Analysis of neurodynamics for diagnosis of mental states

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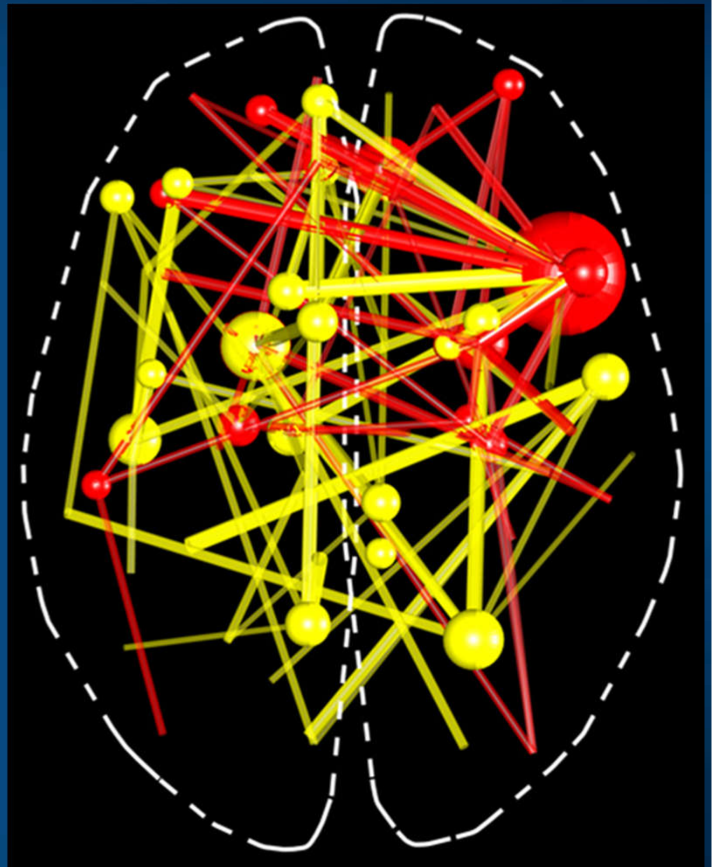
On the threshold of a dream …

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

- Global brain initiatives.
- Human enhancement or why is this important
- Mind/Brain at many levels.
- Brain networks – space for neurodynamics.
- Fingerprints of Mental Activity.
- Dynamic functional brain networks.
- Simulation of brain networks.

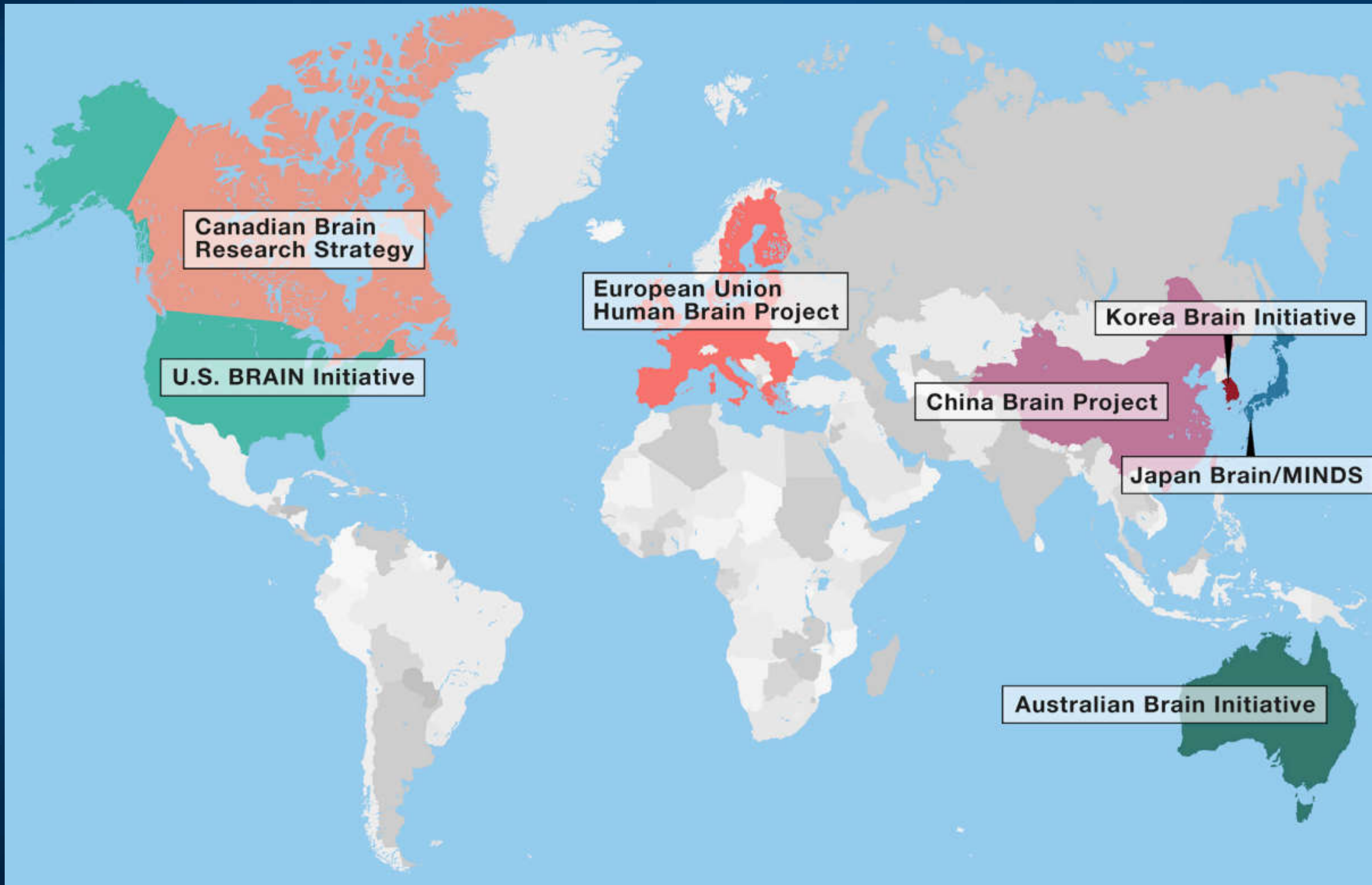


Final goal: Use your brain to the max!
Optimization of brain processes?

Duch W. (2012) Mind-Brain Relations, Geometric Perspective and Neurophenomenology, American Philosophical Association Newsletter 12(1), 1-7.

Global Brain Initiatives

International Brain Initiatives



Costs of brain diseases

European Brain Council (EBC) reports (2010; 2014).
Consensus Statement on European Brain Research (2015) includes a chapter on Computational Neuroscience, data repositories and analytics.

179 million, or 1/3 of all European citizens, had at least one brain disorder.
45% of the total annual health budget of Europe!

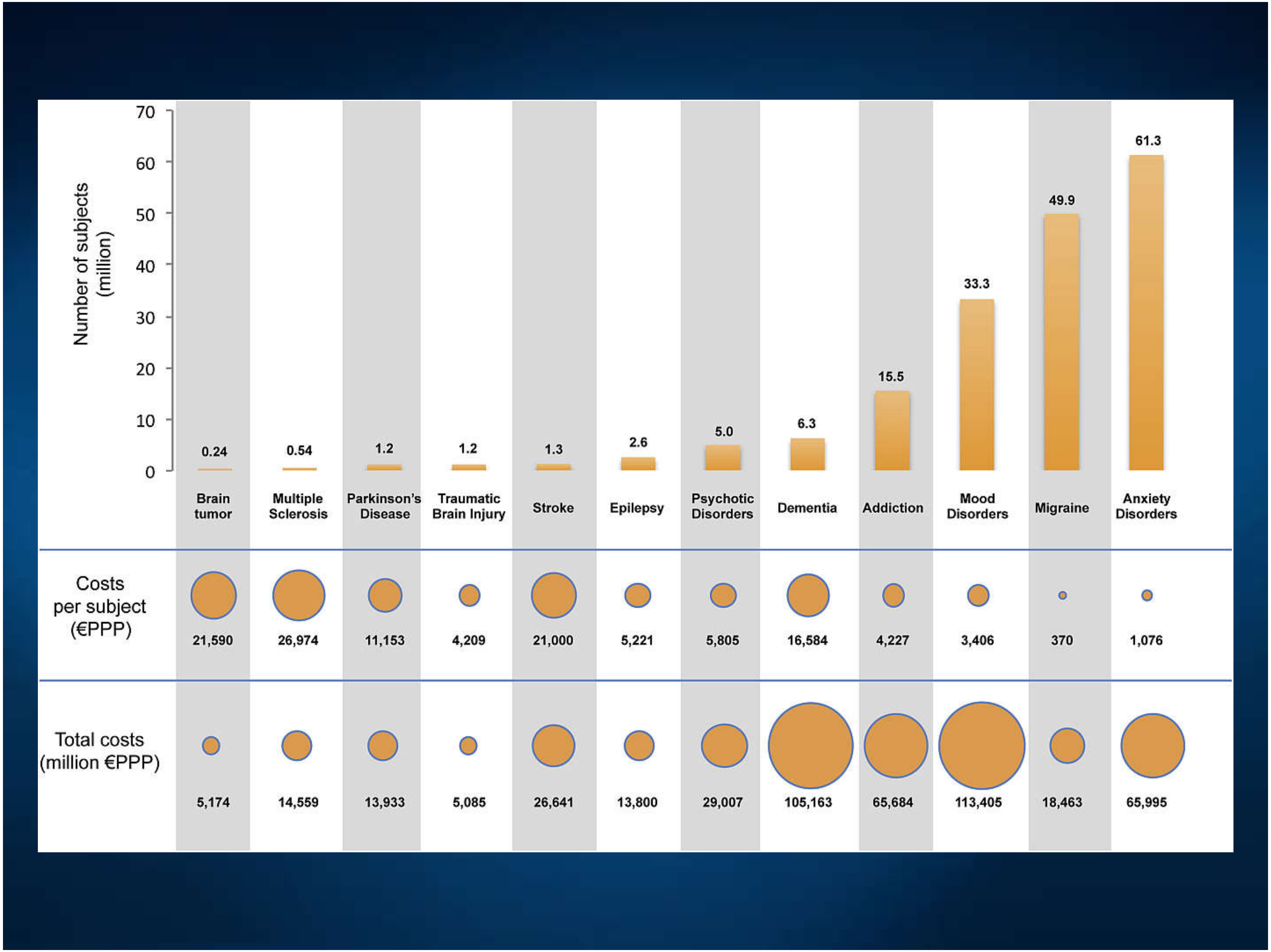
Total cost of brain disorders in EU estimated in 2010: 798 billion €/year, average direct health care costs represent 37%,
direct nonmedical costs 23%, and indirect costs 40%.

China: >20% of population (~250 mln) suffering from some mental disorder.

Total costs of disorders of the brain in Poland, 2010 estimates.

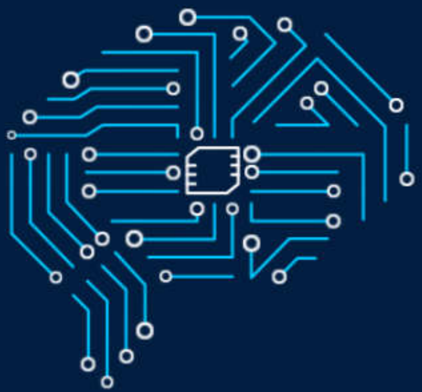
Addiction	Anxiety	Dementia	Epilepsy	Headache	Mood	Psychotic	Stroke	x1000
1 201	5 261	358	298	12 025	2 499	371	503	# people
2 501	2 882	2 480	745	1 559	4 489	3 723	2 187	mln €

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



Number of subjects (million)
70
60
50
40
30
20
10
0
0.24
0.54
1.2
1.2
1.3
2.6
5.0
6.3
15.5
33.3
49.9
61.3
Brain tumor
Multiple Sclerosis
Parkinson's Disease
Traumatic Brain Injury
Stroke
Epilepsy
Psychotic Disorders
Dementia
Addiction
Mood Disorders
Migraine
Anxiety Disorders
Costs per subject (€PPP)
21,590
26,974
11,153
4,209
21,000
5,221
5,805
16,584
4,227
3,406
370
1,076
Total costs (million €PPP)
5,174
14,559
13,933
5,085
26,641
13,800
29,007
105,163
65,684
113,405
18,463
65,995

BRAIN
INITIATIVE



Advance Neurotechnologies

Accelerate the development and application of new neurotechnologies.

Support multi-disciplinary teams and stimulate research to rapidly enhance current neuroscience technologies and catalyze innovative scientific breakthroughs.

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

"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."

Since 2013 numerous exciting developments in neurotechnology and our understanding of the brain have been made by scientists across the globe.

G20+/N20+ WORLD BRAIN MAPPING & THERAPEUTICS INITIATIVE

IEEE brain

IEEE brain

Join the IEEE Brain Community

JOIN FREE

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**, International 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.

Workshop on Brain-Machine Interface Systems
Global Current and Emerging Brain Initiative Meeting
Brain Hackathon

IEEE SMC Systems, Man, and Cybernetics Society

Part of the Brain-Machines Interface Workshop and SMC2018.

The IEEE SMC Society and the IEEE President, James Jefferies, are proud to invite you on to a special meeting of **Global Current and Emerging Brain Initiative leaders** and representatives from other groups working on large-scale multi-year brain projects from Australia, Canada, China, Europe (HBP), Japan, Korea, New Zealand, **Poland**, Russia, and US (NSF and NIH), with representatives from the **IEEE Brain Initiative**, International Neuroethics Society, industry, and other stakeholders.

IEEE welcomes collaborative discussions with all stakeholders to better align and integrate IEEE with other existing brain efforts.

incf

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.

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

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

We hope to become a full member of INCF by that time.

Polish Brain Council (Polska Rada Mózgu) started in 2013, working on “Brain Plan for Poland – Strategy for People with Brain Diseases”.

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 led to many applications.

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

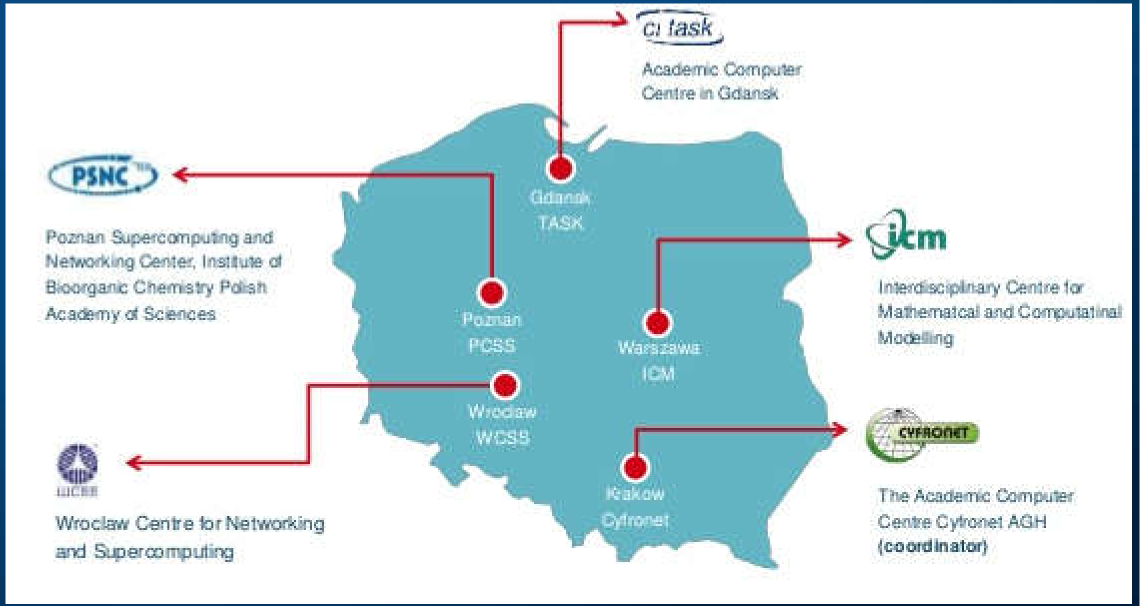
Amoset al. (2018). **Learning Awareness Models**. *ArXiv:1804.06318*.

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) Neurobiological models of **synaptic consolidation** and the elastic weight consolidation (EWC) algorithm.

PL-Grid HPC Infrastructure

- AI and neuroinformatics needs big data and computing power for analytics.
- The Polish Grid Infrastructure (NGI) connects 5 supercomputing centers, enabling research in various domains of e-Science.
- Supports research, integrating experimental data and results of advanced computer simulations in over 24 domains.
- A part of a pan-European infrastructure built in the framework of the EGI (European Grid Initiative). In future access to exaflop power.
- INCF-PL is working on creation of national neuroscience gateway.
- Collaboration with HBP medical platform: prof. R. Frackowiak, prof. P. Bogorodzki.



ORNL

- ORNL, since 1943 as part of the Manhattan Project, largest US Department of Energy laboratory. Budget $1.4 billion, Summit ~1.9 Eflop!
  10.07.2019: High-Performance Computing and Artificial Intelligence for Mental Illness, Suicide Prevention, and Substance Abuse Research Summit.

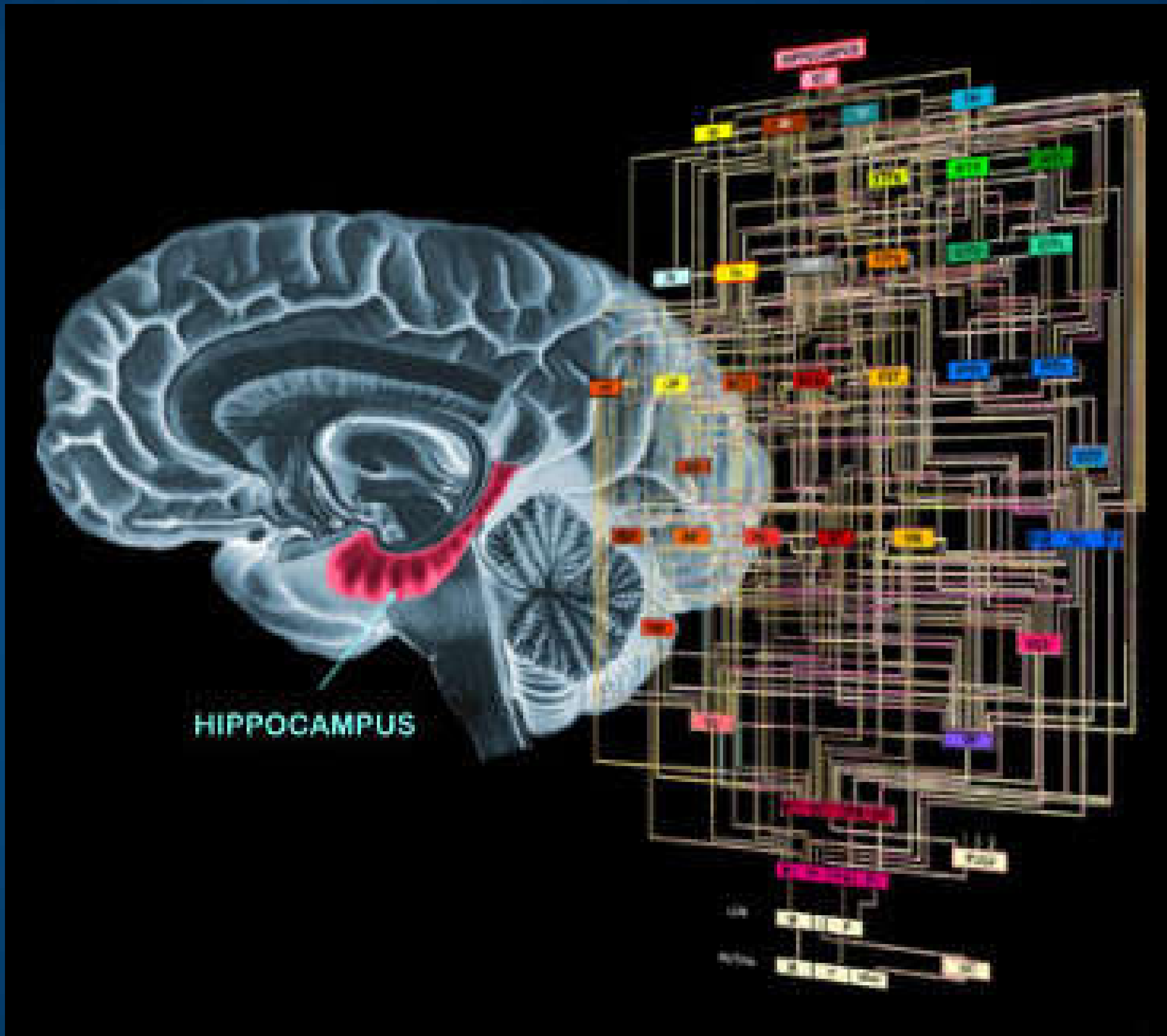
BICA, Brain-Inspired Cognitive Architecture

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

Cognitive informatics, Neurocognitive Informatics.

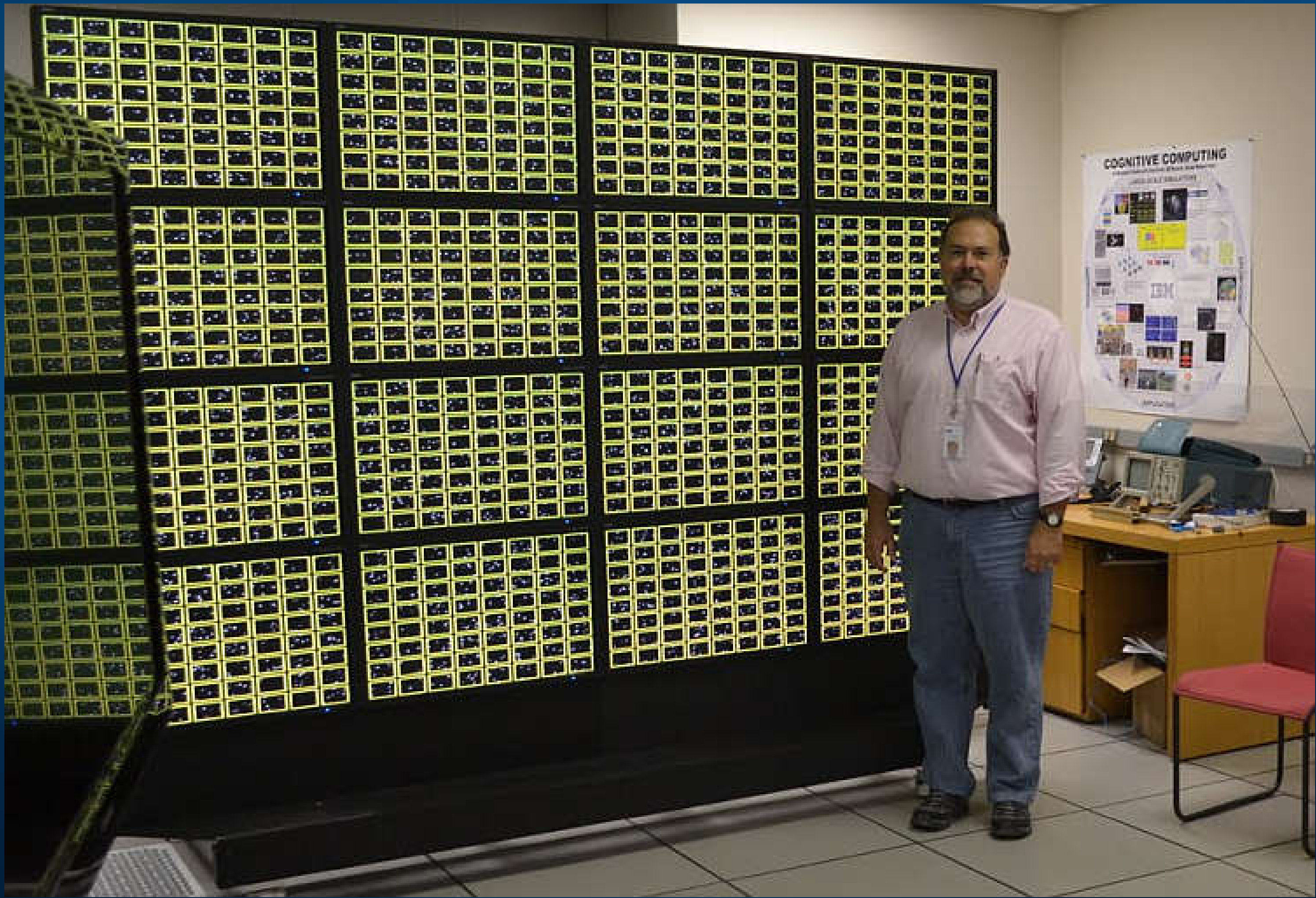
BICA = Brain Inspired Cognitive Architecture.

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



Neuromorphic wall

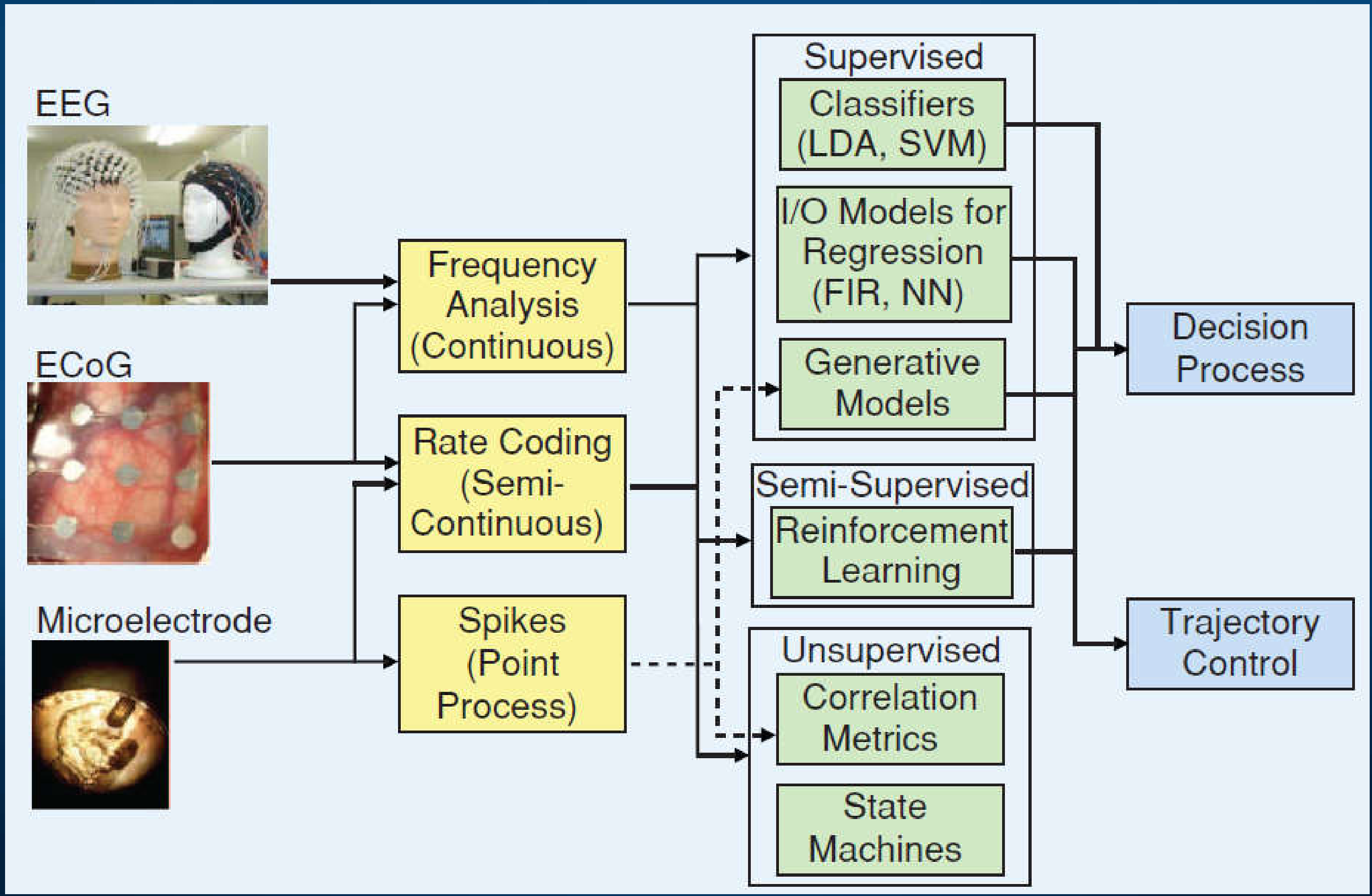
1024 TN chips, or 1 B neurons and 256 B synapses.
Complexity of horse brain, 1/4 gorilla, 1/6 chimpanse.



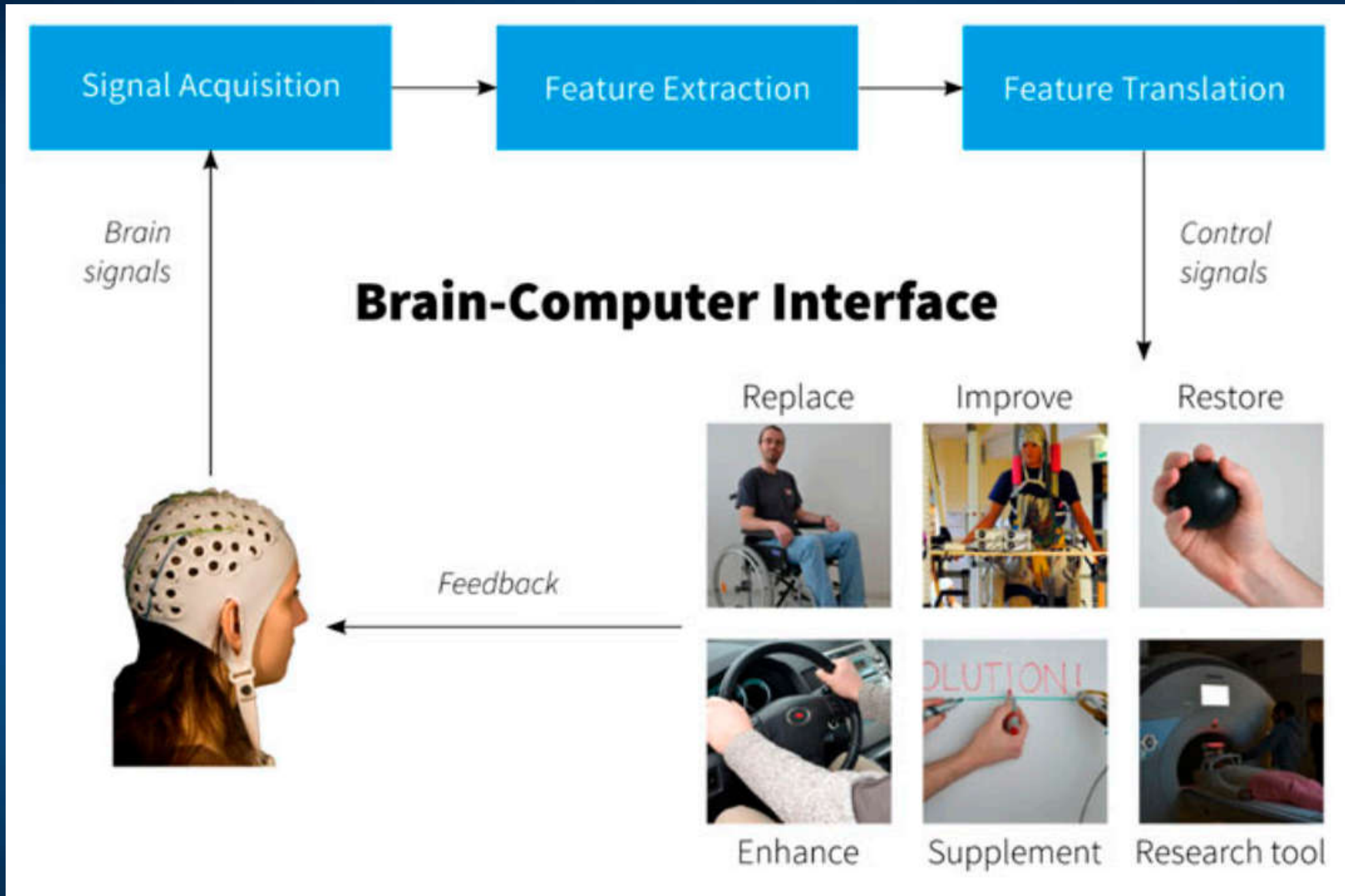
Human Enhancement
and
Optimization of Brain Processes

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!

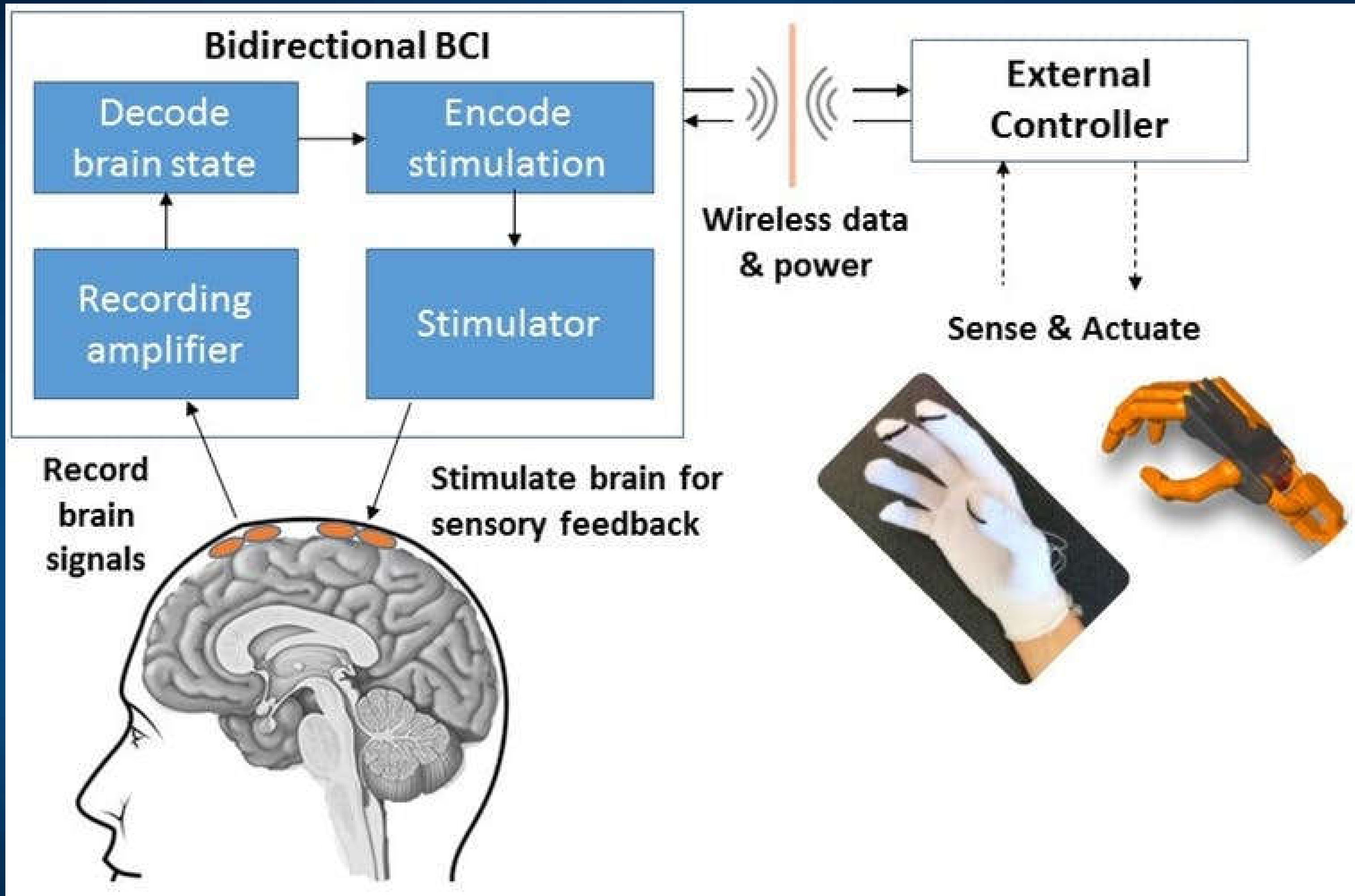


BCI Applications



Signals: invasive (brain implants), partially invasive (ECoG), and non-invasive.

Brain-Computer-Brain Interfaces



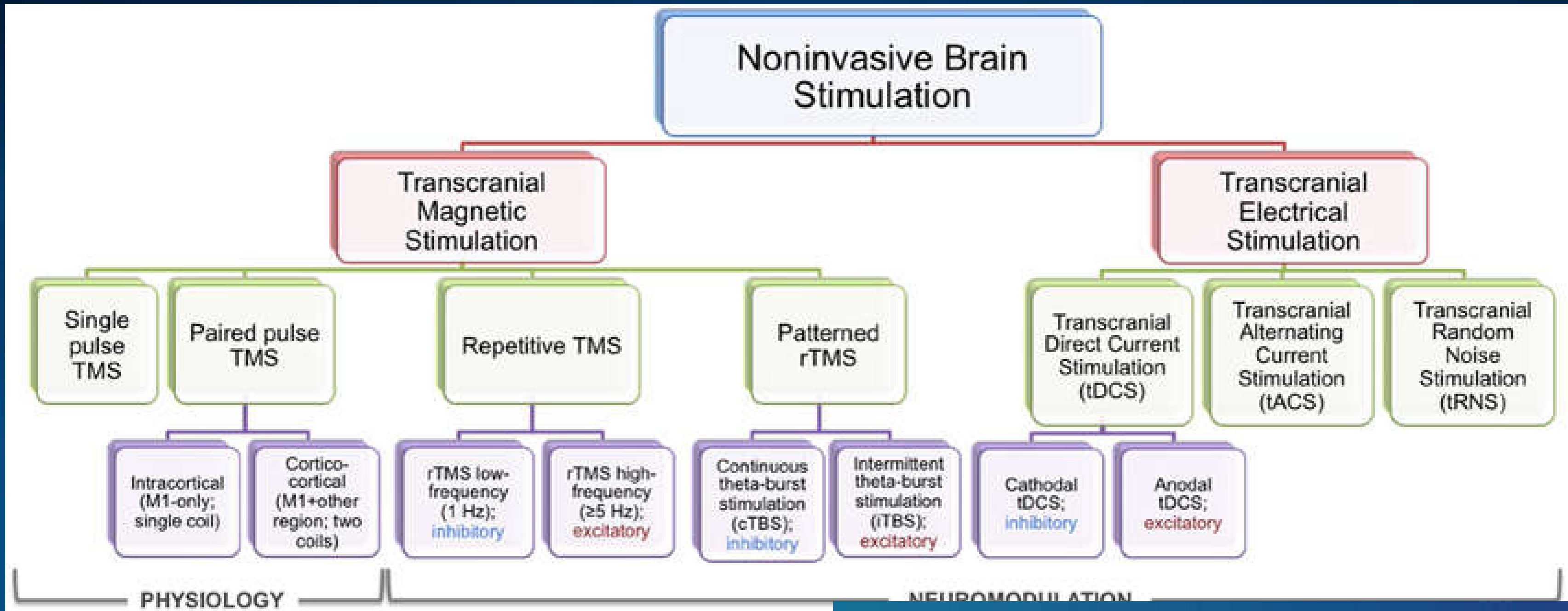
Closed loop system with brain stimulation for self-regulation.
Body may be replaced by sensory signals in Virtual Reality.

BCBI for learning

Your brain knows better what is interesting than you do! Information relevance inferred directly from brain signals to model search intent.

1. Eugster et al. (2016). Natural brain-information interfaces: Recommending information by relevance inferred from human brain signals.
2. Externally induced frontoparietal synchronization modulates network dynamics and enhances working memory performance (Violante et al. 2017).
3. **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. *Neuron*, *96*(6), 1282–1289.e4.
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.

Brain stimulation



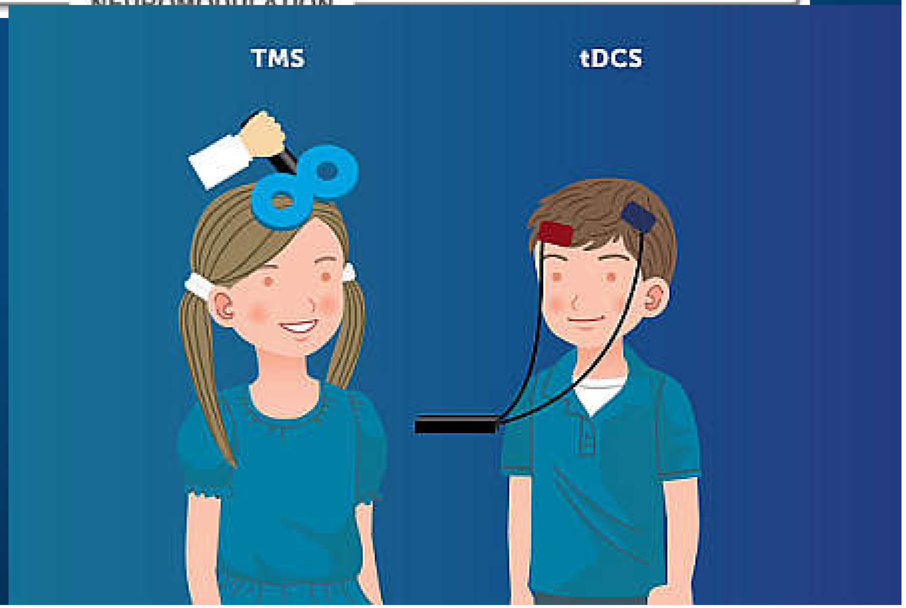
ECT – Electroconvulsive Therapy

VNS – Vagus Nerve Stimulation

Ultrasound, laser … stimulation.

Complex techniques, but portable phones are also complex.

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



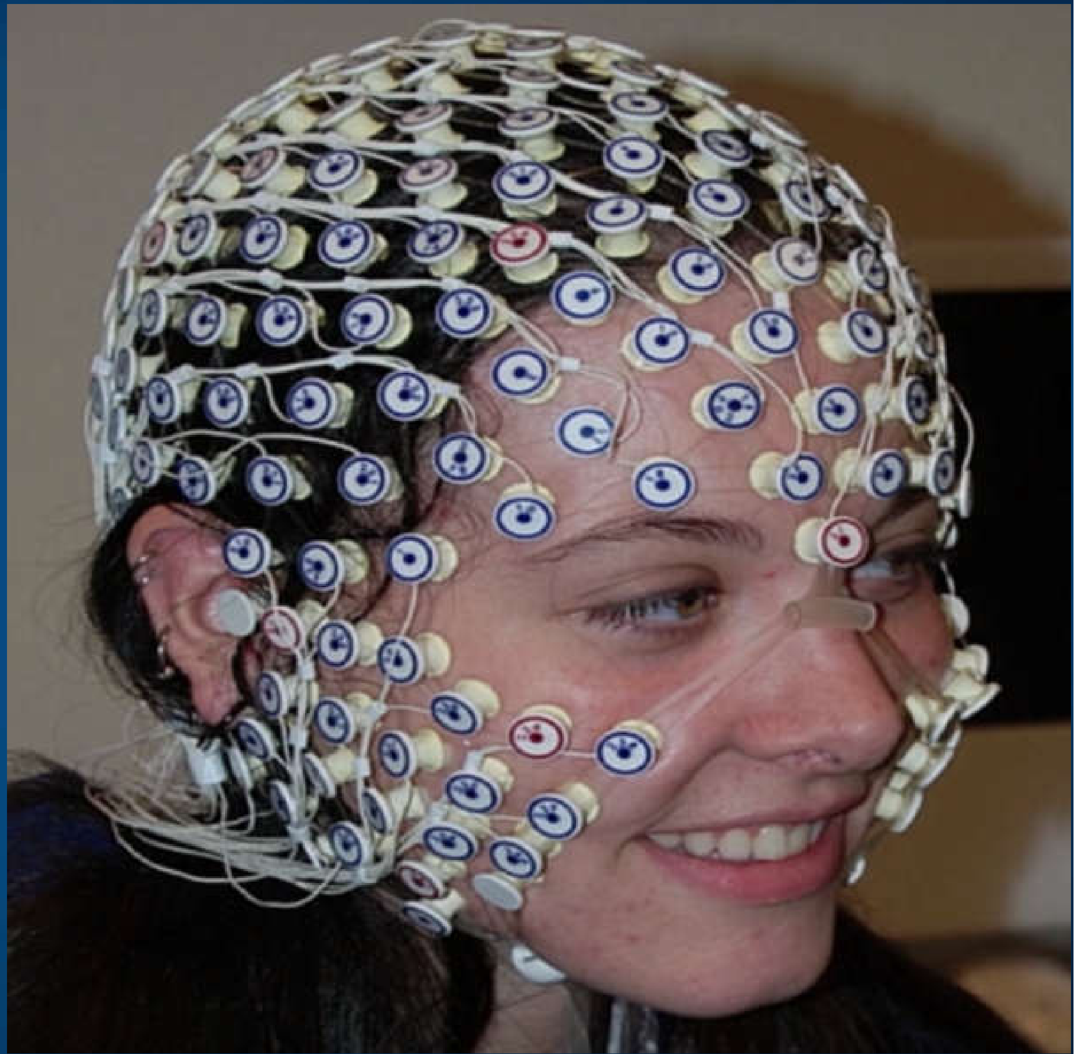
HD EEG/DCS?

EEG electrodes + DCS.

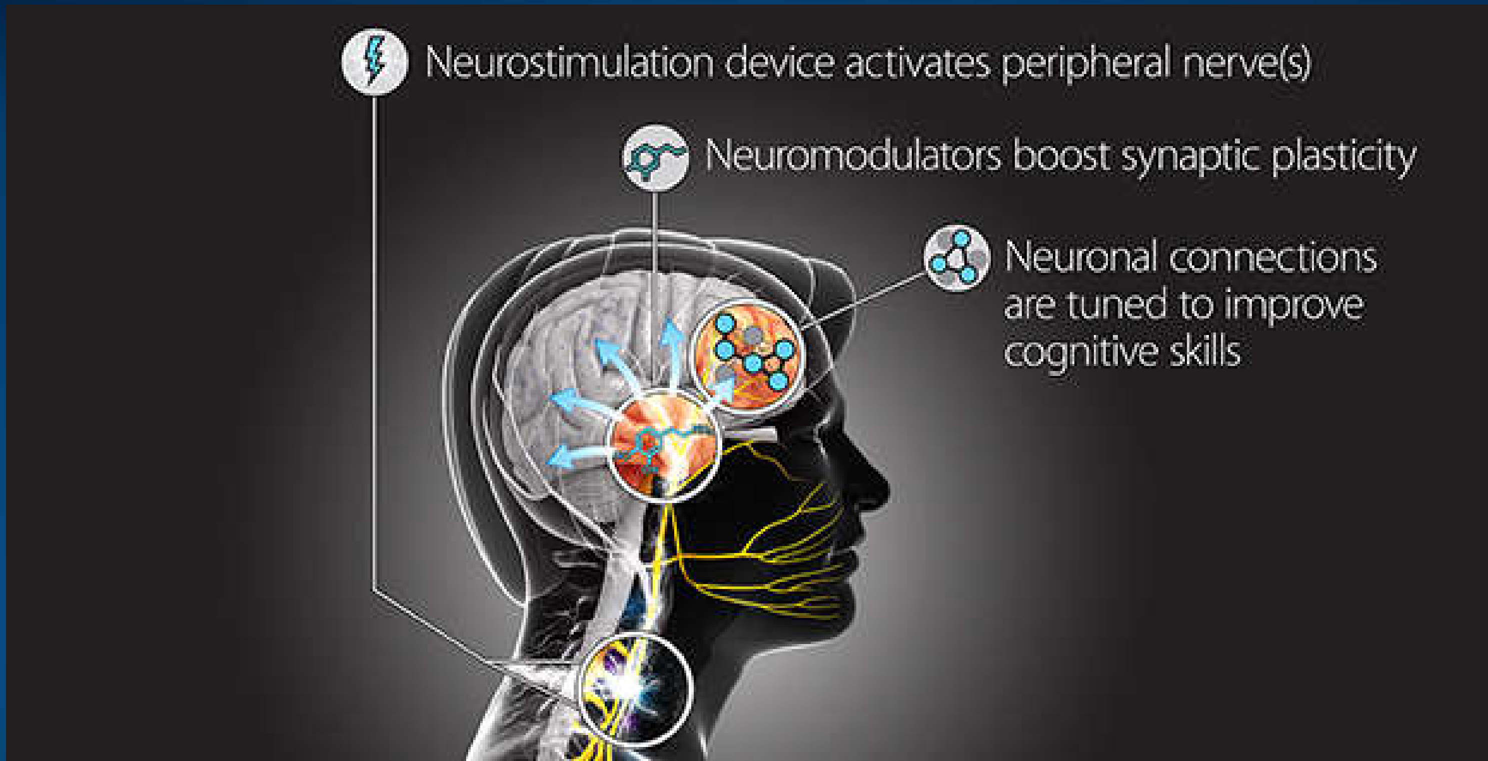
Reading brain states
=> transforming to common space
=> duplicating in other brains
Applications:

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

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



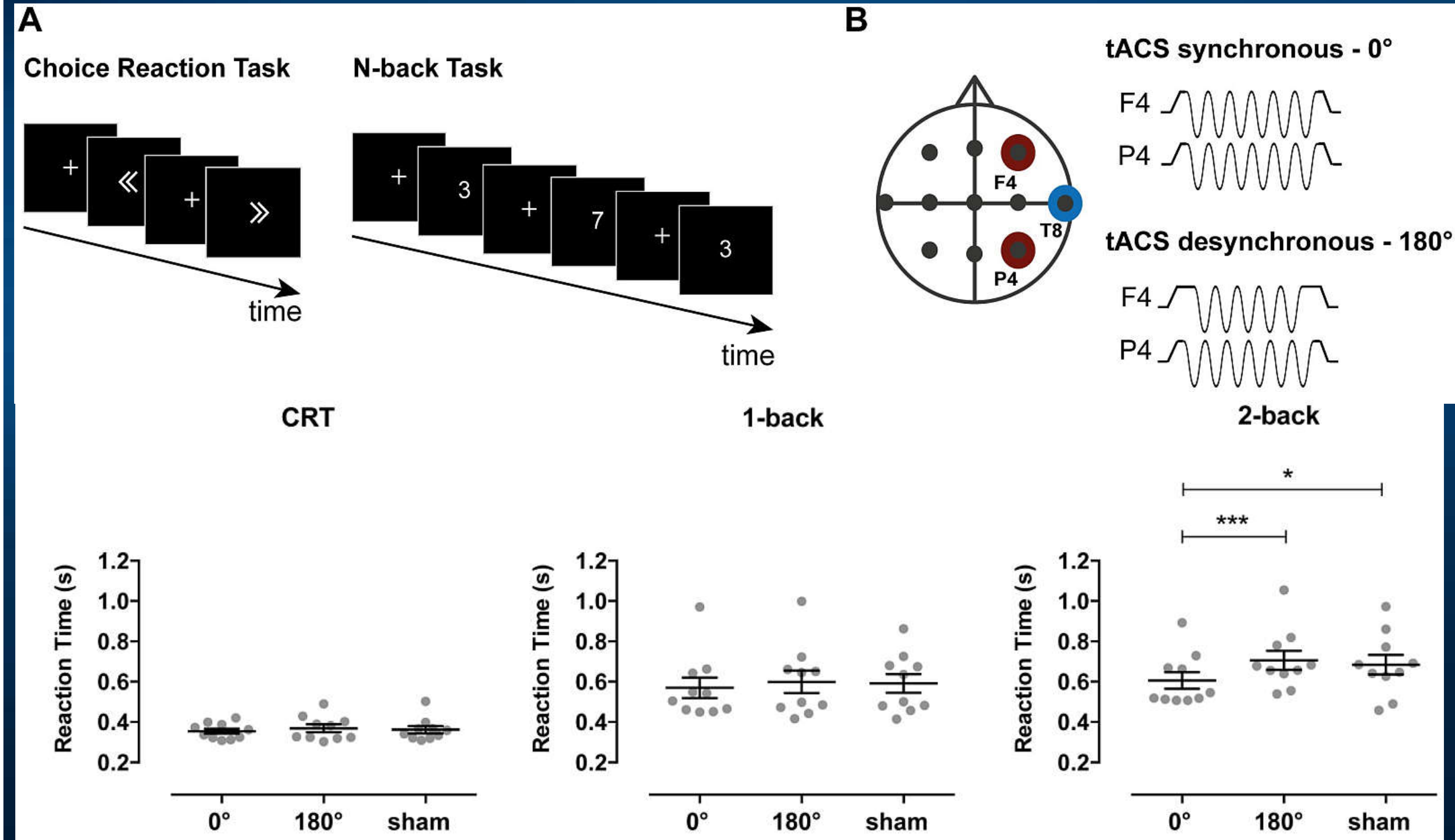
Targeted Neuroplasticity Training



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.

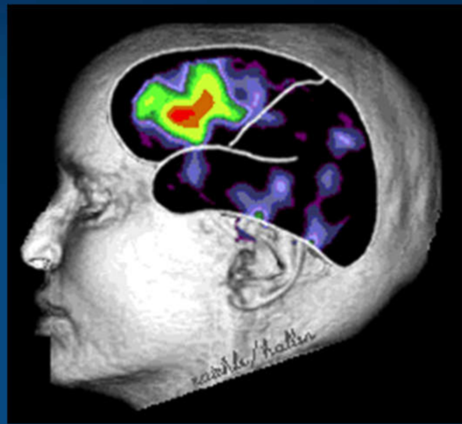
Synchronize PFC/PC

Violante, I.R. et al. Externally induced frontoparietal synchronization modulates network dynamics and enhances working memory performance. ELife, 6 (2017).



Mind/brain at many levels

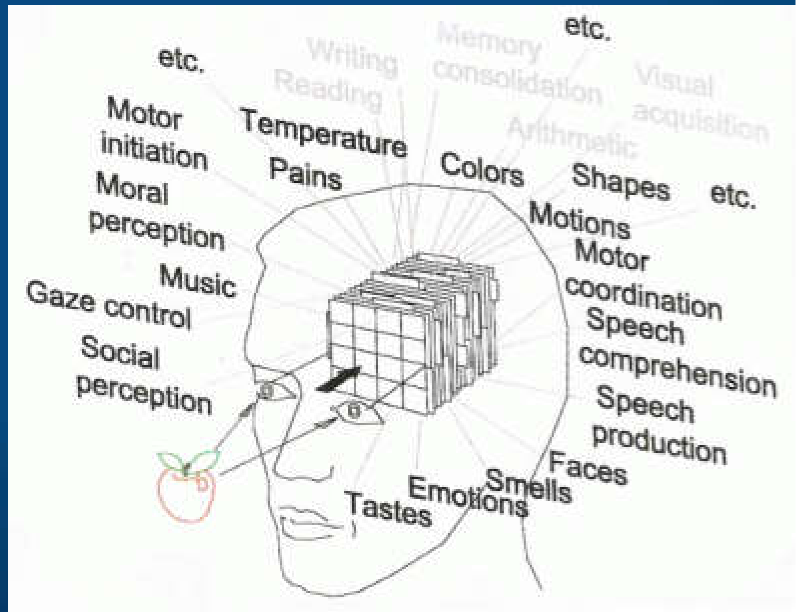
Brains ⇔ Minds



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 our 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.

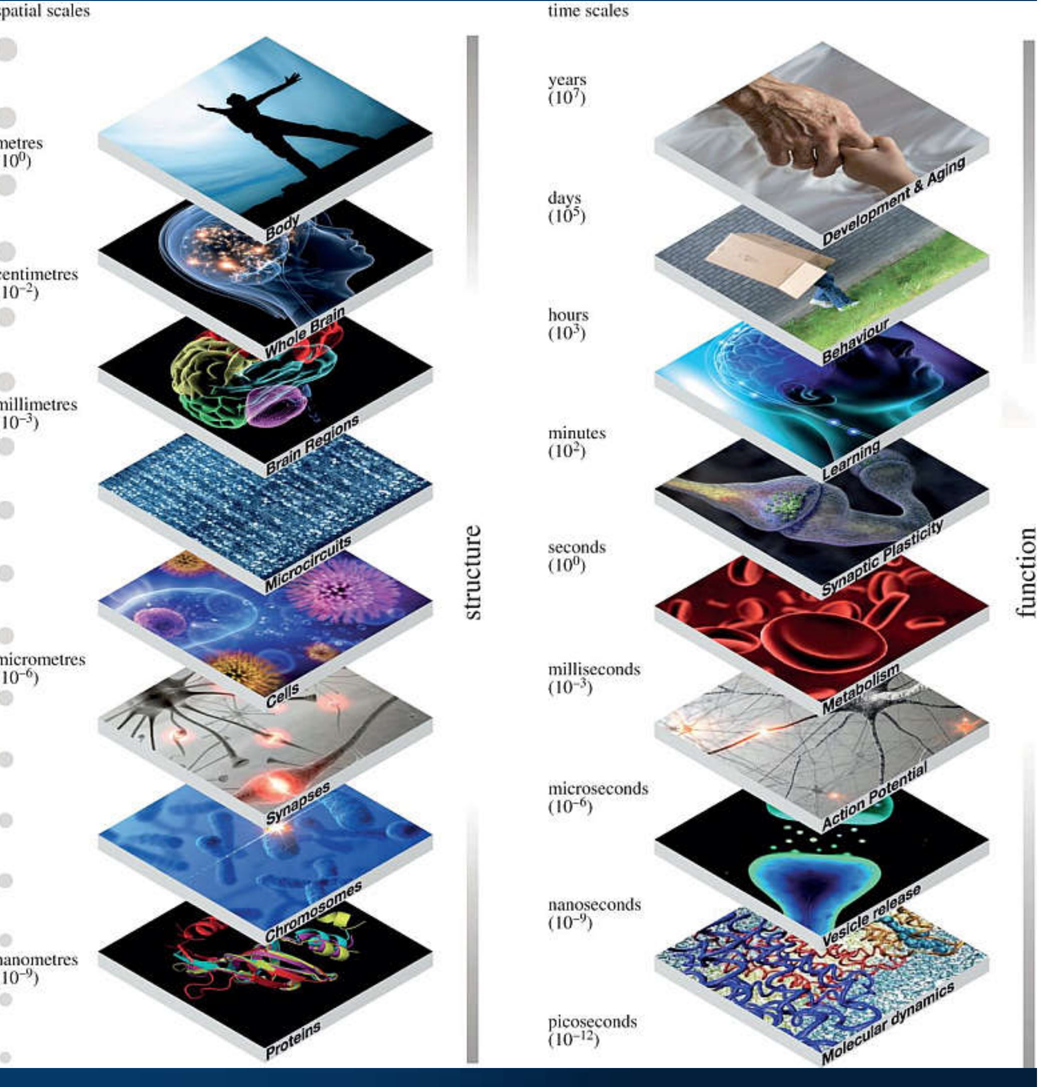
Neuropsychiatric phenomics

2008: The Consortium for Neuropsychiatric Phenomics

"… categories, based upon presenting signs and symptoms, may not capture fundamental underlying mechanisms of dysfunction" (Insel et al., 2010).

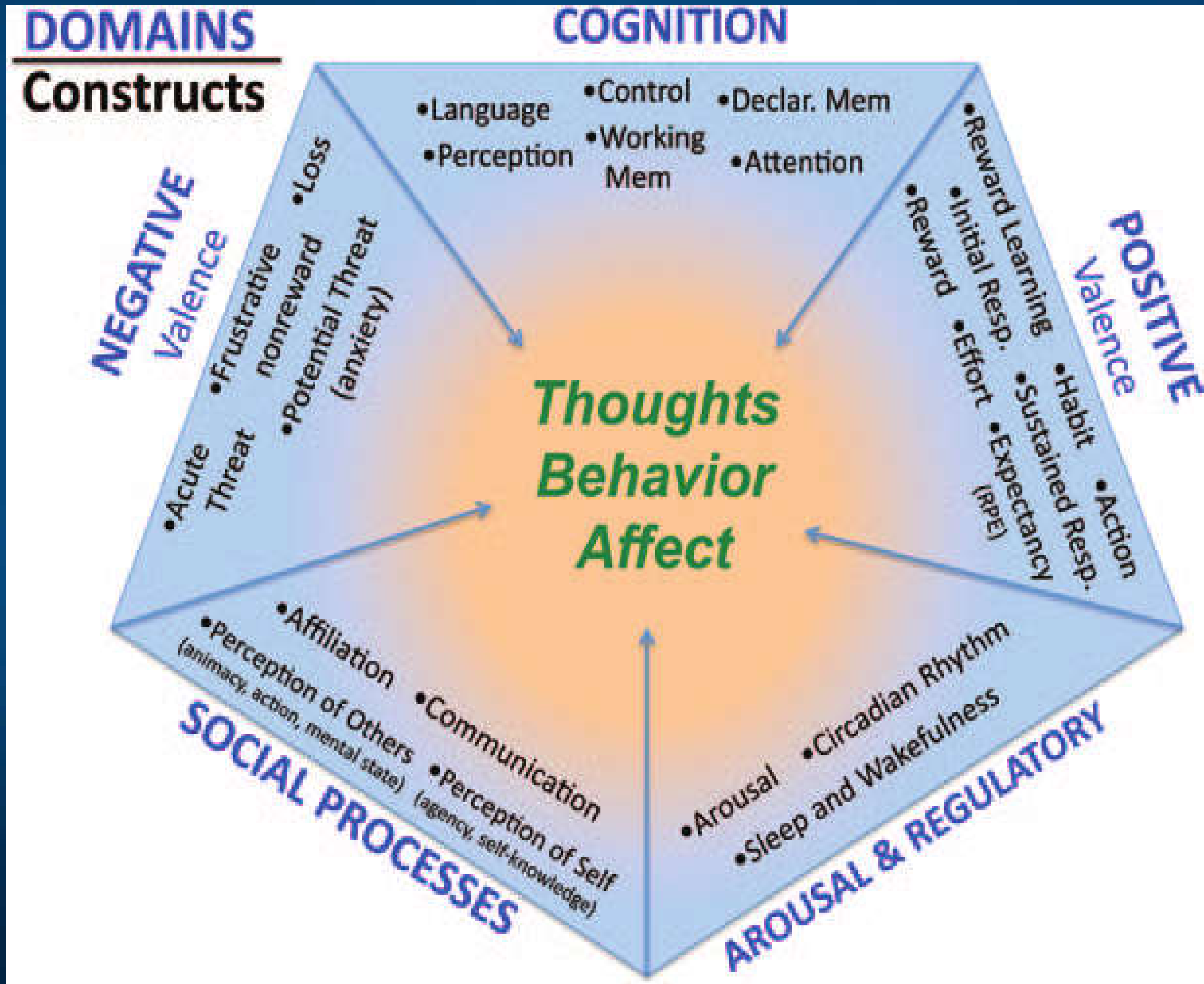
New approach: RDOC NIMH.

Description of organisms at different levels will help to answer different types of questions.
Network level is in the middle and can be connected to the mental level via computational models.



Research Domain Criteria Initiative

NIMH RDoC Matrix for deregulation of 5 large brain systems.



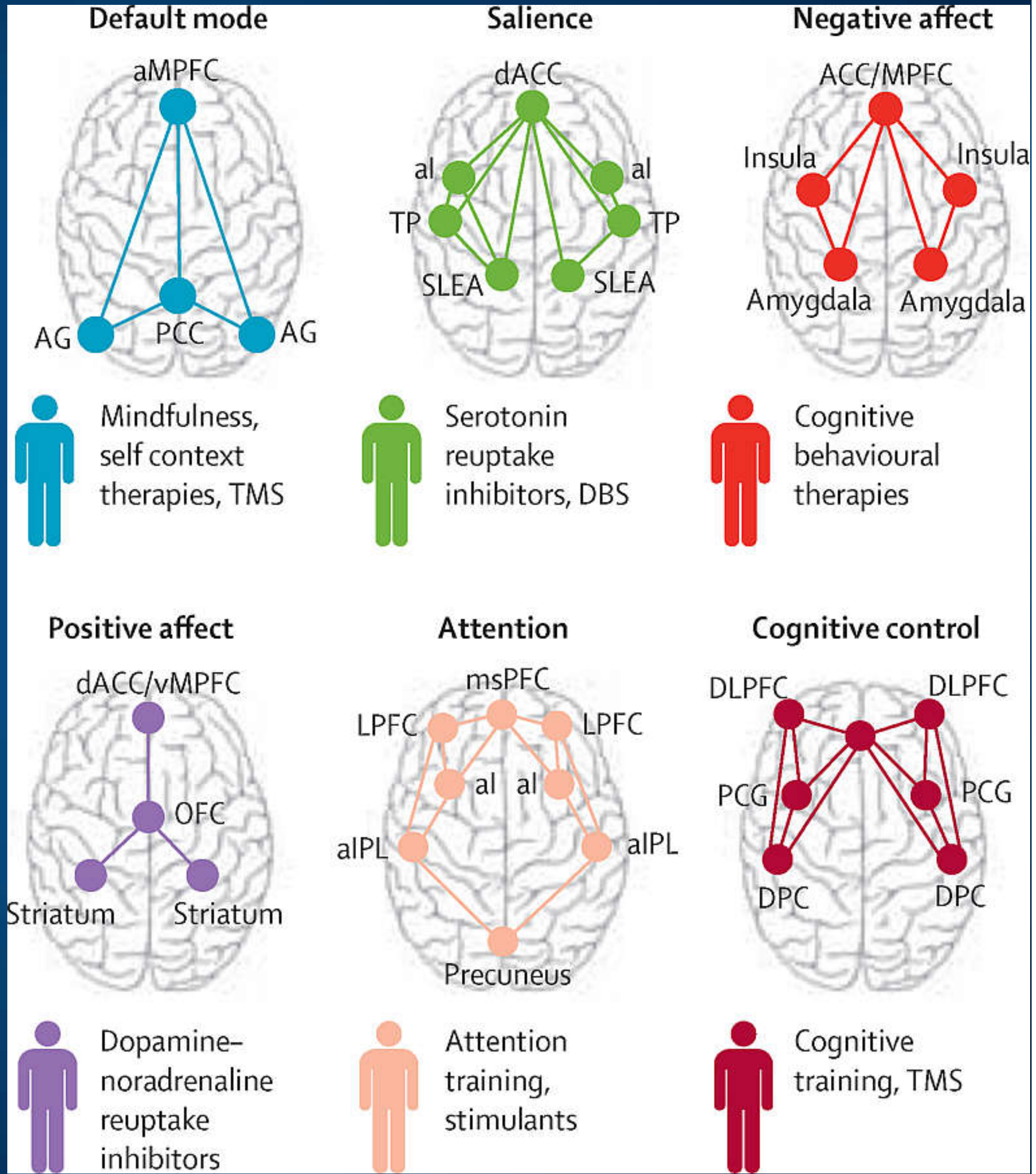
Multi-level phenomics

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.

M. Minsky, Society of mind (1986)

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

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



NIMH RDoC Matrix for deregulation of 6 large brain systems.

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

1. **Negative Valence Systems**, primarily responsible for responses to aversive situations or context, such as fear, anxiety, and loss.
2. **Positive Valence Systems** are primarily responsible for responses to positive motivational situations or contexts, such as reward seeking, consummatory behavior, and reward/habit learning.
3. **Cognitive Systems** are responsible for various cognitive processes.
4. **Social Processes Systems** mediate responses in interpersonal settings of various types, including perception and interpretation of others' actions.
5. **Arousal/Regulatory Systems** - generating activation of neural systems in various contexts, homeostatic regulation, energy balance and sleep.
6. **Sensorimotor systems** responsible for the control and execution of motor behaviors, and their refinement during learning and development.

RDoC Matrix for „cognitive domain”

Construct/Subconstruct		Genes	Molecules	Cells	Circuits	Physiology	Behavior	Self-Report	Paradigms
Attention		Elements	Elements	Elements	Elements	Elements	Elements		Elements
Perception	Visual Perception	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Auditory Perception	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Olfactory/Somatosensory/Multimodal/Perception								Elements
Declarative Memory		Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
Language		Elements			Elements	Elements	Elements	Elements	Elements
Cognitive Control	Goal Selection; Updating, Representation, and Maintenance ⇒ Focus 1 of 2 ⇒ Goal Selection				Elements			Elements	Elements
	Goal Selection; Updating, Representation, and Maintenance ⇒ Focus 2 of 2 ⇒ Updating, Representation, and Maintenance	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Response Selection; Inhibition/Suppression ⇒ Focus 1 of 2 ⇒ Response Selection	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Response Selection; Inhibition/Suppression ⇒ Focus 2 of 2 ⇒ Inhibition/Suppression	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Performance Monitoring	Elements	Elements		Elements	Elements	Elements	Elements	Elements
Working Memory	Active Maintenance	Elements	Elements	Elements	Elements	Elements			Elements
	Flexible Updating	Elements	Elements	Elements	Elements	Elements			Elements
	Limited Capacity	Elements	Elements		Elements	Elements			Elements
	Interference Control	Elements	Elements	Elements	Elements	Elements			Elements

Possible form of Brain Fingerprints

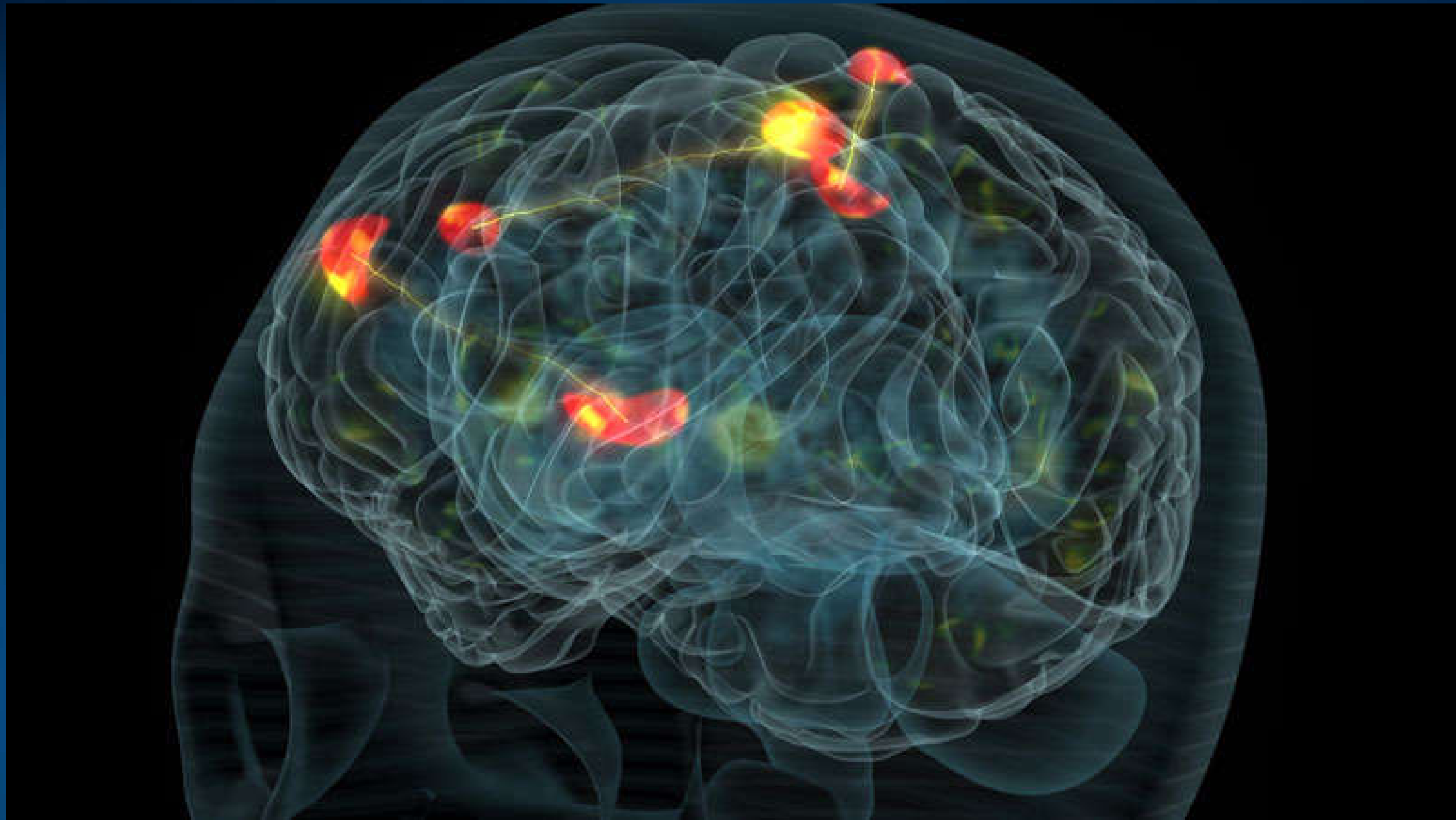
fMRI: BFP is based on **V(X,t)** voxel intensity of fMRI BOLD signal changes, contrasted between task and reference activity or resting state.
EEG: spatial, spatio-temporal, ERP maps/shapes, coherence, various phase synchronization indices.

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(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. Model-based: **The Virtual Brain**, integrating EEG/neuroimaging data.
8. Spectral fingerprinting (MEG, EEG), power distributions.

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

Brain networks:
space for neurodynamics

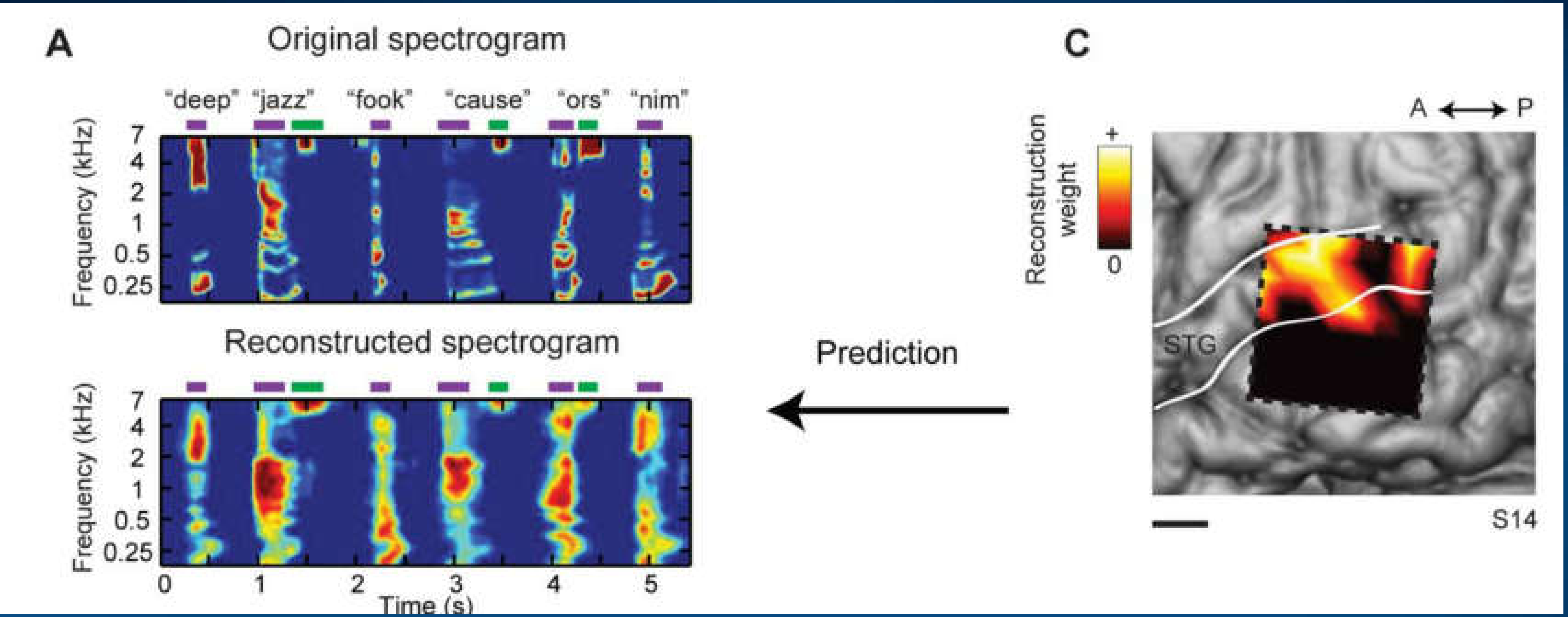
Mental state: strong coherent activation



Many processes go on in parallel, controlling homeostasis and behavior. Most are automatic, hidden from our Self. What goes on in my head?

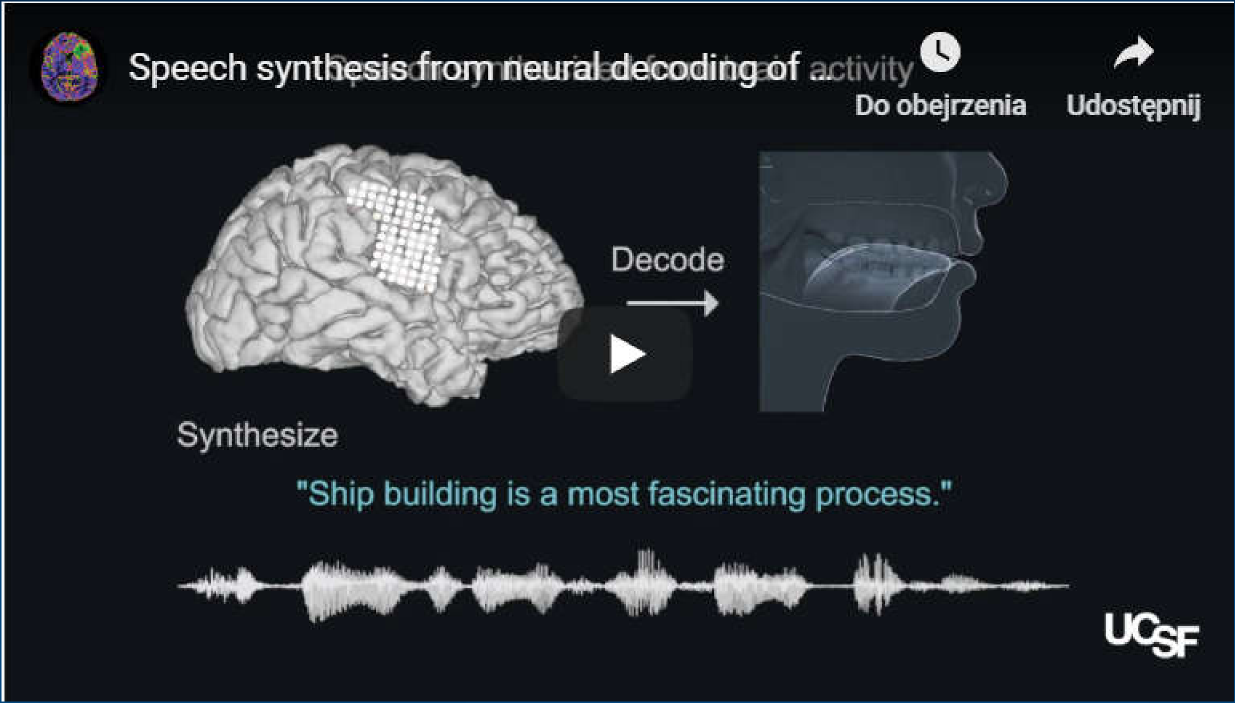
Various subnetworks compete for access to the highest level of control - consciousness, the winner-takes-most mechanism leaves only the strongest. How to extract stable intentions from such chaos? BCI is never easy.

Though: time, position, energy, frequency



Spectrogram of words – distribution of energy in space/time/frequency – may be reconstructed from local field potentials measured using electrocorticography, and then used to activate voice synthesizer, changing brain activations to speech.

Listing to thoughts

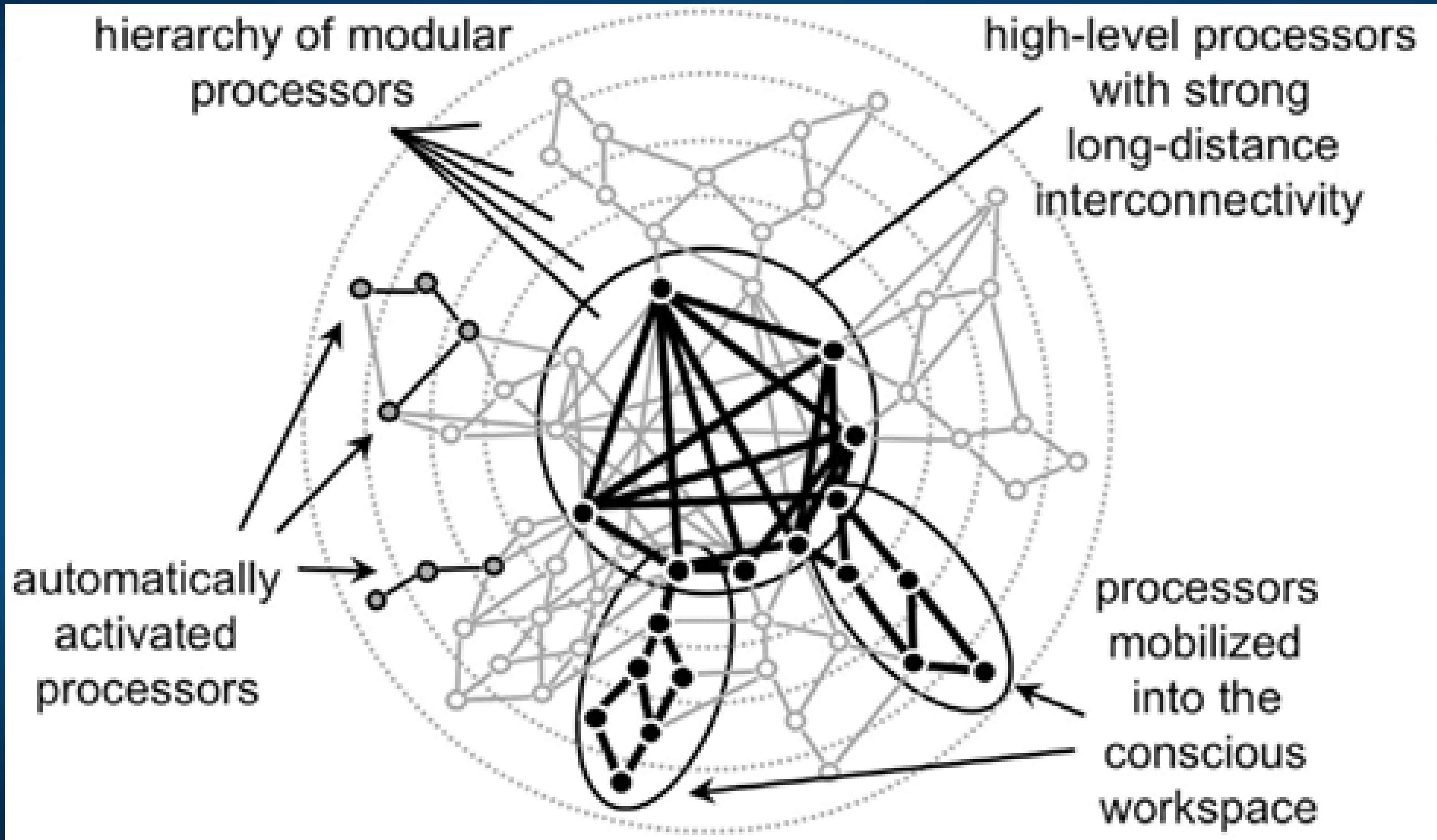


Patterns of cortical activations in higher order human auditory cortex allows for neural decoding of speech acoustic parameters, decoder is used to synthesize speech when a participant silently mimed sentences.

Pasley et al. (2012); G.K. Anumanchipalli, J. Chartier, E.F. Chang, Speech synthesis from neural decoding of spoken sentences. Nature 24/4/2019

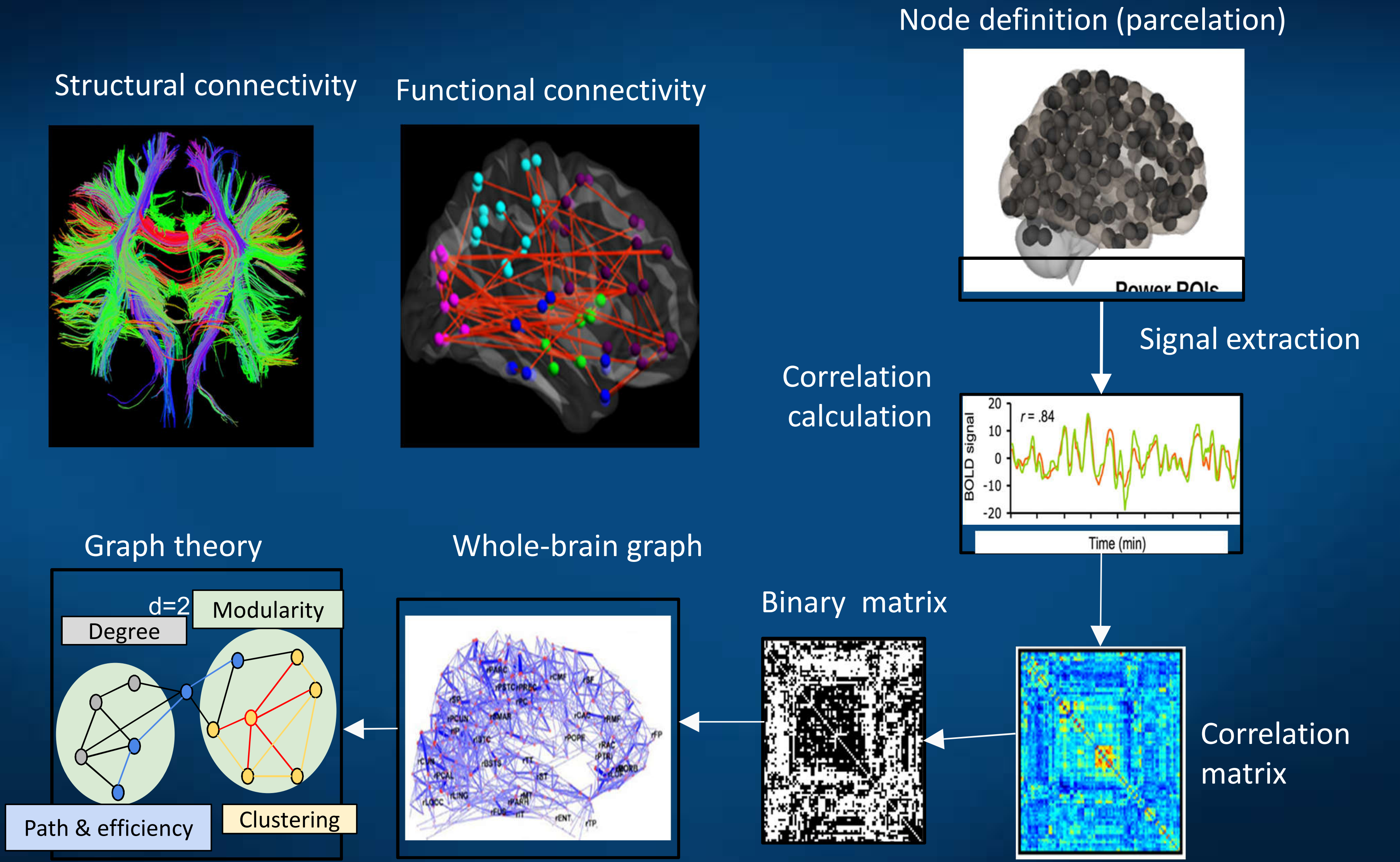
GNWT

Global Neuronal Workspace Theory (Dehaene et al. 1998)



Brain is a substrate in which thoughts, feelings and intentions arise.

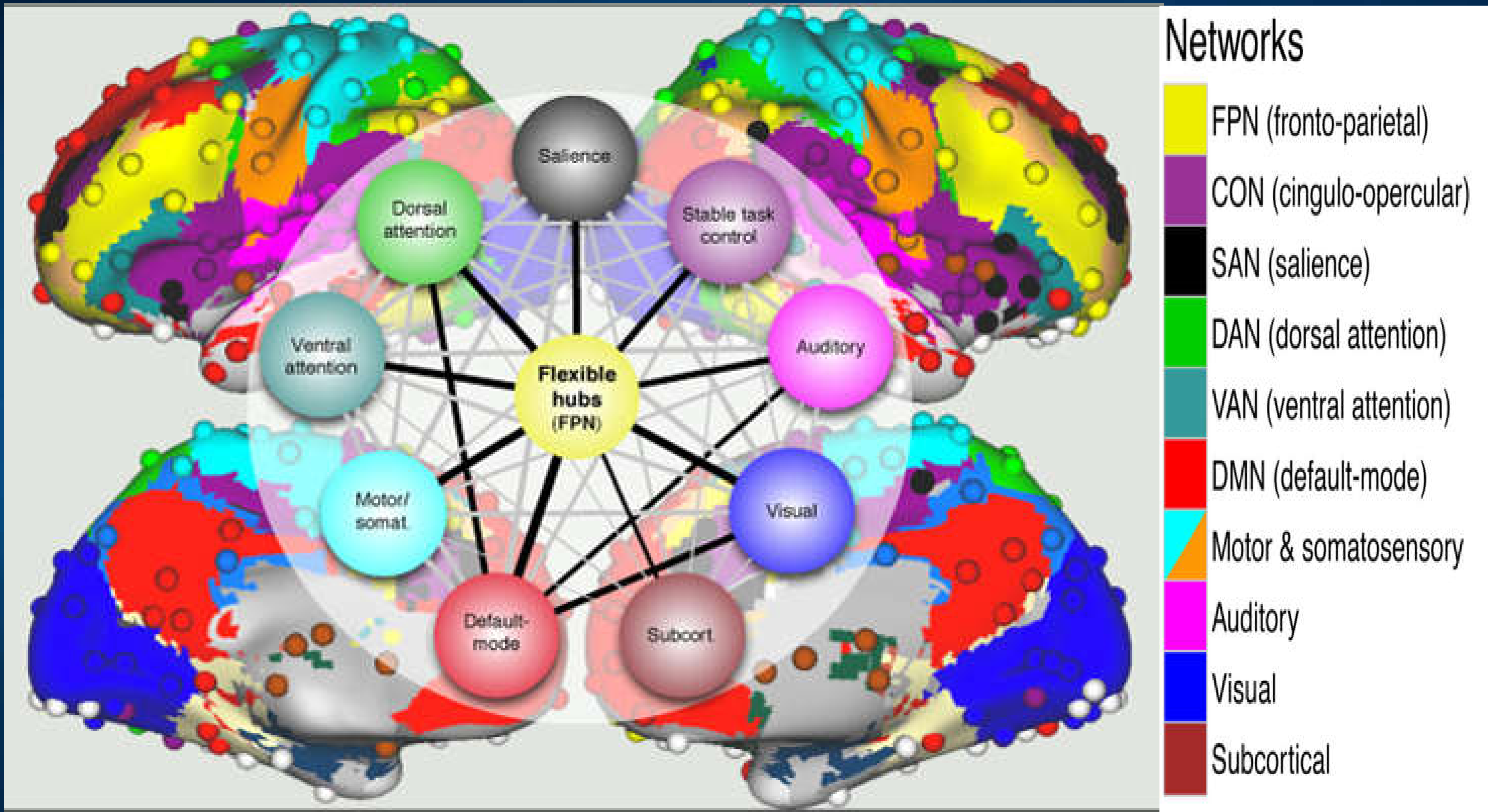
Human connectome and MRI/fMRI



Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

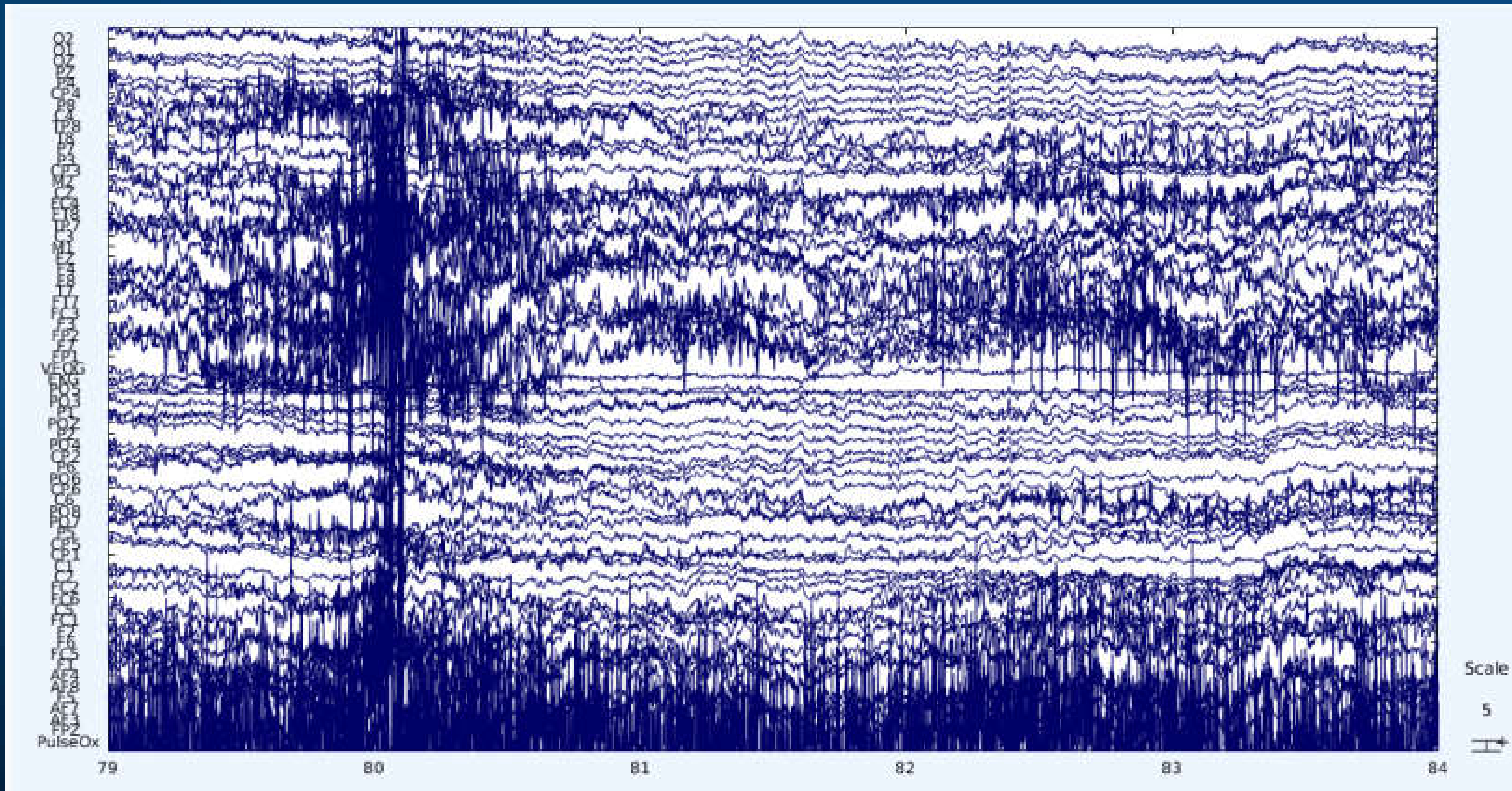
Neurocognitive Basis of Cognitive Control



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).

EEG

Removal of artefacts is only partially automatic, it involves a lot of manual work. Usually only a subset of electrodes is selected.

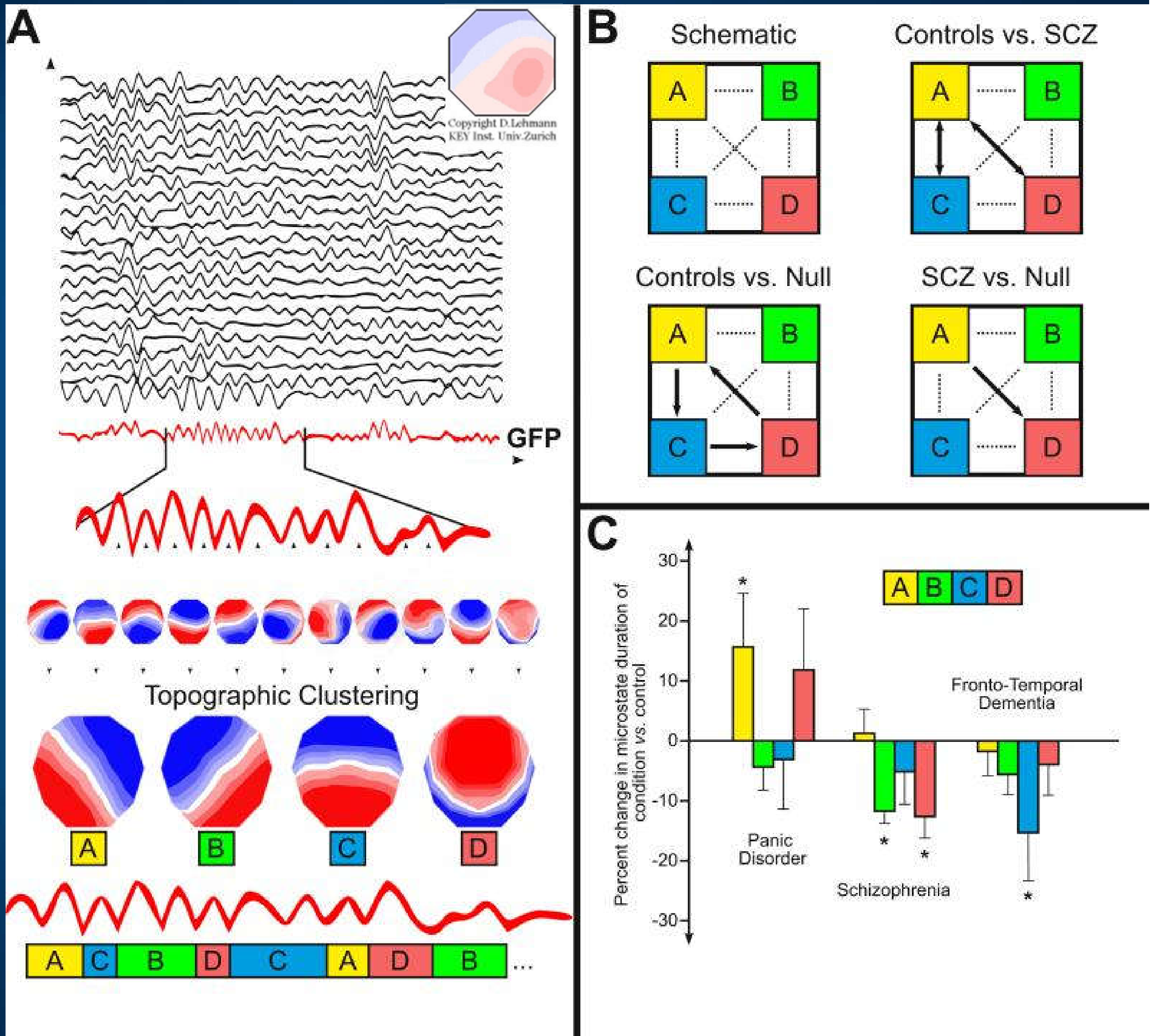


Microstates

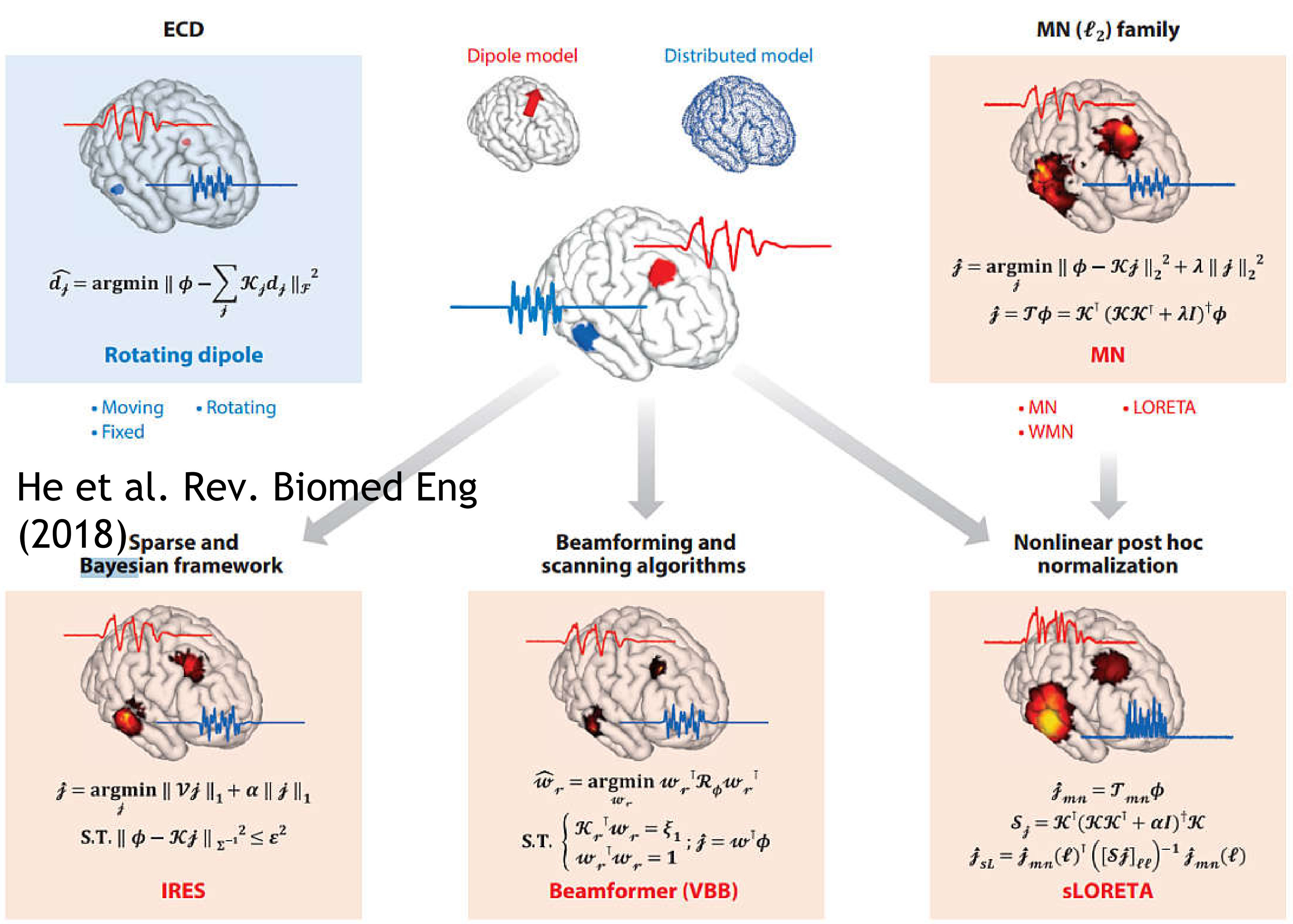
Lehmann et al.
EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia.
Psychiatry Research Neuroimaging, 2005

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

4-7 states 60-150 ms
Symbolic dynamics.



EEG localization and reconstruction

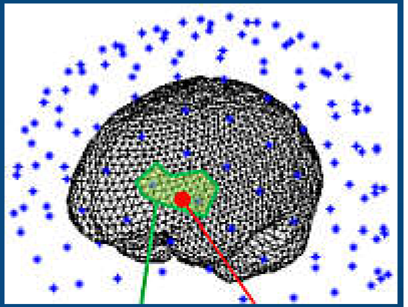


He et al. Rev. Biomed Eng (2018)

Spatial filters

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

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



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.

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.

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

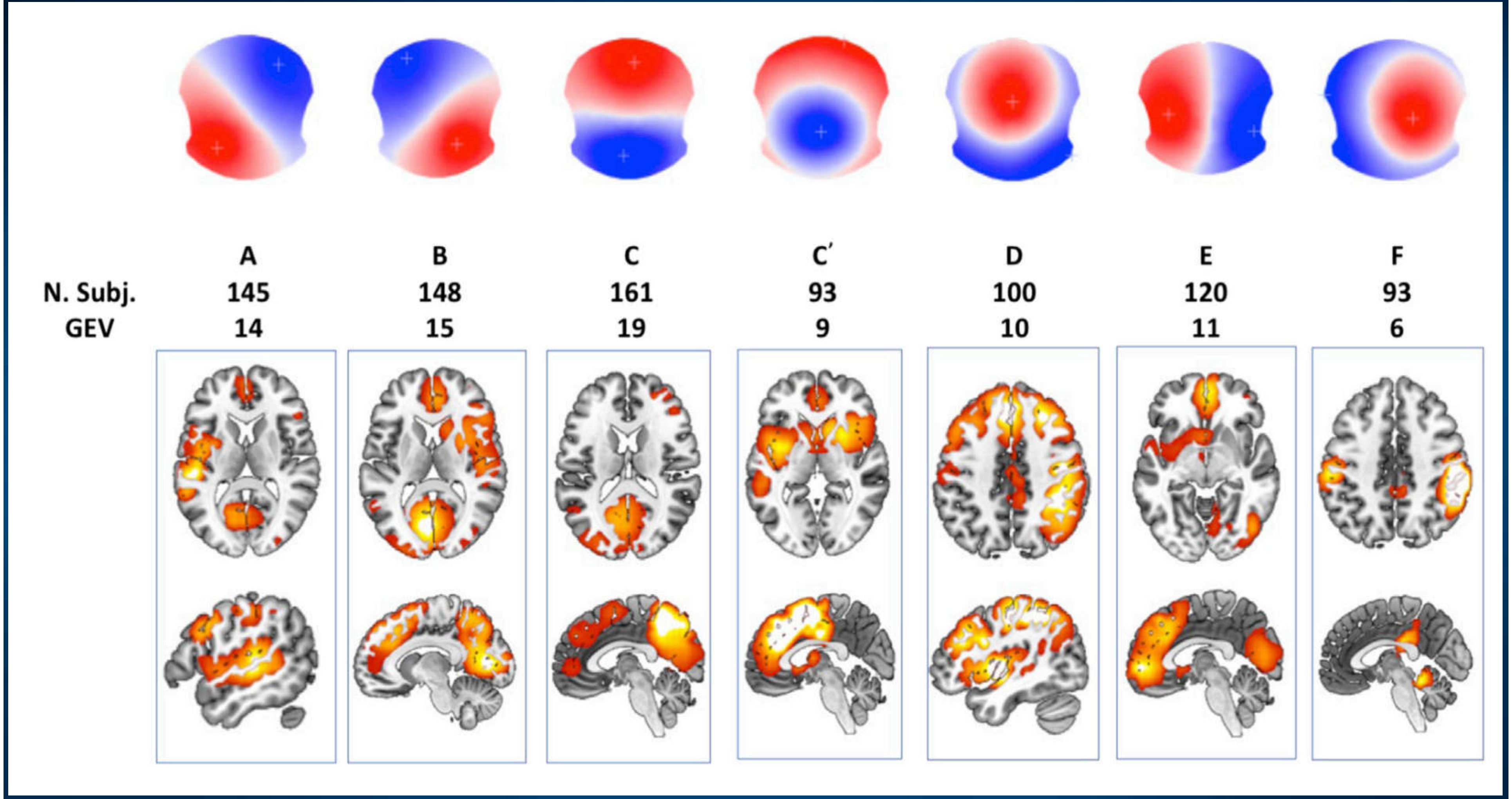
$$B := H_{Src,N} := N^{-1/2} H \tag{35}$$

```
%%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, K., Nikadon, J., Duch, W., & Piotrowski, T. (2019). *BioRxiv, 618694*

Microstates sources



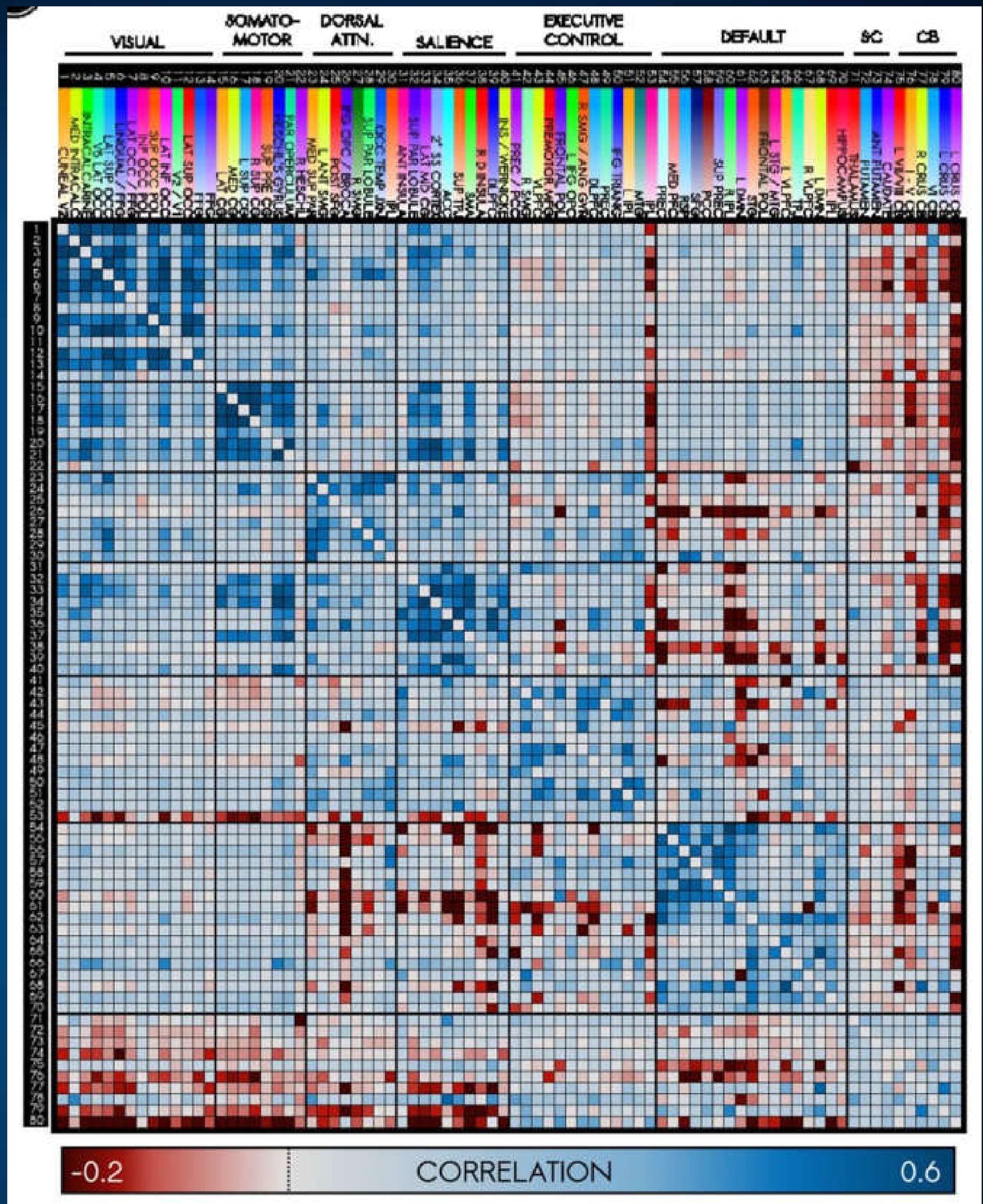
Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593. https://doi.org/10.1016/j.neuroimage.2017.11.062

Ciric et.al. (2017). Contextual connectivity: A framework for understanding the intrinsic dynamic architecture of large-scale functional brain networks. *Scientific Reports*.

Correlations of 6 canonical networks.

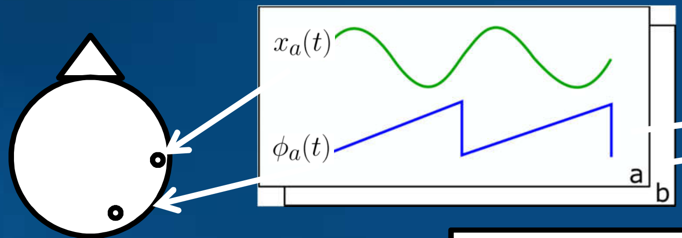
Perception,
Action-attention
DMN (Default Mode Network)

Each has up to 10 different network connectivity states (NC-states), rather stable for single subjects, ex.
DMN has usually 7-9.



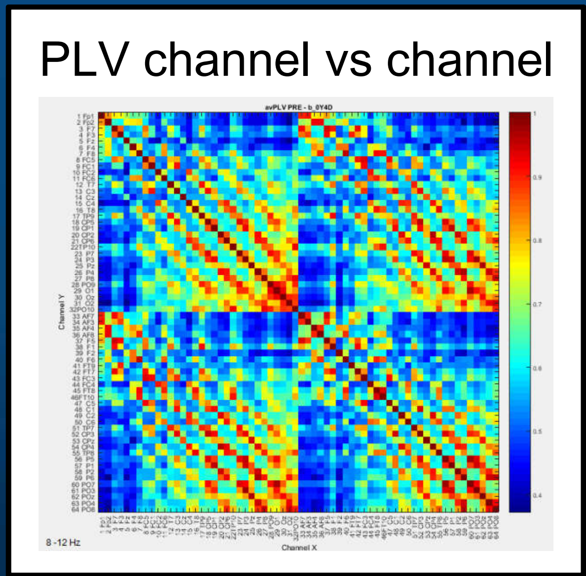
Functional connectivity changes

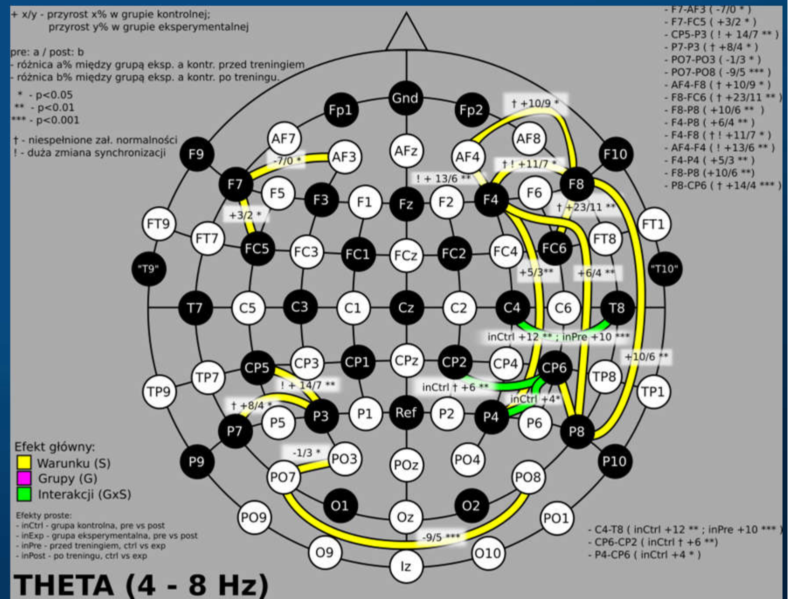
Influence of brain games on functional connectivity: **Phase Locking Value** (Burgess, 2013; Lachaux 1999), phase differences between signals measured at each electrode. PLV => synchronization maps, info flow.



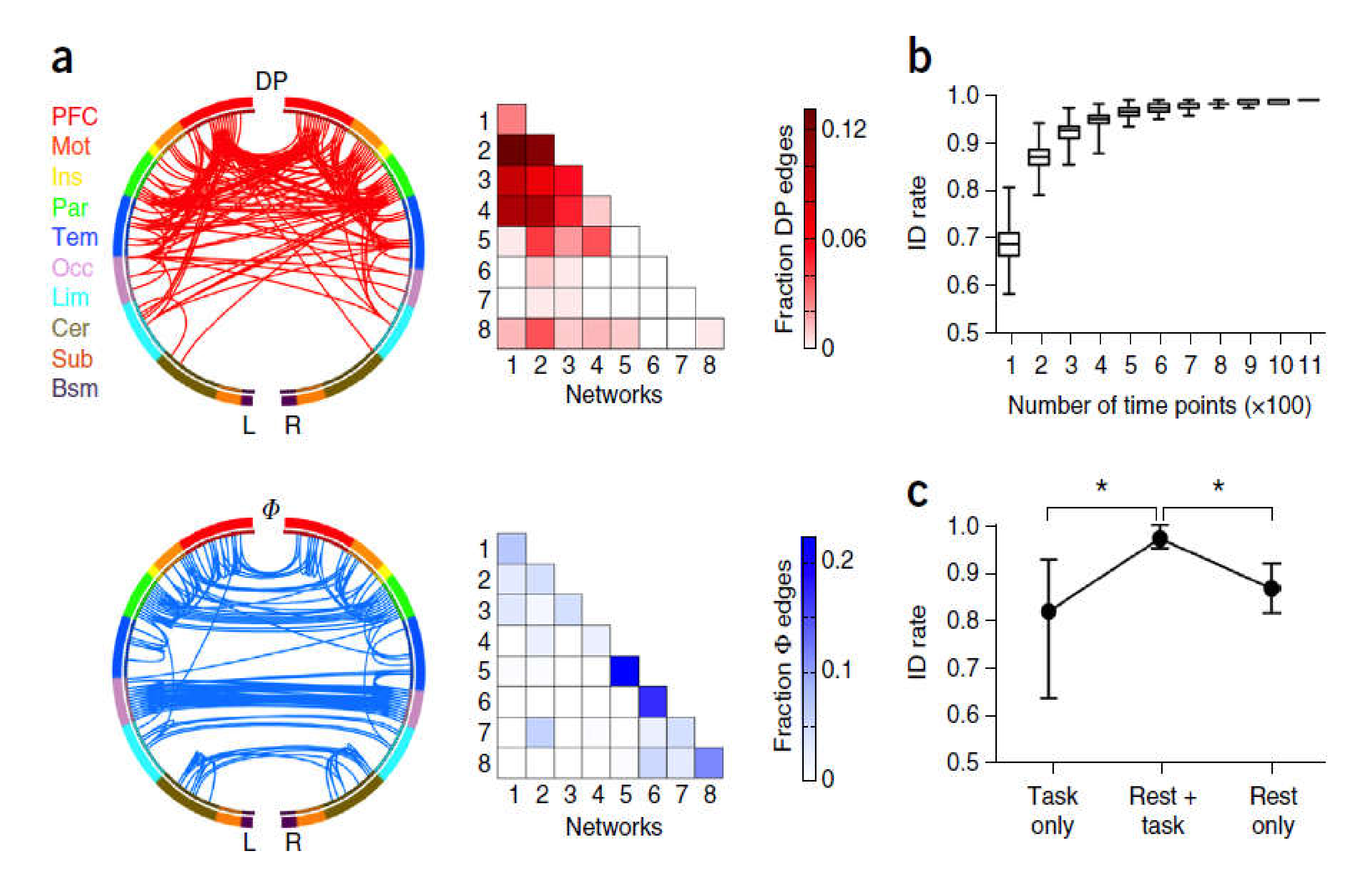
$$\Phi(t) = \phi_a(t) - \phi_b(t)$$

$$PLV(a,b) = \frac{1}{T}\left|\sum_{t}^{T} e^{i\Phi(t)}\right|$$





Finn et al. (2015), **Functional connectome fingerprinting**: identifying individuals using patterns of brain connectivity. Nature Neuroscience. Top: highly unique; Bottom: highly consistent connections.



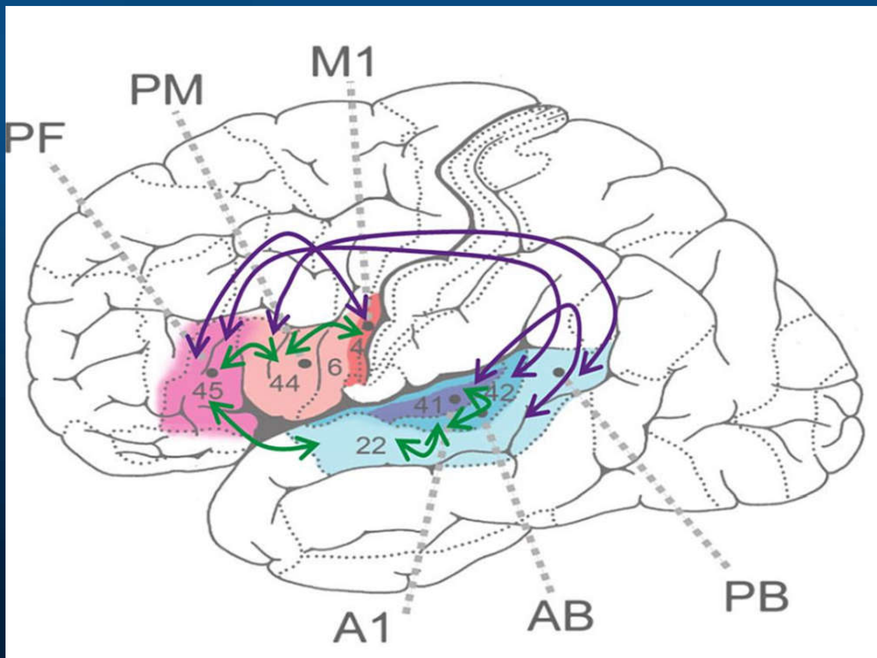
Fluid nature

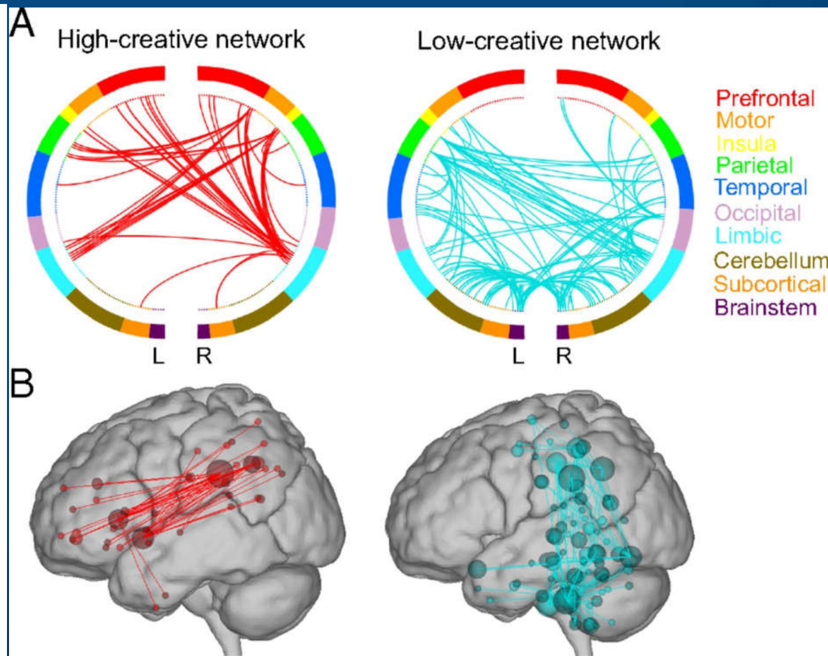
BABY Connectome Project
a UNC / UMN collaboration

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, pre-linguistic (our BabyLab).



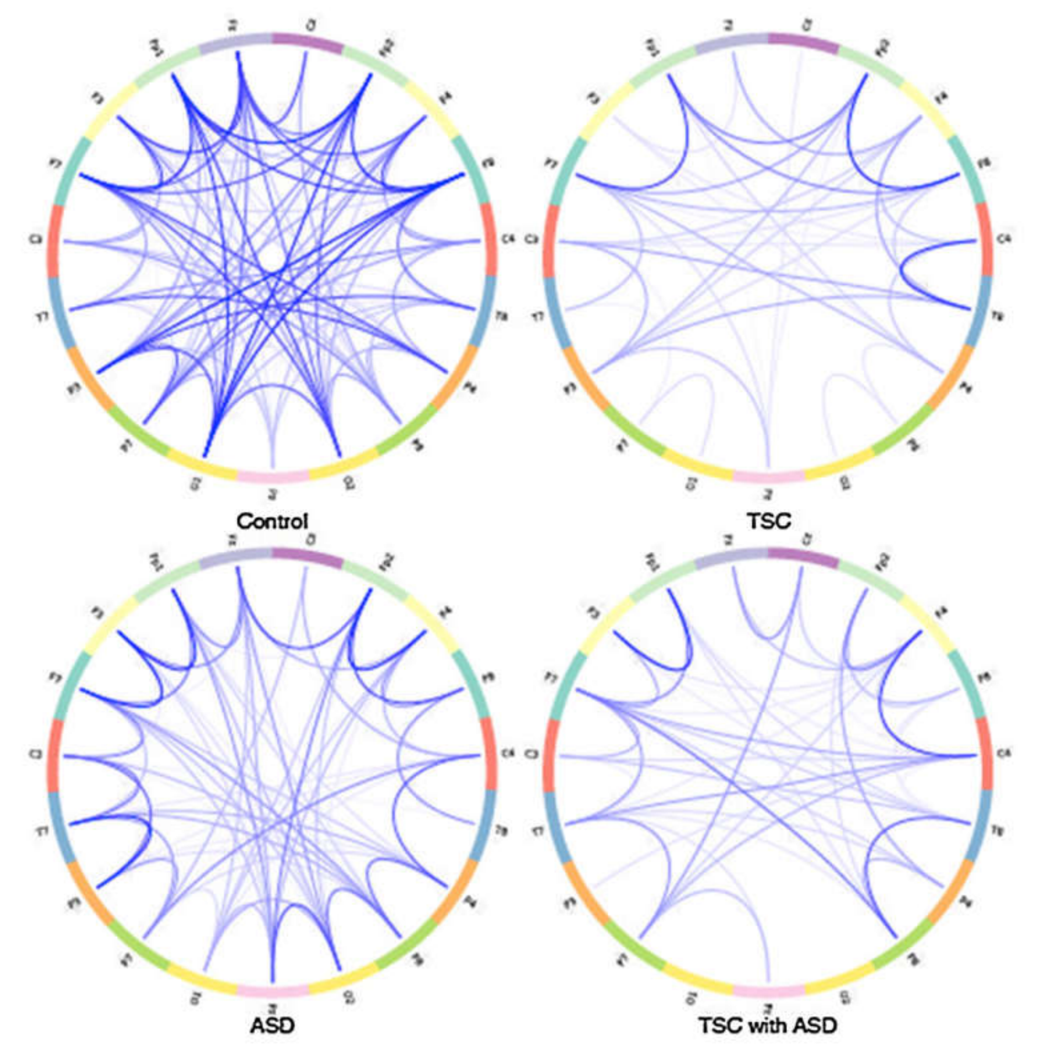


ASD: pathological connections

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

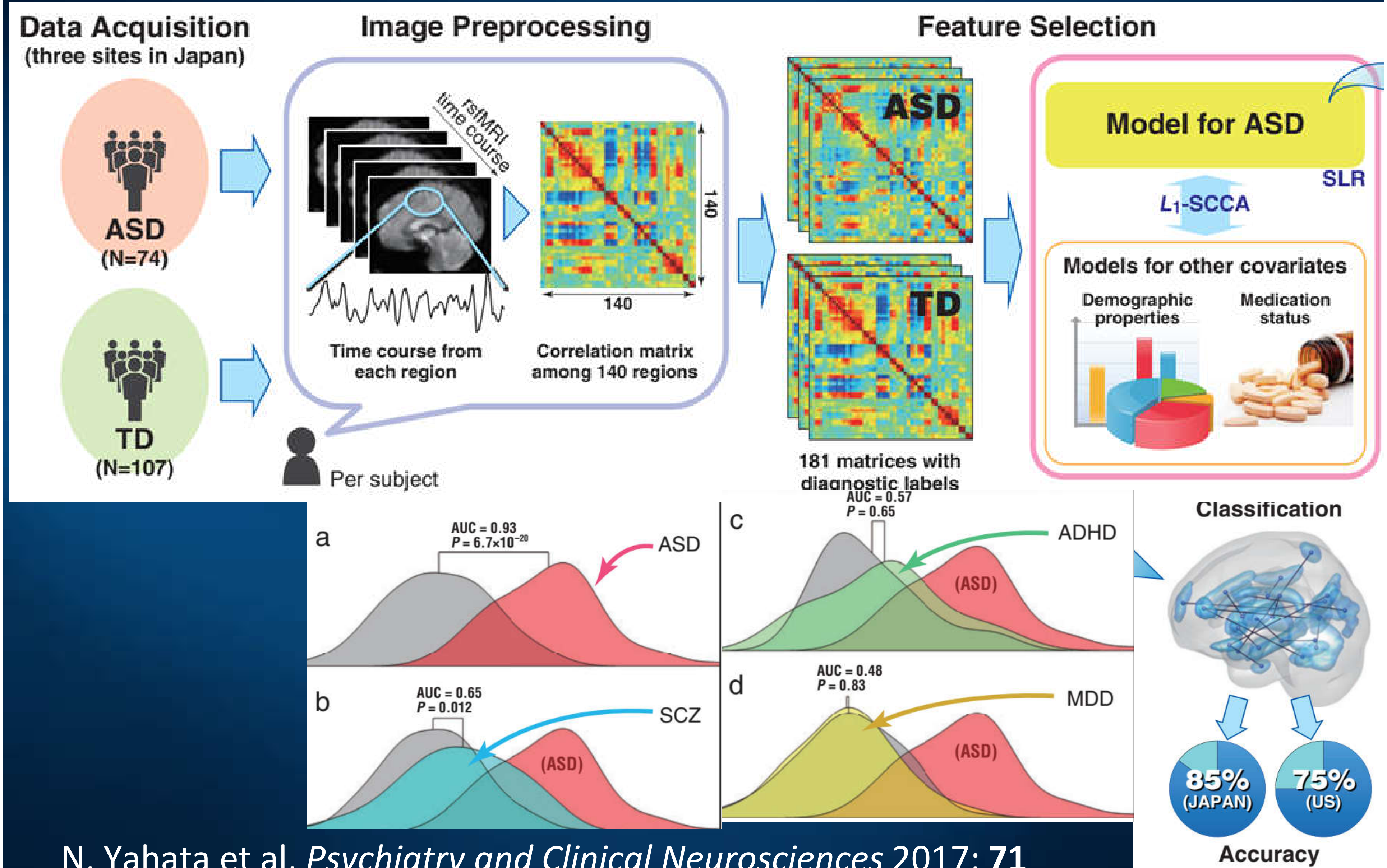
Coherence between electrodes. Weak or missing connections between distant regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

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



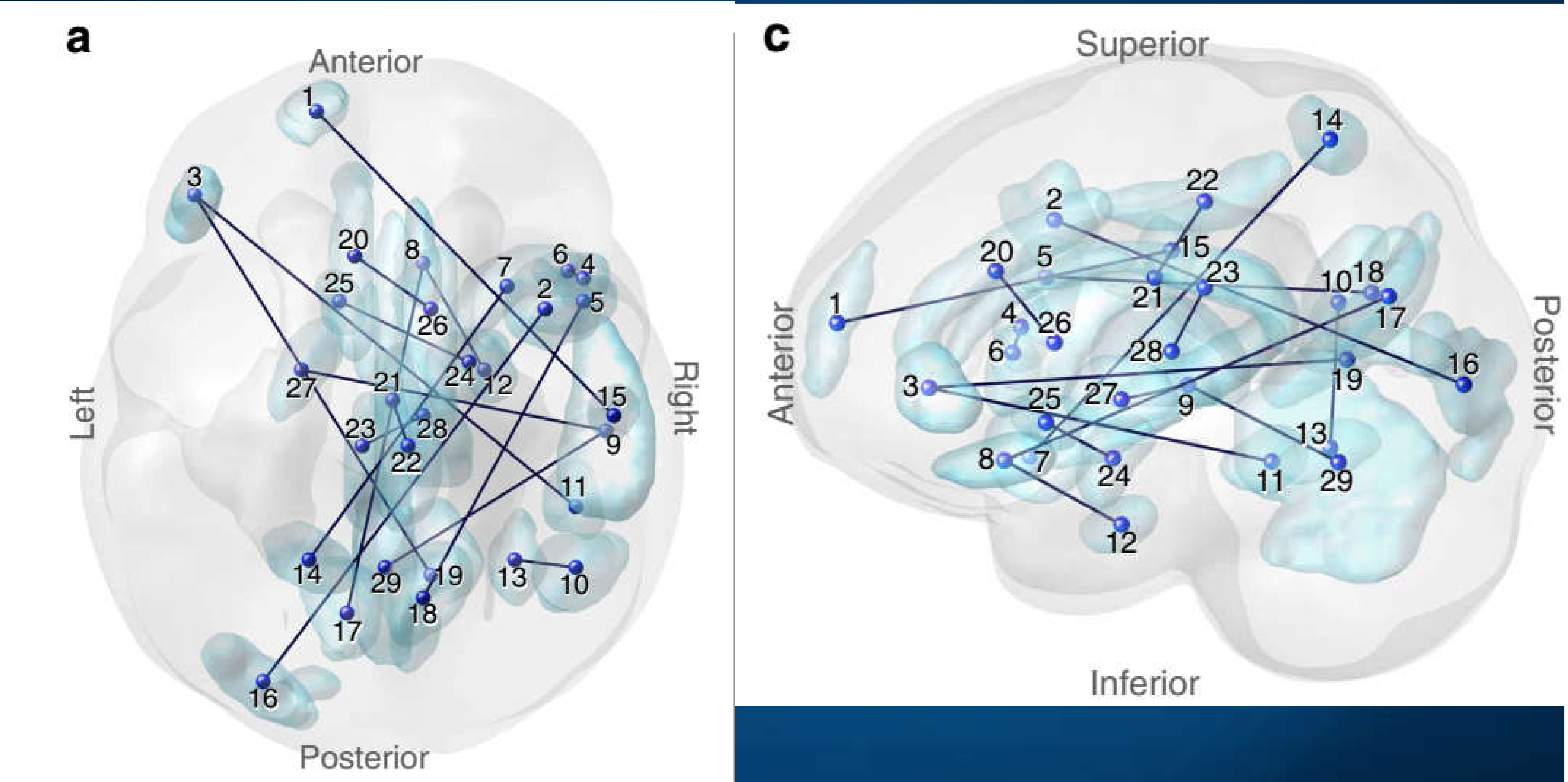
J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

Biomarkers from neuroimaging



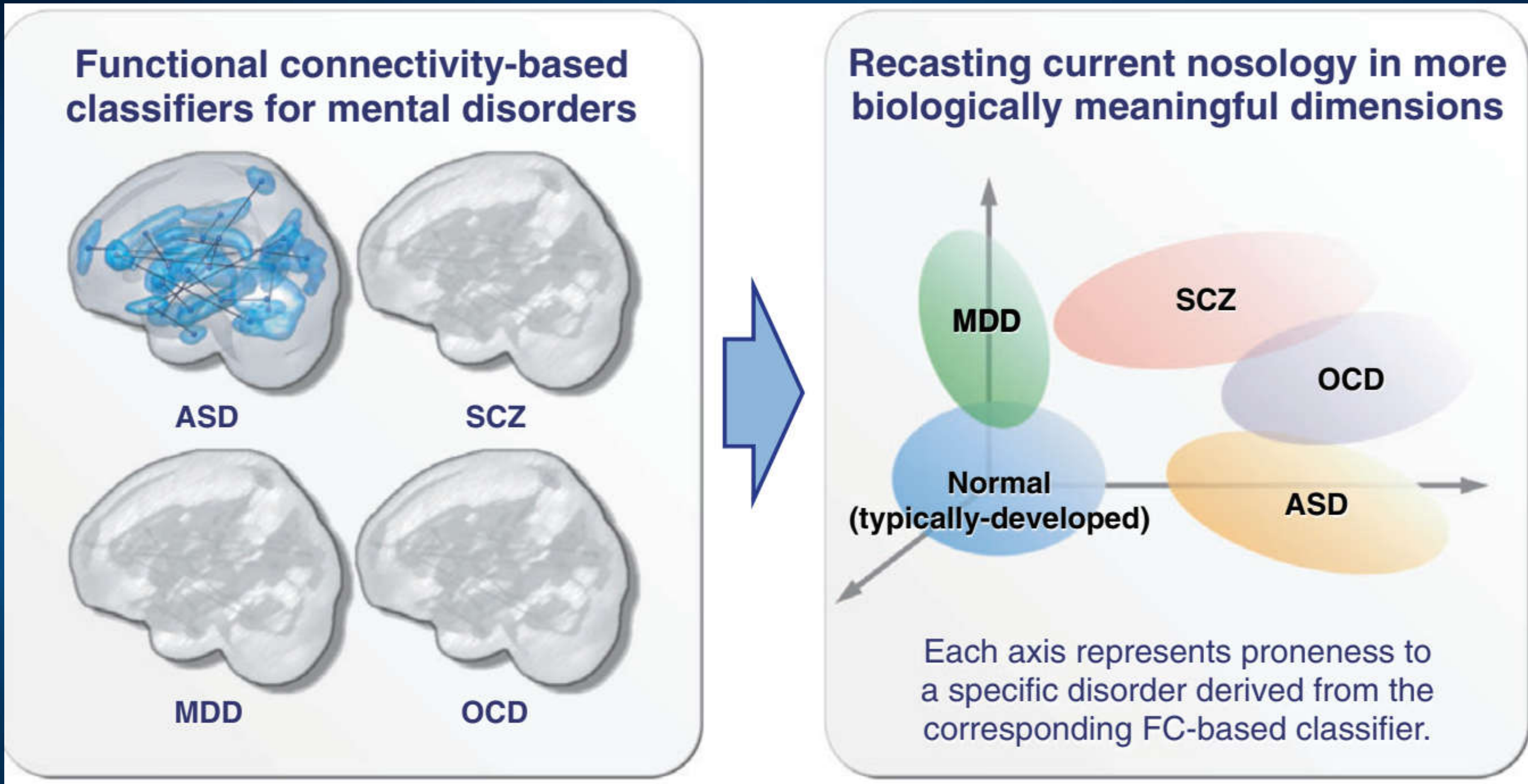
N. Yahata et al, *Psychiatry and Clinical Neurosciences* 2017: **71**

Selected connections



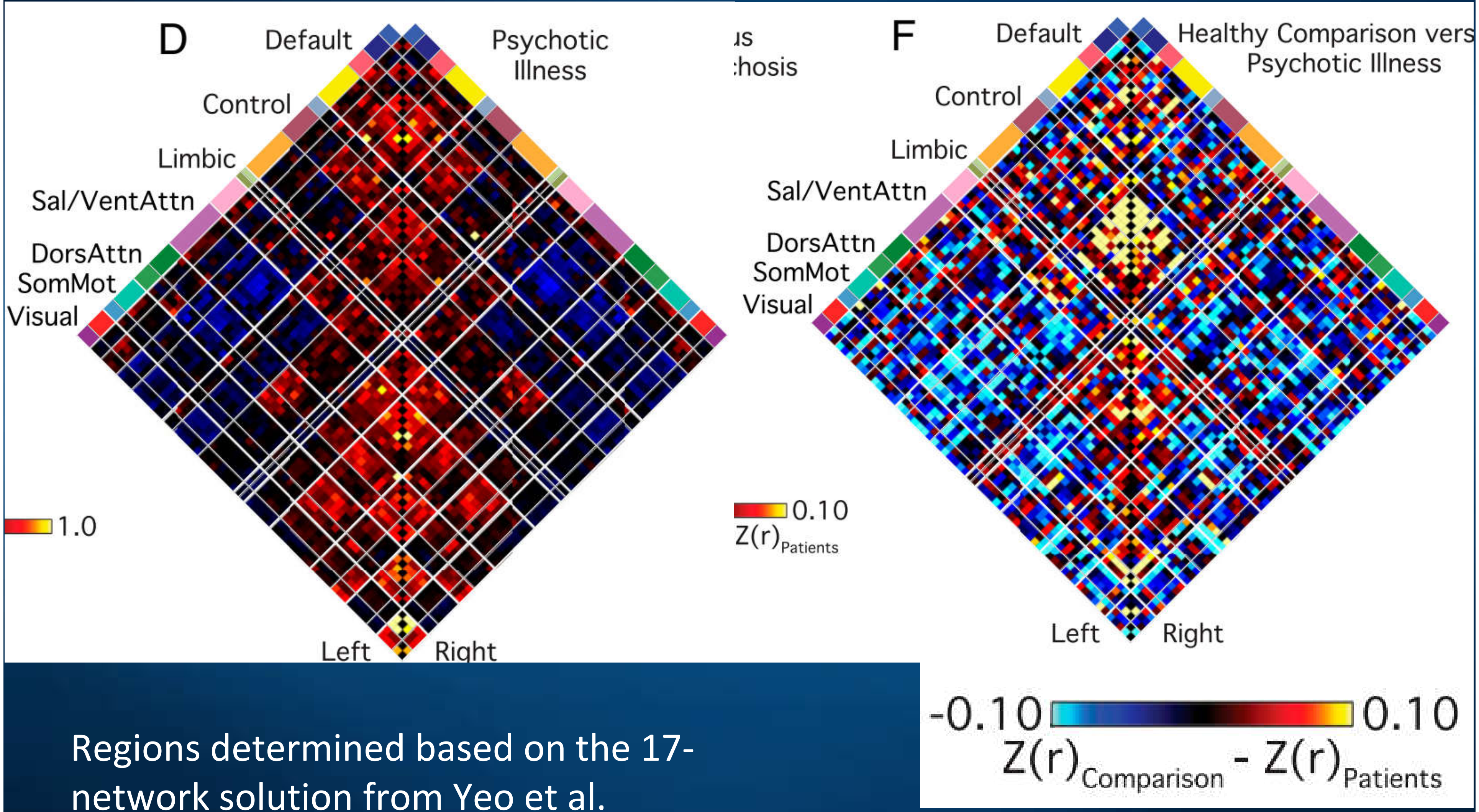
N. Yahata et al (2016): 29 selected regions (ROI) and 16 connections are sufficient to recognize ASD with 85% accuracy in 74 Japanese adult patients vs. 107 people in control group; without re-training accuracy was 75% on US patients.

Biomarkers of mental disorders



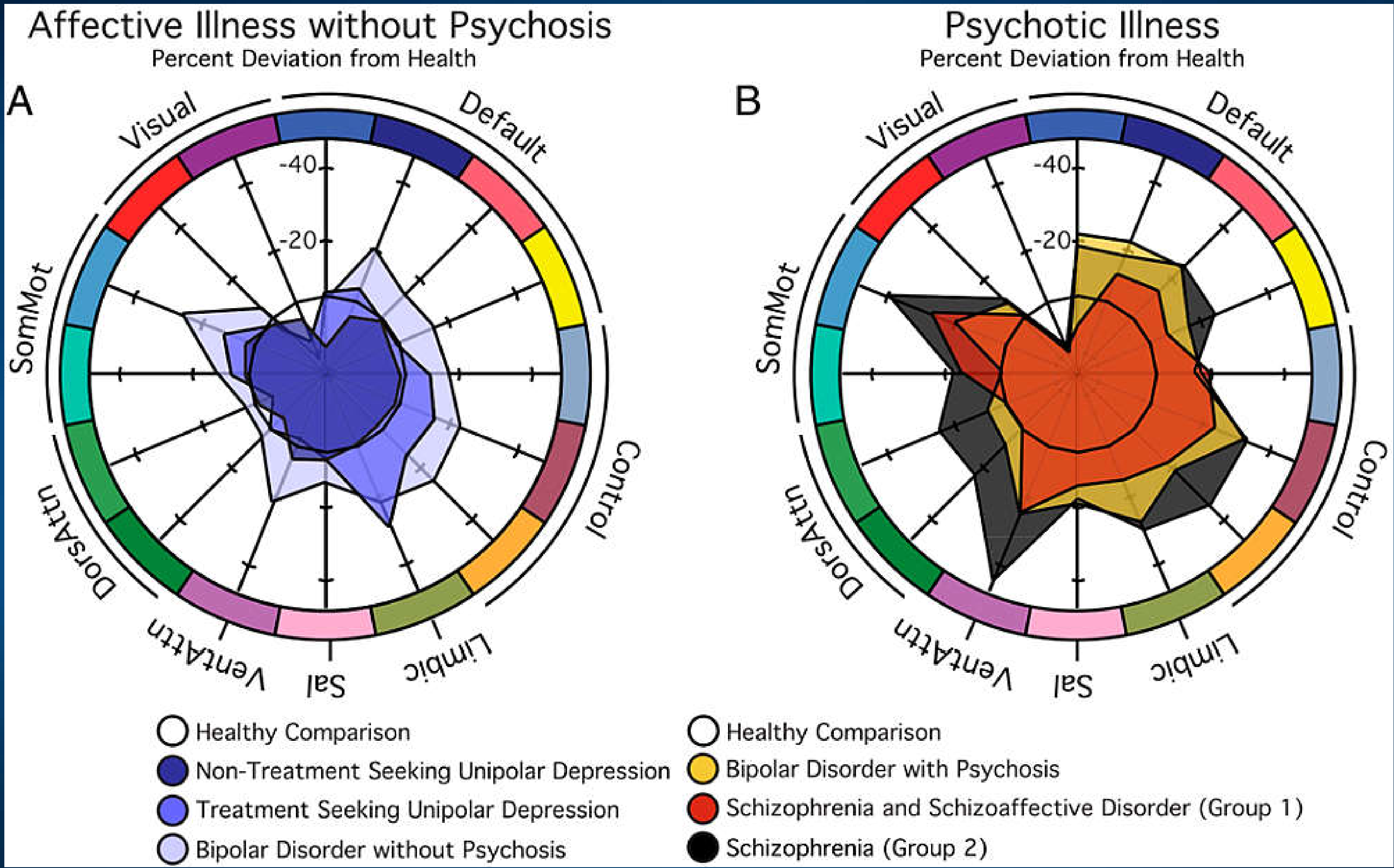
MDD, deep depression, SCZ, schizophrenia, OCD, obsessive-compulsive disorder, ASD autism spectrum disorder. fMRI biomarkers allow for objective diagnosis.
N. Yahata et al, *Psychiatry & Clinical Neurosciences* 2017; **71**: 215–237

Connectivity in patients vs healthy



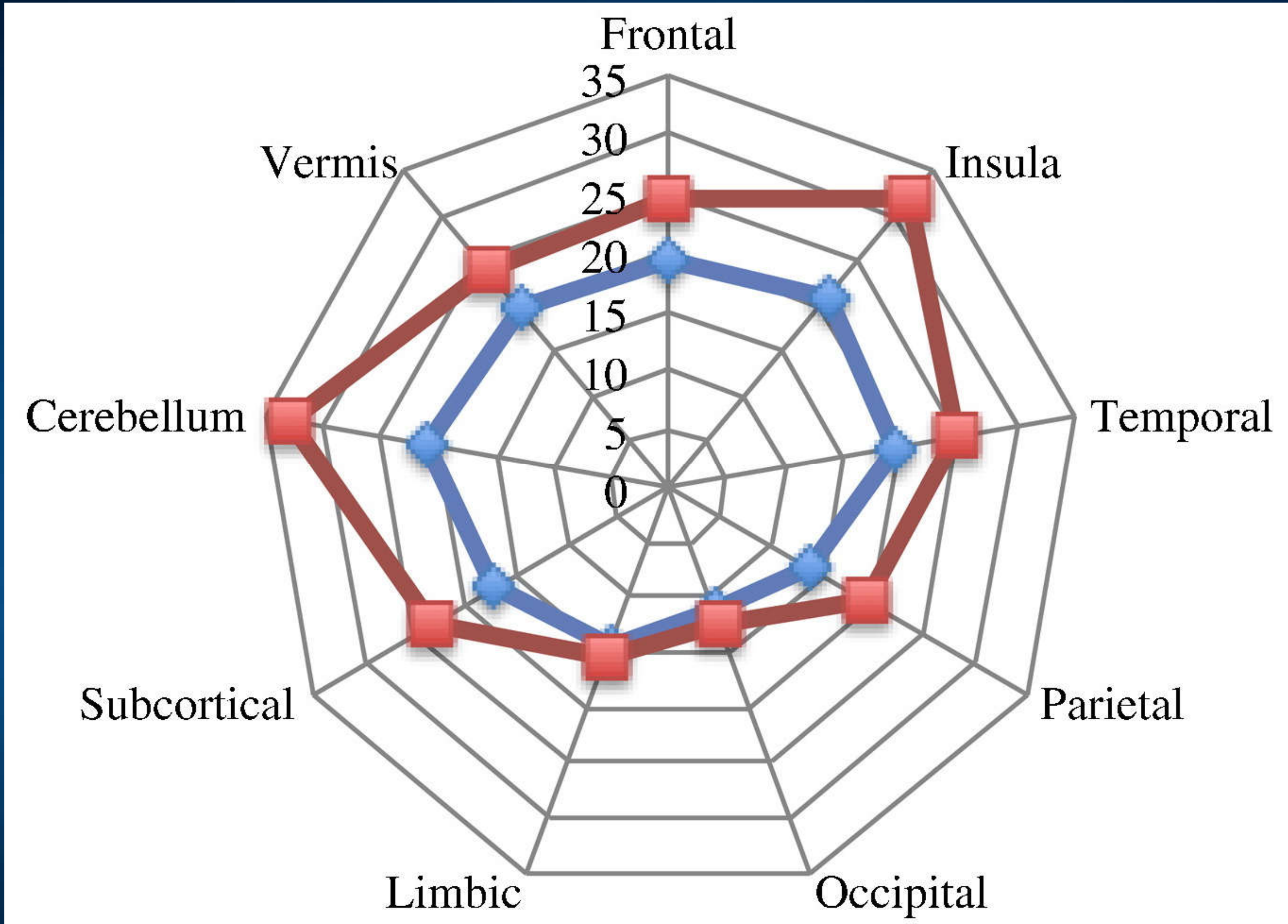
Regions determined based on the 17-network solution from Yeo et al.

Connectivity in patients vs healthy



Regions determined based on the 17-network solution from Yeo et al.

Negative connections in MCI patients



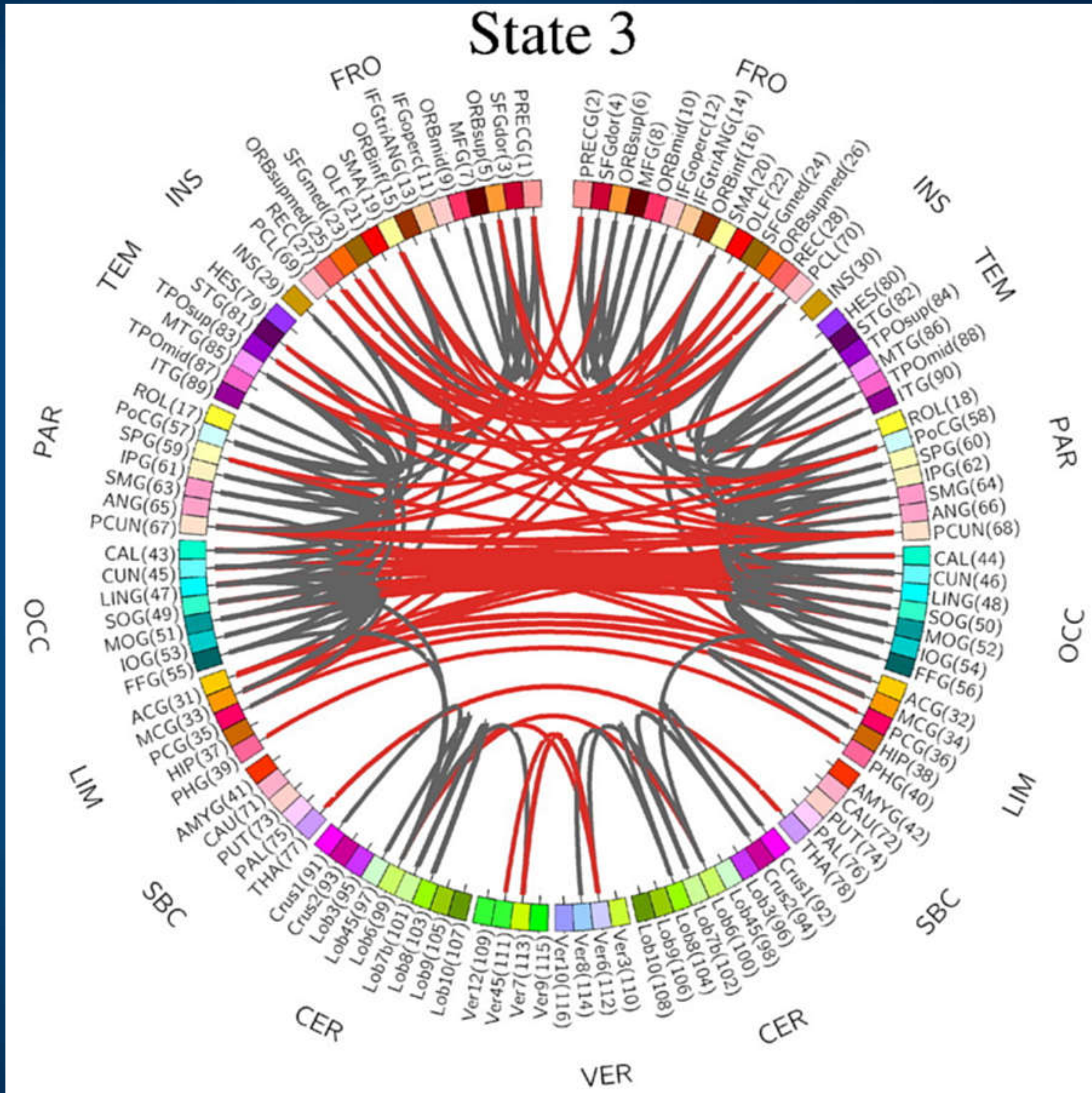
MCI, Mild cognitive Impairment. Red MCI, blue controls.
Significant differences in negatively correlated functional brain areas.
Deep Auto-Encoder (DAE) + HMM models, Suk et al. Neuroimage (2016)

Functional connections in controls

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)

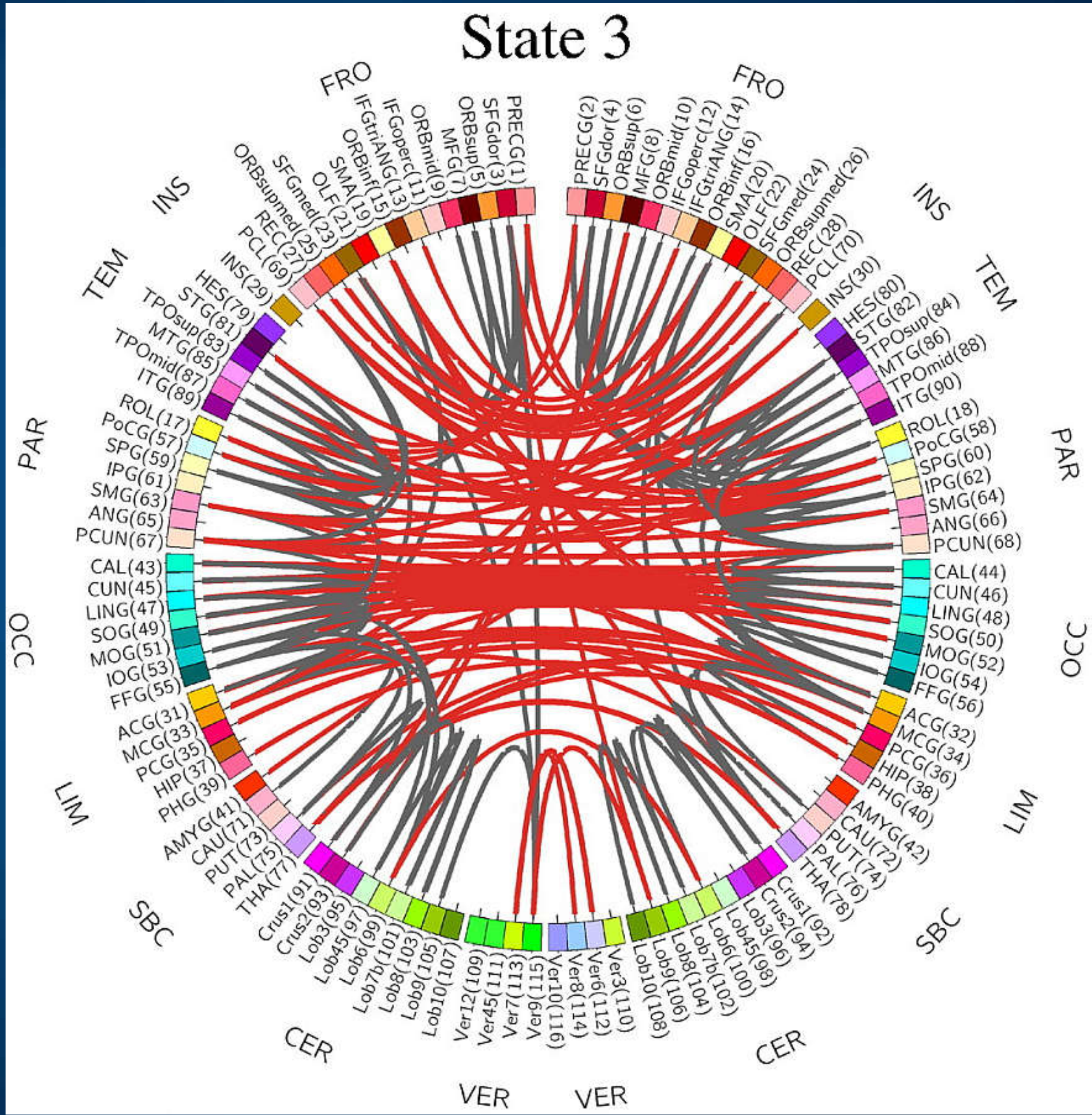


Negative connections in MCI patients

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

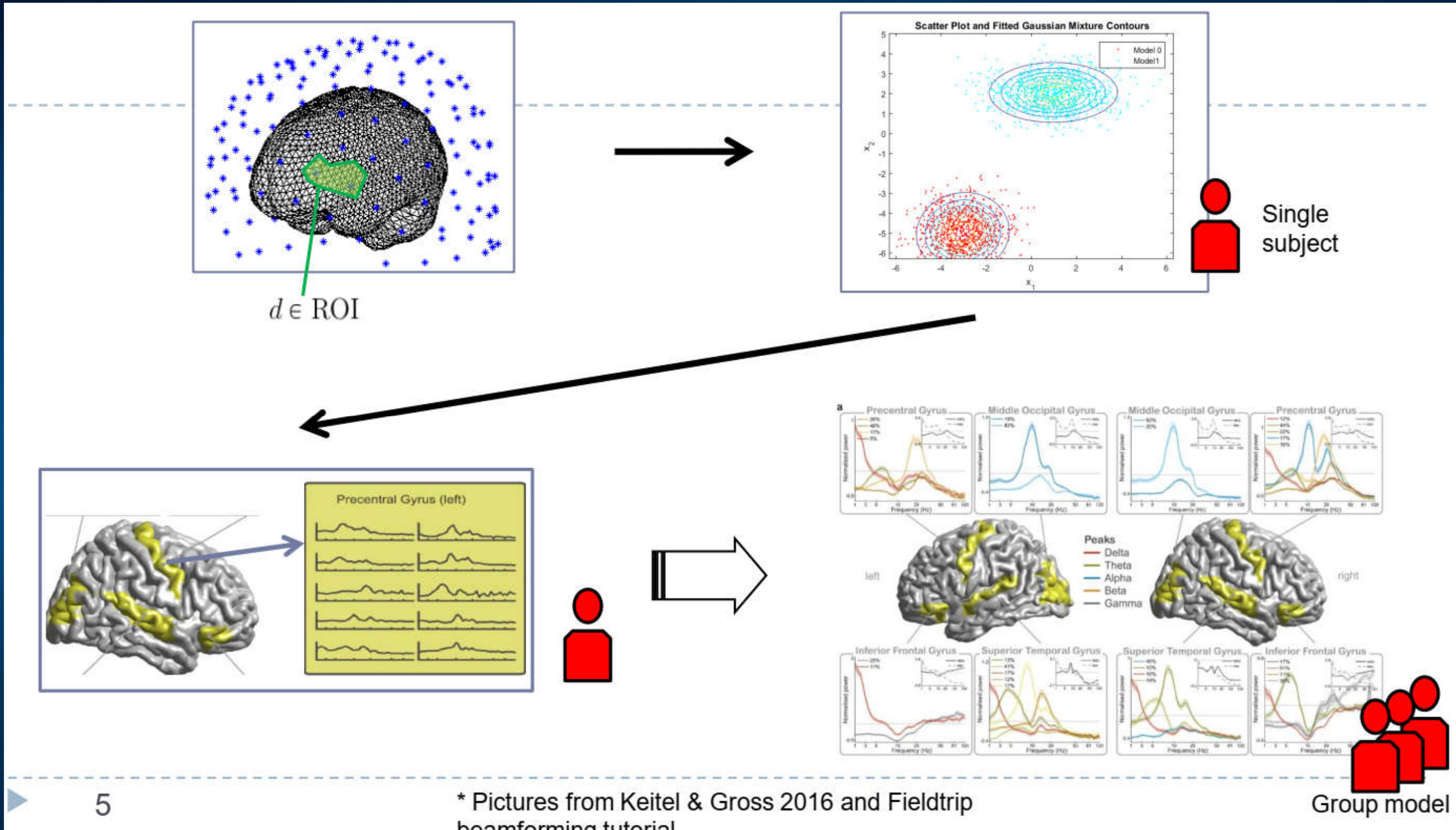
Connections |W|>0.65.

Suk et al. Neuroimage (2016)



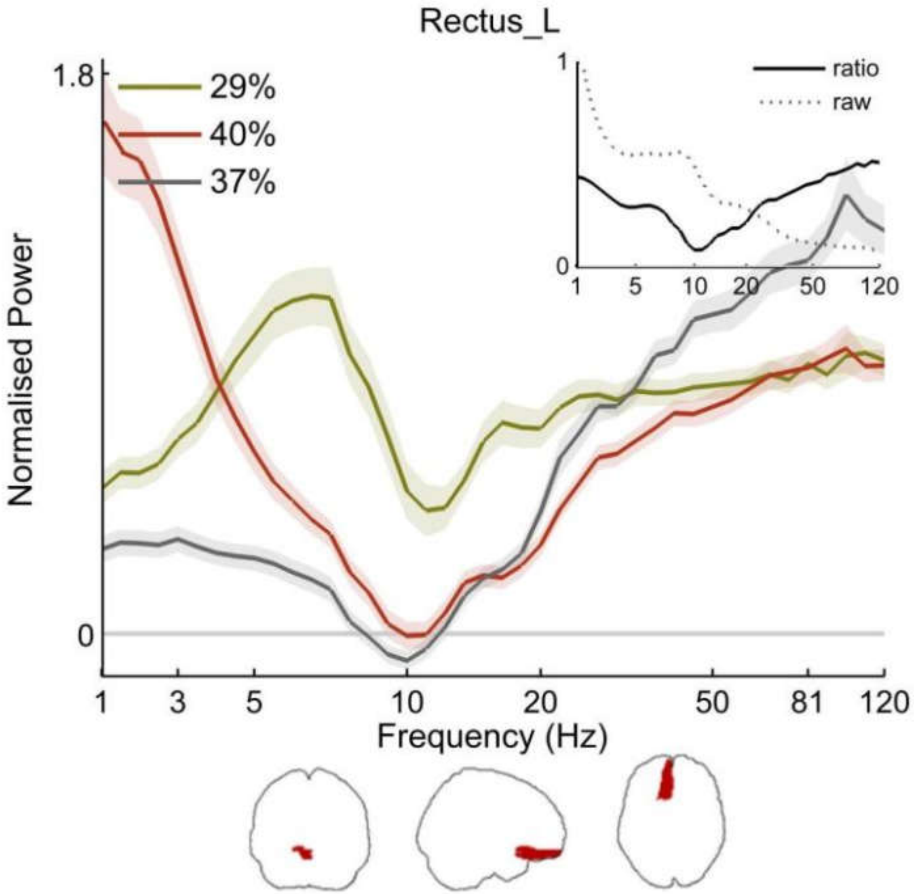
Fingerprints of mental activity

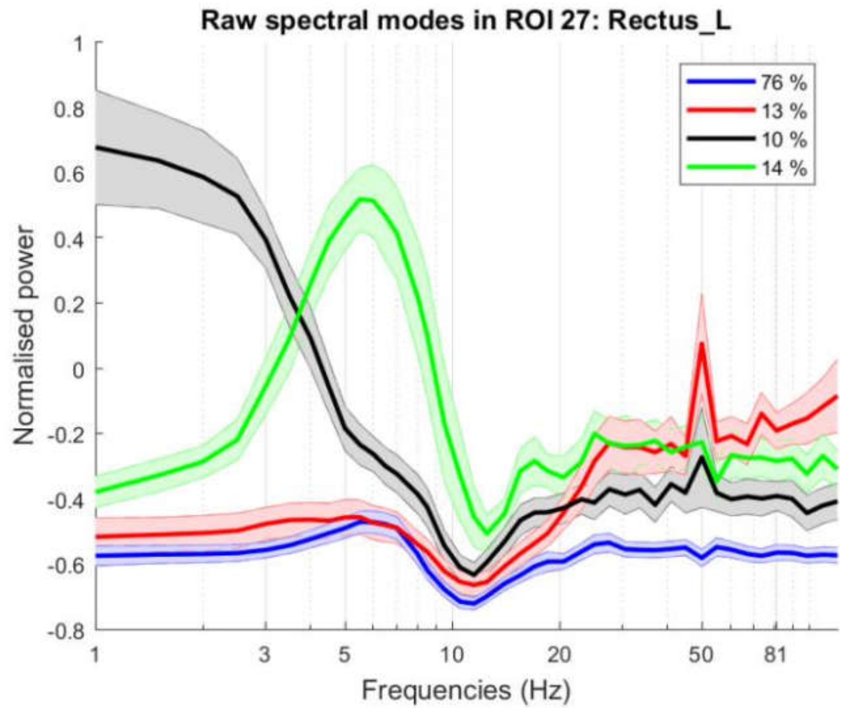
Spectral fingerprints



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

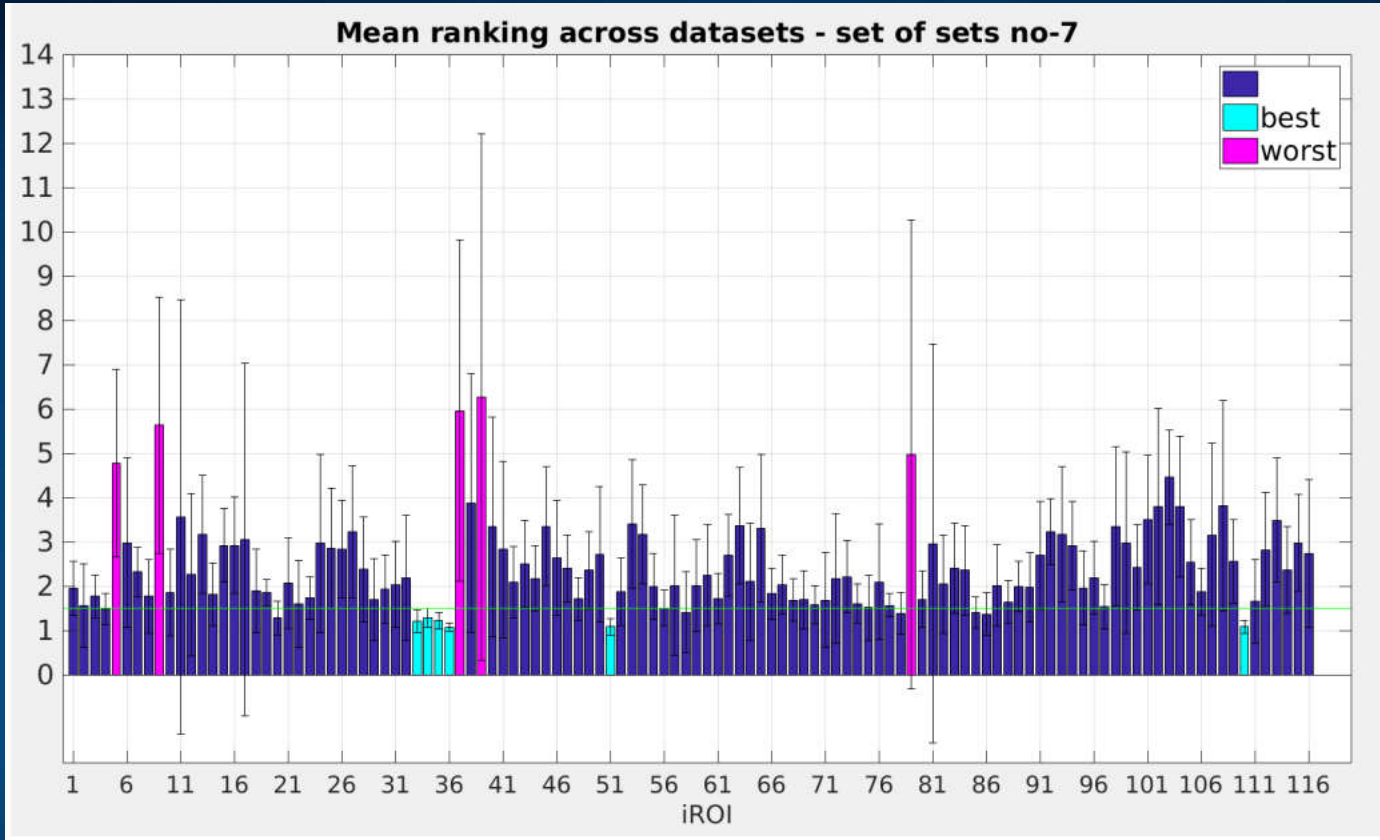
Spectral fingerprints





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

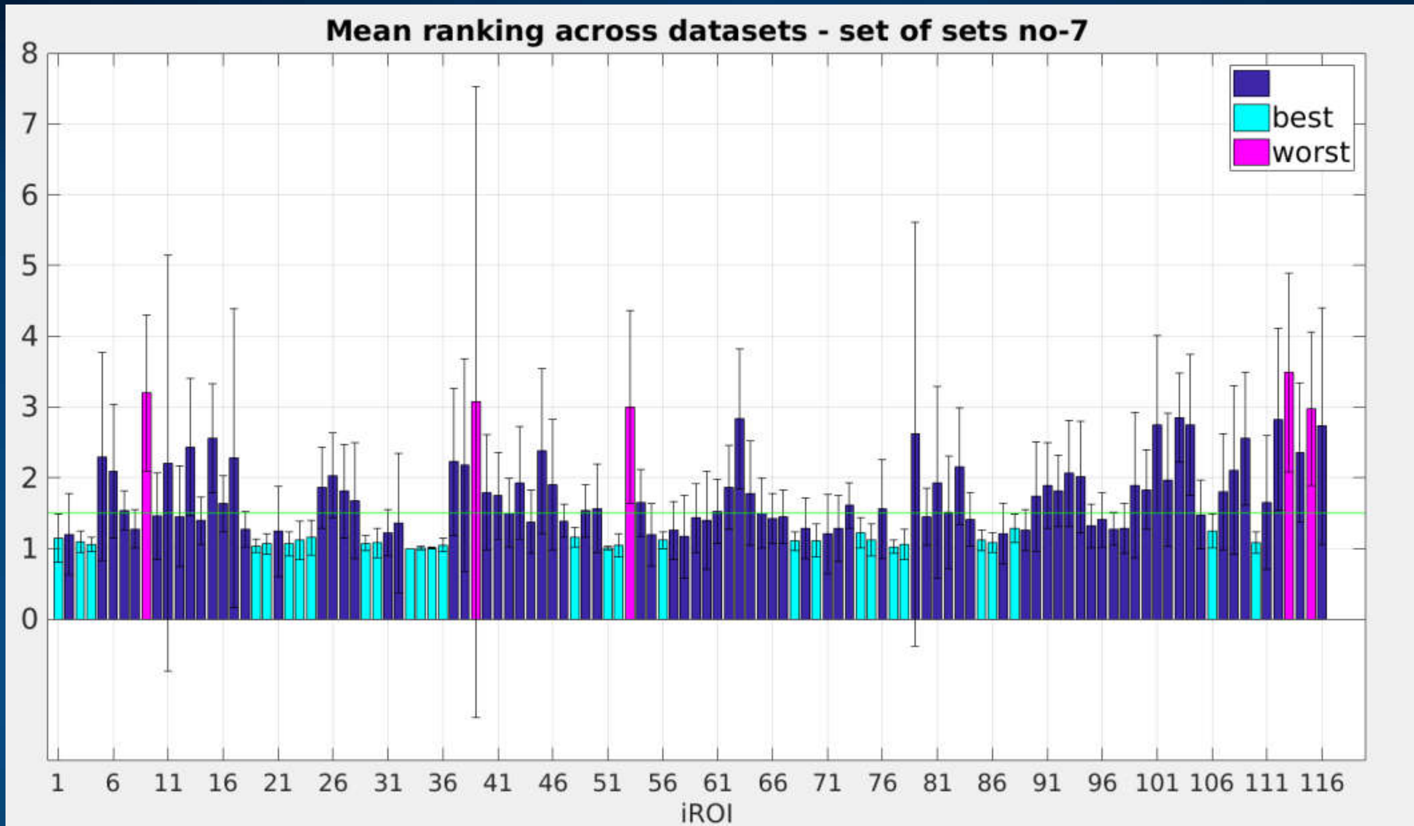
Reliability of ROI identification



Rank one means that ROI is uniquely identified (blue).

Some errors are due to homologous ROIs (left-right) and have mean rank <2.

Reliability of ROI identification

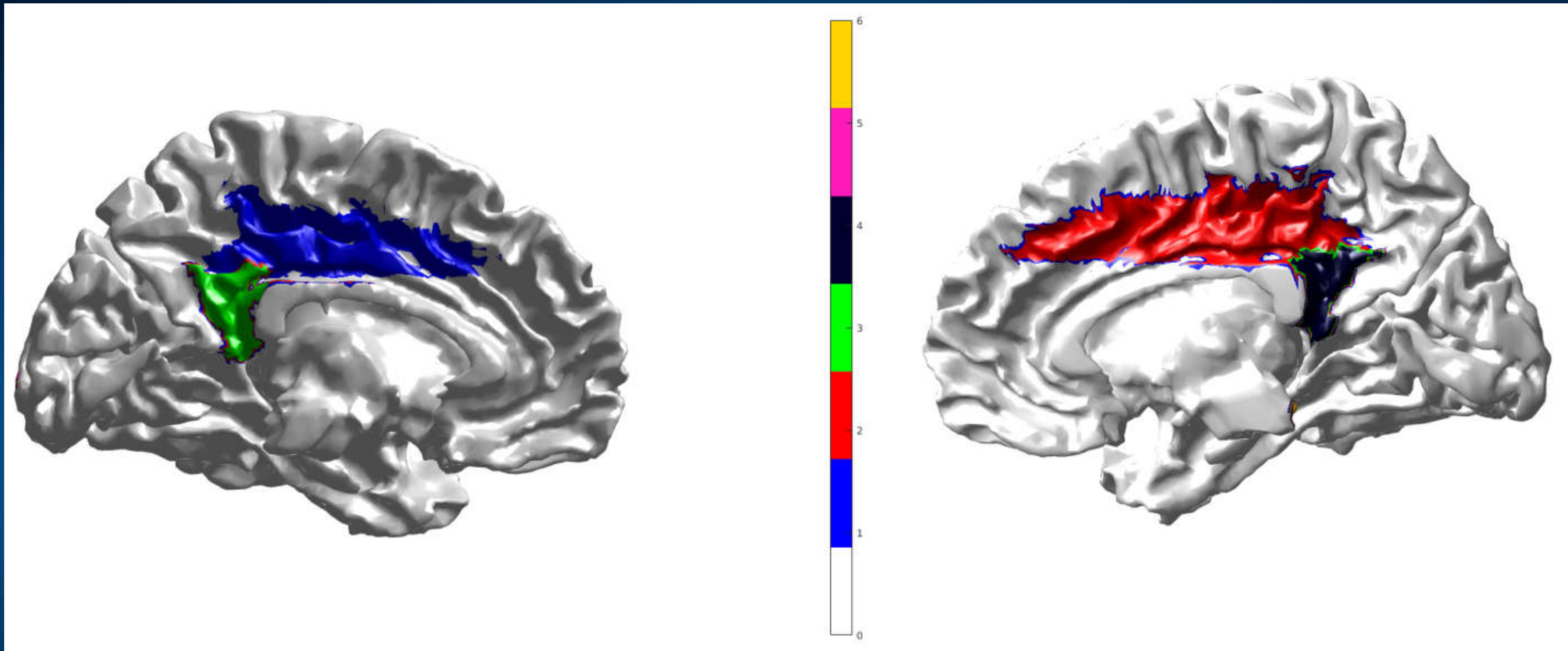


Some errors are due to homologous ROIs (left-right) and have mean rank <2.

Number of ROIs that can be reliably identified this way is much larger.

Some regions are hard to identify: S/N is different depending on cortex folding and MEG/EEG measures. MEG can see cingulate cortex activity, EEG is better for flat cortex on the surface.

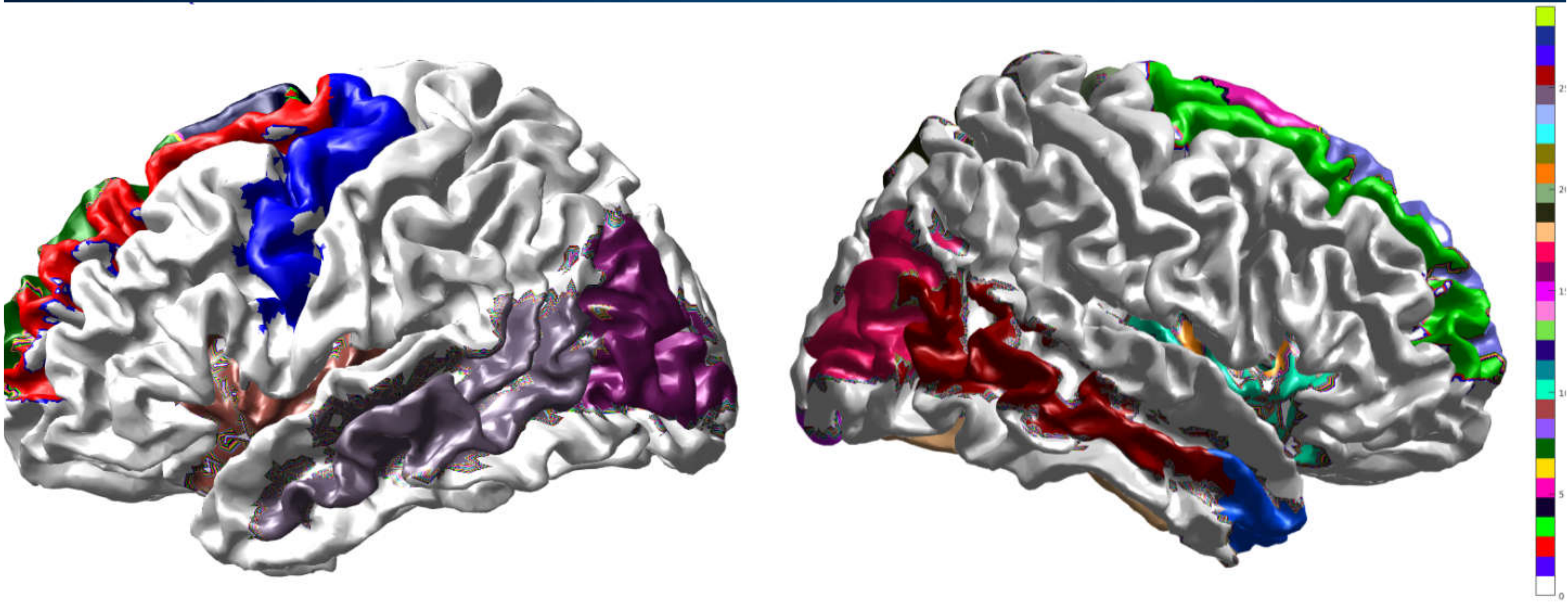
Most reliable ROI



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

Most reliable ROI, homologous ≤ 1.5

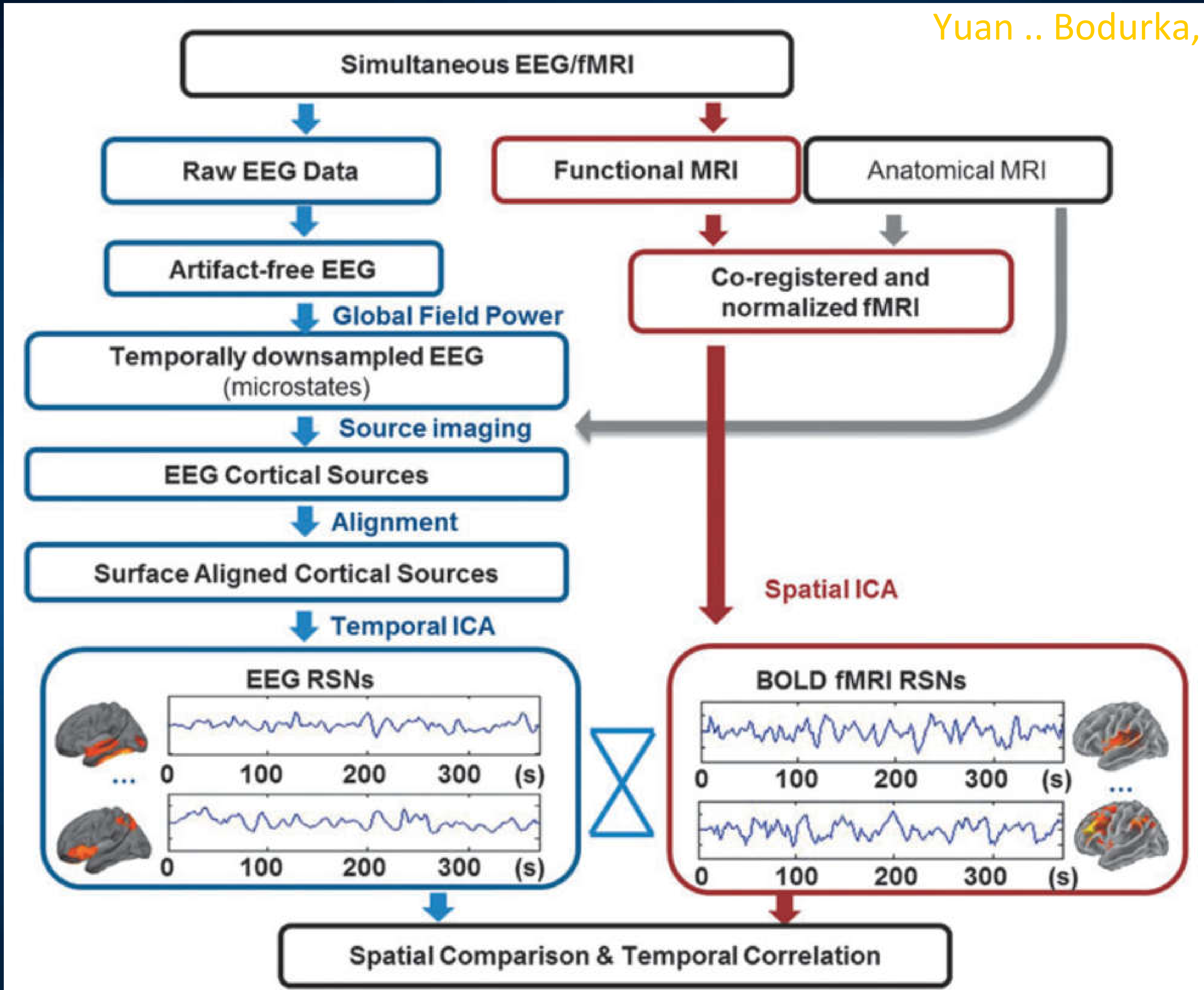


MEG data from the Human Connectome Project (HCP) for 1200 subjects.

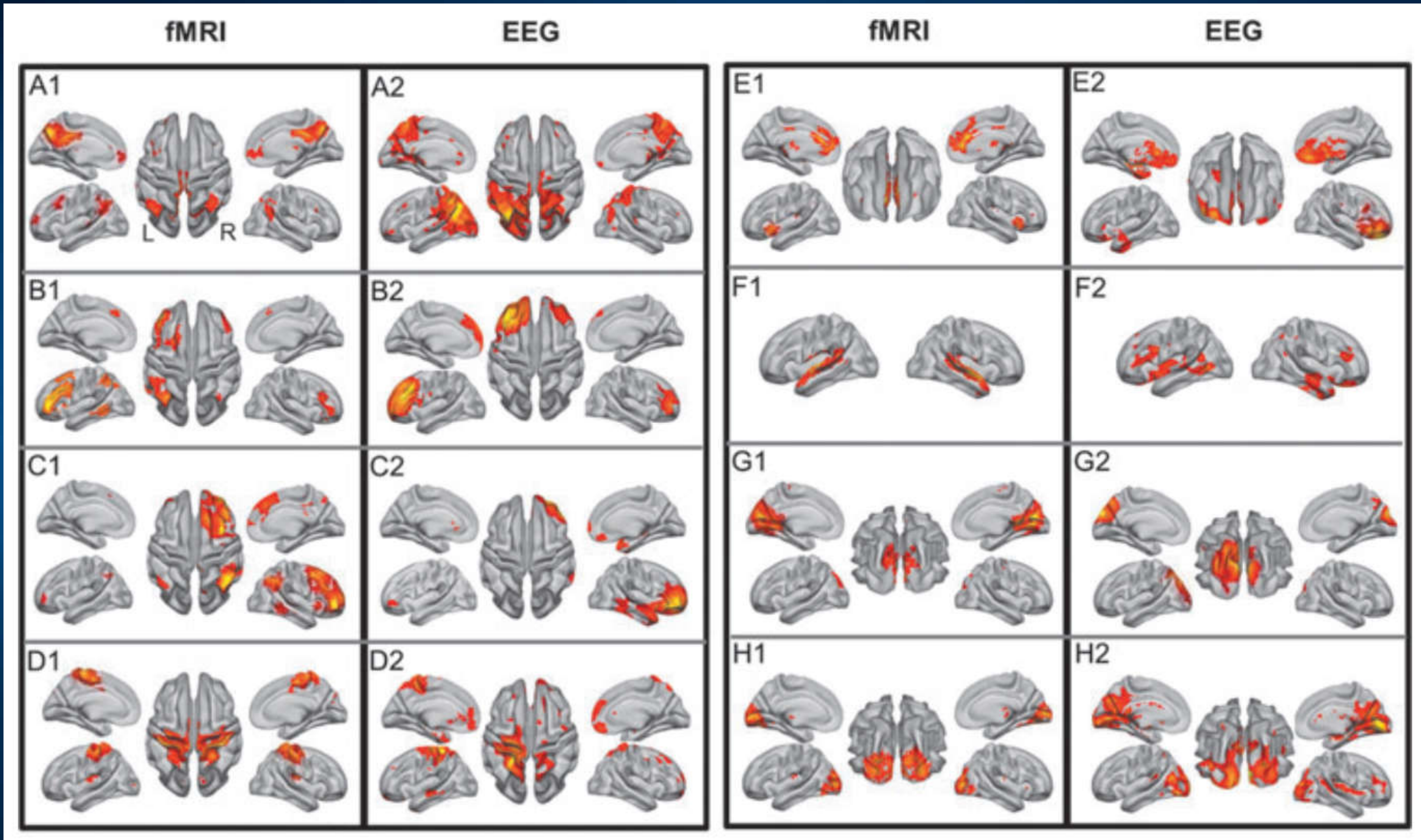
Some ROI can be recognized quite reliably.

If homologues are not distinguished we have 29 ROIs, many sub-cortical.

Yuan .. Bodurka, 2015

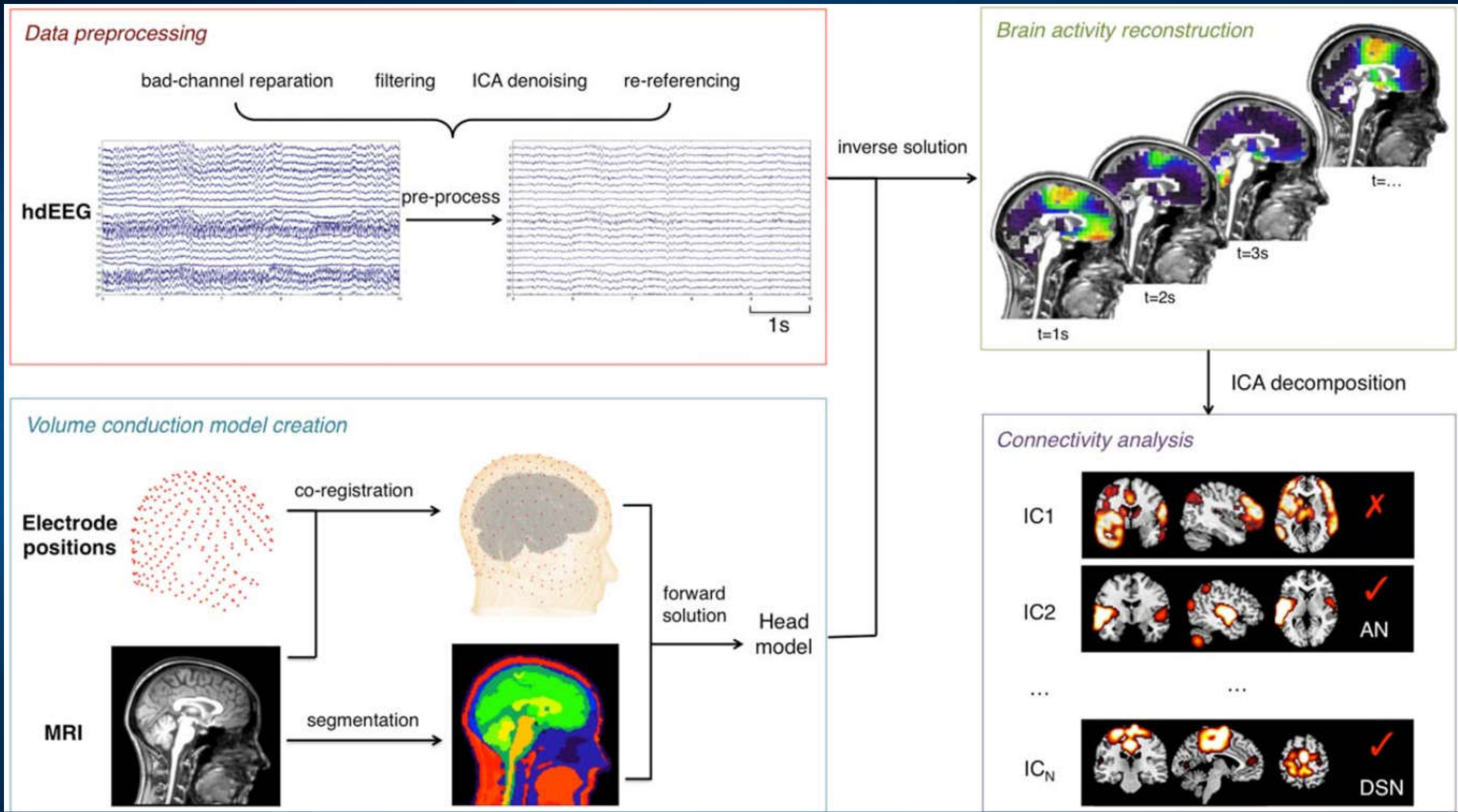


8 large networks from BOLD-EEG

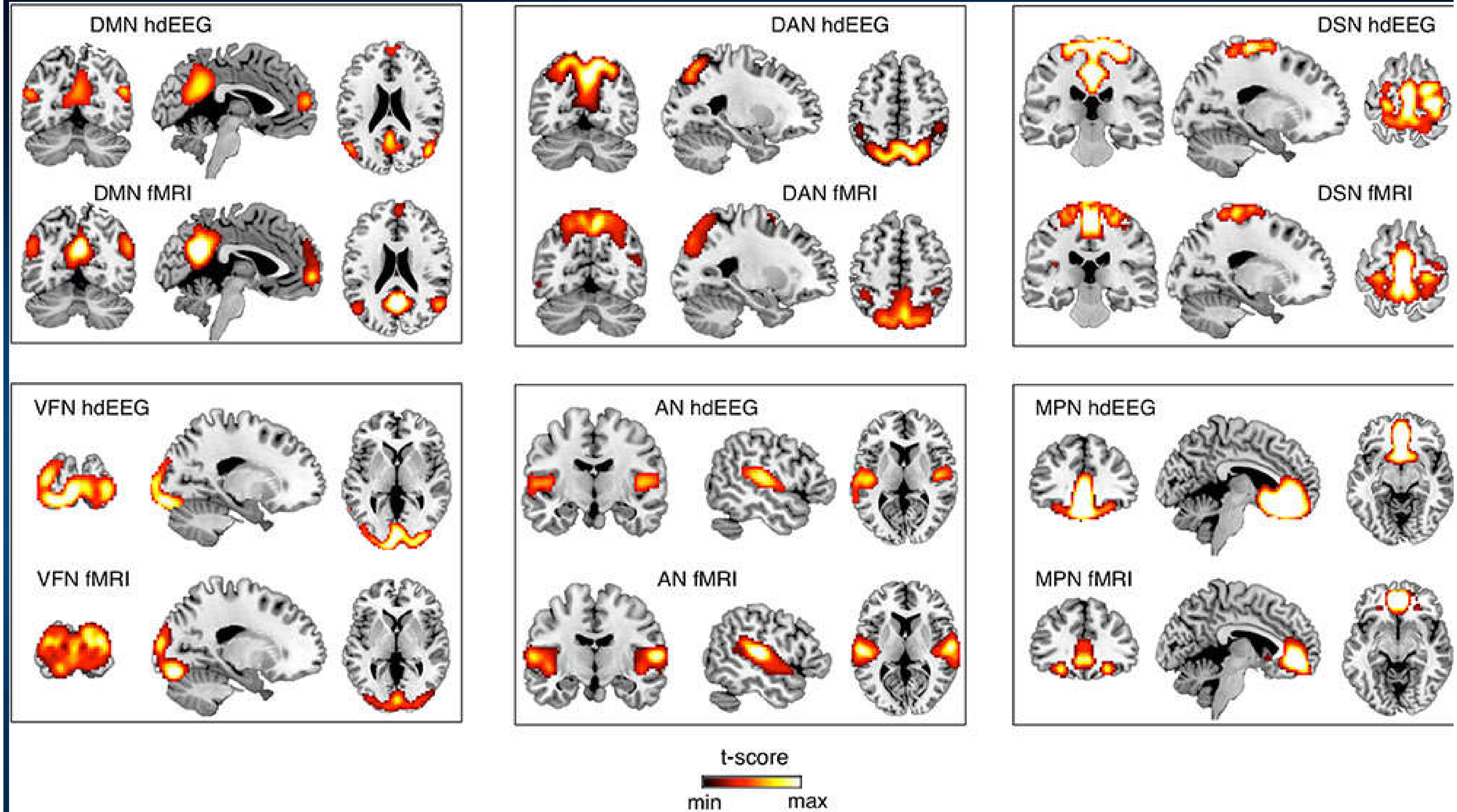


DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral).   Yuan … Bodurka (2015)

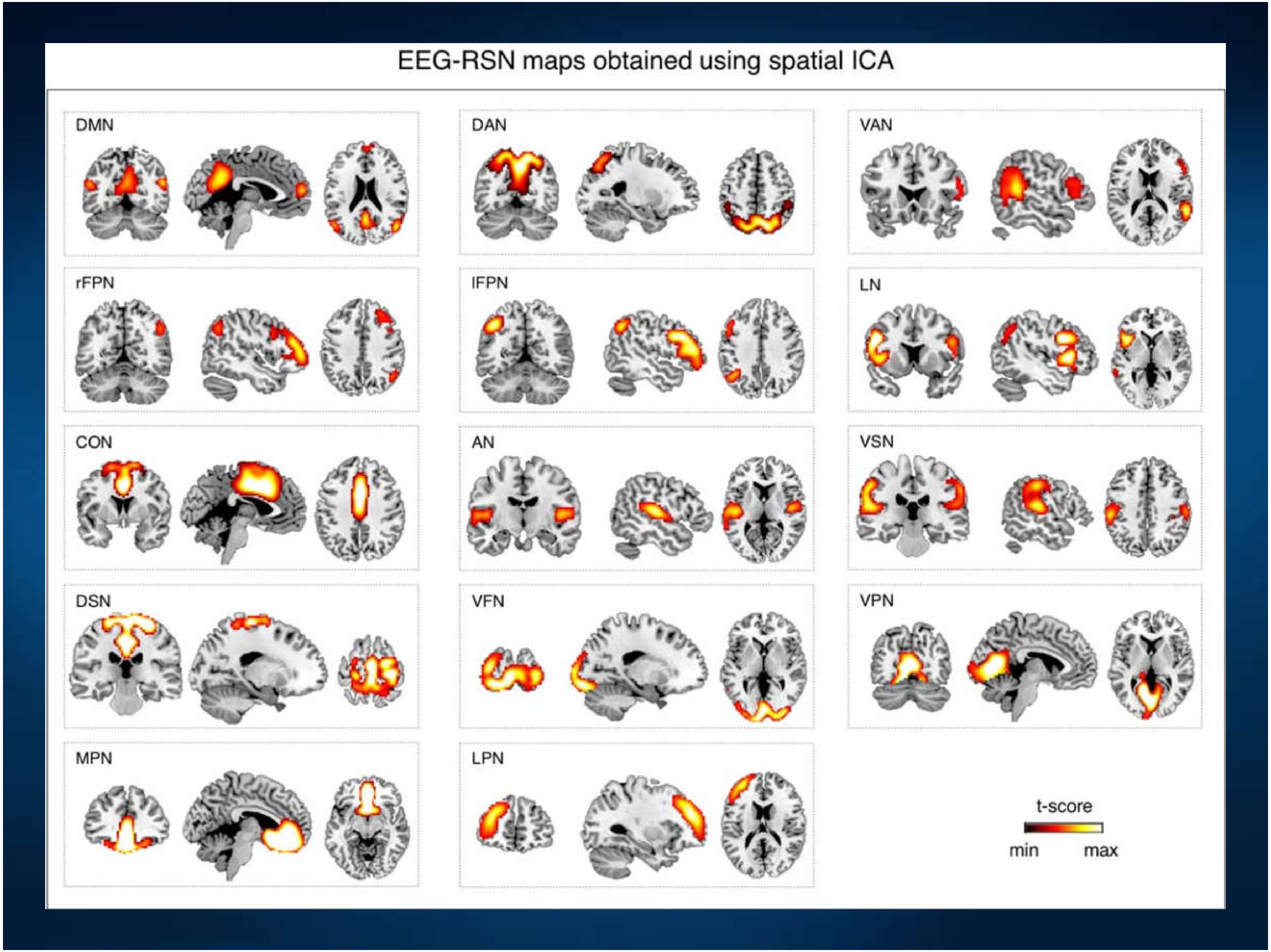
14 networks from BOLD-EEG



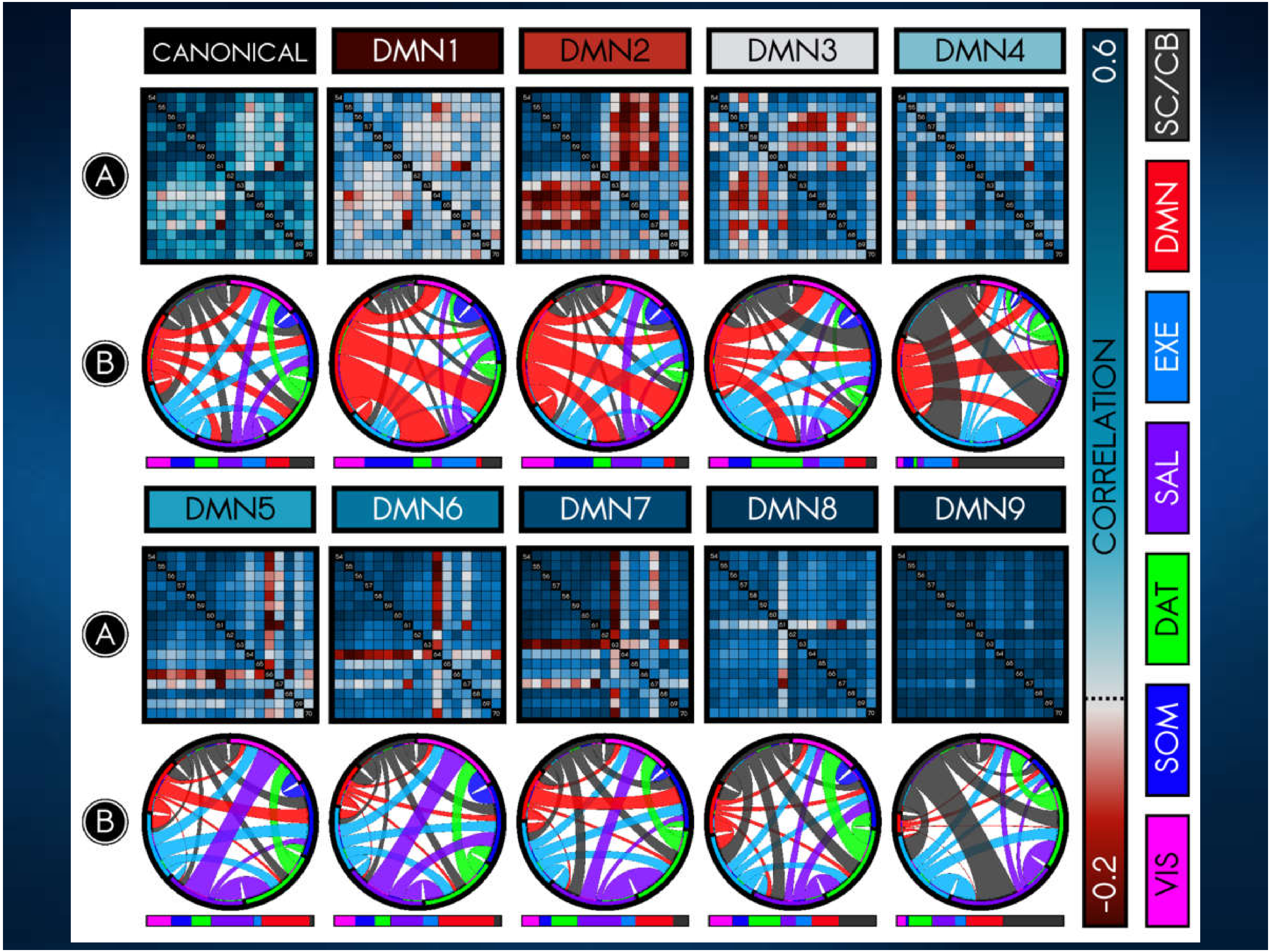
Liu et al. Detecting large-scale networks in the human brain. HBM (2017; 2018).

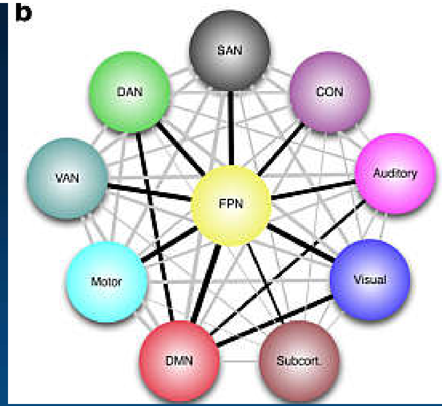


sICA on 10-min fMRI data ($N = 24$, threshold: $p < 0.01$, TFCE corrected). DMN, default mode network; DAN, dorsal attention network; DSN, dorsal somatomotor network; VFN, visual foveal network; AN, auditory network; MPN, medial prefrontal network.


EEG-RSN maps obtained using spatial ICA
DMN
DAN
VAN
rFPN
lFPN
LN
CON
AN
VSN
DSN
VFN
VPN
MPN
LPN
t-score
min
max

Dynamic functional brain networks


CANONICAL
DMN1
DMN2
DMN3
DMN4
DMN5
DMN6
DMN7
DMN8
DMN9
A
B
A
B
CORRELATION
0.6
-0.2
SC/CB
DMN
EXE
SAL
DAT
SOM
VIS



Questions

Global Neuronal Workspace Theory (Deahene et al. 1998): brain processes underlying effortful tasks require two main computational spaces:

- a set of specialized and modular perceptual, motor, memory, evaluative, and attentional processors;
- a unique global workspace 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), mobilize or suppress contribution of specific processor neurons.

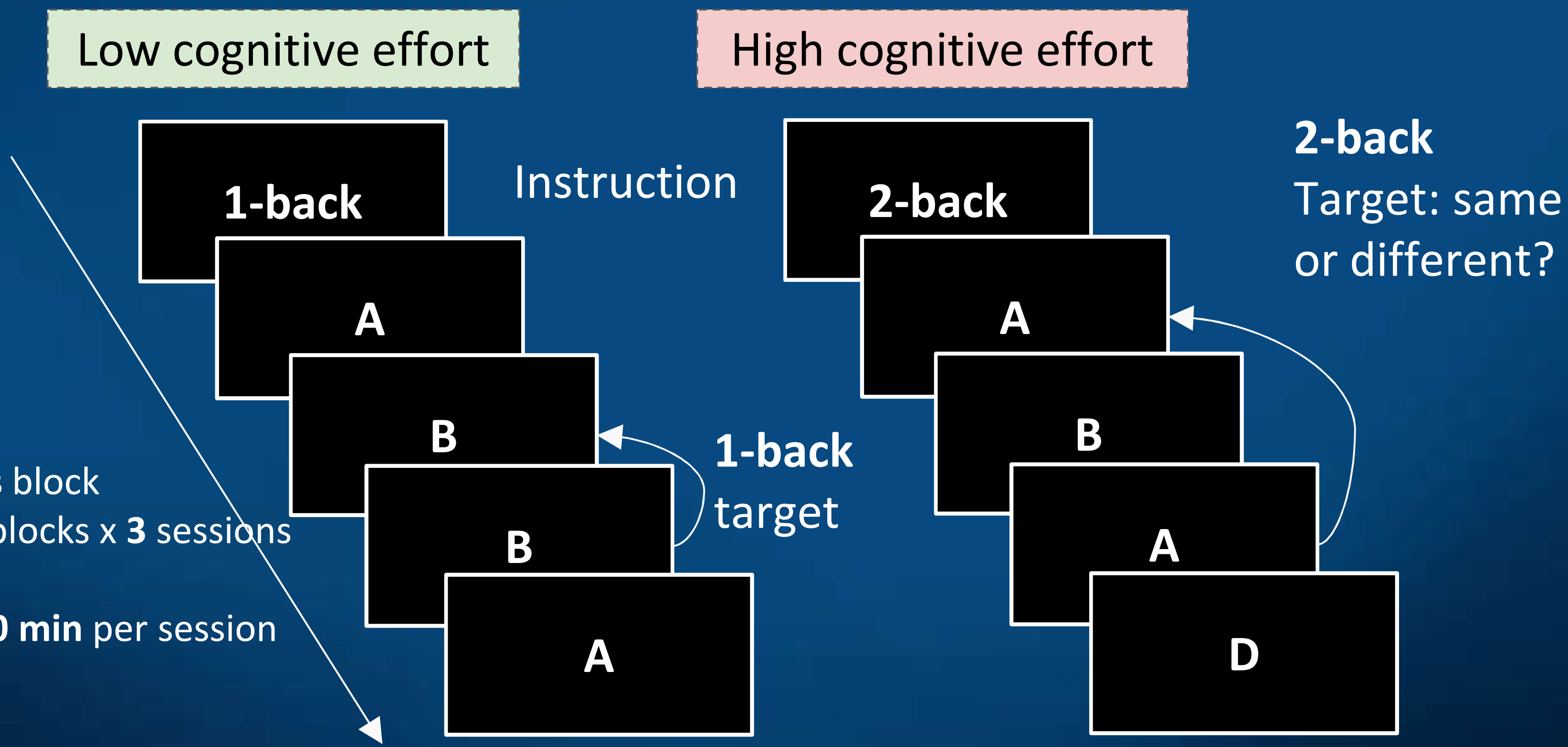
1. Can the whole-brain network properties change during performance?
2. Do modularity, path length, global, local efficiency and other network measures dependent on the cognitive load?

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.

Cognitive load on whole-brain network

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

Letter *n*-back task



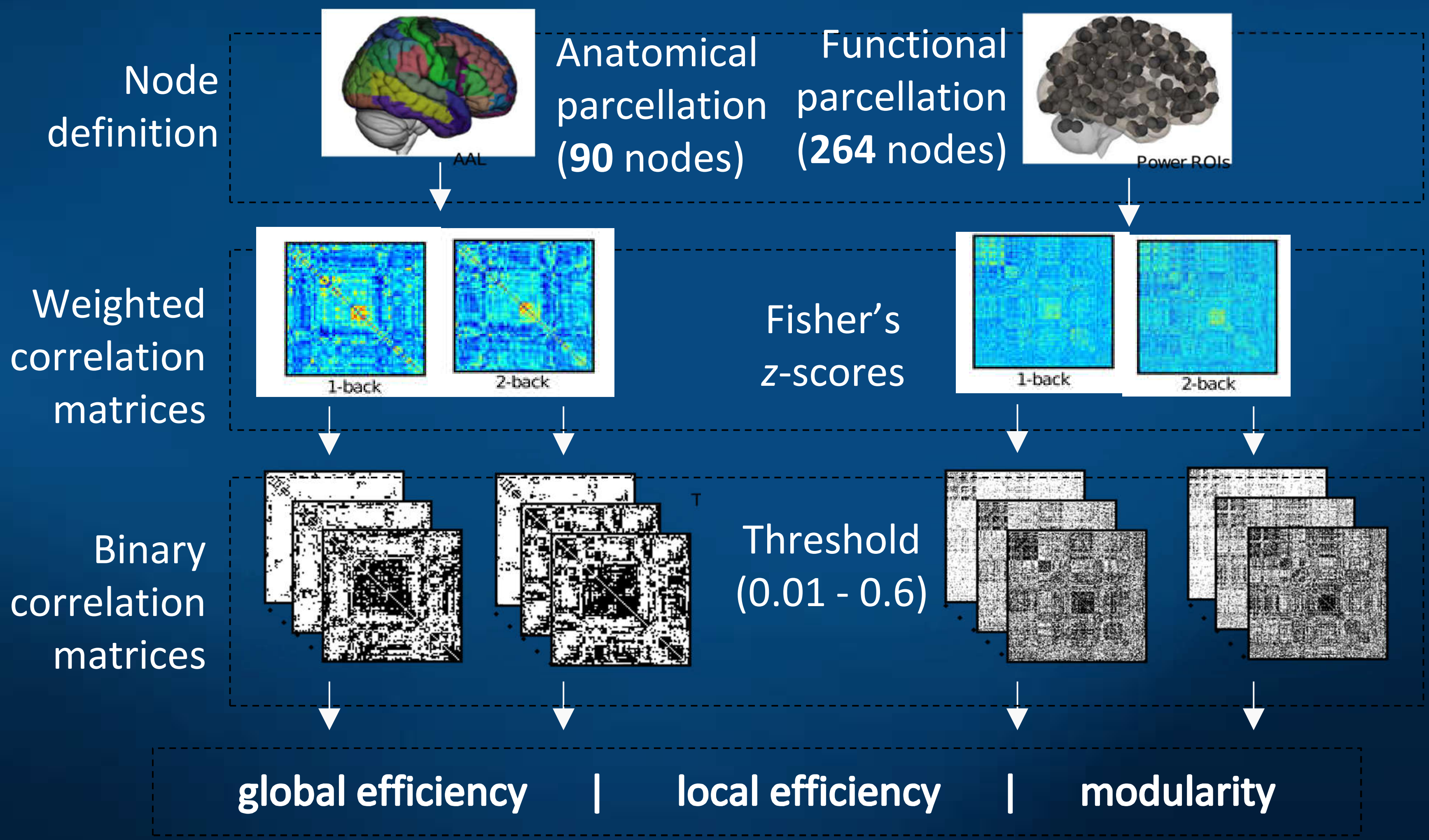
30 s block
10 blocks x **3** sessions

5:30 min per session

Finc et al, Human Brain Mapping, 2017

Data workflow

Two experimental conditions: 1-back, 2-back



Brain modules and cognitive processes

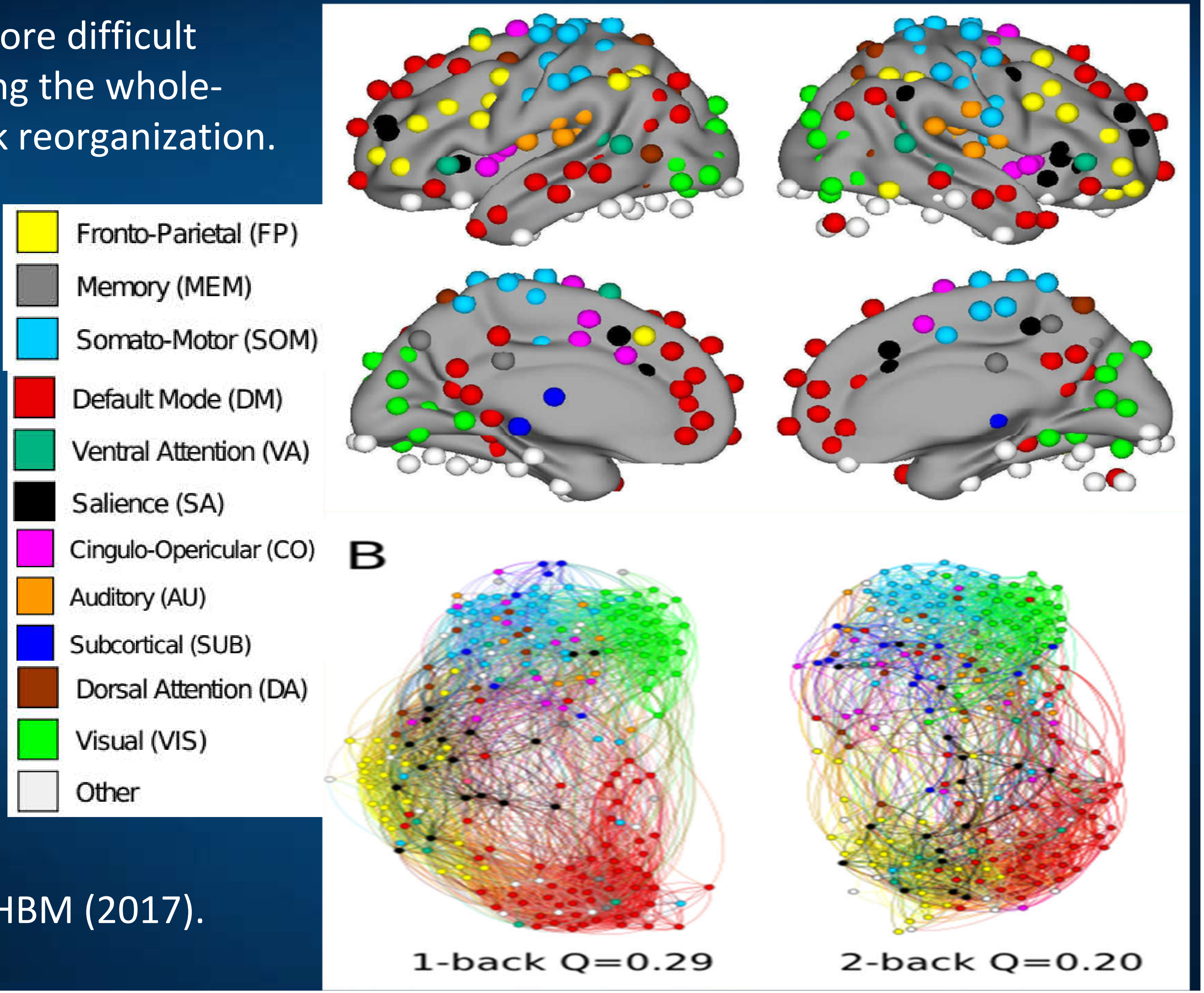
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back

Right: 2-back

Average over 35 participants.

Left and midline sections.



K. Finc et al, HBM (2017).

Brain modules and cognitive processes

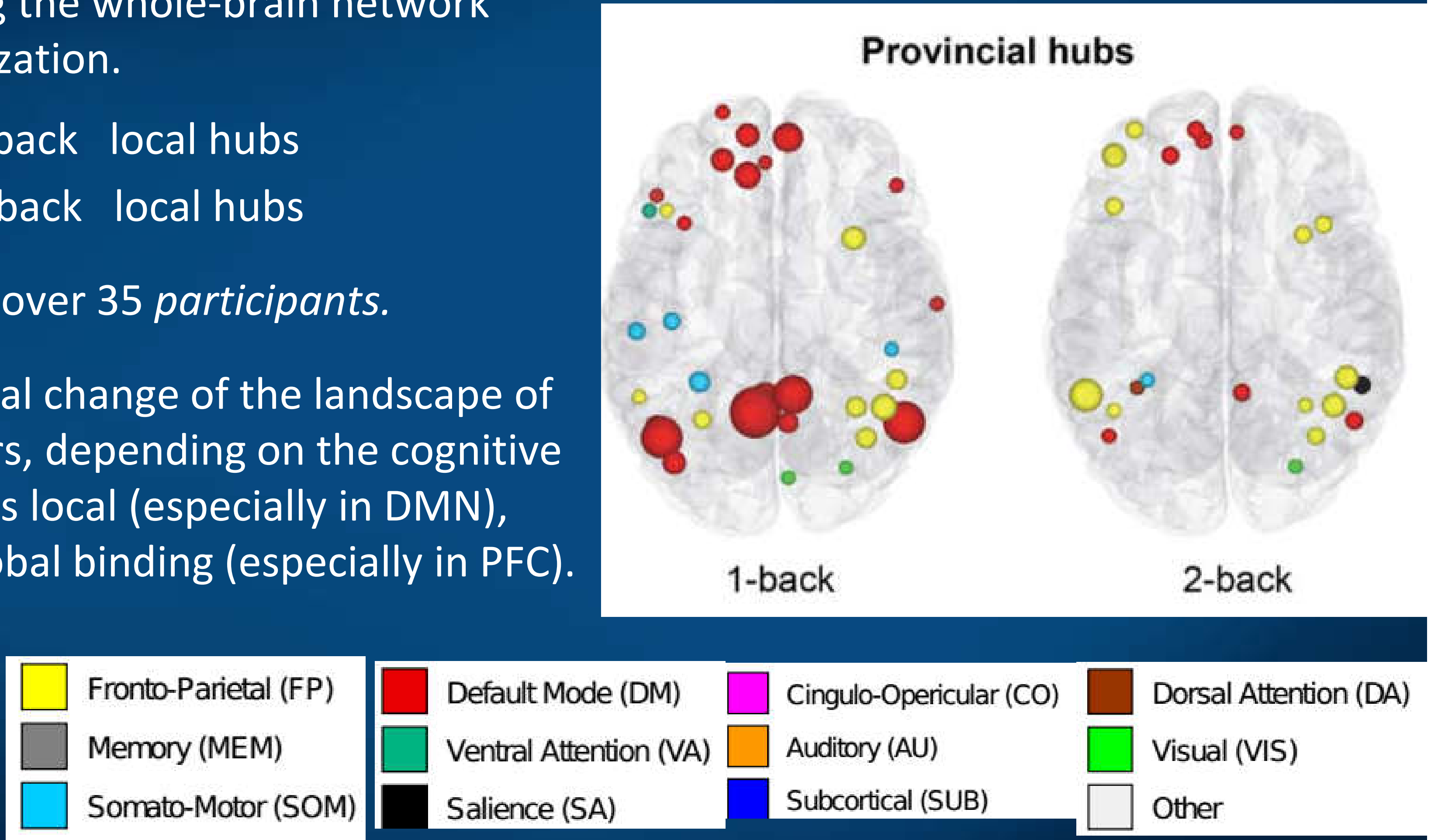
Simple and more difficult tasks, requiring the whole-brain network reorganization.

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).



K. Finc et al, HBM (2017).

Brain modules and cognitive processes

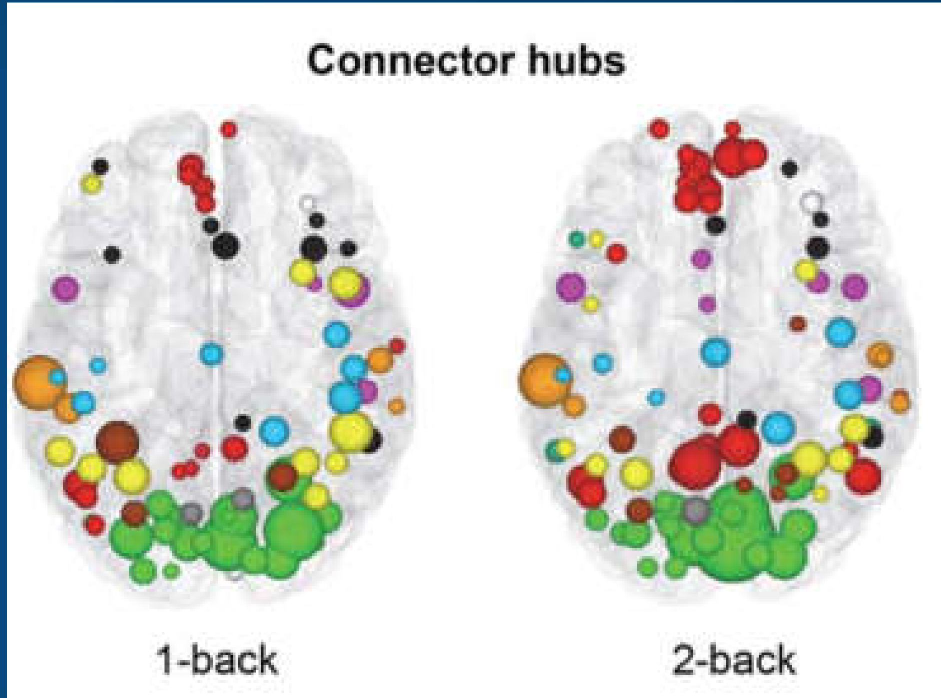
Simple and more difficult tasks, requiring the whole-brain network reorganization.

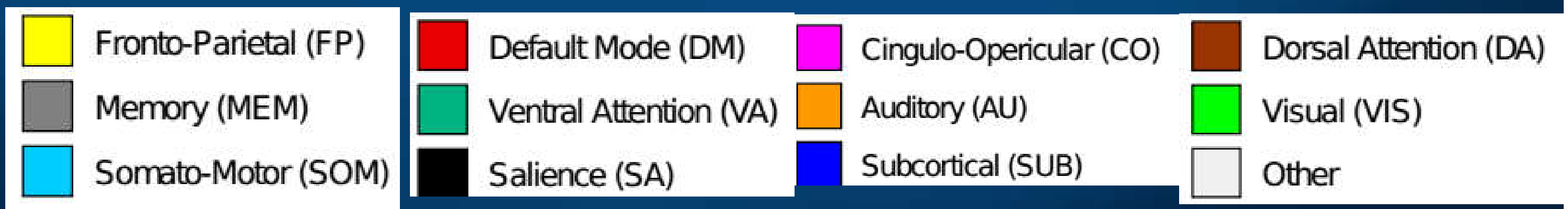
Left: 1-back connector hubs

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!





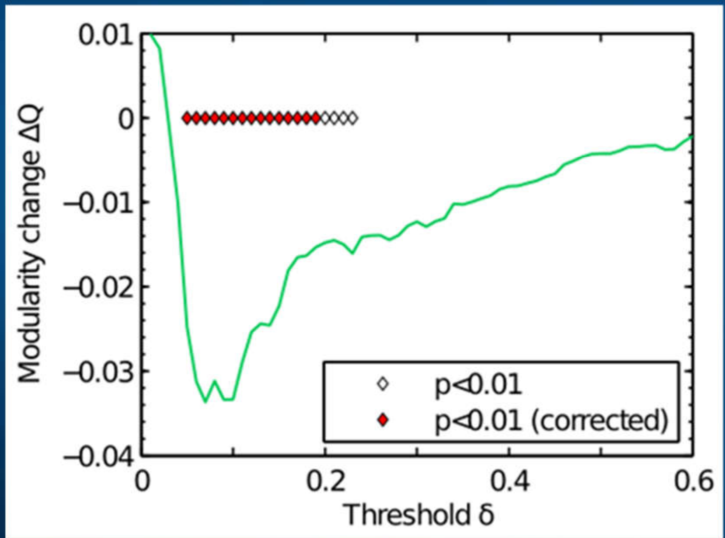
K. Finc et al, HBM (2017).

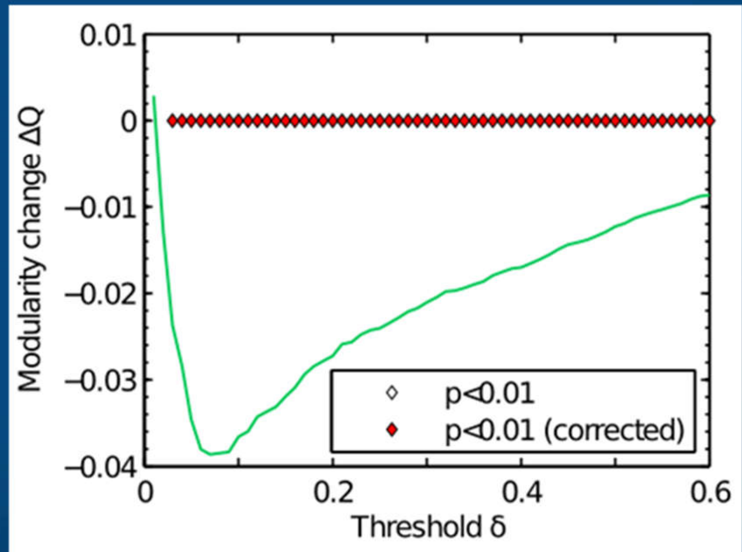
Changes in modularity

Modularity metric: fraction of within-community edges in the network minus such fraction for randomly connected network with unchanged community structure.

Parcellation
AAL, 90 ROI

Parcellation
264 ROI
functional





Modularity for both parcellations significantly decreases for thresholds ~0.1.
Coarse parcellation washes out many effects, especially strong correlations.

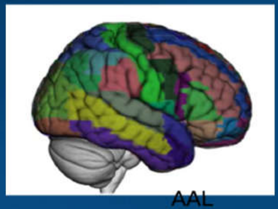
Finc et al, Human Brain Mapping, 2017

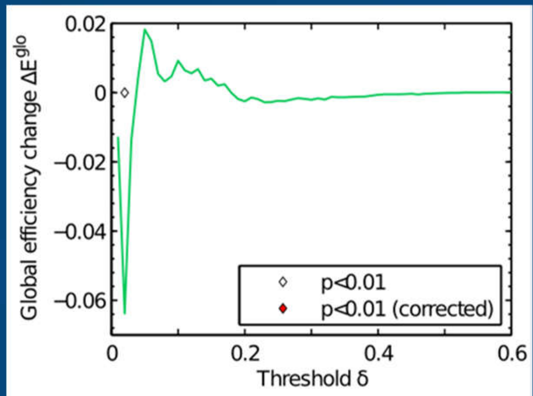
Changes in efficiency

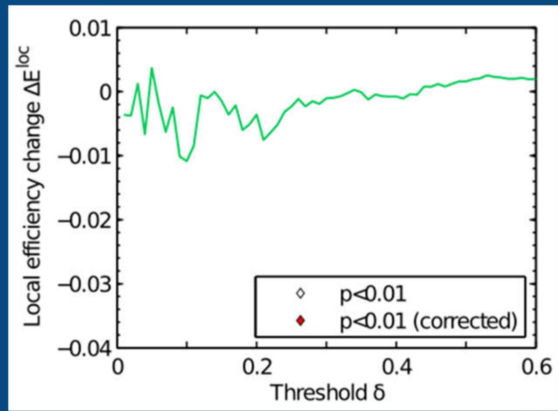
Global efficiency ~ inverse of characteristic path length
Local efficiency ~ clustering coefficient (Latora & Marchiori, 2001).

Global efficiency

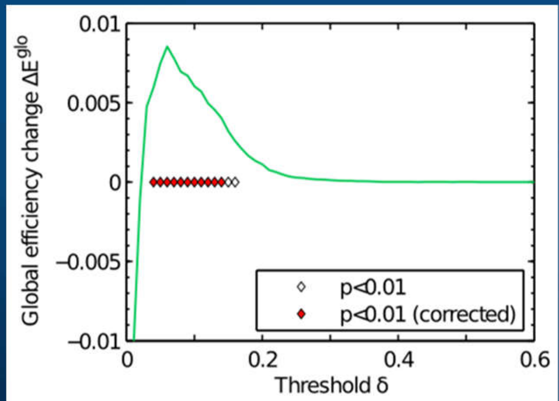
Local efficiency

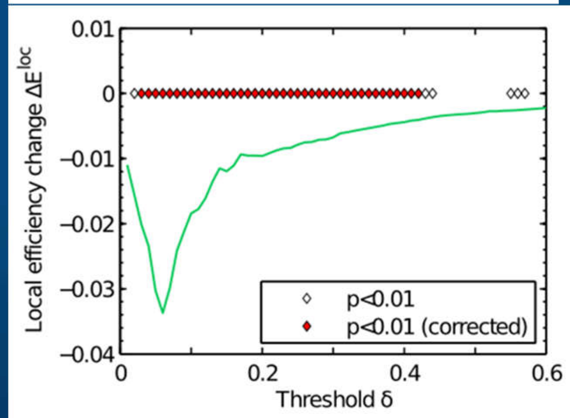






Parcellation
AAL, 90 ROI





Parcellation
264 ROI
functional

Finc et al, Human Brain Mapping, 2017

Cognitive load

Segregated network

Low cognitive effort

Locally specialized processing

↑ global efficiency

↓ local efficiency

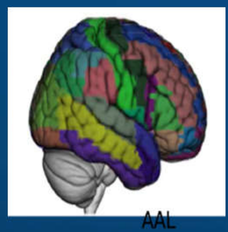
↓ modularity

↓ performance

Integrated network

High cognitive effort

Distributed processing

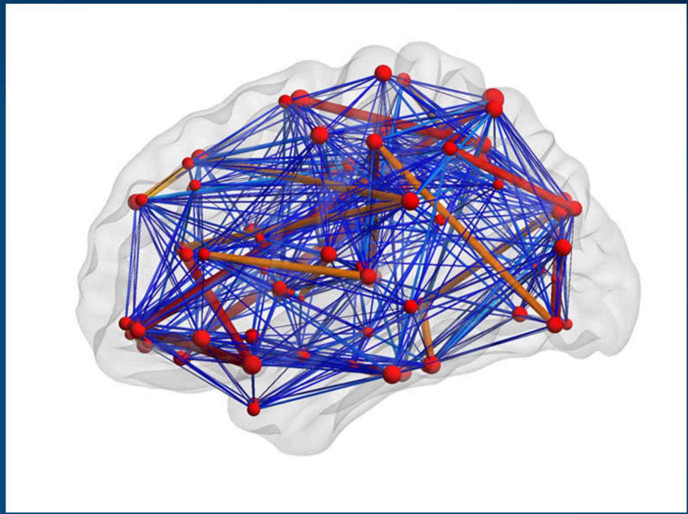


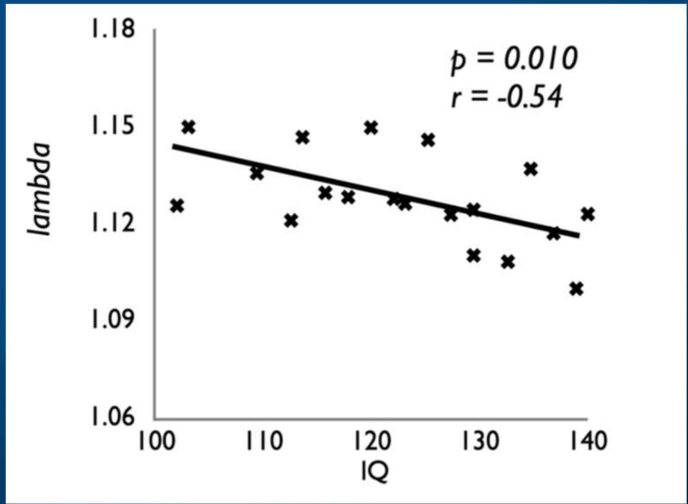
≠

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

Characteristic path length λ	→	Intellectual performance
Modularity	→	Working memory performance
Modularity	→	Working memory capacity



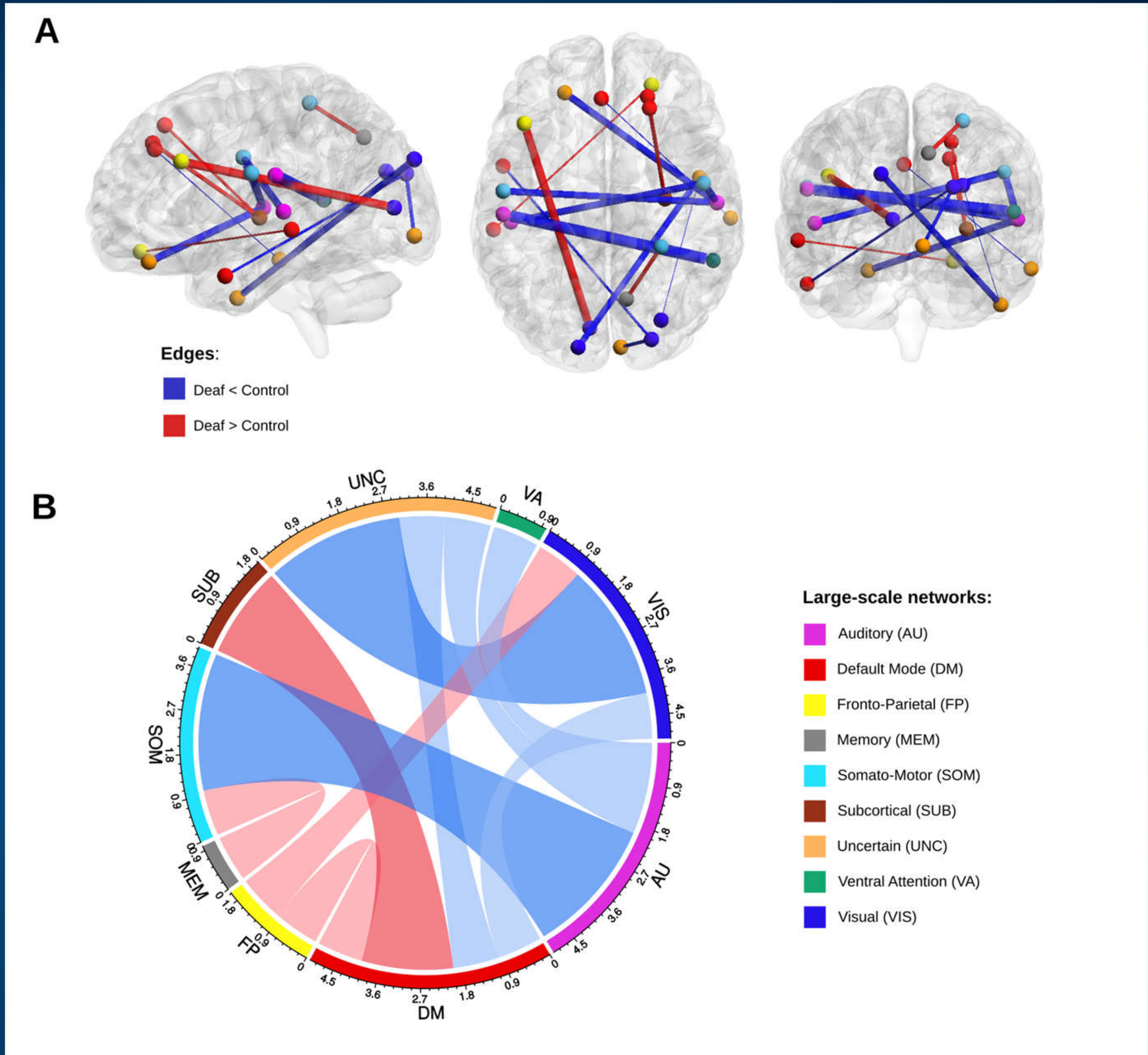


Network modularity ⇔ higher working memory capacity and performance.

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

van den Heuvel *et al.* (2009) | Stevens *et al*. (2012)

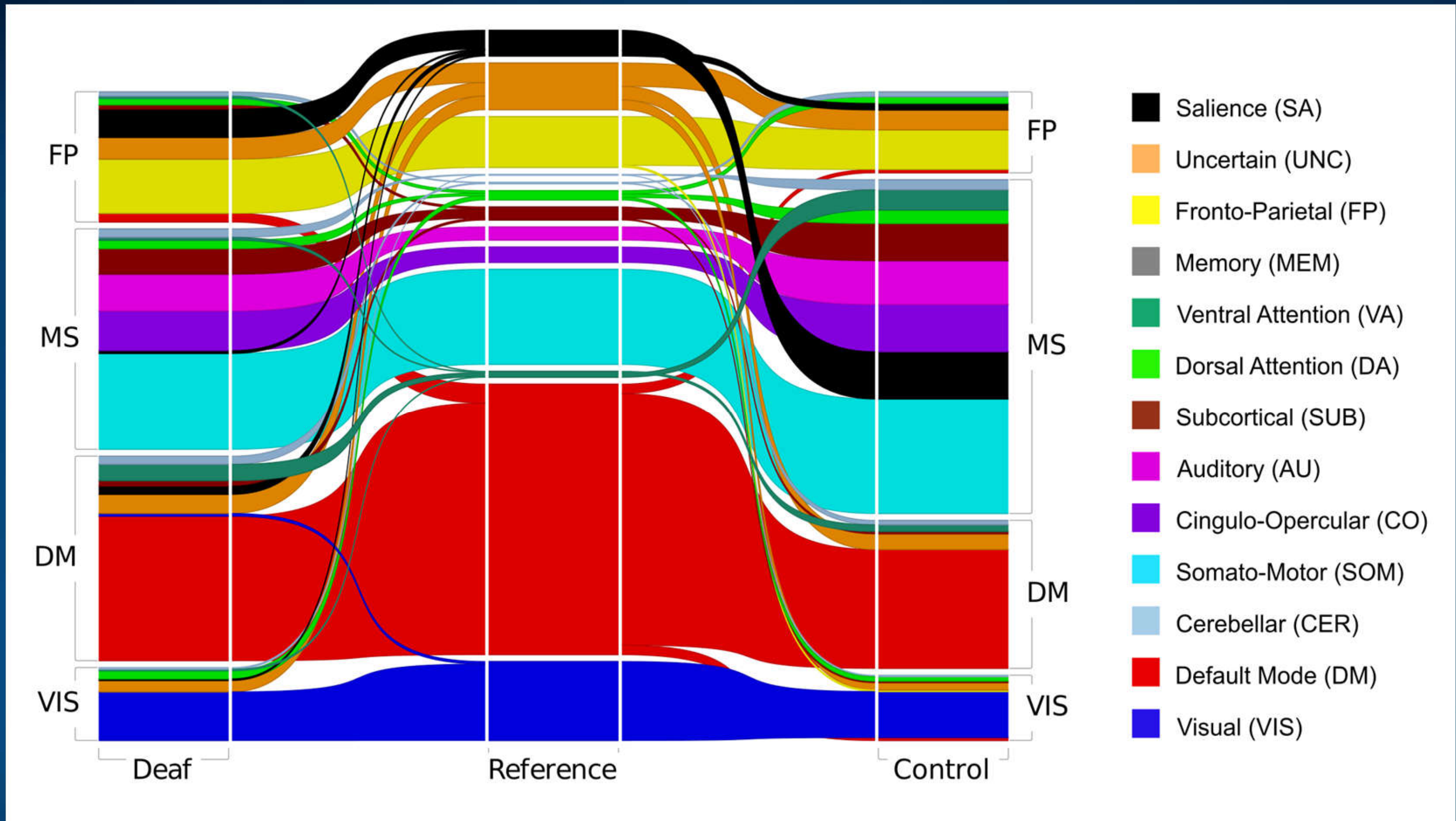
Deaf vs. Control



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

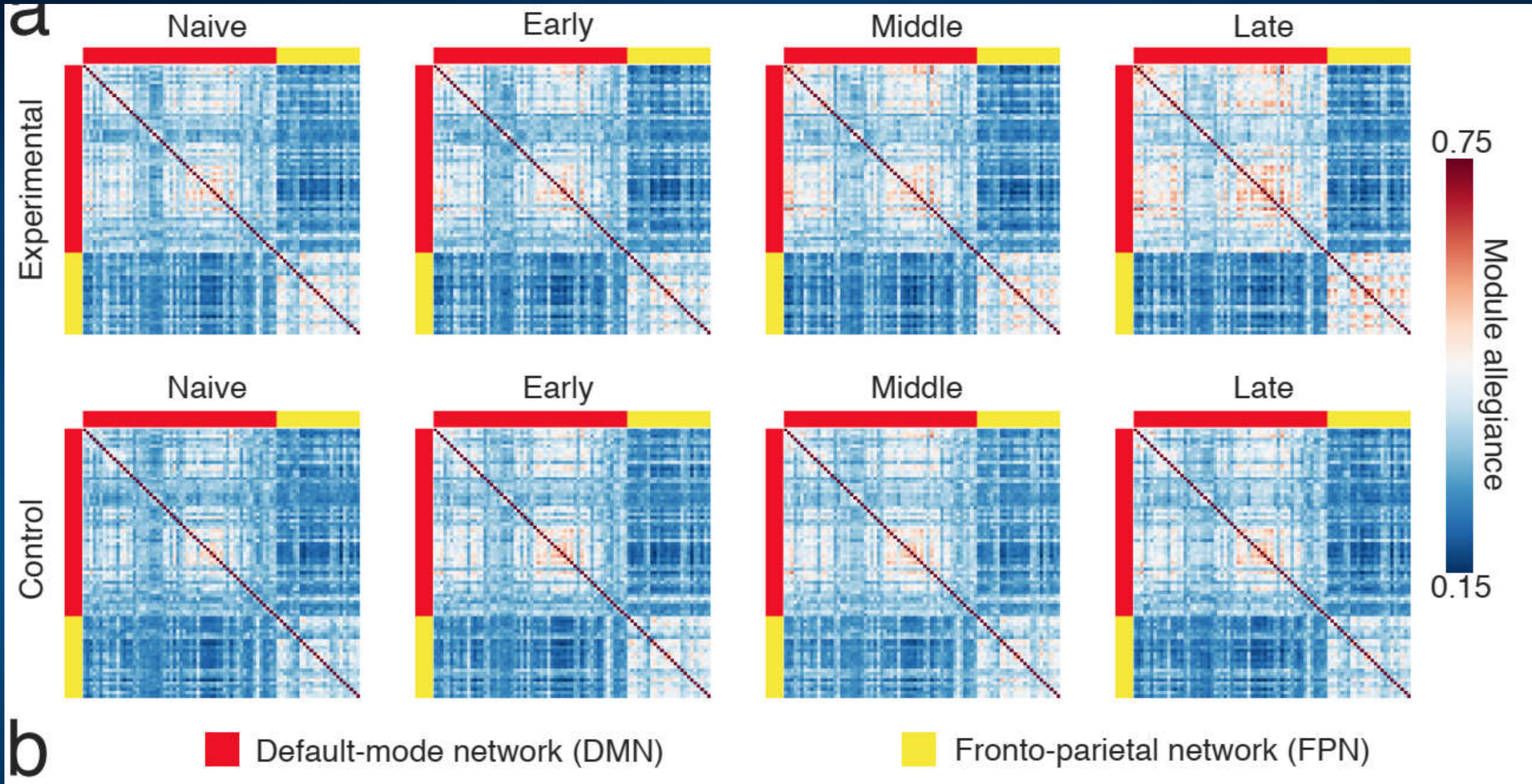
Red bands represent edges with stronger functional connectivity in the deaf compared to hearing control, while blue bands represent edges with weaker functional connectivity. (Bonna, Finc, Szwed et al, in review).

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 deaf group but fall into multi-system (MS) module in control group. Also 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).

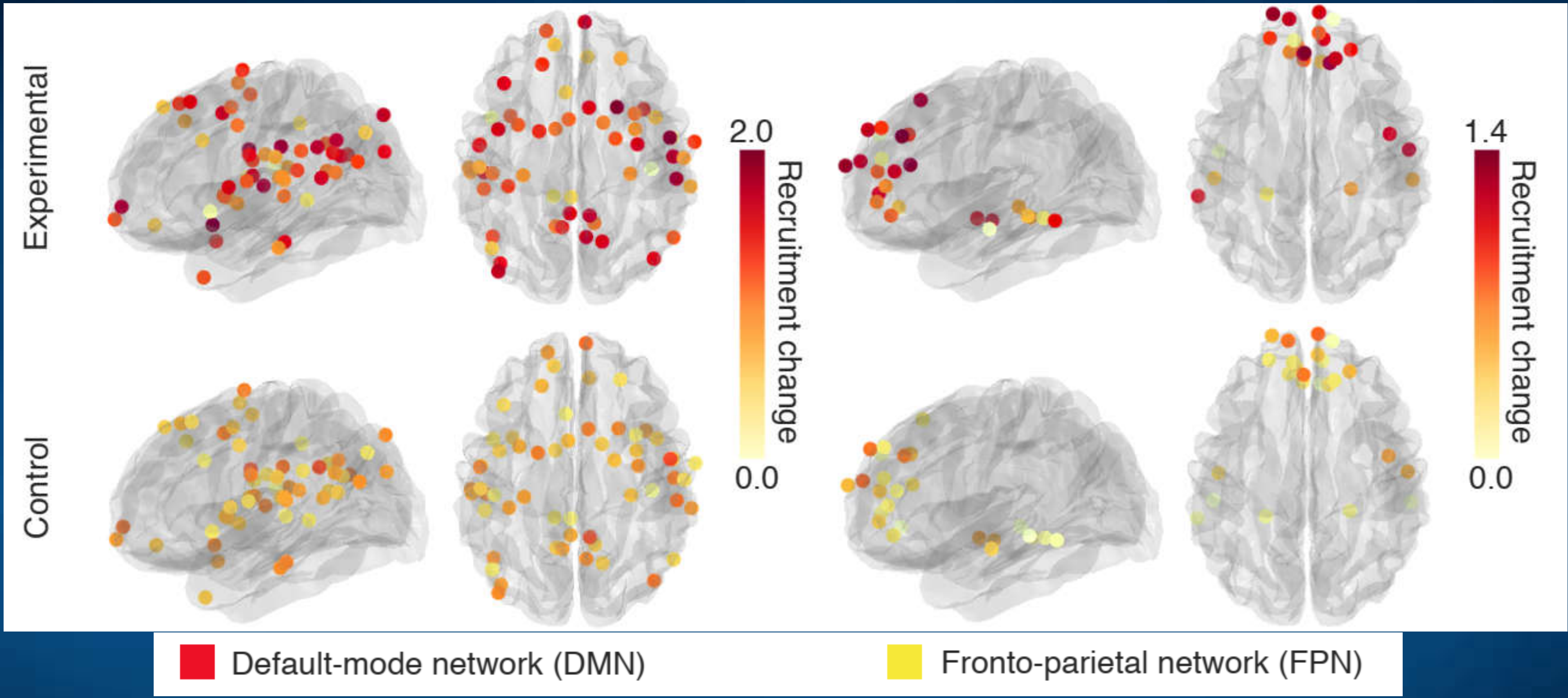
Working memory training



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.

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.

Simulations of brain networks

Model of reading & dyslexia

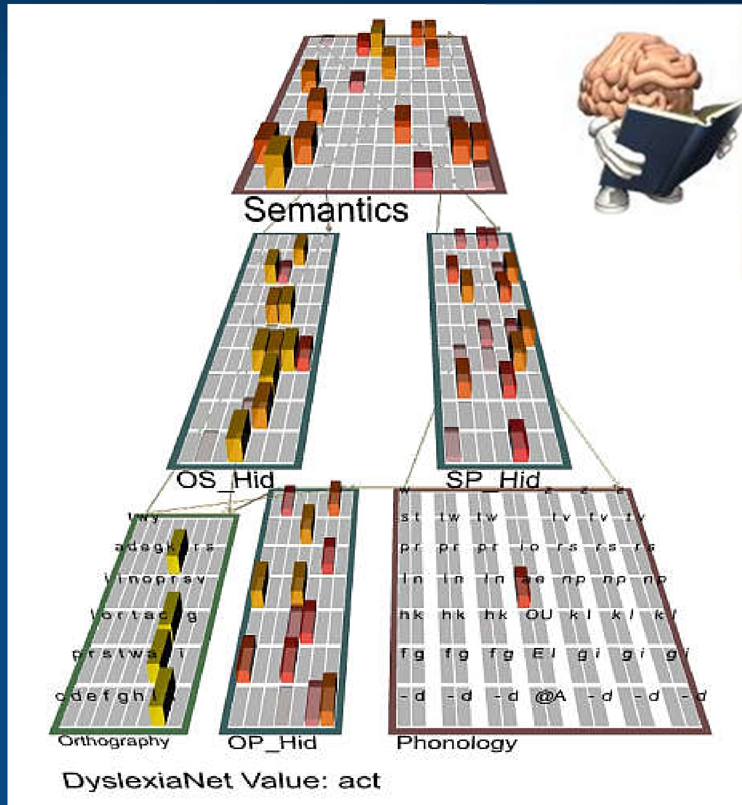
Emergent neural simulator:

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.

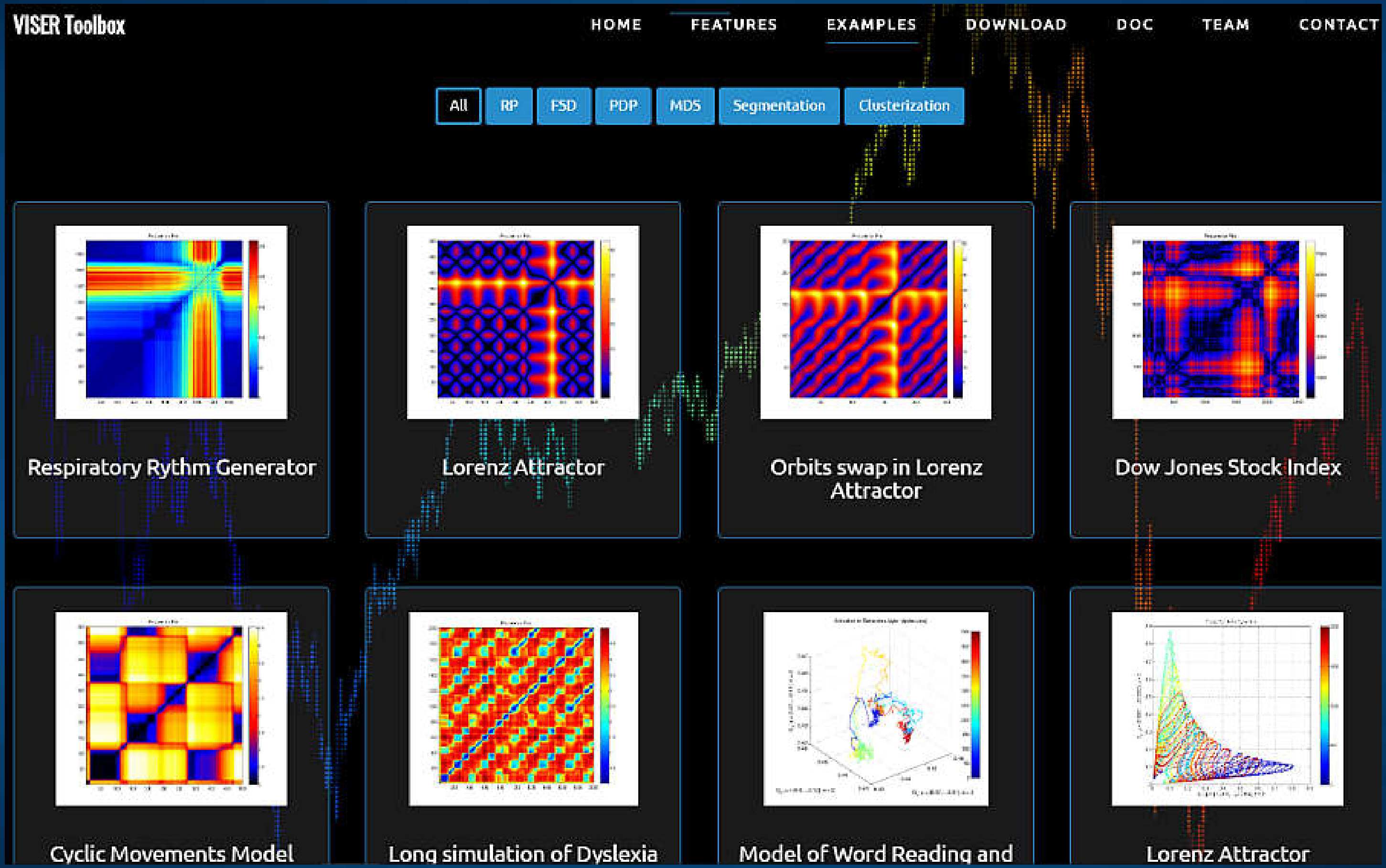


Learning: mapping one of the 3 layers to the other two.

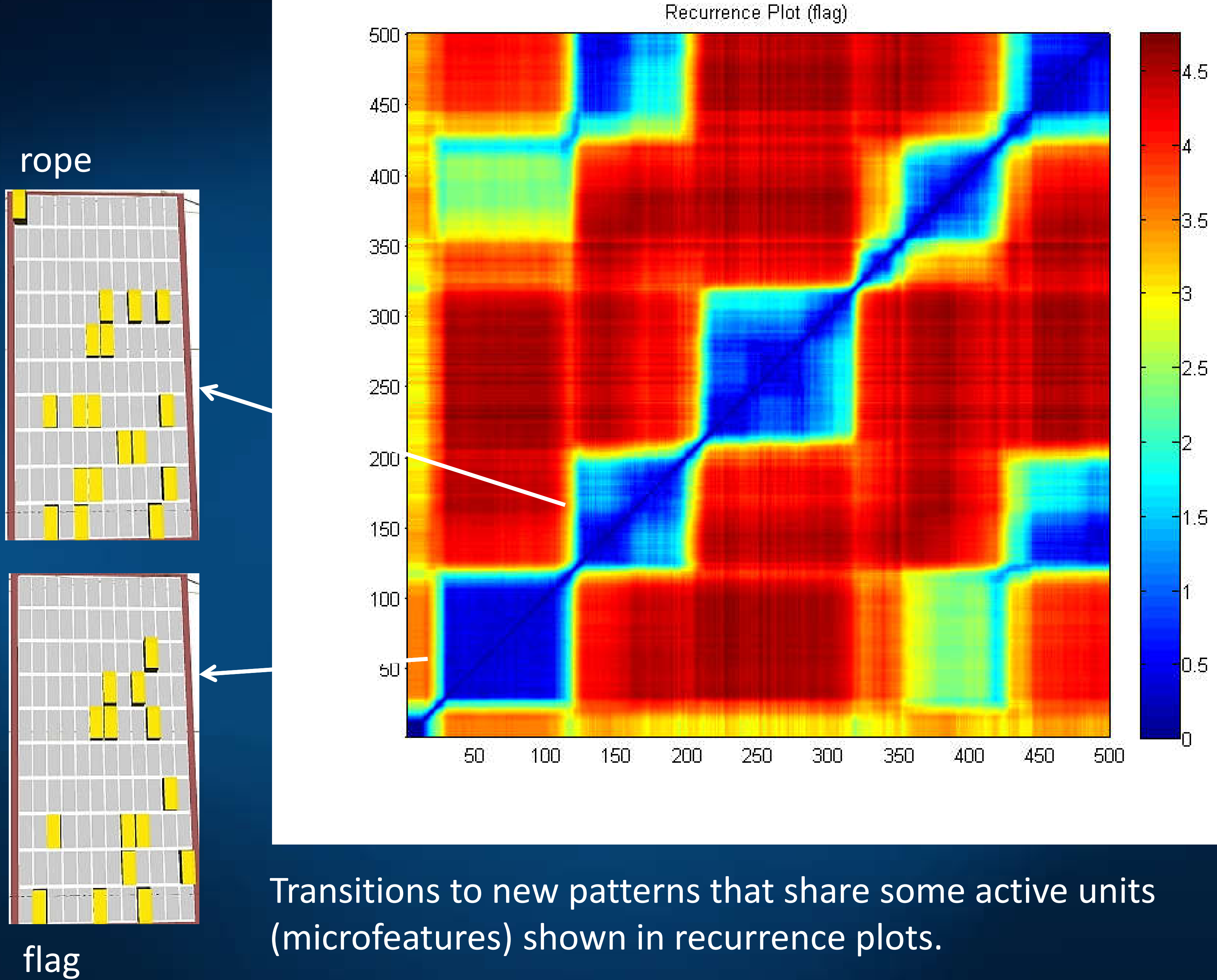
Fluctuations around final configuration = attractors representing concepts.

How to see properties of their basins, their relations?
Model in **Genesis**: more detailed neuron description.

Viser toolbox

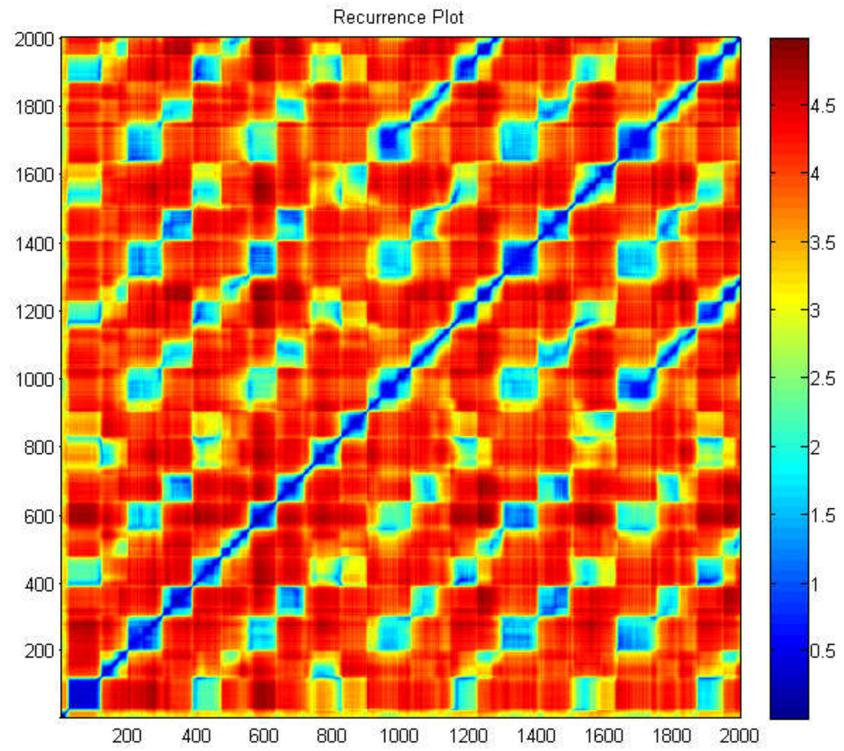


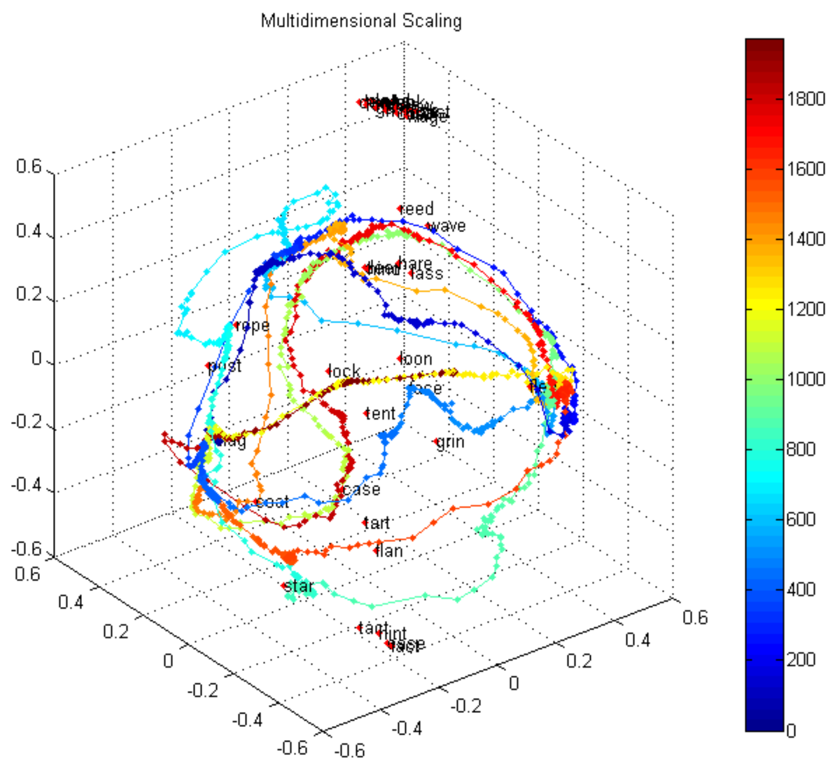
Nasz Viser toolbox (Dobosz, Duch) do wizualizacji szeregów czasowych w wielu wymiarach różnymi technikami.



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

Trajectory visualization

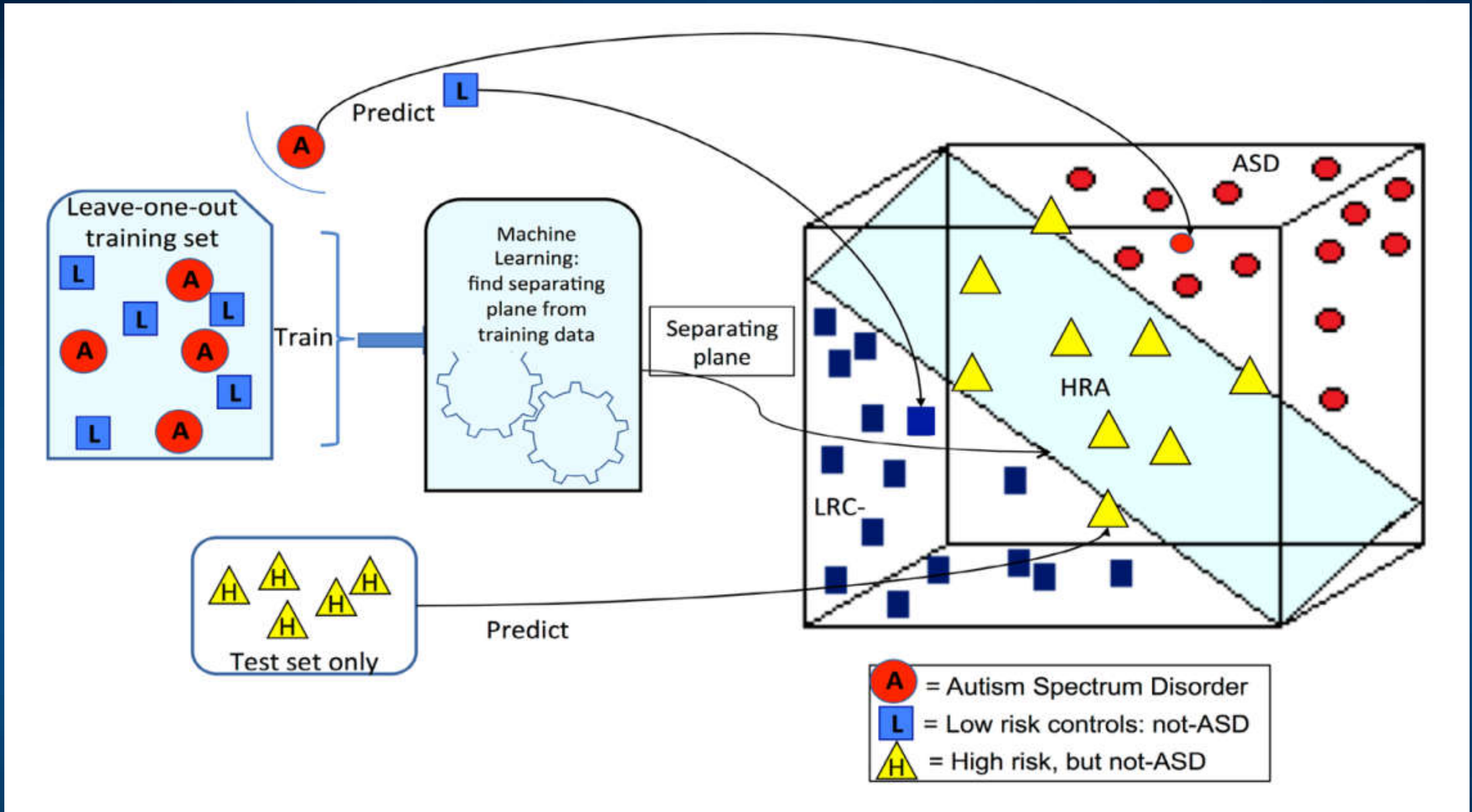




Recurrence plots and MDS/FSD/SNE visualization of trajectories of the brain activity. Here data from 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain, starting with the word “flag”.

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

ASD EEG SVM Classification



Wavelet decomposition, Recurrent Quantification Analysis, feature ranking and machine learning. Nonlinear features are critical to achieve good results, and their correlated with ASD depends on age.

EEG early ASD detection

Bosl, W. J., Tager-Flusberg, H., & Nelson, C. A. (2018). EEG Analytics for Early Detection of Autism Spectrum Disorder: A data-driven approach. Scientific Reports, 8(1), 6828.

EEG of 3 to 36-month old babies, 19 electrodes selected from 64 or 128.

Daubechies (DB4) wavelets transform EEG signal into 6 bands.

7 features from Recurrence Quantitative Analysis (RQA): RP entropy, recurrence rate, laminarity, repetition, max/mean line length, trapping time.

In addition sample entropy and Detrended Fluctuation Analysis was used.

Nonlinear features were computed from EEG signals and used as input to statistical learning methods. Prediction of the clinical diagnostic outcome of ASD or not ASD was highly accurate.

SVM classification with 9 features gave high specificity and sensitivity, exceeding 95% at some ages. Prediction using only EEG data taken as early as 3 months of age was strongly correlated with the actual measured scores.

EEG non-linear features

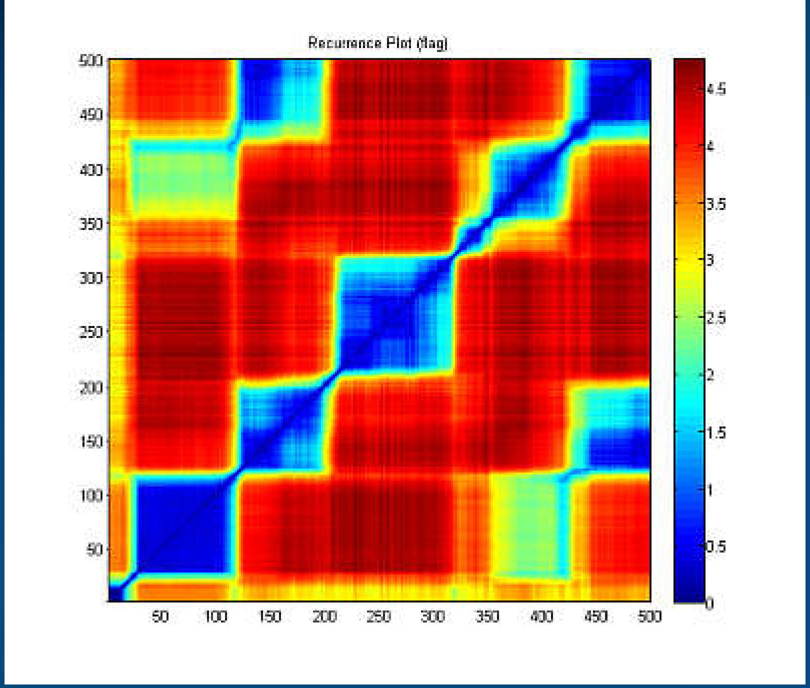
Features: not only structure, but also dynamics.

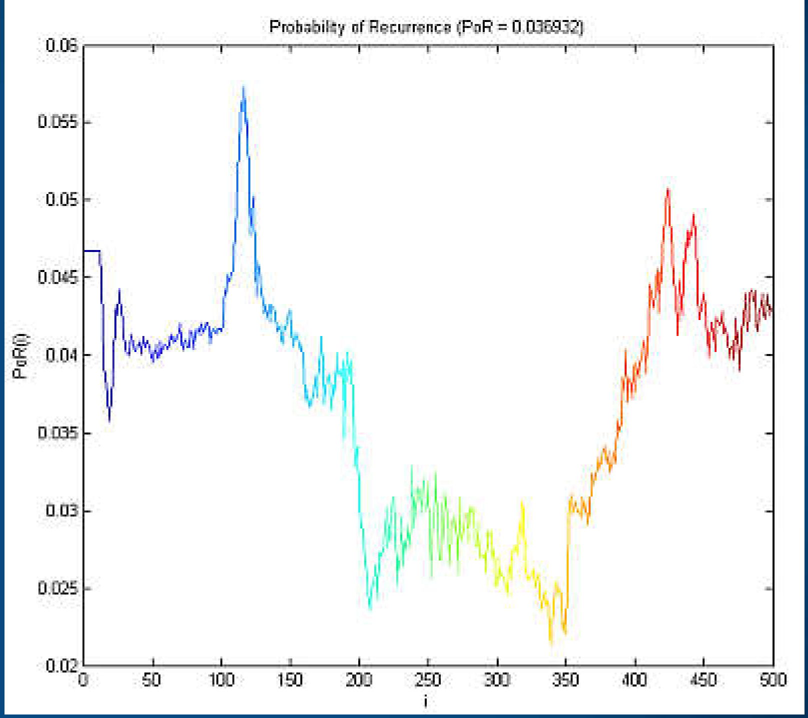
Nonlinear invariant measures of a time series and their physical interpretation, recurrence quantification analysis (RQA).

For example:

1. Sample Entropy (SampE)
2. Entropy derived from recurrence plot (L_entr).
3. Recurrence rate (RR), probability of recurrence.
4. Determinism (DET), repeating patterns in the system.
5. Laminarity (LAM), frequency of transitions between states.
6. Trapping time (TT), time in a given state.

Probability of recurrence





Probability of recurrence may be computed from recurrence plots, or from clusterization of trajectory points, allowing for evaluation how strongly some basins of attractors capture neurodynamics.

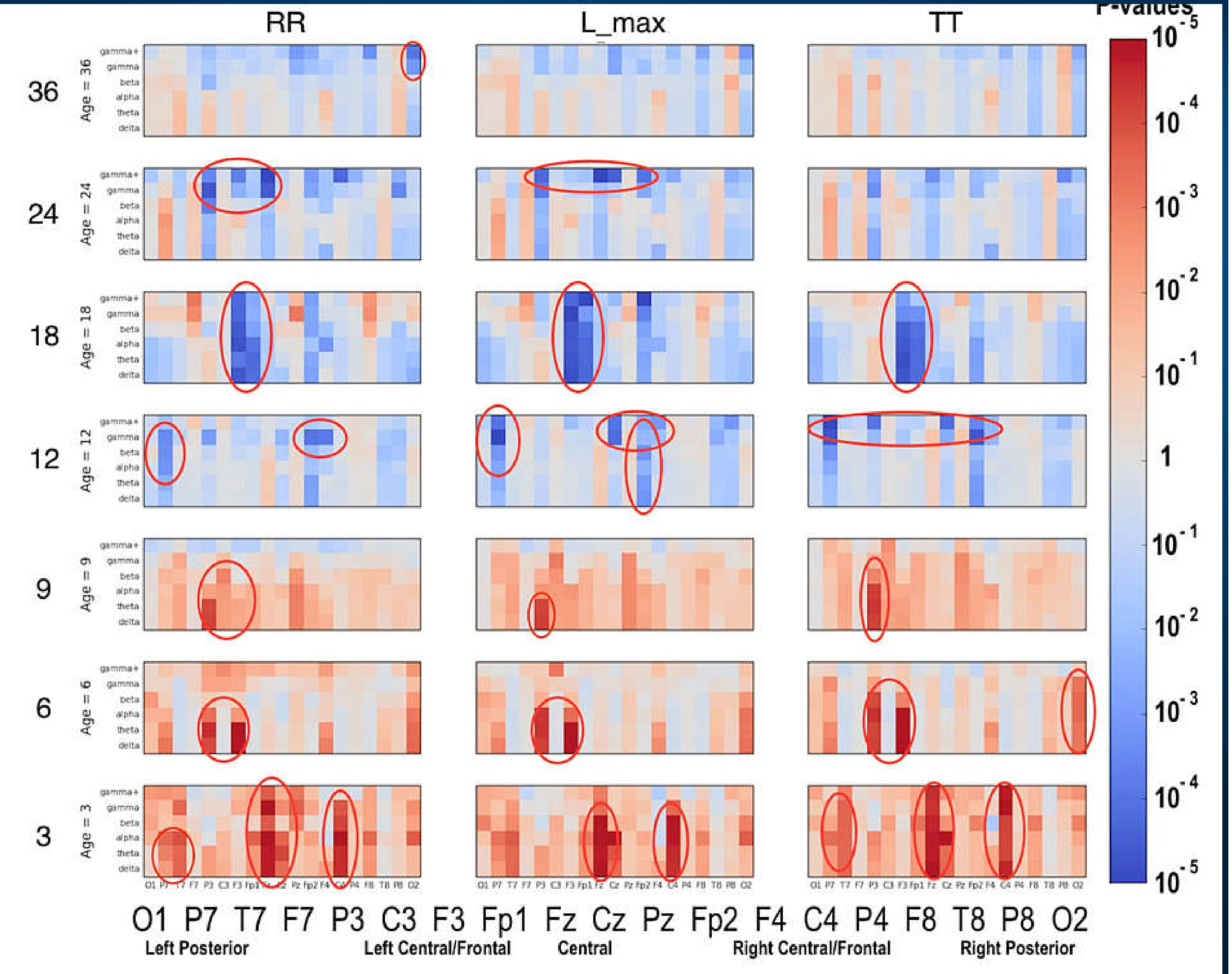
Our Viser Toolbox is used for all visualizations

ASD vs Low Risk Healthy

RR = recurrence rate

L_max = max line length, related to Lyapunov exponent

TT = trapping time

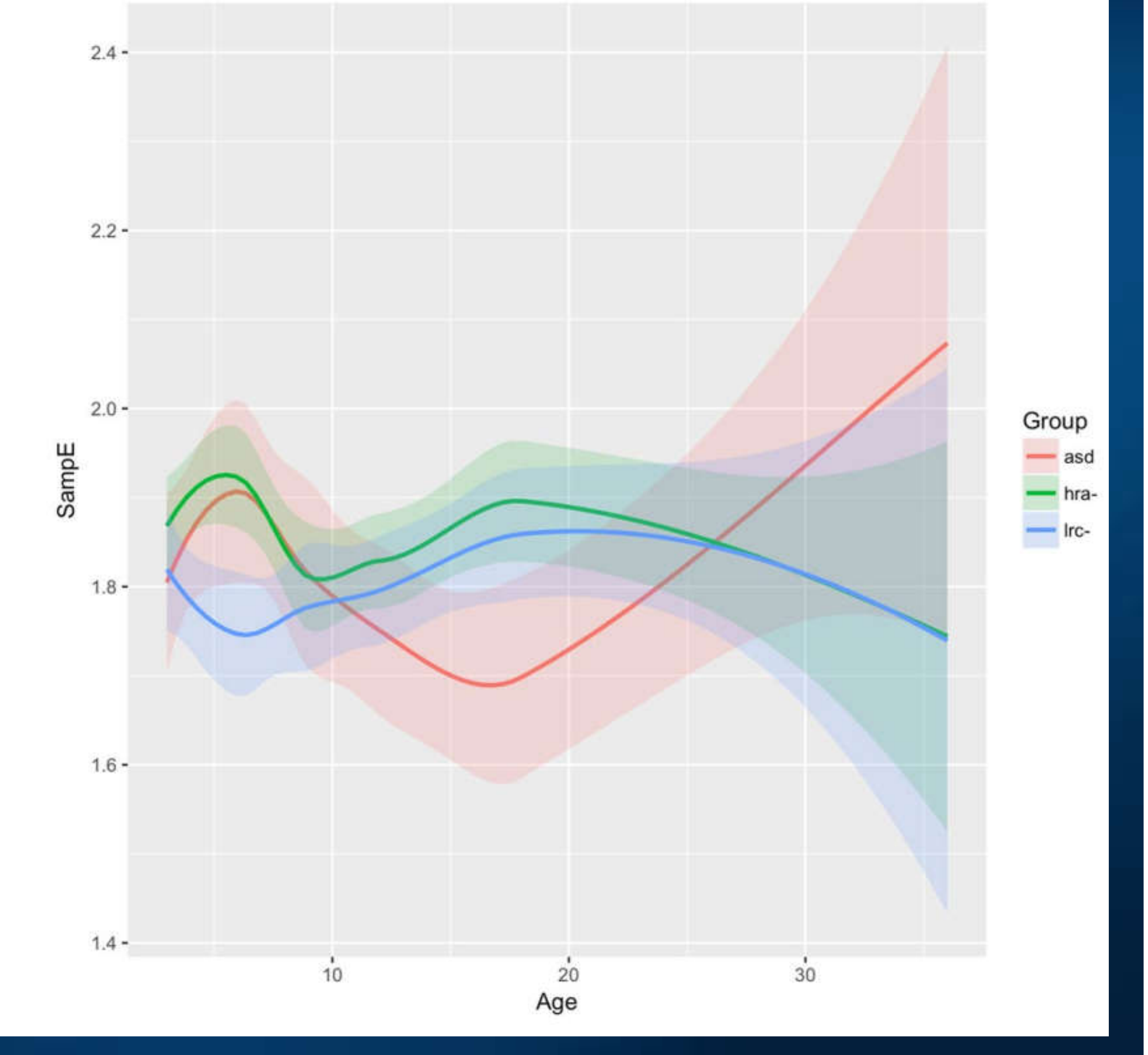


ASD EEG SVM Classification

Developmental trajectories for SampE in the left temporal region (T7 sensor) in higher frequencies (beta+gamma) for ASD, LRC-, and HRA-

LRC low risk controls

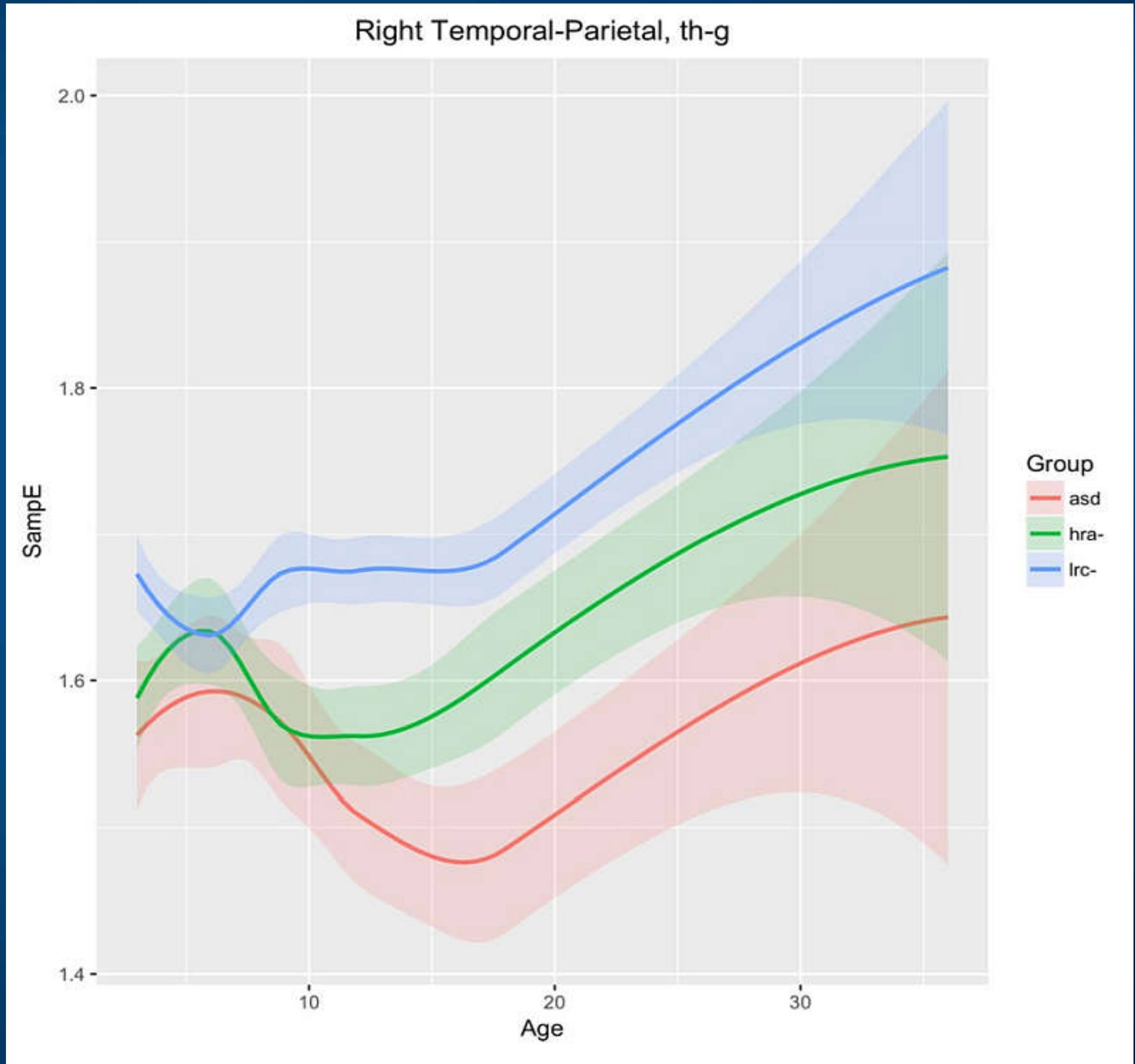
HRA high risk for ASD - no ASD



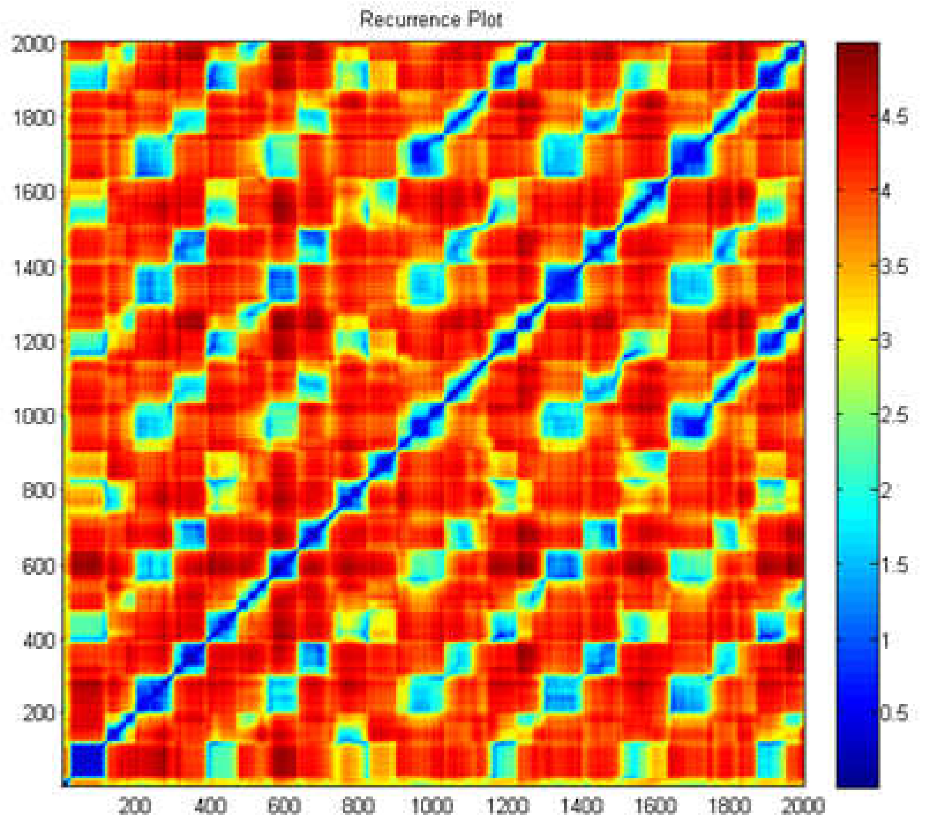
ASD EEG SVM Classification

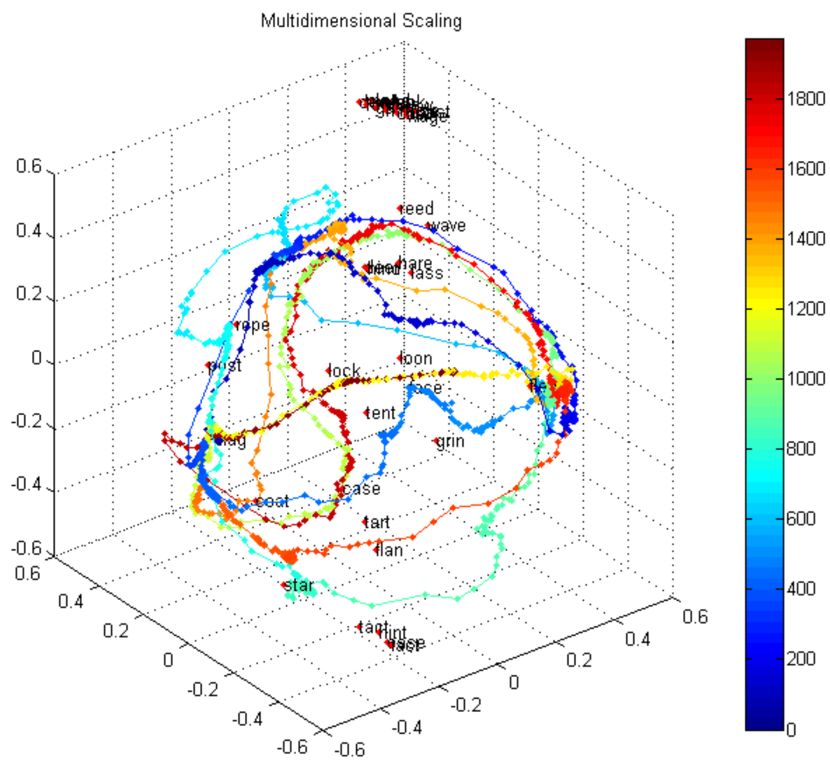
Developmental trajectories for SampE in the right temporal-parietal region

(T8 +P4+P8 sensors) in frequencies theta through gamma for ASD, LRC-, and HRA-.



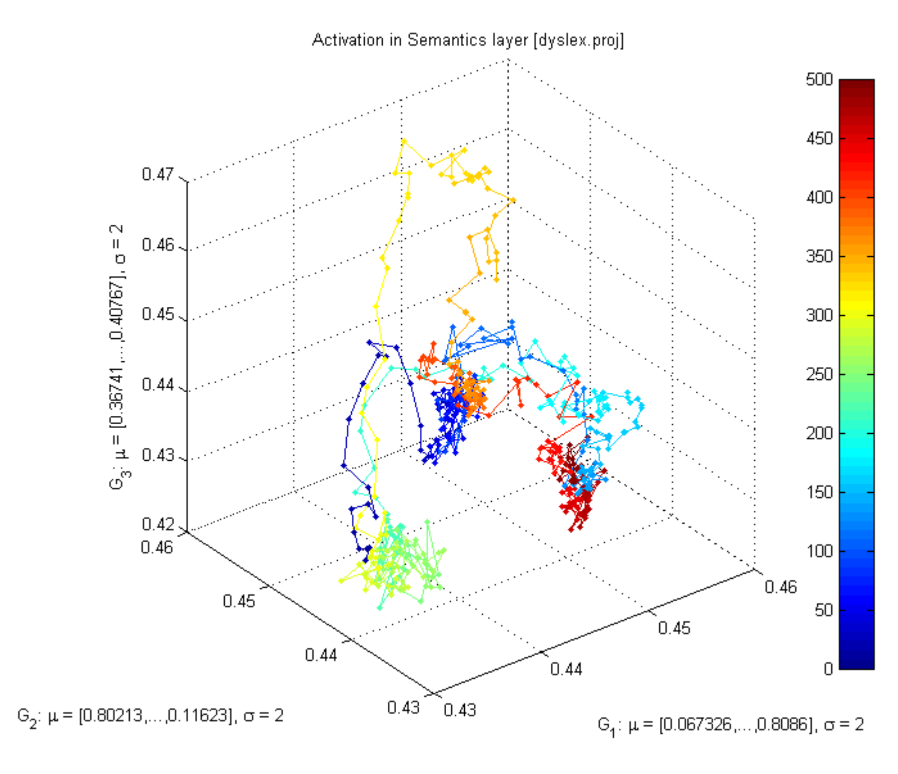
Trajectory visualization

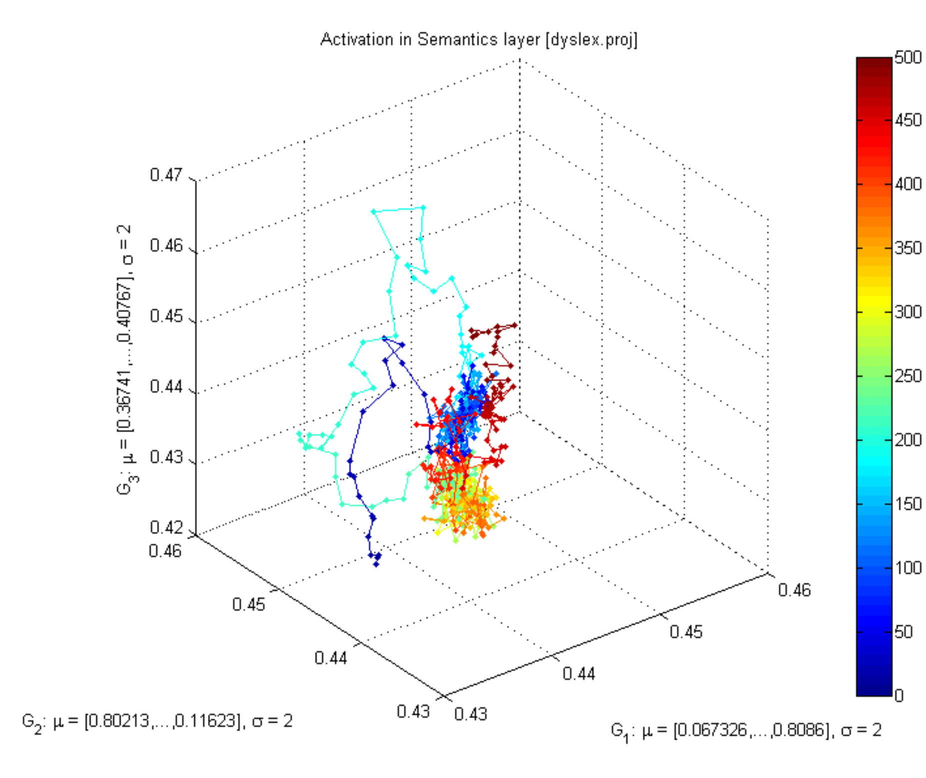




Trajectories may be visualized either using recurrence plots that shows relative changes of the trajectory or some form of visualization showing absolute positions of points on trajectories (MDS/FSD/SNE). Visualization shows transitions between microstates, or attractor states.

Typical Development vs. Autism



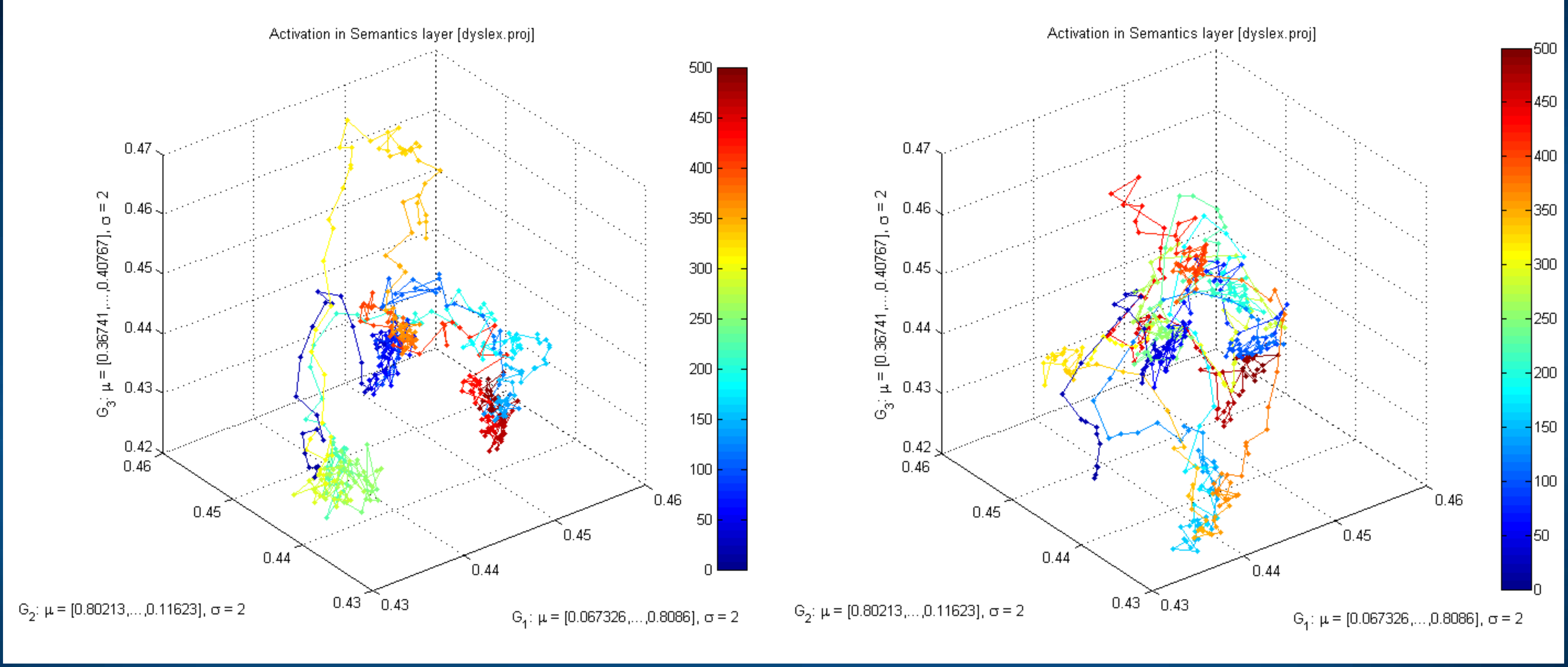


All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. b_inc_dt = 0.01 & b_inc_dt = 0.005

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

Typical Development vs ADHD

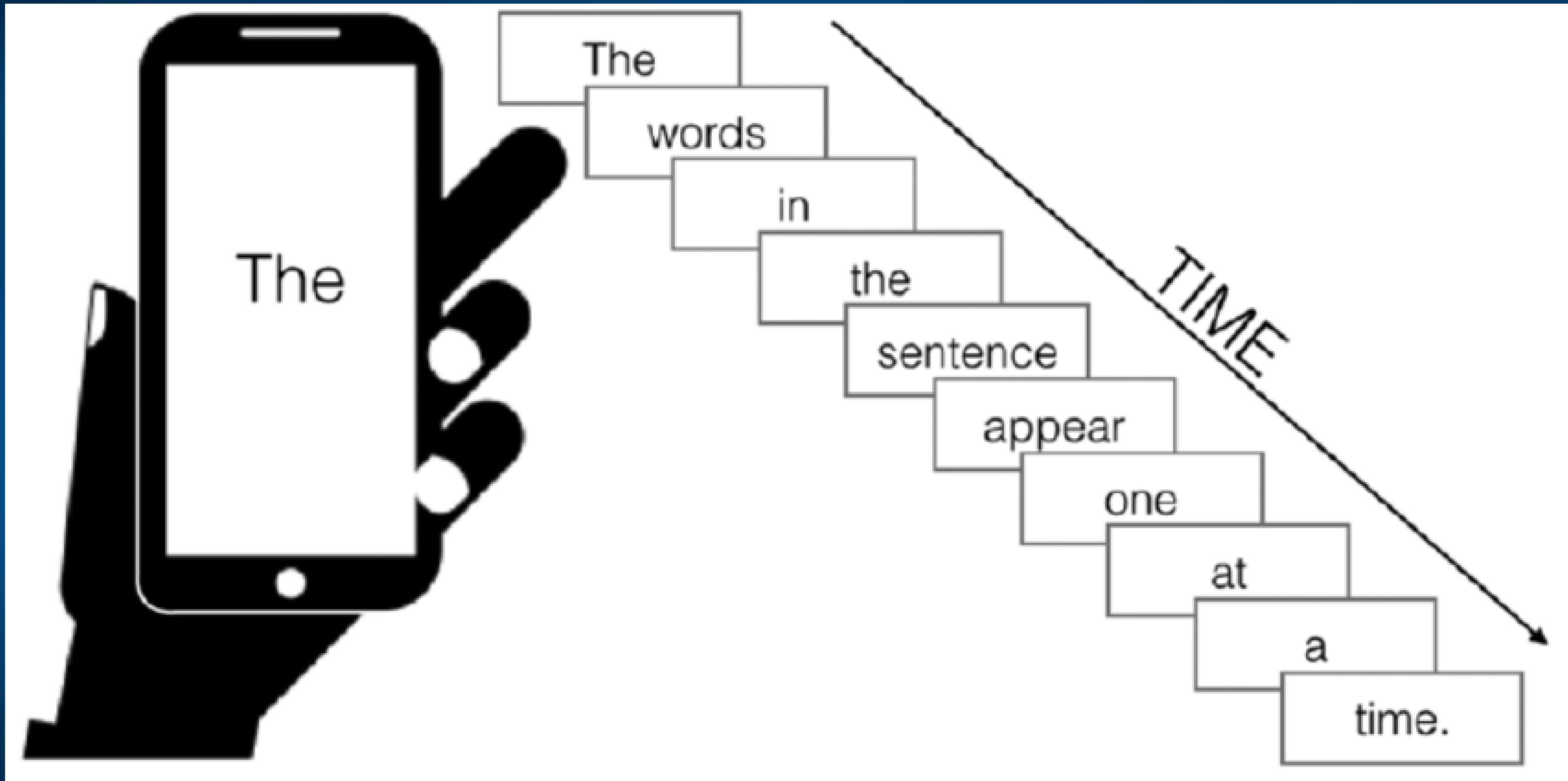


All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. b_inc_dt = 0.01 & b_inc_dt = 0.02.

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

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

Rapid Serial Visual Presentation

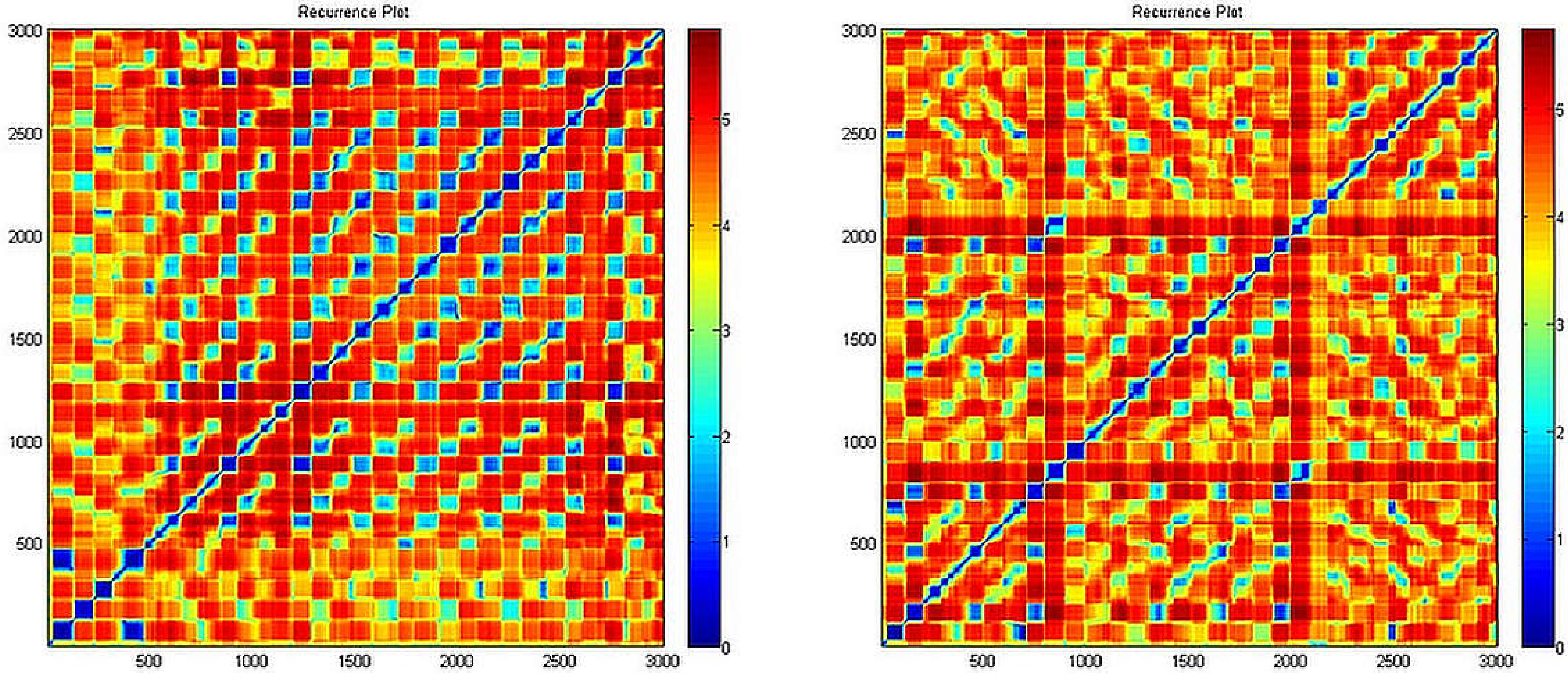


Any RSVP applications for fast reading.

Simulation: showing series of words, looking for attention/associations.

star => flea => tent => lock => tart => hind

RSVP: typical brain



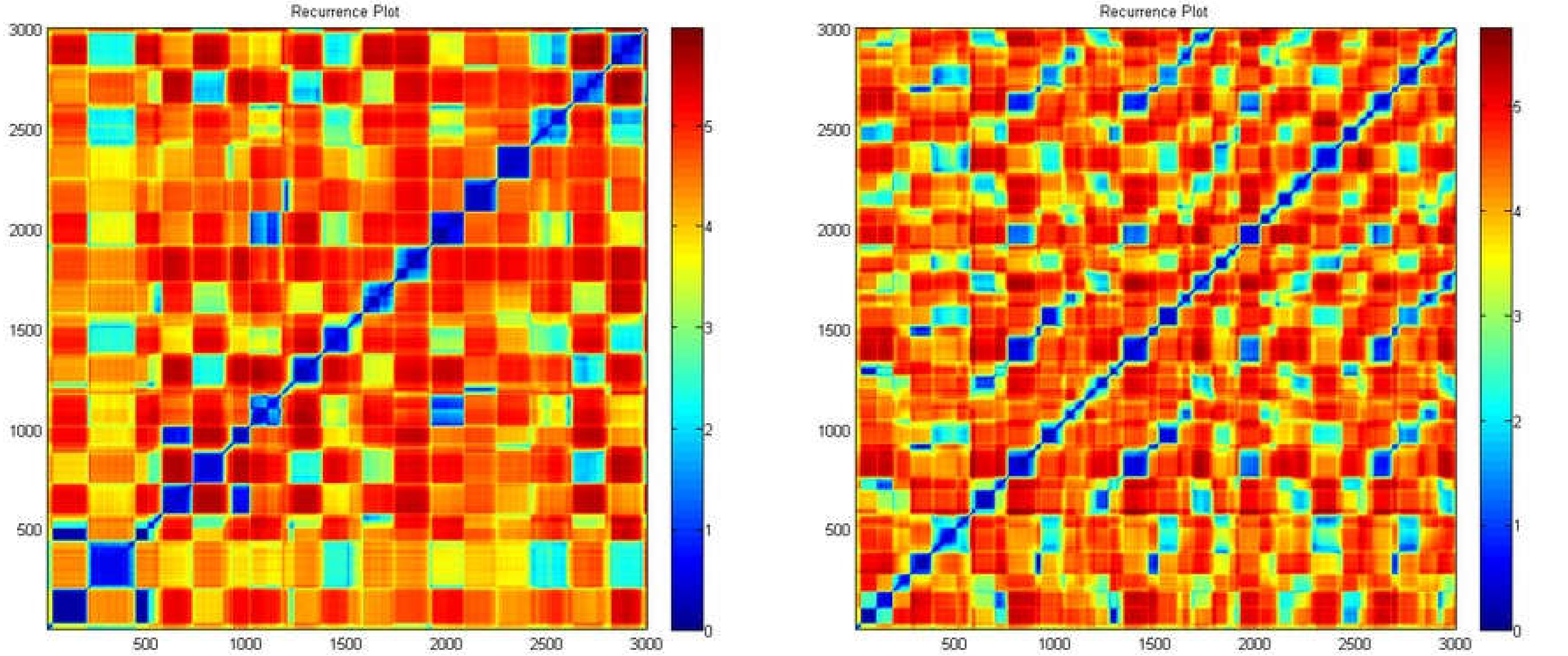
Normal speed
associations, context=>understanding

Some shallow microstates, no associations

too fast, speed 5x
microstates get blurred,

few associations

RSVP simulations: HFA

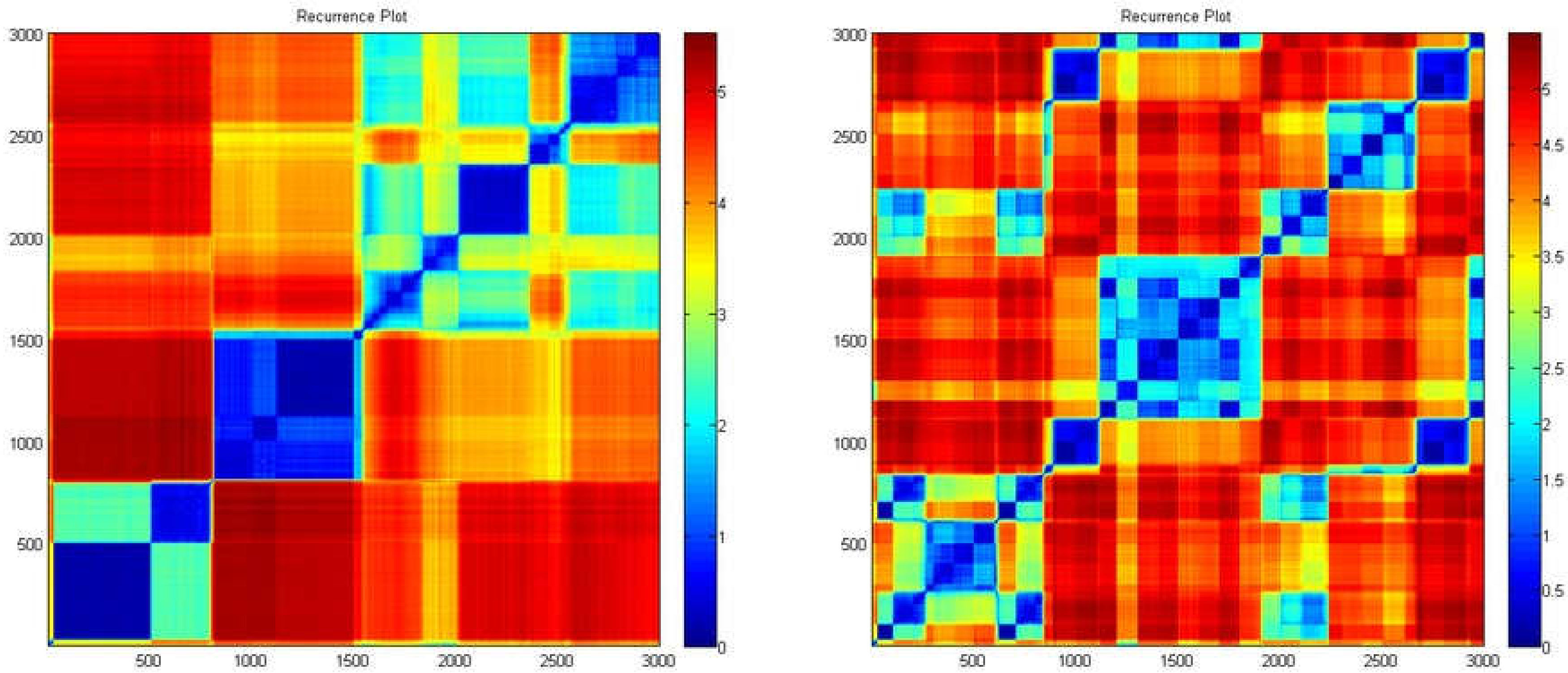


High functioning ASD case (HFA):

normal presentation
long dwelling times

fast presentation
enforced quick resynchronization
more internal stimuli.

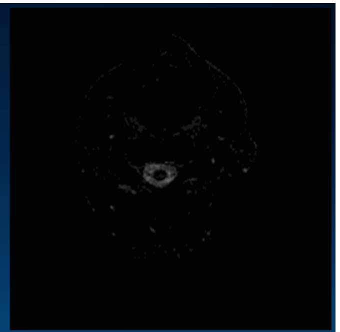
RSVP simulations in deep autism



Normal speed
skipping some words,
no associations

fast presentation
more internal states
some associations arise

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 ⇔ models of whole brain (TVB) ⇔ networks, neurodynamics ⇔ interpretation, mental states: S(B) ⇔ S(M).
- Neurodynamics is the key to understanding mental states; it creates dynamical forms, changing states of functional connectomes without re-arranging physical elements. Influence of other phenomics levels on mental states may be understood indirectly, via changes in neurodynamics.
- AI/ML draws inspirations from brain research, but also neural network models and learning algorithms (CNN, recurrence networks, reinforcement learning) help to interpret information processing in the brain.
- Many neurocognitive technologies are coming, helping to diagnose, repair and optimize brain processes.

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

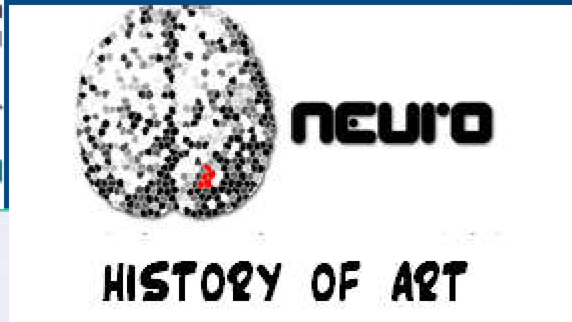
My group of neuro-cog-fanatics

Soul or brain: what makes us human? Interdisciplinary Workshop with theologians, Toruń 19-21.10.2016

Monthly international developmental seminars (2017): Infants, learning, and cognitive development

Disorders of consciousness 17-21.09.2017

Autism: science, therapies 23.05.2017



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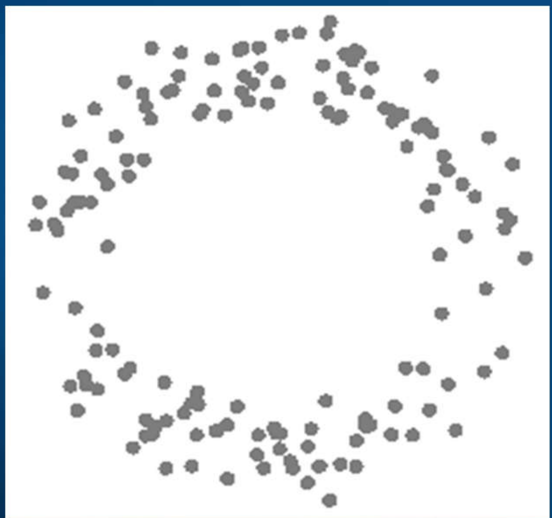
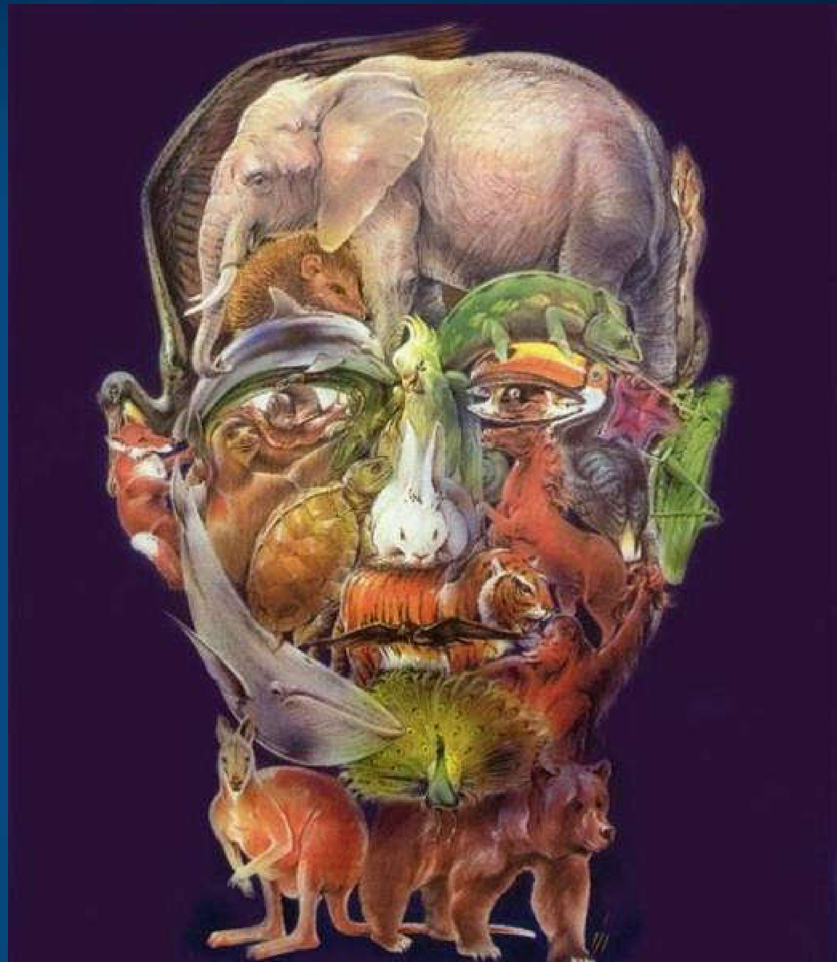
Thank you for synchronization of your neurons





Google: W. Duch

=> talks, papers, lectures, Flipboard …