Challenges and prospects of neuroinformatics

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Statistical Physics in Complex Systems seminar, Wrocław Technical University, 7.05.2021

Neuroinformatics

AI ⇔ Neuroscience

Simulations of Neurodynamics

EEG and Neurodynamics

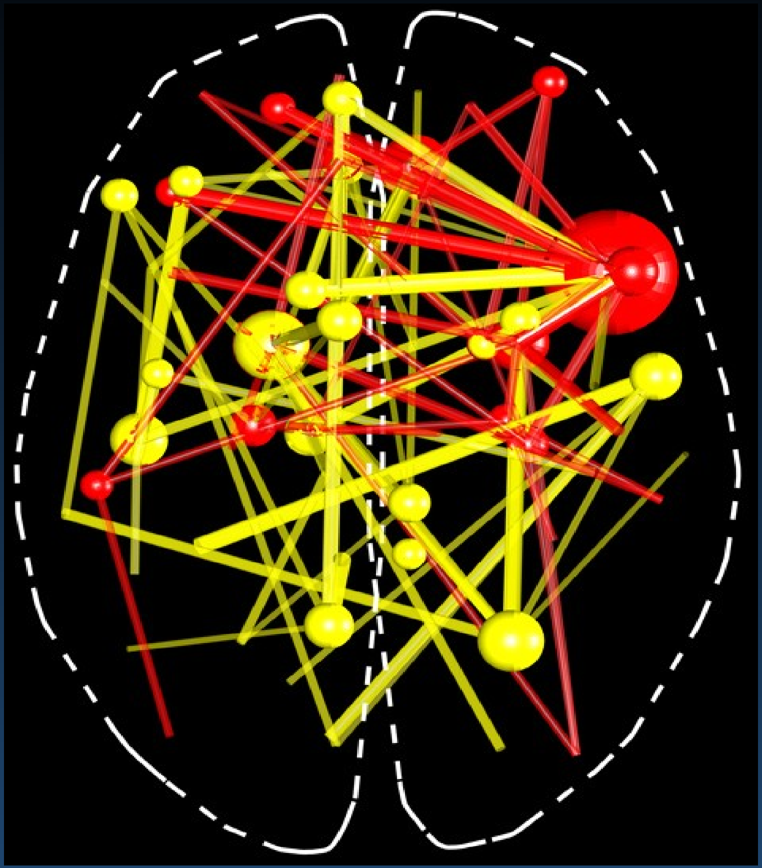
fMRI and Brain functions

On the threshold of a dream …

Unique moment in history of civilizations!

How can 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)

CD DAMSI

University Centre of Excellence (2020)
"Dynamics, mathematical analysis and artificial intelligence".

1. Dynamics and ergodic theory (Math)
2. Computer science – formal languages and concurrency (Theoretical CS)
3. Entangled states and dynamics of open quantum systems (Math Physics)
4. Neuroinformatics and artificial intelligence (Neuroinformatics). Understanding the brain and inspirations for better neural algorithms.

Neuroinformatics is a combination of two important disciplines on the science front: brain research and artificial intelligence. By using machine learning and signal processing methods, new theories and algorithms for brain signal analysis are developed, verifying hypotheses through experiments.

International Neuroinformatics Coordination Facility (INCF.org), coordinated by Karolinska Institutet, Stockholm: 18 countries, 120 institutions. Polish node in IBD PAN (Nenckiego Institute), moved in 2017 to our group.

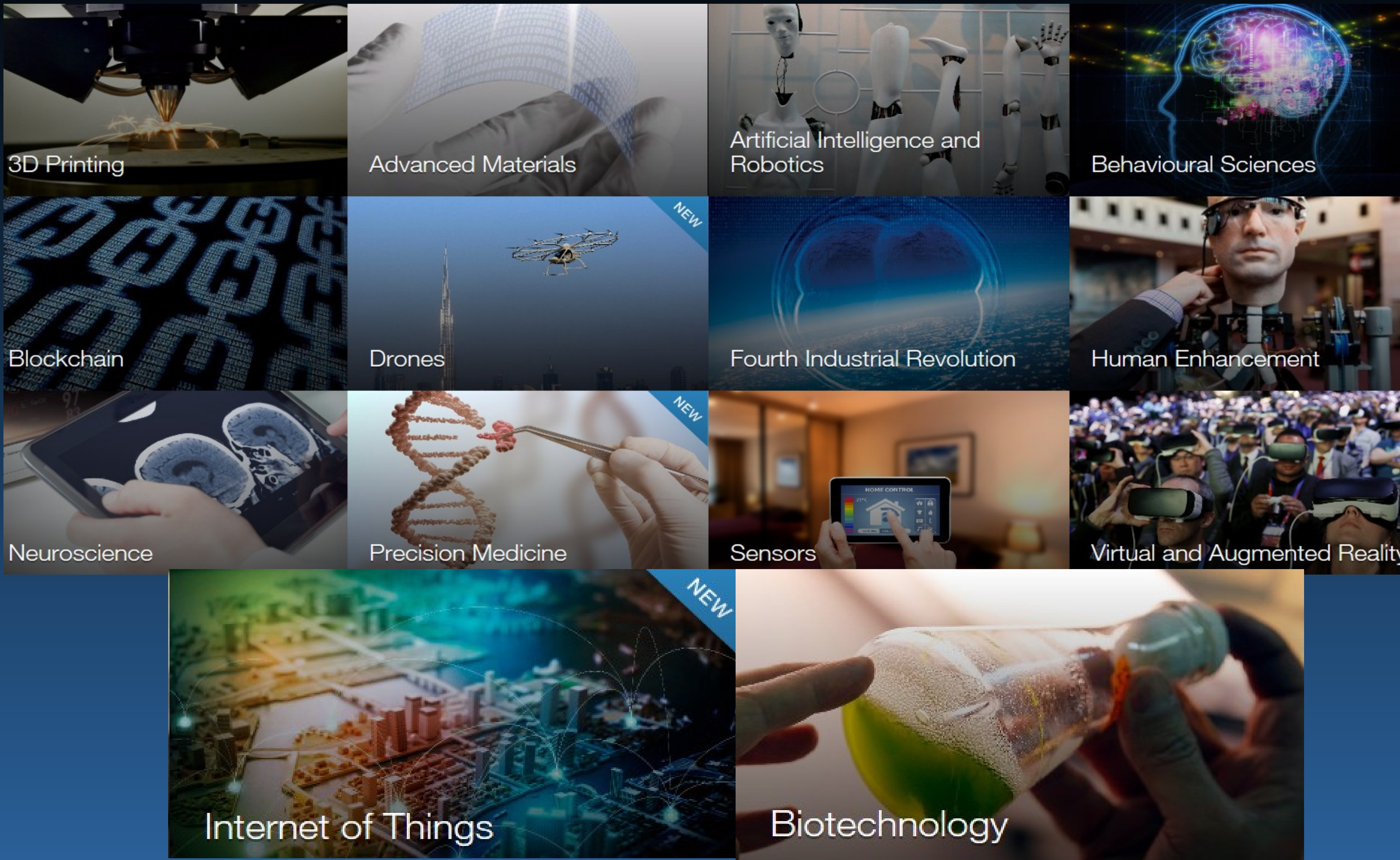
12th INCF Congress on Neuroinformatics and INCF Assembly, Warsaw 9/2019.

Polish Brain Council (2013) – no activity?

PRM Polska Rada Mózgu

BRAIN PLAN dla Polski

WEF: 4th Industrial Revolution driven by AI/neuro



Superhuman AI

Reasoning: 1997–Deep Blue wins in chess; 2016 –AlphaGo wins in Go; 2017-AlphaGo reaches super-human level.

Perception: face recognition, personality, criminal, sexual, political, religious orientation, general image recognition.

Strategy and planning: 2017–OpenAI wins in Pokera and strategic games Dota 2; 2019-Starcraft II, … military?

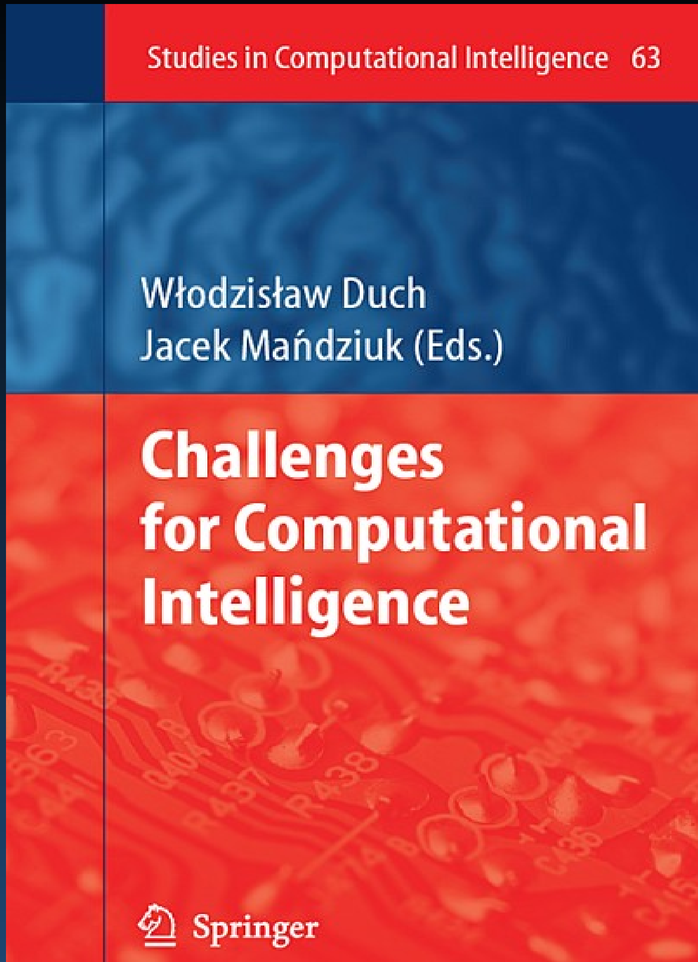
Science: 2015-AI Reverse-Engineers Planarian Regeneration regulatory networks. 2020-AlphaFold 2 for protein folding.

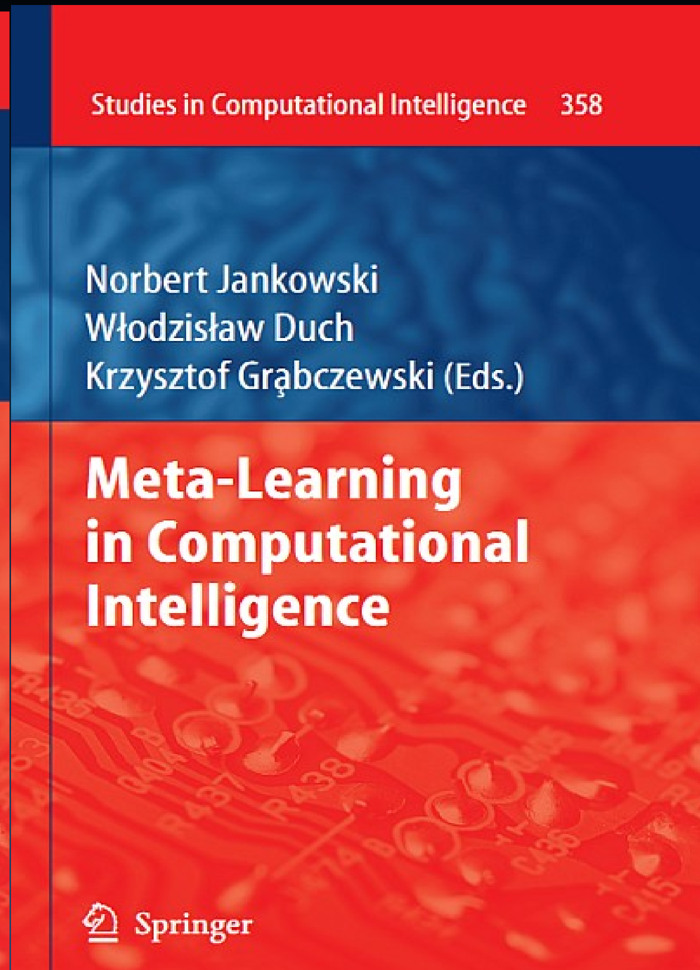
Robotics: 2020 backflip and parcour by Atlas robot, from Boston Dynamics, autonomic vehicles on roads.

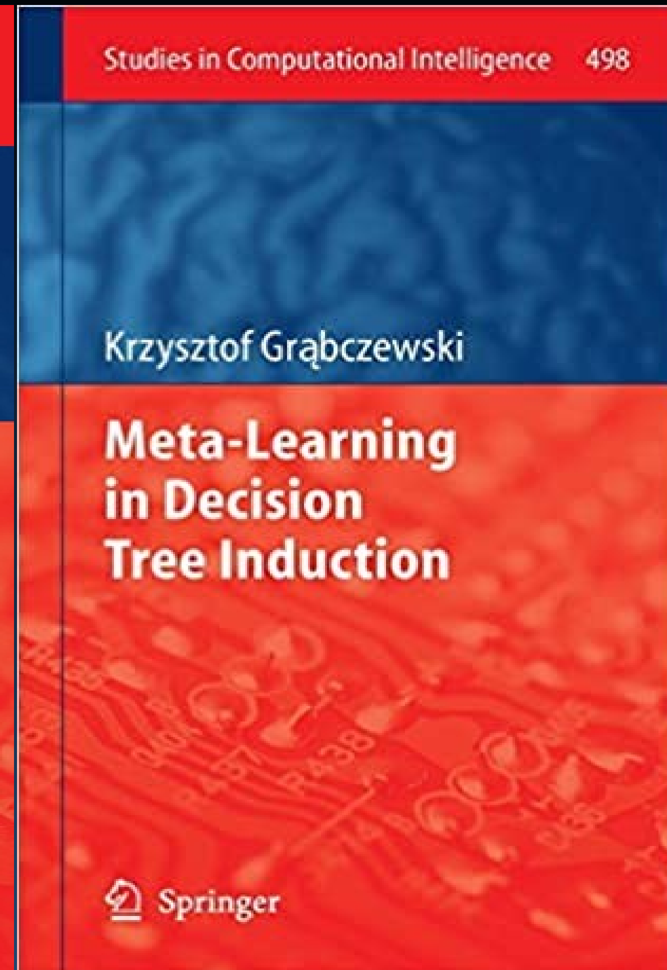
Creativity and imagery: AIVA and other AI composers, DeepArt and painting programs.

Language: 2011–IBM Watson wins in Jeopardy (Va Banque); 2018–Watson Debater wins arguing with philosophers, 2020: BERT answers 100.000 SquAD questions, superhuman level.

Cyborgs: BCI, optimization of human brains is coming ...

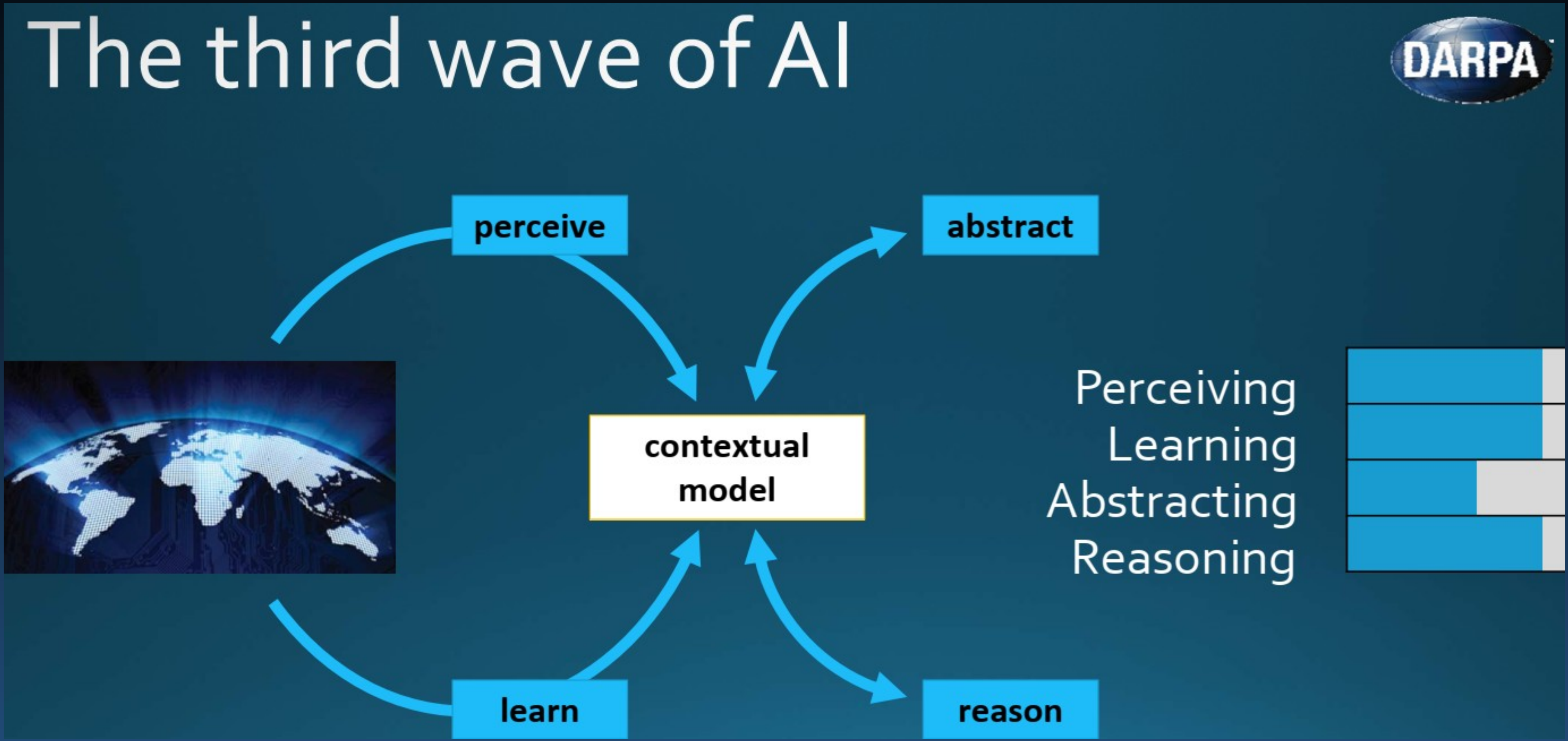






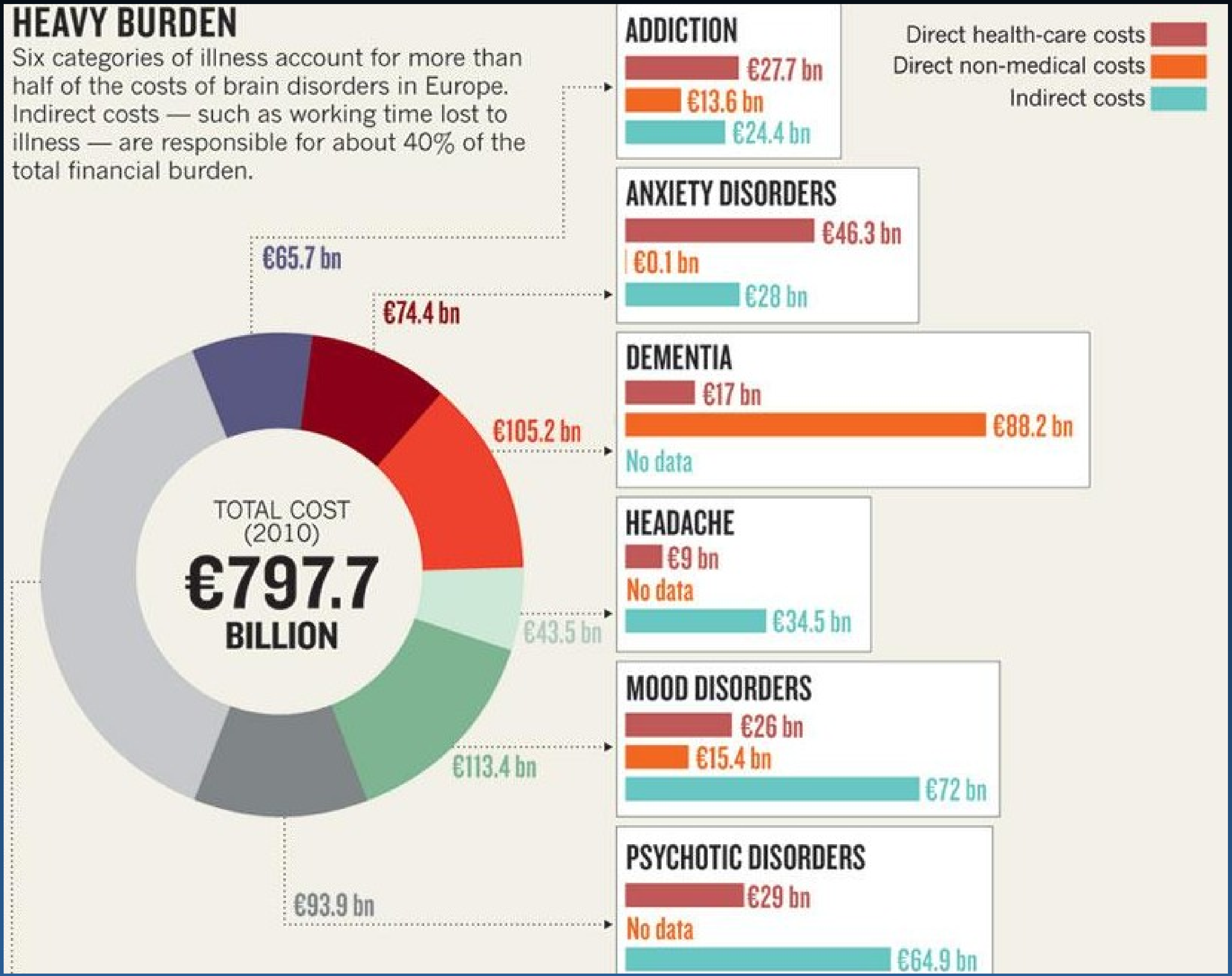
Duch W, Grudziński K. (2001) Meta-learning: searching in the model space
Duch W, Mandziuk J (Eds.), *Challenges for Computational Intelligence*. Springer 2007
Jankowski N, Duch W, Grąbczewski K, *Meta-learning in Computational Intelligence* 2011
Grąbczewski K, Meta-Learning in decision tree induction, 2014.

Third wave of AI



GAN, Generative Adversarial Networks, one network creates false examples distorting learning data, another network learns to distinguish them from natural ones. Building models of objects and situations is the next step.

Brain disorders are costly



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."

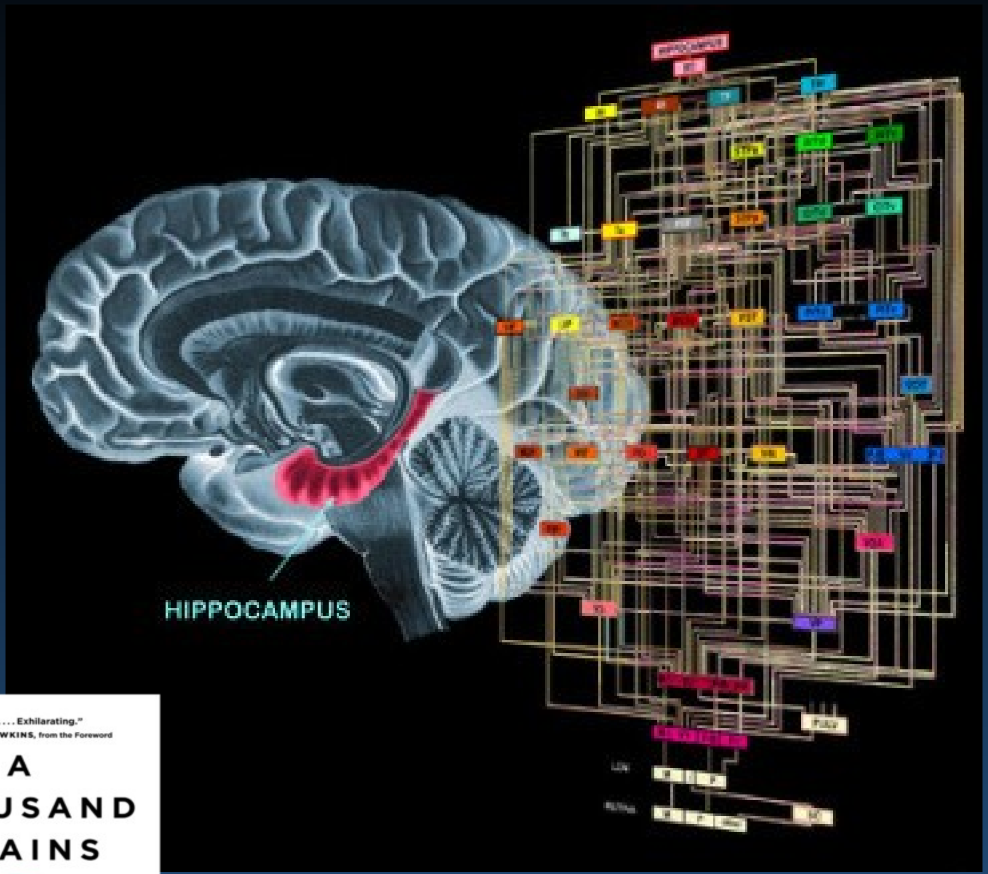
This is joint effort of many IEEE Societies.

BICA, Brain-Inspired Cognitive Architecture

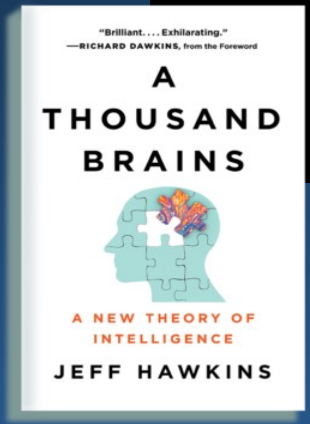
Understanding the brain from engineering perspective means to build a model of the brain showing similar functions.

How to create BICA for flexible intelligence?

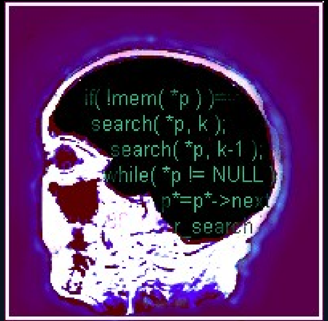
Duch, Oentaryo, Pasquier, [Cognitive architectures:](#) where do we go from here?



"We'll never have true AI without first understanding the brain"
Jeff Hawkins (2020).



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..

AI for Neuroscience & Neuroscience for AI

Irina Rish
AI Foundations
IBM T.J. Watson Research Center

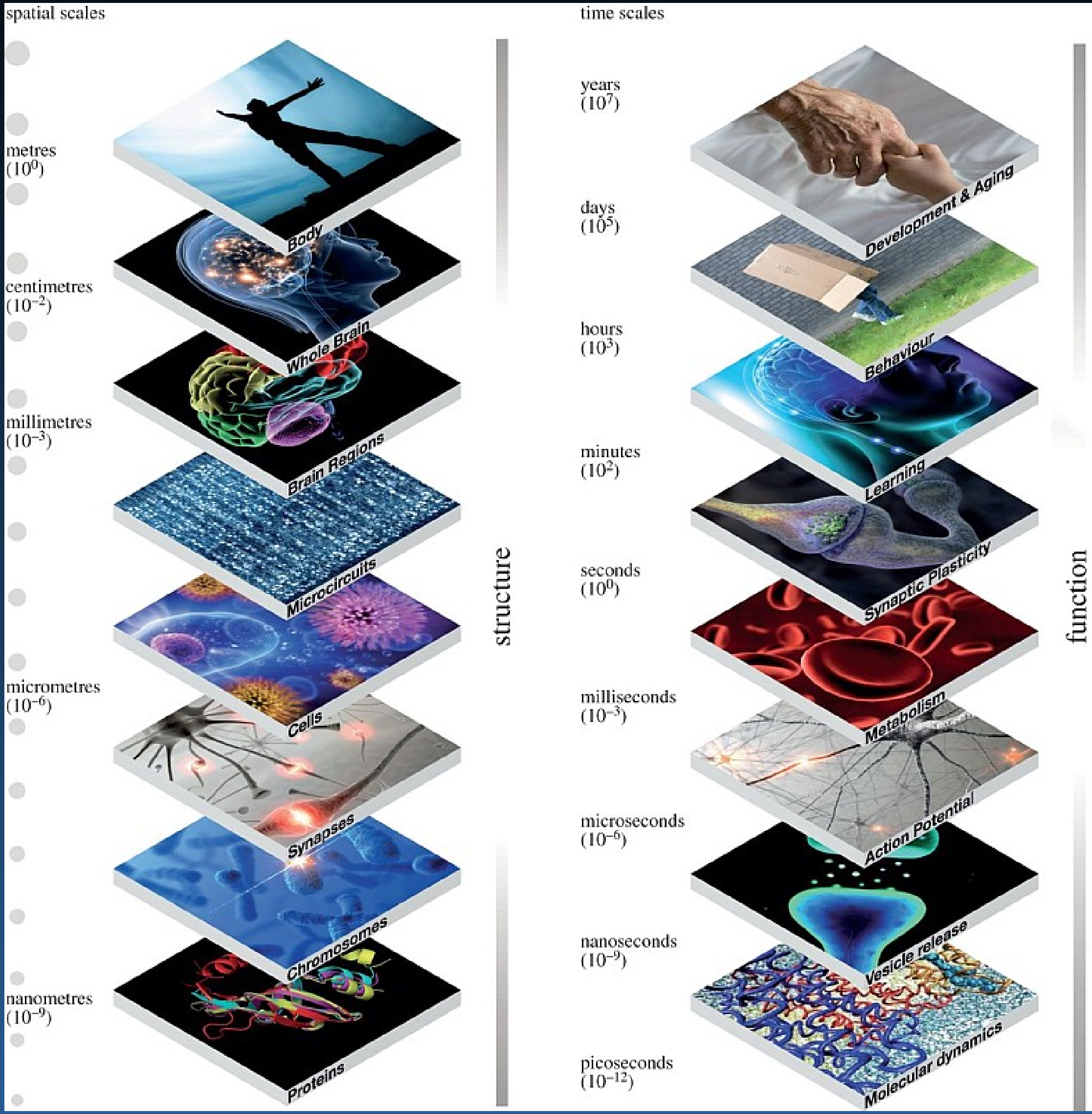
Multi-level phenomics

NIMH: mental disorders result from deregulation of large brain systems. Use **Research Domain Criteria** (RDoC) matrix based on **multi-level neuropsychiatric phenomics**.

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

Decompose neurodynamics into activity of large-scale networks, related to various brain functions.

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



Large-Scale Networks

NIMH: mental disorders result from deregulation of large brain systems. Use **Research Domain Criteria** (RDoC) matrix based on **multi-level neuropsychiatric phenomics**.

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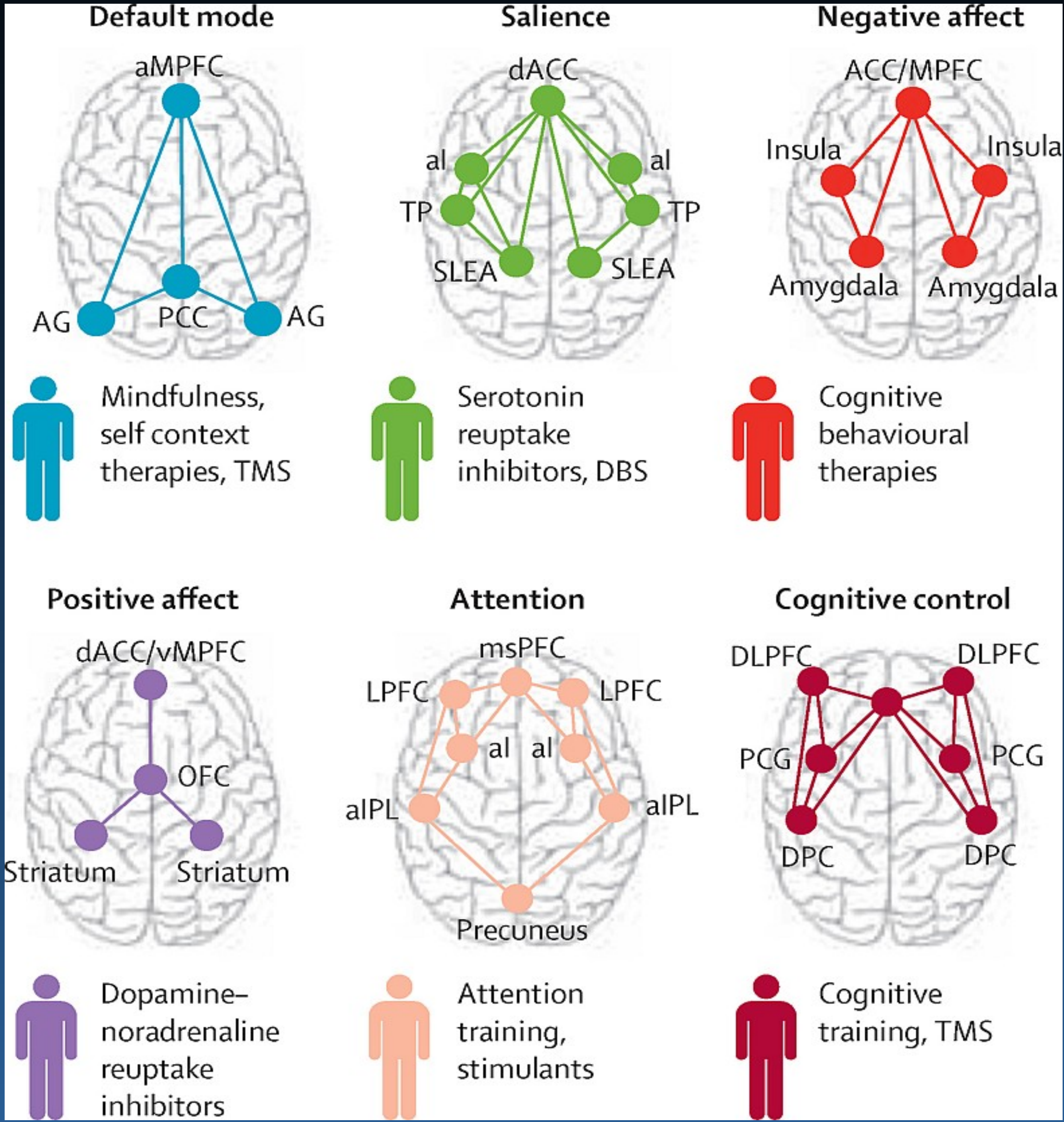
How many? From 7 to



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.

AI⇔ Neuroscience

Machine learning techniques are basic tools for analysis of neuroimaging data.

Ideas from animal psychology helped to give birth to reinforcement learning (RL) research. Now **key concepts from RL inform neuroscience**.

Activity of midbrain dopaminergic neurons in conditioning paradigms has a striking resemblance to temporal difference (TD) generated prediction errors - **brain implements a form of TD learning!**

CNN ⇔ interpret neural representations in high-level ventral visual stream of humans and monkeys, finding evidence for deep supervised networks.

LSTM architecture provides key insights for development of working memory, gating-based maintenance of task-relevant information in the prefrontal cortex.

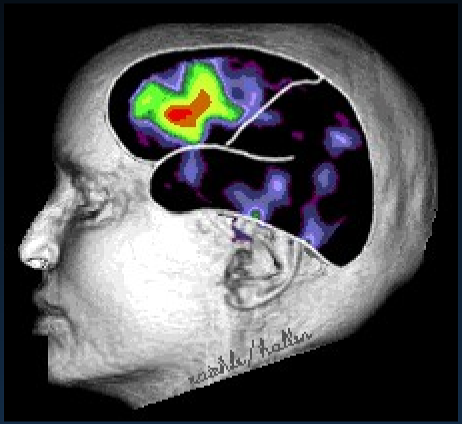
Random backward connections allow the backpropagation algorithm to function effectively adjusting forward weights and using backward projections to transmit useful teaching signals.

Brains ⇔ Minds

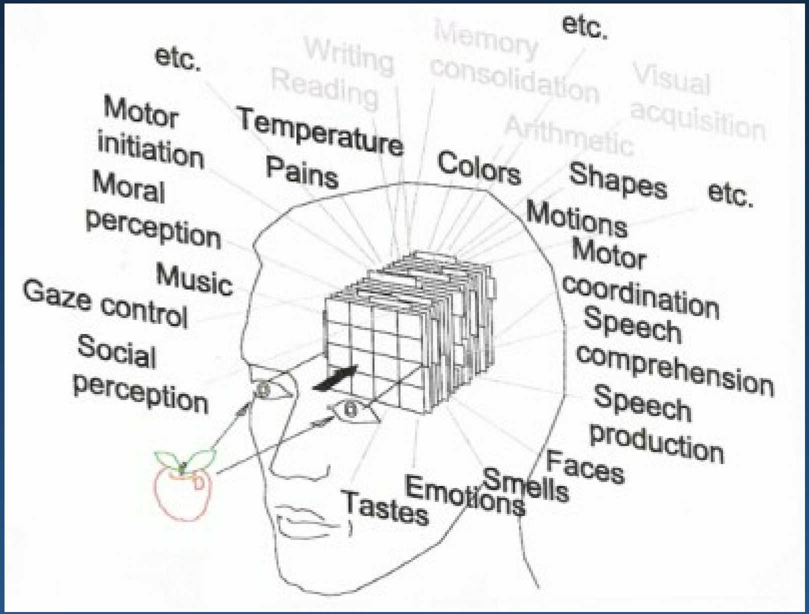
Define mapping S(M)⇔S(B), as in BCI.
How do we describe the state of mind?

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.

RDoC
Research Domain Criteria Initiative

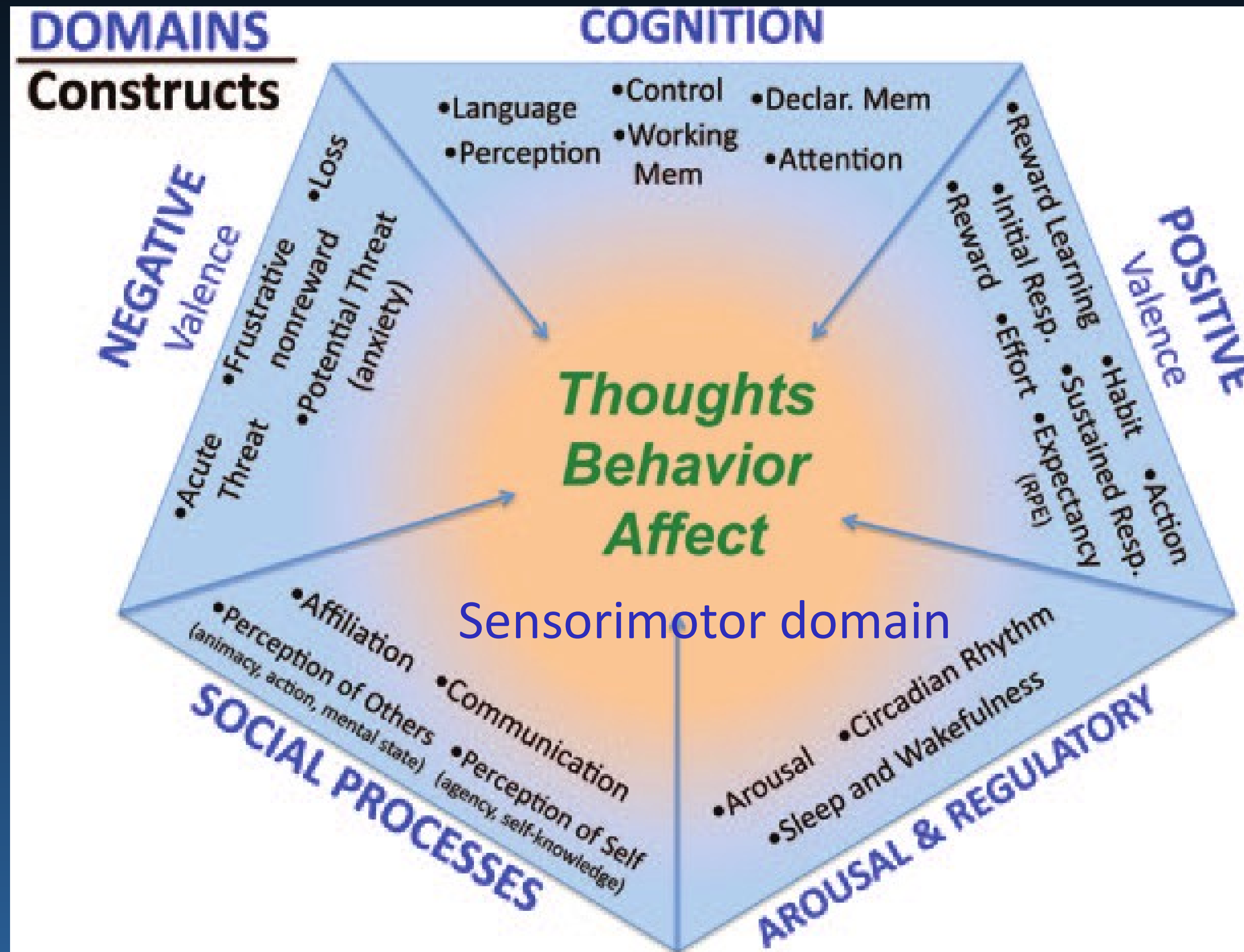
NIMH RDoC Matrix for deregulation of 6 large brain systems.

Psychological constructs are necessary to talk about mental states.

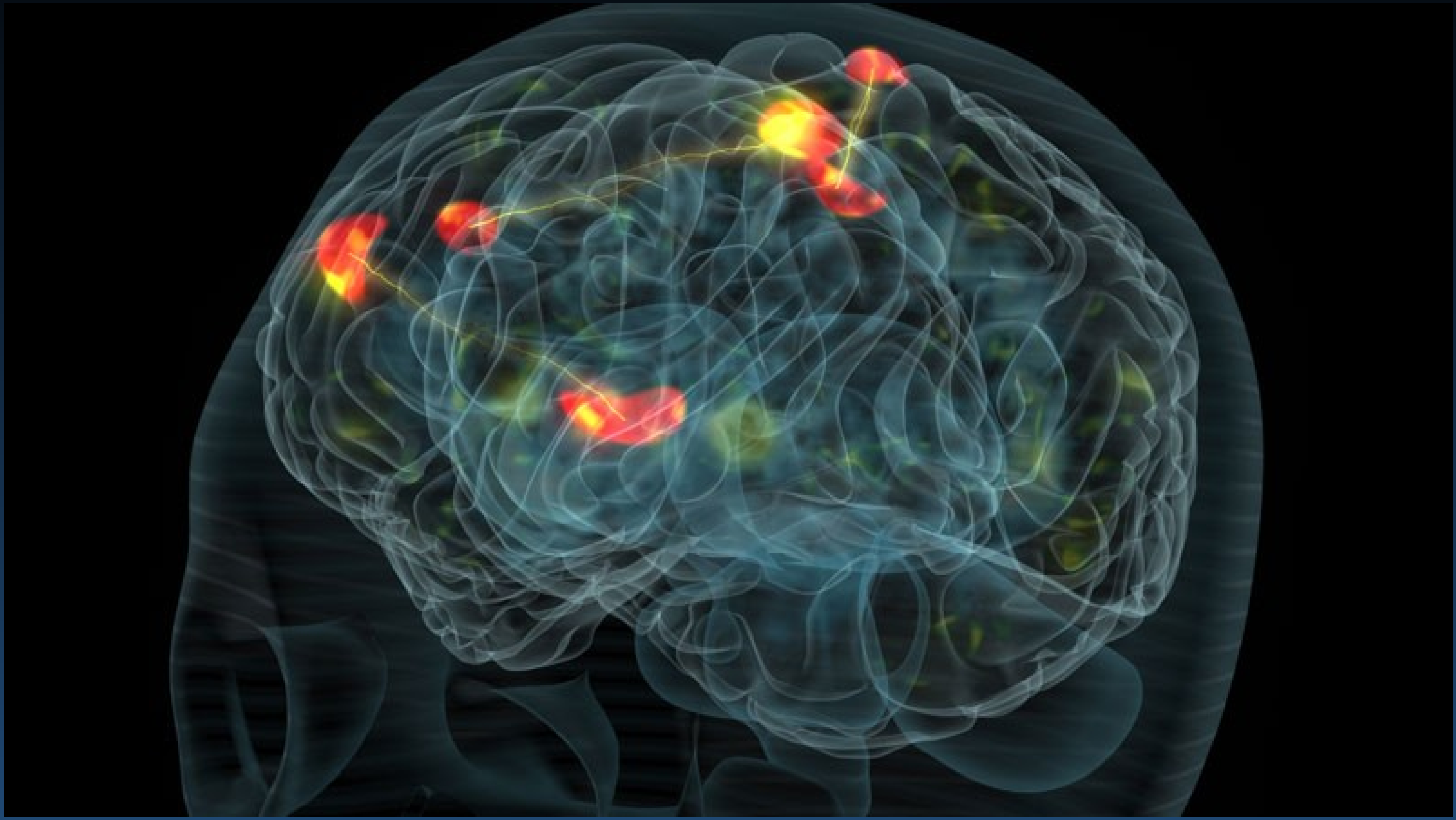
Sensorimotor systems added in Jan. 2019 as sixth brain system.

This is the basis of computational psychiatry.

How are these functions implemented in the brain?



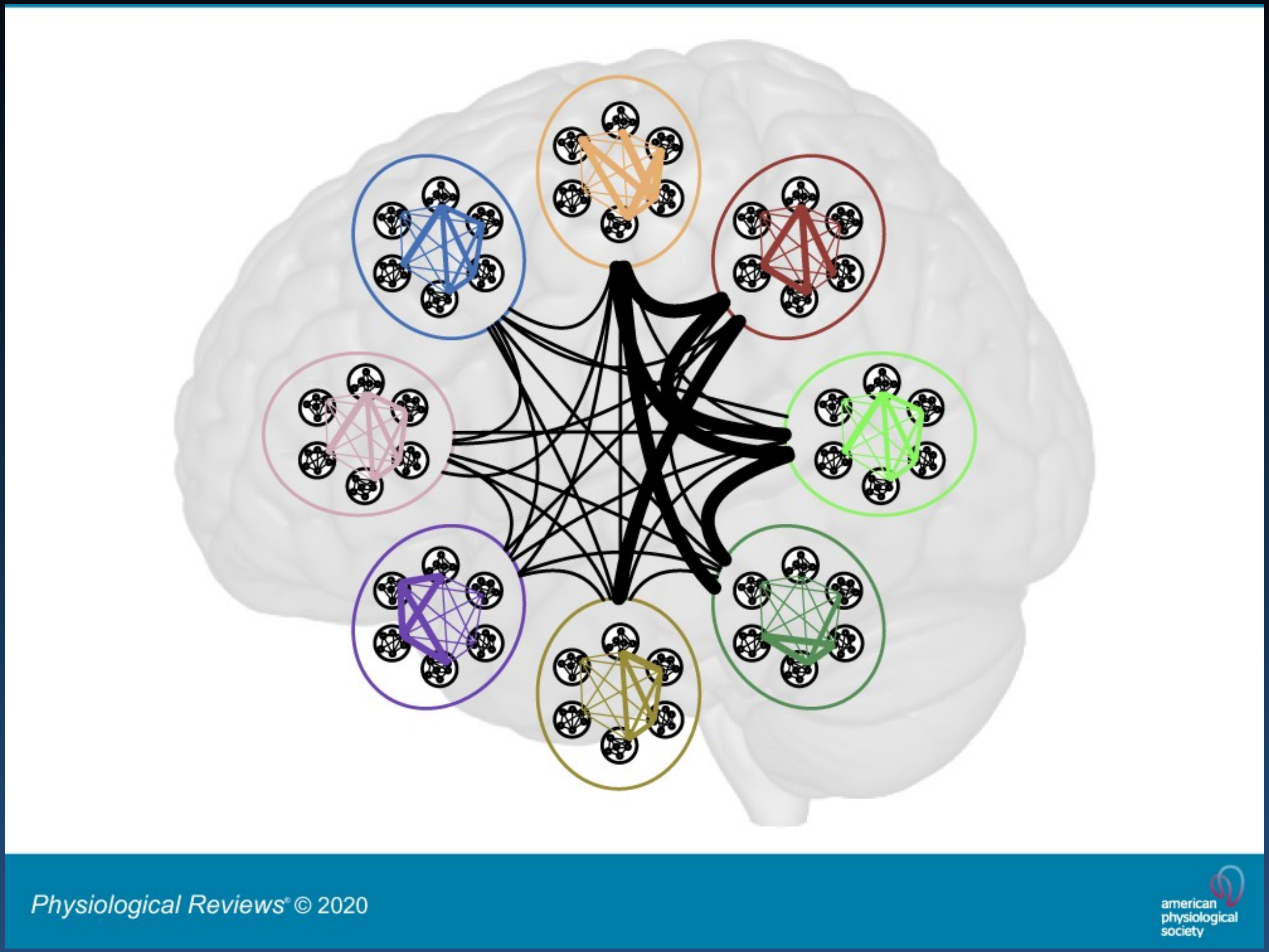
Mental state: strong coherent activation



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

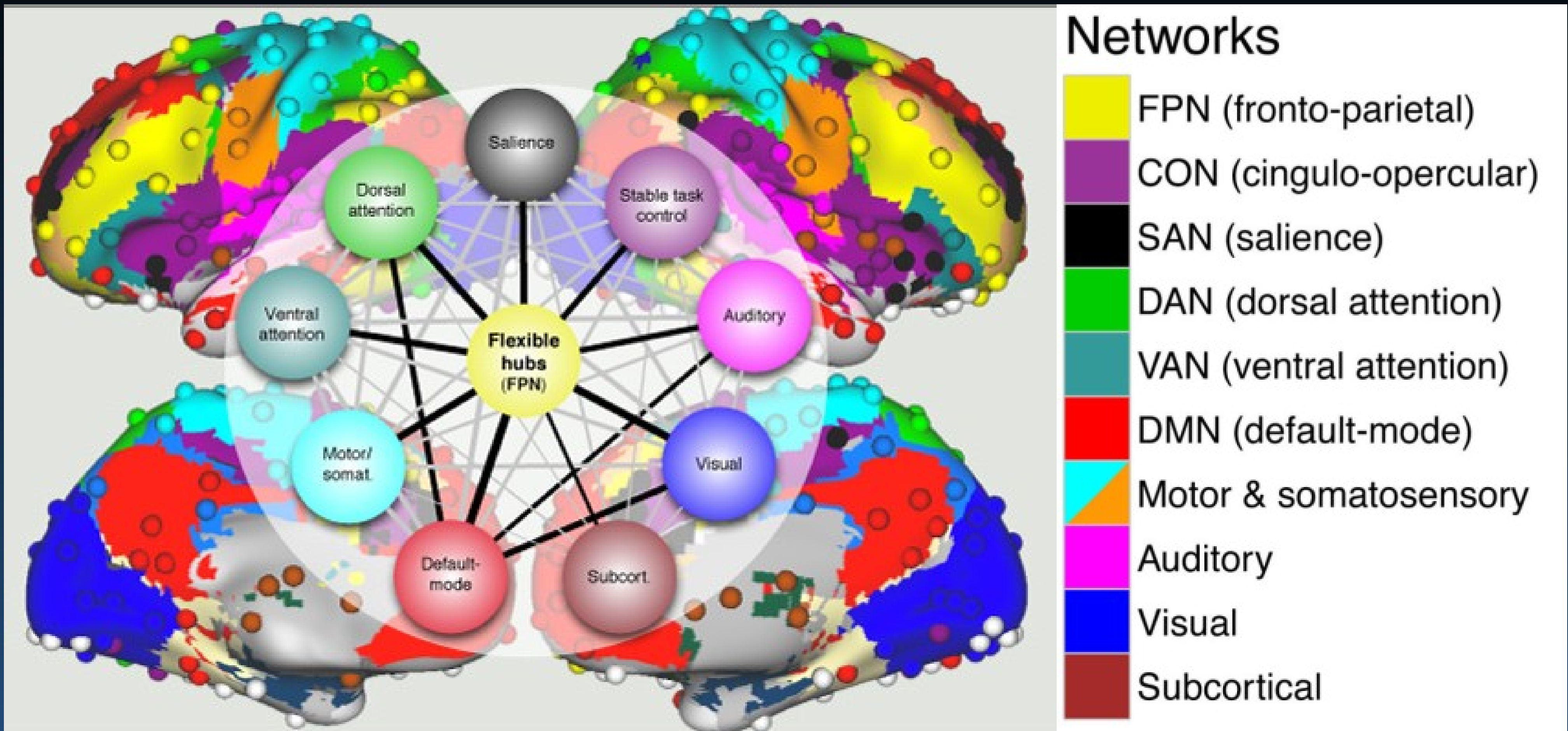
Various subnetworks compete for access to the highest level of control.
Consciousness, the winner-takes-most mechanism leaves only the strongest filtering noise (signal detection theory). How to extract stable intentions from such chaos?

~ Small worlds architecture



All complex functions are based on synchronization of activity among many 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.

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).

Frames, capsules and metastable 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.

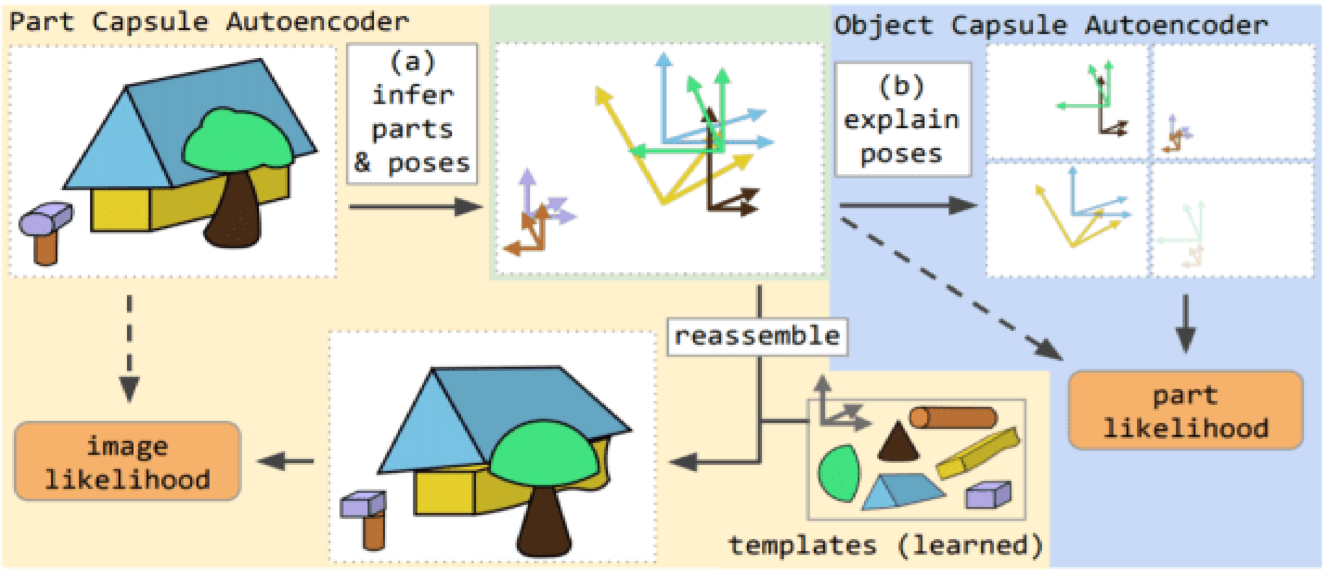
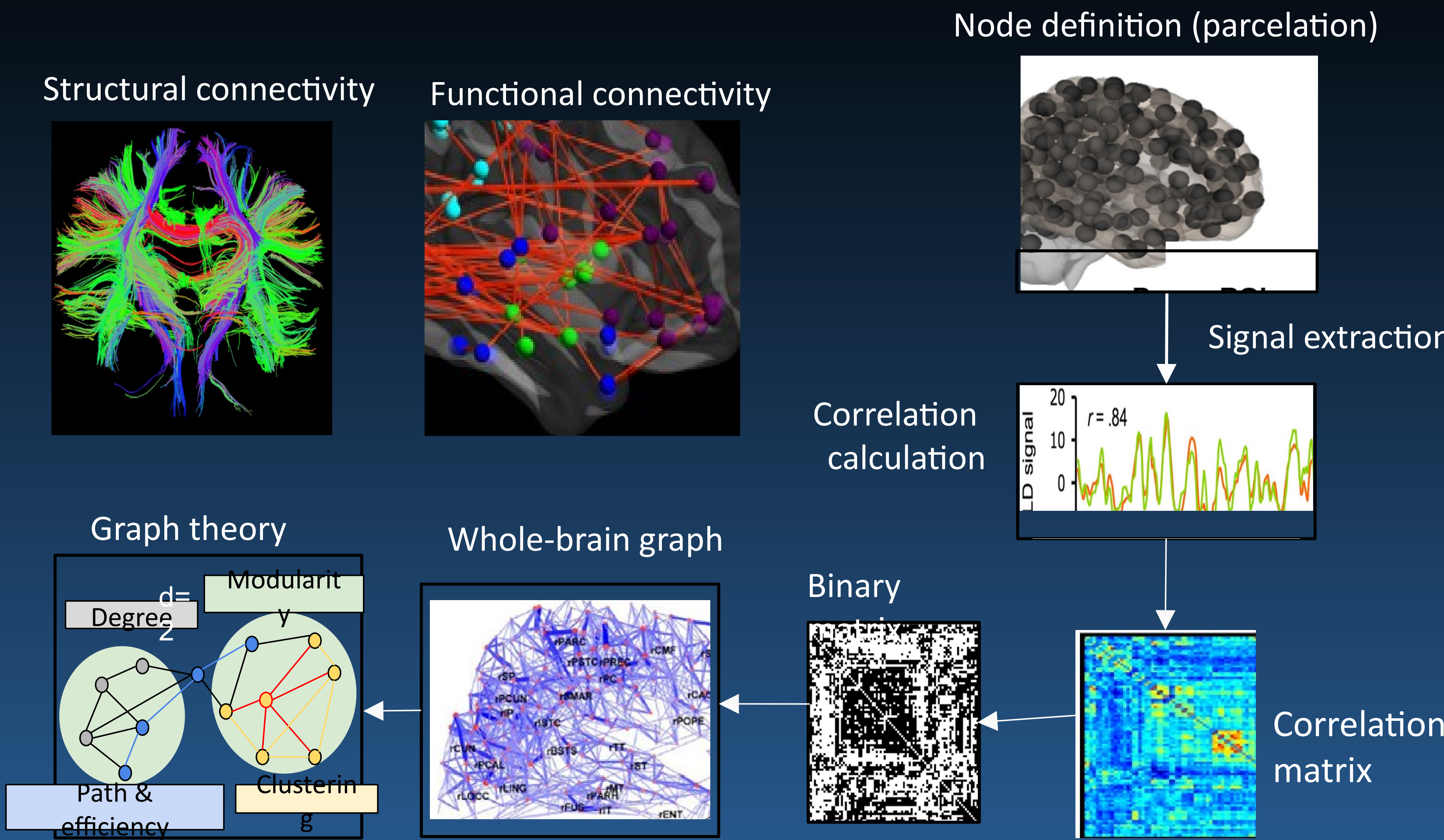


Figure 1: Stacked Capsule Autoencoder (SCAE): (a) *part* capsules segment the input into parts and their poses. The poses are then used to reconstruct the input by affine-transforming learned templates. (b) *object* capsules try to arrange inferred poses into objects, thereby discovering underlying structure.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

Human connectome and MRI/fMRI



Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

Simulations of neurodynamics

Model of reading & dyslexia

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

Fluctuations around final configuration = attractors representing concepts.

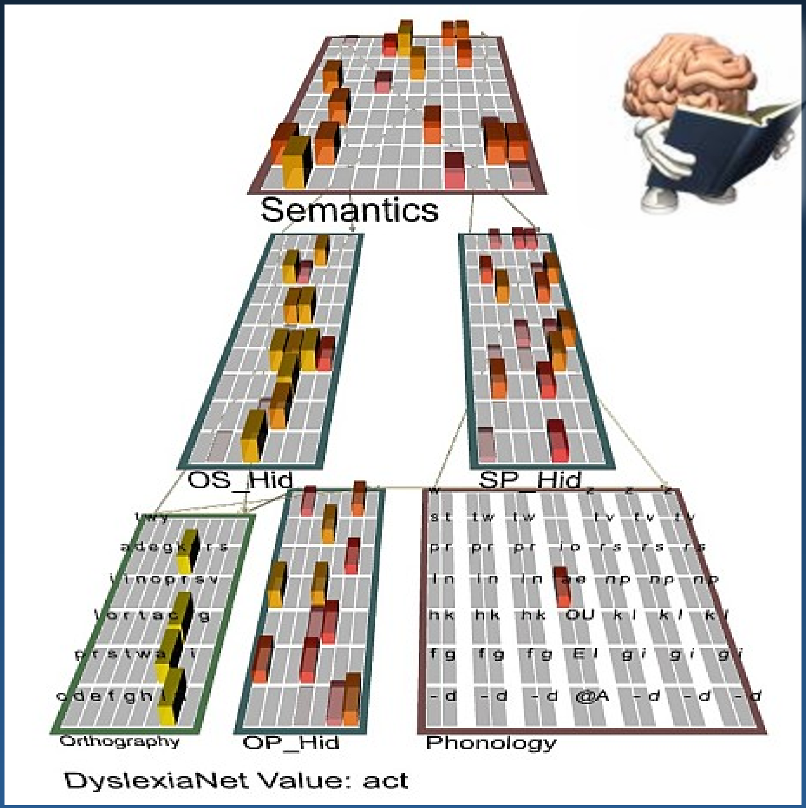
How to see trajectory of neurodynamics, attractor basins, transitions?
Genesis simulator offers more detailed neuron models, but is harder.

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.

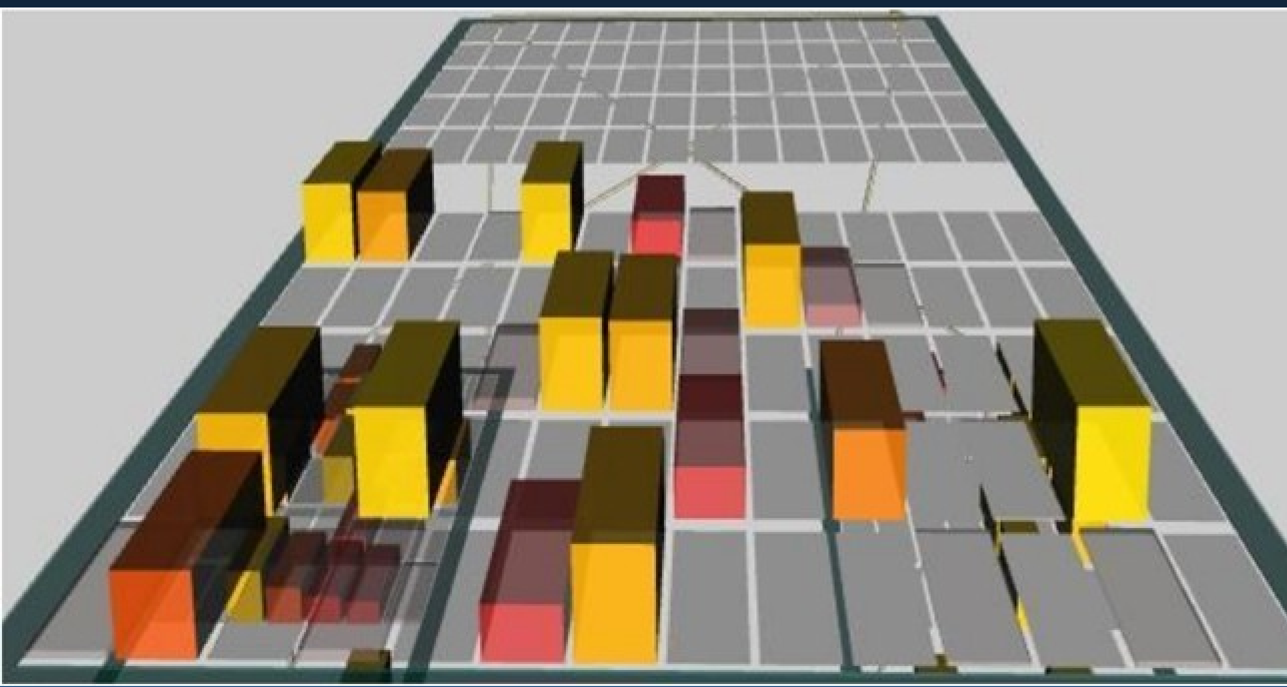
3-layer model of reading:

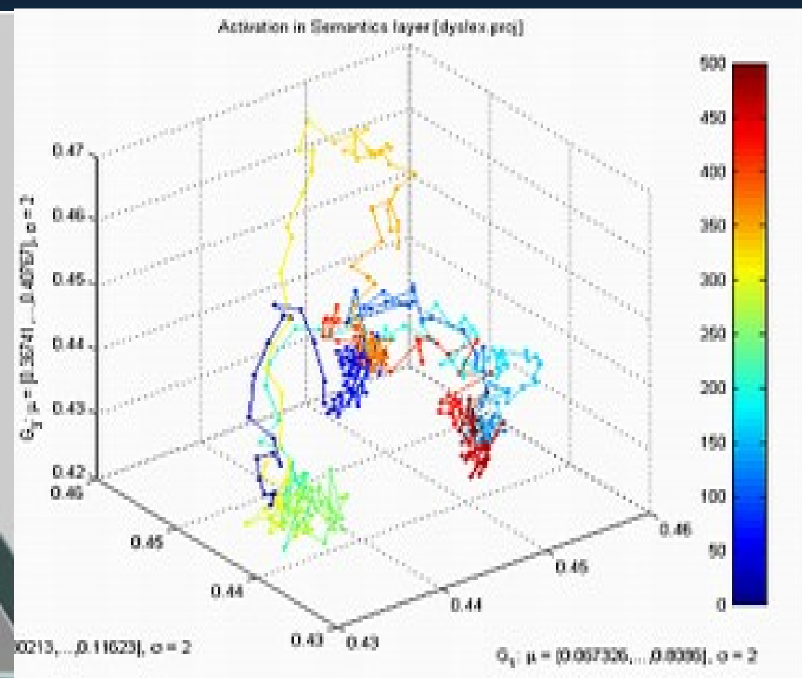
orthography, phonology, semantics =
distribution of activity over
140 microfeatures defining concepts.
Hidden layers OS/OP/SP_Hid in between.
In the brain: microfeature = subnetwork.



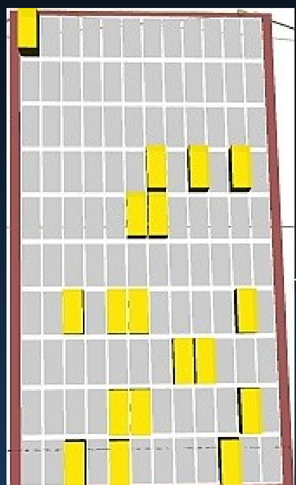
Semantic layer

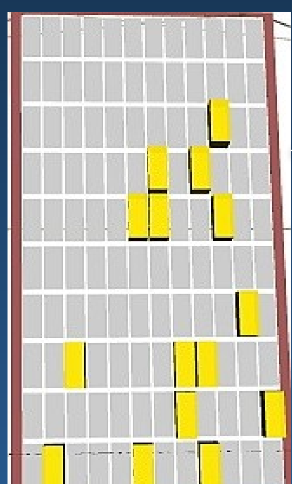
Semantic layer in our simulations has 140 units.
Here activity for the word "case" is shown, upper 70 units code abstract microfeatures, lower physical properties. Representation is sparse.
Concepts/words are identified by a pattern of active features.
Associations = transitions between patterns, can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



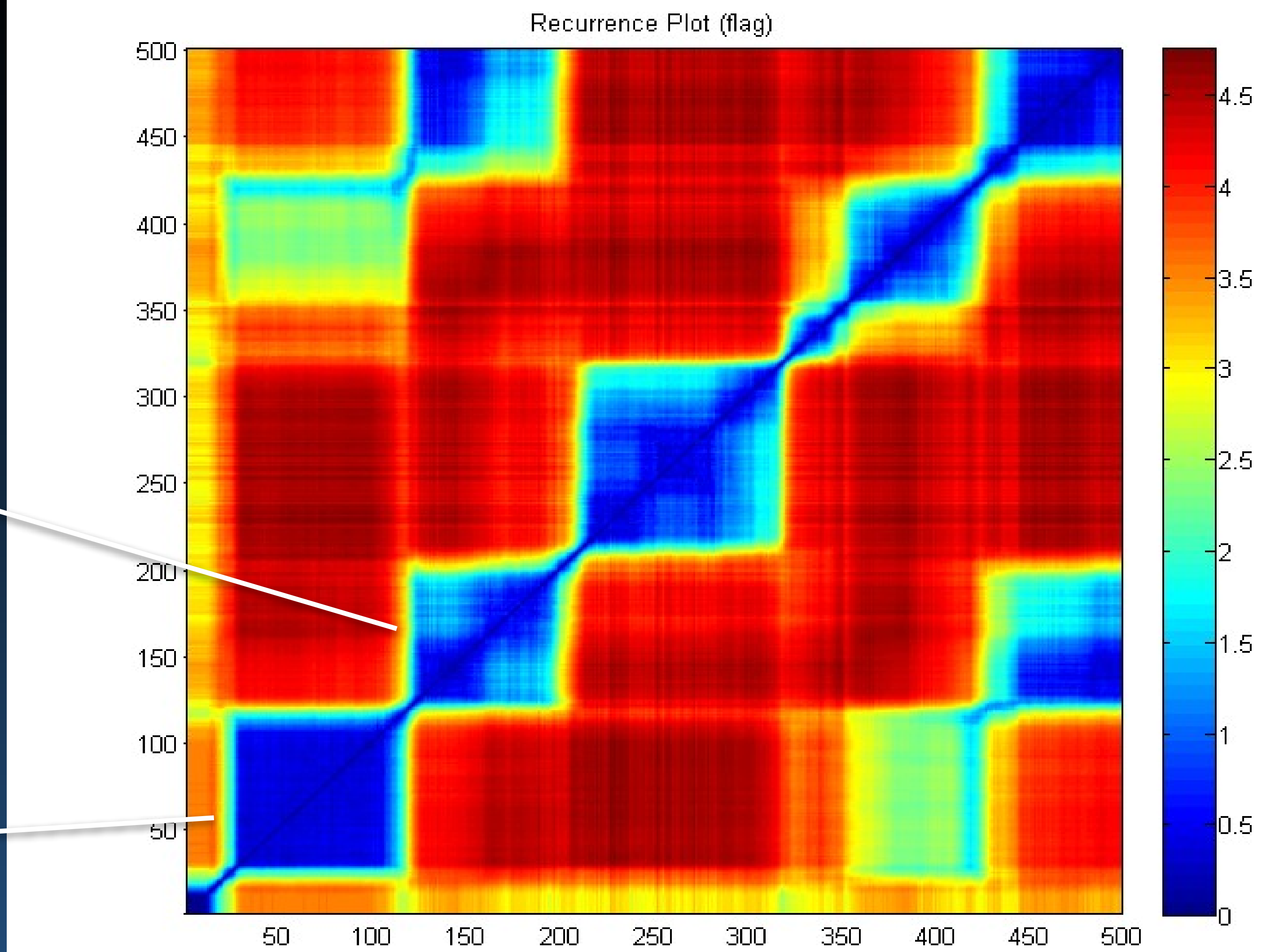


rope



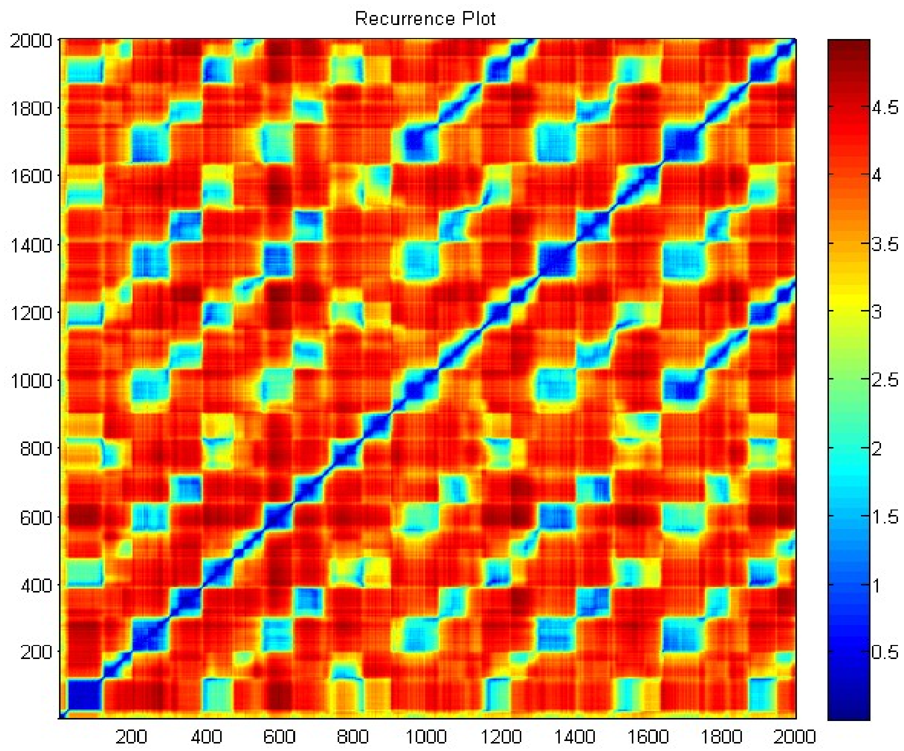


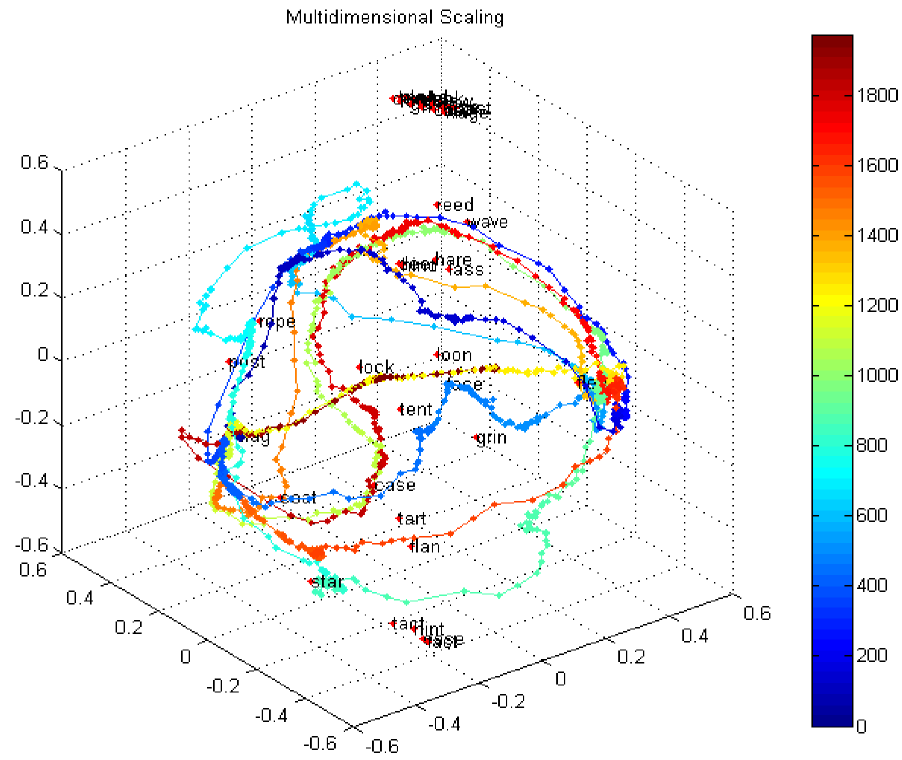
flag



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

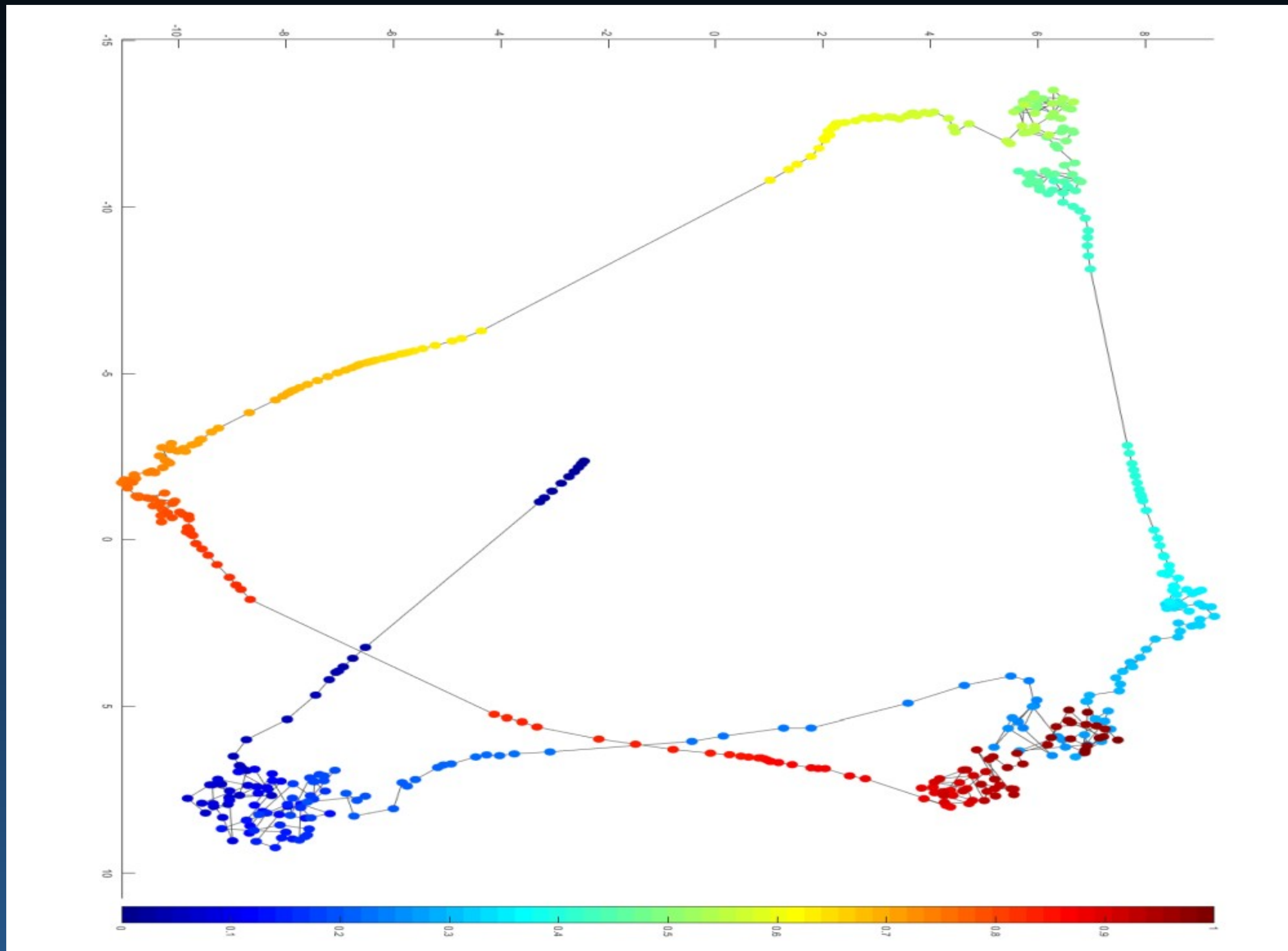
Trajectory visualization





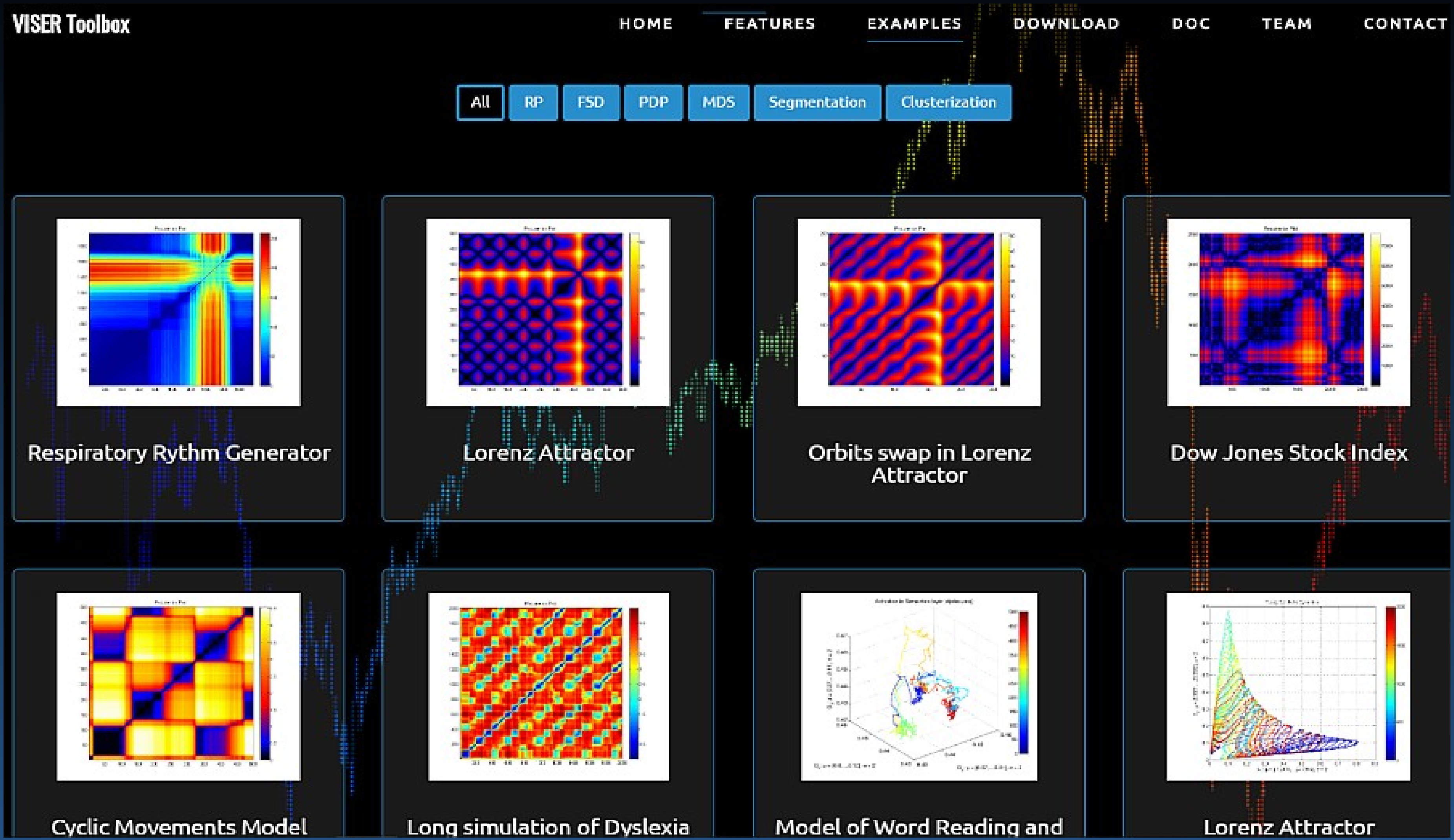
Recurrence plots and MDS visualization of trajectories of the brain activity.
Here evolution of 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain is presented, starting with the word “flag”.
Trajectories may be displayed using tSNE, UMAP, MDS or our FSD visualization.

Trajectory in 2D



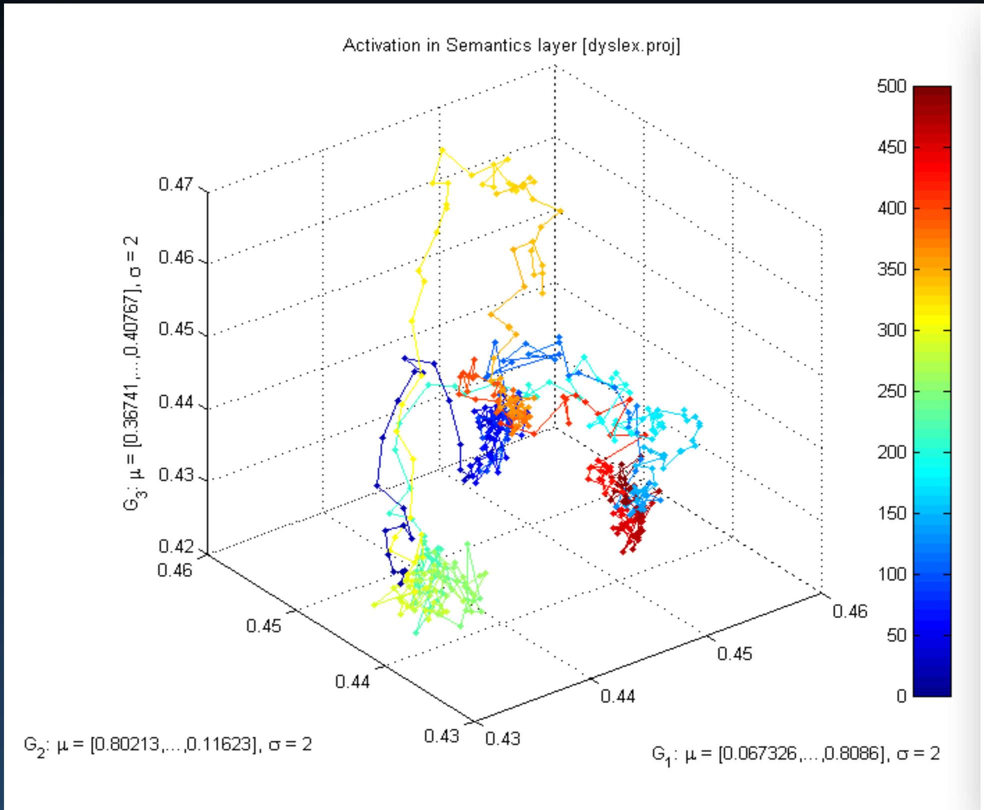
Stochastic Neighbor Embedding (tSNE) visualization, “from thought to thought”.

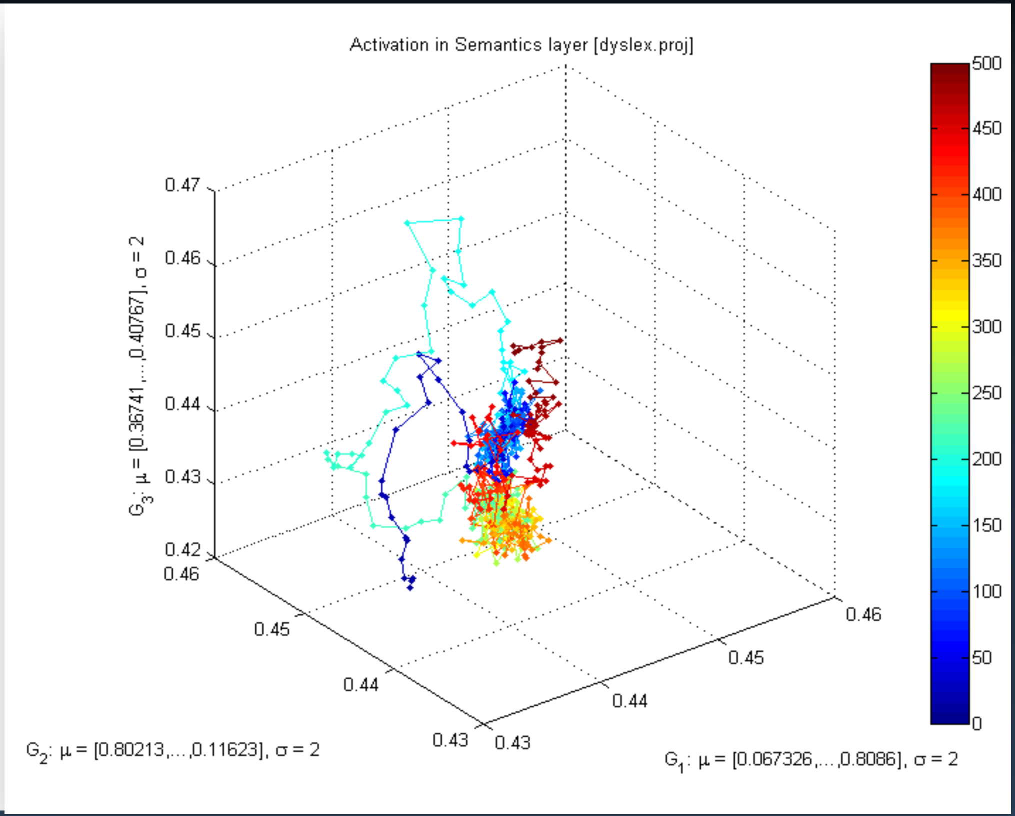
Viser toolbox



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

Typical Development vs. Autism

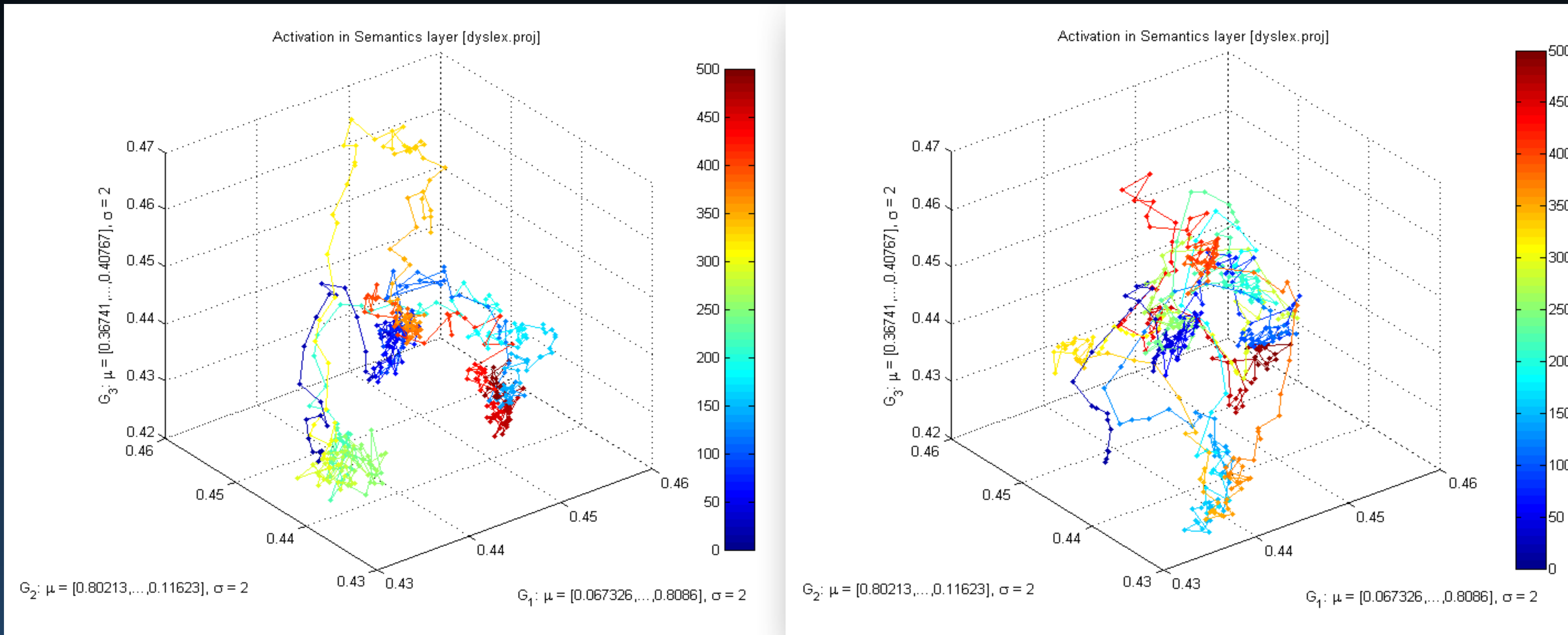




Trajectories show activation of 3 Gaussian functions ($G_1(t)$,$G_2(t)$,$G_3(t)$). Neurodynamics depends on properties of single neurons, noise in the system.

Start from "flag". Parameter b_inc_dt is related to voltage-dependent leak channels that determines depolarization of neurons, b_inc_dt = 0.01 in normal case vs. b_inc_dt = 0.005, long trapping times and a few states, slow Hebbian learning.

Typical Development vs ADHD



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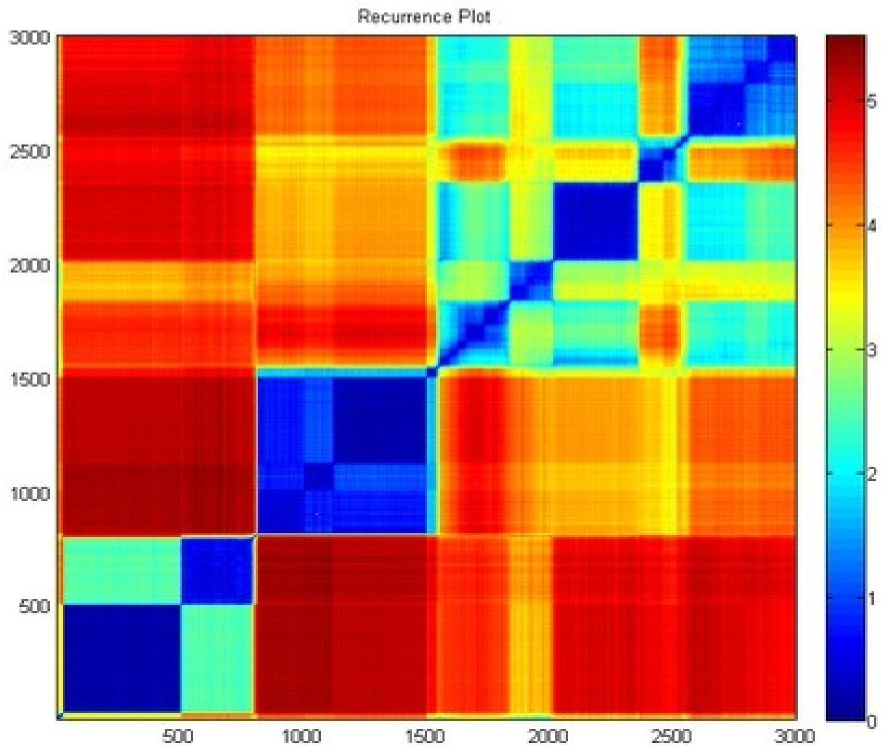
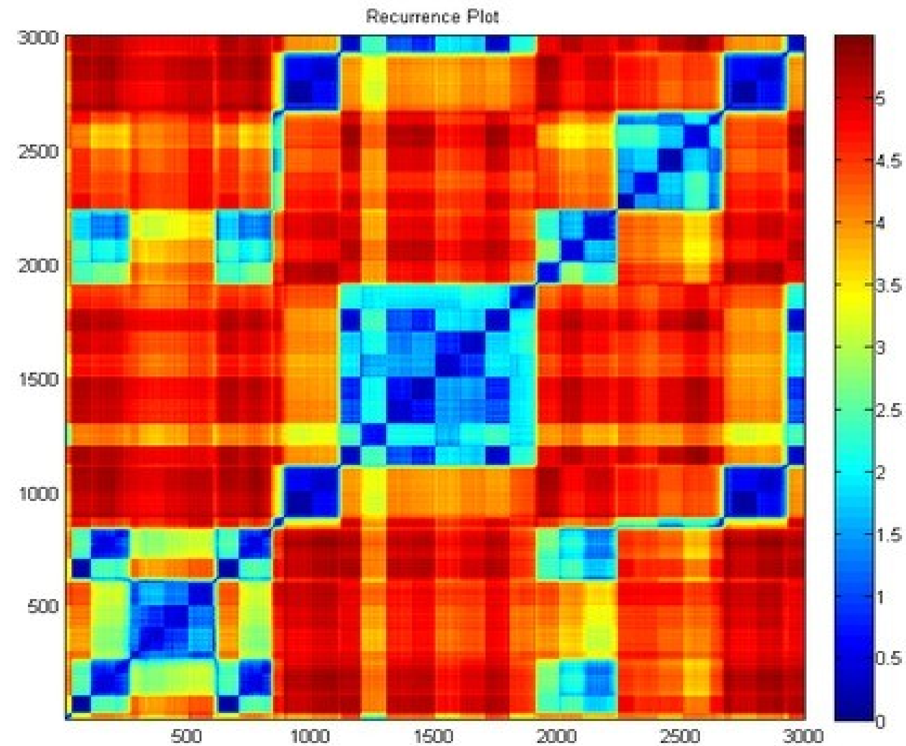
Neurodynamics depends on properties of single neurons, noise in the system.

Start from "flag". Parameter b_inc_dt is related to voltage-dependent leak channels that determines depolarization of neurons, b_inc_dt = 0.01 in normal case vs. b_inc_dt = 0.02, short trapping times and a many states, slow Hebbian learning.

Simulations of rapid stimulation in autism





Normal speed
skipping some words,
no associations

fast presentation
more complex internal states
some associations arise (off-diagonal)

EEG and neurodynamics

Brain Fingerprinting

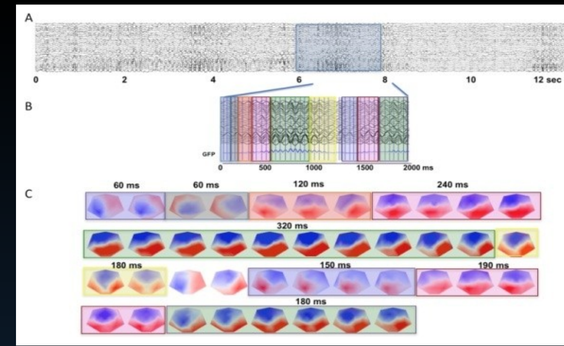
find unique patterns of brain activity that should help to identify:

- brain regions of interest (ROI)
- active neural networks
- mental states, tasks.

Several approaches:

1. Microstates and their transitions (Michel & Koenig 2018)
2. Reconfigurable task-dependent modes (Krienen et al. 2014)
3. Contextual Connectivity (Ciric et al. 2018)
4. Spectral Fingerprints (Keitel & Gross 2016)
5. A few more …

1



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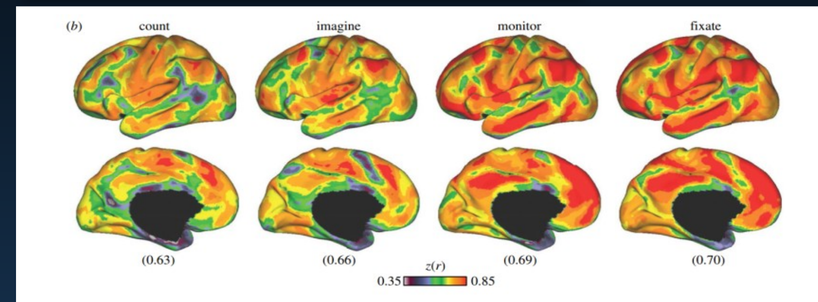

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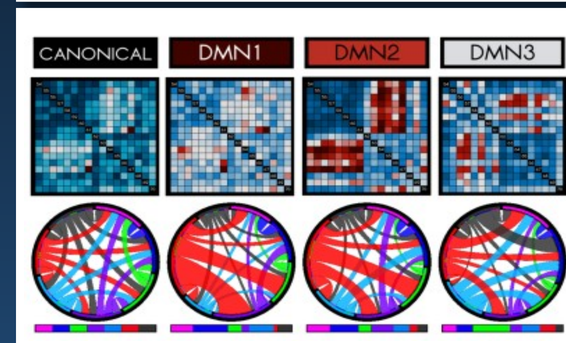

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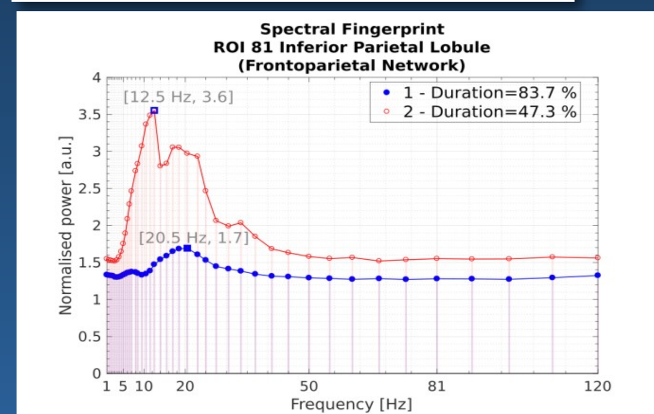


EEG microstates for diagnostics

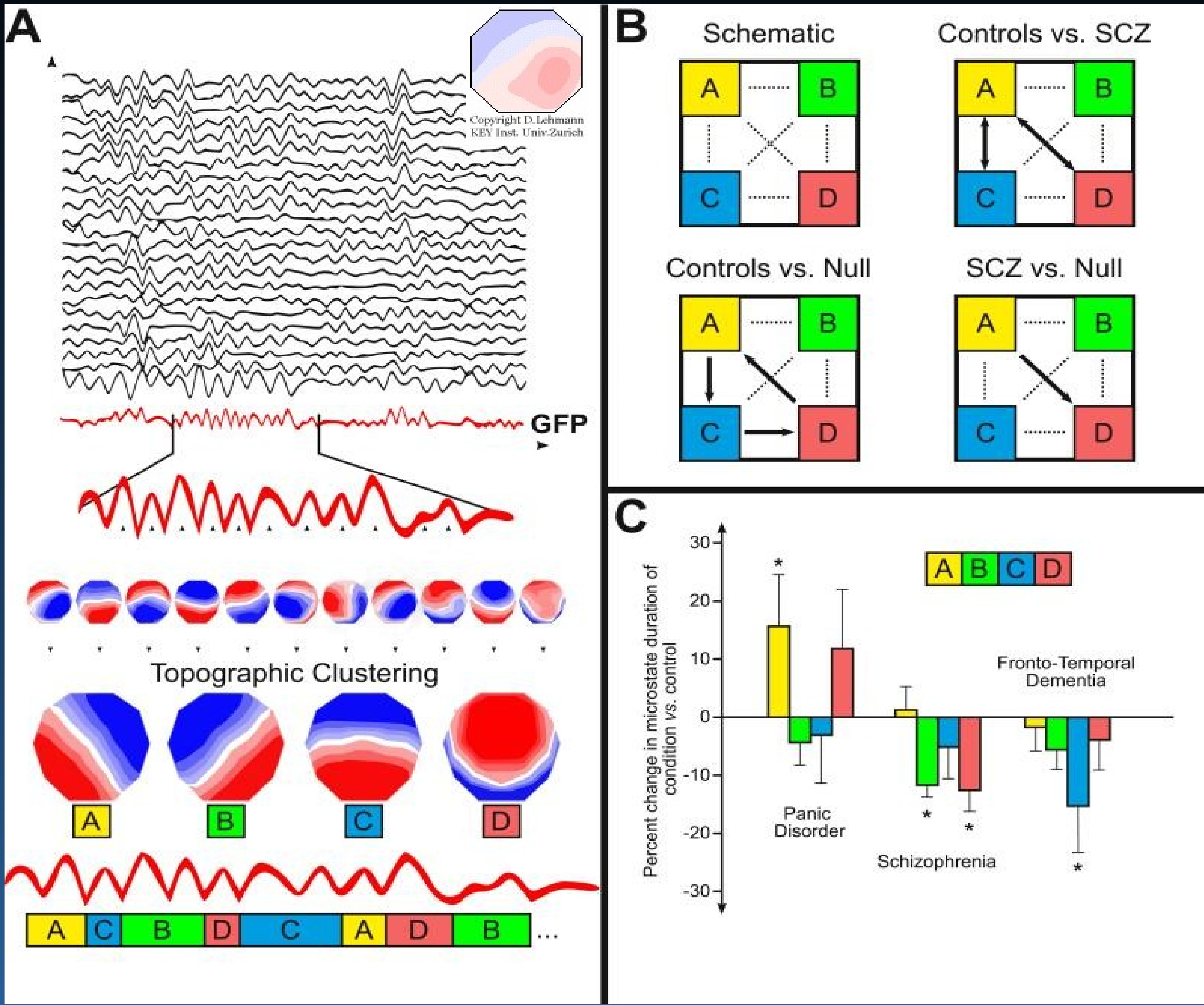
Global EEG Power.

Lehmann et al.
EEG microstate duration and syntax in [...] schizophrenia. Psychiatry Research Neuroimaging, 2005

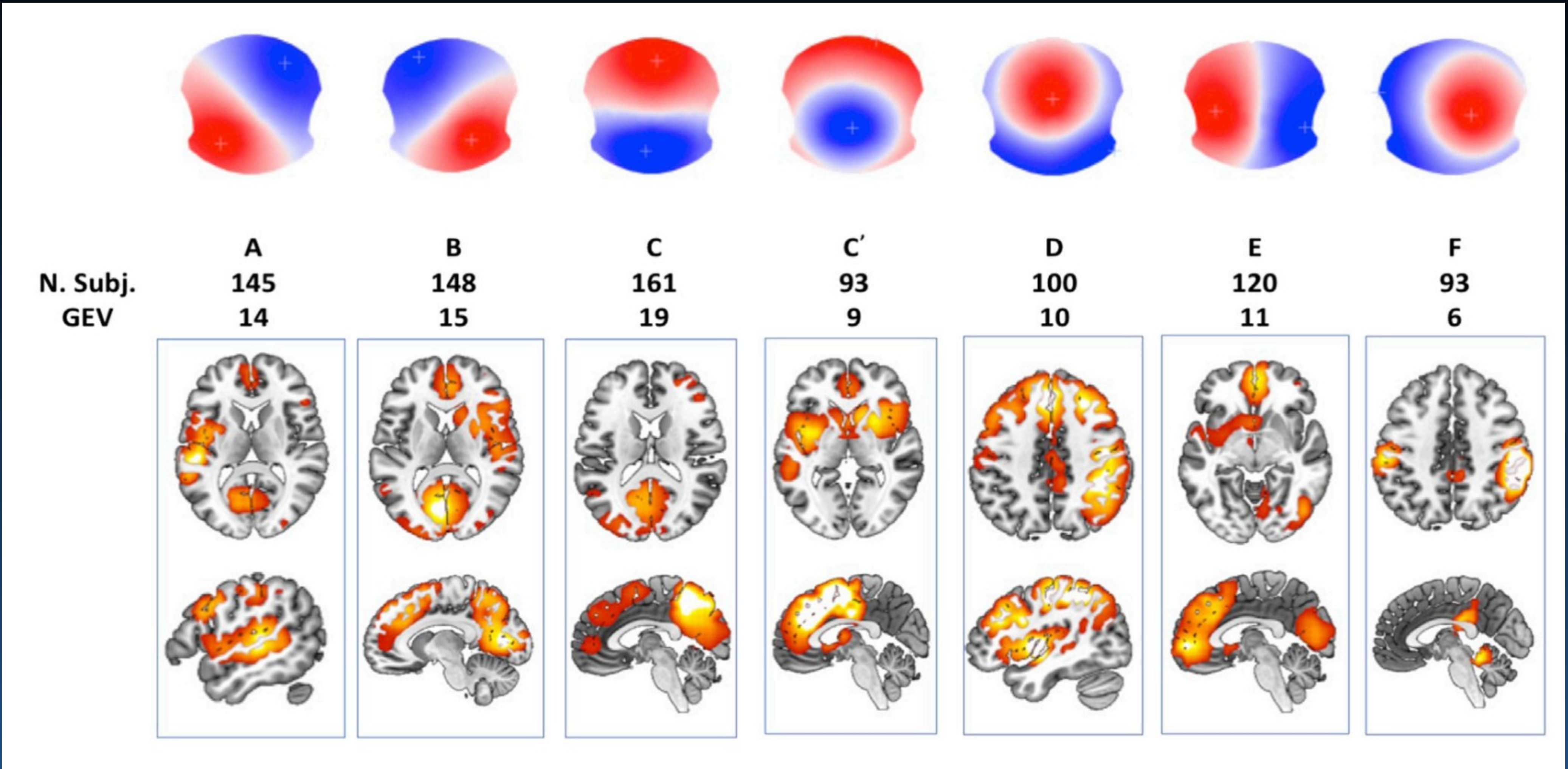
Khanna et al.
Microstates in Resting-State EEG. *Neuroscience and Biobehavioral Reviews*, 2015

4-7 states 60-150 ms

Symbolic dynamics.

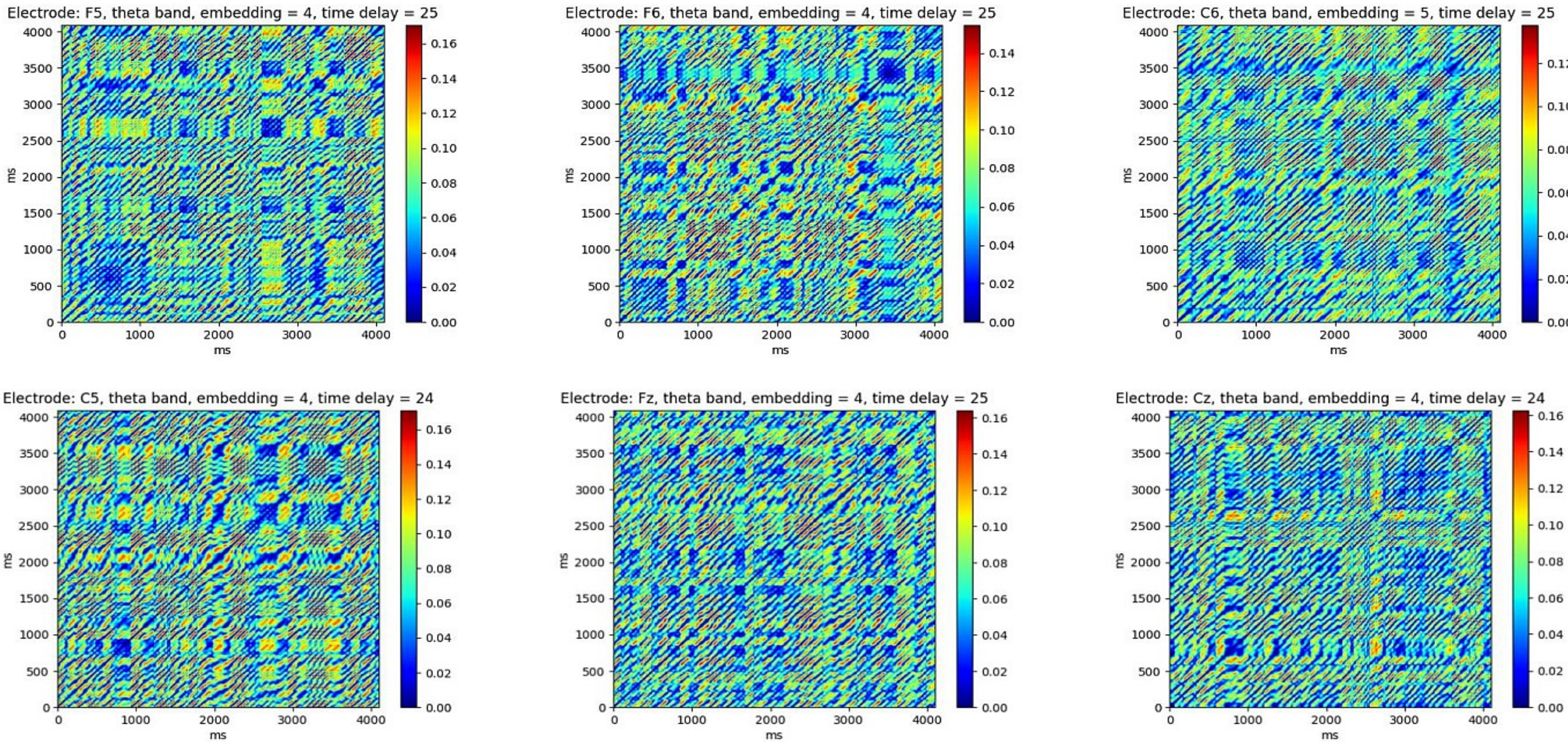


Microstates and their sources



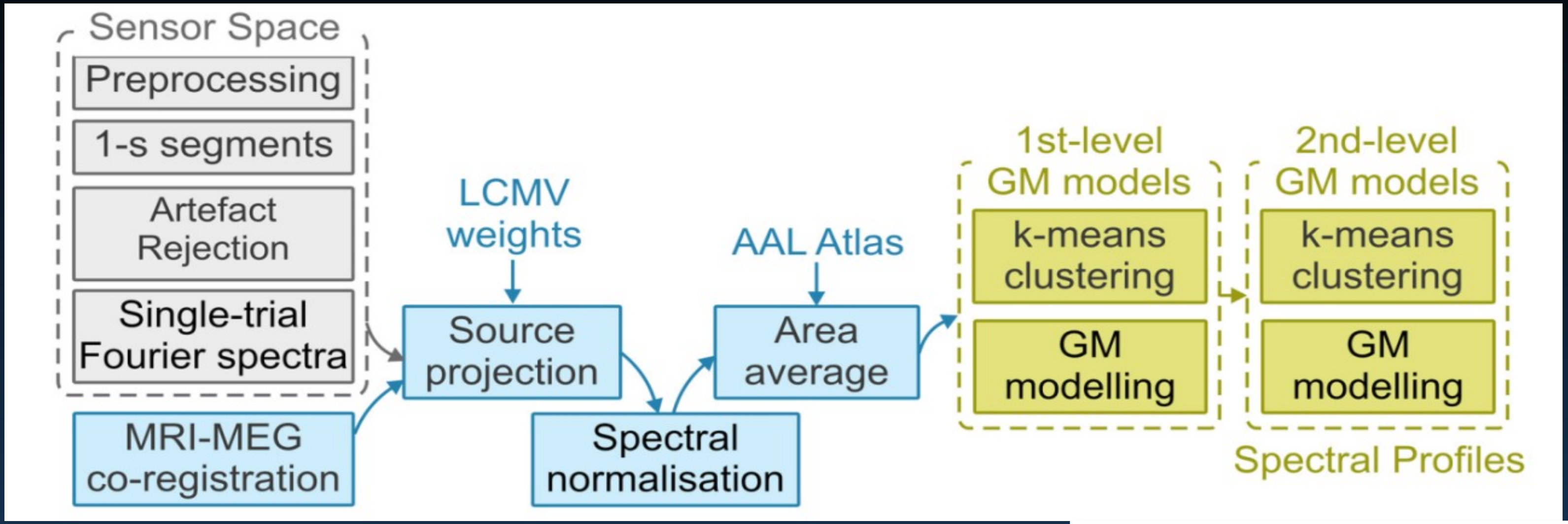
Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593. https://doi.org/10.1016/j.neuroimage.2017.11.062

EEG resting state



We would like to see activity of subnetworks.
HD EEG, selected 6 channels in theta band. Attractor reconstruction using embedding:
$[y(t),y(t-\tau),y(t-2\tau),\ldots,y(t-2n\tau)]$.

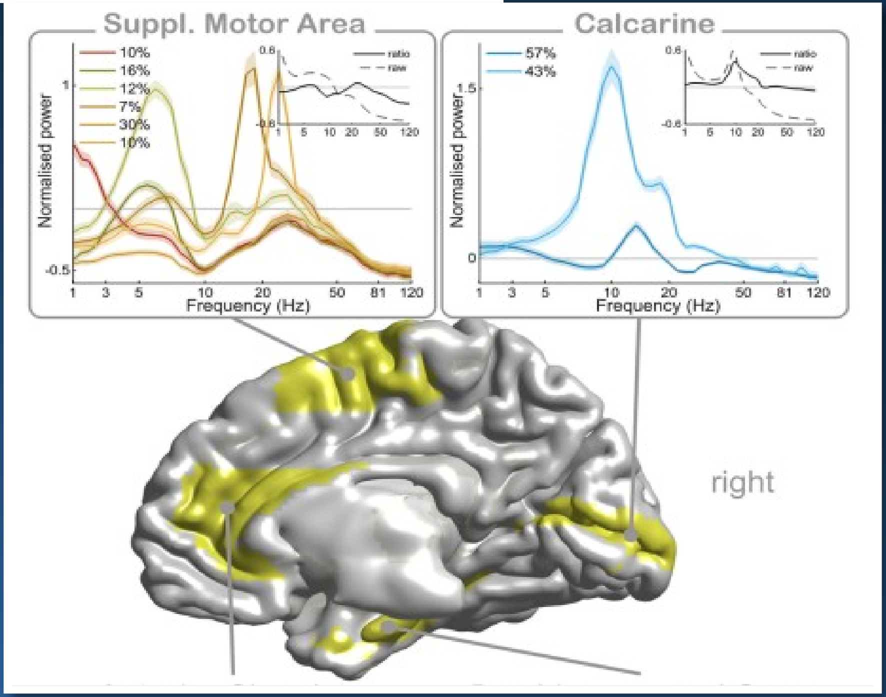
Spectral analysis



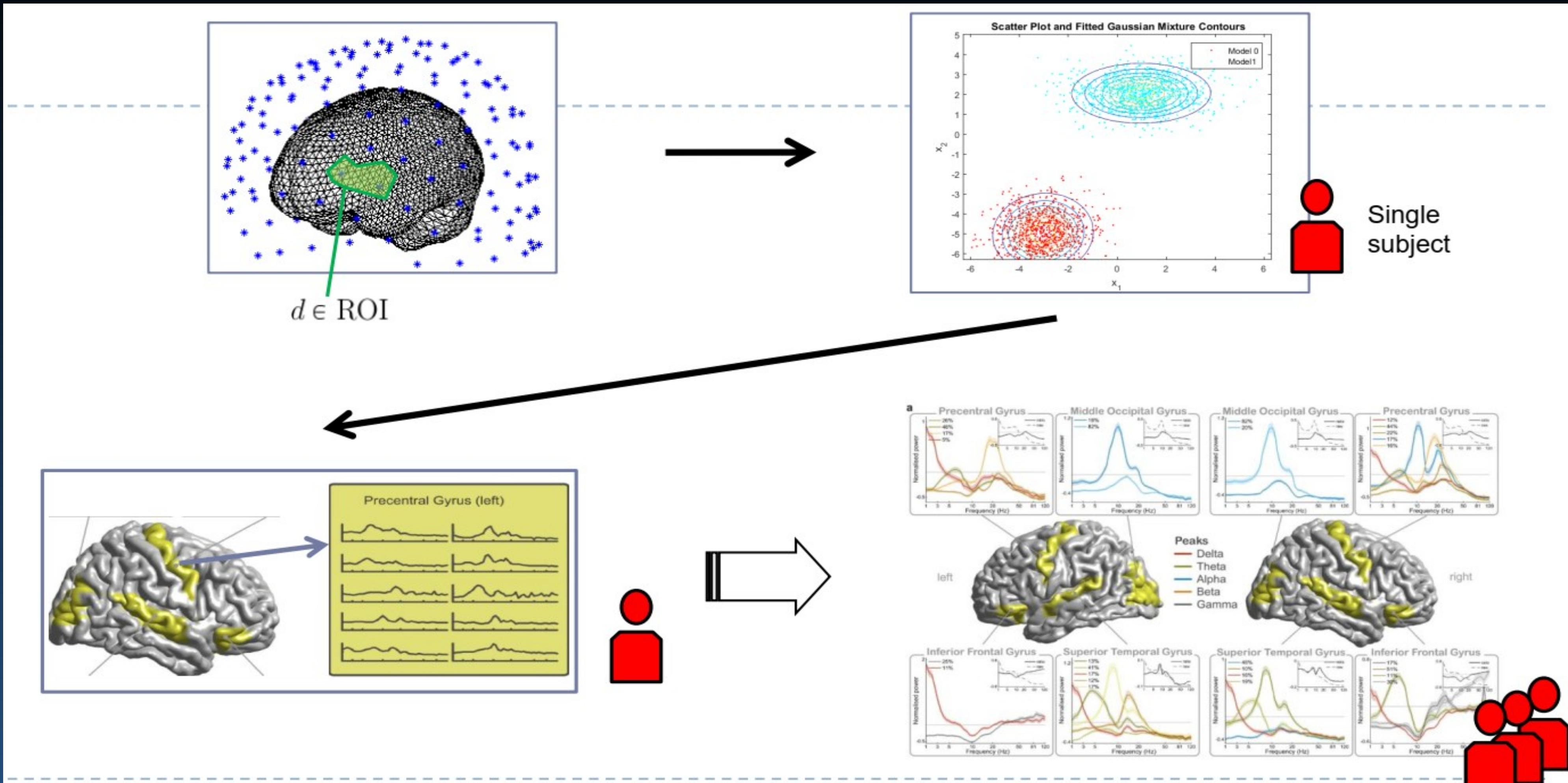
Spectral fingerprints

Monitor EEG/MEG power spectra in 1 sec time windows, project them to source space of ROIs based on brain atlas, and create spectra.

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



Spectral fingerprints

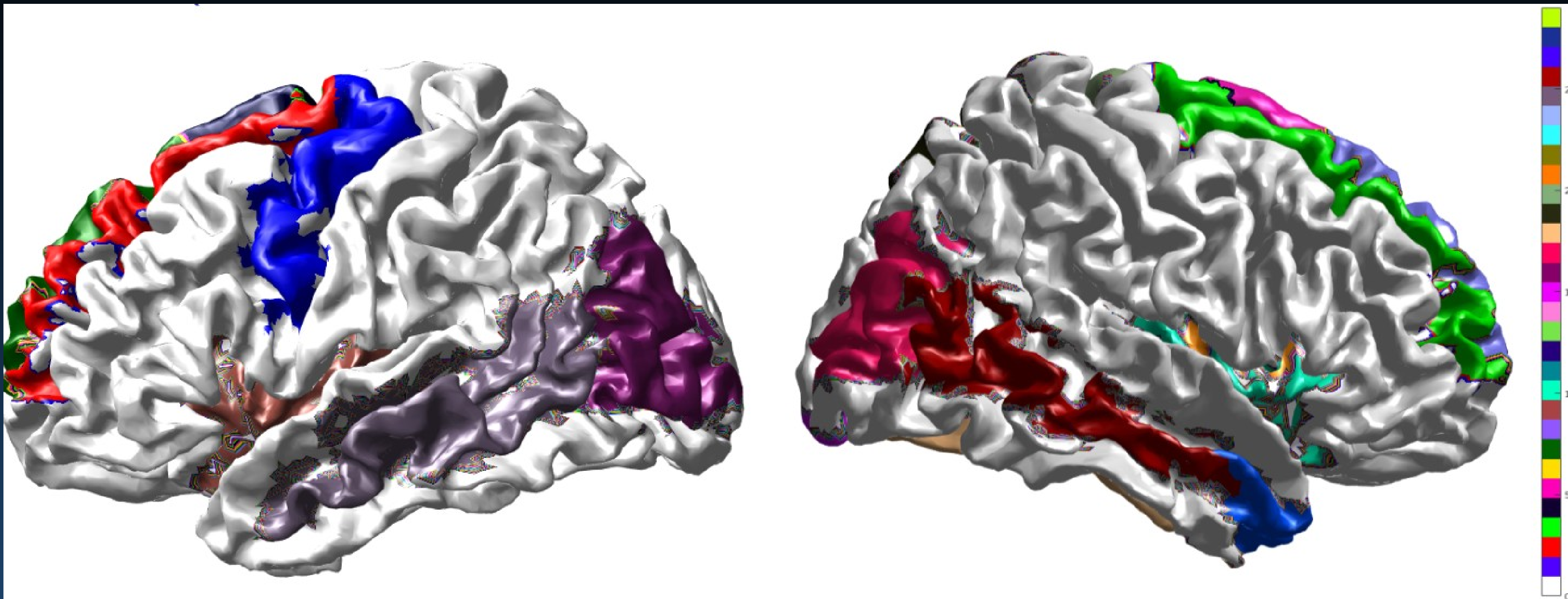


5

* 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

Most reliable ROI, homologous ≤ 1.5



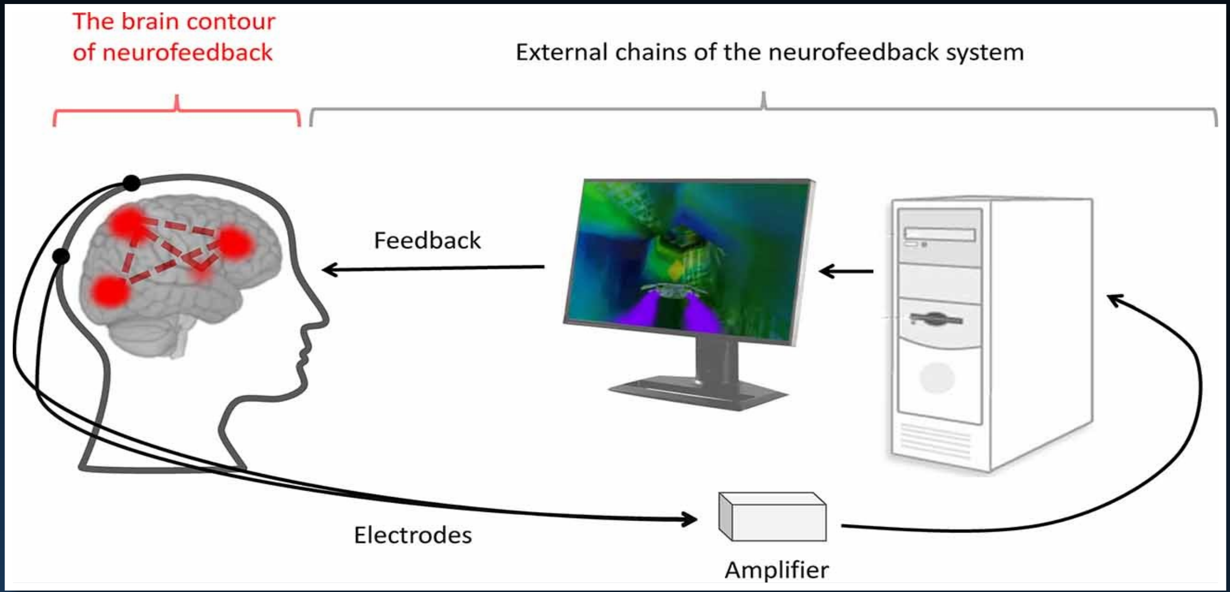
MEG data from the Human Connectome Project (HCP) for 1200 subjects.

Some ROI can be recognized quite reliably.

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

Spectral Fingerprint Challenges

Michał Komorowski



Source: O. R. Dobrushina *et al. Front. Hum. Neurosci.* 14, 2020

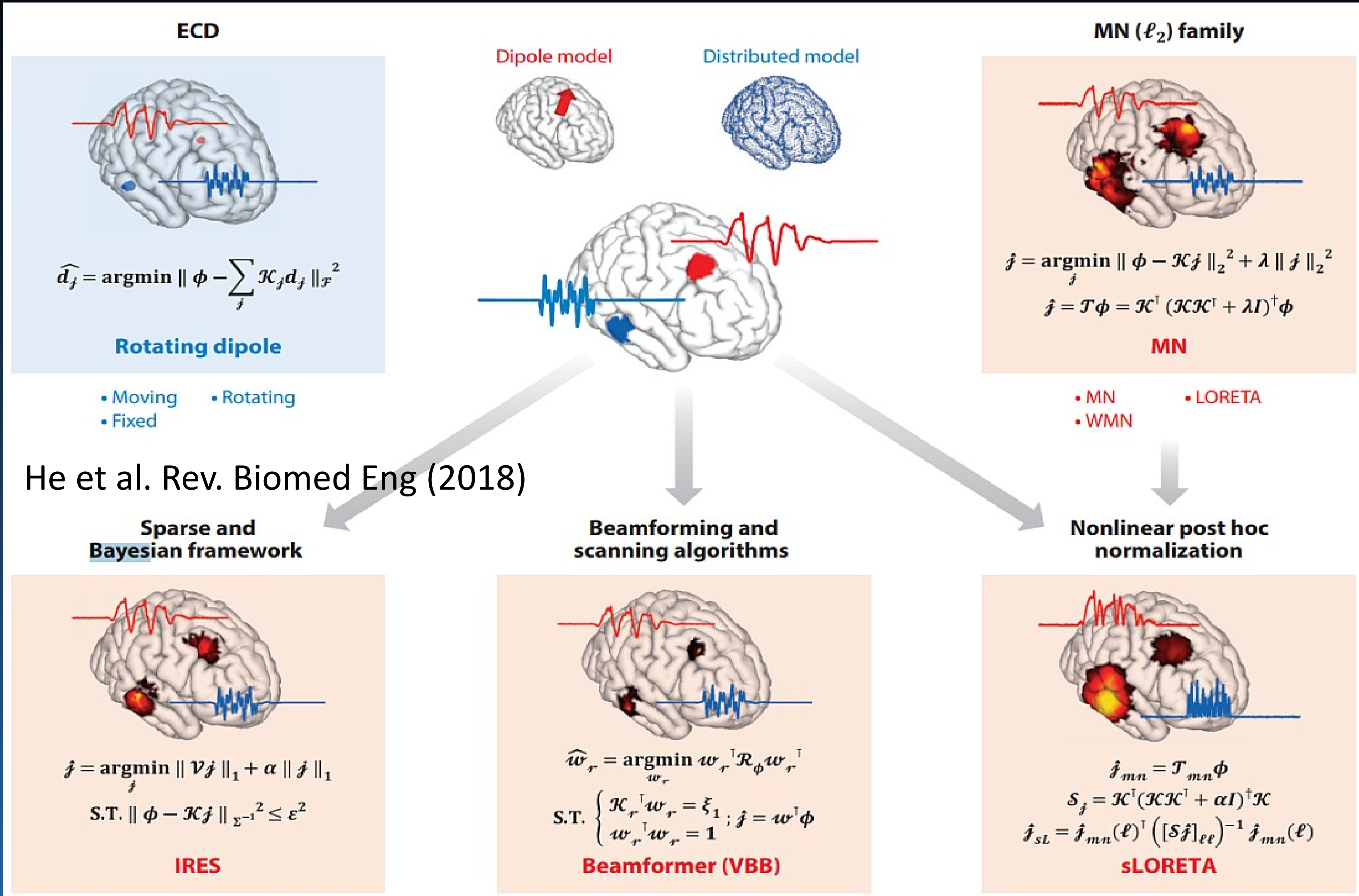
This method was tested for MEG resting-state data, will it work on EEG recordings?

Can we extract features that will be useful as biomarkers for brain disorders?

Can we do it in real time for neurofeedback applications?

Are linear constraint minimum variance (LCMV) sufficient?

EEG localization and reconstruction

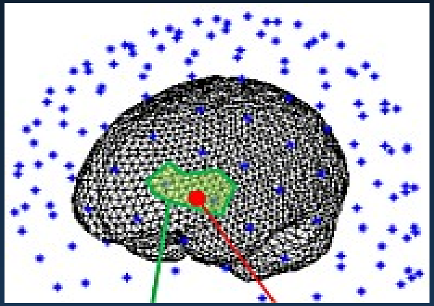


He et al. Rev. Biomed Eng (2018)

Spatial filters

LCMV (Linearly Constrained Minimum Variance), classical reconstruction filter is a solution to the following problem:
K - *lead-field* matrix; θ – dipol positions, *j* – activations; *W* – spatial filter

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



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 (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.

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

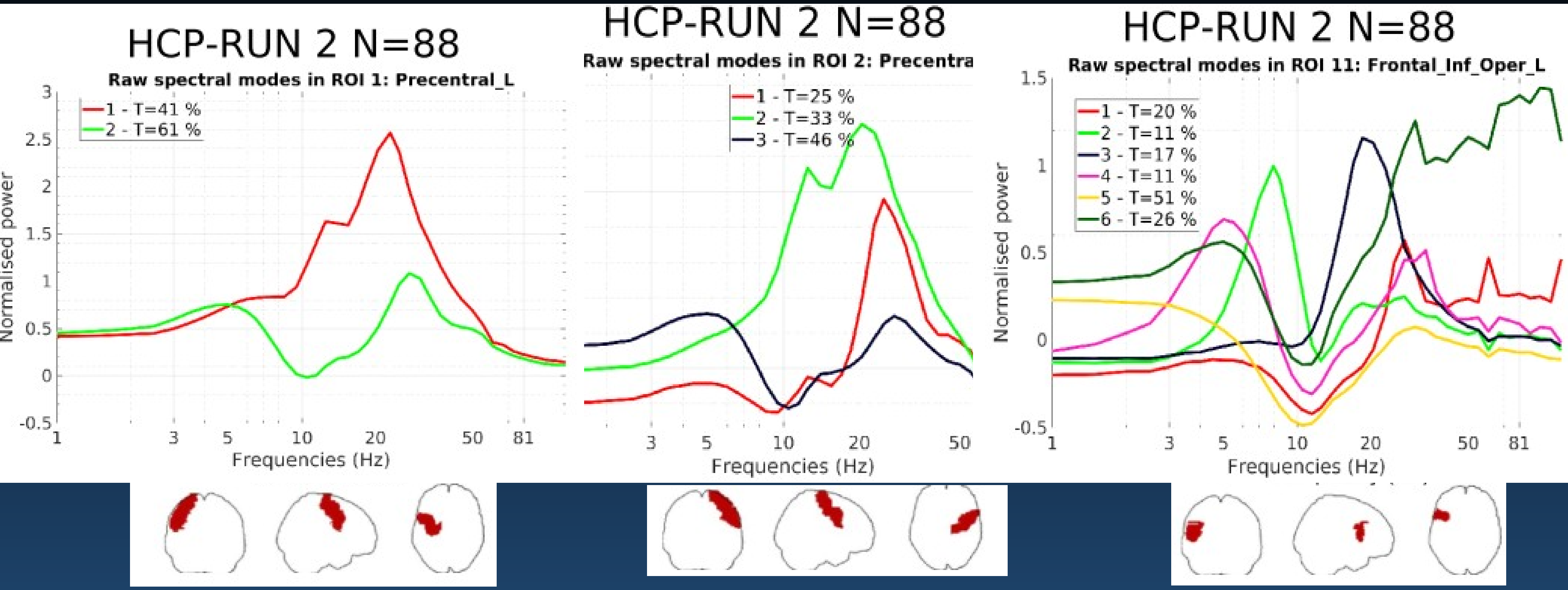
$$B := H_{Src,N} := N^{-1/2} H \quad (35)$$

```
%%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

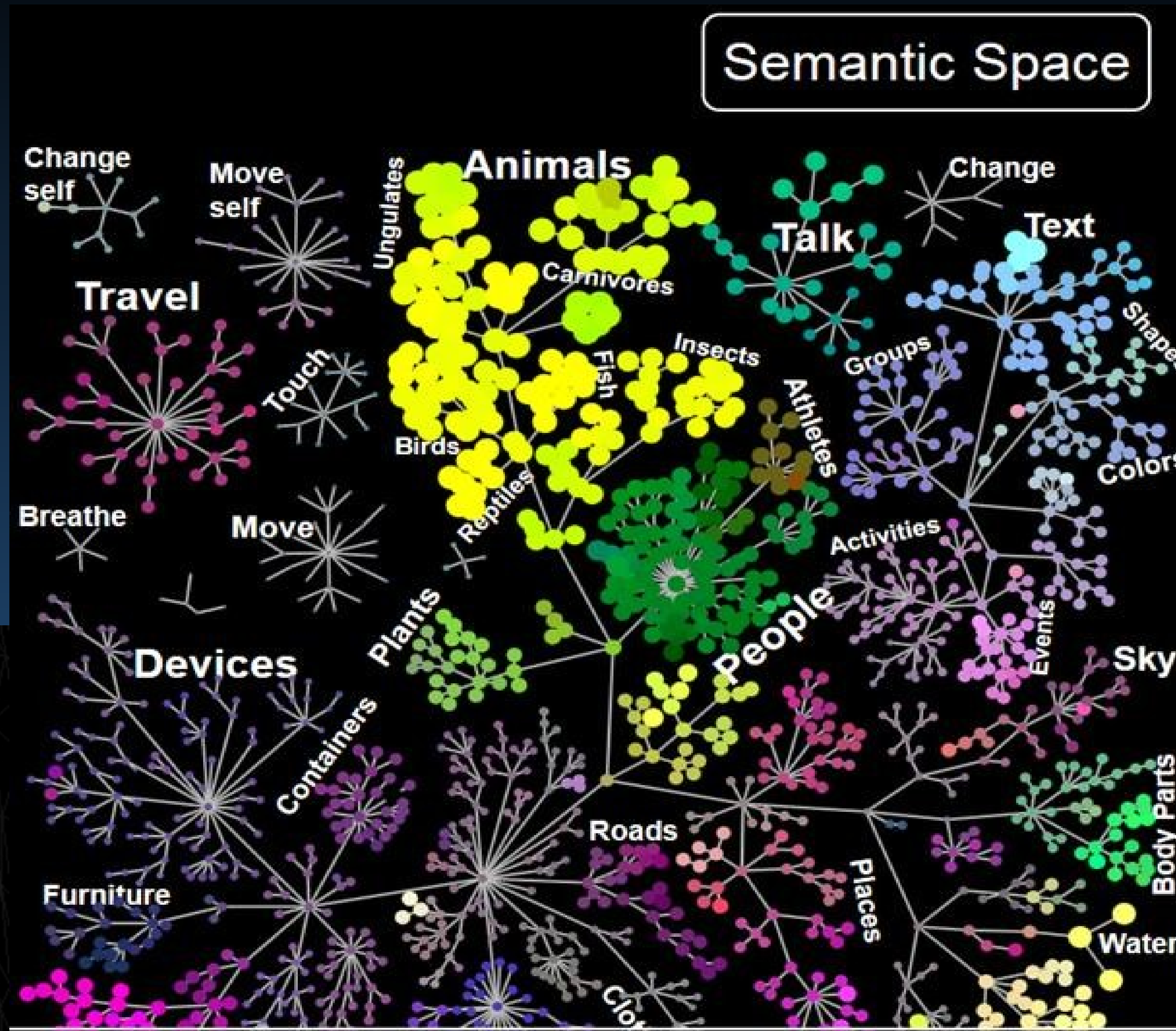


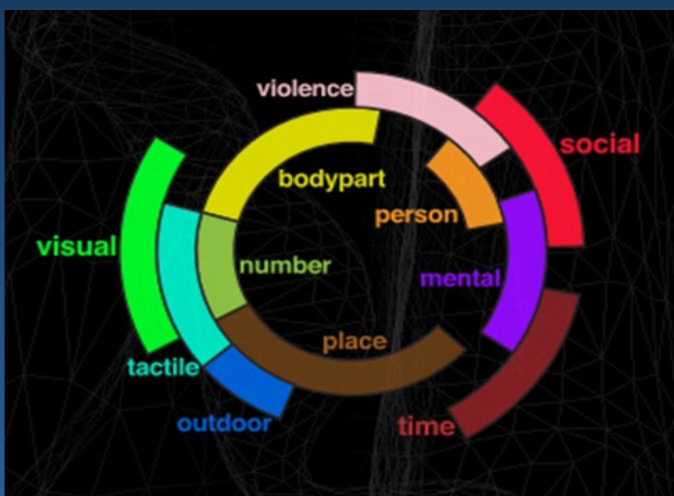
Example of spectra showing modes of oscillation characteristic to precentral left and right gyrus, and much more complex opercular part of inferior frontal gyrus.
MEG data from the Human Connectome Project (HCP).

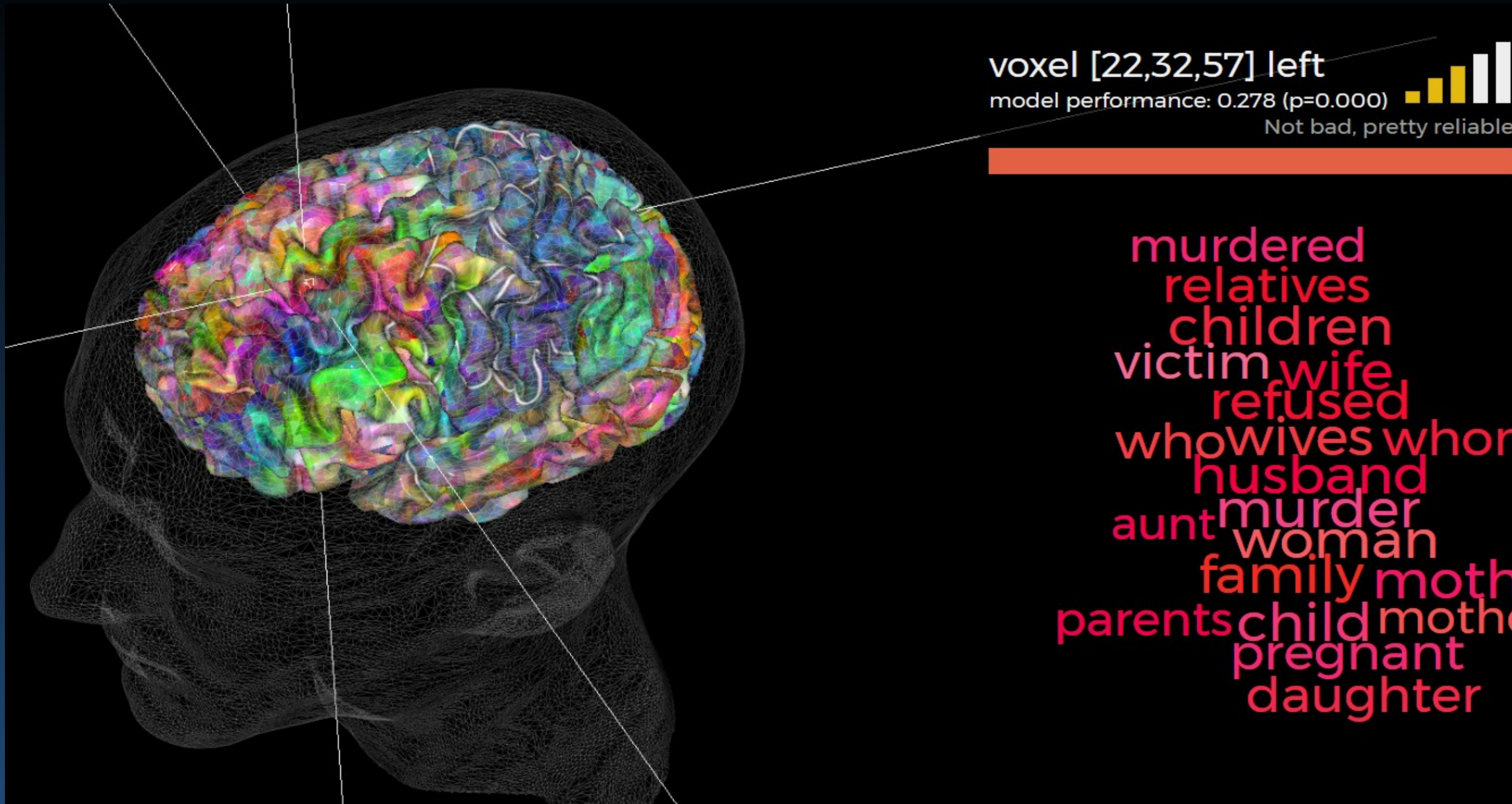
fMRI and brain functions

Semantic neuronal space

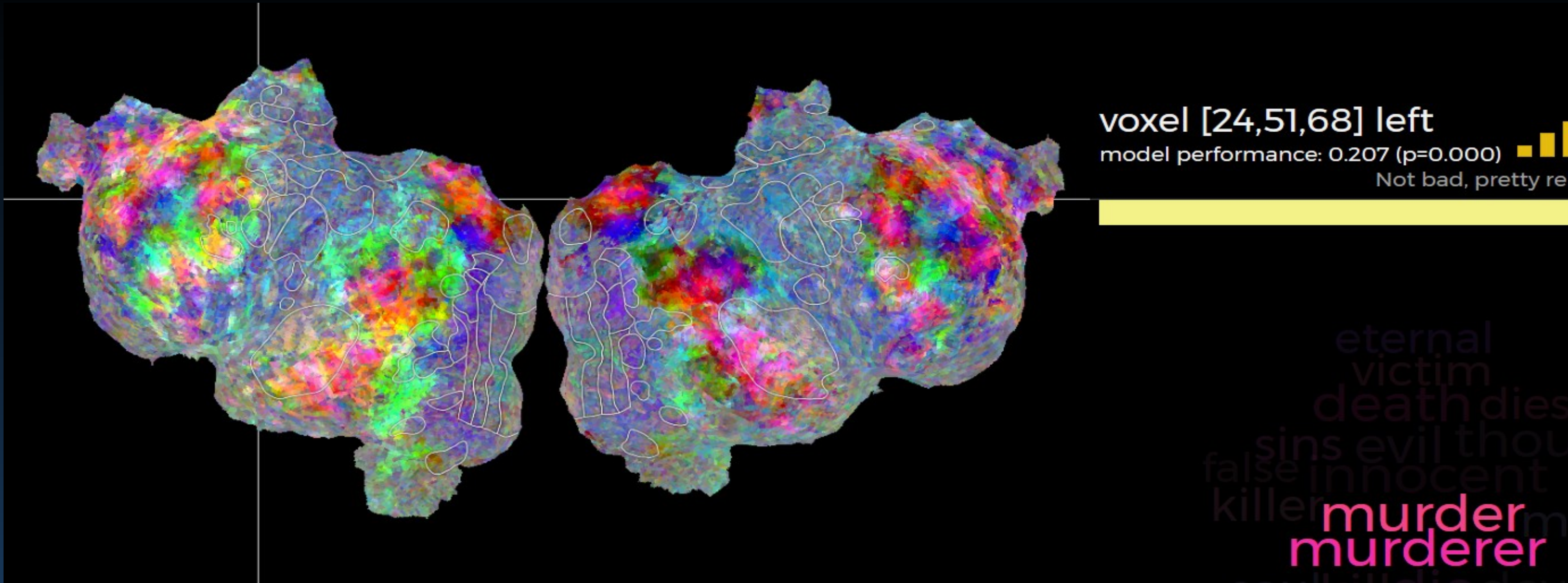
Words in the semantic space are grouped by their similarity.
Words activate specific ROIs, similar words create similar maps
of brain activity.
Video or audio stimuli, fMRI 60.000 voxel).
Gallant lab, Berkeley.







Each voxel responds usually to many related words, whole categories.
http://gallantlab.org/huth2016/
Huth et al. (2016). Decoding the Semantic Content of Natural Movies from Human Brain Activity. Frontiers in Systems Neuroscience 10, pp. 81



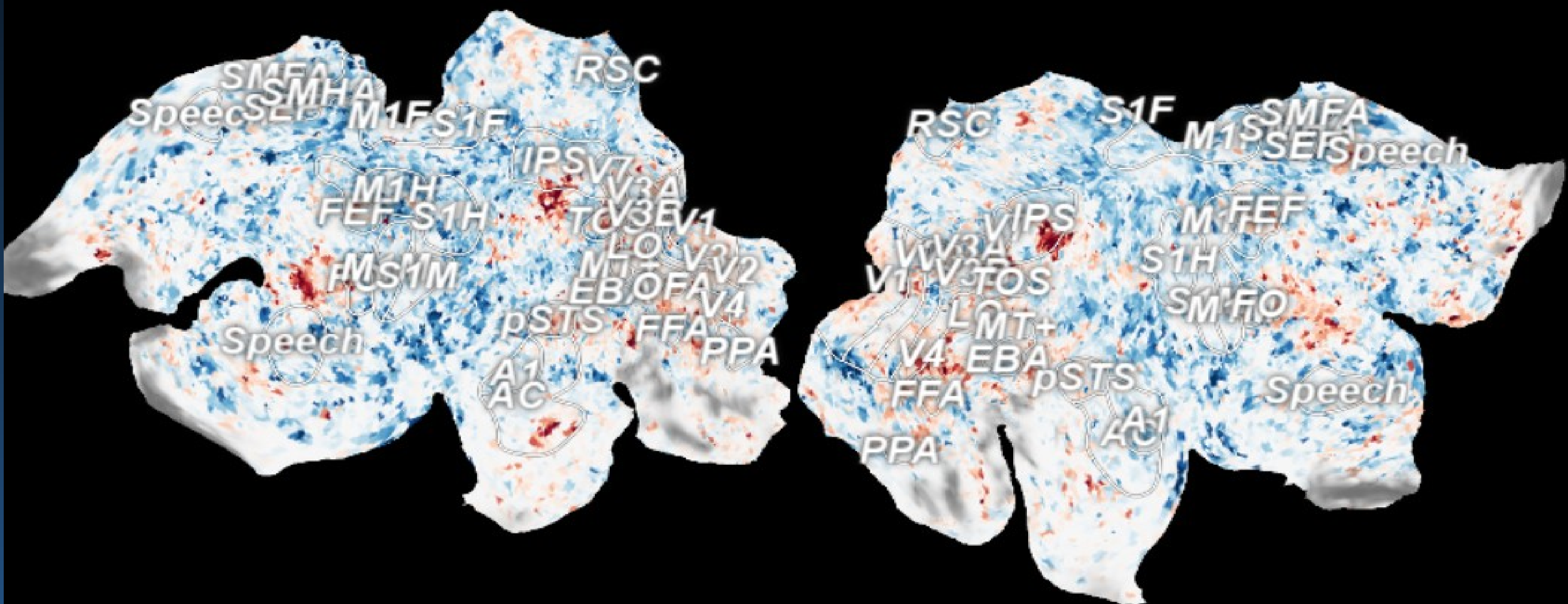
Whole fMRI activity map for the word "murder" shown on the flattened cortex.

Each word activates a whole map of activity in the brain, depending on sensory features, motor actions and affective components associated with this word. Why such activity patterns arise? Brain subnetworks connect active areas.

http://gallantlab.org/huth2016/ and short movie intro.

Can one do something like that with EEG or MEG?

Category traffic light: Passive Viewing



Simple activations for simple objects, colors, shapes, name, movement.

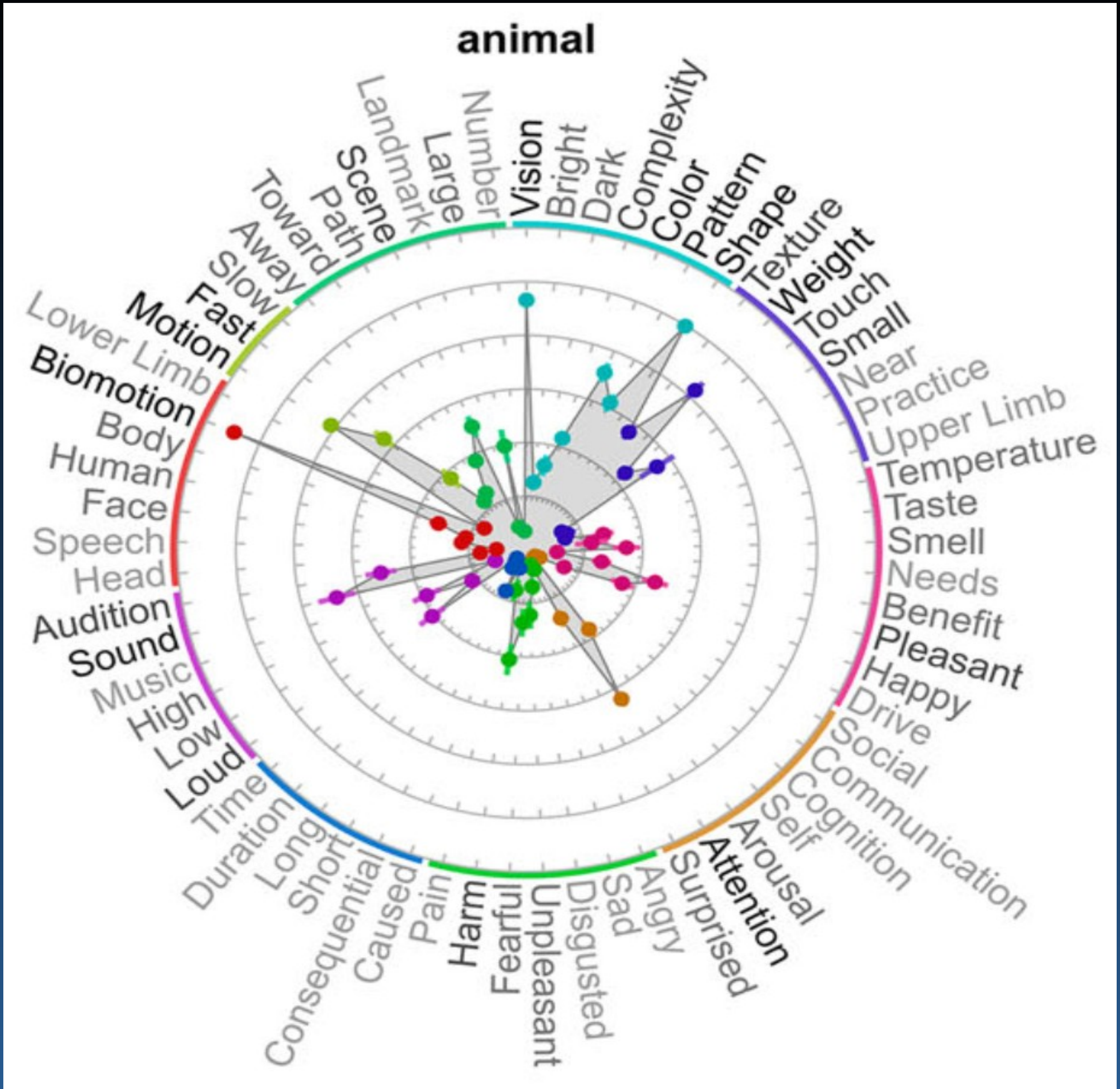
65 attributes related to neural processes;

Colors on circle: general domains.

J.R. Binder et al.

Toward a Brain-Based Componential Semantic Representation, 2016

More than just visual objects!

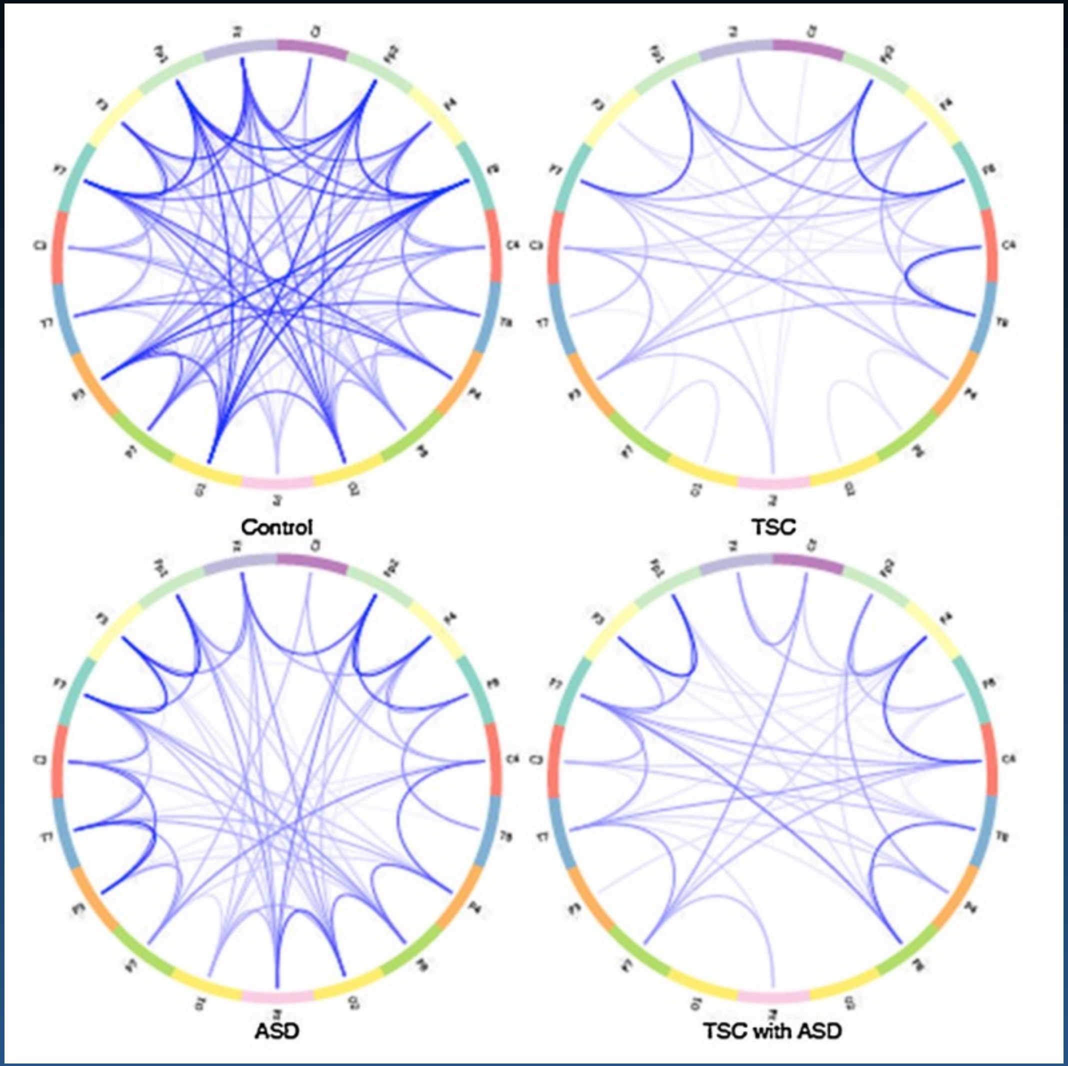


ASD: pathological connections

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**!



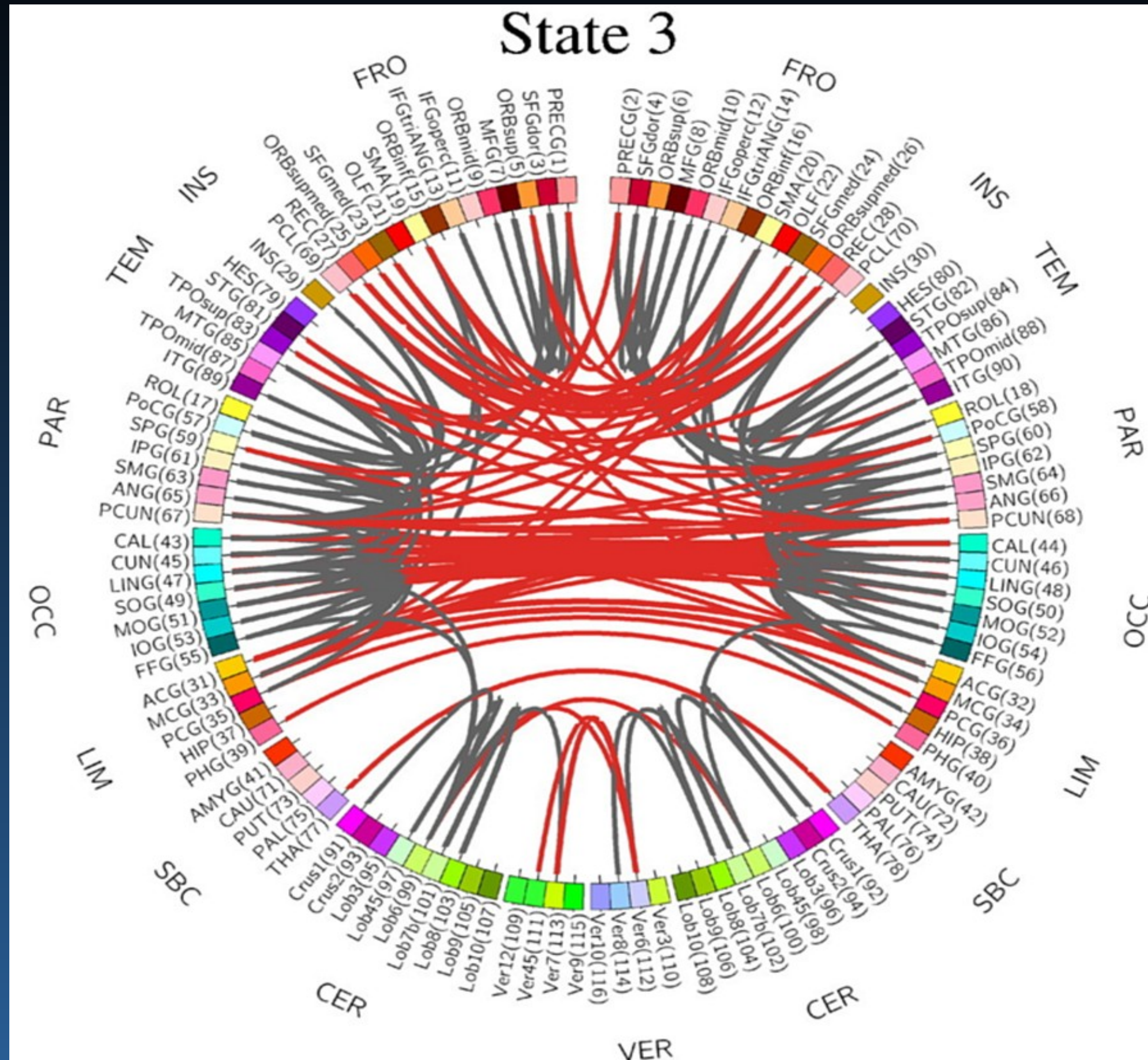
J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

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)



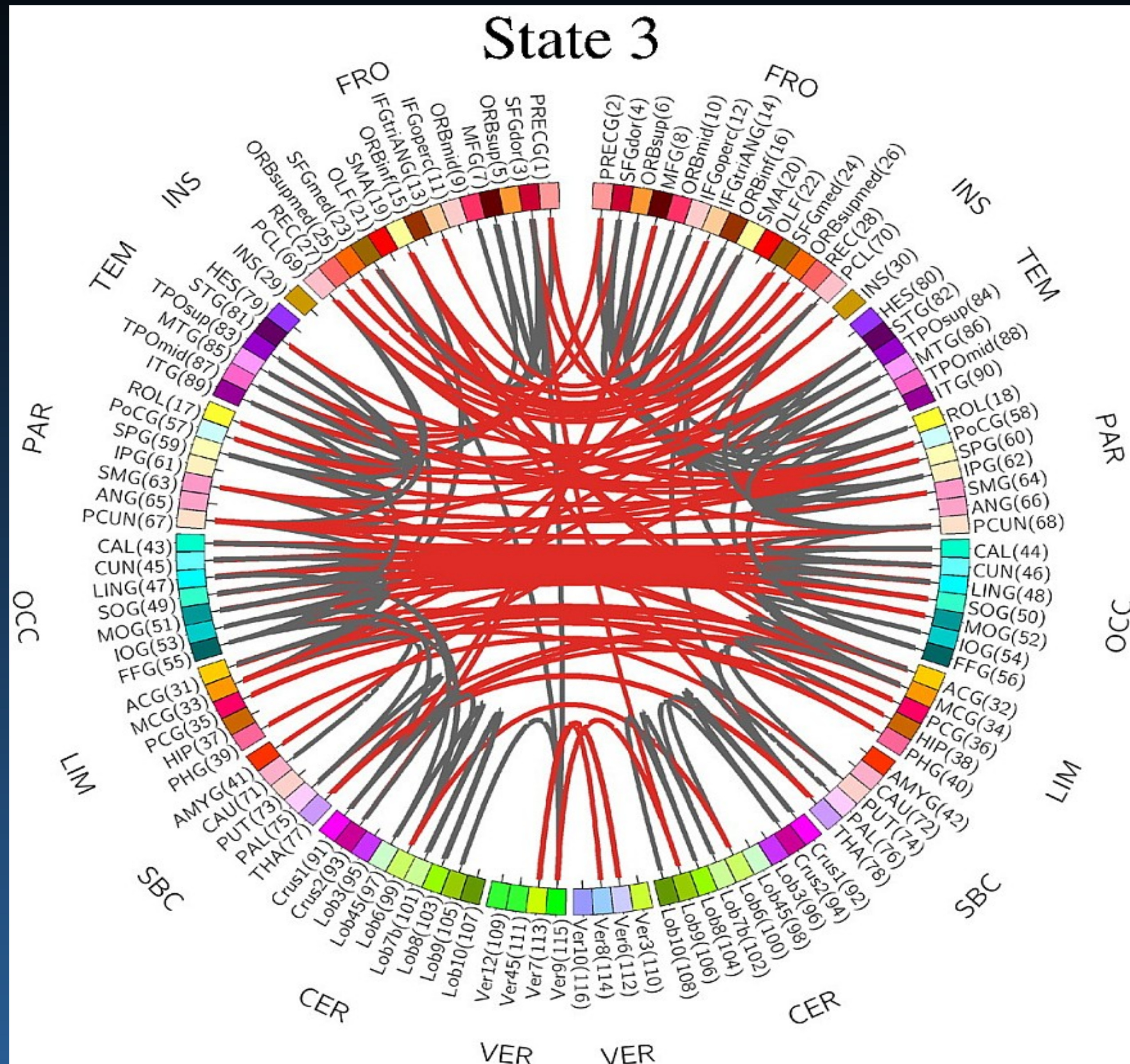
Negative connections in MCI patients

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

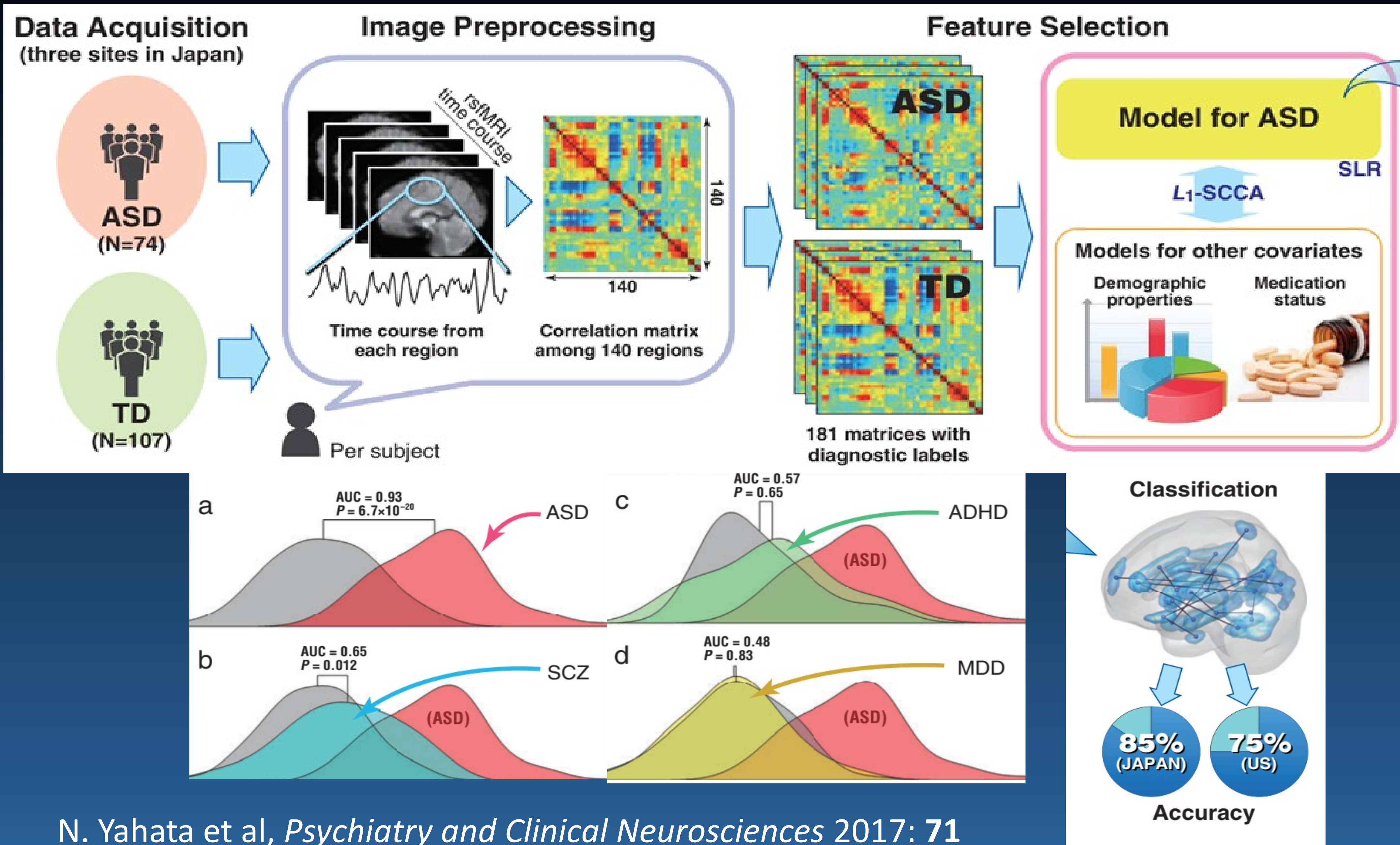
Connections |W|>0.65.

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

Suk et al. Neuroimage (2016)

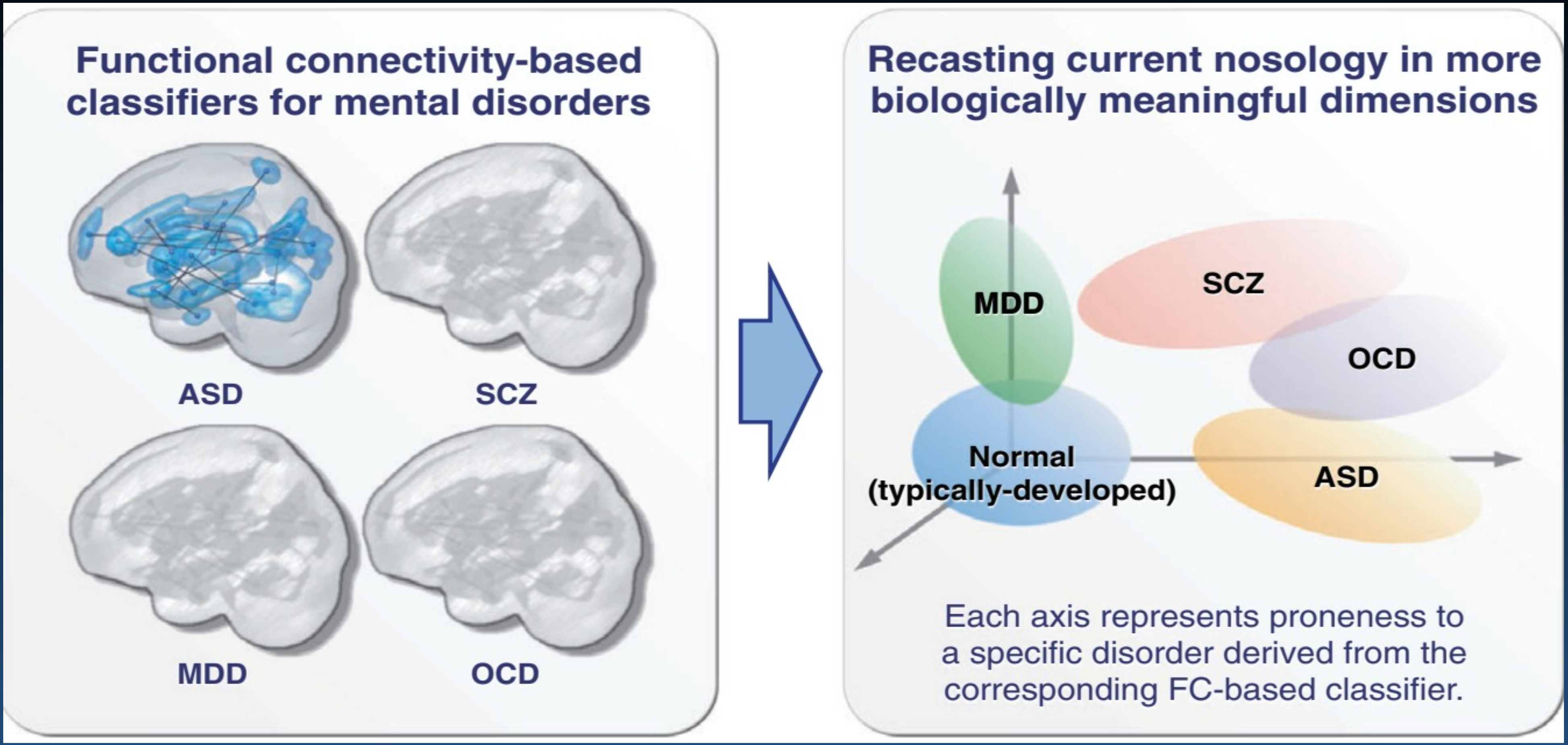


Biomarkers from neuroimaging



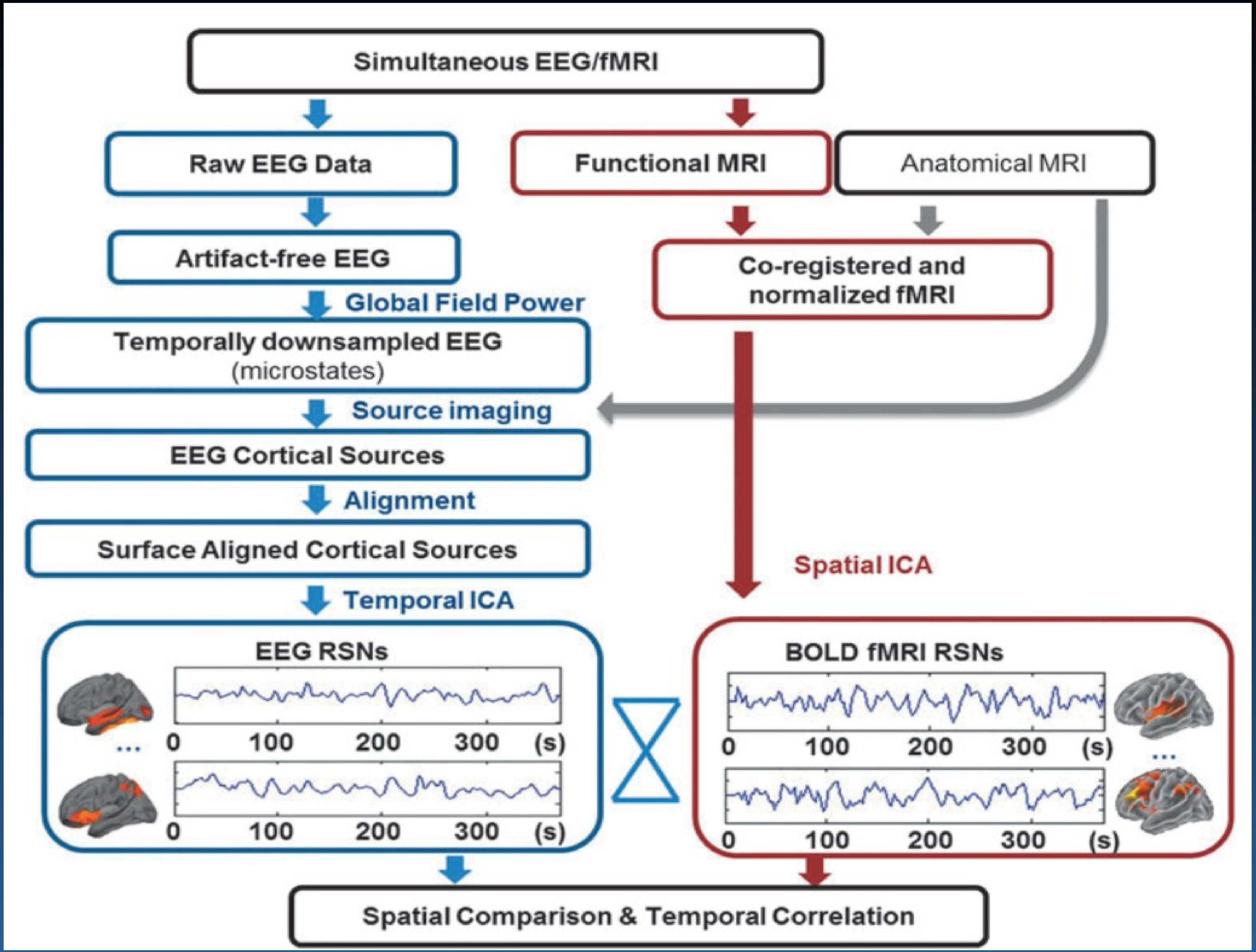
N. Yahata et al, *Psychiatry and Clinical Neurosciences* 2017: **71**

Biomarkers of mental disorders

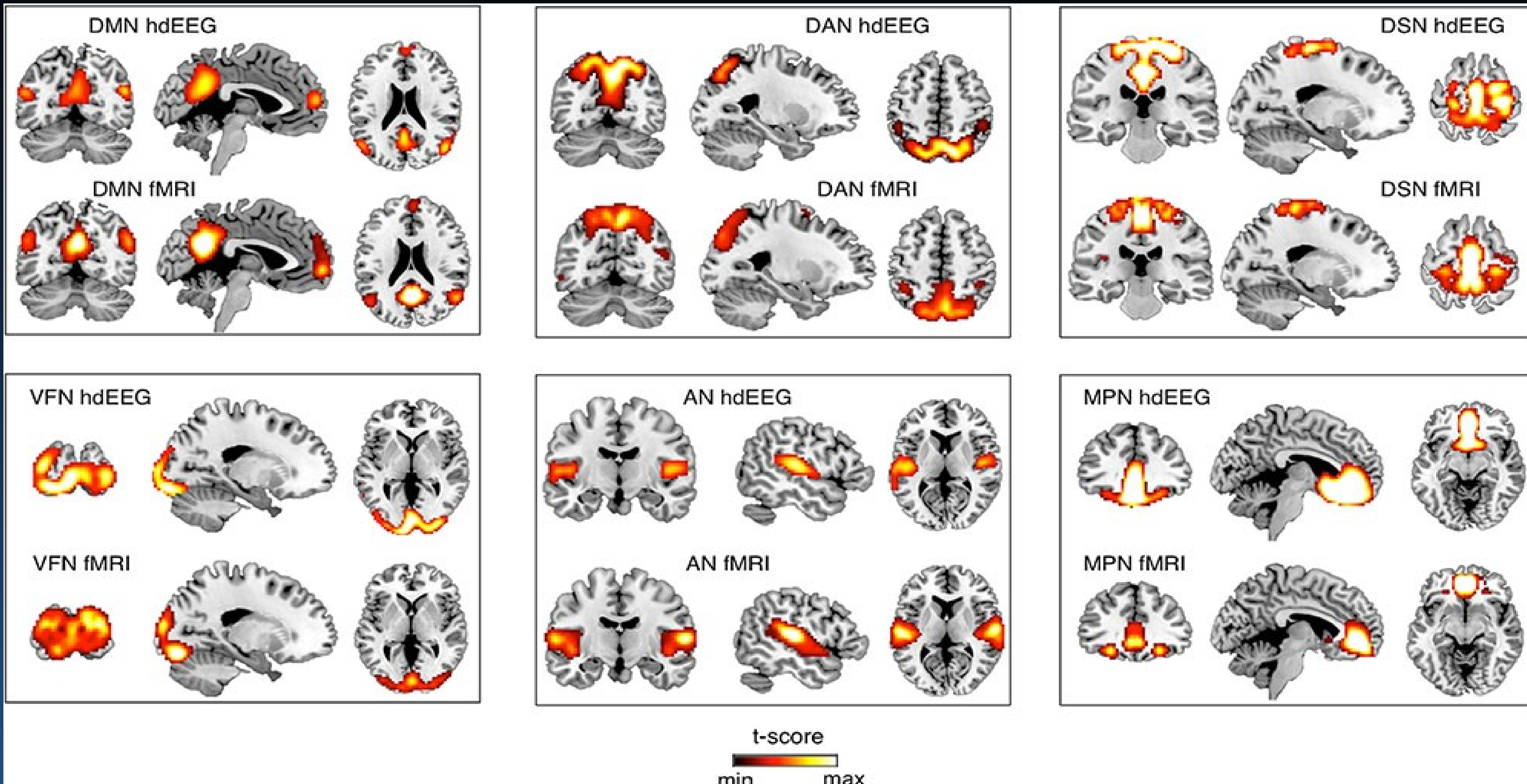


MDD, deep depression, SCZ, schizophrenia, OCD, obsessive-compulsive disorder, ASD autism spectrum disorder. fMRI biomarkers allow for objective diagnosis.
N. Yahata et al, *Psychiatry & Clinical Neurosciences* 2017; **71**: 215–237

Yuan .. Bodurka, 2015-21



14 networks from BOLD-EEG



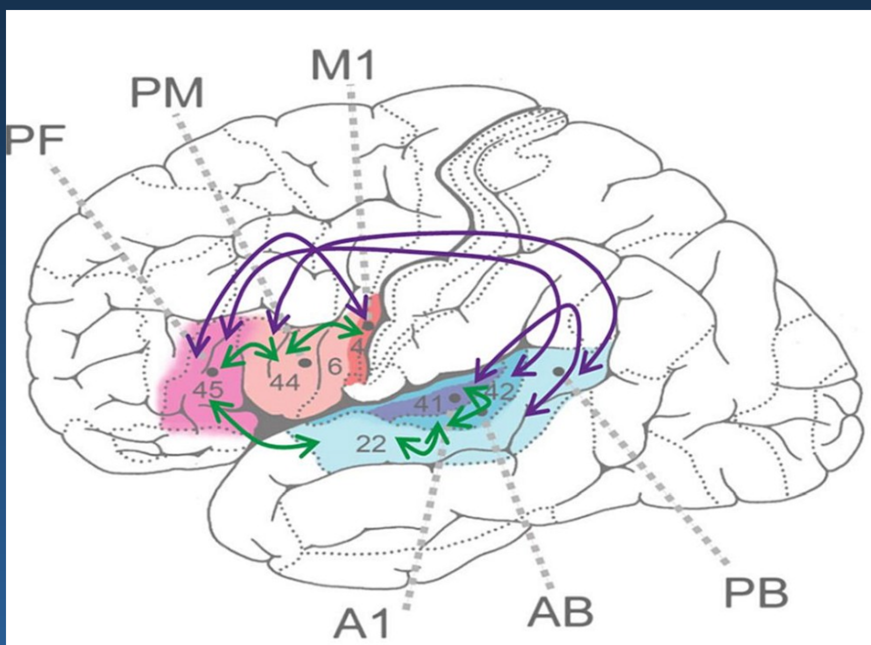
Spatial ICA, 10-min fMRI (*N* = 24). Networks: DMN, default mode; DAN, dorsal attention; DSN, dorsal somatomotor; VFN, visual foveal; AN, auditory; MPN, medial prefrontal.
Liu et al. Detecting large-scale networks in the human brain. HBM (2017; 2018).

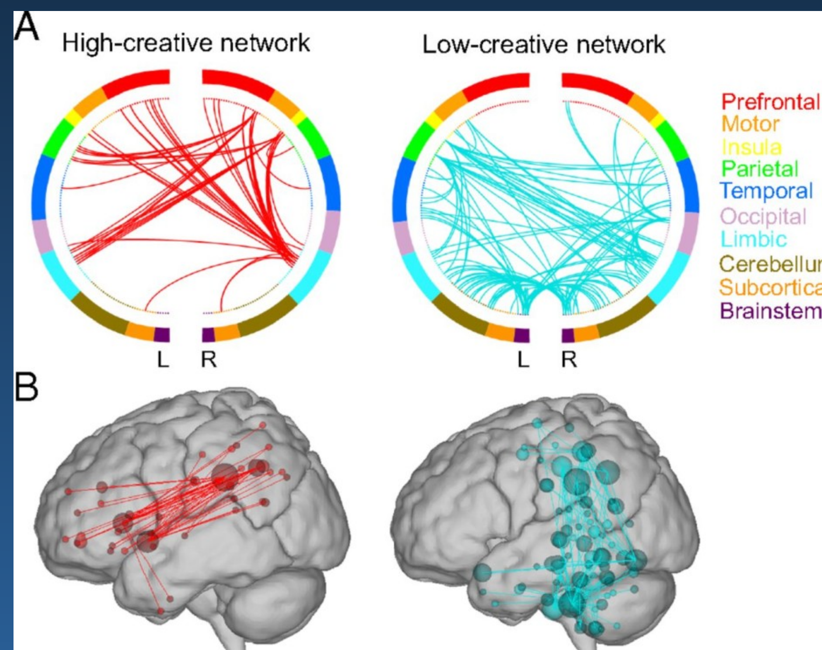
Fluid nature

BABY Connectome Project
a UNC / UMN collaboration

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

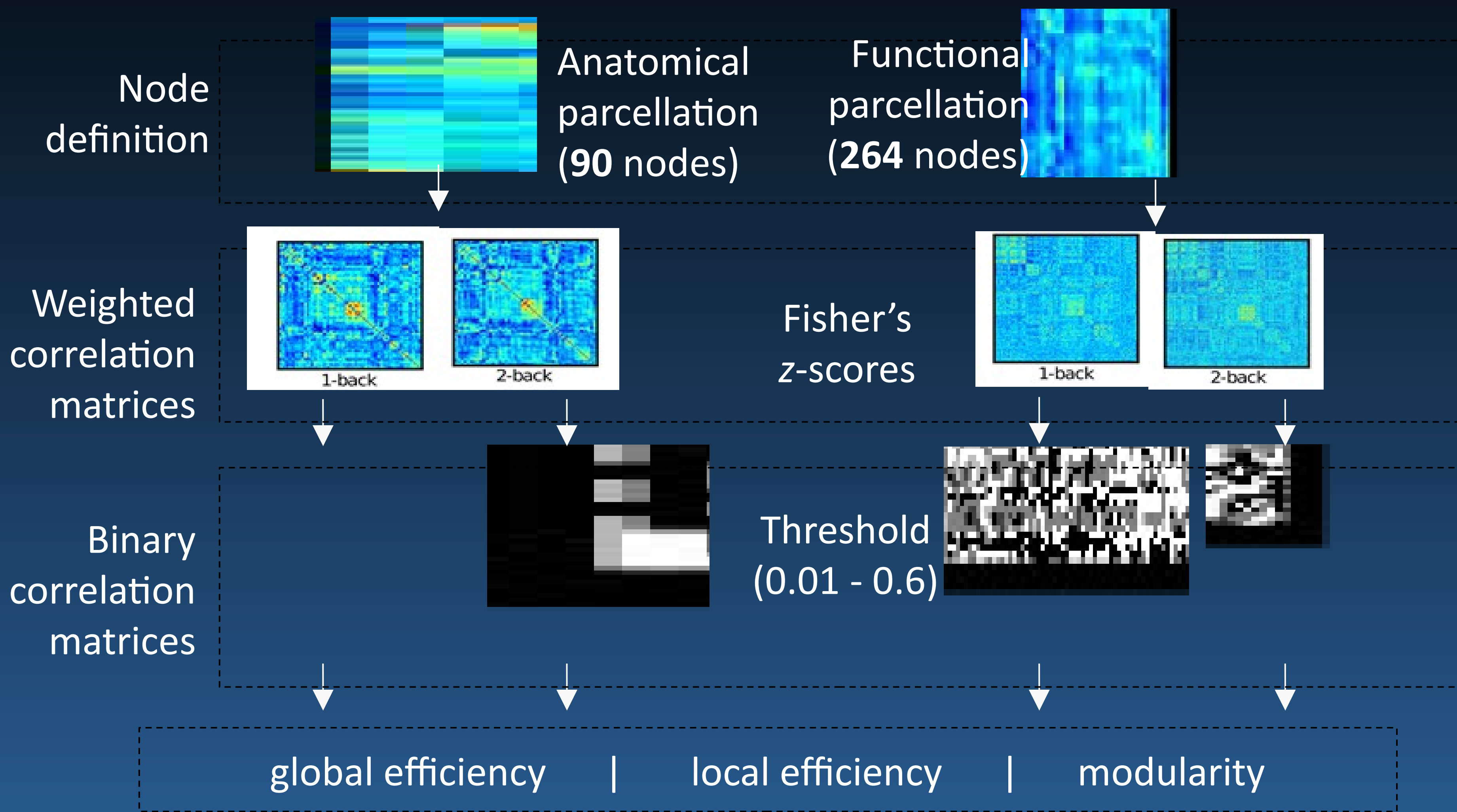
The Developing Human Connectome Project: create a dynamic map of human brain connectivity from 20 to 44 weeks post-conceptional age, which will link together imaging, clinical, behavioral, and genetic information.
Pointing, gestures, lead to connectome development in pre-linguistic children (our BabyLab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





Hard problem – recruit more regions!

Two experimental conditions: 1-back, 2-back, 35 subjects, letter N-back.



Finc, Bonna, Lewandowska, Wolak, Nikadon, Dreszer, Duch, Kühn, Human Brain Mapping (2017).

Brain modules and cognitive processes

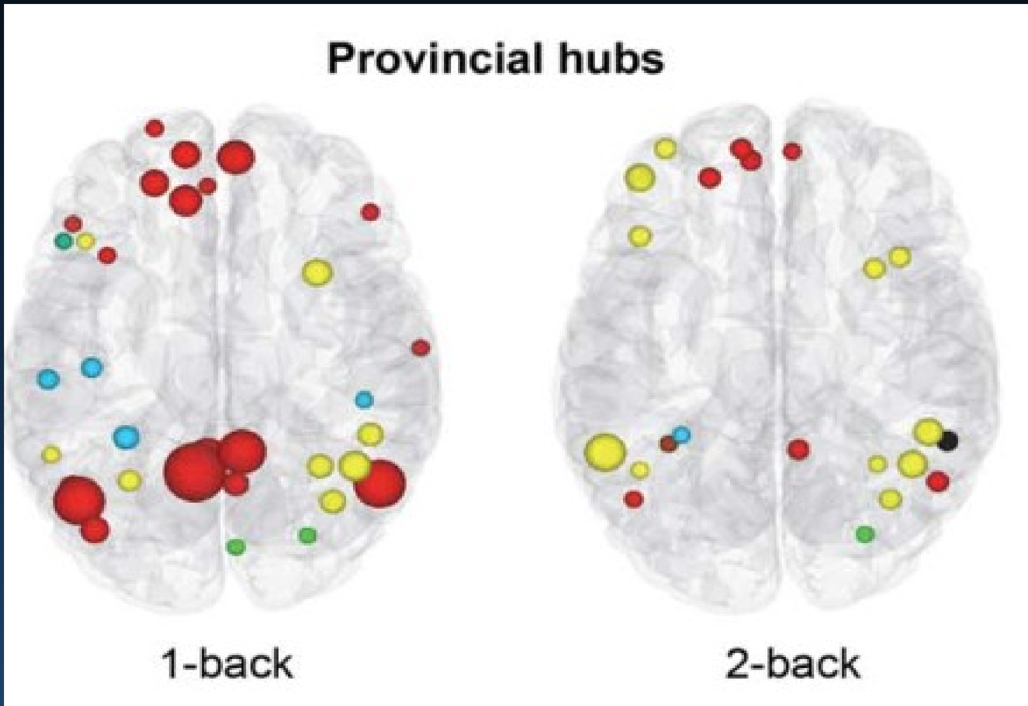
Simple and more difficult tasks, requiring the whole-brain network reorganization.

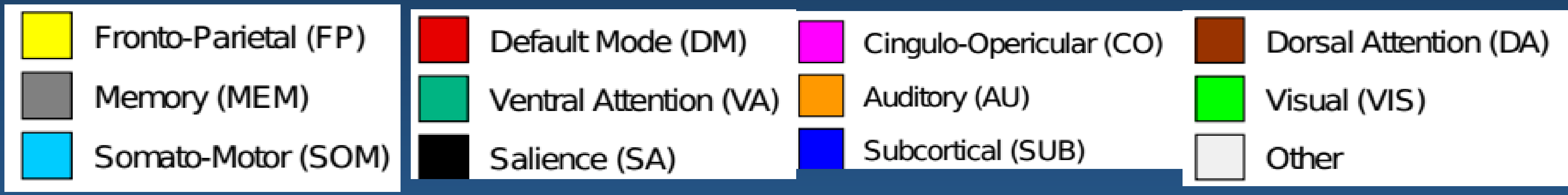
Left: 1-back local hubs

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).

Effect of cognitive load on info flow

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

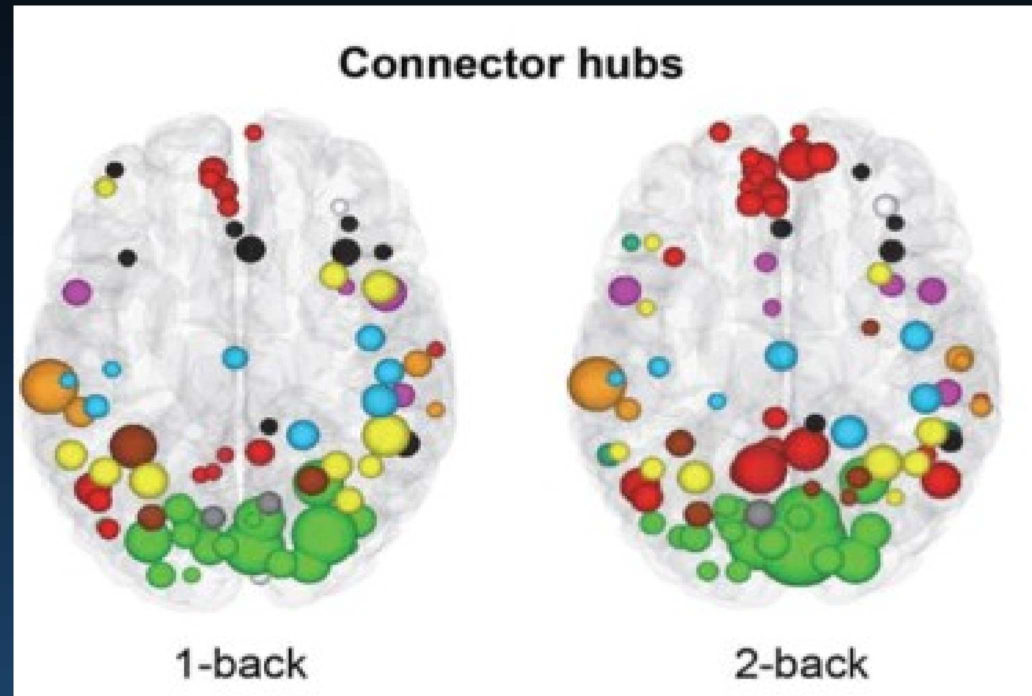
Left: 1-back connector hubs

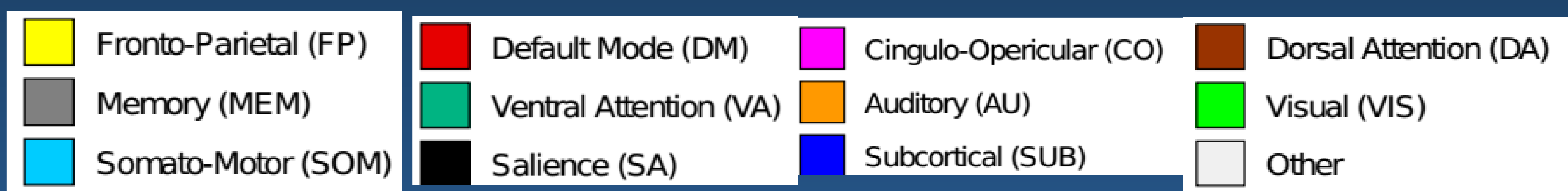
Right: 2-back connector hubs

Average over 35 *participants.*

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

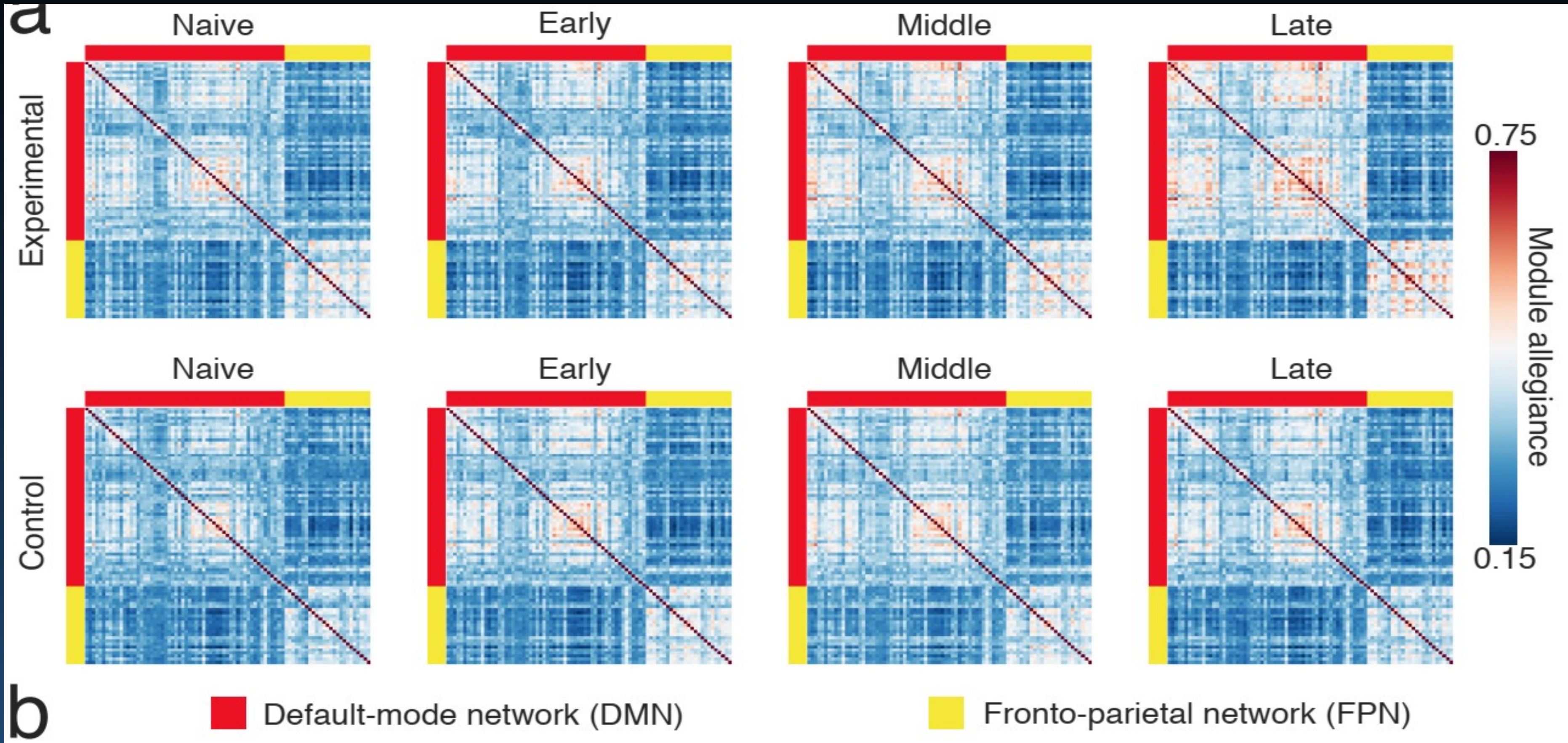
DMN areas engaged in global binding!





Finc, Bonna, Lewandowska, Wolak, Nikadon, Dreszer, Duch, Kühn. Transition of the functional brain network related to increasing cognitive demands. Human Brain Mapping 38, 3659–3674, 2017.

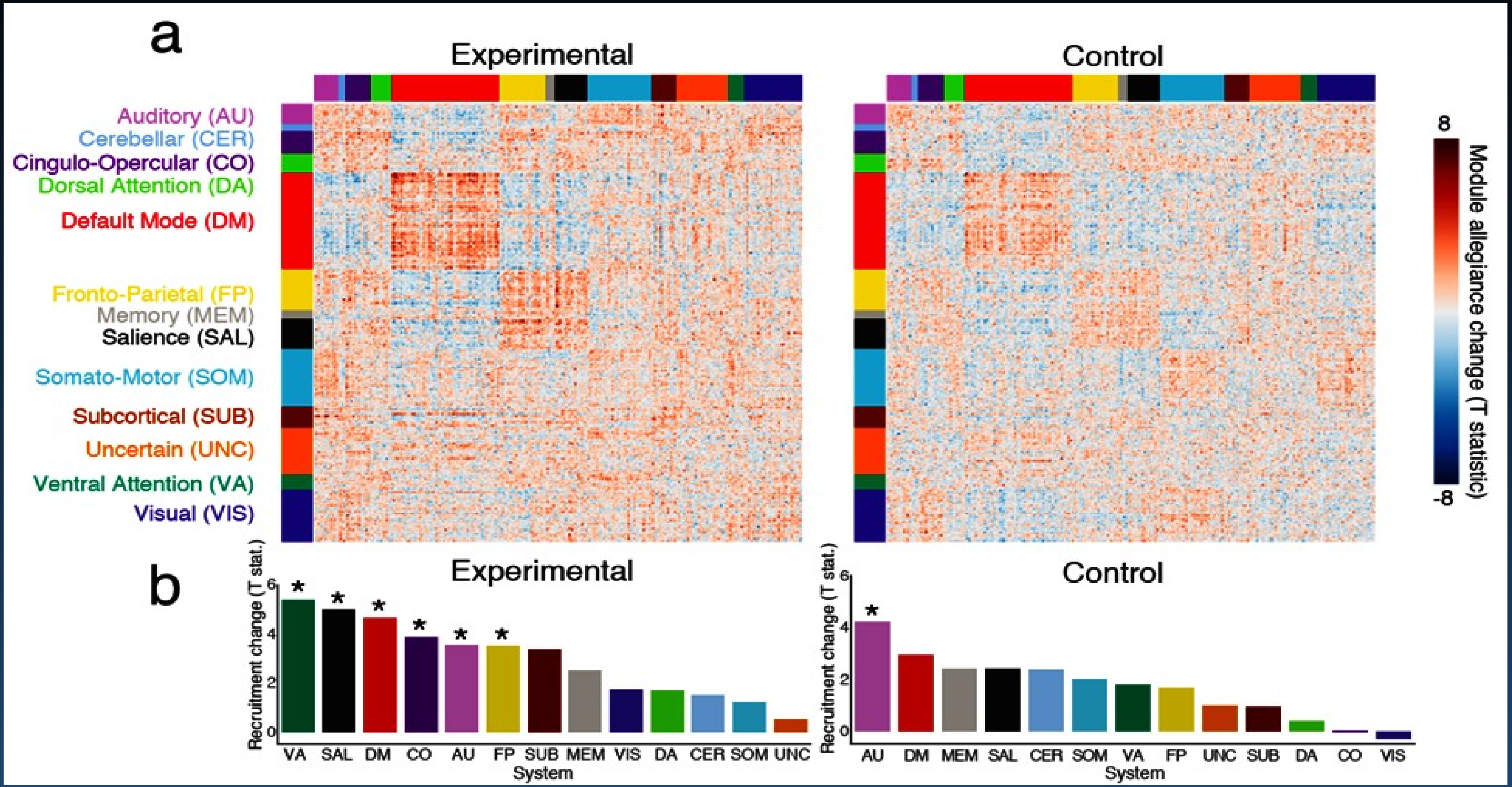
Working memory training



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.

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.

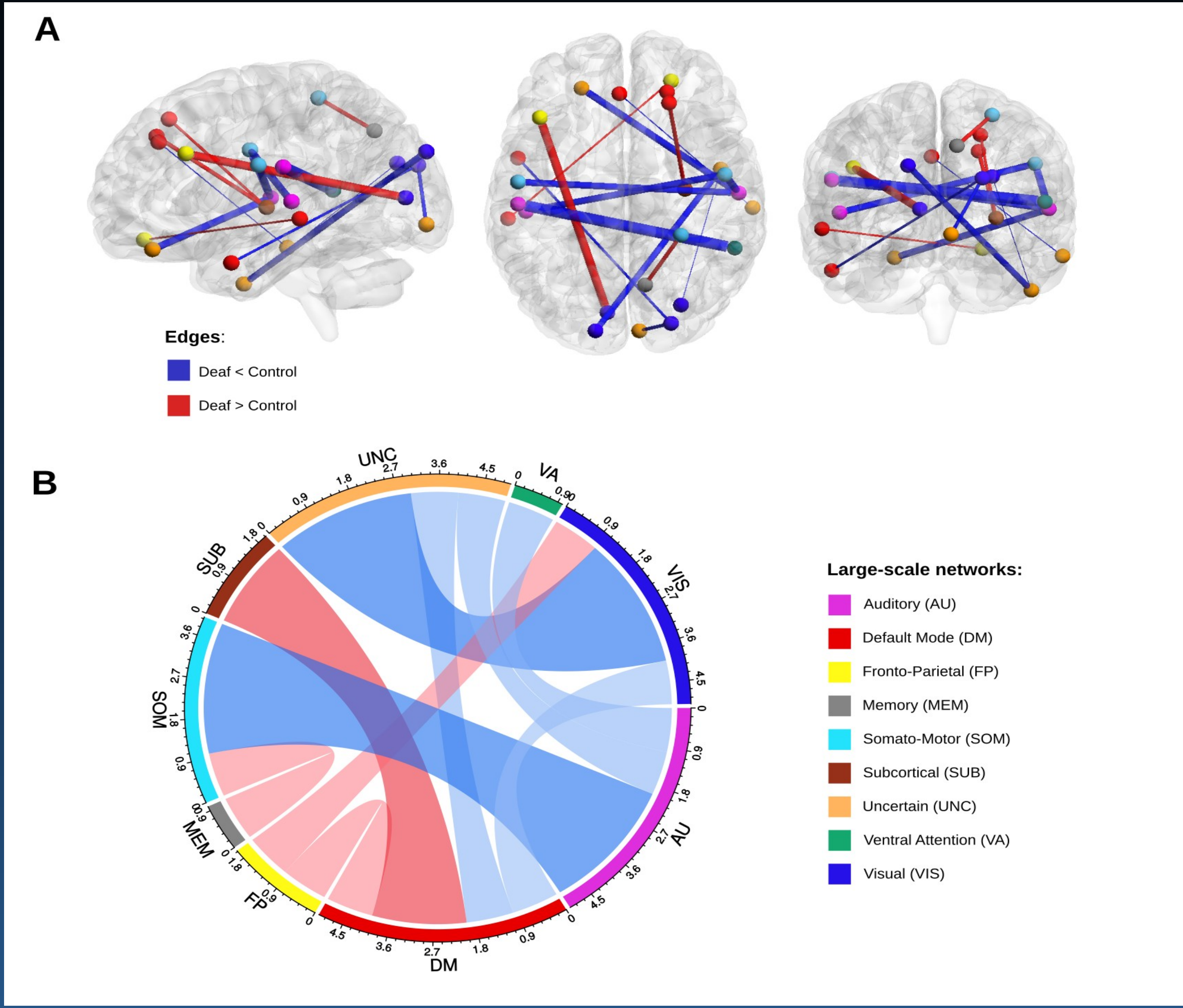
(b) Significant increase * in the default mode DM, fronto-parietal ventral attention VA, salience SAL, cingulo-opercular CO, and auditory systems AU recruitment.

Finc, Bonna, He, Lydon-Staley, Kühn, Duch, Bassett, Nature Communications 11 (2020).

Deaf vs. Control

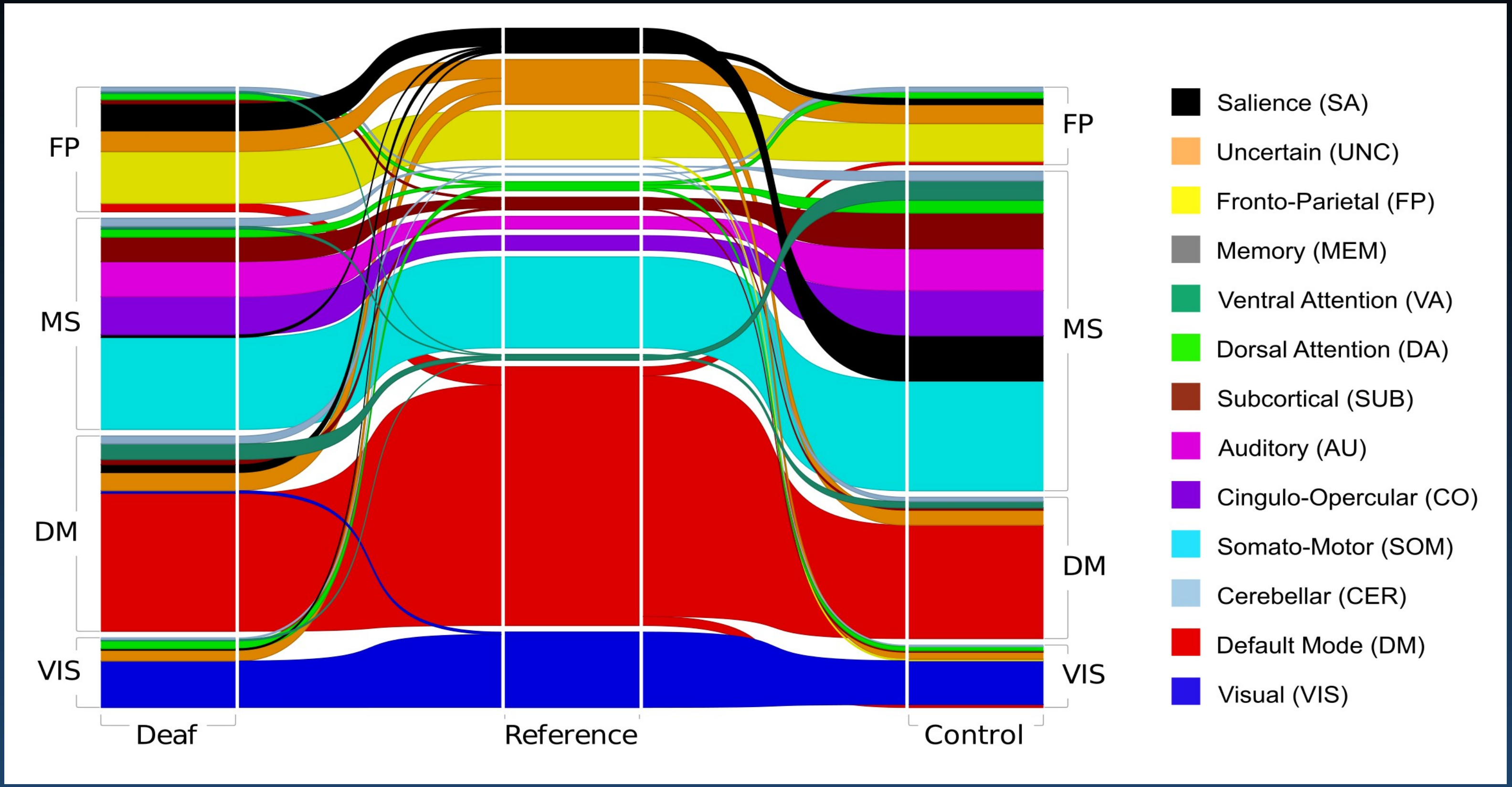
Edge-wise functional connectivity network differences visualized in the brain space.
(A). Connections that are significantly stronger (red) or weaker (blue) in deaf. Edge thickness reflects t-test statistic strength.
(B) Number of significant edges between different large-scale networks.

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).

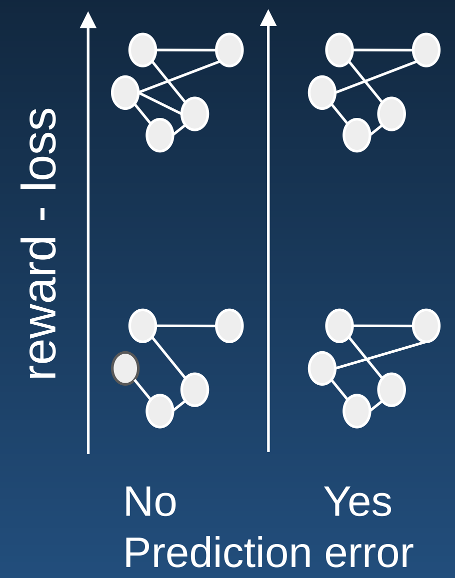
DecideNet

Does functional brain network organization during learning depend on prediction error and reward / punishment context?

Experiment: 32 subjects in the fMRI (GE 3T) were tested on *probabilistic reversal learning* (PRL) task, and after the session filled psychometric tests (Barratt Impulsiveness Scale BIS-11, Specific Risk Taking Scale DOSPERT).

Questions (Kamil Bonna):

1) How functional orgnaization of brain networks changes depending on prediction error in context of reward or loss?
2) Can we notice changes in modular orgnaization of networks?
3) Which other networks interact with networks involved in predictions?



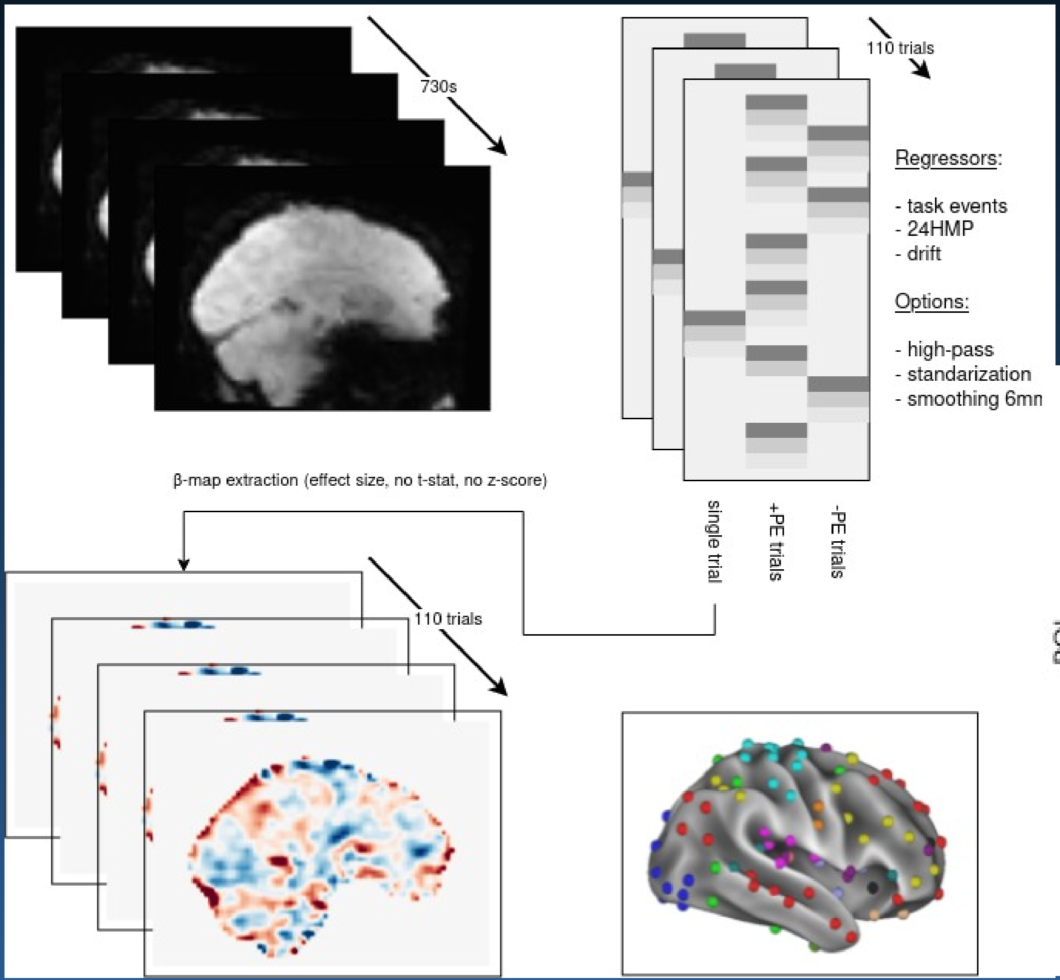
Beta series correlation

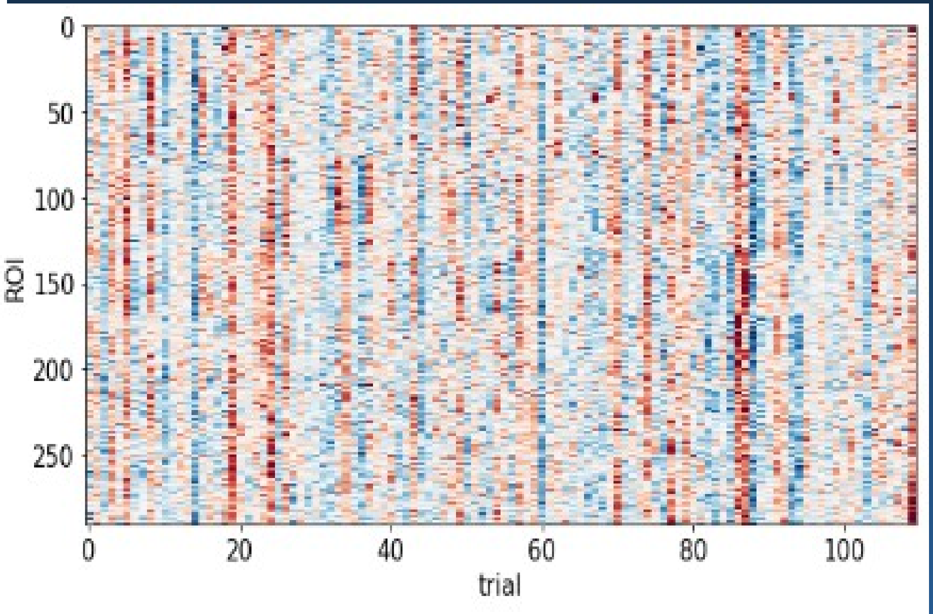
Investigation of inter-regional functional connectivity in event-related fMRI data, allows for assessing the modulation of functional connectivity by an experimental condition.

Analysis requires many steps:

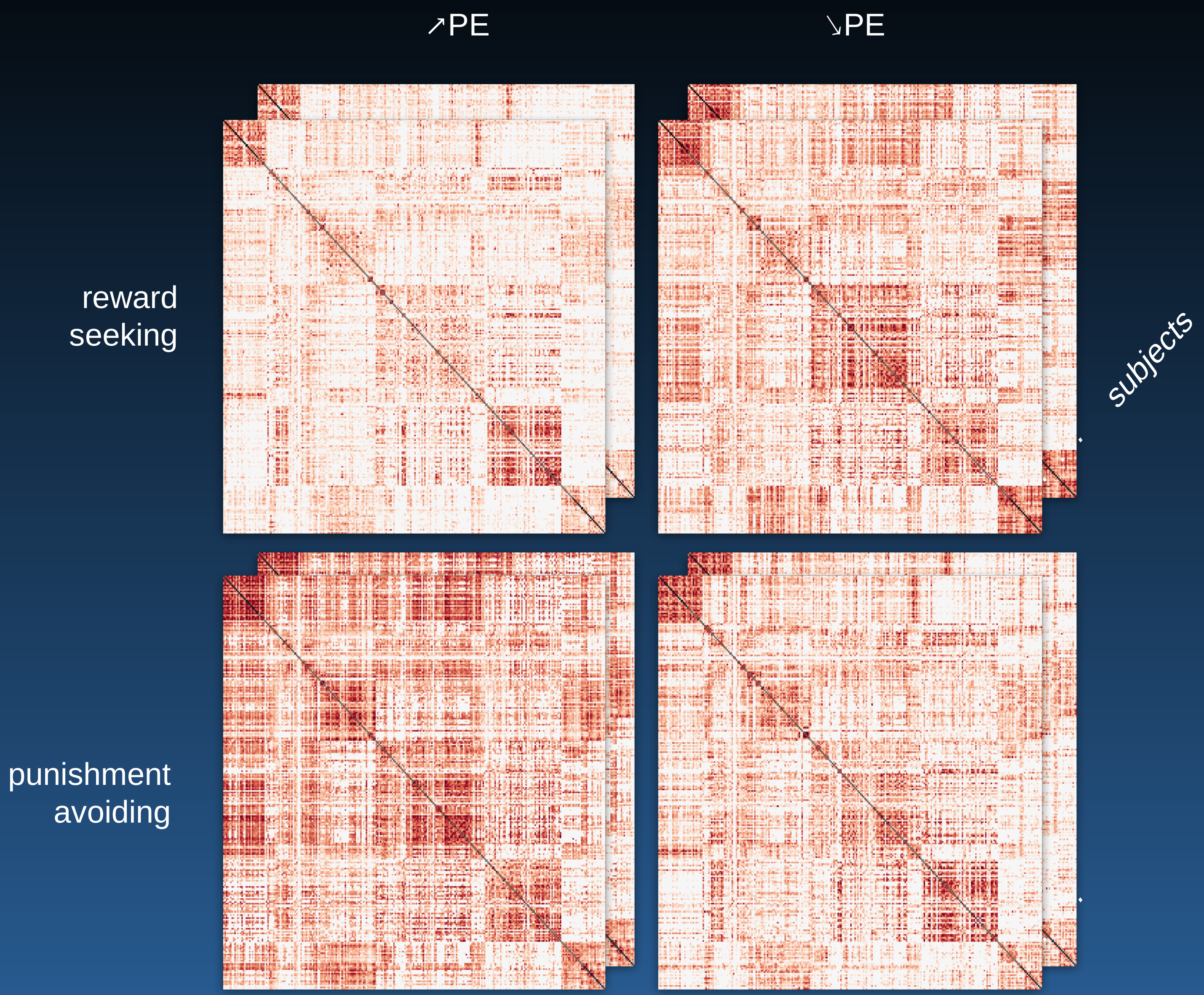
Power Atlas with 264 ROI parcelation, plus 30 new ROIs from meta-analysis of data, a total of 272 ROI +15 networks.

Many corrections of signals, tresholding, denoising, tests of statistical significance. The whole pipeline is on Github.



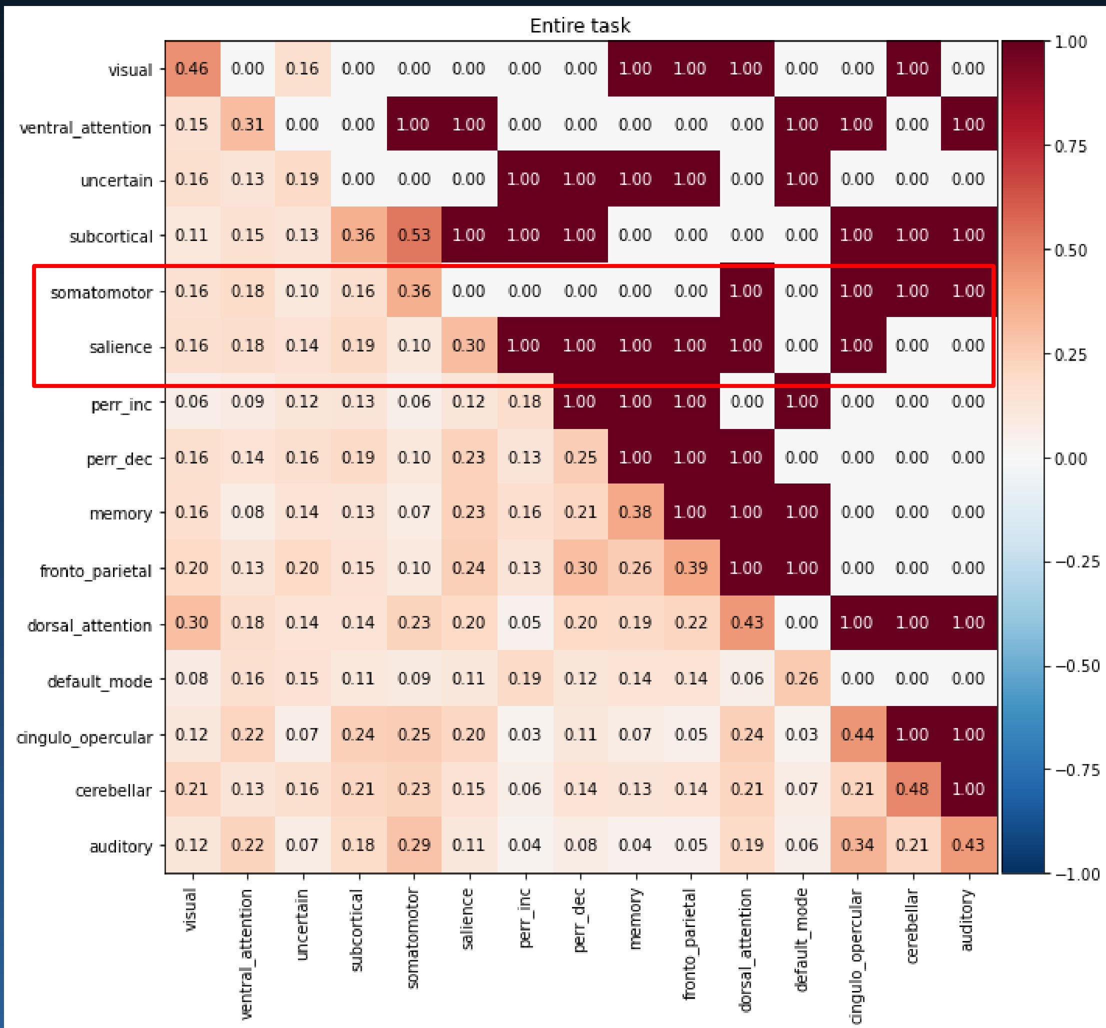


Changes, 4 situations



Interactions with other networks

For each real network create set of random networks to serve as null distribution of connection strengths between modules and compare real LSN ↔ LSN interactions with null distribution. Mean was ~0.1, real interactions 0.47.



↗PE network interacts with:

- itself and ↘PE network
- memory network
- fronto-parietal network
- default mode network

↘PE network interacts with:

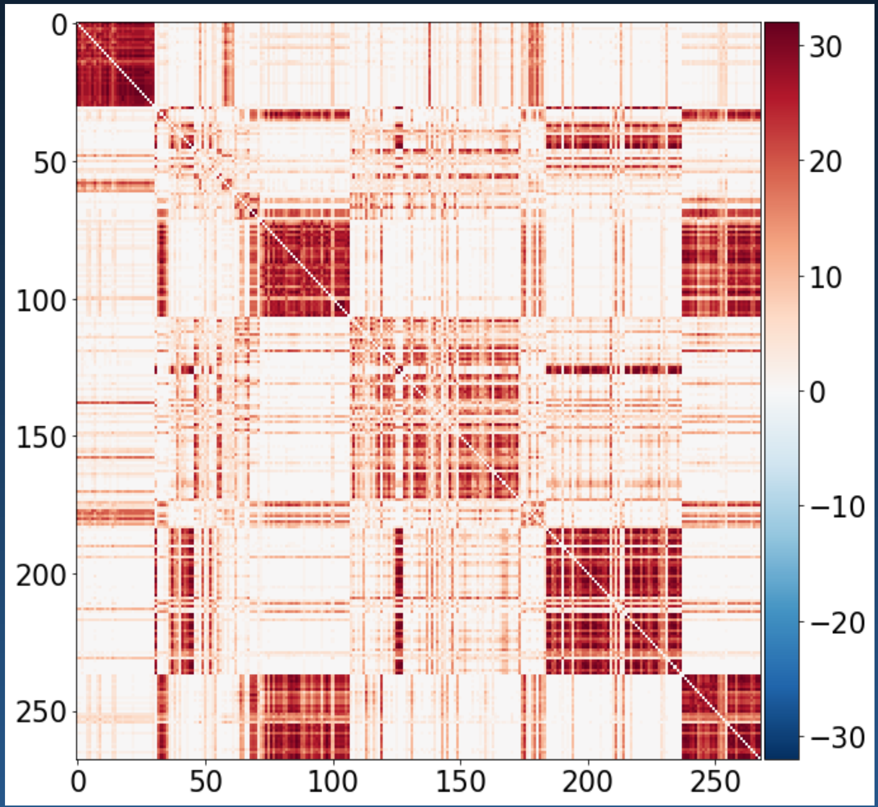
- itself and ↗PE network
- memory network
- fronto-parietal network
- dorsal attention network

Network organization and its modular structure

Method: for 272 ROIs

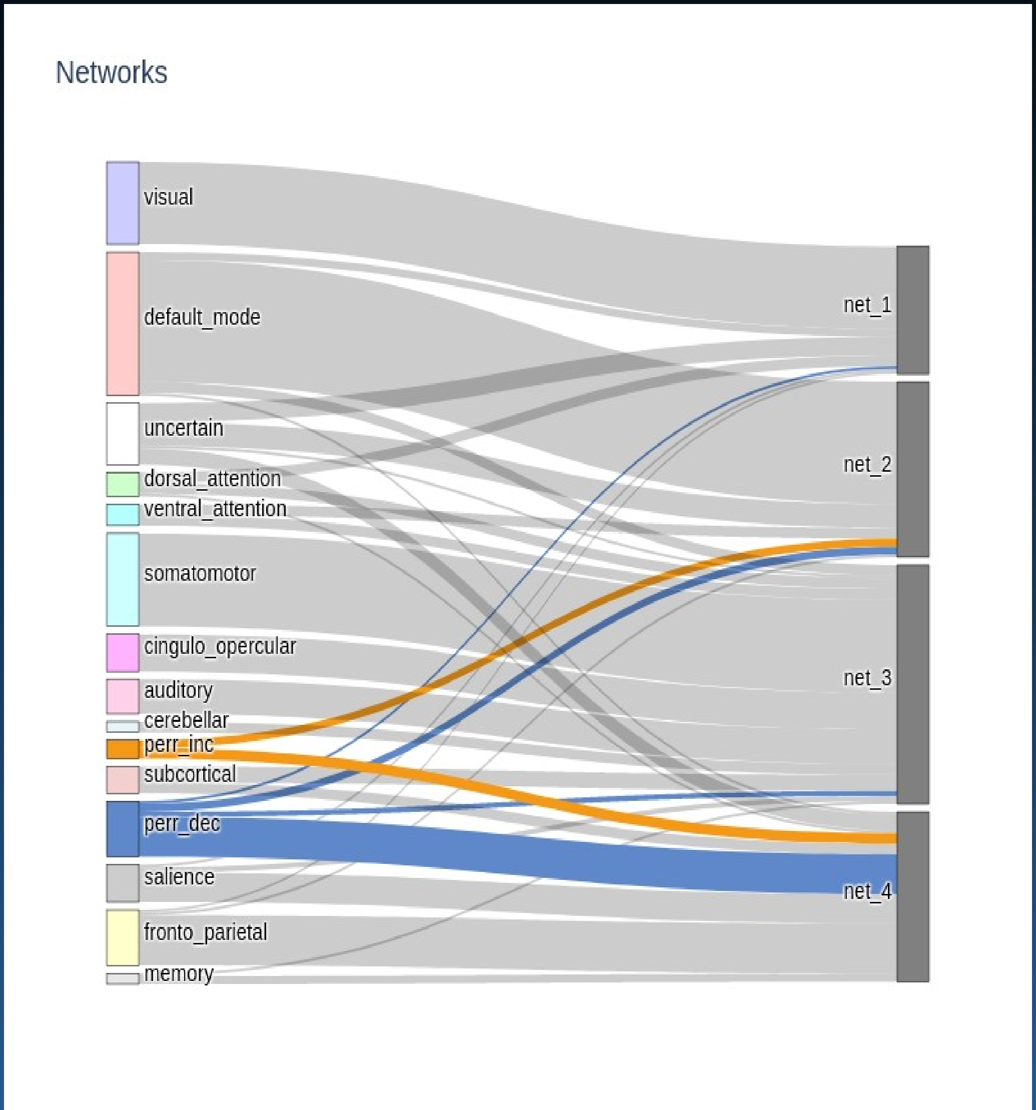
- for each network calculate modularity and community structure,
- compute consensus clustering (single representative partition).

agreement matrix



reclustering

Networks involved in making decisions

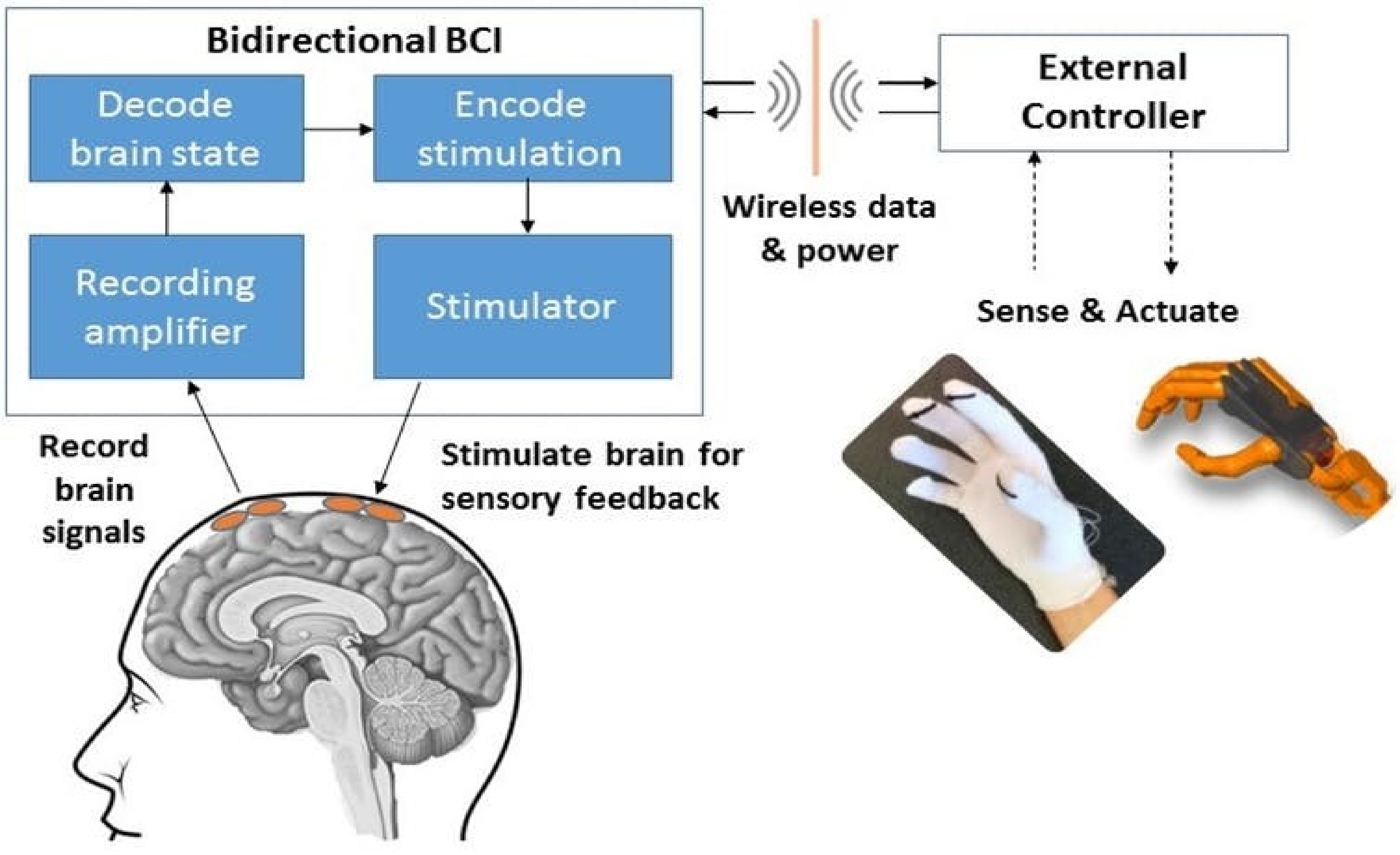


4 main LSNs contribute to PE networks:

- visual network
- default mode network
- somatosensory network
- task network

- ↗PE network is part of
  - task network (57%)
  - default mode network (43%)
- ↘PE network is part of
  - task network (71%)
  - default mode network (14%)

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?

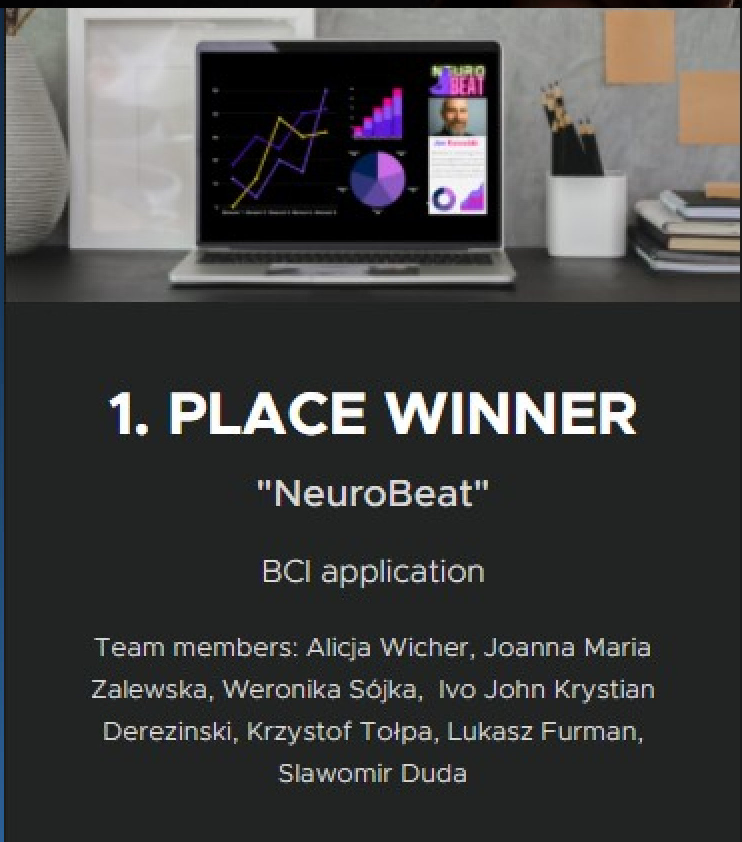
EEG electrodes + DCS.

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

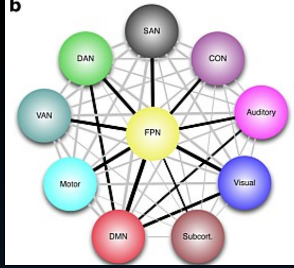
depression, neuro-plasticity, pain, psychosomatic disorders, teaching!

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


VIRTUAL BR41N.IO HACKATHON
April 17-18, 2021
during the
Spring School 2021*
IEEE brain
g.tec
*BR41N.IO and Spring School 2021 are part of g.tec's Teaching Plan 2021 with more than 140 hours of online courses and lectures.


1. PLACE WINNER
"NeuroBeat"
BCI application
Team members: Alicja Wicher, Joanna Maria Zalewska, Weronika Sójka, Ivo John Krystian Derezinski, Krzystof Tołpa, Lukasz Furman, Slawomir Duda


IMPROVING HUMAN DAILY LIFE FUNCTIONING
NEUROHACKATOR 2021
21. - 23. MAY 2021 // ONLINE
FRIDAY
Organisers presentation
workshops with Judges
SATURDAY
Project development in groups
STARTS 10 a.m.
SUNDAY
Evaluation
ENDS 10 a.m.
working 24h
REQUIREMENTS:
1. Create a team consisting of 3-5 people.
2. Fill in the Registration Form (available on Facebook event).
DO YOU HAVE ANY QUESTIONS?
Write an e-mail:
NEUROTECHTOR@GMAIL.COM
Neurotechnology Scientific Club
Center for Modern Interdisciplinary Technologies
at Nicolaus Copernicus University in Toruń
Wileńska 4 Street



2020 in our lab

- Finc K, … Bassett, D.S. (2020). Dynamic reconfiguration of functional brain networks during working memory training. **Nature Communications** 11, 2435.
- Esteban, O. … Gorgolewski, K. J. (2020). Analysis of task-based functional MRI data preprocessed with fMRIPrep. **Nature Protocols** 15, 2186–2202
- Thompson, W.H. … Poldrack, R. A. (2020). Time-varying nodal measures with temporal community structure: A cautionary note to avoid misinterpretation. **Human Brain Mapping**, 41(9), 2347-2356.
- Bonna, K … Szwed, M. (2020). Early deafness leads to re-shaping of global functional connectivity beyond the auditory cortex. Brain Imaging and Behaviour.
- Asanowicz, D. … Binder, M. (2020). The response relevance of visual stimuli modulates the P3 component and the underlying sensorimotor network. Sci. Reports, 10(1), 1-20.
- Rykaczewski, K. … Piotrowski, T. (2020). SupFunSim: spatial filtering toolbox for EEG. **Neuroinformatics** 19, 107–125
- Dreszer J. ... Piotrowski T. (2020) . Spatiotemporal Complexity Patterns of Resting-state Bioelectrical Activity Explain Fluid Intelligence: Sex Matters. Human Brain Mapping 41(17), 4846-4865.
- Duch. W. (2020) IDyOT architecture - is this how minds operate? Physics of Life Reviews, 34–35

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

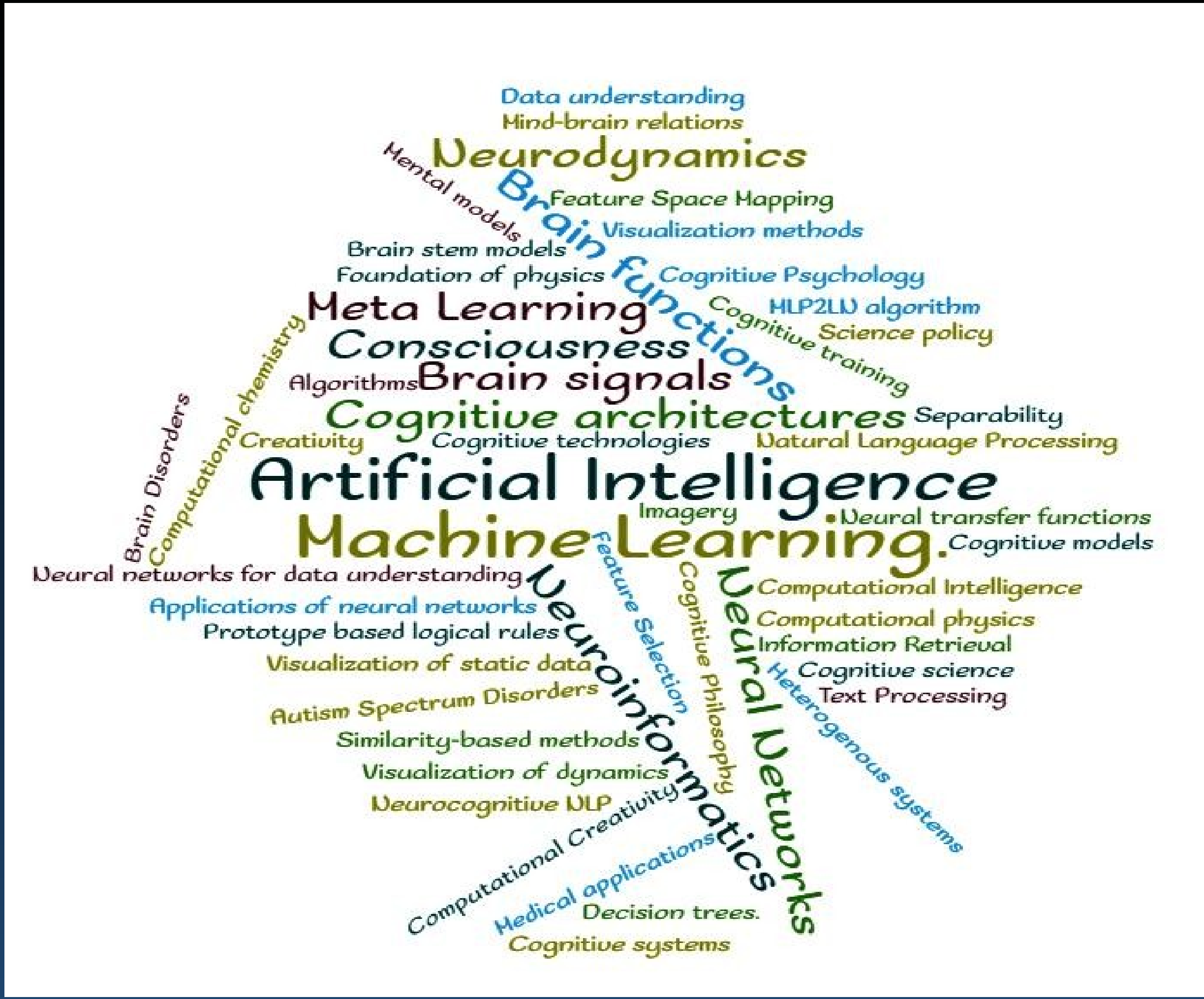
nencki institute of experimental biology

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
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