Mental states in brains and computers

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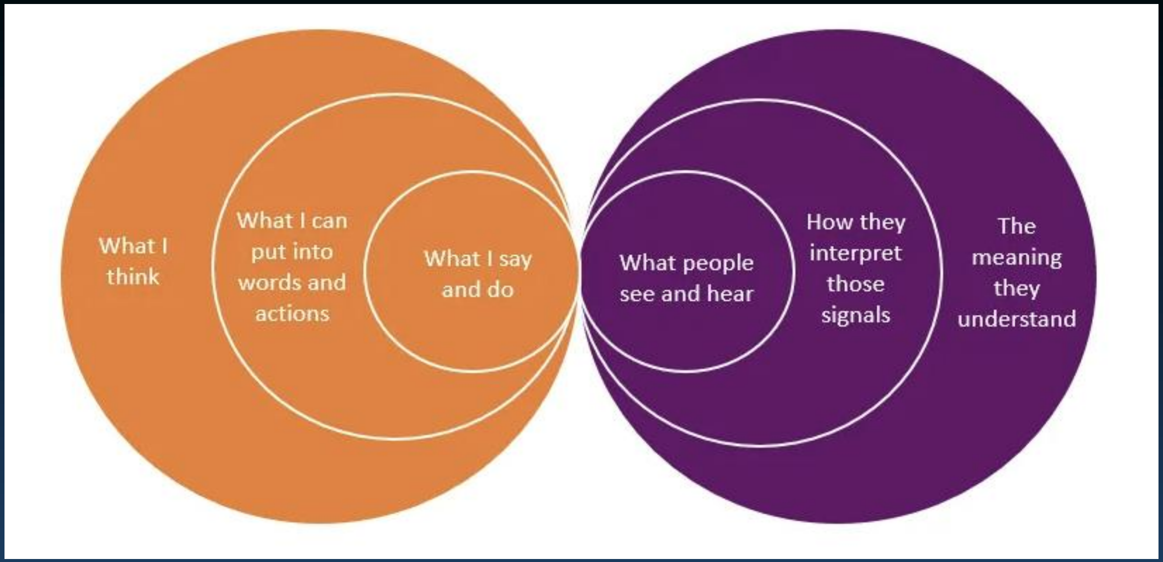
On the threshold of a dream …

Unique moment in history of civilizations!

~~Space~~ Brains: The final frontier.

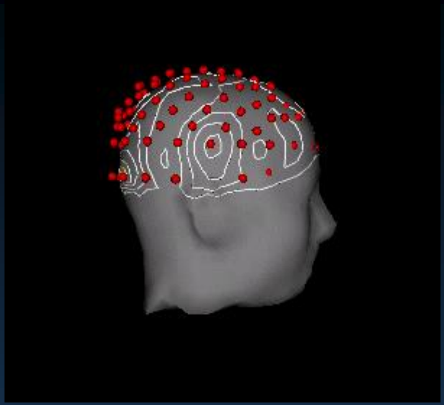
- We are beginning to understand how mental states arise from specific activity of the brain networks.
- This leads us to better AI systems, Cognitive Architectures.
- Final goal:
  Correct and optimize brain processes!
  Use full potential of your brain!
  Let the robots work for us!

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



1. Geometrical models of brain states.
2. Phenomics and attractor network models.
3. Learning from simulations and visualizations.
4. Memetics and conspiracies.
5. Neuroimaging of real brains.
6. EEG brain fingerprinting.
7. Cognitive maps.
8. Towards theory of mental processes.

Brains ⇔ Minds



Neurodynamics: measure bioelectrical activity of the brain, try to find fingerprints of mental states – ex. BCI.

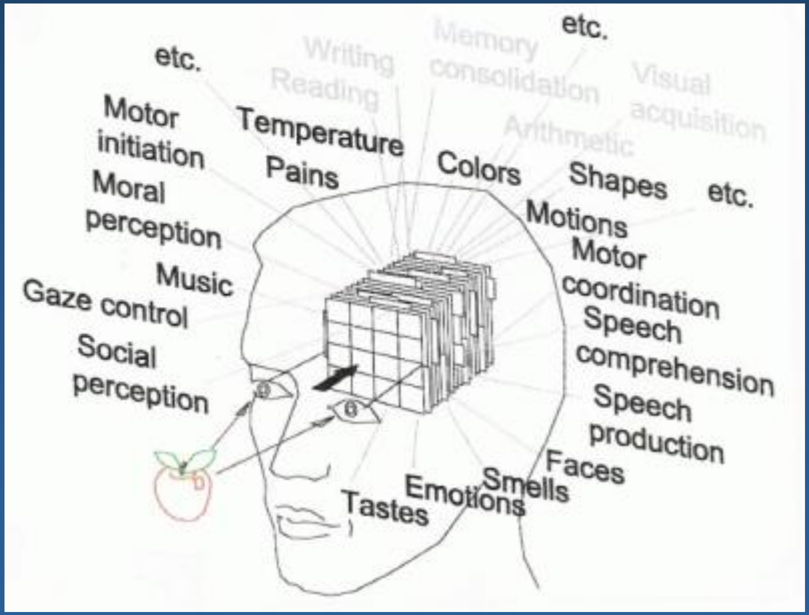
Define mapping S(B)⇔S(M). How to describe M, state of mind? Verbal description is not sufficient.

Neurosemantic decoding: embed symbolic words (ex: Word2Vec) in vector space, relate dimensions to different aspects of experience.

Stream of mental states, movement of thoughts corresponds to trajectories in some psychological spaces.

Two problems:

1. Discretization of continuous brain states to link them with psychological constructs.
2. Lack of good phenomenology – we are not able to describe details of our own mental states.

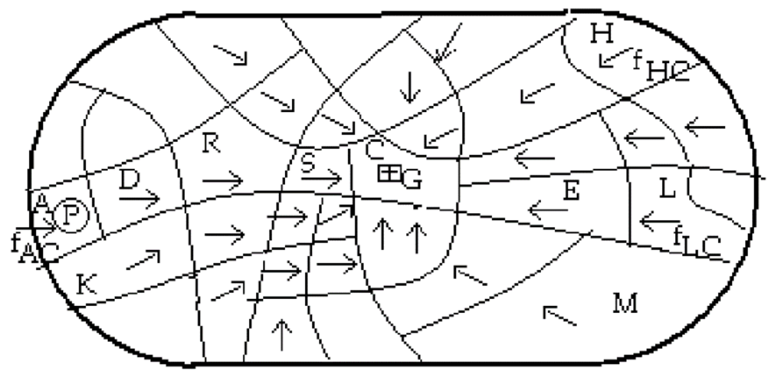


E. Schwitzgabel, Perplexities of Consciousness. MIT 2011

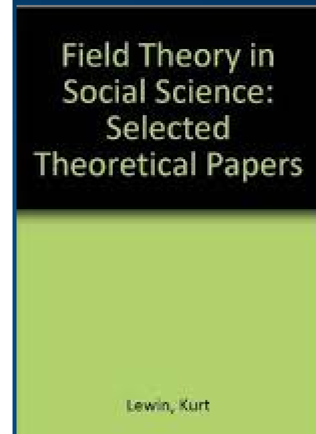
WD: Computational physics of the mind.
Computer Physics Communications 97, 136-153, 1996

Kurt Lewin: psychological forces

Fig. 5. "Positive central force field corresponding to a positive valence (Va>0)" (Lewin, fig. 33)



"G, region of a positive valence (Va(G)>0), located in C; P, person; the forces $f_{A,C}$, $f_{H,C}$, or $f_{L,C}$ correspond to Va(G) in case P is located at A, H, or L, respectively; $f_{X,Y} = f_{X,G}$."



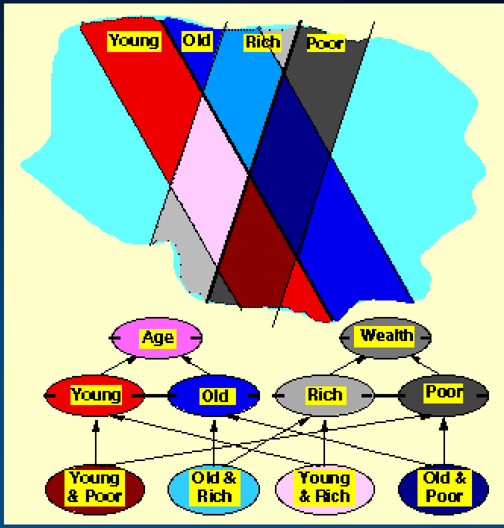
Kurt Lewin, founder of social psychology, analyzed interactions between people and their environment creating psychology inspired by field theory.

Transitions between mental states are due to the psychological forces.
Regions of positive valence are in basins of **attractors of neurodynamics**.

Books by K. Lewin: *Principles of Topological Psychology* (1936);
Field Theory in Social Science (1951).

Duch W. (2018), Kurt Lewin, psychological constructs and sources of brain cognitive activity. Polish Psychological Forum 23(1), 5-19.

Psychological spaces



Psychological spaces:

George Kelly (1955), personal construct psychology, geometry of psychological spaces as alternative to logic.

A complete theory of cognition, action, learning and intention.

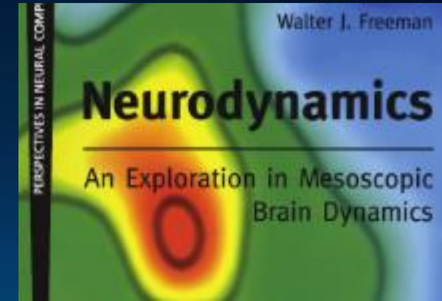
P-space: region in which we may place and classify elements of our experience, constructed and evolving, „a space without distance”, divided by dichotomies. The idea of P-spaces was developed by R. Shepard (1957-2001):

- minimal dimensionality
- distances should monotonically decrease with increasing similarity, as in the multi-dimensional non-metric scaling representation.

Many attempts were made to introduce dynamical cognition in P-spaces:

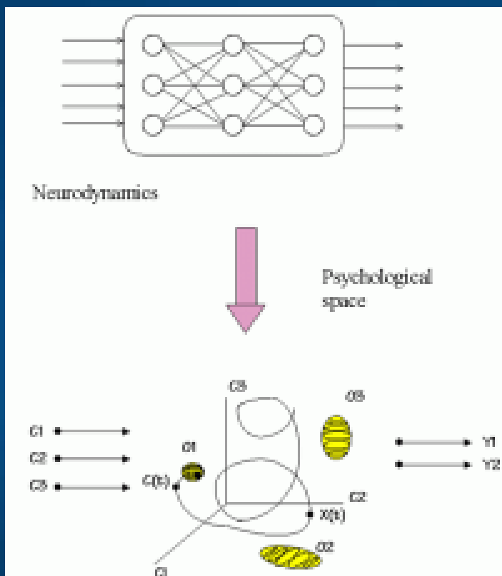
R.F. Port, T. van Gelder, Eds. (1995) Mind as motion. MIT Press.
G. Fauconnier (1994) Mental Spaces. Cambridge UP.
J. Elman (1997) Language as a dynamical system. San Diego UP.
M. J. Spivey (2007) The Continuity of Mind. Oxford UP.
P. Gärdenfors (2004) Conceptual Spaces: The Geometry of Thought, MIT Press.
P.G. (2014) The Geometry of Meaning: Semantics Based on Conceptual Spaces. MIT Press.

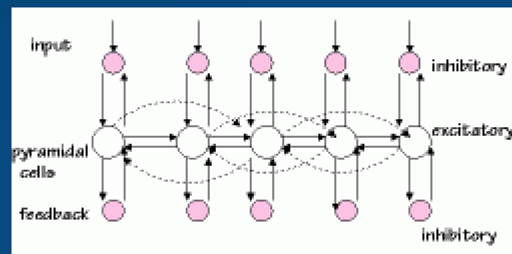
From neurodynamics to P-spaces

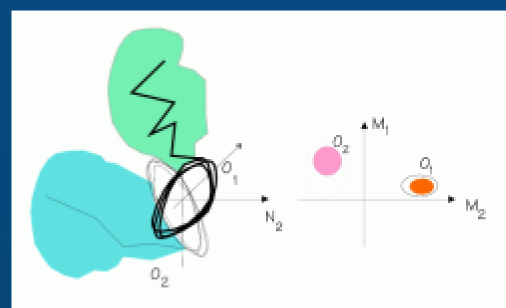


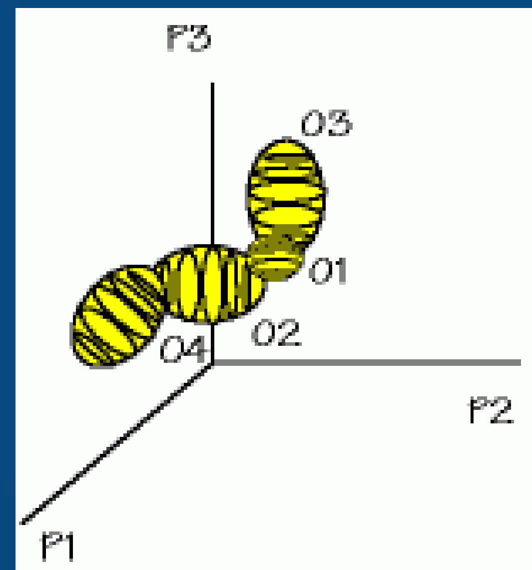
Walter Freeman (2000): model of olfaction in rabbits, 5 types of odors elicited stable 5 types of behavior, but different EEG maps .

Relational memory model: network may use arbitrary internal representations, but maintain fixed input/output relations between memory states.







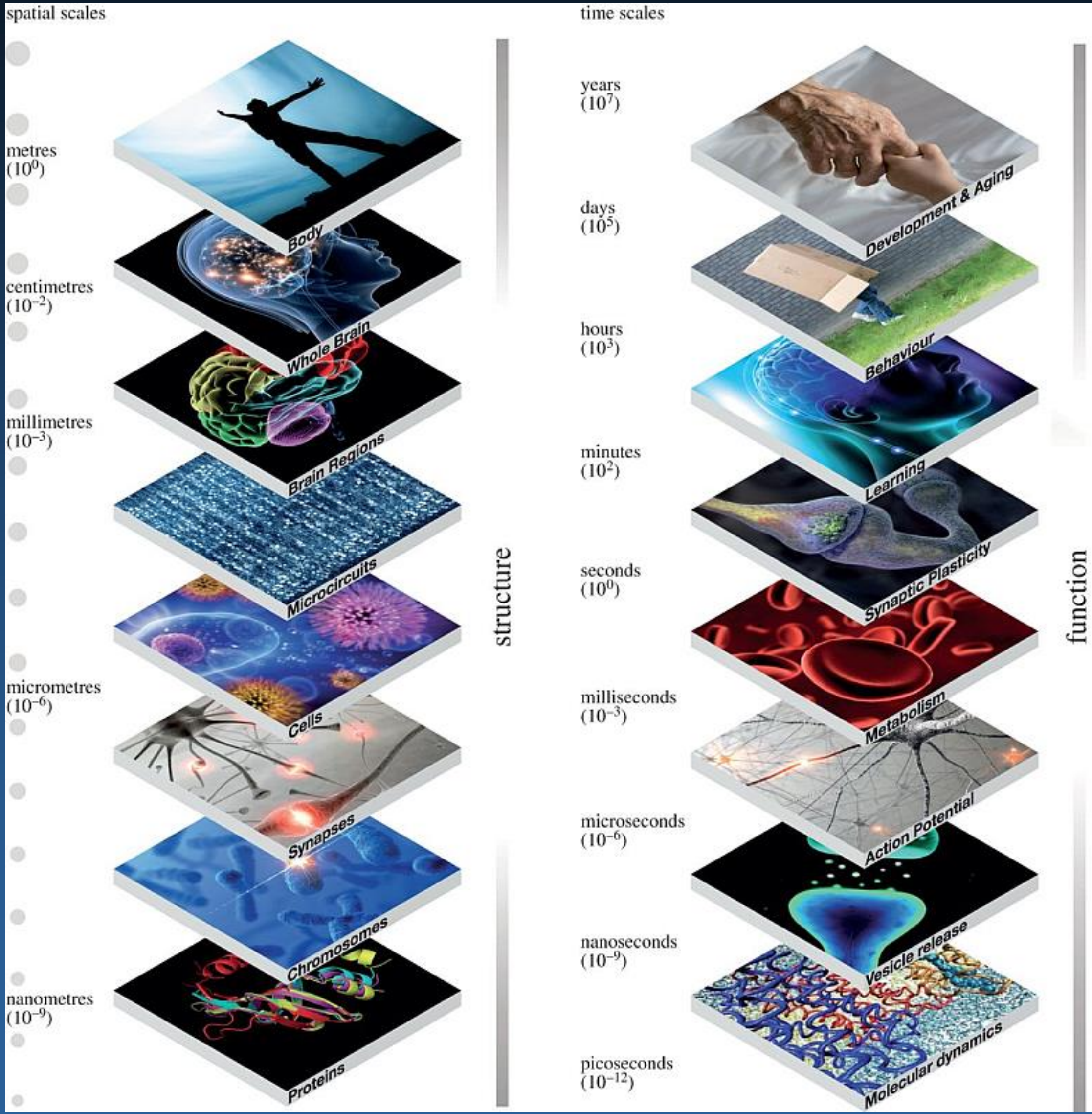


Attractors of dynamics in high-dimensional spaces create “mind objects”, fuzzy prototypes of brain activity, modeled using separable functions (FSM).
Fuzzy Symbolic Dynamics (FSD): follows probability density (PDF) in feature spaces.

Duch W, Diercksen GHF (1995) Feature Space Mapping as a universal adaptive system. Computer Physics Communications 87: 341-371

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 networks related to specific brain functions.
- M. Minsky, Society of mind (1986) Intelligent AI Agent = subnetworks implementing specific function.



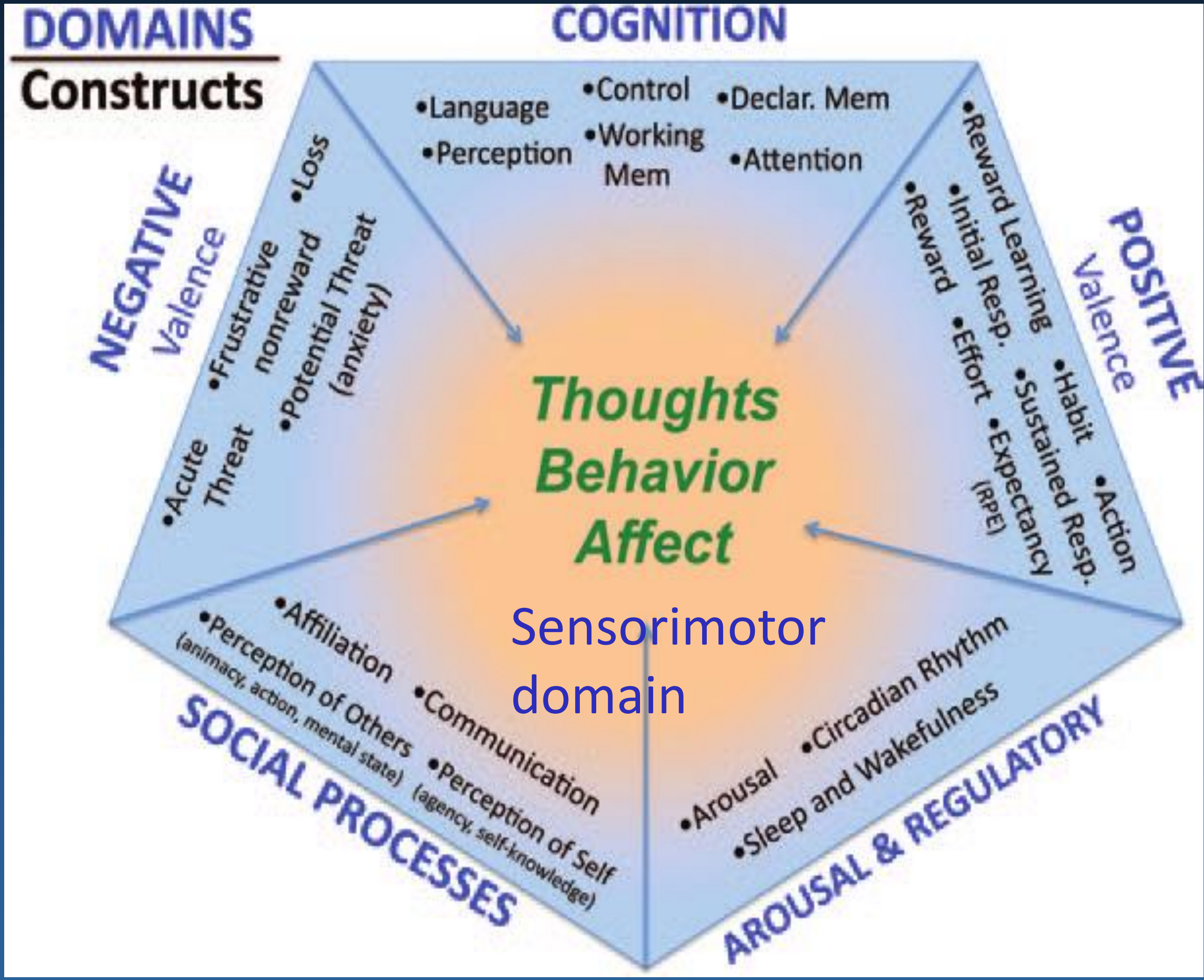
NIMH RDoC Matrix for deregulation of 6 large brain systems.

Psychological constructs are necessary to talk about mental states.

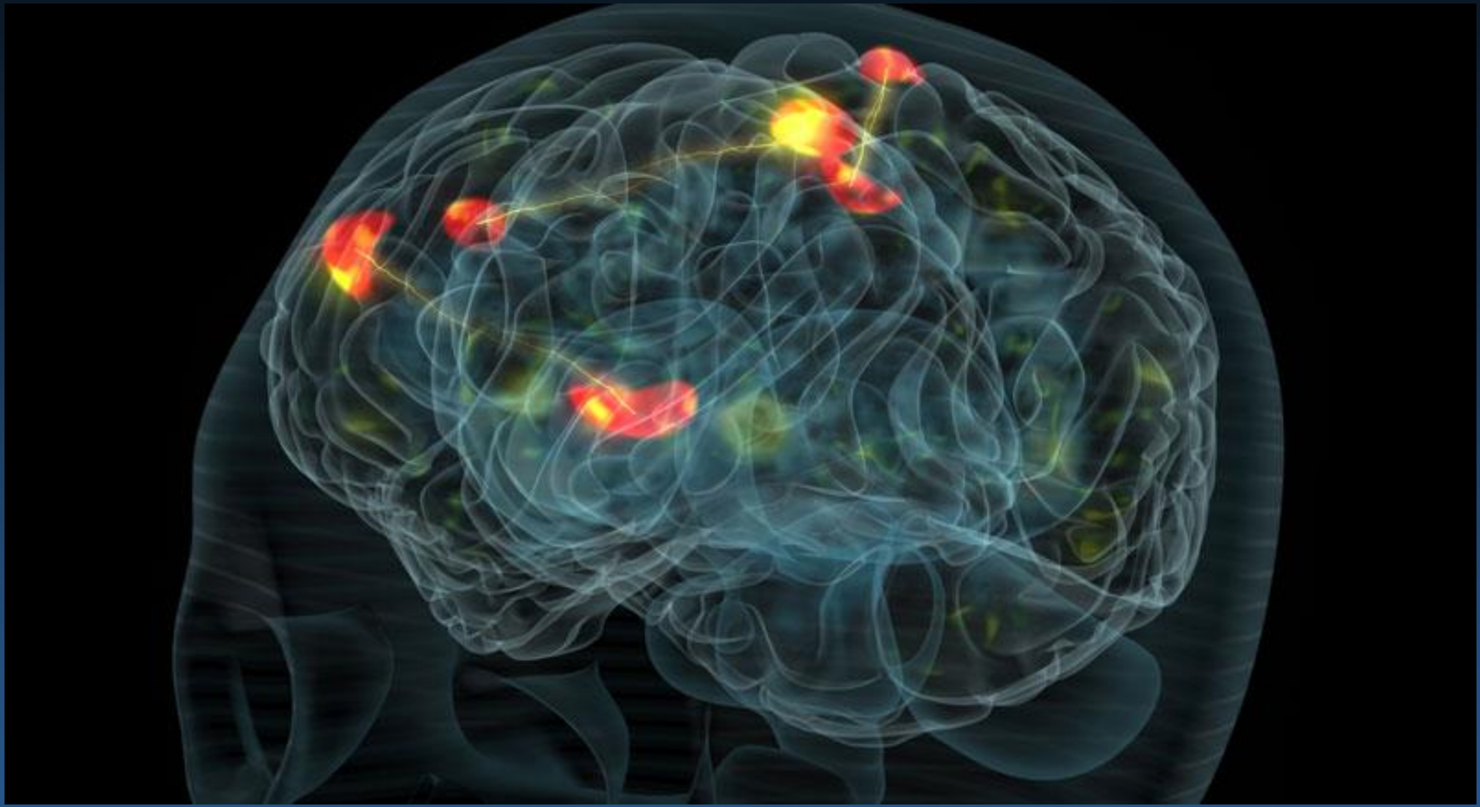
Sensorimotor systems added in 2019 as the 6th system.

This is the basis of computational psychiatry.

How are these functions implemented in the brain?



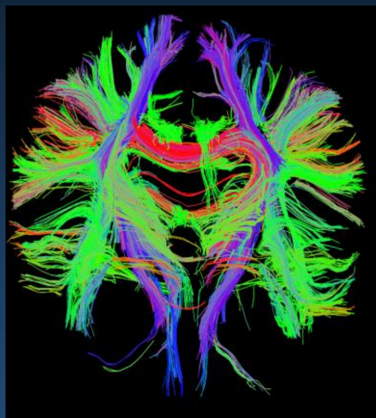
Mental state: strong coherent activation



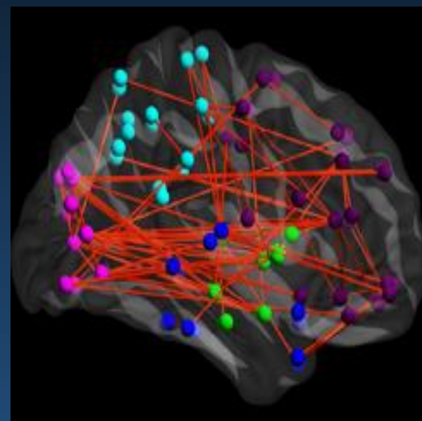
- Many processes go on in parallel, controlling homeostasis and behavior. Most are automatic, hidden from our perception. What goes on in my head?
- Various subnetworks compete for access to the highest level of control. The winner-takes-most mechanism leaves only the strongest activations, filtering noise (signal detection theory), enabling conscious reactions of the whole organism. How to extract metastable intentions from such chaos?

Human connectome and MRI/fMRI

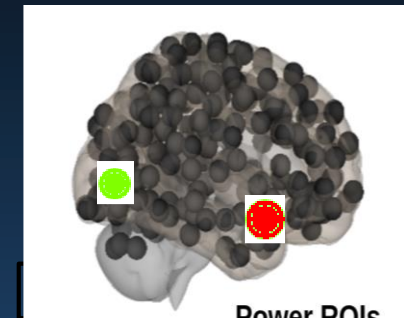
Structural connectivity



Functional connectivity

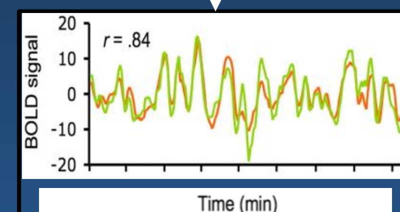


Node definition (parcelation)

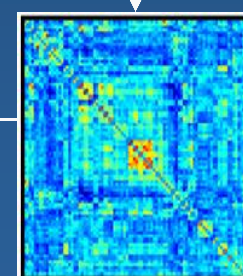


Signal extraction

Correlation calculation

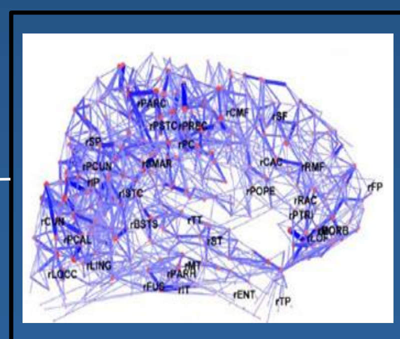


Correlation matrix

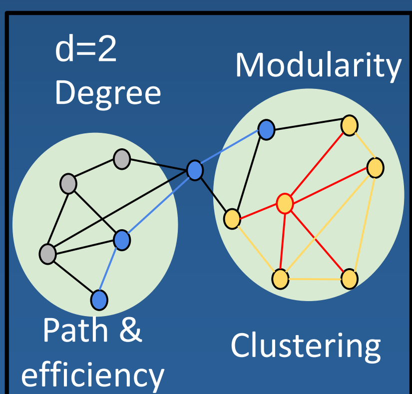


Binary matrix

Whole-brain graph



Graph theory



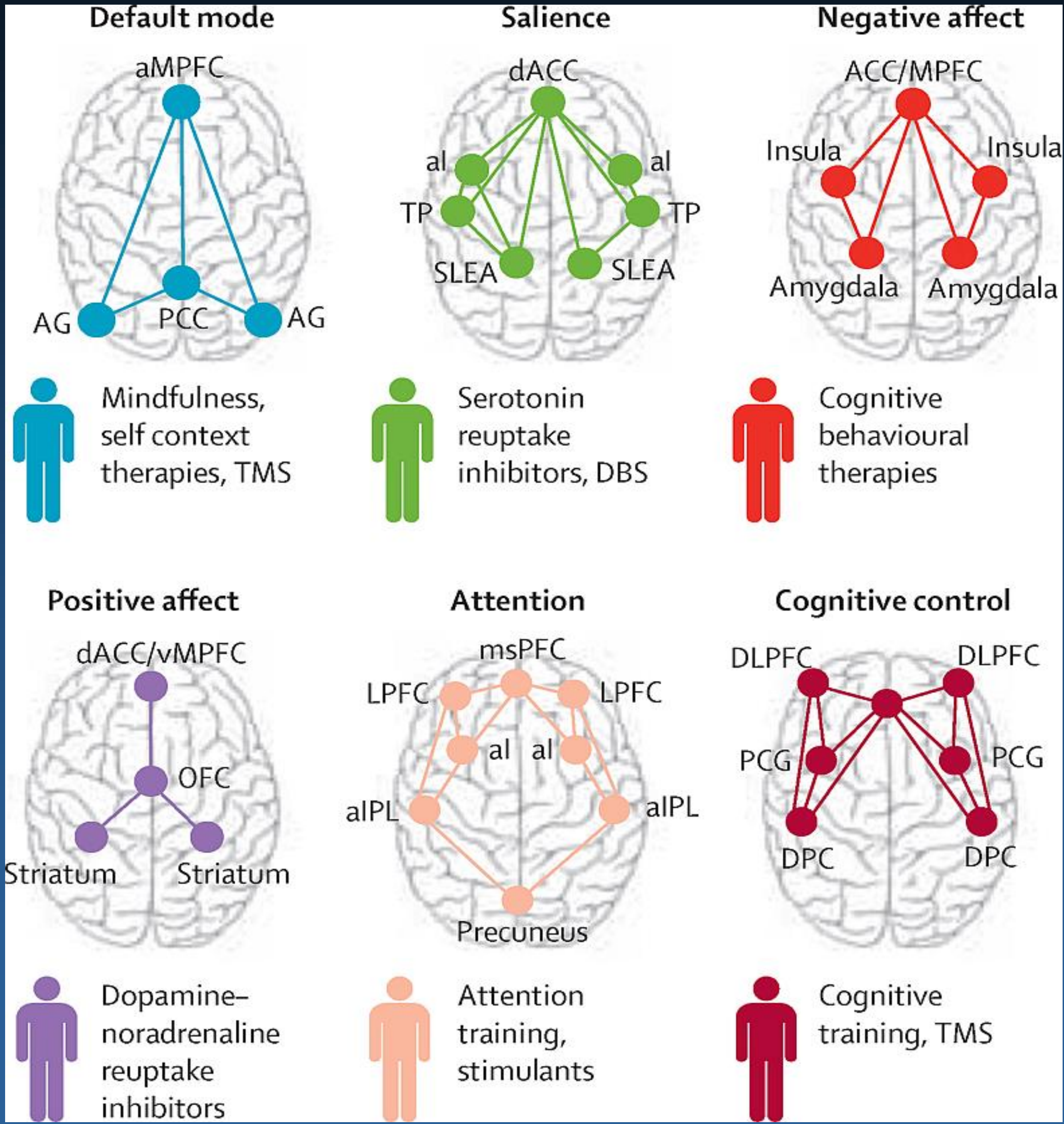
Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

Large-Scale Networks

- Large brain systems depend on coordination of activity in many brain regions.
- Decompose neurodynamics into activity of large-scale networks, related to various brain functions.
- LSN or intrinsic brain networks are derived from functional connectivity by statistical analysis of various neuroimaging experiments.
- How many? From 7 to 17 to 3 mln?
- Brain networks have specialized functions, dominating frequencies, dynamics, neurotransmitters.

Network science for complex systems.

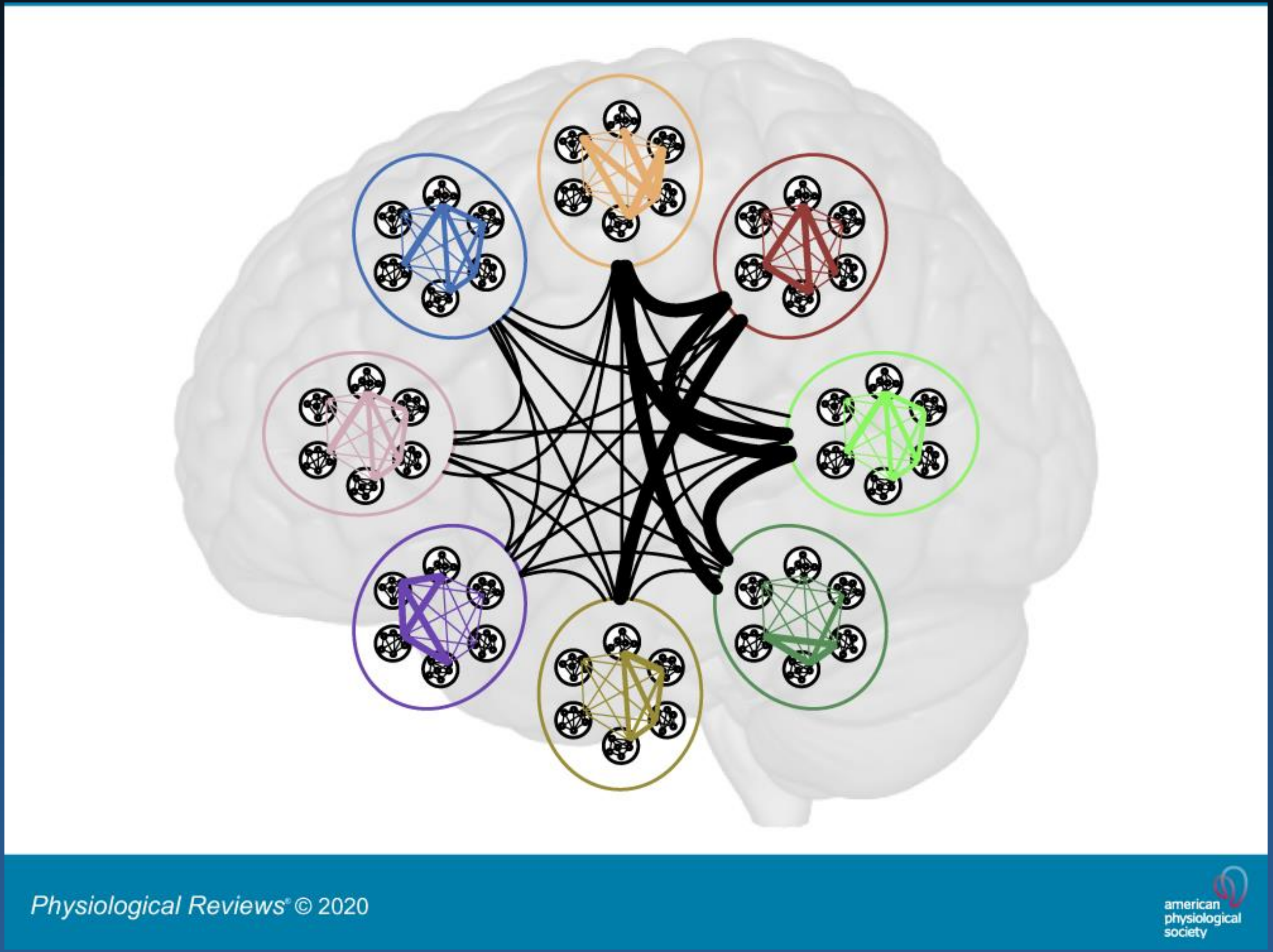


≈ Small worlds architecture

Small world: high levels of clustering, short path lengths, preserved across multiple frequency bands and behavioral tasks.

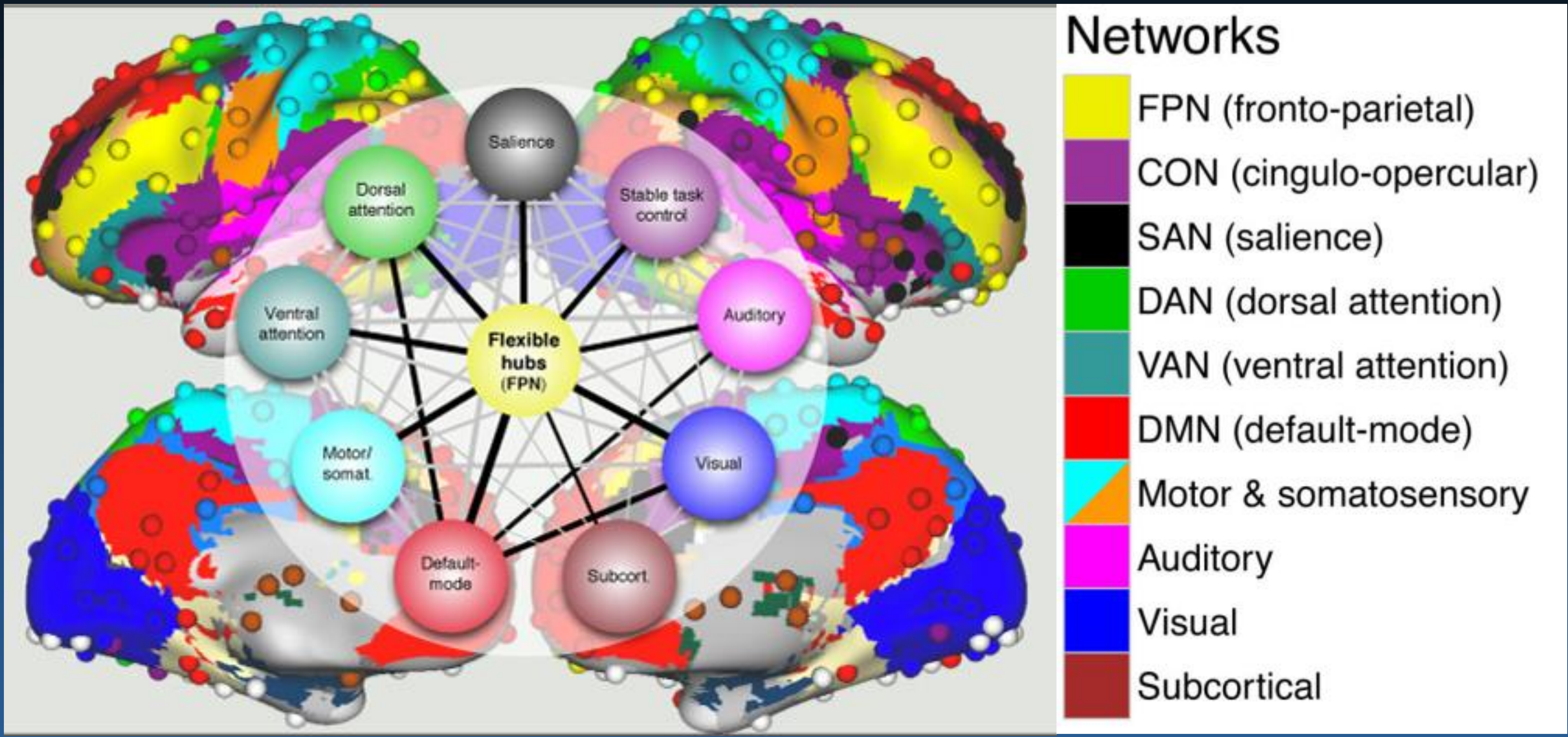
Local modules are densely connected, extract relevant information from sensory data, salience, memory associations, orchestrate motor actions.

Needs a switchboard.



All complex functions are based on synchronization of activity among many brain areas. Memory, personality or consciousness are processes engaging a collection of functions, like multi-agent systems or the "society of mind", or GWT, Global Workspace Theory. Psychological constructs should be "deconstructed" and linked to 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.

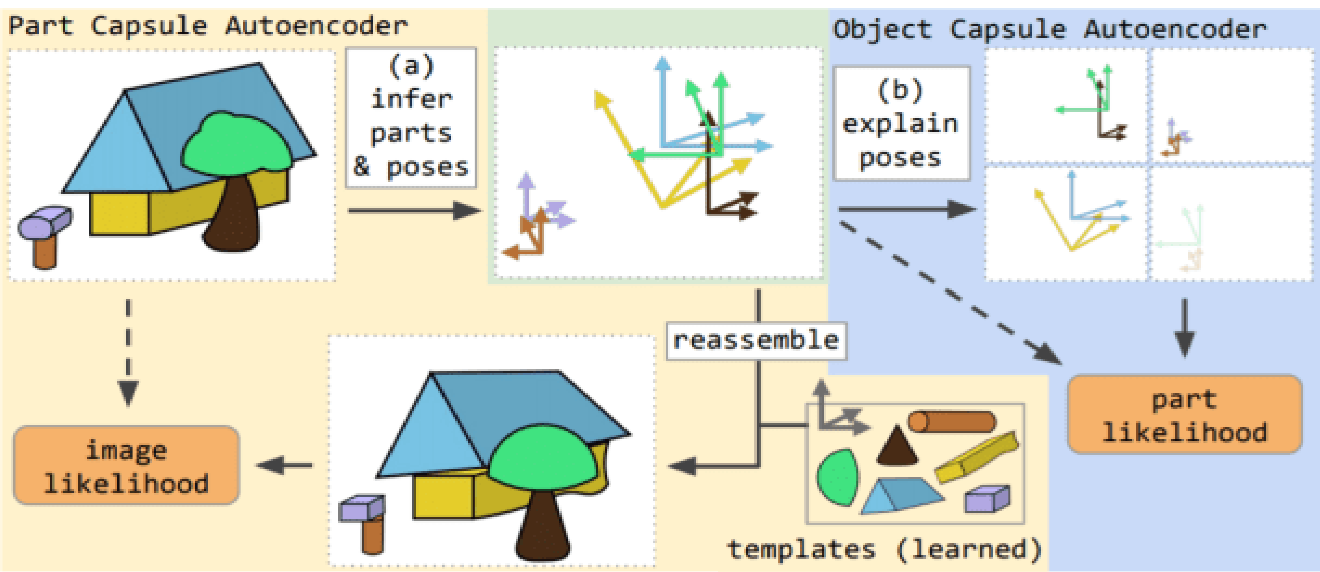


Figure 1: Stacked Capsule Autoencoder (SCAE): (a) *part* capsules segment the input into parts and their poses. The poses are then used to reconstruct the input by affine-transforming learned templates. (b) *object* capsules try to arrange inferred poses into objects, thereby discovering underlying structure.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

Simulations of neurodynamics

Computational Models

Models at various level of detail.

- Minimal model includes neurons with 3 types of ion channels, ex, inh, leak.

Models of attention:

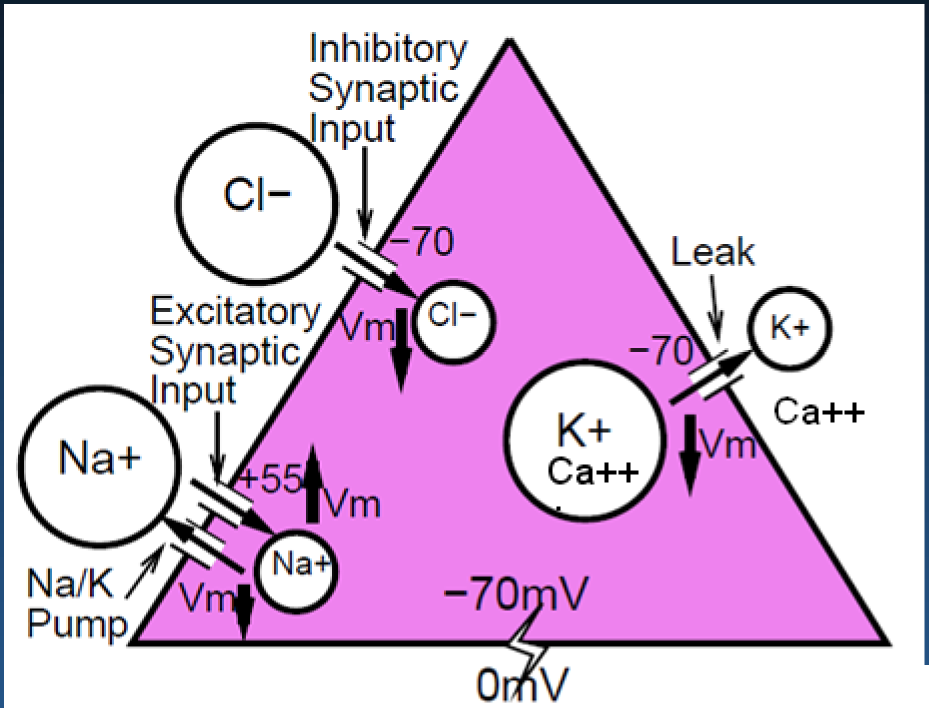
- Posner spatial attention;
- attention shift between visual objects.

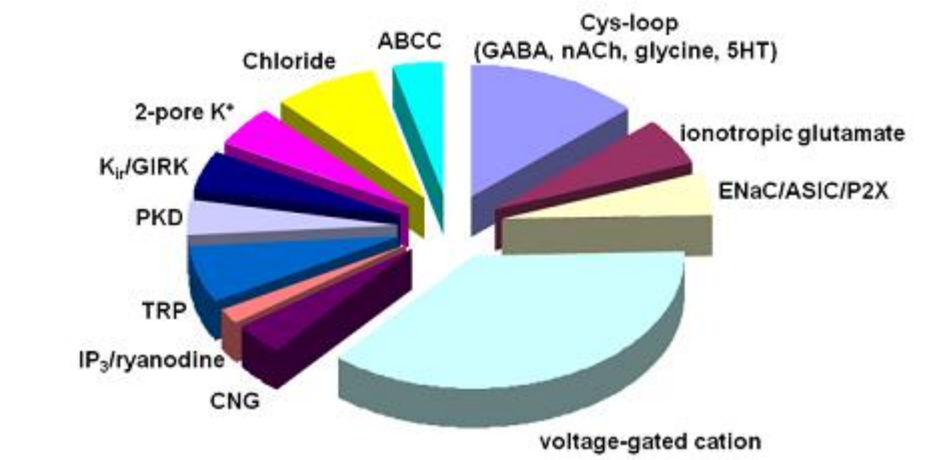
Models of word associations:

- sequence of spontaneous thoughts.

Models of motor control.

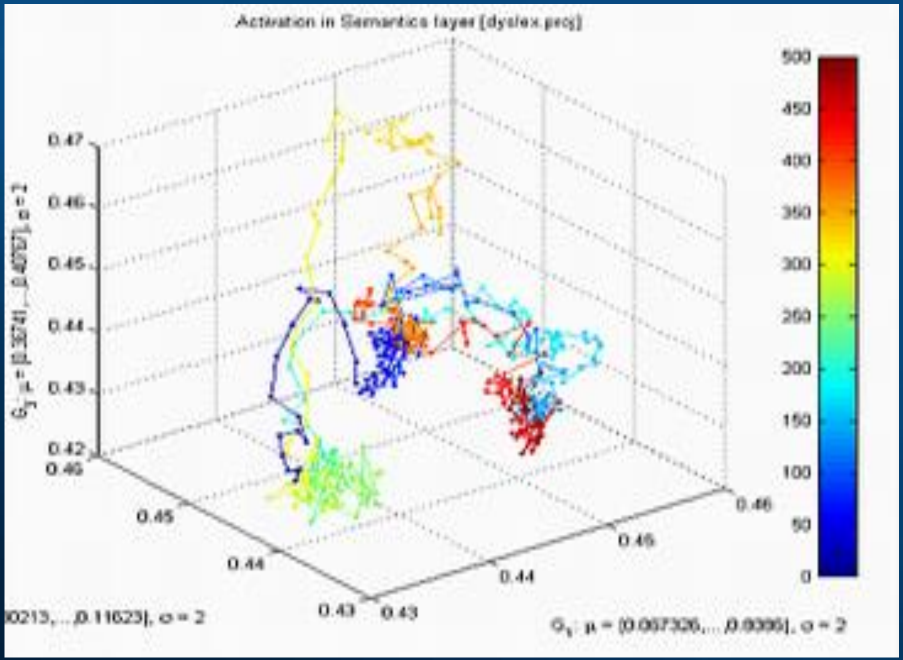
Initial focus: the leak channels,
2-pore K^+, looking for genes/proteins.
Critical: control of the increase in intracellular calcium, which builds up slowly as a function of activation.

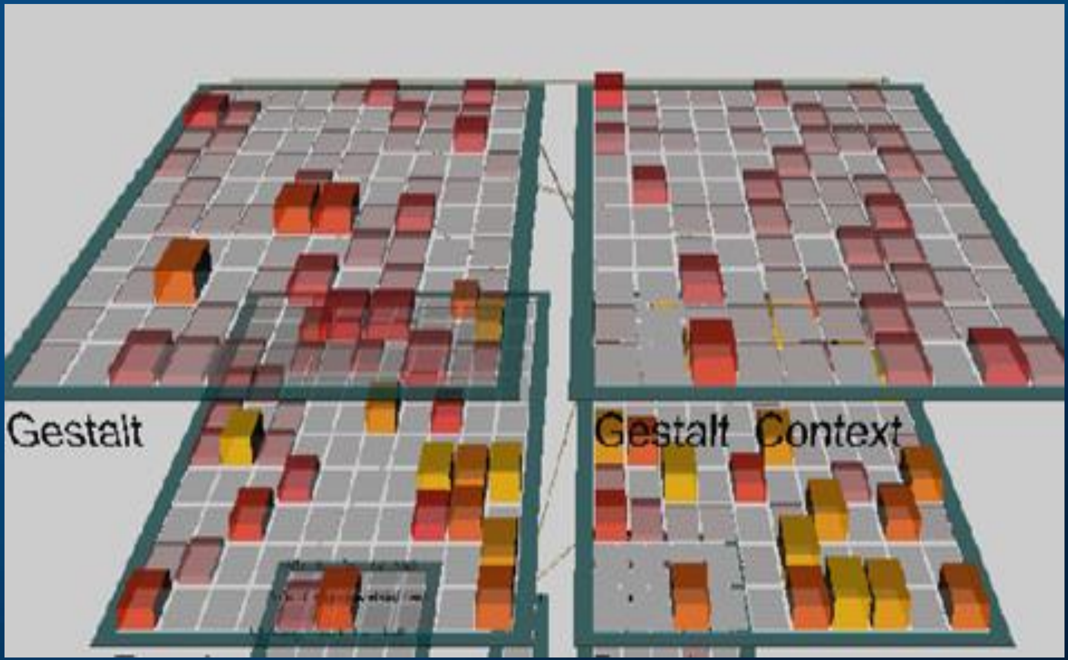




Brain as a substrate of mind

- Brain: substrate for the mind, a maze of mutual activations.
- Conscious impressions result from strong coherent activations, a shadow of neurodynamics that can be linked to phonological representations.
- Without phonological representation of brain states there will be no language, precise thoughts and logic, only direct associative actions.
- Psychology based on verbal description cannot describe brain processes.
- Follow brain activations to label metastable states, select view points.





Model of reading & dyslexia

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

Fluctuations around final configuration = attractors representing concepts.

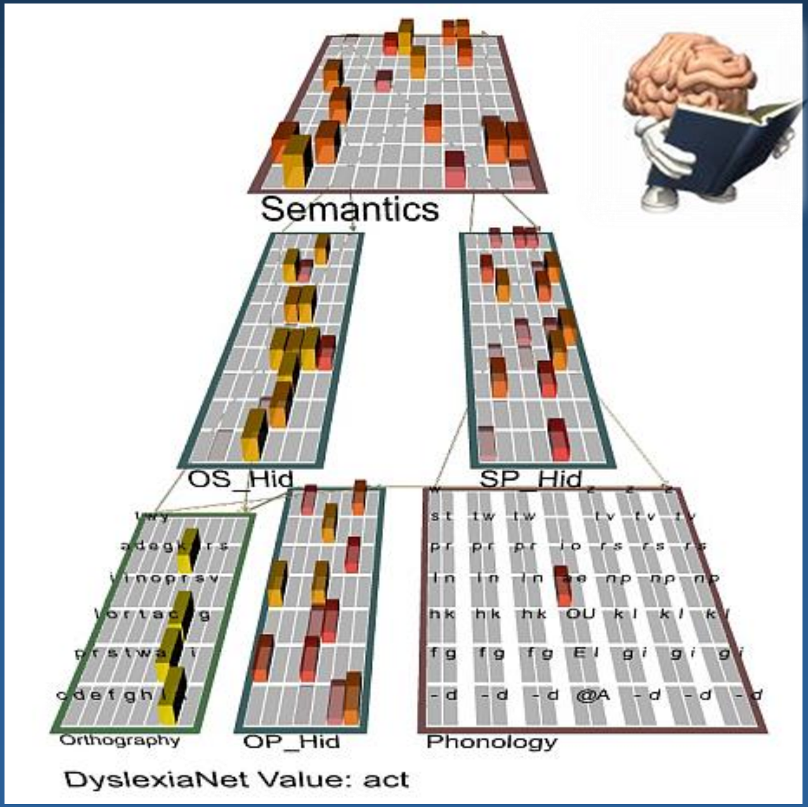
How to see trajectory of neurodynamics, attractor basins, transitions?
Genesis simulator offers more detailed neuron models, but is harder.

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.

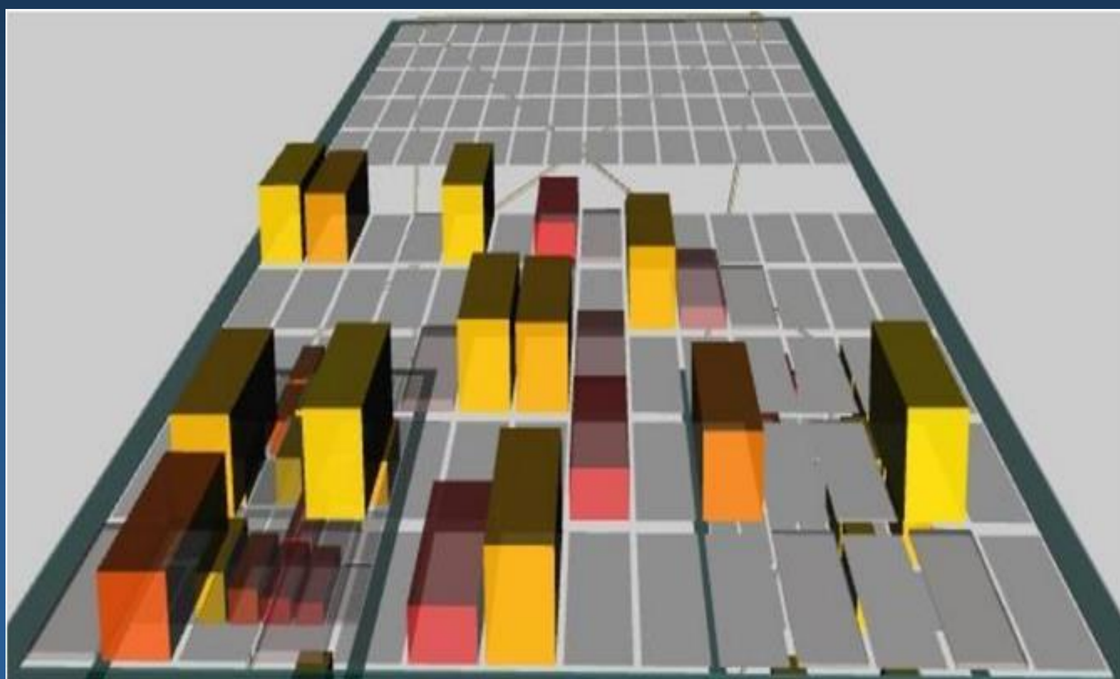
3-layer model of reading:

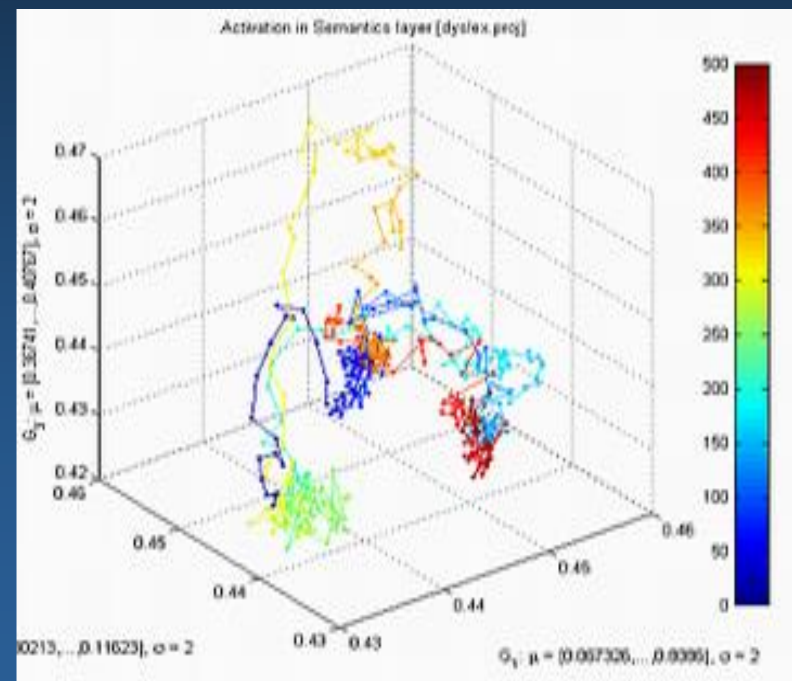
orthography, phonology, semantics
= distribution of activity over
140 microfeatures defining concepts.
Hidden layers O-S/O-P/S-P_Hid.
Brain subnetworks => microfeatures.



Semantic layer

Semantic layer in our simulations has 140 units. Attractor states = patterns. 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 relations** between patterns of active features. Associations = transitions between patterns, can be formed in many ways.





Recurrence plots

Trajectory of dynamical system (neural activities) may be visualized using recurrence plots (RP).

$$\mathrm{u}(t) = \{u_i(t)\}$$

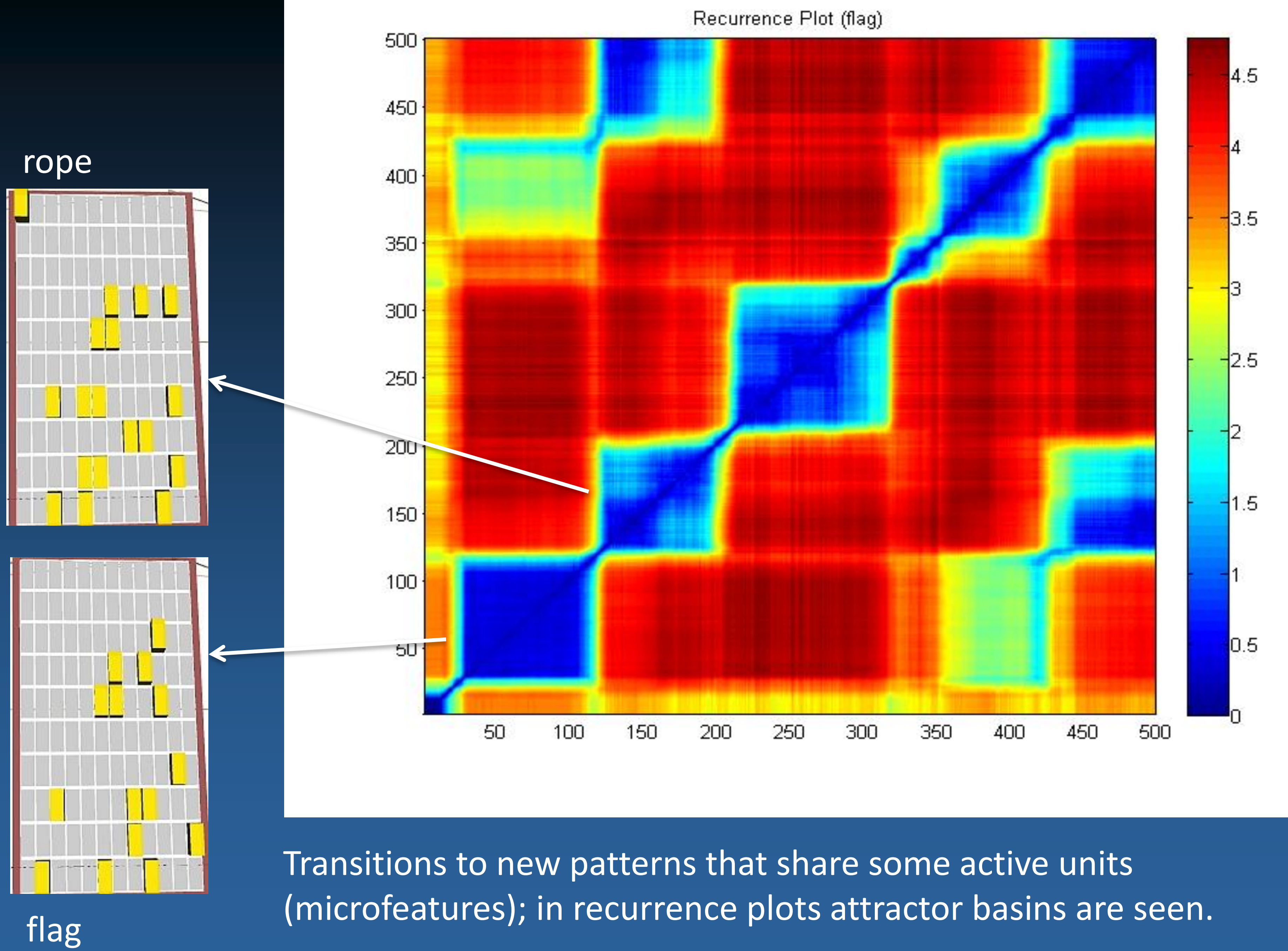
F. Takens' (1981) delay embedding theorem showed that a smooth attractor can be reconstructed from observations of time-delayed multiple points on the trajectory, in particular values of a single component $x_i=(u(t), u(t+\tau),\ldots u(t+d\tau))$.

$$R_{ij} = \begin{cases} 1: x_i \approx x_j \\ 0: x_i \not\approx x_j \end{cases} \quad i, j = 1 \cdots N$$

R is recurrence matrix based on approximate equality of N trajectory points of *d*-dimensional vectors. For discretized time steps binary matrix $\boldsymbol{R}_{ij}$ is obtained.

Many measures of complexity and dynamical invariants are derived from RP matrices: generalized entropies, correlation dimensions, mutual information, redundancies, etc.

N. Marwan et al, Recurrence plots for the analysis of complex system. Physics Reports 438 (2007) 237–329



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

Fuzzy Symbolic Dynamics (FSD)

$$R(t,t';\varepsilon)=\Theta\left(\varepsilon-\left\|x(t)-x(t')\right\|\right)$$

R matrix: distances between points, or from reference points for trajectory $x(t)$:

$$S(\mathbf{x}(t),\mathbf{x}_0)=G\left(-\left\|\mathbf{x}(t)-\mathbf{x}_0\right\|\right)$$

G function for non-linear scaling of distances.

1. Standardize original data in high dimensional space.
2. Find cluster centers (e.g. by clusterization): $\mu_1, \mu_2 \ldots \mu_d$
3. Use non-linear mapping to reduce dimensionality to *d*, for example:

$$y_k(t;\mu_k,\Sigma_k)=\exp\left(-\left(x-\mu_k\right)^{\mathrm{T}}\Sigma_k^{-1}\left(x-\mu_k\right)\right)$$

Localized membership functions $y_k(t;W_k)$:

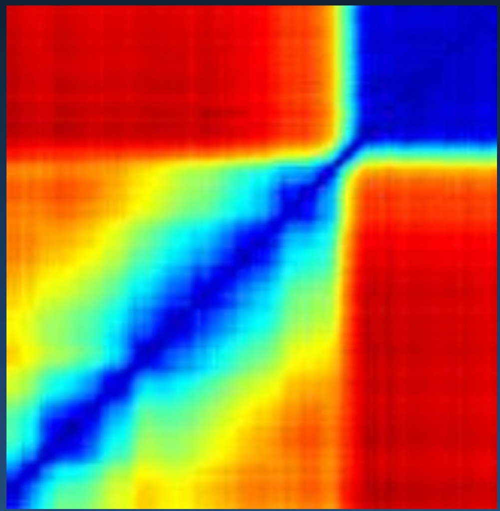
sharp indicator functions => symbolic dynamics; $x(t)$ => strings of symbols;

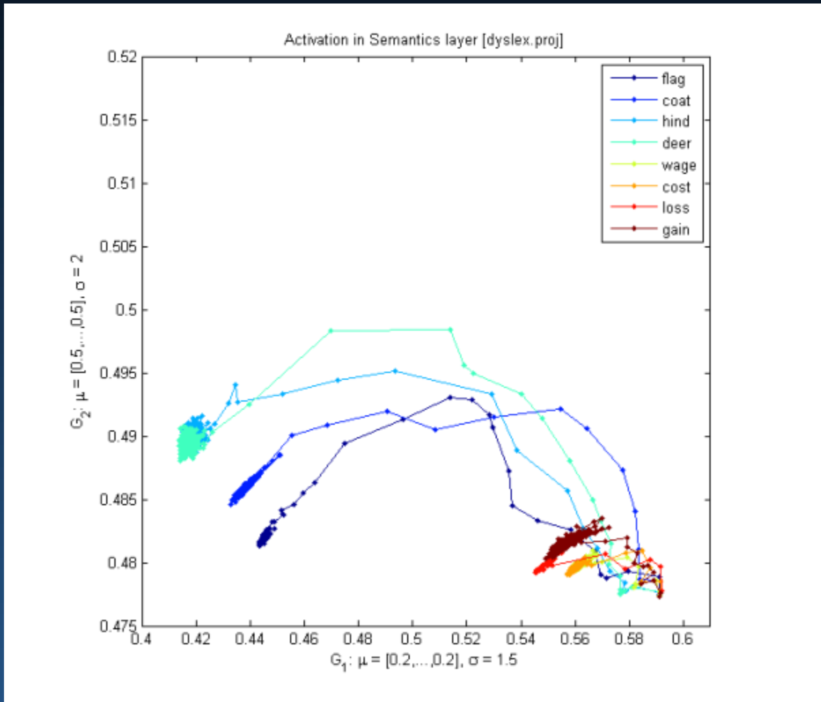
soft functions => fuzzy symbolic dynamics, dimensionality reduction

$Y(t)=(y_1(t;W_1), y_2(t;W_2))$ => 2D mapping of high-dimensional data, choose your parameters to find useful view point.

Fuzzy Symbolic Dynamics (FSD)

FSD complements RP information



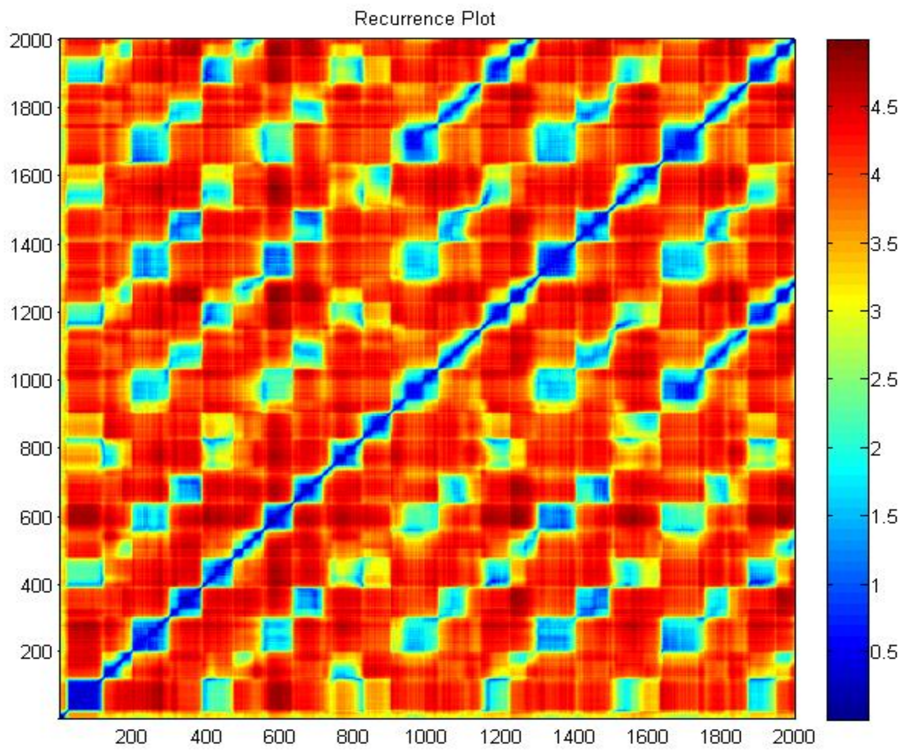


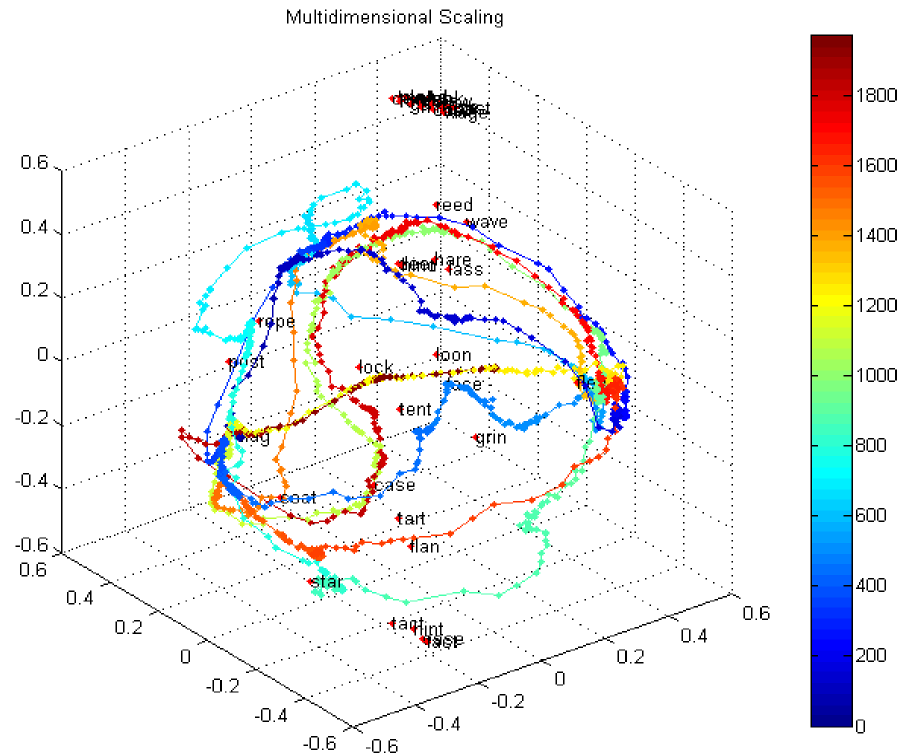
Find good reference points to see the dynamics, distinguish important basins of attraction, states that should be monitored.

Dobosz, K., & Duch, W. (2010). Understanding neurodynamical systems via fuzzy symbolic dynamics. *Neural Networks*, *23*(4), 487–496.

Duch, W., & Dobosz, K. (2011). Visualization for understanding of neurodynamical systems. *Cognitive Neurodynamics*, *5*(2), 145–160

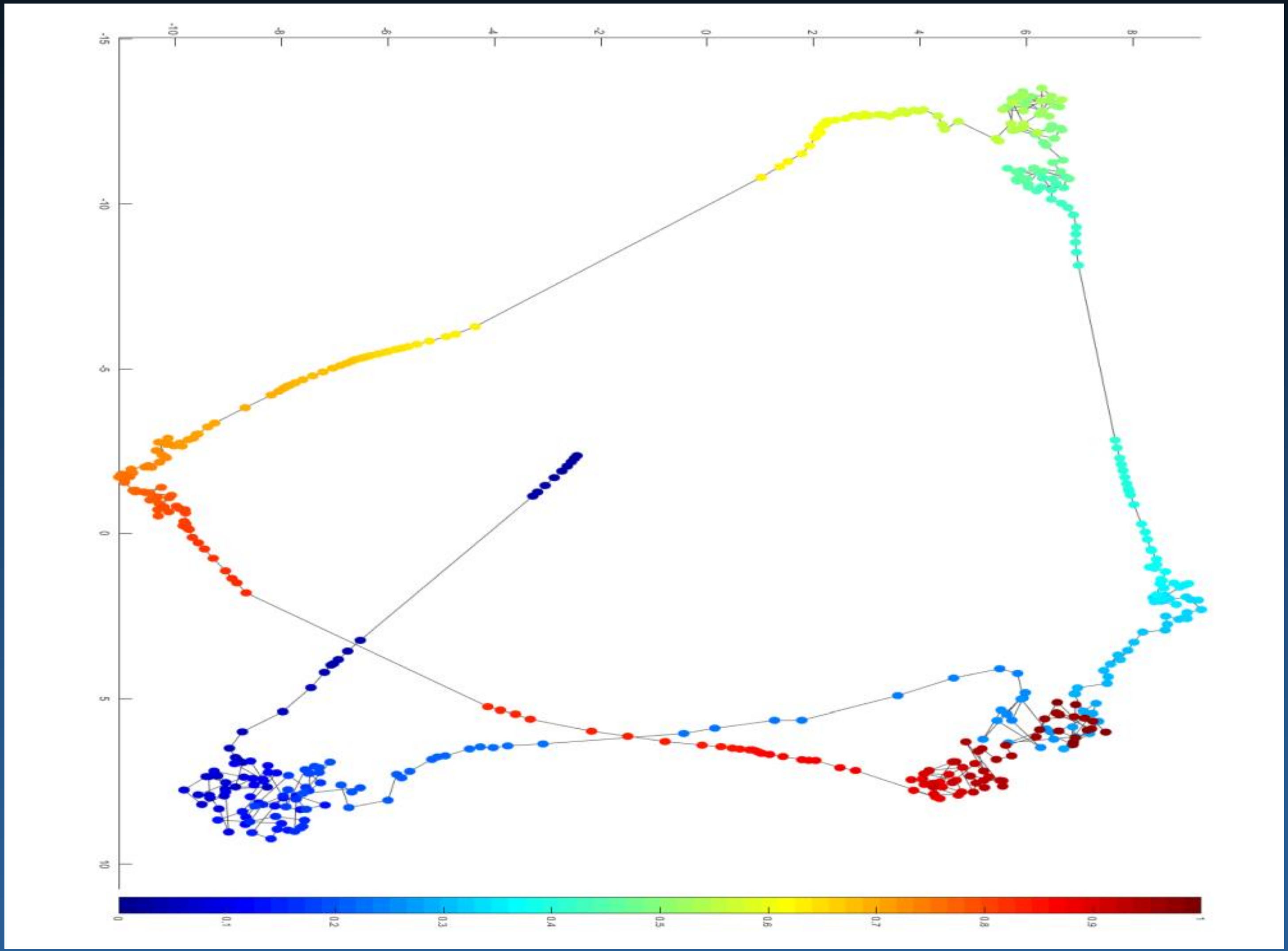
Trajectory visualization





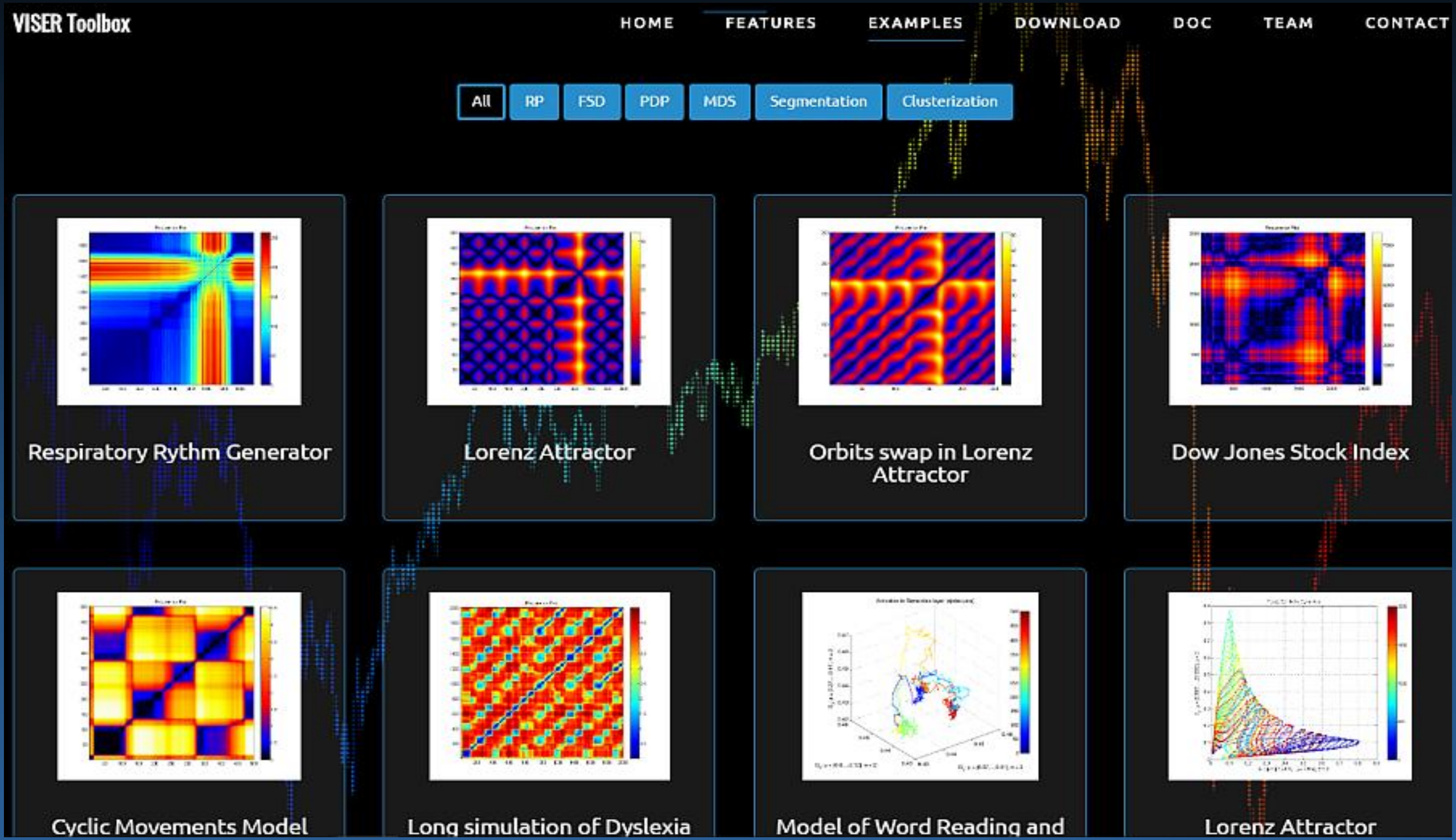
Recurrence plots and MDS visualization of trajectories of the brain activity.
Here evolution of 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain is presented, starting with the word “flag”.
Trajectories may be displayed using tSNE, UMAP, MDS or our FSD visualization.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

Trajectory in 2D



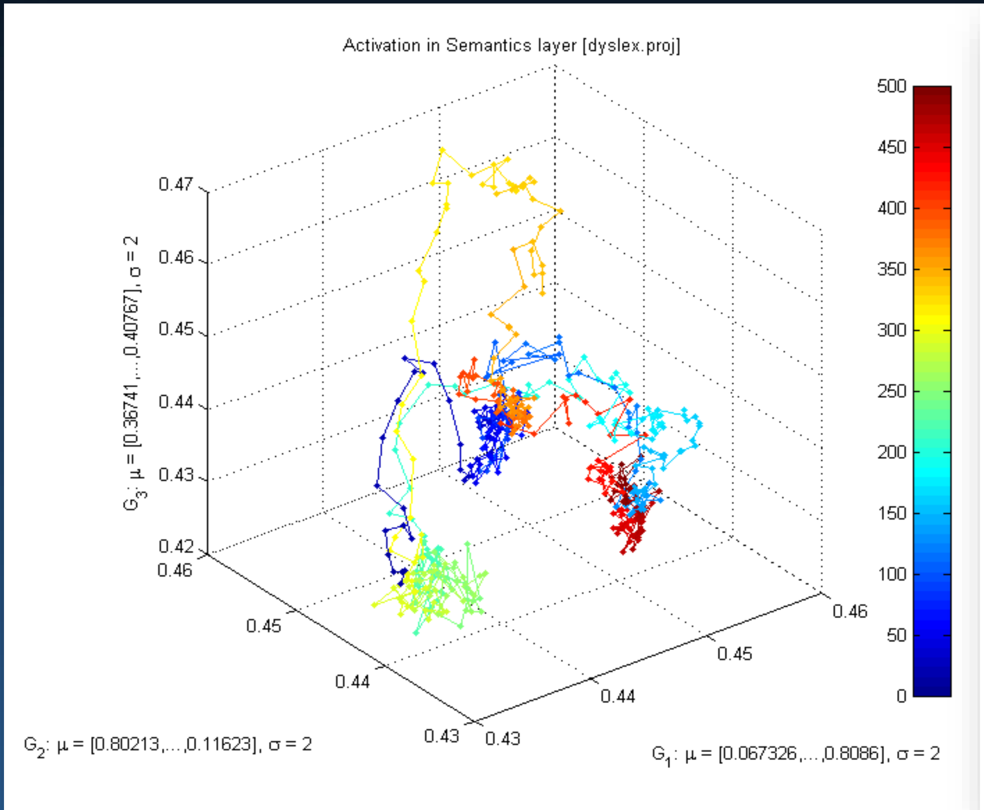
tSNE visualization of 140 dim trajectories, going “from thought to thought”.

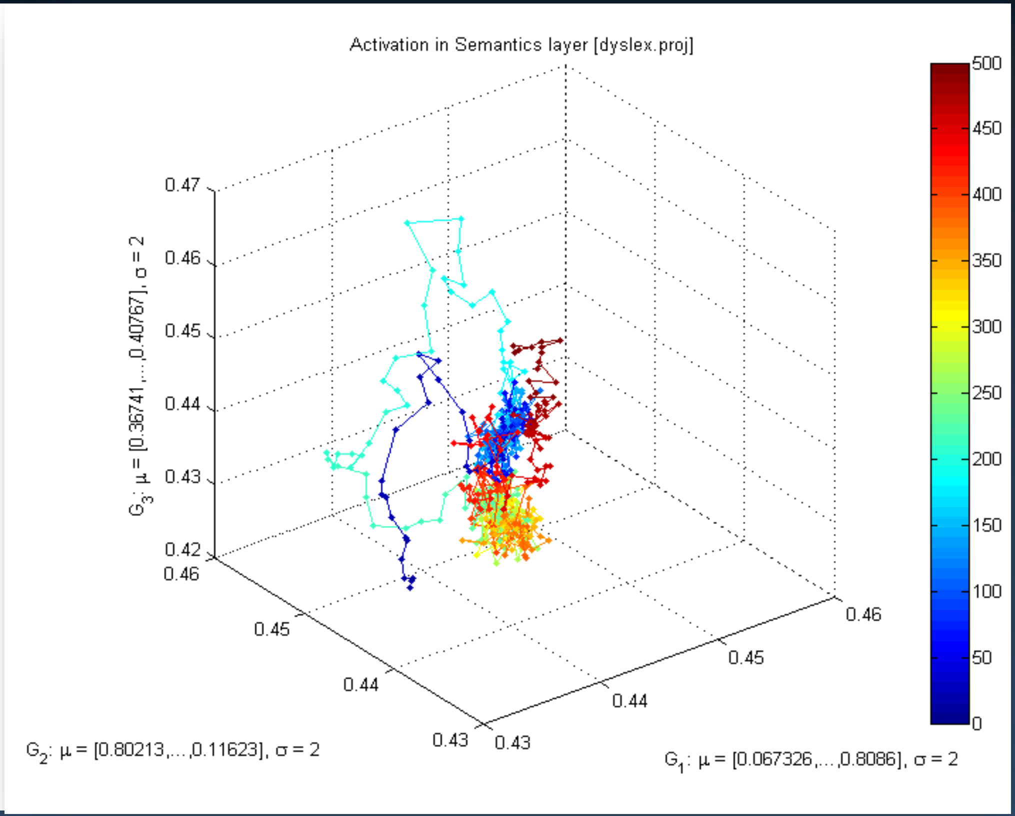
Viser toolbox



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

Typical Development vs. Autism

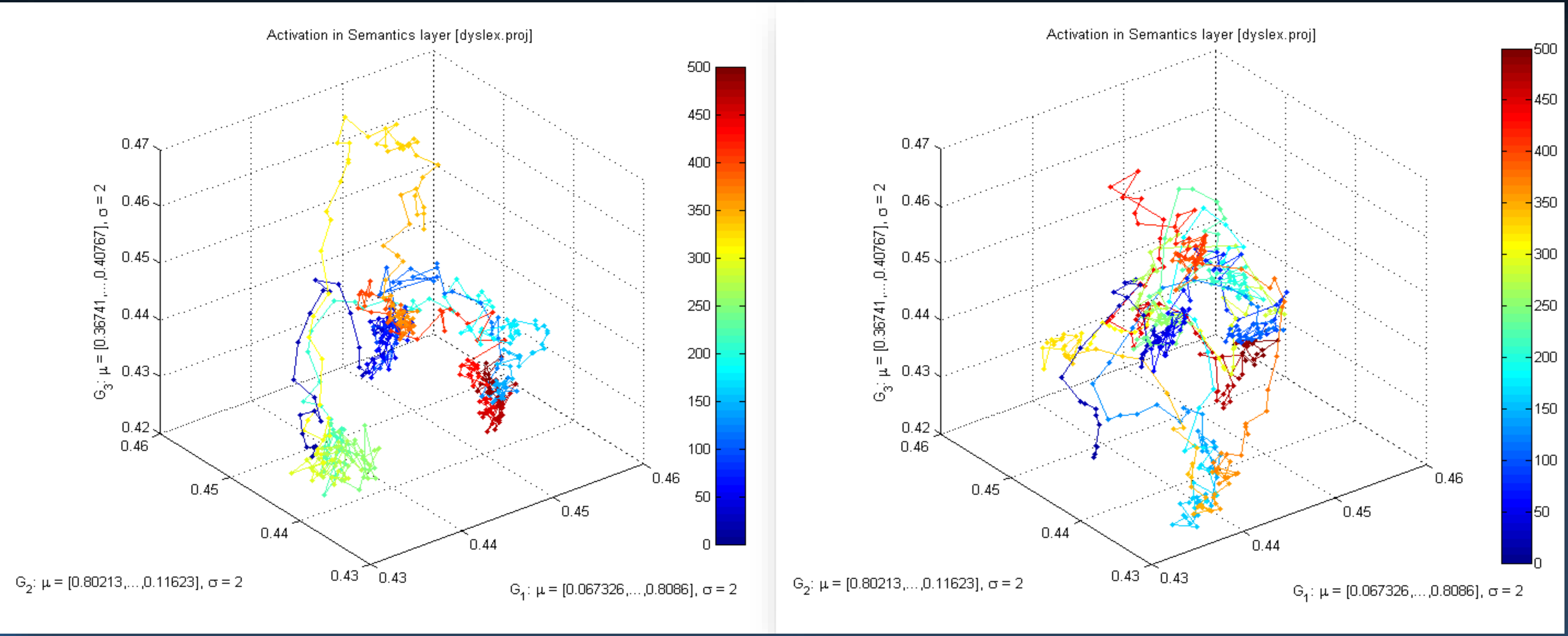




Trajectories show activation of 3 Gaussian prototypes ($G_1(t)$,$G_2(t)$,$G_3(t)$). Neurodynamics depends on properties of single neurons, noise in the system.

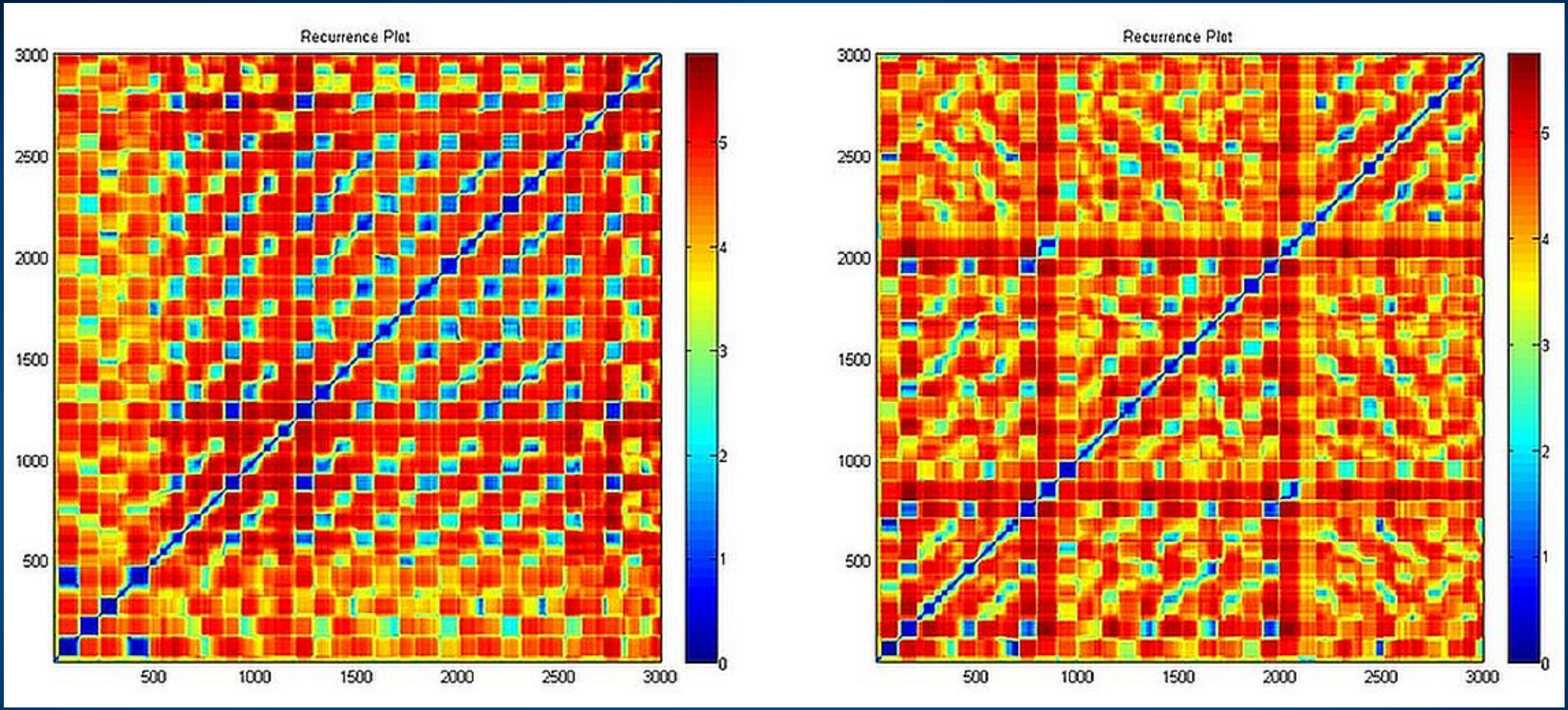
Starting from "flag". Voltage-dependent leak channel parameter determines rate of spontaneous depolarization of neurons, $b_{inc\_dt} = 0.01$ is normal case, $b_{inc\_dt} = 0.005$ slows depolarization, trapping times are long, fewer states, slow Hebbian learning.

Typical Development vs ADHD



Starting from the word "flag". Voltage-dependent leak channel parameter determines rate of spontaneous depolarization of neurons, b_{inc_dt} = 0.01 is normal case, b_{inc_dt} = 0.02 leads to fast depolarization. Trapping times are short, many weak attractors are formed, "fleeting thoughts" end in shallow associations, the system needs stimulants to increase synchronization. Surprising, but this is probably why stimulants like Ritalin are used to treat ADHD.

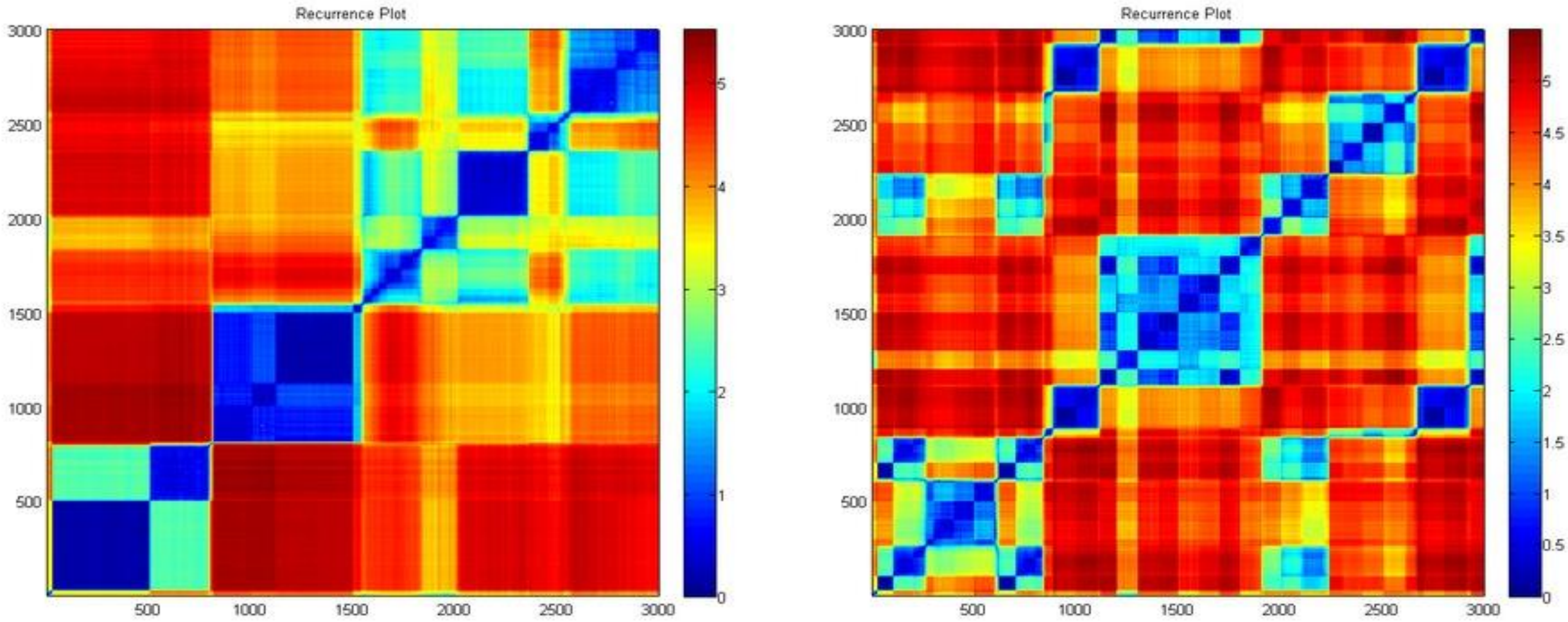
RSVP: normal case



Normal presentation speed
associations, words in context, good
good understanding

5x faster presentation, weak priming
context states are weakly activated
no time for associations/understanding.

Simulations of rapid stimulation in autism



Normal speed
skipping some words,
no associations

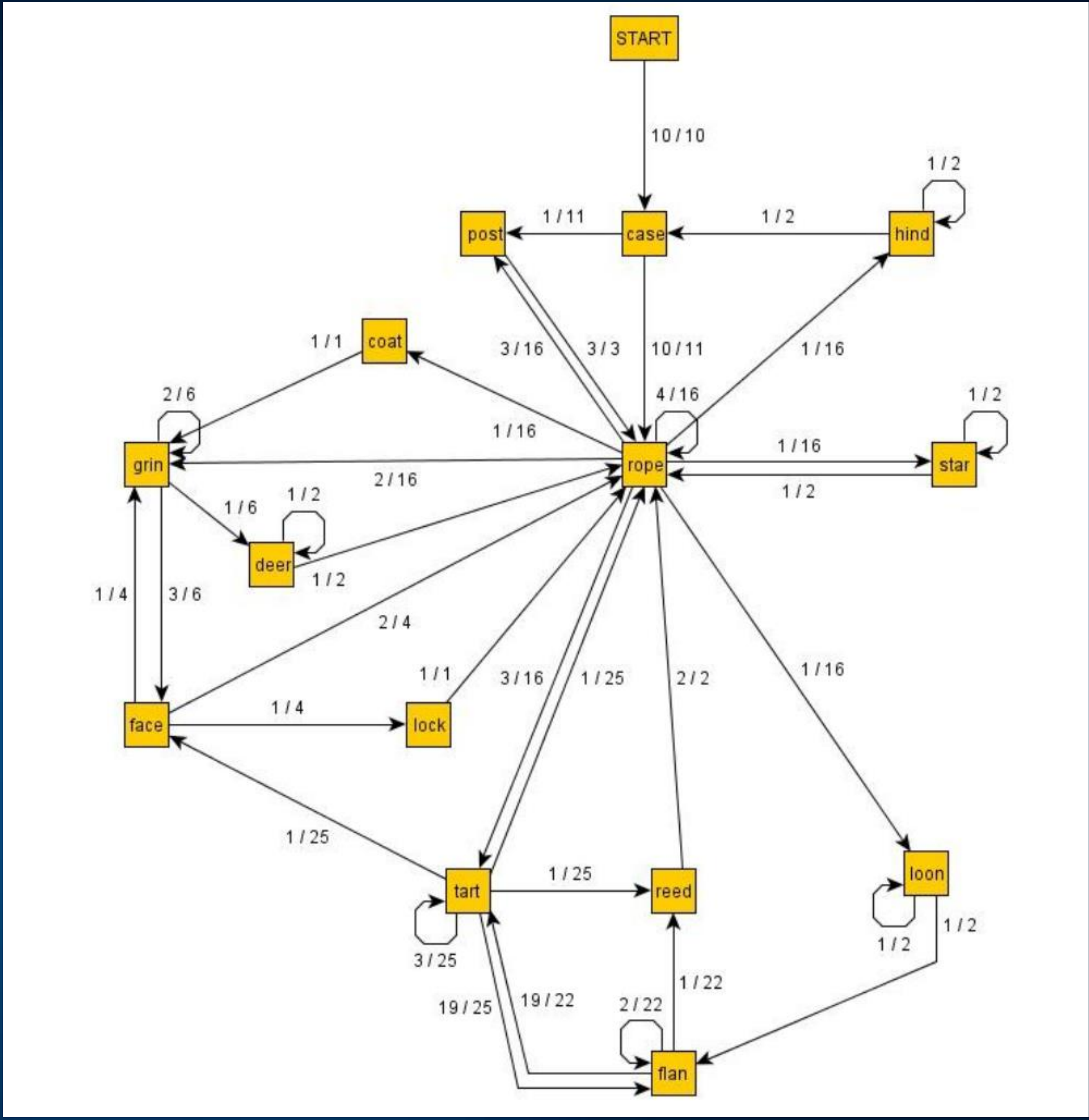
fast presentation, richer dynamics,
more complex internal states,
some associations arise (off-diagonal)

More states/time window = better connectome development.

Multiple starts from the same word lead to different trajectories. Calculate transition probabilities between metastable states from frequency of transitions.

Why such transitions?

Linked state have patterns sharing few features, that recruit less active, but strongly connected neurons, and relax those currently active, making the previous state inaccessible for some time (refractory period).



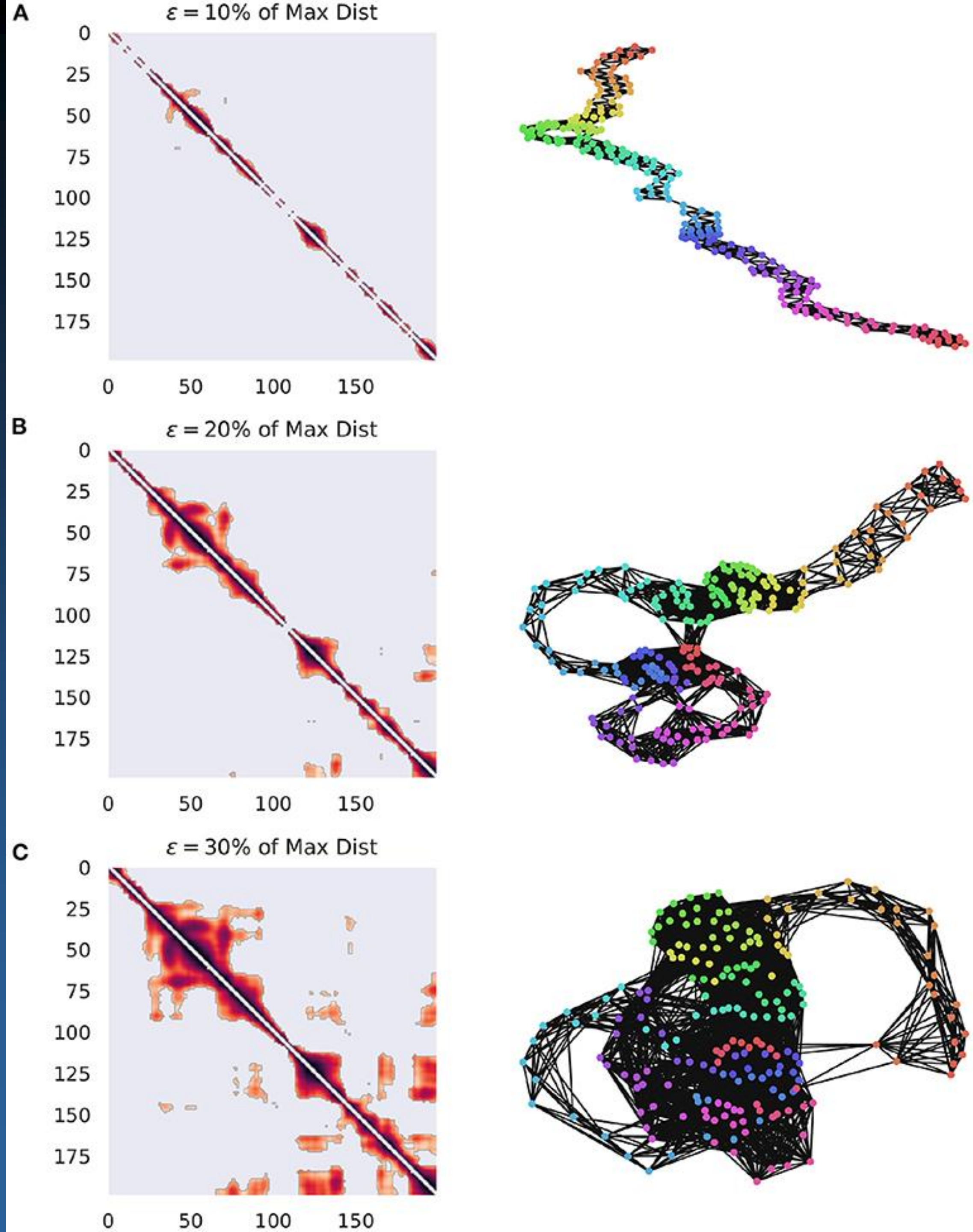
Recurrence network

Real brains, ECoG data: recurrence plots depend on the similarity threshold ε, cosine distance, Takens embedding of oscillatory data with dimension *d* and lag τ, .

Varley, T. F., & Sporns, O. (2022). Network Analysis of Time Series: Novel Approaches to Network Neuroscience. *Frontiers in Neuroscience, 15*. 10.3389/fnins.2021.787068

For mathematically inclined:

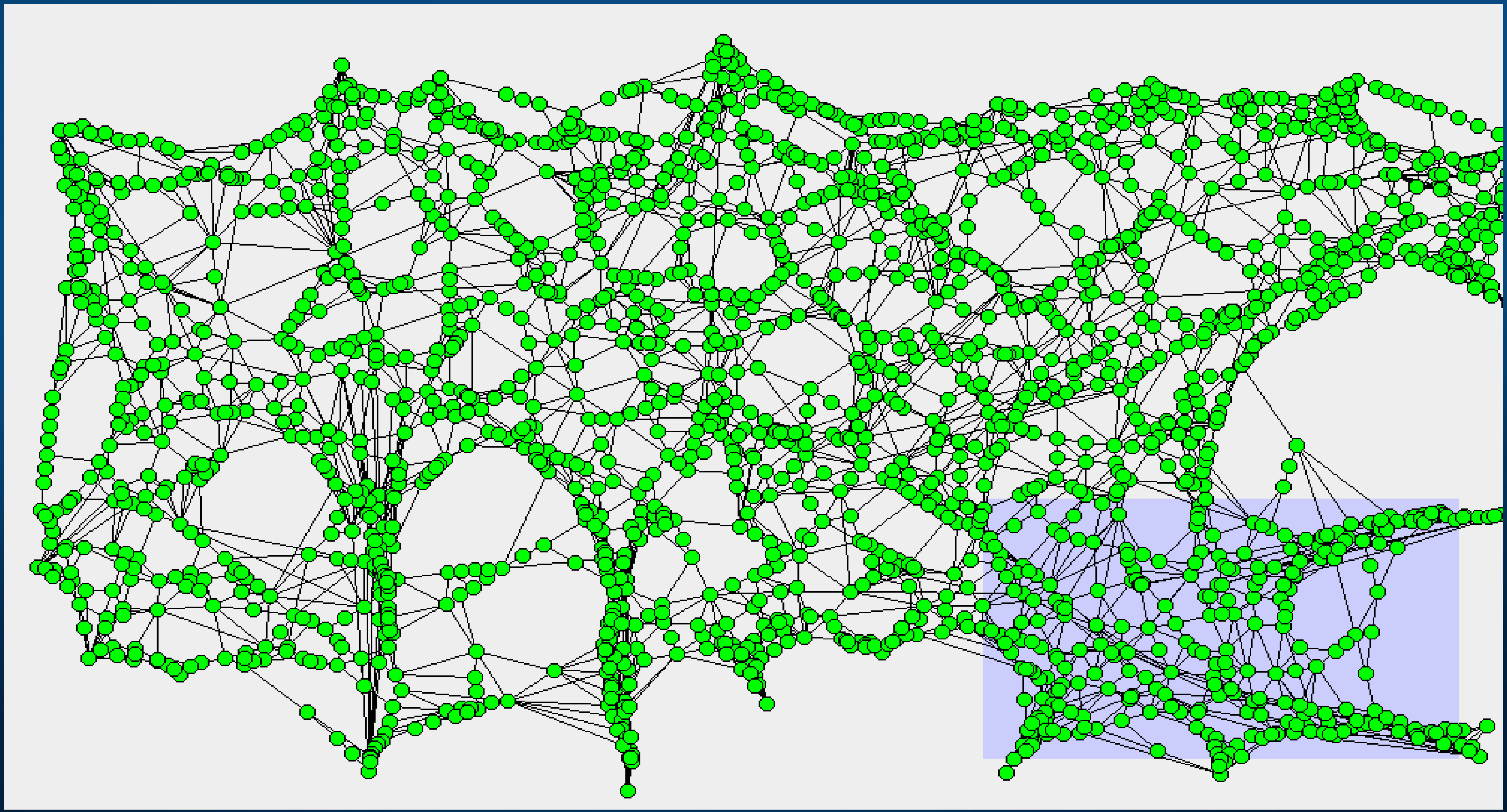
Caputi, L., Pidnebesna, A., & Hlinka, J. (2021). Promises and pitfalls of topological data analysis for brain connectivity analysis. *NeuroImage*, *238*, 118245.



Learning in real situations

Learning complex information creates conceptual grid, each node = metastable brain state, links = associations, thinking = transitions between states, following associations. Conceptual grid approximates environmental states, but **rapid learning distorts relations**. Strong emotions increase neuroplasticity, but may lead to accidental associations, save mental energy, creating „sinks" that attract many unrelated episodic memory states.

Growing Neural Gas model, trained on blue patches.

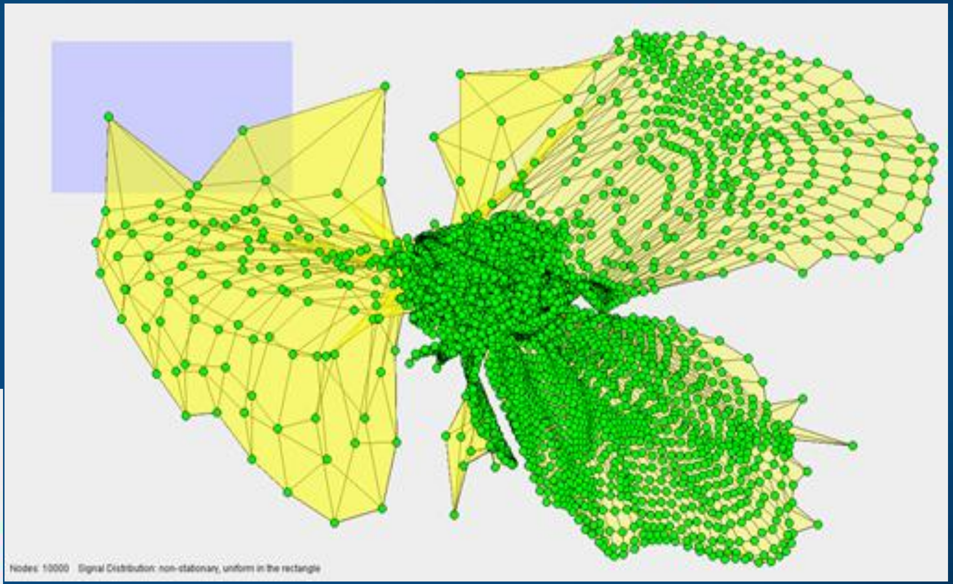


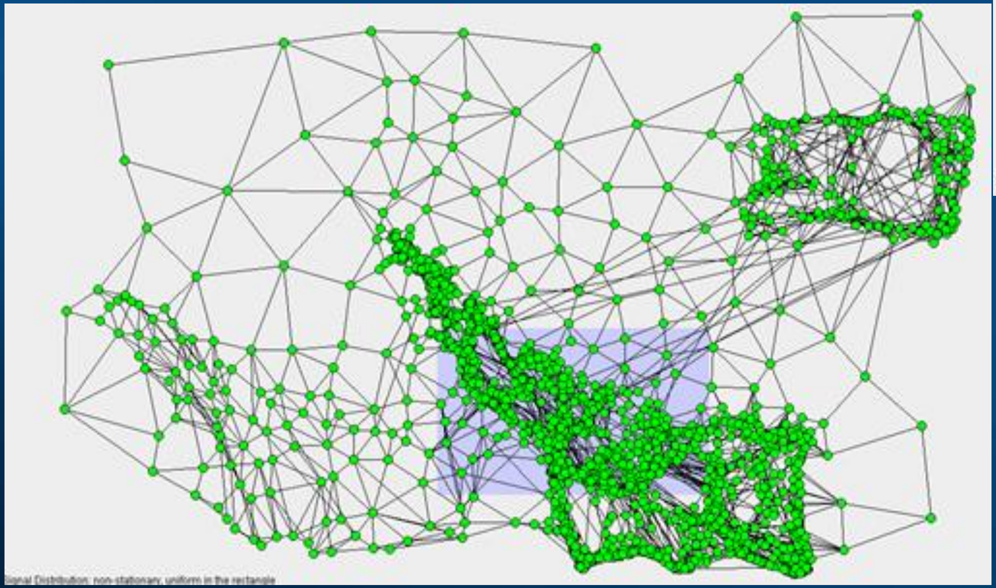
Memoids …

In extreme cases everything is associated with one great idea or cause.
"A lie that is repeated a thousand times becomes truth".

World view is totally distorted, mind states form one big memplex …

- Extraterrestials, politics, Nazis, religion, apocalypse, vaccines, 5G … anything.
- Simplifies dynamics, saves energy.



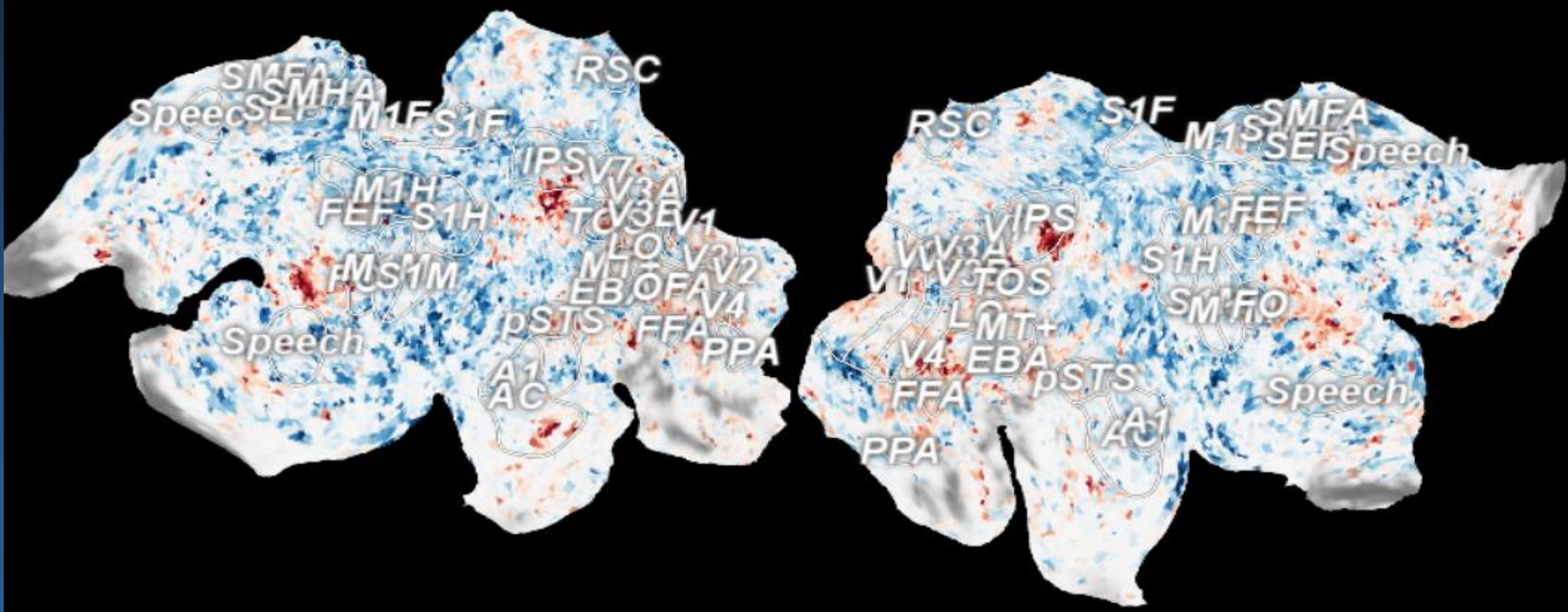


The rapid freezing of high neuroplasticity (RFHN) model. So far only simplest network simulations.

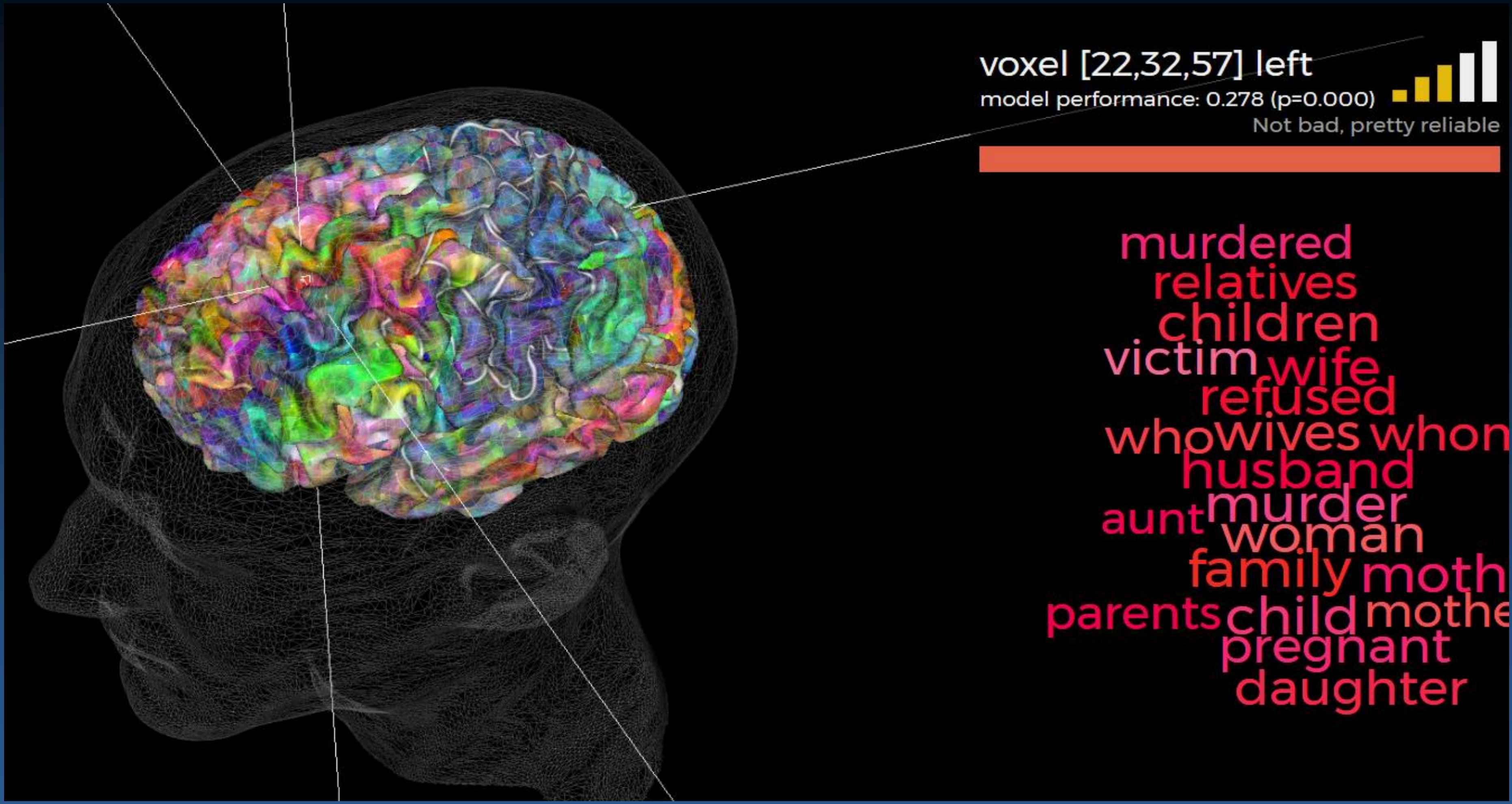
Duch W. (2021) Memetics and Neural Models of Conspiracy Theories. Patterns. Cell Press.

fMRI and neurodynamics

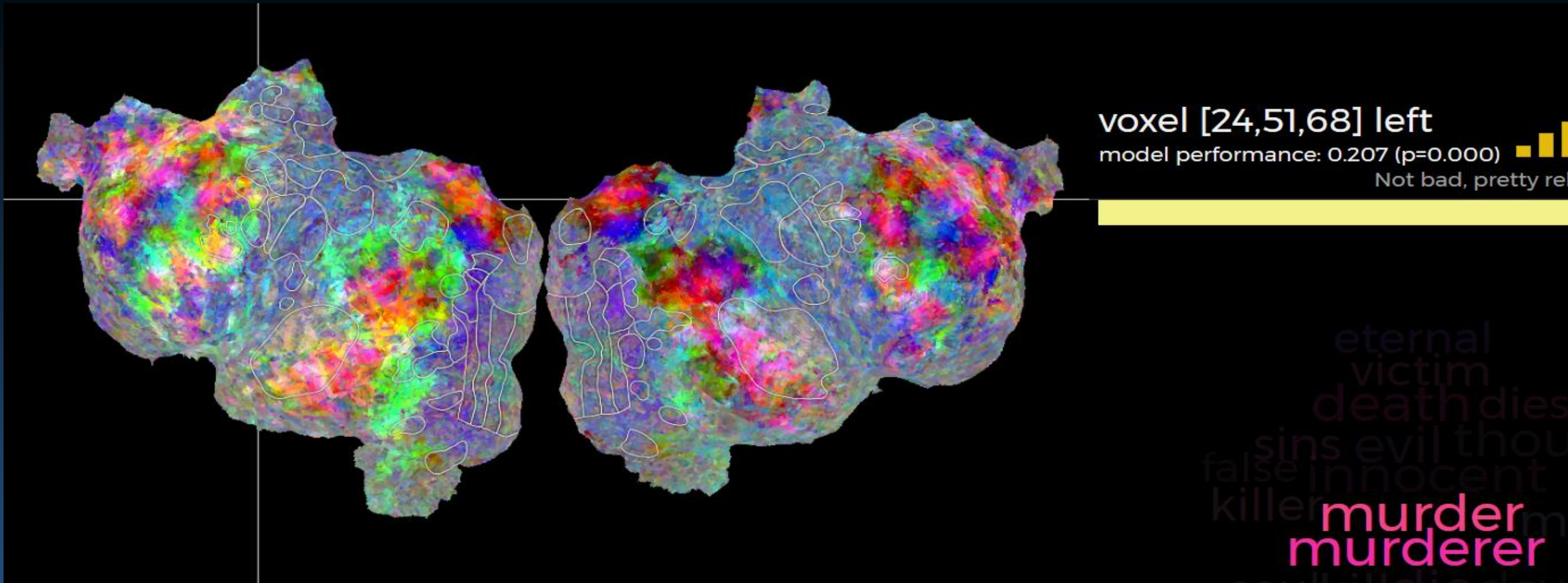
Category traffic light: Passive Viewing



Simple activations in IPS, V4, FFA, for simple objects/actions, we can recognize brain areas responsible for colors, shapes, name, movement.



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.

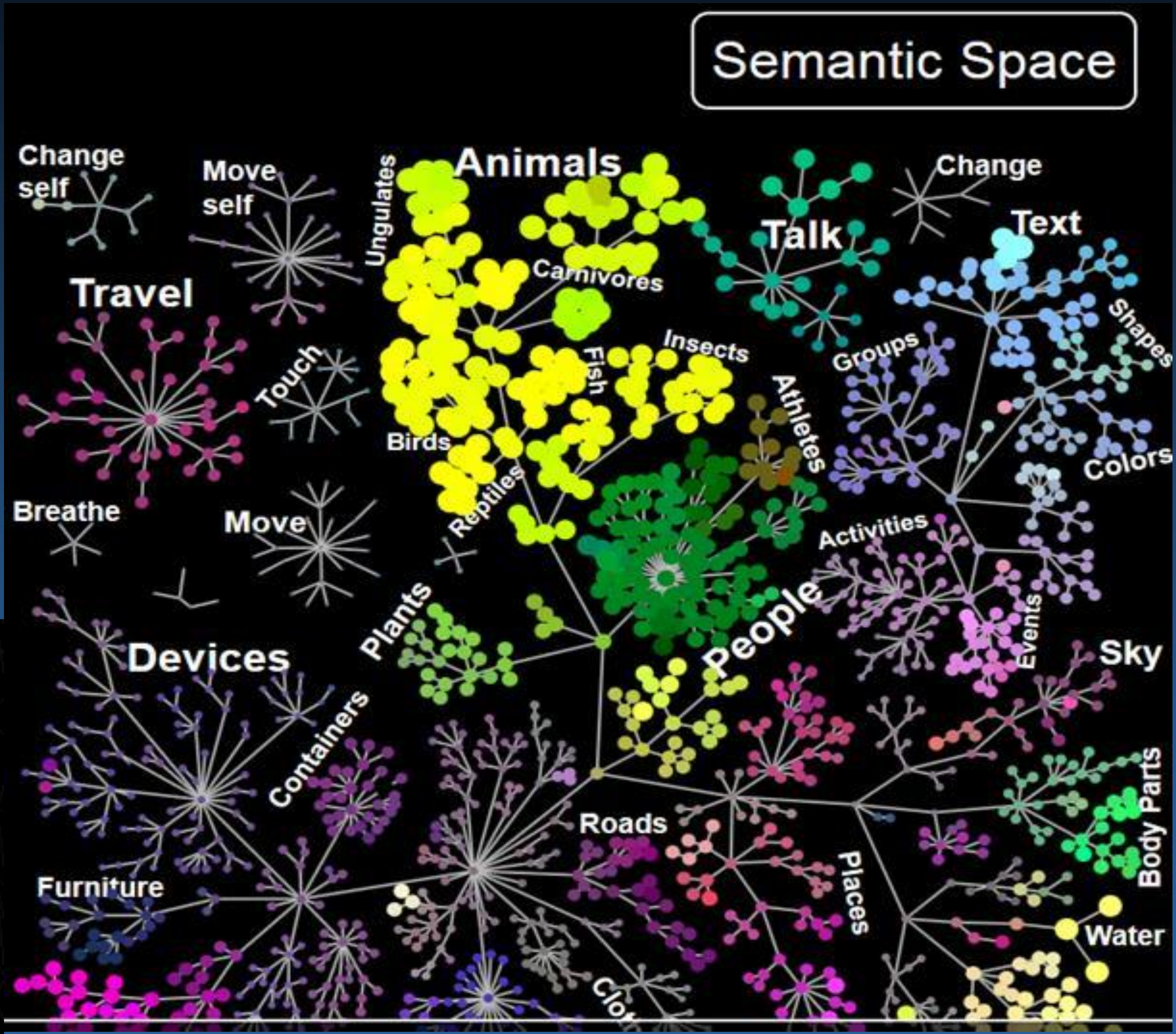
Each word activates a whole map of activity in the brain, depending on sensory features, motor actions and affective components associated with this word.
Why such activity patterns arise? Brain subnetworks connect active areas.

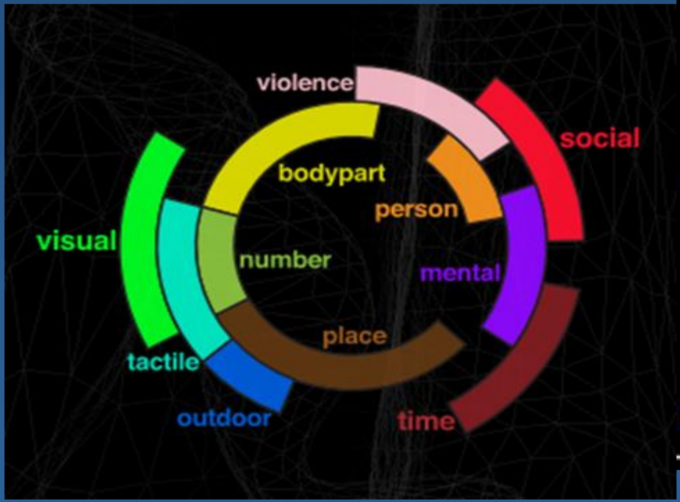
http://gallantlab.org/huth2016/ and short movie intro.

Can one do something like that with EEG or MEG?

Semantic neuronal space

Words in the semantic space are grouped by their similarity.
Words activate specific ROIs, similar words create similar maps (1700 states) of brain activity.
Video or audio stimuli, fMRI 60.000 voxel).
Gallant lab, Berkeley.



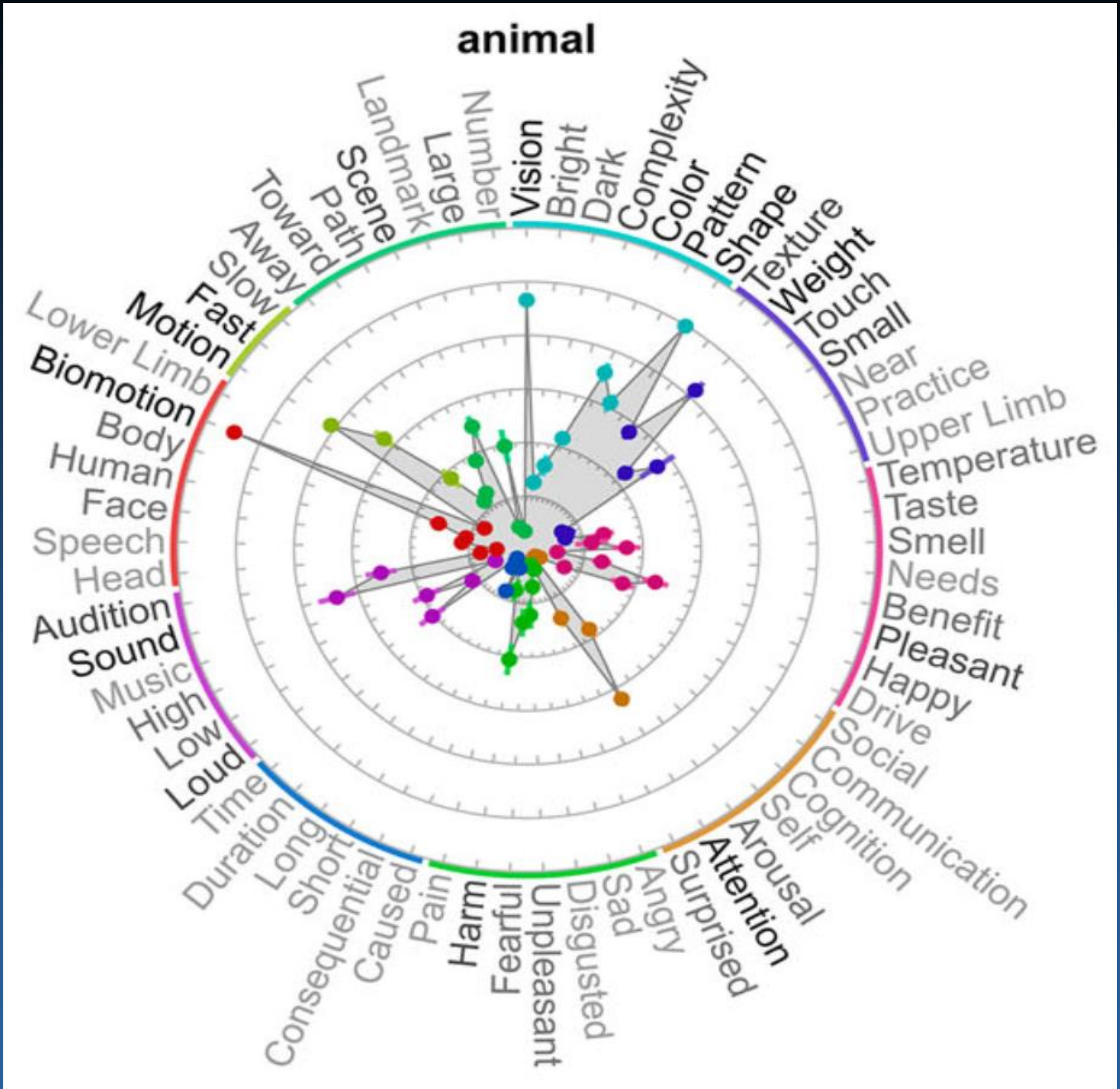


- 65 attributes related to neural activations.
- Colors on circle: general domains.

J.R. Binder et al. (2016) Toward a **Brain-Based Componential Semantic** Representation, Cognitive Neuropsychology 33, 130-174

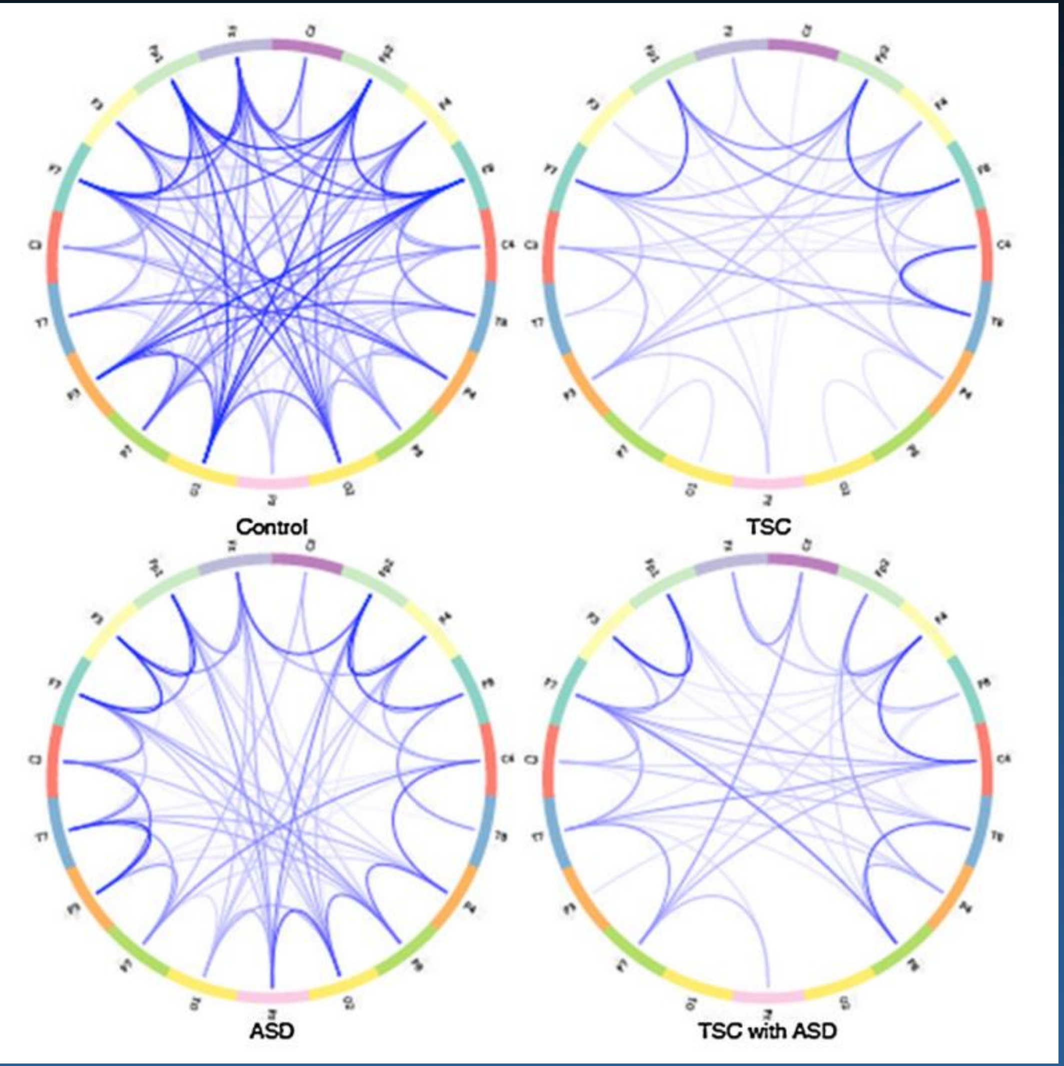
E. Chersoni et al. (2021). Decoding Word Embeddings with Brain-Based Semantic Features. *Computational Linguistics*, *47*(3), 663-698

10 embedding methods with up to 1024 dim vs BBS.



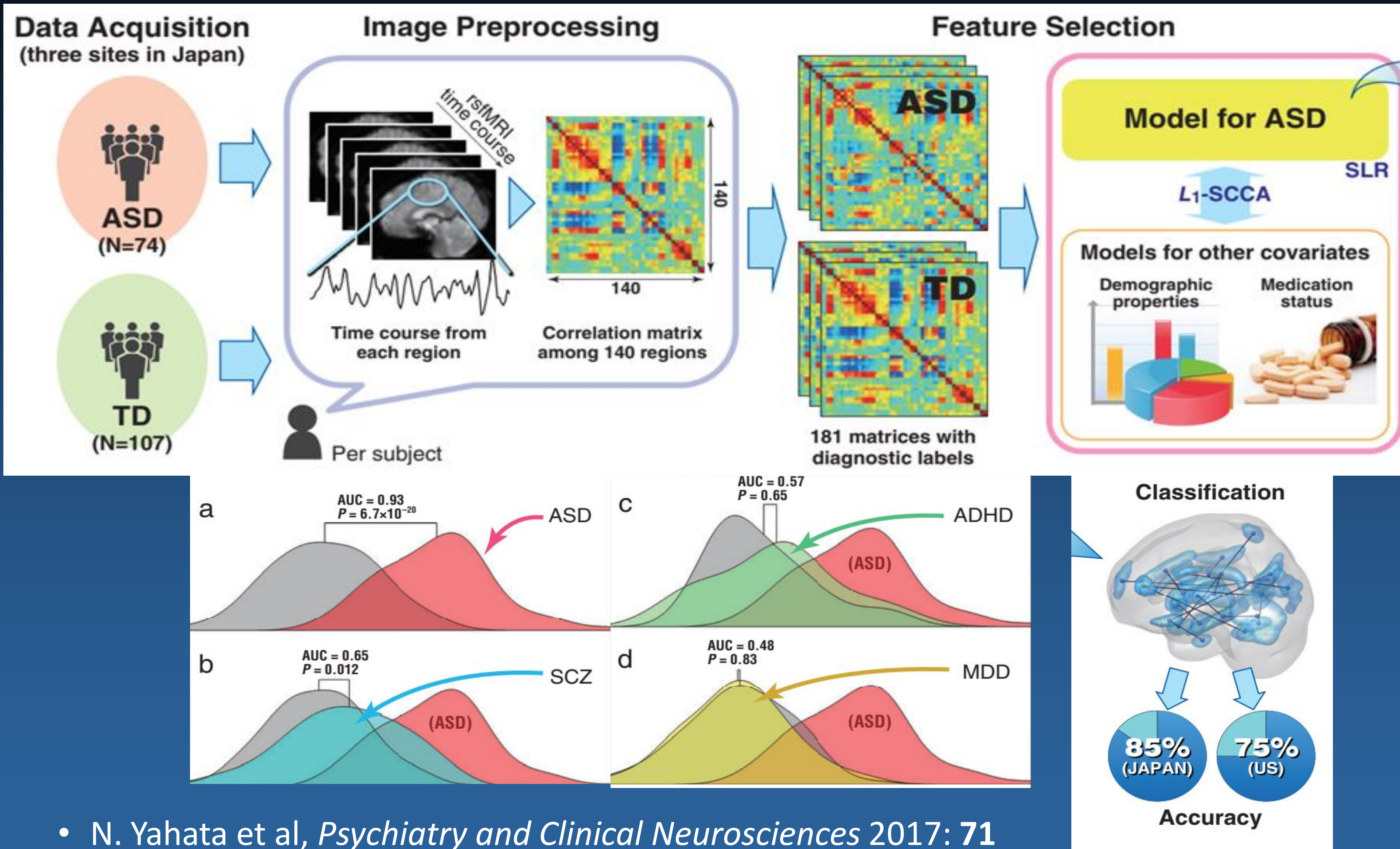
ASD: pathological connections

- 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**!



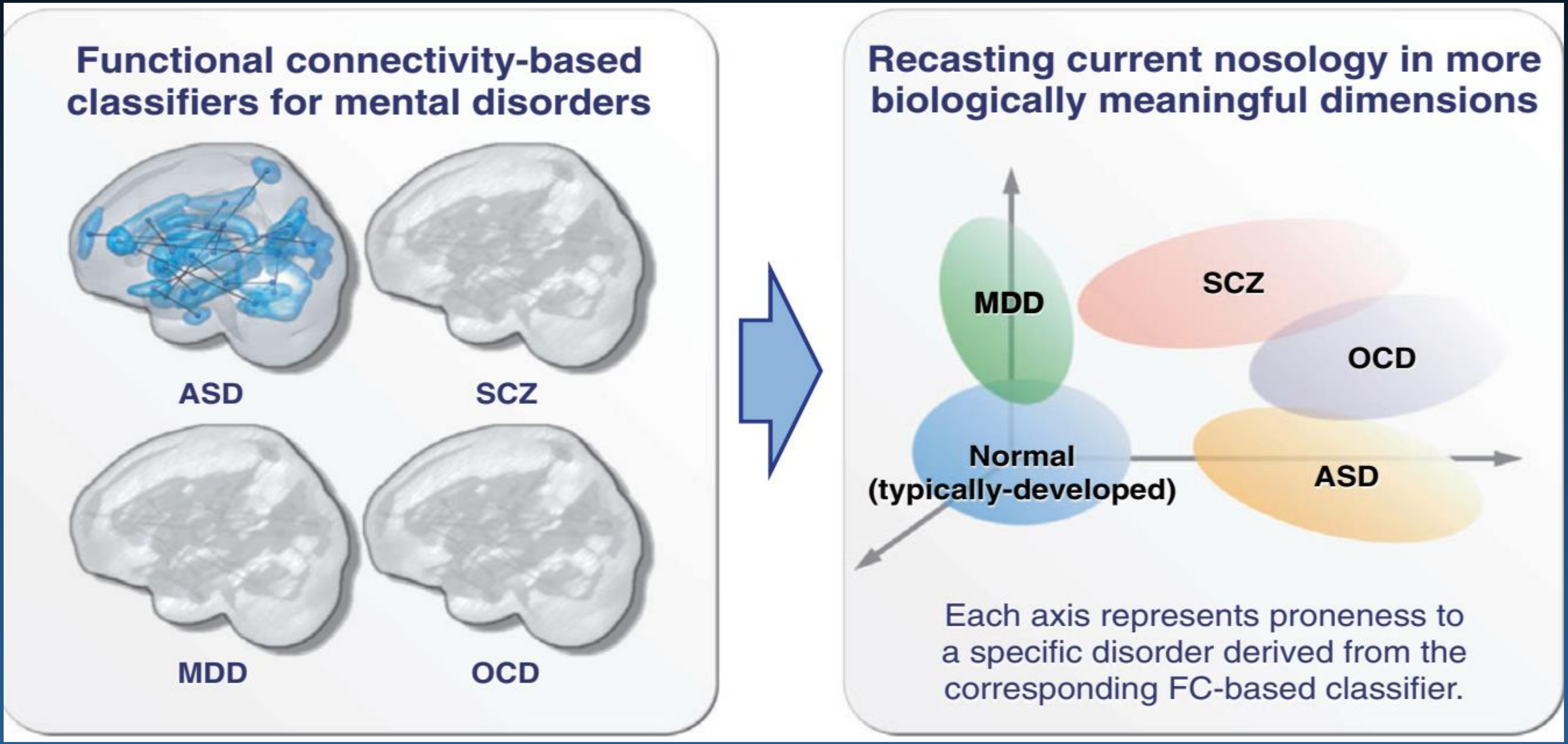
- J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

Biomarkers from neuroimaging



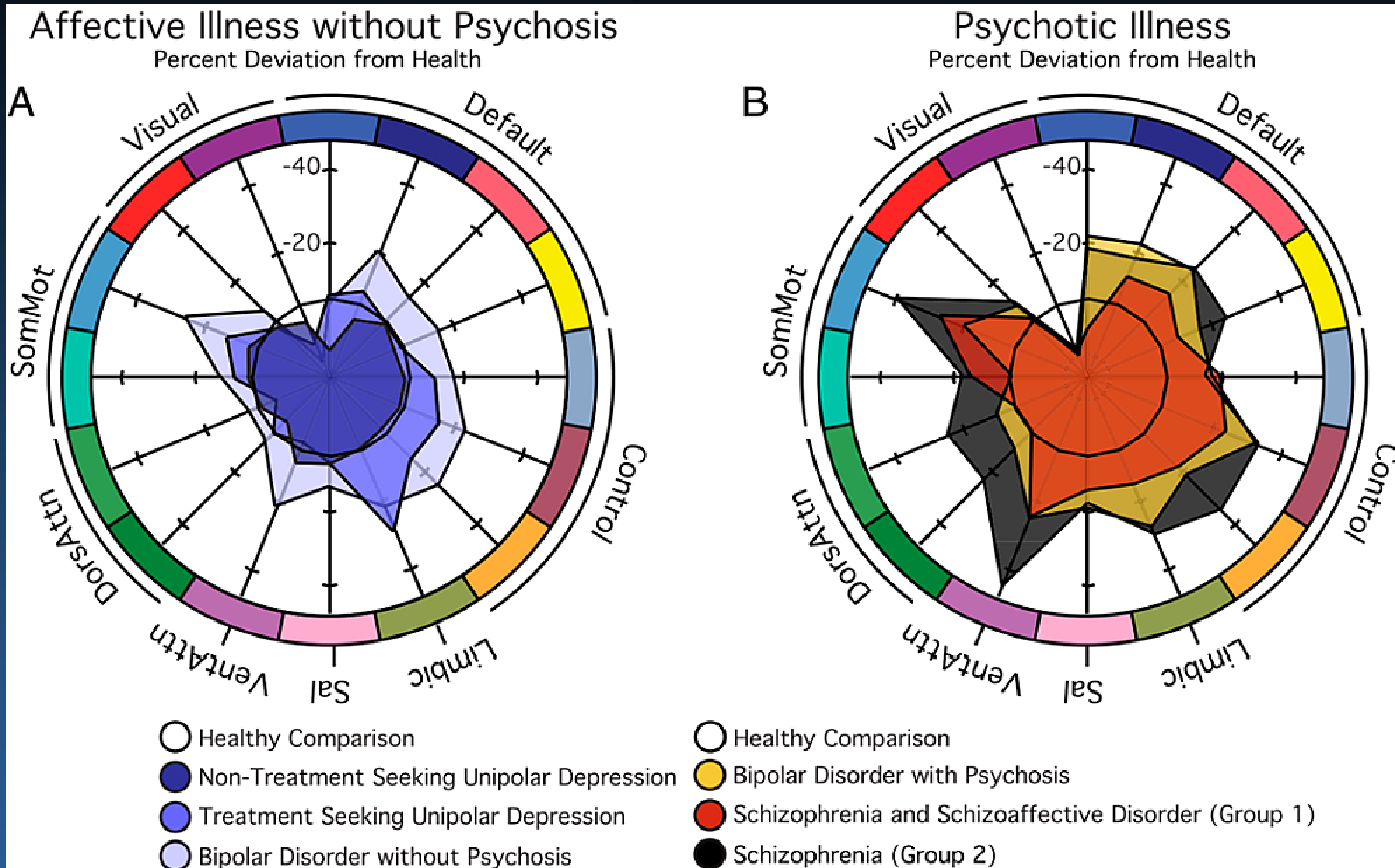
- N. Yahata et al, *Psychiatry and Clinical Neurosciences* 2017: **71**

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

Psychosis

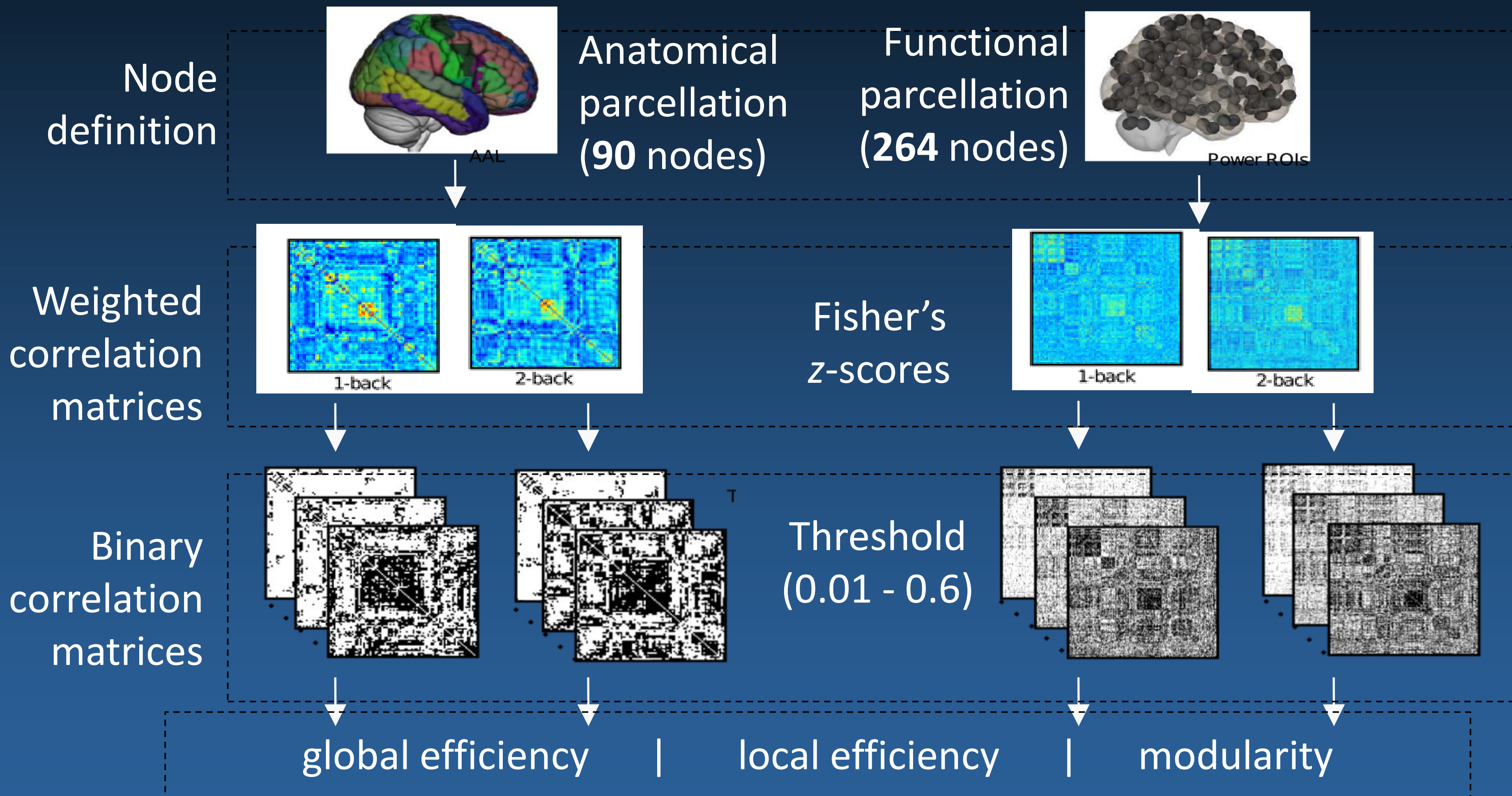


Difference in mean network connectivity for patients with affective illnesses without psychosis or psychotic illnesses relative to healthy participants.

J.T. Baker et al. (2019). Functional connectomics of affective and psychotic pathology. *PNAS* 116(18), 9050–9059.

Effects of load and training.

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



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.

Brain modules and cognitive processes

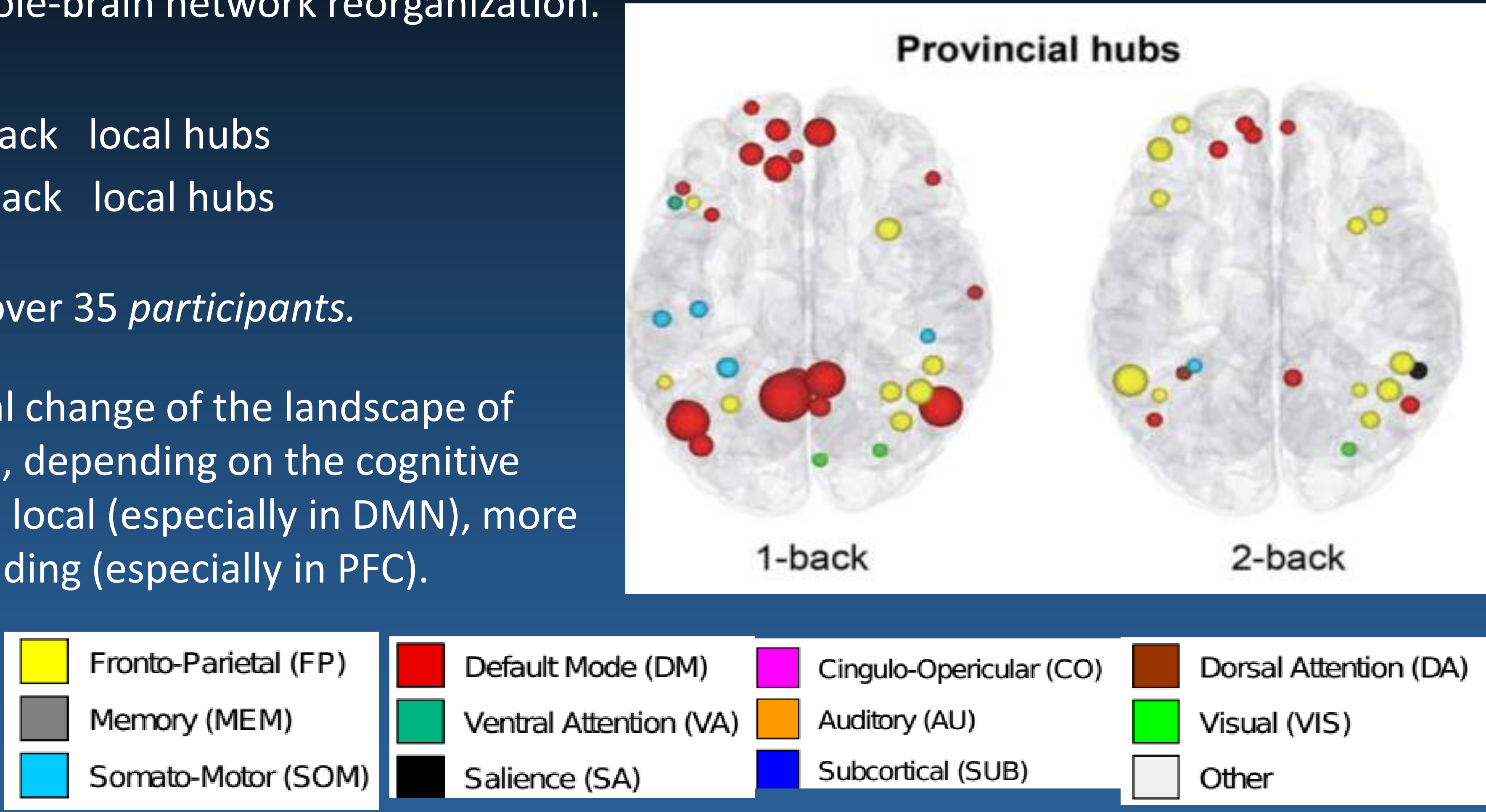
- Simple and more difficult tasks, requiring the whole-brain network reorganization.

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. Transition of the functional brain … Human Brain Mapping 38, 3659–3674, 2017.

Effect of cognitive load on info flow

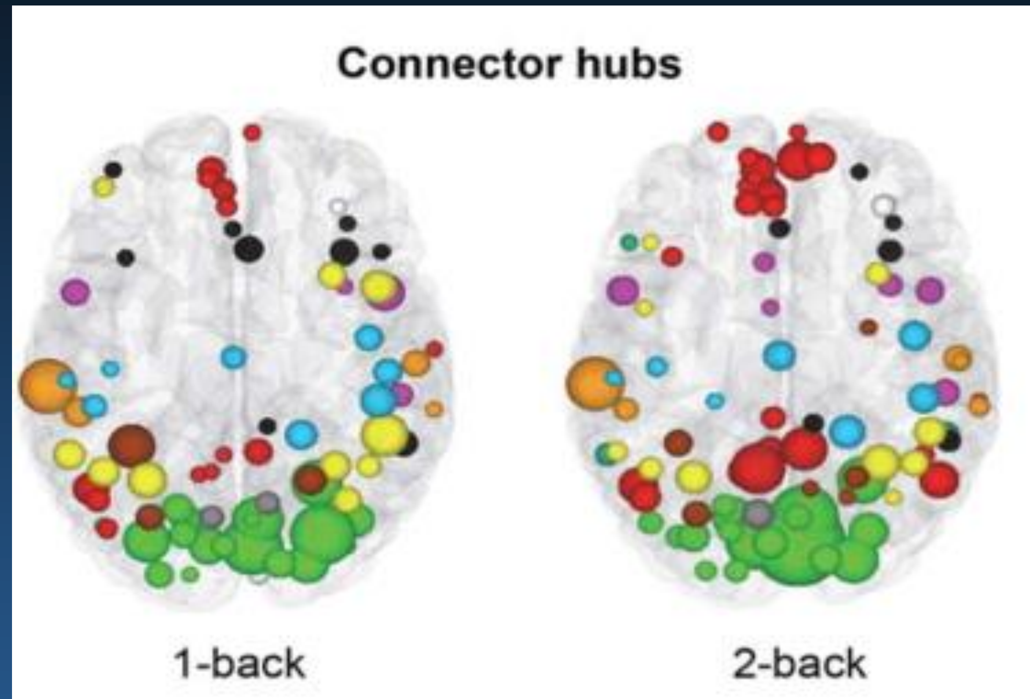
- Simple and more difficult tasks, requiring the whole-brain network reorganization.

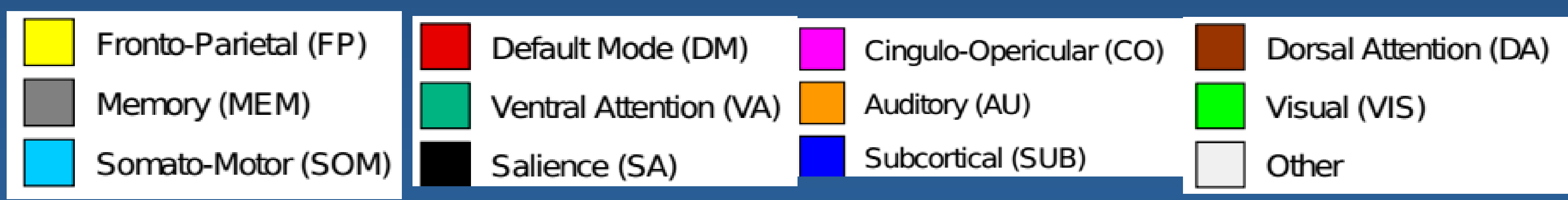
Left: 1-back connector hubs

Right: 2-back connector hubs

Average over 35 *participants.*

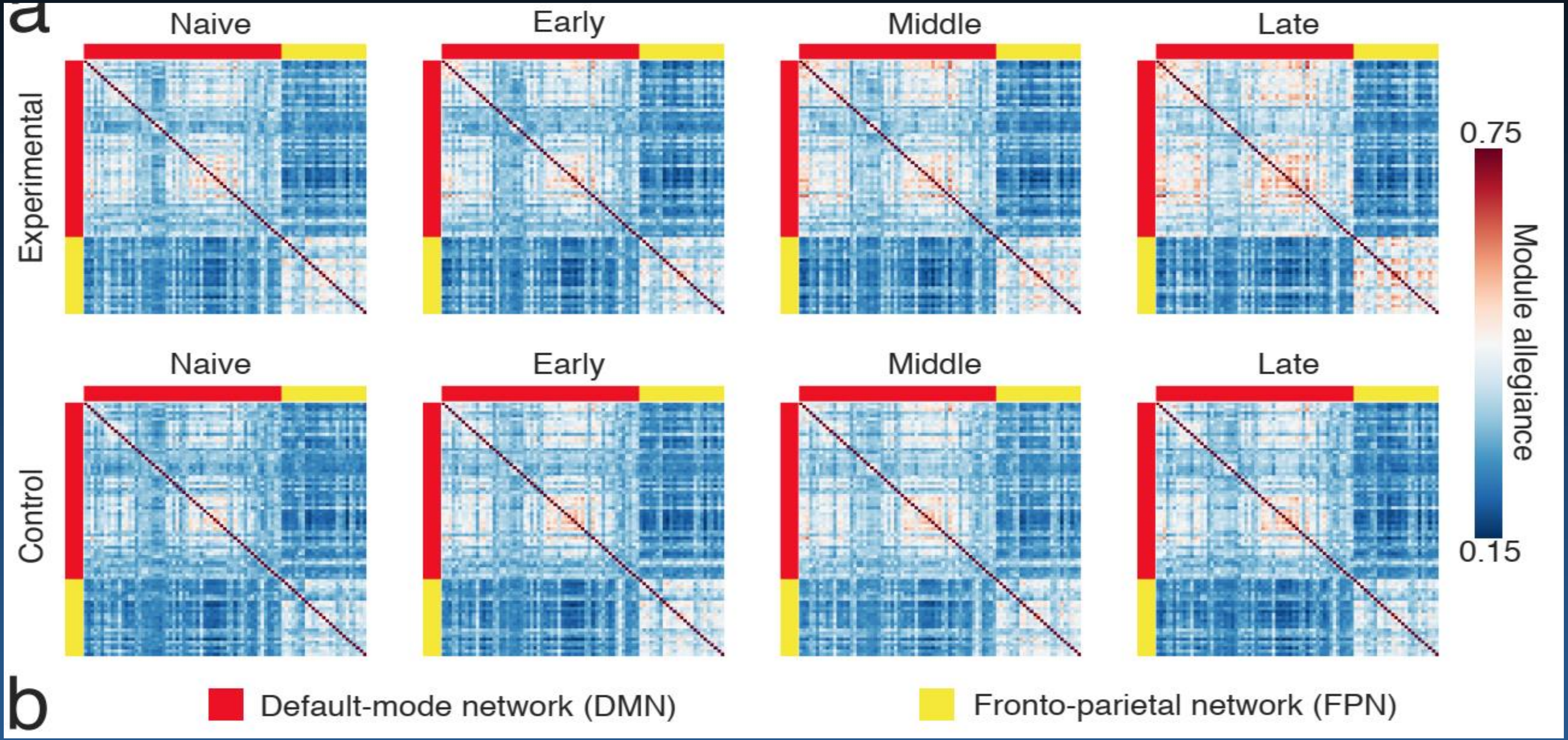
Dynamical change of the landscape of attractors, depending on the cognitive load – System 2 (D. Khaneman).
DMN areas engaged in global binding!





K. Finc, et al. Transition of the functional brain … Human Brain Mapping 38, 3659–3674, 2017.

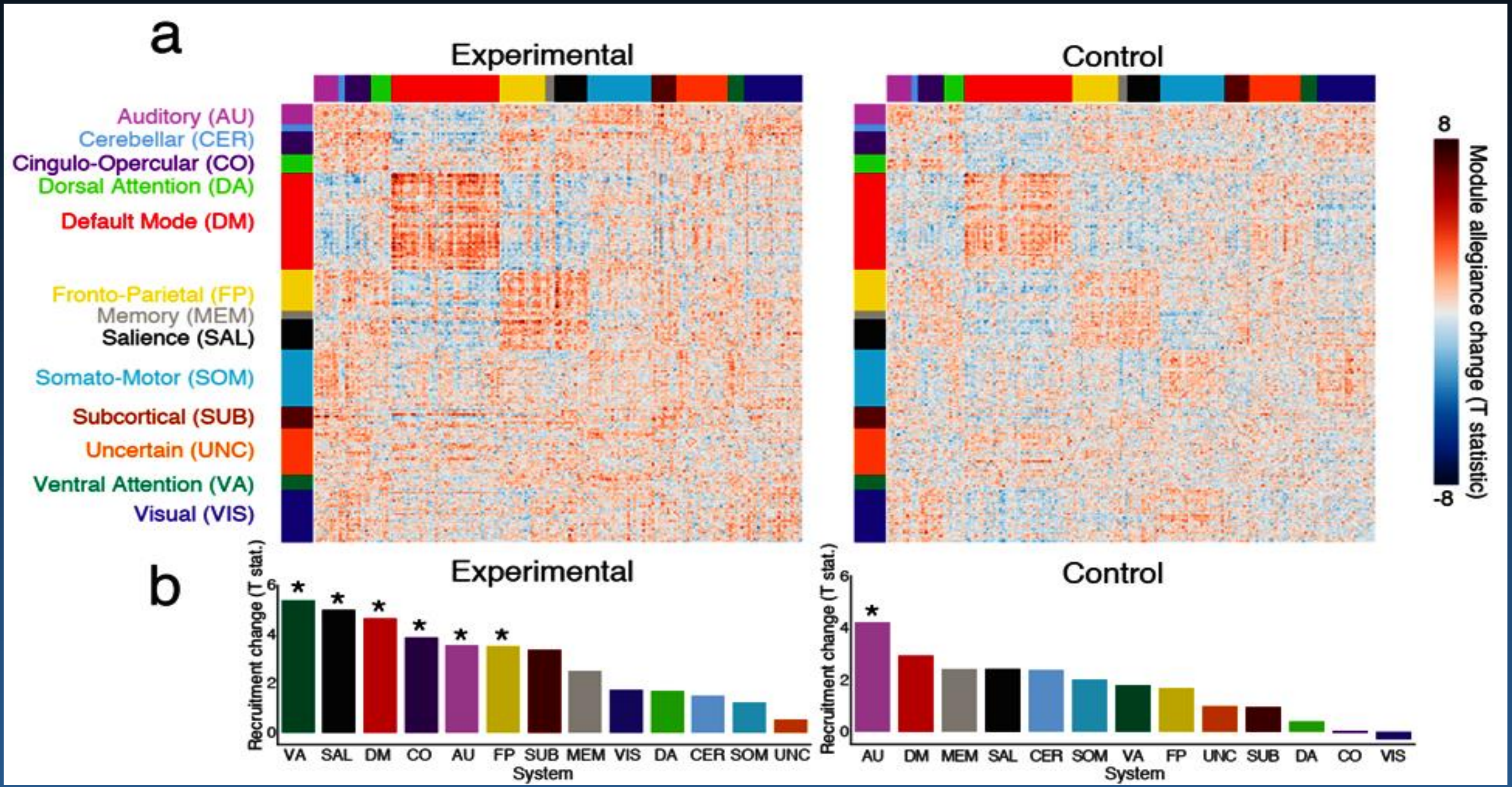
Working memory training



6-week training, dual n-back task (visual+auditory), 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.

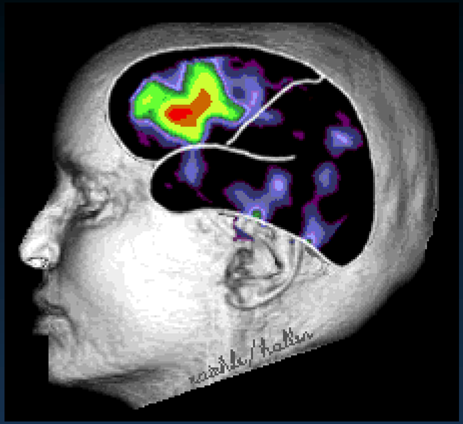
Segregation of task-relevant DMN and FPN regions is a result of training and complex task automation, i.e. from conscious to automated processing.

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, Dynamic reconfiguration of functional brain networks during working memory training. Nature Communications 11 (2020).



EEG and neurodynamics

Brain fingerprinting

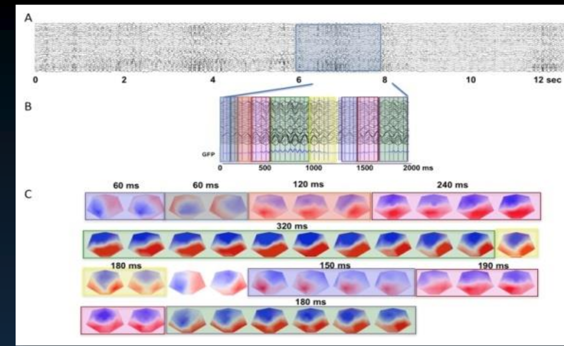
Find unique patterns of brain activity to identify:
- brain regions of interest (ROI)
- active neural networks
- mental states, tasks, processes.

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. fMRI networks (Yuan … Bodurka, 2015).
6. Recurrence quantification analysis.

\+ many more approaches…

1



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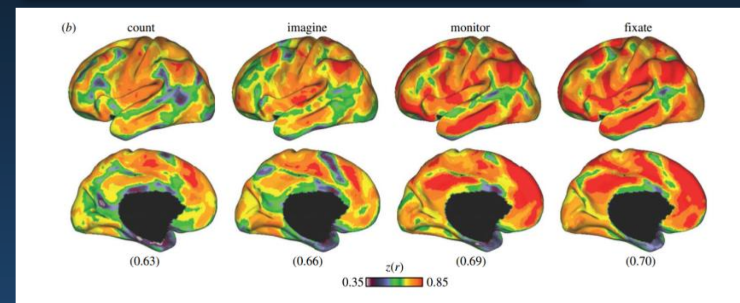

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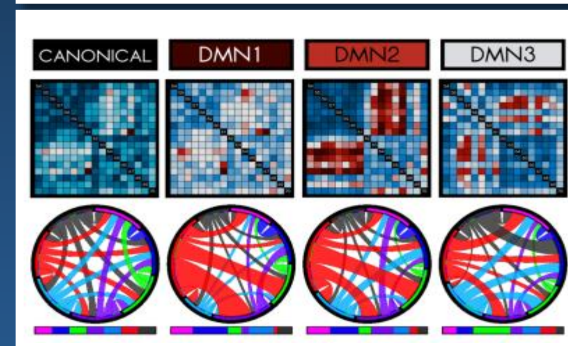

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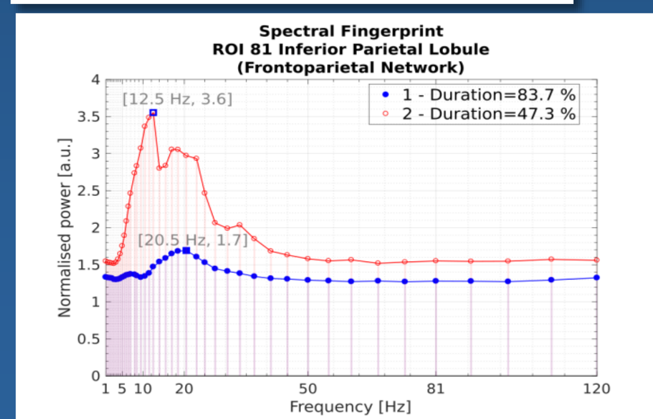


EEG microstates for diagnostics

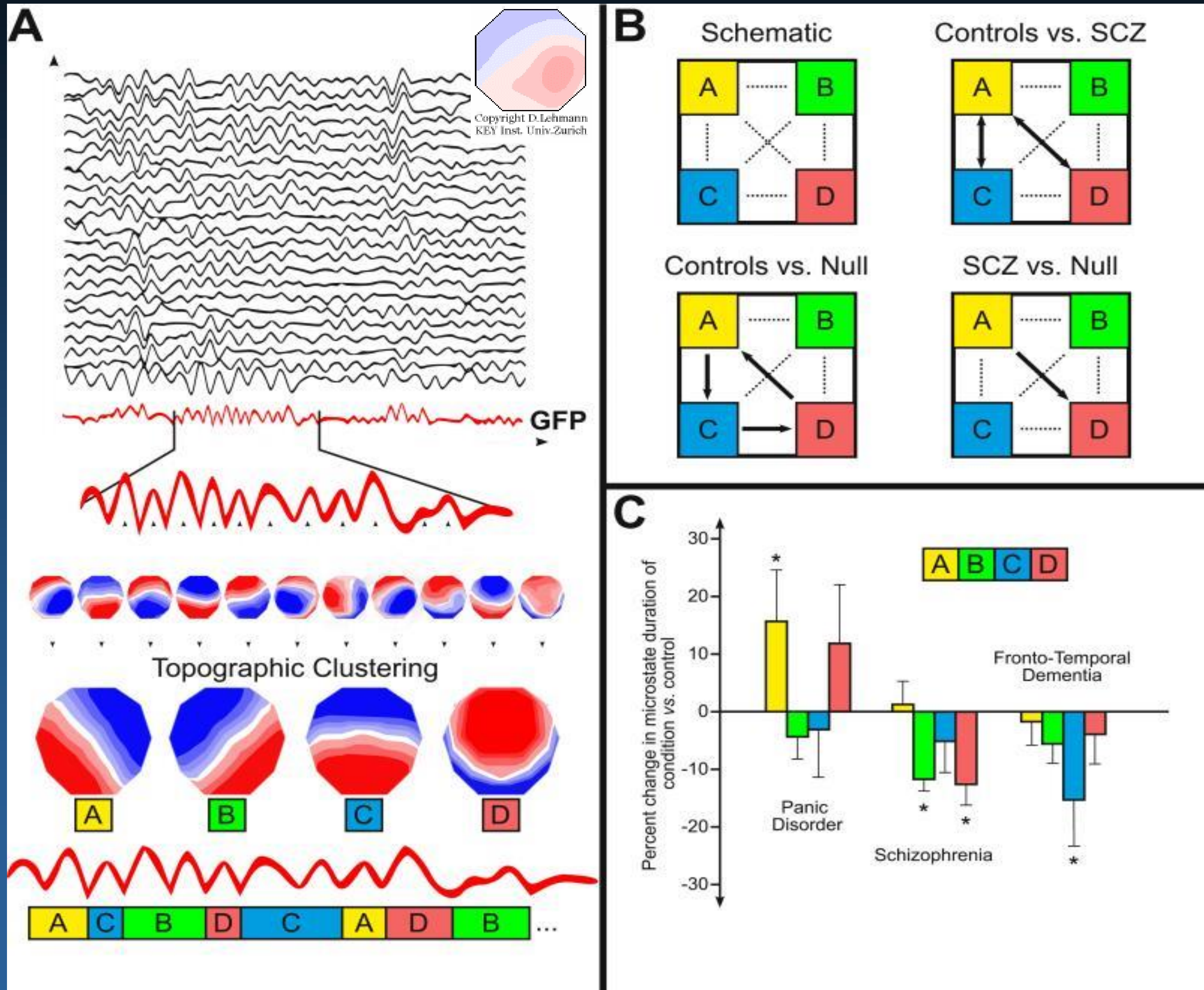
Global EEG Power.
4-7 states, 60-150 ms.

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

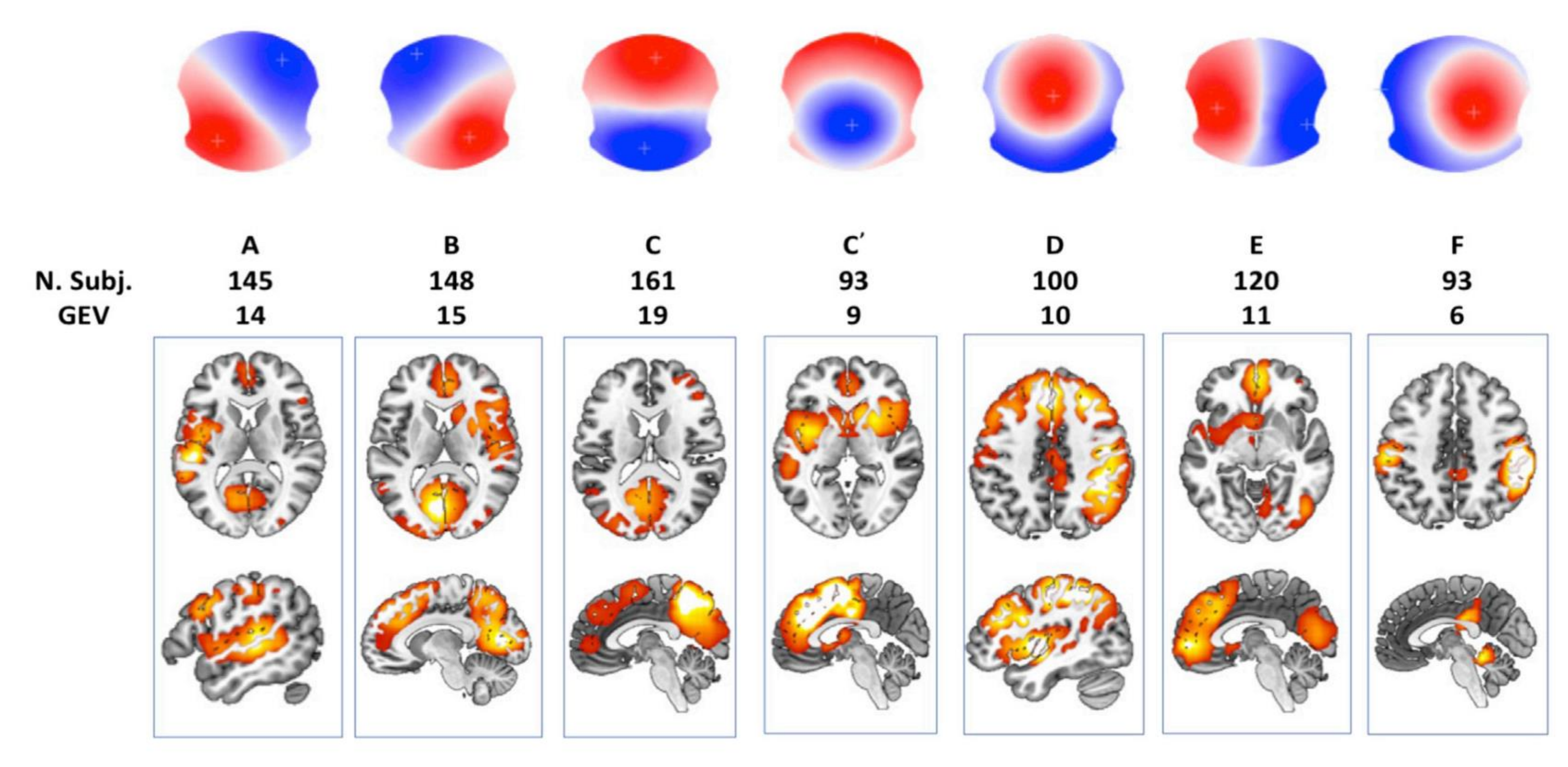
Symbolic dynamics: statistics of A-D symbol strings. Fuzzy Symbolic Dynamics (FSD) + visualizations.

Duch W, Dobosz K. (2011). Cognitive Neurodynamics 5, 145

Dobosz K, Duch W. (2010). Neural Networks, 23(4), 487–496.



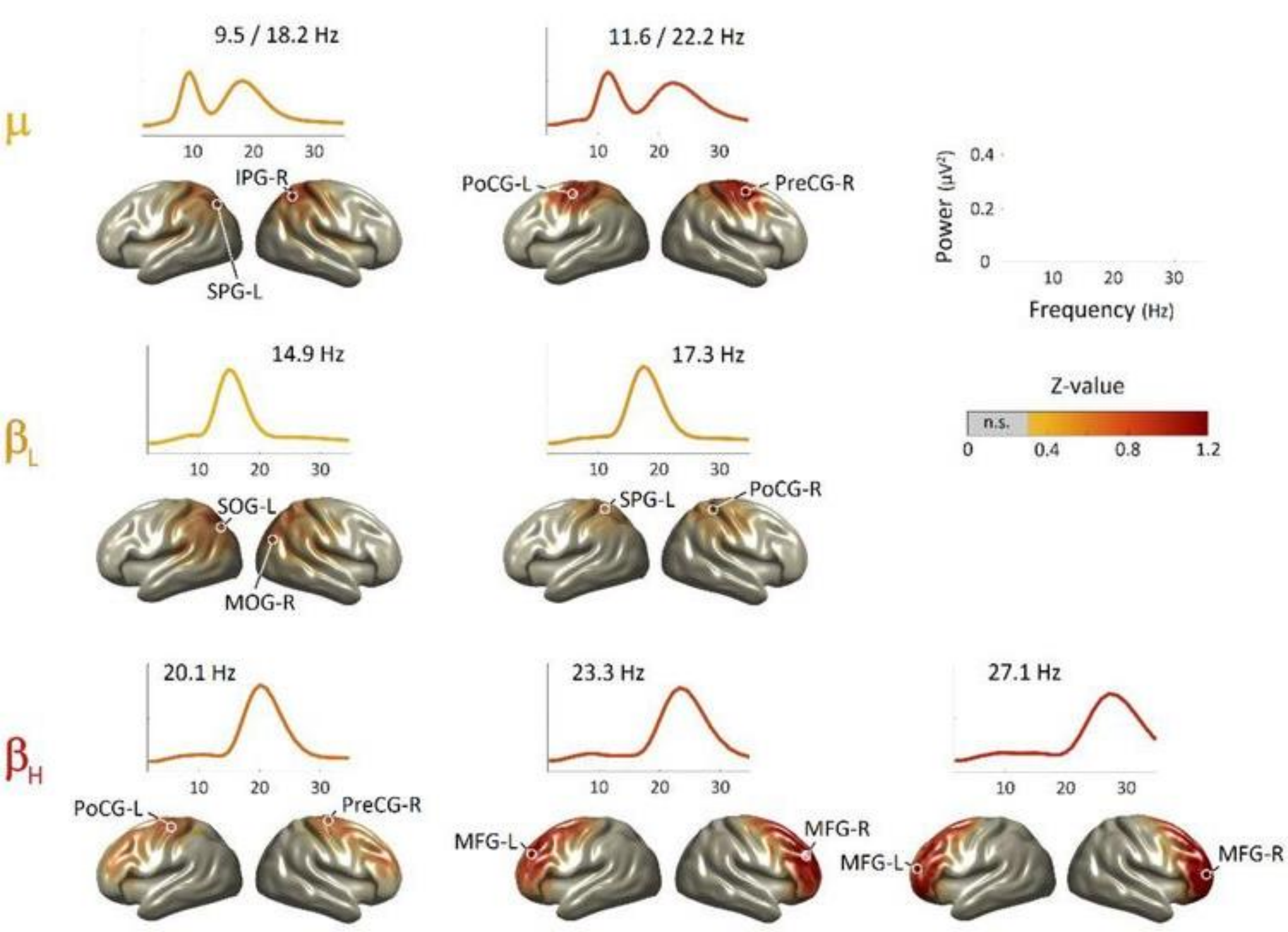
Microstates and their sources



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.

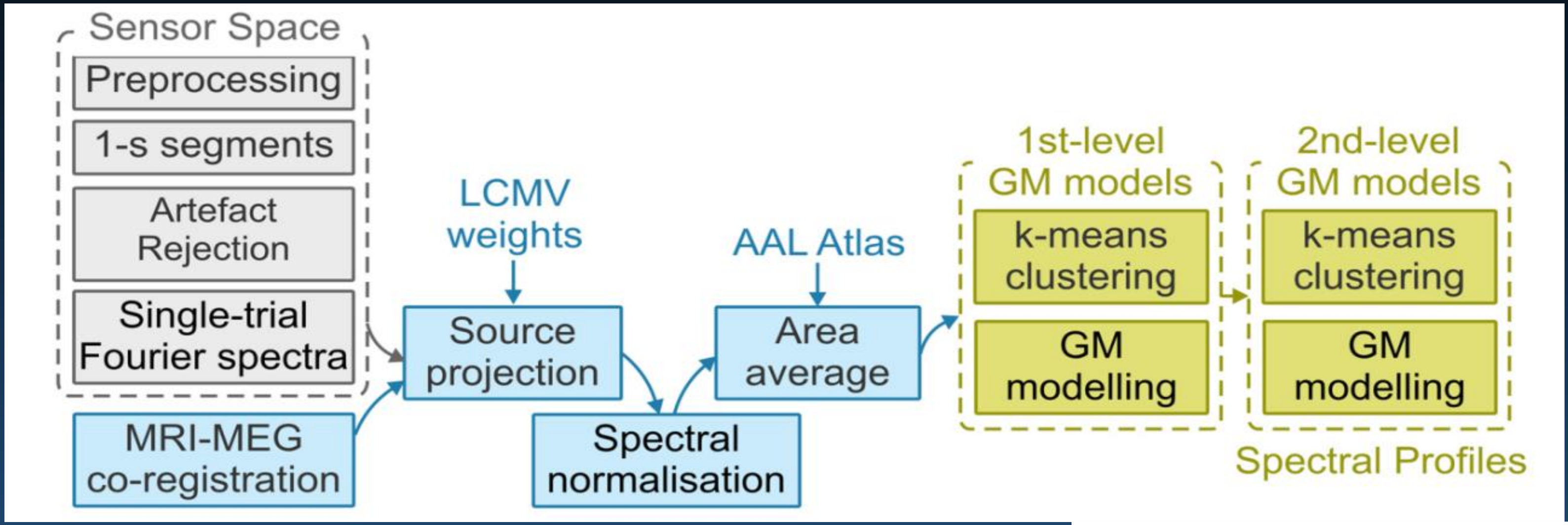
Atlas of the natural frequencies, resting brain

Peak frequencies in selected brain areas observed using MEG in the resting brain.



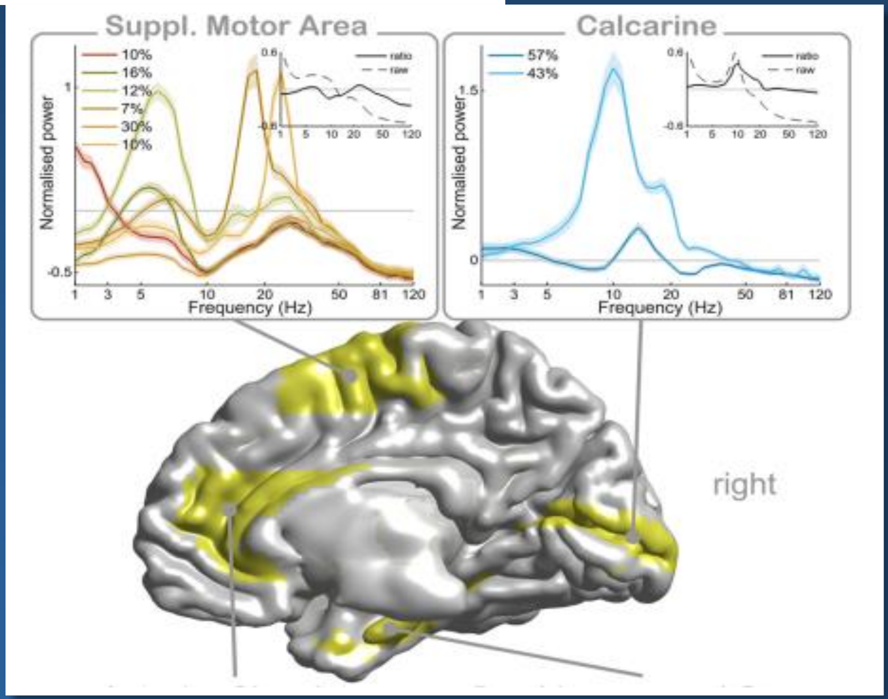
Capilla, A., Arana, L., García-Huéscar, M., Melcón, M., Gross, J., & Campo, P. (2021). *The natural frequencies of the resting human brain: An MEG-based atlas.* BioRxiv 2021 11.17.468973

Spectral analysis

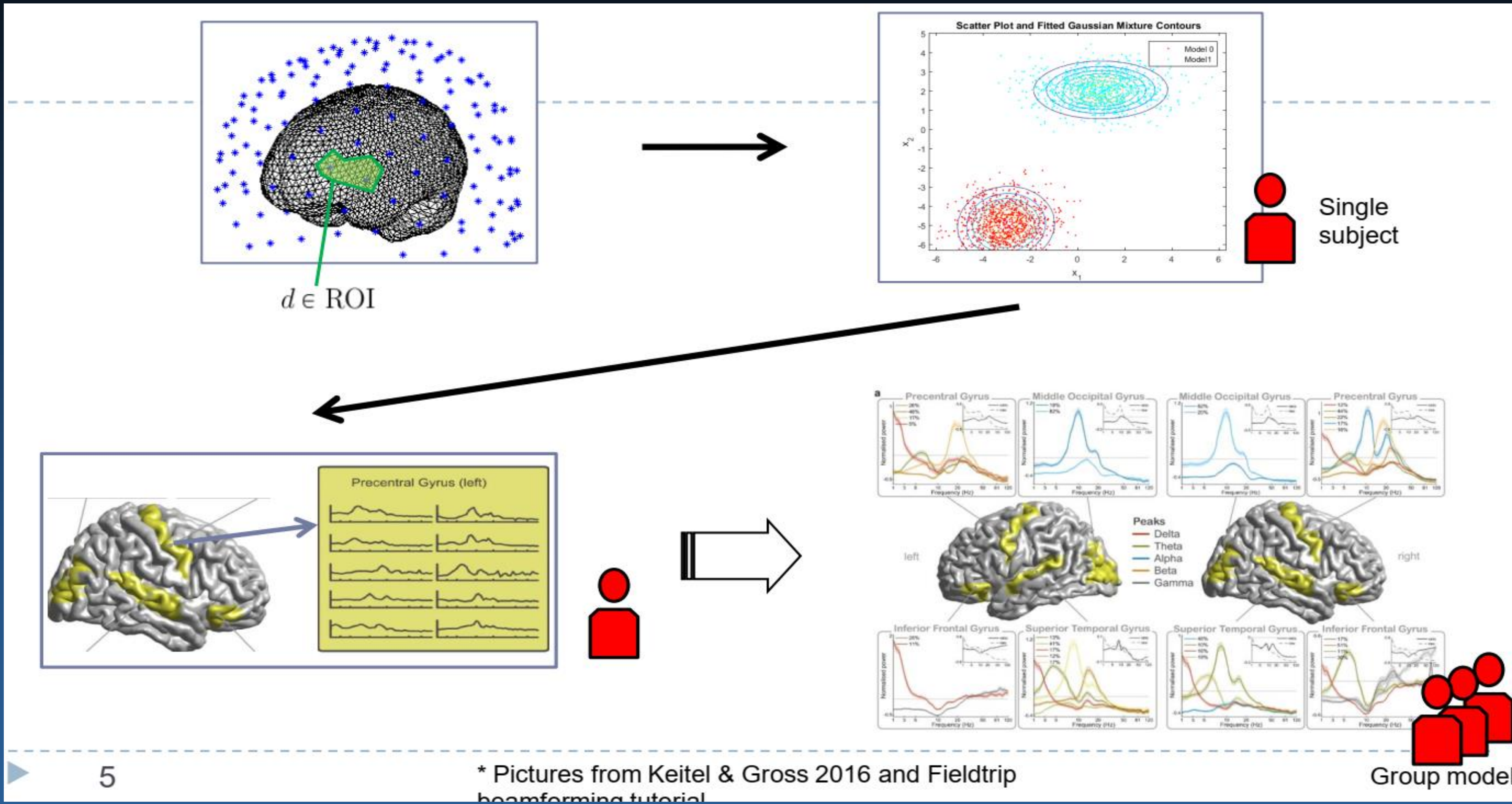


Create spectral fingerprints of ROIs.

- Analyze EEG/MEG power spectra in 1 sec time windows; project them to the source space of ROIs based on brain atlas; clusterize individual/group to create spectra.
- A. Keitel & J. Gross. Individual human brain areas can be identified from their characteristic spectral activation fingerprints. *PLoS Biol* 14, e1002498, 2016



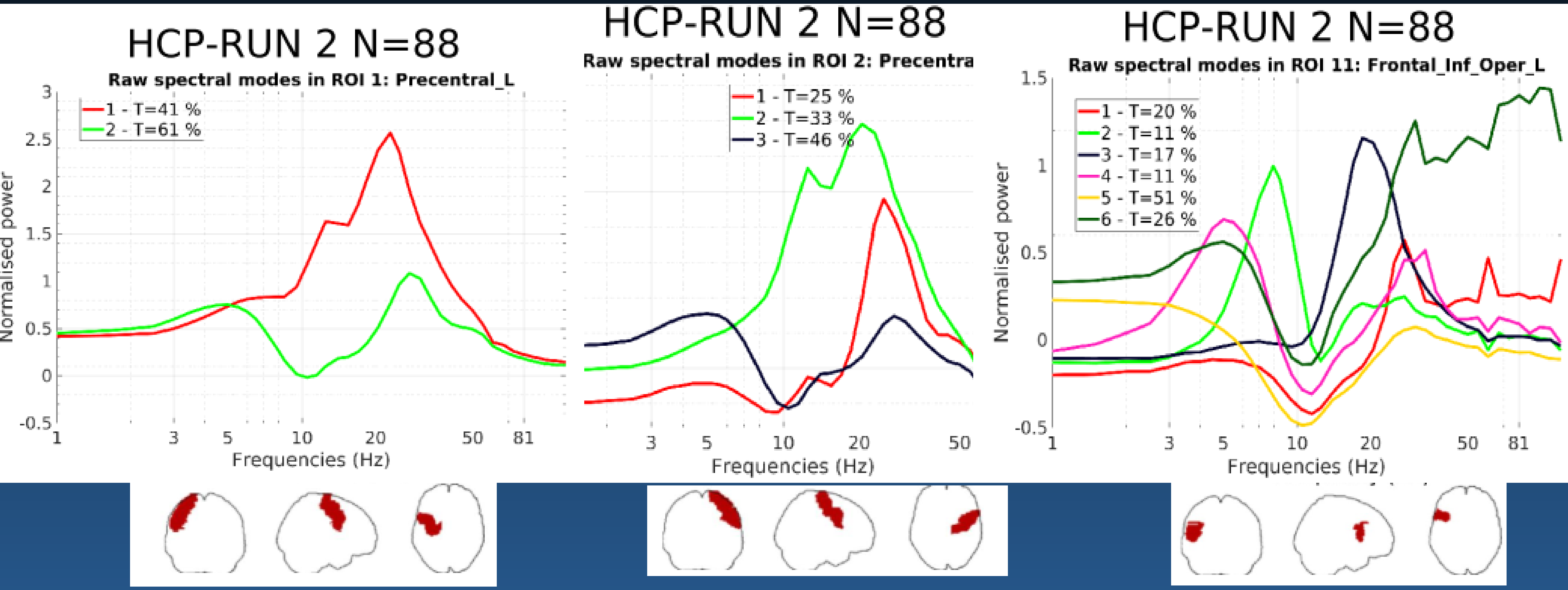
Spectral fingerprints



One ROI, two or more spectra. Static picture showing natural frequencies.

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

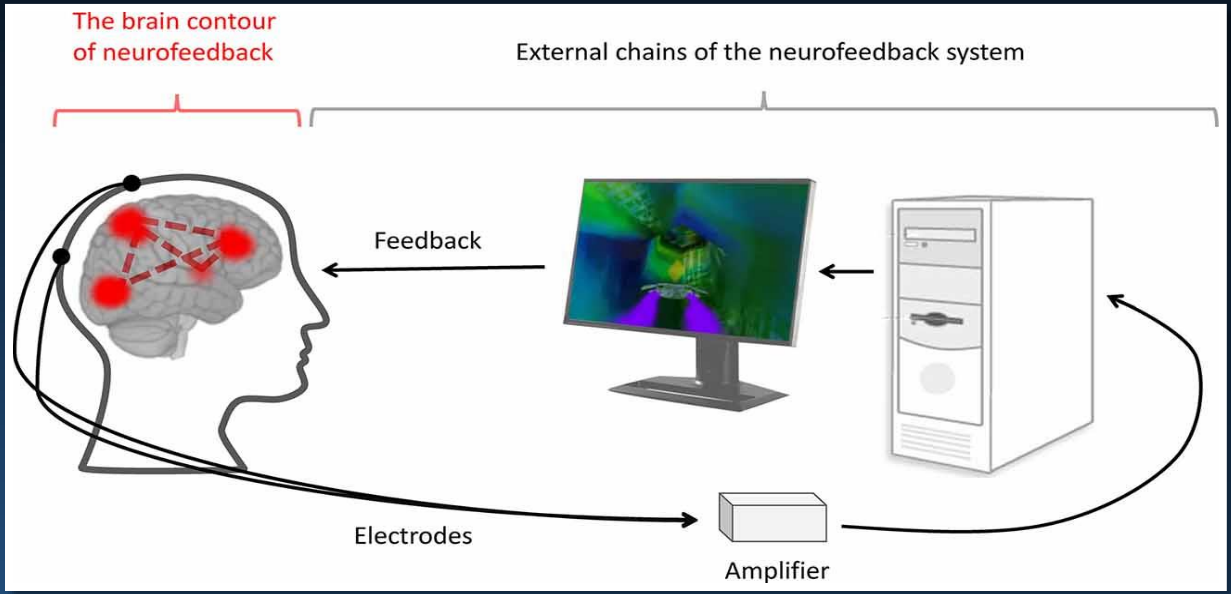
Spectral fingerprints



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

Spectral Fingerprint Challenges

Michał Komorowski



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

Method was tested for MEG resting-state data, will it work for 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 filters (LCMV) sufficient for signal reconstruction?

M.K. Komorowski, K. Rykaczewski, T. Piotrowski, K. Jurewicz, J. Wojciechowski, A. Keitel, J. Dreszer, W. Duch (2021) ToFFi - Toolbox for Frequency-based Fingerprinting of Brain Signals. Neurocomputing (revised 5/2022).

Spectral fingerprints of cognitive processes

Find subnetworks binding ROIs at specific frequencies.
Oscillations can rapidly change, one ROI is engaged in different subnetworks for short time periods.
This is reflected very crudely in microstates, recurrence plots show more precise information.

Siegel, M., Donner, T. H., & Engel, A. K. (2012). Spectral fingerprints of large-scale neuronal interactions. *Nature Reviews Neuroscience*, *13*(2), 121–134.

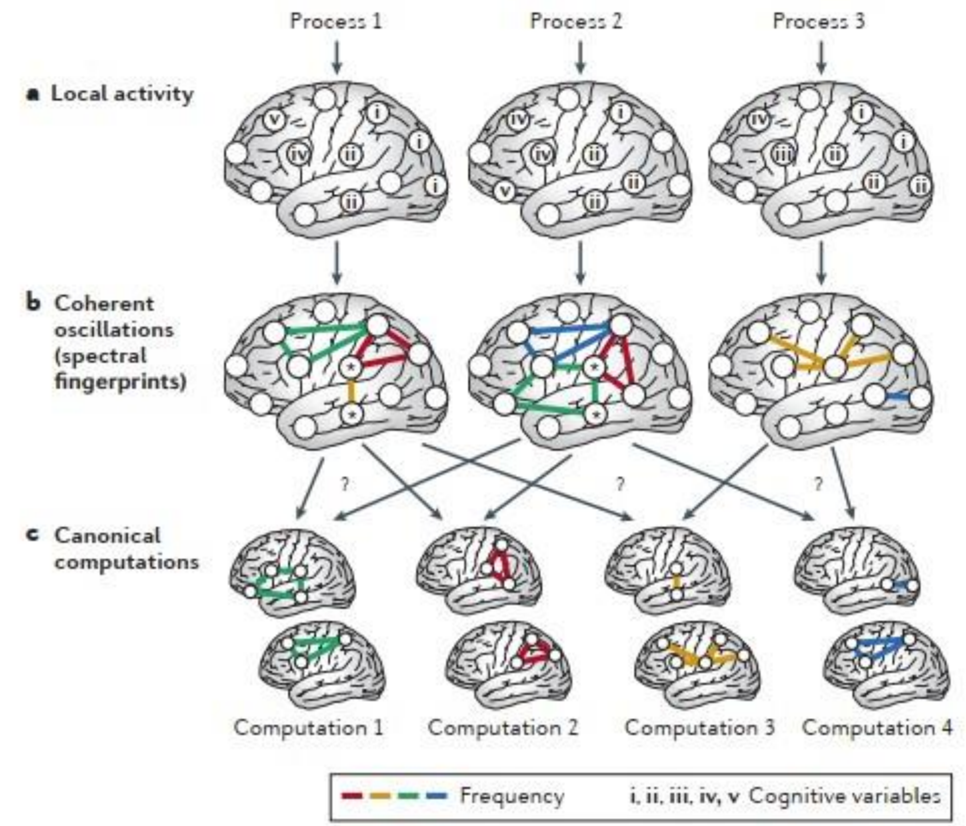
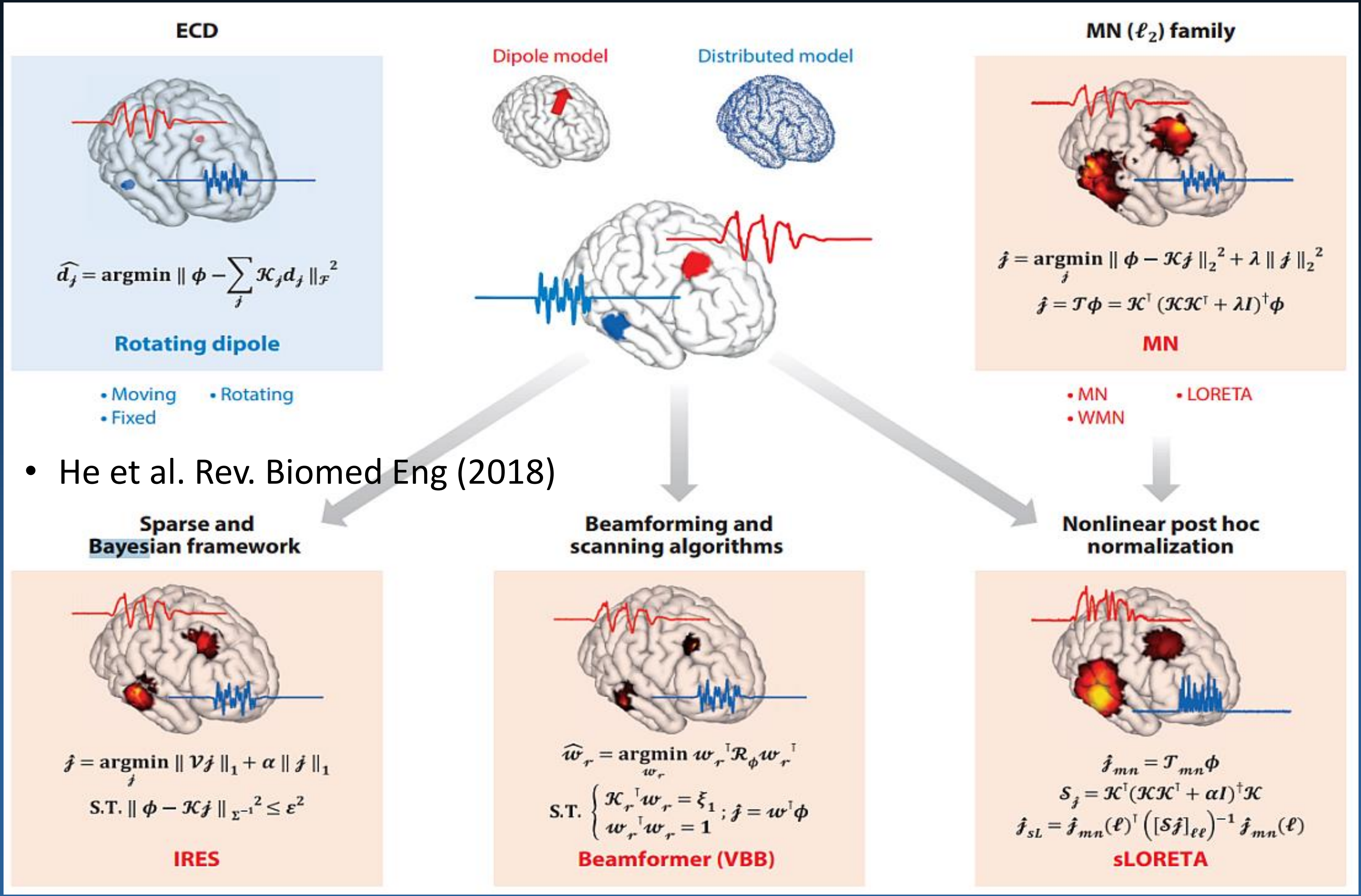


Figure 4 | **Large-scale spectral fingerprints of cognitive processes.** Schematic illustration of how coherent oscillations provide 'spectral fingerprints' for regrouping of cognitive processes 1–3. **a** | Studies of neuronal activity in individual brain regions (circles) elucidate the activation of different regions (bold circles) and the encoding of various cognitive variables (Roman numerals) during different cognitive processes. Several cognitive variables (for example, different sensory features) are simultaneously encoded in each region, but for simplicity only one variable is depicted per region. Note that the pattern of local activity and encoding can be similar between processes. **b** | Coherent oscillations allow for the characterization of the interactions between different brain regions (coloured lines) during different cognitive processes. The frequency of these oscillations (indicated by the colours) allows the corresponding network

EEG localization and reconstruction

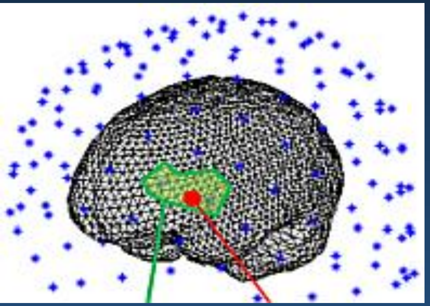


- He et al. Rev. Biomed Eng (2018)

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, leadfiled

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



- LCMV has large error if:
  - sources are correlated,
  - signal to noise ratio (SNR) is low, or
  - forward problem is ill-conditioned.

- Minimum variance pseudo-unbiased reduced-rank, MV-PURE:
  T. Piotrowski, I. 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).

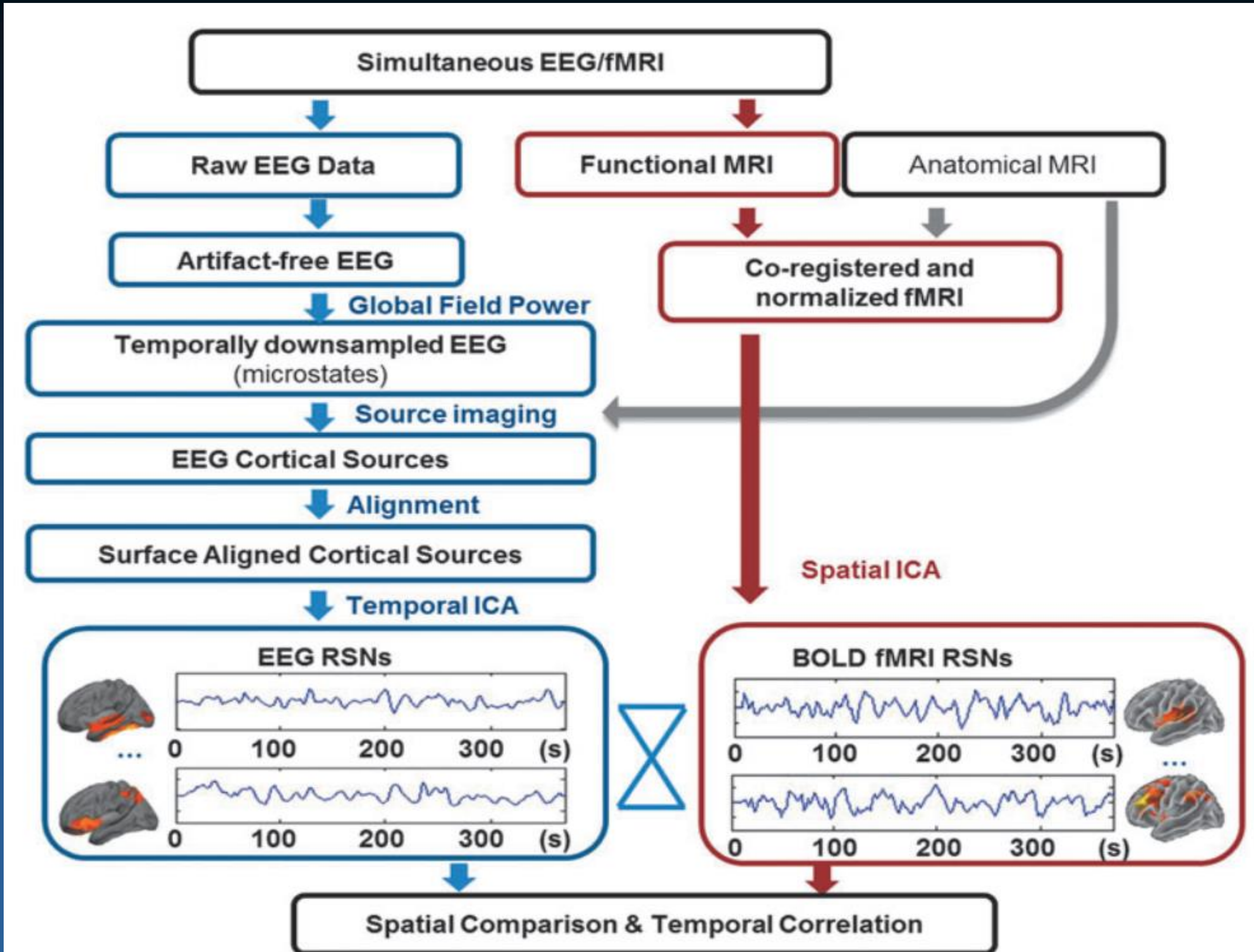
SupFunSim

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

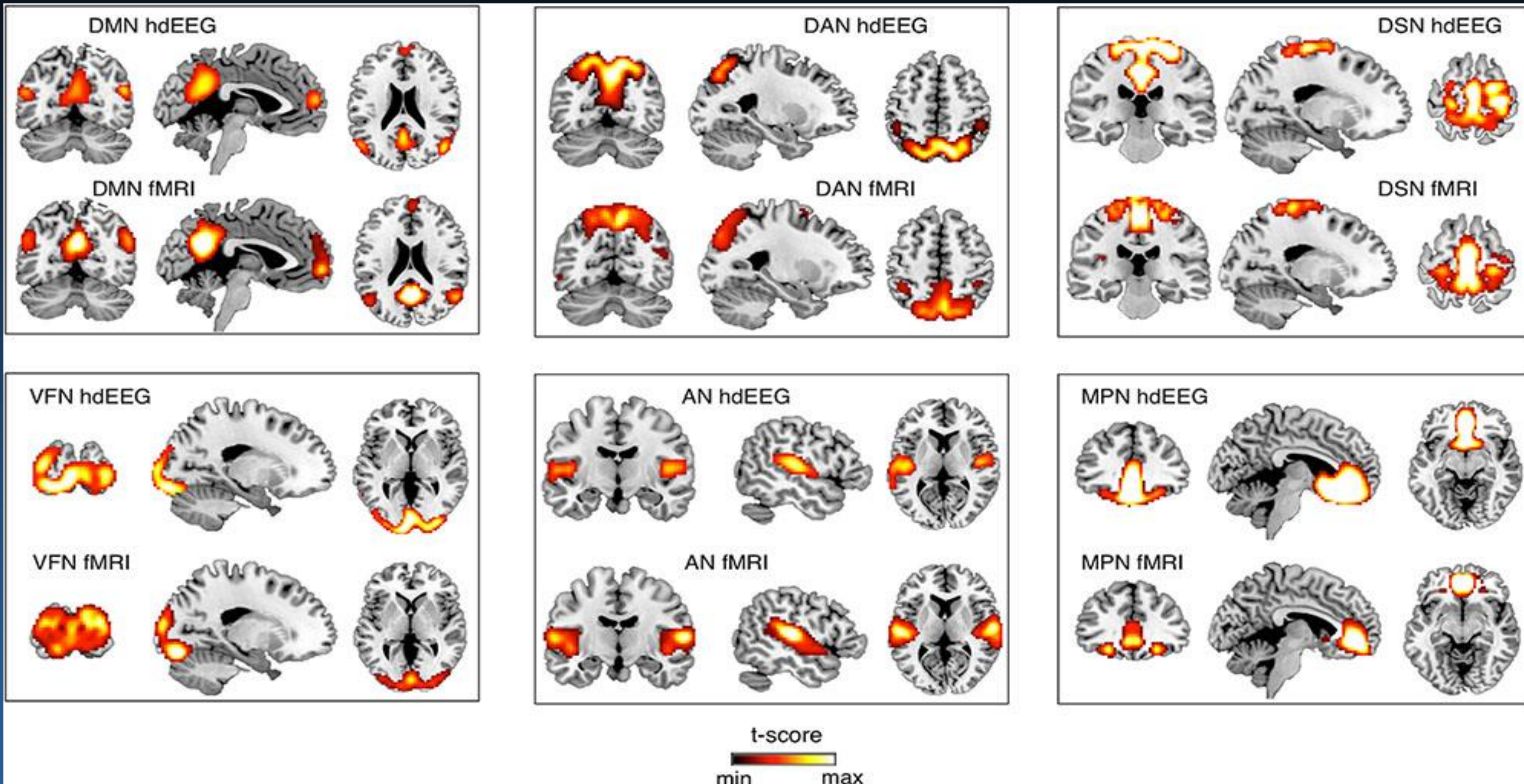
```
%%file calculate_H_Src.m
function model = calculate_H_Src(MODEL)
    model = MODEL;

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

- K. Rykaczewski, J. Nikadon, W. Duch, T. Piotrowski, *Neuroinformatics* **19**, 107-125, 2021.

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).

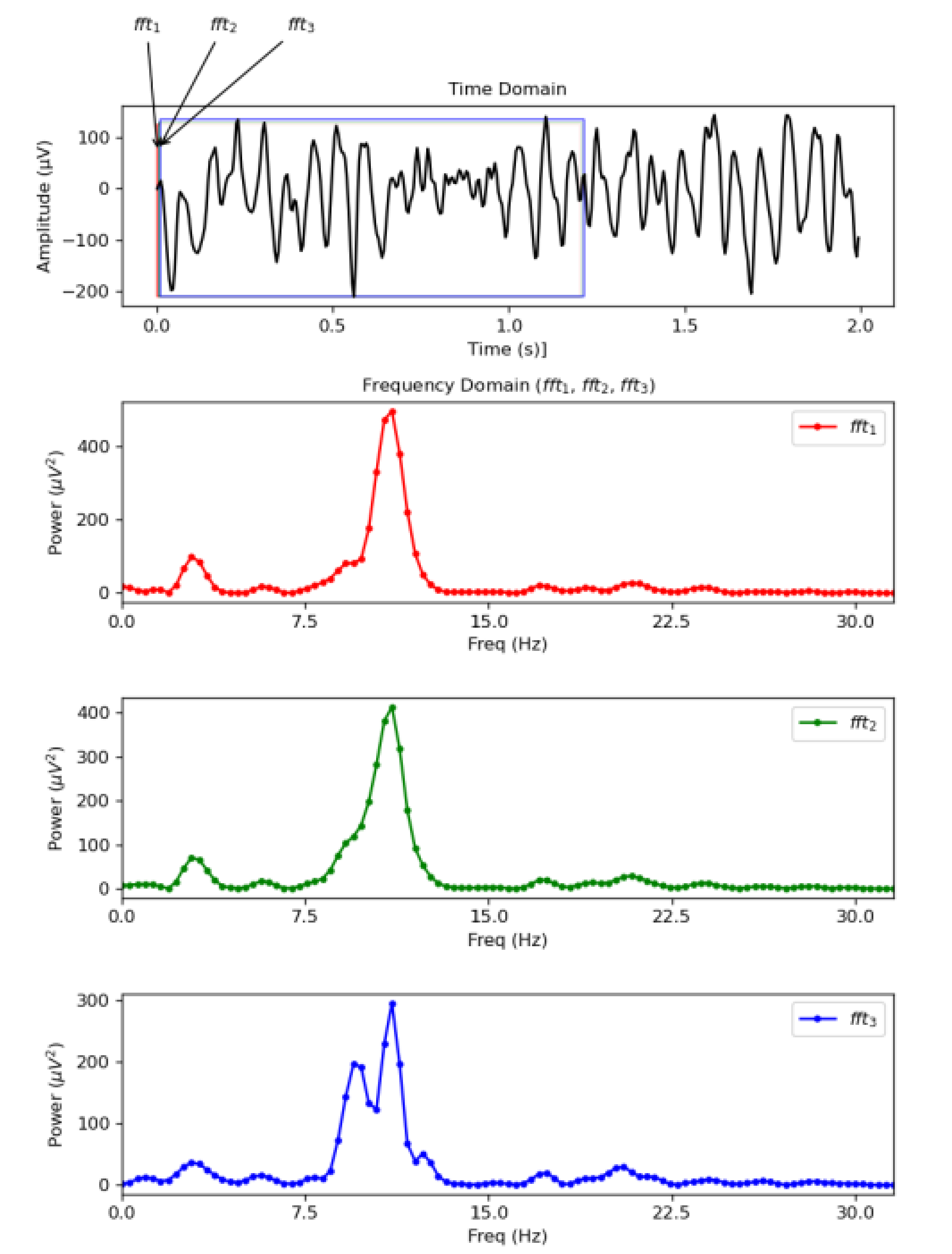
Recurrence analysis

STFT vs. embedding

Takens theorem: attractors are recreated from signals sampled using time-delay embedding, vectors $\mathbf{x}_i = (u_i, u_{i+\tau}, \ldots, u_{i+(m-1)\tau\Delta t})$. Here m is the embedding dimension, and τ is an index enumerating time delays, $\tau\Delta t$.

Alternative representation: STFT, shows power distribution in subsequent time windows. Here changes of spectrum every 100 ms, O1 electrode.

W. Duch, Ł. Furman, K. Tołpa, L. Minati, Short-Time Fourier Transform and Embedding Method for Recurrence Quantification Analysis of EEG Time Series. The European Physical Journal Special Topics (sub. 4/2022)



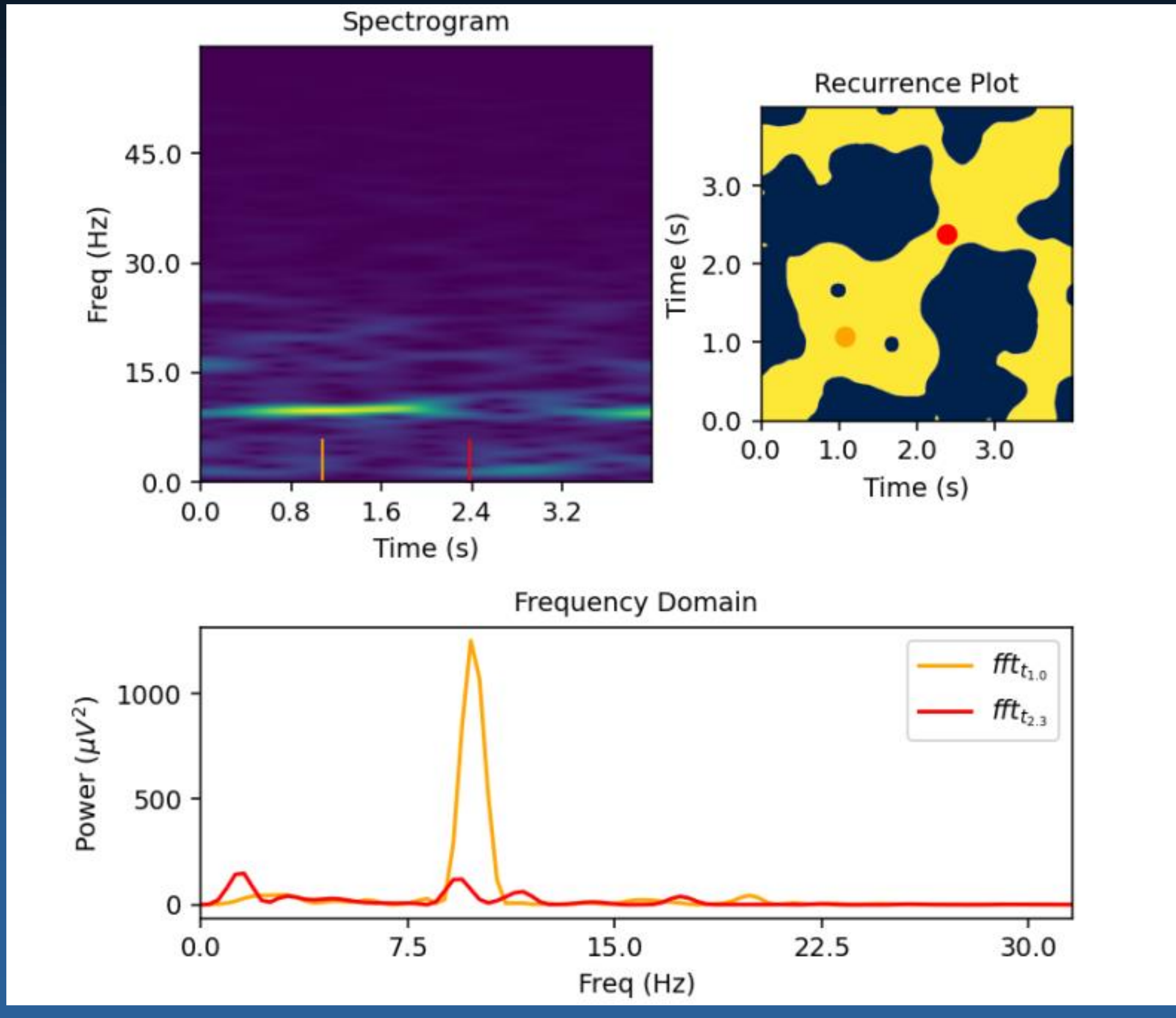
Time/frequency spectrograms & RPs

Information in t/f spectrograms is represented in recurrence plots, that can be analyzed using RQA, recurrence quantification analysis to extract non-linear features characterizing dynamics, see recurrence-plot.tk

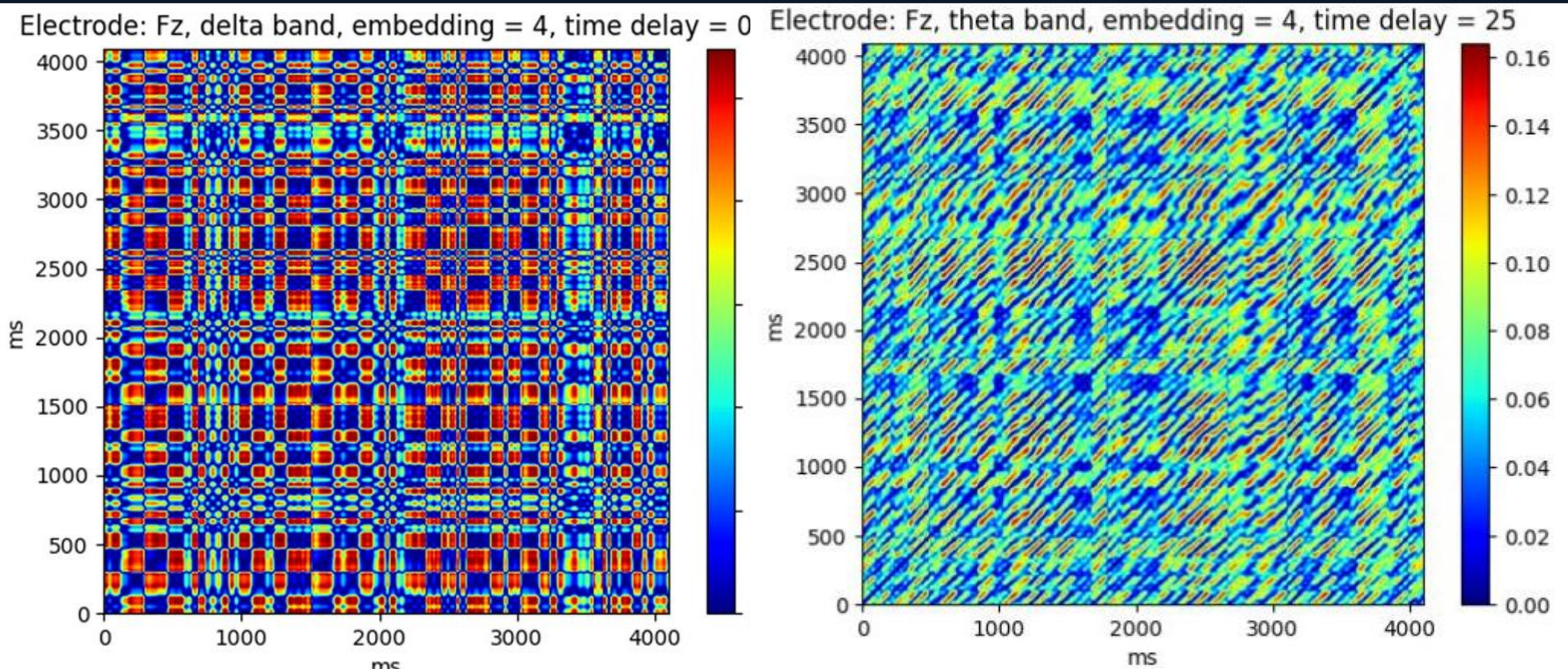
Pipelines: raw signal to X (emb) or Y (STFT) to recurrence matrix to non-linear features.

U=>X=>RX=>FX

U=>Y=>RS=>FS.

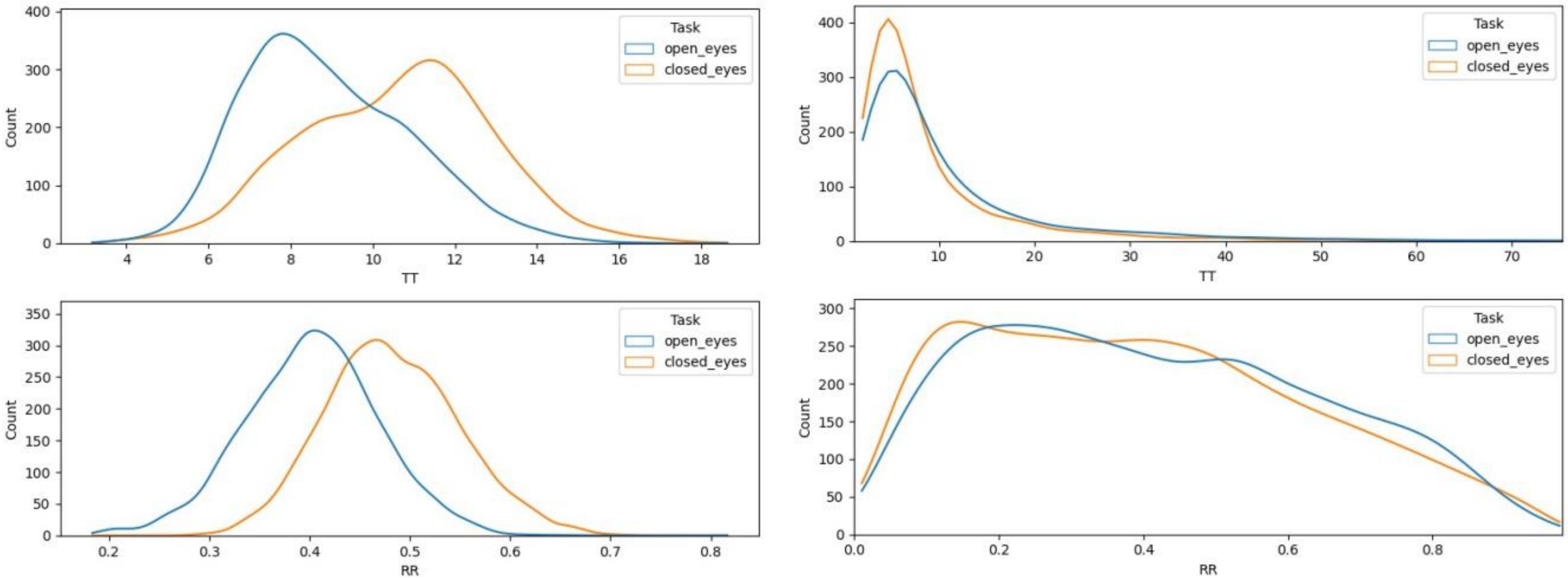


Recurrence plots δ, θ



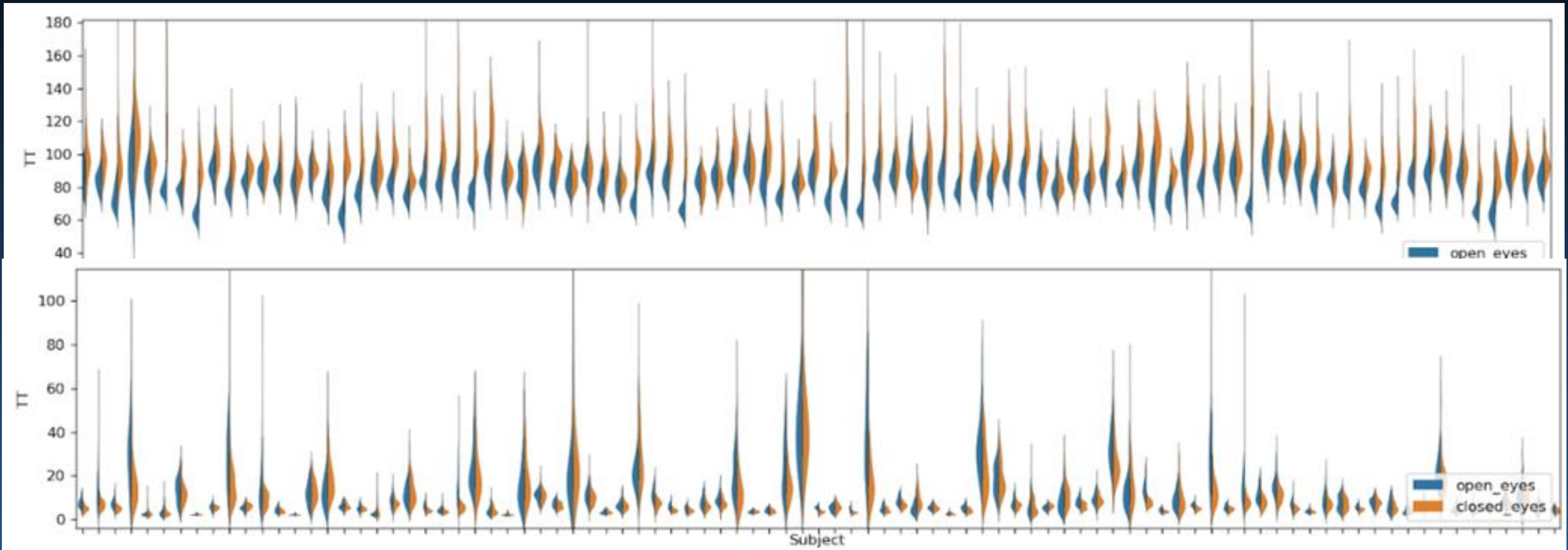
Unthreshold RPs for delta and theta bands, Fz electrode.
Distance scale changes parameters of the metastable states along diagonal, and influence non-linear parameters. Łukasz Furman builds BrainPulse tools for analysis of RPs. This movie shows changes of t/f spectra, RPs and STFT power spectra.

Features for classification



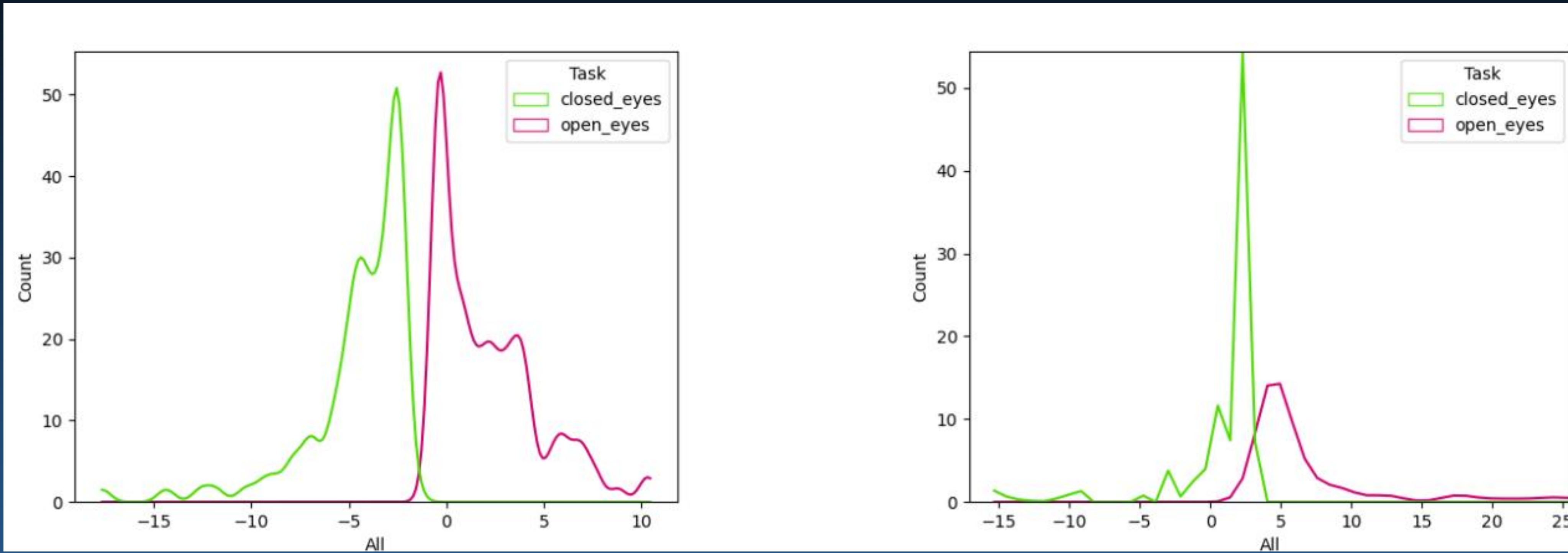
Example of distribution of values of trapping time (TT) and recurrence rate (RR), calculated from 31 seconds of EEG, each containing about 5000 samples per channel, 90 people, in two conditions: eyes closed and open.
Left side: STFT representation, right side embedding with d=2, τ=9.
We have used 6 out of 12 non-linear RQA features for classification.

RQA features for 64 electrodes



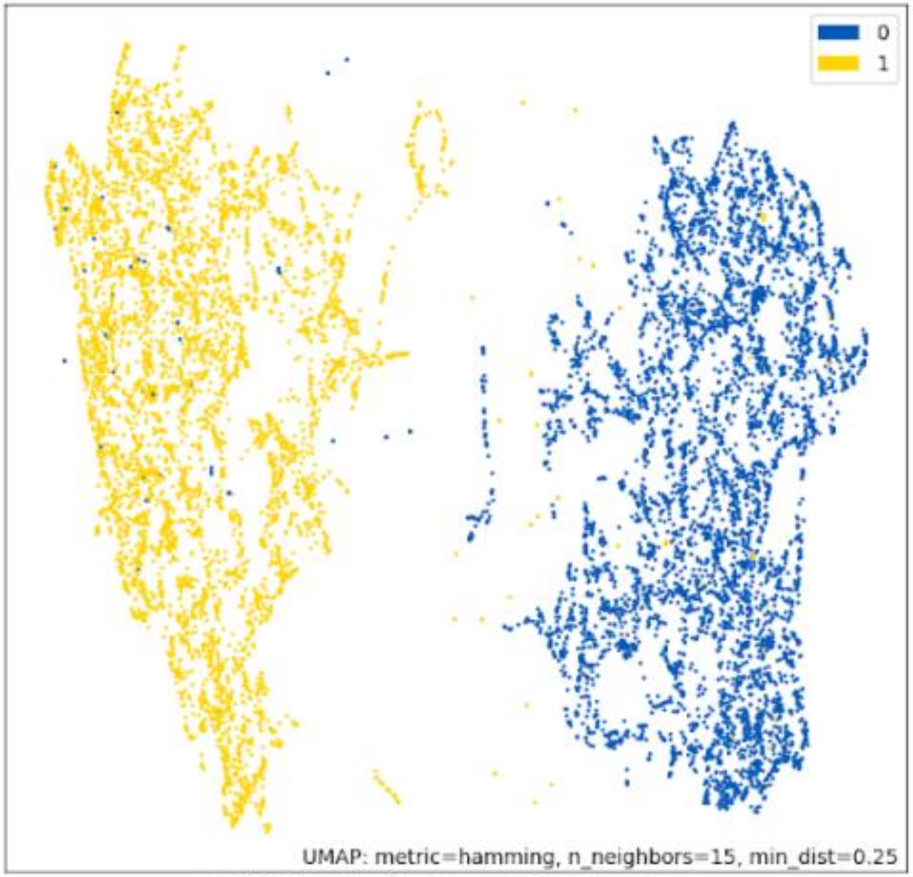
Distribution of trapping time values for 64 electrodes shown for all 90 subjects.
Top: STFT, bottom: optimized embedding.
For some people STFT allows for easy separation of the two conditions using a single RQA feature. Variance is very different, depending on the person.
Linear SVM provides weights for (feature, electrode), facilitating selection of relevant combinations and reducing number of EEG channels.

LSVM classification

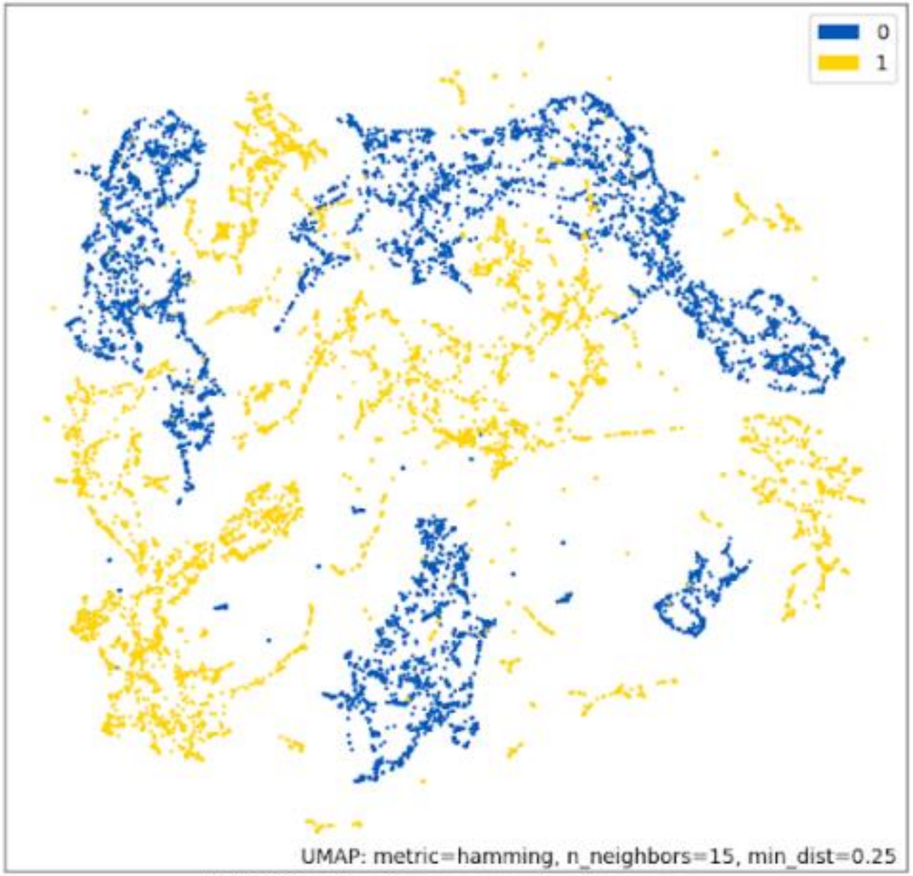


Projection in the direction perpendicular to the LSVM hyperplane, for all data for 90 subjects.
Input has 384 features = 6 RQA features x 64 electrodes.
Left - STFT, window 240 samples (6.2 ms each), test accuracy 90% (open 80%, closed 100%).
Right - embedding dim=2, delay = 9, test accuracy 61% (open 67%, closed 55%).

UMAP distribution



(a) RS. Condition 0 - open eyes, 1 - closed eyes



(b) RX. Condition 0 - open eyes, 1 - closed eyes

Left: UMAP Visualization of 6 features for 64 electrodes and 90 subjects, STFT representation.
Right: UMAP Visualization of 6 features for 64 electrodes and 90 subjects, embedding.

Labeling states

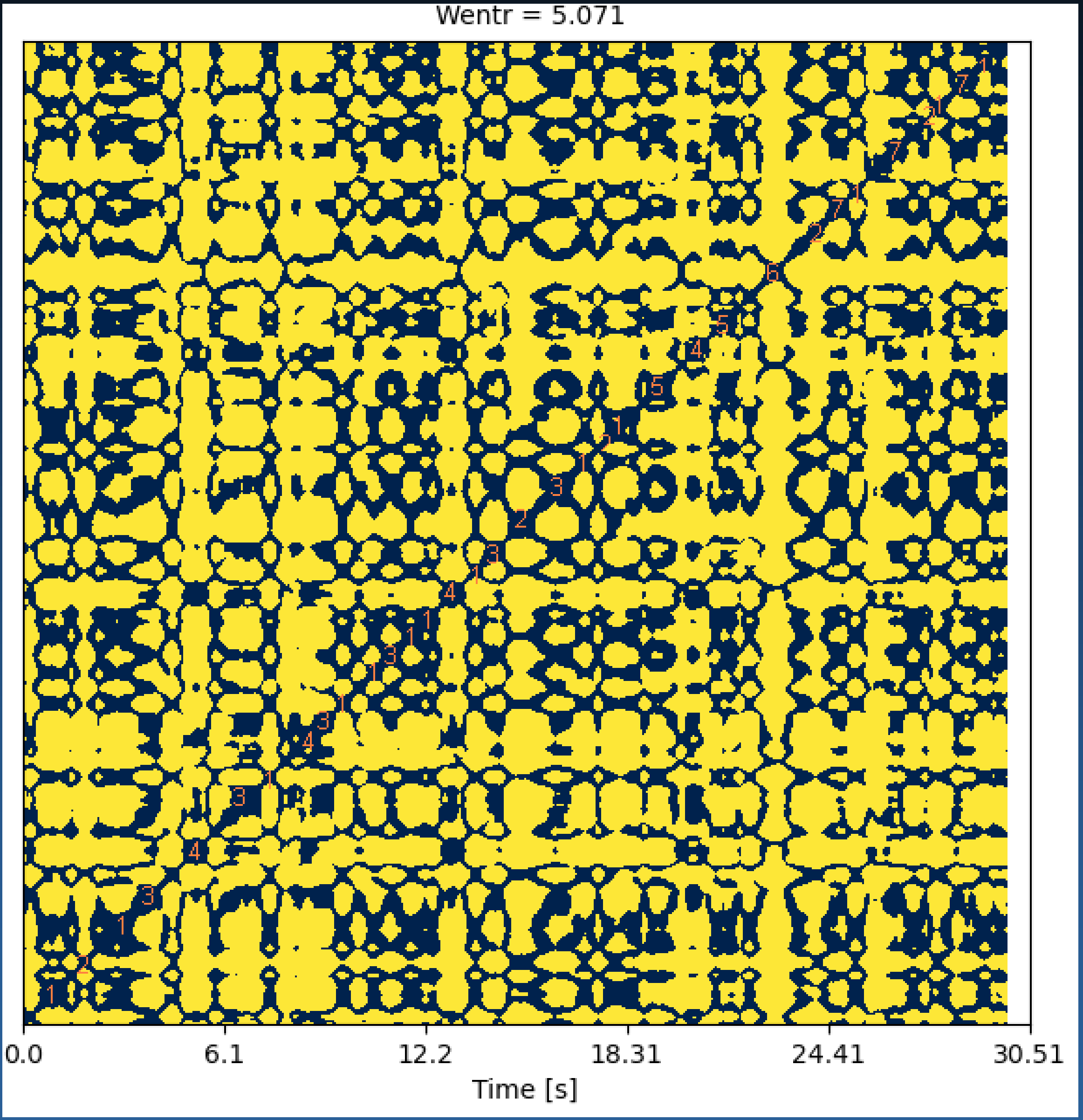
Automatic labeling of states and estimation of their recurrence may be important for biofeedback.

Metabolic costs of transitions between states may be important.

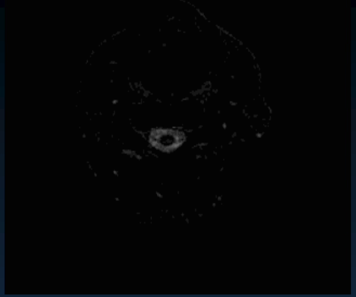
Ruminations? Pain states? How external stimuli influence this dynamics?

Needs automatic method for recognition of metastable, multivariate states.

More precise than micorstates.



Conclusions



- Neurodynamics is the key to understanding mental states.
- Simulations help to understand how attractor networks create metastable states, how to understand global trajectories, form hypothesis that can be tested (autism, ADHD, mechanism of memory distortion, conspiracy theories).
- Brain networks are dynamic, change due to priming, history, refraction, cognitive load, memory training, emotional arousal, aging.
- Many brain fingerprinting methods exists; we have focused on microstates, spectral fingerprinting and recurrence analysis, in order of increased precision.
- Neuroimaging & analysis of EEG/MEG/ECoG should help to understand network neurodynamics and enable interpretation of mental states: $S(B) \Leftrightarrow S(M)$.
- Neurocognitive technologies may help to diagnose, repair and optimize brain processes, improve AI algorithms. Potential of such methods is enormous.
- We are working on new neurofeedback approaches, and with clinical psychologists hope to include direct DTS/TMS neuromodulation for therapy.

CD DAMSI

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

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

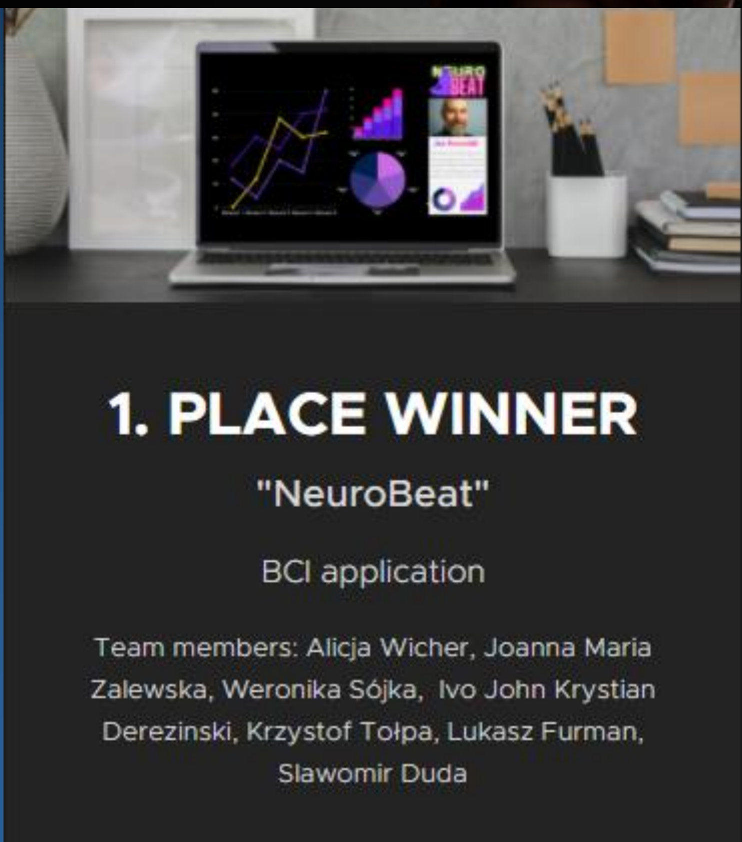
Neuroinformatics is a combination of two important disciplines on the science front: brain research and artificial intelligence.

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 as of 2022?


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
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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

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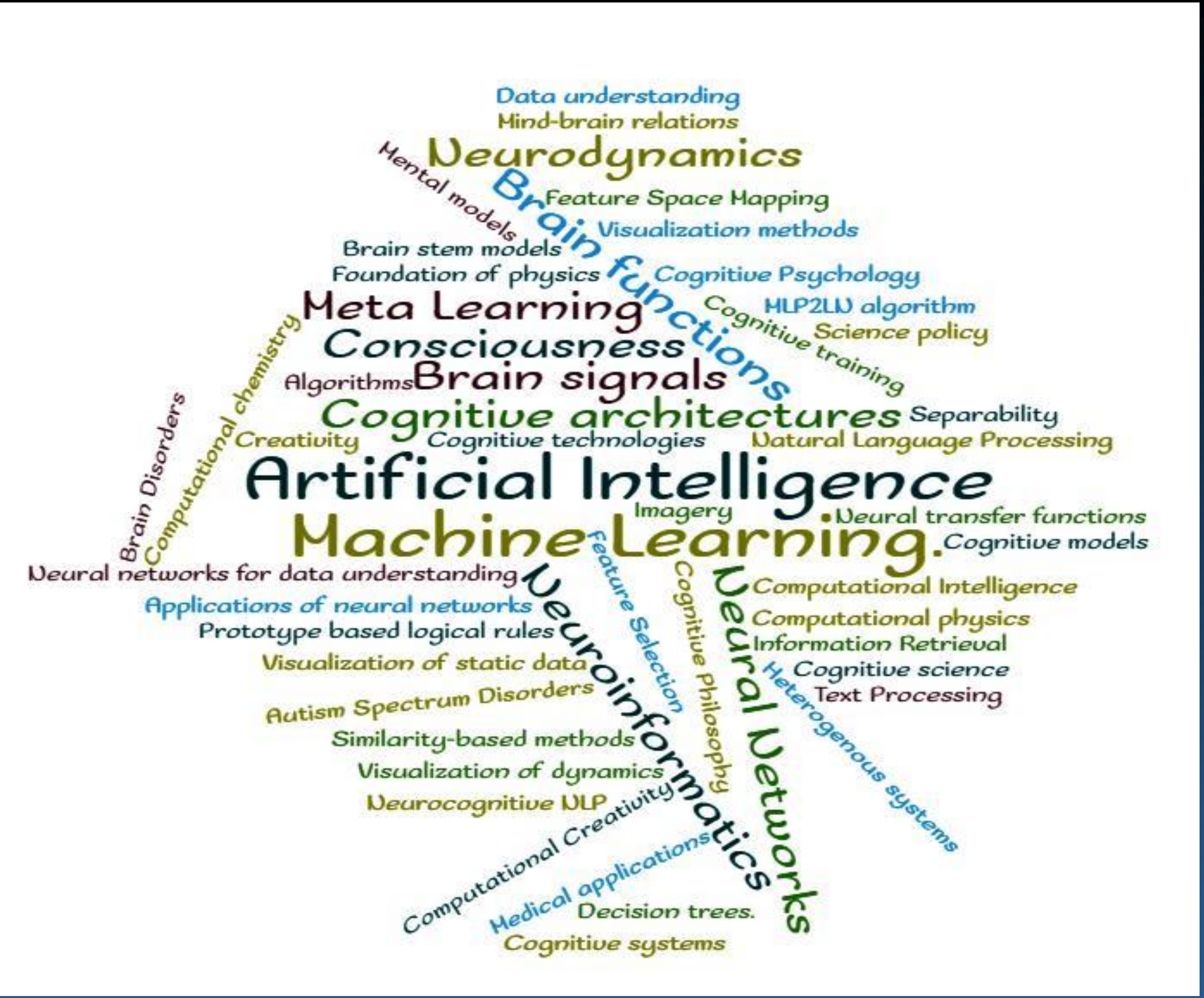
nencki institute of experimental biology

- 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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