Understanding real brain neurodynamics using recurrence analysis

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22nd Int. Conf. on Artificial Intelligence and Soft Computing, 18-22.06.2023

AI ⇔ Brain

Simple neurons => artificial neural networks.

Neurodynamics => RNNs, LLMs, high-level mechanisms.

AI and brains

- Large Language Models.
- Generative Pretrained Transformers (GPT).
- Understanding brain dynamics and distributed artificial brains (DABs).

Brains

- Spatial distributions, spectral fingerprinting.
- Temporal activity: recurrence, microstates.
- Recurrence analysis.
- Human enhancement with **neurocognitive technologies**.

AI and Neuroscience

AGI & BICA

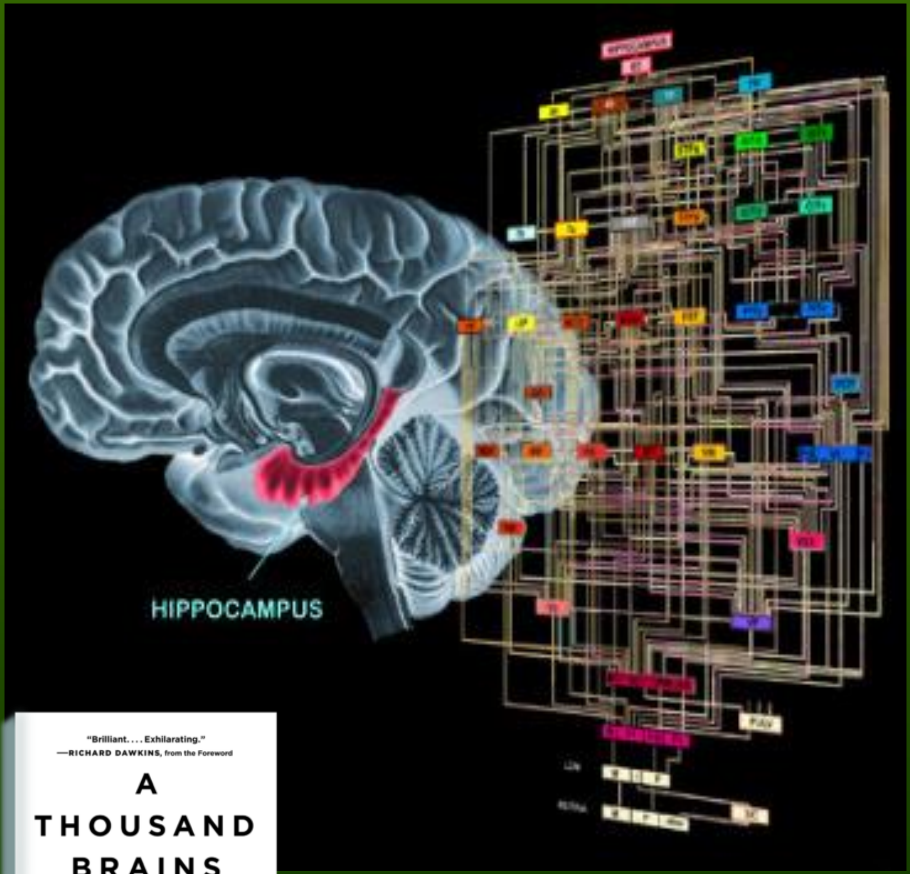
From an engineer's perspective,
to understand the brain is to build a working model that exhibits the same functions. Needed: spatial models of phenomena, actions and their causes, real world imagery.

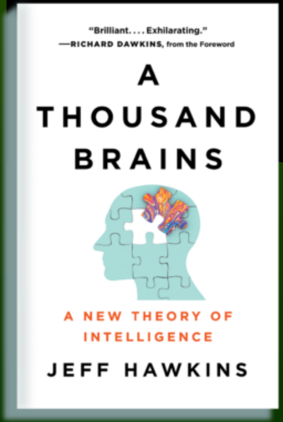
AGI = Artificial General Intelligence, learn many different things.

BICA (Brain-Inspired Cognitive Architecture) brain-like 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).





Neuroscience ⇔ AI

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

Affiliations: **Google DeepMind**, Gatsby, ICN, UCL, Oxford.

Attention, awareness models, consciousness, complementary learning systems, various types of memory, reinforcement learning are used in machine learning.

Key concepts from RL inform neuroscience and ML techniques are basic tools for analysis and interpretation of brain neuroimaging data. Ex:

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.

All this will help in development of **neurocognitive technologies**.

Towards Human-like Intelligence

IEEE Computational Intelligence Society Task Force (Mandziuk, Duch, M. Woźniak),
Towards Human-like Intelligence

IEEE Symposium on Computational Intelligence for Human-like Intelligence (IEEE SSCI CIHLI), 12/2022 in Singapore, 12/2023 in Mexico City.
Distributed Artificial Brains (DAB) session (Duch, Mandziuk, Woźniak).

AGI: conference, 6/2023 in Stockholm
Journal of Artificial General Intelligence comments on Cognitive Architectures and Autonomy: A Comparative Review (eds. Tan, Franklin, Duch).

BICA: Annual International Conf. on Biologically Inspired Cognitive Architectures, 13th Annual Meeting of the BICA Society, Guadalajara, Mexico 2023.

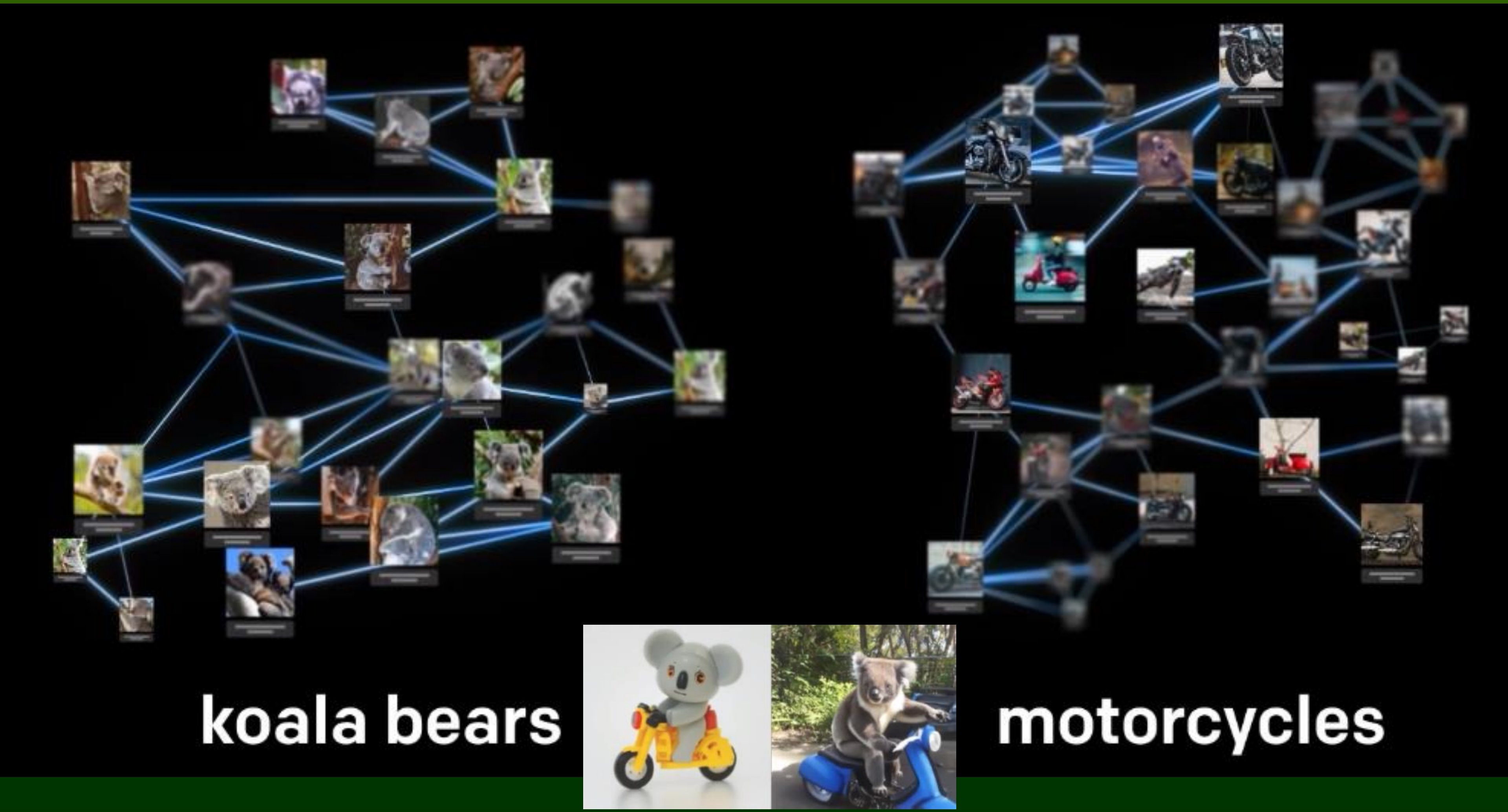
LLM algorithms

Language models: encoding of words in rich context in complex network structures. Google BERT (2018) was pre-trained on a very large text corpus.

- **Bidirectional Encoder Representations from Transformers** (**BERT**). Transformer-based machine learning technique for (NLP) pre-training.
- English-language BERT: 340M parameters in 24-layers; trained on the BooksCorpus with 800M words, and Wikipedia with 2,500M words. In 2019 BERT worked already in 70 languages – LLMs era.
- LLMs are fine-tuned for specific NLP tasks such as question answering or semantic information retrieval.
- The network learns to predict masked words (images, signals):
  Input: the man went to the [MASK1]. He bought a [MASK2] of milk.
  Labels: [MASK1] = store; [MASK2] = gallon.
- Can we have LLMs for brain signals?

Vision-language models

Vision-Language Pre-Trained Models (VL-PTMs): convergence of language, vision, and multimodal pretraining => general-purpose foundation models can be easily adapted to multiple diverse tasks with zero-shot learning.

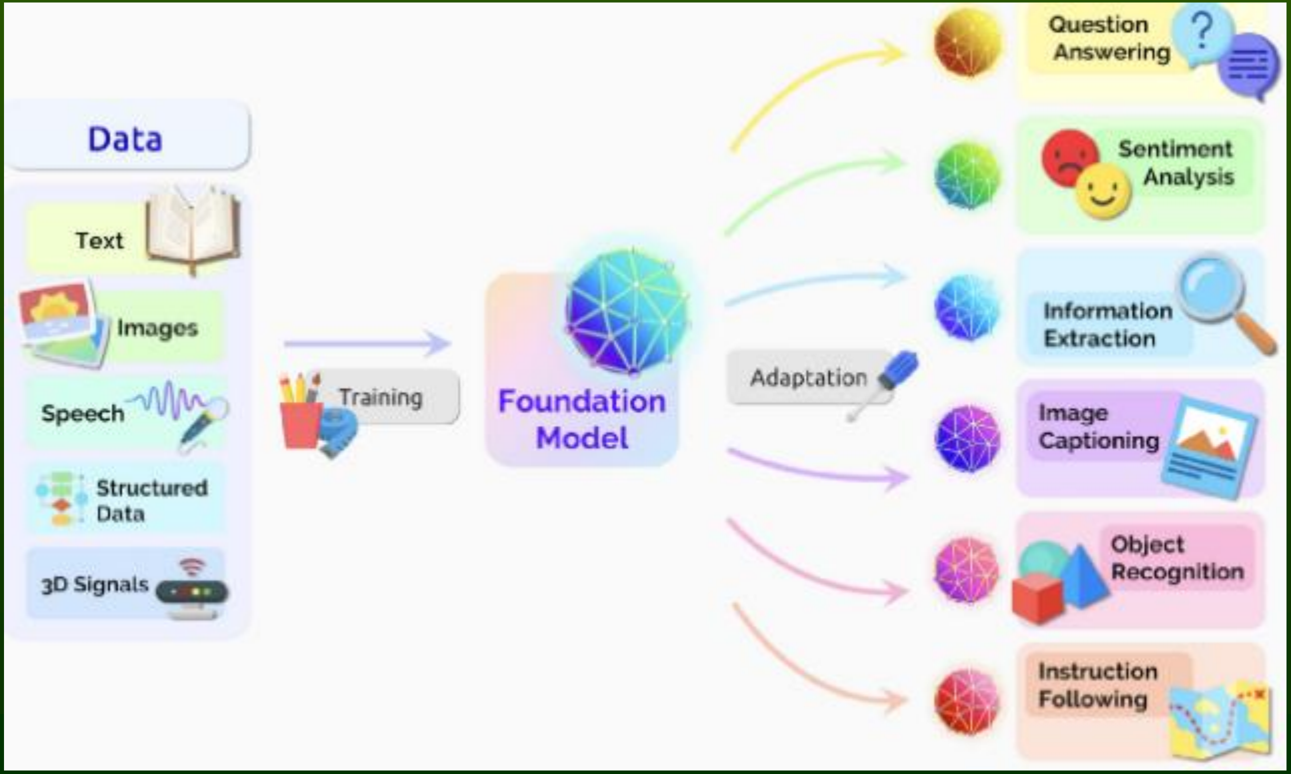


Multimodal models

Multimodal learning – different types of modalities with different statistical properties, embedded in **the same model**.

- **Multimodal Affective Computing (MAC)**, sentiment analysis.
- **Natural Language for Visual Reasoning (NLVR)**.
- **Multimodal Machine Translation (MMT)**.
- **Visual Retrieval (VR)** and **Vision-Language Navigation (VLN)**.

Image: Center for Research on Foundation Models (CRFM), Stanford Institute for Human-Centered Artificial Intelligence (HAI)



BEiT: Image as a Foreign Language

MS BEiT-3 (BERT Pretraining of Image Transformers), a general-purpose state-of-the-art multimodal foundation model for vision-language tasks (2022).

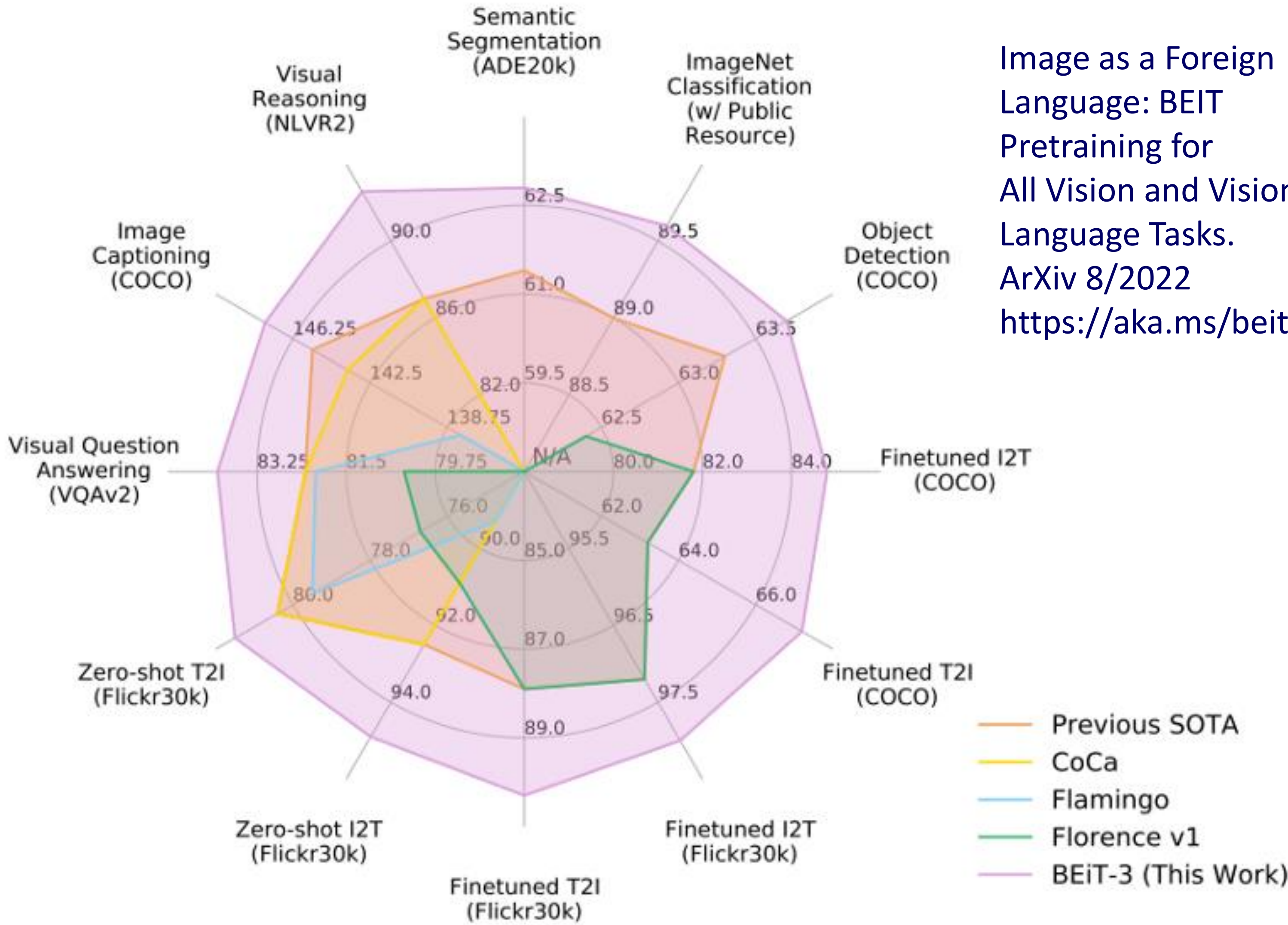


Image as a Foreign Language: BEIT Pretraining for All Vision and Vision-Language Tasks. ArXiv 8/2022 https://aka.ms/beit-3

Brains and BCI

On the threshold of a dream …

Final goal: optimize brain processes!

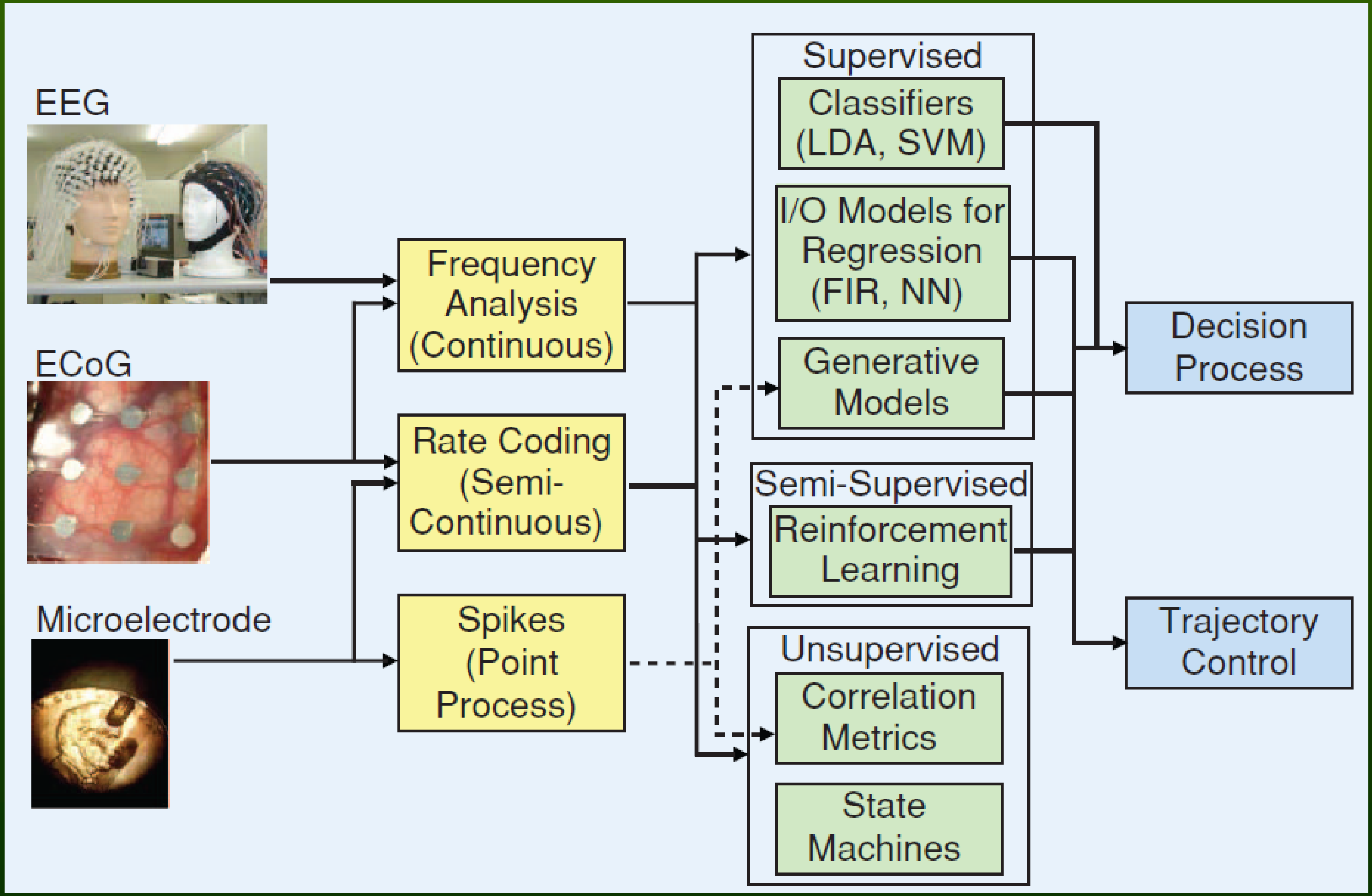
Although whole brain is always active we are far from achieving full human potential.
Repair damaged brains, increase efficiency of healthy brains! First we need to understand brain processes:

1. Find fingerprints of specific activity of brain structures using new neurotechnologies.
2. Create models of cognitive architectures that help to understand information processing in the brain.
3. Create new diagnostic and therapeutic procedures.
4. Use neurofeedback based on decoding and changes in connectivity to stimulate the brain.
5. Stimulate neuroplasticity by monitoring brain activity and directly stimulating it (TMS, DCS, EM).

G-tec wireless NIRS/EEG on my head.

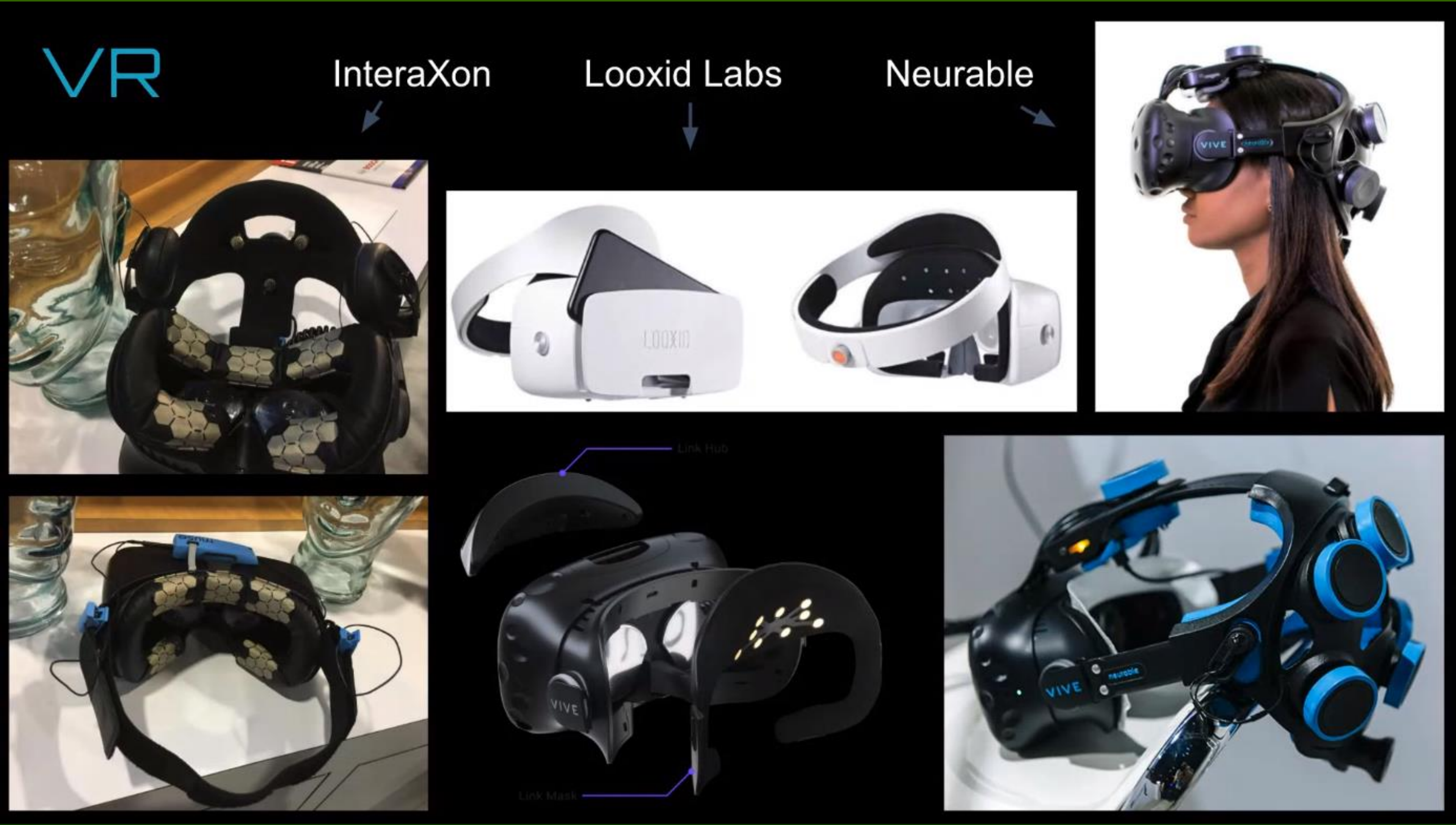
BCI: time to connect our brains …

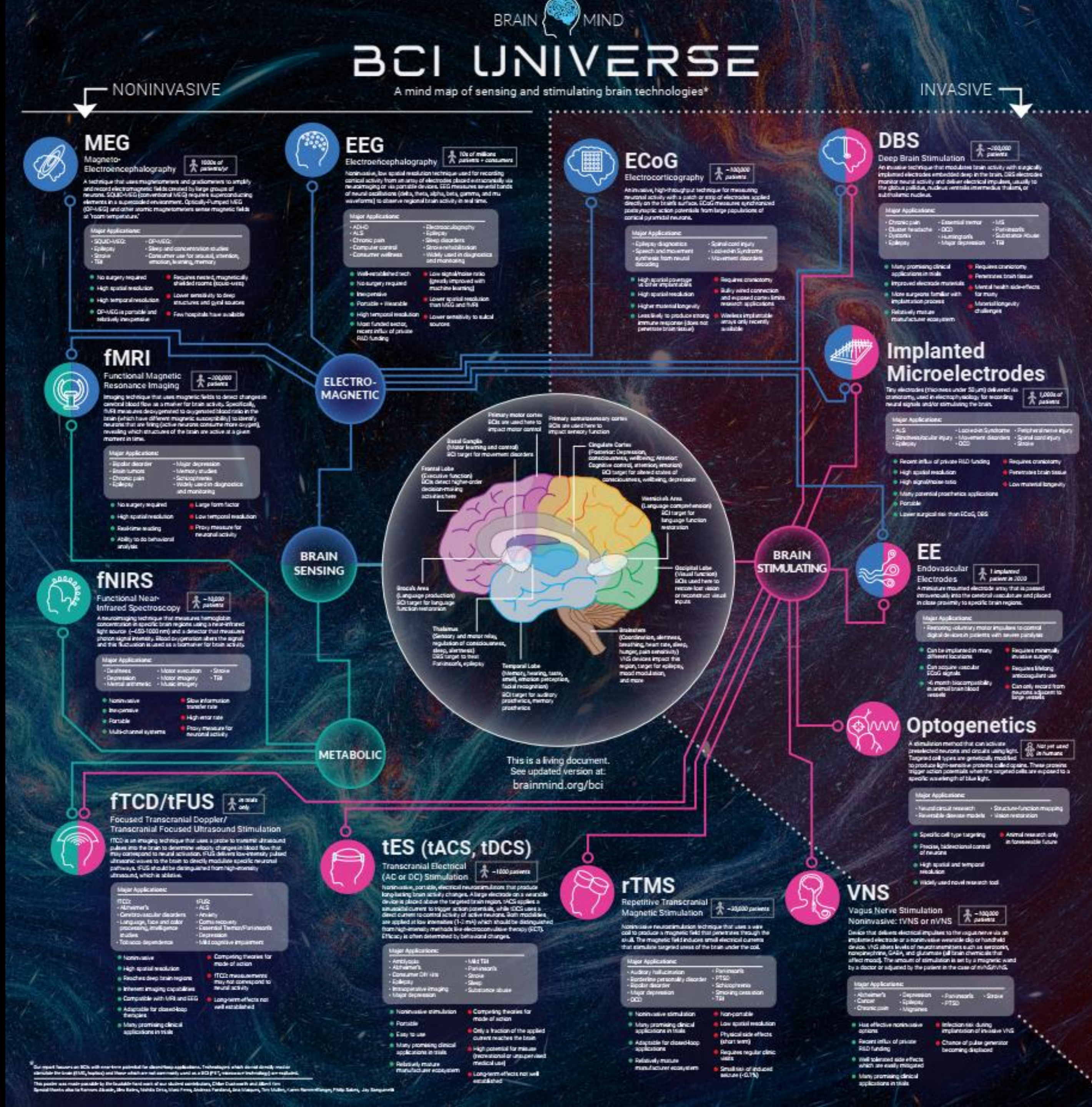
Non-invasive, partially invasive and invasive methods carry increasing amount of information, but are also more difficult to implement. EEG+ML still reigns supreme!



BCI tools

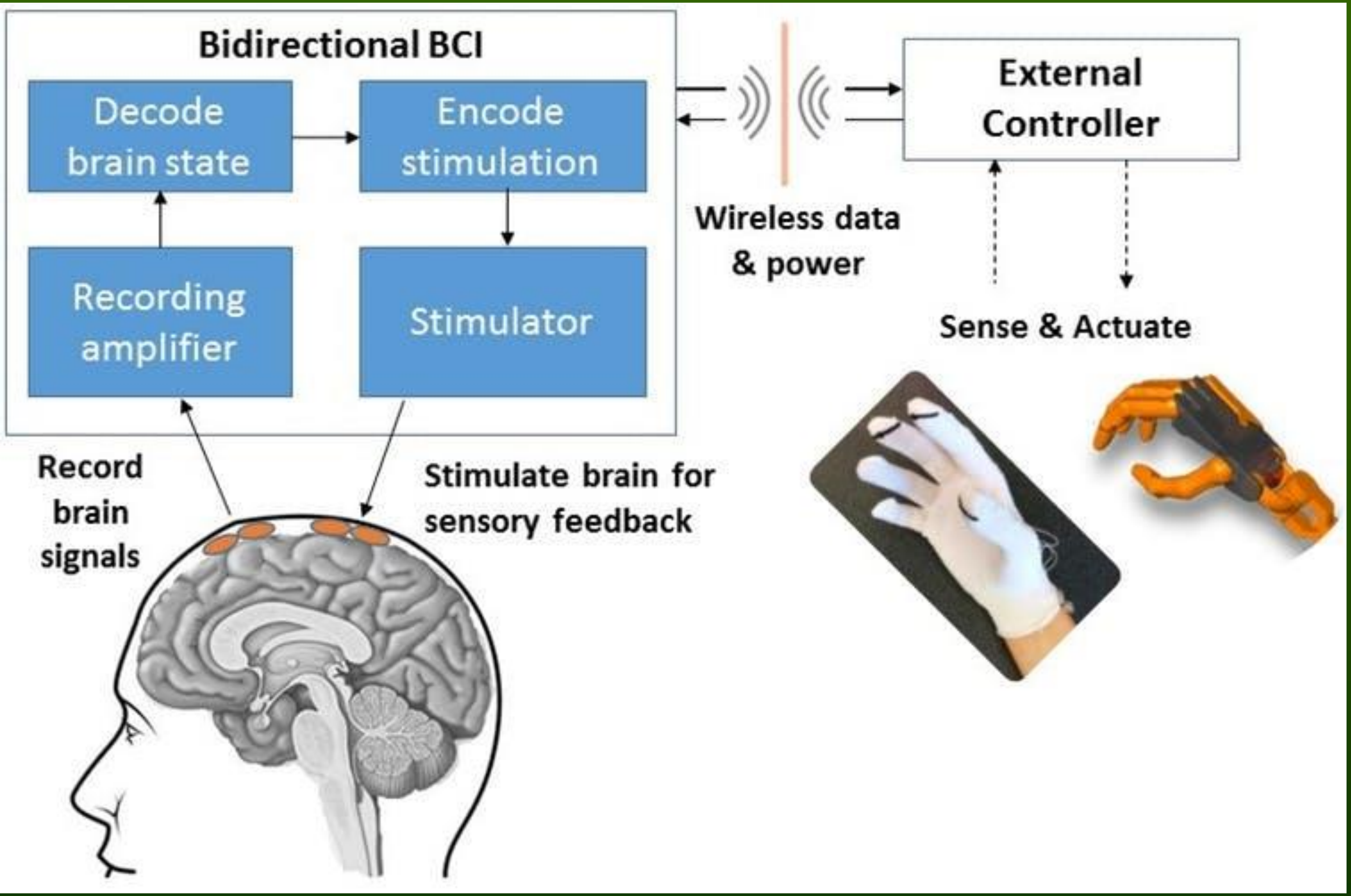
Combination of Virtual Reality with BCI has great potential.





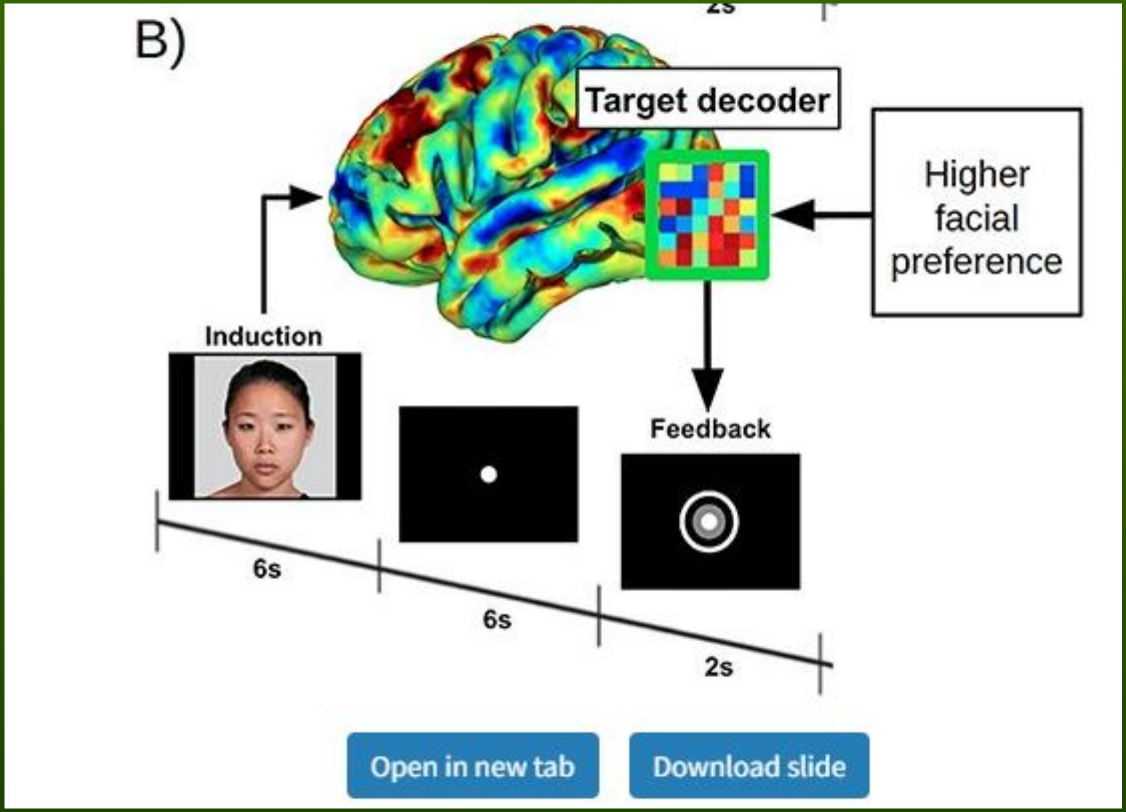
BRAIN MIND
BCI UNIVERSE
A mind map of sensing and stimulating brain technologies*
NONINVASIVE
INVASIVE
MEG
Magneto-Electroencephalography
EEG
Electroencephalography
ECoG
Electrocorticography
DBS
Deep Brain Stimulation
fMRI
Functional Magnetic Resonance Imaging
ELECTRO-MAGNETIC
Implanted Microelectrodes
BRAIN SENSING
BRAIN STIMULATING
fNIRS
Functional Near-Infrared Spectroscopy
EE
Endovascular Electrodes
Optogenetics
METABOLIC
This is a living document. See updated version at: brainmind.org/bci
fTCD/tFUS
Focused Transcranial Doppler/ Transcranial Focused Ultrasound Stimulation
tES (tACS, tDCS)
Transcranial Electrical (AC or DC) Stimulation
rTMS
Repetitive Transcranial Magnetic Stimulation
VNS
Vagus Nerve Stimulation
Noninvasive: tVNS or nVNS

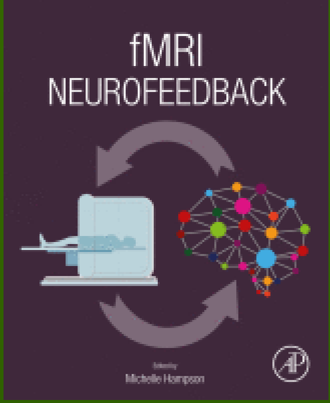
BCBI: Brain-Computer-Brain



BCI + brain stimulation = BCBI – a closed loop through which the brain begins to restructure itself. The body can be replaced by signals in Virtual Reality.

fMRI neurofeedback

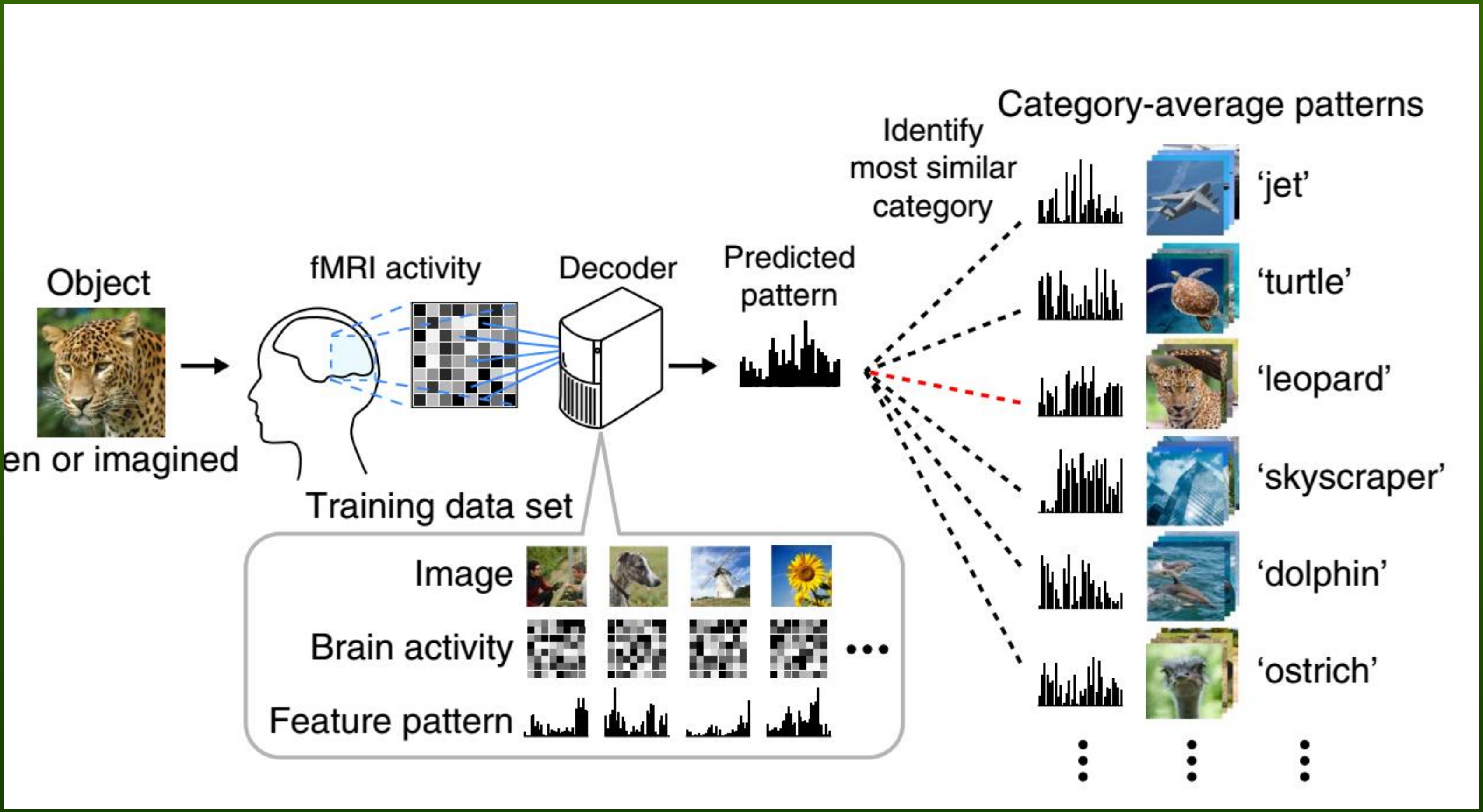




- Decoded Neurofeedback (DecNef).
  Target ROIs or occurrences of specific multivoxel representations.
- Functional Connectivity Neurofeedback (FCNef).

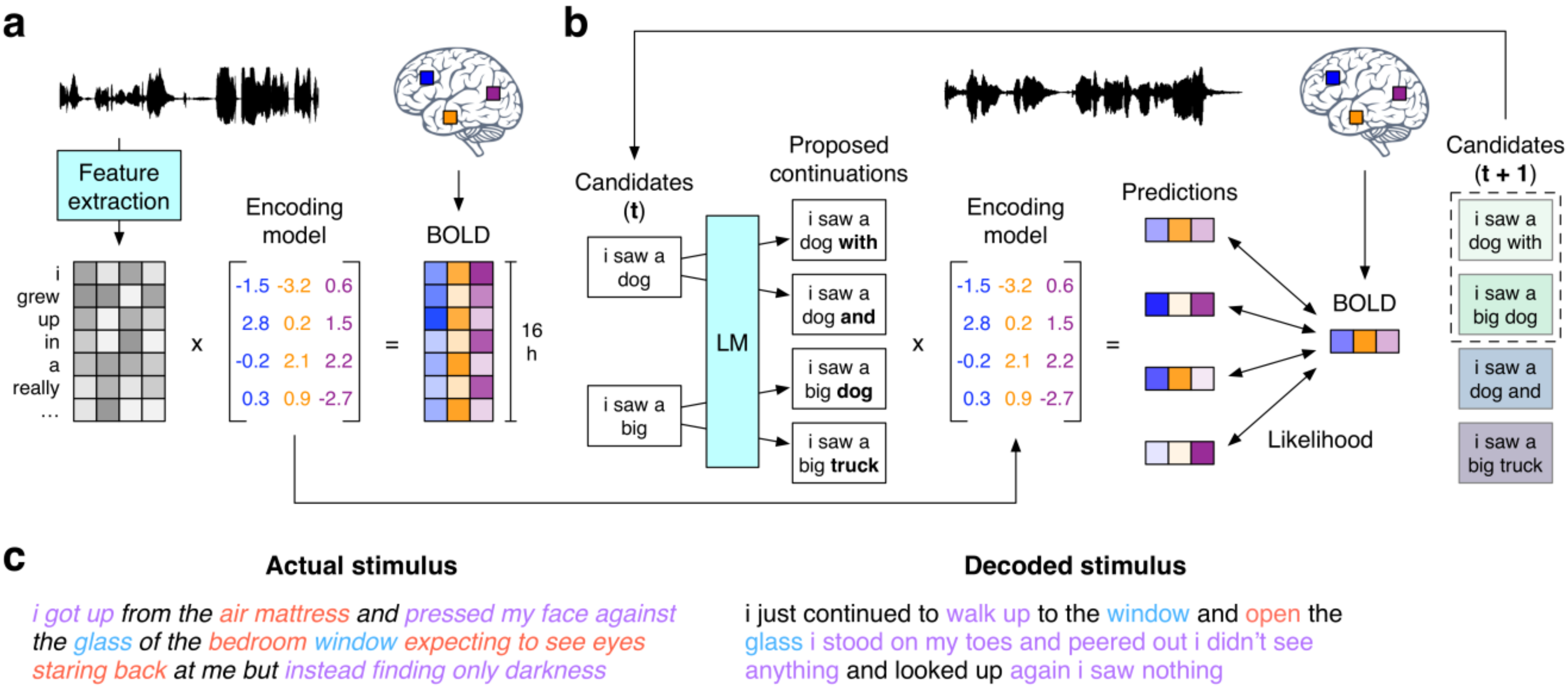
Taschereau-Dumouchel, V., Cortese, A., Lau, H., & Kawato, M. (2021). Conducting decoded neurofeedback studies. *Social Cognitive & Affective Neuroscience 16*, 838–848.

Images in the brain



fMRI activity => deep CNN network features => identify similar images.
Horikawa, Kamitani, Generic decoding of seen and imagined objects using hierarchical visual features. Nature Communications, 2017.

Listening to stories



fMRI responses, 3 subjects 16 h of 100 narrative stories.
(a) Encoding: predict brain responses, semantic 101 features of stimulus words.
(**b**) Language reconstruction from novel brain recordings: the decoder maintains a set of 102 candidate word sequences, predicts most probable.

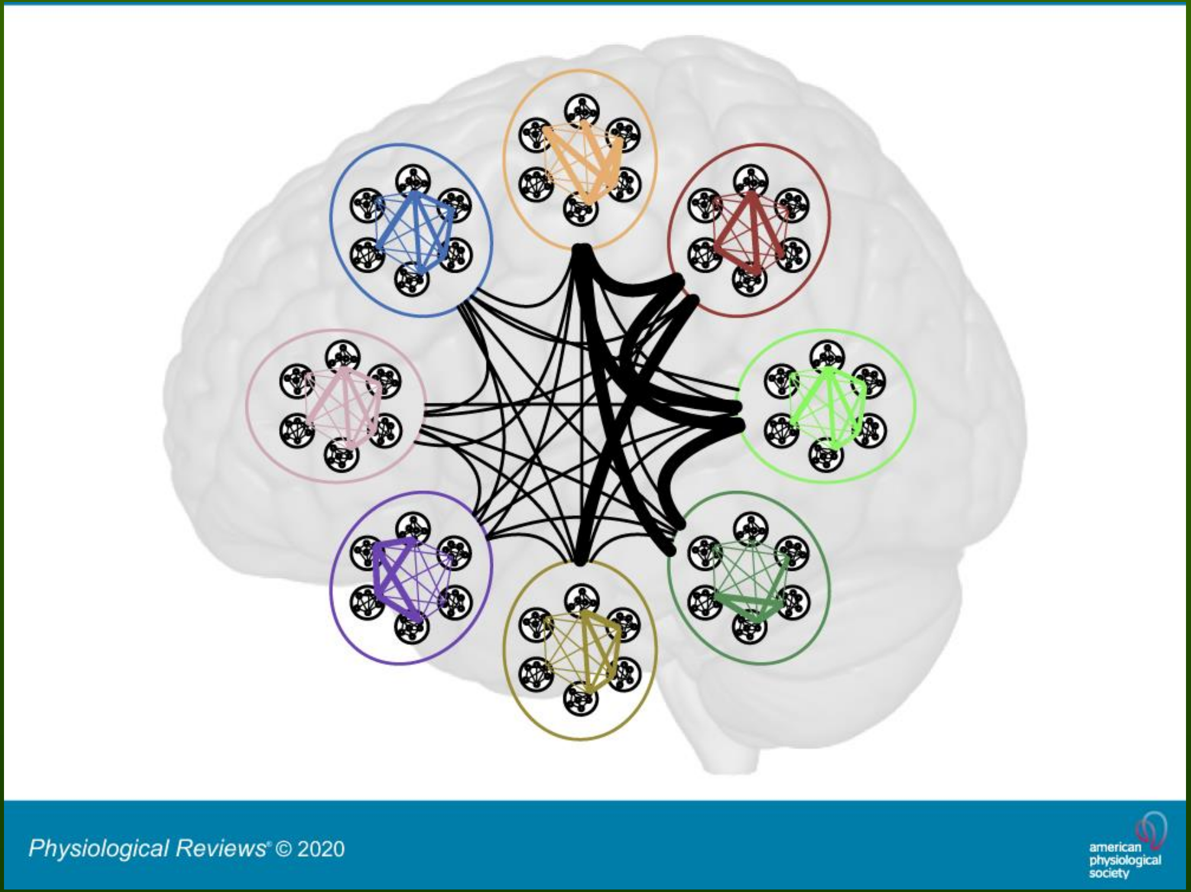
Tang wt al. (2023). *Nature Neuroscience*, *26*(5), Article 5.

≈ Small worlds architecture

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

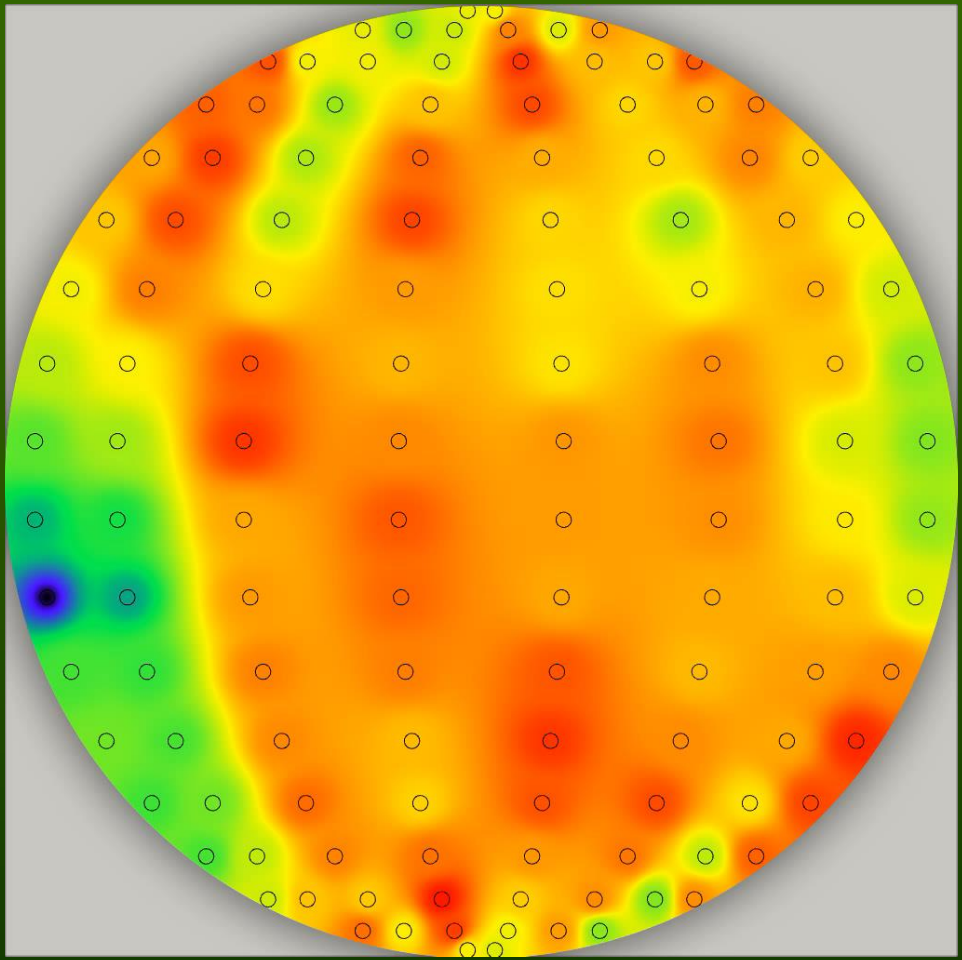
Local modules are densely connected, extract relevant information from sensory data, salience, memory associations, orchestrate motor actions.

Needs a switchboard?



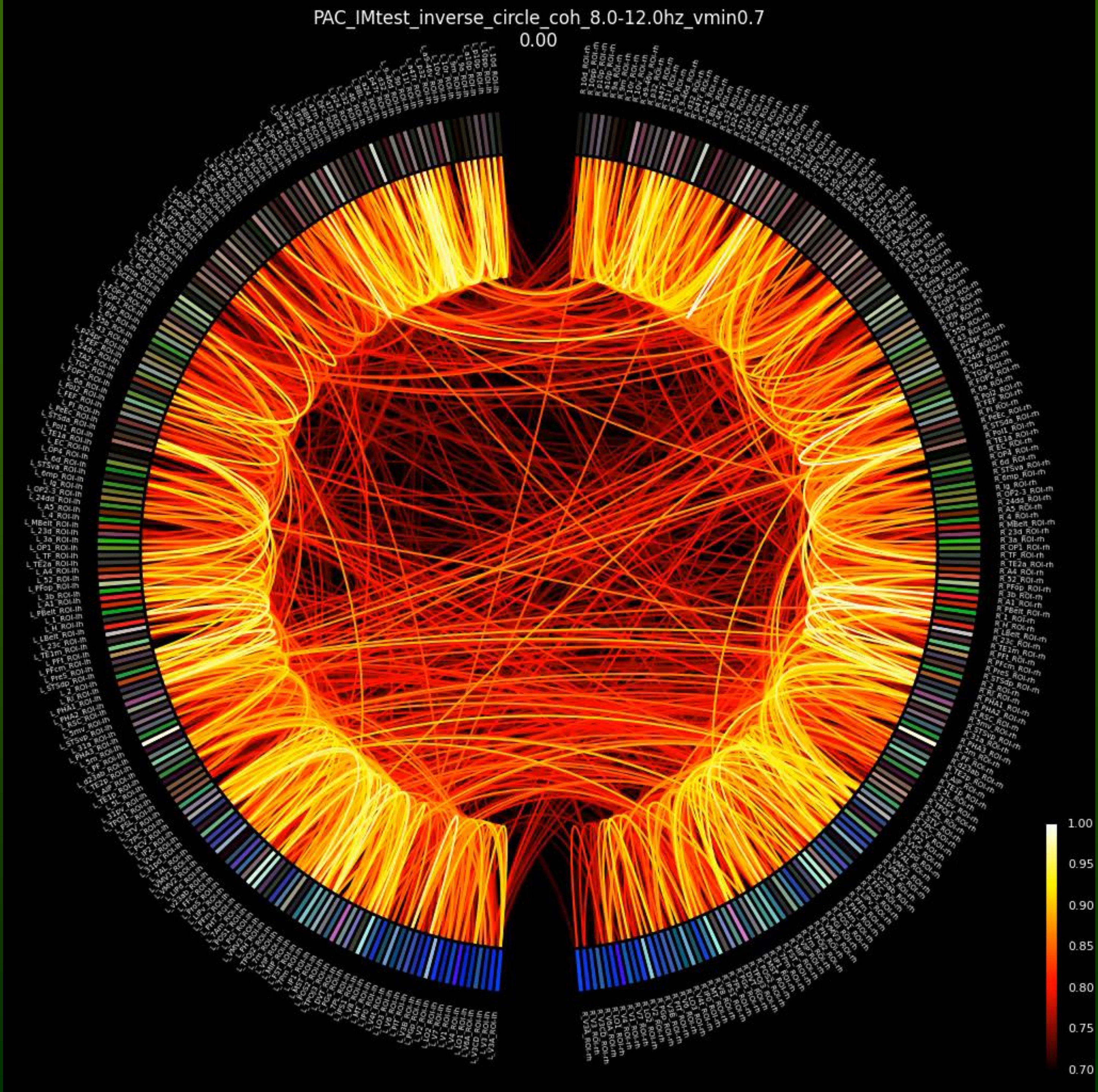
All complex functions are based on synchronization of activity among brain areas. Memory, personality, or consciousness are processes engaging many functions. Similar to multi-agent systems, the "society of mind", or the Global Workspace Theory. "Deconstruct" psychological constructs, link them to the brain processes.

Dynamics



Asymptotic power may show hypo/hyperactive brain regions, summarize overall functions. Dynamics should be taken into account averaging activity of subnetworks.

Motifs?


PAC_IMtest_inverse_circle_coh_8.0-12.0hz_vmin0.7
0.00
1.00
0.95
0.90
0.85
0.80
0.75
0.70

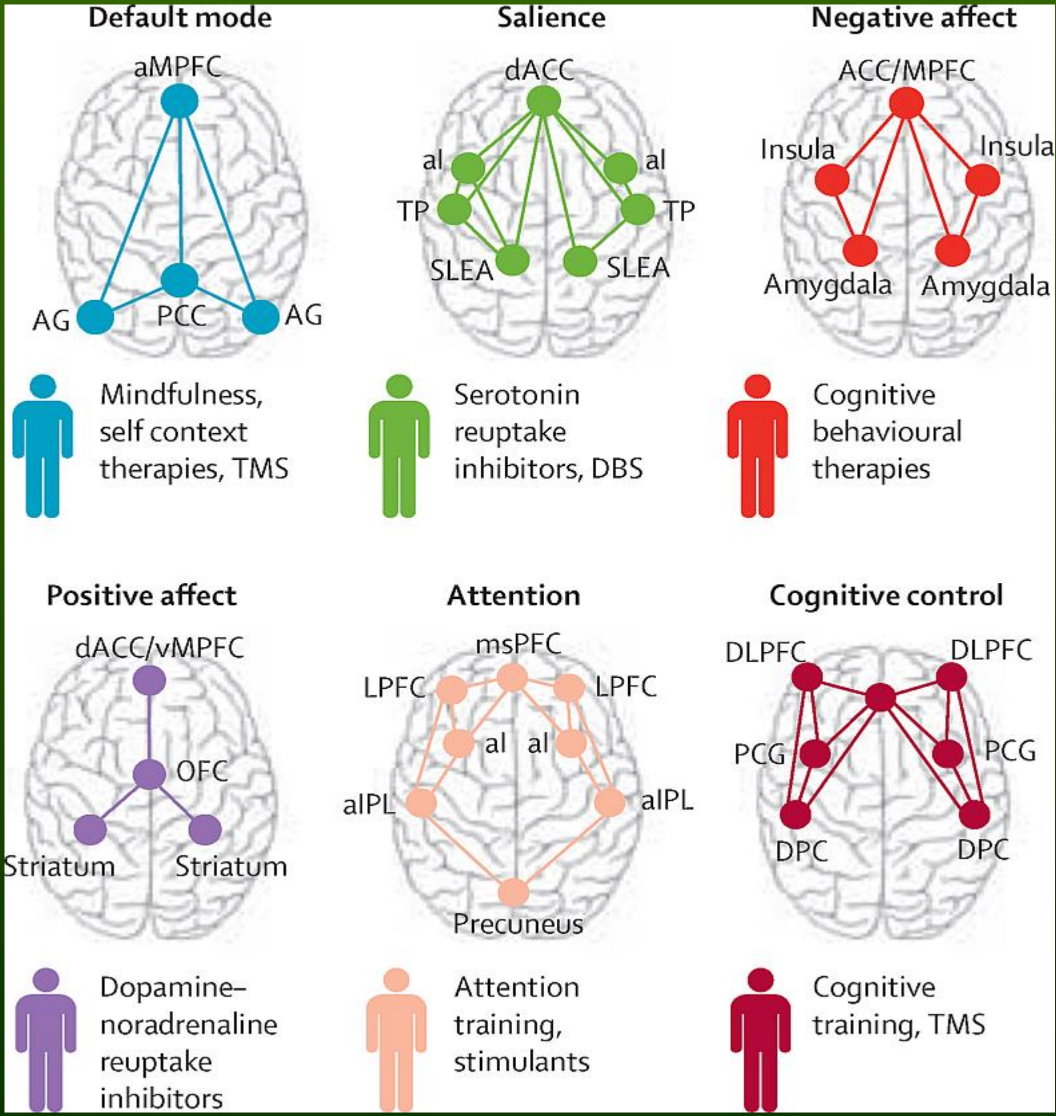
Large-scale brain networks

Classification of mental diseases by **Research Domain Criteria** (RDoC), matrix based on **multi-level neuropsychiatric phenomics** describing 6 large brain systems.

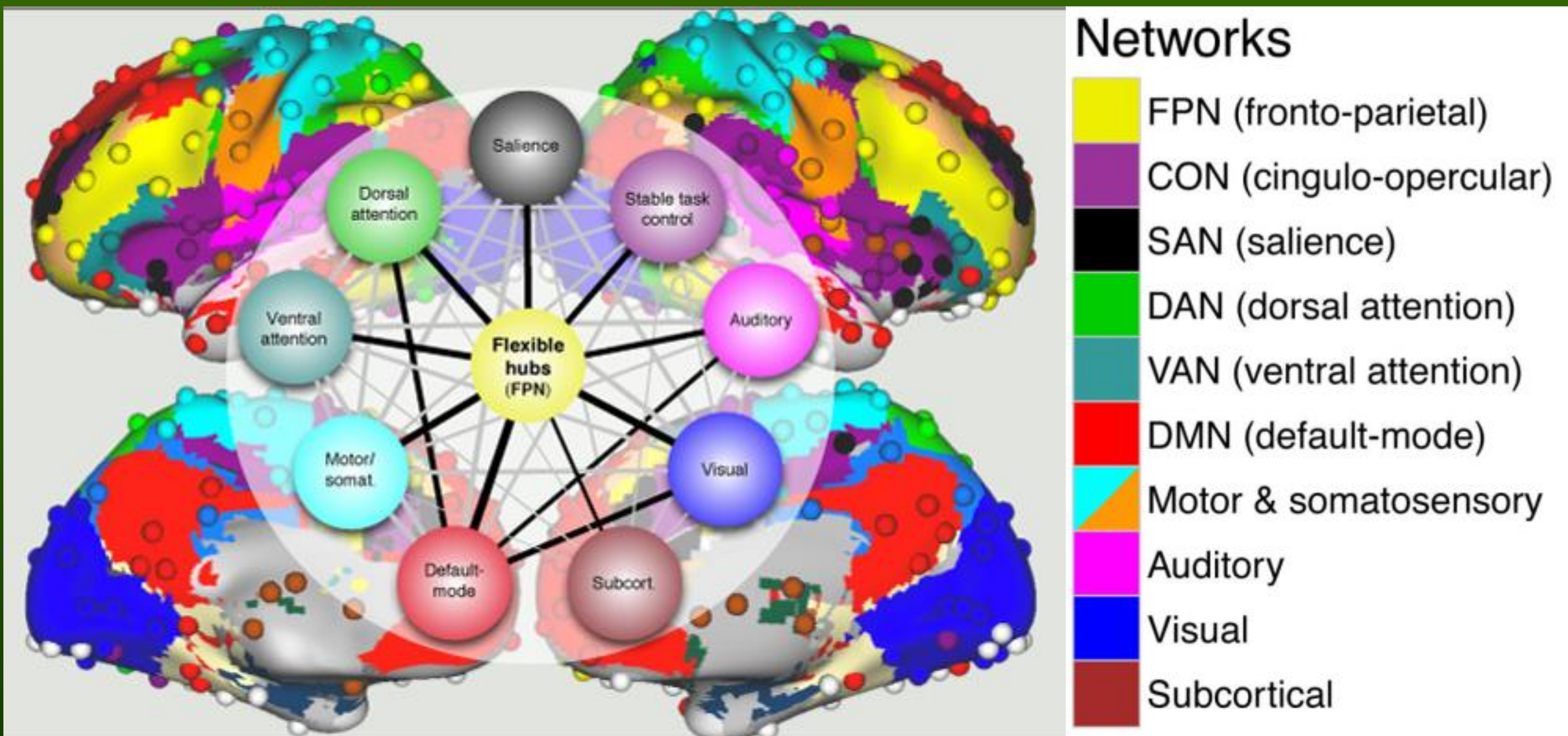
fMRI data led to identification of large-scale networks responsible for specific brain function activity.

These networks depend on genes, many types of neurons, **circuits**, neurotransmitters, physiology, are responsible for behavior, and brain disorders.

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



Neurocognitive Basis of Cognitive Control



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

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

Brain: sequence planning + many tools

Music playing engages whole brain.

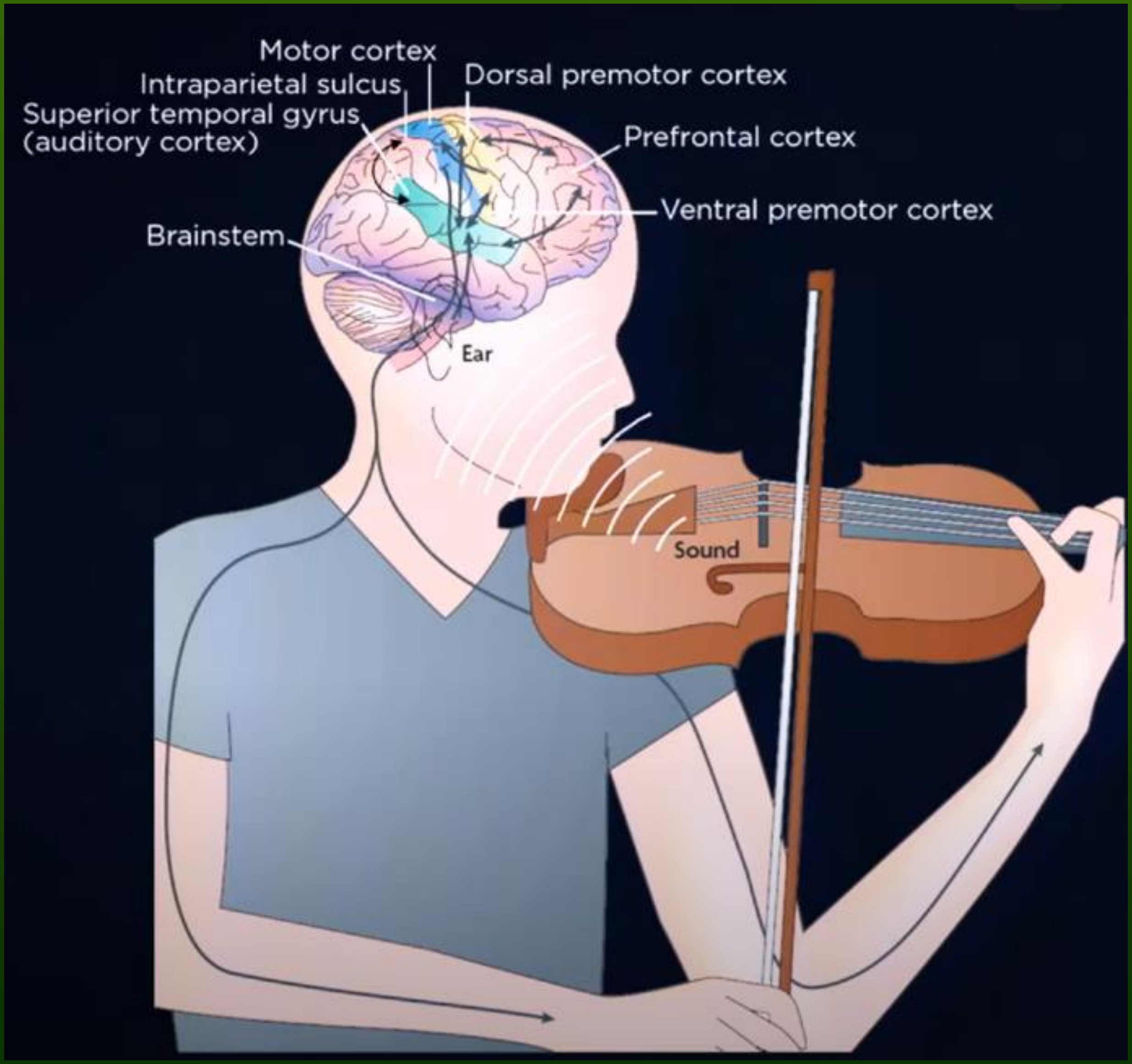
Our central executive system **plans** and recruits specialized systems, tools to do the job.

Best model of intelligence:

P-FIT, parieto-frontal integration theory.

Can LLM do the same?

Give AI tools and teach how to use them.



Distributed Artificial Brain (DAB)

Hugging Face
> 10000 tools

FutureTools.io
~2000

ChatGPT
Plugins

LLMs

Planning, reflection, chains of thoughts

Generative Tools

Programming Tools

Language Tools

Search Tools

Math/Stat Tools

Brain fingerprinting

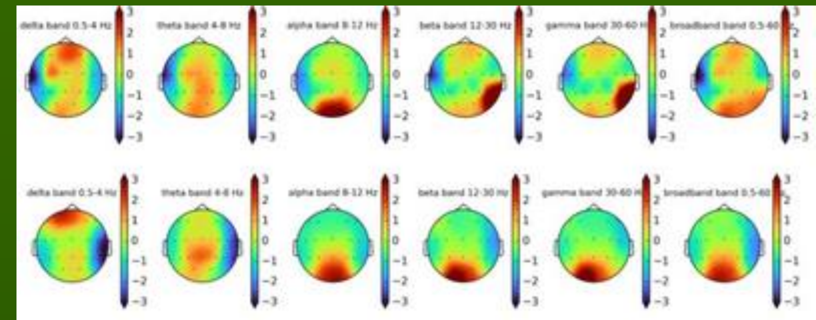
Find unique patterns of brain activity:

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

Several approaches:

1. Spatial distributions, power maps and spectral fingerprints (Keitel & Gross 2016)
2. Large scale networks seen in fMRI can be recreated from EEG (Yuan et al, 2015).
3. Temporal information, microstates and their transitions (Michel & Koenig 2018)
4. Recurrence plots and RQA, recurrence quantification analysis.
5. Connectivity, functional correlations and many more approaches…

1



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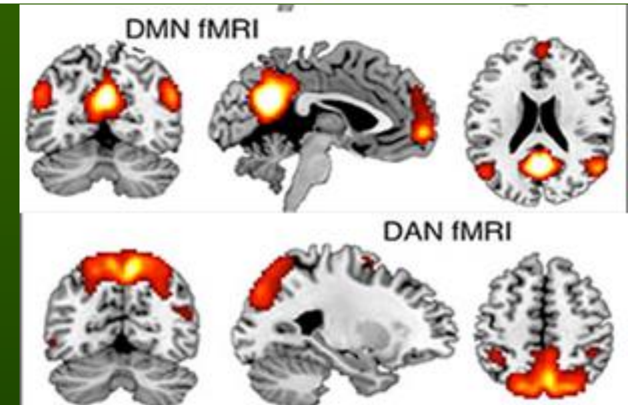

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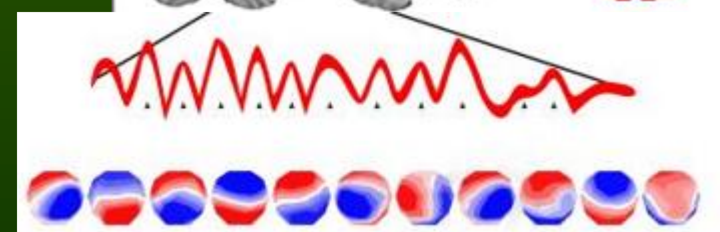

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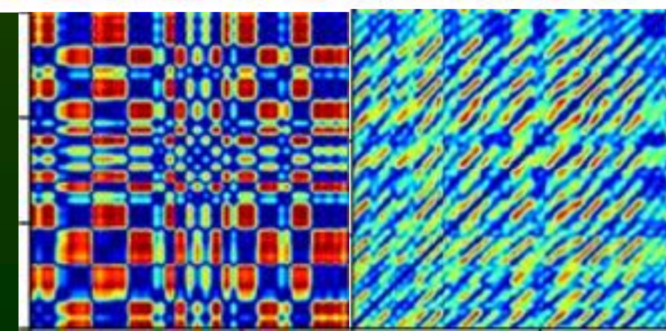


Brains – spatial aspects

Spectral fingerprints of cognitive processes

Decompose neurodynamics.
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.

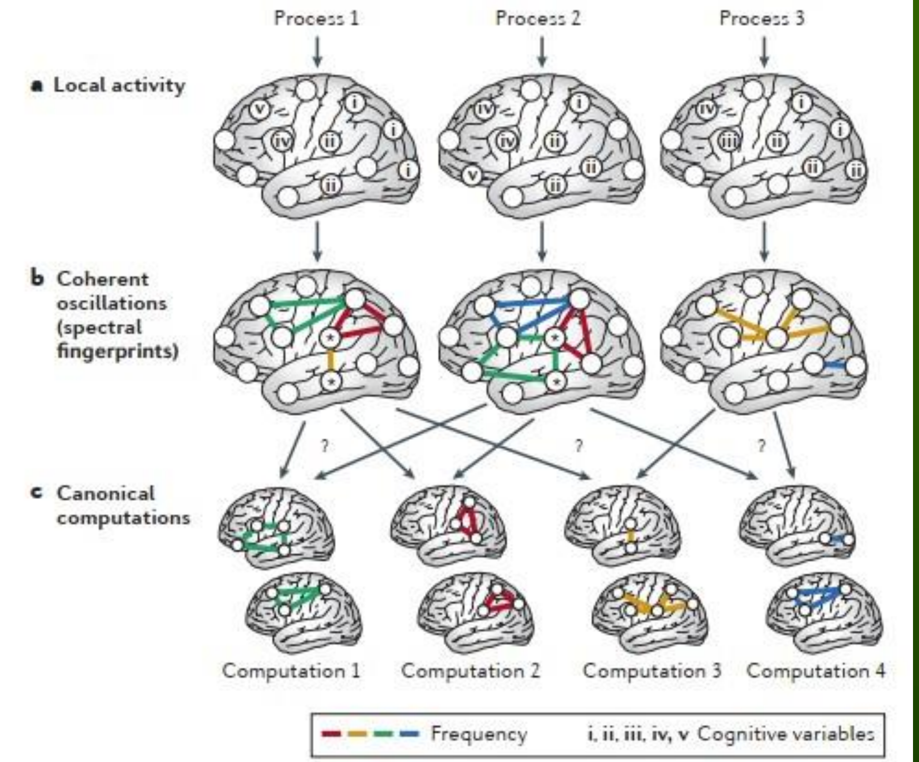
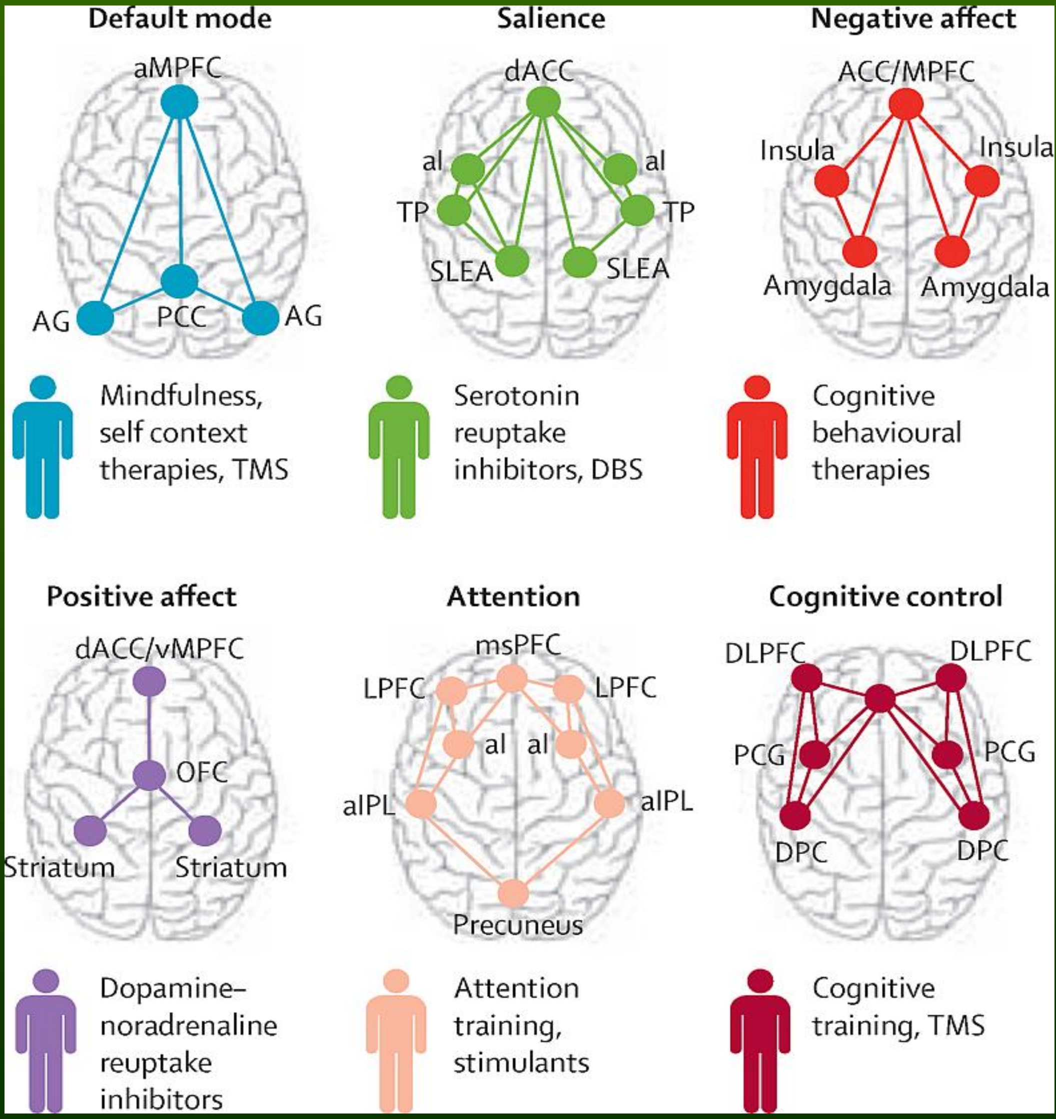


Figure 4 | **Large-scale spectral fingerprints of cognitive processes.** Schematic illustration of how coherent oscillations provide 'spectral fingerprints' for regrouping of cognitive processes 1–3. **a** | Studies of neuronal activity in individual brain regions (circles) elucidate the activation of 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

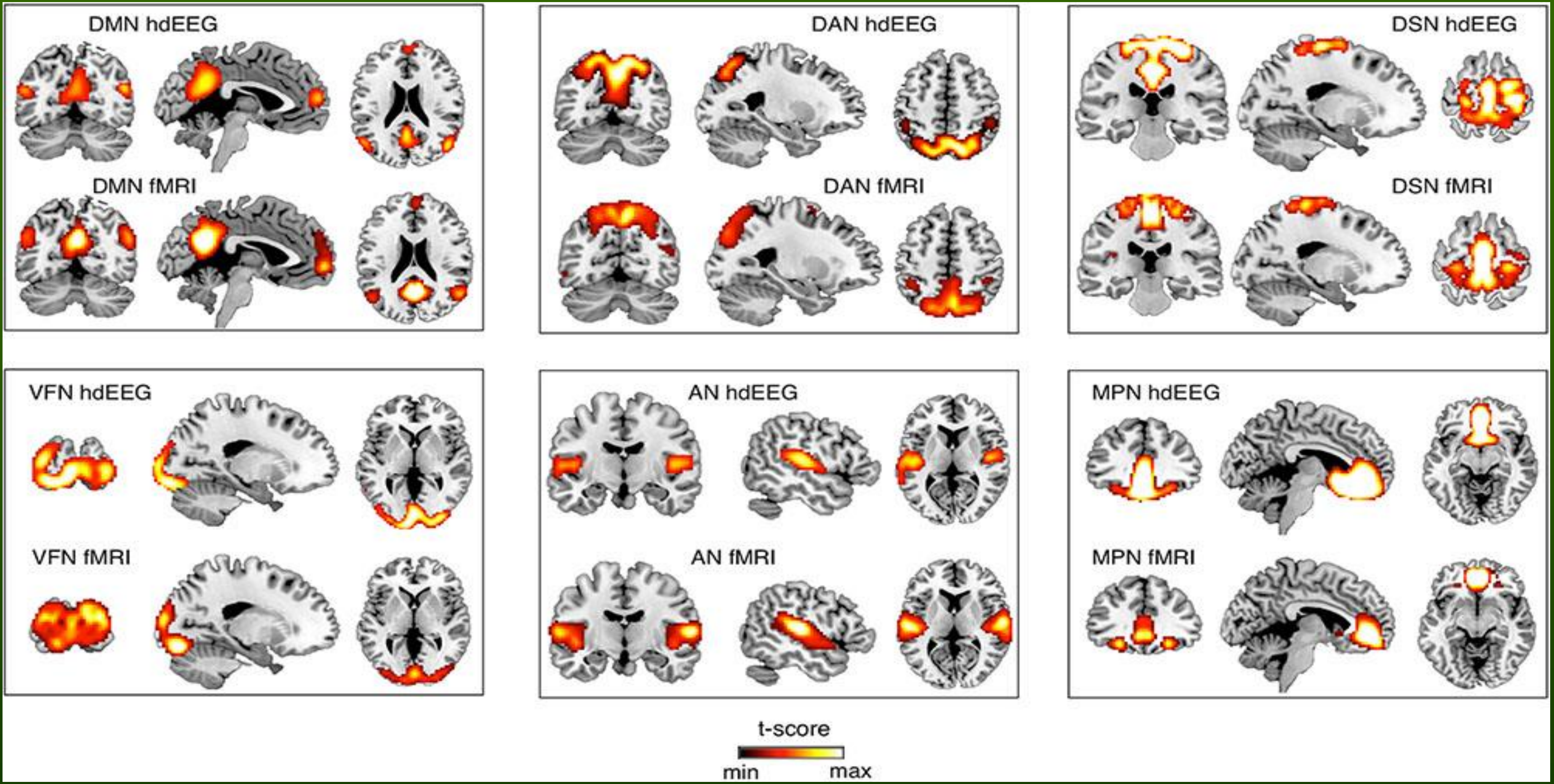
Large-Scale Networks from fMRI

- 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 120, or much more (3 mln minicolumn)
- Brain networks have specialized functions, dominating frequencies, dynamics, neurotransmitters.

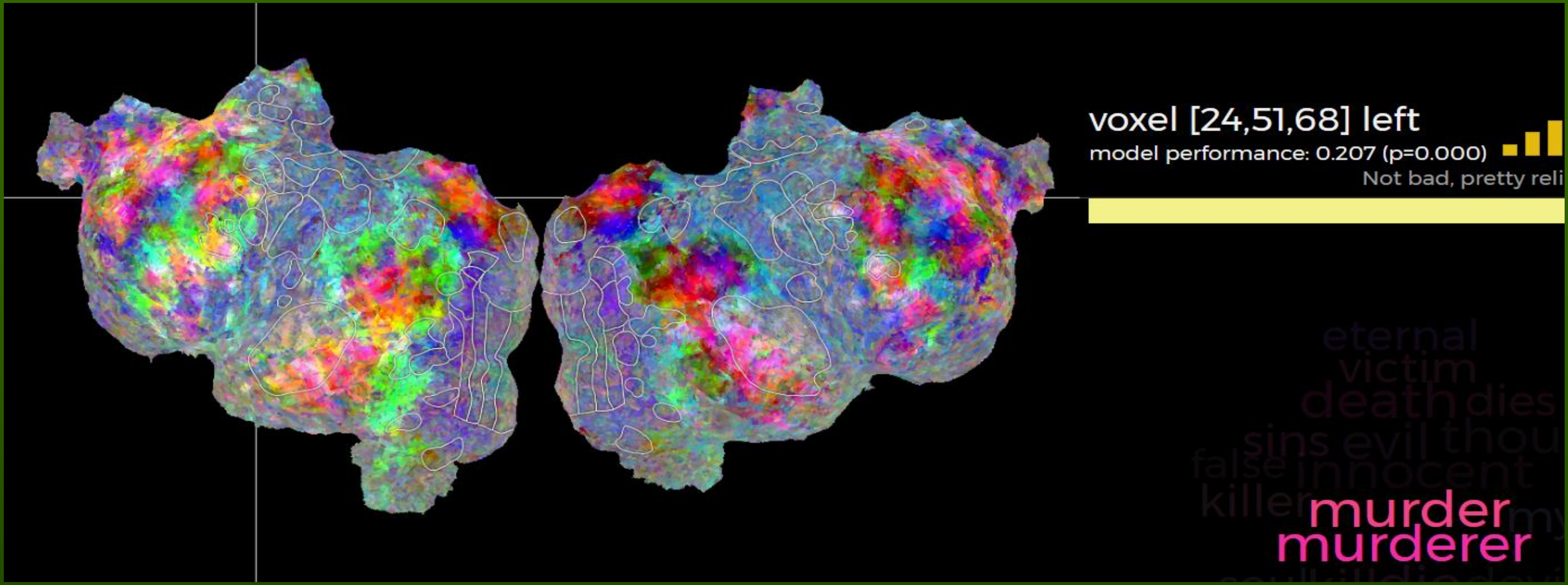
Network science for complex systems.



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).
Dynamics? Specific frequencies?



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?
Prompts invoke specific activation in LLMs.

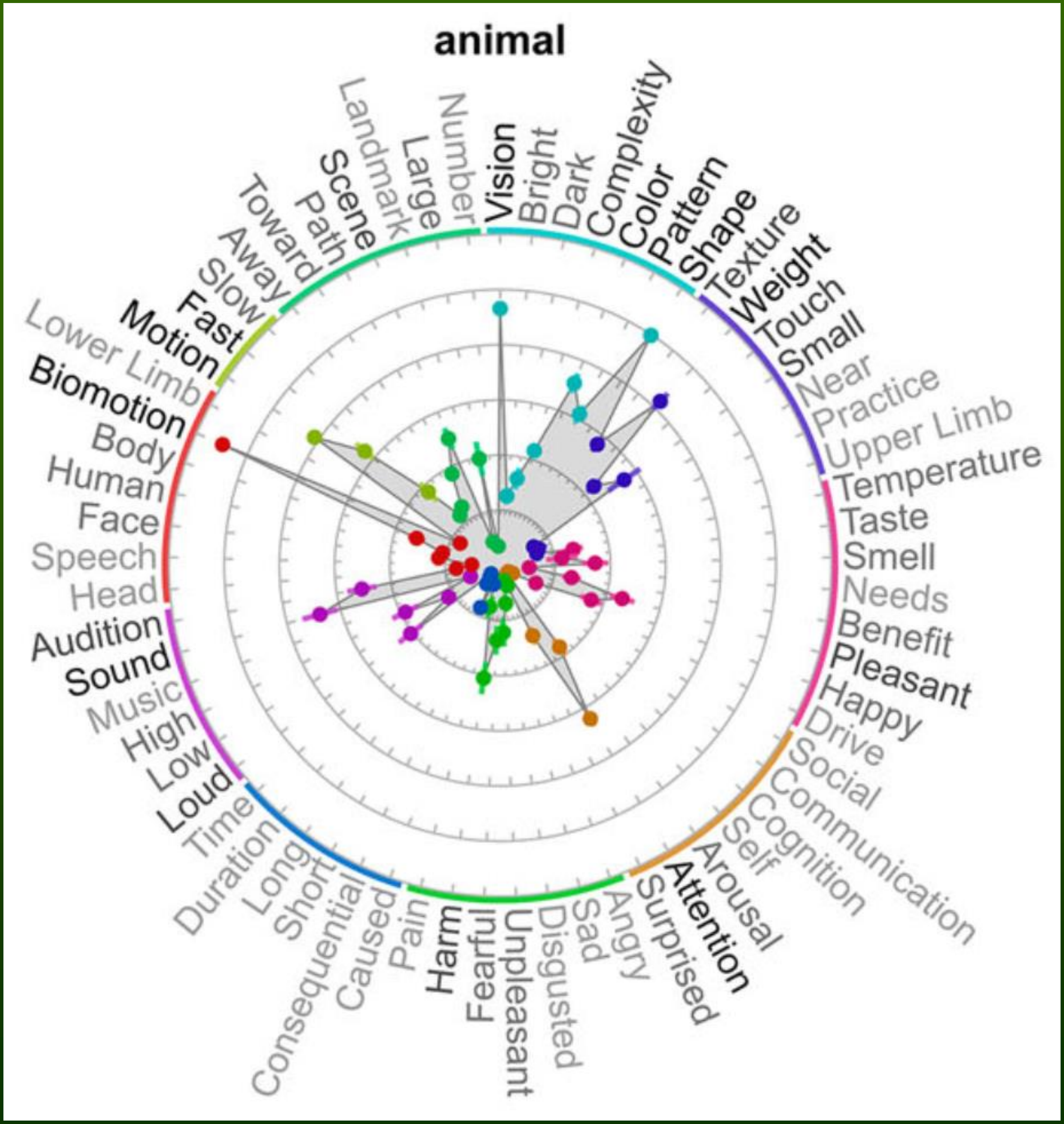
J.R. Binder et al.
Toward a Brain-Based Componential Semantic Representation, 2016

65 attributes related to neural processes;

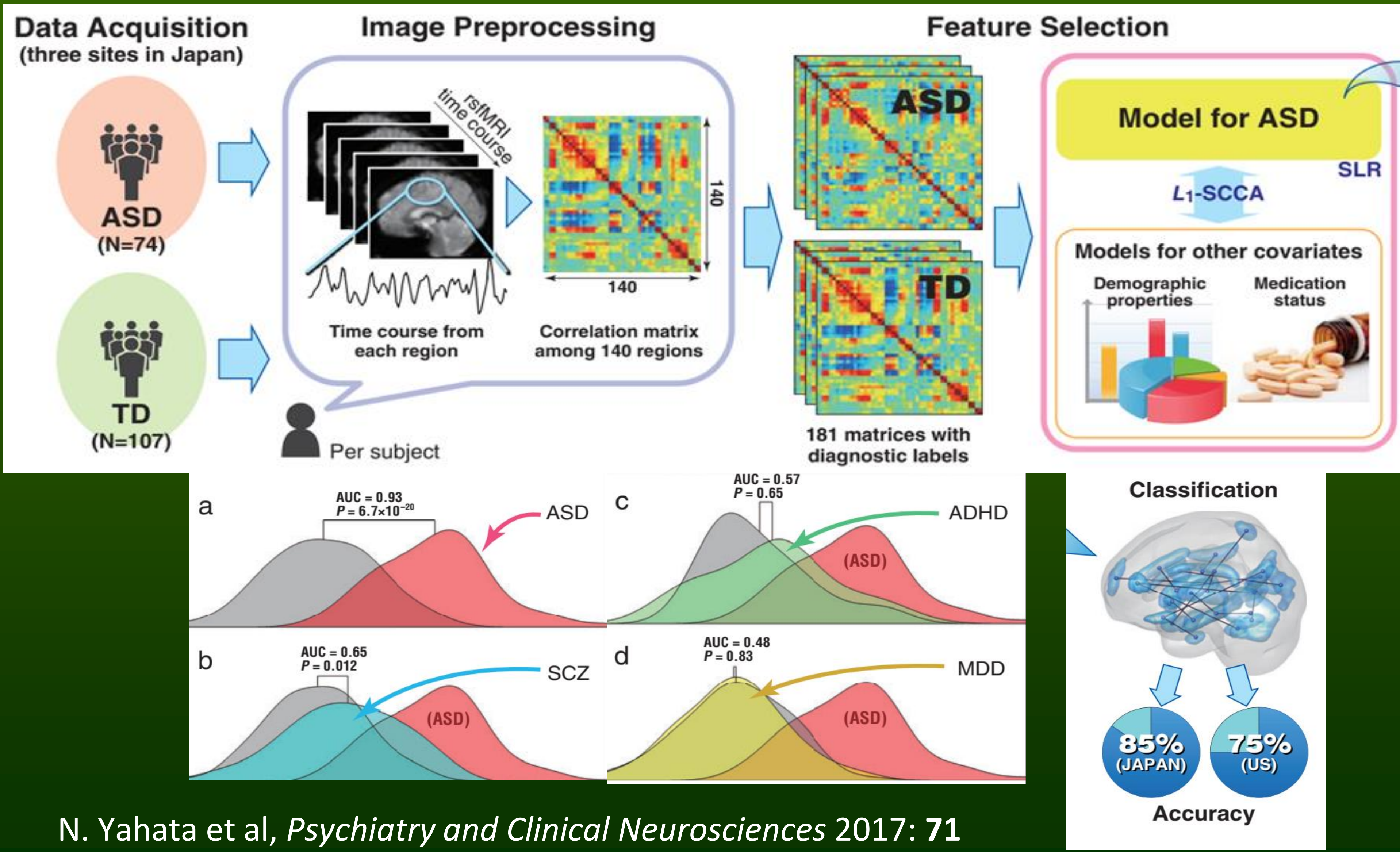
Colors on circle: general domains.

More than just visual objects!

Decompose brain signals for a given concept into components coding these attributes.

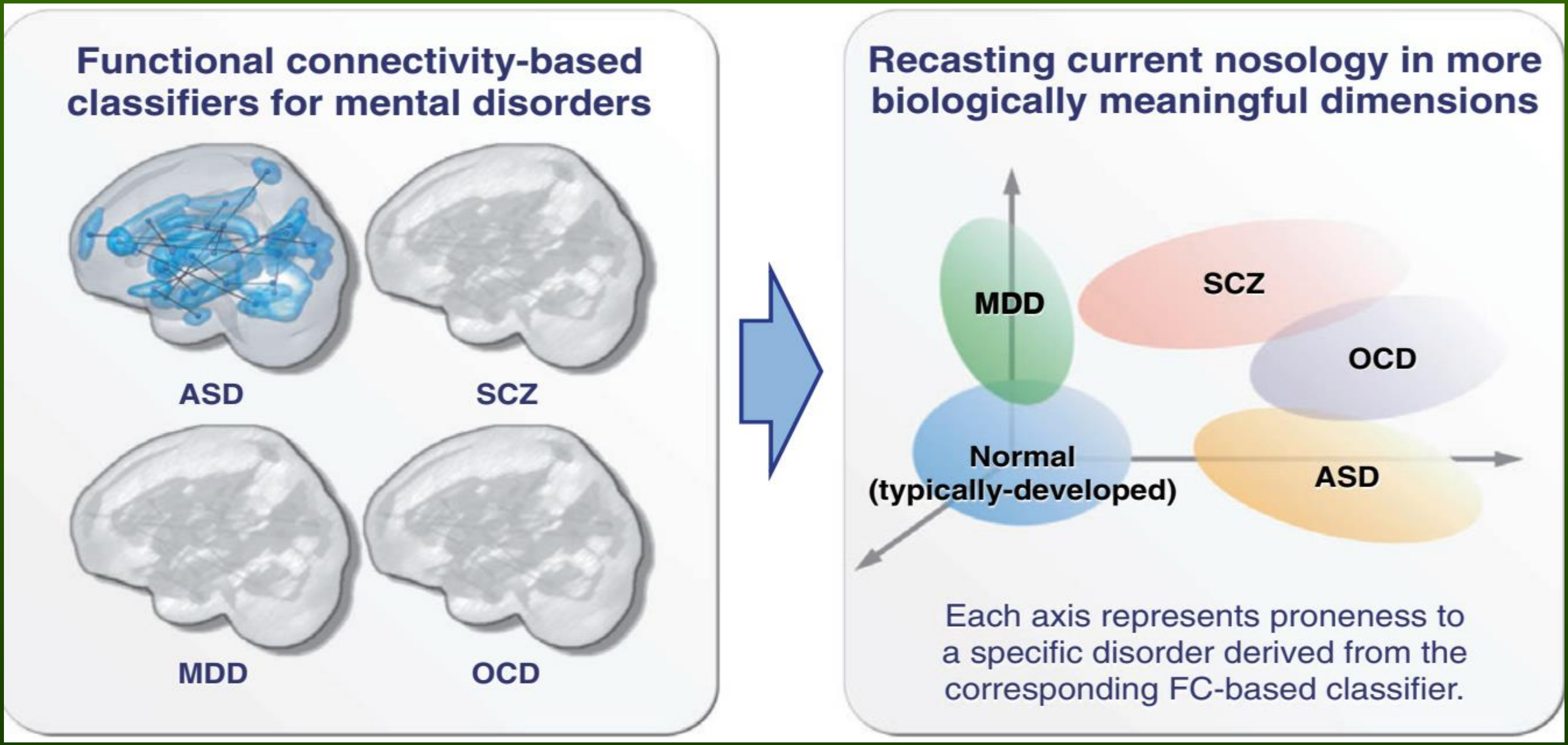


Biomarkers from neuroimaging



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

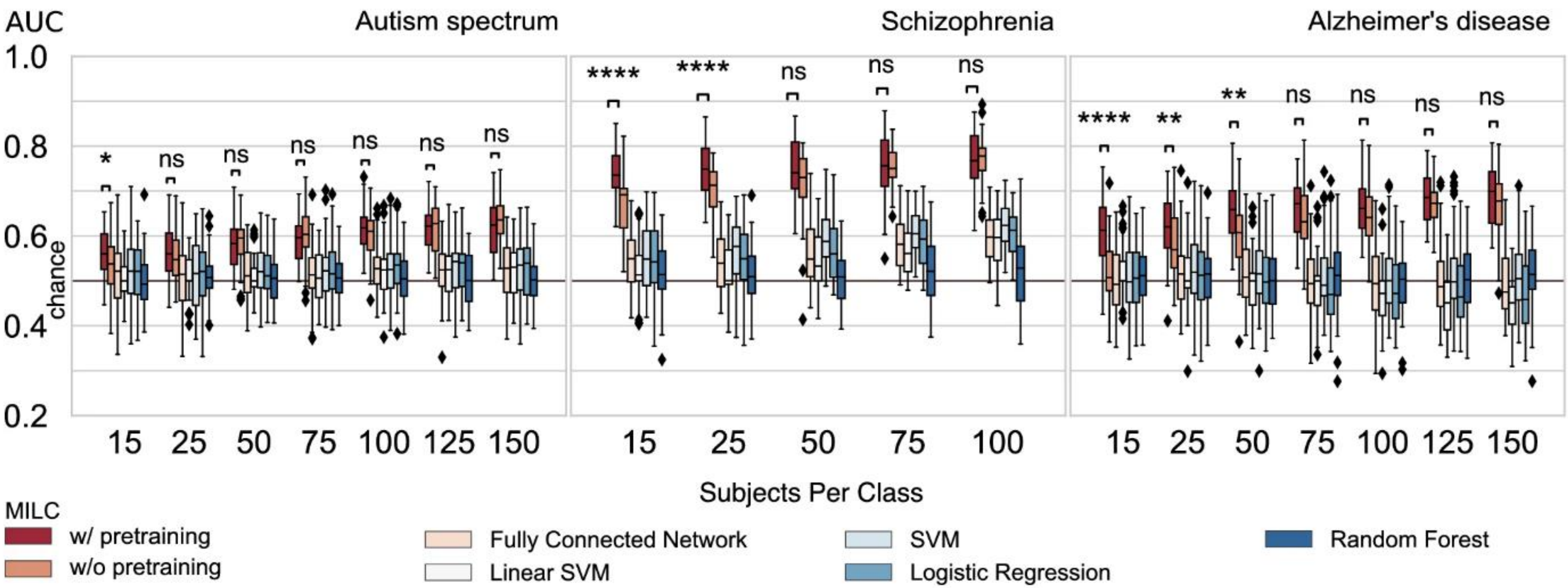
Biomarkers of mental disorders



fMRI biomarkers allow for objective diagnosis. MDD, deep depression, SCZ, schizophrenia, OCD, obsessive-compulsive disorder, ASD autism spectrum disorder. This should be most effective neurofeedback approach.

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

MILC model



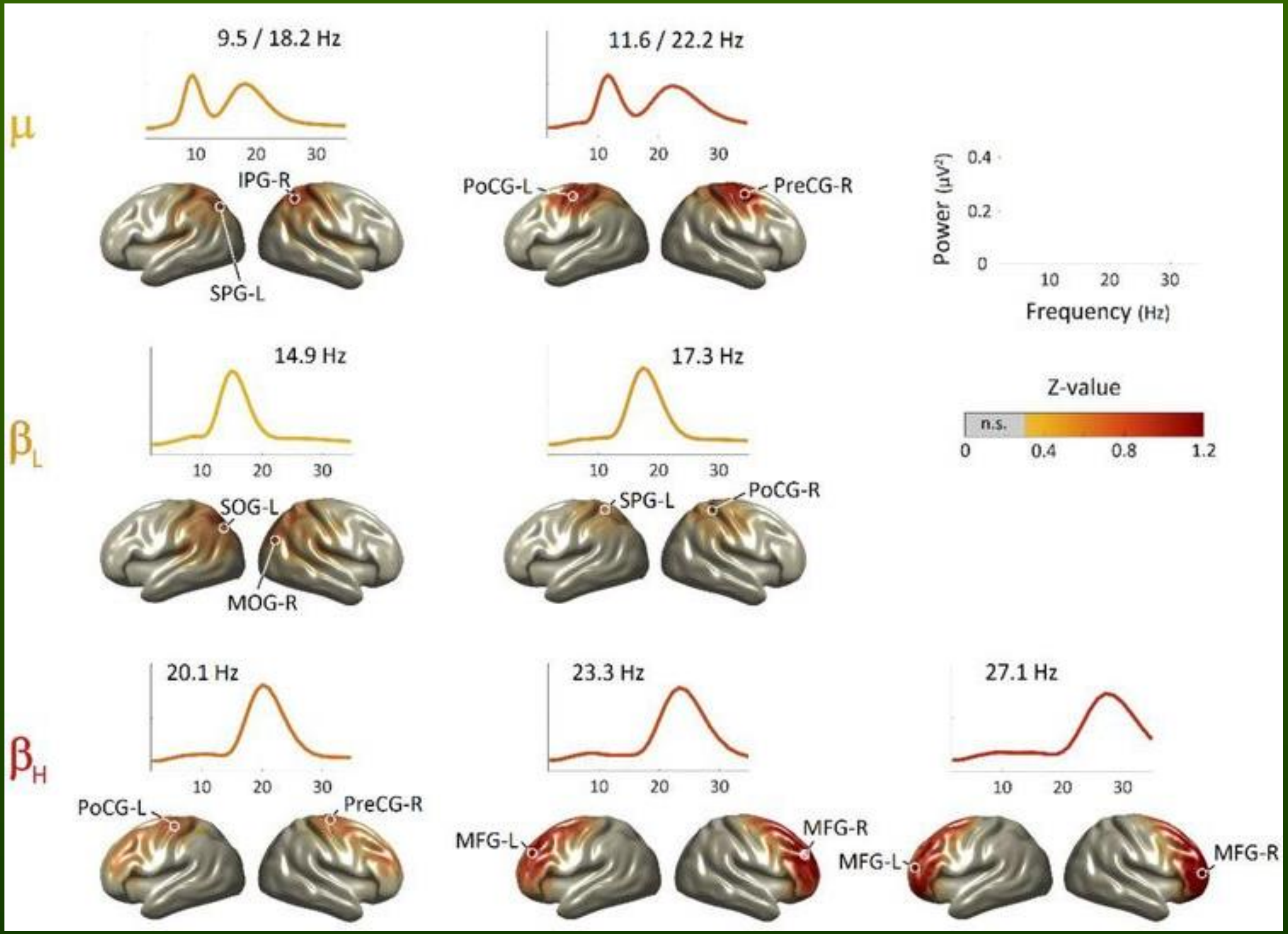
Rahman, … & Plis, S. M. (2022). Interpreting models interpreting brain dynamics. *Scientific Reports*, *12*(1), 12023. Supervised pretraining scheme, which maximizes "Mutual Information Local to (whole) Context" (MILC).

After pre-training on large fMRI data deep learning + MILC can learn directly from high-dimensional signal dynamics, even in small datasets (15 subjects).

Mutual information maximization between the whole sequence (context embedding) and local windows (local embedding) from the same sequence.

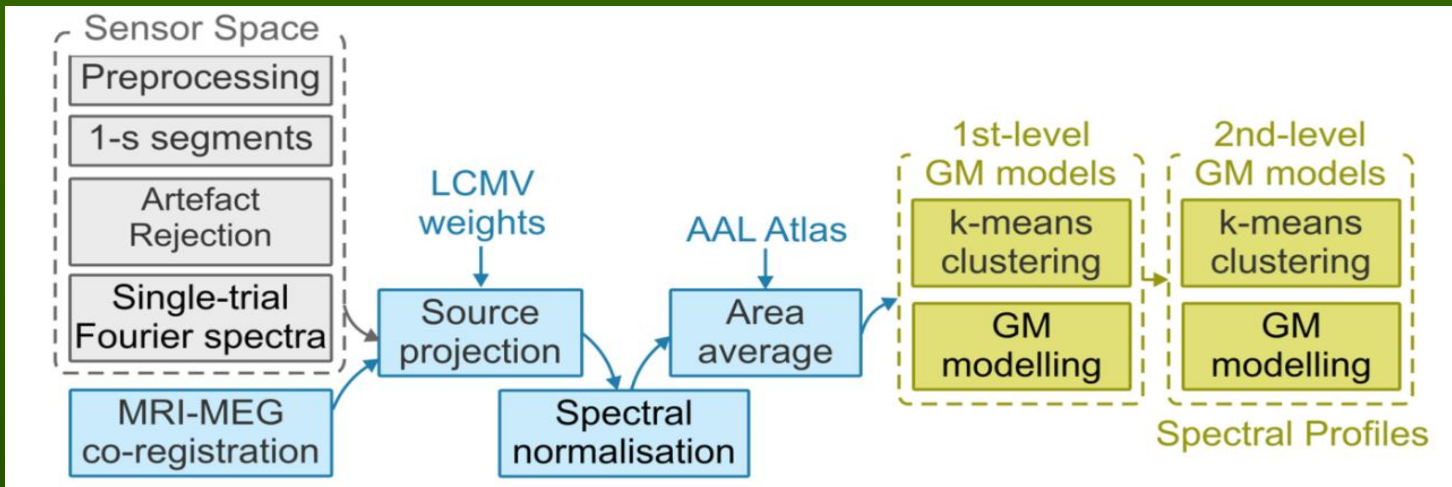
Atlas of the natural frequencies, resting brain

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

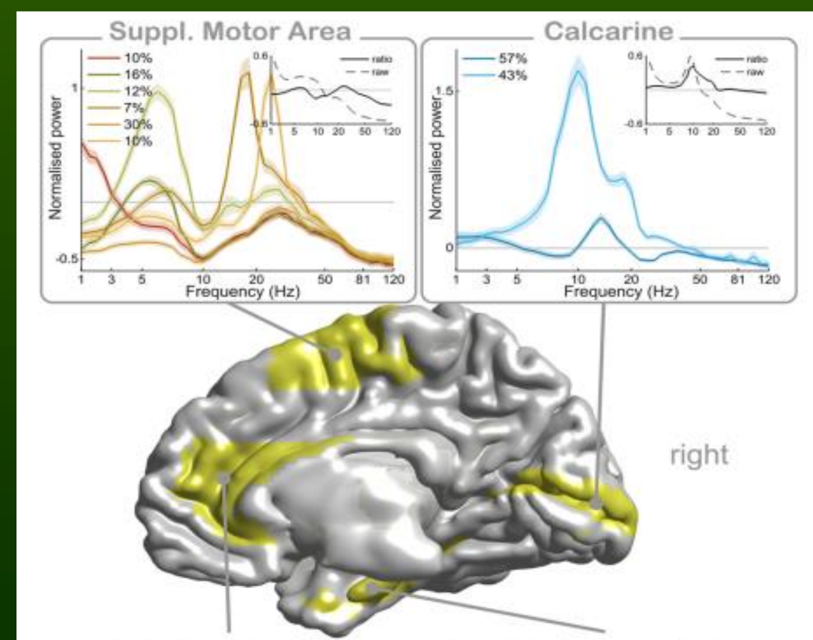


Create spectral fingerprints of ROIs.

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. *PLoS Biol* 14, e1002498, 2016

Komorowski … Duch (2023). ToFFi – Toolbox for frequency-based fingerprinting of brain signals. *Neurocomputing*, *544*, 126236. ToFFi toolbox



Schizotypical and schizoaffective disorders

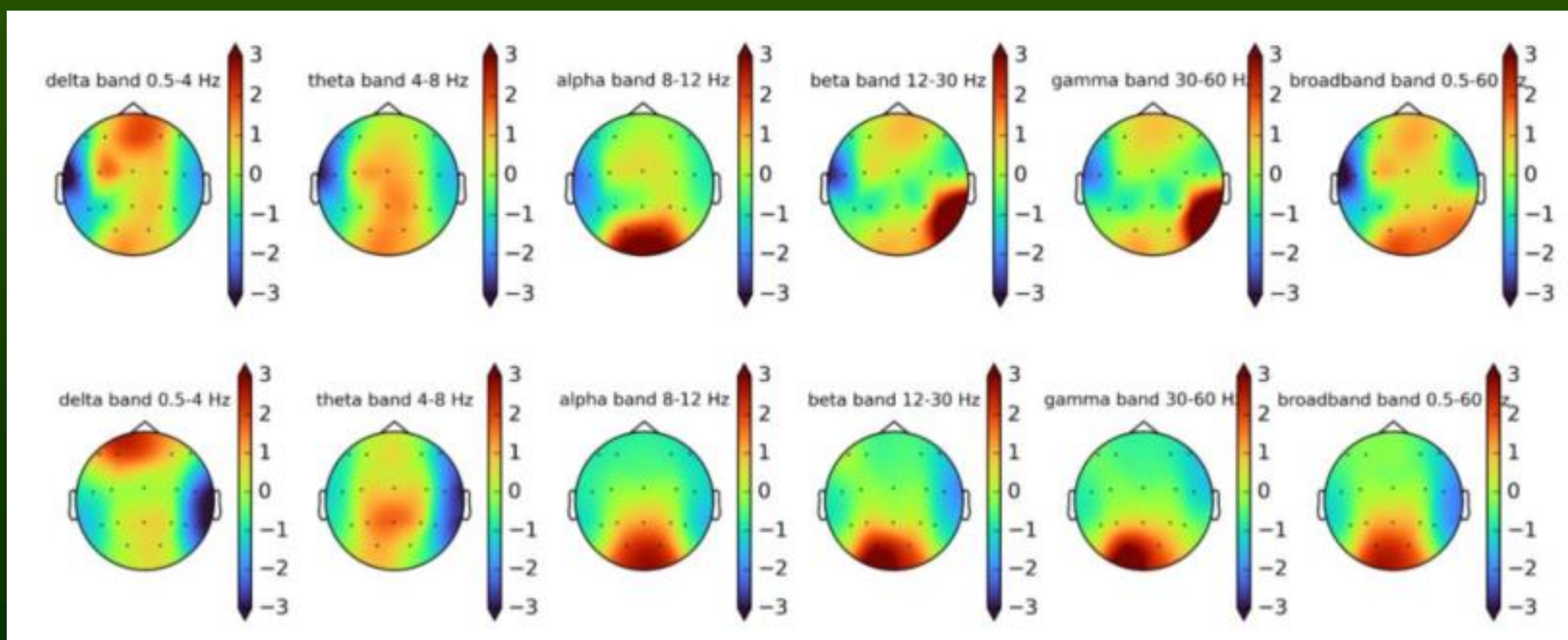
Diagnostic utility of resting-state EEG spatial power distribution maps. Long-term temporal averaging of signals in each channel. Asymptotic values of average power distribuitons (**avPP)** shows activations of different brain regions.

Schizophrenia patients: 45 boys (10-14 y) diagnosed with schizophrenia and 39 healthy controls (Borisov et al. Human Physiology, 2005).

EEG: 16 electrodes, 125 Hz sampling rate, 60 sec. sequences.
Maps for 5 bands + broadband, 5x16=80 features for classification.

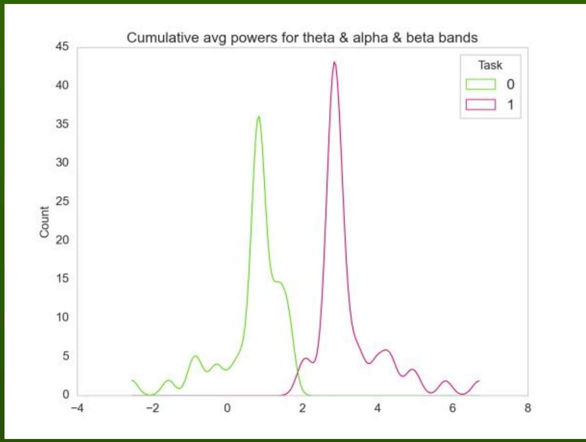
Schizo

Control



Schizophrenia 5xCV classification

Bands	Dim	All %	Norm %	Schizo %	
broadband	9	72.6	72.5	73.3	
delta-gamma	42	86.9	87.5	86.7	
theta & beta	13	85.7	92.5	80.0	
delta-theta	27	84.7	80	88.9	
delta-alpha	48	83.3	87.5	80.0	
theta-beta	6	77.4	70	84.4	
STFT RQA	16	82.2	82.1	82.2	
4 microstates	3	78.5	69.3	86.7	TAAHC
10 microstates	67	94.0±5.9	92.1	95.6	K-means



CNN CN	170	81.0±4.4	network topology graphs (TDA)
CNN VAR	1280	81.0	time-domain vector autoregressive
CNN PDC	1280	89.2	freq. domain partial directed coherence
SVM PDC	1280	88.0	freq. domain partial directed coherence
VAR+PDC+CN	2730	91.7	best CNN (Phang et al. IEEE JBHI 2020).

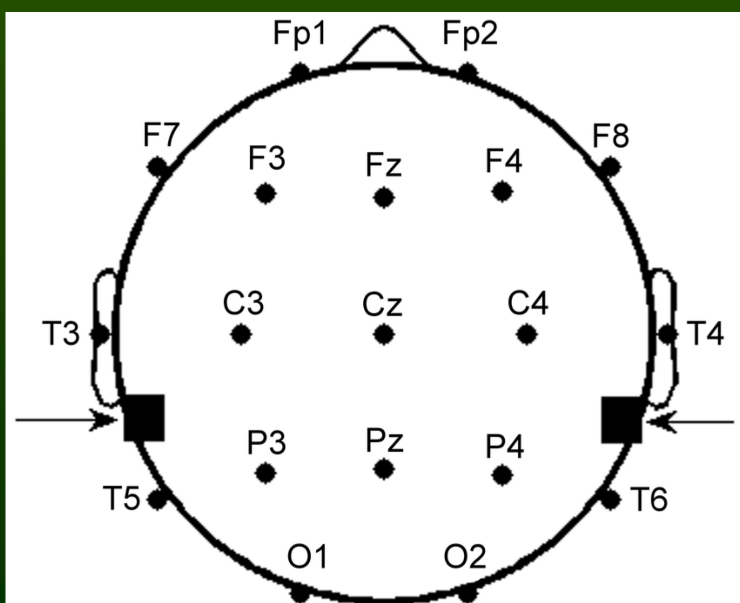
Schizophrenia avPP

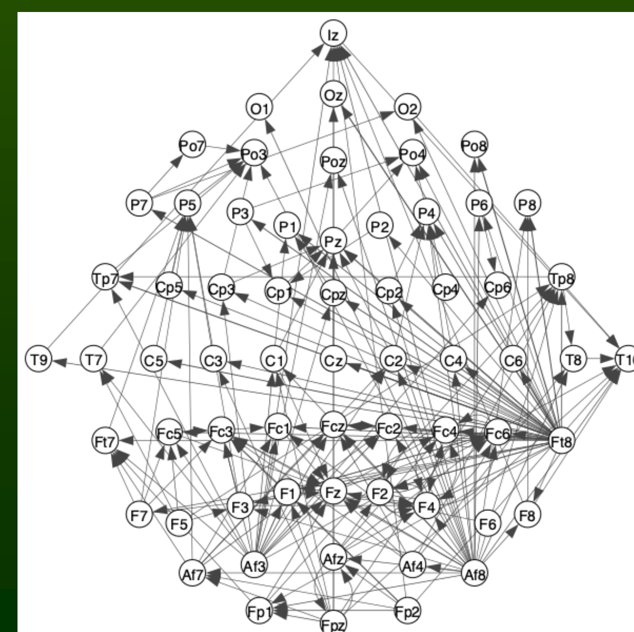
Simple method, useful in clinical settings.

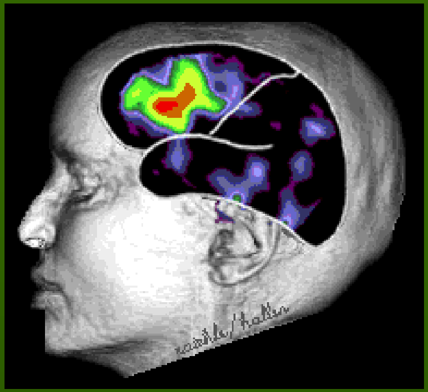
The power distribution maps are relatively stable for each individual, with clusters distinguishing schizophrenia patients vs. control subjects.
Electrode/frequency band selection based on linear SVM weights.
The top 10 combinations :

T4 α, F8 α, P3 β, C3 β, O2 α, Pz α, F8 θ, P4 θ, T4 θ, T3 θ

Improve: add dynamics + coherence + topological data analysis.







Brains – temporal aspects

Understanding brains: microstates

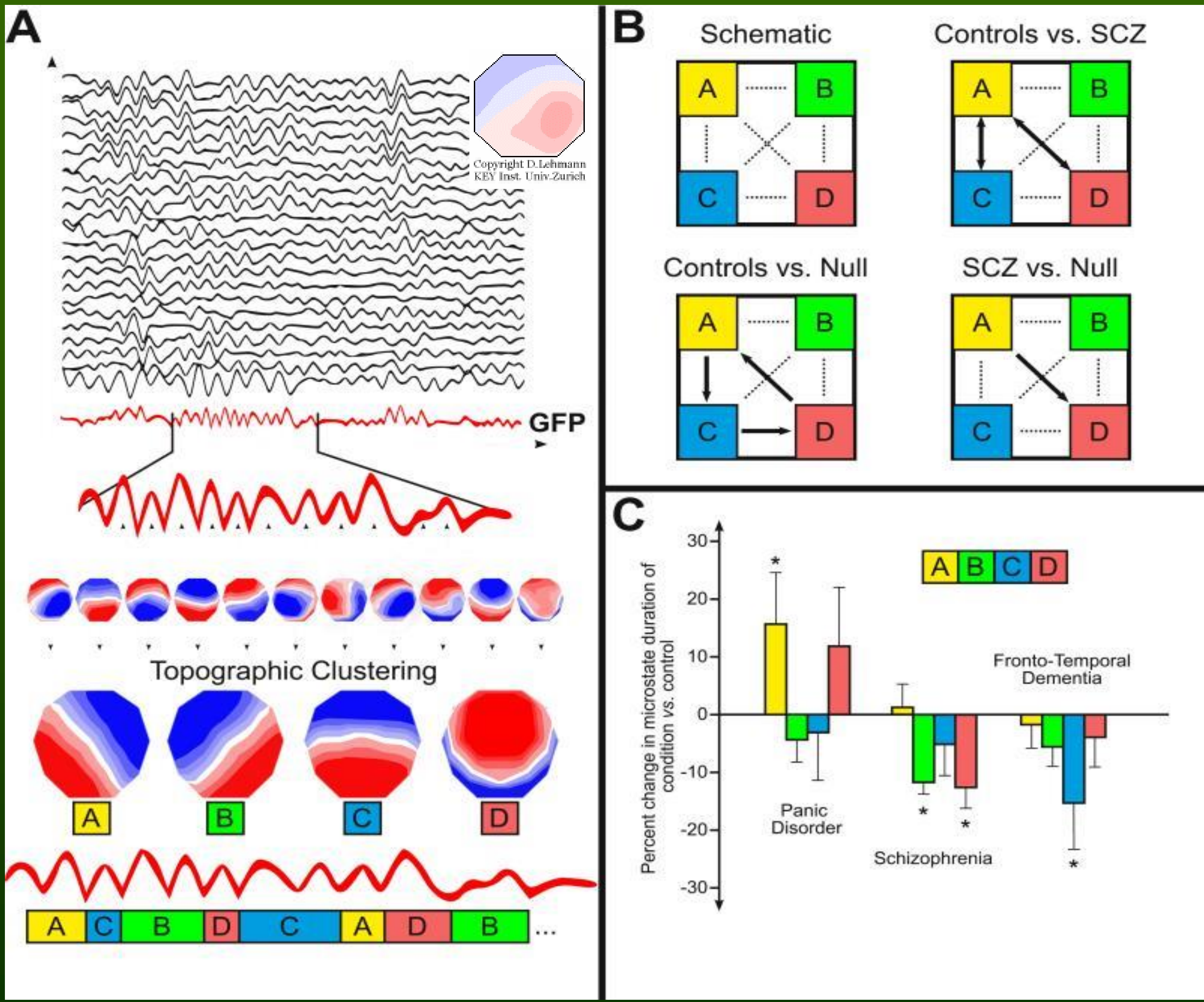
Global Field Power.
4-7 states, 60-150 ms.

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

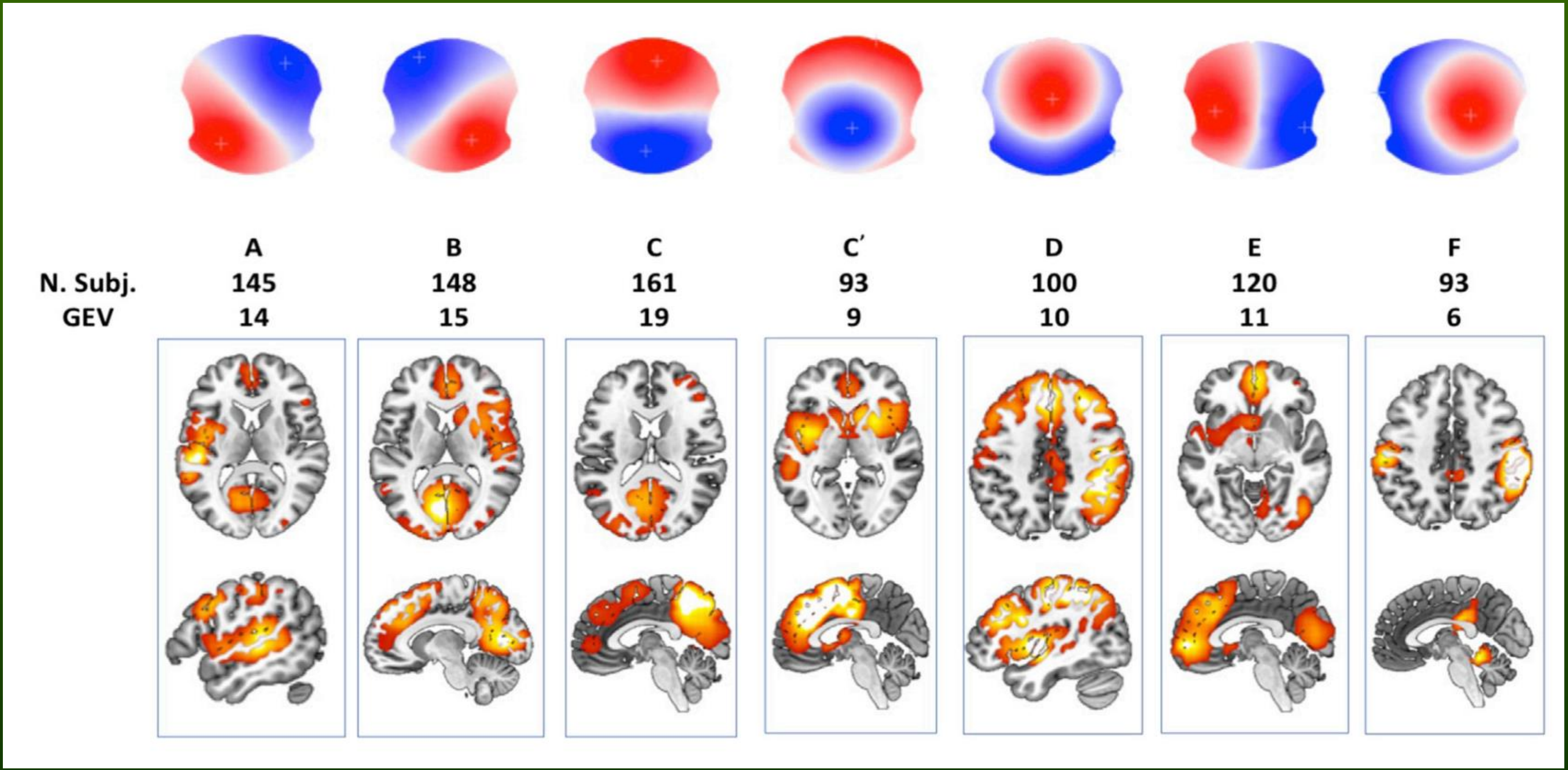
Symbolic dynamics: statistics of A-D symbol strings. Fuzzy Symbolic Dynamics (FSD) + visualizations.

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

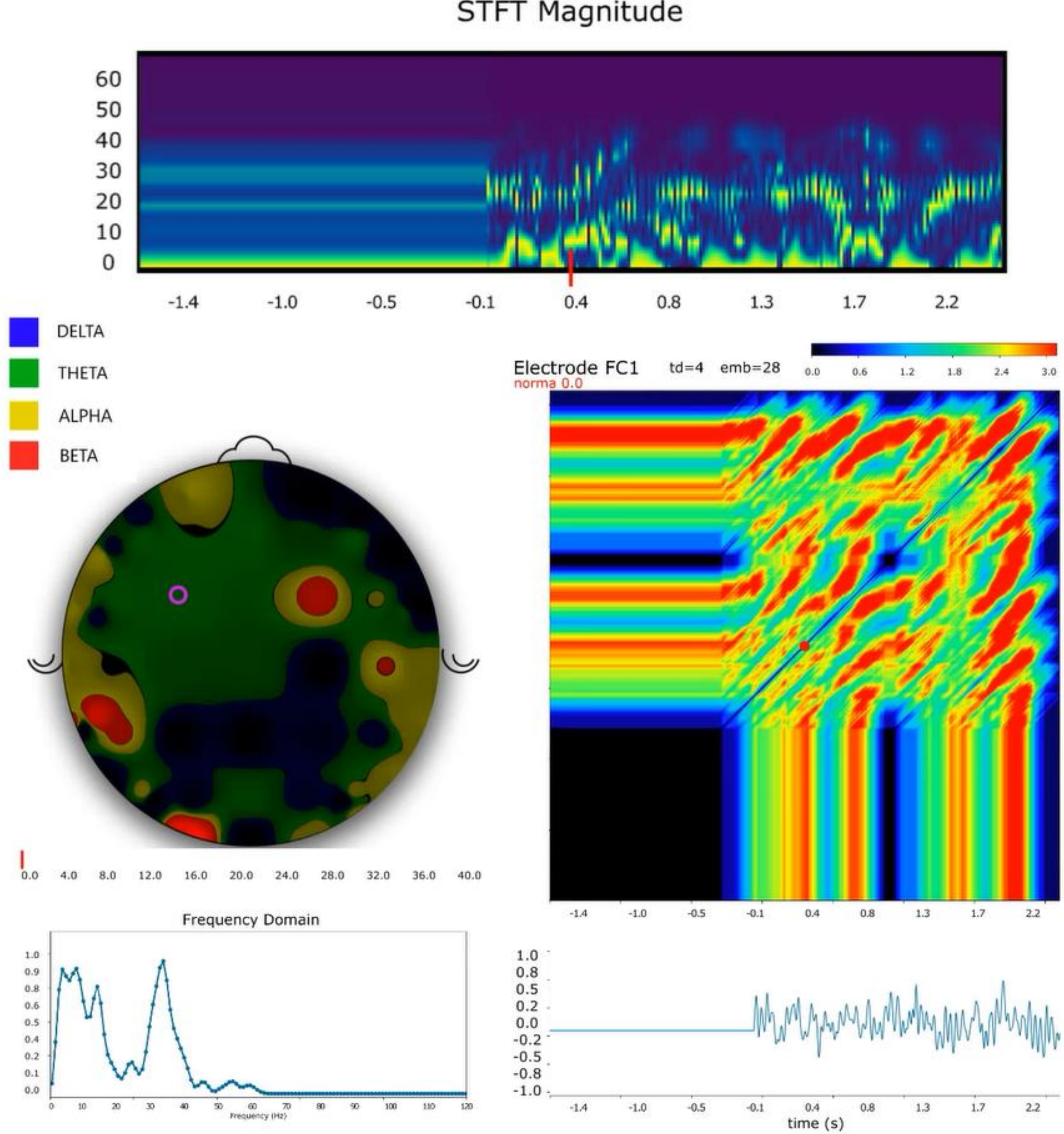
Dobosz K, Duch W. (2010). Neural Networks, 23(4), 487–496.



Microstates and their sources



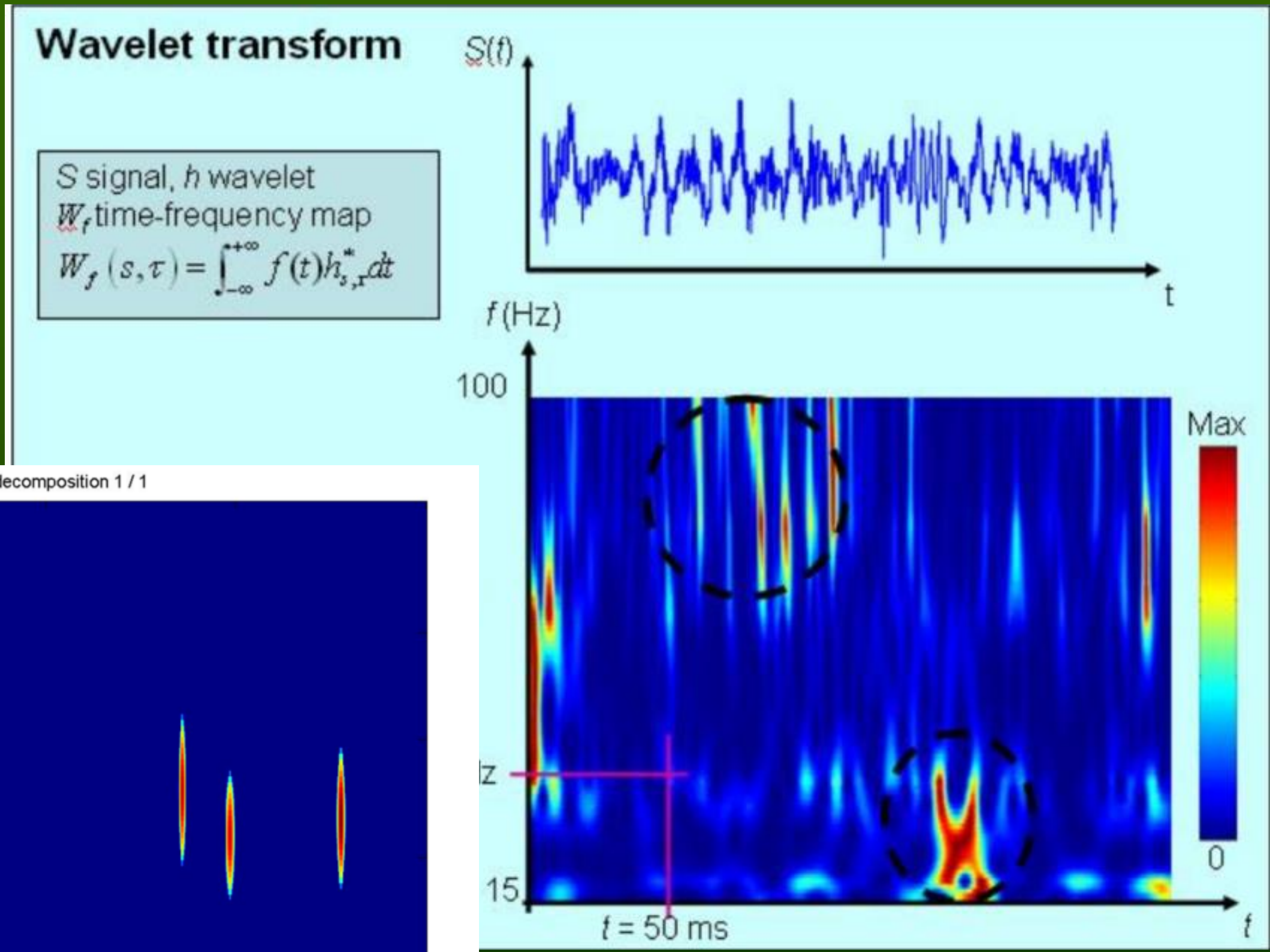
Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593.
Ewa Ratajczak, PhD thesis "Microstate neurodynamics in HRV biofeedback“ (2022)

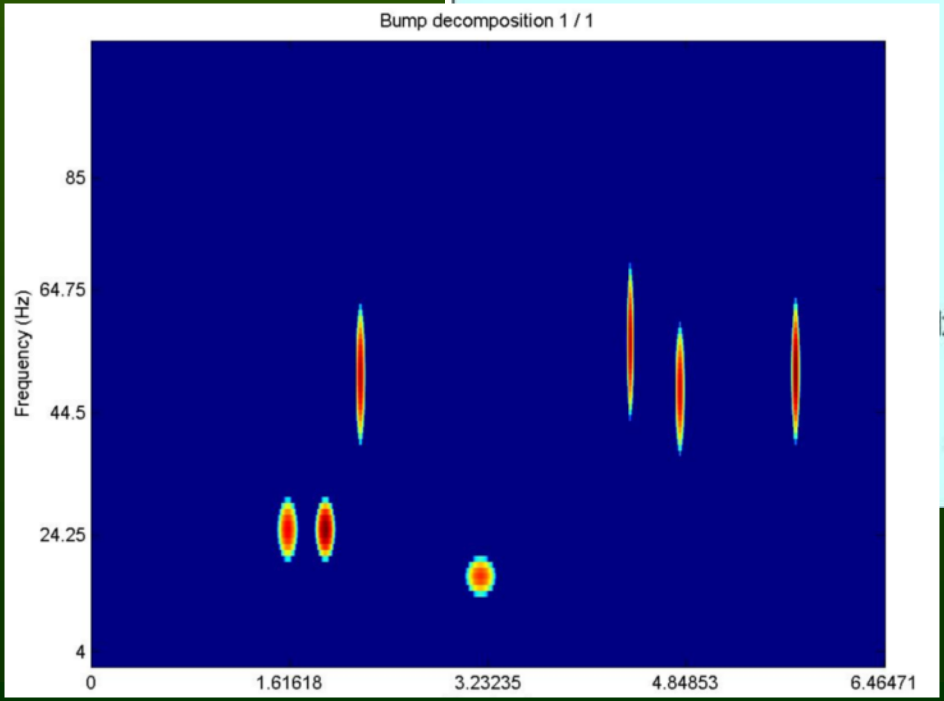

STFT Magnitude
60
50
40
30
20
10
0
-1.4
-1.0
-0.5
-0.1
0.4
0.8
1.3
1.7
2.2
DELTA
THETA
ALPHA
BETA
Electrode FC1
td=4
emb=28
norma 0.0
0.0
0.6
1.2
1.8
2.4
3.0
0.0
4.0
8.0
12.0
16.0
20.0
24.0
28.0
32.0
36.0
40.0
Frequency Domain
1.0
0.9
0.8
0.6
0.5
0.4
0.2
0.1
0.0
Frequency (Hz)
0.5
0.2
0.0
-0.2
-0.5
-0.8
-1.0
time (s)

Brains – spatiotemporal aspects

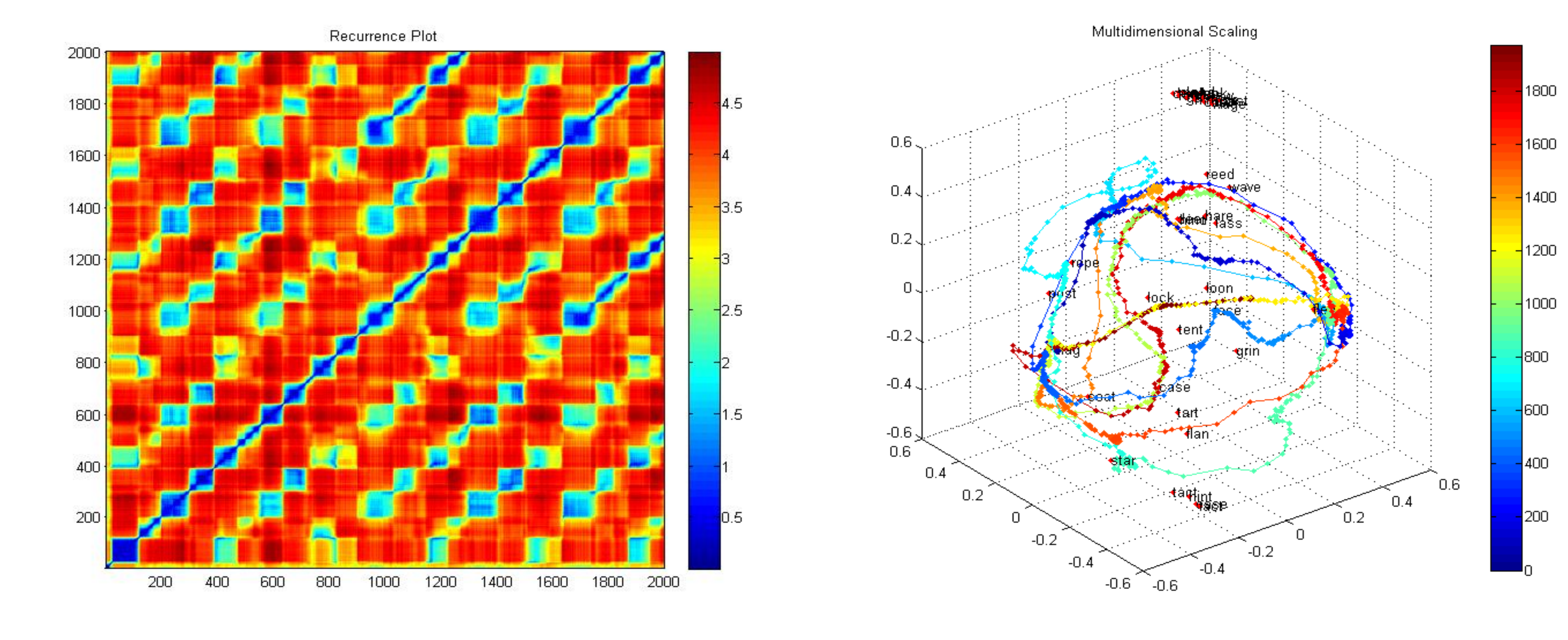
t/f rep and bumps

High frequency intermittent signals, and low beta strong activation, ECoG data, BCI Competition III . Msc thesis of M Szupke (2011), using EEGLab.





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 ...

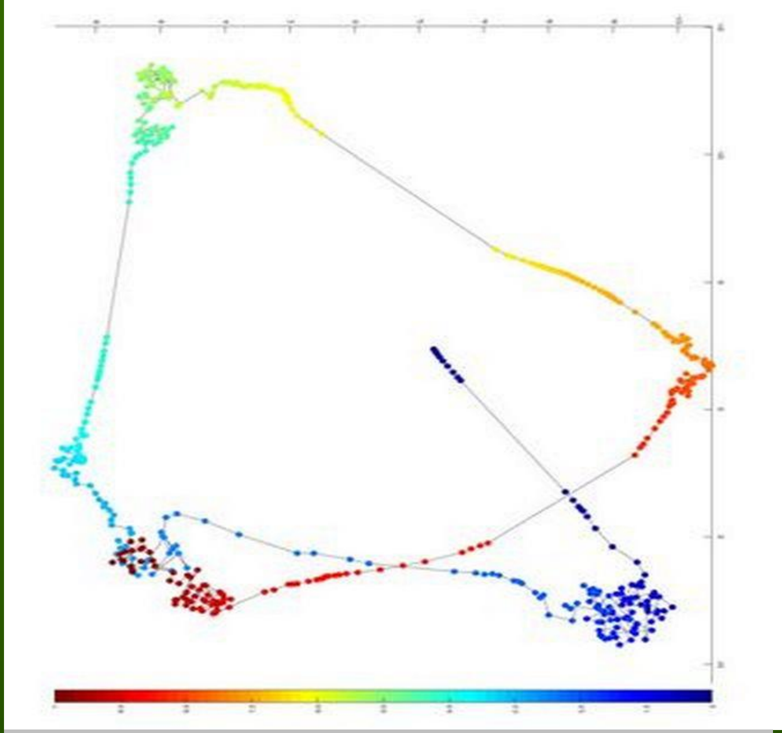
Trajectories

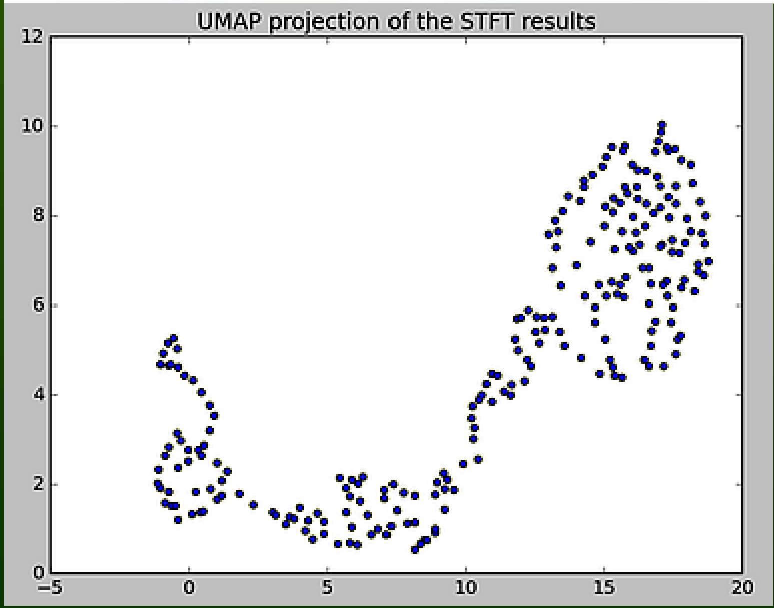
Can we characterize attractor states of the brain using EEG data?

tSNE for simulated attractor network, color=time, each dot represents 140 ROIs. Large and small attractor basins, large clusters = long trapping time, fast transitions between some states, Recurrence near the end.

UMAP STFT visualization of real EEG data, single channels/sources.

Some transitions and clusterization, but several subnetworks with individual trajectories (working memory patterns) with separate trajectories (work in progress).

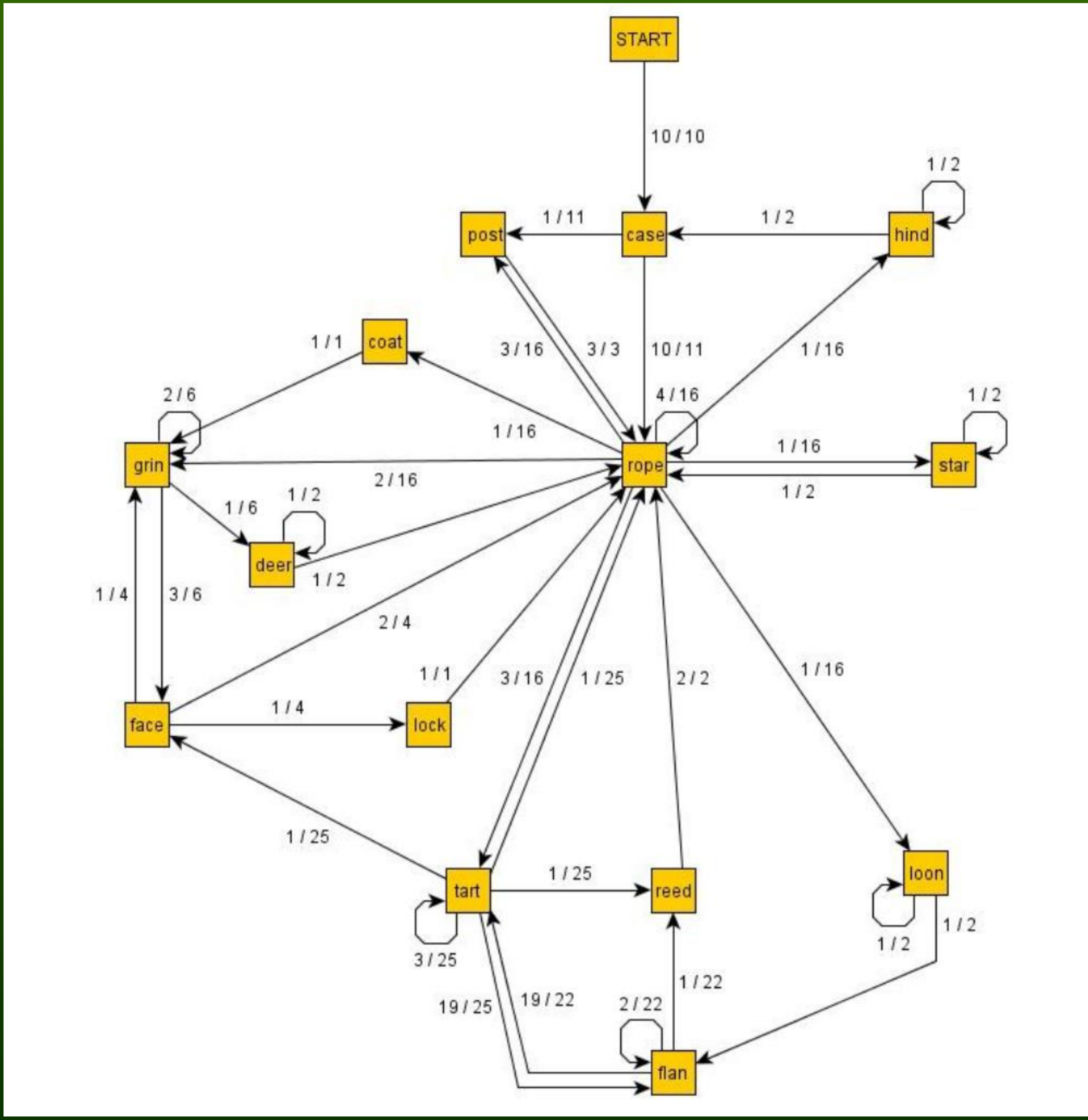




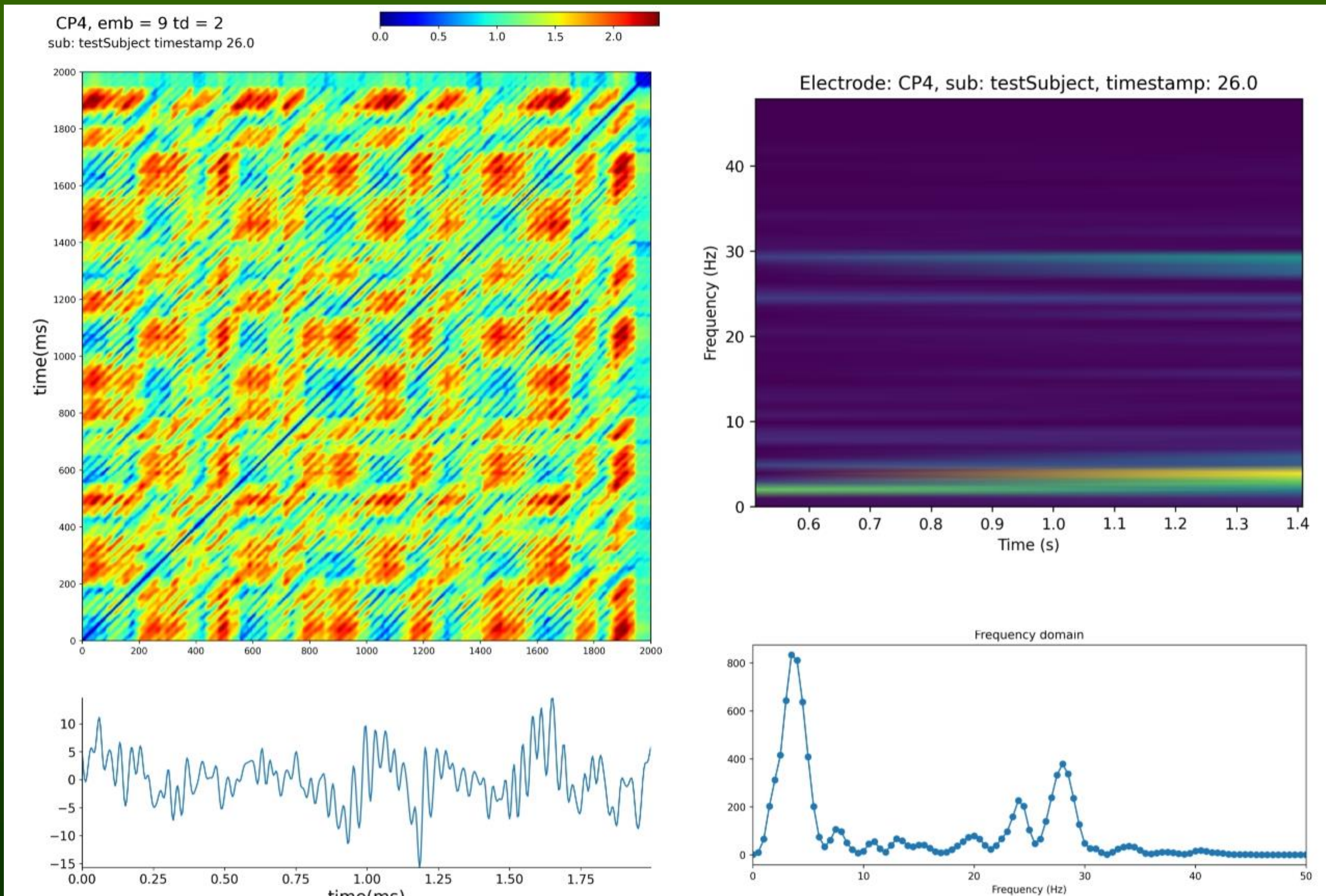
Multiple starts from the same word lead to different trajectories. Calculate transition probabilities between metastable states from frequency of transitions.

Why such transitions?

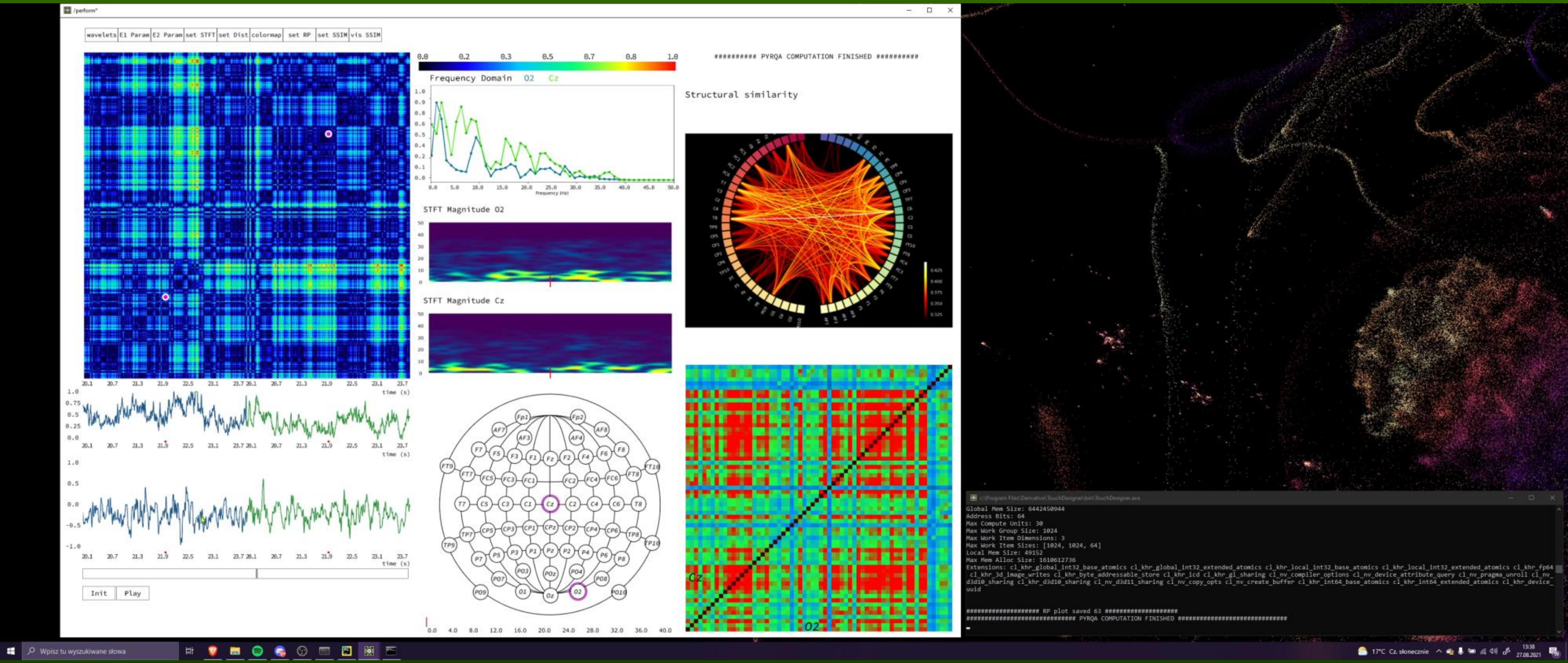
Linked state have patterns sharing few features, that recruit less active, but strongly connected neurons, and relax those currently active, making the previous state inaccessible for some time (refractory period).



Representations



STFT EEG in real time



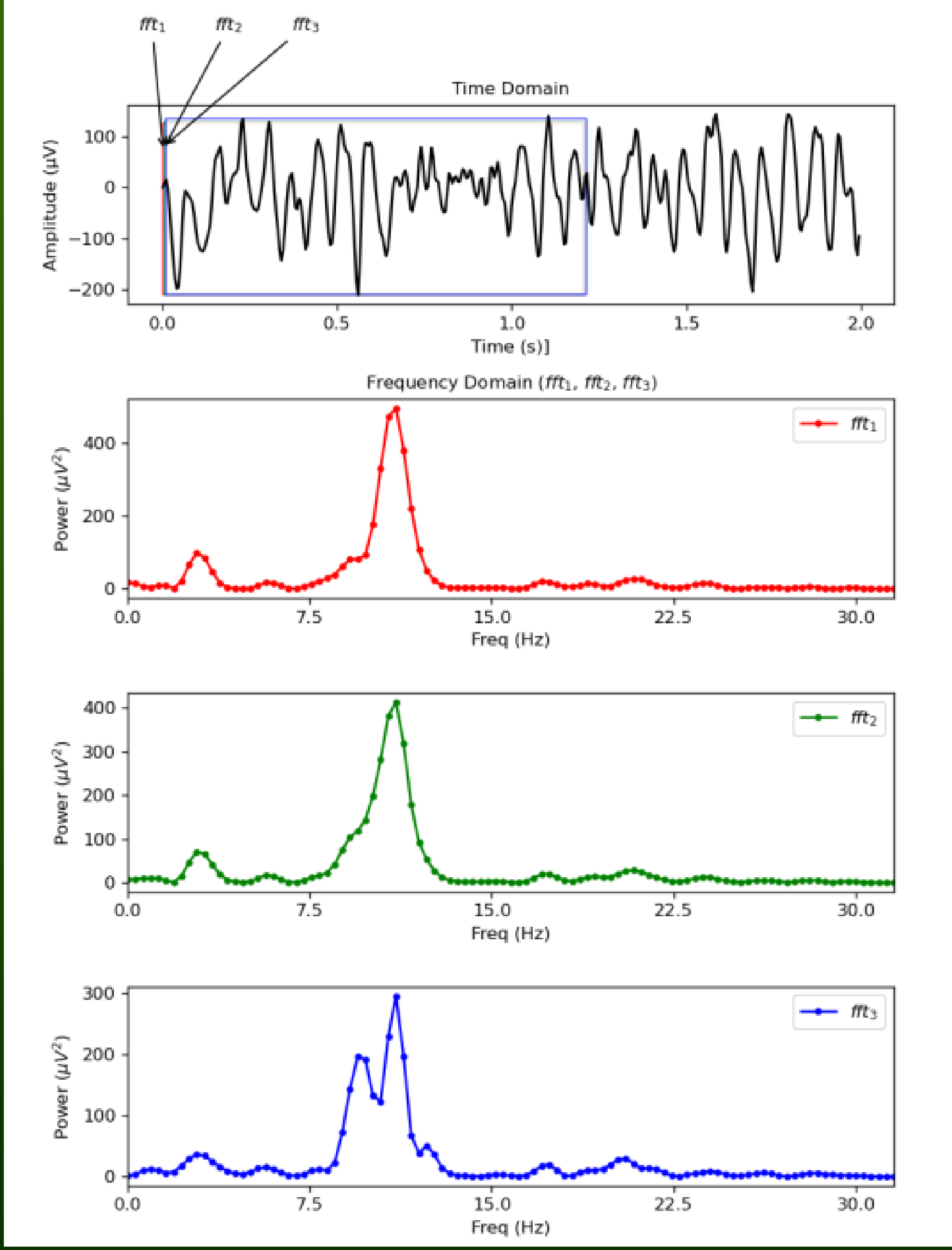
EEG data, 128 channels, recursion graphs, power spectrum for two electrodes, information flow and correlations between brain regions.
BrainPulse (in development, Łukasz Furman).

Labeling states

Example of STFT vectors, time windows ~ 1.5-sec, showing a shift and split of the α peak frequency after 200 ms. O1 electrode (occipital area), eyes closed.

Compare spectra S_1, S_2: many types of similarity measures may be used. Which channels have similar spectra? How long they are metastable (trapping time)? How frequent are transitions? Recurrence to the same state?

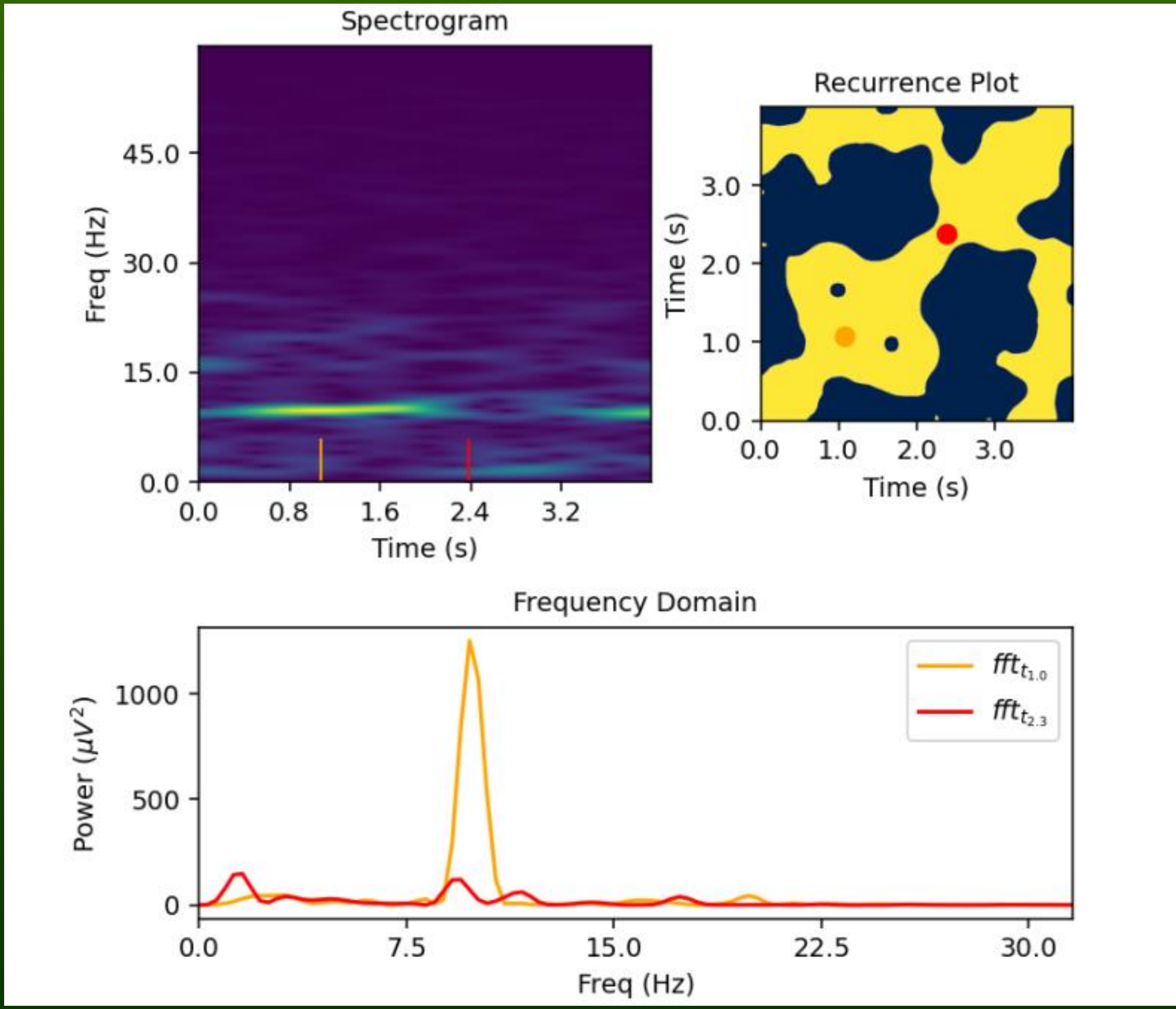
Ł. Furman, W. Duch, L. Minati, K. Tołpa, Short-Time Fourier Transform and Embedding Method for Recurrence Quantification Analysis of EEG Time Series. The European Physical Journal Special Topics (2022, p. 1-15).



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.



RQA measures

RR, **recurrence rate**, density of recurrence points in a recurrence plot:

$$\mathrm{RR} = \frac{1}{N^2} \sum_{i,j=1}^{N} R(i,j).$$

percentage of recurrence points which form diagonal lines in the recurrence plot of minimal length ℓ_{min} or predictability of the dynamical system.

$$\mathrm{DET} = \frac{\sum_{\ell=\ell_{\min}}^{N} \ell\, P(\ell)}{\sum_{\ell=1}^{N} \ell P(\ell)},$$

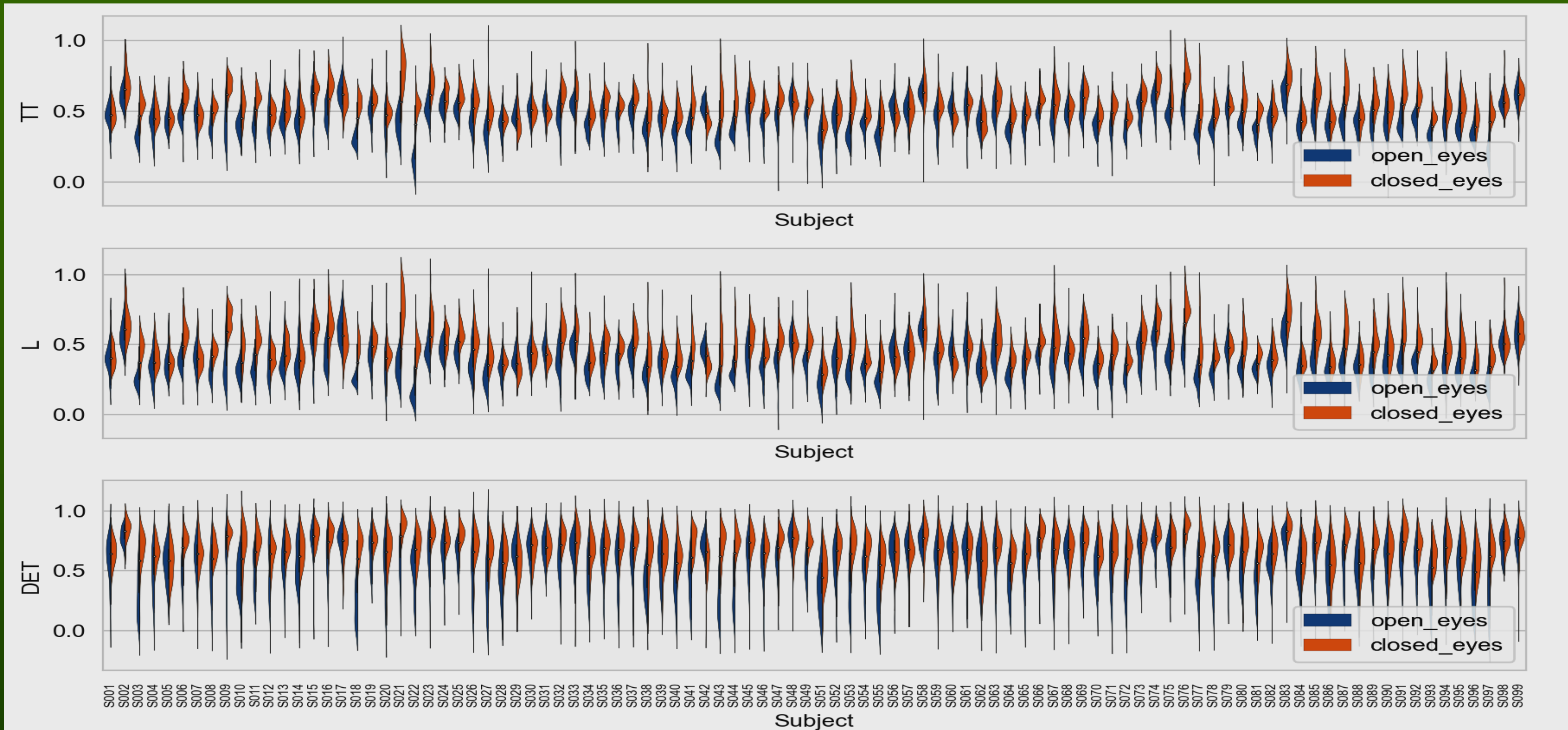
The averaged diagonal line length:

$$\mathrm{L} = \frac{\sum_{\ell=\ell_{\min}}^{N} \ell\, P(\ell)}{\sum_{\ell=\ell_{\min}}^{N} P(\ell)}$$

Trapping time, measuring the average length of the vertical lines

$$TT = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=v_{\min}}^{N} P(v)}$$

RQA features for 64 electrodes



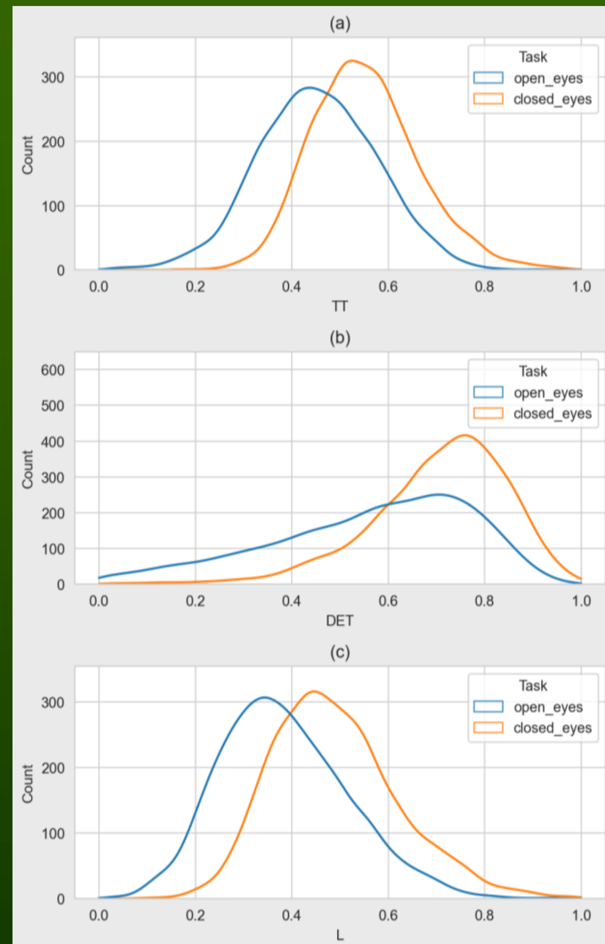
Distribution of trapping time, av. line length and determinism values for 64 electrodes shown for all 98 subjects. In some cases a single RQA feature allows for an easy separation of the two conditions. Variance is very different (focus? dreaming?), depending on the person. Linear SVM provides weights for (feature, electrode), facilitating selection of relevant EEG channels.

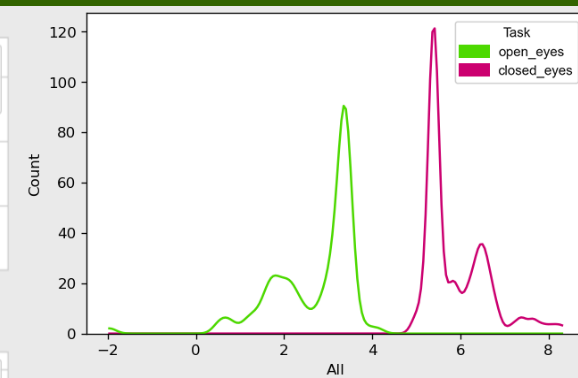
RQA features for 64 electrodes

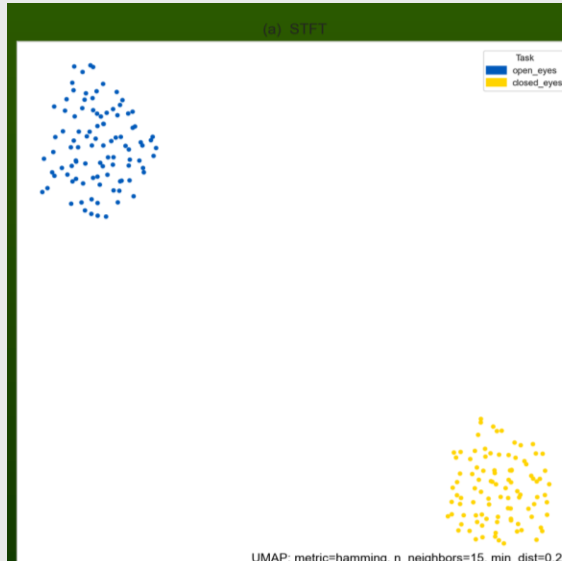
Histograms of the RQA features for all 98 subjects:
TT (trapping time),
DET (determinism),
L (average diagonal line length).

Histograms of the projection of 320 FS feature values (5 RQA features x 64 electrodes), for all subjects, LSVM projection, for all data.

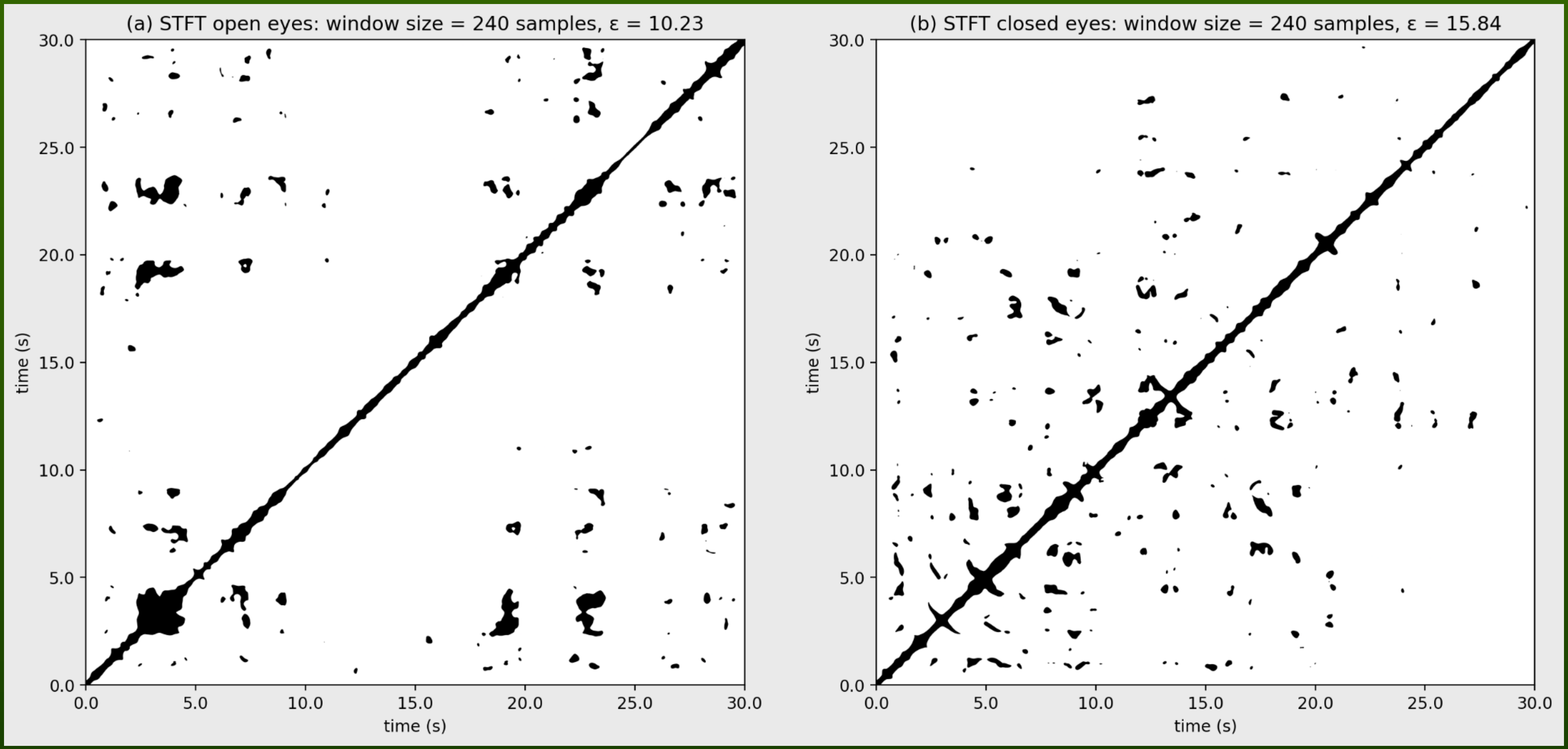
UMAP visualization of the 320-dimensional Z column vectors.







RPs, O1 electrode



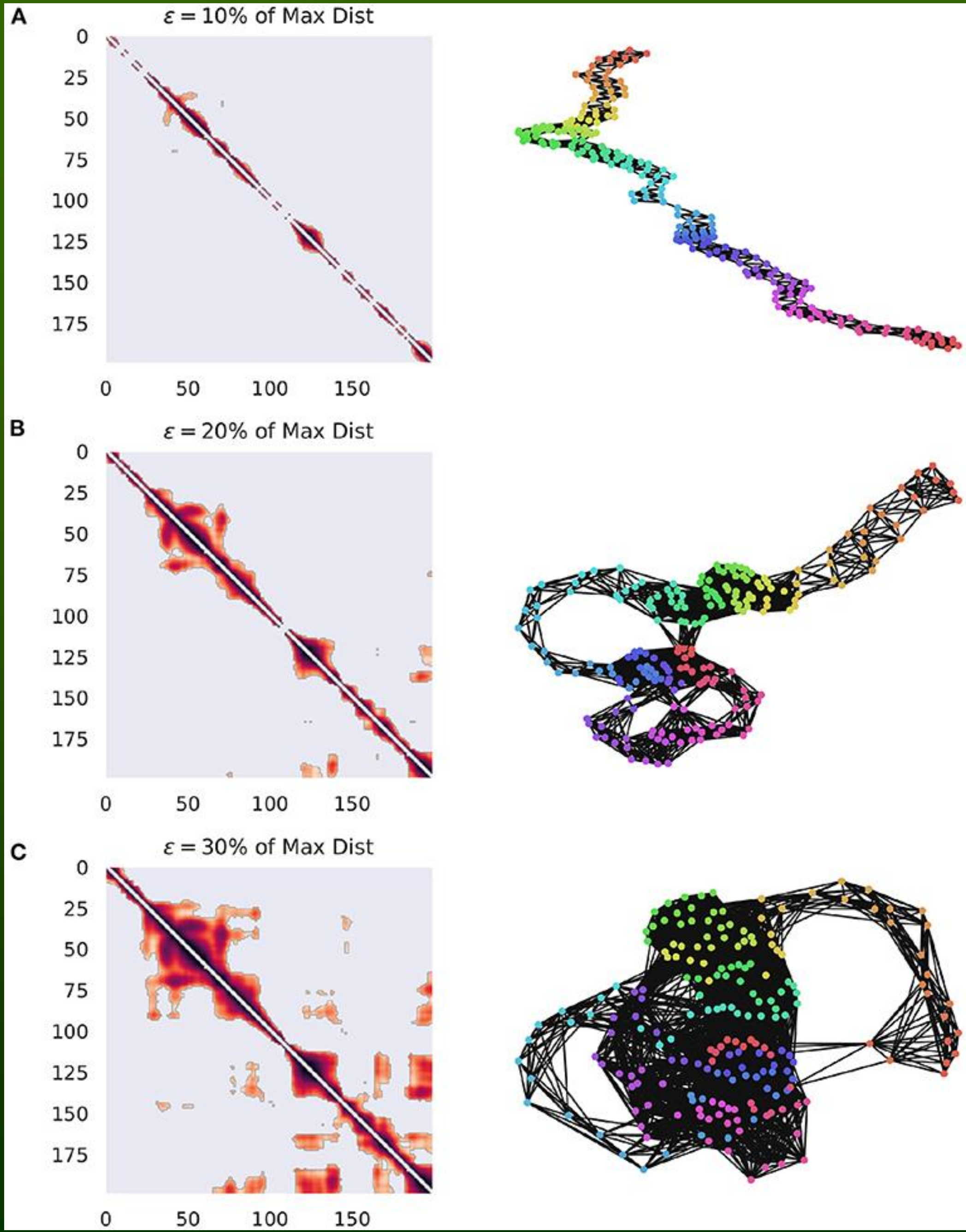
Example of recurrence plots, 30 s, electrode O1, subject S001.
Dark dots show distances inside small ε neighborhood.

TDA

TDA quantifies complex network topology graphs.
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.

Caputi et al. (2021). Promises and pitfalls of Topological Data Analysis for brain connectivity analysis. *NeuroImage*, *238*, 118245.

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



Labeling states

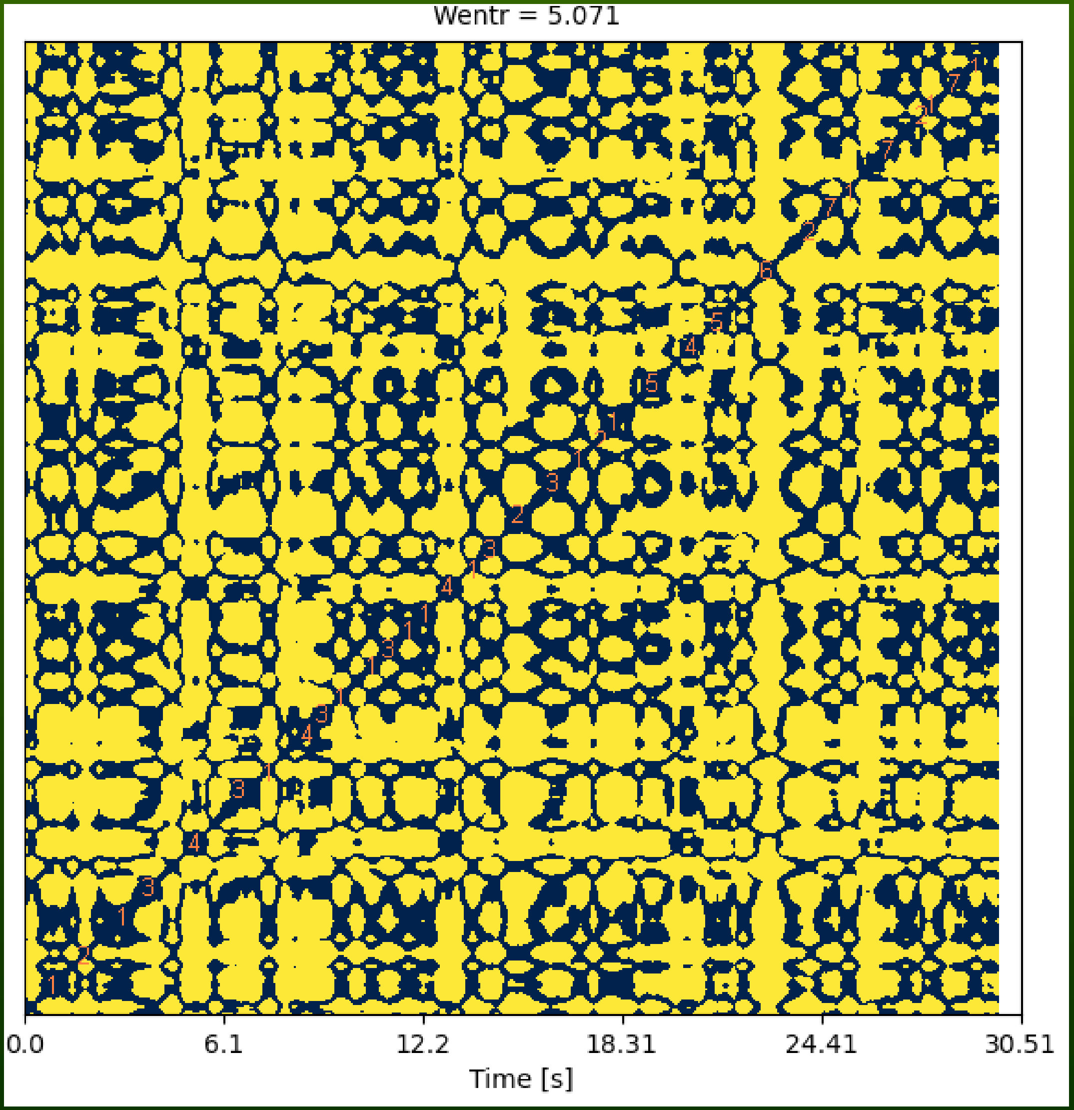
Automatic labeling of states and estimation of their recurrence may be important for biofeedback.

Metabolic costs of transitions between states may be important.

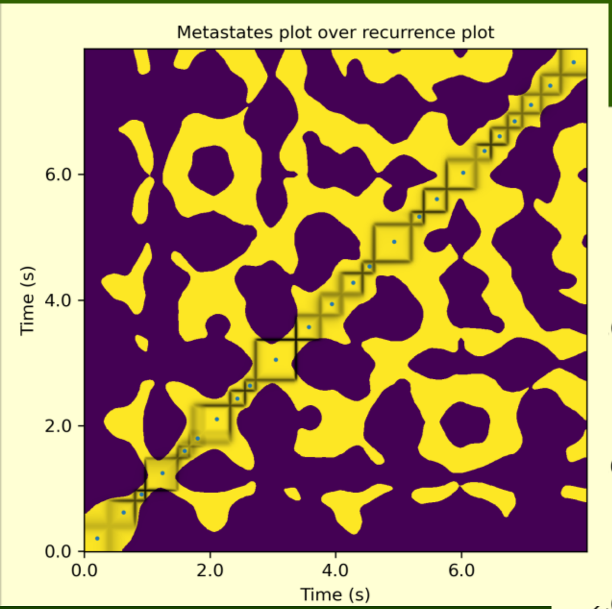
Ruminations? Pain states? How external stimuli influence this dynamics?

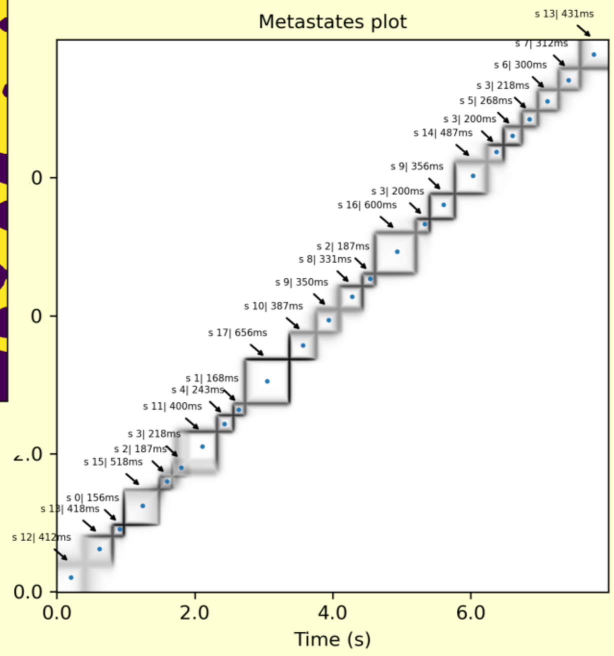
Needs automatic method for recognition of metastable, multivariate states.

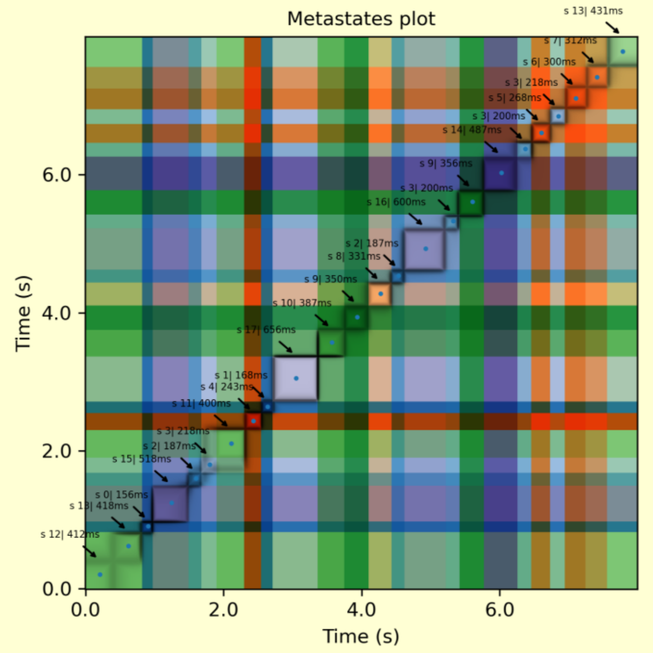
More precise than microstates.



Segmentation of states







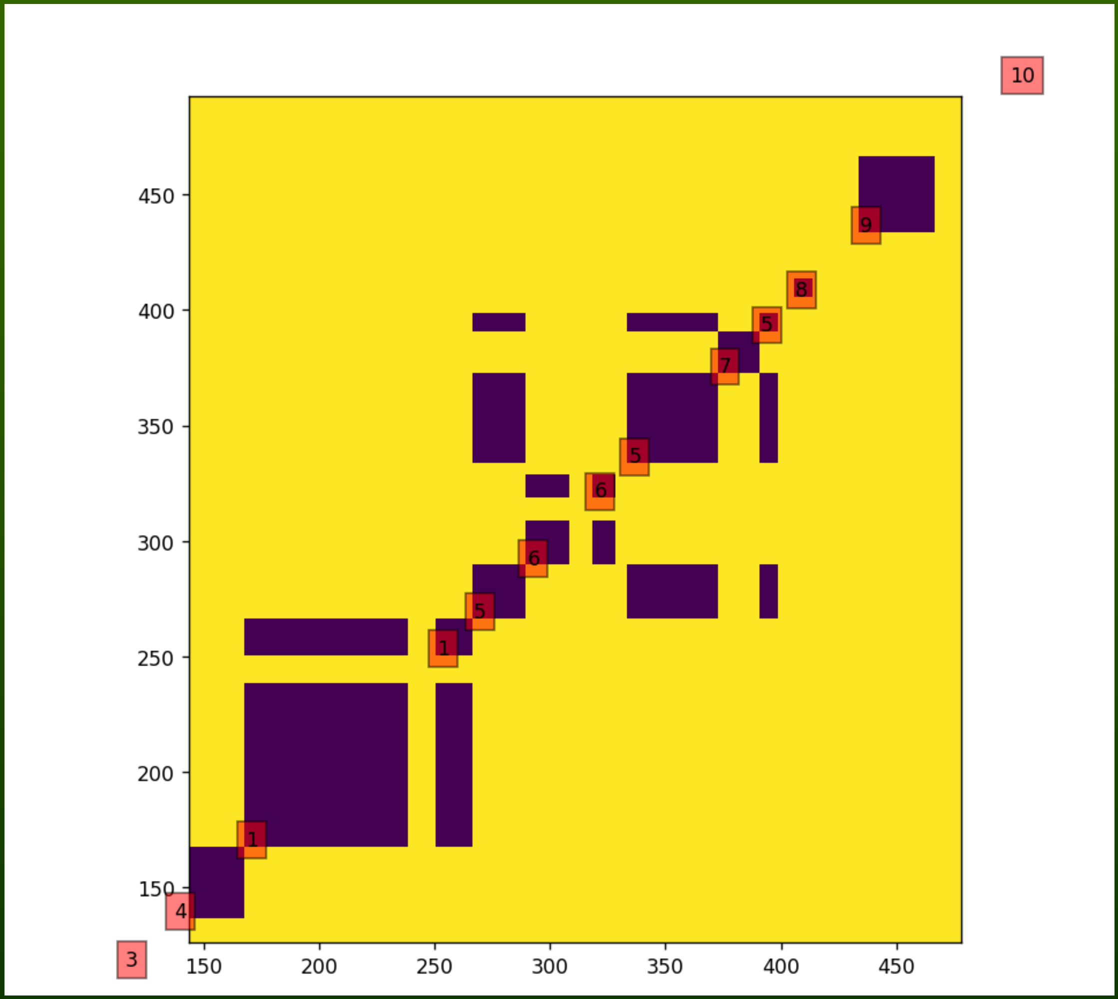
Labeling RPs

STFT rep, 1-50 Hz, represented by vectors X with 150 components.

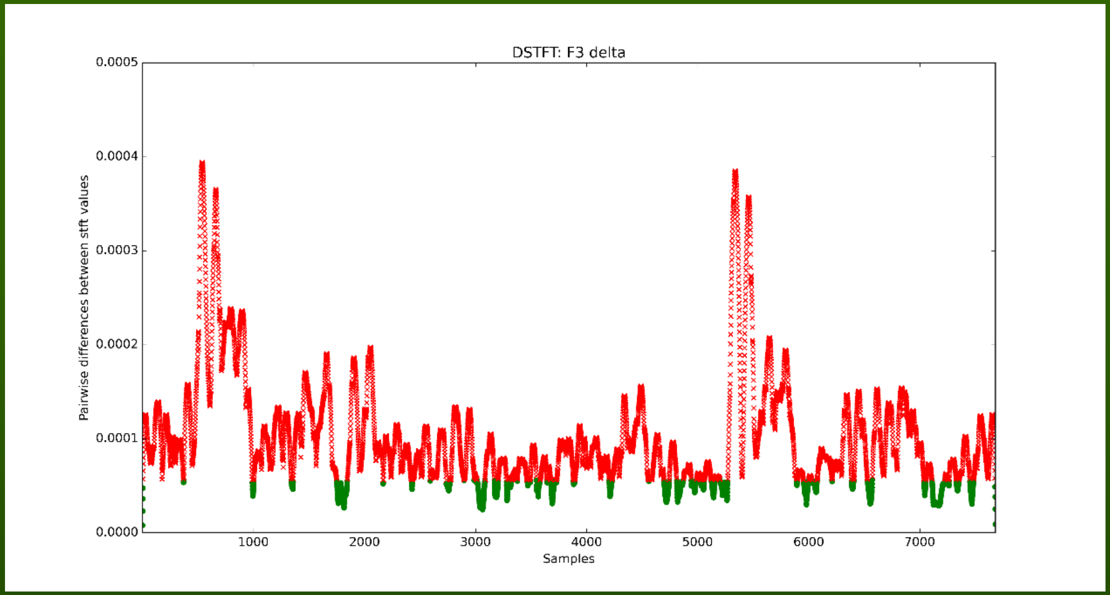
Create RP matrices.
Smooth/erode data.
Identify stable regions along the diagonal.
New state: no similar spectra in the past (row in upper part of the RP plot).

Problem: setting the threshold.

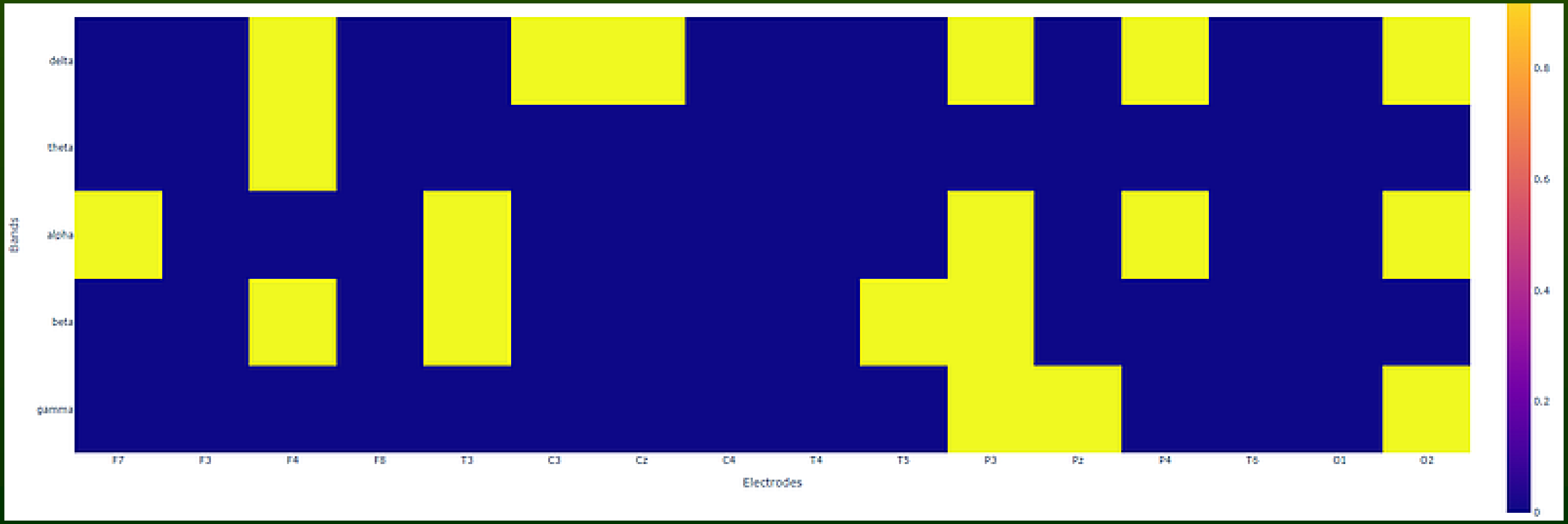
Compute power for individual states.



Labeling recurrent states

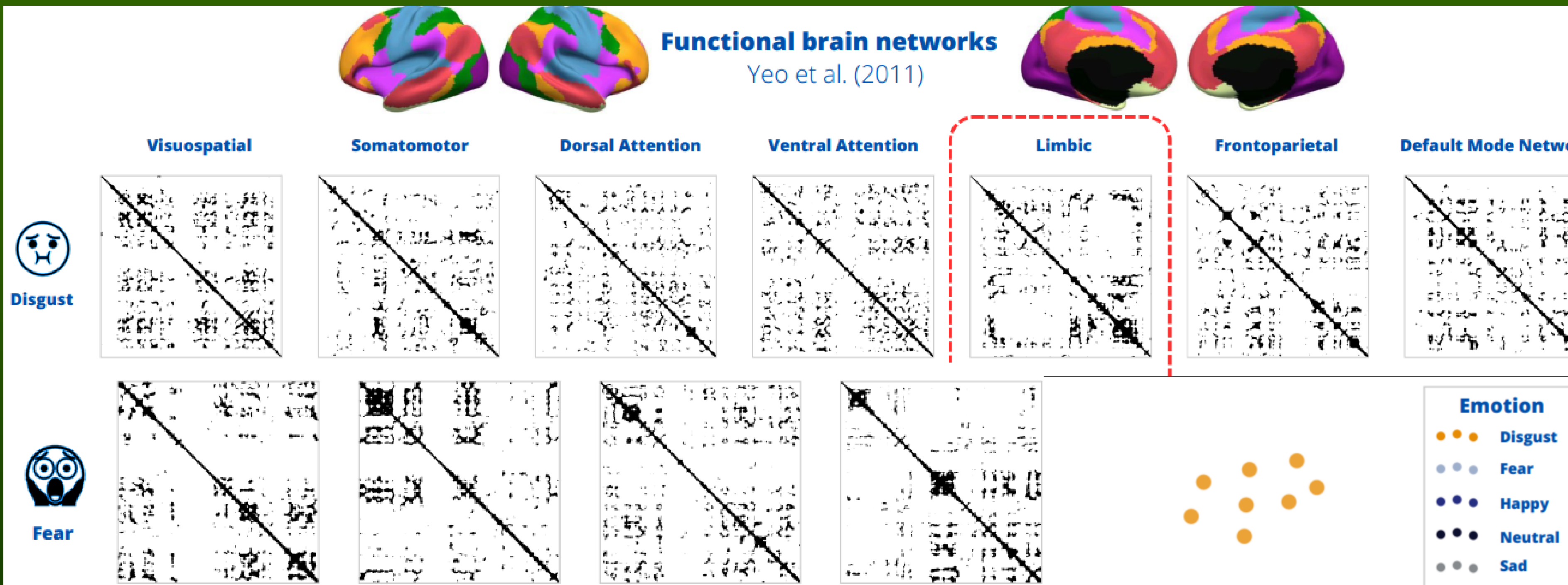


STFT rep, 1-50 Hz, represented by vectors X with 150 components.



Emotions from EEG

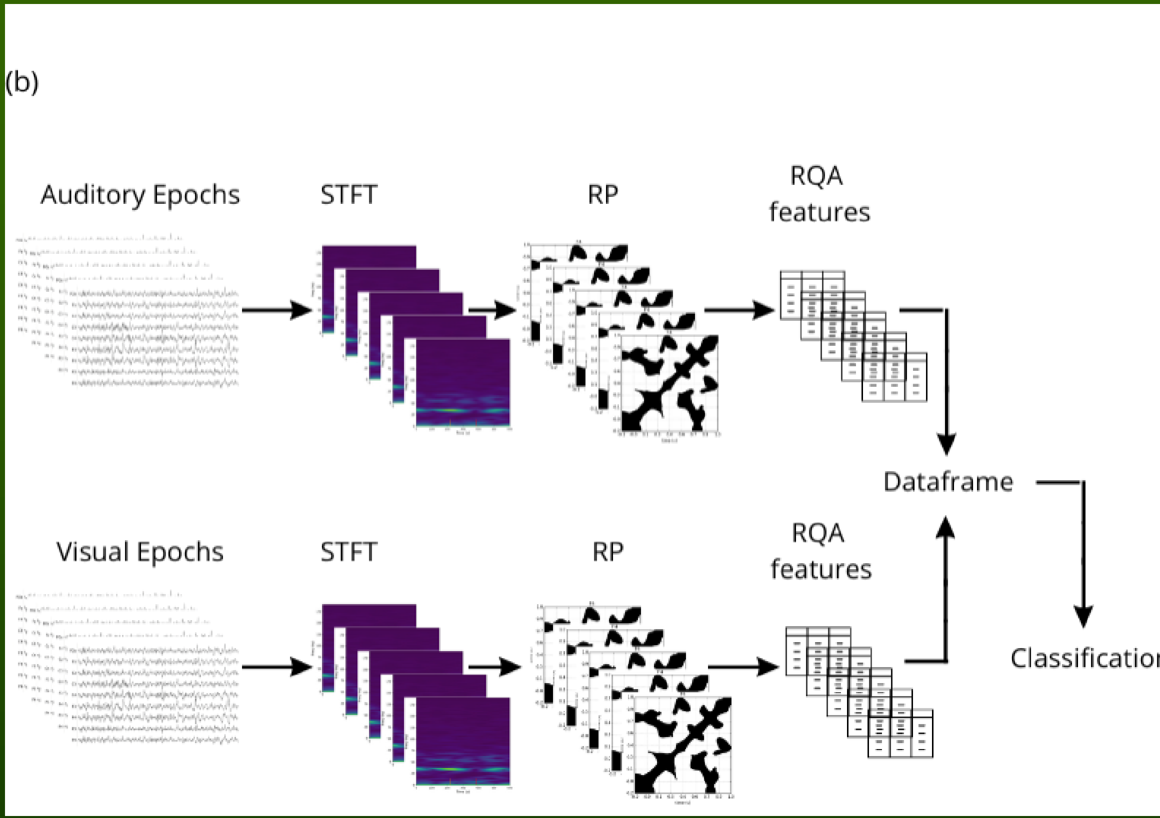
SEEDV data (Liu et al 2021), 62 channel EEG, 7 functional networks, 5 emotions.



Ł. Furman, K. Tołpa, L. Alexandre, W. Duch (2023). Recurrence analysis of brain neurodynamics. Nonlinear Data Analysis and Modeling: Advances, Applications, Perspectives 15–17.03.2023, Potsdam.

ERP classification pipeline

RQA classification pipeline for analysis of event-related auditory and visual potentials (ERPs).
STFT - Short-Time Fourier Transformation,
RP - Recurrence Plots,
RQA - Recurrence Quantification Analysis features.



Dereziński K, Tołpa K, Furman Ł, Rutkowski T.M, Duch W. (2022)
Time-frequency analysis combined with recurrence quantification for classification of onset of dementia using data from the oddball BCI paradigm.
Proc. of the 2022 Joint 12th Int. Conf. on Soft Computing and Intelligent Systems, and 23rd Int. Symposium on Advanced Intelligent Systems (SCIS/ISIS 2022), Ise-Shima, Mie, Japan. IEEE Press, p. 1-6.

Brains – future or hype?

Brain Robotic Interface

- Australia, UTS: VR to control robotic dogs using EEG.
  Dry graphene sensors, not as accurate as wet. Can it be useful?

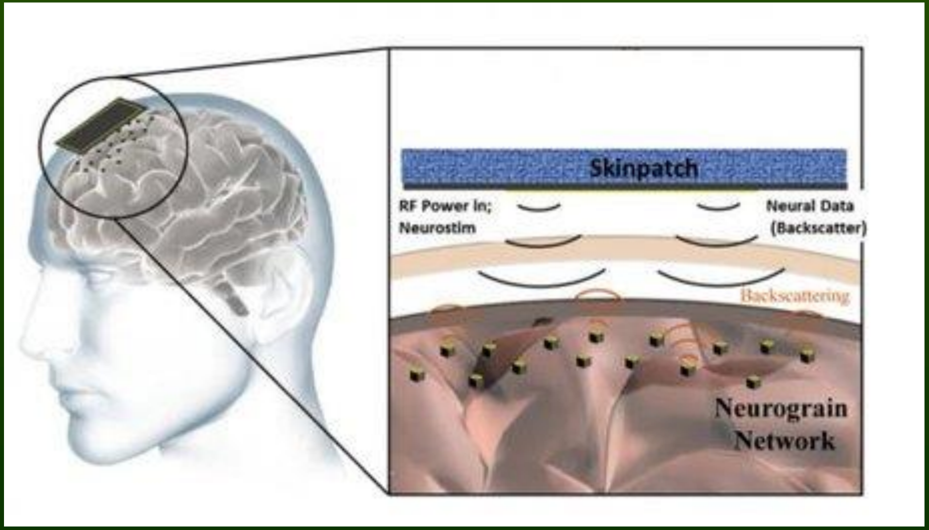
A million nanowires in the brain?

DARPA initiatives: **Neural Engineering System Design (NESD)** and other projects.

An interface that reads the impulses of 10^6 neurons, stimulates 10^5 neurons, simultaneously reads and stimulates 10^3 neurons.

DARPA awarded grants to research groups for projects under the program Electrical Prescriptions (ElectRx), whose aim is to develop BCBI systems modulating the activity of peripheral nerves for therapeutic purposes.

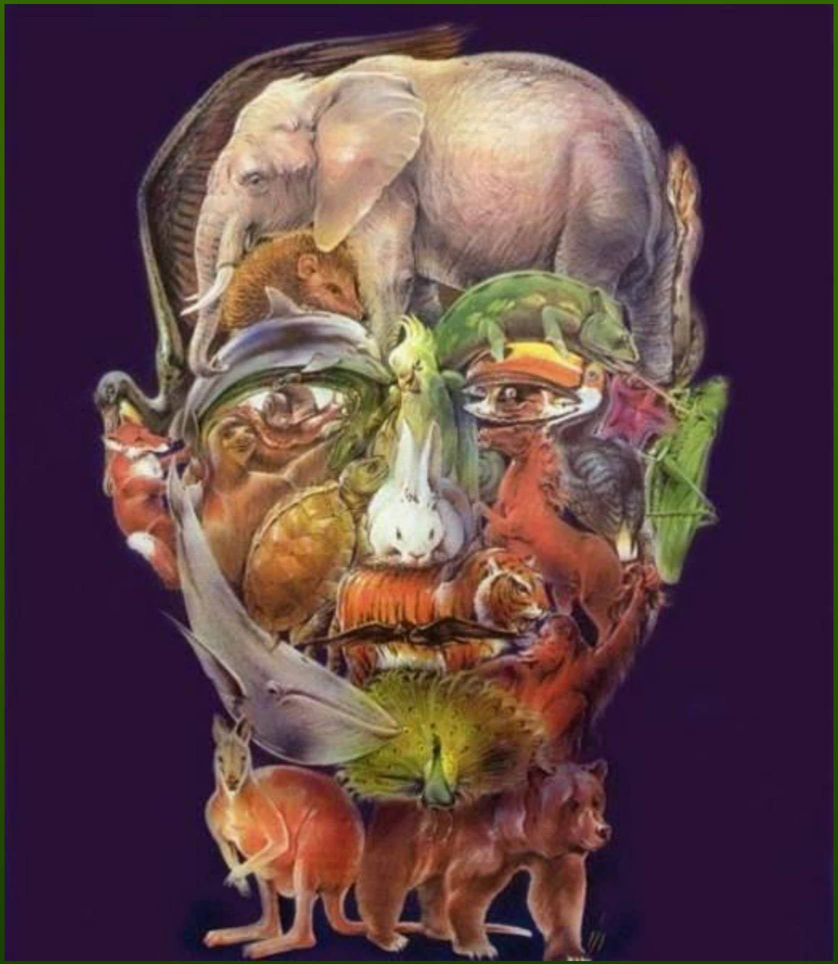
Neural dust – microscopic wireless sensors in the brain.
Elon Musk promised neuralink (neural lace). FDA refuses human trials.



Perspectives

- Optimization of brain processes is our biggest challenge! Medical diagnostics and closed loop systems for therapy of brain disorders are the driving forces.
- Simple robust methods have may be used in clinical applications. Asymptotic spatial distributions give remarkably high diagnostic accuracy.
- Spatial, temporal and structural aspects of brain signals should be integrated. Recurrence quantification analysis based on signal representation using Fourier spectra is a promising way.
- DecNef (spatial localization) and FCNef (connectivity) approaches used by rt-FMRI should be developed for EEG. Neurocognitive technologies will ultimately restore normal functions and optimize normal brain processes, but there is a lot of hype in the BCI field.
- AI is now inspired by high-level brain processes, but we need better methods for understanding brain activity. Large language models can do much more than generate language and images, multimodal models can include brain signals.

Intelligence?



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