Limits of spatial, temporal, and recurrence analysis of EEG signals

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2nd Int. Workshop on Complex Systems Science & Health Neuroscience, 25.09.2023

On the threshold of a dream …

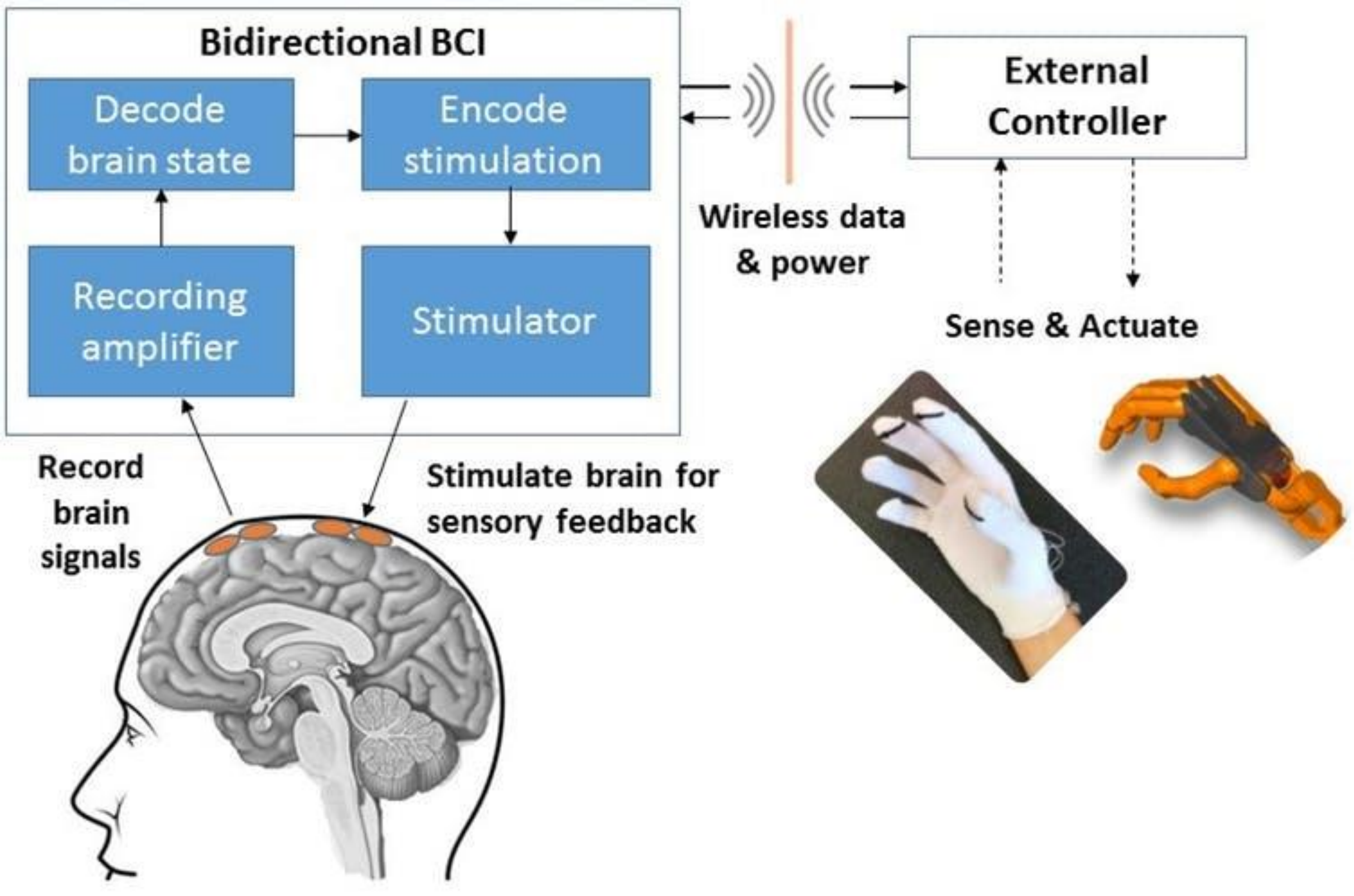
Motivation: optimize brain processes!

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 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).

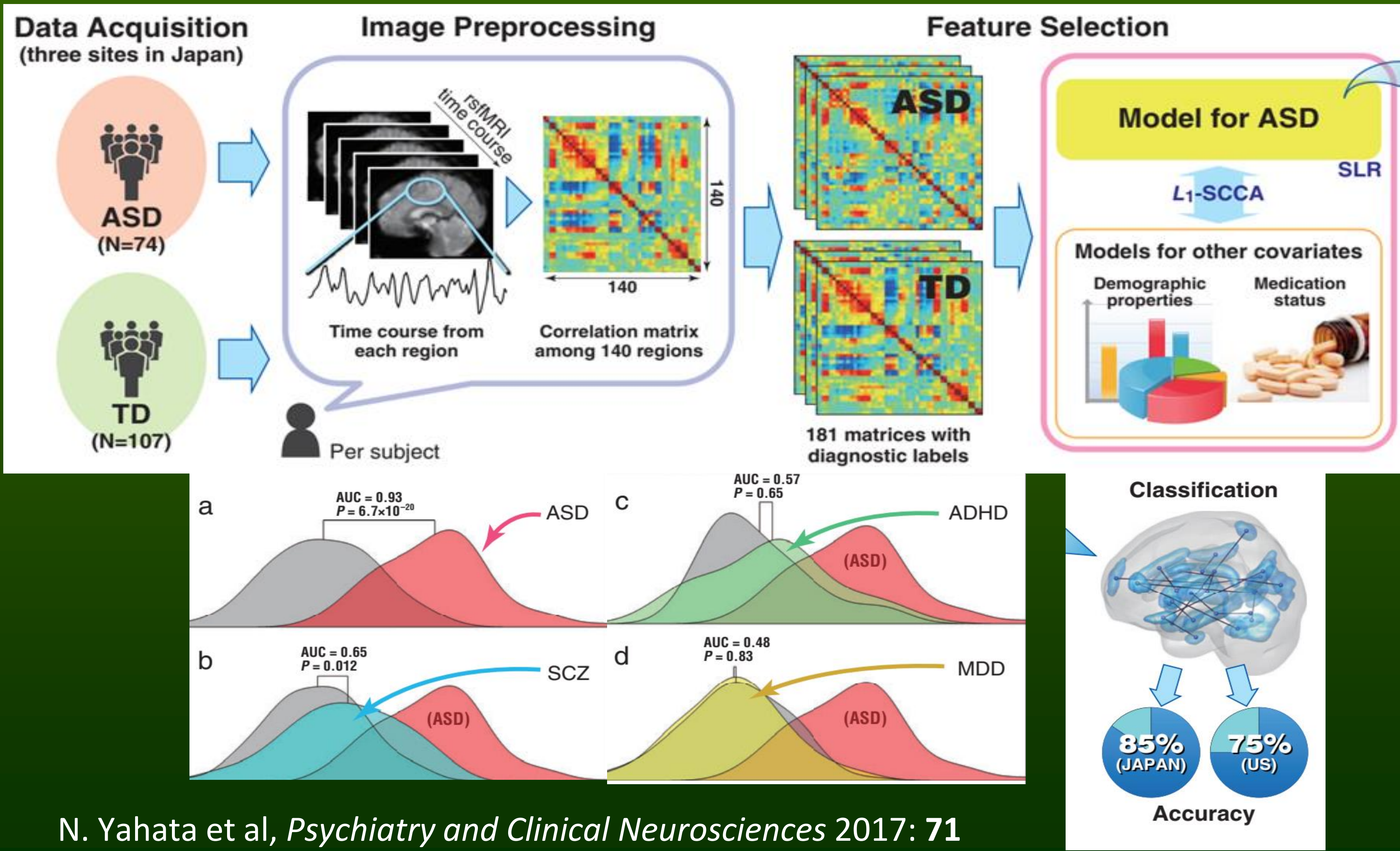
G-tec wireless NIRS/EEG on my head.

BCBI: Brain-Computer-Brain



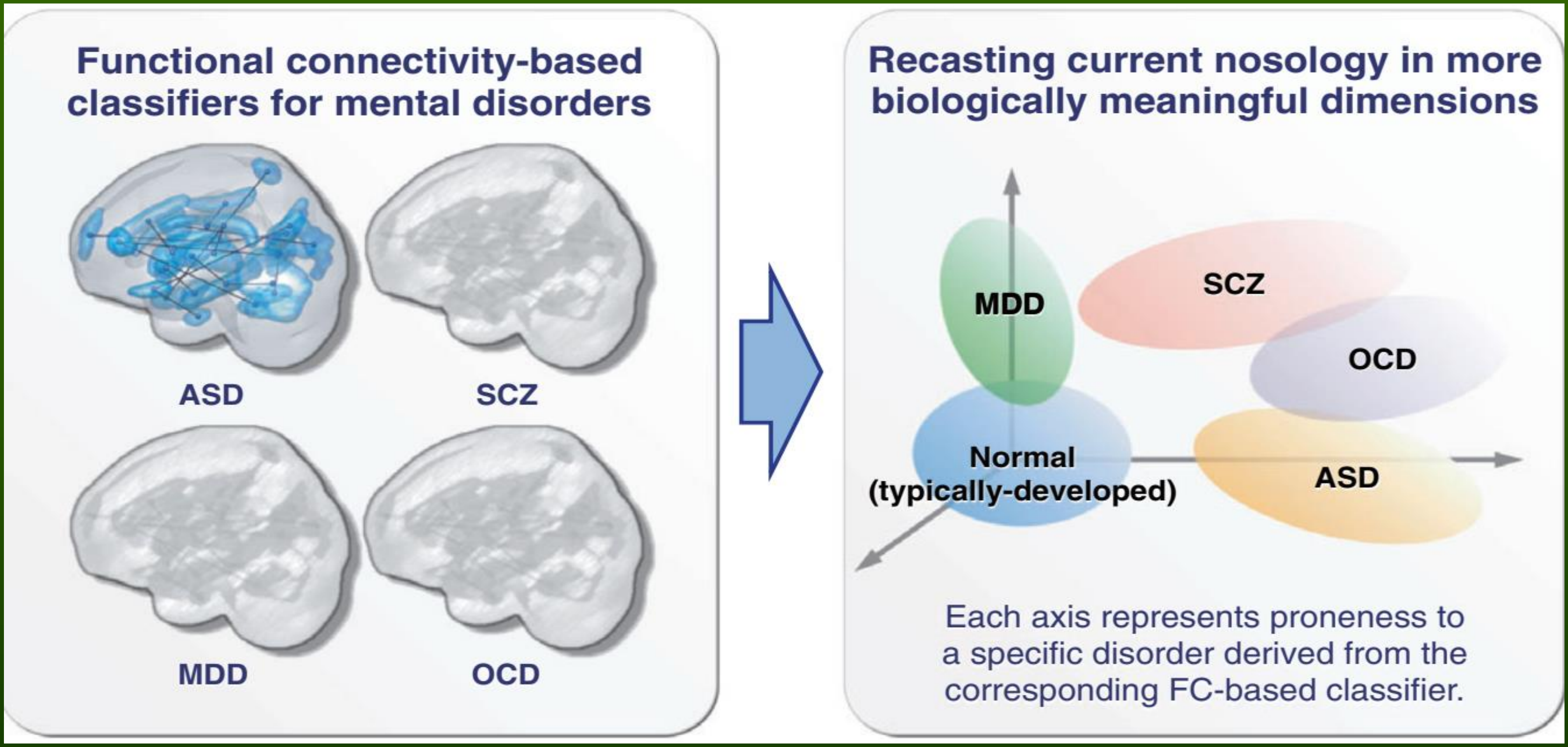
BCI + brain stimulation = BCBI – a closed loop through which the brain begins to restructure itself. The body can be replaced by signals in Virtual Reality.

Biomarkers from fMRI FCs



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

Problems with EEG

- Sophisticated EEG analysis is rarely used in clinical practice
- Reliable biomarkers for diagnosis of brain disorders are still unknown.

Why?

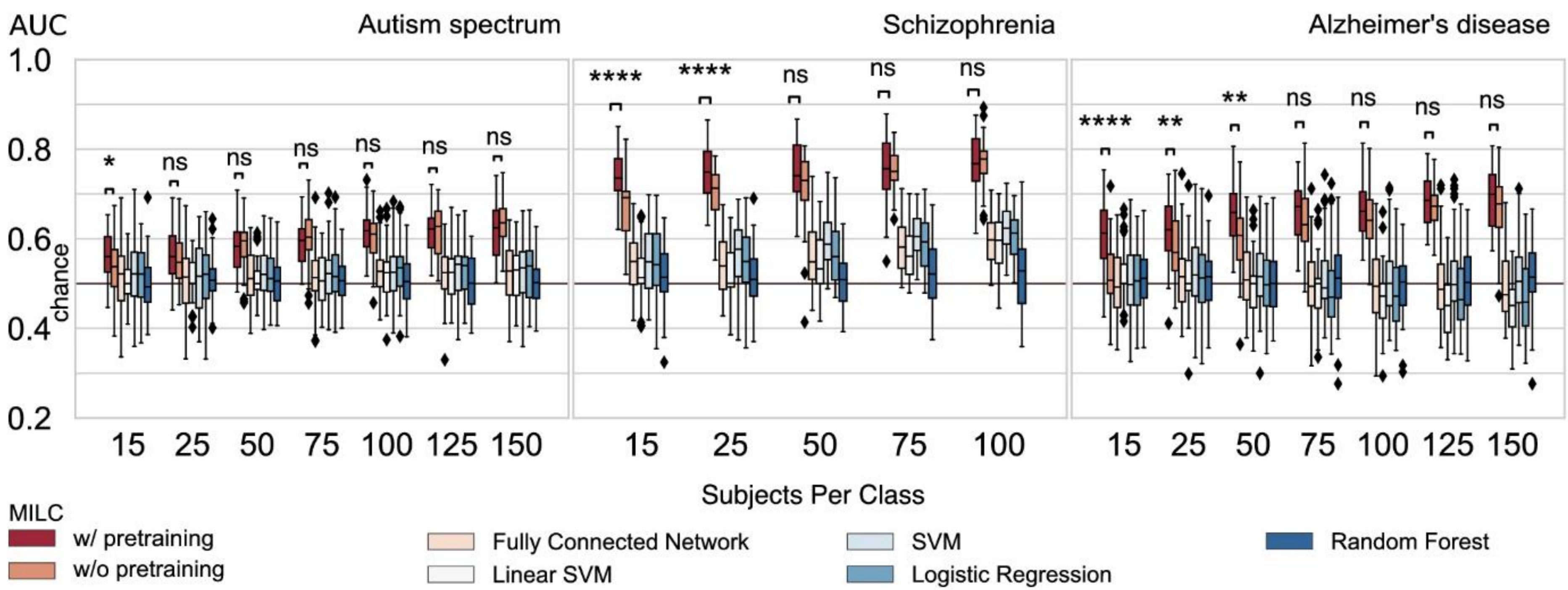
- Signals are non-stationary, even during short periods.
- Individual differences are quite large.
- Neurodynamics, especially in the resting state, depends on hundreds of confounds.
- Methods tested on a small datasets in real life do not generalize well. 100% accuracy on small datasets ~ little chance of being useful.

Why?

SFARI Human Gene Module contains 1140 genes related to ASD, and still new genes are added. Very large number of people had to be tested.

EEG diagnosis: without very large EEG databases of such heterogenic disorders as schizophrenia or MCI we shall not create good biomarkers.

MILC model



Rahman, … & Plis, S. M. (2022). Interpreting models interpreting brain dynamics. *Scientific Reports*, *12*(1), 12023.

Mutual information maximization between the whole sequence (~300 context embedding) and local windows (local embedding) from the same sequence.

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-dim signal dynamics, even in small datasets.

Our goals

Understand:

- Limits of spatial averaging of power in the narrow frequency bands.
- Limits of temporal characterization of brain processes using a large number of microstates.
- Combination of spatial, temporal and frequency data in recurrence analysis.
- Show big influence of rare cases feature selection done on the whole data and just strictly on training partitions in CV on classification results.

Tests were made on a typical, small EEG dataset of 45 schizophrenic adolescents + 39 controls. Several papers can get 100% accuracy on such datasets. Perfect accuracy is reached when features are selected on the whole data, before training a classifier (which is a common practice).

Feature selection on the cross-validation training partition does not allow to identify rare cases that should be inspected separately.

Recent work

Where to look for information in EEG?

- Spatial distribution of power.
- Temporal dynamics.
- Frequency.

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

Duch W, Tołpa K, Ratajczak E, Hajnowski M, Furman Ł, Alexandre L.A.

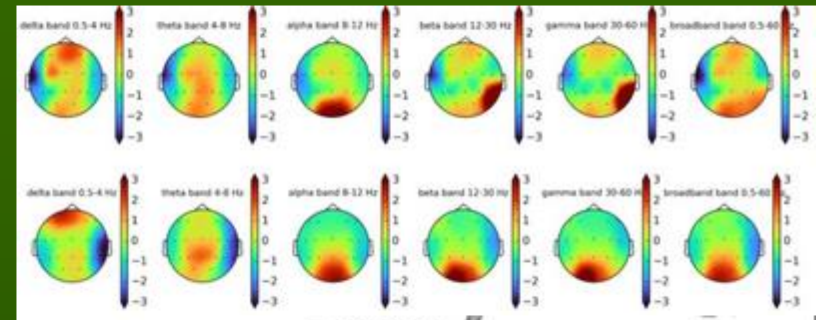
Asymptotic spatiotemporal averaging of the power of EEG signals for schizophrenia diagnostics.

2023 International Conference on Neural Information Processing (ICONIP2023), Changsha, China

Brain fingerprinting

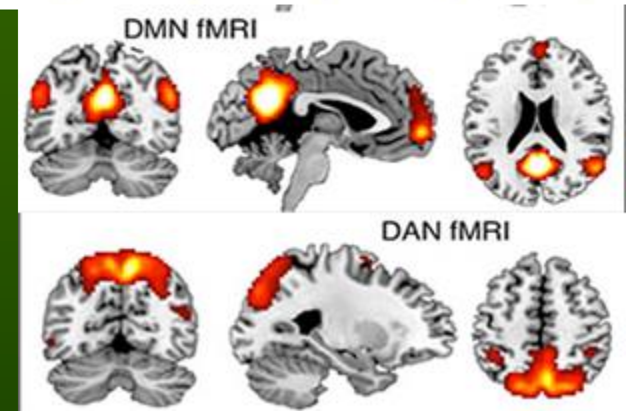
Find unique patterns of brain activity:

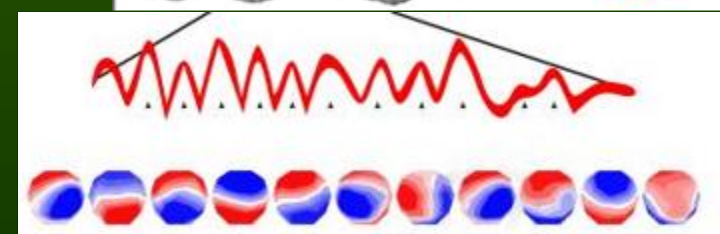
- brain regions of interest (ROI),
- active neural networks,
- mental states, tasks, processes.

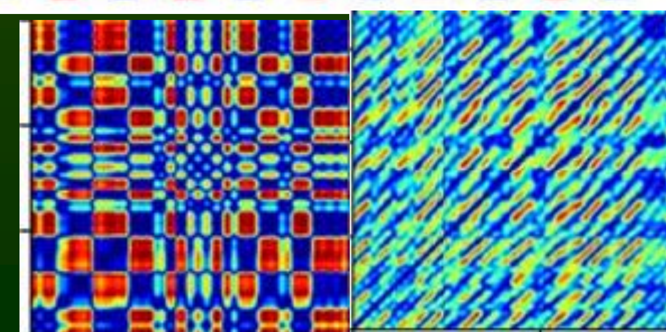


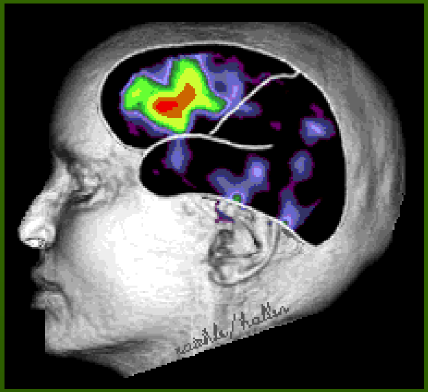
Several approaches:

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…

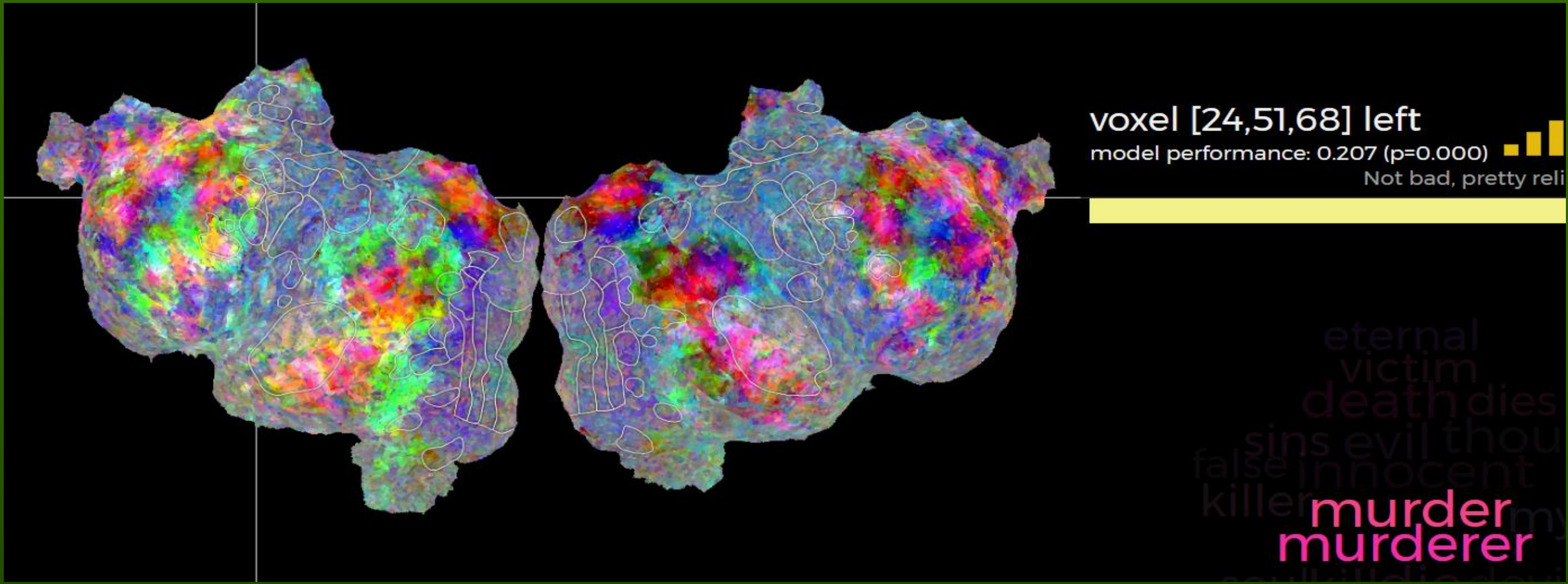








Brains: spatial aspects



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.

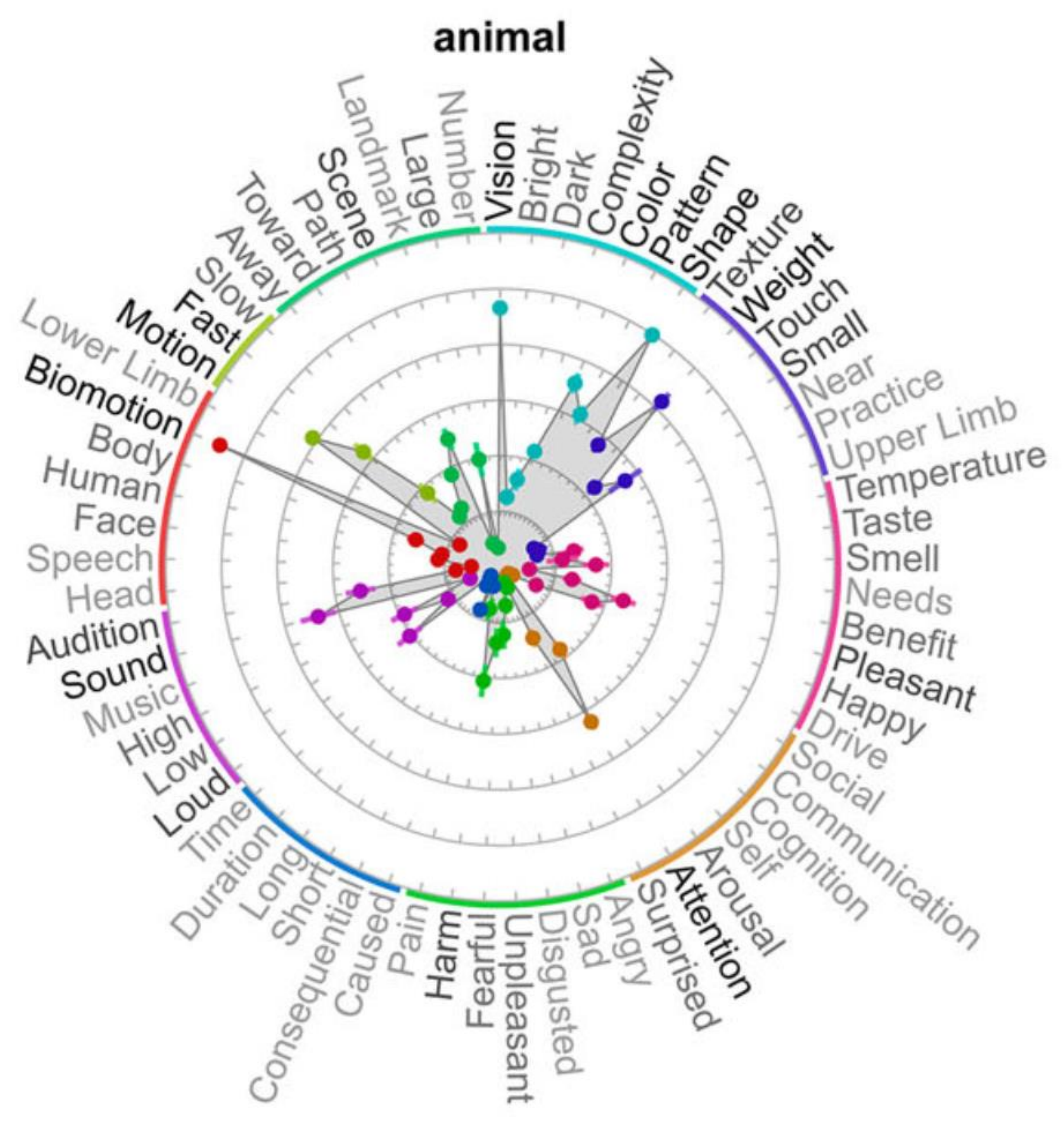
J.R. Binder et al.
Toward a Brain-Based Componential Semantic Representation, 2016

65 attributes related to neural processes;

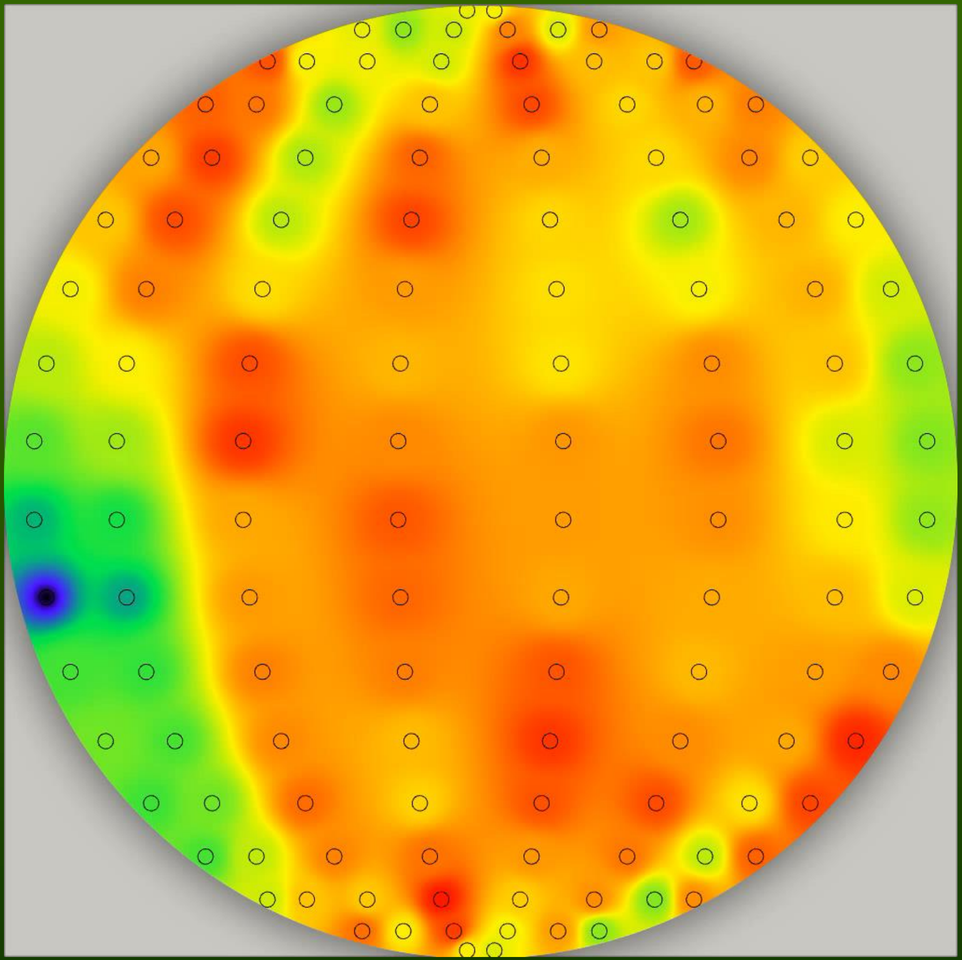
Colors on circle: general domains.

More than just visual objects!

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

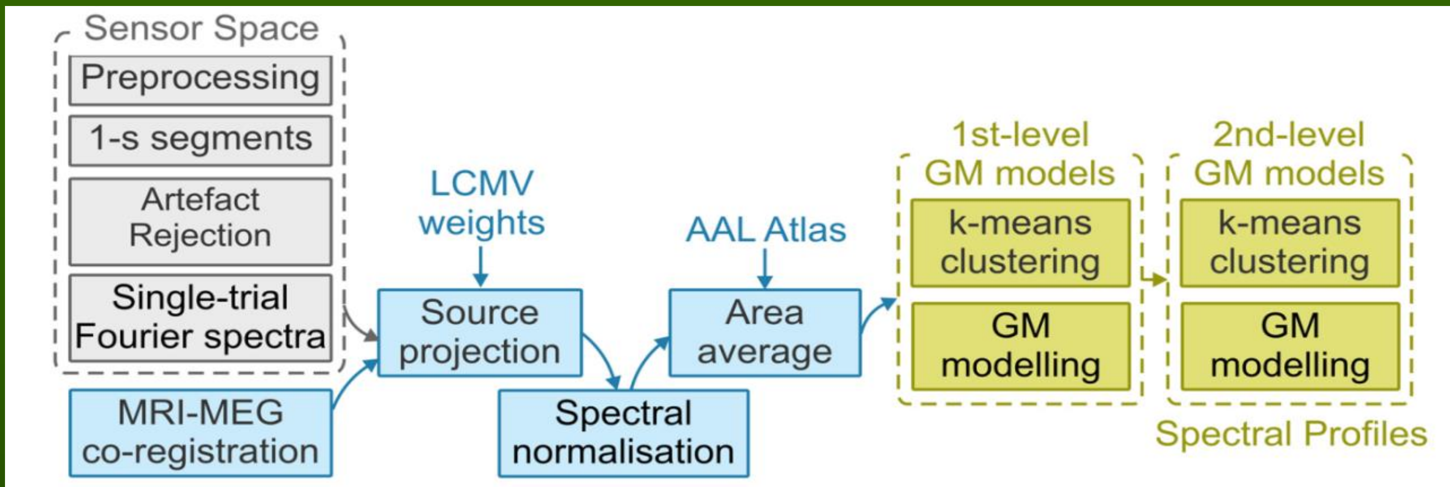


Dynamics



Asymptotic EEG power in the resting state may show hypo/hyperactive brain regions, summarize overall brain activity. How well can it distinguish between brain disorders? Dynamics should be taken into account averaging activity of subnetworks.

Spectral analysis

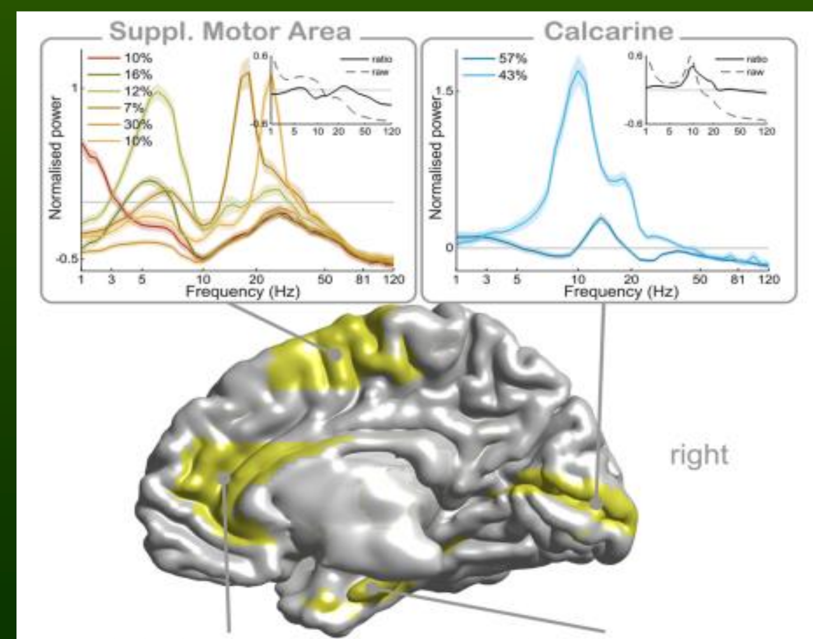


Create spectral fingerprints of ROIs.

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



Schizo reference results

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.

Phang et al. A Multi-Domain Connectome Convolutional Neural Network for Identifying Schizophrenia from EEG Connectivity Patterns, IEEE JBHI 2020.

3 types of features:
Time-domain (VAR) autoregressive model coefficients,
Frequency-domain (PDC) partial directed coherence,
Network topology-based complex network (CN) measures.
Total dim=((2 × 16 × 16) + 34) × 5 =2730

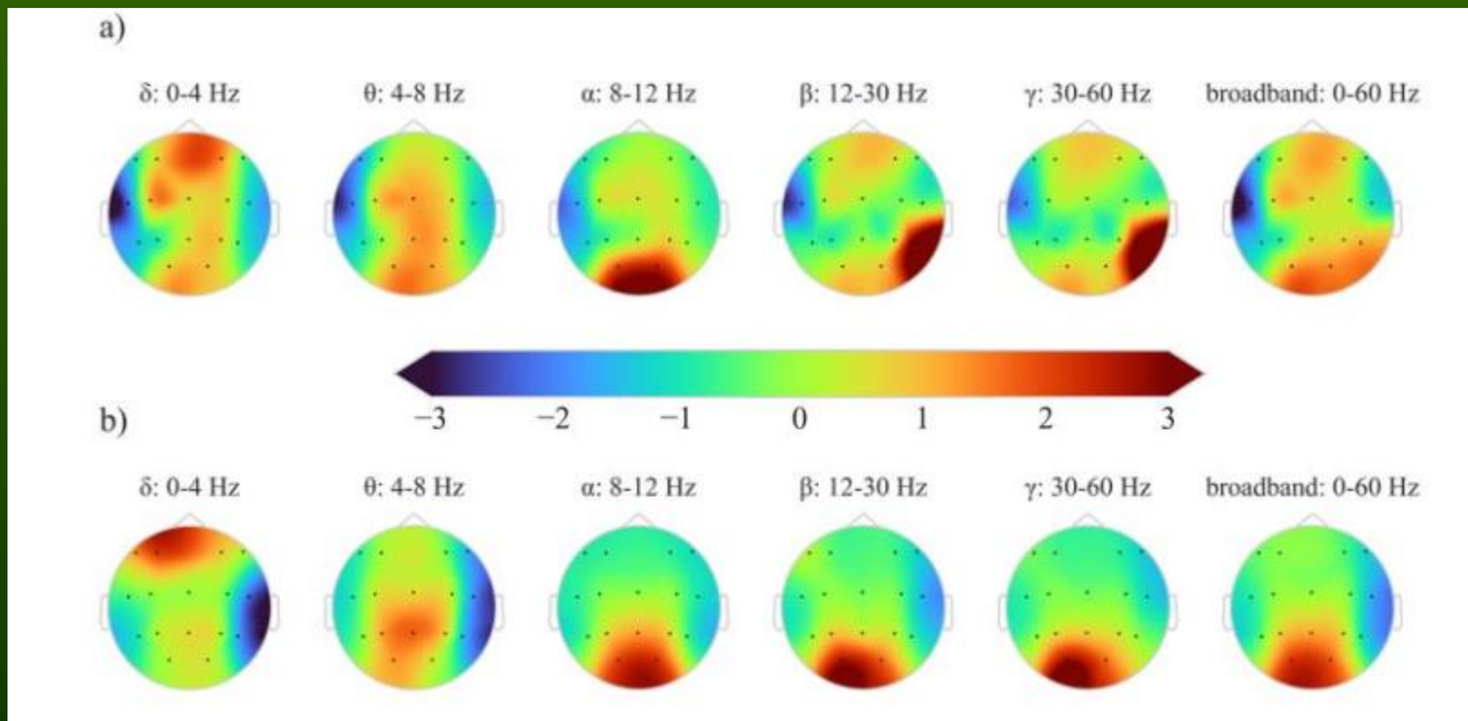
CNN CN	170	81.0±4.4	network topology graphs (TDA)
CNN VAR	1280	81.0	time-domain VAR
CNN PDC	1280	89.2	freq. domain PDC
SVM PDC	1280	88.0	freq. domain PDC
VAR+PDC+CN	2730	**91.7±4.7**	best CNN

Average Power Plots (avPP)

Long-term temporal averaging of signals in each channel. Asymptotic values of average power distributions (**avPP)** shows activations of different brain regions for each frequency bands. We also have such maps in 1 Hz bands.

Schizo
S27w1

Control
719w1

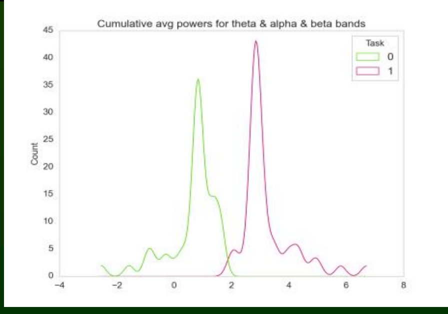


Example of average resting state power in 60 sec segment for two subjects. Cumulative power is relatively stable. Individual differences are large.

L-SVM 5xCV avPP classification

EEG bands	Selection on all data		Selection on training	
	N dim	Acc±Var %	N dim	Acc±Var %
Broadband	10	72.5±20.6	10	68.0±22.8
$\beta+\gamma$	3	73.8±19.6	3	72.7±20.5
$\theta+\beta$	23	74.9±18.4	23	65.4±23.0
$\delta+\theta$	19	68.9±21.0	19	65.6±23.6
$\delta+\theta+\alpha$	19	90.5±8.6	19	76.2±19.2
$\delta+\theta+\alpha+\beta$	21	**95.2±4.6**	21	78.5±17.8
$\delta+\theta+\alpha+\beta+\gamma$	71	79.5±15.5	71	**79.8±17.1**

Number of features has been fixed for all folds, although in case of selection on the training partition features were different in each CV fold.



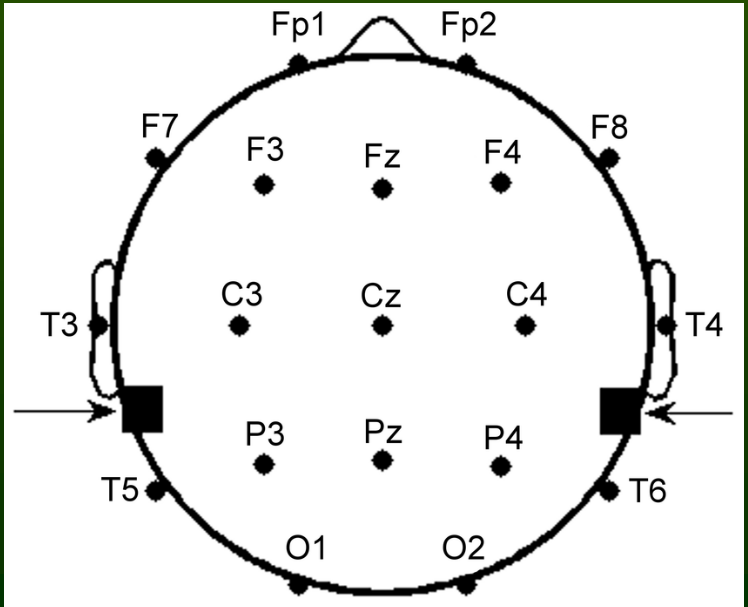
Schizophrenia avPP

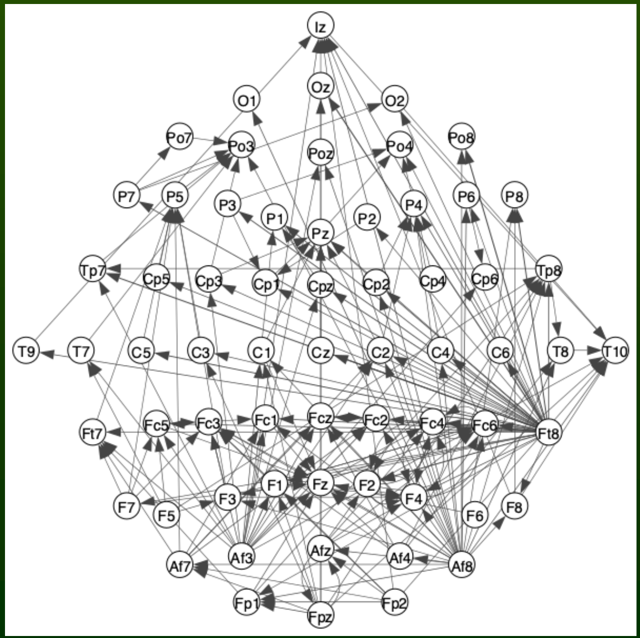
Simple method, may be useful in clinical settings.

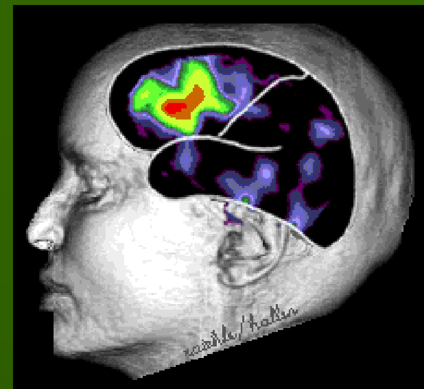
The power distribution maps are relatively stable for each individual, with clusters distinguishing schizophrenia patients vs. control subjects. Electrode/frequency band selection is based on linear SVM weights. The top 10 combinations :

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

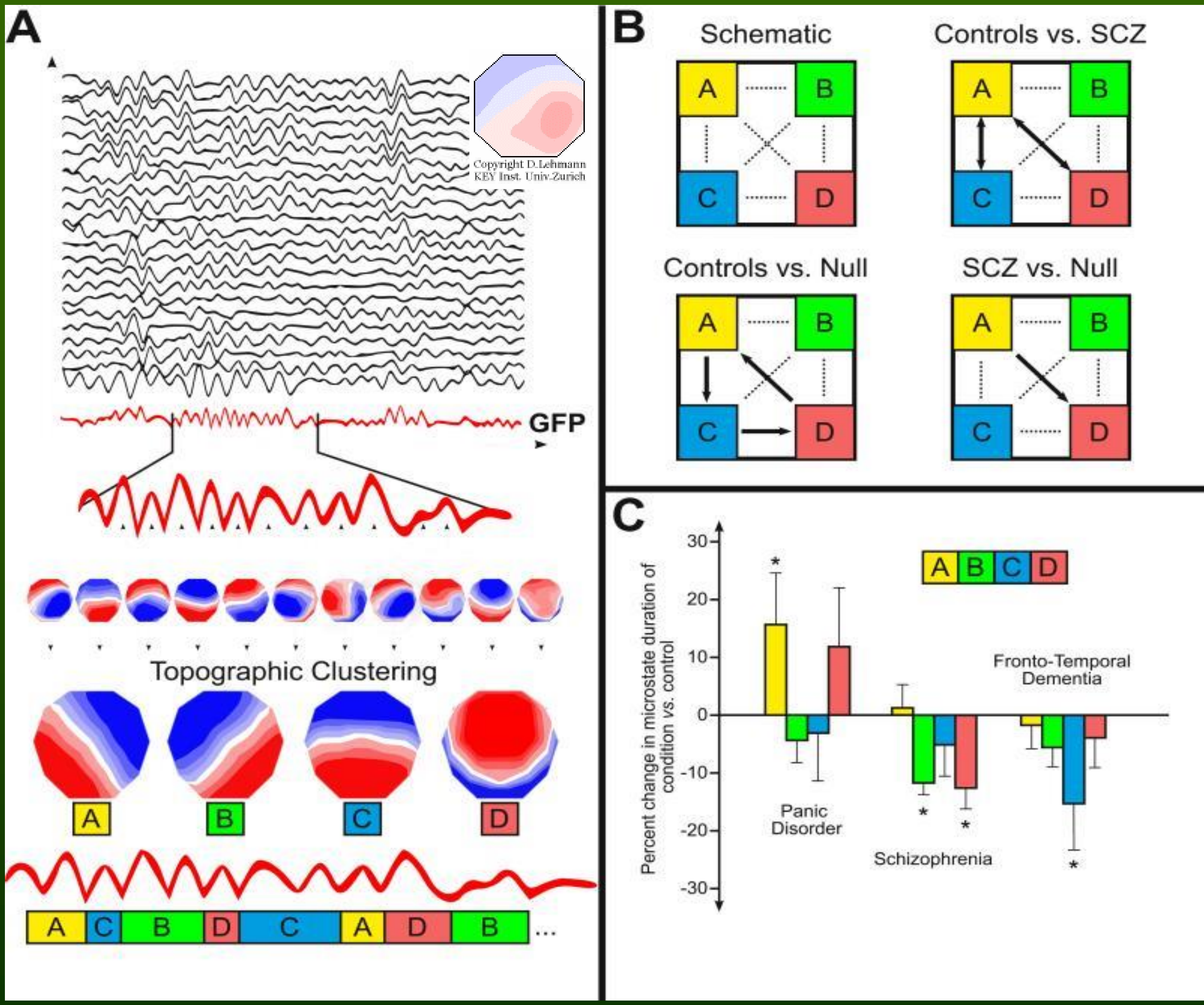
Global Field Power.
4-7 states, 60-150 ms.

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

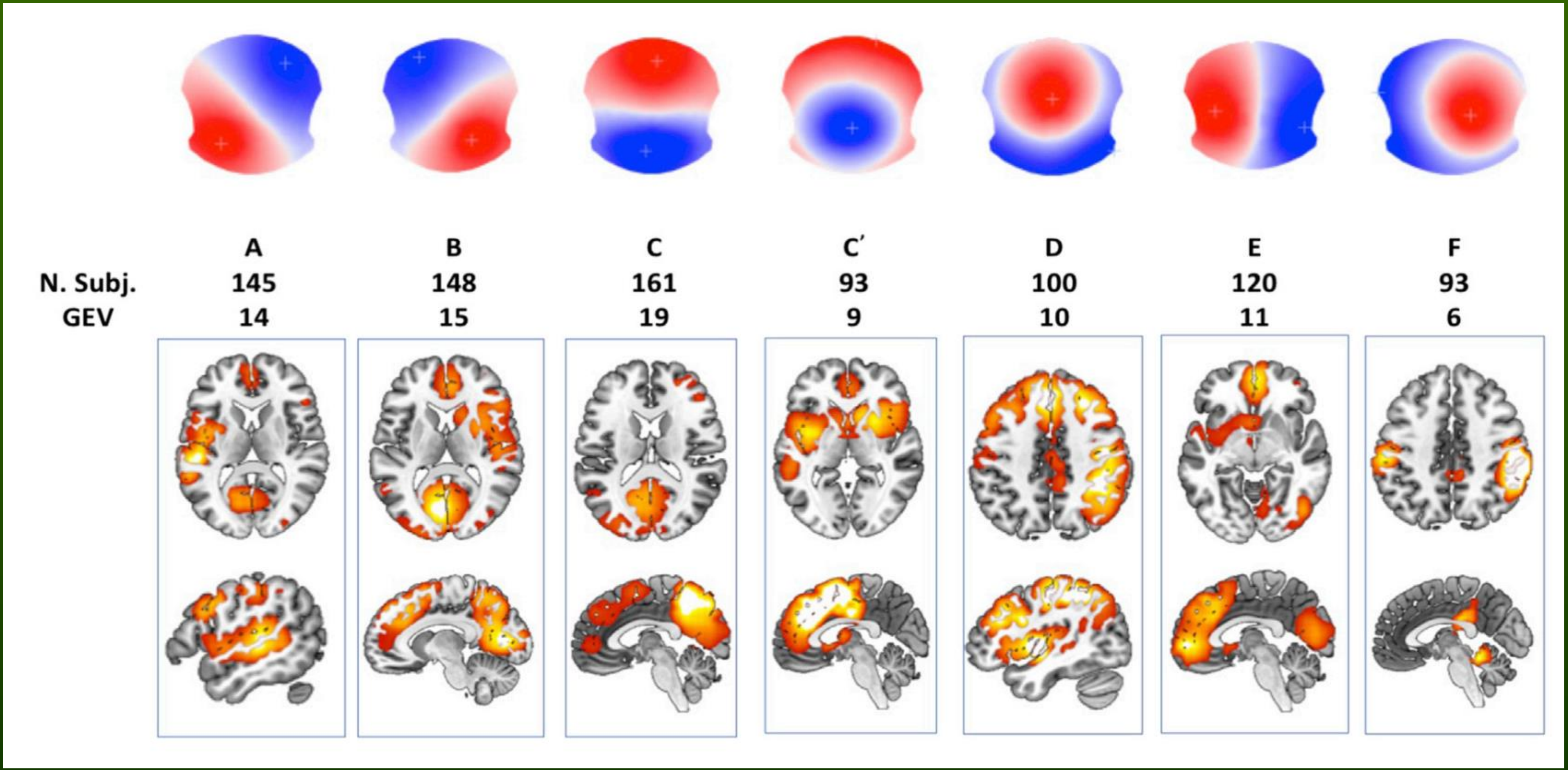
Symbolic dynamics: statistics of A-D symbol strings. Fuzzy Symbolic Dynamics (FSD) + visualizations.

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

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



Microstates and their sources

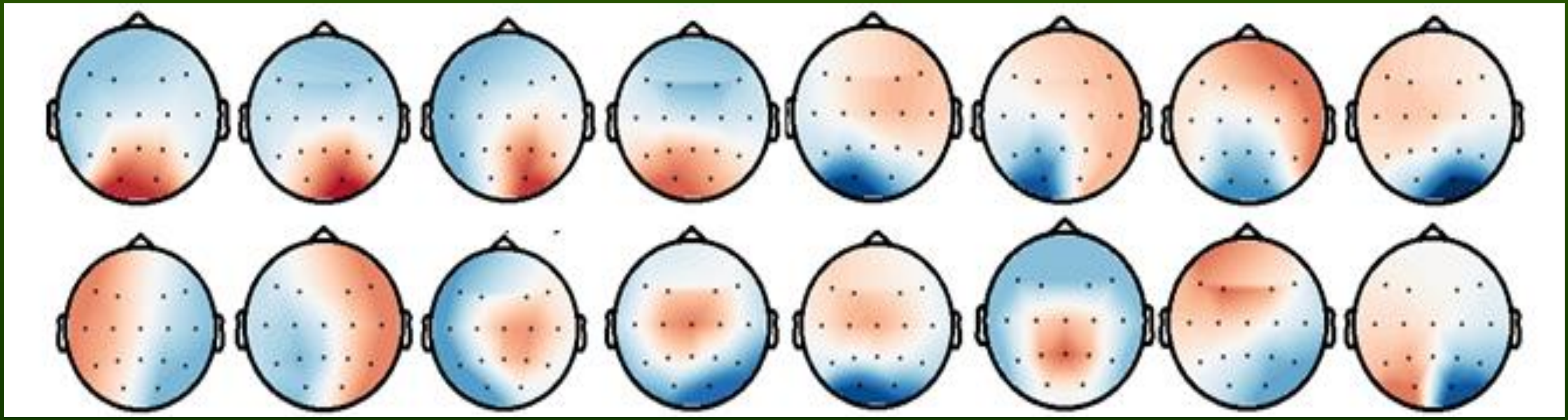


Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593.
Ewa Ratajczak, PhD thesis "Microstate neurodynamics in HRV biofeedback“ (2022)

Microstates limits

T\We have created 4-20 microstates using two clusterization procedures. Features include occurrence (OCC), duration (DUR), coverage (Cov), global field potential (GFP), global explained variation (GEV), mean spatial correlation (MSC), transition probabilities between microstate classes (TP, 16x16).

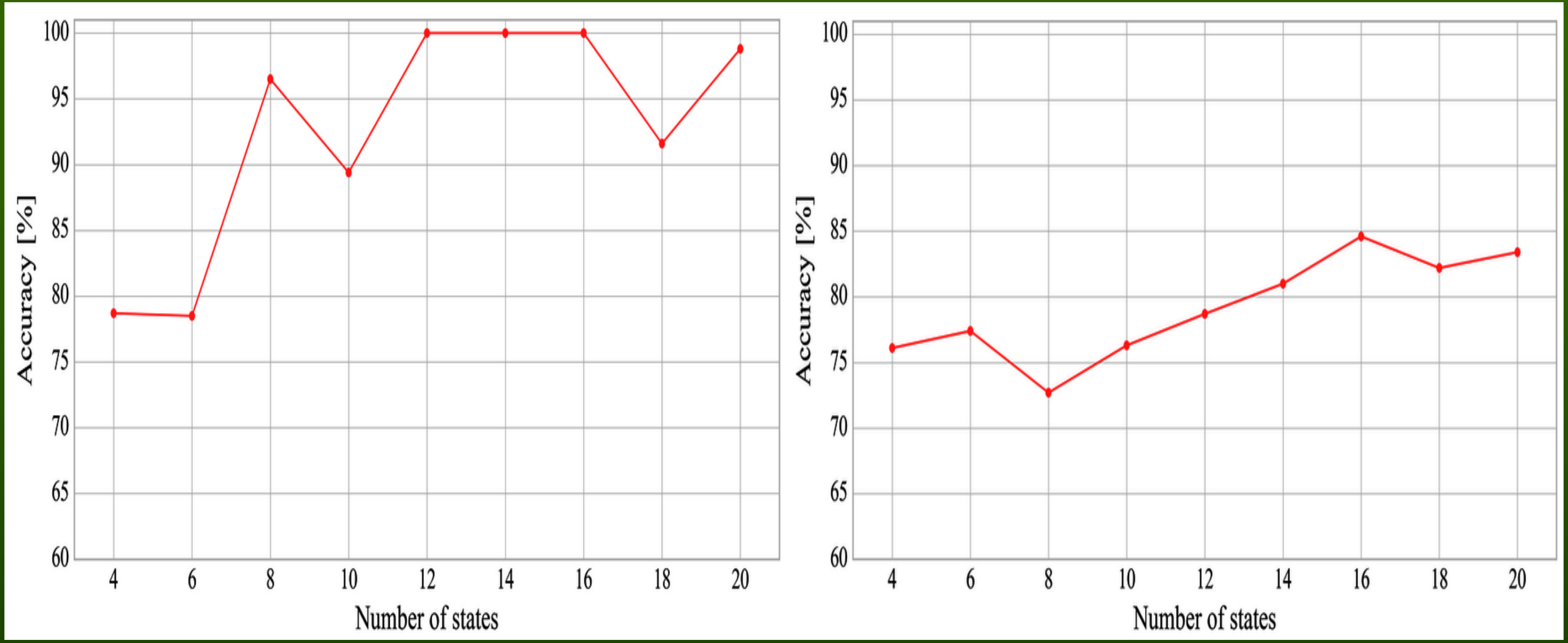
Below – 16 microstate example for schizophrenia. They hardly differ. Another choice: use avPP states as prototypes.



Microstates for classification

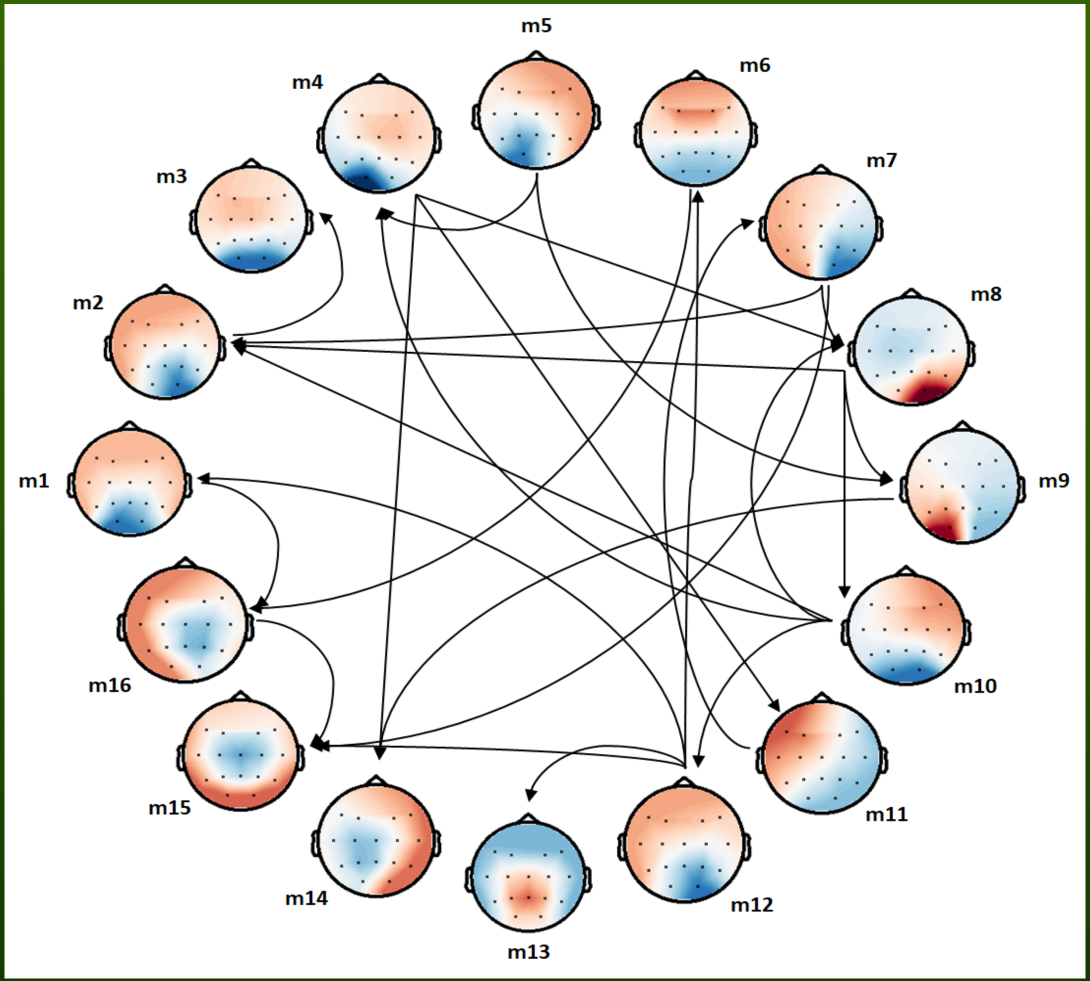
Microstates		Selection on all data		Selection on training only		
N states	Type	N dim	Acc±Var %	Type	Ndim	Acc±Var %
4	TAAHC	4	78.7±17.2	TAAHC	4	76.1±18.6
6	TAAHC	52	78.5±17.7	TAAHC	52	77.4±17.7
8	TAAHC	17	96.5±3.4	TAAHC	17	72.7±20.2
10	TAAHC	93	89.4±9.4	TAAHC	93	76.3±18.5
12	K-means	55	100	K-means	55	78.7±17.5
14	K-means	90	100	K-means	90	81.0±15.9
16	TAAHC	42	100	K-means	17	84.6±13.0
18	TAAHC	281	91.6±7.8	TAAHC	281	82.2±14.0
20	TAAHC	221	98.8±1.2	TAAHC	221	83.4±14.3

Microstates for classification

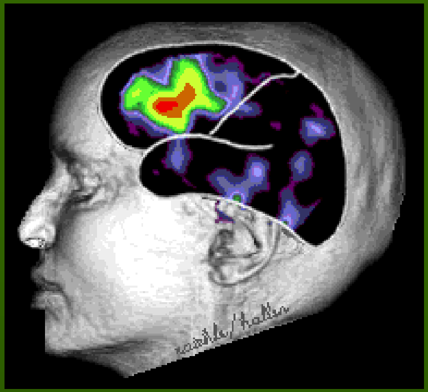


Left: features selected on the whole data, before training of LSVM.
Right: features selected on the training partition.
In both cases training of LSVM is in stratified crossvalidation.

Microstate transitions

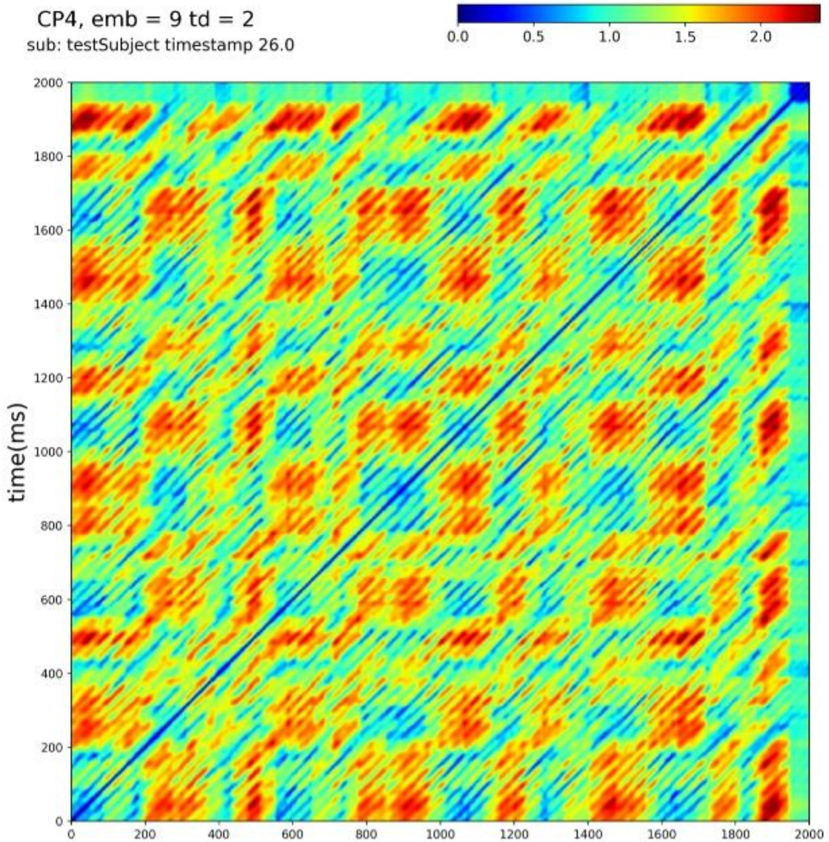


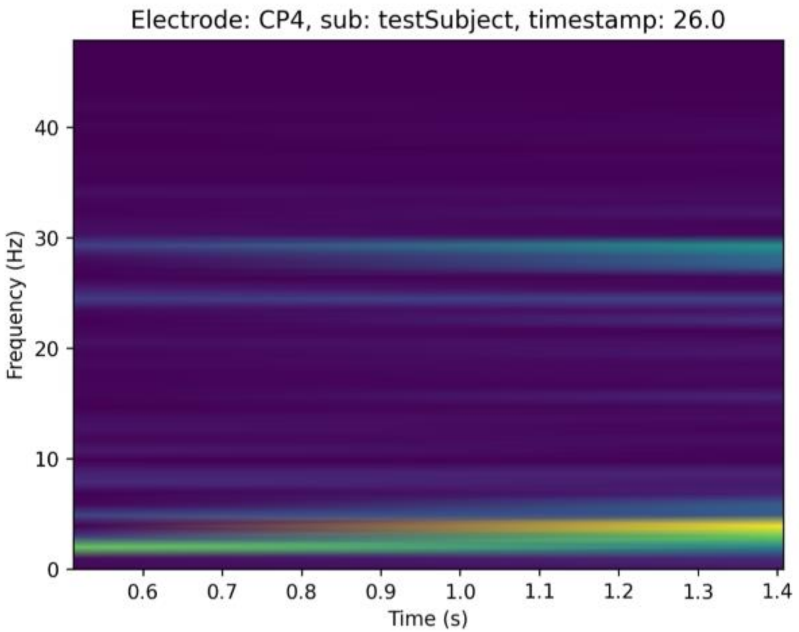
These transitions were selected most often.

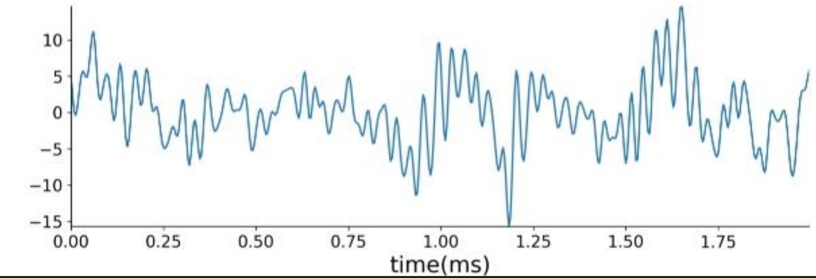


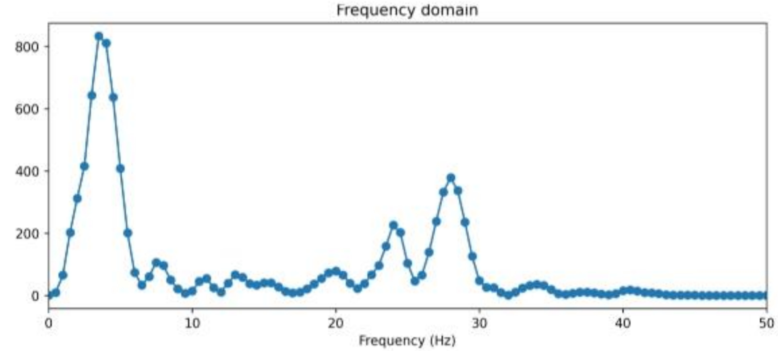
Brains: spatio-temporal aspects

Representations

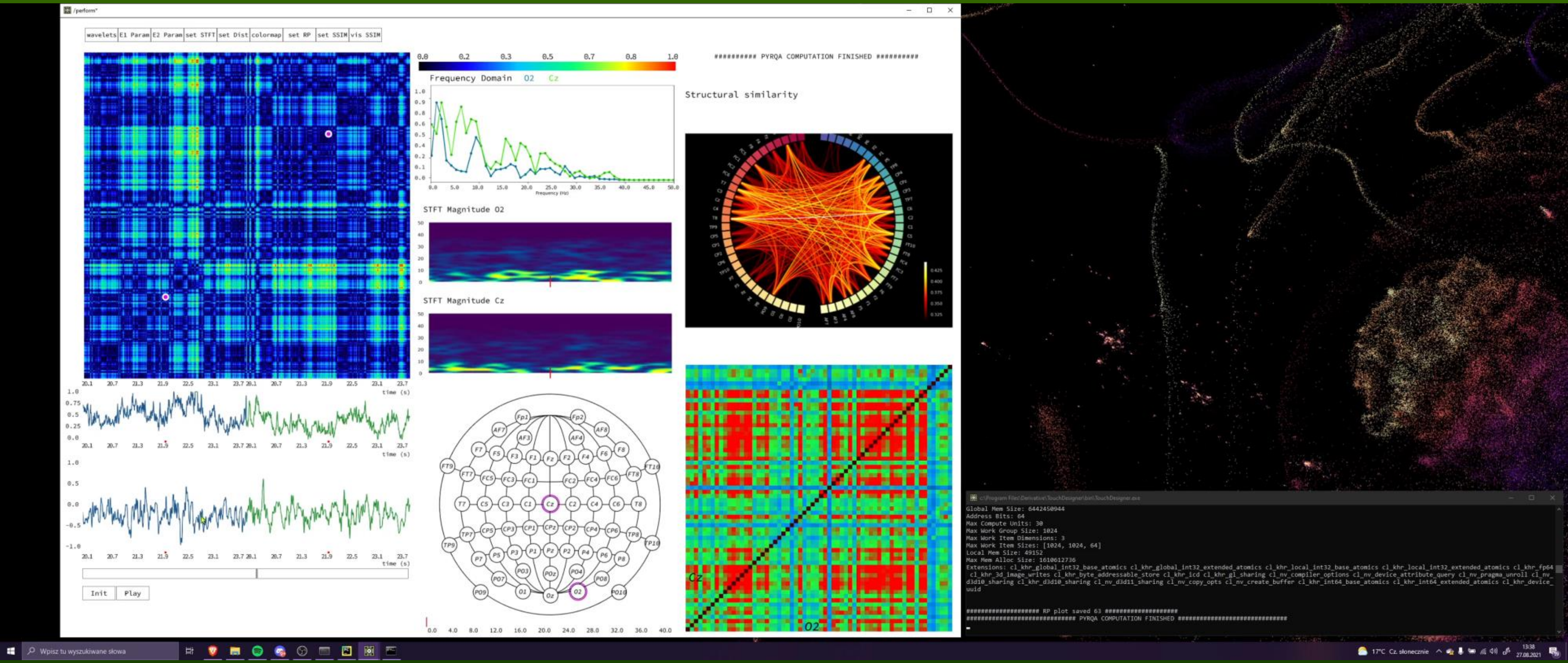




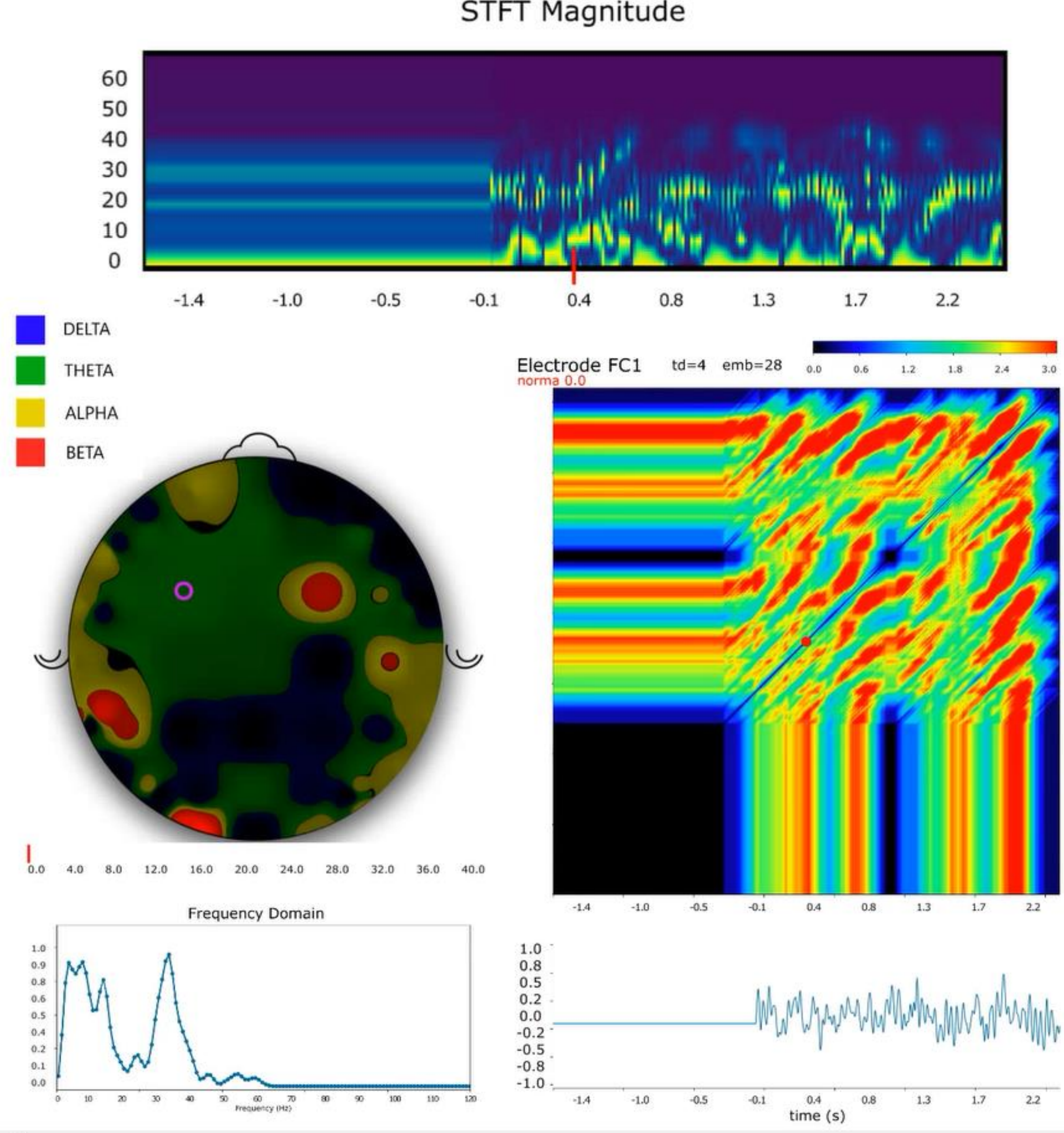


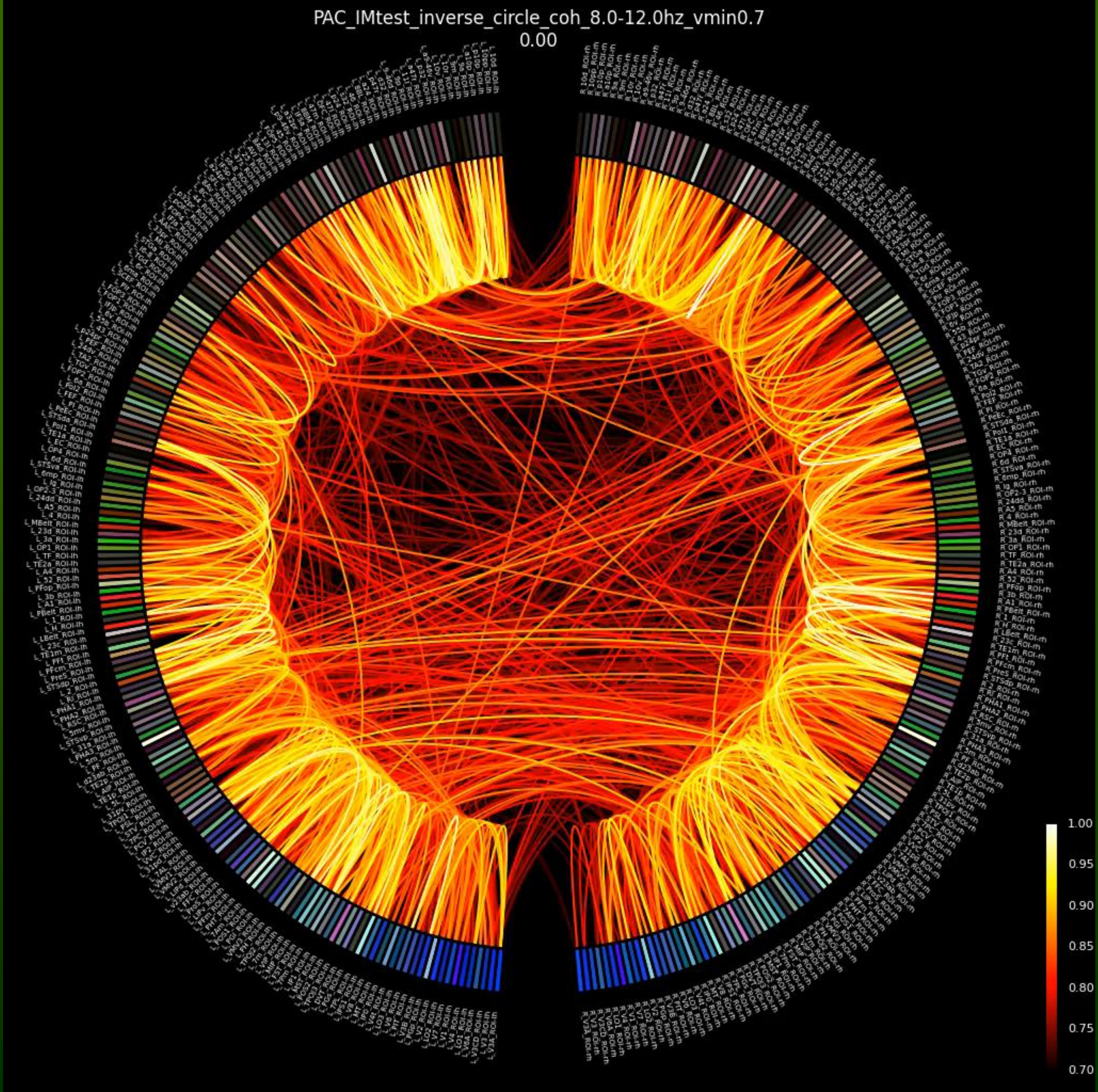


STFT EEG in real time



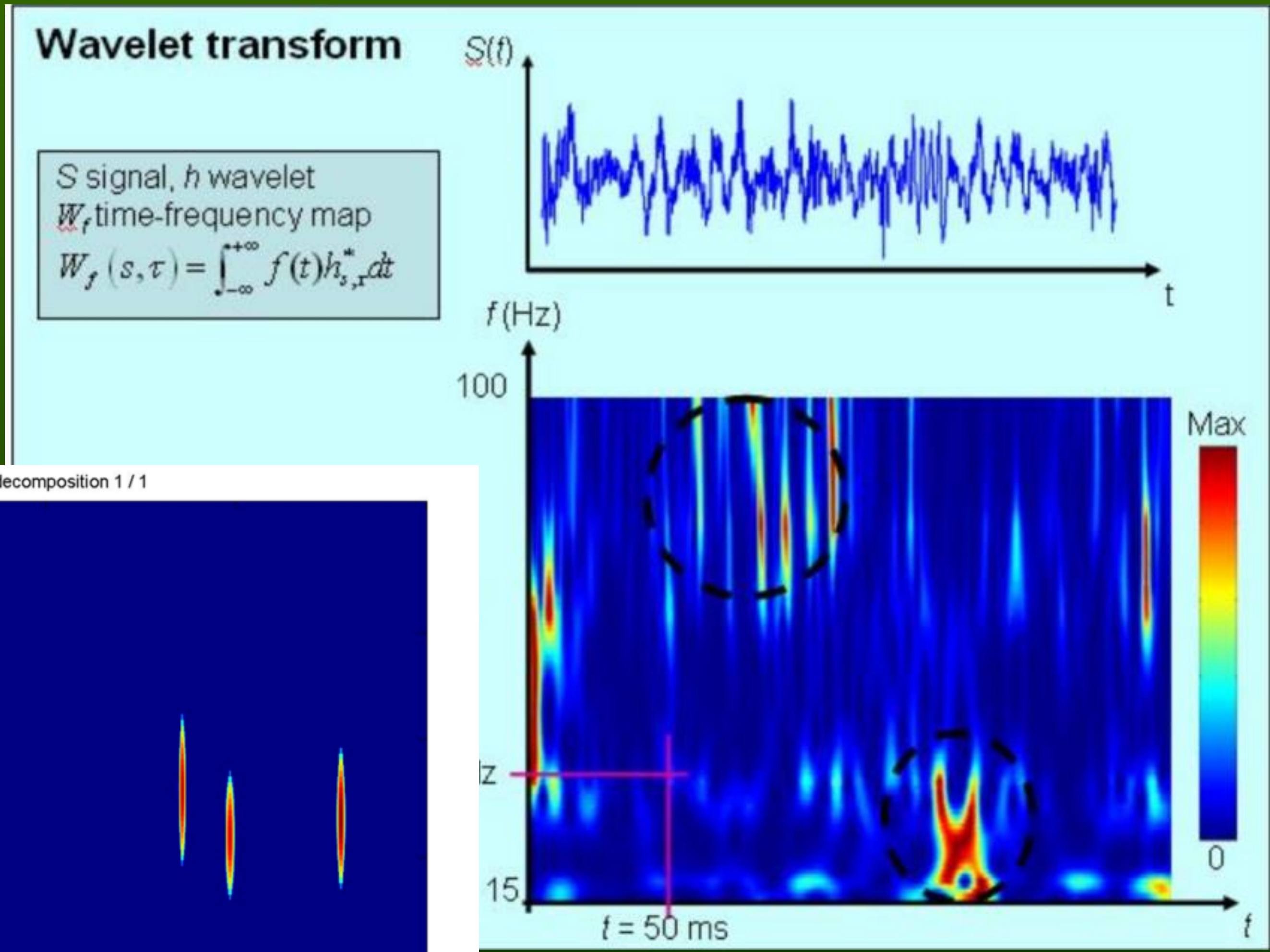
EEG data, 128 channels, recursion graphs, power spectrum for two electrodes, information flow and correlations between brain regions.
BrainPulse (in development, Łukasz Furman).

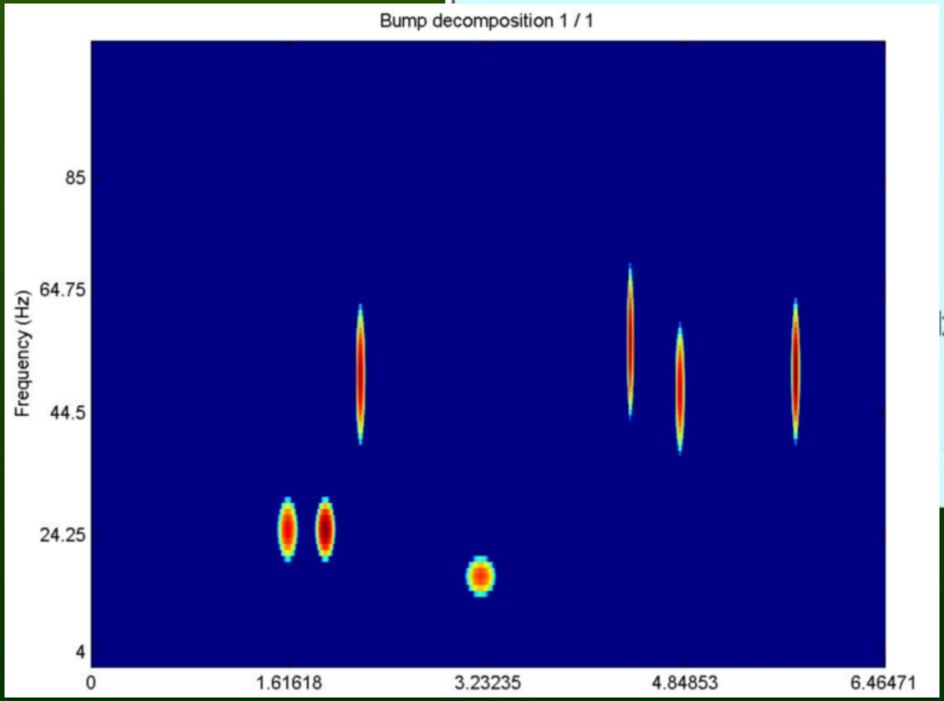

STFT Magnitude
DELTA
THETA
ALPHA
BETA
Electrode FC1
td=4
emb=28
norma 0.0
Frequency Domain
Frequency (Hz)
time (s)


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

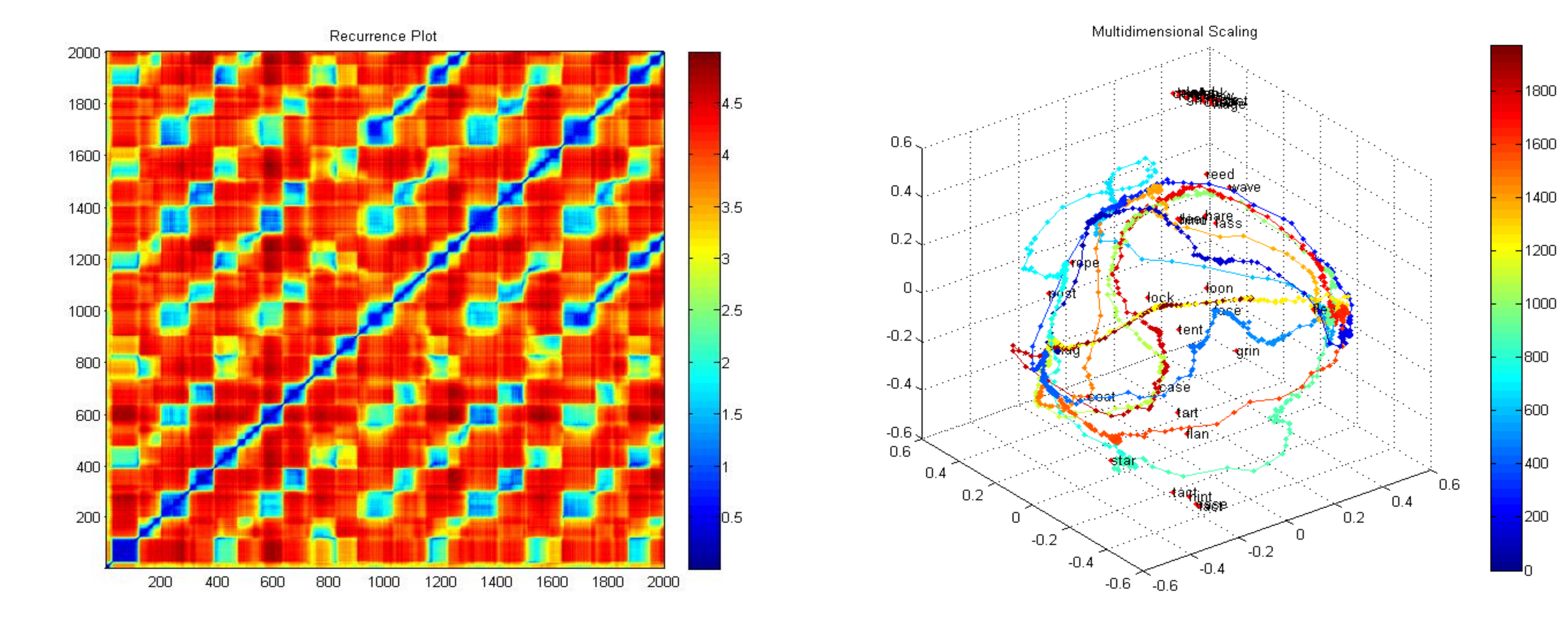
t/f rep and bumps

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





Recurrence and 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 ...

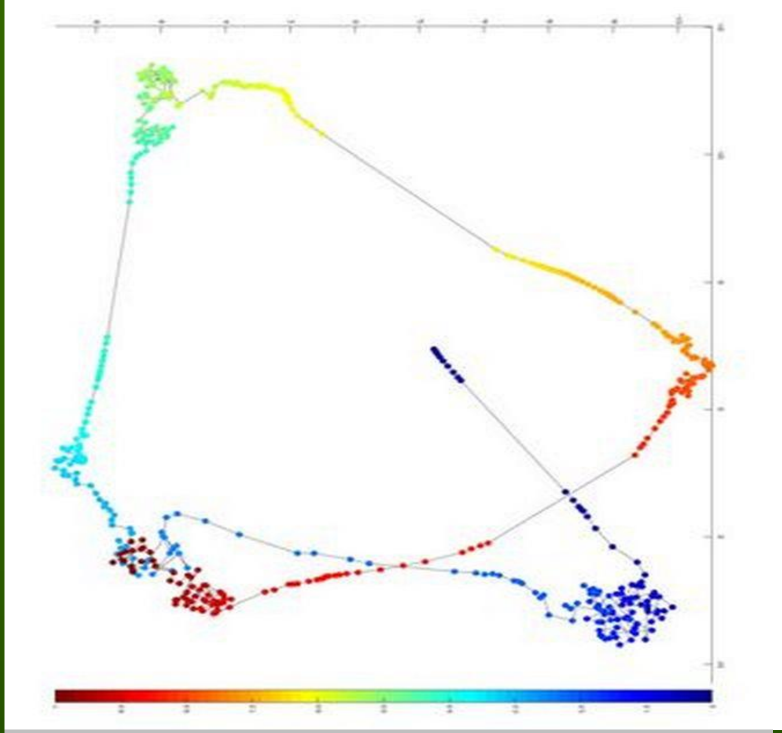
Trajectories

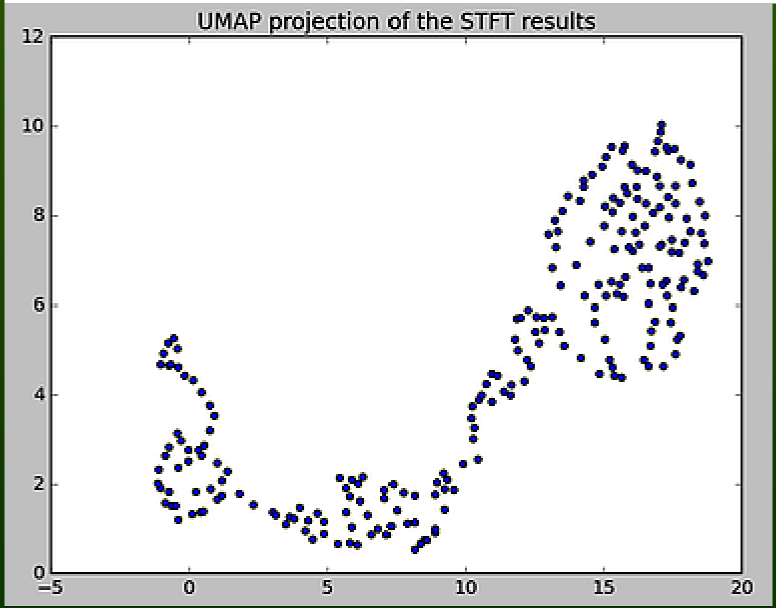
Can we characterize attractor states of the brain using EEG data?

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).



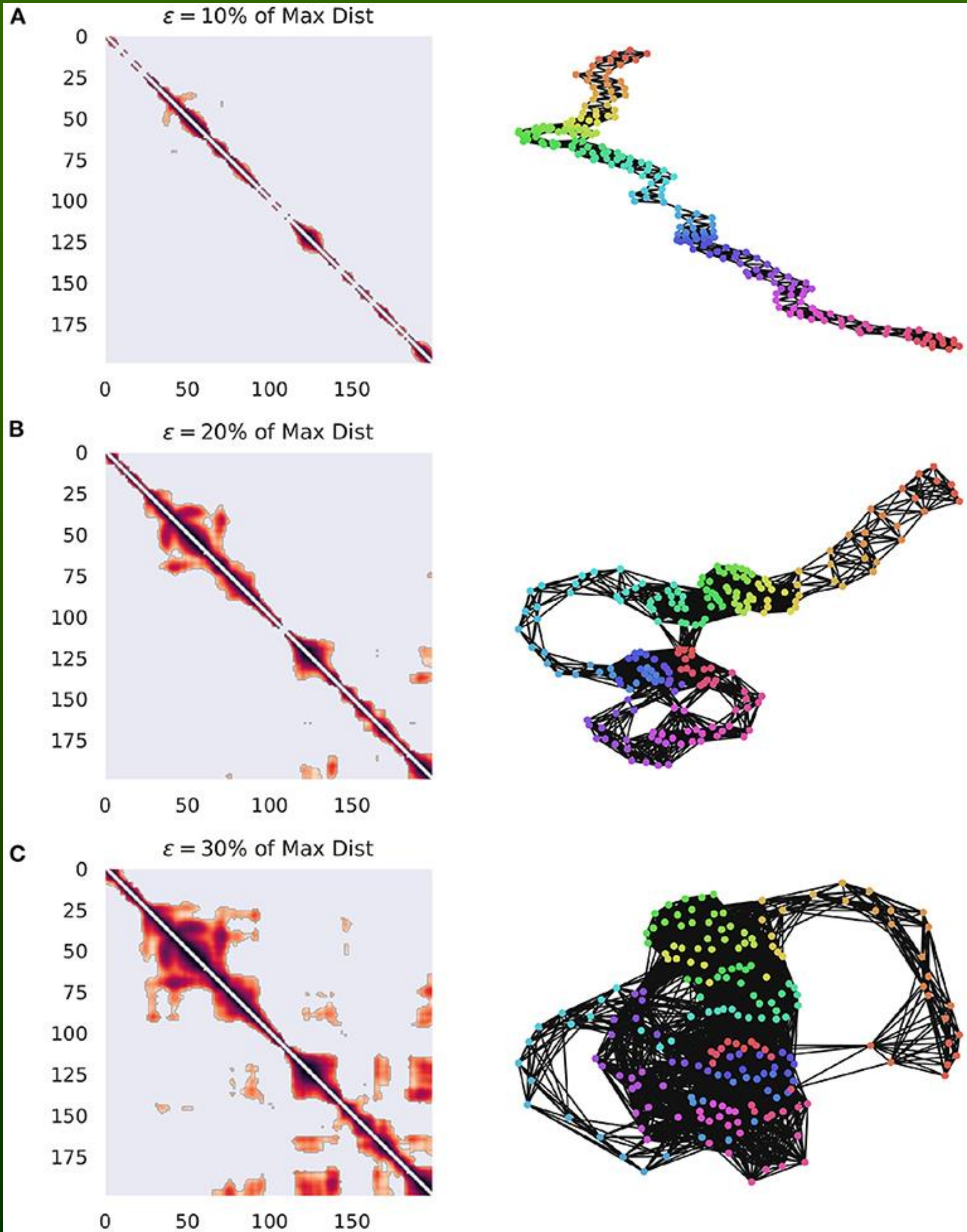


TDA

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.

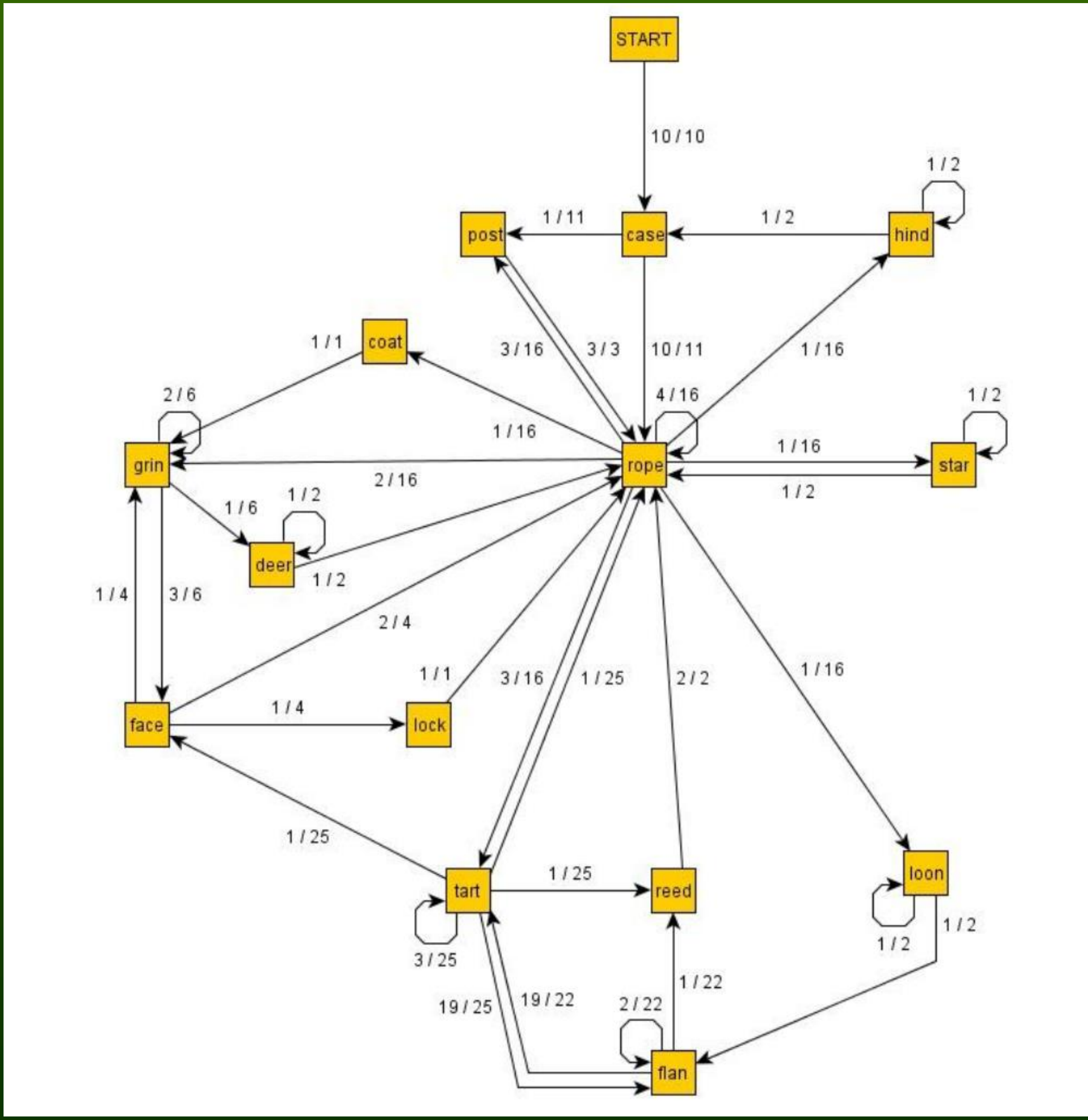
Varley, T. F., & Sporns, O. (2022). Network Analysis of Time Series: Novel Approaches to Network Neuroscience. [*Frontiers in Neuroscience, 15*]().



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).

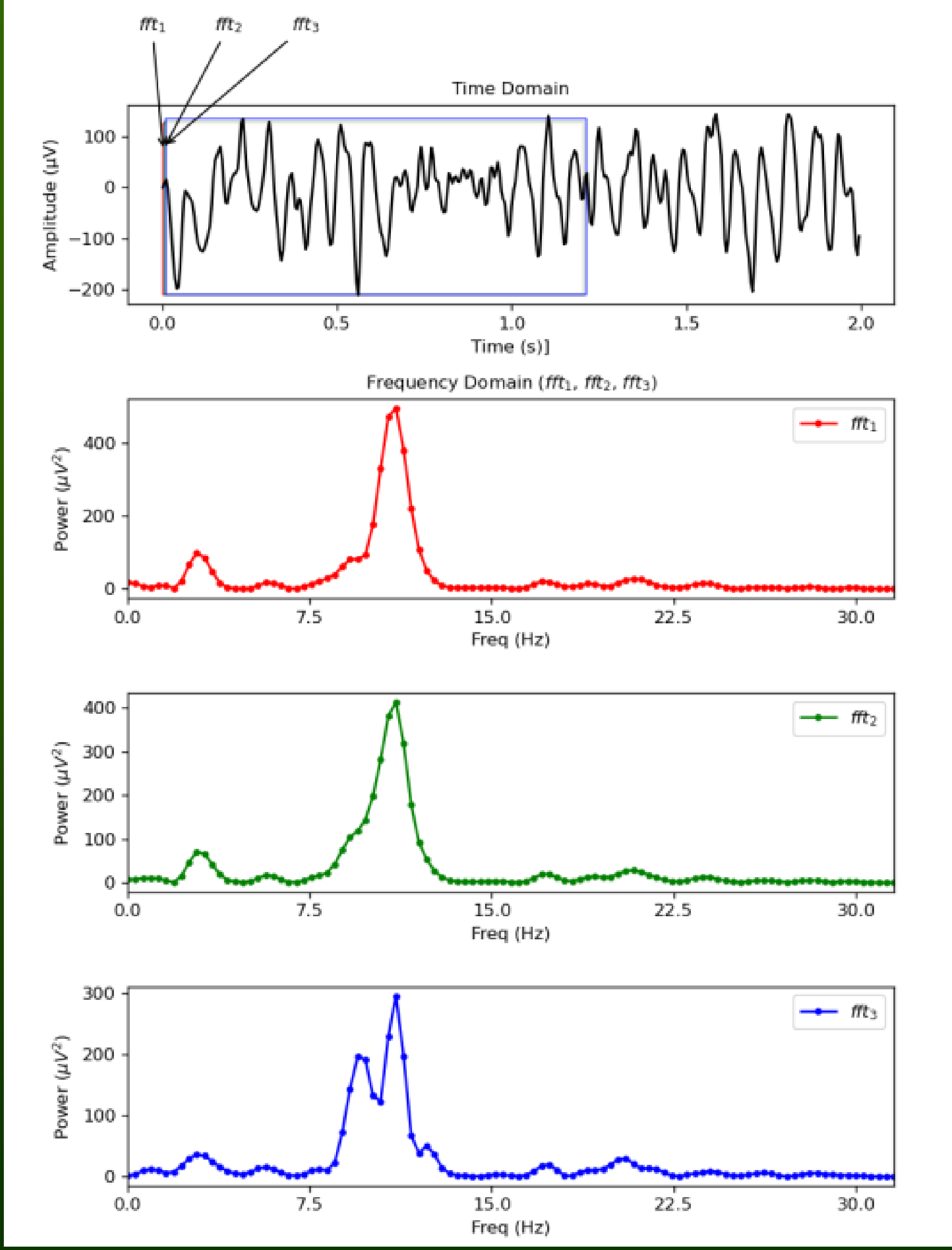


Labeling states

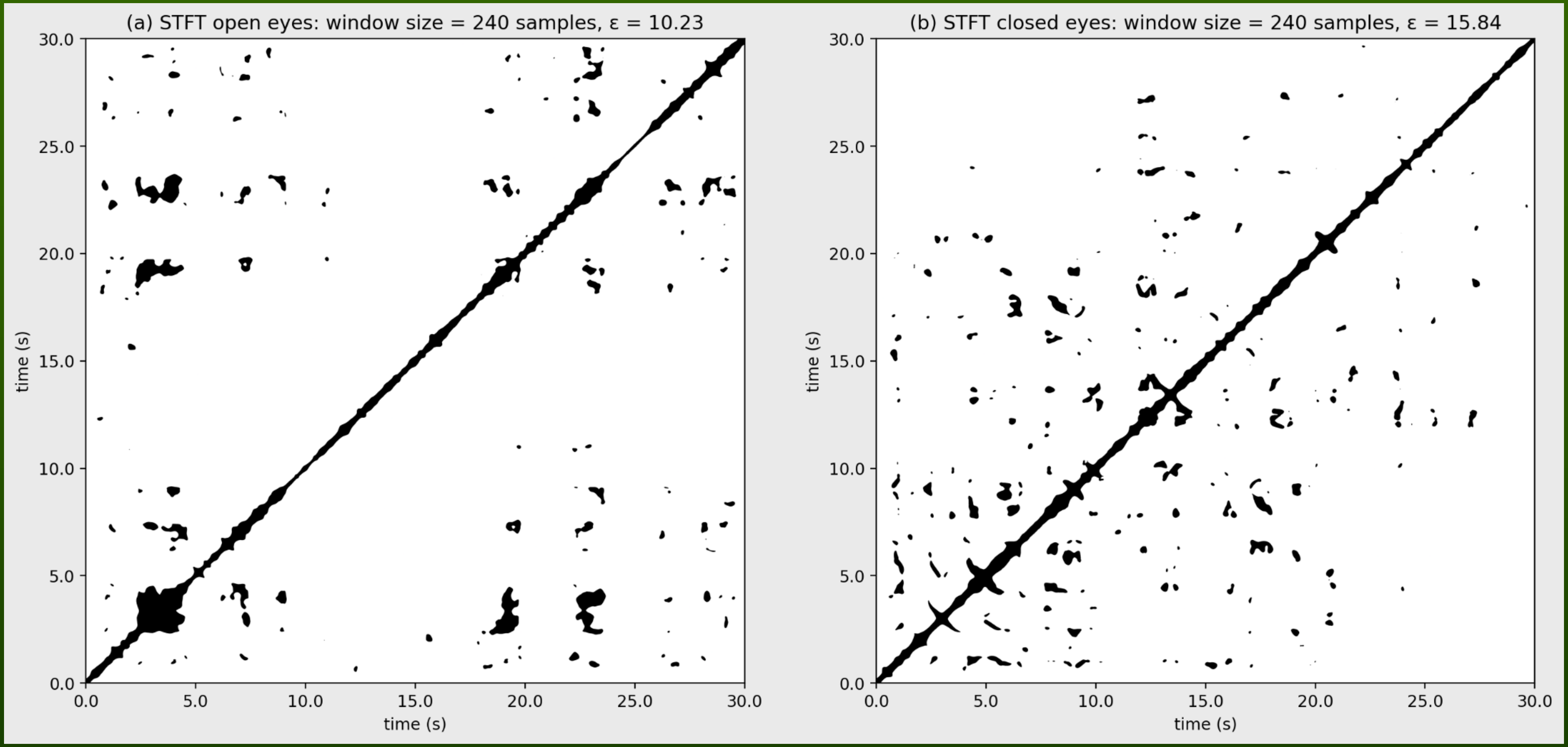
Example of STFT vectors, time windows ~ 1.5-sec, showing a shift and split of the α peak frequency after 200 ms. O1 electrode (occipital area), eyes closed.

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).



RPs, O1 electrode



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

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.

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

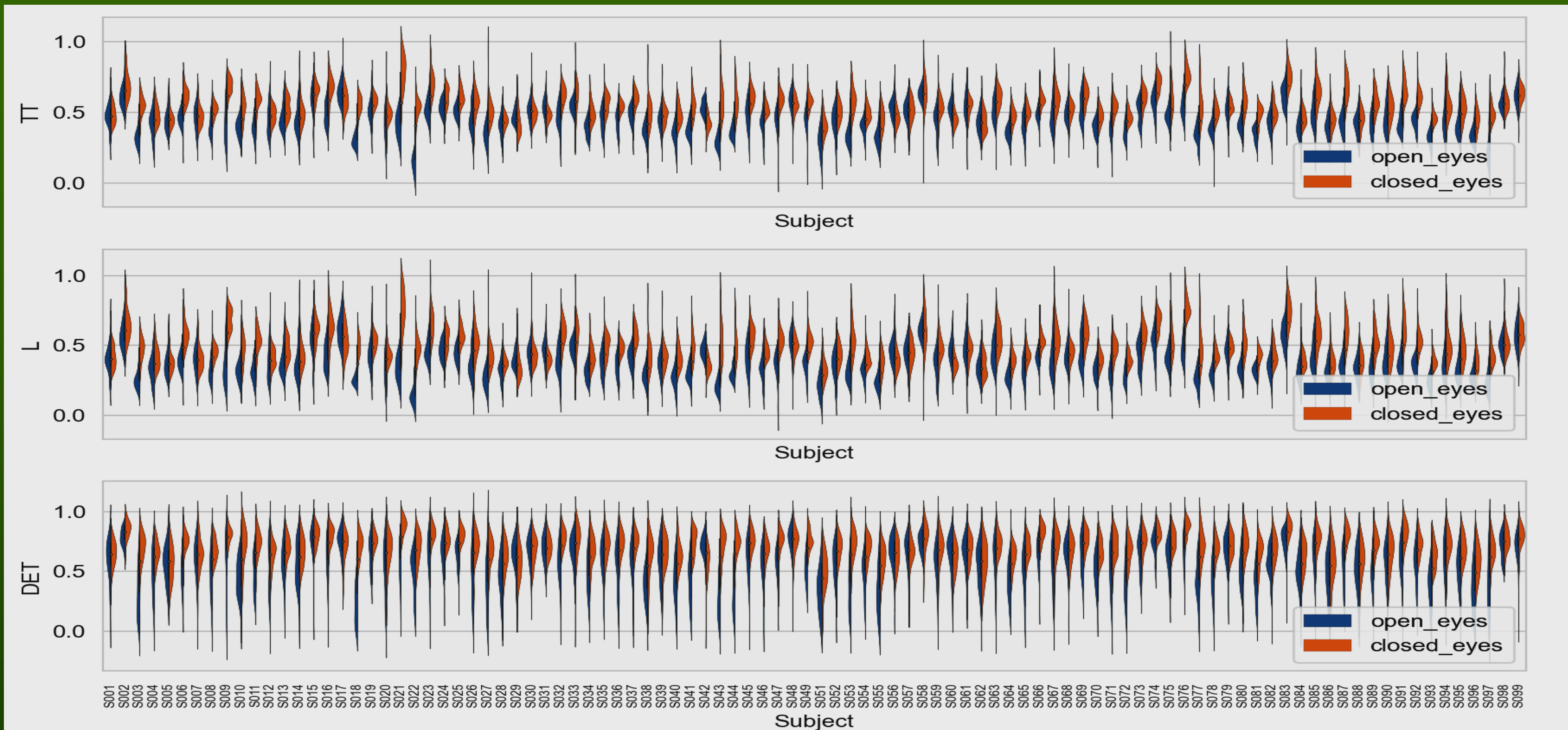
The averaged diagonal line length:

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

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



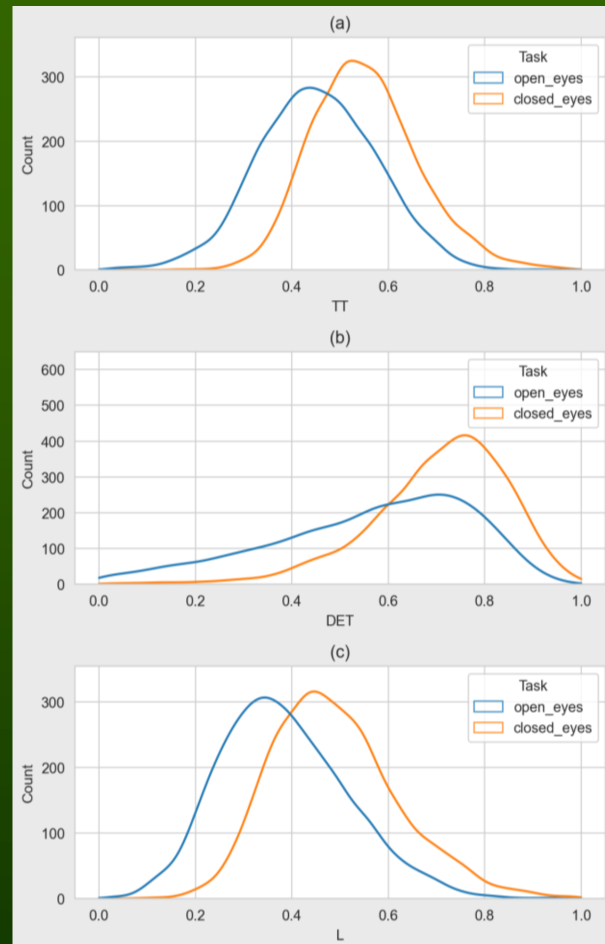
Distribution of trapping time, av. line length and determinism values for 64 electrodes shown for all 98 subjects. In some cases a single RQA feature allows for an easy separation of the two conditions. Variance is very different (focus? dreaming?), depending on the person. Linear SVM provides weights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

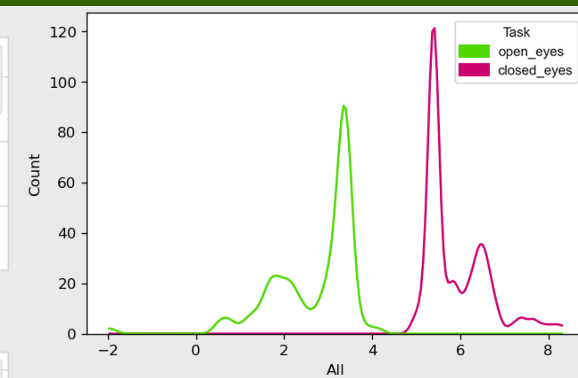
RQA features for 64 electrodes

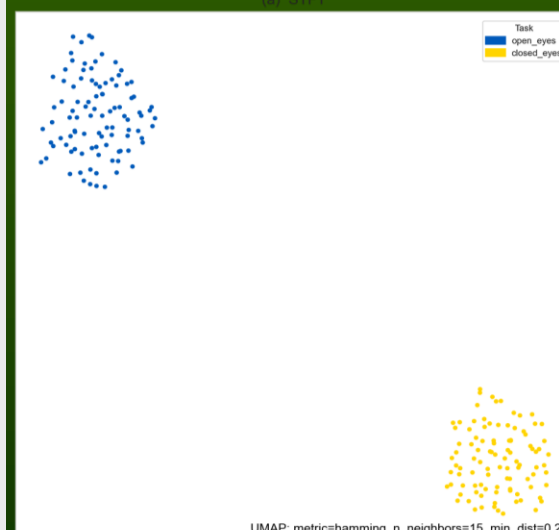
Histograms of the RQA features for all 98 subjects:
TT (trapping time),
DET (determinism),
L (average diagonal line length).

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.







Labeling states

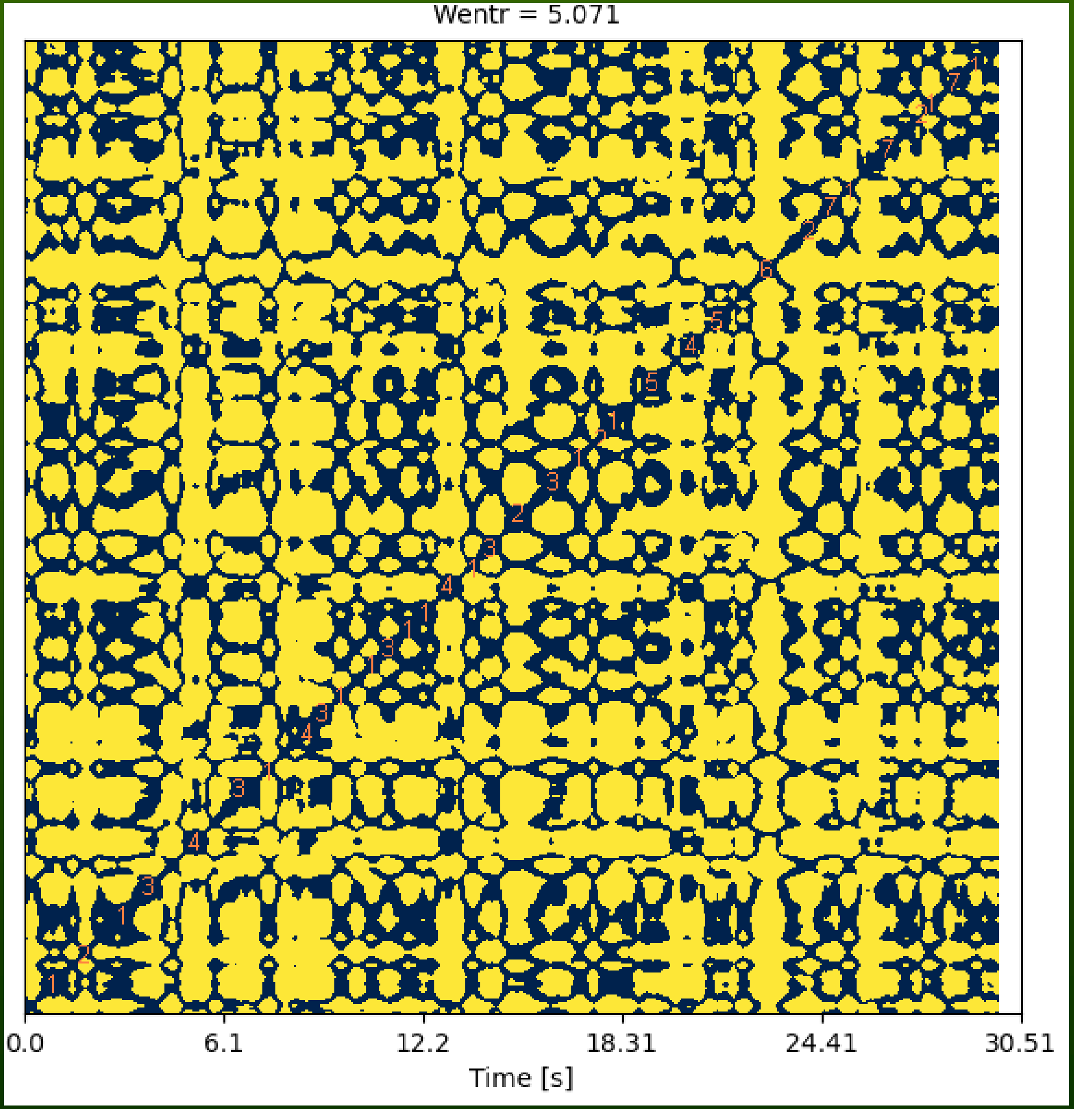
Automatic labeling of states and estimation of their recurrence may be important for biofeedback.

Metabolic costs of transitions between states may be important.

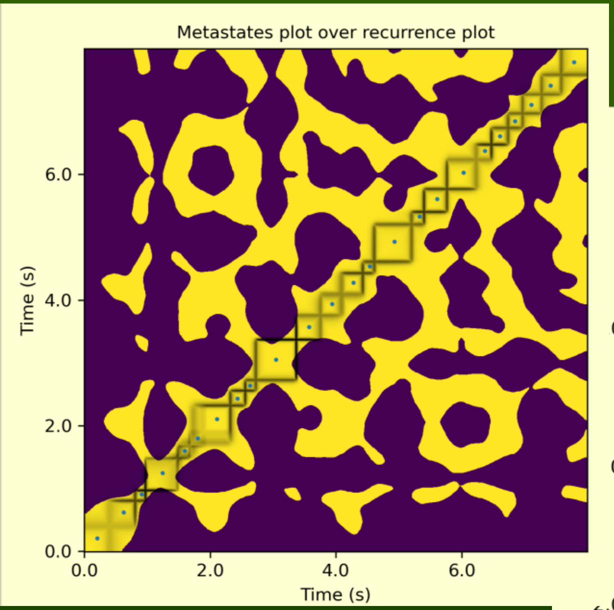
Ruminations? Pain states? How external stimuli influence this dynamics?

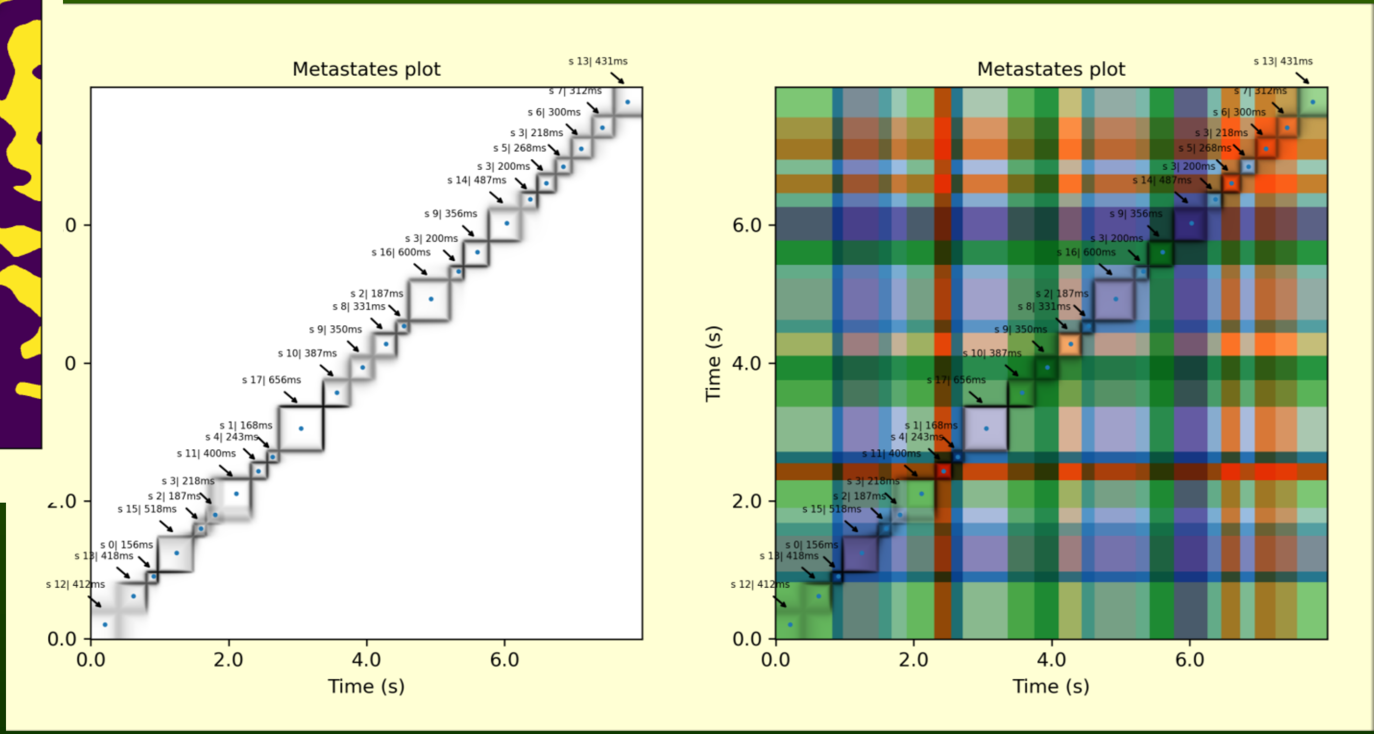
Needs automatic method for recognition of metastable, multivariate states.

More precise than microstates.



Segmentation of states





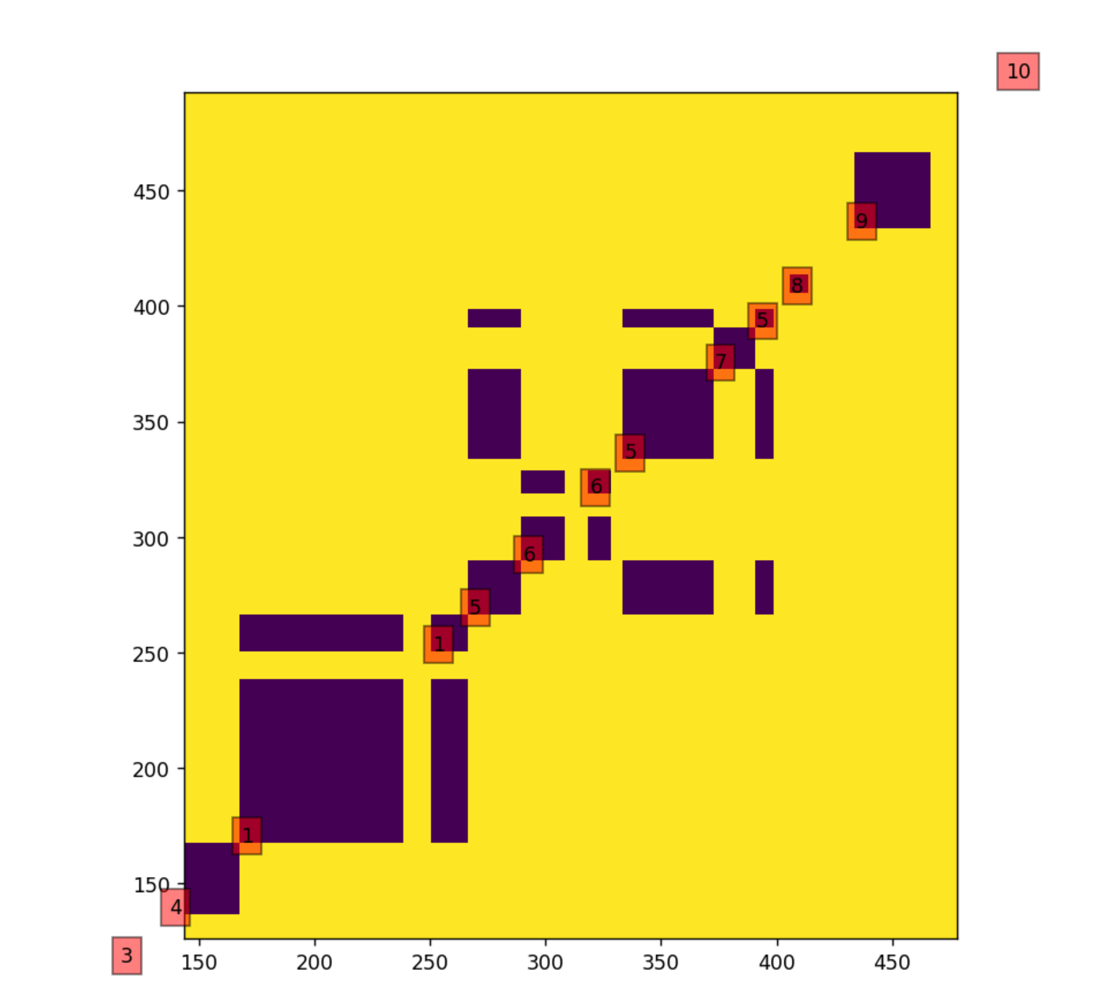
Labeling RPs

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

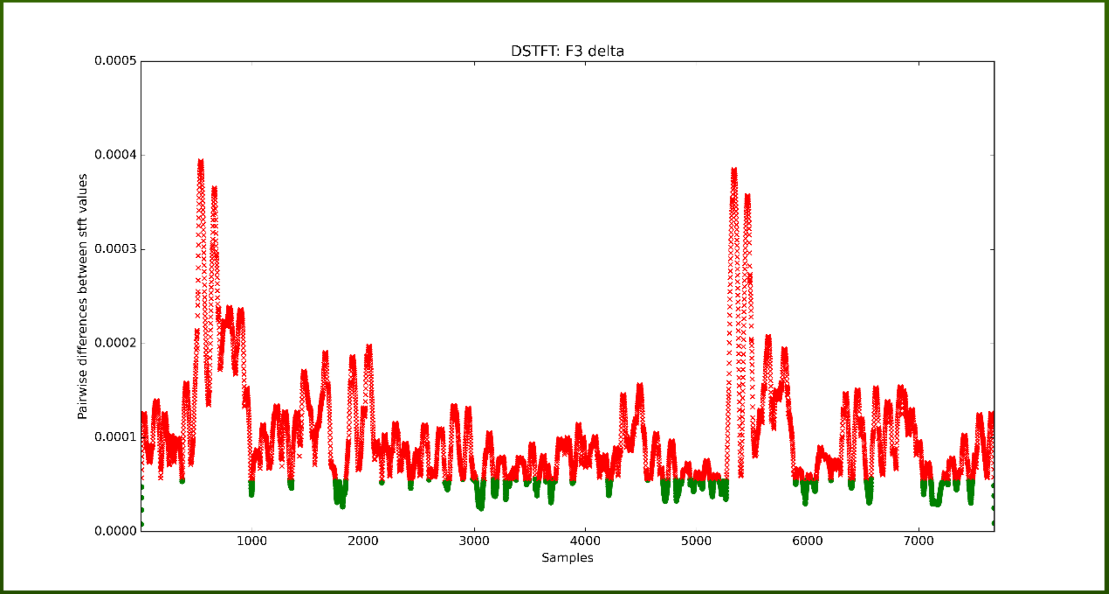
Create RP matrices.
Smooth/erode data.
Identify stable regions along the diagonal.
New state: no similar spectra in the past (row in upper part of the RP plot).

Problem: setting the threshold.

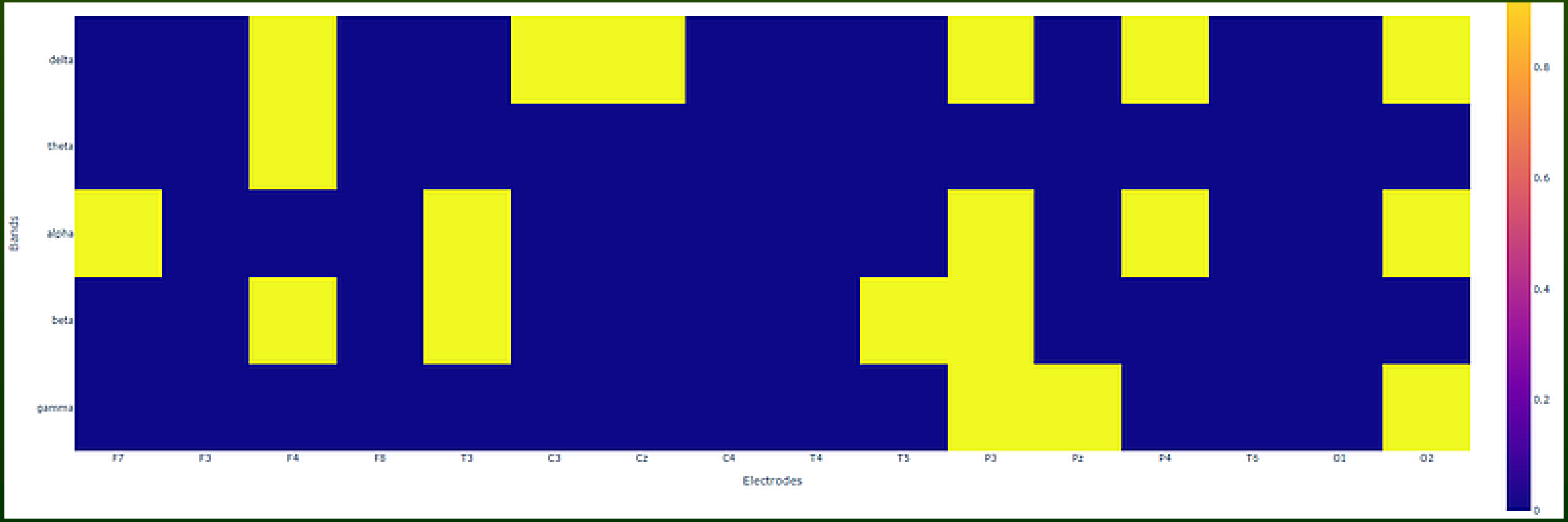
Compute power for individual states.



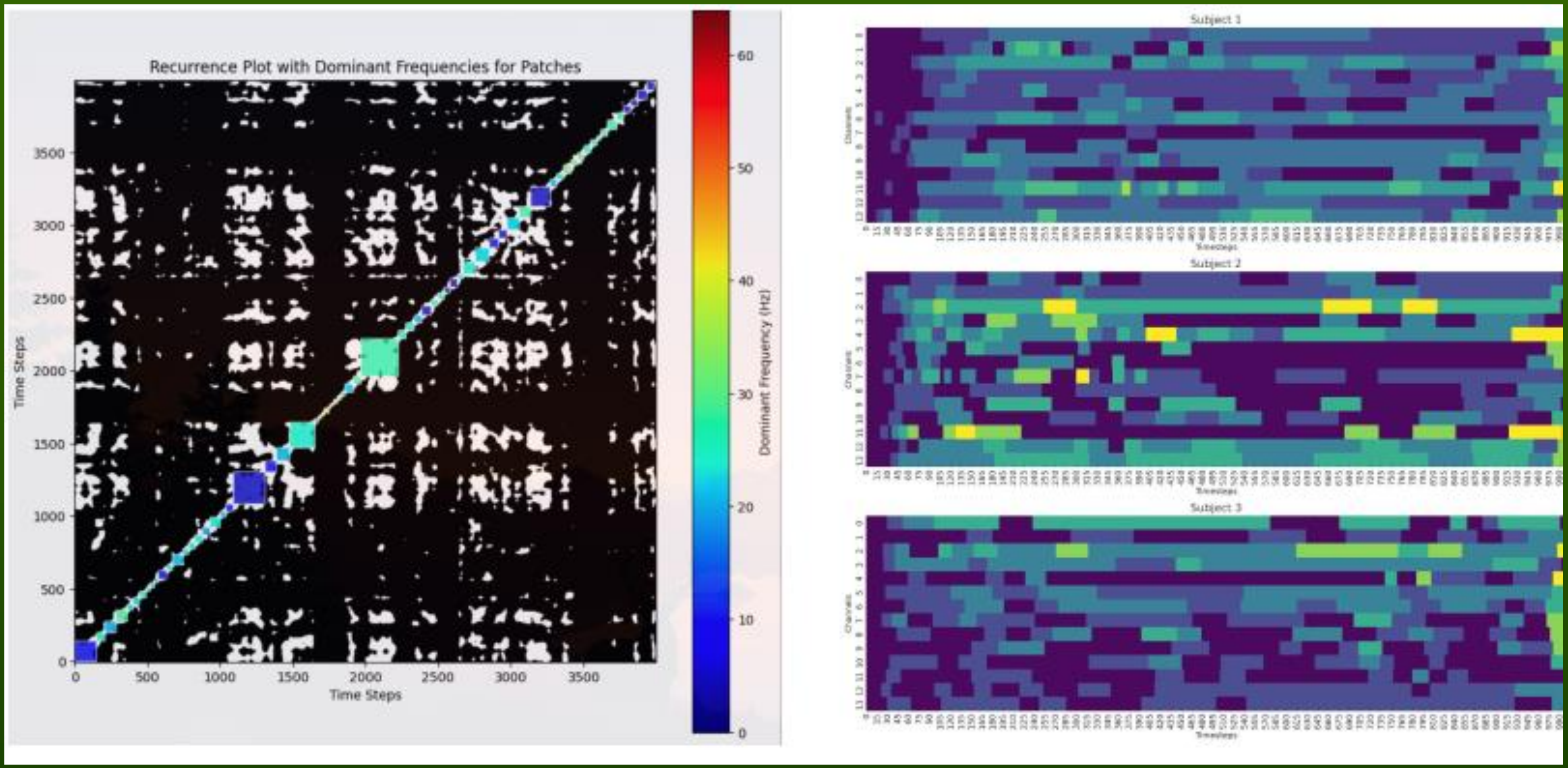
Labeling recurrent states



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



Labeled states



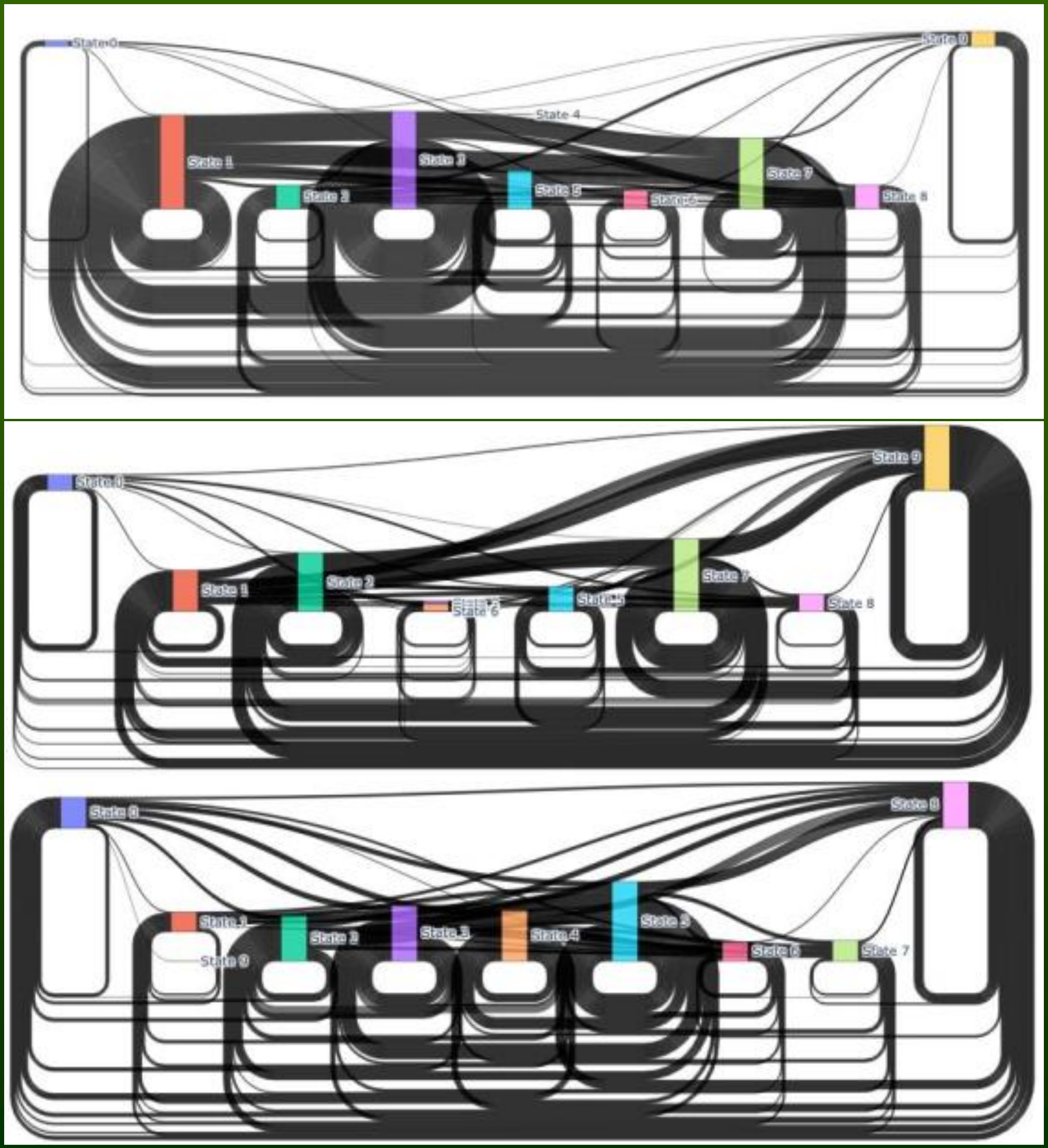
Example of RP with individual states, and patterns of states in discretized time steps for 3 subjects, 14 electrodes.

Sankey diagrams of dynamics

Control

ADHD

Schizophrenia



Classification using symbolic dynamics

Transformer network with multi-head architecture attention mechanism, applied to the state vectors.

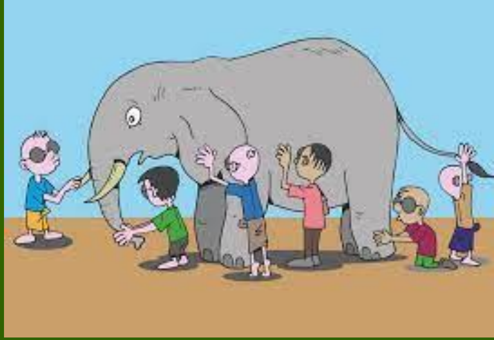
Classification results (5xCV):
16-19 Electrodes

Schizophrenia dataset, 45/39 adolescent boys (10-14 years old).
Accuracy: 96.15%, Precision: 0.93-1.00, Recall: 0.92-1.00, F1-Score: 0.96-0.97

ADHD dataset, 61/60 control children 7-12 years old
Accuracy: 97.30%, Precision: 0.95-1.00, Recall: 0.95-1.00, F1-Score: 0.97

BCI Dataset, Motor imagery, hands vs feets, 106 subjects:
Accuracy: 99.72%, Precision: 0.99-1.00, Recall: 0.99-1.00, F1-Score: 1.0

Perspectives



- Optimization of brain processes is our biggest challenge! Medical diagnostics and closed loop systems for therapy of the brain disorders are the driving forces.
- Simple robust methods may be used in clinical applications. Asymptotic spatial distributions and temporal dynamics based on large number of microstates give surprisingly high diagnostic accuracy.
- Spatial, temporal and structural aspects of brain signals should be integrated.
- Promising way to such integration may be based on recurrence quantification analysis using spectral signal representation, RQA combined with microstates, and graphs of transitions between dynamical states.
- RQA may be based on comparison with different reference states, including microstates or avPP states.
- Feature selection done within crossvalidation partition may identify untypical cases that are not correctly recognized if specific features are not used.
- Models trained on small data will not give biomarkers of clinical value. Large databases are needed to handle idiosyncratic cases.

Towards Human-like Intelligence

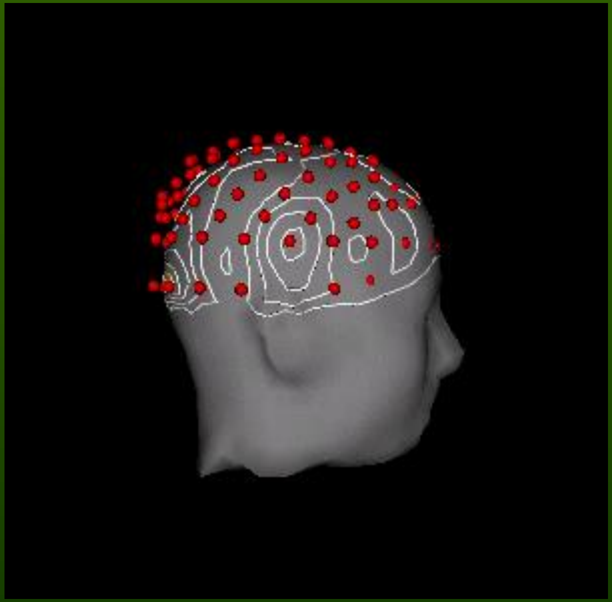
IEEE Computational Intelligence Society Task Force (Mandziuk, Duch, M. Woźniak),
Towards Human-like Intelligence

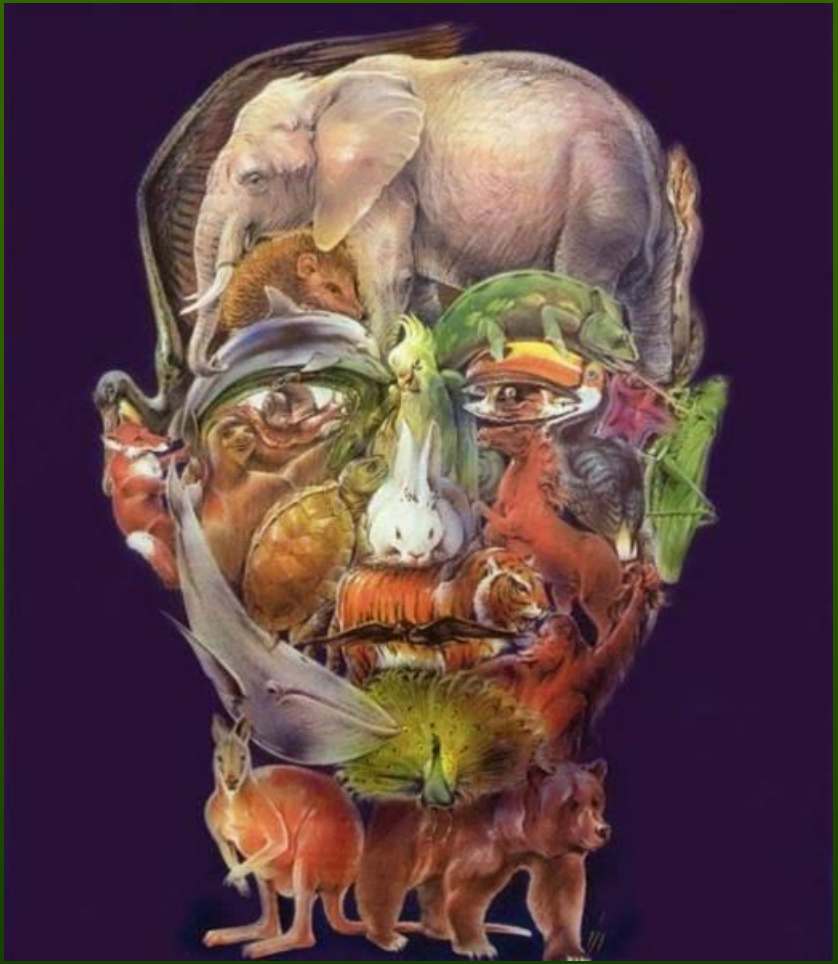
IEEE Symposium on Computational Intelligence for Human-like Intelligence
(IEEE SSCI CIHLI), 12/2022 in Singapore, 12/2023 in Mexico City.
Distributed Artificial Brains (DAB) session (Duch, Mandziuk, Woźniak).

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.

Thank you for synchronization of your neurons.





Search: Wlodek Duch

=> talks, papers, lectures, YouTube ...

1. PLACE WINNER

"NeuroBeat"

BCI application

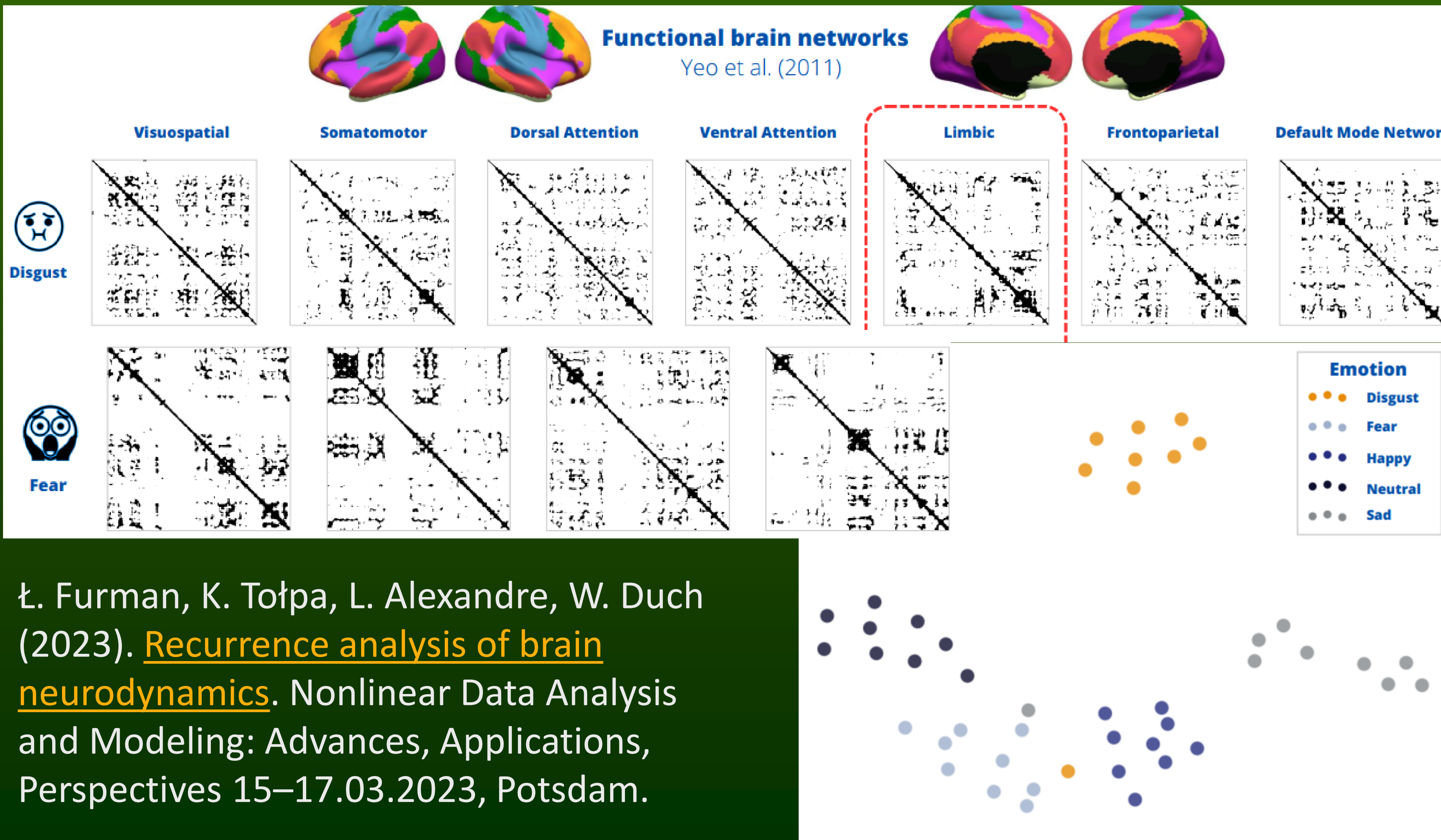
Team members: Alicja Wicher, Joanna Maria Zalewska, Weronika Sójka, Ivo John Krystian Derezinski, Krzystof Tołpa, Lukasz Furman, Slawomir Duda

Private Information in BCIs

K. Xia, W. Duch, Y. Sun, K. Xu, W. Fang, H. Luo, Y. Zhang, D. Sang, D. Wu, X. Xu, F-Y Wang, Privacy-Preserving Brain-Computer Interfaces: A Systematic Review, IEEE Trans. on Computational Social Systems, 2022

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.

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.

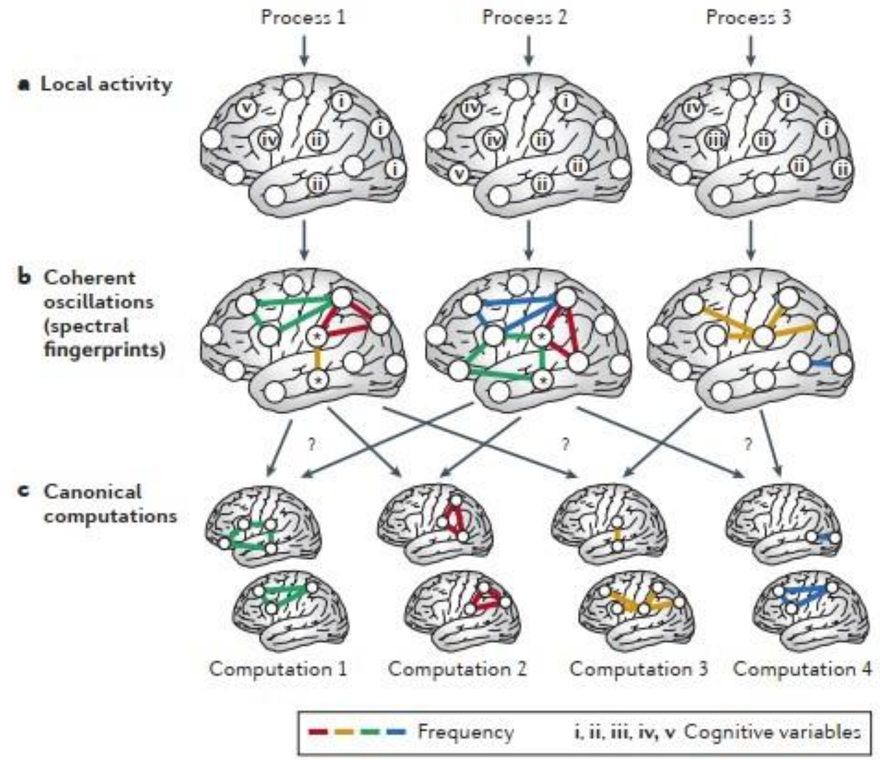
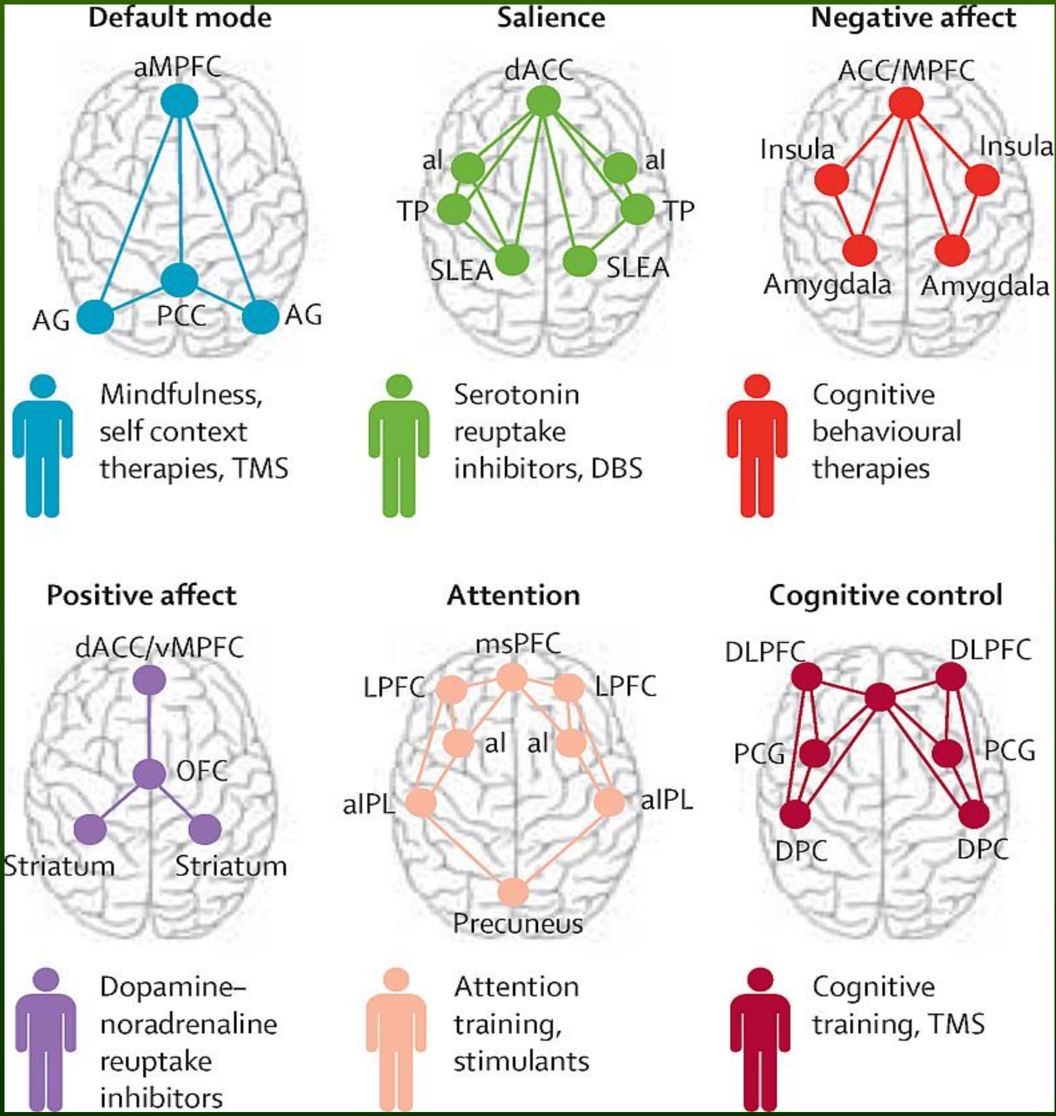


Figure 4 | **Large-scale spectral fingerprints of cognitive processes.** Schematic illustration of how coherent oscillations provide 'spectral fingerprints' for regrouping of cognitive processes 1–3. **a** | Studies of neuronal activity in individual brain regions (circles) elucidate the activation of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

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

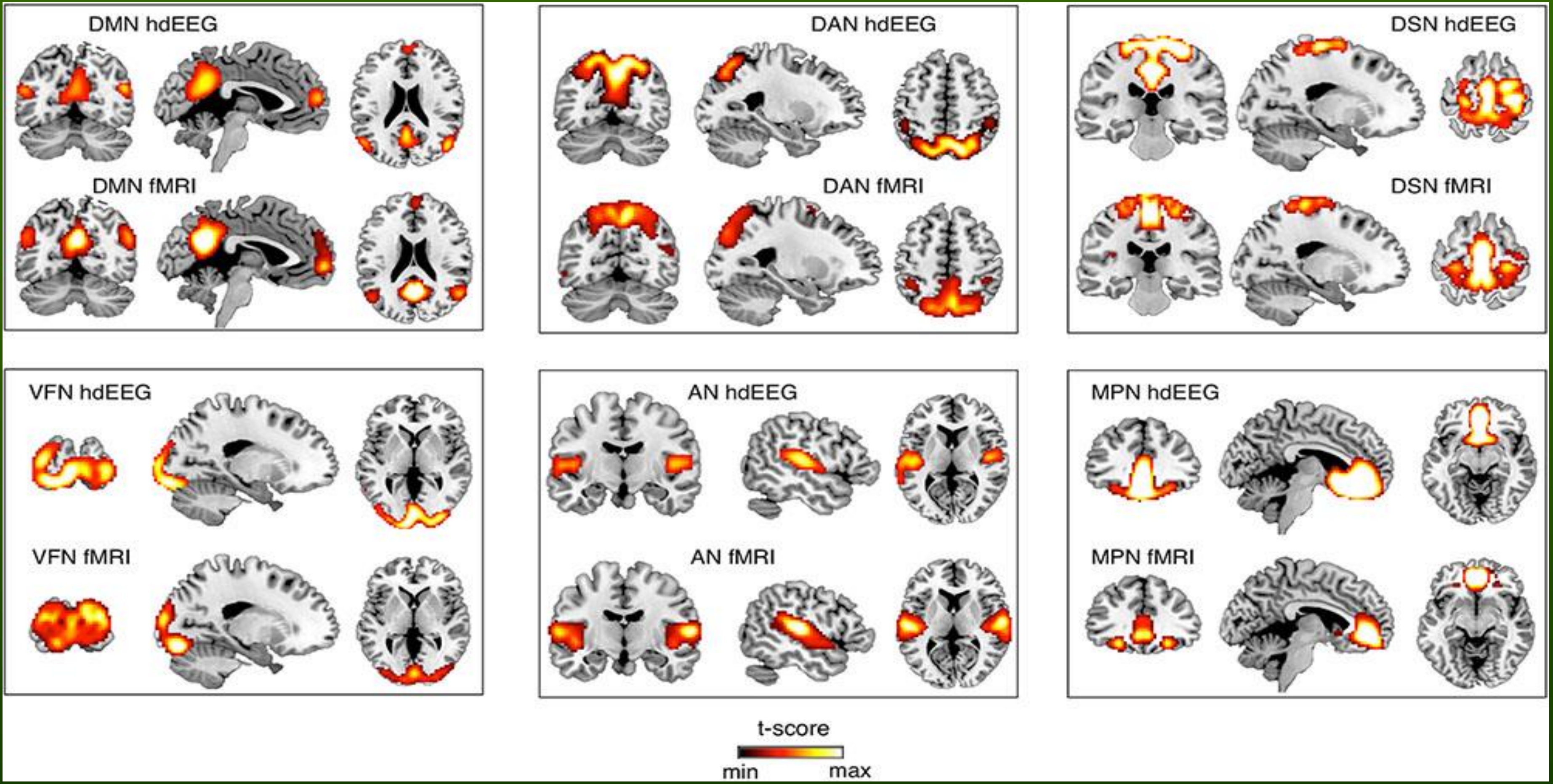
Large-Scale Networks from fMRI

- 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.

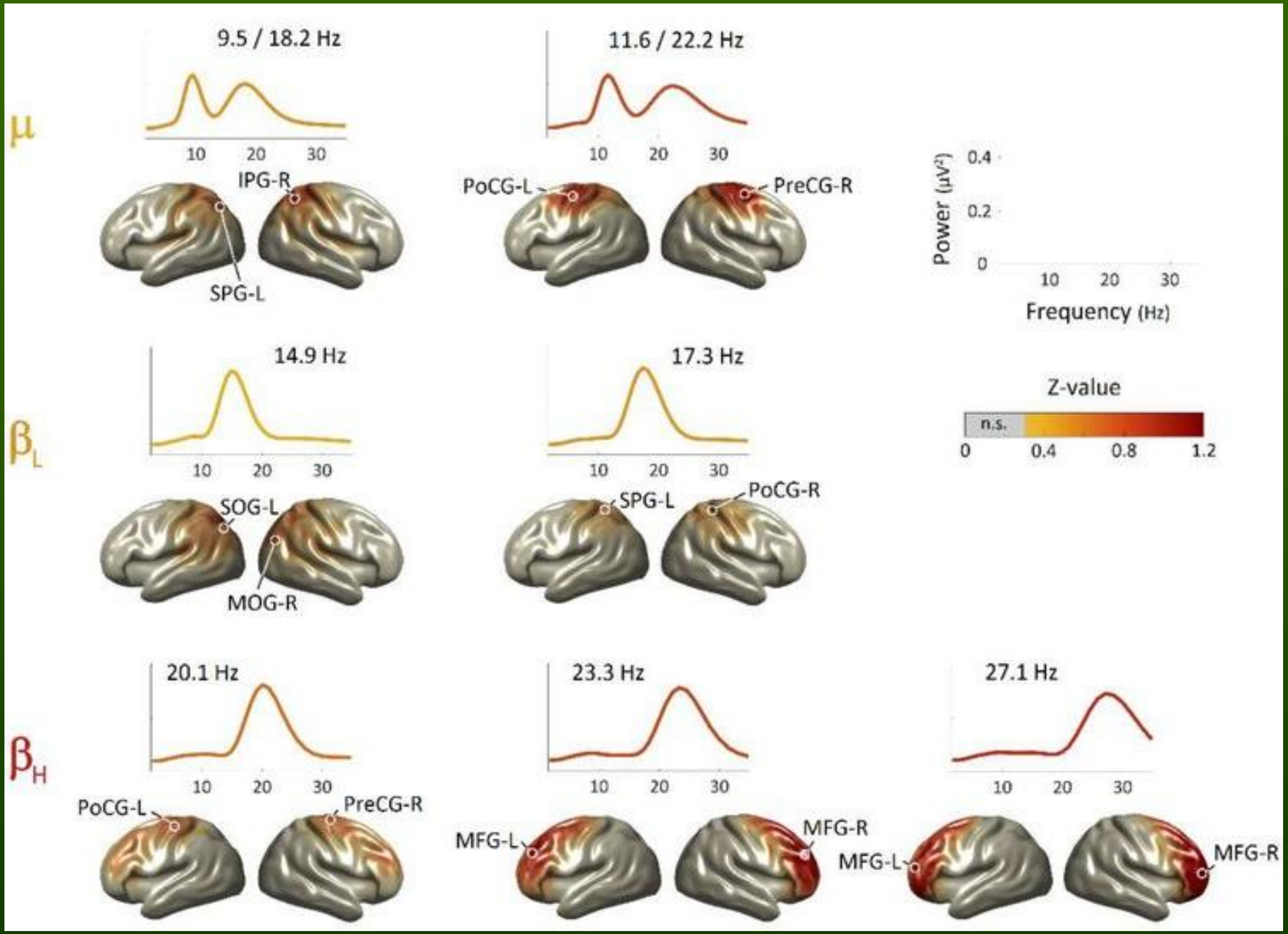
14 networks from BOLD-EEG



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?

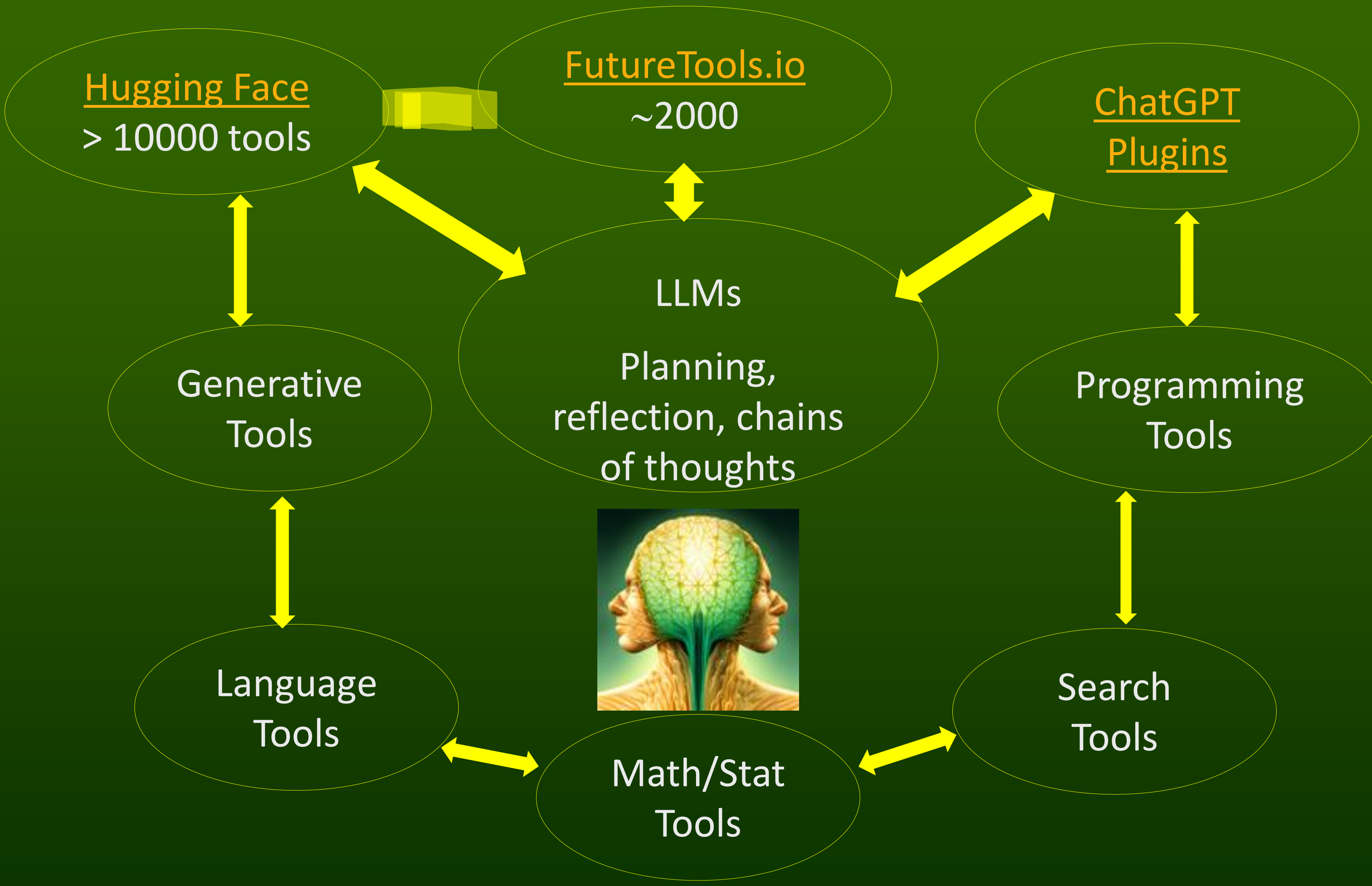
Atlas of the natural frequencies, resting brain

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

Distributed Artificial Brain (DAB)



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?