Neurodynamics and recurrence quantification for analysis of EEG data.

Włodzisław Duch

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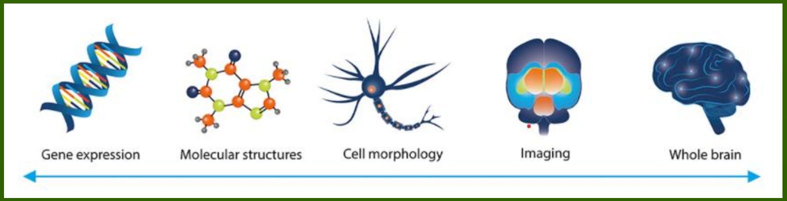
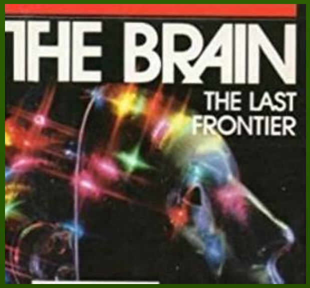
Google: Wlodzislaw Duch

Komisja Informatyki i Automatyki PAN, Poznań, 25/11/2022

Neuroinformatics





- Zespół :Neuroinformatics and Artificial Intelligence”, w ramach Uniwersyteckiego Centrum Doskonałości (2020) IDUB “Dynamika, analiza matematyczna i sztuczna inteligencja”. Zrozumienie procesów w mózgu i inspiracje dla algorytmów AI.
- Komitet Informatyki PAN: Sekcja Nauk Obliczeniowych, Bio i Neuro-informatyki.
- Neuroinformatyka to chyba jedyna specjalność informatyki, w której można dostać Nagrodę Nobla (A. Cormack, G.Hounsfield, 1979 Computer Tomography)
- Symulacje + Interpretacja sygnałów, czyli jak działają mózgi.
- Perspektywy neurotechnologii.
- Planujemy z UW/IPPT++ co roku podsumowanie działań w Polsce.

On the threshold of a dream …

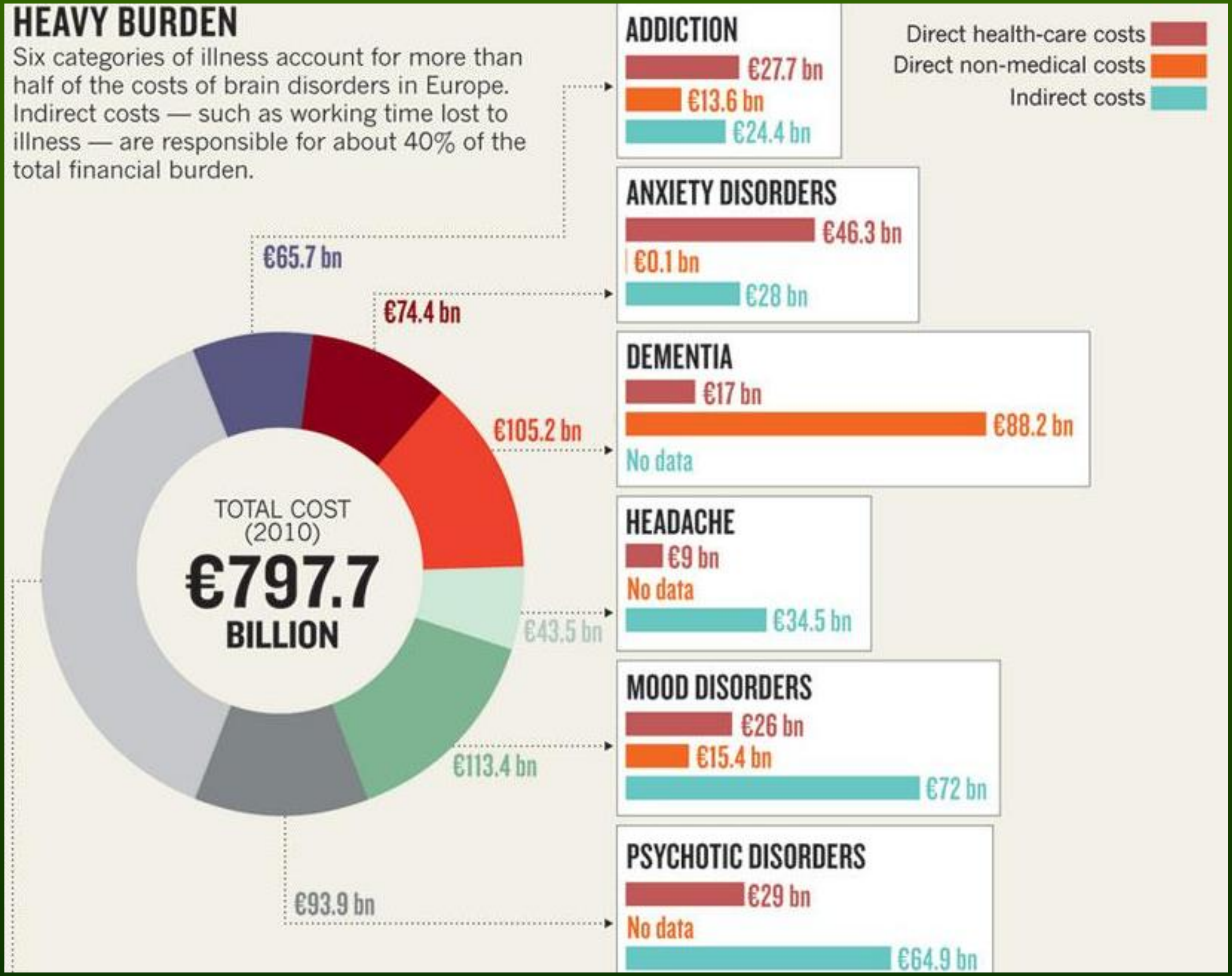
Final goal: optimize brain processes!

To repair damaged brains and increase efficiency of healthy brains we need to understand brain processes:

1. Create models of cognitive architectures that help to understand information processing in the brain.
2. Find fingerprints of specific brain activity (regions, subnetworks) using neurotechnologies.
3. Create diagnostic and therapeutic procedures.
4. Use neurofeedback decoding local activity and functional connectivity to stimulate the brain.
5. Stimulate neuroplasticity in a closed loop, monitoring brain activity and applying TMS, DCS, EM and other forms of neuromodulation.

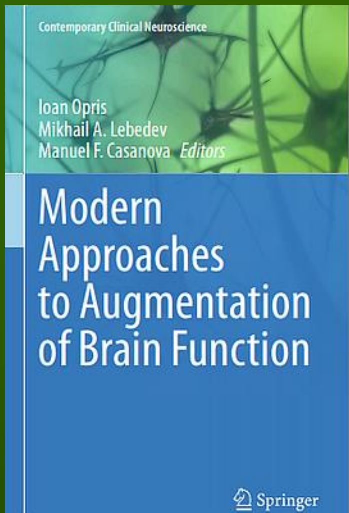
G-tec wireless NIRS/EEG on my head.

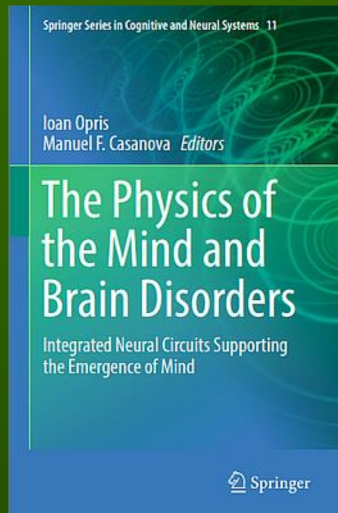
Brain disorders are costly

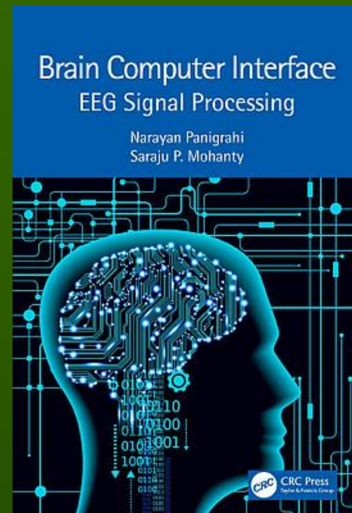


Current costs - well over 1000 bn?

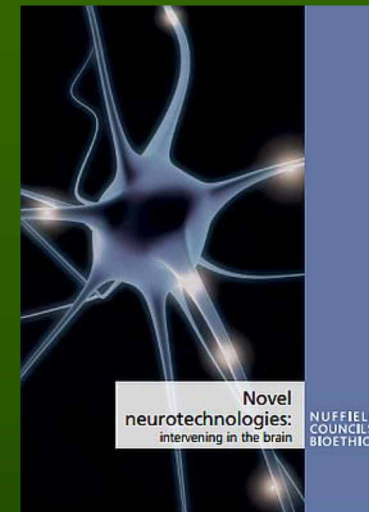
Books

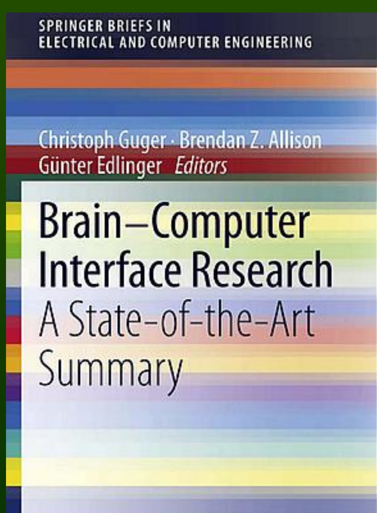

Contemporary Clinical Neuroscience
Ioan Opris
Mikhail A. Lebedev
Manuel F. Casanova Editors
Modern Approaches to Augmentation of Brain Function
Springer

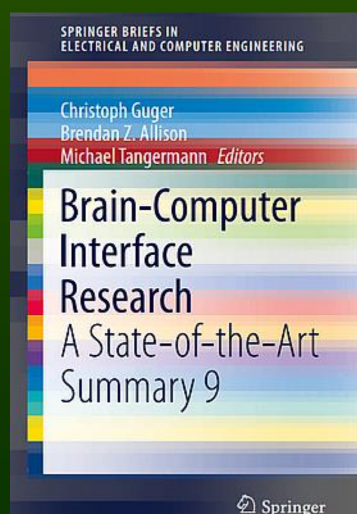

Springer Series in Cognitive and Neural Systems 11
Ioan Opris
Manuel F. Casanova Editors
The Physics of the Mind and Brain Disorders
Integrated Neural Circuits Supporting the Emergence of Mind
Springer

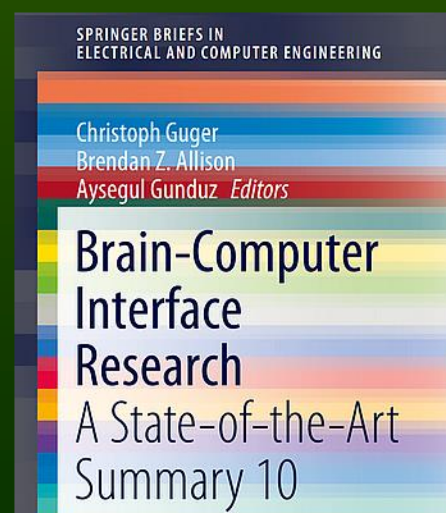

Brain Computer Interface
EEG Signal Processing
Narayan Panigrahi
Saraju P. Mohanty
CRC Press

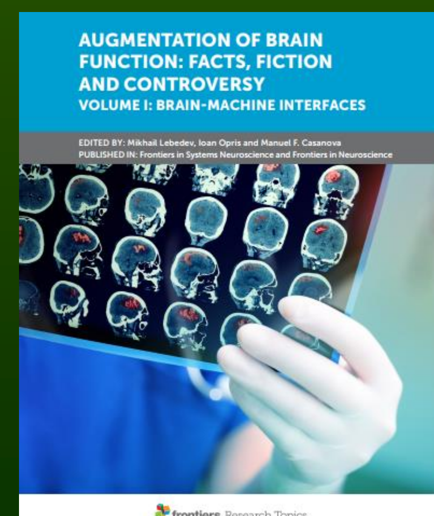

Vahid Asadpour
Andries Engelbrecht
Brain-Computer Interface


Novel neurotechnologies:
intervening in the brain
NUFFIELD COUNCIL ON BIOETHICS


SPRINGER BRIEFS IN ELECTRICAL AND COMPUTER ENGINEERING
Christoph Guger · Brendan Z. Allison
Günter Edlinger Editors
Brain–Computer Interface Research
A State-of-the-Art Summary

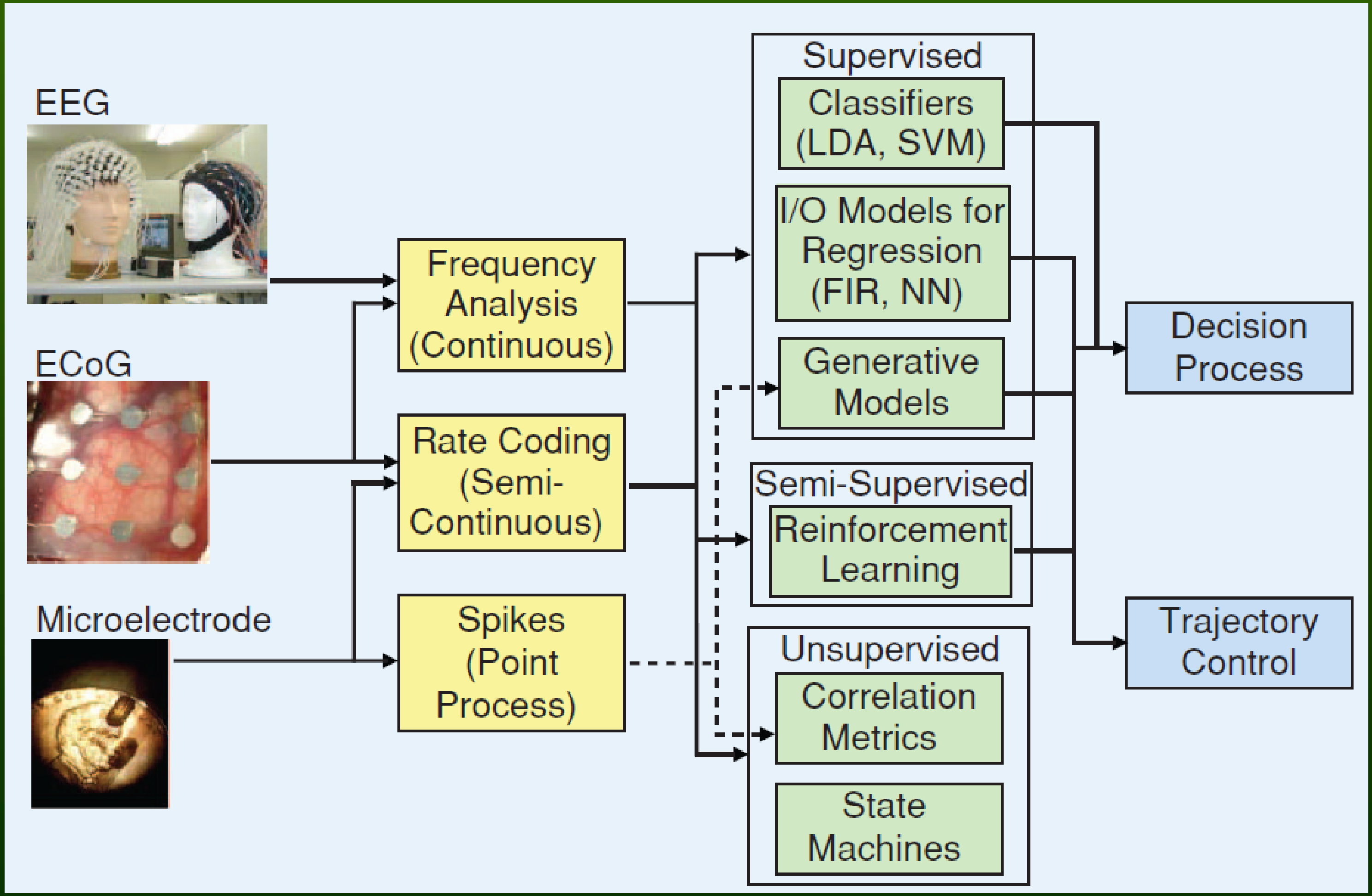

SPRINGER BRIEFS IN ELECTRICAL AND COMPUTER ENGINEERING
Christoph Guger
Brendan Z. Allison
Michael Tangermann Editors
Brain-Computer Interface Research
A State-of-the-Art Summary 9
Springer

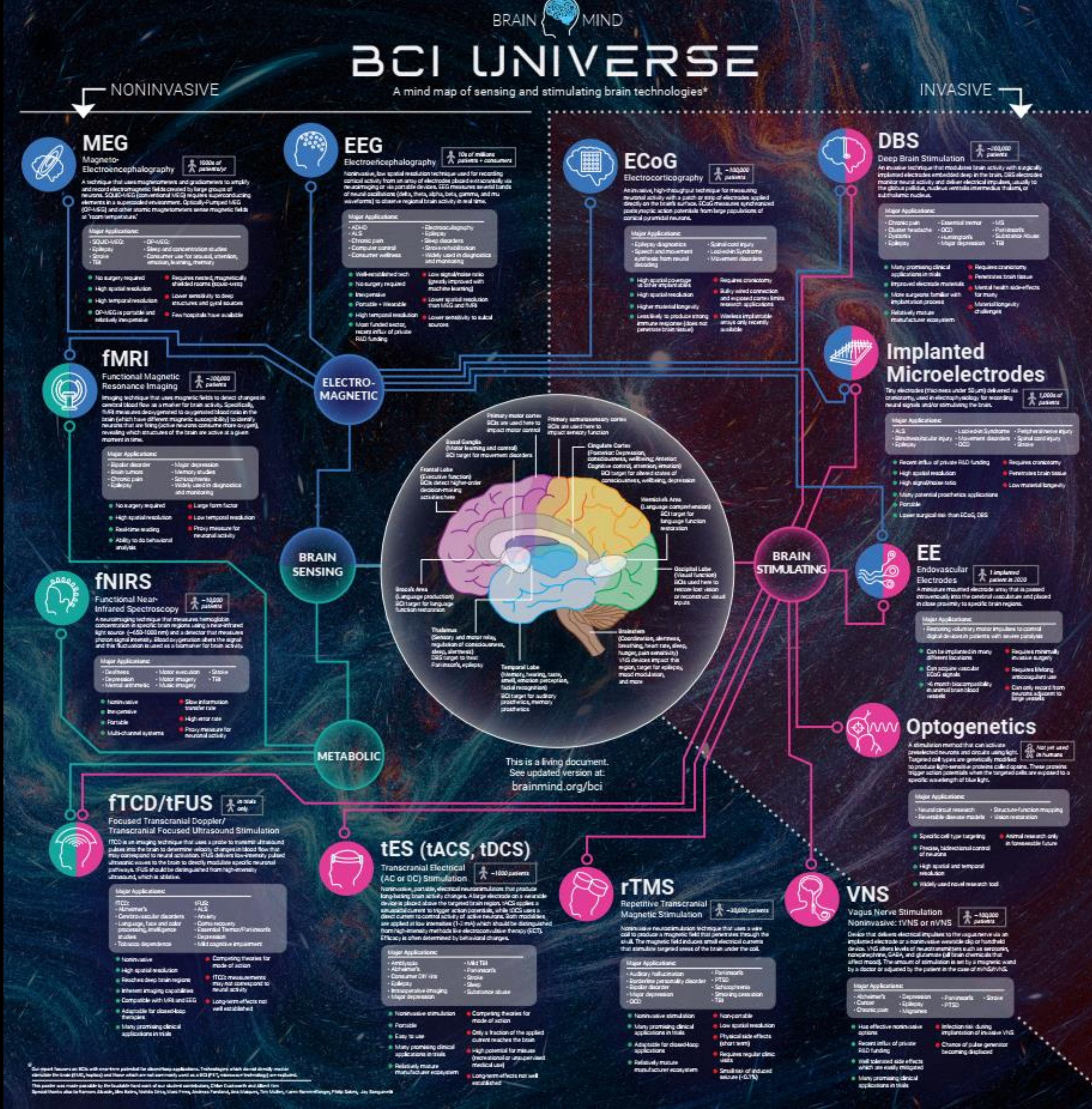

SPRINGER BRIEFS IN ELECTRICAL AND COMPUTER ENGINEERING
Christoph Guger
Brendan Z. Allison
Aysegul Gunduz Editors
Brain-Computer Interface Research
A State-of-the-Art Summary 10


AUGMENTATION OF BRAIN FUNCTION: FACTS, FICTION AND CONTROVERSY
VOLUME I: BRAIN-MACHINE INTERFACES
EDITED BY: Mikhail Lebedev, Ioan Opris and Manuel F. Casanova
PUBLISHED IN: Frontiers in Systems Neuroscience and Frontiers in Neuroscience
frontiers Research Topics

BMI: time to connect our brains …

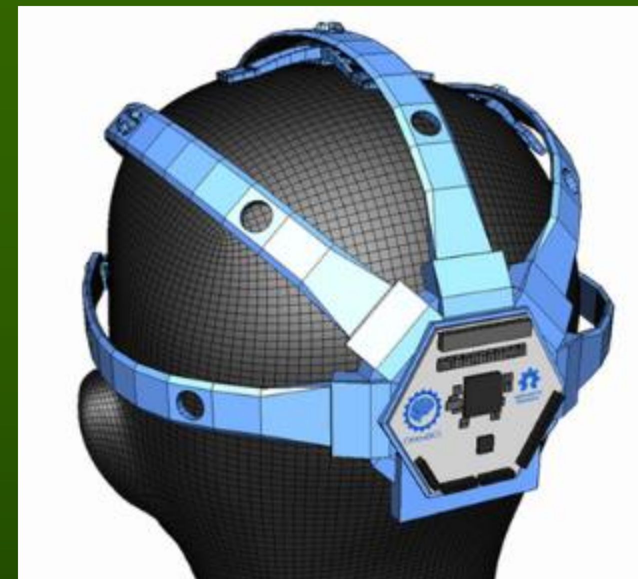
Non-invasive, partially invasive and invasive methods carry increasing amount of information, but are more difficult to implement.
EEG+ML still reigns supreme!




BRAIN MIND
BCI UNIVERSE
A mind map of sensing and stimulating brain technologies*
NONINVASIVE
INVASIVE
MEG
Magneto-Electroencephalography
1000s of patients/yr
A technique that uses magnetometers and gradiometers to amplify and record electromagnetic fields created by large groups of neurons. SQUID-MEG (conventional MEG) requires superconducting elements in a supercooled environment. Optically-Pumped MEG (OP-MEG) and other atomic magnetometers sense magnetic fields at "room temperature."
Major Applications:
SQUID-MEG: Epilepsy, Stroke, TBI
OP-MEG: Sleep and concentration studies, Consumer use for arousal, attention, emotion, learning, memory
No surgery required
High spatial resolution
High temporal resolution
OP-MEG is portable and relatively inexpensive
Requires nested, magnetically shielded rooms (SQUID-MEG)
Lower sensitivity to deep structures and gyral sources
Few hospitals have available
EEG
Electroencephalography
10s of millions patients + consumers
ECoG
Electrocorticography
~100,000 patients
DBS
Deep Brain Stimulation
~200,000 patients
fMRI
Functional Magnetic Resonance Imaging
~200,000 patients
Implanted Microelectrodes
ELECTRO-MAGNETIC
BRAIN SENSING
BRAIN STIMULATING
METABOLIC
fNIRS
Functional Near-Infrared Spectroscopy
~10,000 patients
EE
Endovascular Electrodes
Optogenetics
fTCD/tFUS
Focused Transcranial Doppler/
Transcranial Focused Ultrasound Stimulation
tES (tACS, tDCS)
Transcranial Electrical (AC or DC) Stimulation
~1000 patients
rTMS
Repetitive Transcranial Magnetic Stimulation
~10,000 patients
VNS
Vagus Nerve Stimulation
Noninvasive: tVNS or nVNS
~100,000 patients
This is a living document.
See updated version at:
brainmind.org/bci

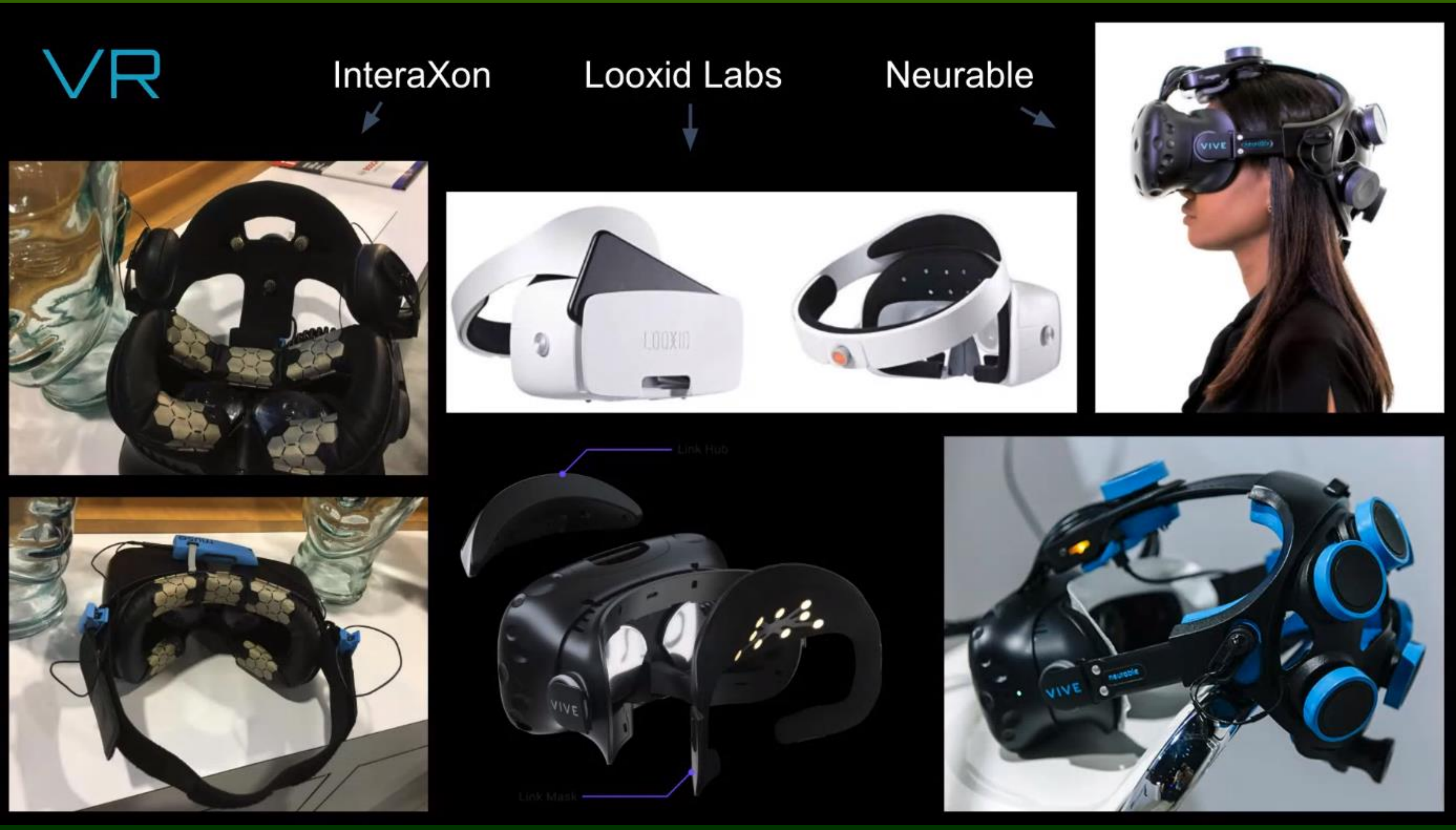
Over 30 companies

Neurosky-MindWave Mobile 2; G-Tec, OpenBCI,
ANT-neuro, Waveguard, Google Wireless EEG …



BCI tools

Combination of Virtual Reality with BCI has great potential.



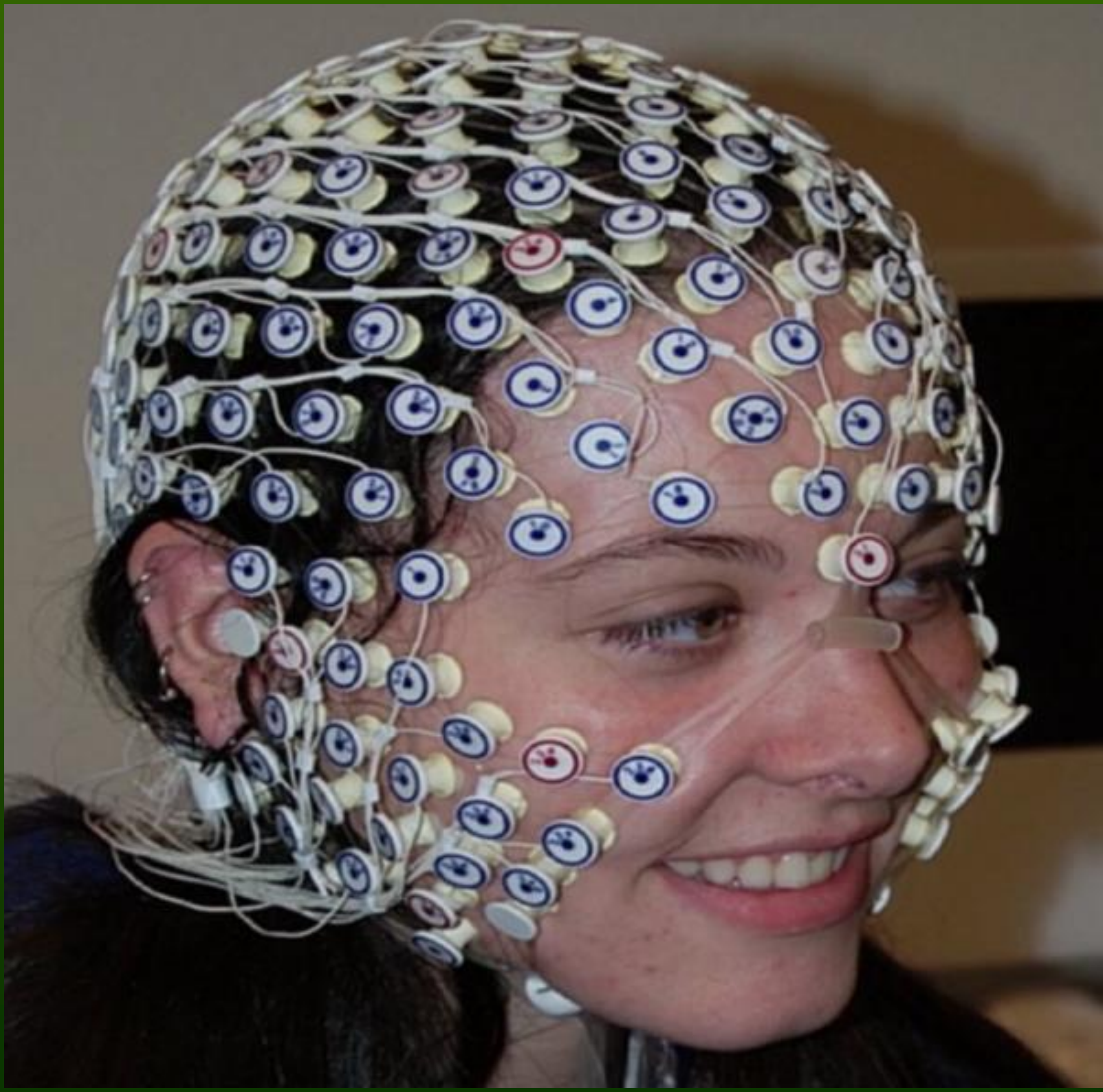
HD DCS for BCBI

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

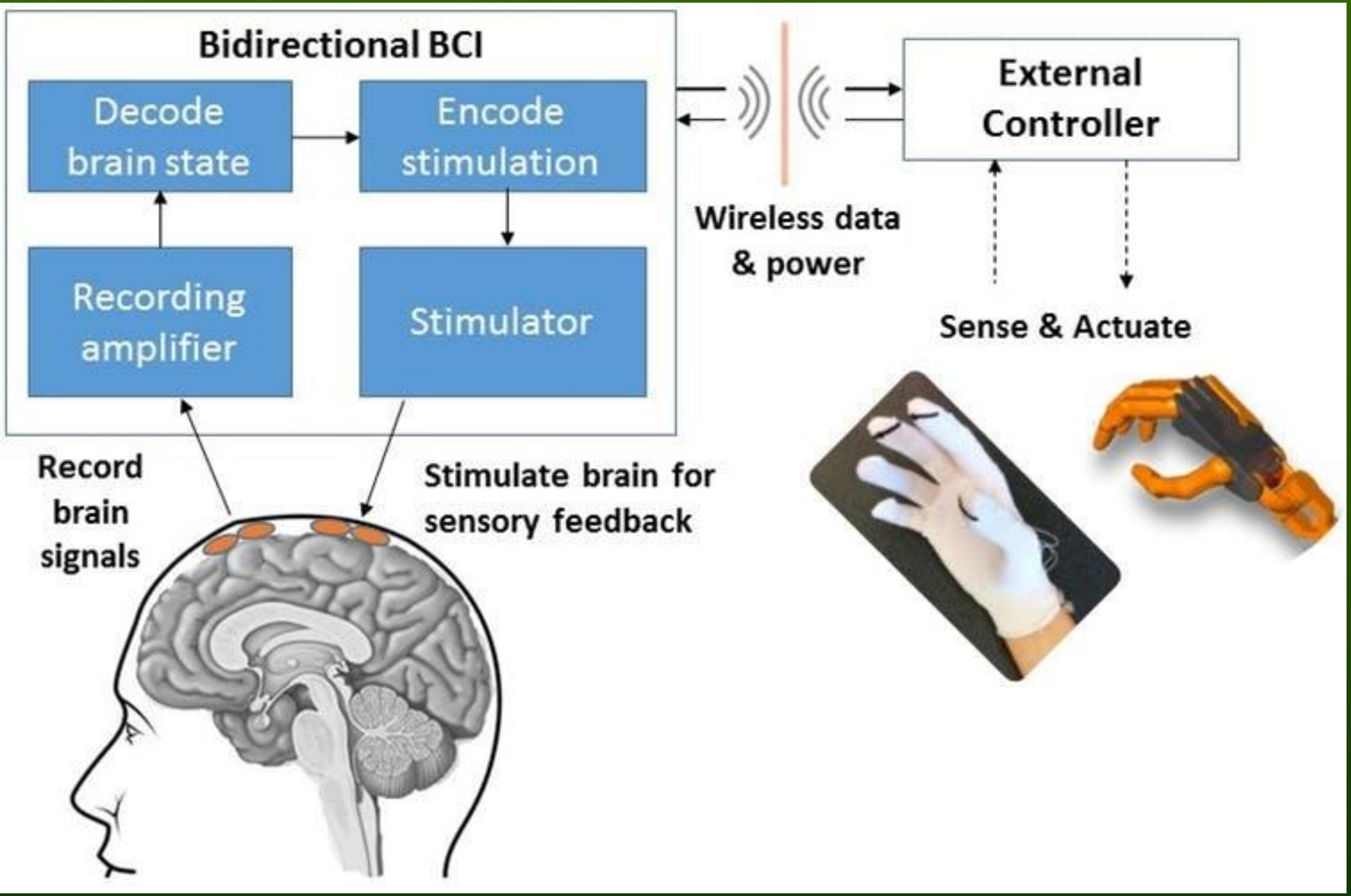
Depression, neuro-plasticity, pain, psychosomatic disorders, teaching!

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

But **no-one really knows** why it works …

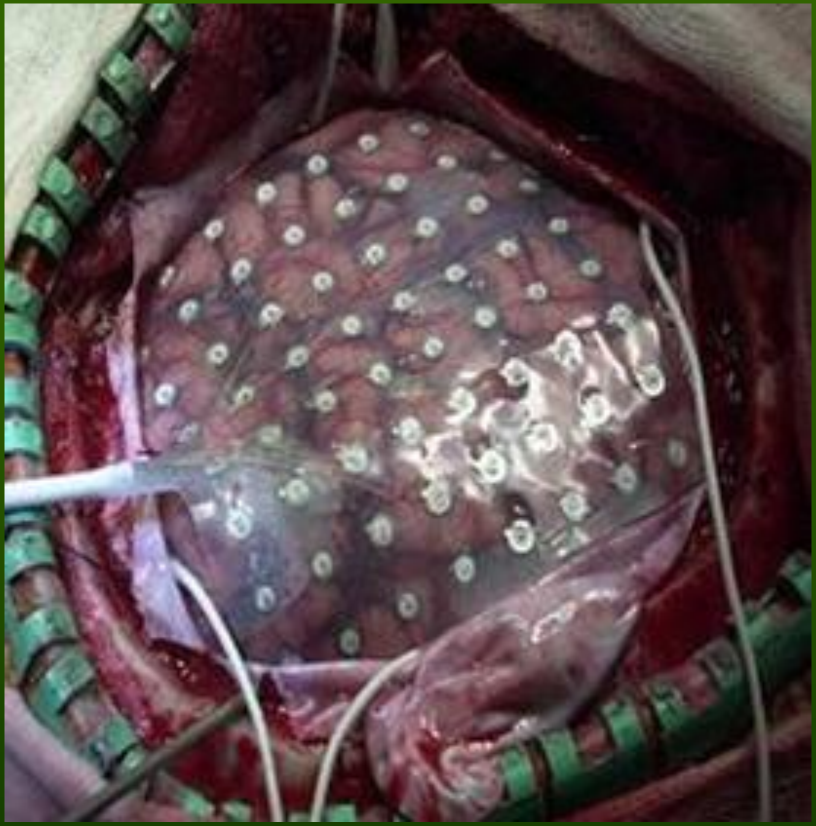


BCBI: Brain-Computer-Brain



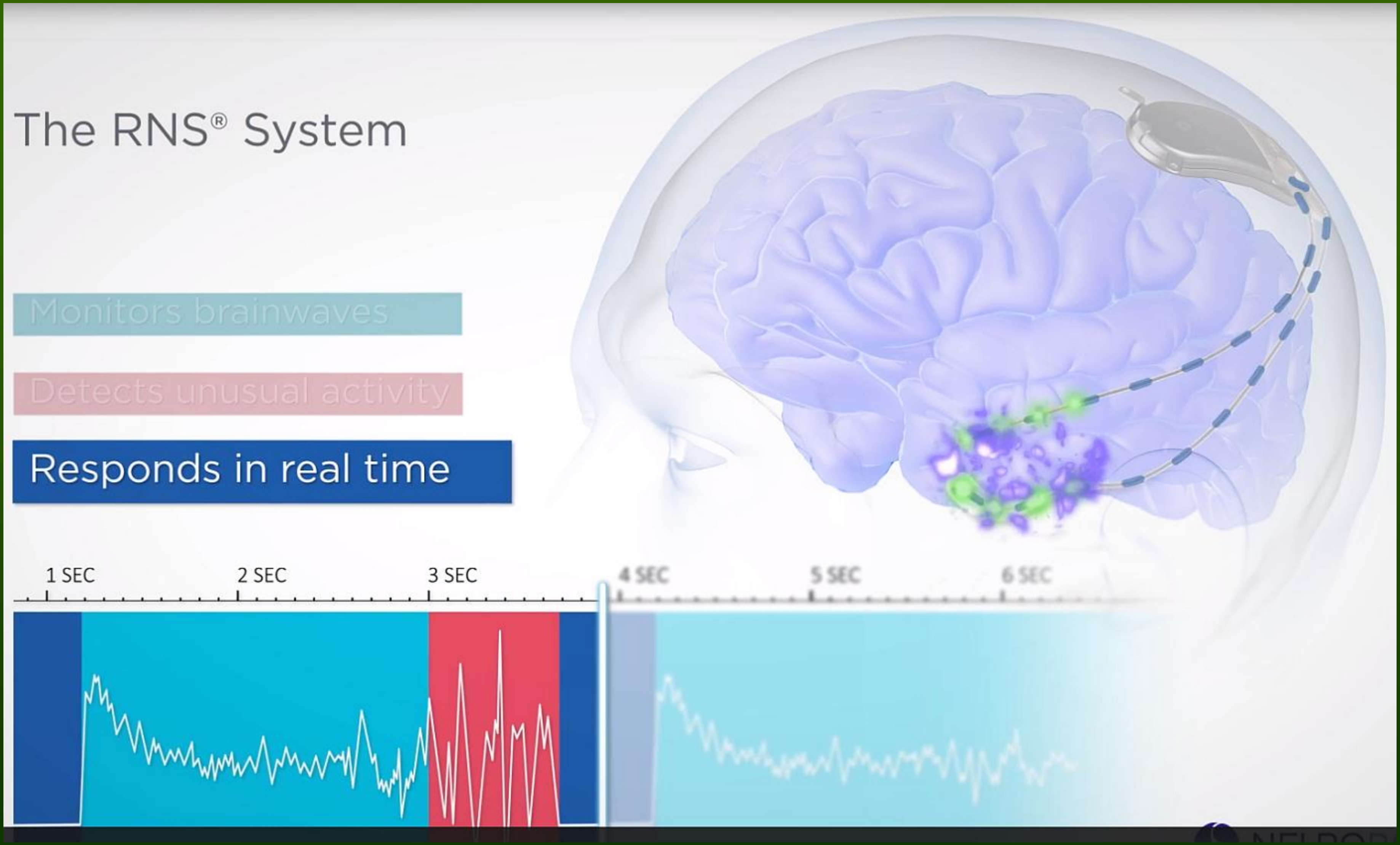
BCI + brain stimulation = BCBI – a closed loop through which the brain begins to restructure itself. The body can be replaced by signals in Virtual Reality.

Invasive brain computer interfaces



People with Parkinson's disease or compulsive-obsessive disorder who have pacemakers implanted in their brain can regulate their behavior with an external controller.

Epilepsy



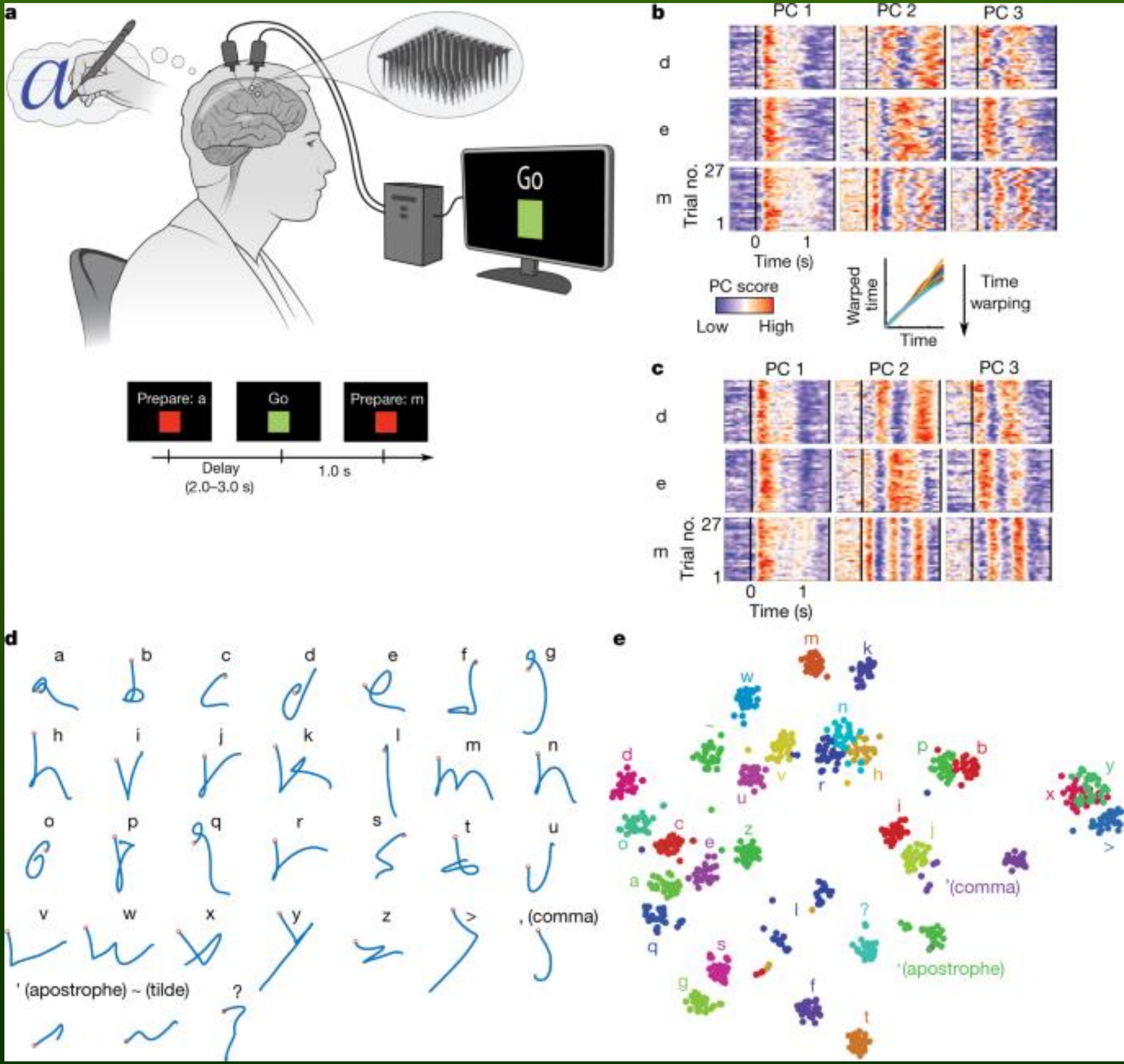
The neurostimulator and detector stops attacks of drug-resistant epilepsy before cramps occur. About 1% of people in the world have epilepsy.

Intracortical array with 192 electrodes.

Decoded pen trajectories are shown for all 31 characters.
Time wrapping (shift + scale) is essential for denoising.

Speech: 90 char/min!

Willett, F.R. …. & Shenoy, K.V.(2021) High-performance brain-to-text communication via handwriting. *Nature*, *593*, 249



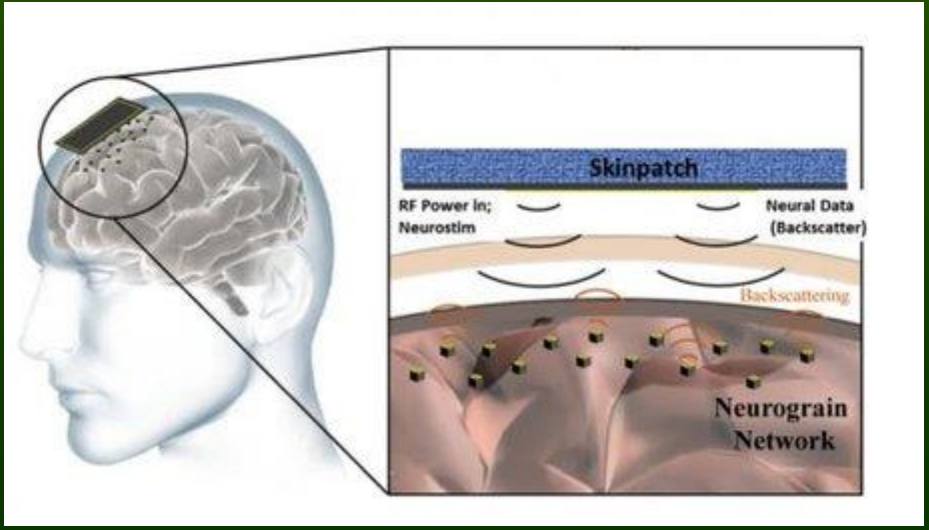
A million nanowires in the brain?

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

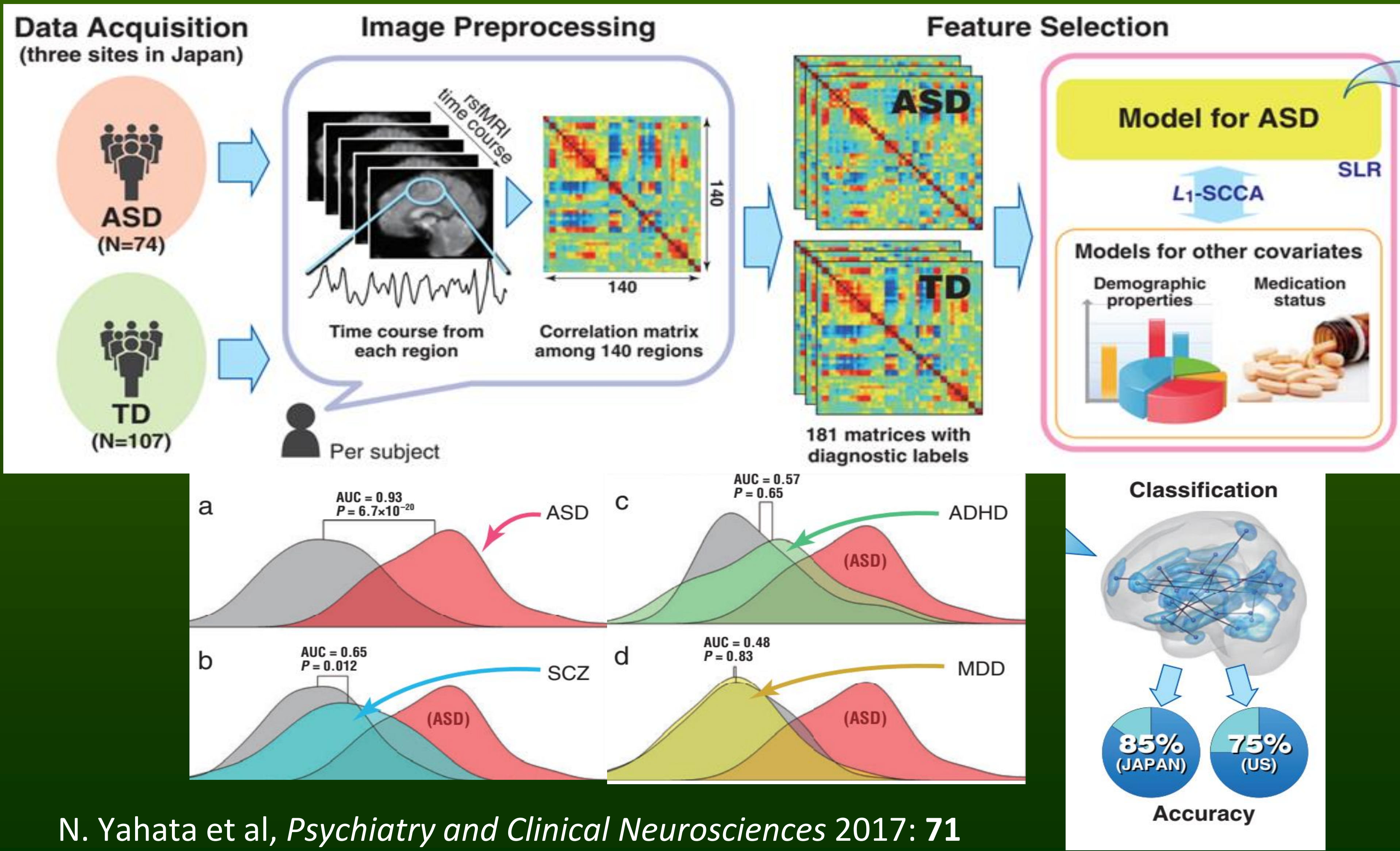
An interface that reads the impulses of 10^6 neurons, stimulates 10^5 neurons, simultaneously reads and stimulates 10^3 neurons.

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 and the much-heralded technology neuralink (neural lace).

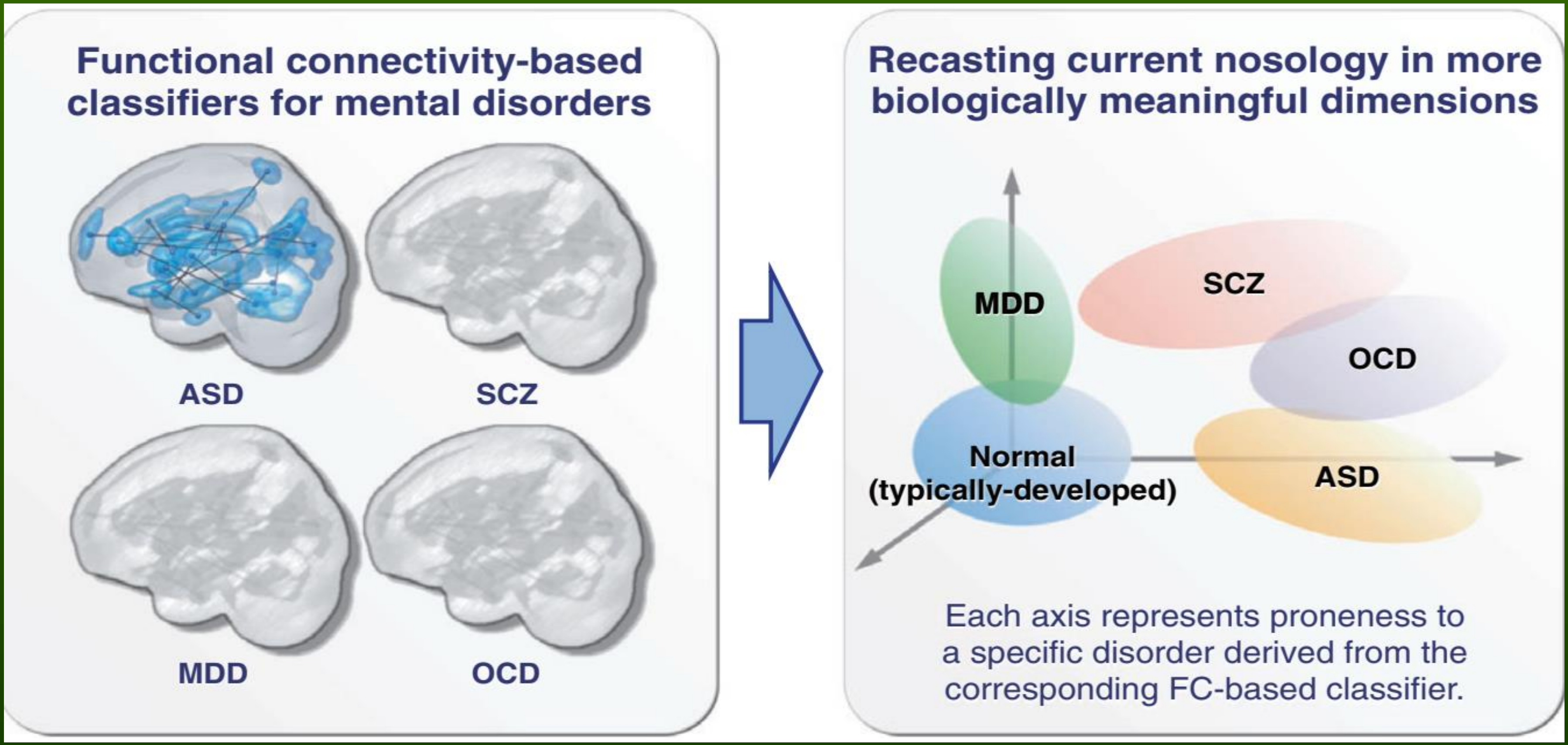


Biomarkers from fMRI



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

Use it in neurofeedback.

Understanding the brain

Recent PhDs

- Kamil Bonna, Neural correlates of prediction errors during reward and punishment learning (UMK Toruń).

- Michał Komorowski, Locally specific human brain dynamics automatically modeled using spectral features of MEG/EEG signals (IPPT PAN, Warszawa).

- Ewa Ratajczak, Microstate neurodynamics in HRV biofeedback (UMK Toruń).

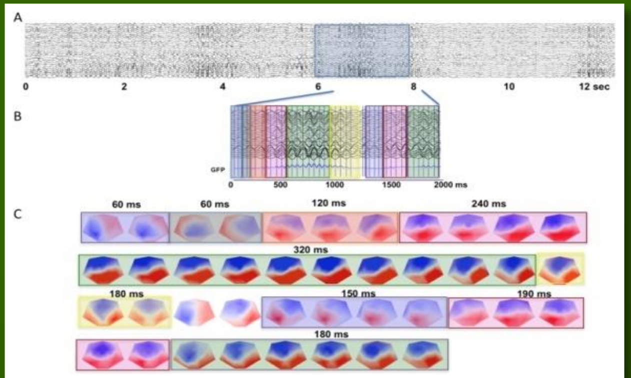
Brain fingerprinting

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

Several approaches:

- 1. Microstates and their transitions, GFP+SD (Michel & Koenig 2018)
- 2. Spectral Fingerprints (Keitel & Gross 2016)
- 3. Recurrence quantification analysis.
- 4. fMRI networks (Yuan … Bodurka, 2015).
- 5. Contextual Connectivity (Ciric et al. 2018)
- 6. Reconfigurable task-dependent modes (Krienen et al. 2014)
- + TDA, many more approaches…

1



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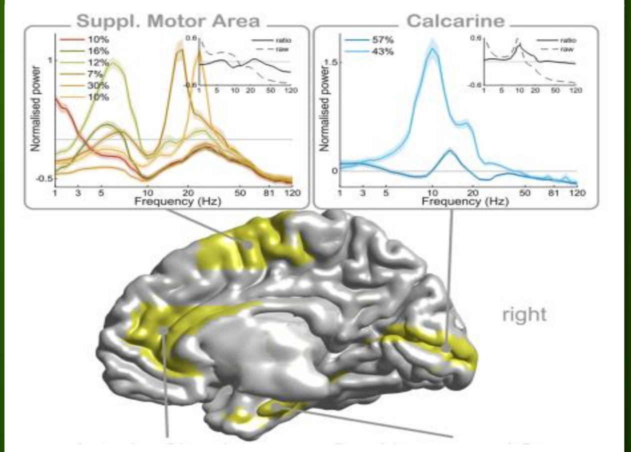

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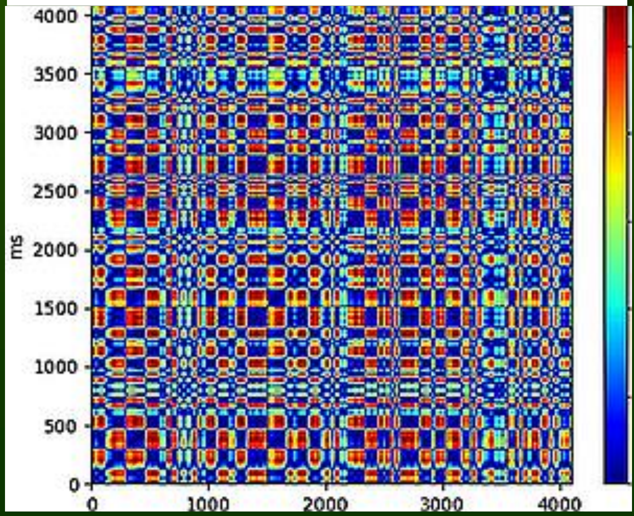
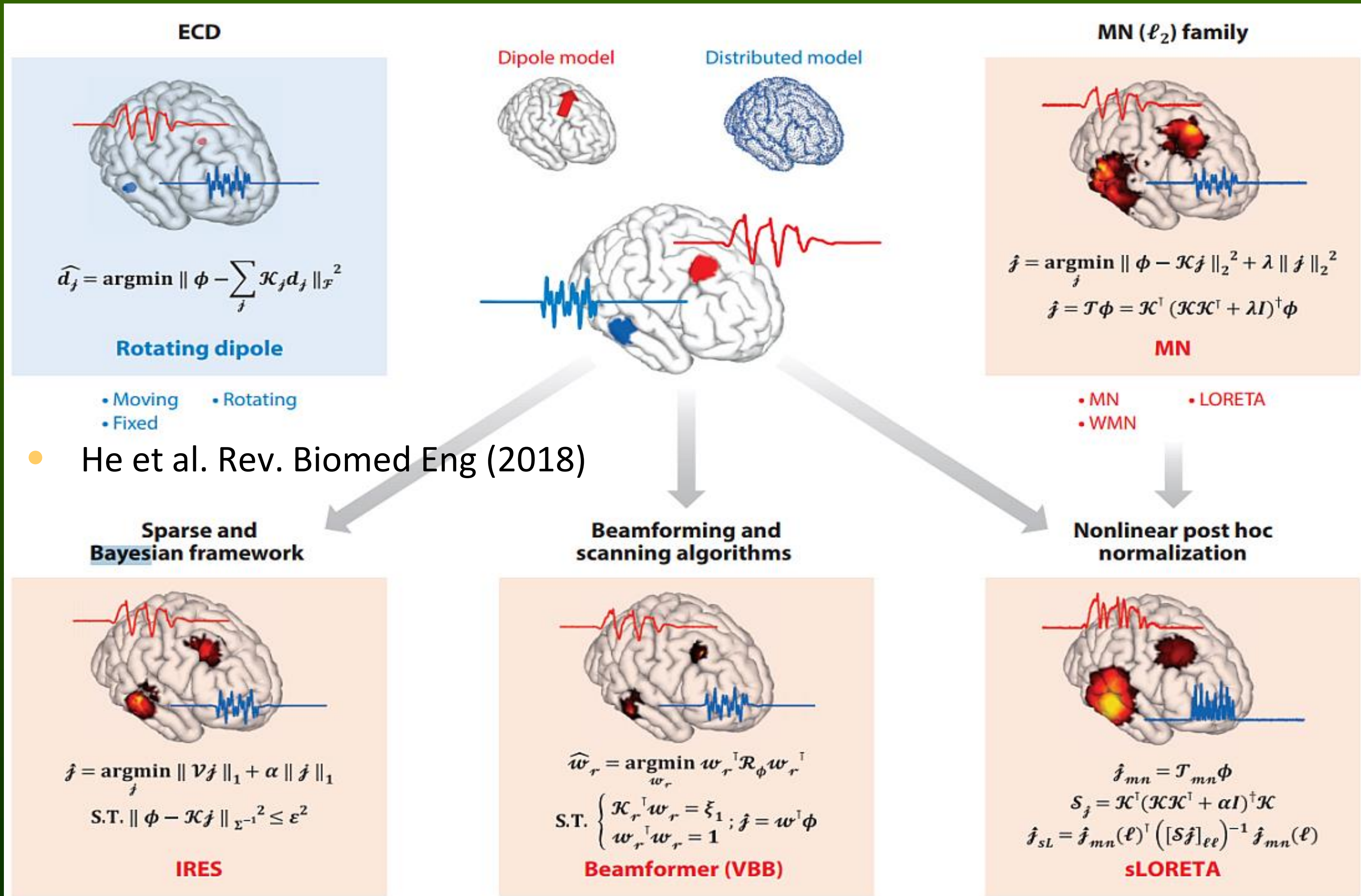


EEG localization and reconstruction

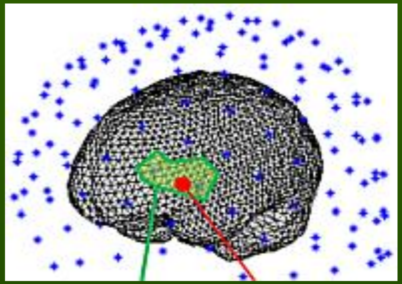


- He et al. Rev. Biomed Eng (2018)

Spatial filters

- LCMV (Linearly Constrained Minimum Variance), classical reconstruction filter, is a solution to the following problem: how measured Φ on scalp relate to sources. *K* - *lead-field* matrix; θ – dipole positions, *j* – activations; *W* – spatial filter, leadfield

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



- 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

$$W = \bigcap_{j \in \Upsilon} \operatorname*{arg\,min}_{\hat{W} \in X_r} \left\| \hat{W} K(\theta) - \mathrm{I}_l \right\|_j^2$$

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.

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

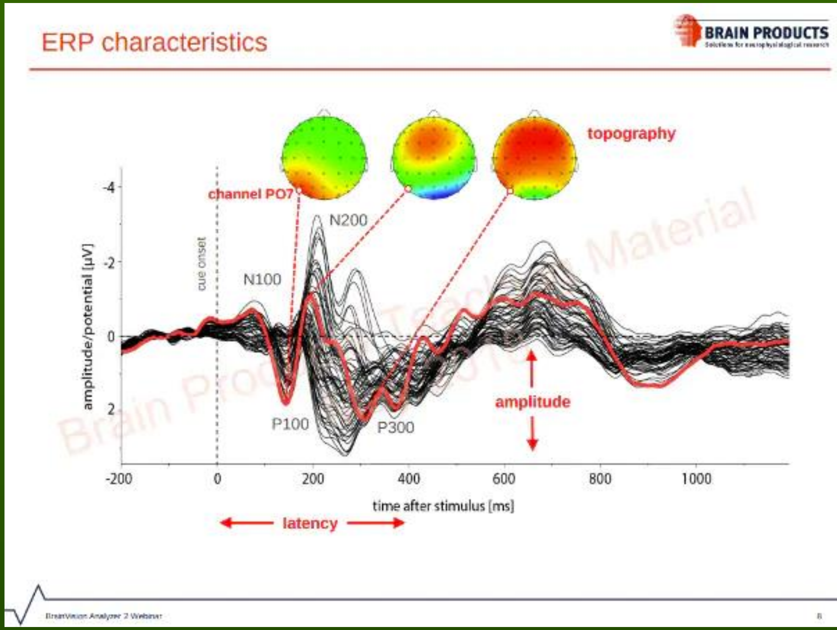
$$B := H_{Src,N} := N^{-1/2}H \tag{35}$$

```
%%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.

Understanding brains: ERP



What do brain signals tell us?

Evoked potentials:

- Visual evoked potential VEP, SSVEP
- Auditory evoked potential AEP
- Somatosensory evoked potential SEP
- Motor evoked potentials MEP

Event-Related Potentials, higher cognitive processing.

ERP – most popular, average of many trials.

- Negativity: N100 • Visual N1 • N170 • N200 • N2pc • N400
- Positivity: P200 • P300 • P3a • P3b • Late positive component • P600
- Contingent negative variation (CNV), Error-related negativity (ERN)
- Mismatch Negativity (MMN), Centro-parietal positivity (CPP)

Understanding brains: microstates

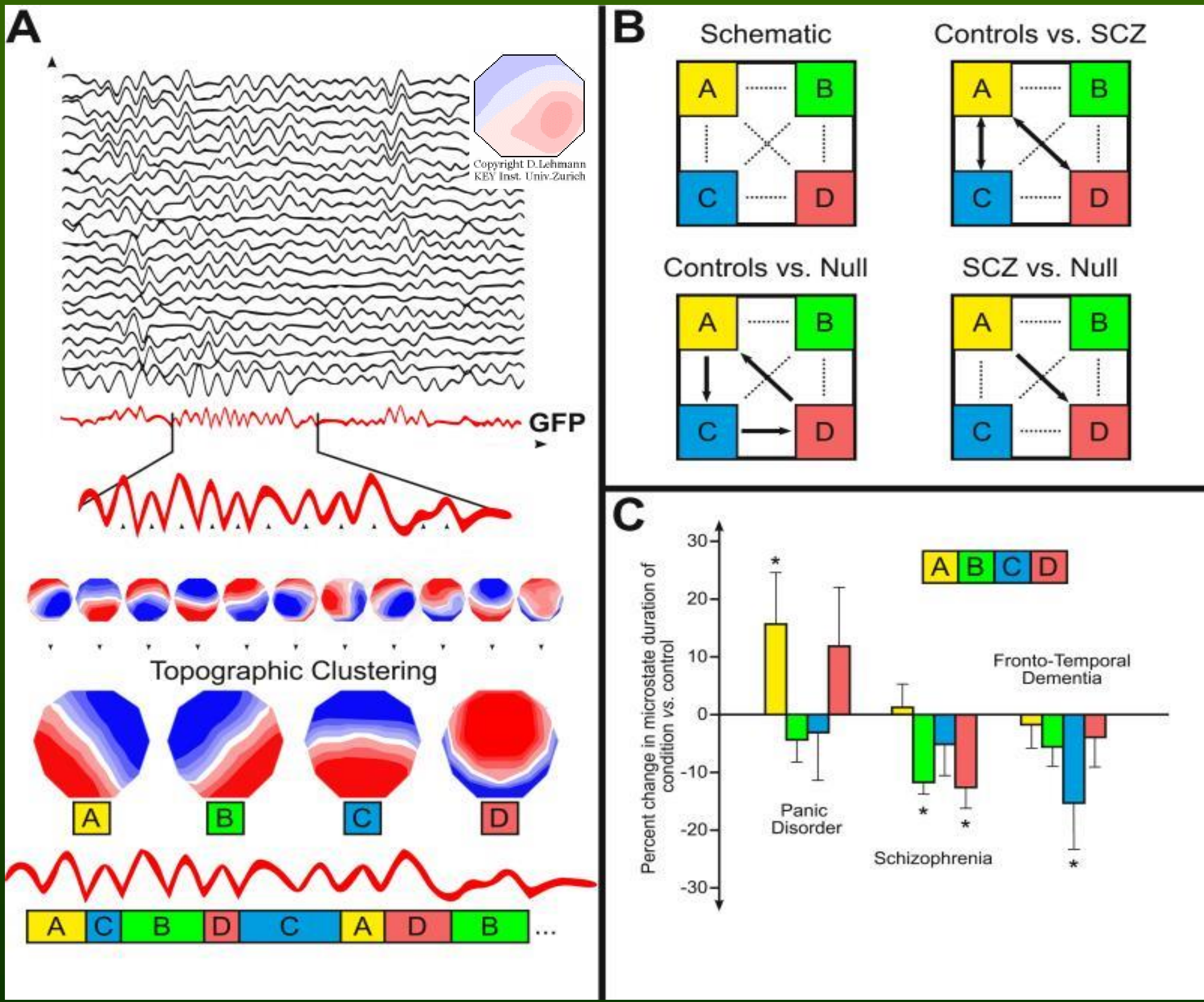
Global EEG Power.
4-7 states, 60-150 ms.

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

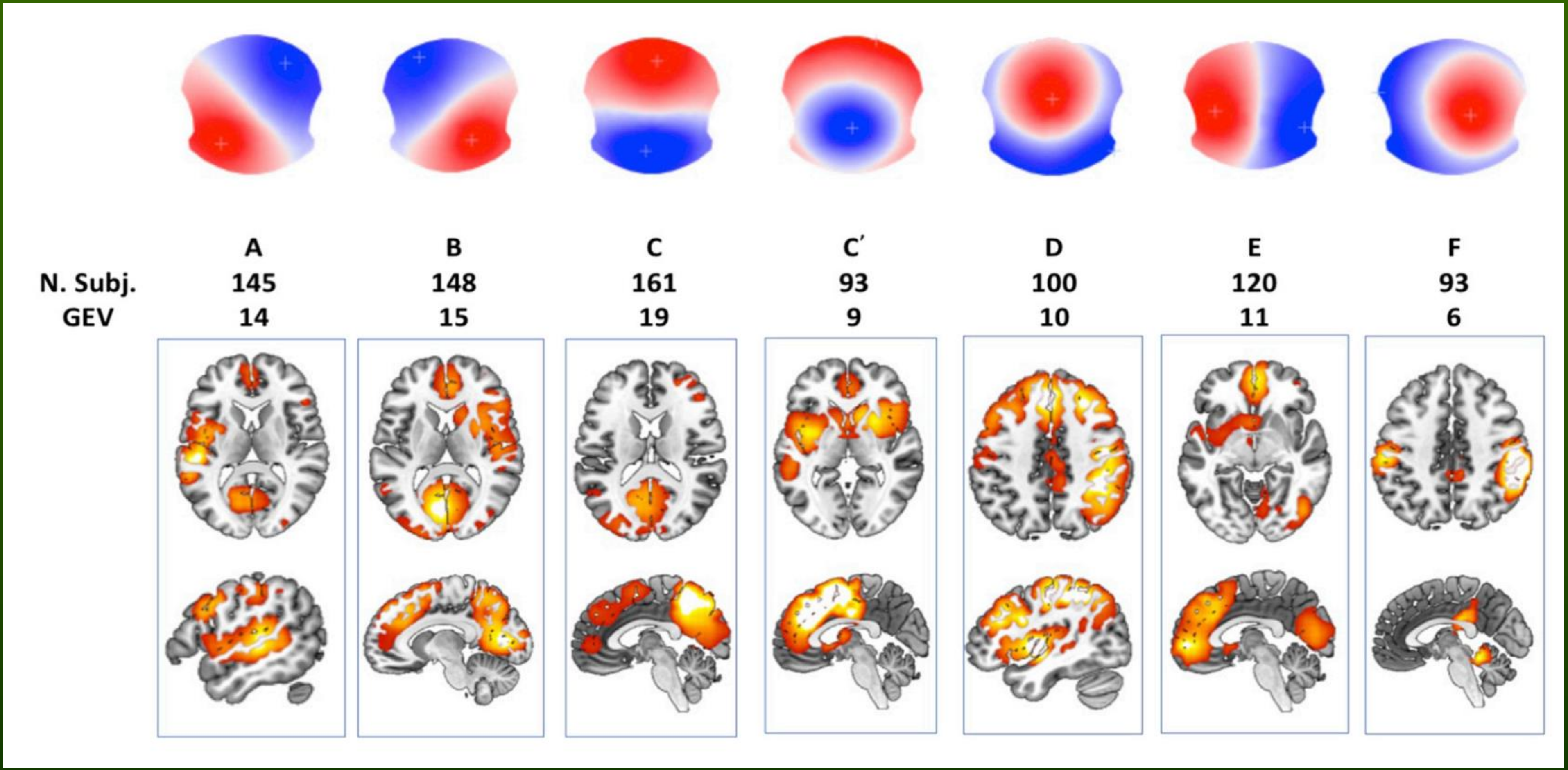
Symbolic dynamics: statistics of A-D symbol strings. Fuzzy Symbolic Dynamics (FSD) + visualizations.

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.

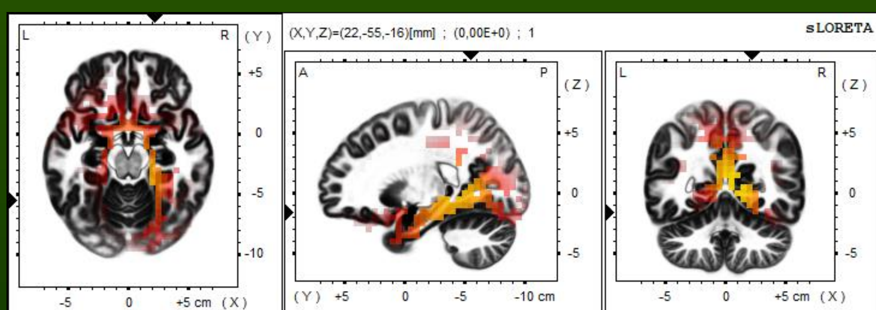
HRV-EEG-feedback

Influence of HRV biofeedback training on microstates and fluent intelligence (PhD of **Ewa Ratajczak**):

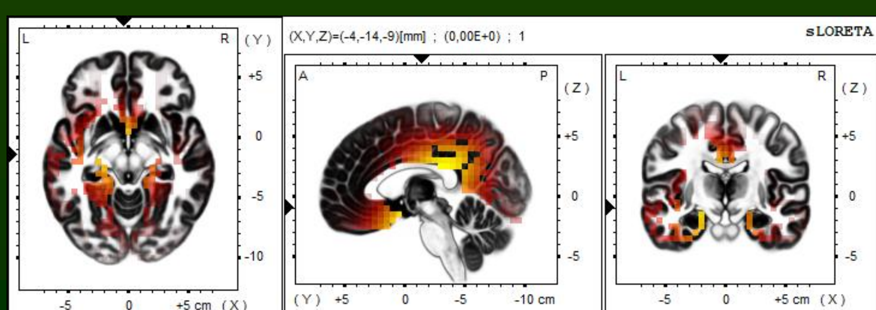
- distinguished 9 microstates during HRV-BFB;
- #5 (G): prefrontal and right temporoparietal areas;
- #9 (E): left hemispheric prefrontal cortex, insular cortex and temporoparietal cortex

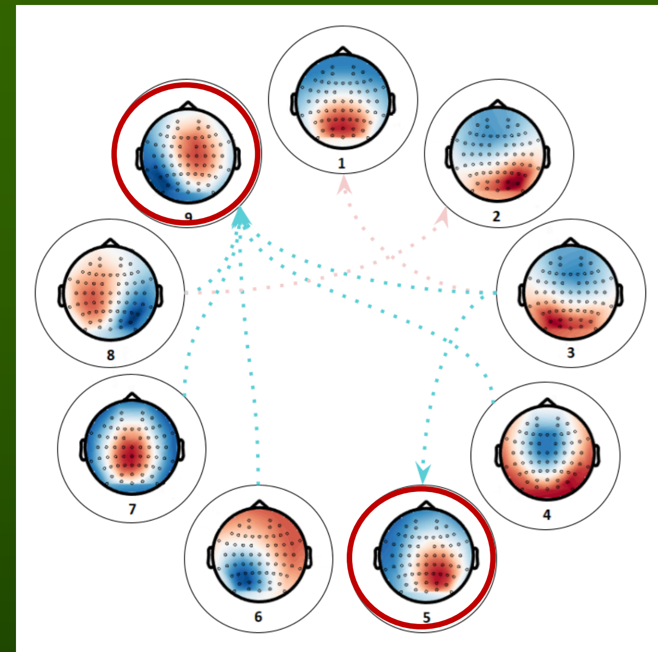
Visually guided somatosensory and affective control.

#5 (G)



#9 (E)



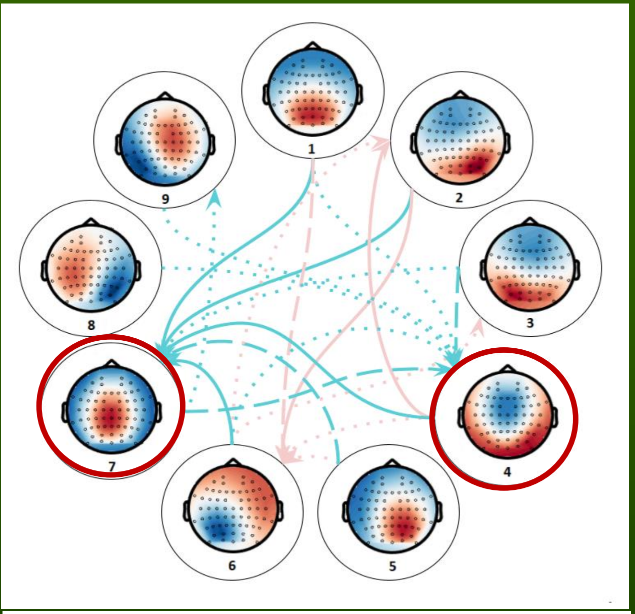


Index	Microstate								
	#1	#2	#3	#4	#5	#6	#7	#8	#9
	C	B	A	D	G	H	F	I	E
Occ	↓				↑				↑
Dur			↓		↑				↑
Cov		↓	↓		↑				↑
GEV		↓			↑				↑
MSC	↓								↑
GFP									

HRV-EEG-training

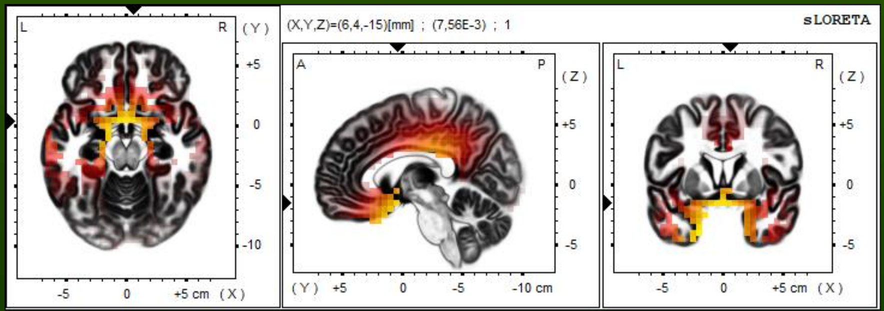
HRV-BFB training increased activation of microstates

- #4 (D): attentional/cognitive control network
- #7 (F): insula/circuit network
- Related to neural activity in EEG θ and δ bands, neuroplasticity.
- Switching between external/internal attention networks, enhanced cognitive control.

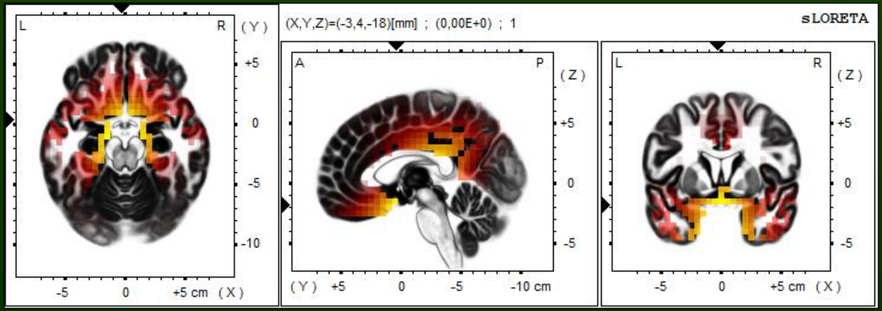


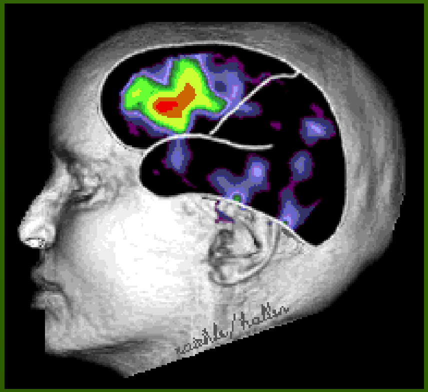
Index	Microstate								
	#1	#2	#3	#4	#5	#6	#7	#8	#9
	C	B	A	D	G	H	F	I	E
Occ		↓	↓	↑		↓	↑		
Dur		↓	↓	↑		↓	↑		
Cov		↓	↓	↑		↓	↑		
GEV		↓		↑		↓	↑		
MSC				↑	↑		↑		↑
GFP									

#4 (D)



#7 (F)



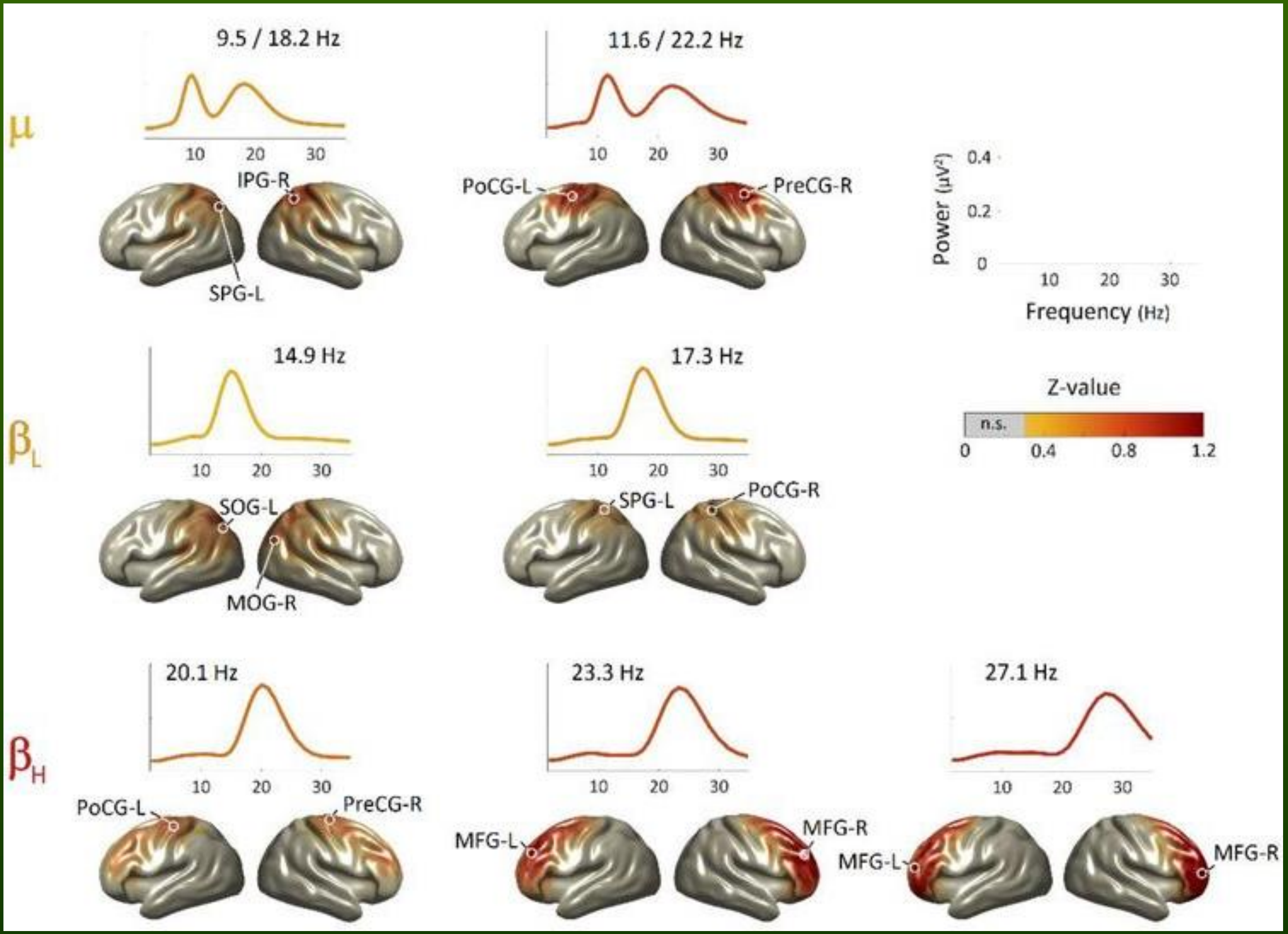


EEG and neurodynamics

Atlas of the natural frequencies, resting brain

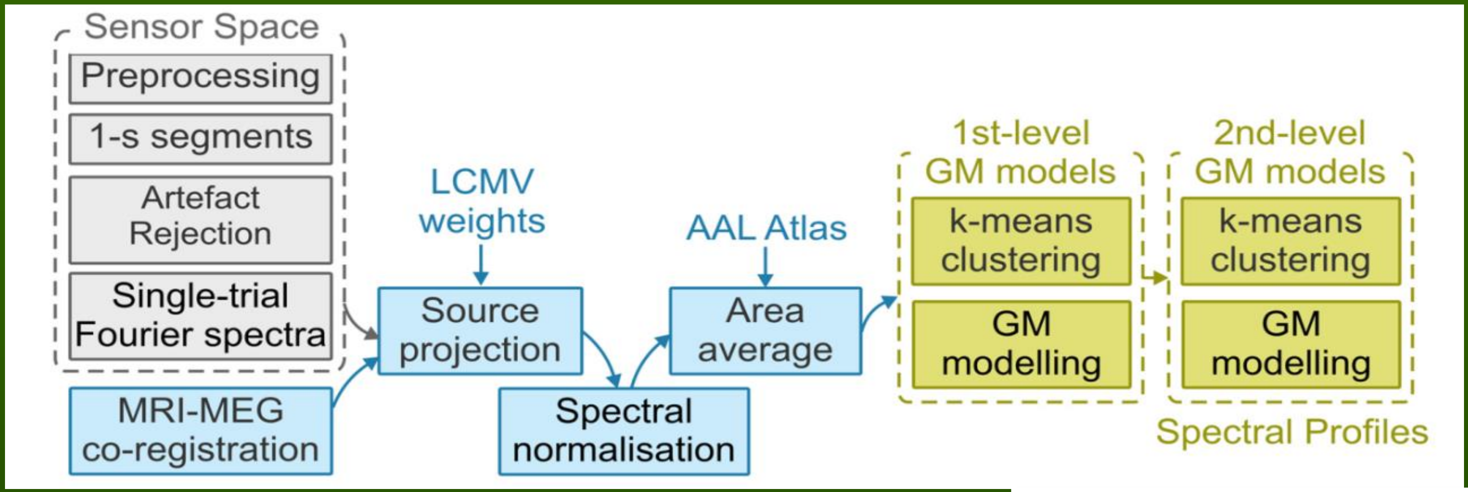
Peak frequencies in selected brain areas observed using MEG in the resting brain, averaged over 128 people.

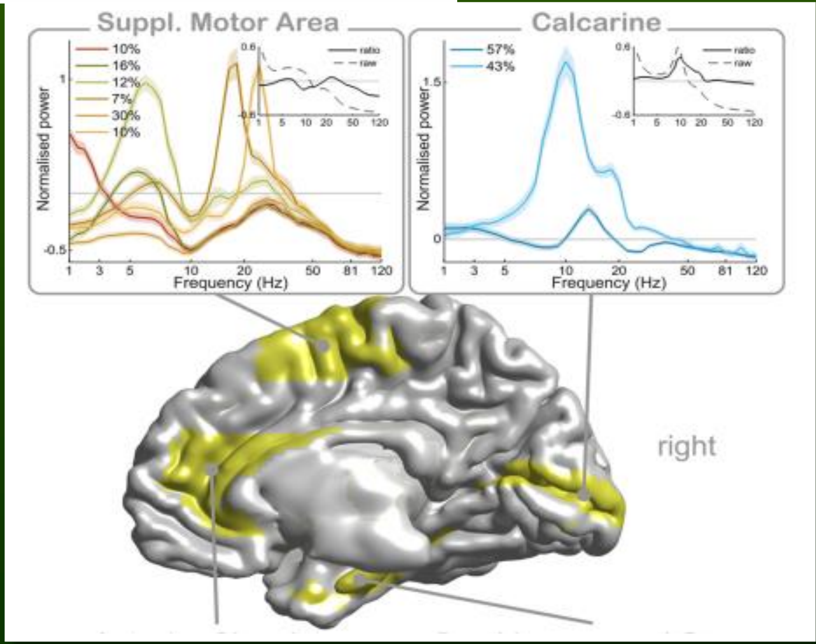
Individual differences?
Brain disorders?



Capilla, A., Arana, L., García-Huéscar, M., Melcón, M., Gross, J., & Campo, P.
The natural frequencies of the resting human brain: An MEG-based atlas.
NeuroImage 258 (2022) 119373

Spectral analysis



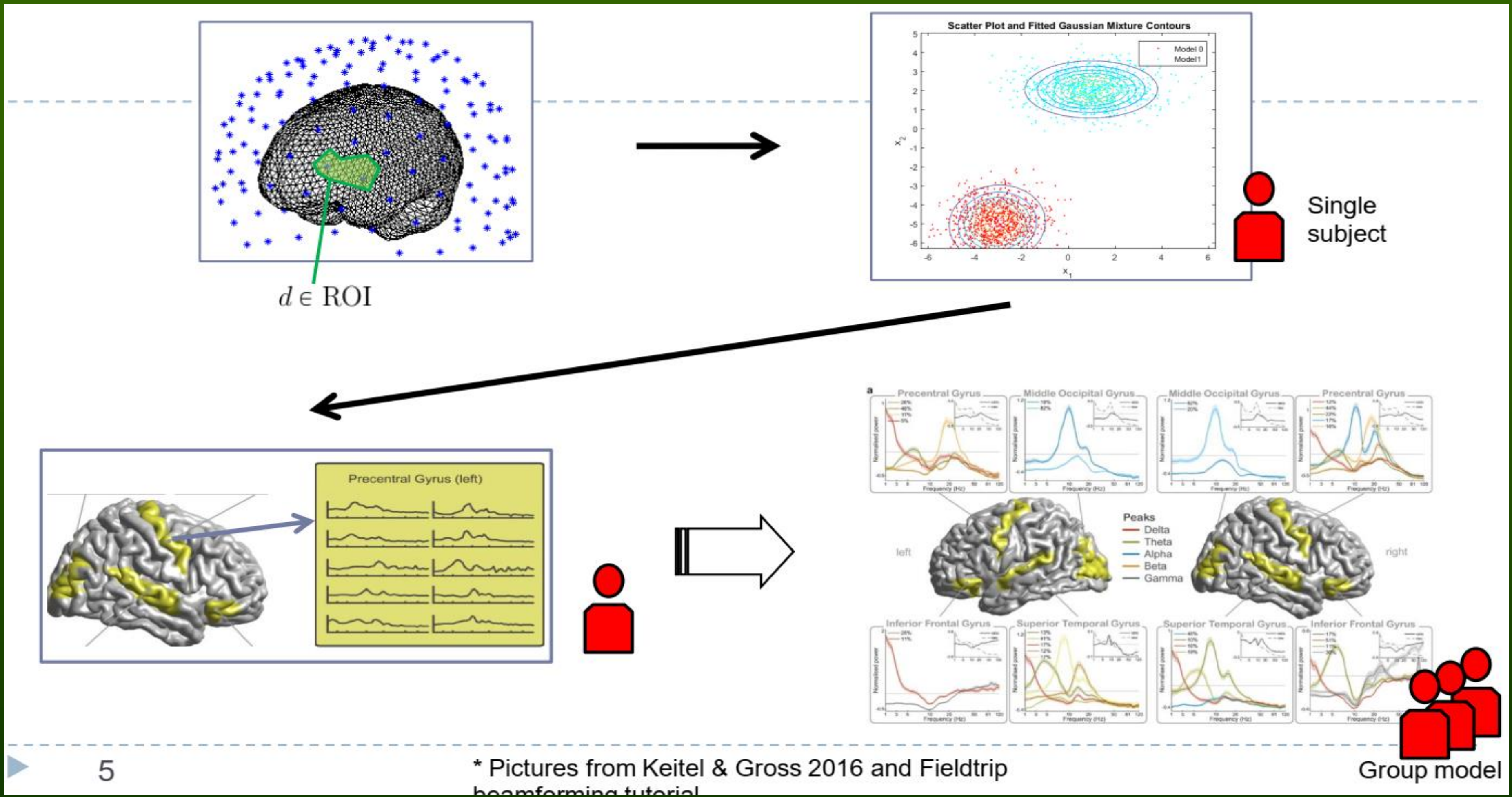


Create spectral fingerprints of all ROIs.

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

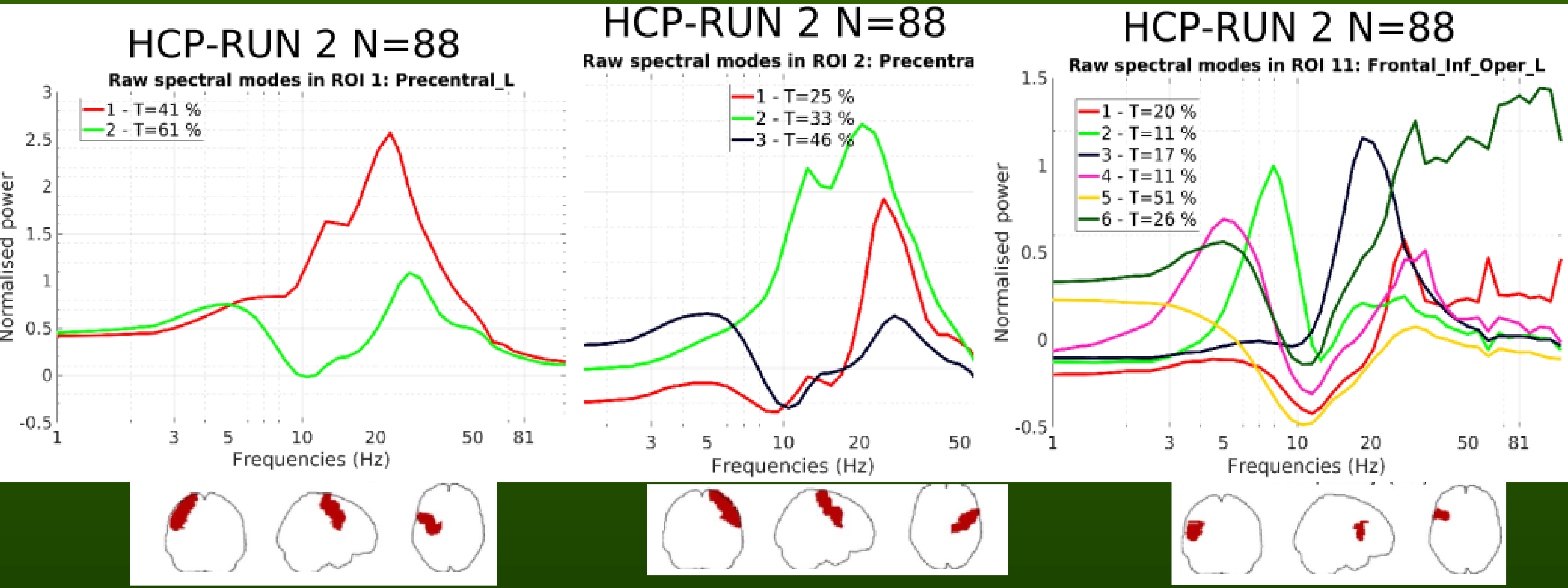
Spectral fingerprints



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

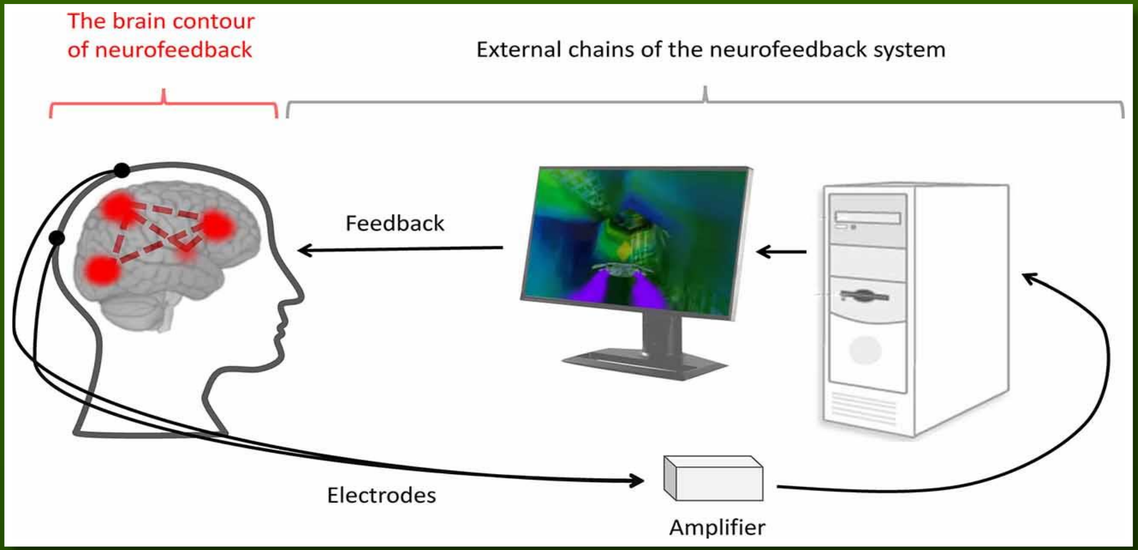
Spectral fingerprints



- 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, now applied to 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. … W. Duch (2022)
ToFFi - Toolbox for Frequency-based Fingerprinting of Brain Signals. Neurocomputing (revised + Arxives).

Spectral fingerprints of cognitive processes

Decompose neurodynamics into

activations of subnetworks binding ROIs at specific frequencies.

Oscillations can rapidly change, each ROI is engaged in different subnetworks for short time periods. This is reflected very crudely in microstates, recurrence plots show more precise information.

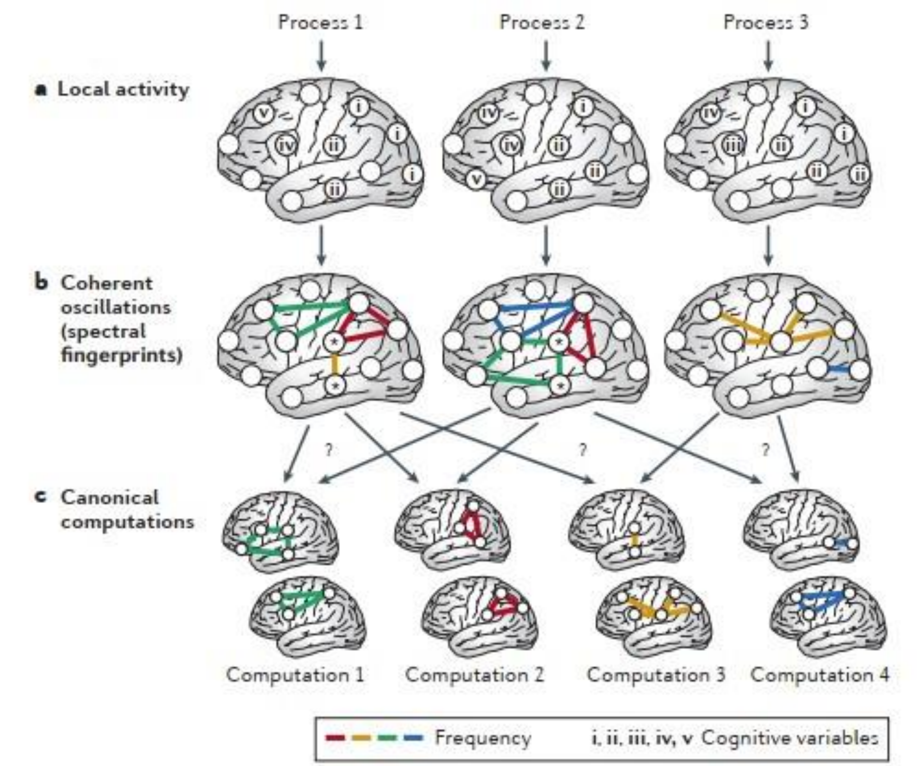


Figure 4 | **Large-scale spectral fingerprints of cognitive processes.** Schematic illustration of how coherent oscillations provide 'spectral fingerprints' for regrouping of cognitive processes 1–3. **a** | Studies of neuronal activity in individual brain regions (circles) elucidate the activation of 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*, 121

Recurrence analysis

Recurrence Quantification Analysis

Signal representation: up to 256 channels, sampling 512 Hz.
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, $\tau\Delta t$.

Works for simple dynamical systems, but EEG/MEG is not simple at all.

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

Recurrence matrices: 1 if closer than ε, 0 otherwise; or use color for distance.

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

Recurrence plots: plot matrices to see the dynamics.
Visualize trajectories.
RQA: calculate various statistical measures based on recurrence matrices.

Simulations

Emergent neural simulator:

Aisa, B., Mingus, B., and O'Reilly, R.
The emergent neural modeling system.
Neural Networks, 21, 1045, 2008.
Point neurons with 3 kinds of ion channels.

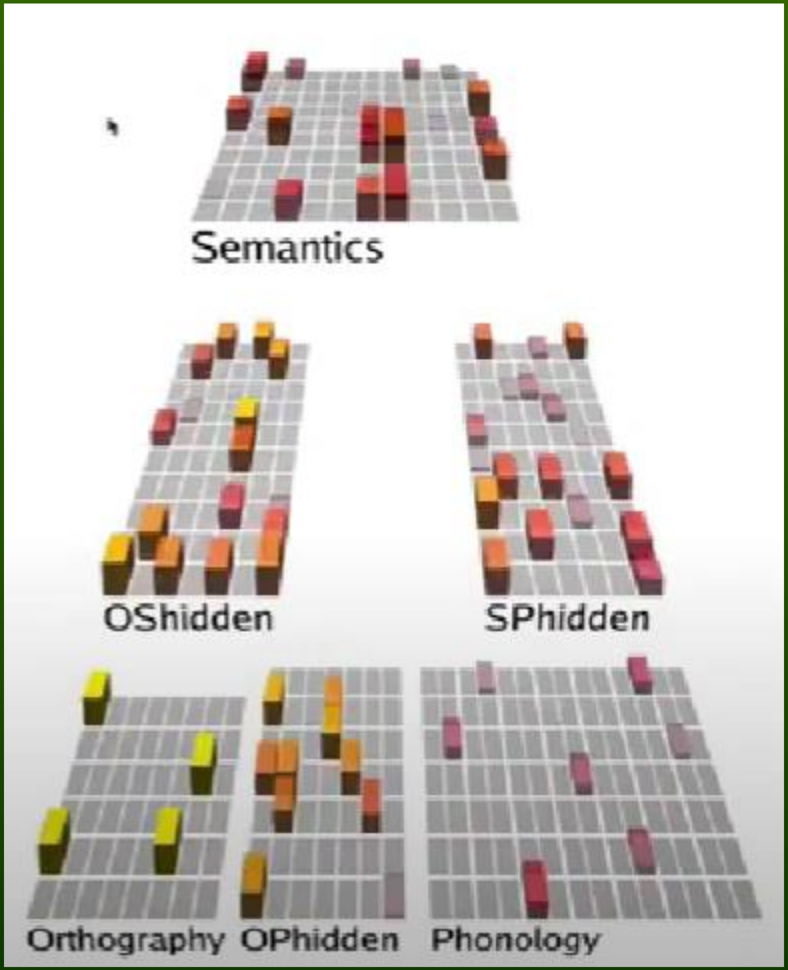
3-layer model of reading:

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

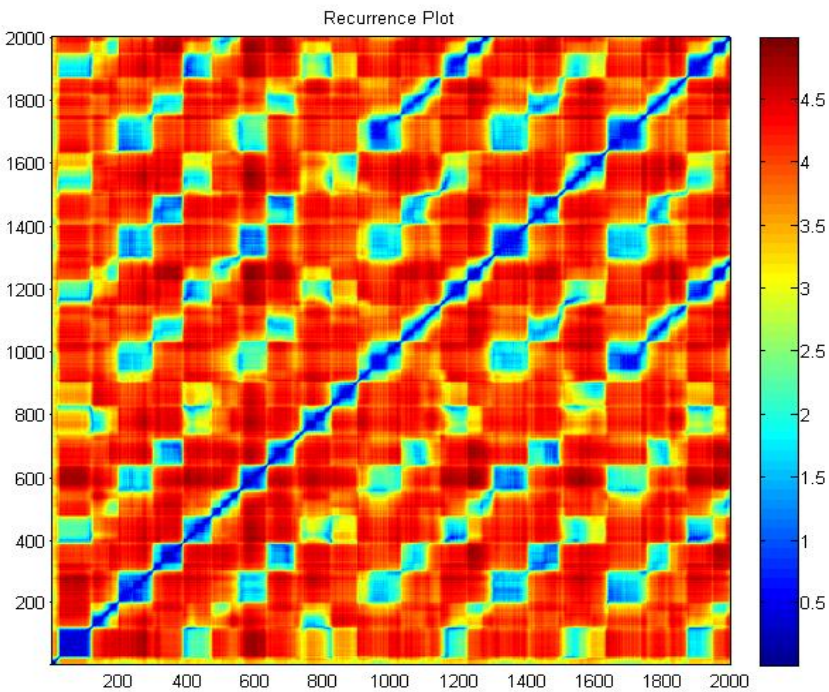
Learning: mapping one of the 3 layers to
the other two, LEABRA algorithm.

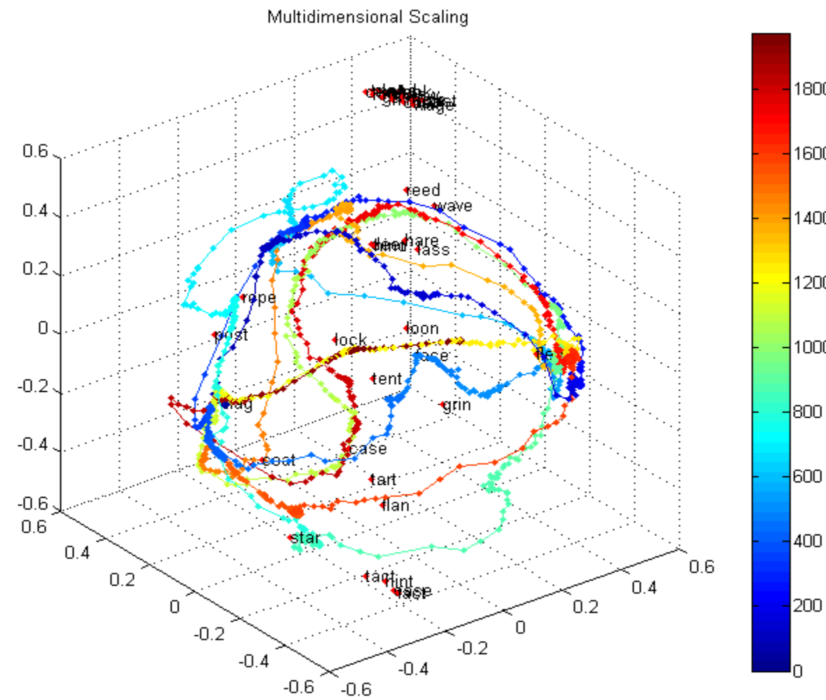
Fluctuations around final configuration =
attractors representing concepts.

How to see trajectory of neurodynamics,
attractor basins, transitions?



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 ...

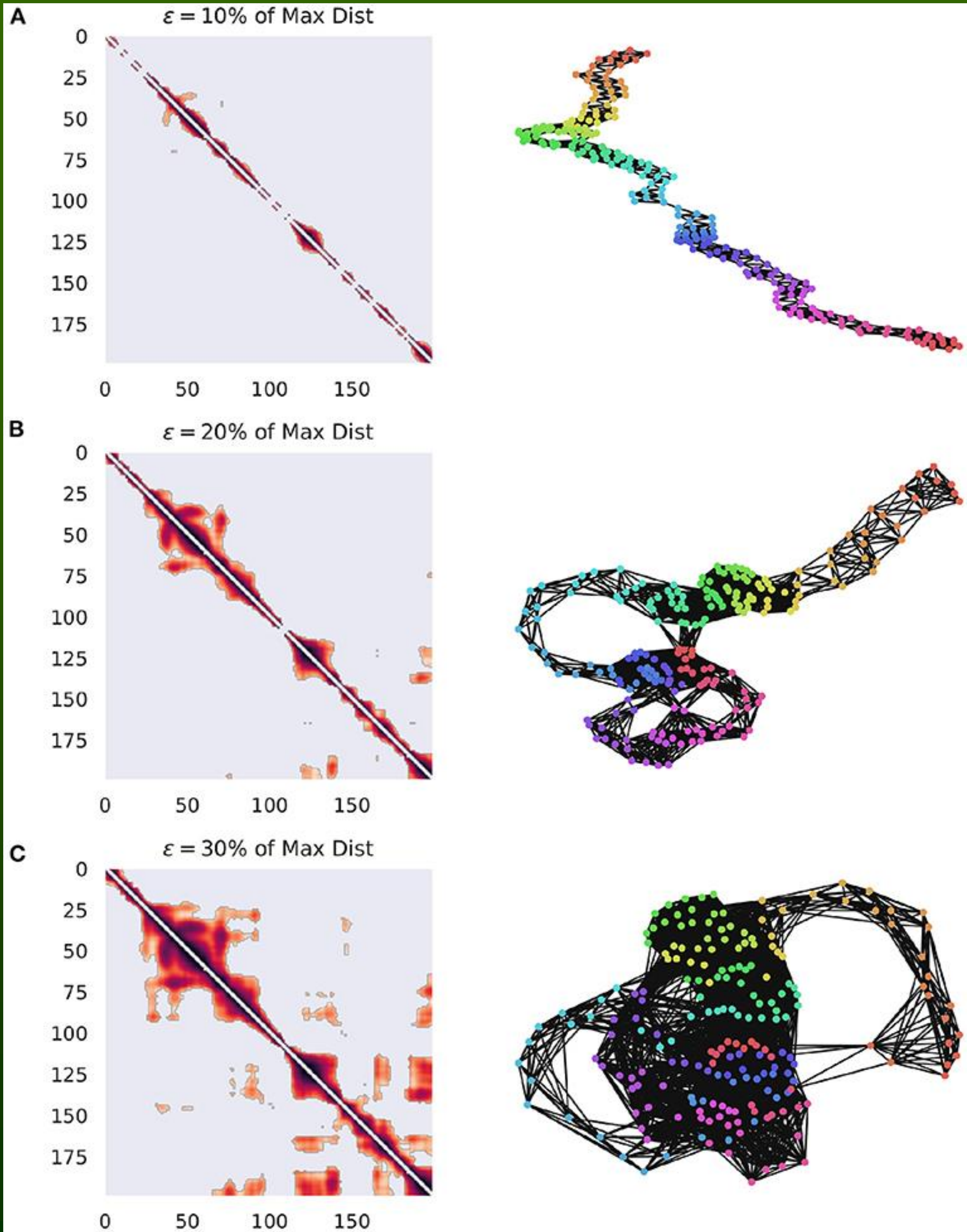
Recurrence network

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](https://doi.org/10.3389/fnins.2021.787068)

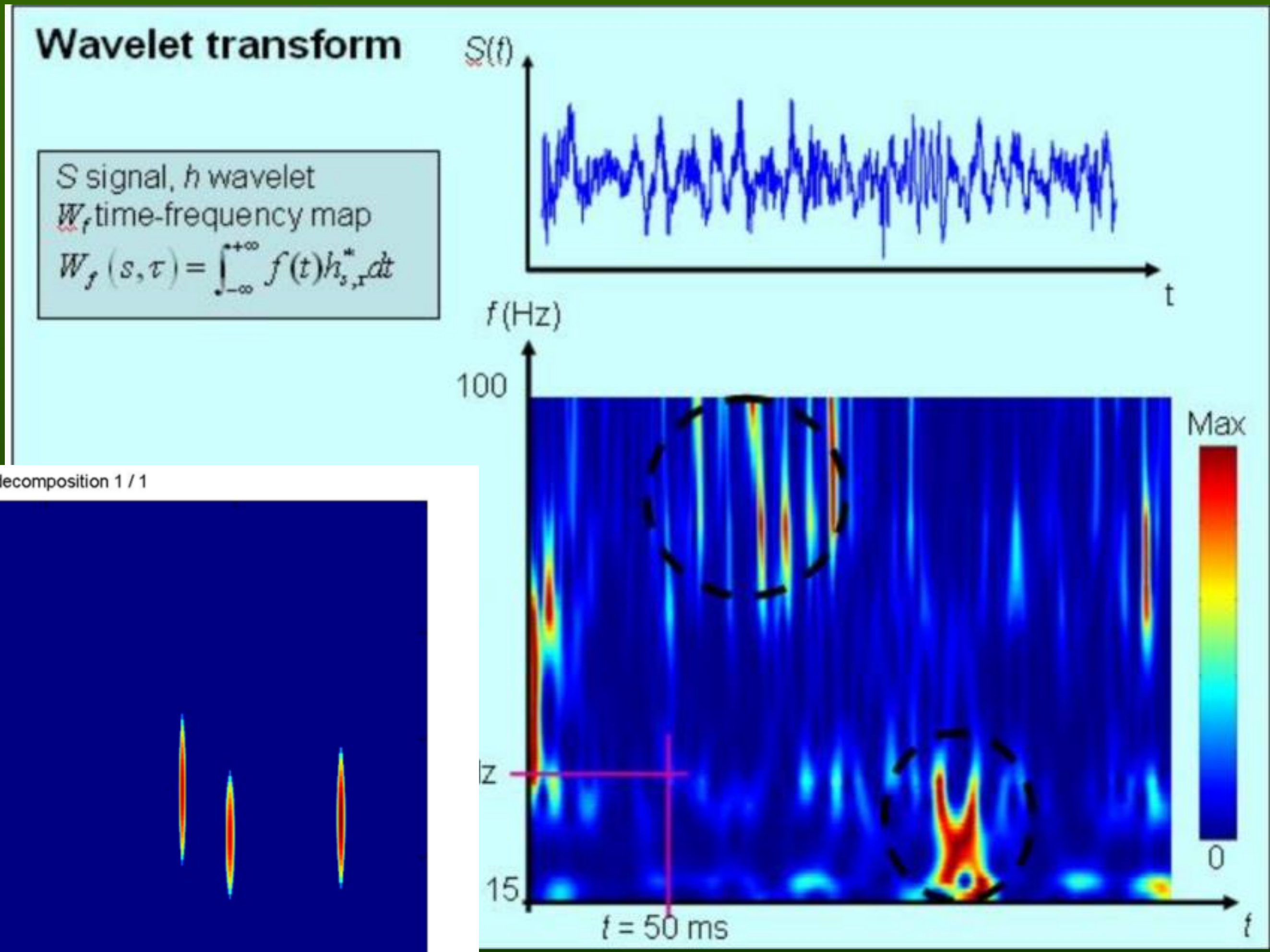
For mathematically inclined:

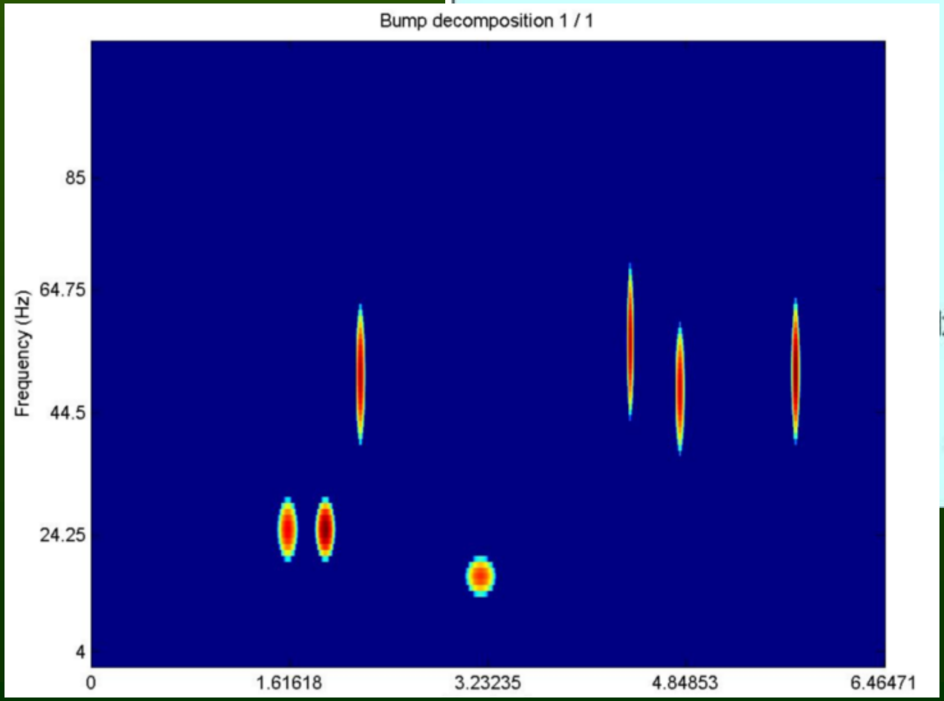
Caputi, L., Pidnebesna, A., & Hlinka, J. (2021). Promises and pitfalls of topological data analysis for brain connectivity analysis. *NeuroImage*, *238*, 118245.



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.



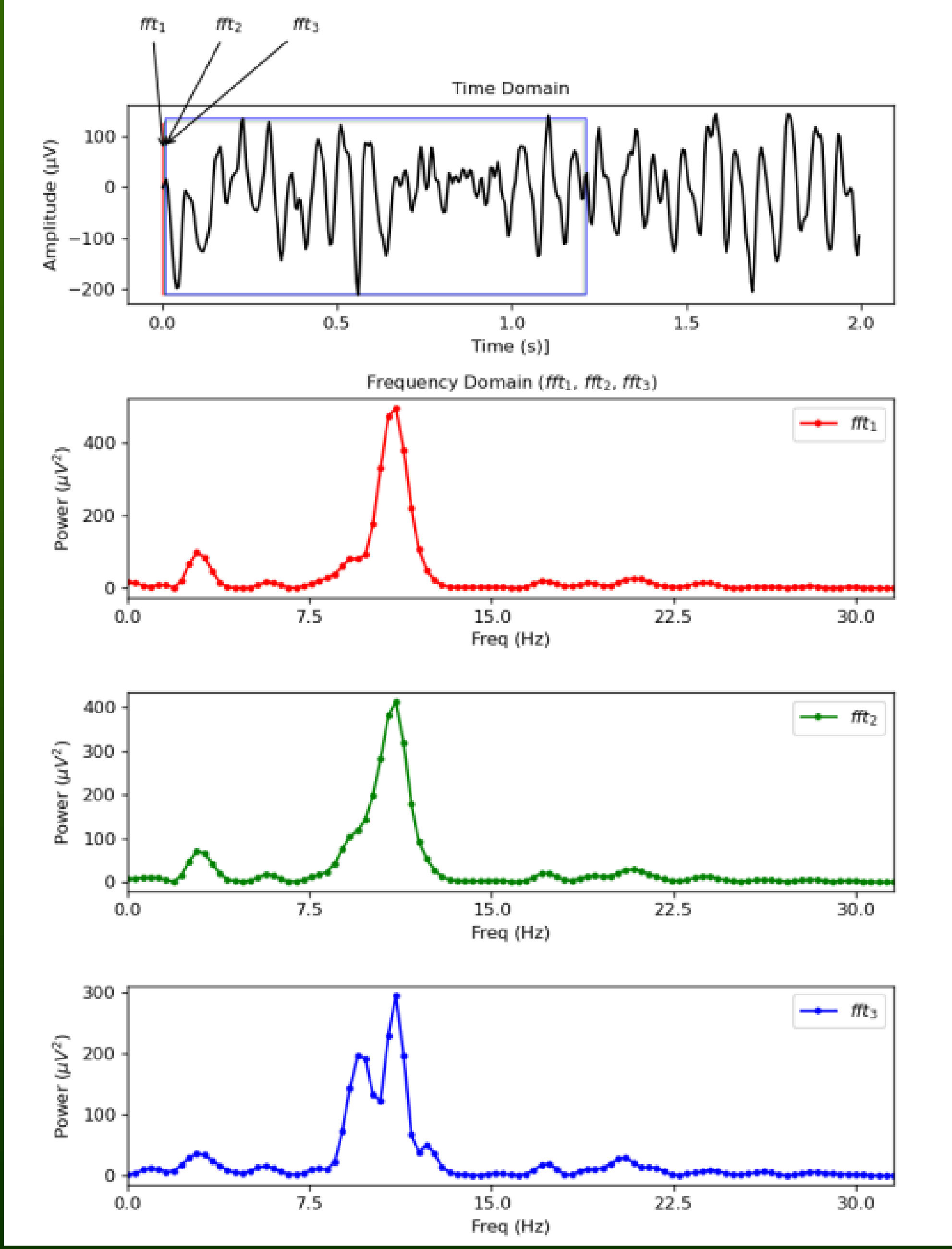


STFT vs. embedding

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.

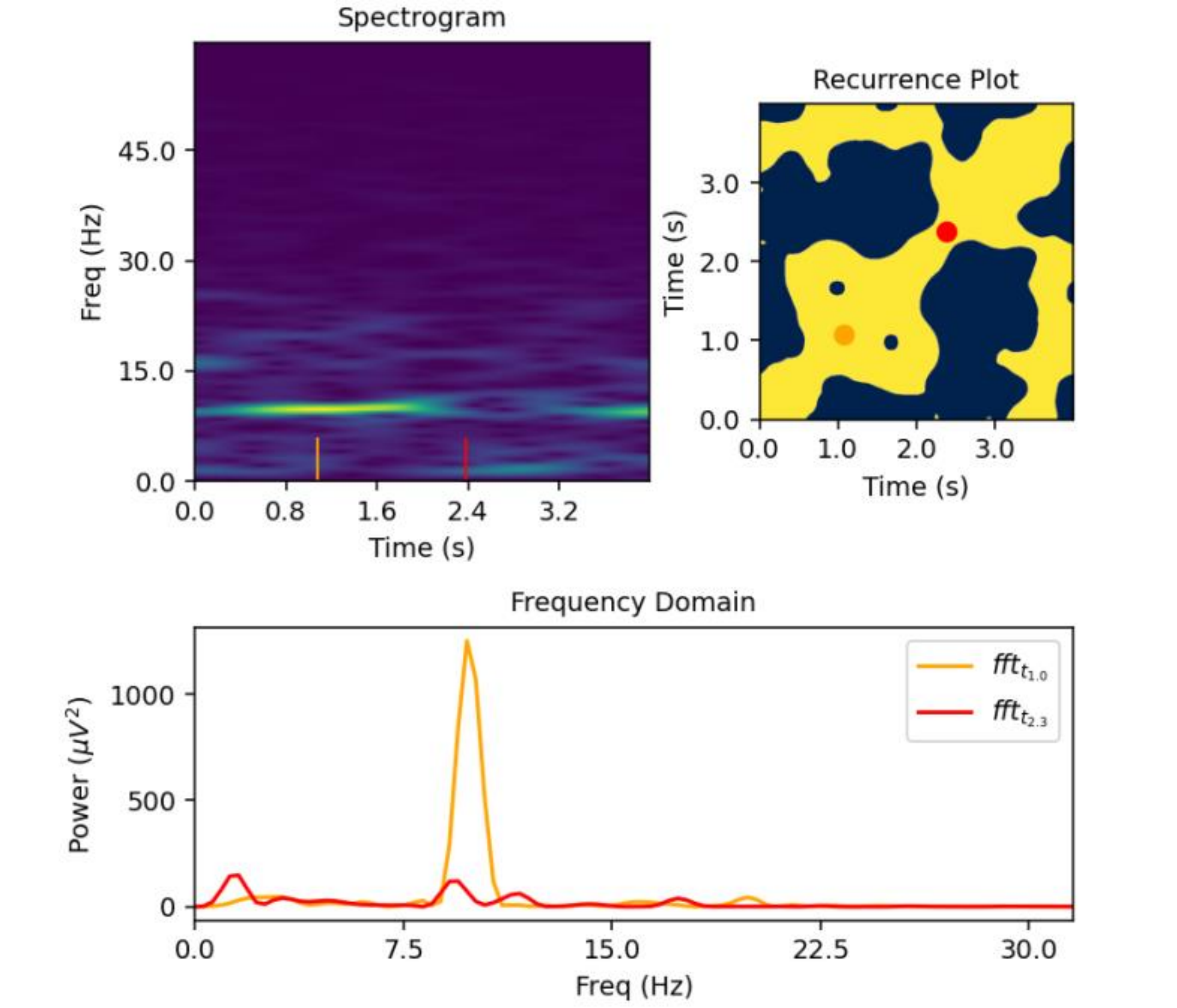
W. Duch, Ł. Furman, K. Tołpa, L. Minati, Short-Time Fourier Transform and Embedding Method for Recurrence Quantification Analysis of EEG Time Series. The European Physical Journal DOI: 10.1140/epjs/s11734-022-00683-7



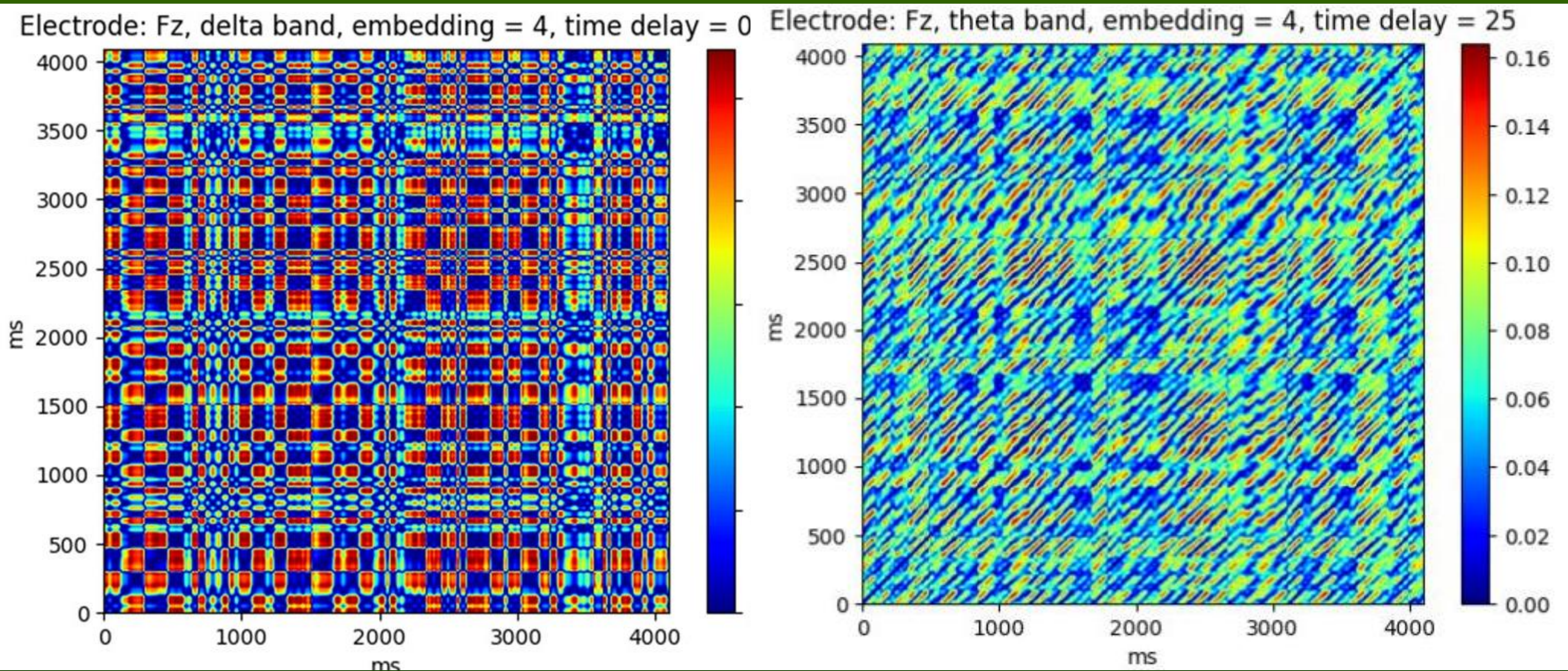
Time/frequency spectrograms & RPs

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.

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:

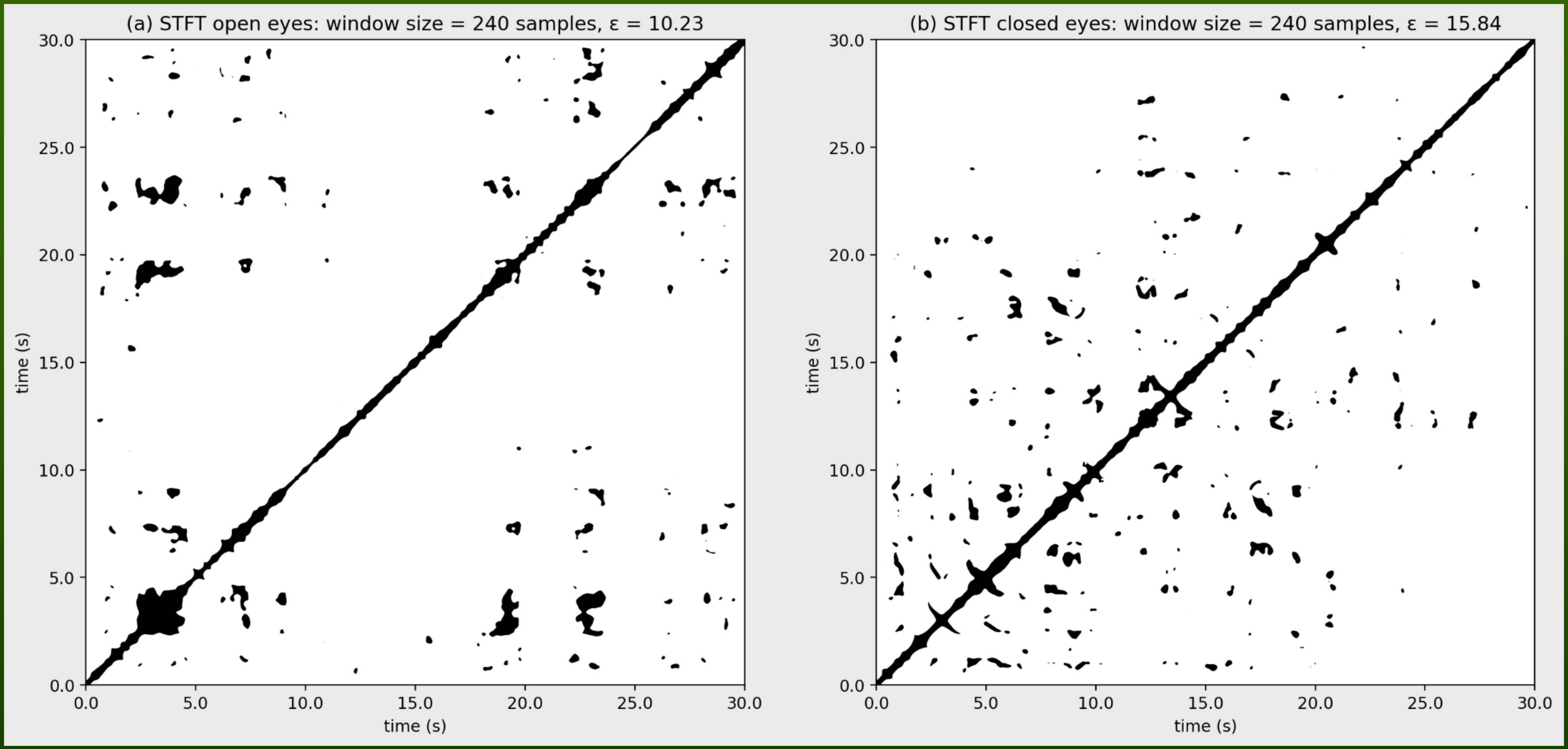
$$\mathrm{L} = \frac{\sum_{\ell=\ell_{\min}}^{N} \ell\, P(\ell)}{\sum_{\ell=\ell_{\min}}^{N} P(\ell)}$$

Trapping time, measuring the average length of the vertical lines:

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

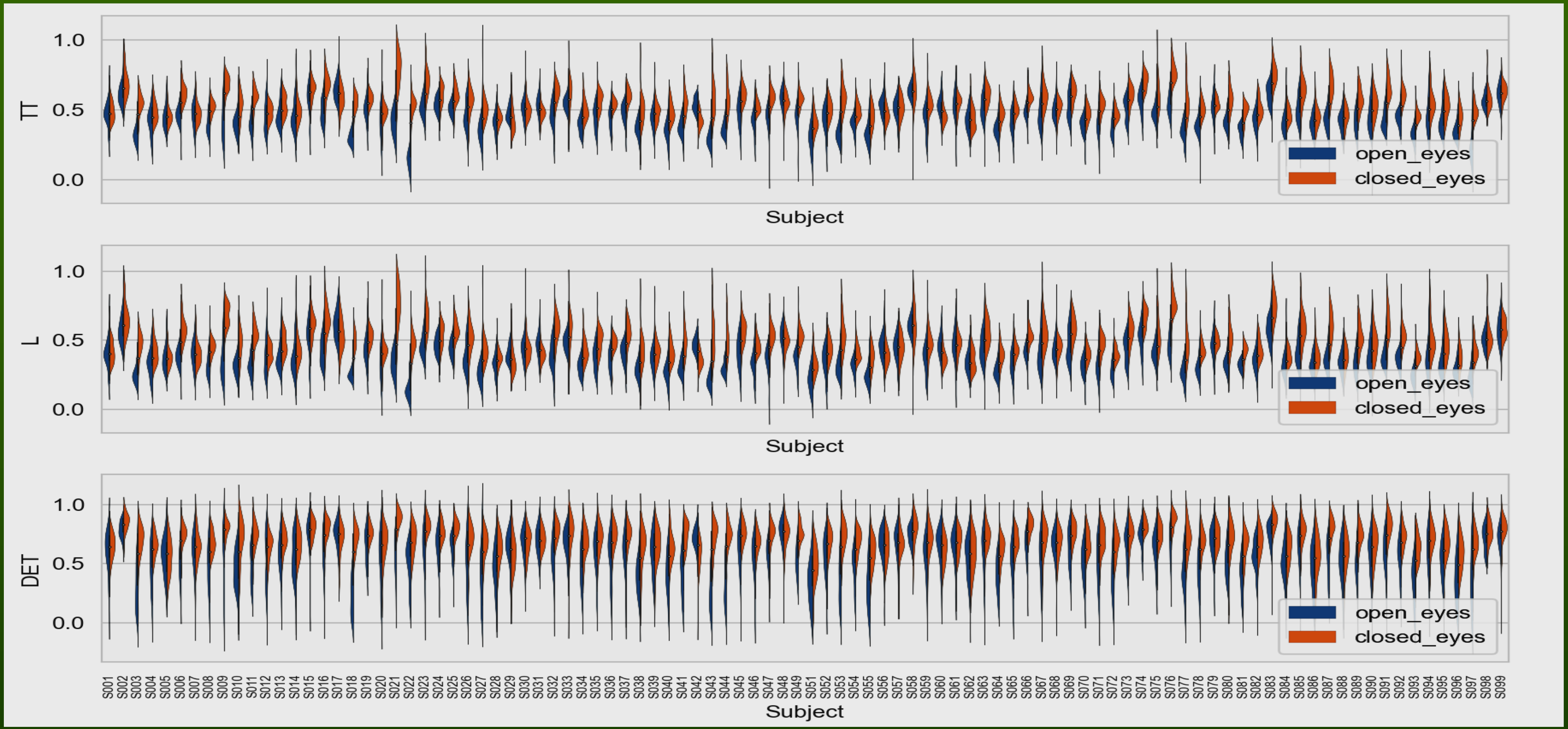
+ 10 other measures.
Unthreshold measures?

RPs, O1 electrode



Example of recurrence plots, 30 s, resting state, electrode O1, subject S001.
Dark dots show distances inside small ε neighborhood.
How to avoid thresholds?

RQA features for 64 electrodes



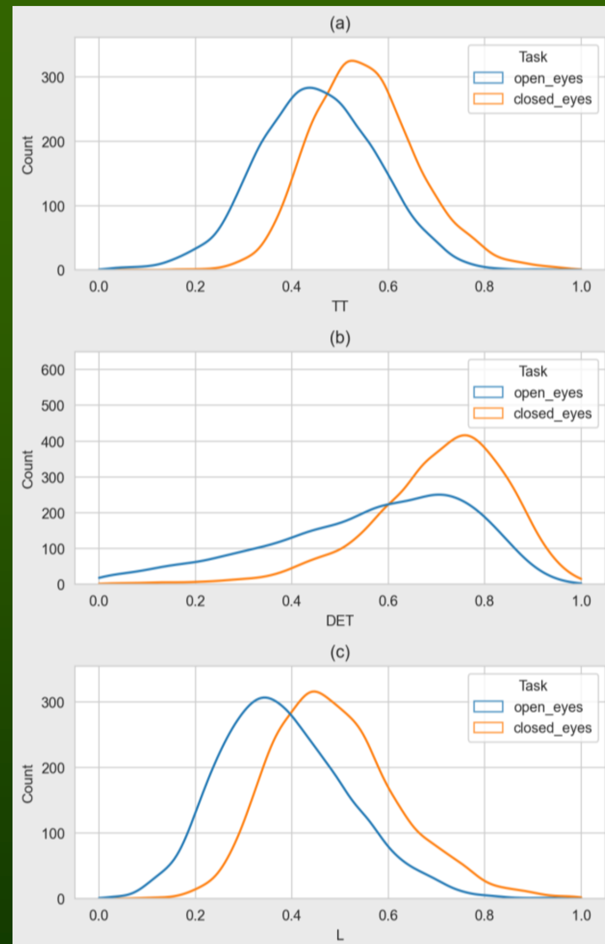
Distribution of trapping time, av. line length and determinism values for 64 electrodes shown for all 98 subjects. In some cases a single RQA feature allows for an easy separation of the two conditions. Variance is very different (focus? dreaming?), depending on the person. Linear SVM provides weights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

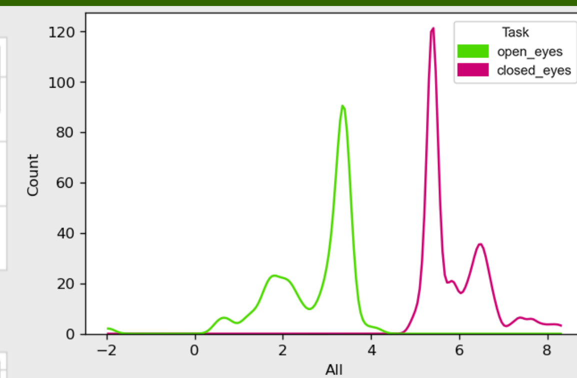
RQA features for 64 electrodes

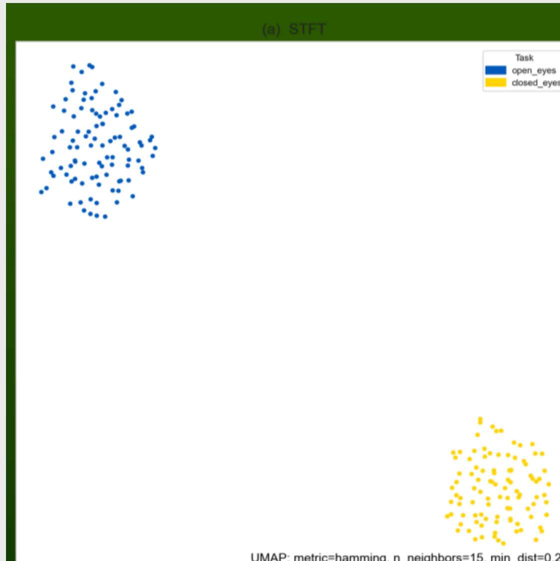
Histograms of the RQA features for all 98 subjects:
TT (trapping time),
DET (determinism),
L (average diagonal line length).

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

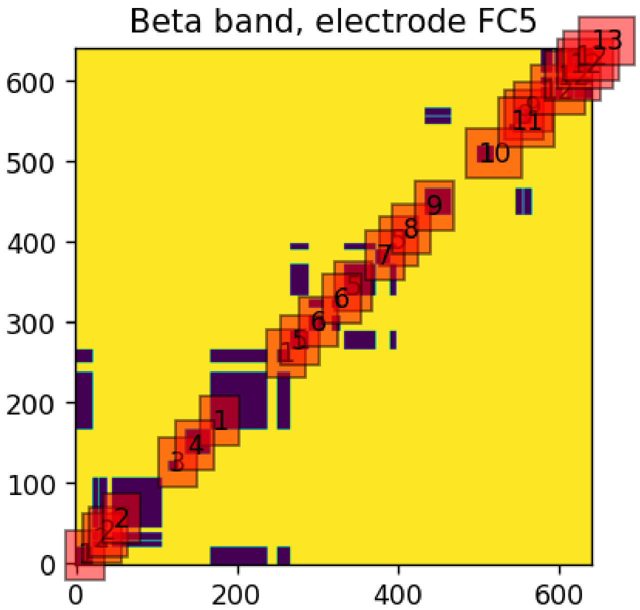
UMAP visualization of the 320-dimensional Z column vectors.

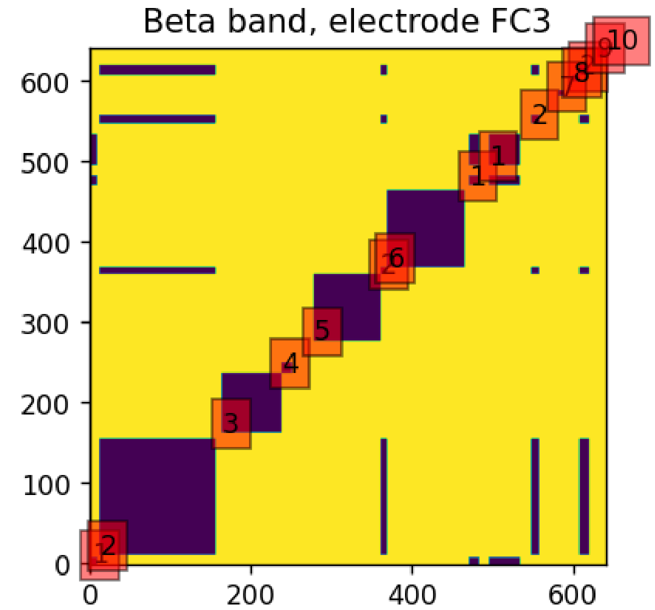


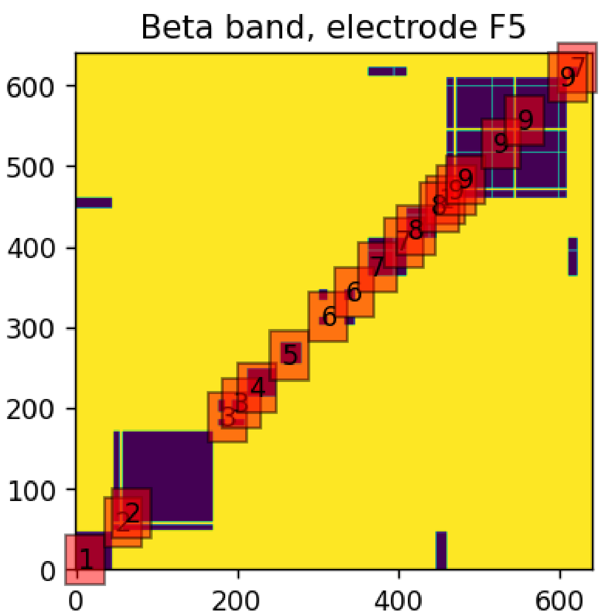


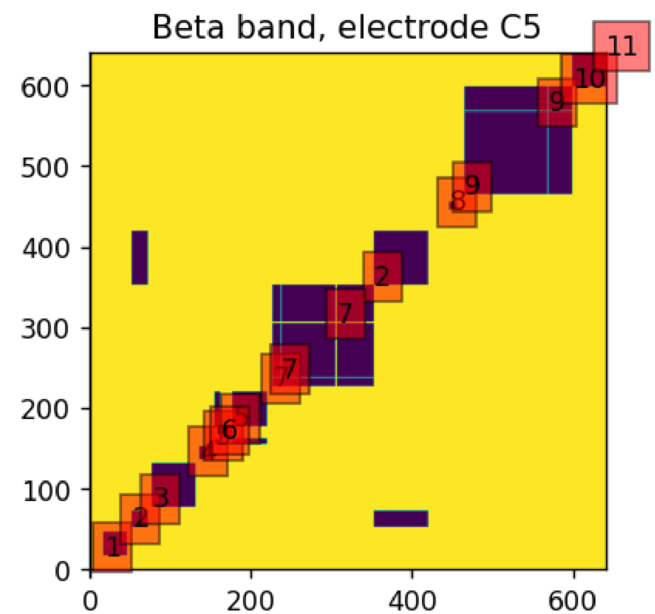


Cross-recurrence

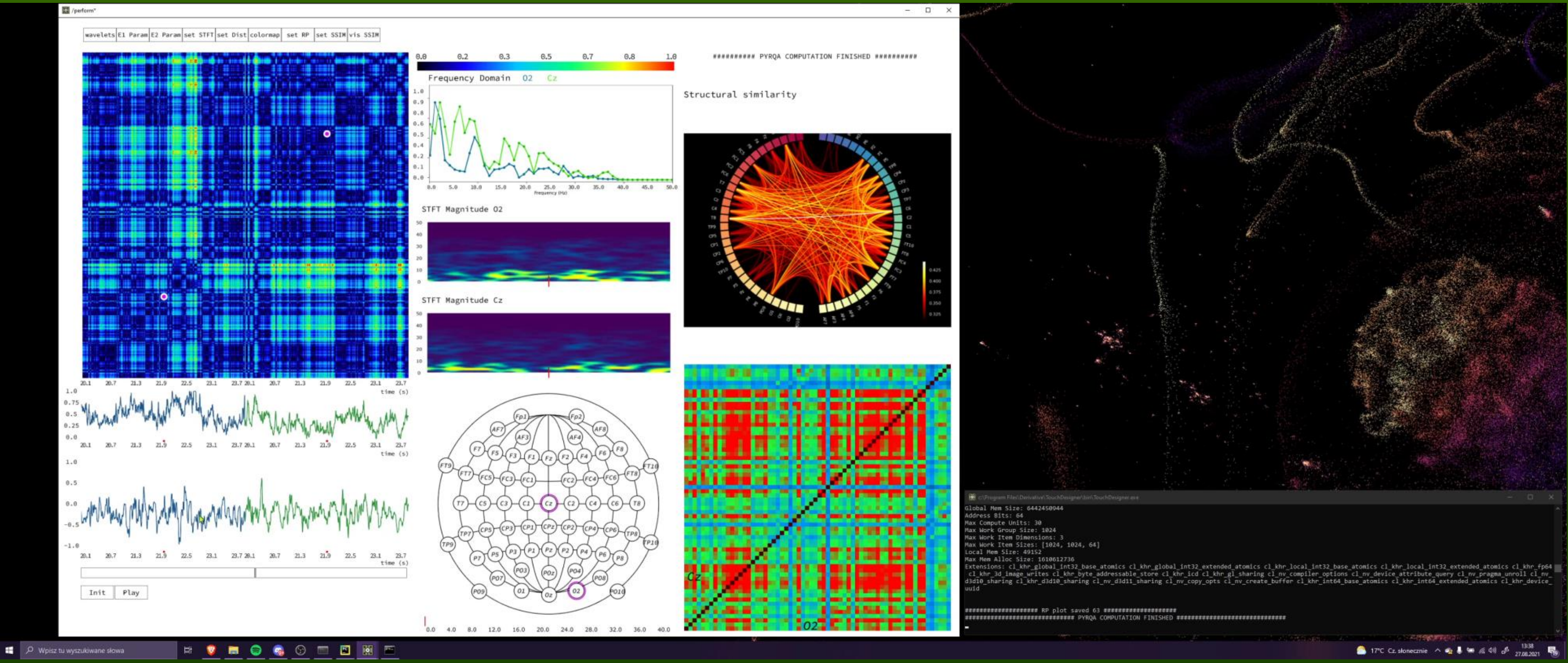




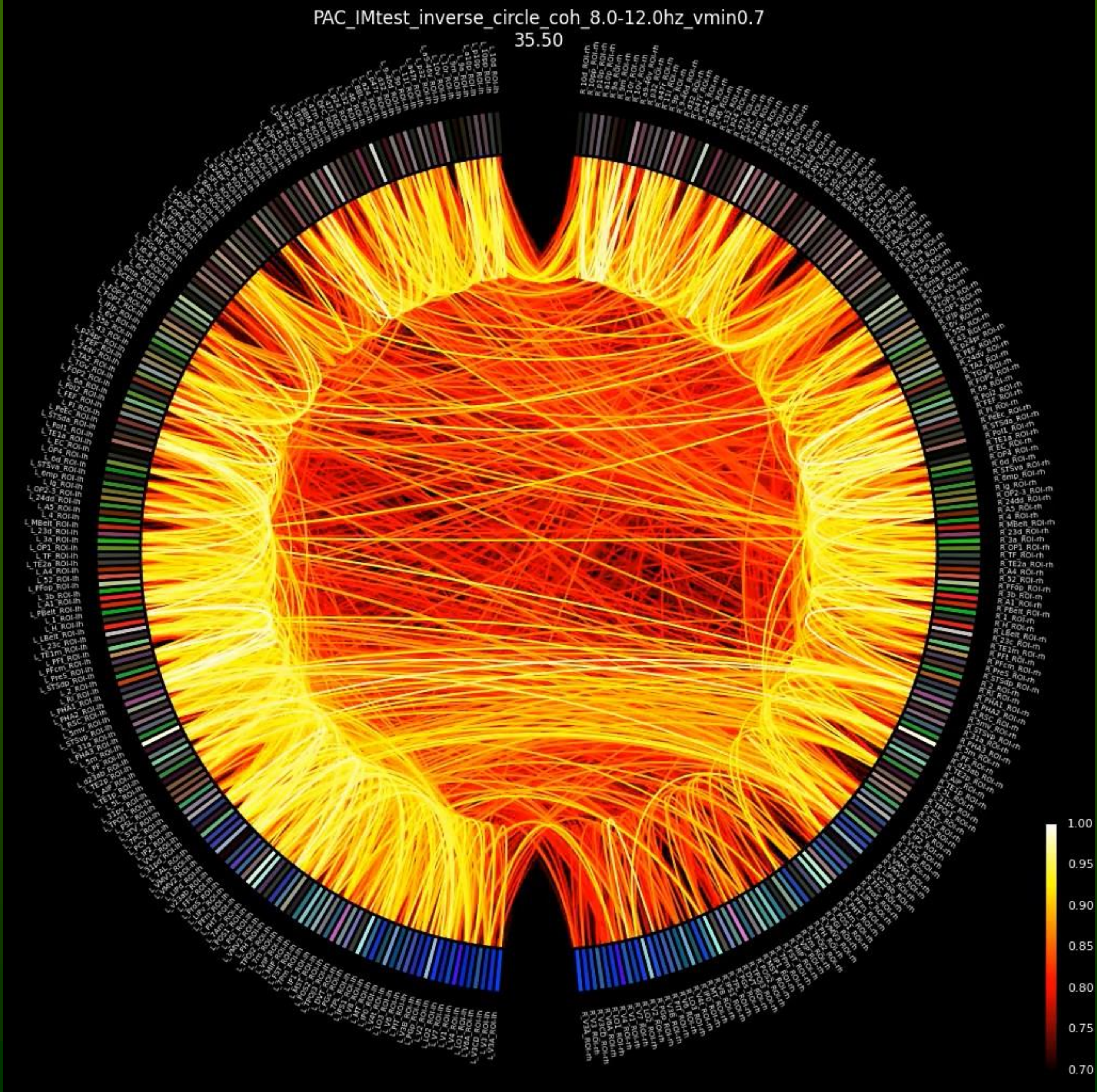


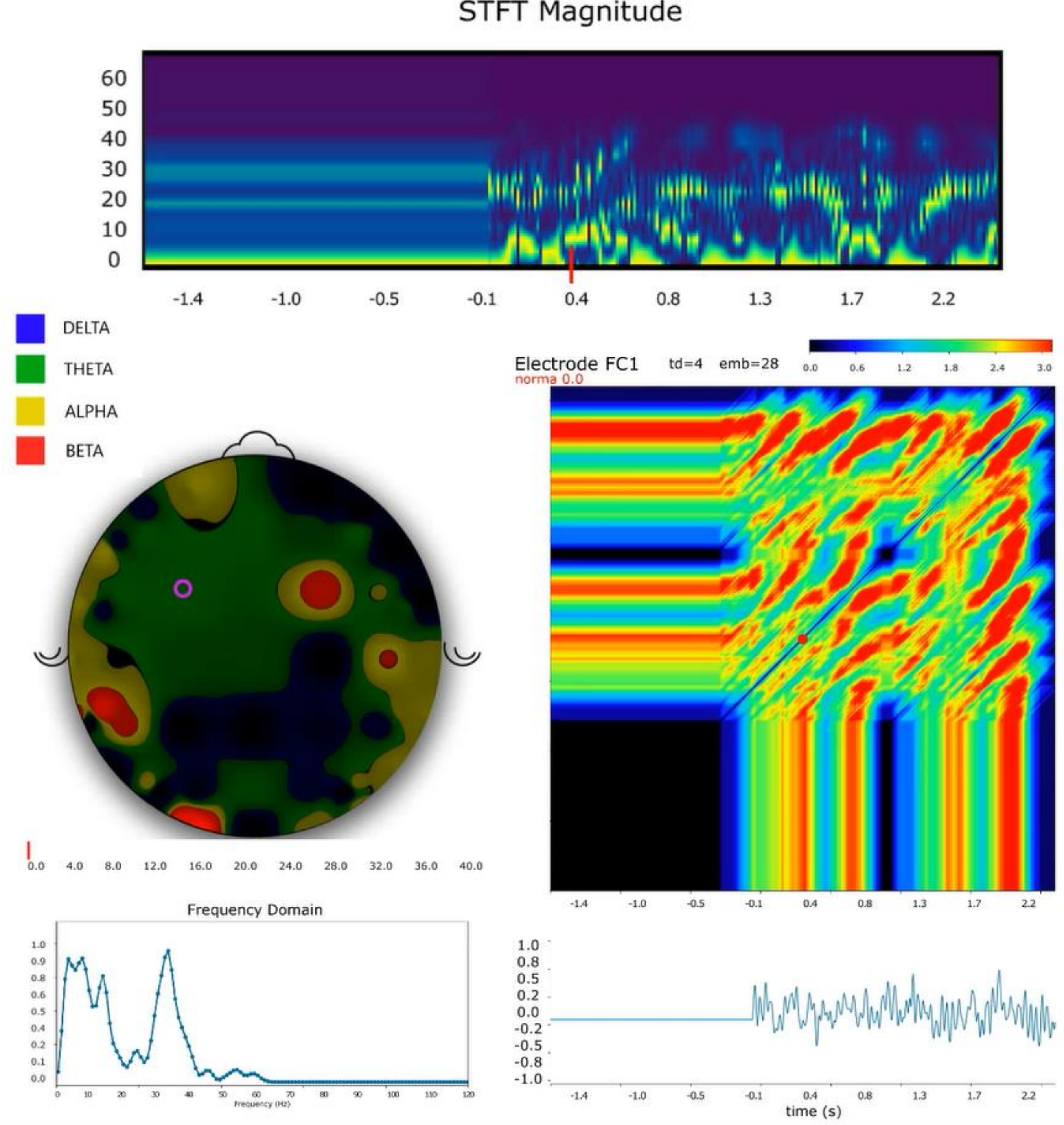


EEG analysis



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


PAC_IMtest_inverse_circle_coh_8.0-12.0hz_vmin0.7
35.50
1.00
0.95
0.90
0.85
0.80
0.75
0.70



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
Frequency (Hz)
time (s)

Labeling states

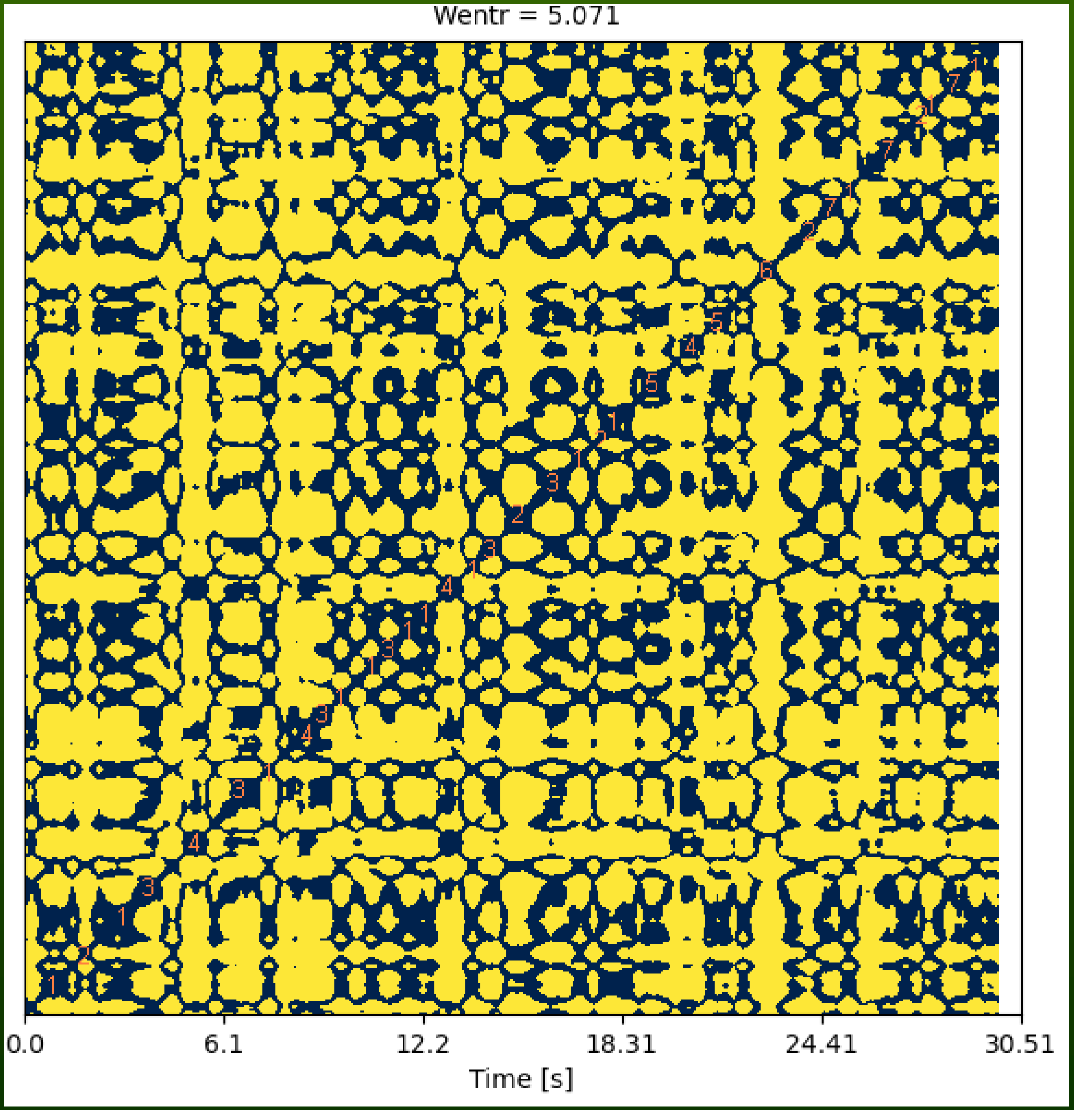
Automatic labeling of states and estimation of their recurrence may be important for biofeedback.

Metabolic costs of transitions between states may be important.

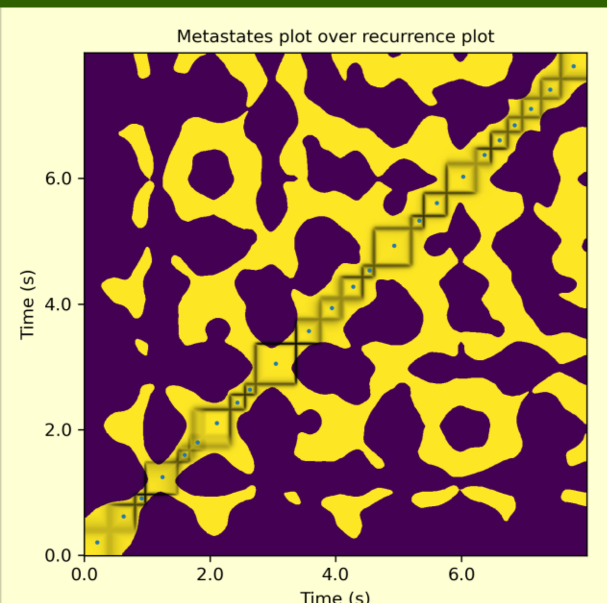
Ruminations? Pain states? How external stimuli influence this dynamics?

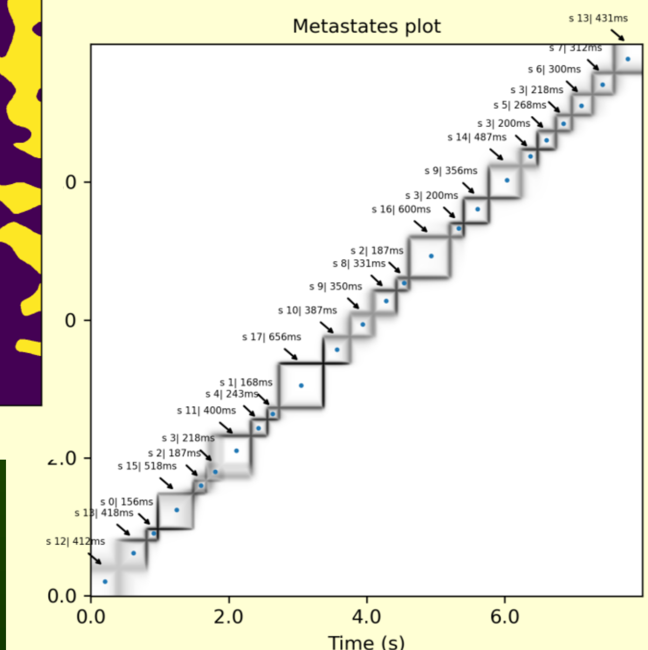
Needs automatic method for recognition of metastable, multivariate states.

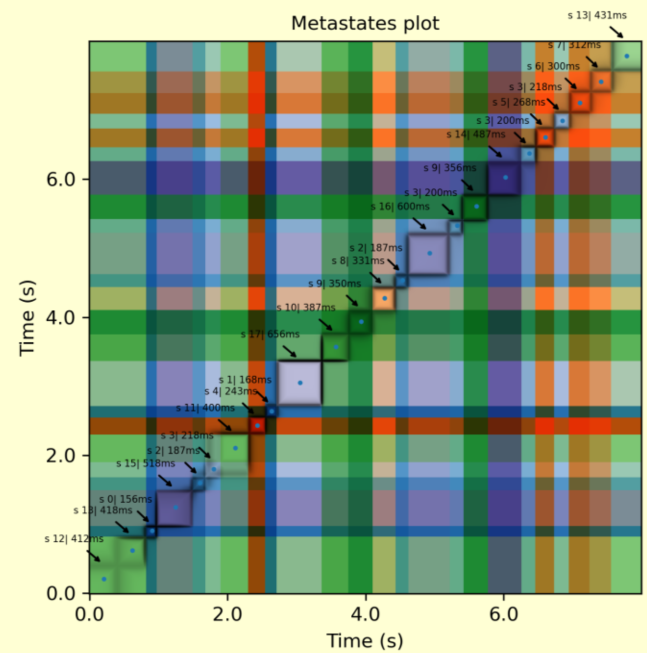
More precise than microstates.



Segmentation of states



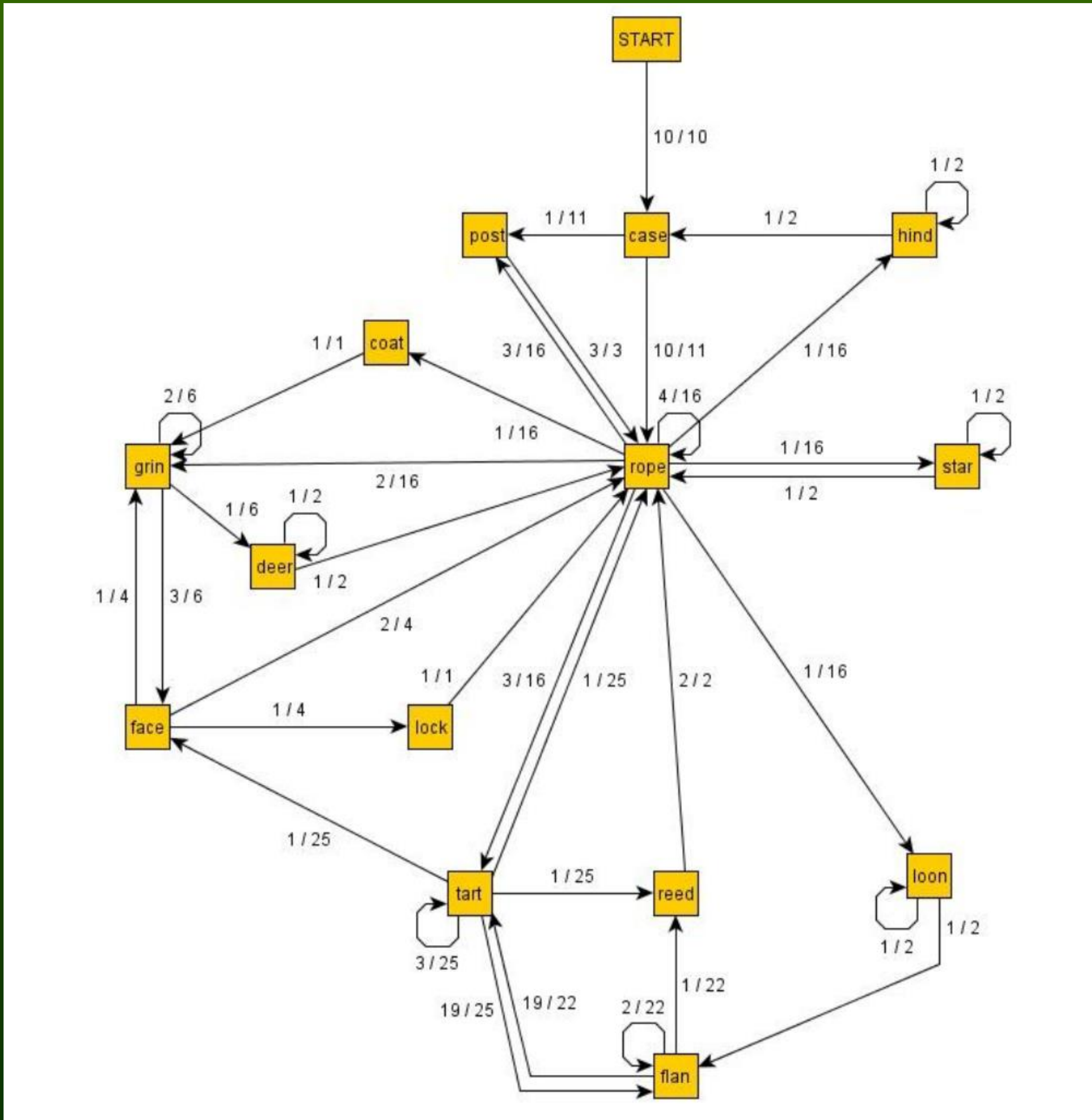




Multiple starts from the same word lead to different trajectories. Calculate transition probabilities between metastable states from frequency of transitions.

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).



To do: visualization and measures

Include max information in the RPs (recurrence plots).

- V1. Use color and show threshold as contours on the color plot.
- V2. Use 4 color schemes to show frequency of the dominating amplitude, i.e. distance = intensity, color = band.
- V3. Use lower parts of RP plots for additional information.
- V3.1 Select frequency band and show only changes for this band.
- V3.2 Show distance to peaks of a chosen band.
- V4. Use fixed reference states, ex. to the most frequent state, or fix rare reference state in oddball paradigm.
- Count RR frequency for each unique state; it should show ruminations in OCD, craving addicts or depression.
- V6. Fuzzy symbolic dynamics (FSD) or UMAP for plotting trajectories.
- V7. HMM for state labeling, identification of states.
- ….

To do list

- Find good MCI data for testing our approach.
- Experiment with simple similarity functions for STFT.
- Develop fuzzy version of RQA features.
- Automatic labeling of metastable states.
- Check method for automatic embedding parameters (Marwan et al).
- Check the effects of RPs smoothing on RQA parameters.
- Create new RQA features based on labeled states, ex. distribution of different states, most common states, metabolic costs!
- Consider Pade approximants instead of STFT to define "oscillons".
- Consider multivariate matching pursuit for discovery of patterns based on oscillons.
- Average RQA to get SFP, use RQA instead of clustering in SFP.
- Other signal decompositions: EMD, wavelets, spatio-temporal ICA...
- Source representation vs. electrodes.
- Multivariate options, synchronization to find subnetworks and RPs in network space.
- Cross-recurrence correlations, multivariate synchronization for subnetworks ... coherence and information flow.

To do: applications

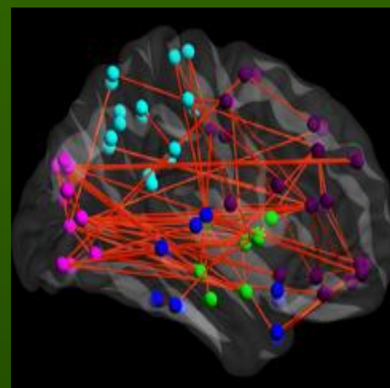
- A1. Pathological spectral fingerprints - using ToFFI on patient's data suffering from various problems: autism, Alzheimer, MCI ...
- A2. Pathological RPs to analyze dynamics of switching that lead after averaging to spectral fingerprints.
- A3. Relations to microstate transitions for diagnosis.
- A4. Synchronization of fronto-parietal theta as a sign of inhibition control.
- A5. Craving in addictions and frontal theta desynchronization.
- A6. Analysis of psychosomatic problems for our clinical psychologists.
- Analysis of real-time BCI applications.

fMRI and neurodynamics

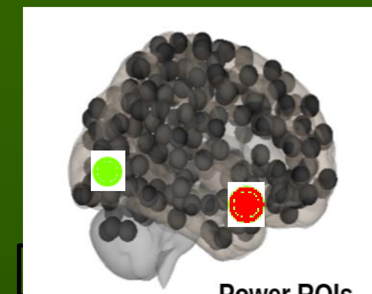
Human connectome and MRI/fMRI

Structural connectivity

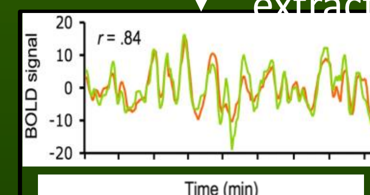
Functional connectivity



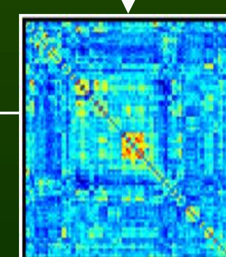
Node definition (parcelation)



Signal extraction



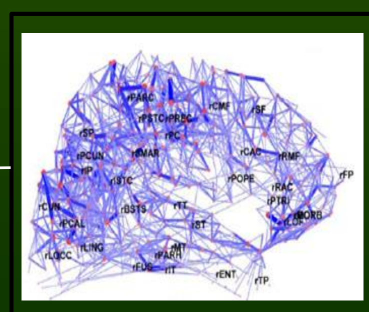
Correlation calculation



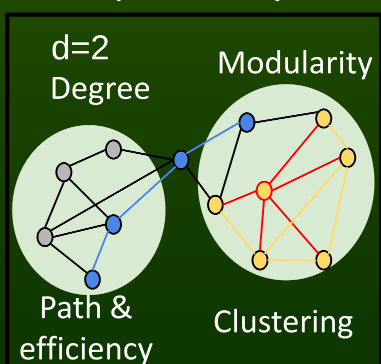
Correlation matrix

Binary matrix

Whole-brain graph



Graph theory

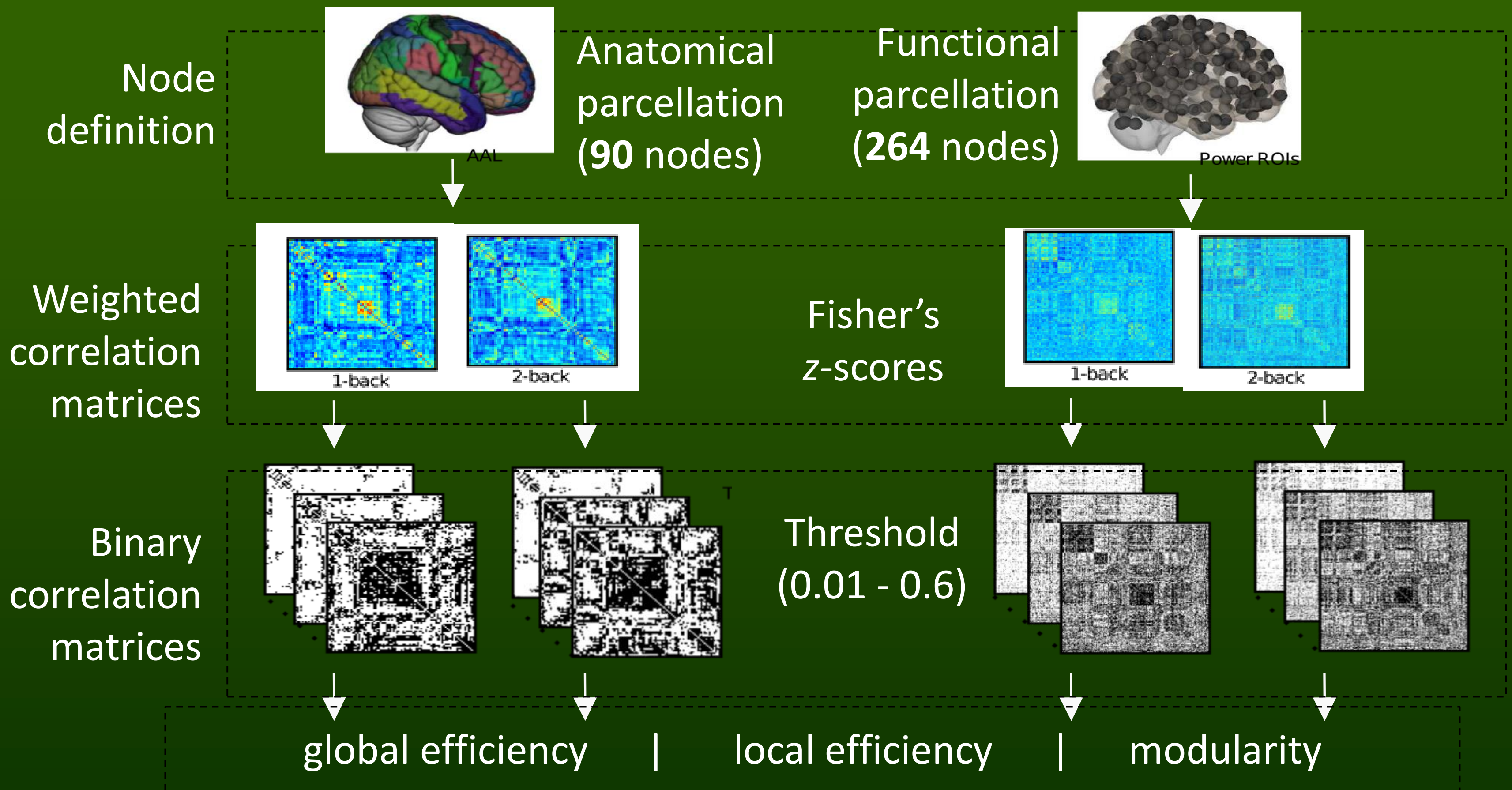


Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

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

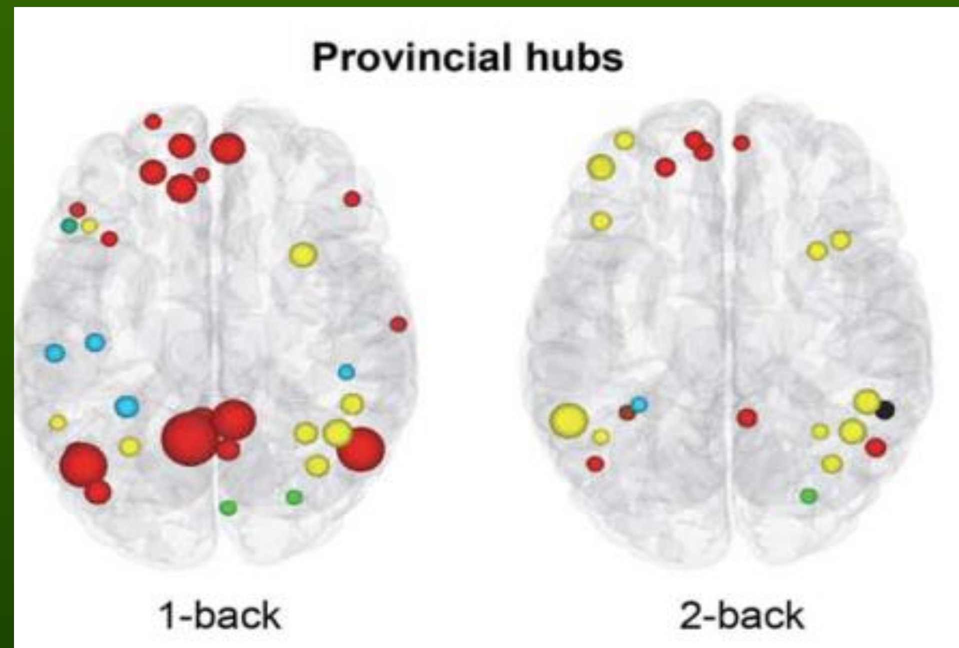
- Simple and more difficult tasks, requiring the whole-brain network reorganization.

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

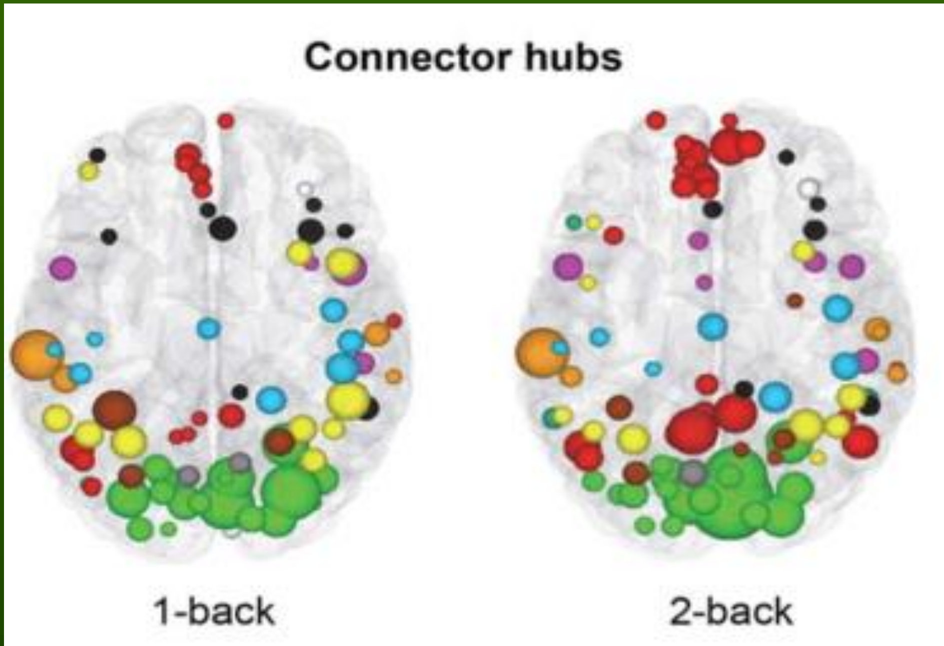
- Simple and more difficult tasks, requiring the whole-brain network reorganization.

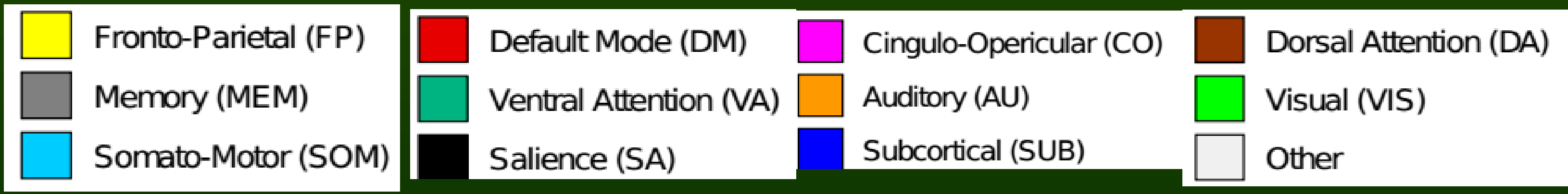
Left: 1-back connector hubs

Right: 2-back connector hubs

Average over 35 *participants.*

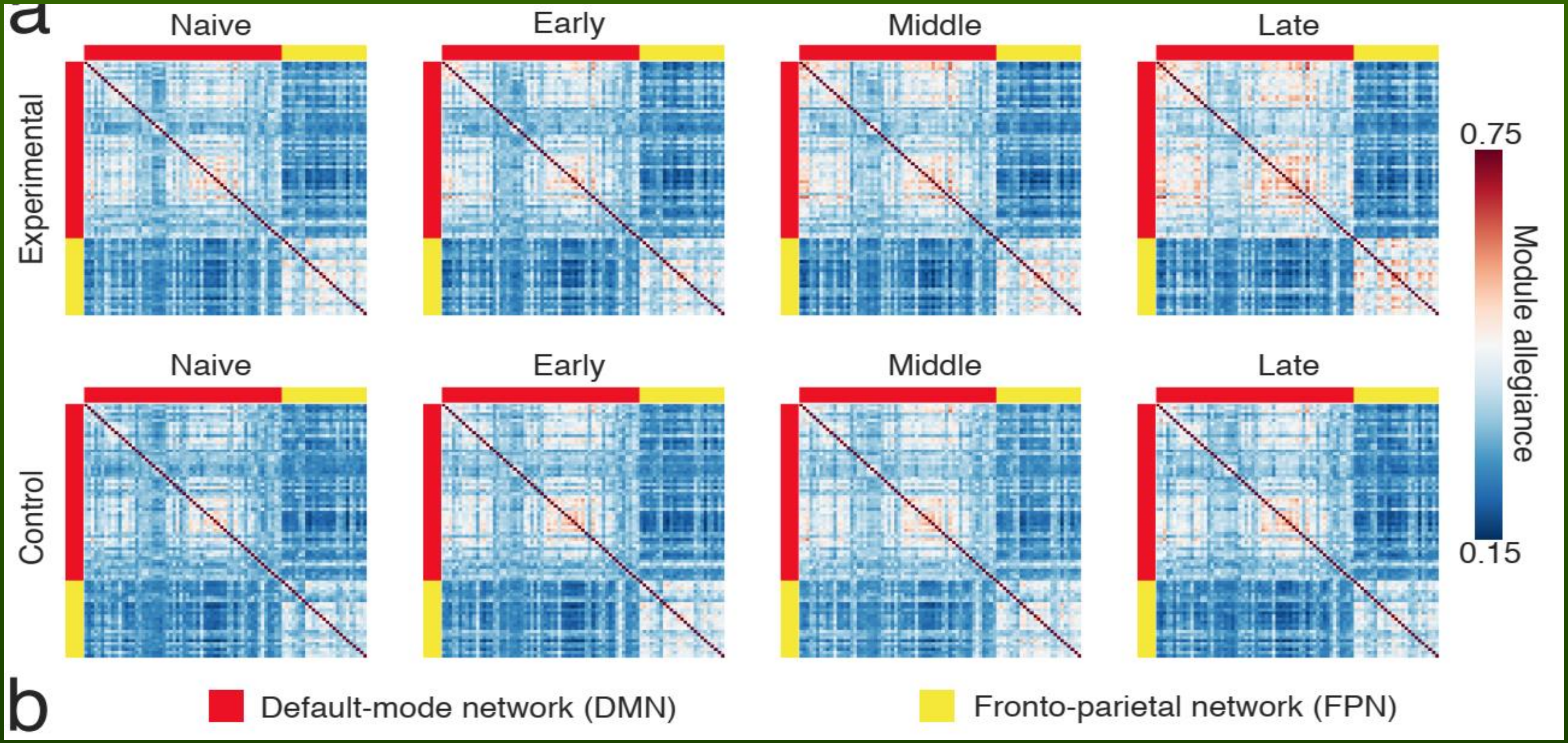
Dynamical change of the landscape of attractors, depending on the cognitive load – System 2 (D. Khaneman).
DMN areas engaged in global binding!





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

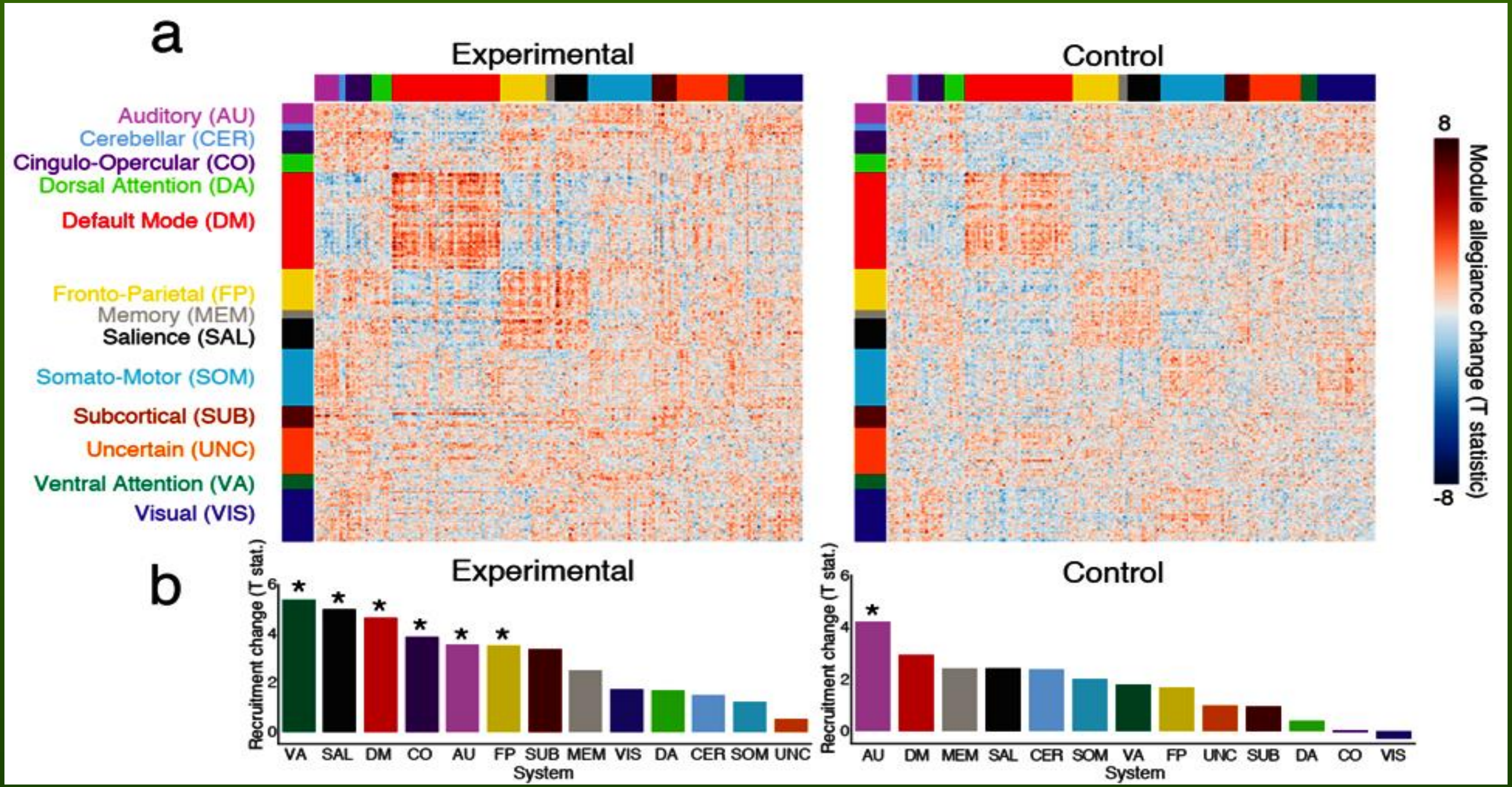
Working memory training



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).

Simulations of neurodynamics

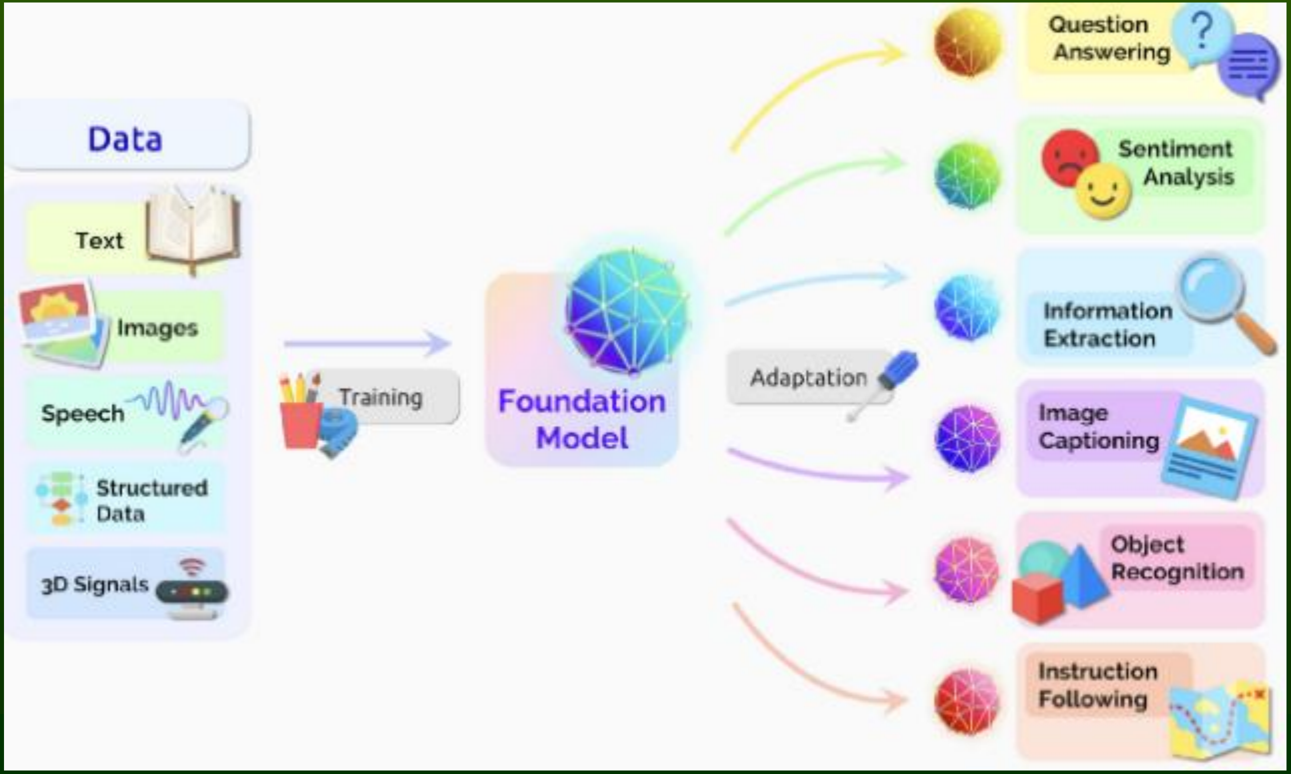
Mulitimodal foundational models

Multimodal transfer 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).

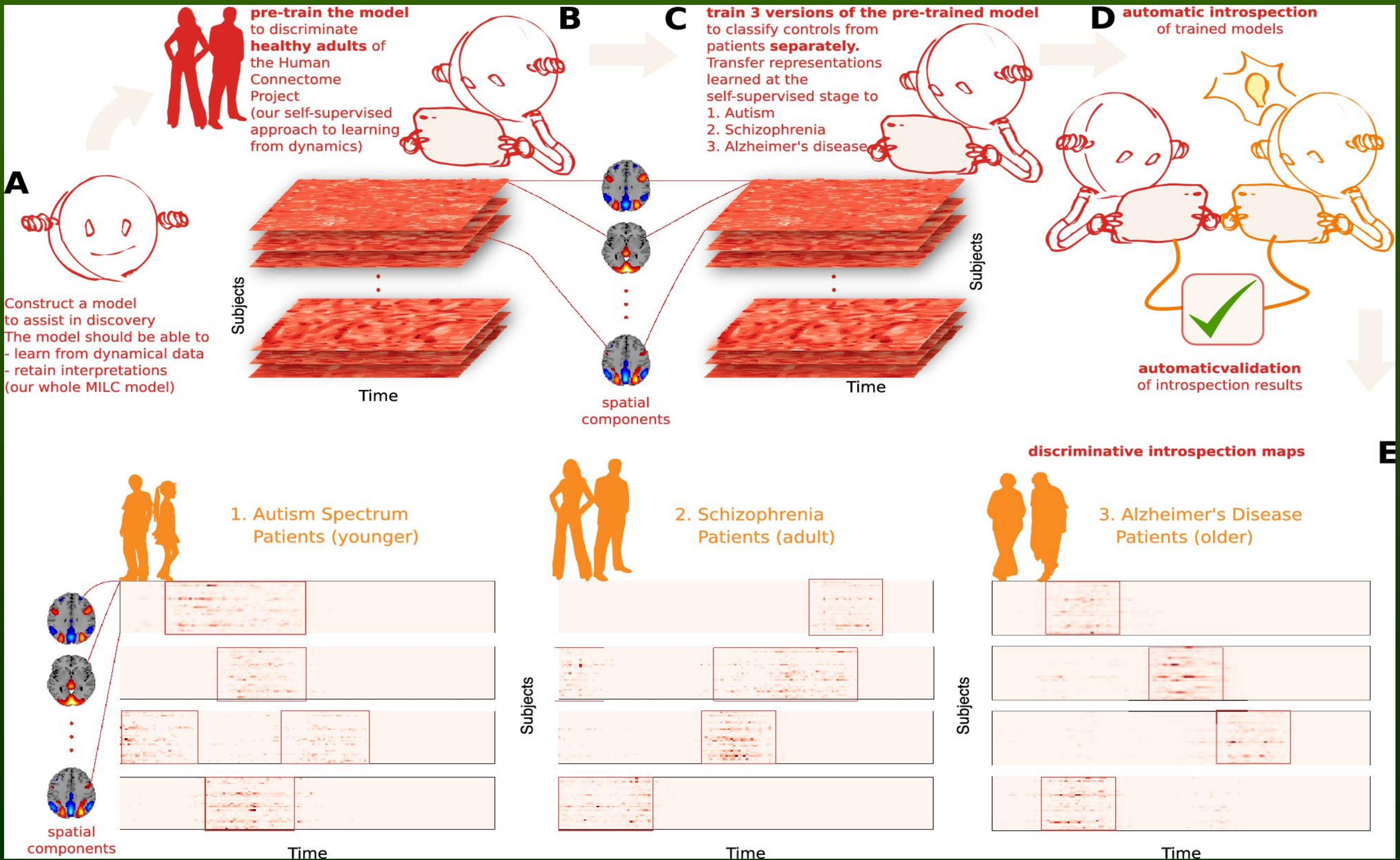
Image: Center for Research on Foundation Models (CRFM), Stanford Institute for Human-Centered Artificial Intelligence (HAI)

Can this be used to analyze brain signal patterns?

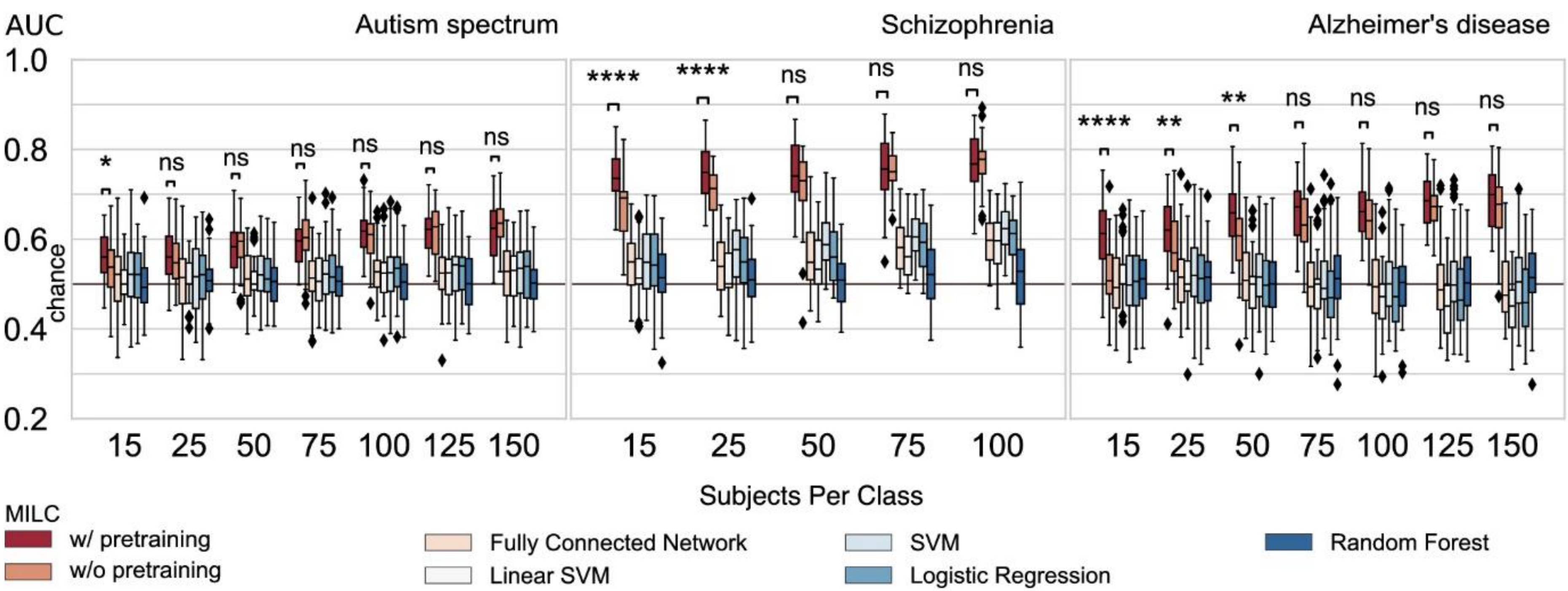


MILC model

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).



MILC model results



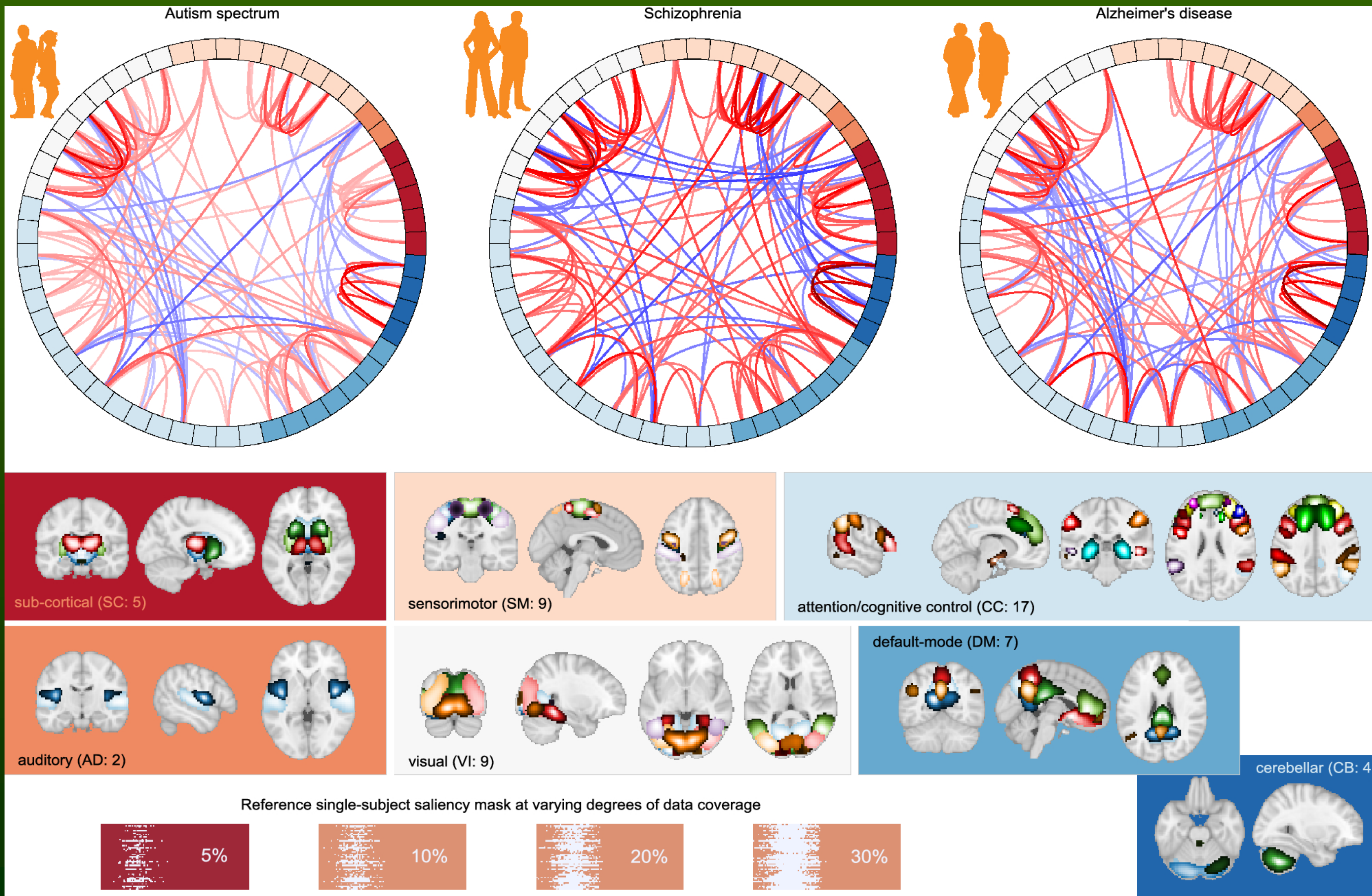
Deep learning + MILC can learn directly from high-dimensional signal dynamics even in small datasets (15 subjects), after pre-training on large data.

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

FNC (Functional Network Connectivity) was computed as Pearson's correlations between time courses of the components obtained by spatial independent component analysis (sICA).

MILC diagnosis

Top 10% FNC for patients computed using most 5% of the salient data as thresholded using feature attribution maps (saliency maps) for 3 disorders.



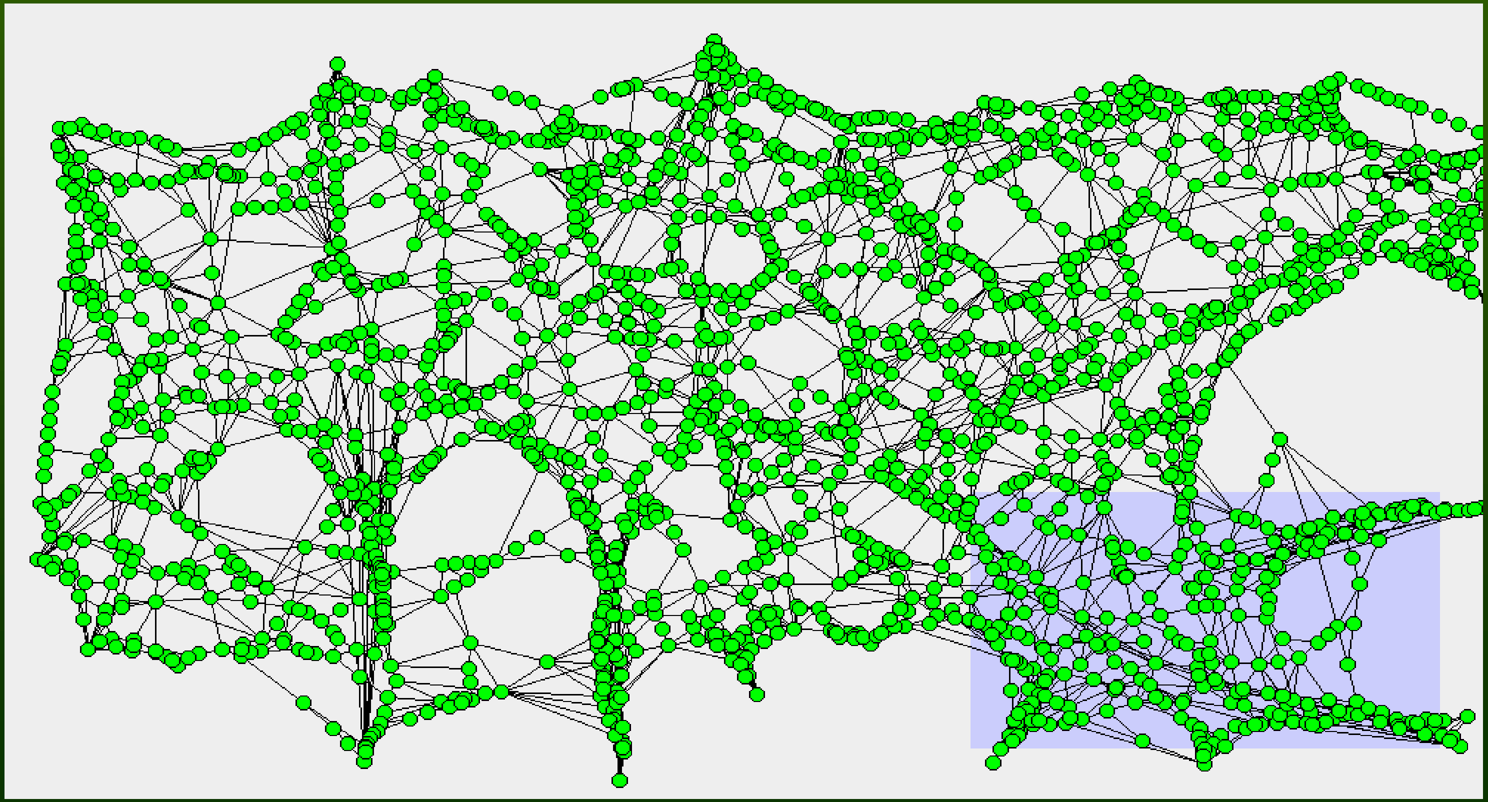
Learning in real situations

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.

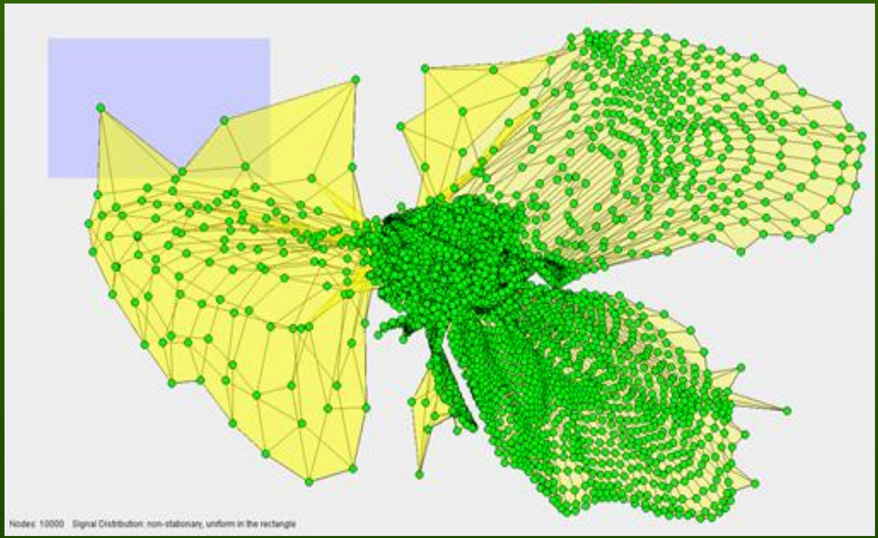


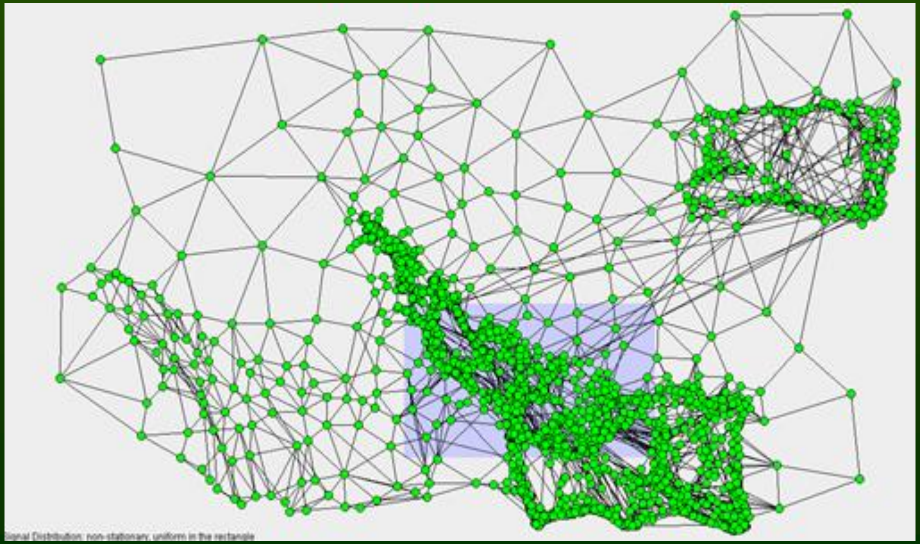
Memoids …

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. Overtraining => inhibition of alternatives!

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

Conclusions

- Neurodynamics is the key to understanding mental states.
  BMI has now hundreds of applications, medical, entertainment,
  but does not use cognitive architectures to build better models.
- Simulations show how attractor networks create metastable states, behavioral trajectories, test hypothesis (autism, ADHD, belief formation).
- Brain networks have fluid nature: 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.
- Neurocognitive technologies may help to diagnose, repair and optimize brain processes, improve AI algorithms. Develop close-loop systems based on DecNef and FCNef approaches.

Neurocognitive technologies will profoundly change ourselves.
The integration of brains with AI becomes feasible. Memory implants?
Brain synchronization? Metaverse? Impossible yesterday common tomorrow.

BMI perspectives

- BMI has now hundreds of applications, from medical to entertainment.
- Neuroprothesis and neurorehabilitation are coming of age.
- ECoG and intracortical recordings show what is possible with direct access to cortex.
- Hippocampal memory prothesis is a step towards deep future.
- Medical diagnostics and closed loop systems for therapy of brain disorders are the driving forces.
- DecNef and FCNef approaches used by rt-FMRI should be converted to EEG
- AI development, especially foundational models, should help in creation of more accurate models, enable transfer learning.
- Neurocognitive technologies will profoundly change our selves.
  The integration of brains with AI becomes feasible.
- Metaverse? Brain synch?
- What was impossible yesterday tomorrow will be common.
  The singularity may come faster than we think!

Towards Human-like Intelligence

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

IEEE SSCI CIHLI 2022 Symposium on Computational Intelligence for Human-like Intelligence, Singapore.

AGI: conference, 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, 11th Annual Meeting of the BICA Society, Natal, Brazil, 2020.

Brain-Mind Institute Schools, International Conference on Brain-Mind (ICBM) and Brain-Mind Magazine (Juyang Weng, Michigan SU).

In search of sources of brain's cognitive activity

Project „Symfonia", NCN, Kraków, 18.07.2016

FACULTY OF PHYSICS, ASTRONOMY AND INFORMATICS

CENTRE FOR MODERN INTERDISCIPLINARY TECHNOLOGIES

INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

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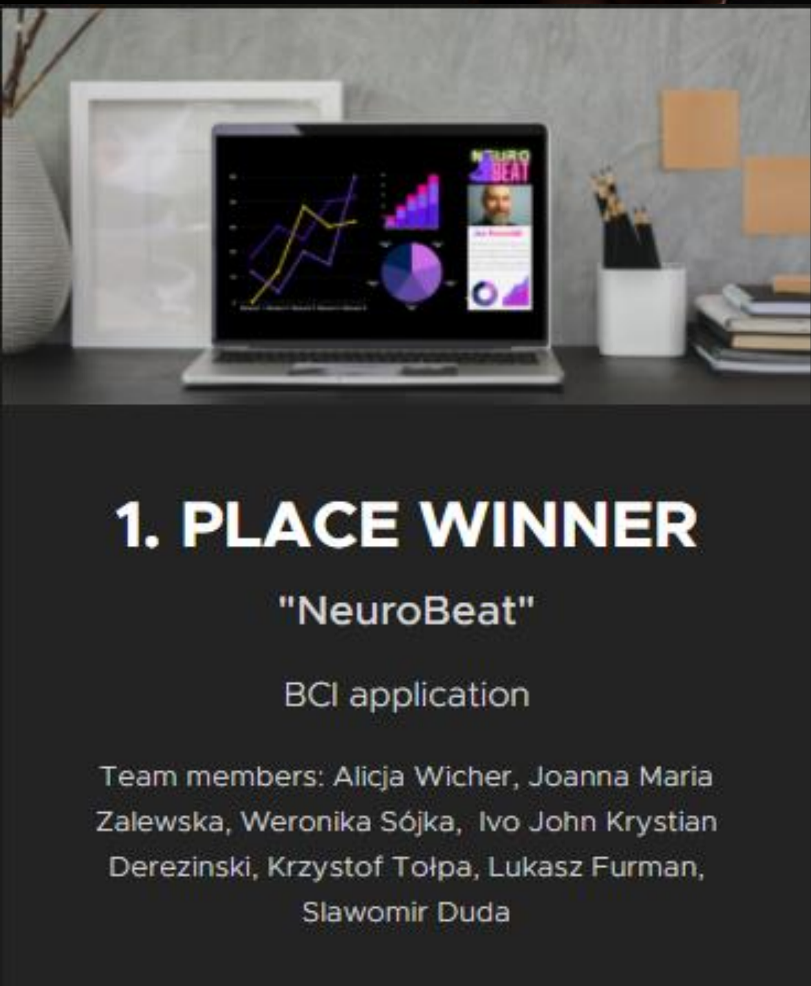
VIRTUAL BR41N.IO HACKATHON
April 17-18, 2021
during the
Spring School 2021*
IEEE brain
g.tec
*BR41N.IO and Spring School 2021 are part of g.tec's Teaching Plan 2021 with more than 140 hours of online courses and lectures.


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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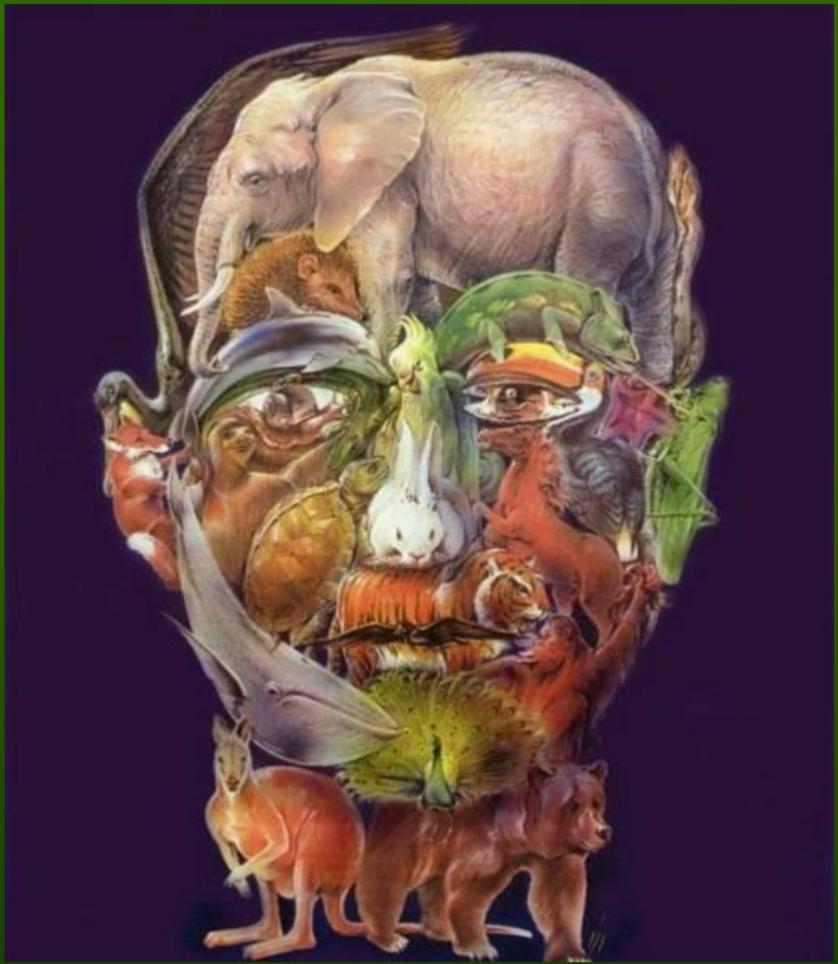
Intelligence?



Google: Wlodek Duch

=> talks, papers, lectures ...