



How can we understand brain activity?

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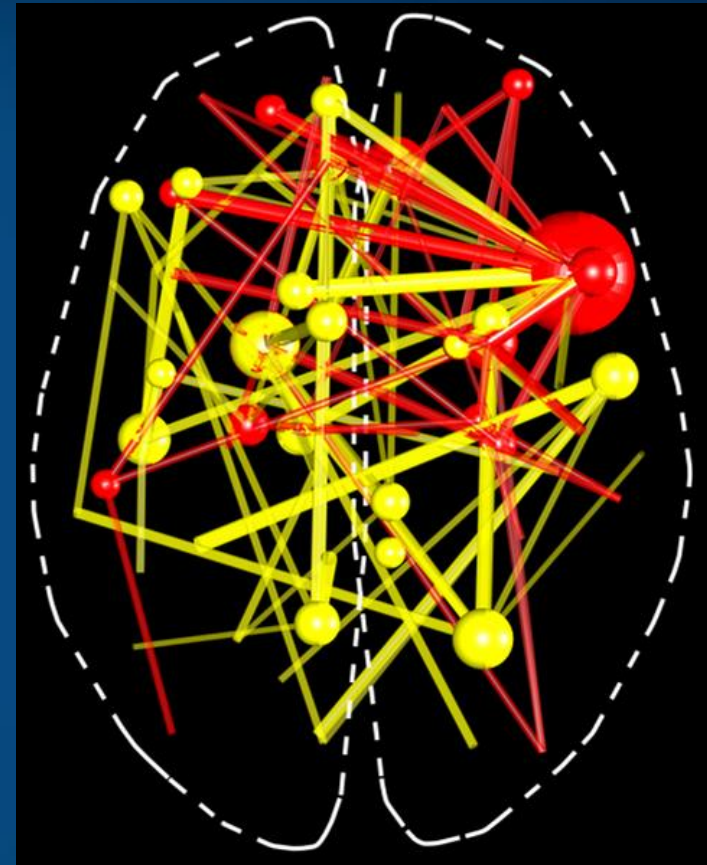
10 years of CS in Toruń, 29-30.05.19

On the threshold of a dream ...

How mental states arise from specific activity of the brain networks?

- AI and models of mind/brain.
- Brain \Leftrightarrow Mind relations.
- Brain networks – space for neurodynamics.
- Fingerprints of Mental Activity.
- Dynamic functional brain networks.
- Neurocognitive technologies.

Final goal: Use your brain to the max!
Optimization of brain processes?



Duch W. (2012) Mind-Brain Relations, Geometric Perspective and Neurophenomenology, American Philosophical Association Newsletter 12(1), 1-7.

In search of the sources of brain's cognitive activity

Project „Symfonia”, 2016-21



AI and abstract models of mind/brain

Neuropsychiatric phenomics

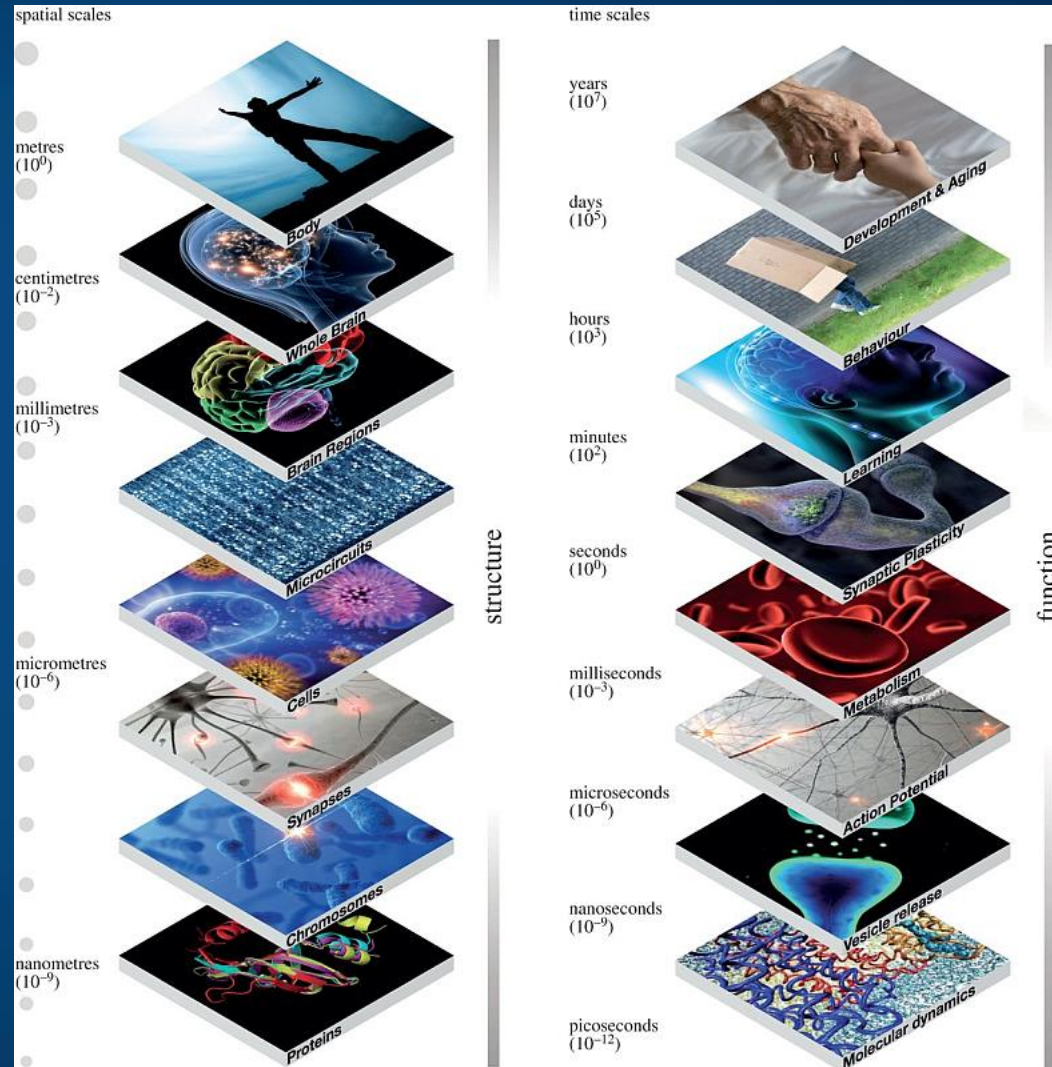
2008: The Consortium for Neuropsychiatric Phenomics

“... categories, based upon presenting signs and symptoms, may not capture fundamental underlying mechanisms of dysfunction” (Insel et al., 2010).

New approach: RDOC NIMH.

Description of organisms at different levels will help to answer different types of questions.

Network level is in the middle and can be connected to the mental level via computational models.



RDoC Matrix for „cognitive domain”

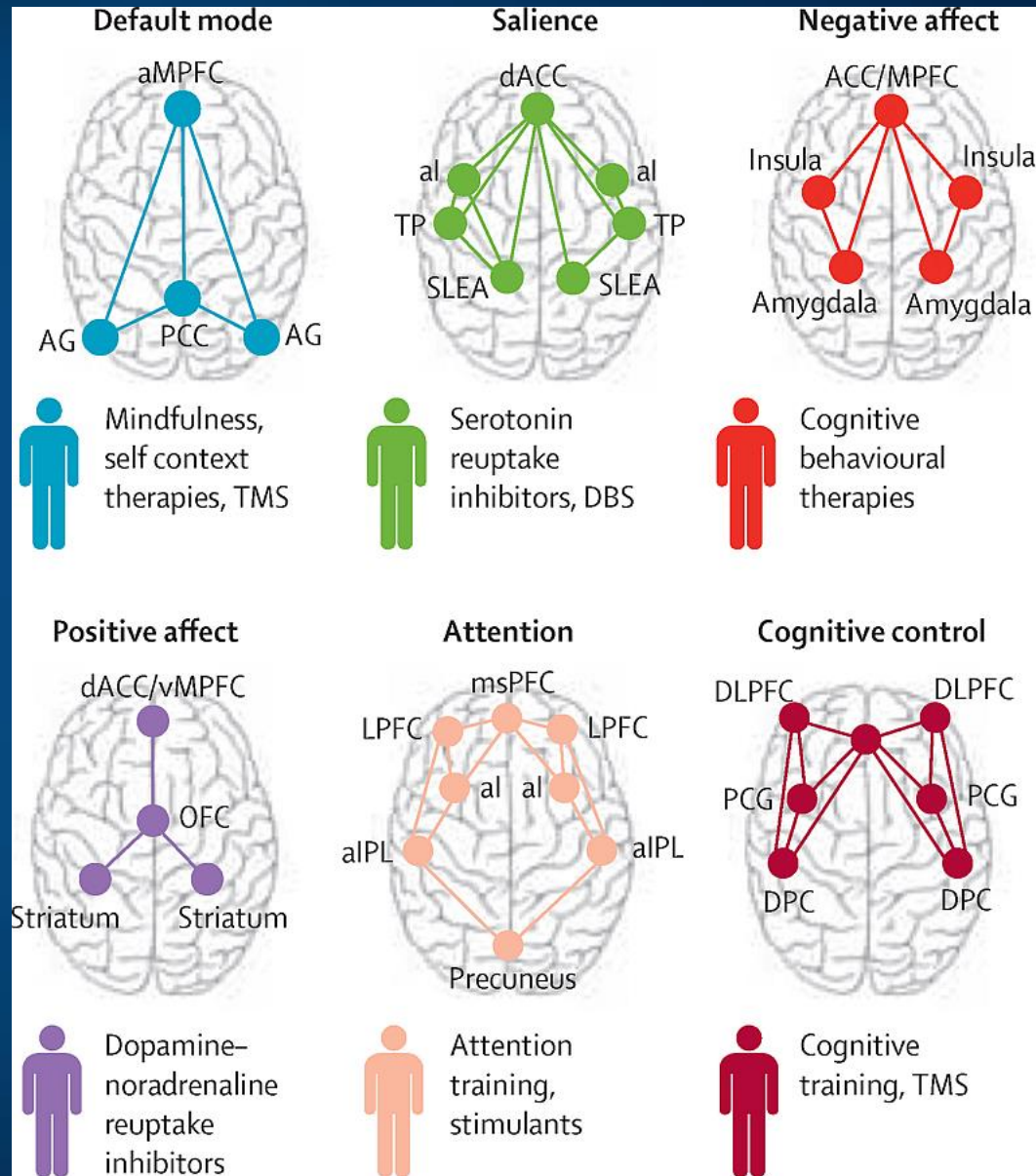
Construct/Subconstruct		Genes	Molecules	Cells	Circuits	Physiology	Behavior	Self-Report	Paradigms
Attention		Elements	Elements	Elements	Elements	Elements	Elements		Elements
Perception	Visual Perception	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Auditory Perception	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Olfactory/Somatosensory/Multimodal/Perception								Elements
Declarative Memory		Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
Language		Elements			Elements	Elements	Elements	Elements	Elements
Cognitive Control	Goal Selection; Updating, Representation, and Maintenance ⇒ Focus 1 of 2 ⇒ Goal Selection				Elements			Elements	Elements
	Goal Selection; Updating, Representation, and Maintenance ⇒ Focus 2 of 2 ⇒ Updating, Representation, and Maintenance	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Response Selection; Inhibition/Suppression ⇒ Focus 1 of 2 ⇒ Response Selection	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Response Selection; Inhibition/Suppression ⇒ Focus 2 of 2 ⇒ Inhibition/Suppression	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Performance Monitoring	Elements	Elements		Elements	Elements	Elements	Elements	Elements
Working Memory	Active Maintenance	Elements	Elements	Elements	Elements	Elements			Elements
	Flexible Updating	Elements	Elements	Elements	Elements	Elements			Elements
	Limited Capacity	Elements	Elements		Elements	Elements			Elements
	Interference Control	Elements	Elements	Elements	Elements	Elements			Elements

Multi-level phenomics

Instead of classification of mental disease by symptoms use **Research Domain Criteria (RDoC)** matrix based on **multi-level neuropsychiatric phenomics** describing large brain systems deregulation.

1. **Negative Valence Systems,**
2. **Positive Valence Systems**
3. **Cognitive Systems**
4. **Social Processes Systems**
5. **Arousal/Regulatory Systems**

Include genes, molecules, cells, **circuits**, physiology, behavior, self-reports and paradigms describing psychological constructs.



Brains ↔ Minds

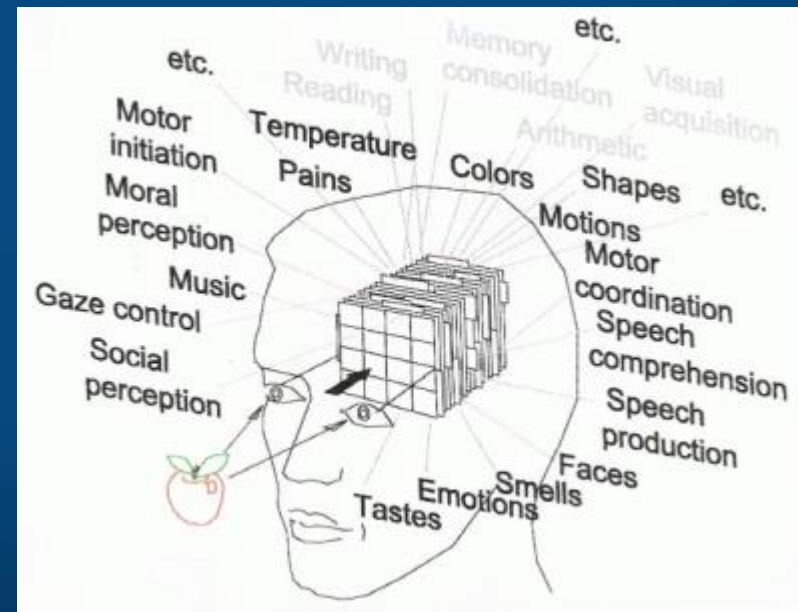
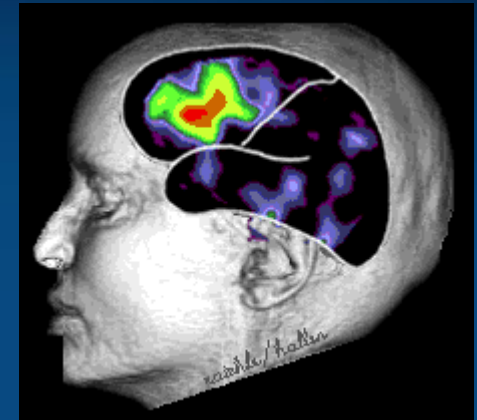
Cognitive neuroscience: map $S(M) \leftrightarrow S(B)$, as in BCI.
How do we describe the state of mind?

Verbal description is not sufficient unless words are represented in a space with dimensions that measure different aspects of experience.

Stream of mental states, movement of thoughts
↔ trajectories in psychological spaces.

Two problems: discretization of continuous processes for symbolic models, and lack of good phenomenology – we are not able to describe our mental states.

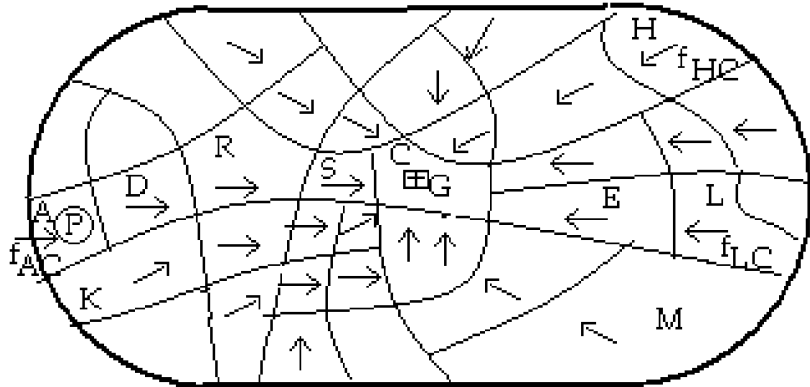
Neurodynamics: bioelectrical activity of the brain, neural activity measured using EEG, MEG, NIRS-OT, PET, fMRI ...



E. Schwitzgabel, Perplexities of Consciousness. MIT Press 2011.

Lewin's psychological forces

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



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

Kurt Lewin, founder of social psychology, analyzed interactions between people and their environment creating psychology inspired by field theory. Transitions between mental states = psychological forces. Regions of positive valence are in basins of attractors of neurodynamics. K. Lewin books: *Principles of Topological Psychology* (1936); *Conceptual Representation & Measurement of Psychological Forces* (1938); *Field Theory in Social Science* (1951).

A Standard Model of the Mind

Laird JE, Lebiere C, & Rosenbloom, PS (2017). A Standard Model of the Mind: Toward a Common Computational Framework across Artificial Intelligence, Cognitive Science, Neuroscience, and Robotics. *AI Magazine*, 38, 13–26.

J. Laird: A mind is a functional entity that can think.

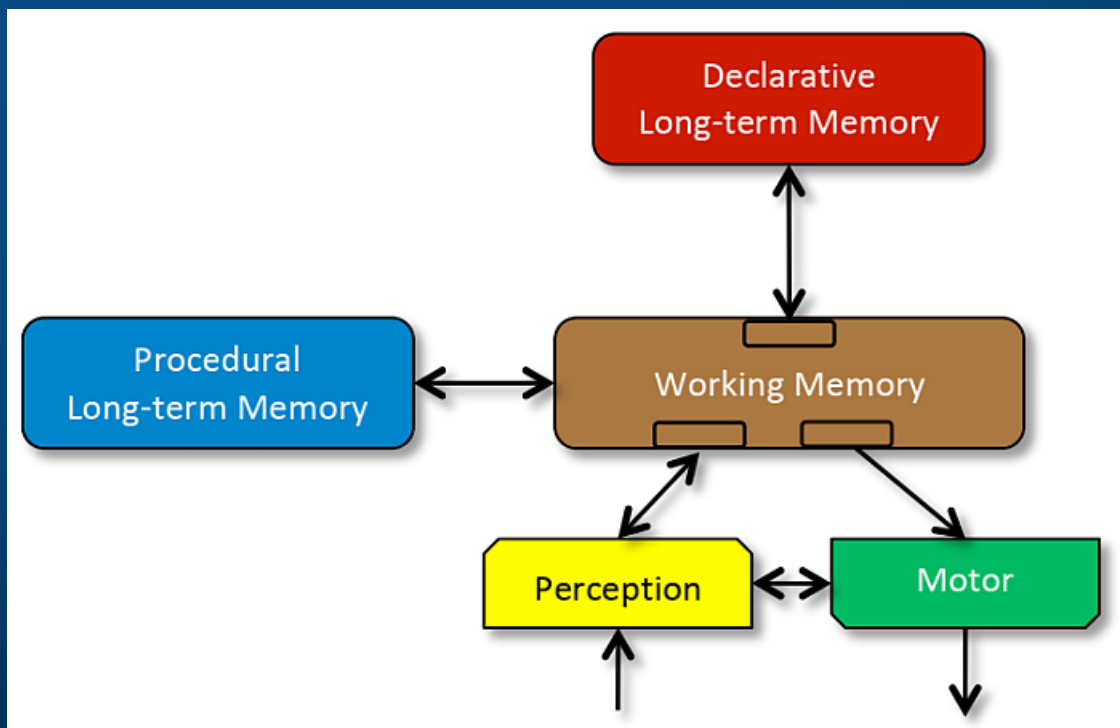
A. Newell: Mind is a control system that determines behavior of organism interacting with complex environment.

Cognitive informatics,
Neurocognitive Informatics

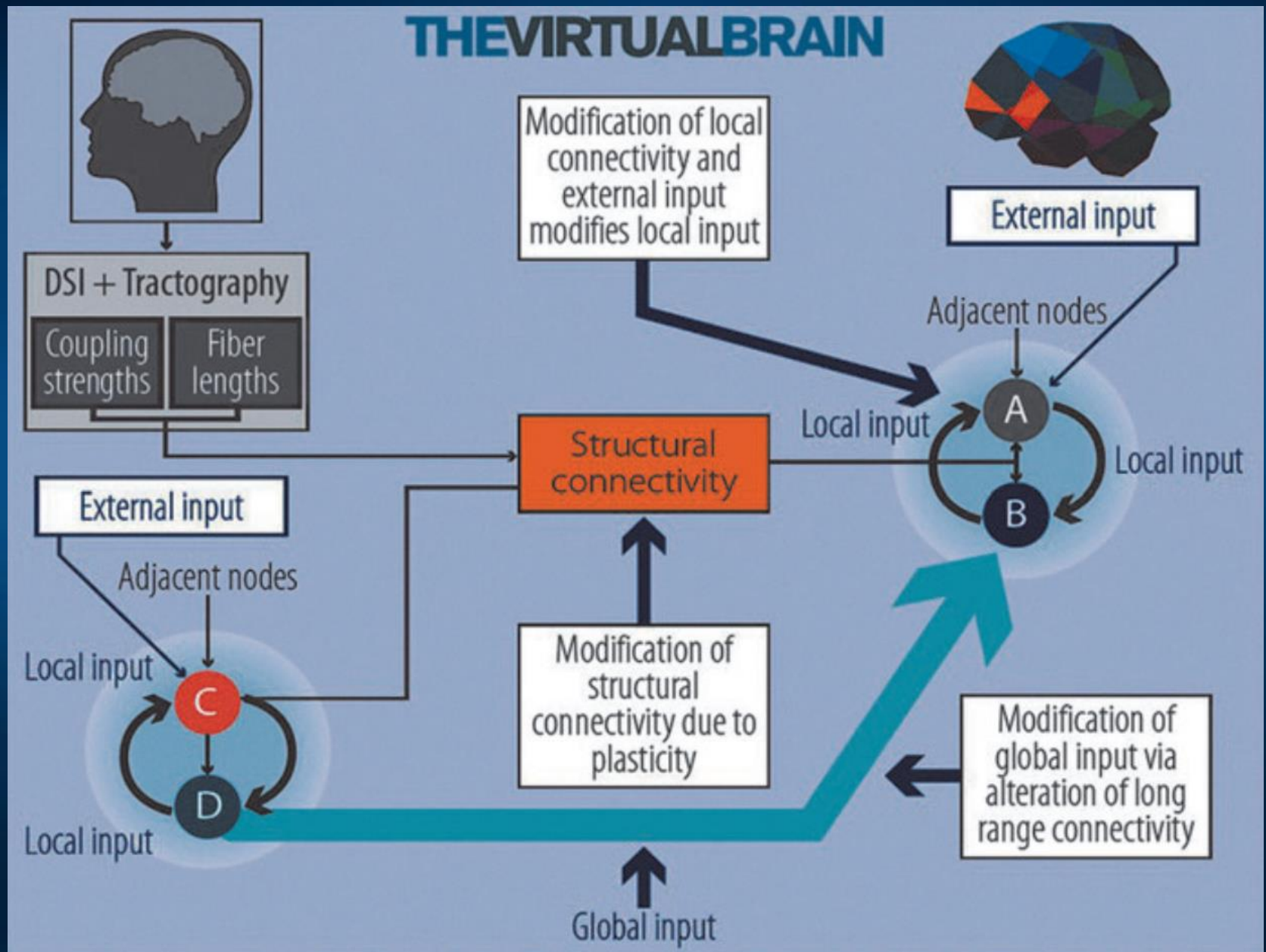
BICA = Brain Inspired
Cognitive Architecture.

Review: Duch, Oentaryo,
Pasquier, Cognitive
architectures: where do we
go from here? 2008

Rules, not dynamics.



Population dynamics TVB model



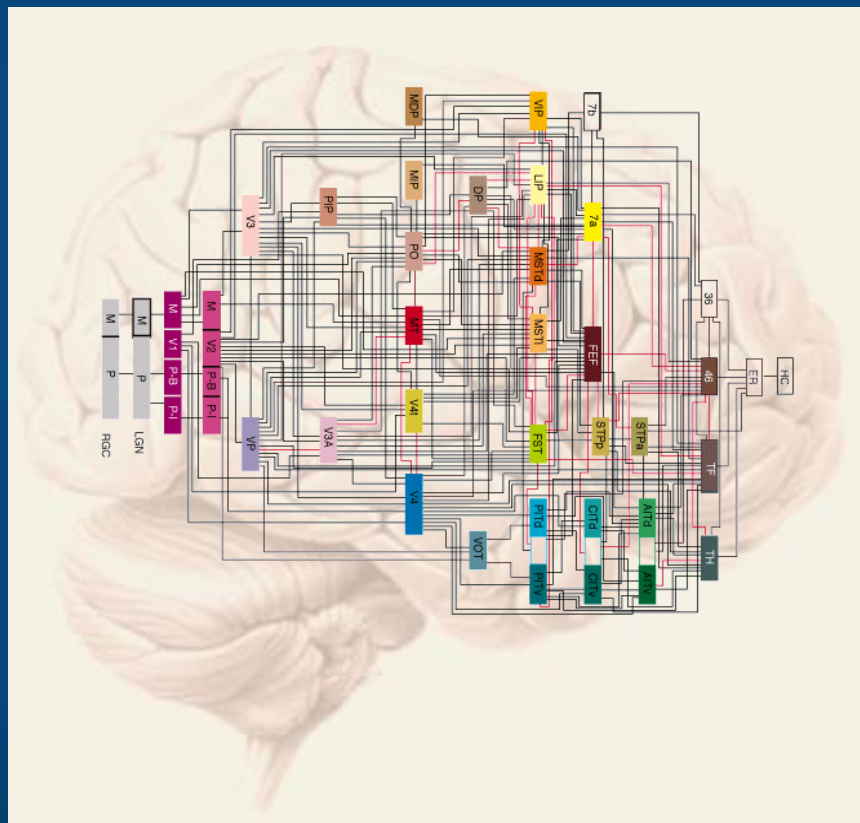
Free energy

The free-energy principle (FEP): any self-organizing system that is at equilibrium with its environment must minimize its free energy – predict => active inference.

Constraints for brain architecture: EST, Evolutionary Systems Theory (Badcock, 2012).

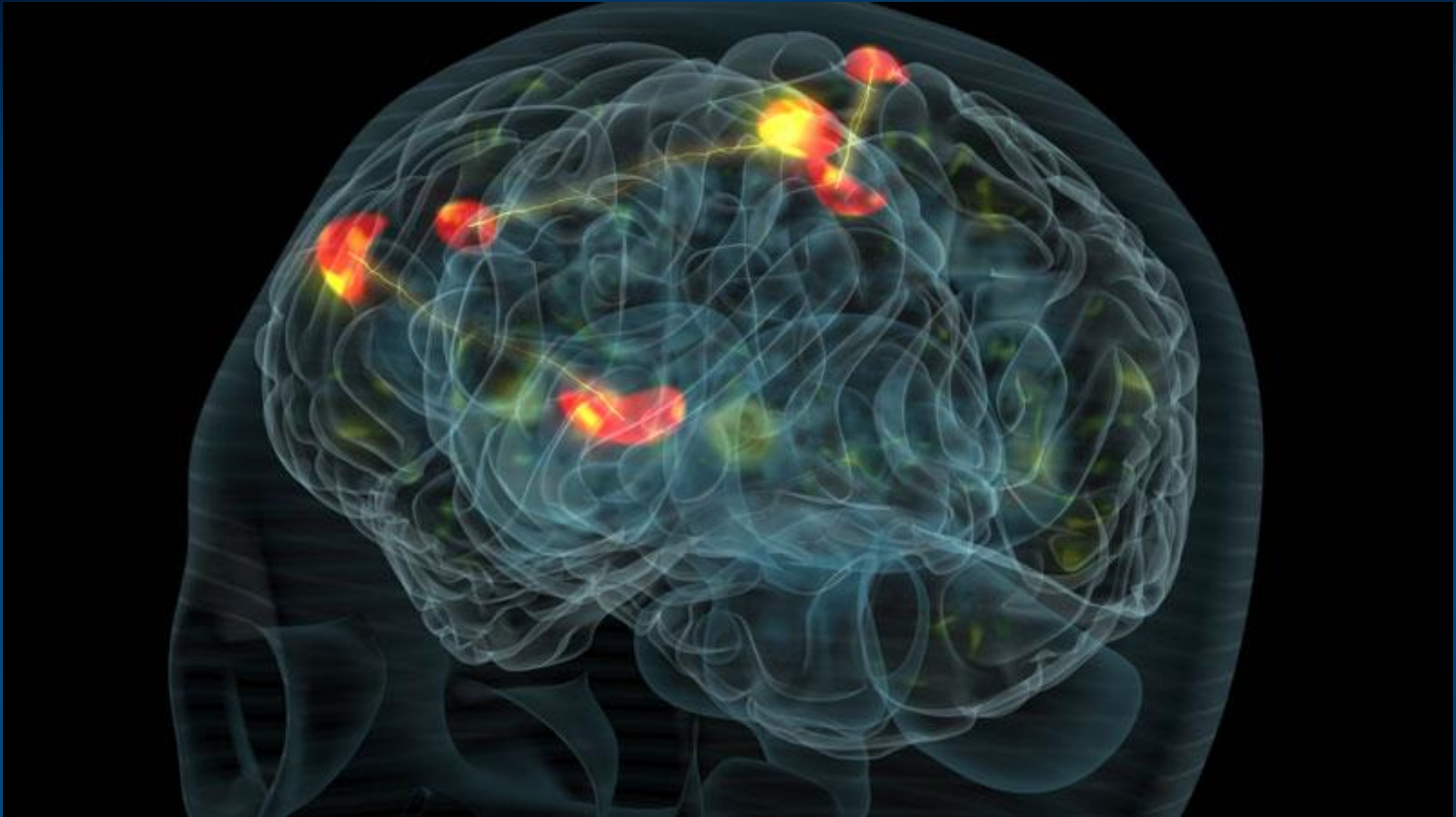
Combination of FEP with EST is a candidate for standard theory of cognitive systems.

Still only a sketch of a theory. Can FEP be derived from computational neuroscience?



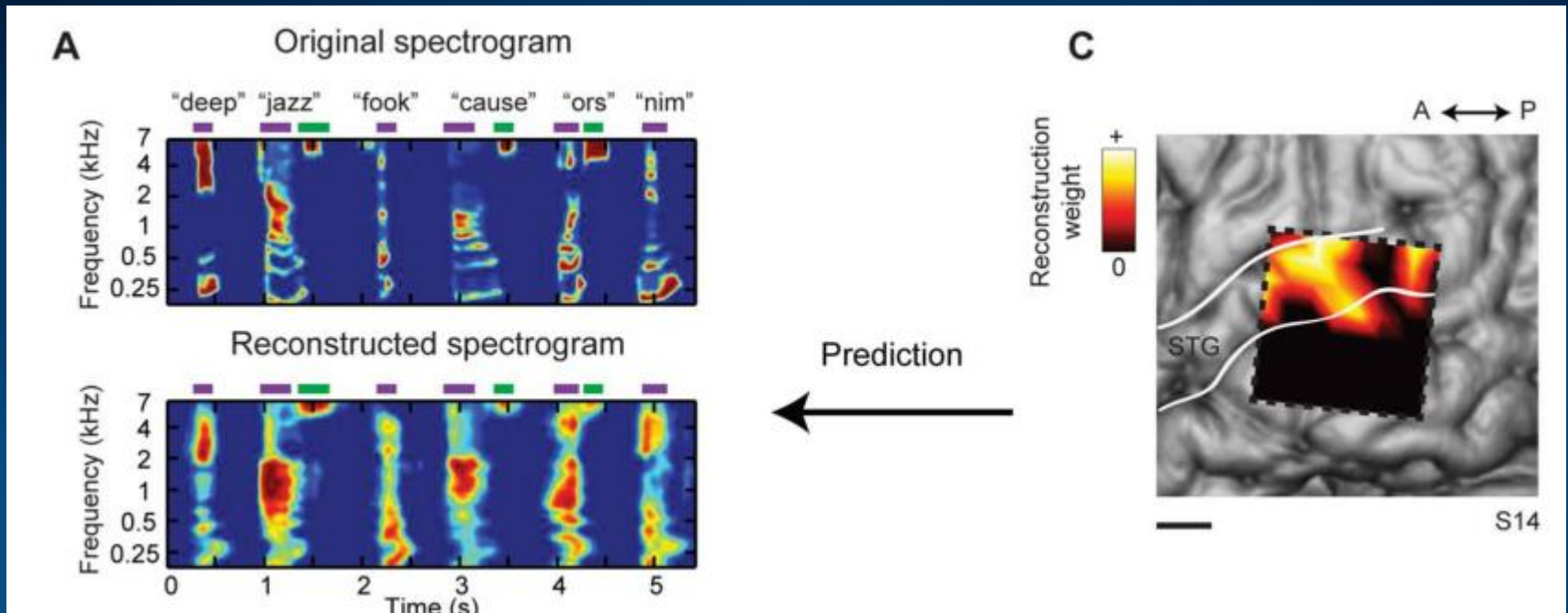
Brain networks:
space for neurodynamics

Mental state: strong coherent activation



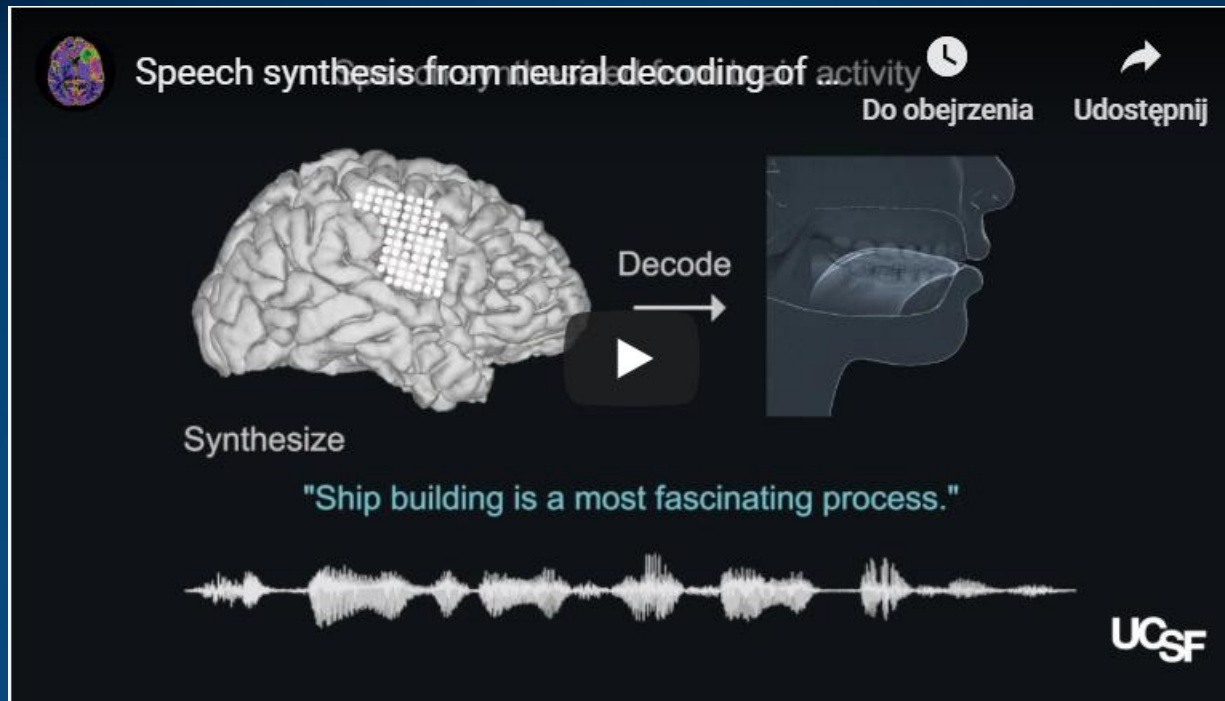
Many processes go on in parallel, controlling homeostasis and behavior. Most are automatic, hidden from our Self. What goes on in my head? Various subnetworks compete for access to the highest level of control - consciousness, the winner-takes-most mechanism leaves only the strongest. How to extract stable intentions from such chaos? BCI is never easy.

Thought: time, position, energy, frequency



Spectrogram of words – distribution of energy in space/time/frequency – may be reconstructed from local field potentials measured using electrocorticography, and then used to activate voice synthesiser, changing brain activations to speech.

Listing to thoughts

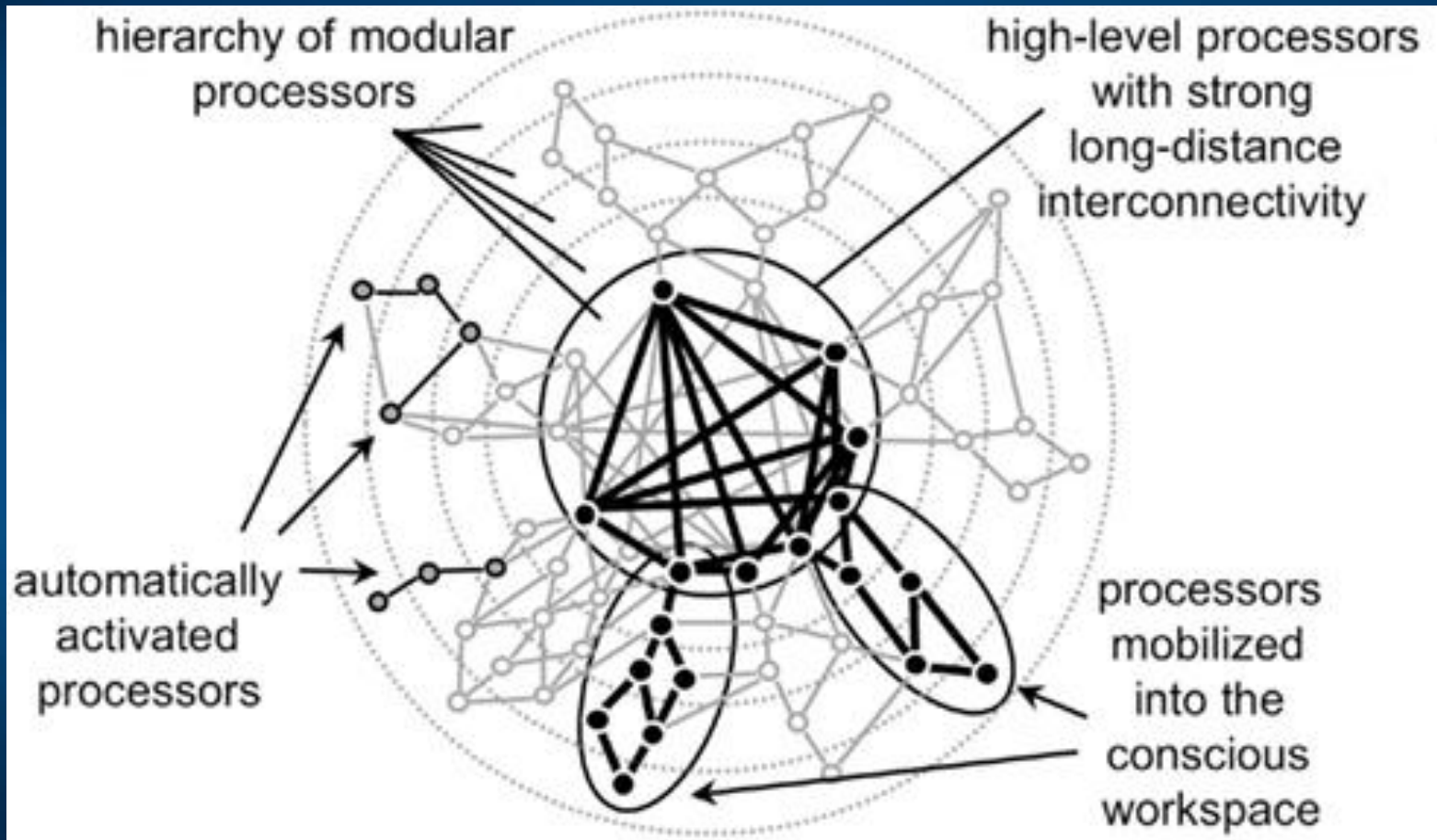


Patterns of cortical activations in higher order human auditory cortex allows for neural decoding of speech acoustic parameters, decoder is used to synthesize speech when a participant silently mimed sentences.

Pasley et al. (2012); G.K. Anumanchipalli, J. Chartier, E.F. Chang, Speech synthesis from neural decoding of spoken sentences. [Nature 24/4/2019](#)

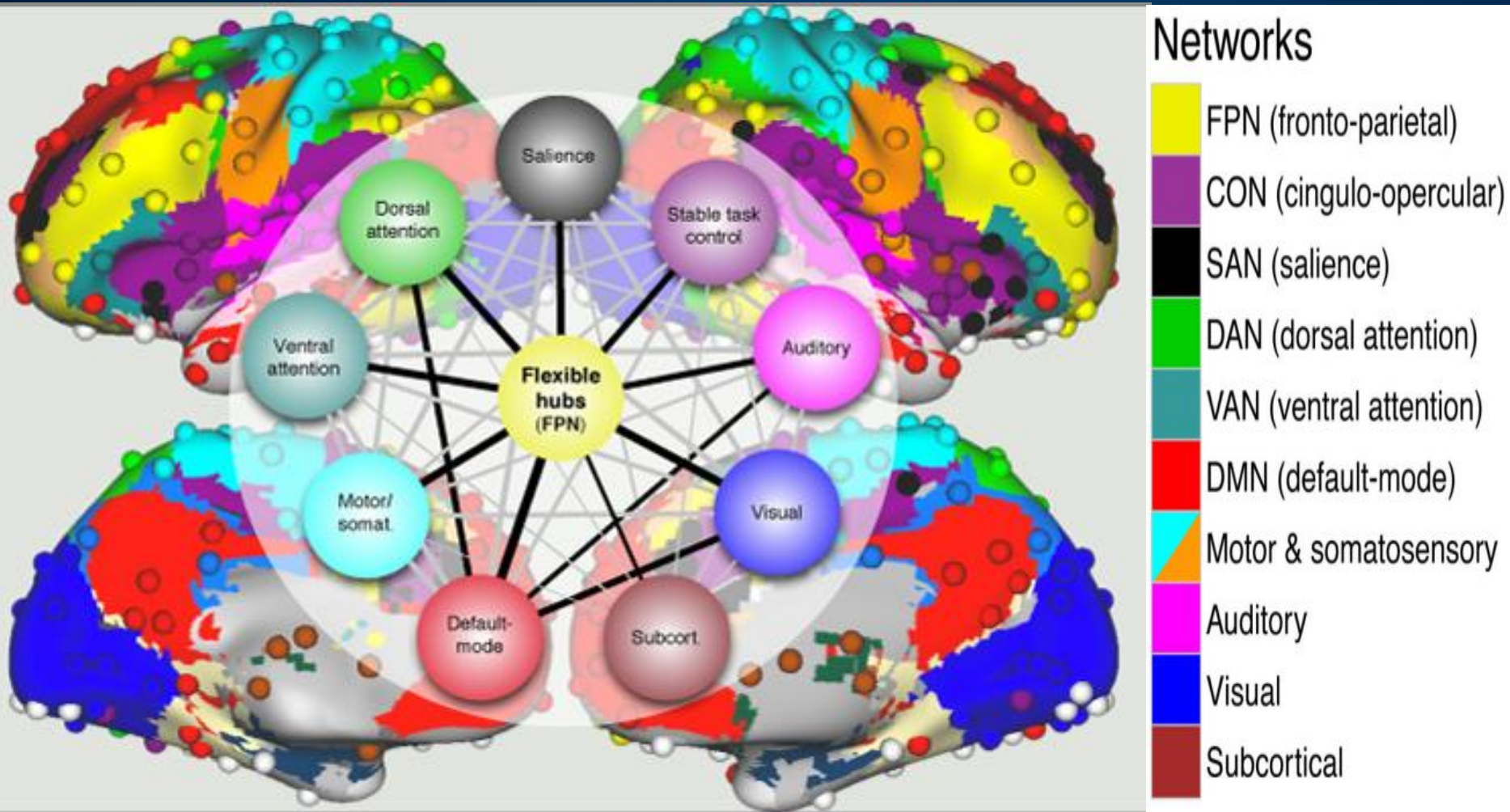
GNWT

Global Neuronal Workspace Theory (Dehaene et al. 1998)



Brain is a substrate in which thoughts, feelings and intentions arise.

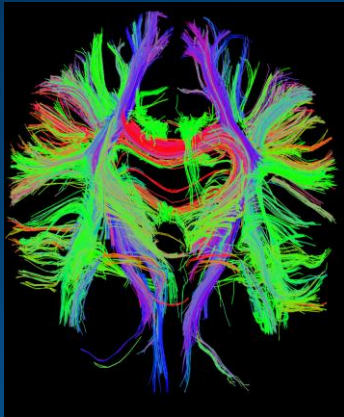
Neurocognitive Basis of Cognitive Control



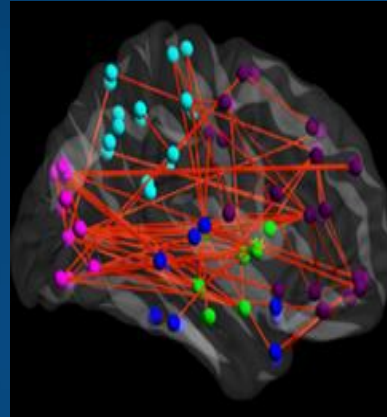
Central role of fronto-parietal (FPN) flexible hubs in cognitive control and adaptive implementation of task demands (black lines=correlations significantly above network average). Cole et al. (2013).

Human connectome and MRI/fMRI

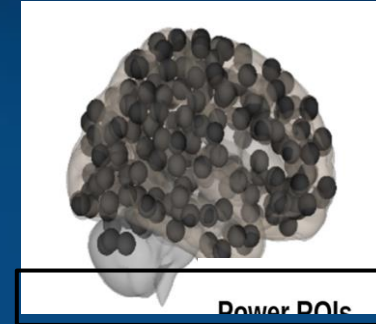
Structural connectivity



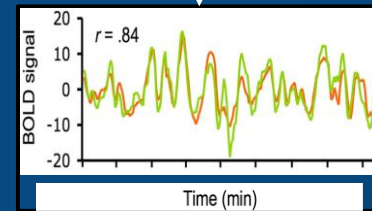
Functional connectivity



Node definition (parcelation)



Signal extraction

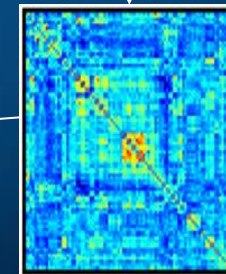


Correlation calculation

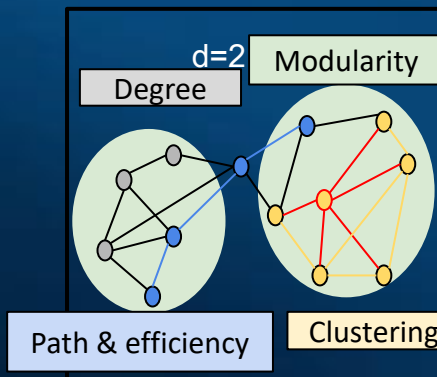
Binary matrix



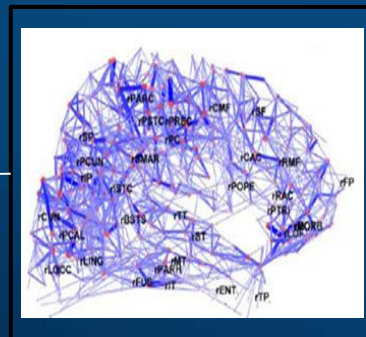
Correlation matrix



Graph theory



Whole-brain graph



Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

Possible form of Brain Fingerprints

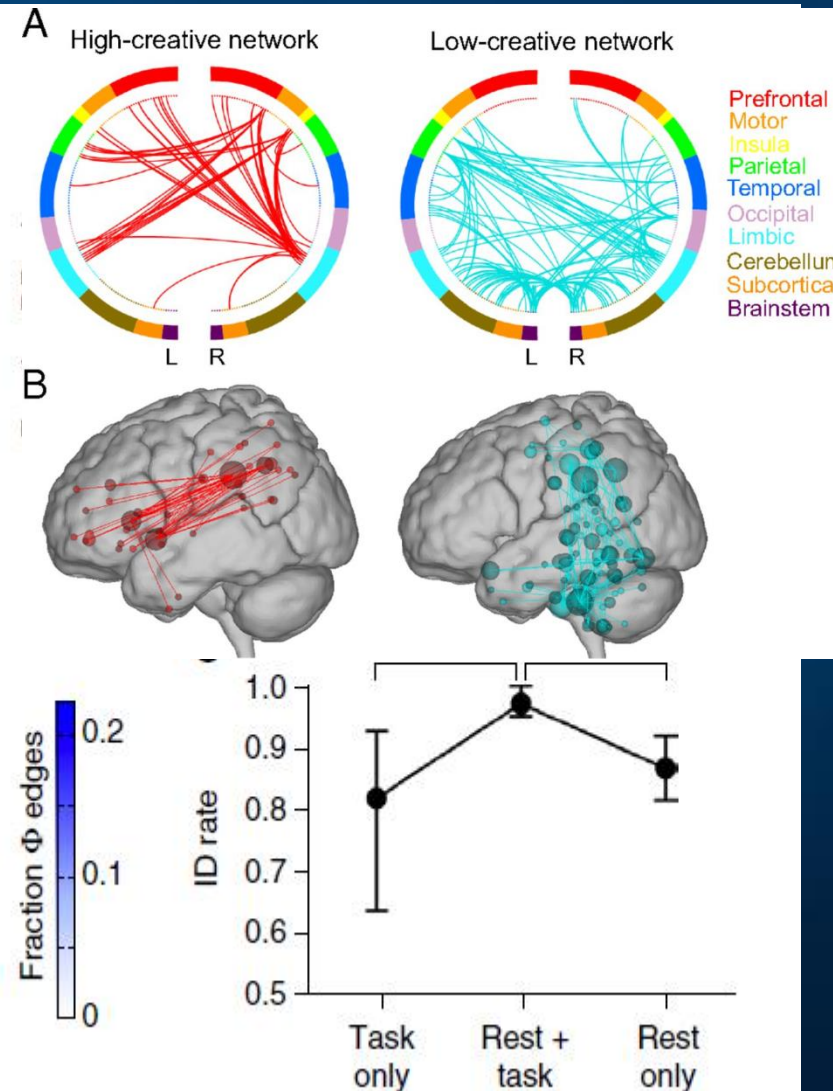
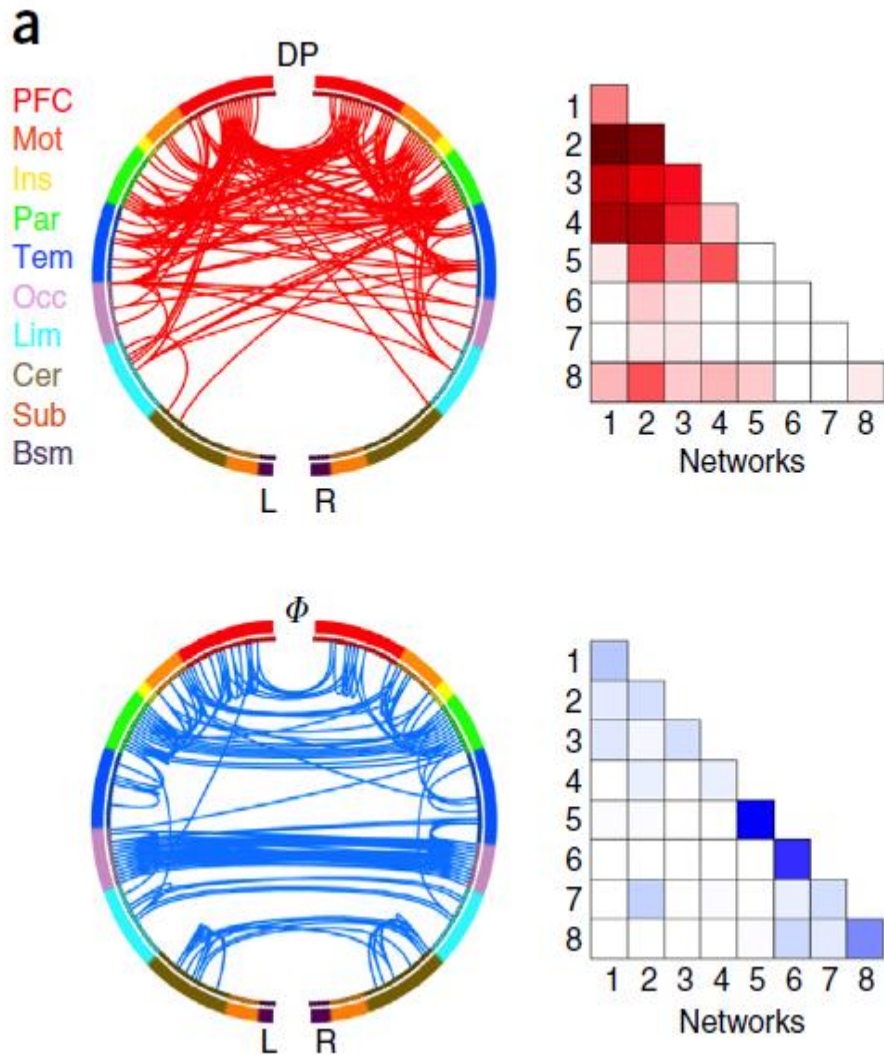
fMRI: BFP is based on $V(\mathbf{X},t)$ voxel intensity of fMRI BOLD signal changes, contrasted between task and reference activity or resting state.

EEG: spatial, spatio-temporal, ERP maps/shapes, coherence, various phase synchronization indices.

1. **Spatial/Power:** direct localization/reconstruction of sources.
2. **Spatial/Synch:** changes in functional graph network structure.
3. **Frequency/Power:** ERS/ERD smoothed patterns $E(\mathbf{X},t,f)$.
4. **ERP power maps:** spatio-temporal averaged energy distributions.
5. **EEG decomposition into components:** ICA, CCA, tensor, RP ...
6. **EEG microstates, sequences & transitions, dynamics in ROI space.**
7. **Model-based: The Virtual Brain,** integrating EEG/neuroimaging data.
8. **Spectral fingerprinting (MEG, EEG), power distributions.**

Neuroplastic changes of connectomes and functional connections as results of training for optimization of brain processes.

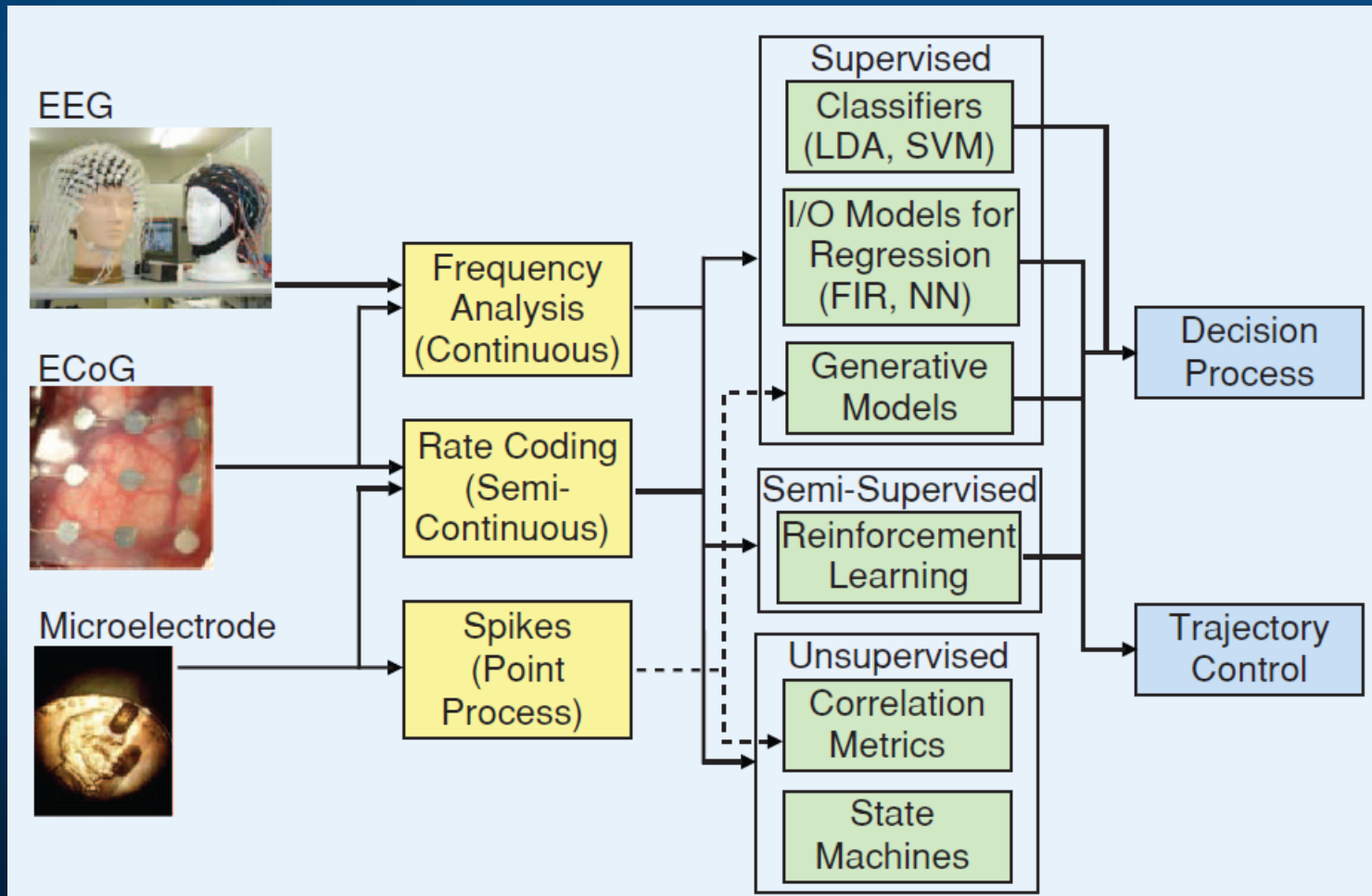
Finn et al. (2015), **Functional connectome fingerprinting**: identifying individuals using patterns of brain connectivity. Nature Neuroscience. Top: highly unique; Bottom: highly consistent connections.



Brain-Computer Interfaces (BCI)

Recognition of brain states (mind reading) to discover intentions, focus of attention, understand mental states.

Better access to neurons = more precise information.

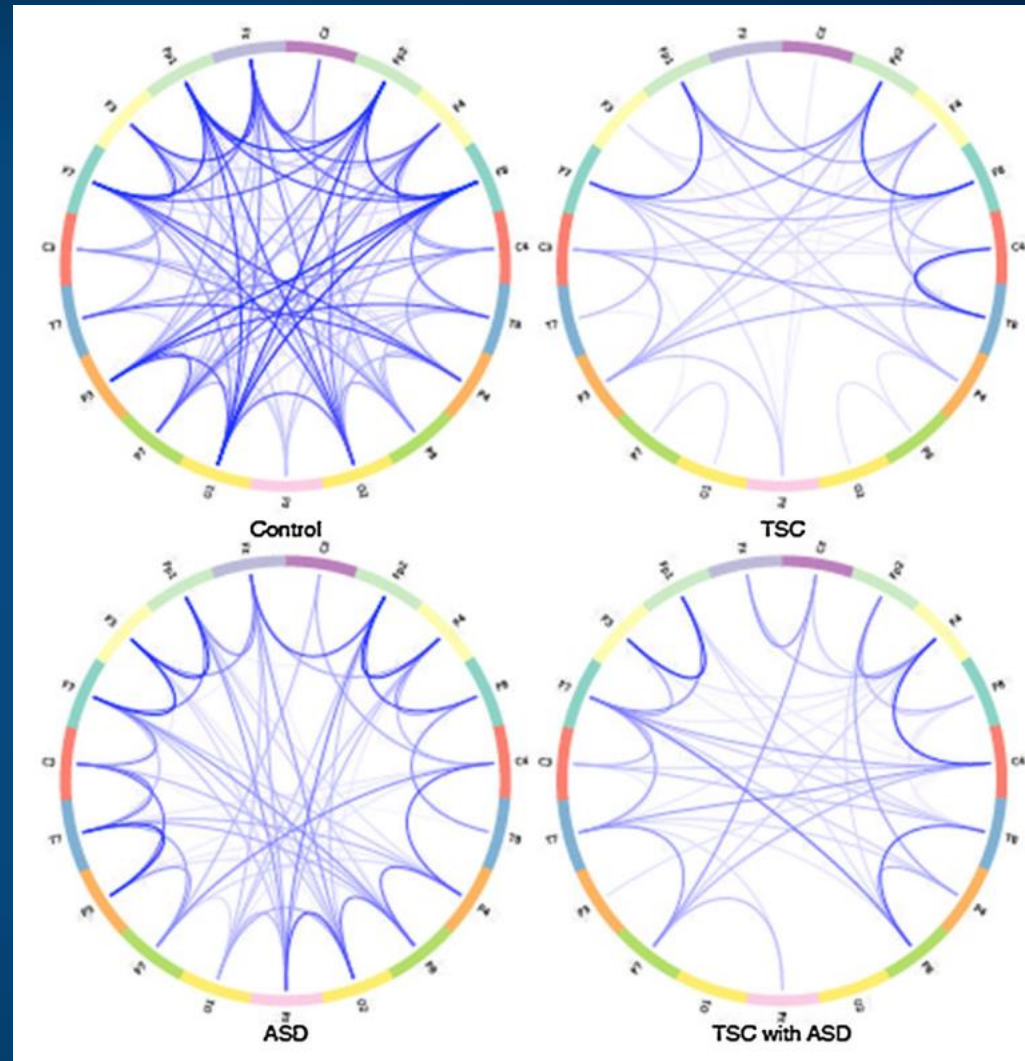


ASD: pathological connections

Comparison of connections for patients with ASD (autism spectrum), TSC (Tuberous Sclerosis), and ASD+TSC.

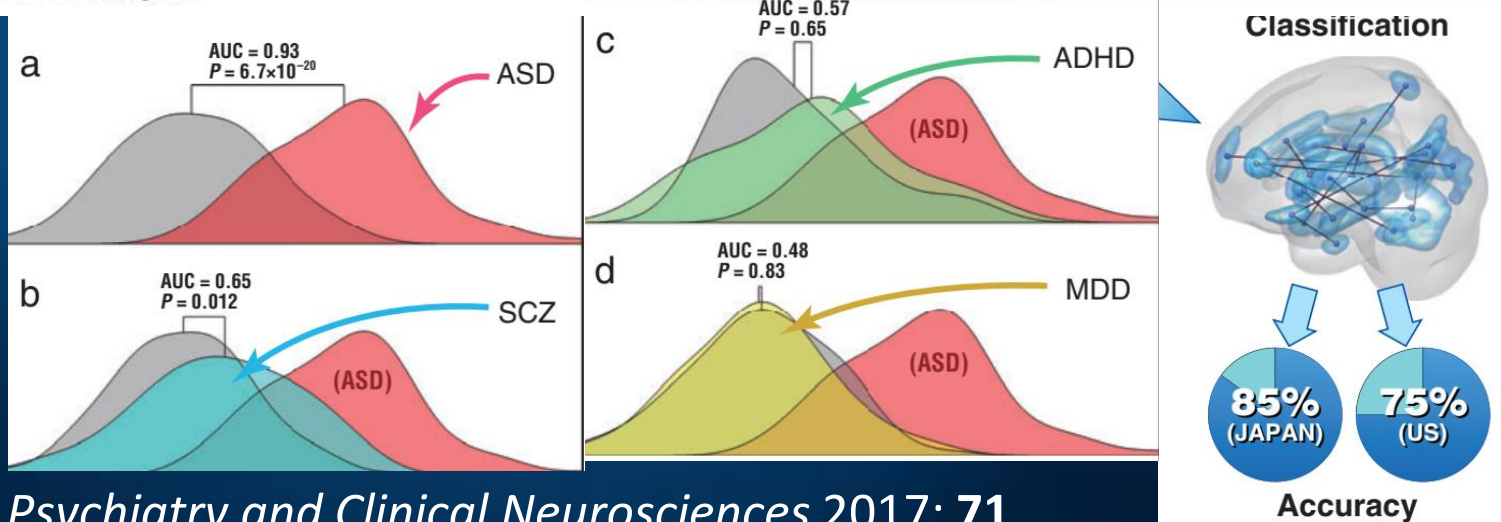
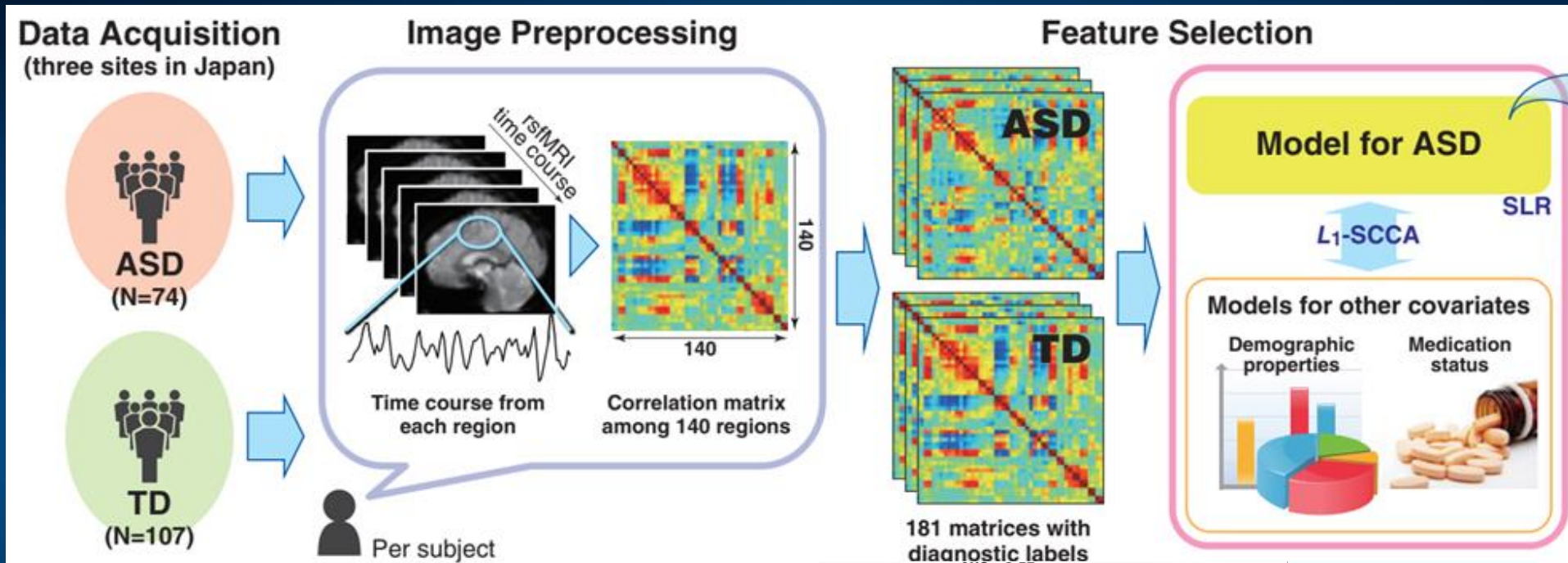
Coherence between electrodes. Weak or missing connections between distant regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

Network analysis becomes very useful for diagnosis of changes due to the disease and learning; **correct your networks!**

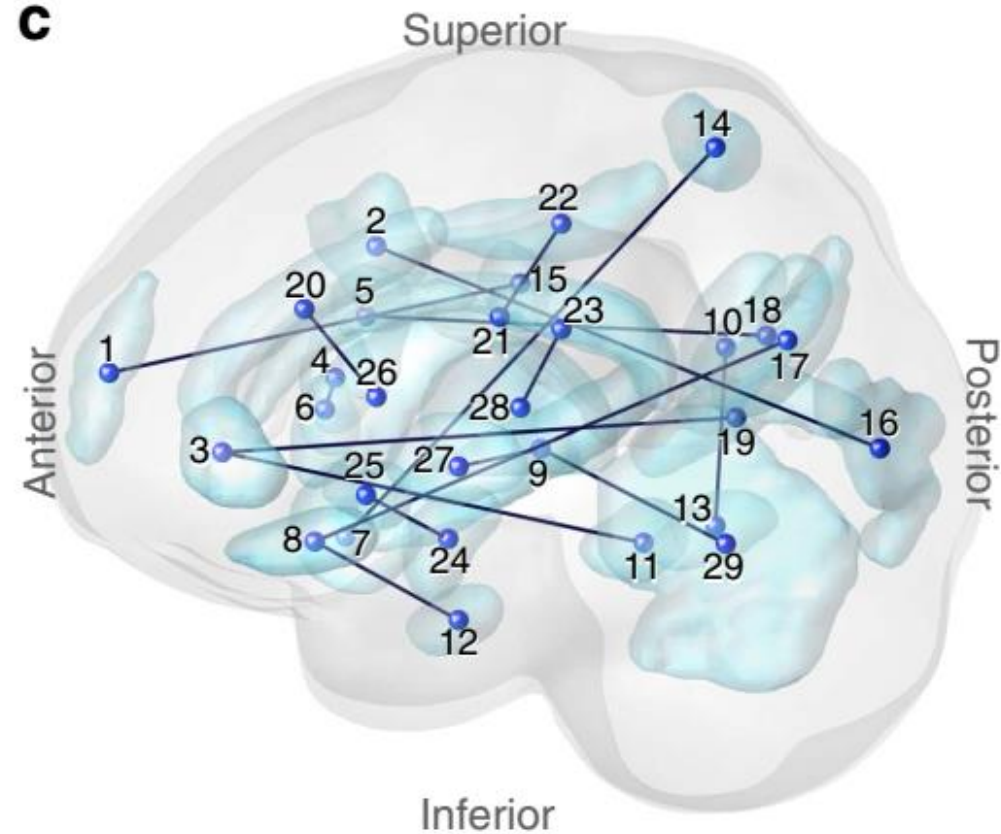
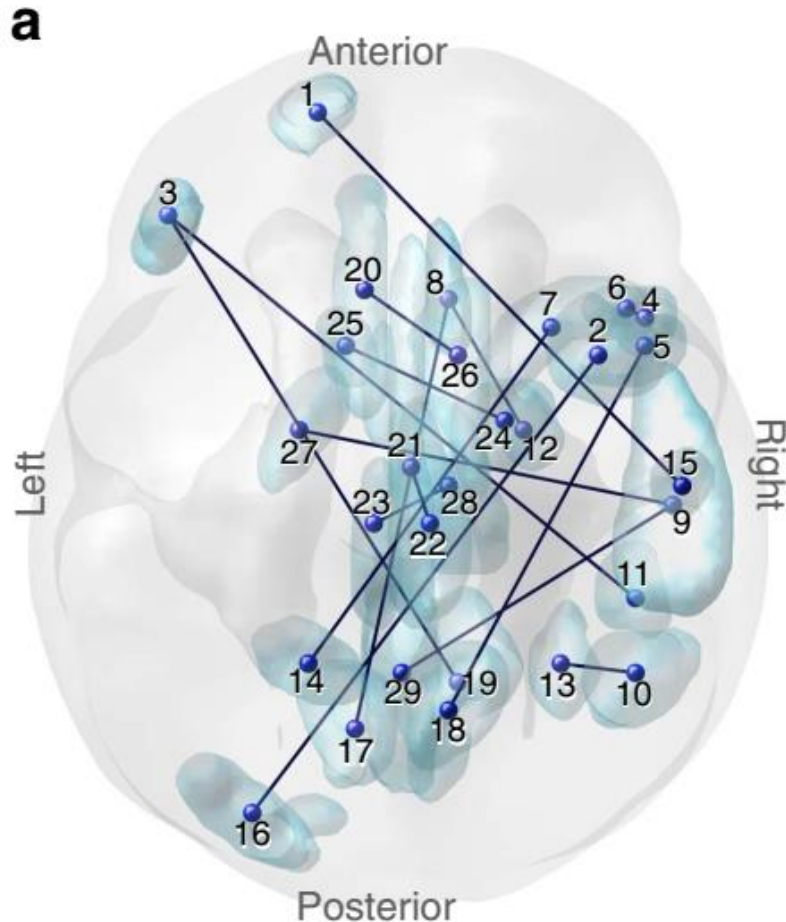


J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. *Cogn Process* (2015) 16:1–16

Biomarkers from neuroimaging



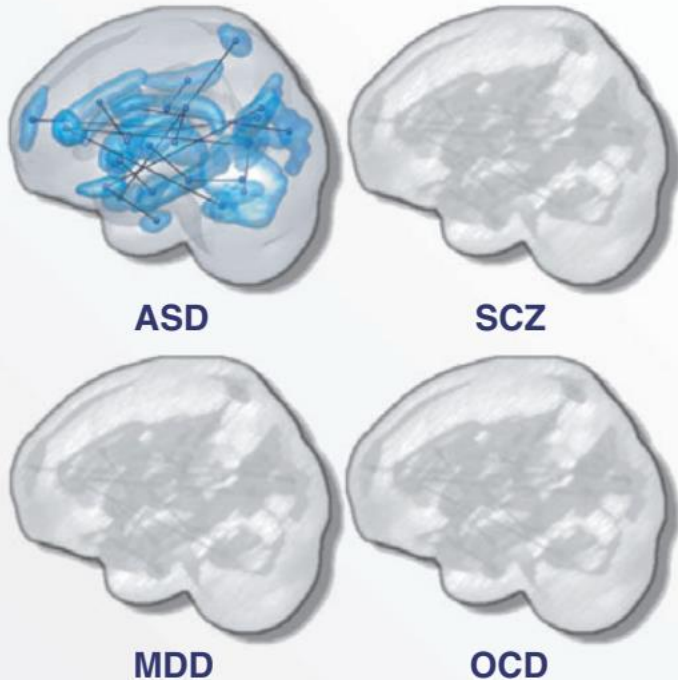
Selected connections



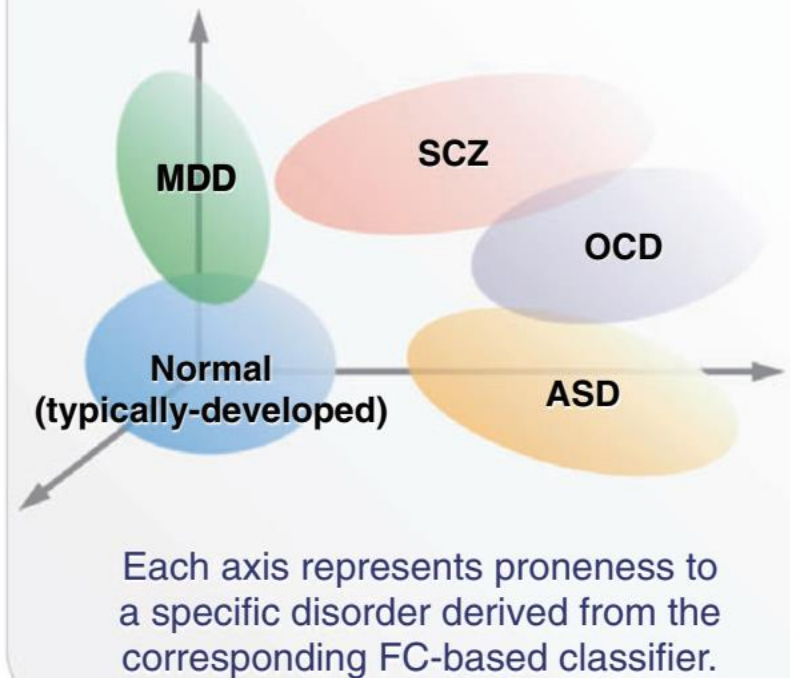
N. Yahata et al (2016): 29 selected regions (ROI) and 16 connections are sufficient to recognize ASD with 85% accuracy in 74 Japanese adult patients vs. 107 people in control group; without re-training accuracy was 75% on US patients.

Biomarkers of mental disorders

Functional connectivity-based classifiers for mental disorders



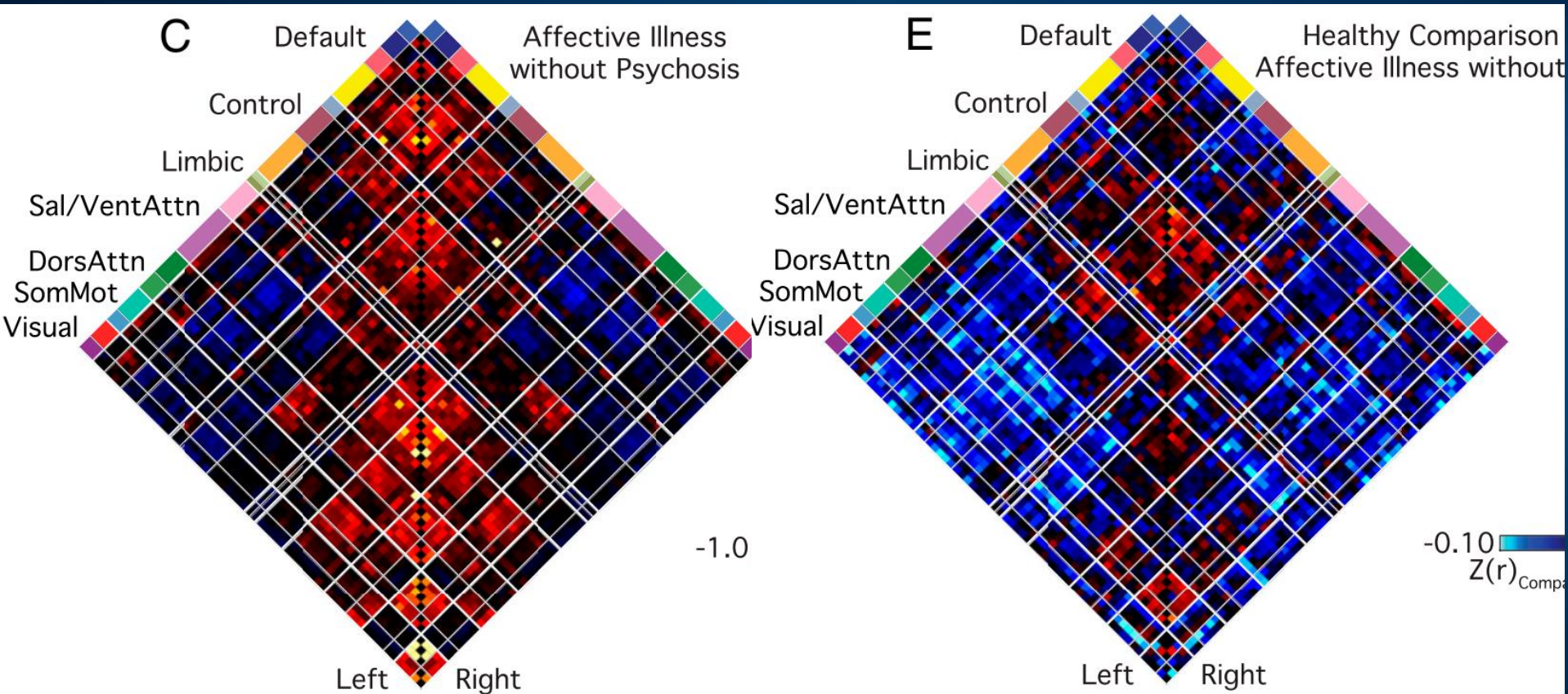
Recasting current nosology in more biologically meaningful dimensions



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

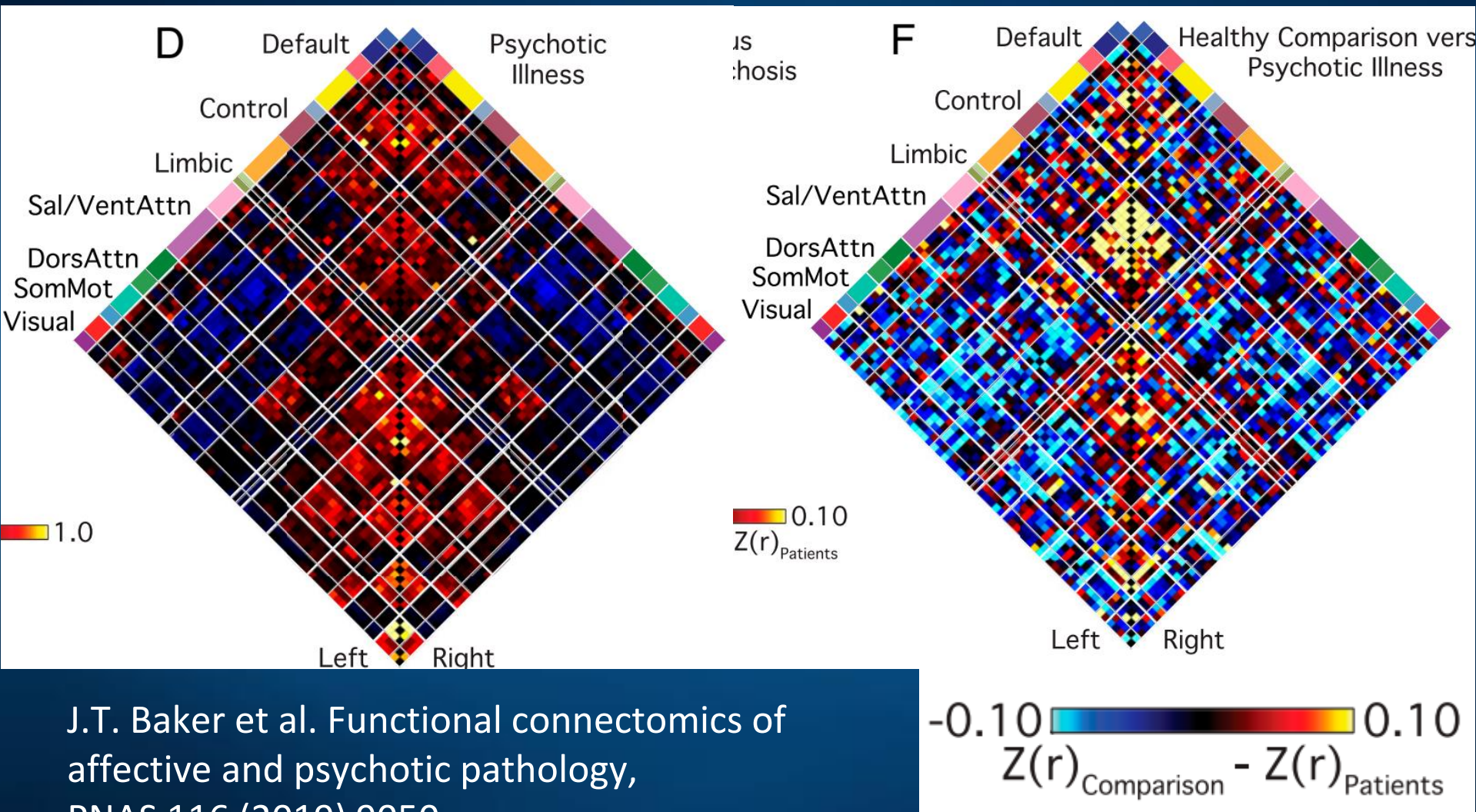
Connectivity in patients vs healthy



MDD, deep depression, SCZ, schizophrenia,
OCD, obsessive-compulsive disorder, ASD autism spectrum disorder.

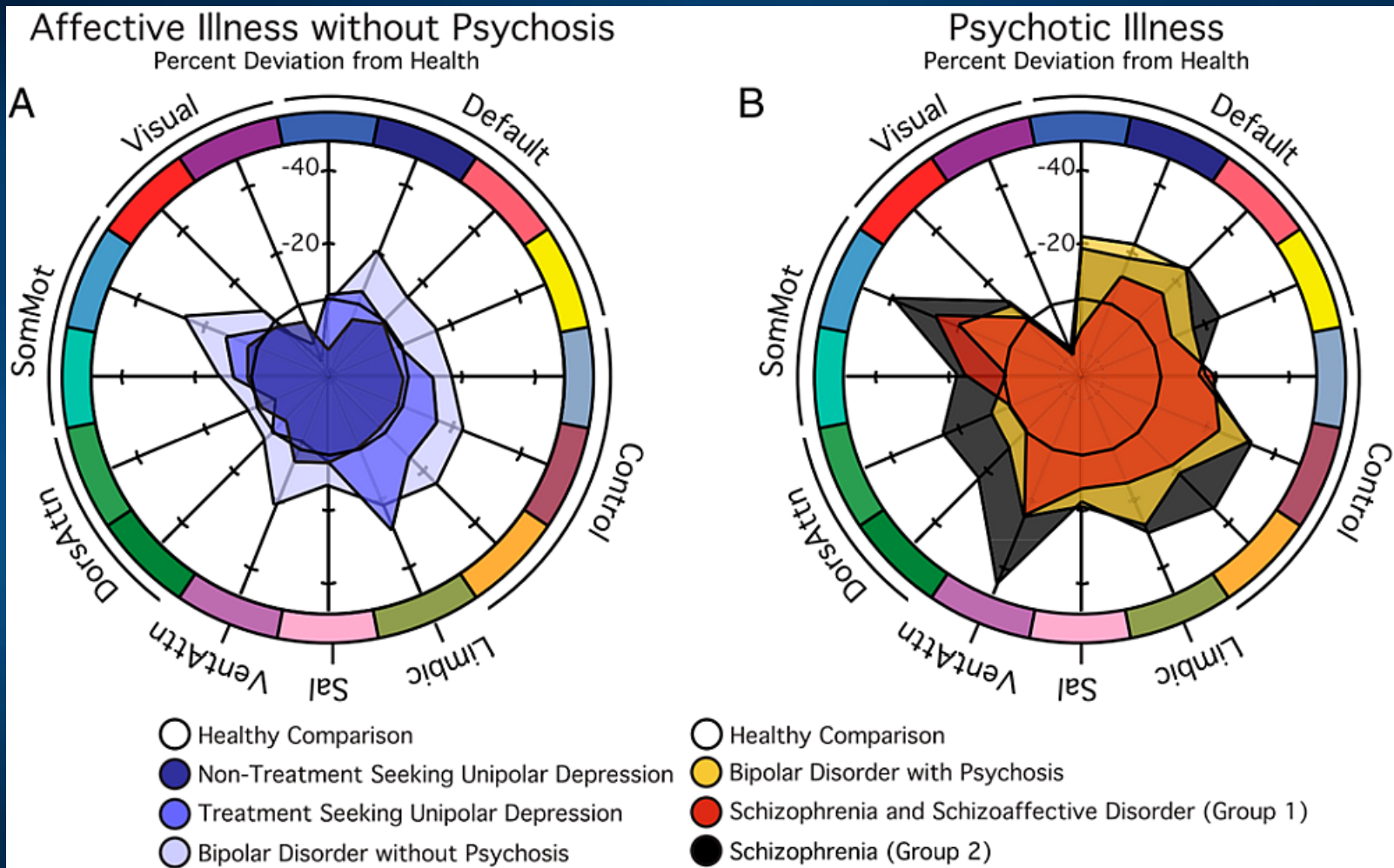
J.T. Baker et al. Functional connectomics of affective and psychotic pathology,
PNAS April 30, 2019

Connectivity in patients vs healthy



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

Connectivity in patients vs healthy



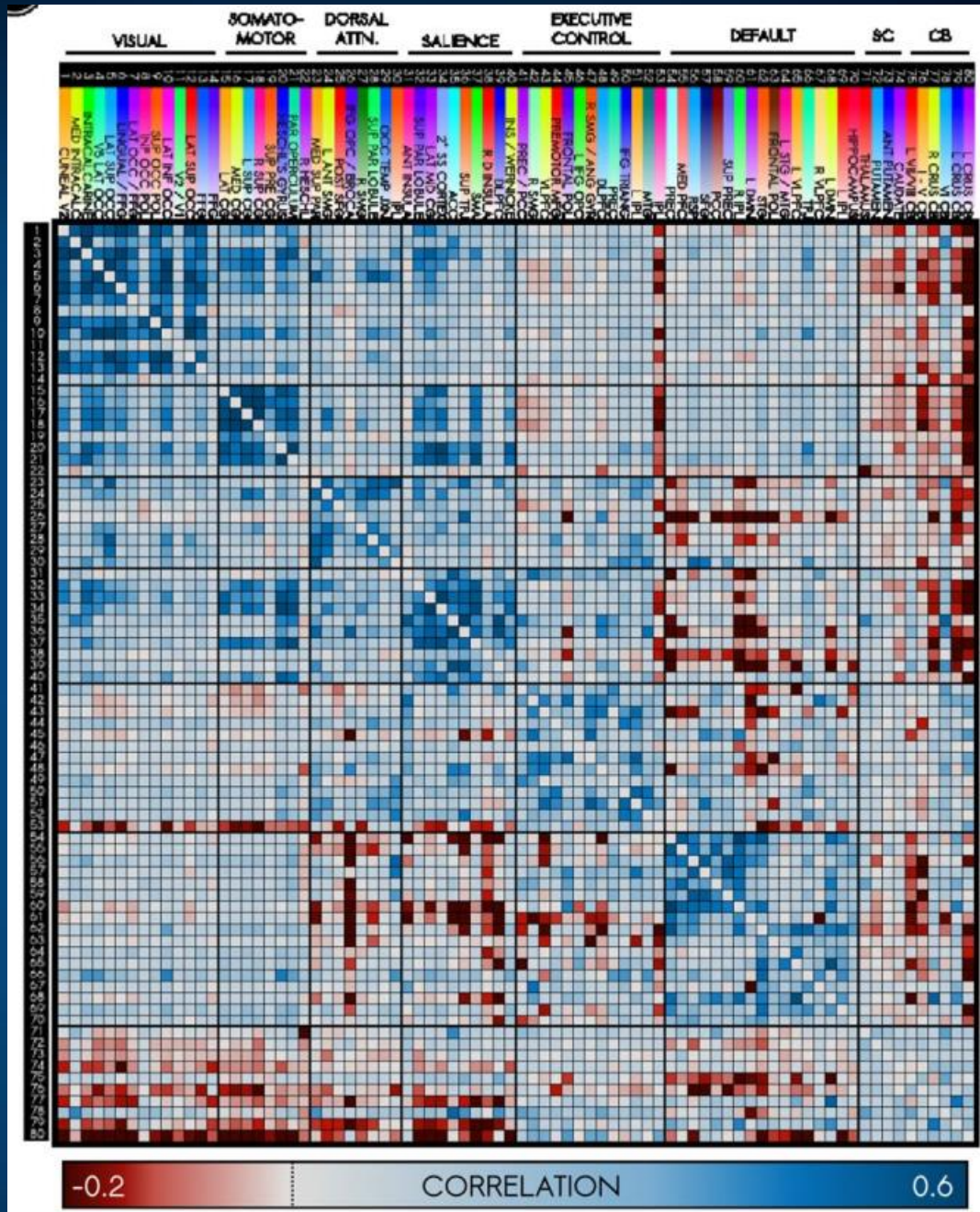
Regions determined based on the 17-network solution from Yeo et al.

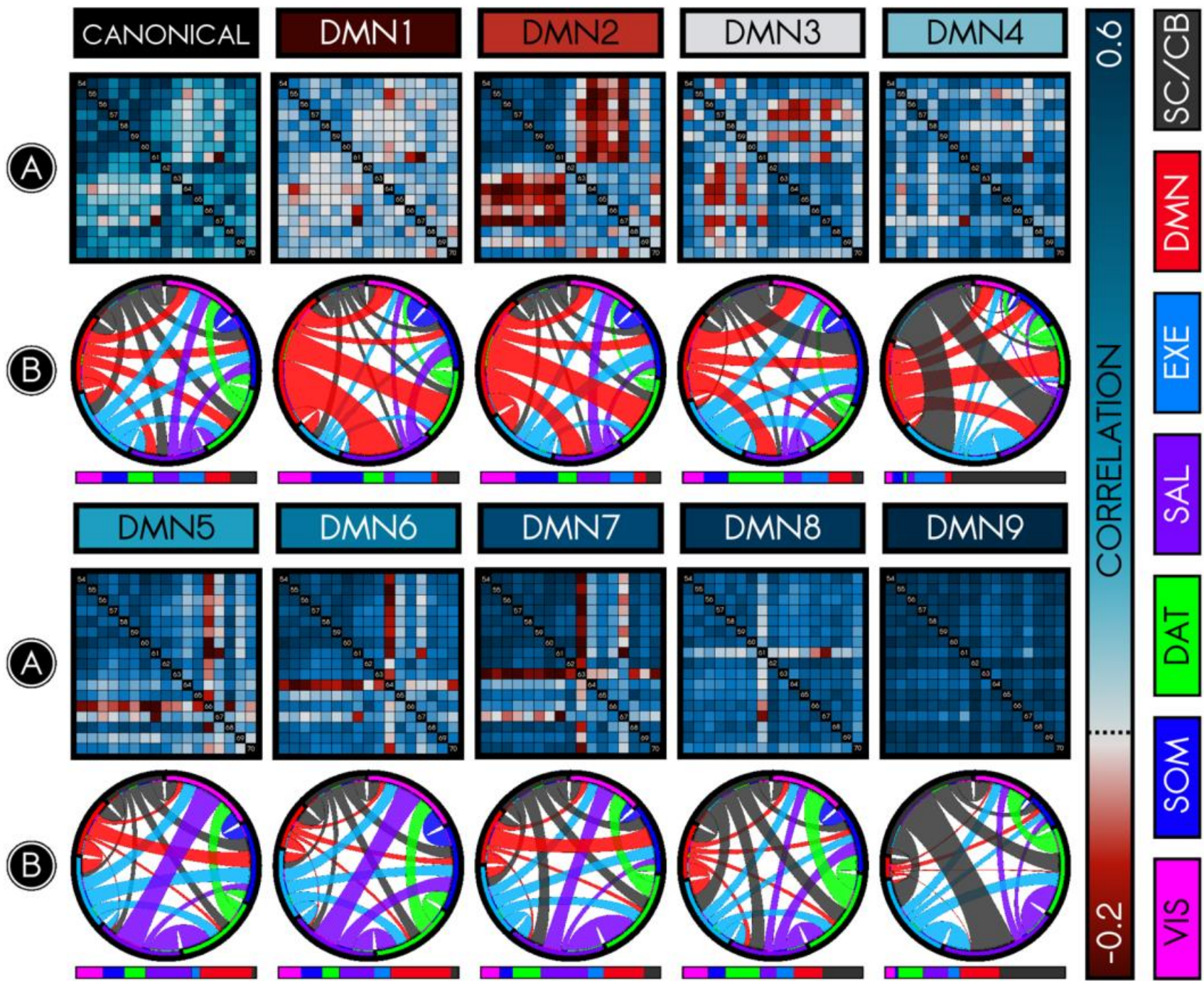
Ciric et.al. (2017). Contextual connectivity: A framework for understanding the intrinsic dynamic architecture of large-scale functional brain networks. *Scientific Reports*.

Correlations of 6 canonical networks.

Perception,
Action-attention
DMN (Default Mode Network)

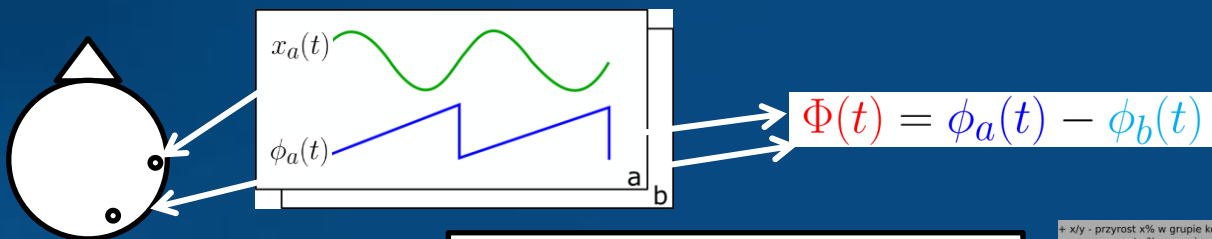
Each has up to 10 different network connectivity states (NC-states), rather stable for single subjects, ex. DMN has usually 7-9.



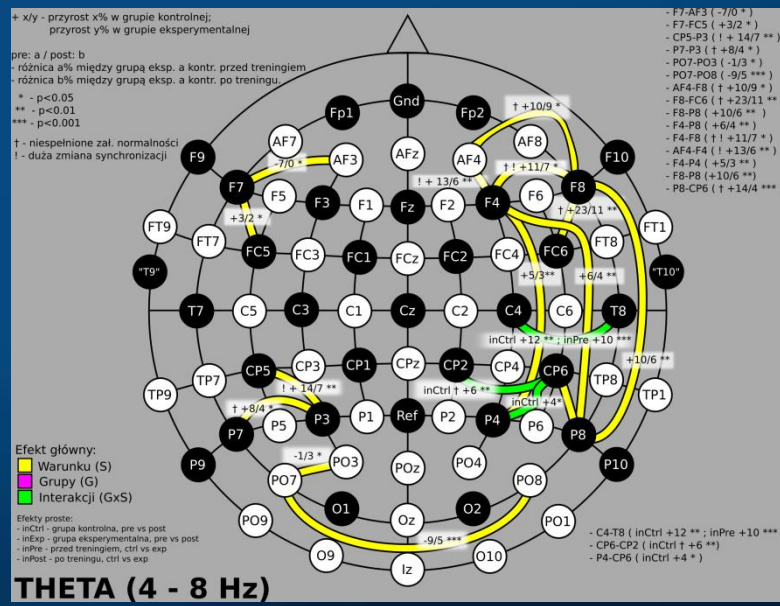
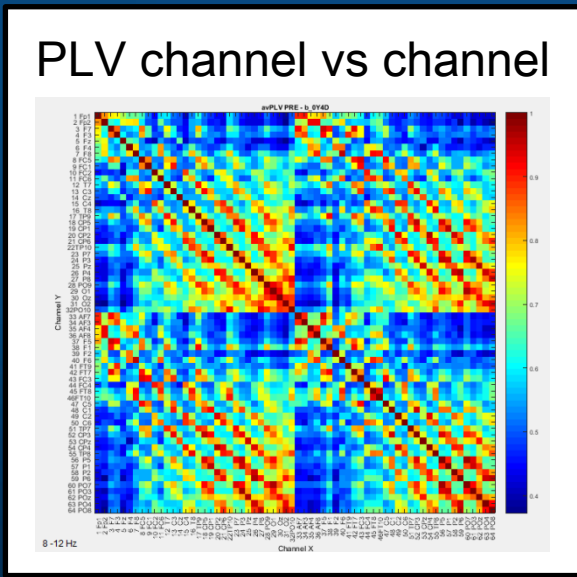


Functional connectivity changes

Influence of brain games on functional connectivity: **Phase Locking Value** (Burgess, 2013; Lachaux 1999), phase differences between signals measured at each electrode. PLV => synchronization maps, info flow.



$$PLV(a, b) = \frac{1}{T} \left| \sum_t e^{i\Phi(t)} \right|$$

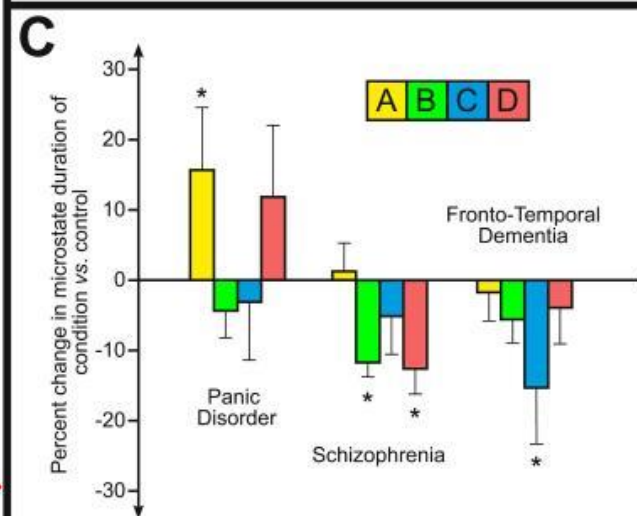
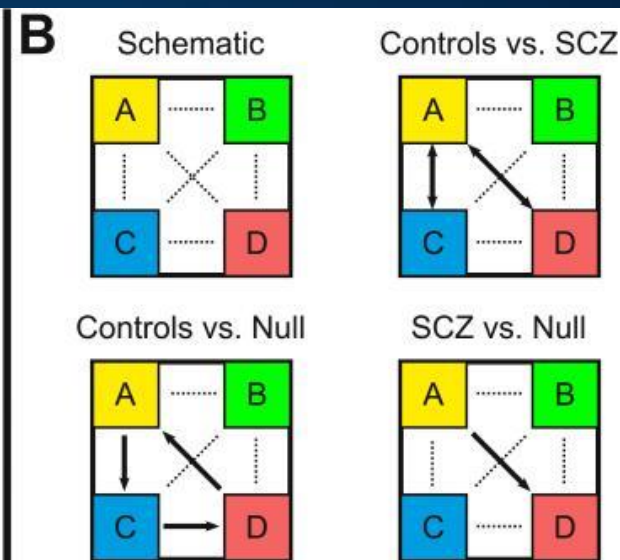
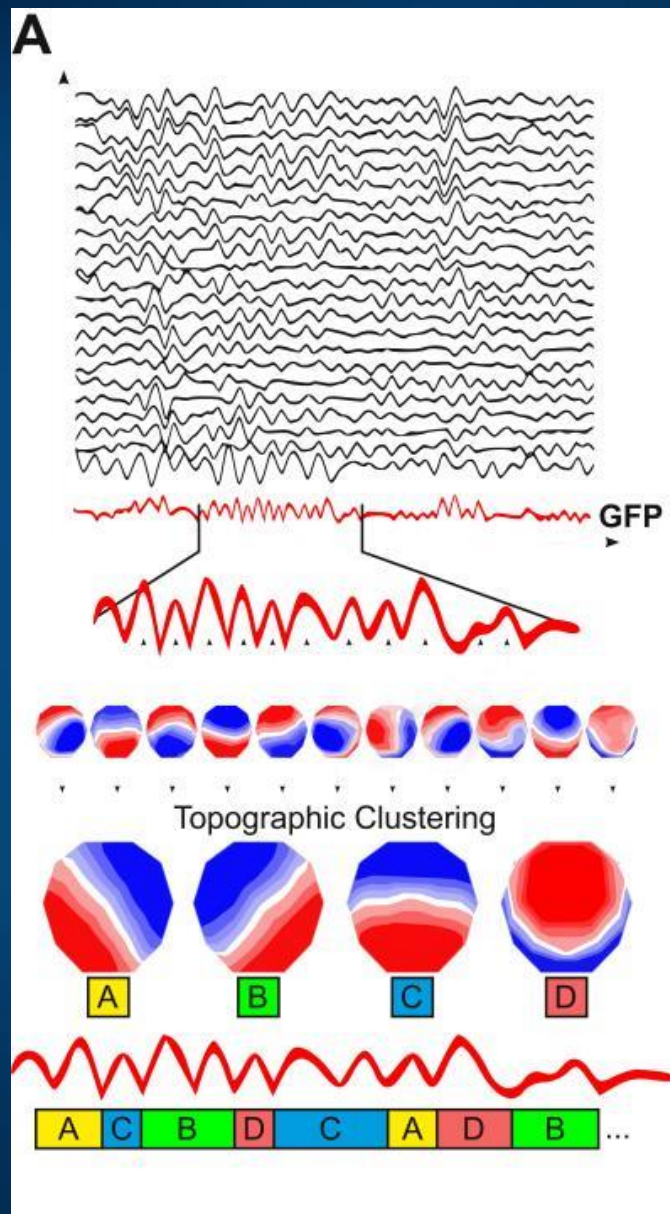


Microstates

Lehmann et al.
 EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia: a multi-center study. *Psychiatry Research Neuroimaging*, 2005

Khanna et al.
 Microstates in Resting-State EEG: Current Status and Future Directions. *Neuroscience and Biobehavioral Reviews*, 2015

Symbolic dynamics.



Model of reading & dyslexia

Emergent neural simulator:

Aisa, B., Mingus, B., and O'Reilly, R. The emergent neural modeling system. *Neural Networks*, 21, 1045, 2008.

3-layer model of reading:

orthography, phonology, semantics, or distribution of activity over **140 microfeatures** defining concepts.

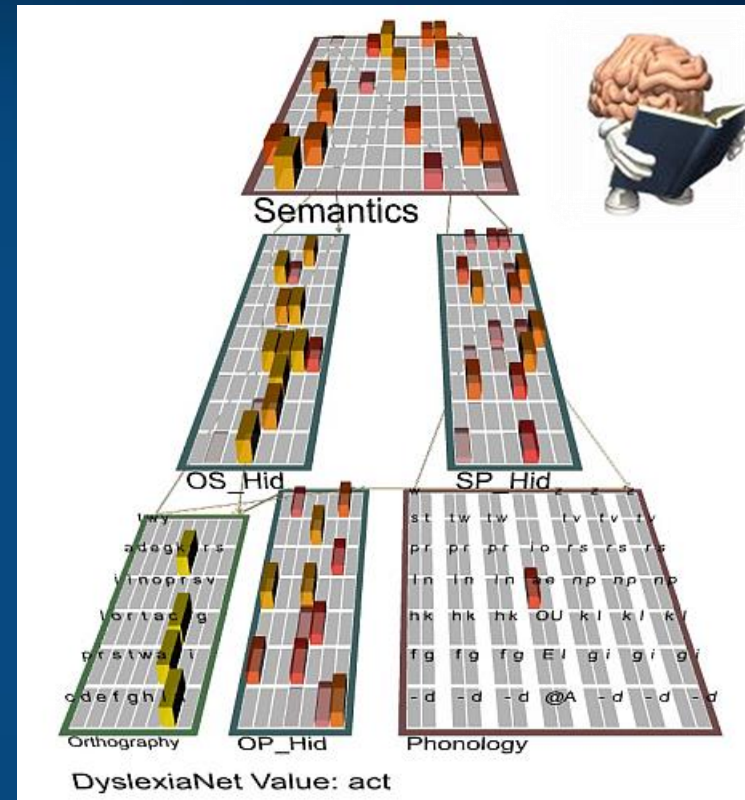
In the brain: microfeature=subnetwork.
Hidden layers OS/OP/SP_Hid in between.

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

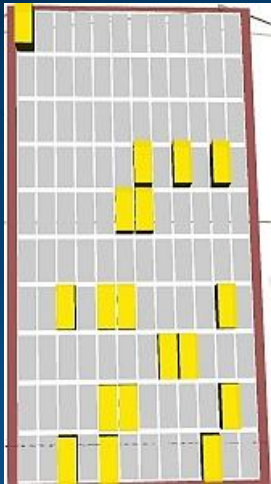
Fluctuations around final configuration = attractors representing concepts.

How to see properties of their basins, their relations?

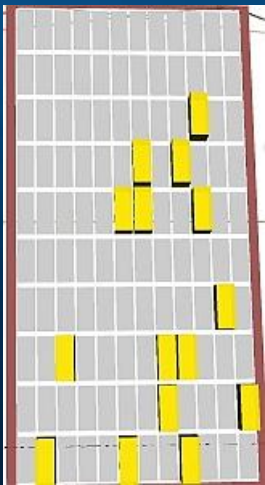
Model in **Genesis**: more detailed neuron description.



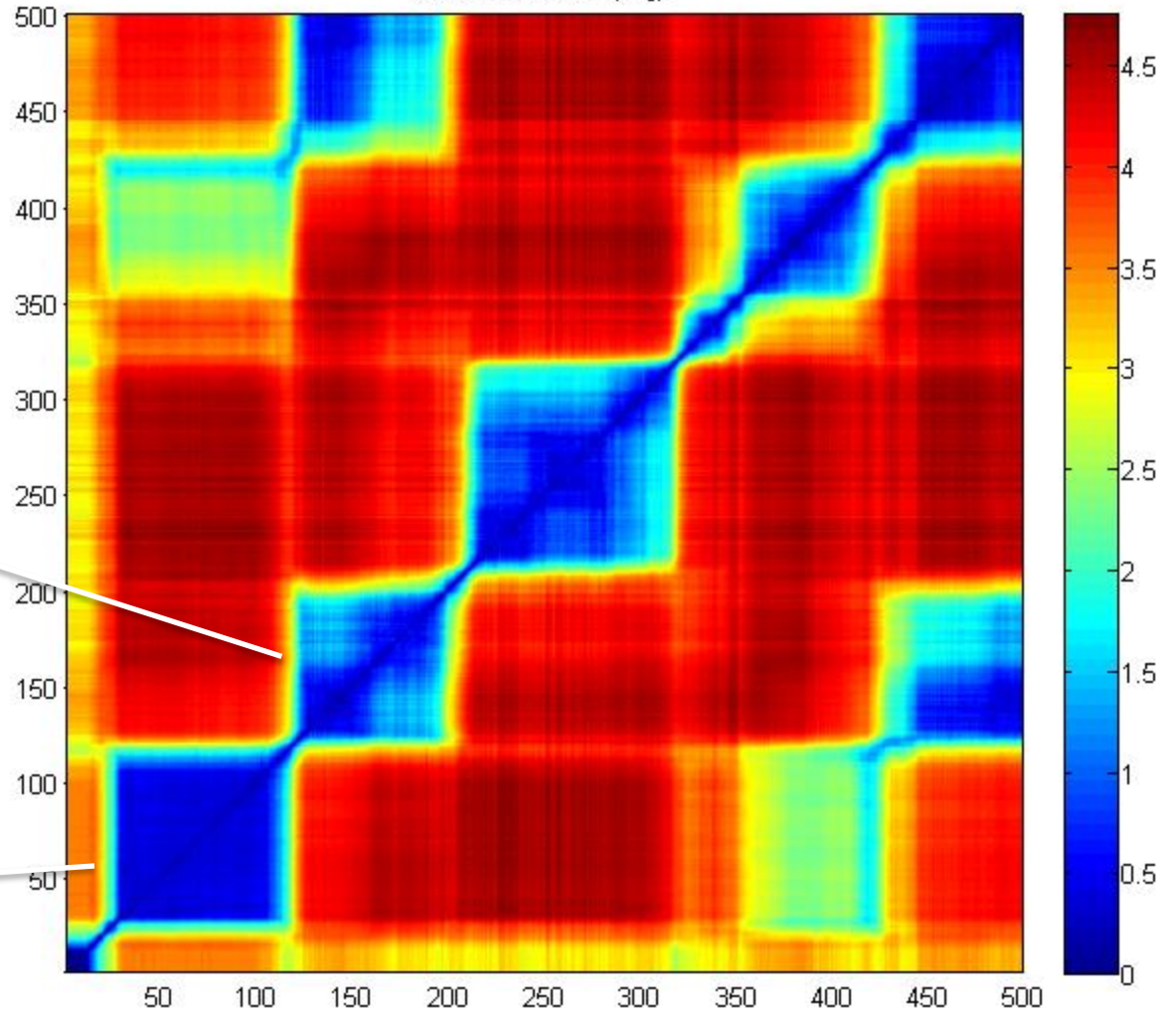
rope



flag

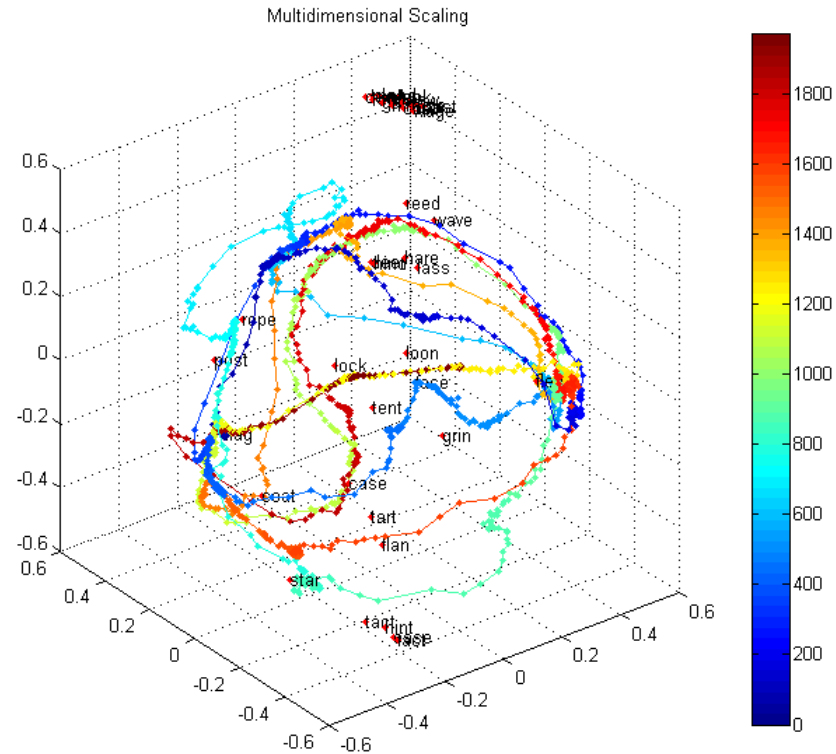
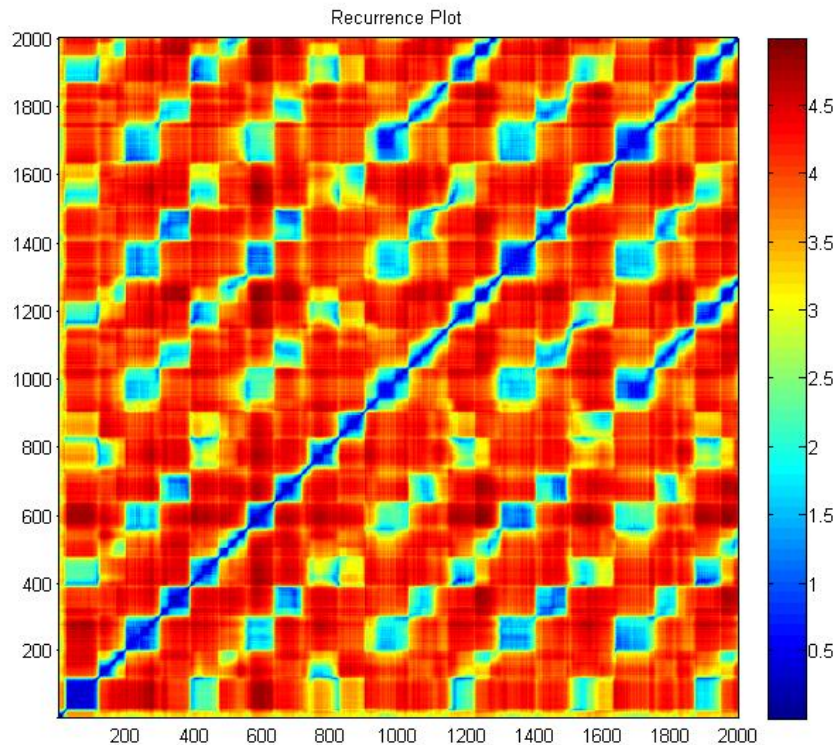


Recurrence Plot (flag)



Transitions to new patterns that share some active units (microfeatures) shown in recurrence plots.

Trajectory visualization



Recurrence plots and MDS/FSD/SNE visualization of trajectories of the brain activity. Here data from 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain, starting with the word “flag”.

Our toolbox: <http://fizyka.umk.pl/~kdobosz/visertoolbox/>

EEG early ASD detection

Bosl, W. J., Tager-Flusberg, H., & Nelson, C. A. (2018). EEG Analytics for Early Detection of Autism Spectrum Disorder: A data-driven approach. *Scientific Reports*, 8(1), 6828.

EEG of 3 to 36-month old babies, 19 electrodes selected from 64 or 128.

Daubechies (DB4) wavelets transform EEG signal into 6 bands.

7 features from **Recurrence Quantitative Analysis** (RQA): RP entropy, recurrence rate, laminarity, repetition, max/mean line length, trapping time.

In addition sample entropy and Detrended Fluctuation Analysis was used.

Nonlinear features were computed from EEG signals and used as input to statistical learning methods. Prediction of the clinical diagnostic outcome of ASD or not ASD was highly accurate.

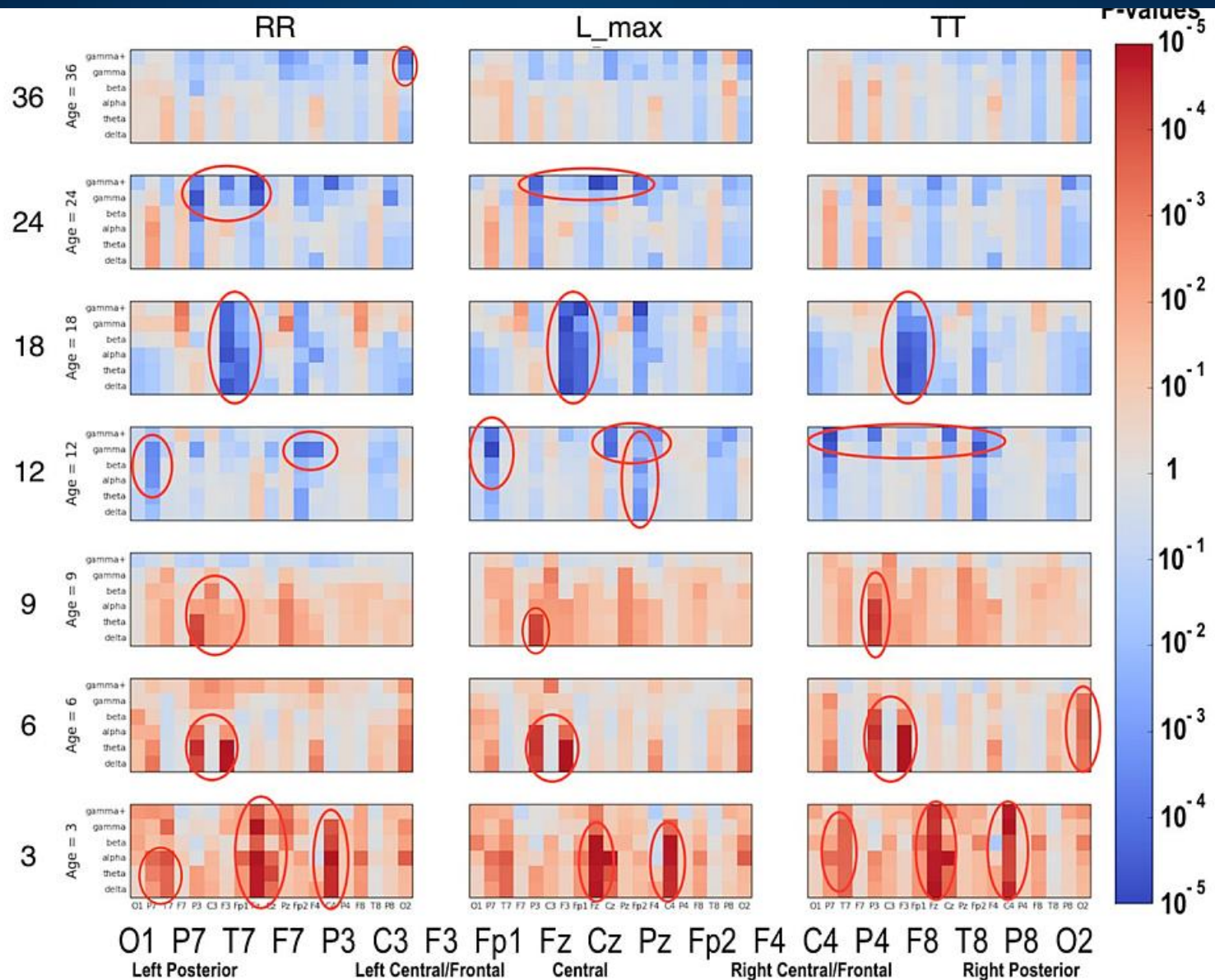
SVM classification with 9 features gave high specificity and sensitivity, **exceeding 95% at some ages**. Prediction using only EEG data taken as early as 3 months of age was strongly correlated with the actual measured scores.

ASD vs Low Risk Healthy

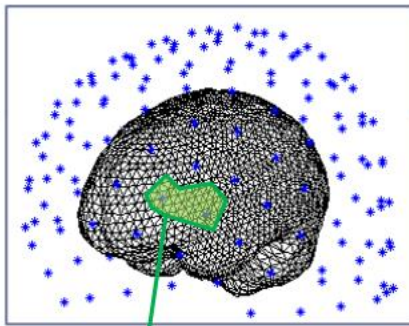
RR =
recurrence
rate

L_max = max
line length,
related to
Lyapunov
exponent

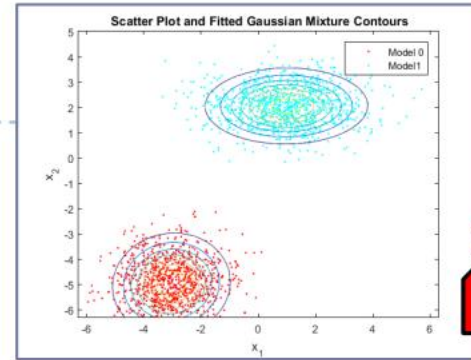
TT = trapping
time



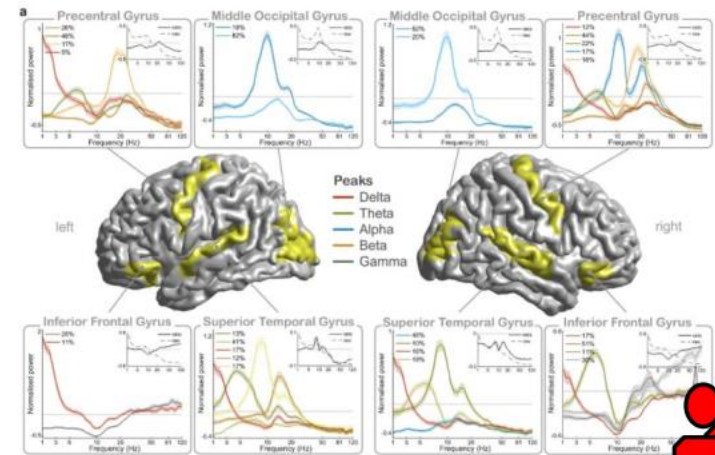
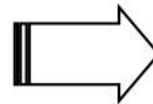
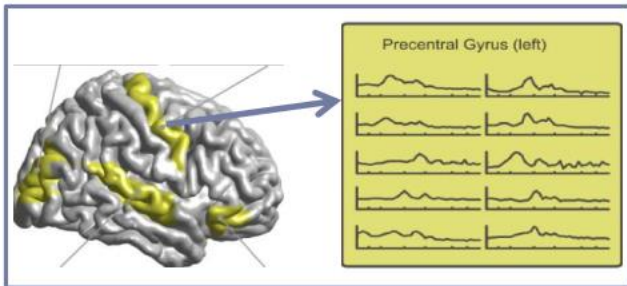
Spectral fingerprints



$d \in \text{ROI}$



Single subject



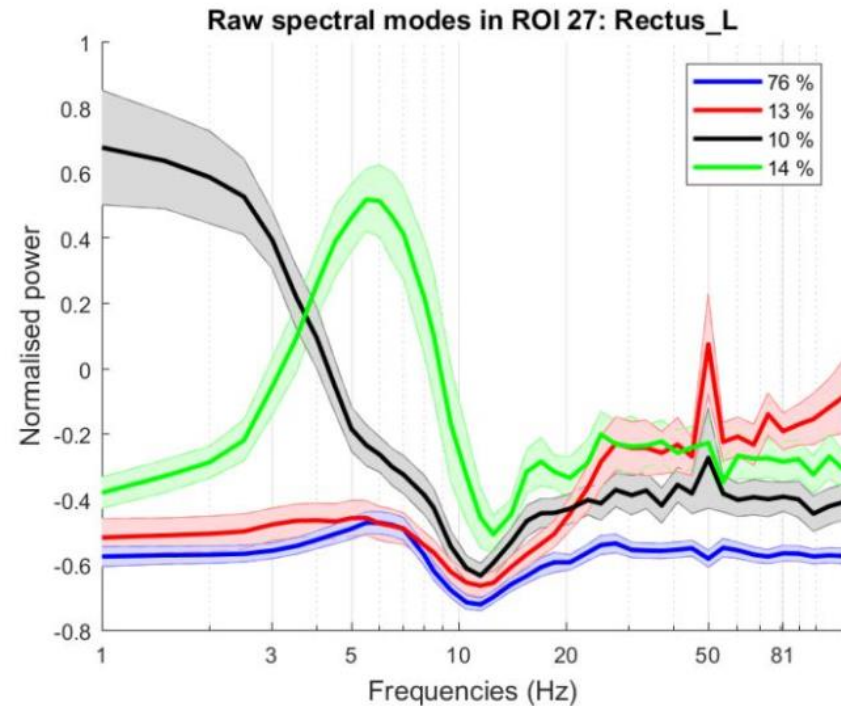
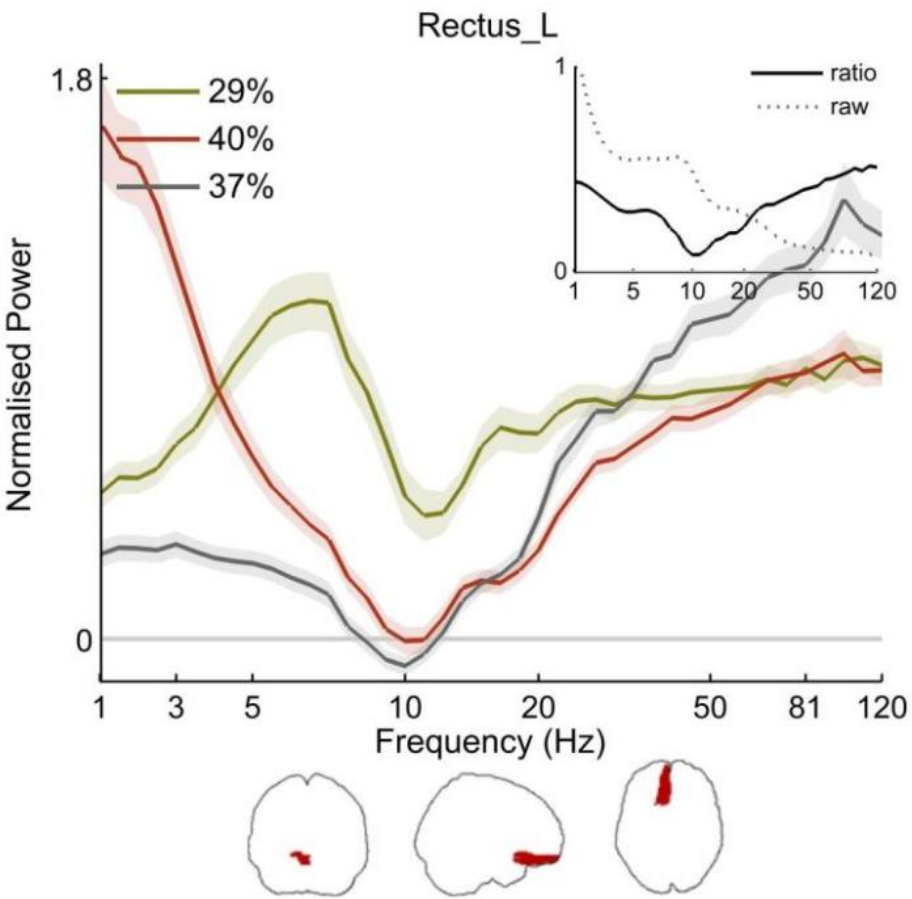
Group model

5

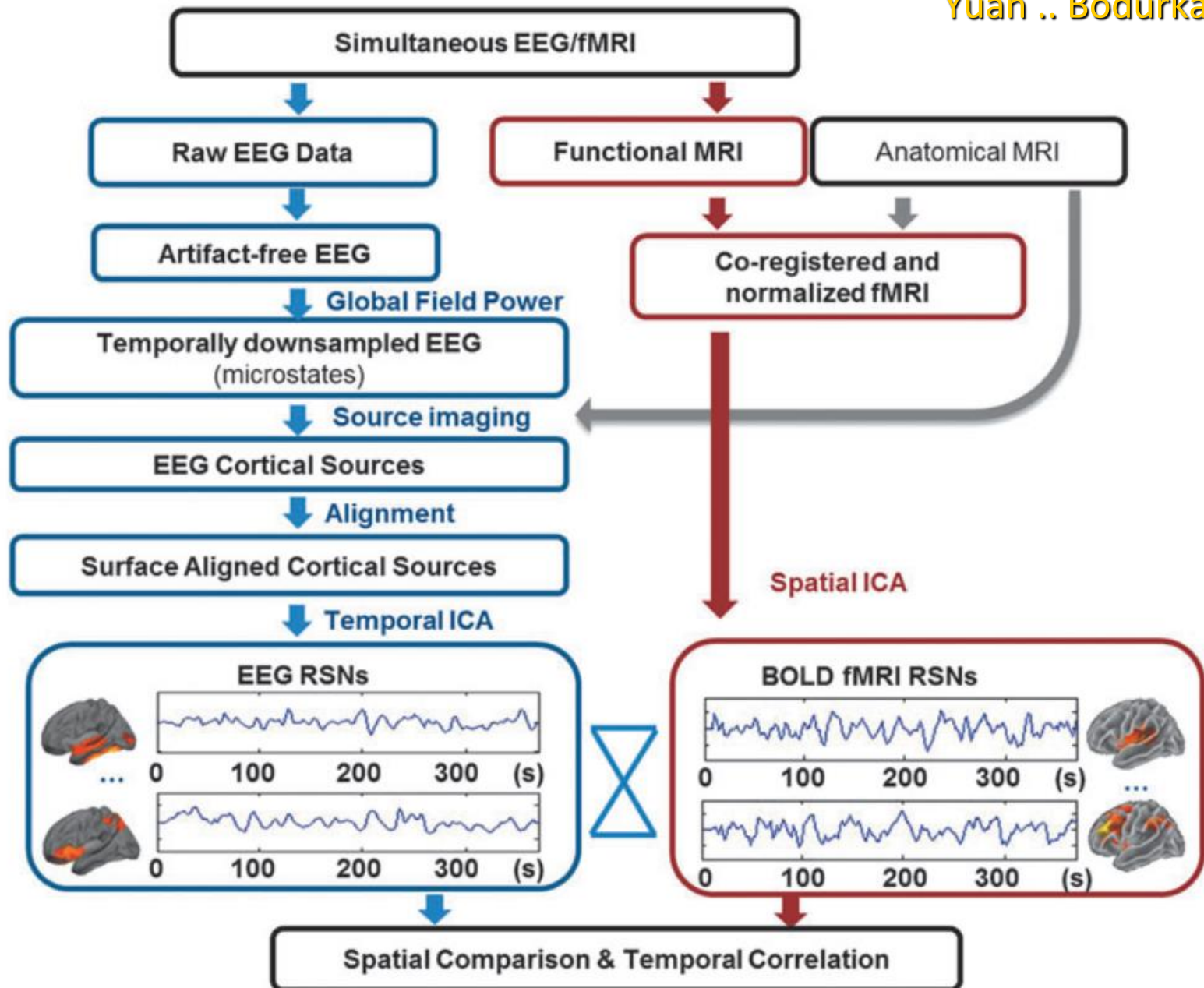
* Pictures from Keitel & Gross 2016 and Fieldtrip beamforming tutorial

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

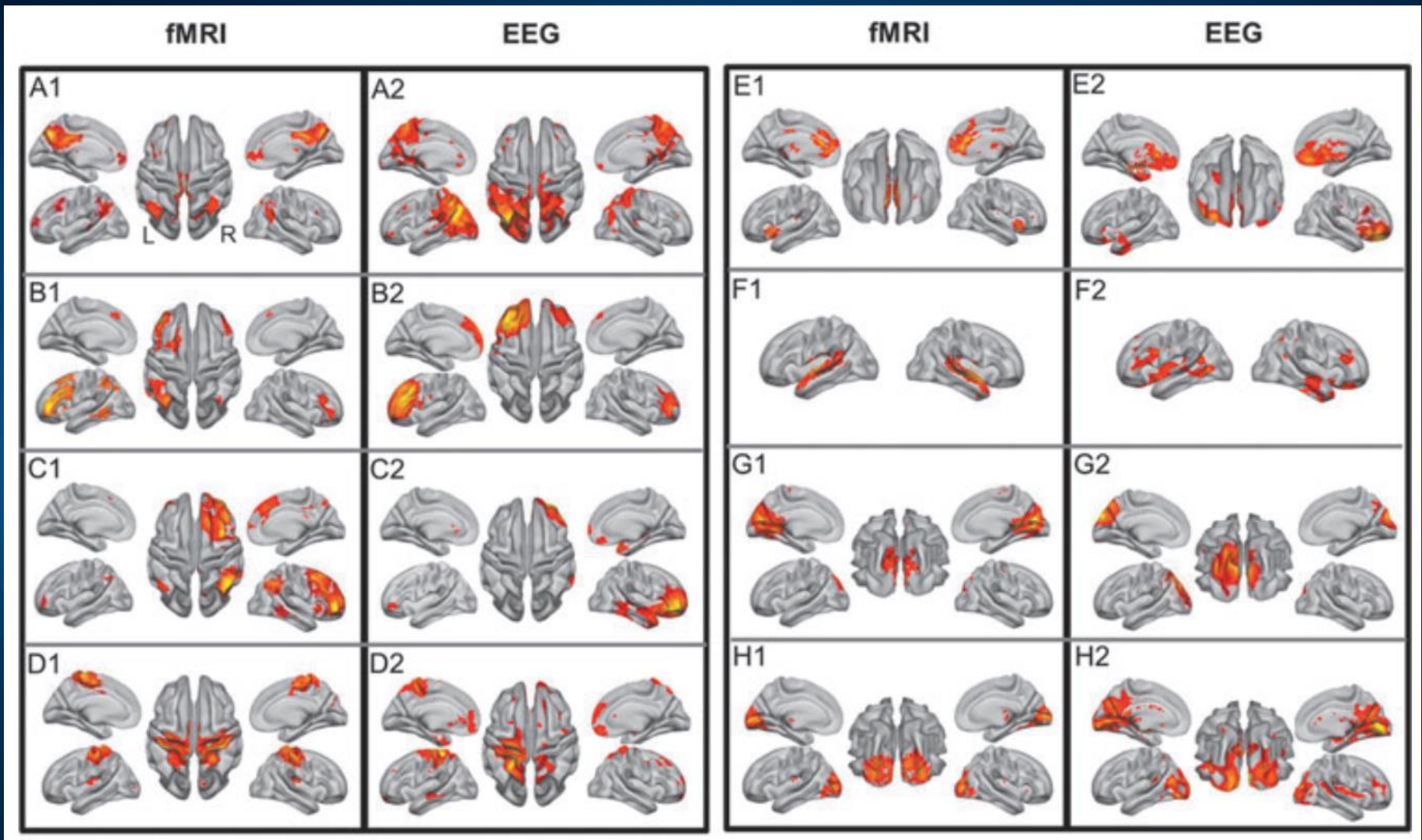
Spectral fingerprints



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

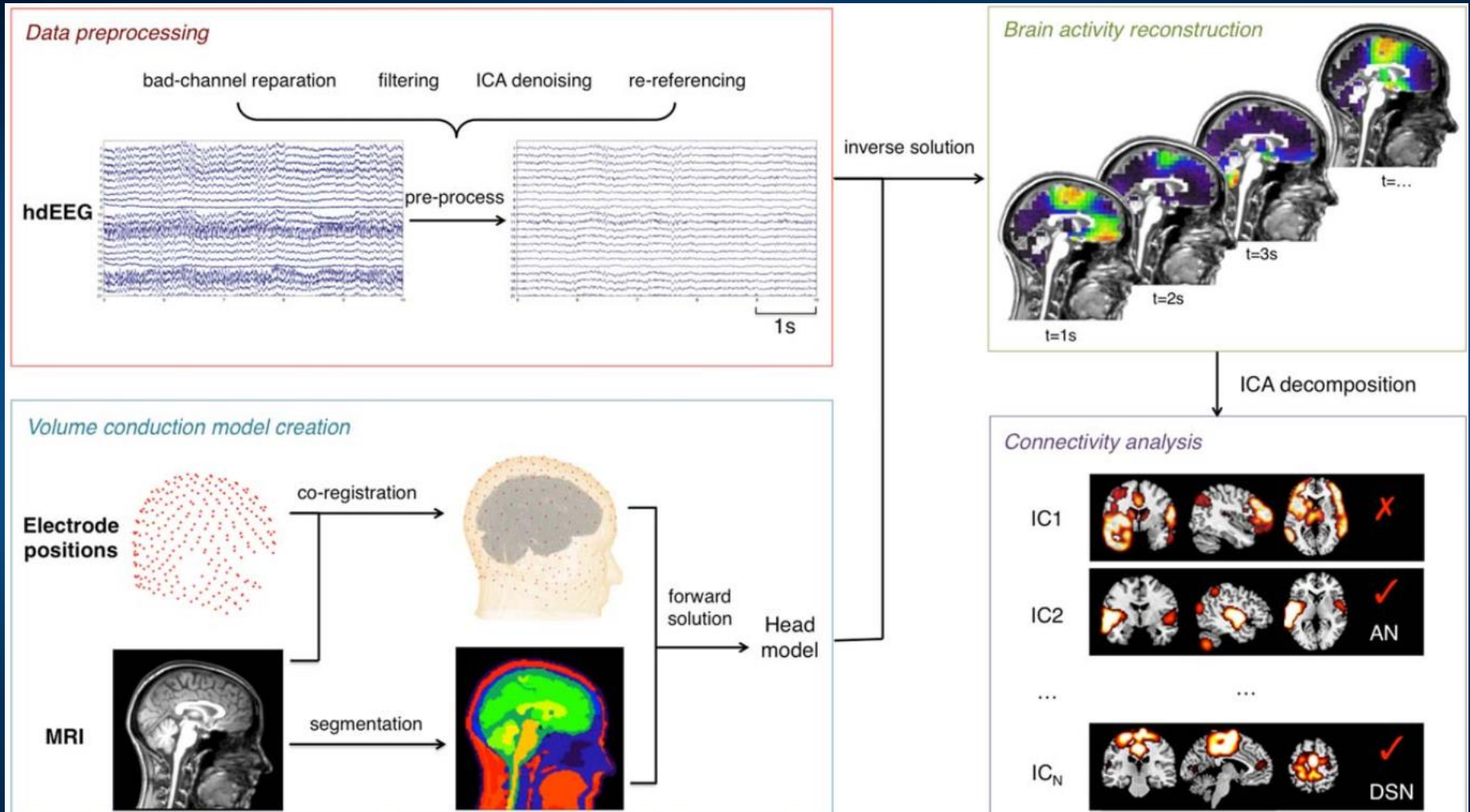


8 large networks from BOLD-EEG

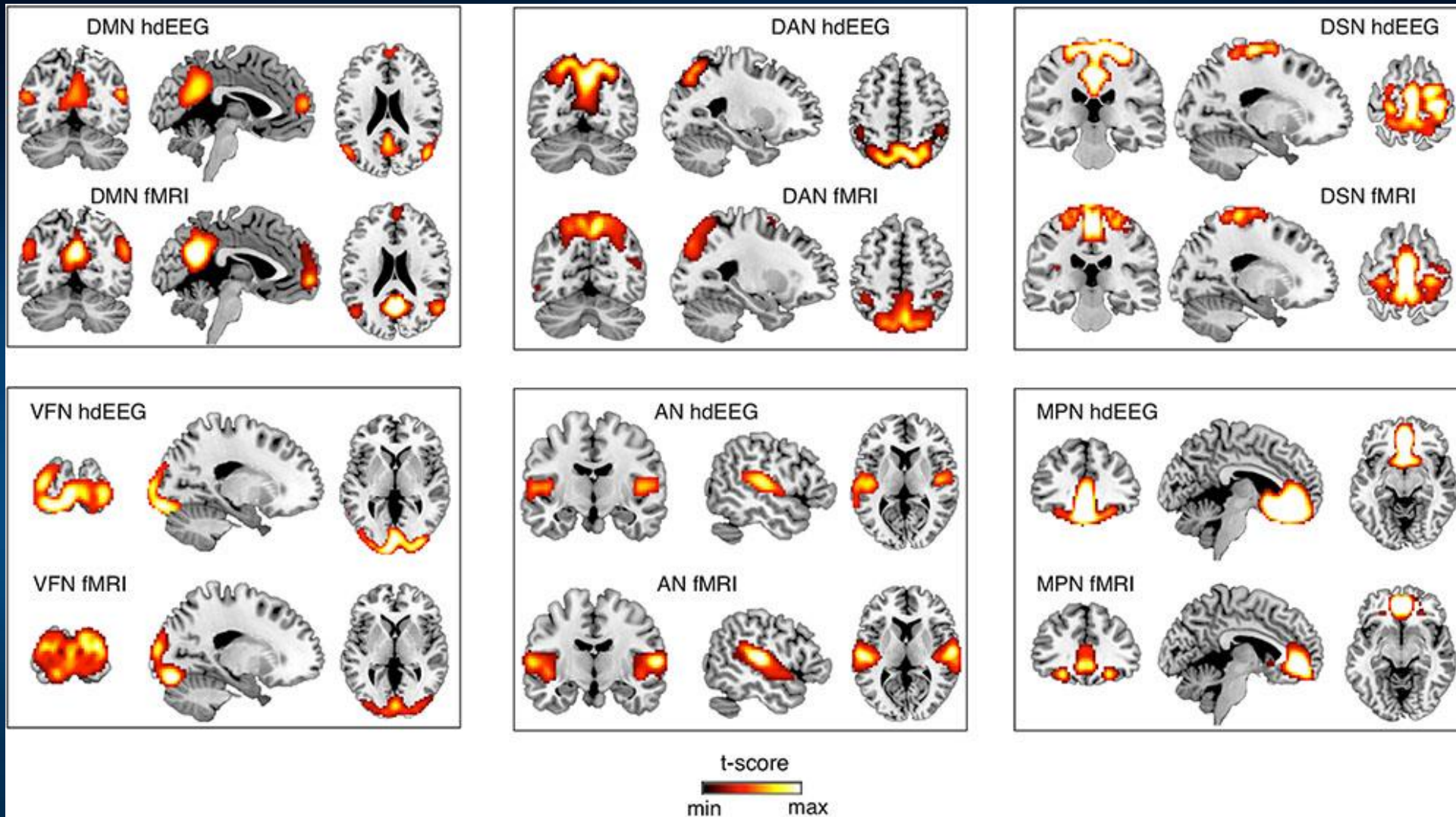


DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral). Yuan ... Bodurka (2015)

14 networks from BOLD-EEG

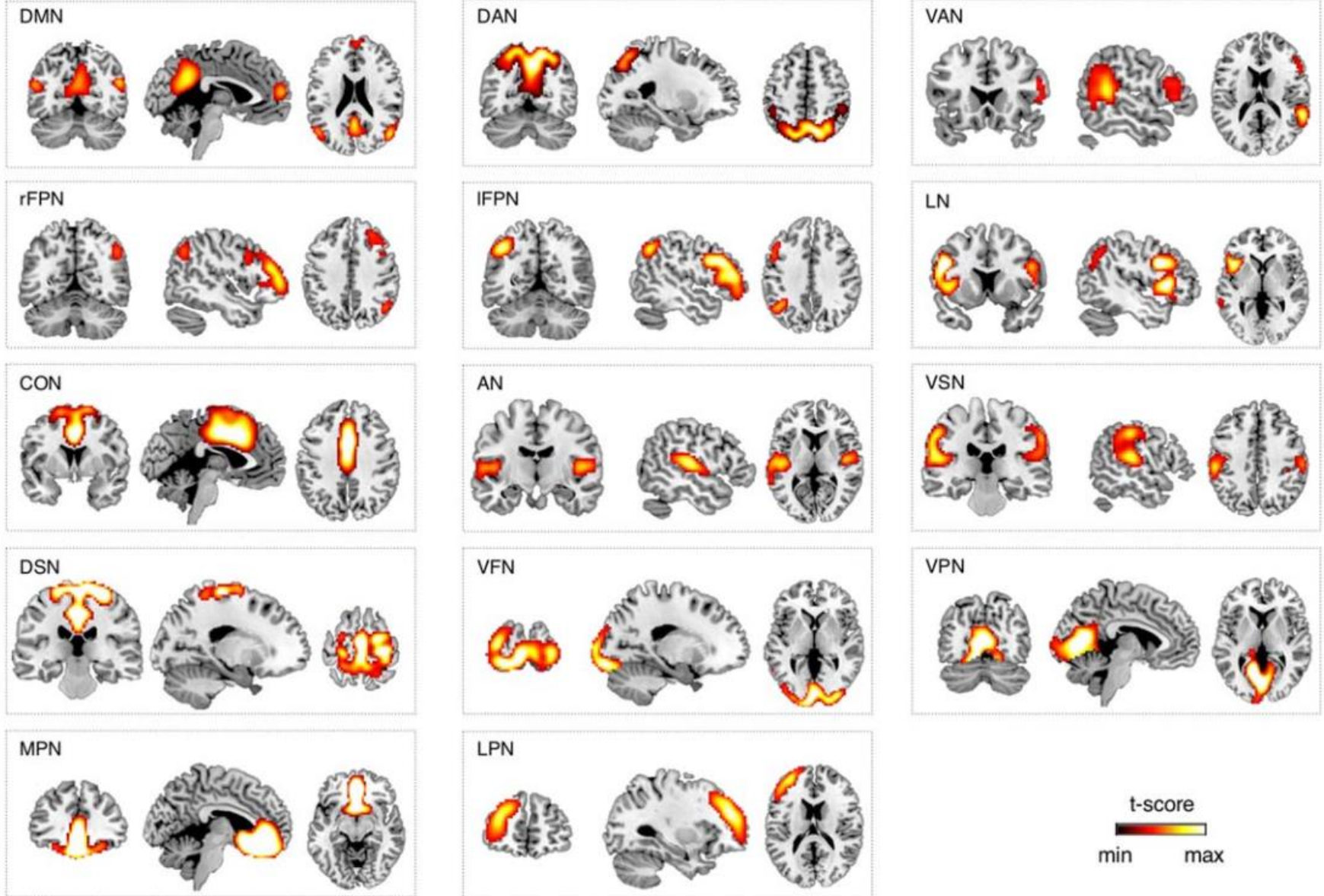


Liu et al. Detecting large-scale networks in the human brain. HBM (2017; 2018).



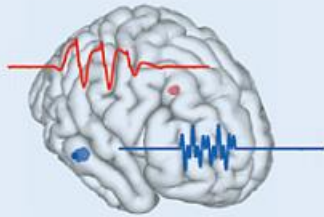
sICA on 10-min fMRI data ($N = 24$, threshold: $p < 0.01$, TFCE corrected). DMN, default mode network; DAN, dorsal attention network; DSN, dorsal somatomotor network; VFN, visual foveal network; AN, auditory network; MPN, medial prefrontal network.

EEG-RSN maps obtained using spatial ICA



EEG localization and reconstruction

ECD



$$\hat{d}_j = \operatorname{argmin} \left\| \phi - \sum_j \mathcal{K}_j d_j \right\|_F^2$$

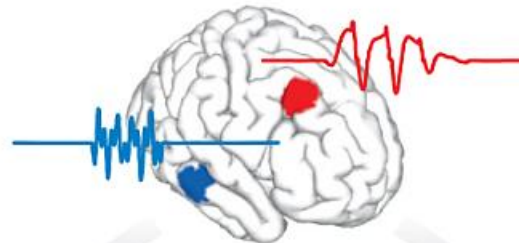
Rotating dipole

- Moving
- Rotating
- Fixed

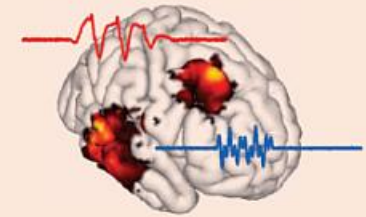
Dipole model



Distributed model



MN (ℓ_2) family



$$\hat{j} = \operatorname{argmin}_j \left\| \phi - \mathcal{K}j \right\|_2^2 + \lambda \left\| j \right\|_2^2$$

$$\hat{j} = \mathcal{T}\phi = \mathcal{K}^\top (\mathcal{K}\mathcal{K}^\top + \lambda I)^{-1} \phi$$

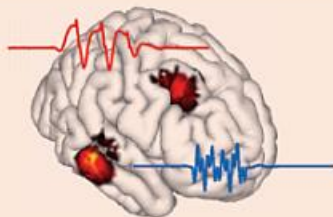
MN

- MN
- WMN
- LORETA

He et al. Rev. Biomed Eng (2018) Sparse and Bayesian framework

Beamforming and scanning algorithms

Nonlinear post hoc normalization



$$\hat{j} = \operatorname{argmin}_j \left\| \mathcal{V}j \right\|_1 + \alpha \left\| j \right\|_1$$

$$\text{S.T. } \left\| \phi - \mathcal{K}j \right\|_{\Sigma^{-1}}^2 \leq \epsilon^2$$

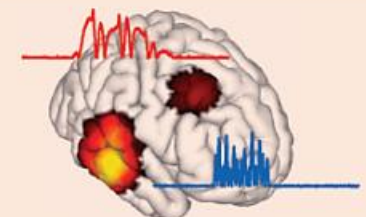
IRES



$$\hat{w}_r = \operatorname{argmin}_{w_r} w_r^\top \mathcal{R}_\phi w_r$$

$$\text{S.T. } \begin{cases} \mathcal{K}_r^\top w_r = \xi_1 \\ w_r^\top w_r = 1 \end{cases}; \hat{j} = w^\top \phi$$

Beamformer (VBB)



$$\hat{j}_{mn} = \mathcal{T}_{mn}\phi$$

$$S_j = \mathcal{K}^\top (\mathcal{K}\mathcal{K}^\top + \alpha I)^{-1} \mathcal{K}$$

$$\hat{j}_{sL} = \hat{j}_{mn}(\ell)^\top \left([S\hat{j}]_{\ell\ell} \right)^{-1} \hat{j}_{mn}(\ell)$$

sLORETA

SupFunSim

SupFunSim: our library/Matlab /toolbox, direct models for EEG/MEG.

Provides many spatial filters for reconstruction of EEG sources: linearly constrained minimum-variance (LCMV), eigenspace LCMV, nulling (NL), minimum-variance pseudo-unbiased reduced-rank (MV-PURE) ...

Source-level directed connectivity analysis: partial directed coherence (PDC), directed transfer function (DTF) measures.

Works with FieldTrip EEG/ MEG software. Modular, object-oriented, using Jupyter notes, allowing for comments and equations in LaTeX.

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

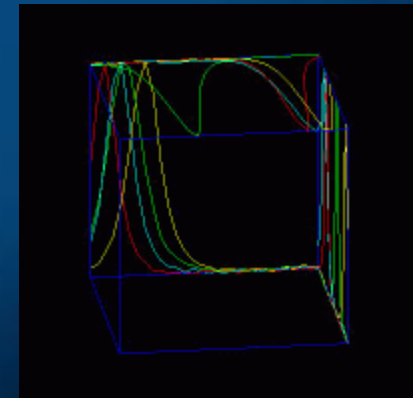
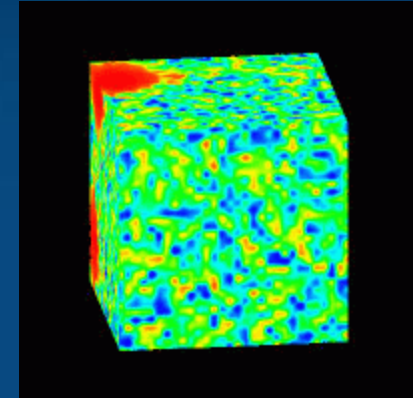
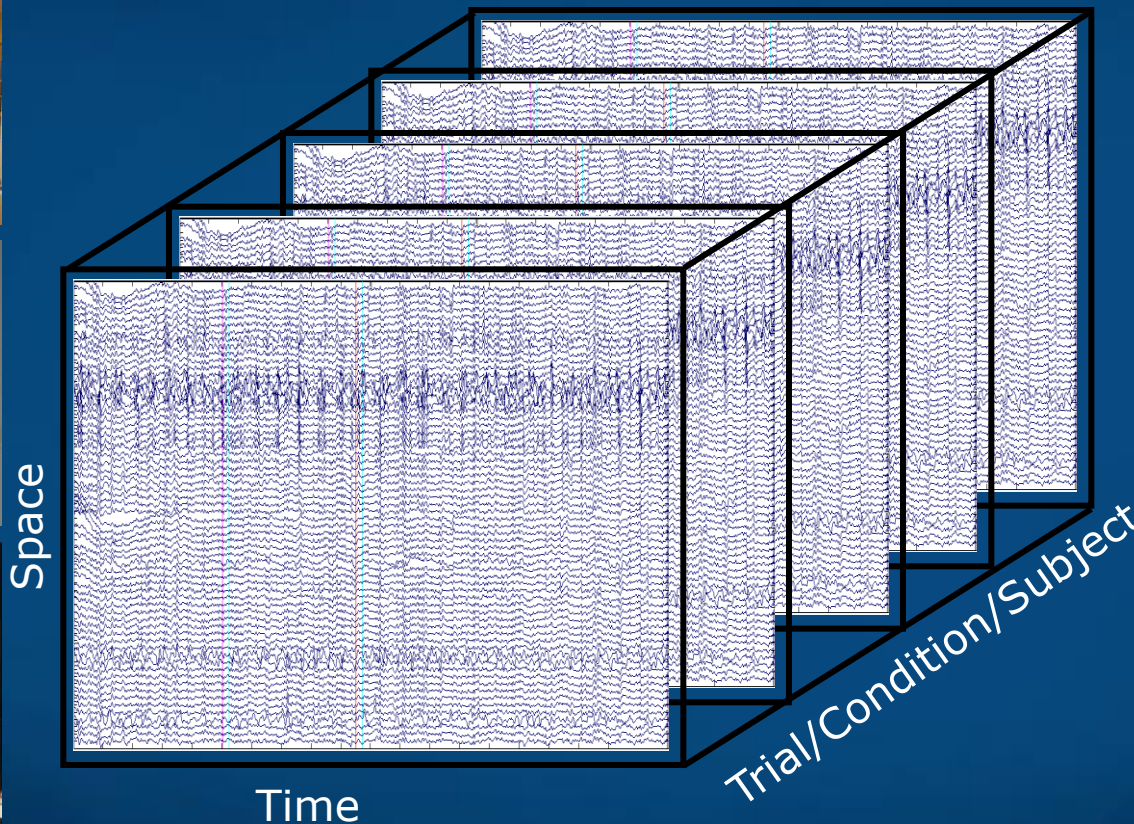
$$B := H_{Src,N} := N^{-1/2} H \quad (35)$$

```
1 %%file calculate_H_Src.m
2 function model = calculate_H_Src(MODEL)
3     model = MODEL;
4
5     model.H_Src_R = pinv(sqrtm(model.R)) * model.H_Src;
6     model.H_Src_N = pinv(sqrtm(model.N)) * model.H_Src;
7 end
```

From Two-way to Multi-way Analysis Integration and Fusion of Various Modalities

EEG+fNIRS +fMRI

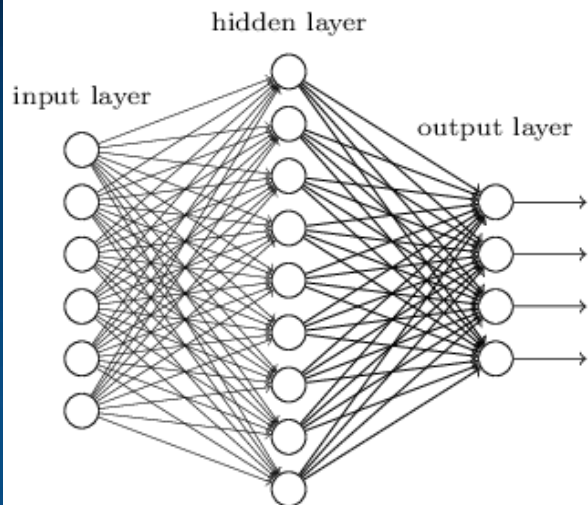
A. Cichocki Lab
RIKEN Brain Science Inst.



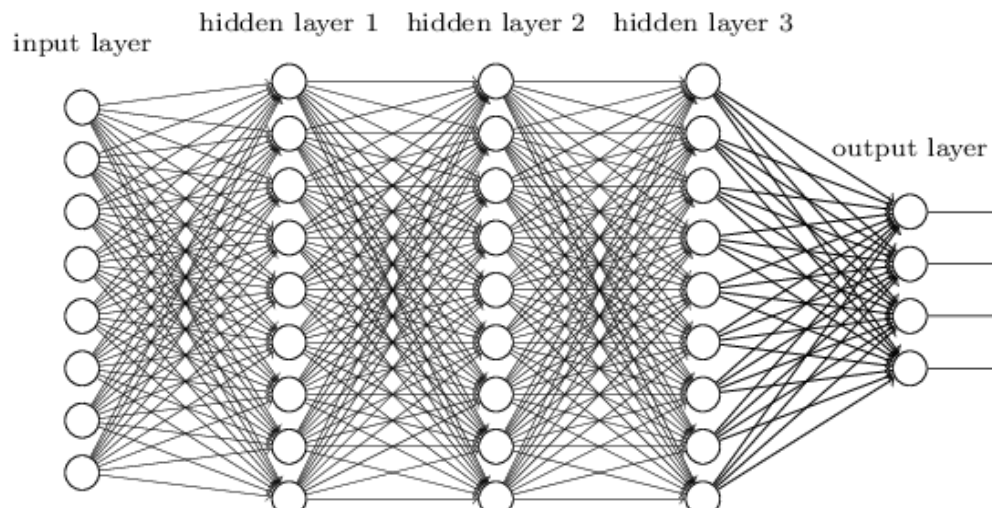
Exploratory and multi-way blind source separation and tensor factorizations: unsupervised learning methods and software to find the hidden causes & underlying hidden structure in the data.

Tensorization of Convolutive Deep Learning NN

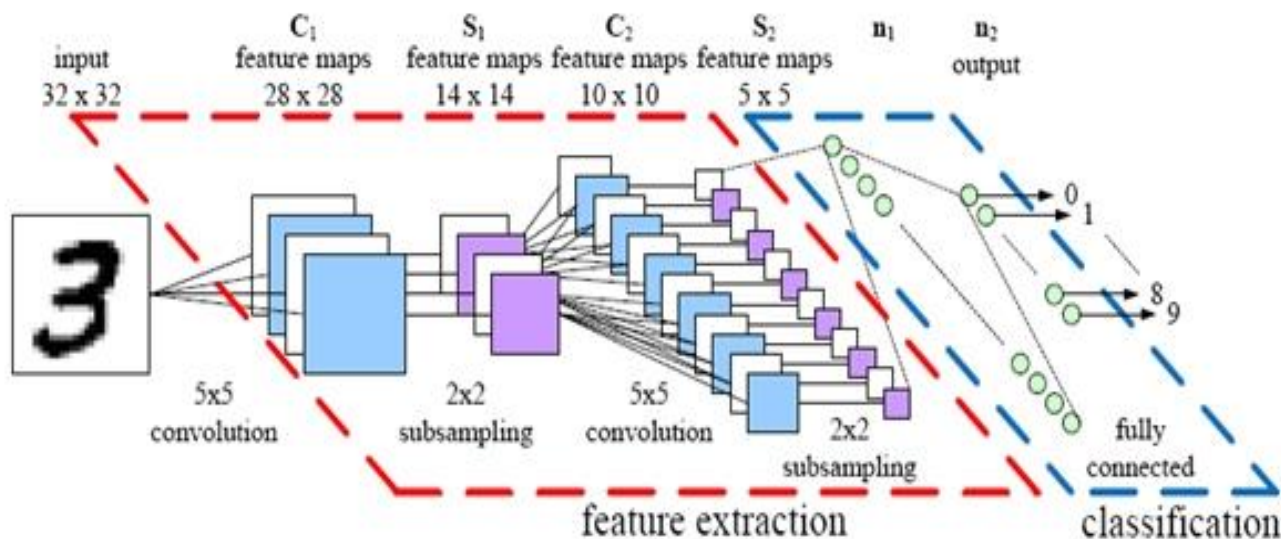
"Non-deep" feedforward neural network



Deep neural network



A. Cichocki Lab
RIKEN BSI



Fingerprints of Mental Activity

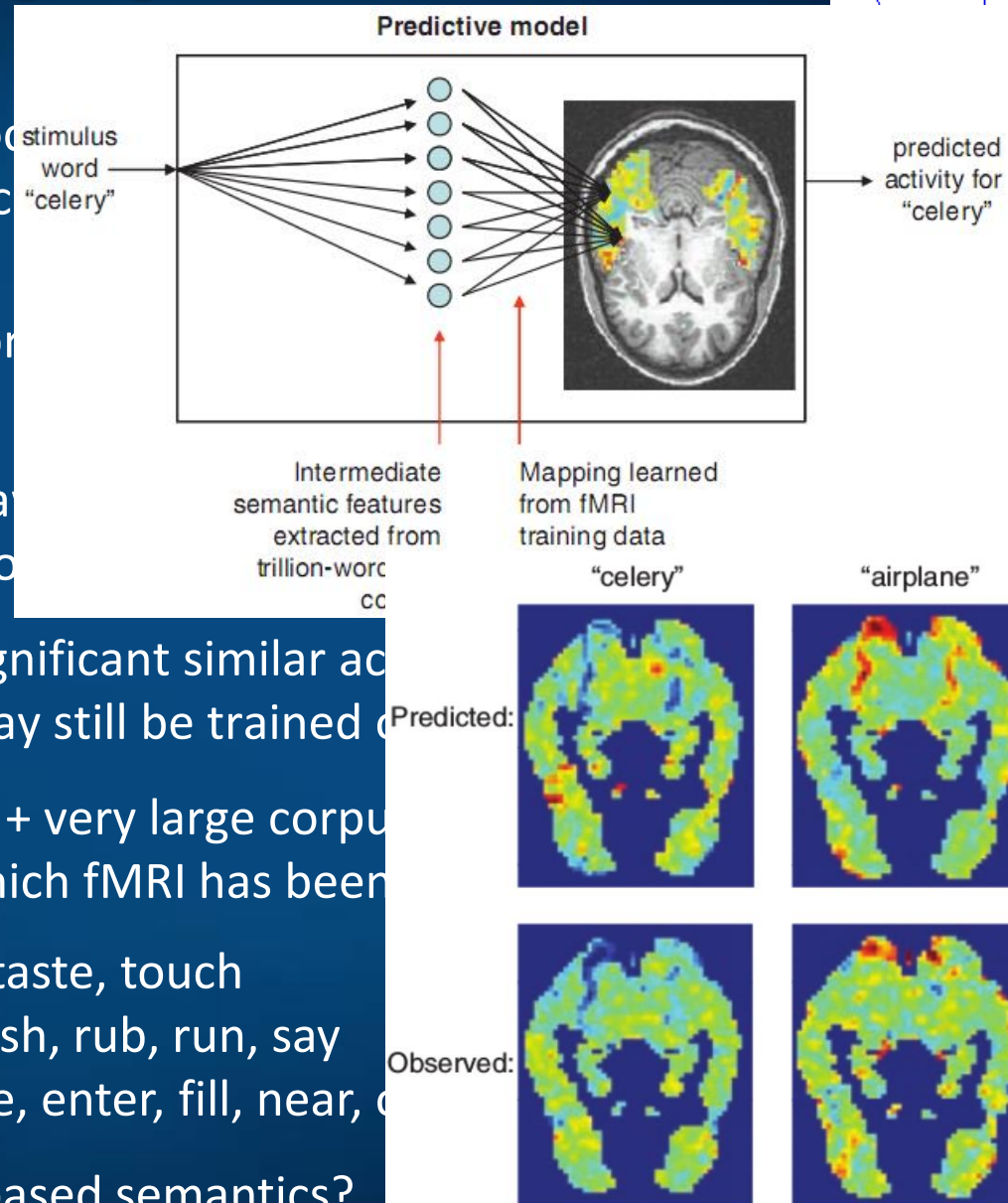
Neuroimaging words



Predicting Human Brain Activity Associated with the Reading of Nouns," T. M. Mitchell et al, Science

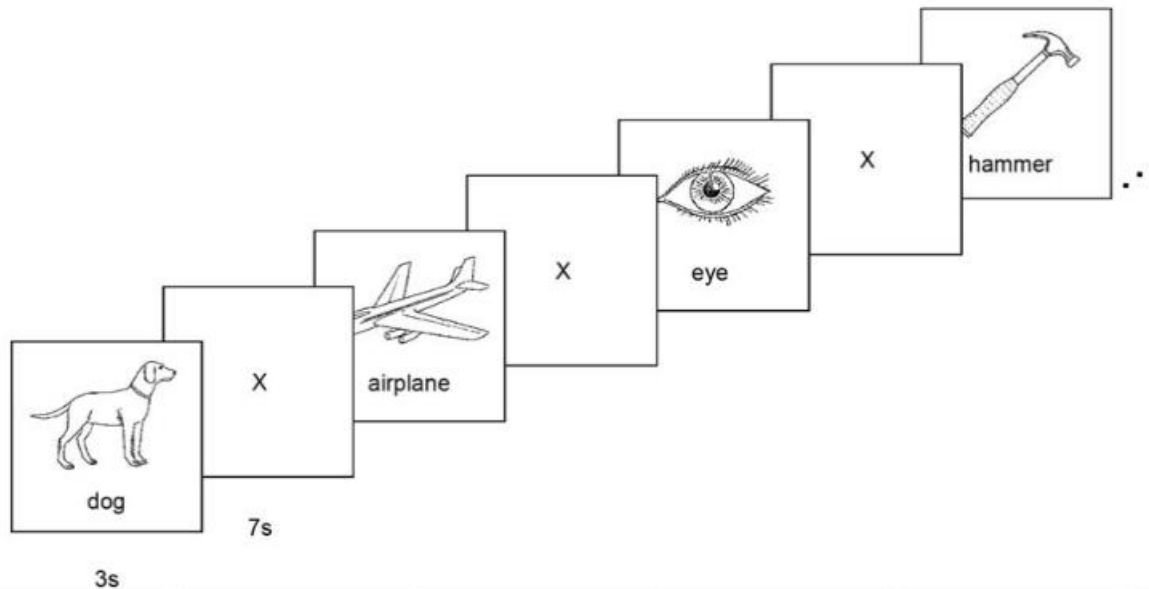
- Clear differences between fMRI brain activity patterns for different nouns.
- Reading words and seeing the drawing of the corresponding object presumably reflecting semantics of the word.
- Although individual variance is significant, similar activity patterns across different people, a classifier may still be trained on the data.
- Model trained on ~10 fMRI scans + very large corpus of text to predict activity for over 100 nouns for which fMRI has been recorded.

Sensory: fear, hear, listen, see, smell, taste, touch
Motor: eat, lift, manipulate, move, push, rub, run, say
Abstract: approach, break, clean, drive, enter, fill, near, open, ...
Are these 25 features defining brain-based semantics?



Quasi-stable brain activations?

Maintain brain activation for longer time. Use pictures, video, sounds ...



Category	Exemplar 1	Exemplar 2	Exemplar 3	Exemplar 4	Exemplar 5
animals	bear	cat	cow	dog	horse
body parts	arm	eye	foot	hand	leg
buildings	apartment	barn	church	house	igloo

Can we induce stable cortical activation? Locate sources in similar areas as BOLD? Interpret brain activations in terms of brain-based semantics?

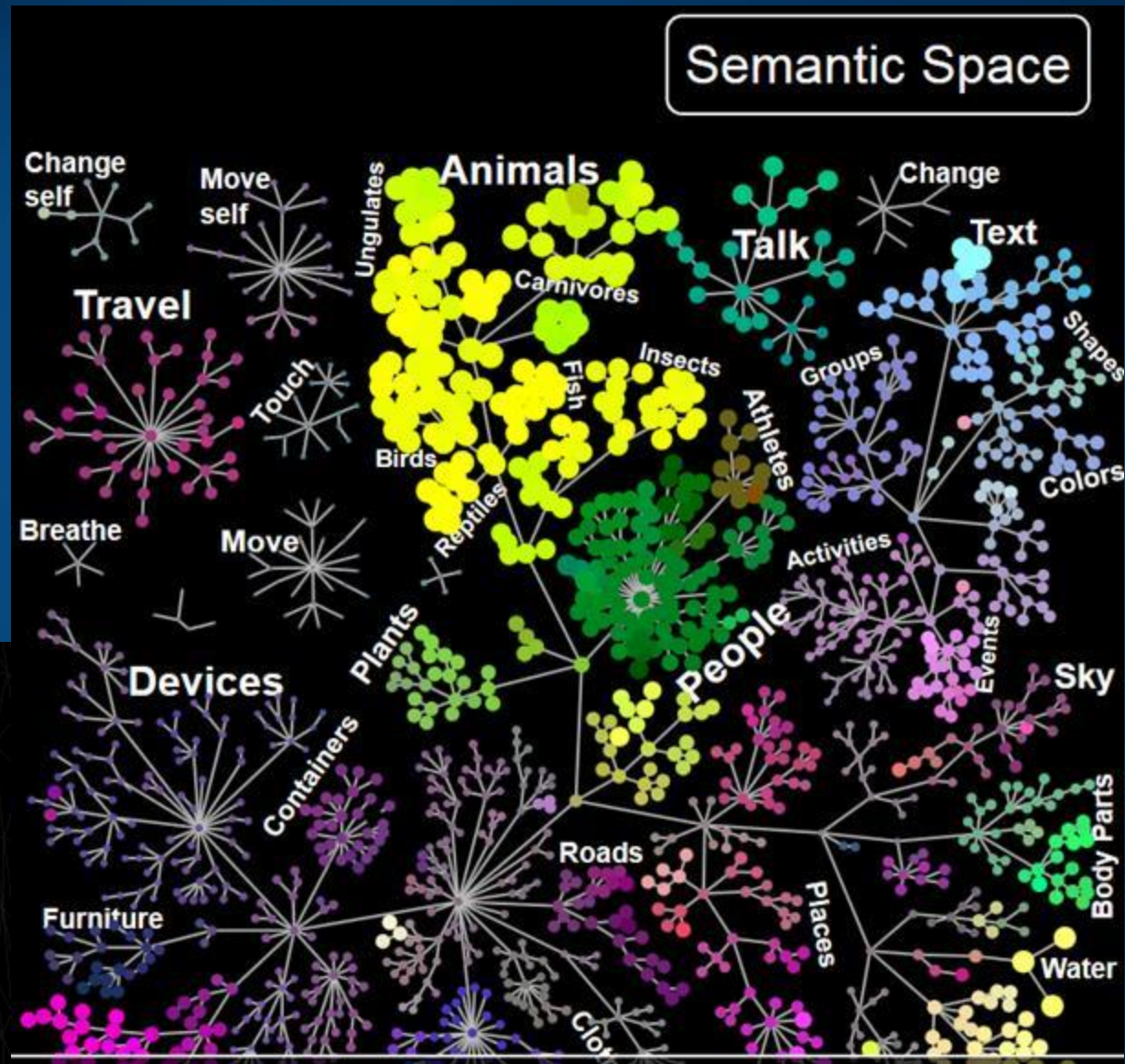
Semantic neuronal space

Words in the semantic space are grouped by their similarity.

Words activate specific ROIs, similar words create similar maps of brain activity.

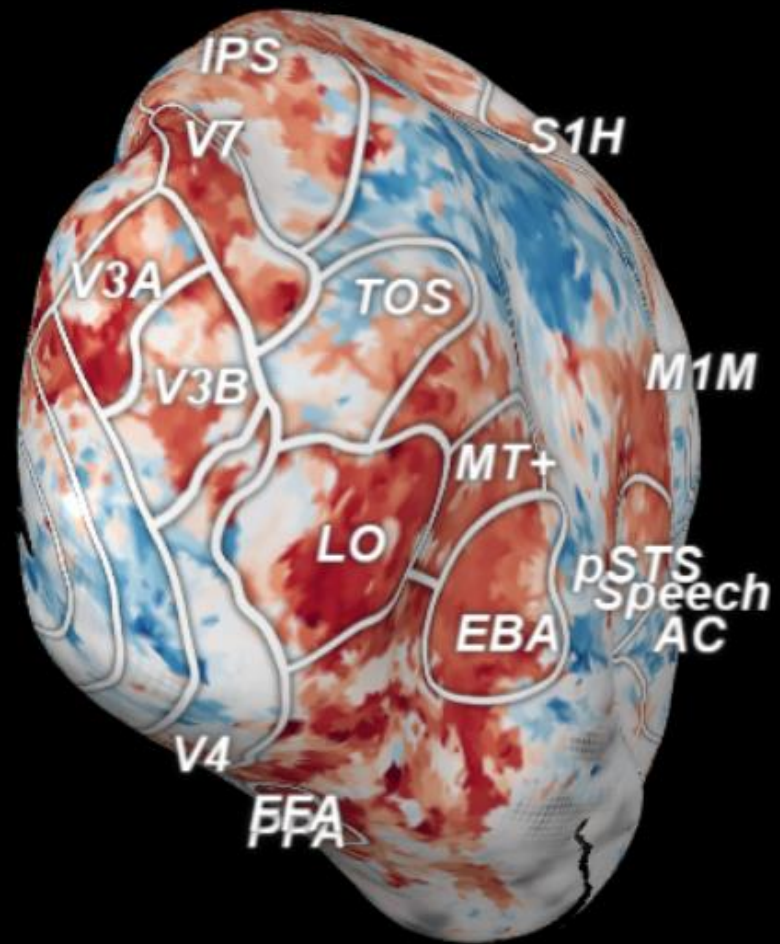
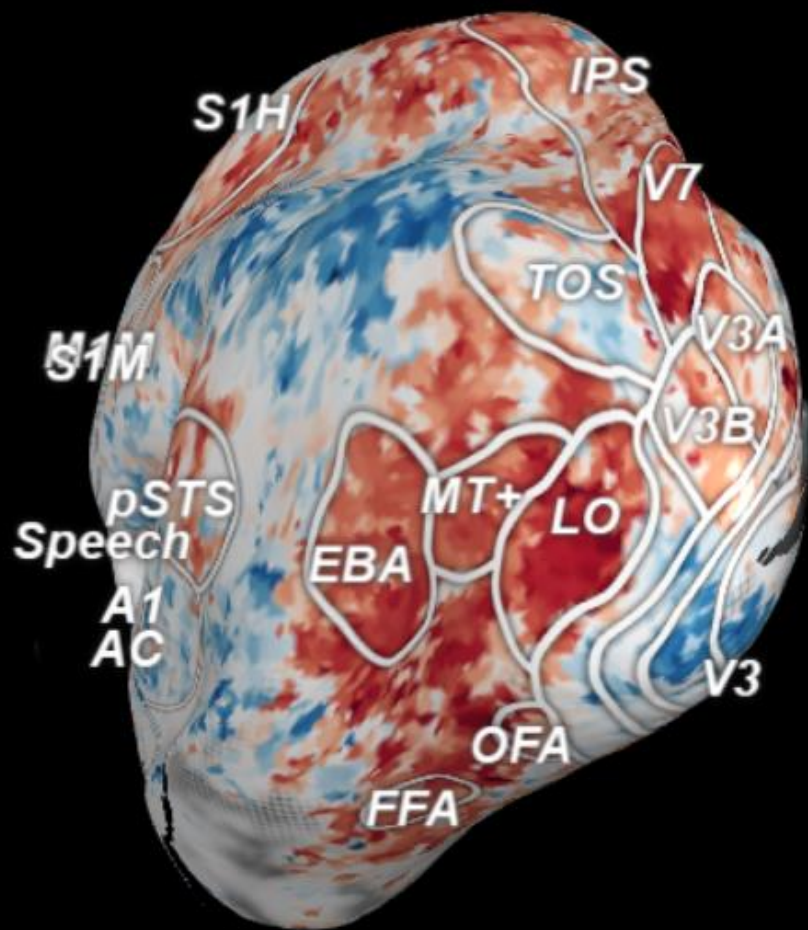
Video or audio stimuli, fMRI (60.000 voxel).

Gallant lab, Berkeley.



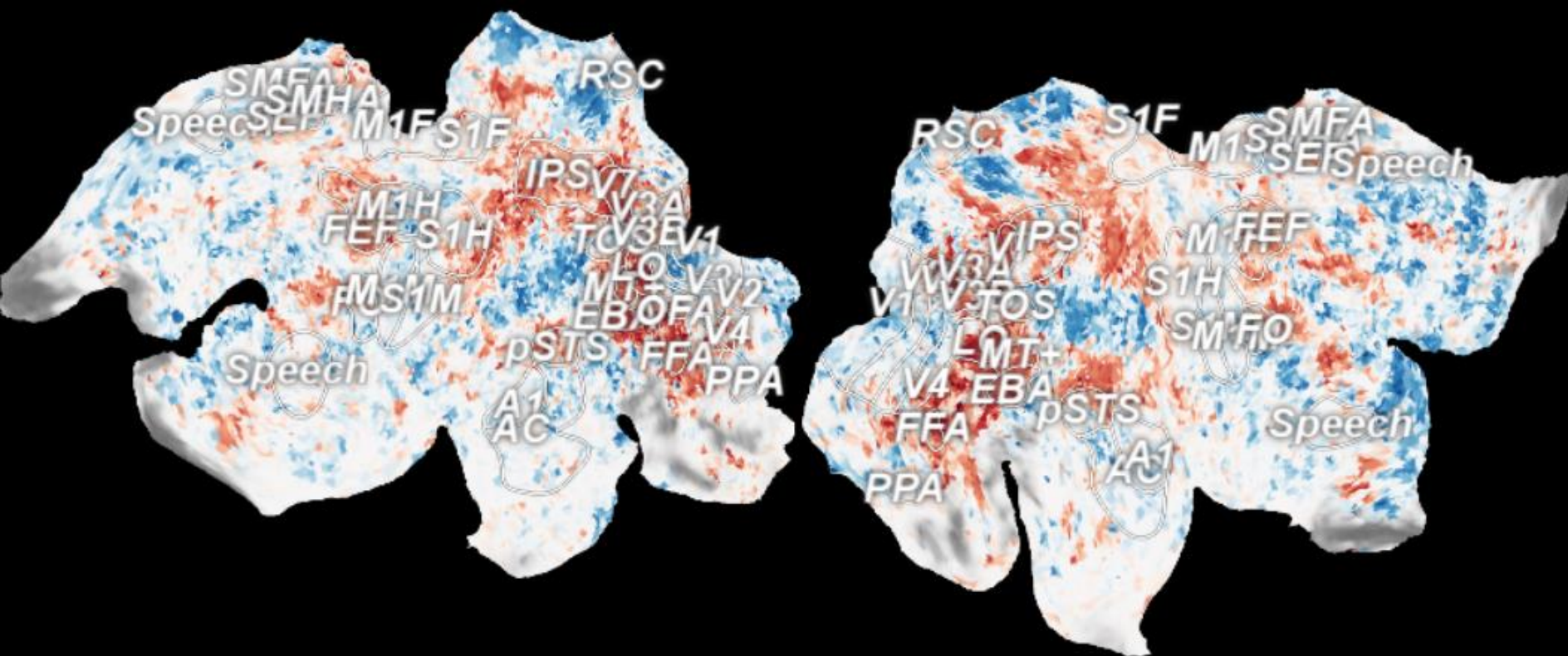


Category zebra: Passive Viewing

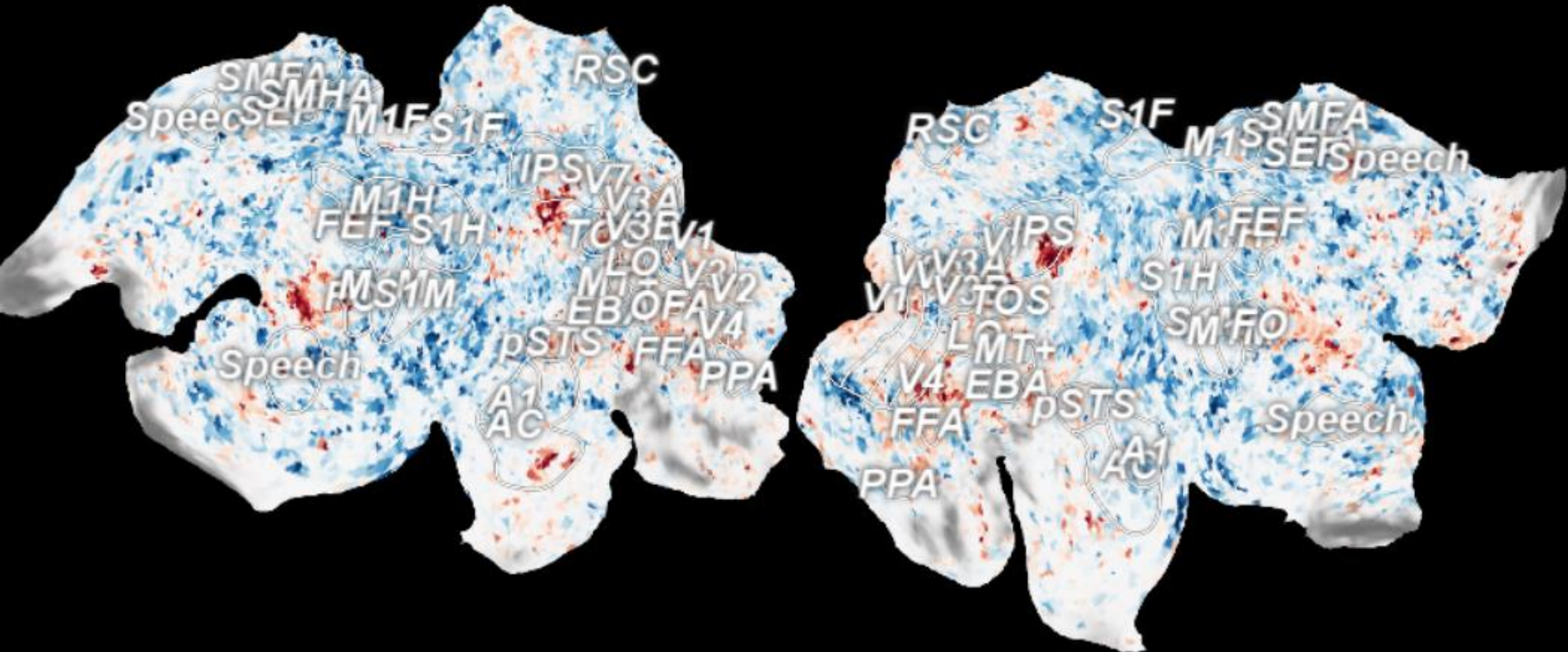


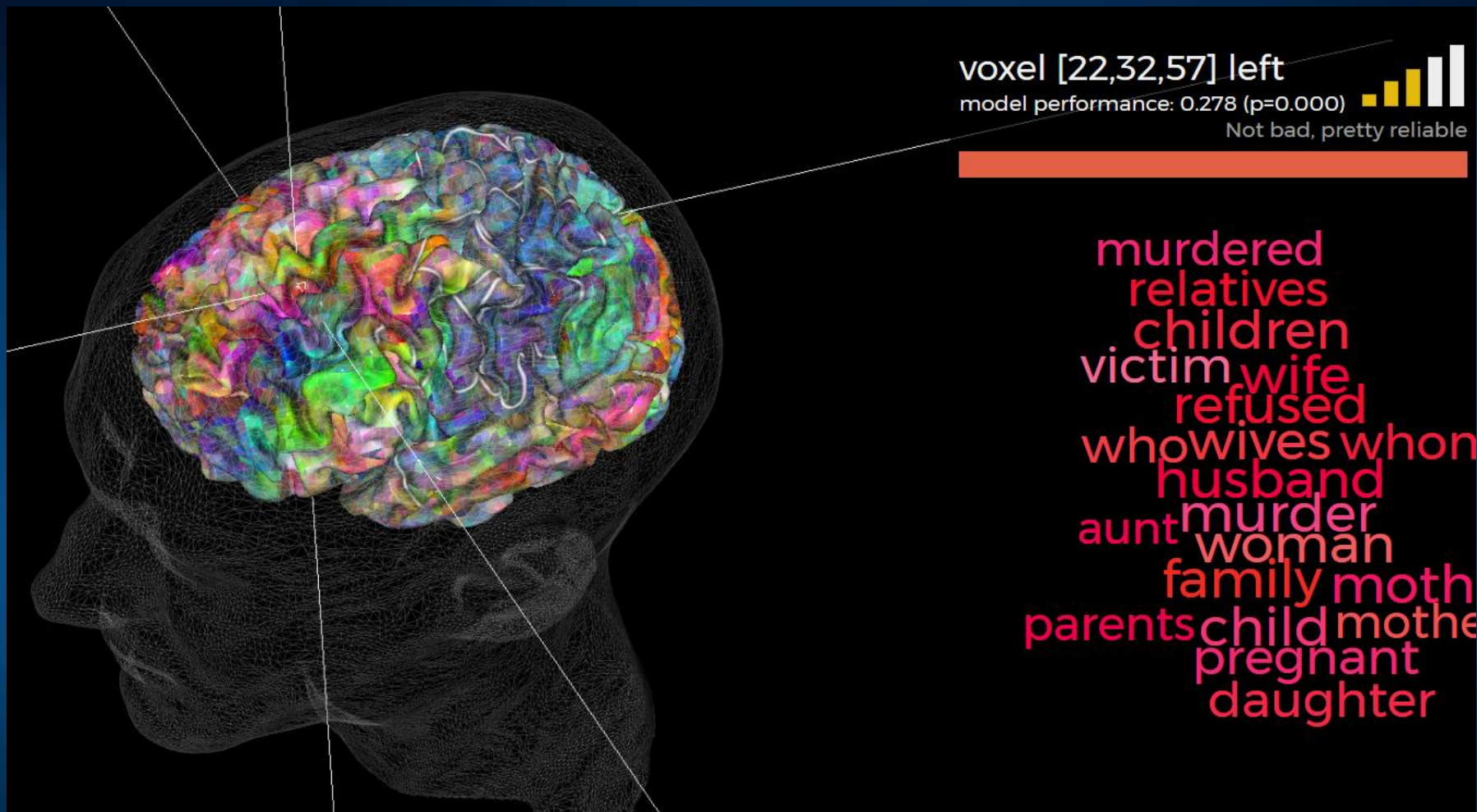


Category zebra: Passive Viewing



Category traffic light: Passive Viewing





Each voxel responds usually to many related words, whole categories.

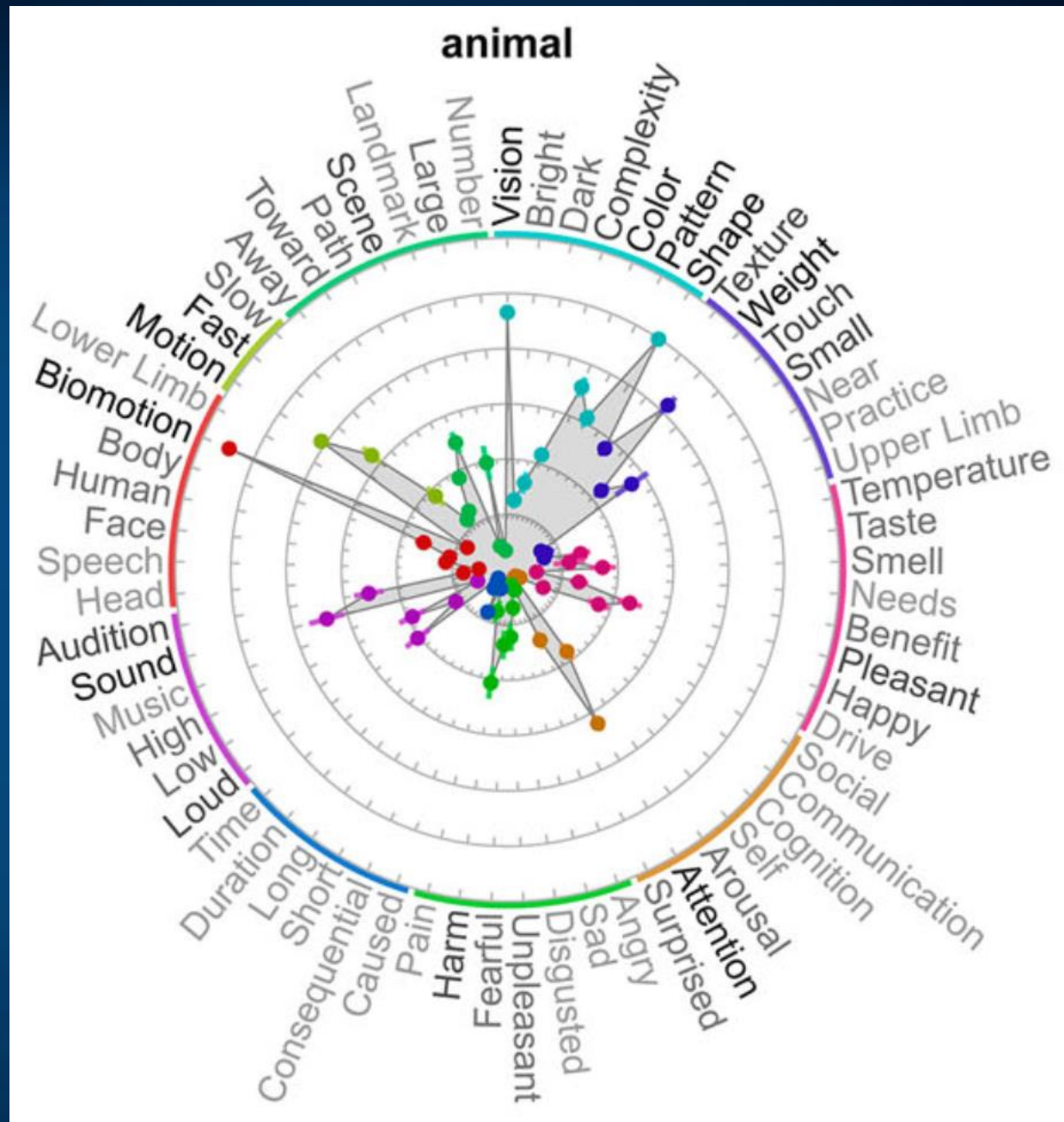
<http://gallantlab.org/huth2016/>

Huth et al. (2016). Decoding the Semantic Content of Natural Movies from Human Brain Activity. *Frontiers in Systems Neuroscience* 10, pp. 81

65 attributes related to neural processes;
Colors on circle: general domains.

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

More than just
visual objects!



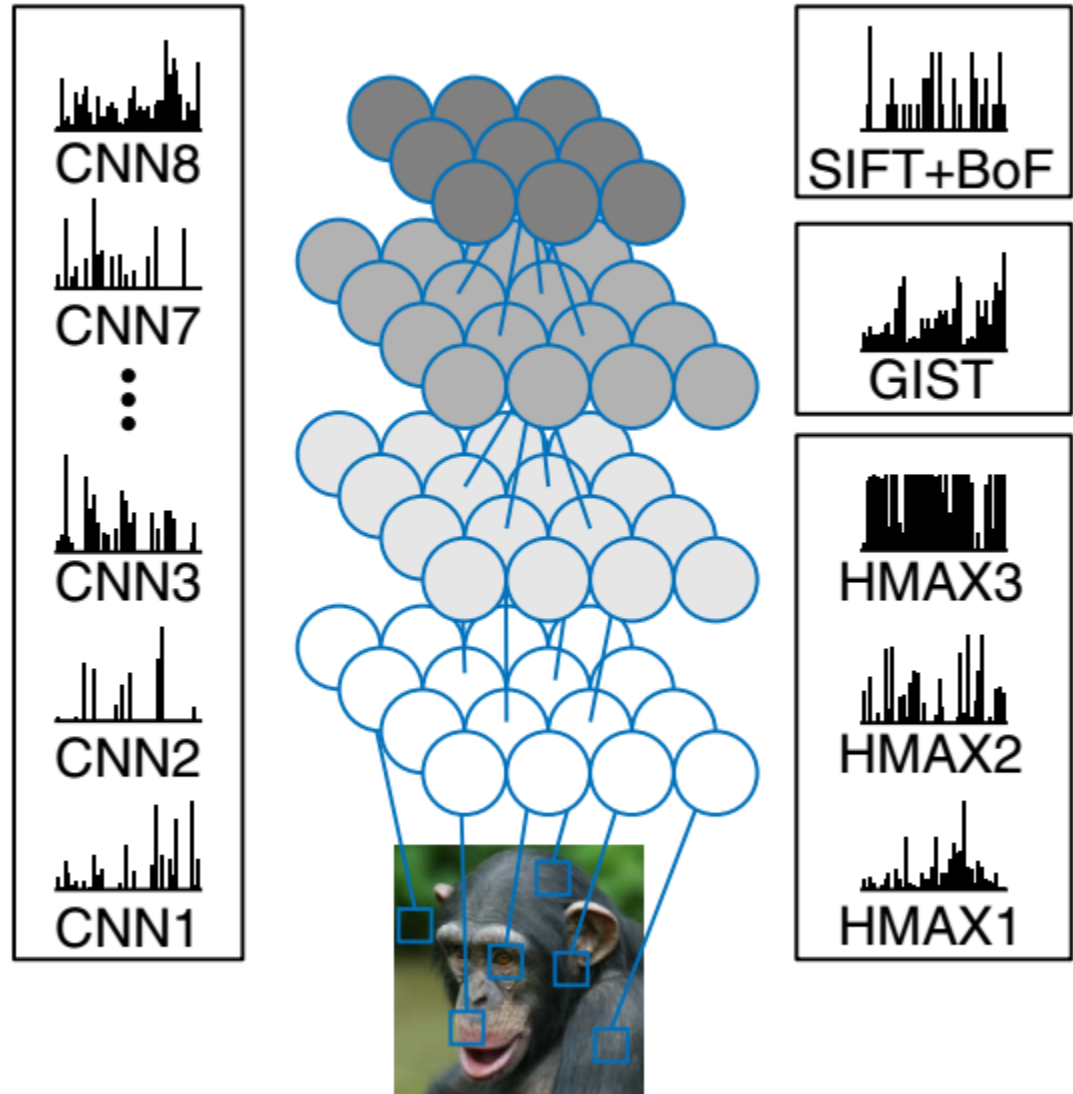
Mental images from brain activity

Can we convert activity of the brain into the mental images that we are conscious of?

Try to estimate features at different layers.

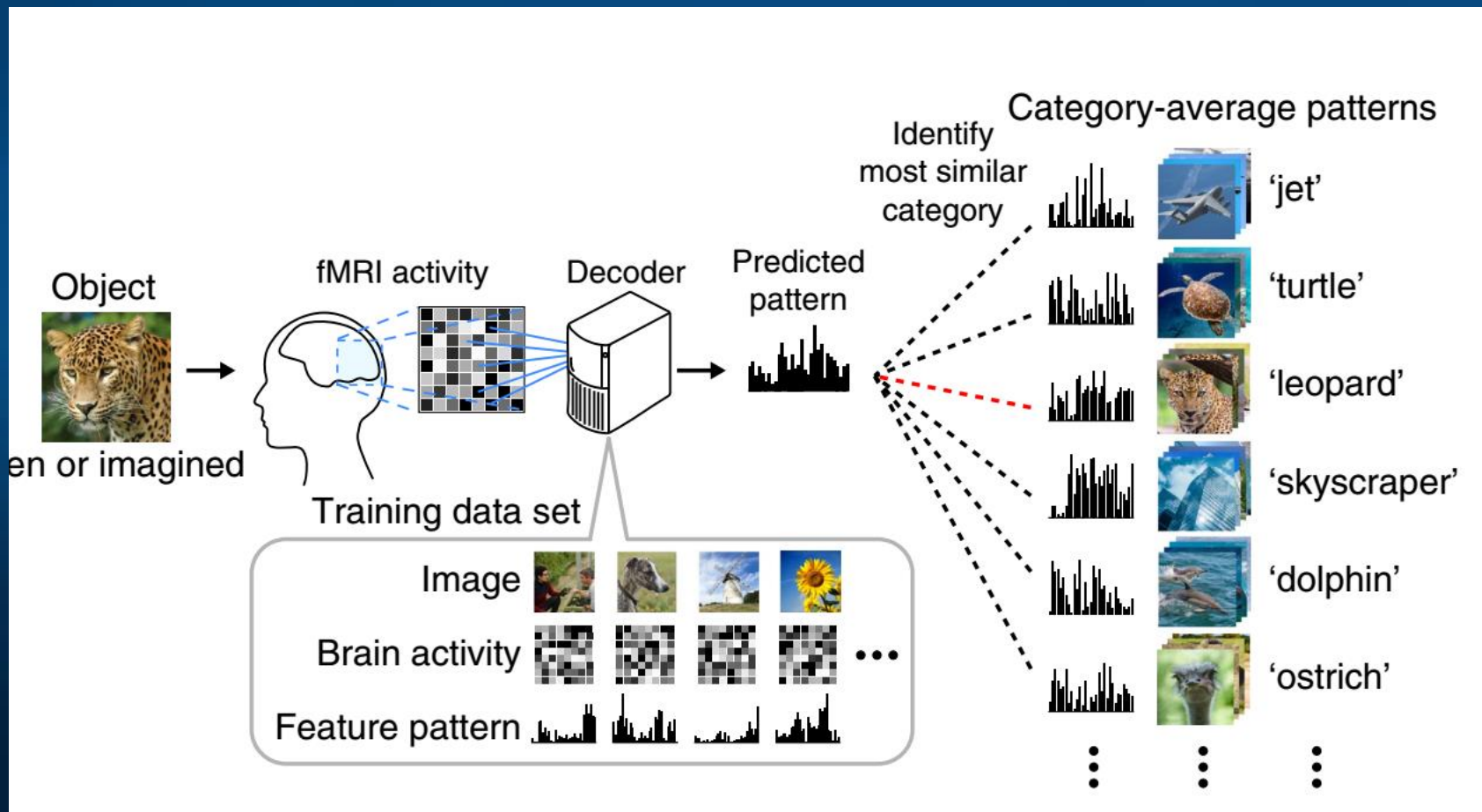
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

Output: 1000 images.



Brain activity \leftrightarrow Mental image

fMRI activity can be correlated with deep CNN network features; using these features closest image from large database is selected. Horikawa, Kamitani, Generic decoding of seen and imagined objects using hierarchical visual features. Nature Comm. 2017.



Decoding Dreams



Decoding Dreams, ATR Kyoto, Kamitani Lab. fMRI images analysed during REM phase or while falling asleep allows for dream categorization (~20 categories).

Dreams, thoughts ... can one hide what has been seen and experienced?

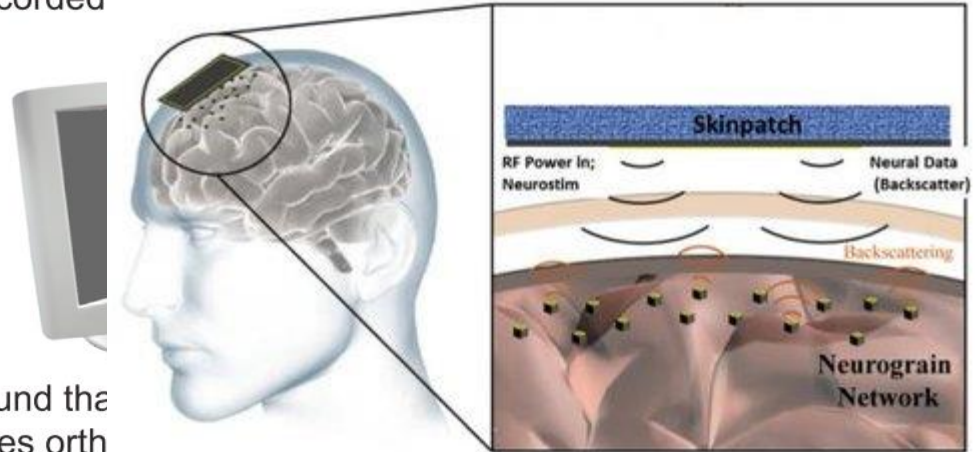
Neural screen

Features are discovered, and their combination remembered as face, but detailed recognition needs detailed recording from neurons – 205 neurons in various visual areas used.

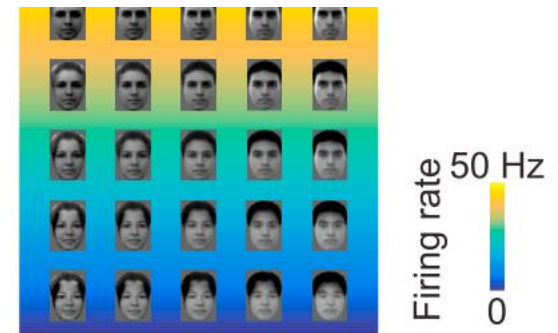
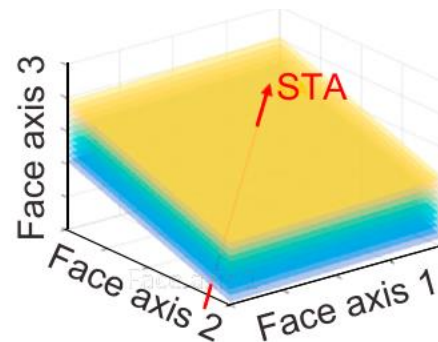
L. Chang and D.Y. Tsao, “The code for facial identity in the primate brain”. *Cell* 2017

DARPA (2016): put million nanowires in the brain!
Use them to read neural responses and 10% of them to activate neurons.

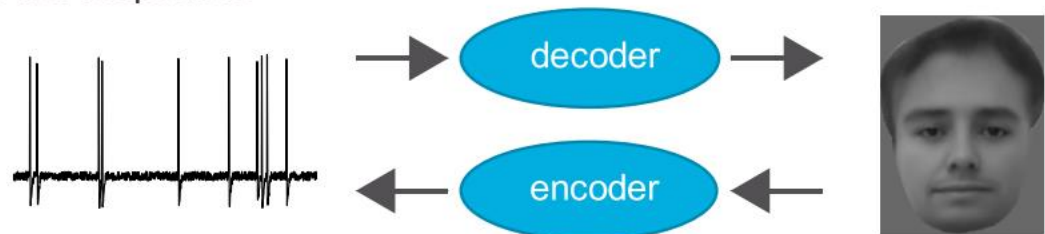
1. We recorded patches



2. We found the to changes orth

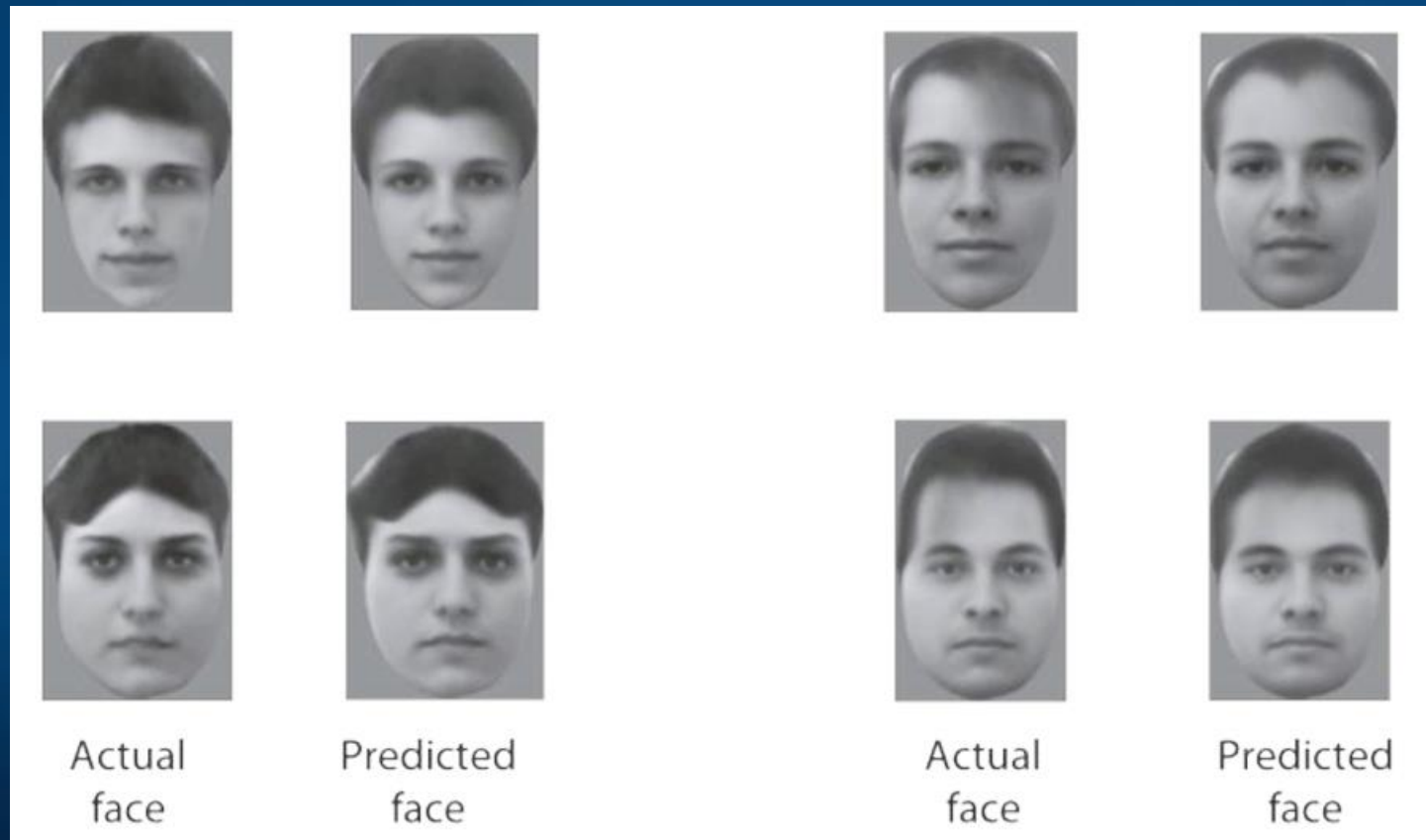


3. We found that an axis model allows precise encoding and decoding of neural responses



Mental images

Facial identity is encoded via a simple neural code that relies on the ability of neurons to distinguish facial features along specific axes in the face space.



Narration

Nicole Speer et al.
 Reading Stories Activates Neural
 Repre-sentations of Visual and
 Motor Experiences. Psychological
 Science 2009; 20(8): 989–999.

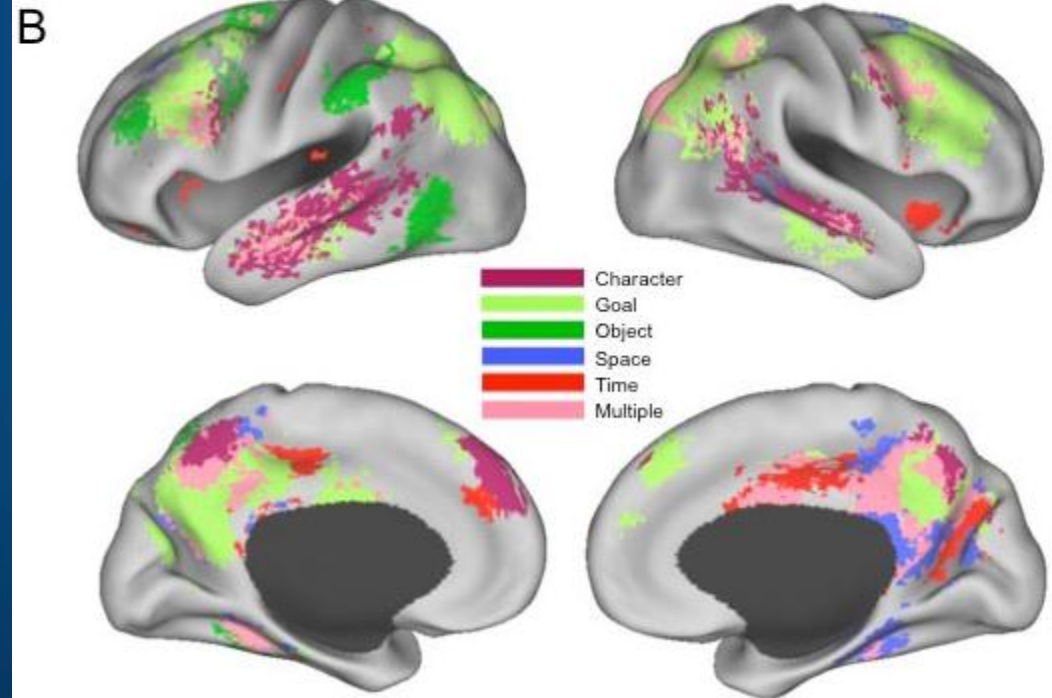
Thought: spatiotemporal pattern

Meaning: always slightly
 different, depending on the
 context, but still may be clustered
 into relatively small number of
 distinct meanings.

Sentences: trajectories in
 semantic space, building scenes,
 mind models with characters,
 objects, spatio-temporal
 relations.

A

Clause	Cause	Character	Goal	Object	Space	Time
...[Mrs. Birch] went through the front door into the kitchen.	●				●	
Mr. Birch came in	●	●			●	
and, after a friendly greeting,	●					●
chatted with her for a minute or so.	●					●
Mrs. Birch needed to awaken Raymond.		●				
Mrs. Birch stepped into Raymond's bedroom, pulled a light cord hanging from the center of the room,			●		●	
and turned to the bed.						
Mrs. Birch said with pleasant casualness, "Raymond, wake up."						
With a little more urgency in her voice she spoke again:						
Son, are you going to school today?						
Raymond didn't respond immediately.		●				●
He screwed up his face			●			
And whimpered a little.						



Dynamic functional brain networks

Brain modules and cognitive processes

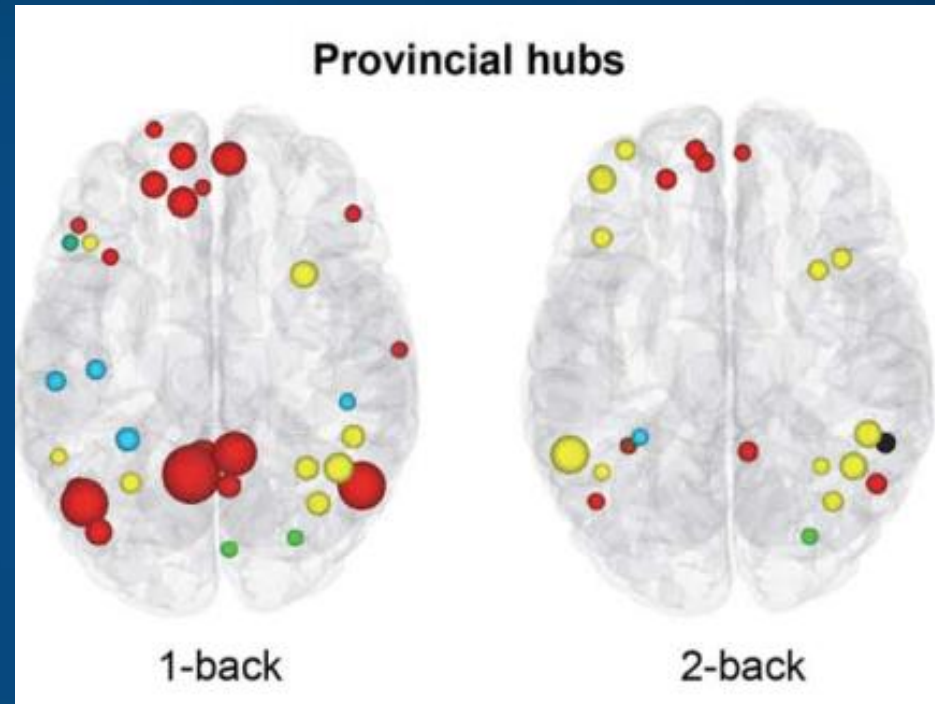
Simple and more difficult tasks, requiring the whole-brain network reorganization.

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. (2017). Transition of the functional brain network related to increasing cognitive demands. *Human Brain Mapping*, 38(7), 3659–3674.

Brain modules and cognitive processes

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

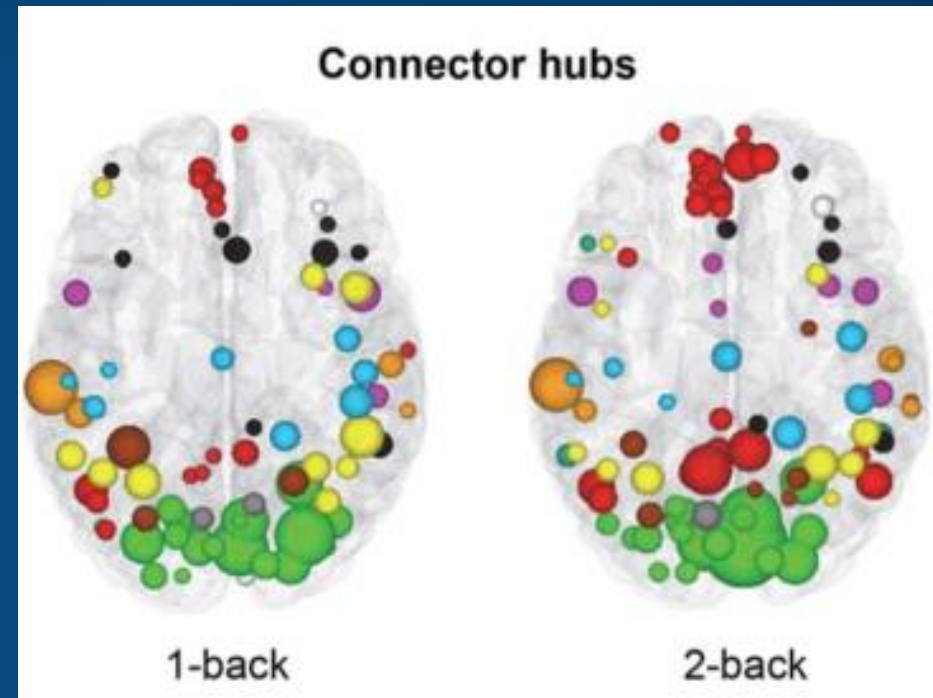
Left: 1-back connector hubs

Right: 2-back connector hubs

Average over 35 *participants*.

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

DMN areas engaged in global binding!

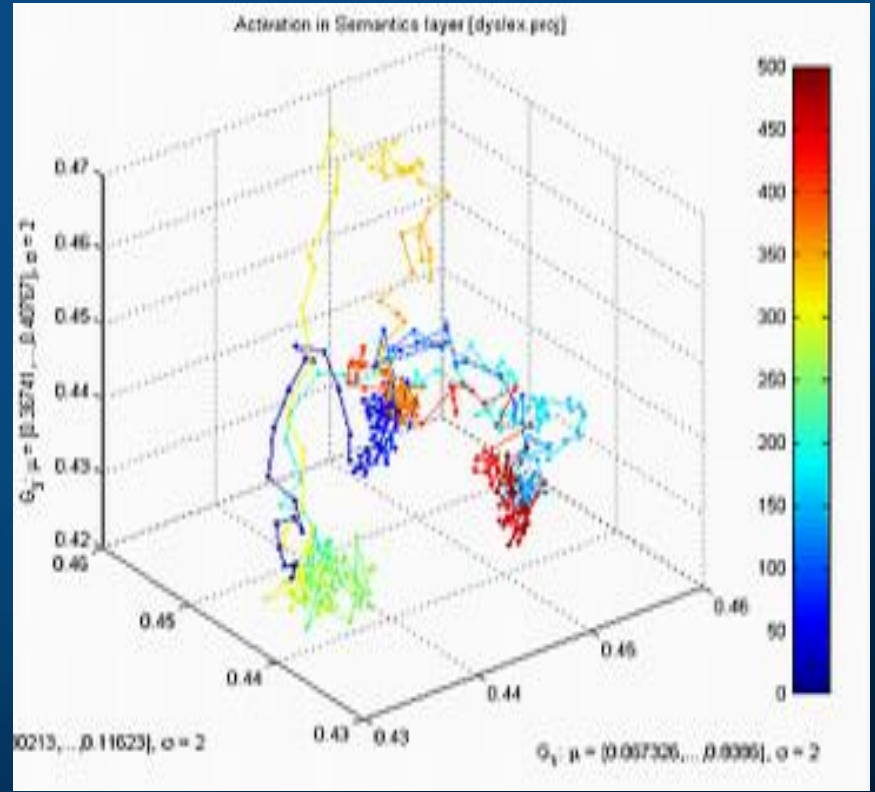
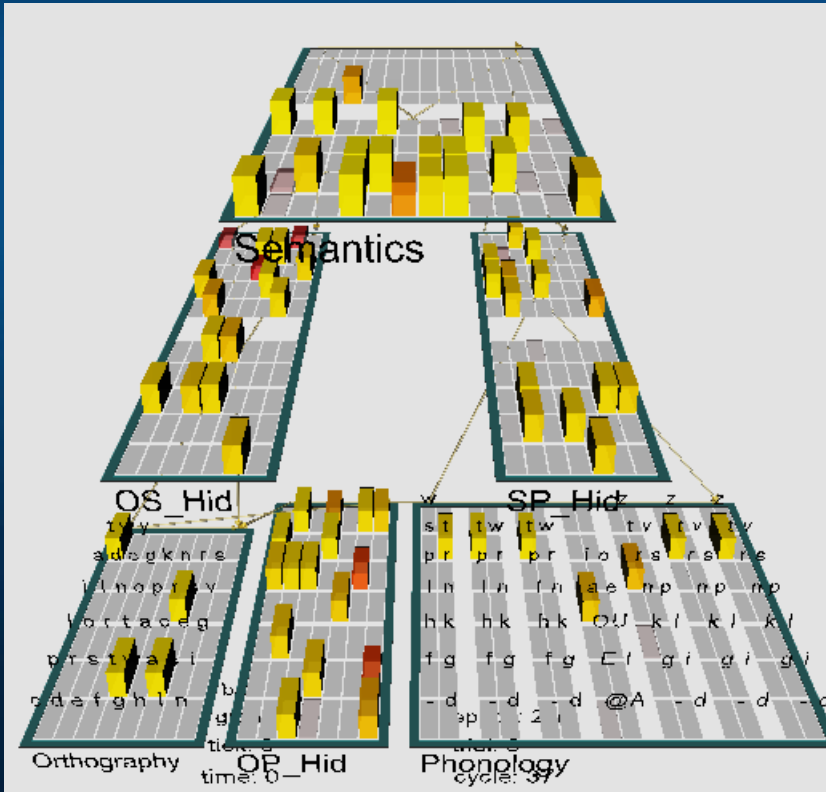


K. Finc et al, HBM (2017).

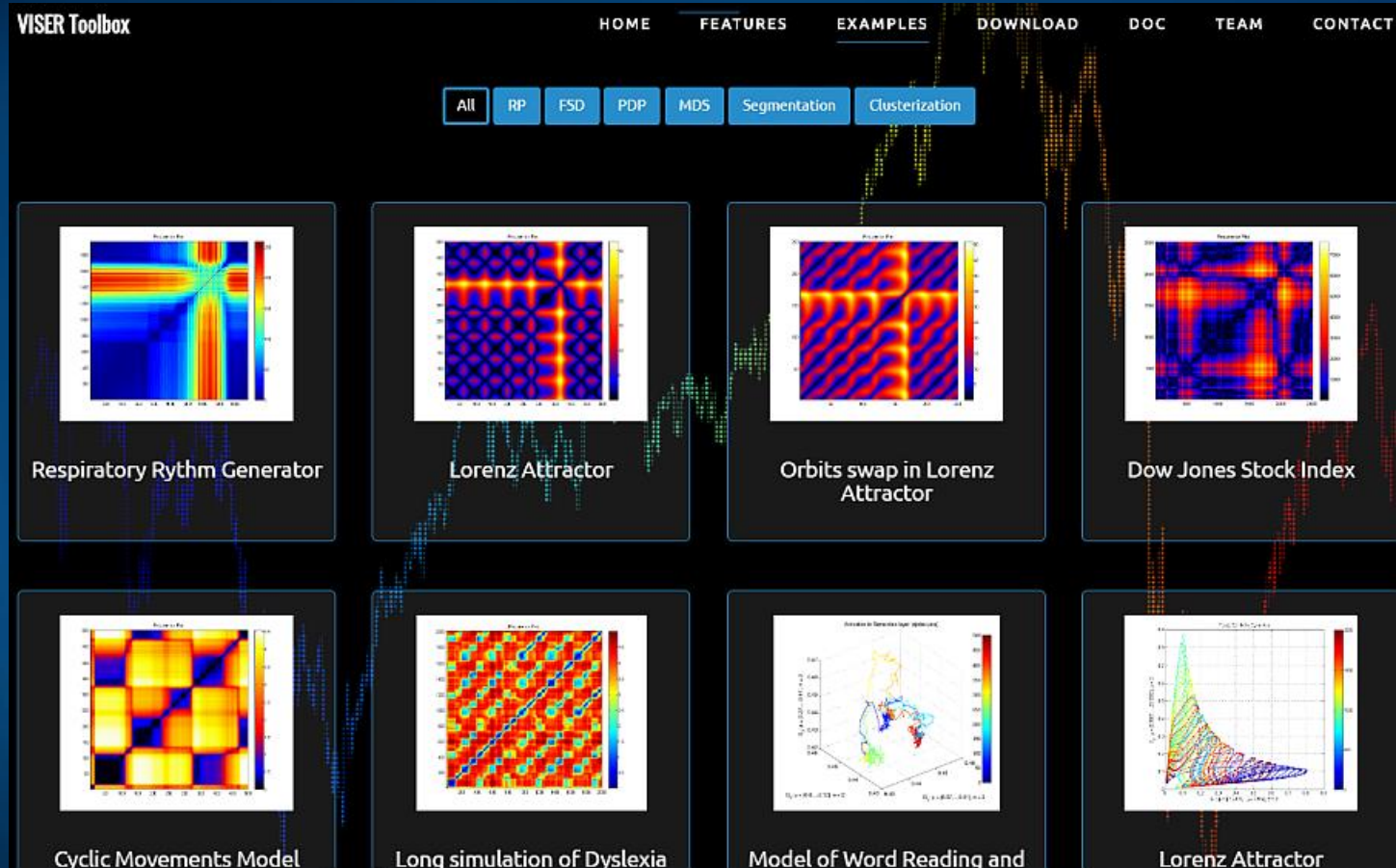
Simulation of reading

Emergent neural simulator: Aisa, B., Mingus, B., and O'Reilly, R. The emergent neural modeling system. *Neural Networks*, 21, 1045-1212, 2008.

Model includes phonology, orthography, semantic layers + 3 hidden layers to map activations between these layers. Trajectories of semantic layer activity in 140D shows transitions between microstates (basins of attractors).

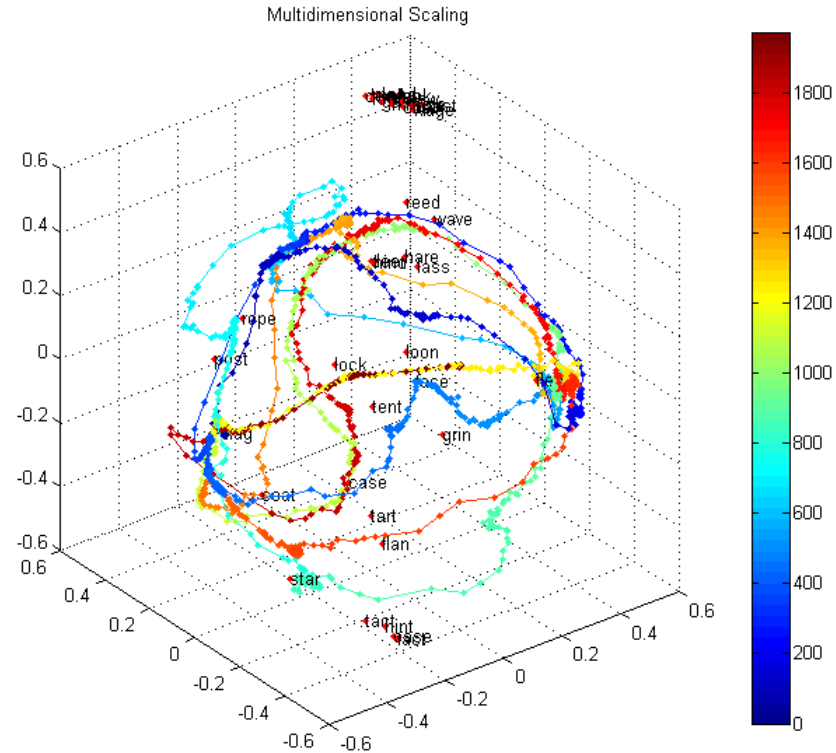
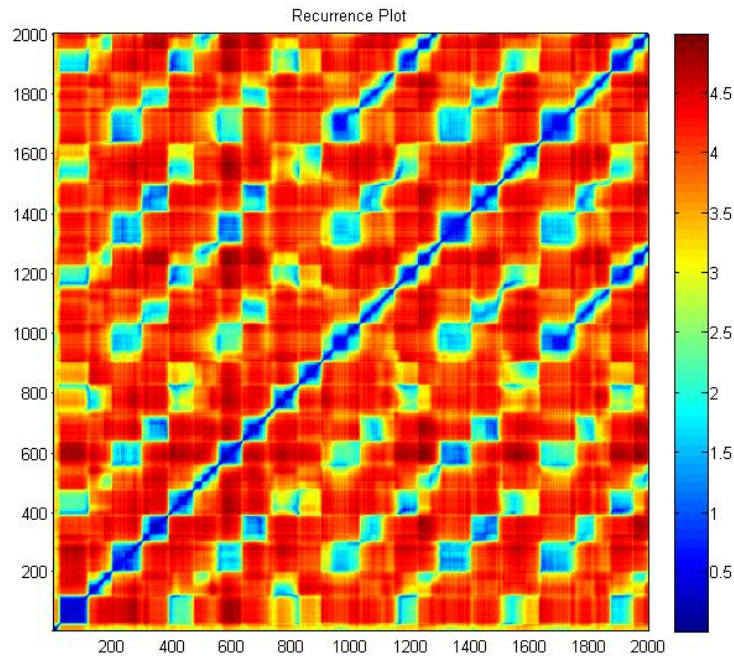


Viser toolbox



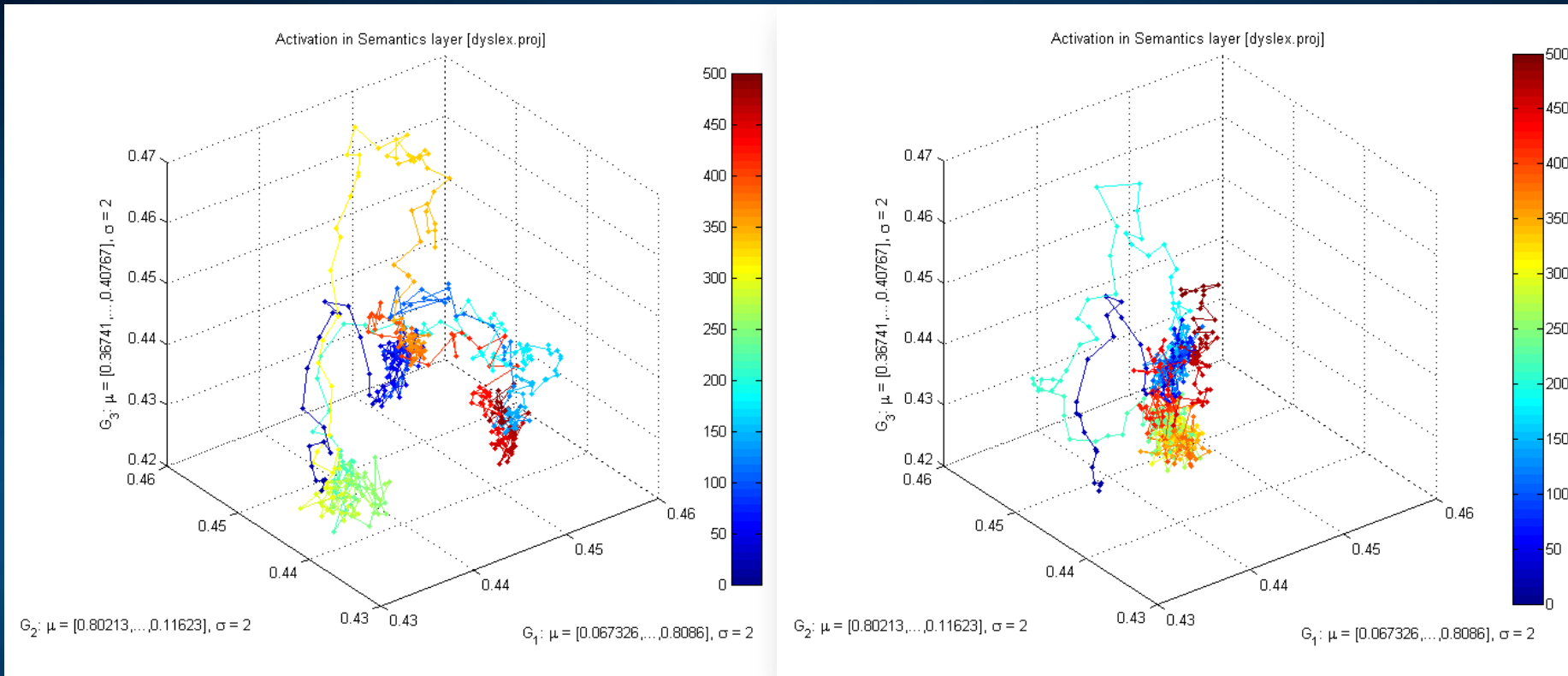
Nasz Viser toolbox (Dobosz, Duch) do wizualizacji szeregów czasowych w wielu wymiarach różnymi technikami.

Trajectory visualization



Wykresy rekurencji i różne formy wizualizacji trajektorii (MDS/FSD/SNE) obrazują przejścia pomiędzy stanami reprezentującymi kolejne stany w sieci nauczonej reprezentacji 40 słów, startując od “flag” widać sekwencję skojarzeń.

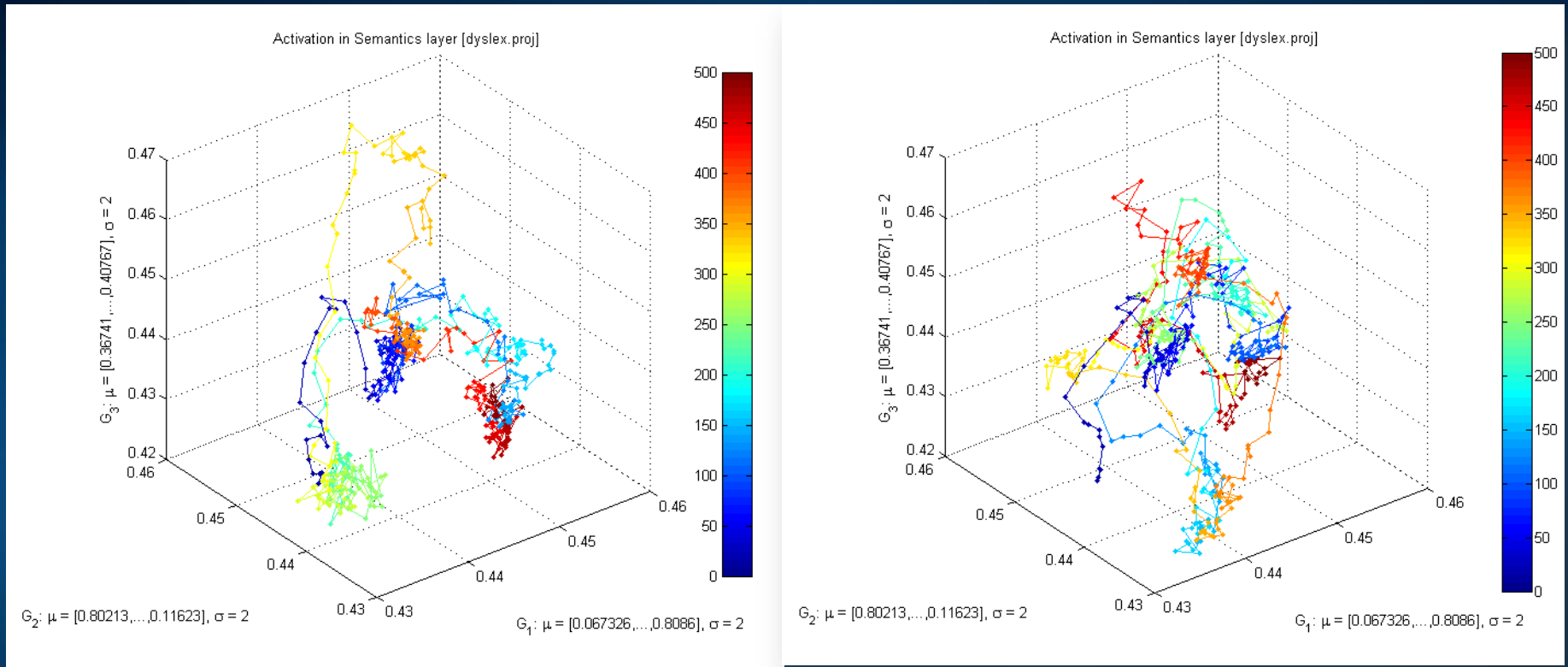
Norma-Autyzm



Trajektoria warstwy semantycznej (140 wym) dla słowa „flag”, różne wartości parametru kontrolującego kanały upływu (zmęczenie neuronów).

Tu neurony wolno się męczą i pozostają na długo zsynchronizowane: rezultat to ubóstwo myśli, problemy z przenoszeniem uwagi, koncentracja na prostych bodźcach, nawrót tej samej myśli, echolalia (powtarzanie bez zrozumienia).

Norma - ADHD

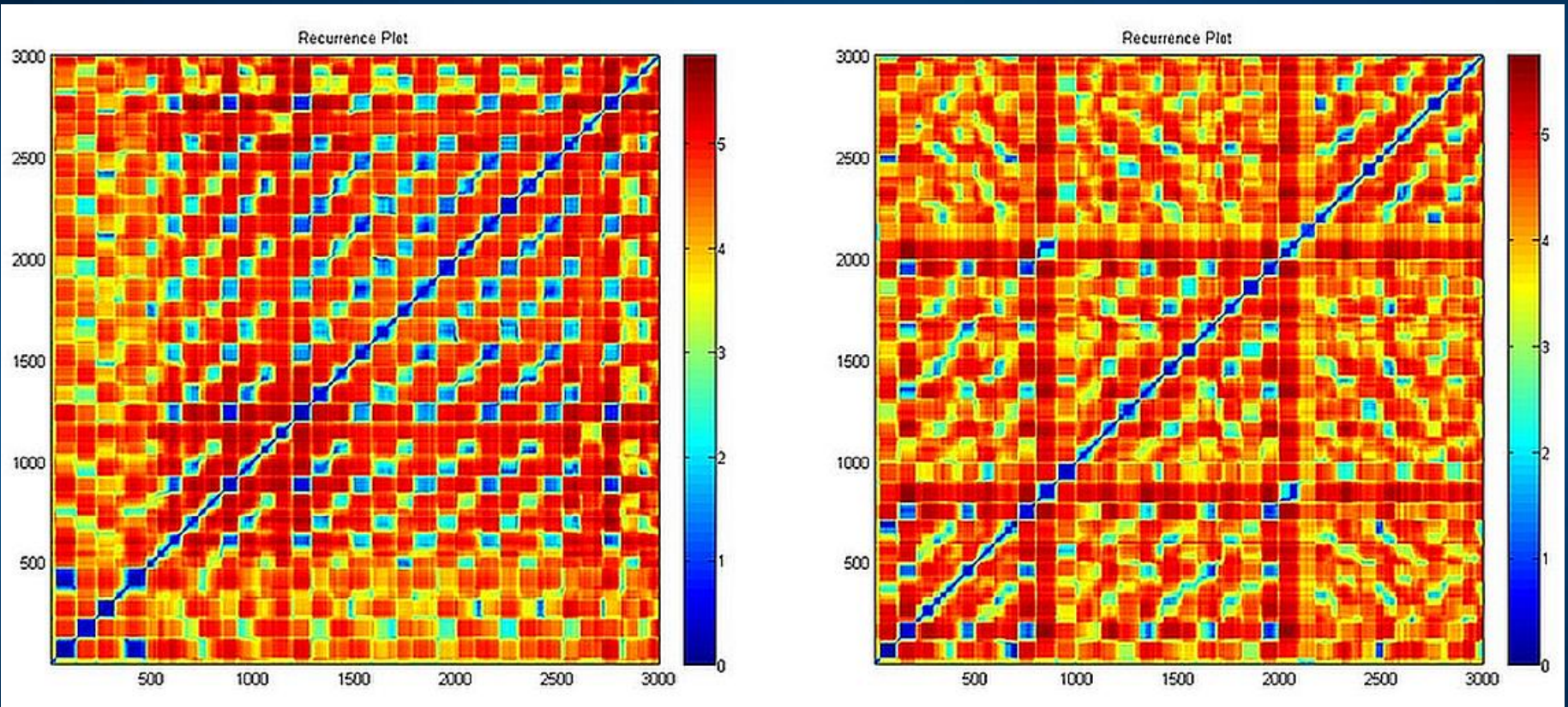


ADHD: dużo więcej i krócej trwających aktywacji wzorców, „ulotne” stany.

ADHD: kanały upływu zbyt otwarte, szybka depolaryzacja neuronów, krótki czas kwazistabilnych stanów atraktorowych.

ASD: kanały upływu zbyt zamknięte, wolna depolaryzacja neuronów, długi czas kwazistabilnych stanów atraktorowych.

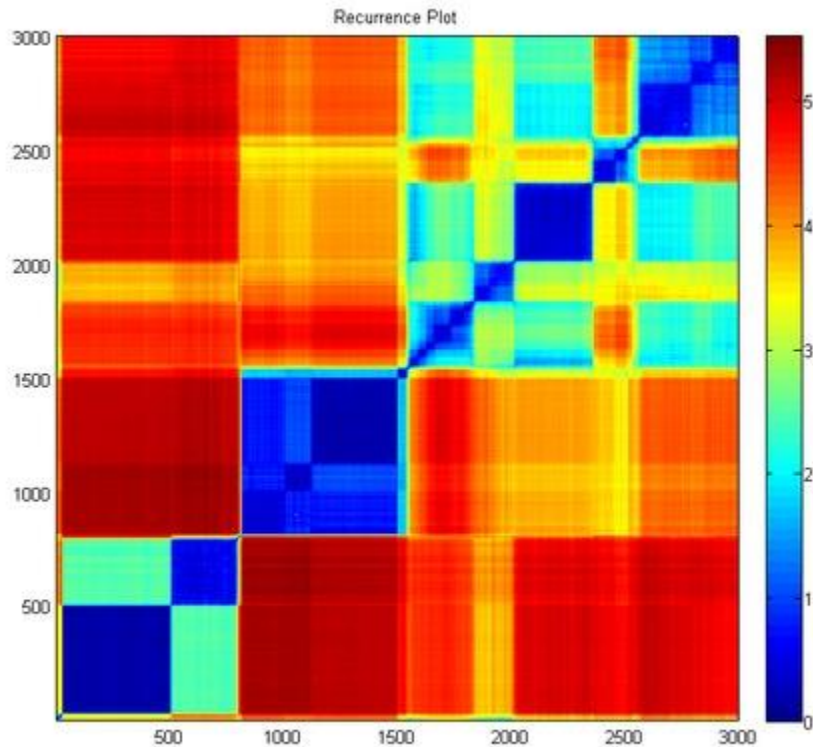
RSVP: normal brain



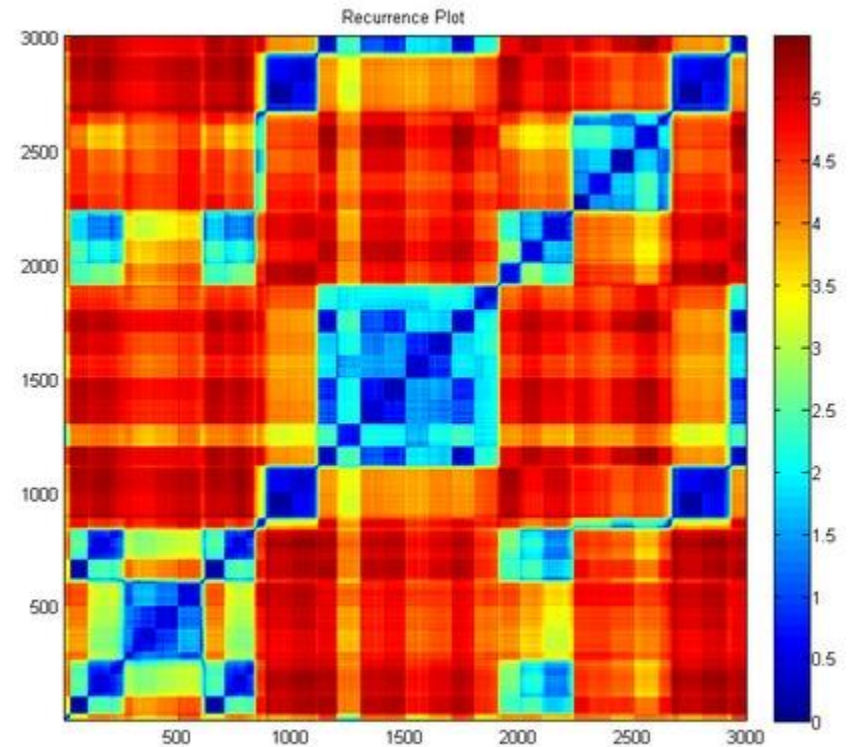
Normal speed
associations, context=>understanding

too fast, speed 5x
microstates get blurred,
few associations

RSVP simulations in deep autism



Normal speed
skipping some words,
no associations



fast presentation
more internal states
some associations arise

Human Enhancement and Optimization of Brain Processes

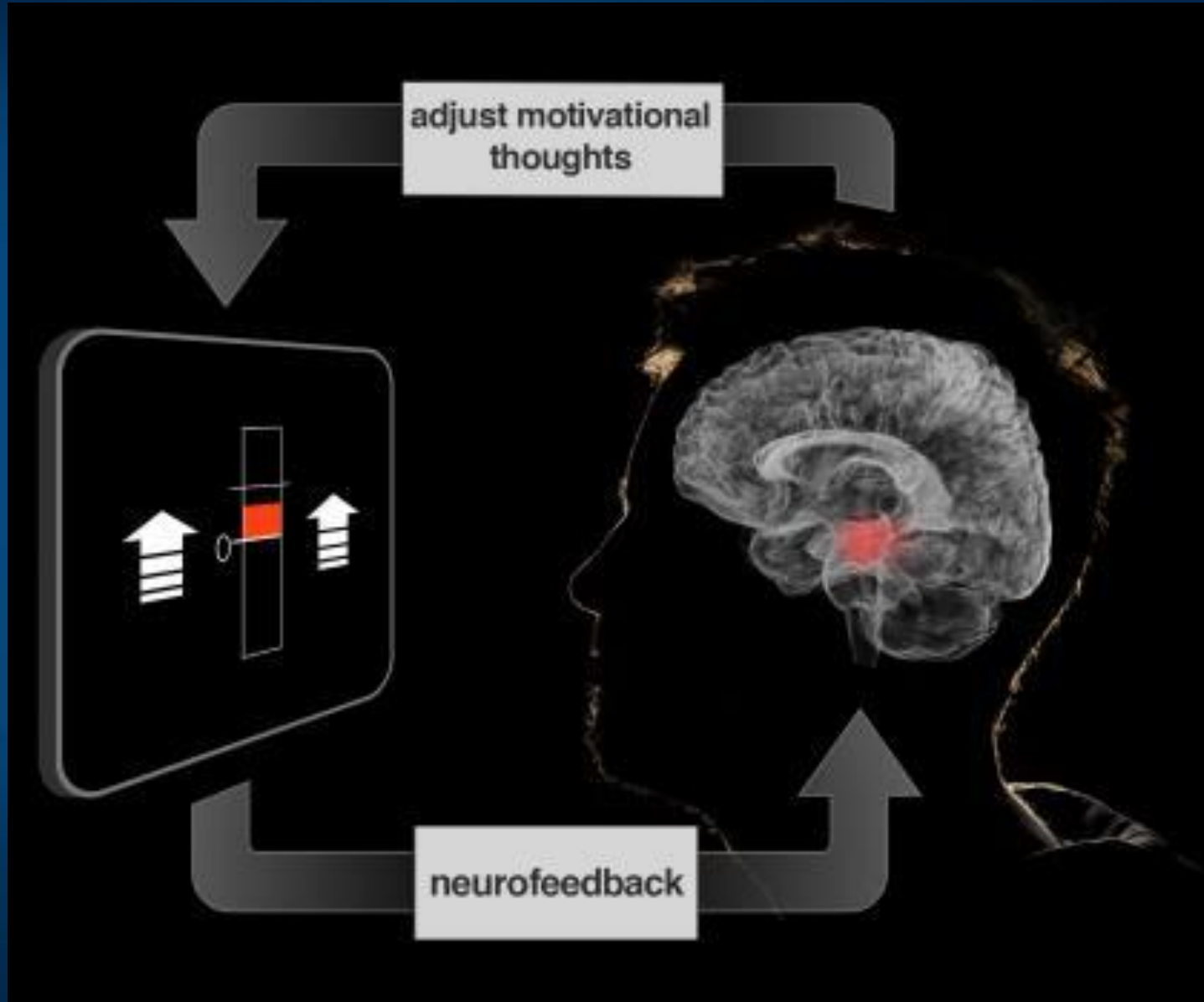
Neurofeedback: first BCI

Used in clinical practice, α/θ rhythms for relaxation.

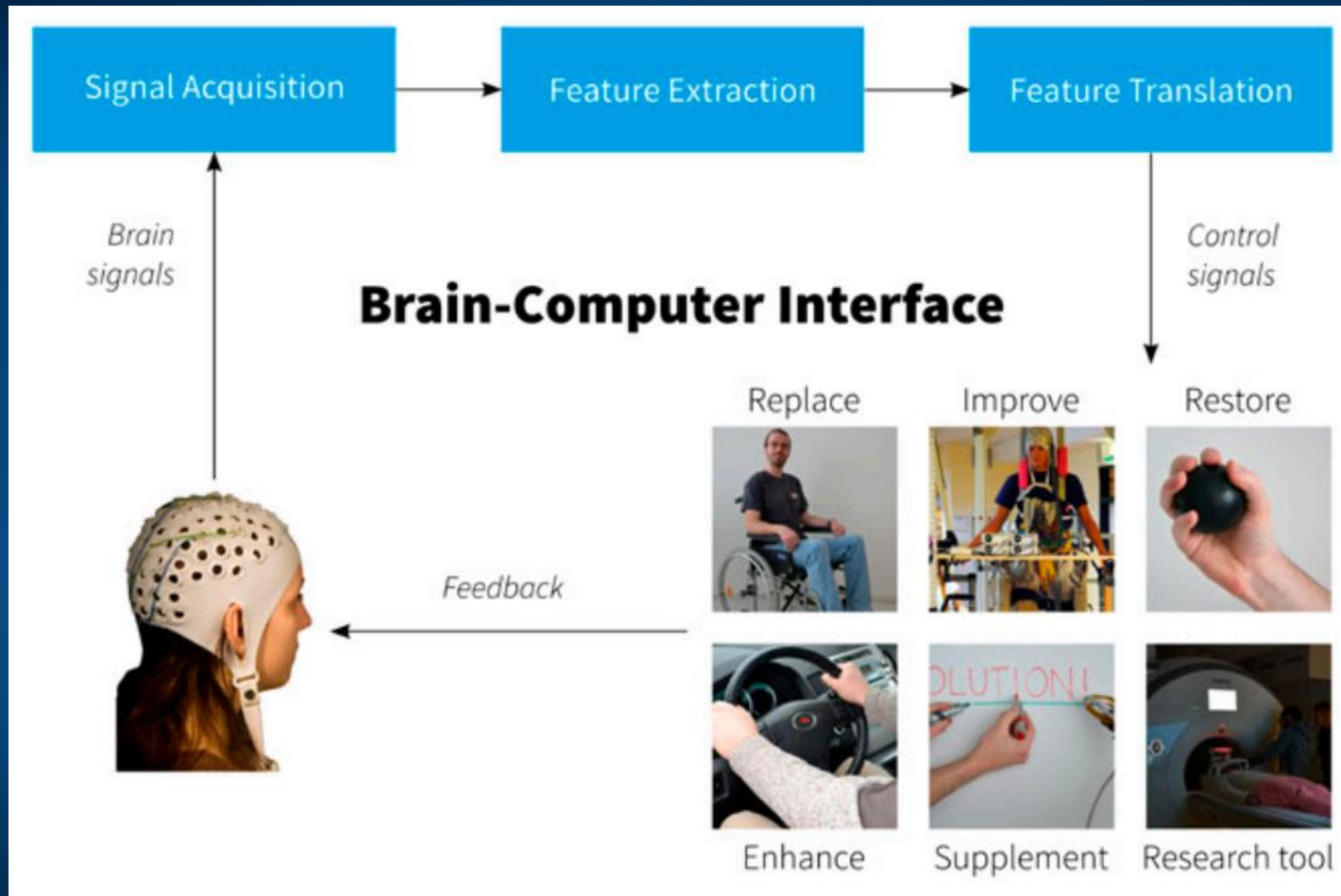
Duch, Elektronika i stresy, 1978!

Critical review of existing literature shows that this is not effective.

New forms based on brain fingerprinting needed.

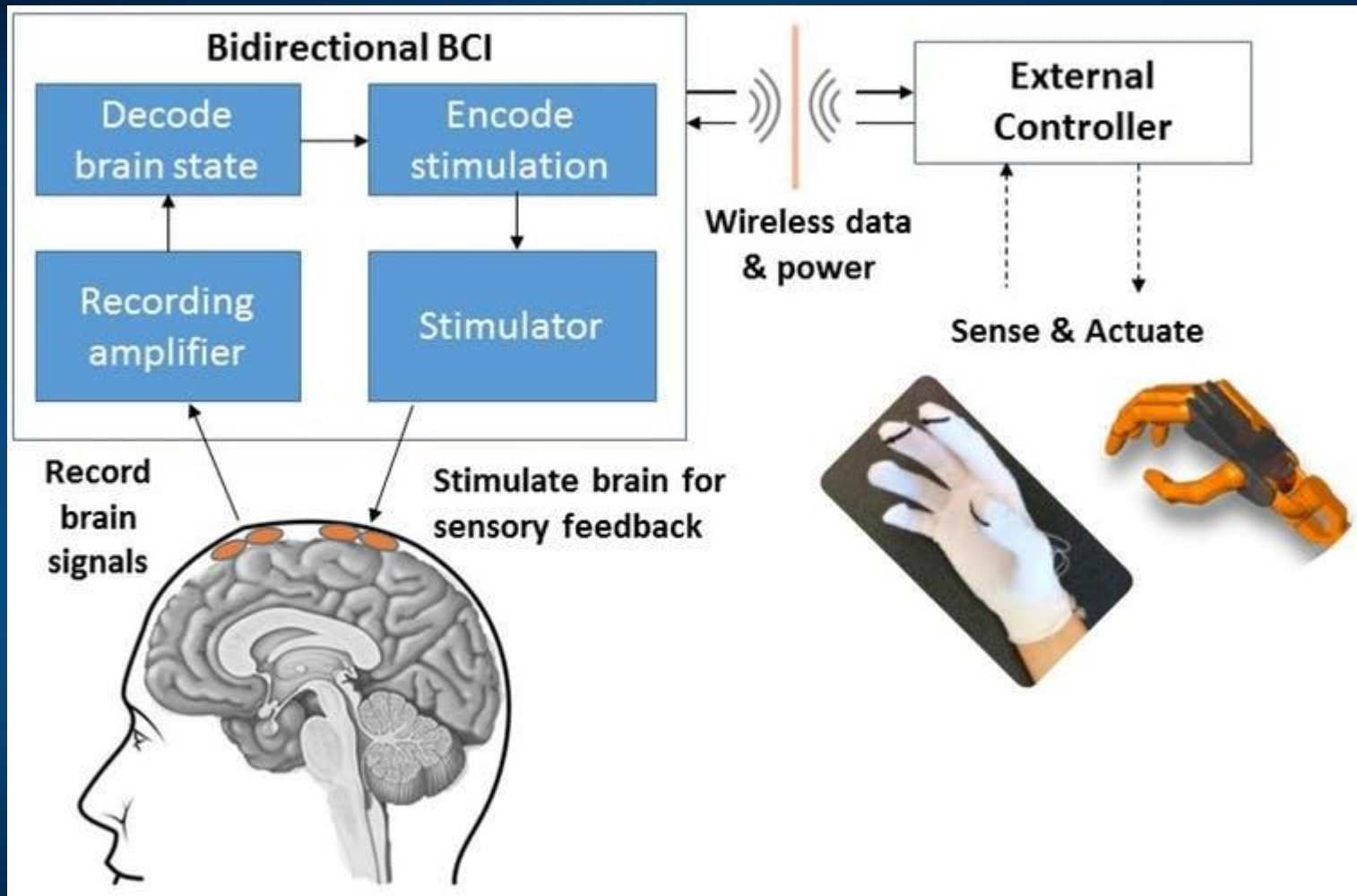


BCI Applications



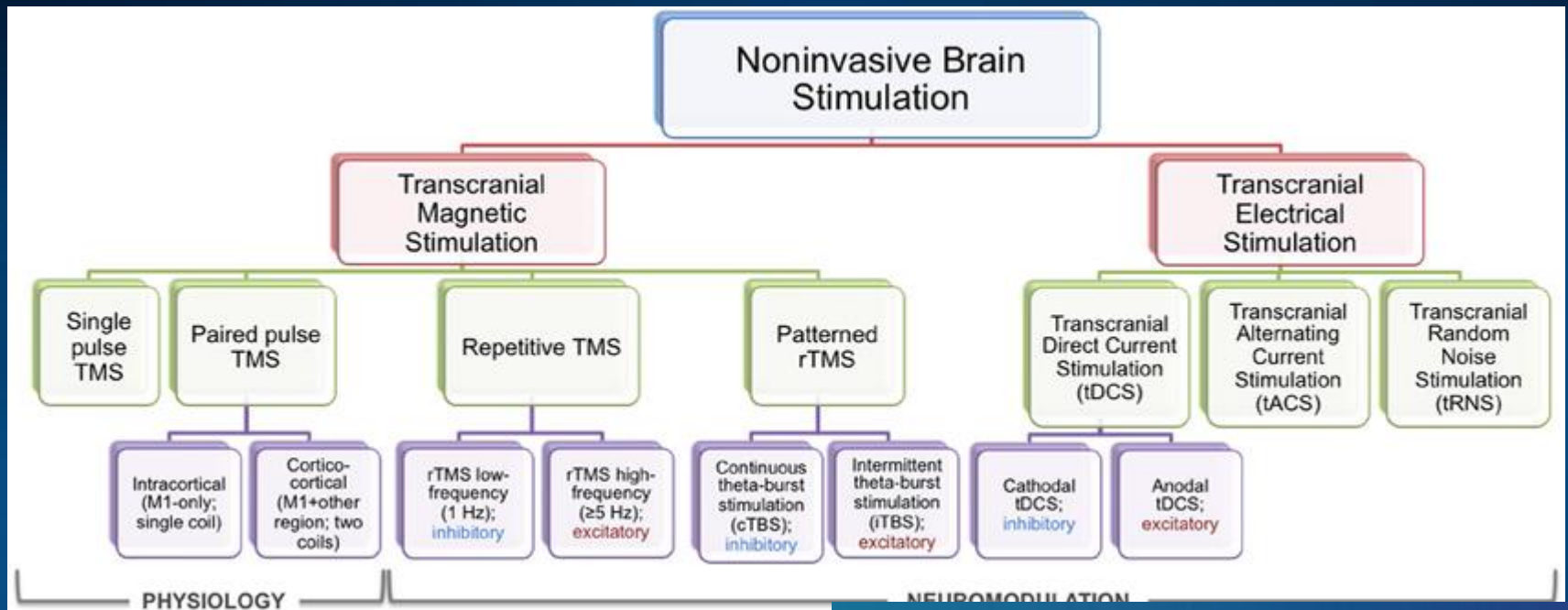
Signals: invasive (brain implants), partially invasive (ECoG), and non-invasive.

Brain-Computer-Brain Interfaces



Closed loop system with brain stimulation for self-regulation.
Body may be replaced by sensory signals in Virtual Reality.

Brain stimulation



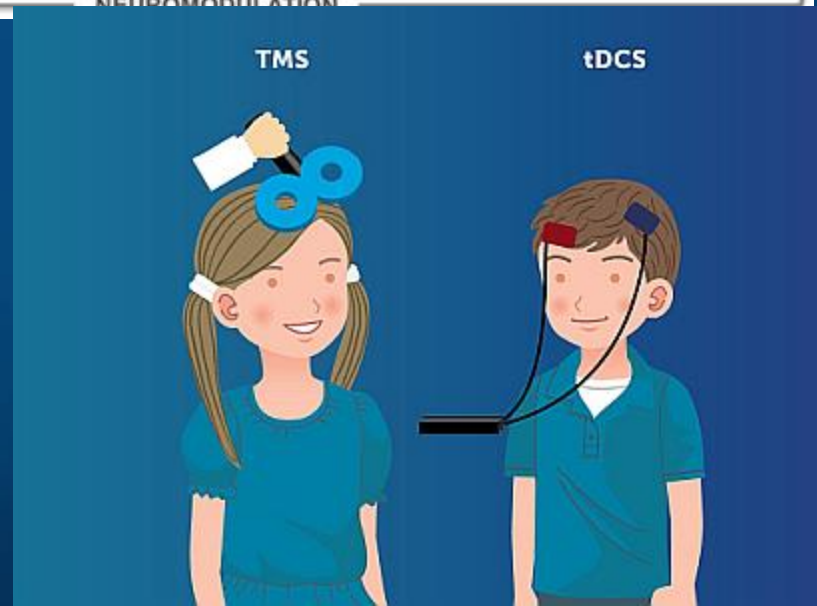
ECT – Electroconvulsive Therapy

VNS – Vagus Nerve Stimulation

Ultrasound, laser ... stimulation.

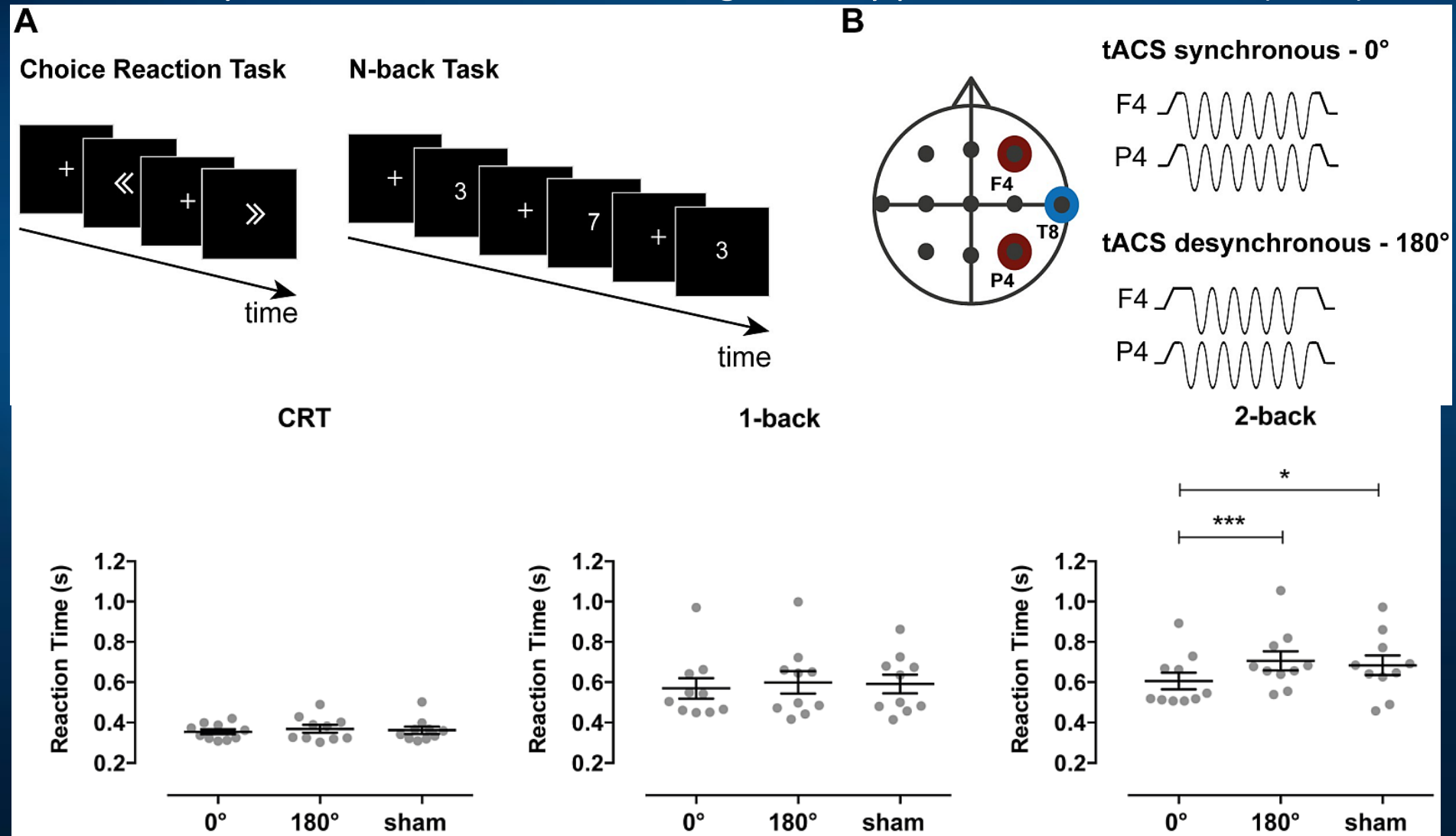
Complex techniques, but portable phones are also complex.

Attention? Just activate your cortex, no effort is needed!



Synchronize PFC/PC

Violante, I.R. et al. Externally induced frontoparietal synchronization modulates network dynamics and enhances working memory performance. *ELife*, 6 (2017).



HD EEG/DCS?

EEG electrodes + DCS.

Reading brain states

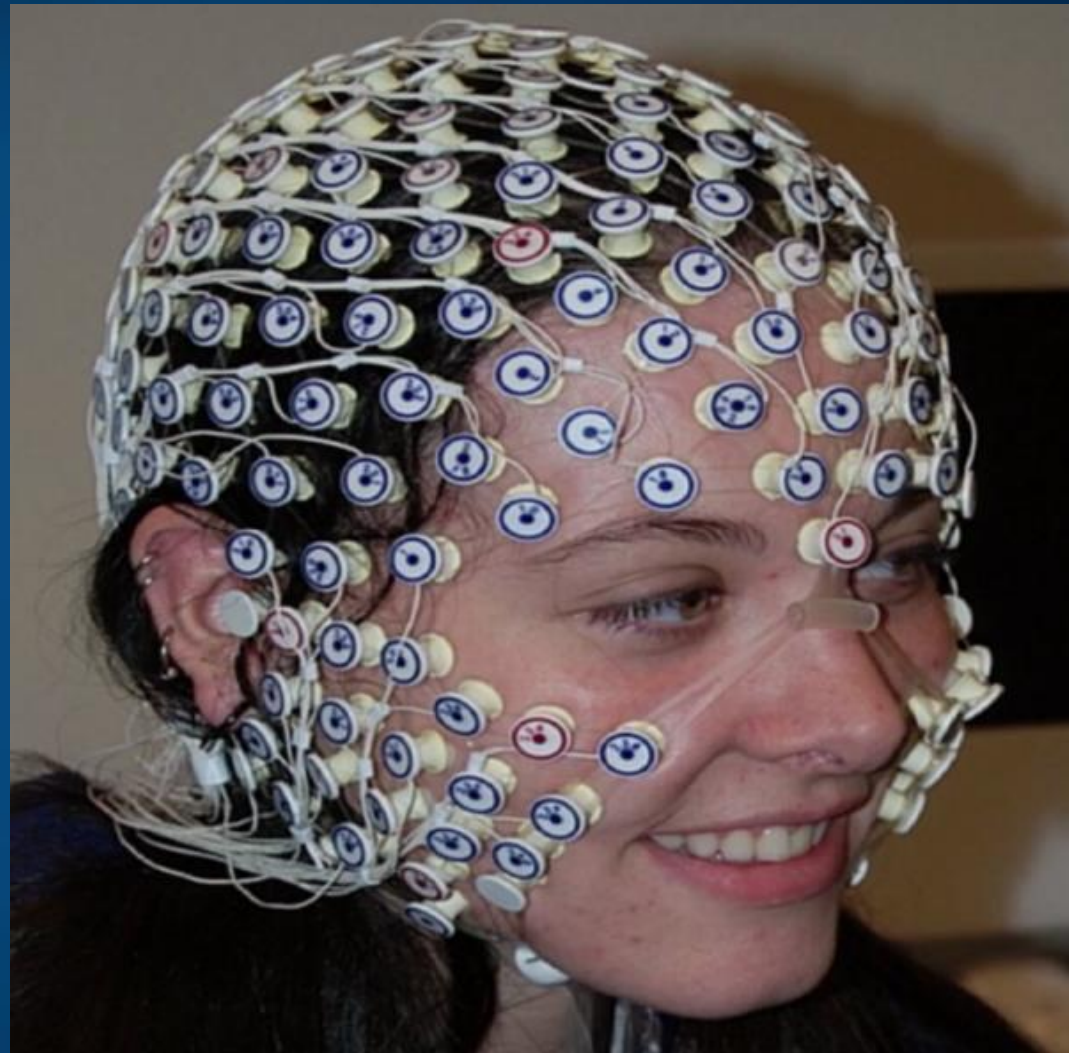
=> transforming to common space

=> duplicating in other brains

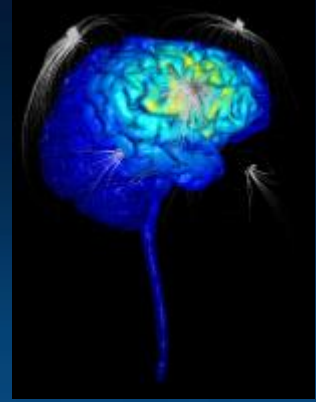
Applications:

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

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



BCBI for learning



Your brain knows better what is interesting than you do!
Information relevance inferred directly from brain signals to
model search intent.

1. Eugster et al. (2016). Natural brain-information interfaces: Recommending information by relevance inferred from human brain signals.
2. Externally induced frontoparietal synchronization modulates network dynamics and enhances working memory performance (Violante et al. 2017).
3. **Teaching skills by stimulating cortex:** microstimulation too low to evoke muscle activation, applied in premotor cortex, instructed specific actions. Mazurek & Schieber (2017). Injecting Instructions into Premotor Cortex. *Neuron*, 96(6), 1282–1289.e4.
4. Neuroimaging based assessment strategy may provide an objective means of evaluating learning outcomes in the application of **Universal Design for Learning (UDL)**, an educational framework created to guide the development of flexible learning environments that adapt to individual learning differences.

Military applications

Engagement Skills Trainer (EST) procedures are used by USA army.

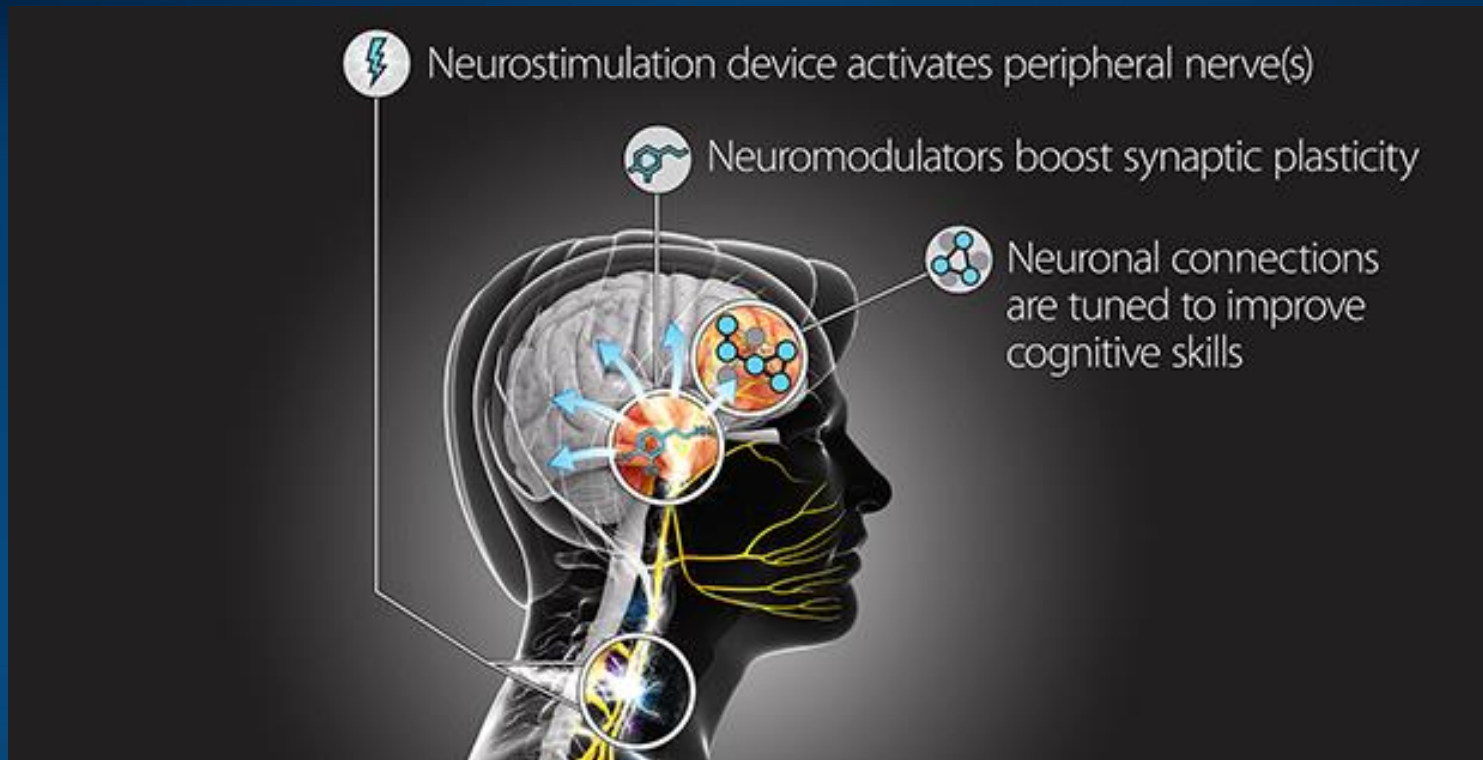
Intific Neuro-EST uses EEG analysis and multi-channel transcranial simulation (HD-DCS) to pre-activate the brain of the novice in areas where the expert brain is active.

Real-life transfer learning ...

HD-tDCS may have 100 channels, neurolace and nanowires much more.

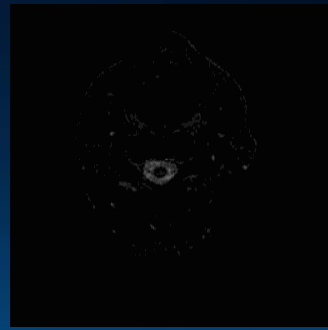


Targeted Neuroplasticity Training



DARPA (2017): Enhance learning of a wide range of cognitive skills, with a goal of reducing the cost and duration of the Defense Department's extensive training regimen, while improving outcomes. TNT could accelerate learning and reduce the time needed to train foreign language specialists, intelligence analysts, cryptographers, and others.

Conclusions



- Many brain states are now linked to specific mental states, and can be transformed into signals that we can understand: motor intentions, plans, images, inner voices ...
- Neuroimaging \Leftrightarrow models of whole brain (TVB) \Leftrightarrow networks, neurodynamics \Leftrightarrow interpretation, mental states: $S(B) \Leftrightarrow S(M)$.
- Neurodynamics is the key to understanding mental states; it creates dynamical forms, changing states of functional connectomes without rearranging physical elements. Influence of other phenomics levels on mental states may be understood indirectly, via changes in neurodynamics.
- AI/ML draws inspirations from brain research, but also neural network models and learning algorithms (CNN, recurrence networks, reinforcement learning) help to interpret information processing in the brain.
- Many neurocognitive technologies are coming, helping to diagnose, repair and optimize brain processes.

My group of neuro-cog-fanatics



Soul or brain: what makes us human?
Interdisciplinary Workshop with theologians,
Toruń 19-21.10.2016



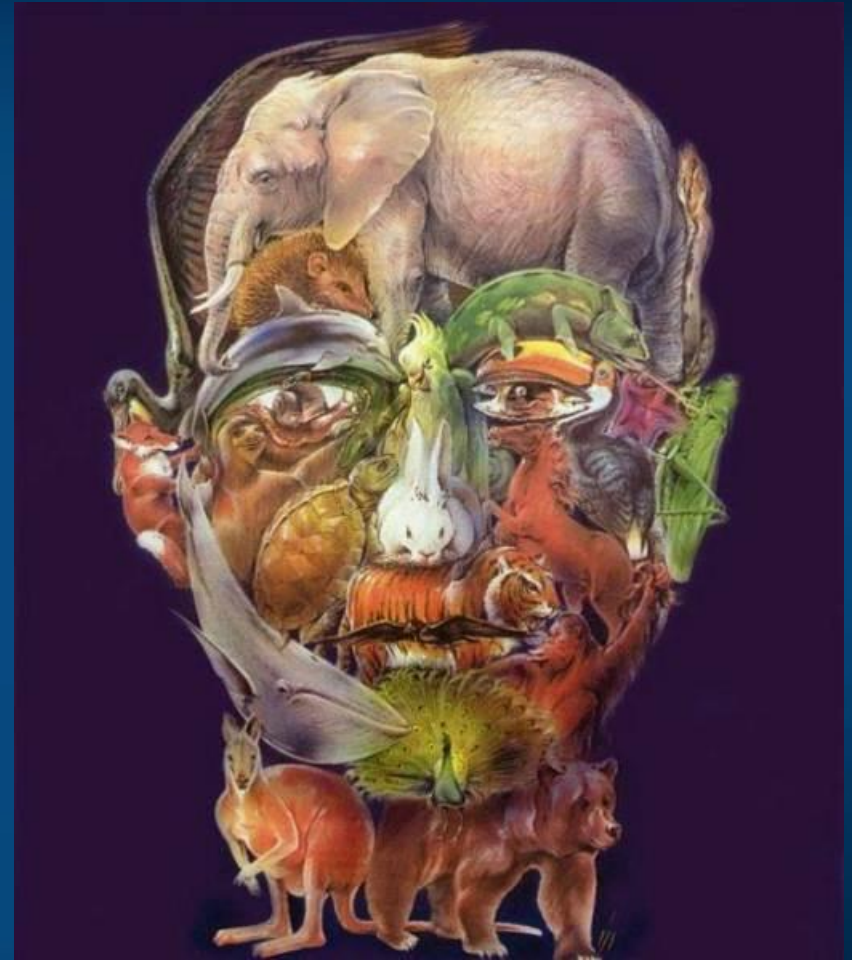
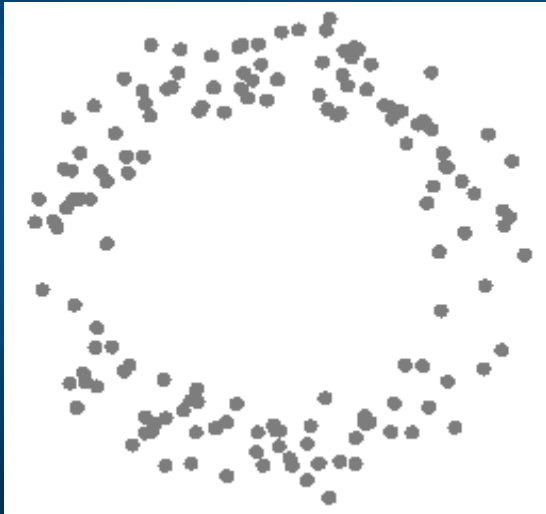
Monthly international
developmental seminars
(2017): Infants, learning,
and cognitive development

Disorders of consciousness
17-21.09.2017

Autism: science, therapies
23.05.2017



Thank you for
synchronization
of your neurons



Google: W. Duch
=> talks, papers, lectures, Flipboard ...

