# Neurocognitive informatics for understanding brain functions

Włodzisław Duch

Neurocognitive Laboratory,
Center for Modern Interdisciplinary Technologies,
Dept. of Informatics, Faculty of Physics, Astronomy & Informatics,
Nicolaus Copernicus University

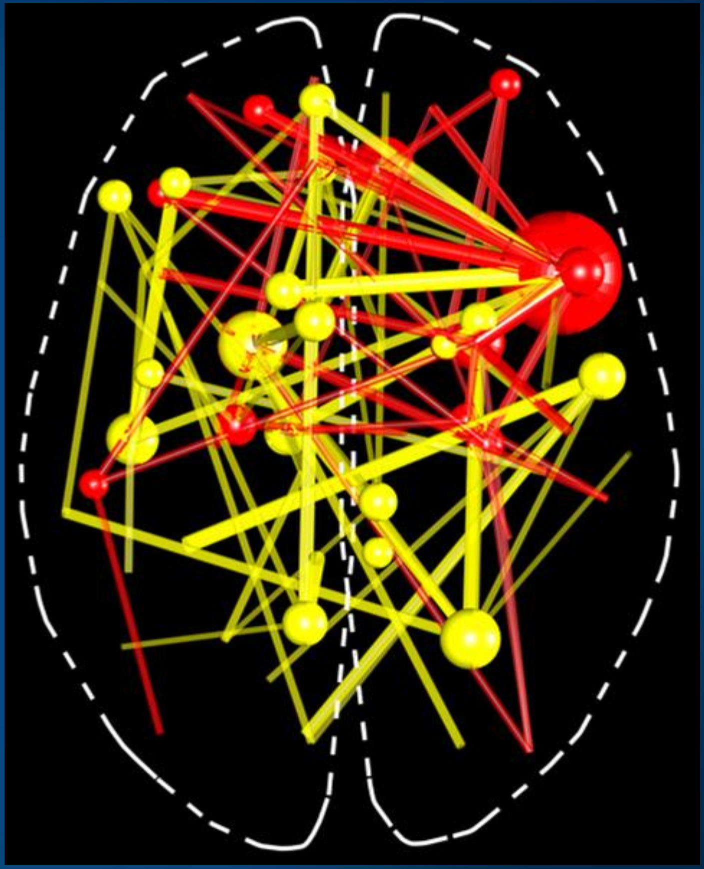
Google: W. Duch

**FedCSIS 2018, 9-12.09, Poznań**

# On the threshold of a dream …

**How can we find fingerprints of specific activity of brain structures (regions, networks)?**

- AI and mind/brain theory.
- Brain ⇔ 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, *Neurocognitive Informatics Manifesto*. In: Series of Information and Management Sciences, California Polytechnic State Univ. 2009.

# AI and abstract models of mind/brain

# AI in Europe

**Communication From The European Commission,** Brussels, 25.4.2018
**Artificial Intelligence for Europe.**

"Like the steam engine or electricity in the past, AI is transforming our world, our society and our industry. AI is one of the most strategic technologies of the 21st century. The stakes could not be higher. The way we approach AI will define the world we live in."

In the period 2014-2017 around 1.1 B€ has been invested in AI-related research and innovation under the Horizon 2020, in big data, health, rehabilitation, transport and space-oriented research. Investments in neuromorphic chips, high-performance computers, flagship projects on quantum technologies and mapping of the human brain are also important.

Public and private EU sectors should aim to invest at least 20 B€ by the end of 2020 and more than EUR 20 billion per year over the following decade.
**Pan-European network of AI excellence centers will be created.**

Is it really AI revolution? Or NN, CI, ML, pattern recognition, signal processing …

# 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.

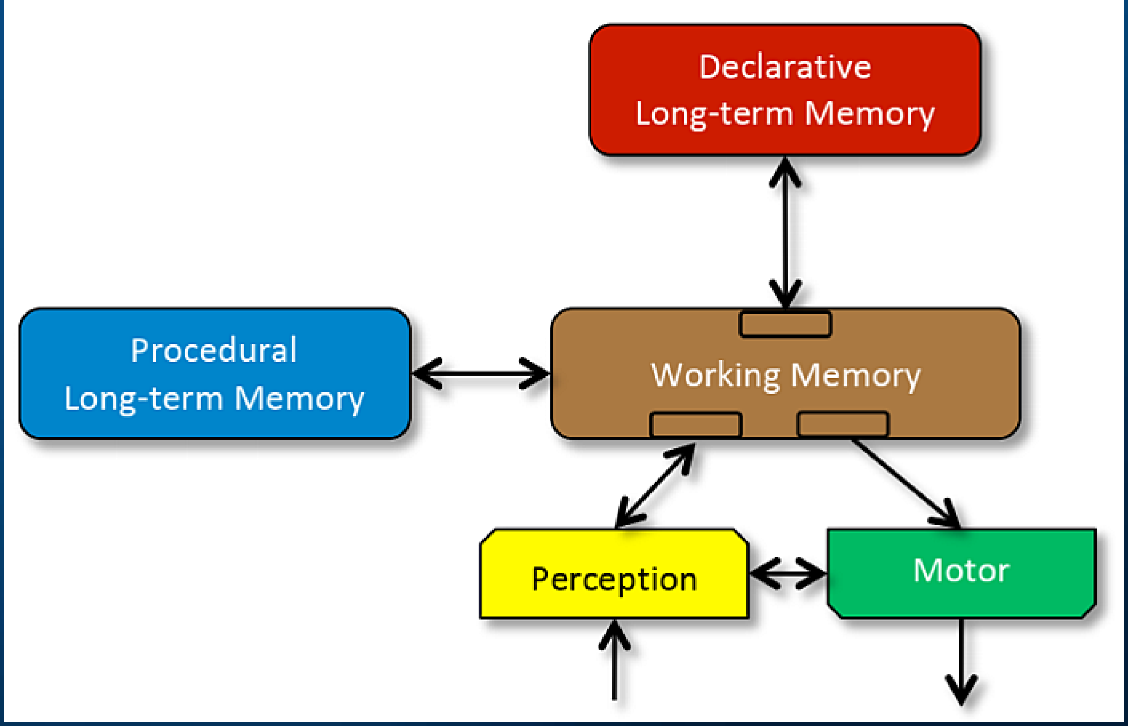
Laird: A mind is a functional entity that can think.

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



# Unified theories of brain functions

**Physics**: principle of least action => laws of mechanics: Newtonian, Lagrangian, Hamiltonian, and general relativity (Hilbert) equations of motion.

**Artificial Intelligence**: search in problem spaces (Newell, Simon).

**Cognitive systems**: minimization of surprise or prediction errors, active inference, self-organization to minimize surprise (sensory), ensure homeostasis, select a limited number of internal action states.

**Mathematical formulation** is based on variational Bayesian methods.

Behavior = F(Brain State, Sensations).

Brain State depends on stimuli $s$ and latent internal parameters $\upsilon$ of the model (agent) $m$ while surprise is measured by entropy:

$$\mathcal{H} = \int_0^T dt\mathcal{L}(m,s,t) = -\int \ln p\big(s(t) \,|\, m\big(\vartheta(t)\big)\big) d\vartheta$$

$$= -\int p(\vartheta \,|\, m) \ln p(\vartheta \,|\, m) d\vartheta$$

# Free energy

We do not know the latent parameters $\upsilon$ of the model, but may estimate free energy to find the upper bound:

$$\mathcal{F}(t) \geq \mathcal{L}(t)$$

**Free energy principle (Friston:** an information theory measure *F* that bounds from above the surprise on sampling some data, given a generative model.

Adaptive systems (animals, brains) resist a natural tendency to disorder. Perception optimizes predictions. Action minimizes prediction errors.

The free-energy principle (FEP): any self-organizing system that is at equilibrium with its environment must minimize its free energy.

Maximum a posteriori estimation (MAP estimation) <= EM (expectation-maximization) algorithm extension from single most probable value of hidden parameters to fully Bayesian estimation of an approximation to the entire posterior distribution $p(\upsilon|s)$ of the parameters and latent variables.

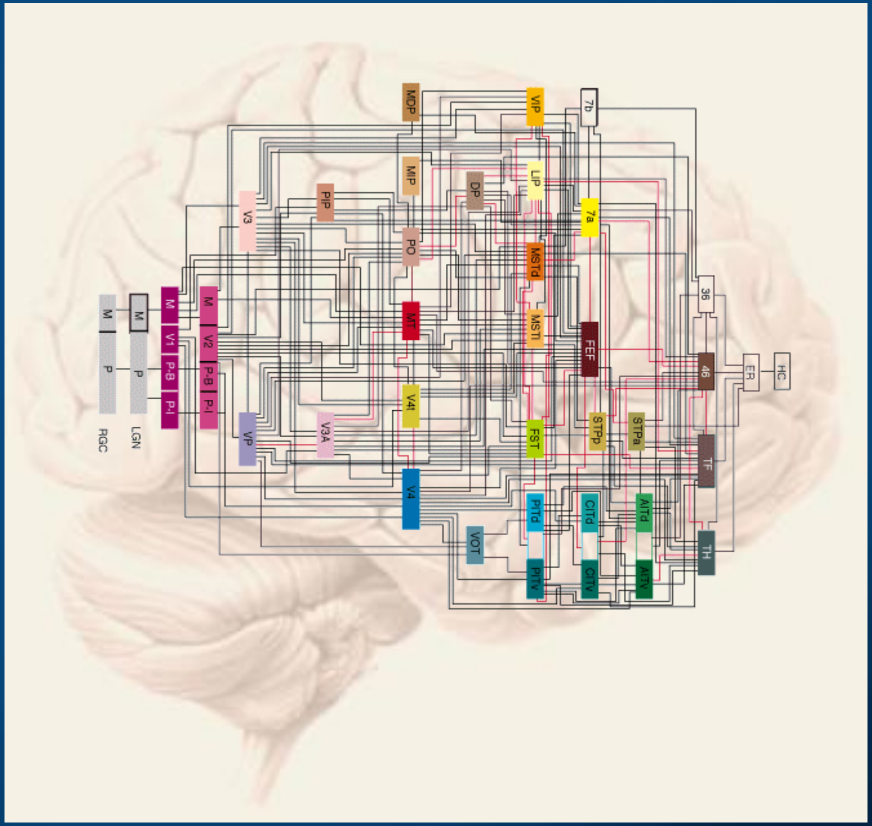
# Free energy

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?

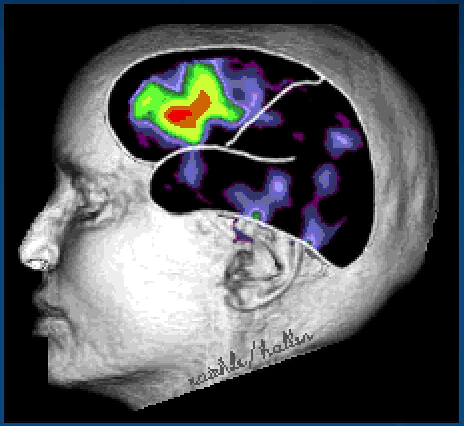


# Brains ⇔ Minds

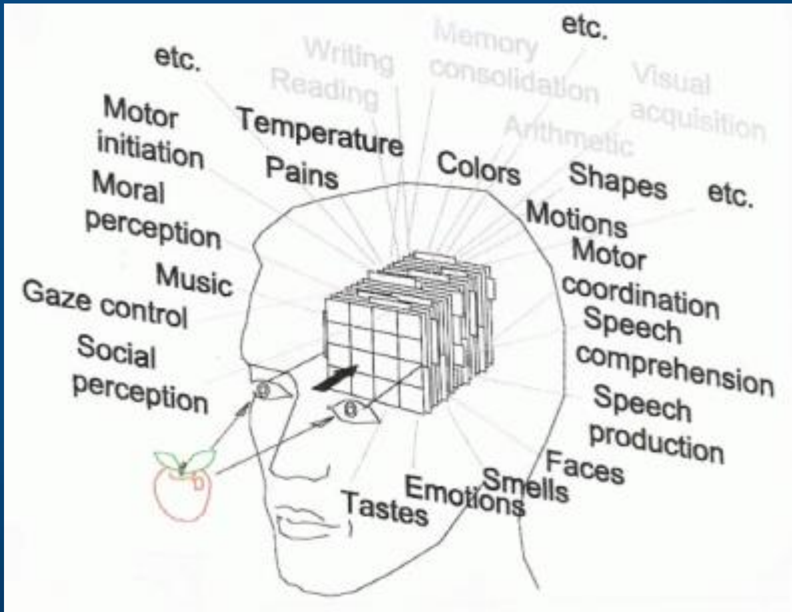
Define mapping S(M)⇔S(B), as in BCI.
How do we describe the state of mind?

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.

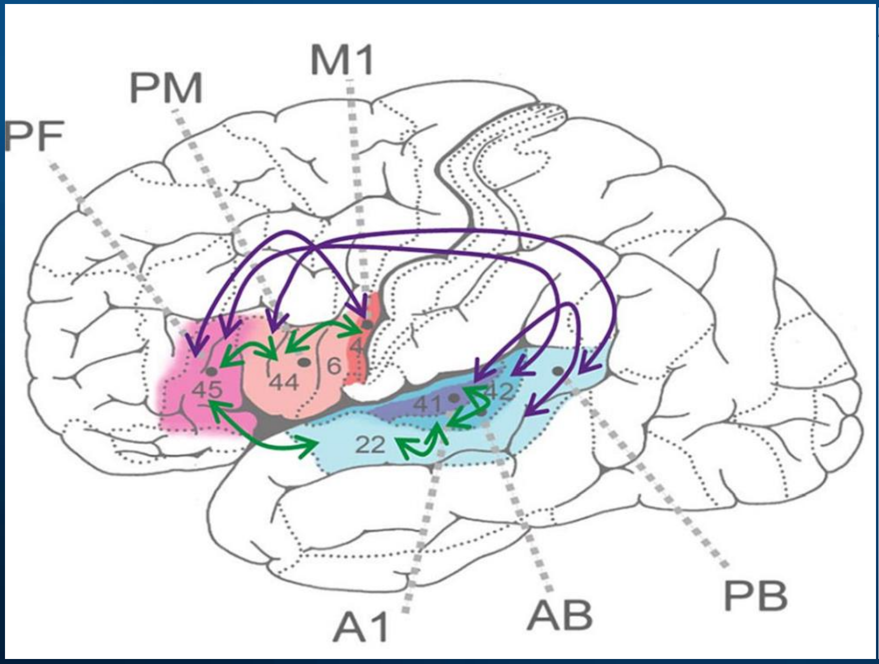
# Brain networks:
# space for neurodynamics

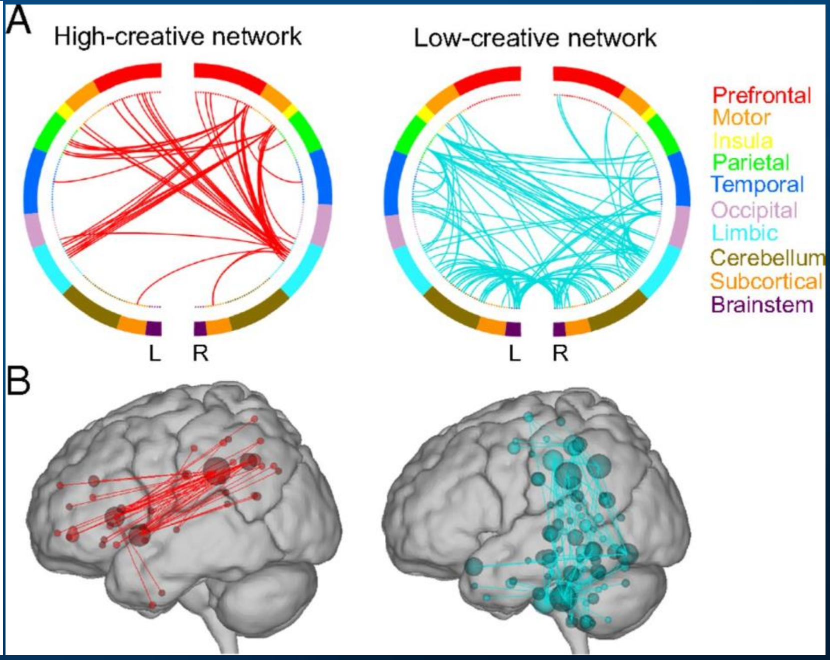
# Fluid nature

Development of brain in infancy: first learning how to move, sensorimotor activity organizes brain network processes.

The Developing Human Connectome Project: create a dynamic map of human brain connectivity from 20 to 44 weeks post-conceptional age, which will link together imaging, clinical, behavioral, and genetic information.

Pointing, gestures, pre-linguistic (our BabyLab).



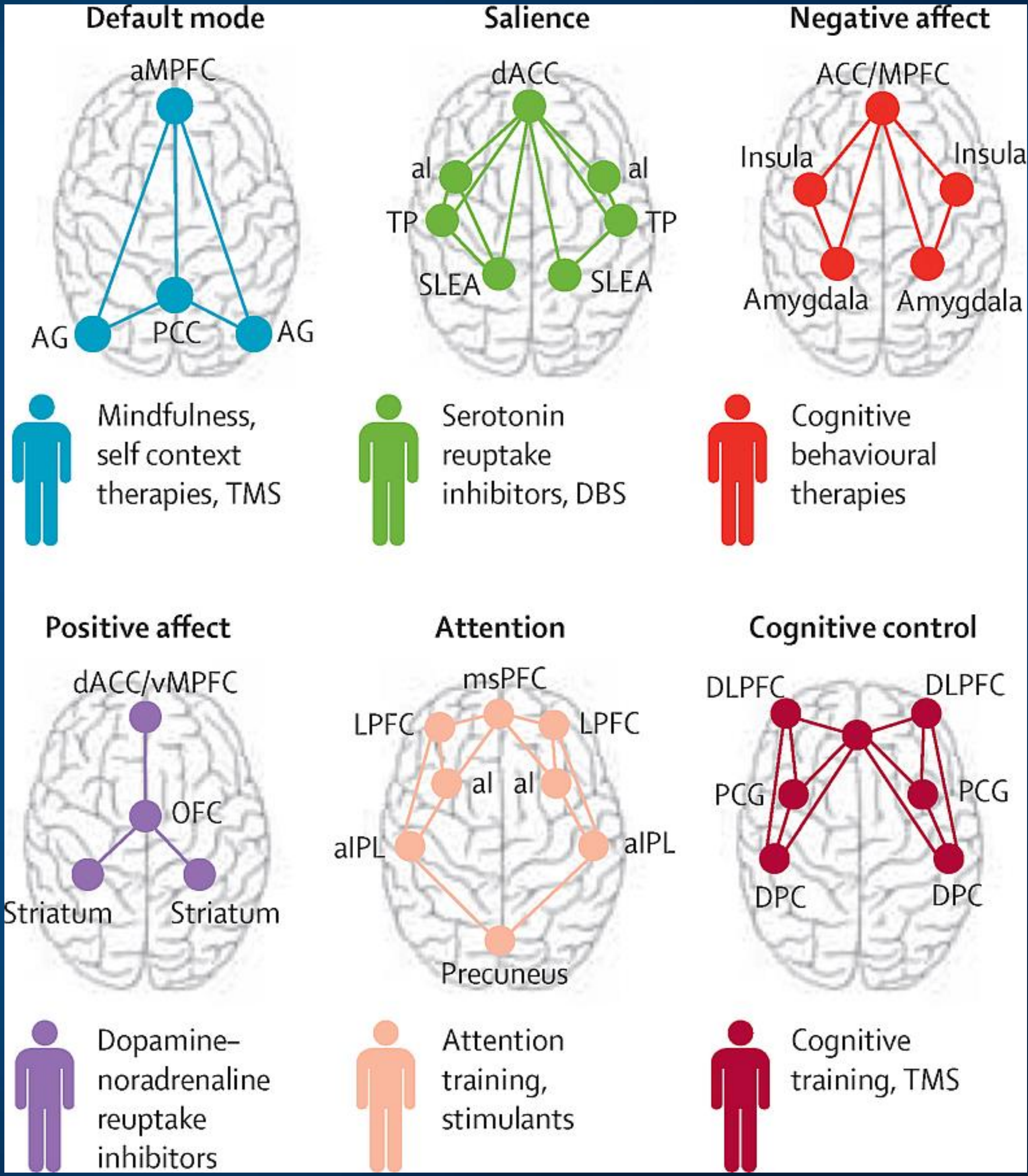



# Multi-level phenomics

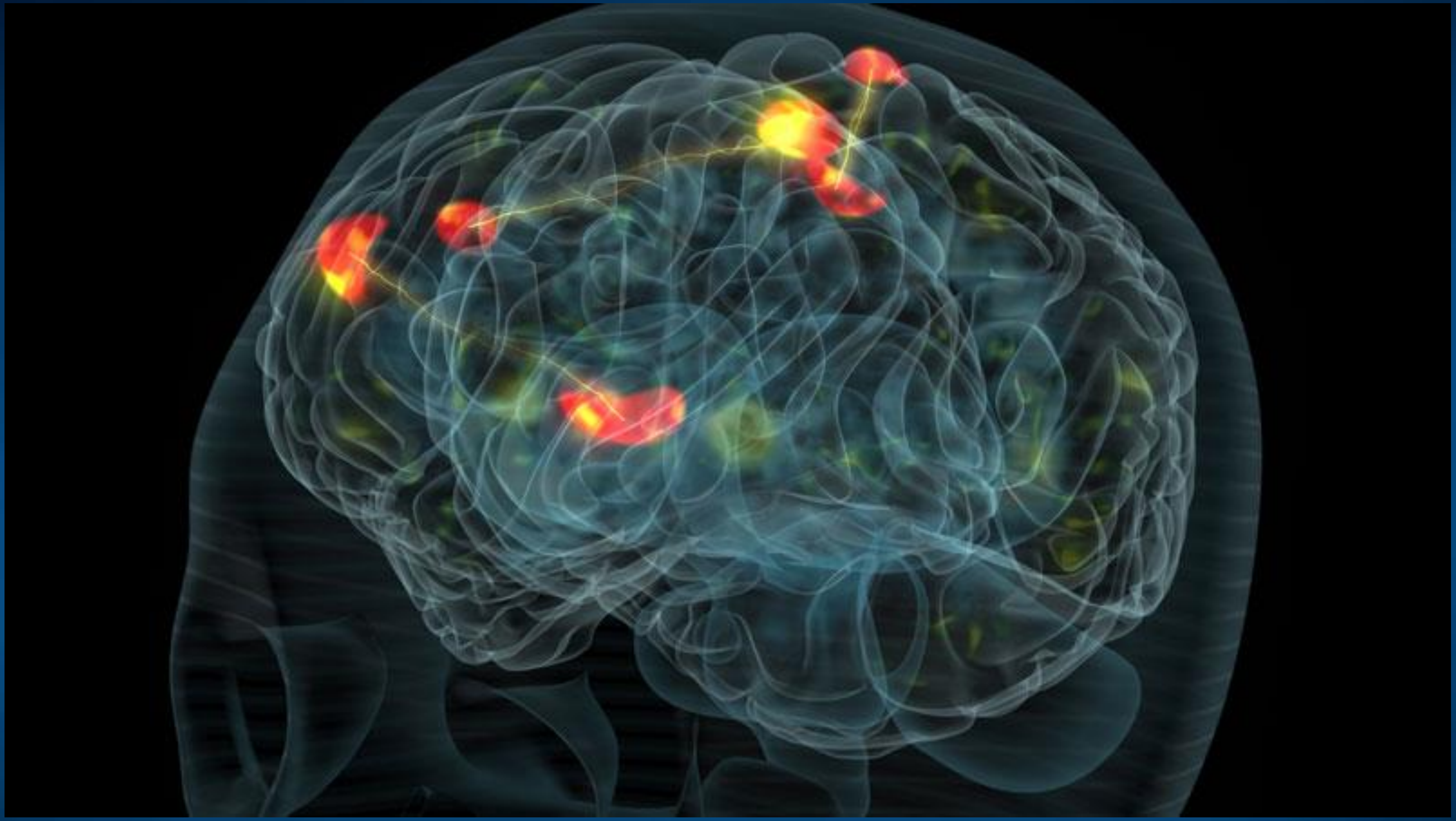
Instead of classification of mental disease by symptoms use **Research Domain Criteria** (RDoC) matrix based on **multi-level neuropsychiatric phenomics** describing large brain systems deregulation.

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.



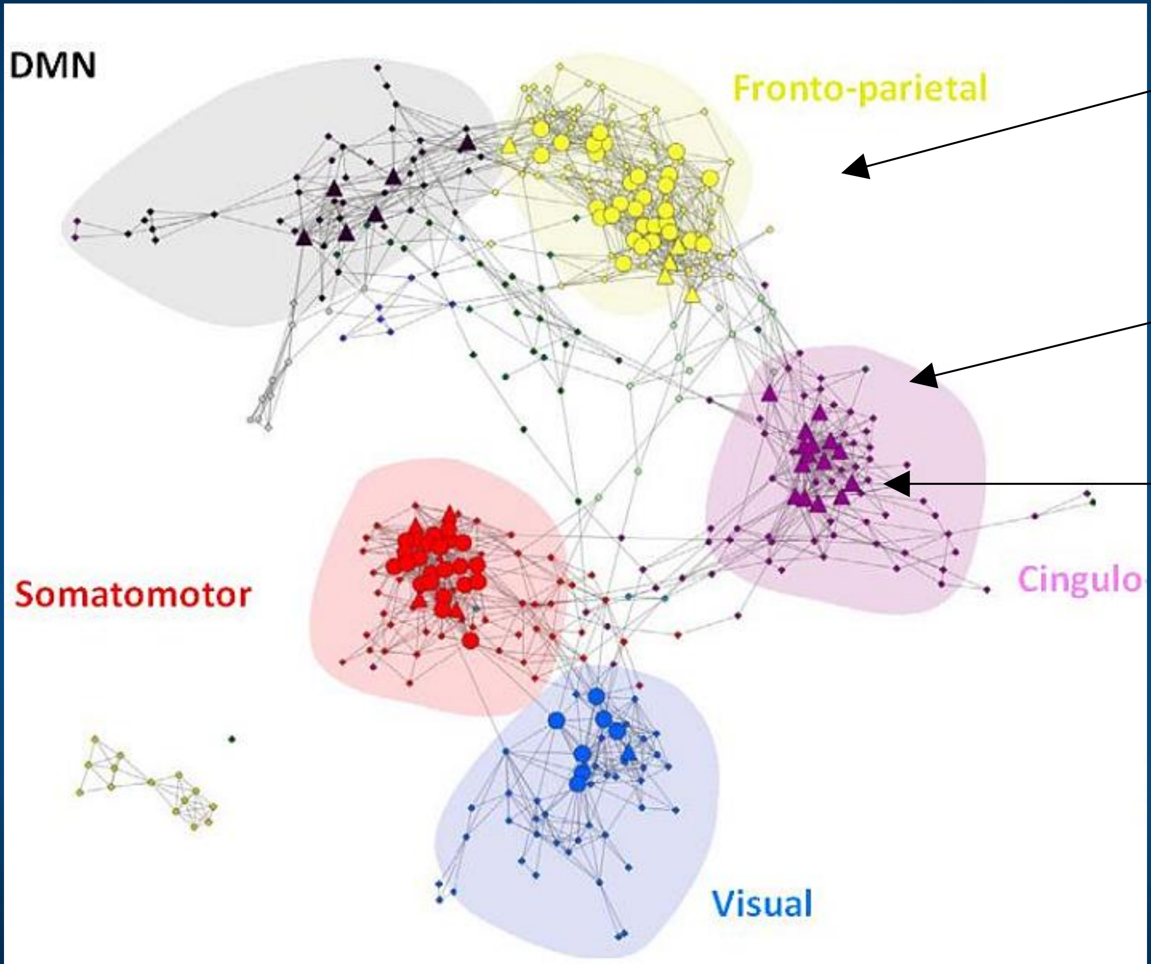
# Mental state: strong coherent activation



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.

# Brain networks: canvas for the mind




ROI=brain Regions of Interest

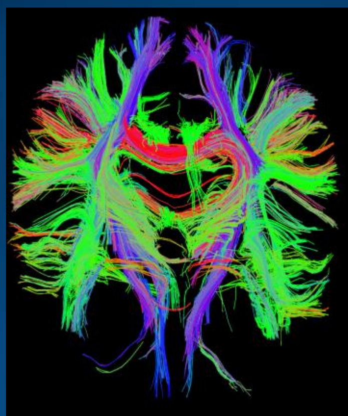
Connections

Nodes

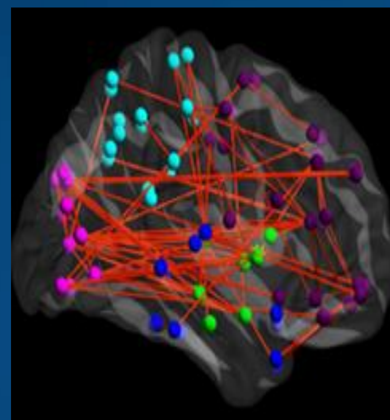
Bassett DS, Sporns O: Network neuroscience. Nature Neuroscience 2017

# Human connectome and MRI/fMRI

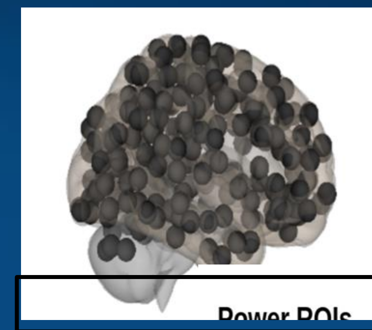
Structural connectivity



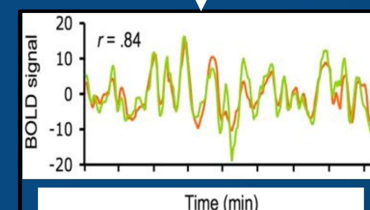
Functional connectivity



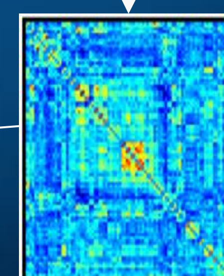
Node definition (parcelation)




Signal extraction



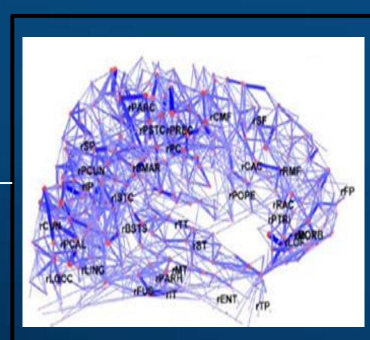

Correlation calculation



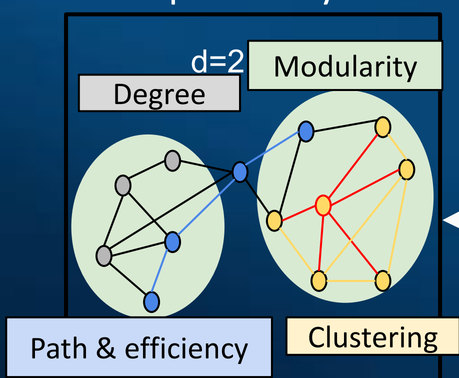
Correlation matrix

Binary matrix

Whole-brain graph



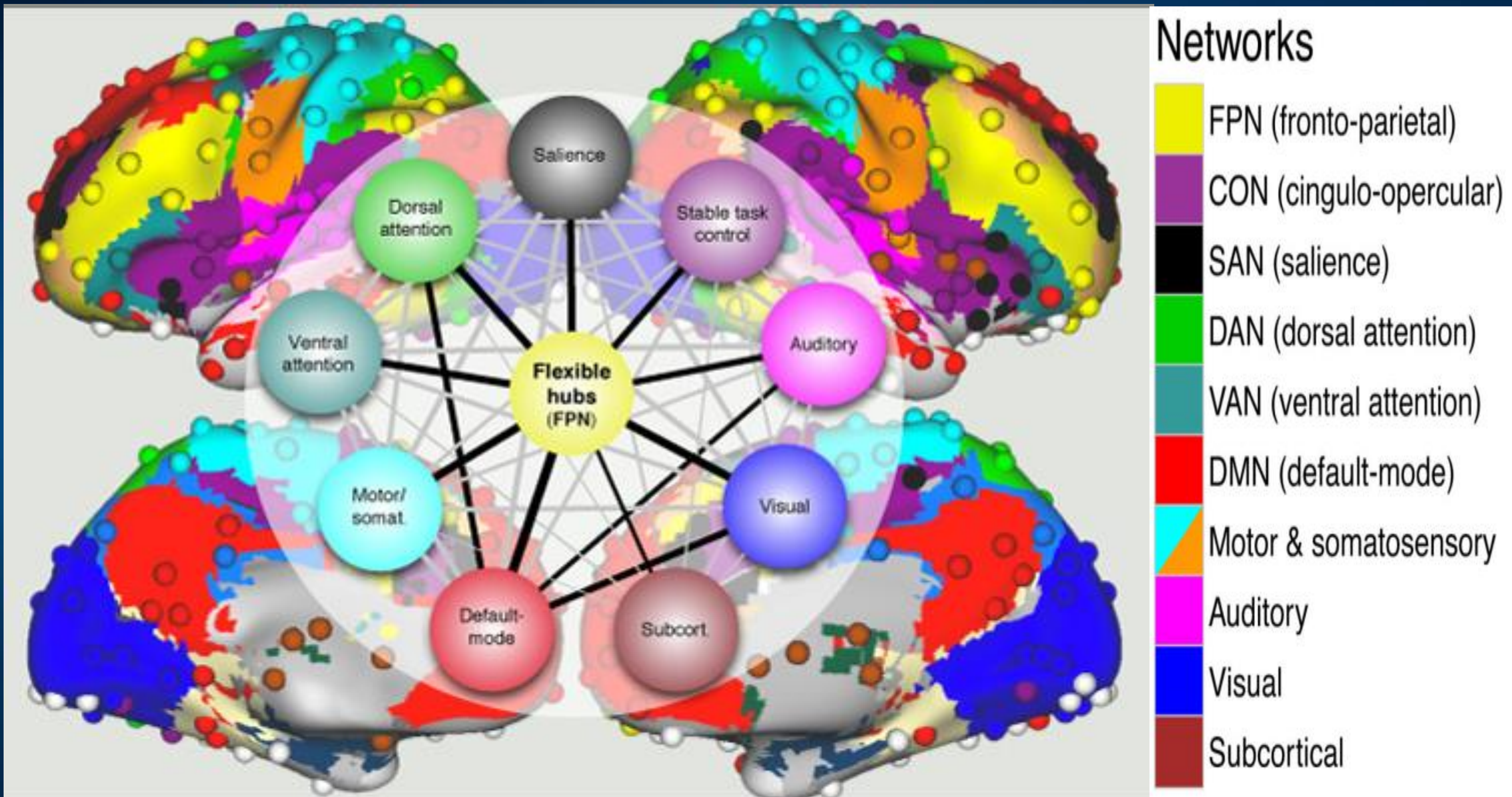
Graph theory




Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

# 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).

# In search of the sources of brain's cognitive activity

## Project „Symfonia”, 2016-21

FACULTY OF PHYSICS, ASTRONOMY AND INFORMATICS

CENTRE FOR MODERN INTERDISCIPLINARY TECHNOLOGIES

INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

nencki institute of experimental biology

# My group of neuro-cog-fanatics

# CMIT: scanner GE Discovery MR750 3T

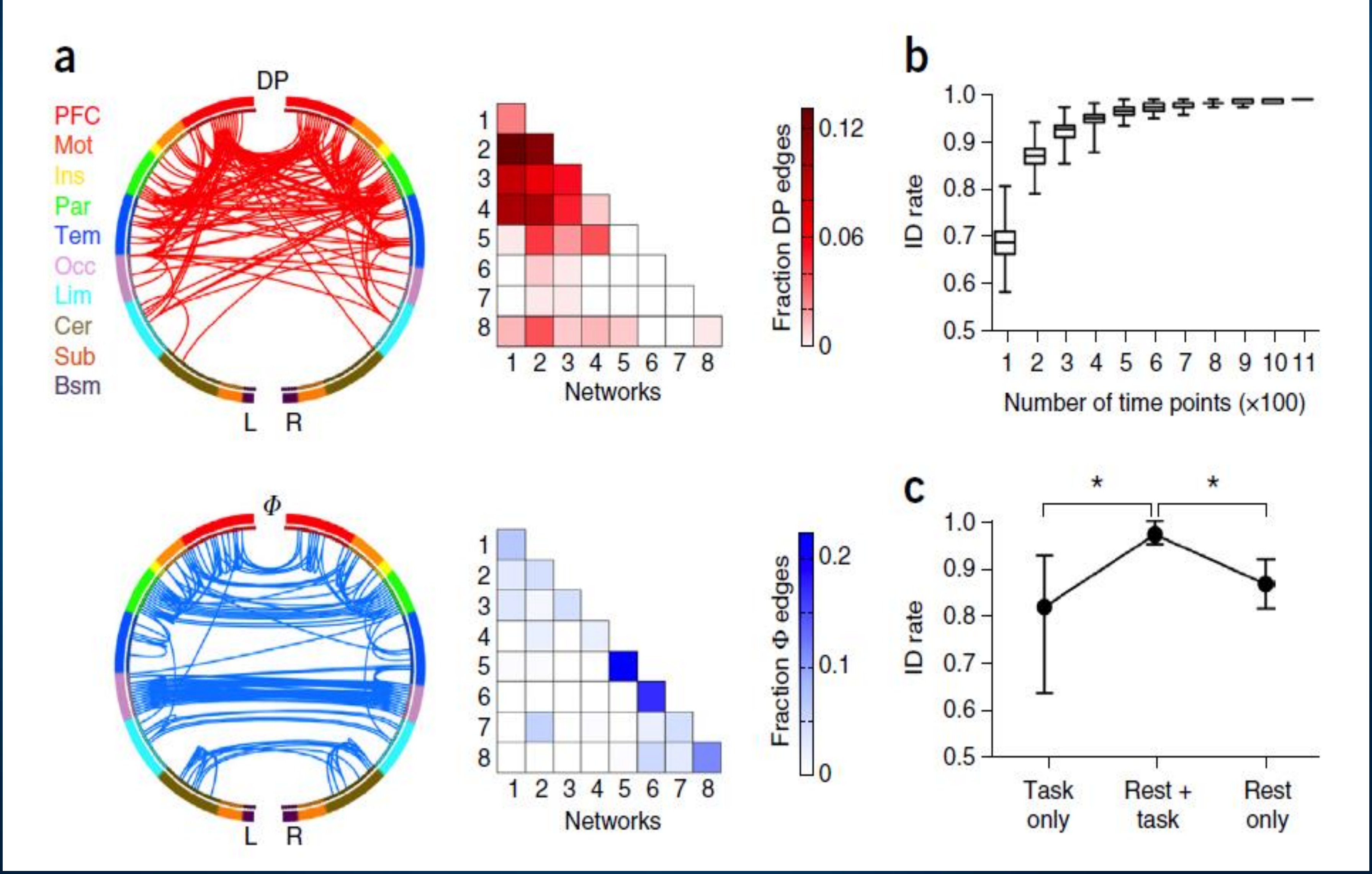
# Possible form of Brain Fingerprints

**fMRI**: BFP is based on **V(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(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.

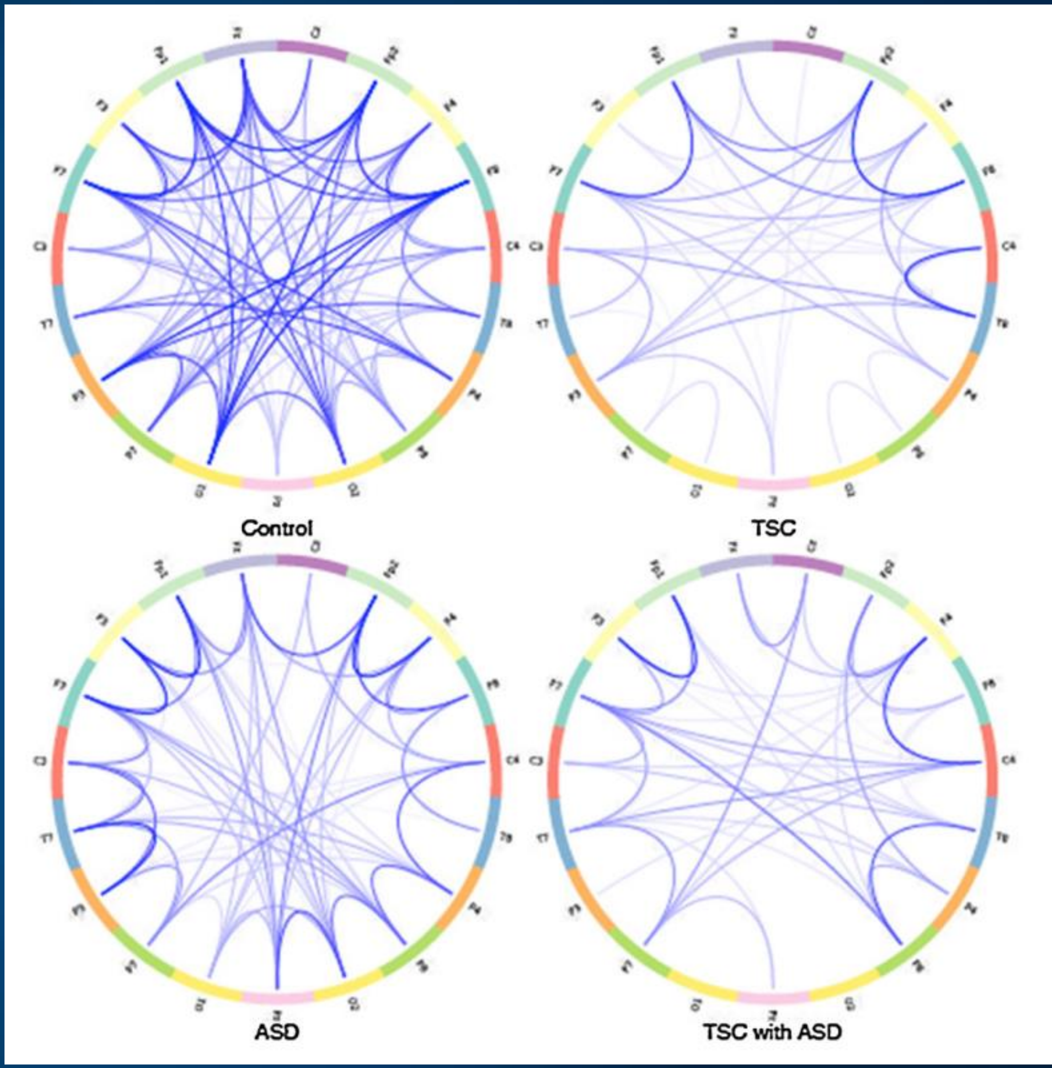


# ASD: pathological connections

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

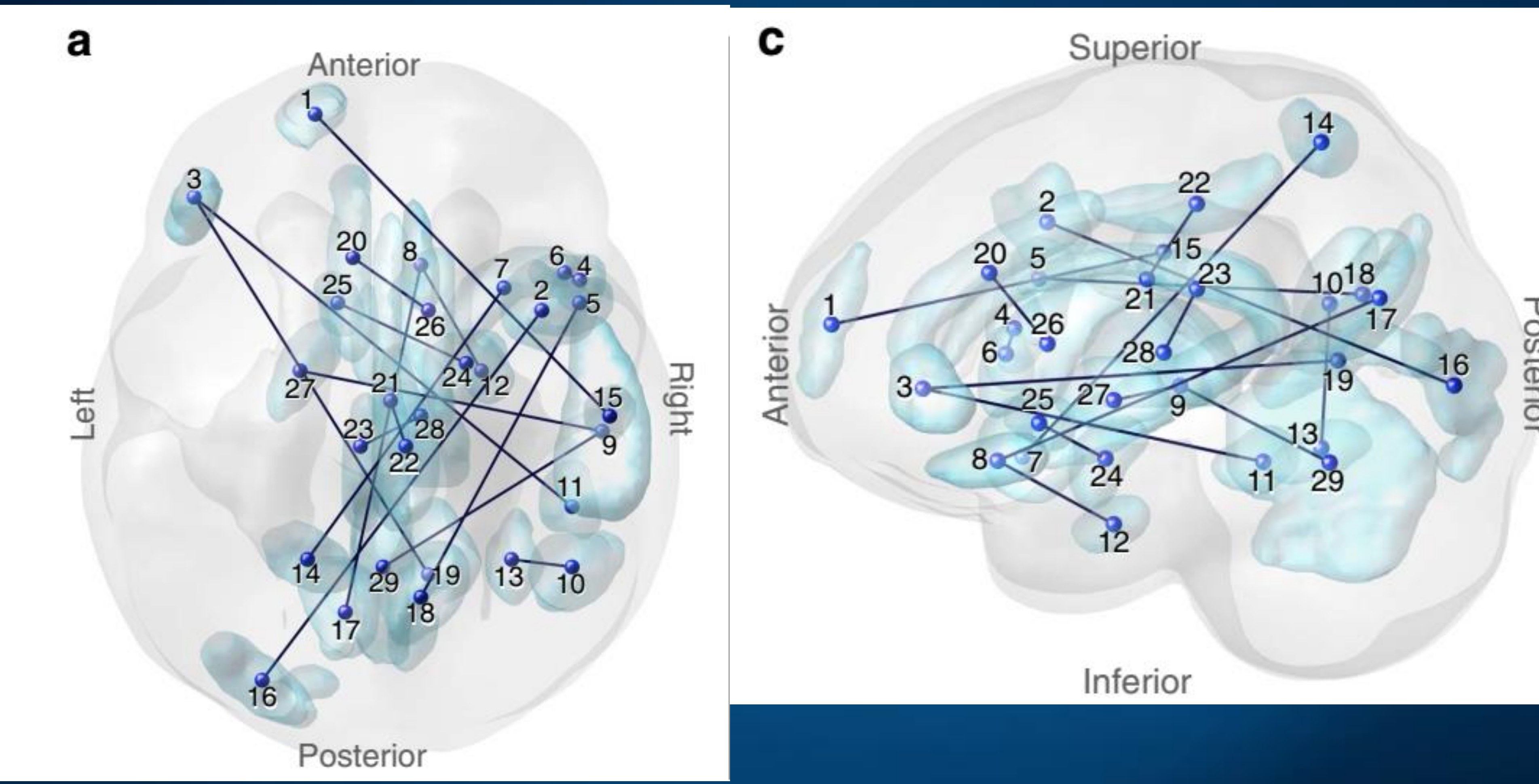
Coherence between electrodes. Weak or missing connections between distant  regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

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

# 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.

# Model of reading & dyslexia

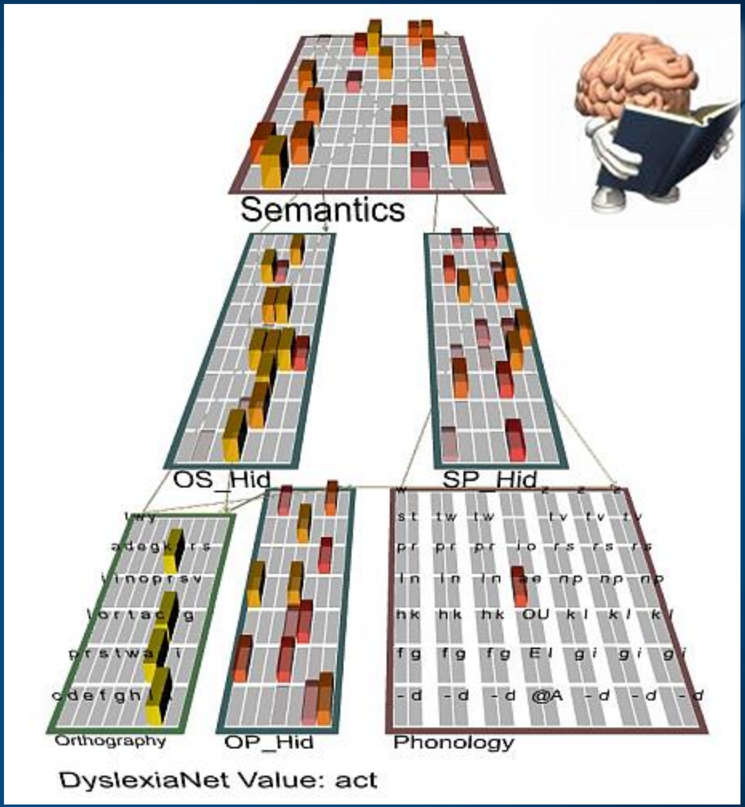
Emergent neural simulator:

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.

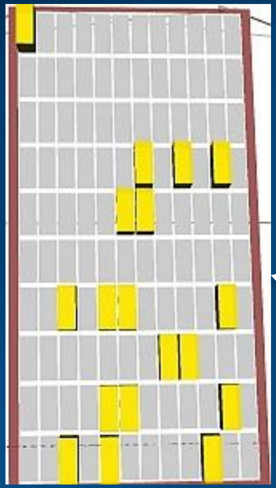


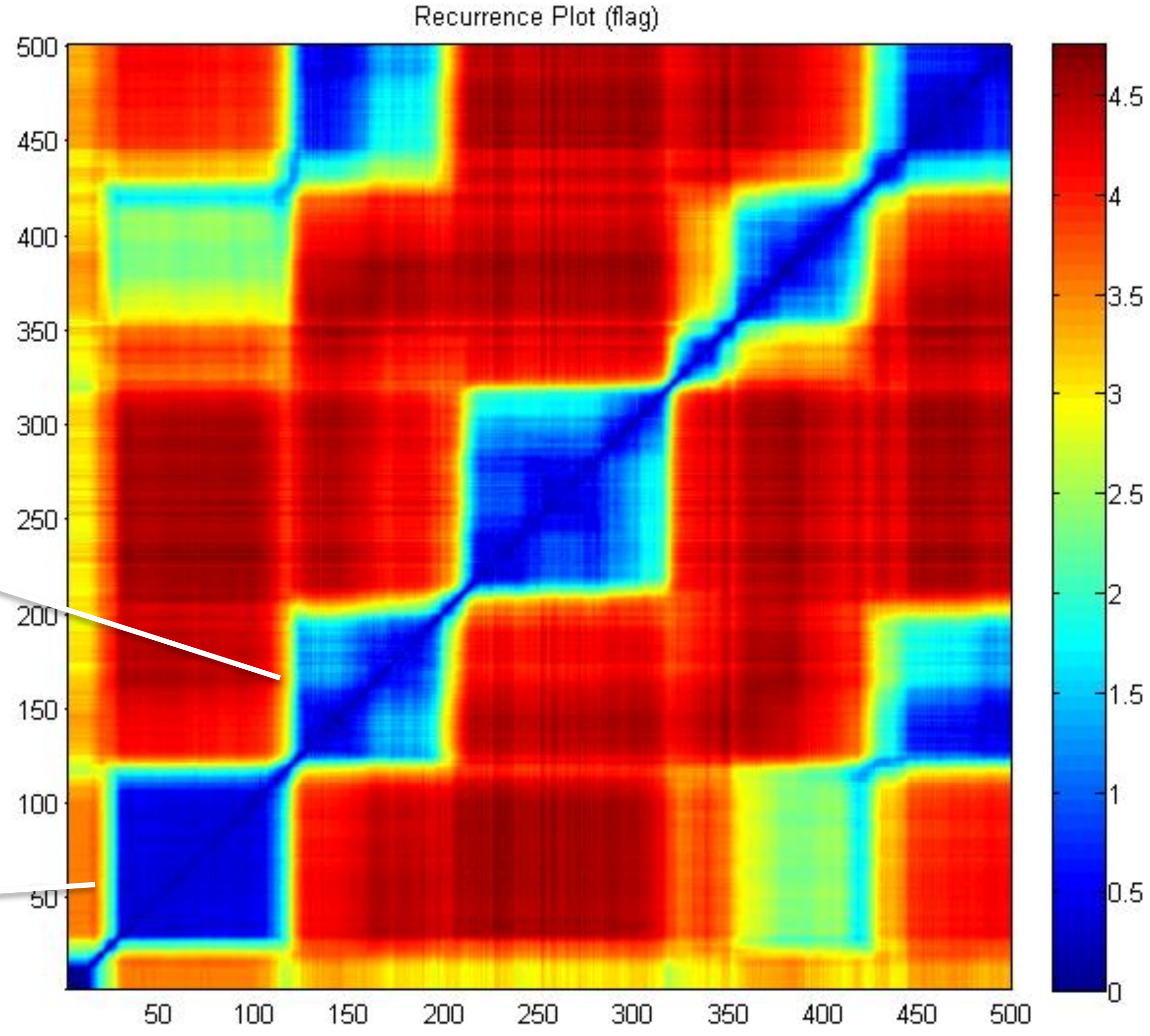

Learning: mapping one of the 3 layers to the other two.

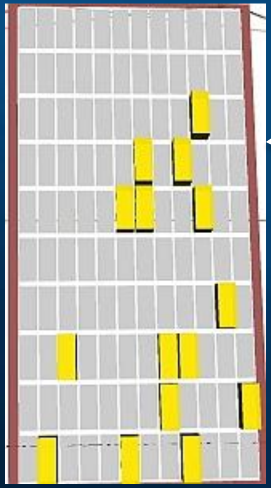
Fluctuations around final configuration = attractors representing concepts.

How to see properties of their basins, their relations?
Model in **Genesis**: more detailed neuron description.

rope



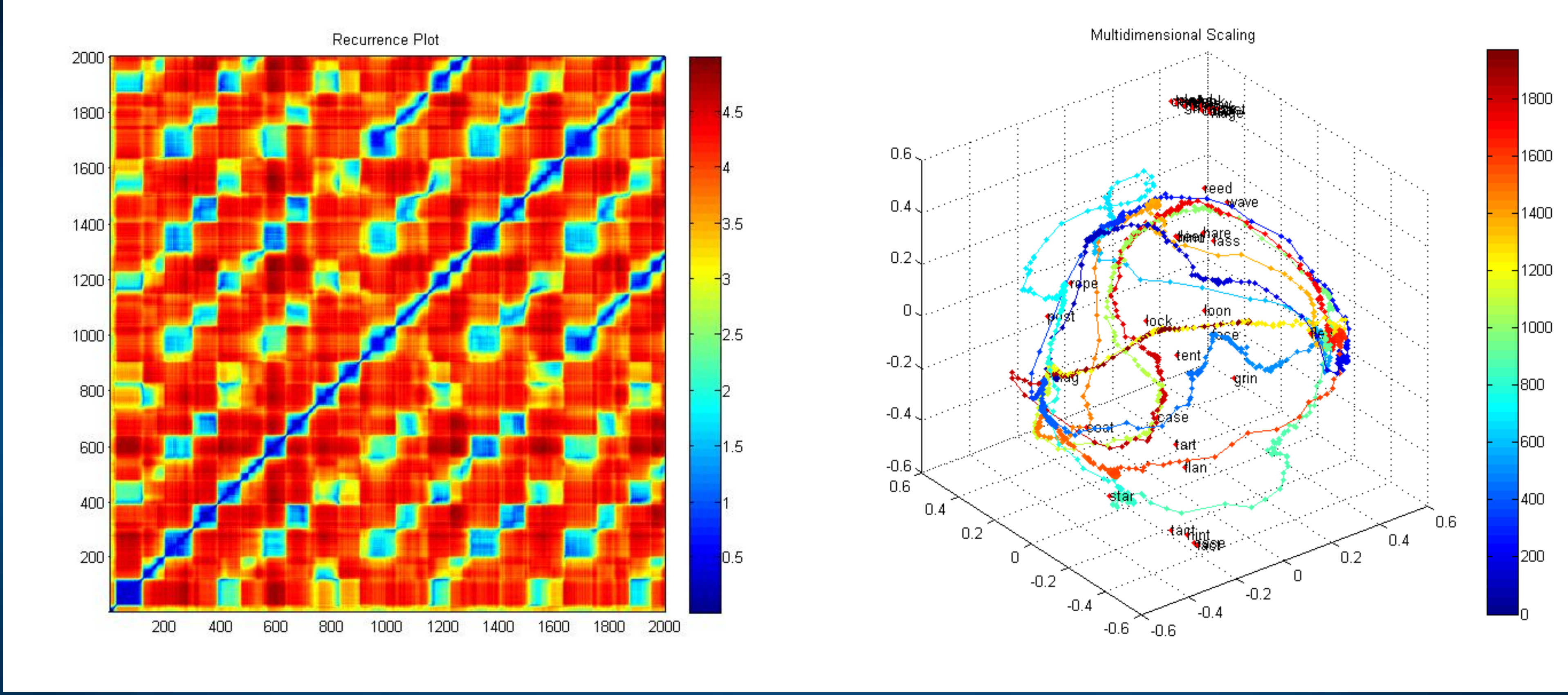


flag

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

# Trajectory visualization

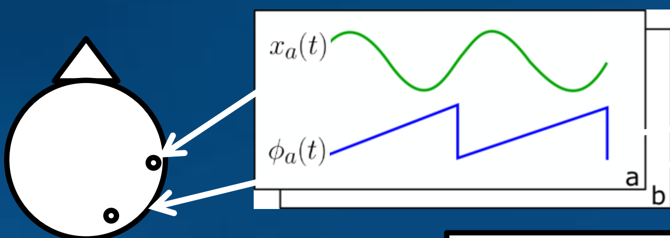



Recurrence plots and MDS/FSD/SNE visualization of trajectories of the brain activity. Here data from 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain, starting with the word “flag”.

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

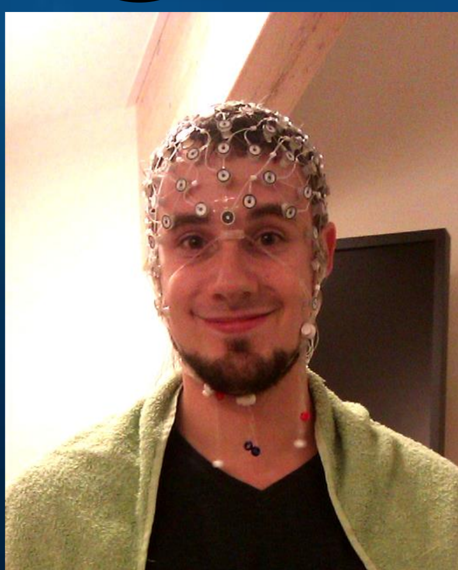
# Functional connectivity changes

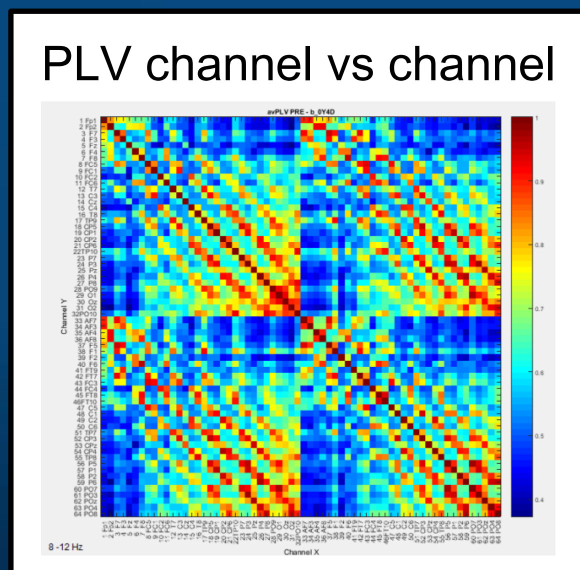
Influence of brain games on functional connectivity: **Phase Locking Value** (Burgess, 2013; Lachaux 1999), phase differences between signals measured at each electrode. PLV => synchronization maps, info flow.

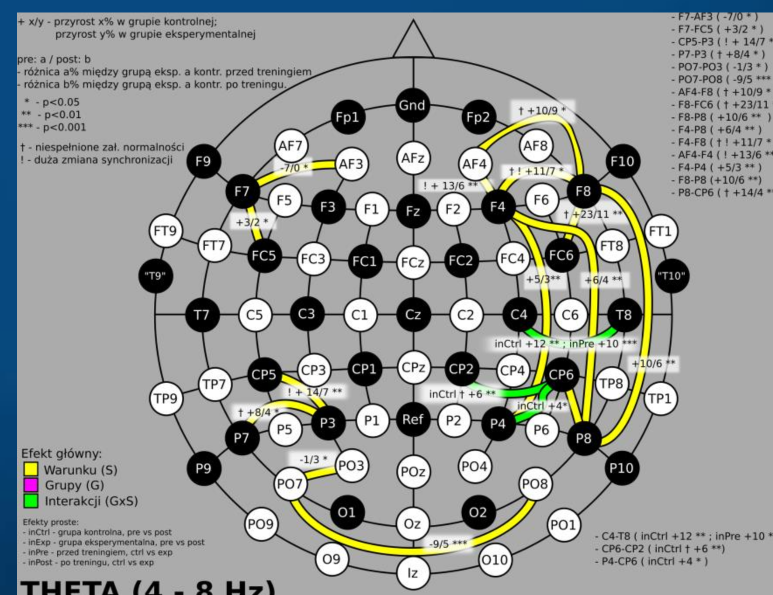



$$\Phi(t) = \phi_a(t) - \phi_b(t)$$

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





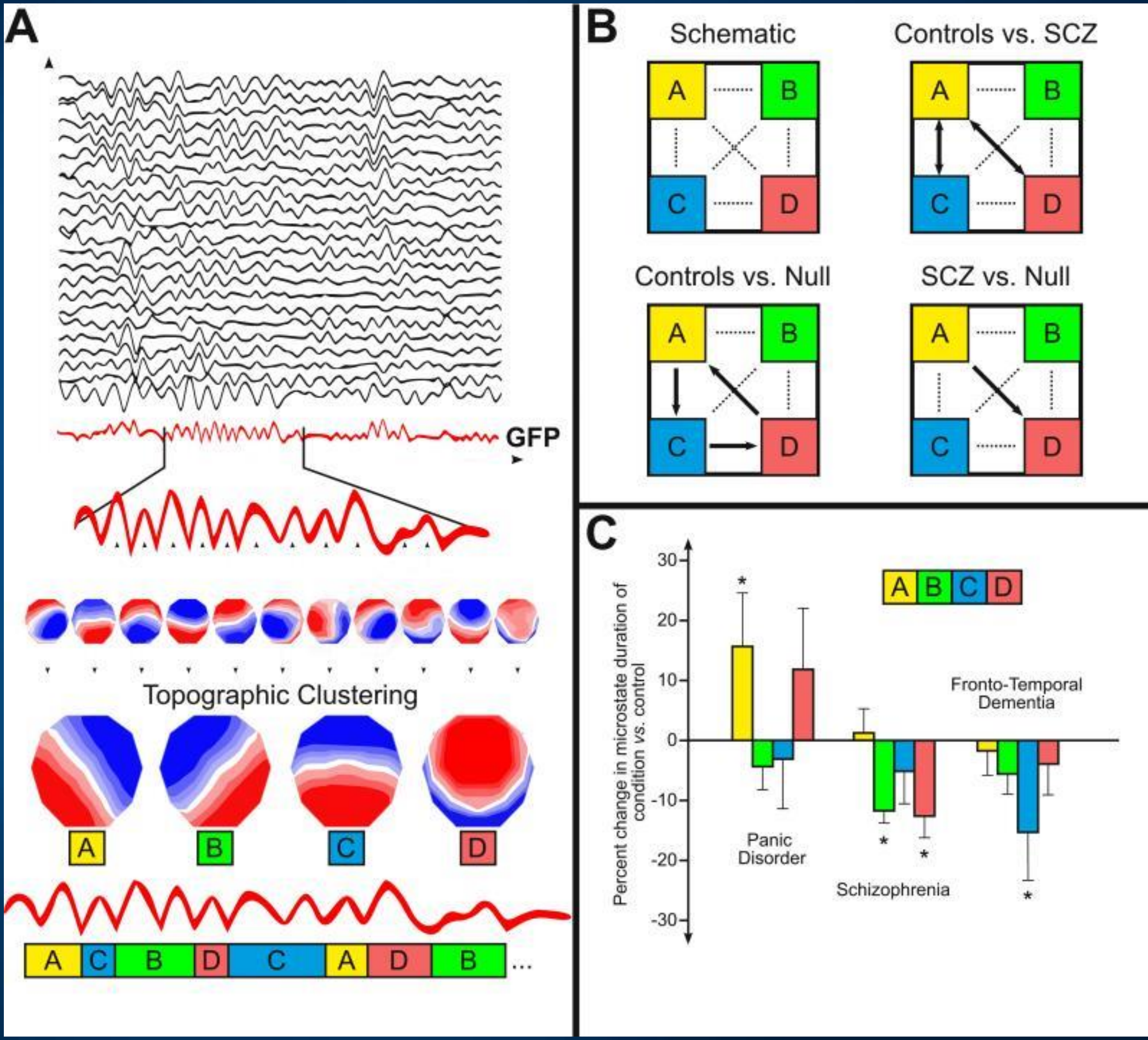



# Microstates

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.

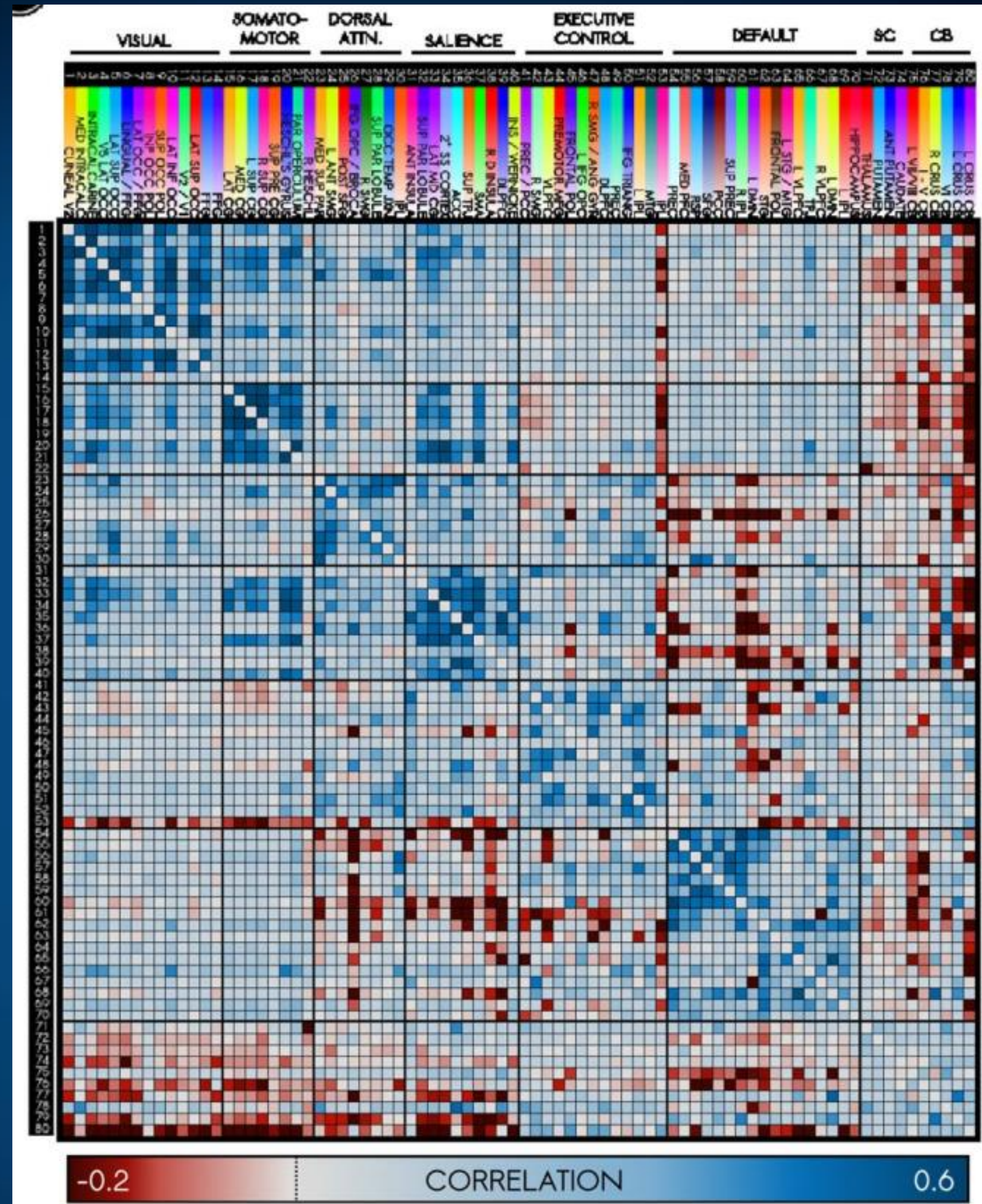


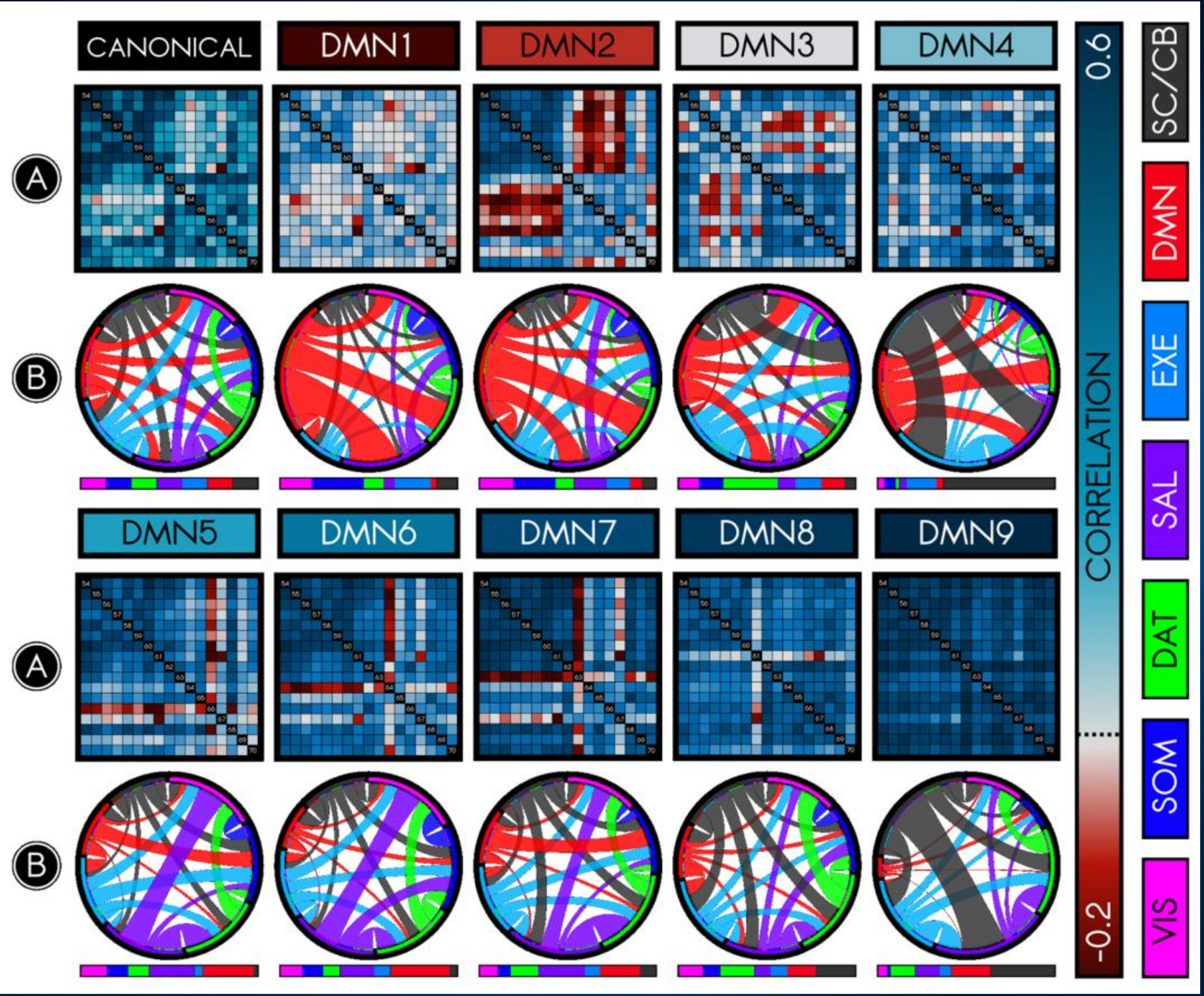
Ciric et.al. (2017). Contextual connectivity: A framework for understanding the intrinsic dynamic architecture of large-scale functional brain networks. *Scientific Reports*.

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.




CANONICAL
DMN1
DMN2
DMN3
DMN4
DMN5
DMN6
DMN7
DMN8
DMN9
A
B
CORRELATION
0.6
-0.2
SC/CB
DMN
EXE
SAL
DAT
SOM
VIS

# 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.

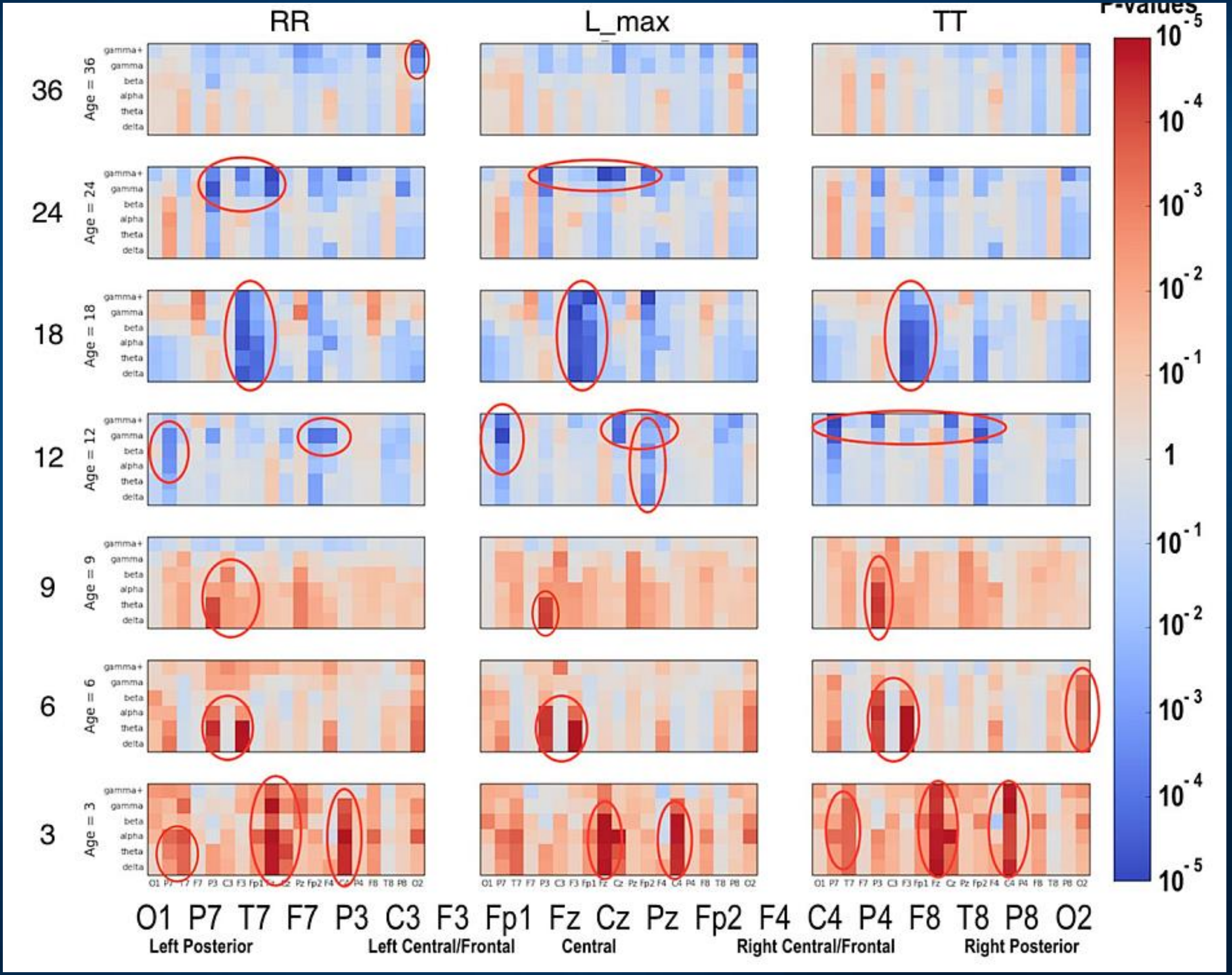
SVM classification with 9 features gave high specificity and sensitivity, exceeding 95% at some ages. Prediction using only EEG data taken as early as 3 months of age was strongly correlated with the actual measured scores.

# ASD vs Low Risk Healthy

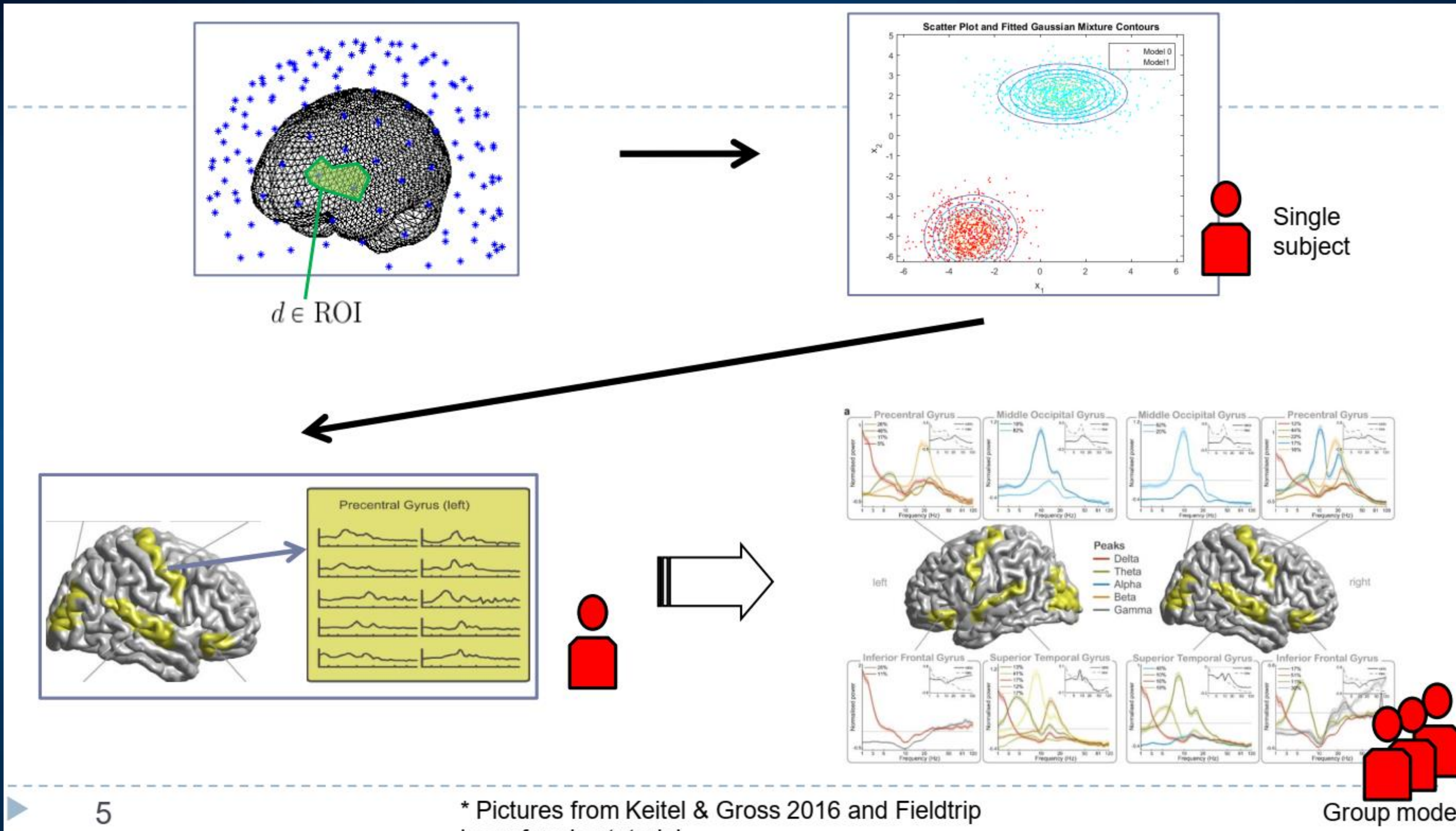
RR = recurrence rate

L_max = max line length, related to Lyapunov exponent

TT = trapping time

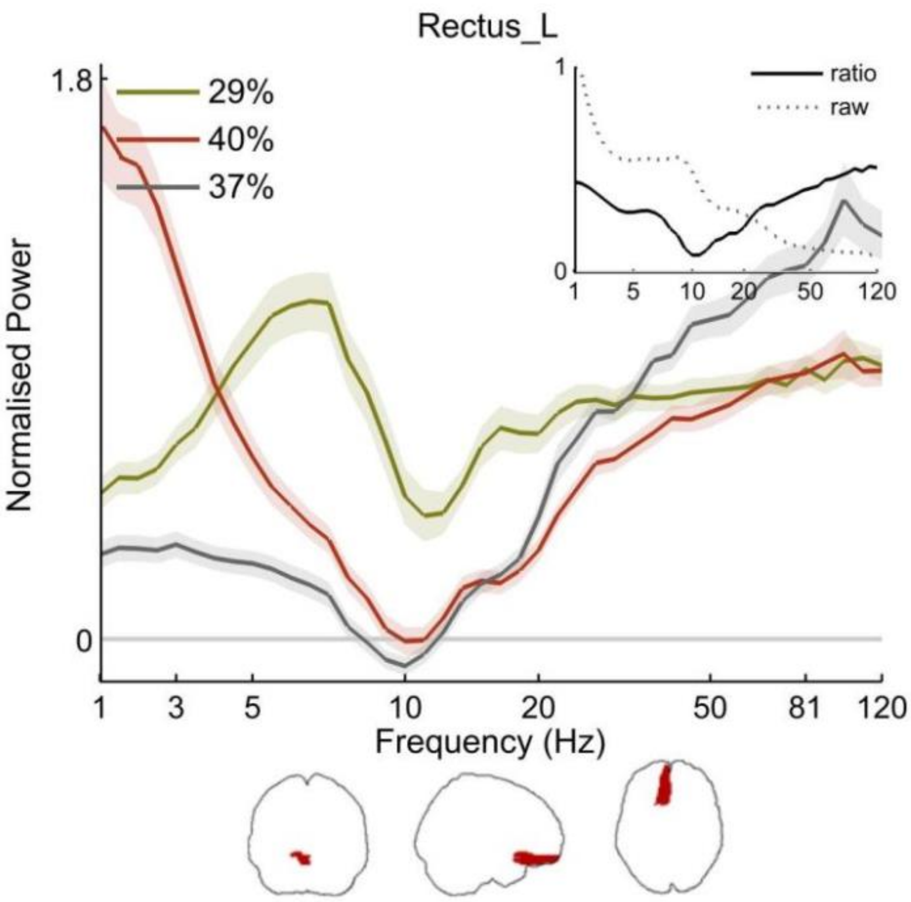


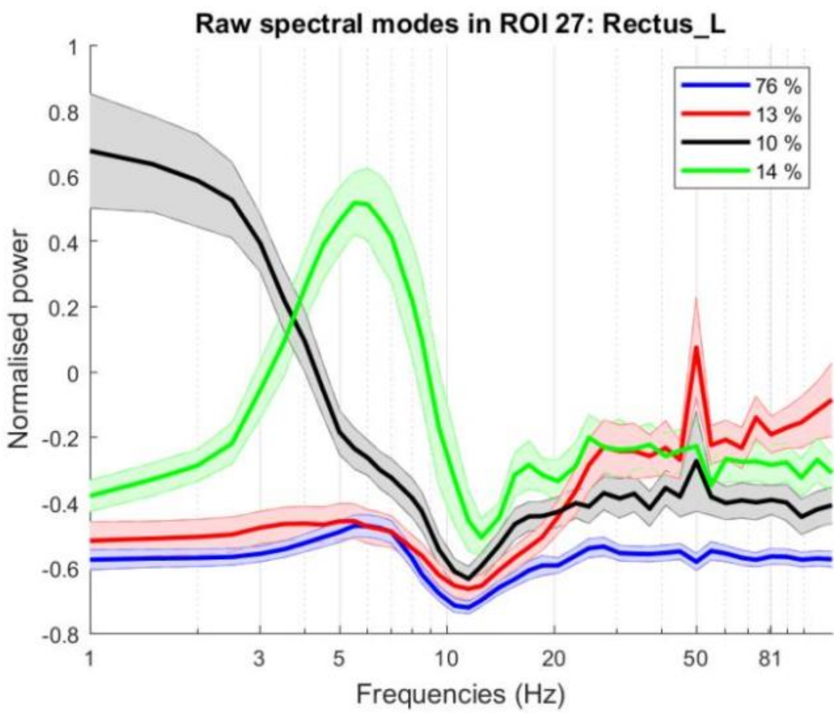
# Spectral fingerprints




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

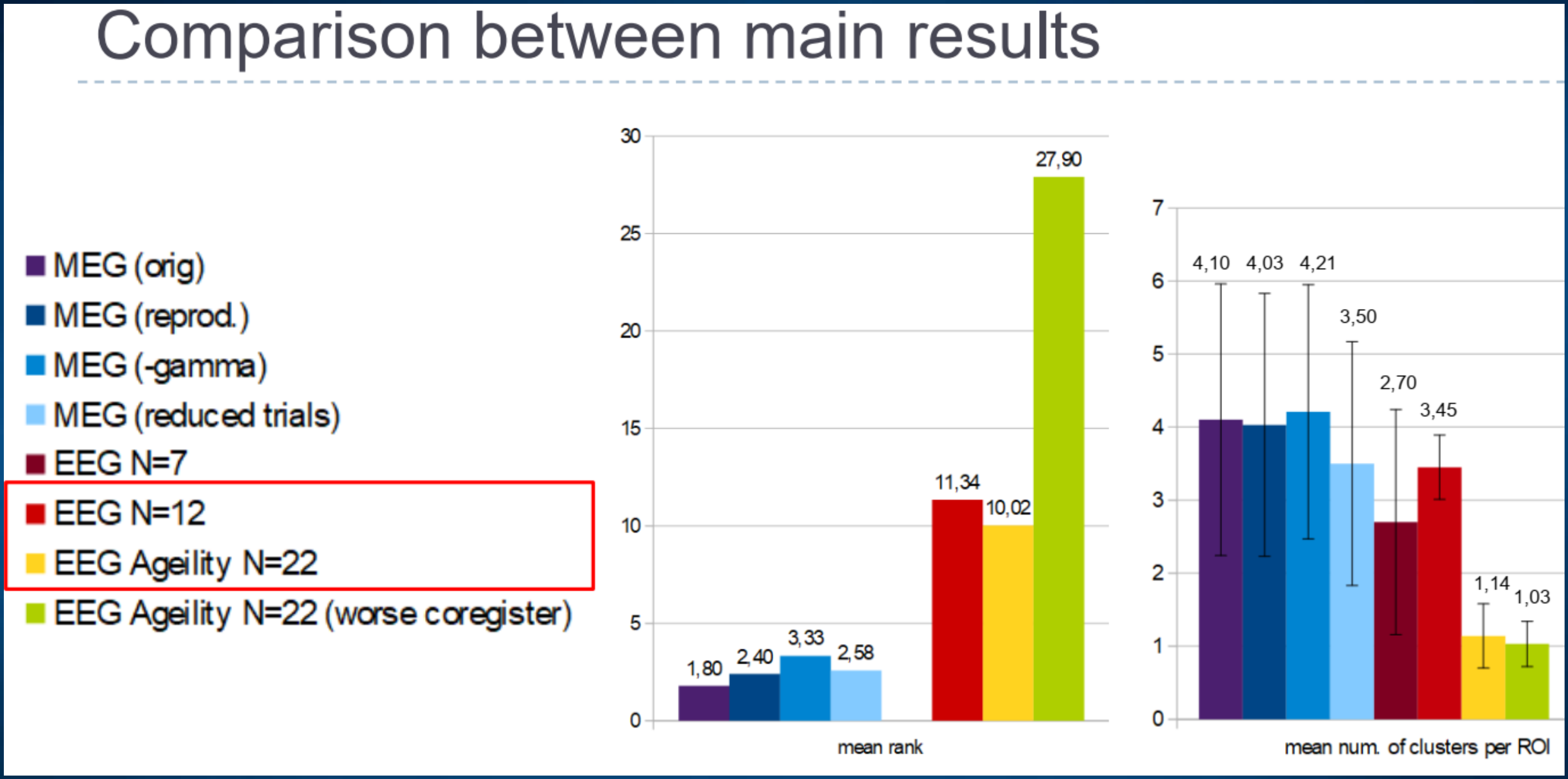
# Spectral fingerprints




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

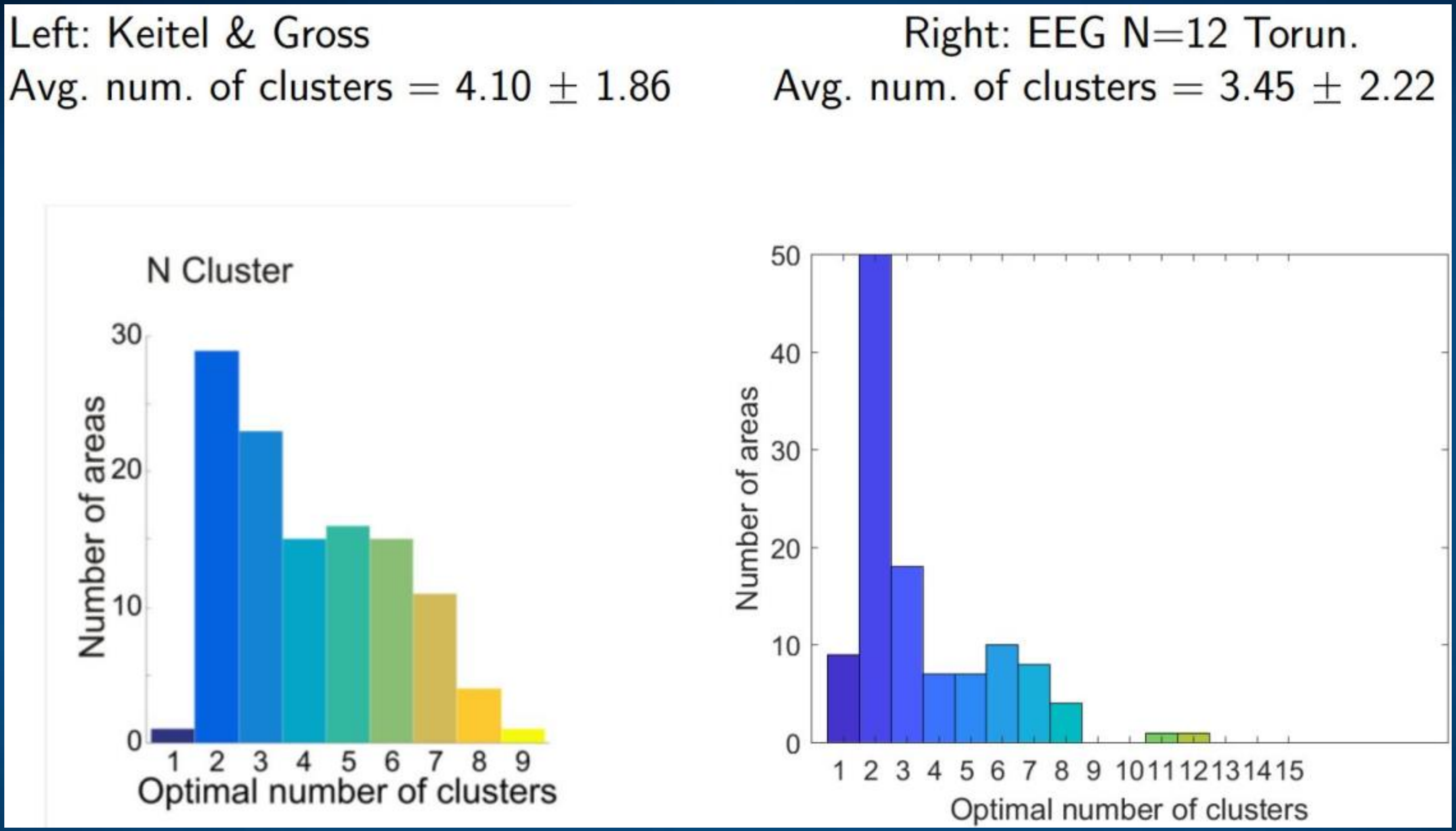
# MEG-EEG preliminary comparison




Ageility data have no information on sensor positions and results (in green) are quite poor; yellow – a bit of guessing where to place sensors on the head.

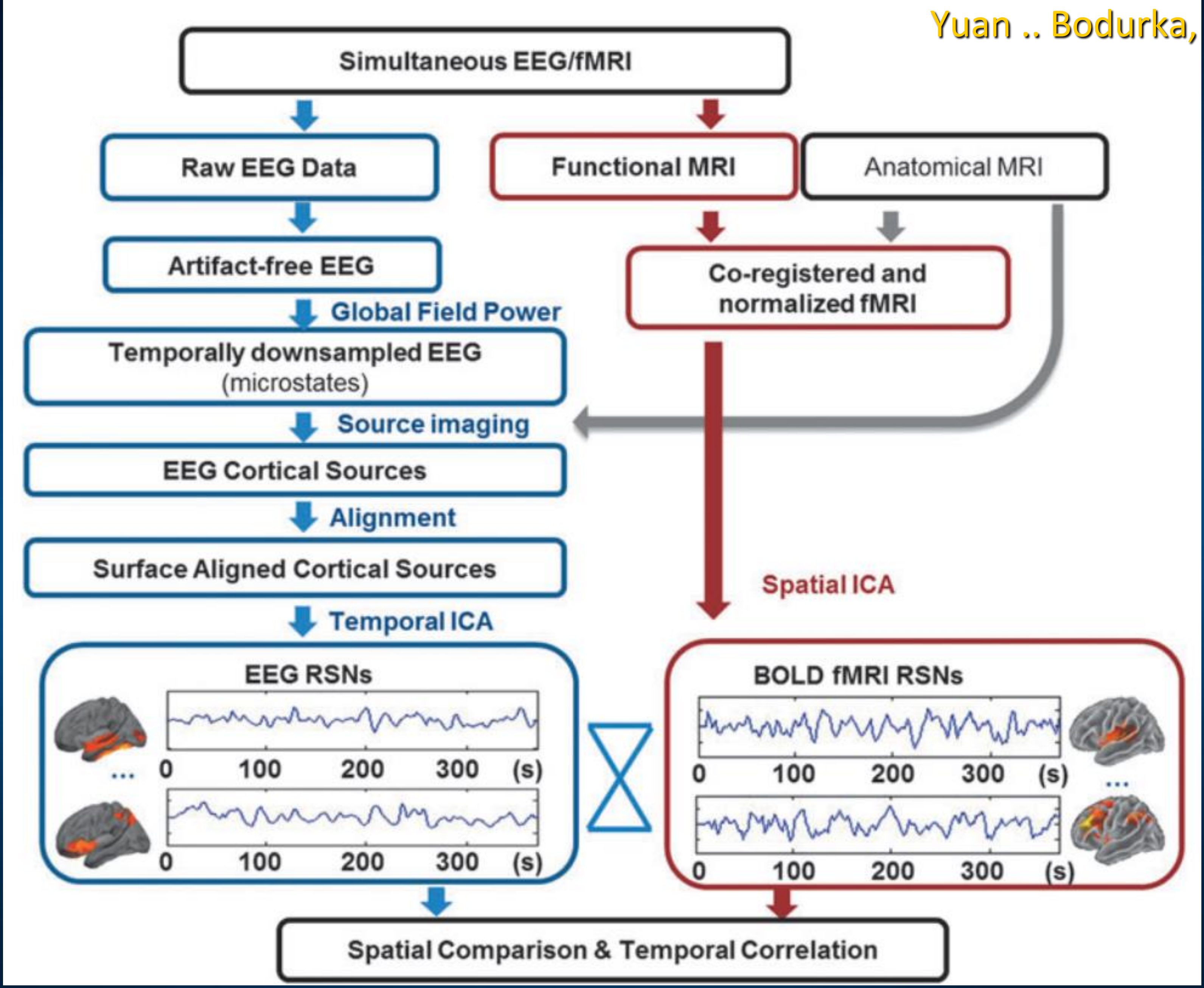
Our own experiment to collect EEG data with precise position of electrodes to enable good source reconstruction for 7 and 12 cases.

# Spectral fingerprints

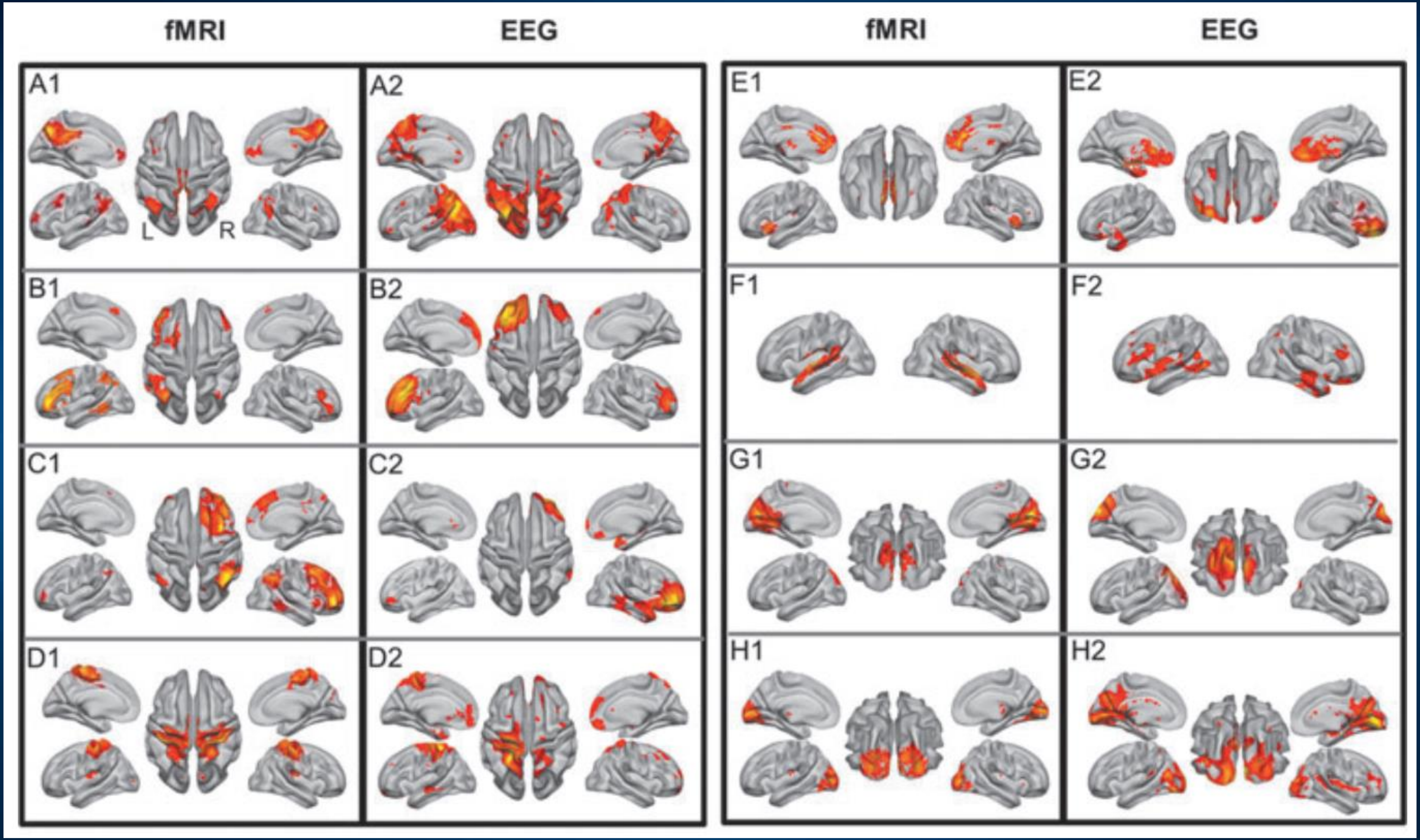



Without proper registration of sensor positions results are quite poor; we are now making our own experiment to collect EEG data with precise position of electrodes to enable good source reconstruction. In some ROI many clusters are found – sign of participation in many processes.

Yuan .. Bodurka, 2015

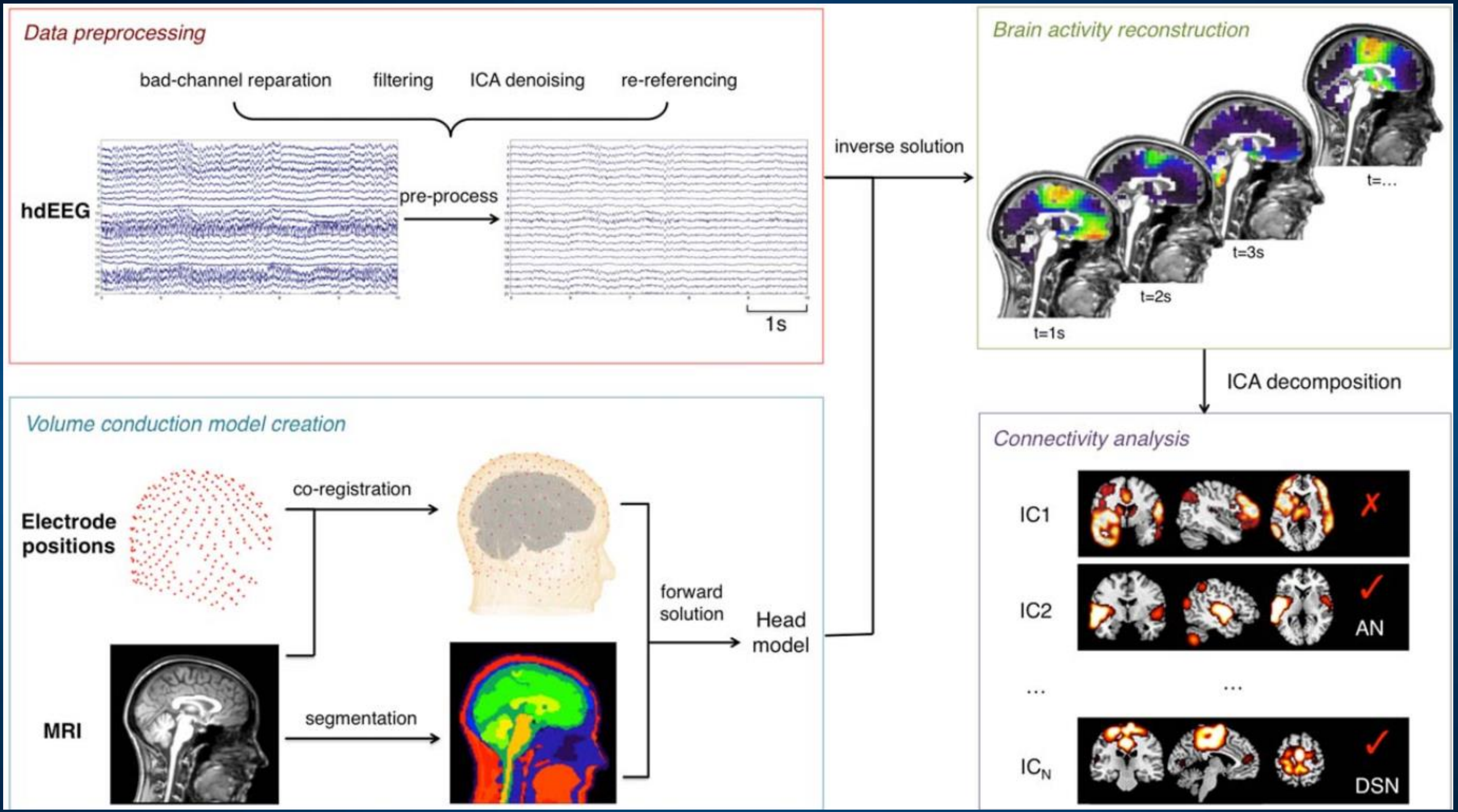


# 8 large networks from BOLD-EEG

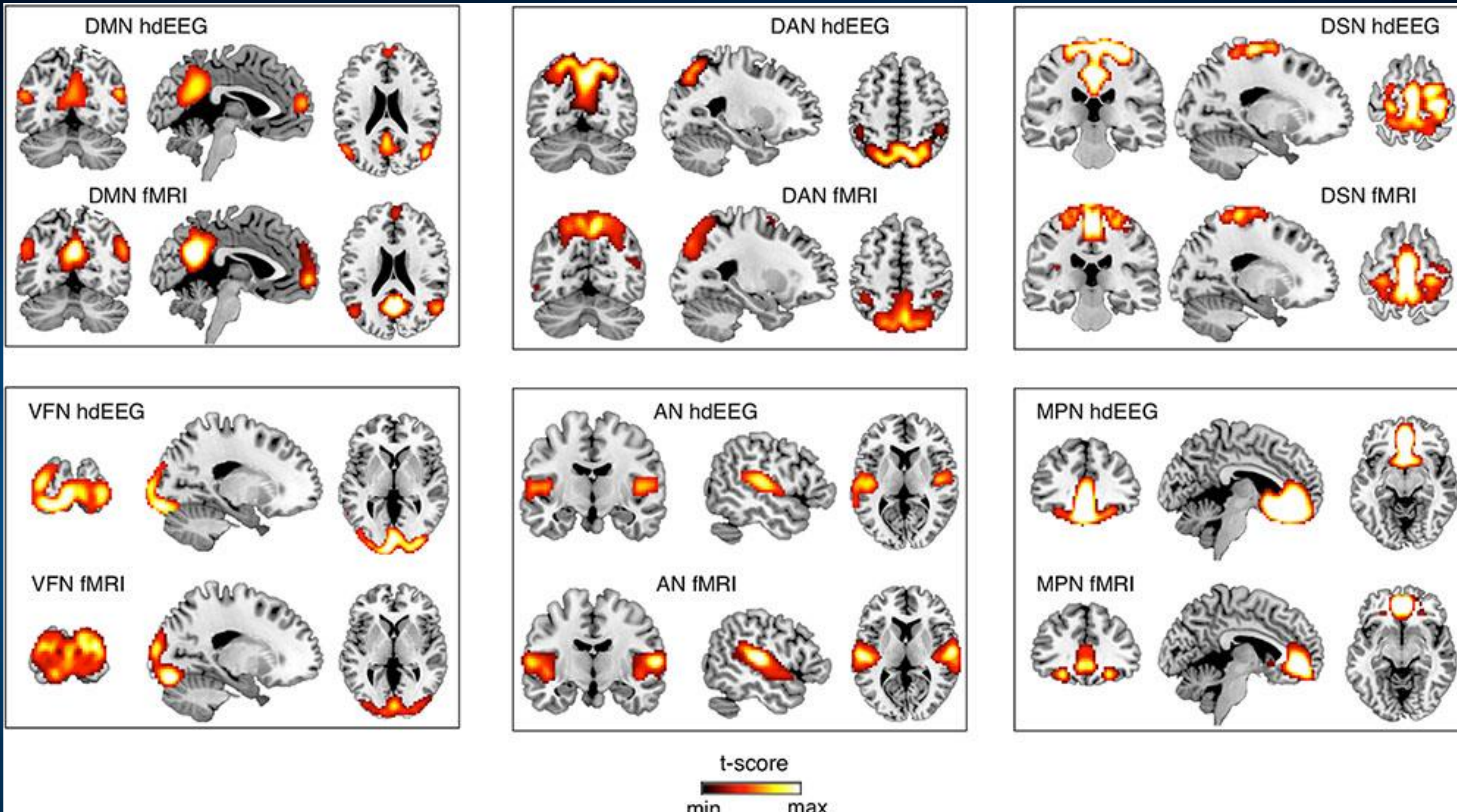



DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral). Yuan … Bodurka (2015)

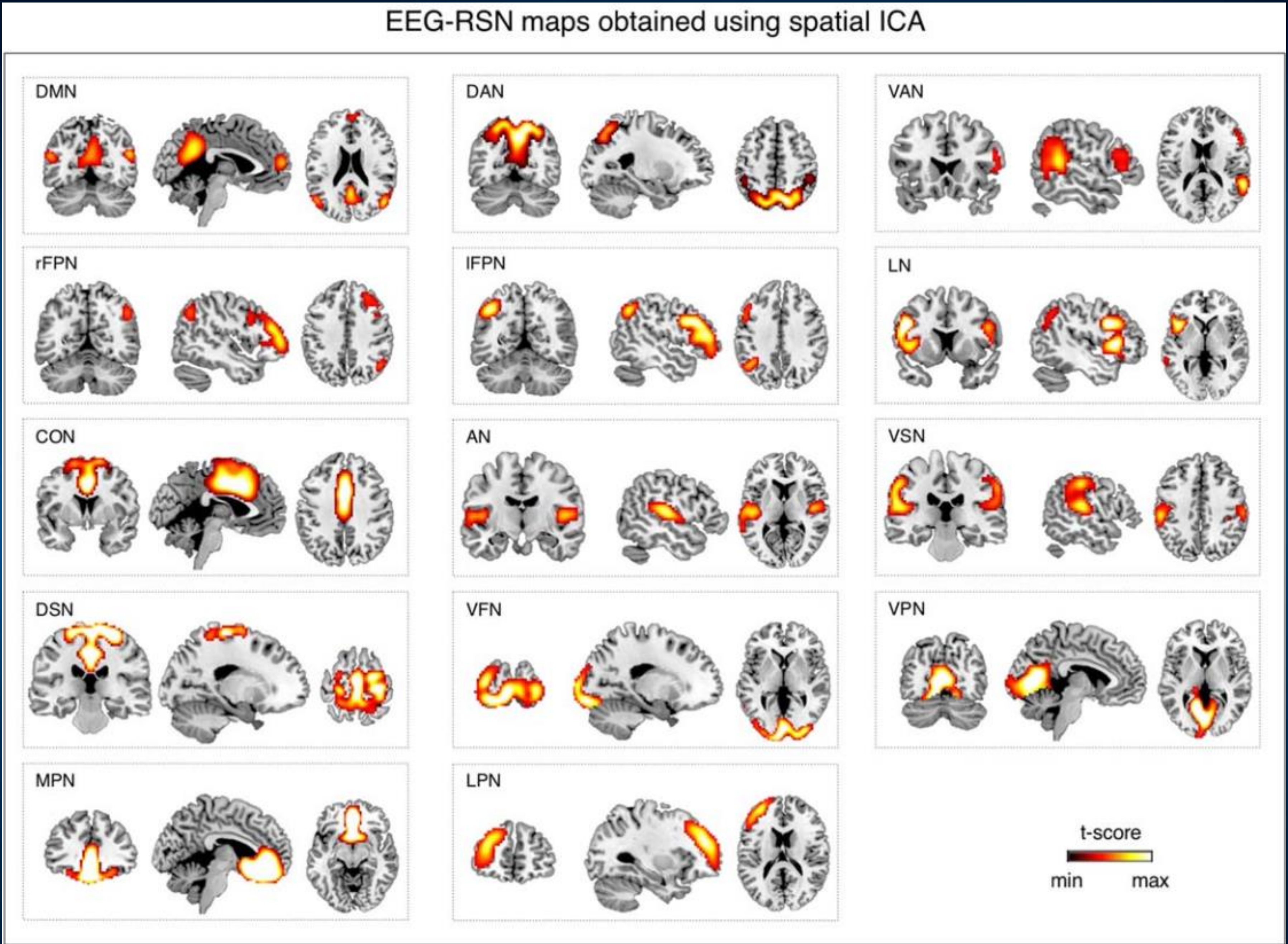
# 14 networks from BOLD-EEG




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

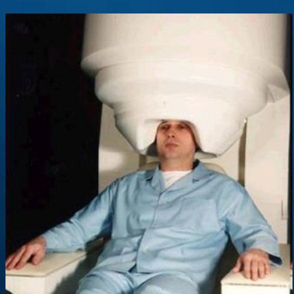


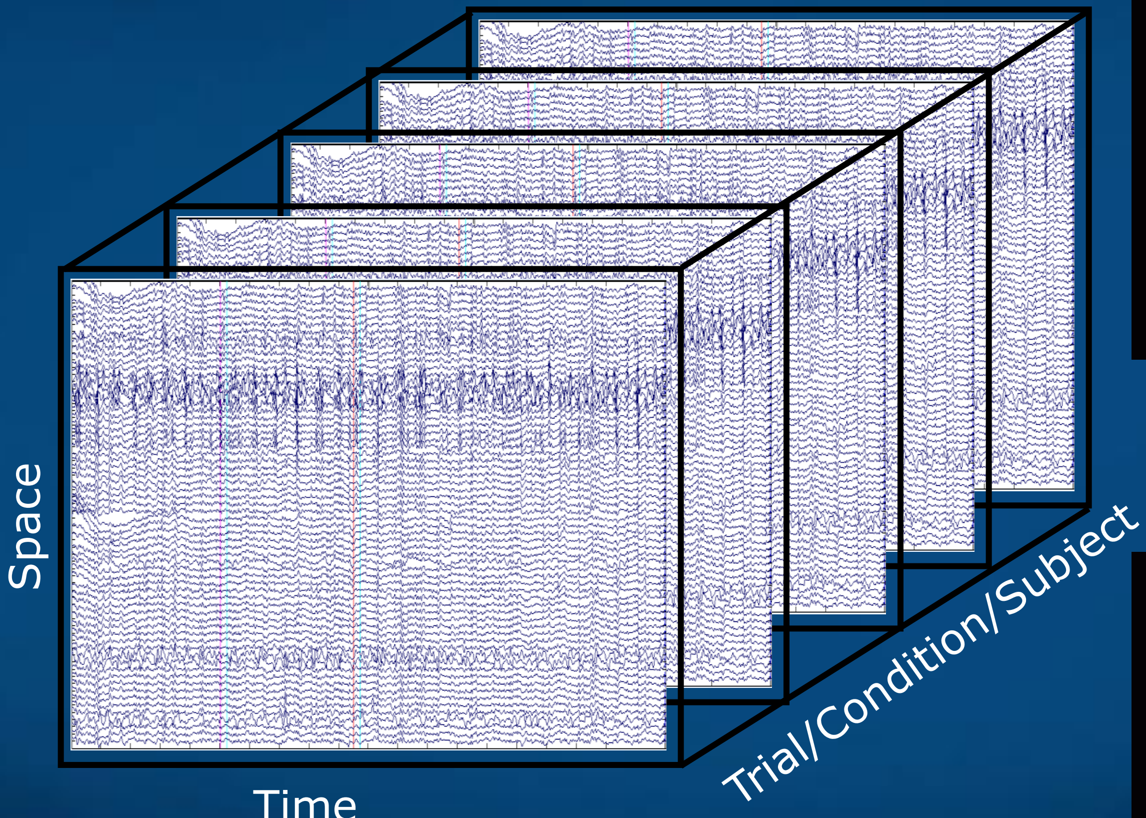

sICA on 10-min fMRI data (*N* = 24, threshold: *p* < 0.01, TFCE corrected). DMN, default mode network; DAN, dorsal attention network; DSN, dorsal somatomotor network; VFN, visual foveal network; AN, auditory network; MPN, medial prefrontal network.

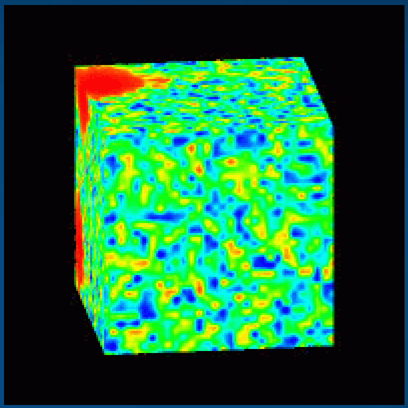

EEG-RSN maps obtained using spatial ICA
DMN
DAN
VAN
rFPN
lFPN
LN
CON
AN
VSN
DSN
VFN
VPN
MPN
LPN
t-score
min
max

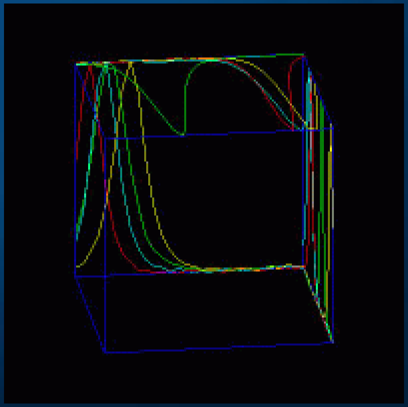
# From Two-way to Multi-way Analysis
# Integration and Fusion of Various Modalites
# EEG+fNIRS +fMRI

A. Cichocki Lab
RIKEN Brain Science Inst.



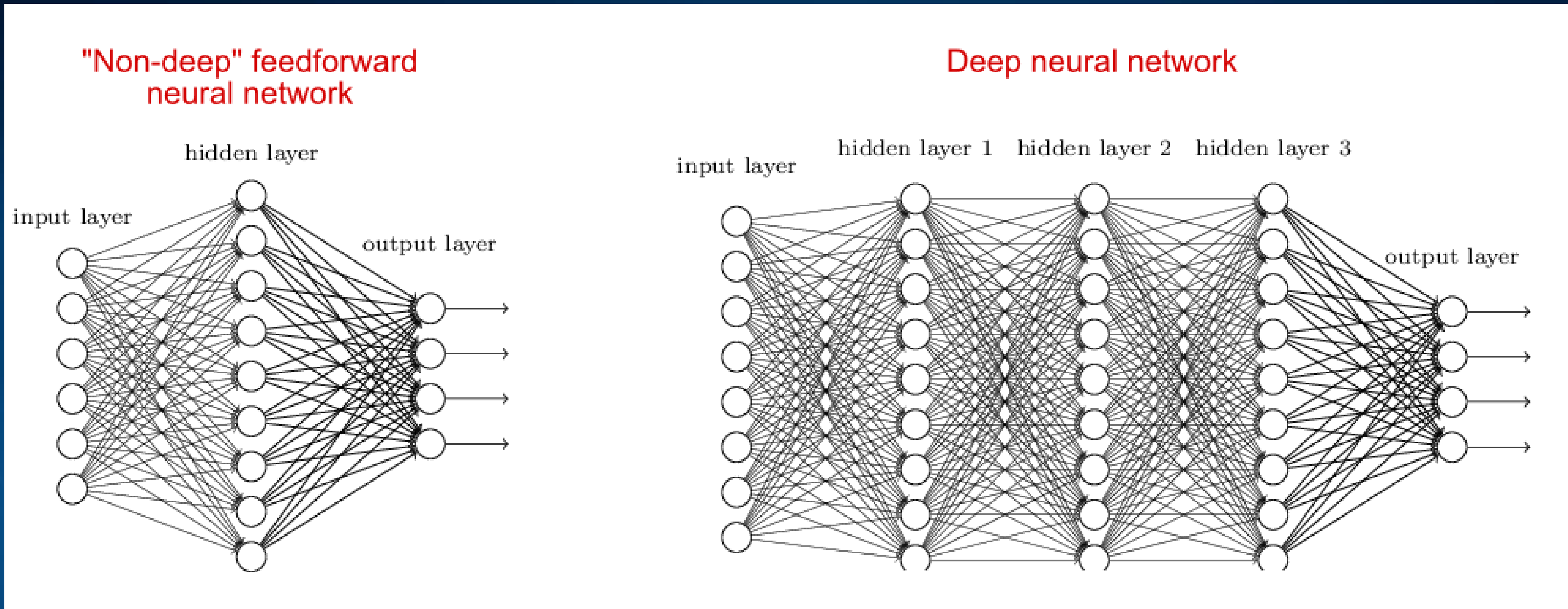


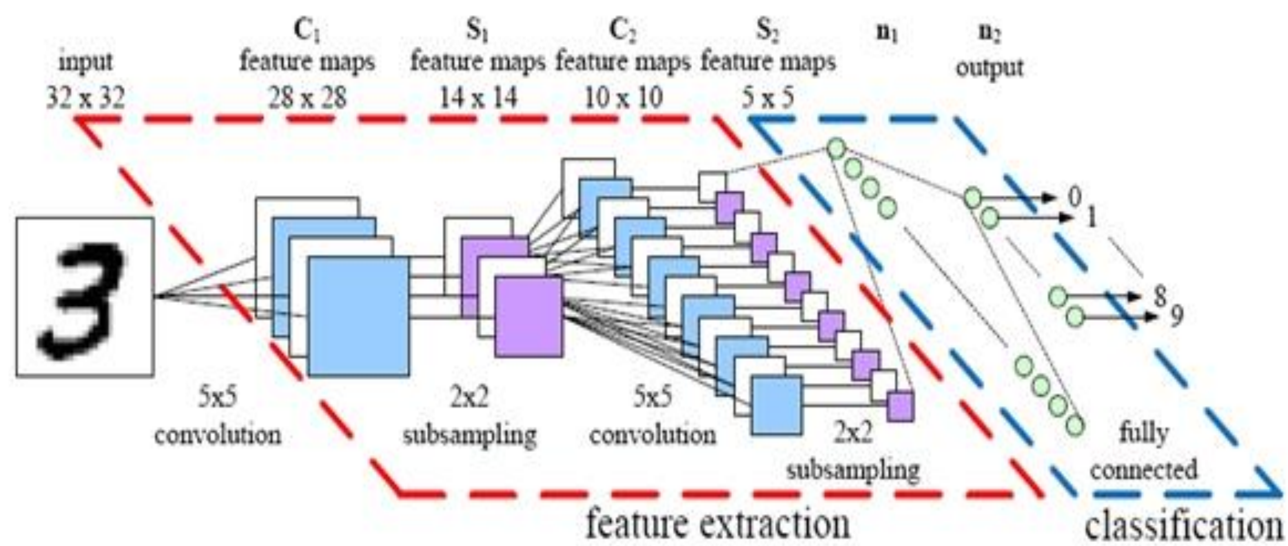





Exploratory and multi-way blind source separation and tensor factorizations: unsupervised learning methods and software to find the hidden causes & underlying hidden structure in the data.

# Tensorization of Convolutive Deep Learning NN




A. Cichocki Lab
RIKEN BSI

# Fingerprints of Mental Activity

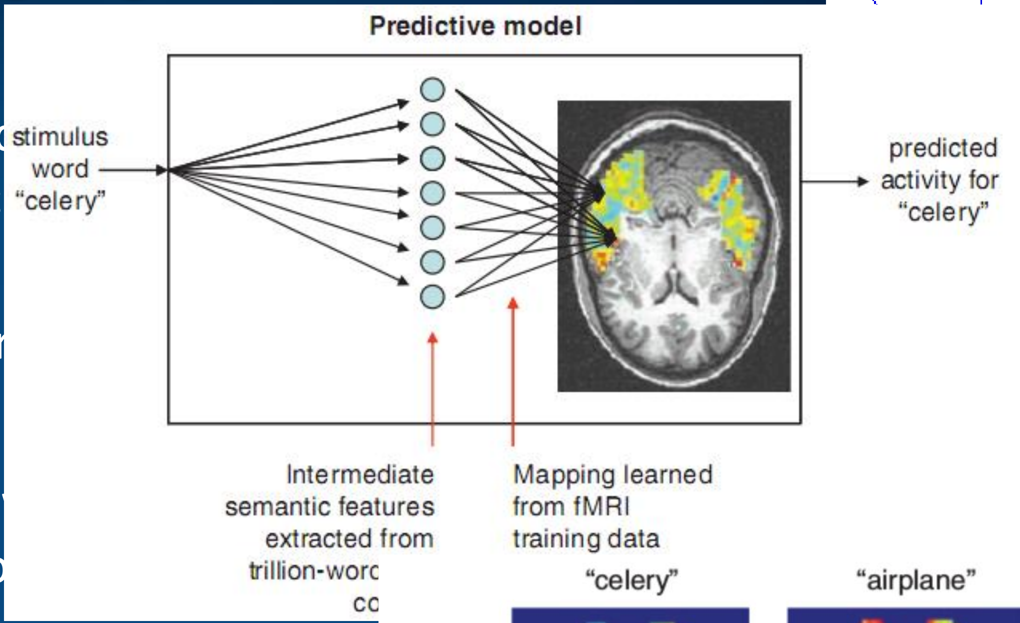
# Neuroimaging words

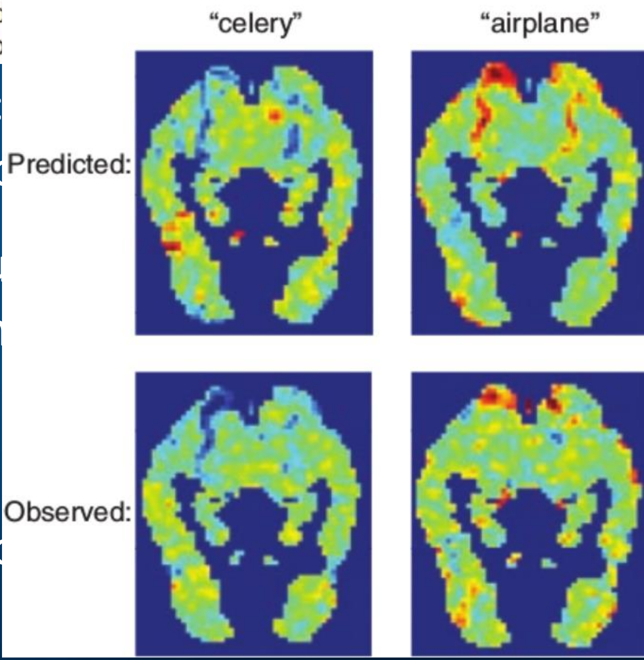
Predicting Human Brain Activity Assoc
of Nouns," T. M. Mitchell et al, Scienc

- Clear differences between fMRI br
about different nouns.
- Reading words and seeing the dra
presumably reflecting semantics o
- Although individual variance is significant similar ac
of different people, a classifier may still be trained c
- Model trained on ~10 fMRI scans + very large corpu
activity for over 100 nouns for which fMRI has been

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, o

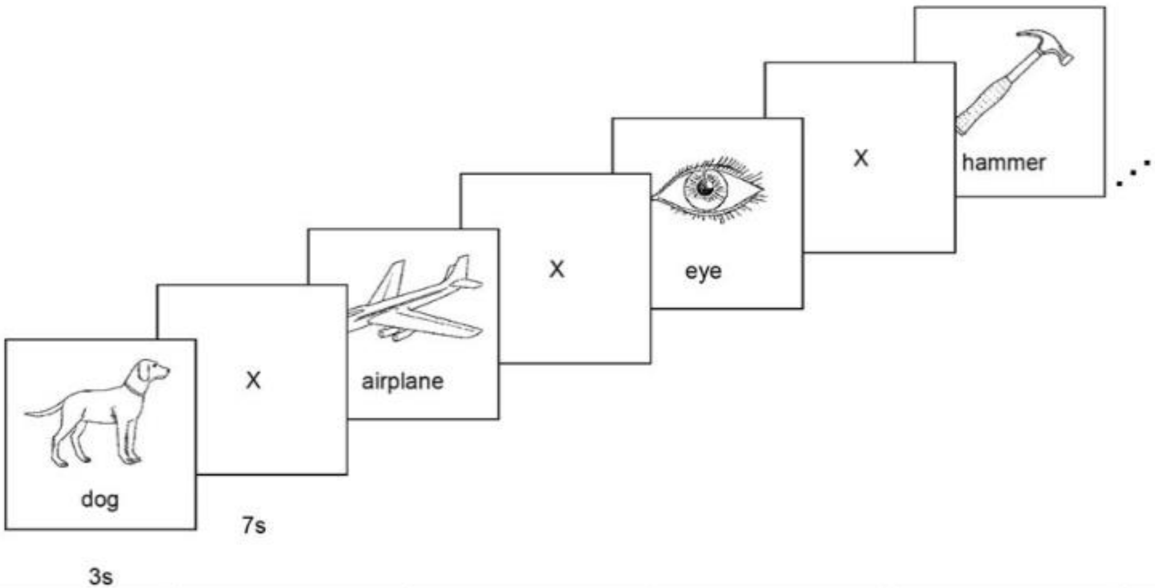
Are these 25 features defining brain-based semantics?



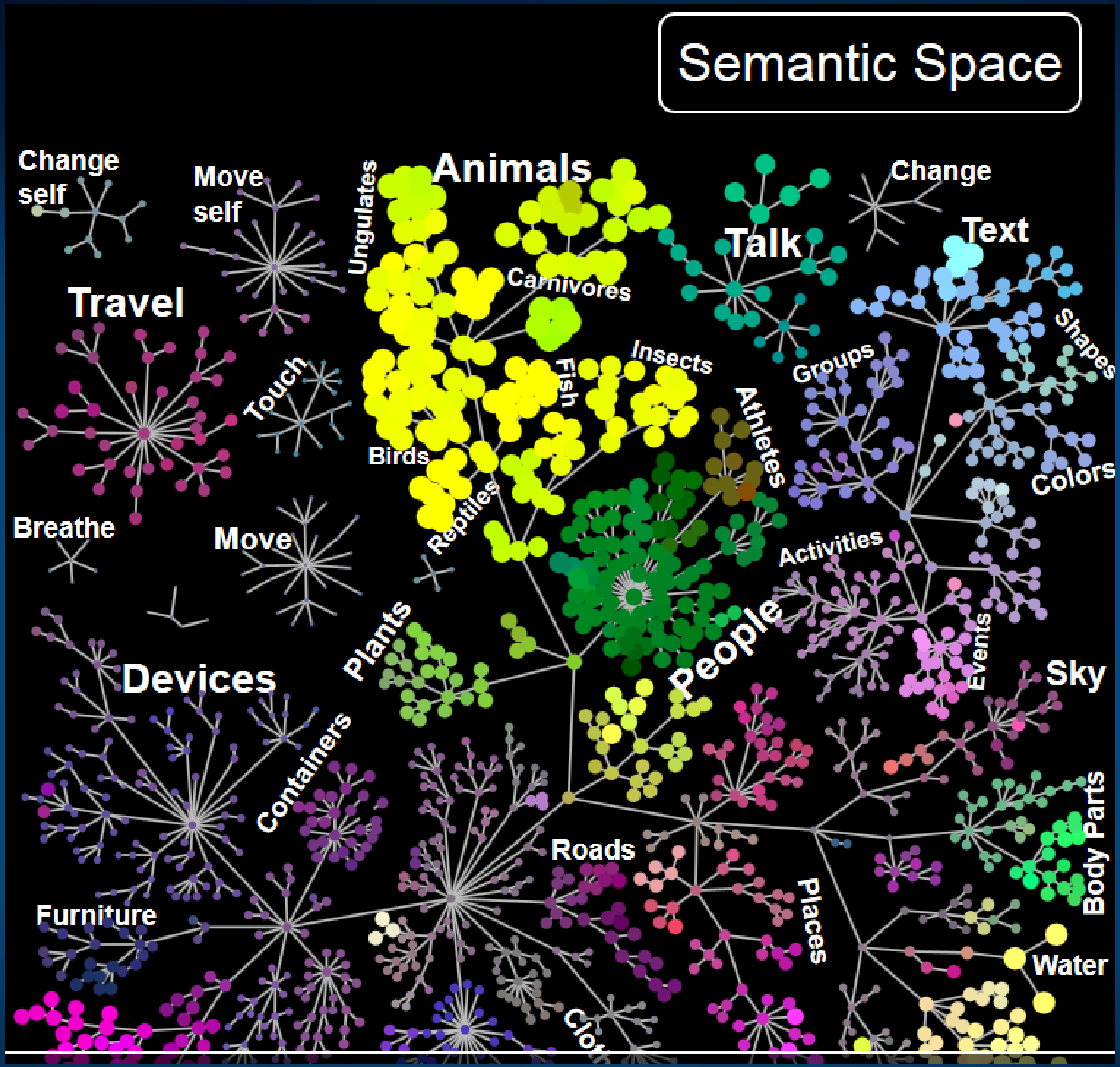
# Quasi-stable brain activations?

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



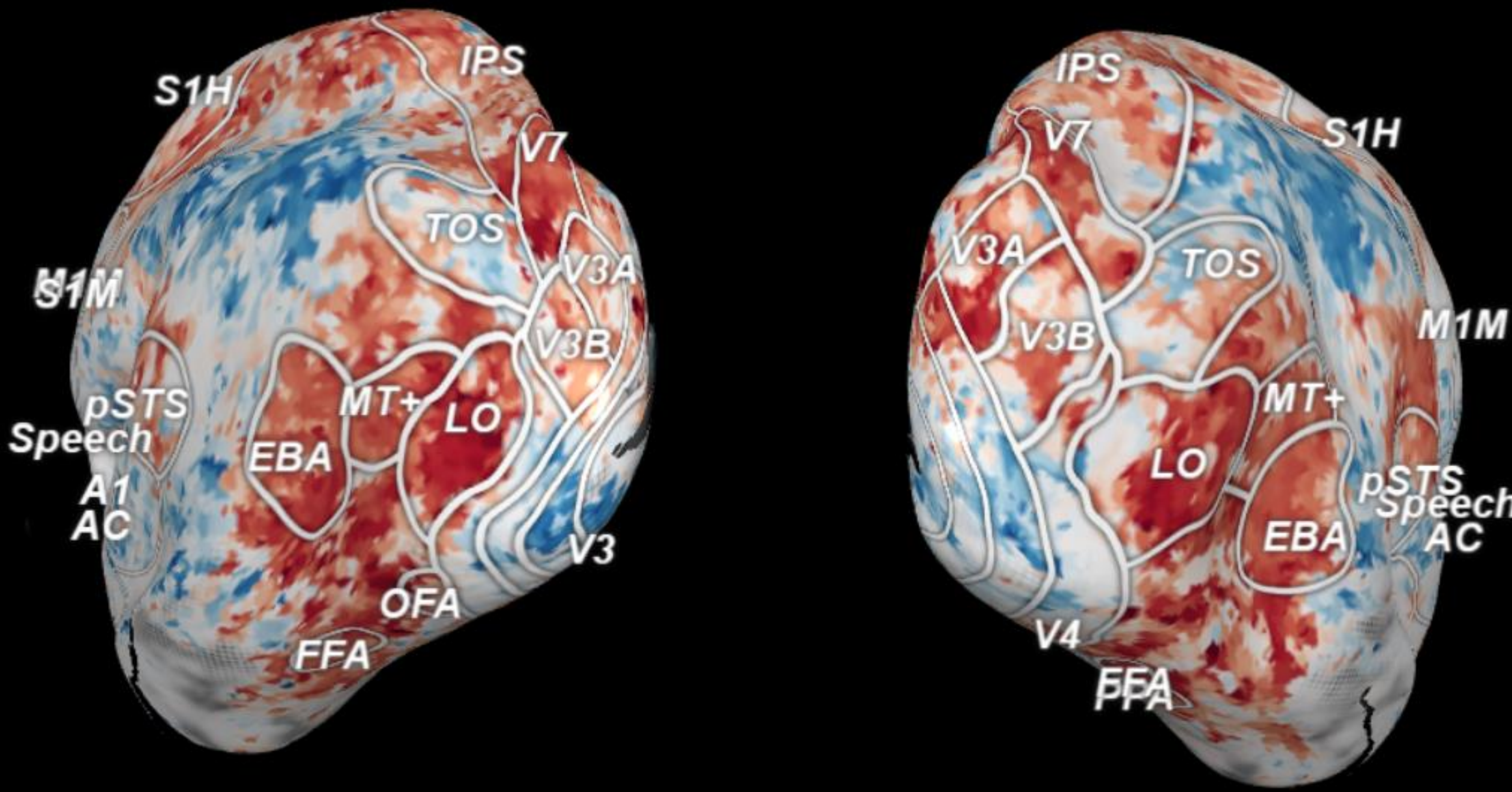

| Category | Exemplar 1 | Exemplar 2 | Exemplar 3 | Exemplar 4 | Exemplar 5 |
|---|---|---|---|---|---|
| animals | bear | cat | cow | dog | horse |
| body parts | arm | eye | foot | hand | leg |
| buildings | apartment | barn | church | house | igloo |

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

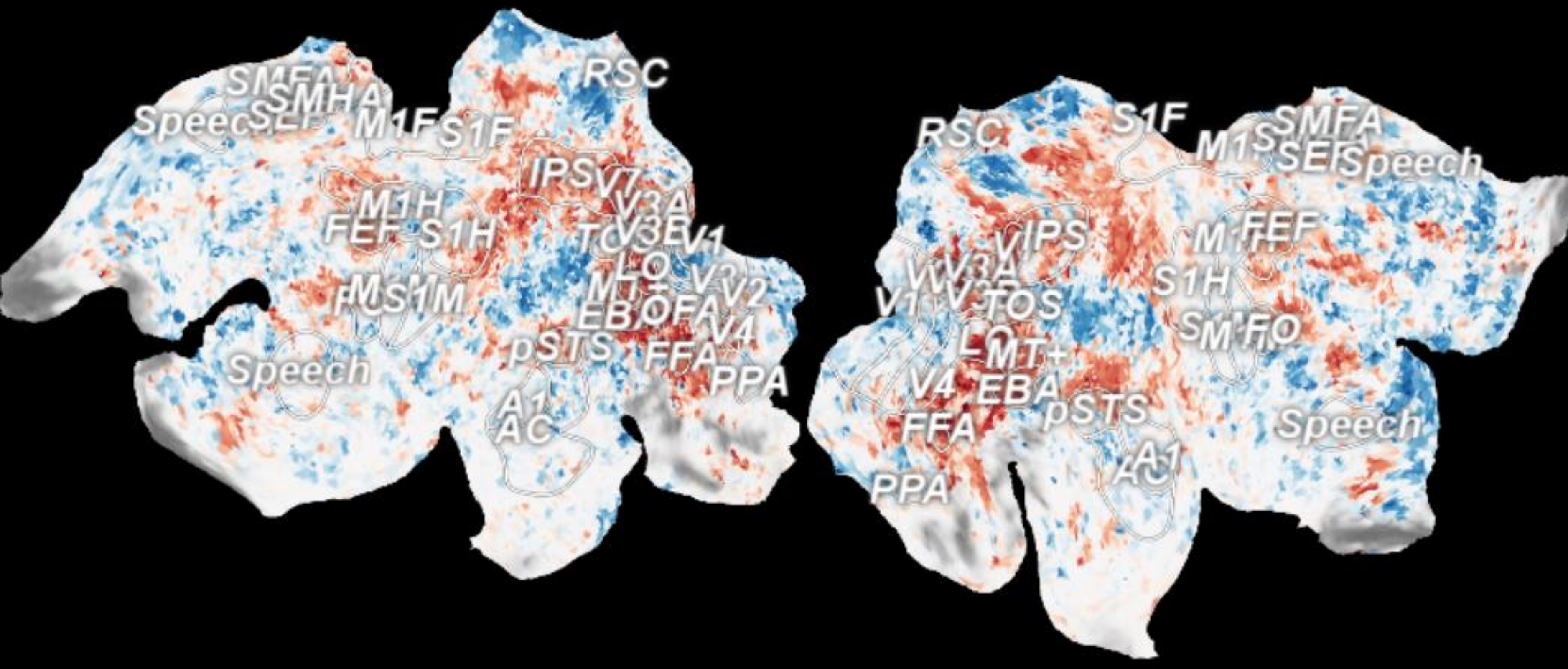



Words in the semantic space are grouped by their similarity (Gallant Lab, 2016).
Words activate specific ROIs, similar words create similar maps of brain activity.
Each voxel may be activated by many words. Video or audio stimuli, fMRI scans.

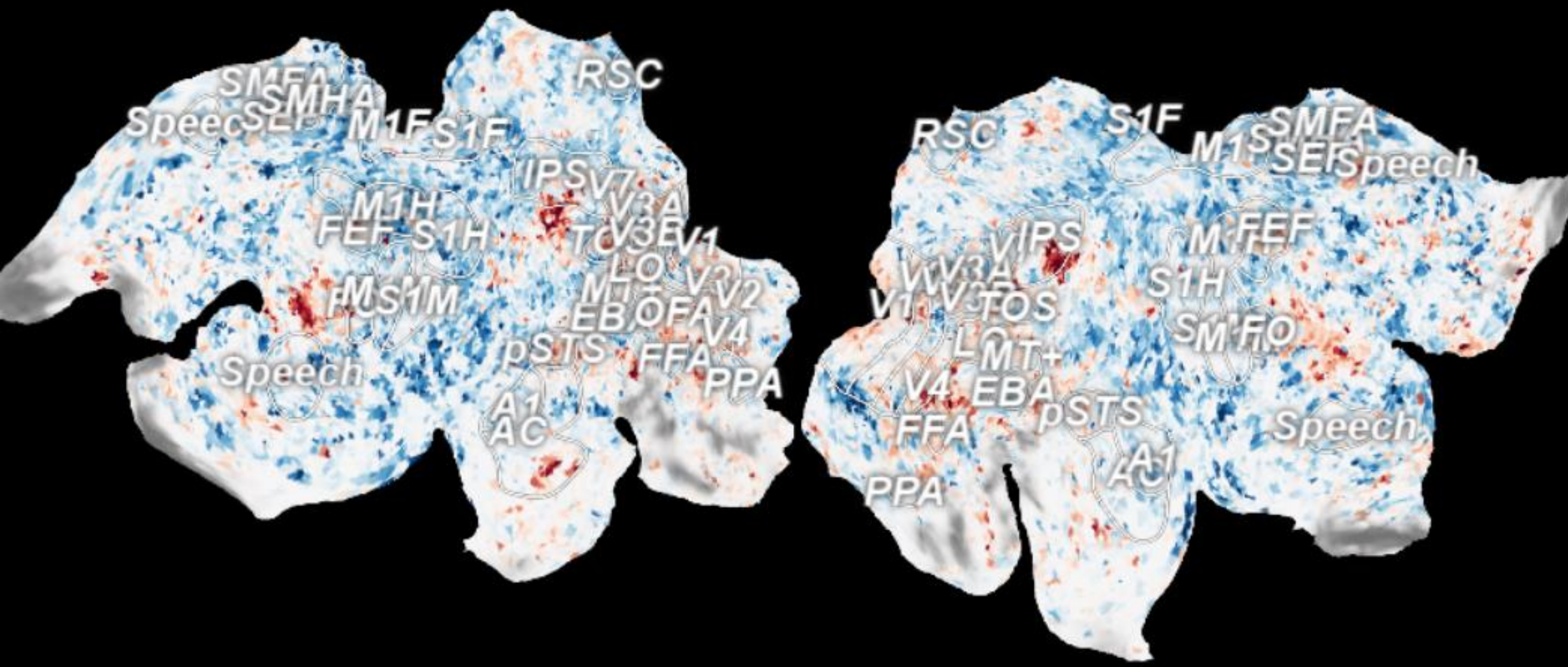
Category zebra: Passive Viewing

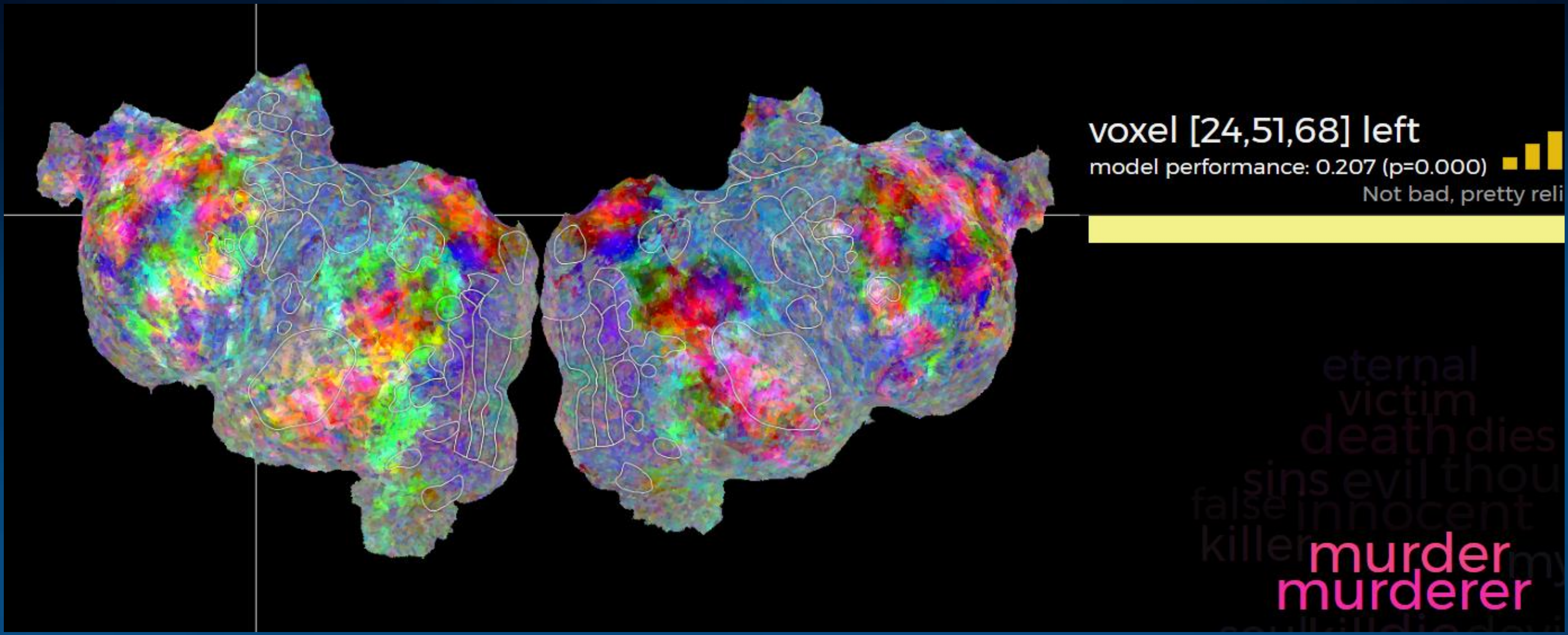


Category zebra: Passive Viewing



Category traffic light: Passive Viewing



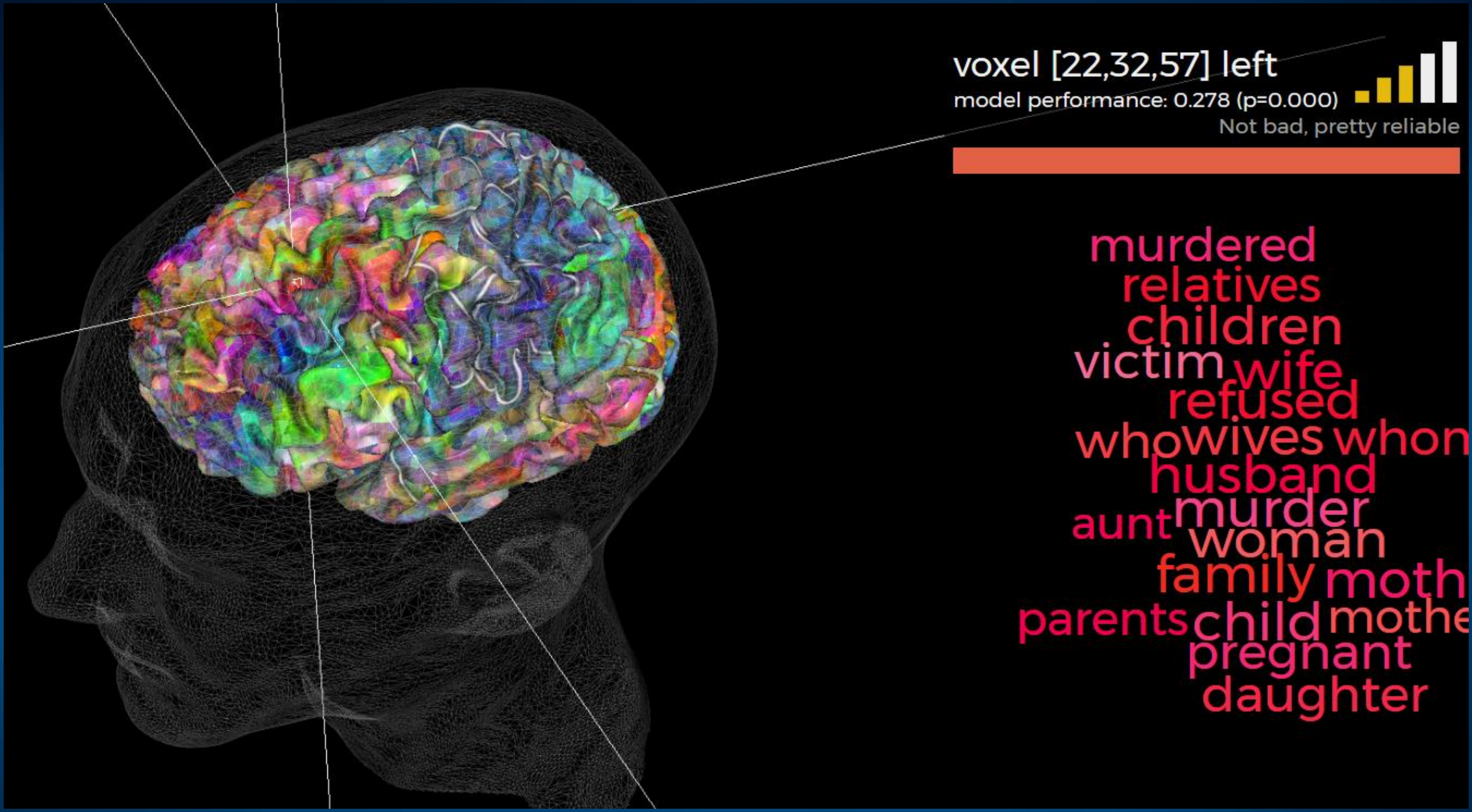



Whole fMRI activity map for the word "murder" shown on the flattened cortex.

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

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

Can one do something like that with EEG or MEG?




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

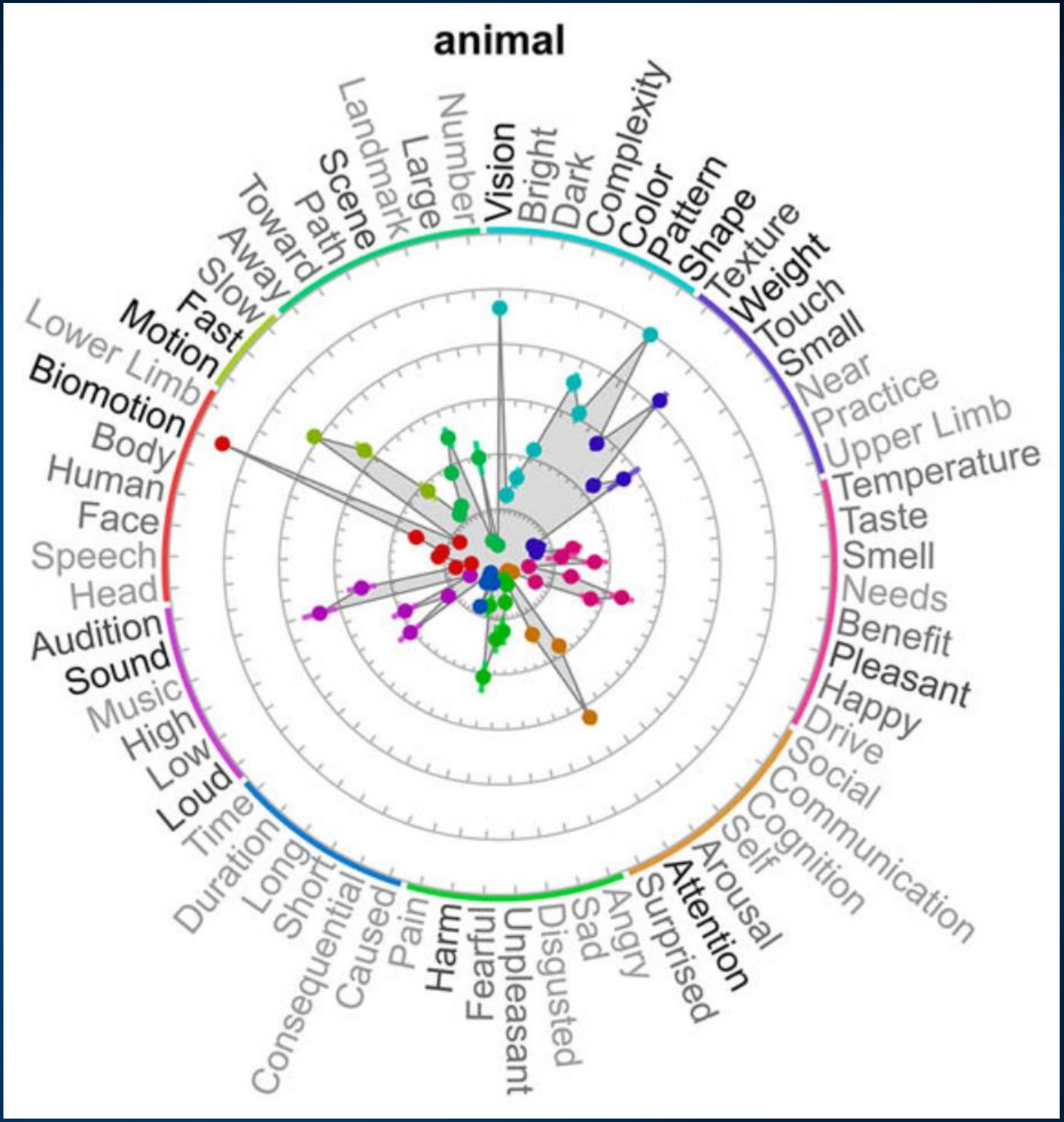
65 attributes related to neural processes;

Colors on circle: general domains.

J.R. Binder et al

Toward a Brain-Based Componential Semantic Representation, 2016

More than just visual objects!



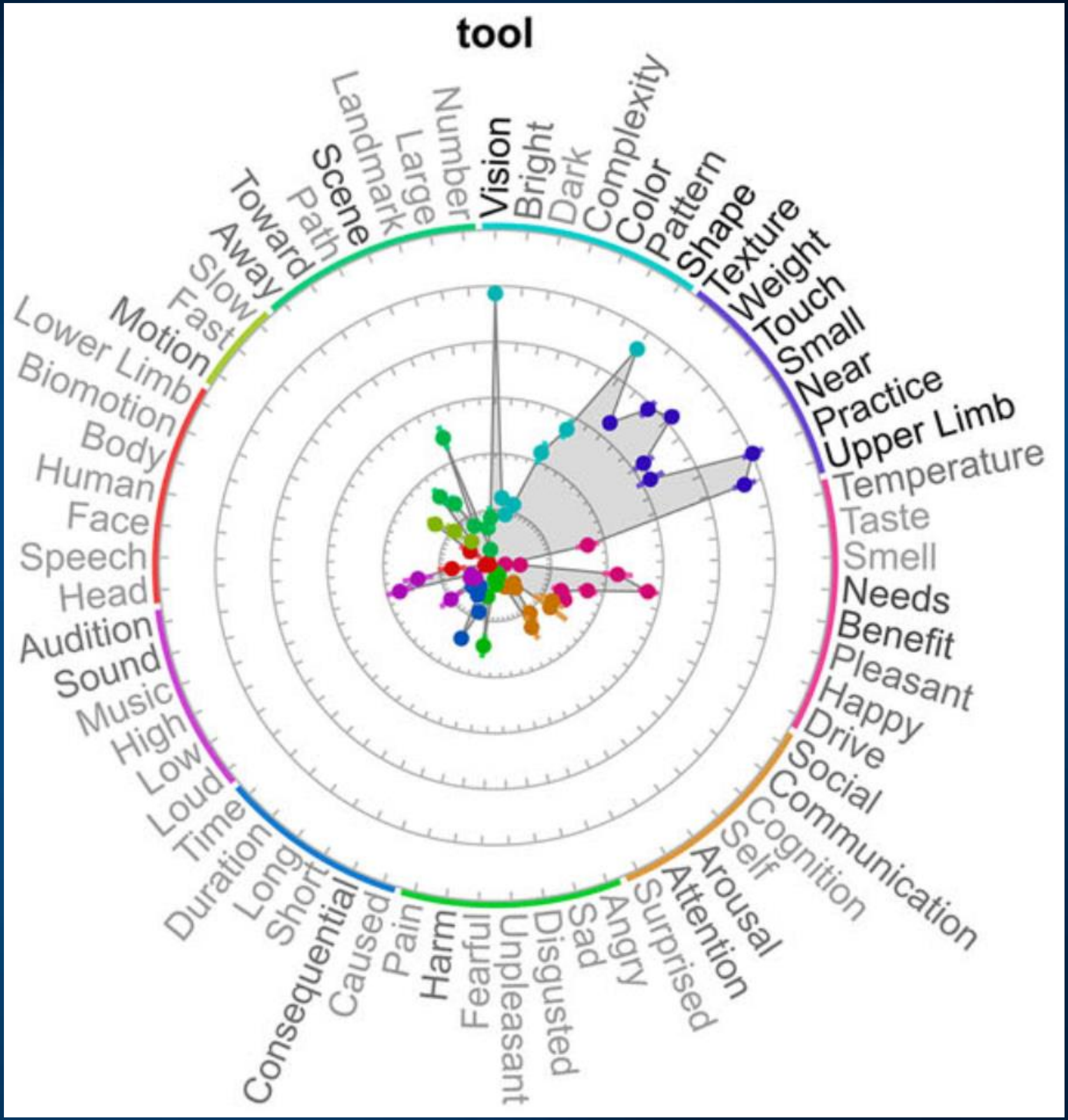
65 attributes related to neural processes.

Brain-Based Representation of tools.

J.R. Binder et al

Toward a Brain-Based Componential Semantic Representation

Cognitive Neuropsychology 2016



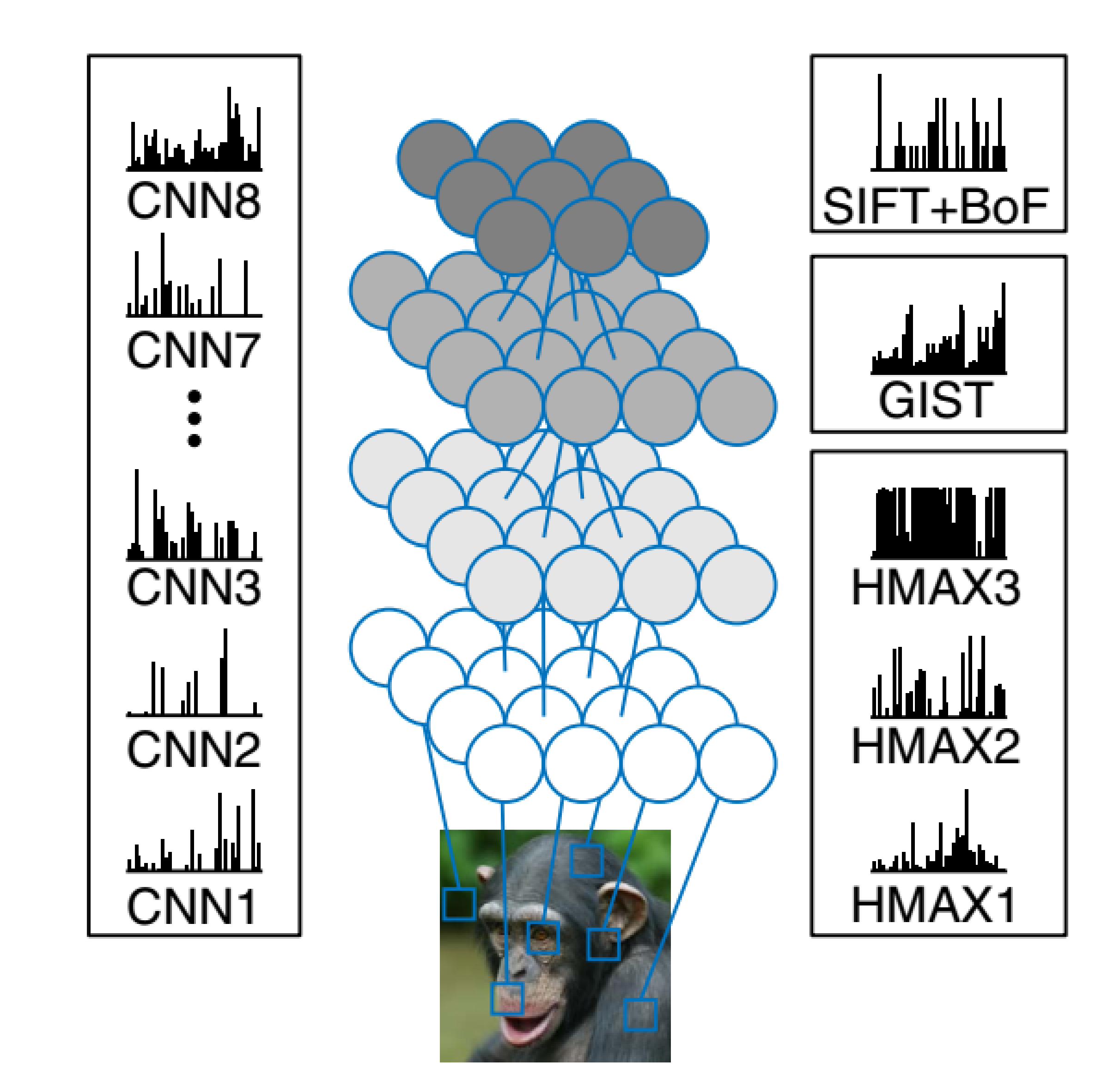
# Mental images from brain activity

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

Try to estimate features at different layers.

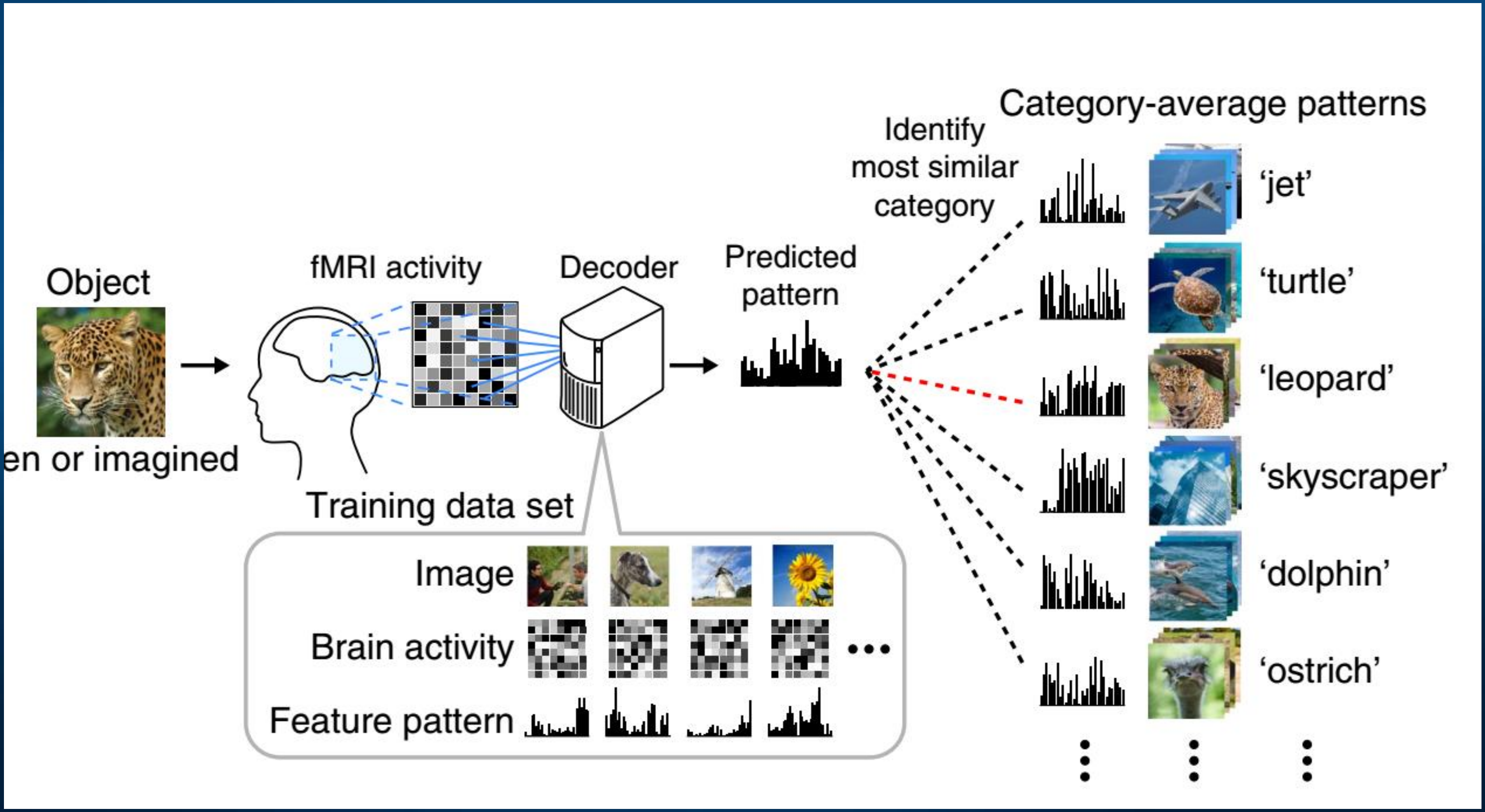
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

Output: 1000 images.



# Brain activity ⇔ 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).

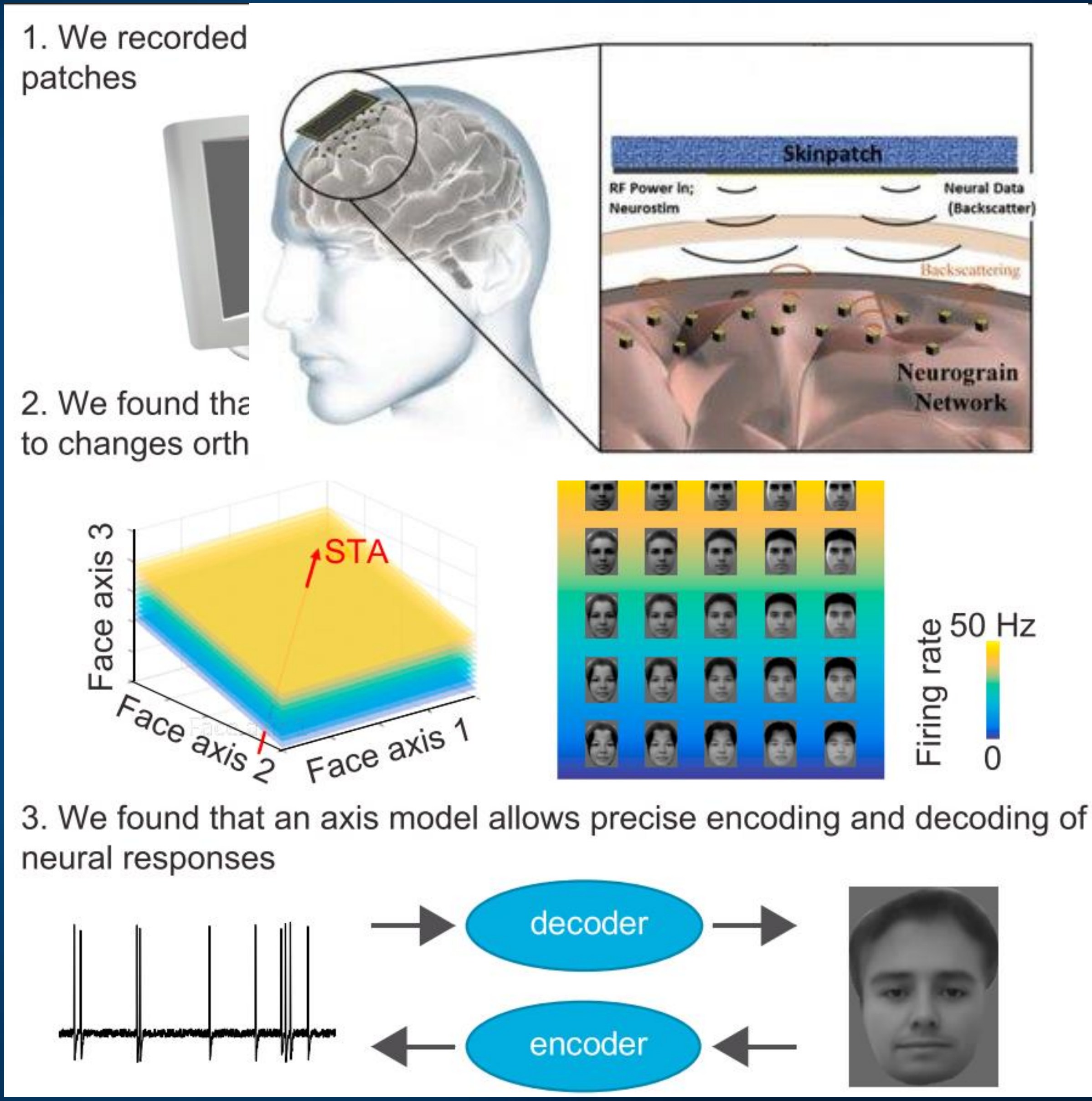
Dreams, thoughts … can one hide what has been seen and experienced?

# 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.

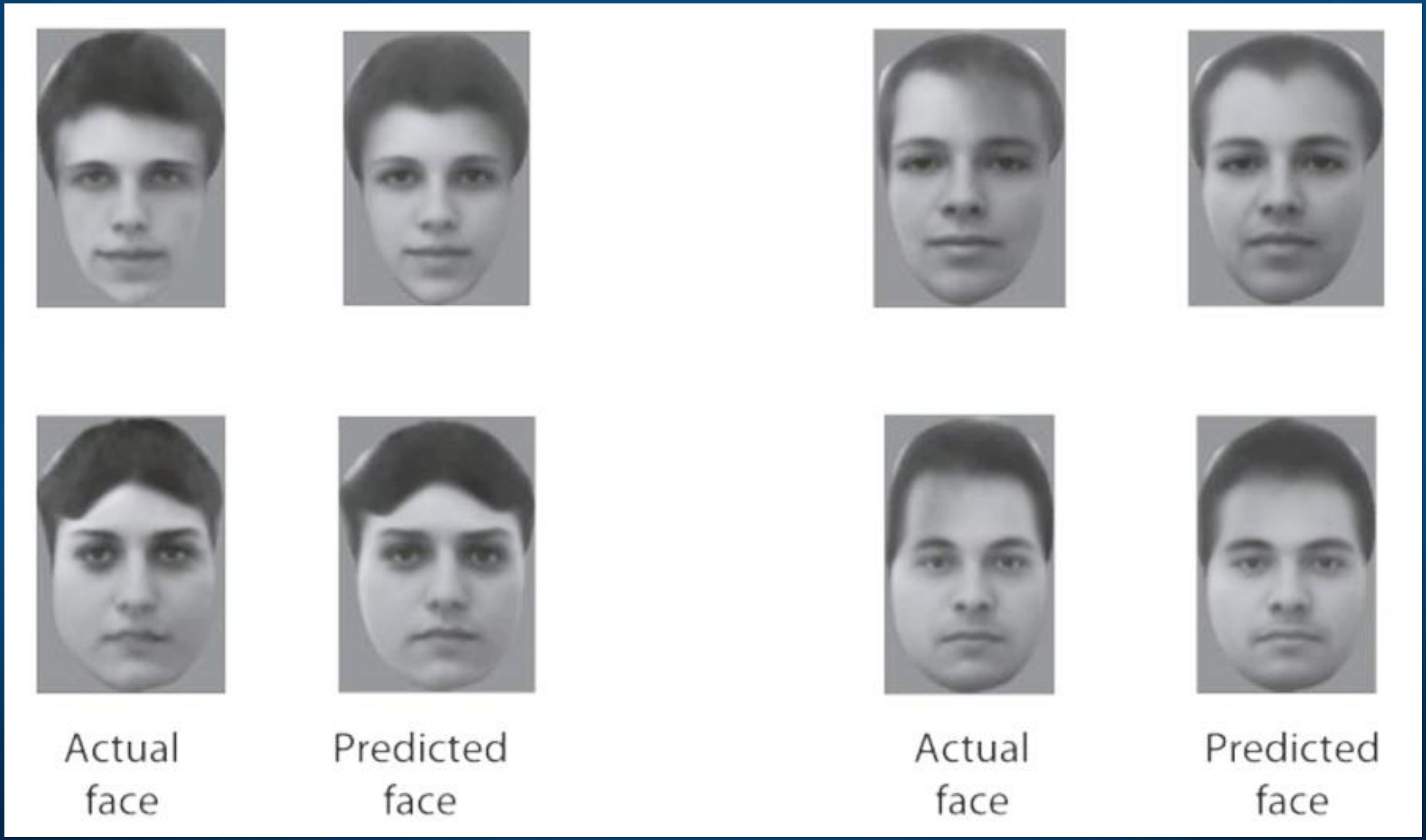
L. Chang and D.Y. Tsao, "The code for facial identity in the primate brain," *Cell* 2017

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



# 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.




L. Chang and D.Y. Tsao, *Cell* 2017

# 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

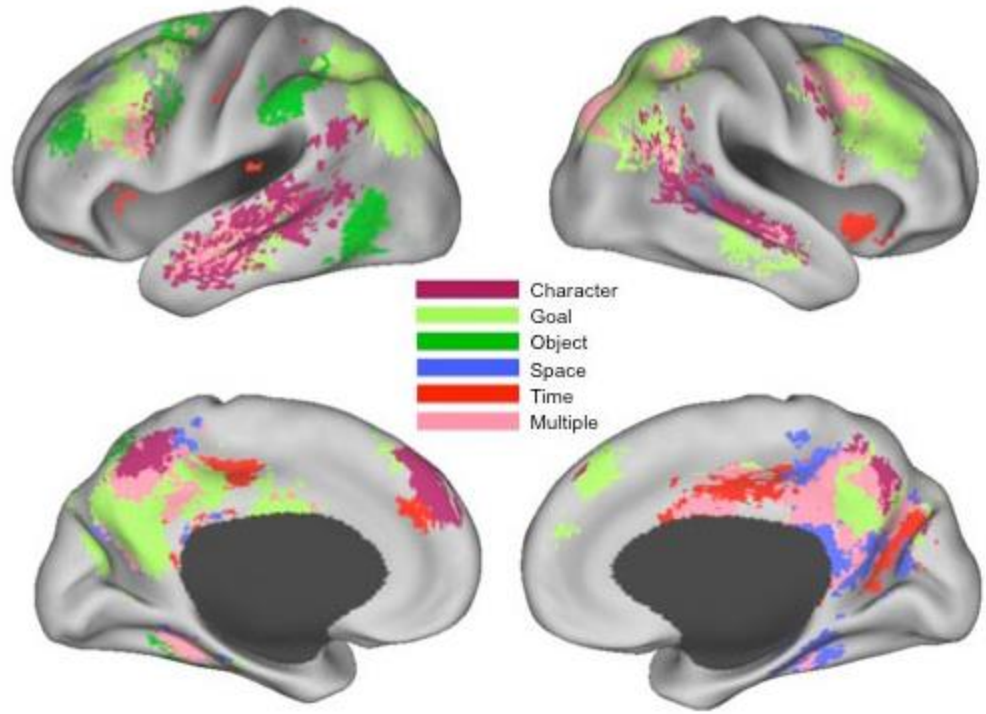
**Meaning**: always slightly different, depending on the context, but still may be clustered into relatively small number of distinct meanings.

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

A

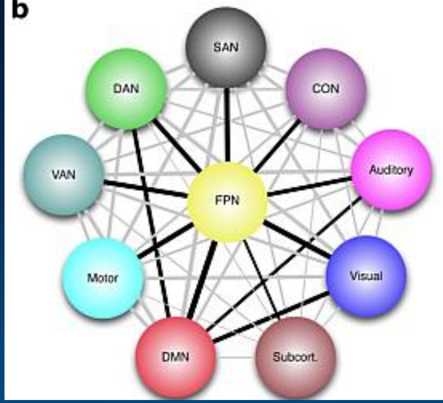
| Clause | Cause | Character | Goal | Object | Space | Time |
|---|---|---|---|---|---|---|
| ...[Mrs. Birch] went through the front door into the kitchen. | ● | | | | ● | |
| Mr. Birch came in | ● | ● | | | ● | |
| and, after a friendly greeting, | ● | | | | | ● |
| chatted with her for a minute or 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. | | | | | | |

B



# Dynamic functional brain networks

# Questions




**Global Neuronal Workspace Theory (Deahene et al. 1998):** brain processes underlying effortful tasks require two main computational spaces:

- a set of specialized and modular perceptual, motor, memory, evaluative, and attentional processors;
- a unique global workspace composed of distributed and heavily interconnected neurons with long-range axons.

Workspace neurons are mobilized in effortful tasks for which the specialized processors (Kahneman's System 1) do not suffice (System 2), mobilize or suppress contribution of specific processor neurons.

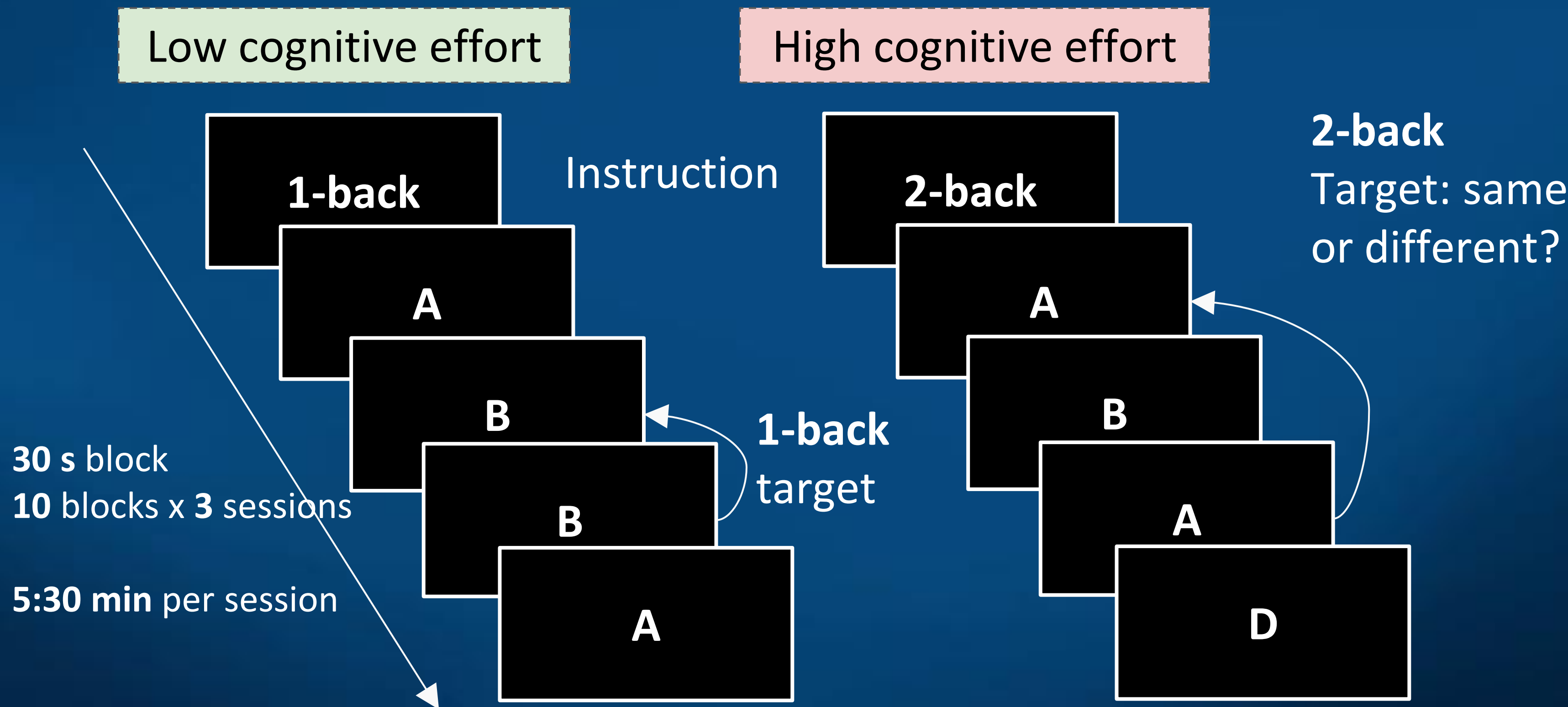
1. Can the whole-brain network properties change during performance?
2. Do modularity, path length, global, local efficiency and other network measures dependent on the cognitive load?

Finc, K., Bonna, K., Lewandowska, M., Wolak, T., Nikadon, J., Dreszer, J., Duch W, Kühn, S. (2017). Transition of the functional brain network related to increasing cognitive demands. Human Brain Mapping, 38(7), 3659–3674.

# Cognitive load on whole-brain network

35 participants (17 females; Mean age = 22.6 ± 3.1; 19-31).

**Letter *n*-back task**




Finc et al, Human Brain Mapping, 2017

# Data workflow

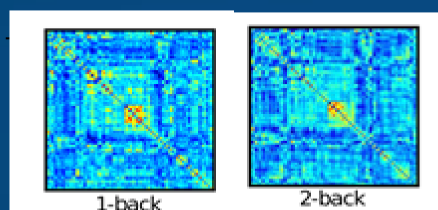
Two experimental conditions: 1-back, 2-back

**Node definition**

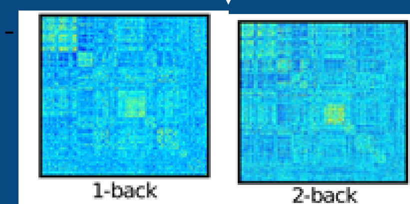

Anatomical parcellation (**90** nodes)

Functional parcellation (**264** nodes)


**Weighted correlation matrices**

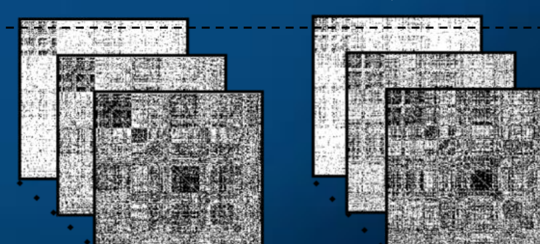



Fisher's *z*-scores




**Binary correlation matrices**

Threshold (0.01 - 0.6)



**global efficiency | local efficiency | modularity**

# Brain modules and cognitive processes

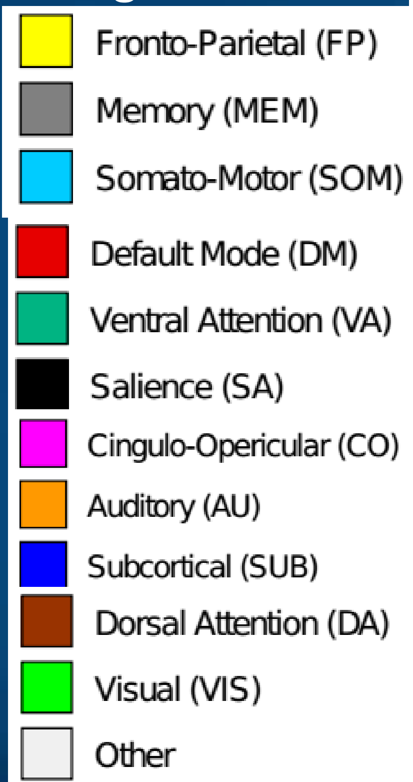
Simple and more difficult tasks, requiring the whole-brain network reorganization.

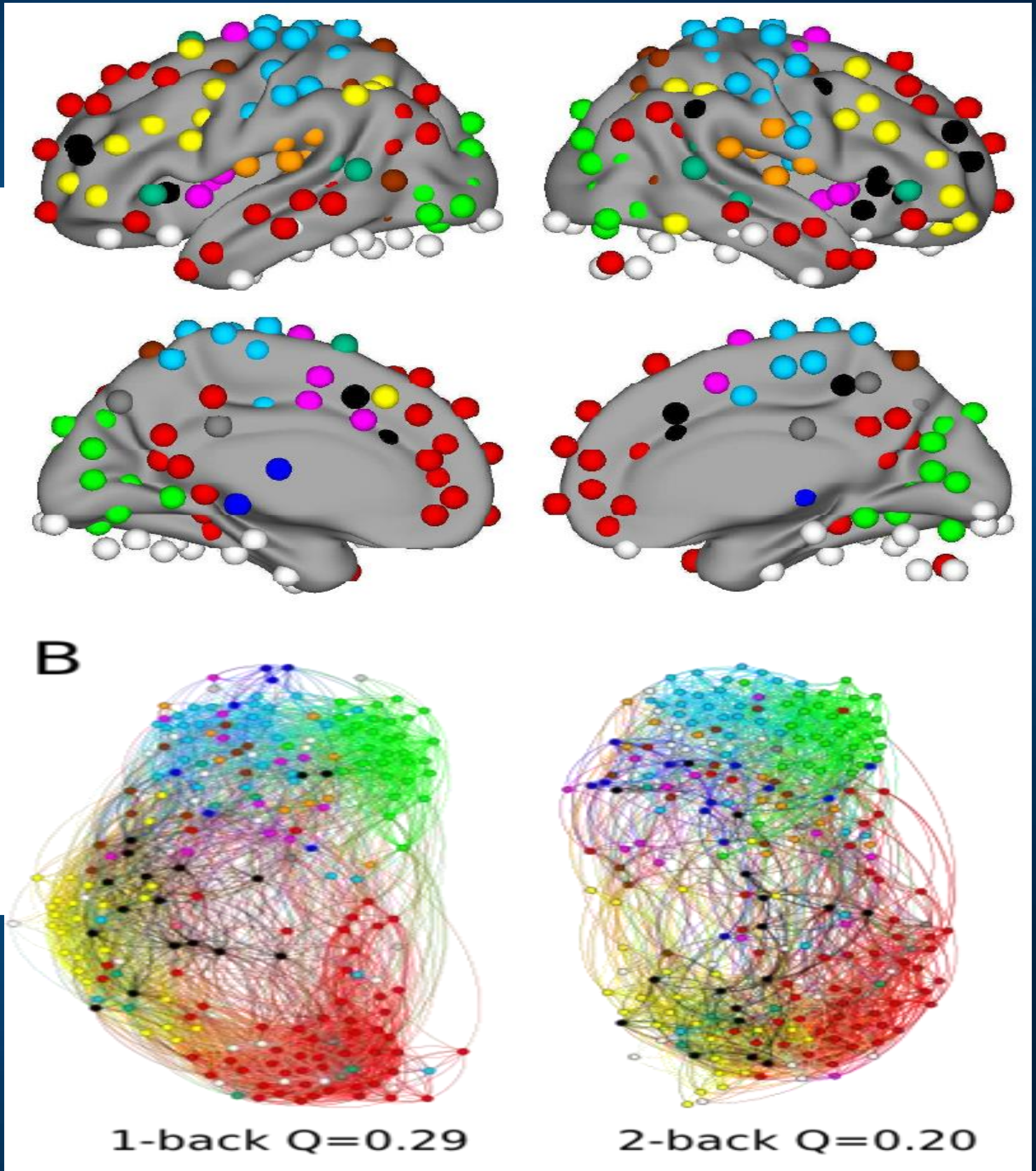
Left: 1-back

Right: 2-back

Average over 35 participants.

Left and midline sections.




K. Finc et al, HBM (2017).

# Brain modules and cognitive processes

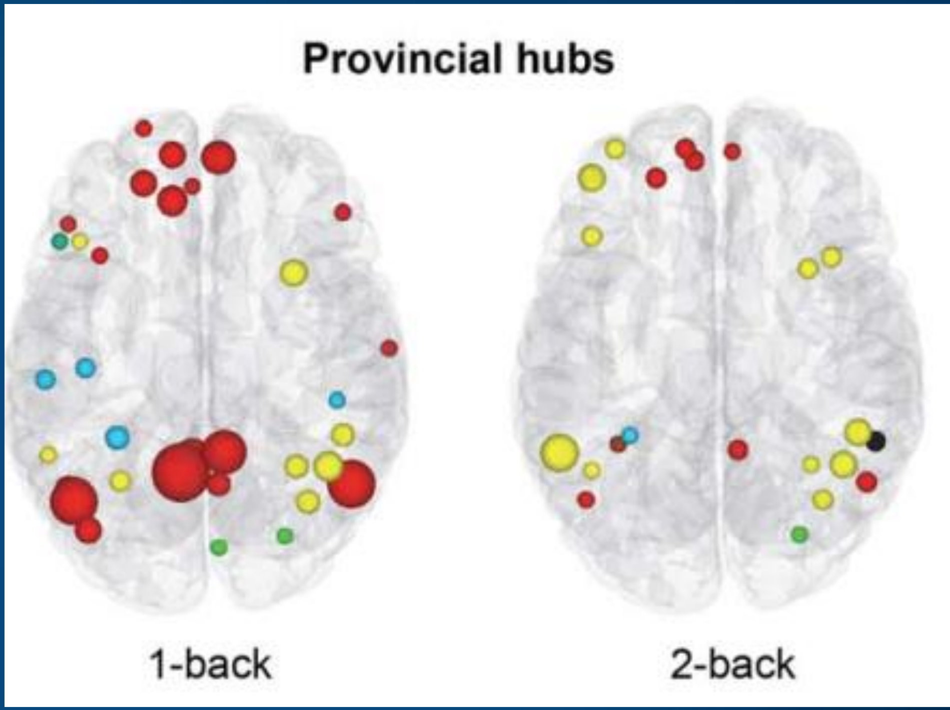
Simple and more difficult tasks, requiring the whole-brain network reorganization.

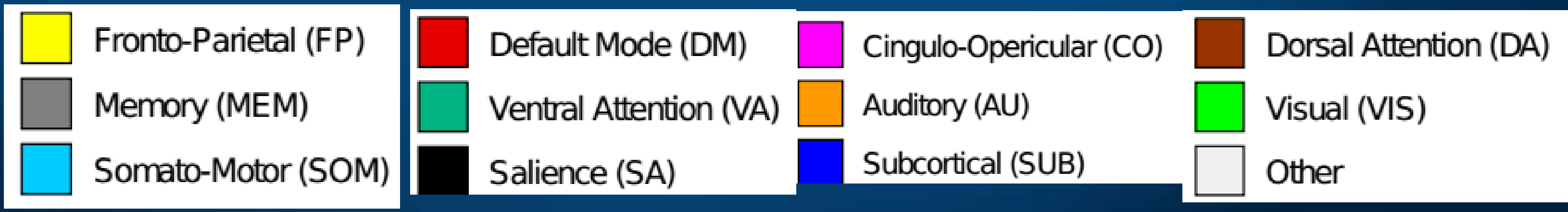
Left: 1-back local hubs

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, HBM (2017).

# Brain modules and cognitive processes

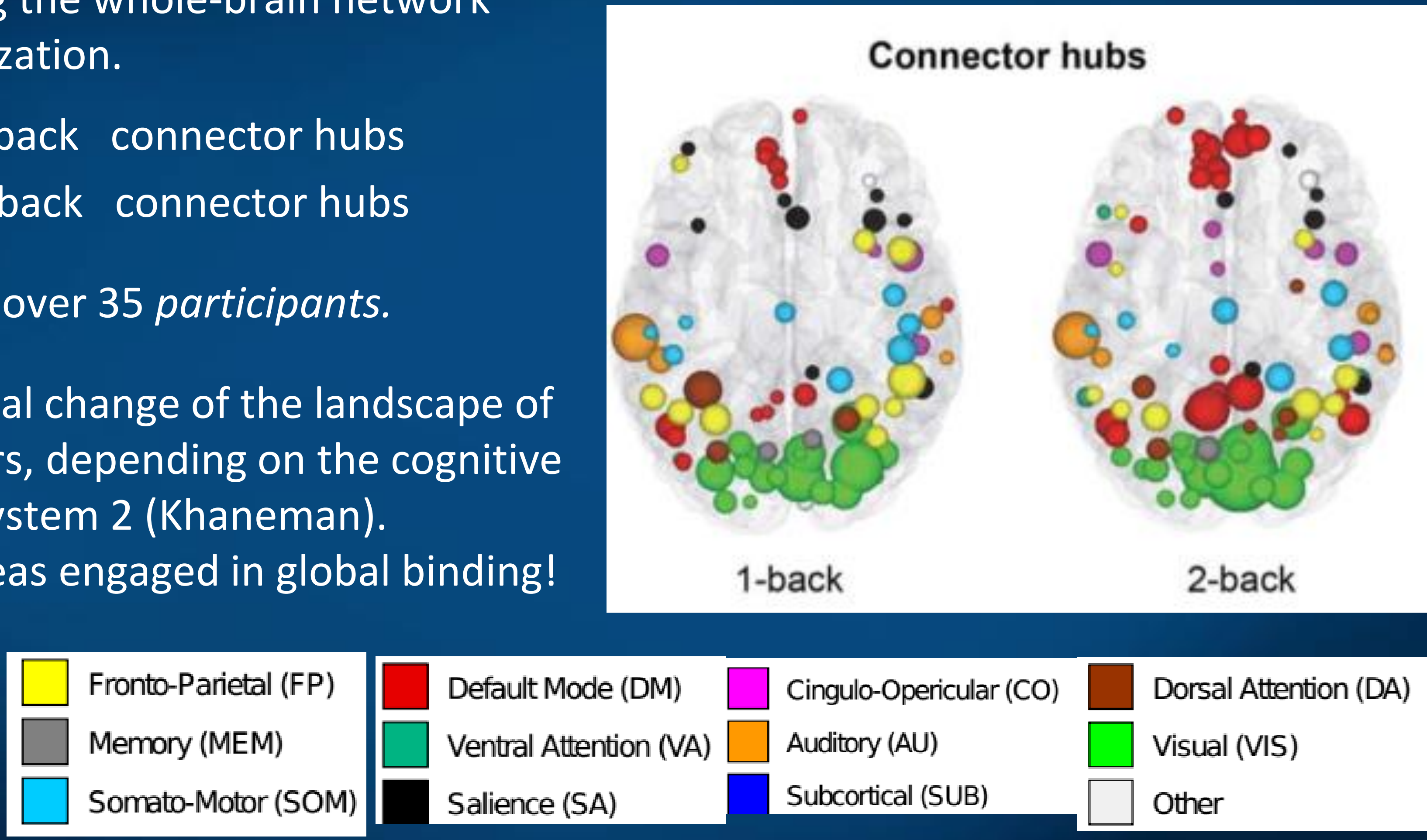
Simple and more difficult tasks, requiring the whole-brain network reorganization.

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!



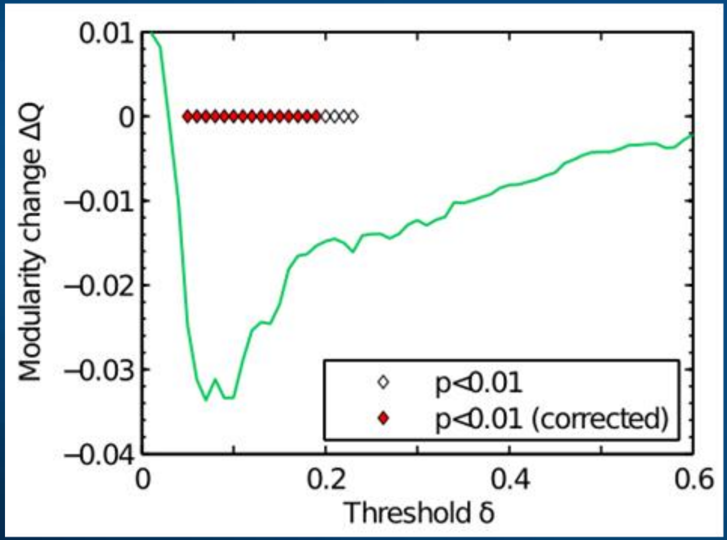

K. Finc et al, HBM (2017).

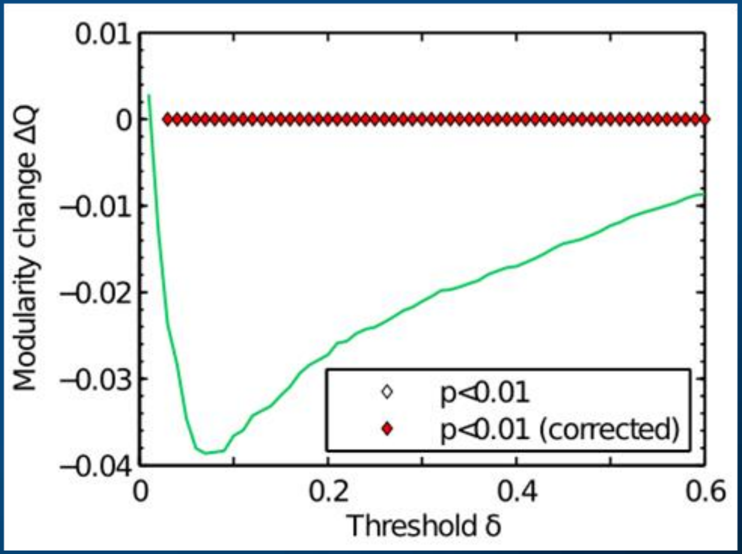
# Changes in modularity

Modularity metric: fraction of within-community edges in the network minus such fraction for randomly connected network with unchanged community structure.


Parcellation
AAL, 90 ROI


Parcellation
264 ROI
functional




Modularity for both parcellations significantly decreases for thresholds ~0.1.
Coarse parcellation washes out many effects, especially strong correlations.

Finc et al, Human Brain Mapping, 2017

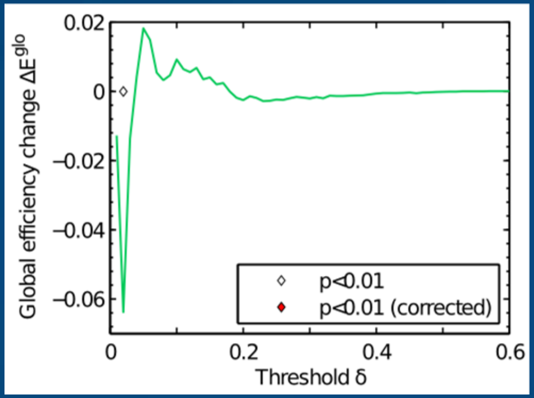
# Changes in efficiency

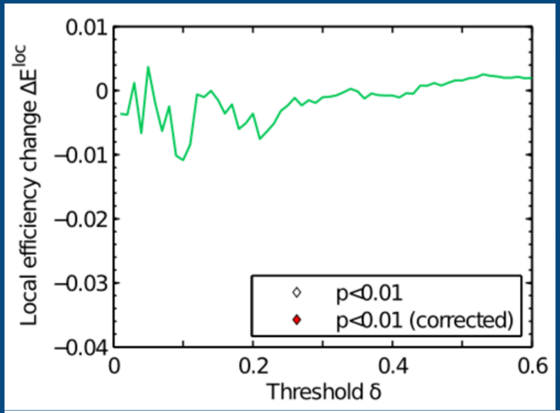
Global efficiency ~ inverse of characteristic path length
Local efficiency ~ clustering coefficient (Latora & Marchiori, 2001).

Global efficiency

Local efficiency

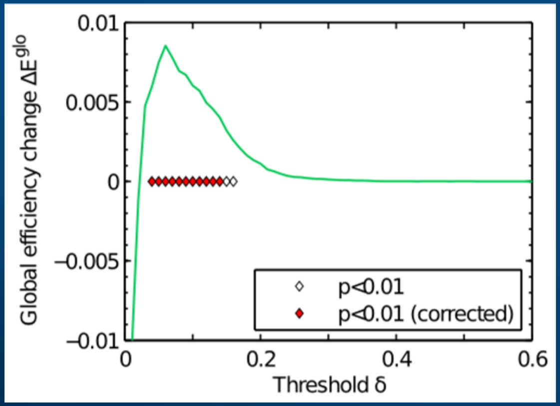

Parcellation
AAL, 90 ROI

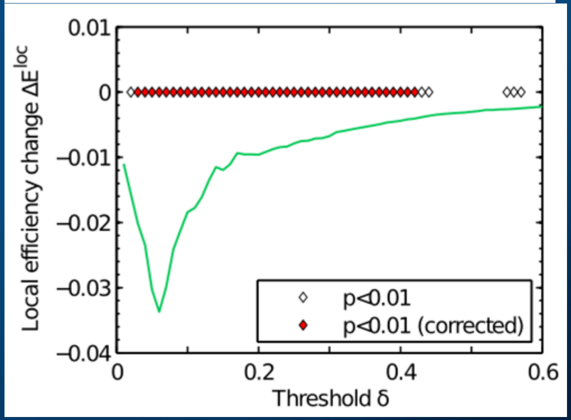




Parcellation
264 ROI
functional




Finc et al, Human Brain Mapping, 2017

# Cognitive load

Segregated network

Low cognitive effort

Locally specialized processing

global efficiency

local efficiency

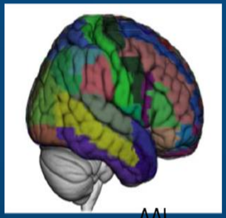
modularity

performance

Integrated network

High cognitive effort

Distributed processing

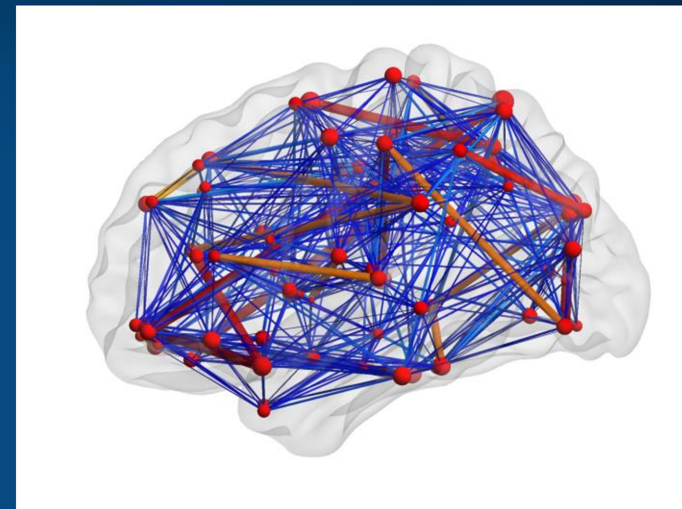


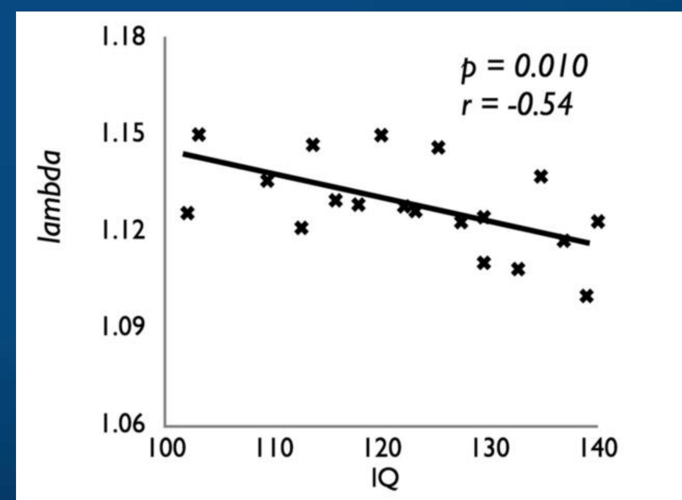

≠


Parcellation into 264 regions (10 mm spheres) shows subnetworks more precisely than for 90 regions; only a small subgroup of neurons in each ROI is strongly correlated.

# Resting state/cognitive performance

| | |
|---|---|
| Characteristic path length λ → | Intellectual performance |
| Modularity → | Working memory performance |
| Modularity → | Working memory capacity |






Network modularity ⇔ higher working memory capacity and performance.

High connectivity within modules and sparse connections between modules increases effective cooperation of brain regions, is associated with higher IQ.

van den Heuvel *et al.* (2009) | Stevens *et al*. (2012)

# Human Enhancement
# and
# Optimization of Brain Processes

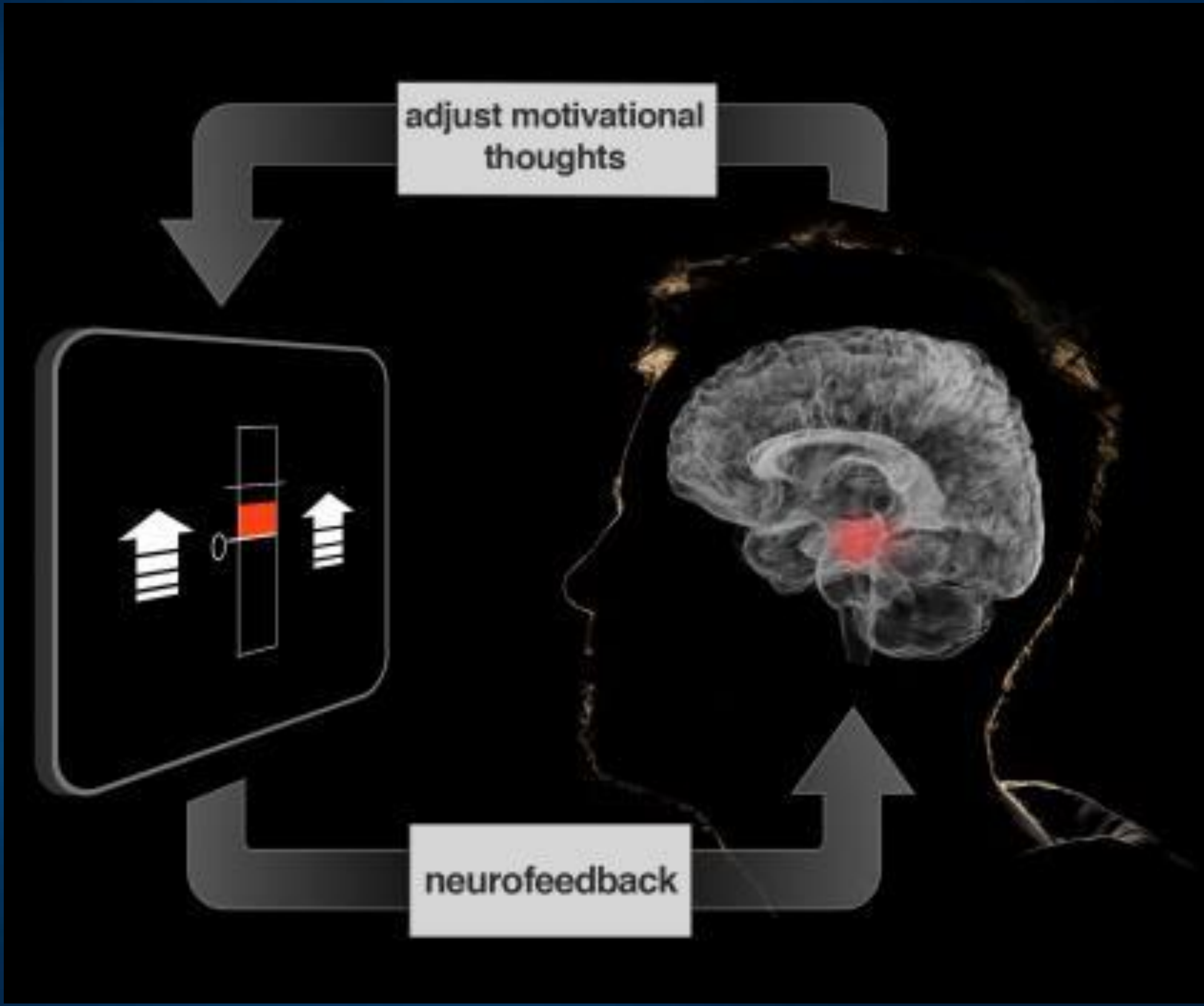
# Neurofeedback: first BCI

Used in clinical practice, $\alpha/\theta$ rhythms for relaxation.

Duch, Elektronika i stresy, 1978!

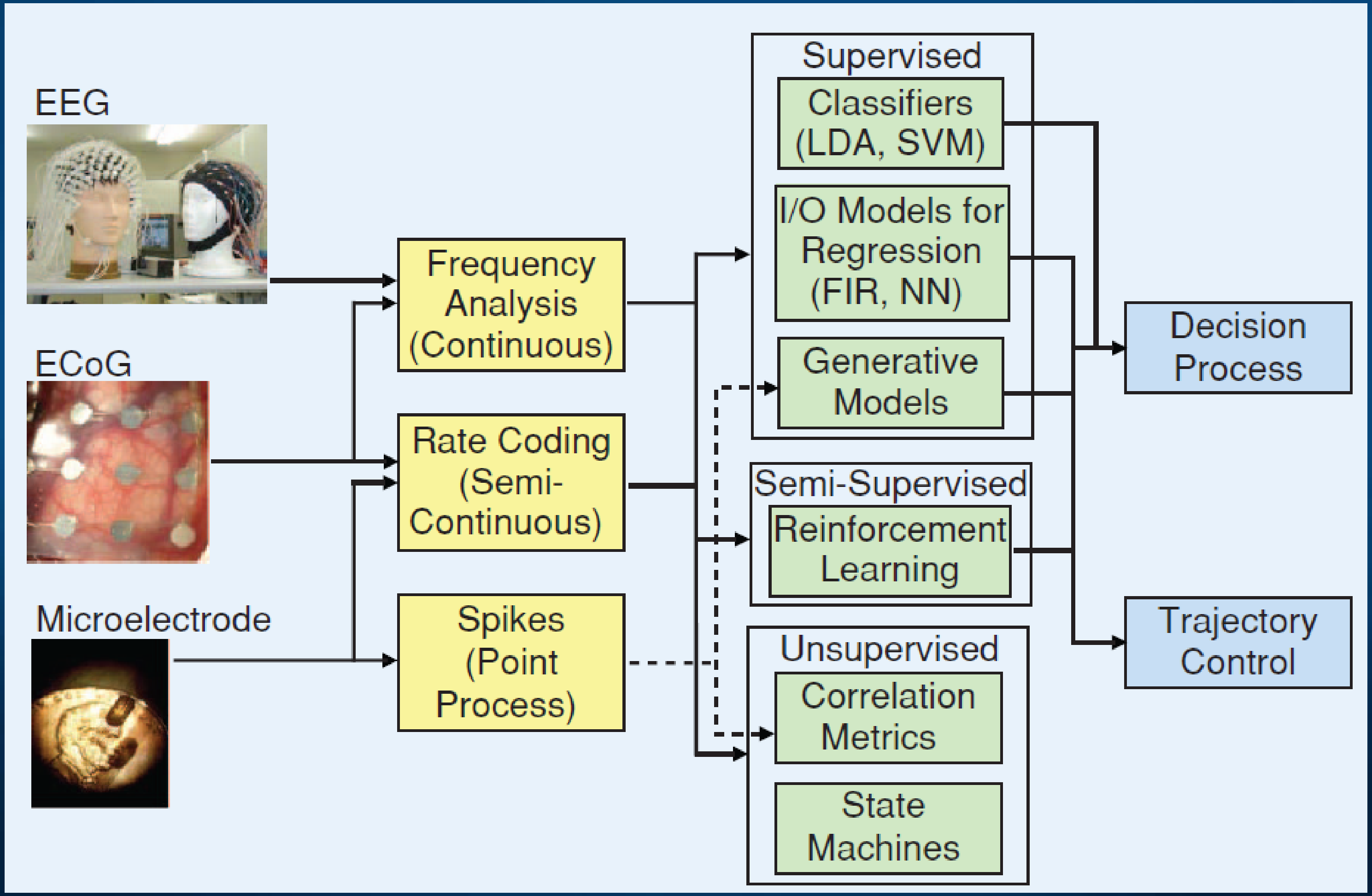
Critical review of existing literature shows that this is not effective.

New forms based on brain fingerprinting needed.

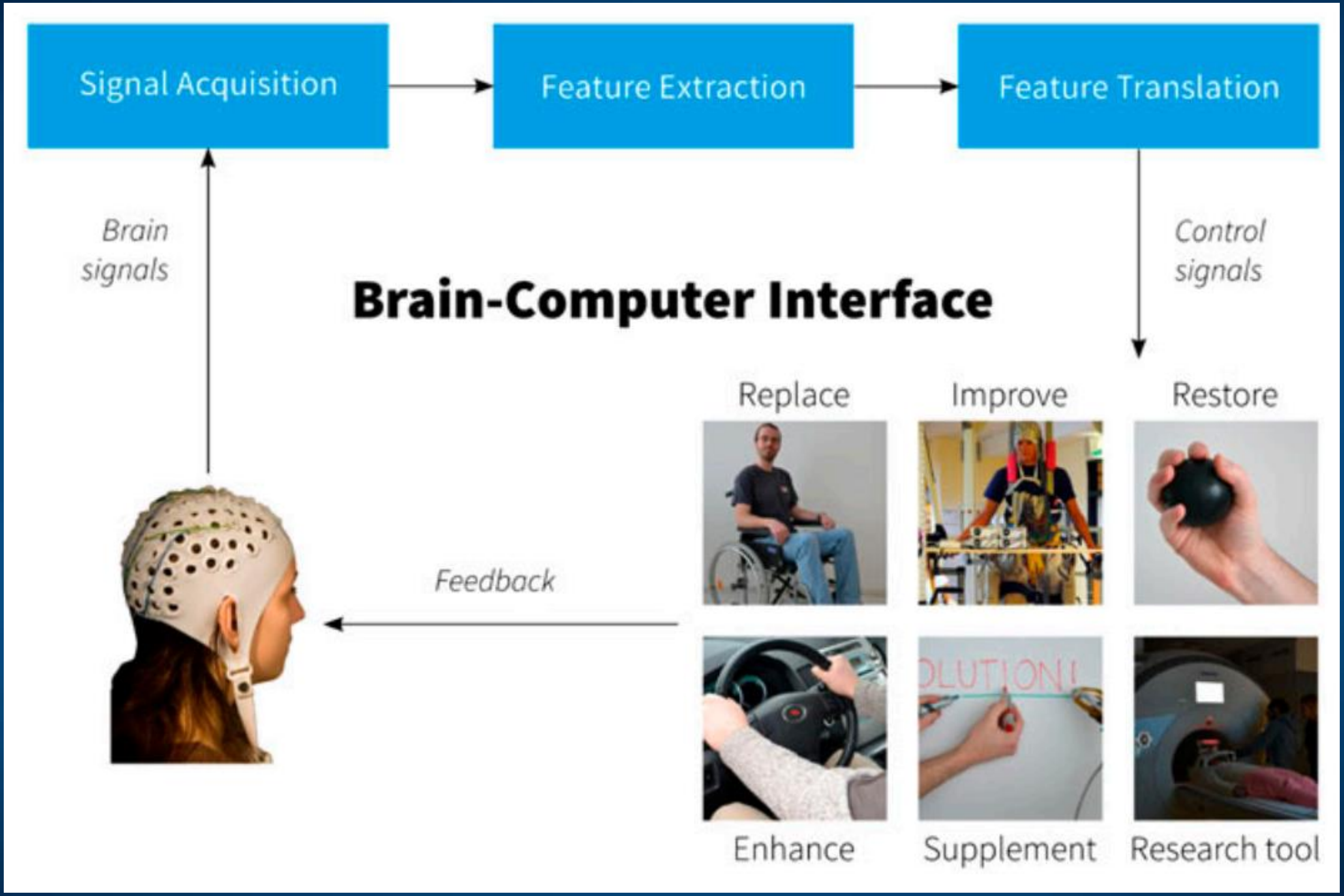


# BCI: wire your brain …

Non-invasive, partially invasive and invasive signals carry progressively more information, but are also harder to implement. EEG is still the king!

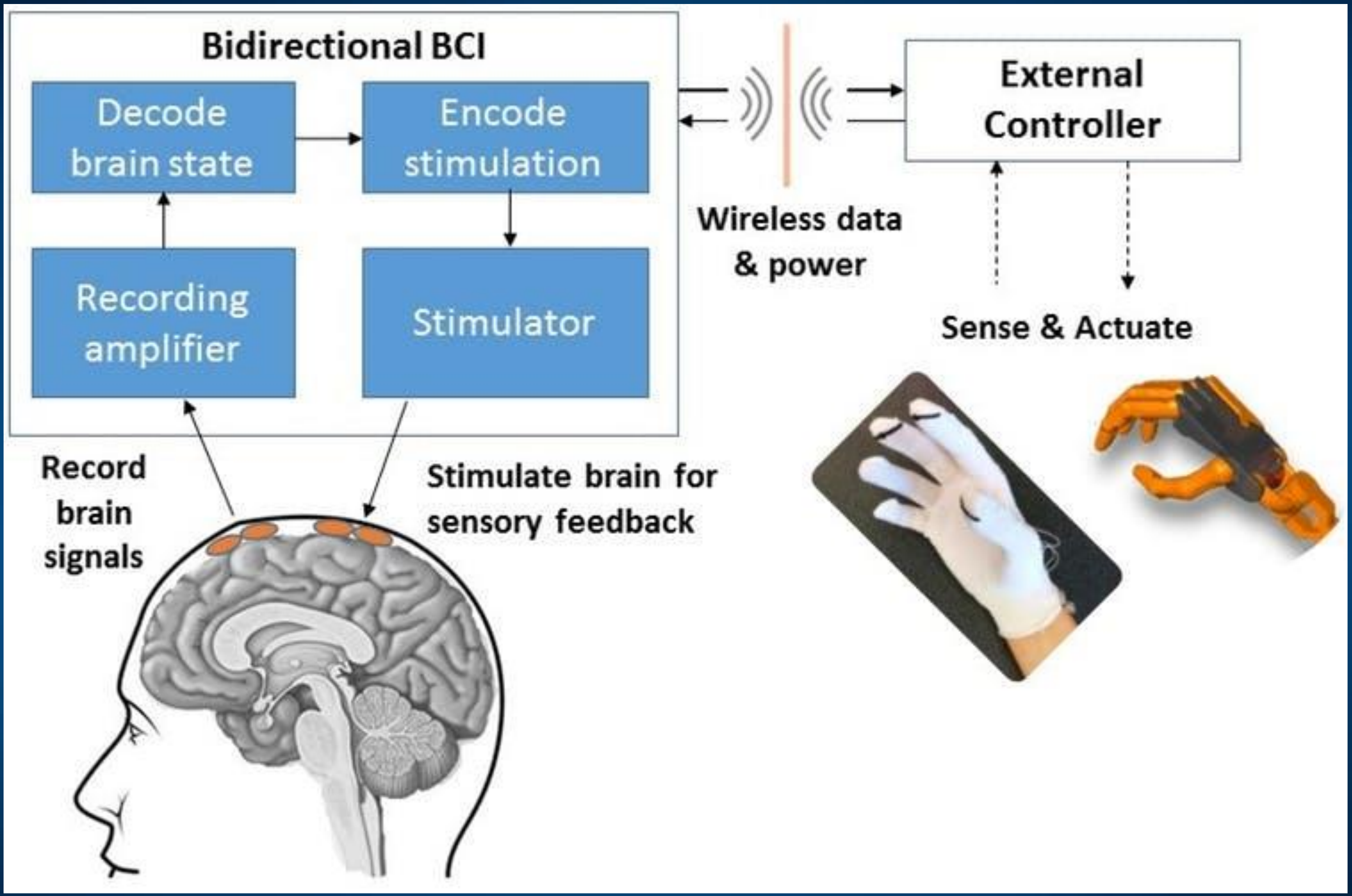


# BCI Applications



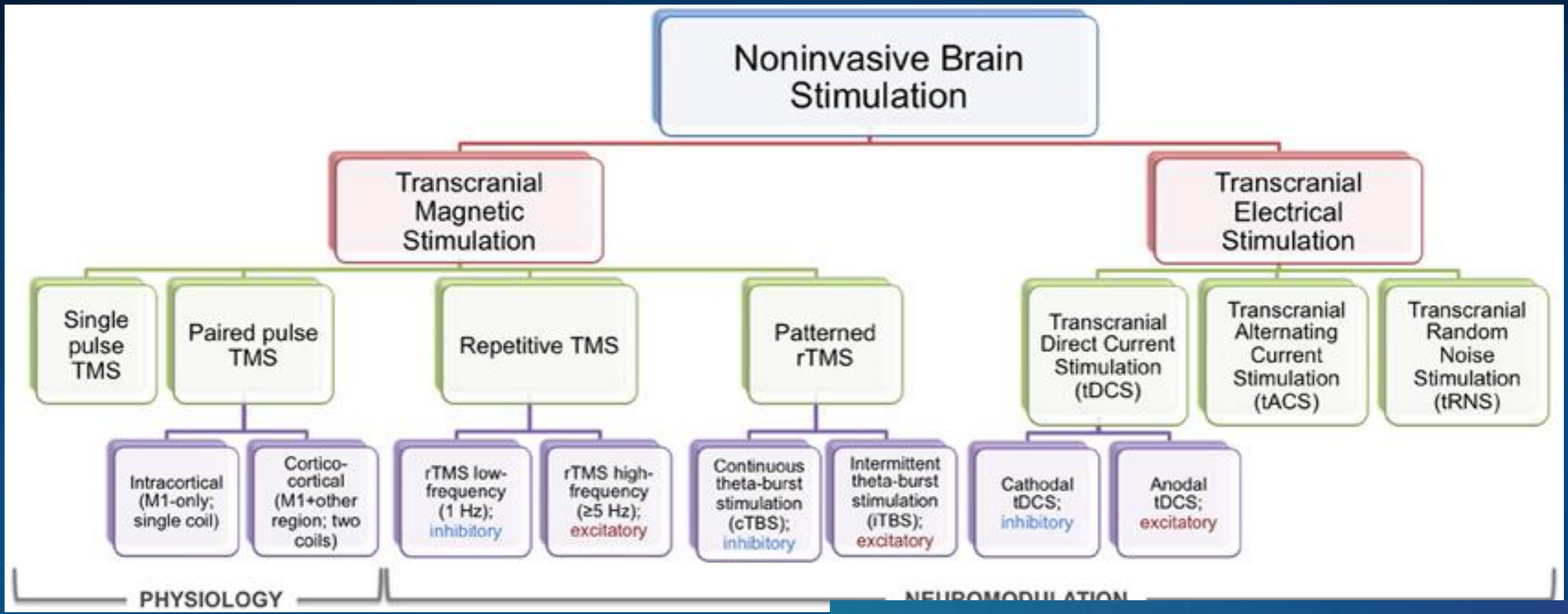

Signals: invasive (brain implants), partially invasive (ECoG), and non-invasive.

# 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



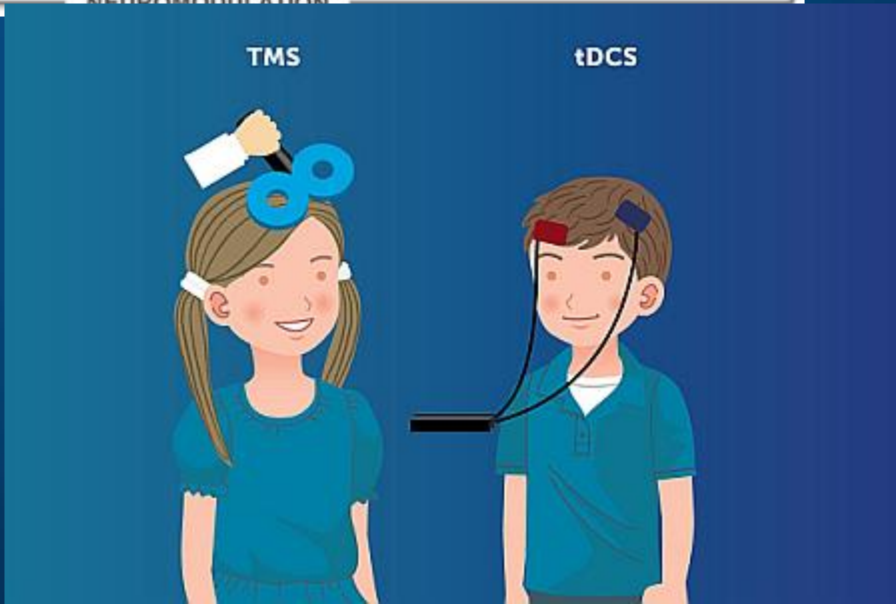

ECT – Electroconvulsive Therapy

VNS – Vagus Nerve Stimulation

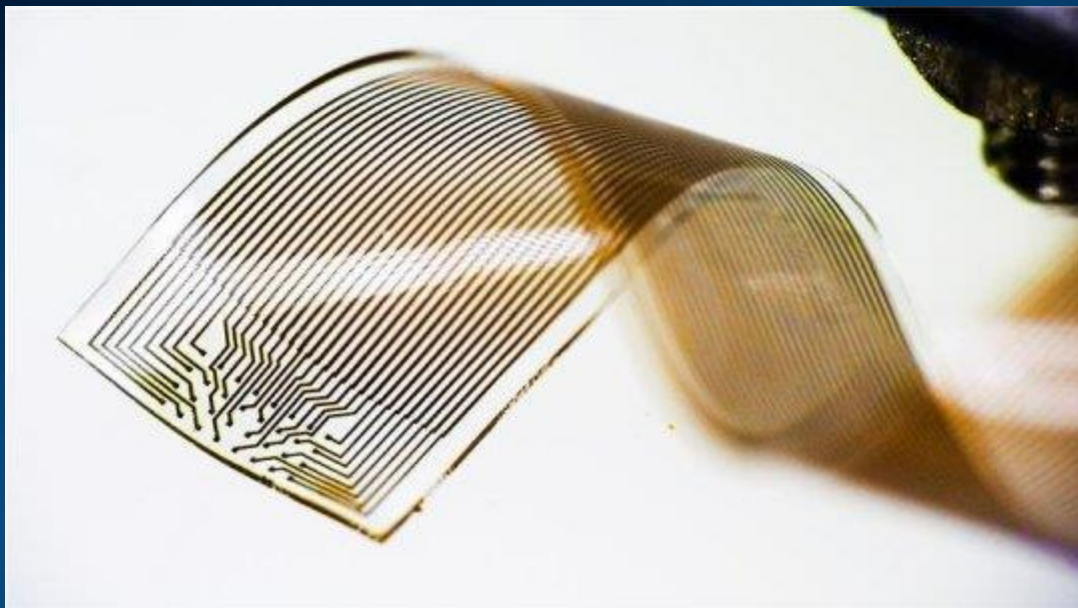
Ultrasound, laser … stimulation.

Complex techniques, but portable phones are also complex.

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



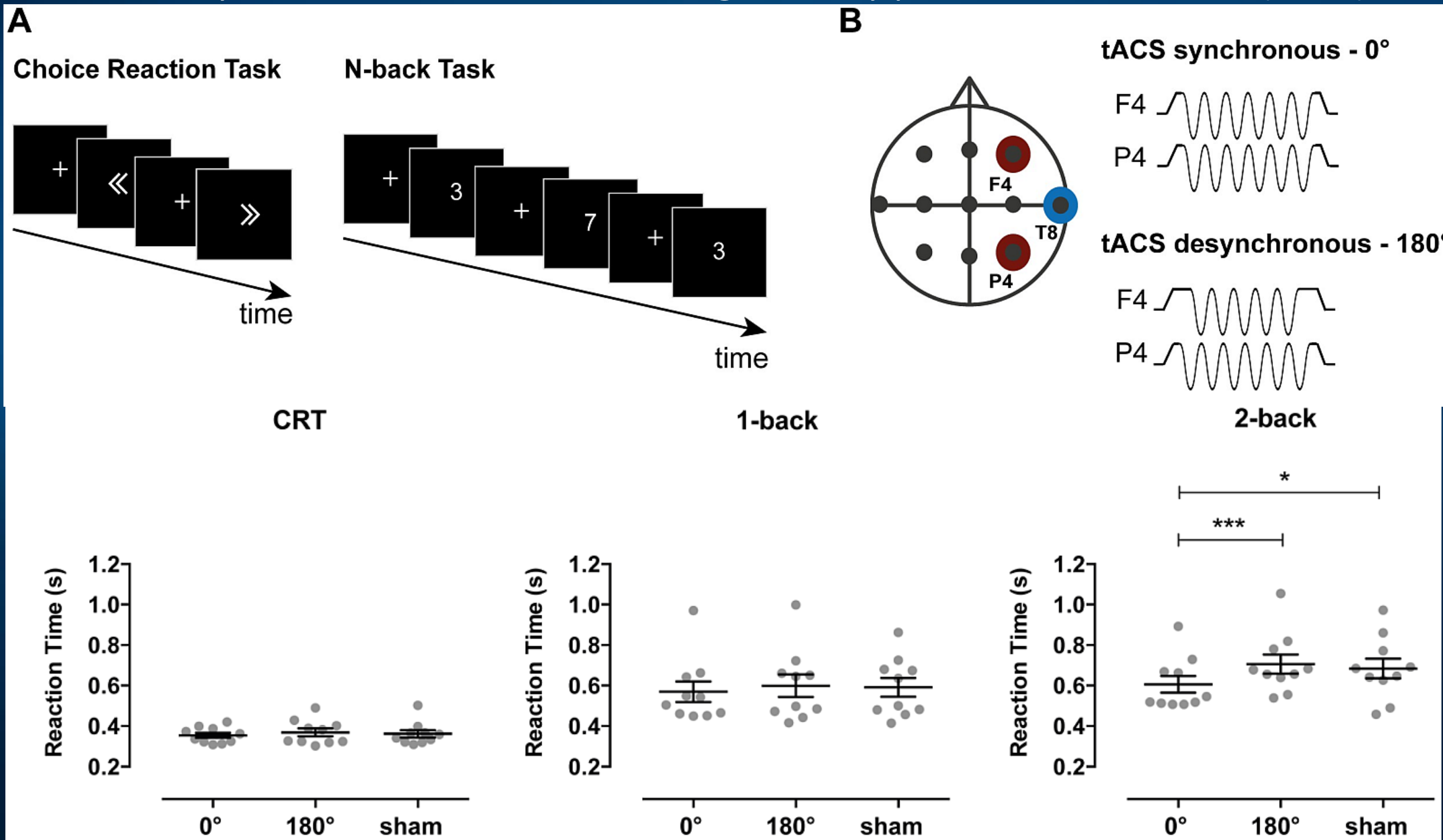
# Partially invasive interfaces



Epilepsy, Obsessive-Compulsive Disorder, Phobias … if you know how to run electric currents through your brain you can control your mental states in a conscious way. New stable electrodes are coming!

# Synchronize PFC/PC

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



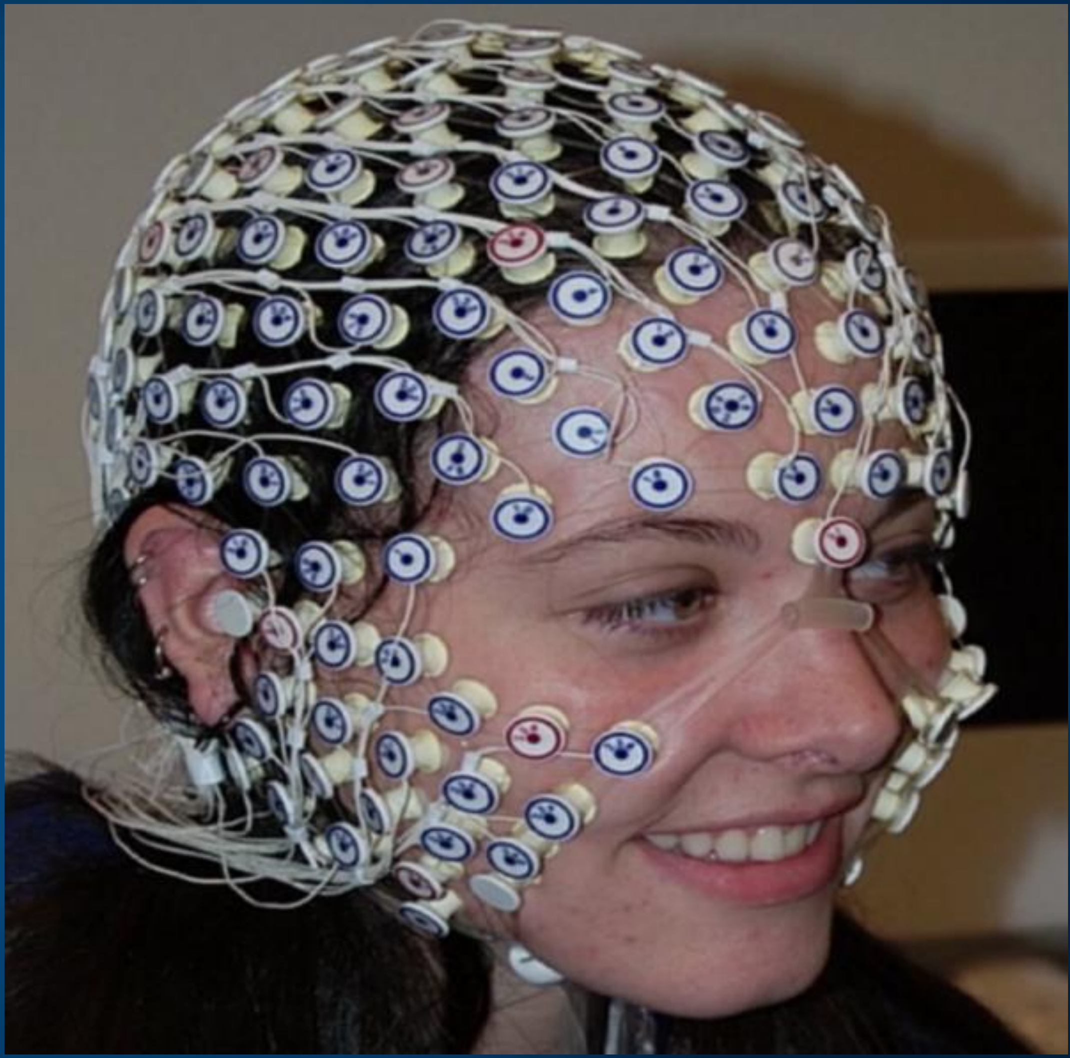
# HD EEG/DCS?

EEG electrodes + DCS.

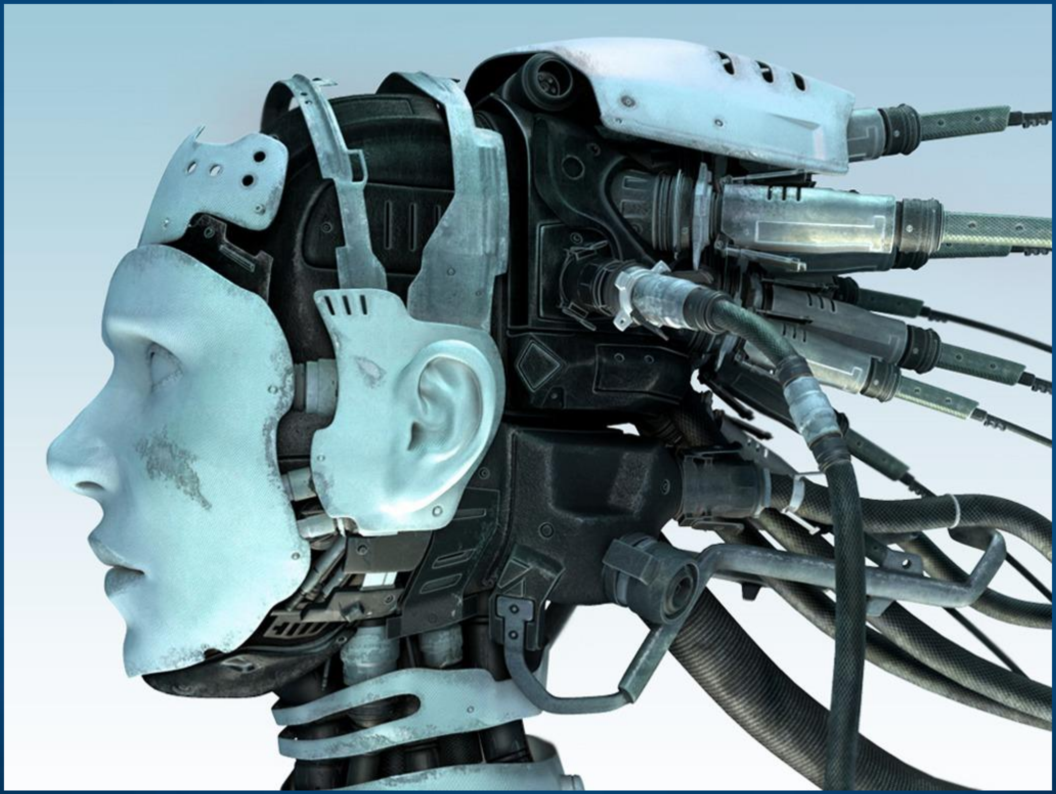
Reading brain states
=> transforming to common space
=> duplicating in other brains
Applications:

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

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



# Neurocognitive technologies



# Neuro-relax

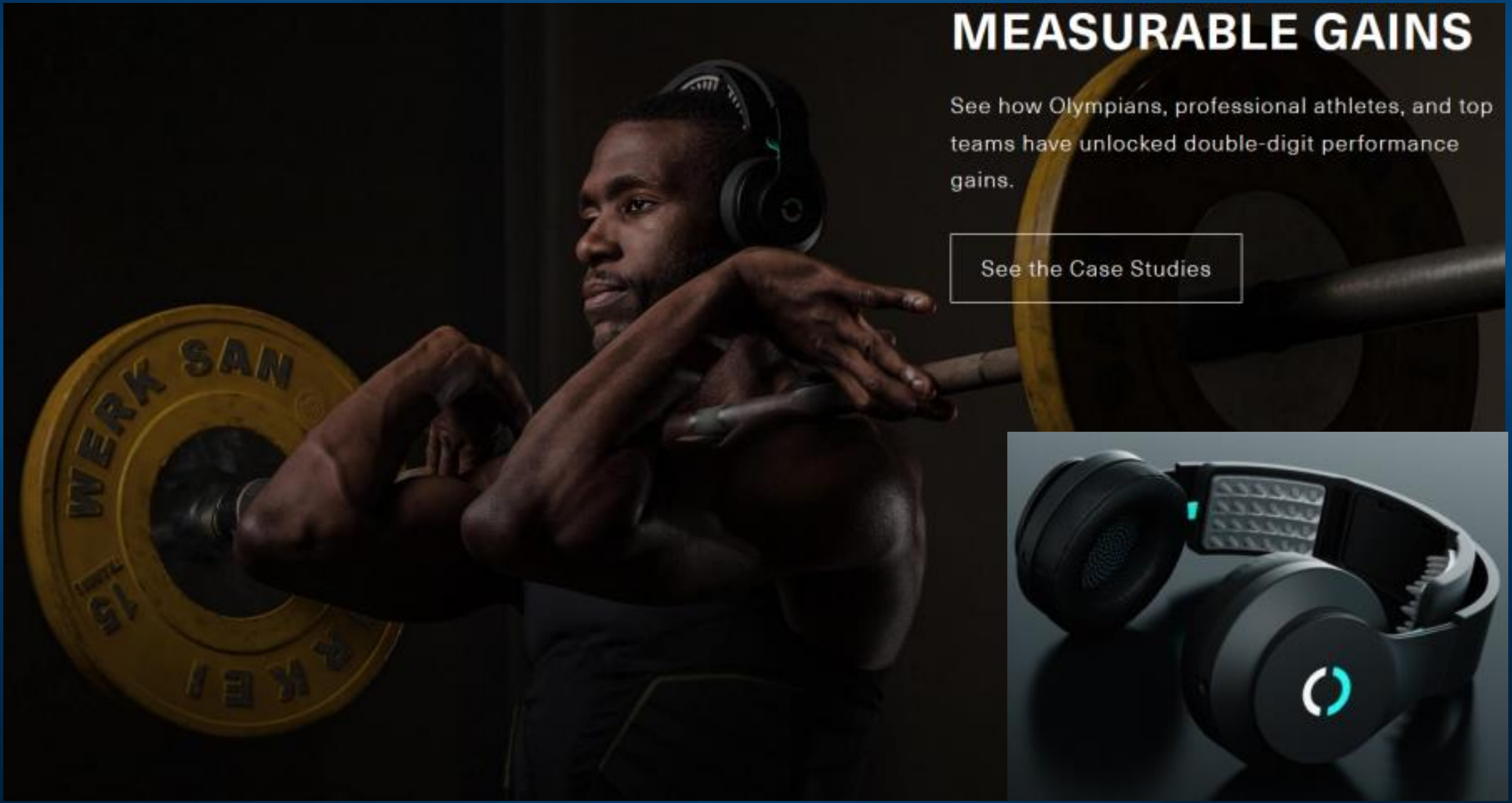
Sounds and music may have arousing or relaxing effects.

Melomind:

Simple EEG determins the relaxation level and adaptively creates sounds to increase it.

# Neuropriming

Effort, stamina, force in sports requires strong activation of muscles by motor cortex. Synchronize your effort with direct current cortex stimulation.

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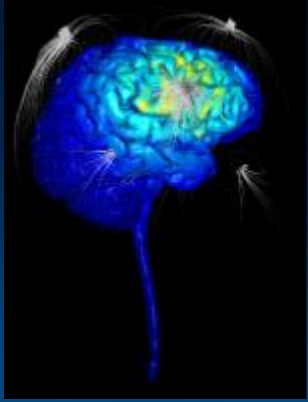
# DCS for attention/relaxation

Focusing attention for a long time requires effort: PFC activates brain regions processing signals from various modalities. External stimulation using alternating currents (tDCS) or magnetic pulses (rTMS) gives good results in case of games, pilots, combat soldiers. Control yourself with a smartphone! **Thync** arouses the brain before action and relaxes after.


# BCBI for learning



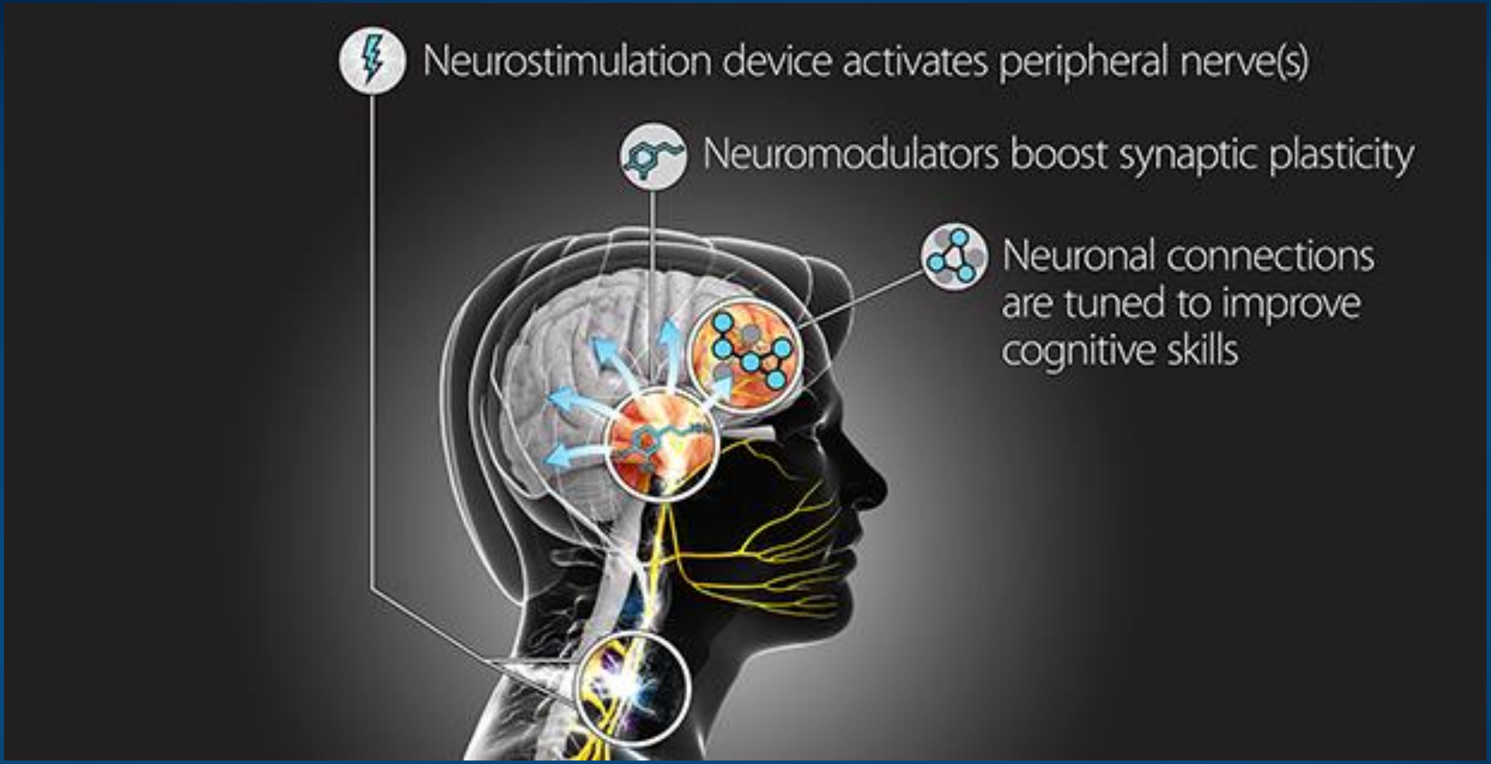
Your brain knows better what is interesting than you do! Information relevance inferred directly from brain signals to model search intent.

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

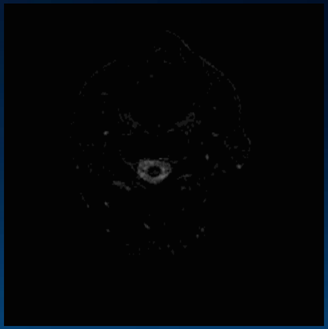
- Engagement Skills Trainer (EST) procedures are used by USA army.
- Intific Neuro-EST uses EEG analysis and mulit-channel transcranial simulation (HD-DCS) to pre-activate the brain of the novice in areas where the expert brain is active.
- Real-life transfer learning …
- HD-tDCS may have 100 channels, 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



- „Optimization" of brain processes should be possible, but first we need to find good methods for discovering brain fingerprints of cognitive activity, mapping between brain and mental states – our main goal.
- **Roadmap**: Brain neuroimaging ⇔ models of brain processes ⇔ links with mental models ⇔ closed loop BCBI for conscious control/brain optimization
- Brain reading, understanding neurodynamics and neurocognitive phenomics, plus computational stimulation are the key to BCBI for voluntary self-regulation of brain functions, and numerous therapeutic applications.
- Neuromorphic hardware with complexity beyond the human brain is coming and will enable construction of new brain models and practical applications.
- Neurocognitive informatics is needed to understand learning processes, creativity, formation of deep beliefs, conspiration theories, diagnose mental problems and improve therapies, increase efficiency of the brain.
  With new global AI initiatives anything is possible!

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

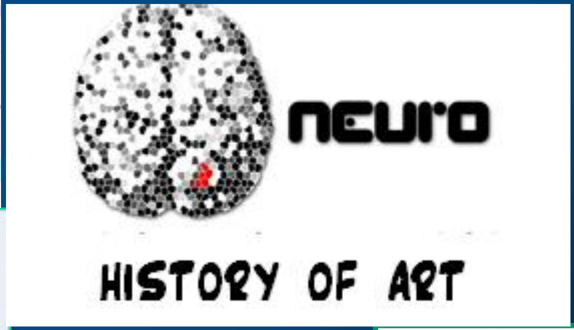




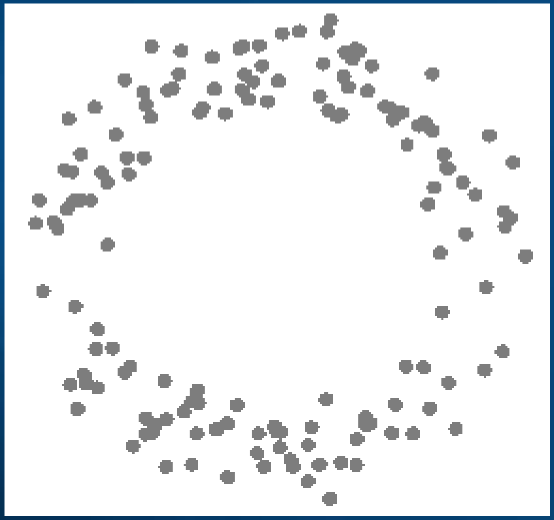
Monthly international developmental seminars (2017): Infants, learning, and cognitive development

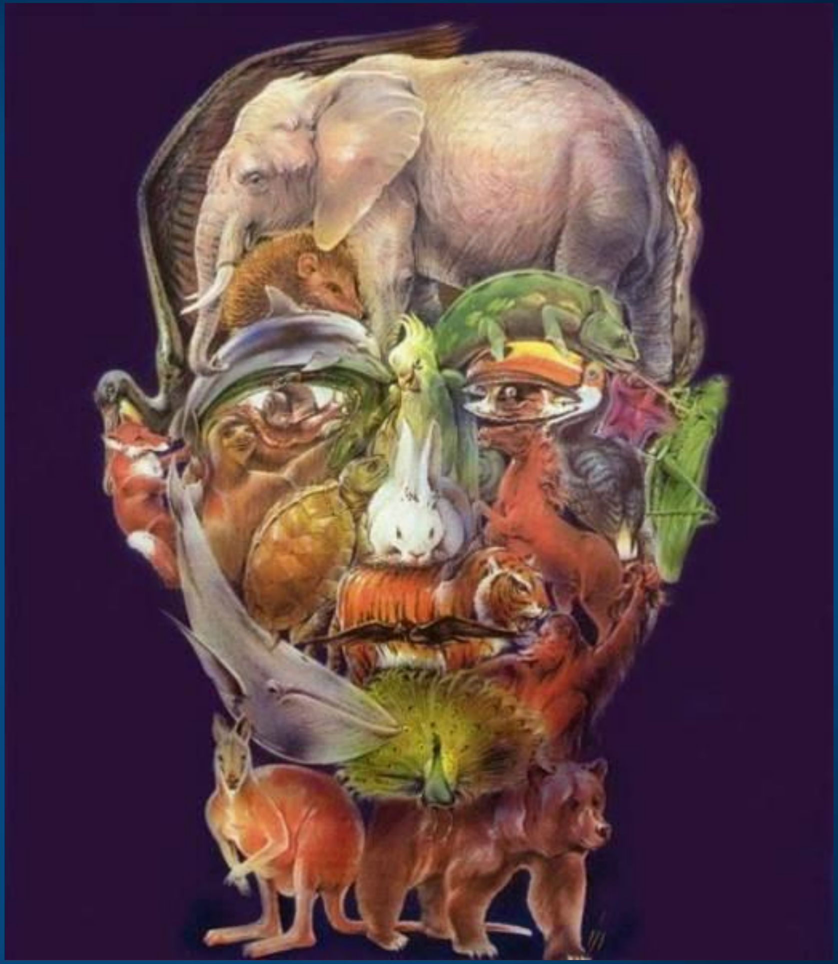
Disorders of consciousness 17-21.09.2017

Autism: science, therapies 23.05.2017




Thank you for synchronization of your neurons





Google: W. Duch

=> talks, papers, lectures, Flipboard …