



AI for better brains

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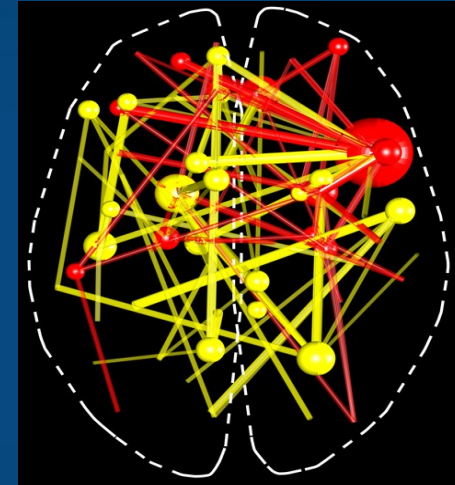
[Google: Wlodek Duch](#)

SISSA, Nov. 12-13, 2019

On the threshold of a dream ... (50 y!)



**Some ideas on how to
optimize and repair
human brains
with AI.**



Duch W. (2012) Mind-Brain Relations, Geometric Perspective and Neurophenomenology, American Phil. Assoc. Newsletter 12(1), 1-7.
Duch, W. (2019) Mind as a shadow of neurodynamics. [Physics of Life Reviews](#)

Krzysztof Grąbczewski

Norbert Jankowski
Włodzisław Duch
Krzysztof Grąbczewski (Eds.)

Włodzisław Duch
Jacek Mańdziuk (Eds.)

Meta-Learning in Decision Tree Induction

Meta-Learning in Computational Intelligence

Challenges for Computational Intelligence

 Springer

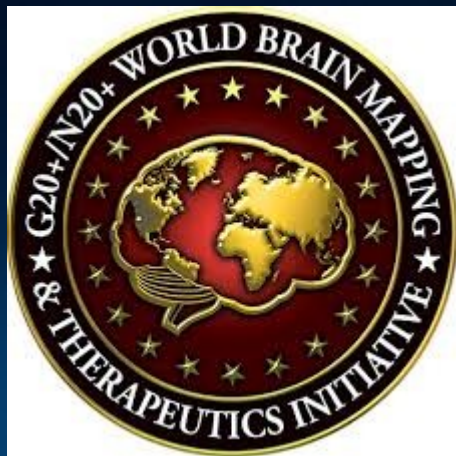
 Springer

 Springer

I've worked on many topics: computational intelligence algorithms, meta-learning in CI, neural networks, data understanding, NLP, similarity based methods, visualization, computational creativity, ASD, neuroinformatics, computational physics/quantum chemistry, philosophy of mind.

<http://www.is.umk.pl/~duch/cv/WD-topics.html>

Global Brain Initiatives,
or why is this so important?



The mission of IEEE Brain is to facilitate cross-disciplinary collaboration and coordination to advance research, standardization and development of technologies in neuroscience to help improve the human condition.

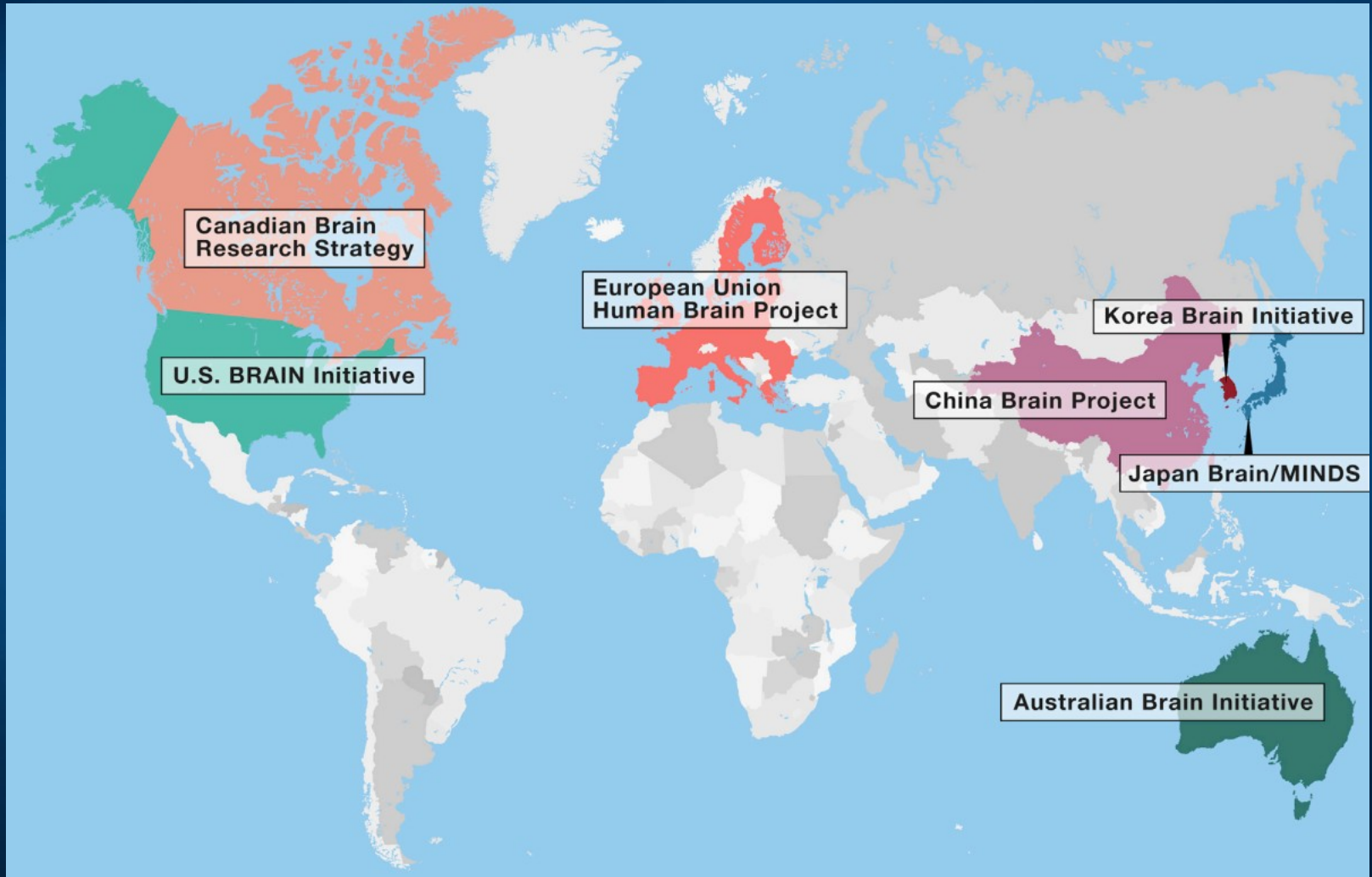
AI-neuroscience convergence! 20 IEEE Societies are involved, including:

IEEE Computational Intelligence Society; Computer Society; Consumer Electronics Society; Digital Senses Initiative; Robotics and Automation Society; Sensors Council; Signal Processing Society; Society on Social Implications of Technology; **Systems, Man, and Cybernetics Society**, International Neuroethics Society, and a few other societies.

Most these societies are also involved in artificial intelligence.

Satya Nadella (CEO, Microsoft): examples of technology that can be applied to empower more than one billion people with disabilities around the world.

International Brain Initiatives



Involvement in large EU Initiatives

2005, Beyond the Horizon TG 5 group:
Intelligent and Cognitive Systems

- **Recommended work on** mind-body co-evolution, materials and growth technologies, morphological computation, emerging behavior.

This was adopted in FP7, I wrote *votum separatum*, recommending work on artificial minds, NLP, bots and avatars, creativity, cognitive architectures.

2011, FET Work Programme, **Human Computer Confluence** panel.
Merging Minds and Machines: Integrating AI with current Brain Research and future Neurotechnologies.

Two FET Flagship projects:

- 2010, **The Mind and Brain Model Project.**
- **2018 Future FET Flagship: Sapiens5.0**, The science and technology for a 22nd-century humanity.

Beyond the Horizon

Anticipating Future and Emerging
Information Society Technologies

Costs of brain diseases

Big ICT companies: Amazon, Apple, Google, Microsoft + Chinese giants Tencent, Baidu, and Alibaba, entering AI in health care (3 T\$ industry).

Brain research is most important: AI ↔ Neuroscience ↔ Neuropsychiatry.

Gustavsson et al. (2011). Cost of disorders of the brain in Europe 2010. *European Neuropsychopharmacology*, 21(10), 718–779.

179 million, or **1/3 of all European citizens**, had at least one brain disorder.
45% of the total annual health budget of Europe!

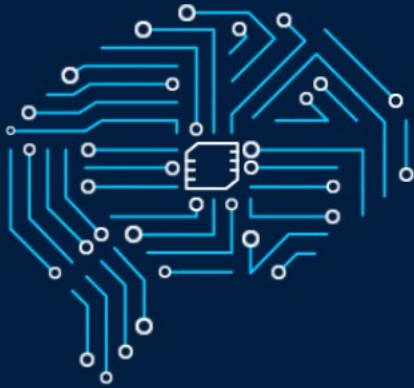
Total cost of brain disorders in EU estimated in 2010: **798 billion €/year**.

China: >20% of population (~250 mln) suffering from some mental disorder.

European Brain Council (EBC) reports (2010; 2014).

Consensus Statement on European Brain Research (2015) includes a chapter on Computational Neuroscience, data repositories and analytics.

BRAIN
INITIATIVE



Advance Neurotechnologies

Accelerate the development and
application of new neurotechnologies.

Support multi-disciplinary teams and
stimulate research to rapidly enhance current
neuroscience technologies and catalyze
innovative scientific breakthroughs.

Human Brain Project, EU Flagship, and Obama BRAIN Initiative (2013):
Brain Research through Advancing Innovative Neurotechnologies.

“Develop new technologies to explore how the brain’s cells and circuits interact at the speed of thought, ultimately uncovering the complex links between brain function and behavior. Explore how the brain records, processes, uses, stores, and retrieves vast quantities of information. Help bring safe and effective products to patients and consumers.”

Since 2013 numerous exciting developments in neurotechnology and our understanding of the brain have been made by scientists across the globe.

Workshop on Brain-Machine Interface Systems

Global Current and Emerging Brain Initiative Meeting

Brain Hackathon

IEEE
SMC
Systems, Man, and Cybernetics Society



This workshop was part of the Brain-Machines Interface Workshop and SMC2018 conference, organized by Mike Smiths (UC Berkeley).

Special meeting of **Global Current and Emerging Brain Initiative leaders** was attended by IEEE President, James Jefferies, President-elect Toshio Fukuda, and representatives from Australia to USA (NSF and NIH), **IEEE Brain Initiative**, International Neuroethics Society, industry, and other stakeholders.

Neuroscience => AI



Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). **Neuroscience-Inspired Artificial Intelligence**. *Neuron*, 95(2), 245–258.

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

Bengio, Y. (2017). The **Consciousness Prior**. *ArXiv:1709.08568*.

Amos et al. (2018). **Learning Awareness Models**. ICRL, *ArXiv:1804.06318*.

AI Systems inspired by Neural Models of Behavior:

- (A) **Visual attention**, foveal locations for multiresolution “retinal” representation, prediction of next location to attend to.
- (B) **Complementary learning systems** and episodic control: fast learning hippocampal system and parametric slow-learning neocortical system.
- (C) Models of **working memory** and the Neural Turing Machine.
- (D) Neurobiological models of **synaptic consolidation**.

SANO, new Centre for Individualized Computational Medicine in Kraków (EU Team project, with Sheffield Uni, Fraunhofer Society, Research Centre Juelich).

BICA, Brain-Inspired Cognitive Architecture

Understanding the brain from engineering perspective means to build a model of the brain showing similar functions.

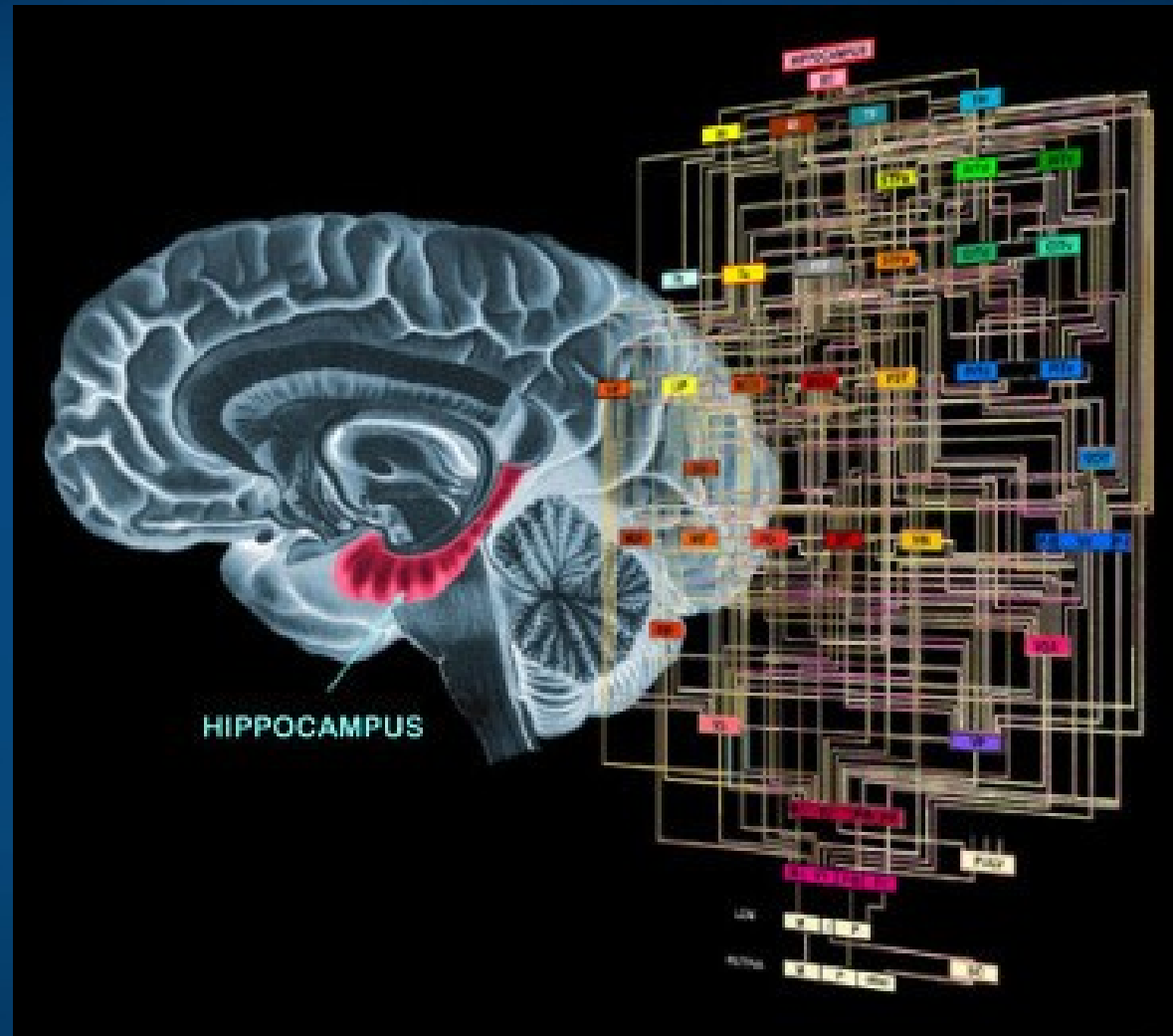
Cognitive informatics,
Neurocognitive Informatics.

BICA = Brain Inspired
Cognitive Architecture.

Review: Duch, Oentaryo,
Pasquier,

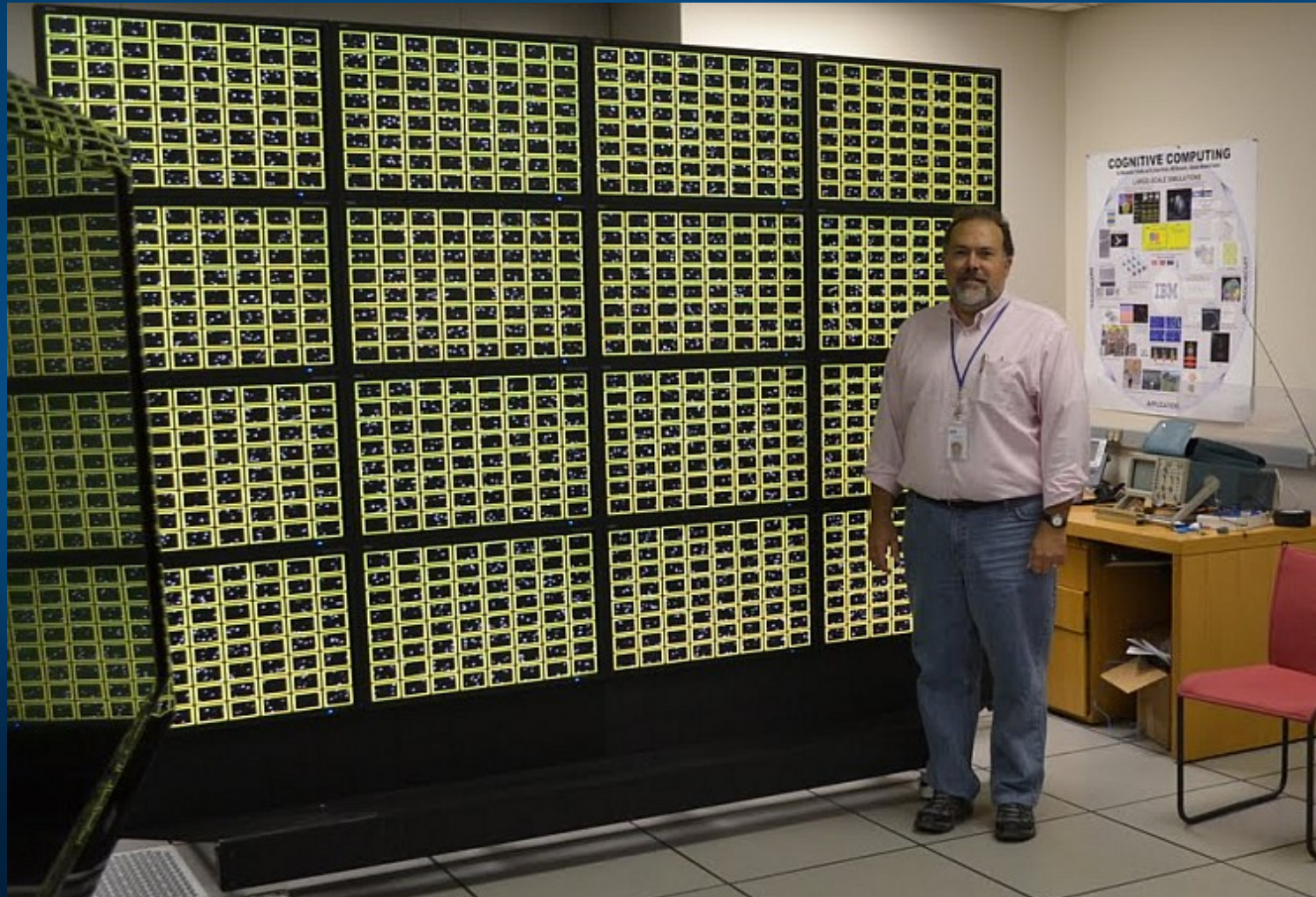
[Cognitive architectures: where do we go from here](#)

? 2008



Neuromorphic wall

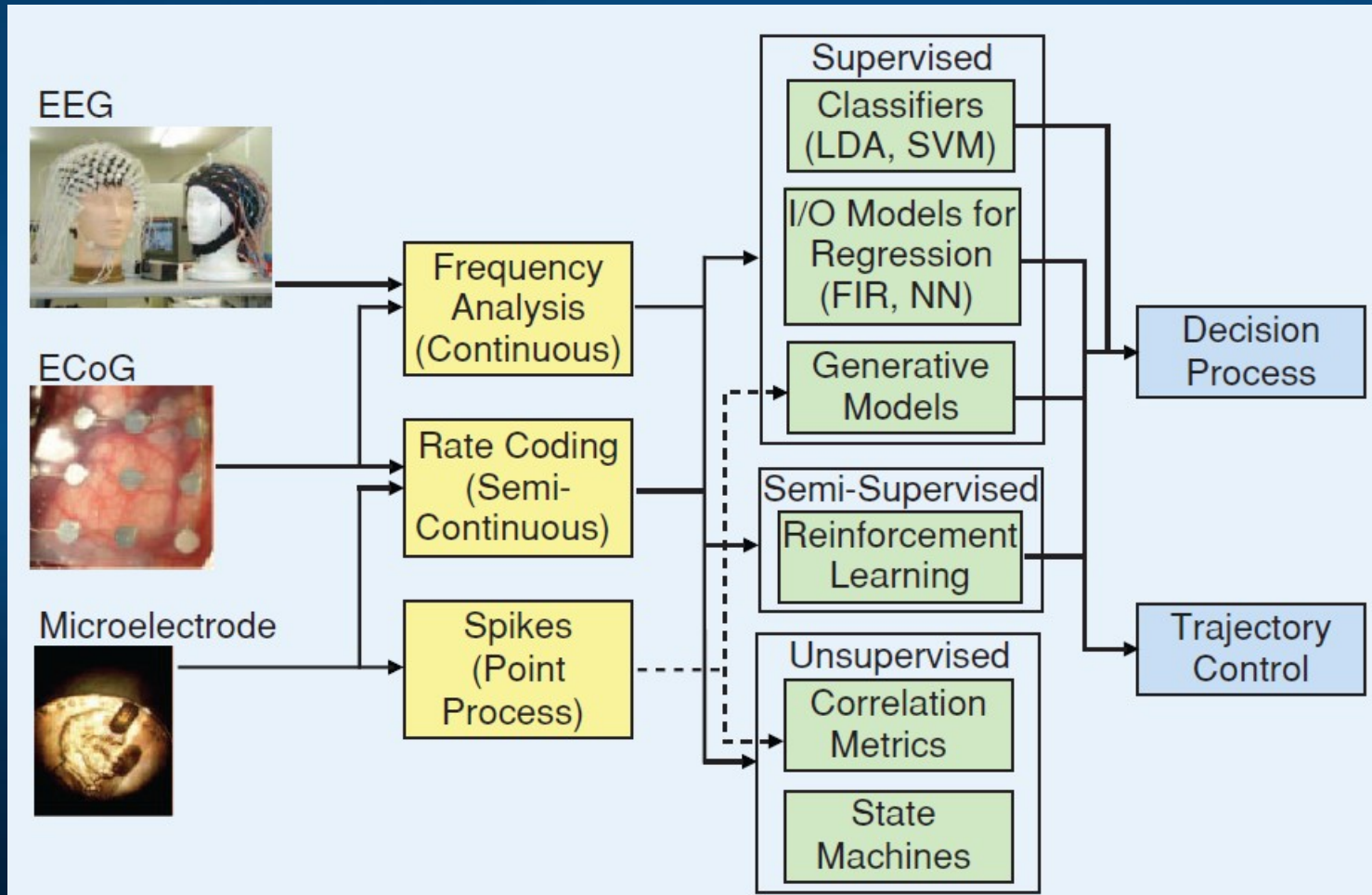
1024 TN neuromorphic chips, or 1B neurons and 256B synapses!
Complexity ~ horse brain, 1/4 gorilla, 1/6 chimpanzee.



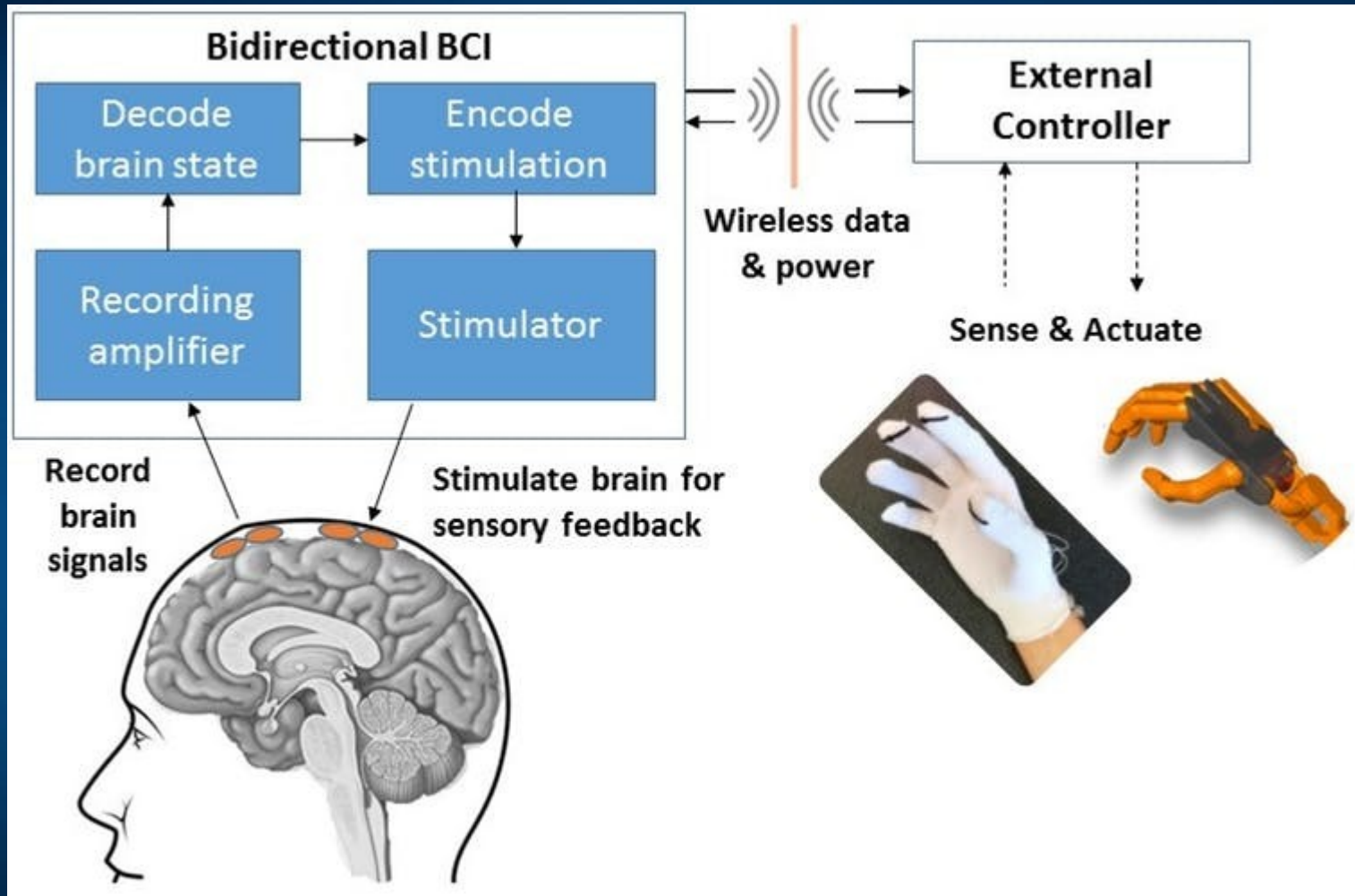
Optimizing brains Neurocognitive technologies

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!

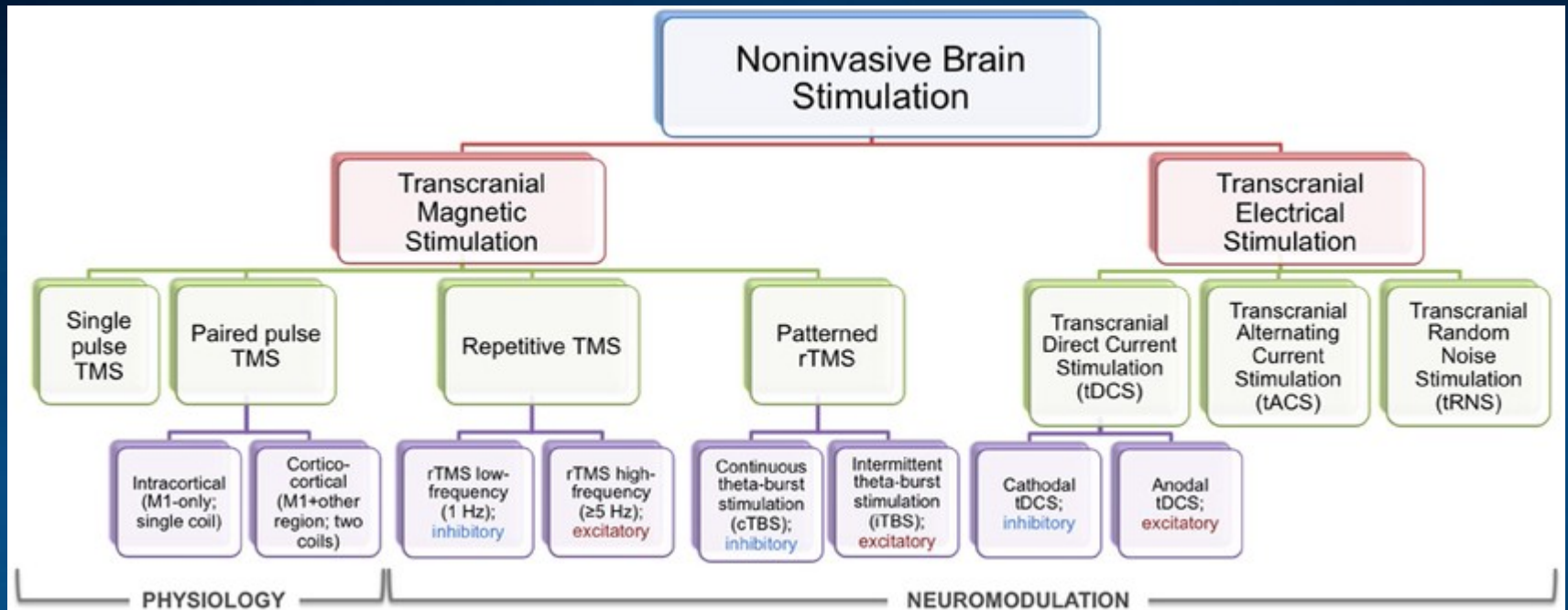


Brain-Computer-Brain Interfaces



Neurofeedback + neuromodulation. Closed loop system with brain reading and stimulation for self-regulation. Sensory signals may come from Virtual Reality.

Brain stimulation



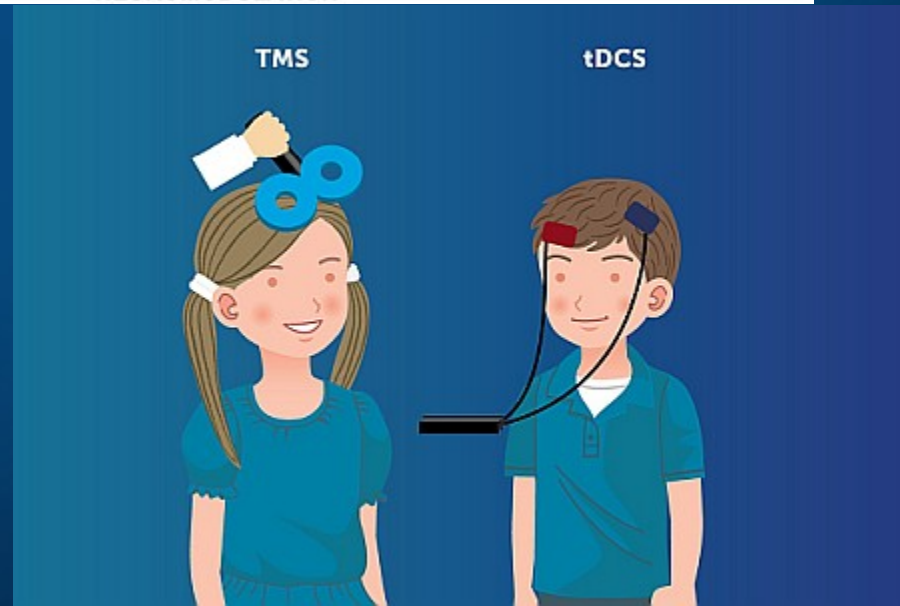
ECT – Electroconvulsive Therapy

VNS – Vagus Nerve Stimulation

Ultrasound, laser ... stimulation.

Complex techniques, but portable phones are also complex.

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



Trenowanie mózgu

Engagement Skills Trainer (EST) to procedury treningu amerykańskich żołnierzy.

Intific Neuro-EST to technologia wykorzystująca analizę EEG i wielokanałowy stymulator przeczaszkowy (MtCS) do transferu umiejętności pomiędzy mistrzem i uczniem.



Epilepsy

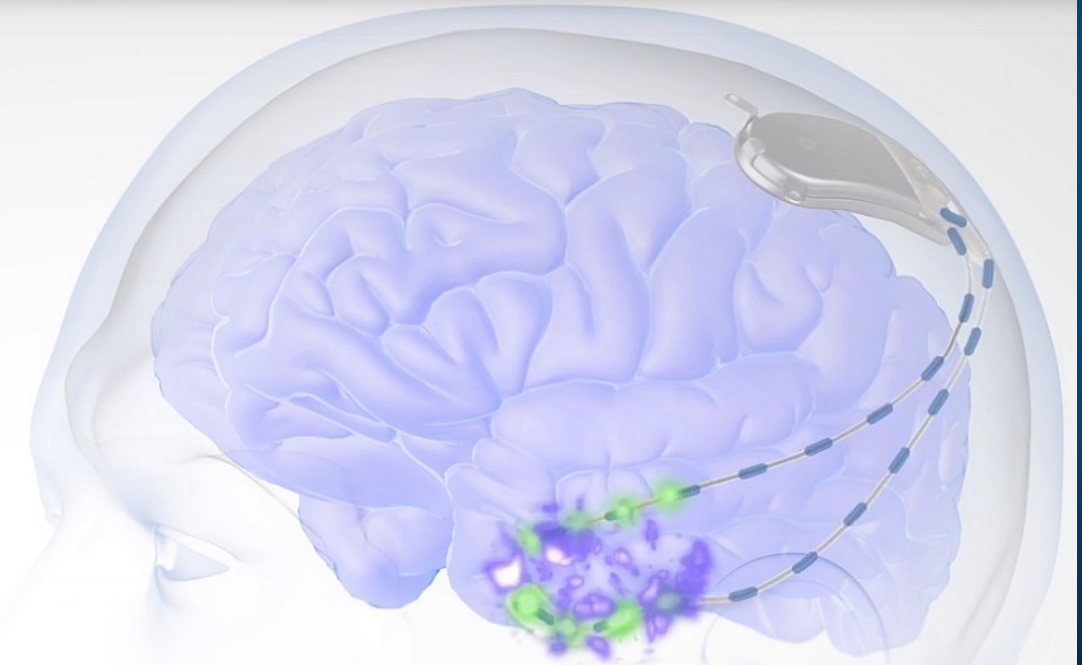
About 1% of people and some mammals suffers from epilepsy. Detector and neurostimulator may discover and stop seizures of drug-resistant epilepsy.

The RNS[®] System

Monitors brainwaves

Detects unusual activity

Responds in real time



1 SEC

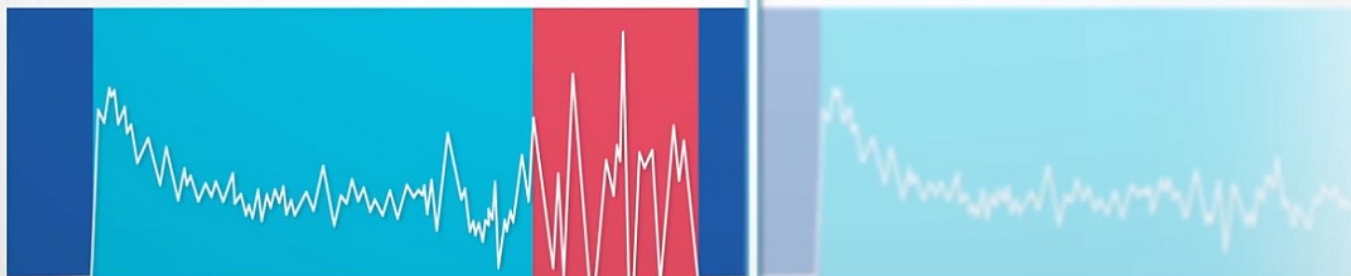
2 SEC

3 SEC

4 SEC

5 SEC

6 SEC



Flow for depression

Complete at-home depression treatment: combining tDCS with behavioral therapy. 24% could overcome depression, 41% claimed 50% improvement.

<https://flowneuroscience.com/>

- Medication free. Home treatment.
- Reduces depression with a brain stimulation headset and free app for behavioural therapy.
- 18 sessions, each 30 min, 6 weeks.
- After 6 weeks, the activity in your frontal lobe is rebalanced and your depressive symptoms will have decreased.
- Approved for medical use in the EU and UK.

Early neurocognitive technology, but more precise analysis of individual brain activity with tDCS is needed for best adaptation.



HD EEG/DCS?

EEG electrodes + DCS.

Reading brain states

=> transforming to common space

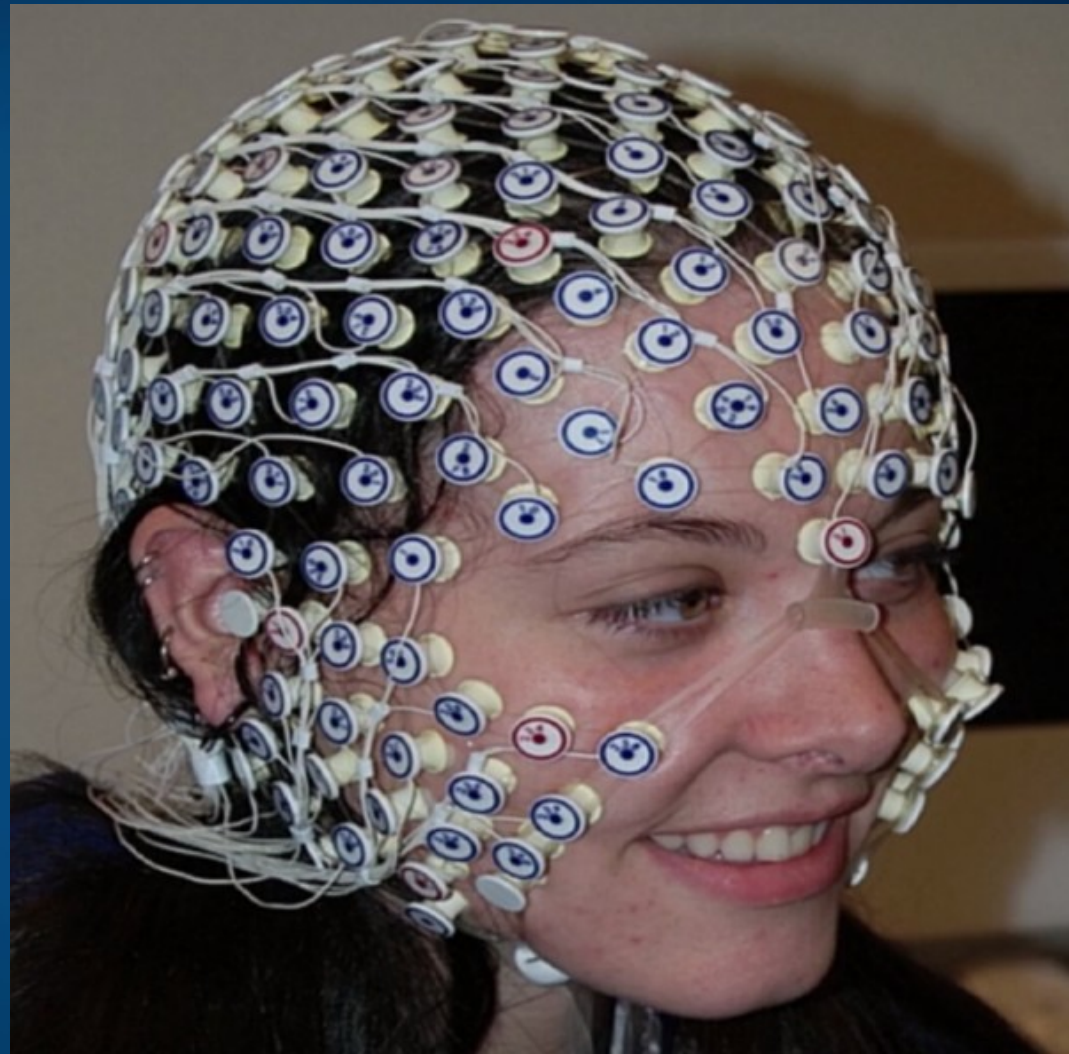
=> duplicating in other brains

Applications:

depression, neuro-plasticity,
new neurofeedback, pain,
psychosomatic disorders!

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

Ex: Phillips Neuro EEG S400.



MemorEM

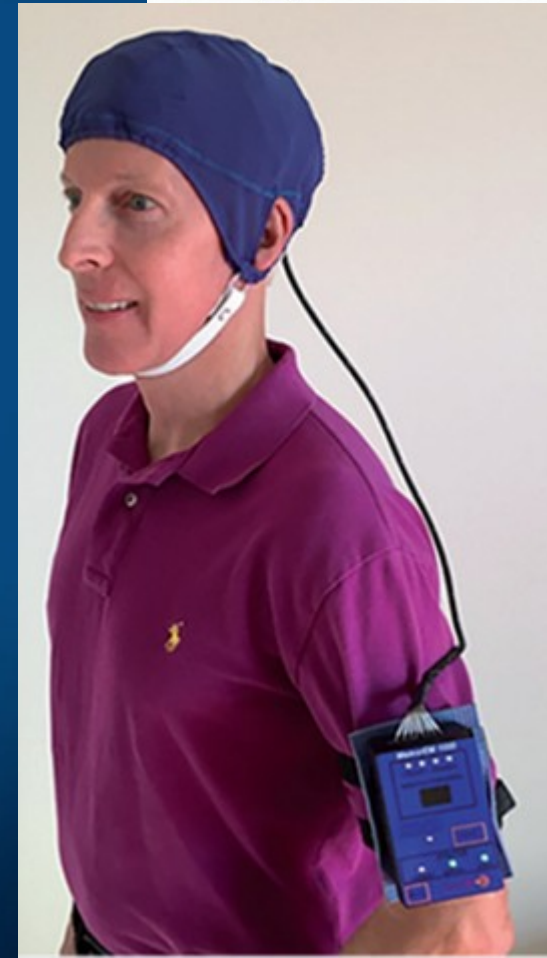
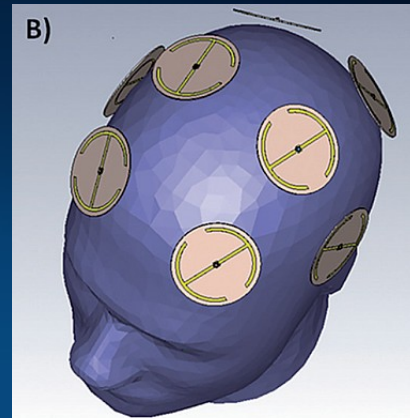
Transcranial Electromagnetic Treatment (TEMT)
MemorEM head device being worn by a subject.
Position of the eight electromagnetic emitters embedded
between the device's two-layered head cap.
8 emitters 915 MHz, pulses 4.6 ms, 1.6 W/kg, provide
global TEMT to the cortex and deeper structures.

In AD transgenic mice TEMT prevents and reverses both
cognitive impairment and brain amyloid- β ($A\beta$)
deposition. TEMT improves cognitive performance in
normal mice. 3 disease-modifying and inter-related
mechanisms of TEMT action:

1) anti- $A\beta$ aggregation, both intraneuronally and
extracellularly; 2) mitochondrial enhancement; and 3)
increased neuronal activity.

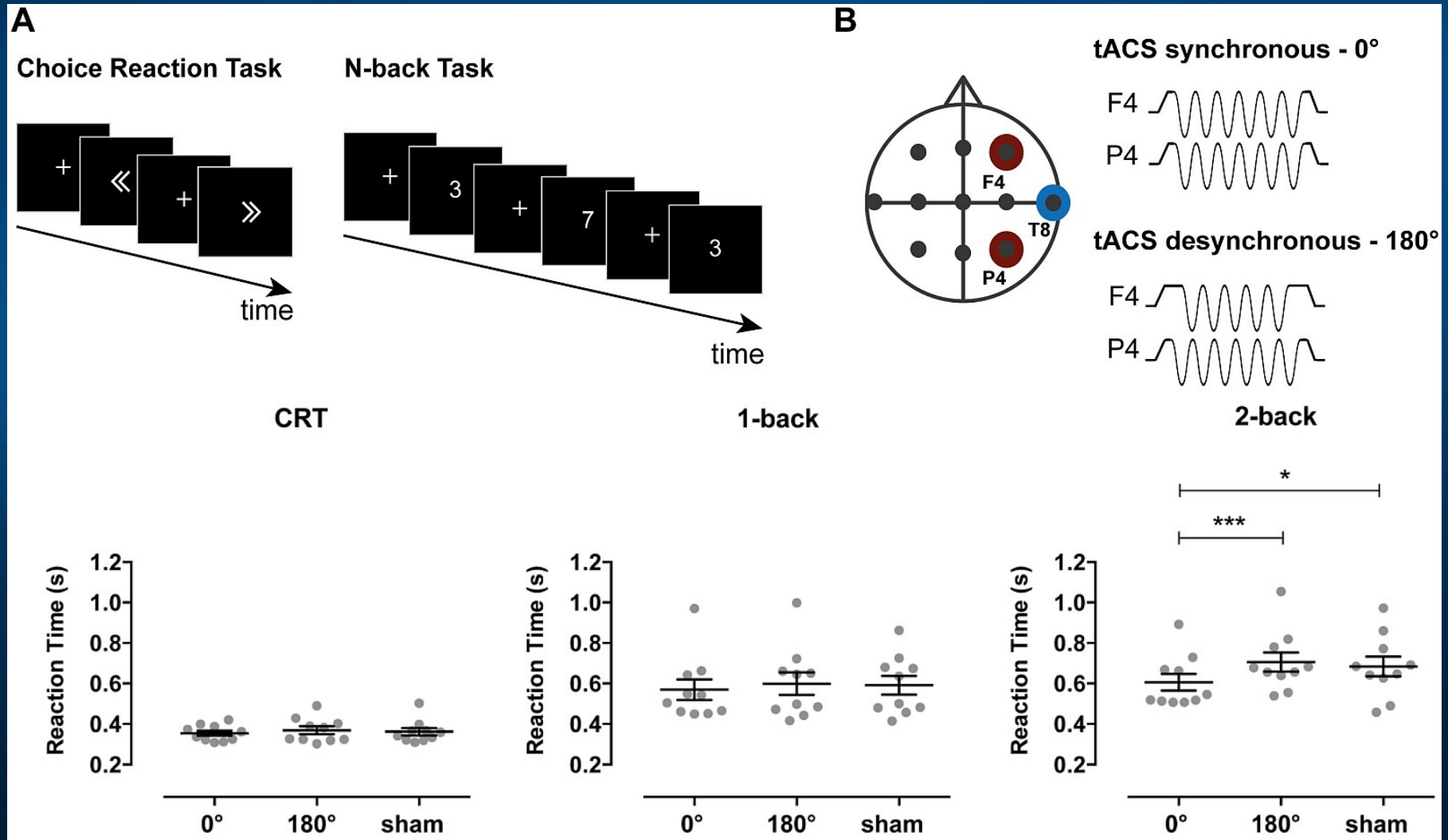
8 mild/moderate AD patients were treated with TEMT,
increased functional connectivity within CC area.

Arendash GW et. al. J. of Alzheimer's Dis 71 (2019) 57



Synchronize PFC/PC to improve WM

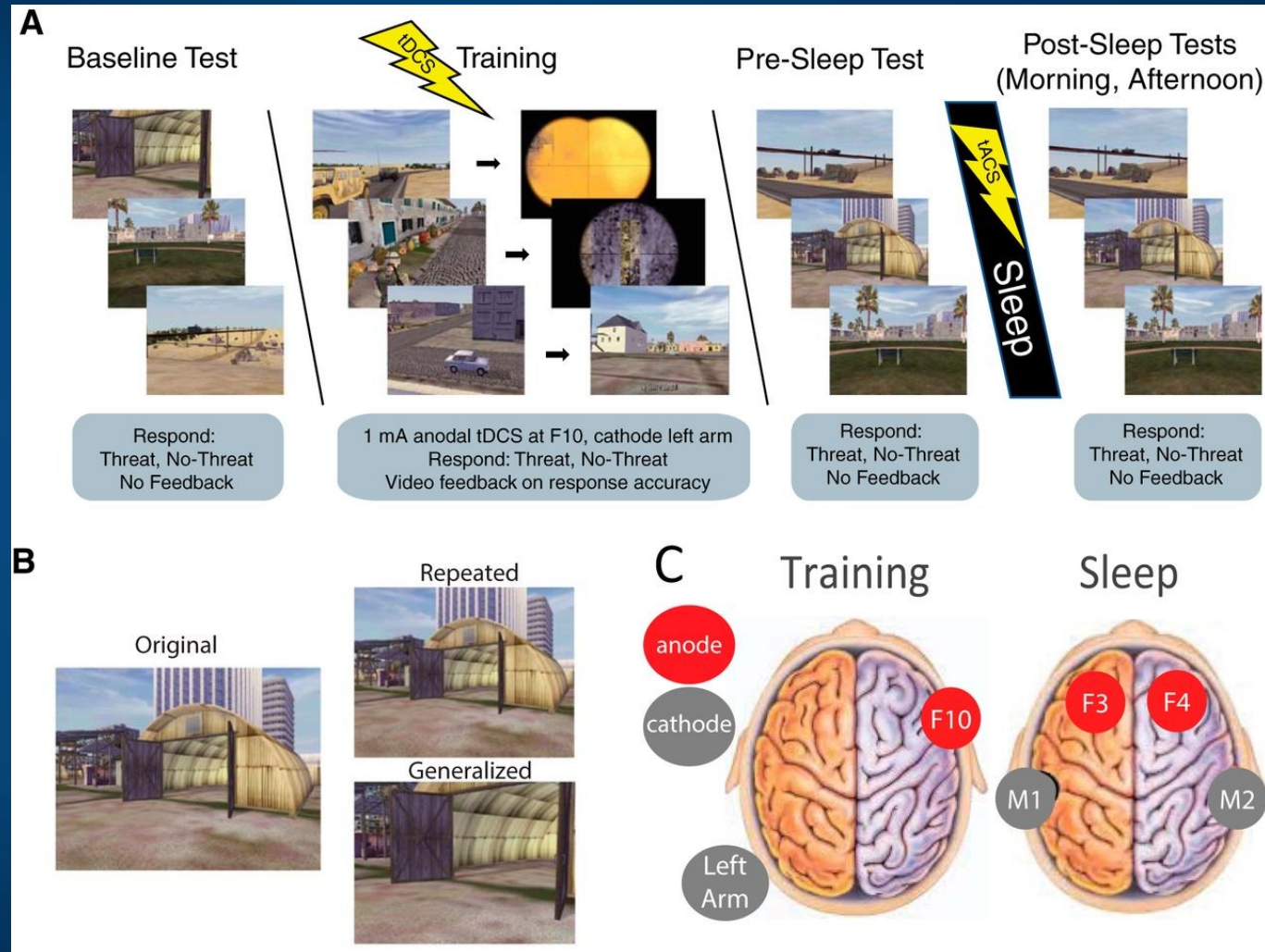
Violante, I.R. et al. Externally induced frontoparietal synchronization modulates network dynamics and enhances working memory performance. *ELife*, 6 (2017).



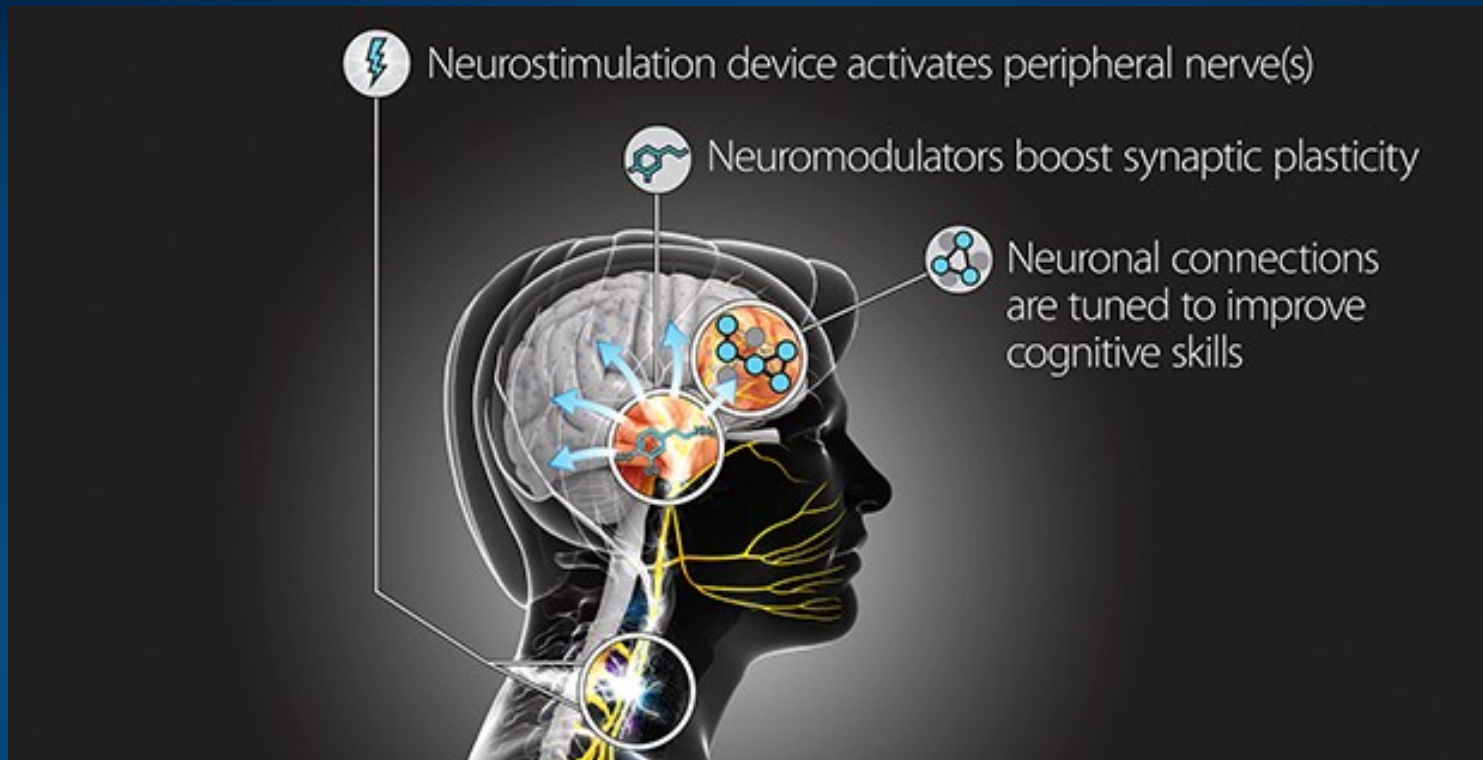
BCBI and memory

N. Ketz et al.,
Closed-Loop Slow-Wave tACS Improves Sleep-Dependent Long-Term Memory Generalization by Modulating Endogenous Oscillations.

J. Neuroscience
8 (33) 2018
Enhances the consolidation of recent experiences into long-term memory.



Targeted Neuroplasticity Training

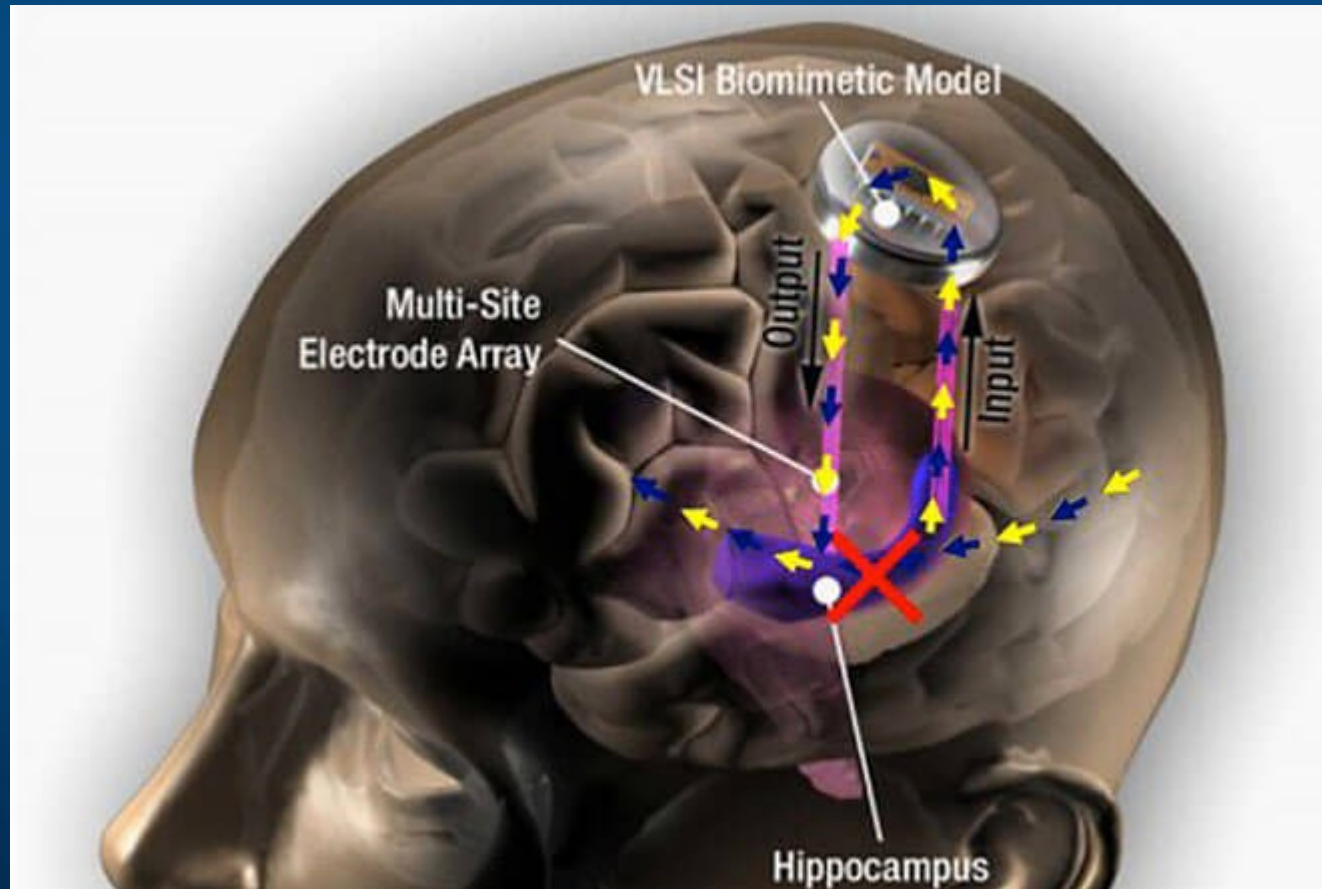


DARPA (2017): Enhance learning of a wide range of cognitive skills, with a goal of reducing the cost and duration of the Defense Department's extensive training regimen, while improving outcomes. TNT could accelerate learning and reduce the time needed to train foreign language specialists, intelligence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

Memory implants

Ted Berger (USC, [Kernel](#)): hippocampal neural prosthetics facilitate human memory encoding and recall using the patient's own hippocampal spatiotemporal neural codes. Tests on rats, monkeys and on people gave memory improvements on about 35% ([J. Neural Engineering 15, 2018](#)).

DARPA: Restoring Active Memory (RAM), new closed-loop, non-invasive systems that leverage the role of neural “replay” in the formation and recall of memory to help individuals better remember specific episodic events and learned skills.



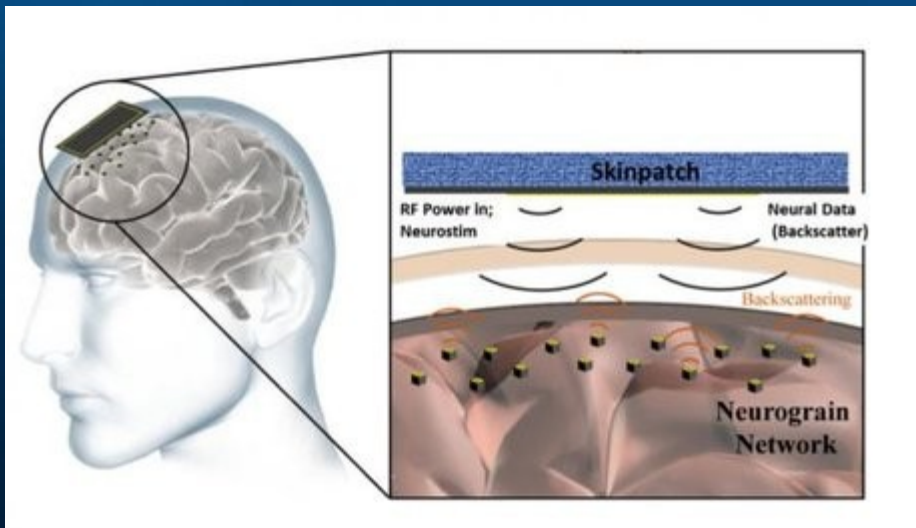
Million nanowires in your brain?

DARPA (2016): **Neural Engineering System Design (NESD)**

Interface that reads impulses of 10^6 neurons, injecting currents to 10^5 neurons, and reading/activating 10^3 neurons.

DARPA Electrical Prescriptions (ElectRx) project enables “artificial modulation of peripheral nerves to restore healthy patterns of signaling in these neural circuits. ElectRx devices and therapeutic systems under development are entering into clinical studies.”

Neural lace i neural dust project for cortex stimulation.



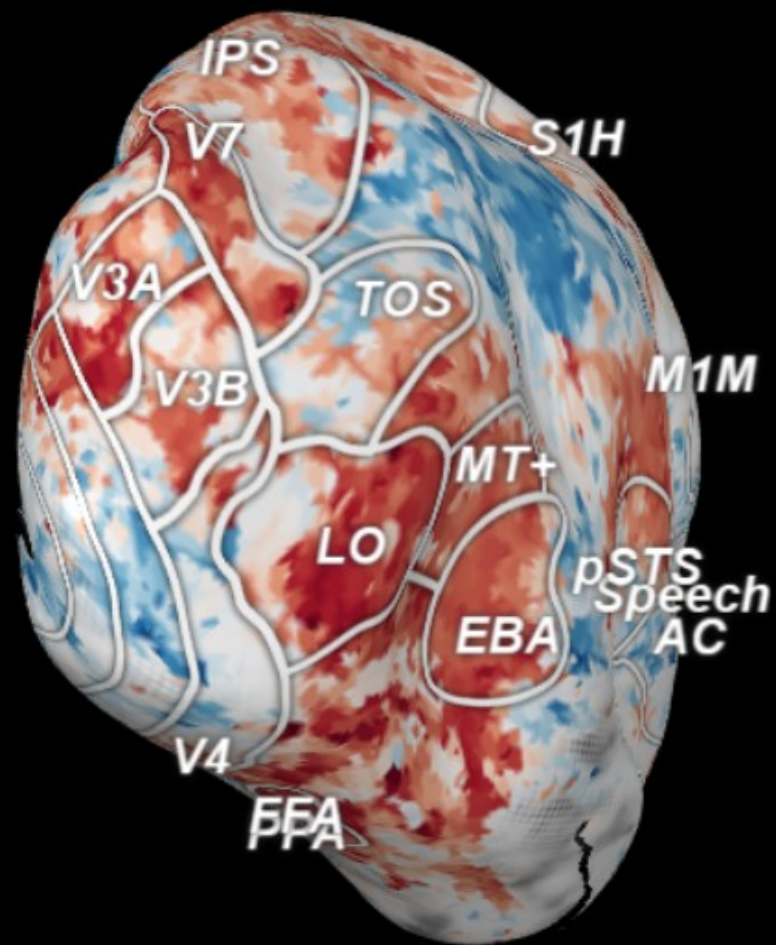
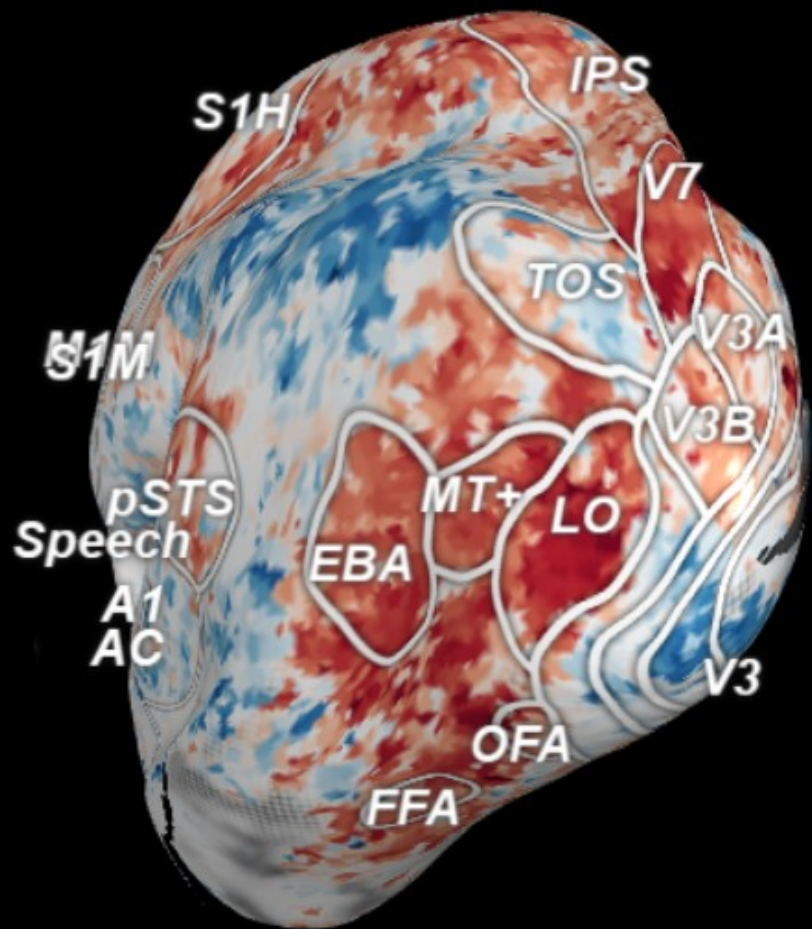
neural
lace
*ultra-thin
mesh*



Decoding mental states

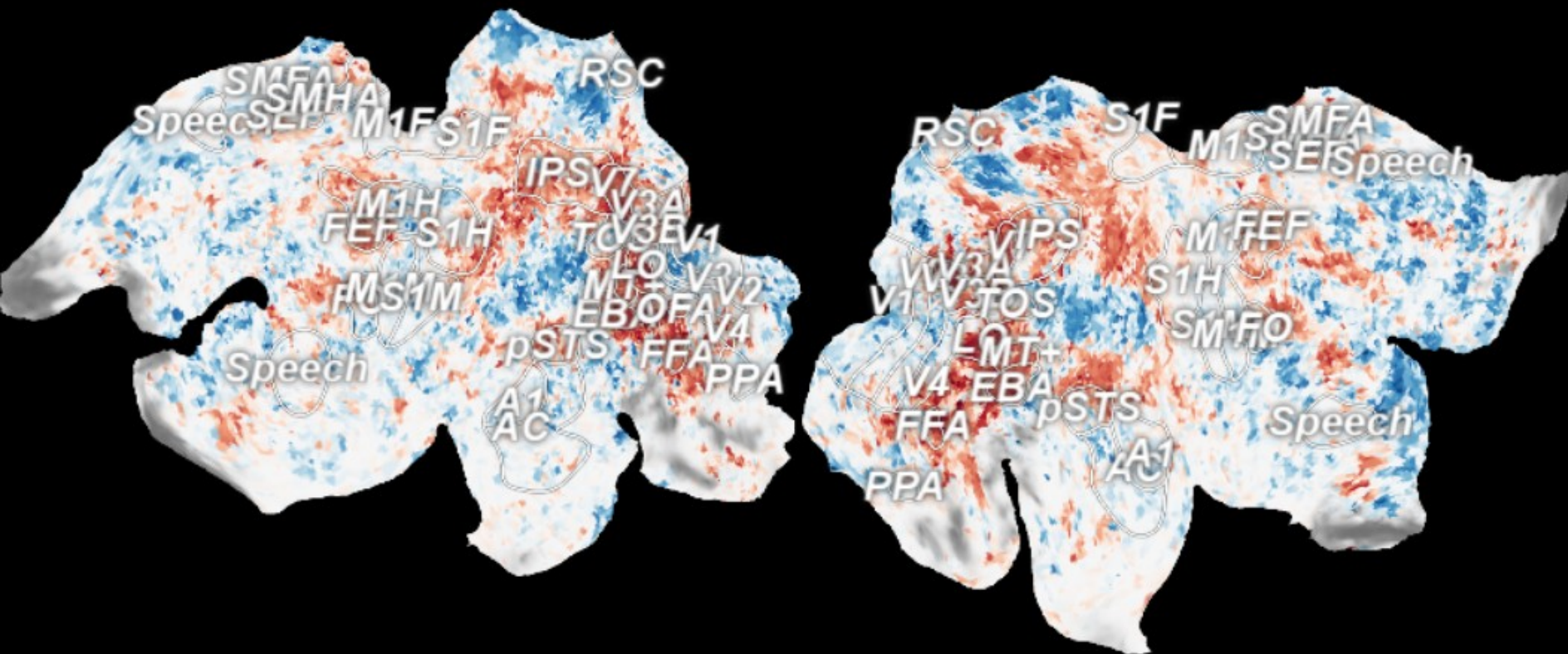


Category zebra: Passive Viewing

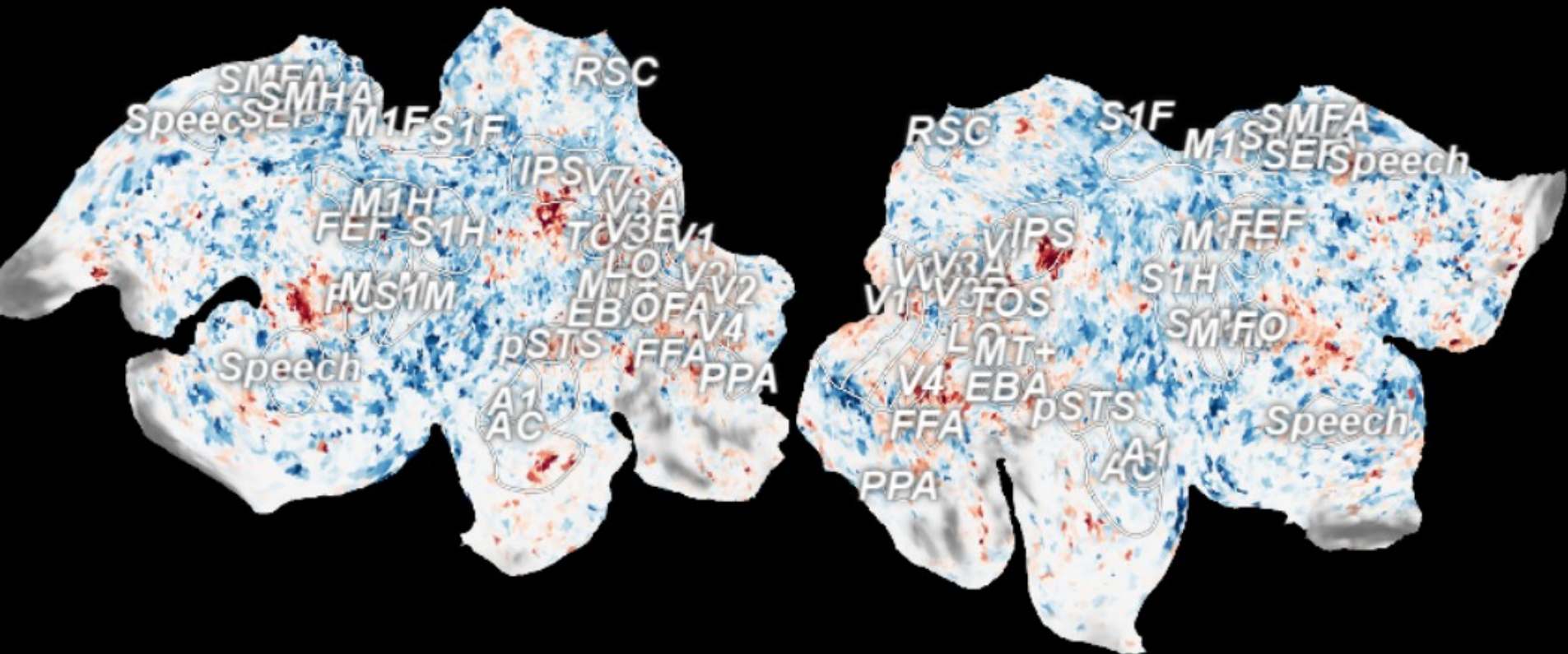




Category zebra: Passive Viewing

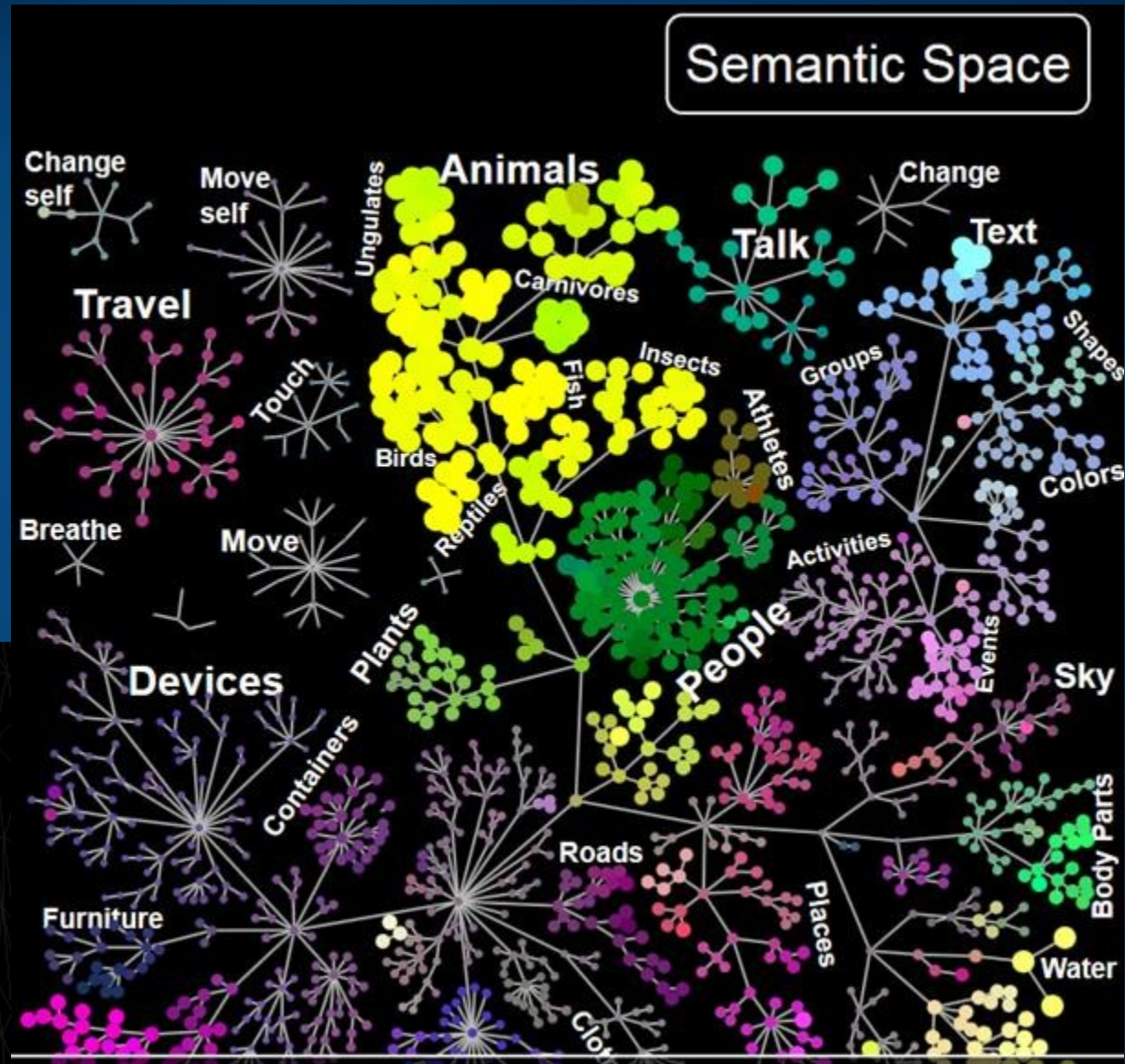


Category traffic light: Passive Viewing



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.](#)

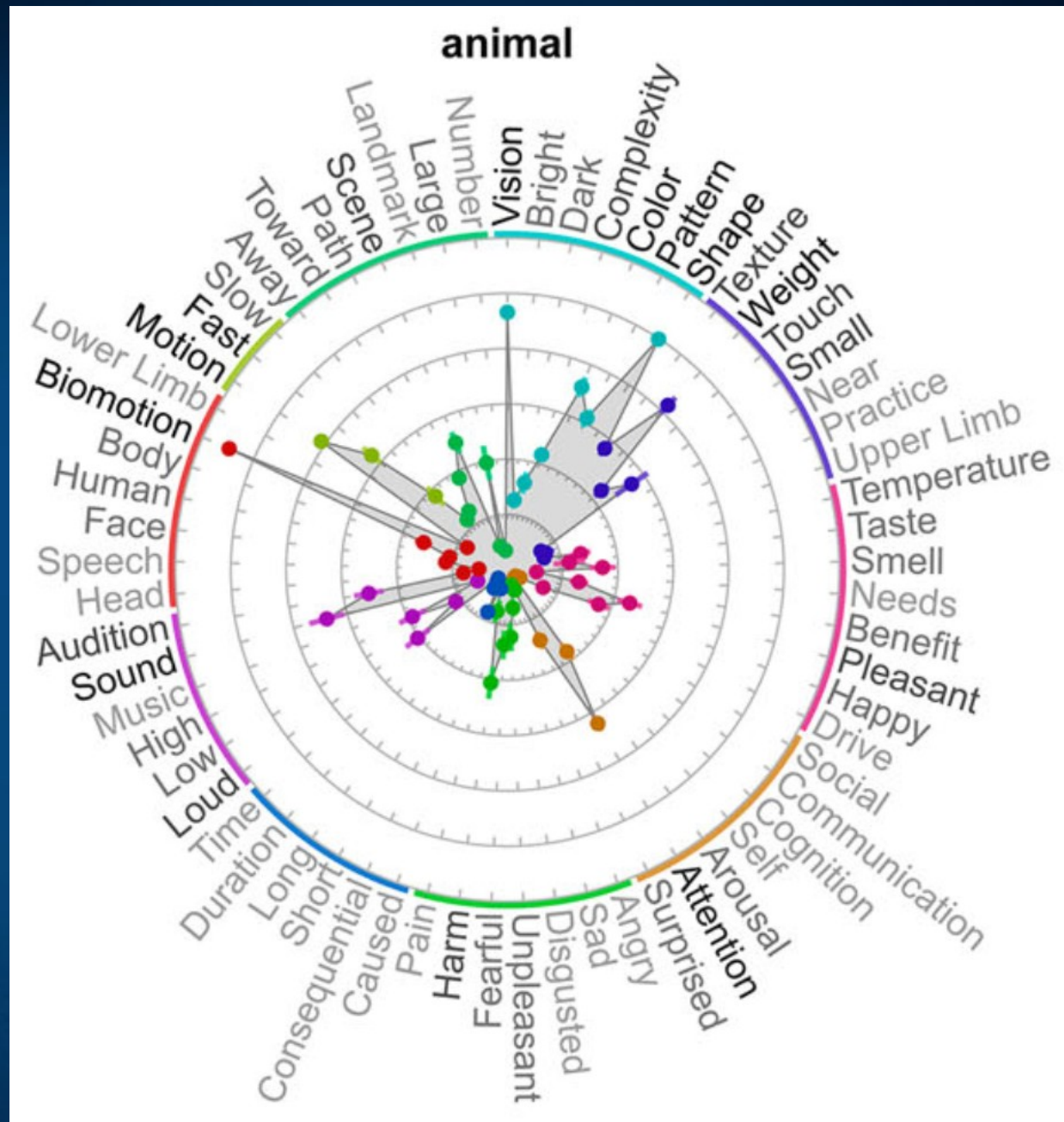


65 attributes related to neural processes;
Colors on circle: general domains.

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

More than just
visual objects!

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



Brains ↔ Minds

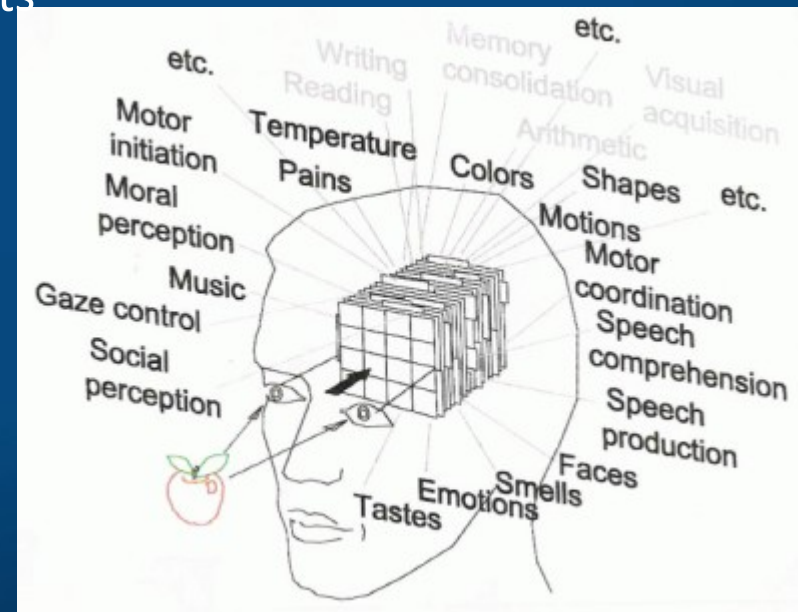
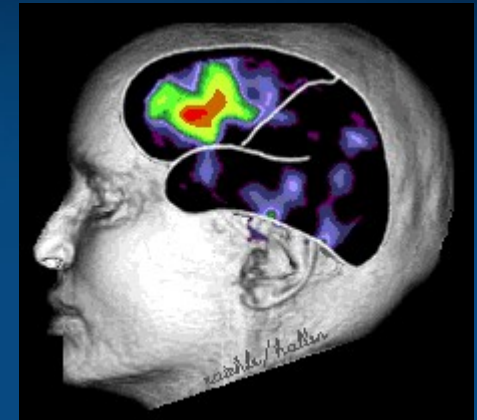
Cognitive neuroscience: map $S(M) \leftrightarrow S(B)$, as in BCI.

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.

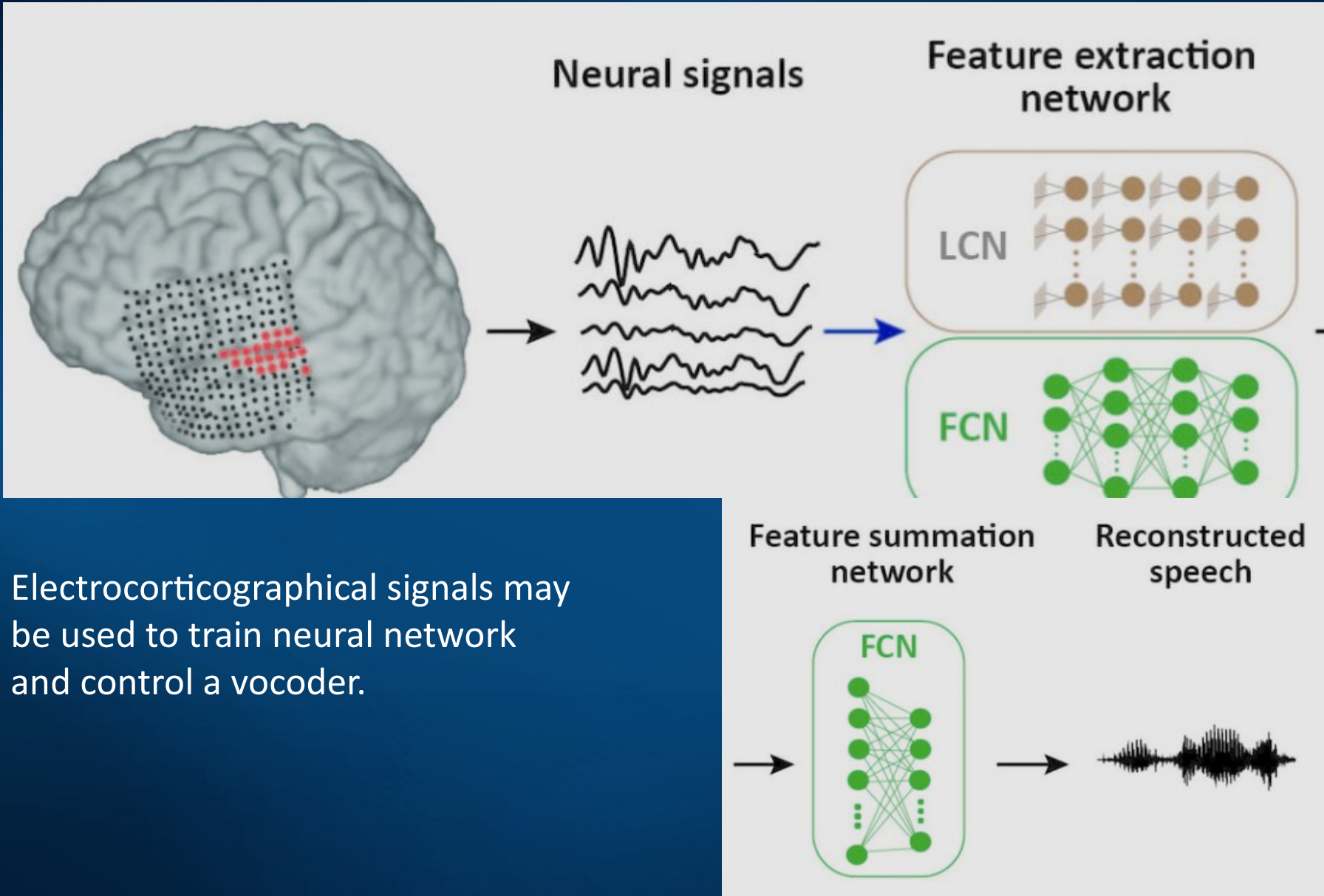
Stream of mental states, movement of thoughts
↔ trajectories in psychological spaces.

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 ...



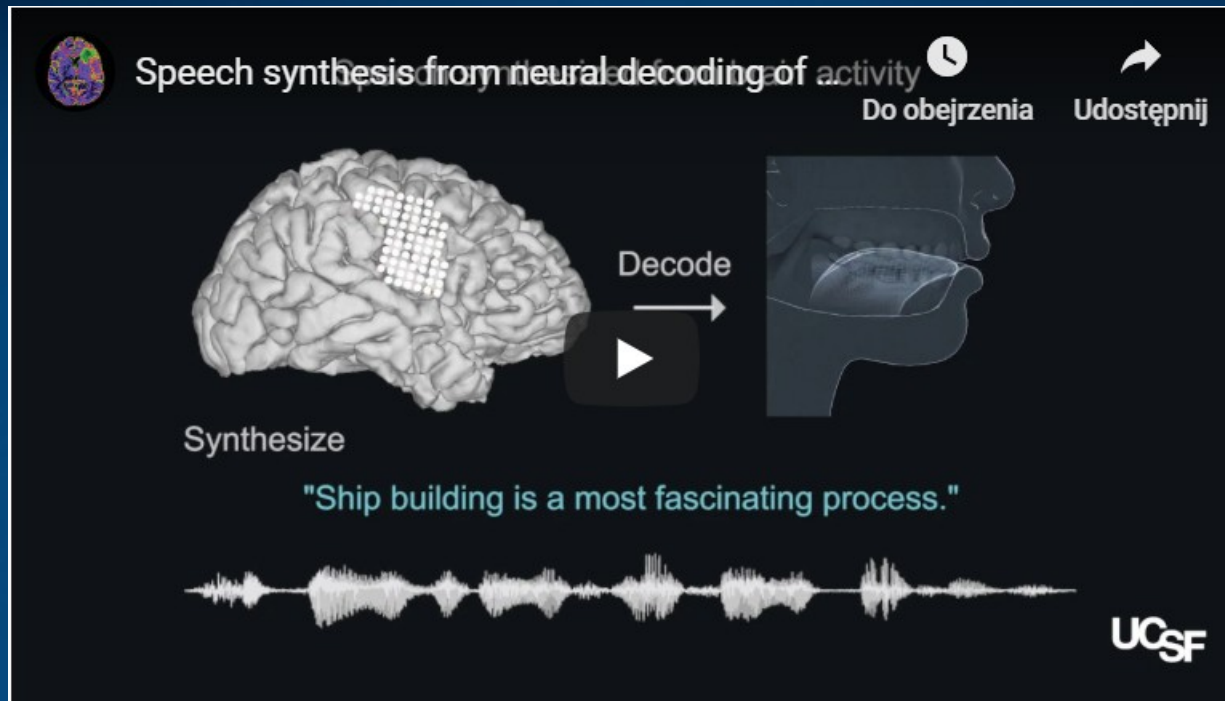
Duch W (1996) Computational physics of the mind. CPC 97: 136-153

Your brain is taking



Electrocorticographical signals may be used to train neural network and control a vocoder.

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](#)

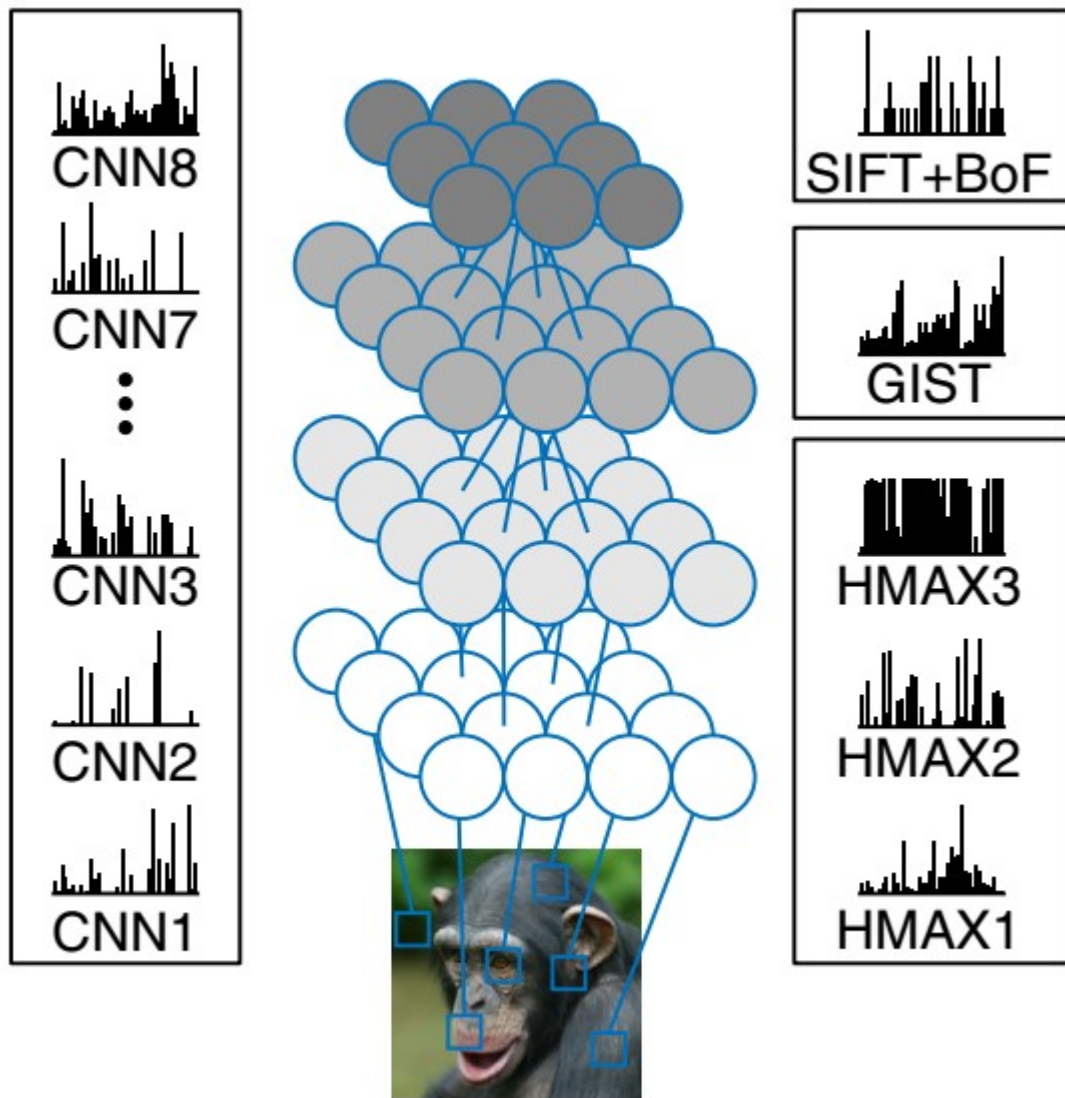
Mental images from brain activity

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

Try to estimate features at different layers.

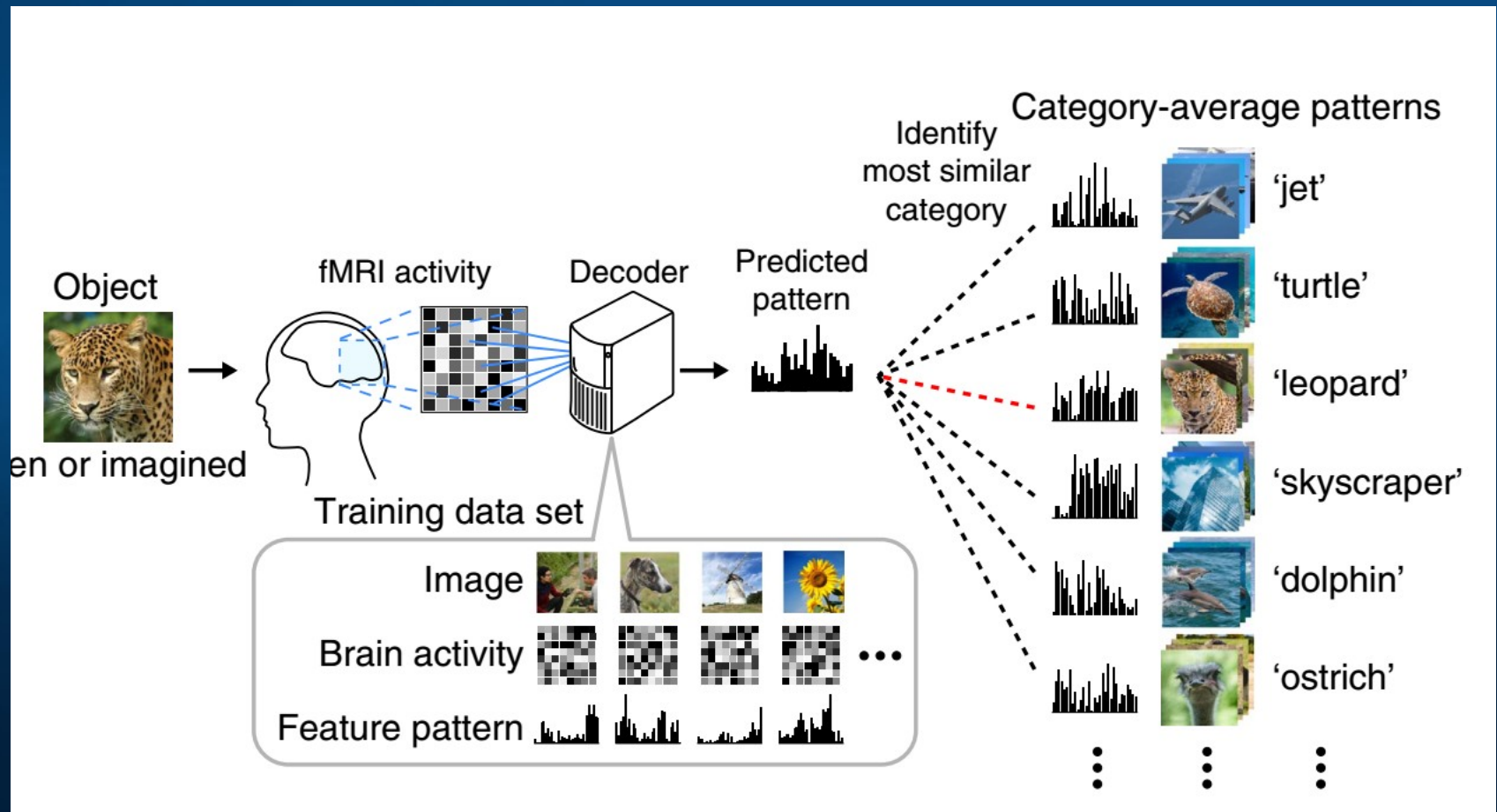
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

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.



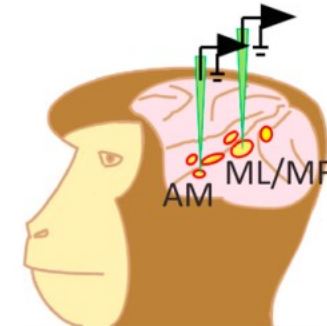
Neural screen

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

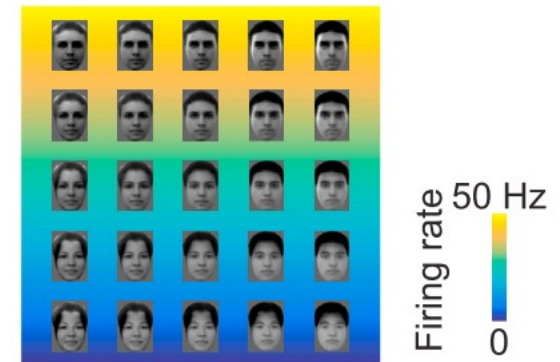
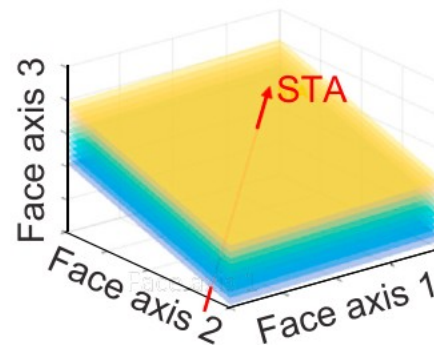
L. Chang and D.Y. Tsao, “The code for facial identity in the primate brain”. *Cell* 2017

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

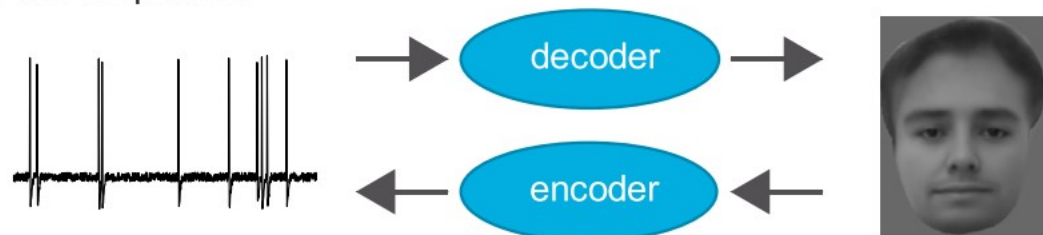
1. We recorded responses to parameterized faces from macaque face patches



2. We found that single cells are tuned to single face axes, and are blind to changes orthogonal to this axis



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



Brain networks

Neuropsychiatric phenomics

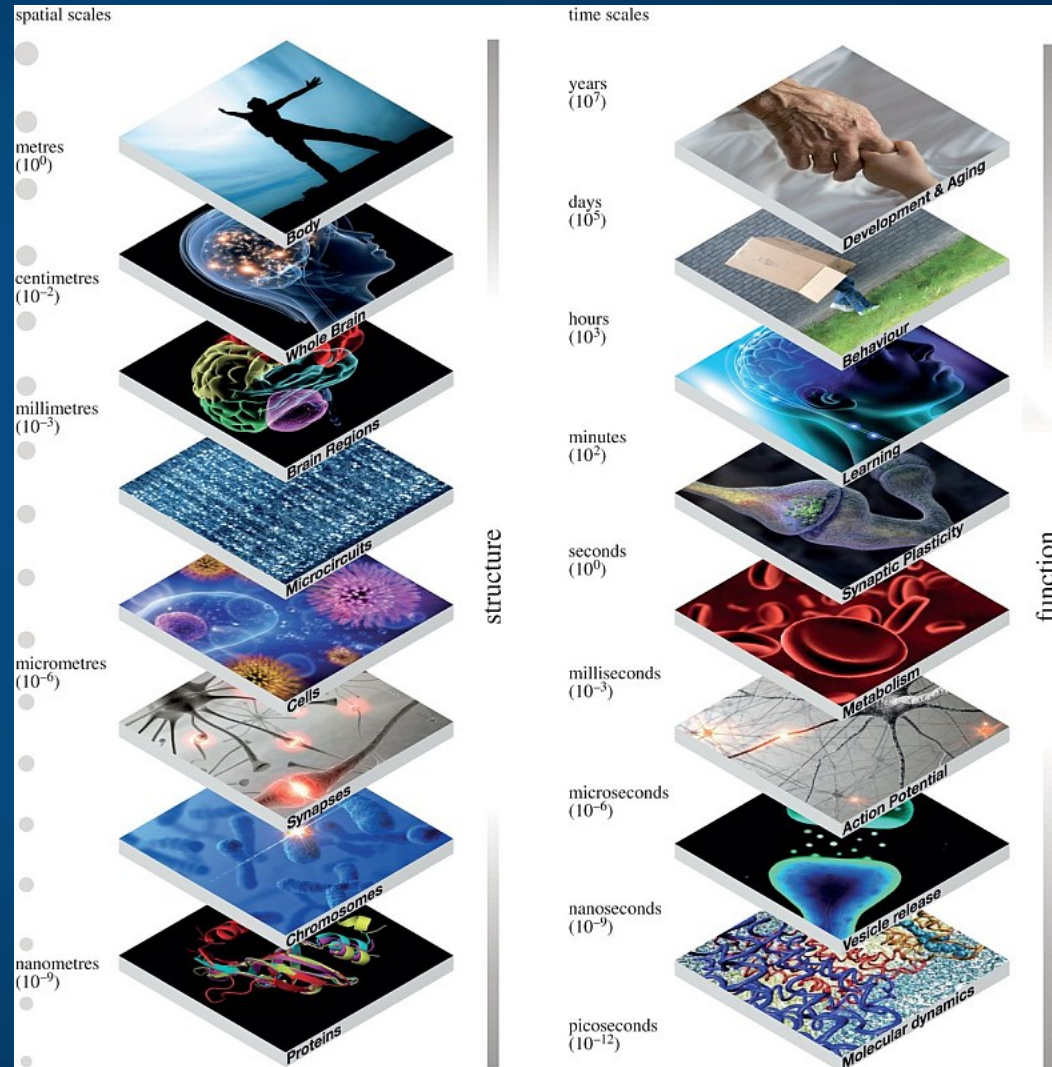
2008: The Consortium for Neuropsychiatric Phenomics

“... 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.

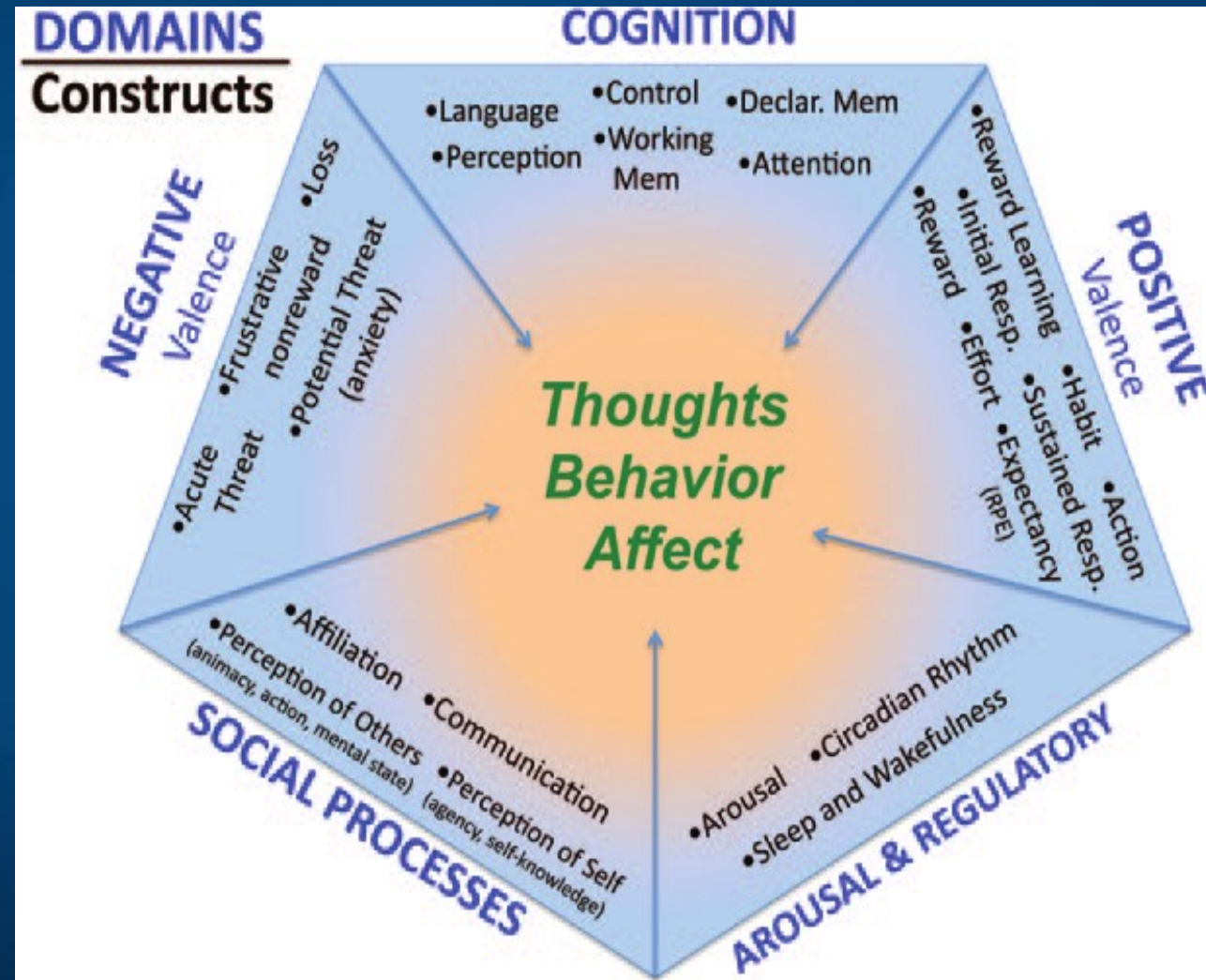
Network level is in the middle and can be connected to the mental level via computational models.



RDoC Matrix for „cognitive domain”

Construct/Subconstruct		Genes XXX	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

NIMH RDoC Matrix for deregulation of 6 large brain systems.



Psychological constructs are necessary to talk about mental states.

Sensorimotor systems added in Jan. 2019 as sixth brain system.

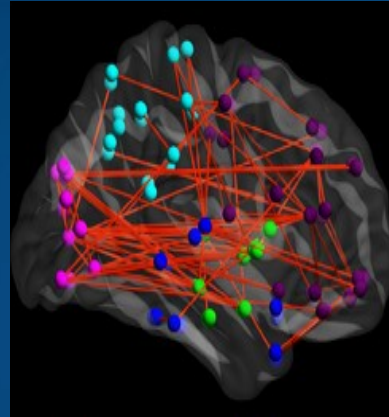
How are they related to physical processes?

Human connectome and MRI/fMRI

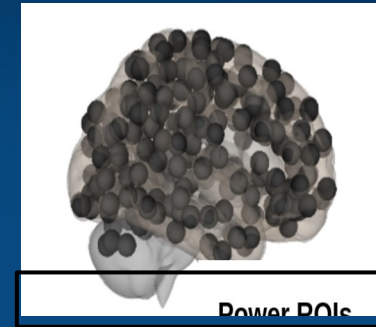
Structural connectivity



Functional connectivity

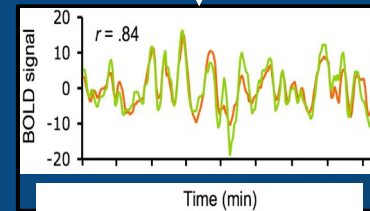


Node definition (parcelation)



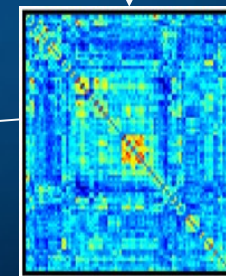
Power ROIs

Signal extraction



Correlation calculation

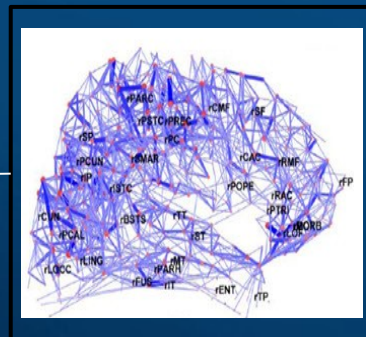
Correlation matrix



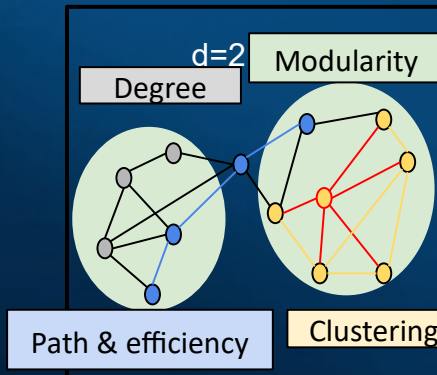
Binary matrix



Whole-brain graph



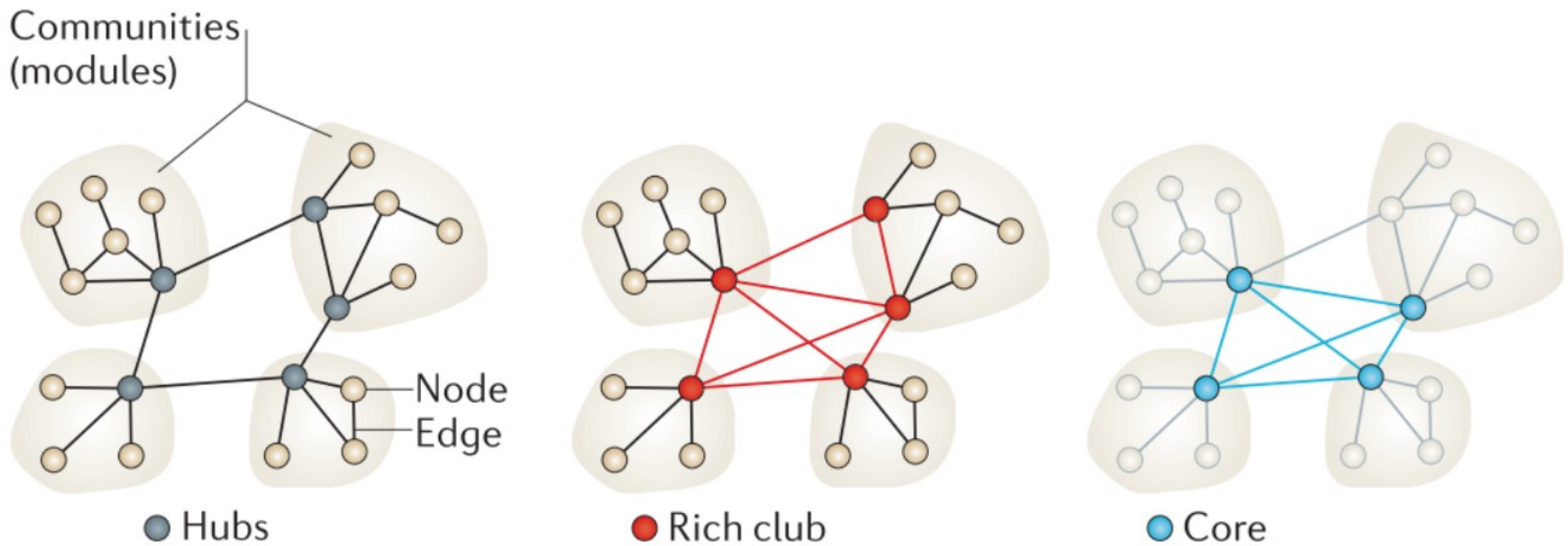
Graph theory



Many toolboxes available for such analysis.

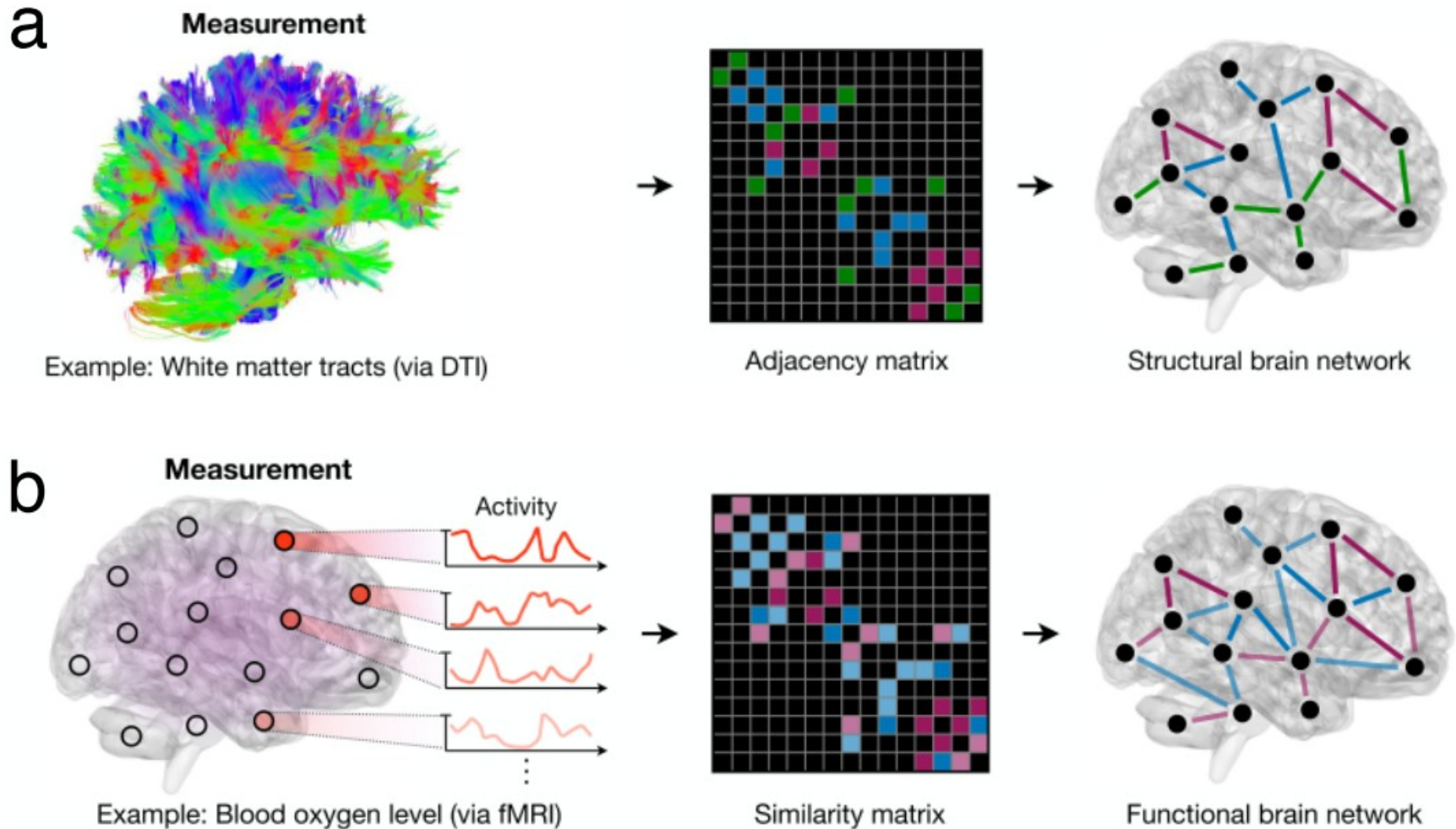
Bullmore & Sporns (2009)

Network Neuroscience

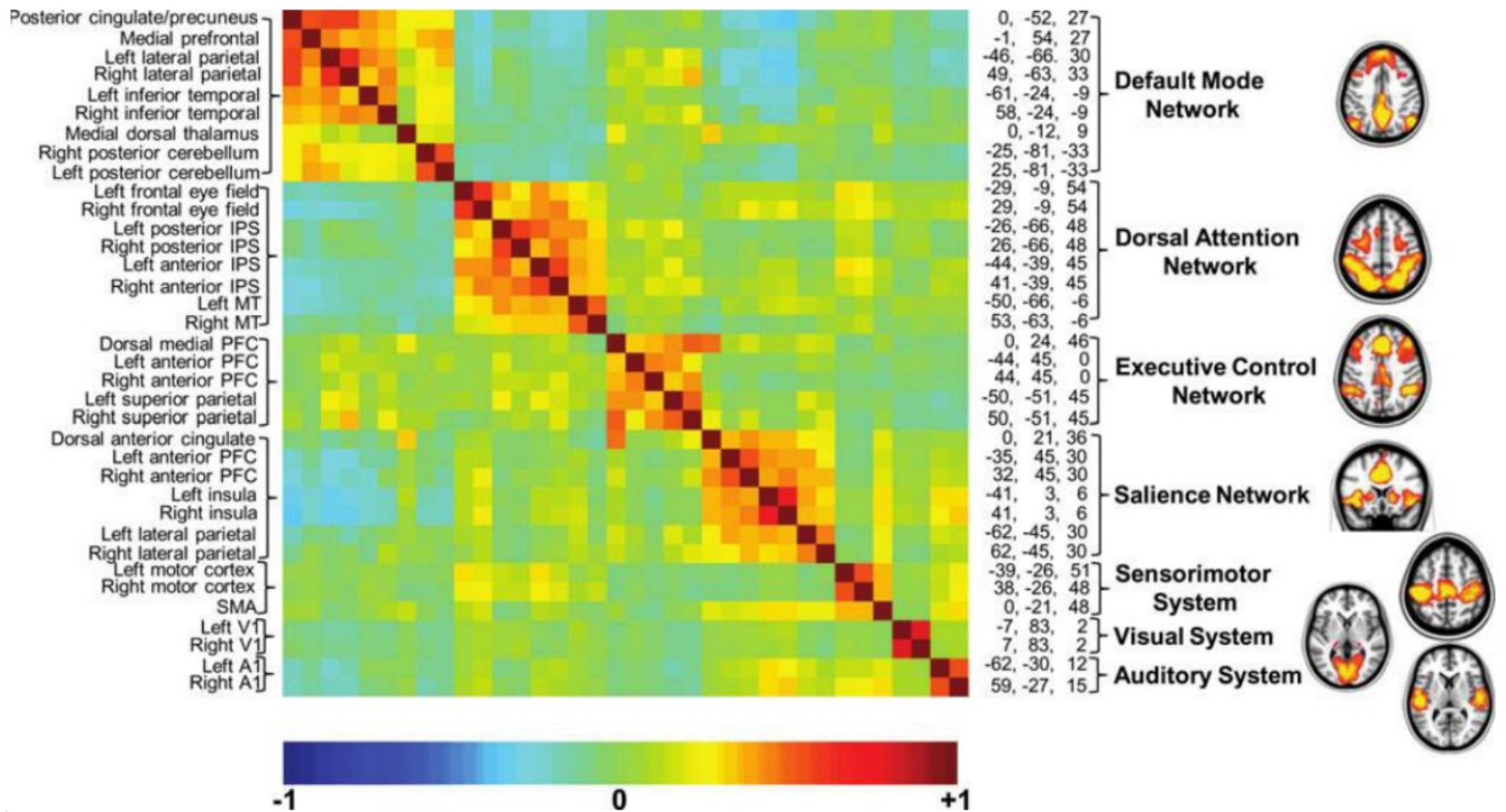


Network neuroscience is focused on identifying network structures, hubs, rich clubs and cores of the network. Hubs connect modules via long-distance connections. Hubs are also often densely interconnected forming so called 'rich club' or integrated core. New ways of quantification of various network structures are being developed.

Bullmore and Sporns (2012) The economy of brain network organization. *Nature Reviews Neuroscience*, 13(5):336.



Lynn and Bassett (2018) The physics of brain network structure, function, and control. arXiv:1809.06441.



Correlation matrix representing resting-state functional connectivity between selected brain regions Shows stronger connectivity for 7 large-scale brain networks: default mode (DM), dorsal attention (DAT), executive control network (FPN, CON), salience (SAL), sensorimotor (SOM), visual (VSN), auditory (ASN). Switching DMN ↔ Salience ↔ FPN

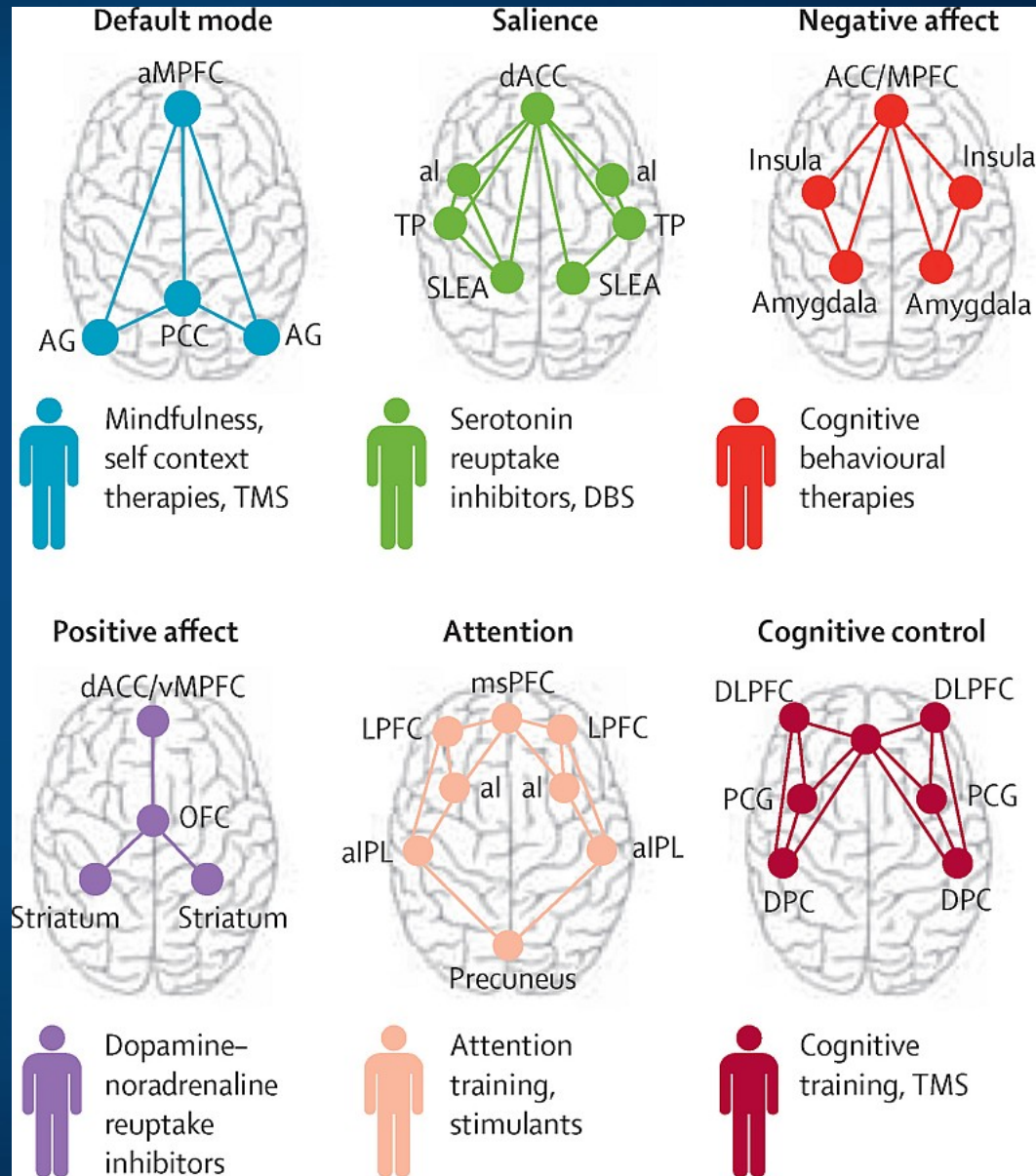
Multi-level phenomics

Research Domain Criteria (RDoC) matrix is based on **multi-level neuropsychiatric phenomics** describing large brain systems deregulation, but links to behavior should be analyzed at the network level, where specialized functions are implemented. **In AI:**

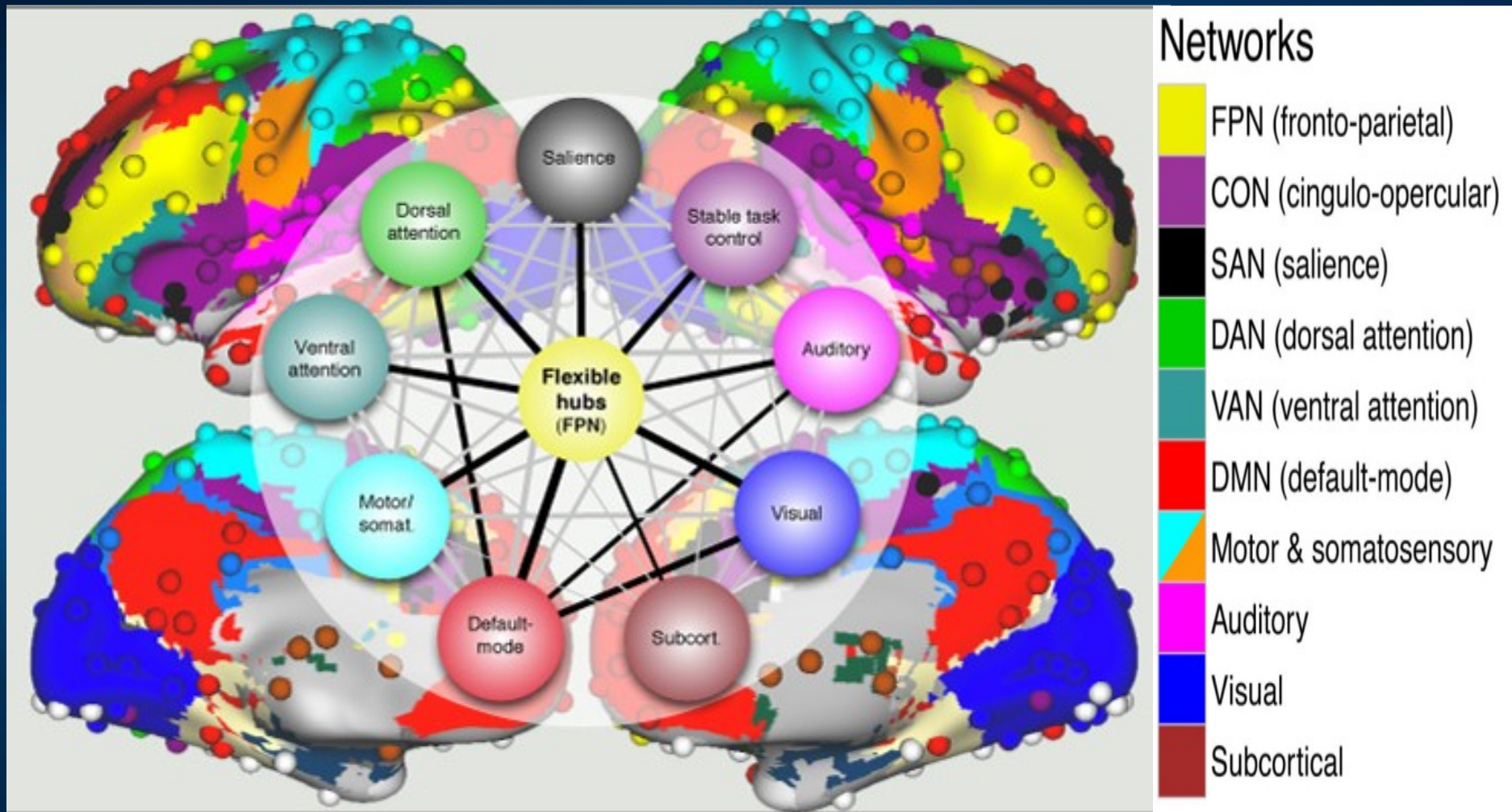
M. Minsky, Society of mind (1986)

Decompose brain network dynamics into meaningful components of activity related to various brain functions.

Include influence of genes, molecules, cells, **circuits**, physiology, behavior, self-reports on network functions.

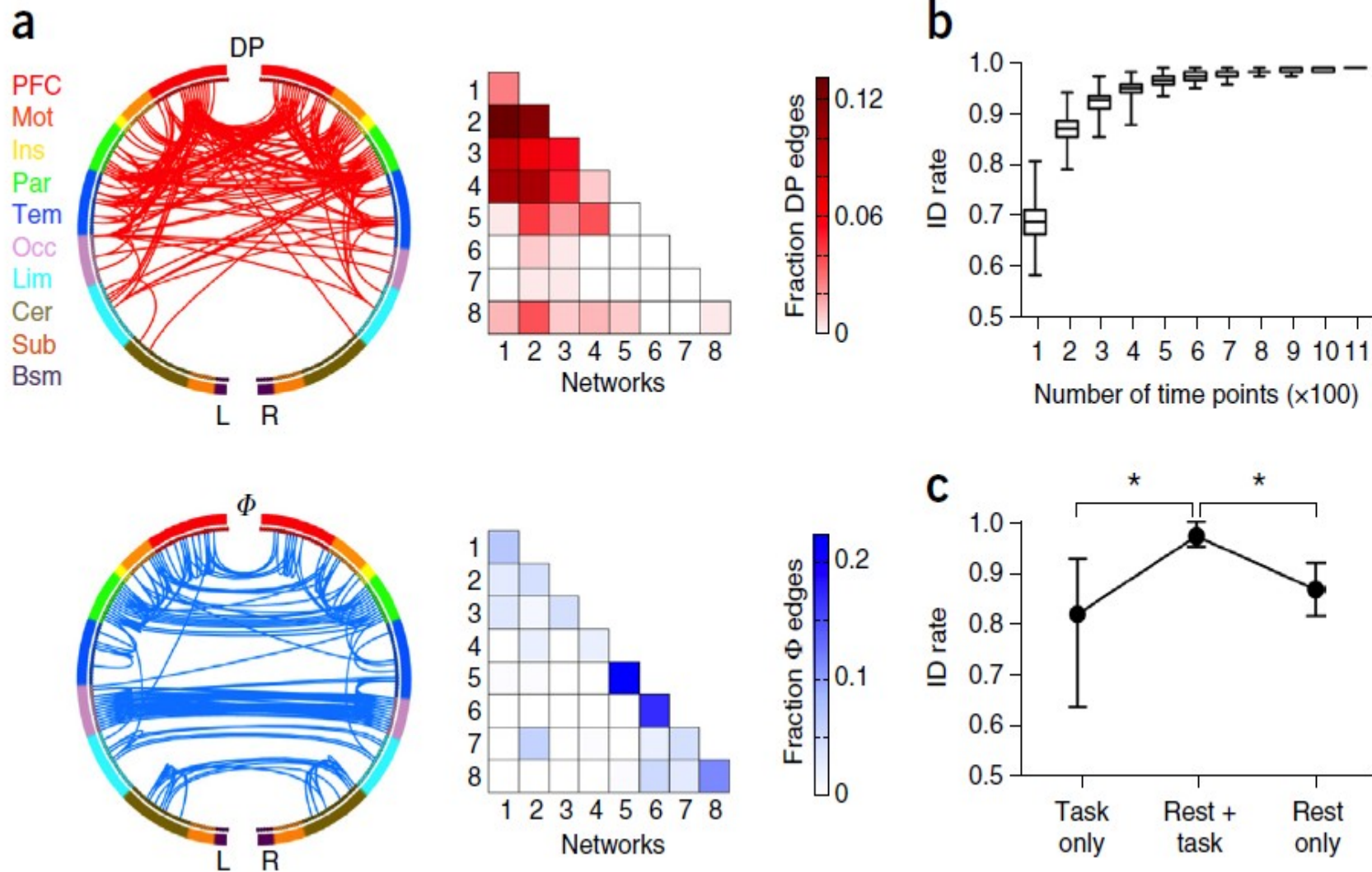


Neurocognitive Basis of Cognitive Control



Large scale canonical networks. 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).

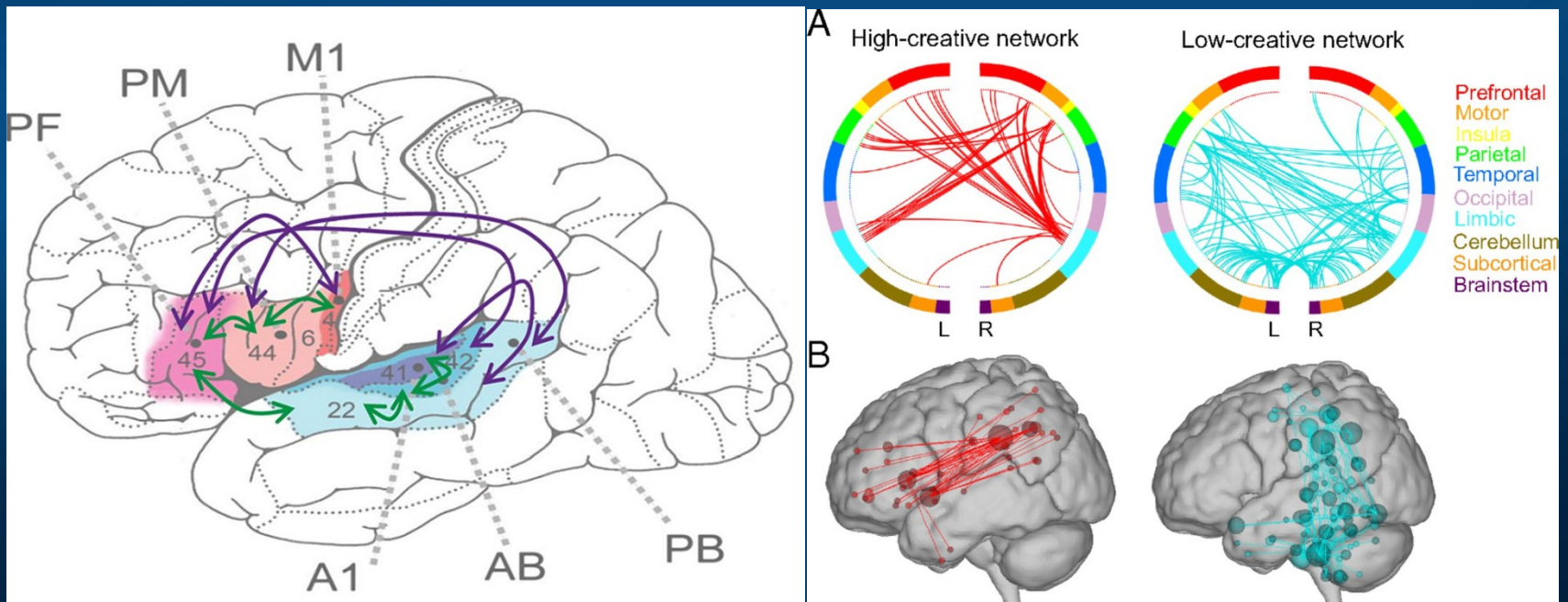
Finn et al. (2015), **Functional connectome fingerprinting**: identifying individuals using patterns of brain connectivity. Nature Neuroscience. Top: highly unique; Bottom: highly consistent connections.



Fluid nature

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

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

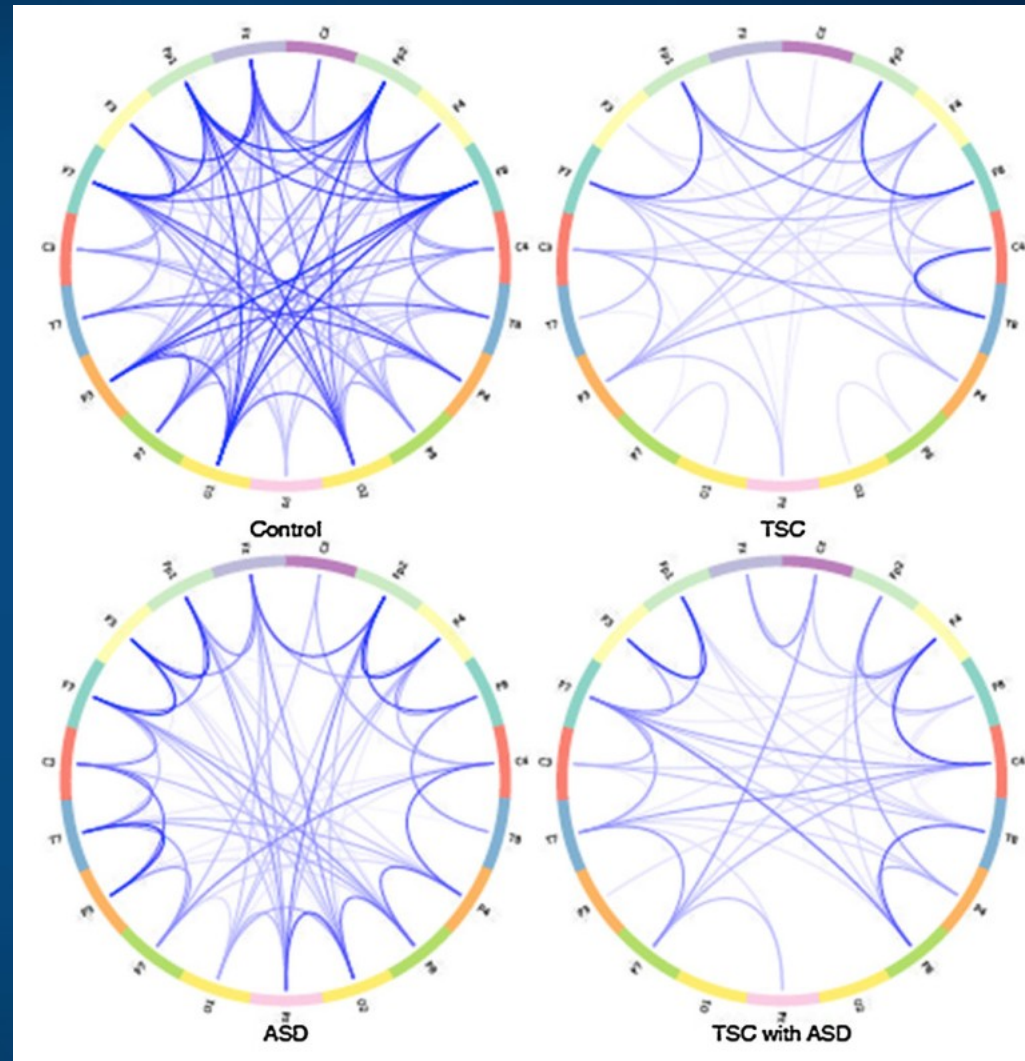


ASD: pathological FC

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

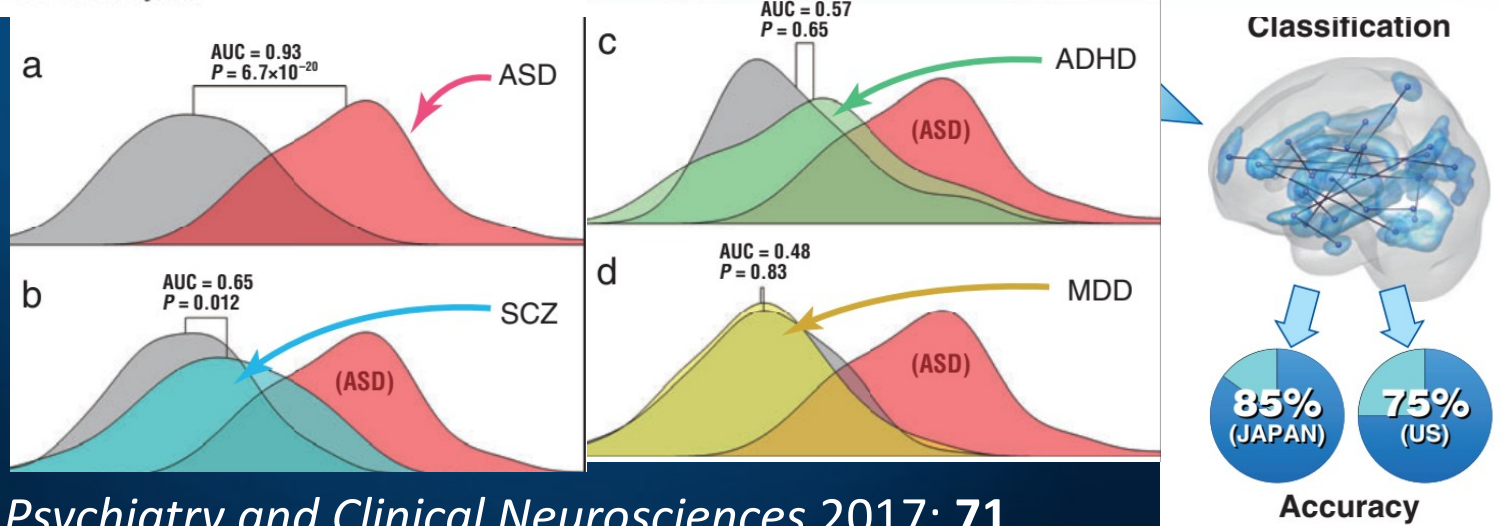
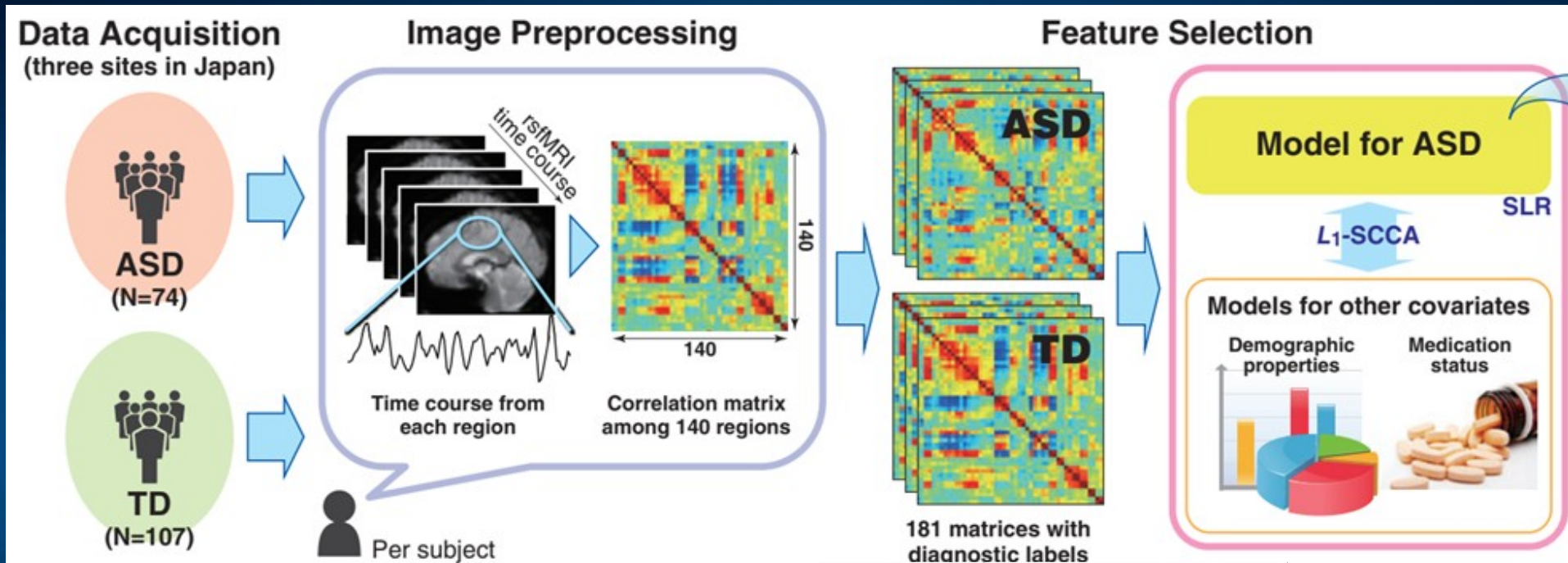
Coherence between electrodes. Weak or missing connections between distant regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

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

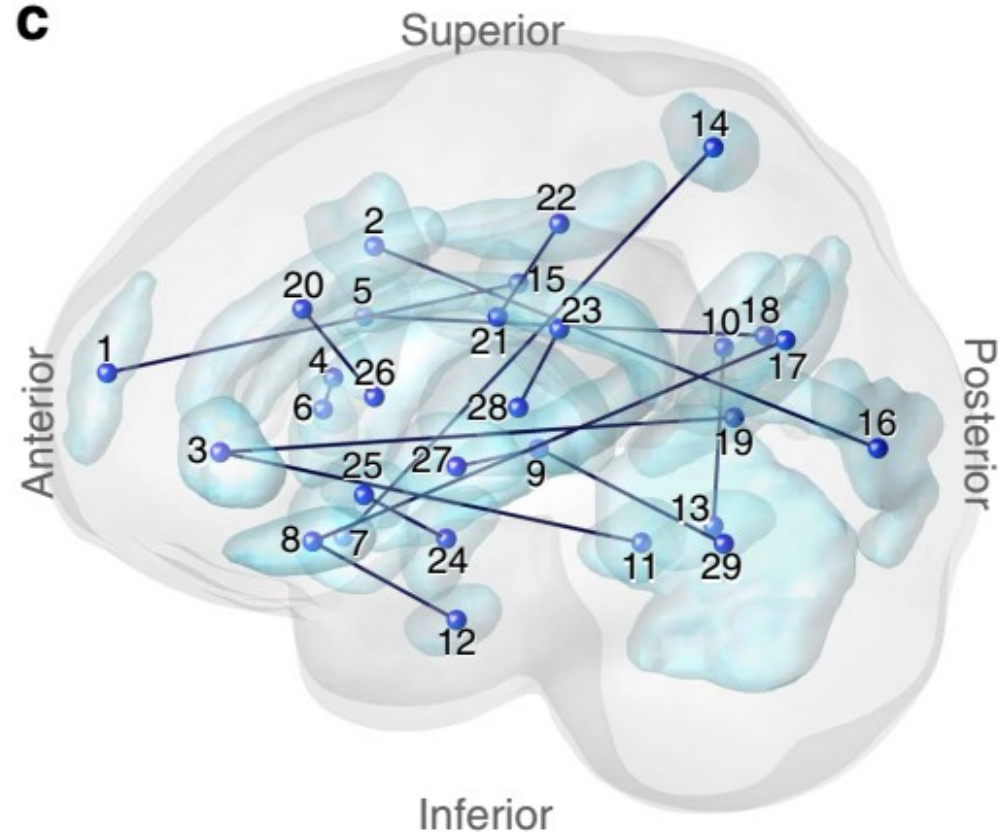
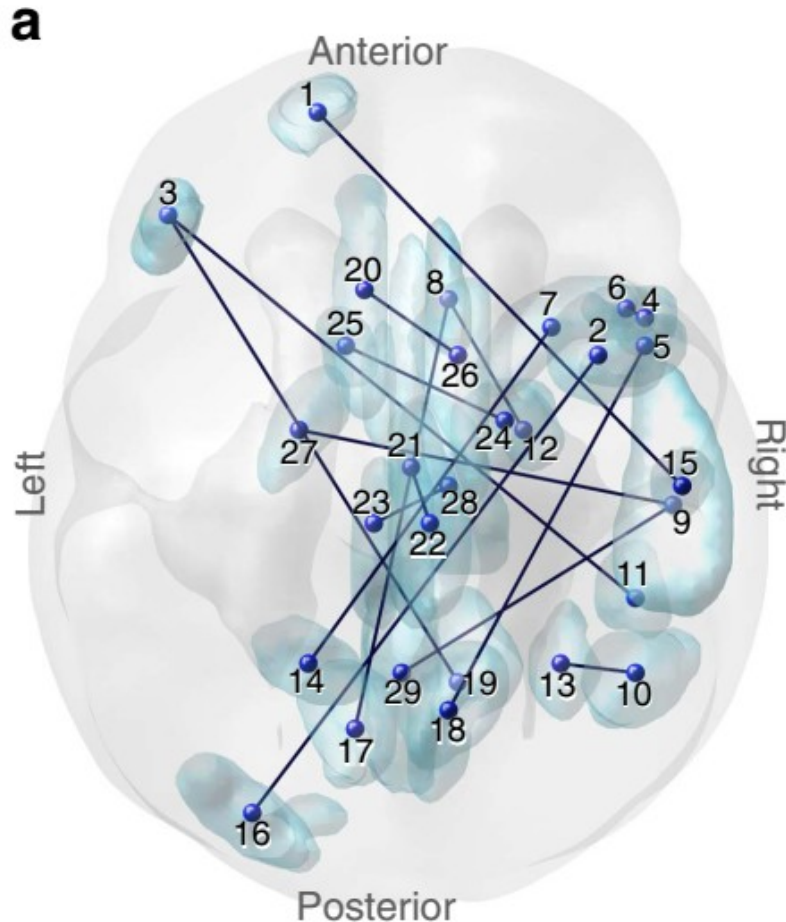


J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. *Cogn Process* (2015) 16:1–16

Biomarkers from neuroimaging



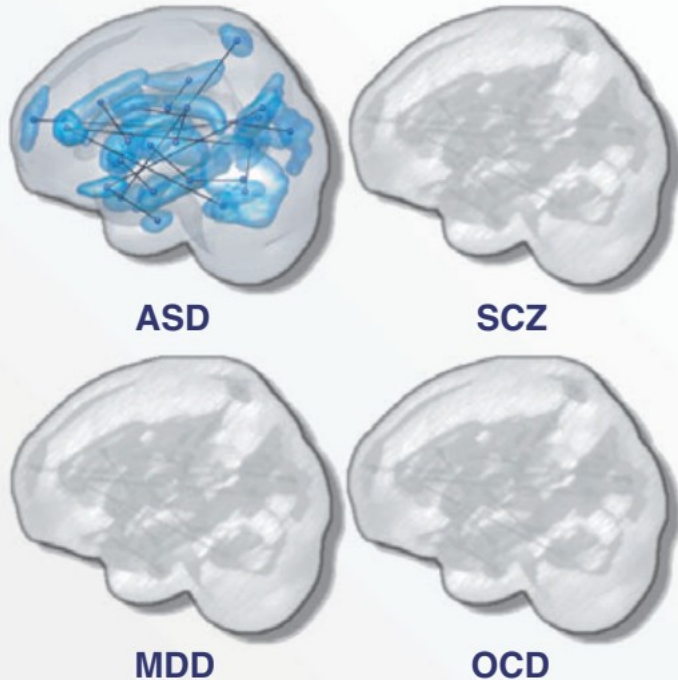
Selected connections



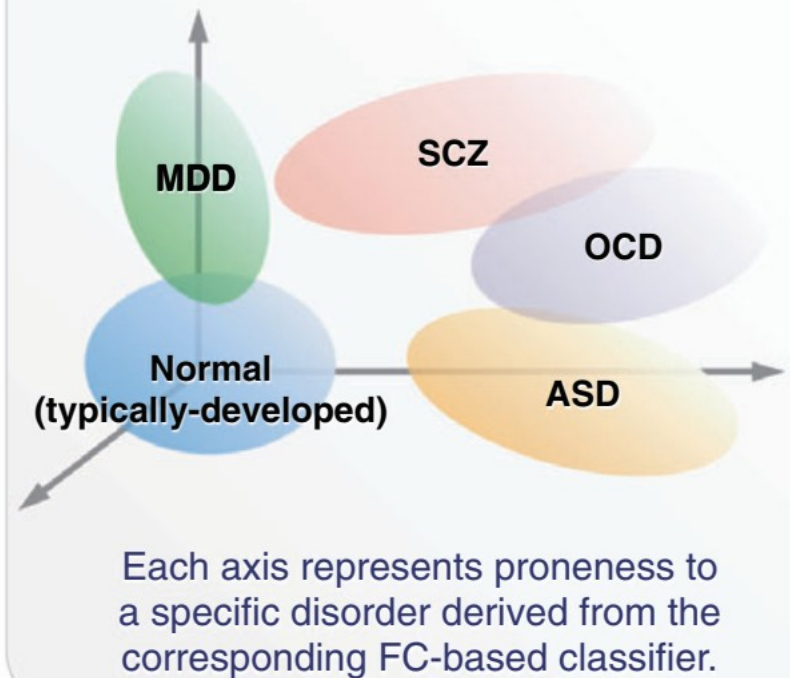
N. Yahata et al (2016): 29 selected regions (ROI) and 16 connections are sufficient to recognize ASD with 85% accuracy in 74 Japanese adult patients vs. 107 people in control group; without re-training accuracy was 75% on US patients.

Biomarkers of mental disorders

Functional connectivity-based classifiers for mental disorders

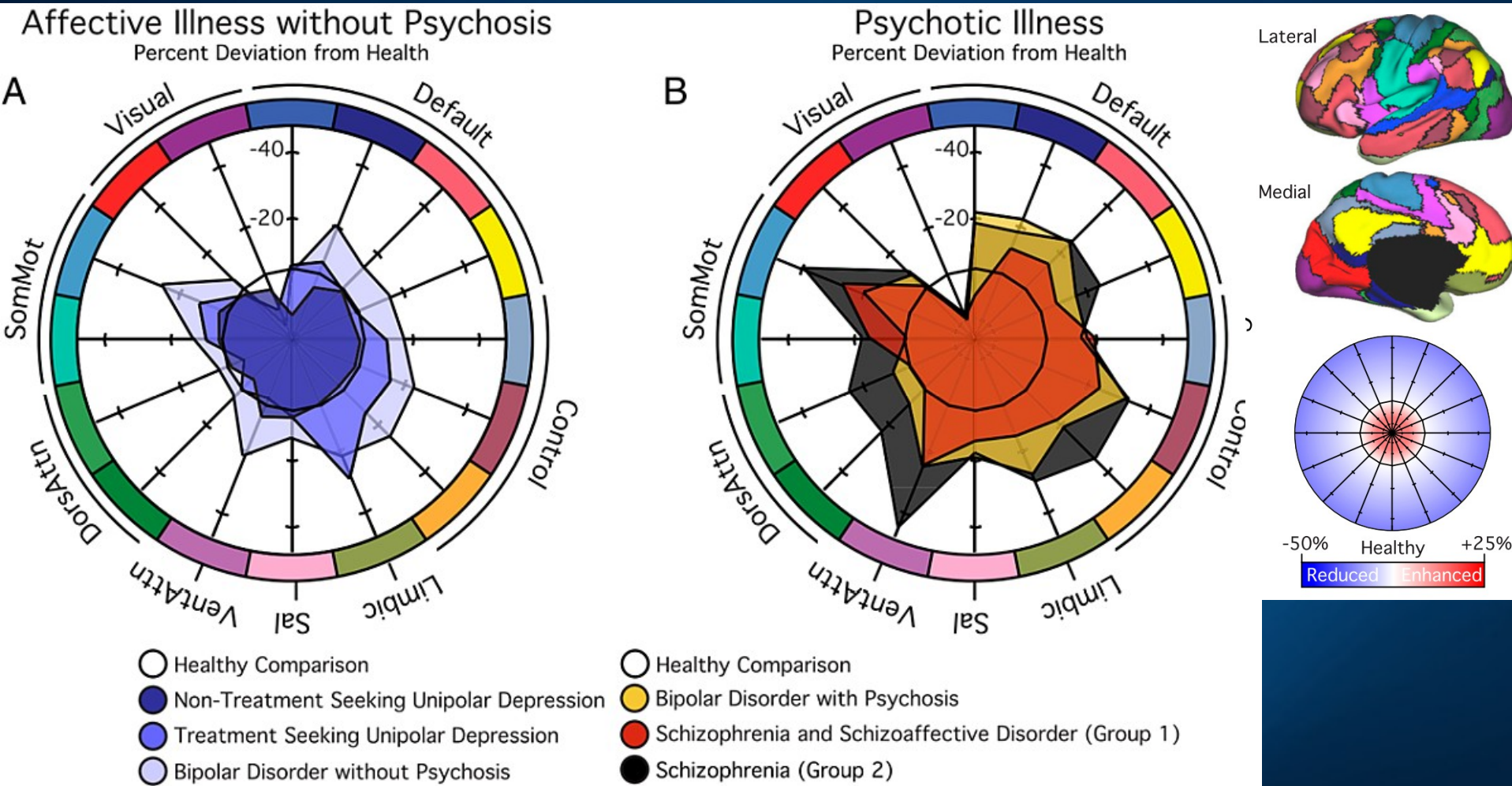


Recasting current nosology in more biologically meaningful dimensions



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



Regions determined based on the 17-network solution from Yeo et al.
Control (health) = circle, % deviation in mean network connectivity shown.

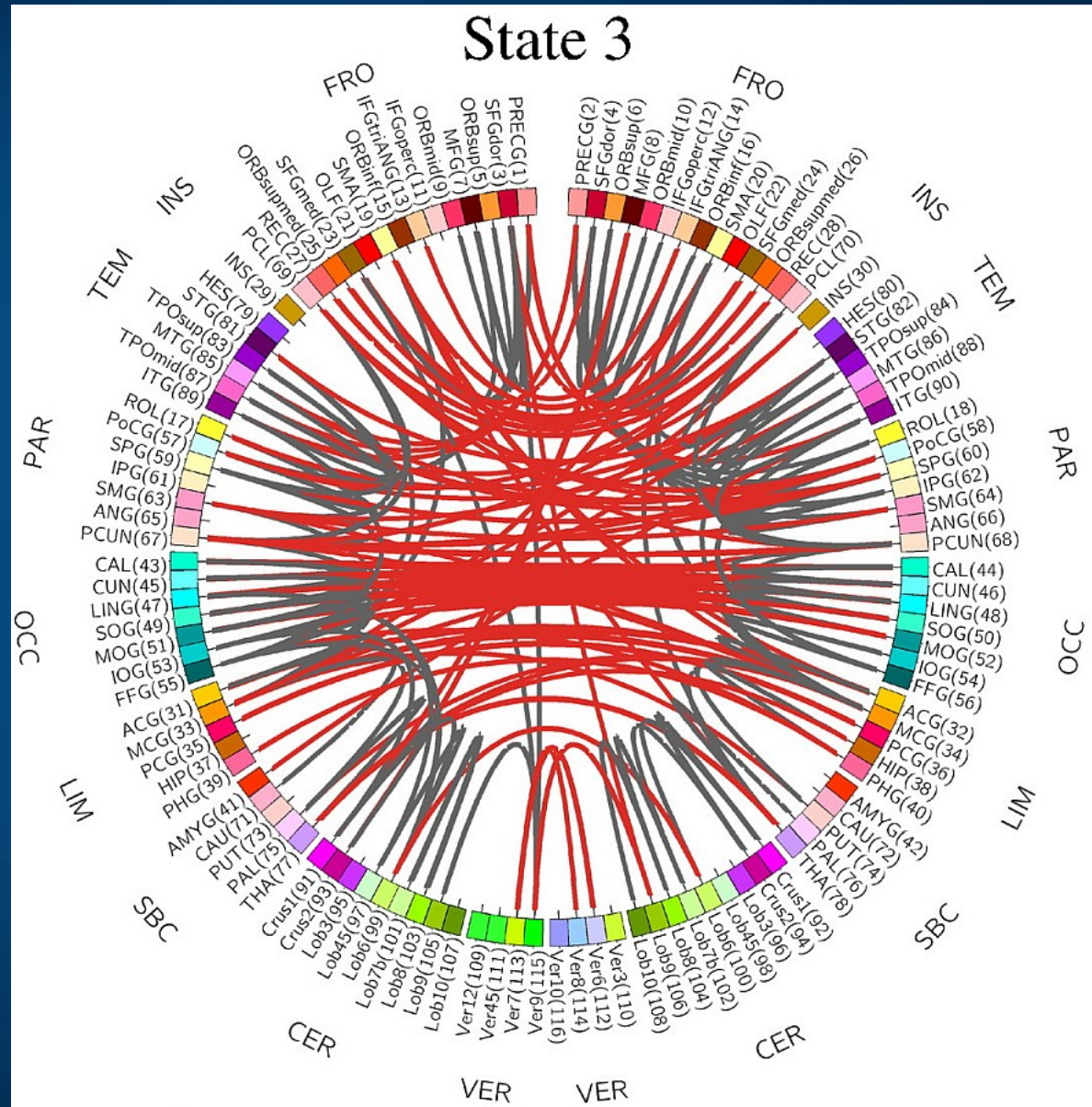
Negative connections in MCI patients

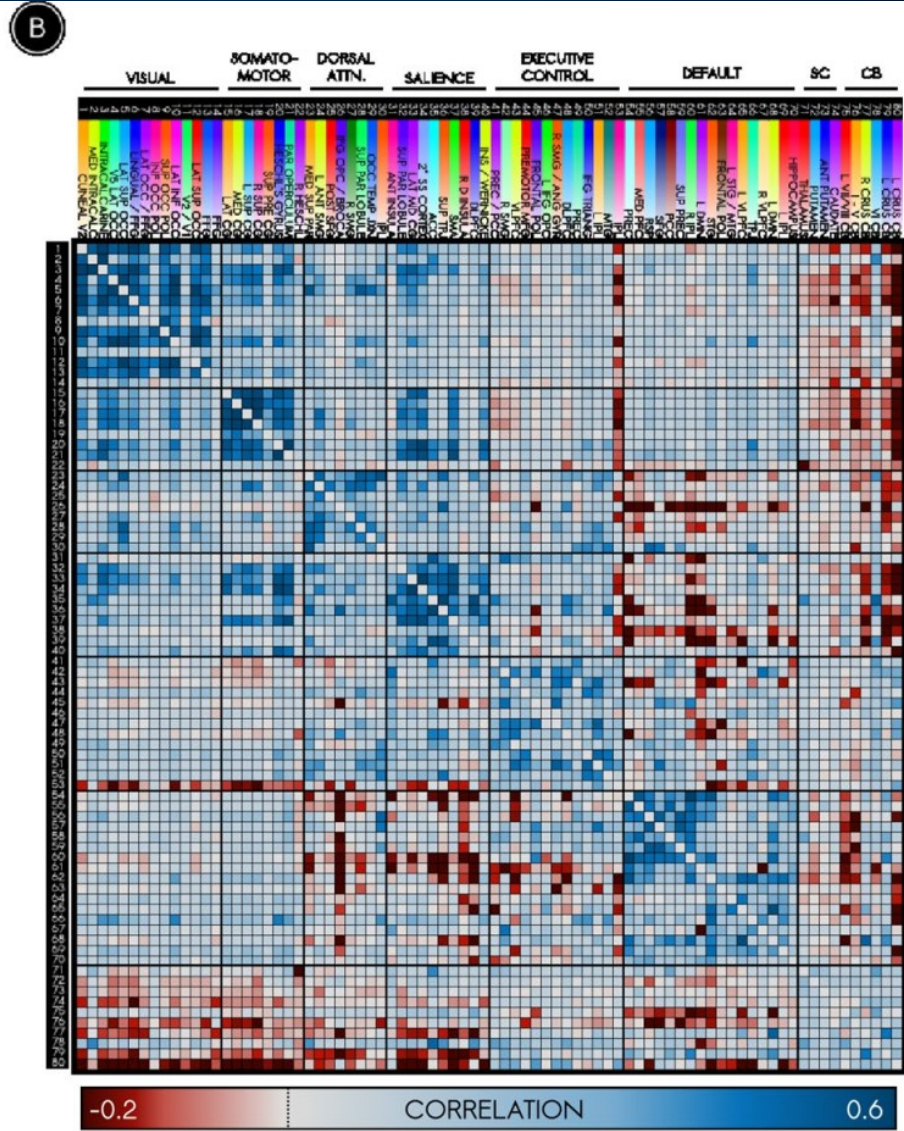
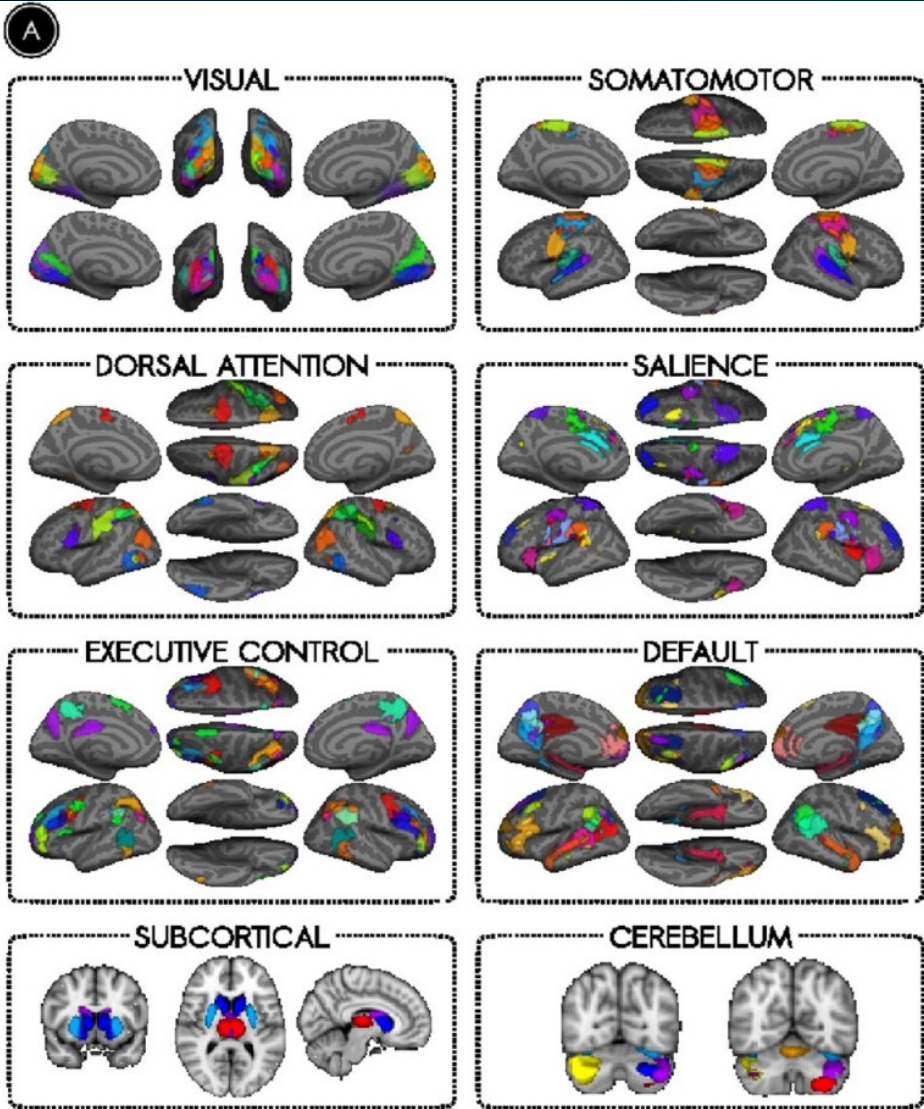
MCI patients (ADNI2), positive and negative functional connections in one of the 5 states of the Deep Auto-Encoder (DAE) + HMM models derived from the rs-fMRI time series.

Connections $|W| > 0.65$.

Accuracy 72.6% with a sensitivity of 70.6% and a specificity of 75%.

Suk et al. Neuroimage (2016)

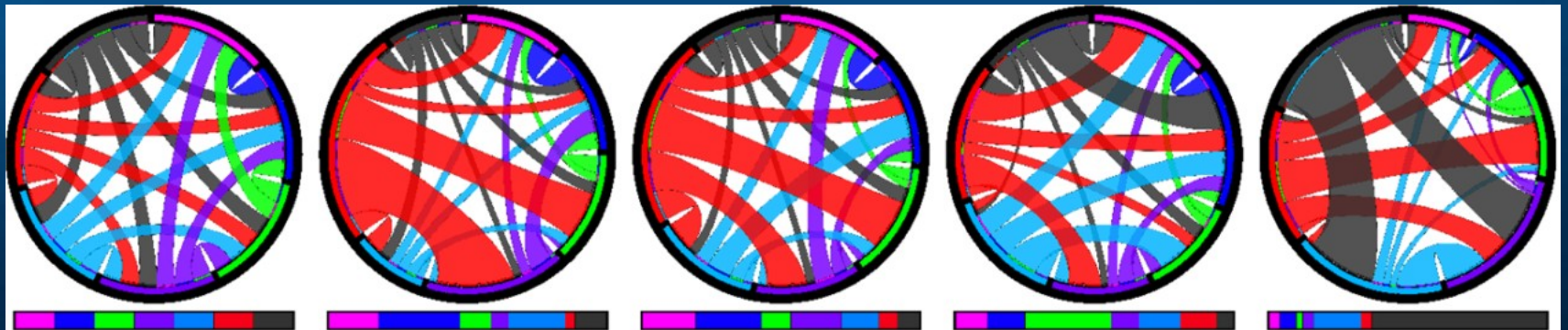


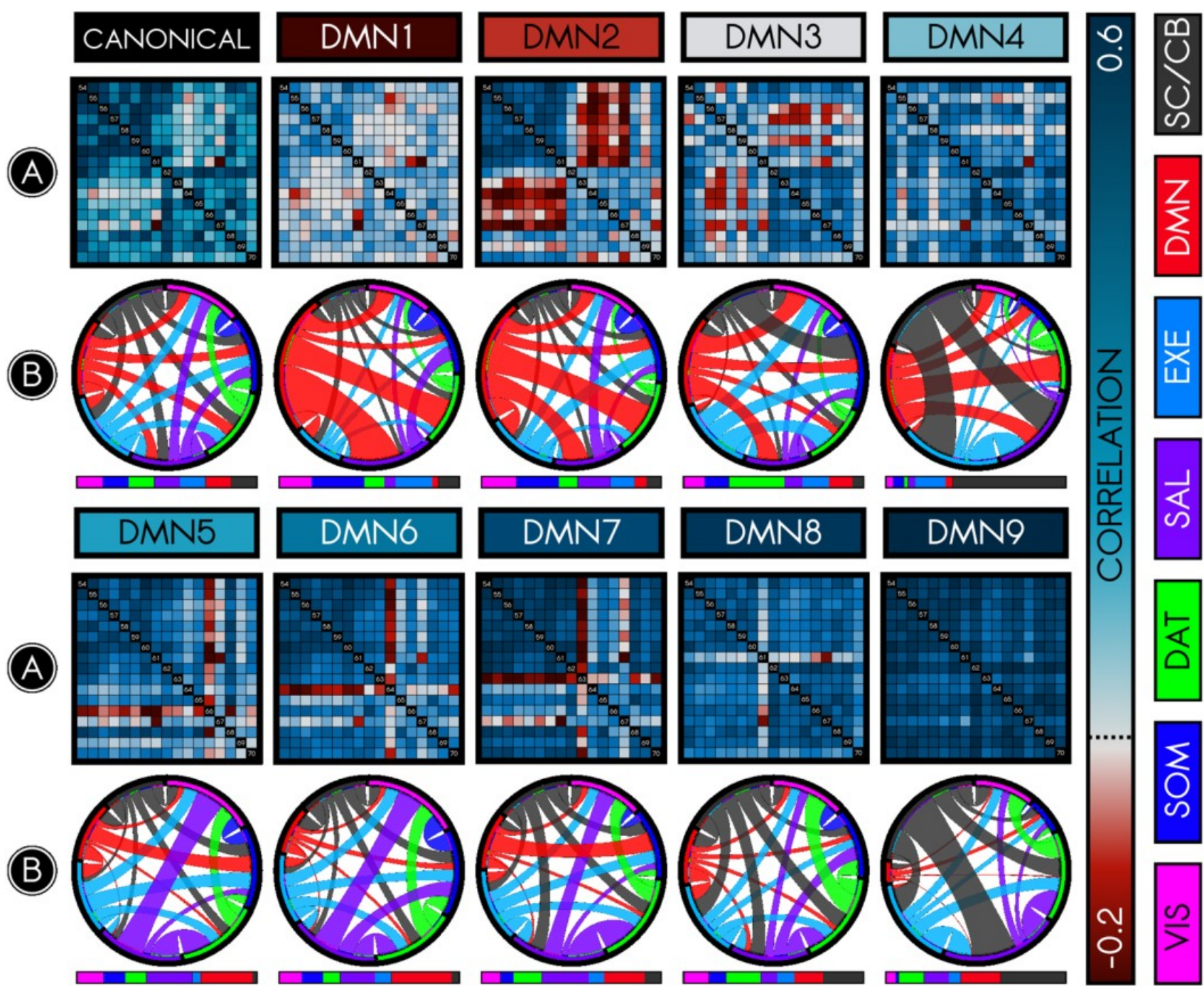


Circic et.al. (2017). Contextual connectivity: A framework for understanding the intrinsic dynamic architecture of large-scale functional brain networks. *Scientific Reports* 7, 6537

DMN time-averaged baseline.

Between-network allegiances (prob. that nodes are in the same community).
Rim colors = canonical networks, rim length = greater allegiance to other networks, size of connections = strength of between-network allegiances.
DMN1: weak within-network allegiance strong to DAT, SAL, and VIS.

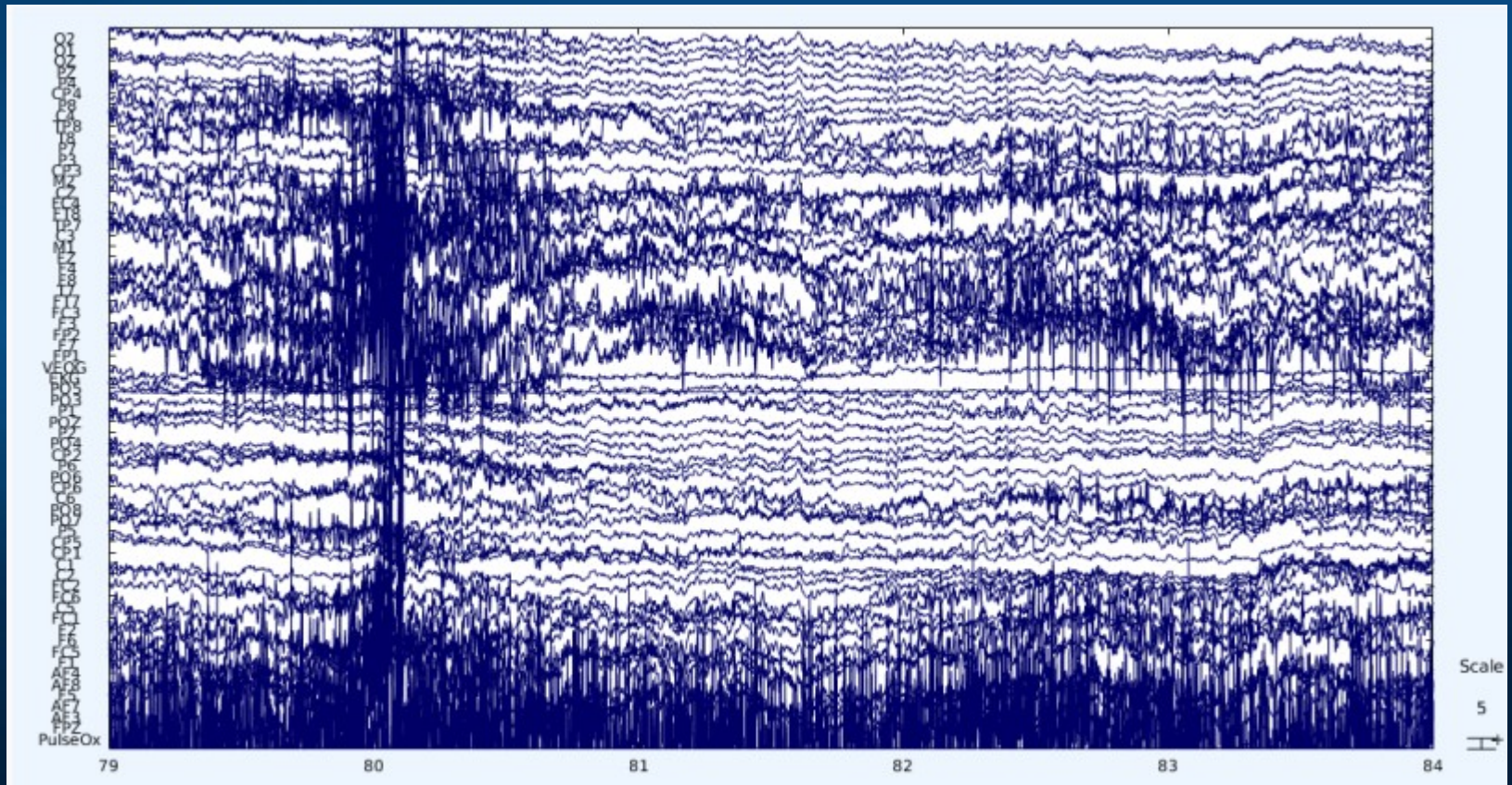




Neurodynamics

EEG

Brain networks from EEG? Technically difficult. Poor spatial resolution, only outer cortex, signals from the sensors are misleading, localization is necessary. Removal of artefacts is only partially automatic, it involves a lot of manual work.



EEG for Brain Fingerprints

fMRI is too costly, difficult to standardize, too slow to follow dynamics.

fMRI BFP are based on $V(X,t)$ voxel intensity of fMRI BOLD signal changes, contrasted between task and reference activity or resting state.

EEG: cheaper and better temporal resolution, use spatio-temporal maps, ERP maps/shapes, coherence, various phase synchronization indices for BFP.

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

Neuroplastic changes of connectomes and functional connections are observed as a result of training to optimize brain processes.

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.

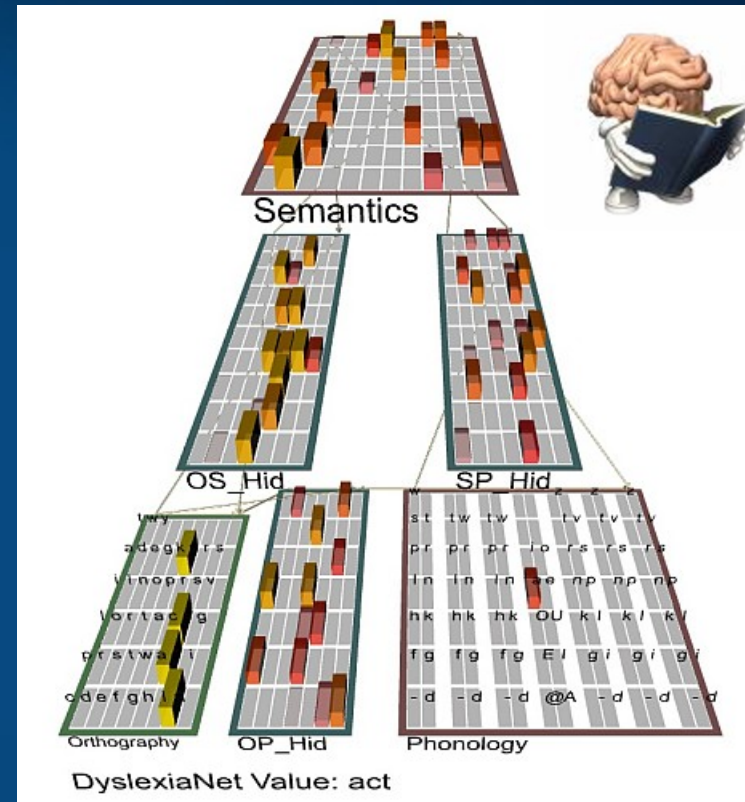
In the brain: microfeature=subnetwork.
Hidden layers OS/OP/SP_Hid in between.

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.



Computational Models

Models at various level of detail.

- Minimal model includes neurons with 3 types of ion channels.

Models of attention:

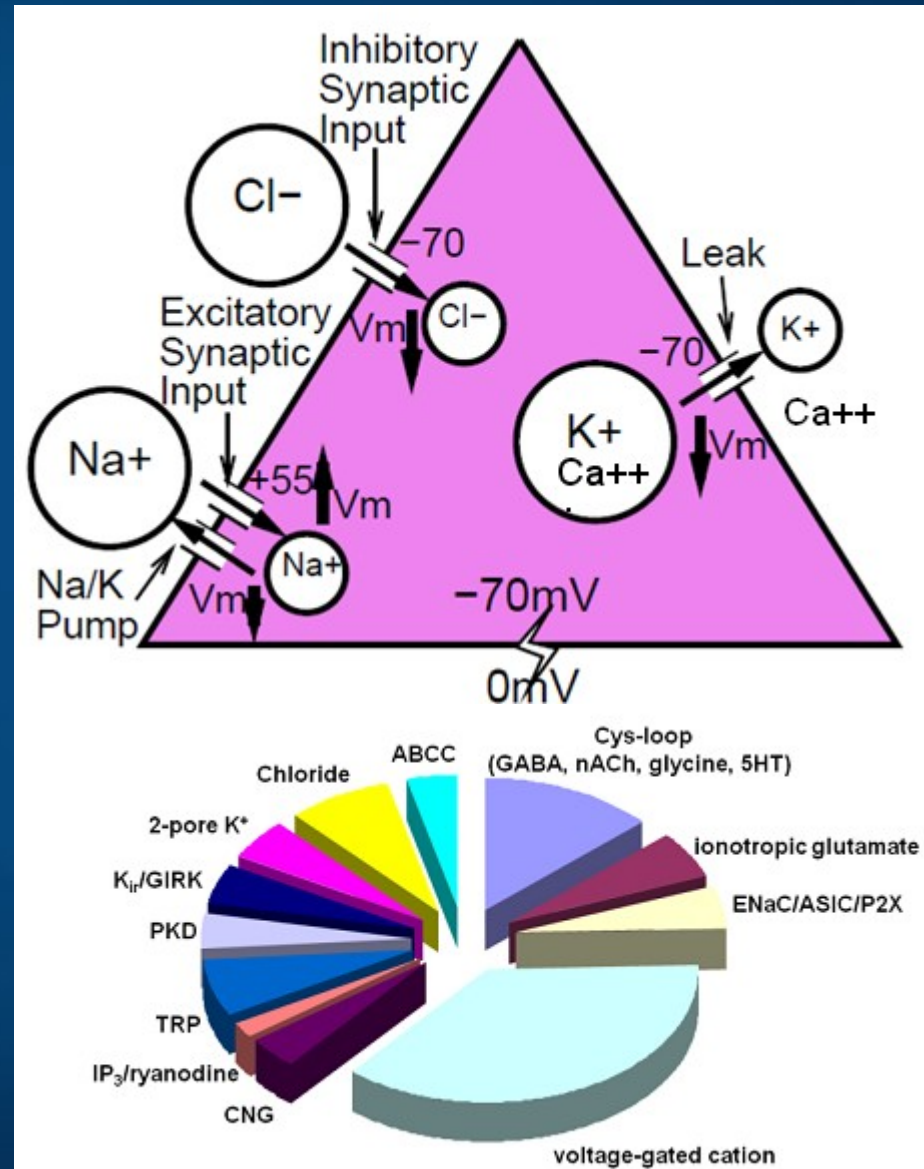
- Posner spatial attention;
- attention shift between visual objects.

Models of word associations:

- sequence of spontaneous thoughts.

Models of motor control.

Critical: control of the increase in intracellular calcium, which builds up slowly as a function of activation. Initial focus on the leak channels, 2-pore K^+ , looking for genes/proteins.



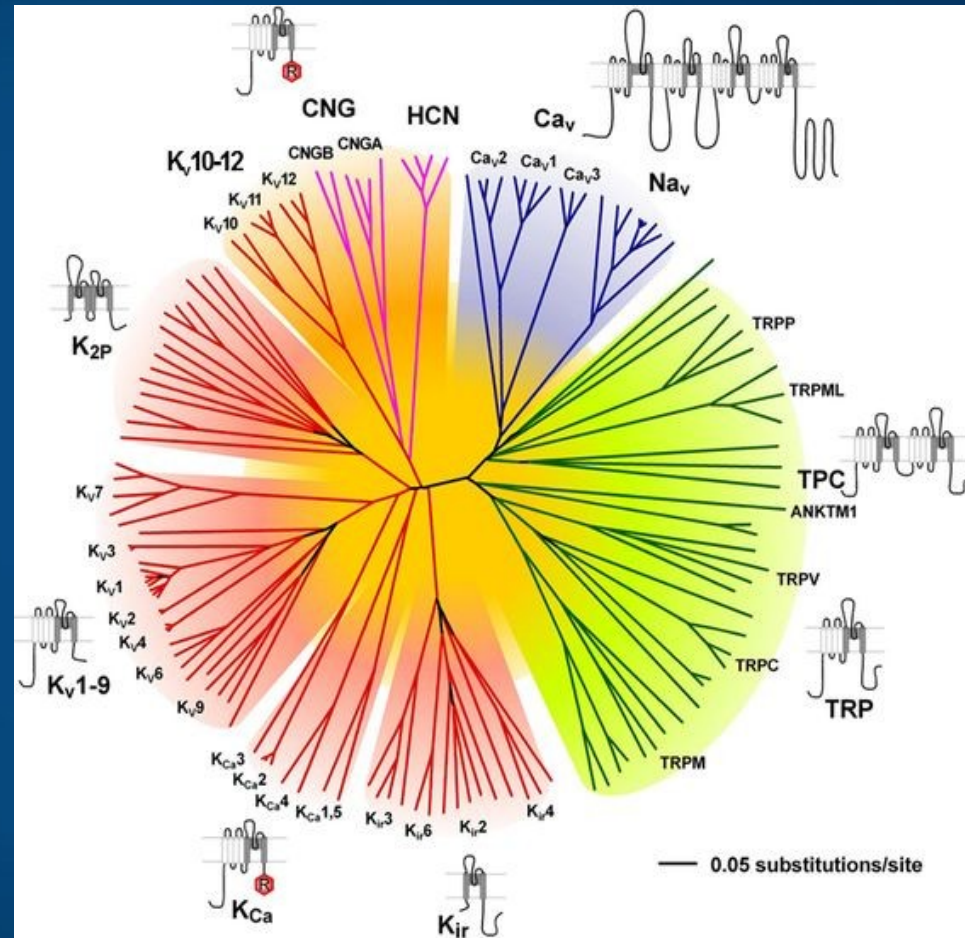
Ion channels

Hundreds of ion channels
have been identified in neurons ...

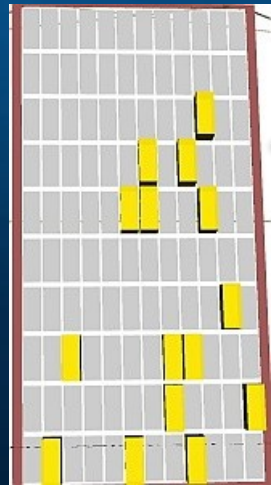
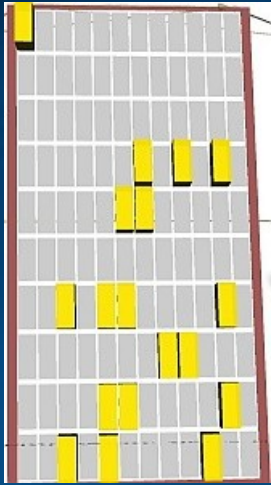
Major challenge for computational
neurosciences:

what happens with the nervous
system when some of them are
dysfunctional?

Leak channels regulate spontaneous
transitions between attractor states.

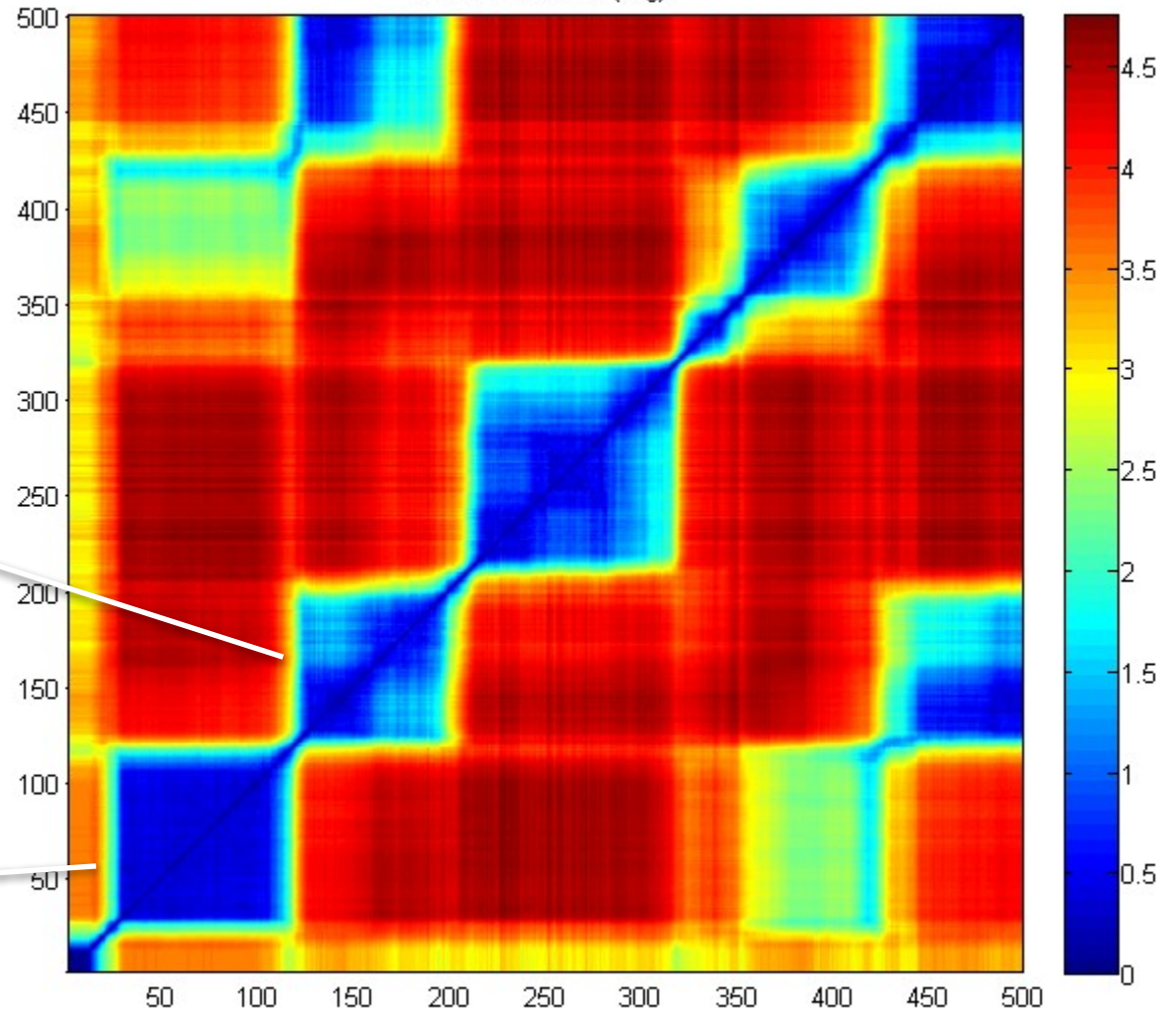


rope



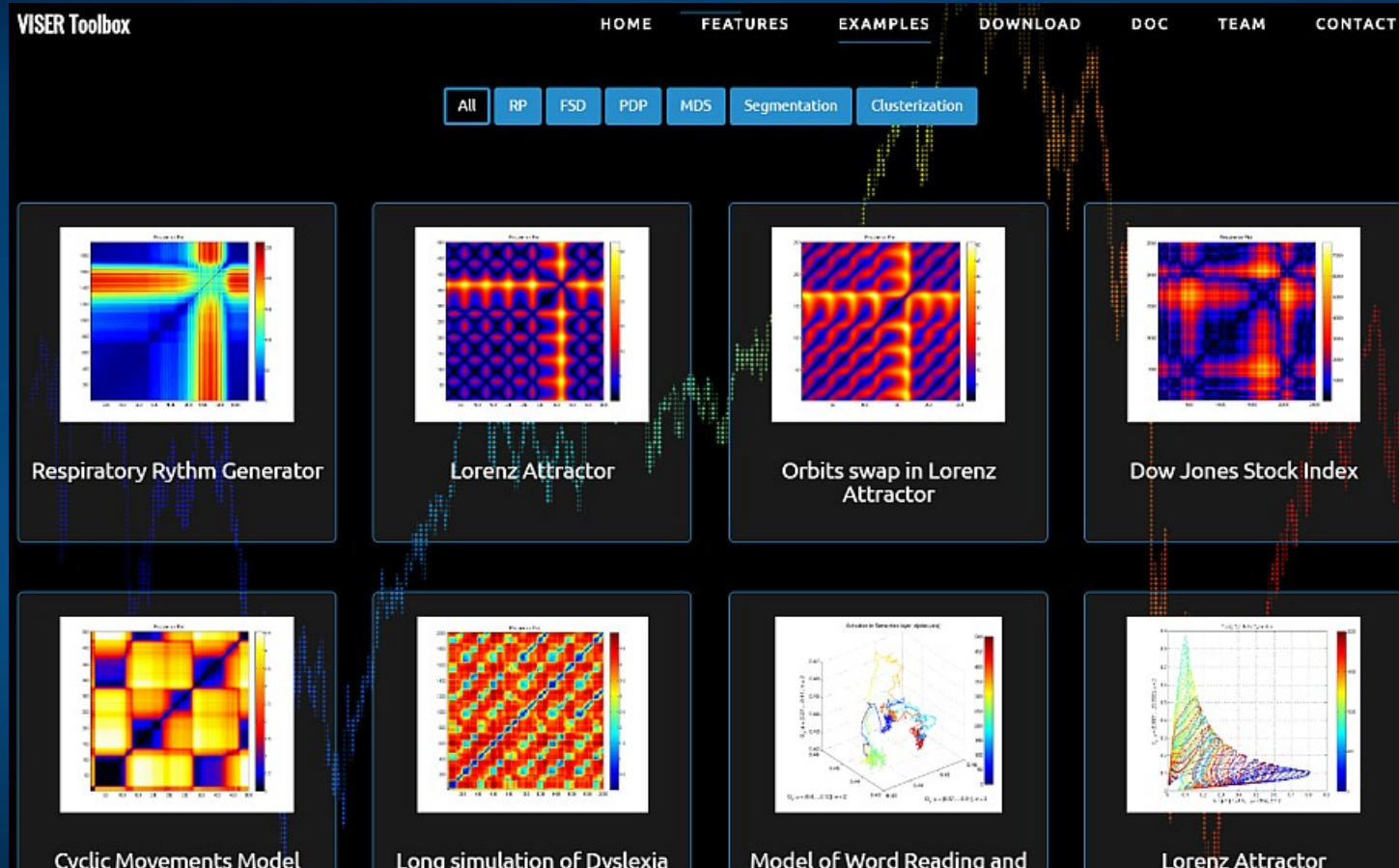
flag

Recurrence Plot (flag)



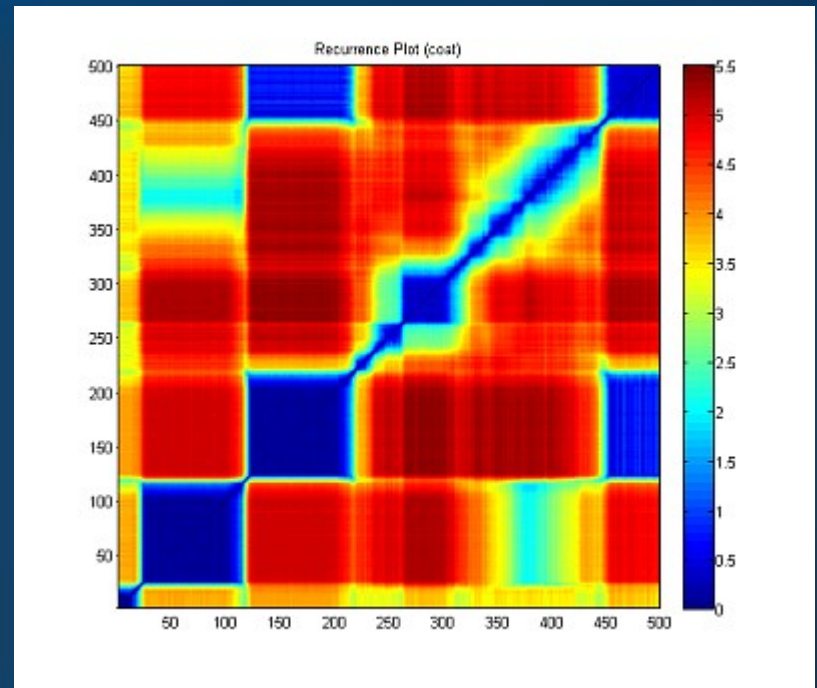
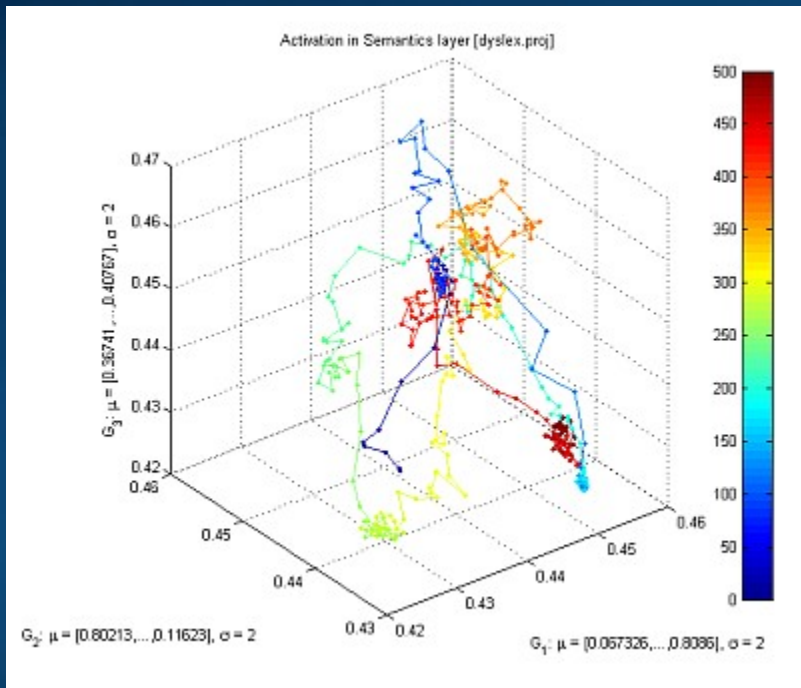
Transitions to new patterns that share some active units (microfeatures) shown in recurrence plots.

Viser toolbox



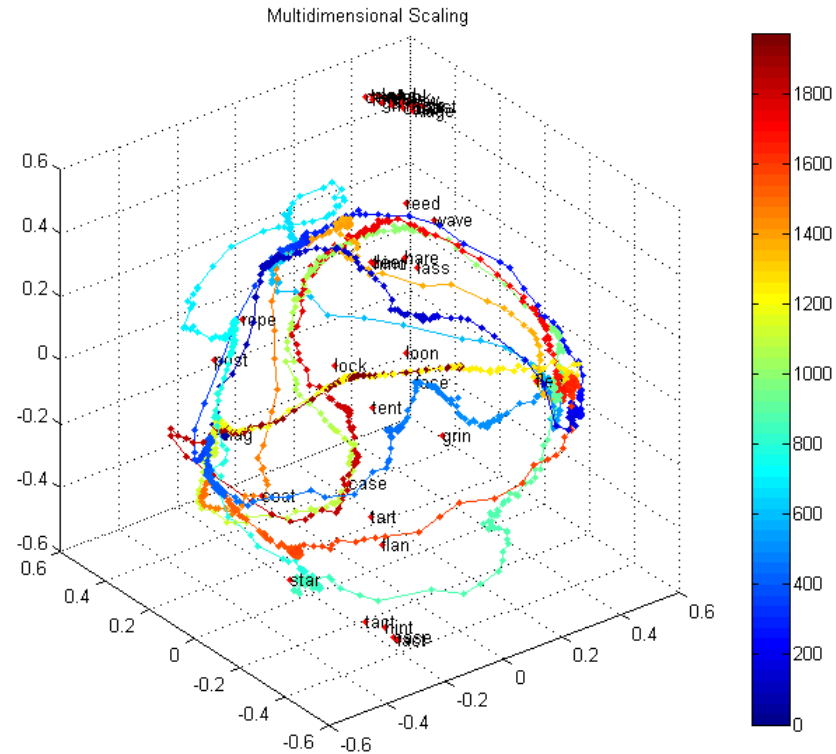
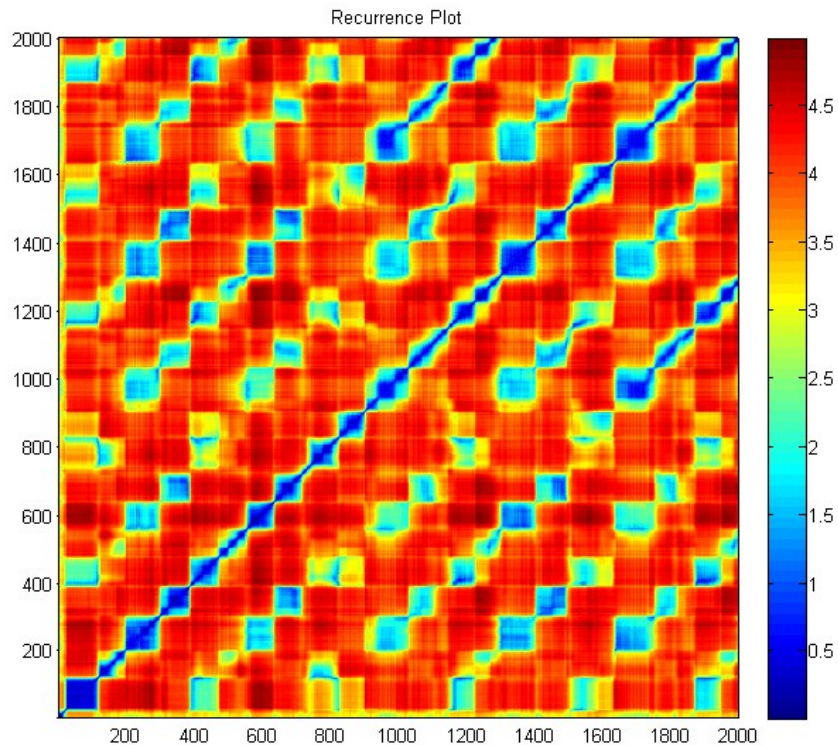
Nasz Viser toolbox (Dobosz, Duch) do wizualizacji szeregów czasowych w wielu wymiarach różnymi technikami.

Fast transitions



Attention is focused only for a brief time and then moved to the next attractor basin, some basins are visited for such a short time that no action may follow, corresponding to the feeling of confusion and not being conscious of fleeting thoughts.

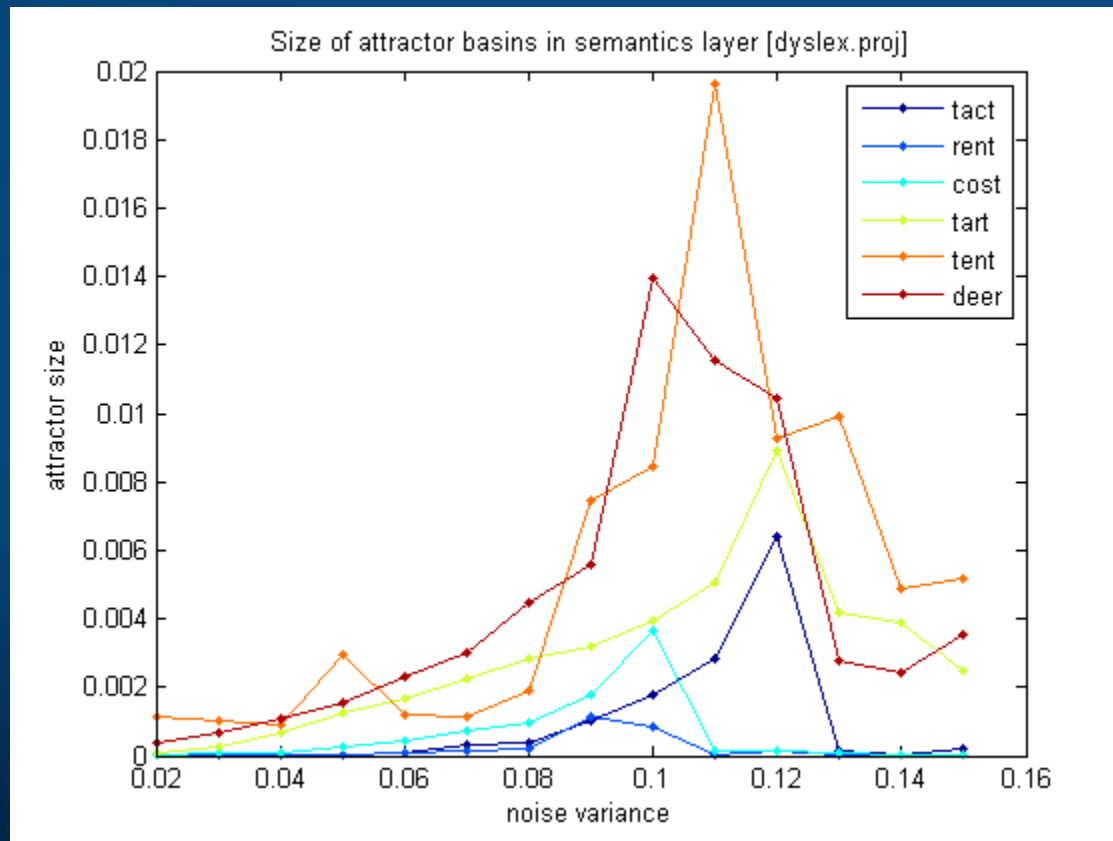
Trajectory visualization



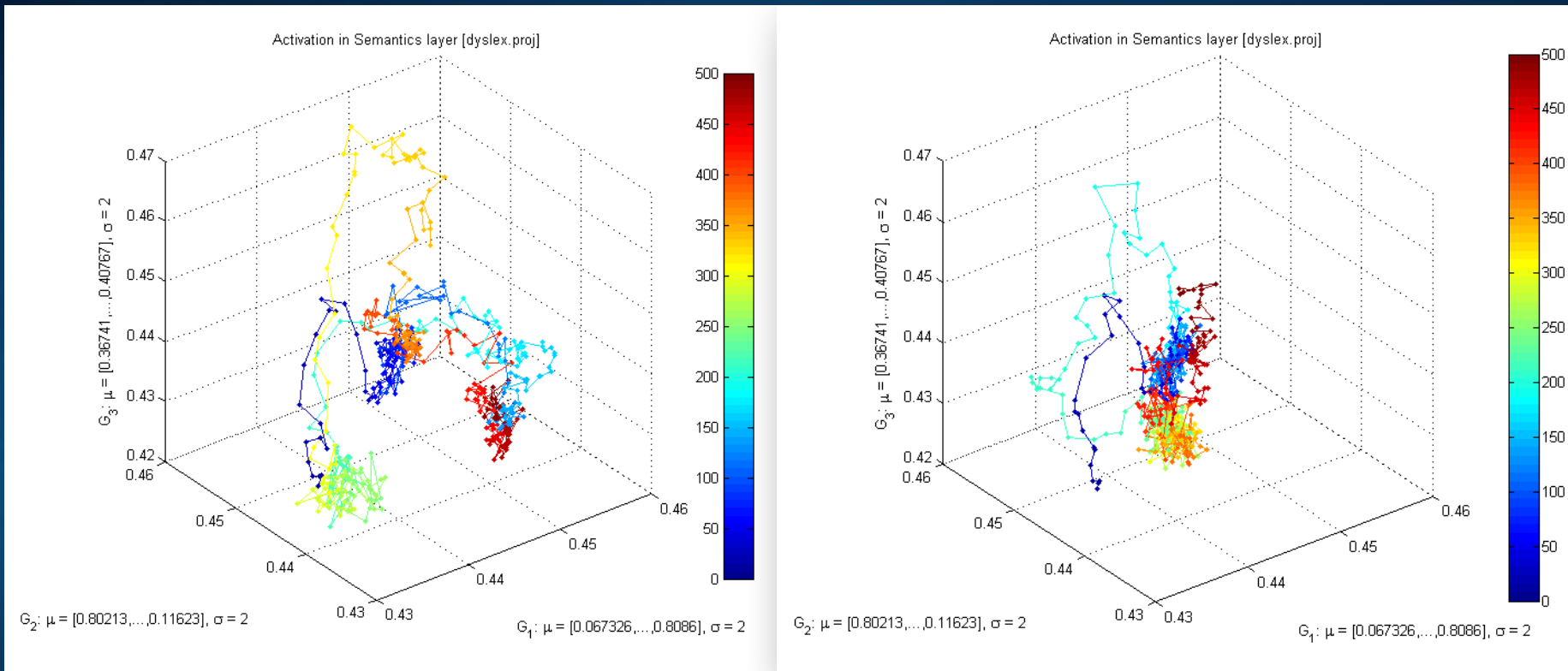
Recurrence plots and MDS/FSD/SNE visualization of trajectories of the brain activity. Here data from 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain, starting with the word “flag”.

Depth of attractor basins

Variance around the center of a cluster grows with synaptic noise; for narrow and deep attractors it will grow slowly, but for wide basins it will grow fast. It may be used to estimate how strong states are entrapped in basins of attractors. Jumping out of the attractor basin reduces the variance due to inhibition of desynchronized neurons.

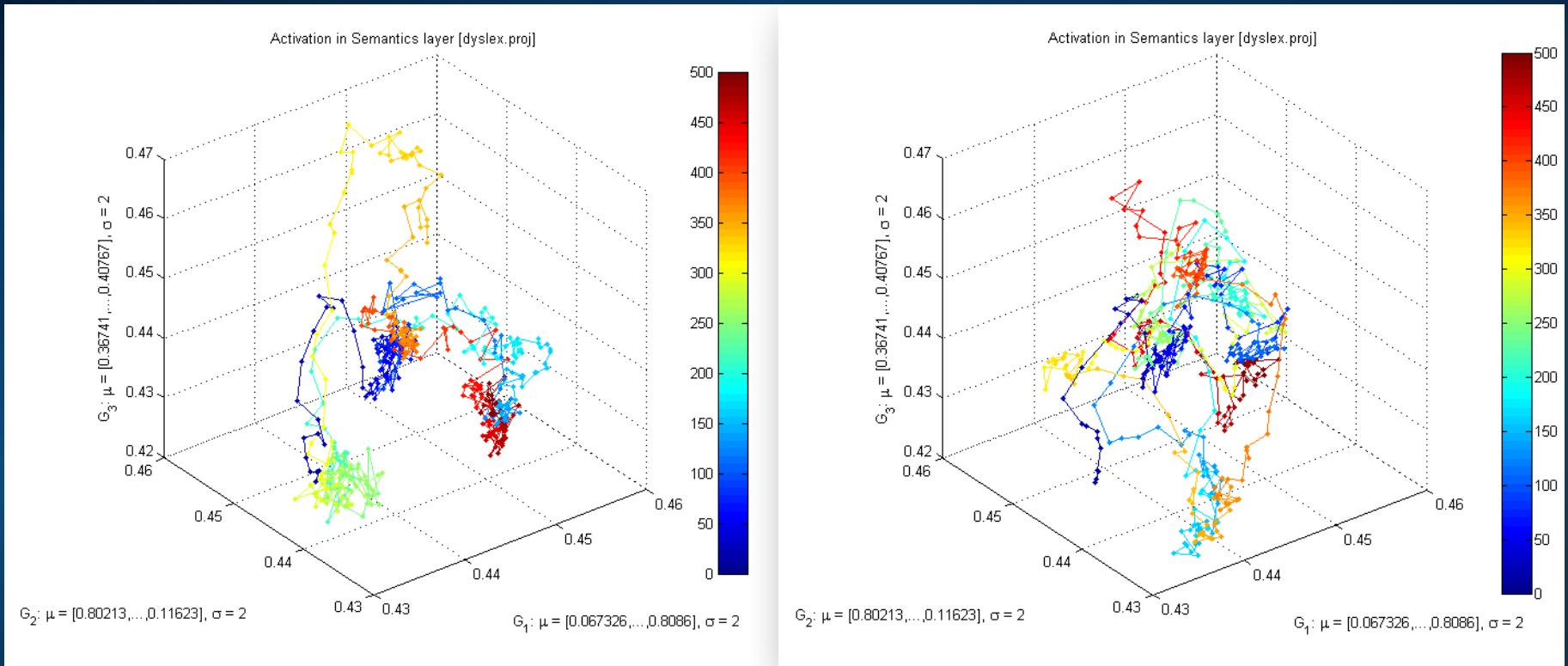


Typical Development vs. Autism



All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. $b_inc_dt = 0.01$ & $b_inc_dt = 0.005$
 $b_inc_dt =$ time constant for increases in intracellular calcium building up slowly as a function of activation, controls voltage-dependent leak channels.
<http://kdobosz.wikidot.com/dyslexia-accommodation-parameters>

Typical Development vs ADHD

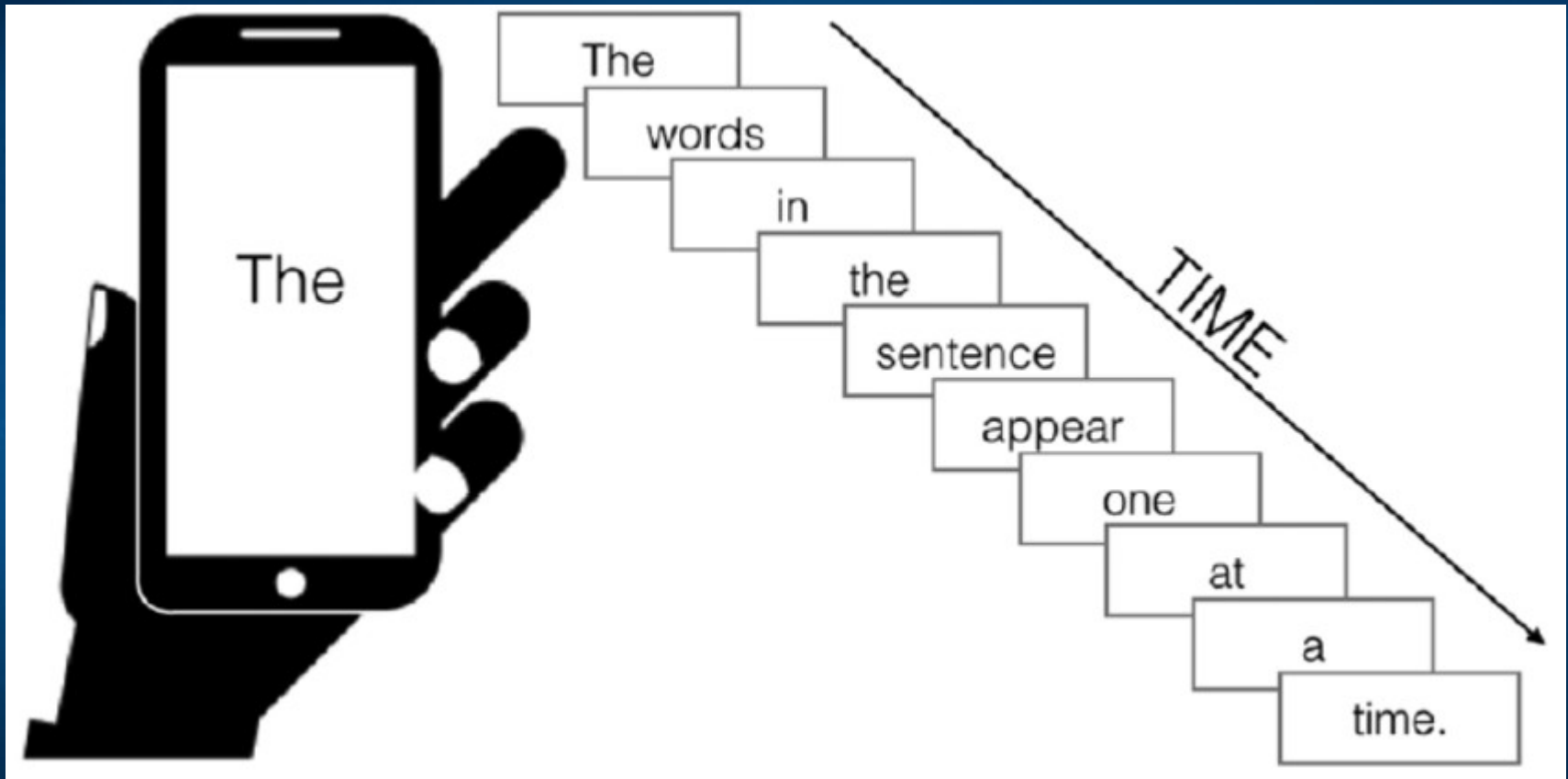


All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. $b_inc_dt = 0.01$ & $b_inc_dt = 0.02$.

b_inc_dt = time constant for increases in intracellular calcium which builds up slowly as a function of activation.

<http://kdobosz.wikidot.com/dyslexia-accommodation-parameters>

Rapid Serial Visual Presentation

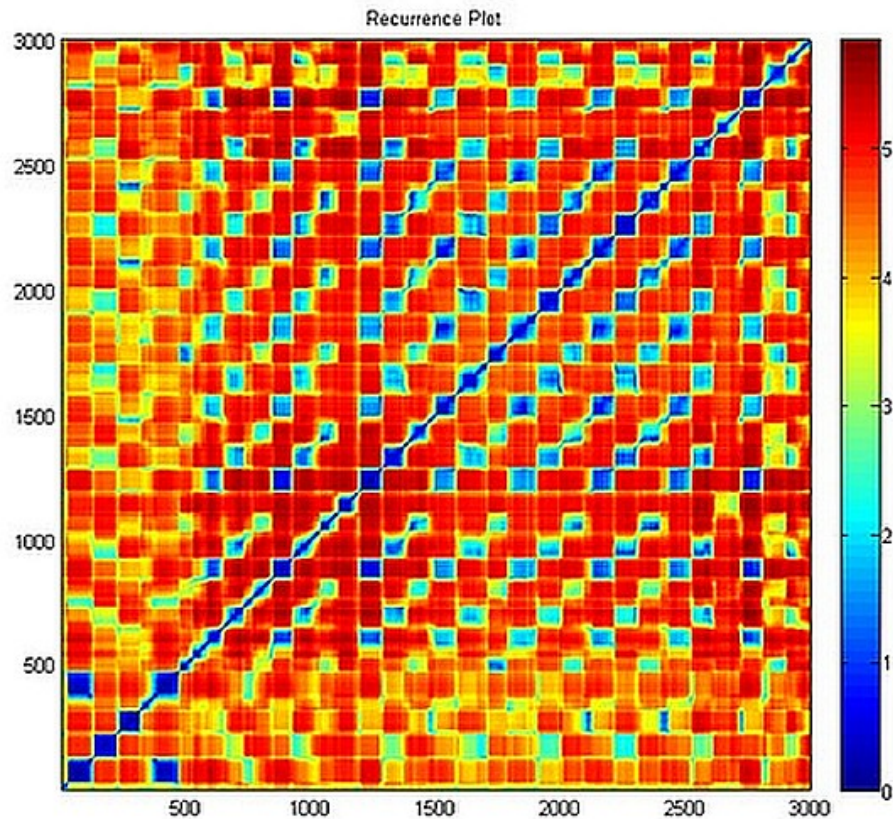


Any RSVP applications for fast reading.

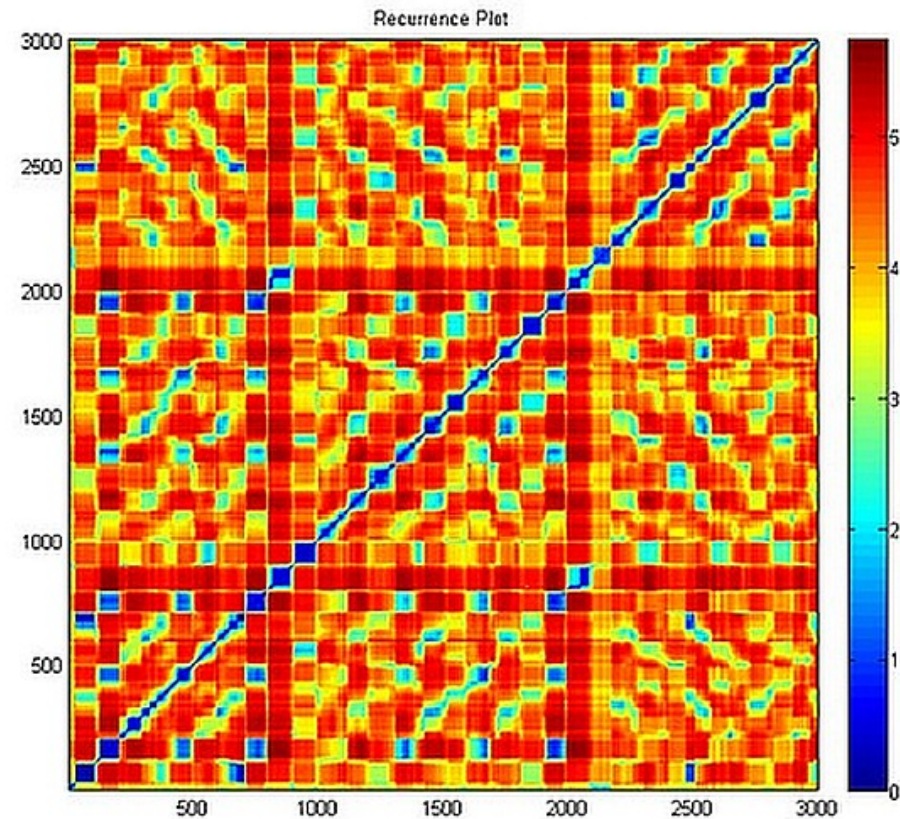
Simulation: showing series of words, looking for attention/associations.

star => flea => tent => lock => tart => hind

RSVP: typical brain

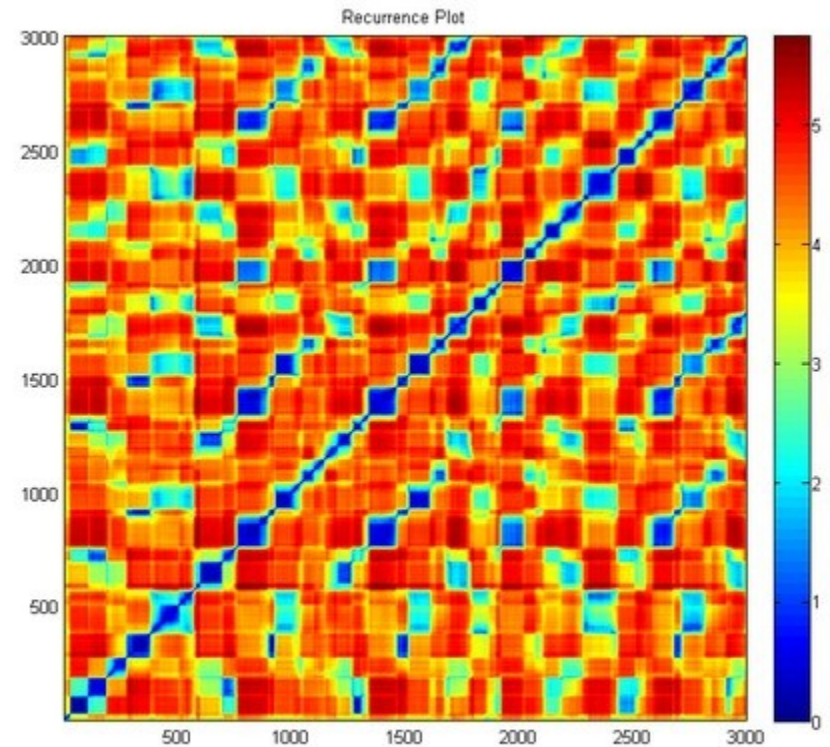
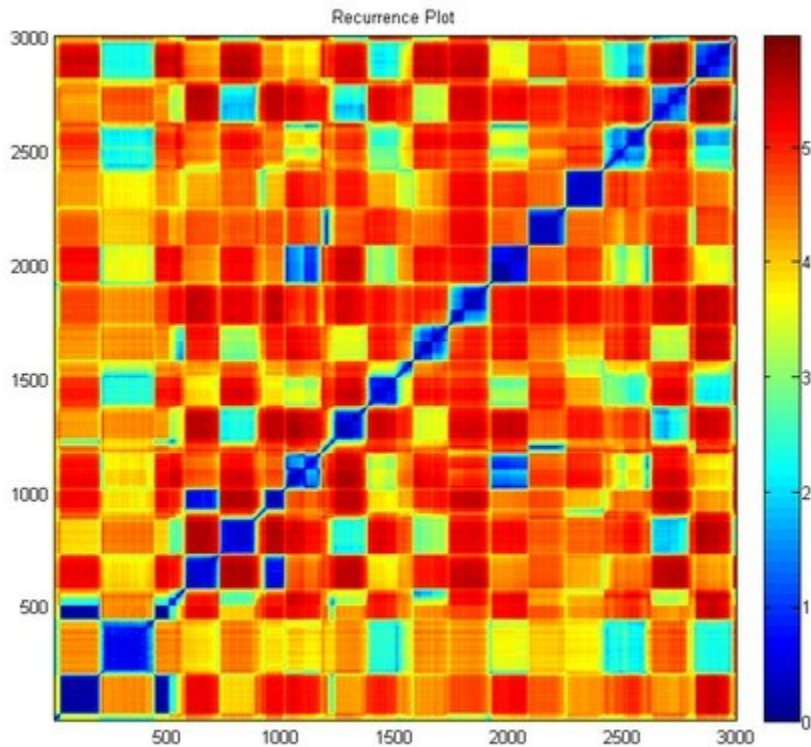


Normal speed
associations, context=>understanding
Some shallow microstates, no associations



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

RSVP simulations: HFA



High functioning ASD case (HFA):

normal presentation

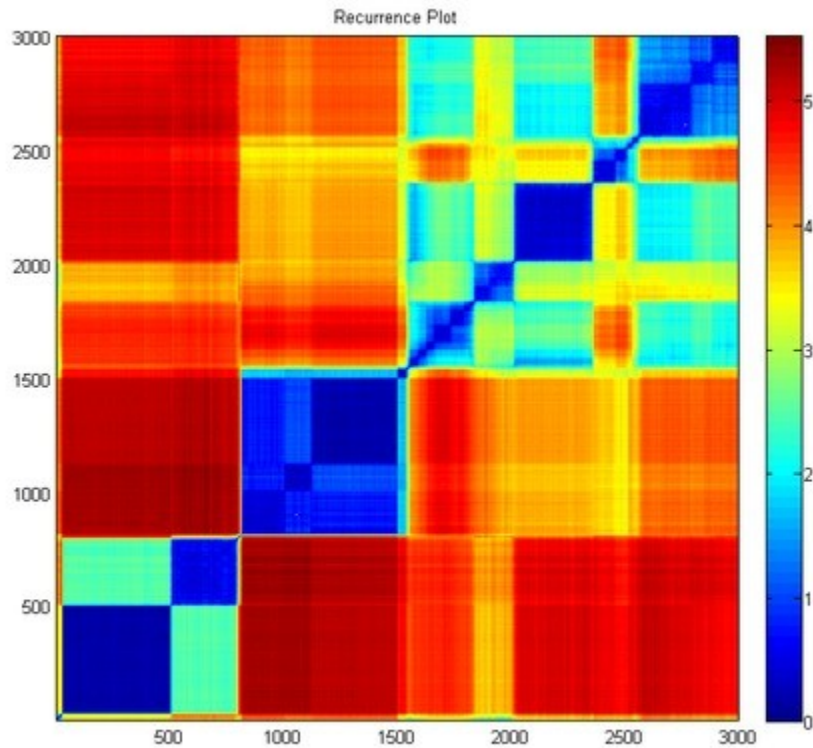
fast presentation

long dwelling times

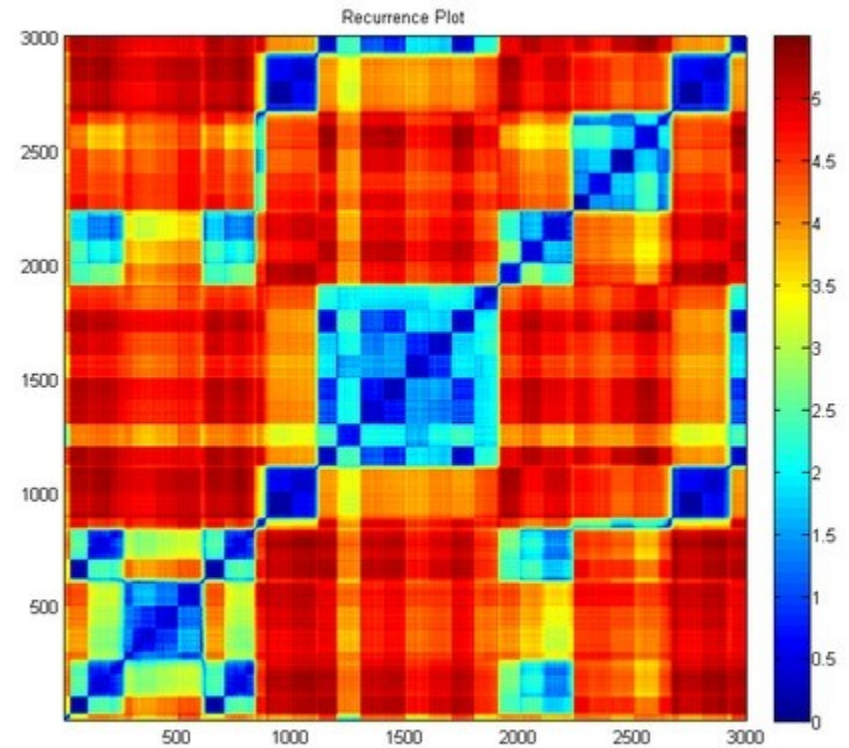
enforced quick resynchronization

more internal stimuli.

RSVP simulations in deep autism

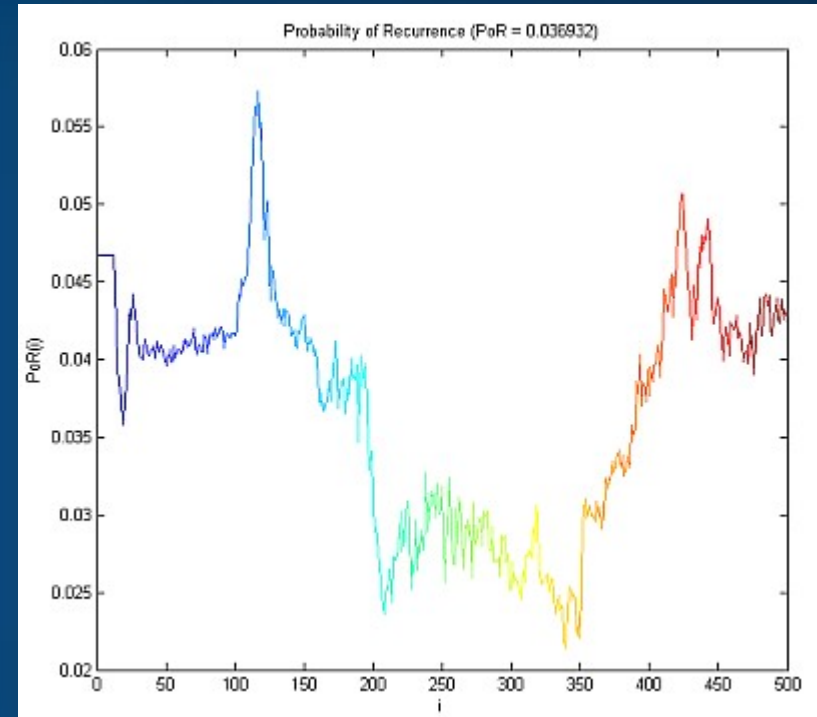
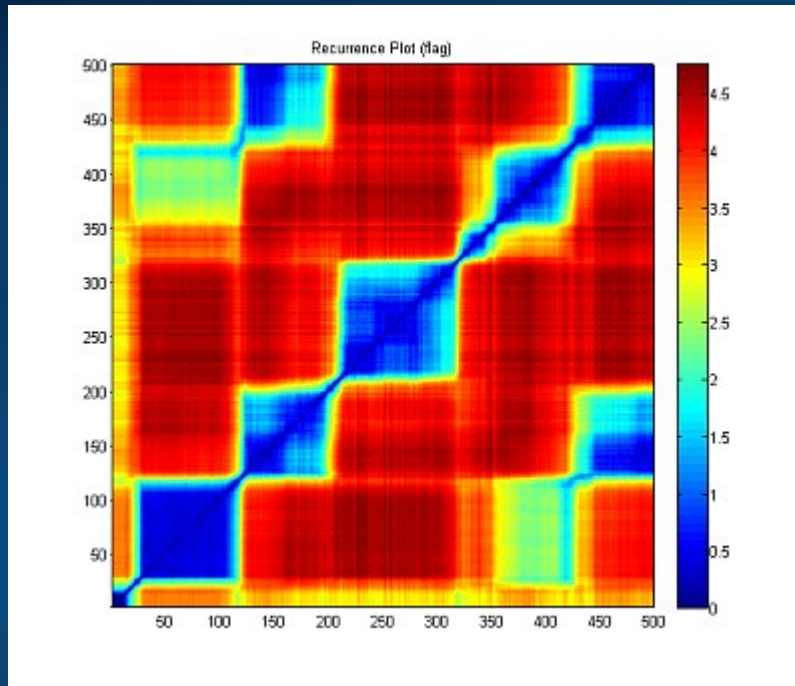


Normal speed
skipping some words,
no associations



fast presentation
more internal states
some associations arise

Probability of recurrence



Probability of recurrence may be computed from recurrence plots, or from clusterization of trajectory points, allowing for evaluation how strongly some basins of attractors capture neurodynamics.

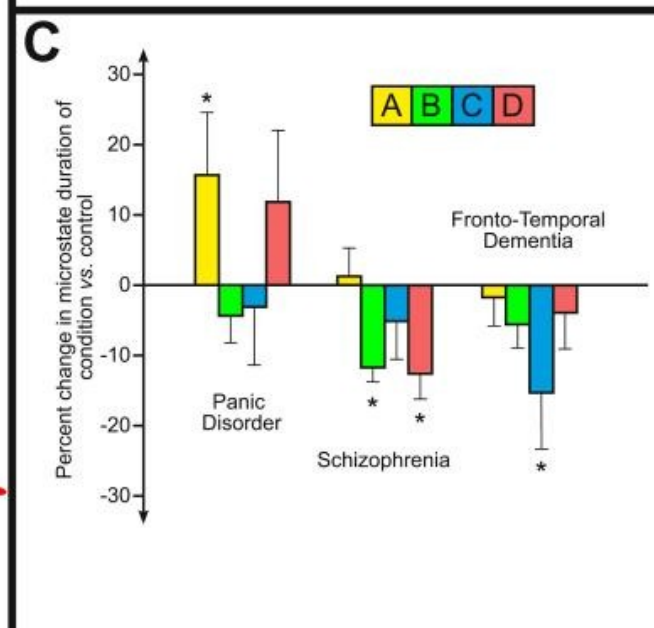
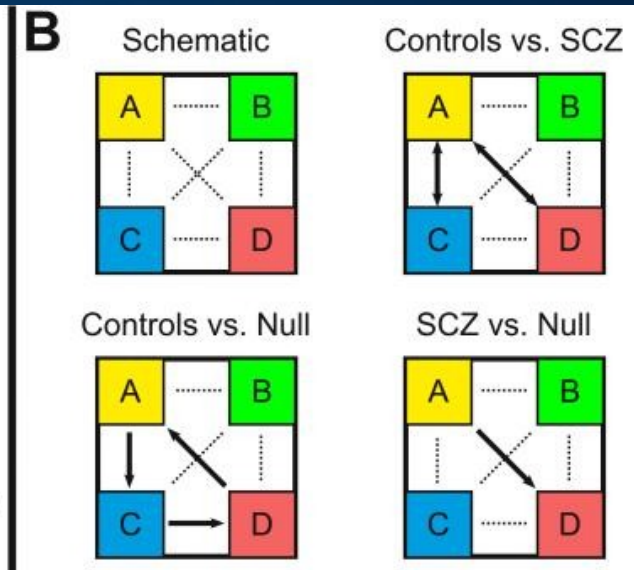
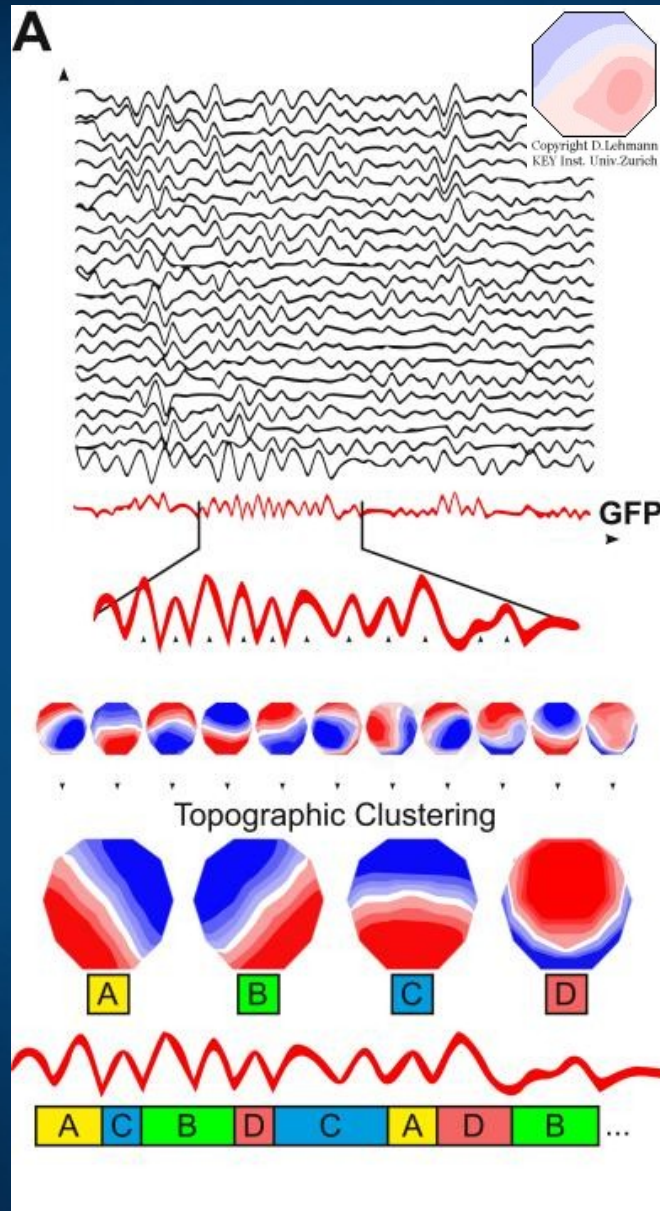
Our Viser Toolbox is used for all visualizations

Microstates in sensor space

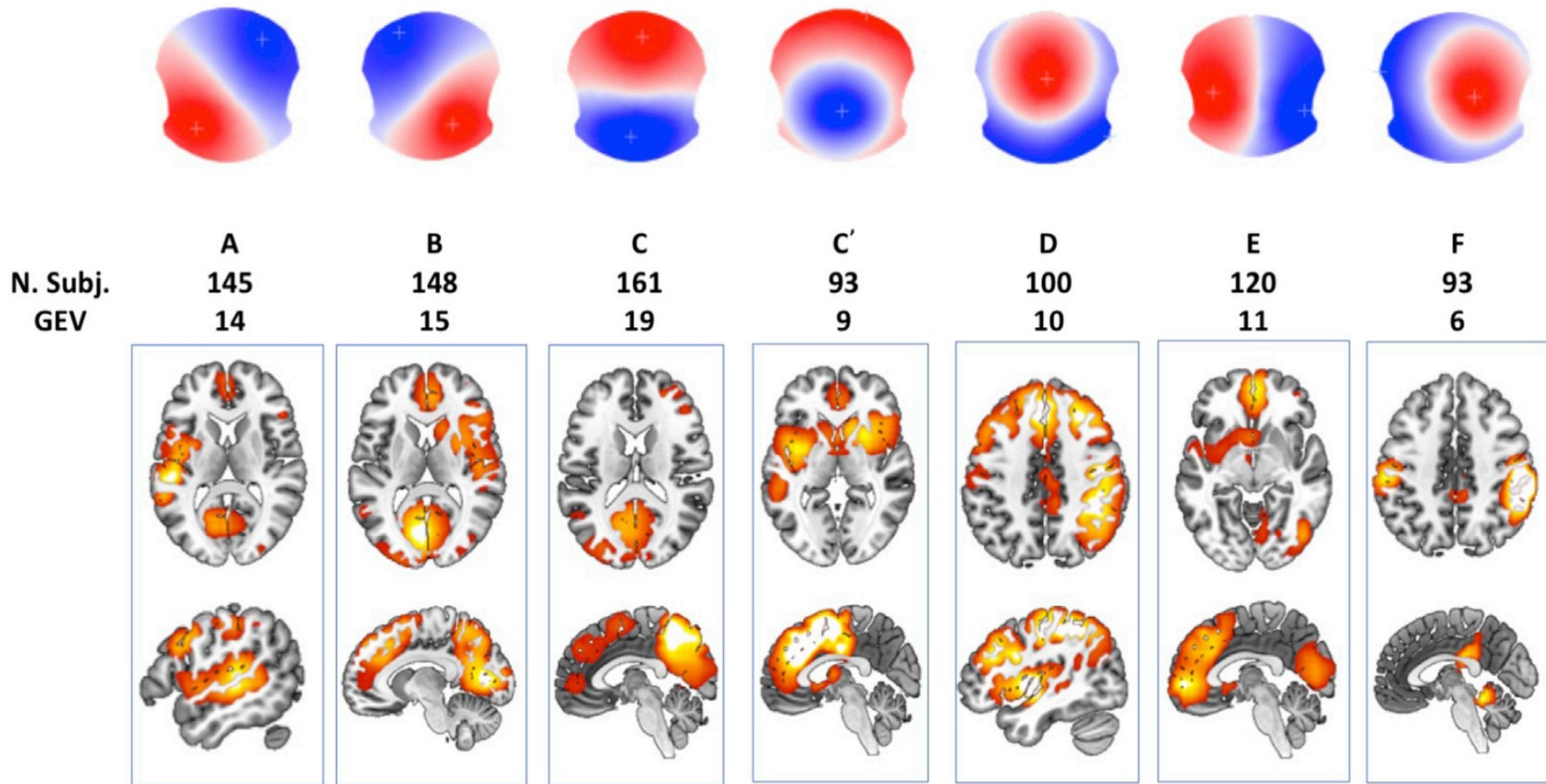
Lehmann et al.
 EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia.
 Psychiatry Research Neuroimaging, 2005

Khanna et al.
 Microstates in Resting-State EEG.
Neuroscience and Biobehavioral Reviews, 2015

4-7 states 60-150 ms
 Symbolic dynamics.



Microstates sources

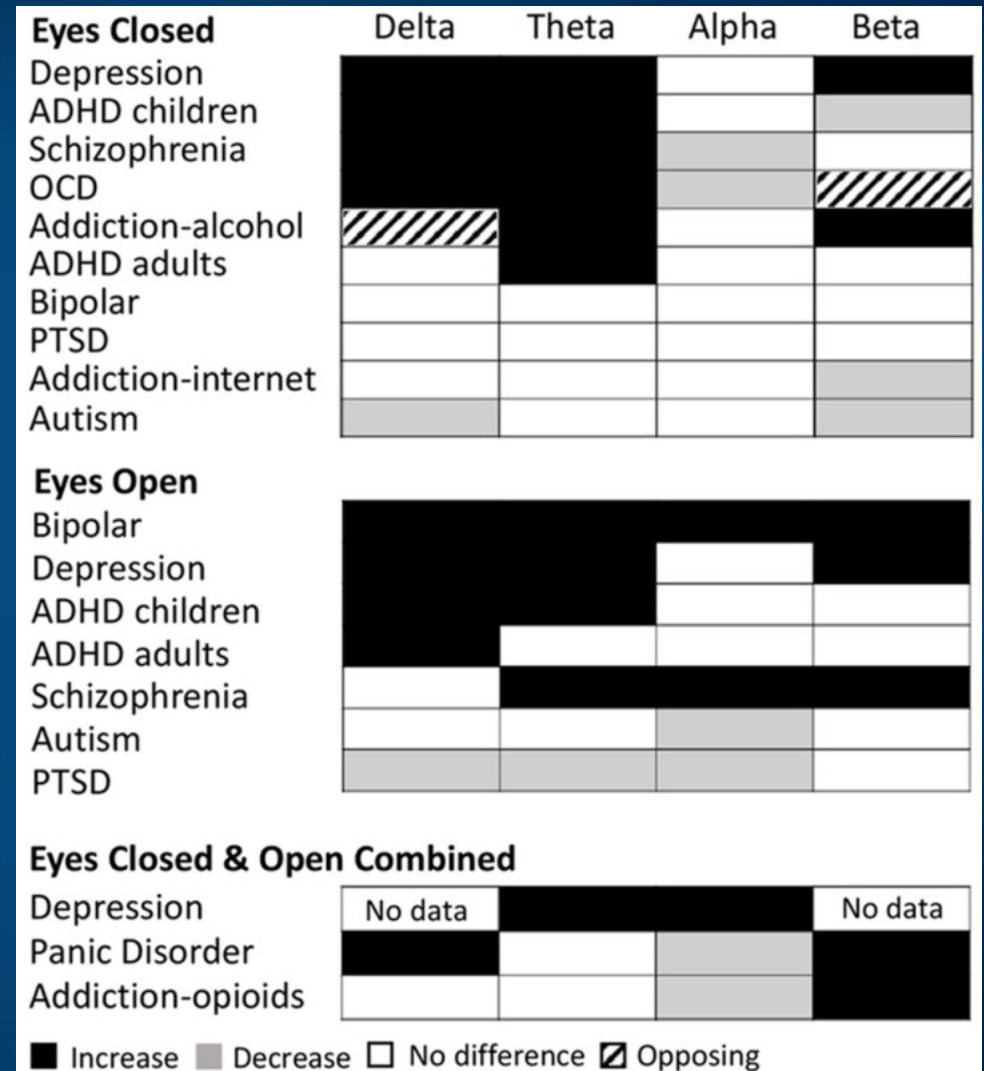


Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593. <https://doi.org/10.1016/j.neuroimage.2017.11.062>

EEG bands and brain disorders

Differences in absolute power for each disorder (relative to control) for eyes closed condition (top), eyes open (middle) and eyes open and eyes closed combined (bottom). White boxes indicate no change, black indicates an increase, and gray indicates a decrease. Hashed boxes - opposing results (contradictory).

Newson & Thiagarajan (2019). EEG Frequency Bands in Psychiatric Disorders: A Review of Resting State Studies. *Frontiers in Human Neuroscience*, 12. <https://doi.org/10.3389/fnhum.2018.0052>



Checkerboard reversal, 5 microstates

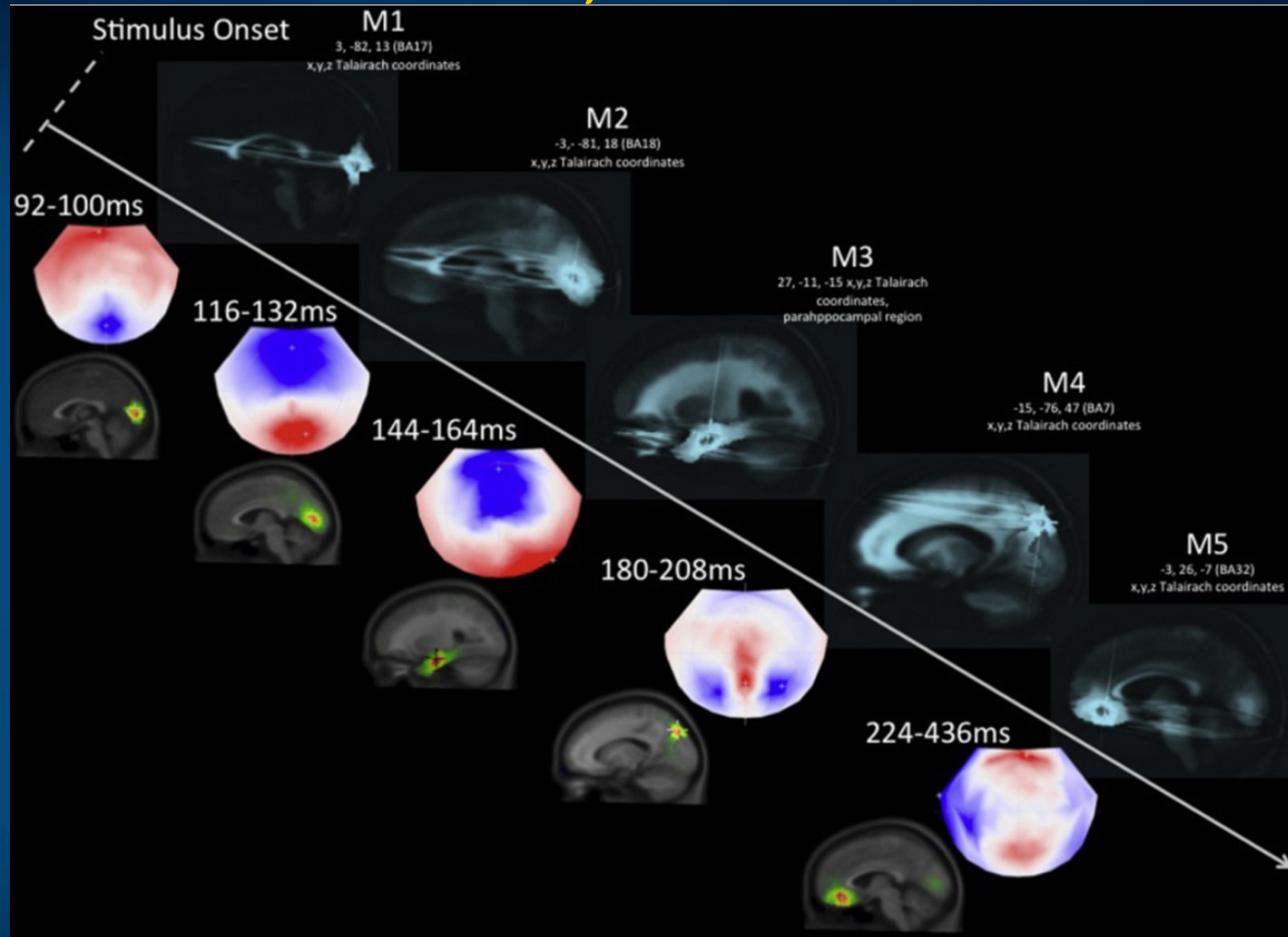
M1 => V1

M2 => V2

M3=>Para-hippocampal

M4=>BA7, left PC, precuneus

M5=>dACC

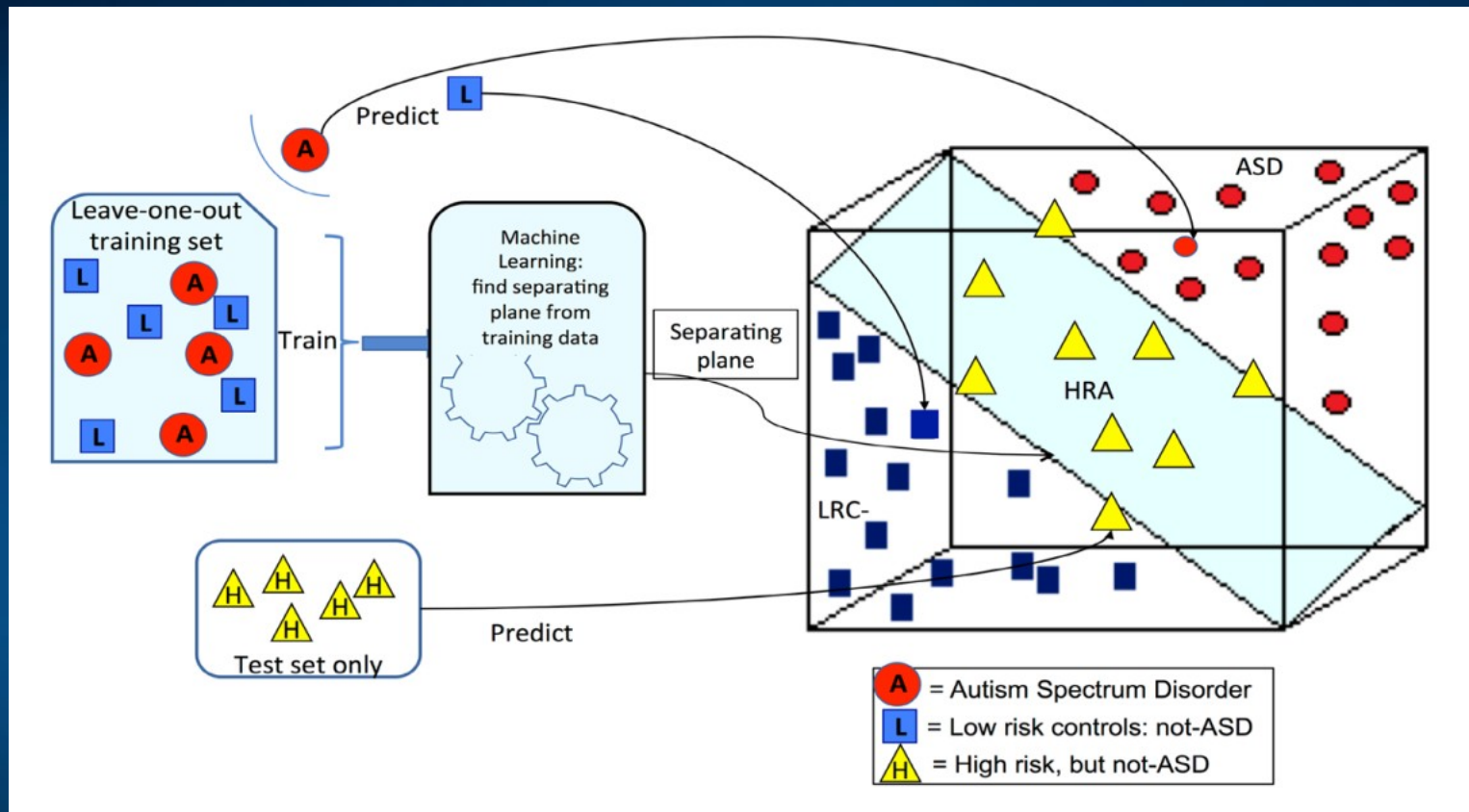


Cacioppo, S., Weiss, R. M., Runesha, H. B., & Cacioppo, J. T. (2014). Dynamic spatiotemporal brain analyses using high performance electrical neuroimaging: Theoretical framework and validation. *J. of Neuroscience Methods*, 238, 11–34.

Plan for action: 8-fold way.

1. Focus on neurodynamics. Include ion channels and other biophysical parameters for neurons/networks in your models.
2. Create simulation of normal functions, ex: attention shifts.
3. Catalogue all possible changes in biophysical parameters that lead to specific deregulation of normal behavior, ex: all types of ion channels.
4. Look for dysfunctional proteins related to biophysical parameters, ex: those proteins that build ion channels.
5. Use gene expression atlases to find correlations of proteins with mutations. Explain diversity of mutations and weak disease signals.
6. Predict changes in real brain signals: EEG/MEG, neuroimaging, intracranial.
7. Analyze existing neuroimaging data, functional and anatomical. Perform new experiments to verify proposed mechanisms leading to dysfunctions.
8. Propose close-loop therapies. Psychosomatic pain is a good target.

ASD EEG SVM Classification



Wavelet decomposition, Recurrent Quantification Analysis, feature ranking and machine learning. Nonlinear features are critical to achieve good results, and their correlated with ASD depends on age.

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.

EEG non-linear features

Features: not only structure, but also dynamics.

Nonlinear invariant measures of a time series and their physical interpretation, recurrence quantification analysis (RQA).

For example:

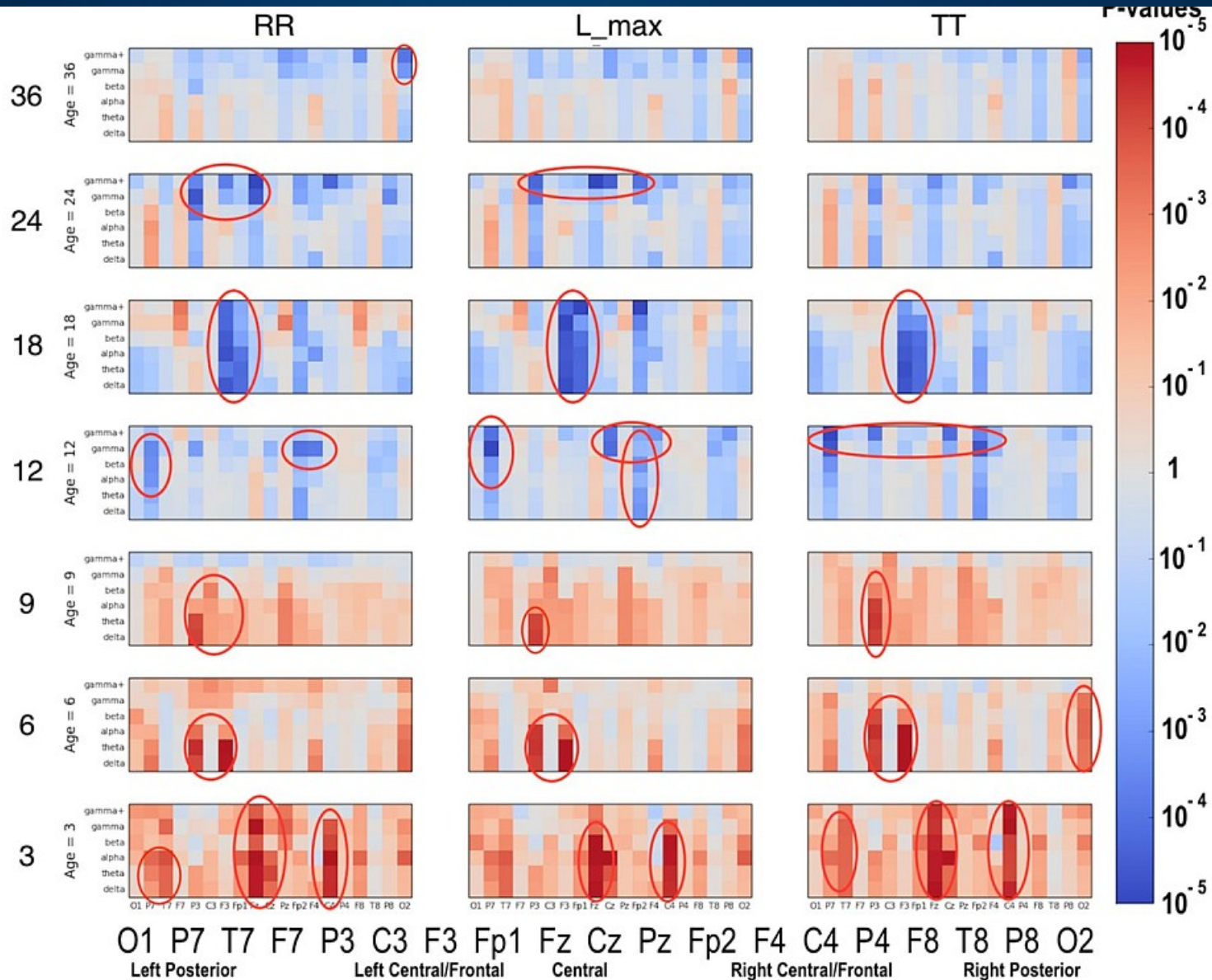
1. Sample Entropy (SampE)
2. Entropy derived from recurrence plot (L_entr).
3. Recurrence rate (RR), probability of recurrence.
4. Determinism (DET), repeating patterns in the system.
5. Laminarity (LAM), frequency of transitions between states.
6. Trapping time (TT), time in a given state.

ASD vs Low Risk Healthy

RR =
recurrence
rate

L_max = max
line length,
related to
Lyapunov
exponent

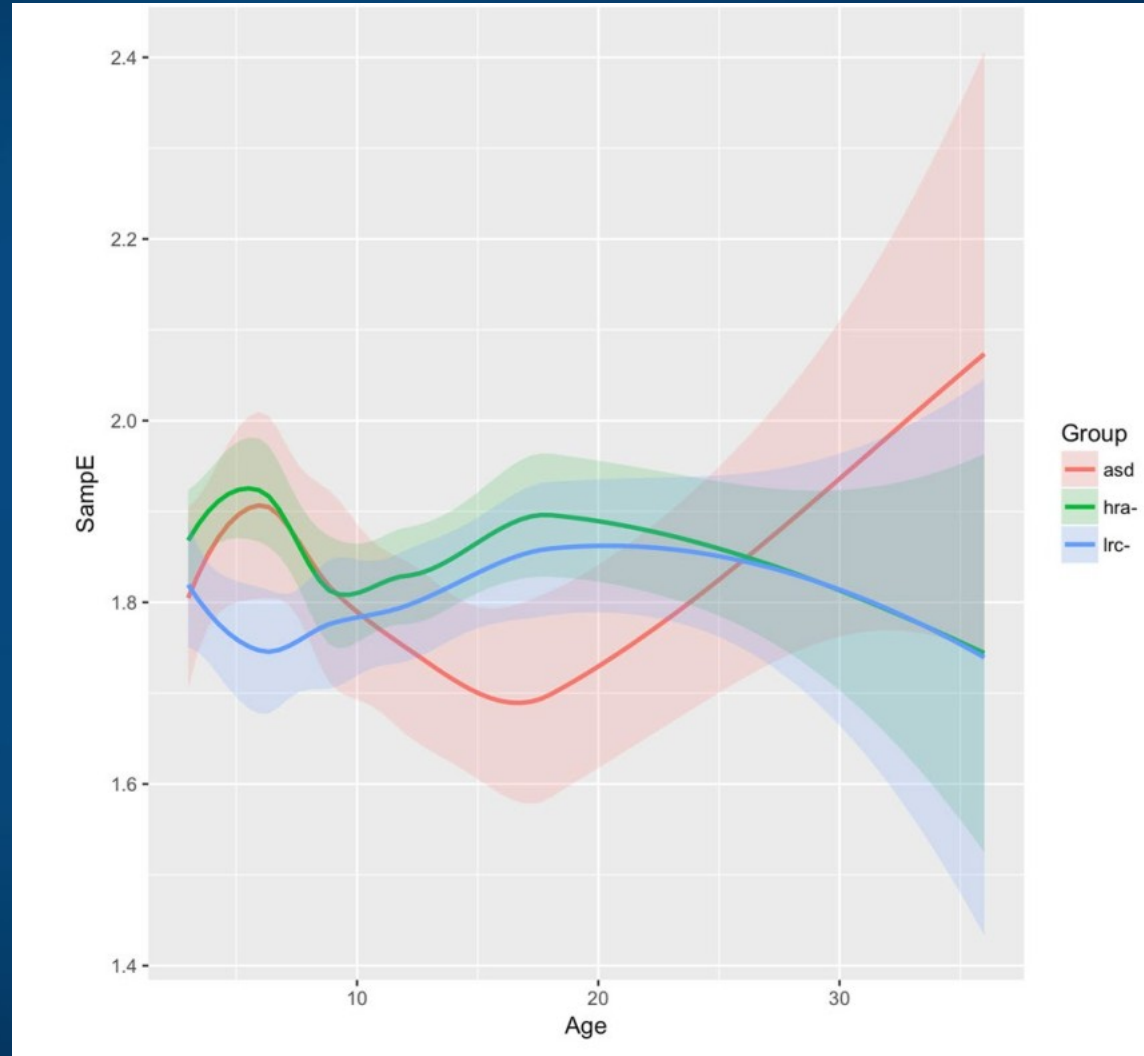
TT = trapping
time



ASD EEG SVM Classification

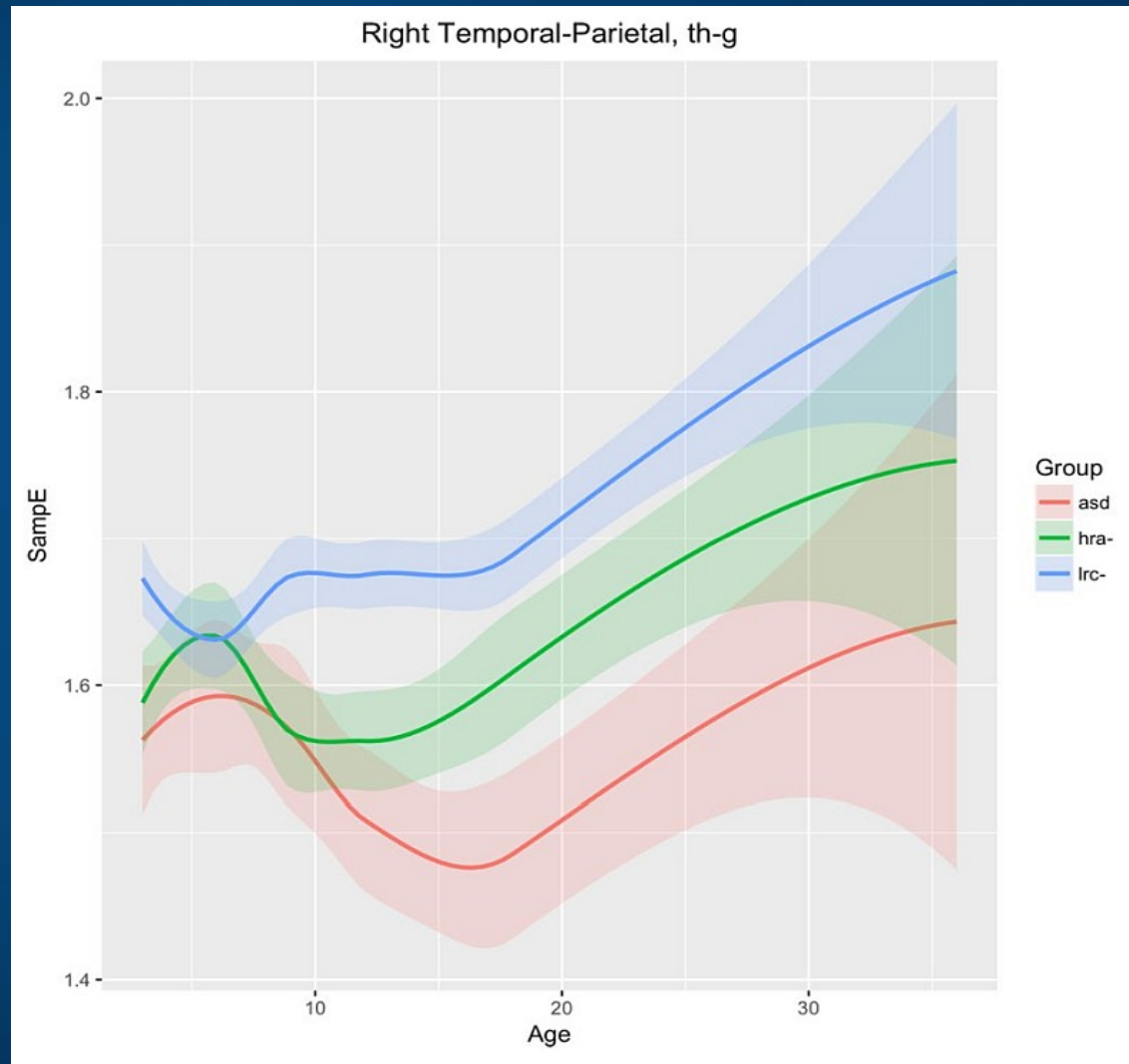
Developmental trajectories for SampE in the left temporal region (T7 sensor) in higher frequencies (beta+gamma) for ASD, LRC-, and HRA-

LRC low risk controls
HRA high risk for ASD
- no ASD



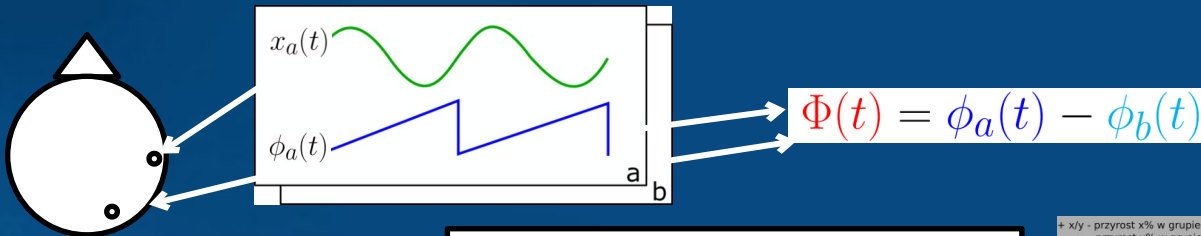
ASD EEG SVM Classification

Developmental trajectories for SampE in the right temporal-parietal region (T8 +P4+P8 sensors) in frequencies theta through gamma for ASD, LRC-, and HRA-.

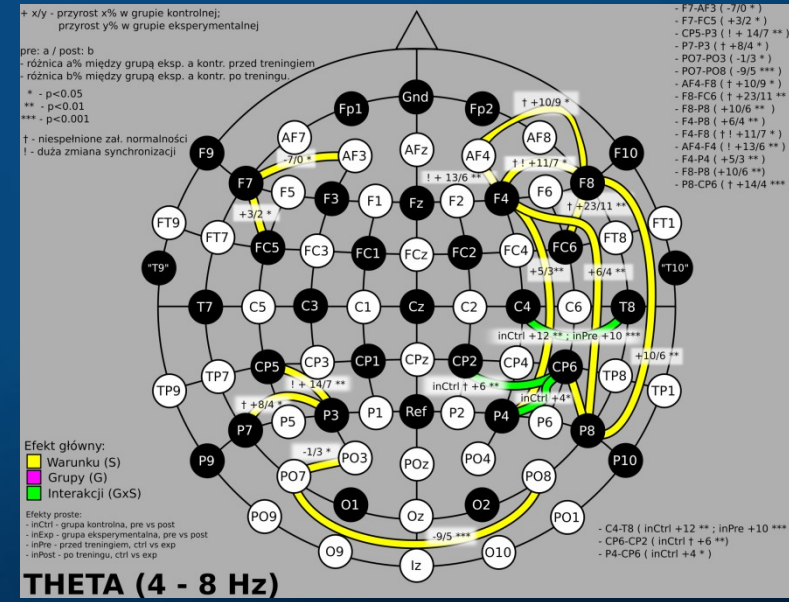
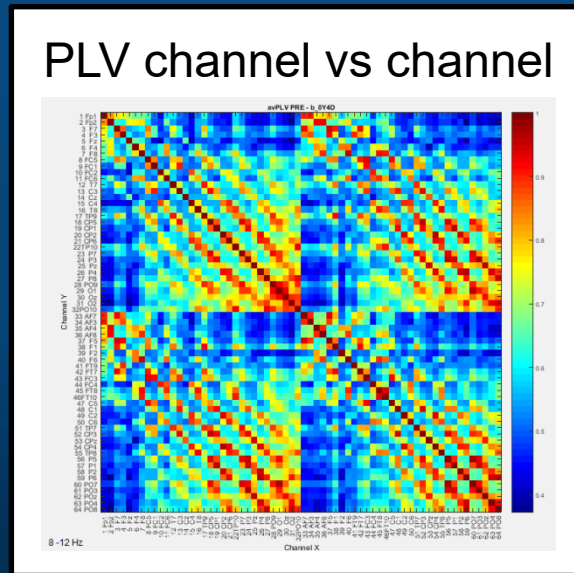


Functional connectivity changes

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.



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



EEG localization and reconstruction

ECD



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

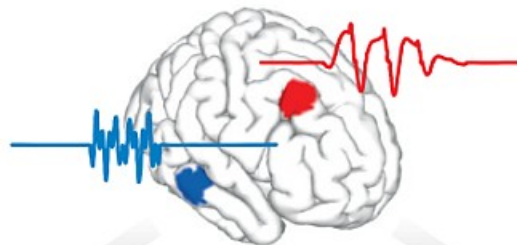
Rotating dipole

- Moving
- Rotating
- Fixed

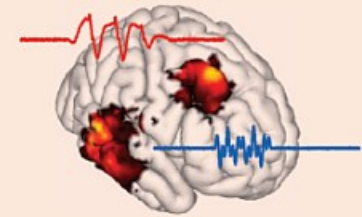
Dipole model



Distributed model



MN (ℓ_2) family



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

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

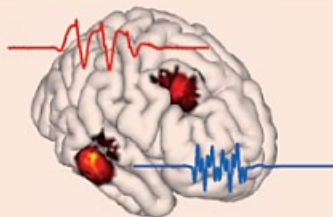
MN

- MN
- WMN
- LORETA

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

Beamforming and scanning algorithms

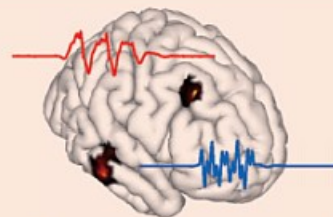
Nonlinear post hoc normalization



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

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

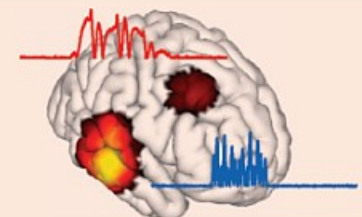
IRES



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

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

Beamformer (VBB)



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

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

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

sLORETA

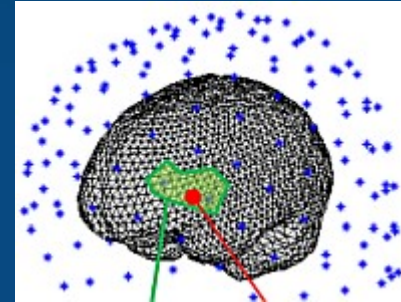
Spatial filters

LCMV (Linearly Constrained Minimum Variance), classical reconstruction filter is a solution to the following problem:

$$W^+ \approx (\theta) \approx I$$

LCMV has large error if:

- sources are correlated,
- SNR (signal to noise ratio) is low, or
- forward problem is ill-conditioned.



Minimum variance pseudo-unbiased reduced-rank (MV-PURE, Piotrowski, Yamada, IEEE Transactions on Signal Processing **56**, 3408-3423, 2008)

$$W = \bigcap_{j \in Y} \arg \min_{\hat{W} \in X_r} \left\| \hat{W} K(\theta) - I_l \right\|_j^2$$

where X_r is a set of all matrices of rank at most r , and set Y denotes all unitary norms. We use 15000 vertex FreeSurfer brain tessellation together with brain atlases that provide parcellation of the mesh elements into 100-240 cortical patches (regions of interest, ROIs).

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.

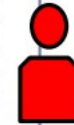
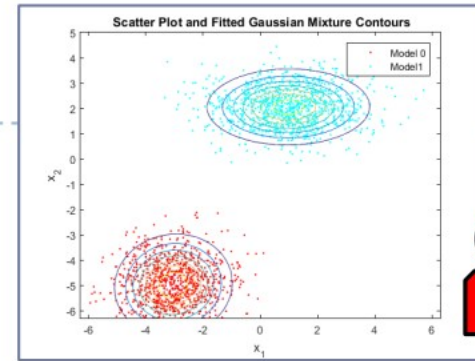
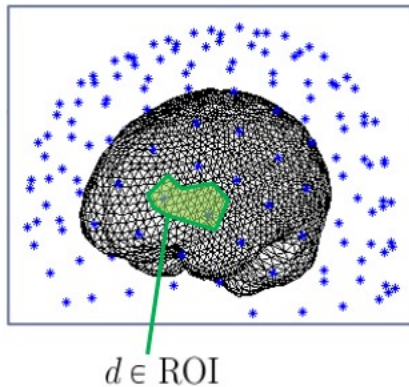
Works with FieldTrip EEG/ MEG software. Modular, object-oriented, using Jupyter notes, allowing for comments and equations in LaTeX.

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

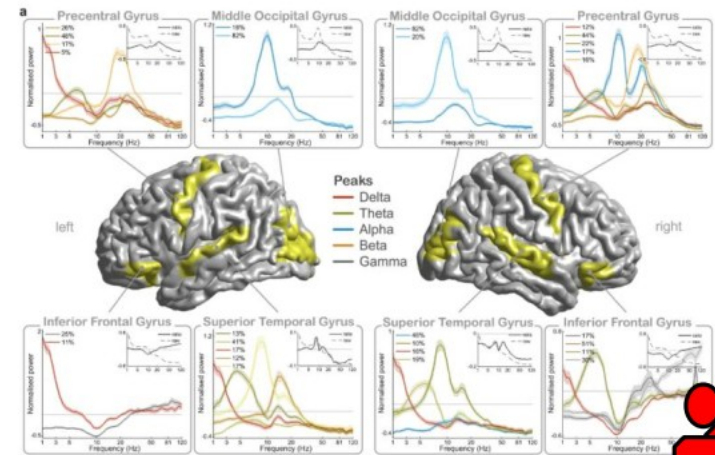
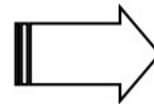
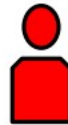
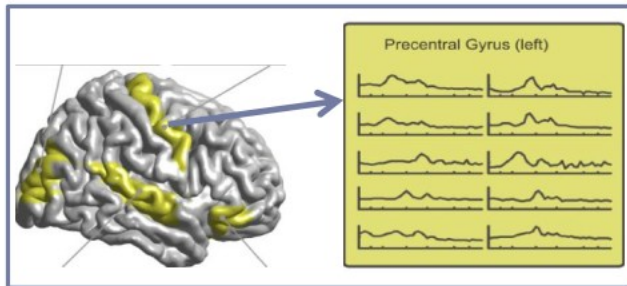
$$B := H_{Src,N} := N^{-1/2} H \quad (35)$$

```
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
```

Spectral fingerprints



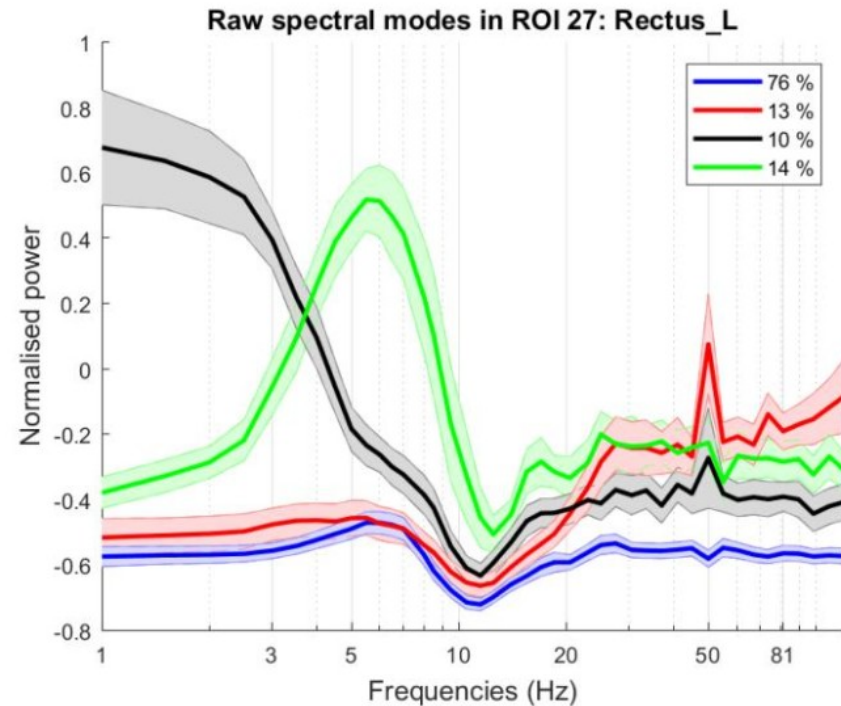
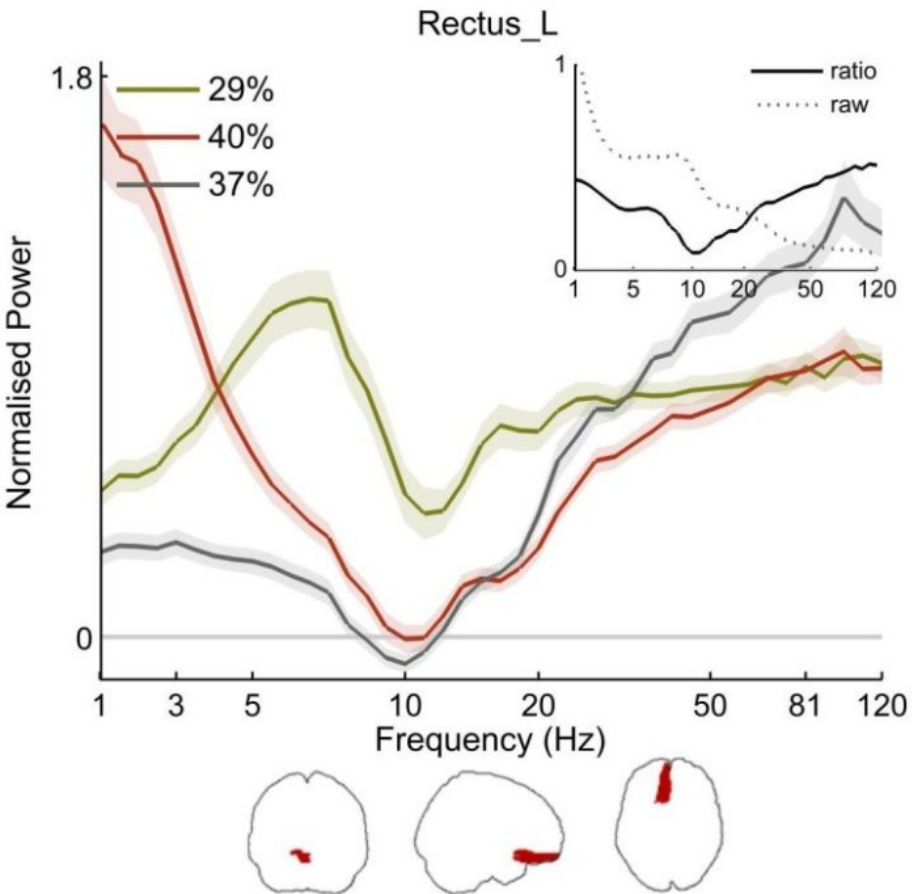
Single subject



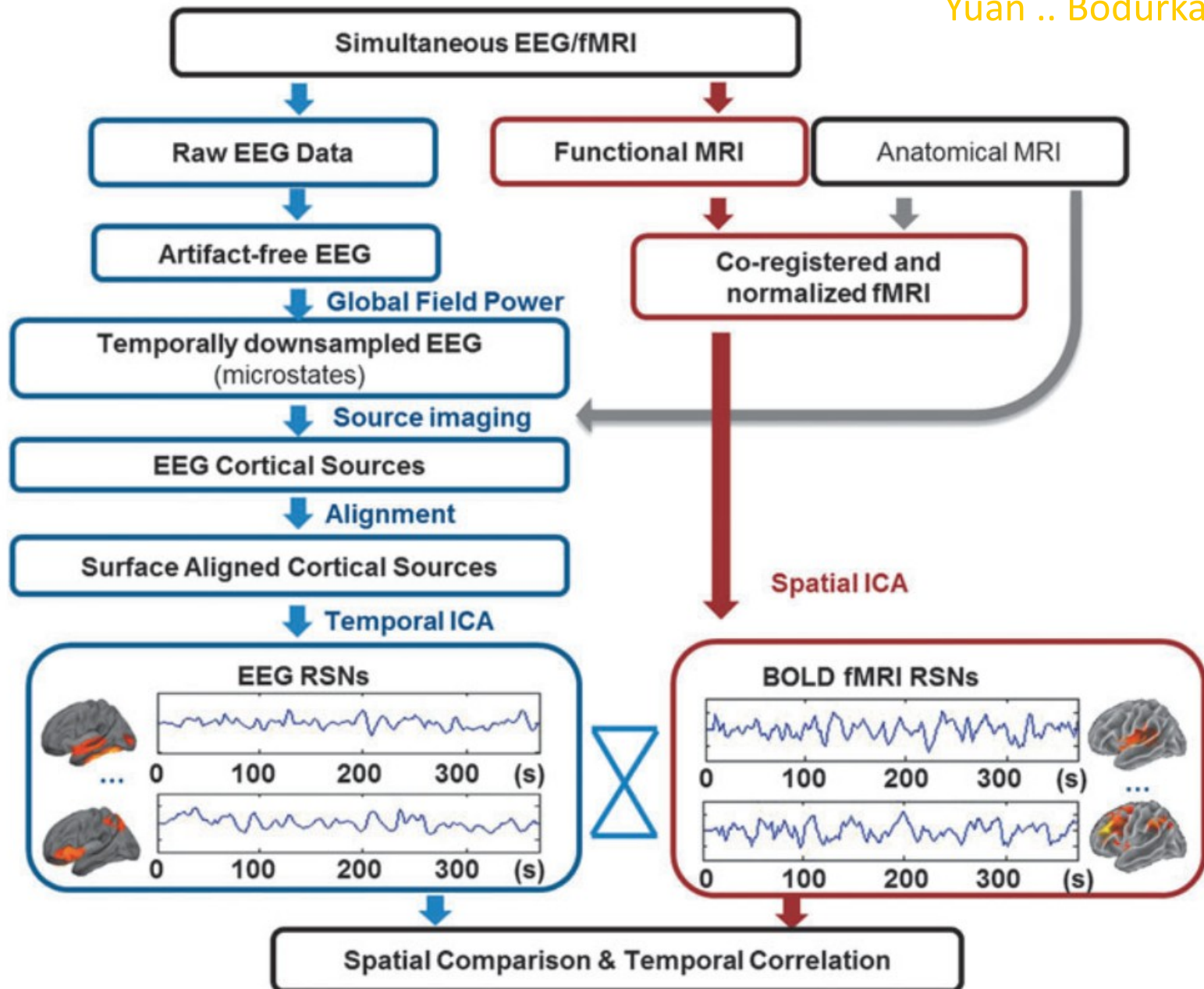
Group model

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

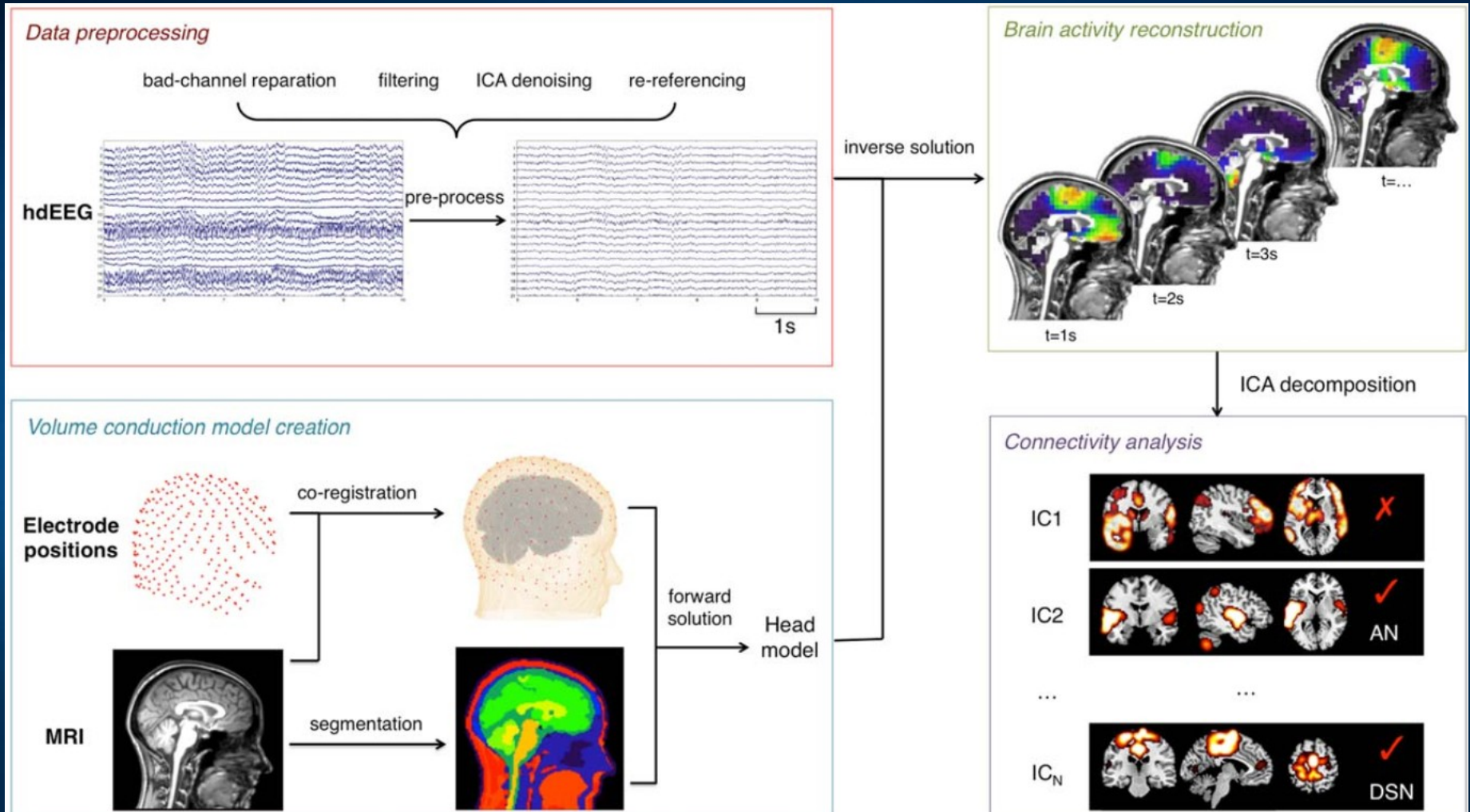
Spectral fingerprints



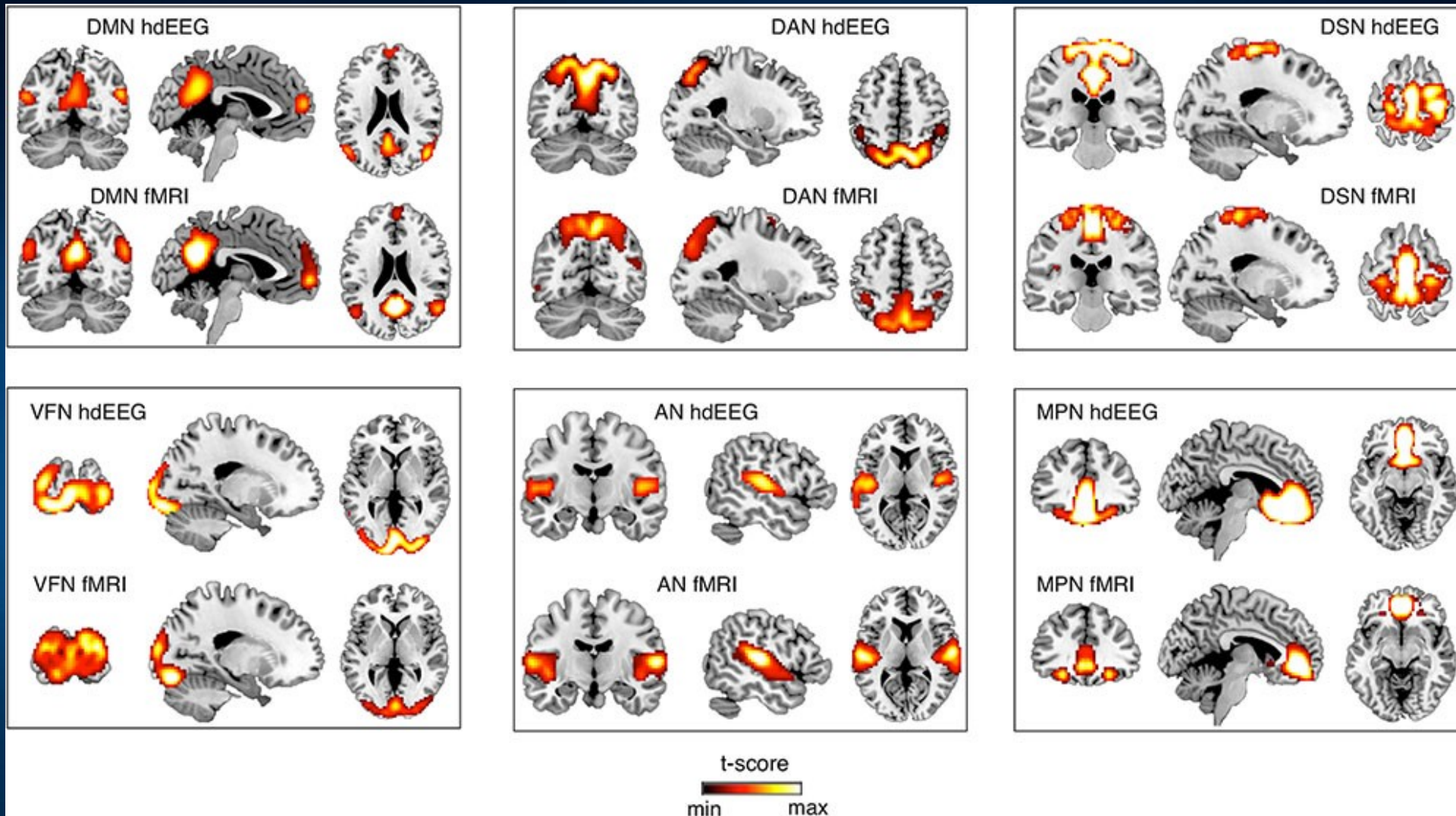
A. Keitel i J. Gross, „Individual human brain areas can be identified from their characteristic spectral activation fingerprints”, *PLoS Biol* 14, e1002498, 2016



14 networks from BOLD-EEG

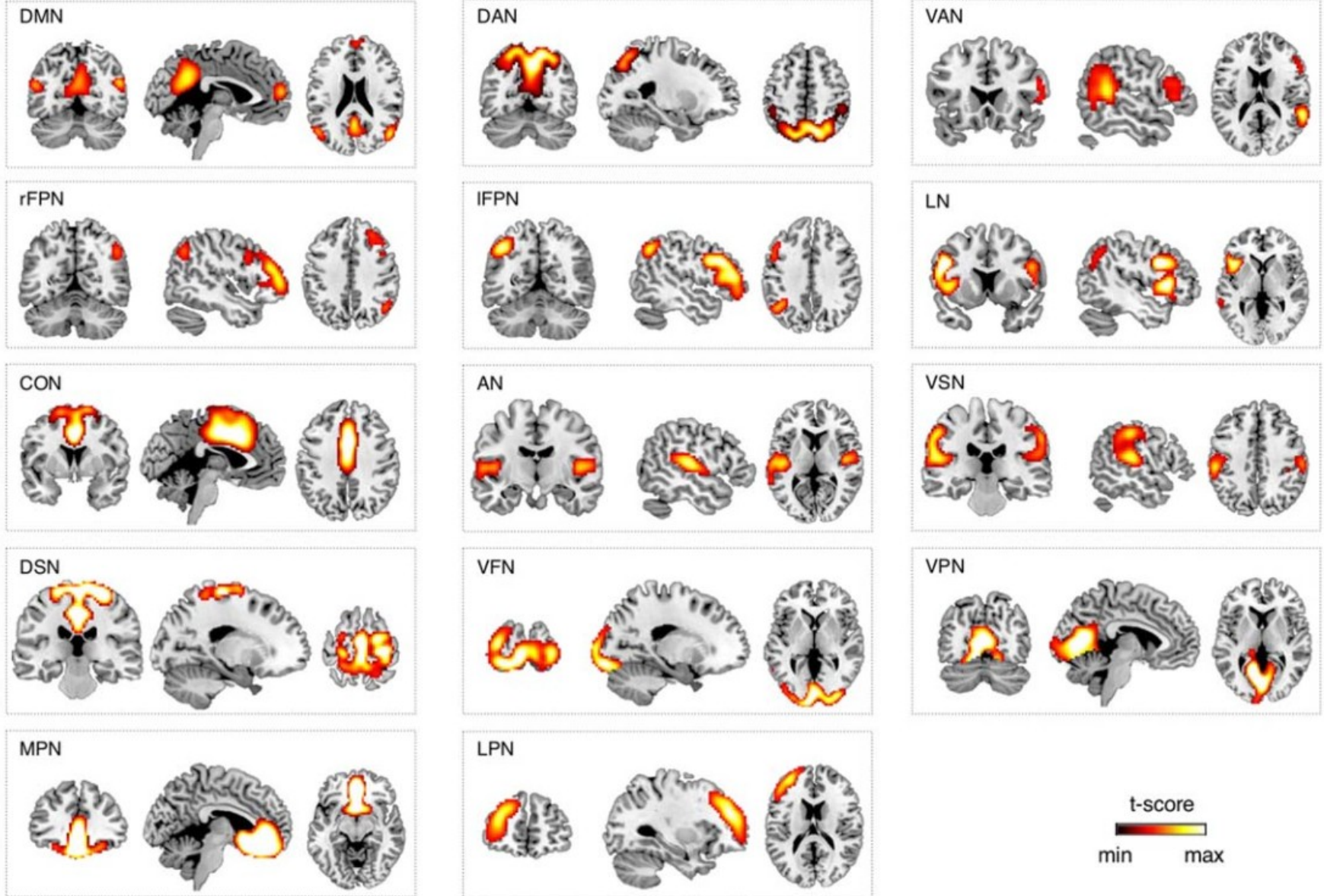


Liu et al. Detecting large-scale networks in the human brain. HBM (2017; 2018).



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.

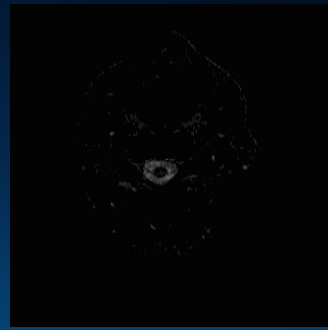
EEG-RSN maps obtained using spatial ICA



Plan for action - lessons from ASD

1. Focus on neurodynamics. Include ion channels and other biophysical parameters for neurons/networks.
2. Create simulation of normal functions, ex: attention shifts.
3. Catalogue all possible changes in biophysical parameters that lead to specific deregulation of normal behavior, ex: all types of ion channels.
4. Look for dysfunctional proteins related to biophysical parameters, ex: those proteins that build ion channels.
5. Use gene expression atlases to find correlations of proteins with mutations. Explain diversity of mutations and weak disease signals.
6. Predict changes in real brain signals: EEG/MEG, neuroimaging, intracranial.
7. Analyze existing neuroimaging data, functional and anatomical. Perform new experiments to verify proposed mechanisms leading to dysfunctions.
8. Propose close-loop therapies. Psychosomatic pain is a good target.

Perspectives



- 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 ...
- Some large-scale functional networks have reasonable (although still not perfect) interpretation, for example sensory networks, dorsal and ventral attention networks, executive control, motor networks.
- Individual differences and many psychological functions are directly linked to connectome and functional networks, including multistable properties.
- 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.

In search of the sources of brain's cognitive activity

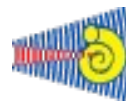
Project „Symfonia”, 2016-21



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Carole Goble, *University of Manchester*
William Grisham, *UCLA*
Michael Hawrylycz, *Allen Institute for Brain Science*
Henry Kennedy, *INSERM*
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Frances Skinner, *University of Toronto*
Pedro Valdes-Sosa, *Cuban Neuroscience Center,
University of Electronic Science and Technology China*
Kirstie Whitaker, *University of Cambridge*
Alexander Woodward, *RIKEN CBS*
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Session themes

- Global brain projects: infrastructure interoperability and sustainability
- Data management and workflows in neuroscience
 - Future of academic publishing
 - Comparative and predictive connectomics
 - Brain Computer Interface (BCI)
- Neuroinformatics challenges in behavioral studies
 - Building open science communities

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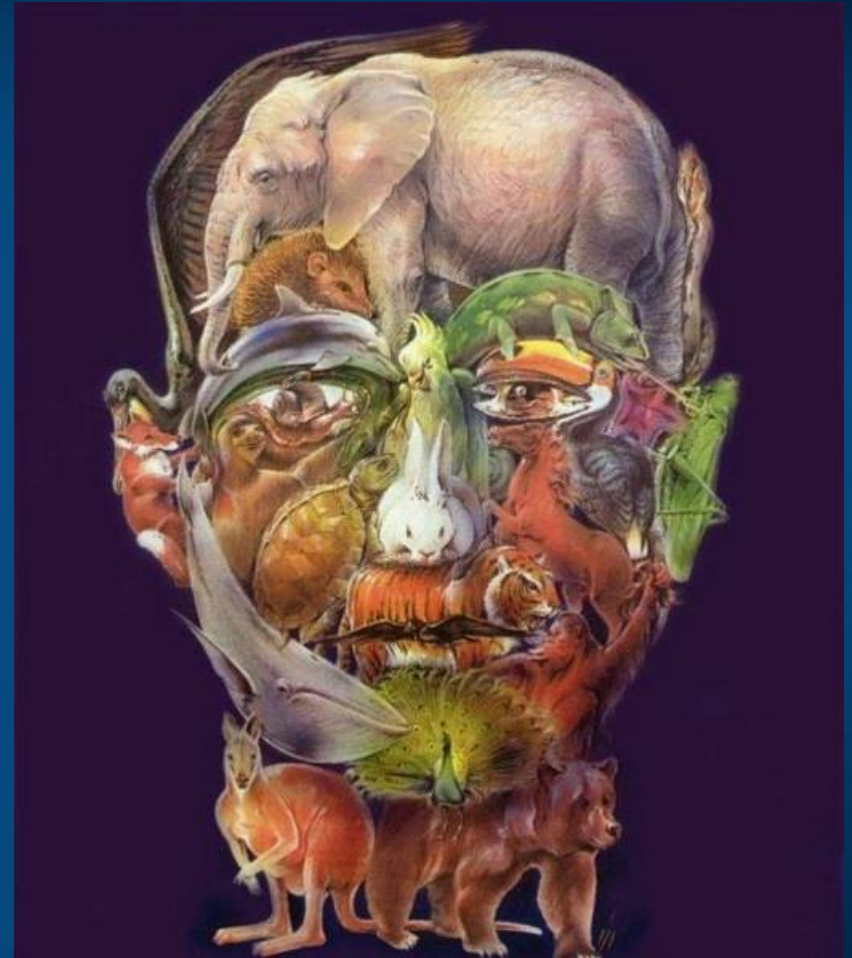
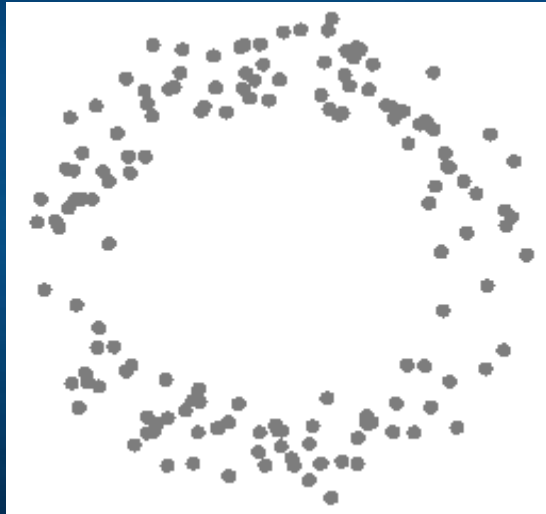
Polskie Porozumienie na rzecz Rozwoju Sztucznej Inteligencji

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