



W poszukiwaniu źródeł aktywności poznawczej mózgu



Włodzisław Duch

Laboratorium Neurokognitywne,
Interdyscyplinarne Centrum Nowoczesnych Technologii,
Katedra Informatyki Stosowanej, Wydział Fizyki, Astronomii i
Informatyki Stosowanej, Uniwersytet Mikołaja Kopernika

Google: W. Duch

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Projekt „Symfonia 4”, NCN, 2016-2021



Geometryczny model mózg-umysł

Mózg \leftrightarrow Umysł

Obiektywne \leftrightarrow Subiektywne

Neurodynamika: aktywność neuronalna mózgu mierzona za pomocą EEG, MEG, NIRS-OT, PET, fMRI i innych technik.

Mapowanie $S(M) \leftrightarrow S(U)$, ale jak można opisać stan umysłu?

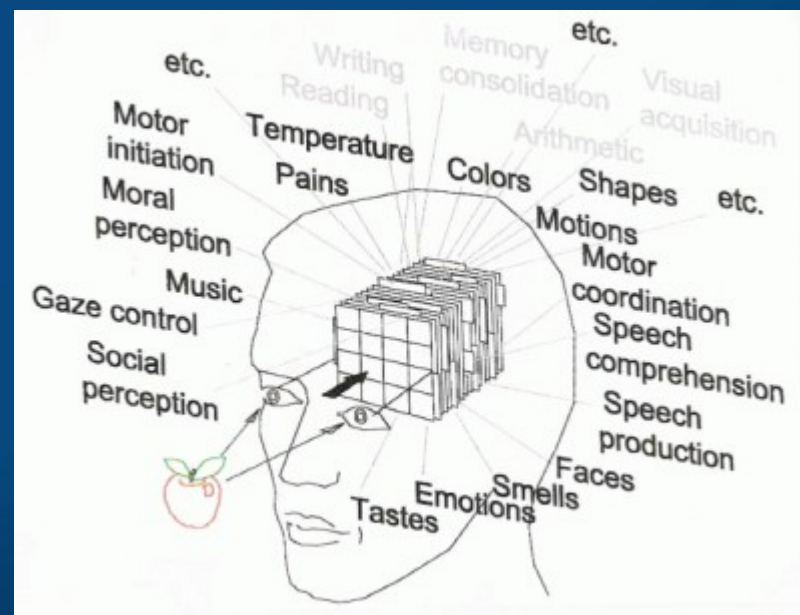
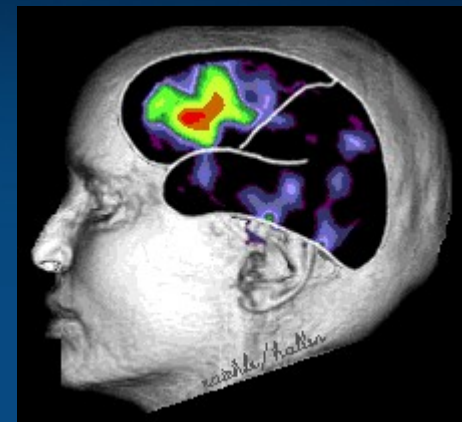
Nie wystarczy opis werbalny, potrzebna jest przestrzeń, której wymiary odpowiadają subiektywnemu doświadczeniu.

Stany umysłowe, ruch myśli \leftrightarrow trajektorie w przestrzeniach psychologicznych.

Problem: nie mamy dobrej fenomenologii.

E. Schwitzgabel, *Perplexities of consciousness* MIT Press 2011.

R.T. Hurlburt & E. Schwitzgabel, *Describing Inner Experience?* MIT Press 2007.



Modele umyśłu

- 1994: Towards Artificial Minds. Pierwsza Konf. Pol. Tow. Sieci Neuronowych
- 1996: Computational physics of the mind. Computer Phys.Comm. 97: 136-153
- 1997: Platonic model of mind as an approximation to neurodynamics. In: Brain-like computing and intelligent information systems, Springer, 491-512
- 2001: Facing the hard question. Commentary on J.A. Gray, BBS 24 (2001)
- 2003: Just bubbles? Com. on S. Lehar, Gestalt Isomorphism and the Primacy of Subjective Conscious Experience: A Gestalt Bubble Model. BBS 26(4)
- 2005: Rules, Similarity, and Threshold Logic. Com. on E.Pothos, The Rules versus Similarity distinction), Behavioral and Brain Sciences, 28 (1): 23
- 2005: Brain-inspired conscious computing architecture. Journal of Mind and Behavior 26(1-2), 1-22.
- 2013: Duch W, Brains and Education: Towards Neurocognitive Phenomics. Book chapter, in: Learning while we are connected, pp. 12-23.
- 2017: Finc K, Bonna K, Lewandowska M, Wolak T, Nikadon J, Dreszer J, Duch W, Kühn S. Transition of the functional brain network related to increasing cognitive demands. Human Brain Mapping 38(7), 3659–3674.

Psychological spaces

Psychological spaces and topological psychology, some ideas from physics:

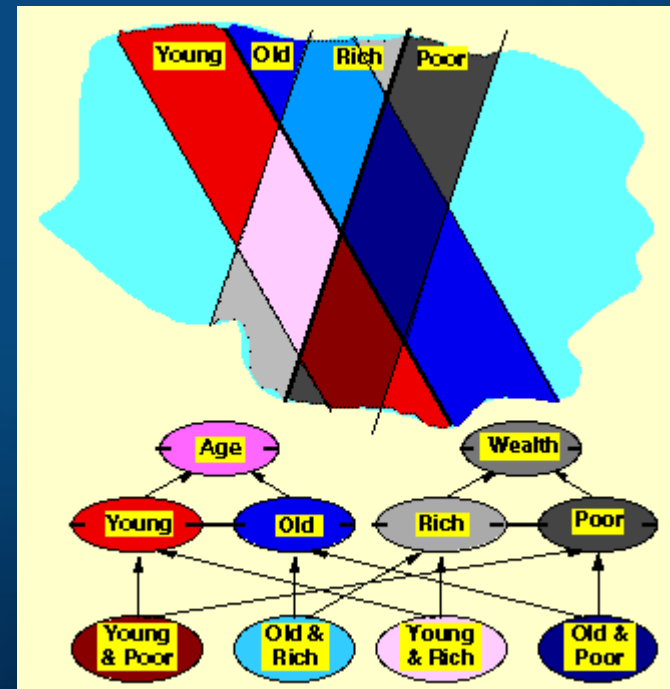
Kurt Lewin, The conceptual representation and the measurement of psychological forces (1938). Idea: cognitive dynamic movement in **phenomenological (hodological) space**. Discrete Process Model (DPM)
Force \sim transition probability between states in valence fields.

George Kelly (1955), **personal construct psychology**, geometry of psychological spaces as alternative to logic. A complete theory of cognition, action, learning and intention.

P-space: region in which we may place and classify elements of our experience, constructed and evolving, „a space without distance”, divided by dichotomies.

Roger Shepard (1957-2001), P-spaces :

- minimal dimensionality
- distances that monotonically decrease with increasing similarity (multi-dimensional non-metric scaling).



Some connections

Geometric/dynamical ideas related to mind may be found in many fields:

Philosophy: Mind as motion, ed. R.F. Port, T. van Gelder (MIT Press 1995)

Linguistics: G. Fauconnier, Mental Spaces (Cambridge U.P. 1994).
Mental spaces and non-classical feature spaces.

J. Elman, Language as a dynamical system (San Diego, 1997).
Stream of thoughts, sentence as a trajectory in P-space.

Psycholinguistics: M.J. Spivey, The Continuity of Mind (OUP 2007)

T. Landauer, S. Dumais, Latent Semantic Analysis Theory, Psych. Rev. (1997)
Semantics requires about 300 dim. to capture associations.

Neuroscience: Anderson, van Essen (1994): Superior Colliculus maps as PDFs

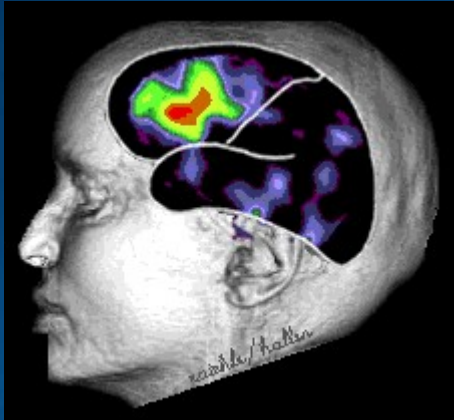
AI: problem spaces - reasoning, problem solving, SOAR, ACT-R

Folk psychology: to put in mind, to have in mind, to keep in mind, to make up one's mind, be of one mind ... (space).



Mapping brain states to mental images

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



Mapping State(Brian) \leftrightarrow State(Mind)
Via intermediate models.



Mental states, movement of thoughts \leftrightarrow trajectories in psychological spaces.

1. From simulations and neuroimaging to mental trajectories.
2. From neuroimaging to mental images.

Phenomics

Why we have such transitions in networks?

Phenomics is the branch of science concerned with identification and description of measurable physical, biochemical and psychological traits of organisms.

Genom, proteom, interactom, exposome, virusom, connectom ... omics.org has a list of over 400 various ...omics !

Human Genome Project, since 1990.

Human Epigenome Project, since 2003.

Human Connectome Project, since 2009.

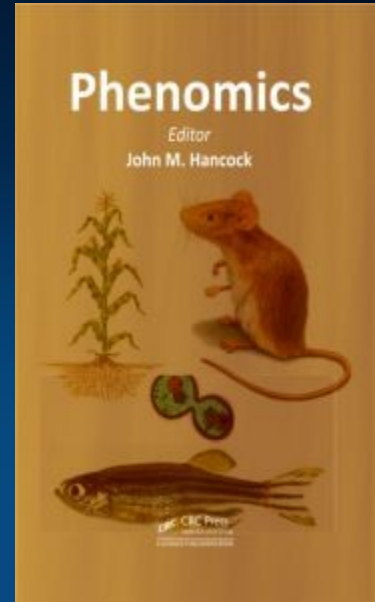
Developing Human Connectome Project, UK 2013 + many others.

Behavior, personality, cognitive abilities \leq phenotypes at all levels.

Still many white spots on maps of various phenomes.

Behaviormetrika (Springer), quantitative approaches to human behaviors.

Can neurocognitive phenomics be developed to understand behavior of people?

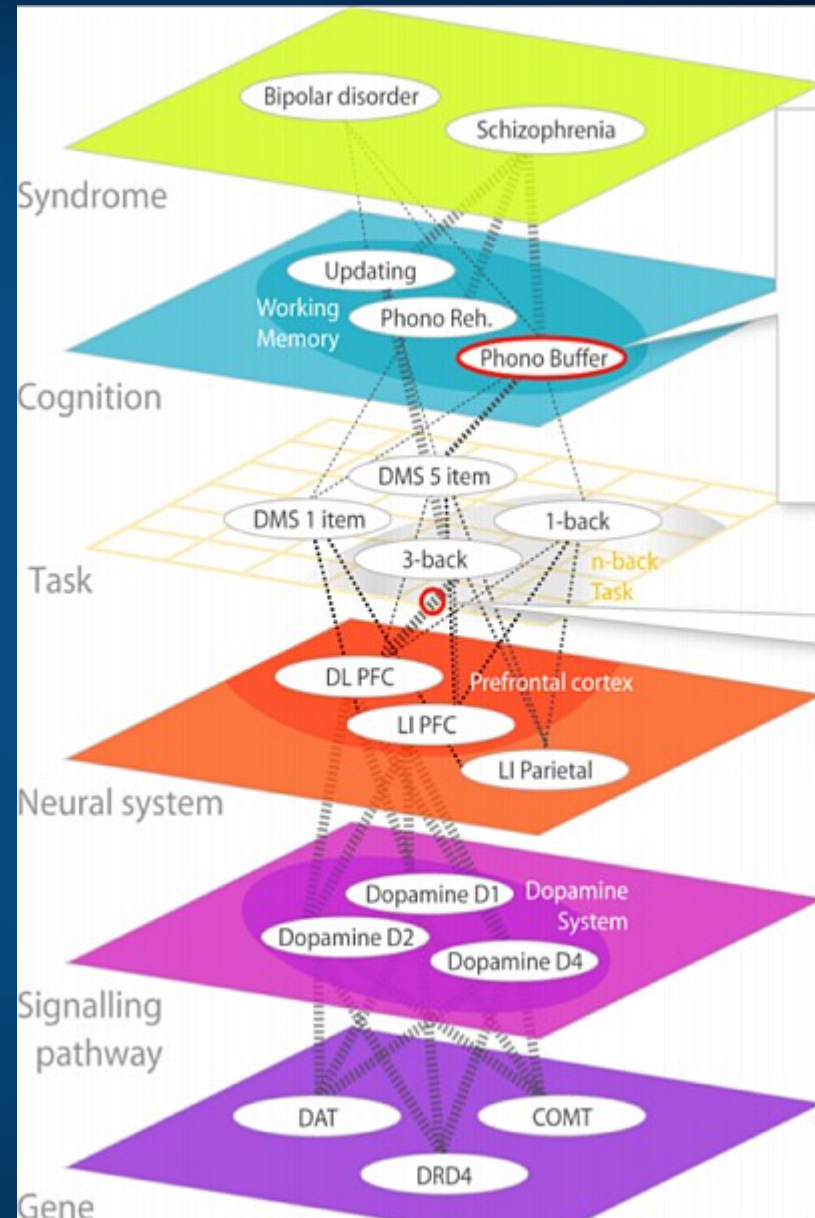


Neuropsychiatric Phenomics in 6 Levels

Consortium for Neuropsychiatric Phenomics (CNP)/NIMH RoDC approach:

Research Domain Criteria (RoDC) analyzes 5 large brain systems – negative/positive valence systems, arousal, cognitive, affective systems – through interaction of Genes, Molecules, Cells, Circuits, Physiology, Behavior, Self-Report, and Research Paradigms.

From genes to cognitive subsystems and behavior, neurons and networks are **right in the middle** of this hierarchy.
=> **Neurodynamics is the key!**





NIMH RD0C Matrix for deregulation of large brain systems.

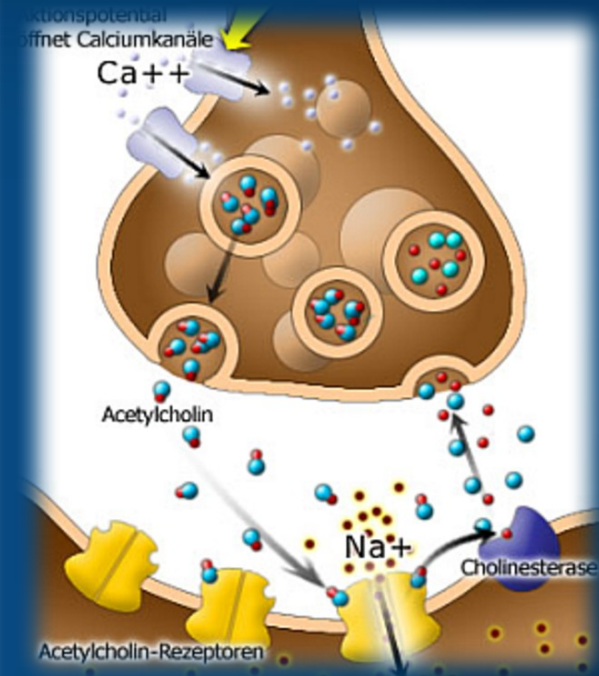
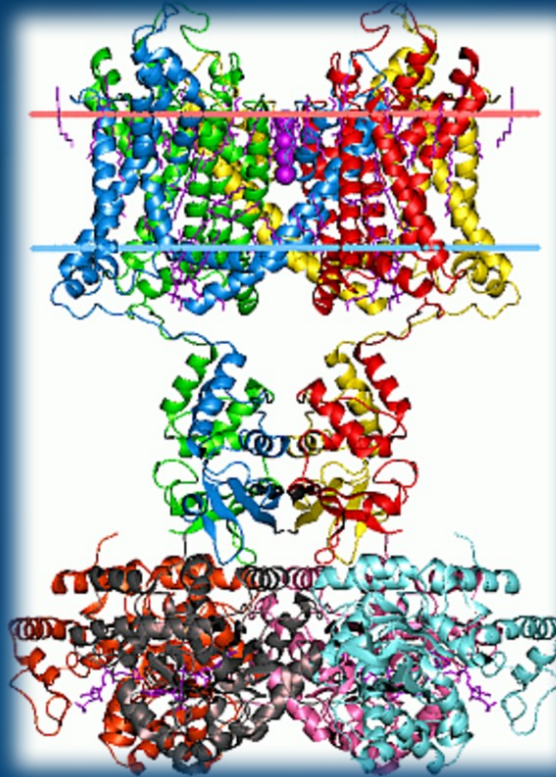
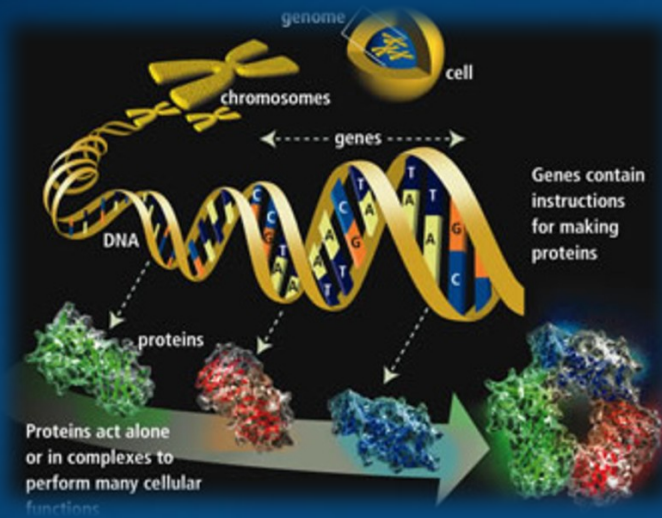
Instead of classification of mental disease by symptoms use **Research Domain Criteria** (RD0C) based on multi-level neuropsychiatric phenomics.

1. **Negative Valence Systems**, primarily responsible for responses to aversive situations or context, such as fear, anxiety, and loss.
2. **Positive Valence Systems** are primarily responsible for responses to positive motivational situations or contexts, such as reward seeking, consummatory behavior, and reward/habit learning.
3. **Cognitive Systems** are responsible for various cognitive processes.
4. **Social Processes Systems** mediate responses in interpersonal settings of various types, including perception and interpretation of others' actions.
5. **Arousal/Regulatory Systems** are responsible for generating activation of neural systems as appropriate for various contexts, providing appropriate homeostatic regulation of such systems as energy balance and sleep.

RDoC Matrix for „cognitive domain”

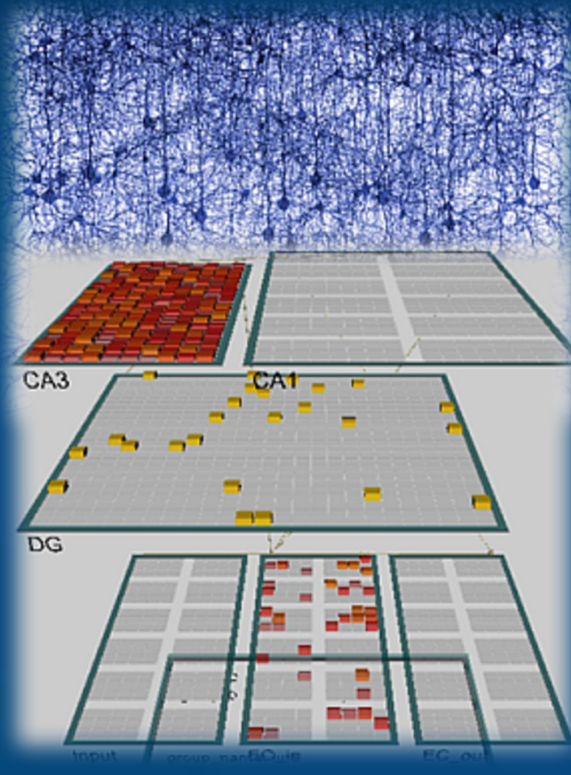
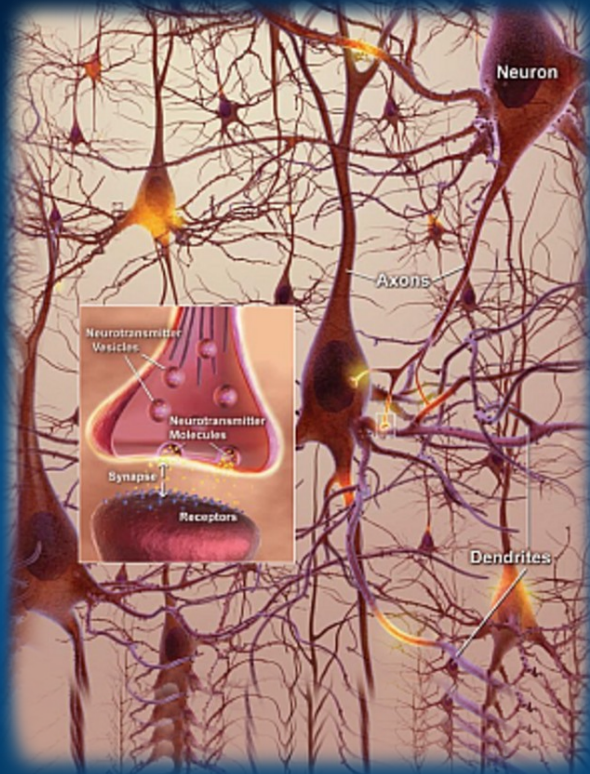
Construct/Subconstruct		Genes	Molecules	Cells	Circuits	Physiology	Behavior	Self-Report	Paradigms
Attention		Elements	Elements	Elements	Elements	Elements	Elements		Elements
Perception	Visual Perception	Elements	Elements	Elements	Elements	Elements	Elements	Elements	Elements
	Auditory Perception	Elements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

From Genes to Neurons



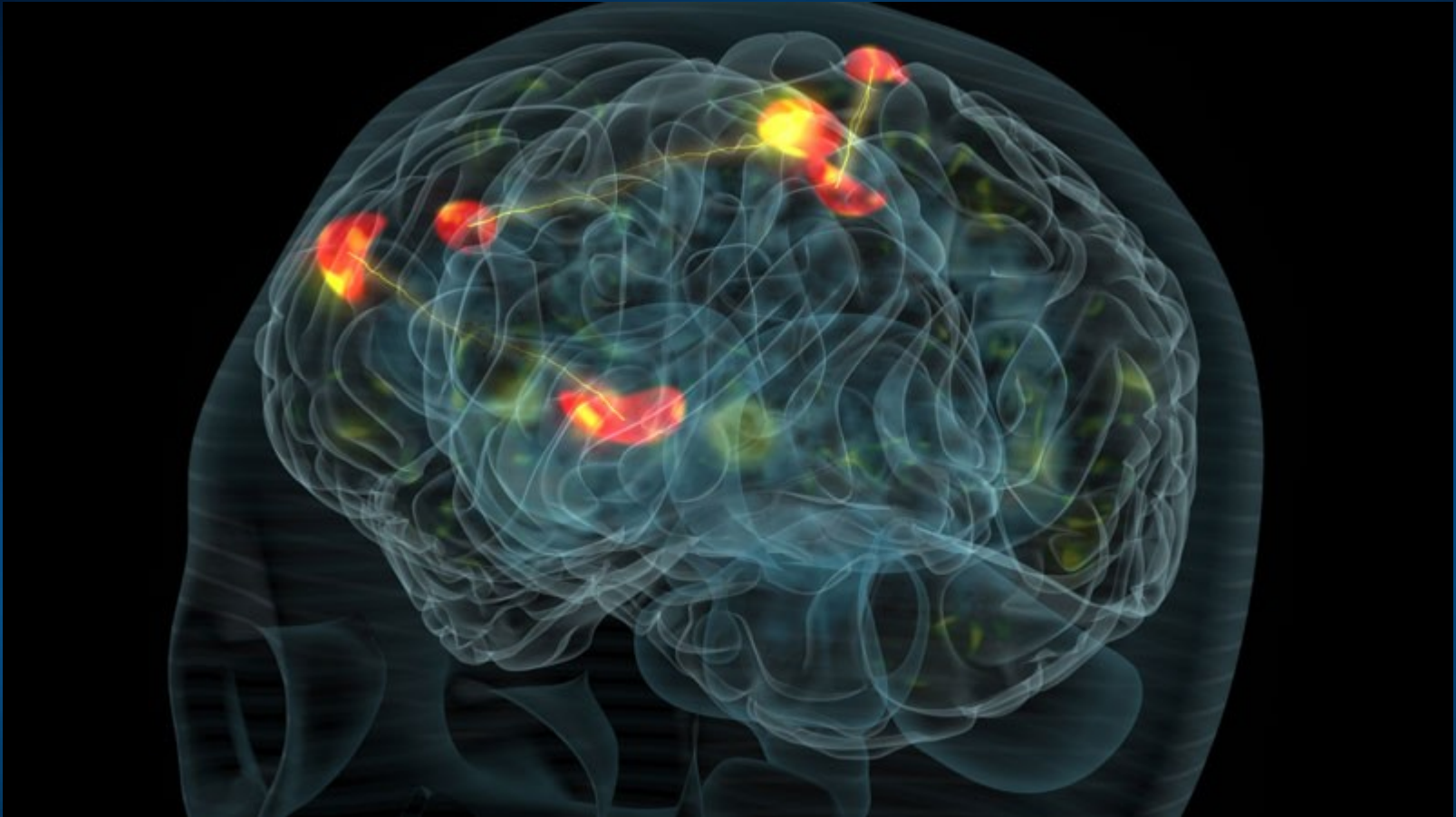
Genes \Rightarrow Proteins \Rightarrow receptors, ion channels, synapses
 \Rightarrow neuron properties, networks, neurodynamics
 \Rightarrow cognitive phenotypes, abnormal behavior, syndromes.

From Neurons to Behavior



Genes => Proteins => receptors, ion channels, synapses
=> neuron properties, networks
=> **neurodynamics** => cognitive phenotypes, abnormal behavior!

Thought: strong, coherent activation



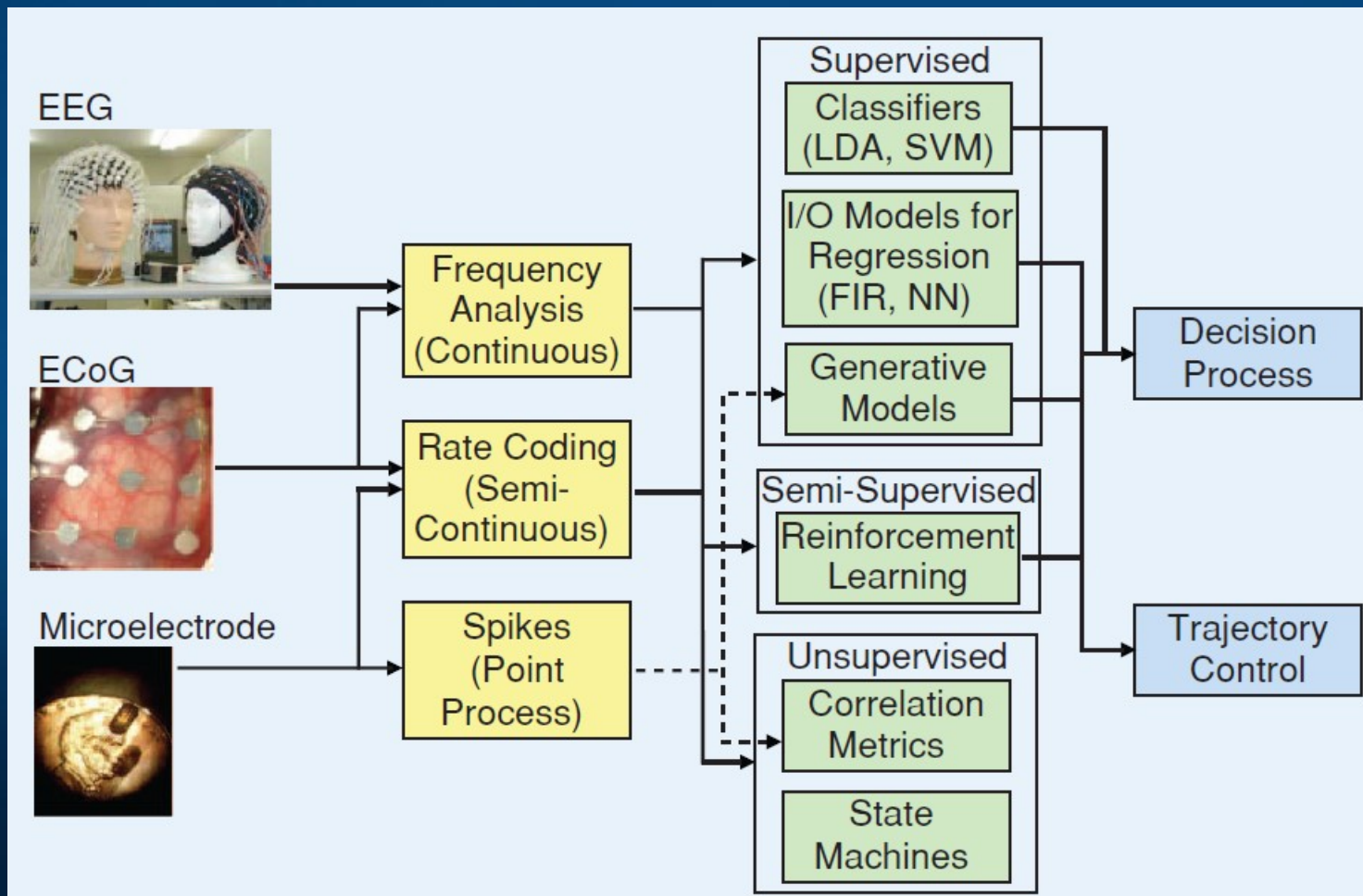
Many processes go on in parallel, controlling the state of our bodies. Most are automatic, hidden from our Self.

Processes implemented by subnetworks compete for access to the highest level of control, consciousness, using the winner-takes-most mechanism. Such processes may activate representation of Self in the brain.

Brain-computer interfaces

Mind reading is an exciting and rapidly developing field. Brain-computer interfaces (BCI) read and interpret some activity of the brain.

Conscious, intentional activity is detected, recognizing a few simple conditions.



Model of reading & dyslexia



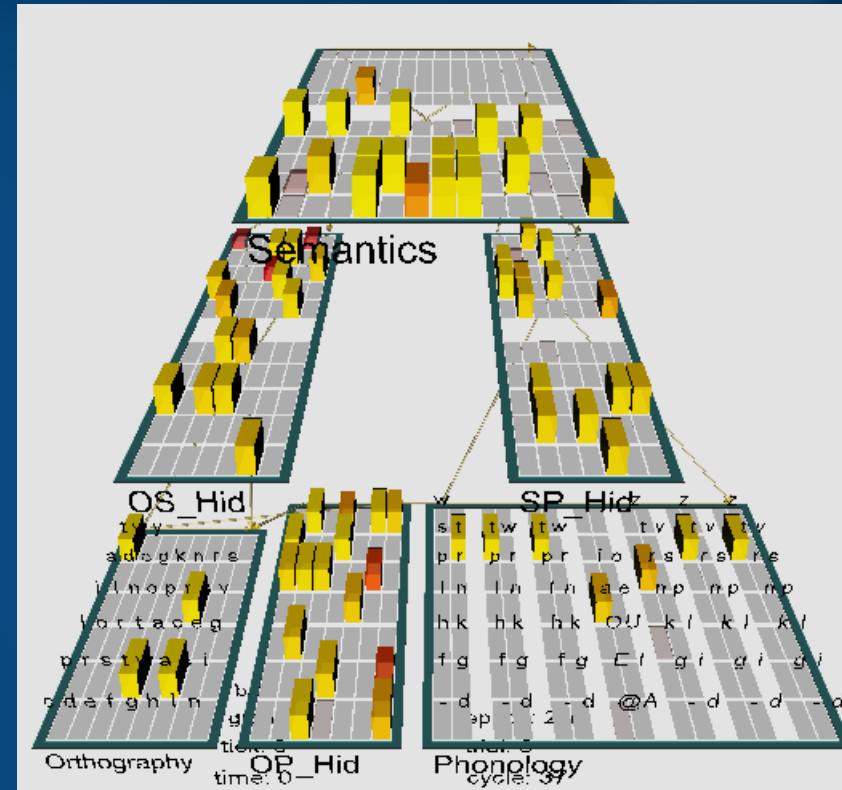
Emergent neural simulator:

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

3-layer model of reading:

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

Hidden layers 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?

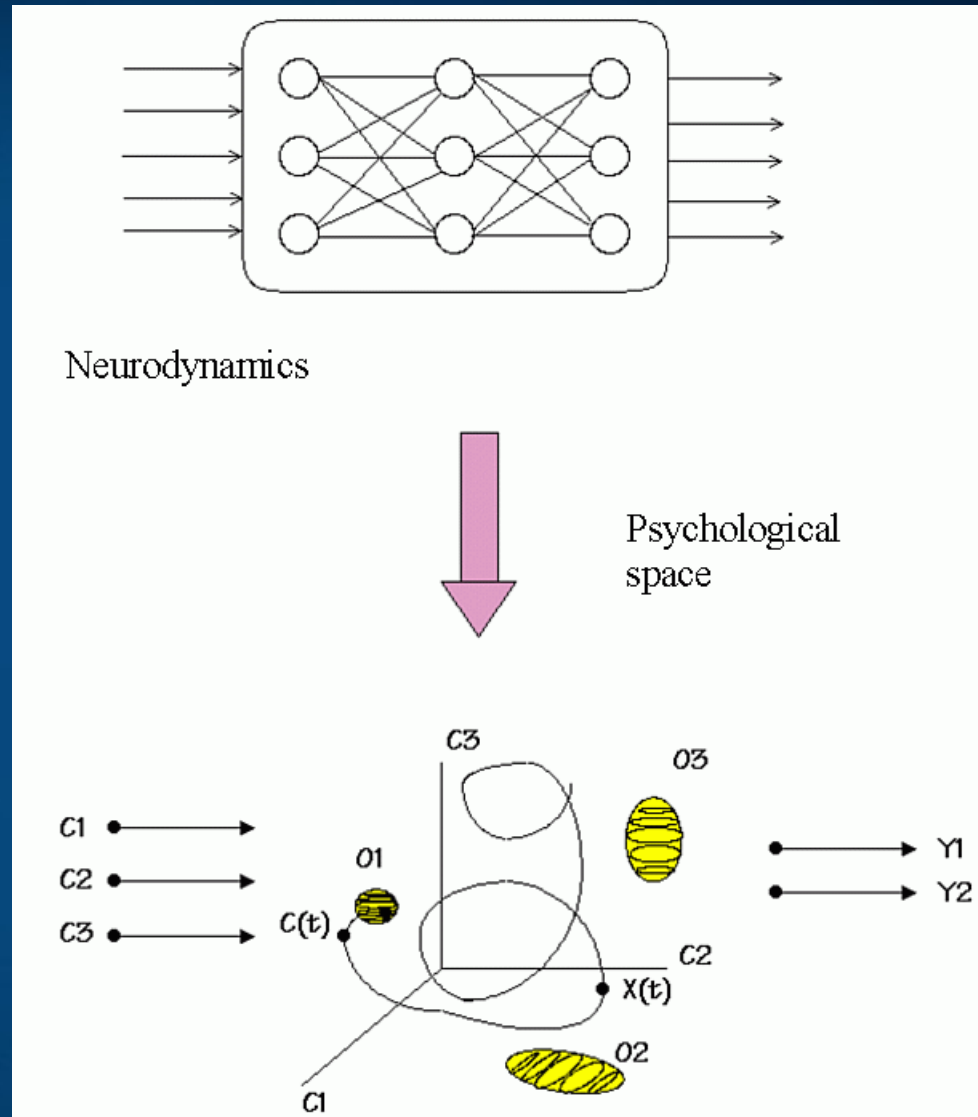
Model in **Genesis**: more detailed neuron description.

Zamiast skomplikowanej neurodynamiki spróbujemy przedstawić stan mózgu jako trajektorię w przestrzeni określonej przez cechy, które dają się zidentyfikować dzięki introspekcji stanów mentalnych.

Stan mózgu => stan umysłu,
Zdefiniowany w przestrzeni psychologicznej.

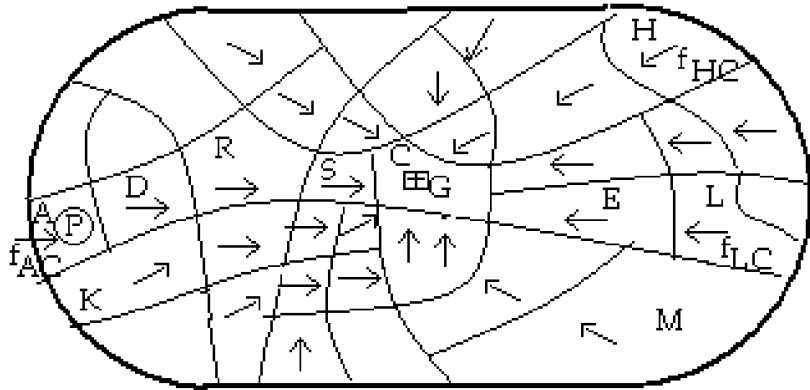
Tu stan mózgu = warstwa semantyczna i pozostałe.

Stan umysłu = wizualizacja trajektorii w przestrzeniach psychologicznych.



Transitions

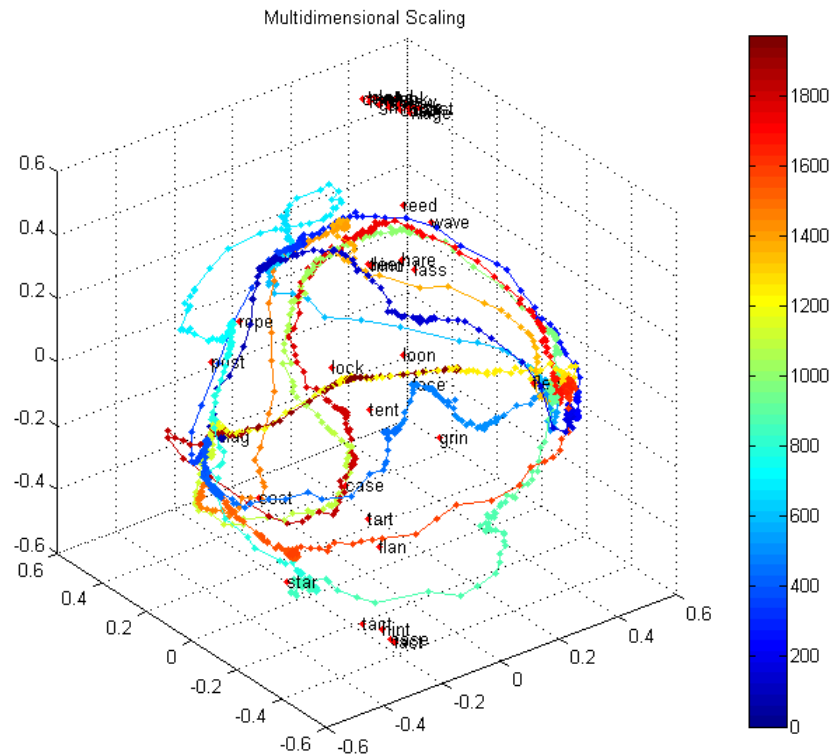
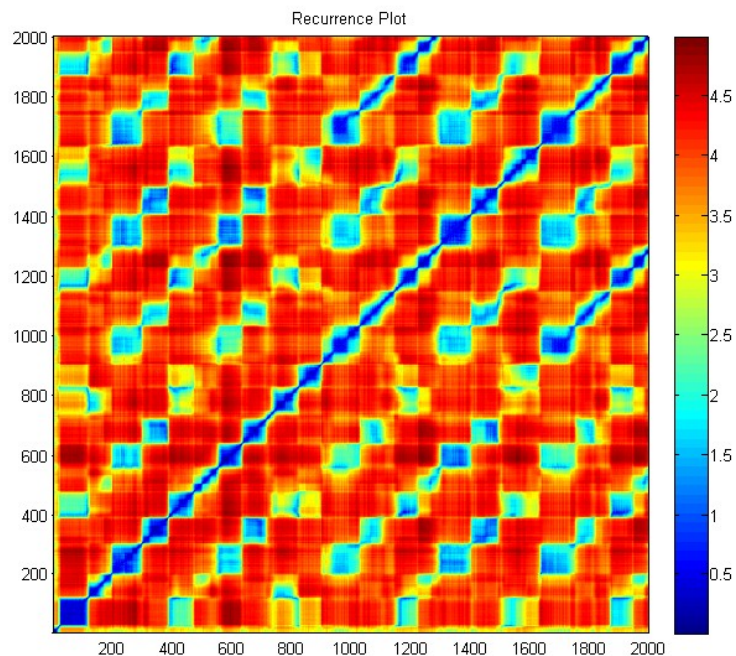
Fig. 5. "Positive central force field corresponding to a positive valence ($V_a > 0$)" (Lewin, fig. 33)



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

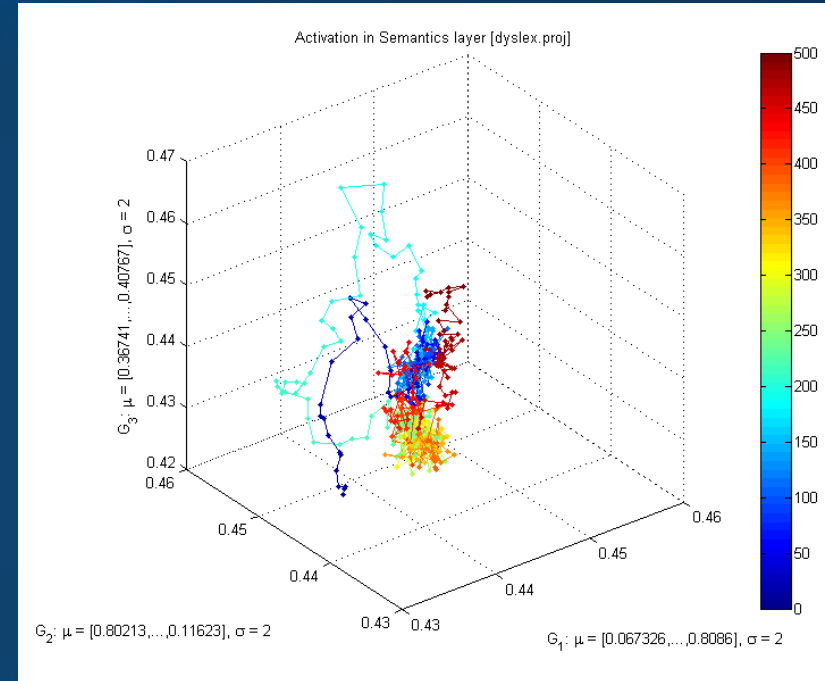
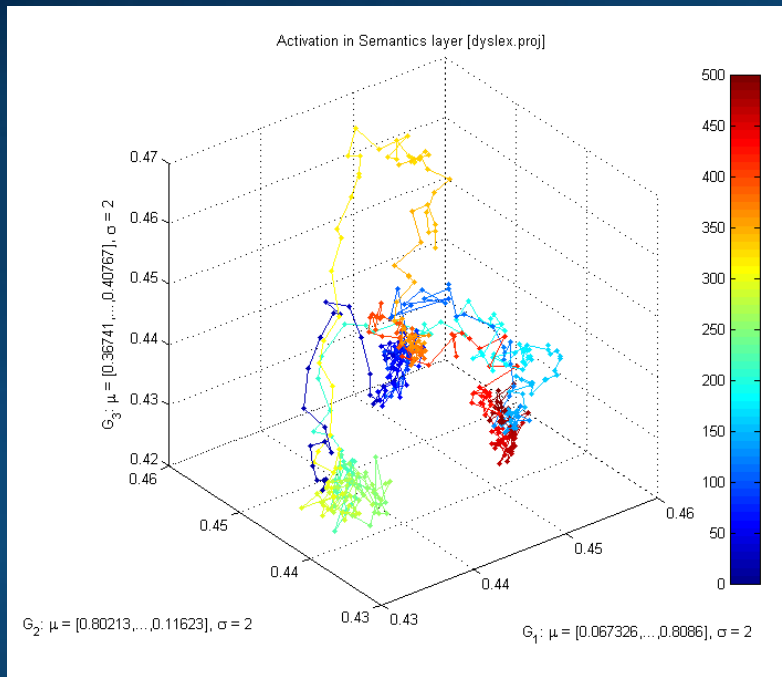
Transitions = Lewin's psychological forces.
Attractors = regions with positive valence.

Transitions



Recurrence plots and MDS visualization of trajectories of the activity in 140-dim semantic layer during spontaneous associations in the 40-words microdomain, starting with the word “flag”. Transitions = Lewin’s psychological forces. Attractors=regions with positive valence.

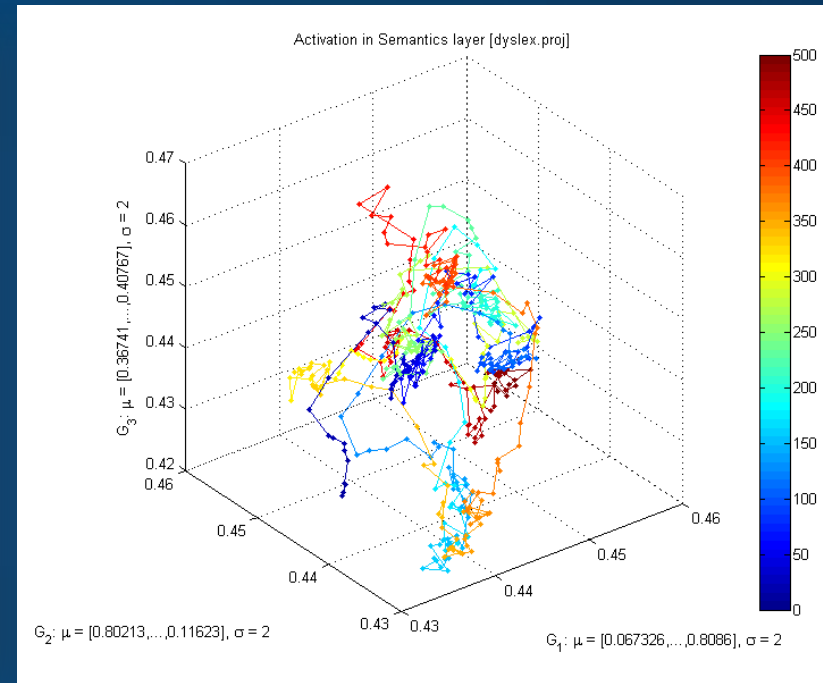
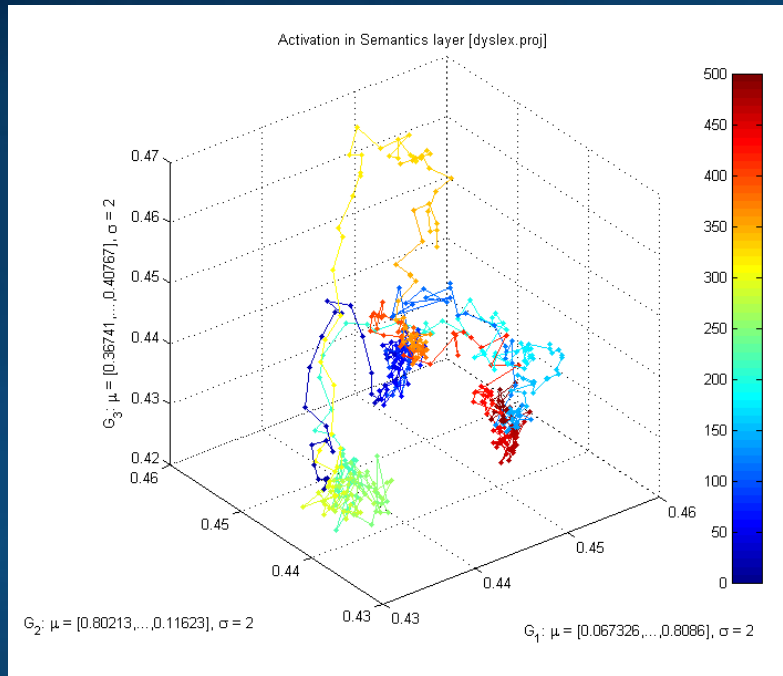
Normal-Autism



Dwell time in attractor basin determines the speed of attention shifts. In case of ASD it is too long, leading to a small number of states, and poor development of long neural projections.

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

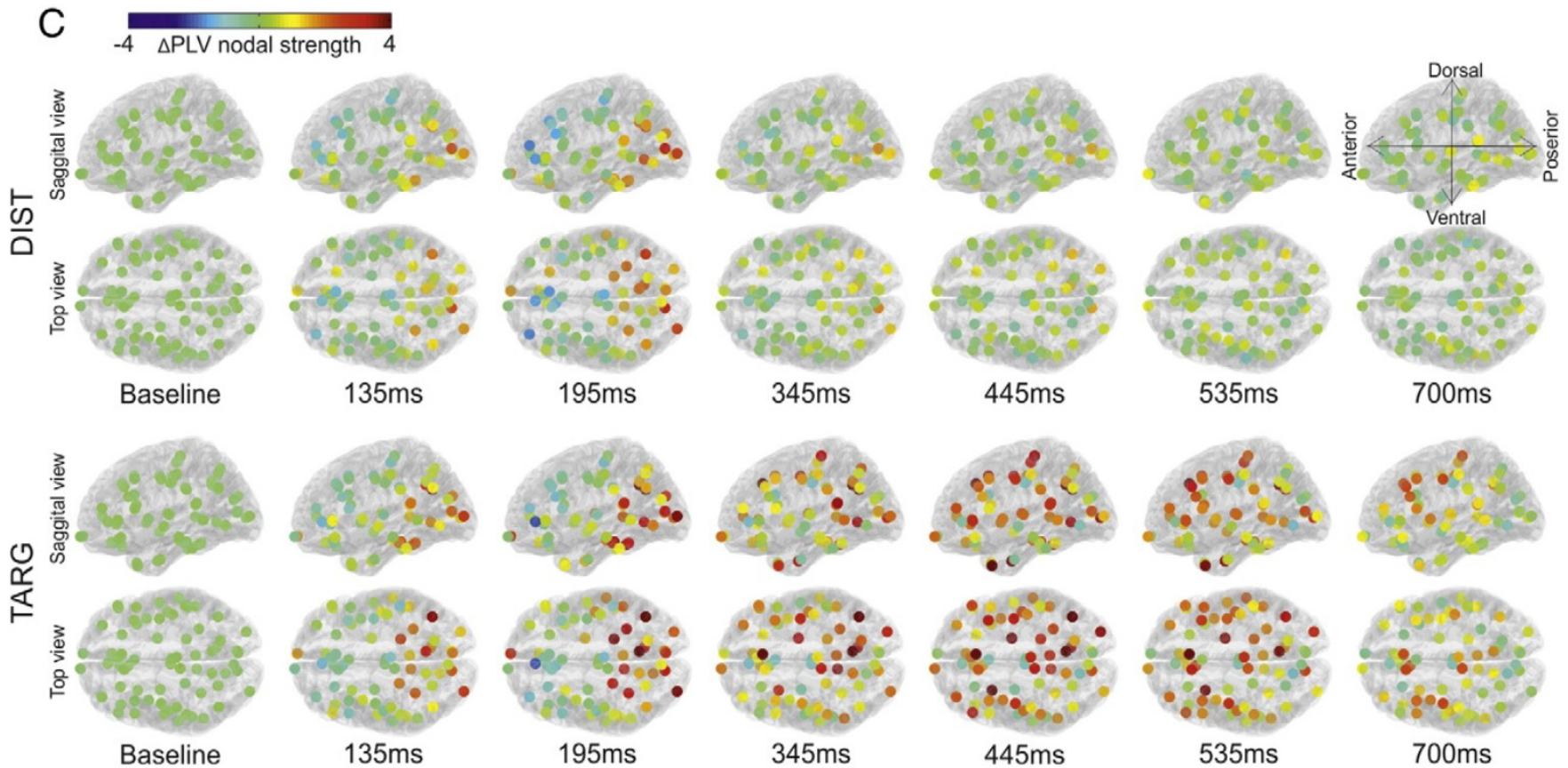
Normal-ADHD



In ADHD dwell time in attractor basins is very short, resulting in hyperactivity.
 b_inc_dt = time constant for increases in intracellular calcium which builds up slowly as a function of activation.

Viser toolbox for time series data visualization (K. Dobosz, W. Duch ++).

Phase Locking Value network analysis



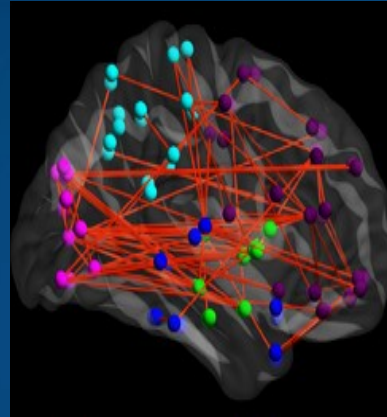
Strength of weighted event-related networks, changes in theta EEG band in the space of phase locking value. Anticipation of stimuli creates weak priming activation that is inhibited if this is not the target stimuli (Bola, Sabel, 2015). Such pre-activation solves the frame problem?

Human connectome and MRI/fMRI

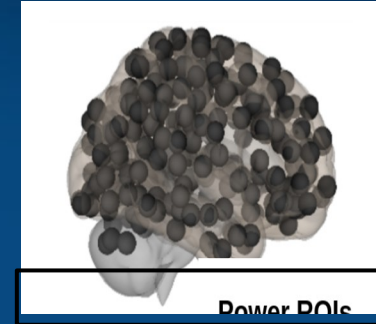
Structural connectivity



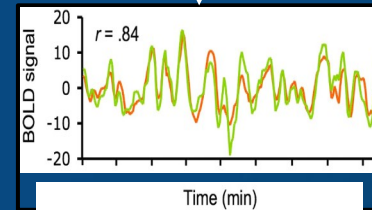
Functional connectivity



Node definition (parcelation)

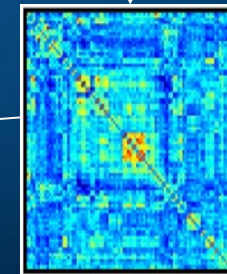


Signal extraction



Correlation calculation

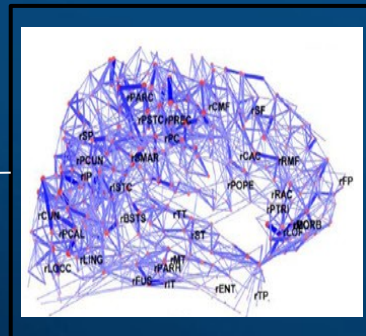
Correlation matrix



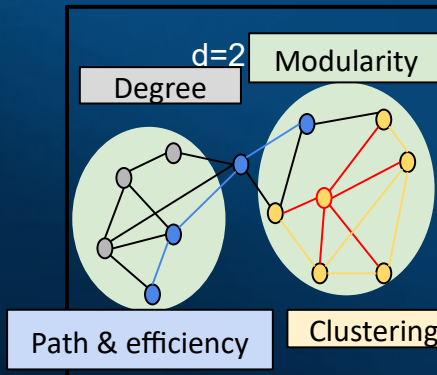
Binary matrix



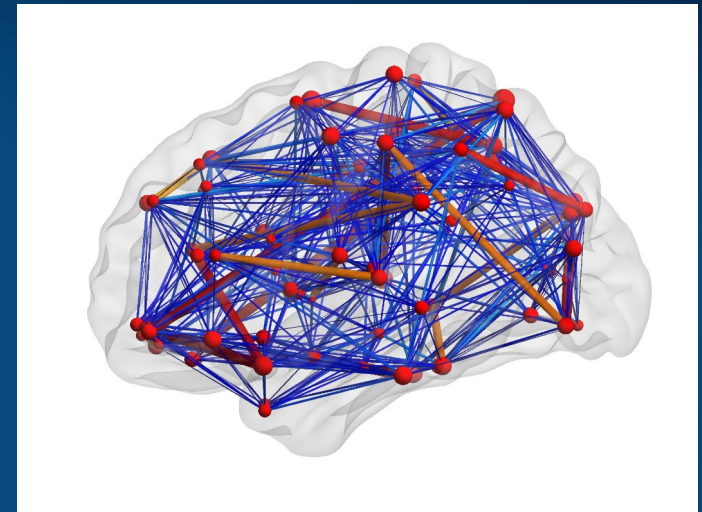
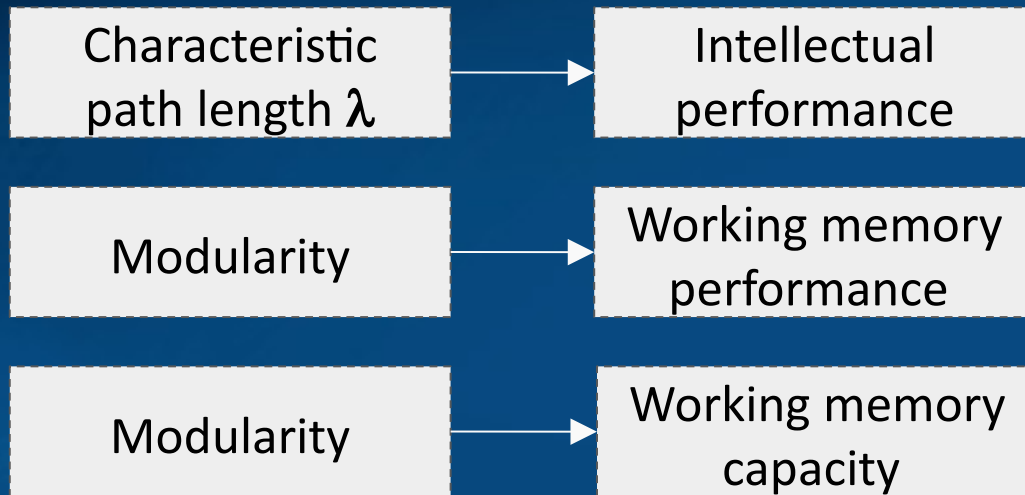
Whole-brain graph



Graph theory

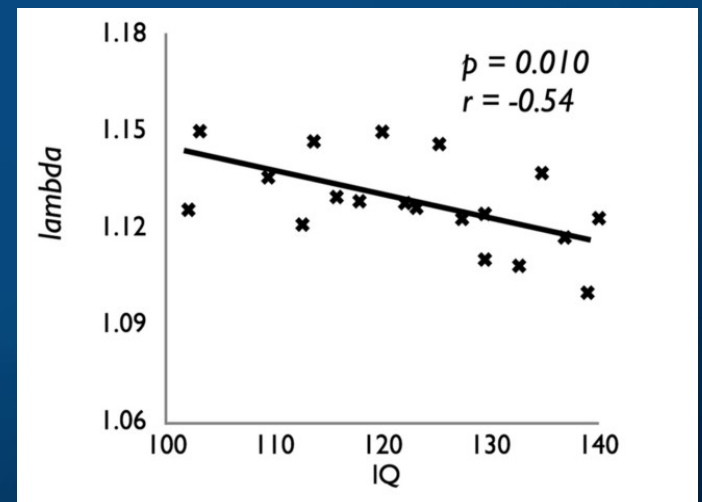


Resting state/cognitive performance



Network modularity \Leftrightarrow 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.



Questions for our study

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

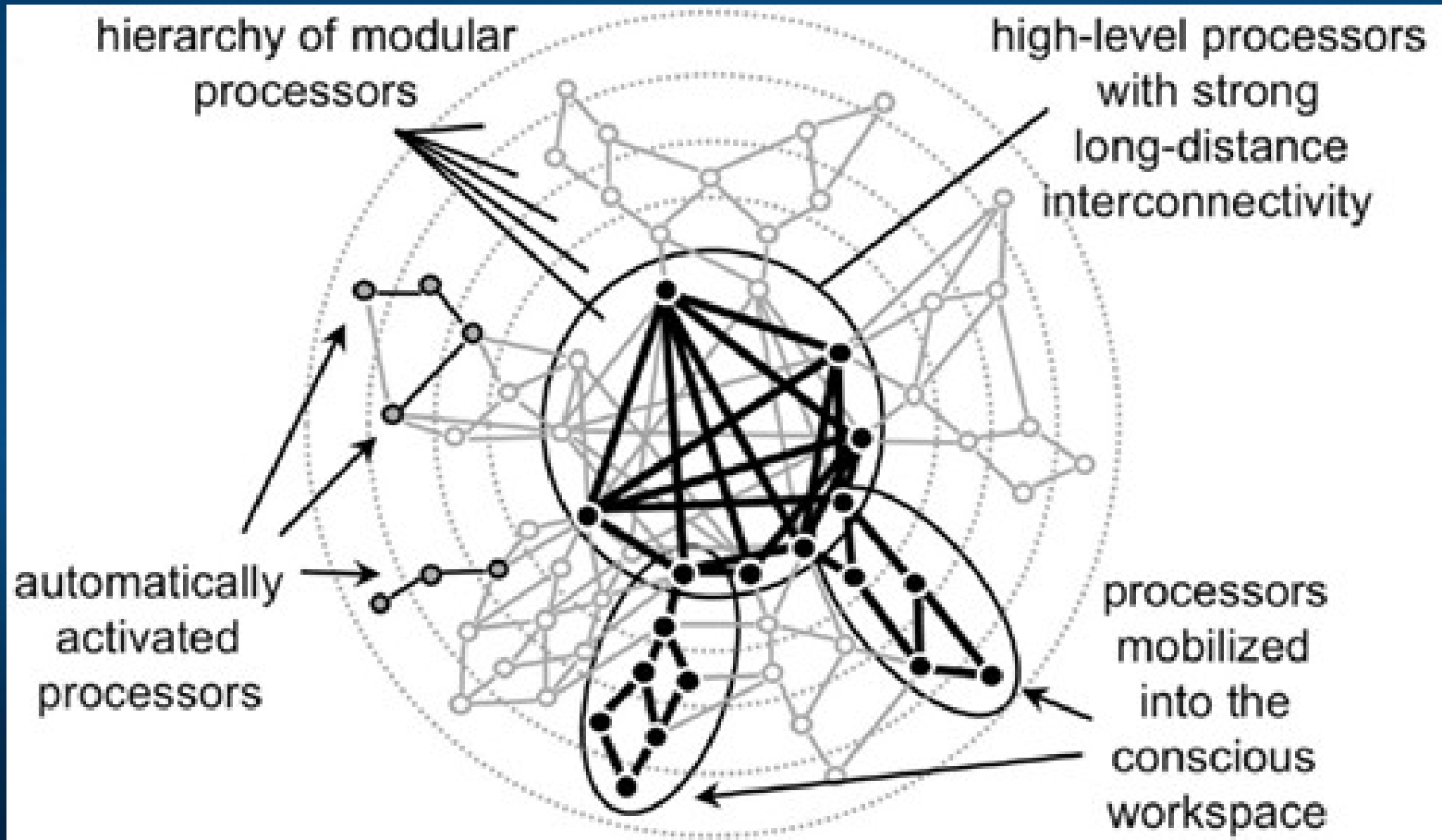
Global Neuronal Workspace Theory (Dehaene et al. 1998): brain processes underlying effortful tasks require two main computational spaces:

- 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 do not suffice. They selectively mobilize or suppress, through descending connections, the contribution of specific processor neurons.

GNWT

Global Neuronal Workspace Theory (Dehaene et al. 1998)



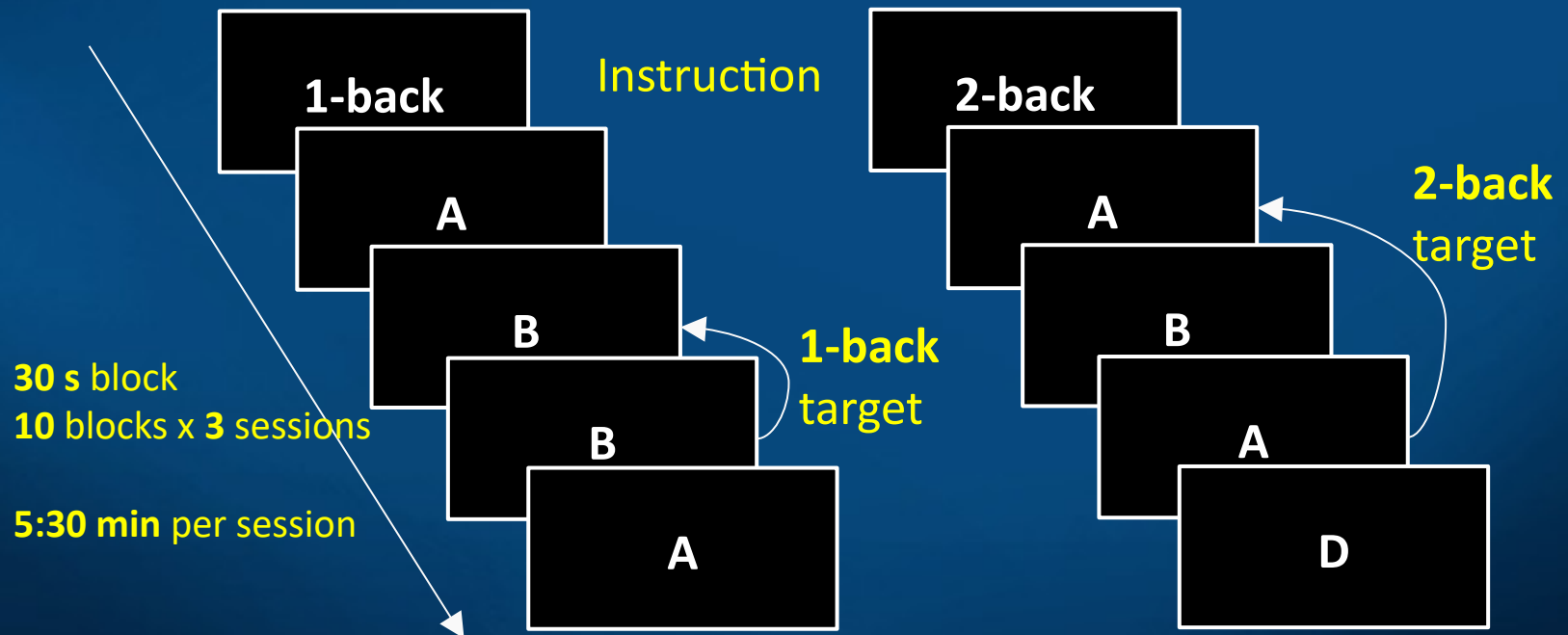
Cognitive load on whole-brain network

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

Letter *n*-back task

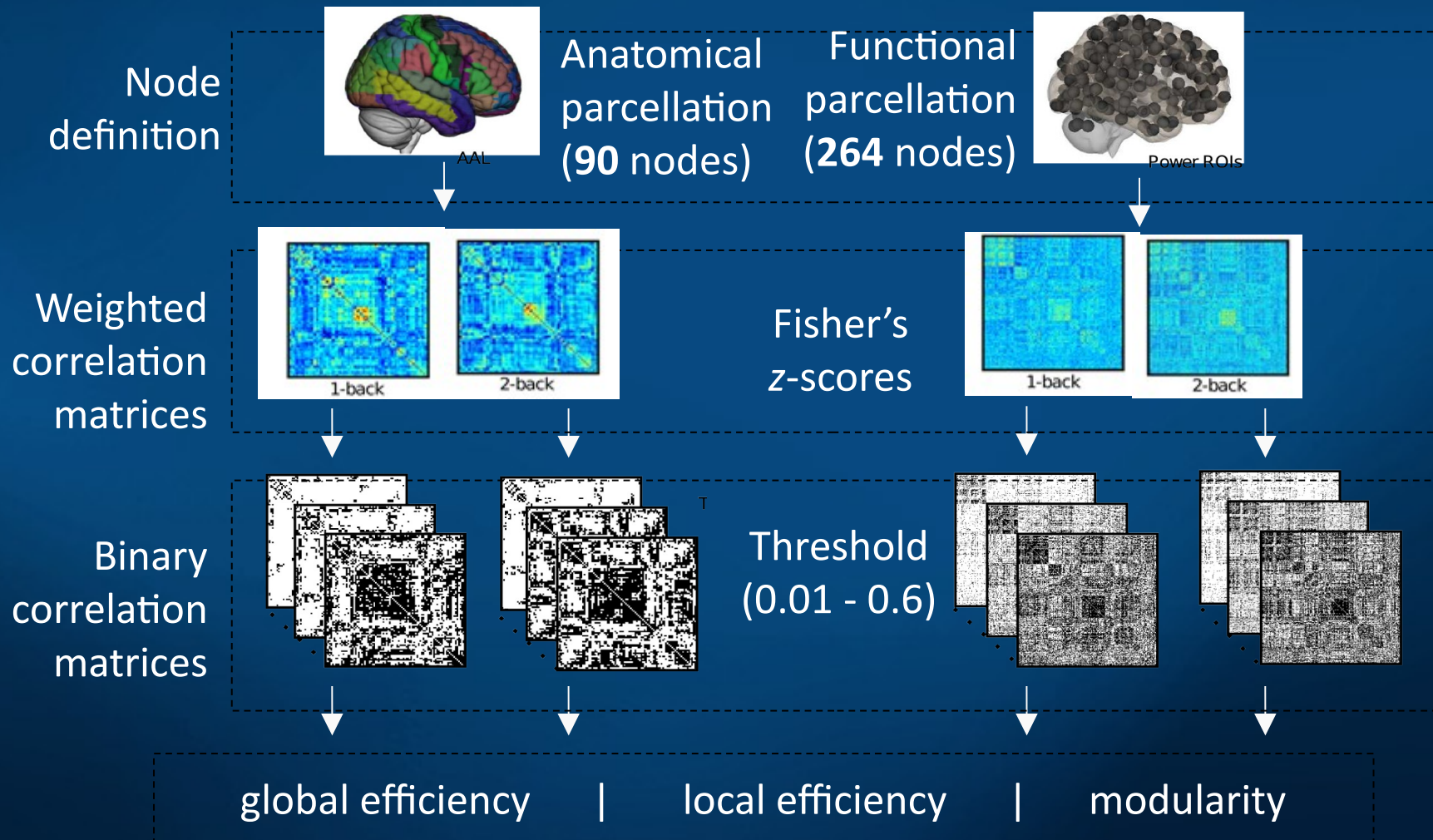
Low cognitive effort

High cognitive effort



Data workflow

Two experimental conditions: 1-back, 2-back

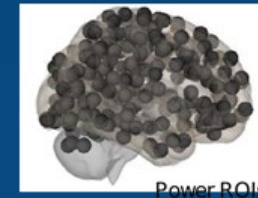


Changes in modularity

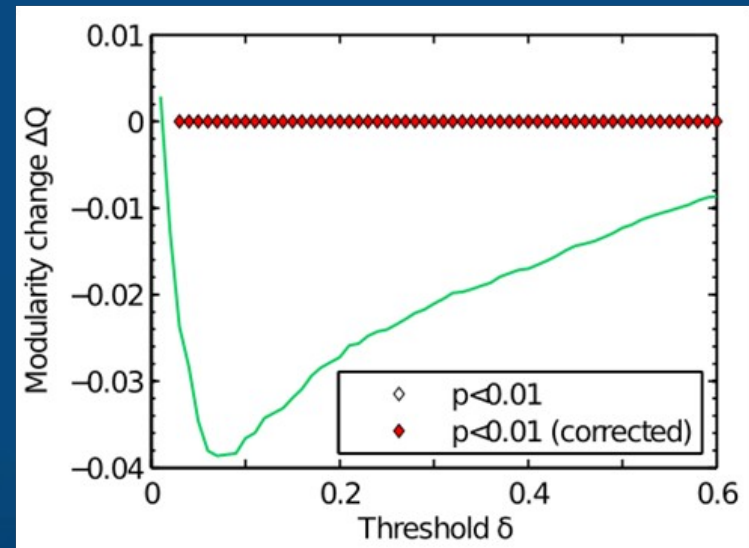
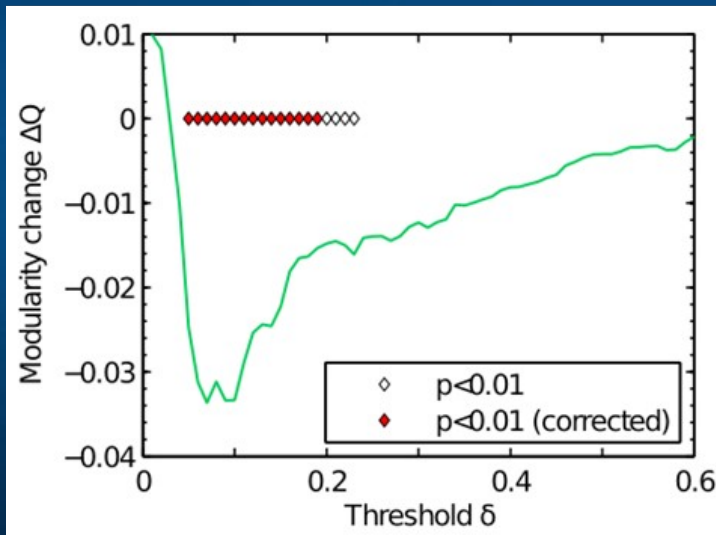
Modularity metric: fraction of within-community edges in the network minus such fraction for randomly connected network with unchanged community structure.



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.

Changes in efficiency

Global efficiency \sim inverse characteristic path length

Local efficiency \sim clustering coefficient (Latora & Marchiori, 2001).



AAL

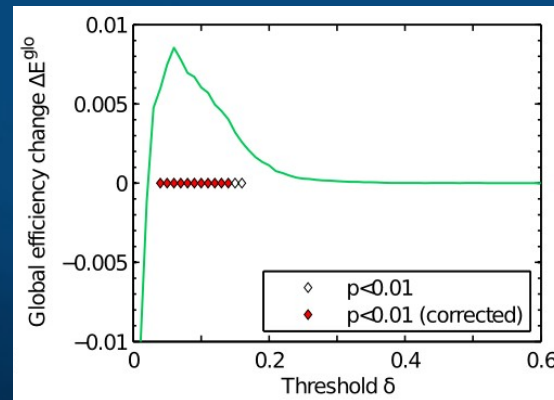
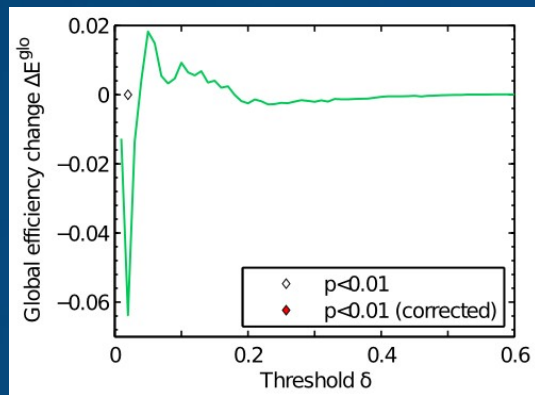
Parcelation
AAL, 90 ROI



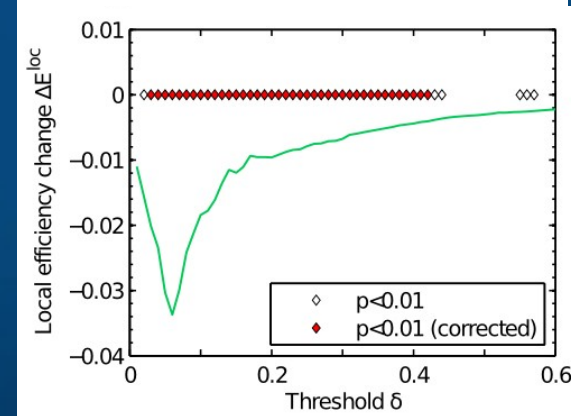
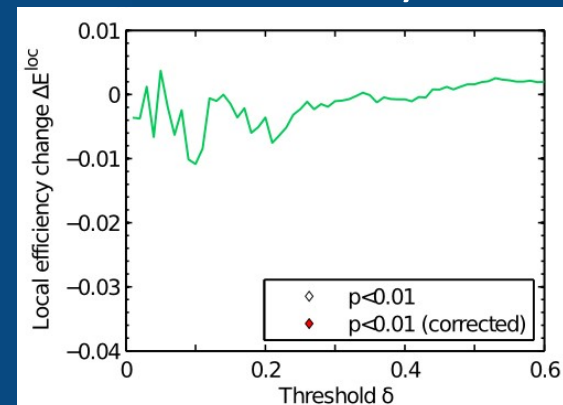
Power ROIs

Parcelation
264 ROI
functional

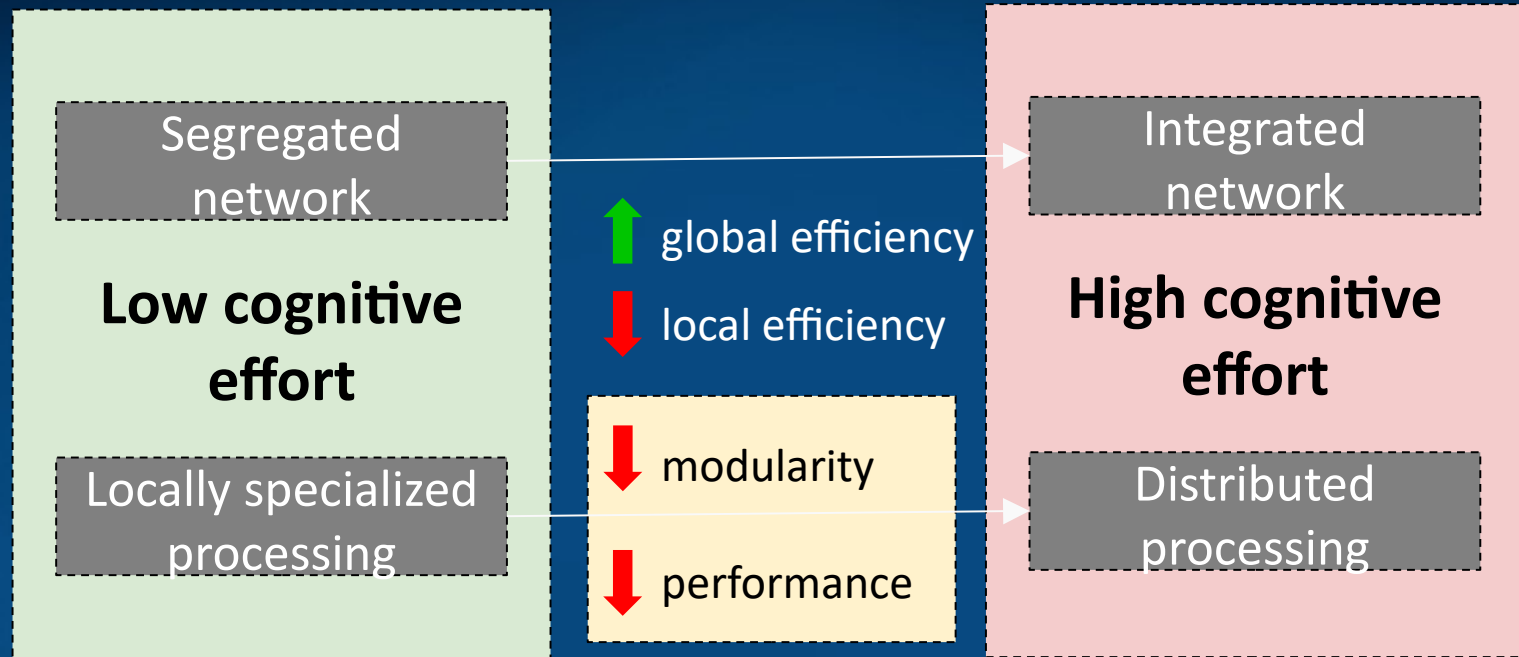
Global efficiency



Local efficiency



Conclusions



≠



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.

Brain modules and cognitive processes

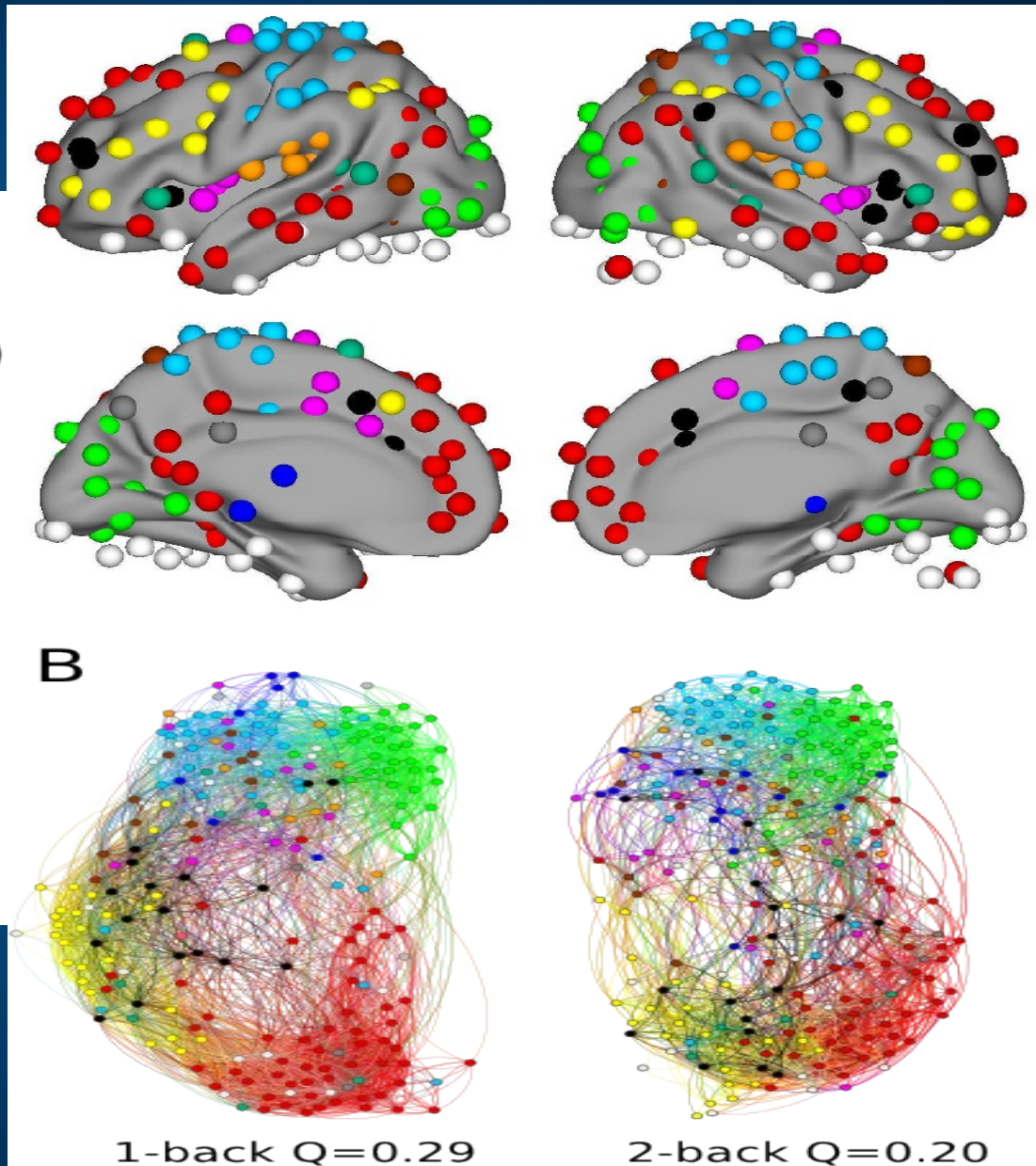
Simple and more difficult tasks, requiring the whole-brain network reorganization.

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

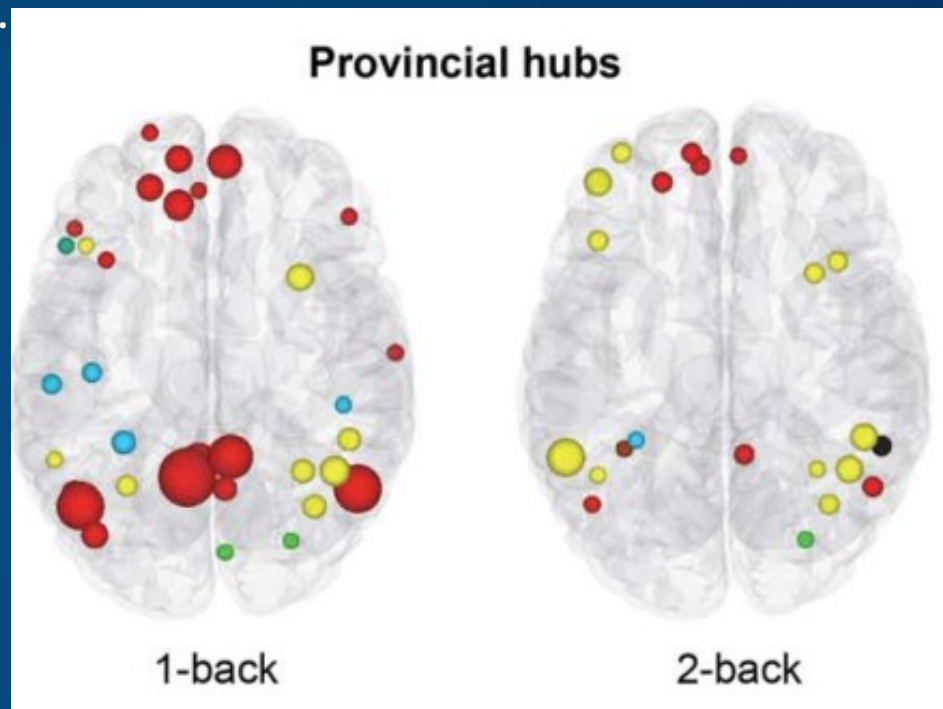
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back Top: connector hubs
 Right: 2-back Bottom: 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).



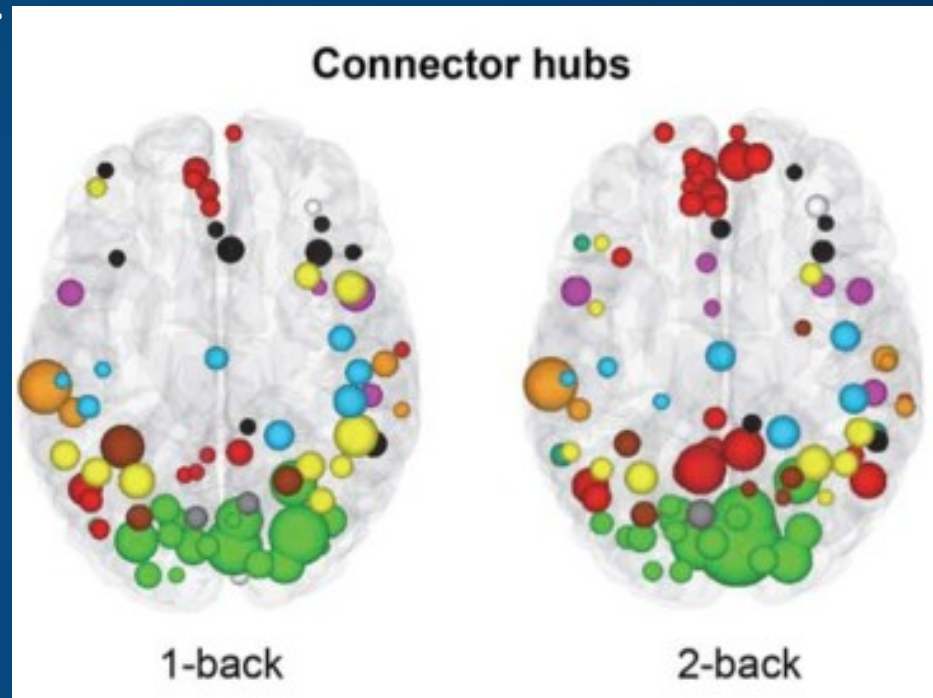
Brain modules and cognitive processes

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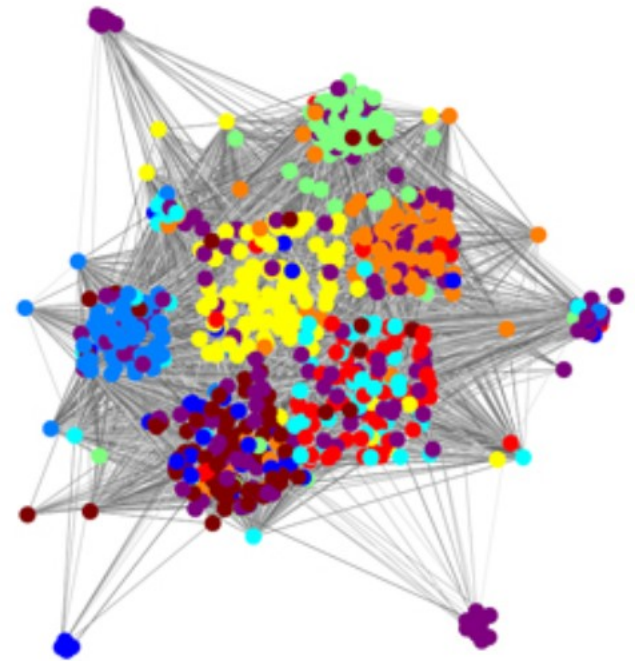
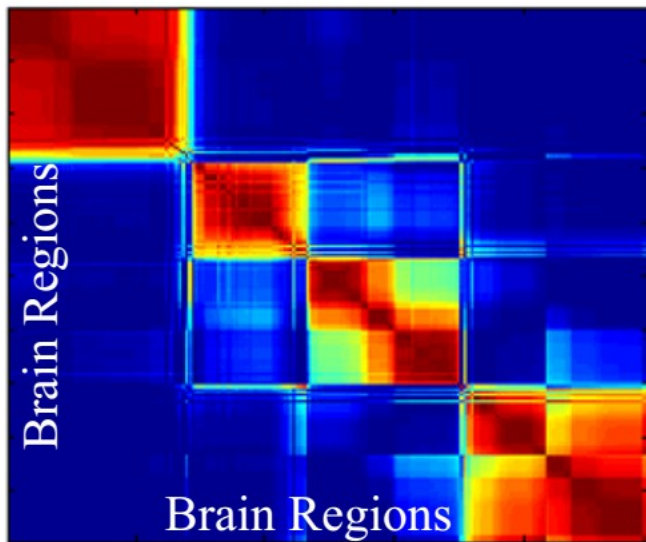
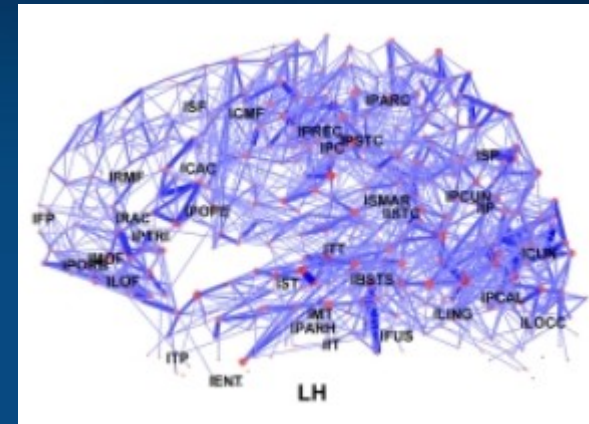
Dynamical change of the landscape of attractors, depending on the cognitive load. DMN areas engaged in global binding!



Neuronal subnetworks

Hierarchy and modularity is observed at large scale: several subnetworks responsible for arousal, attention, positive/negative valence, perception.

At the microcircuit level similar hierarchy/modularity is seen.

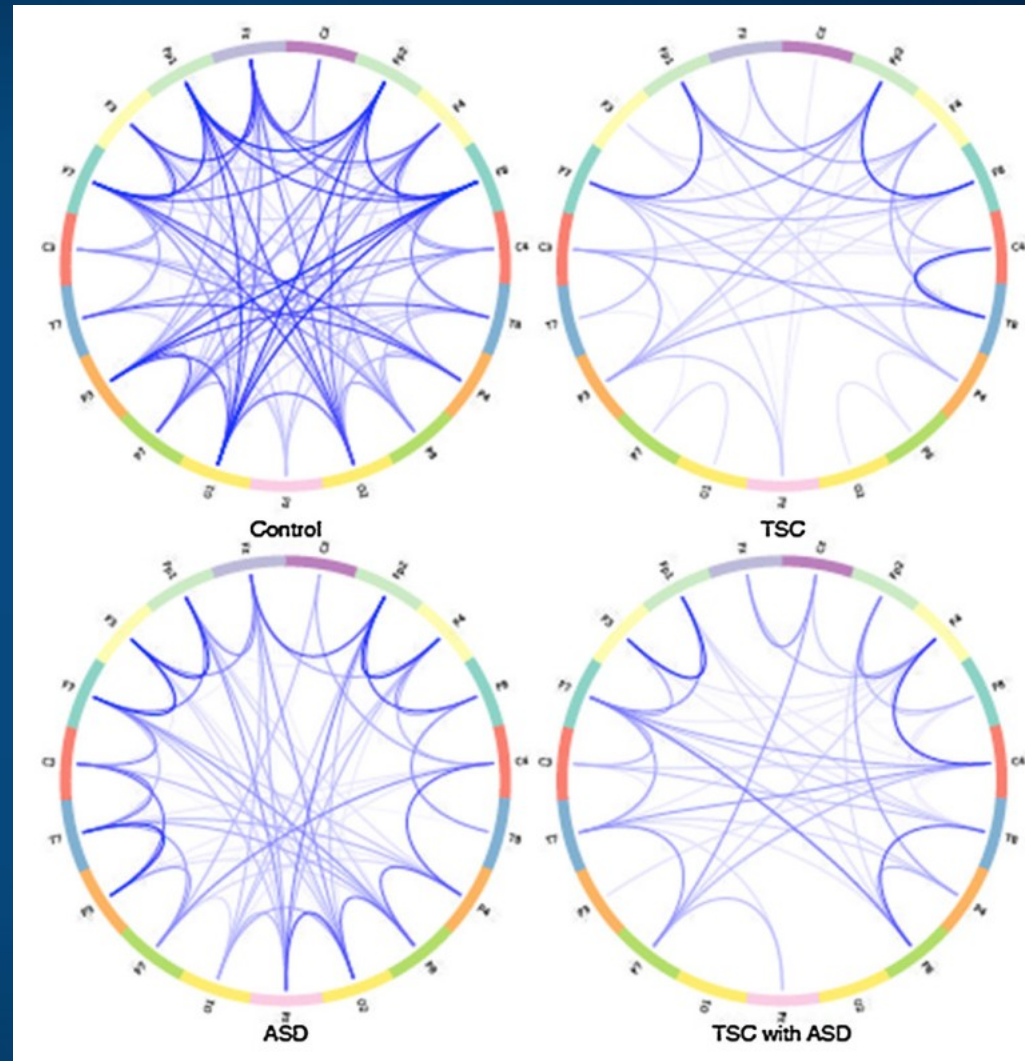


ASD: pathological connections

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

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.

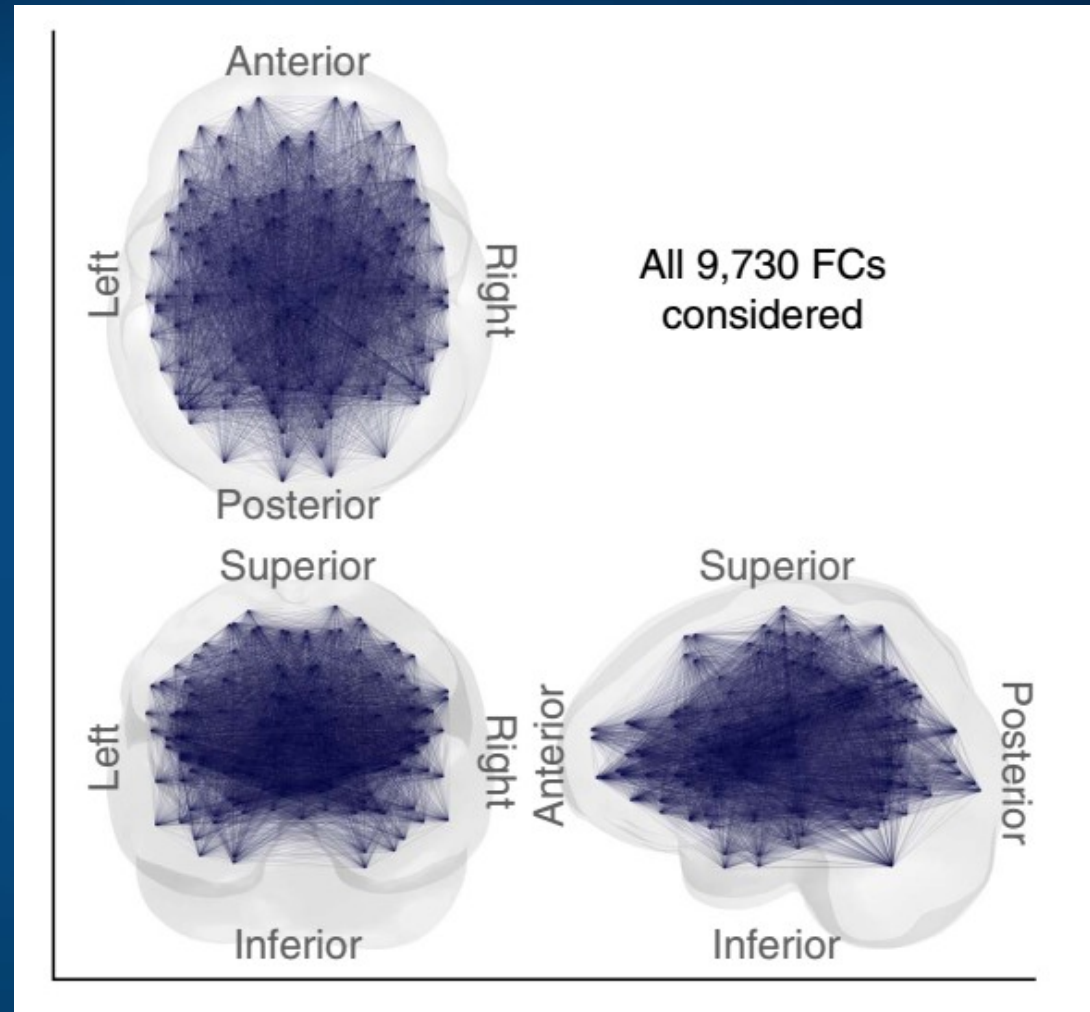


J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. *Cogn Process* (2015) 16:1–16

ASD connectome

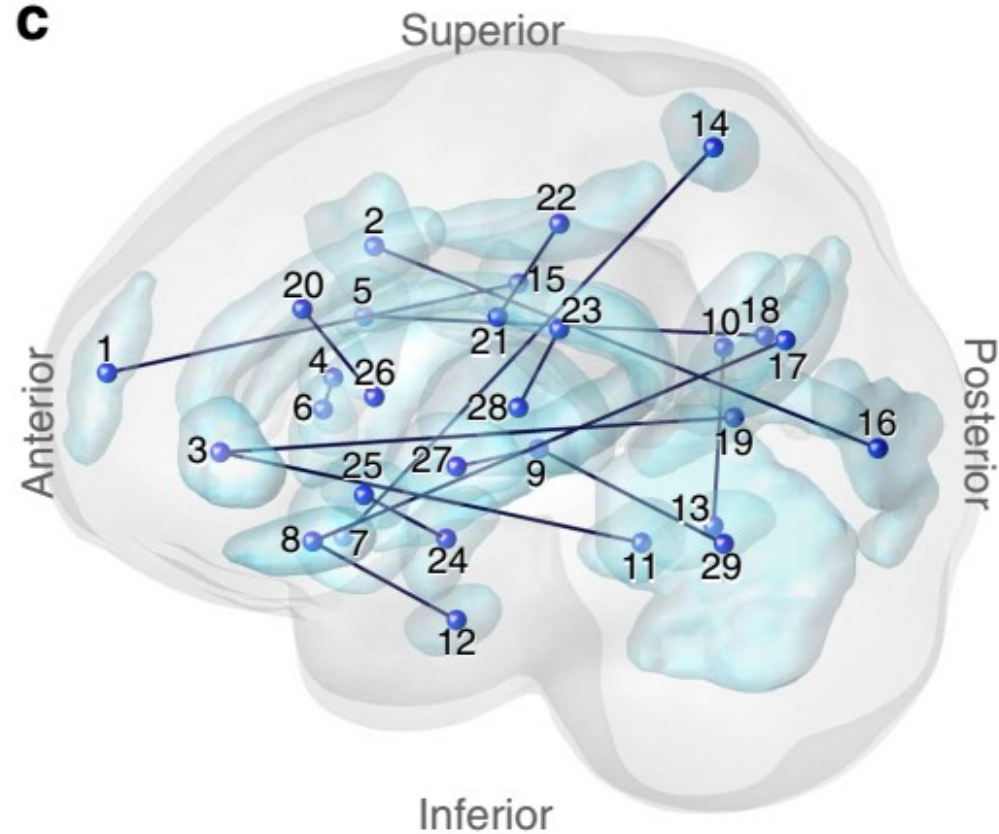
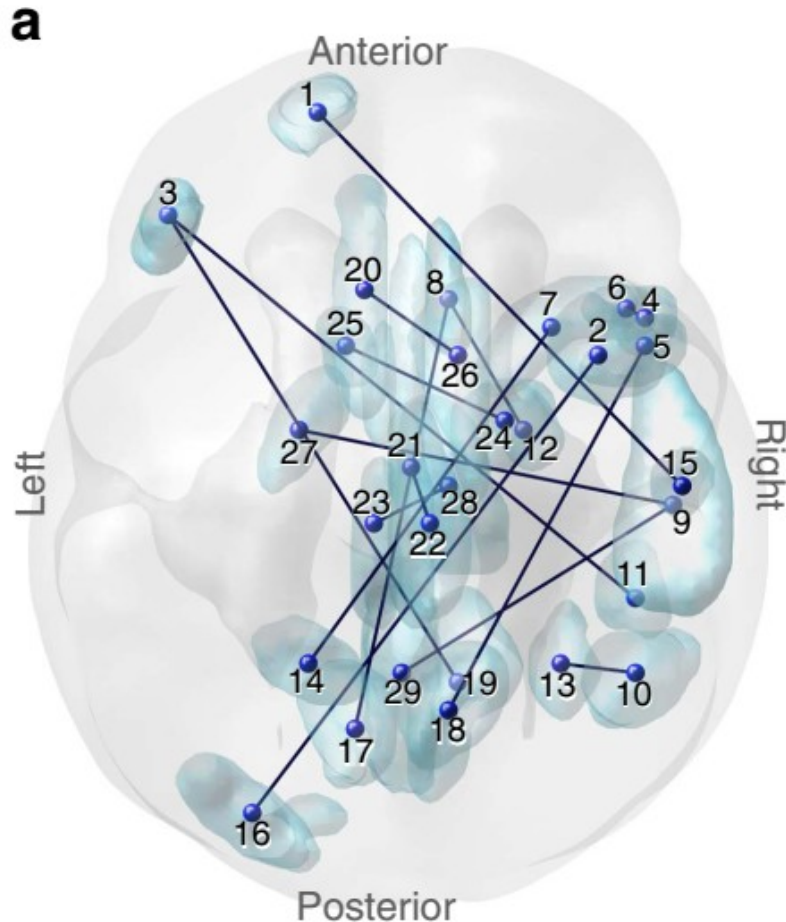
Analysis of functional connections (correlated activity) between brain regions measured using fMRI in the resting state between 140 ROIs has 9730 possible interactions.

Selecting the most important and using L1-SCCA classifier 16 connections were left, sufficient to reach 85% of accuracy distinguishing ASD people from the healthy ones.



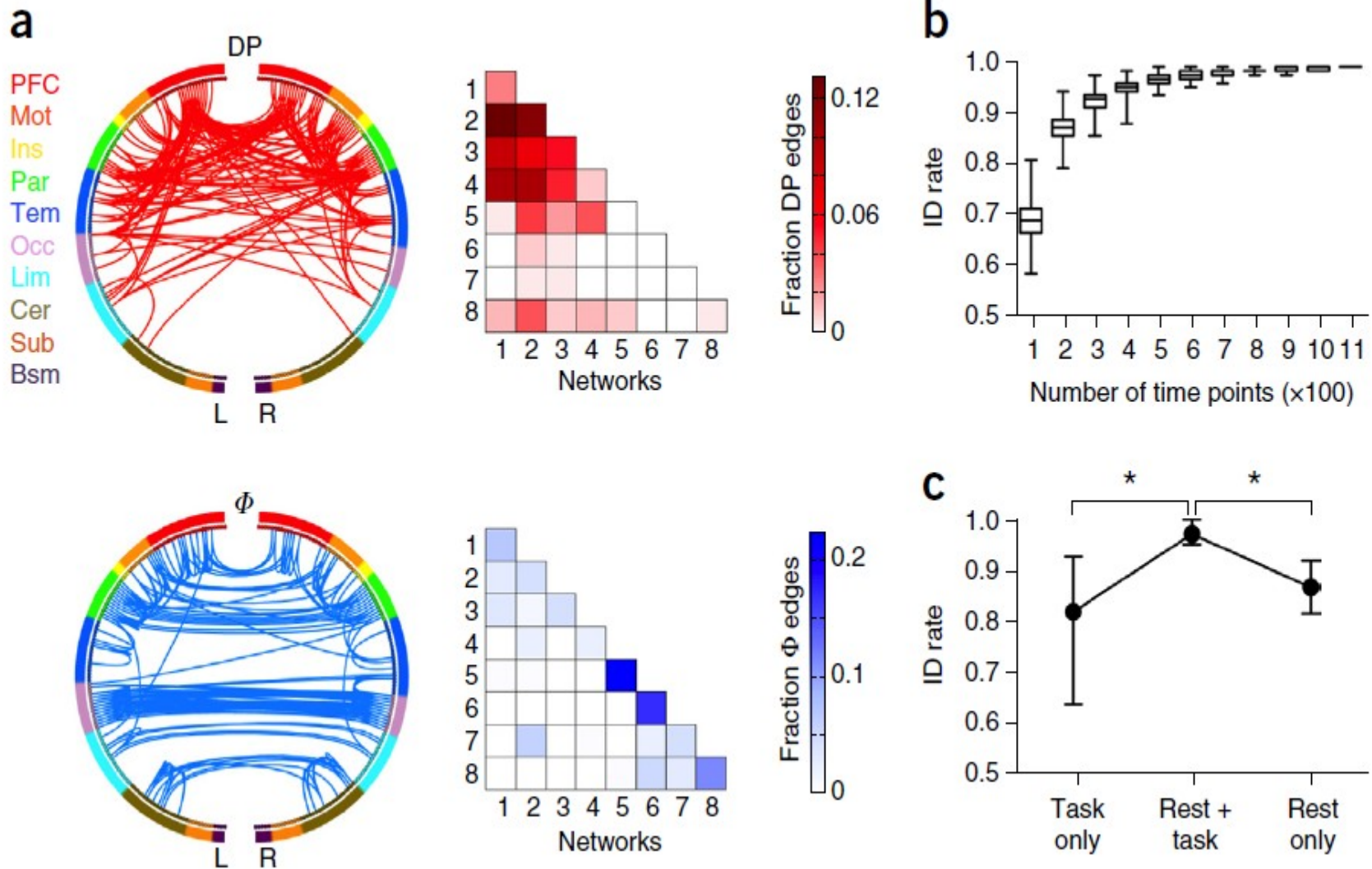
N. Yahata *et al.*, A small number of abnormal brain connections predicts adult autism spectrum disorder. *Nature Communications* (2016)

Selected connections



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

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

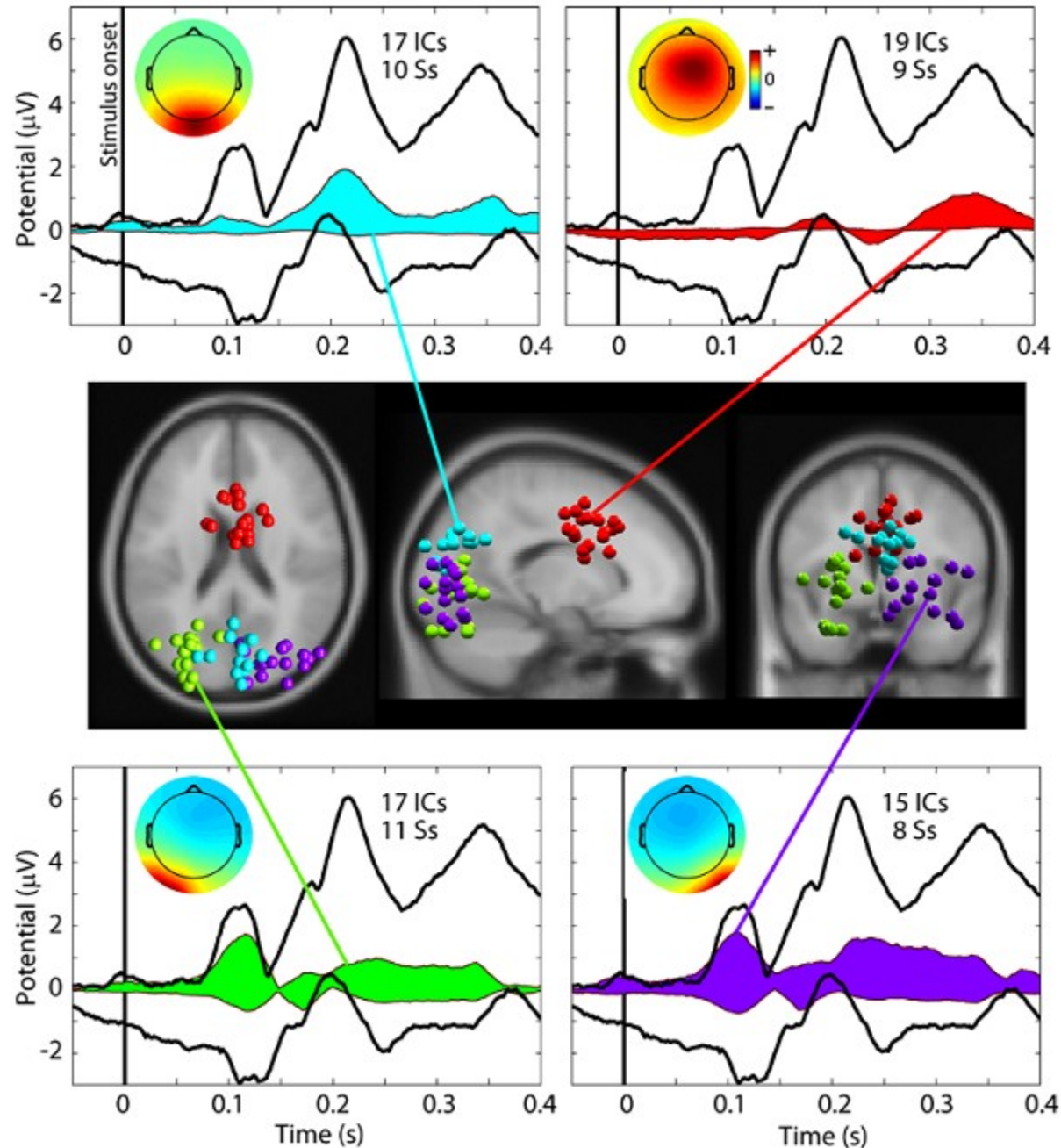


Brain fingerprinting:

discover in EEG specific patterns of attractor dynamics = subnetwork or specific structure activations. Ex:

Visual attention-shift experiment. 4 (of 22) IC (Independent Comp.) cluster contributions to a visual stimulus ERP. Equivalent model dipole locations, mean scalp maps, and cluster projection envelopes, av. over 12 subjects.

Fig. from: Makeig, Onton (2009)



8 selected approaches to BFP

1. **Source Reconstruction/Localization**, from fMRI to EEG.
2. **Graph-based approaches**: phase locking PLV, analysis of CC, RCC and other coefficients showing subnetwork activity.
3. **Connectome-based**: influence of network topography on signal propagation and system function; dynamic changes in network architecture, functional cartography.
4. **Spatio-temporal EEG maps using ERD/ERS**
 $(t, f, E, X) \Rightarrow \text{ERS/ERD} \Rightarrow \text{bumps} \Rightarrow \text{relevant dimensions (subnetworks)} \Rightarrow$
analysis of trajectories in this space.
5. **EEG component analysis**: ICA, EMD, ERM, tensor decomposition ...
6. **ERP shape analysis in component space.**
7. **Model-based approaches**
Mapping fMRI/EEG activity on network models of the brain, ex. TVB
8. **Feature-based approaches** – microstates, specific $x(t)$ signatures.

Words in the brain



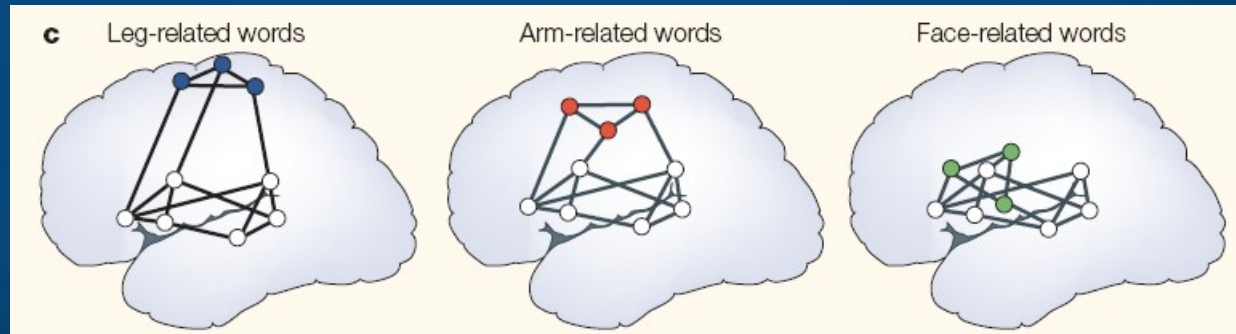
Psycholinguistic experiments show that phonological representations activate categorical representations.

Acoustic signal => phoneme => words => semantic concepts.

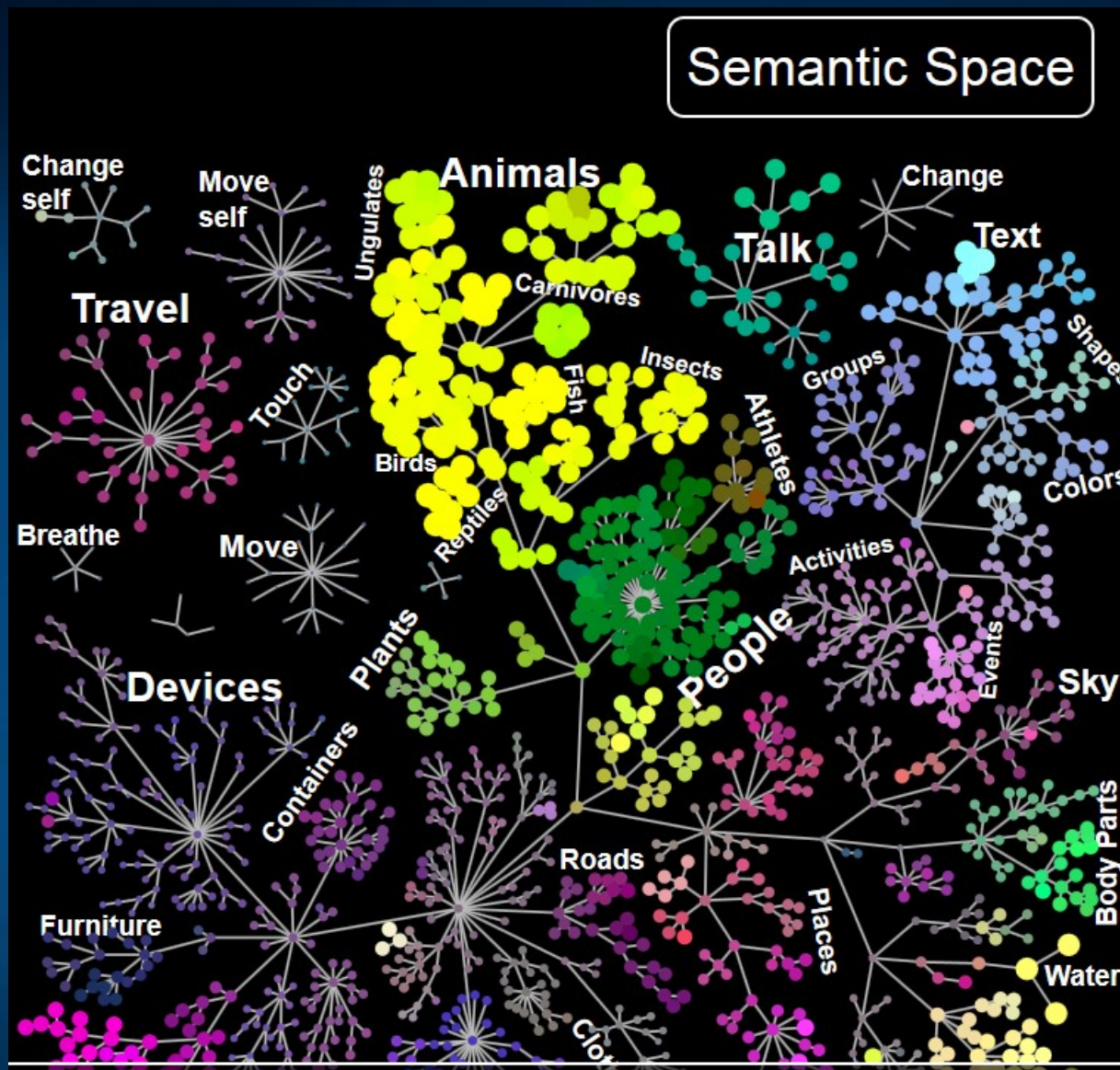
Phonological processing precedes semantic by 90 ms (from N200 ERPs).

F. Pulvermuller (2003) *The Neuroscience of Language. On Brain Circuits of Words and Serial Order*. Cambridge University Press.

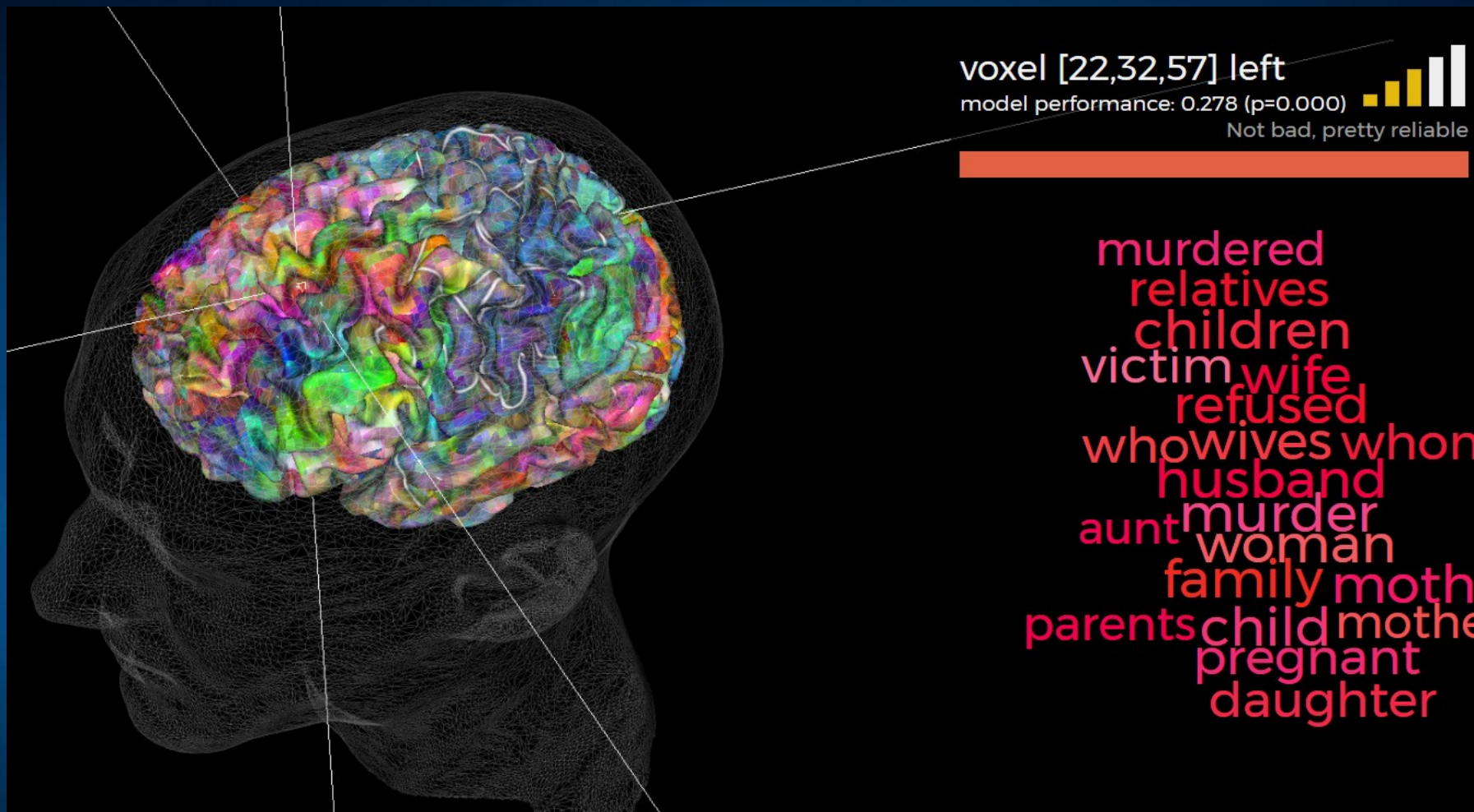
Action-perception networks inferred from ERP and fMRI



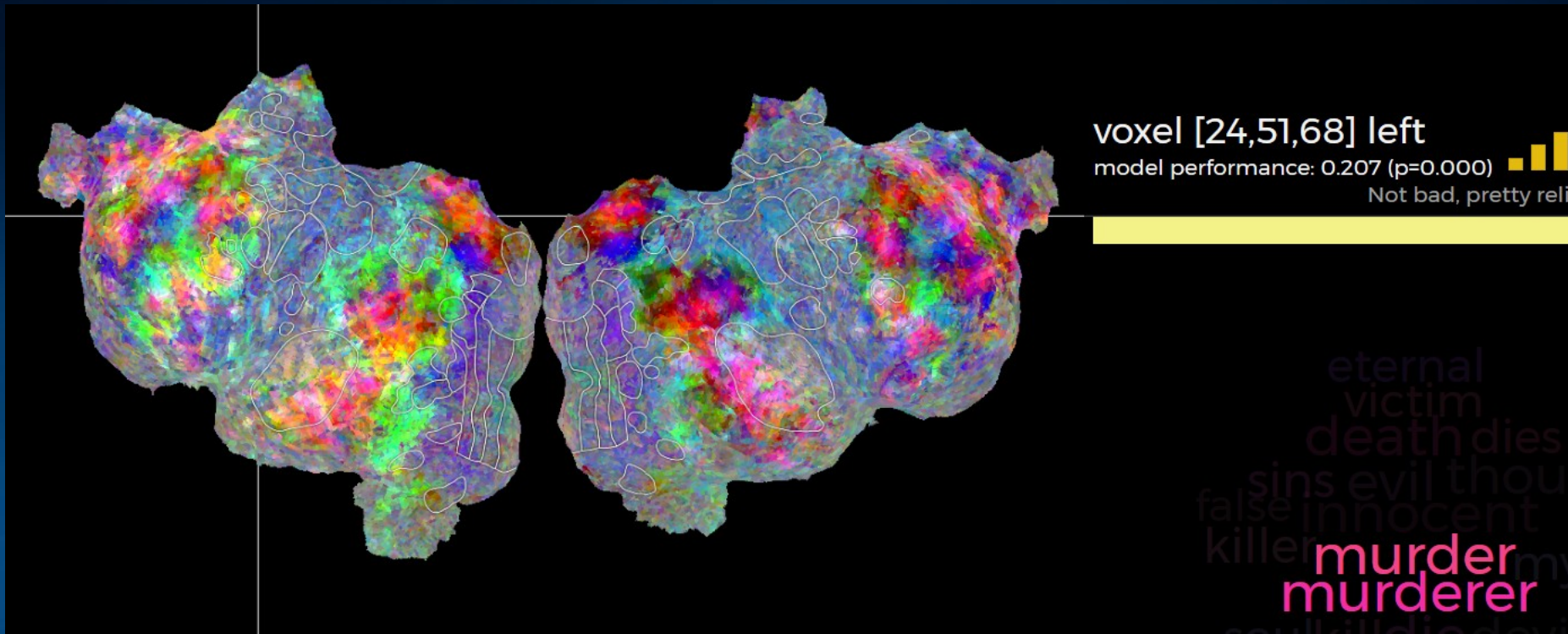
Left hemisphere: precise representations of symbols, including phonological components. Right hemisphere sees clusters of concepts, the gist.



Words in the semantic space are grouped by their similarity. Words activate specific brain maps, similar words create similar maps. Each pixel may be activated by many words.



Each voxel responds usually to many related words, whole categories, but some voxels are quite specific. <http://gallantlab.org/huth2016/>



Each word activates a whole map of activity in the brain.

Whole map for the word “murder” shown on the flattened cortex.

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? If yes, there will be great application opportunities.

Narration

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

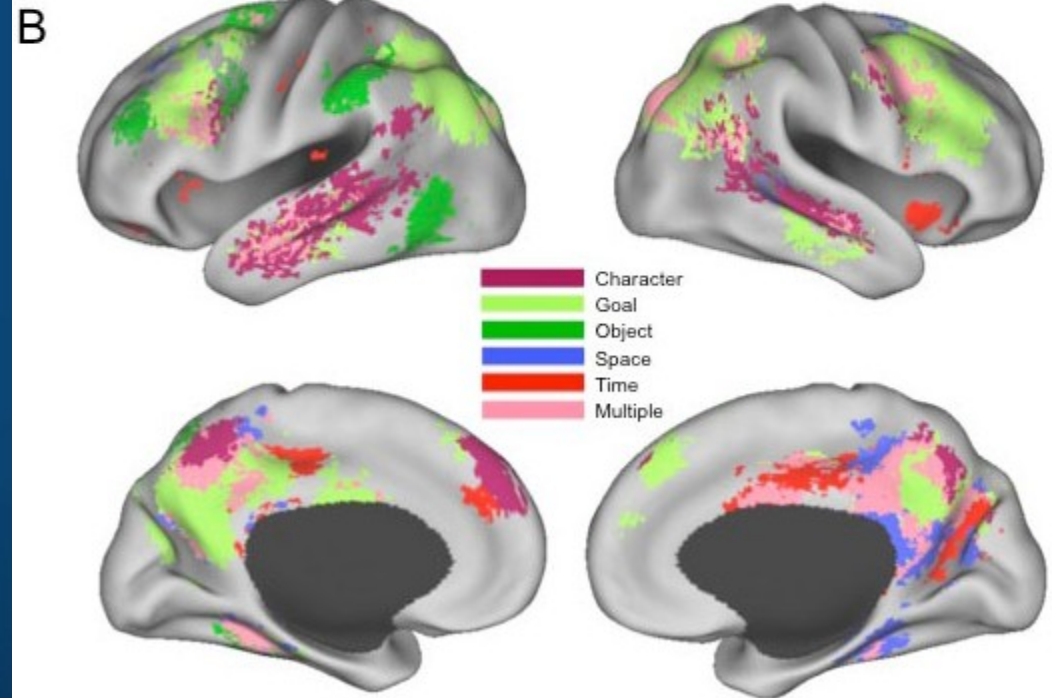
Thought: spatiotemporal pattern

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

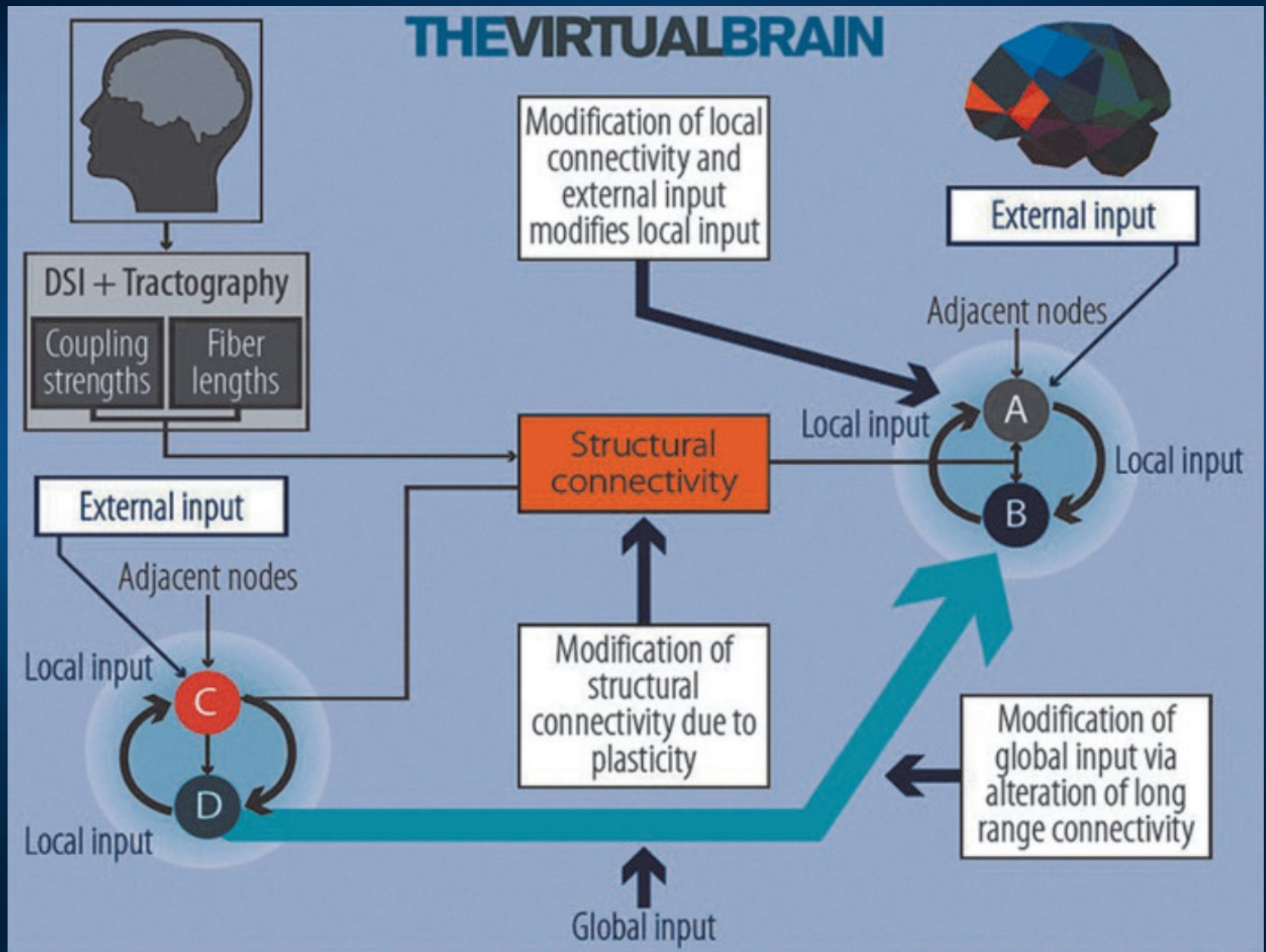
Sentences: trajectories in
 semantic space, building scenes,
 mind models with characters,
 objects, spatio-temporal
 relations.

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.						

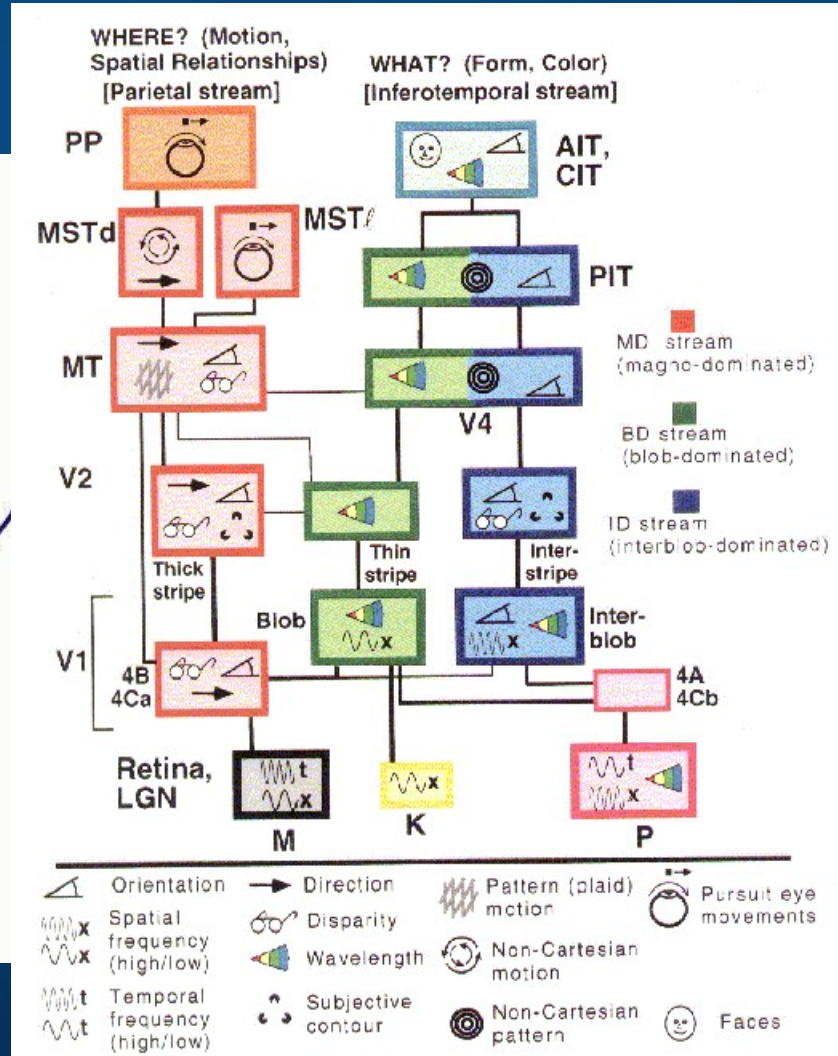
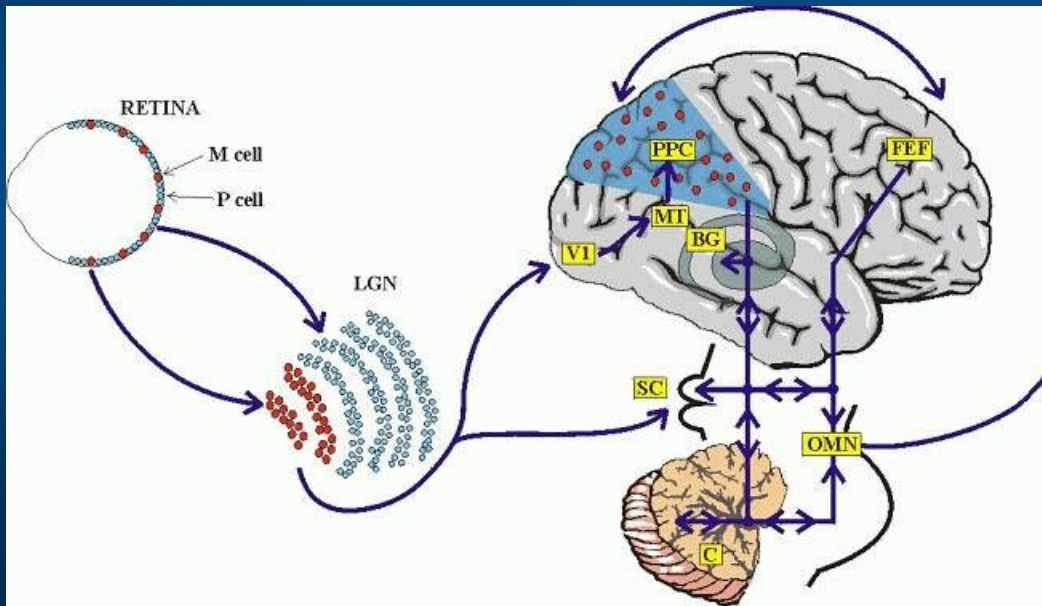


Population dynamics TVB model



Mental images - Vision

From retina through LGN (thalamus, lateral geniculate body) to the primary visual cortex V1, through dorsal and ventral pathways, information flows through many layers, receptive fields react to the complex stimuli in an invariant way.



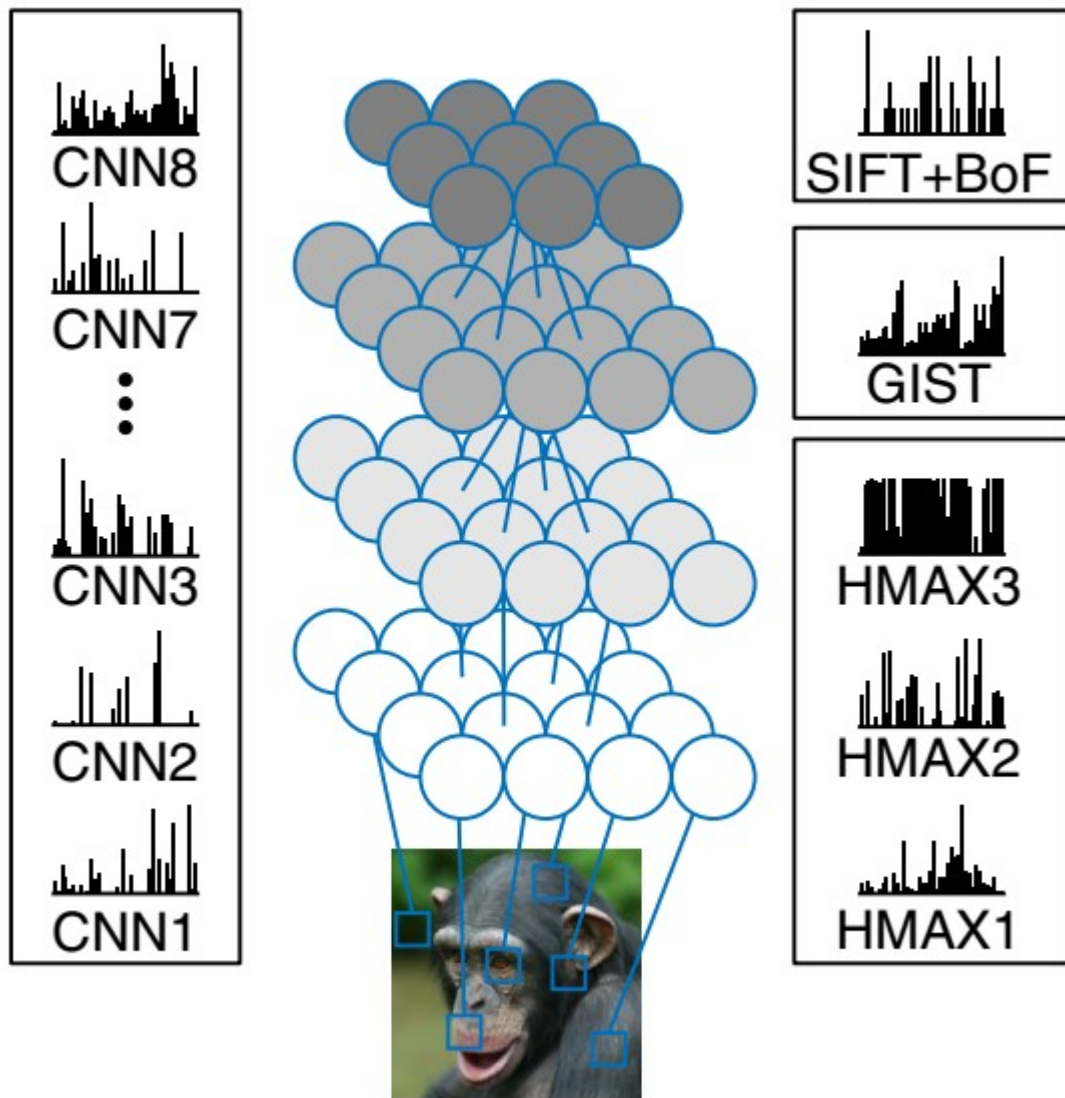
Mental images from brain activity

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

Try to estimate features at different layers.

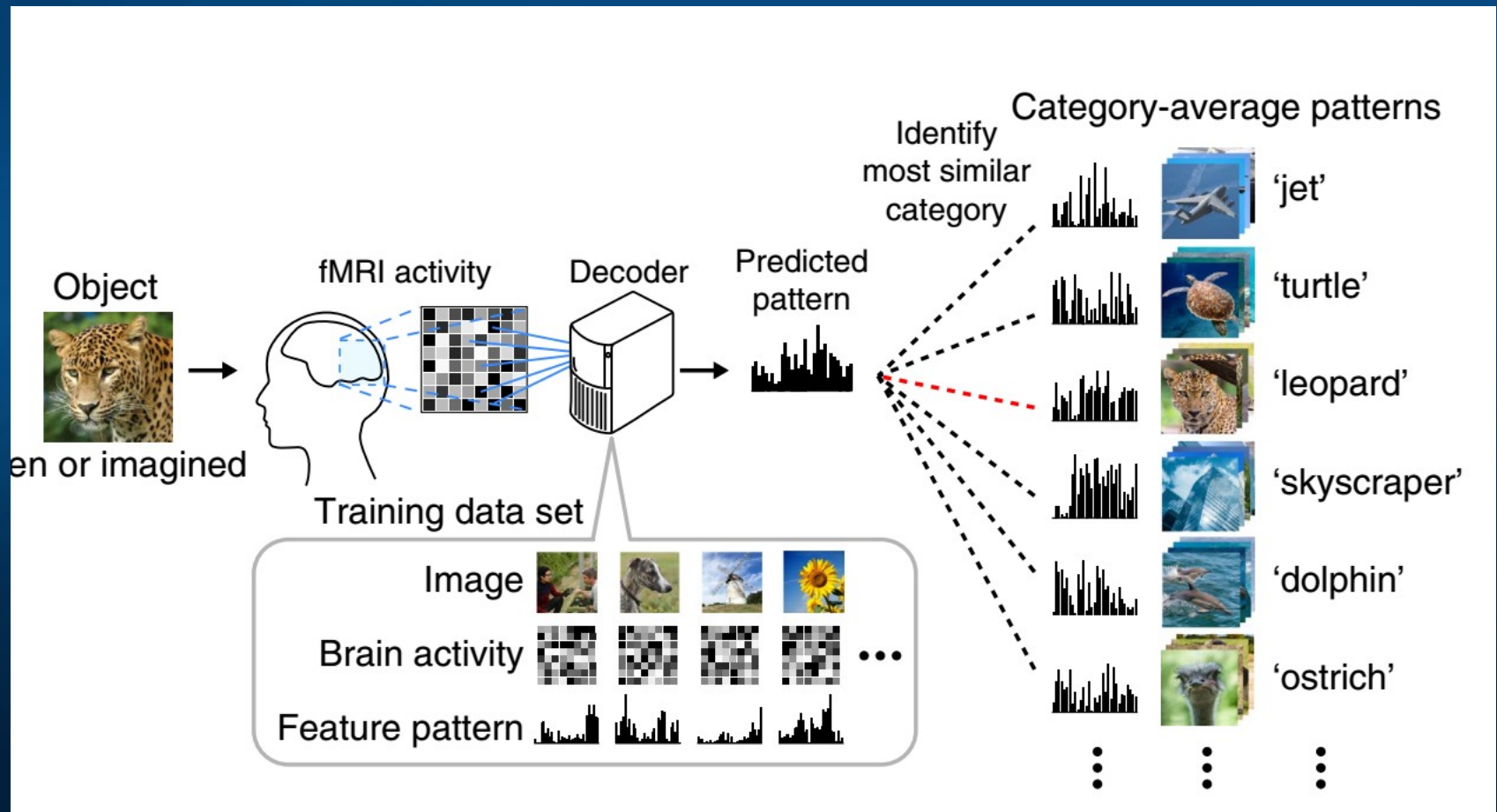
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

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.



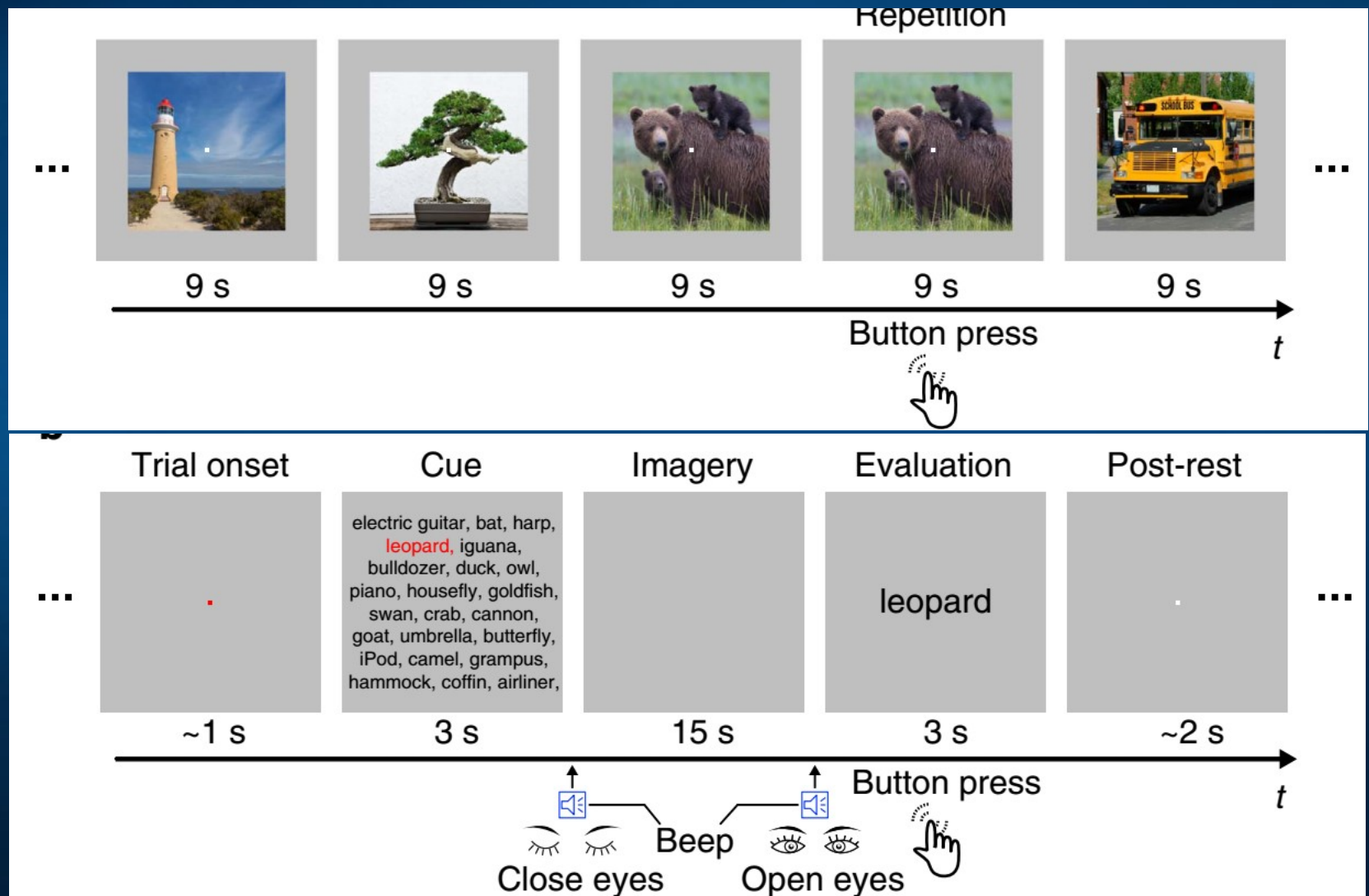
fMRI ↔ CNN

Generic decoding: recognizing also images that did not appear in training.
Data from dreams, imagery, visual activity.

1. Use CNN to analyze >15.000 images O_i from ImagNet database classifying them into 1000 categories; for each image generate 13 types of features (CNN1–8, HMAX1–3, GIST and SIFT + BoF) coded as template feature vectors $V(O_i)$ for images.
2. Analyze fMRI data $F(O_i)$ for 150 image categories (8 examples in each), select 500 voxels for V1–V4, LOC, FFA and PPA responding strongly to images vs scrambled images; decode feature values $V(O_i)$ using regression analysis $R[F(O_i)] = V(O_i)$.
3. For a new image O_n (test, imagery, dream) use regression to calculate feature vector $R[F(O_n)] = V(O_n)$.
4. Find in the database vector $V(O)$ for category of images most similar to the predicted $V(O_n)$, representing mental image, or recreate using activation maximization method an image from $V(O_n)$ vector.

Recognizing mental image

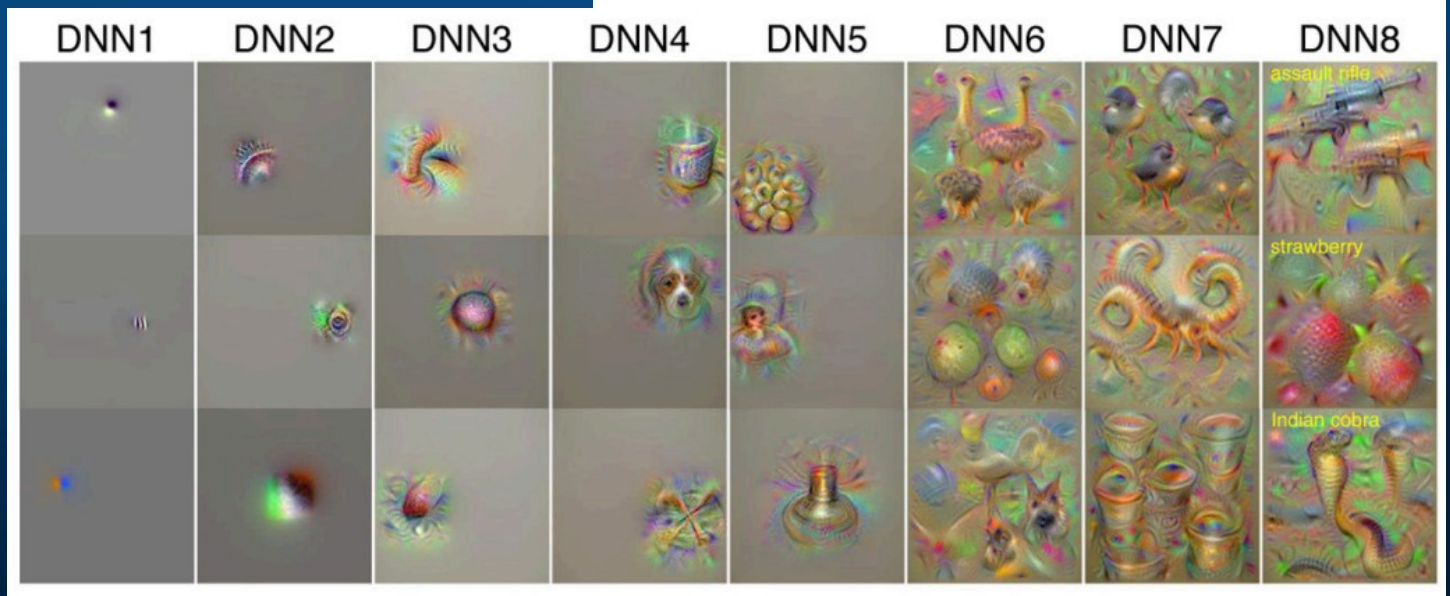
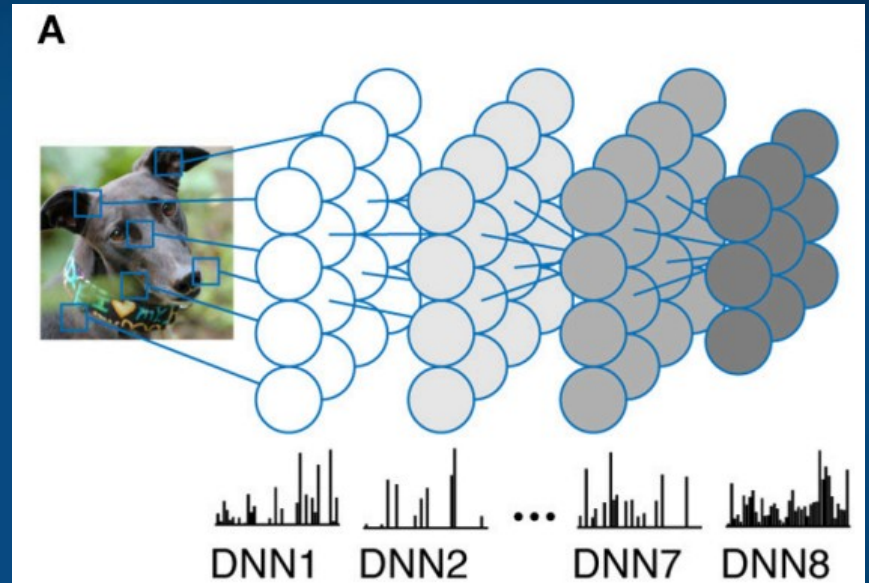
Horikawa, Kamitani, Nature Comm. 2017.



fMRI \leftrightarrow CNN

CNN with 8 layers,
~1000 units selected/layer;
layers 6, 7, 8 are fully connected,
synthesis of preferred images by
the output layer was done using
activation maximization method.

Same approach was used to
decode dreams (Horikawa,
Kamitani, FCN 2017)



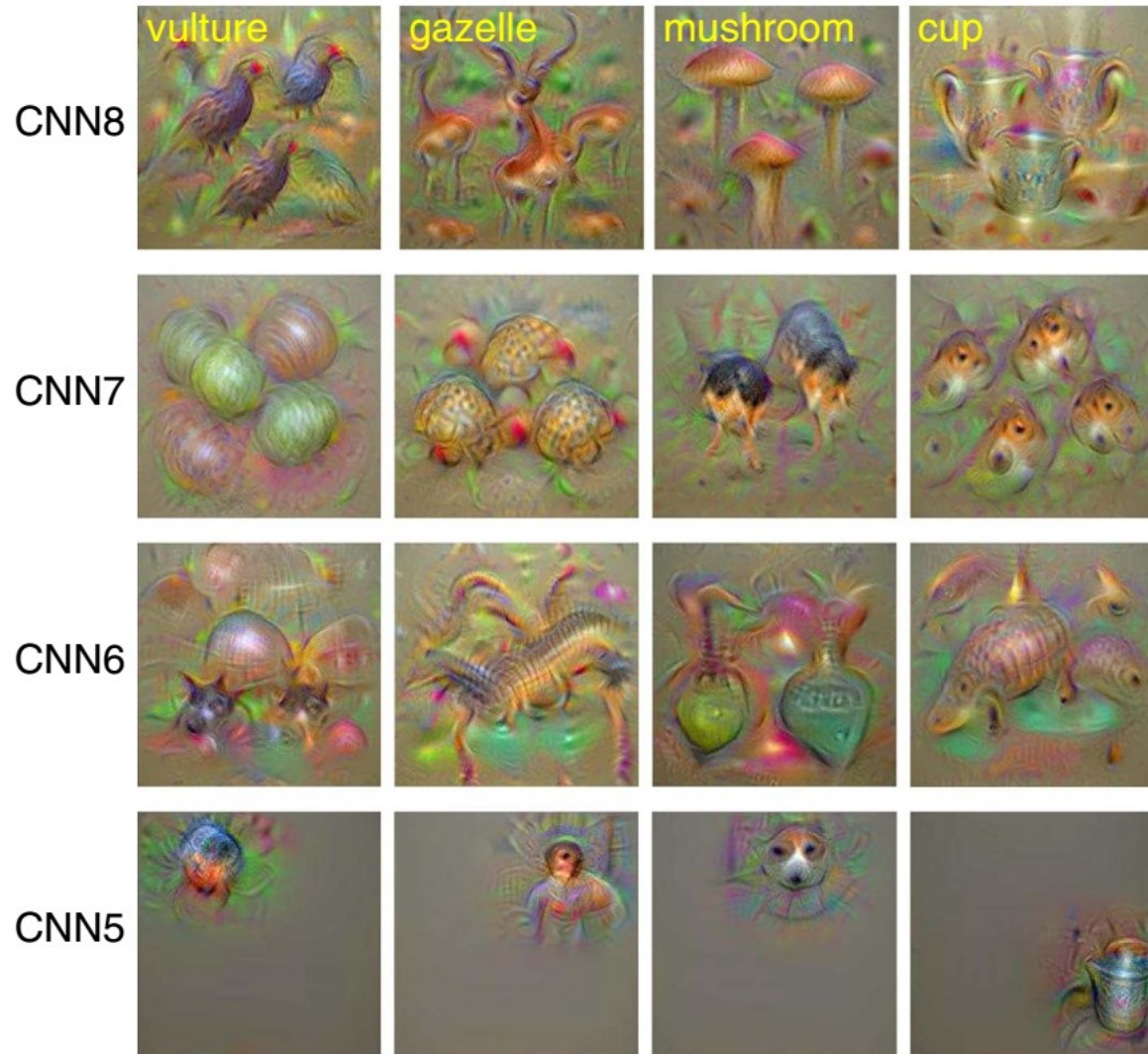
fMRI \leftrightarrow CNN

4 units randomly selected from 1000 in each layer.

Complexity and invariance (rotation, translation, scaling) grows in each layer.

CNN8 has labels for 1000 categories.

Accuracy of seen object can reach >92% and for imagined objects >72%.



CNN preferowane obrazy

CNN8



CNN7



CNN6

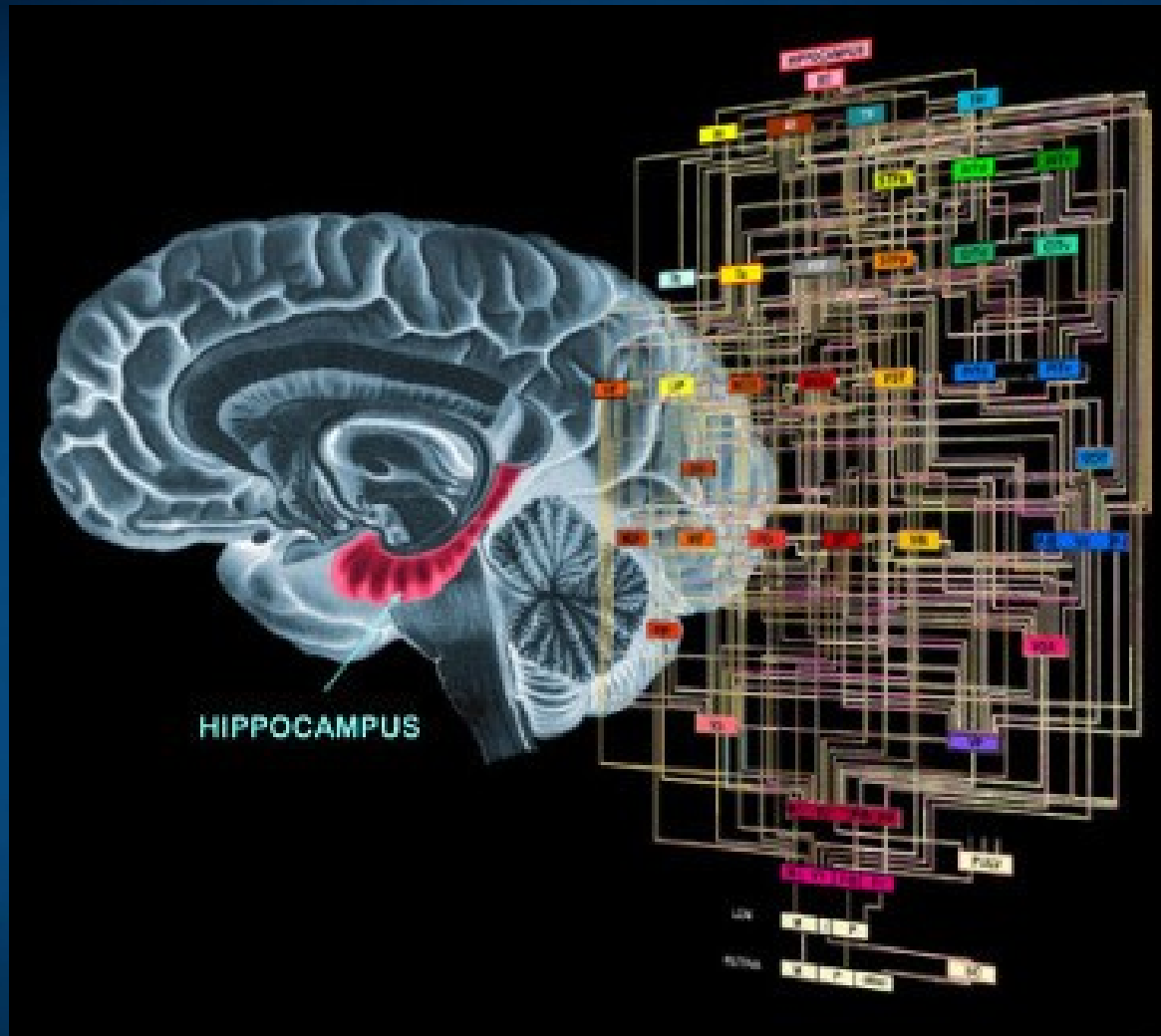


Understanding by creating brains

- “Here, we aim to understand the brain to the extent that we can make humanoid robots solve tasks typically solved by the human brain by essentially the same principles. I postulate that this ‘**Understanding the Brain by Creating the Brain**’ approach is the only way to fully understand neural mechanisms in a rigorous sense.”
- M. Kawato, From ‘Understanding the Brain by Creating the Brain’ towards manipulative neuroscience.
Phil. Trans. R. Soc. B 27 June 2008 vol. 363 no. 1500, pp. 2201-2214
- Humanoid robot may be used for exploring and examining neuroscience theories about human brain.
- Engineering goal: build artificial devices at the brain level of competence.

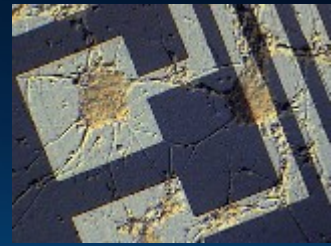


BICA, Brain-Inspired Cognitive Architecture



Understanding subtle mental processes requires a model that should show how internal states create narrative “stream of consciousness”.

The Great Artificial Brain Race



BLUE BRAIN, HBP: École Polytechnique Fédérale de Lausanne, in Switzerland, use an IBM supercomputer to simulate minicolumn.

C2: 2009 IBM Almaden built a cortical simulator on Dawn, a Blue Gene/P supercomputer at Lawrence Livermore National Lab. C2 simulator re-creates 10^9 neurons connected by 10^{13} synapses, small mammal brain.

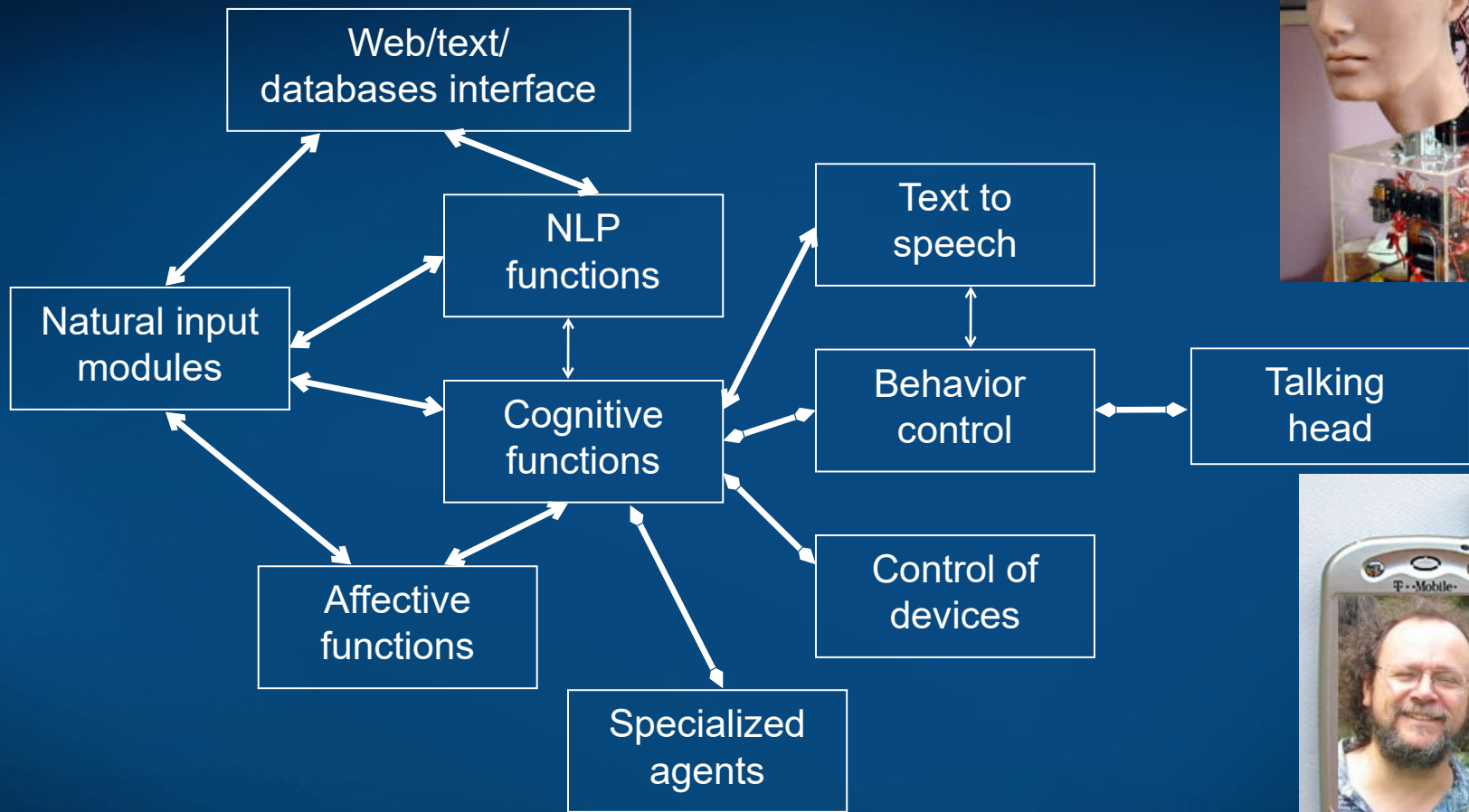
NEUROGRID: Stanford (K. Boahen), developing chip for $\sim 10^6$ neurons and $\sim 10^{10}$ synapses, aiming at artificial retinas for the blind.

IFAT 4G: Johns Hopkins Uni (R.Etienne-Cummings) Integrate and Fire Array Transceiver, over 60K neurons with 120M connections, visual cortex model.

Brain Corporation: San Diego (E. Izhakievich), neuromorphic vision.

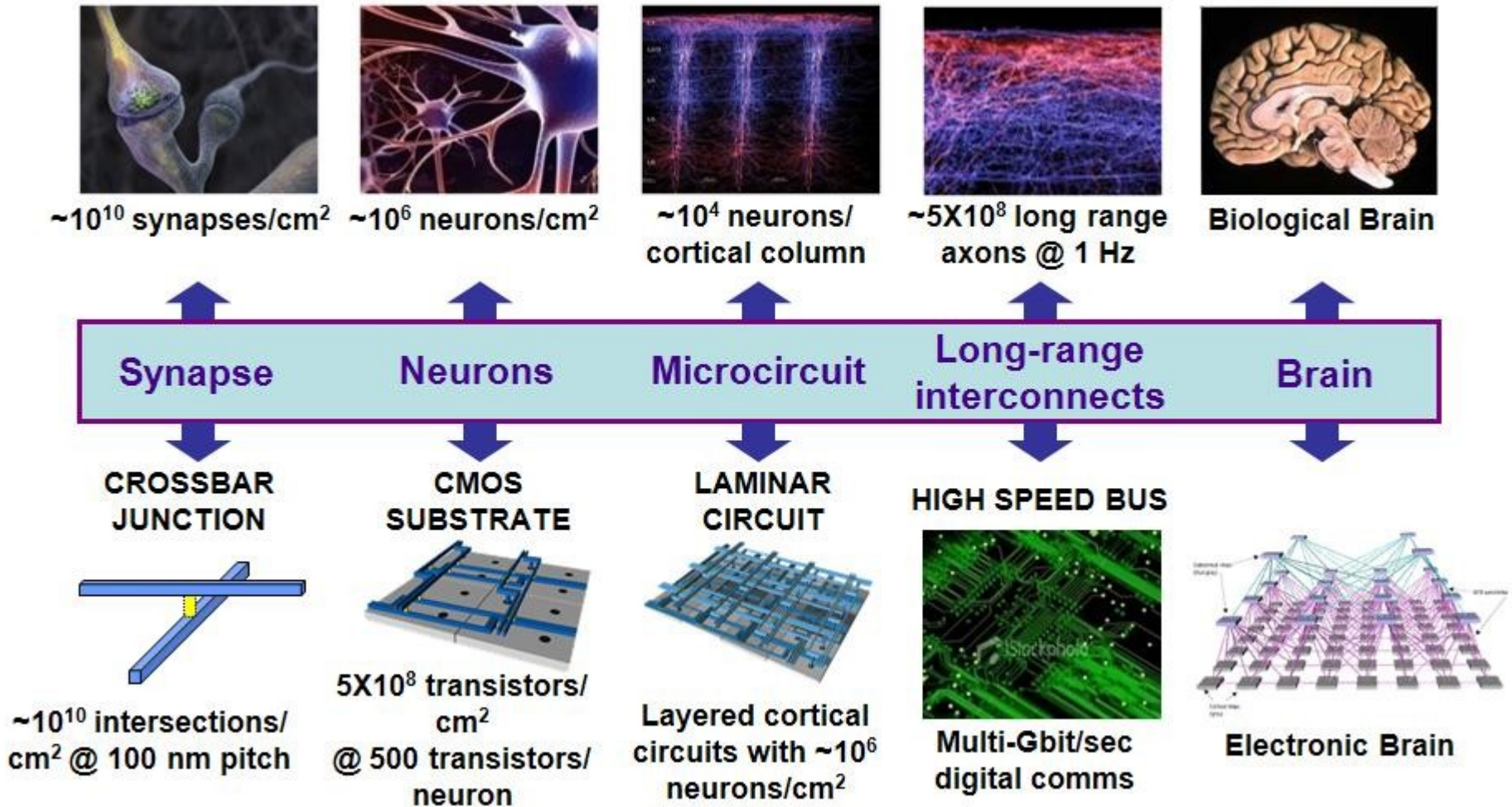
BRAINSCALES: EU neuromorphic chip project, FACETS, Fast Analog Computing with Emergent Transient States, now BrainScaleS, complex neuron model $\sim 16K$ synaptic inputs/neuron, integrated closed loop network-of-networks mimicking a distributed hierarchy of sensory, decision and motor cortical areas, linking perception to action.

DREAM top-level architecture



DREAM project (2003), focused on perception (visual, auditory, text inputs), cognitive functions (reasoning based on perceptions), natural language communication in well defined contexts, real time control of the simulated/physical head. Now Amazon, Google, Apple do it ...

From brains to machines



Source: DARPA Synapse project

Neuromorphic computers

Synapse 2015: IBM TrueNorth chip:

~1M neurons and ¼G synapses, 5.4G transistors, 70 mW.

NS16e module=16 chips=16M neurons, >4G synapses, requires only 1.1 W!

Scaling: 256 modules, ~4G neurons, ~1T= 10^{12} synapses < 300 W power!

IBM Neuromorphic System can reach **complexity of the human brain**.

Integrate & fire neurons,
programming of such
devices will not be easy.

IBM Research created
SyNAPSE University.

Samsung Dynamic Vision
Sensor (DVS) for phones is
based on TN.

Simulation with 5×10^{11}
neurons and $> 10^{14}$
synapses done, 1500x
slower than real time.



Few Steps Towards HLI

IEEE Computational Intelligence Society Task Force (J. Mandziuk & W. Duch),
Towards Human-like Intelligence.

IEEE SSCI The 5th IEEE Symposium on Computational Intelligence for Human-like Intelligence, Honolulu, HAWAII, USA, Nov. 27 – Dec. 1, 2017.

World Congress of Computational Intelligence 2014, Special Session:
Towards Human-like Intelligence (A-H Tan, J. Mandziuk, W. Duch)



AGI: conference, Journal of Artificial General Intelligence comments on Cognitive Architectures and Autonomy: A Comparative Review (eds. Tan, Franklin, Duch).

BICA: Annual International Conf. on Biologically Inspired Cognitive Architectures, 8rd Annual Meeting of the BICA Society, Moscow, August 1-5, 2017

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

Conclusions



- We begin to understand the mappings between brain states and mental images – but its still a tip of iceberg.
- Neurodynamics and neurocognitive phenomics are the key.
- Brains solve the frame problem by creating dynamical search spaces that restrict all plausible interpretations/solutions.
- Brain neuroimaging \Leftrightarrow The Virtual Brain, graphical models \Leftrightarrow mental models.
- Neuromorphic hardware is coming and will enable construction of new brain models and many applications.

Is there a shorter route
to deep understanding of human behavior?

My group of neuro-cog-fanatics



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

konferencja studencko-doktorancka
NeuroMania IV
28-29 maja 2016, Toruń



HOMO COMMUNICATIVUS
WSPÓŁCZESNE OBlicZA KOMUNIKACJI I INFORMACJI

Toruń, 24-25 VI 2013 r.



Cognitivist Autumn in Toruń 2011
PHANTOMOLOGY:
the virtual reality of the body
2011 Torun, Poland



Cognitivist Autumn in Toruń 2010
MIRROR NEURONS:
from action to empathy
April, 14-16 2010 Torun, Poland



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

Disorders of consciousness
17-21.09.2017

Autism: science, therapies
22.05.2017



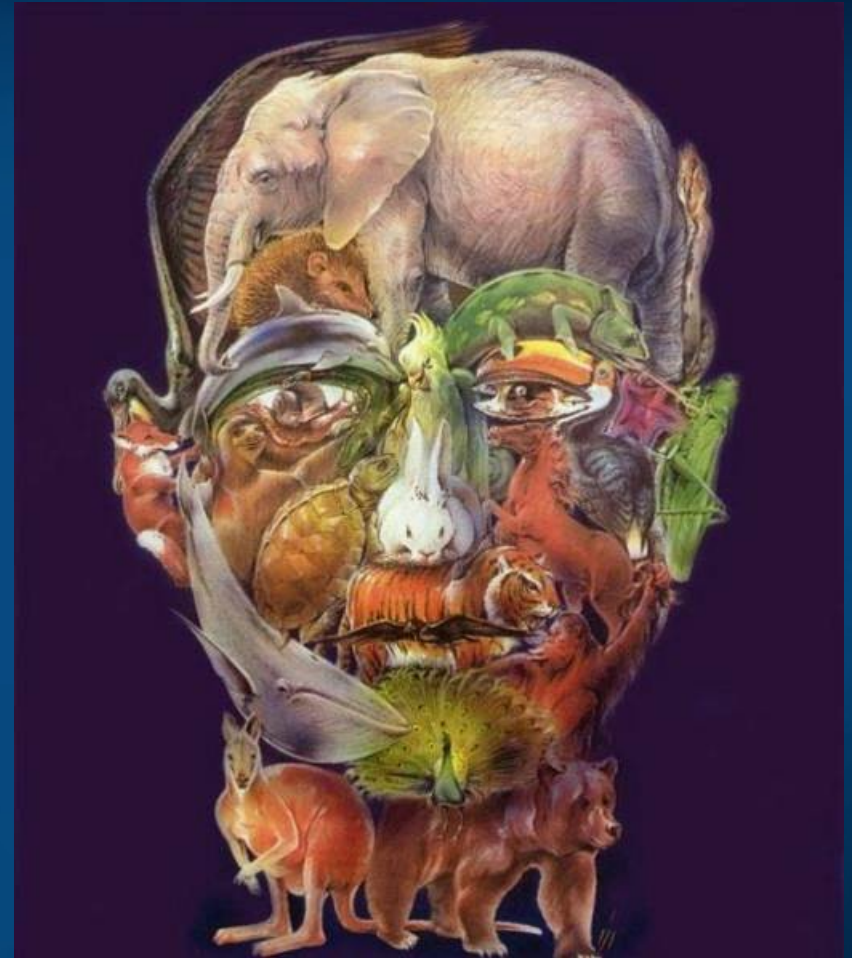
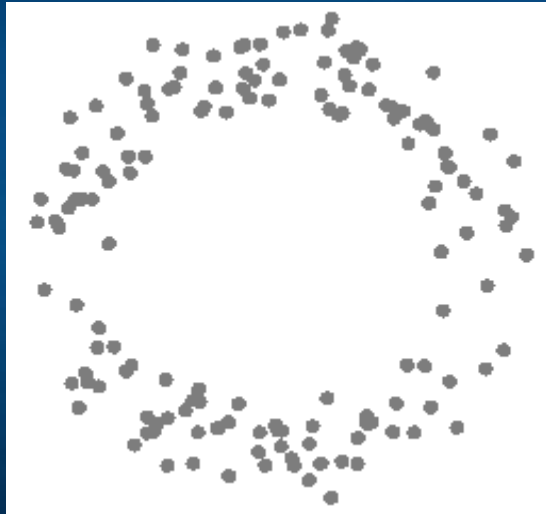
NEURO

HISTORY OF ART



**COGNITIVIST
AUTUMN IN
TORUŃ**

Thank for
synchronization
of your neurons



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

Projekty

Google W. Duch => Projects => List of Projects

1. In the quest of sources of brain cognitive activity, NCN 2016-21
2. Platonic theory of mind as a shadow of neurodynamics
3. Understanding neurodynamics through visualization
4. Development of phonematic hearing and working memory in infants and children (NeuroPerKog). NCN 2013-18
5. Neurocognitive approach to language
6. Conspiracy theories and formation of beliefs
7. Imagery agnosia
8. Computational creativity
9. Semantic spaces and word games
10. A test-bed for integration of different Humanized Interface Technologies
11. Meta-learning, or learning how to learn

Książki

Książki (+16 red. Artificial Neural Networks):

- 1999: Duch W, Kucharski T, Gomuła J, Adamczak R, *Metody uczenia maszynowego w analizie danych psychometrycznych. Zastosowanie do wielowymiarowego kwestionariusza osobowości MMPI-WISKAD*, 650 str.
- 2000: Duch W, Korbicz J, Rutkowski L, Tadeusiewicz R (Eds), *Sieci neuronowe. Seria: Biocybernetyka i Inżynieria Biomedyczna, Tom 6: AOW EXIT*, 850 str.
- 2007: Duch W, Mandziuk J (Eds.), *Challenges for Computational Intelligence*. Springer, 488 pp.
- 2011: Jankowski N, Duch W, Grąbczewski K, *Meta-learning in Computational Intelligence*. Springer, 362 pp.
- 2013: *Sieci neuronowe w inżynierii biomedycznej. Red. Tadeusiewicz R, Korbicz J, Rutkowski L, Duch W.* Wyd. Exit, Warszawa, str. 775.
- 2017: Mikołajewski D, Duch W, *Pień mózgu. Przybliżenie aspektów medycznych dzięki modelowaniu biocybernetycznemu*. WN UMK, 220 str.

Granty

Trzy granty doktorantów:

- Ewa Ratajczak - grant Preludium: BrainHeart. BrainHeart. Wpływ treningu HRV-biofeedback na dynamikę procesów uwagowych oraz myślenie dywergencyjne" (2016-17).
- Jan Nikadon - diamentowy grant "Kierunkowe związki przyczynowe pomiędzy zrekonstruowaną aktywnością bioelektryczną węzłów sieci uwagowej: nowa metoda i przykład jej praktycznego zastosowania w badaniu EEG".
- Karolina Finc – grant Preludium, Dynamika czasowa w przebiegu zmian połączeń funkcjonalnych indukowanych przez trening poznawczy. Rola różnic indywidualnych.
- W.D. Autyzm: zintegrowane ujęcie. Grant MNiSW (2010-2012).

EU Projects

- 2014-2006 EUCog 1, 2, 3 - European Network for the Advancement of Artificial Cognitive Systems, Interaction and Robotic, FP7 coordination action.
- 2012, SINTELNET, EU FET Coordination Project in Social Intelligence (with R. Wójcickim, M. Miłkowskim, IFIS PAN).
- 2012, Confluence of humans and computers, EU FP7 FET Proactive Consultation Panel.
- 2009-2012, 2nd European Network for the Advancement of Artificial Cognitive Systems, Interaction and Robotics, FP7 EU Networks Project.
- 2008-2012, COST Action BM0605 "Consciousness: A Transdisciplinary, Integrated Approach" , EU COST Project
- 2008-2012, COST Action BM0601 NeuroMath "Advanced Methods For The Estimation Of Human Brain Activity And Connectivity", EU COST Project
- 2008-2010, Argumentation as cognitive process, UMK - Rutgers University
- 2005-2007, COST Action B27 Group, "Electric neuronal oscillations and cognition (ENOC)", EU COST Project.

Zajęcia

Obecnie:

- Wstęp do kognitywistyki, część I: Natura umysłów.
- Wstęp do kognitywistyki, część II: Mózg, umysł i zachowanie.
- Sieci neuronowe - wykład dla IS, S2.
- Sztuczna Inteligencja i systemy ekspertowe - wykład kursowy IS S1

Wcześniej:

- Przetwarzanie informacji przez mózgi - wykład monograficzny (2012).
- Modelowanie Funkcji Mózgu - wykład monograficzny.
- Jak działa mózg (2008/2009).
- Neuropsychologia komputerowa, SWPS 2007, 30 g+15 g lab.