Mapping psychological concepts on higher order brain dynamics

Włodzisław Duch

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

Google: Wlodzislaw Duch

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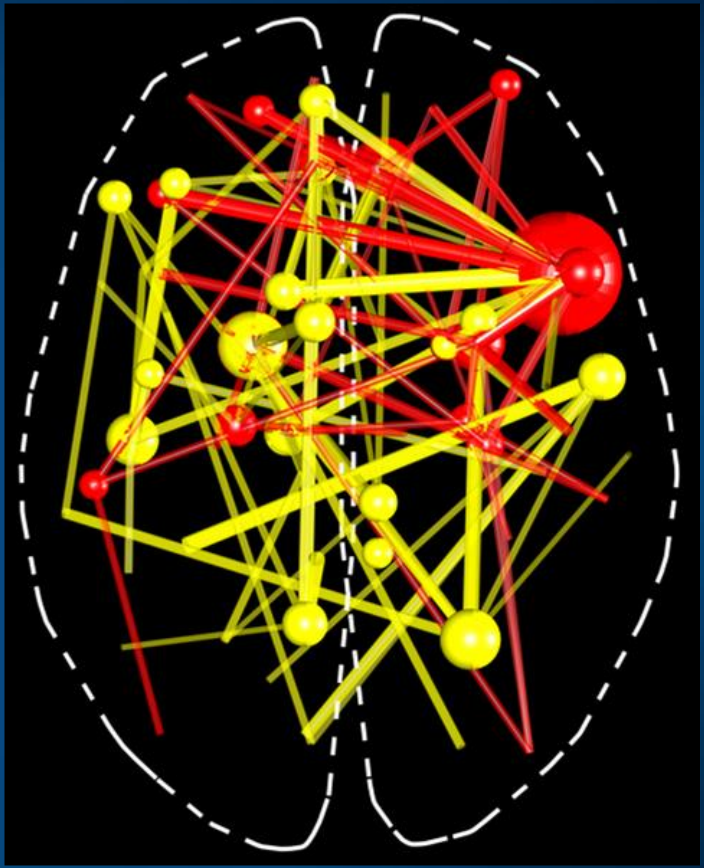
Questions

What is the best way to understand and create human-like intelligence?

- What is a proper level for understanding brain-behavior relations?
- How to decompose brain dynamics in a meaningful way?
- Do functional brain networks change with the cognitive load?
- Can we see mental images in the brain?
- Will it help to create brain-inspired cognitive architectures?



Duch W (1994) Towards Artificial Minds. First PNNS Conference, Kule 1994

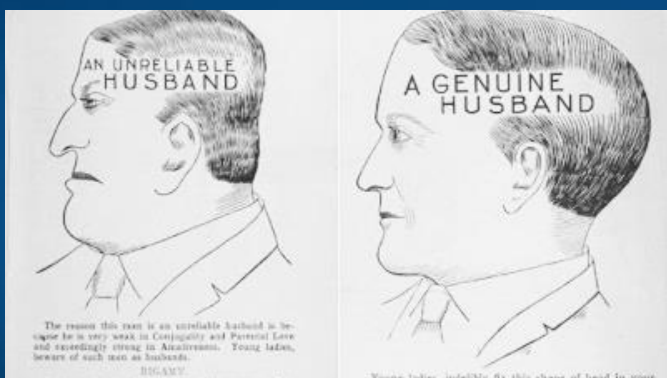
Duch W (2009), Neurocognitive Informatics Manifesto. California Polytechnic State University, pp. 264-282.

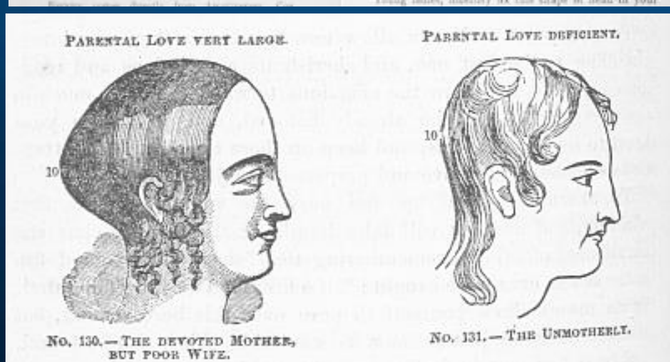
My favorite organ! Where is mind?

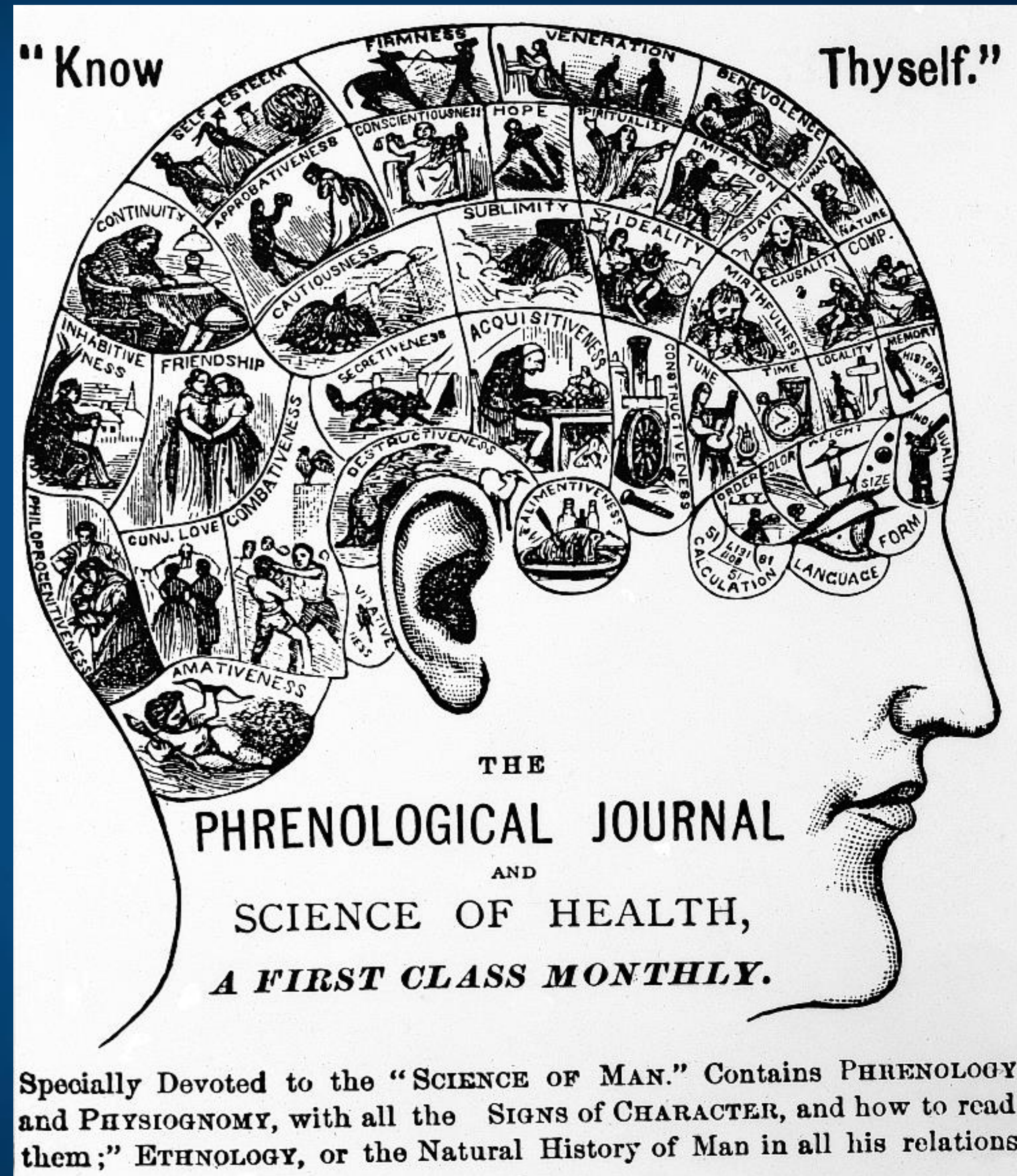
Phrenology

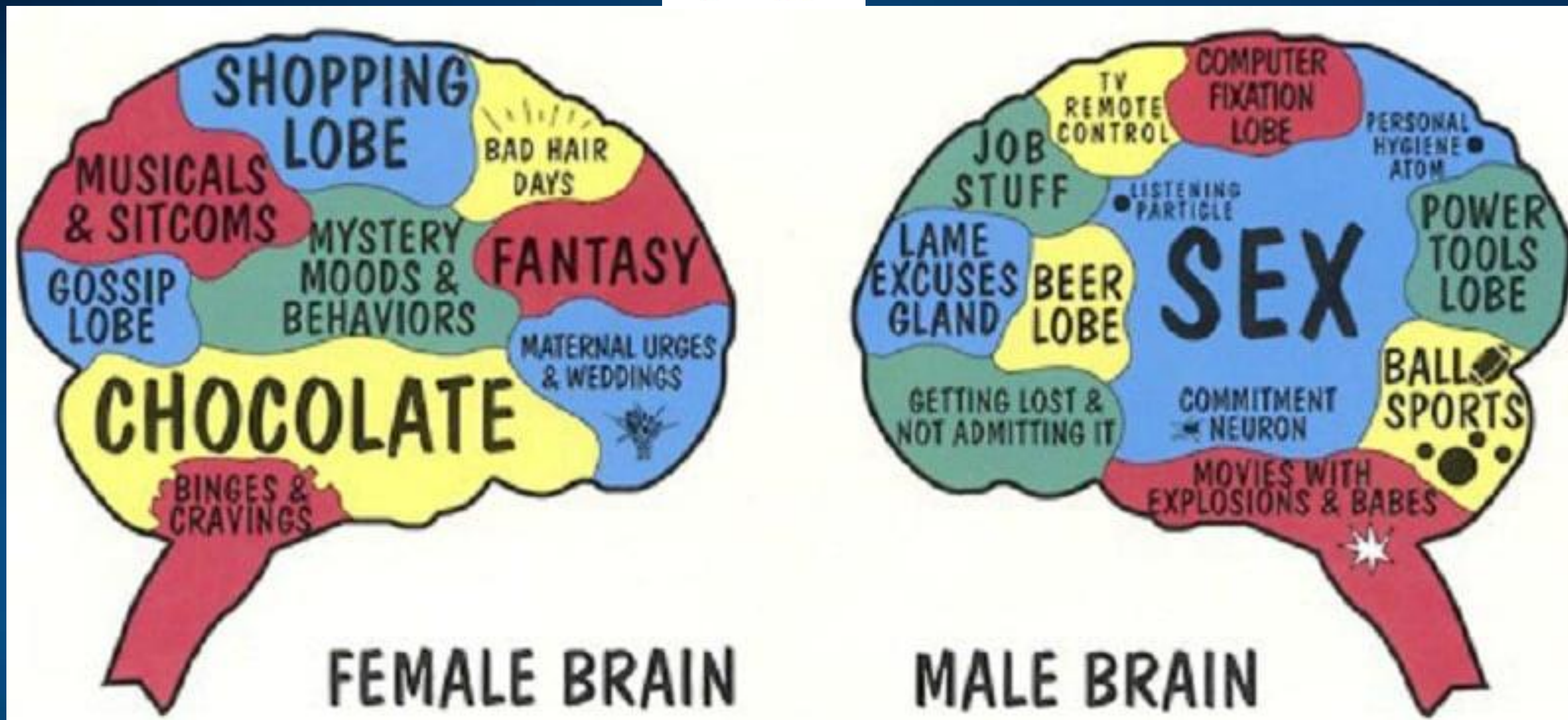
Phrenology was popular in 19 century. The scull was divided in 35 areas with specific functions.

Amativness, friendship, self esteem, hope, wit, veneration …









This is also not what we have in the brain …

But there are many neuromyth and pseudo-scientific organizations that promote ideas at this level.

Ex: Structogram Training System, Genetic Code for Personality.

Phenomics

Phenomics is the branch of science concerned
with identification and description of measurable
physical, biochemical and psychological traits of organisms.
Gen*om, 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 <= phenotypes at all levels.
Still many white spots on maps of various phenomes.

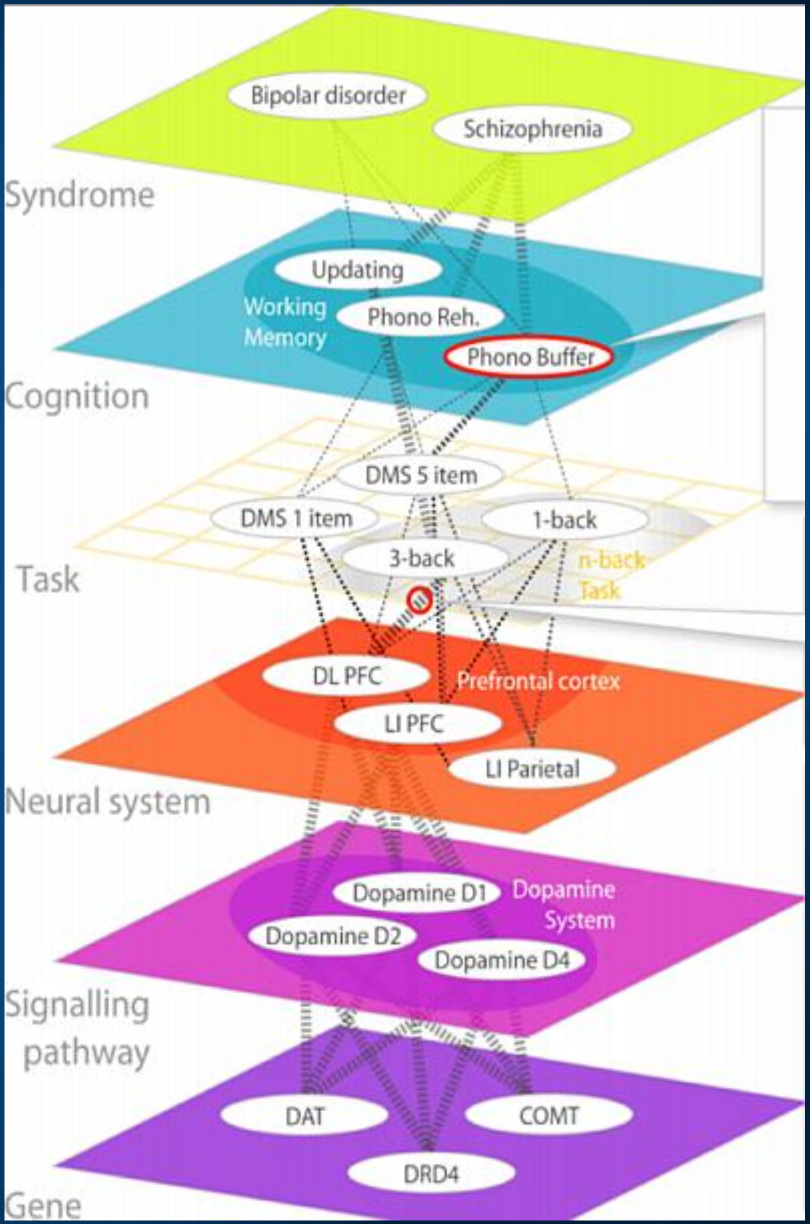
Can neurocognitive phenomics be developed to understand general behavior of people and find better ways for flexible artificial intelligence?

Neuropsychiatric Phenomics in 6 Levels

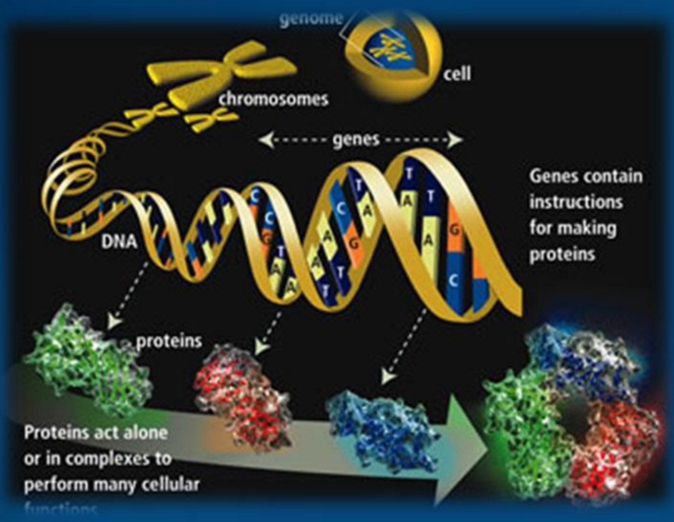
Consortium for Neuropsychiatric Phenomics (CNP)/NIMH RoDC approach:

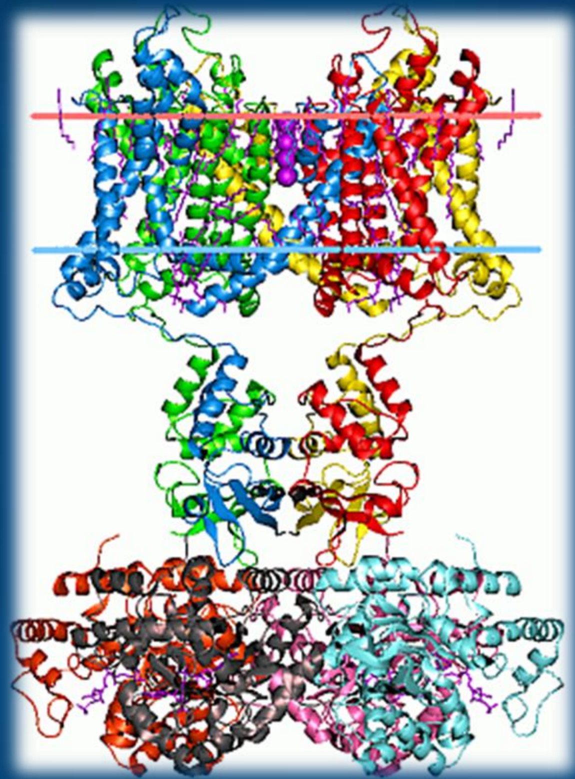
Research Domain Criteria (RoDC) analyzes 5 large brain systems – negative/positive valence systems, arousal, cognitive, affective systems – through interaction of Genes, Molecules, Cells, Circuits, Physiology, Behavior, Self-Report, and Research Paradigms.

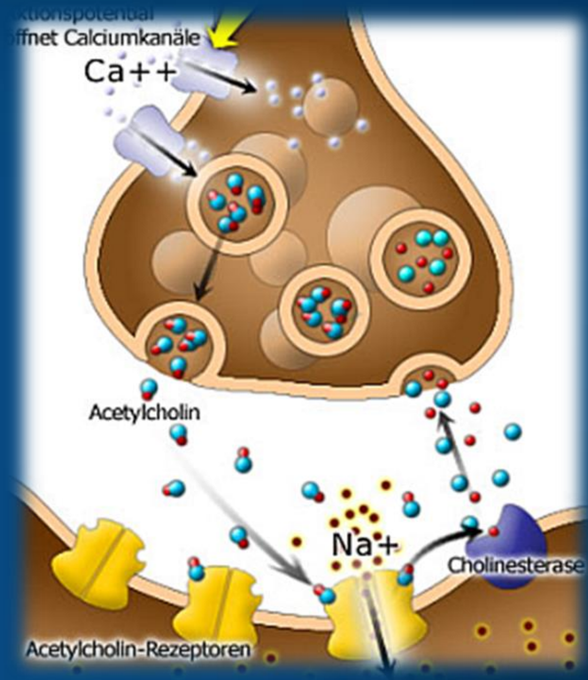
From genes to cognitive subsystems and behavior, neurons and networks are right in the middle of this hierarchy.
=> Neurodynamics is the key!



From Genes to Neurons

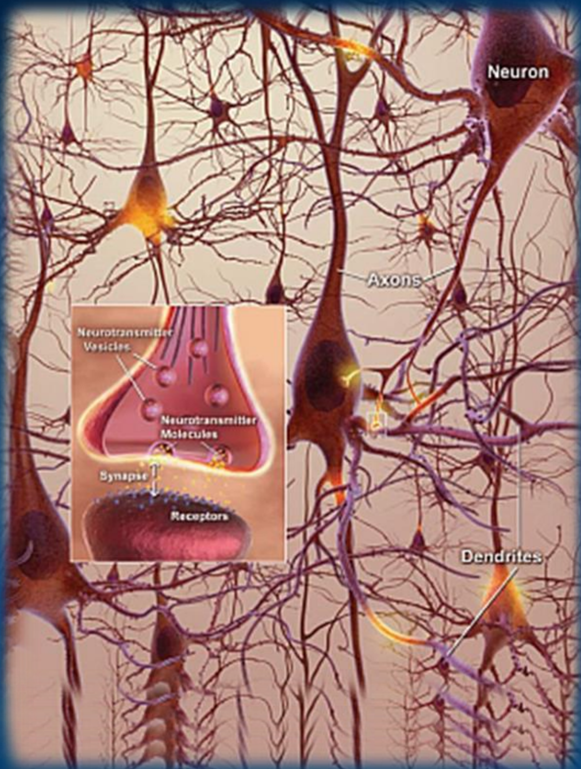


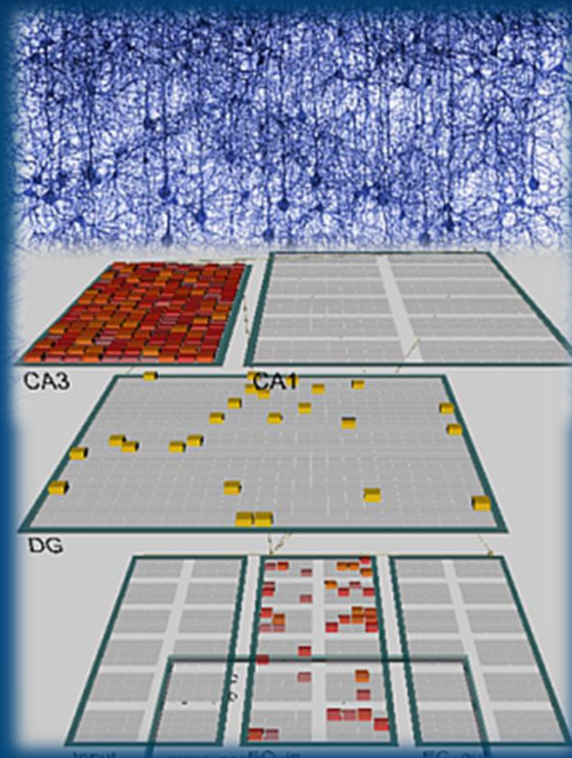




Genes => Proteins => receptors, ion channels, synapses
=> neuron properties, networks, neurodynamics
=> cognitive phenotypes, abnormal behavior, syndromes.

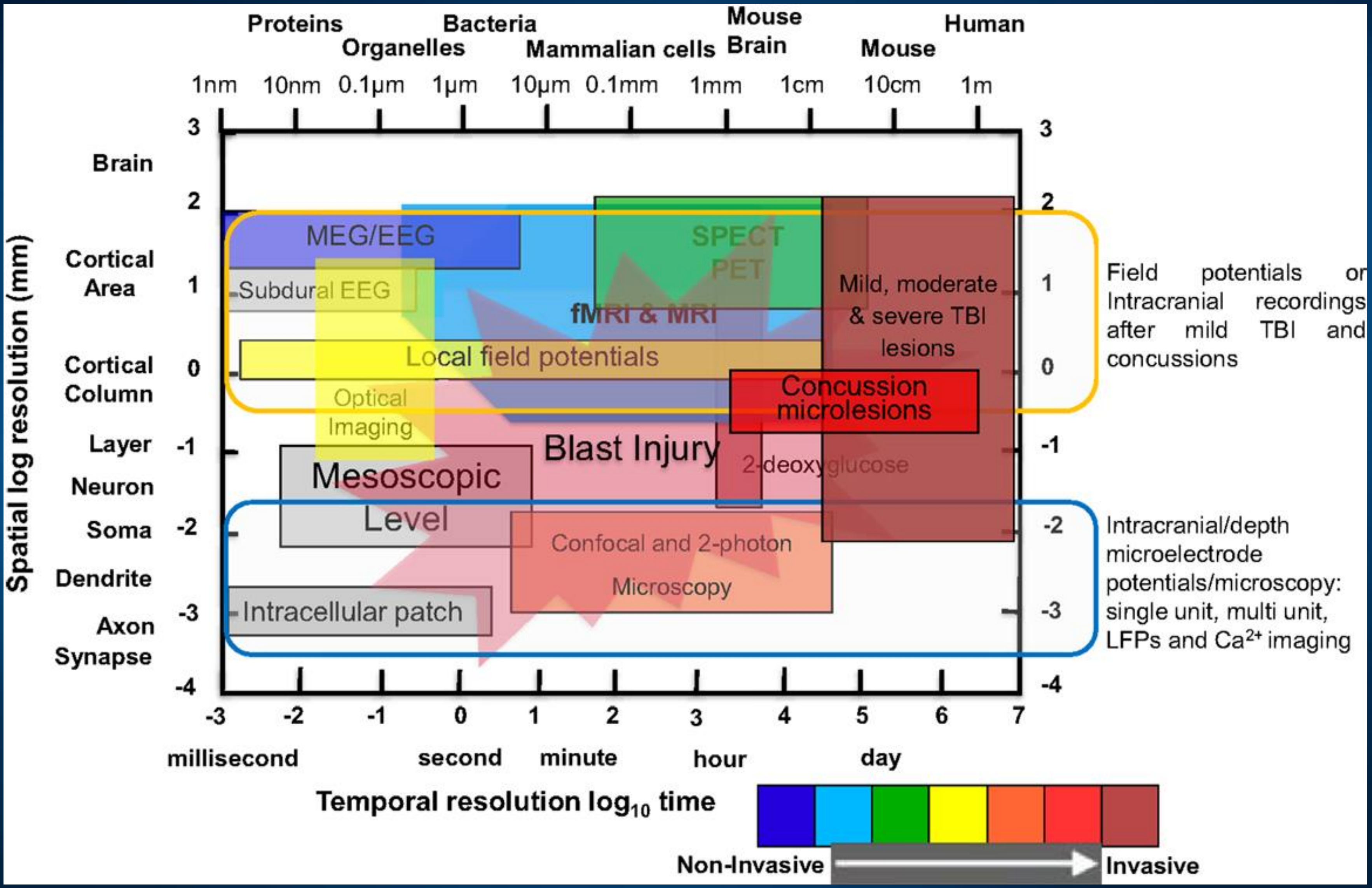
From Neurons to Behavior



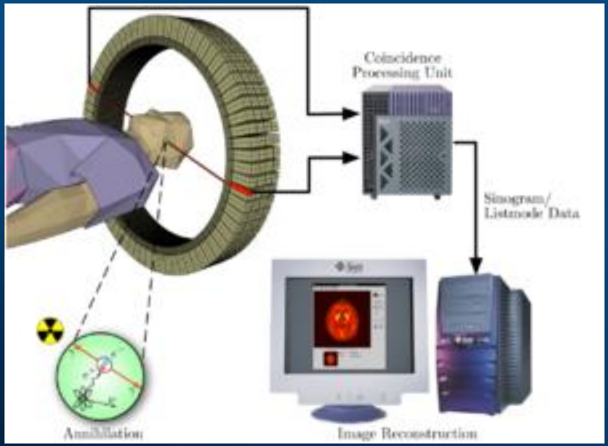


Genes => Proteins => receptors, ion channels, synapses
=> neuron properties, networks
=> neurodynamics => cognitive phenotypes, abnormal behavior!

Experimental techniques

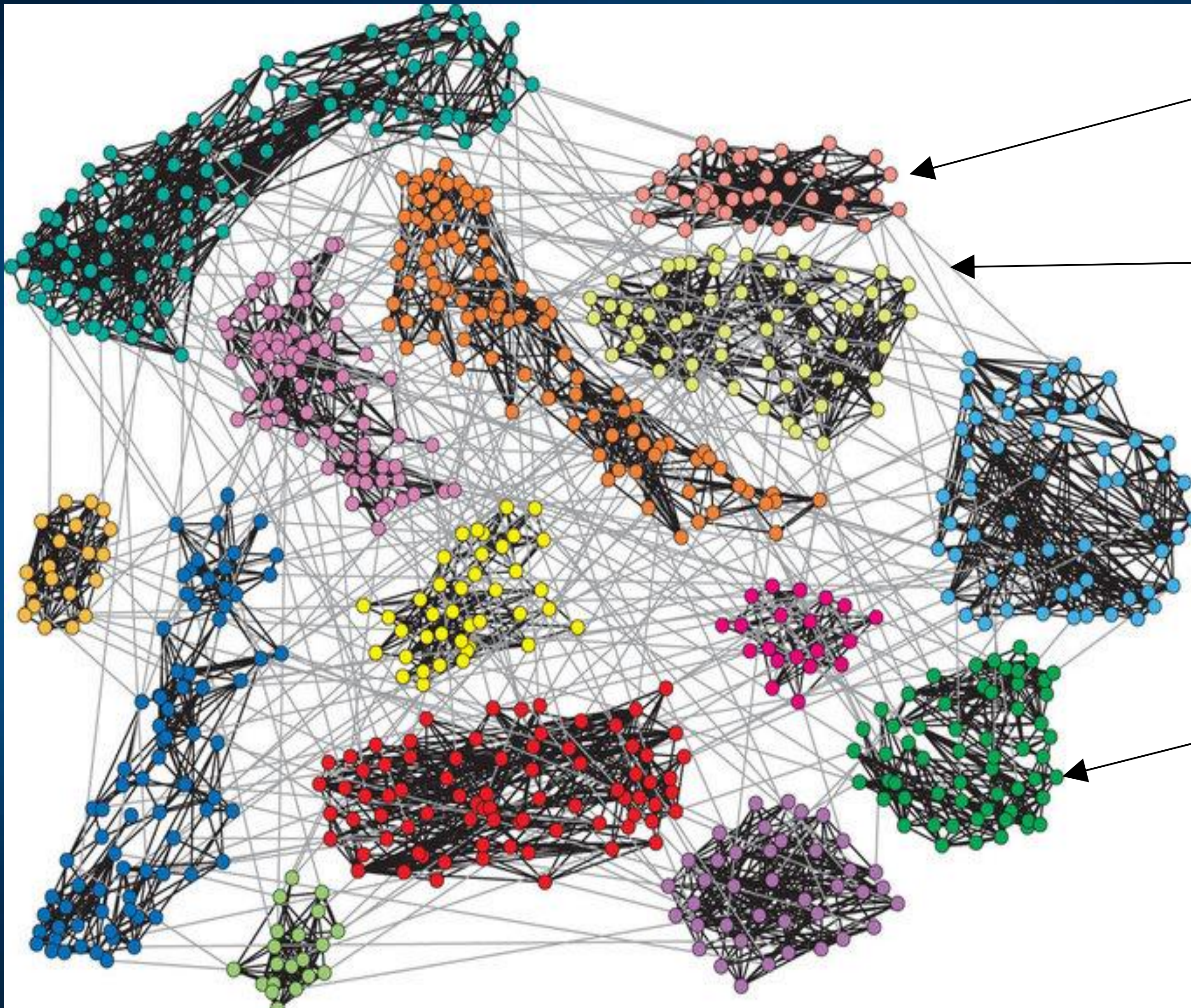


Neuroimaging



ICNT: scanner GE Discovery MR750 3T

Brain networks

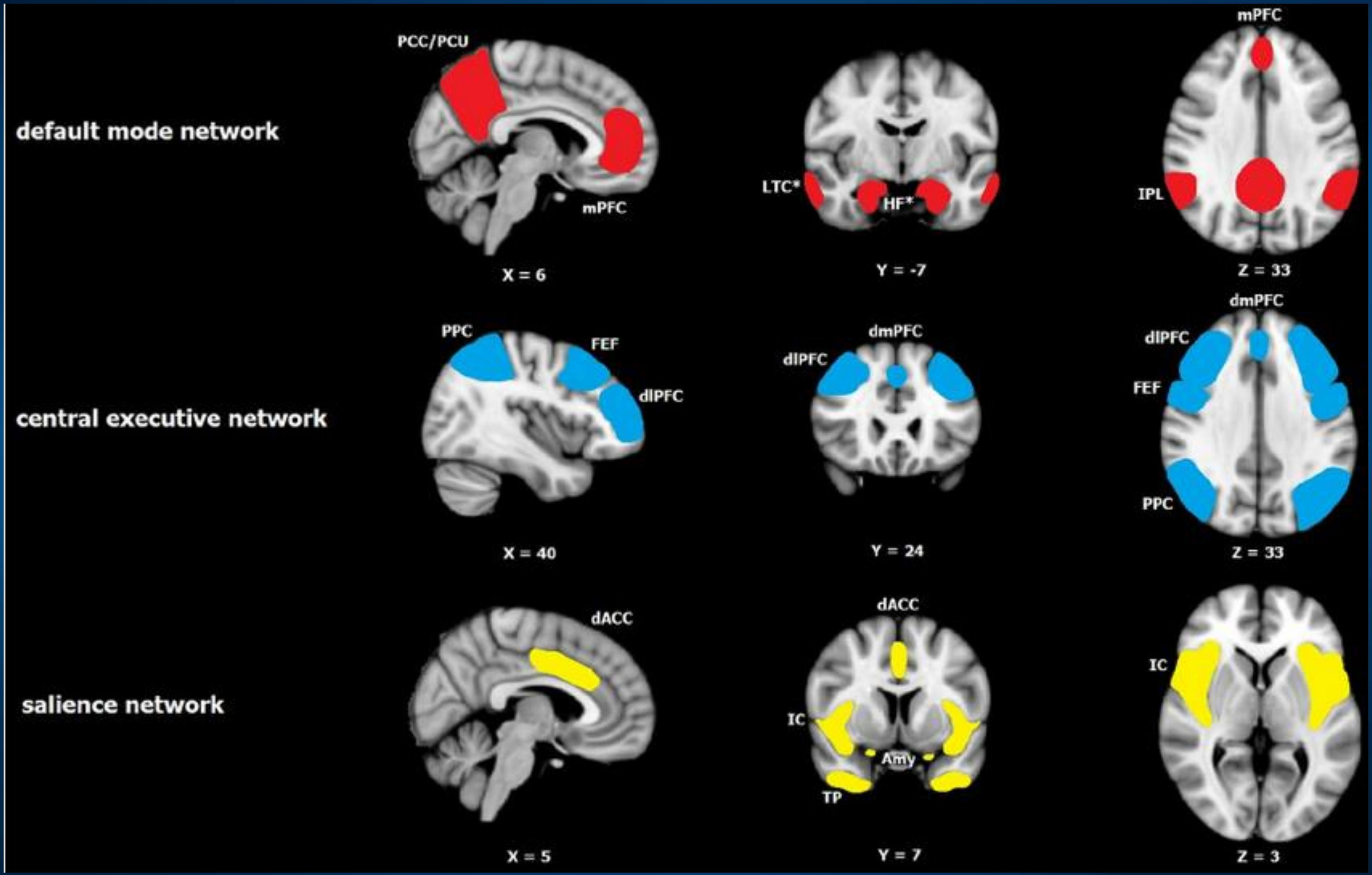


Brain regions

Connections

Nodes

DMN, CEN and SN networks



Mulders et al. (2015)

RDoC

Research Domain Criteria Initiative

NIMH RDoC Matrix for deregulation of large brain systems.

Instead of classification of mental disease by symptoms use **Research Domain Criteria** (RDoC) 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.

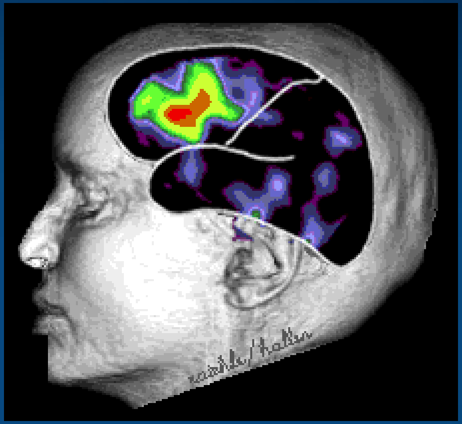
RDoC Matrix for „cognitive domain”

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

Geometric model of mind

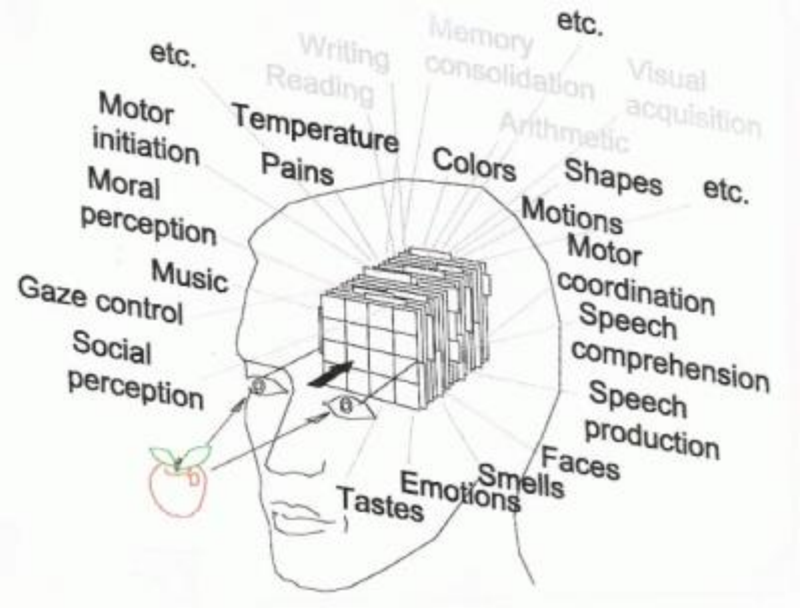
Brain ⇔ Psyche

Objective ⇔ Subjective



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

Mapping S(M)⇔S(B) but how do we describe the state of mind?



Verbal description is not sufficient.
A space with dimensions that measure different aspects of experience is needed.

Mental states, movement of thoughts ⇔ trajectories in psychological spaces.

Problem: good phenomenology. We are not able to describe our mental states.

Hurlburt & Schwitzgabel, Describing Inner Experience? MIT Press 2007

Psychological spaces

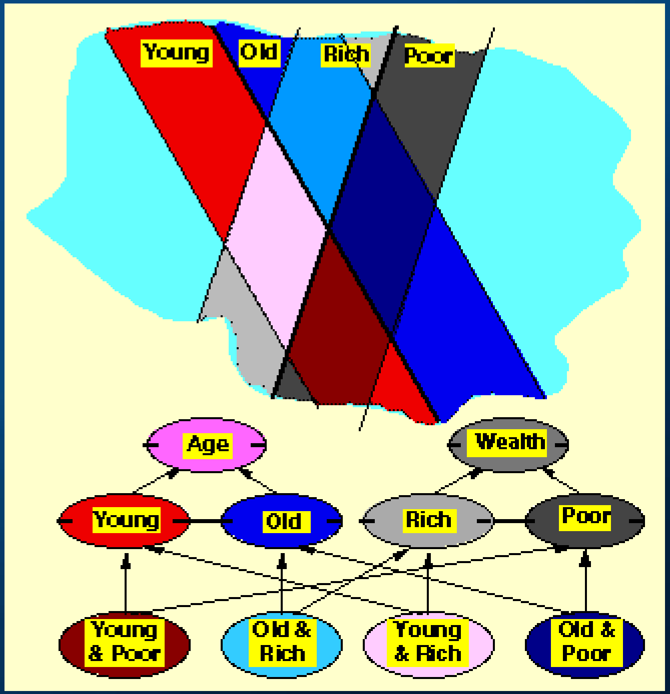
Psychological spaces:

Kurt Lewin, The conceptual representation and the measurement of psychological forces (1938), cognitive dynamic movement in **phenomenological space**.

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.



P-spaces (Roger Shepard 1957-2001):
- 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: T. Landauer, S. Dumais, Latent Semantic Analysis Theory, Psych. Rev. (1997) Semantics requires about 300 dim. to capture associations.

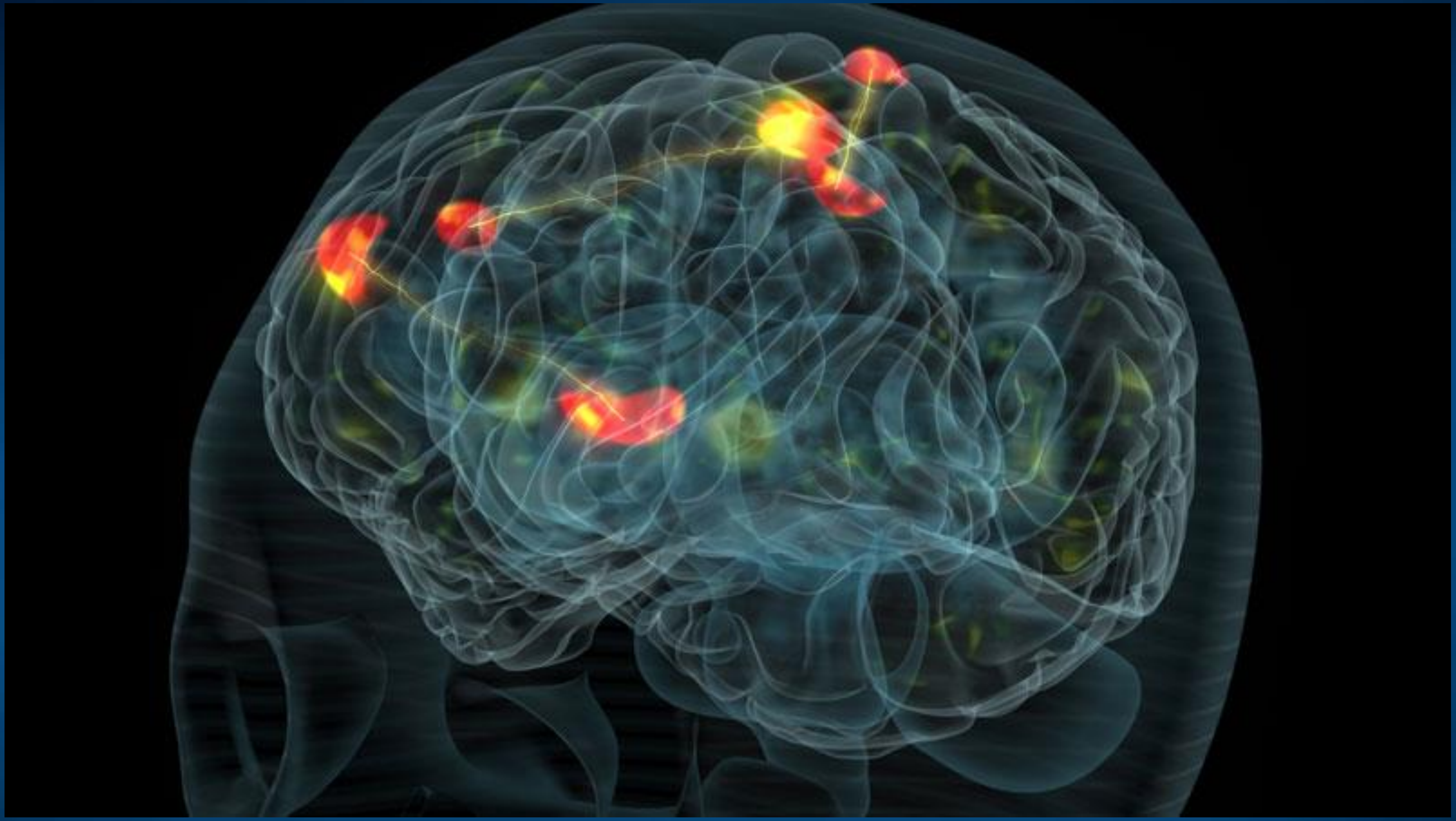
M.J. Spivey, The Continuity of Mind (OUP 2007)

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).

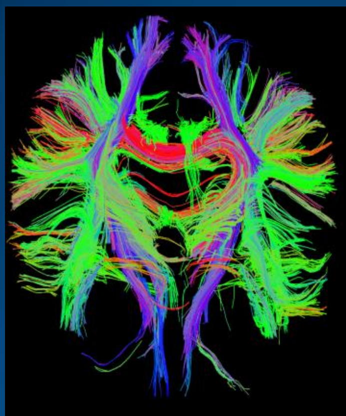
Thought: strong, coherent activation



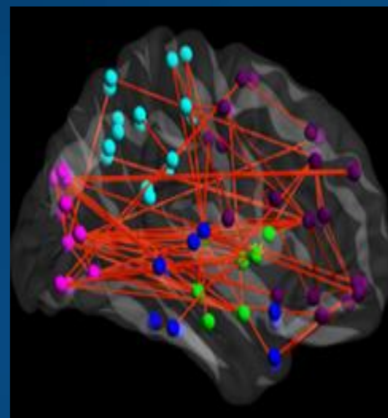
Many processes go on in parallel, controlling the state of our bodies.
Most are automatic, hidden from our Self.
Processes implemented by subnetworks compete for access to the highest level of control, consciousness, using the winner-takes-most mechanism.
Such processes may activate representation of Self in the brain.

Human connectome and MRI/fMRI

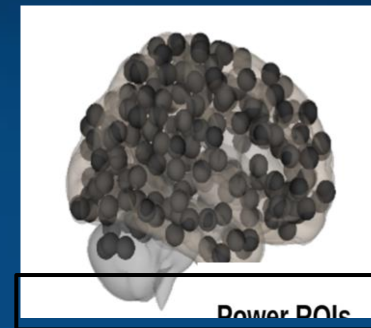
Structural connectivity



Functional connectivity

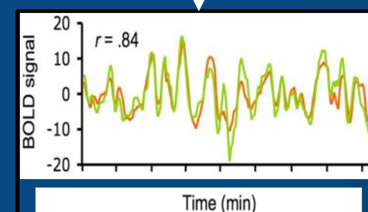


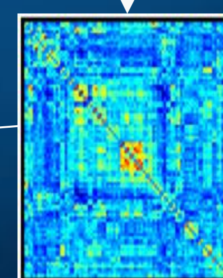
Node definition (parcelation)



Signal extraction

Correlation calculation

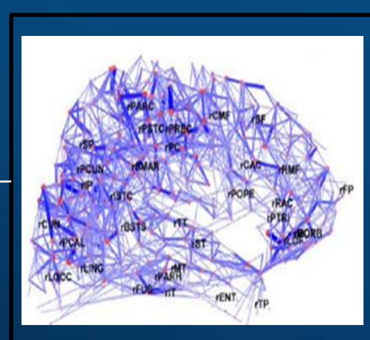




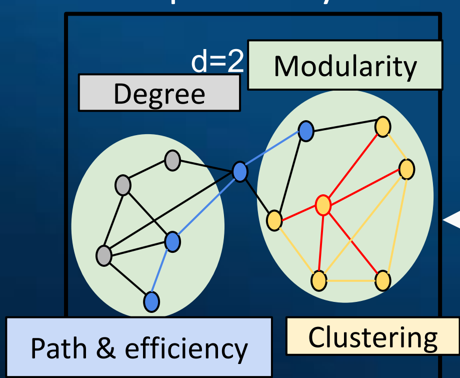
Correlation matrix

Binary matrix

Whole-brain graph



Graph theory



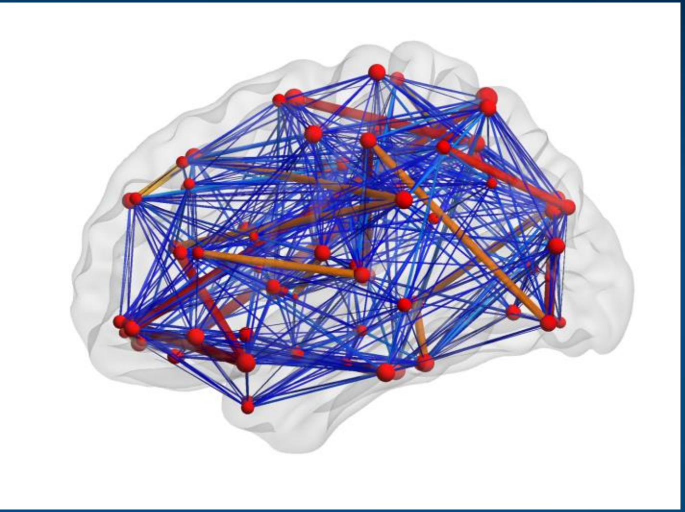
Bullmore & Sporns (2009)

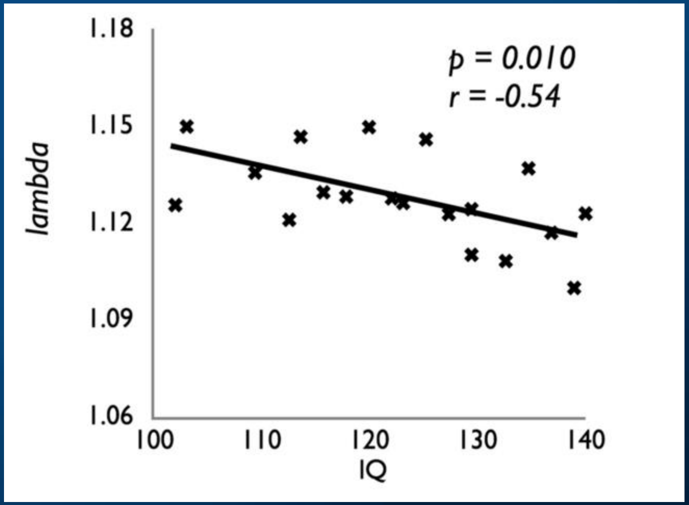
Resting state/cognitive performance

Characteristic path length λ → Intellectual performance

Modularity → Working memory performance

Modularity → Working memory capacity





Network modularity ⇔ higher working memory capacity and performance.

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

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

Questions

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?

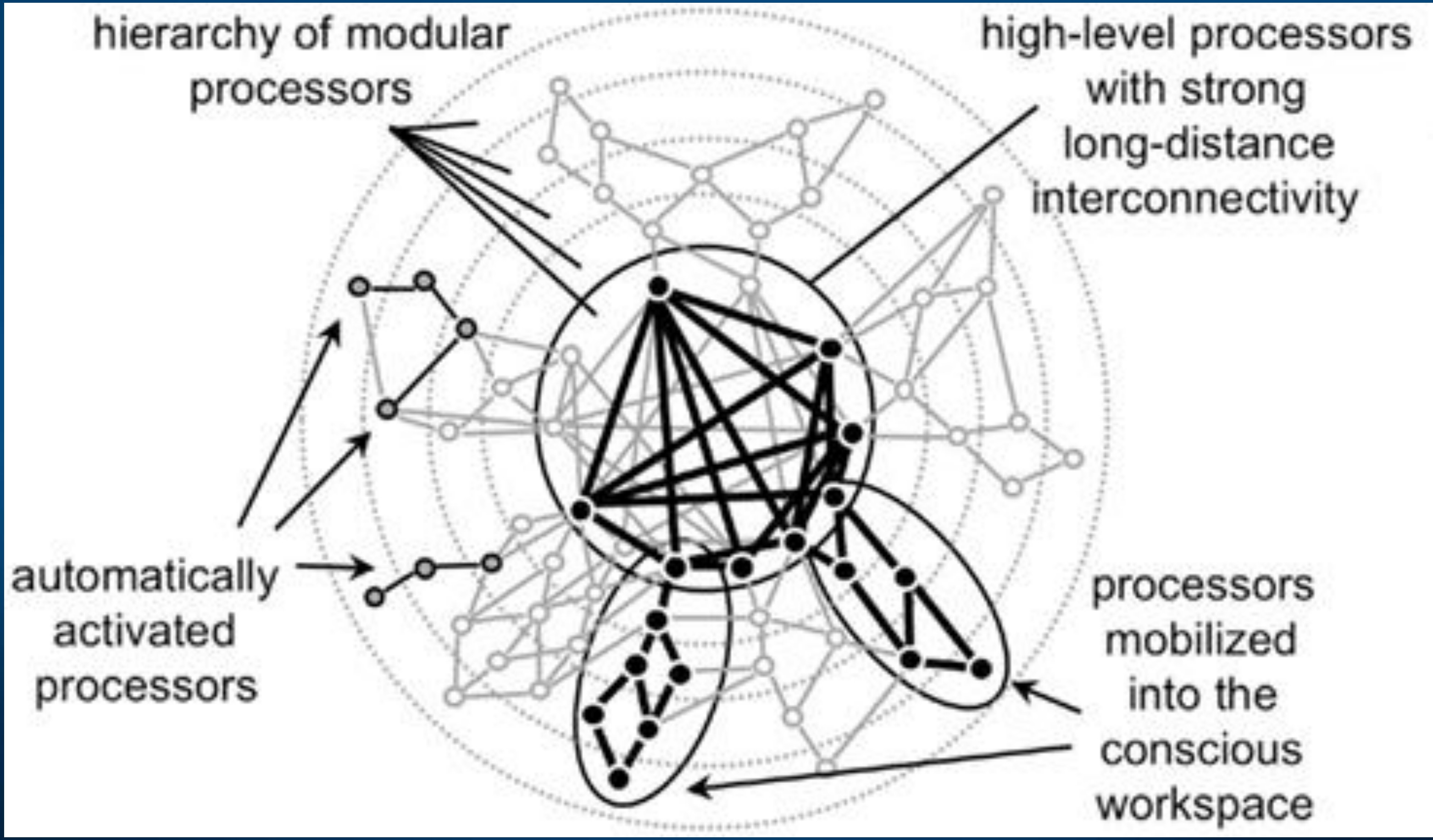
Global Neuronal Workspace Theory (Deahene et al. 1998): brain processes underlying effortful tasks require two main computational spaces:

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

Workspace neurons are mobilized in effortful tasks for which the specialized processors do not suffice. They selectively mobilize or suppress, through descending connections, the contribution of specific processor neurons.

GNWT

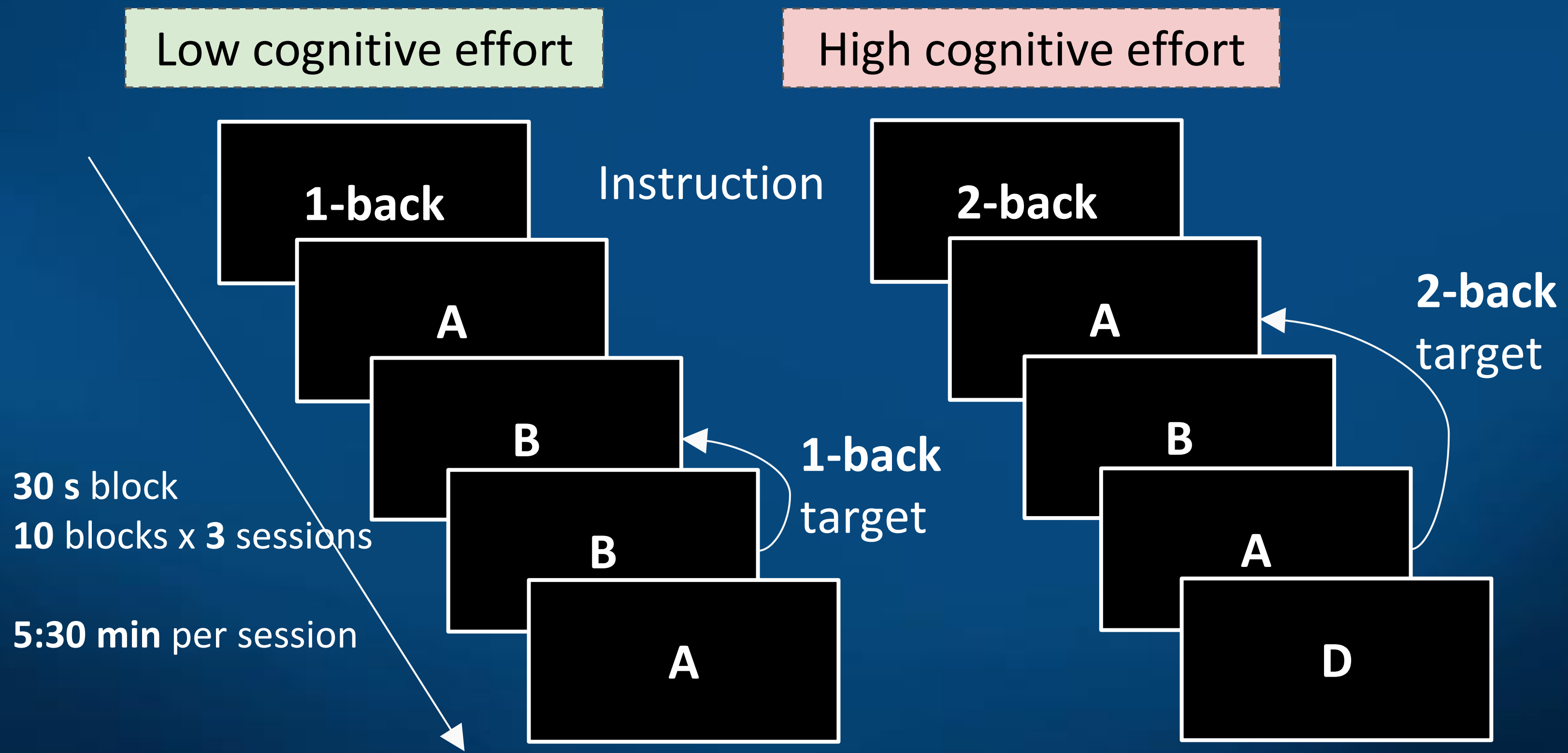
Global Neuronal Workspace Theory (Dehaene et al. 1998)



Cognitive load on whole-brain network

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

Letter *n*-back task



Finc et al, Human Brain Mapping, 2017

Data workflow

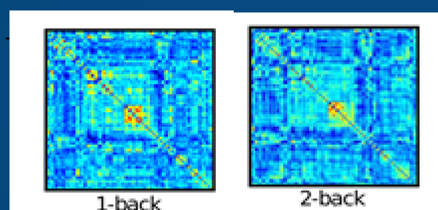
Two experimental conditions: 1-back, 2-back

Node definition

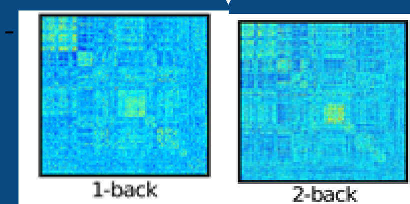
Anatomical parcellation (**90** nodes)

Functional parcellation (**264** nodes)

Weighted correlation matrices

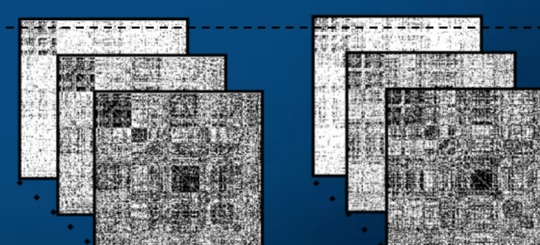


Fisher's *z*-scores



Binary correlation matrices

Threshold (0.01 - 0.6)



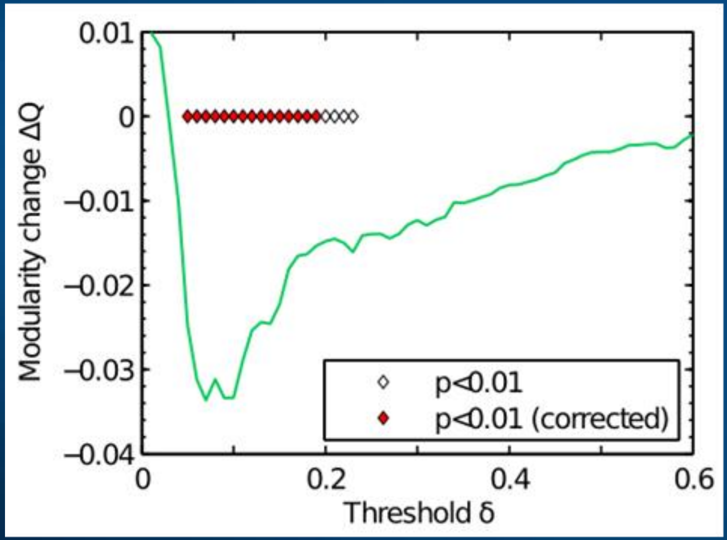
global efficiency | local efficiency | modularity

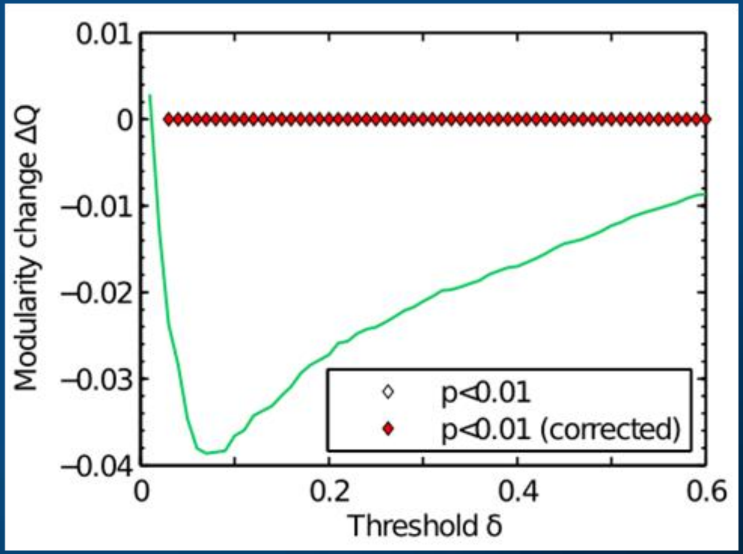
Changes in modularity

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

Parcellation
AAL, 90 ROI

Parcellation
264 ROI
functional





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

Finc et al, Human Brain Mapping, 2017

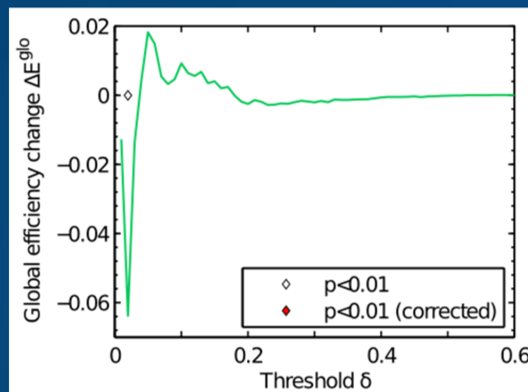
Changes in efficiency

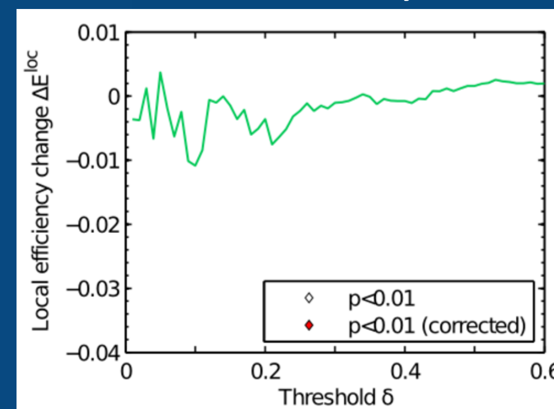
Global efficiency ~ inverse characteristic path length
Local efficiency ~ clustering coefficient (Latora & Marchiori, 2001).

Global efficiency

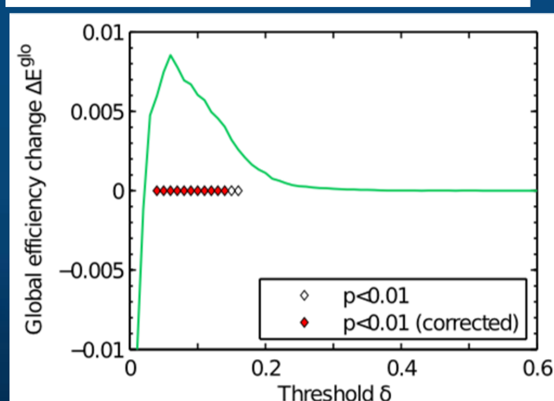
Local efficiency

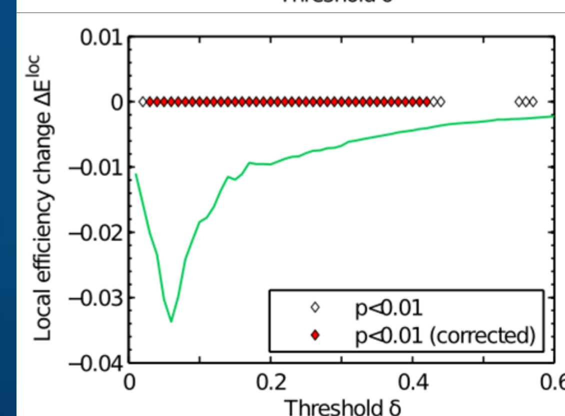
Parcelation
AAL, 90 ROI





Parcelation
264 ROI
functional





Finc et al, Human Brain Mapping, 2017

Conclusions

Segregated network

Low cognitive effort

Locally specialized processing

↑ global efficiency

↓ local efficiency

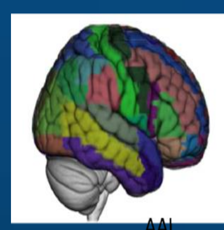
↓ modularity

↓ performance

Integrated network

High cognitive effort

Distributed processing



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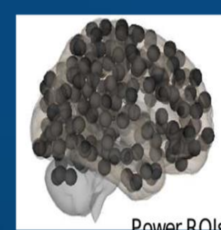


Parcellation into 264 regions (10 mm spheres) shows subnetworks more precisely than for 90 regions; only a small subgroup of neurons in each ROI is strongly correlated.

Brain modules and cognitive processes

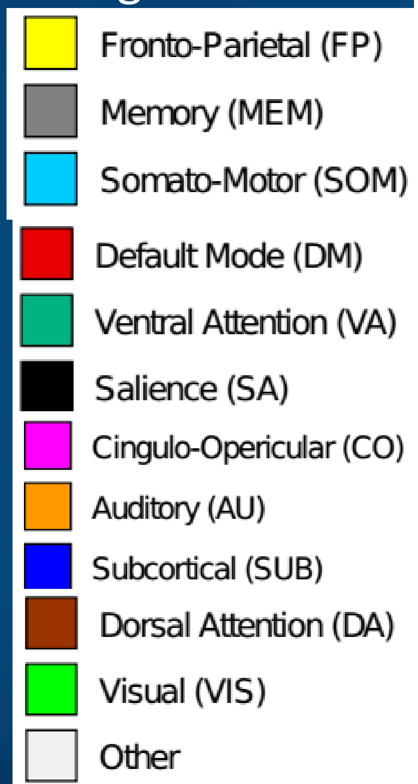
Simple and more difficult tasks, requiring the whole-brain network reorganization.

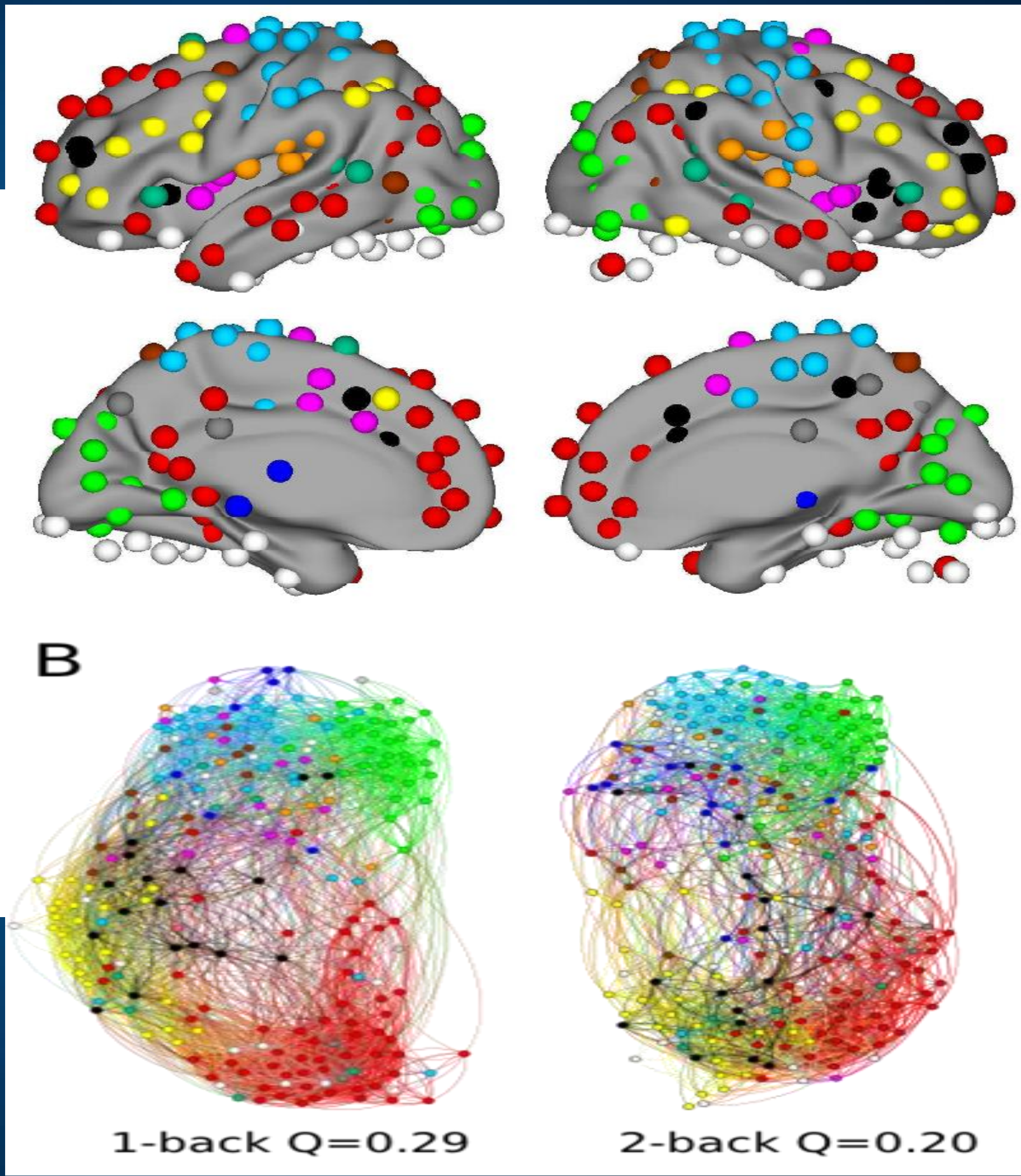
Left: 1-back

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.

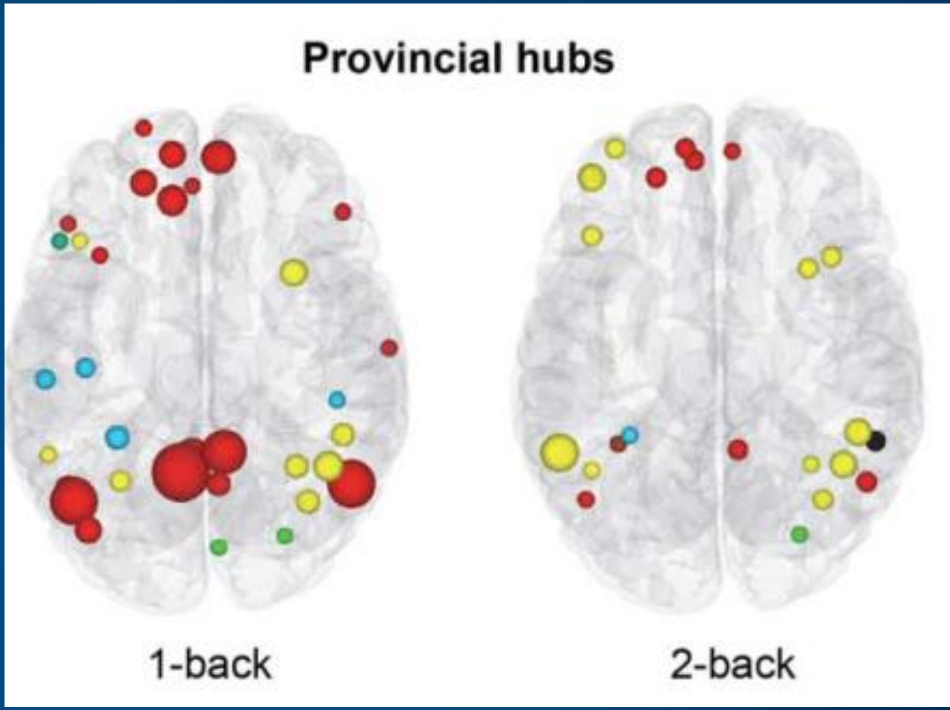
Left: 1-back Top: connector hubs

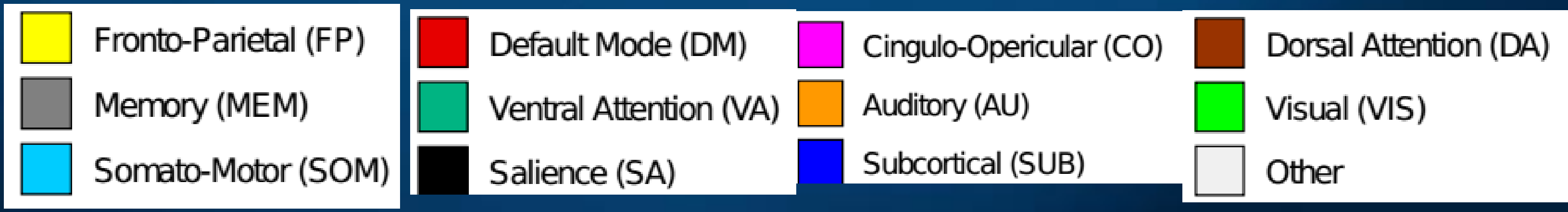
Right: 2-back Bottom: local hubs

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).





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Brain modules and cognitive processes

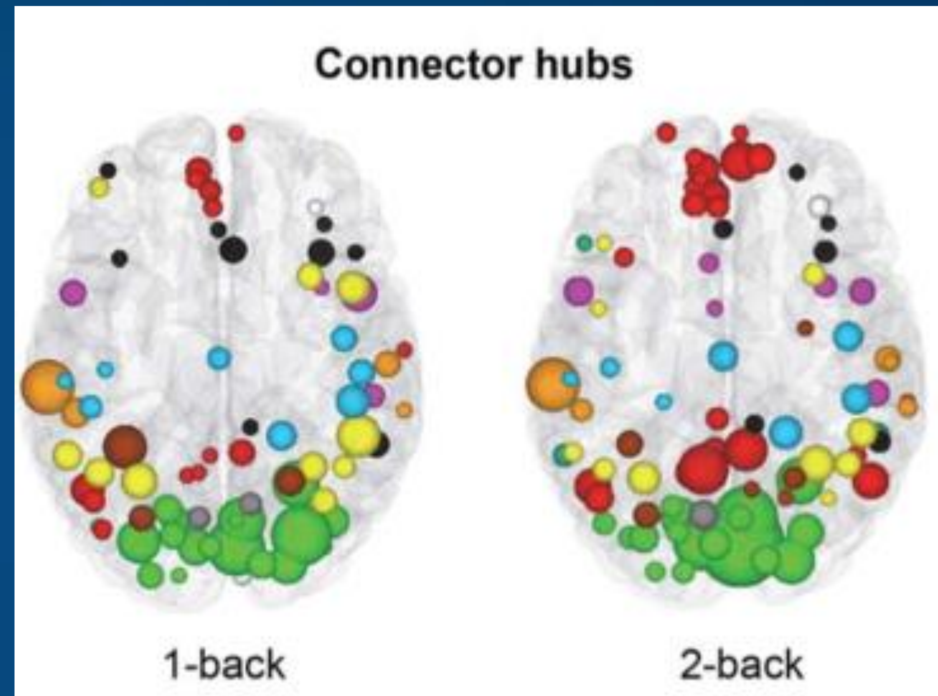
Simple and more difficult tasks, requiring the whole-brain network reorganization.

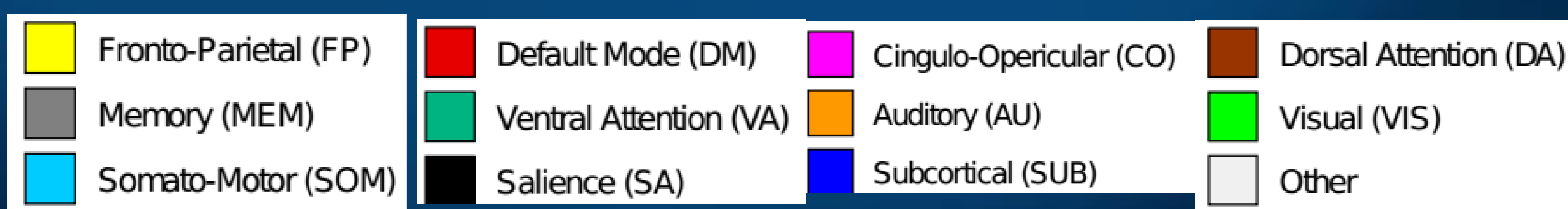
Left: 1-back Top: connector hubs

Right: 2-back Bottom: local hubs

Average over 35 *participants.*

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





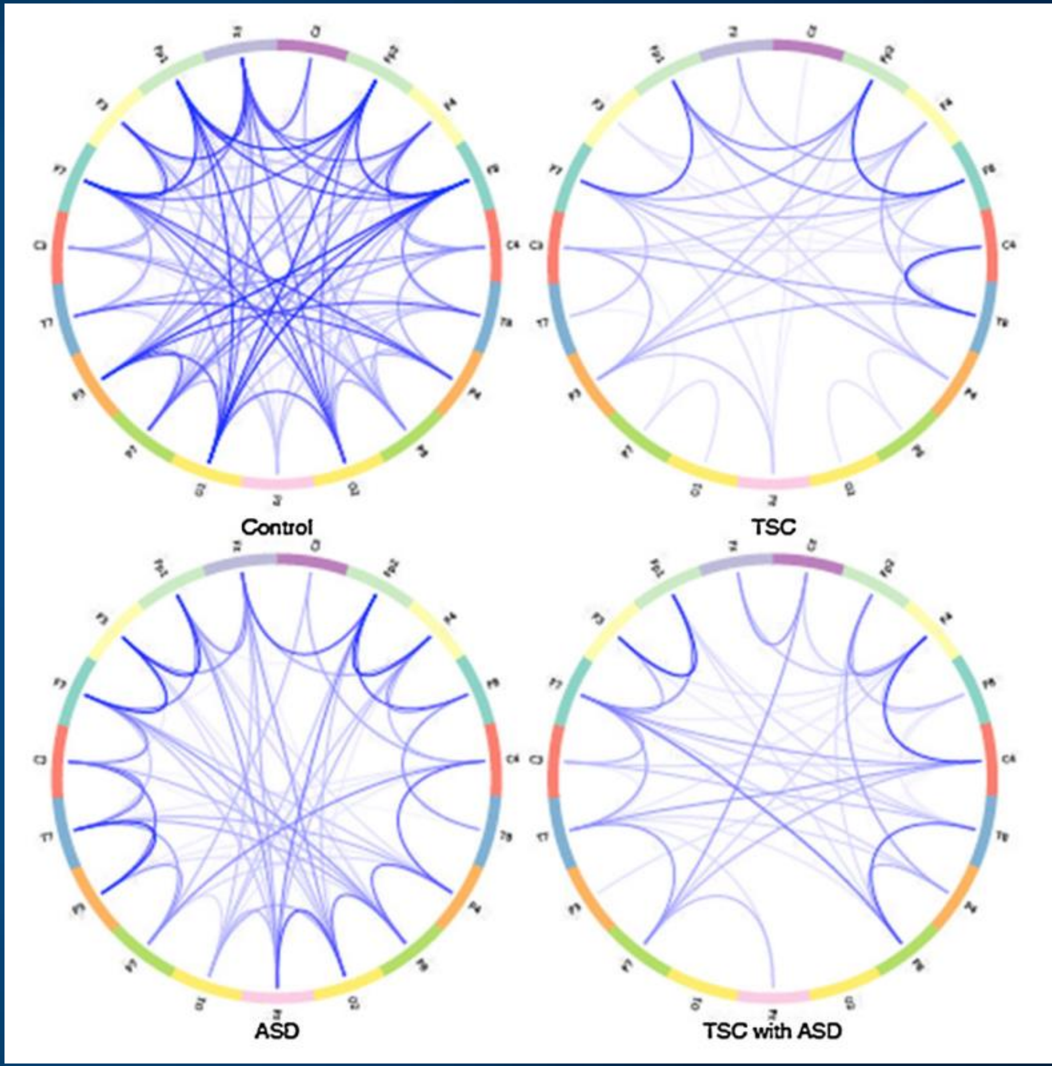
K. Finc et al, HBM (2017).

ASD: pathological connections

Comparison of connections for patients with ASD (autism spectrum), TSC (Tuberous Scelrosis), 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.

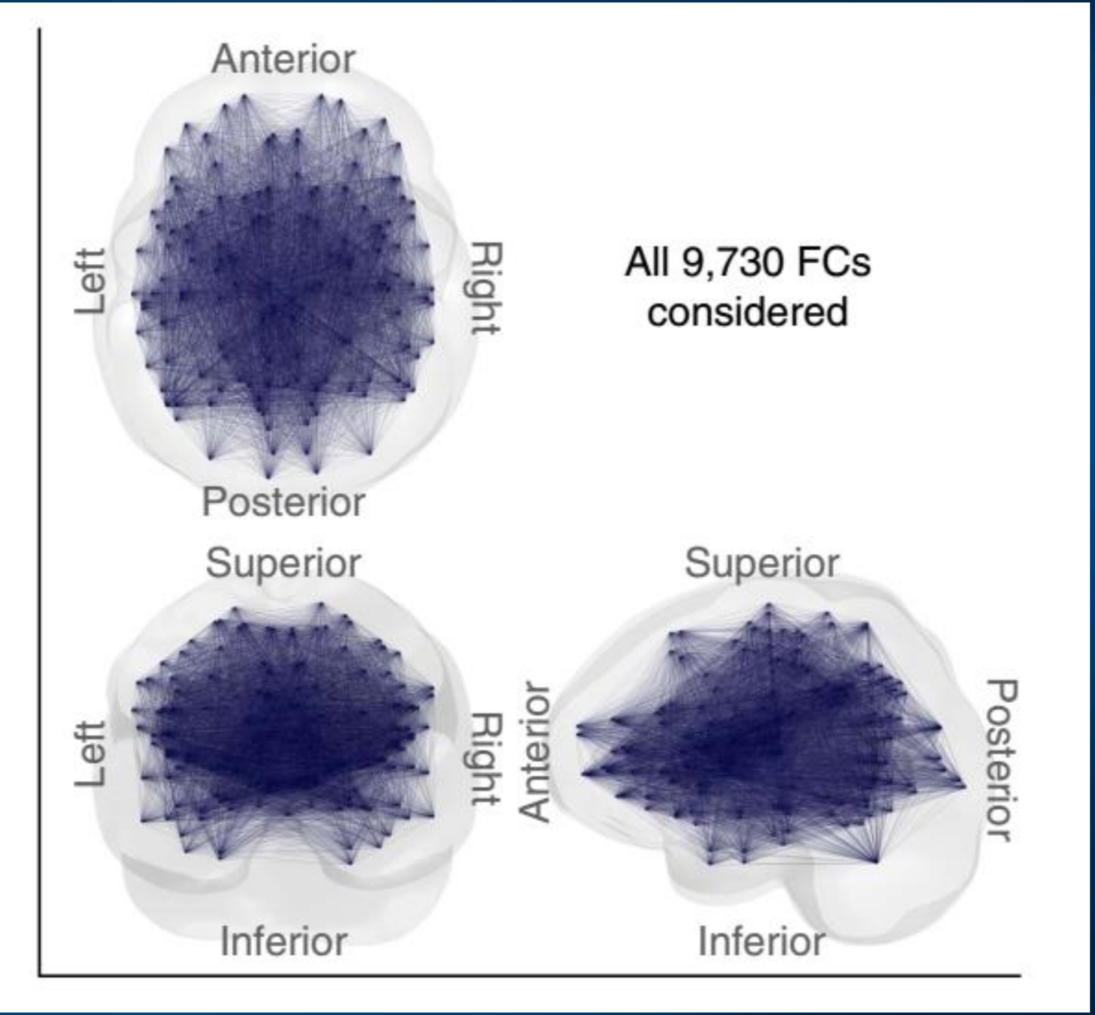


J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

ASD connectome

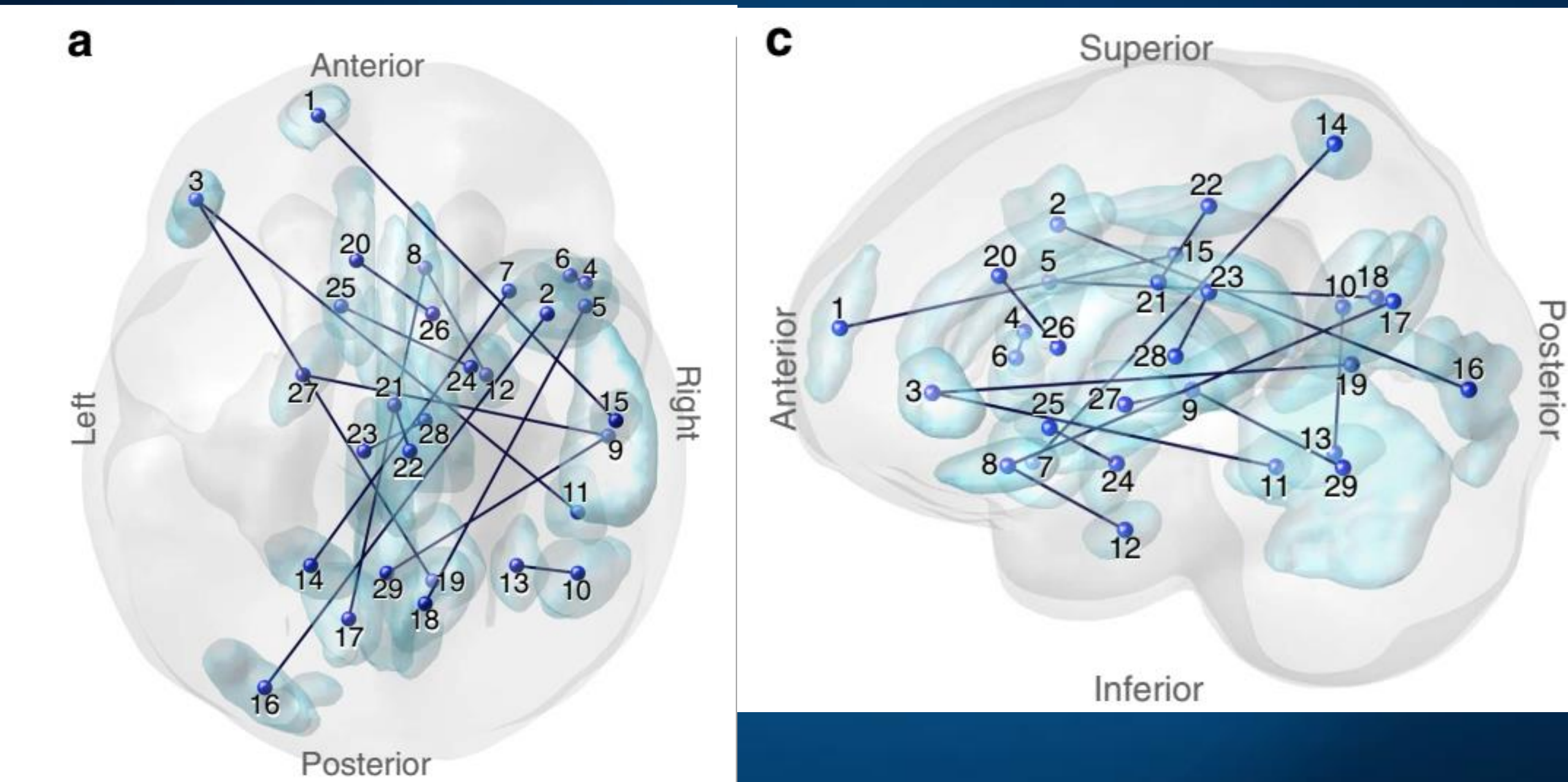
Analysis of functional connections (correlated activity) between brain regions measured using fMRI in the resting state between 140 ROIs has 9730 possible interactions.

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



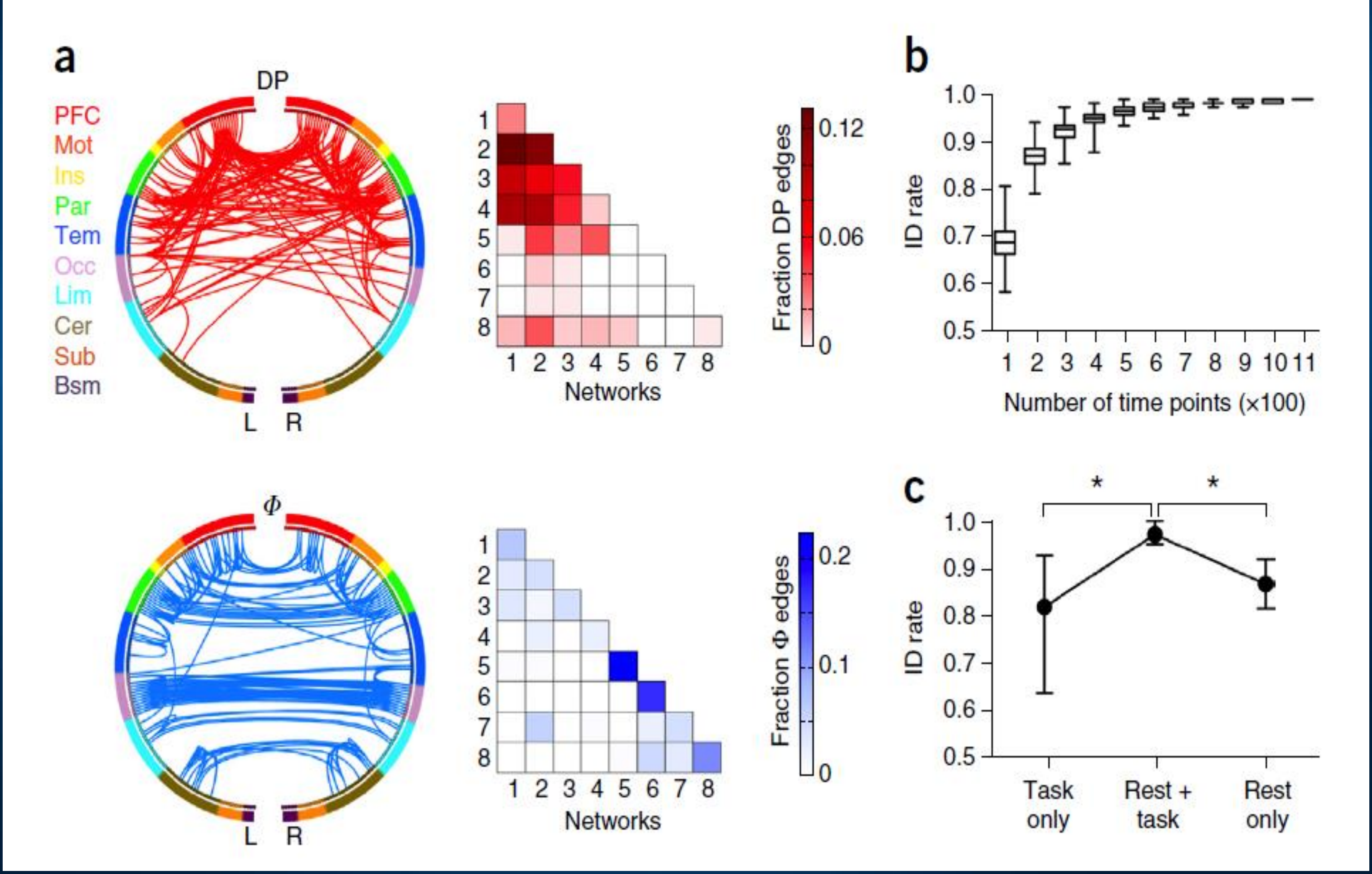
N. Yahata i inn, A small number of abnormal brain connections predicts adult autism spectrum disorder. Nature Communications (2016)

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.

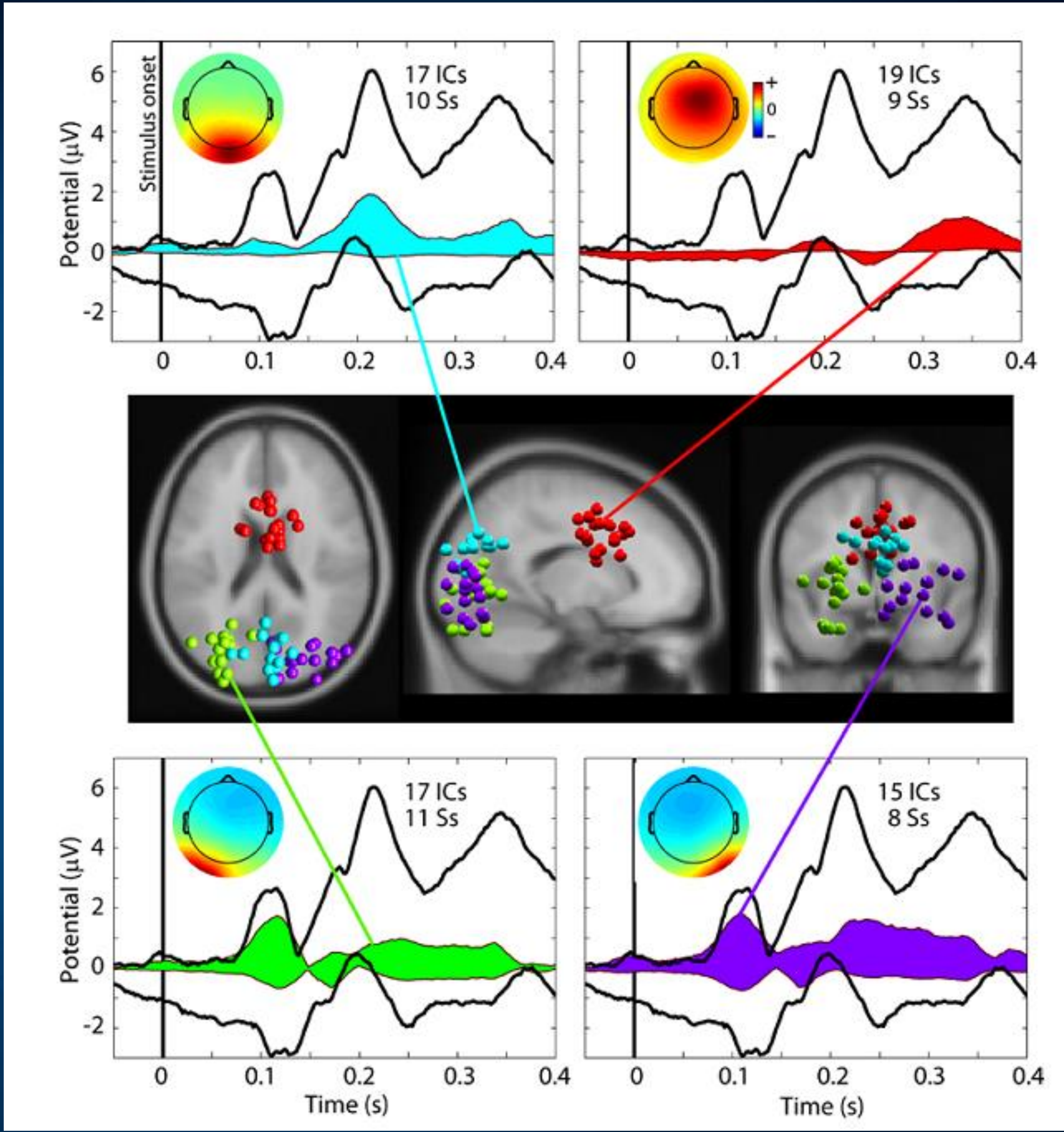


Source localization maps brain activity to attractor dynamics.

Problem: these sources pop up and vanish in different places.

Fig. from:
Makeig, Onton, 2009
ERP Features and
EEG Dynamics:
An ICA Perspective.

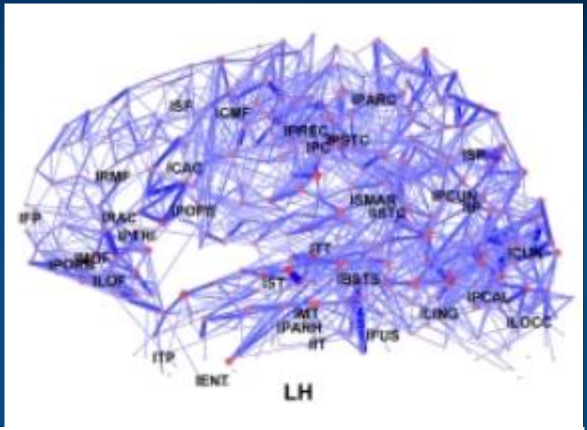
Brain fingerprinting: discover in EEG specific patterns for attractor dynamics = subnetwork activation.

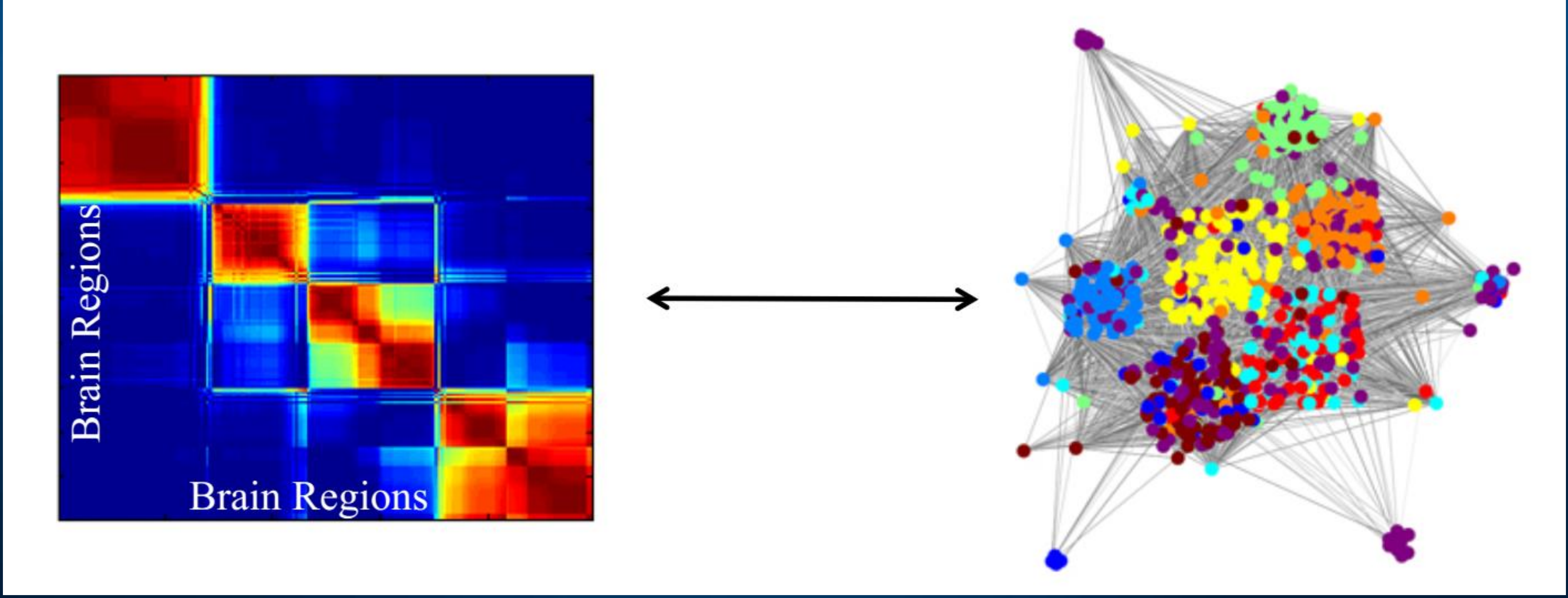


Neuronal subnetworks

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

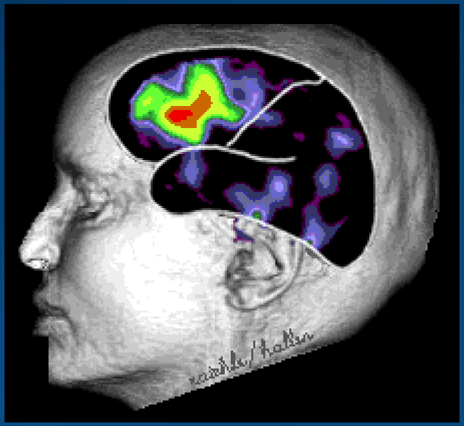
At the microcircuit level similar hierarchy/modularity is seen.





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)⇔State(Mind)

Via intermediate models.

Mental states, movement of thoughts ⇔ trajectories in psychological spaces.

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

Model of reading & dyslexia

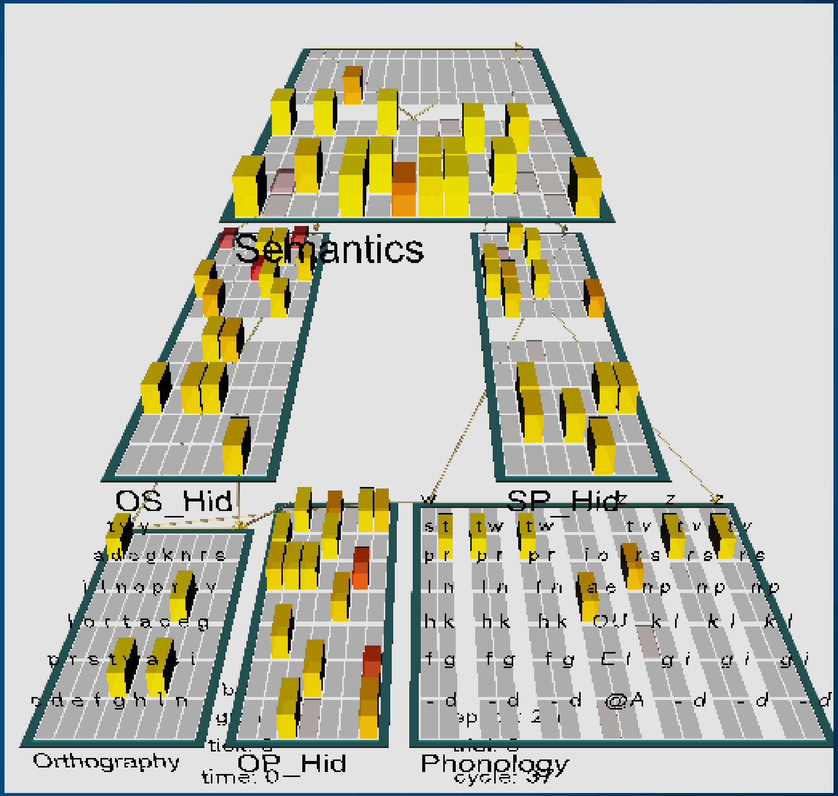
Emergent neural simulator:

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.

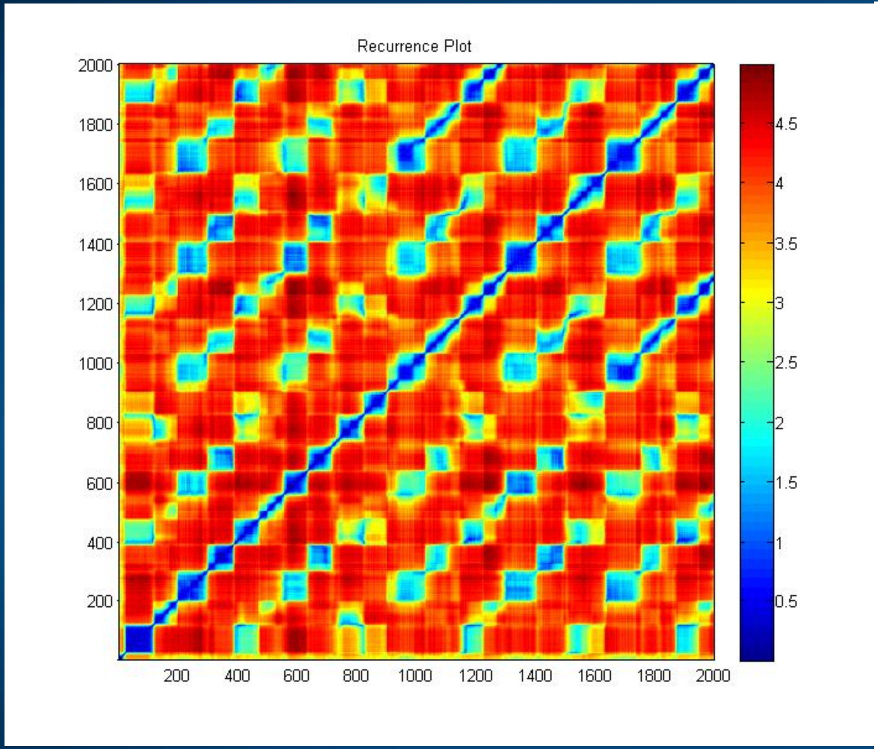


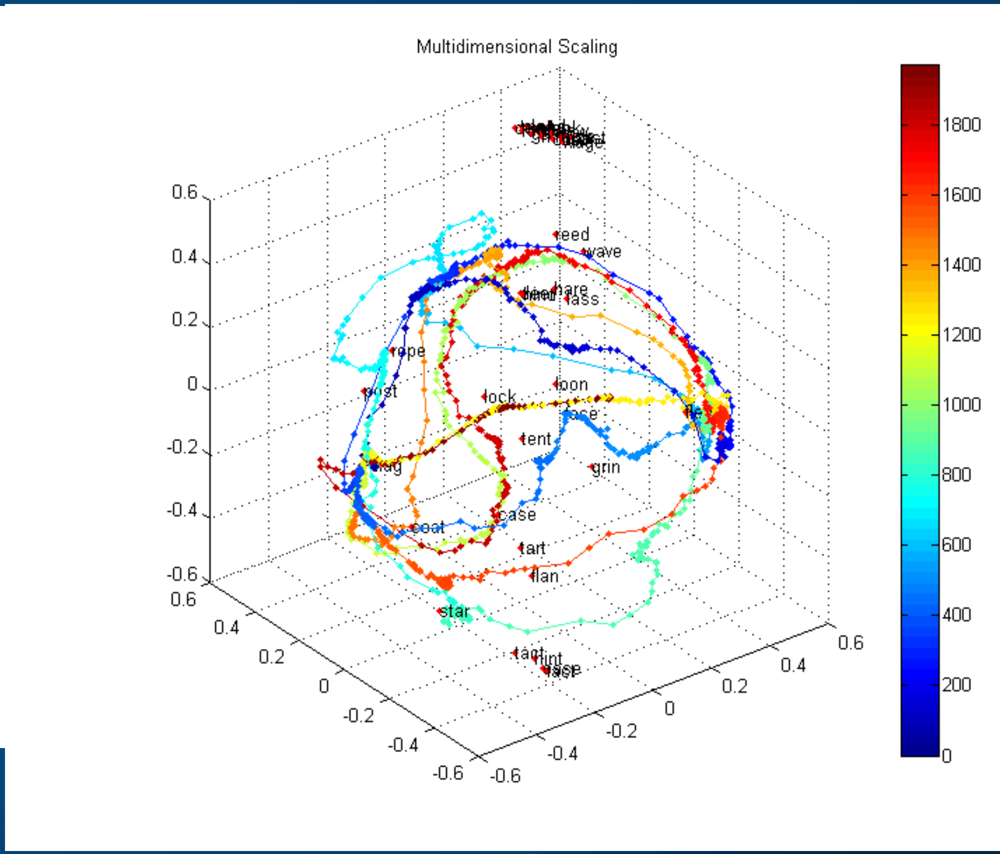
Learning: mapping one of the 3 layers to the other two.

Fluctuations around final configuration = attractors representing concepts.

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

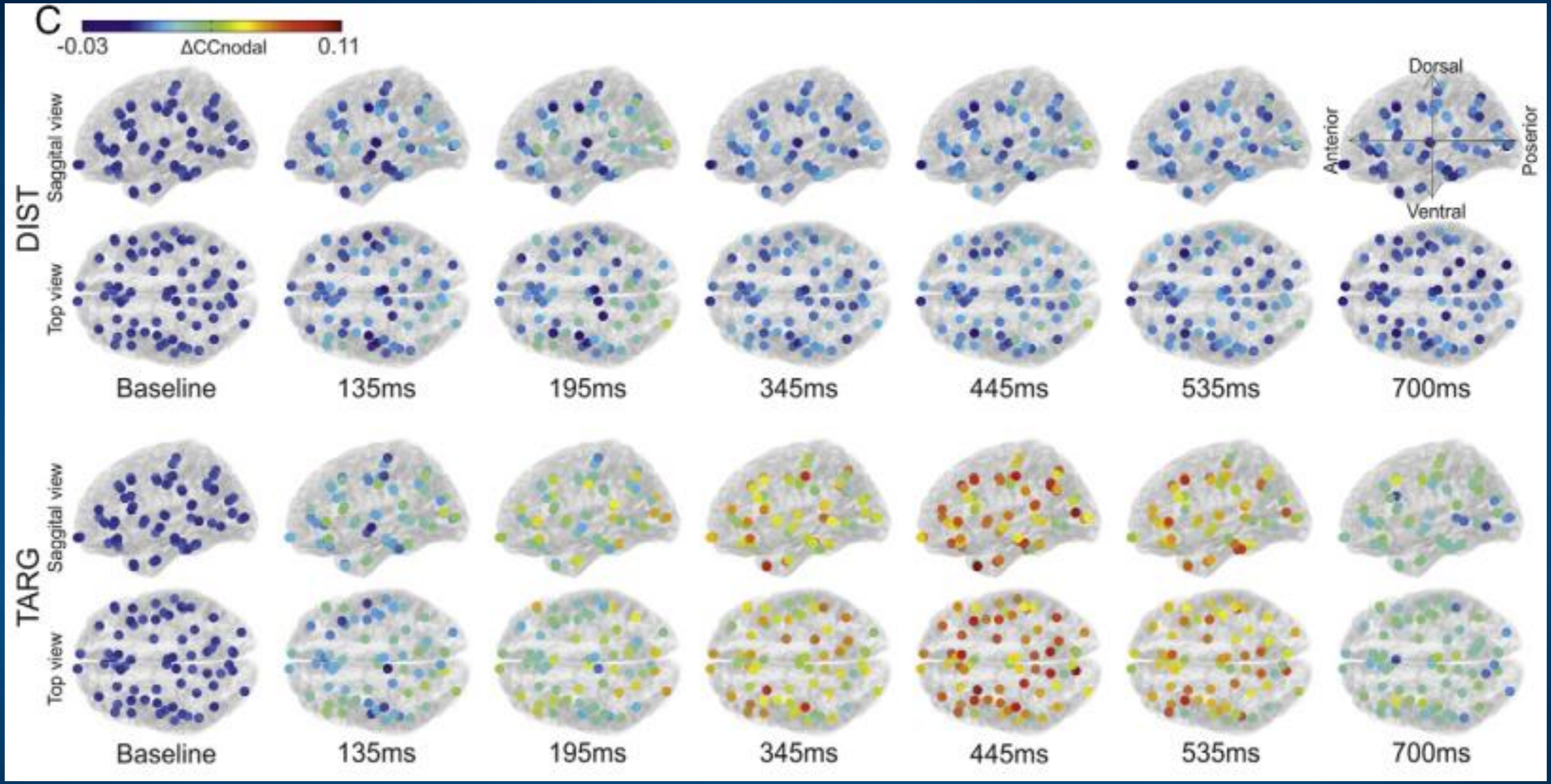
Long trajectories





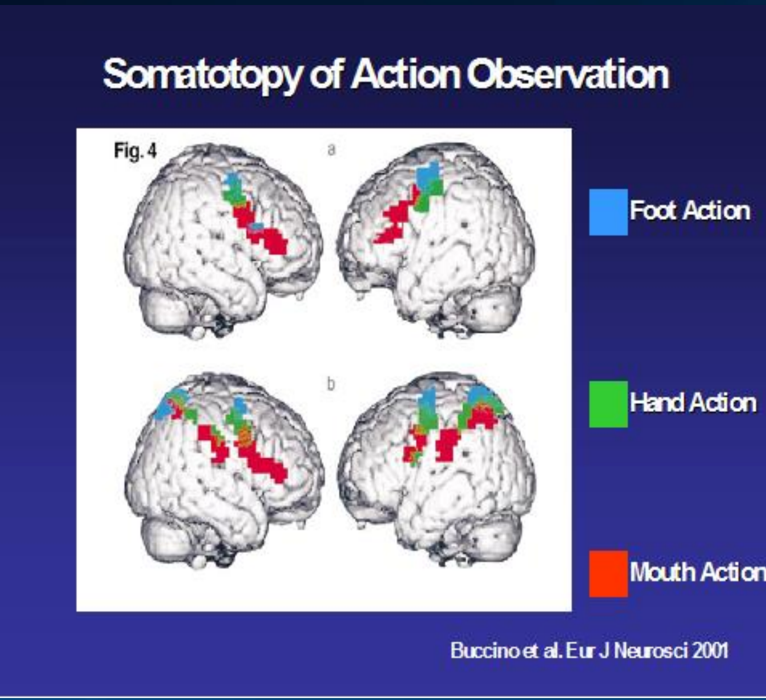
Recurrence plots and MDS visualization of trajectories of the activity in 140-dim semantic layer during spontaneous associations in the 40-words microdomain, starting with the word "flag".

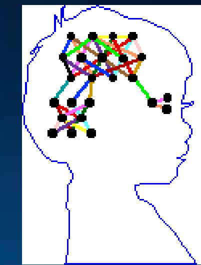
Phase Locking Value analysis



Changes in theta EEG band in the space of cluster coefficients. Anticipation of stimuli creates weak priming activation that is inhibited if this is not the target stimuli (Bola, Sabel, 2015). Pre-activation solves the frame problem?

ds in the brain





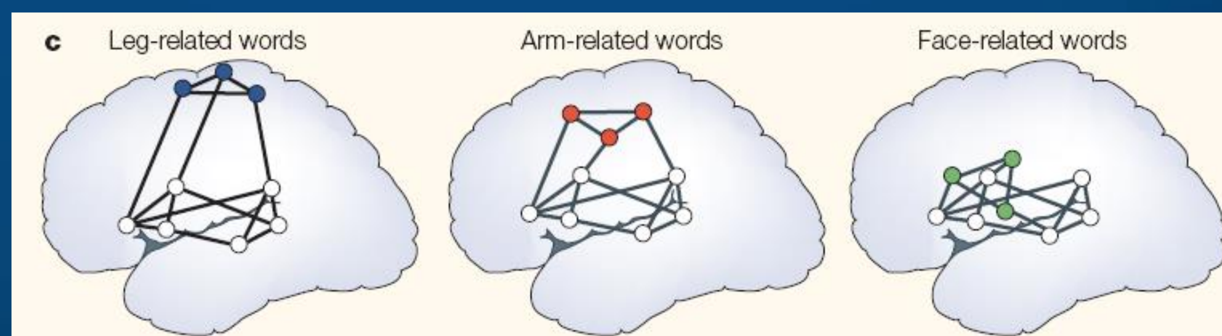
show that phonological
jorical representations.

=> words => semantic concepts.

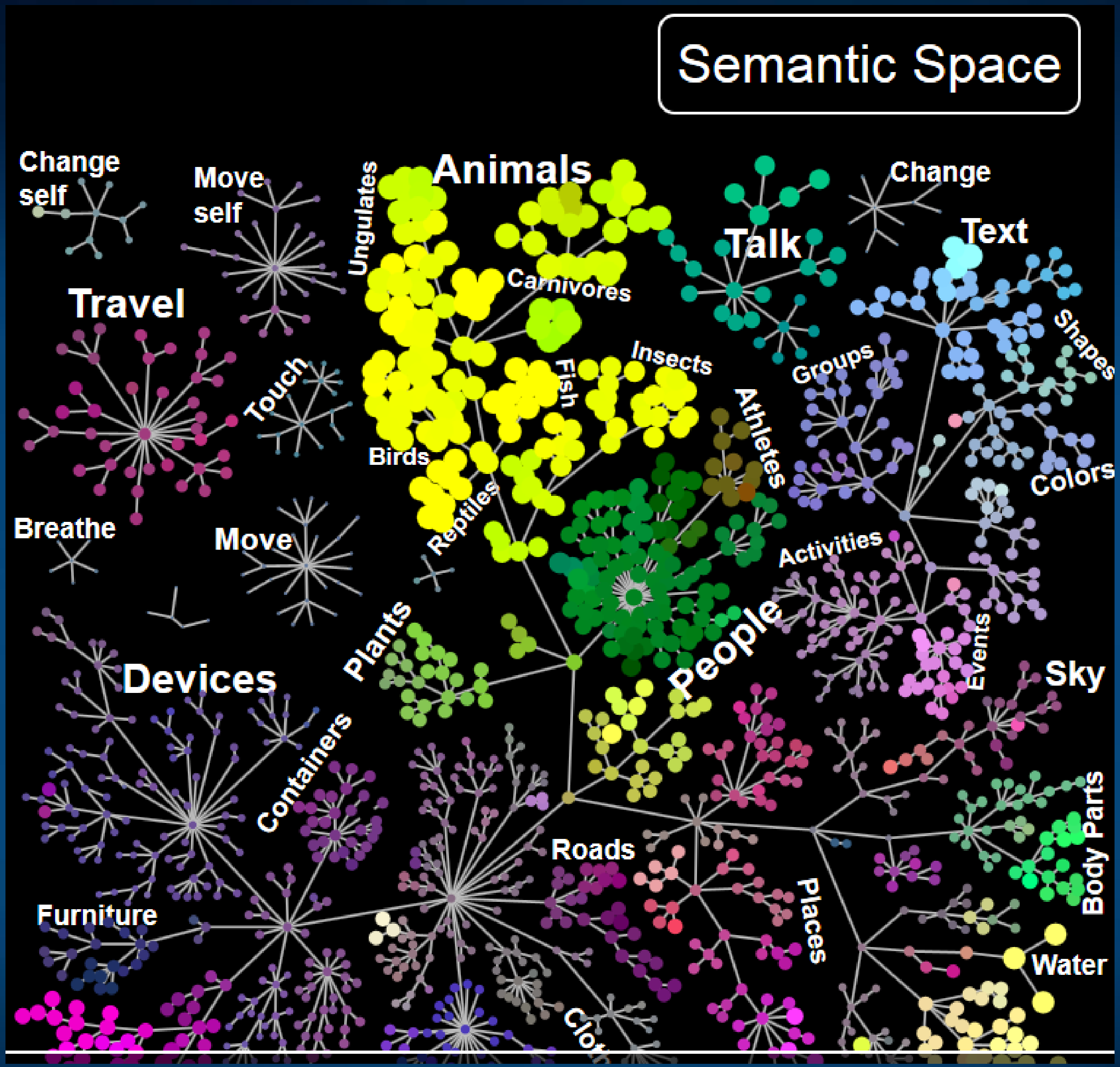
edes semantic by 90 ms (from N200 ERPs).

euroscience of Language. On Brain Circuits of
bridge University Press.

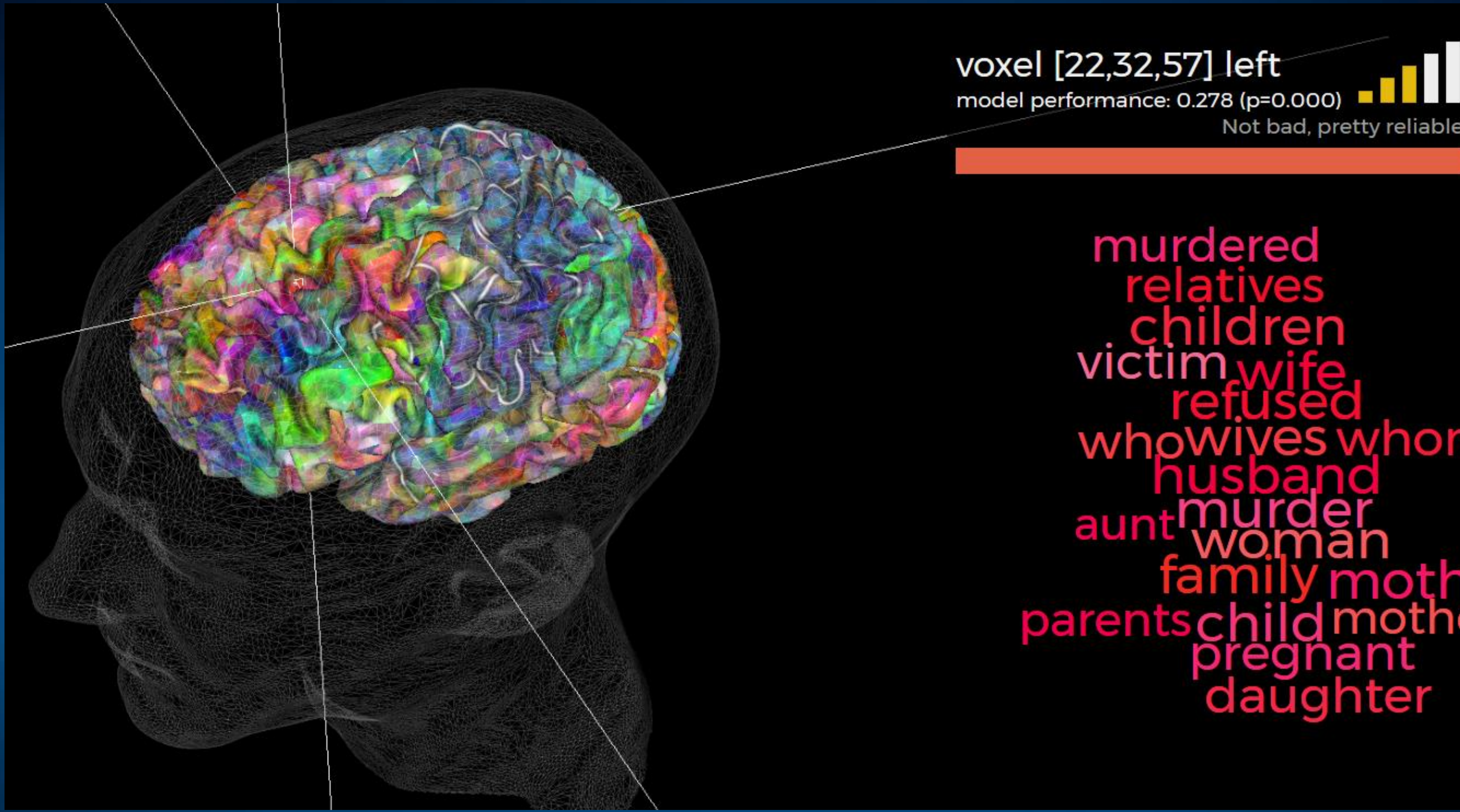
Action-perception networks inferred from ERP and fMRI



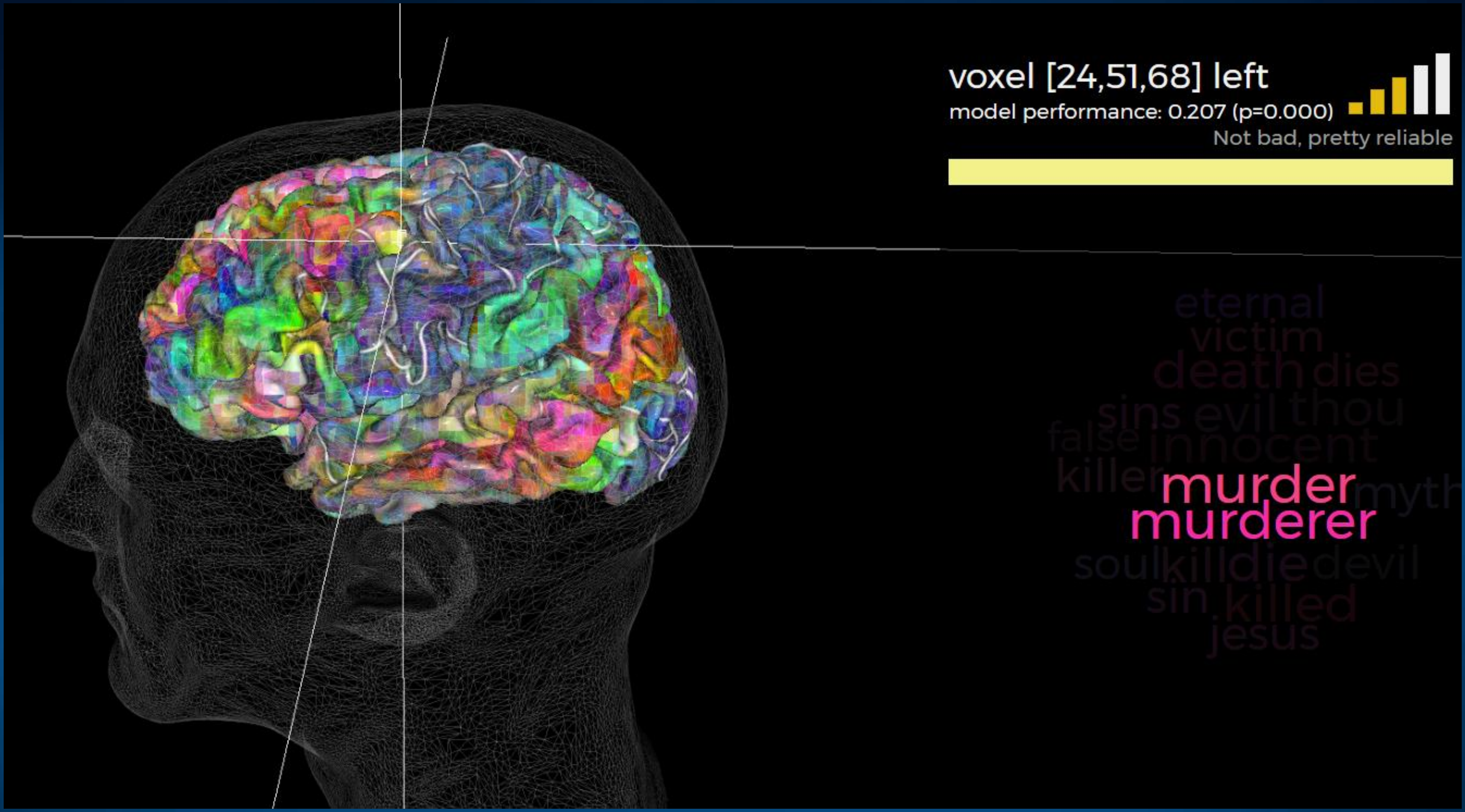
Left hemisphere: precise representations of symbols, including phonological components. Right hemisphere sees clusters of concepts, the gist.



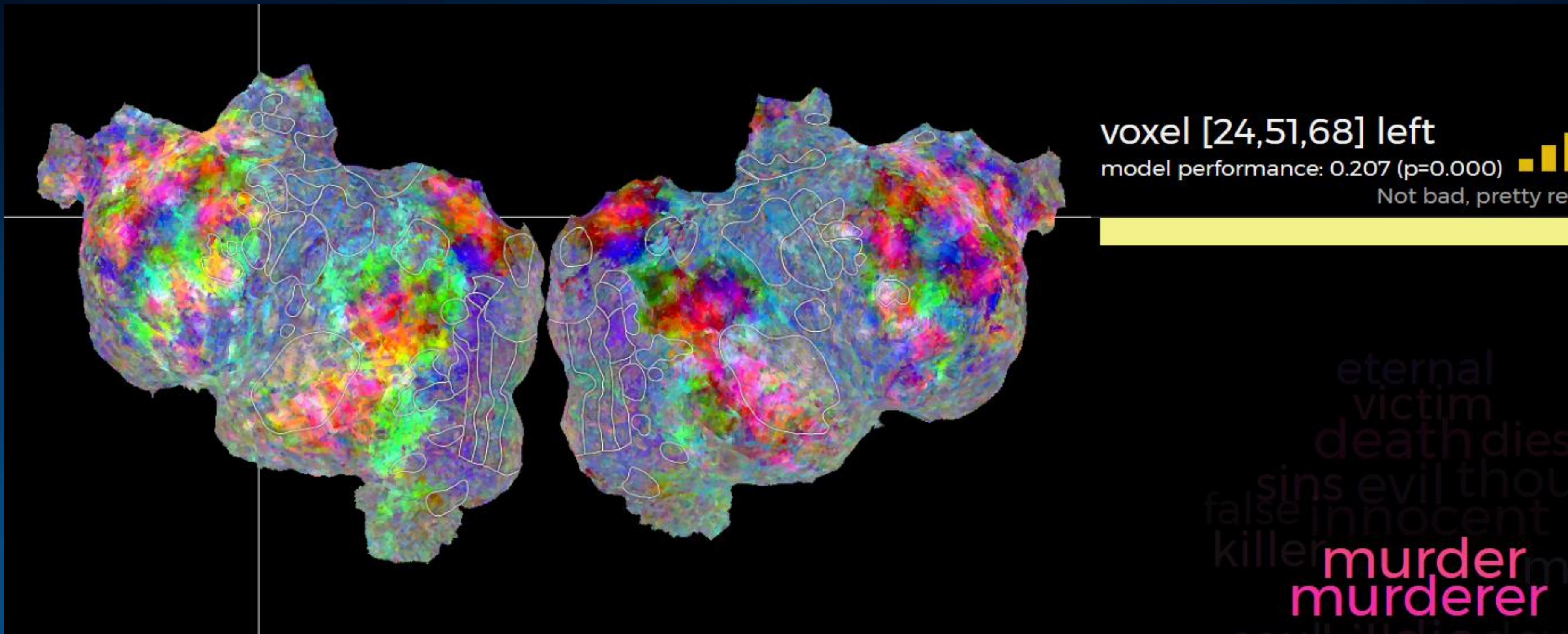
Words in the semantic space are grouped by their similarity.
Words activate specific brain maps, similar words create similar maps.
Each pixel may be activated by many words.



Each voxel responds usually to many related words, whole categories.
http://gallantlab.org/huth2016/



Voxel may also responds in quite specific way.
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.

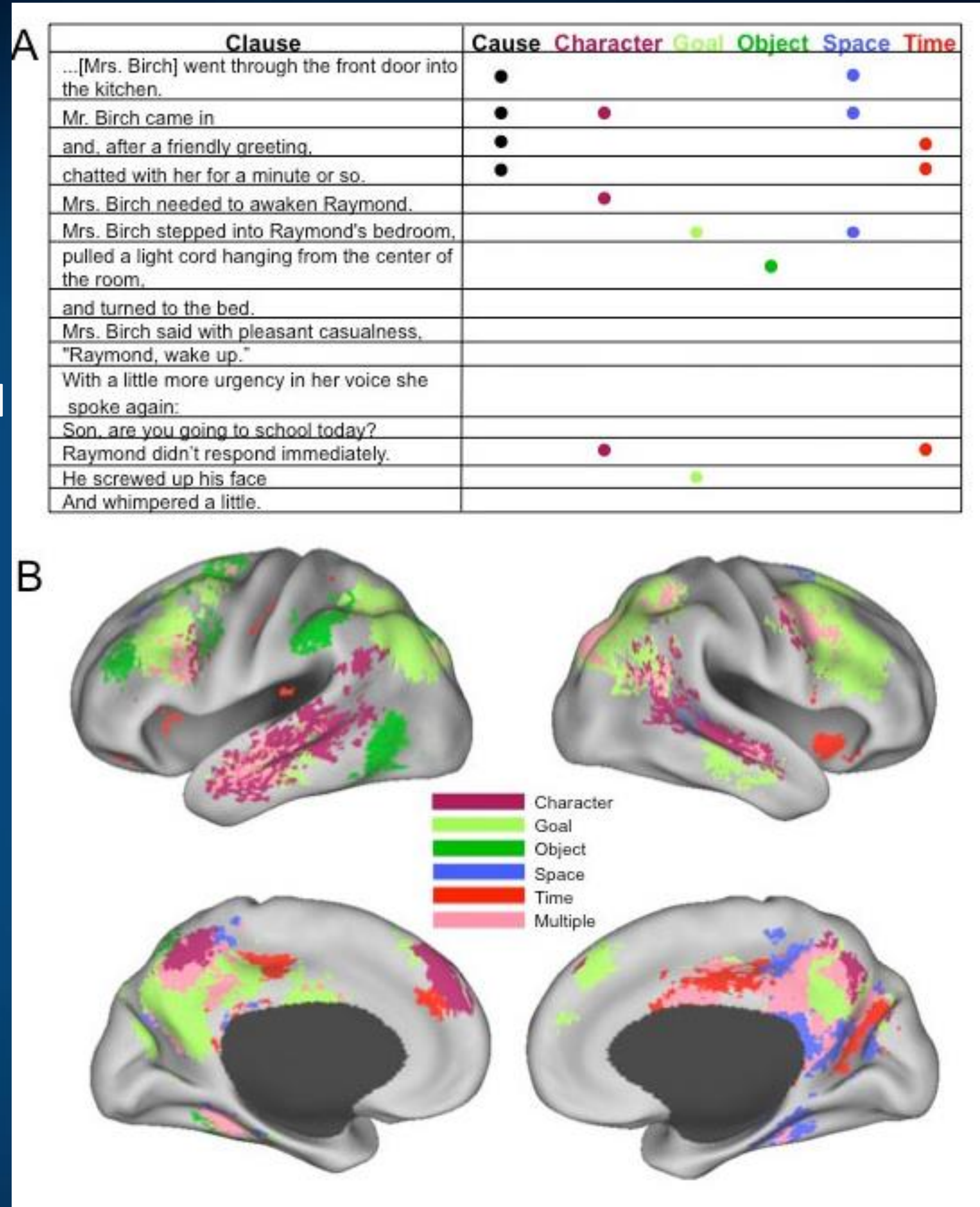
Narration

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

Thought: spatiotemporal pattern

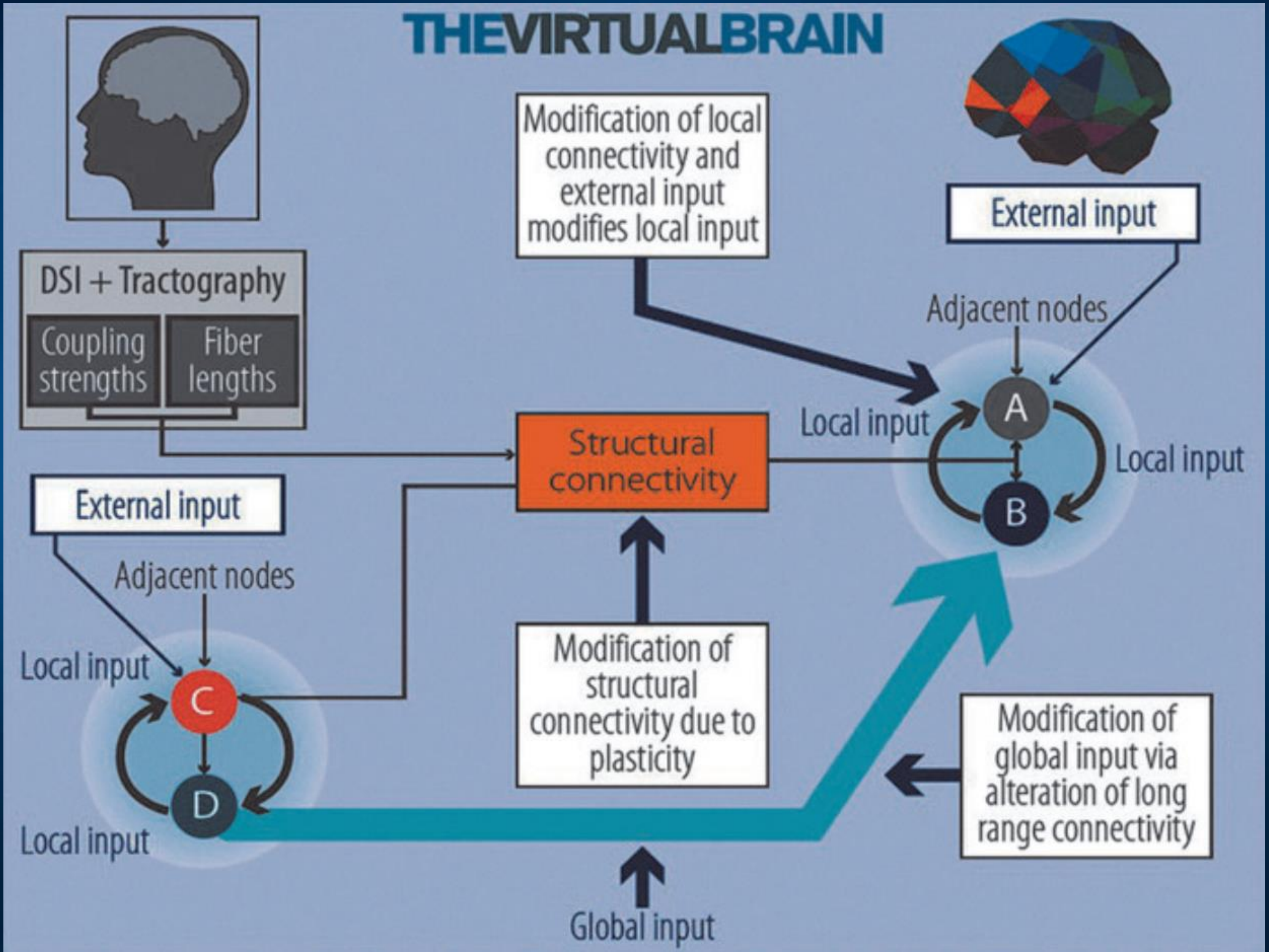
Meaning: always slightly different, depending on the context, but still may be clusterized into relatively small number of distinct meanings.

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


A

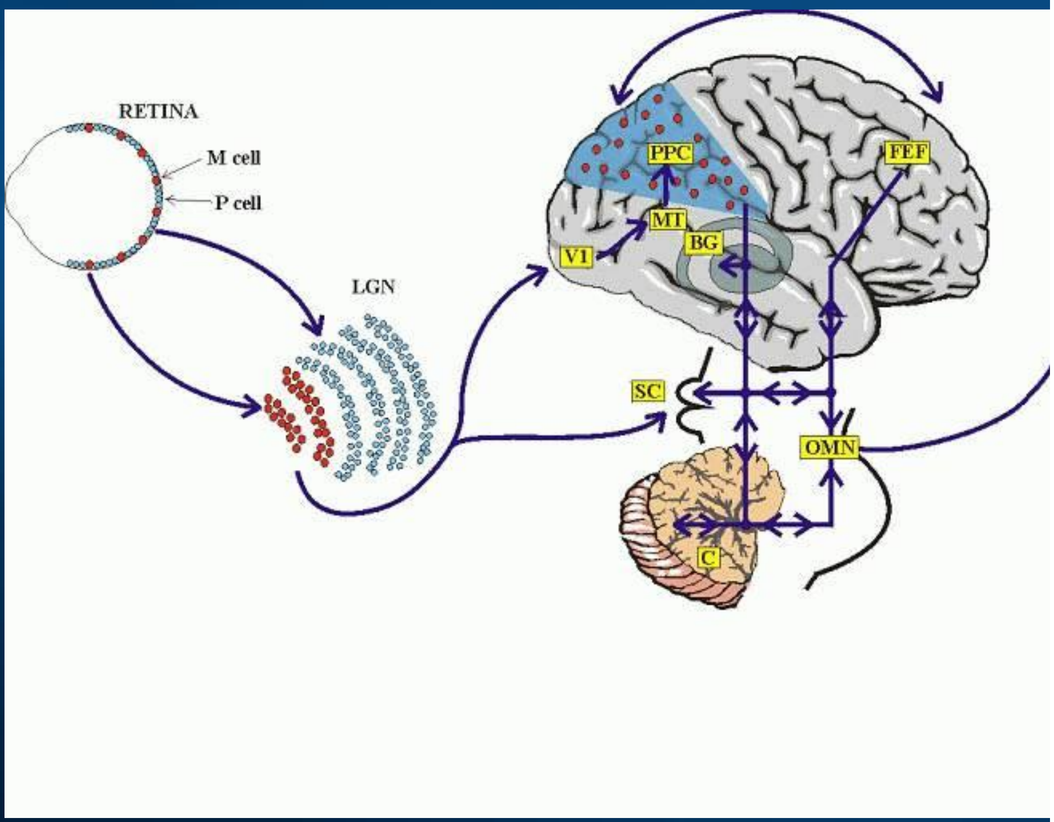
Clause	Cause	Character	Goal	Object	Space	Time
...[Mrs. Birch] went through the front door into the kitchen.	•				•	
Mr. Birch came in	•	•			•	
and, after a friendly greeting,	•					•
chatted with her for a minute or so.	•					•
Mrs. Birch needed to awaken Raymond.		•				
Mrs. Birch stepped into Raymond's 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.						

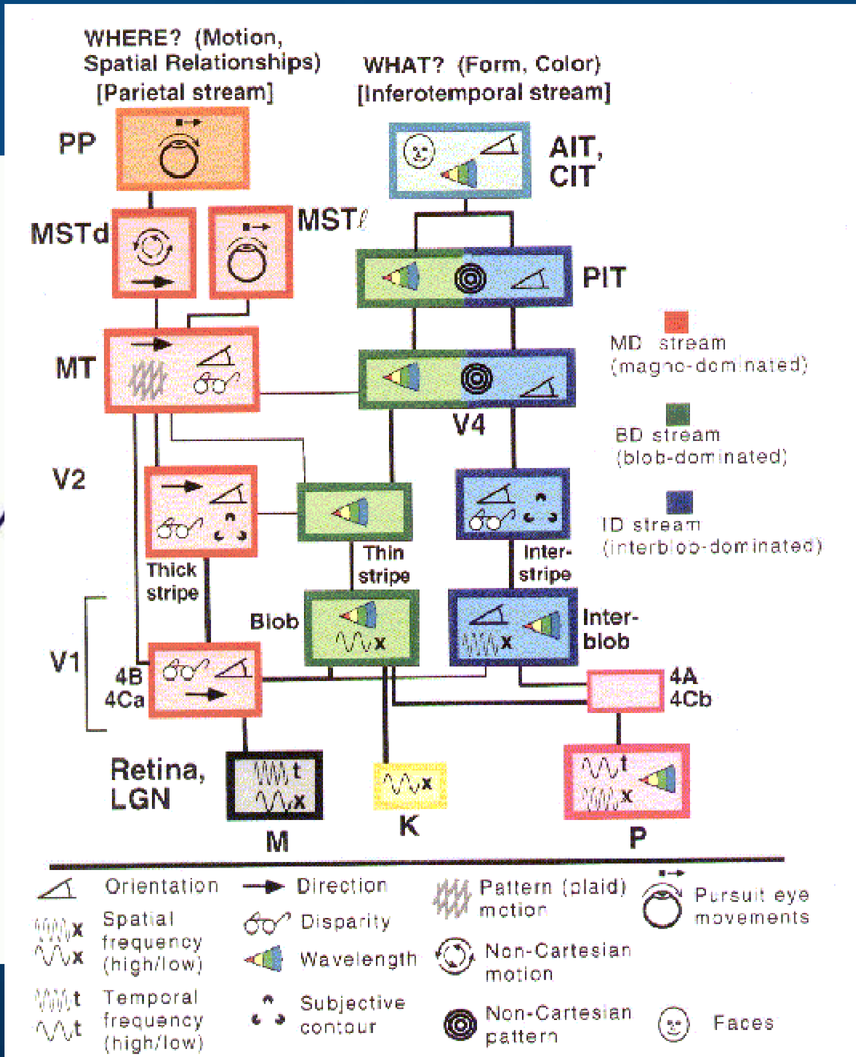
Population dynamics TVB model



Mental images - Vision

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





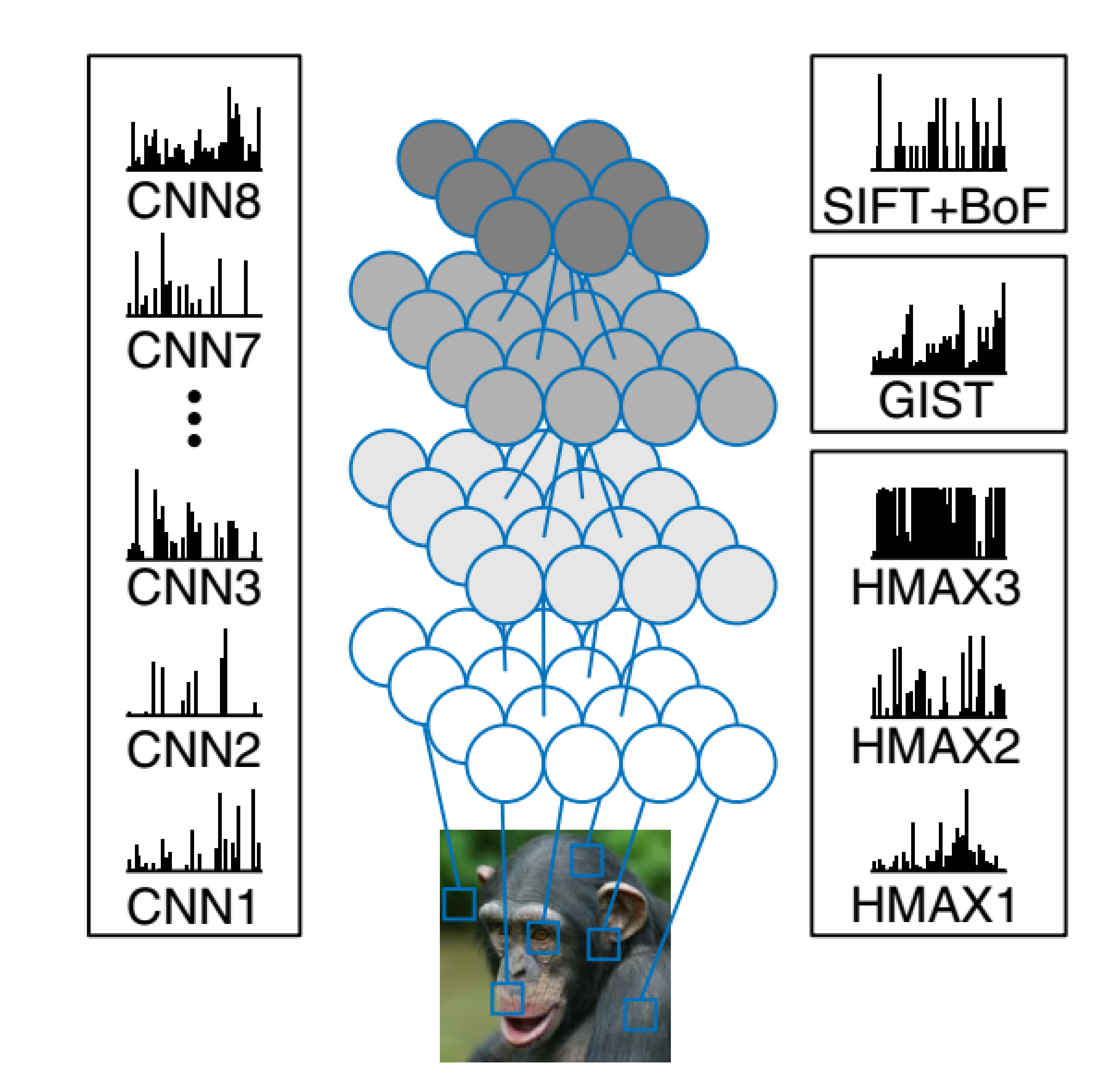
Mental images from brain activity

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

Try to estimate features at different layers.

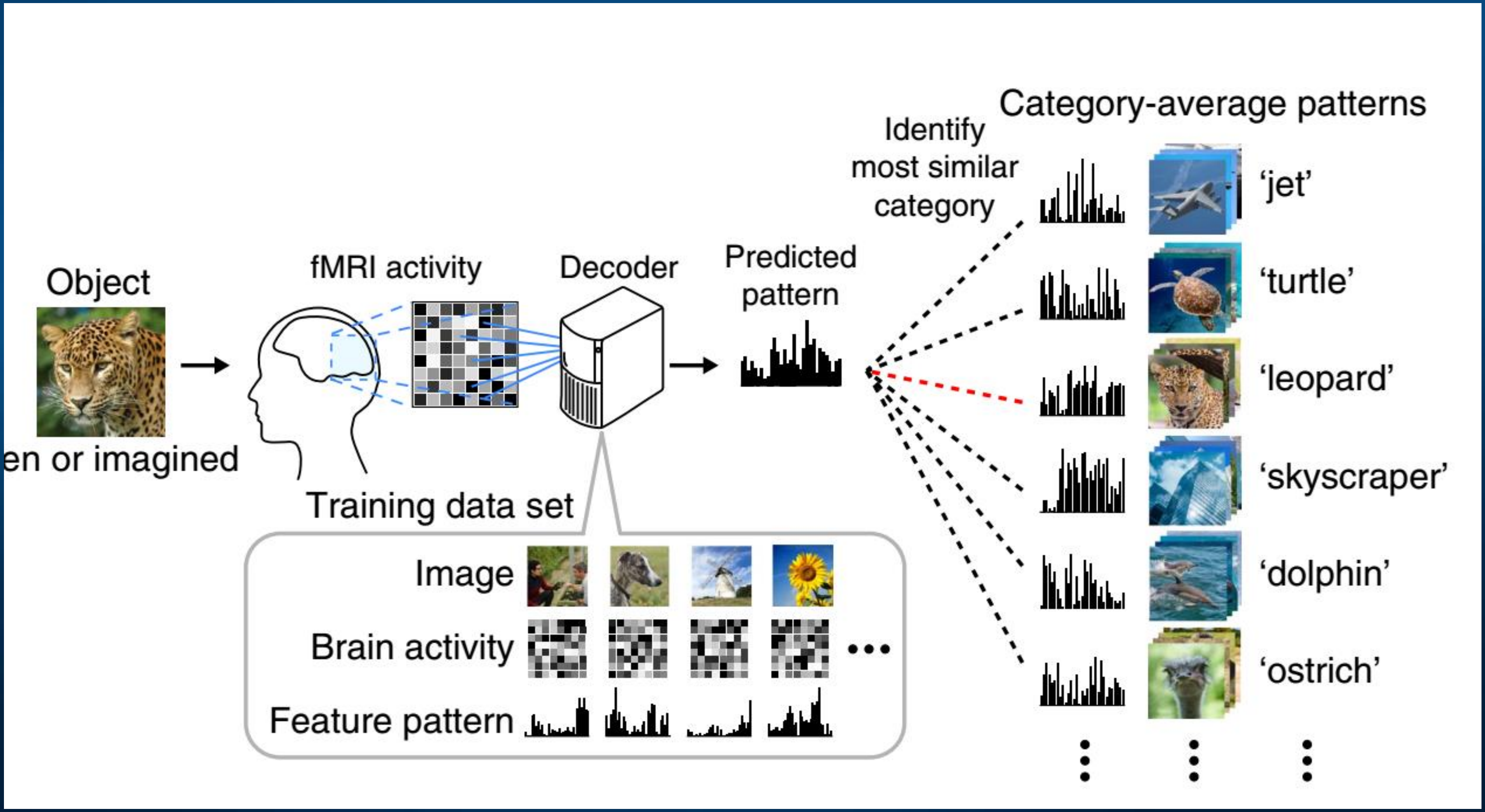
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

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.

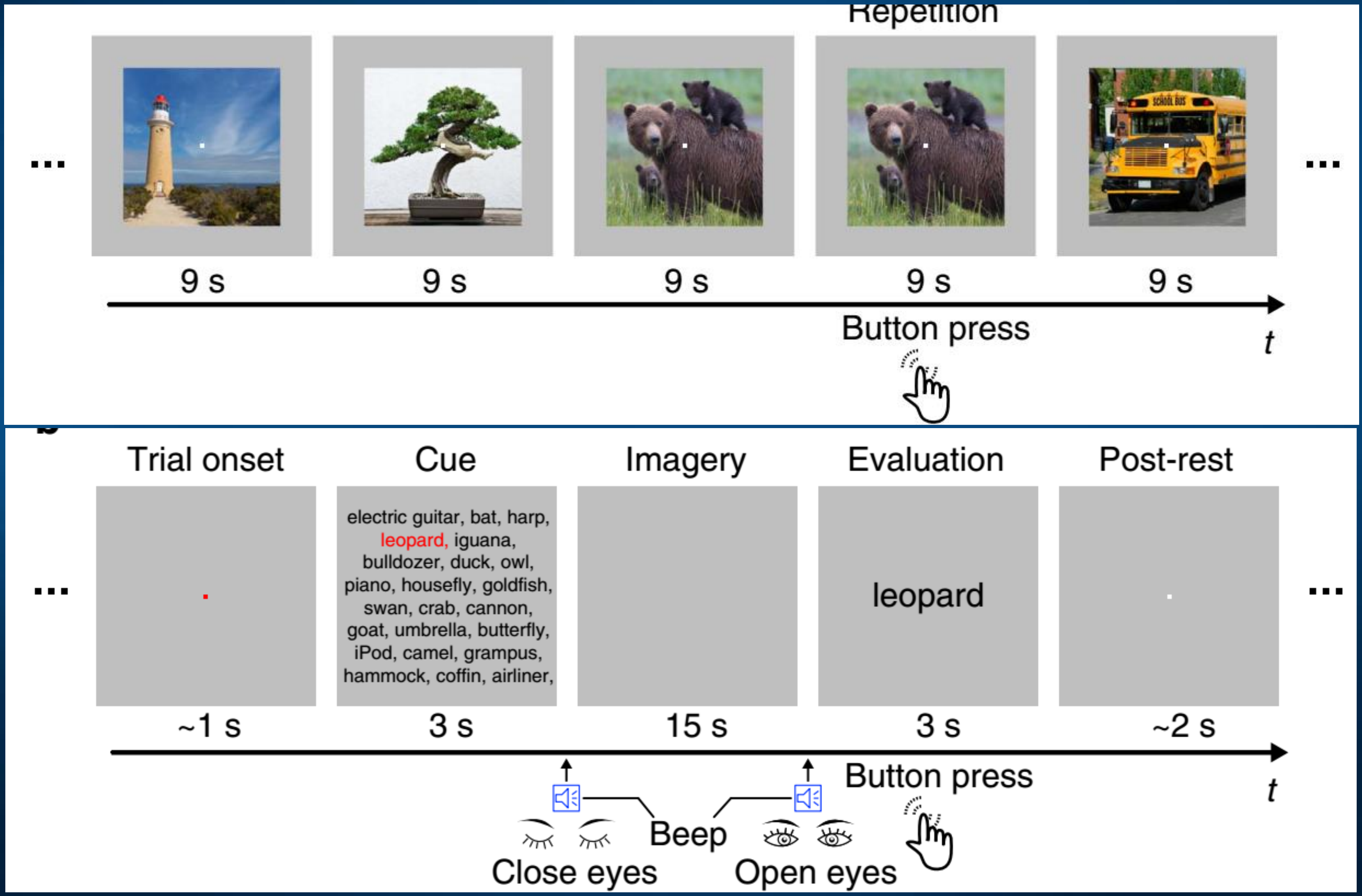
2. Analyze fMRI data $F(O_i)$ for 150 image categories (8 examples in each), select 500 voxels for V1–V4, LOC, FFA and PPA responding strongly to images vs scrambled images; decode feature values $V(O_i)$ using regression analysis $\mathrm{R}[F(O_i)] = V(O_i)$.

3. For a new image O_n (test, imagery, dream) use regression to calculate feature vector $\mathrm{R}[F(O_n)] = V(O_n)$.

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

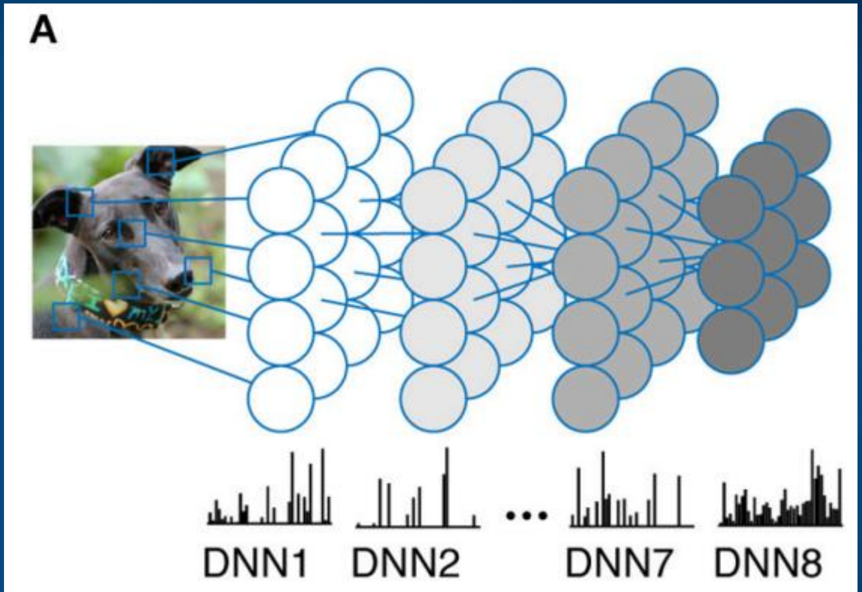
Horikawa, Kamitani, Nature Comm. 2017.

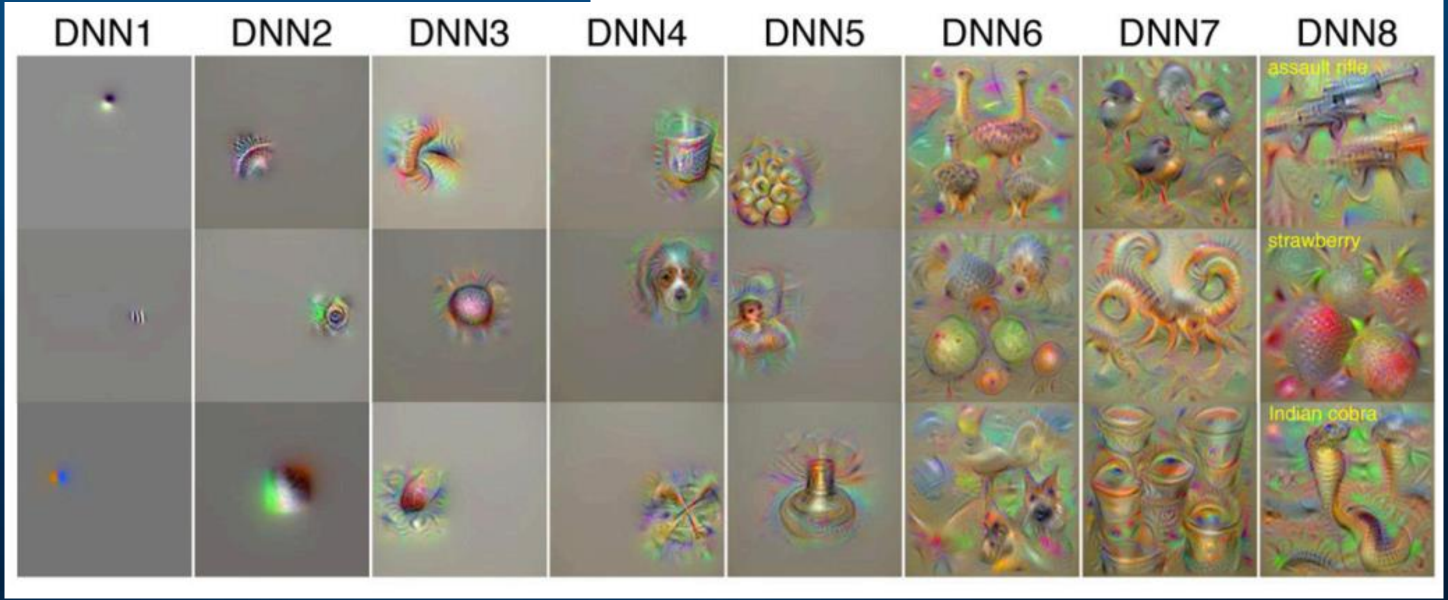


fMRI ⇔ CNN

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)





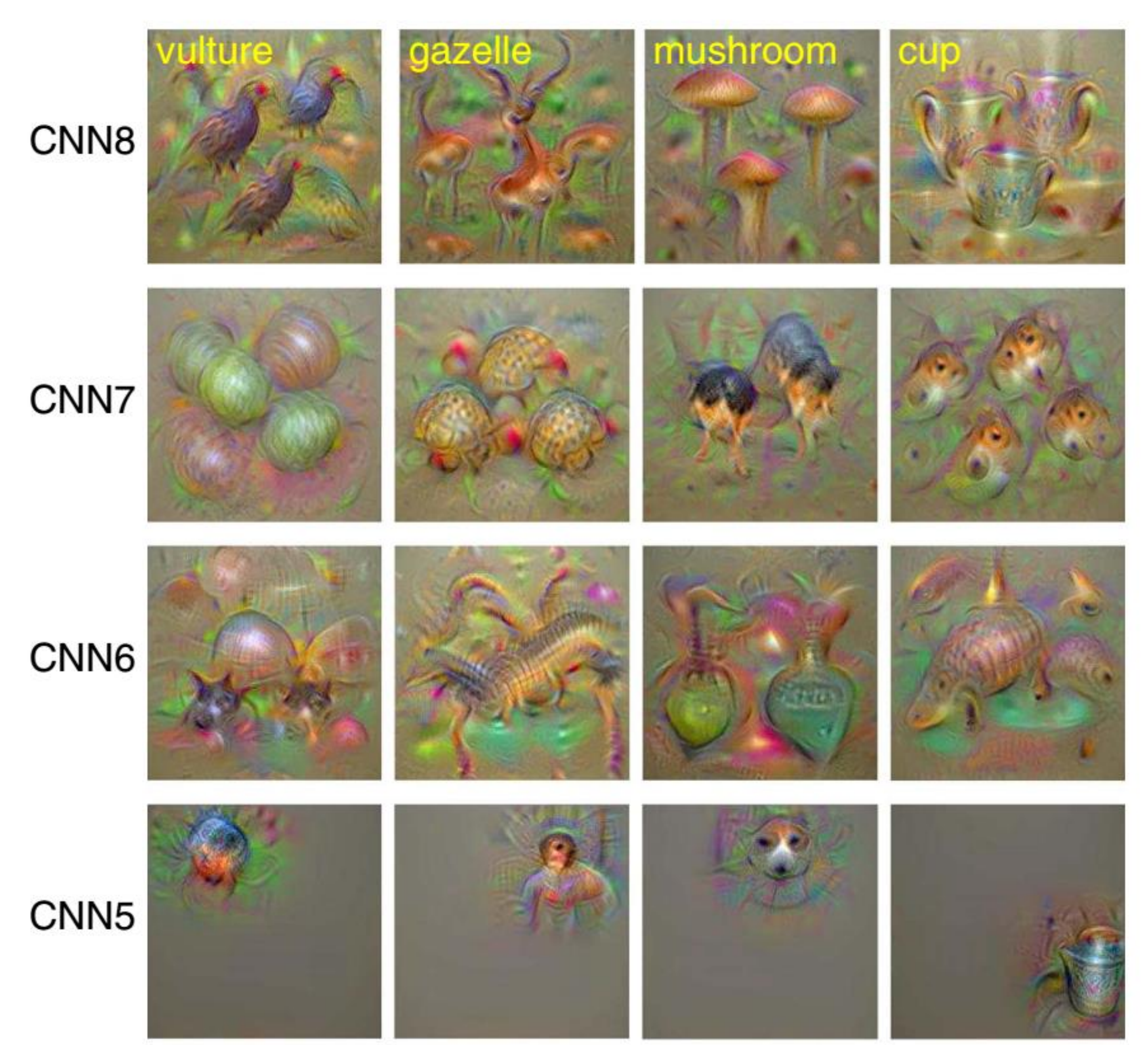
fMRI ⇔ CNN

4 units randomly selected from 1000 in each layer.

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

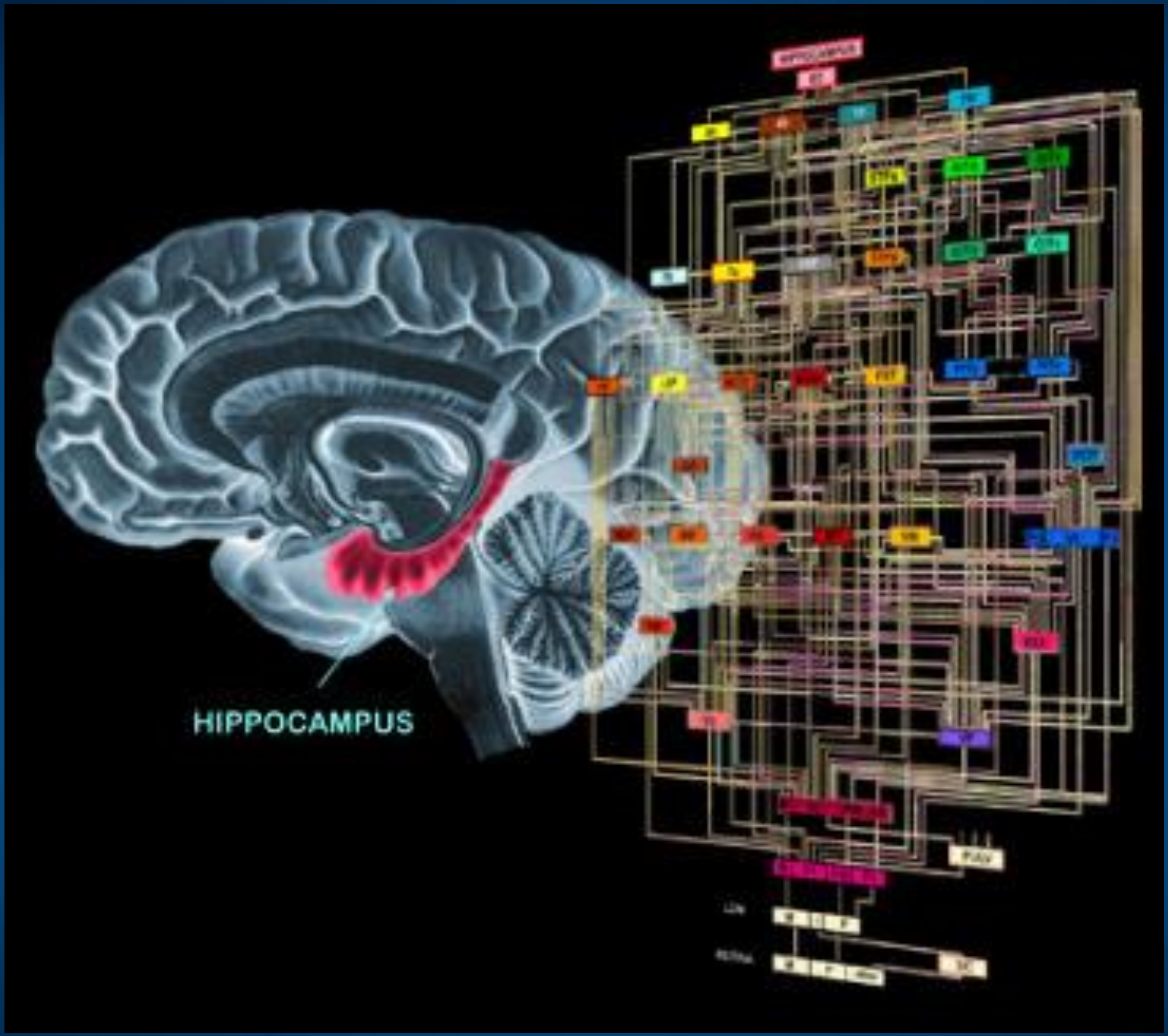
CNN8 has labels for 1000 categories.

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



CNN preferowane obrazy

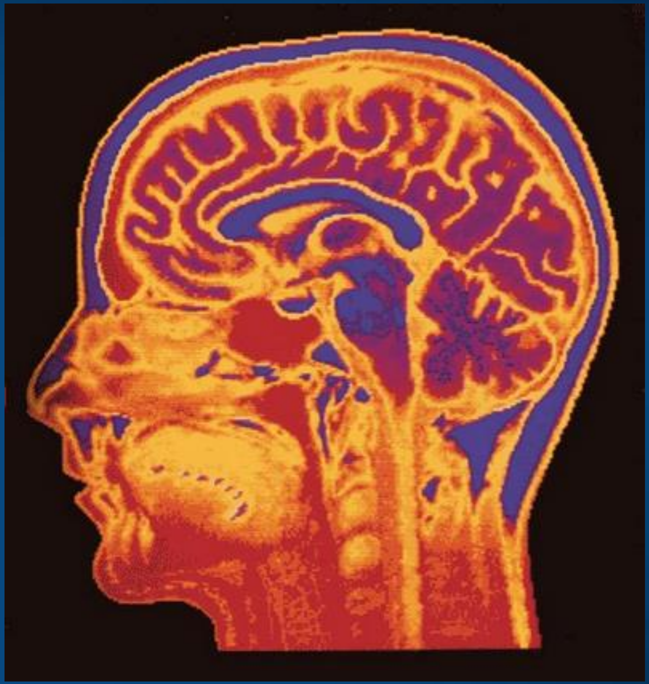
BICA, Brain-Inspired Cognitive Architecture



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

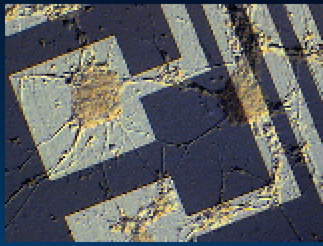
Understanding by creating brains

- "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.

The Great Artificial Brain Race



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

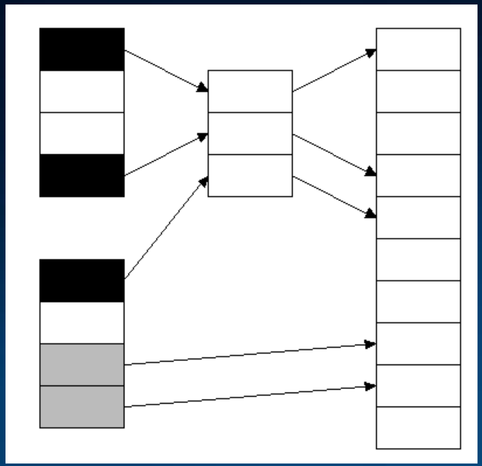
C2: 2009 IBM Almaden built a cortical simulator on Dawn, a Blue Gene/P supercomputer at Lawrence Livermore National Lab. C2 simulator re-creates 10^9 neurons connected by 10^{13} synapses, small mammal brain.

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

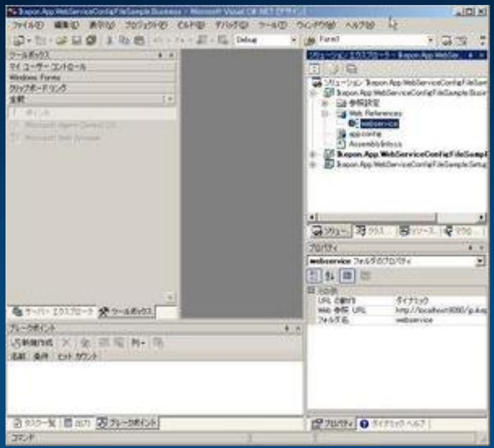
IFAT 4G: Johns Hopkins Uni (R.Etienne-Cummings) Integrate and Fire Array Transceiver, over 60K neurons with 120M connections, visual cortex model.

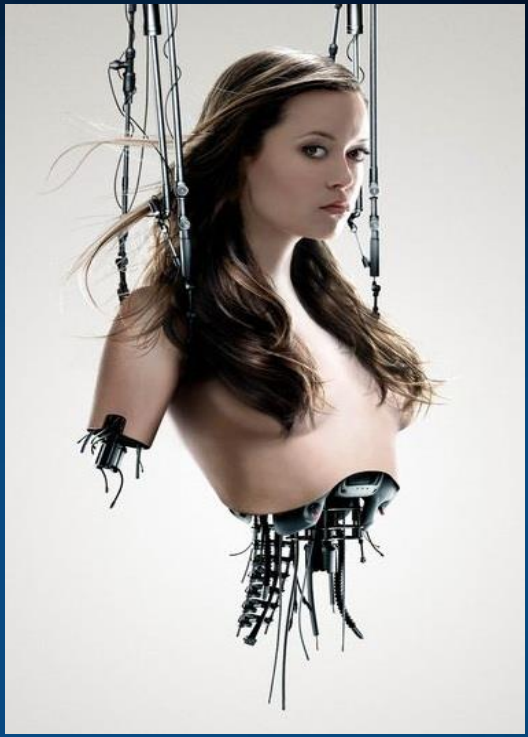
Brain Corporation: San Diego (E. Izhakievich), neuromorphic vision.

BRAINSCALES: EU neuromorphic chip project, FACETS, Fast Analog Computing with Emergent Transient States, now BrainScaleS, complex neuron model ~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.



Query

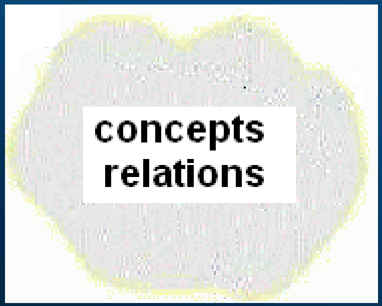




Semantic memory

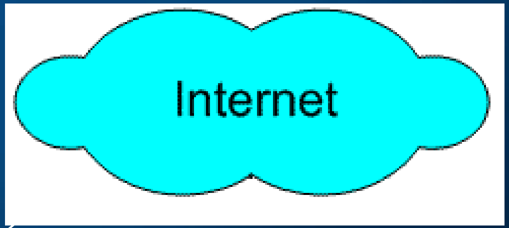
Applications, search,
20 questions game.

Store



Part of speech tagger
& phrase extractor

verification

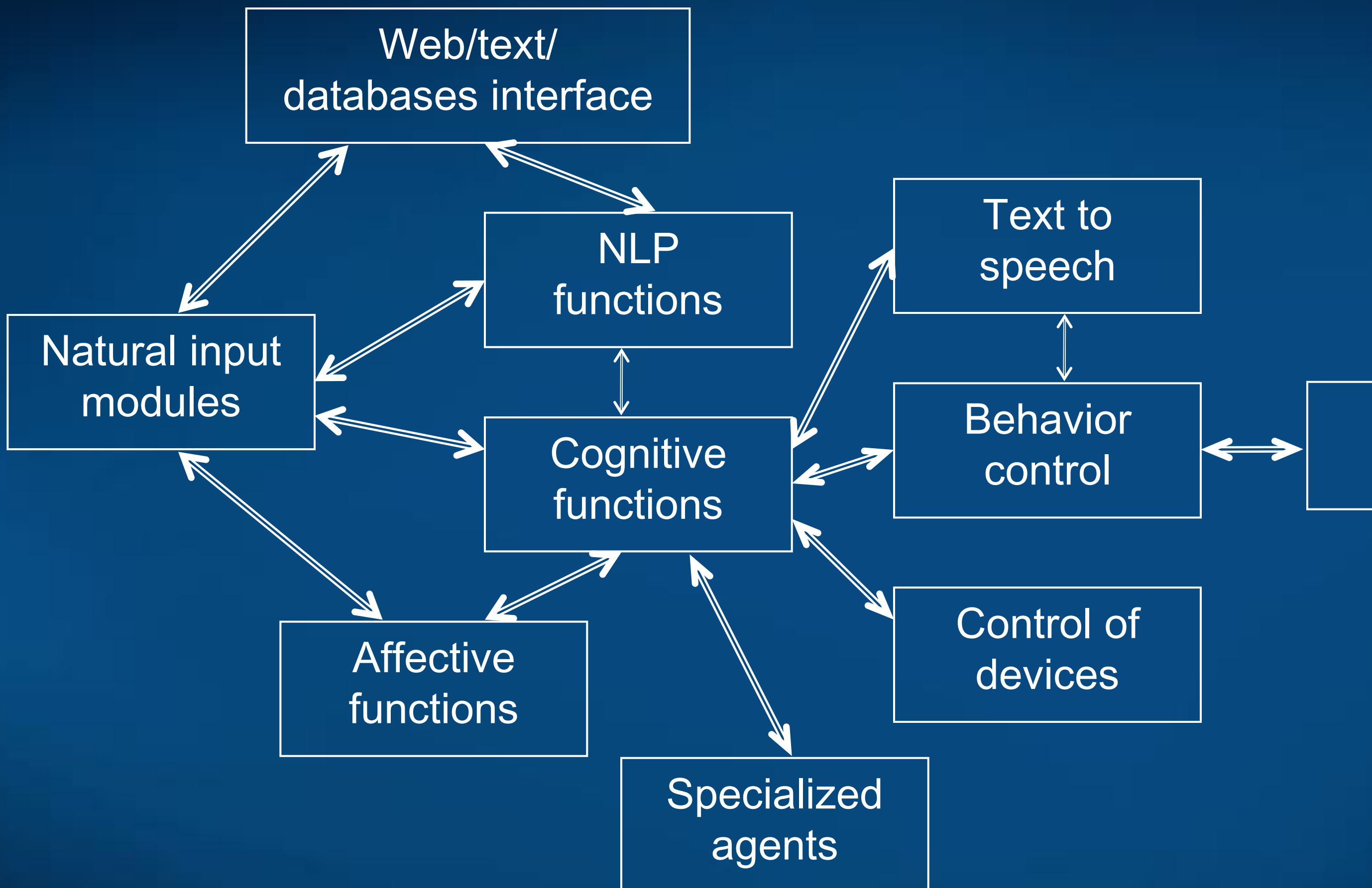


On line dictionaries
Active search and
dialogues with users

Parser

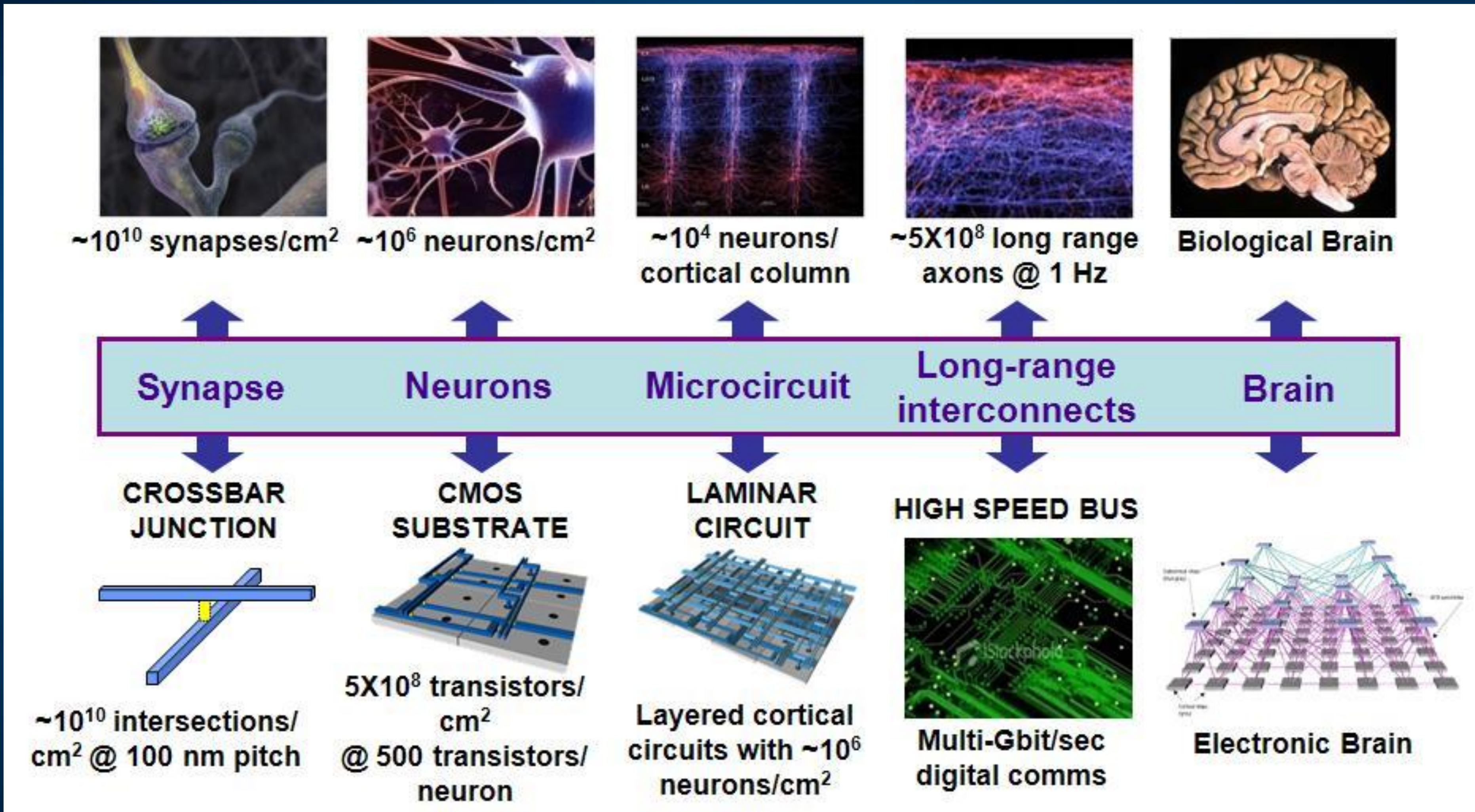
Manual

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

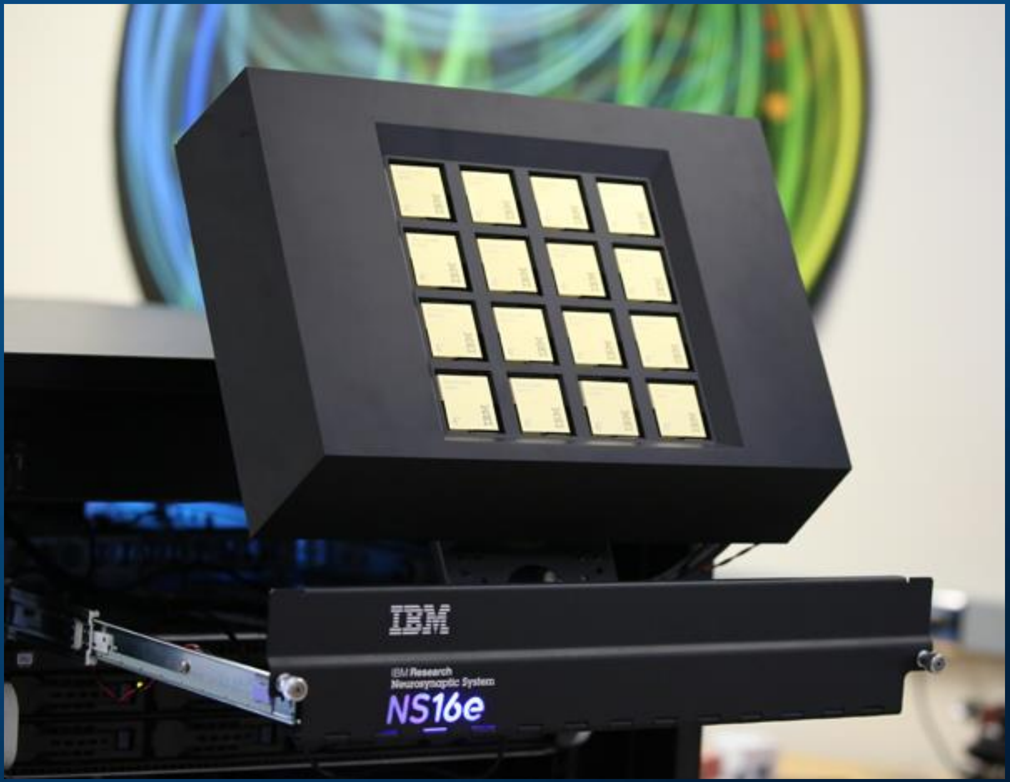
Synapse 2015: IBM TrueNorth chip:
~1M neurons and ¼G synapses, 5.4G transistors, 70 mW.
NS16e module=16 chips=16M neurons, >4G synapses, requires only 1.1 W!
Scaling: 256 modules, ~4G neurons, ~1T= 10^{12} synapses < 300 W power!
IBM Neuromorphic System can reach complexity of the human brain.

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 ⇔ The Virtual Brain, graphical models ⇔ mental models.
- Neuromorphic hardware is coming and will enable construction of new brain models and many applications.

Is there a shorter route
to understand human behavior?

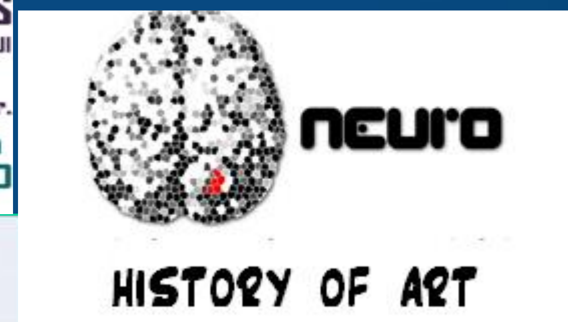
My group of neuro-cog-fanatics

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

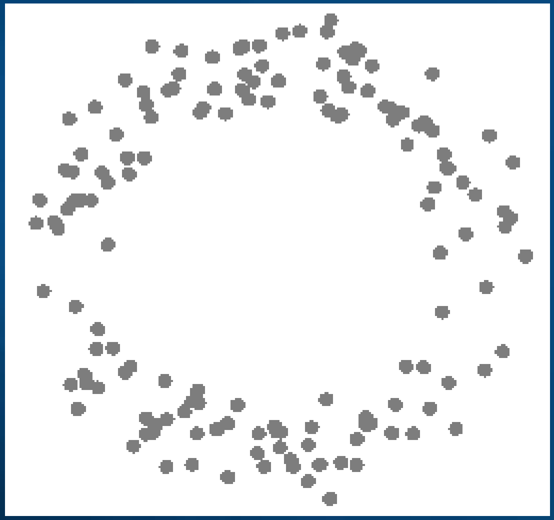
Monthly international developmental seminars (2017): Infants, learning, and cognitive development

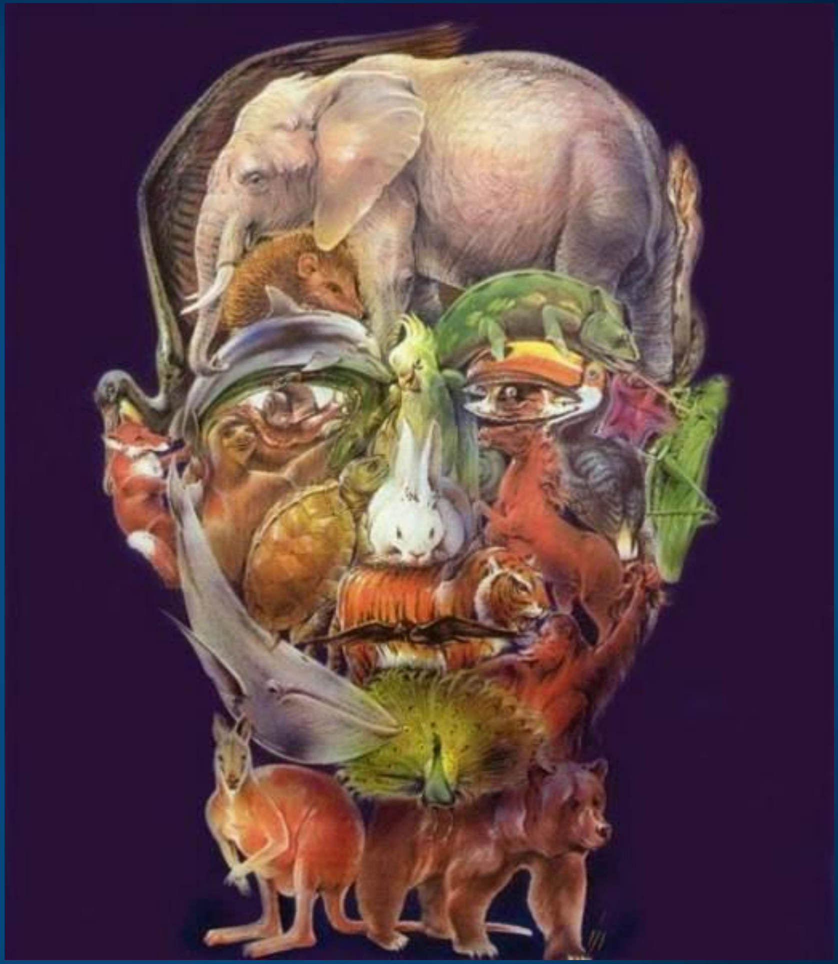
Disorders of consciousness 17-21.09.2017

Autism: science, therapies 23.05.2017



Thank for synchronization of your neurons





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

jacekzurada.org