Multi-level explanations in neuroscience: from genes to subjective experiences.

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Cracow School of Theoretical Physics, LVIII Course, Zakopane, 15-23 June,
Neuroscience: Machine Learning Meets Fundamental Theory

On the threshold of a dream …

From mind to AI to NN to multi-level phenomics.

Part I: Brain and ML inspirations.

Brain ⇔ Mind relations, phenomics, **RDoC**.

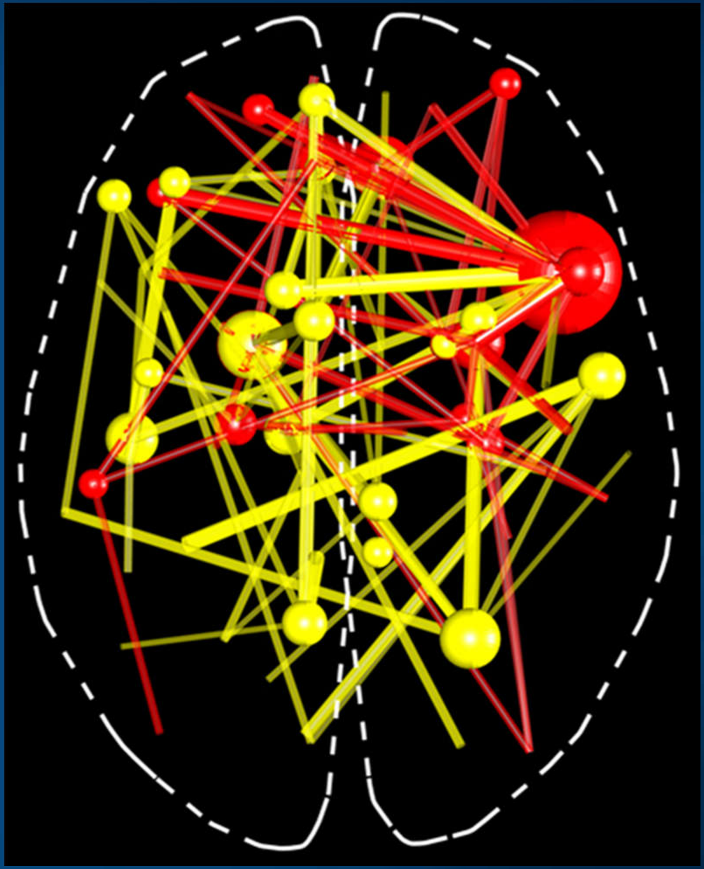
Part II: Neurodynamics.

Brain simulations at different levels.

Part III: **Fingerprints of mental activity**.

Neurodynamics on real brain networks.

Past, present, future overview.

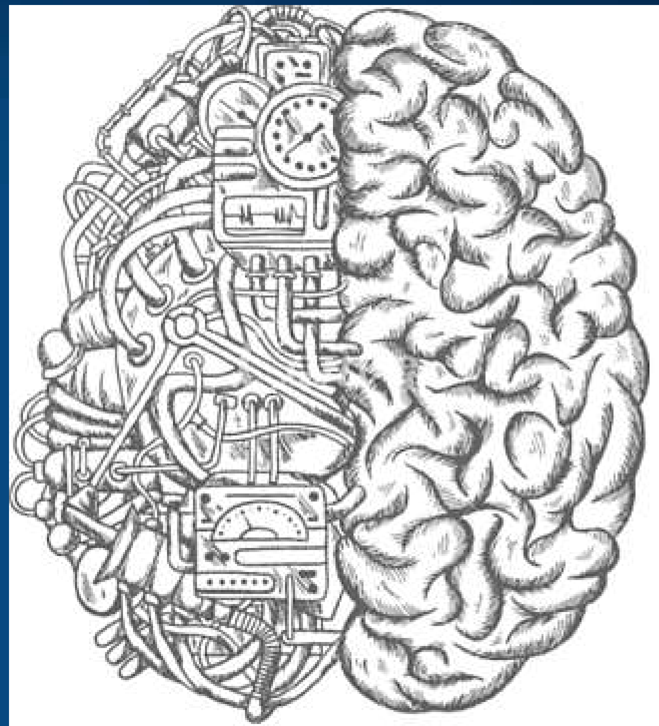


Part III: Fingerprints of mental activity

Goal: understanding brains and minds, relations:

Environment ⇔ Brain ⇔ Mind

Real brain networks, many ways to measure,
but what do we understand?



Brain networks

State transitions

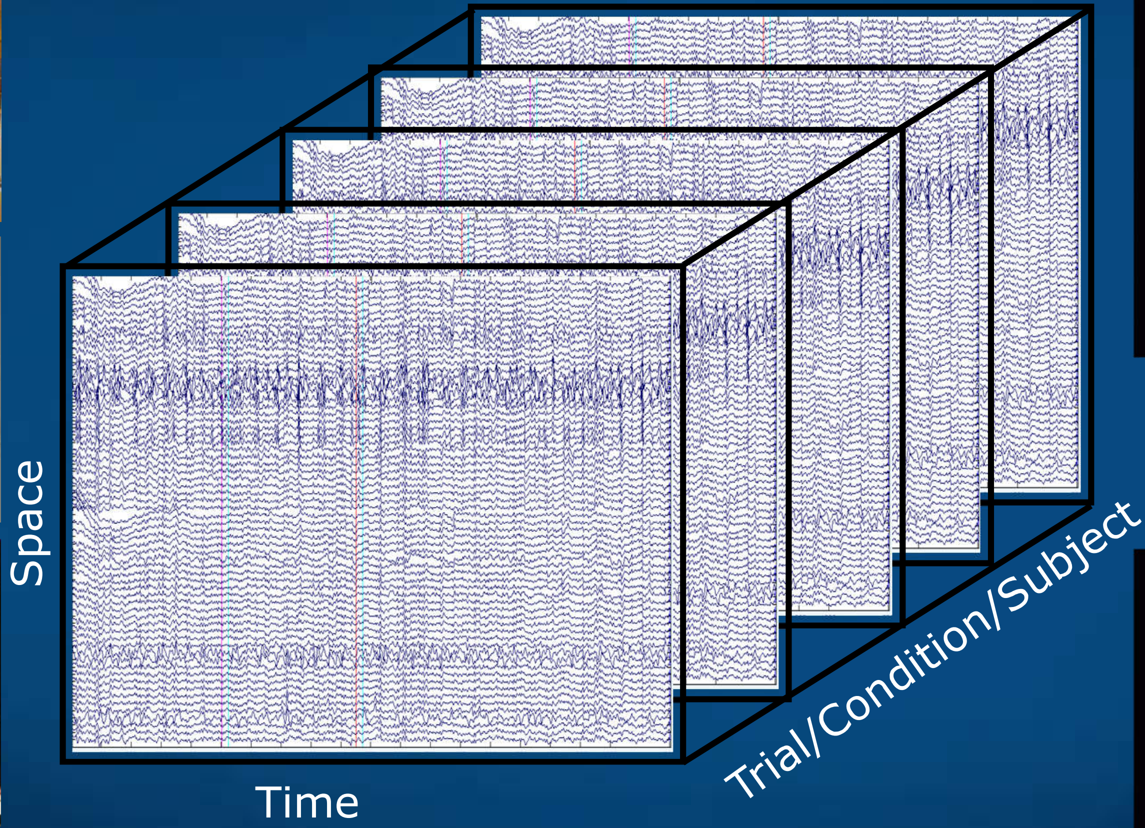
Dynamics on brain networks

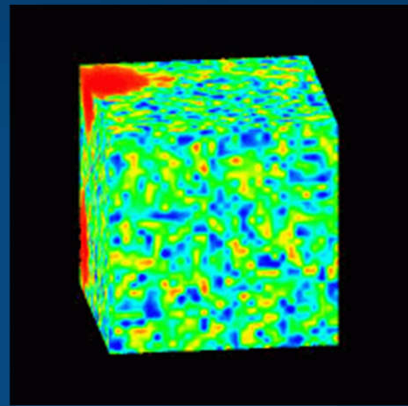
Understanding brain states

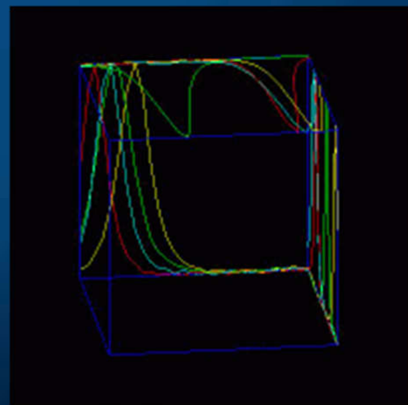
Conspiracy theories …

From Two-way to Multi-way Data Analysis
EEG+fNIRS +fMRI

A. Cichocki Lab
RIKEN Brain Science Inst.

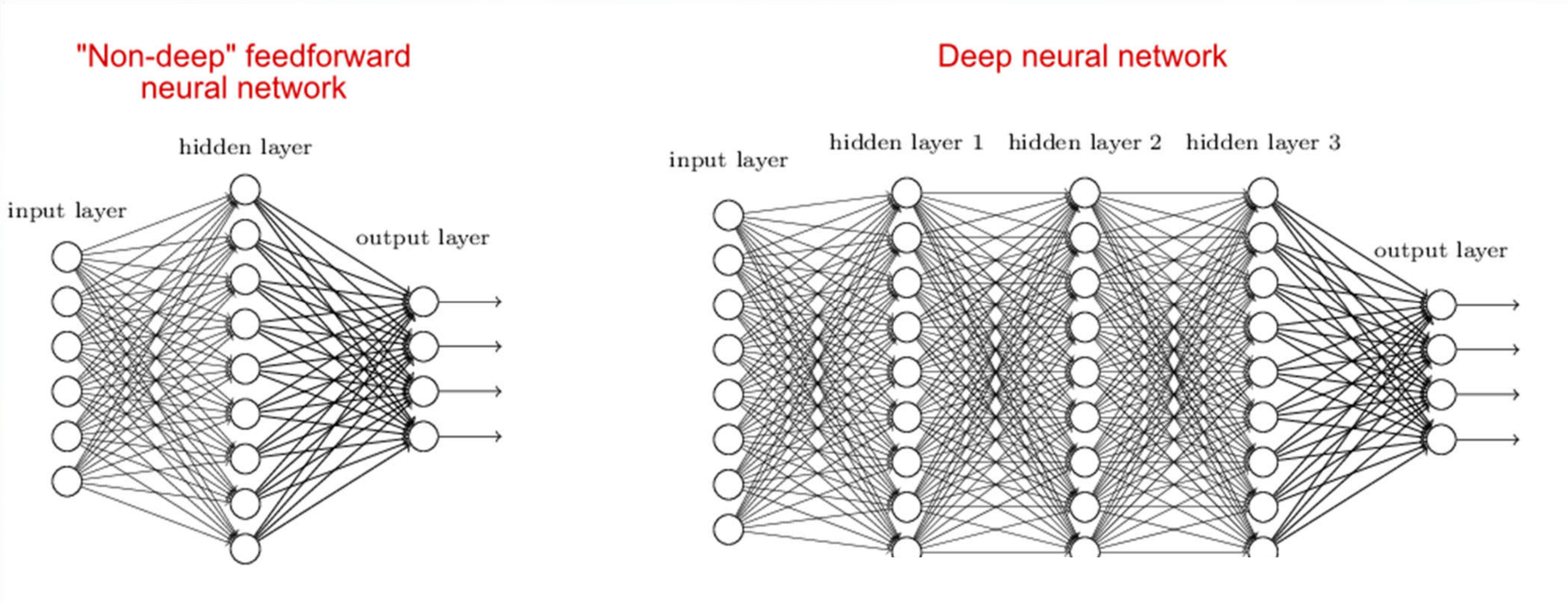




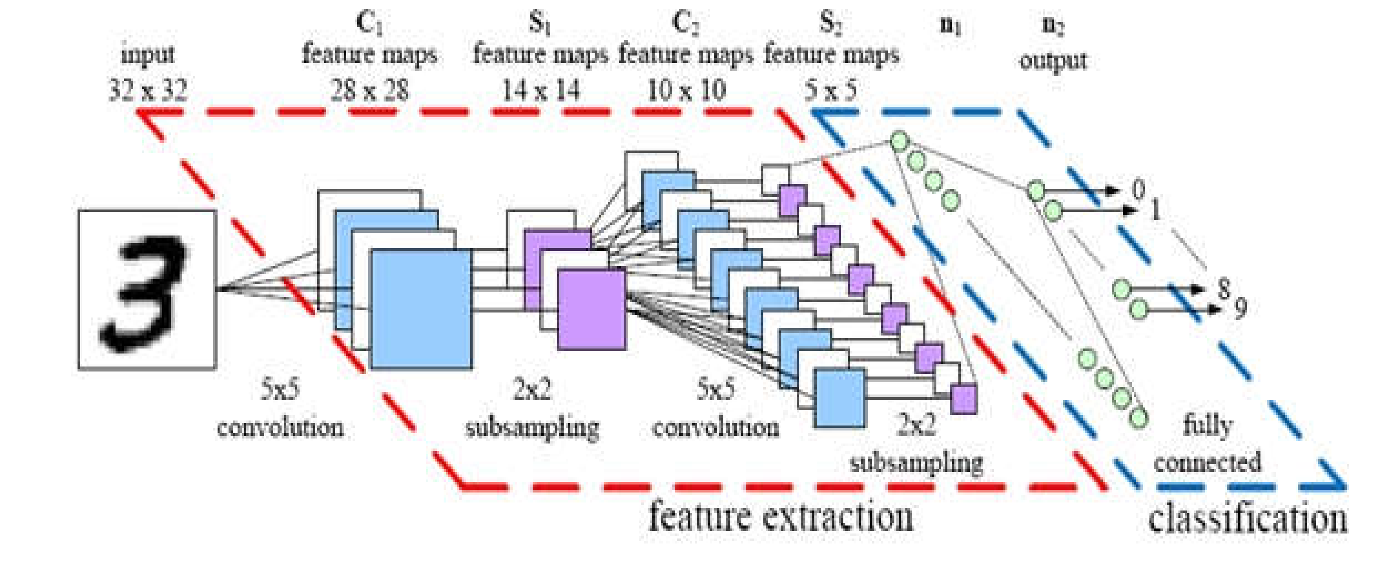


Exploratory and multi-way blind source separation and tensor factorizations: unsupervised learning methods and software to find the hidden causes & underlying hidden structure in the data.

Tensorization of Deep Learning NN



A. Cichocki Lab
RIKEN BSI



EEG fingerprints applications

Recognition of specific brain activity using EEG should allow for regulation of brain neurodynamics, using either biofeedback or closed-loop DCS/TMS, brain-computer-brain interfaces.

Rt-fMRI neurofeedback is more effective than EEG neurofeedback, can we get similar results based on EEG?

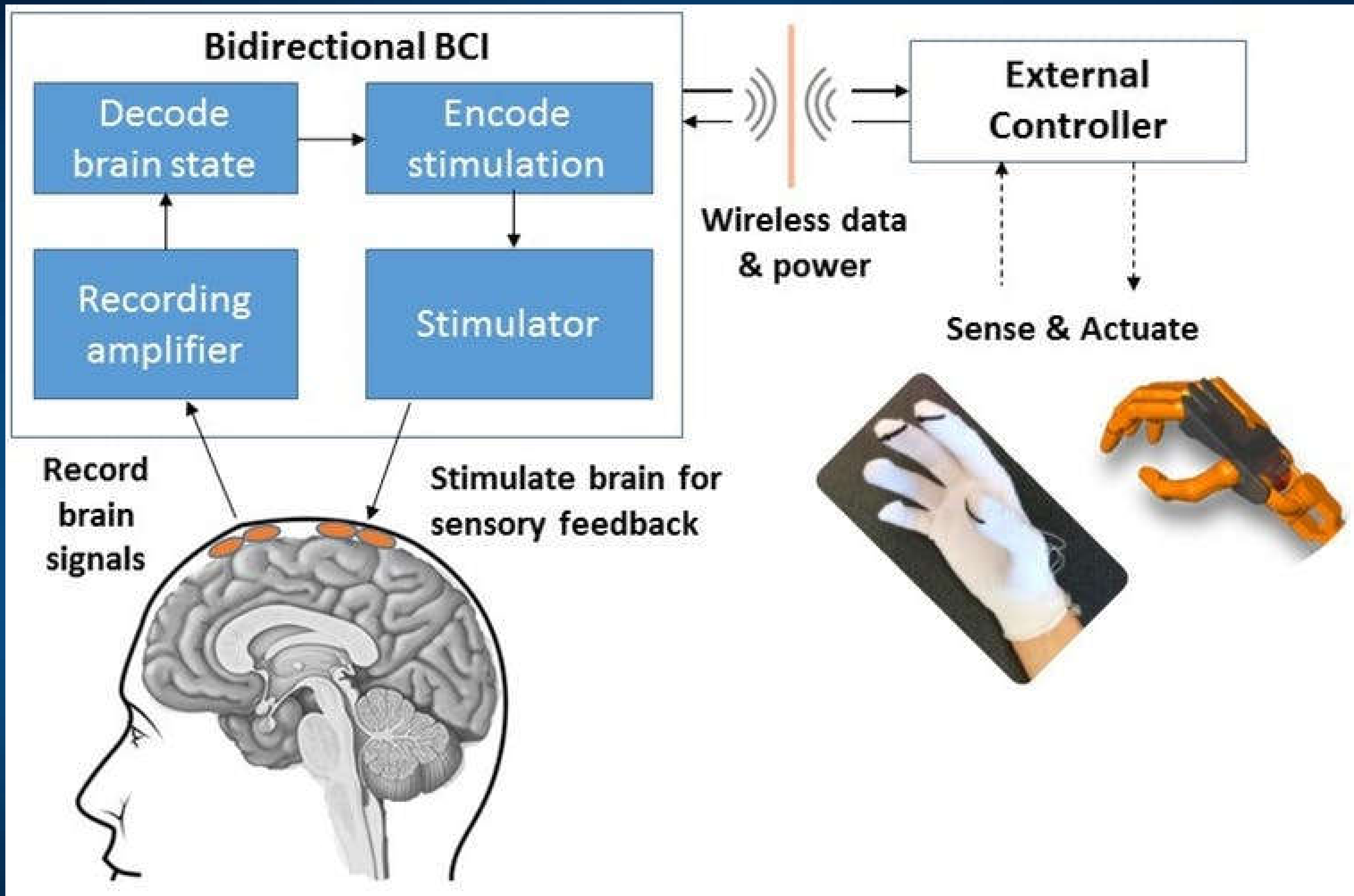
Enhance/inhibit selected brain structures/networks.
Enhance/inhibit connections between brain structures/networks.

Use in neurorehabilitation: stroke, motor impairments, assistive robotics …

Use if to boost specific skills, creativity, memory, learning, reading ...

Use in therapy: psychosomatic disease, various forms of pain, OCD, PTSD, specific developmental disorders …

Brain-Computer-Brain interfaces



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

Brain networks.
Space for neurodynamics.

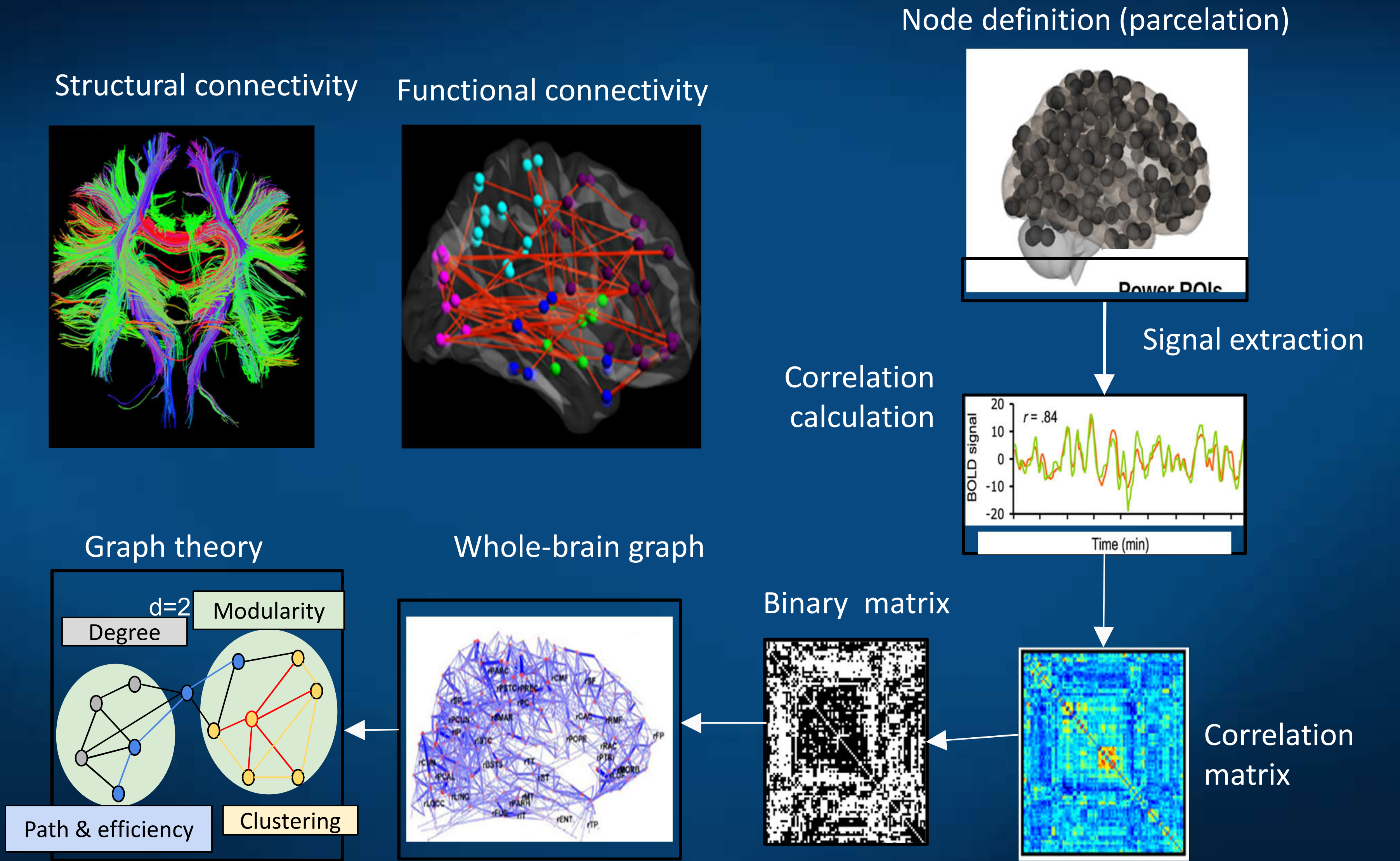
Possible form of Brain Fingerprints

fMRI: BFP is based on **V(X,t)** voxel intensity BOLD signal changes, contrasted between task and reference activity or resting state.
EEG: spatial, spatio-temporal, ERP maps/shapes, coherence, various phase synchronization indices.

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

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

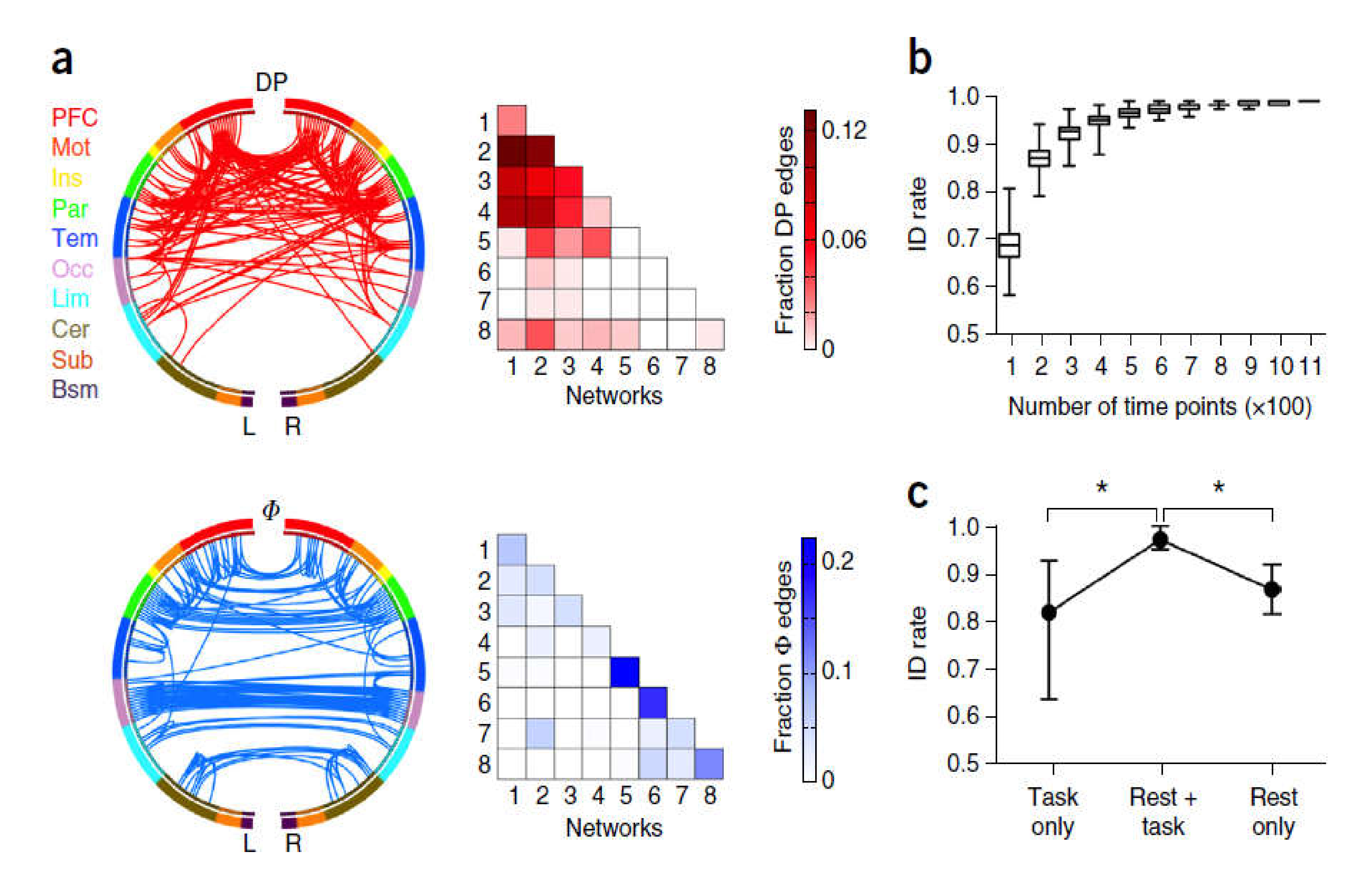
Human connectome and MRI/fMRI



Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

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

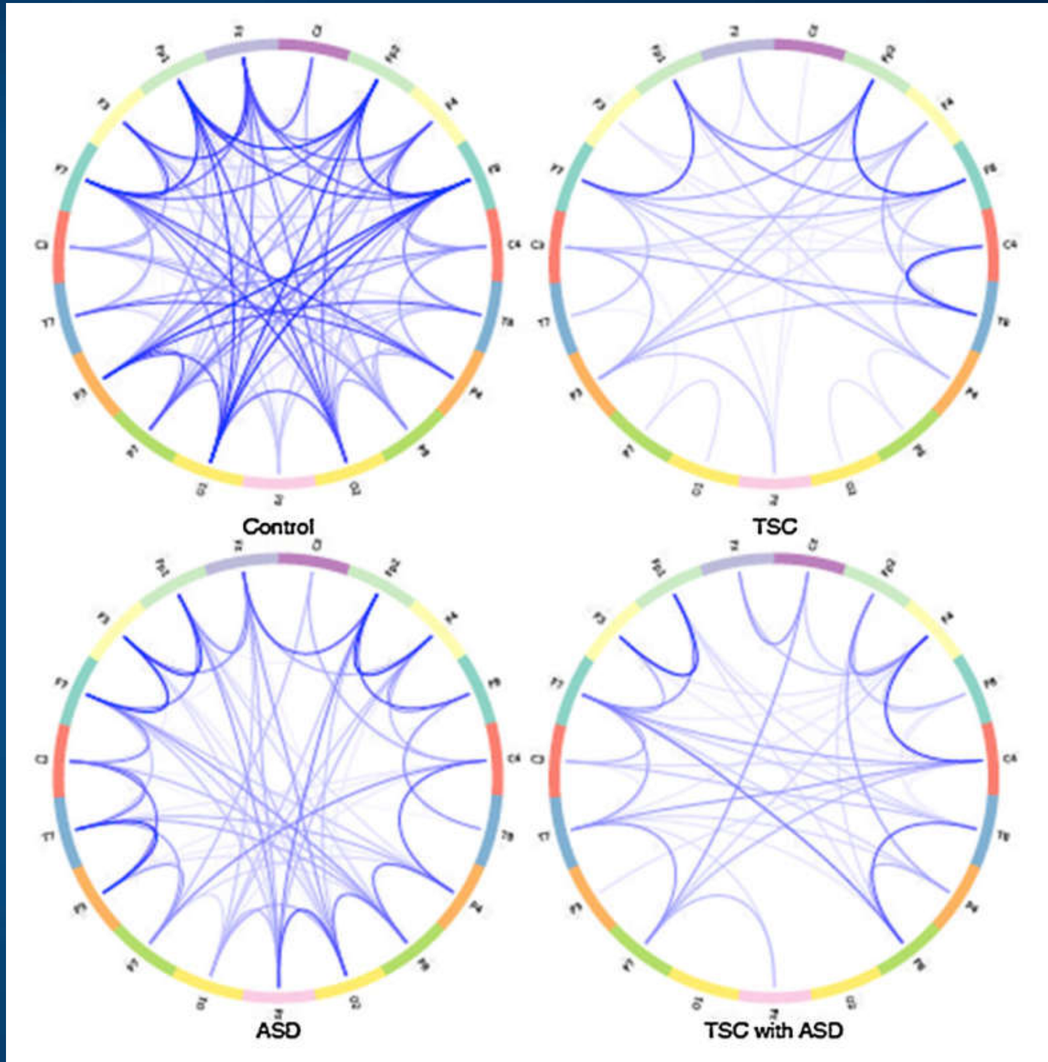


ASD: pathological connections

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

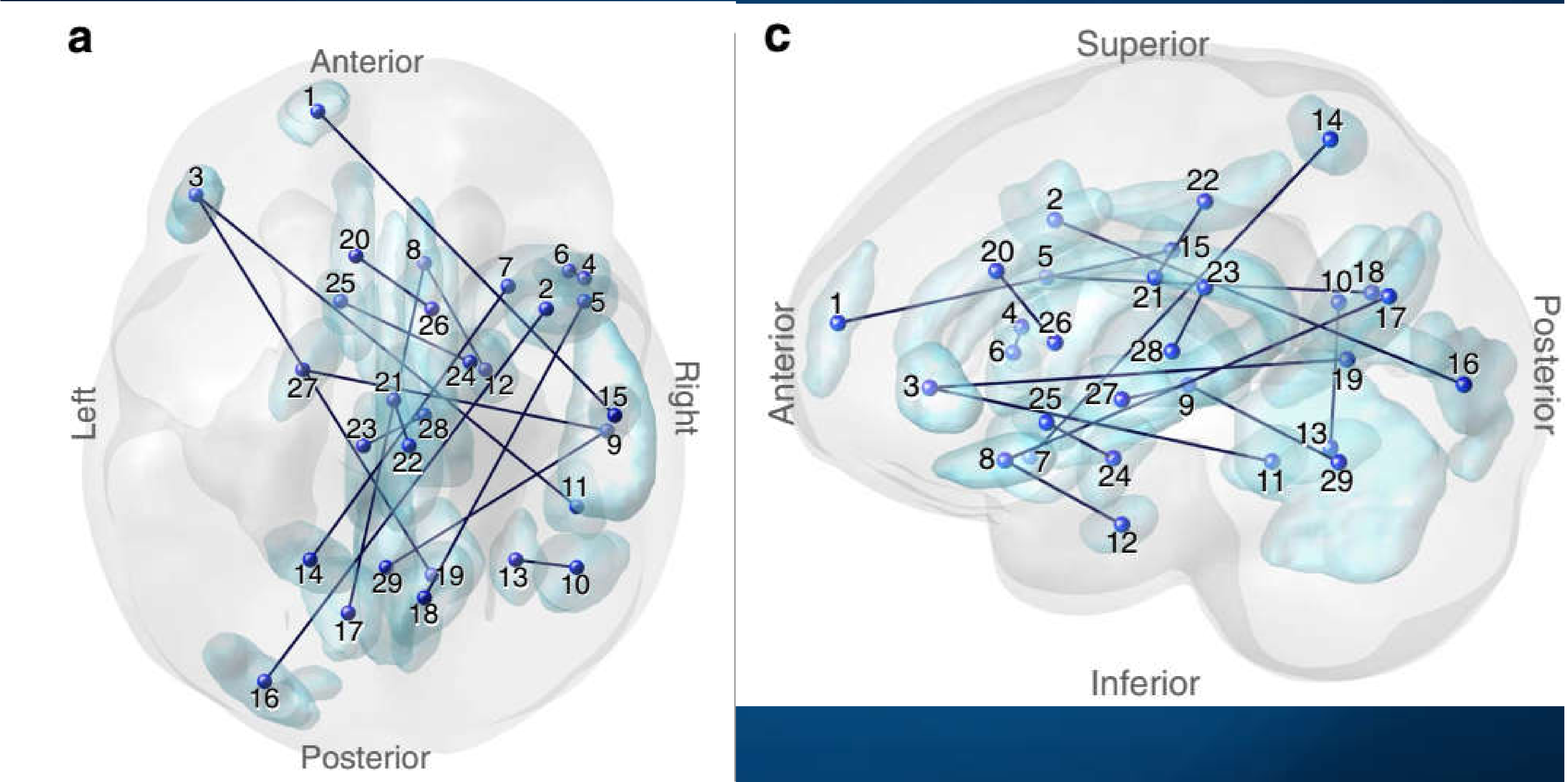
Coherence between electrodes. Weak or missing connections between distant regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

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



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

Selected connections



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

Age differences

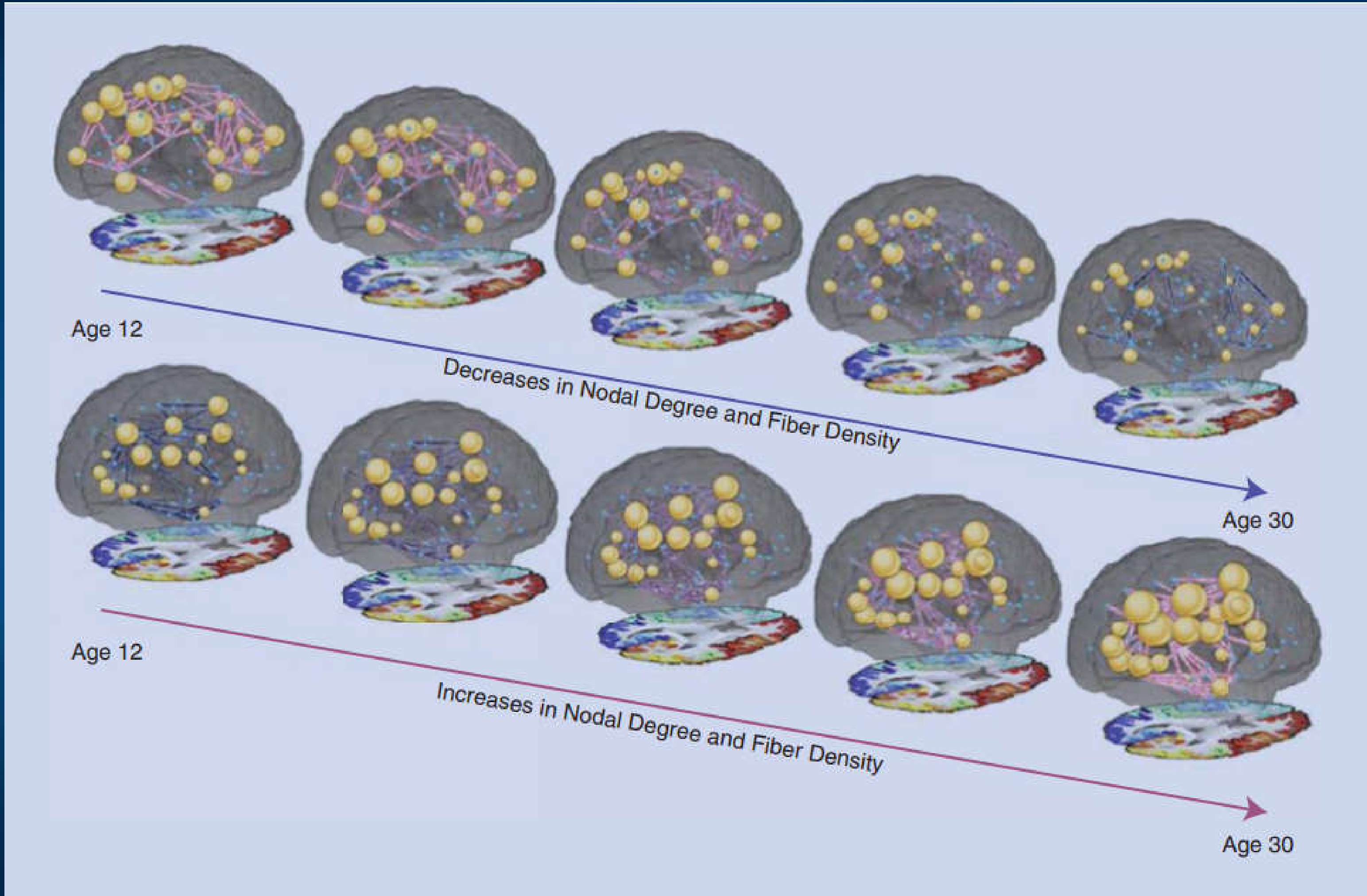


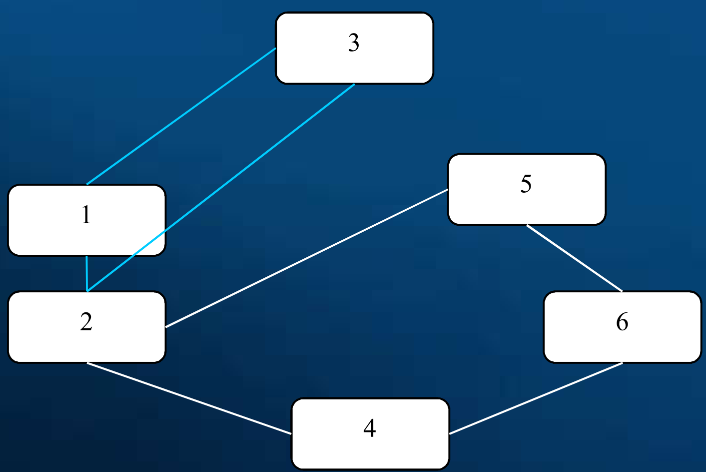
FIGURE 16. Dennis et al. [49] compared the brains of 439 individuals aged 12–30 years by high angular resolution diffusion imaging and found that not all connections are strengthened during development, but some are pruned. Only the connections with significant correlations with age are shown. The node size is proportional to the number of connections, and the thickness of the connection edges is proportional to relative fiber density. (Figure reprinted from [49] with permission.)

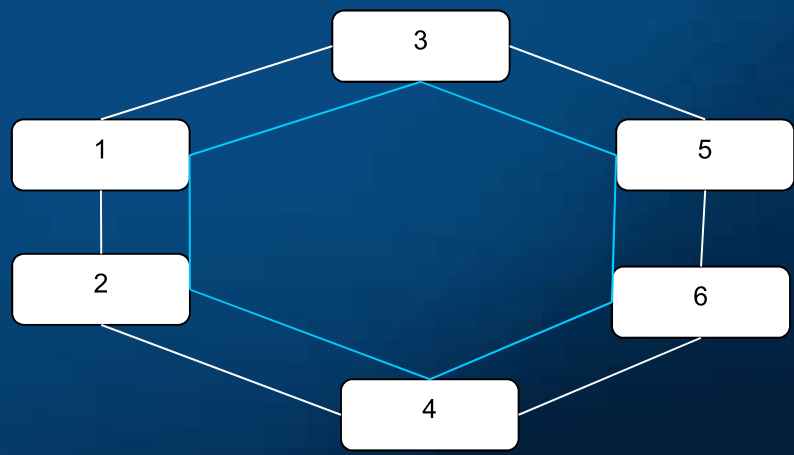
Functions and regions

Localization:
Is every region of the brain endowed with specialized tasks, and every tasks done by a fixed subset of specialized regions?

Holism:
Or is the whole brain working on the tasks?

Neither.





Recycling ?

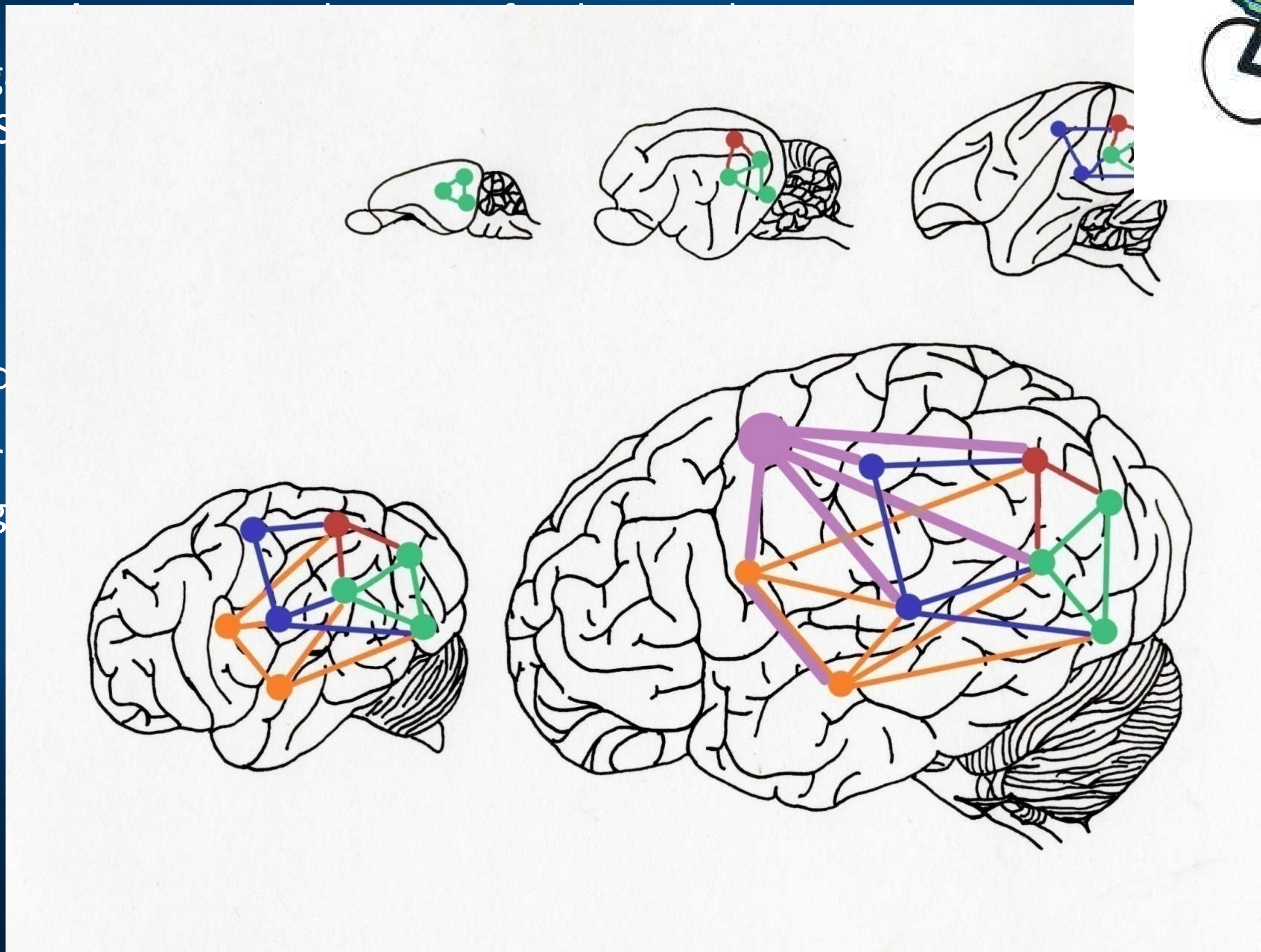
M. Anderson, Neural reuse: a fundamental organizational principle of the brain.
BBS 33, 245–313 (2010)

Endogenesis.

Formation of columns from resonators responsible for movements, from wiggling in worms to salamander out of phase RPGs.

Recycling ?

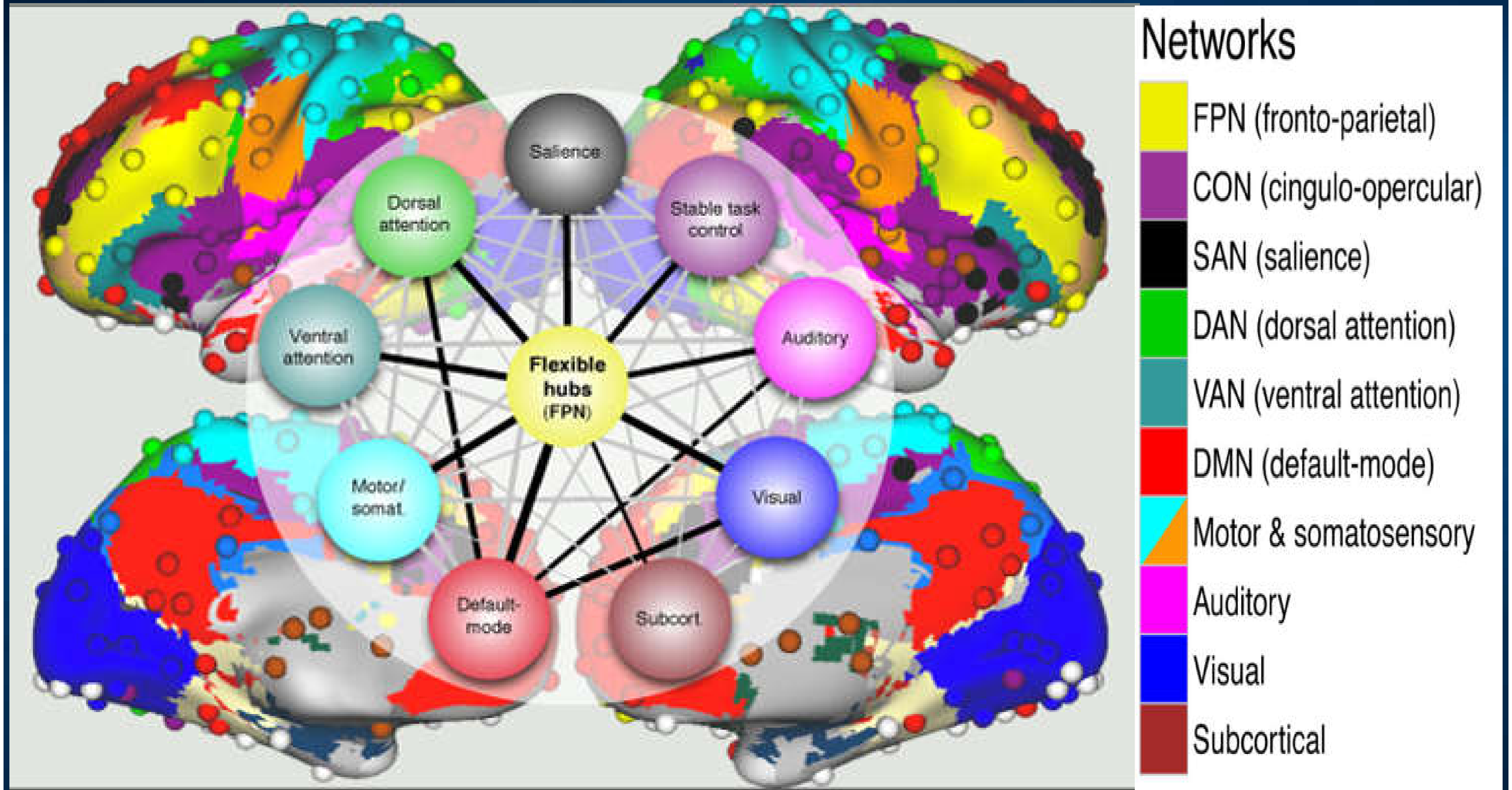
M.
org
BBS



End

For m
wig

Neurocognitive Basis of Cognitive Control

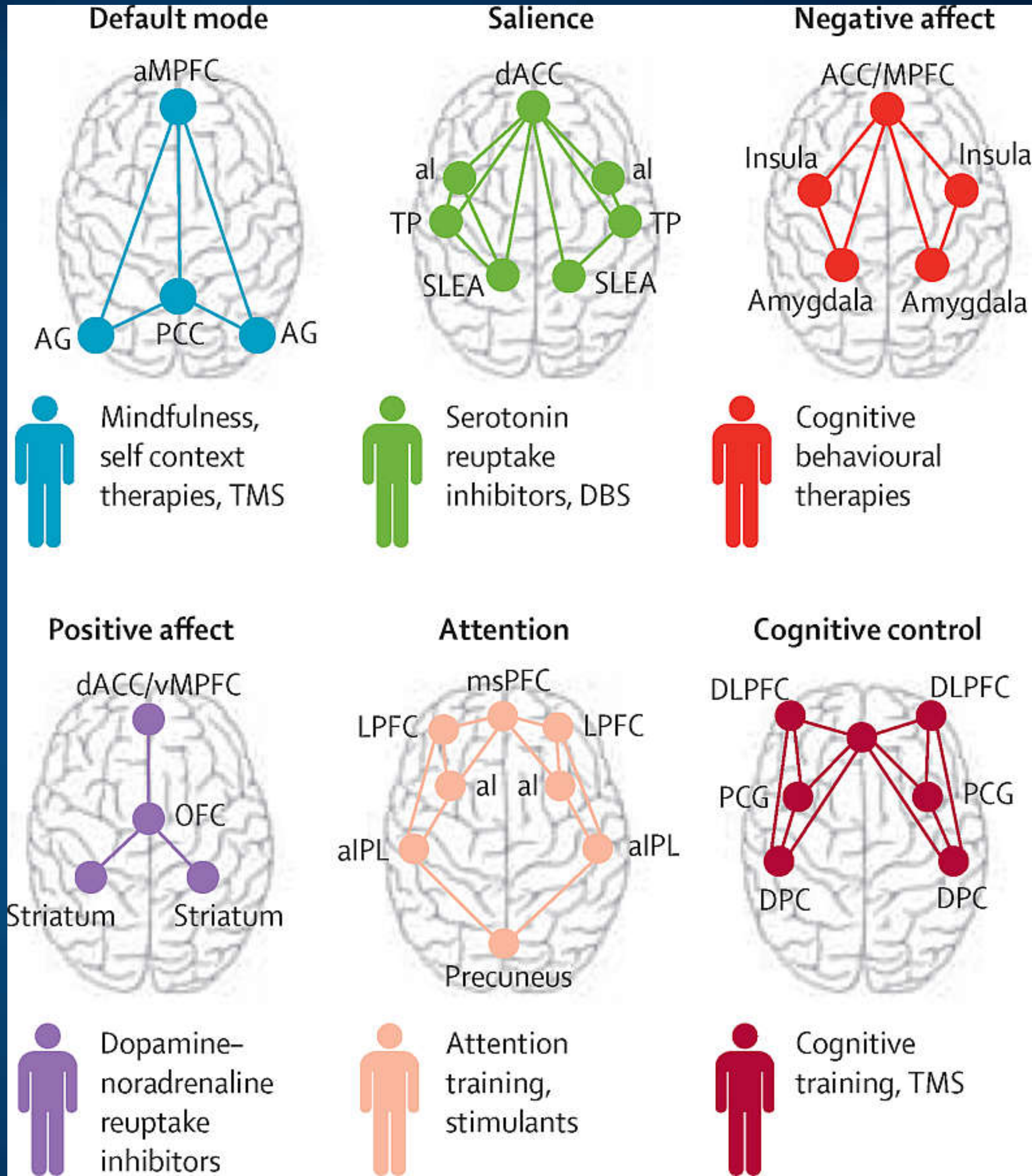


Central role for fronto-parietal (FPN) flexible hubs in cognitive control and adaptive implementation of task demands (black lines=correlations significantly above network average). Cole et al. (2013).

RDoC networks

aMPFC=anterior medial PFC
AG=angular gyrus. PCC=posterior cingulate cortex; dACC=dorsal anterior CC; aI=anterior insula. TP=temporal pole. SLEA=sublenticular extended amygdala.
LPFC=lateral PFC, M=medial v=ventral, ms=medial superior, vM =ventromedial, aIPL=anterior inferior parietal lobule.

OFC=orbitofrontal cortex. ACC=anterior cingulate cortex. DLPFC=dorsolateral PCG=precentral gyrus. DPC=dorsal parietal cortex.



fMRI BOLD-MEG signals

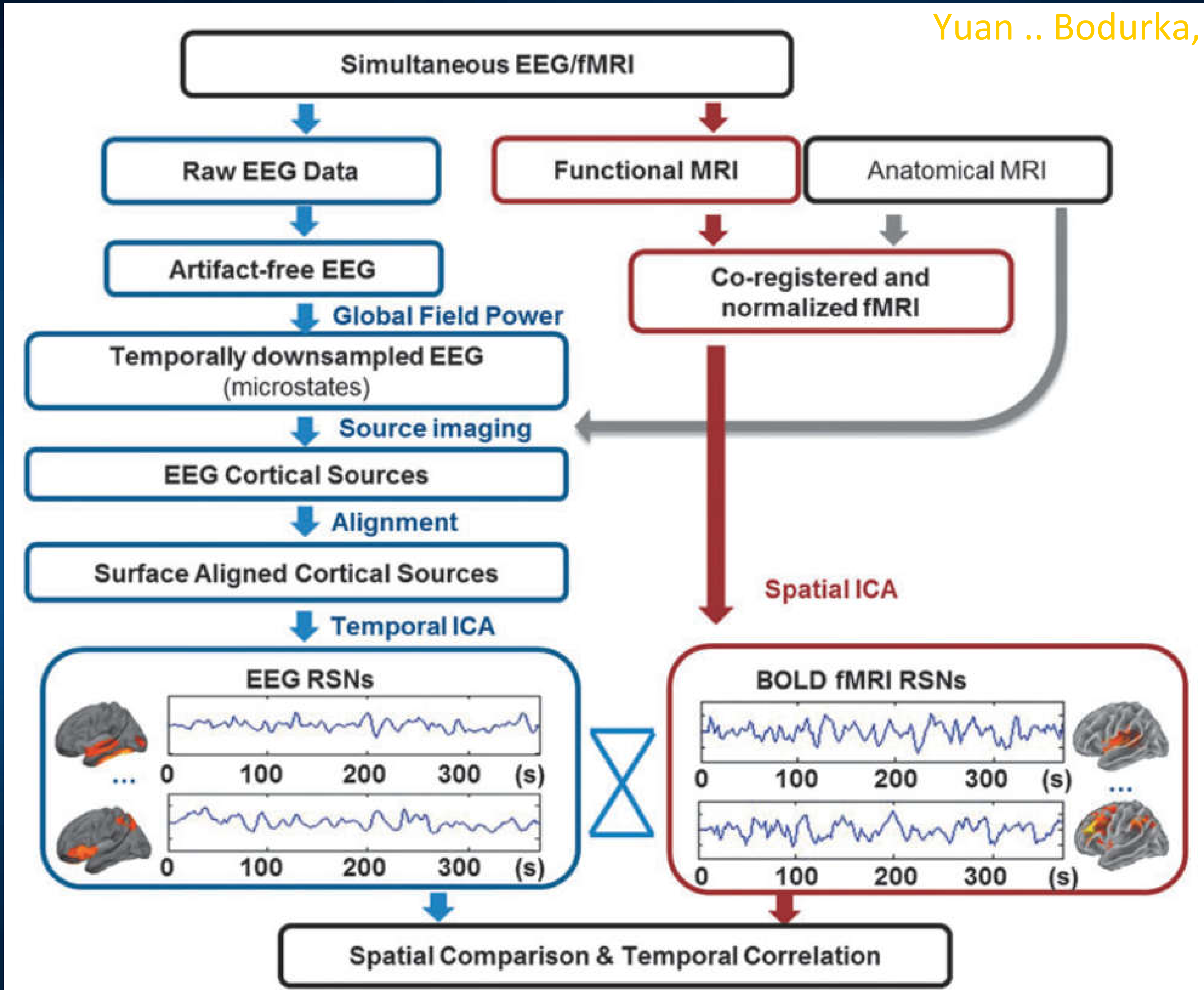
Zumer, J.M., Brookes, M.J., Stevenson, C.M., Francis, S.T., & Morris, P.G. (2010) Relating BOLD fMRI and neural oscillations through convolution and optimal linear weighting. *NeuroImage*, *49*(2), 1479–1489.

… several recent findings, recorded invasively in both humans and monkeys, show a positive correlation of BOLD to high-frequency (30–150 Hz) oscillatory power changes and a negative correlation to low-frequency (8–30 Hz) power changes.

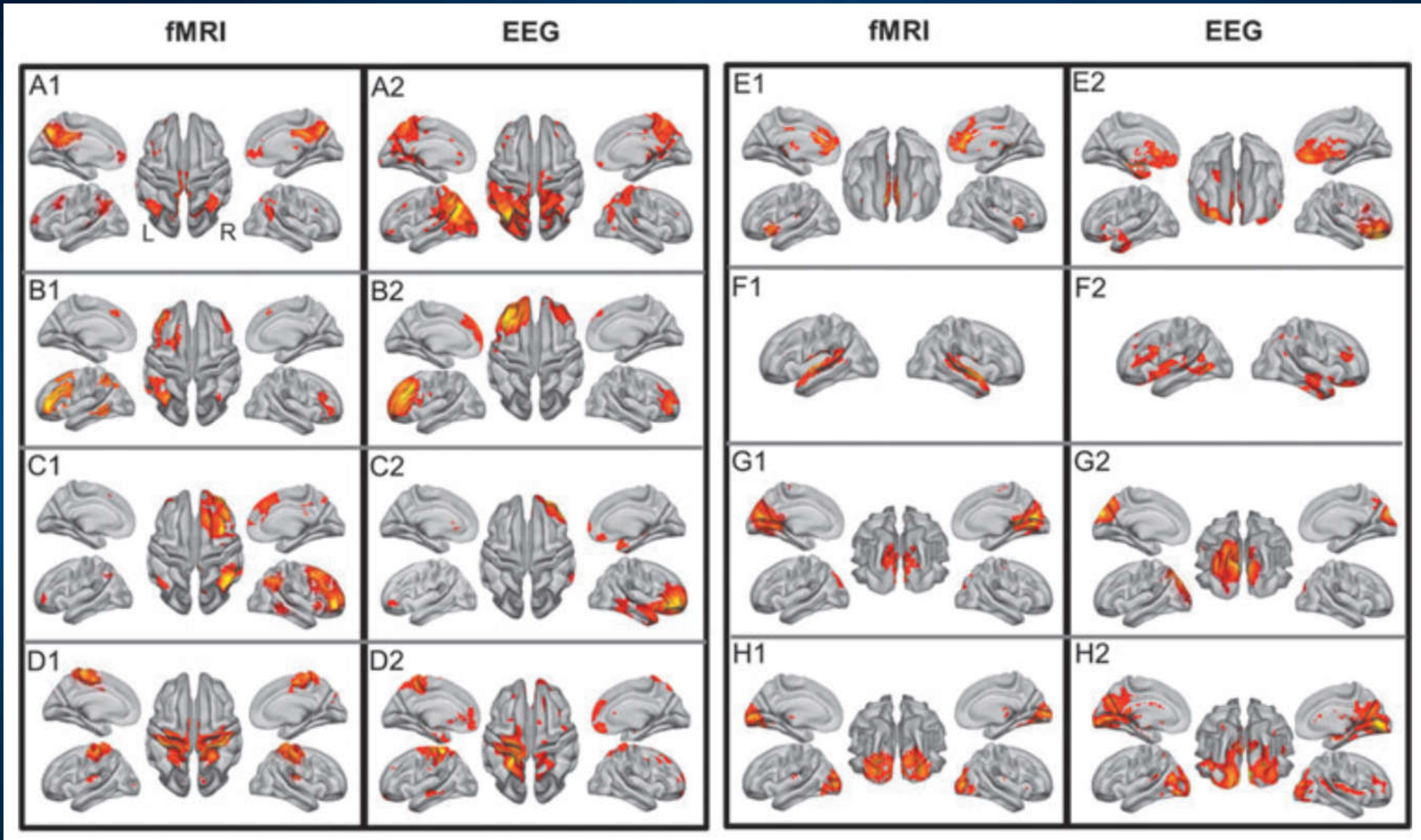
MEG replicates findings from invasive recordings with regard to time series correlations with BOLD data. Conversely, deconvolution of BOLD data provides a neural estimate which correlates well with measured neural effects as a function of neural oscillation frequency.

Can EEG also be correlated with BOLD and help to discover large-scale networks? Many recent papers show that this is possible.

Yuan .. Bodurka, 2015

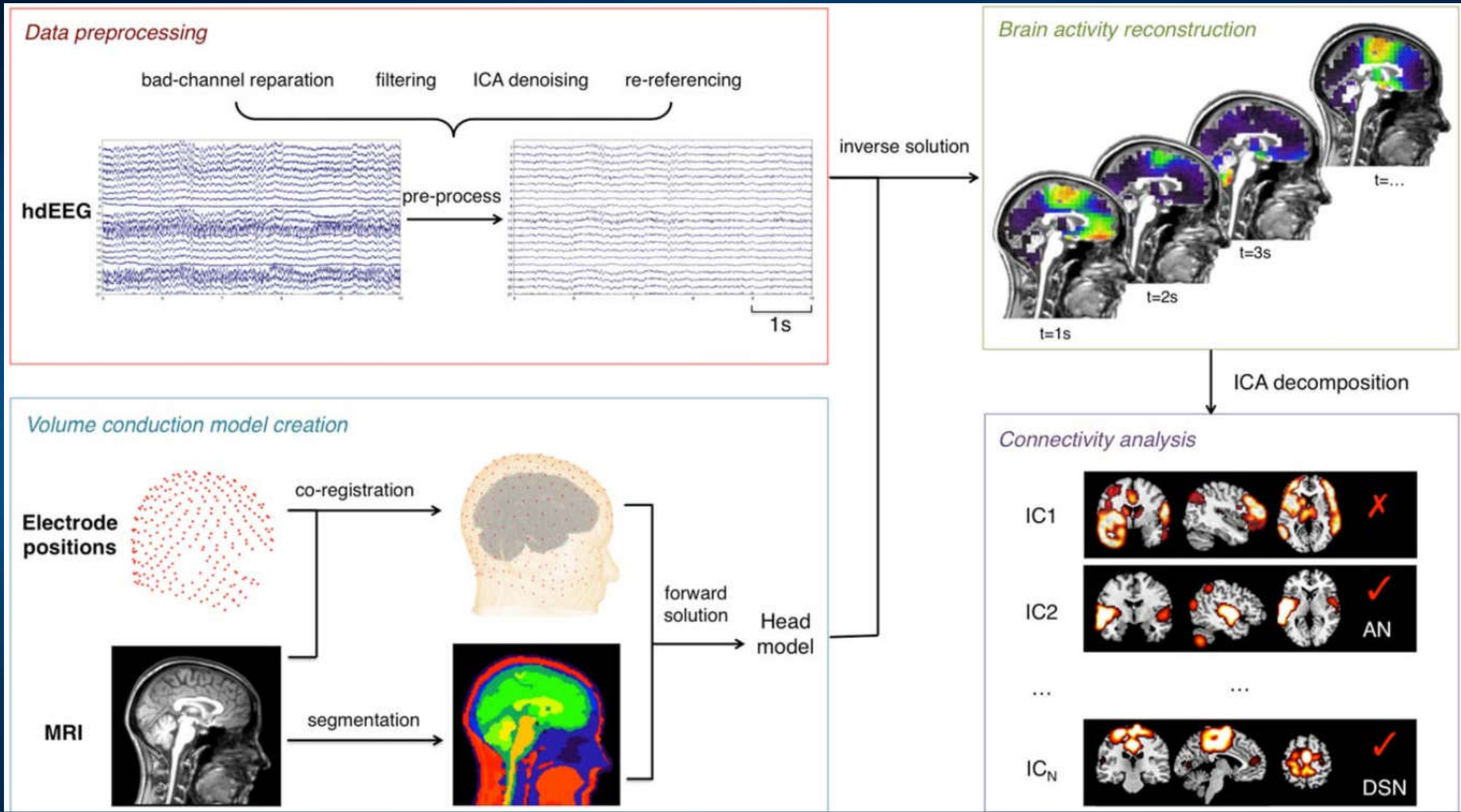


8 networks from BOLD-EEG

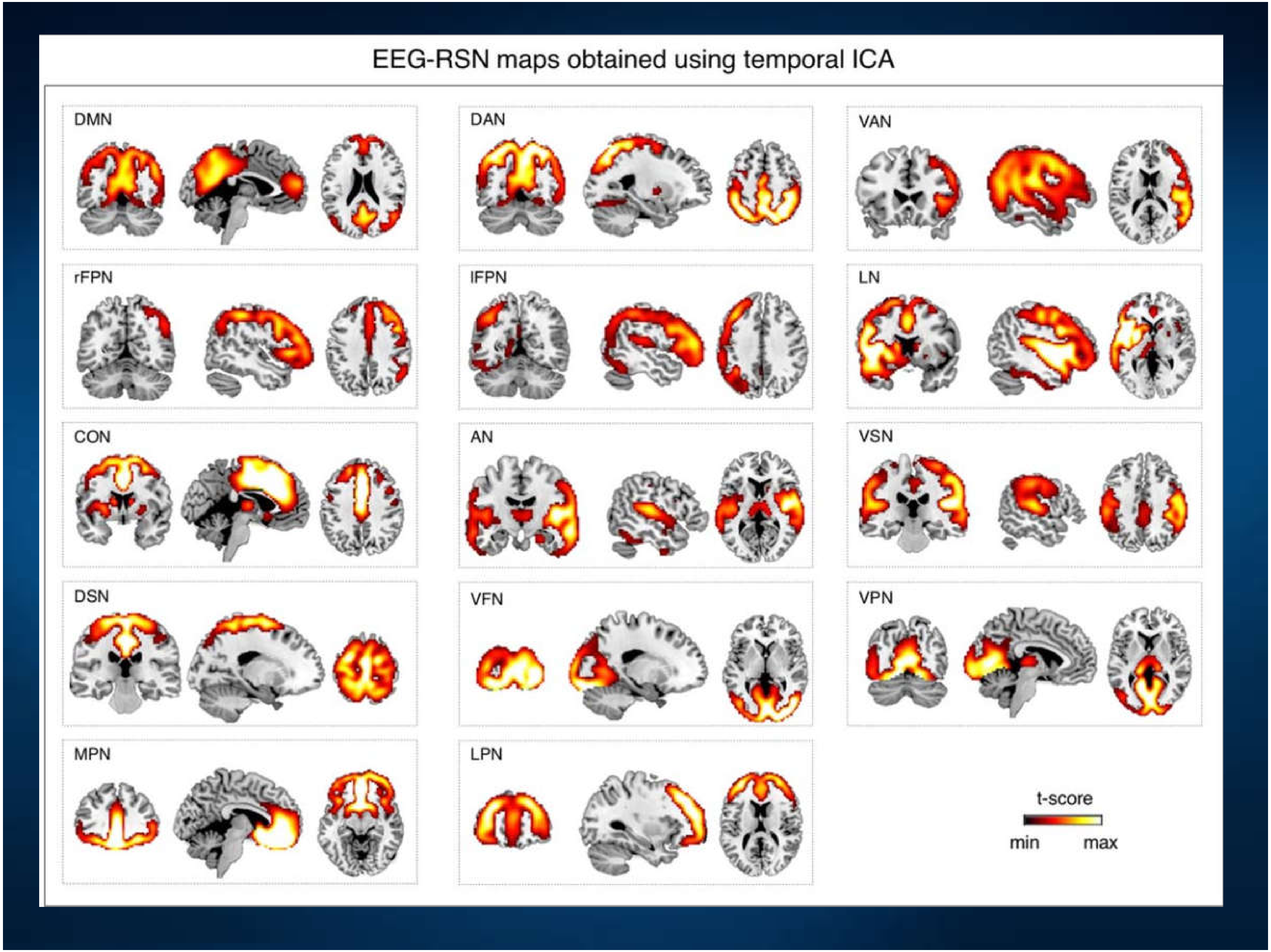


DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral).

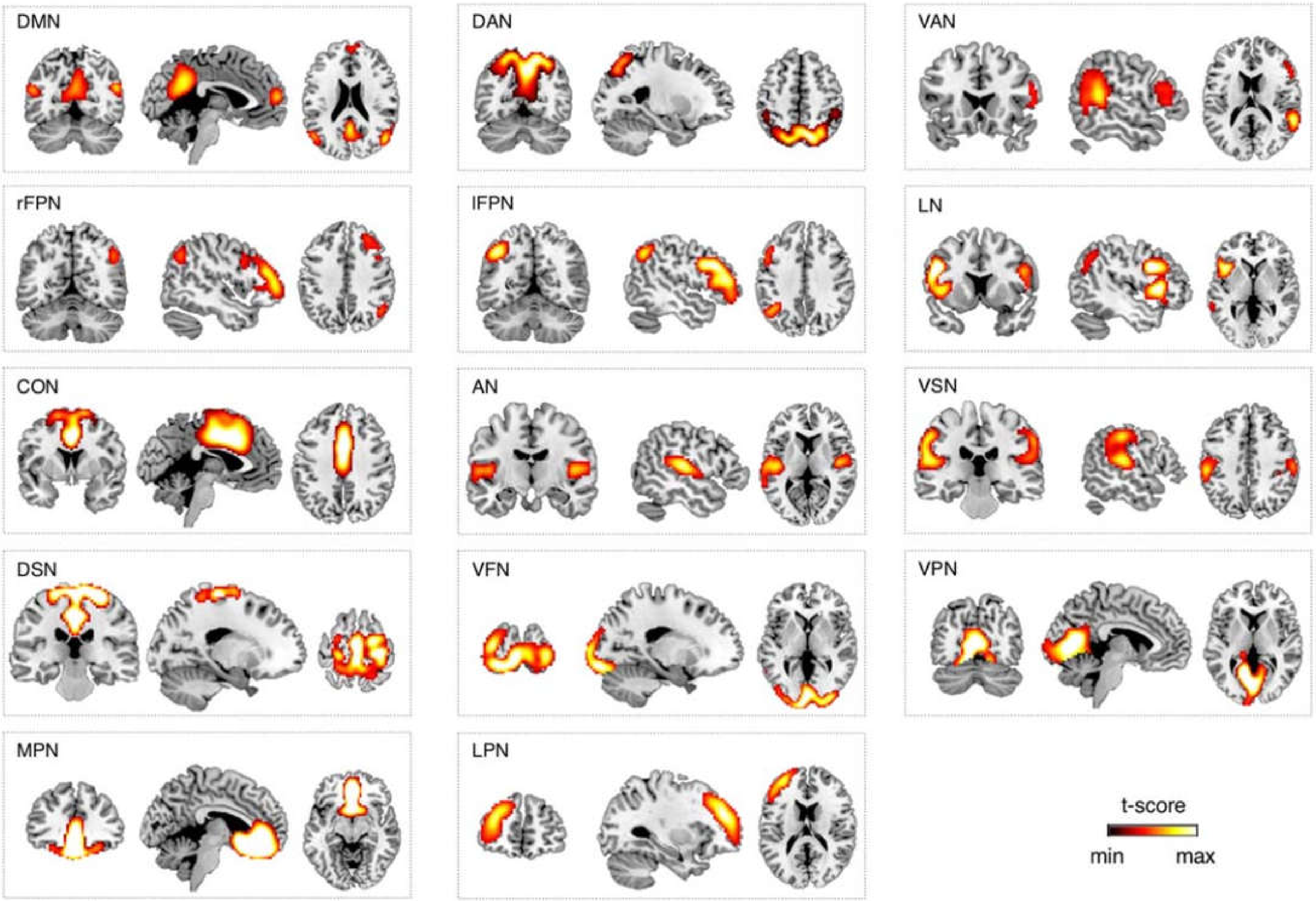
14 large networks from BOLD-EEG



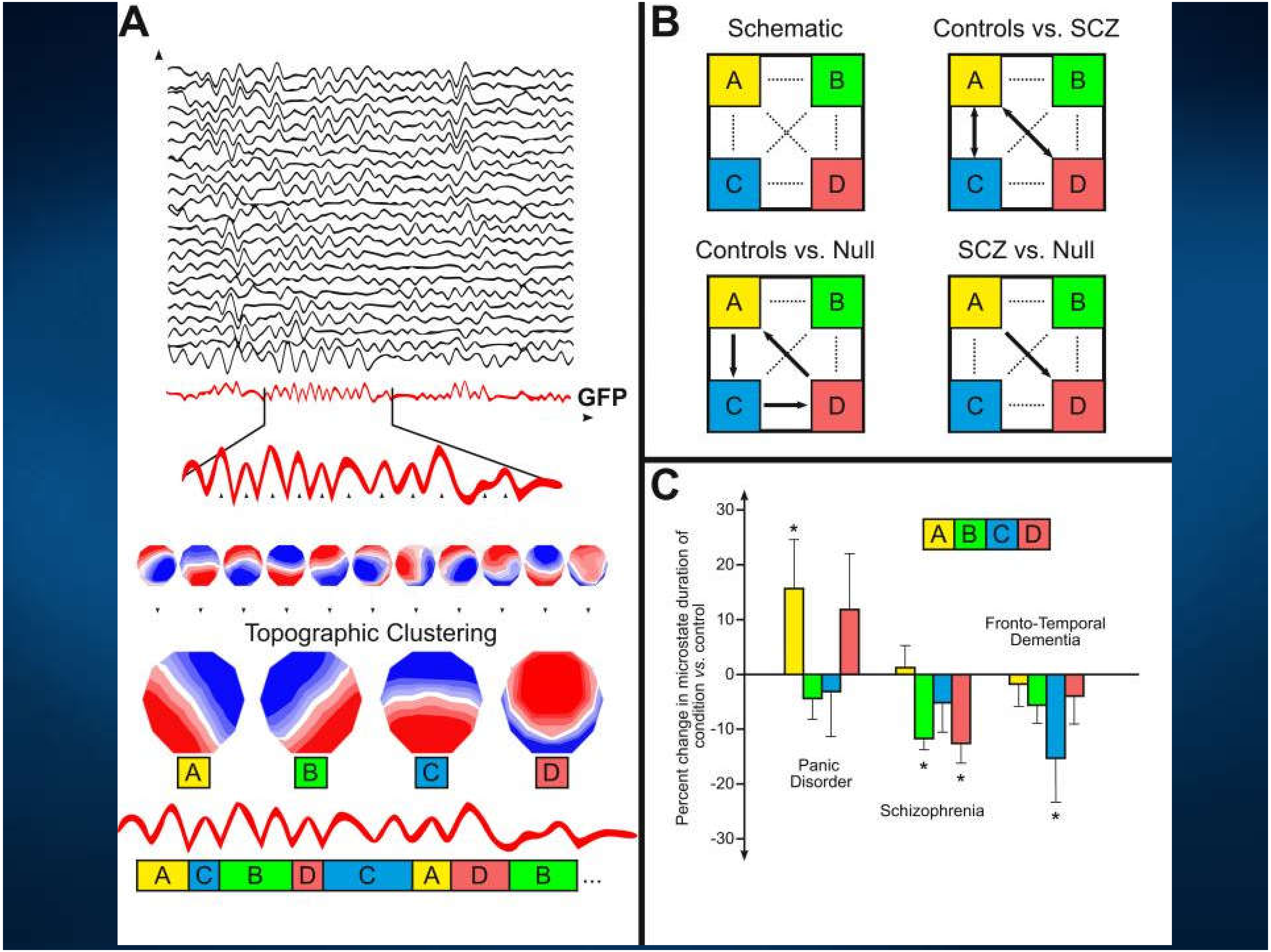
DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral). Liu et al, Human Brain Mapping (2017)


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

EEG-RSN maps obtained using spatial ICA



State Transitions



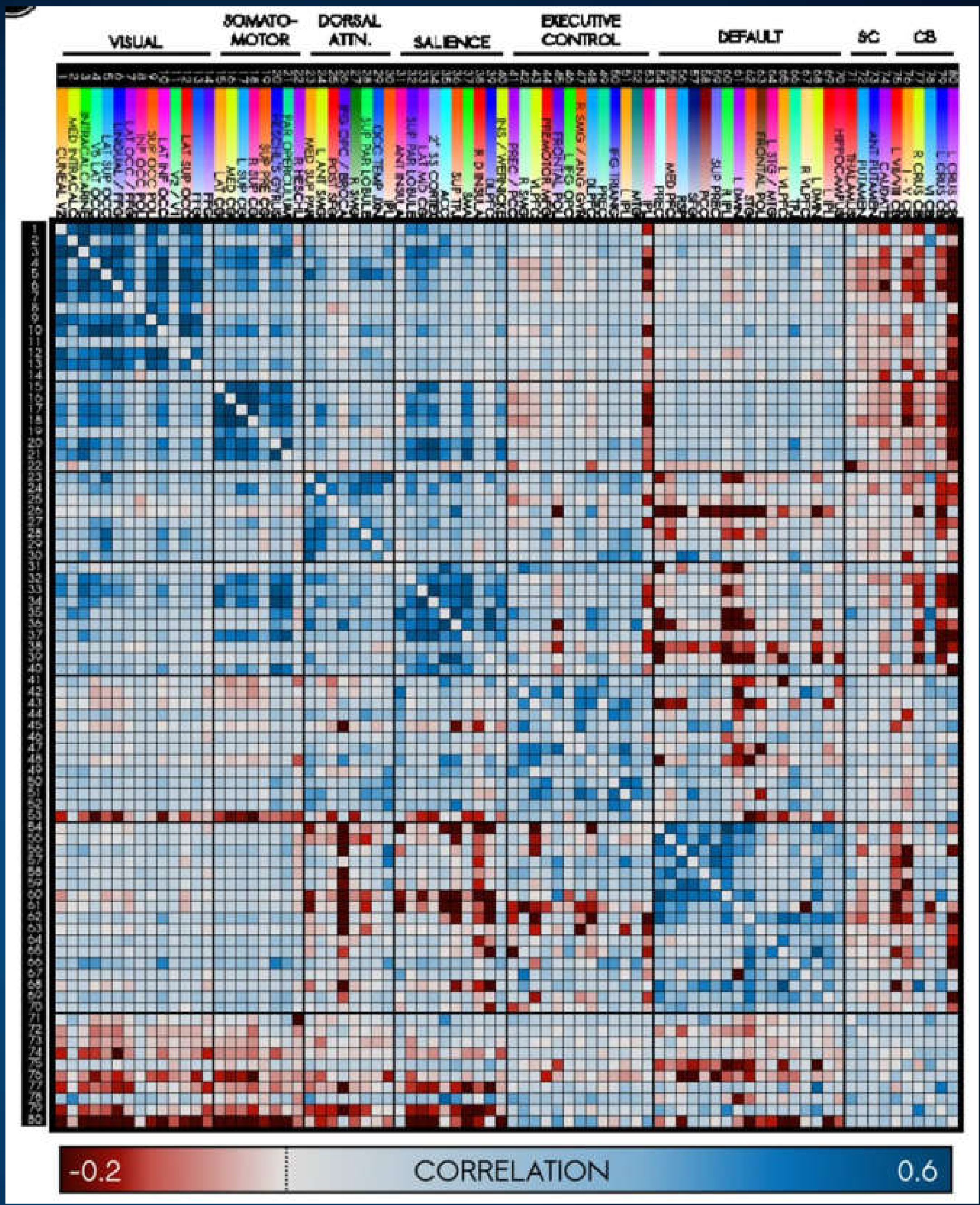
A
GFP
Topographic Clustering
A
B
C
D
A C B D C A D B ...
B
Schematic
Controls vs. SCZ
Controls vs. Null
SCZ vs. Null
C
Percent change in microstate duration of condition vs. control
30
20
10
0
-10
-20
-30
Panic Disorder
Schizophrenia
Fronto-Temporal Dementia

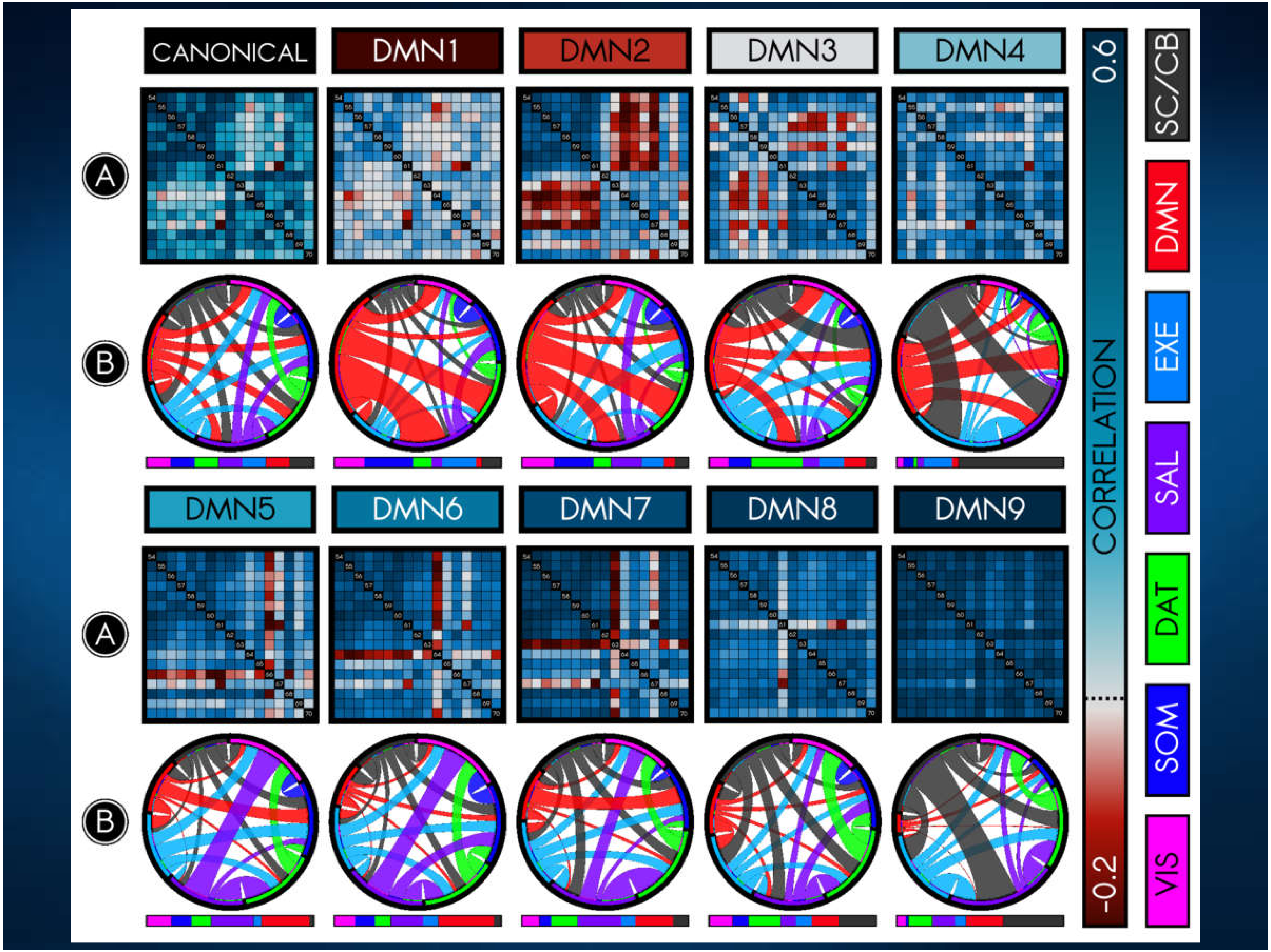
Ciric et.al. (2017). Contextual connectivity: A framework for understanding the intrinsic dynamic architecture of large-scale functional brain networks. *Scientific Reports*.

Correlations of 6 canonical networks.

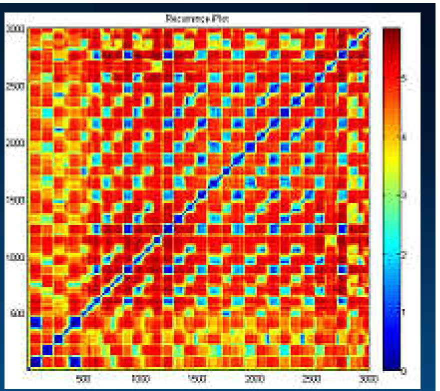
Perception,
Action-attention
DMN (Default Mode Network)

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




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

EEG early ASD detection



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

EEG of 3-month old, 19 electrodes (from 64 or 128) selected.

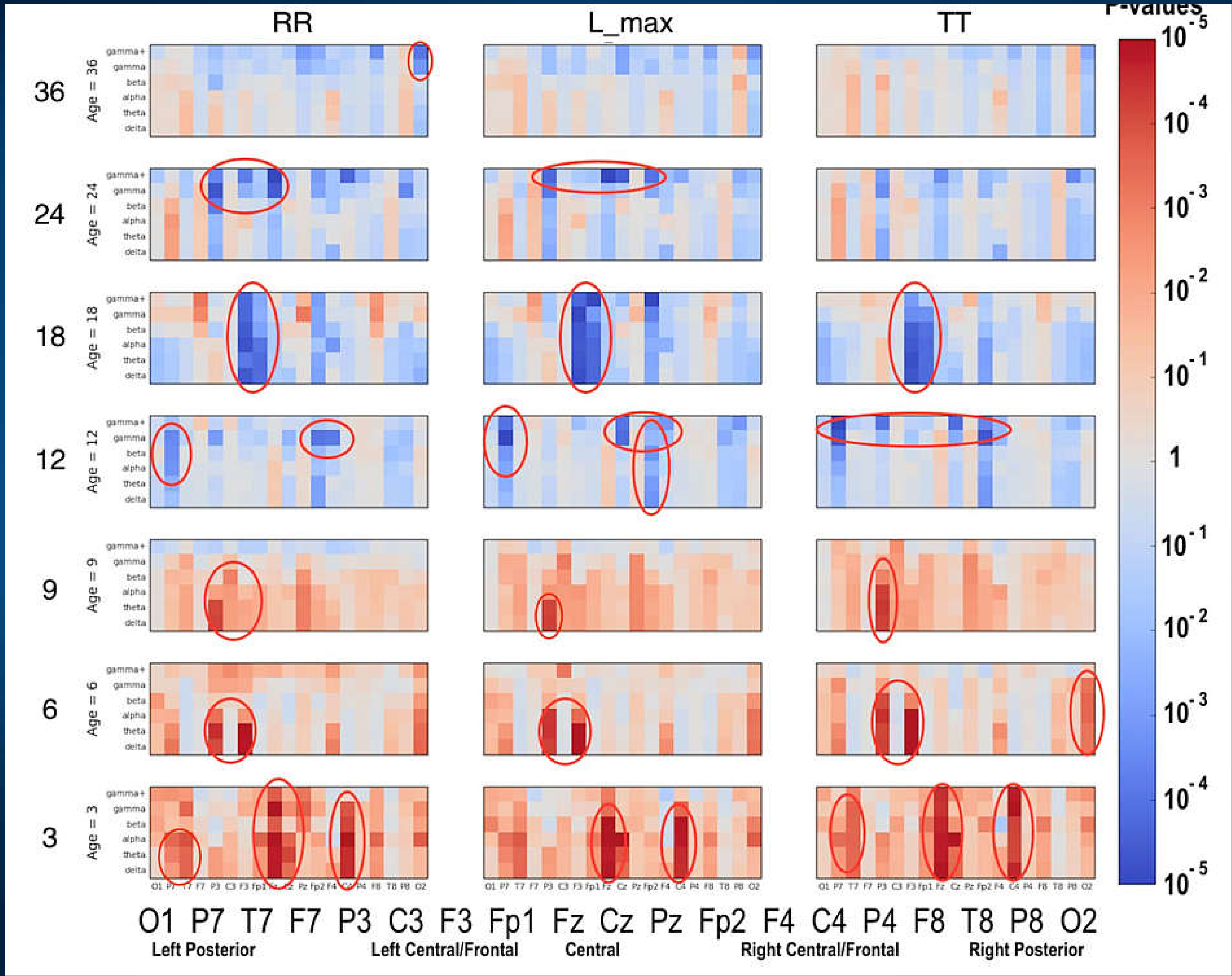
Daubechies (DB4) wavelets transform EEG signal into 6 bands.

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

In addition sample entropy and Detrended Fluctuation Analysis was used.

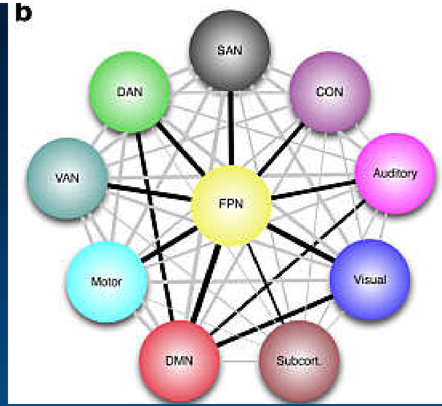
Nonlinear features were computed from EEG signals and used as input to statistical learning methods. Prediction of the clinical diagnostic outcome of ASD or not ASD was highly accurate when using EEG measurements from as early as 3 months of age. SVM on 9 features gave specificity, sensitivity and PPV were high, exceeding 95% at some ages. Prediction of ADOS calibrated severity ASD scores for all infants in the study using only EEG data taken as early as 3 months of age was strongly correlated with the actual measured scores.

ASD vs Low Risk Healthy



Dynamic functional brain networks

Questions



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

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

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

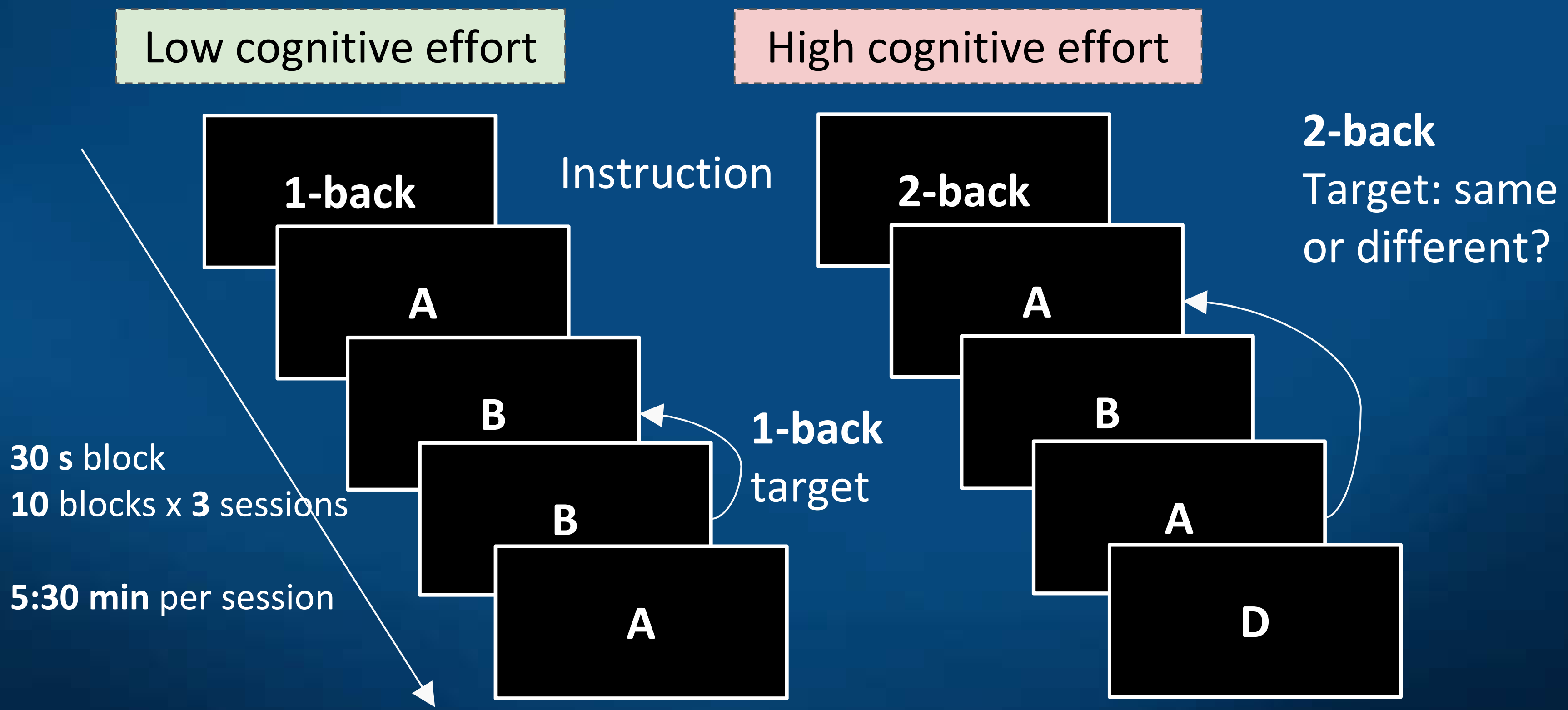
1. Can the whole-brain network properties change during performance?
2. Do modularity, path length, global, local efficiency and other network measures dependent on the cognitive load?

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

Cognitive load on whole-brain network

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

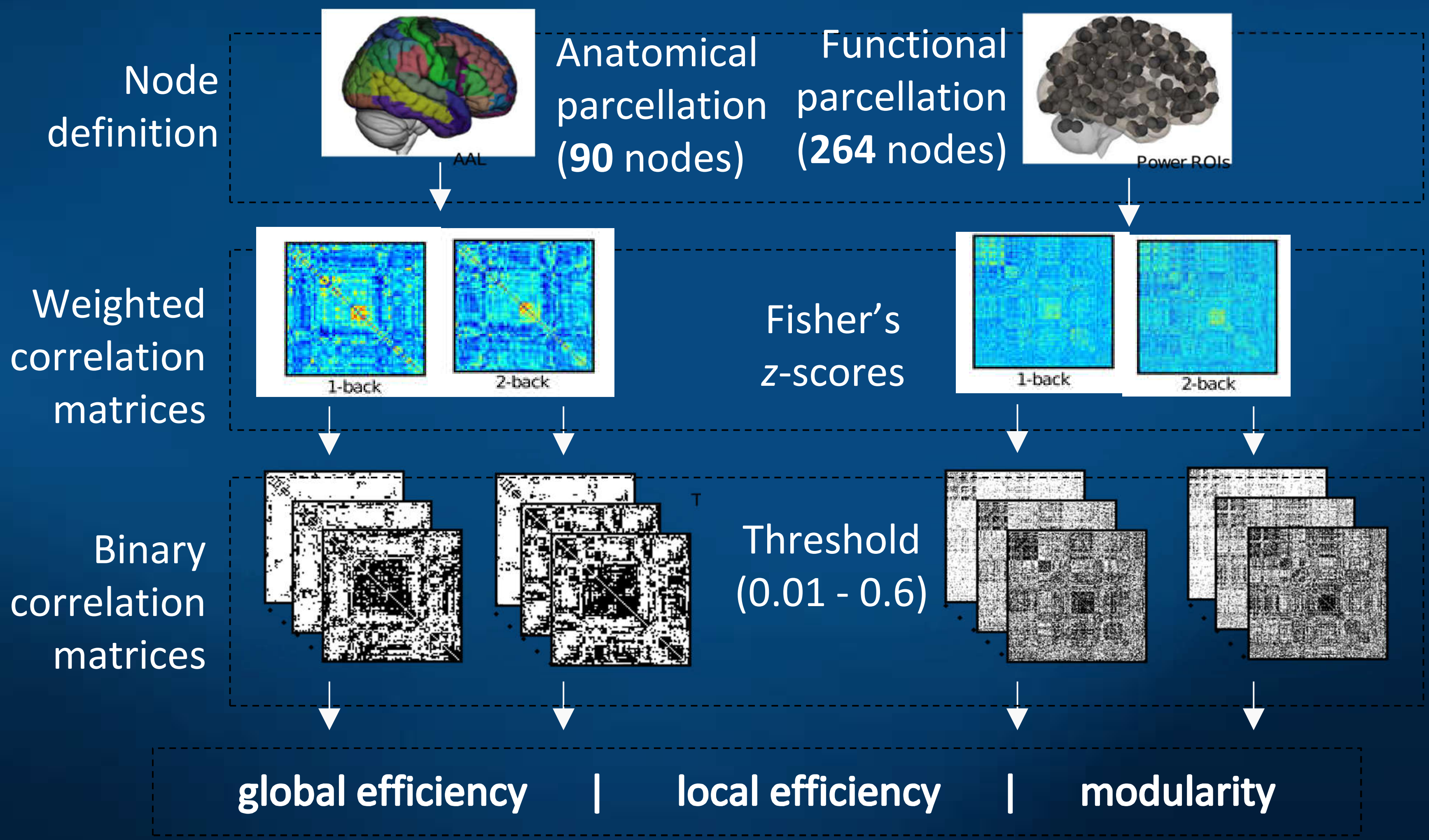
Letter *n*-back task



Finc et al, Human Brain Mapping, 2017

Data workflow

Two experimental conditions: 1-back, 2-back



Brain modules and cognitive processes

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

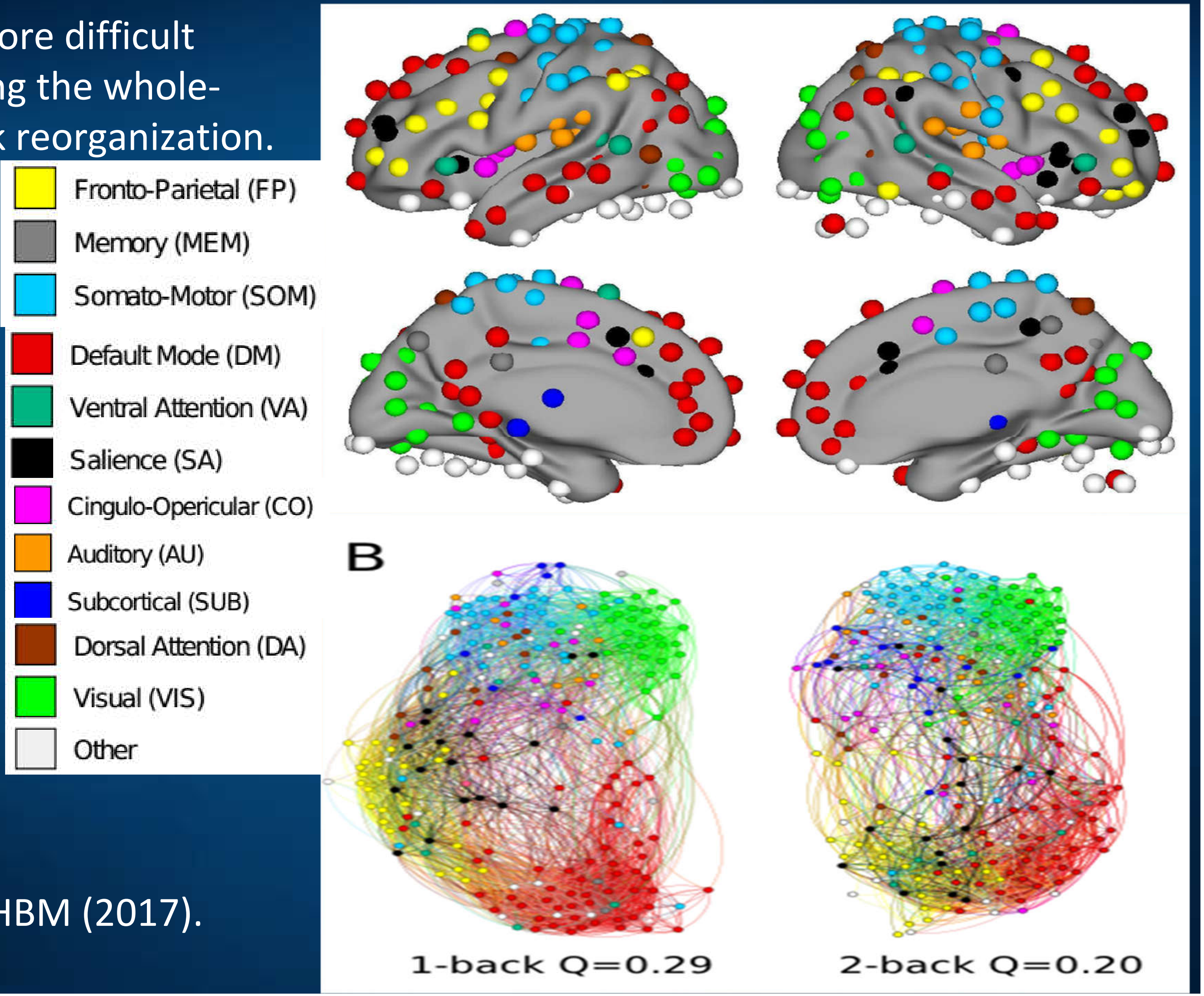
Left: 1-back

Right: 2-back

Average over 35 participants.

Left and midline sections.

K. Finc et al, HBM (2017).



Brain modules and cognitive processes

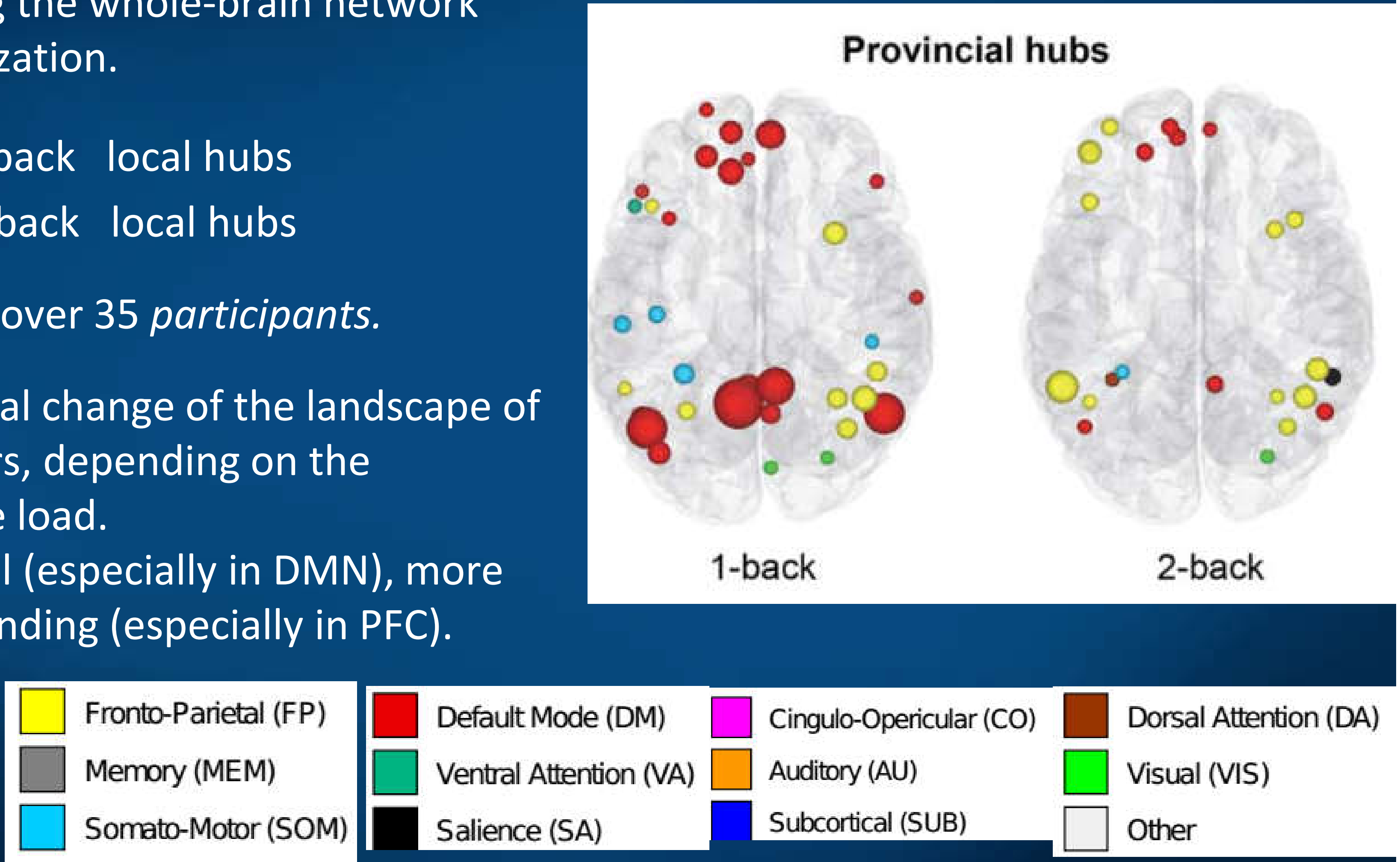
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back local hubs

Right: 2-back local hubs

Average over 35 *participants.*

Dynamical change of the landscape of attractors, depending on the cognitive load.
Less local (especially in DMN), more global binding (especially in PFC).



K. Finc et al, HBM (2017).

Brain modules and cognitive processes

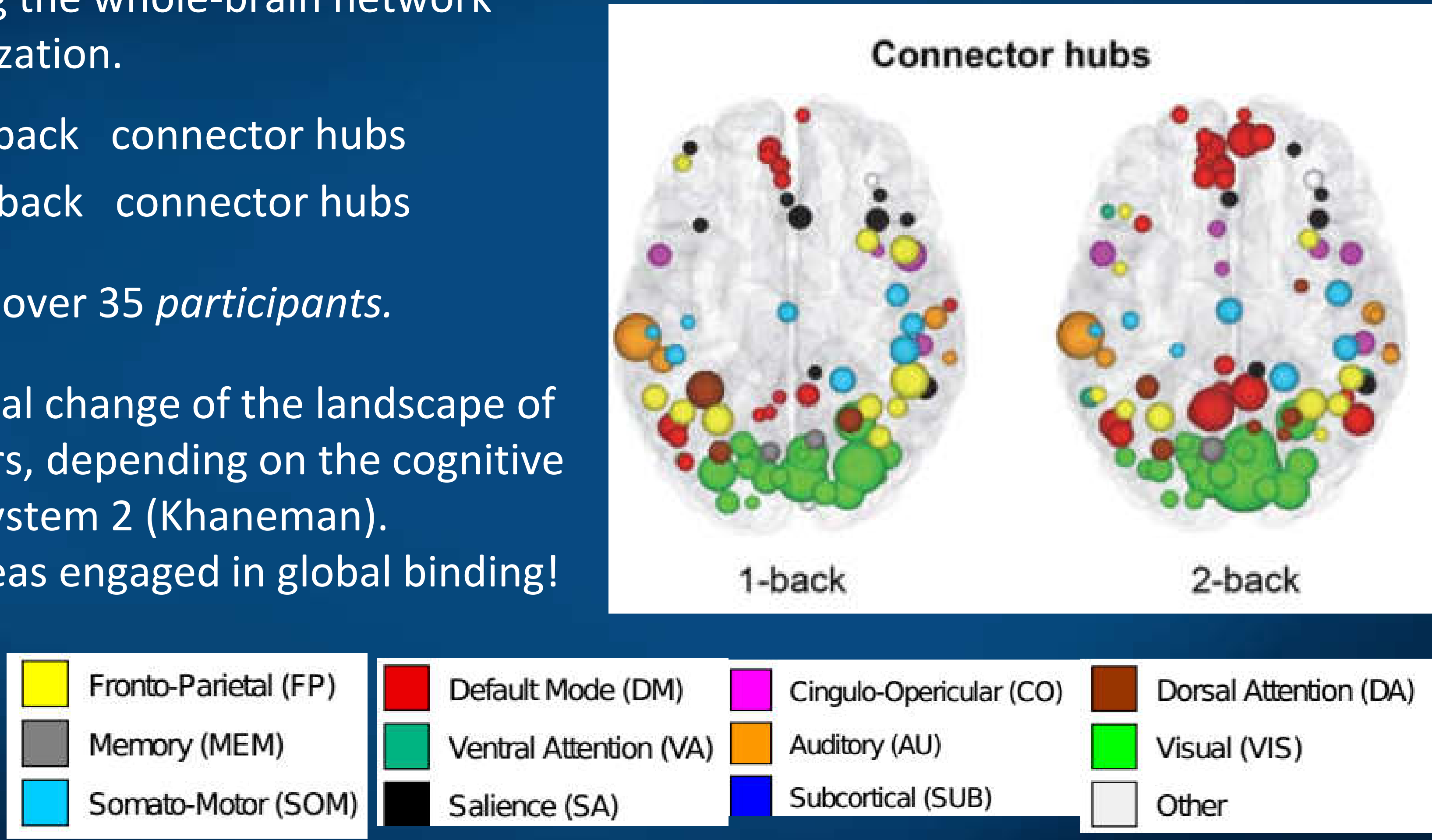
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back connector hubs

Right: 2-back connector hubs

Average over 35 *participants.*

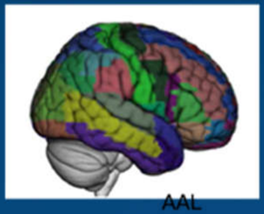
Dynamical change of the landscape of attractors, depending on the cognitive load – System 2 (Khaneman).
DMN areas engaged in global binding!



K. Finc et al, HBM (2017).

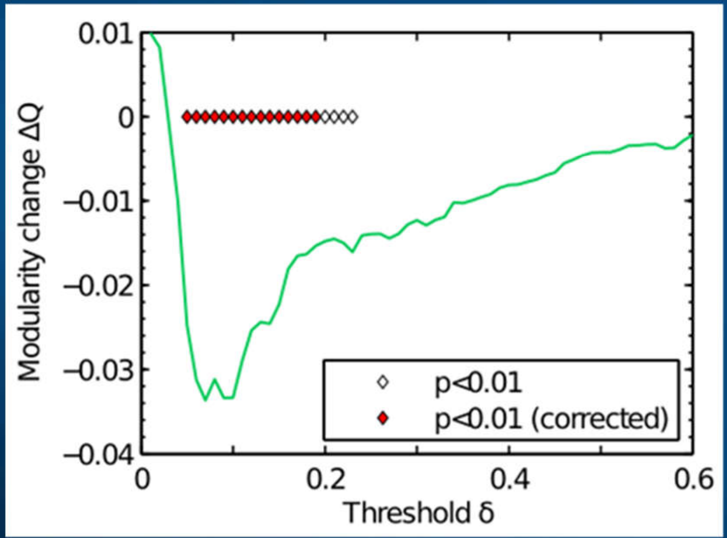
Changes in modularity

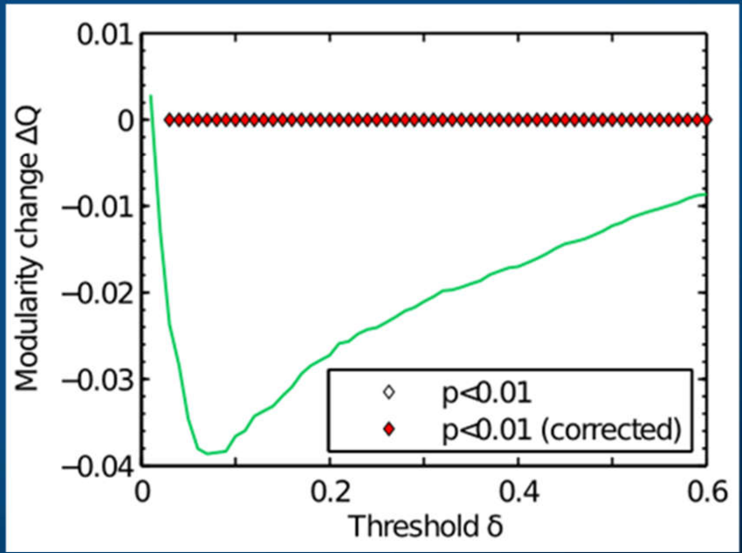
Modularity metric: fraction of within-community edges in the network minus such fraction for randomly connected network with unchanged community structure.



Parcellation
AAL, 90 ROI

Parcellation
264 ROI
functional





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

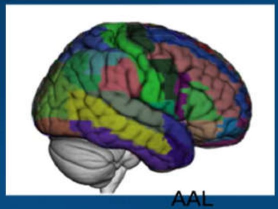
Finc et al, Human Brain Mapping, 2017

Changes in efficiency

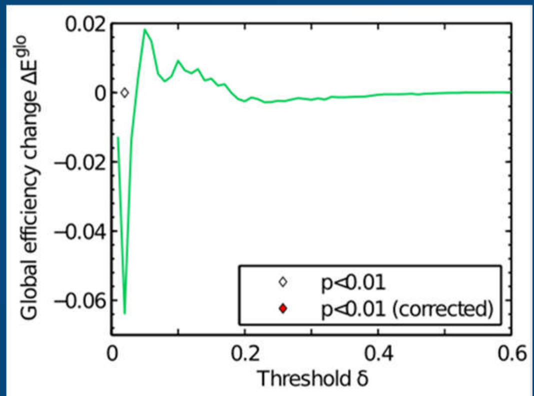
Global efficiency ~ inverse of characteristic path length
Local efficiency ~ clustering coefficient (Latora & Marchiori, 2001).

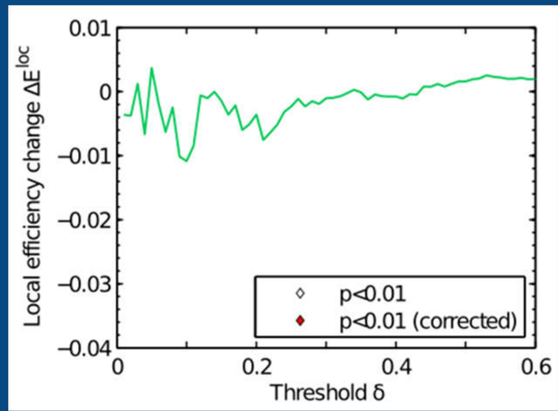
Global efficiency

Local efficiency

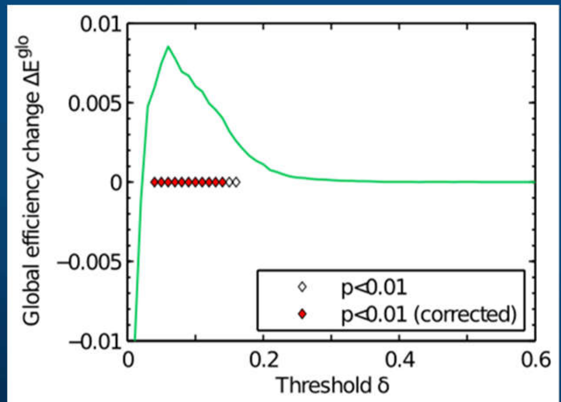


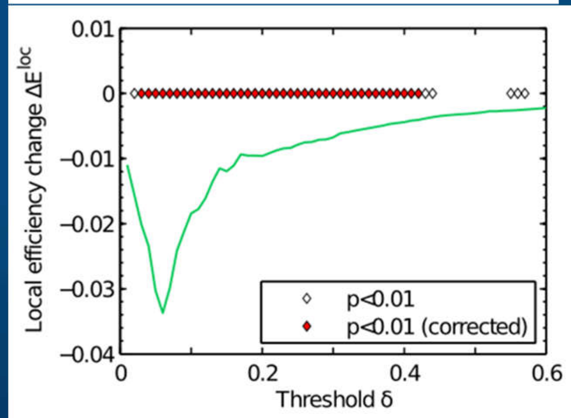
Parcellation
AAL, 90 ROI





Parcellation
264 ROI
functional





Finc et al, Human Brain Mapping, 2017

Cognitive load

Segregated network

Locally specialized processing

Low cognitive effort

global efficiency ↑

local efficiency ↓

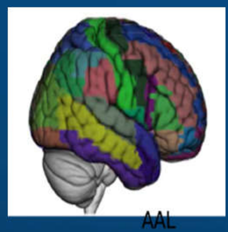
modularity ↓

performance ↓

Integrated network

Distributed processing

High cognitive effort



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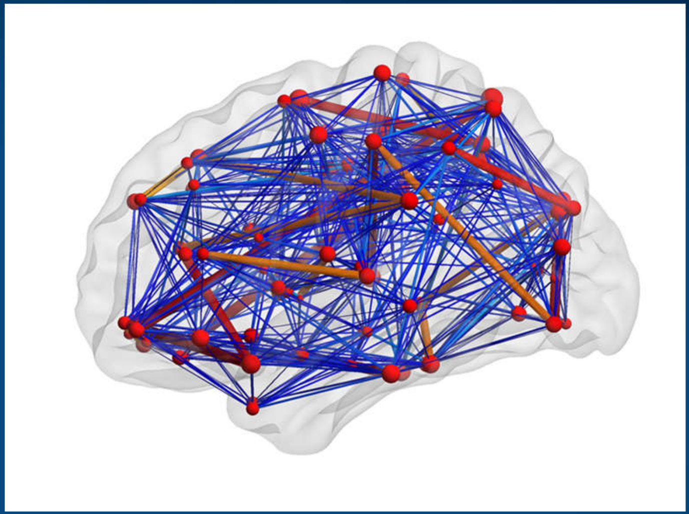
Parcellation into 264 regions (10 mm spheres) shows subnetworks more precisely than for 90 regions; only a small subgroup of neurons in each ROI is strongly correlated.

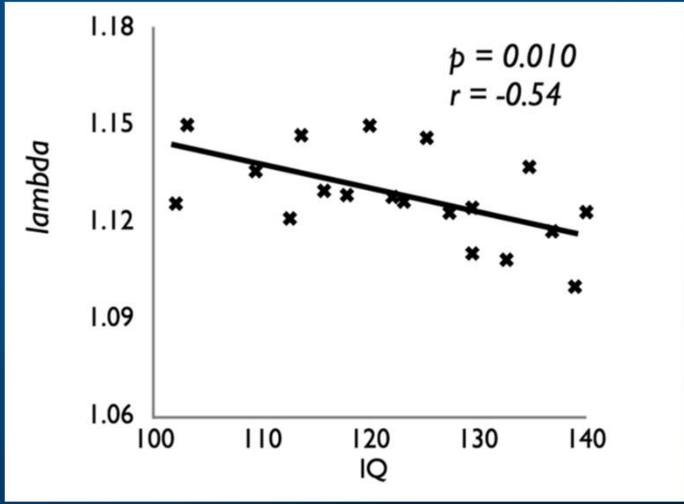
Resting state/cognitive performance

Characteristic path length λ → Intellectual performance

Modularity → Working memory performance

Modularity → Working memory capacity





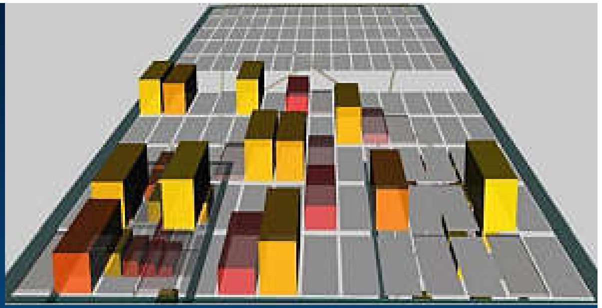
Network modularity ⇔ higher working memory capacity and performance.

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)

Understanding Brain Activity

Mitchell/Just 2008



Predicting Human Brain Activity Associated with the Meanings of Nouns," T. M. Mitchell et al, Science, 320, 1191, May 30, 2008

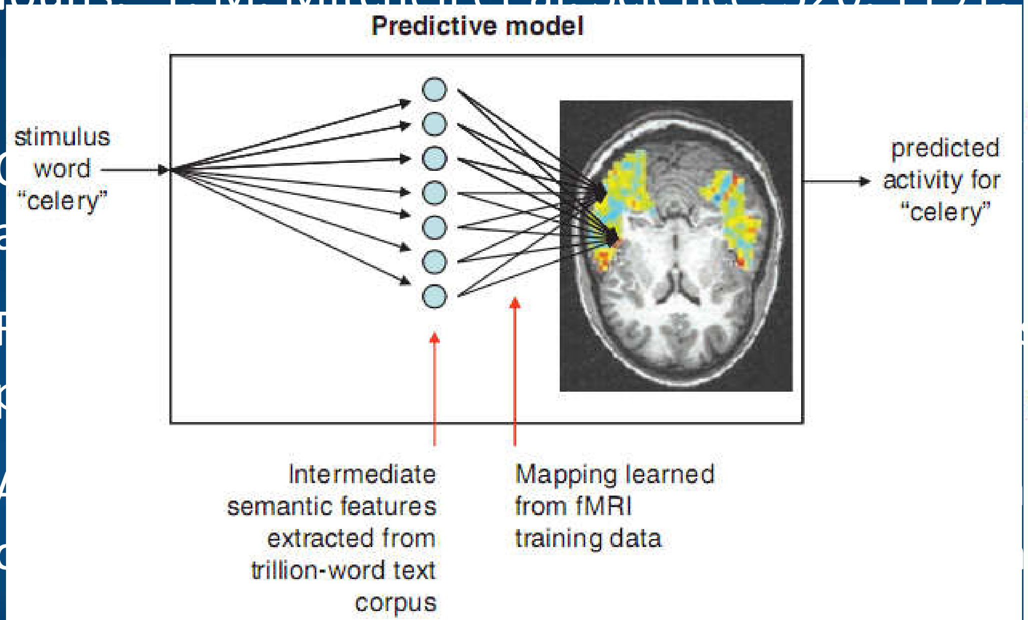
- Clear differences between fMRI brain activity when people read and think about different nouns.
- Reading words and seeing the drawing invokes similar brain activations, presumably reflecting semantics of concepts.
- Although individual variance is significant similar activations are found in brains of different people, a classifier may still be trained on pooled data.
- Model trained on ~10 fMRI scans + very large corpus (10^{12}) predicts brain activity for over 100 nouns for which fMRI has been done.

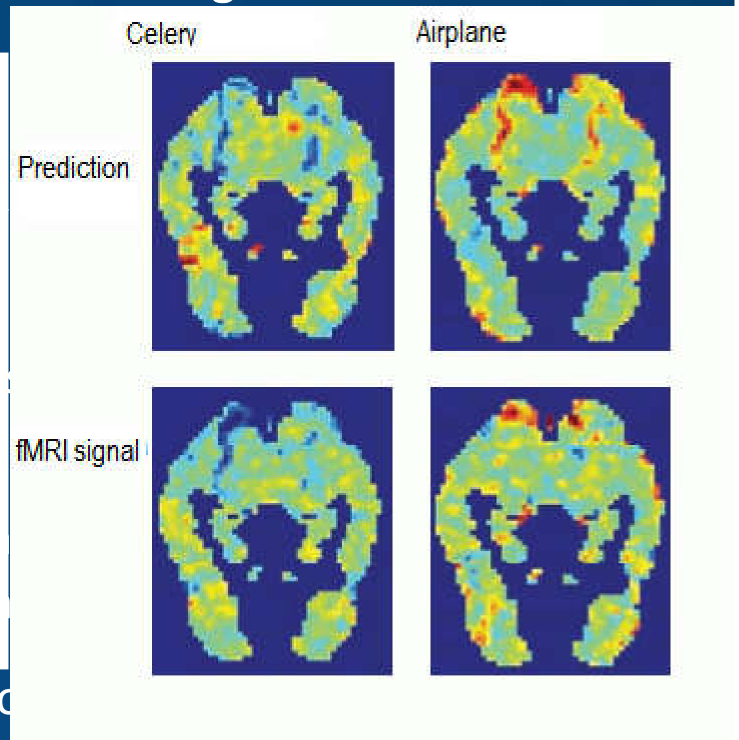
Sensory: fear, hear, listen, see, smell, taste, touch
Motor: eat, lift, manipulate, move, push, rub, run, say
Abstract: approach, break, clean, drive, enter, fill, near, open, ride, wear.

Are these 25 features defining brain-based semantics?

Mitchell/Just 2008

Predicting Human Brain Activity Associated with the Meanings of Nouns," T. M. Mitchell et al. Science, 320, 1191





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Are these 25 features defining brain-based semantics?

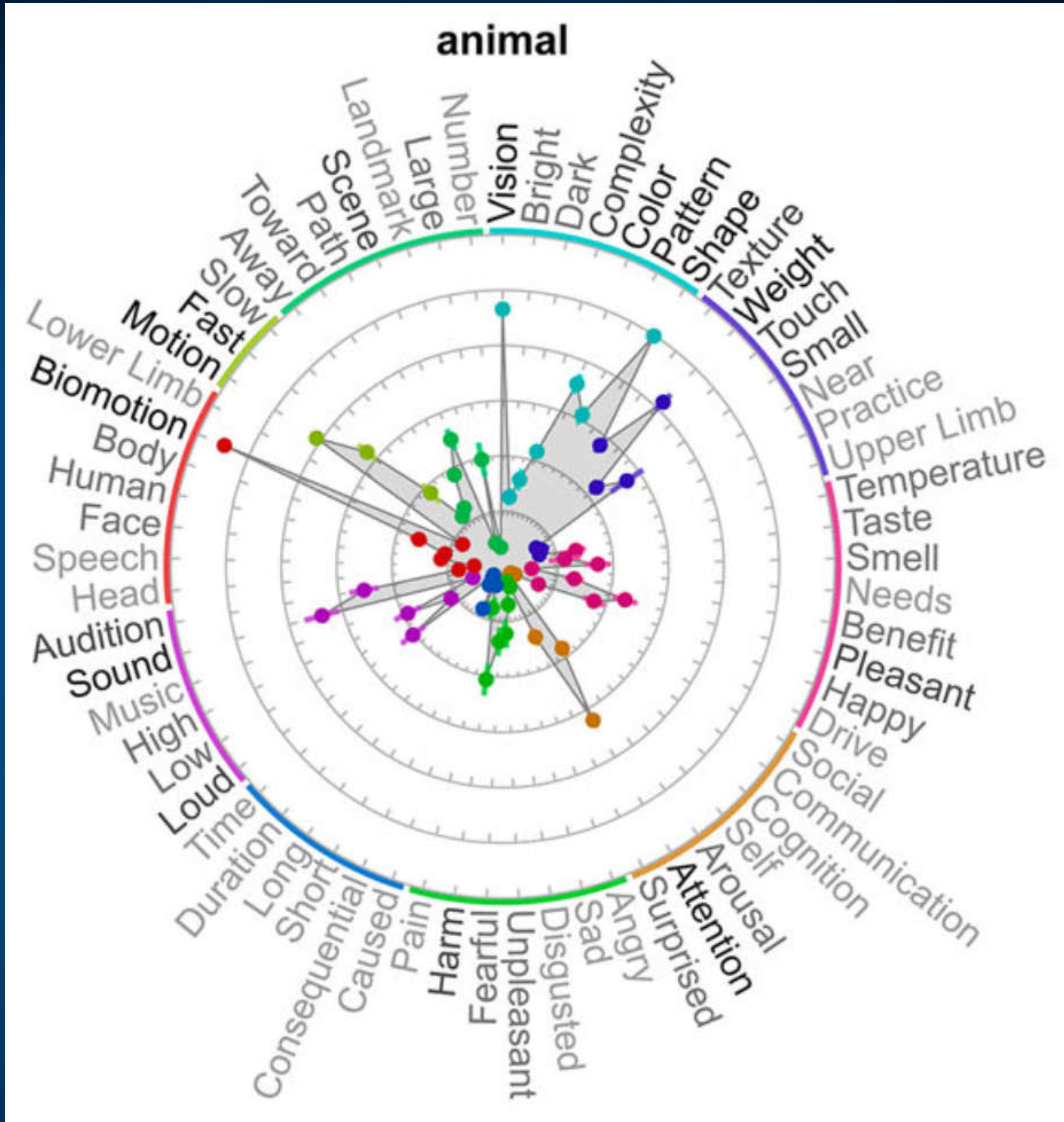
65 attributes related to neural processes;

Colors on circle: general domains.

J.R. Binder et al

Toward a Brain-Based Componential Semantic Representation 2016

More than visual objects!



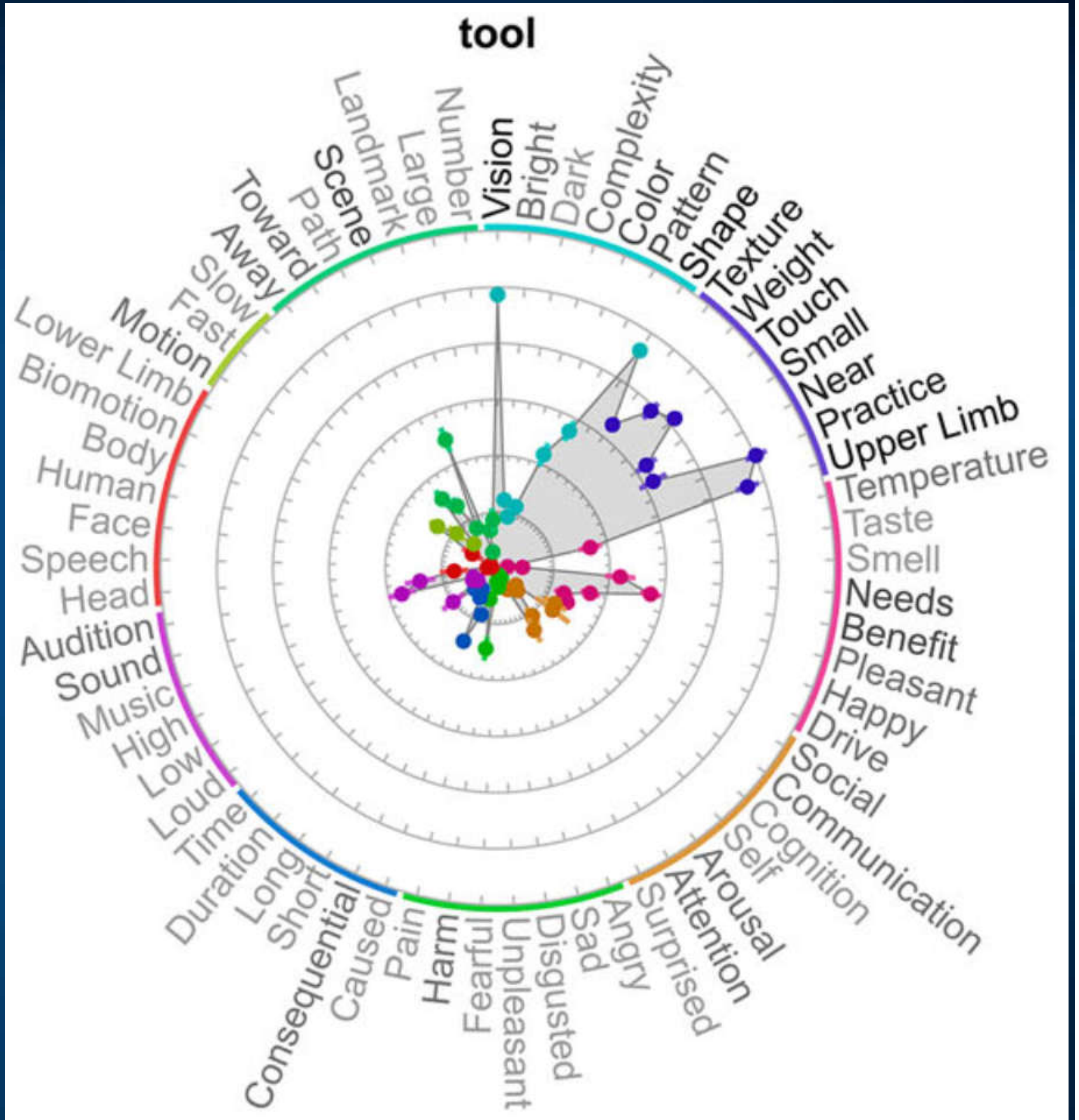
65 attributes related to neural processes.

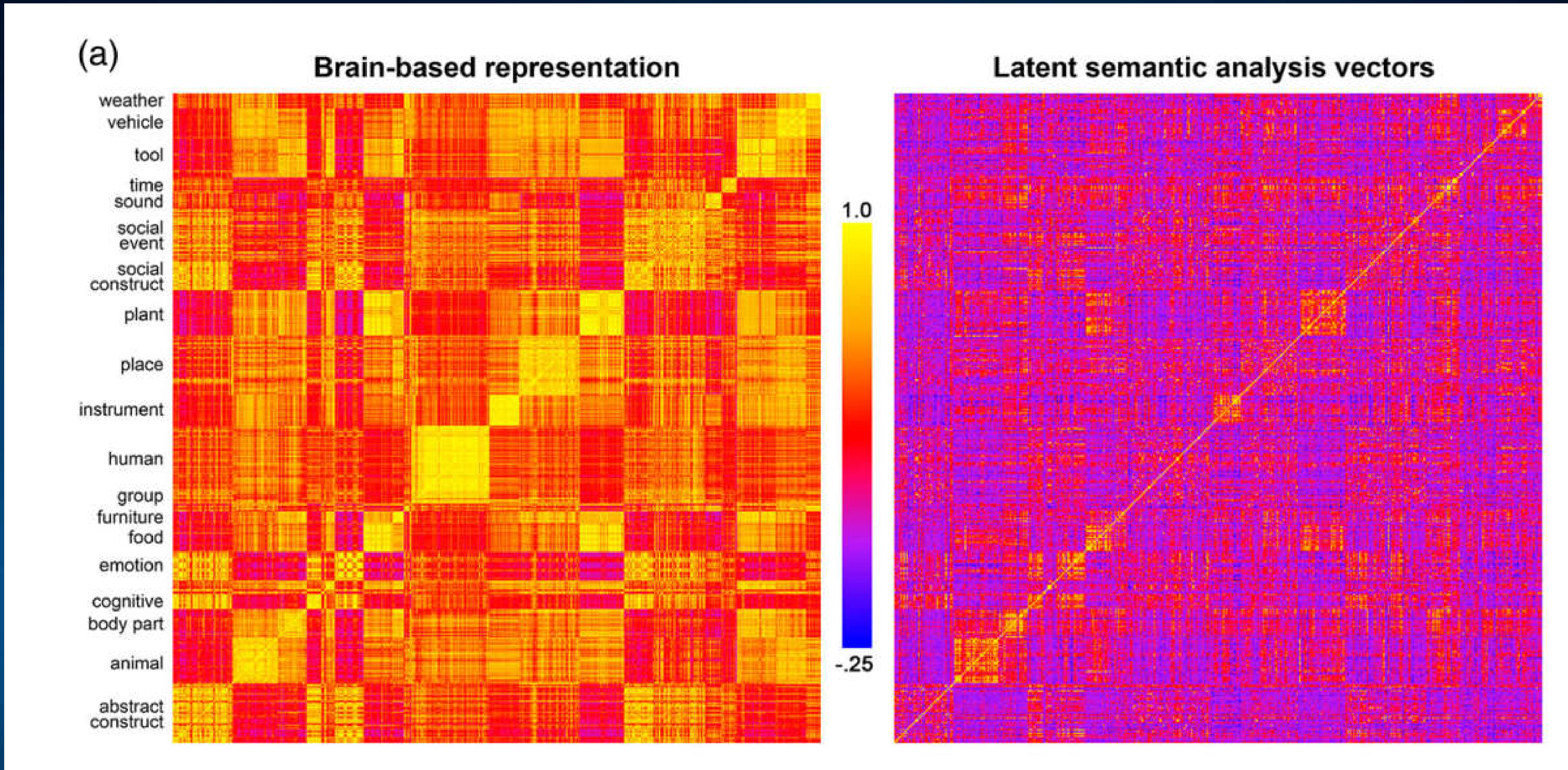
Brain-Based Representation of tools.

J.R. Binder et al

Toward a Brain-Based Componential Semantic Representation

Cognitive Neuropsychology 2016



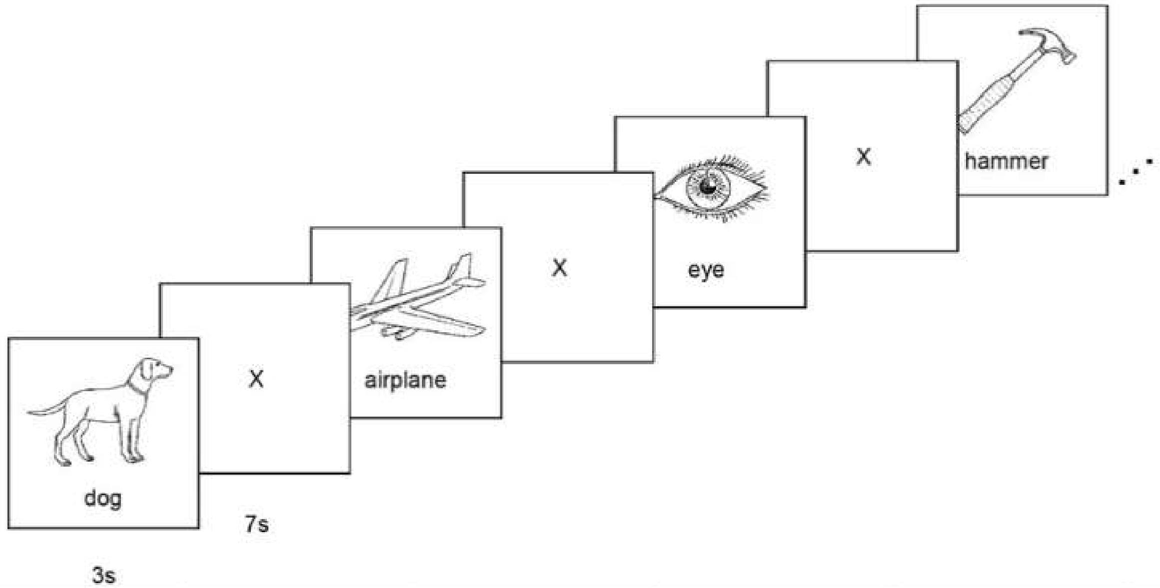


Cosine similarities, 434 nouns grouped by superordinate category.
Left: brain-based vectors, right: latent semantic analysis vectors from large corpus (typical NLP). Yellow = greater similarity. Similarities within categories are much stronger for BBR (no brain signals, just NLP).

Wang, S., Zhang, J., Lin, N., & Zong, C. (2017). Investigating Inner Properties of **Multimodal Representation** and Semantic Compositionality with Brain-based Componential Semantics.

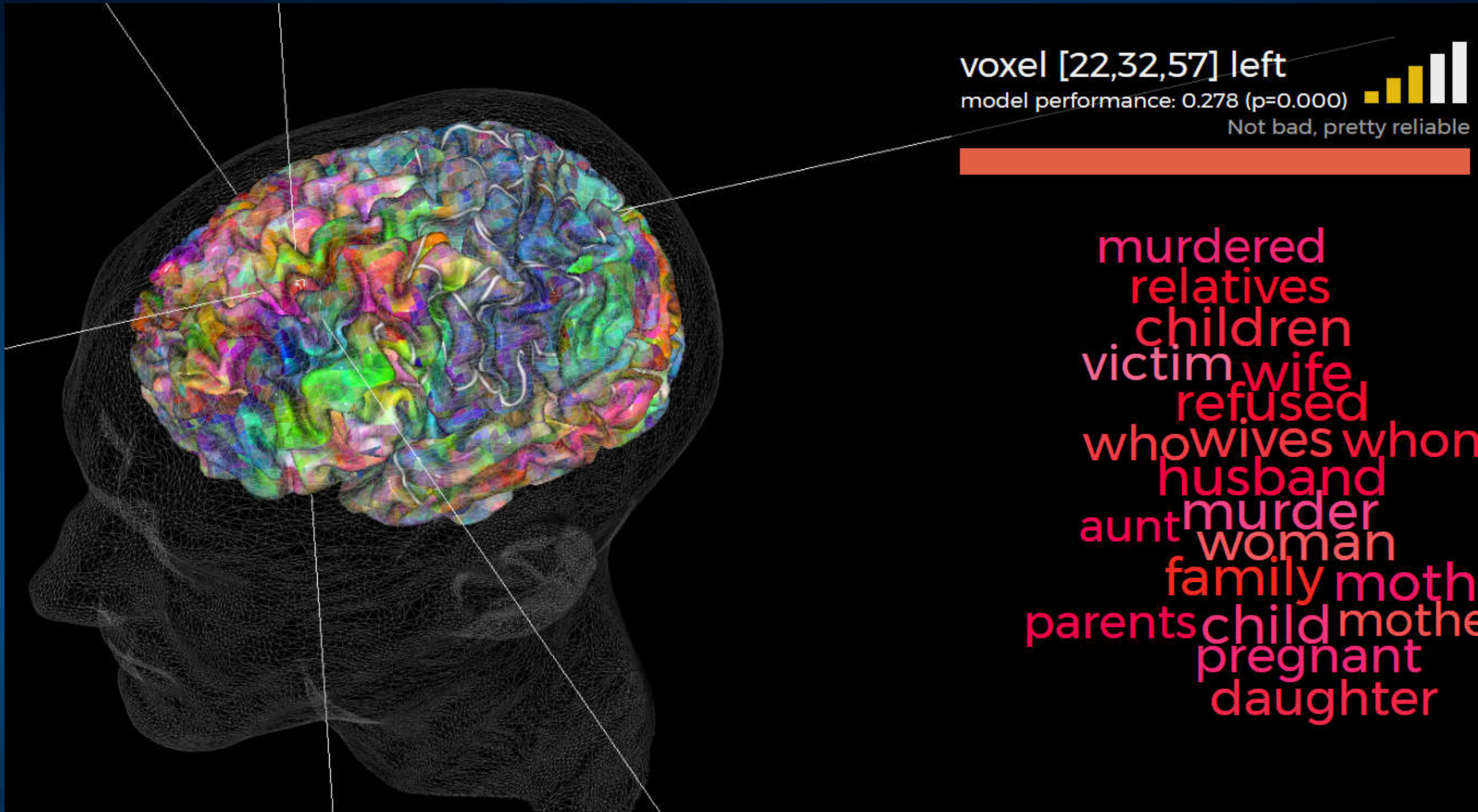
Quasi-stable brain activations?

Maintain brain activation **for longer time**. Pictures, moving pictures, sounds …



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

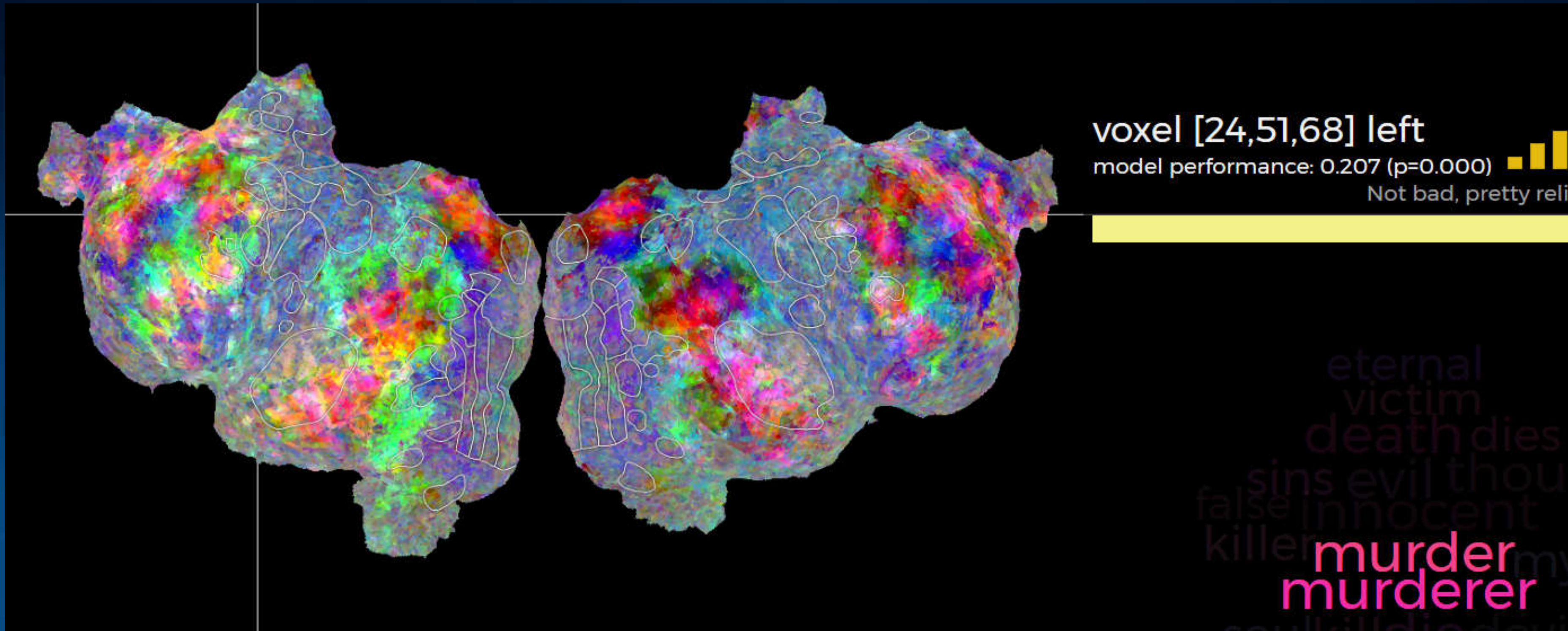
Can we induce stable cortical activation? Locate sources in similar areas as BOLD? Interpret brain activations in terms of brain-based semantics?



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

http://gallantlab.org/huth2016/

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

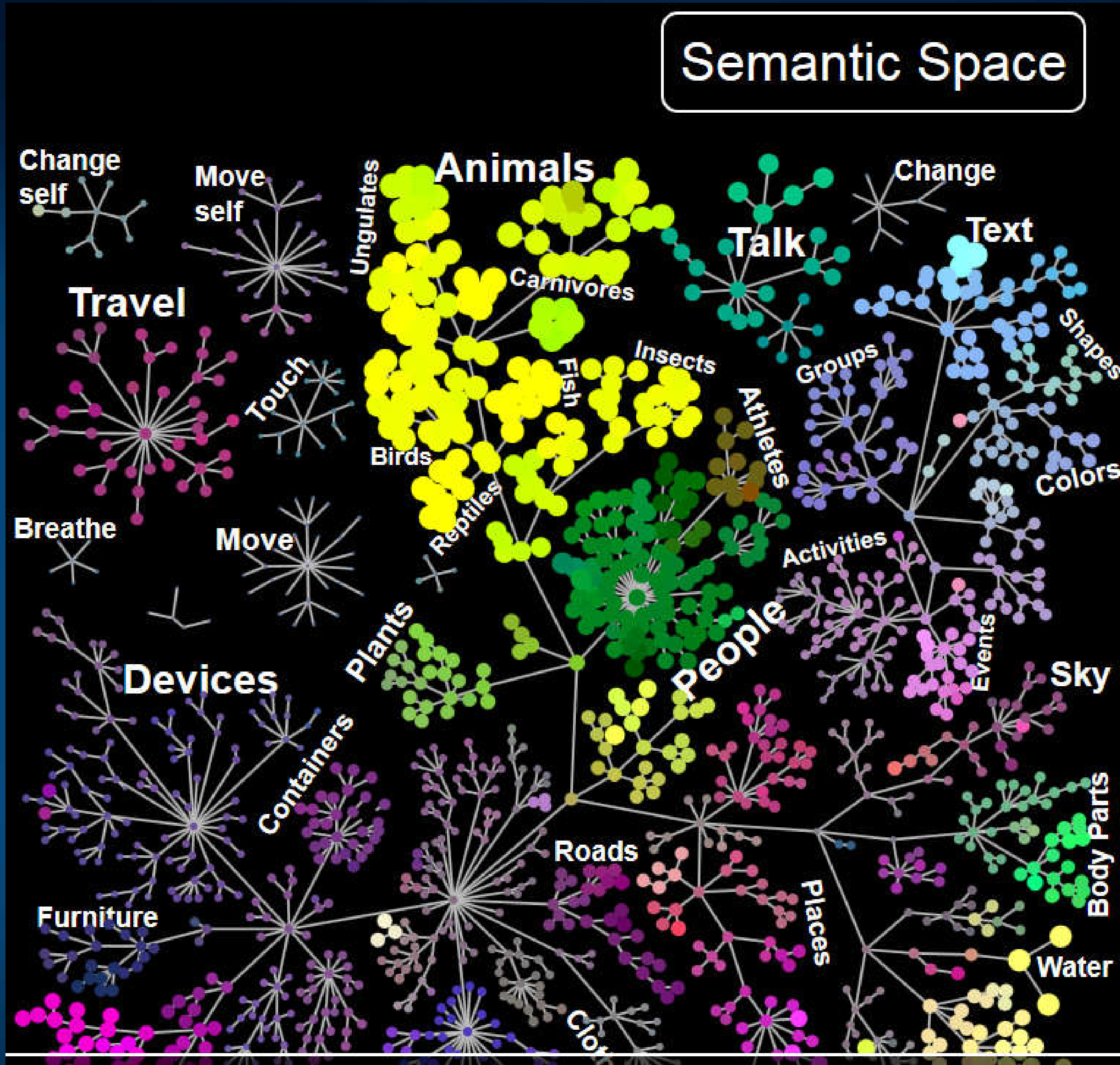


Whole fMRI activity map for the word “murder” shown on the flattened cortex.

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

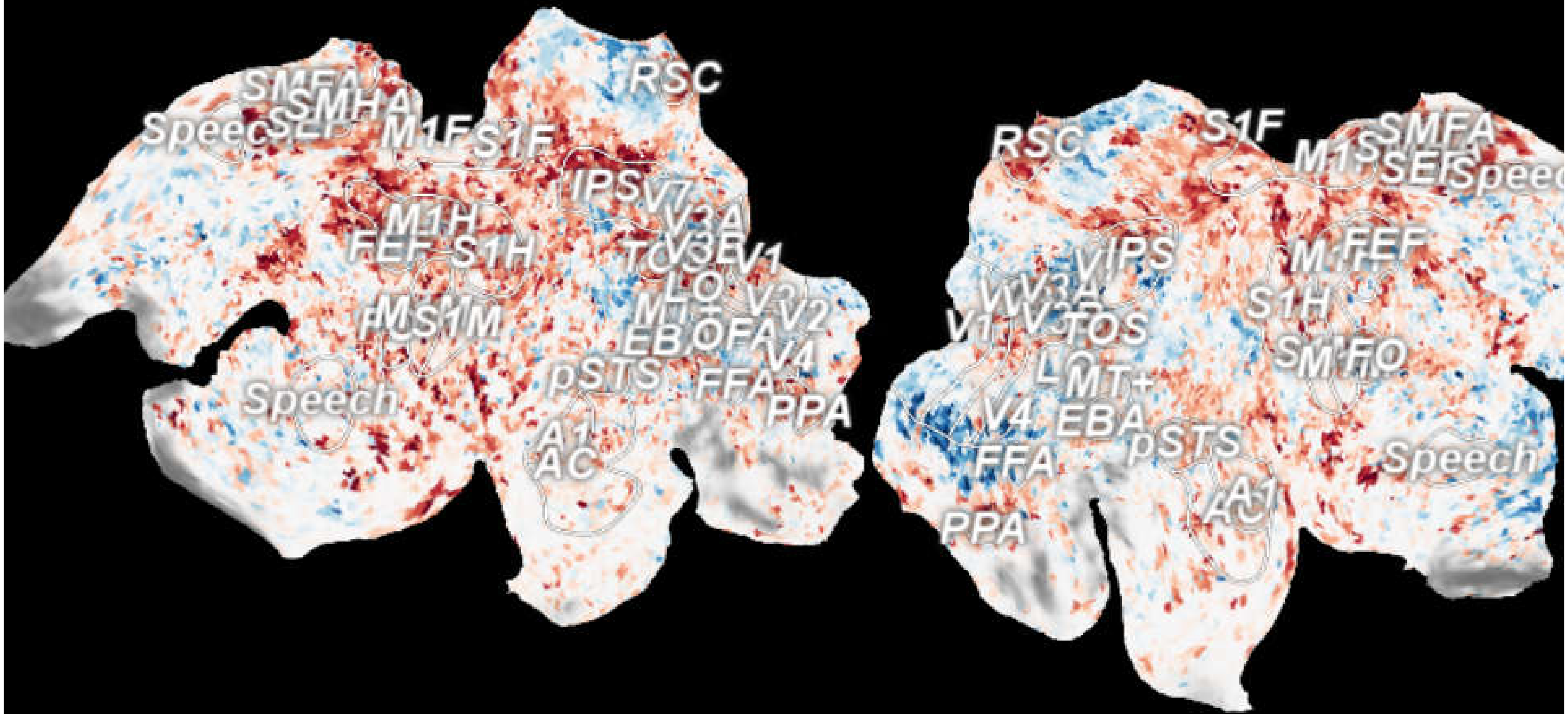
http://gallantlab.org/huth2016/ and short movie intro.

Can one do something like that with EEG or MEG?

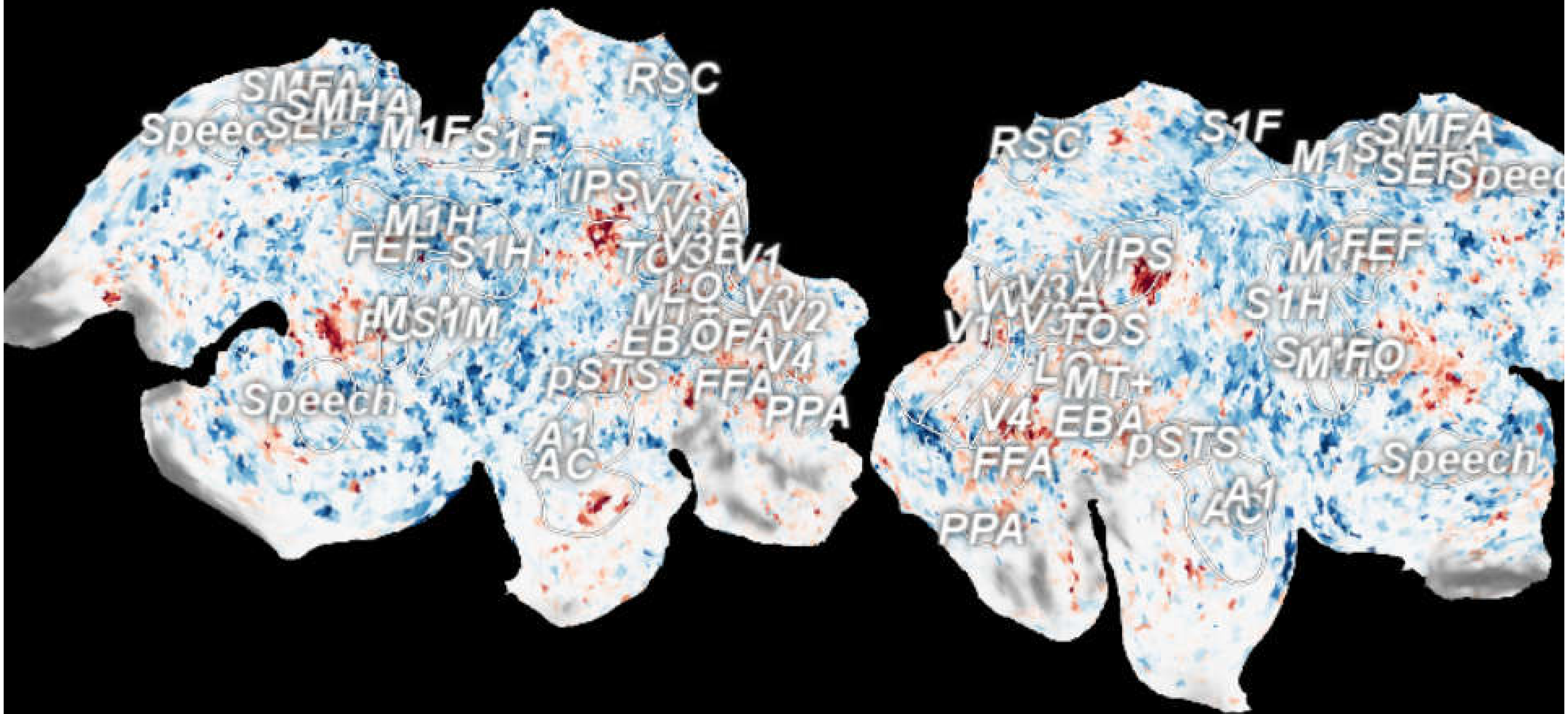


Words in the semantic space are grouped by their similarity (Gallant Lab, 2016).
Words activate specific ROIs, similar words create similar maps of brain activity.
Each voxel may be activated by many words. Video or audio stimuli, fMRI scans.

Category natural depression: Passive Viewing



Category traffic light: Passive Viewing



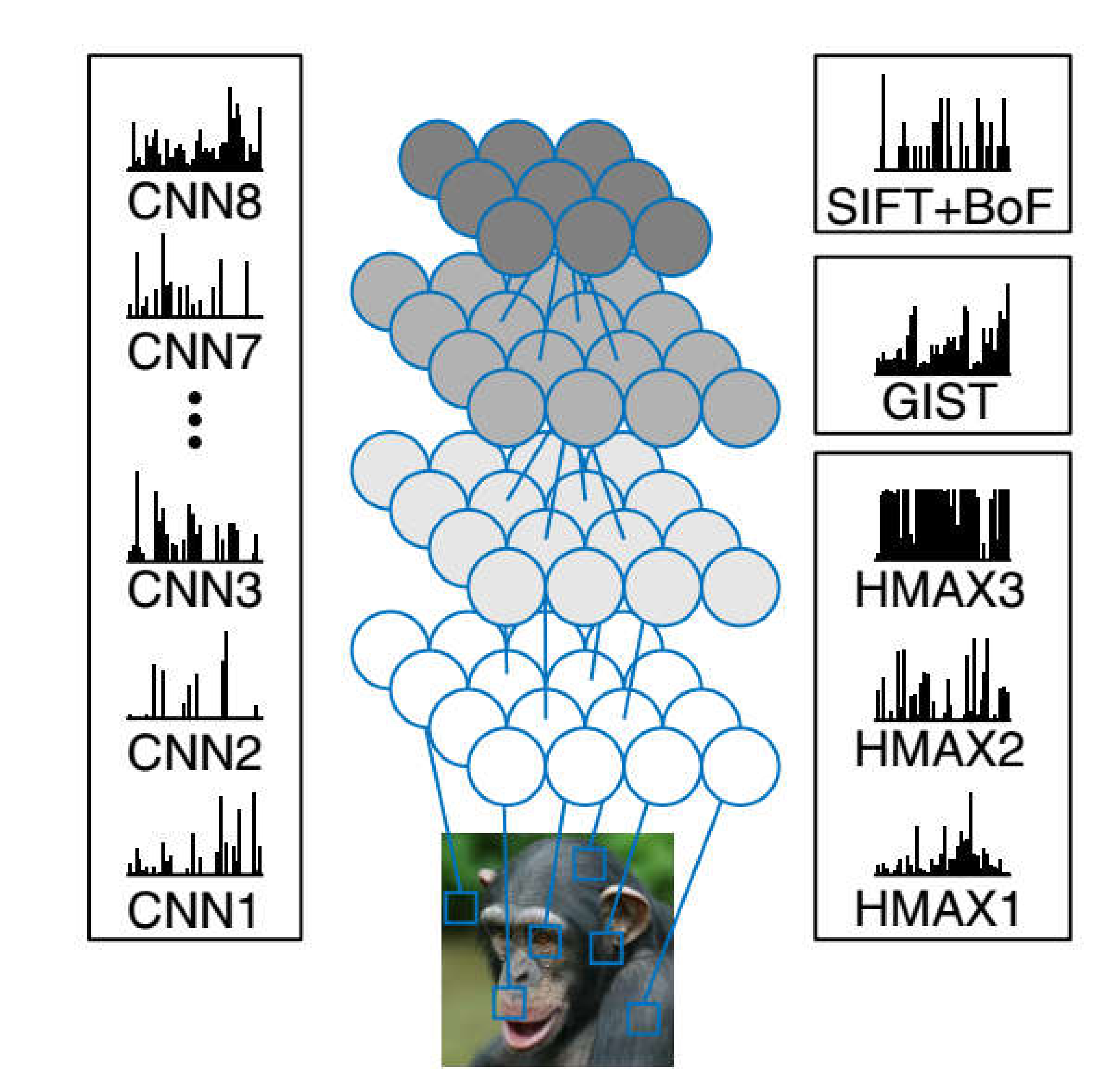
Mental images from brain activity

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

Try to estimate features at different layers.

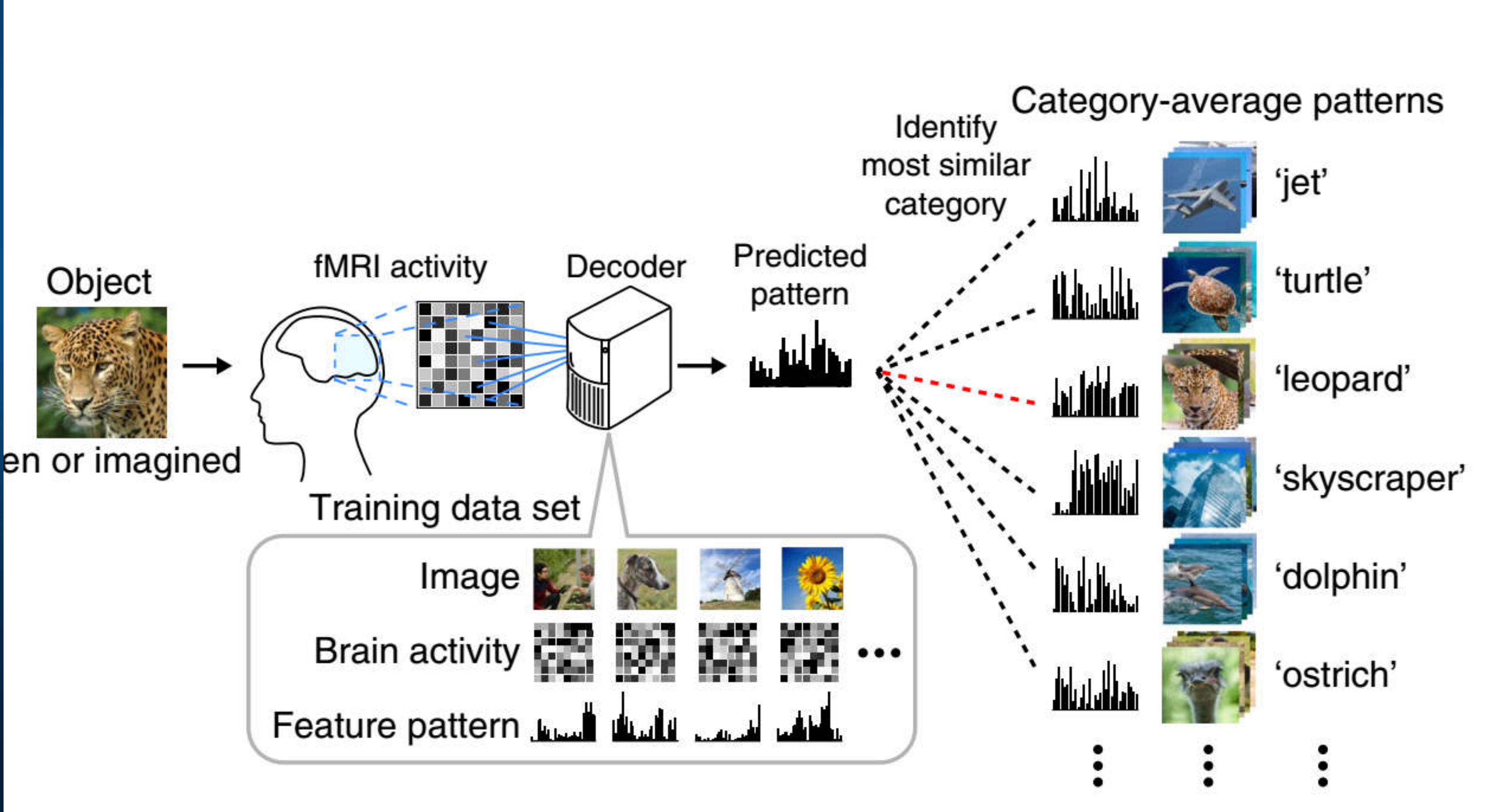
8-layer convolution network, ~60 mln parameters, feature vectors from randomly selected 1000 units in each layer to simplify calculations.

Output: 1000 images.



Brain activity ⇔ Mental image

fMRI activity can be correlated with deep CNN network & other features; using feature pattern closest image from large database is selected.
Horikawa, Kamitani, **Generic decoding** of seen and imagined objects using hierarchical visual features. Nature Communications 5/2017.



Decoding Dreams

Decoding Dreams, ATR Kyoto, Kamitani Lab. fMRI images analysed during REM phase or while falling asleep allows for dream categorisation.

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

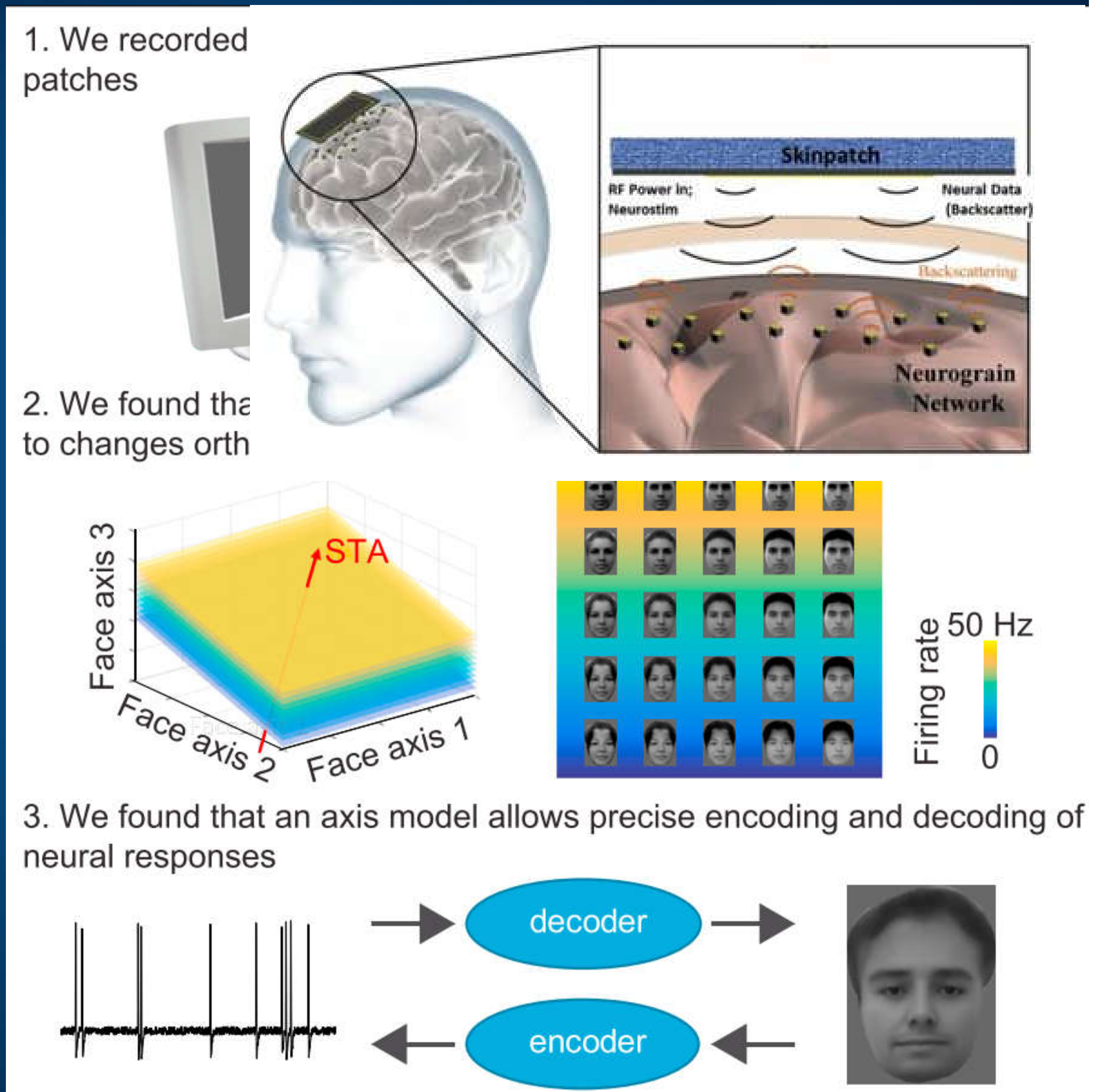
Understanding Brain Activity
Near Future

Neural screen

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

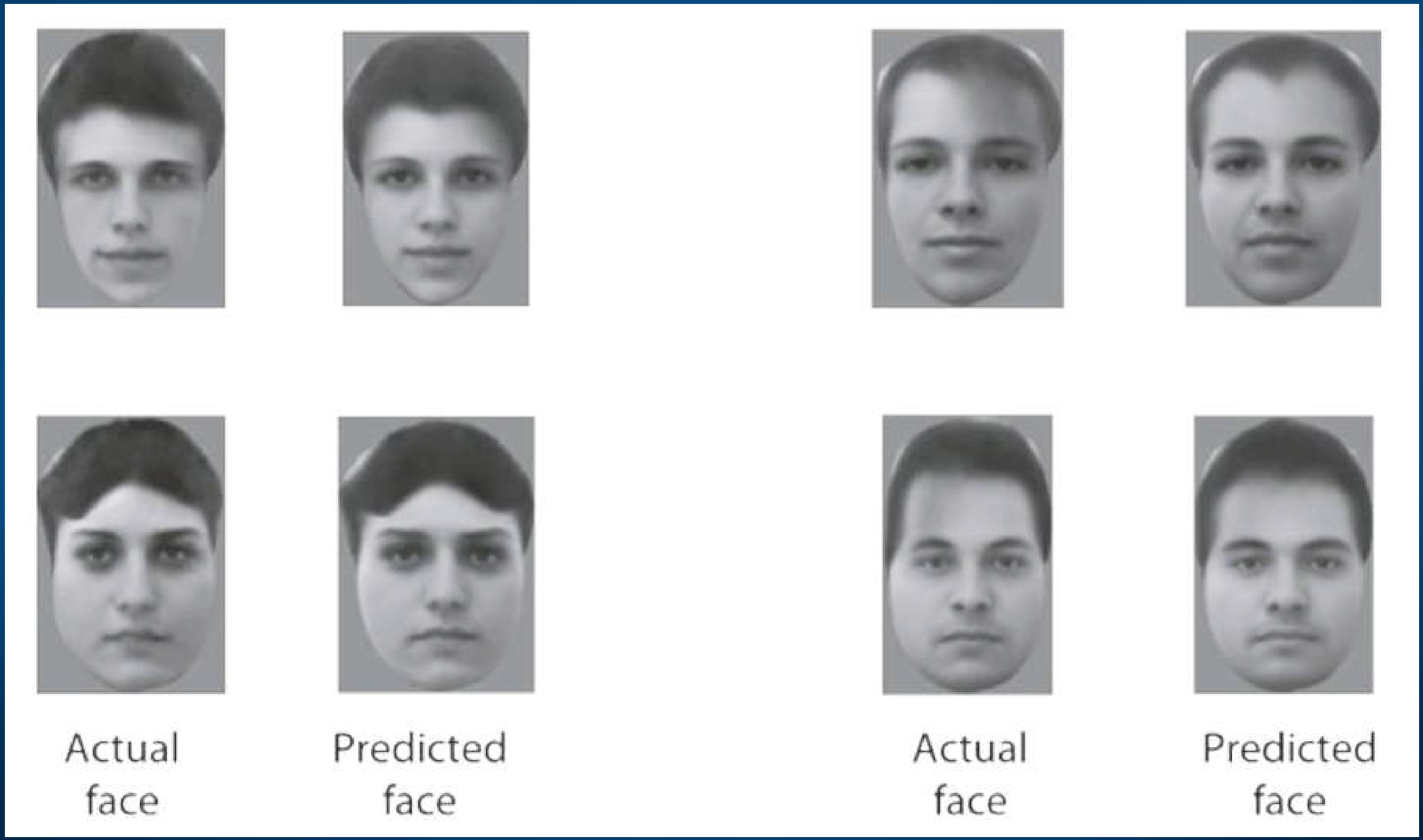
L. Chang and D.Y. Tsao, “The code for facial identity in the primate brain,” *Cell* 2017

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



Mental images

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



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

Conspiracy in the brain

Formation of deep beliefs, distorted memory, memetics, conspiracy ...

Slow and rapid scenarios are possible, here only rapid presented:

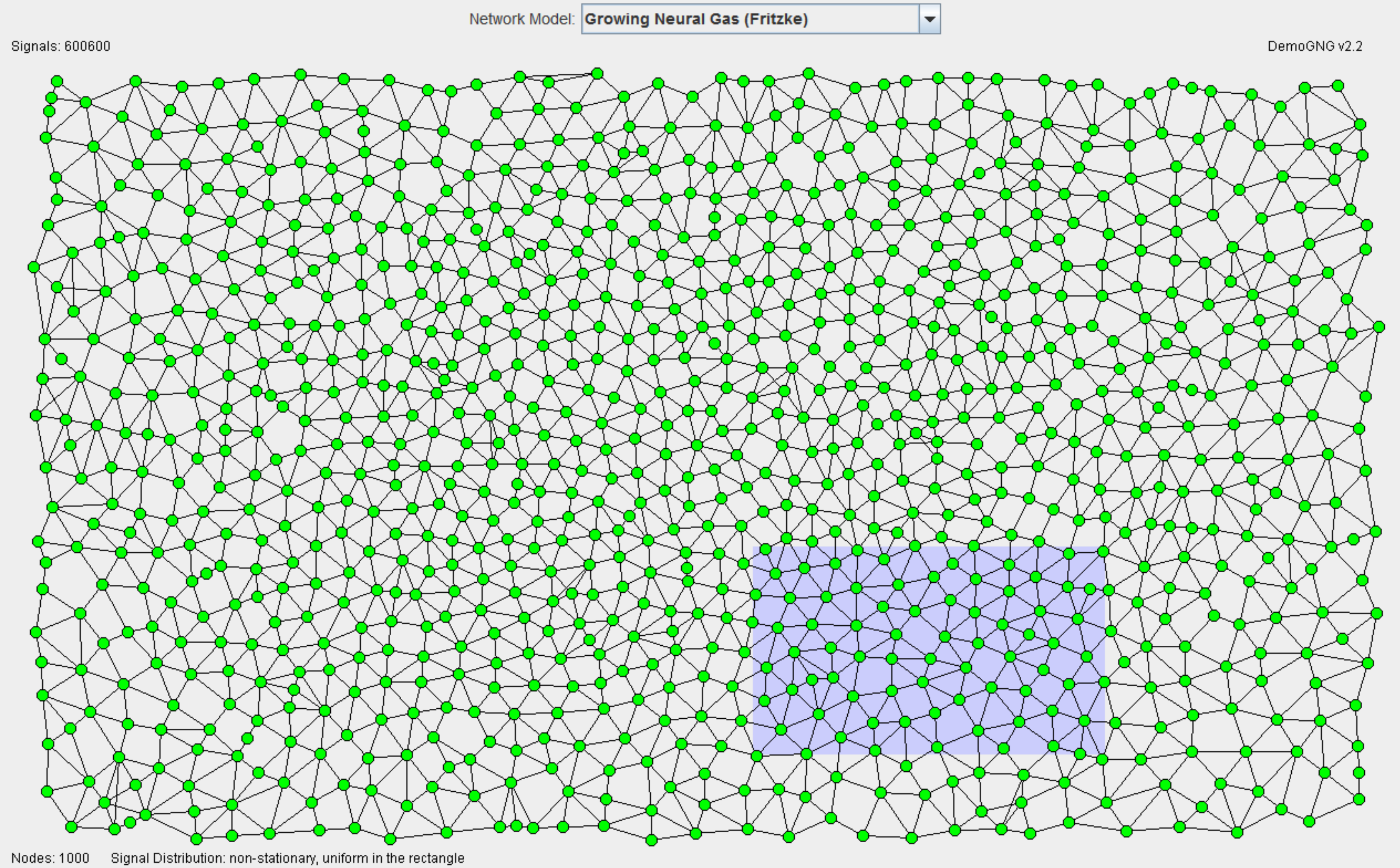
- Emotional situations => neurotransmitters => neuroplasticity => fast learning, must be important.
- Fast learning => high probability of wrong interpretation.
- Traumatic experiences, hopelessness, decrease brain plasticity only strongest association – strongly connected pathways.

- Conspiracy theories form around such associations, "frozen" pathways lead to brain activations forming strong attractors, distorting rational thinking.
- Such strong associations save brain energy and cannot be changed by rational arguments, that influence weaker associations only.
- This explanation becomes so obviously obvious …

Model: concept vectors derived from a corpus + MDS or Growing Neural Gas visualization (Martinetz & Schulten, 1991).

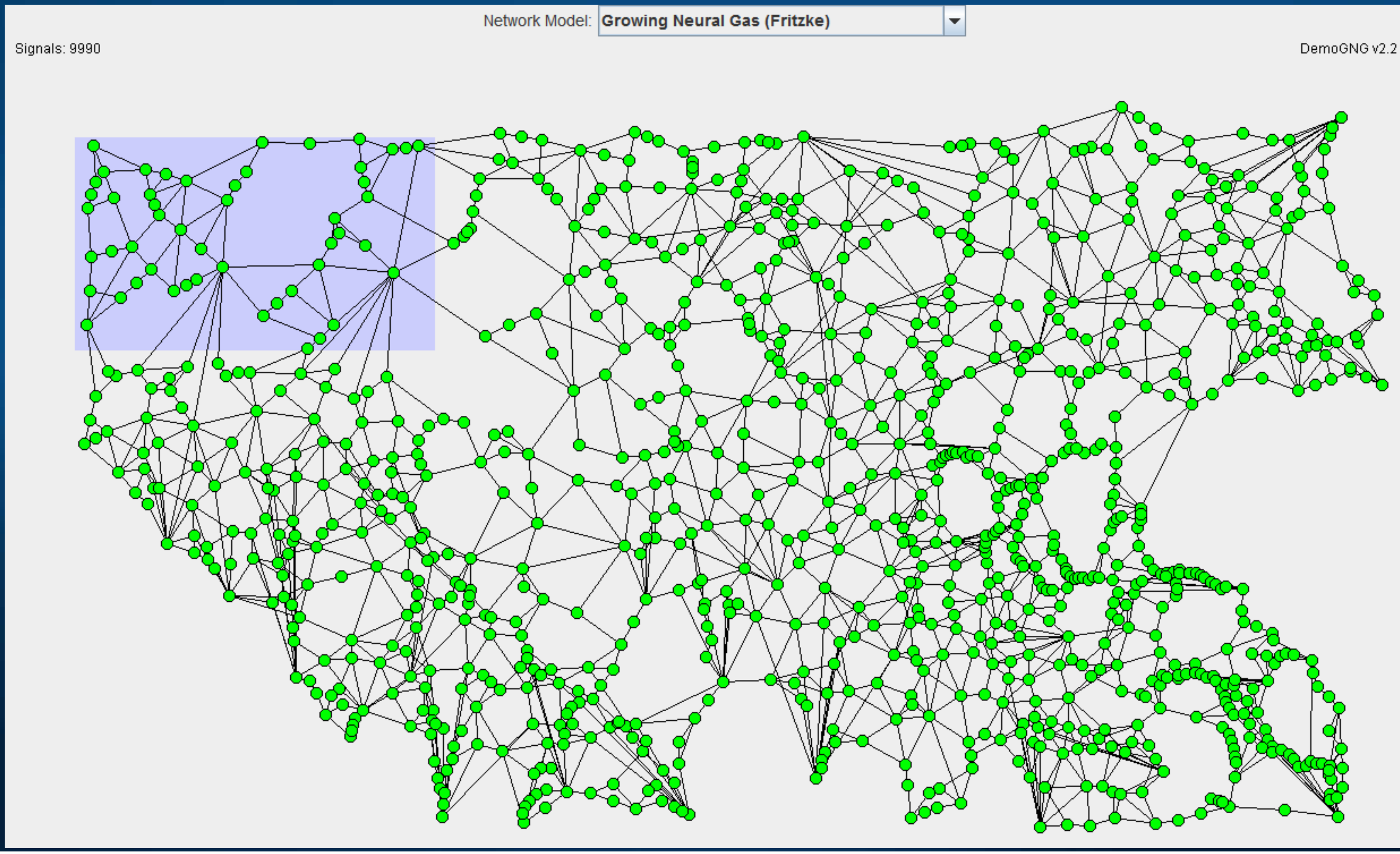
Internalization of environment

Episodes are remembered and serve as reference points, if observations are unbiased they reflect reality.



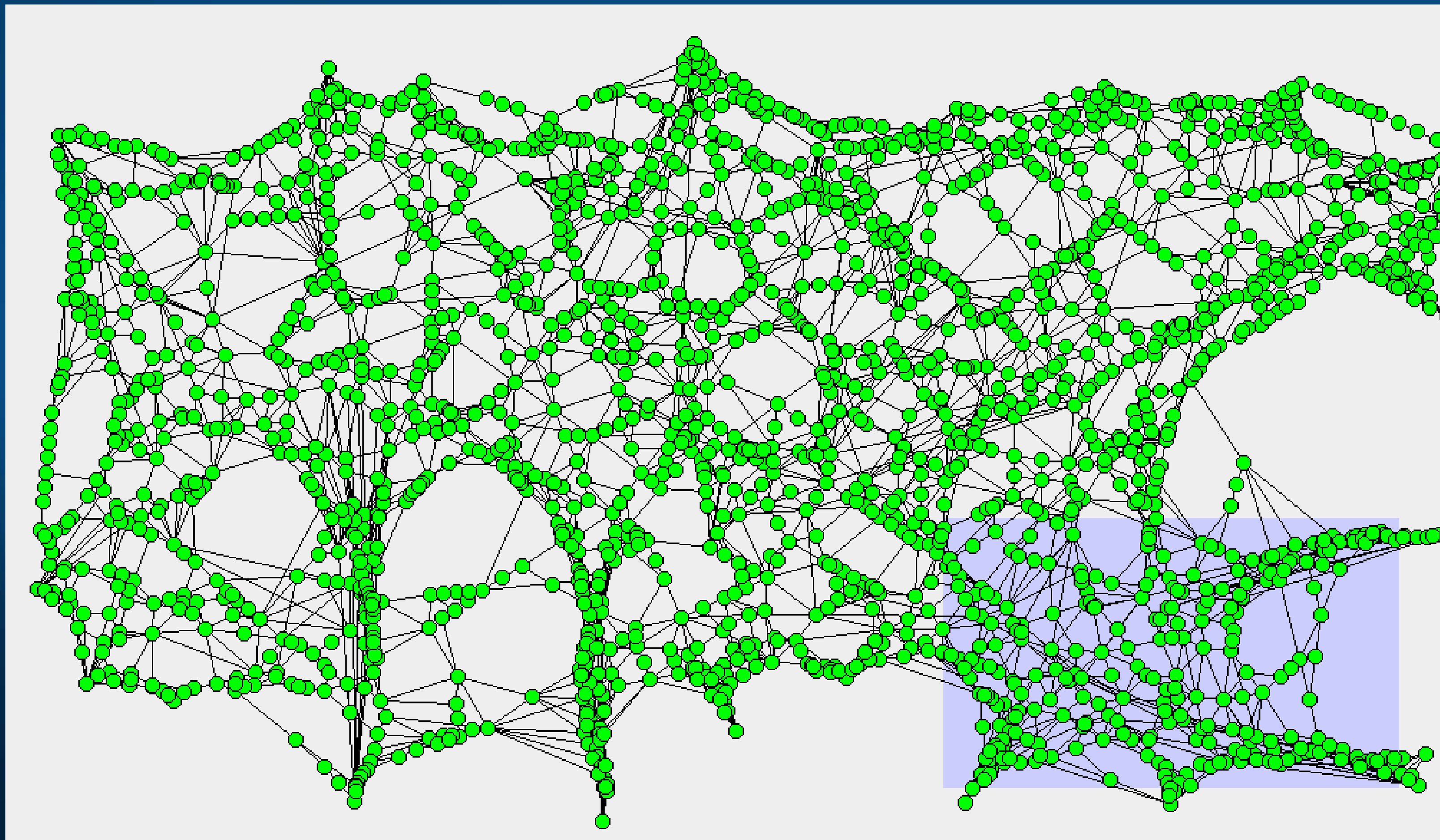
Extreme plasticity

Brain plasticity (learning) is increased if long, Slow strong emotions are involved. Followed by depressive mood it leads to severe distortions, false associations, simplistic understanding.



Conspiracy views

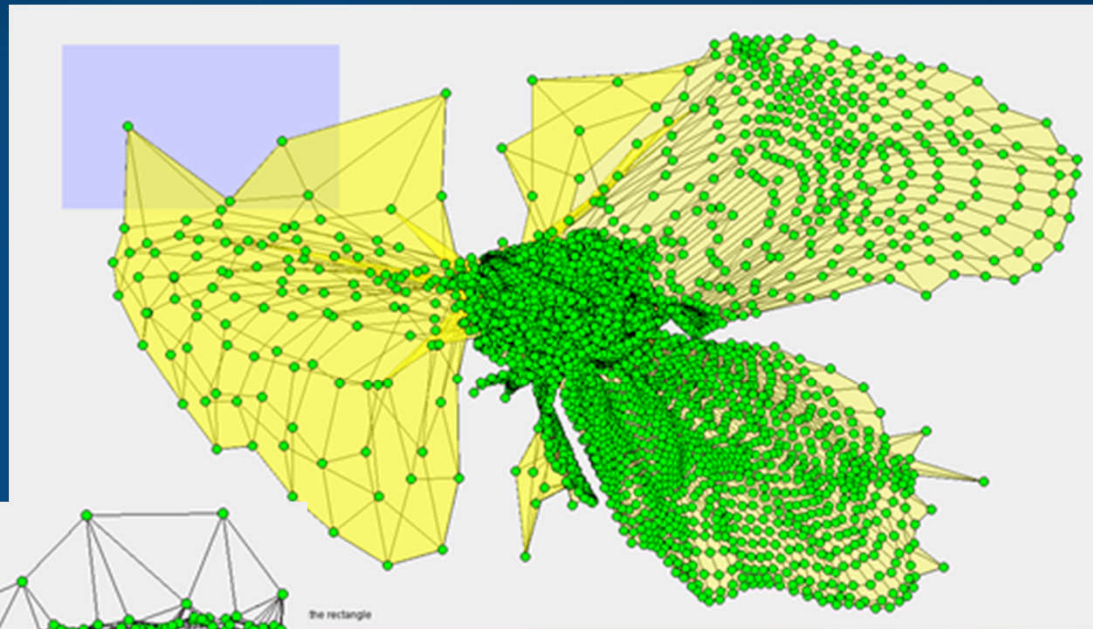
Illuminati, masons, Jews, UFOs, or twisted view of the world leaves big holes and admits simple explanations that save mental energy, creating „sinks” that attract many unrelated episodes.

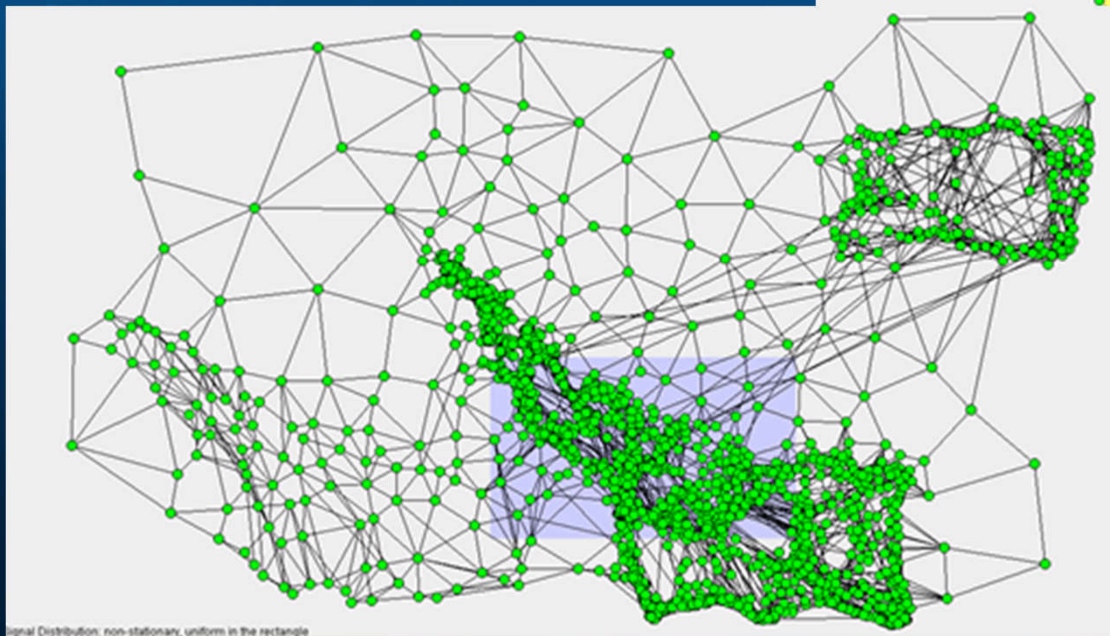


Memoids …

Totally distorted world view, mind changed into a memplex.

Ready for sacrifice.

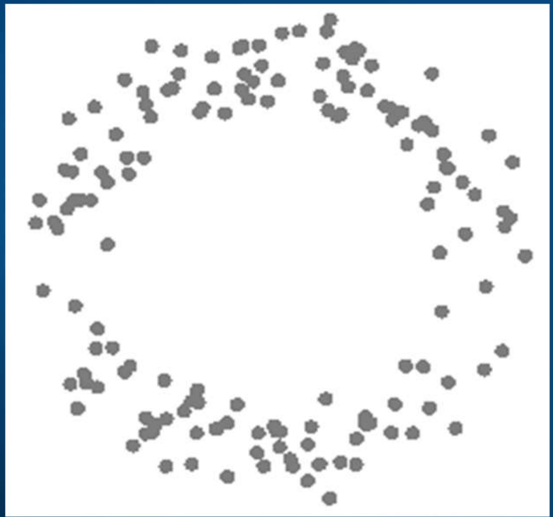


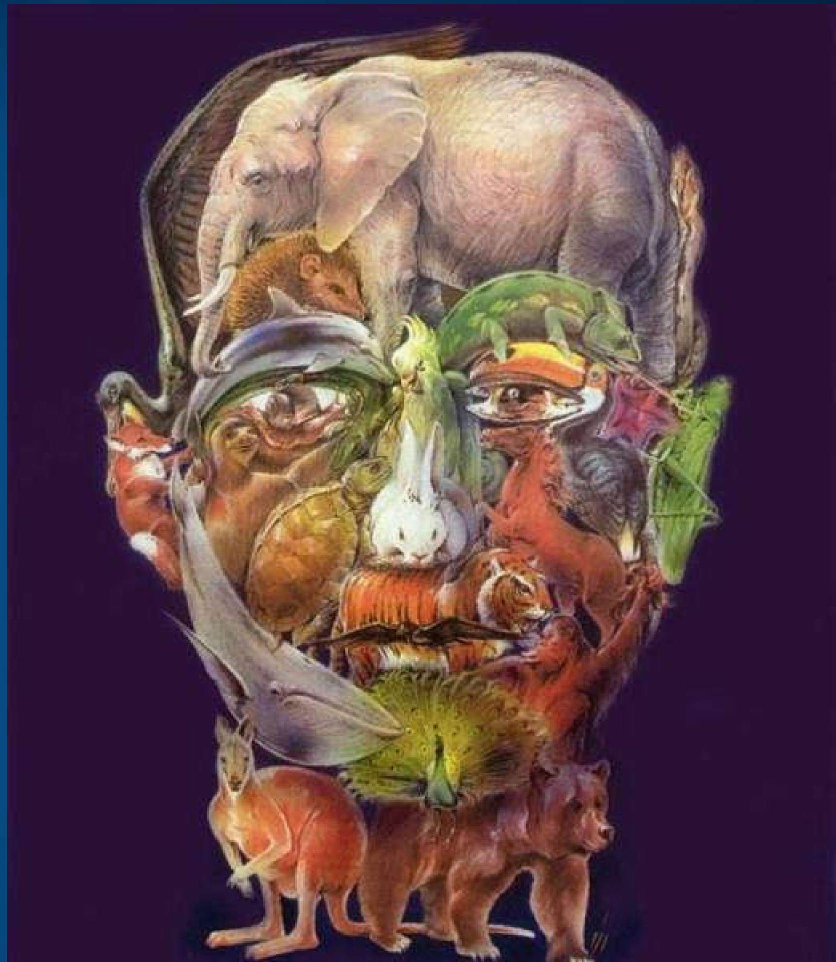


WD: Memetics and Neural Models of Conspiracy Theories

arXiv:1508.04561

Thank for
synchronization
of your neurons





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