Brain-inspired cognitive computing

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ICAISC 21/06/2021

CD DAMSI

University Centre of Excellence (2020) in the research area "Dynamics, mathematical analysis and artificial intelligence".

1. Dynamics and ergodic theory (Math)
2. Computer science – formal languages and concurrency (Theoretical CS)
3. Entangled states and dynamics of open quantum systems (Math Physics)
4. Neuroinformatics and artificial intelligence (Neuroinformatics)

Neuroinformatics is on the front of brain research and AI.
Signal processing methods + machine learning models
⇨ new theories and algorithms for brain signal analysis/brain functions
⇨ experimental verification, construction of cognitive models.

Goals of our group:
1) understanding brain processes through experiments, analysis of brain signals, and computational modeling;
2) inspirations from brain research for better AI algorithms.

In search of the sources of brain's cognitive activity

Project „Symfonia”, NCN, Kraków, 18.07.2016

FACULTY OF PHYSICS, ASTRONOMY AND INFORMATICS

CENTRE FOR MODERN INTERDISCIPLINARY TECHNOLOGIES

INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

nencki institute of experimental biology

Publications 2020

- Duch. W. (2020) IDyOT architecture – is this how minds operate? **Physics of Life Reviews** (IF 13.8)
- Rykaczewski, K, Nikadon, J, Duch, W, Piotrowski, T. (2020). SupFunSim: spatial filtering toolbox for EEG. **Neuroinformatics** (IF 5.1).
- Finc, K, Bonna, K, He, X, Lydon-Staley, D.M, Kühn, S, Duch, W, & Bassett, D. S. (2020). Dynamic reconfiguration of functional brain networks during working memory training. **Nature Communications** 11, 2435 (IF 11.8)
- Dreszer J, Grochowski M, Lewandowska M, Nikadon J, Gorgol J, Bałaj B, Finc K, Duch W, Kałamała P, Chuderski A, Piotrowski T. (2020). Spatiotemporal Complexity Patterns of Resting-state Bioelectrical Activity Explain Fluid Intelligence: Sex Matters. **Human Brain Mapping** (IF 4.5)
- Bonna, K, Finc, K, … Duch, W, Marchewka, A, Jednoróg, K, Szwed, M. (2020). Early deafness leads to re-shaping of global functional connectivity beyond the auditory cortex. **Brain Imaging and Behaviour**, 1-14 (IF 3.6).
- Duch W, Mikołajewski D. (2020) Modelling effects of consciousness disorders in brainstem computational model – Preliminary findings. **Bio-Algorithms and Med-Systems** 16(2).

History and future

Unique moment in history of civilizations!

Superstitions, magical thinking
⇨ causal theories, empirical knowledge
⇨ mathematical models, physics
⇨ computer simulations of complex systems
⇨ AI algorithms/applications
⇨ understanding brains, computer models
⇨ autonomous cognitive systems, BICA
⇨ optimization and enhancement of brain processes.

Q: Why is it so difficult to understand/build artificial brains?

- From simple neuroscience inspirations to ML algorithms.
- From brain activity to some ideas useful in ML.
- Fingerprints of real mental activity.
- Dynamic functional brain networks.

Superhuman AI in many domains

Reasoning: 1997–Deep Blue wins in chess;
2016 –AlphaGo wins in Go; 2017-AlphaGo super-human.

Perception: face recognition, personality, criminal, sexual, political, religious orientation, image recognition.

Strategy and planning: 2017–OpenAI wins in Poker, strategic games Dota 2; 2019-Starcraft II, … war games?

Science: 2015-AI Reverse-Engineers Planarian networks. 2020-AlphaFold 2 for protein folding.

Robotics: 2020 backflip and parcour by Boston Dynamics Atlas robot, autonomic vehicles are coming.

Creativity and imagery: AIVA and other AI composers, DeepArt and painting programs.

Language: 2011–IBM Watson wins in Jeopardy;
2018–Watson Debater wins with philosophers,
2020: BERT answers 100.000 SquAD questions, WuDao.

Cyborgs: BCI, optimization of human brains is coming ...

AGI and BICA

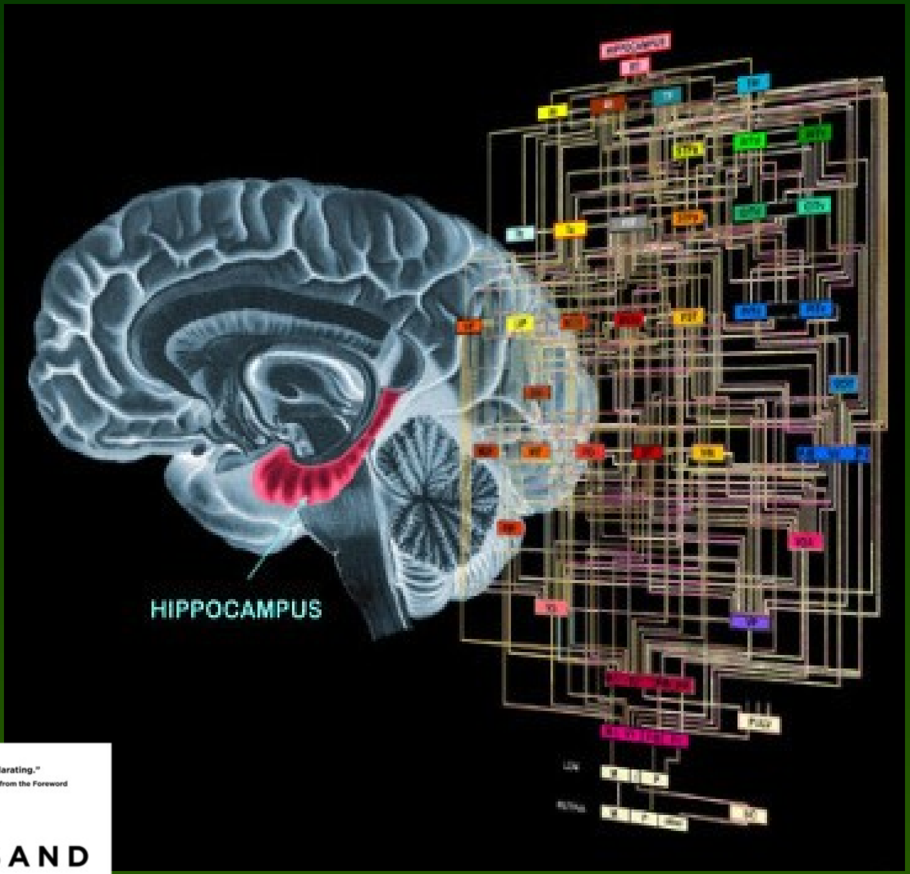
Understanding the brain from engineering perspective
⇔ build a model of the brain capable of all brain functions.
Build causal models of the world.

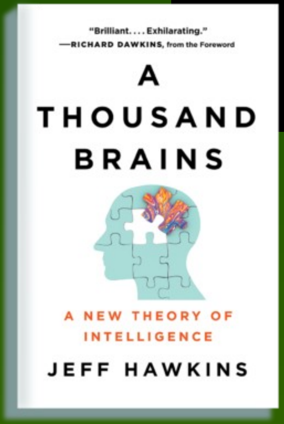
AGI = Artificial General Intelligence, learn many different tasks (2008).

BICA (Brain-Inspired Cognitive Architecture) for flexible intelligence.

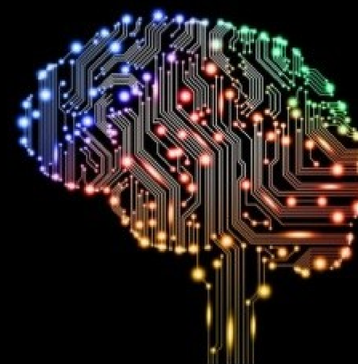
Duch, Oentaryo, Pasquier, [Cognitive architectures:] where do we go from here?

"We'll never have true AI without first understanding the brain"
Jeff Hawkins (2020).

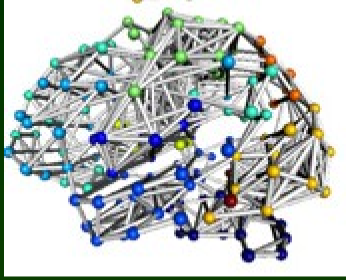




AI for Neuroscience
&
Neuroscience for AI



Irina Rish
AI Foundations
IBM T.J. Watson Research Center



Neuroscience inspirations

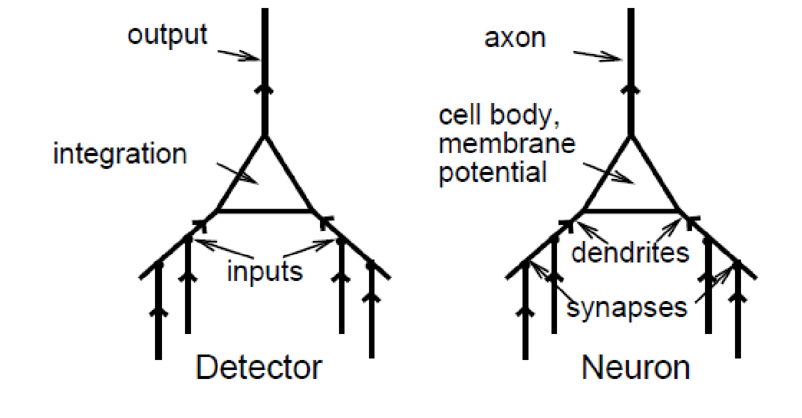
1. Simple neurons: single internal parameter (bias), fixed synaptic connections
   $\Rightarrow$ perceptrons, MLPs, deep networks.

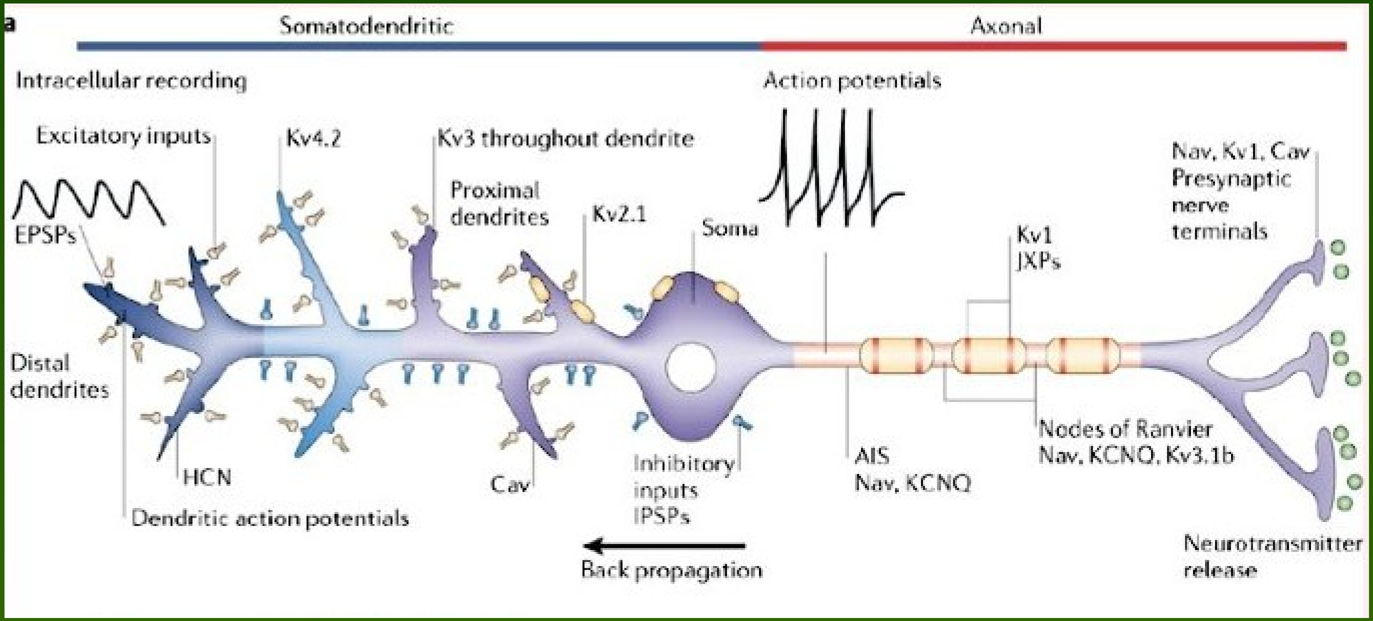
Neurons

Simplest inspiration: neurons (100 G) => perceptron function $\sigma(W*X+\theta)$

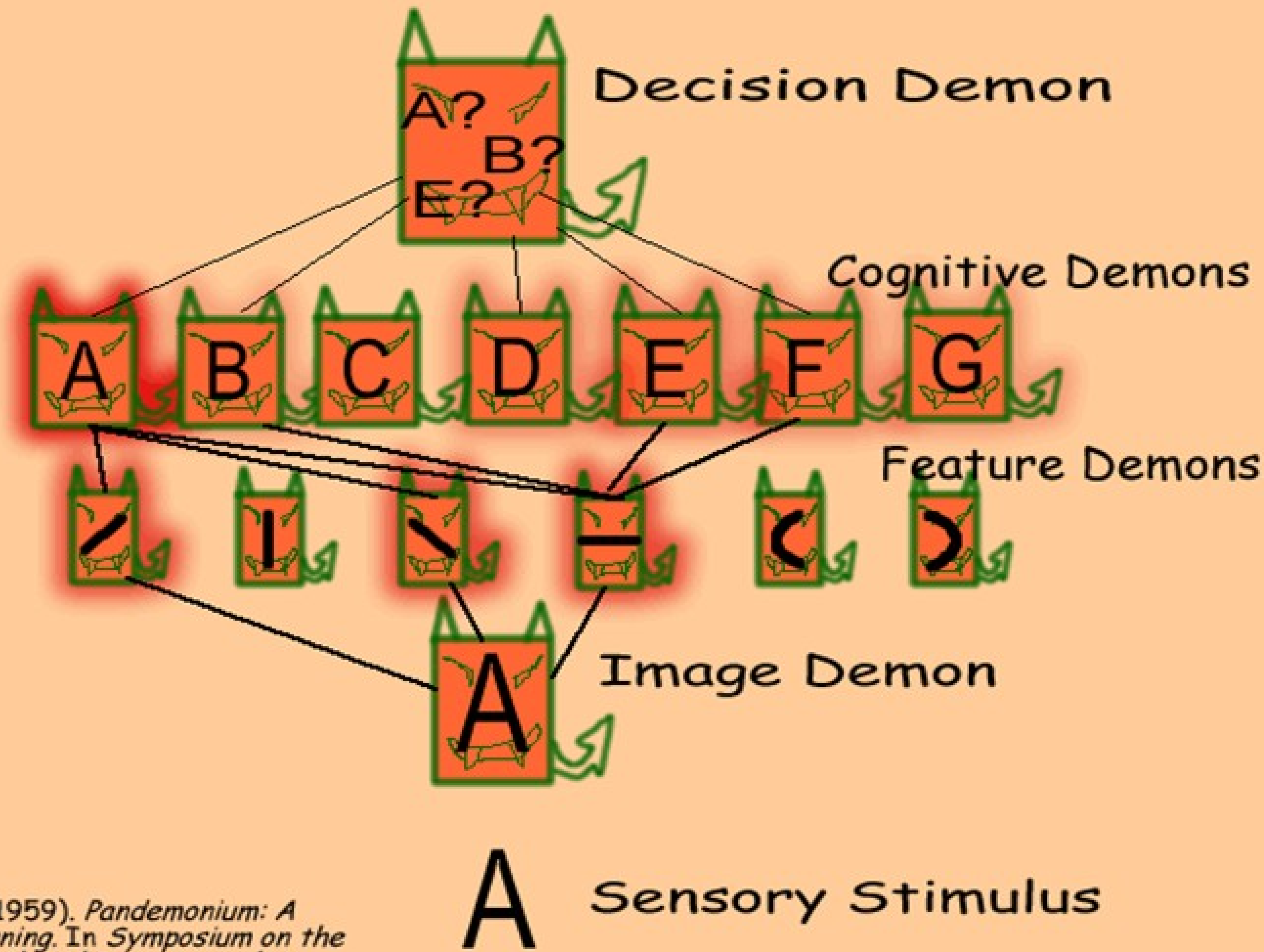
Reality: diverse types, >100 ion channels, complex neurochemistry & spatio-temporal integration, $\approx$10 K inputs …

Detailed biophysical models of neurons are required for neuropsychiatric disorders, influence of neurotransmitters, drugs, etc.





Selfridge's Model (1959)



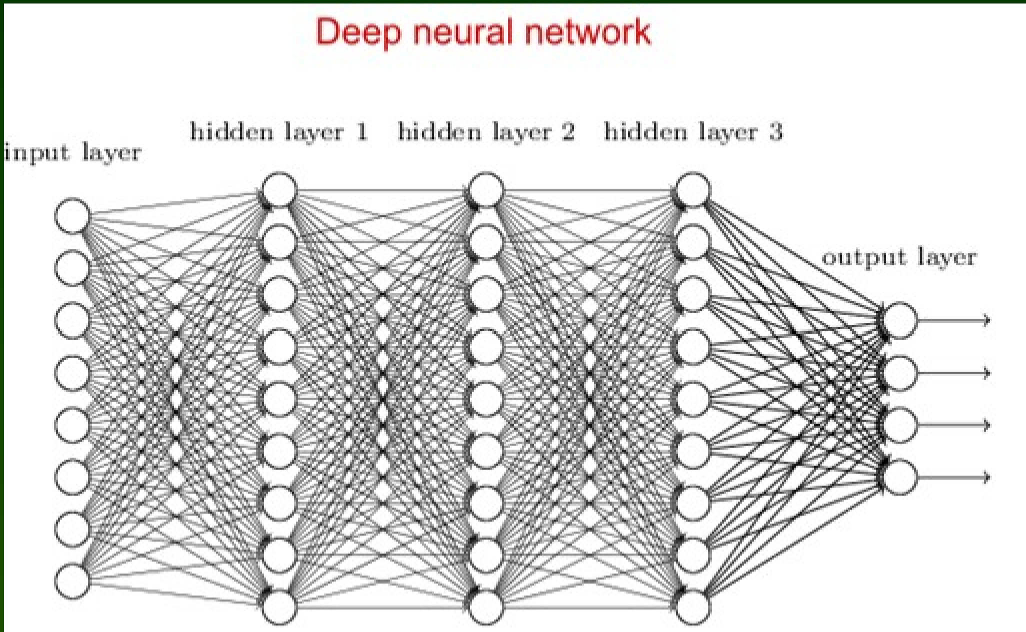
Based on:

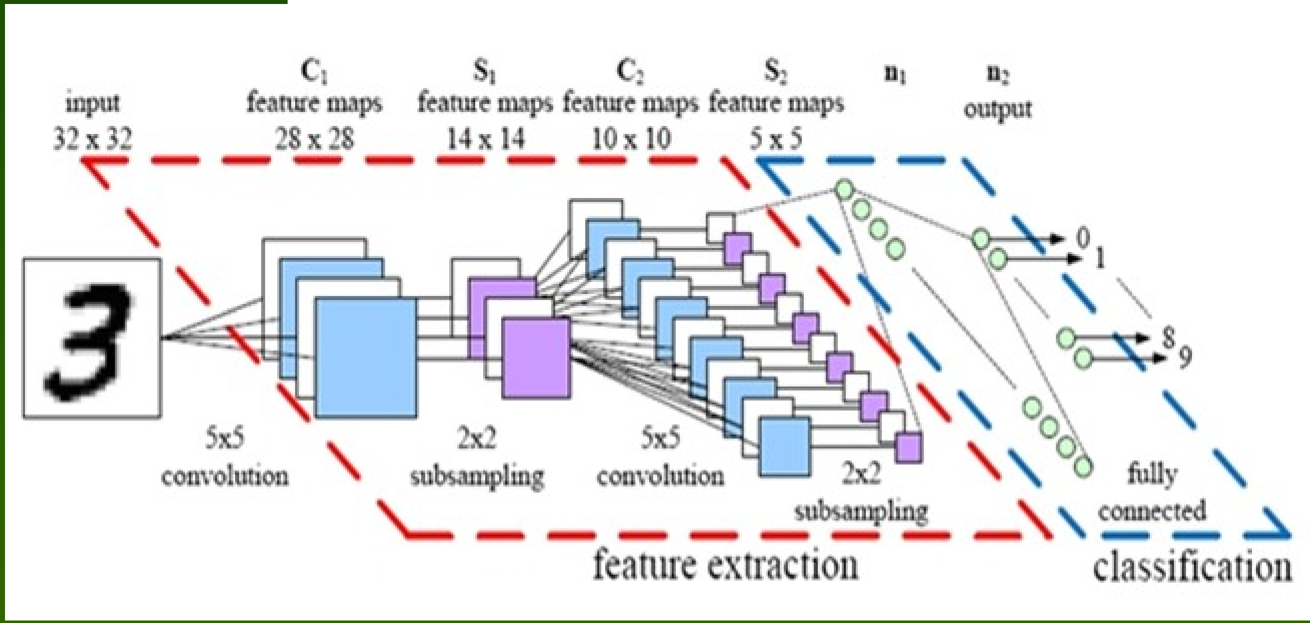
Selfridge, O. G. (1959). *Pandemonium: A paradigm for learning.* In *Symposium on the mechanization of thought processes* (pp. 513-526). London: HM Stationery Office.

Deep Learning for NN

Most neural models are networks of simple non-linear neurons (recently ReLu, simplest), exchanging information via fixed connections, adapting simple parameters to learn vector mappings.
But backprop like learning has no biological justification.

Ex: tensor networks
Cichocki Lab, RIKEN BSI





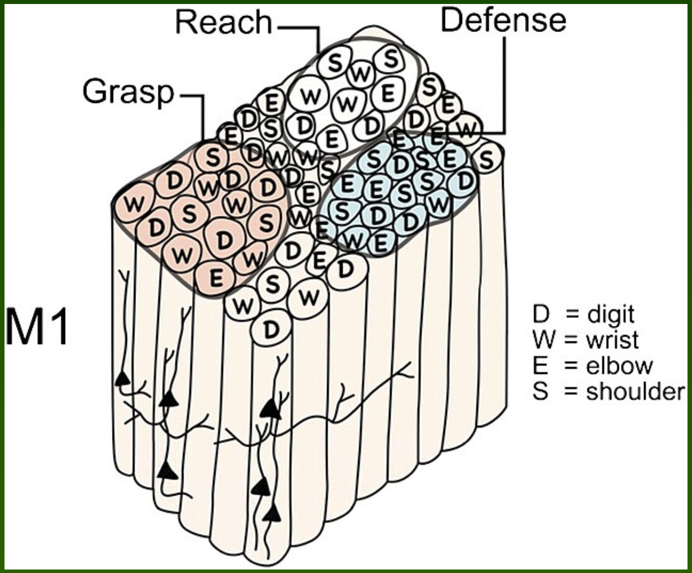
From simple neurons to neural ensembles

Neuroscience inspirations

1. Simple neurons, 1 parameter, fixed synaptic connections
   $\Rightarrow$ perceptrons, MLPs, deep networks.

   Universal learning algorithm in the cortex, can handle any sensory data.

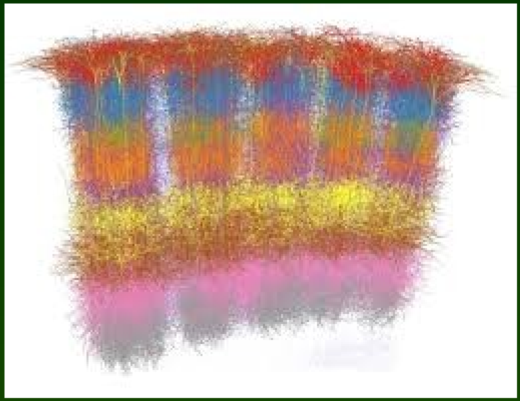
2. Complex neurons and microcircuits,
   small neural cortical ensembles with structural connections
   (fixed, or slowly changing).



Functional organization of the hand–forearm segment of primary motor cortex (M1) in monkeys and primates.

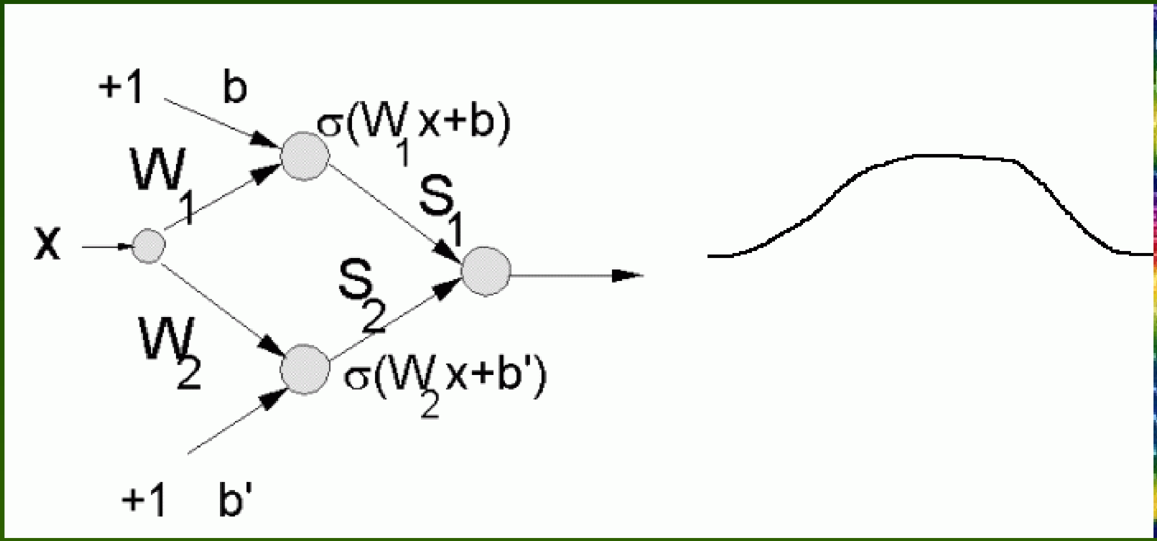
J.H. Kaas PNAS 2012;109: Supplement 1:10655-10660

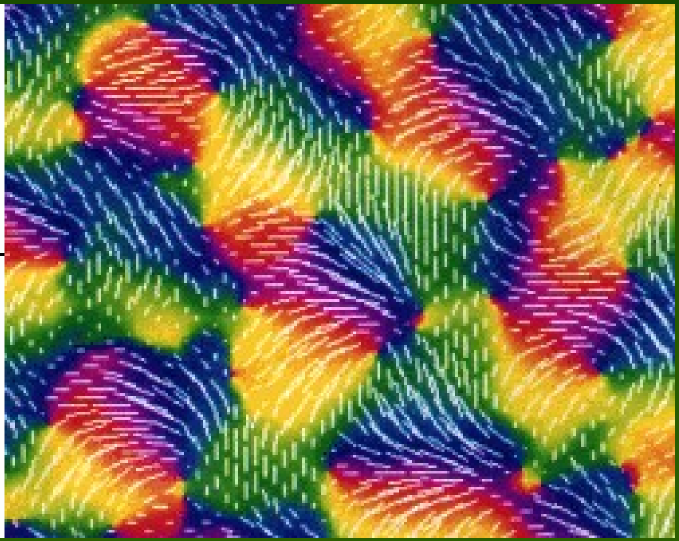
Cell ensembles



Neural Cell Ensembles (NCE) or neuronal ensembles, introduced by D. Hebb, 1949.

Two neurons create soft trapezoidal function, bicentral transfer function. Ensembles of bicentral neurons that implement localized functions G(W*X), model resonances in cortical columns. Ex: primary visual cortex has columns reacting to orientation and ocular dominance (Hubel and Wiesel, Nobel 1981).

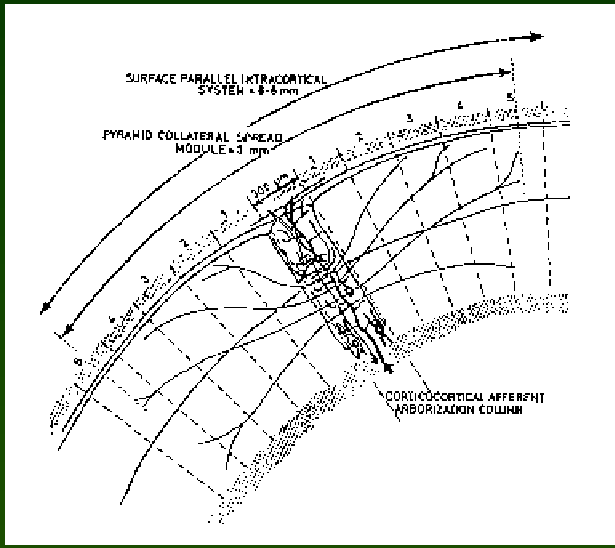




Basis for networks: modules, not neurons, but still fixed connections.

Cortical columns

Cortical columns may learn to respond to stimuli resonating in different way, with complex logic.



Liquid state machine (LSM; Maas, Markram 2004) – large spiking recurrent neural network, randomly connected. Now reservoir computing.

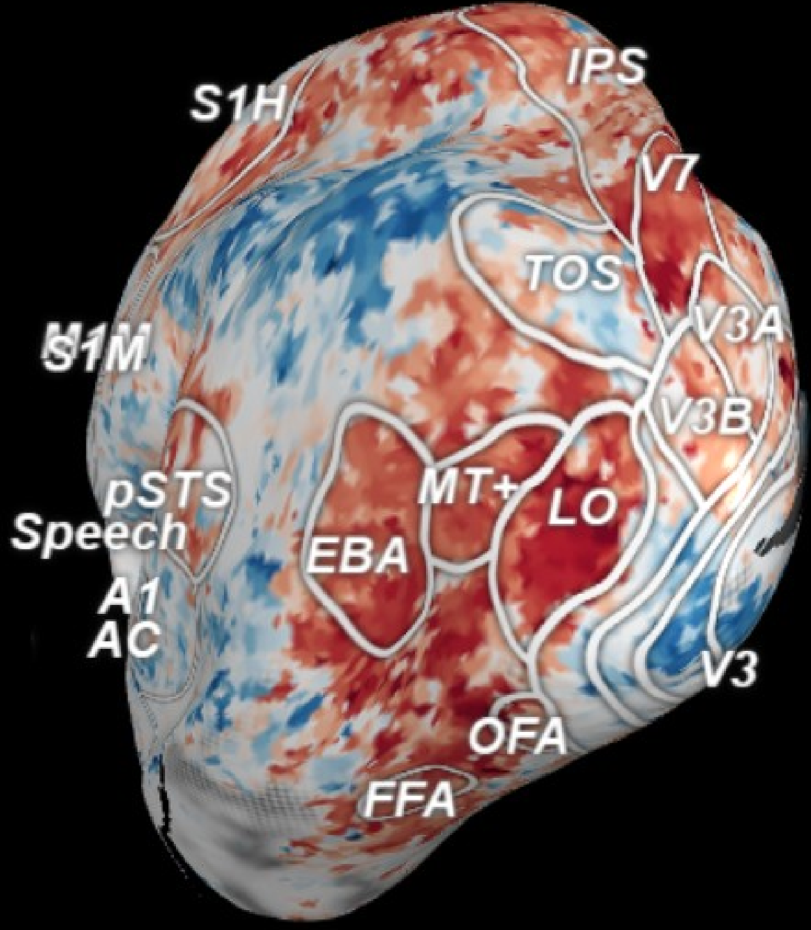
S(t) => LSM (x,t), spatio-temporal pattern of activations, creating separable high dimensional projections that perceptron can handle.

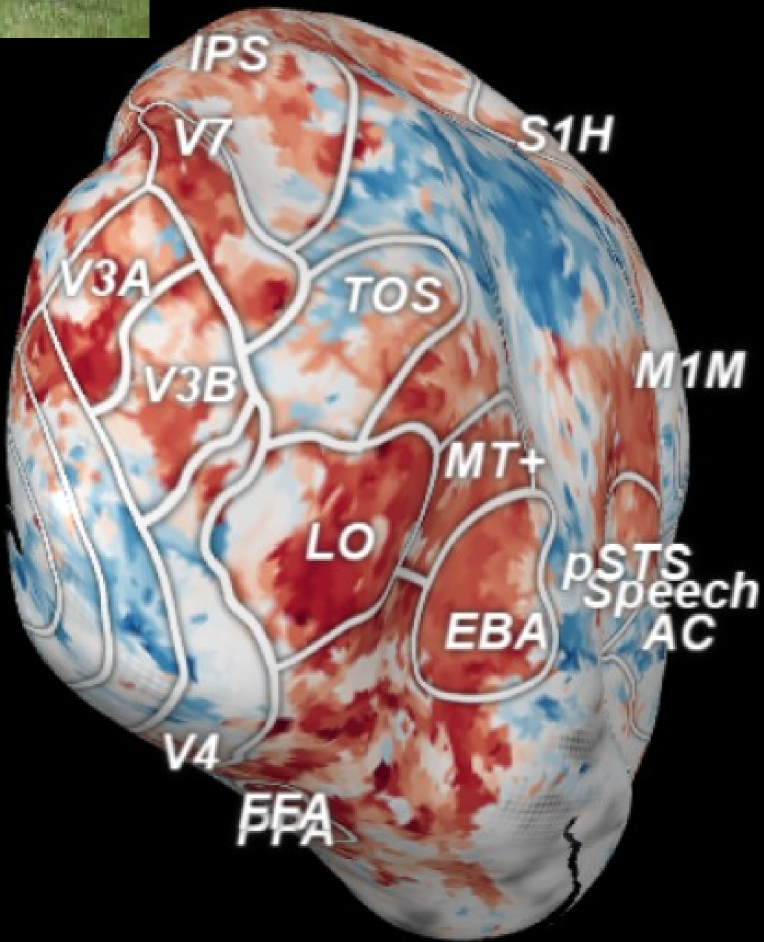
Blue Brain detailed simulation of minicolumn (~10K neurons, 100M synapses) but it was not very useful to create simple abstractions. Simplification for static data:

1) Oscillators based on combination of two neurons $\sigma(W\cdot X\text{-}b) - \sigma(W\cdot X\text{-}b')$ give localized projections ⇔ specific resonant states!
2) Single hidden layer constructive network based on random projection.
Used in our **MLP2LN architecture** for extraction of logical rules from data.

Brain activity beyond visual cortex

Category zebra: Passive Viewing

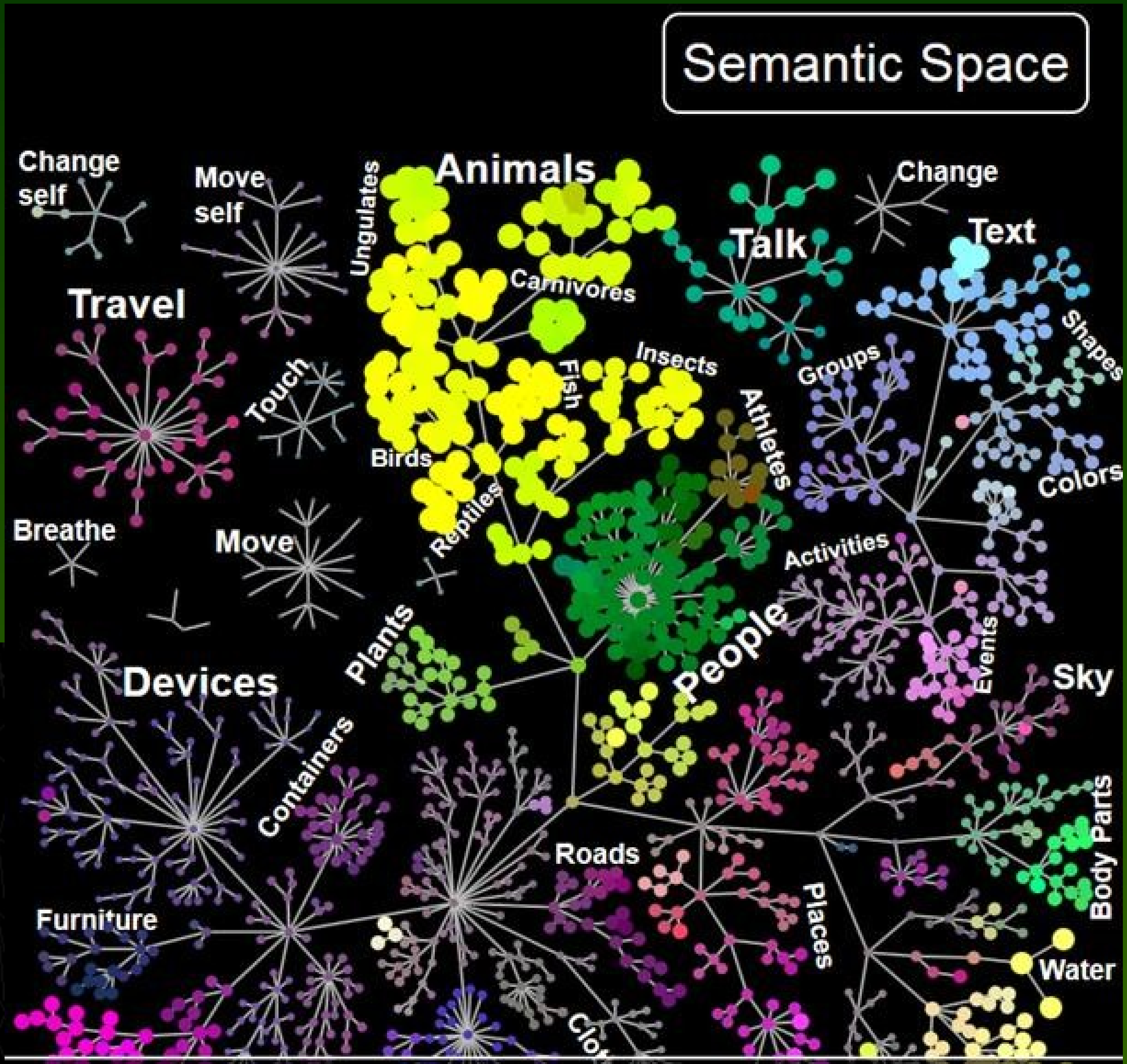


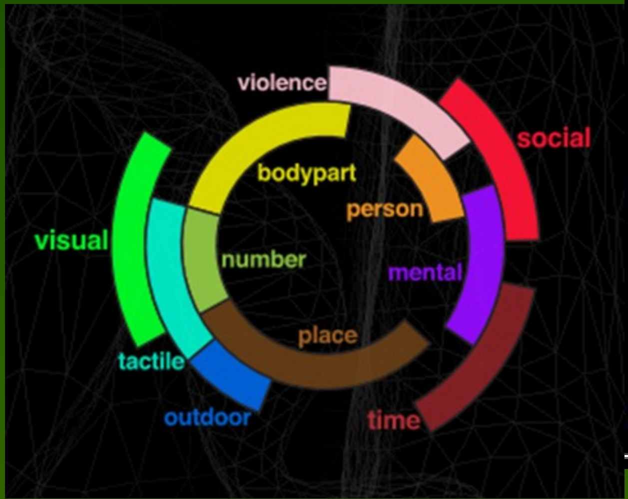


Semantic neuronal space

Words = labels for brain activation patterns.
Understanding words = activation of patterns.
Similar words create similar activity maps.

Video or audio stimuli, fMRI 60.000 voxel).
Gallant lab, Berkeley.





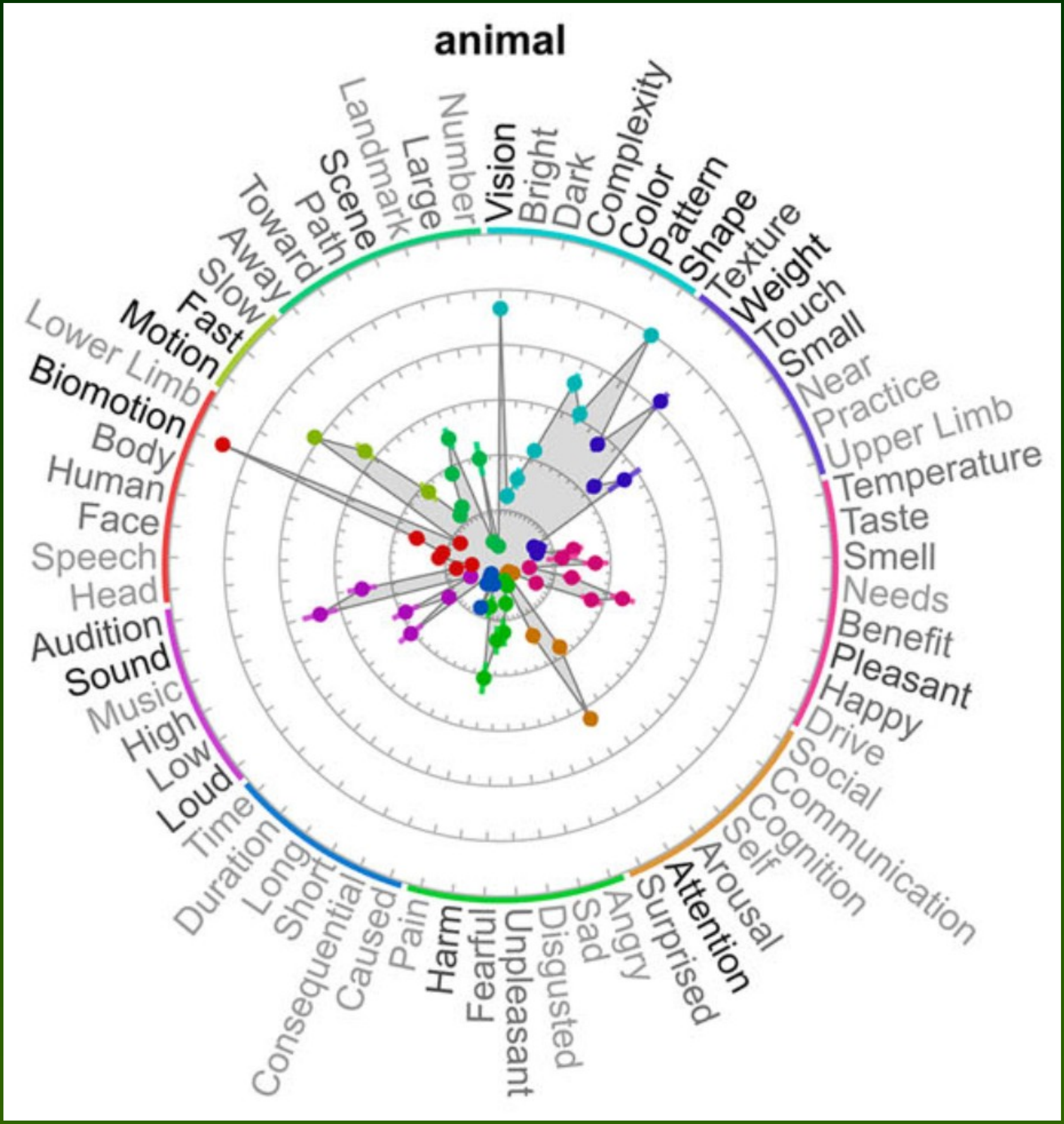
65 attributes related to neural processes;

Colors in circle: general domains. Concept = many patterns.

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

This is general, not than just physical objects

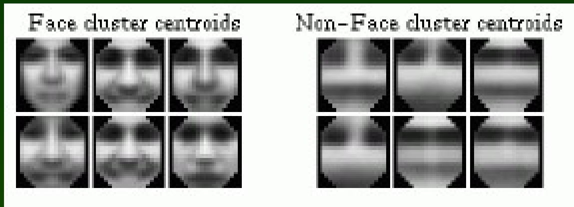
Maps are different in each brain, reflecting subjective individual differences.

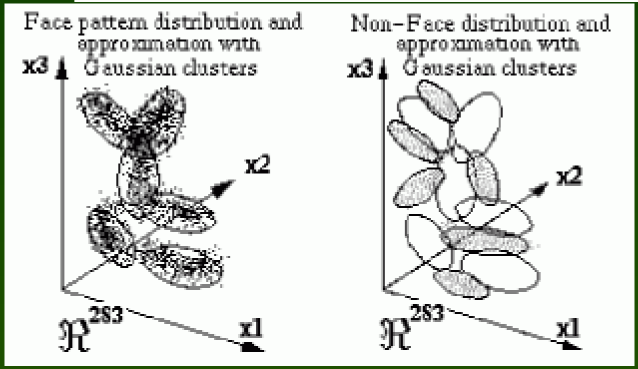


From neural ensembles to simple algorithms

Separable Basis Functions

Feature Space Mapping (FSM) constructive neurofuzzy system. Neural adaptation, estimation of probability density distribution (PDF) using single hidden layer network (RBF-like), with nodes realizing separable basis functions (SBF networks):





$$RBF(X;P) = \sum_i W_i \left\| X_i - P_i \right\|$$

$$FSM(X;P) = \sum_i W_i \prod_{j=1} G_{ij}\left(X_{ij} - P_{ij}\right)$$

Model of mental processes–FSM nodes representing attractors, mental events.

Duch W, Diercksen GHF (1995) Feature Space Mapping as a universal adaptive system. Computer Physics Communications 87: 341-371

Duch W (1997) Platonic model of mind as an approximation to neurodynamics. In: Brain-like computing and intelligent information systems, ed. S-i. Amari, N. Kasabov (Springer, Singapore 1997), chap. 20

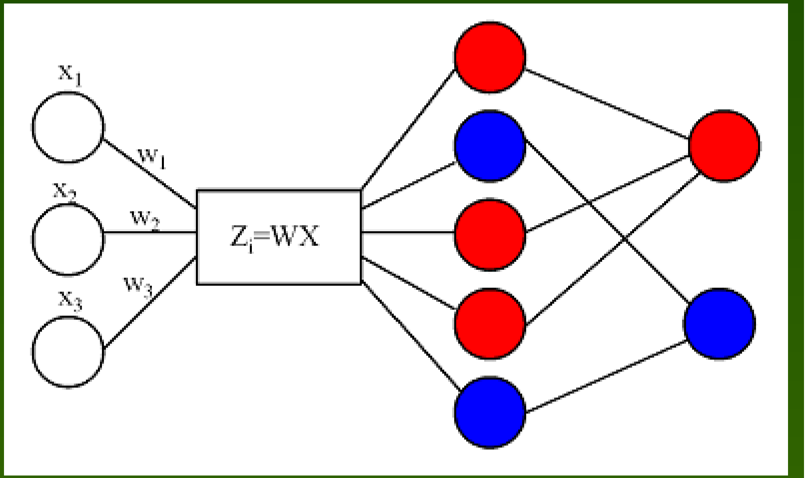
aRPM

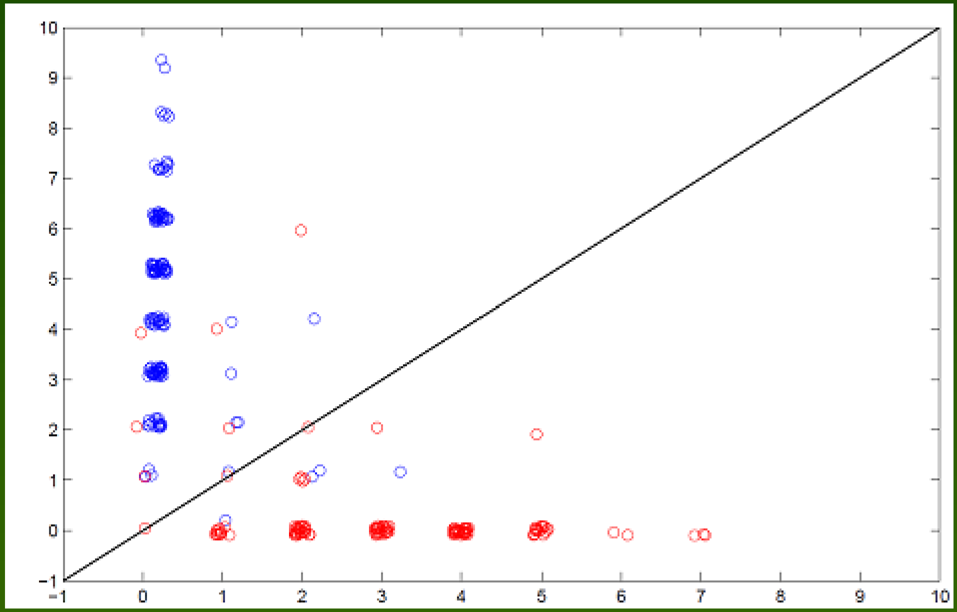
Brain has ~3 mln cortical columns, initially not tuned to input signals.

aRMP, almost Random Projection Machine (with implicit Hebbian learning):

- generate random combinations of inputs (line projection) $z(X)=W{\cdot}X$,
- find and isolate pure cluster $h(X)=G(z(X))$; use localized kernel on projections, estimate relevance of $h(X)$, ex. $MI(h(X),C)$,
- accept only relevant nodes, other contribute only to noise;
- continue until each input vector activates minimum k hidden nodes.

Count how many nodes vote for each class and plot: one-shot learning! Trust those far from diagonal!





Taxonomy of TF

Bicentral (2Slope, Rot2Slope, …) (29, 30, [12])
Act: $A2$–$A4$, Out: $\prod(Ai^-, Ai^+, \sigma)$

G-Conic (27)
Act: $I + D^b$, Out: σ

G-Ridella (28)
Act: $I^+ + D^+$, Out: σ

Bicentral (25,26)
Act: $A1, A3$, Out: $\prod(Ai^-, Ai^+, \sigma)$

Conic (22)
Act: $I + D$, Out: σ

Ridella (21)
Act: $I^+ + D^+$, Out: σ

C_{GL1} (23)
Act: $I + D$, Out: $\frac{1}{1+A}$

C_{GL1} (23)
Act: $I + D$, Out: $\frac{1}{1+A}$

Multivariate Gaussian (13)
Act: D^b, Out: G

Multivariate Sigmoid (14)
Act: D^b, Out: σ

$\bar{G}_2$ (15)
Act: D_i, Out: $\prod \frac{1}{1+A}$

$\bar{G}_3$ (16)
Act: D_i, Out: $\frac{1}{1+\sum A}$

Gaussian-bar (17)
Act: D^b, Out: $\sum G$

Sigmoidal-bar (18)
Act: D^b, Out: $\sum \sigma$

Lorentzian (19)
Act: I, Out: $\frac{1}{1+\sum A}$

Window (20)
Act: I, Out: G

Gaussian (11)
Act: D, Out: G

Radial coordinate (8)
Act: D, Out: A

Multiquadratics (9)
Act: D, Out: $(b^2 + D^2)^\alpha$

Thin-plate spline (10)
Act: D, Out: $(bD)^2 \ln(bD)$

Gaussian Approximations (12)
Act: D, Out: $G_1 = 2 - 2\sigma(r^2)$, $G_2 = \tanh(r^2)$, $G_{2n} = \frac{1}{1+r^{2n}}$, splines approx. [12]

Logistic (5)
Act: I, Out: σ

Other Sigmoids
Act: I, Out: tanh, arctan

Sigmoids Approximations ($s2, s3$) (6–7)
Act: I, Out: $\Theta(I)\frac{I}{I+s} - \Theta(-I)\frac{I}{I-s}$, $\frac{sI}{1+\sqrt{1+s^2I^2}}$, $\frac{sI}{1+|sI|}$, $\frac{sI}{\sqrt{1+s^2I^2}}$

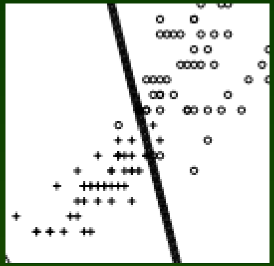
Heaviside (2)
Act: I, Out: $\Theta(I;\theta)$

Multistep (3)
Act: I, Out: $\varsigma(I)$

Semi-linear (4)
Act: I, Out: $s_l(I;\theta_1,\theta_2)$

Heterogeneous decision trees

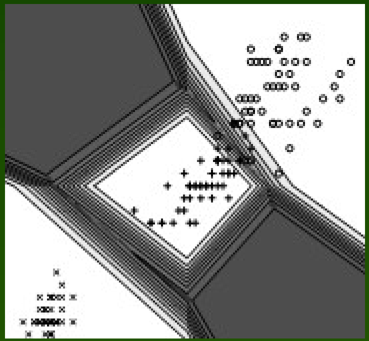
Decision trees select the best feature/threshold value
for univariate and multivariate trees:



$$X_i < \theta_k \text{ or } T\left(\mathbf{X};\mathbf{W},\theta_k\right) = \sum_i W_i X_i < \theta_k$$

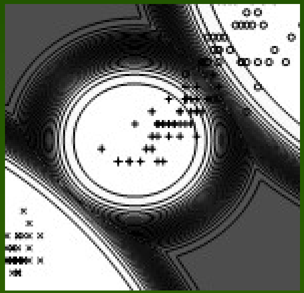
Decision borders: hyperplanes.

Introducing tests based on L_α Minkovsky metric.



$$T\left(\mathbf{X};\mathbf{R},\theta_R\right) = \left\|\mathbf{X}-\mathbf{R}\right\|_\alpha = \sum_i \left|X_i - R_i\right|^{1/\alpha} < \theta_R$$

Such DT use radial kernel features!



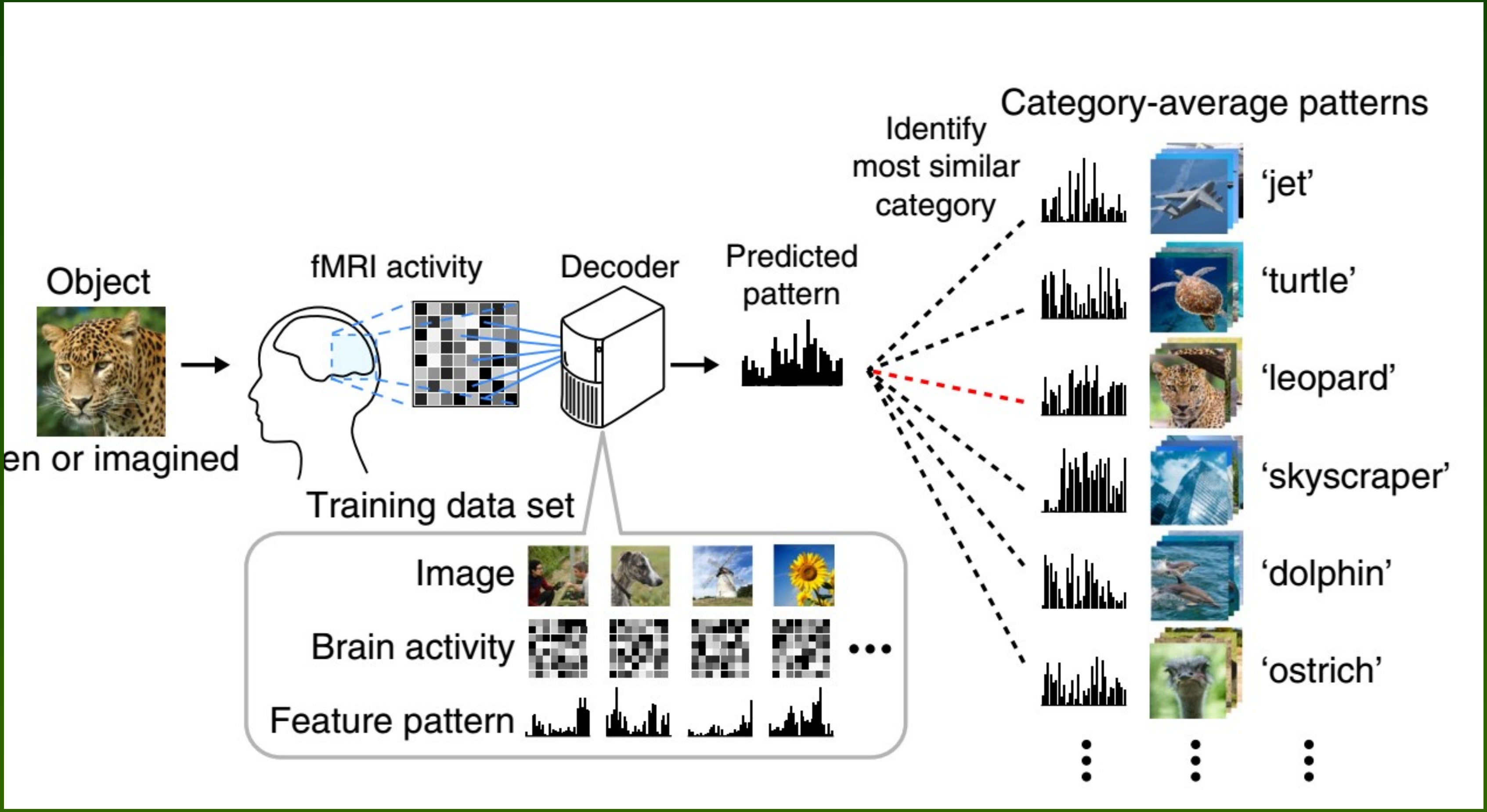
For L_2 spherical decision border are produced.

For L_∞ rectangular border are produced.

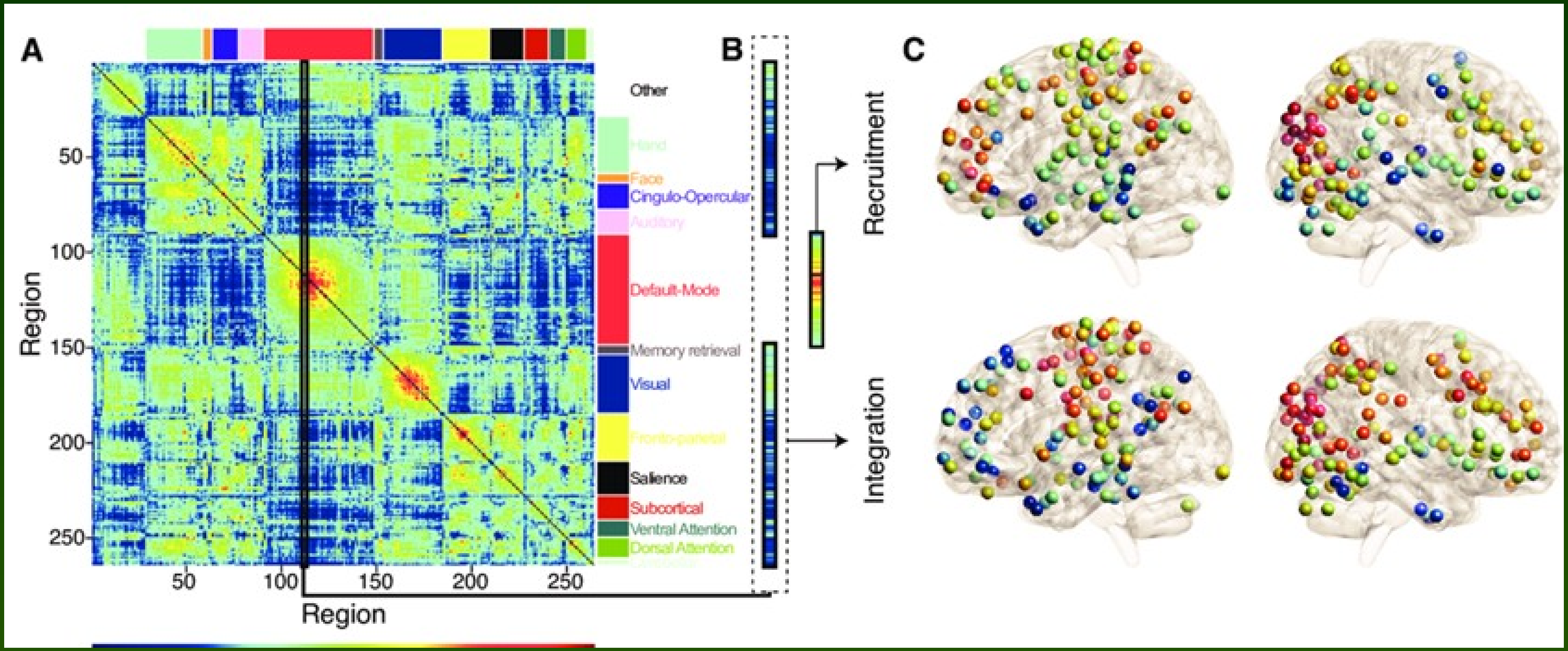
For large databases first cluster data to get candidate references **R**.

Brain activity ⇔ Mental image

fMRI voxel activity (2^3 mm) 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 Communications 2017.



Much more complex logic …

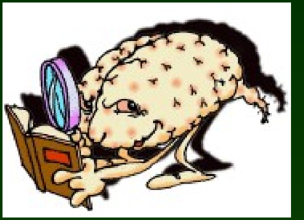


Different activations => many ways to express/do specific task.
Same cognitive functions in different context lead to different activations, to learn from from this type of data complex logic is required.

Mattar, M. G, Cole, M. W, Thompson-Schill, S. L, & Bassett, D. S. (2015). A **Functional Cartography of Cognitive Systems**. *PLOS Computational Biology*, *11*(12), e1004533.

From bain activations
to complex algorithms

Goal of learning



MLP/RBF/SVM kernel methods transform data to high dimensional spaces, “flatten” non-linear decision borders, achieving separability.

In AI logical reasoning problems, visual/auditory perception, object recognition, text analysis, bioinformatics this is not sufficient.

For complex logic networks with localized functions need exponentially large number of nodes. Training MLPs is hopeless.

Linear separation is too difficult, set an easier goal. Brains learn patterns.
Linear separation: projection on 2 half-lines in the kernel space:
line $y=WX$, with $y<0$ for class – and $y>0$ for class +.

Two solutions that brains/AI may use:

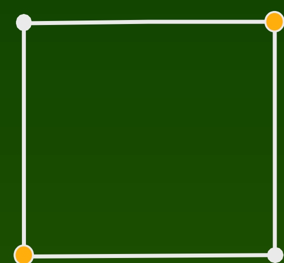
1) Transform data to a unique distribution that can be easily analyzed.
2) Simplest approach: **separate data into k-intervals, or k-separability**.

For parity: find direction W with minimum # of intervals, $y=W\cdot X$

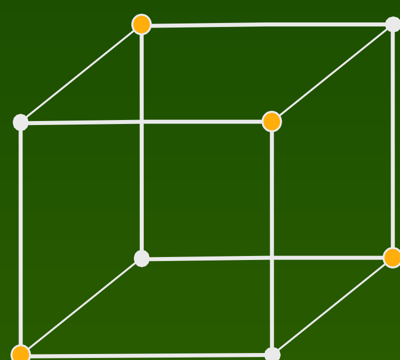
Neurons learning complex logic

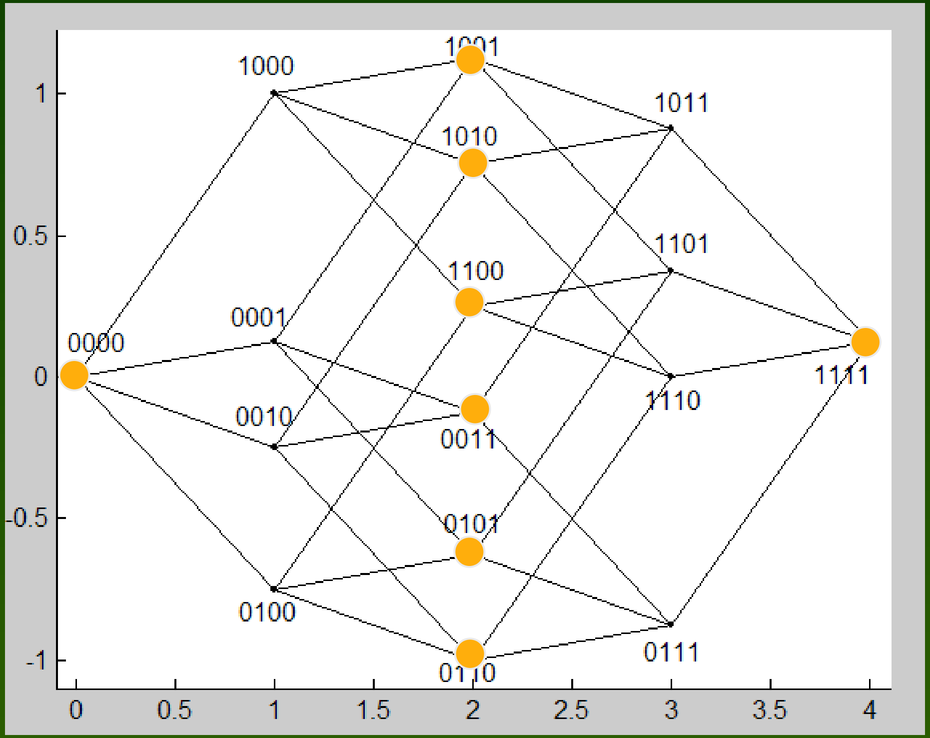
Boole'an functions are difficult to learn, n bits but 2^n nodes => combinatorial complexity; similarity is not useful, for parity all neighbors are from the wrong class. MLP networks have difficulty to learn functions that are highly non-separable.

Ex. of 2-4D parity problems.



Neural logic can solve it without counting; find a good point of view.



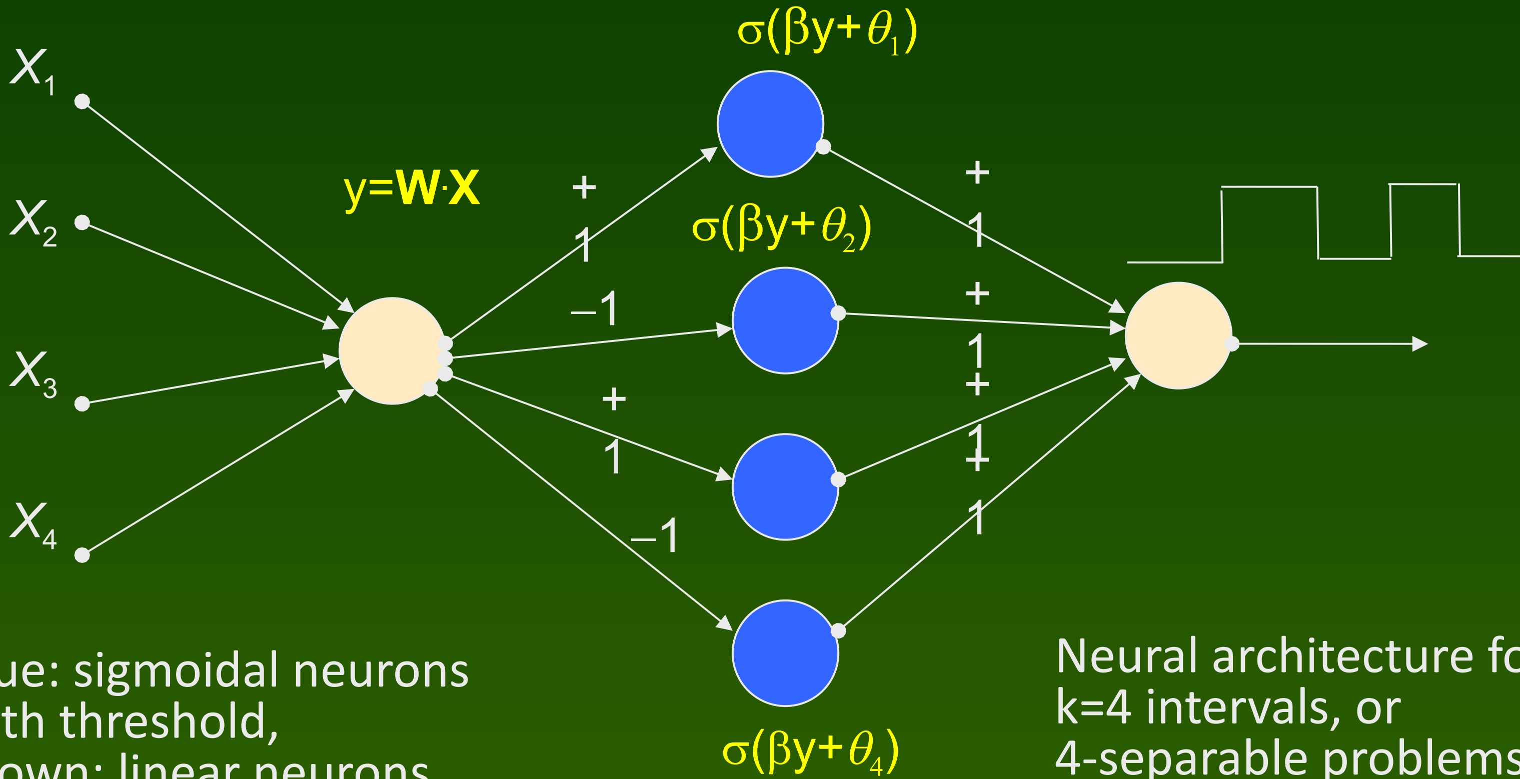


Projection on W=(111 ... 111) gives clusters with 0, 1, 2 ... n bits; solution requires abstract imagination + easy categorization.

k-separability

Can one learn complex Boolean functions, not just parity?

Problems may be classified as 2-separable (linear separability);
non separable problems may be broken into k-separable, k>2.



Blue: sigmoidal neurons
with threshold,
brown: linear neurons.

Neural architecture for
k=4 intervals, or
4-separable problems.

QPC, Projection Pursuit

What is needed to learn data with complex logic?

- cluster non-local areas in the X space, use W·X
- capture local clusters after transformation, use G(W·X-θ)

SVMs fail because the number of directions W that should be considered grows exponentially with the size of the problem *n*.

What will solve it? Projected clusters (M. Grochowski PhD)!

1. A class of constructive neural network solution with G(W·X-θ) functions combining non-local/local projections, with special training algorithms.
2. Maximize the leave-one-out error after projection: take some localized function *G*, count in a soft way cases from the same class as X_k.

$$Q(\mathbf{W}) = \sum_{\mathbf{X}} \left[A^{+} \sum_{\mathbf{X}_k \in C} G\left(\mathbf{W} \cdot (\mathbf{X} - \mathbf{X}_k)\right) - A^{-} \sum_{\mathbf{X}_k \notin C} G\left(\mathbf{W} \cdot (\mathbf{X} - \mathbf{X}_k)\right) \right]$$

Grouping and separation; projection may be done directly to 1 or 2D for visualization, or higher D for dimensionality reduction, if W has *d* columns.

Similarity-based framework

Search for good models requires a frameworks to build and evaluate them.

$p(C_i|X;M)$ posterior classification probability or $y(X;M)$ approximators, models M are parameterized in increasingly sophisticated way.

Similarity-Based Learning (SBL) or S-B Methods provide such framework.

(Dis)similarity:

- more general than feature-based description,
- no need for vector spaces (structured objects),
- more general than fuzzy approach (F-rules are reduced to P-rules),
- includes nearest neighbor algorithms, MLPs, RBFs, separable function networks, SVMs, kernel methods, specialized kernels, and many others!

A systematic search (greedy, beam), or evolutionary search in the space of all SBL models is used to select optimal combination of parameters & procedures, opening different types of optimization channels,
trying to discover appropriate bias for a given problem.

Result: several candidate models are created, already first very limited version gave best results in 7 out of 12 Stalog problems.

Prototypes for images

Stable and transparent interpretation, based on similarity.

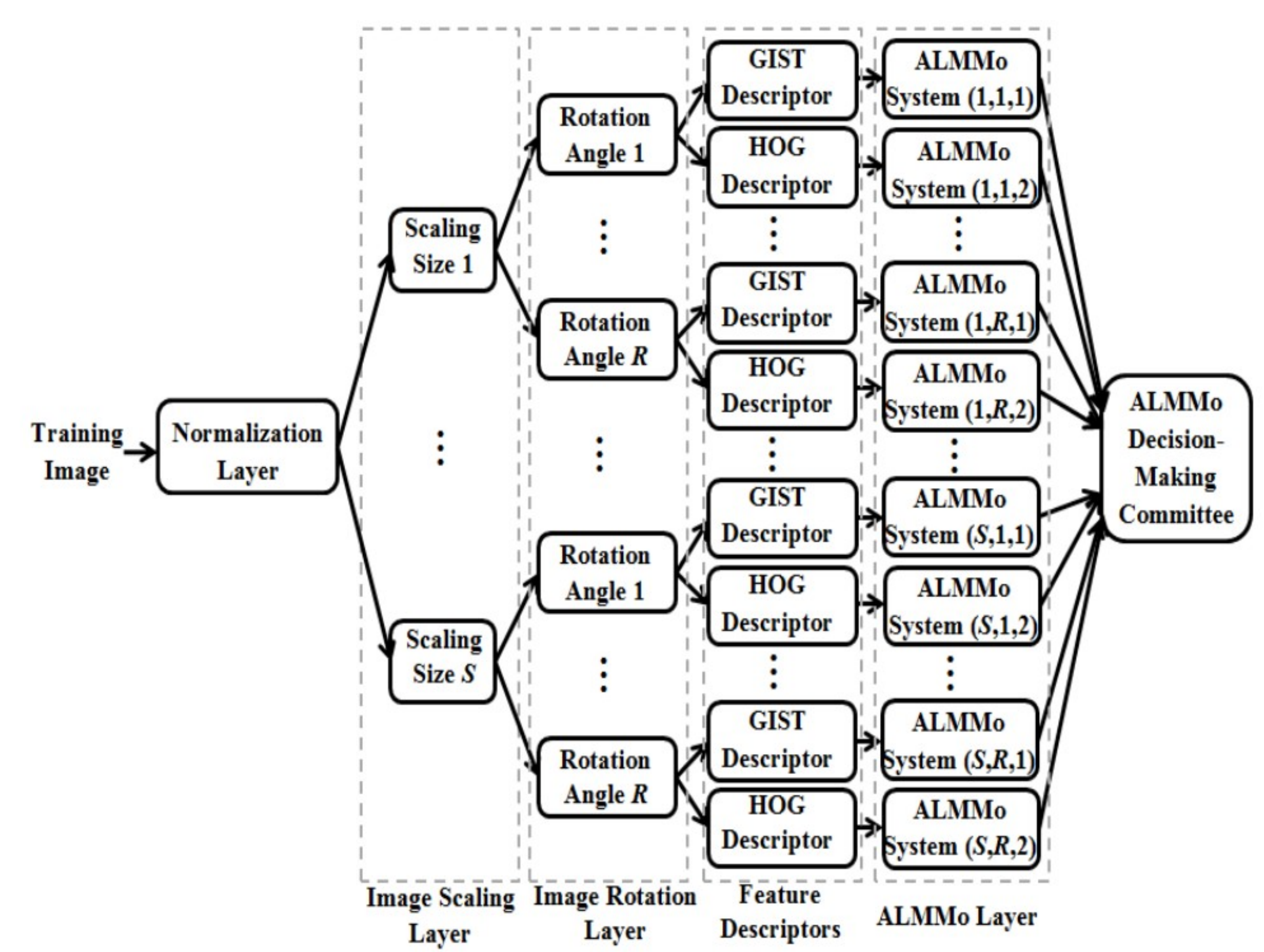
Lazy learning.

Almost as good as deep learning on hand written digits (NIPS data).

~ Pandemonium architecture, Selfridge 1959!

P. Angelov, X. Gu, MICE: **Multi-layer Multi-model Images Classifier. Ensemble**,

CYBCONF 2017



Transformation-based framework

Find simplest model that is suitable for a given data, creating non-sep. that is easy to handle: simpler models generalize better, interpretation.

Compose transformations (neural layers), for example:

- Matching pursuit network for signal decomposition, QPC index.
- PCA network, with each node computing principal component.
- LDA nets, each node computes LDA direction (including FDA).
- ICA network, nodes computing independent components.
- KL, or Kullback-Leibler network with orthogonal or non-orthogonal components; max. of mutual information is a special case.
- c^2 and other statistical tests for dependency to aggregate features.
- Factor analysis network, computing common and unique factors.

Evolving Transformation Systems (Goldfarb 1990-2008), giving unified paradigm for inductive learning, structural processes as representations.

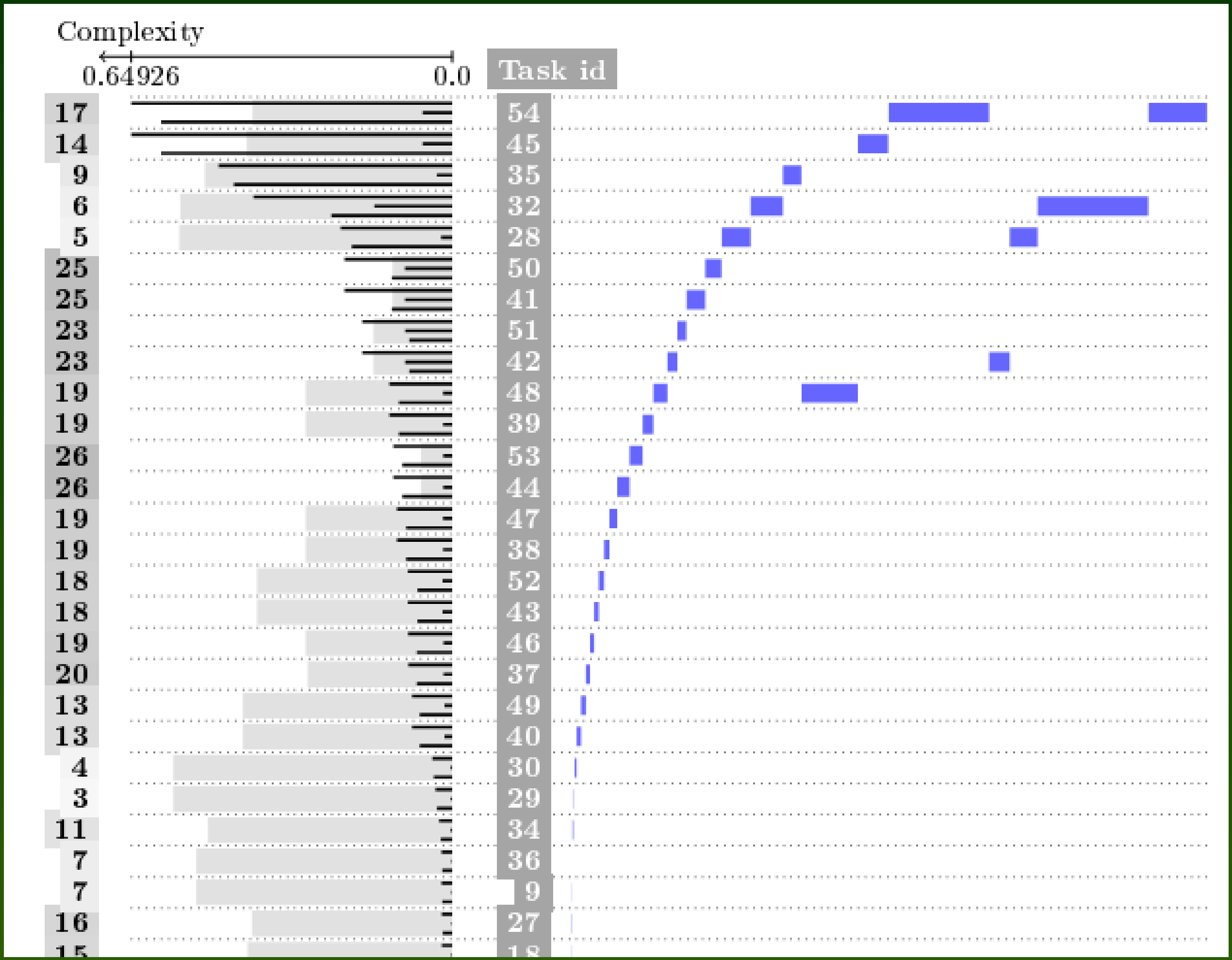
Meta-learning with complex machines

Number on far left
= final ranking.

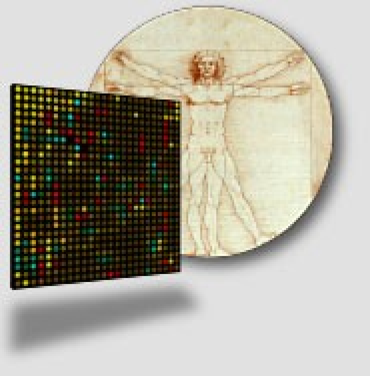
Gray bar
= accuracy

Small bars (up-down)
show estimation of:
total complexity,
time,
memory.

Numbers in the middle
= process id
(refer to models in the
previous table).



Universal Learning Machines



ULM is composed from two main modules:

- feature constructors,
- simple classifiers.

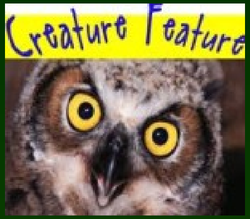
In machine learning features are used to calculate:

- linear combinations of feature values,
- calculate distances (dissimilarites), scaled (includes selection)

Is this sufficient?

- No, non-linear functions of features carry information that cannot be easily recovered by CI methods.
- Kernel approaches: linear solutions in the kernel space, implicitly add new features based on similarity $K(X,S_V)$.
- ULM idea: create potentially useful, redundant set of futures.
  How? Learn what other models do well! Implement transfer learning.
- Learn from others, not only on your own errors! Cf. pre-training in GPT-3.

Support Feature Machines



General principle: complementarity of information processed by parallel interacting streams with hierarchical organization (Grossberg, 2000).

Cortical minicolumns provide various features for higher processes.

Create information that is easily used by various ML algorithms: explicitly build enhanced space adding more transformations.

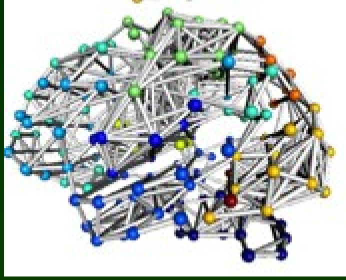
- X , original features
- Z=WX, random linear projections, other projections (PCA< ICA, PP)
- Q = optimized Z using Quality of Projected Clusters or other PP techniques.
- $H=[Z_1,Z_2]$, intervals containing pure clusters on projections.
- $K=K(X,X_i)$, kernel features.
- $HK=[K_1,K_2]$, intervals on kernel features

Kernel-based SVM ⇔ linear SVM in the explicitly constructed kernel space, enhancing this space leads to improvement of results.
LDA is one option, but many other algorithms benefit from information in enhanced feature spaces; best results in various combination X+Z+Q+H+K+HK.

More on this page: https://www.is.umk.pl/~duch/cv/WD-topics.html

Dynamics of real brain networks

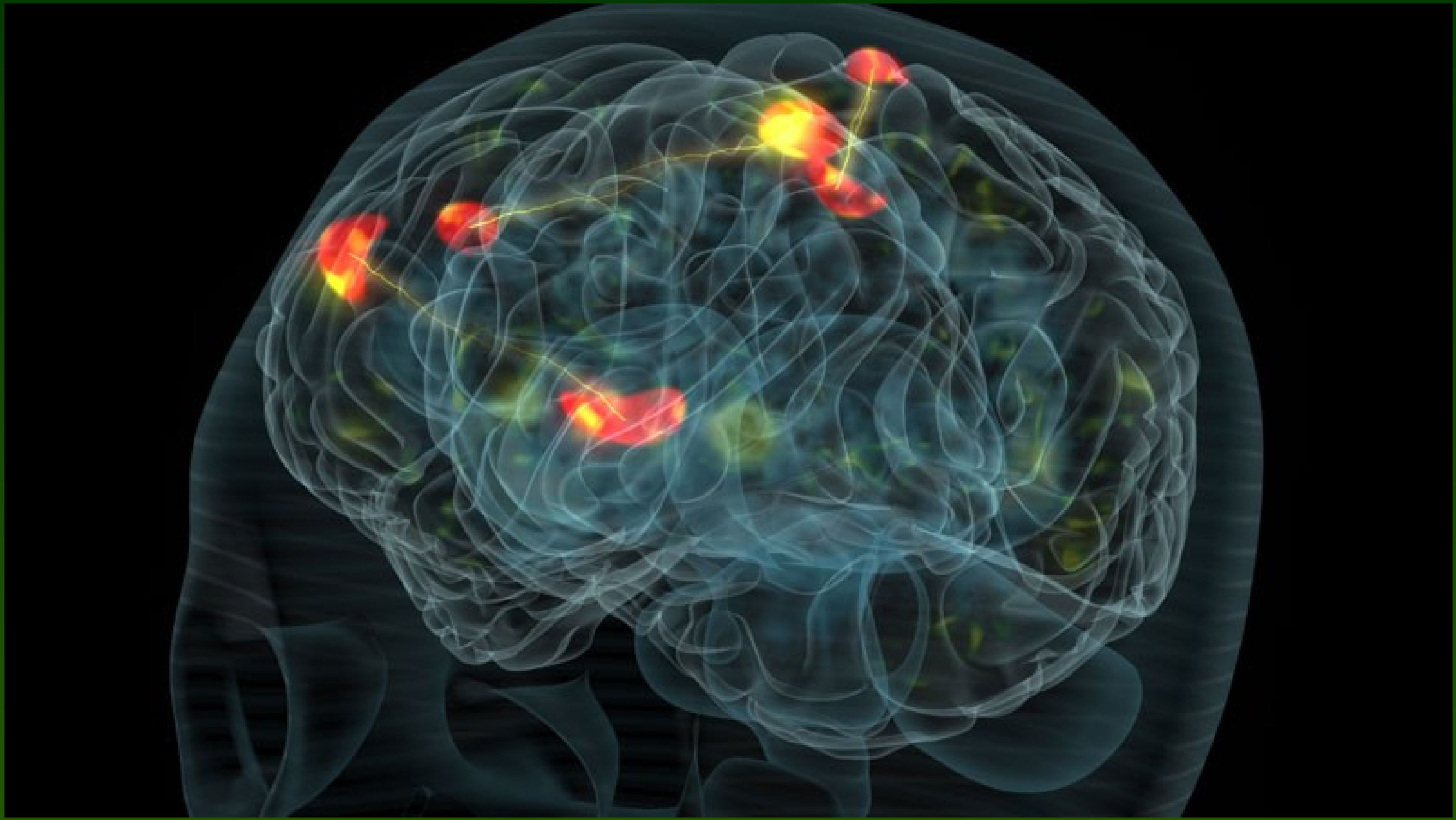
More neuroscience inspirations



1. Simple neurons, 1 parameter, fixed synaptic connections
   ⇒ perceptrons, MLPs, deep networks.
2. Complex neurons, microcircuits, small neural cortical ensembles with structural connections (fixed, or slowly changing).
3. Complex network states: rich internal knowledge in modules interacting in a flexible way, functional connections activated by priming, working memory control. Attractors of neurodynamics that synchronize many cortical ensembles, solving novel combinatorial problems.
4. Society of minds: for different tasks using flexible arrangement of functional connections between specialized brain regions, a lot of knowledge in such modules, no fixed connections. Multiagent systems.
5. Society of brains: collaboration between brains on symbolic level.
   CyC friends, complex specialized agents with common ontology.

These inspirations led me to creation of many interesting ideas/algorithms.

Mental state: strong coherent activation



Many processes go on in parallel, controlling homeostasis and behavior. Most are automatic, hidden from our Self. What goes on in my head?

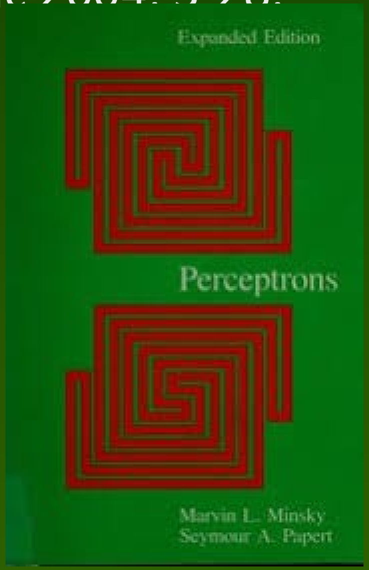
Various subnetworks compete for access to the highest level of control - consciousness, the winner-takes-most mechanism leaves only the strongest. How to extract stable intentions from such chaos? BCI is never easy.

The Society of Mind

NN people ignored AI people (and vv). Will more sophisticated version of pandemonium – based on deep learning – lead to AGI?

The Society of Mind (Minsky 1986) presents theory of natural intelligence based on interactions of mindless agents constituting a "society of mind", or multi-agent model, but at the symbolic level.

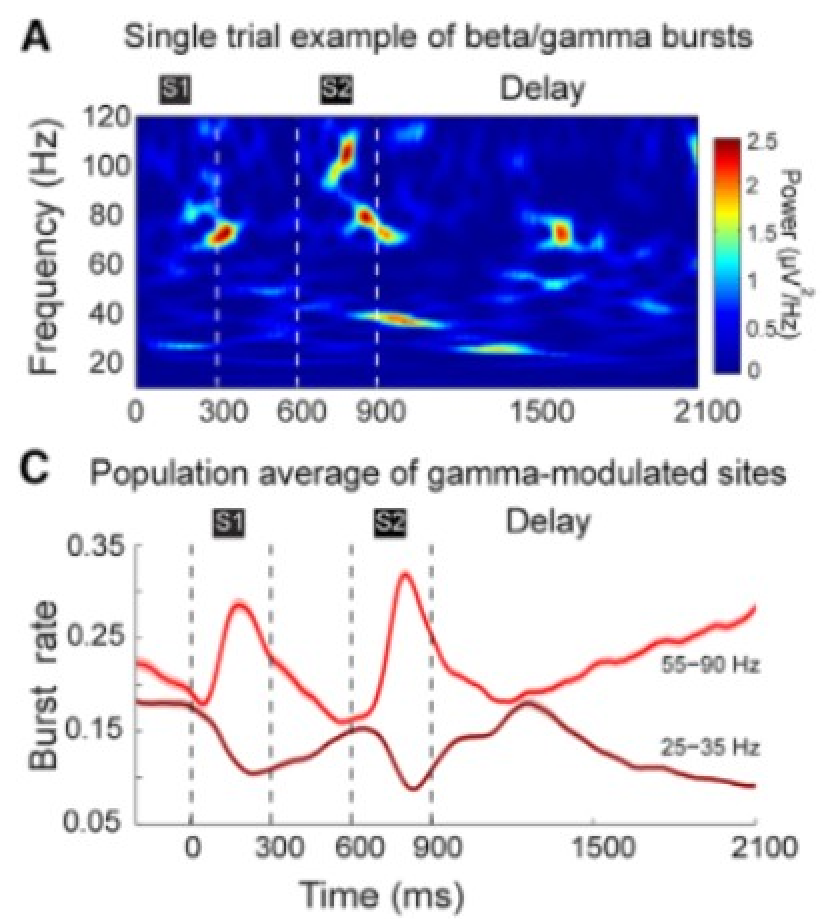
Duch W, Mandziuk J, *Quo Vadis Computational Intelligence*? Advances in Fuzzy Systems - Applications and Theory Vol. 21, World Scientific 2004, 3-28.



Minsky+Papert – MLPs is universal approximator but cannot solve connectedness problem.

⇒ NCE, modules, more internal knowledge, adding phase solves it, opens new complexity problem class.
This shows importance of various transfer functions and led to the FSM model with separable transfer functions.

Working Memory



Where is the secret of cognitive flexibility?

Active networks in the brain –
aka working memory, are realized by brief beta and gamma bursts of activity. Slower oscillations in theta (3-7 Hz) and alpha range (8-12 Hz) open communication channels. Short burst transmit information.

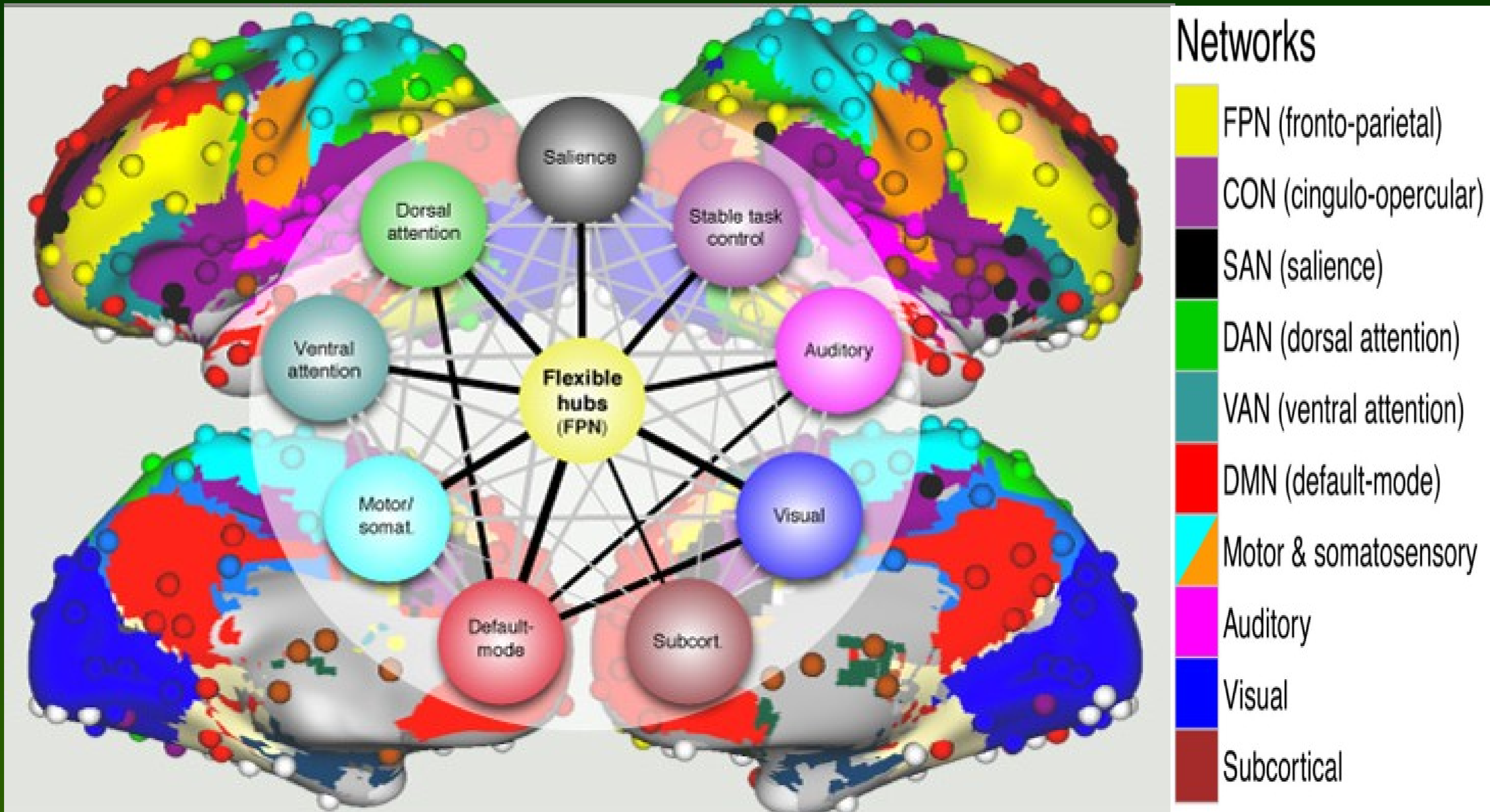
Classical view: cognitive processes = sustained neural activity, stationary states (like in fMRI maps).

Novel analysis: instantaneous frequency and phase of neural oscillations, linked to successive sensory stimuli/mental events.

Cognitive processes unfold in discrete windows within/across oscillatory cycles.

Lundqvist, M., & Wutz, A. (2021, in print). New methods for oscillation analyses push new theories of discrete cognition. Psychophysiology, e13827.

Neurocognitive Basis of Cognitive Control



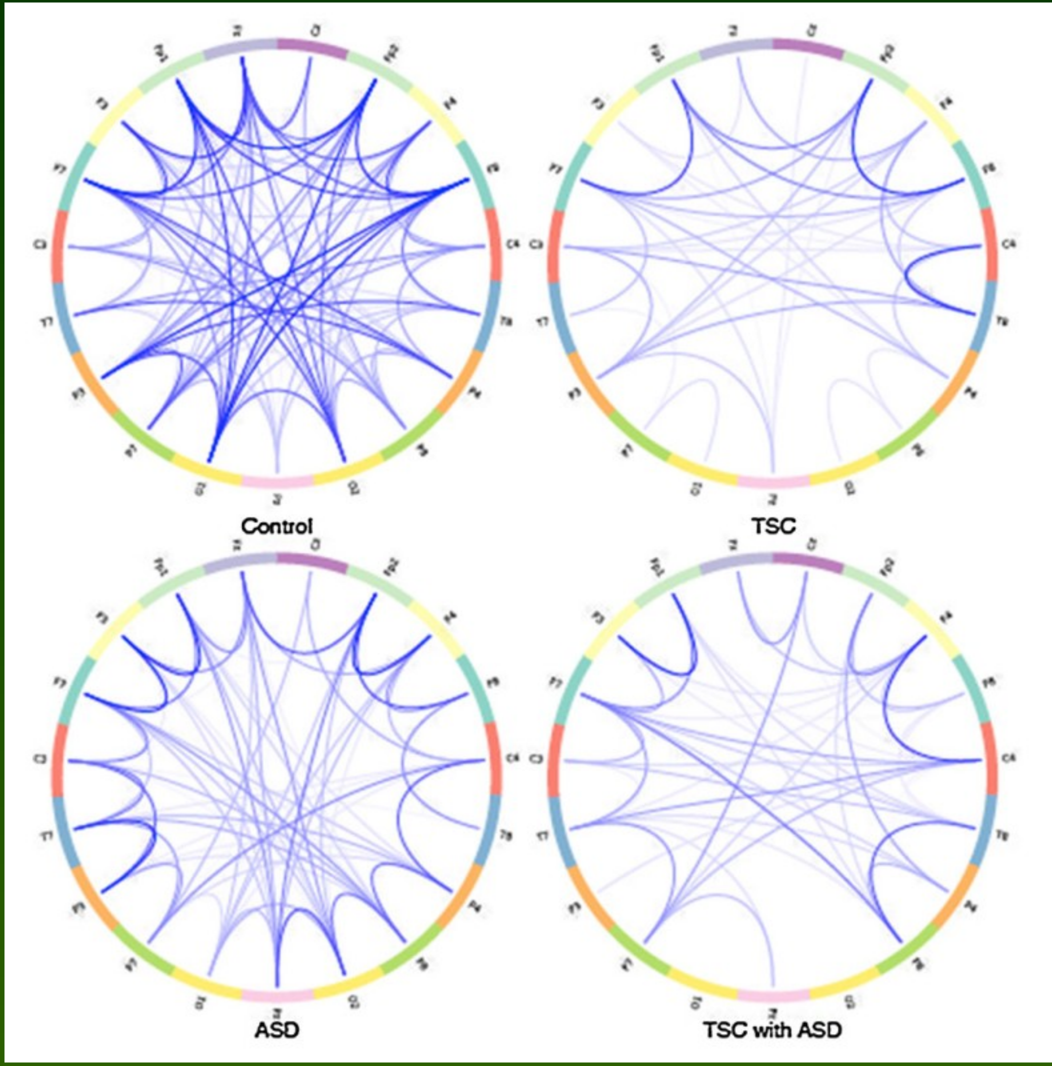
Fronto-parietal (FPN) flexible hubs provide cognitive control, implementing global neuronal workspace, adaptive implementation of task demands (black lines=correlations significantly above network average). Cole et al. (2013).

Pathological functional 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

Brain Fingerprinting

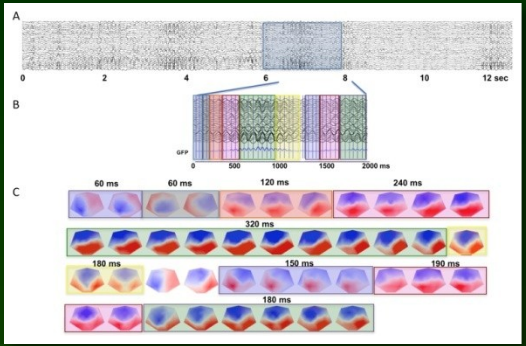
Find unique patterns of brain activity that should help to identify:

- brain regions of interest (ROI)
- dynamics of active neural networks
- link it to mental states, tasks.

Several approaches:

1. Microstates and their transitions (Michel & Koenig 2018)
2. Reconfigurable task-dependent modes (Krienen et al. 2014)
3. Contextual Connectivity (Ciric et al. 2018)
4. Spectral Fingerprints (Keitel & Gross 2016)
5. A few more …

1



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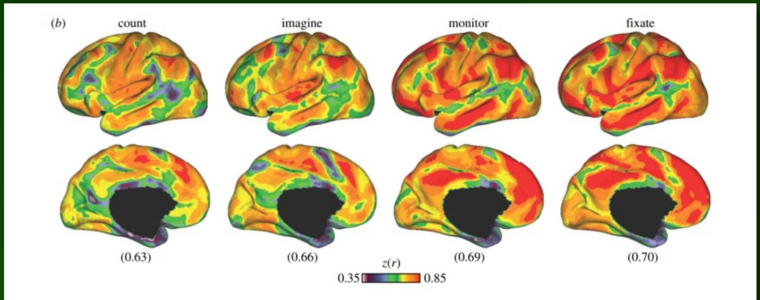

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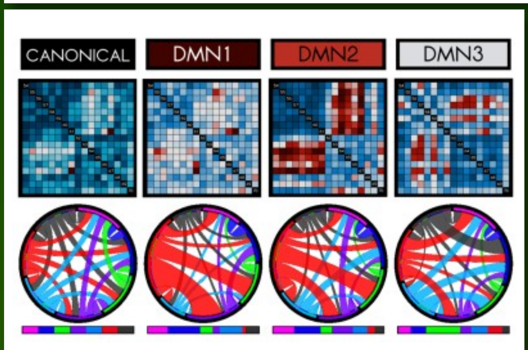

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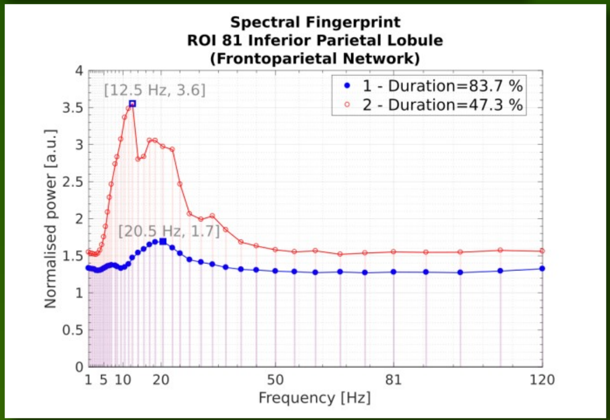


Effect of cognitive load

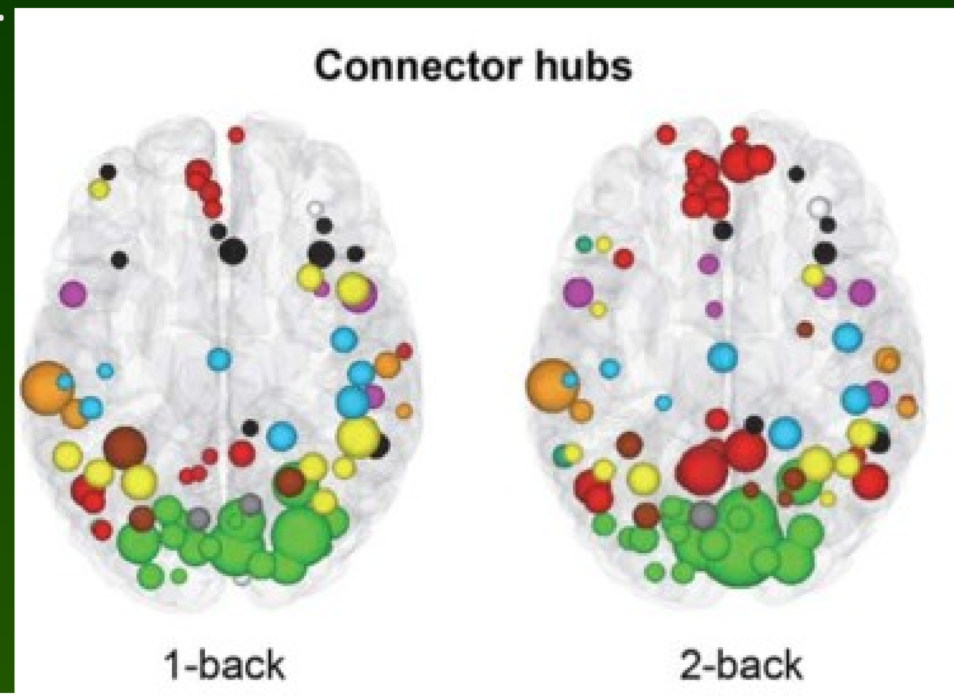
Simple and more difficult tasks, requiring the whole-brain network reorganization.

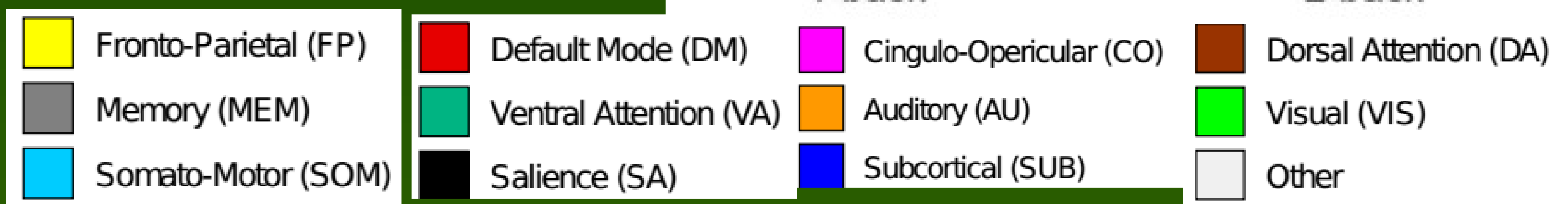
Left: 1-back Top: connector hubs

Right: 2-back Bottom: local hubs

Average over 35 *participants.*

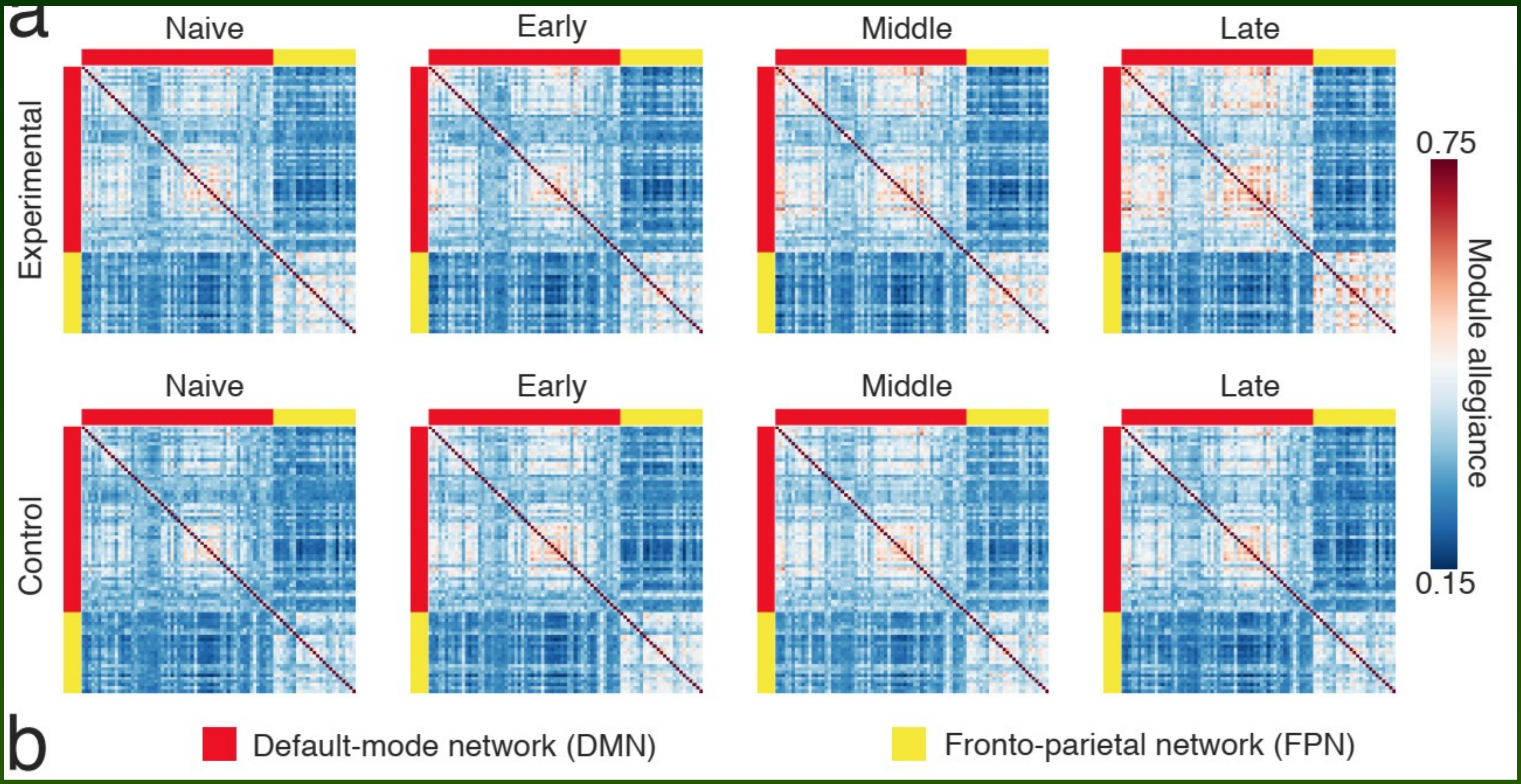
Dynamical change of the landscape of attractors, depending on the cognitive load. DMN areas are recruited when load is high in global networks!





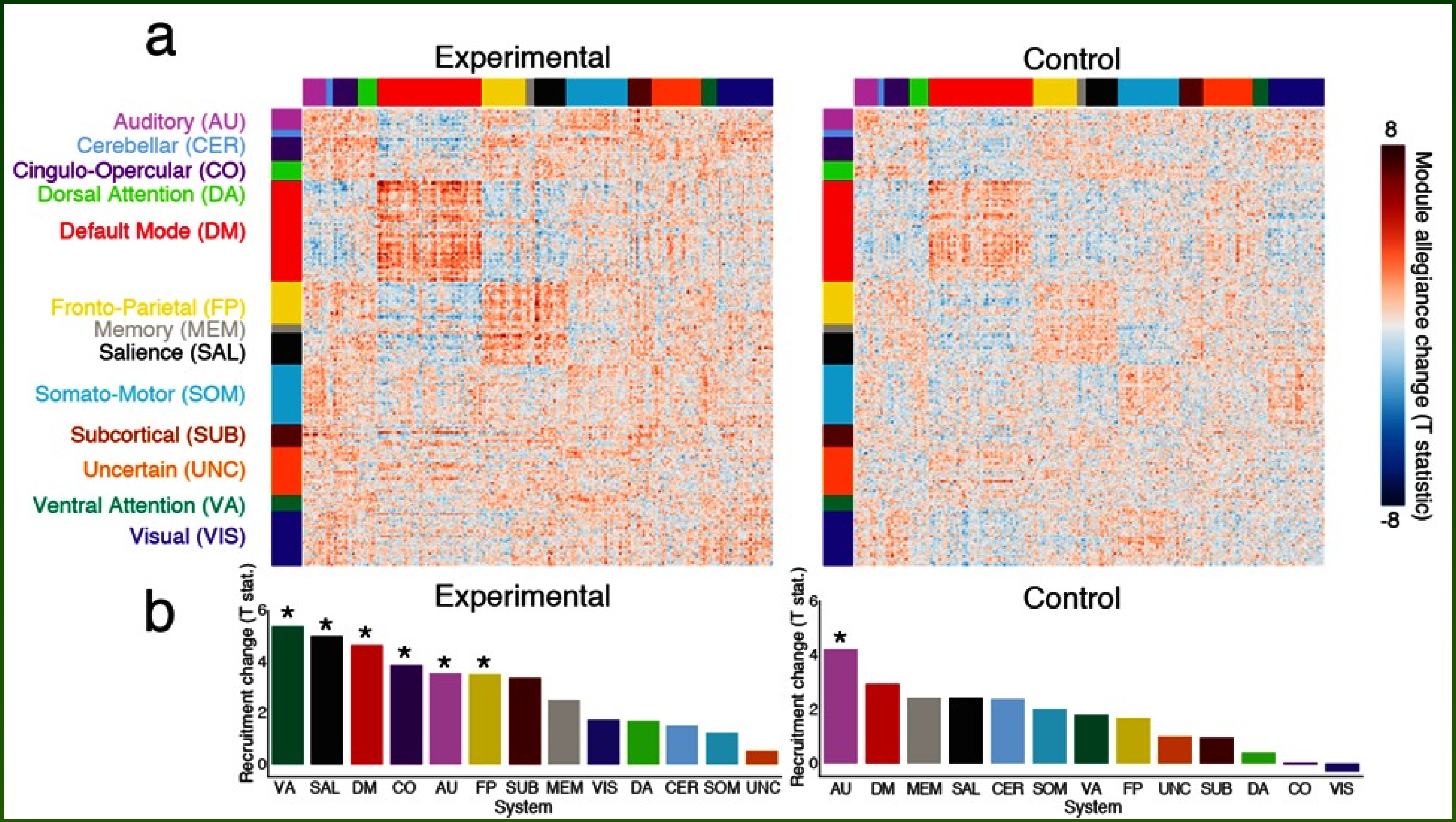
Finc, Bonna, Lewandowska, Wolak, Nikadon, Dreszer, Duch, Kühn. Transition of the functional brain network related to increasing cognitive demands. Human Brain Mapping 38, 3659–3674, 2017.

Working memory training



6-week training, dual n-back task, **changes in module allegiance of fronto-parietal and default-mode networks.** Each matrix element represents the probability that the pair of nodes is assigned to the same community. Segregation of task-relevant DMN and FPN regions is a result of training and complex task automation, i.e. from conscious to automated processing.

Training influence on the brain



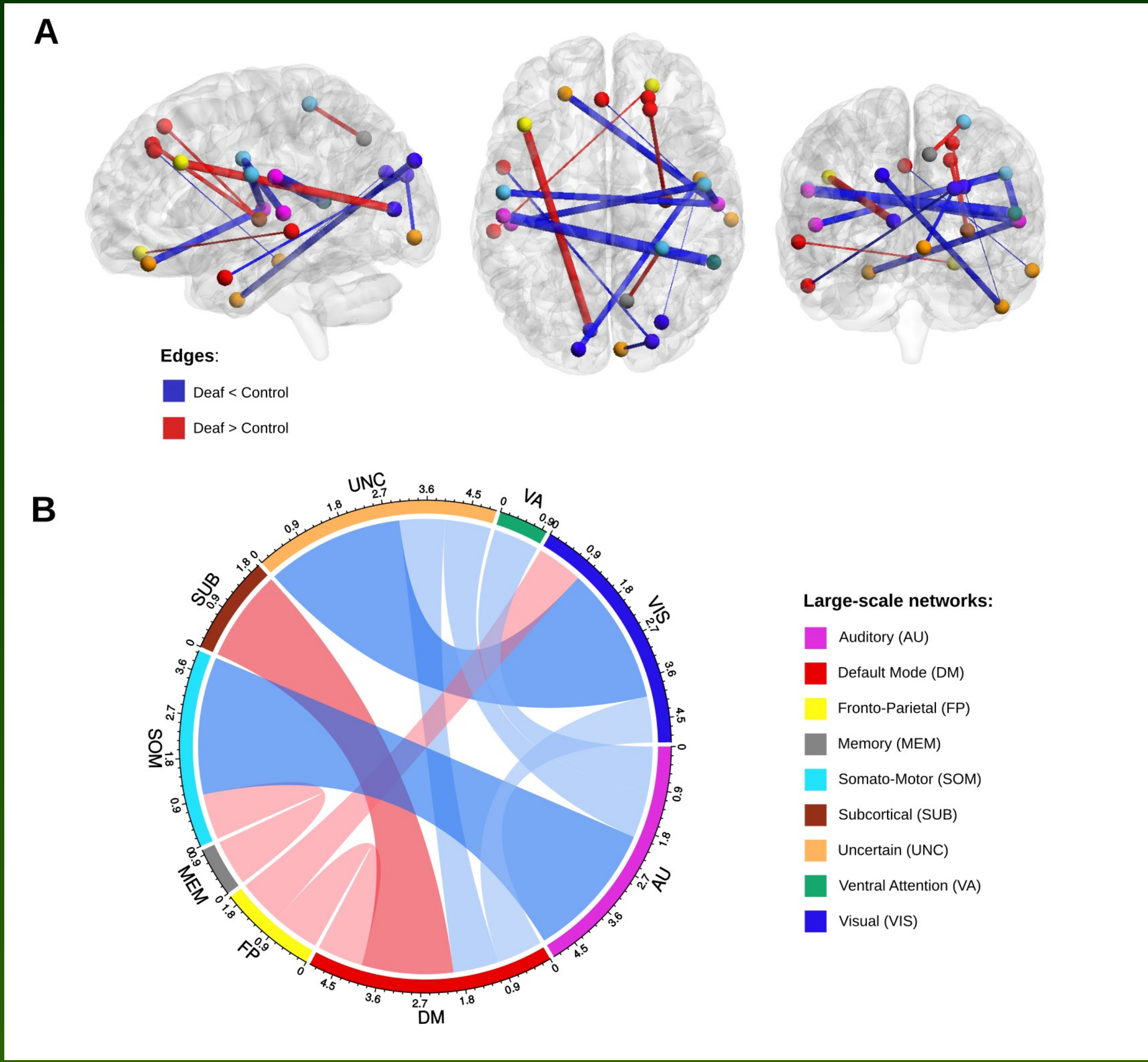
Whole-brain changes in module allegiance after 6-week of WM training.
(a) Changes in node allegiance as reflected in the two-tailed *t*-test.
(b) Significant increase * in the recruitment of default mode DM, fronto-parietal ventral attention VA, salience SAL, cingulo-opercular CO, auditory systems AU.

Finc, Bonna, He, Lydon-Staley, Kühn, Duch, Bassett, Nature Communic. 11 (2020)

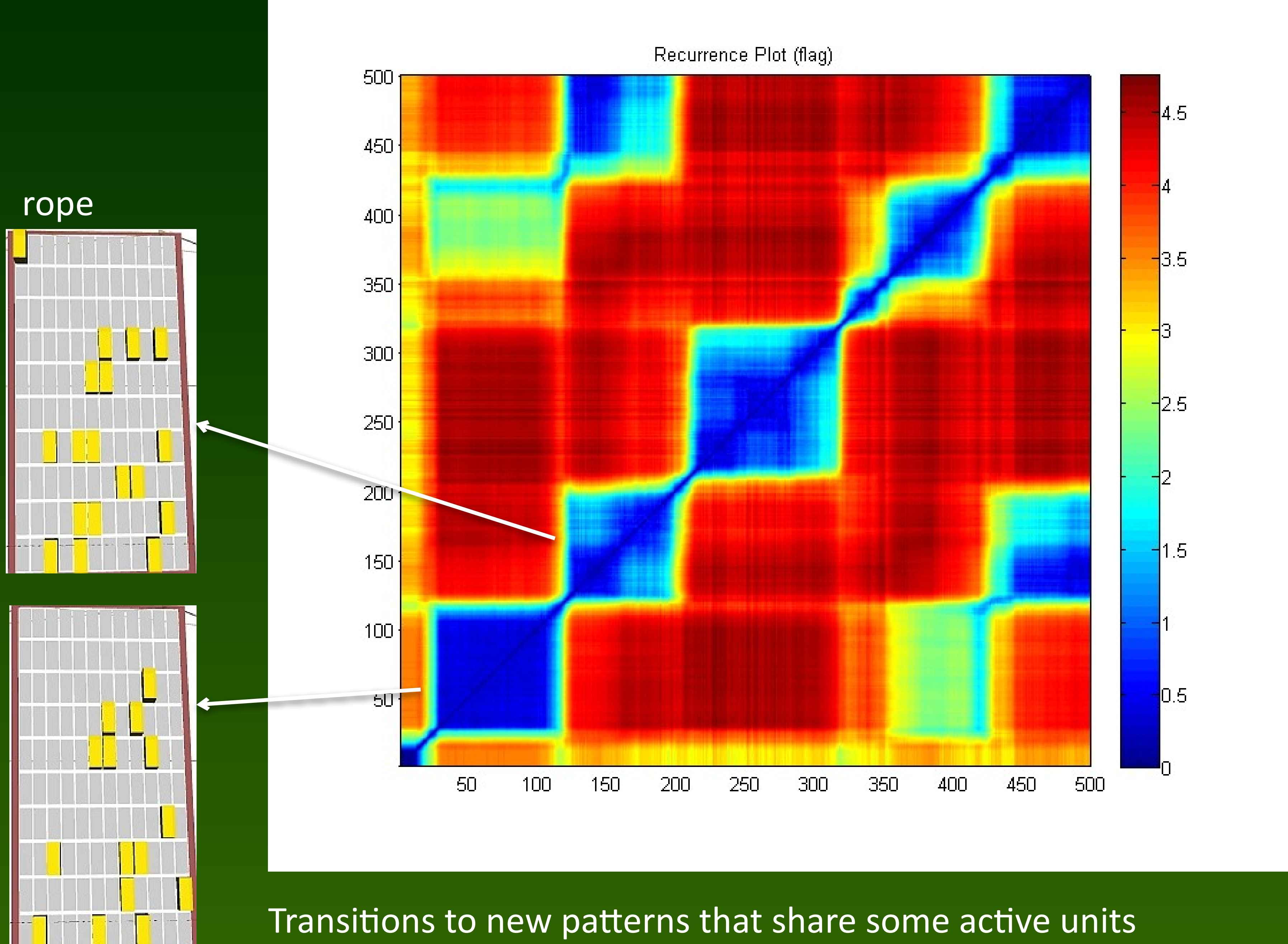
Deaf vs. Control

Edge-wise functional connectivity network differences visualized in the brain space.
(A) Connections that are significantly stronger or weaker (red/blue) in deaf. Edge thickness reflects t-test statistic strength.
(B) Number of significant edges between different large-scale networks.

Red bands = edges stronger in the deaf vs. hearing control, blue bands with weaker functional connectivity.

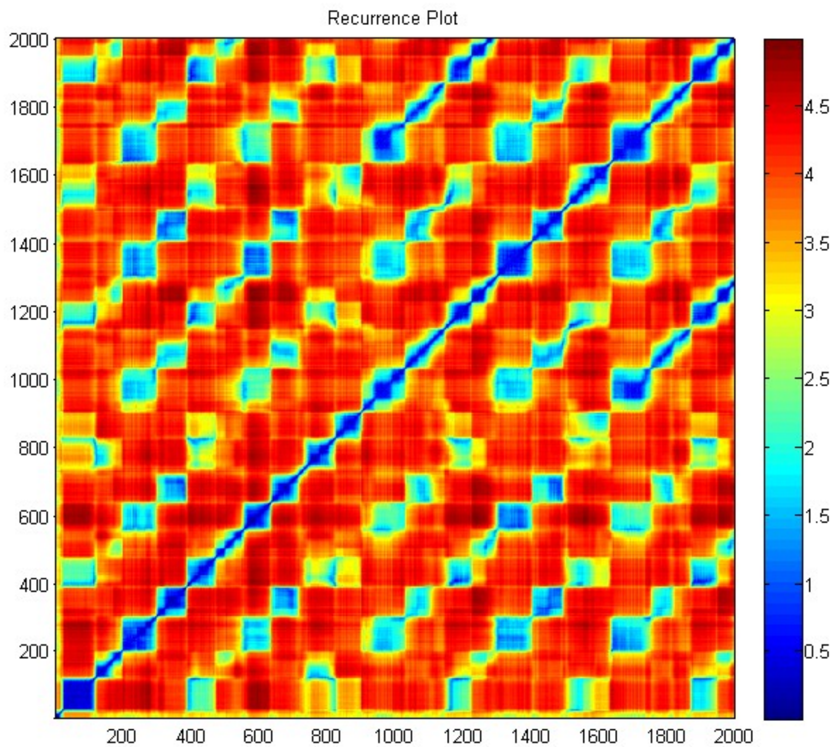


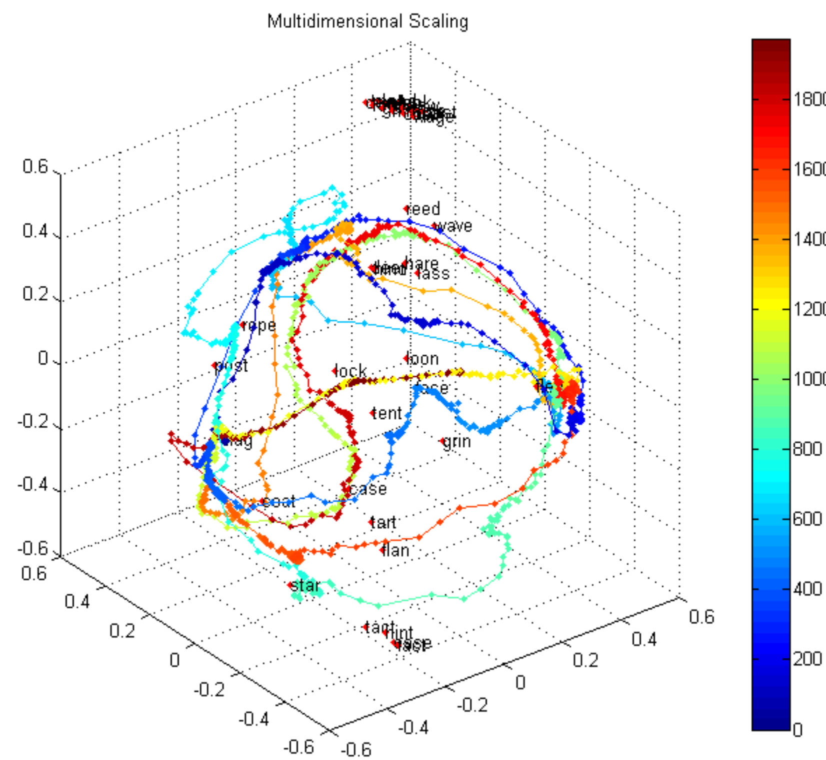
Bonna, Finc et al. Early deafness leads to re-shaping of global functional connectivity beyond the auditory cortex. Brain Imaging and Behavior 2020).



Transitions to new patterns that share some active units (microfeatures); in recurrence plots attractor basins are seen.

Trajectory visualization

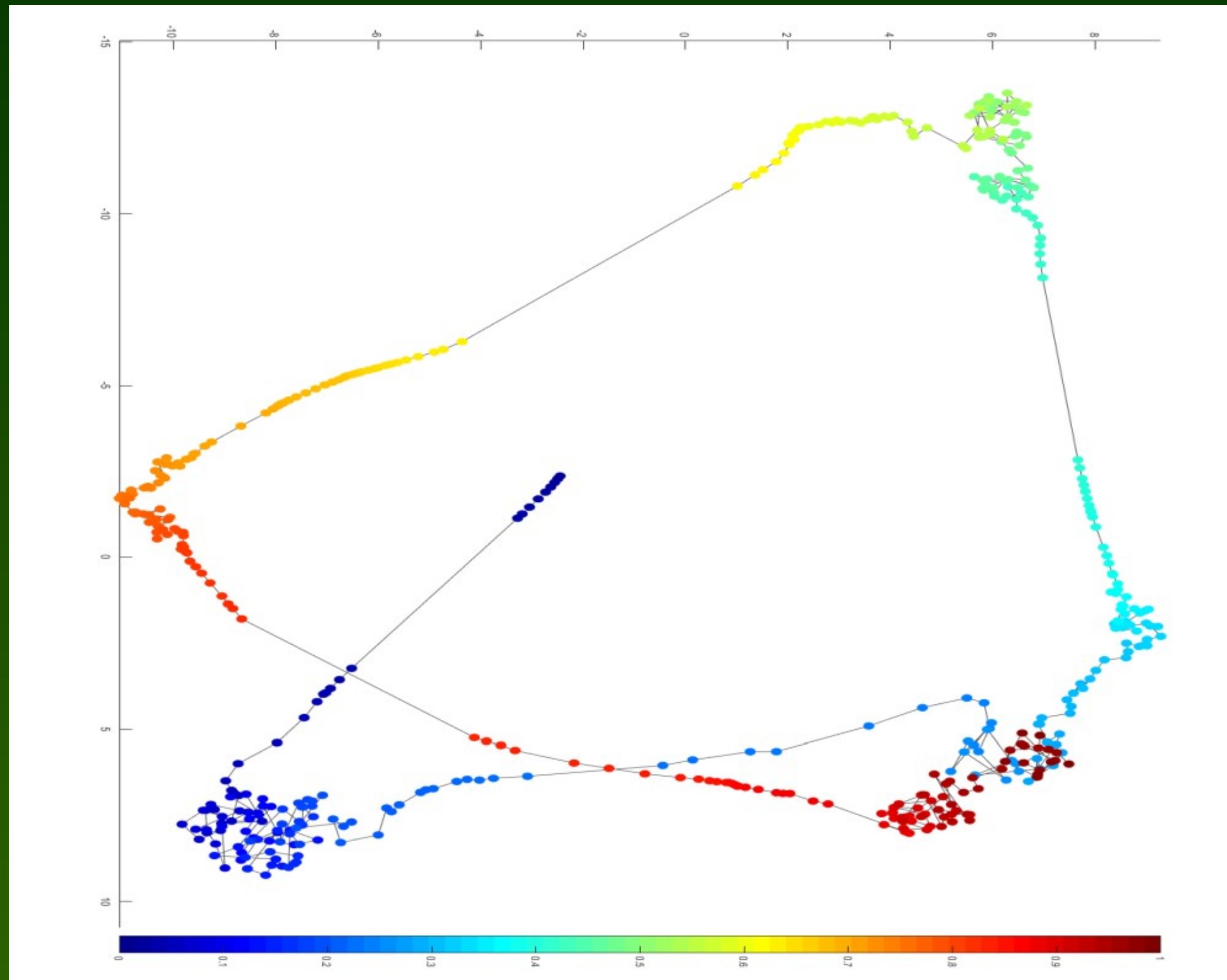




Recurrence plots and visualization of trajectories of the brain activity. Evolution of 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain is presented, starting with the word “flag”. Trajectories may be displayed using tSNE, UMAP, MDS or our FSD visualization.

Trajectory in 2D

Stochastic Neighbor Embedding (tSNE) visualization, “from thought to thought”.
Such graphs are deceiving:
1) only a subset of states is available;
2) only relations between attractor basins are roughly preserved – brain representations drift, as shown by W. Freeman for olfaction.



EEG microstates for diagnostics

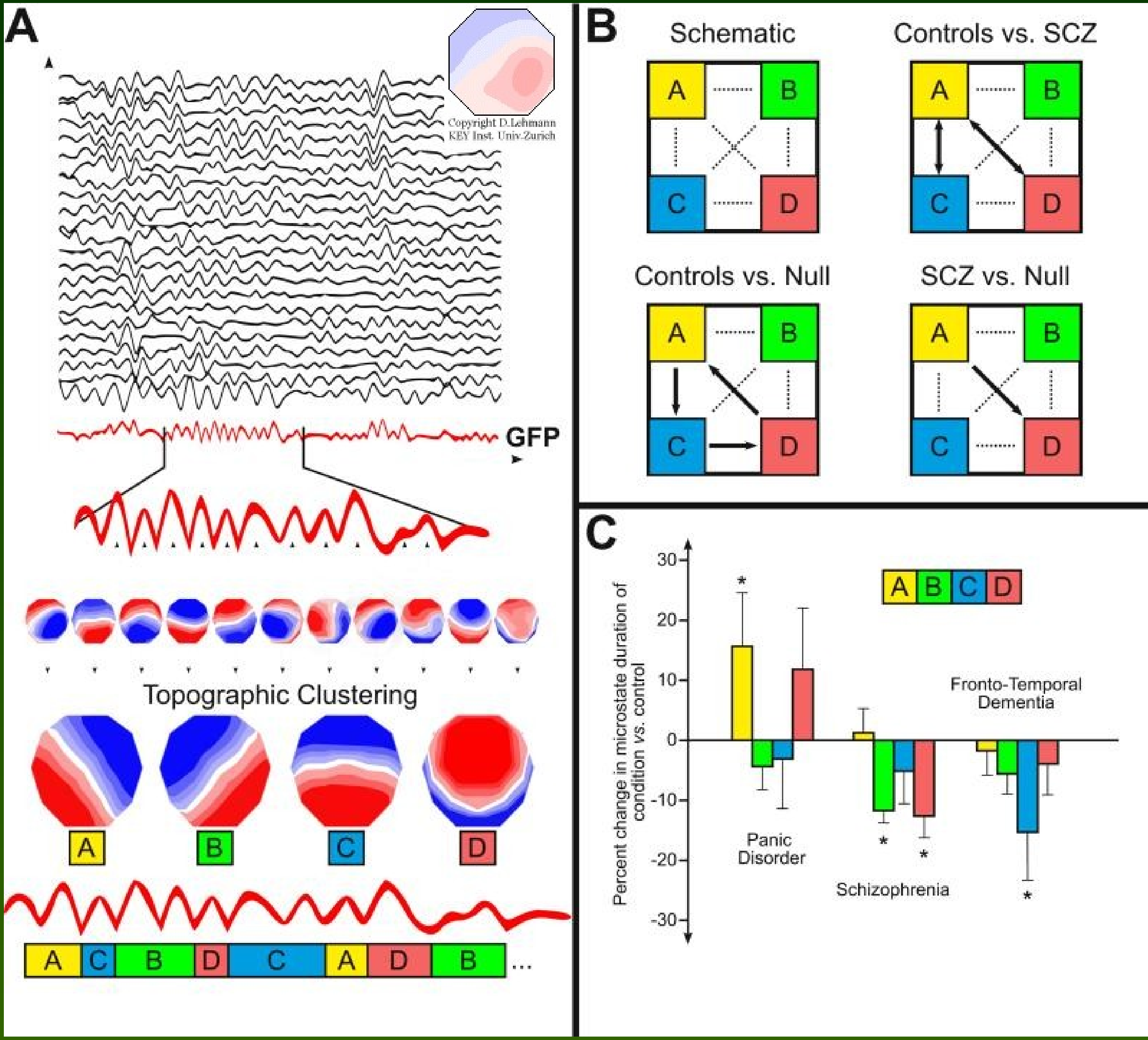
Global EEG Power.

Lehmann et al.
EEG microstate duration and syntax in [.] schizophrenia. Psychiatry Research Neuroimaging, 2005

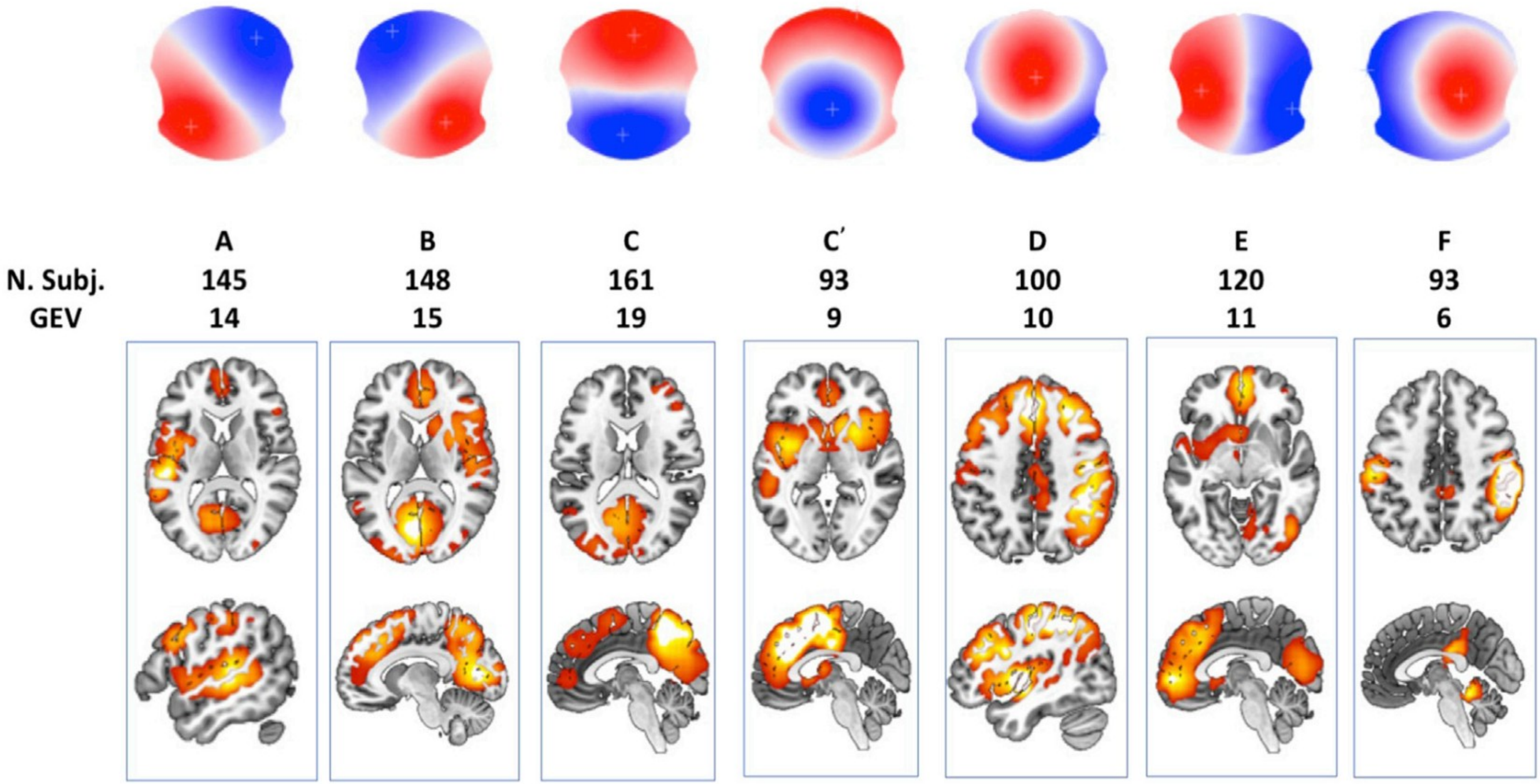
Khanna et al.
Microstates in Resting-State EEG. *Neuroscience and Biobehavioral Reviews*, 2015

4-7 states 60-150 ms

Symbolic dynamics.

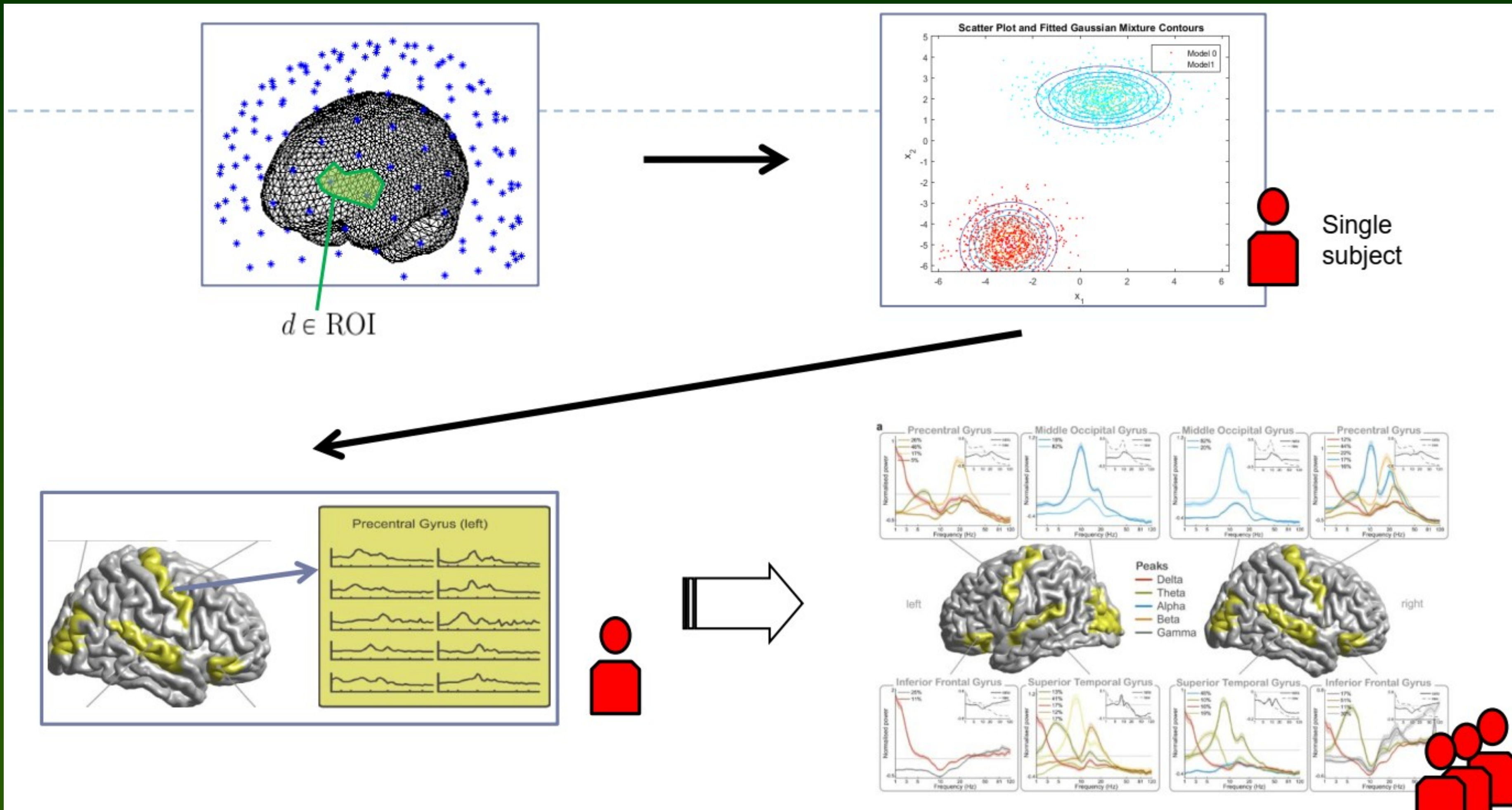


Microstates and their sources



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

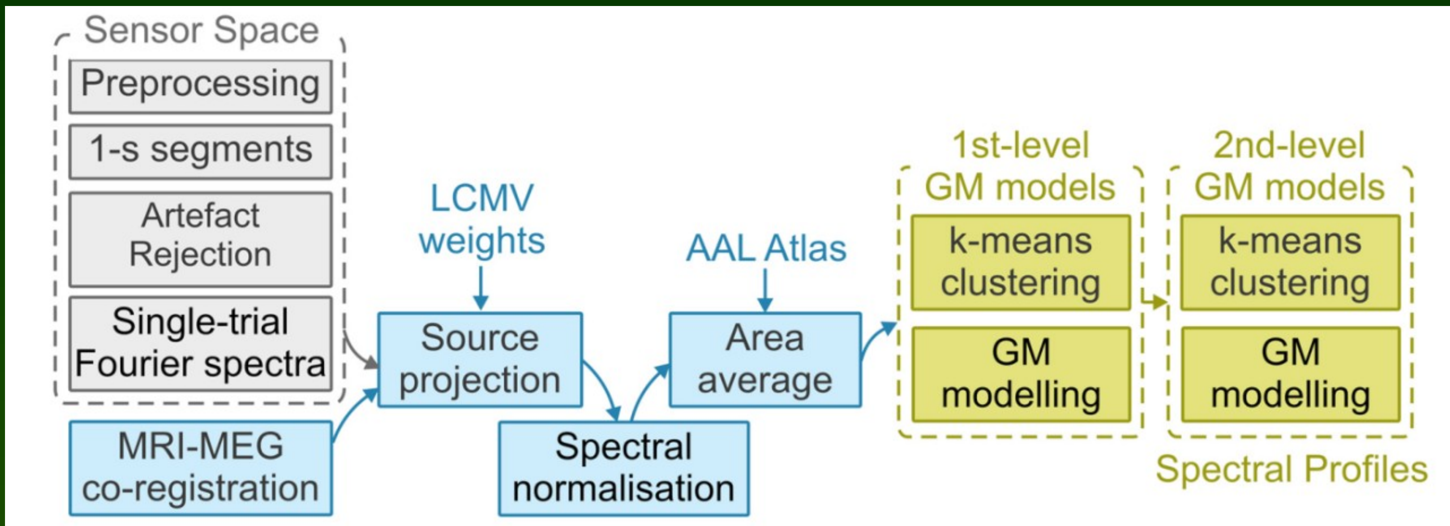
Spectral fingerprints



* Pictures from Keitel & Gross 2016 and Fieldtrip beamforming tutorial

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

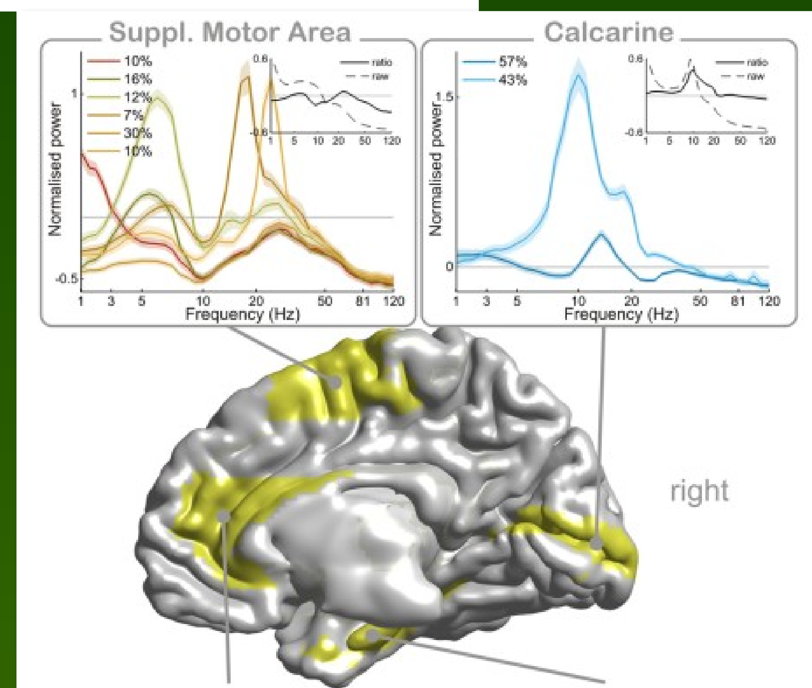
Spectral analysis



Spectral fingerprints

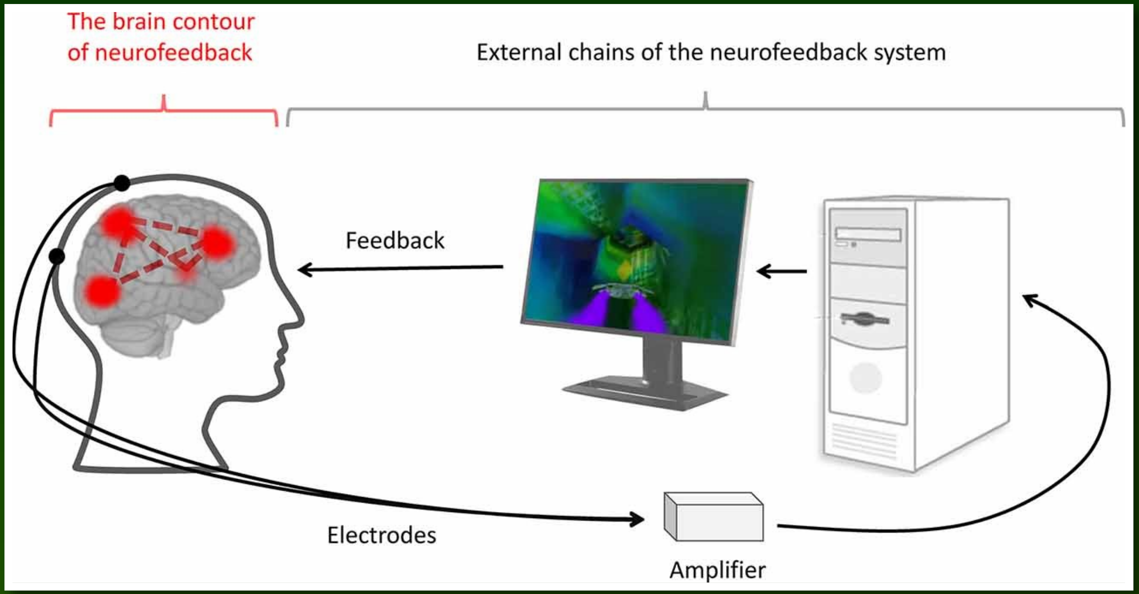
Monitor EEG/MEG power spectra in 1 sec time windows, project them to source space of ROIs based on brain atlas, and create spectra.

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



Spectral Fingerprint Challenges

Michał Komorowski



Source: O. R. Dobrushina *et al. Front. Hum. Neurosci.* 14, 2020

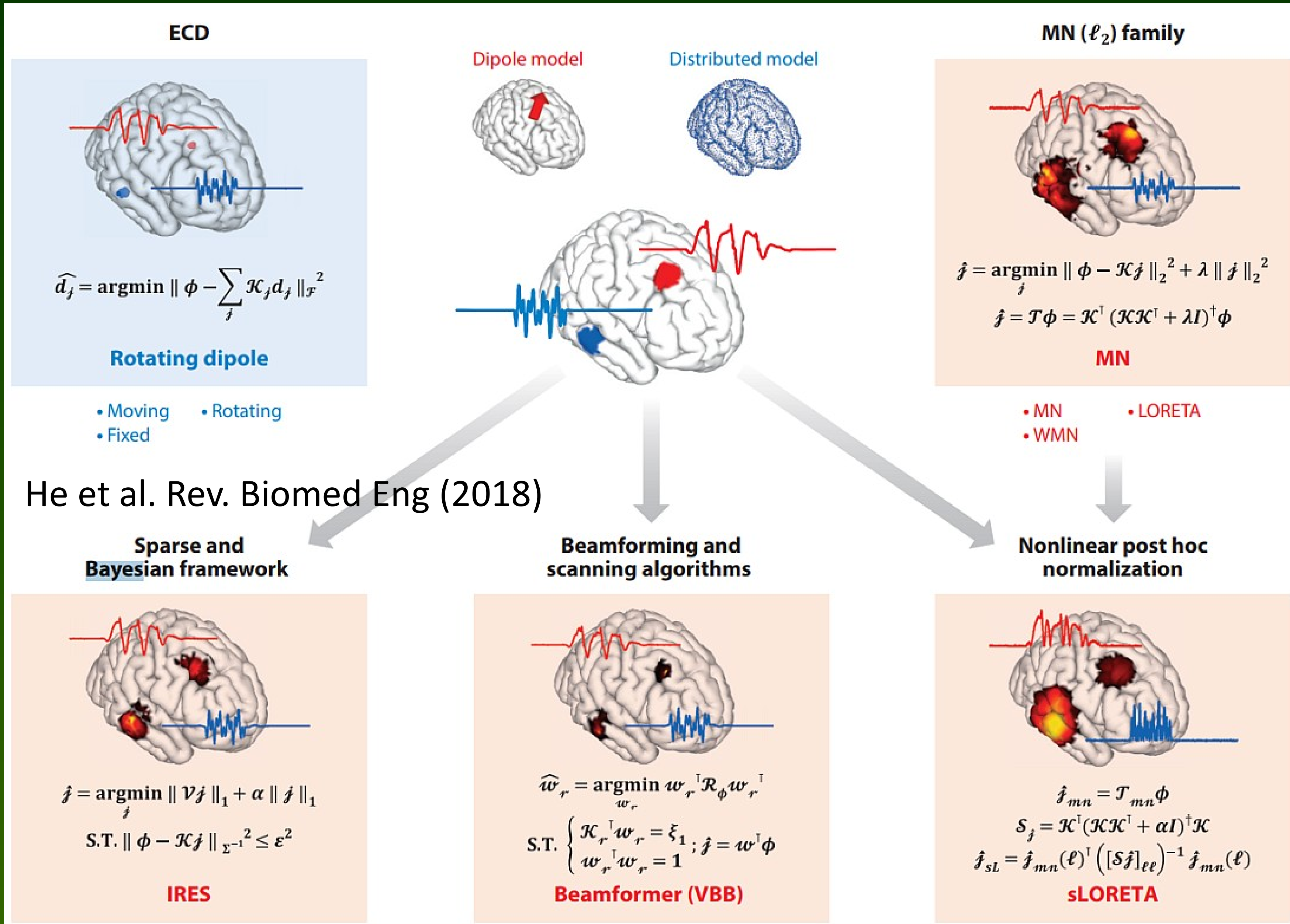
This method was tested for MEG resting-state data, will it work on EEG recordings?

Can we extract features that will be useful as biomarkers for brain disorders?

Can we do it in real time for neurofeedback applications?

Are linear constraint minimum variance (LCMV) sufficient?

EEG localization and reconstruction

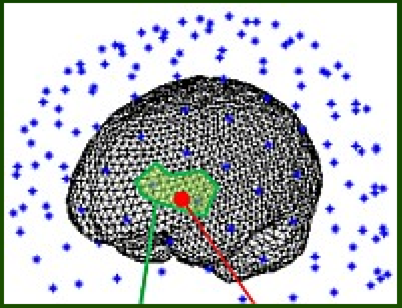


He et al. Rev. Biomed Eng (2018)

Spatial filters

LCMV (Linearly Constrained Minimum Variance), classical reconstruction filter is a solution to the following problem:
K - *lead-field* matrix; θ – dipol positions, j – activation potential; W – spatial filter

- $\Phi = K(\theta)j + n,\ j \approx W\Phi,\ WK(\theta) \approx \mathrm{I}$



LCMV has large error if:
- sources are correlated,
- SNR (signal to to noise ratio) is low, or
- forward problem is ill-conditioned.

Minimum variance pseudo-unbiased reduced-rank for inverse problem, MV-PURE: Piotrowski, Yamada, IEEE Trans.s on Signal Processing **56**, 3408-3423, 2008

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

where X_r is a set of all matrices of rank at most r, set Υ denotes all unitary norms.
FreeSurfer brain tessellation in 15000 vertex, brain atlases provide parcellation of the mesh elements into 100-240 cortical patches (ROIs).

SupFunSim

SupFunSim: our library/Matlab toolbox, direct models for EEG/MEG, on GitHub.

Provides many spatial filters for reconstruction of EEG sources: linearly constrained minimum-variance (LCMV), eigenspace LCMV, nulling (NL), minimum-variance pseudo-unbiased reduced-rank (MV-PURE) …

Source-level directed connectivity analysis: partial directed coherence (PDC), directed transfer function (DTF) measures.

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

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

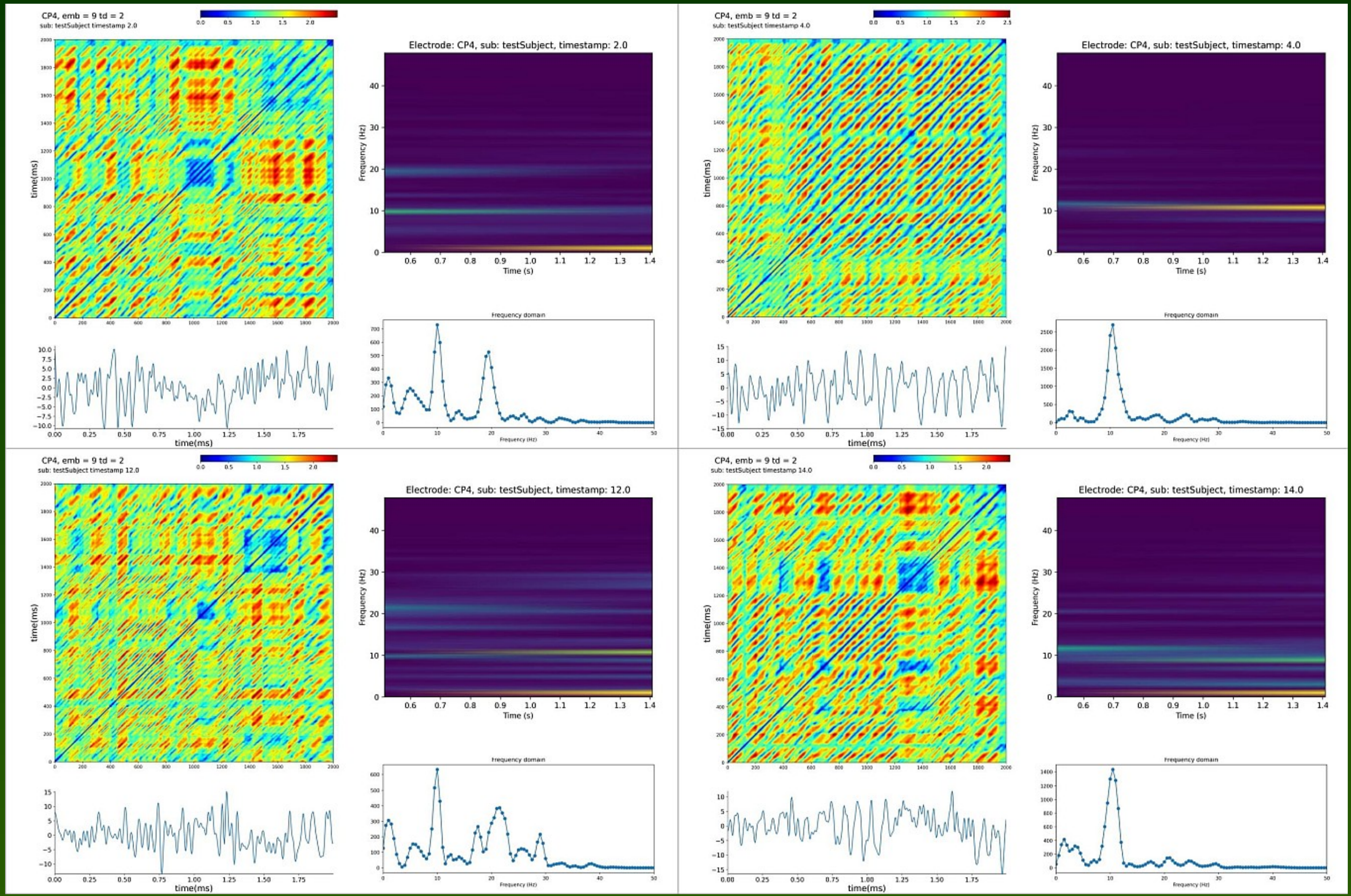
$$B := H_{Src,N} := N^{-1/2} H \tag{35}$$

```
%%file calculate_H_Src.m
function model = calculate_H_Src(MODEL)
    model = MODEL;

    model.H_Src_R = pinv(sqrtm(model.R)) * model.H_Src;
    model.H_Src_N = pinv(sqrtm(model.N)) * model.H_Src;
end
```

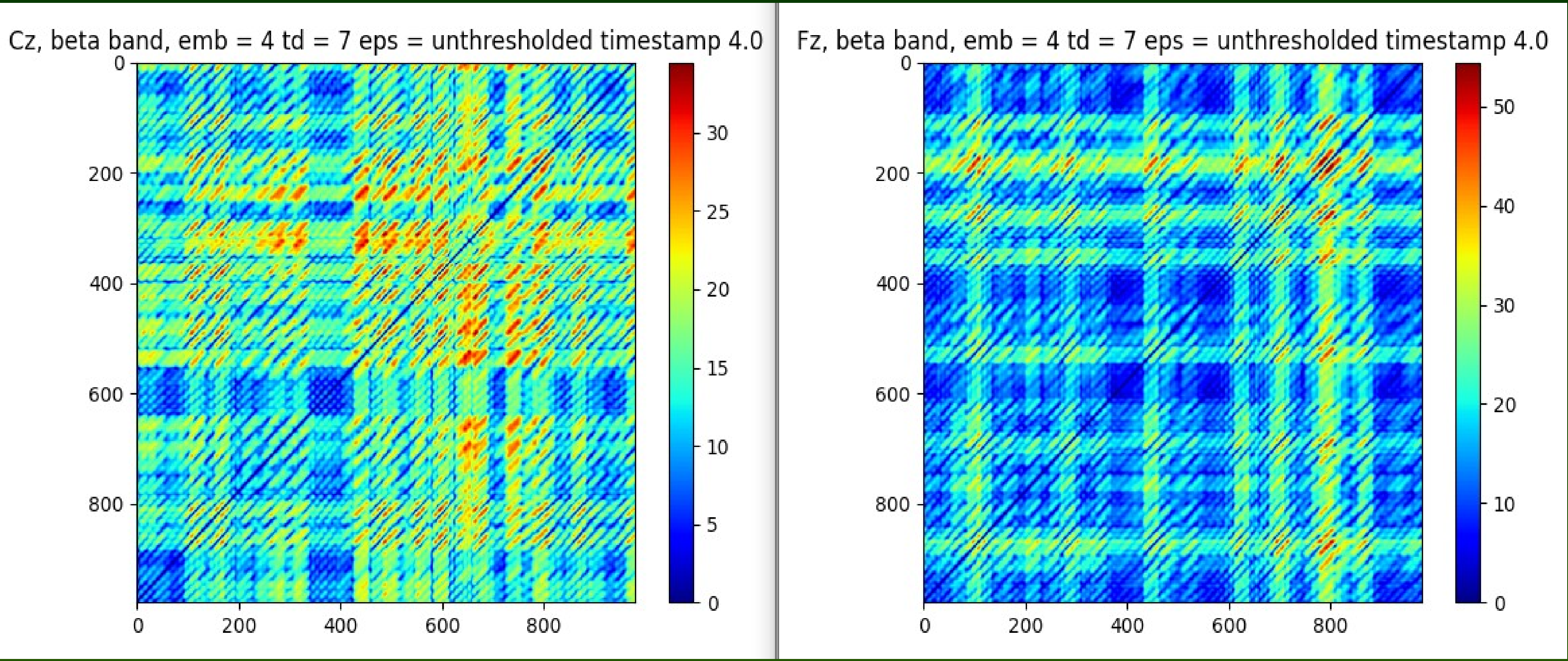
Rykaczewski, Nikadon, Duch, Piotrowski, *Neuroinformatics* **19**, 107-125, 2021.

EEG resting state



Recurrence plot, time/frequency, signal and SFT for single channel, 2 sec. HD Full spectrum EEG. Burst of beta oscillations create blue squares. Local movie. Attractor reconstruction using embedding: $[y(t), y(t-\tau), y(t-2\tau), \ldots, y(t-2n\tau)]$.

EEG and brain activity patterns



Synchronization of two channels in EEG resting state in several time windows. Cz channel between 420-700 ms is desynchronized, but Fz participates in different subnetworks. Metastable states last about 100 ms.
fMRI 128 functional networks of cognition/behavior have been identified, their dynamics is unknown (Sung et al. A Set of Functional Brain Networks for the Comprehensive Evaluation of Human Characteristics. FiN, 12, 2018.

Neuroscience ⇔ AI

Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). Neuroscience-Inspired Artificial Intelligence. *Neuron*, *95*(2), 245–258.
Collaboration of: Google DeepMind, Gatsby Computational Neuroscience, Institute of Cognitive Neuroscience, Uni. College London, Uni. of Oxford.

Artificial neural networks – simple inspirations, but led to many applications.

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

Amoset al. (2018). **Learning Awareness Models**. *ArXiv:1804.06318*.

AI Systems inspired by Neural Models of Behavior:
(A) **Visual attention**, foveal locations for multiresolution ‘‘retinal’’ representation, prediction of next location to attend to.
(B) **Complementary learning systems** and episodic control: fast learning hippocampal system and parametric slow-learning neocortical system.
(C) Models of **working memory** and the Neural Turing Machine.

(D) Numenta Hierarchical temporal memory (HTM), Jeff Hawkins theory of the neocortex, new book (3/2021) „A thousand brains” with more ideas.

AI ⇔ Neuroscience

Machine learning techniques are basic tools for analysis of neuroimaging data.

Ideas from animal psychology helped to give birth to reinforcement learning (RL) research. Now **key concepts from RL inform neuroscience**.

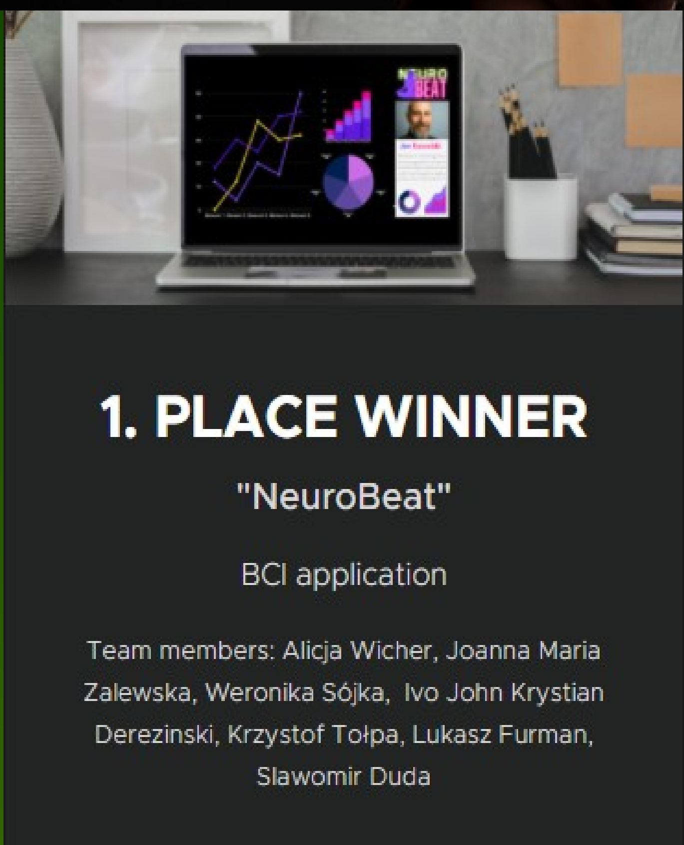
Activity of midbrain dopaminergic neurons in conditioning paradigms has a striking resemblance to temporal difference (TD) generated prediction errors - **brain implements a form of TD learning!**

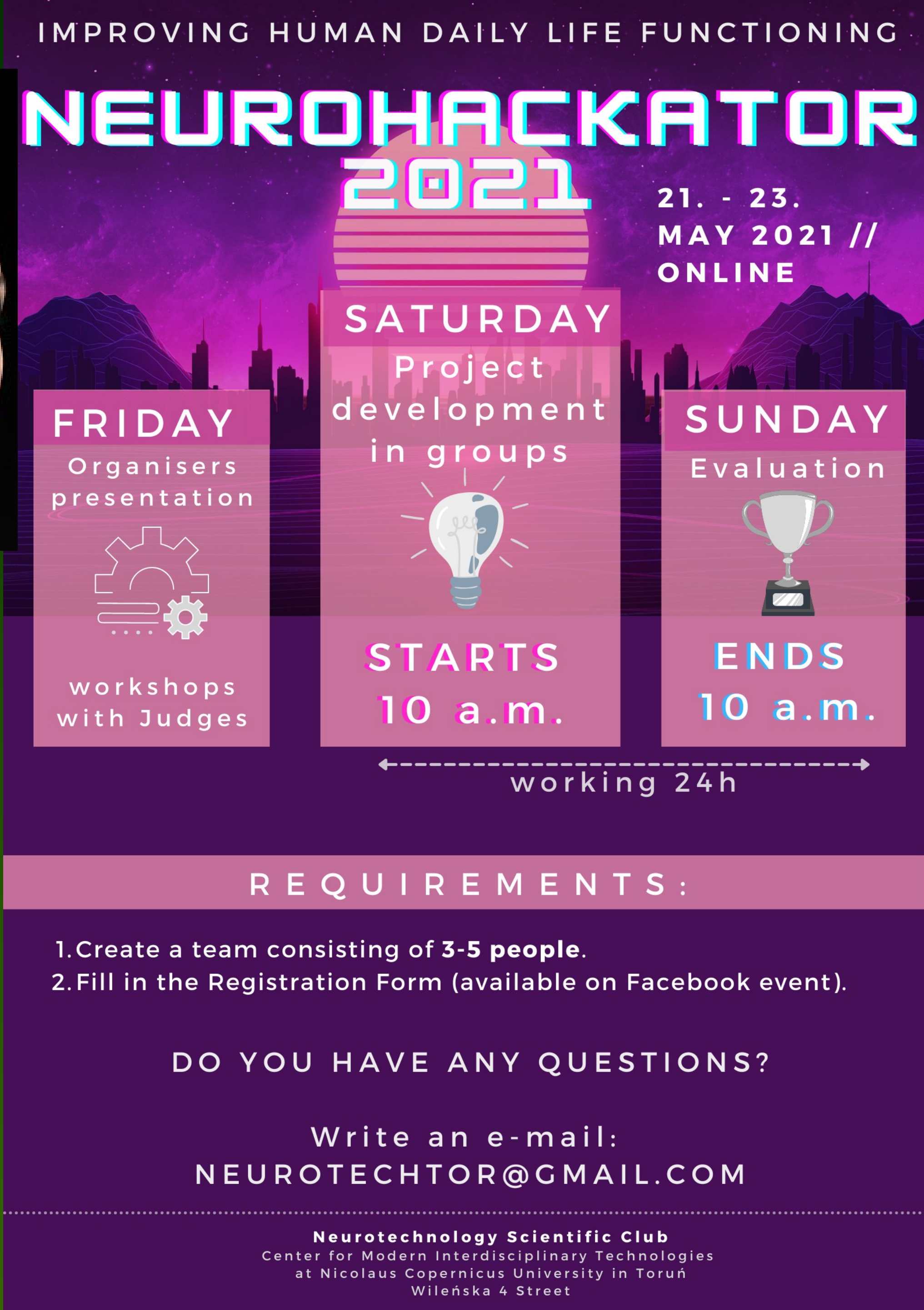
CNN ⇔ interpret neural representations in high-level ventral visual stream of humans and monkeys, finding evidence for deep supervised networks.

LSTM architecture provides key insights for development of working memory, gating-based maintenance of task-relevant information in the prefrontal cortex.

Random backward connections allow the backpropagation algorithm to function effectively adjusting forward weights and using backward projections to transmit useful teaching signals.


VIRTUAL BR41N.IO
HACKATHON
April 17-18, 2021
during the
Spring School 2021*
IEEE brain
g.tec
*BR41N.IO and Spring School 2021 are part of g.tec's Teaching Plan 2021
with more than 140 hours of online courses and lectures.


1. PLACE WINNER
"NeuroBeat"
BCI application
Team members: Alicja Wicher, Joanna Maria Zalewska, Weronika Sójka, Ivo John Krystian Derezinski, Krzystof Tołpa, Lukasz Furman, Slawomir Duda


IMPROVING HUMAN DAILY LIFE FUNCTIONING
NEUROHACKATOR
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21. - 23.
MAY 2021 //
ONLINE
FRIDAY
Organisers presentation
workshops with Judges
SATURDAY
Project development in groups
STARTS
10 a.m.
SUNDAY
Evaluation
ENDS
10 a.m.
working 24h
REQUIREMENTS:
1. Create a team consisting of 3-5 people.
2. Fill in the Registration Form (available on Facebook event).
DO YOU HAVE ANY QUESTIONS?
Write an e-mail:
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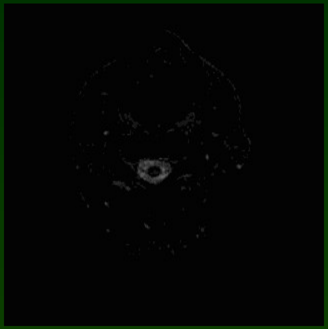
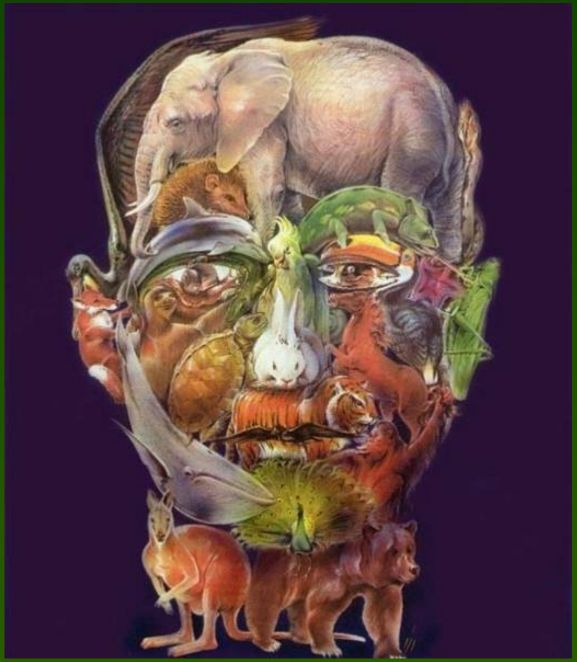
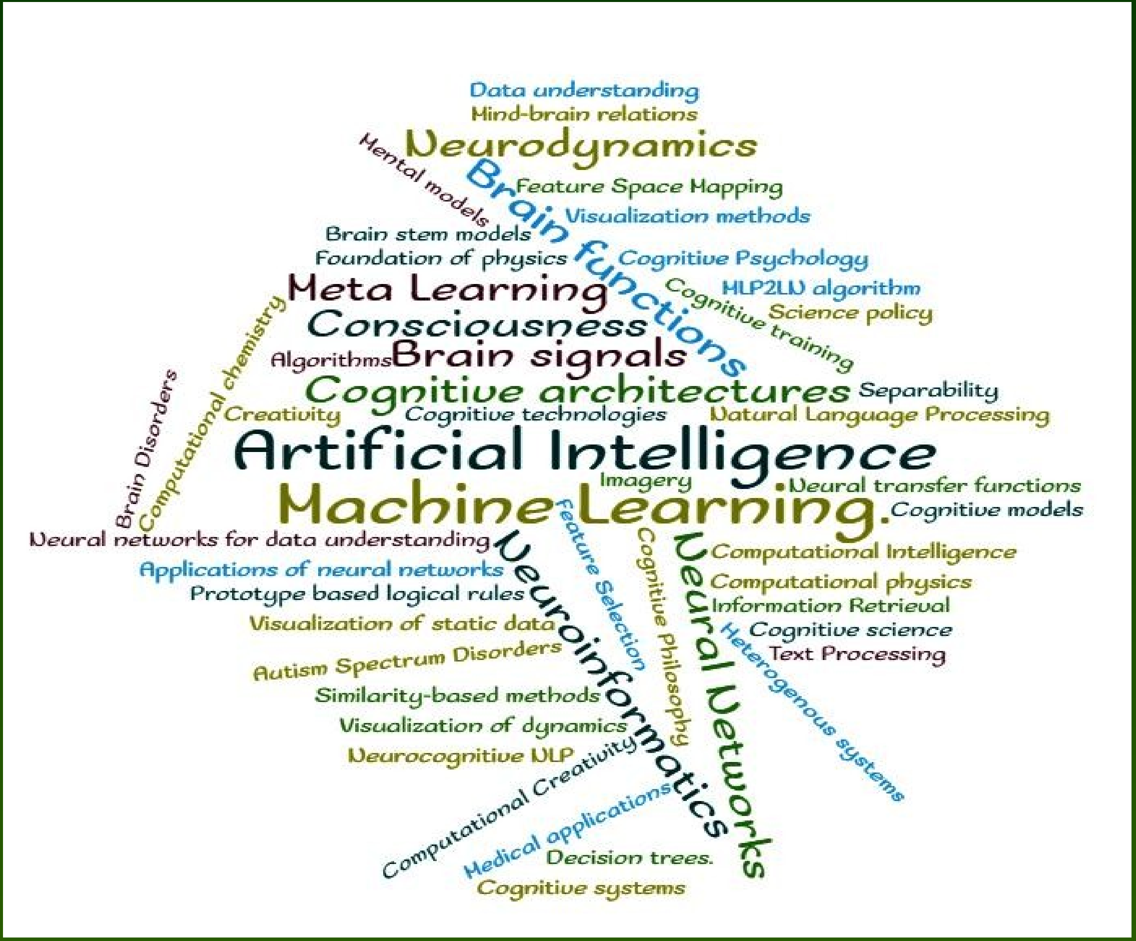
Conclusions



- We need BICA architectures for flexible AI, brain-like. Simplify brain processes. This is our GREAT challenge!
- AI/ML ⇔ brain research, neural network models and learning algorithms (recurrence networks, reinforcement learning, capsule nets) help to interpret information processing in the brain.
- Neurodynamics is the key to understanding mental states. Neuroimaging & analysis of EEG/MEG ⇔ helps to understand network neurodynamics ⇔ interpretation, mental states: S(B) ⇔ S(M).
- Great progress in EEG analysis has been achieved in recent years.
- Potential of such methods is enormous, not only in improving AI. Disorders of the brain are one of the greatest burdens on the society in every country.
- Neurocognitive technologies are coming, helping to diagnose, repair and improve brain processes.

Let us thank our neurons for synchronization





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⇨ talks, papers, projects, Flipboard, lectures …