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

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Google: W. Duch

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

Overview

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

Part I: Brain and ML inspirations.

Brain ⇔ Mind relations, phenomics.

Part II: Neurodynamics.

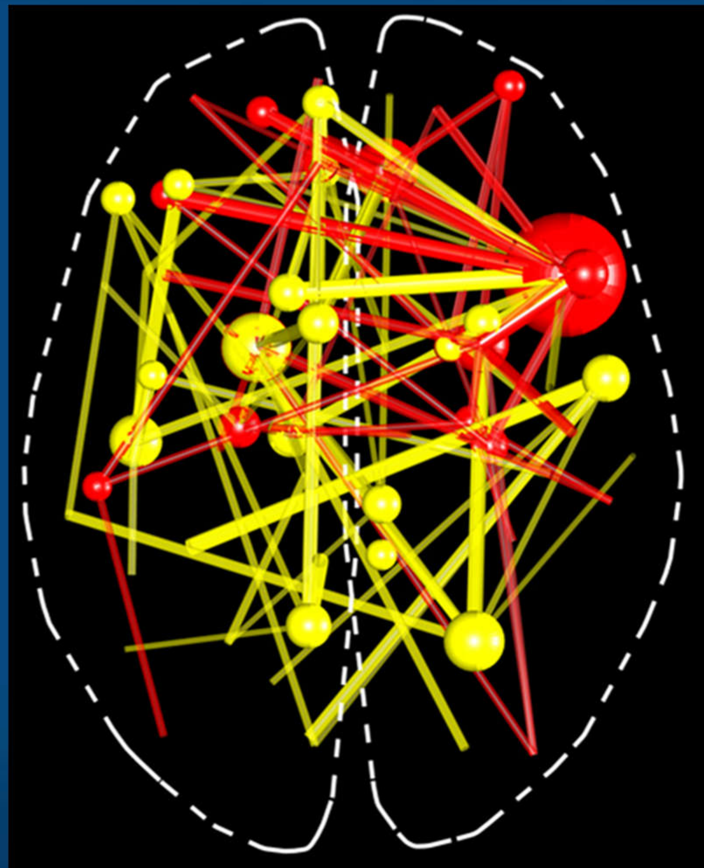
Brain simulations at different levels.

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

Neurodynamics on real brain networks.

Past, present, future overview.

2018 OHBM Paris/Singapore brain hackathons overlap with our school …



Center for Modern Interdisciplinary Technologies

Why am I interested in this?

Bio + Neuro + Cog Sci + Physics =>

NeuroCognitive Lab.

Other labs: molecular biology, chemical analytics, nanotech and electronics.

Main theme: maximizing human potential.
Goal: understanding brain-mind relations, with a lot of help from computational modeling and neuroimaging; pushing the limits of brain plasticity.
Big challenge! Funding: national/EU grants.

My group of neuro-cog-fanatics

NeuroCog Lab

10 units, diverse projects.

1. **BabyLab** – infant EEG, phonematic hearing, working memory
2. **NeuroInfo Unit** – brain signal analysis, simulations of brain functions
3. **fMRI Unit** – neuroimaging projects, neuroplasticity, network science
4. **EEG Lab** – biofeedback, HRV, creativity
5. **GameLab** – therapeutic games, dyscalculia, autism, gaze interaction
6. **Cognitive Video Processing unit** – neurorehabilitation
7. **MoveLab** – analysis of movement, accelerometry
8. **MedLab** – pain research, medical aspects
9. **InterDoctor** – coma patients
10. **EyeTracking unit** – humans and animals

Machine Learning: see A few machine learning algorithms worth further development.
Many good unfinished -;) ideas in Machine Learning.
INCF Poland node in Toruń (2017). ICNF 2019 Congress in Warsaw/Toruń?

CMIT: scanner GE Discovery MR750 3T

In search of the sources of brain's cognitive activity

Project „Symfonia”, NCN, Kraków, 18 July 2016

Looking for a postdock (5/2018)!

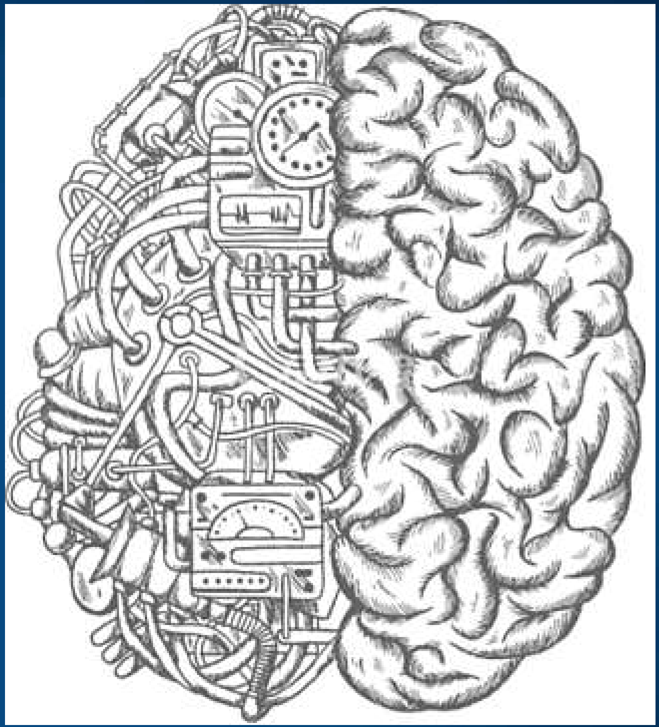
FACULTY OF PHYSICS, ASTRONOMY AND INFORMATICS

CENTRE FOR MODERN INTERDISCIPLINARY TECHNOLOGIES

INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

nencki institute of experimental biology

Part I: Brain and ML inspirations



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

What do we want to achieve?

Understanding brains and minds, relations:
Environment ⇔ Brain ⇔ Mind

High-level description, simple, verbalized
=> cognitive architectures.

Brain, Mind => NN principles, architectures.

Duch, W. (1996). Computational physics of the mind.
Computer Physics Communications, *97*(1), 136–153.

Editor: … We hope our readers will find inspiration in these more unusual contributions, such as that of Duch on "Computational Physics of the Mind".

Now „Physics of Life Reviews" has special issue on the physics of mind .

Goals & levels of understanding

Full understanding of all aspects of cognition/behavior - too difficult?
RIKEN BSI: understand, maintain, develop, create brains.

- Create artificial intelligence => AI, cognitive informatics, brain-inspired.
- Understand cognitive/affective functions, network level.
- Understand details of brain functions: genetic, cellular, neural level.
- Cure and support healthy brain …

AI has focused on intelligent behavior: problem solving, thinking, knowledge representation, searching at symbolic level.

IBM: Cognitive informatics, Watson technologies.

WD: Neurocognitive Informatics manifesto (2009).

AI based on computing with percepts, patterns, not just symbols.

AI-NN-ML-SC-PR communities may one day join in problem-oriented, not method oriented, large-scale projects.

Phenomics

Phenomics

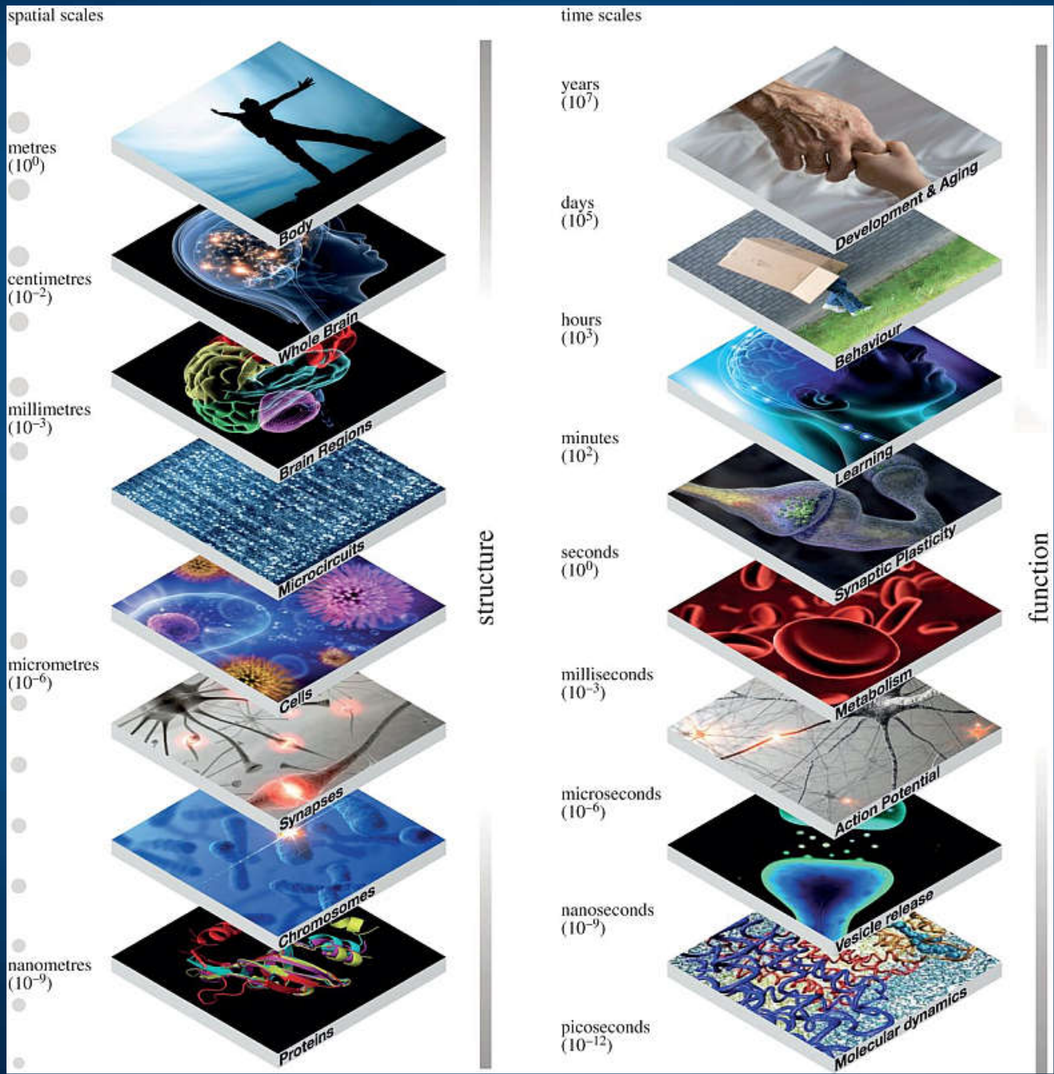
Phenomics is the branch of science concerned with identification and description of measurable physical, biochemical and psychological traits of organisms.
Genom, *proteom*, *phenom, interactom, exposome, virusom … omics.org* has a list of over 400 various … *omics*.

Human Phenome Project, since 2003.
Human Epigenome Project, since 2003.
Human Connectome Project, since 2009.
Developing Human Connectome Project, UK 2013

Consortium for Neuropsychiatric Phenomics, since 2008 investigates phenotypes of people suffering from serious mental disorders at all possible levels.

Can neurocognitive phenomics be developed to understand general behavior of people? At which level? That depends on questions asked.

Phenomics: levels in space and time



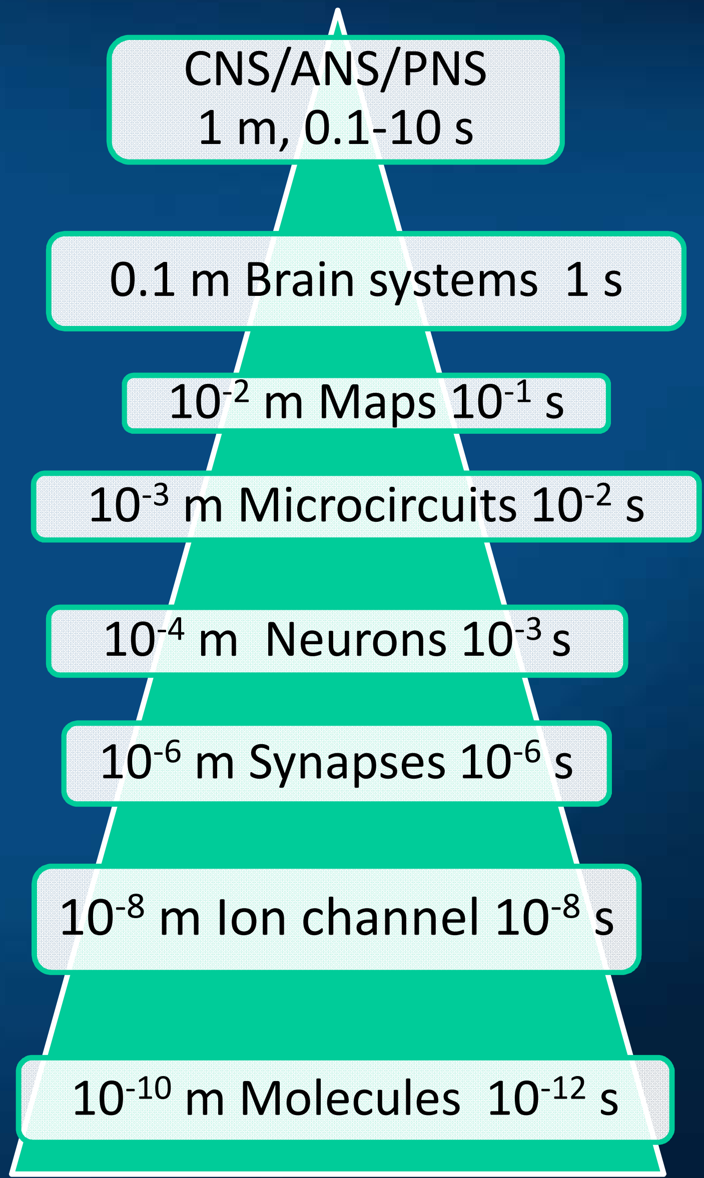
Space/time scales

Spatiotemporal resolution:

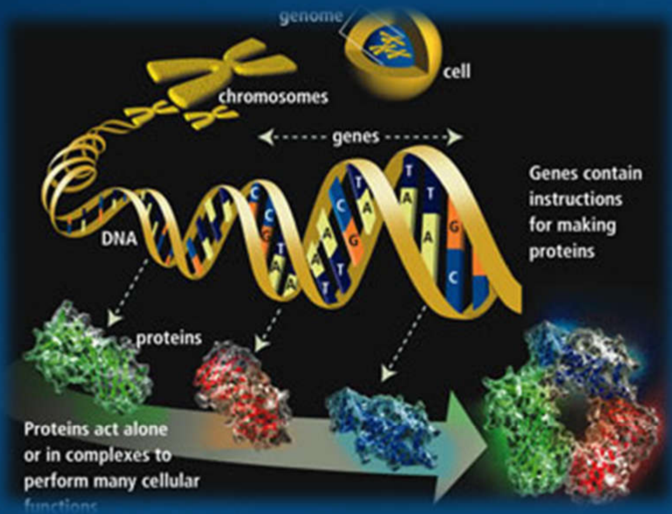
- spatial scale: 10 orders of magnitude, from 10^{-10} m to 1 m.
- temporal scale: 10 or more orders of magnitude, from 10^{-10} s to 1 s.

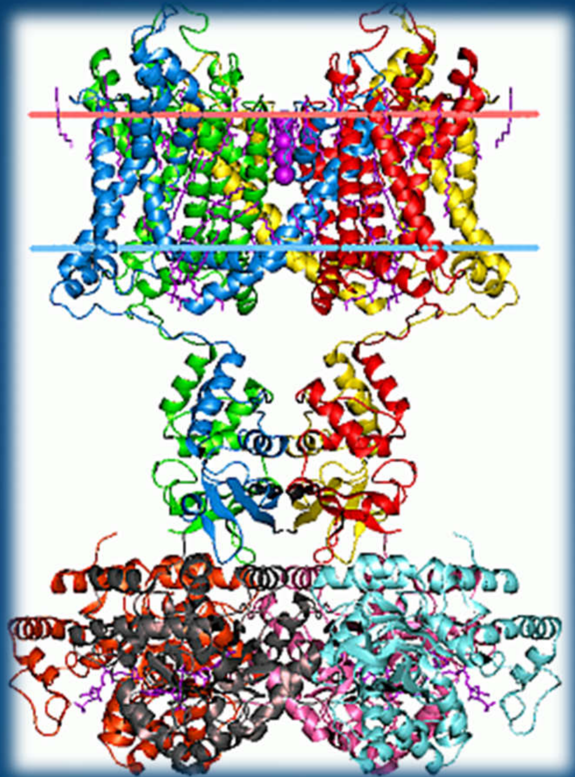
Architecture:

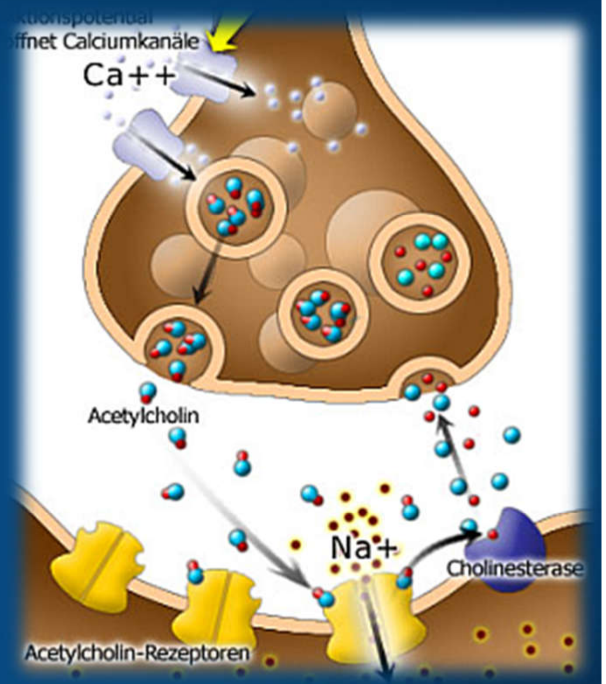
- hierarchical and modular
- ordered in large scale, chaotic in small;
- specific projections: interacting regions wired to each other;
- diffused: regions interact through hormones and neurotransmitters;
- functional:
  subnetworks dedicated to specific tasks.



From Genes to Neurons

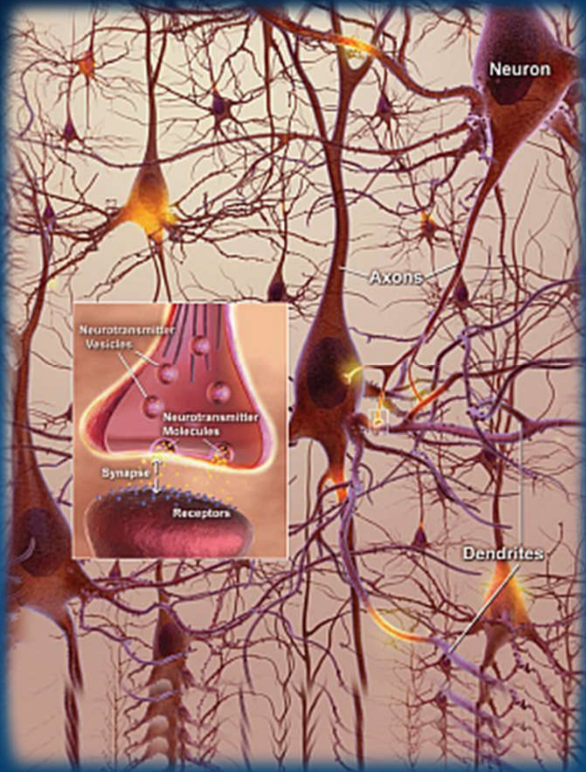


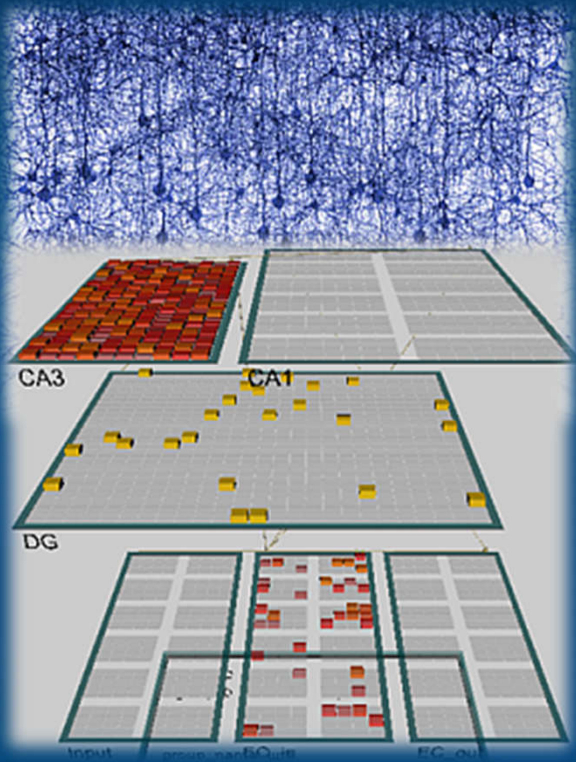


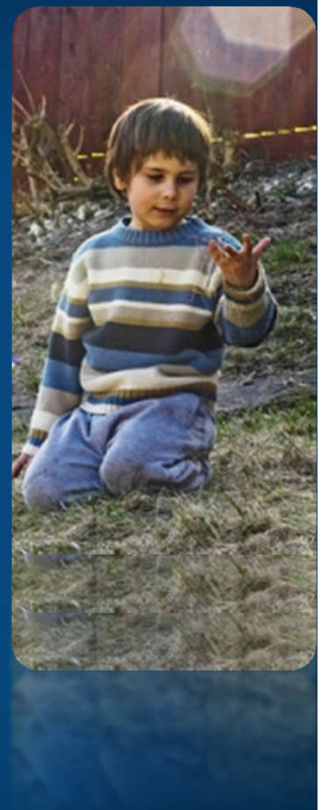


Genes => Proteins => receptors, ion channels, synapses
=> neuron properties, networks, neurodynamics
=> cognitive phenotypes, abnormal behavior, syndromes.

From Neurons to Behavior







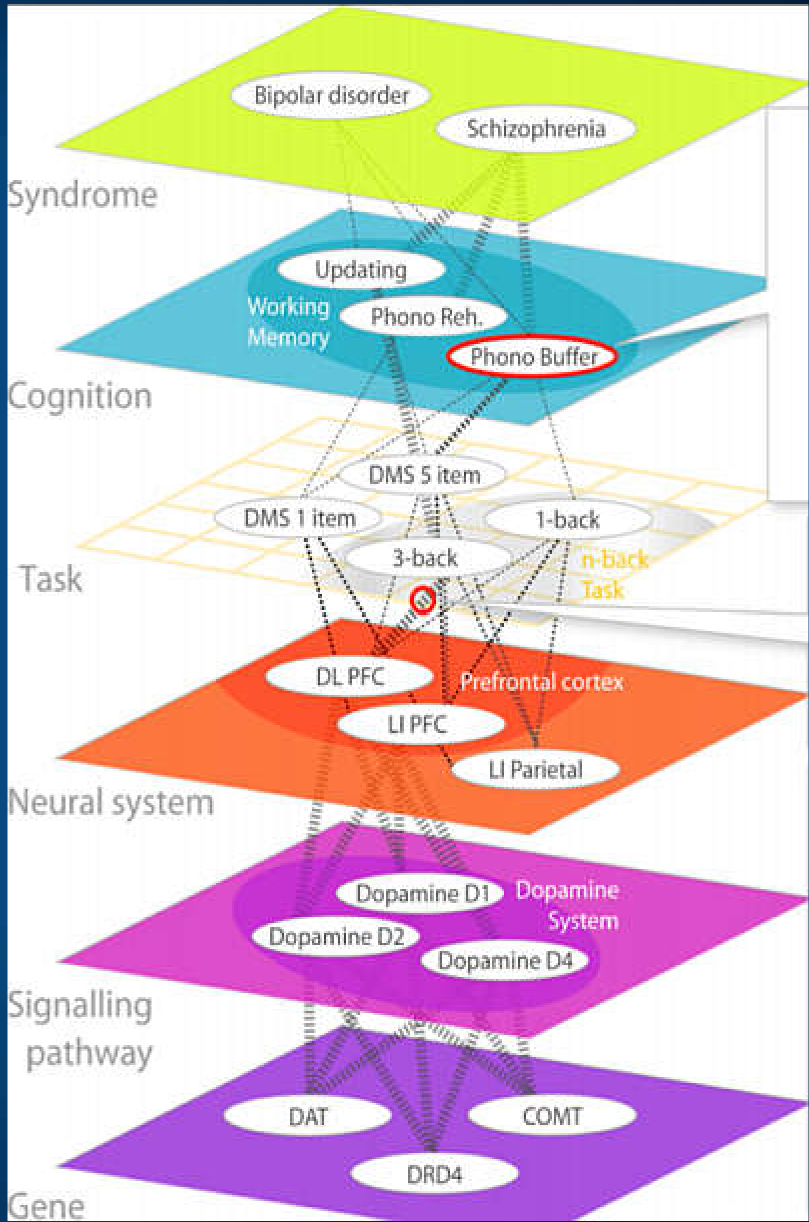
Genes => Proteins => receptors, ion channels, synapses
=> neuron properties, networks
=> neurodynamics => cognitive phenotypes, abnormal behavior!

Neuropsychiatric Phenomics in 6 Levels

According to
The Consortium for Neuropsychiatric Phenomics (CNP), 2008
http://www.phenomics.ucla.edu

From genes to molecules to neurons and their systems to tasks, cognitive subsystems and syndromes.

Neurons and networks are right in the middle of this hierarchy.



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.

Still in poor shape -;)

Report: Behavioral Assessment Methods for RDoC Constructs, NIMH 2016

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

Strategy for Phenomics Research

The Consortium for Neuropsychiatric Phenomics: research should provide bridges between all levels, one at a time, from environment to syndromes.

Strategy: identify biophysical parameters of neurons required for normal neural network functions and leading to abnormal cognitive phenotypes, symptoms and syndromes.

Create models of cognitive function that may reflect some of the symptoms of the disease, ex. problems with attention, relating them to model biophysical properties of neurons.

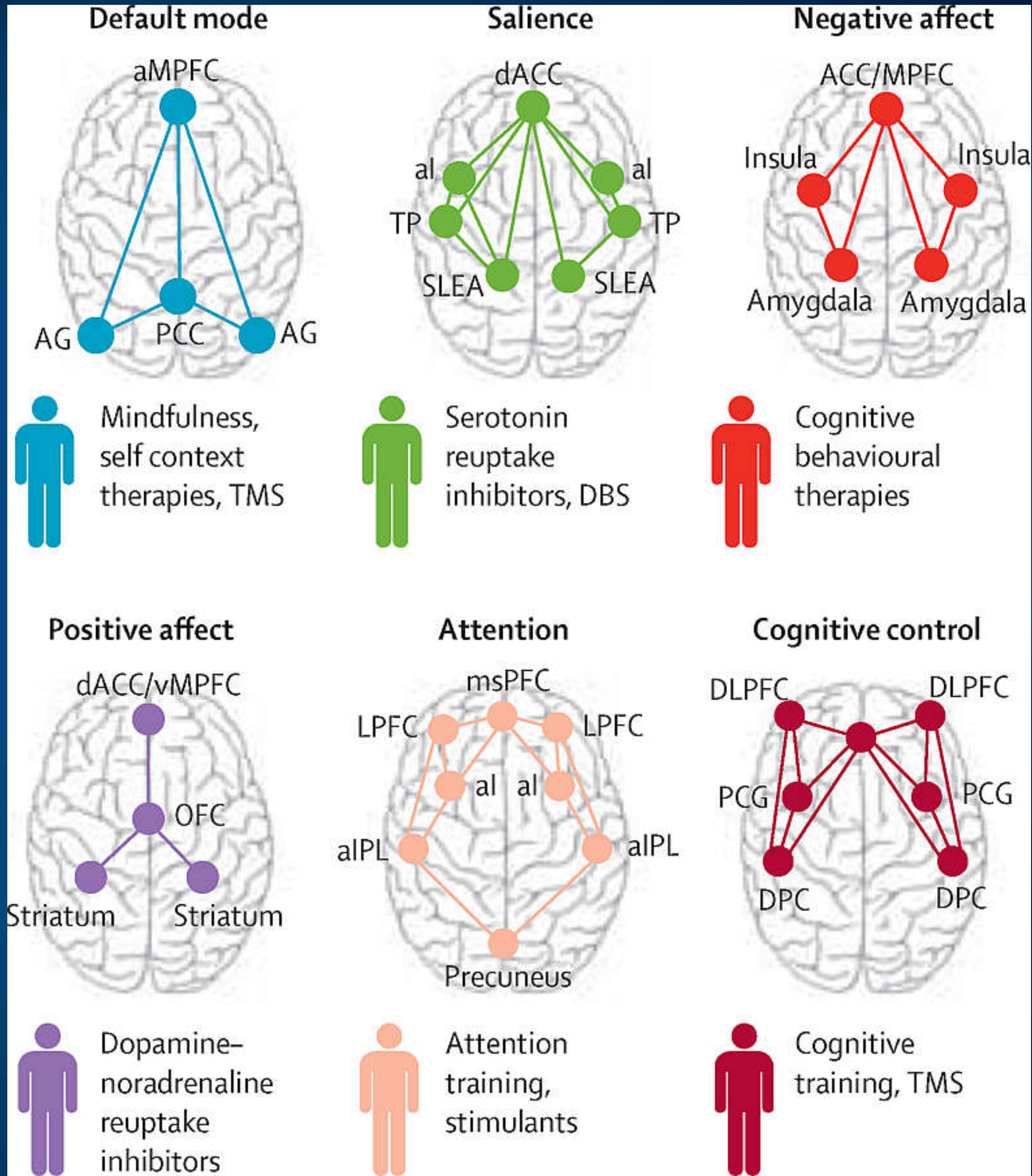
Result: mental events at the network level are linked to neurodynamics and it depends on the lower-level neural properties.
Ex: why drugs that stimulate the brain help in ADHD case? Relation of ASD/ADHD symptoms to neural accommodation.

Neuropsychiatric perspective.

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.



Neurocognitive Phenomics

Phenotypes may be described at many levels. Here from top down we have learning/education, psychiatry & psychology,

neurophysiology,
neural networks,

biology & neurobiology,

biophysics, biochemistry & bioinformatics.

Neurocognitive phenomics is even greater challenge than neuropsychiatric phenomics.

Effects are more subtle but this is the only way to understand fully human/animal behavior.

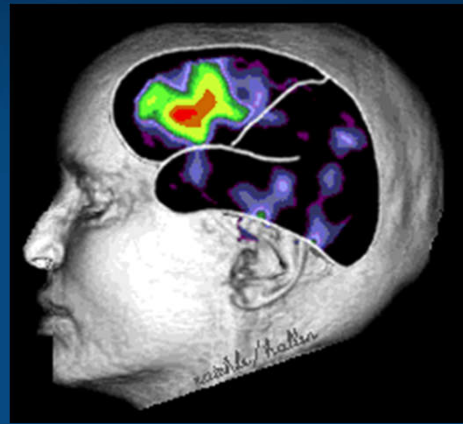
Learning styles, strategies	Learning styles
Memory types, attention …	Cognition
Sensory & motor activity, N-back …	Tasks, reactions
Specialized brain areas, minicolumns	Neural networks
Many types of neurons	Synapses, neurons & glia cells
Neurotransmitters & modulators	Signaling pathways
Genes & proteins, building blocks	Genes, proteins, epigenetics

Geometric model of mind

Brain ⇔ Psyche

Objective ⇔ Subjective

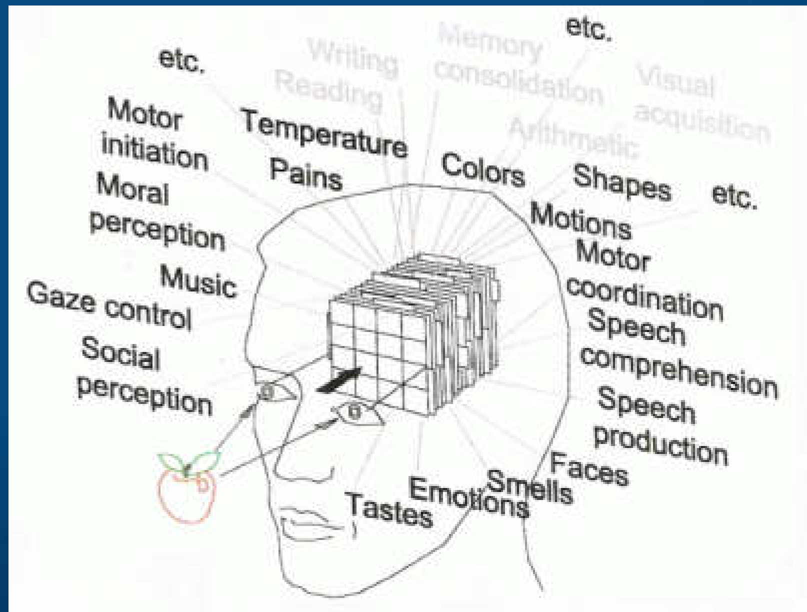
Neurodynamics: bioelectrical activity of the brain, neural activity measured using EEG, MEG, NIRS-OT, PET, fMRI, other techniques.



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.

Hurlbut & Schwitzgabel, Describing Inner Experience? MIT Press 2007

AI/NN inspirations from mind/brain

AI/DNN Milestones

1995 – Chinook wins 6:0 in checkers

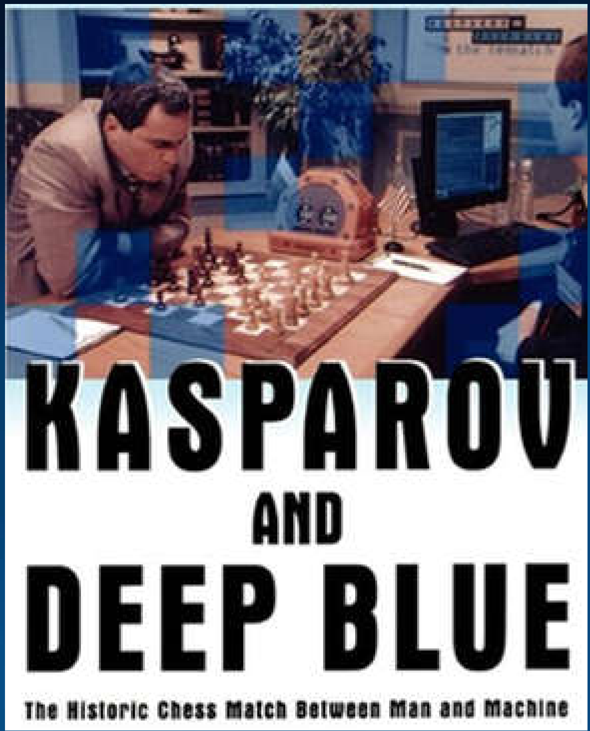
1997 – Deep Blue wins with Kasparov in chess

2011 – IBM Watson wins in Jeopardy.

2015 – robotic lab + AI software discovers genetic and signal pathways regenerating planaria.

2016 – Google AlphaGo wins with world champion Lee Sedol 4:1, and AlphaGoZero beats it 100:0

2017 – Libratus (CM) wins in professional poker
OpenAI wins in Dota 2 with pro player.



Mind in AI

AI/CI simple definition:

branch of science that tries to solve problems for which there are no effective algorithms.

AI – focused on higher cognitive functions; CI includes sensory pattern recognition

Allen Newell, Unified Theories of Cognition (1990):
Mind is a control system that determines behavior of organism interacting with complex environment.

John Laird: mind is a functional entity that can think.

Laird JE, Lebiere C, & Rosenbloom, PS (2017). A Standard Model of the Mind: Toward a Common Computational Framework across Artificial Intelligence, Cognitive Science, Neuroscience, and Robotics. *AI Magazine*, *38*, 13–26.

No reference to brains, minds may be implemented in many ways.

A Standard Model of the Mind

Laird JE, Lebiere C, & Rosenbloom, PS (2017). A Standard Model of the Mind: Toward a Common Computational Framework across Artificial Intelligence, Cognitive Science, Neuroscience, and Robotics. *AI Magazine*, *38*, 13–26.

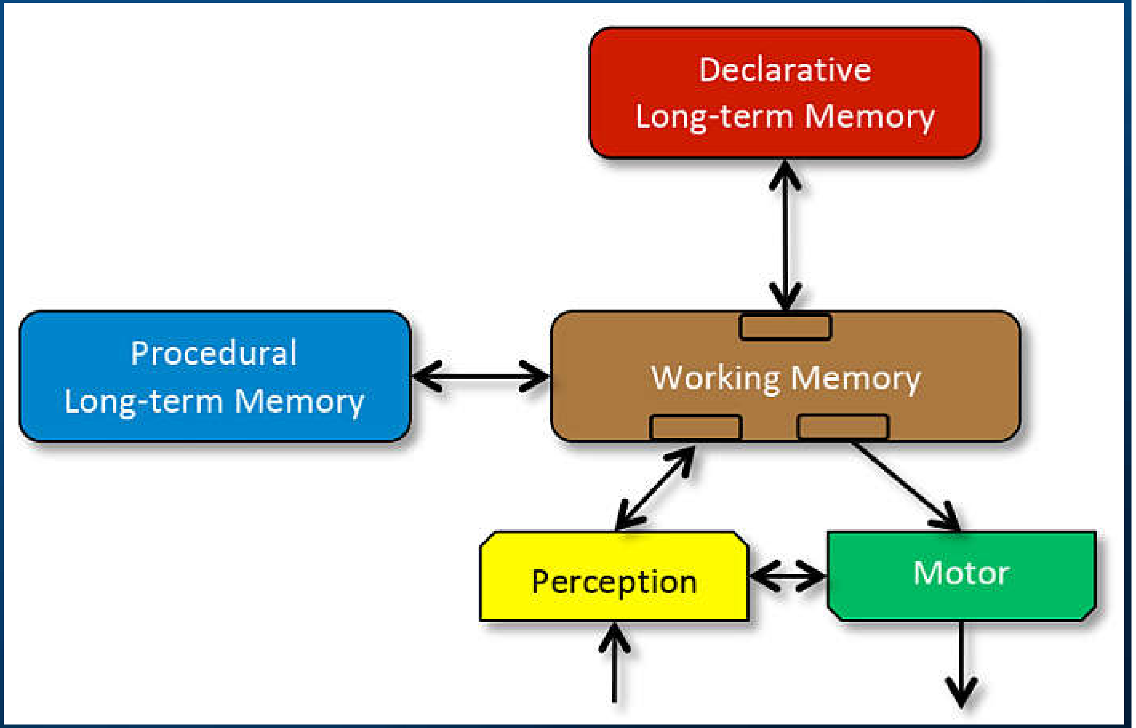
Laird: A mind is a functional entity that can think.

Newell: Mind is a control system that determines behavior of organism interacting with complex environment.

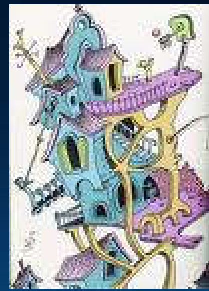
Cognitive informatics
Neurocognitive Informatics

(Deep Mind, OpenAI).

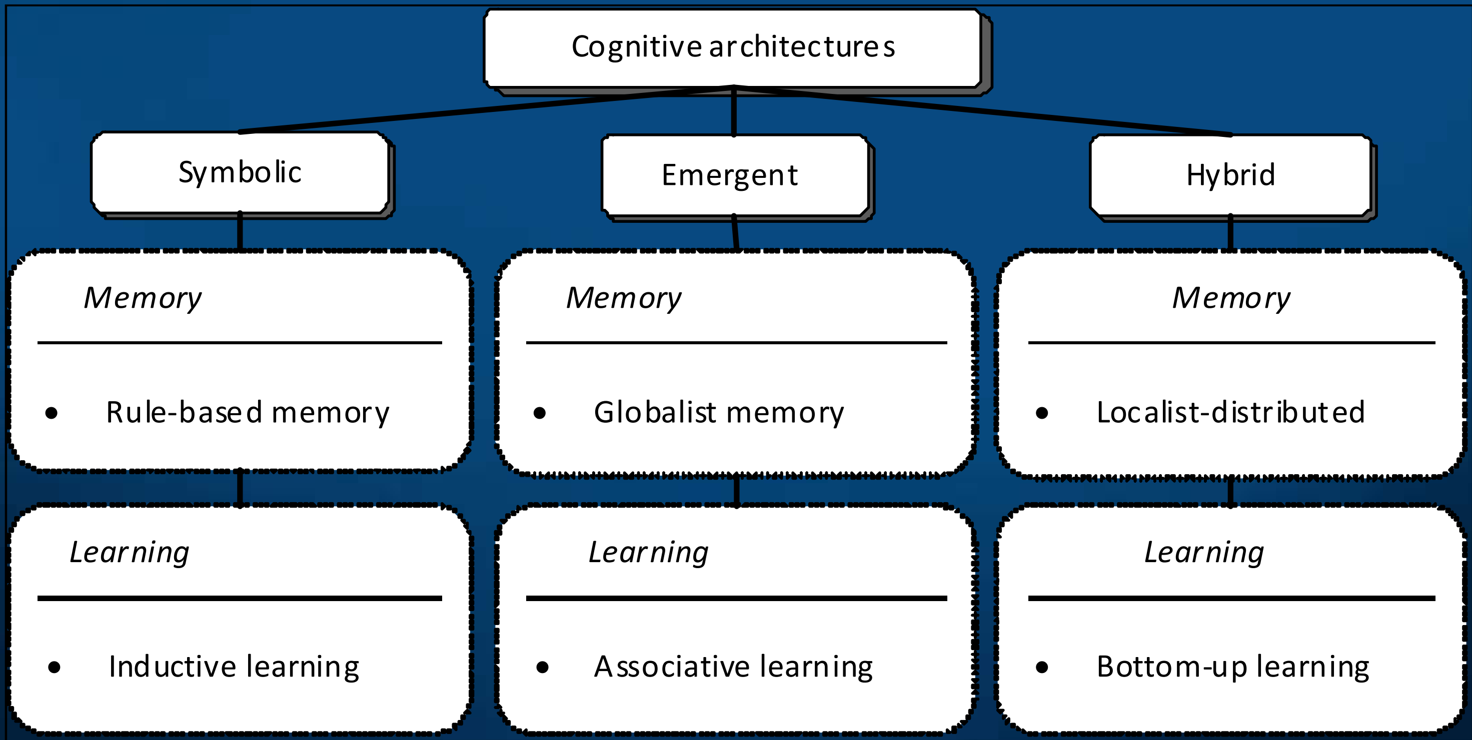
AI-NN-ML-SC-PR communities will finally join in problem-oriented, not method oriented, large-scale projects.



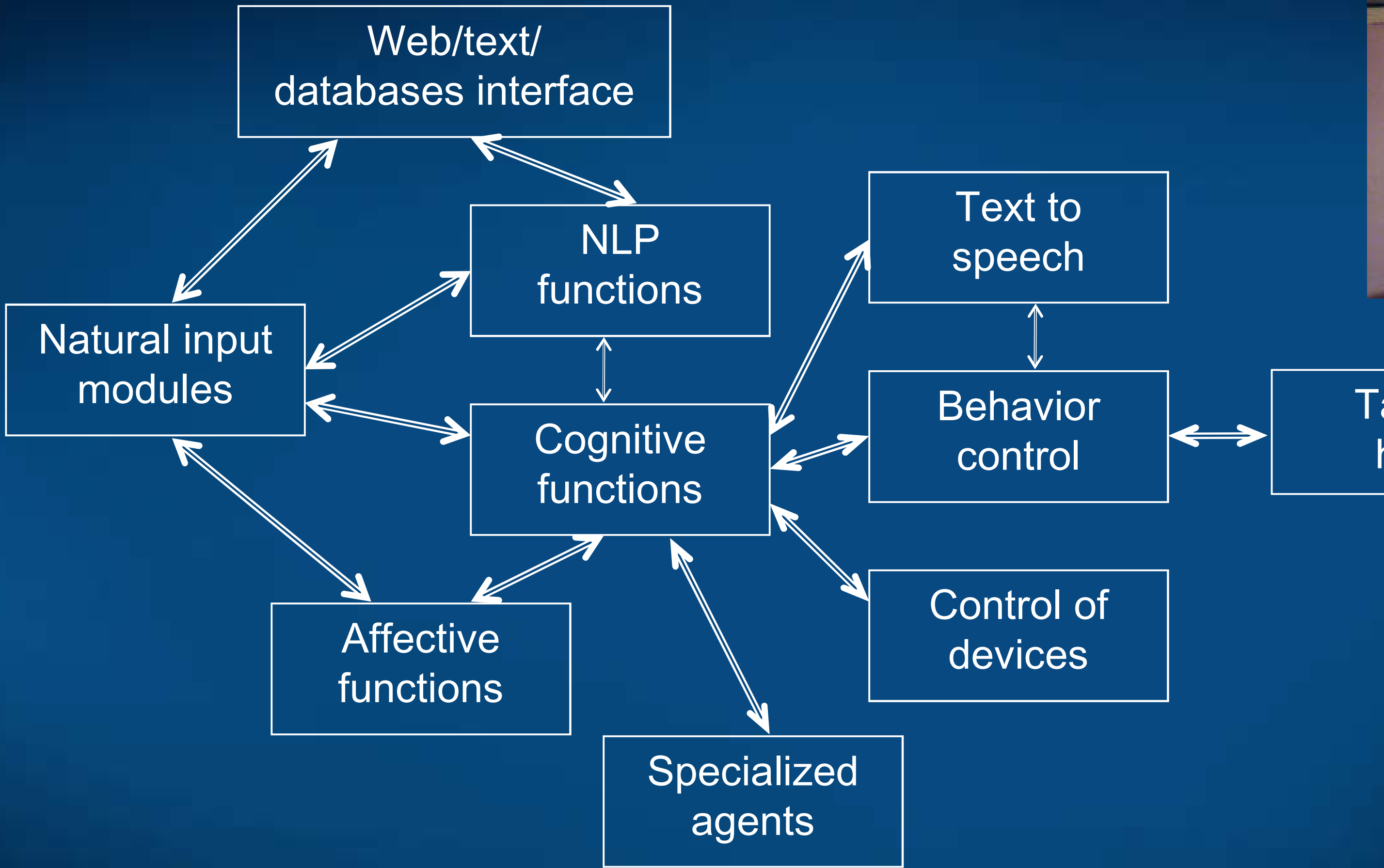
Cognitive architectures



- CA frequently created to model human performance in multimodal multiple task situations, rather than AGI.
- Newell, *Unified Theories of Cognition* (1990), 12 criteria for CS: behavioral: adaptive, dynamic, flexible; development, evolution, learning, knowledge integration, vast knowledge base, natural language, real-time performance, and brain realization.



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 …

A roadmap to human level intelligence

workshop organized by:

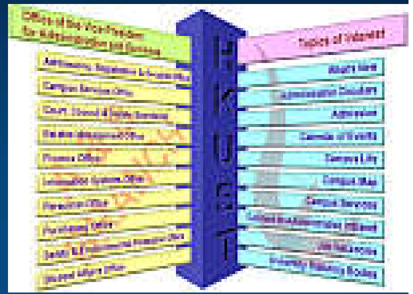
Włodzisław Duch (Google: W. Duch)
Department of Informatics, Nicolaus Copernicus University, Torun, Poland
& School of Computer Engineering, Nanyang Technological Uni, Singapore

Nikola Kasabov (http://www.kedri.info)
KEDRI, Auckland, New Zealand

James Anderson, Paul Allopenna, Robert Hecht-Nielsen, Andrew Coward,
Alexei Samsonovich, Giorgio Ascoli, Kenneth De Jong, Ben Goertzel

WCCI'2006, Vancouver, , British Columbia, Canada, July 17, 2006

Steps Toward an AGI Roadmap



Artificial General Intelligence (AGI, 2007 Memphis): architectures that can solve many problems and transfer knowledge between the tasks.

Roadmaps:

- A Ten Year Roadmap to Machines with Common Sense (Push Singh, Marvin Minsky, 2002)
- Euron (EU Robotics) Research Roadmap (2004)
- Neuro-IT Roadmap (EU, A. Knoll, M de Kamps, 2006)

Challenges: Word games of increasing complexity:

- 20Q is the simplest, only object description.
- Yes/No game to understand situation.
- Logical entailment competitions.

Panel with J. Laird, S. Franklin, B. Goertzel, J. Bell
Conference series, AGI journal, AGI movement.

Newer Initiatives

IEEE Computational Intelligence Society Task Force (J. Mandziuk & W. Duch), CI for Human-like Intelligence (J. Mandziuk & W. Duch), 2013-18

Brain-Mind Institute School (since 2012), International Conference on Brain-Mind (ICBM) and Brain-Mind Magazine (Juyang Weng, Michigan SU).

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

BICA: Annual International Conf on Biologically Inspired Cognitive Architectures, 3rd Annual Meeting of the BICA Society, Palermo, Italy, 31.10- 3.11.2012

Duch W, Oentaryo R.J, Pasquier M, *Cognitive architectures: where do we go from here?* 2008

Attention-Based Artificial Cognitive Control Understanding System (ABACCUS)

Large EU integrated project (2005) with 9 participants, later FET Flagship candidate (but never started):

- King's College London (John G. Taylor, coordinator), UK
- Centre for Brain & Cognitive Development, Berkbeck College, University of London, UK
- Cognition and Brain Sciences Unit, Medical Research Council, UK
- Robotics and Embedded Systems, Technical University of Munich, G
- Institute of Neurophysiology and Pathophysiology, Universitätsklinikum Hamburg-Eppendorf, G
- Institute of Computer Science, Foundation for Research and Technology – Hellas, Heraklion, Crete, GR
- National Center for Scientific Research "Demokritos", Athens, GR
- Dip. di Informatica, Sistemistica, Telematica, Universita di Genova, I
- Dep. of Informatics, Nicolaus Copernicus University, Torun, PL

Mind/brain inspirations for Machine Learning

ML: RBF-discovering the wheel

Early ideas, 1990-95 - before the Internet and repositories of papers …

RBF rediscovery (1993): extract high-level neural processing principles.
What should artificial neural units do? Discriminate (MLP), compute probability density (RBF) or estimate similarity (SBM)? Depends on the point of view …

$$\sigma\left(\sum_i W_i x_i - \theta\right) \Leftrightarrow \sigma\left(\mathbf{W}\cdot\mathbf{X}-\theta\right) = \sigma\left(\frac{1}{2}\left\|\mathbf{W}-\mathbf{X}\right\|^2 - \theta'\left(\left|\mathbf{W}\right|,\left|\mathbf{X}\right|\right)\right) \sim d\left(\mathbf{W},\mathbf{X}\right)$$

Duch W (1994) Floating Gaussian Mapping: a new model of adaptive systems. Neural Network World 4:645-654

But … approximation theory has been developed in 1950-60.
Network implementation led to models of probability density:

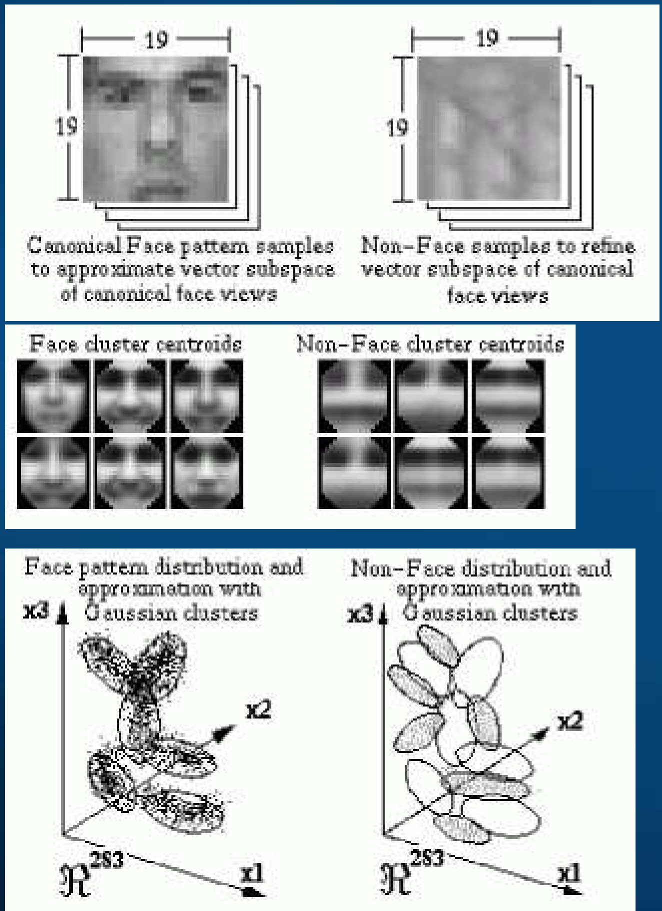
D.S. Broomhead & D. Lowe (1988), Multivariable functional interpolation and adaptive networks. Complex Systems 2: 321–355.
T. Poggio and F. Girosi, Networks for approximation and learning. Proc. IEEE 78(9), 1484-1487 (1990).

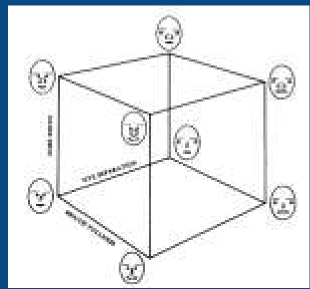
Object recognition

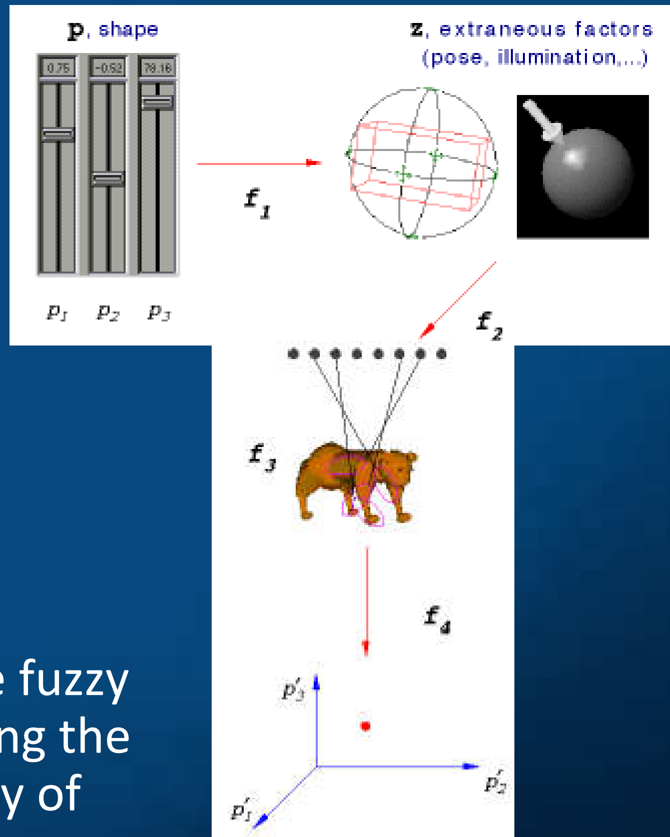
Object recognition theory, S. Edelman (1997)

Second-order similarity in low-dimensional (<300) space is sufficient.

Population of columns as weak classifiers working in chorus - stacking.







Exemplars create fuzzy prototypes, solving the problem in theory of categorization.

Object recognition

Object recognition theory, S. Edelman (1997)

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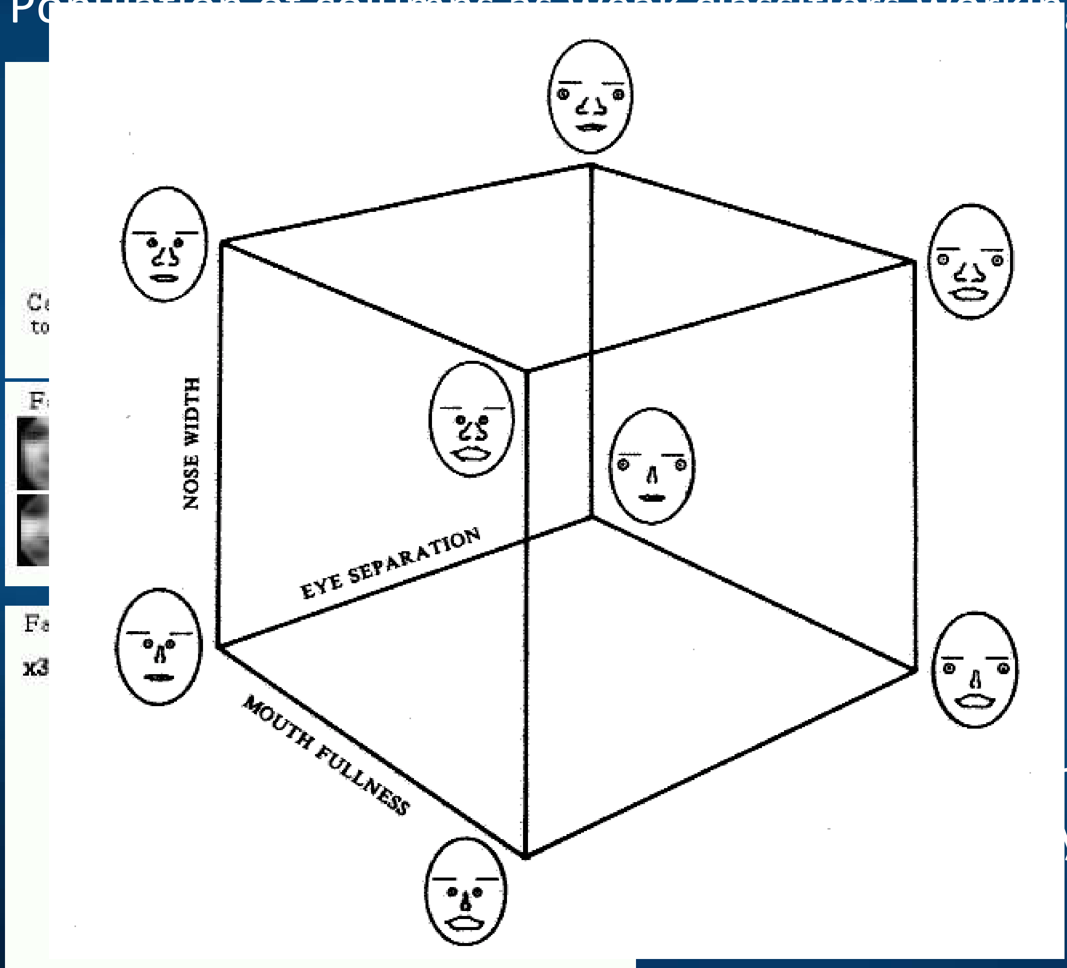

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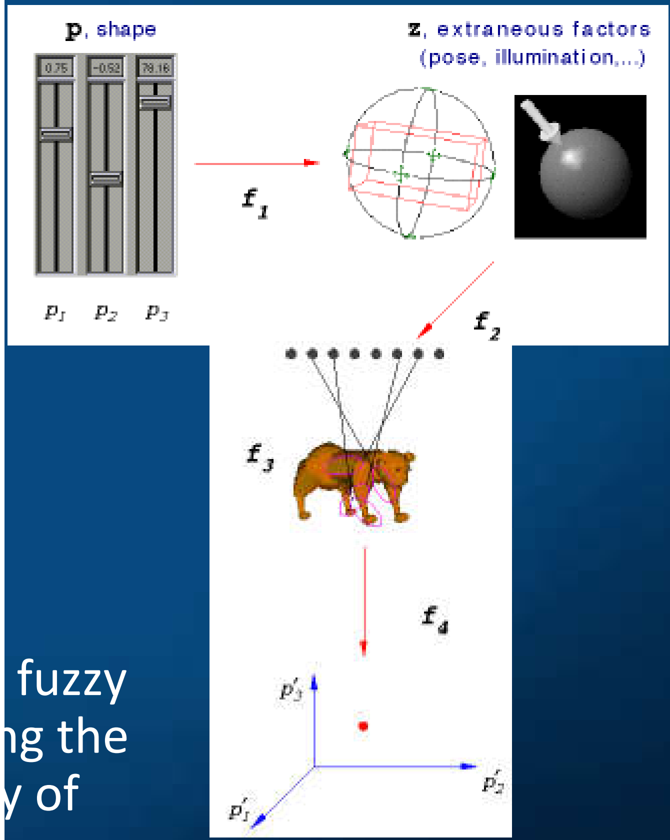
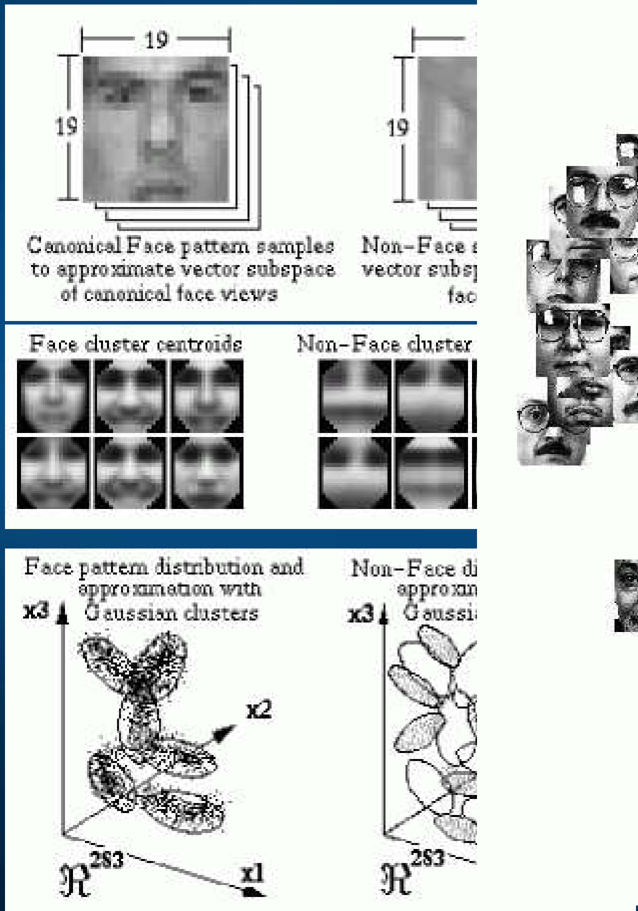


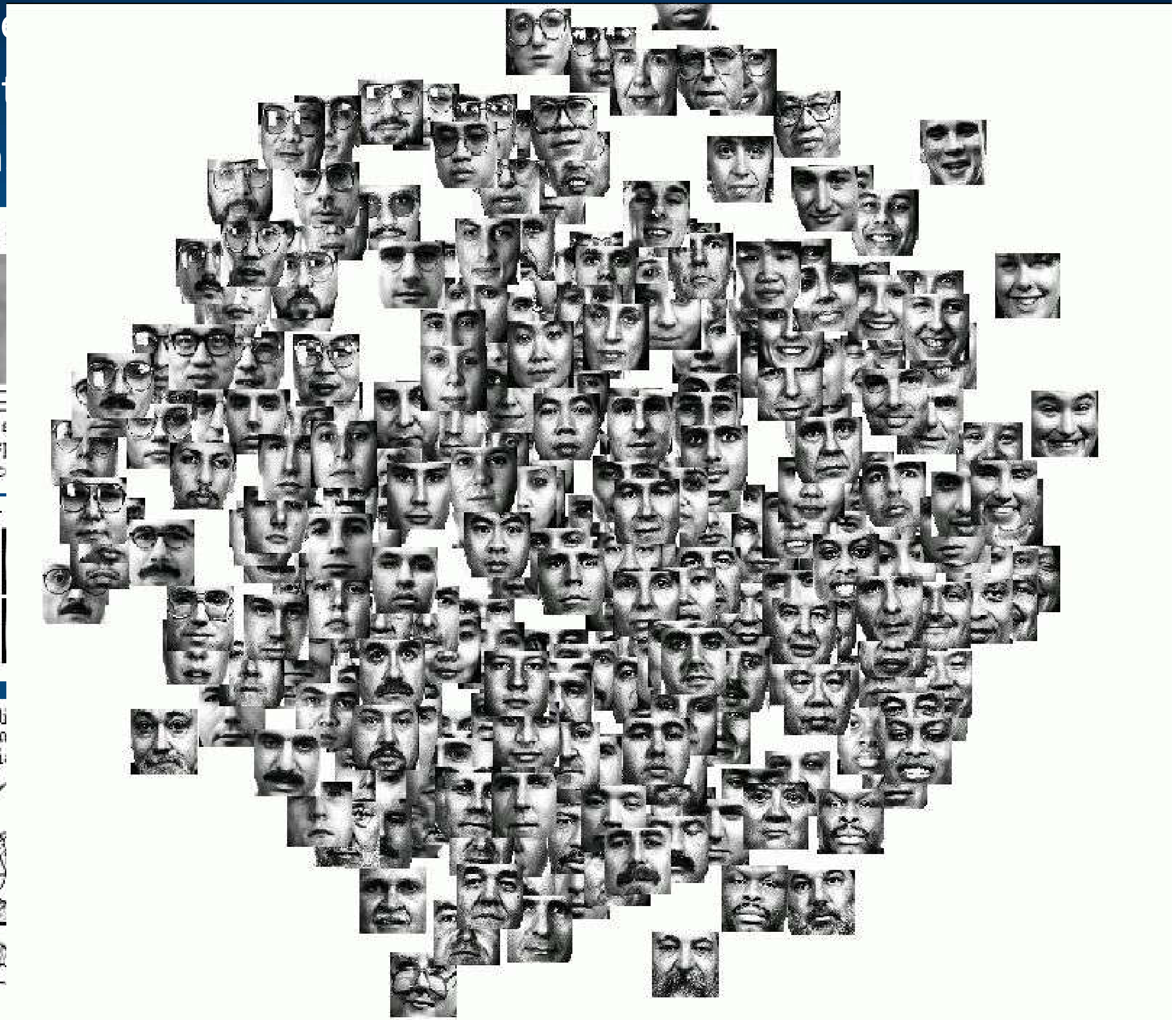
Object recognition

Object recognition the

Second-order similarit

Population of column



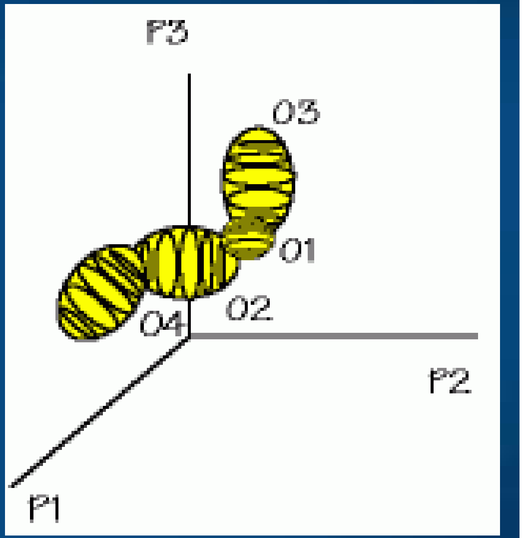


FSM - neurofuzzy systems

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):

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

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



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

Separable functions: interpretation based on fuzzy rules, RBF – just intuition.

Implementation: resource allocation constructive FSM network, stable.

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

P-rules

Euclidean distance leads to a Gaussian fuzzy membership functions + product as T-norm. In this case SBF = RBF.

$$D(\mathbf{X},\mathbf{P}) = \sum_i d(X_i, P_i) = \sum_i W_i (X_i - P_i)^2$$

$$\mu_P(\mathbf{X}) = e^{-D(\mathbf{X},\mathbf{P})} = e^{-\sum_i d(X_i,P_i)} = \prod_i e^{-W_i (X_i - P_i)^2} = \prod_i \mu_i(X_i, P_i)$$

Manhattan function => $\mu(X;P) = \exp\{-|X-P|\}$

Various distance functions lead to different MF; P-rules are more than fuzzy!
Ex. data-dependent probabilistic distance functions for symbolic data:

$$D_{VDM}(\mathbf{X},\mathbf{Y}) = \sum_i \left[\sum_j \left| p(C_j | X_i) - p(C_j | Y_i) \right| \right]$$

$$D_{PDF}(\mathbf{X},\mathbf{Y}) = \sum_i \left[\sum_j \left| p(X_i | C_j) - p(C_j | Y_i) \right| \right]$$

Density modelling

But … *E.M. Pothos, The Rules versus Similarity distinction.* Behavioral and Brain Sciences, Vol. 28 (1): 1-14, 2005

Problem is solved by networks implementing P-rules.

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, 1997, chap. 20, pp. 491-512

Duch, W. Mind as a shadow of neurodynamics. Physics of Life Reviews, special issue "Physics of mind", Ed. F. Schoeller (submitted, 5/2018).

http://www.is.umk.pl/~duch/projects/projects/platonic.html

More on brain inspirations for ML in my presentations here.

What feedforward NN really do?

Vector mappings from the input space to hidden space(s), and finally to the output space where data should be separable.

Hidden-Output mapping done usually by perceptrons.
Brain performs many transformations, Eye=>LGN=>V1=>V2…=>V5=>IT

$T = \{X^i\}$ training data, N-dimensional.

$H = \{h_j(X^i)\}$ T image in the hidden space, j =1 .. N_H-dim.

$Y = \{y_k\{h(X^i)\}$ T image in the output space, k =1 .. N_C-dim.

NN goal: scatterograms of H, the image of T in the hidden space should be **linearly separable and stable**; internal representations will determine network generalization capabilities and other properties.

Is this a good goal? Can it be easily achieved?
"Universal approximator" theorem is not helpful.

Discovering the wheel - reverse

Although we have Internet some people have yet to rediscover my ideas …

- Duch W (1996) Computational physics of the mind. Computer Physics Communication 97: 136-15
- Perlovsky, L. I. (2016). Physics of the Mind. Frontiers in Systems Neuroscience, 10. fnsys.2016.00084

- o Duch W, Diercksen GHF (1995) Feature Space Mapping as a universal adaptive system. Computer Physics Comm. 87: 341-371
- o Perlovsky LI. Neural networks and intellect: Using model based concepts. New York: Oxford University Press; 2001.

Same with meta-learning, prototype-based learning, transfer functions, creativity and intuition, and a few other ideas.

- Duch W (2007), Intuition, Insight, Imagination and Creativity. IEEE Computational Intelligence Magazine 2(3), 40-52
- Cognitive informatics: HITs, DREAMs & Perfect Babies. A*STAR Cognitive Science Symposium, Singapore, September 26, 2005

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.

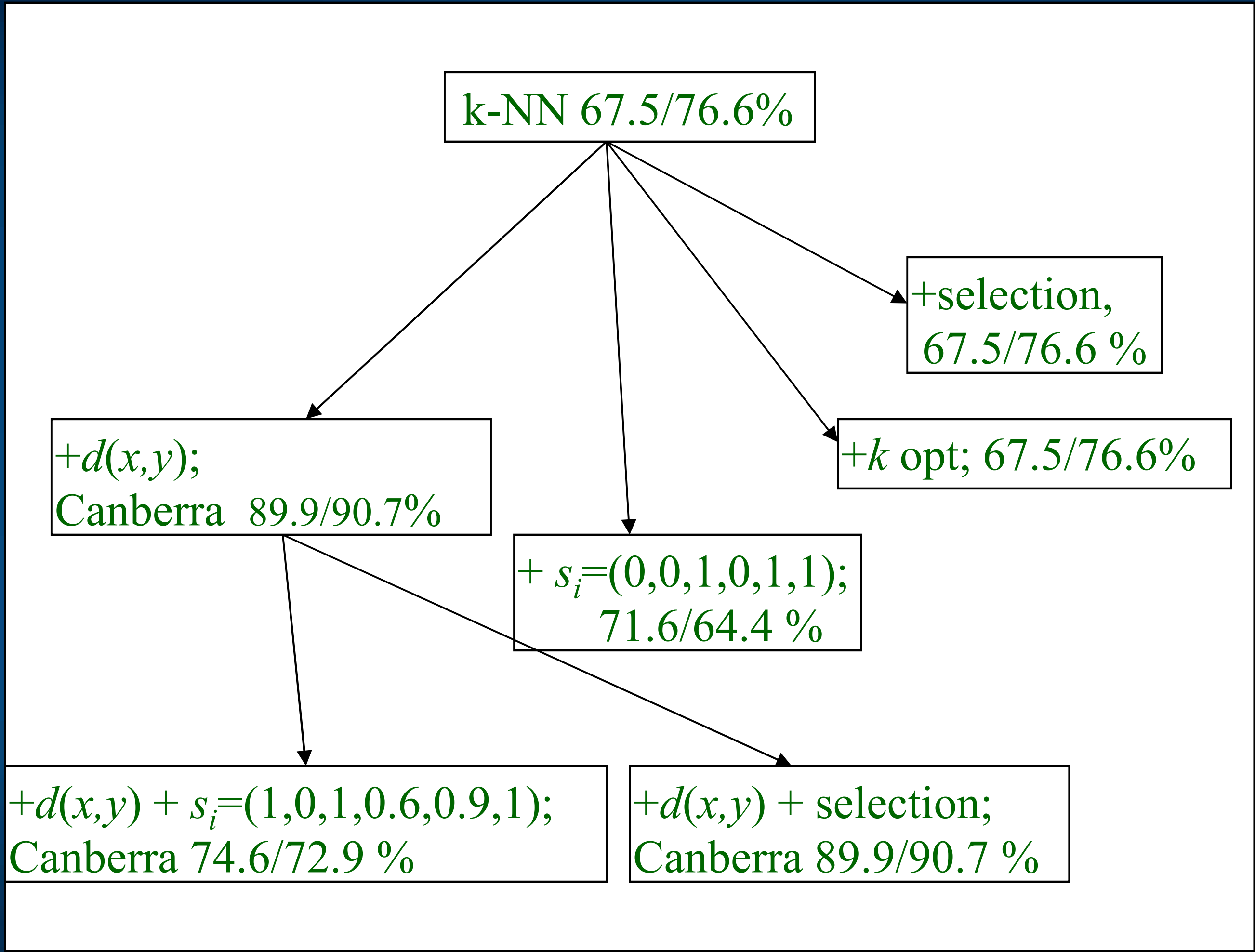
(Dis)similarity:

- more general than feature-based description,
- no need for vector spaces (enables 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, to discover appropriate bias for a given problem. Problem => discover appropriate method!

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

Meta-learning in SBL scheme



Accuracy/complexity measures for model selection.
SBL program with many options developed by Karol Grudziński.


Krzysztof Grąbczewski
Meta-Learning in Decision Tree Induction
Springer
Studies in Computational Intelligence 358
Norbert Jankowski
Włodzisław Duch
Krzysztof Grąbczewski (Eds.)
Meta-Learning in Computational Intelligence
Springer
Studies in Computational Intelligence 63
Włodzisław Duch
Jacek Mańdziuk (Eds.)
Challenges for Computational Intelligence
Springer

Prototypes for images

Stable and transparent interpretation, based on similarity.

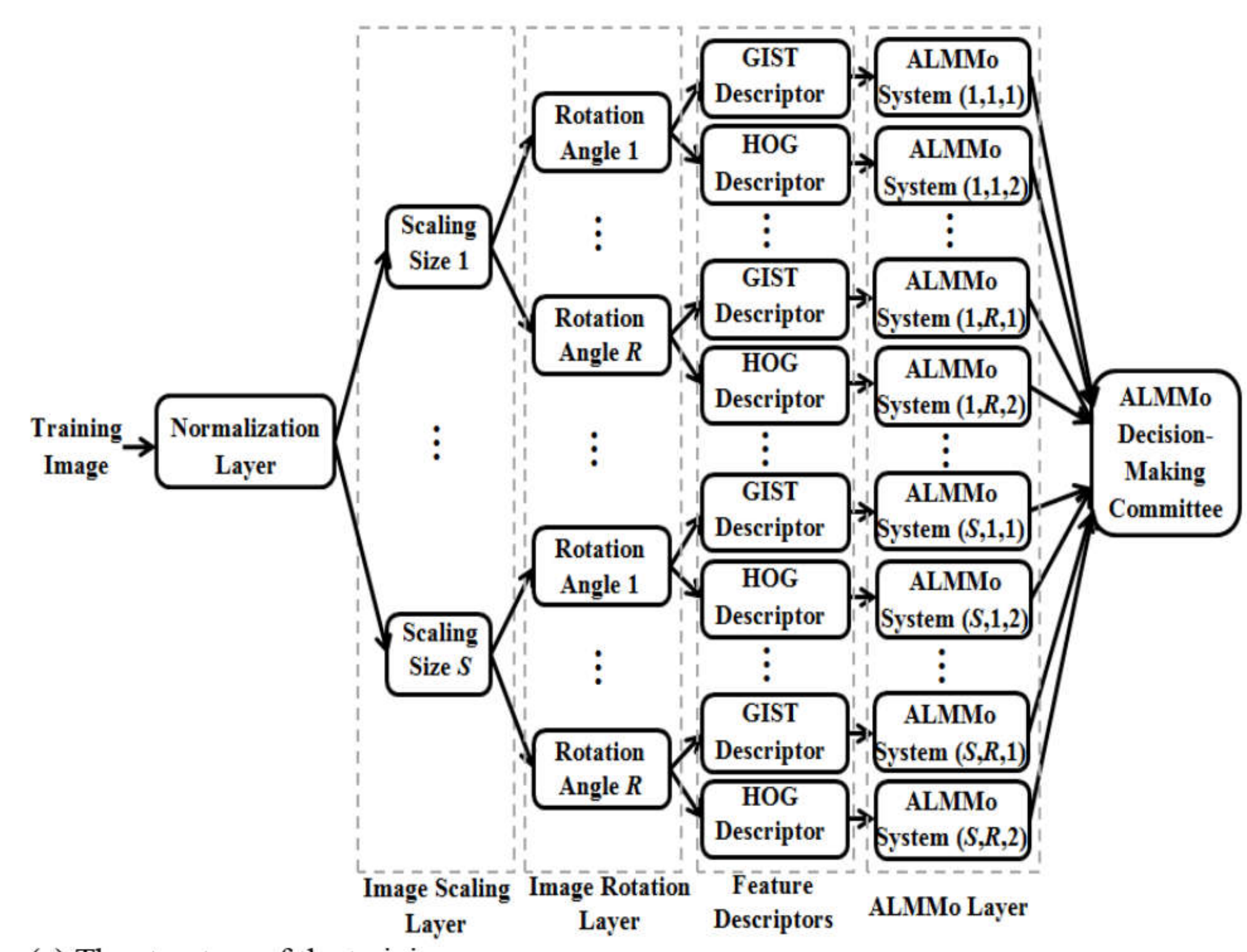
Lazy learning.

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

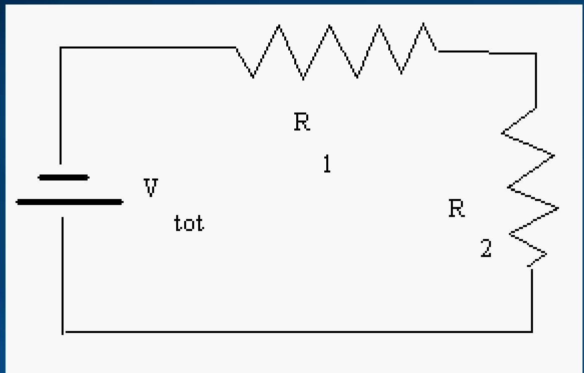
~ Pandemonium architecture, Selfridge 1959!

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

CYBCONF 2017



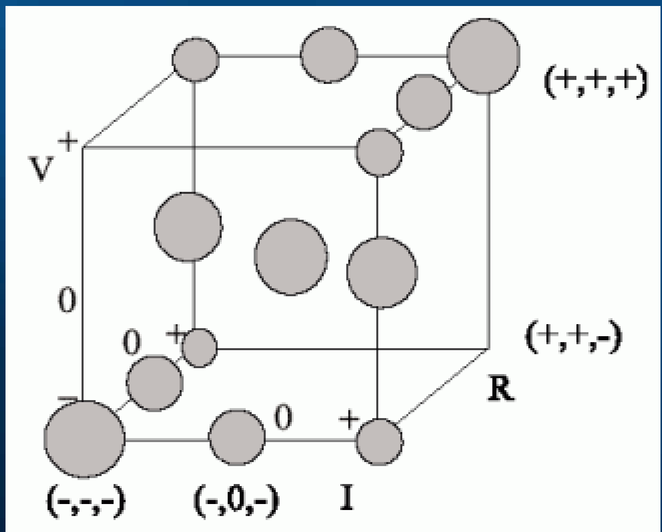
P-rules and intuitive thinking



Question in qualitative physics (PDP book):
if R_2 increases, R_1 and V_t are constant, what will happen with current and V_1, V_2 ?

Learning from partial observations:

Ohm's law $V=I\times R$; Kirhoff's $V=V_1+V_2$.



Geometric representation of qualitative facts:

+ increasing, 0 constant, - decreasing.

True (I_-,V_-,R_0), (I_+,V_+,R_0), false (I_+,V_-,R_0).

5 laws: 3 Ohm's 2 Kirhoff's laws.

All laws $A=B+C$, $A=B\times C$, $A^{-1}=B^{-1}+C^{-1}$, have identical geometric interpretation!

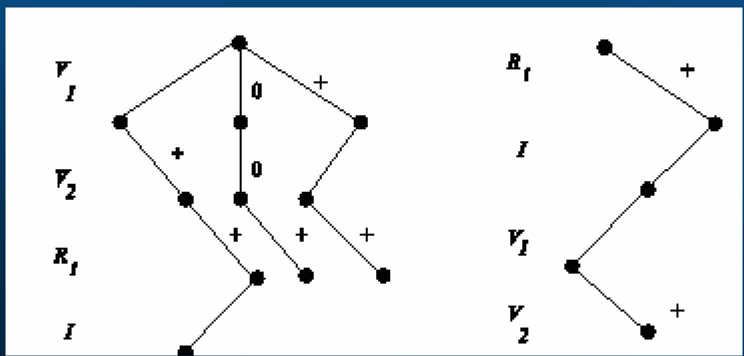
13 true, 14 false facts; simple P-space, but complex neurodynamics.

Intuitive reasoning

5 laws are simultaneously fulfilled, all have the same representation:

$$F(V_t, R, I, V_1, V_2, R_1, R_2) = \prod_{i=1}^{5} F_i(A_i, B_i, C_i)$$

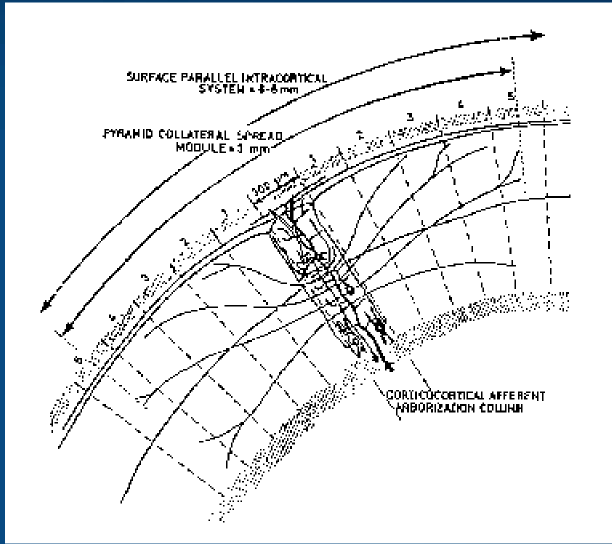
Question: If R_2=+, R_1=0 and V =0, what can be said about I, V_1, V_2 ?
Find missing value giving $F(V{=}0, R, I, V_1, V_2, R_1{=}0, R_2{=}+) > 0$
Assume that one of the variable takes value X = +, is it possible?
Not if $F(V{=}0, R, I, V_1, V_2, R_1{=}0, R_2{=}+) = 0$, i.e. one law is not fulfilled.
If nothing is known 111 consistent combinations out of 2187 (5%) exist.



Intuitive reasoning, without manipulation of symbols.
Heuristics: select variable giving unique answer, like R_t.
Soft constraints or semi-quantitative => small $|F(X)|$ values.

Biological inspirations

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



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

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

Simplifications 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!
Used in MLP2LN architecture for extraction of logical rules from data.

2) Single hidden layer constructive network based on random projections.

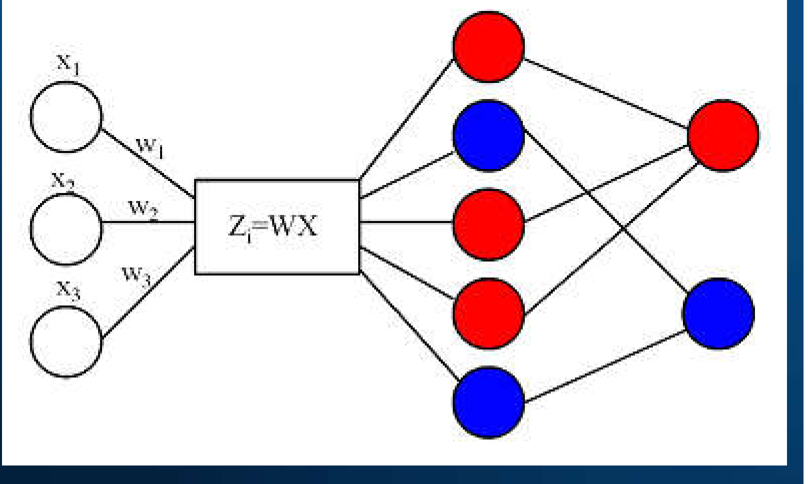
aRPM

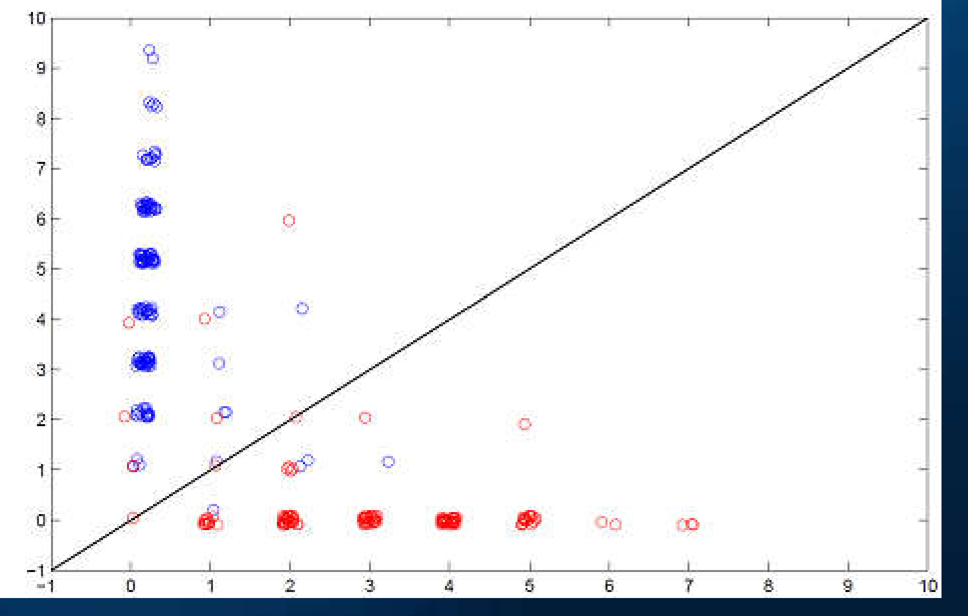
aRMP, Almost Random Projection Machine (with Hebbian learning):

generate random combinations of inputs (line projection) $z(X)=W \cdot X$,

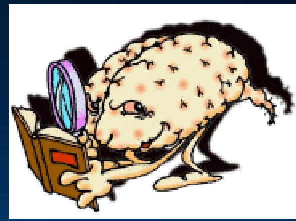
find and isolate pure cluster $h(X)=G(z(X))$; localized kernel on projections, estimate relevance of $h(X)$, ex. $MI(h(X),C)$,
leave only good nodes and continue until each vector activates minimum k hidden nodes.

Count how many nodes vote for each class and plot: no LDA needed!
Learning – only output biases.





Goal of learning



If simple topological deformation of decision borders is sufficient linear separation is achieved in high dimensional spaces, “flattening” non-linear decision borders; this is frequently the case in pattern recognition problems. RBF/MLP networks with one hidden layer solve the problem.

For complex logic this is not sufficient; networks with localized functions need exponentially large number of nodes.

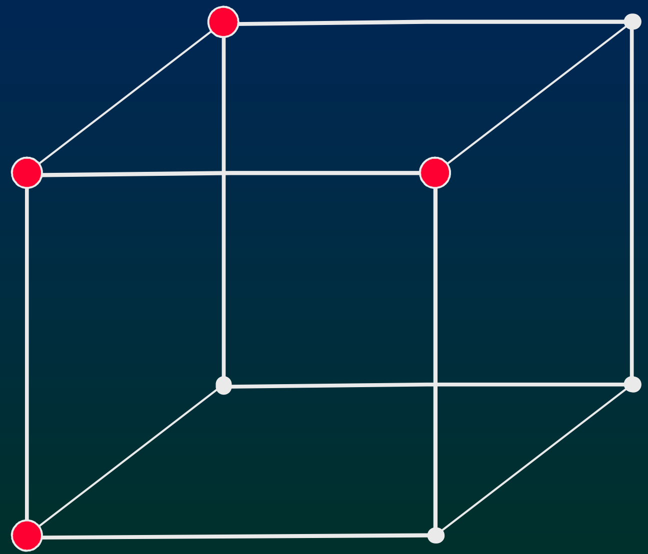
Such situations arise in AI reasoning problems, real perception, object recognition, text analysis, bioinformatics ...

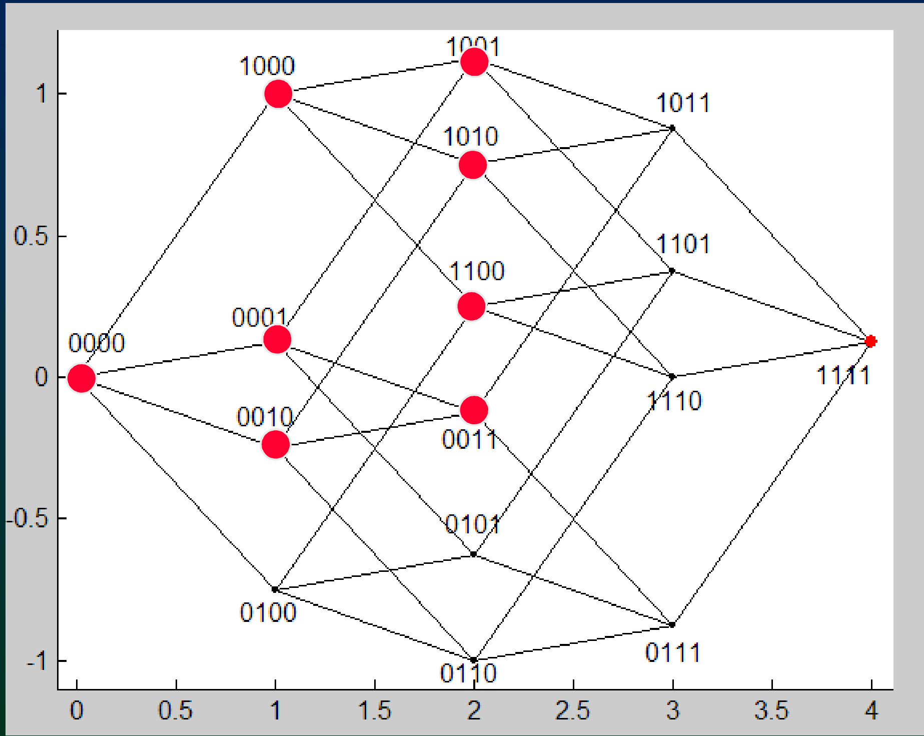
Linear separation is too difficult, set an easier goal.
Linear separation: projection on 2 half-lines in the kernel space:
line $y=WX$, with $y<0$ for class – and $y>0$ for class +.

Simplest extension: **separation into k-intervals, or k-separability**.
For parity: find direction W with minimum # of intervals, $y=W \cdot X$

What can be learned?

Linearly separable or almost separable problems are relatively simple – deform planes or add dimensions to make data separable.



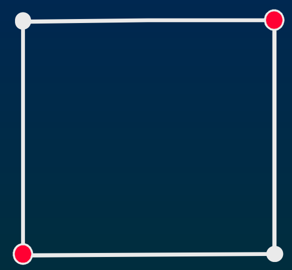


How to define “slightly non-separable”, or relatively easy to learn?
Now we have only separable problems and one vast realm of the rest.

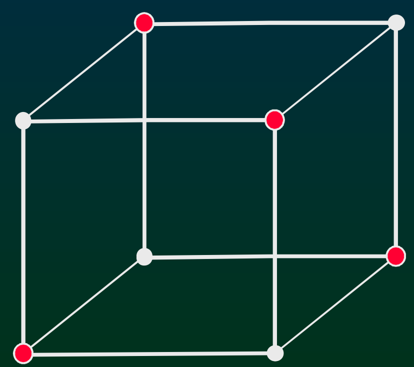
Neurons learning complex logic

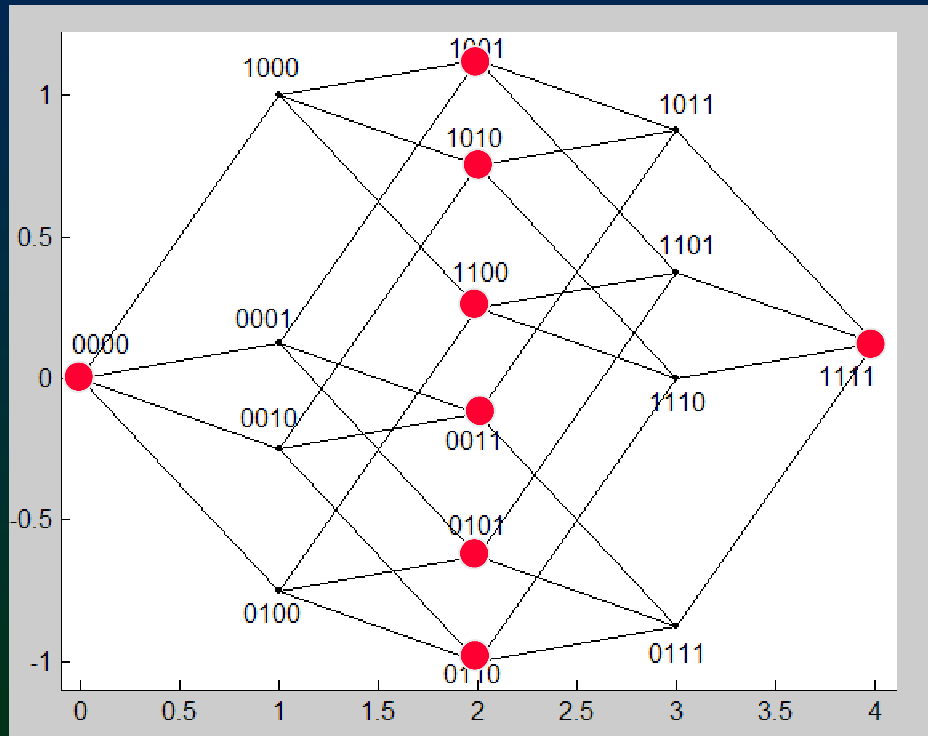
Boole'an functions are difficult to learn, n bits but 2^n nodes => combinatorial complexity; similarity is not useful, for parity all neighbors are from the wrong class. MLP networks have difficulty to learn functions that are highly non-separable.

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.

Boolean functions

n=2, 16 functions, 12 separable, 4 not separable.

n=3, 256 f, 104 separable (41%), 152 not separable.

n=4, 64K=65536, only 1880 separable (3%)

n=5, 4G, but << 1% separable ... bad news!

Most bioinformatics or neuroimaging data may require n >100.

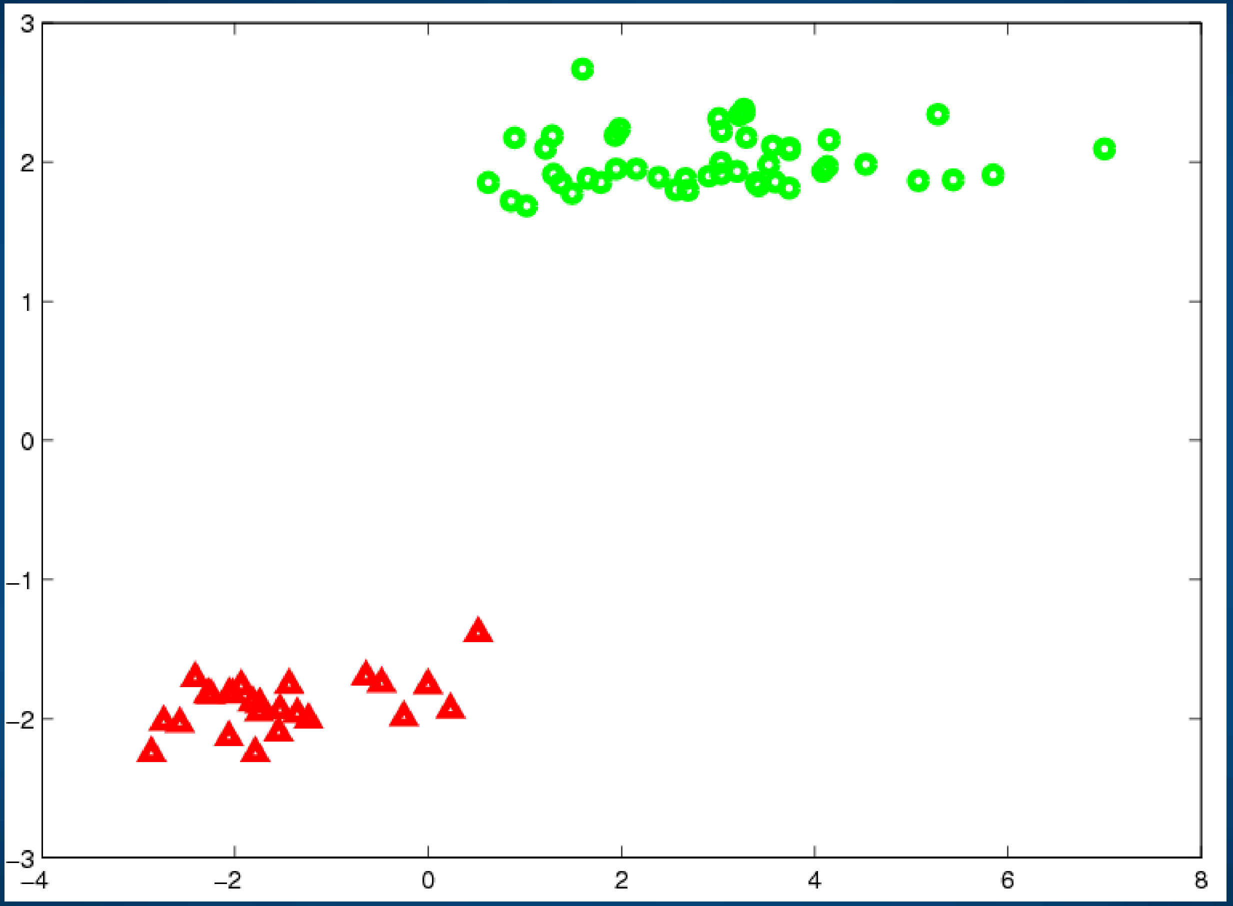
Existing methods may learn some non-separable functions,
but most functions cannot be learned !

Example: *n*-bit parity problem; many papers in top journals.
No off-the-shelf systems are able to solve such problems.

For all parity problems SVM is below base rate!
Such problems are solved only by special neural architectures or special classifiers – if the type of function is known.

But parity is still trivial ... solved by $y = \cos\left(\omega \sum_{i=1}^{n} b_i\right)$

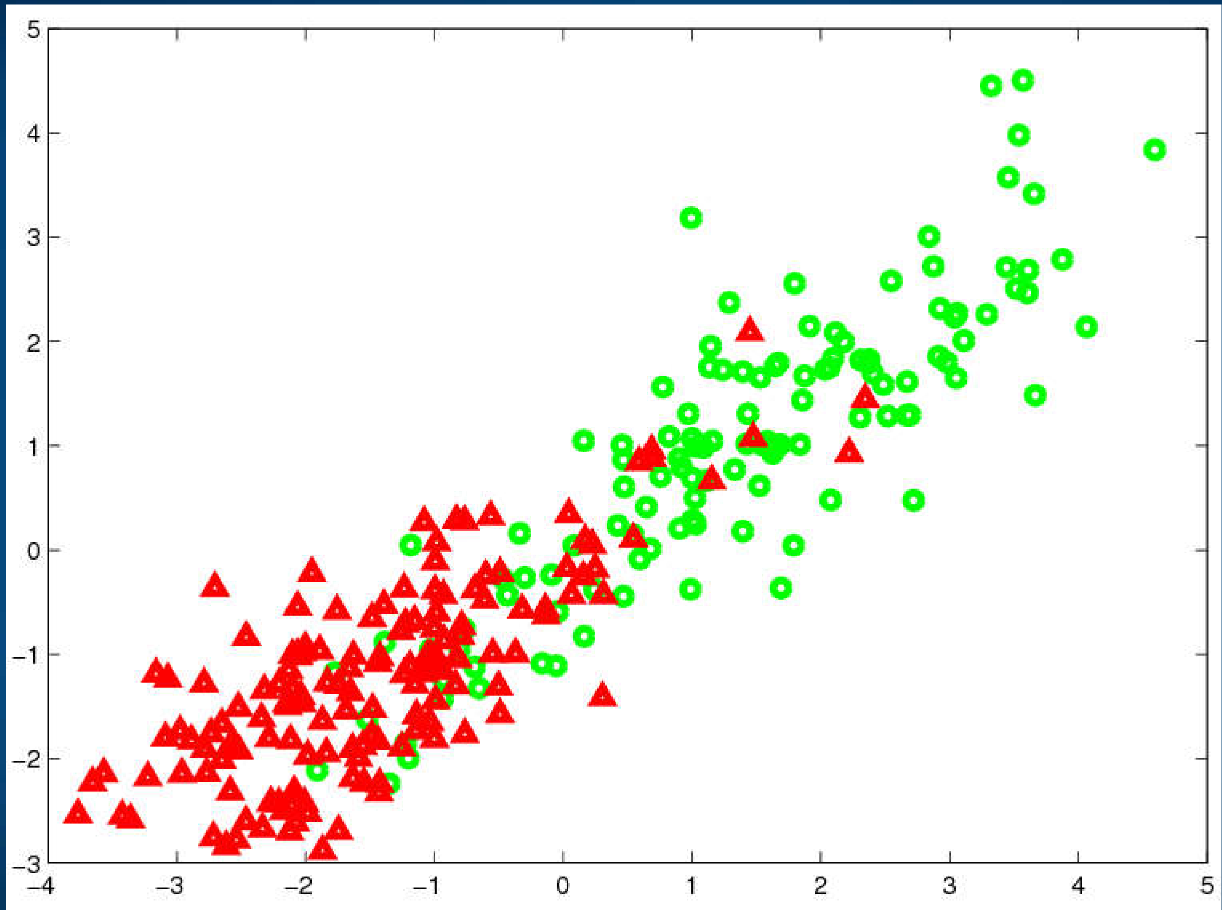
Linear separability



SVM visualization of Leukemia microarray data,

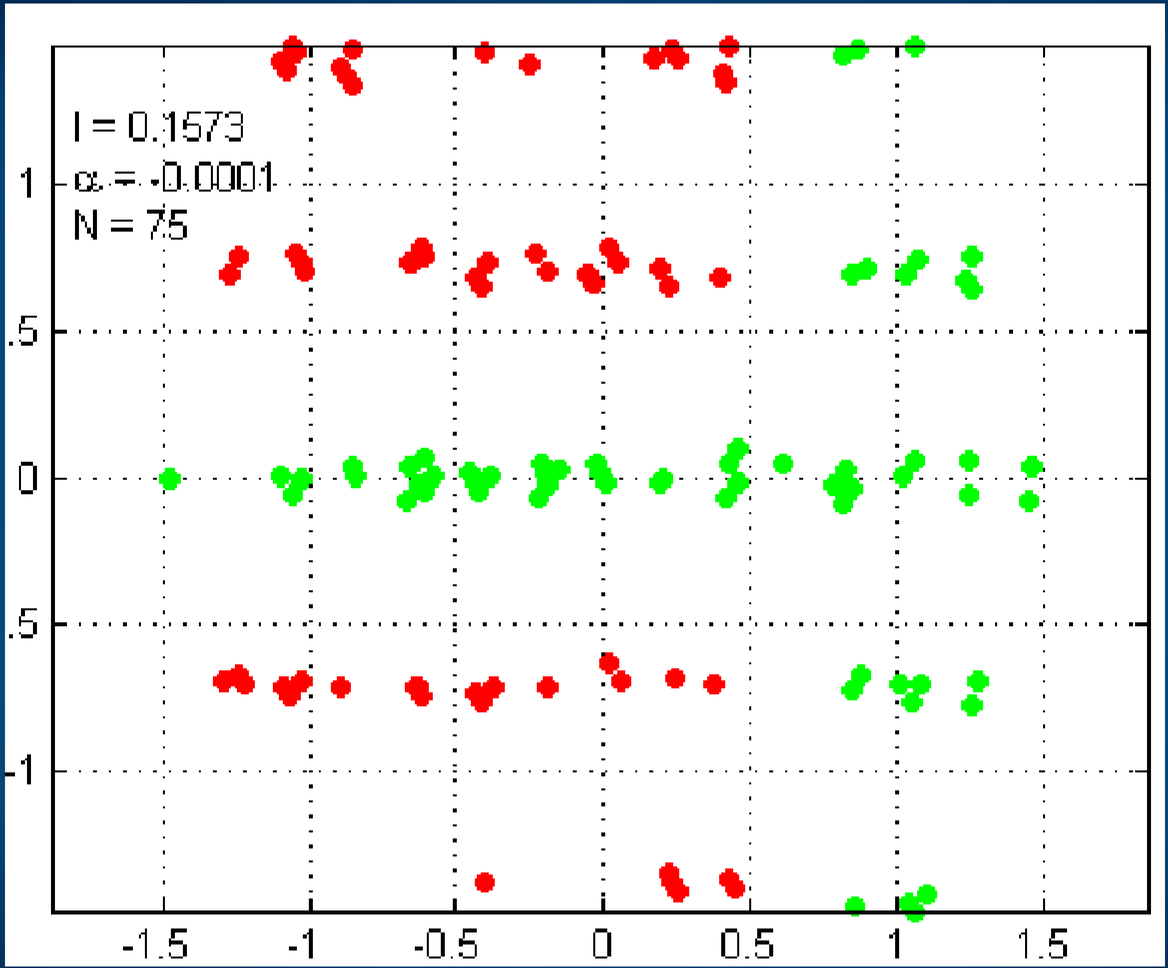
Horizontal axis x=WX, vertical - orthogonal projection.

Approximate separability



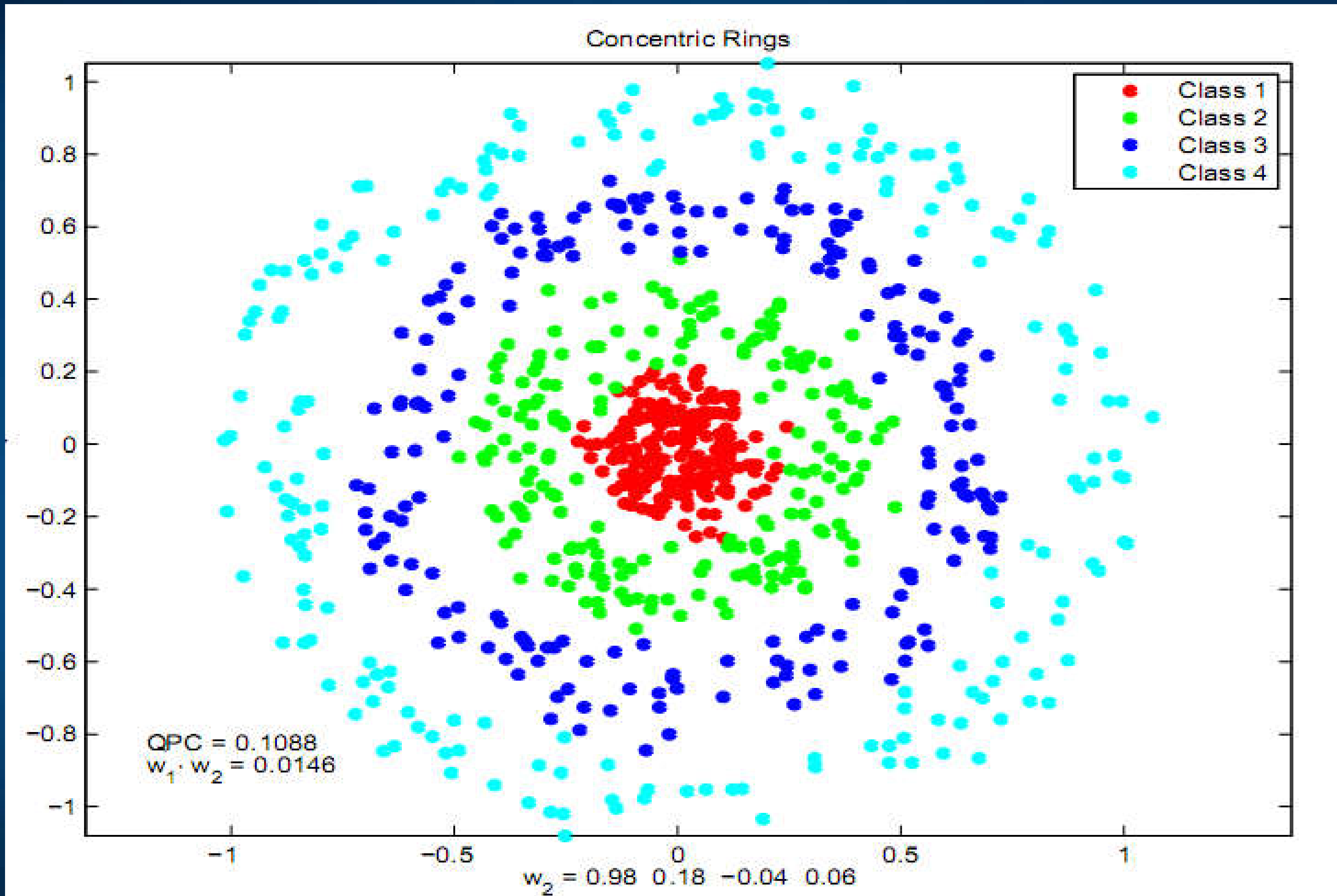
SVM visualization of Heart dataset, overlapping clusters, information in the data is insufficient for perfect classification.

Rules



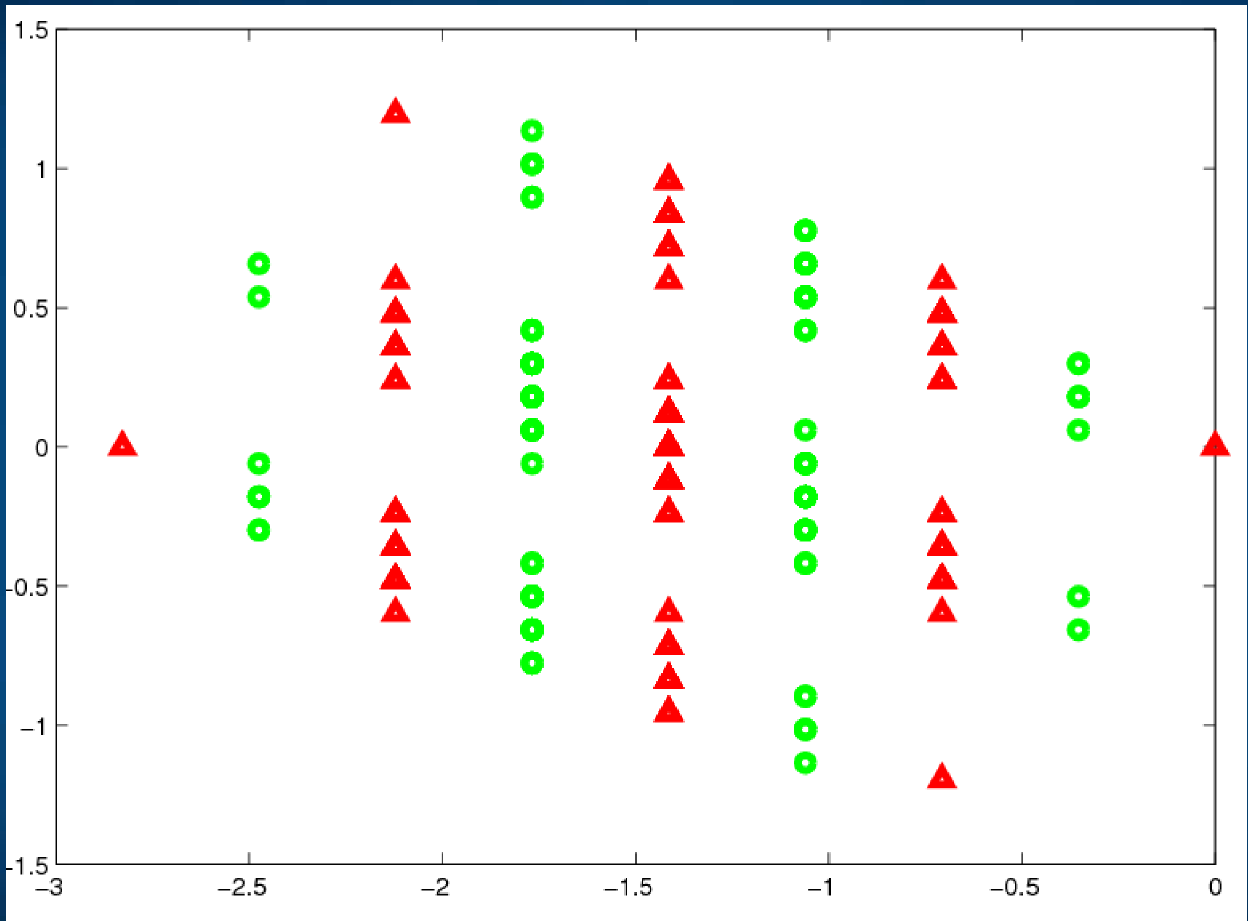
QPC visualization of Monks dataset with simple logical structure, two logical rules are needed, or combination of two projections.

Complex distribution



QPC visualization of concentric rings in 2D with strong noise in remaining 2D; transform: nearest neighbor solutions, combinations of ellipsoidal densities.

Interval transformation



8-bit parity data: 9-separability is much easier to achieve than full linear separability; almost impossible to train MLP on such data.

k-sep learning

Try to find lowest k with good solution (simple methods frequently work):

- Assume k=2 (linear separability), try to find a good solution;
  MSE error criterion
  $$E(\mathbf{W},\theta)=\sum_{\mathbf{X}}\left(y(\mathbf{X};\mathbf{W})-C(\mathbf{X})\right)^2$$
- if k=2 is not sufficient, try k=3; two possibilities are C_+,C_-,C_+ and C_-, C_+, C_- this requires only one interval for the middle class;
- if k<4 is not sufficient, try k=4; two possibilities are C_+, C_-, C_+, C_- and C_-, C_+, C_-, C_+ this requires one closed and one open interval.

Network solution ⇔ to minimization of specific cost function.

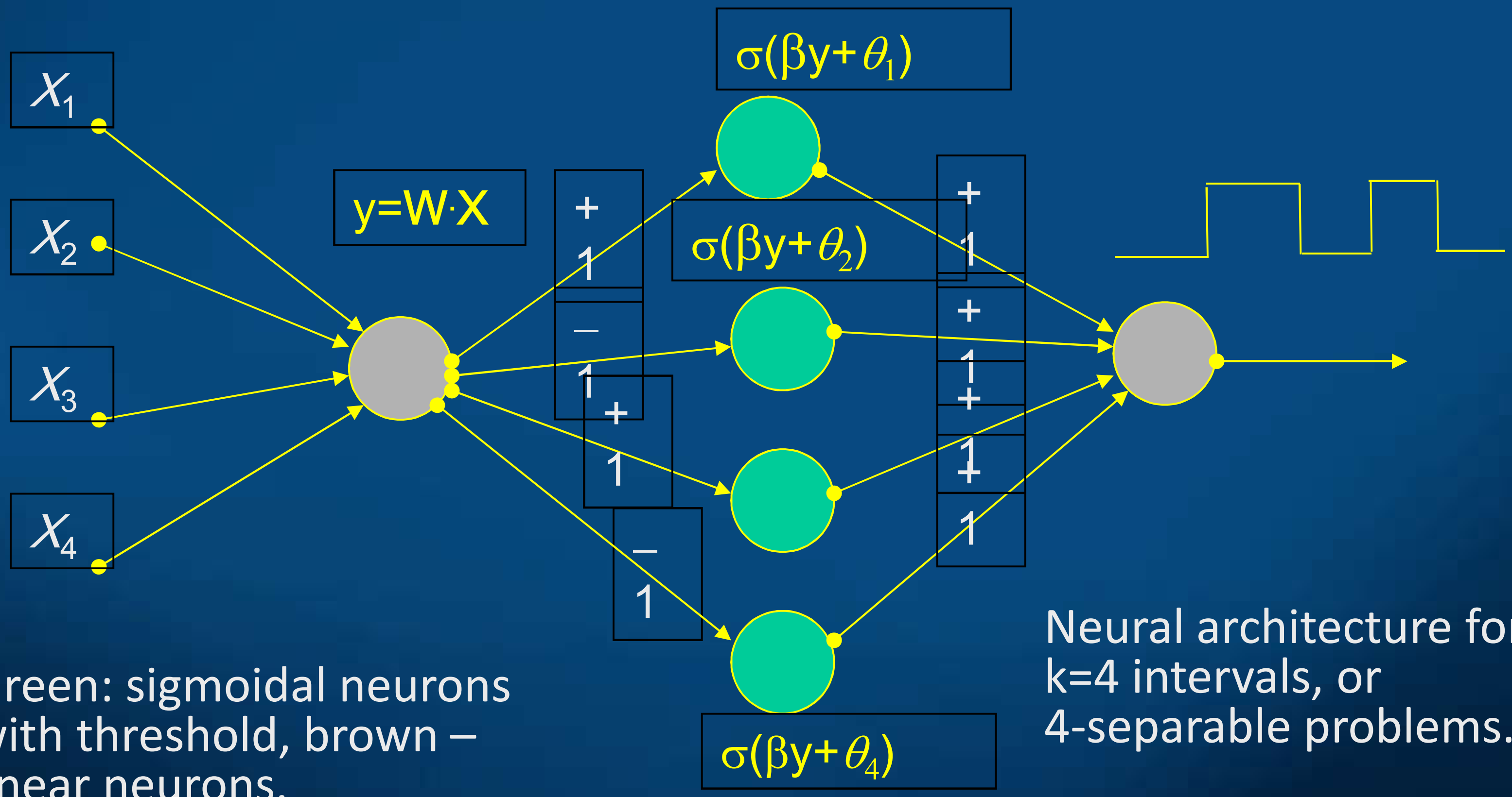
$$E(\mathbf{W},\lambda_1,\lambda_2)=\sum_{\mathbf{X}}\left(y(\mathbf{X};\mathbf{W})-C(\mathbf{X})\right)^2+\lambda_1\sum_{\mathbf{X}}\left(1-C(\mathbf{X})\right)y(\mathbf{X};\mathbf{W})$$
$$-\lambda_2\sum_{\mathbf{X}}C(\mathbf{X})y(\mathbf{X};\mathbf{W})$$

First term = MSE, second penalty for “impure” clusters, third term = reward for the large clusters.

k-separability

How to learn complex Boolean functions?

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

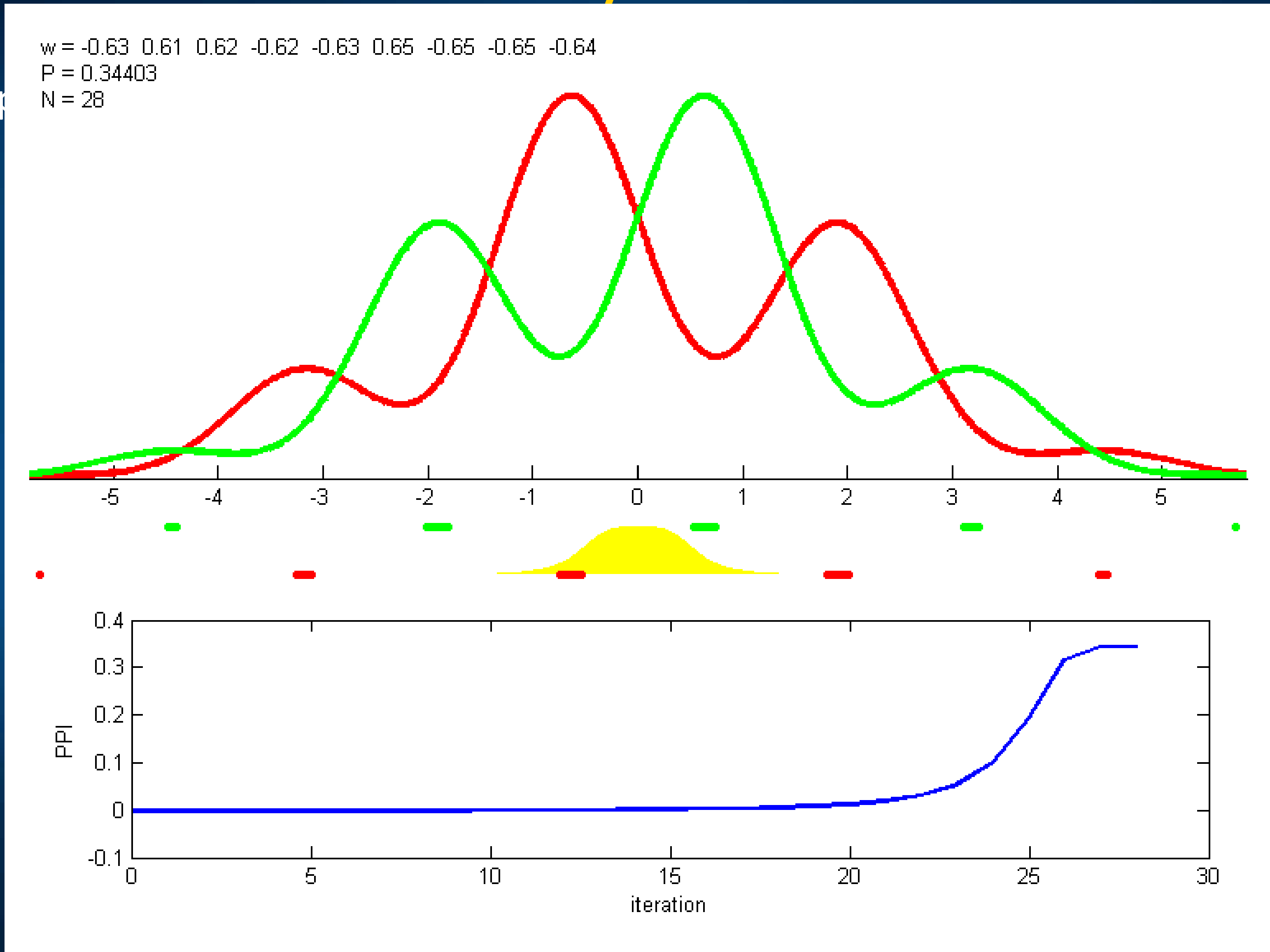


Green: sigmoidal neurons with threshold, brown – linear neurons.

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

Parity n=9

Simp



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.

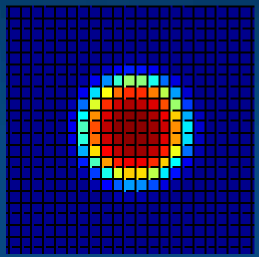
Compose transformations (neural layers), for example:

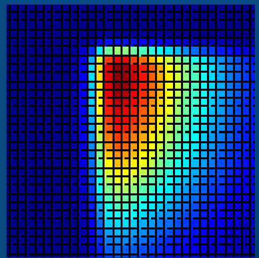
- Matching pursuit network for signal decomposition, QPC index.
- PCA network, with each node computing principal component.
- LDA nets, each node computes LDA direction (including FDA).
- ICA network, nodes computing independent components.
- KL, or Kullback-Leibler network with orthogonal or non-orthogonal 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.

Heterogeneous systems

Next step: use components from different models.
Problems requiring different scales (multiresolution).





2-class problems, two situations:

C_1 inside the sphere, C_2 outside.

MLP: at least N+1 hyperplanes, $O(N^2)$ parameters.

RBF: 1 Gaussian, O(N) parameters.

C_1 in the corner defined by (1,1 ... 1) hyperplane, C_2 outside.

MLP: 1 hyperplane, O(N) parameters.

RBF: many Gaussians, $O(N^2)$ parameters, poor approx.

Combination: needs both hyperplane and hypersphere!

Logical rule: IF $x_1>0$ & $x_2>0$ THEN C_1 Else C_2
is not represented properly neither by MLP nor RBF!

Different types of functions in one model, first step beyond inspirations from single neurons => heterogeneous models are inspired by neural minicolumns, more complex information processing.

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 is equivalent to 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.

Unified theories of brain functions

Physics: principle of least action => laws of mechanics: Newtonian, Lagrangian, Hamiltonian, and general relativity (Hilbert) equations of motion.

Artificial Intelligence: search in problem spaces (Newell, Simon).

Cognitive systems: minimization of surprise or prediction errors, active inference, self-organization to minimize surprise (sensory), ensure homeostasis, select a limited number of internal action states.

Mathematical formulation is based on variational Bayesian methods.

Behavior = F(Brain State, Sensations).

Brain State depends on stimuli *s* and latent internal parameters υ of the model (agent) *m* while surprise is measured by entropy:

$$\mathcal{H} = \int_0^T dt \mathcal{L}(m, s, t) = -\int \ln p\Big(s\big(t\big) \,|\, m\Big(\vartheta\big(t\big)\Big)\Big) d\vartheta$$

$$= -\int p(\vartheta \,|\, m) \ln p(\vartheta \,|\, m) d\vartheta$$

Free energy

We do not know the latent parameters υ of the model, but may estimate free energy to find the upper bound:

$$\mathcal{F}(t) \geq \mathcal{L}(t)$$

Free energy principle (Friston: an information theory measure *F* that bounds from above the surprise on sampling some data, given a generative model.

Maximum a posteriori estimation (MAP estimation) <= EM (expectation-maximization) algorithm extension from single most probable value of hidden parameters to fully Bayesian estimation of an approximation to the entire posterior distribution $p(\upsilon|s)$ of the parameters and latent variables.

Adaptive systems (animals, brains) resist a natural tendency to disorder. Perception optimizes predictions. Action minimizes prediction errors.

The free-energy principle (FEP): any self-organizing system that is at equilibrium with its environment must minimize its free energy.

Lester Ingber, Generic mesoscopic neural networks based on statistical mechanics of neocortical interactions

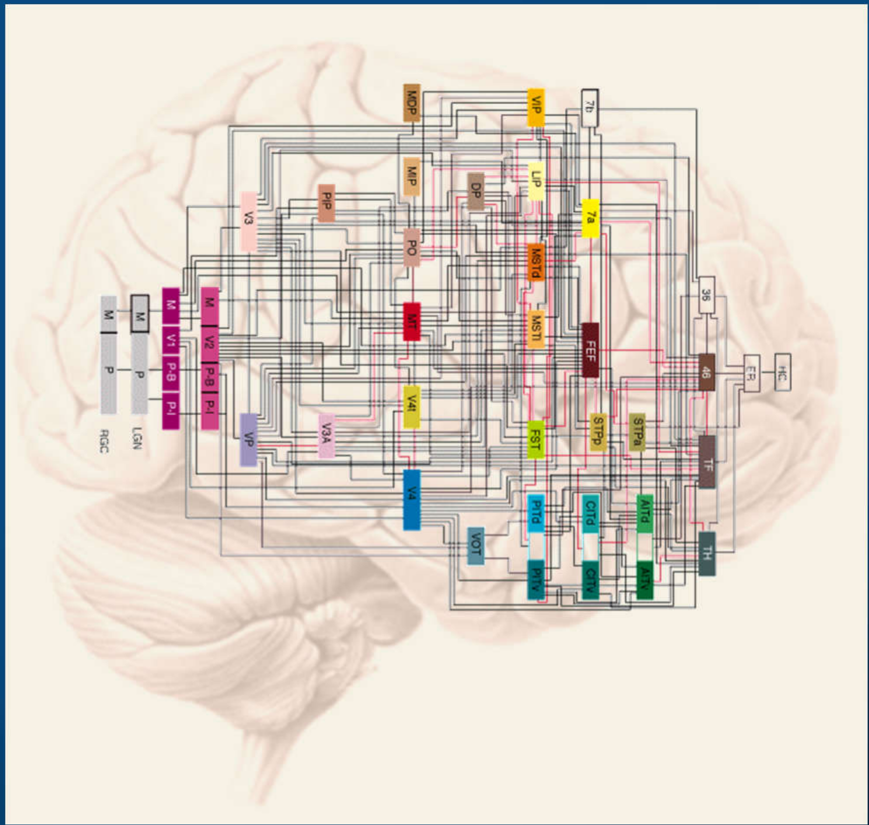
Free energy

The free-energy principle (FEP): any self-organizing system that is at equilibrium with its environment must minimize its free energy – predict = active inference.

Constraints for brain architecture: EST, Evolutionary Systems Theory (Badcock, 2012).

Combination of FEP with EST is a candidate for standard theory of cognitive systems.

Still only a sketch of a theory. Can FEP be derived from computational neuroscience?



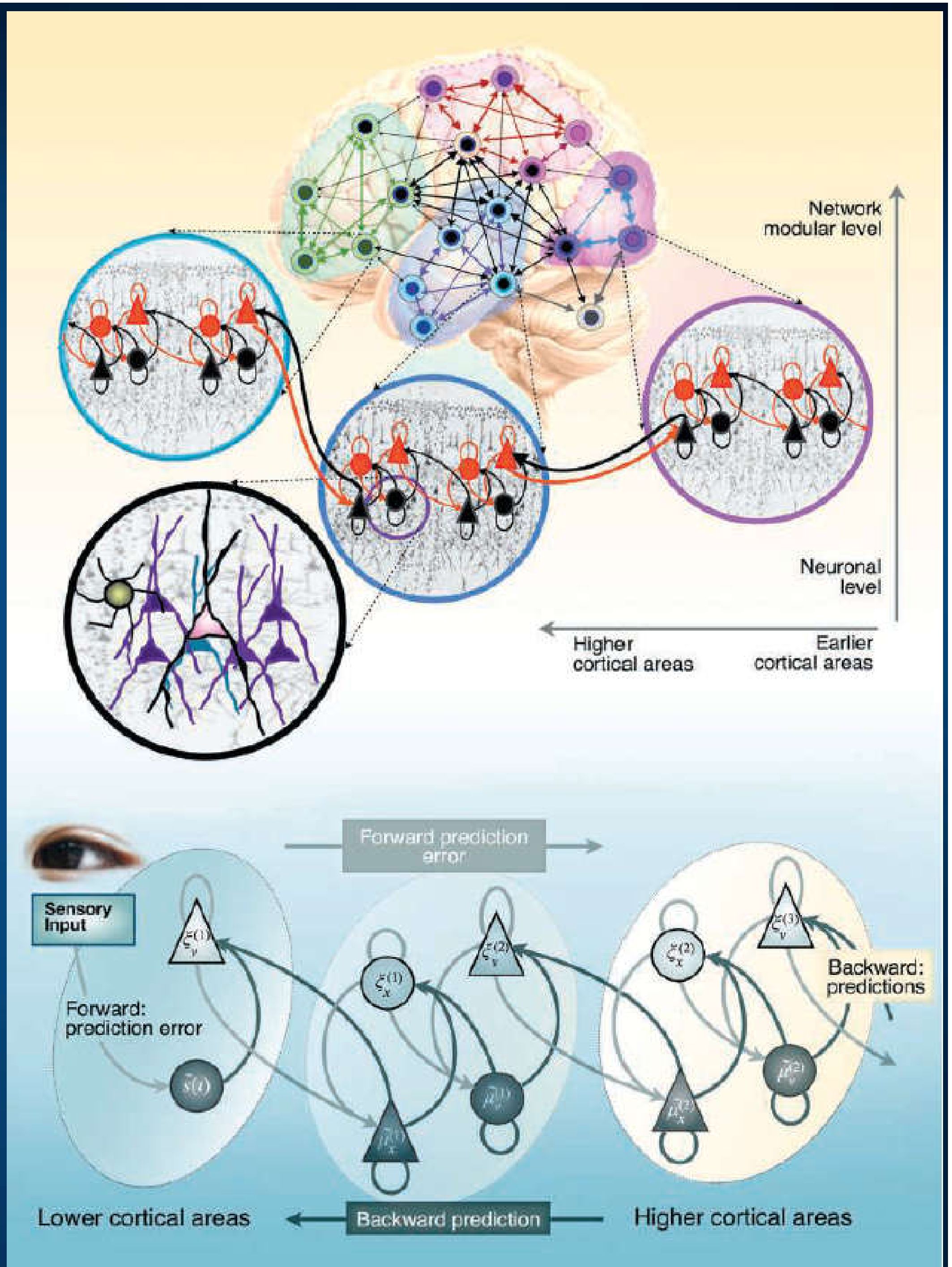
Hierarchical brain structure

Back of the brain – forward prediction error.

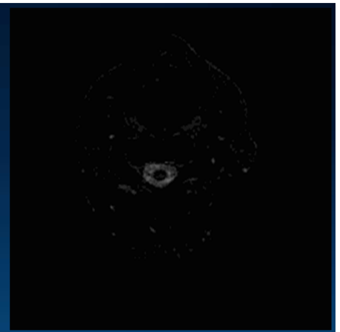
Front of the brain – backward predictions.

Park H-J, Friston K.

Structural and functional brain networks: from connections to cognition. Science. 2013;342



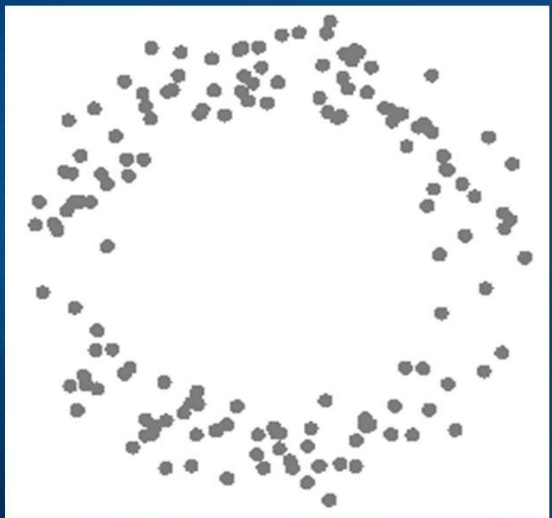
Conclusions I

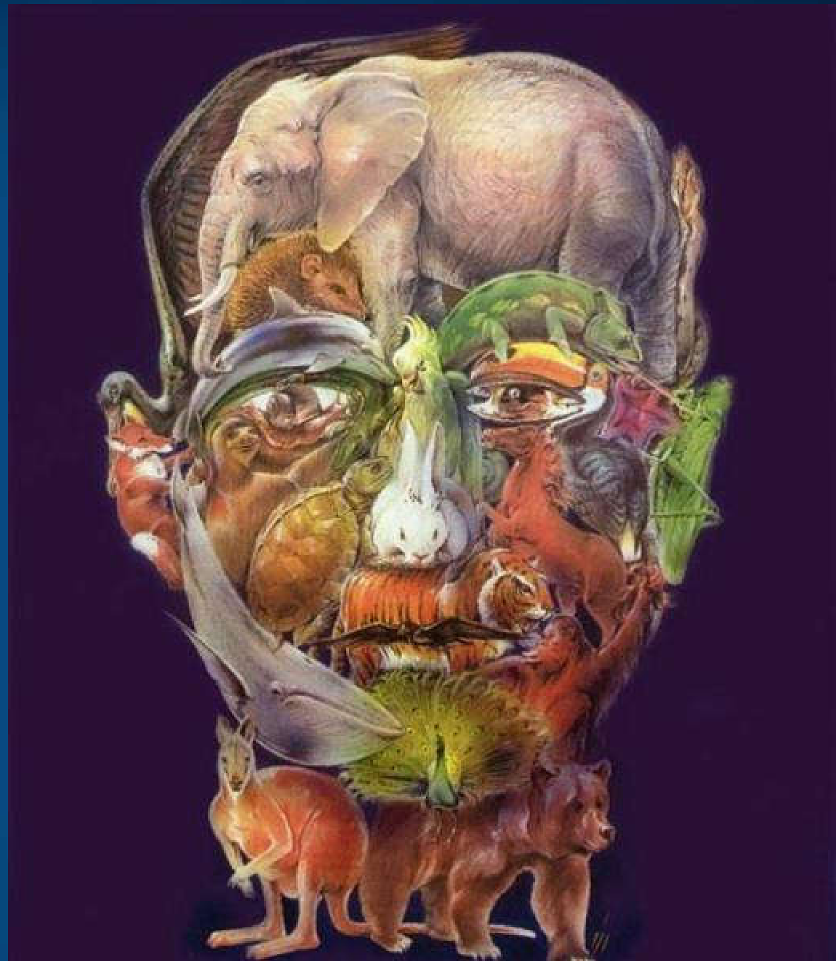


- Cognitive architectures and interesting ML inspirations follow from thinking about the brain and neuron functions.
- Goal of learning should be redefined.
- Simple projections may work as well as backprop MLPs.
- Similarity-based framework, transformation based learning and support feature machines should be used in meta-learning schemes.
- P-rules solve many problems, are more general than F-rules.
- Intuitive solving of complex problems is possible with simple networks.
- Practical methods need to be derived from general principles like FEP.
- With new global AI initiatives everything will be possible!

Next:
Brain networks.
Space for neurodynamics.

Thank for synchronization of your neurons





Google: W. Duch

=> talks, papers, lectures, Flipboard …