Informatyka neurokognitywna. Stan obecny, zastosowania, perspektywy.

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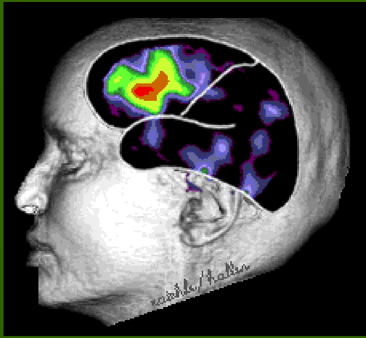
Google: Wlodzislaw Duch

Seminarium Pol. Wrocławska, RD ITiT, Wrocław 10/02/2021

CD DAMSI



Uniwersyteckie Centrum Doskonałości (2020) w ramach IDUB "Dynamika, analiza matematyczna i sztuczna inteligencja".

- Dynamika i teoria ergodyczna.
- Informatyka – języki formalne i współbieżność.
- Neuroinformatyka i sztuczna inteligencja.
- Stany splątane i dynamika otwartych układów kwantowych.

Neuroinformatyka jest kombinacją dwóch ważnych dyscyplin na froncie nauki: badań nad mózgiem i sztucznej inteligencji. Wykorzystując metody uczenia maszynowego i przetwarzania sygnałów, rozwijane są nowe teorie i algorytmy analizy sygnałów mózgu, hipotezy weryfikowane za pomocą eksperymentów.

Nasza grupa: zrozumienie procesów w mózgu i inspiracje dla algorytmów AI.
Komitet Informatyki PAN: Sekcja Nauk Obliczeniowych, Bio- i Neuroinformatyki.

Myślenie i rozwój cywilizacji

To nadzwyczajny moment w historii świata!

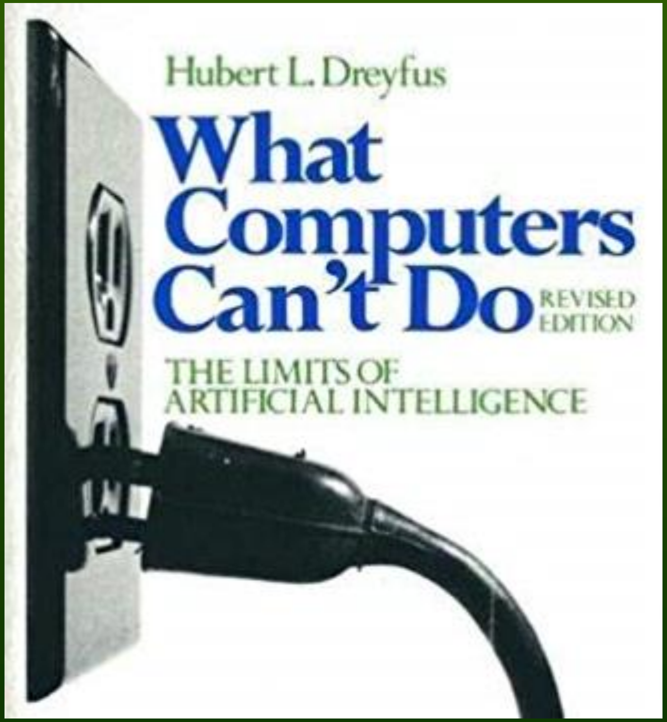
Epoki rozwoju cywilizacji i rozumienia rzeczywistości:

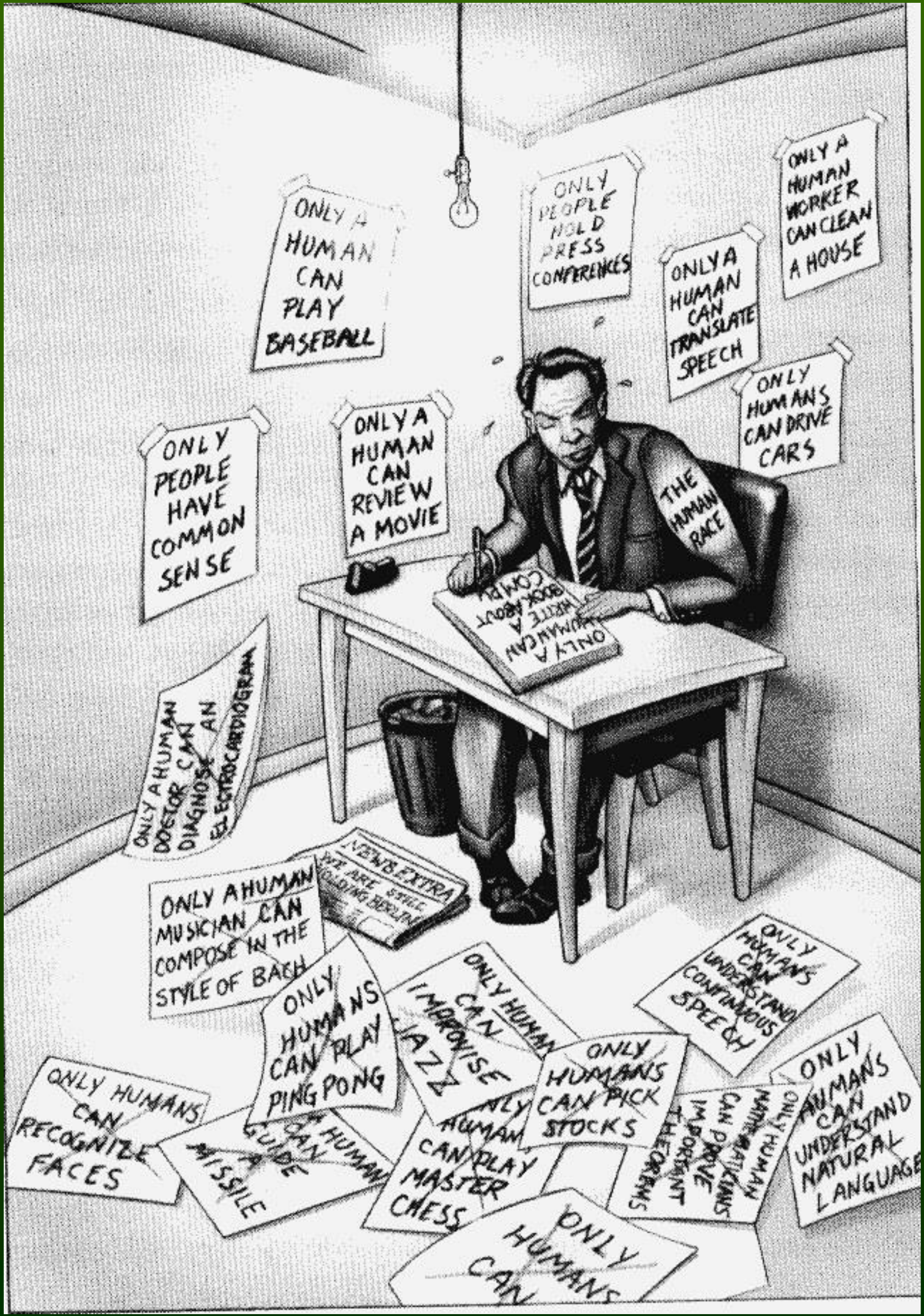
1. Myślenie magiczne, kaprysy bogów, fatalizm.
2. Przyczynowość i empiryczne obserwacje, wiedza opisowa.
3. Teorie i rozumienie mechanizmów, weryfikacja, matematyka i statystyka.
4. Symulacje komputerowe i „nowy rodzaj nauki” Wolframa.
5. Wiedza z danych, gromadzenie i dostęp do wszystkich informacji.
6. Sztuczna inteligencja wspiera ludzkie myślenie.
7. Autonomiczna sztuczna inteligencja.

5 paradygmatów rozwoju nauki wg IBM: empiryczny, teoretyczny, symulacyjny, wiedzy z danych (data driven), oraz przyspieszonych odkryć.

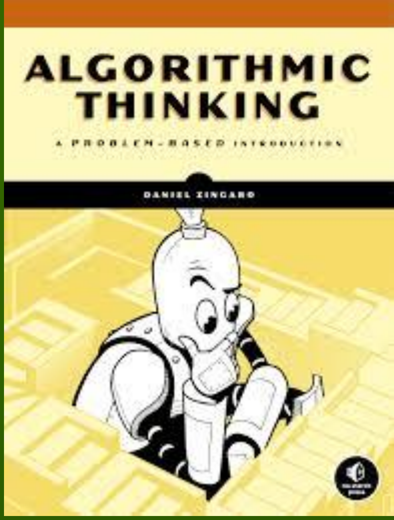
Coraz bardziej złożone modele: IBM Watson, CyC, GPT-3, Google Mixture of Experts (MoE), model z 1 trylionem parametrów …

Inteligencja to tylko to, czego jeszcze nie potrafią sztuczne systemy AI?





AI: definicja informatyka



Sztuczna Inteligencja (Artificial Intelligence, AI) to dział informatyki zajmujący się rozwiązywaniem problemów, dla których nie ma **efektywnych algorytmów.**

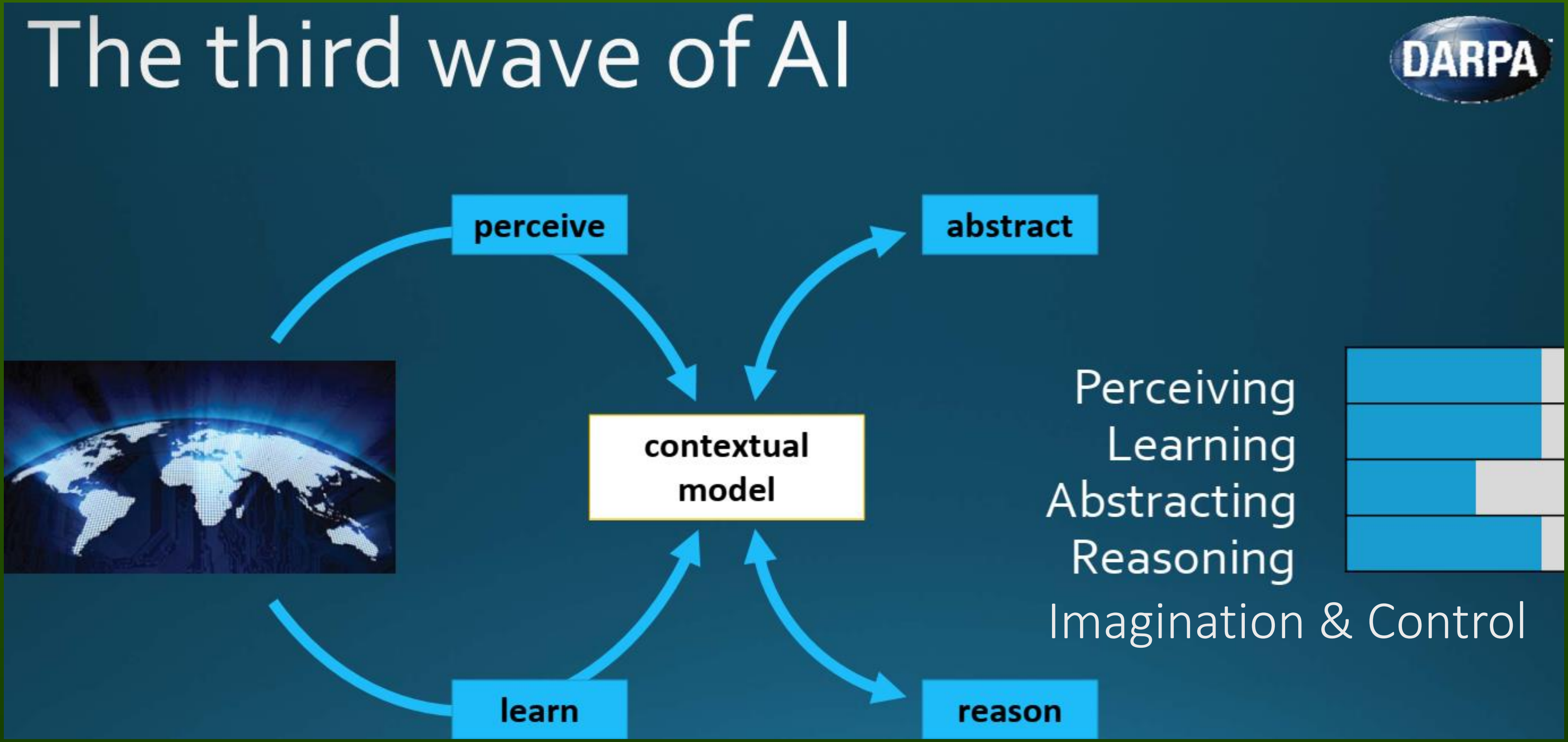
Dawniej: w oparciu o modelowanie wiedzy, przedstawianej w werbalnie opisywany, symboliczny sposób, głównie zajmująca się rozumowaniem na poziomie koncepcyjnym.

Obecnie (ostatnie dekady): AI jest niemal utożsamiana z uczeniem maszynowym, czyli rozpoznawaniem obrazów, odkrywaniem wiedzy w dużych zbiorach danych, funkcjom realizowanym intuicyjnie.

Najważniejszą techniką stały się wielowarstwowe sieci neuronowe. Technologie neurokognitywne: neuro => cogito.

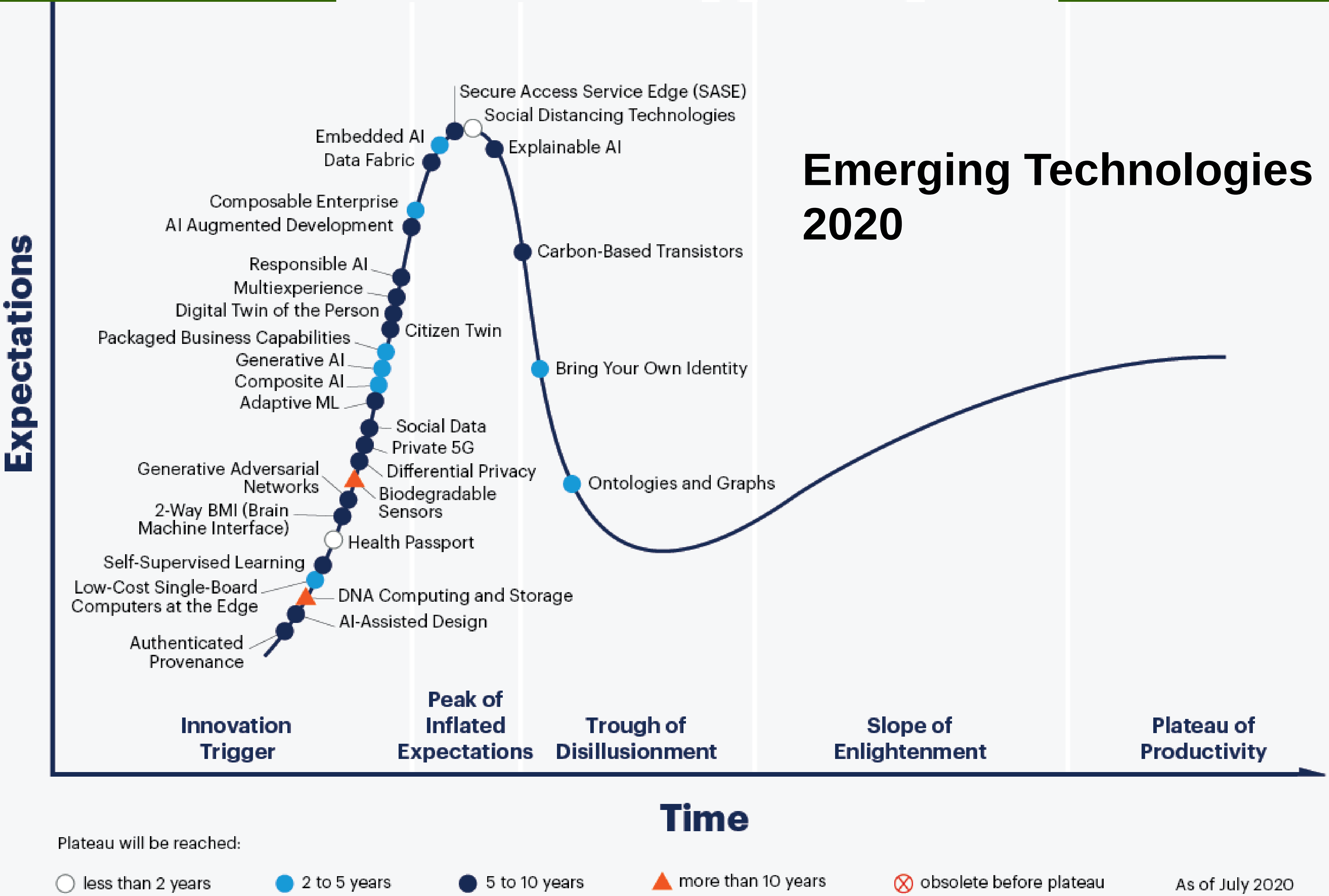
Regulacja AI? To jak regulacja matematyki.

Third wave of AI

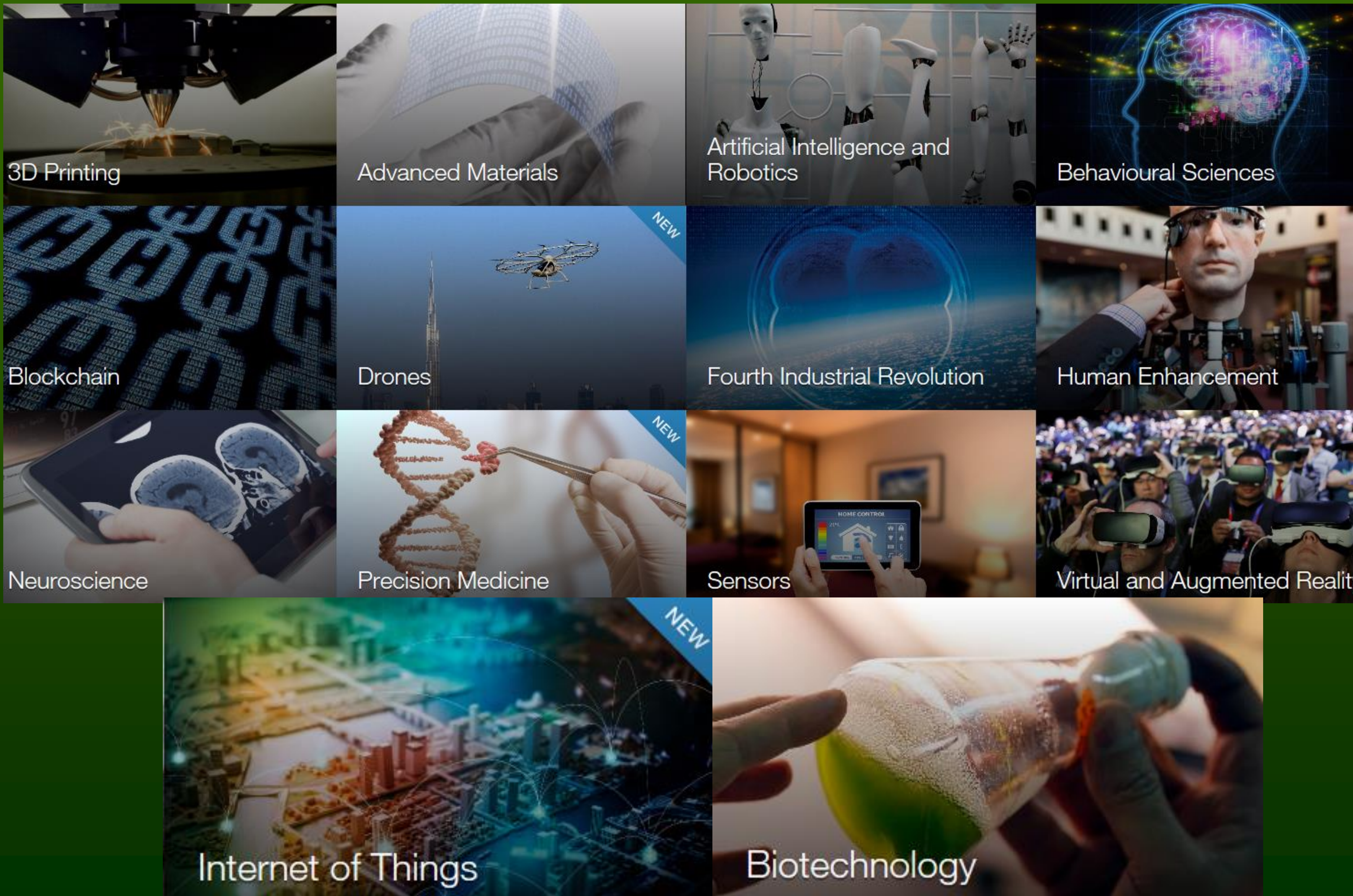


After rule-based (first wave) and statistical approaches (second wave), building causal models of objects and situations is the next step.
GAN, Generative Adversarial Networks, artificial imagination!

Gartner Hype Cycle



WEF: 4th Industrial Revolution driven by AI/neuro



Kogni
Nauki kognitywne

Biohybrydy

Bio

Lab neuro-kognitywne

Nano
Fizyka Kwantowa

Info
Informatyka, inteligencja obliczeniowa/sztuczna, uczenie maszynowe, sieci neuronowe

Neuromorficzna przyszłość

Ściana mieści 1024 chipy TN, czyli 1 mld neuronów i 256 mld synaps, ok. 1/4 mózgu goryla, 1/6 szympansa. Cerebras CS-1 chip ma 1200 mld tranzystorów!

Integracja:

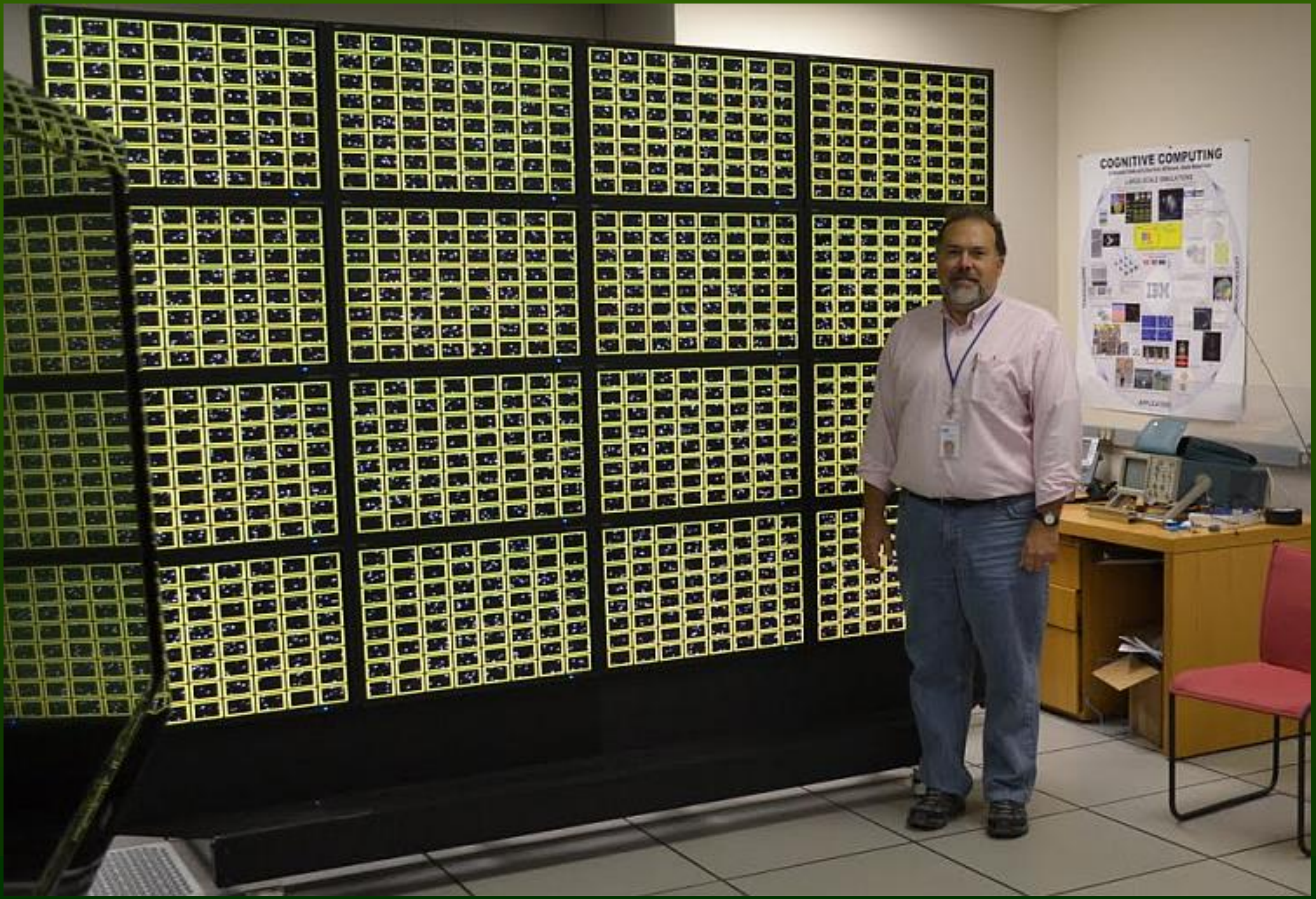
Nano +

Neuro +

Info +

Kogni

Neural accelerators for PC



Nano: hybrydowe chmury

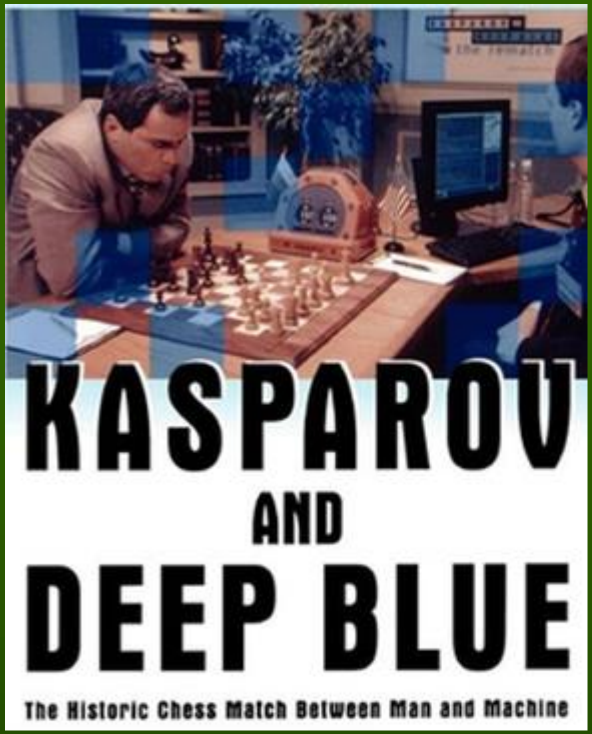
Science is moving beyond dedicated advanced compute systems to make greater use of hybrid cloud: local, public & private, traditional + new ways of computing.

Heterogeneity to support seamless workflows across highly diverse resources including scientific instruments, sensors, physical devices, and entire labs and research organizations.
Distributed farms, data flow machines, FPGA, quantum computing, neuromorphic computing, high-end network …

European Open Science Cloud (2018) Helix Nebula Science Cloud run by CERN.
U.S. Department of Energy's Research Hybrid Cloud at Oak Ridge National Lab

COVID-19 High Performance Computing, huge consortium donating free computer time: 50.000 GPUs, 6.8 mln cores, 600 Pflops, 100 projects.
43 consortium members: USA national labs, NASA, NSF, NIH, Amazon, Google, Dell, HP, Intel, Microsoft, Nvidia, RIKEN …

Info/neuro+nano: AI/DNN



1997 – szachy, Deep Blue wygrywa z Kasparowem.

2011 – IBM Watson wygrywa z dwoma mistrzami teleturnieju Jeopardy (Va Banque)

2015 – zrobotyzowane laboratorium + AI odkrywa ścieżki genetyczne/sygnałowe regeneracji płazińców

2016 – Google AlphaGo wygrywa z Lee Sedolem

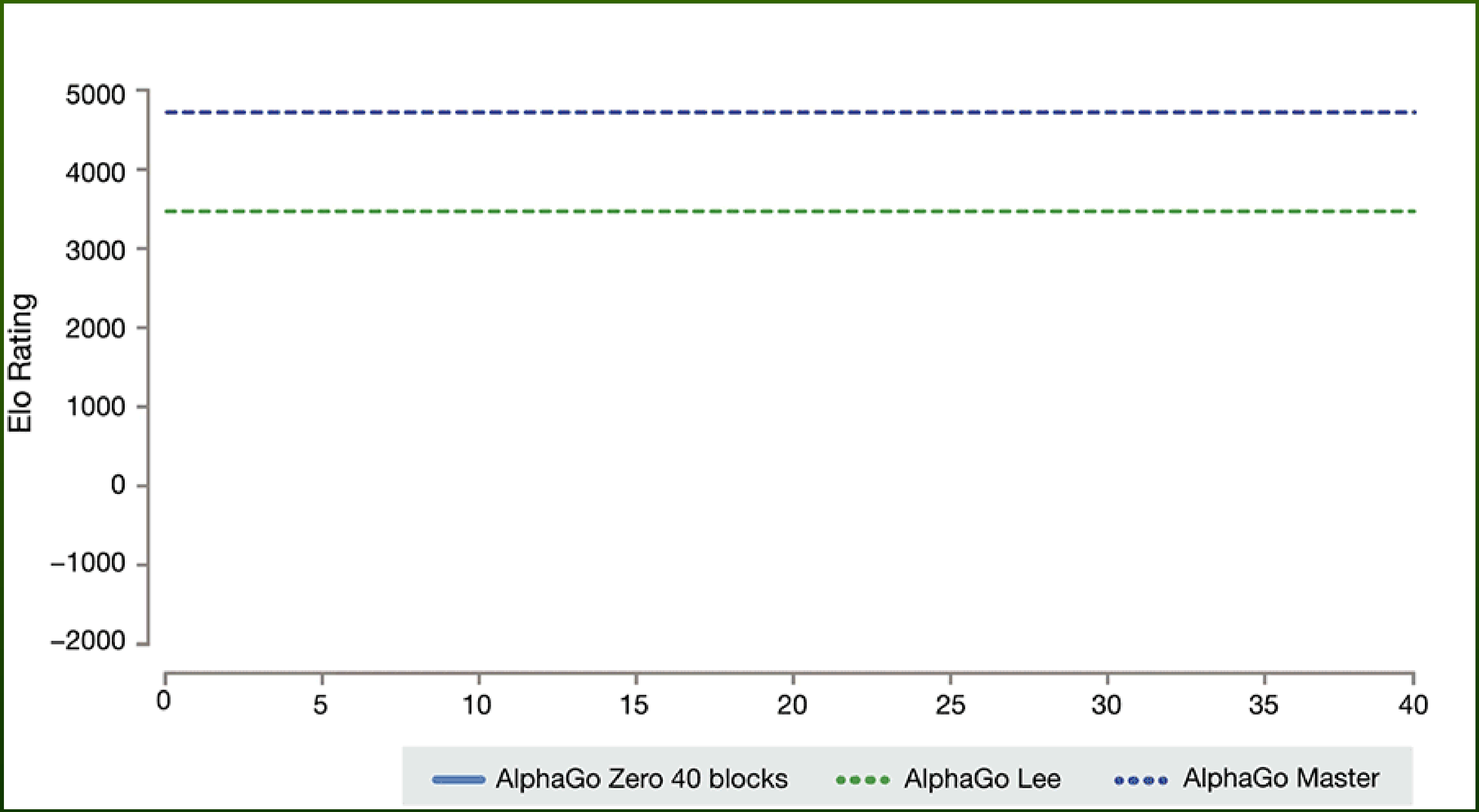
2017 – Libratus (CM) wygrywa z ludźmi w pokera
OpenAI wygrywa w Dota 2 z profesjonalistą.

2018 – Watson Debater wygrywa z filozofami.

2019 – Dota2 drużynowa, Starcraft II … co zostało?

Artificial General Intelligence (AGI), Memphis 2008

Reasoning: AlphaGo zero learns from 0!

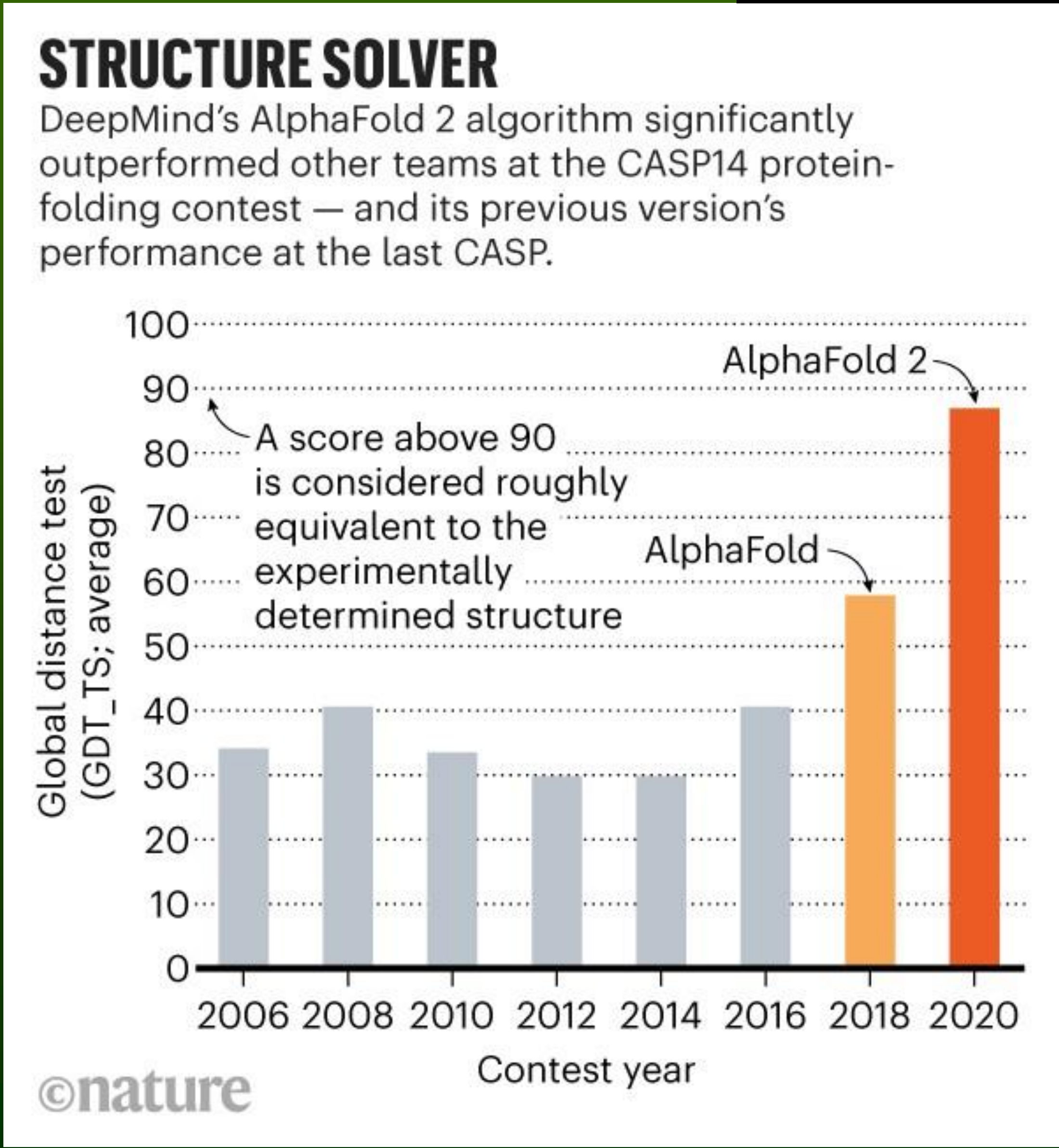


Playing against itself, now at superhuman level, beats all human experience.

Deep NN for protein folding

The ability to accurately predict protein structures from their amino-acid sequence will vastly accelerate efforts to understand the building blocks of cells, and enable quicker and more advanced drug discovery.

AlphaFold 2 using deep neural networks has made great improvement, over 2/3 of predicted structures are equivalent to experimental! [Nature, 30.11.2020]()
Perception+learning+reason.



Perception: superhuman

Automatic analysis of face images: prediction of **physical properties**: gender, age, race, emotions, BMI.

Surprise! Social and **psychological properties** are also predicted with much higher accuracy than humans can: sexual preferences, criminality, political and religious attitudes.

Gay/hetero men in 91% of cases, and in 83% for women (5 images per person). 35 human judges guessed 61% men/54% for women

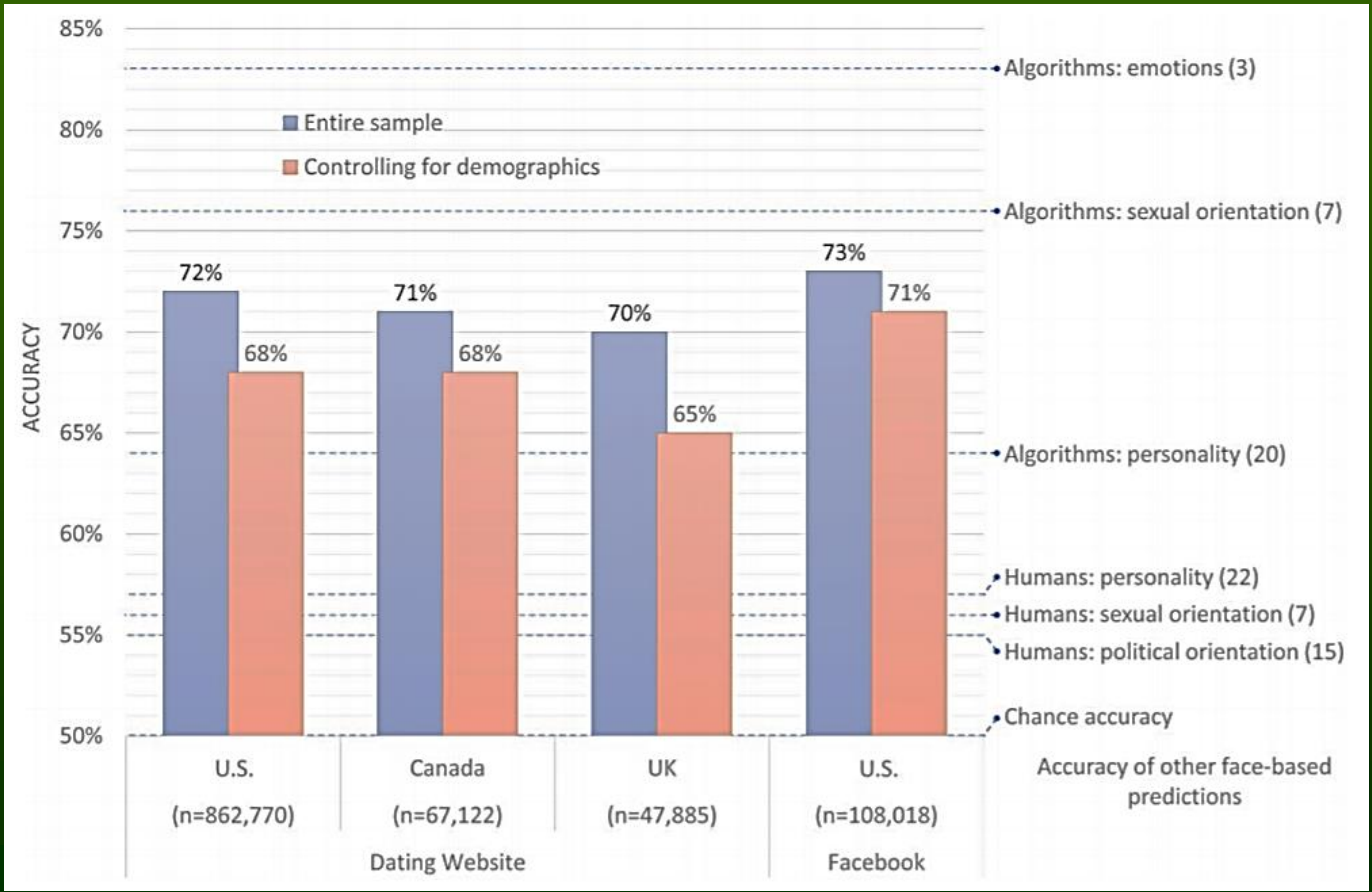
(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

Facial recognition applied to images of >1M individuals predicts with 72% accuracy liberal–conservative orientation; human accuracy is 55%. Criminal tendencies tested on 10,000 facial images, CNN achieved 97% test accuracy (paper retraced due to the lack of ethical committee approval).

Political preference is in your face?

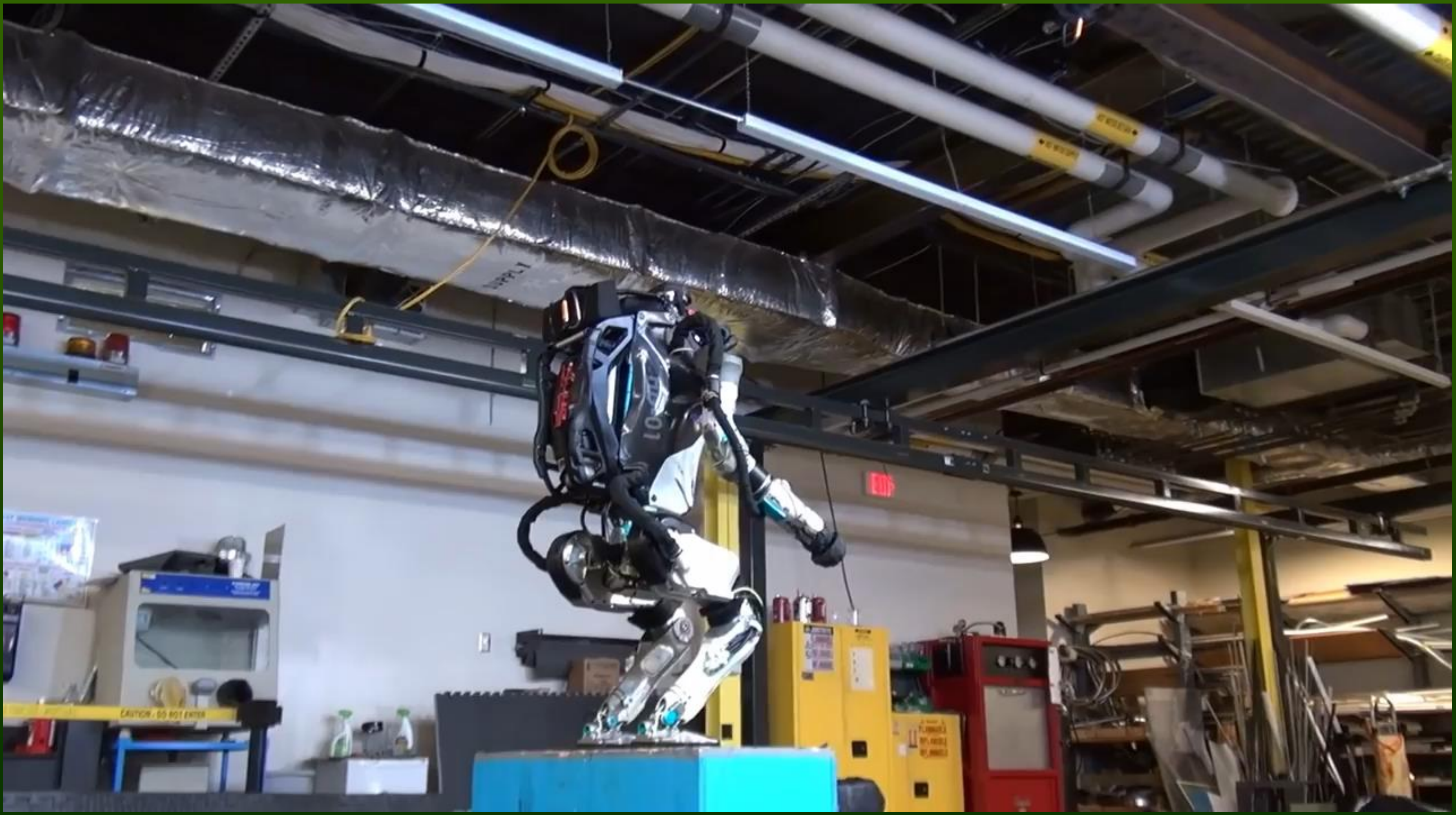
Facial recognition of >1M individuals predicts with 72% accuracy liberal–conservative orientation; humans 55% (M. Kosiński, Sci. Rep. 2021).



Control: robot movements

Behavioral intelligence: build robot and teach it like a child.

Cog MIT project, Rodney Brooks lab, since 1994.

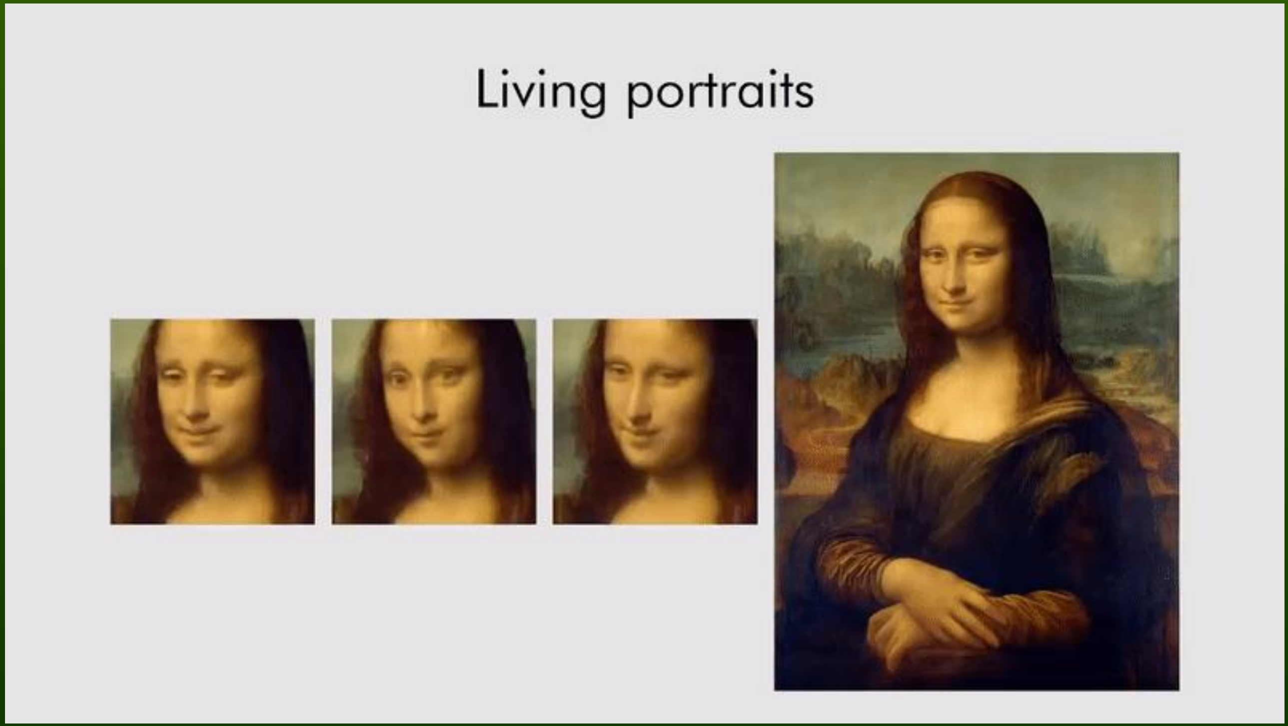


GAN, Generative Adversarial Networks

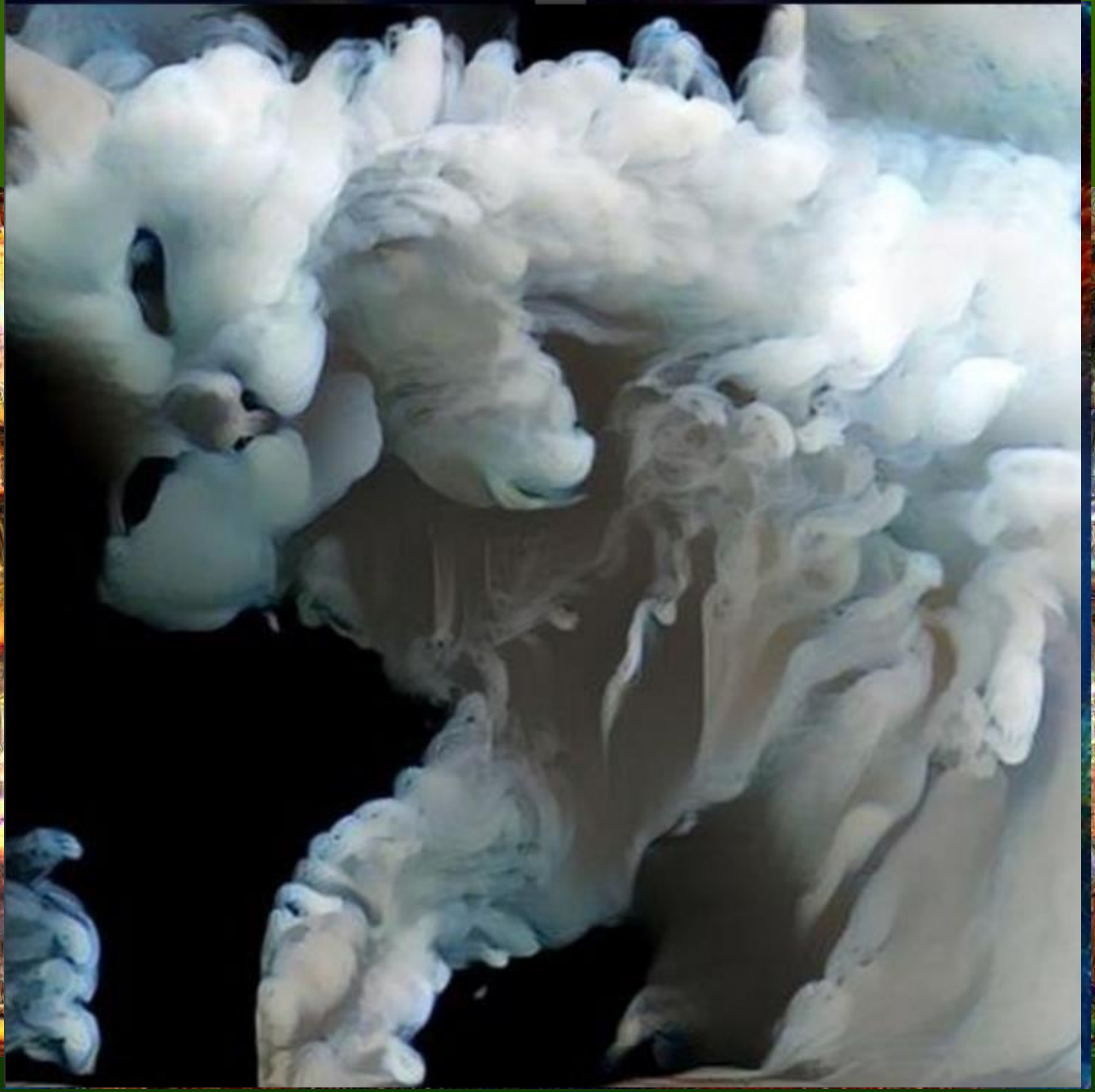
Idea (2014): one network creates false examples distorting learning data in latent space, another learns to distinguish them from natural ones. **Imagination**!

GAN-animacja

Obrazy można ożywić lub zamienić automatycznie w karykatury.
Realistyczny model wymaga kilku zdjęć lub obrazów.
Można też dodać różną ekspresje imitując osobowość i głos.
Każdy może stworzyć „deep fake”.



Deepfake Videos Are Getting Real, Gender swap of composers
Google Deep Dream



Google Deep Dream/Deep Style & Generator, Gallery
LA Gatys, AS Ecker, M Bethge, A Neural Algorithm of Artistic Style (2015)

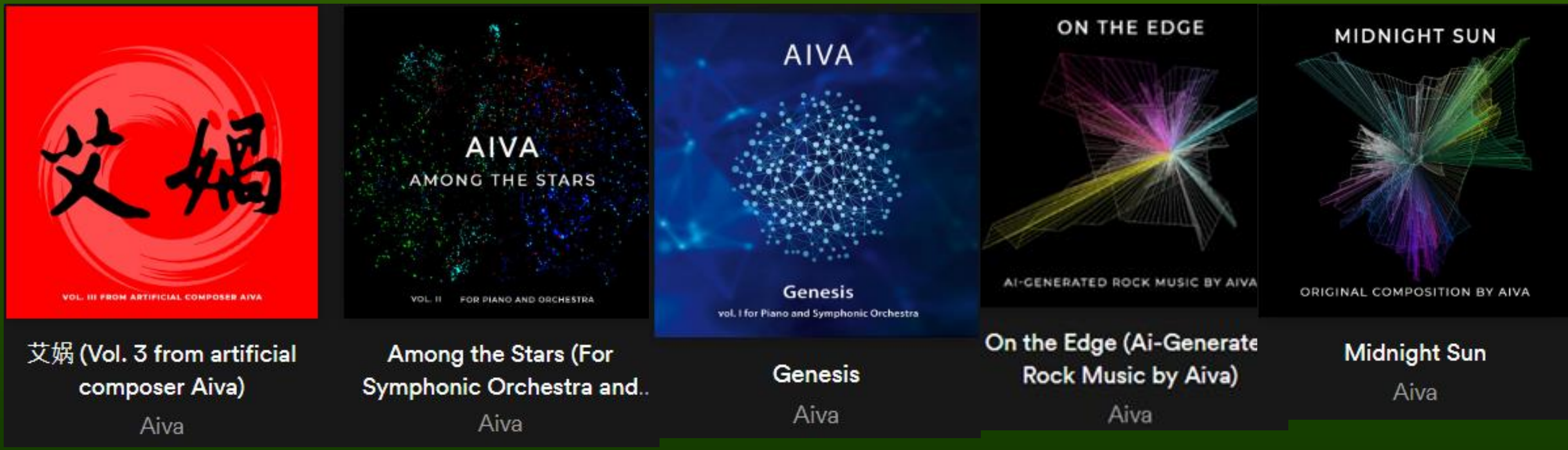
Creativity: AI Virtual Artist

AIVA – AI Virtual Artist, member of author's rights society (SACEM), 206 works.

AIVA YouTube channel, Youtube „Letz make it happen", Op. 23

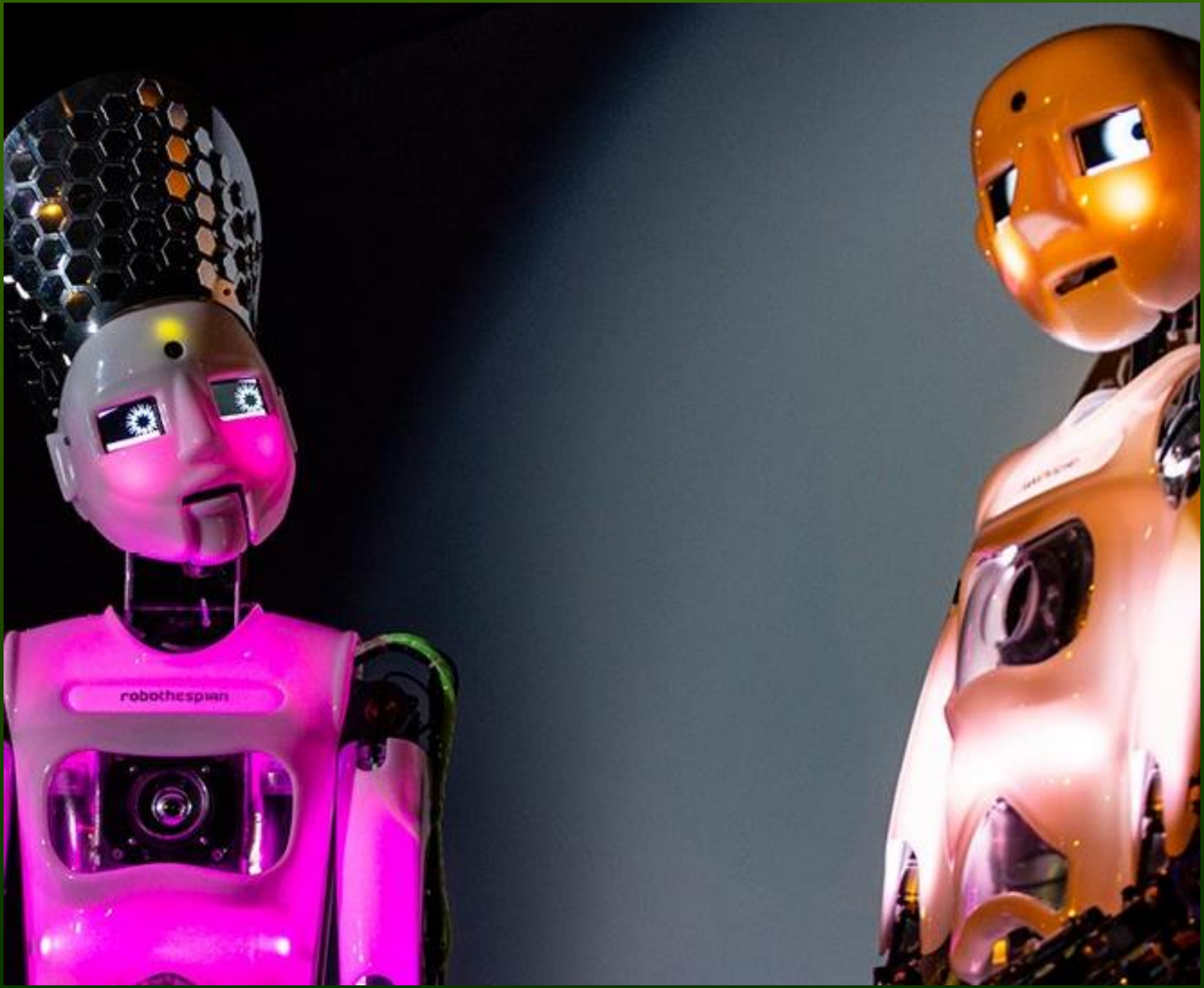
SoundCloud channel

Spotify and Apple channel

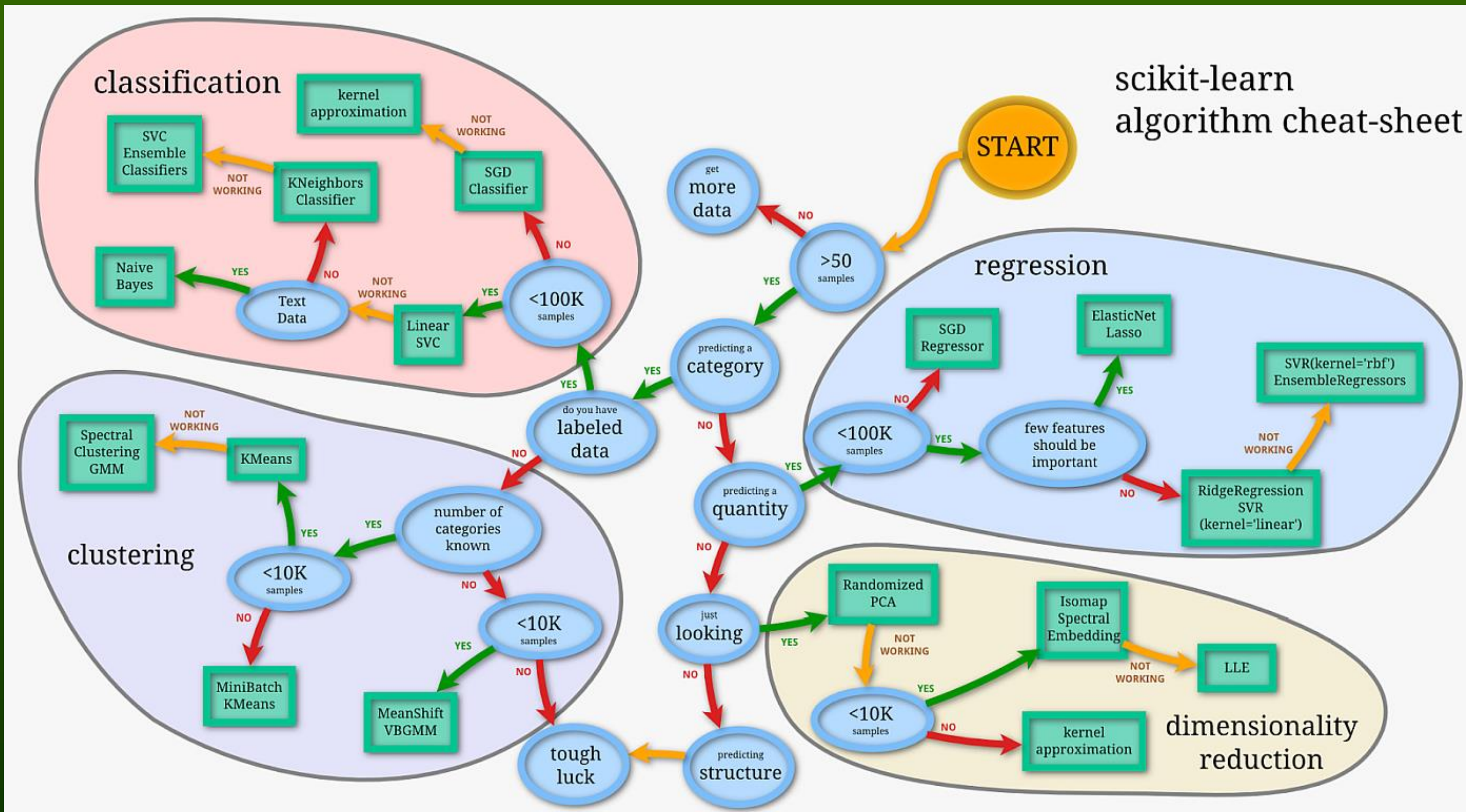


Duch W, *Intuition, Insight, Imagination and Creativity*.
IEEE Computational Intelligence Magazine 2(3), August 2007, pp. 40-52

S. Lem: O królewiczu Ferrycym i królewnie Krystali. Inteligentne bladawce? Czy to możliwe?



Just choose your method



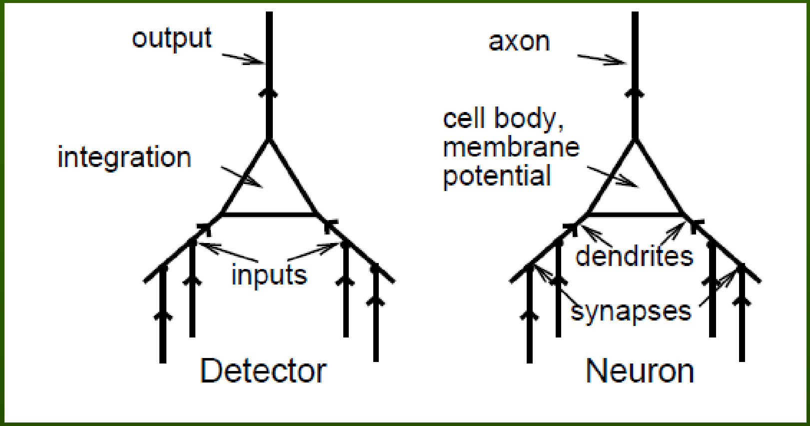
Applications of machine learning **become rather easy**, with hundreds of open software packages and thousands of applications.

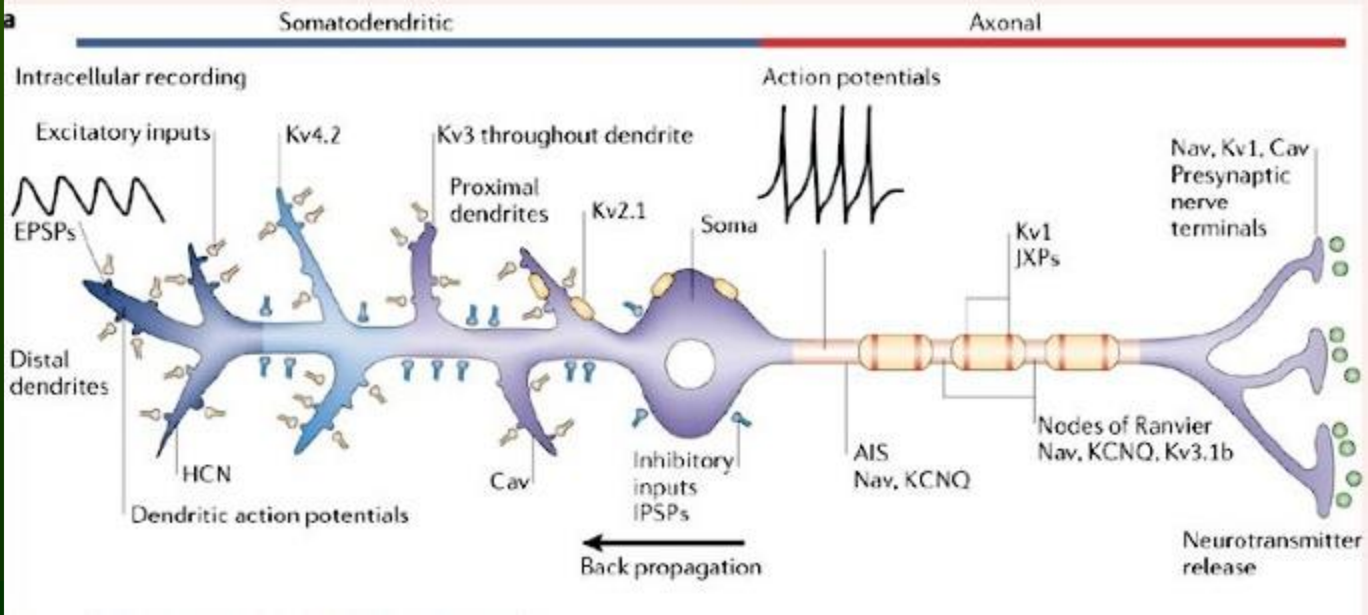
Neurons

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

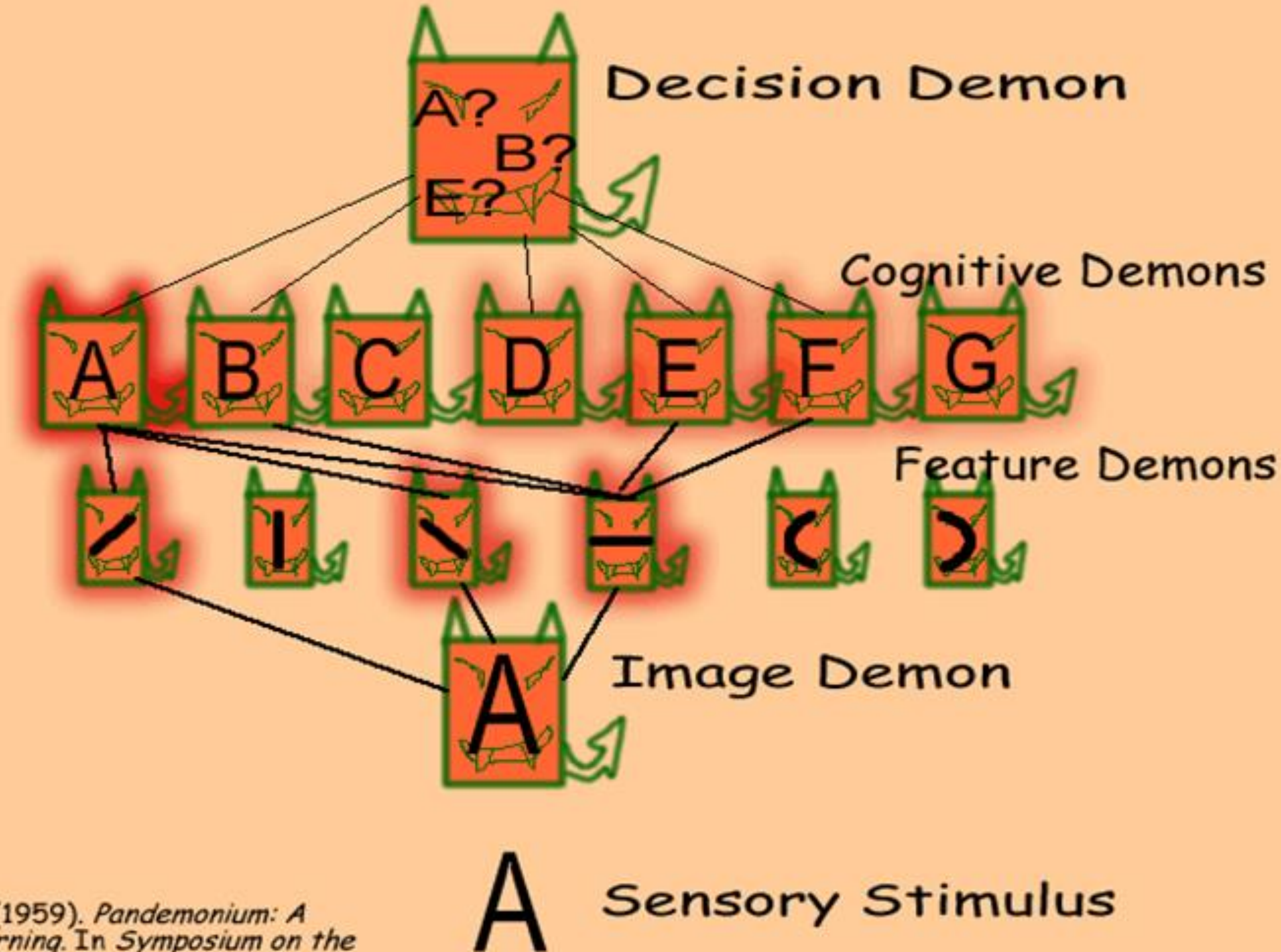
Reality: diverse types, ion channels, neurochemistry, complex spatio-temporal integration, >10 K inputs …

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





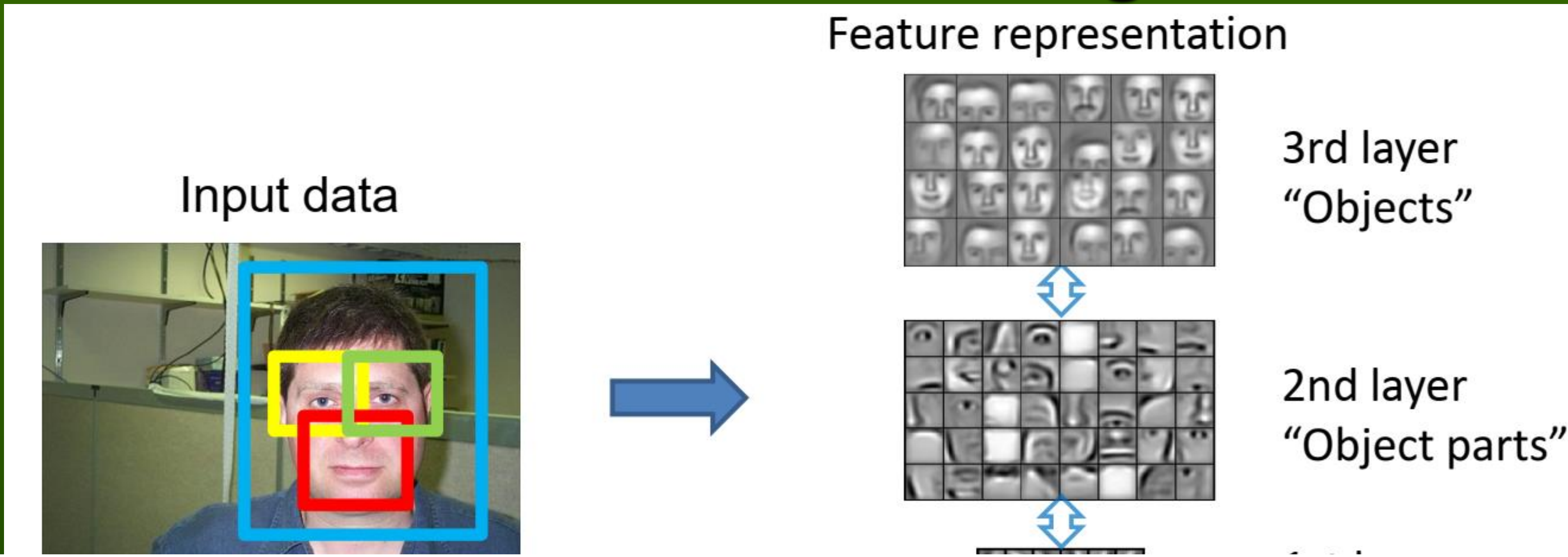
Neural Networks: Selfridge's Model (1959)

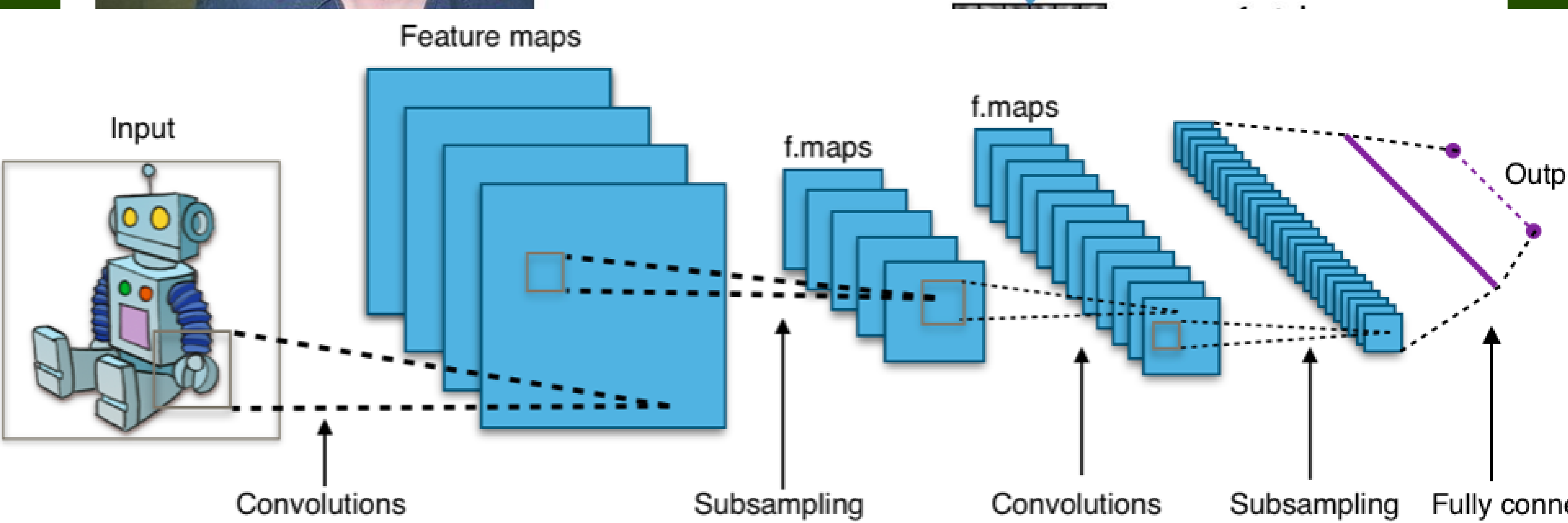


Based on:

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

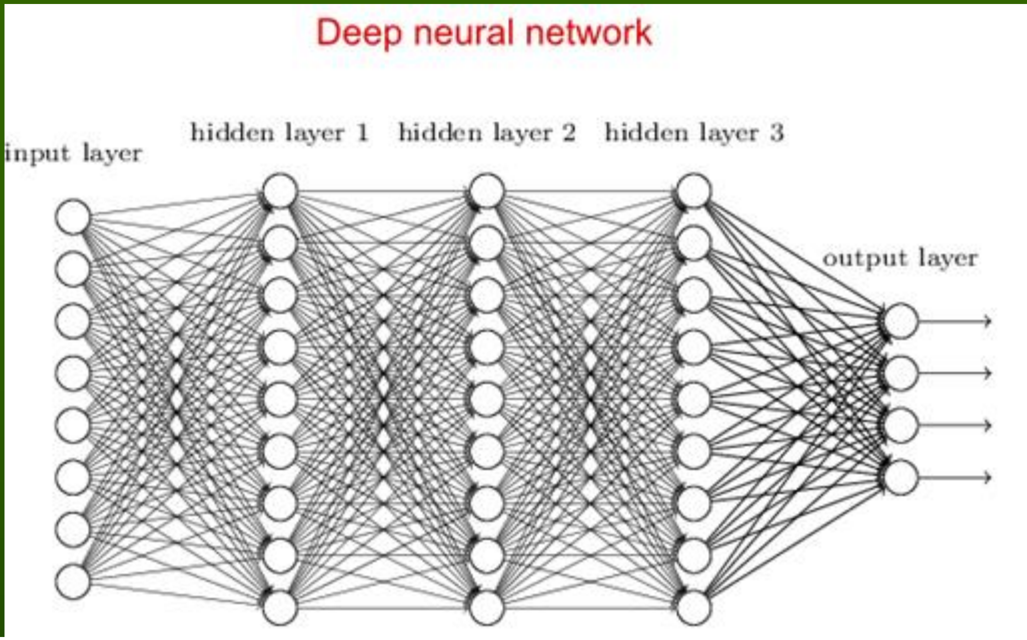
Methods: NN for images



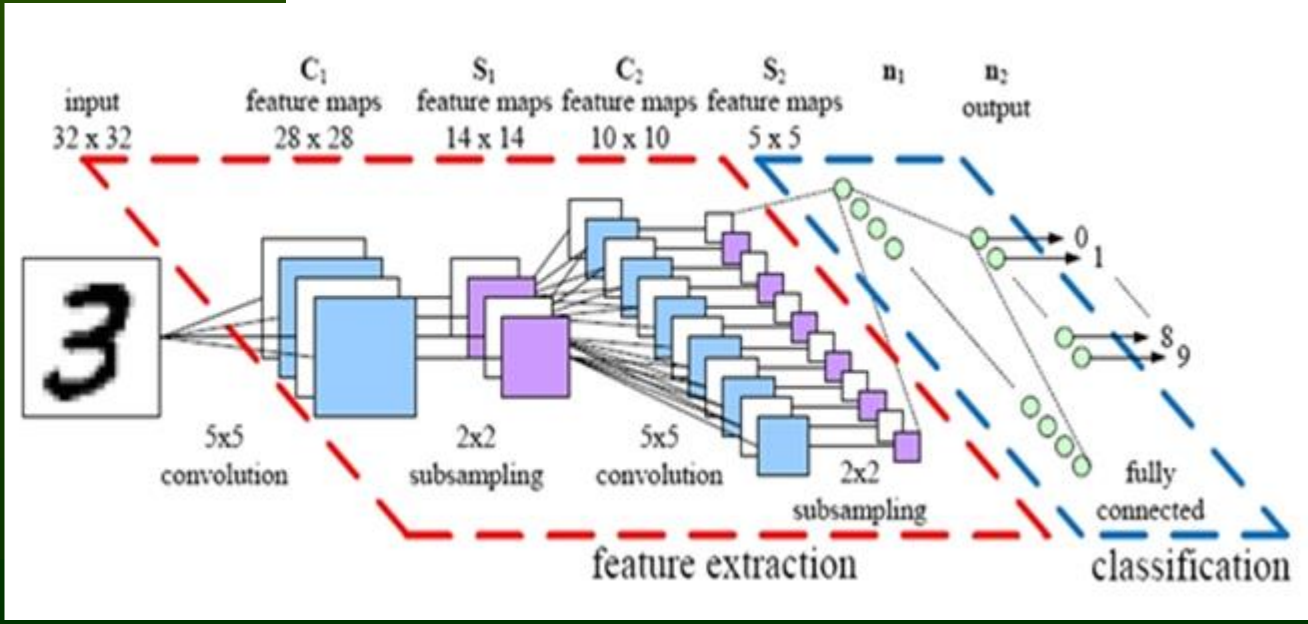


Tensorization of Convolutive Deep Learning NN

Most neural models: 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



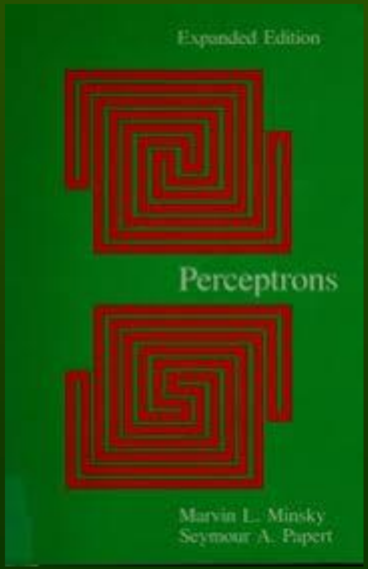
Support Feature Machines (2011).
We do not know how to use oscillators for computations.

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.

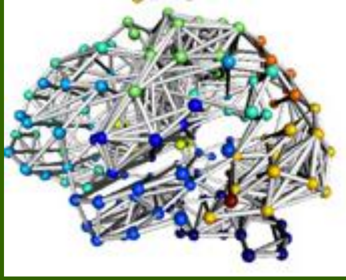
Duch W, Mandziuk J, *Quo Vadis Computational Intelligence?* Advances in Fuzzy Systems - Applications and Theory Vol. 21, World Scientific 2004, 3-28.



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

$\Rightarrow$ 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.

Brain Inspirations



1. Simple neurons, 1 parameter, fixed synaptic connections
   ⇒ perceptrons, MLPs.
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.
5. Society of brains: collaboration between brains on symbolic level.

These inspirations led me to creation of many interesting ideas and algorithms. Some ideas are now verified experimentally using neuroimaging.

Still, we do not know how to compute using oscillations.

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.

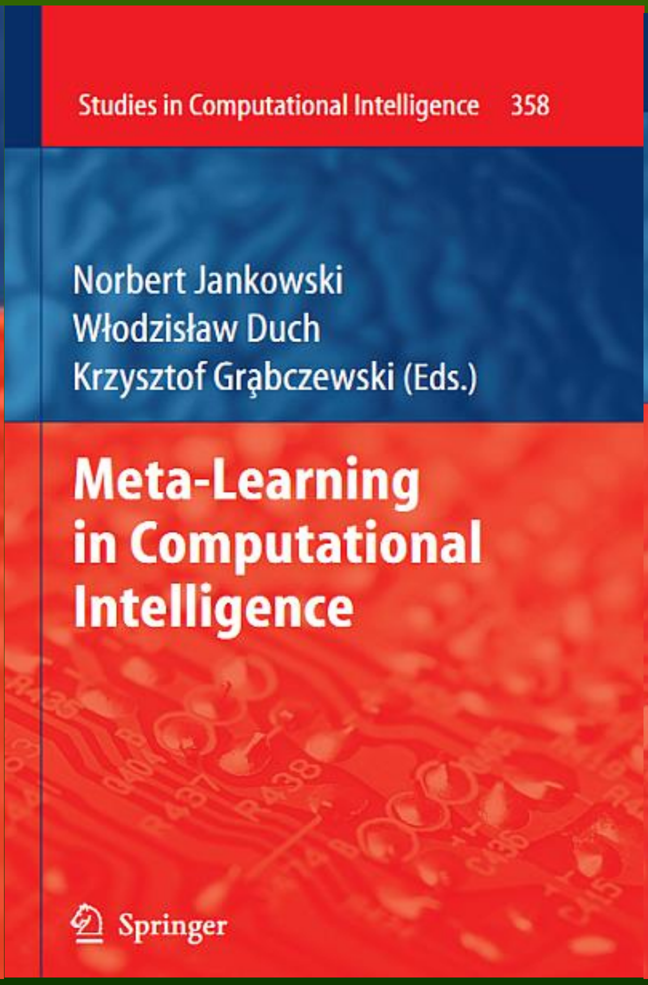
T-based meta-learning

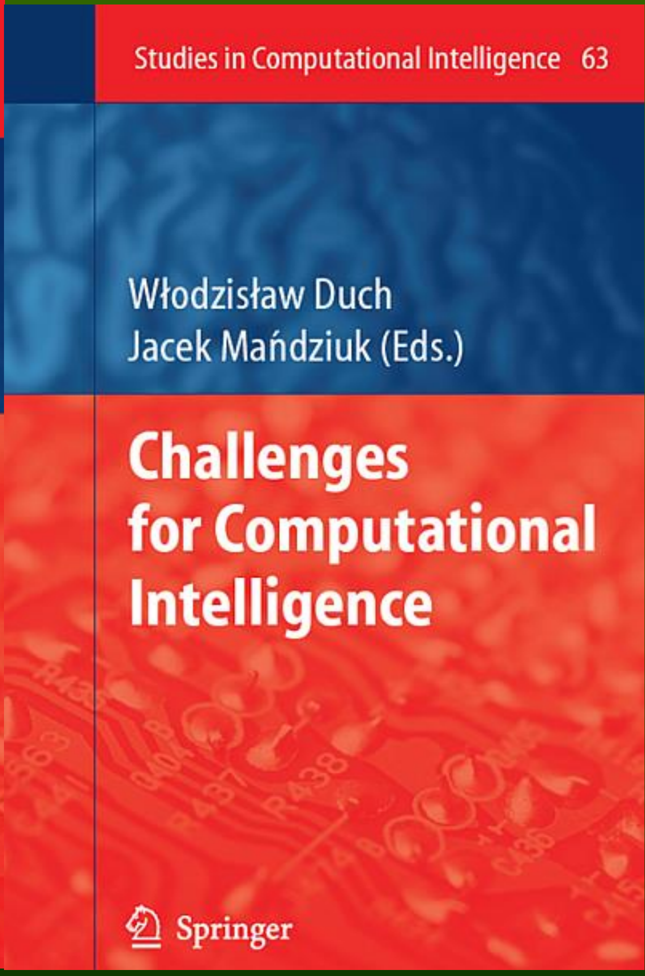
To create successful meta-learning through search in the model space fine granulation of methods is needed, extracting info using support features, learning from others, knowledge transfer and deep learning.

Learn to compose, using complexity guided search, various transformations (neural or processing layers), for example:

- Creation of new support features: linear, radial, cylindrical, restricted localized projections, binarized … feature selection or weighting.
- Specialized transformations in a given field: text, bio, signal analysis, ….
- Matching pursuit networks for signal decomposition, QPC index, PCA or ICA components, LDA, FDA, max. of mutual information etc.
- Transfer learning, granular computing, learning from successes: discovering interesting higher-order patterns created by initial models of the data.
- Stacked models: learning from the failures of other methods.
- Schemes constraining search, learning from the history of previous runs at the meta-level.

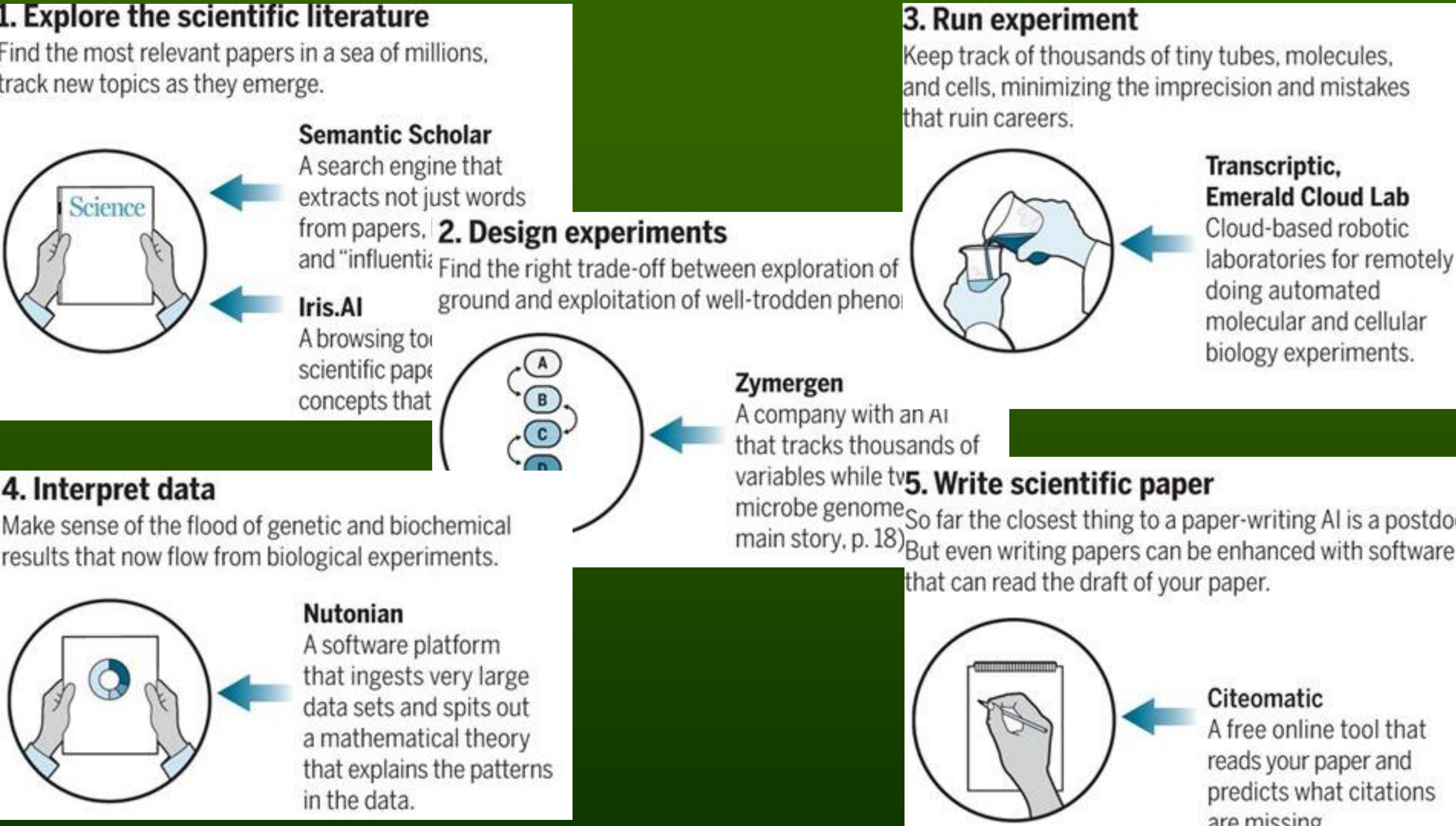

Krzysztof Grąbczewski
Meta-Learning in Decision Tree Induction
Springer


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

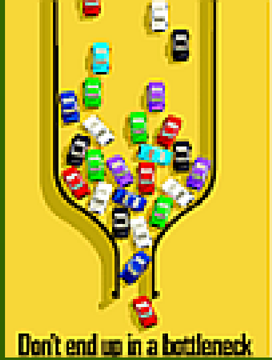
AI for science

Science cycle



HOW MUCH OF SCIENCE can be delegated to machine-learning systems?
Science 2017, Cyberscientist: … the ultimate goal is "to get rid of human intuition".

Discovery bottlenecks



Human-expert-driven and episodic, depending on the field of study.

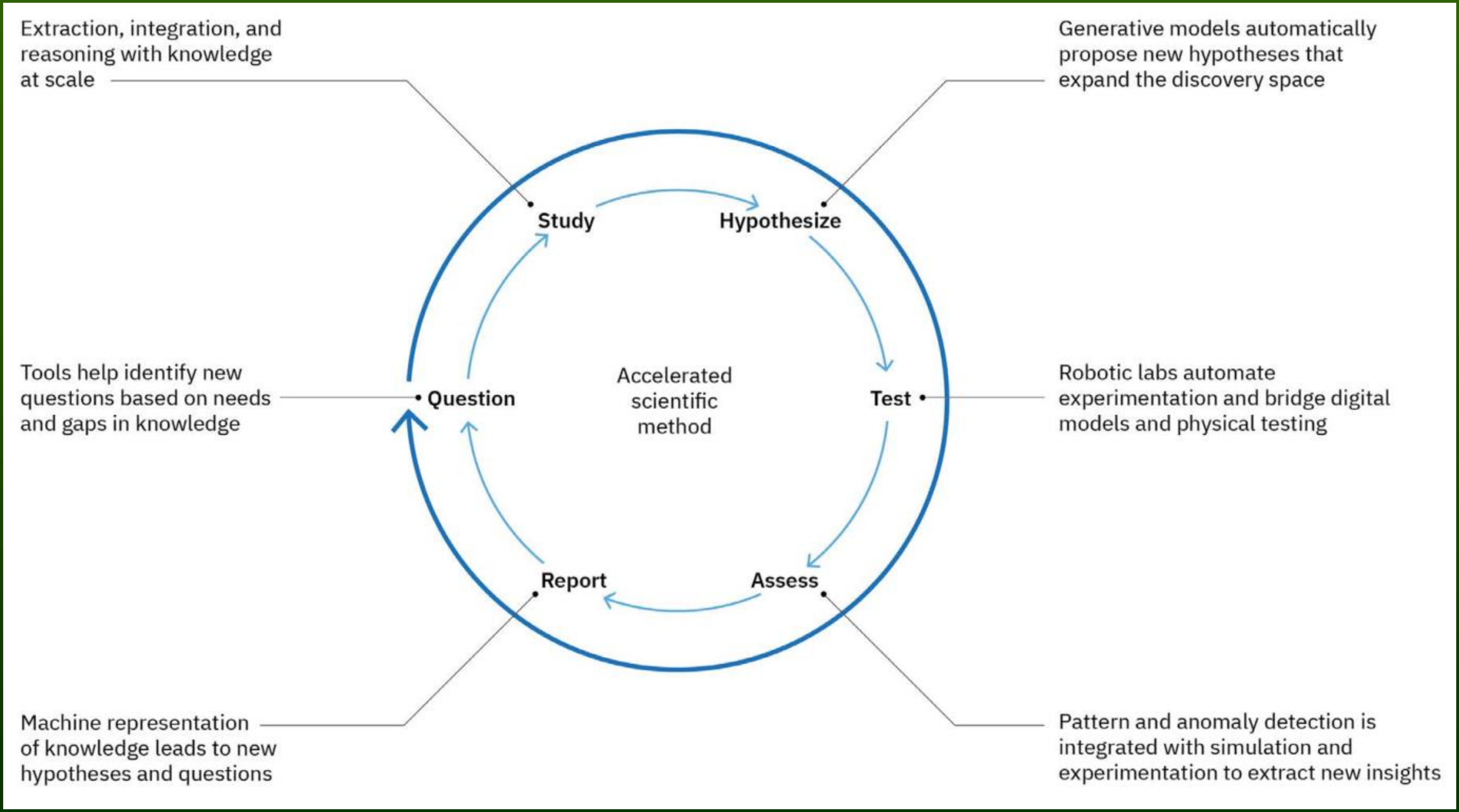
- **Finding good questions** require increasingly deep and broad expertise.
- **Flood of scientific papers** and growing knowledge: > 2 million articles in 30,000 scientific journals each year, >74,000 new COVID-19 papers added to the PubMed in 2020.
- **Challenges in developing hypotheses**: there are about 10^{63} potential drug-like molecules, our knowledge is incredibly sparse compared to that.
- There are **gaps in testing**, including bridging digital models/physical testing.
- **Ensuring reproducibility** is hard, especially in social science, medicine, psychology: 70% of scientists have at least once failed to replicate experiments of other scientists. Statistics conceals individual differences.
- Scale-out, or **translation into practice** is slow.

AI enables knowledge extraction, integration, reasoning at a large scale with knowledge from real data. The steps in scientific method are accelerating.

Speed-up, scale-up and scale out!

Accelerated discoveries

AI tools support discovery process at every step, from questions to reports.
Try Labworm list of tools.



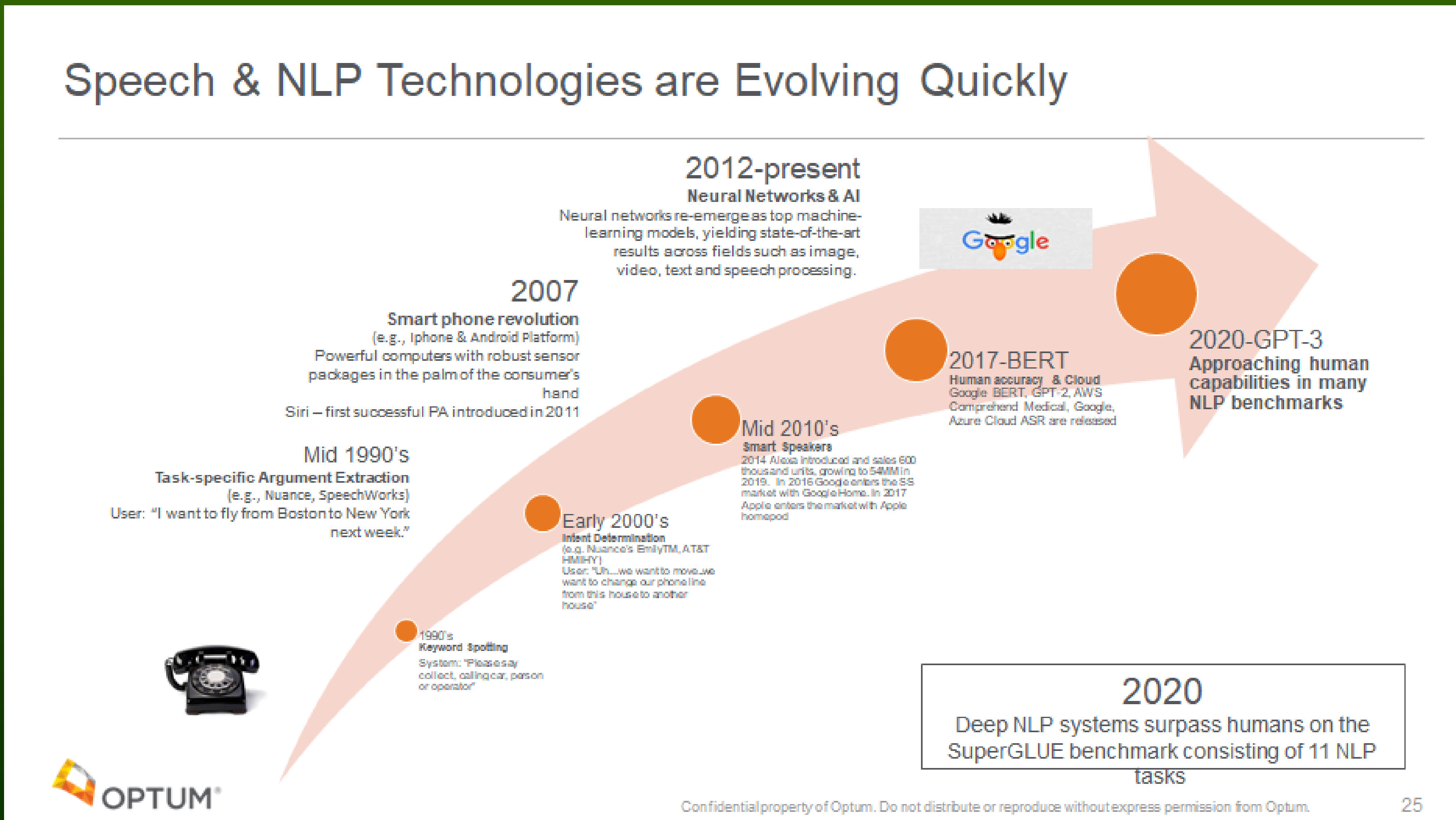
BERT

Language models may encode knowledge about relation of words in complex network structures. In 2018 Google group created BERT, language model pre-trained on a large text corpus to gain a general-purpose "language understanding". That model is then fine-tuned for specific NLP tasks such as question answering or semantic information retrieval.

- **Bidirectional Encoder Representations from Transformers** (**BERT**). Transformer-based machine learning technique for (NLP) pre-training.
- English-language BERT: two networks, smaller 110M parameters, and larger model, a 24-layer 340M parameter architecture; trained on the BooksCorpus with 800M words, and Wikipedia with 2,500M words.
- 12/2019 BERT worked in 70 languages, in 2020 many smaller pre-trained models with the whole word masking open software models were published in GitHub repository.
- Masking some words the system learns to predict them, ex:
  Input: the man went to the [MASK1] . he bought a [MASK2] of milk.
  Labels: [MASK1] = store; [MASK2] = gallon
- Super-human Q/A on Stanford Question Answering Dataset (SQuAD)

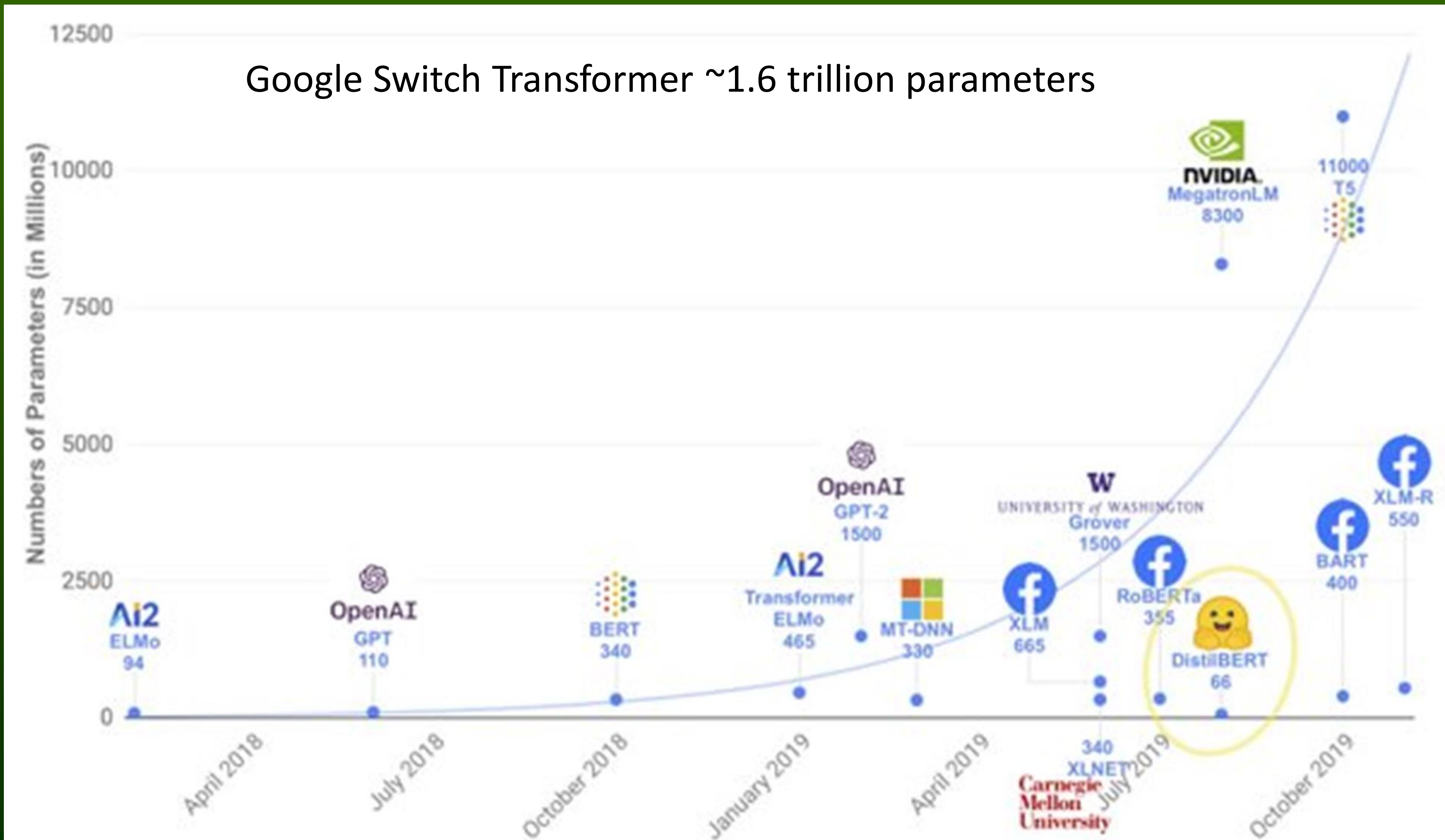
State of the art

- Super-human Q/A on Stanford Question Answering Dataset (SQuAD)



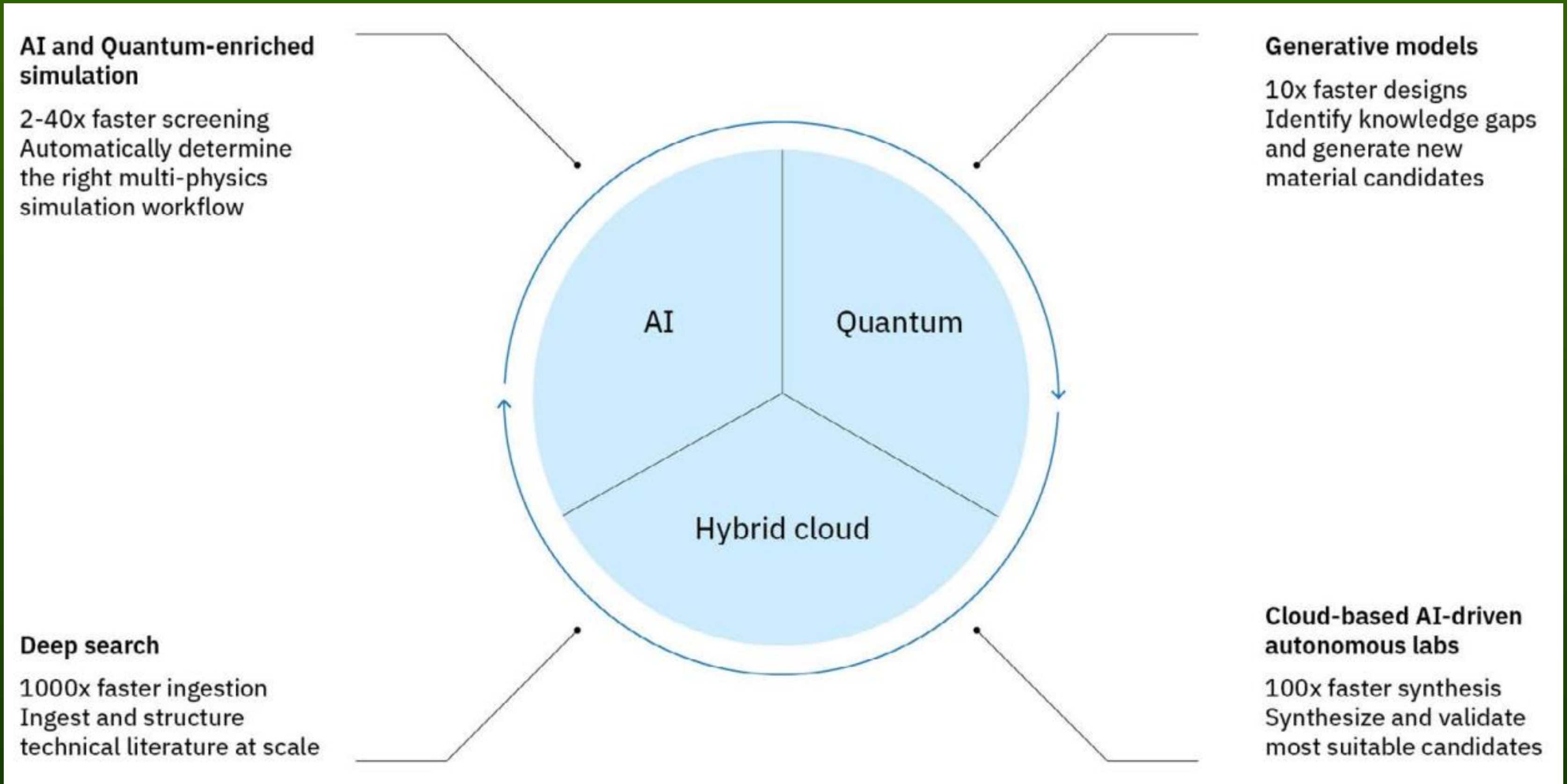
NLP supermodels

OpenAI GPT-3 model with 175 B parameters! See it in action here.



Accelerated discoveries (IBM)

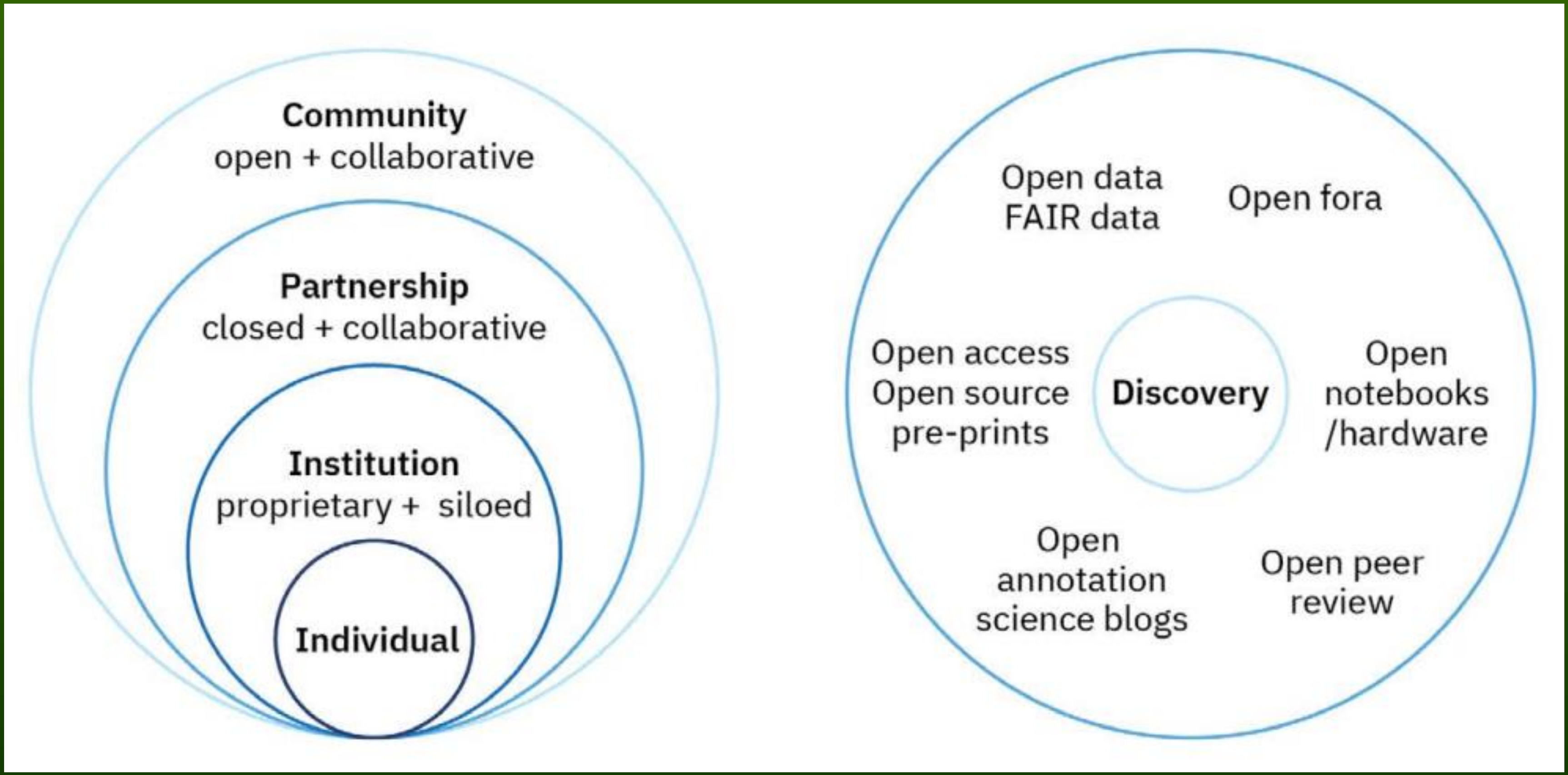
AI support in materials design.



Communities of Discovery are becoming the new paradigm for the practice and advancement of scientific discovery.

Communities of Discovery

Sharing resources and skills in an open collaborative environment.



COVID-19 High Performance Computing, huge public-private partnership in molecular medicine, protein interaction, epidemiology, dozens of consortium members from top government, industry, and academia institutions.

JEDI challenge, 54 billion molecules against COVID-19 screened in phase 1 of 3

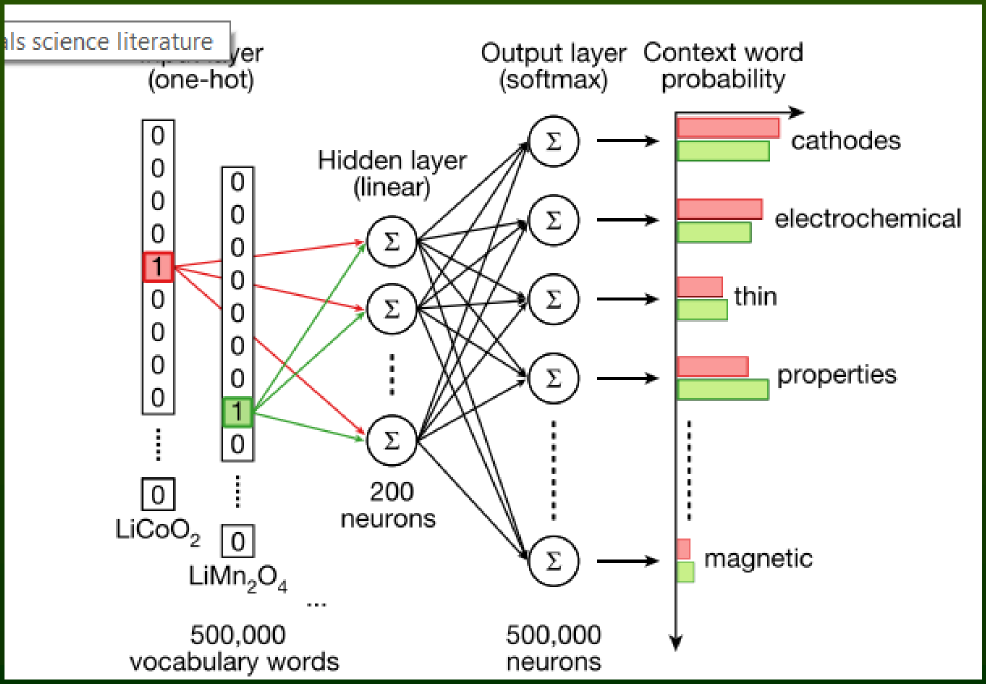
Serious application

Tshitoyan, V. … Jain, A. (2019). Unsupervised word embeddings capture latent knowledge from materials science literature. Nature, 571(7763), 95.

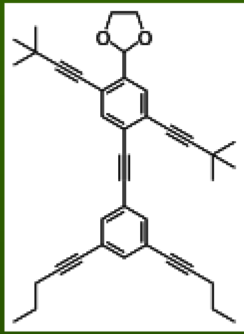
Materials science knowledge present in the published literature can be efficiently encoded as information-dense word embeddings without human supervision. Without any explicit insertion of chemical knowledge, these embeddings capture complex materials science concepts such as the underlying structure of the periodic table and structure–property relationships in materials.

An unsupervised method can recommend materials for functional applications several years before their discovery.

GPT Crush: see applications in business, design, education, philosophy, research, creative writing and many other areas.



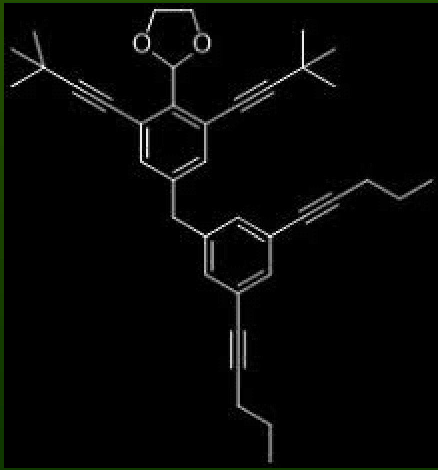
Applications in chemistry/materials



- A. C. Vaucher, F. Zipoli, J. Geluykens, V. H. Nair, P. Schwaller, T. Laino, Automated extraction of chemical synthesis actions from experimental procedures. *Nature Communications*, 2020.
- P. B. Jørgensen, M. N. Schmidt, O. Winther, Deep Generative Models for Molecular Science. *Molecular Informatics*, 2018.
- D. Schwalbe-Koda, R. Gomez-Bombarelli, "Generative Models for Automatic Chemical Design," arXiv:1907.01632v1 , 2019
- T. Maziarka, A. Pocha, J. Kaczmarski, K. Rataj, T. Danel, M. Warchoł, Mol-CycleGAN: a generative model for molecular optimization, *Journal of Cheminformatics*, 2020.
- C.W. Coley, N.S. Eyke, K.F. Jensenz, Autonomous discovery in the chemical sciences part I: Progress, part II: Outlook. *arXiv:2003.13754v1*, 2020.
- E. O. Pyzer-Knapp, T. Laino (eds), "Machine Learning in Chemistry: Data-Driven Algorithms, Learning Systems, and Predictions," 1326, 2019.
- P. Schwaller, T. Laino, T. Gaudin, P. Bolgar, C. A. Hunter, C. Bekas, A. A. Lee, "Molecular Transformer: A Model for Uncertainty-Calibrated Chemical Reaction Prediction," *ACS Cent. Sci.*, 5, 1572-1583, 2019.

More chemistry/materials

- N. Nosengo, "Can you teach old drugs new tricks?" *Nature*, 534, (2016), 314
- L. Himanen, A. Geurts, A. S. Foster, P. Rinke, Data-Driven Materials Science: Status, Challenges, and Perspectives. *Advanced Science*, 2019.
- D. C. Elton, Z. Boukouvalas, M. D. Fuge, P. W. Chung, "Deep learning for molecular design—a review of the state of the art," *arXiv:1903.04388v3,* [cs. LG], 2019.
- P. Staar, M. Dolfi, C. Auer. Corpus Processing Service: A Knowledge Graph Platform to perform deep data exploration on corpora. *Authorea* 2020.
- S. Takeda, et al, Molecular Inverse-Design Platform for Material Industries. *Proc. ACM KDD-2020*.
- Ł. Maziarka, T. Danel, S. Mucha, K. Rataj, J. Tabor, S. Jastrzebski. Molecule Attention Transformer. *arXiv:2002.08264v1* [cs.LG], 2020.



Duch W and Diercksen GHF (1994) *Neural networks as tools to solve problems in physics and chemistry*. CPC 82, 91-103.

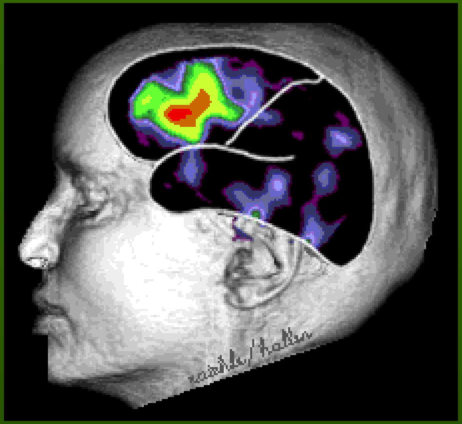
Brains and minds

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.

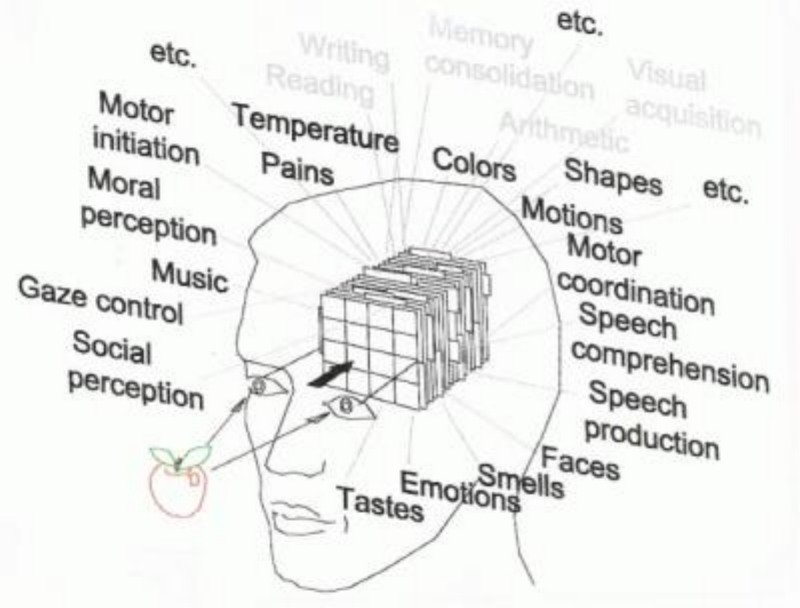


Mapping S(M)⇔S(B) but how to describe the state of mind? Brain fingerprints?

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

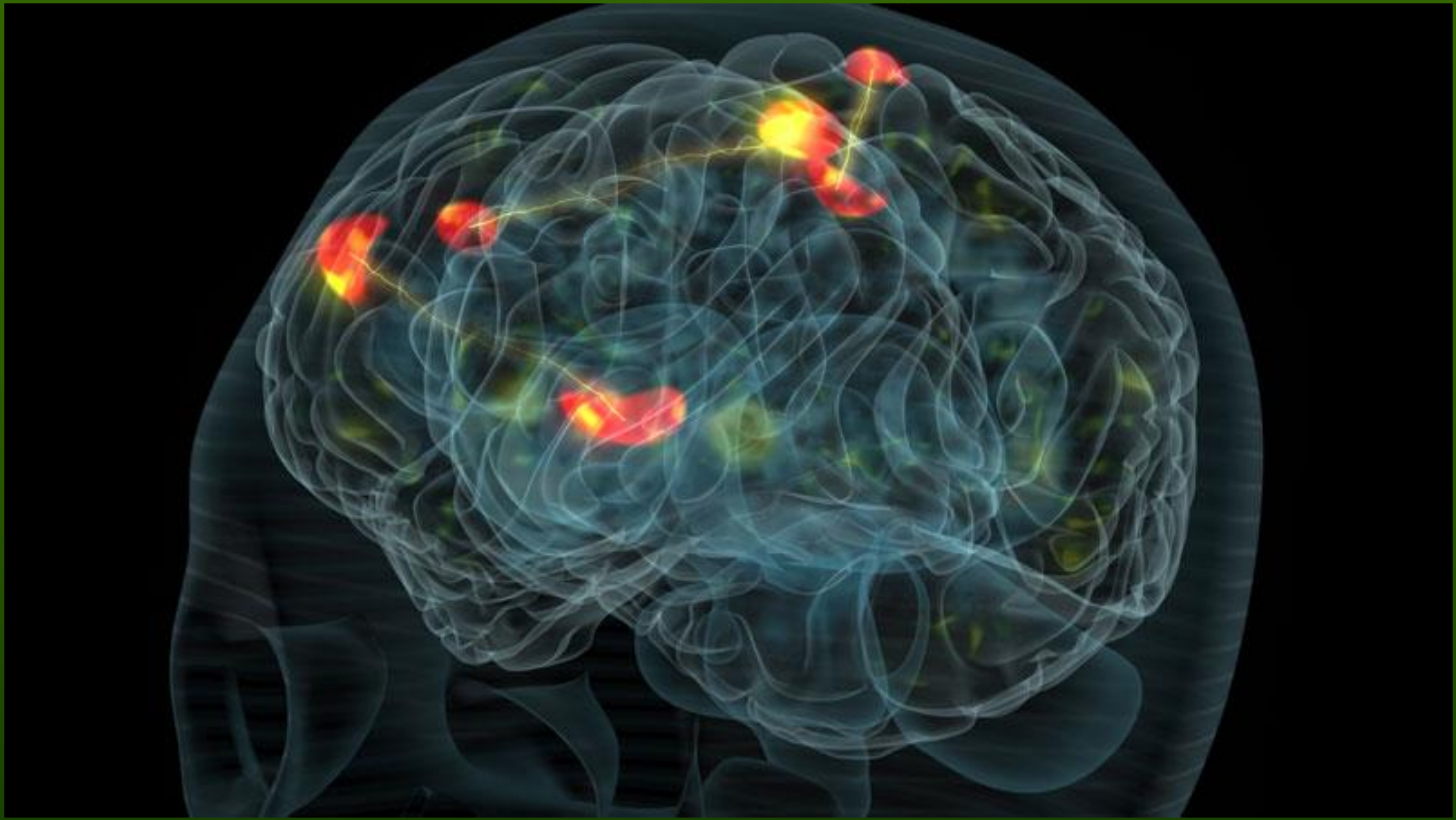
Mental states, movement of thoughts ⇔ trajectories in psychological spaces.

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



Hurlburt & Schwitzgabel, Describing Inner Experience? MIT Press 2007

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.

On the threshold of a dream …

Final goal: **optimize brain processes**!

Although whole brain is always active we are far from achieving full human potential. To repair damaged brains and increase efficiency of healthy brains we need to understand brain processes:

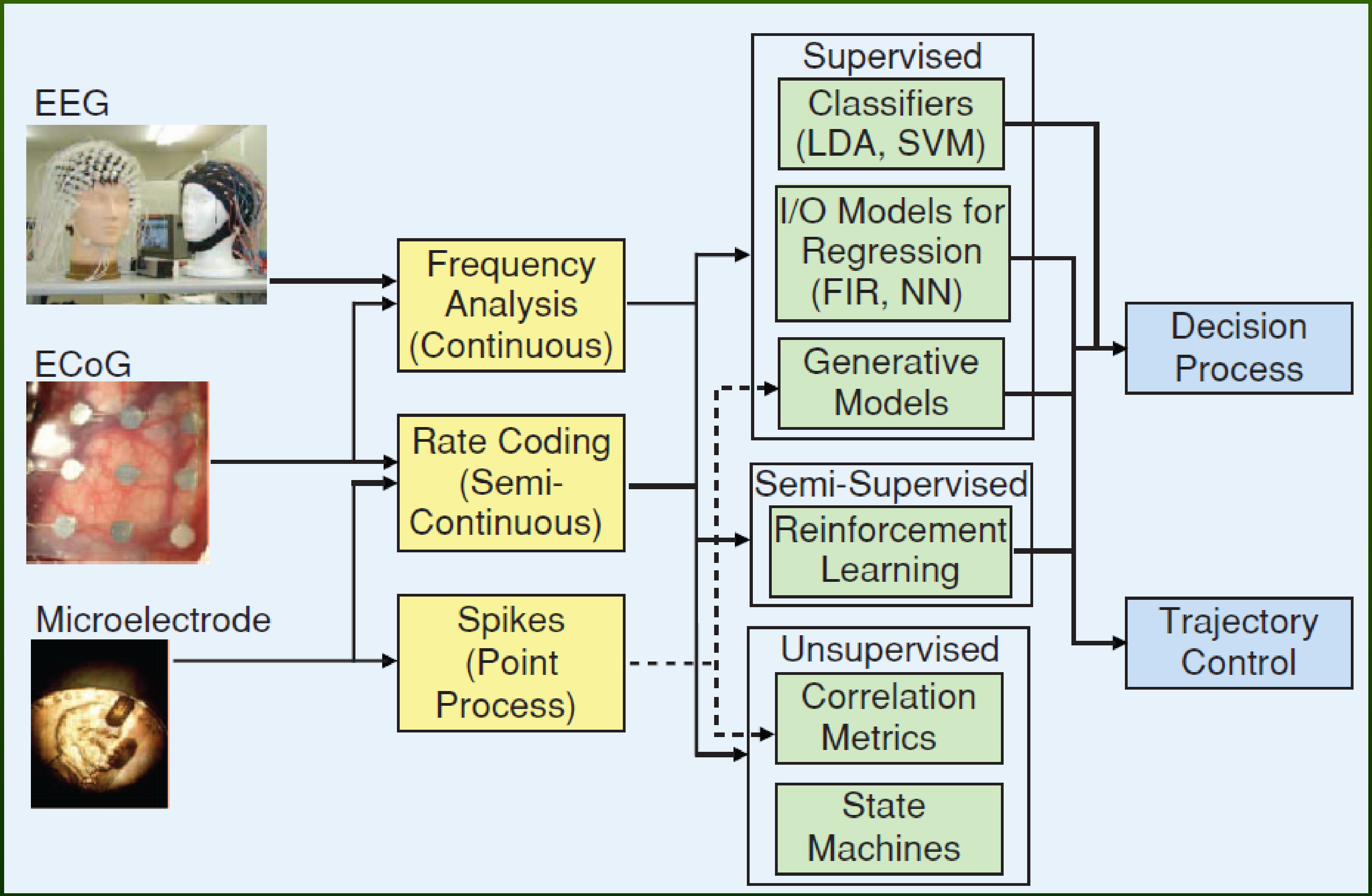
1. Find fingerprints of specific activity of brain structures (regions, networks) using neuroimaging technology (and new neurotechnologies).
2. Create models of cognitive architectures that help to understand information processing in the brain.
3. Create new diagnostic and therapeutic procedures.
4. Use neurofeedback based on decoding and changes in connectivity and close-loop system that directly stimulate the brain.

G-tec wireless NIRS/EEG on my head.

Duch W, *Brains and Education: Towards Neurocognitive Phenomics*. 2013

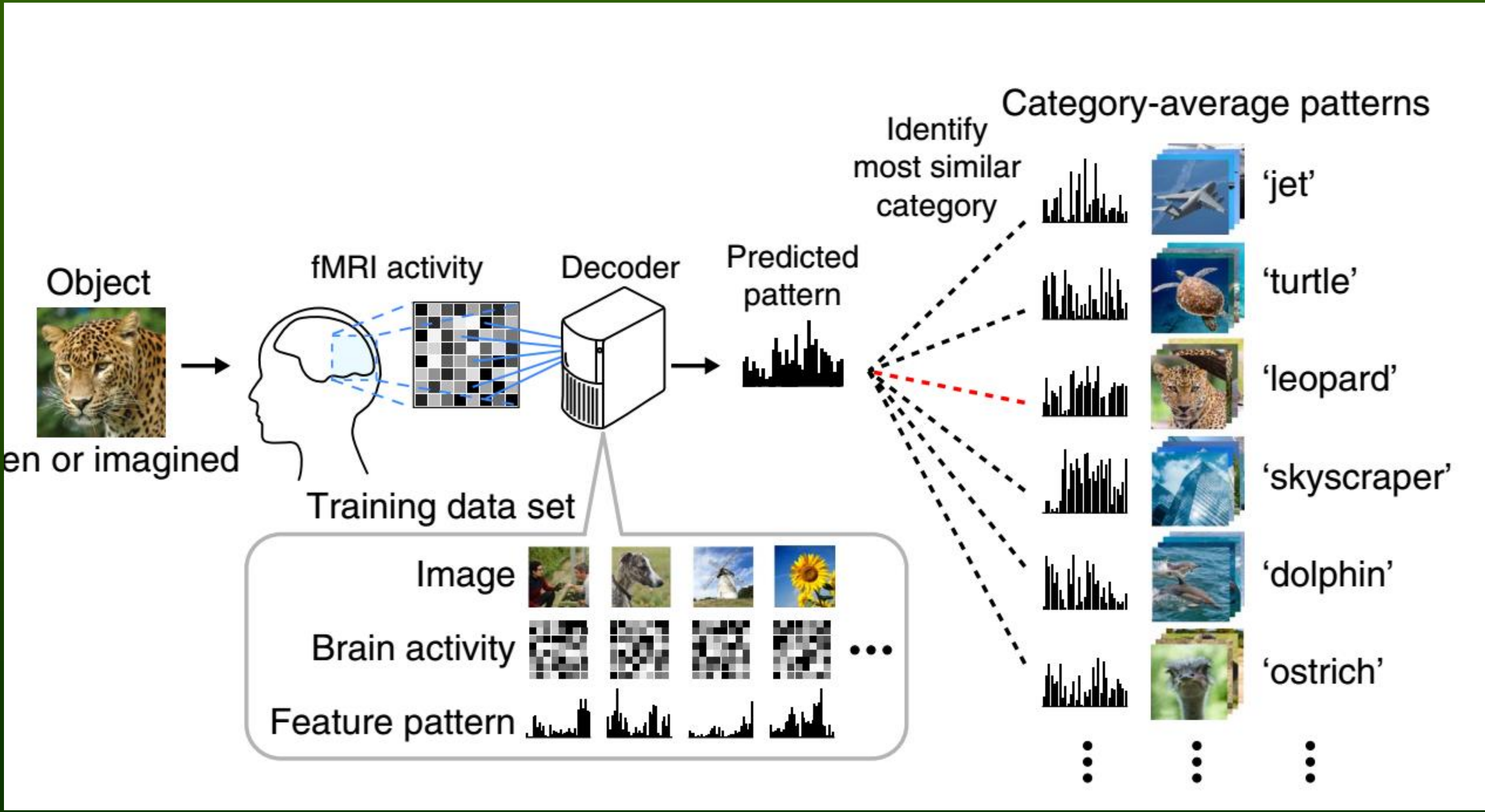
BCI: wire your brain …

Non-invasive, partially invasive and invasive signals carry progressively more information, but are also harder to implement. EEG is still the king!



Brain activity ⇔ Mental image

fMRI activity can be correlated with deep CNN network features;
using these features closest image from large database is selected.
Horikawa, Kamitani, Generic decoding of seen and imagined objects using hierarchical visual features. Nature Comm. 2017.



Decoding Dreams

Decoding Dreams, ATR Kyoto, Kamitani Lab. fMRI images analysed during REM phase or while falling asleep allows for dream categorization (~20 categories).

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

Neuroscience => AI

Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). **Neuroscience-Inspired Artificial Intelligence**. *Neuron*, *95*(2), 245–258.

Affiliations: **Google DeepMind**, Gatsby, ICN, UCL, Oxford.

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

Amoset al. (2018). **Learning Awareness Models**. ICRL, *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.

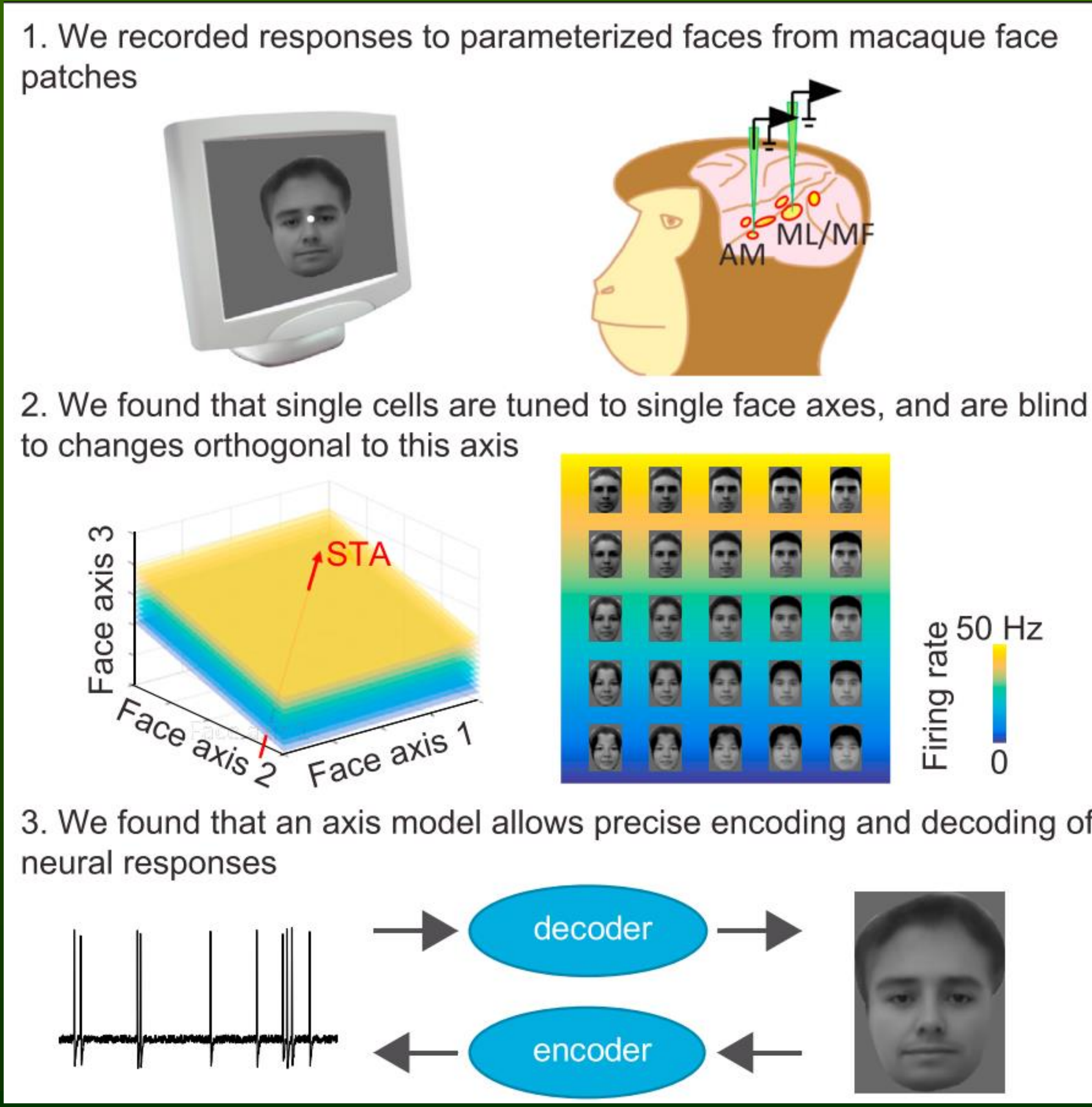
(D) Neurobiological models of **synaptic consolidation**.

SANO, new Centre for Individualized Computational Medicine in Kraków (EU Team project, with Sheffield Uni, Fraunhofer Society, Research Centre Juelich.

Neural screen

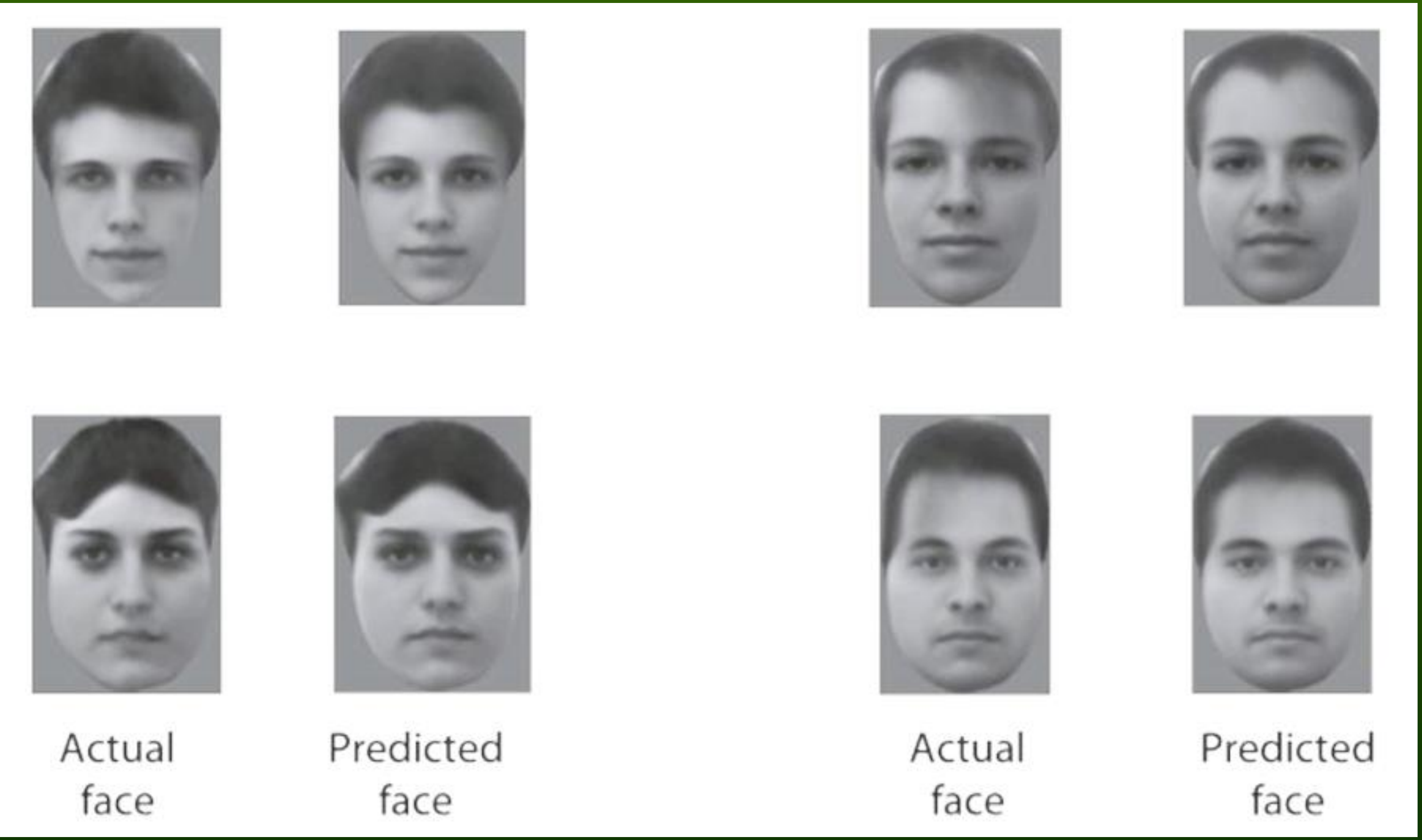
Features are discovered, and their combination remembered as face, but precise recognition needs detailed recording from neurons – only 205 neurons in a few visual areas used.

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



Mental images

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



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

AI=>Neuroscience

ML 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!**

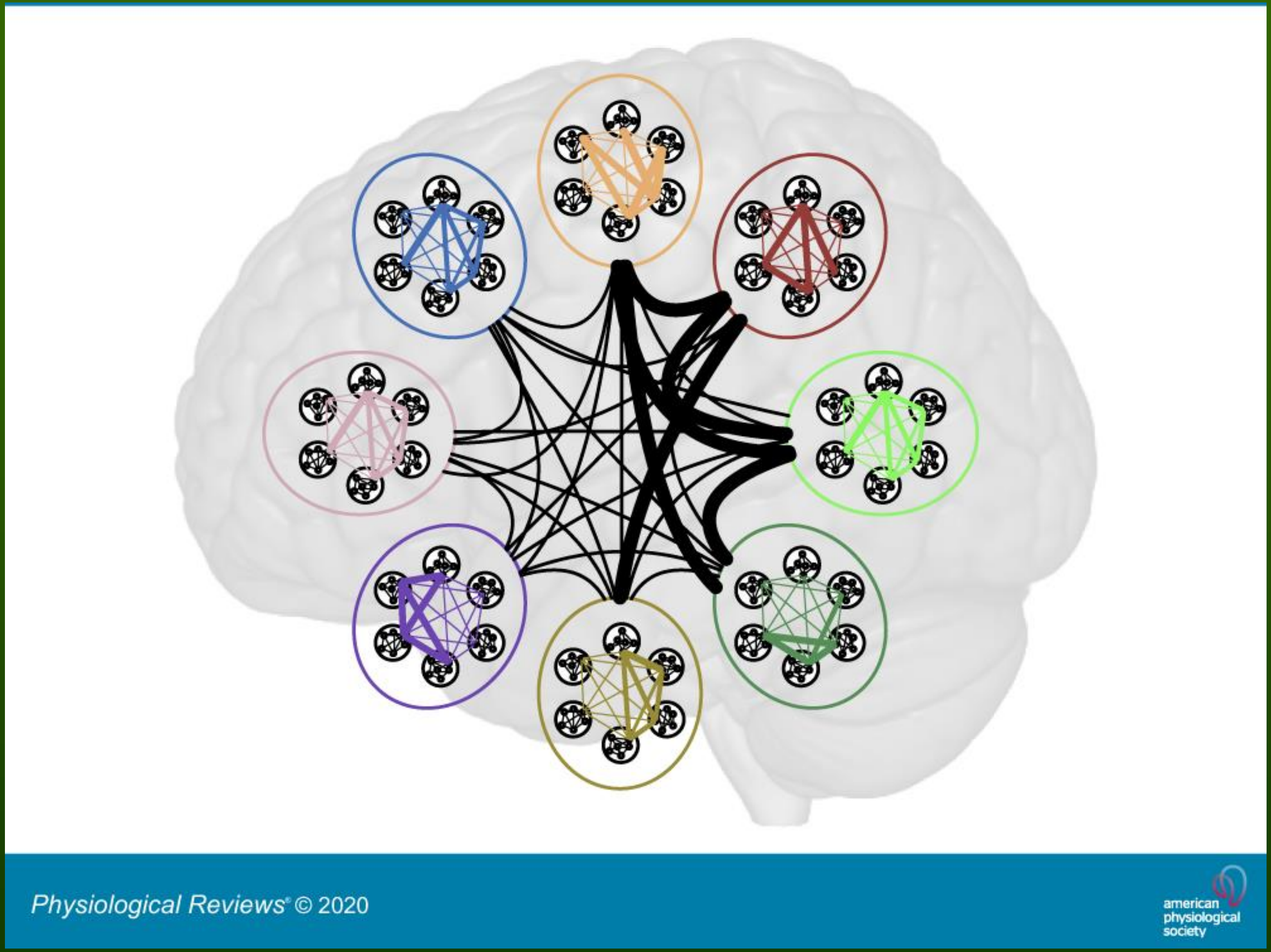
CNN ⬄ interpret neural representations in high-level ventral visual stream of humans and monkeys, finding evidence for deep supervised networks.

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

Backpropagation with symmetric feedback and feedforward connectivity is not realistic, but random backward connections allow the backpropagation algorithm to function effectively through a process whereby adjustment of the forward weights allows backward projections to transmit useful teaching signals.

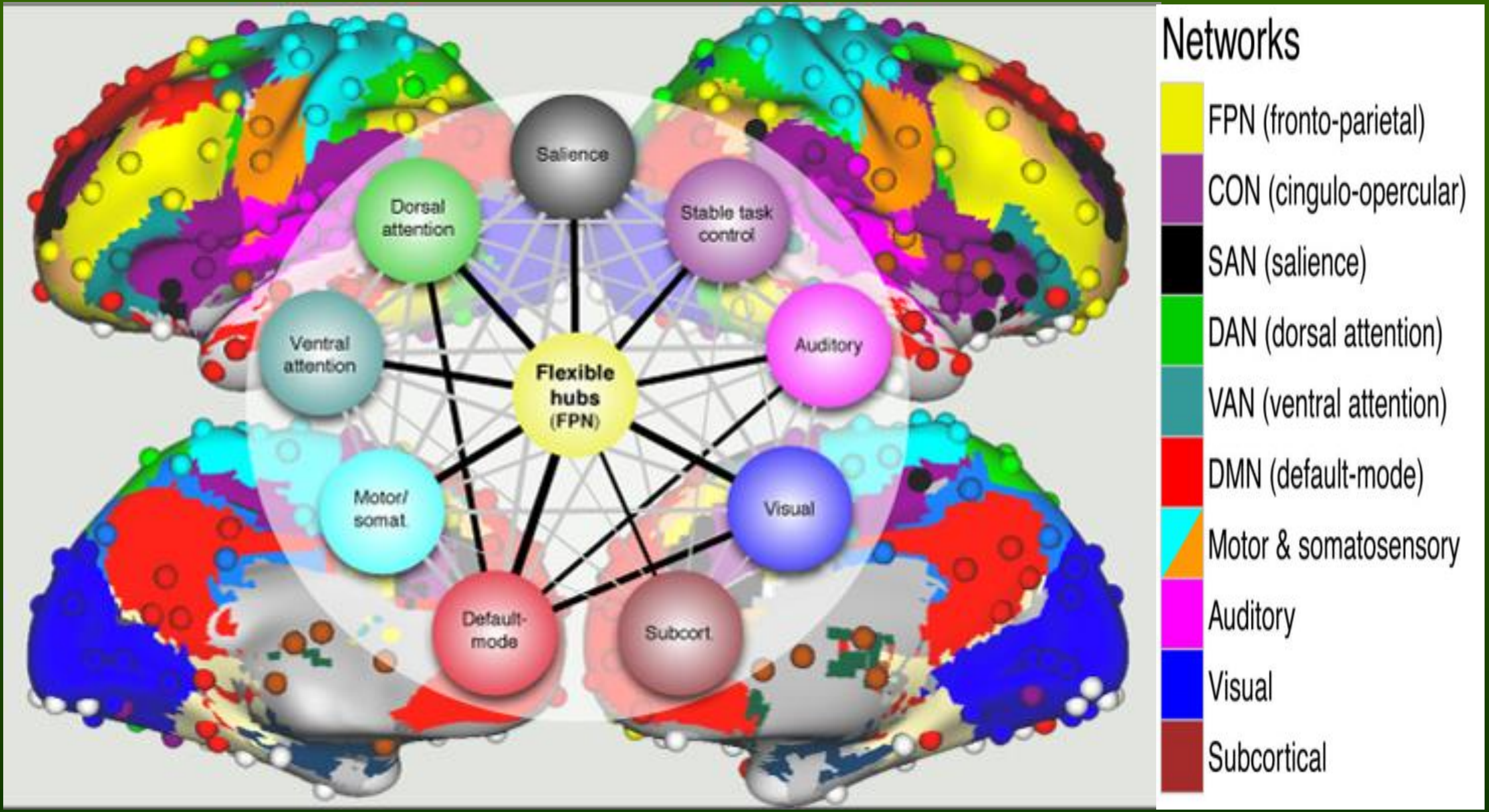
Functional brain networks

~ Small worlds architecture



All complex functions are based on synchronization of many distributed brain areas. Memory, personality or consciousness are collection of functions, like multi-agent systems or the “society of mind”. Psychological constructs should be “deconstructed” to connect them with specific brain processes.

Neurocognitive Basis of Cognitive Control



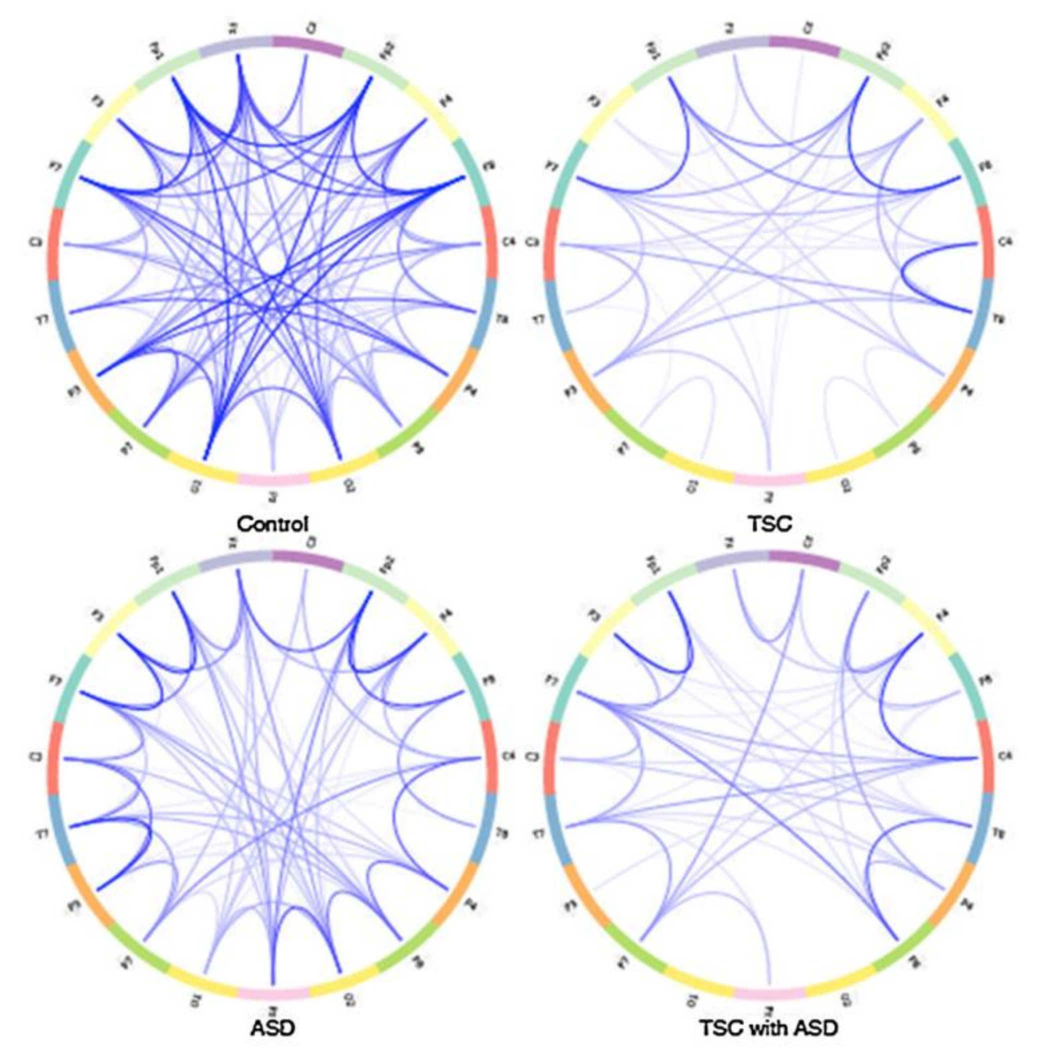
Central role of fronto-parietal (FPN) flexible hubs in cognitive control and adaptive implementation of task demands (black lines=correlations significantly above network average). Cole et al. (2013).

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.

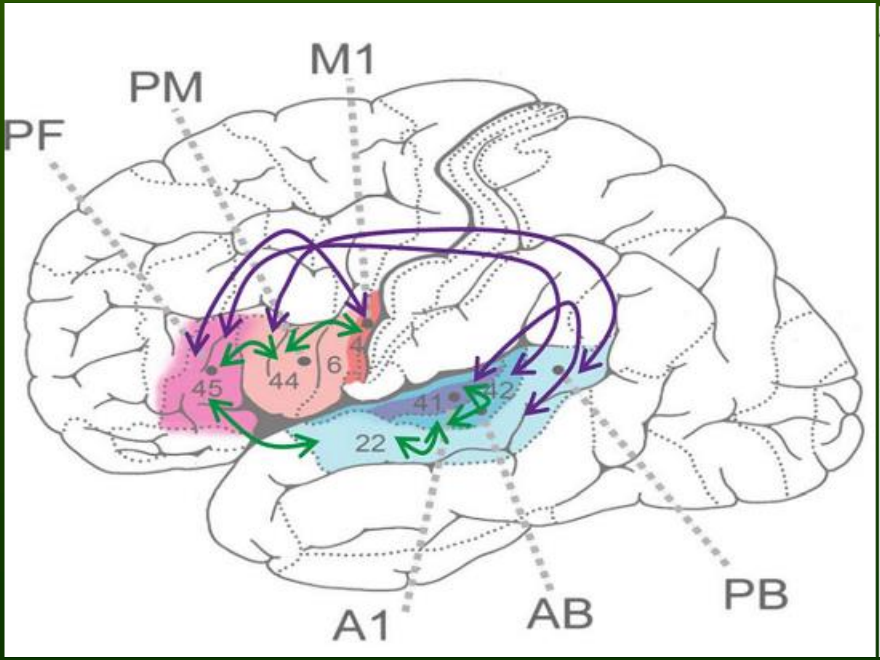


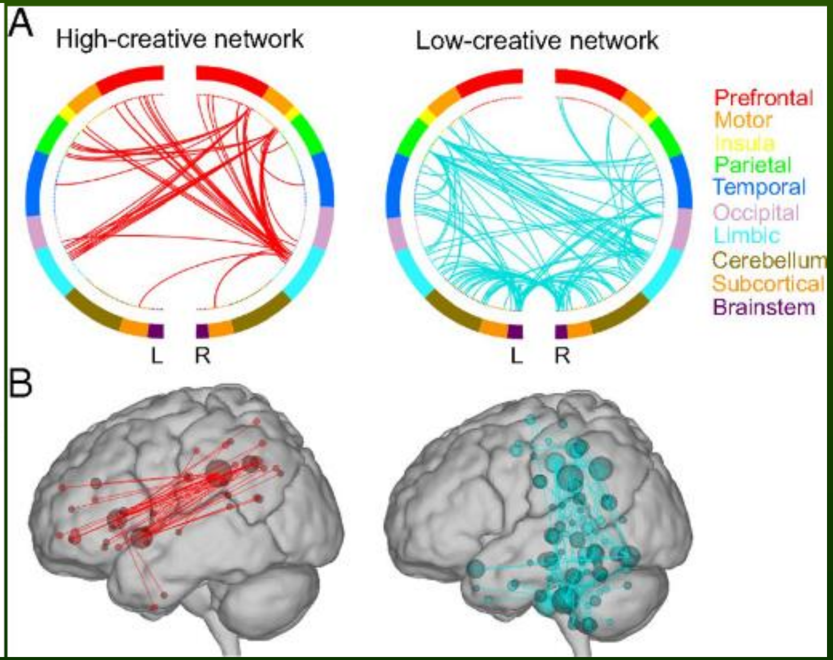
J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

Rozwój inteligencji

W okresie niemowlęcym najpierw ruch i związane z nim wrażenia wpływają na organizację przepływu informacji przez mózg. Zanim dziecko zacznie wymawiać słowa pokazuje swoje intencje gestami (nauka .

The Developing Human Connectome Project: jak rozwija się konektom, sieć połączeń w mózgu w okresie pre-natalnym, 20 - 44 tygodnia ciąży? Badania za pomocą neuroobrazowania (fMRI, EEG), obserwacji ruchów i reakcji płodu, genetyce. Neurony wysyłają impulsy dopiero w 24 tyg. ciąży.





Effect of cognitive load

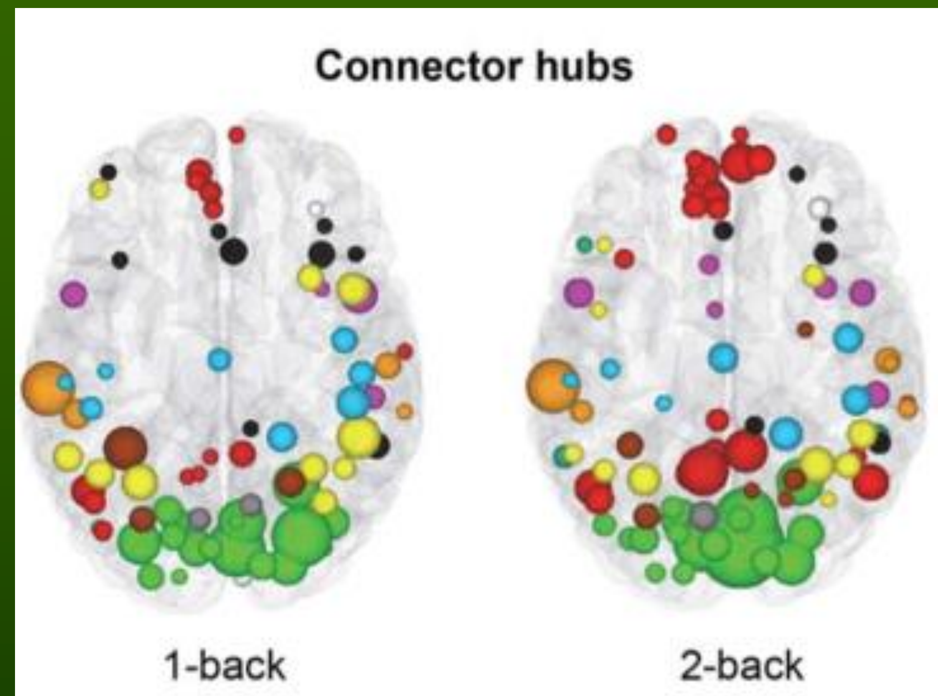
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back Top: connector hubs

Right: 2-back Bottom: local hubs

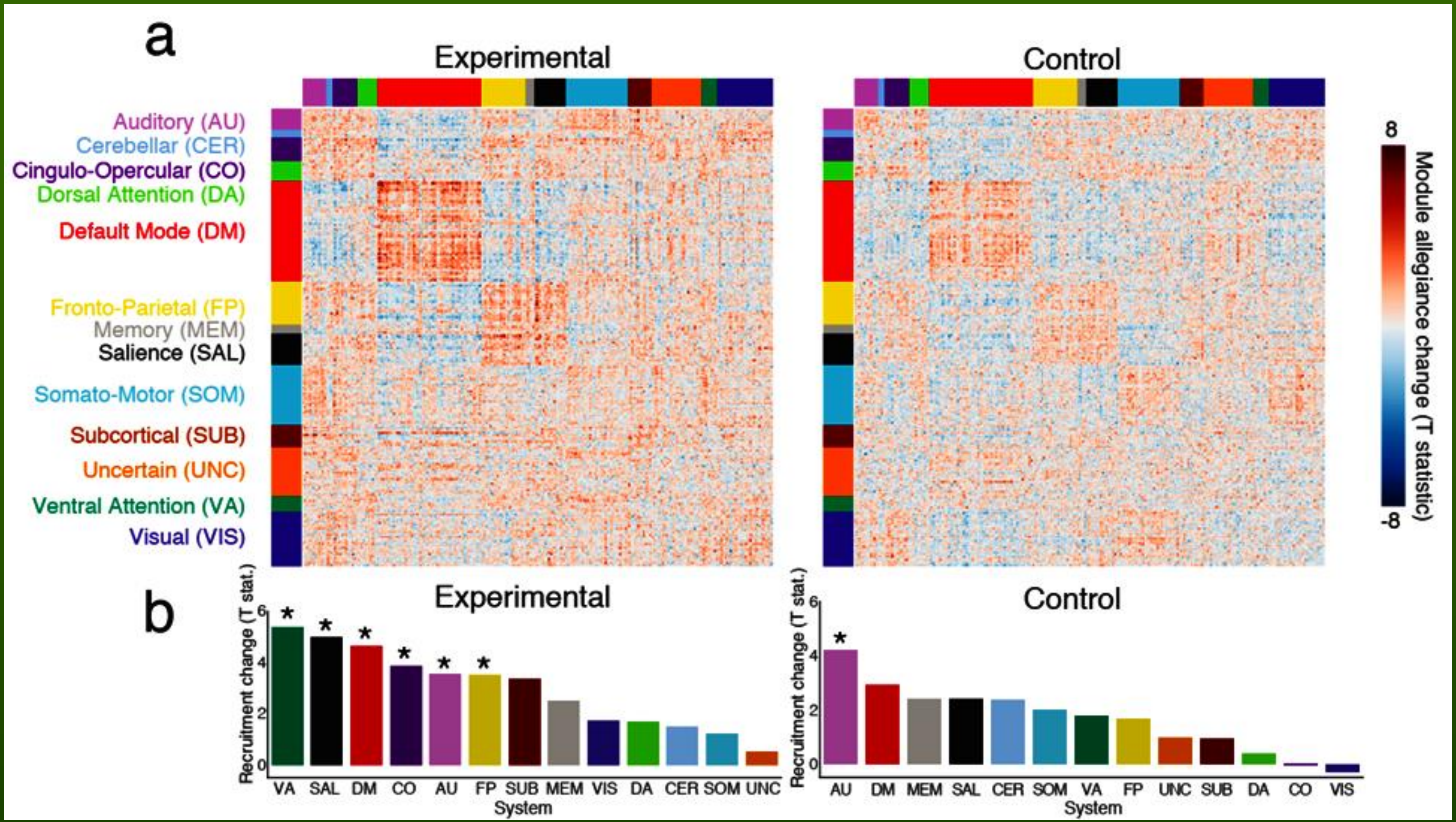
Average over 35 *participants.*

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



K. Finc et al, HBM (2017).

Working memory training



Whole-brain changes in module allegiance between the ‘Naive’ and ‘Late’ 6-week working memory training stages.

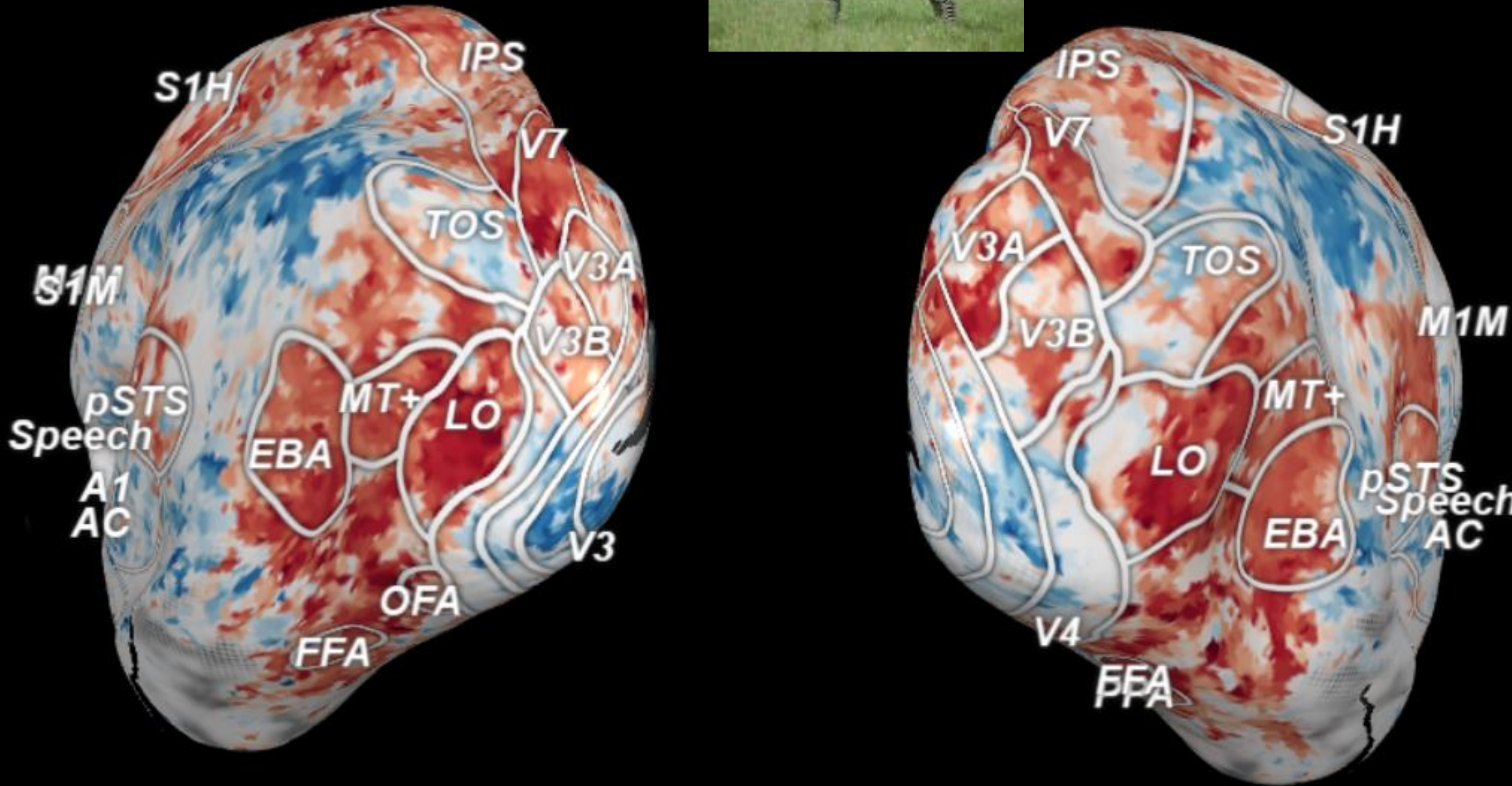
(**a**) Changes in node allegiance as reflected in the two-tailed *t*-test.

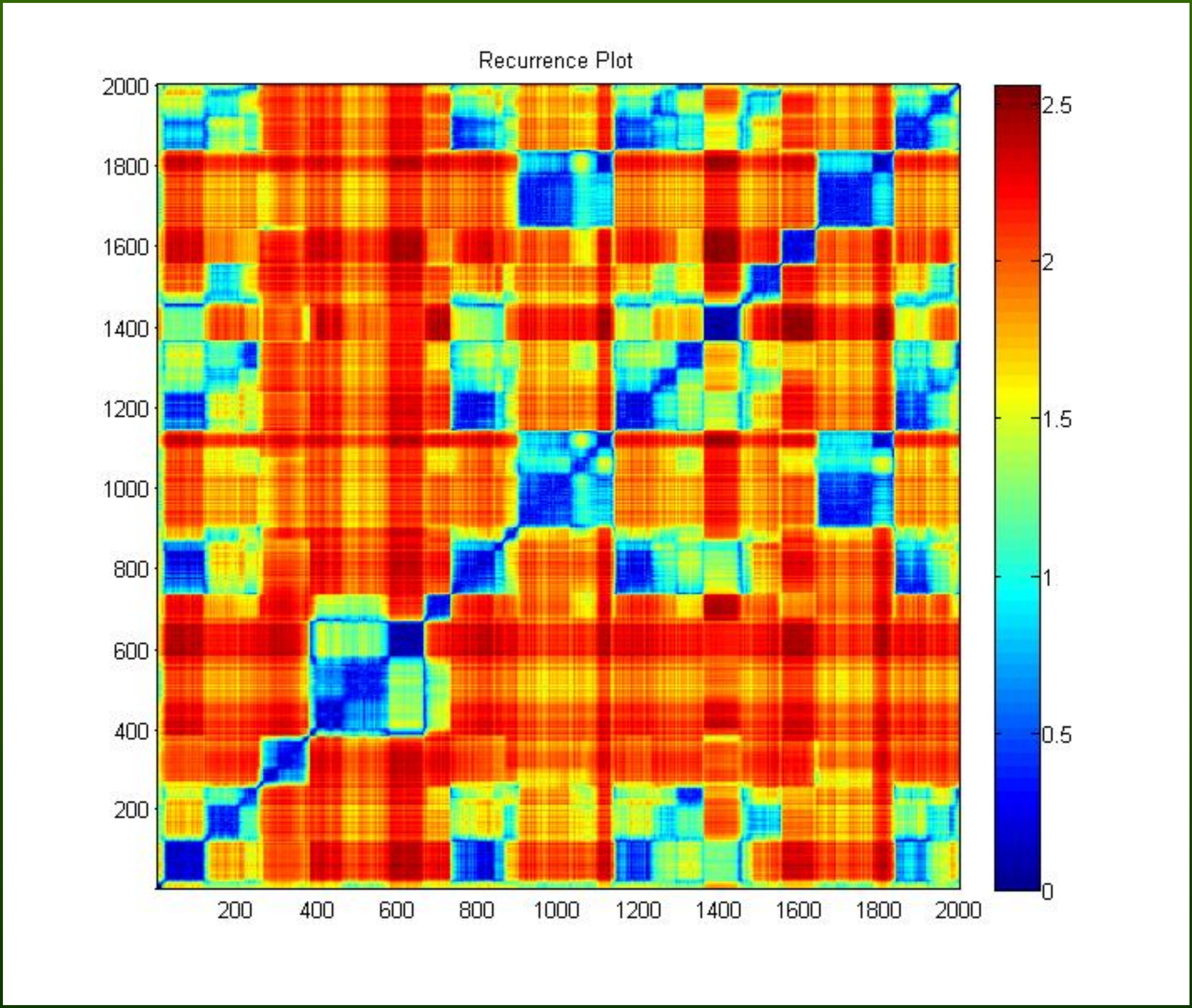
(**b**) Significant increase * in the default mode, fronto-parietal ventral attention, salience, cingulo-opercular, and auditory systems recruitment.

K. Finc et al, Nature Communications (2020).

Brain activity beyond visual cortex: Gallant Lab

Category zebra: Passive Viewing





Activation of 140 semantic layer units starting from the word „gain": rapid transitions between a sequence of related concepts is seen. Real EEG is coming.

The Virtual Brain (TVB) and its neural population models

Not in TVB

Cellular models

Hodgkin-Huxley

Morris-Lécar

In TVB

Local Field Potential, synaptic activity

Stefanescu-Jirsa 2D

Stefanescu-Jirsa 3D

Wong-Wang

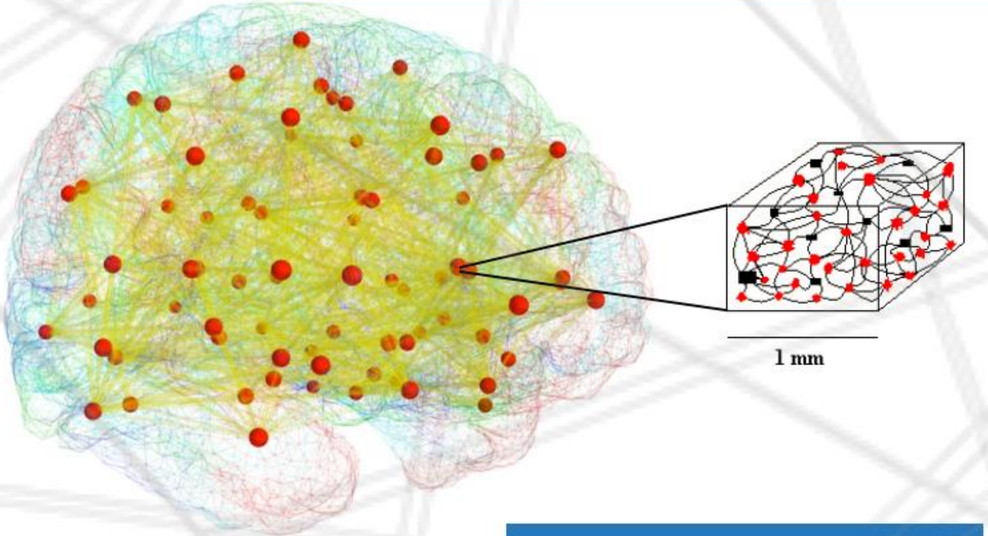
Firing rate

Wilson-Cowan

Brunel-Wang

Jansen-Rit

All models can be described by nonlinear dynamic systems via differential equations



Phenomenological

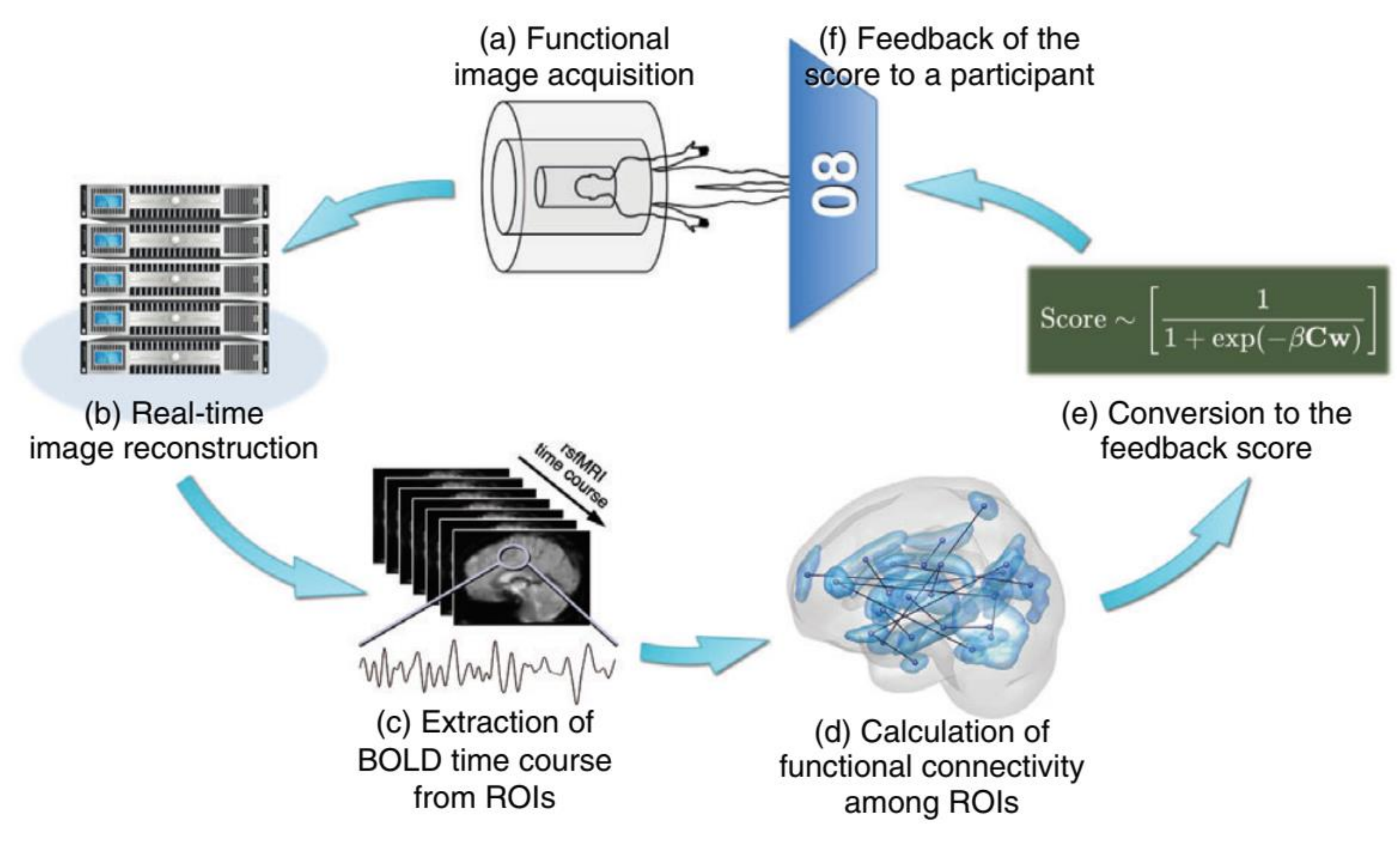
Generic 2D

Kuramoto

Epileptor

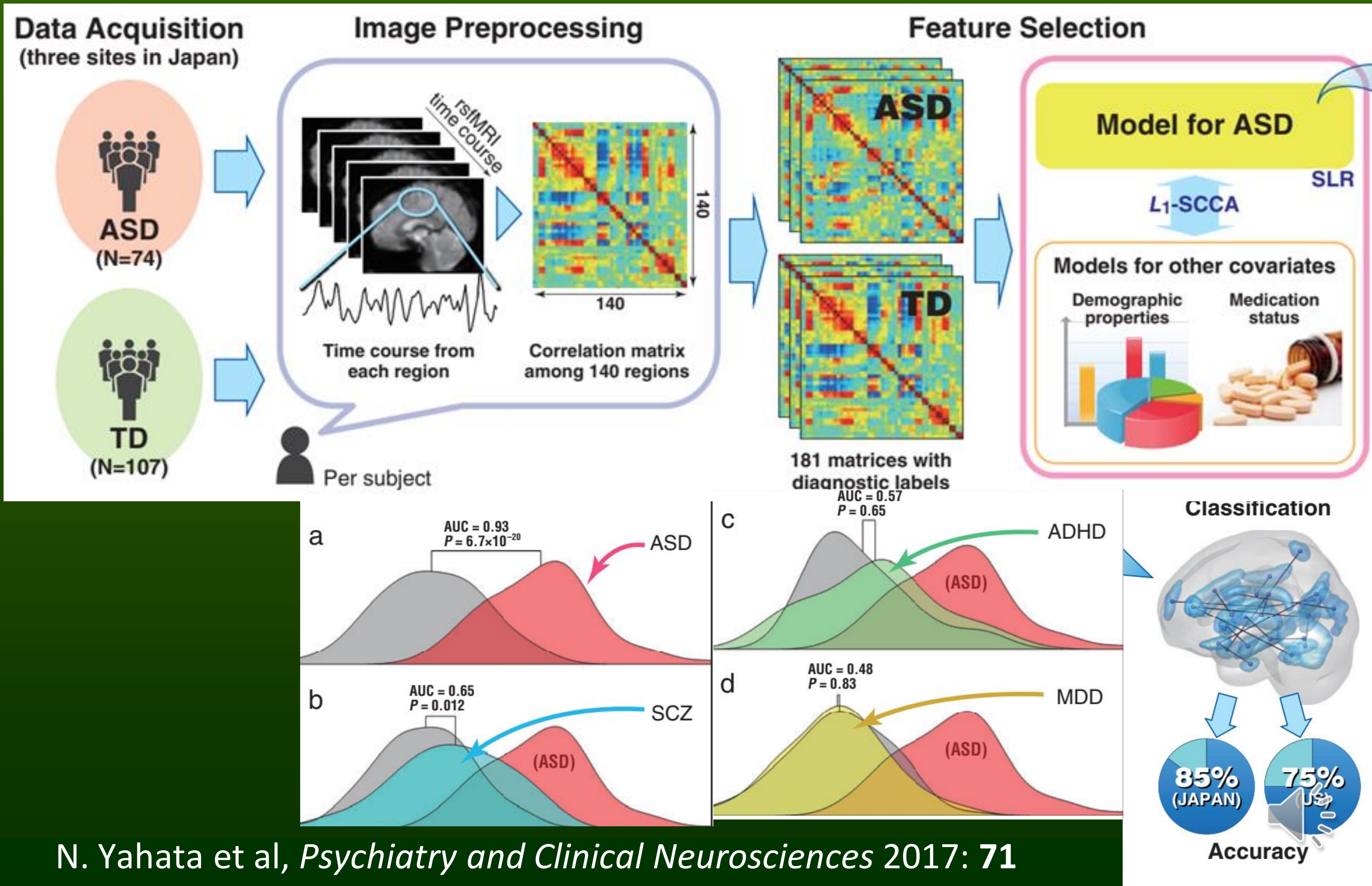
Sanz Leon et al Front NeuroInformatics 2013

Neurofeedback may repair network?



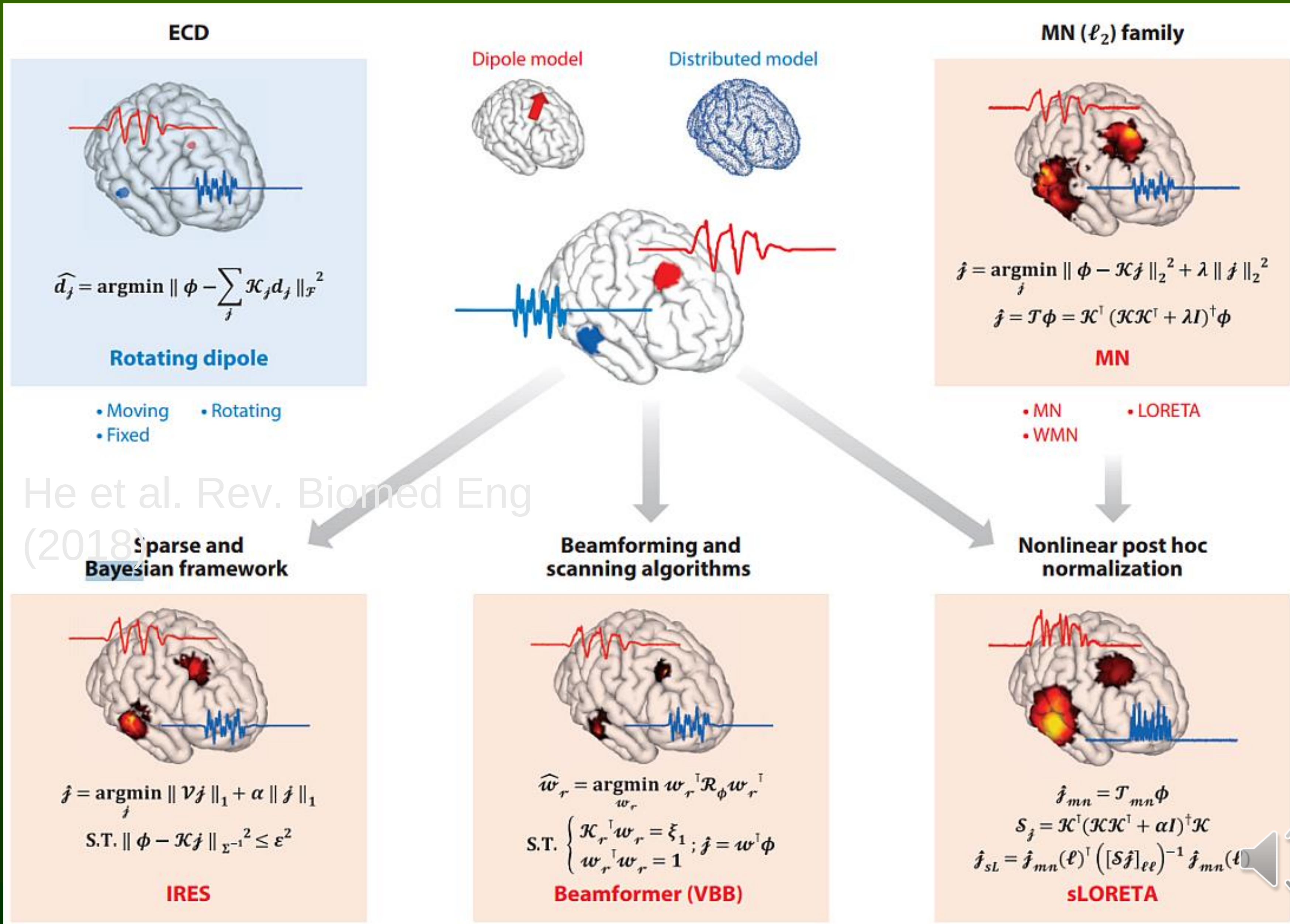
Megumi F, Yamashita A, Kawato M, Imamizu H. Functional MRI neurofeedback training on connectivity between two regions induces long-lasting changes in intrinsic functional network. *Front. Hum. Neurosci.* 2015; **9**: 160.

Biomarkers from neuroimaging



N. Yahata et al, *Psychiatry and Clinical Neurosciences* 2017: **71**

EEG localization and reconstruction



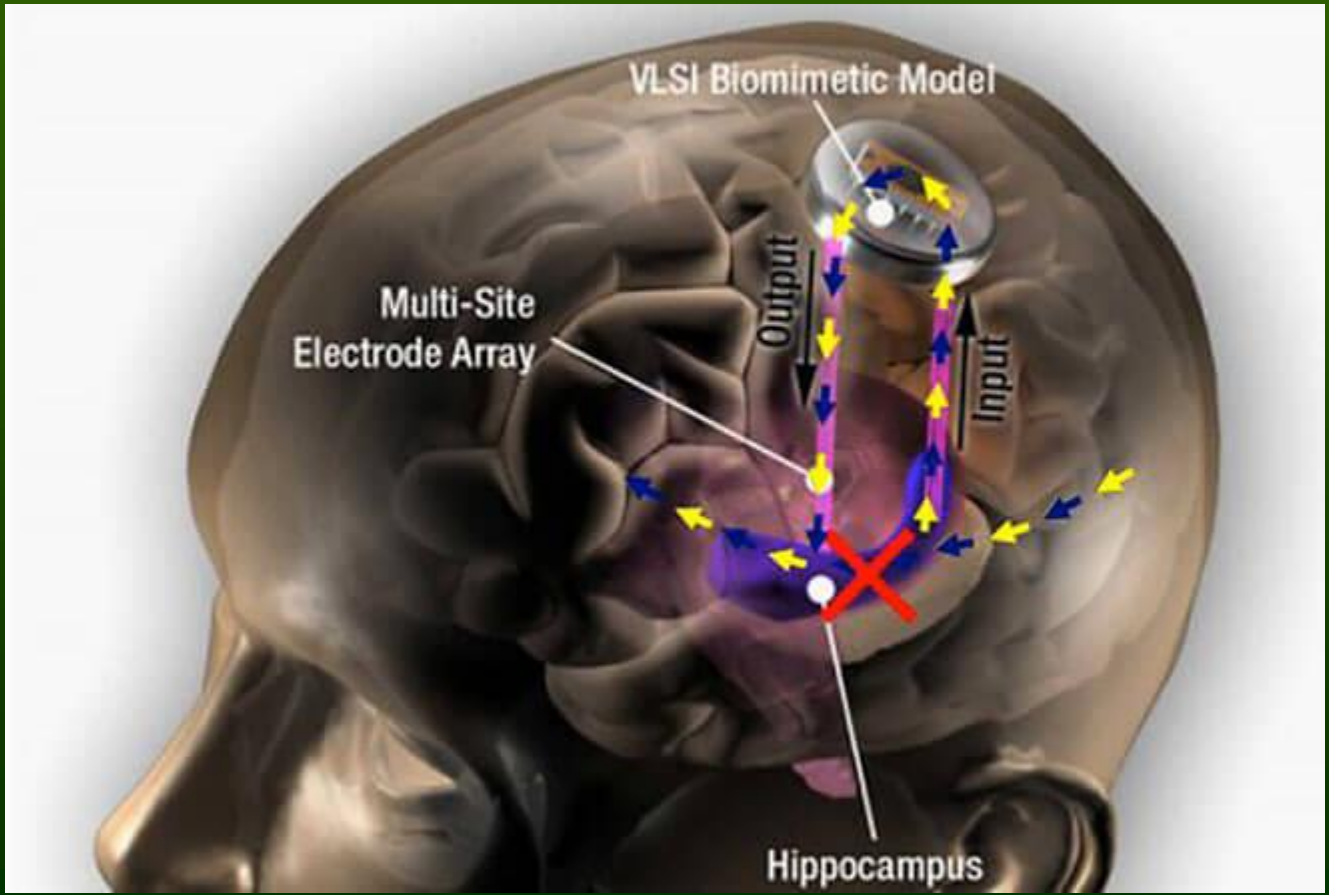
He et al. Rev. Biomed Eng (2018)

Memory implants

Ted Berger (USC, Kernel): hippocampal neural prosthetics facilitate human memory encoding and recall using the patient's own hippocampal spatiotemporal neural codes. Tests on rats, monkeys and on people gave memory improvements on about 35% (J. Neural Engineering 15, 2018).

DARPA: Restoring Active Memory (RAM), new closed-loop, non-invasive systems that leverage the role of neural “replay” in the formation and recall of memory to help remember specific episodic events and learned skills.

RNS for epilepsy!

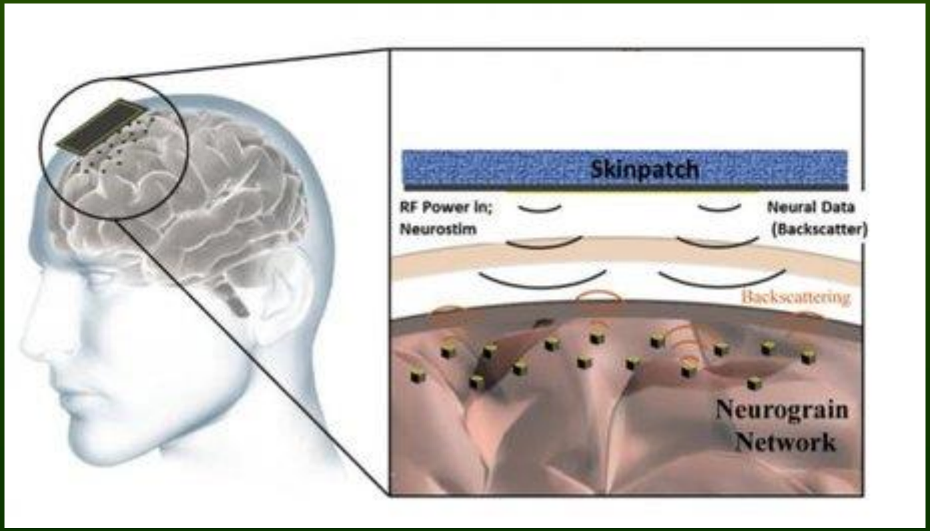


Million nanowires in your brain?

DARPA (2016): **Neural Engineering System Design (NESD)**
Interface that reads impulses of 10^6 neurons, injecting currents to 10^5 neurons, and reading/activating 10^3 neurons.

DARPA Electrical Prescriptions (ElectRx) project enables “artificial modulation of peripheral nerves to restore healthy patterns of signaling in these neural circuits. ElectRx devices and therapeutic systems under development are entering into clinical studies.”

Neural lace i neural dust project for cortex stimulation.



Internet of Bodies

Internet of Bodies (IoB) network based on: medical devices (pacemakers, insulin pumps, pulse, SPO2, temperature sensors), consumer tech (wireless earbuds, smartwatches, fitness trackers), all send data beyond the range of the human body, but they can use the common medium of the body itself to send signals.

From: [Turning the Body Into a Wire](), IEEE Spectrum 11/2020.

Perspektywy

- Sztuczna inteligencja zmienia sposób uprawiania nauki, nie da się uniknąć dominacji wielkich firm i globalnych konsorcjów.
- To co wczoraj było niemożliwe jutro będzie codziennością, postrzeganie świata i rozumienie języka doprowadzi do autonomicznej formy AI.
- Automatyzacja wymusi wielkie zmiany społeczne.
- 3 wymiary i czas będą dla AI mało interesujące – ewolucja myśli przeniesie się w światy wielowymiarowe, artilekty będą uczyć się szybko od siebie, a nowa wiedza stanie się niezrozumiała dla ludzi.
- Maszyny będą twierdzić, że są świadome, a większość ludzi to akceptuje; prawny status cyborgów jest już teraz dyskutowany.
- Technologie neurokognitywne głęboko zmienią człowieka.
- Dzięki implantom wirtualna rzeczywistość nie będzie się różnić od wrażeń realnych; część osób może się w niej całkiem zagubić; sposób przeżywania swojego istnienia stanie się radykalnie odmienny od obecnego.
- Integracja mózgów z systemami sztucznymi stanie się stopniowo możliwa ... W końcu nadejdzie osobliwość!

Wielka zmiana?

Nie wszyscy zauważyli, że się coś zmieniło.
Polowanie i walka trwa nadal, tylko zniszczenia są coraz większe.

Few Steps Towards Human-like Intelligence

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

IEEE SSCI CIHLI 2021 Symposium on Computational Intelligence for Human-like Intelligence, Orlando, FL, USA.

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

BICA: Annual International Conf. on Biologically Inspired Cognitive Architectures, 11th Annual Meeting of the BICA Society, Natal, Brazil, 2020.

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

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).

Referaty po polsku + talks in English – on my page, Google Wlodek Duch

2020:

- Sztuczna inteligencja i przyszłość cywilizacji
- Zastosowania edukacyjne wykorzystujące osiągnięcia neuronauk
- Sztuczna inteligencja i przyszłość cywilizacji

2019:

- Mózg człowieka i sztuczna inteligencja
- Jak możemy zrozumieć aktywność mózgu?
- Sztuczna inteligencja i technologie neurokognitywne
- Fizyka umysłu
- Autyzm - sposoby komunikacji
- Taniec i mózgi
- Sztuczna inteligencja i przyszłość ludzkości
- Sztuczna inteligencja: gdzie jesteśmy i dokąd zmierzamy?

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

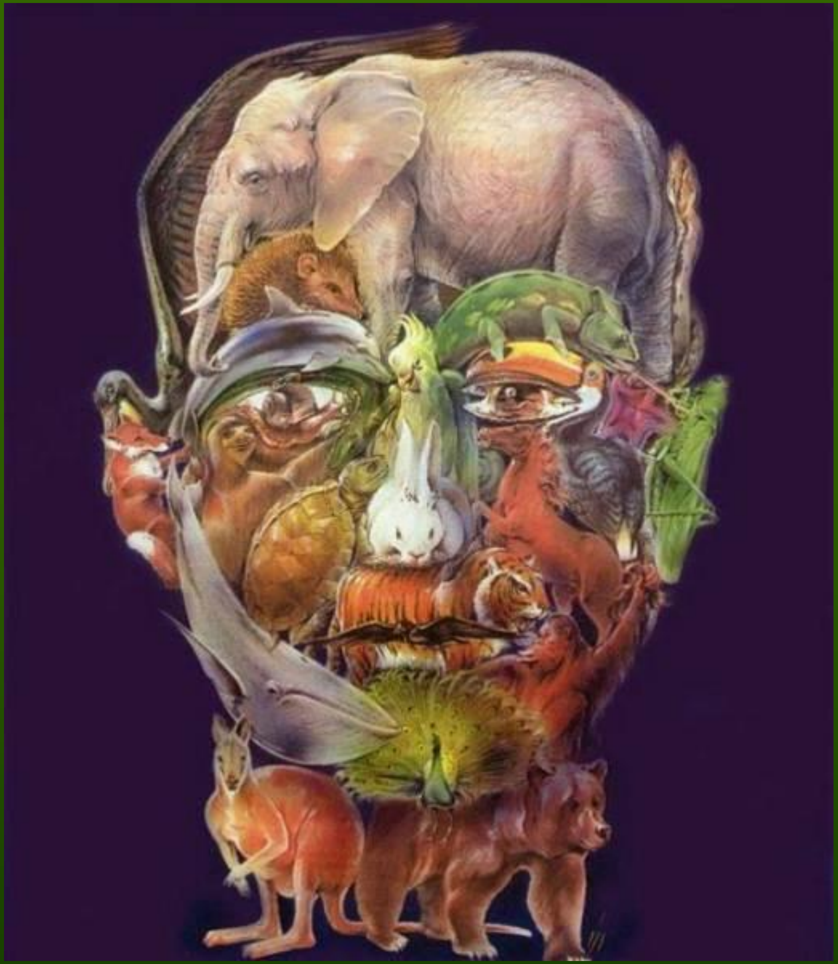
INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

nencki institute of experimental biology

My group of neuro-cog-fanatics

Graduates of: cognitive science, computer science, engineering, mathematics, neuroscience, philosophy, physics, psychology.

Inteligencja?



Google: Wlodek Duch
=> referaty, prace, wykłady …

Centra doskonałości AI

Komunikat Komisji Europejskiej (4/2018): „Sposób w jaki podejdziemy do sztucznej inteligencji zdefiniuje rzeczywistość, w jakiej będziemy żyć.”

European Network of Artificial Intelligence (AI) Excellence Centers, €50m
Konsorcja (10/2020) – dobry wzór dla Polski?

- AI4Media: ethical and trustworthy AI, beneficial technology in the service of society and media.
- ELISE: invites all ways of reasoning, considering all types of data, striving for explainable and trustworthy outcomes.
- HumanE-AI-Net: supports technologies for human-level interaction, empower individuals with new abilities for creativity and experience.
- TAILOR: builds an academic-public-industrial research network for Trustworthy AI, combining learning, optimization and reasoning.
- VISION: to foster exchange between the selected projects and other relevant initiatives, ensuring synergy and overcoming fragmentation in EU.