From Aristoteles to AI Today

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HĪKINA WHAKATUTUKI

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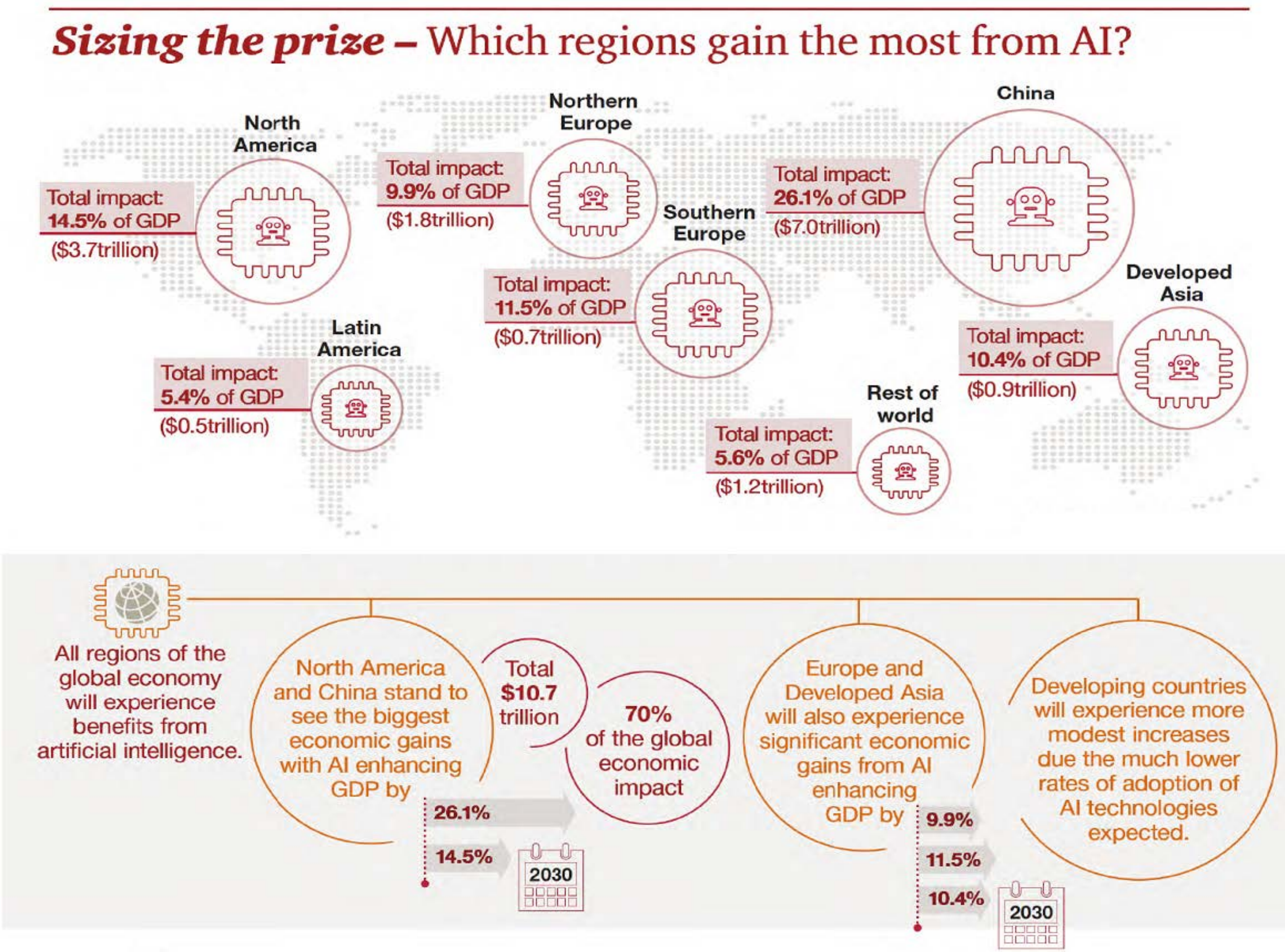
2. From Aristoteles' epistemology to von Neumann information theory
3. Deep neural networks and brain-inspired AI
4. The future of AI ?

Main reference:

N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer, 2019, https://www.springer.com/gp/book/9783662577134

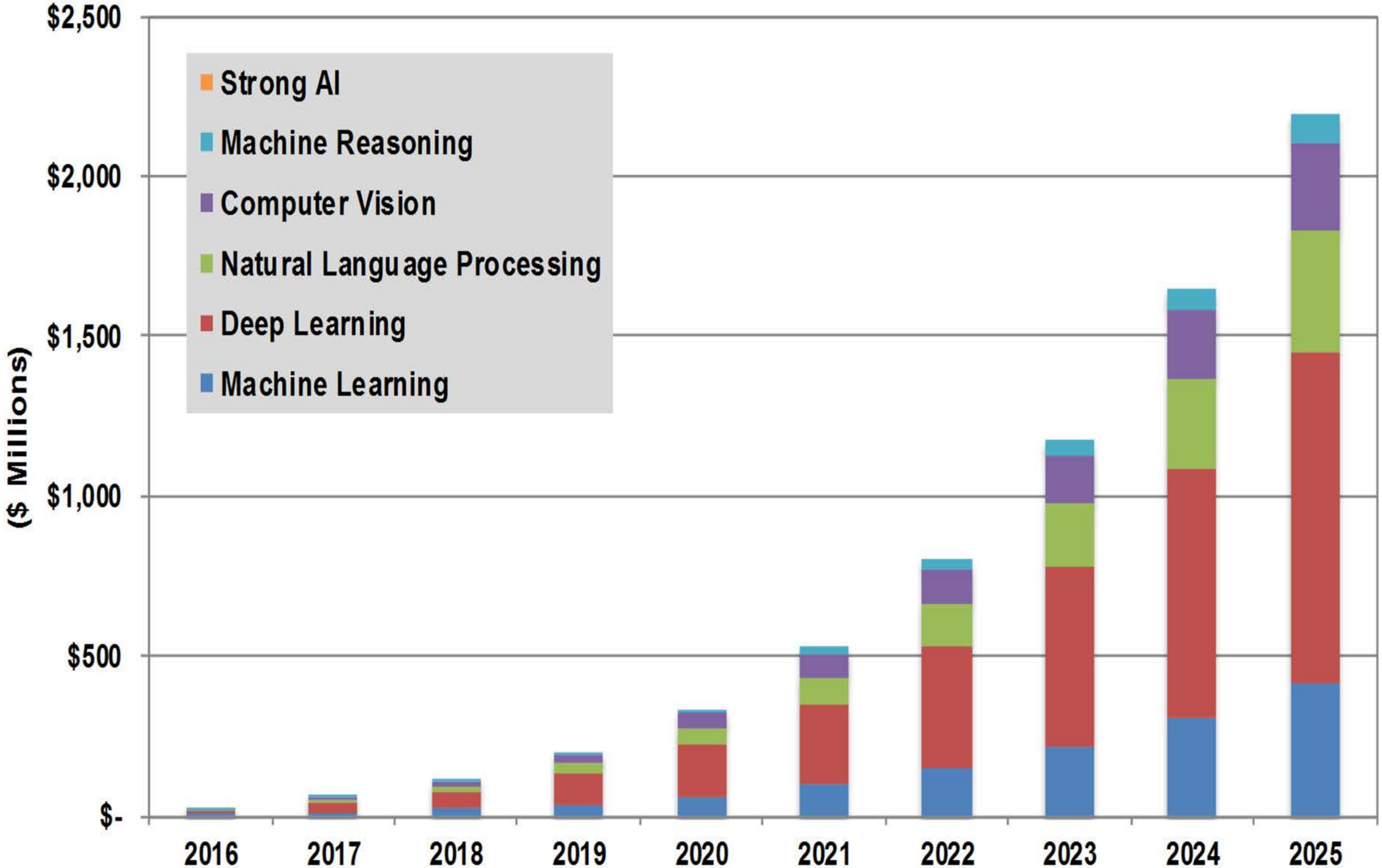
1. What is AI?

- AI is Part of the interdisciplinary information sciences area that develops and implements methods and systems that manifest cognitive behaviour.
- Main features of AI are: learning, adaptation, generalisation, inductive and deductive reasoning, human-like communication.
- Some more features are currently being developed: consciousness, self-assembly, self-reproduction, AI social networks,....
- A fast development of AI is expected in the years to come



Sizing the prize – Which regions gain the most from AI?
North America
Total impact: 14.5% of GDP ($3.7trillion)
Northern Europe
Total impact: 9.9% of GDP ($1.8trillion)
Southern Europe
Total impact: 11.5% of GDP ($0.7trillion)
China
Total impact: 26.1% of GDP ($7.0trillion)
Developed Asia
Total impact: 10.4% of GDP ($0.9trillion)
Latin America
Total impact: 5.4% of GDP ($0.5trillion)
Rest of world
Total impact: 5.6% of GDP ($1.2trillion)
All regions of the global economy will experience benefits from artificial intelligence.
North America and China stand to see the biggest economic gains with AI enhancing GDP by
26.1%
14.5%
2030
Total $10.7 trillion
70% of the global economic impact
Europe and Developed Asia will also experience significant economic gains from AI enhancing GDP by
9.9%
11.5%
10.4%
2030
Developing countries will experience more modest increases due the much lower rates of adoption of AI technologies expected.

AI Revenue by Technology, World Markets: 2016-2025

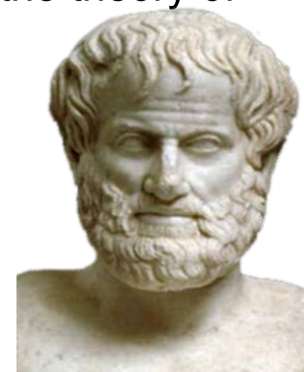


Tractica, White paper, 2017

2. From Aristoteles' epistemology to von Neumann information theory

To understand the current and future AI we need to understand its roots, its principles and its trends...

Aristoteles (384-322 BC) was a pupil of Plato and teacher of Alexander the Great. He is credited with the earliest study of formal logic. Aristotle introduced the theory of propositional knowledge *deductive reasoning*.



Example:

All humans are mortal (i.e. IF human THEN mortal)

New fact: Socrates is a human

Deducted inference: Socrates is mortal

Aristotle introduced *epistemology* which is based on the study of particular phenomena which leads to the articulation of knowledge (rules, formulas) across sciences: botany, zoology, physics, astronomy, chemistry, meteorology, psychology, etc. According to Aristotle this knowledge was not supposed to change *in time* (becomes dogma)!

In places, Aristotle goes too far in deriving 'general laws of the universe' from simple observations and over-stretched the reasons and conclusions. Because he was perhaps the philosopher most respected by European thinkers during and after the Renaissance, these thinkers along with institutions often took Aristotle's erroneous positions, such inferior roles of women, which held back science and social progress for a long time.

The birth and the boom of symbolic AI: Logic, rules and deductive reasoning

Ada Lovelace (1815-1852)

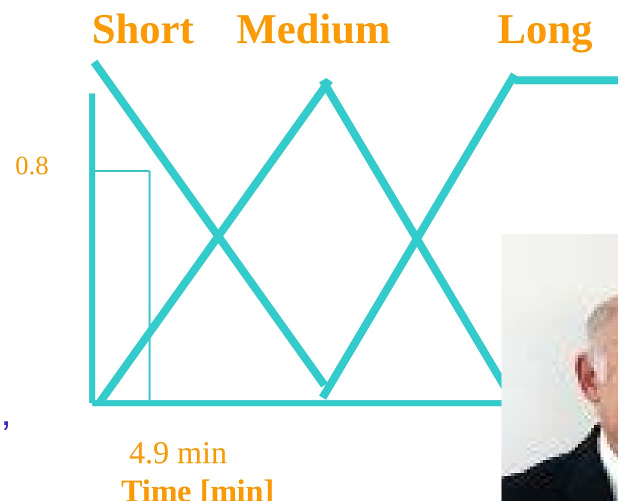
- Machine can deal with symbols (Ada Lovelace)
- Types of knowledge representation and reasoning systems:
  - Relations and implications, e.g.:
    - A-> (implies) B,
  - Propositional (true/false) logic, e.g.:
    - IF (A and B) or C THEN D
  - Boolean logic (George Boole)
  - Predicate logic: PROLOG
  - Probabilistic logic:
    - e.g. Bayes formula: p(A ! C)) = p (C ! A) . p(A) / p(C)
  - Rule based systems; expert systems, e.g. MYCIN.
  - Temporal and spatio-temporal rules.

Logic systems and rules are too rigid to represent the uncertainty in the natural phenomena; they are difficult to articulate, and not adaptive to change.

Fuzzy Logic: Accounting for uncertainties in a human-like, linguistically represented knowledge

(L.Zadeh, 1920 - 2018)

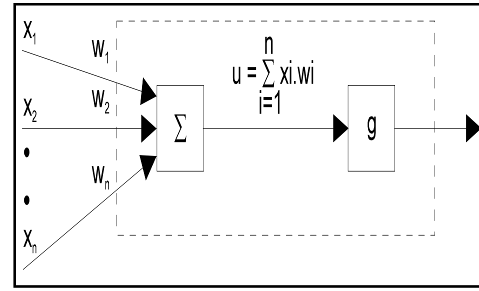
- Fuzzy logic (1965) represents information uncertainties and tolerance in a linguistic form:
  - fuzzy rules, containing fuzzy propositions;
  - fuzzy inference
- Fuzzy propositions can have truth values between true (1) and false (0), e.g. the proposition “washing time is short” is true to a degree of 0.8 if the time is 4.9 min, where *Short* is represented as a *fuzzy set* with its *membership function*
- Fuzzy rules can be used to represent human knowledge and reasoning, e.g. “*IF wash load is small THEN washing time is short*”. Fuzzy inference systems: Calculate outputs based on input data an a set of fuzzy rules
- Contributions from: T.Yamakawa, L.Koczy, I.Rudash and many others



However, fuzzy rules need to be articulated in the first instance, they need to change, adapt, evolve through learning, to reflect the way human knowledge evolves.

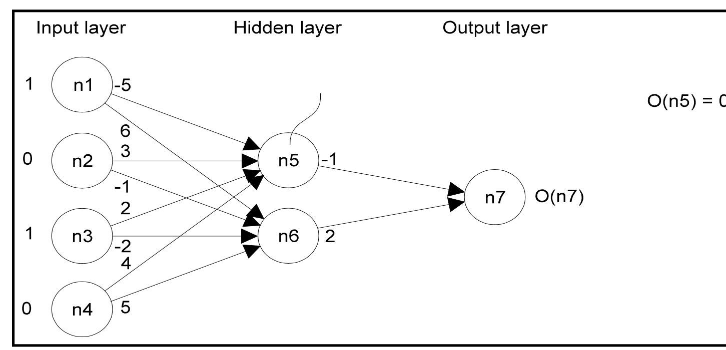
Artificial Neural Networks

- ANN are computational models that mimic the nervous system in its main function of adaptive learning and *generalisation.*
- ANN are *universal computational models*
- 1943, McCulloch and Pitts neuron
- 1962, Rosenblatt - Perceptron
- 1971- 1986, Amari, Rumelhart, Werbos: Multilayer perceptron
- Many engineering applications.



Franc Roseblatt (1928 -1971)

- Early NN were ‘black boxes’ and also - once trained, difficult to adapt to new data without much ‘forgetting’. Lack of knowledge representation.

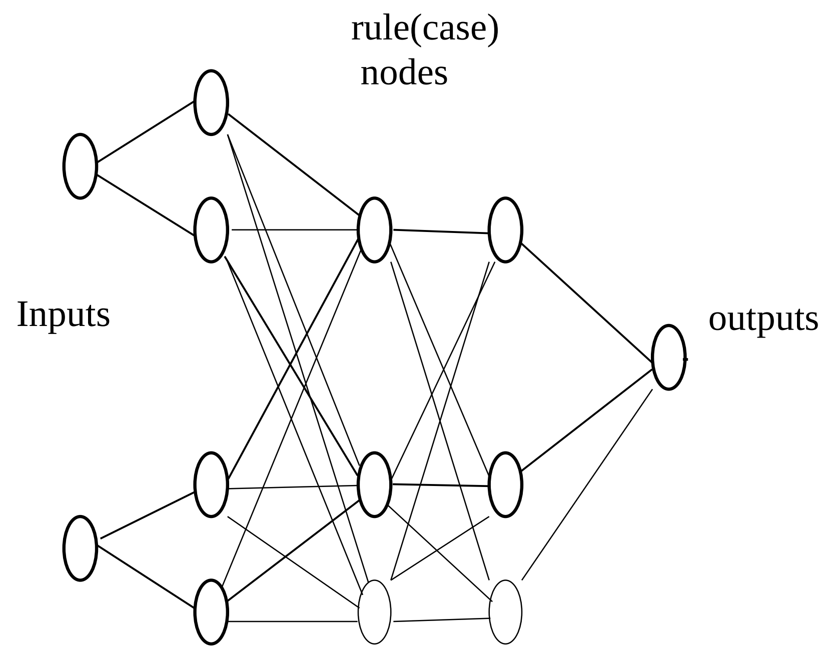


Evolving Connectionist Systems (ECOS)

Adaptive neural networks for incremental learning and rule extraction
The neuro-fuzzy systems (no more the “black box curse”)

- Evolve their structure and functionality.
- Knowledge-based !!

- Neuro-fuzzy systems
- As a general case, input and/or output variables can be non-fuzzy (crisp) or fuzzy
- Fuzzy variables, e.g. Gaussian MF
- Early works:
  - Yamakawa (1992)
  - EFuNN, DENFIS, N. Kasabov, 2001/2002
- Incremental, supervised clustering
- Fuzzy rules can be extracted from a trained NN and the rules can change (evolve) as further training goes:



IF Input 1 is High and Input 2 is Low
THEN Output is Very High (static knowledge)

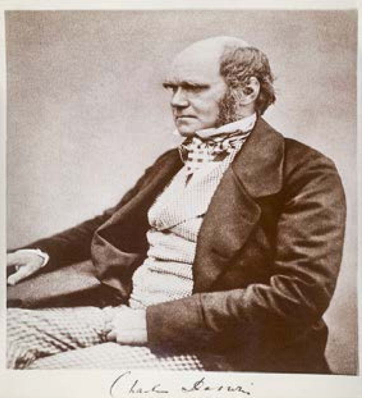
24 Centuries after Aristotle, now we can automate the process of rule extraction and knowledge discovery from data!

Machine learning inspired by Nurture (the brain) and by Nature (Evolution)

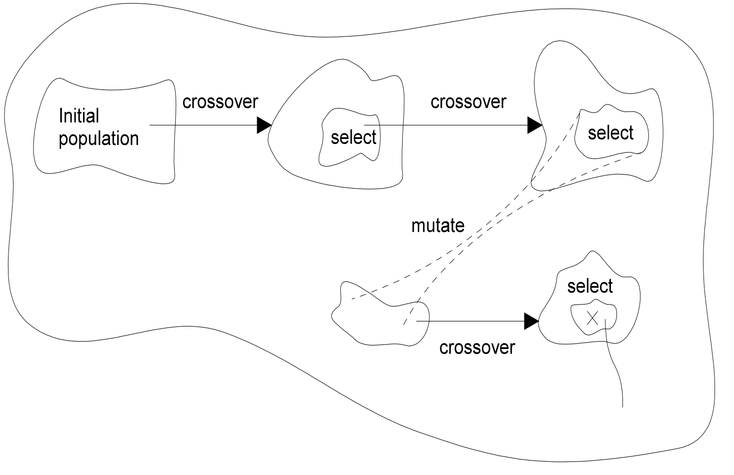
Evolutionary computation: Learning through evolution

- Species learn to adapt through genetic evolution (e.g. crossover and mutation of genes) in populations over generations.
- Genes are carrier of information: stability vs plasticity
- A set of chromosomes define an individual
- Survival of the fittest individuals within a population
- Evolutionary computation (EC) as part of AI is population/generation based optimisation method.

EC can be used to optimise parameters (genes) of learning systems.



Charles Darwin (1809-1882)



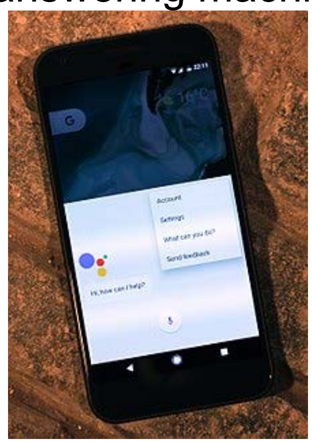
Teaching machines to communicate like humans

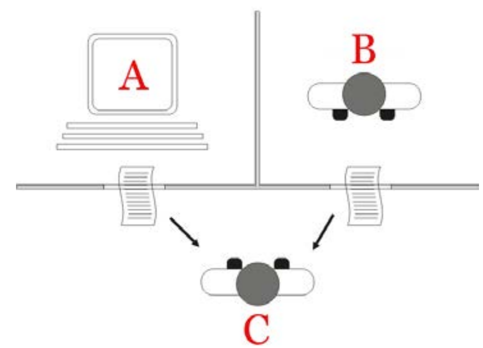
Alan Turing (1912-1954)

Alan Turing (1912-1954) posed a question in 1950: Can computers have general intelligence to communicate like humans?

The Turing test has been too difficult to achieve, but simple communications are now possible in limited natural language.

ChatBot: A computer systems that can communicate on a specific topic in a *natural language* with users and give them answeres to specific questions (question answering machine).





Challenge: ChatBots need AI to collect and learn a large amount of heterogeneous data (e.g. clinical, EEG, fMRI, Xrays, etc) in order to create a personalised model of the user and to suggest the best options to this user.

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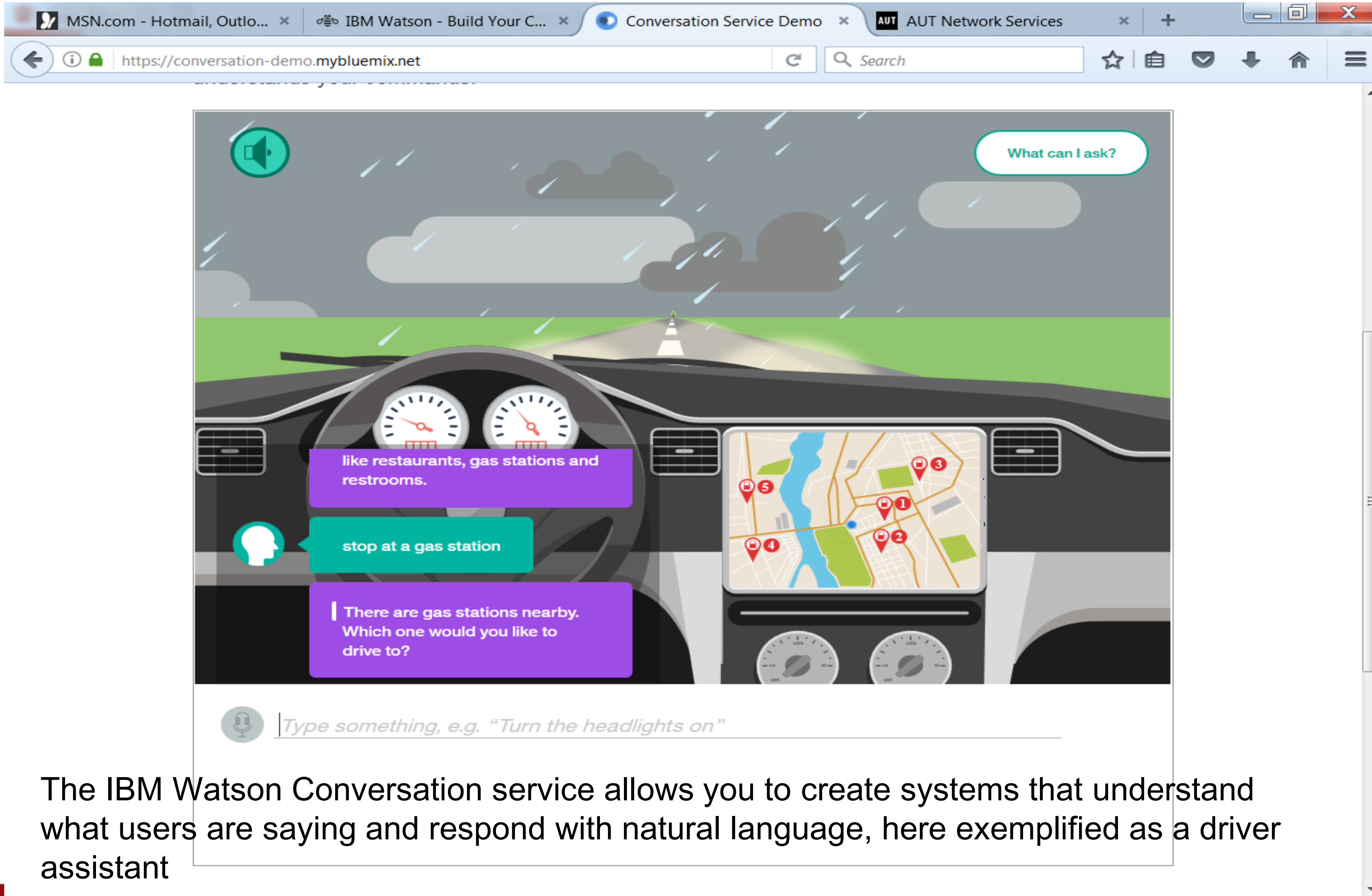
Natural language processing
Example: Driver assistance



The IBM Watson Conversation service allows you to create systems that understand what users are saying and respond with natural language, here exemplified as a driver assistant

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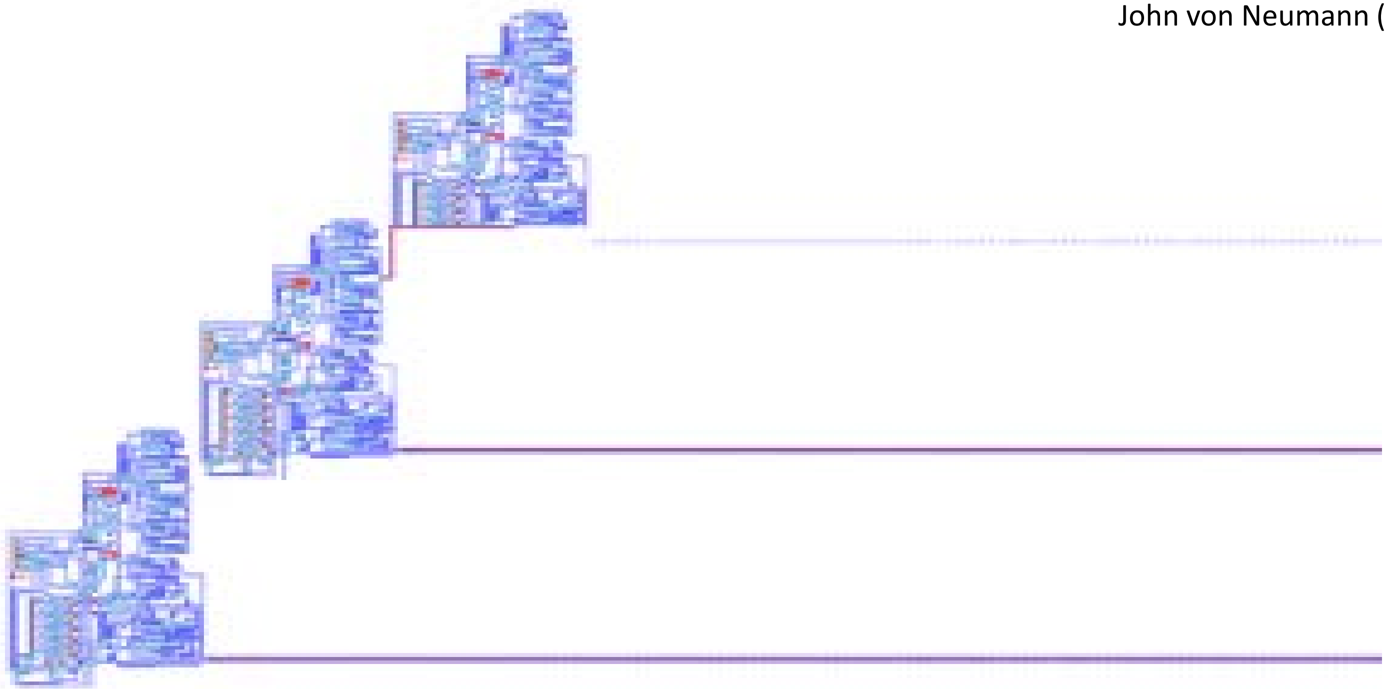
Cellular automata, DNA and the universal constructor

John von Neumann created the theory of cellular automata without the aid of computers, constructing the first self-replicating automata with pencil and graph paper.

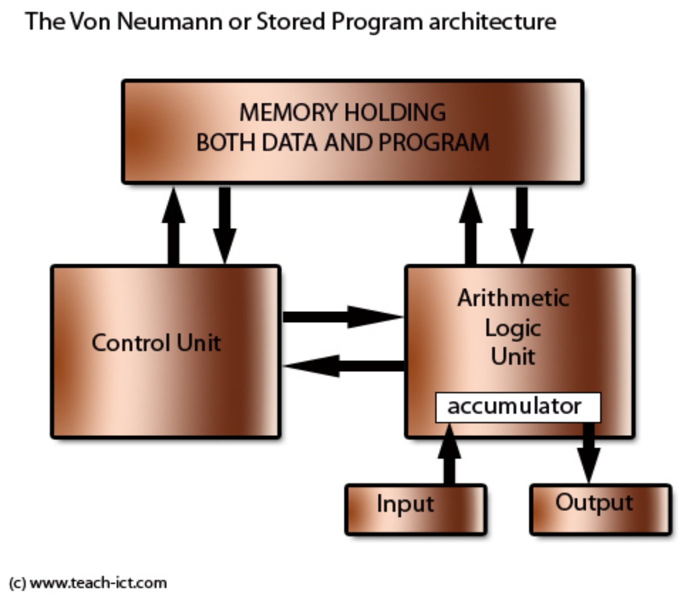
The detailed proposal for a physical non-biological self-replicating system was first put forward in lectures Von Neumann delivered in 1948 and 1949, when he first proposed a kinematic self-reproducing automaton.

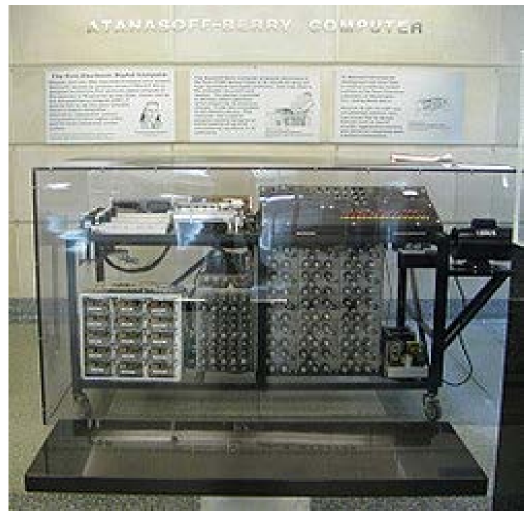
John von Neumann (1903-1957)

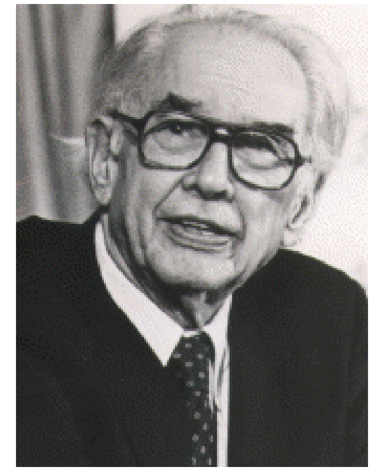


The von Neumann principles and Atanasoff's ABC Machine

The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*.







John Atanasoff (1903-1995)

First electrical machine ABC by John Atanassoff and Clifford Berry (1937)

Unfinished book by John von Neumann: The Computer and the Brain (first published 1958) already pointed towards the current development of the brain-like AI.

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3. Deep neural networks and brain-inspired AI

The brain (80bln neurons, 100 trillions of connections, 200 mln years of evolution) is the ultimate information processing machine

Three, mutually interacting, memory types:

- short term (membrane potential);
- long term (synaptic weights);
- genetic (genes in the nuclei).

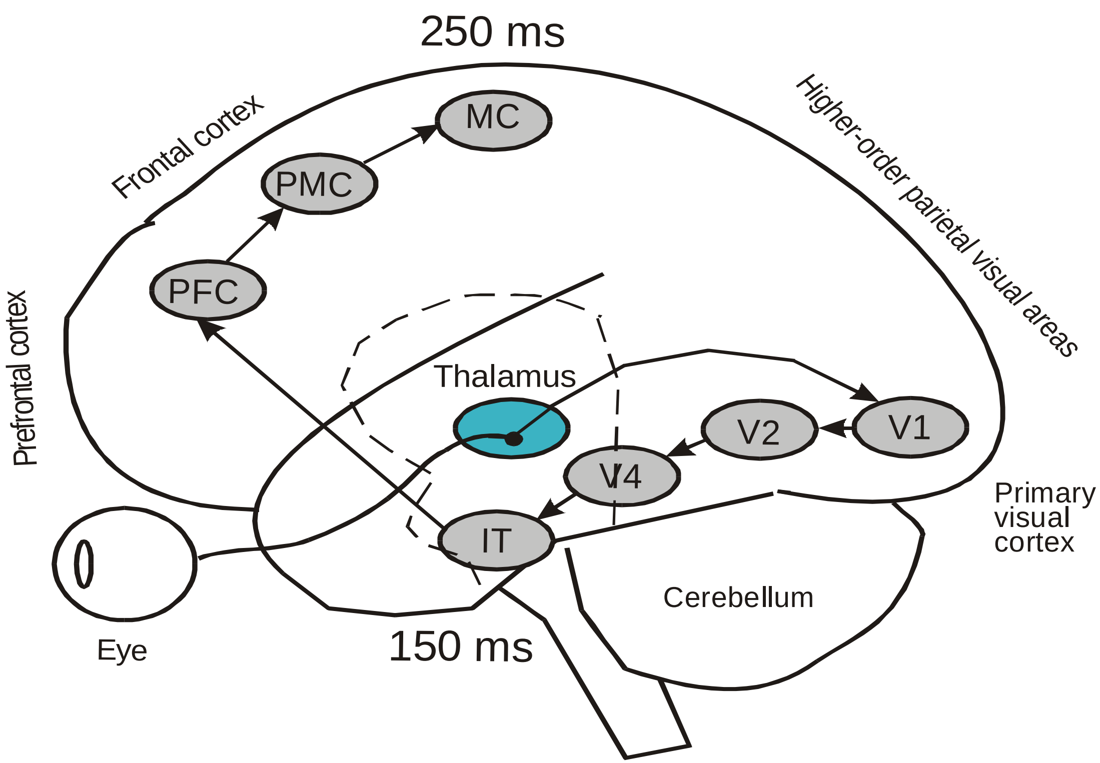
Temporal data at different *time scales:*

- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

A single neuron is a very sophisticated information processing machine, e.g. time-; frequency-; phase- information.

Can we make AI to learn from data like deep learning and knowledge representation in the brain?

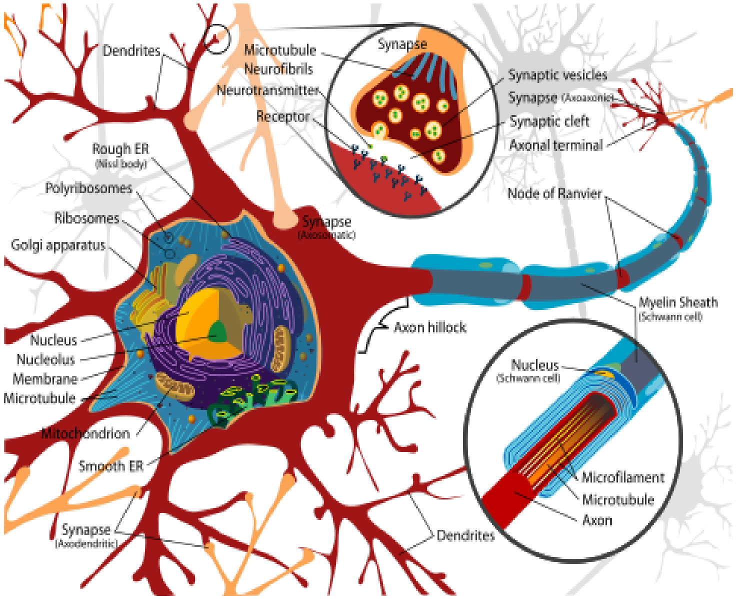
Deep learning and knowledge representation in the brain: Image recognition

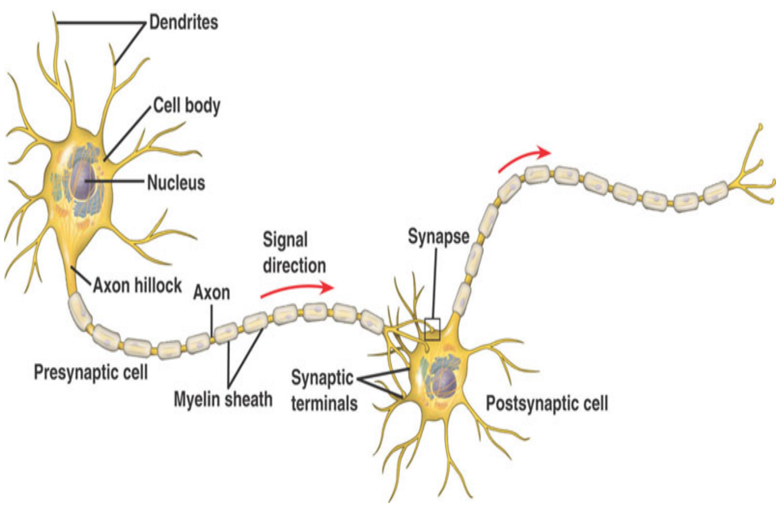


Deep serial processing of visual stimuli in humans for image classification represents human knowledge.
Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex.

(L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

Deep learning is a result of chain-fire activity of millions of neurons





A single neuron is very rich of temporal information processing:

- Nanoseconds (quantum particles);
- Micro and milliseconds (spikes);
- Minutes, hours, days (synapses);
- Years, million of years (genes).

Three, mutually interacting, memory types and learning mechanisms:

- short term (neuronal membranes);
- long term (synapses);
- genetic (genes)

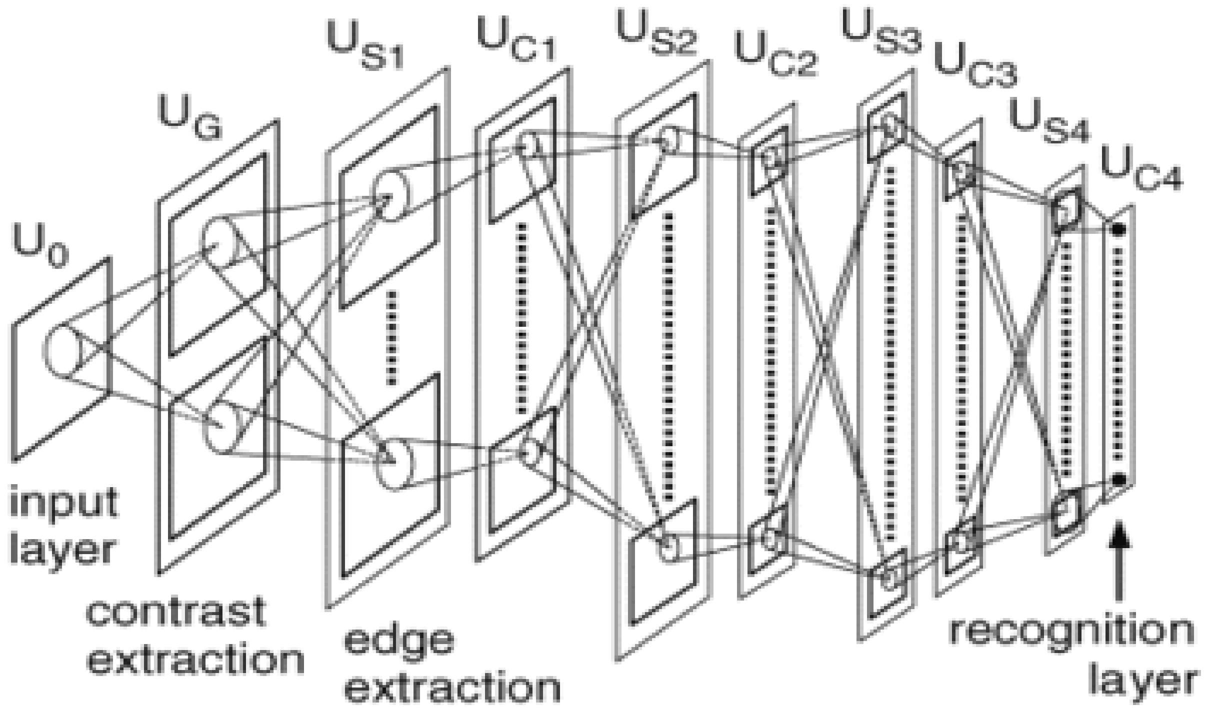
Brain NN can accommodate both spatial and temporal information as location of neurons/synapses and their spiking activity over time.

Complex connectivity in the brain as a result of learning and genetics (trillions of connections)

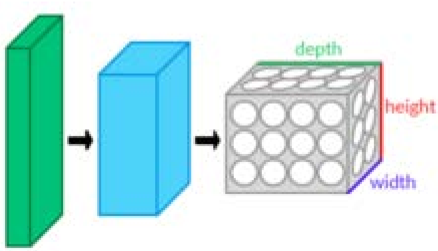
Early deep convolutional NN in computer vision

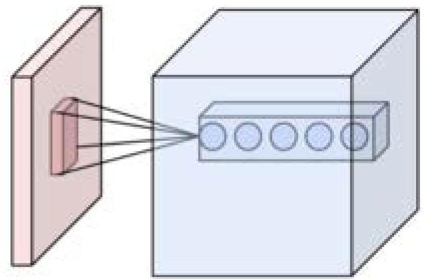
Spatial features are represented (learned) in different layers of neurons

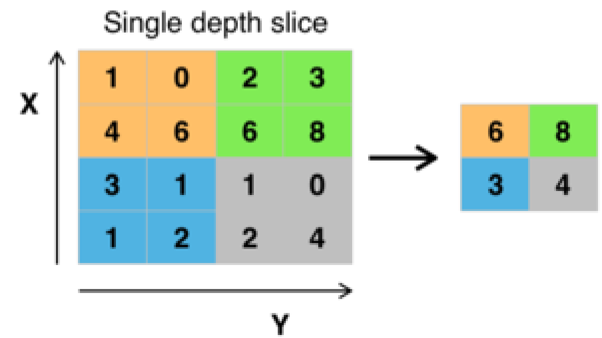
Fukushima's Cognitron (1975) and Neocognitron (1980) for image processing

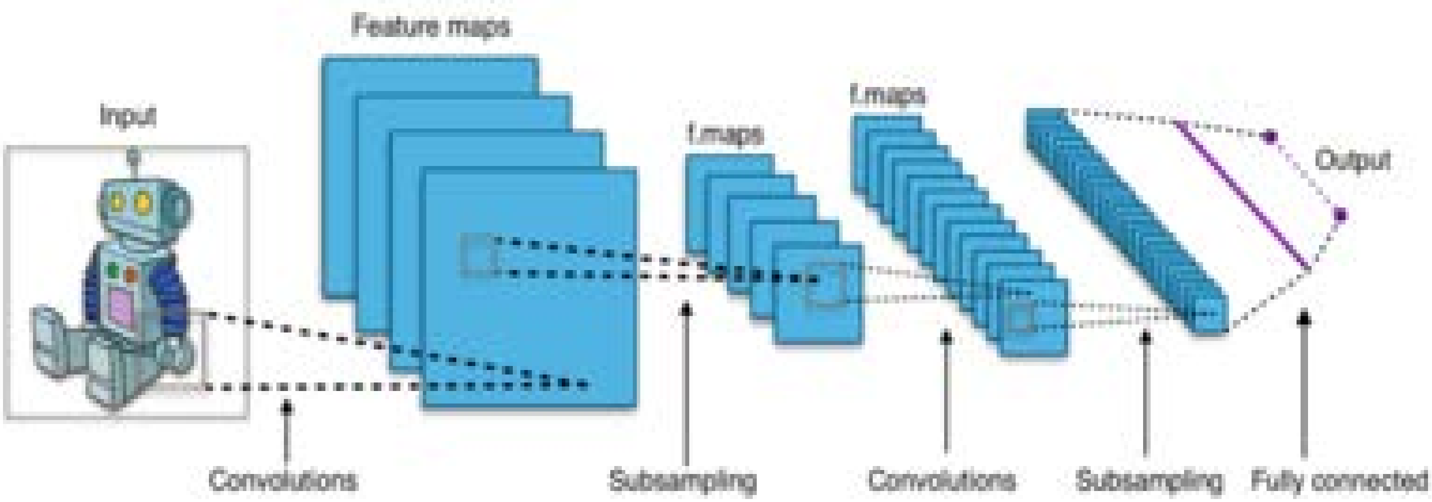


Principles of deep convolutional neural networks



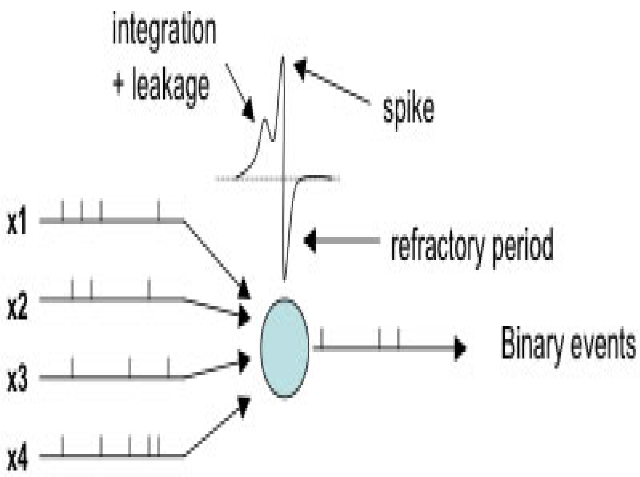




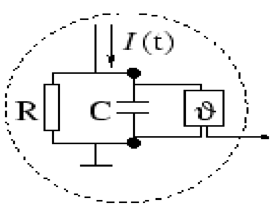


Deep NN are excellent for vector, frame- based data (e.g. image recognition), but not for TSTD. There is no *time of asynchronous events* learned in the model; difficult to adapt to new data and the structures are not flexible. How deep should they be? Who decides? The do not facilitate knowledge transfer!

Spiking Neural Networks



$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$



Information processing principles in neurons and neural networks:

- Trains of spikes
- Time, frequency and space
- Synchronisation and stochasticity
- Evolvability…

Spiking neural networks (SNN)

- Leaky Integrate-and-fire
- Probabilistic model
- Neurogenetic model

They offer the potential for:

- Spatio-temporal data processing
- Bridging higher level functions and “lower” level genetics
- Integration of modalities

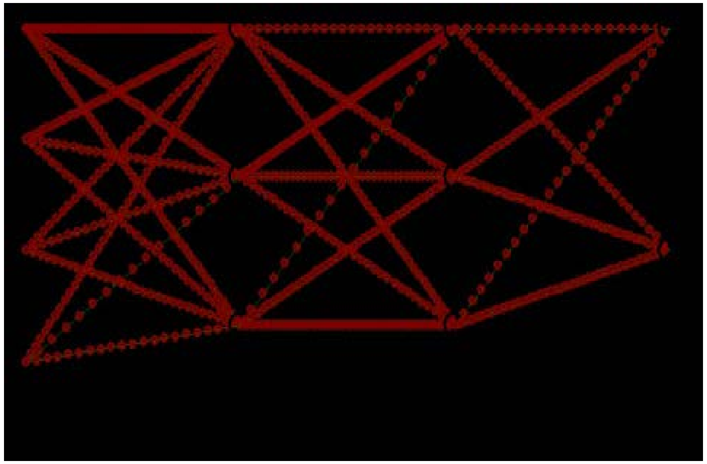
SNN open the field of brain-inspired (cognitive, neuromorphic) computing.

“*The goal of brain-inspired computing is to deliver a scalable neural network substrate while approaching fundamental limits of time, space, and energy,*” IBM Fellow **Dharmendra Modha**, chief scientist of Brain-inspired Computing at IBM Research,

Spiking neural network architectures: From local neuronal learning to global knowledge representation through building connectivity

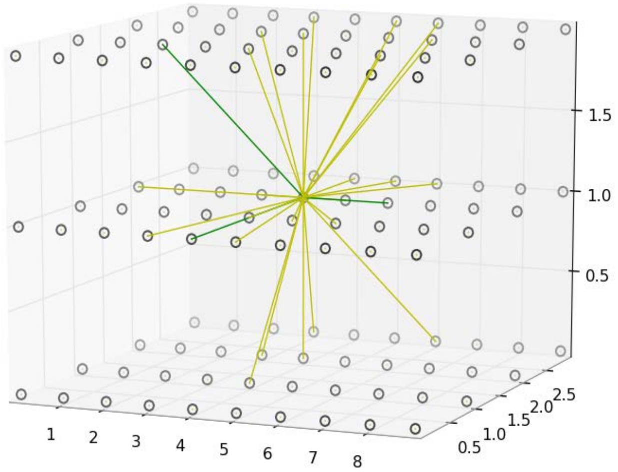
Generic SNN structures:

- Feedforward
- Recurrent
- Evolving
- Convolutional
- Reservoir
- Liquid sate-machines

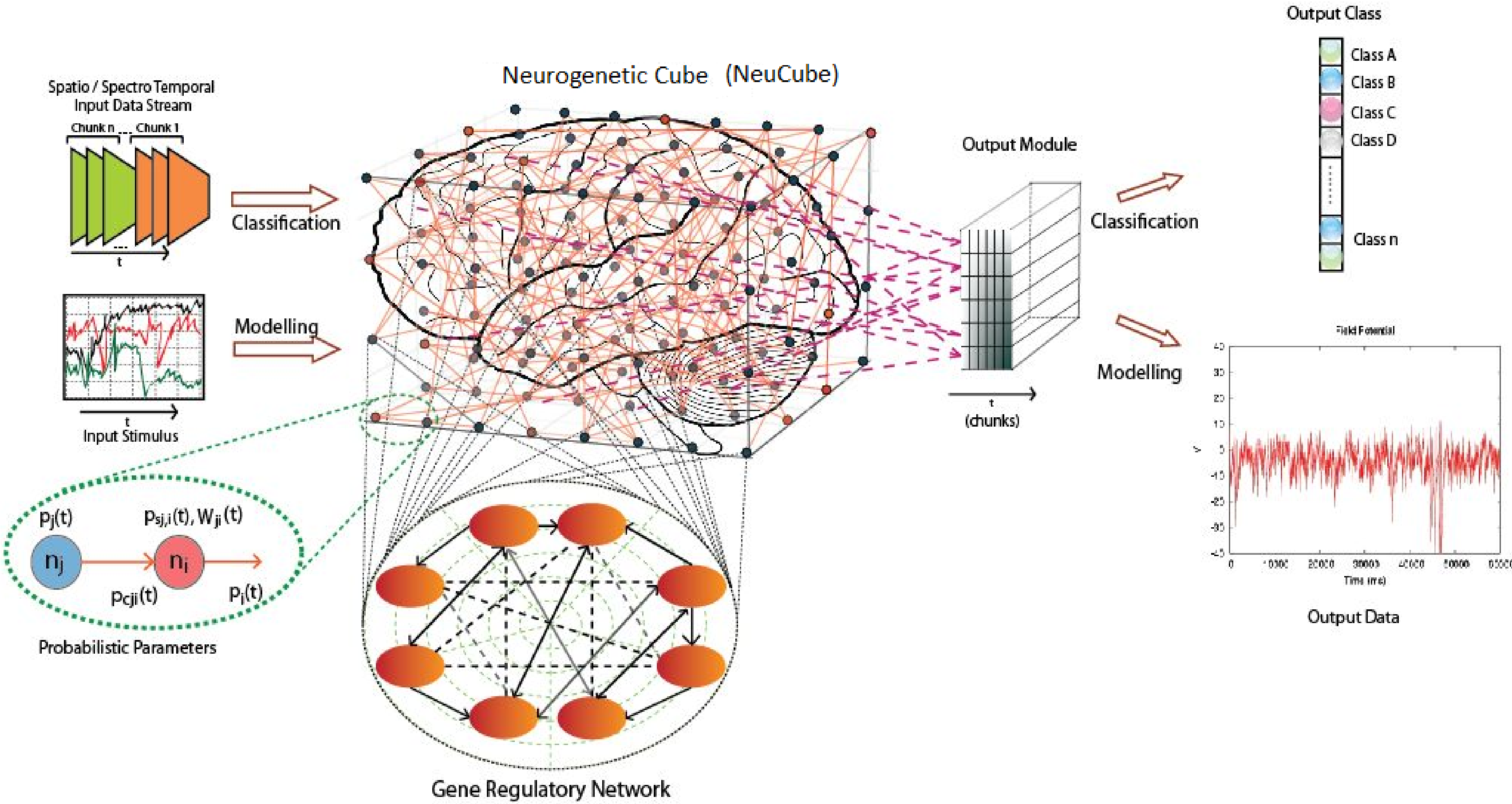


Task oriented structures:

- Classification
- Regression
- Prediction



Brain-inspired architectures: NeuCube



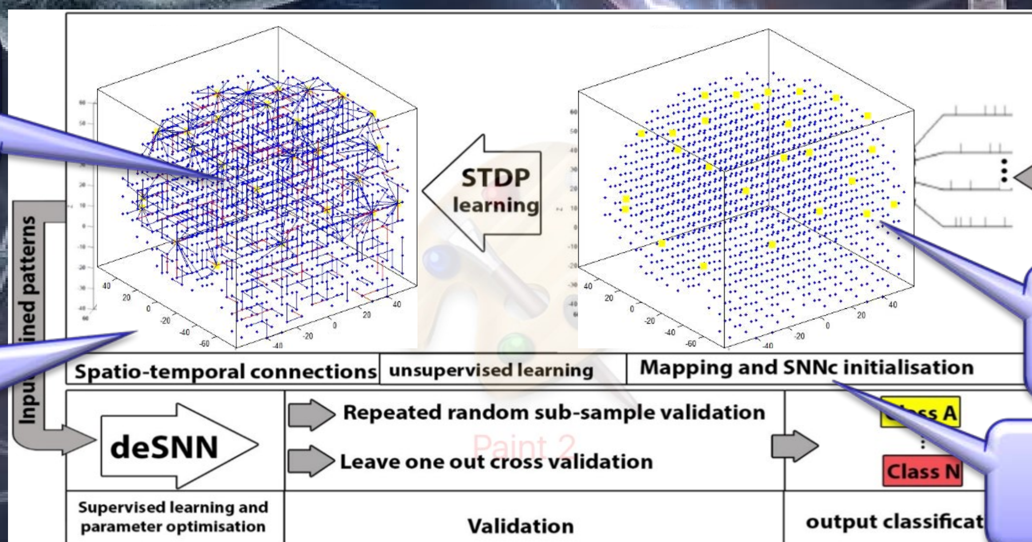
Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

N.Kasabov, V.Feigin, Z.Hou, Y.Chen, Improved method and system for predicting outcomes based on spatio/spectro-temporal data, PCT patent WO2015/030606 A2, US2016/0210552 A1**.** Granted/Publication date: 21 July 2016.

Deep learning in NeuCube

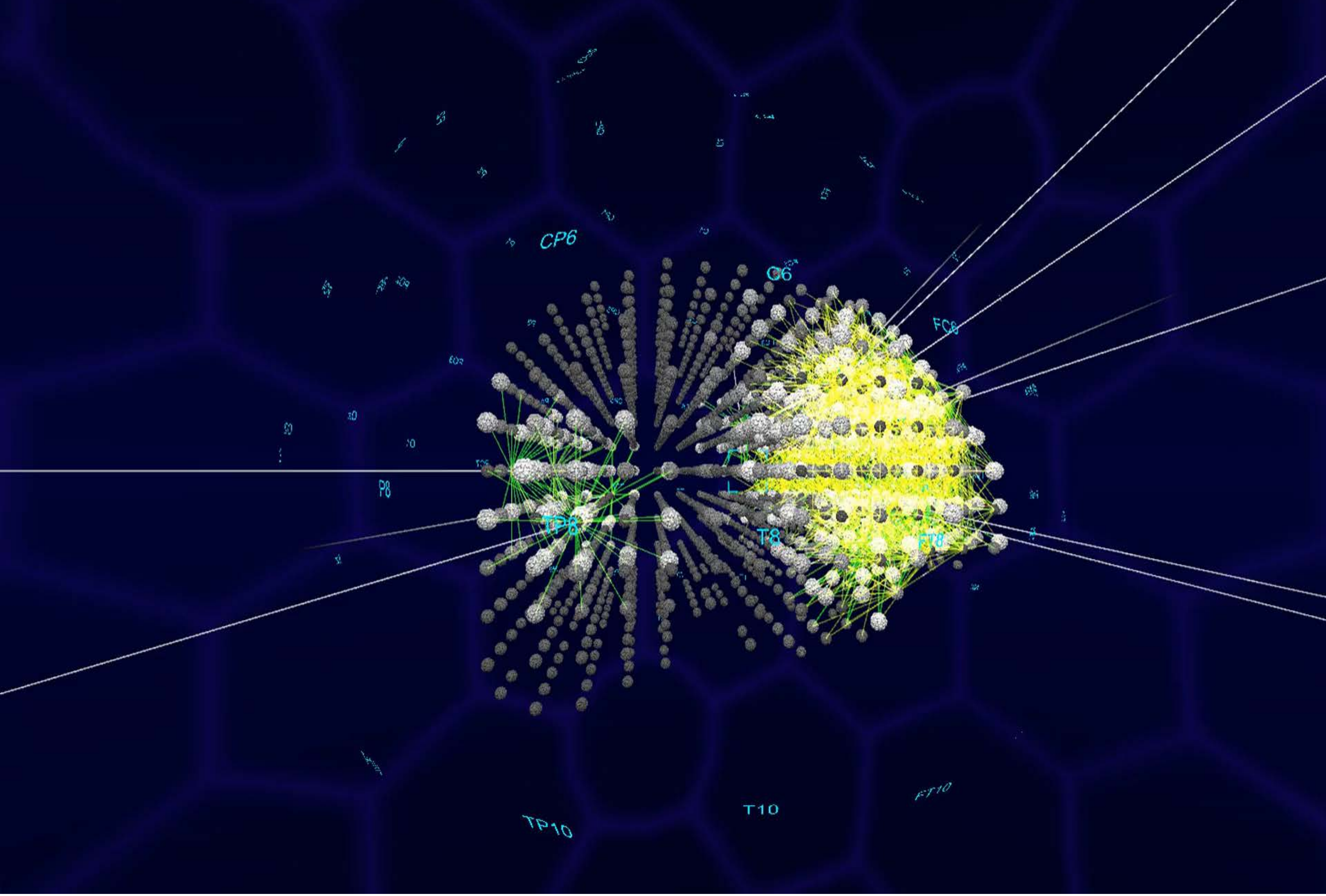
Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created



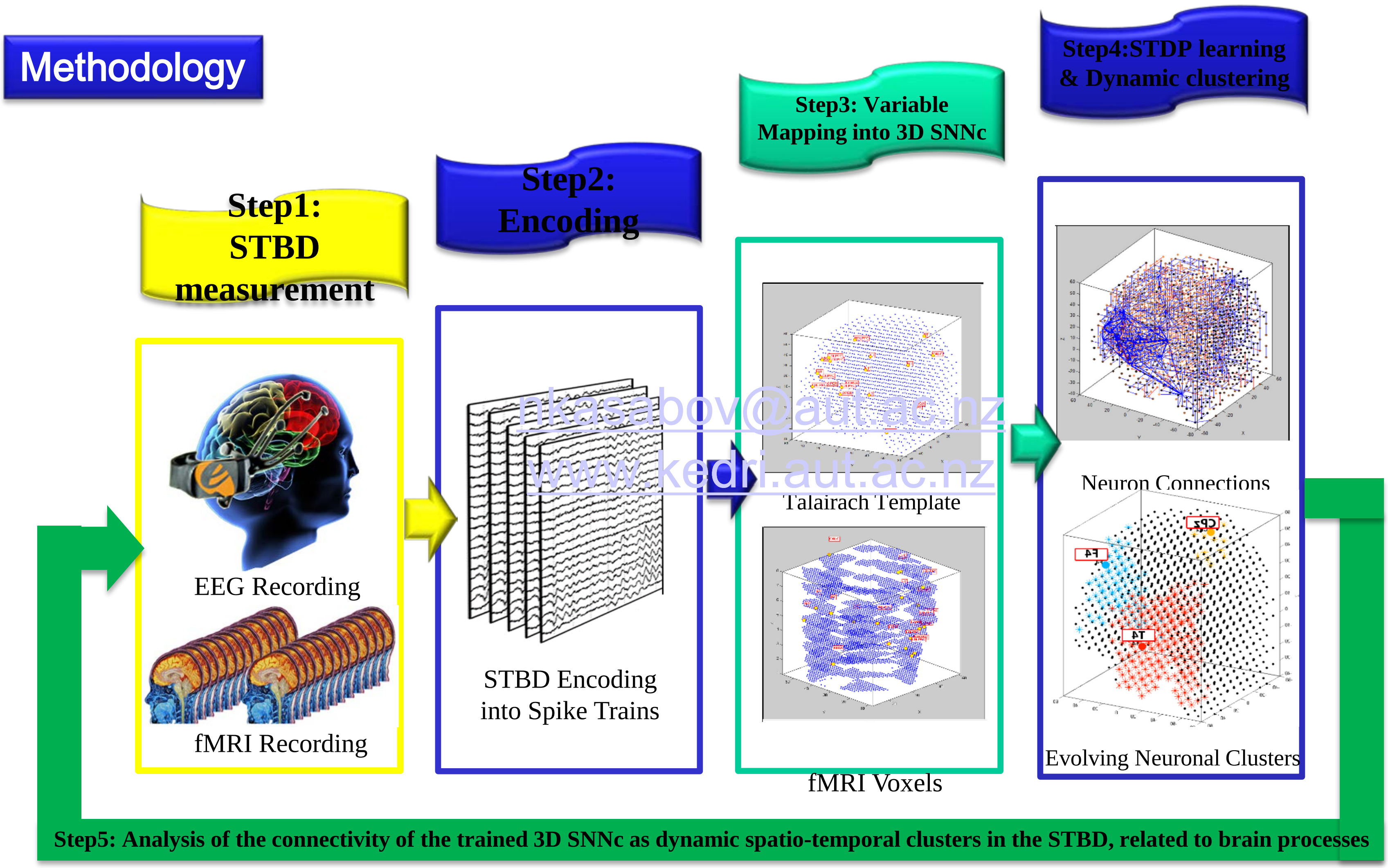
Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning


CP6
C6
FC6
P8
TP8
T8
FT8
TP10
T10
FT10

The KEDRI NeuCube software/hardware development environment

Deep learning of brain data and knowledge representation in NeuCube

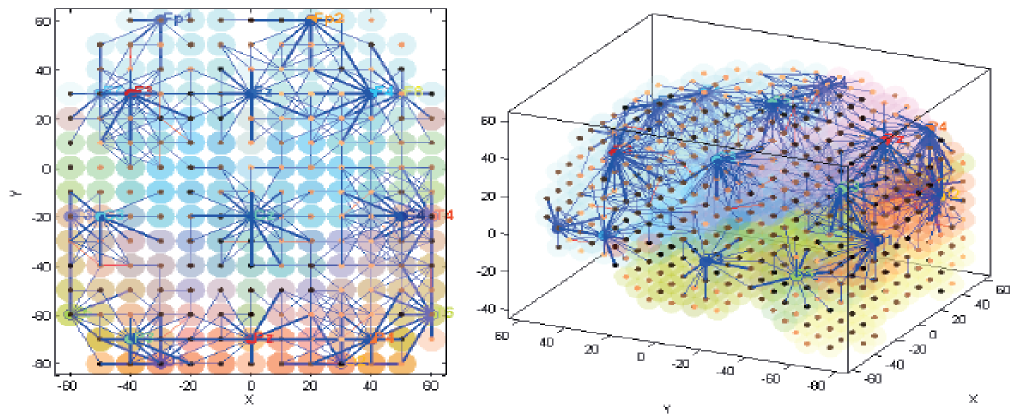


Applications in Neuromarketing

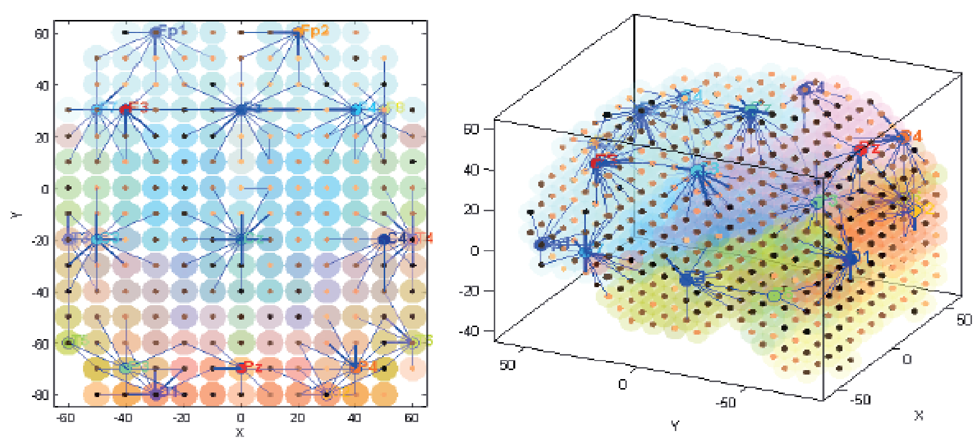
Z.Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich, Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Predicting progression of MCI to AD

E.Capecci, Z.Doborjeh, N.Mammone, F. La Foresta, F.C. Morabito and N. Kasabov, Longitudinal Study of Alzheimer's Disease Degeneration through EEG Data Analysis with a NeuCube Spiking Neural Network Model, Proc. WCCI - IJCNN 2016, Vancouver, 24-29.07.2016, IEEE Press.



(a) EEG signal collected at t_0.



(b) EEG signal collected at t_1.

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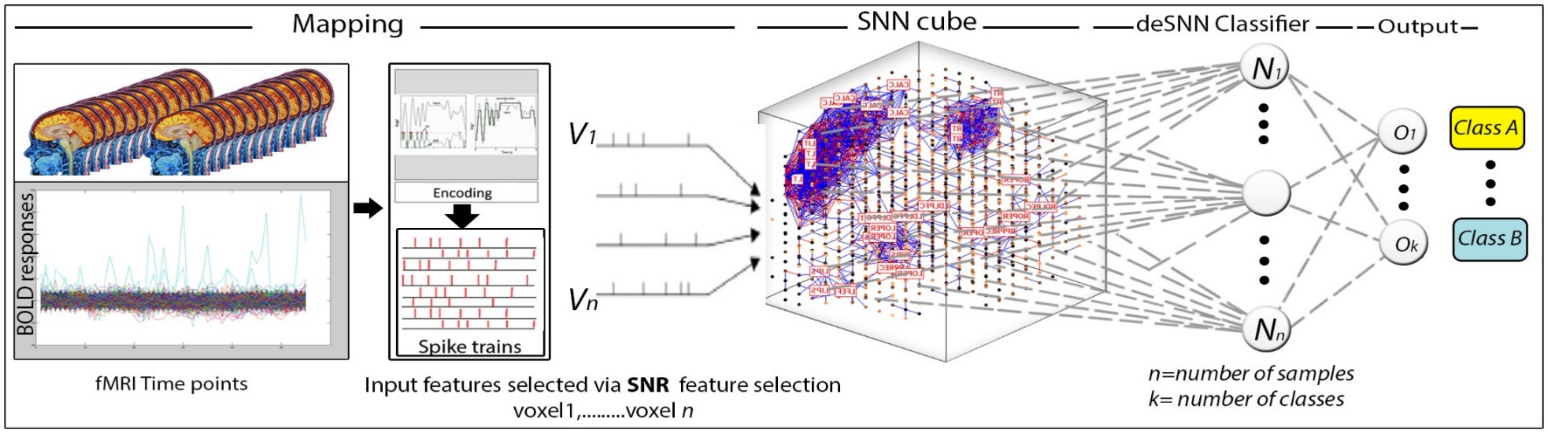
fMRI data modelling

(b) Spatial mapping of fMRI voxels into a 3D SNN cube after conversion into Talairach coordinates.

N.Kasabov, **M.Doborjeh, Z.Doborjeh**, IEEE Transactions of Neural Networks and Learning Systems, DOI: 10.1109/TNNLS.2016.2612890 Manuscript Number: TNNLS-2016-P-6356, 2016



Method / Subject	SVM	MLP	NEUCUBE[B]
04799	50(20,80)	35(30,40)	90(100,80)
04820	40(30,50)	75(80,70)	90(80,100)
04847	45(60,30)	65(70,60)	90(100,80)
05675	60(40,80)	30(20,40)	80(100,60)
05680	40(70,10)	50(40,60)	90(80,100)
05710	55(60,50)	50(50,50)	90(100,80)

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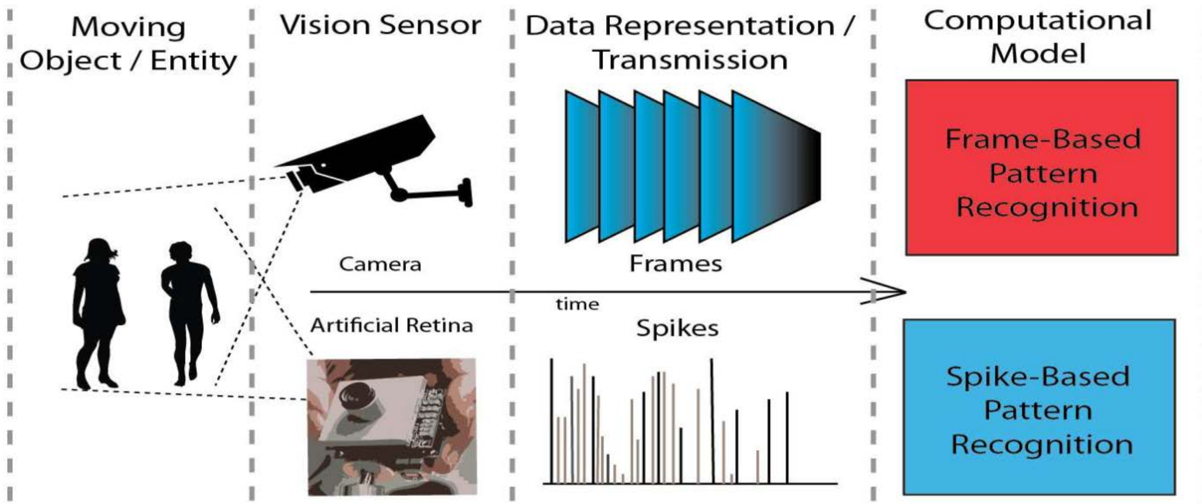
Deep learning of audio-/visual information



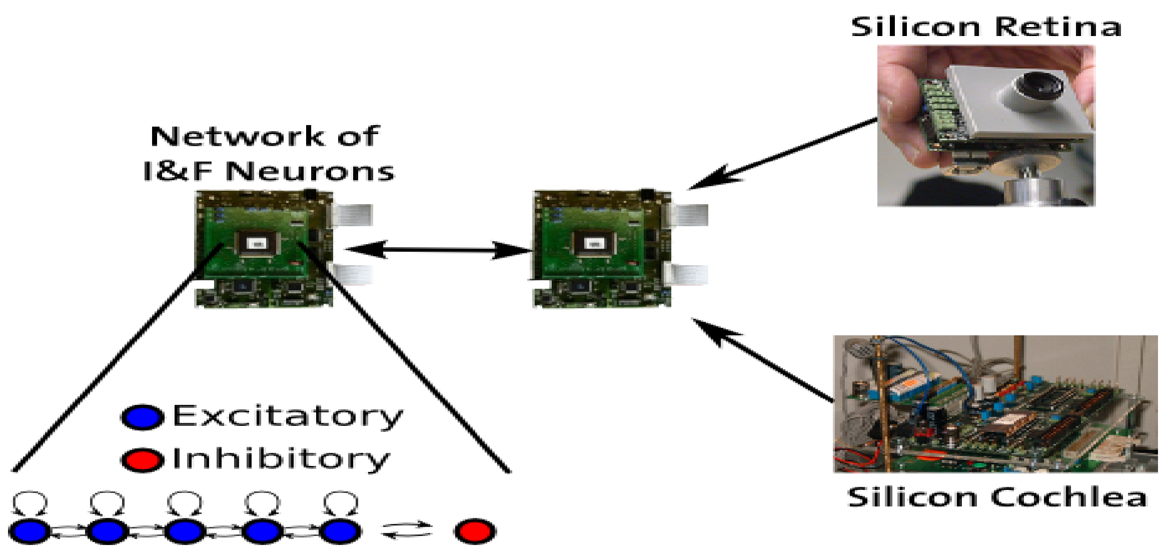


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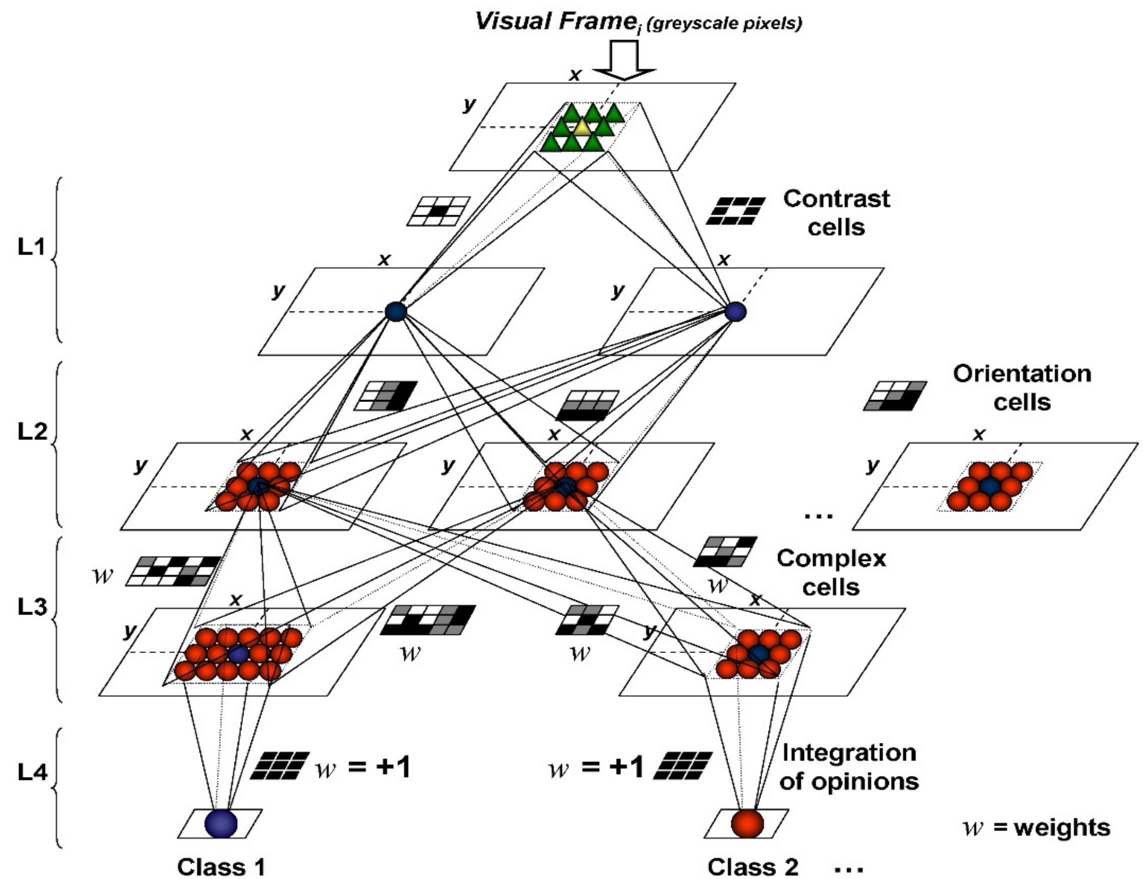
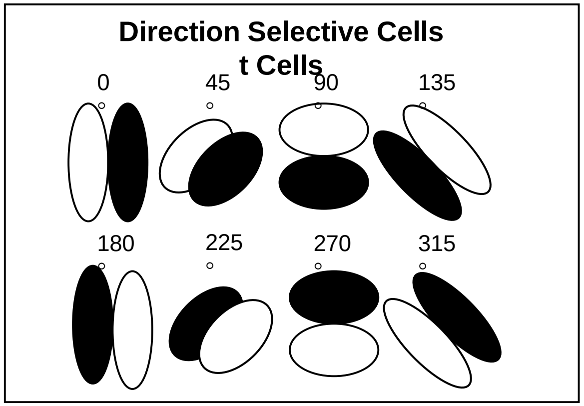
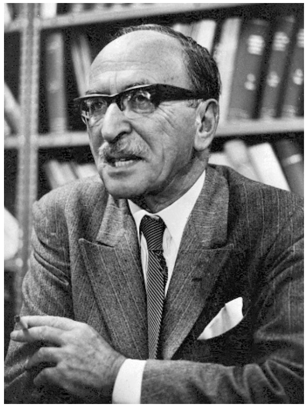
Image Processing using CSNN and Gabor filters.





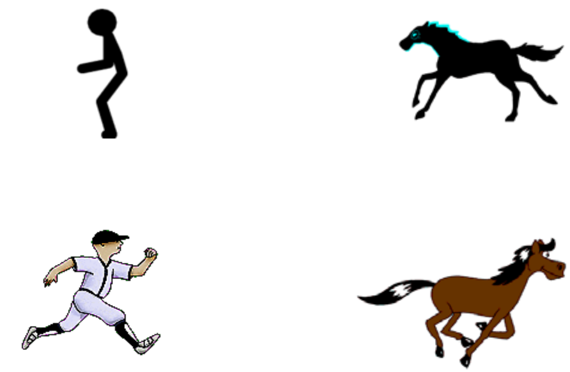


Dennis Gabor (1900-1979)

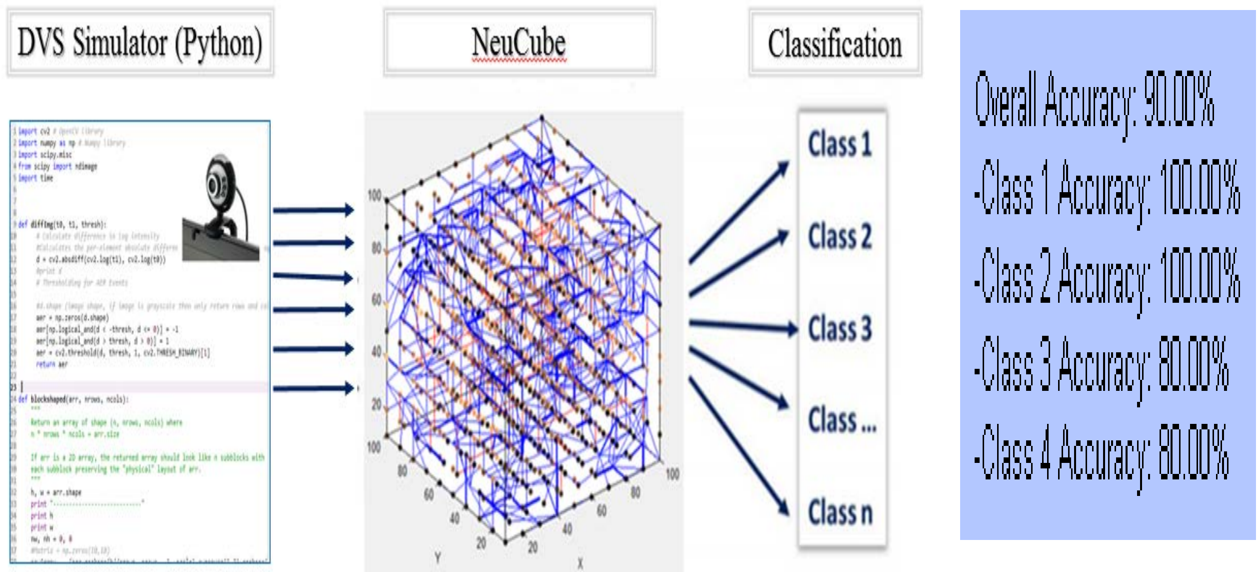
(Wysoski, S., L.Benuskova, N.Kasabov, Evolving Spiking Neural Networks for Audio-Visual Information Processing, Neural Networks, 23, 7, 819-835, 2013).

Fast moving object recognition using DVS and NeuCube

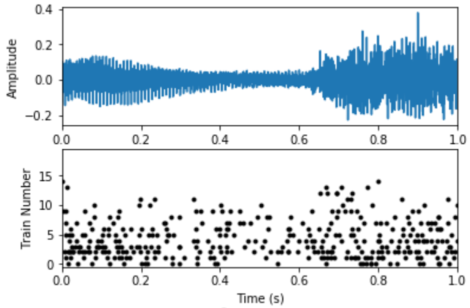
Examples: Cars on the road; Flying Airplanes; Running Animals; Rotating Pens; Fast Moving Barcode; Fast Human Actions; Bouncing Pin Pang Balls; Rockets; etc.

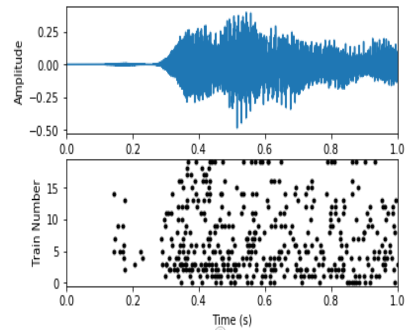


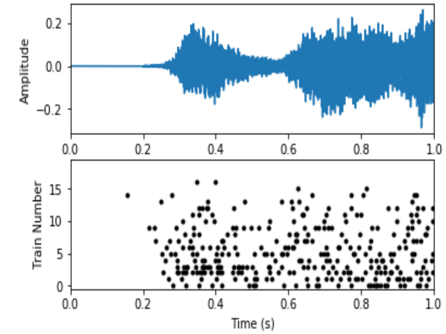
Applications: Surveillance systems; Cybersecurity; Military applications; Autonomous vehicles

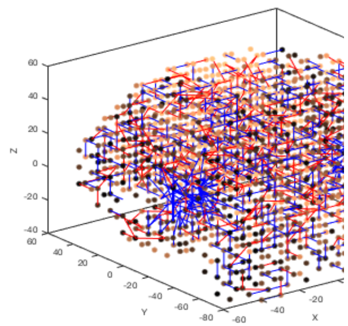


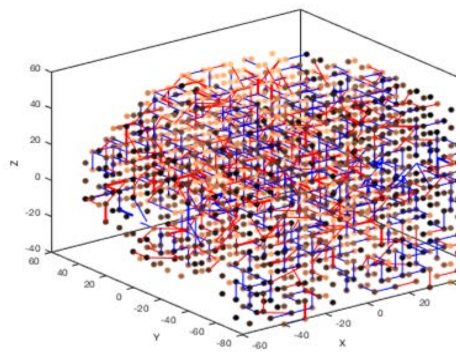
Sound, speech and music recognition with tonotopic, *stereo* mapping

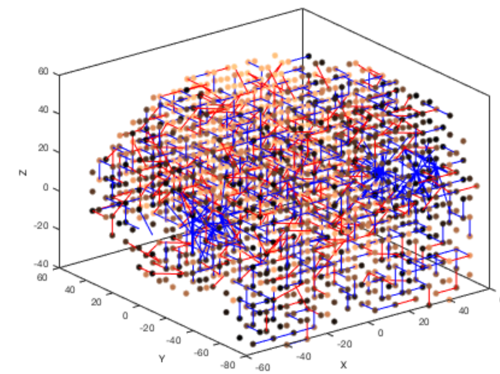












	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

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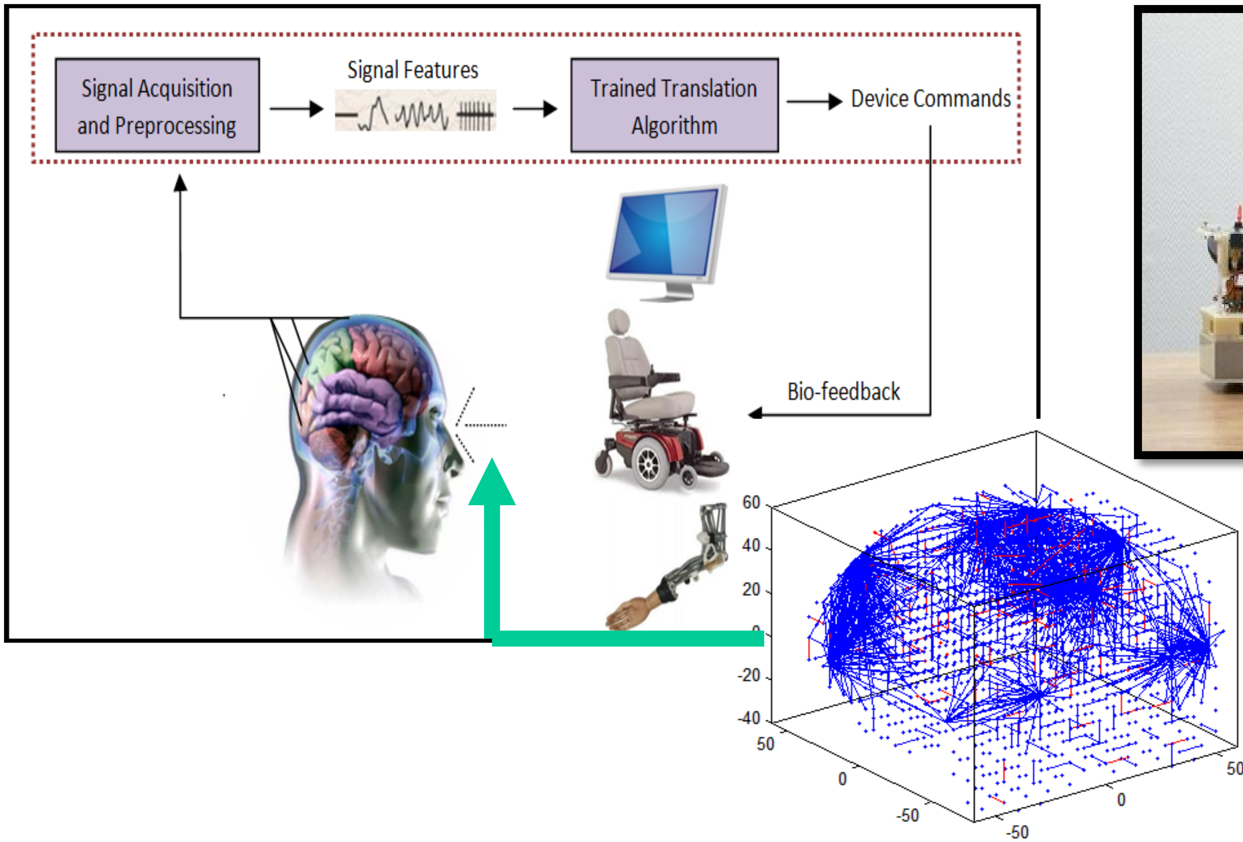
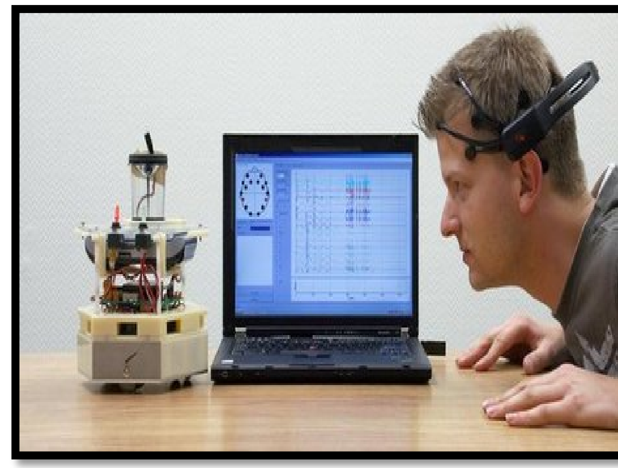
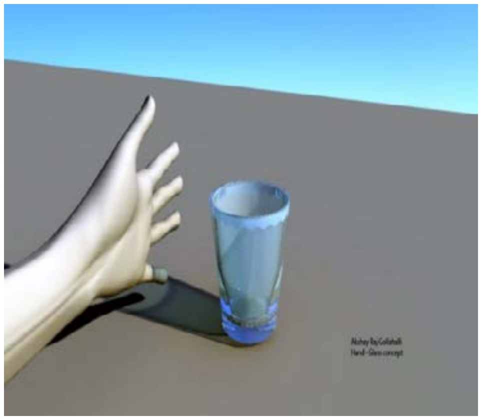
Brain-Inspired Brain Computer Interfaces (BCI)

Brain-Computer Interfaces (BCIs) are interfaces that allow humans to communicate directly with computers or external devices through their brains (e.g. EEG signals)



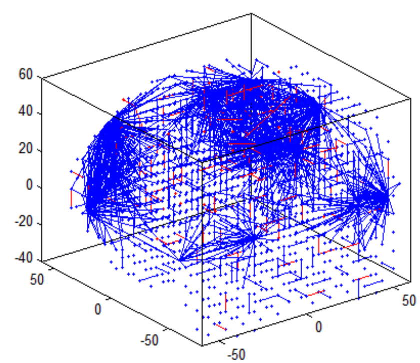


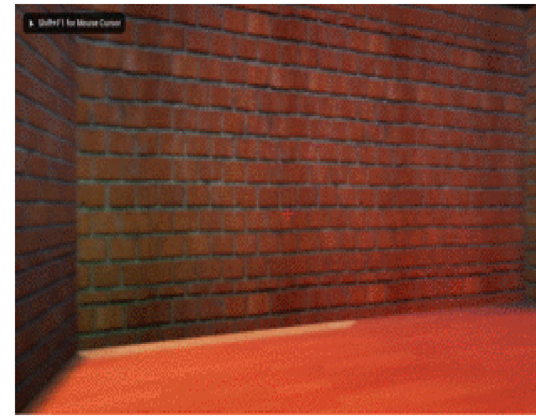
Interactive assistive devices and cognitive games



A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

A virtual environment to control a quadrotor using EEG signals.

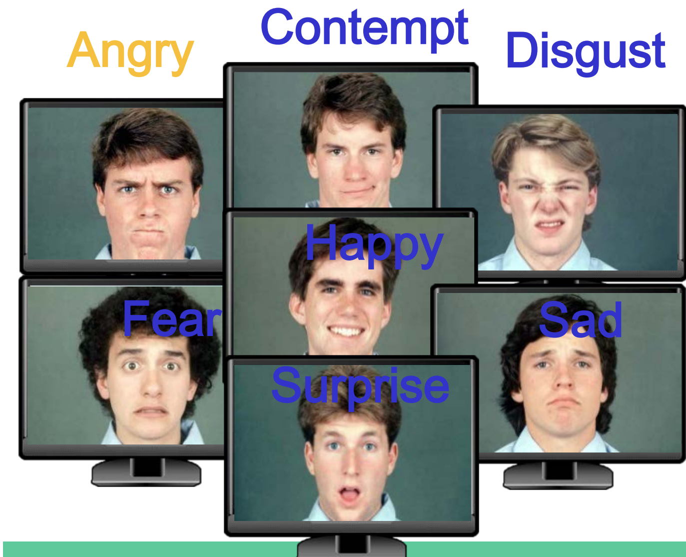


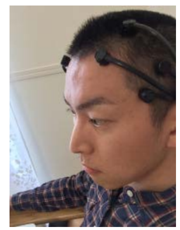


A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG signals.

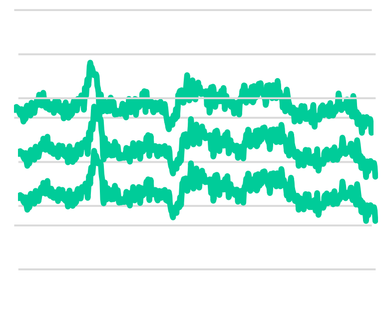
Deep learning and knowledge representation of perception and expression of human emotion

Facial Expression Perception Task

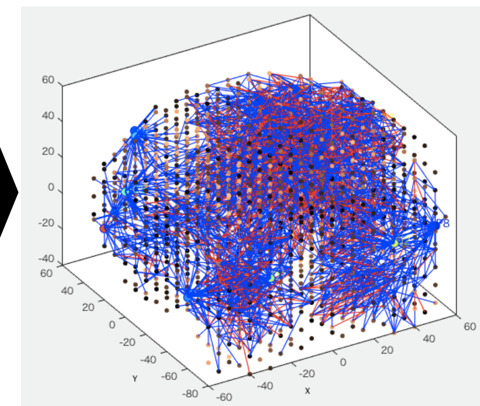




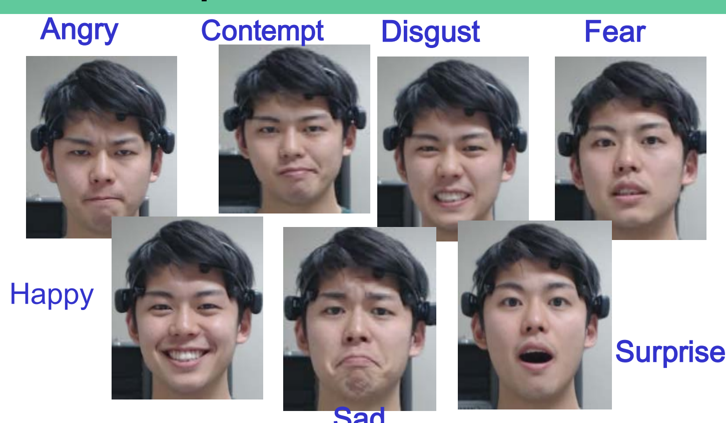
14ch EEG



94.3 %

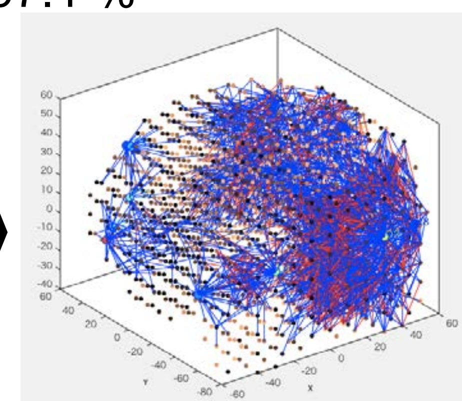


Face Expression Production Task



14ch EEG

97.1 % NeuCube

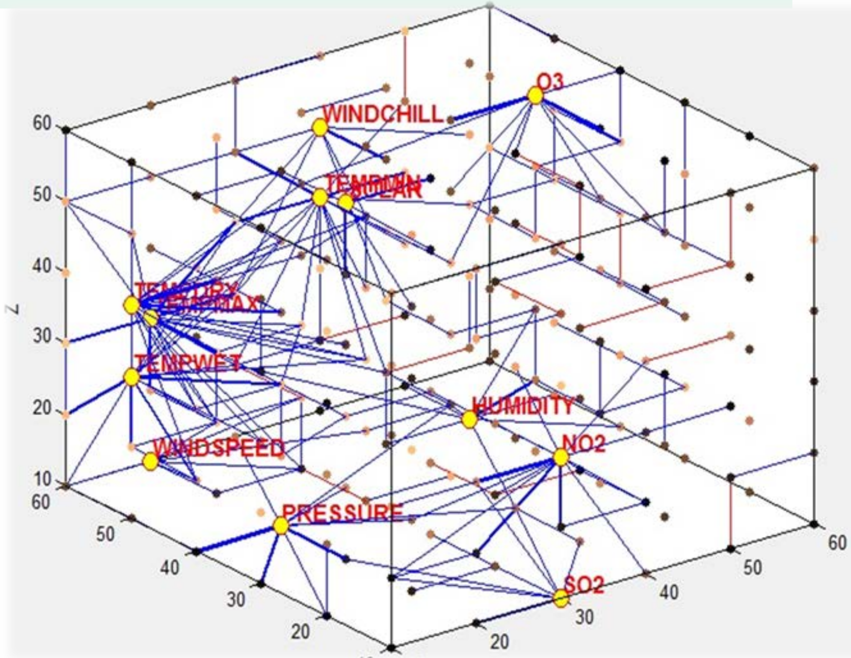


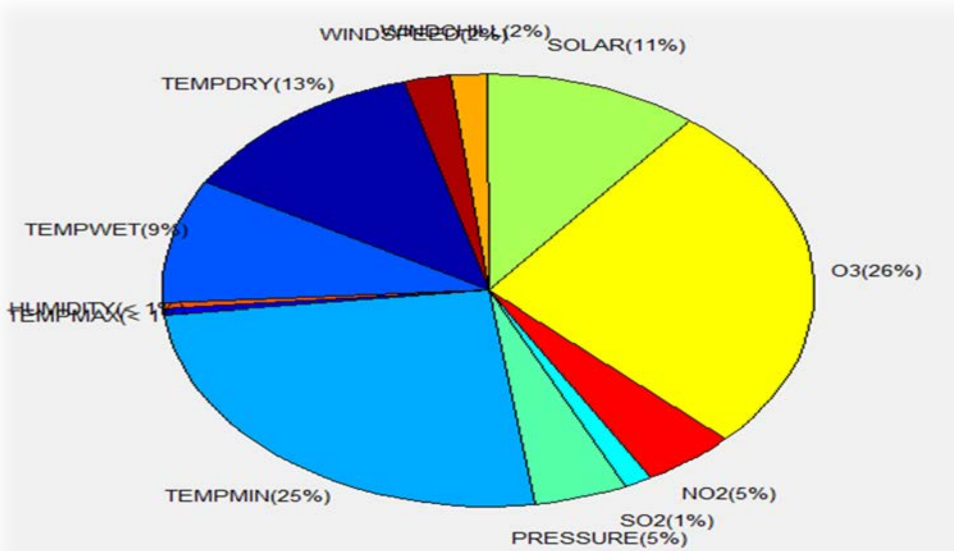
Kawano, H., Seo, A., **Gholami, Z.,** Kasabov, N., G. Doborjeh, M, "Analysis of Similarity and Differences in Brain Activities between Perception and Production of Facial Expressions Using EEG Data and the NeuCube Spiking Neural Network Architecture", ICONIP, Kyoto, 2016, Springer LNCS, 2016.

Personalised prediction of risk for stroke days ahead

(N.Kasabov, M. Othman, V.Feigin, R.Krishnamurti, Z Hou et al - Neurocomputing 2014)

Methods	*SVM*	*MLP*	*KNN*	*WKNN*	*NeuCube^ST^*
1 day earlier (%)	55 *(70,40)*	30 *(50,10)*	40 *(50,30)*	50 *(70,30)*	**95** ***(90,100)***
6 days earlier (%)	50 *(70,30)*	25 *(20,30)*	40 *(60,20)*	40 *(60,20)*	**70** ***(70,70)***
11 days earlier (%)	50 *(50,50)*	25 *(30, 20)*	45 *(60,30)*	45 *(60,30)*	**70** ***(70,70)***





(d) Neuron proportion based on spike transmission

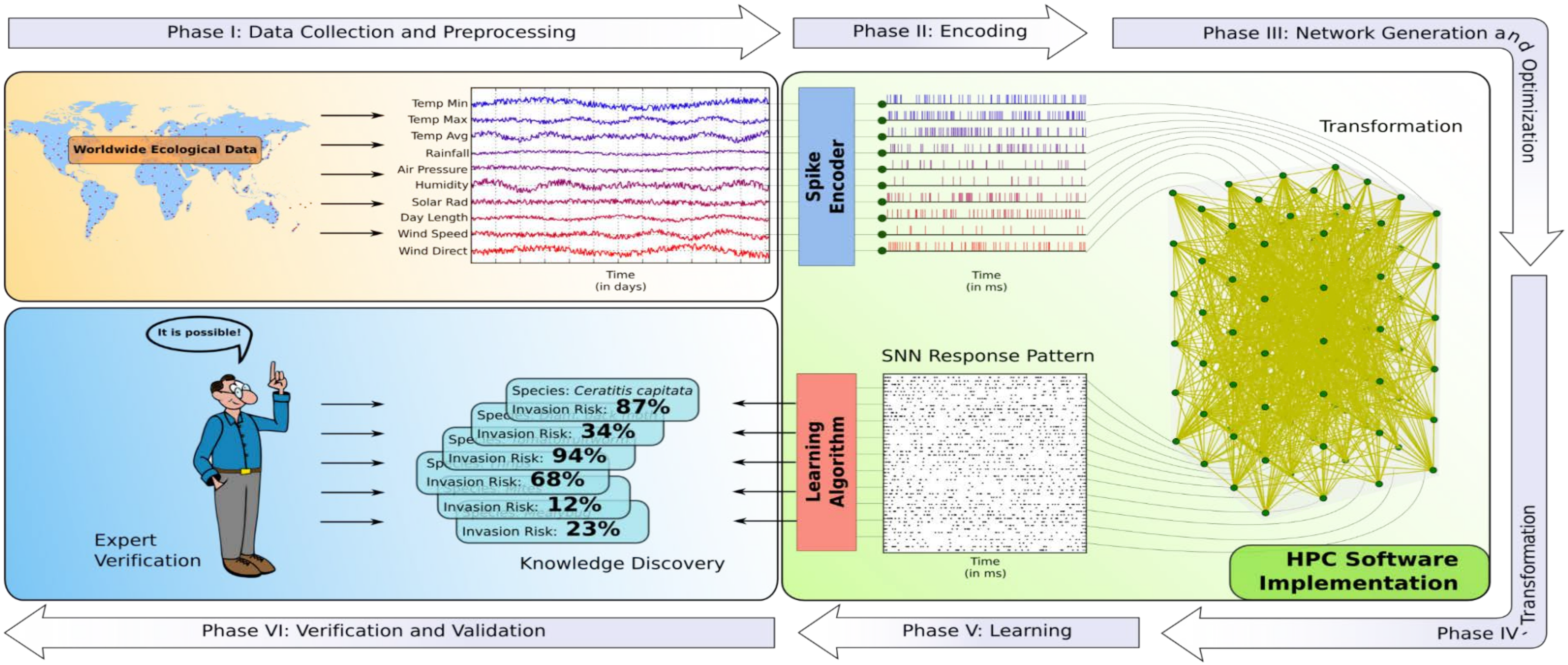
- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods
- New information found about the predictive relationship of variables

Multisensory Predictive Modelling of Time Series Data

- Pre-processing (e.g. Kalman filter)
- Predictive learning (e.g. NuCube)

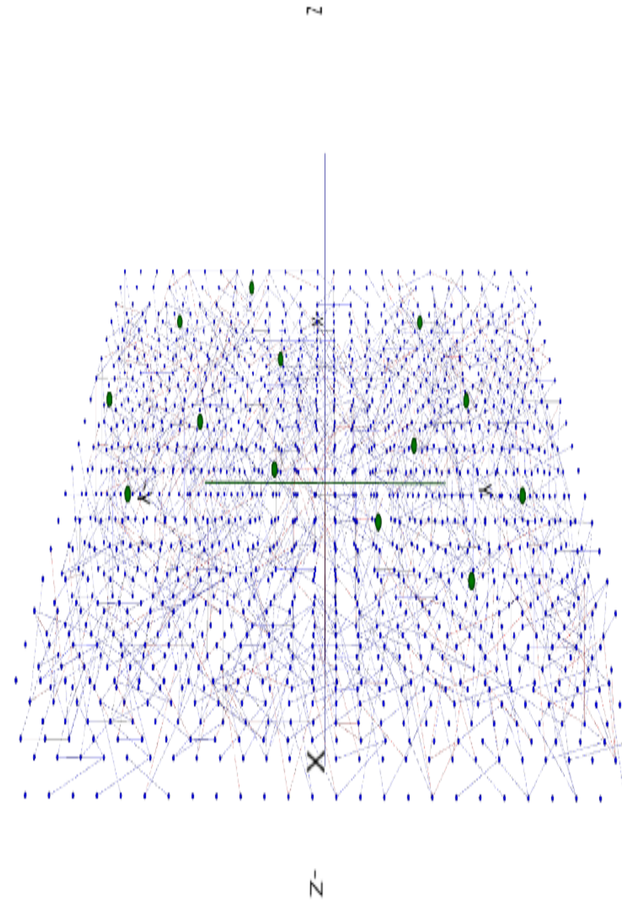
Example: Predicting establishment of harmful species based on temporal climate data streams

Rudolf Kalman (1930-2016)



Wind energy prediction from wind turbines

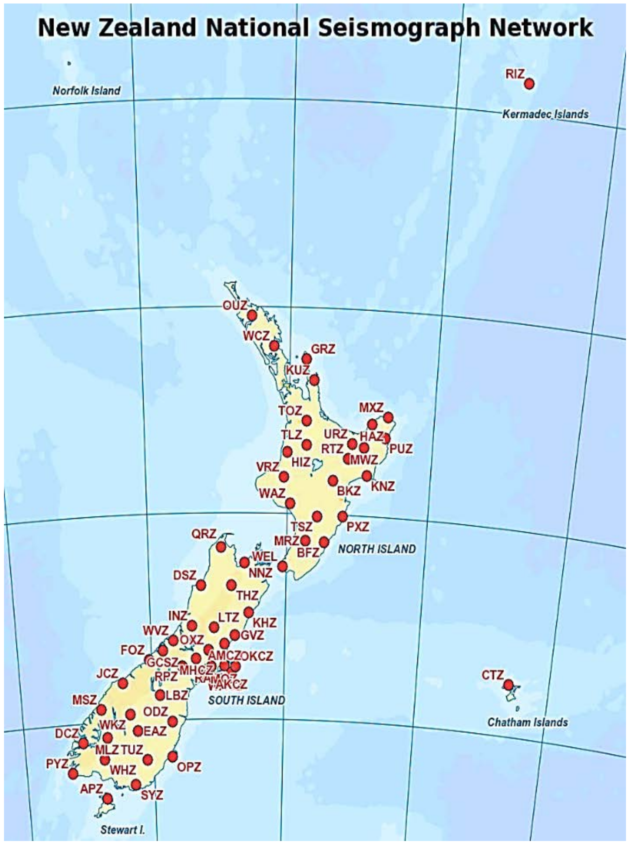
New Zealand

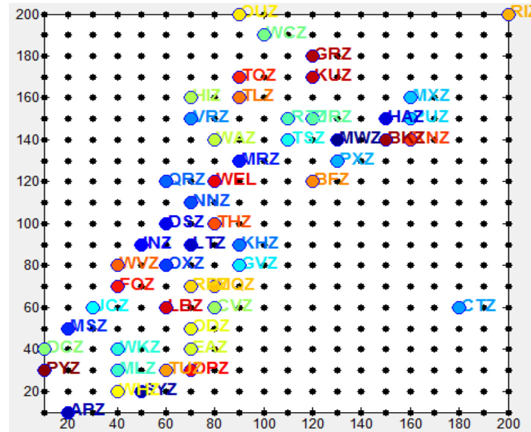


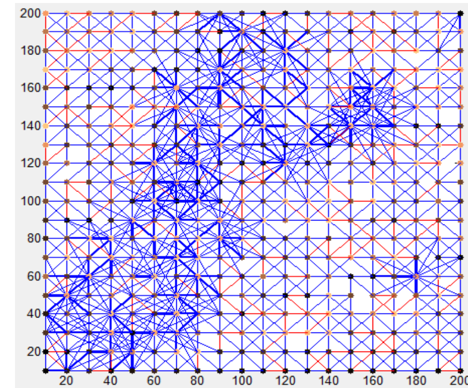
Xinjiang, China (中国新疆)

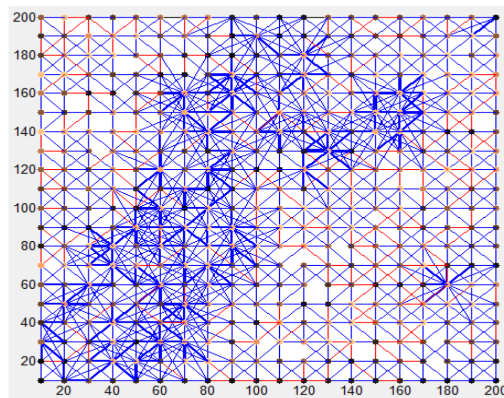
Seismic SSTD modelling for earthquake prediction

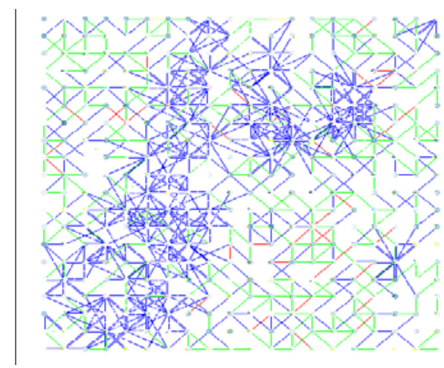
N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.











Measure	NeuCube	SVM	MLP
1h ahead	**91.36%**	65%	60%
6h ahead	**83%**	53%	47%
12h ahead	**75%**	43%	46%

Predicting risk for earthquakes, tsunami, land slides, floods – how early and how accurate?

Predicting extreme weather conditions using satellite image data

(AUT/KEDRI + Met Services NZ)

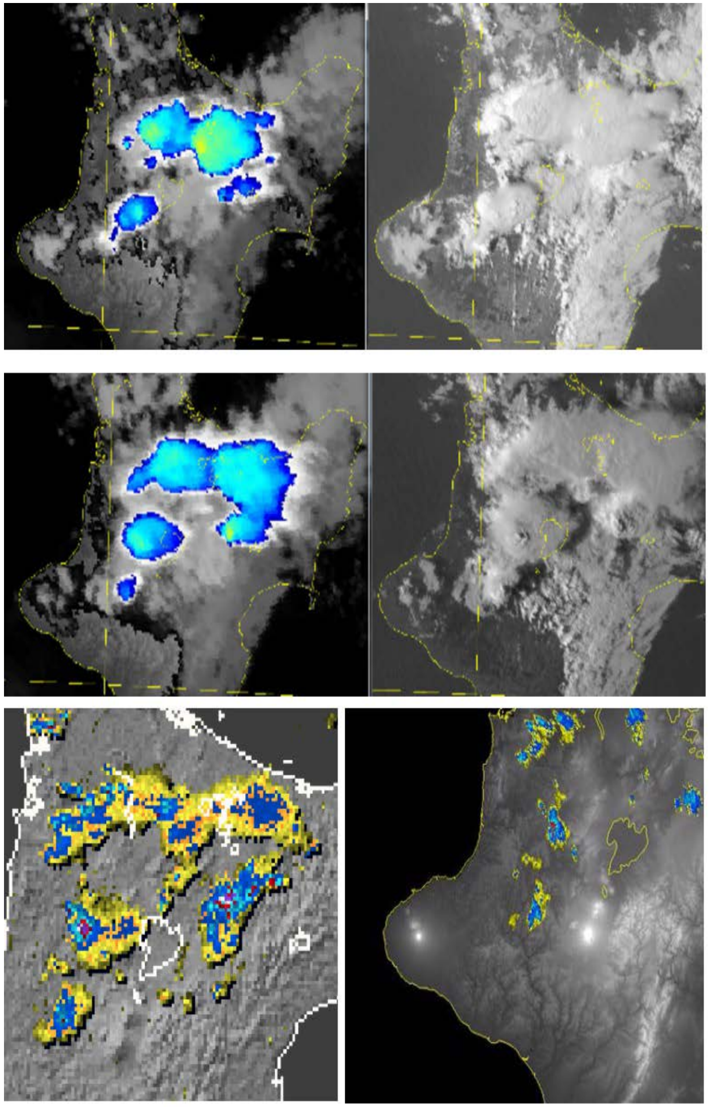


Figure 2. Example of infrared (top left) and visible band (top right) Himawari 8 imagery of a developing convective system. The middle row shows thesame view an hour later as the cloud clusters continue to evolve. The bottom images are rain radar images of the later time showing areas of intenserainfall associated with the convective activity.

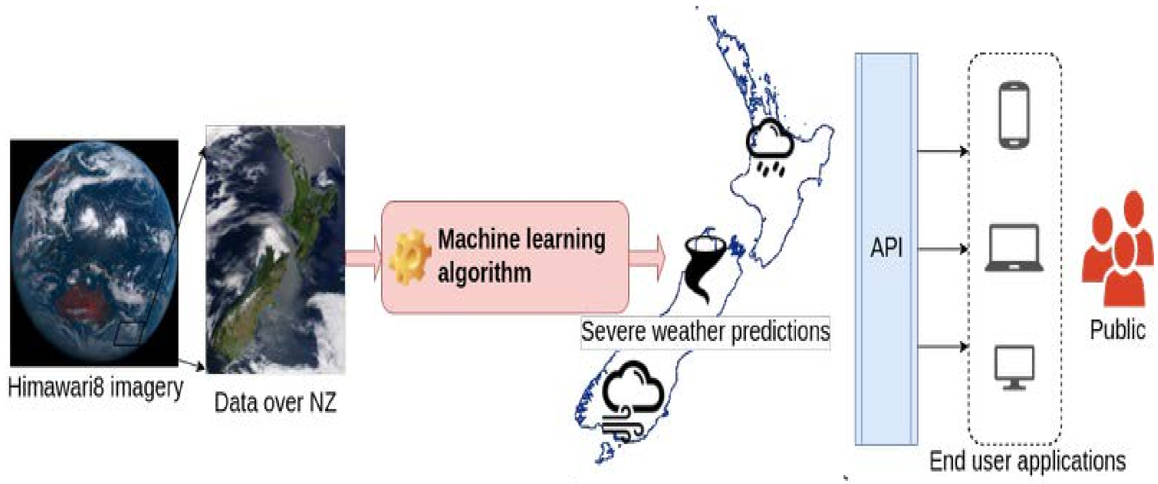


Figure 3. Overview of the implementation pathway to transform satellite imagery into end-user tools.

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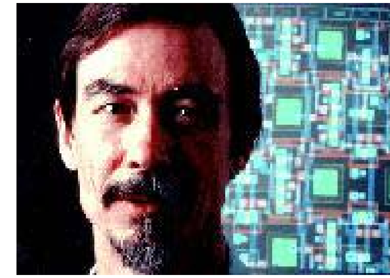
Neuromorphic hardware/software systems



Hodgin- Huxley model (1952)

Carver Mead (1989): A hardware model of an IF neuron;

Misha Mahowald: Silicon retina

FPGA SNN realisations (McGinnity, UNT);

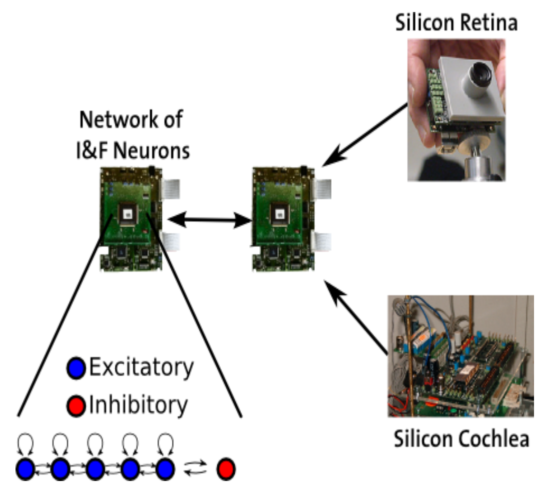
The IBM True North (D.Modha et al, 2016): 1mln neurons and 1 billion of synapses (Merolla, P.A., J.V. Arhur, R. Alvarez-Icaza, A.S.Cassidy, J.Sawada, F.Akopyan, D.Moda et al, “A million spiking neuron integrated circuit with a scalable communication networks and interface”, Science, vol.345, no.6197, pp. 668-673, Aug. 2014).

Misha Mahowald (1963 -1996)

INI Zurich SNN chips (Giacomo Indiveri, 2008 and 2012)
Silicon retina (the DVS) and silicon cochlea (ETH, Zurich)

The Stanford U. NeuroGrid (Kwabena Boahen et al), 1mln neurons on a board, 63 bln connections ; hybrid - analogue /digital)

High speed and low power consumption.



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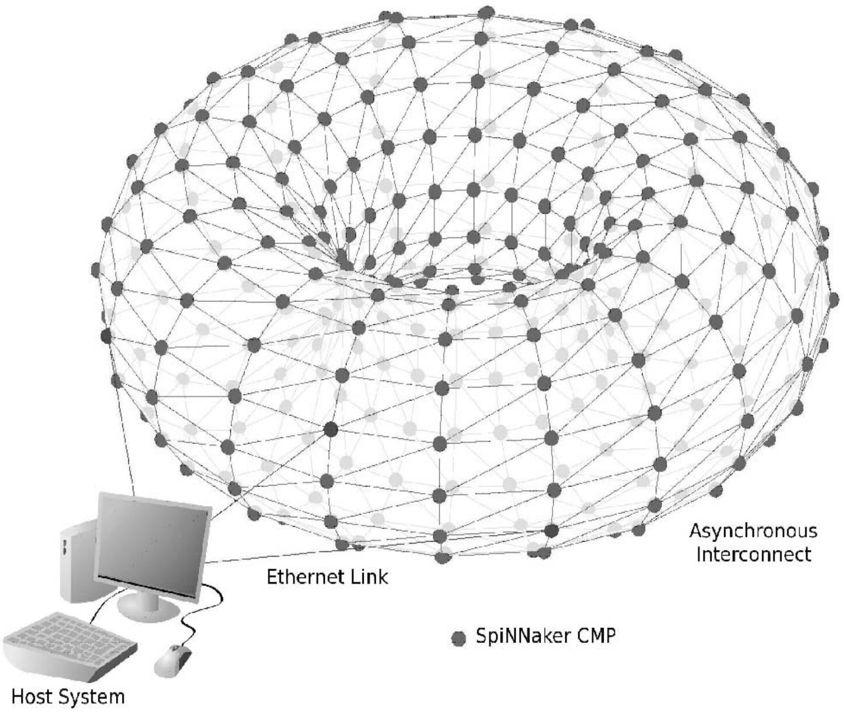
SpiNNaker

Furber, S., To Build a Brain, IEEE Spectrum, vol.49, Number 8, 39-41, 2012.

- U. Manchester, Prof. **Steve Furber**;
- General-purpose, scalable, multichip multicore platform for the real-time massively parallel simulation of large scale SNN;
- 18 ARM968 subsystems responsible for modelling up to one thousand neurons per core;
- Spikes are propagated using a multicast routing scheme through packet-switched links;
- Modular system – boards can be added or removed based on desired system size;
- 1 mln neurons – 2014;
- 100mln neurons - 2018



Quantum (or quantum inspired) computation

Quantum information principles: superposition; entanglement, interference, parallelism (M.Planck, A.Einstein, Niels Bohr, W.Heisenberg, John von Neumann, **E. Rutherford**)

- *Quantum bits (qu-bits)*

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

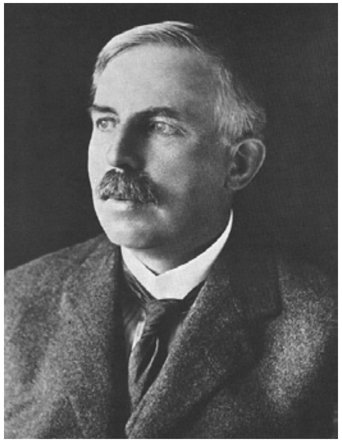
$$|\alpha|^2 + |\beta|^2 = 1$$

- *Quantum vectors (qu-vectors)*

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \ldots & \alpha_m \\ \beta_1 & \beta_2 & \ldots & \beta_m \end{array}\right]$$

- *Quantum gates*

$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix}$$



Ernest Rutherford (1871-1937)

- **Applications:**
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), O($N^{1/2}$) vs O(N) complexity)
  - Quantum associative memories

4. The Future of AI?

- Artificial General Intelligence?
  - Machines that can perform any intellectual task that humans can do.
- Technological *singularity*?
  - Machines become super intelligent that they take over from humans and develop on their own, beyond which point the human societies collapse in their present forms, which may ultimately lead to the perish of humanity.
  - **Stephen Hawking**: “I believe there is no real difference between what can be achieved by a biological brain and what can be achieved by a computer. AI will be able to redesign itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn't compete and could be superseded by AI. AI could be either the best or the worst thing ever to happen to humanity…”

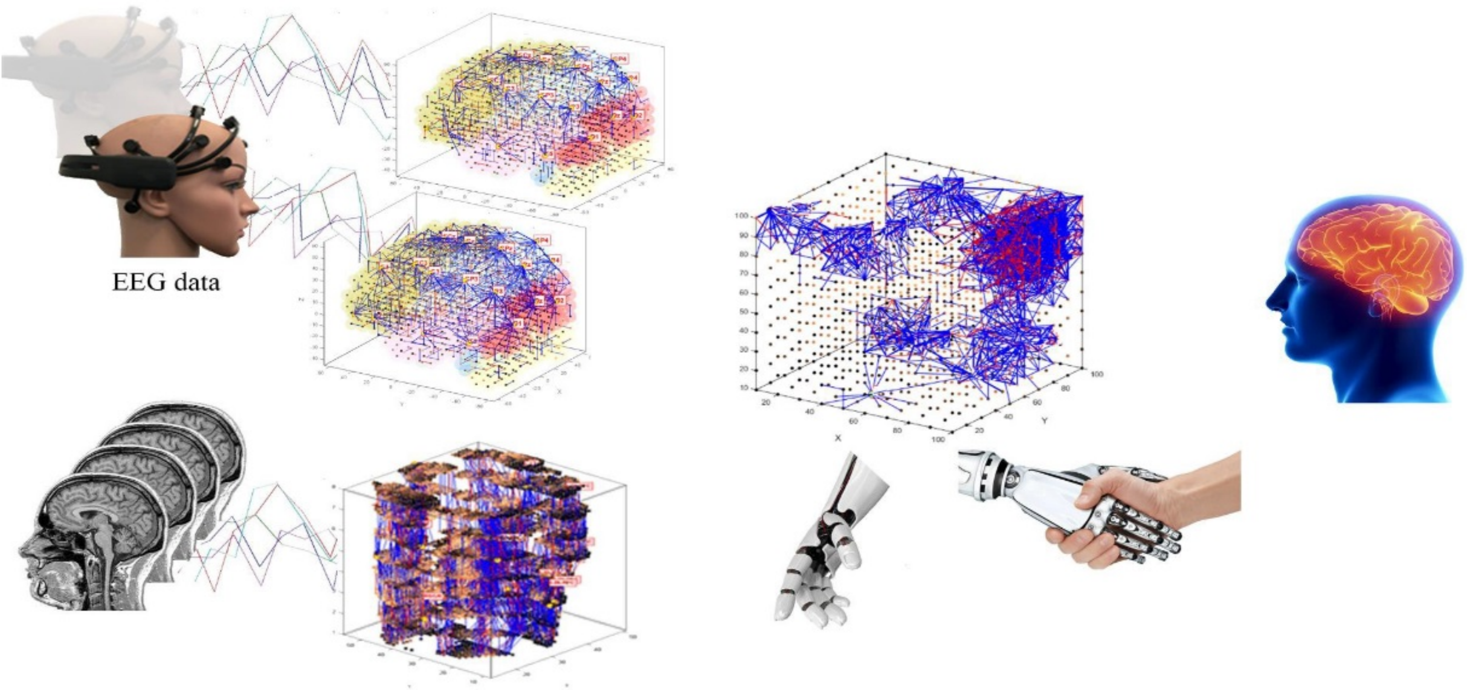
- Or, a tremendous technological progress:
  - Early disease diagnosis and disease prevention
  - Robots for homes and for elderly
  - Improved productivity
  - Improved human intelligence and creativity
  - Improved lives and longevity

Stephen Hawking (1942 - 2018)

- Symbiosis between HI (Human Intelligence) and AI for the benefit of the humanity, being at the same time aware of the potential risk for devastating consequences if AI is misused.

- Knowledge transfer between humans and machines.

- Open and transparent AI systems.



AUT AI Initiative: http://www.aut.ac.nz/aii

https://www.aut.ac.nz/aut-artificial-intelligence

AUT Artificial Intelligence I...

AUT Artificial Intelligence Initiative

This section describes the AUT AI Initiative's objectives, activities and research related to AI at AUT.

AUT: leading the response to a technological revolution

Artificial intelligence (AI) is the current technological revolution in the world. A recent report by PricewaterhouseCoopers predicts that AI will significantly increase the GDP of the world – up to 26% for China, 16% for the USA, and 10% for countries like New Zealand. AI is expected to change the professional activities of millions, threatening thousands of traditional jobs and creating job opportunities in new exciting areas.

Stephen Hawking said: "AI could be either the best or the worst thing ever to happen to humanity". Professor Nikola Kasabov's view is that it will be neither, and perhaps in 20 years' time, AI will become a common tool just as spread sheets are now. Regardless of the views, there are currently many activities world-wide and also starting in NZ that address both technological and societal issues of AI. Companies are in a race to develop new AI technologies in order to keep their competitive edge. Hence, AUT as a university promoting new technologies and innovation, and embracing the motto "for the changing world", is leading the response to this technological revolution.

In this section:

- AI research projects around AUT
- AI-related research across AUT (institutes, centres and groups)
- Staff: researchers in the AI Initiative

Upcoming events

Find out about upcoming events including seminars, workshops and conferences.

EVENTS DETAILS

Contact us

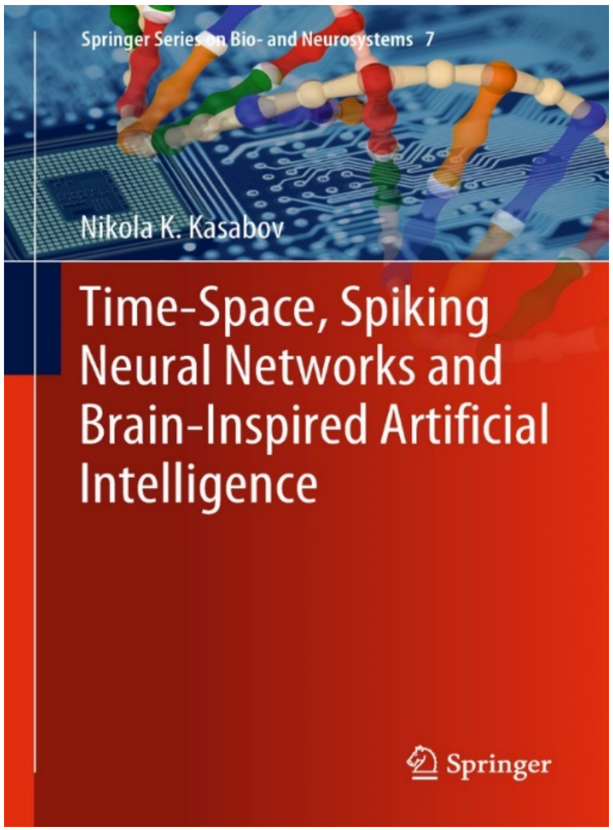
Anne Abbott
Email: anne.abbott@aut.ac.nz

Co-founders

The co-founders of the AUT AI Initiative are:

- Professor Nikola Kasabov
- Associate Professor Dave Parry

N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer, 2019, https://www.springer.com/gp/book/9783662577134



" Времето е в нас и ние сме във времето"

"Time lives inside us and we live inside Time.'

Vasil Levski-Apostola (1837-1873)
Bulgarian educator and revolutionary

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