Gibbon's Lecture 1, 2017

# AI: From Aristotle to Deep Learning Machines and Beyond


Nikola Kasabov, FIEEE, FRSNZ, FIITP

Knowledge Engineering and Discovery Research Institute (KEDRI)
School of Engineering, Computing and Mathematical Sciences
Auckland University of Technology, New Zealand
nkasabov@aut.ac.nz

**http://www.kedri.aut.ac.nz**

# AI

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,....

# Overview

1. The evolution of AI methods: From early deductionism to deep learning machines
2. The evolution of computing platforms to support AI
3. Applications of AI
4. AI in New Zealand
5. The future of AI
6. Selected references

# 1. The evolution of AI methods: From early deductionism to deep learning machines

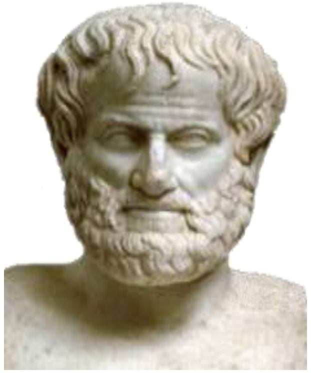
Aristoteles (384-322 BC) was a pupil of Plato and teacher of Alexander the Great. He is credited with the earliest study of formal logic. Aristotle introduced the theory of *deductive reasoning*.

*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 (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.

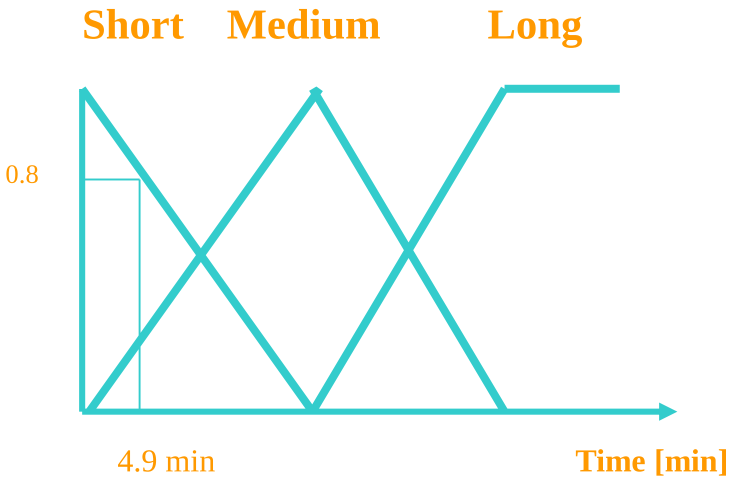
# The boom of symbolic AI:
## Logic, rules and deductive reasoning

- 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

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, linguistic form

- (L.Zadeh, 1965)
- Fuzzy logic 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



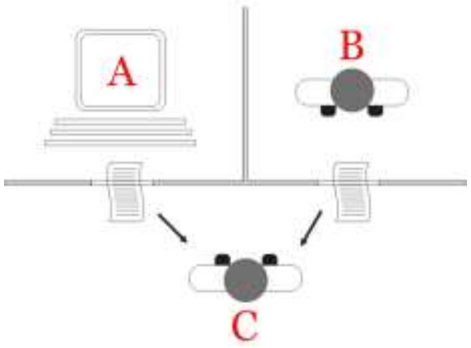

However, fuzzy rules need to be articulated in the first instance, they need to change, adapt, evolve through learning, to reflect the way human knowledge evolves.

# The Turing Test for AI

## Can computers have general intelligence to communicate like humans?

Alan Turing (1912-1954) posed a question in 1950: Can machines think?

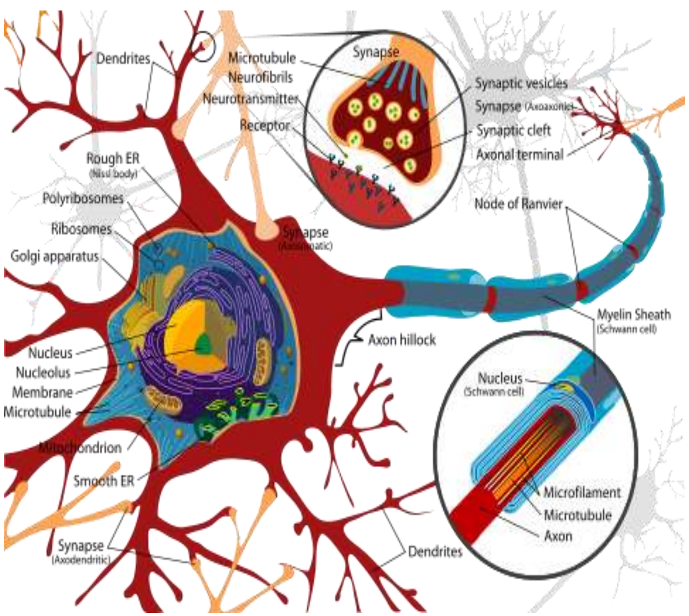
Then it was formulated as “Can machines play imitation games?”, known now as the **Turing test for AI.** It is a test of a machine's ability to exhibit intelligent behaviour equivalent to, or indistinguishable from, that of a human, evaluated by a human ( C on the diagram) .




The Turing test has been both highly influential and widely criticised. However, it has become an important concept in the philosophy of artificial intelligence.

The test though was  too difficult to achieve without *machine learning* in an adaptive, incremental way.

# Learning from data inspired by the human brain – the most sophisticated product of the evolution as an information processing machine




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.

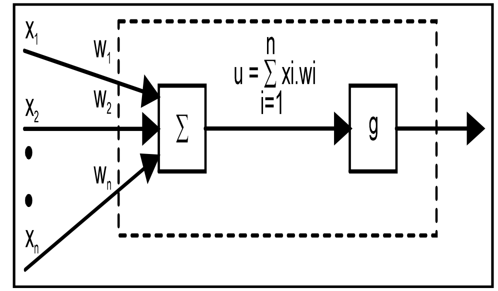
A single neuron is a very sophisticated information processing machine, e.g. time-; frequency-; phase- information.

Can we make AI to learn from data like the brain?

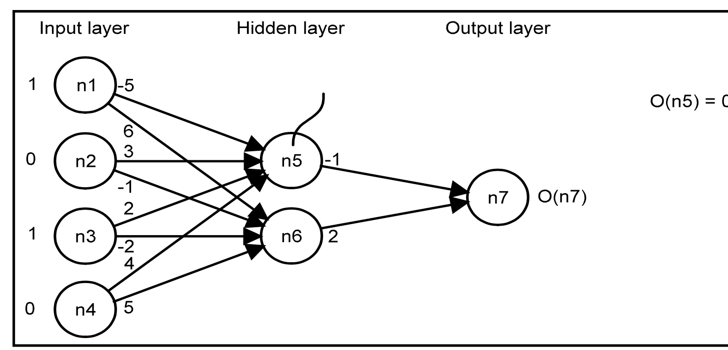
nkasabov@aut.ac.nz

# Early 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: Multilayer perceptron
- Many engineering applications.

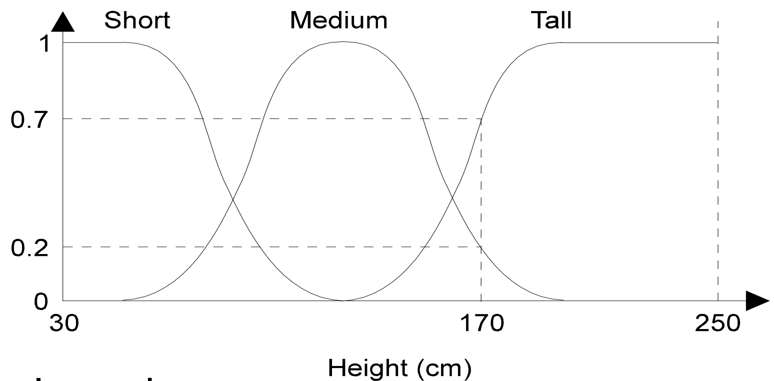



- Early NN were ‘black boxes’ and also - once trained, difficult to adapt to new data without much ‘forgetting’.



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

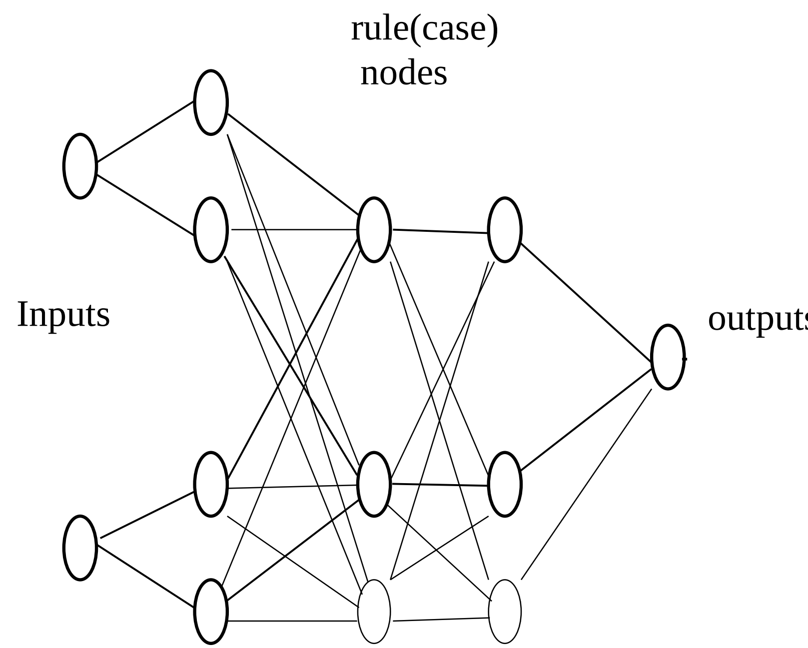
- As a general case, input and/or output variables can be non-fuzzy (crisp) or fuzzy
- Fuzzy variables, e.g. Gaussian MF




- Early works:
  - Yamakawa (1992)
  - EFuNN, DENFIS, N. Kasabov, 2001/2002
- Incremental, supervised clustering

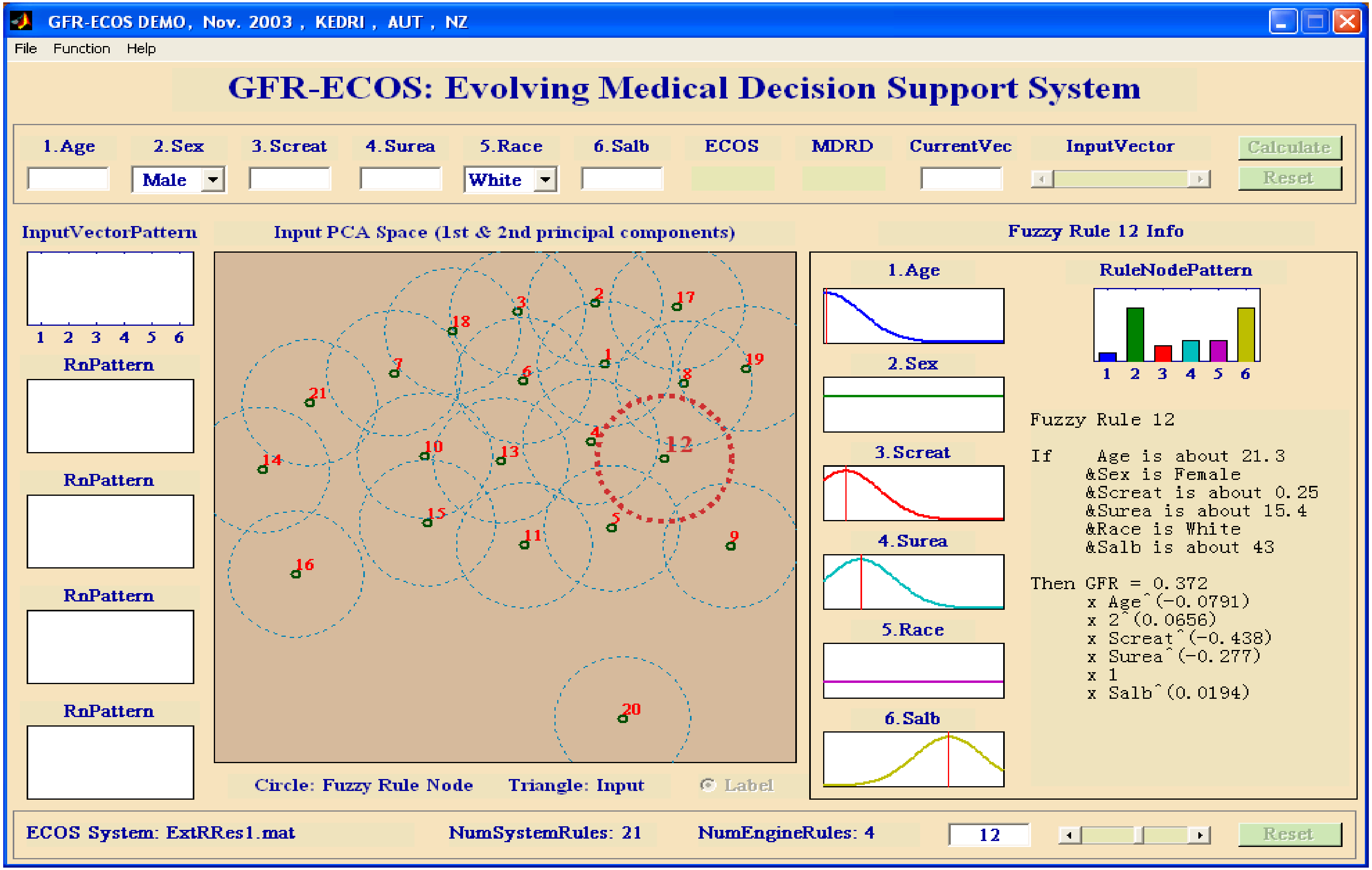
- Fuzzy rules can be extracted from a trained NN and the rules can change (evolve) as further training goes:

  *IF Input 1 is High and Input 2 is Low*
  *THEN Output is Very High*

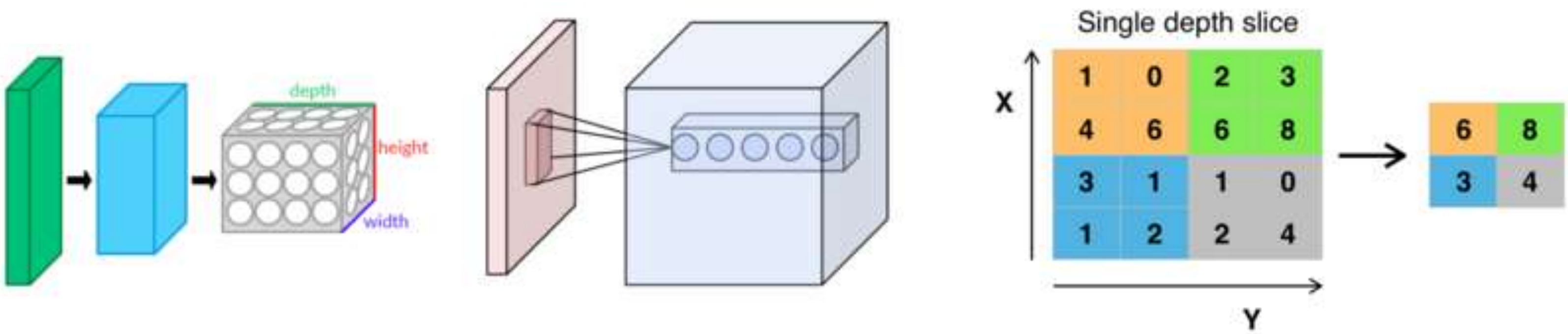


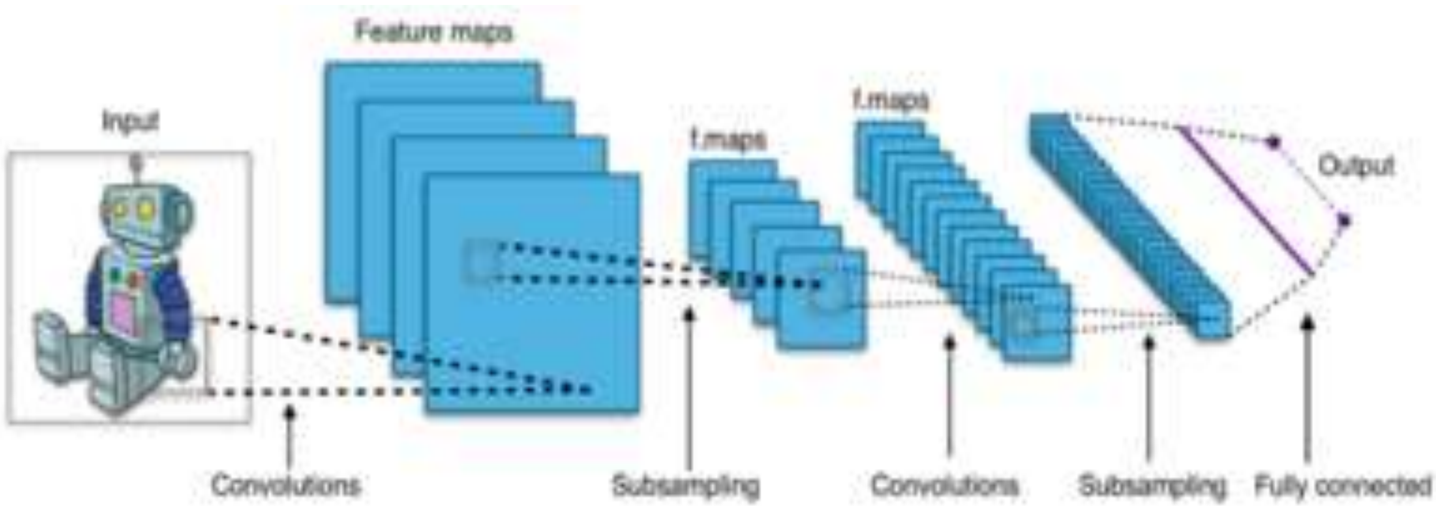
# Example: Extracting adaptable fuzzy rules from medical data

(Mark Marshal, Song, Ma, McDonell and Kasabov, Kidney International, May 2005)



# Deep neural networks

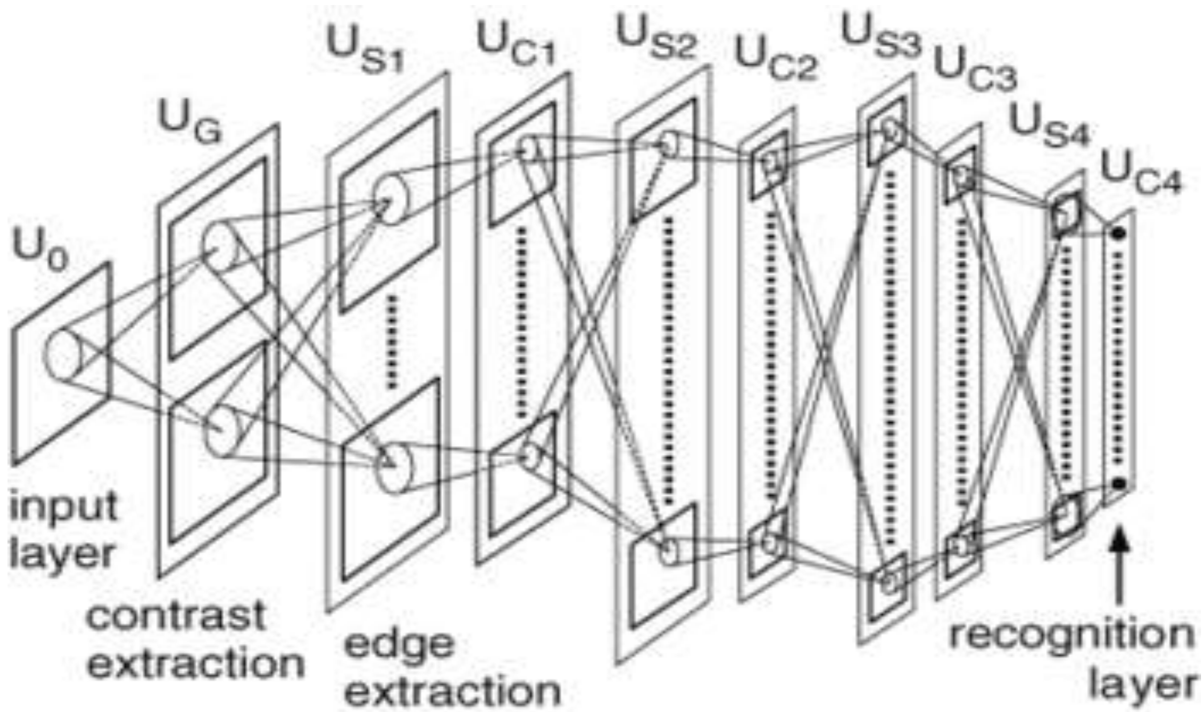


# Deep convolutional NN in computer vision

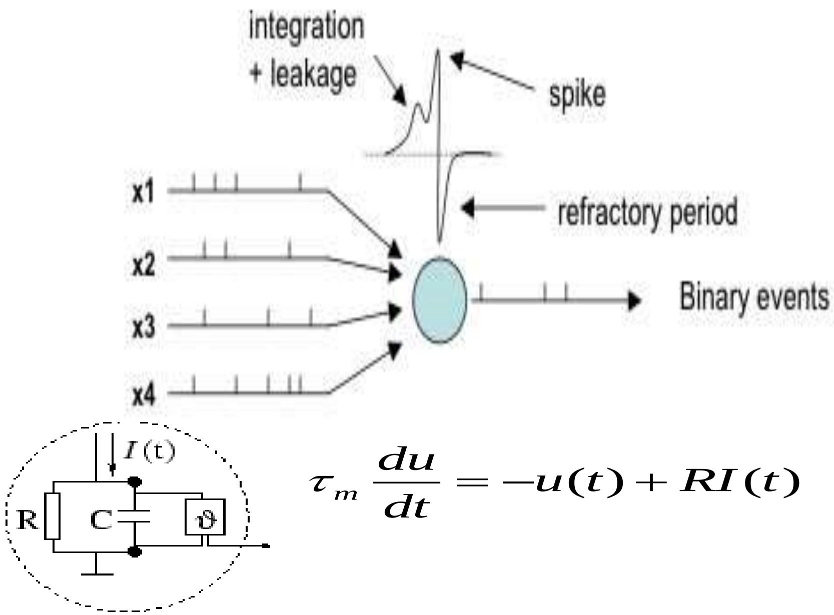
## Spatial features are represented (learned) in different layers of neurons

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

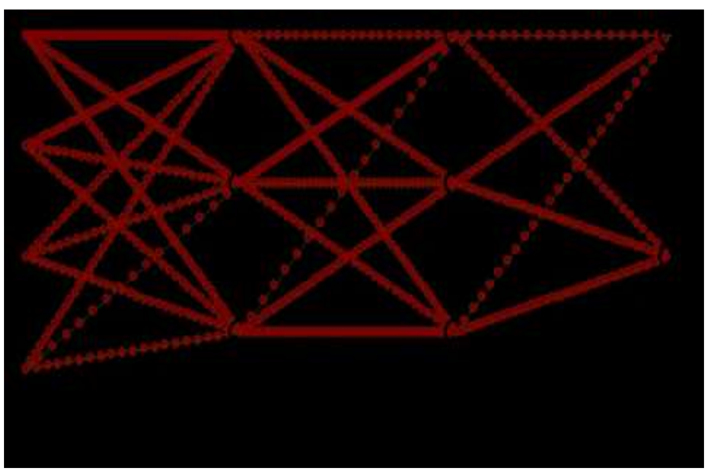



Deep NN are excellent for vector-, frame-based data, but not much for temporal (or spatio/spectro temporal data). There is no *time of asynchronous events* learned in the model; difficult to adapt to new data and the structures are not flexible. How deep should they be? Who decides? (See Lecture 3 by Marcus Freen)

# Spiking Neural Networks can learn temporal patterns




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



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:

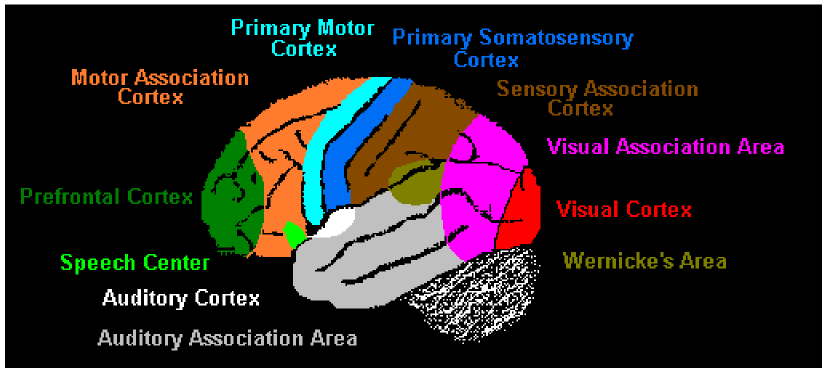
- Spatio-temporal data processing
- Bridging higher level functions and "lower" level genetics
- Integration of modalities

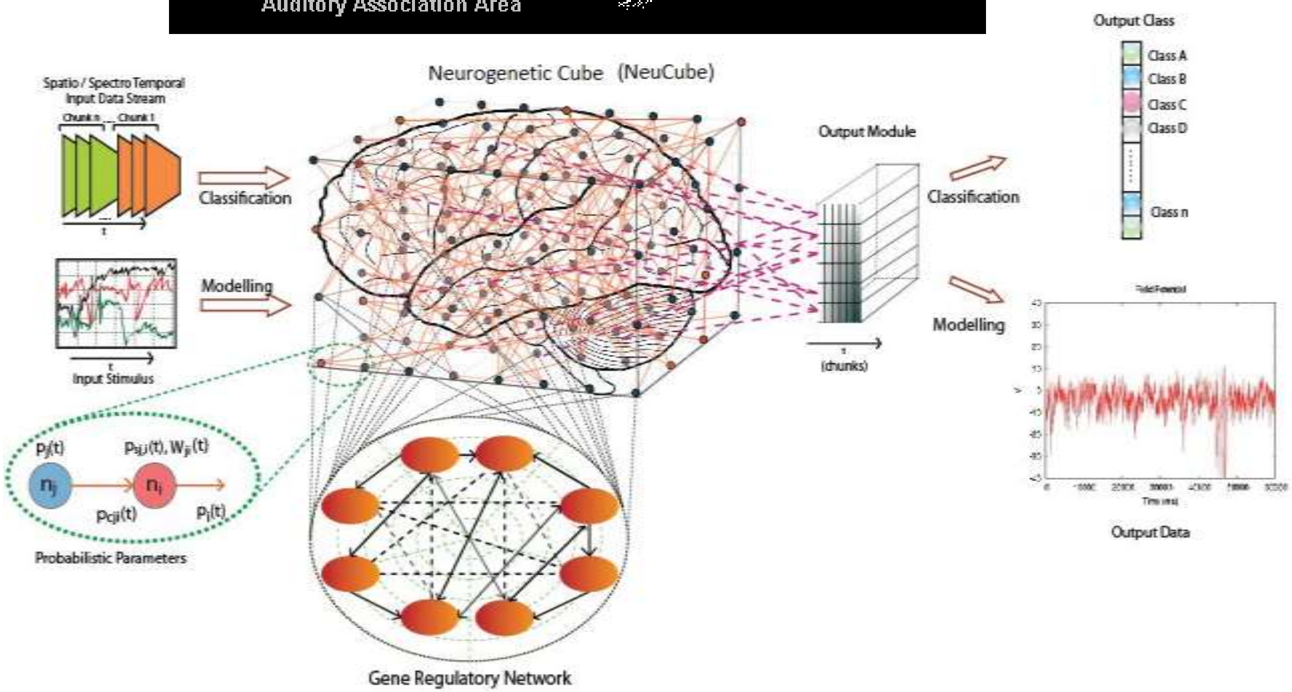
SNN opened the field of brain-inspired (cognitive, neuromorphic) computing.

"*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,

# The deep learning brain-like (neuromorphic, cognitive) spatio-temporal data machine NeuCube

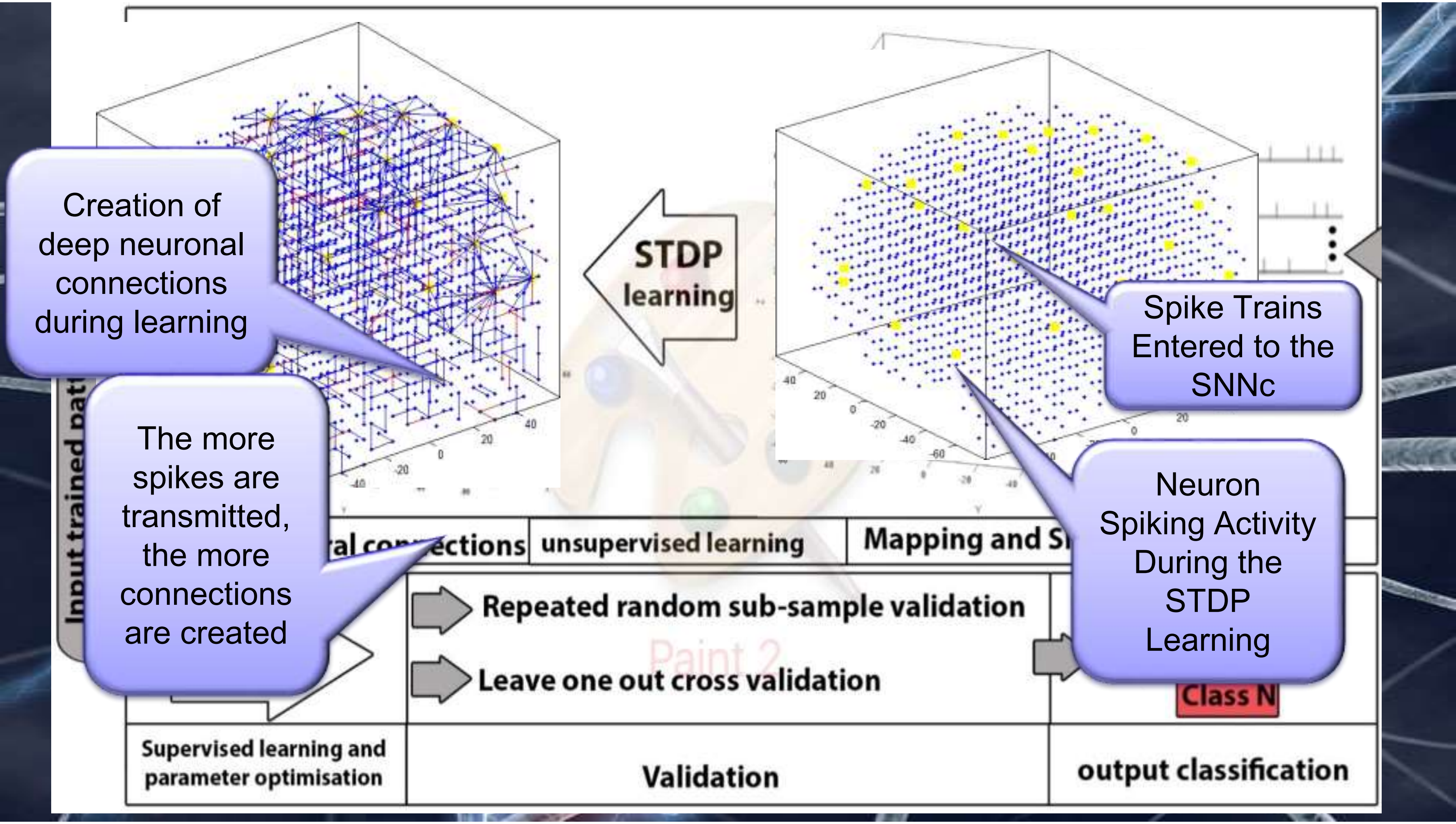
N.Kasabov et al, Improved method and system for predicting outcomes based on spatio/spectro-temporal data, PCT patent, WO2015/030606 A2, priority date: 26.08.2013; Kasabov, Neural Networks, vol.52, 2014, 62-76;



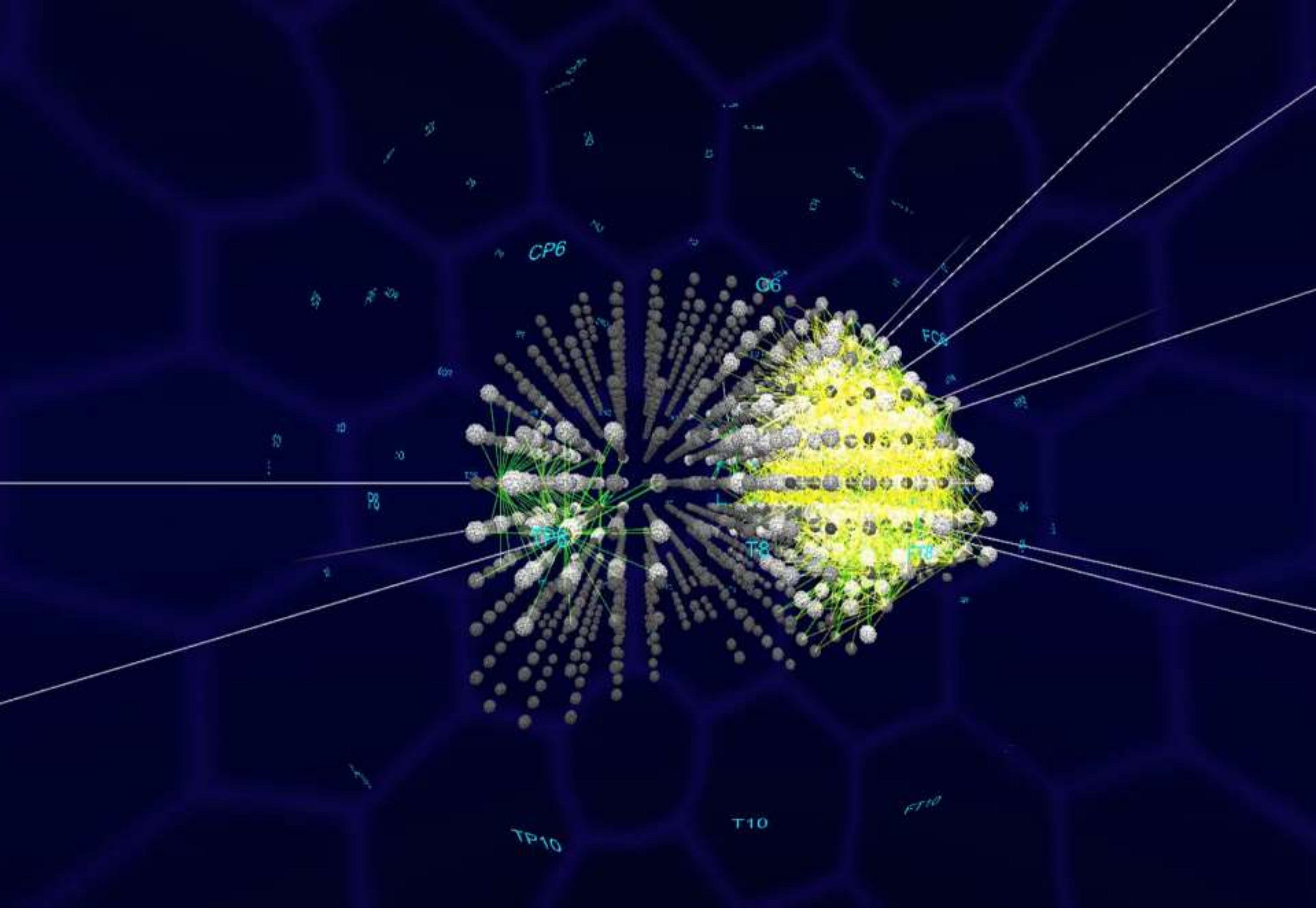

nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

# How deep is the deep learning in the NeuCube brain-like architecture?




nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

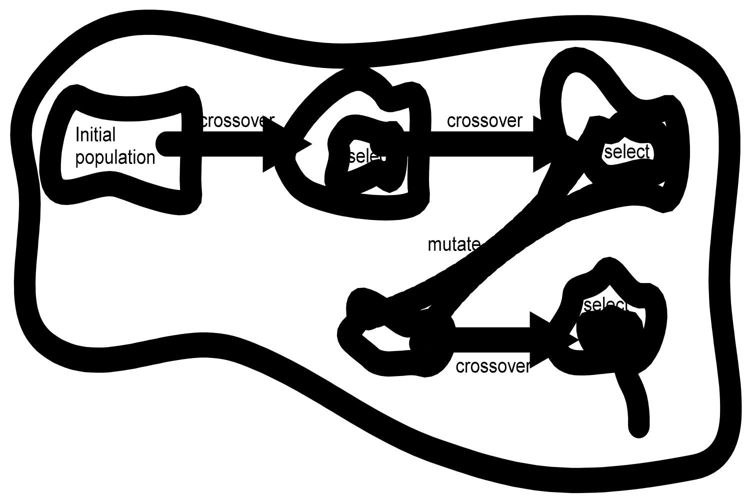
# NeuCube as application development environment for deep learning of spatio-spectro temporal data


CP6
C6
FC6
T8
FT8
TP10
T10
FT10

# 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.

# 2. The evolution of computer platforms to support AI applications

## From von Neumann to neuromorphic and quantum (inspired) architectures

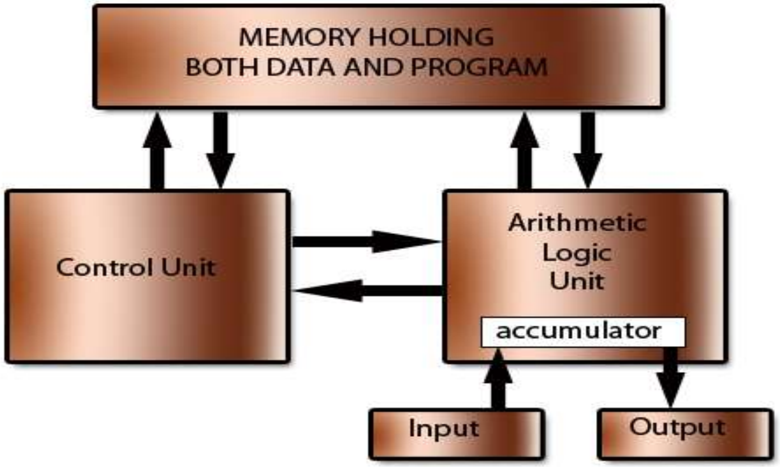
- The *von Neumann computer architecture* separates data and programmes (kept in the memory unit) from the computation (ALU) and the control. Using bits as *static* information.

- Realised as:
  - General purpose computers;
  - Specialised fast computers: GPUs, TPUs
  - Cloud-based computing platforms
- A *neuromorphic computational architecture* integrates data, programs and computation in a SNN structure, similar to how the brain works.

- A quantum (inspired) architecture uses quantum bits, which are in a quantum *superposition* between 1 and 0.

AI models can be simulated using any of the architectures (if available) but with various efficiency.

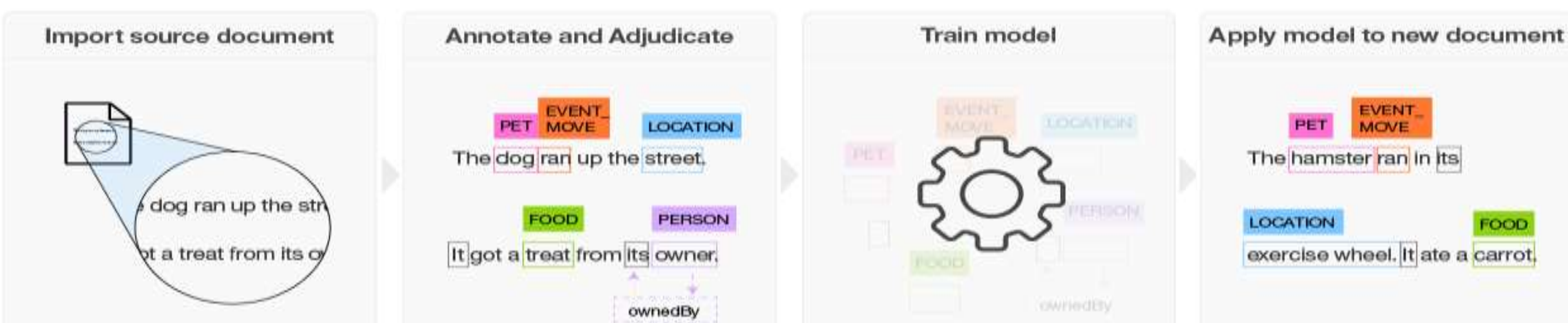
The Von Neumann or Stored Program architecture




(c) www.teach-ict.com

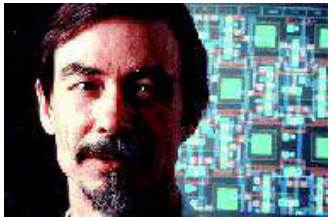
# Cloud-based platforms for machine learning and AI application development

They make it possible to rapidly build cognitive, cloud-based exploration applications based on data. Such systems have been released by competing rivals for world domination: Google, Facebook, Microsoft, IBM, Baidu, Amazon.
Example: The IBM Watson Discovery services
https://www.ibm.com/watson/developercloud/doc/discovery/index.html


Useful, but limited set of methods, mainly for off-line data analysis.
Not suitable for processing streaming data.

# Neuromorphic hardware systems



Hodgin- Huxley model (1952)

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

Misha Mahowald (1963-1996): The first silicon retina

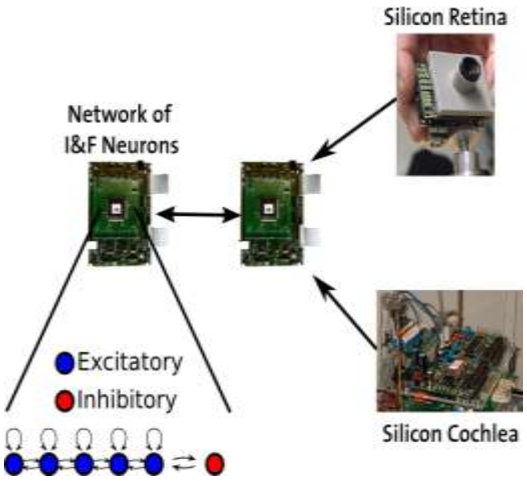
INI Zurich SNN chips (Giacomo Indivery, 2008 and 2012)

FPGA SNN realisations (McGinnity, UNT);

The IBM True North (D.Modha et al, 2016): 1mln neurons and 1 billion of synapses.

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)

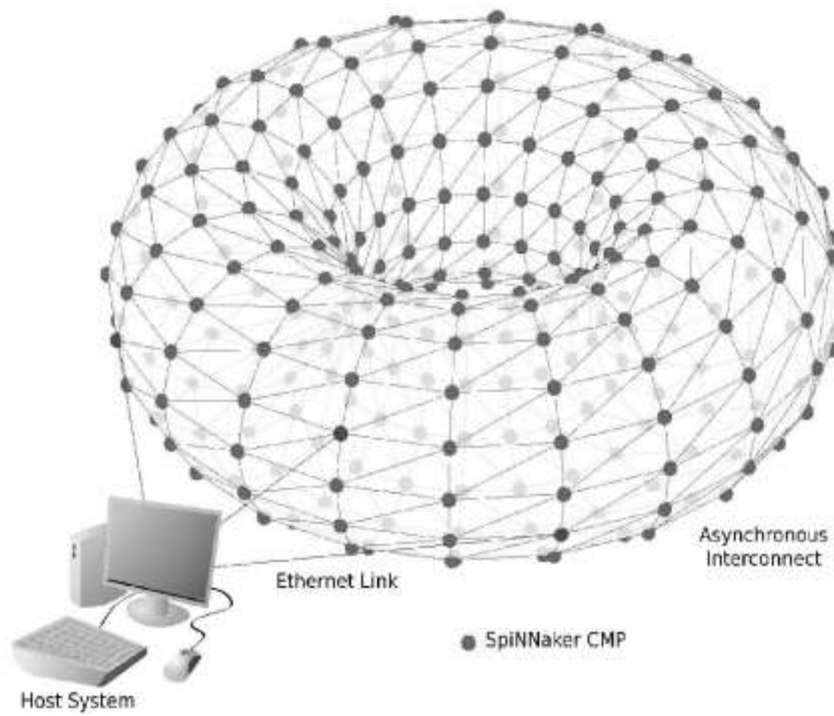



Massive parallelism, high speed and low power consumption.

# 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;
- 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 – 2016;
- 100mln neurons – 2020




Neuromorphic hardware systems require suitable computational models for efficient applications.

# The next step in the AI evolution of methods, tools and platforms: Quantum (inspired) computation?

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

- *Quantum bits (qu-bits)*

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

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

- *Quantum vectors (qu-vectors)*

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

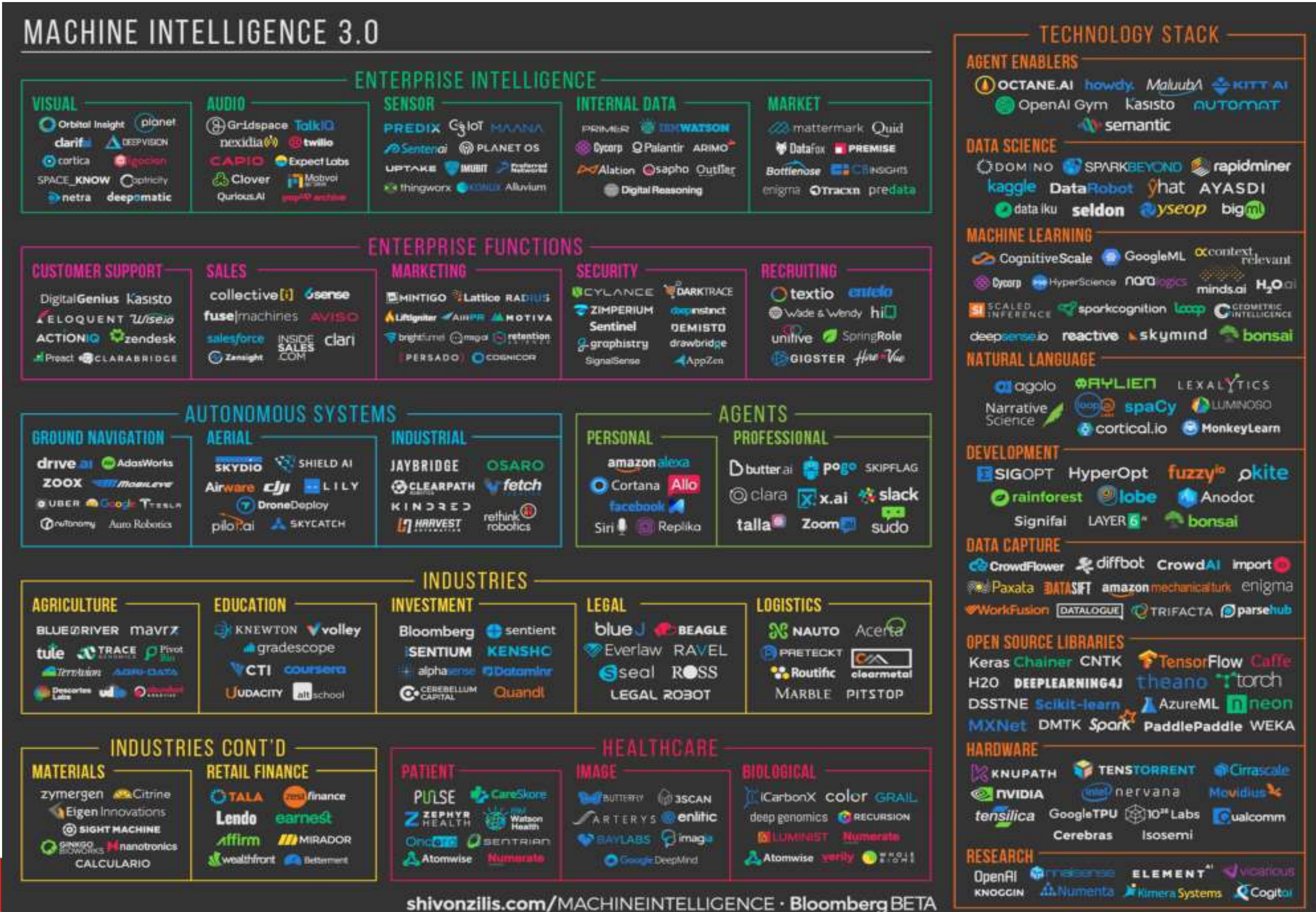
- *Quantum gates*

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

- **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

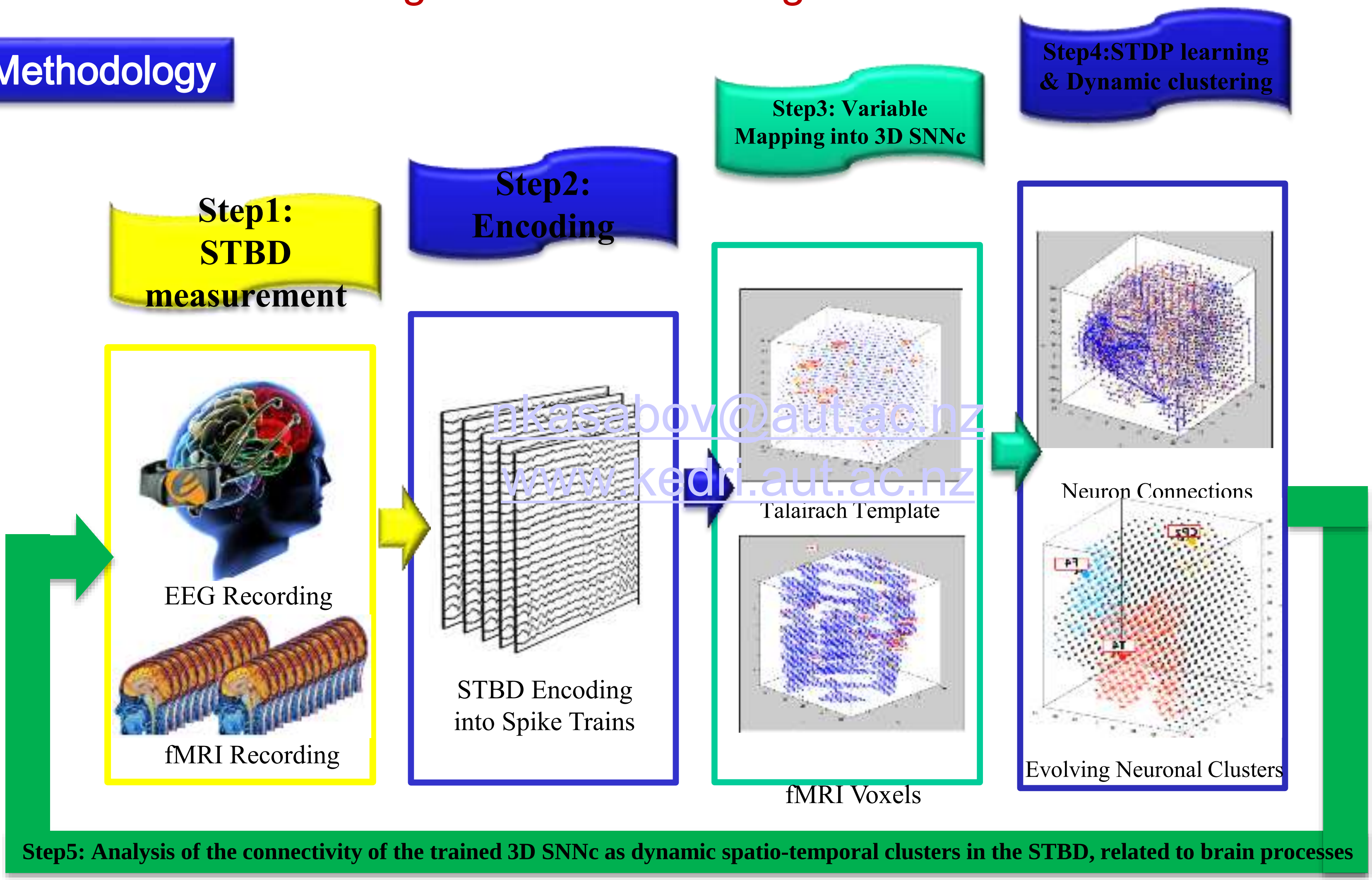
Quantum inspired evolutionary algorithms and neural networks and quantum inspired optimisation of deep learning machines are still in their infancies. Quantum computers – not available yet.

# 3. Applications of AI



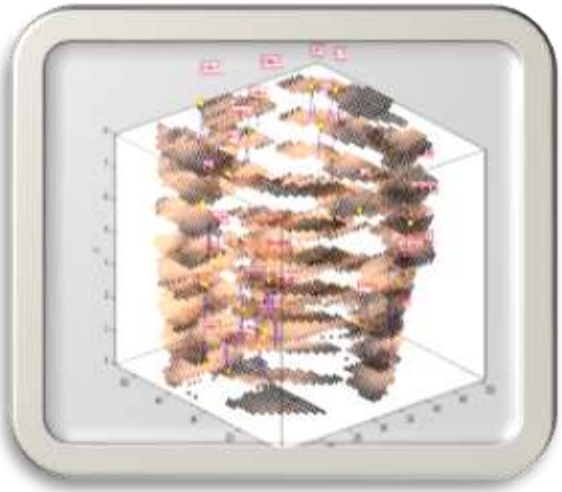
# AI applications in medicine
## Modelling and understanding the brain

**Methodology**

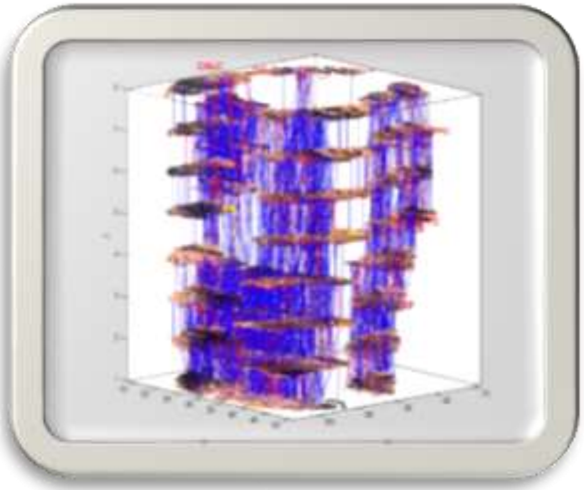


# Modelling brain fMRI data

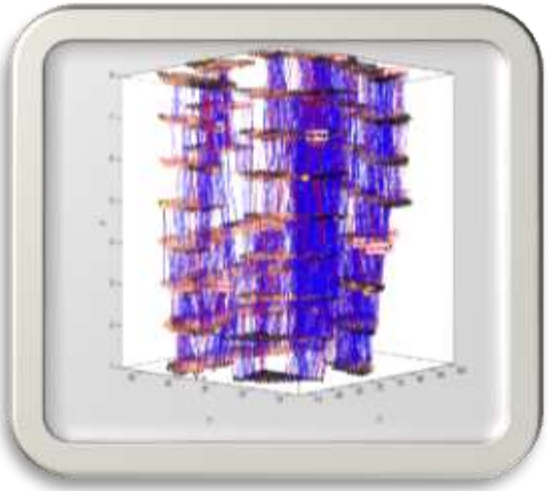
A case study on a person's data related to cognitive tasks.
A trained model reveals spatio-temporal functional connectivity that can be analysed for a better understanding of brain cognitive functions.



Initial SNNc



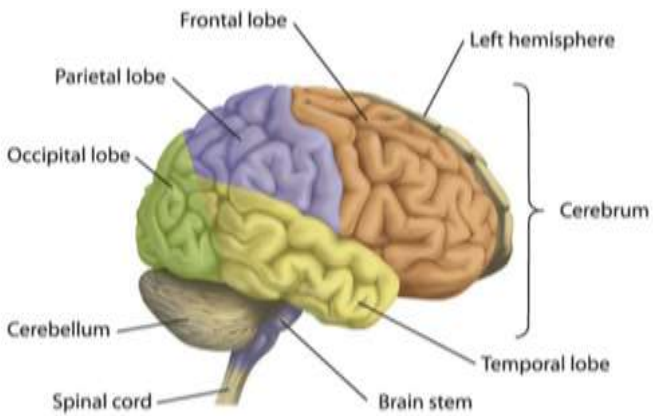
Seeing a Picture

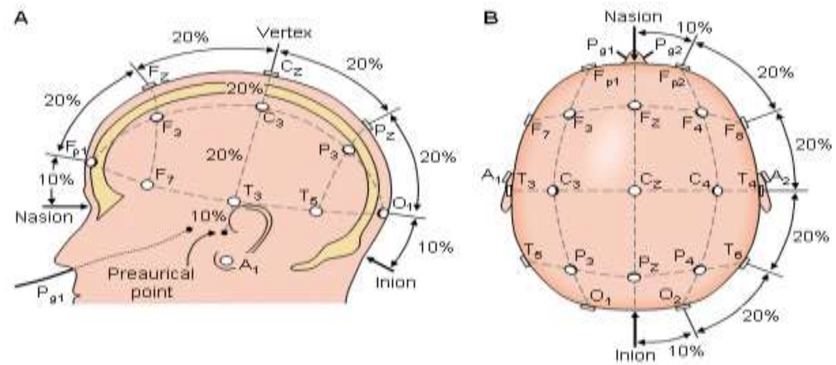


Reading a Sentence

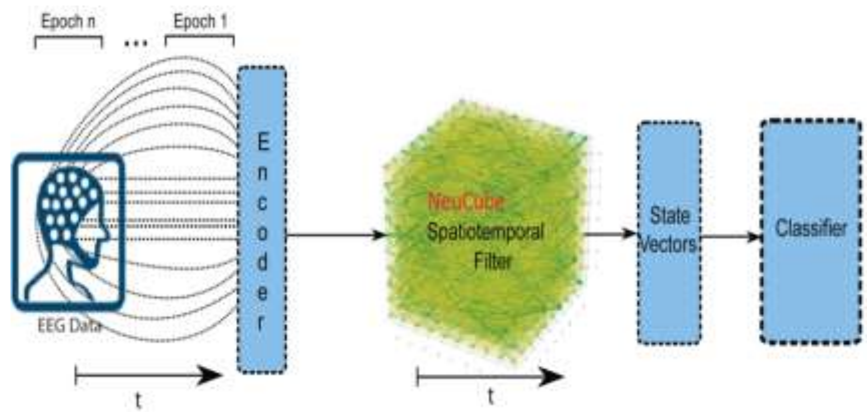
# EEG and MEG data acquisition and modelling

## (the 10-20 system of electrode placement)



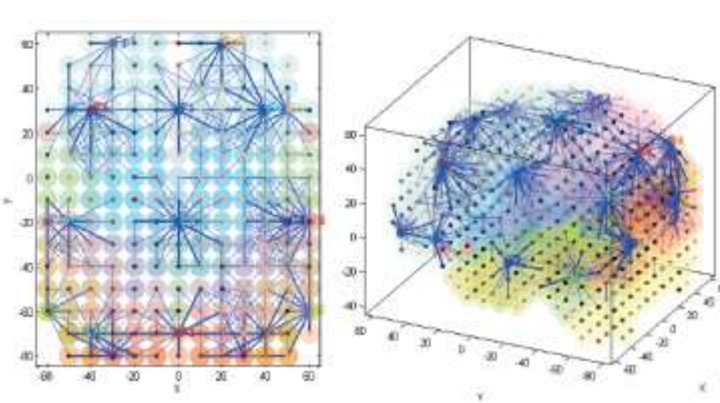




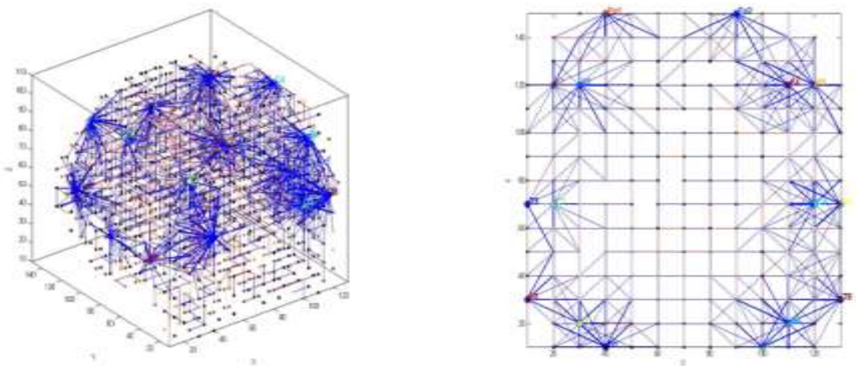
# Predictive modelling of brain changes over time using EEG datra

Predicting progression of MCI to AD (in months)
(with Morabito, Reggio di Calabria)

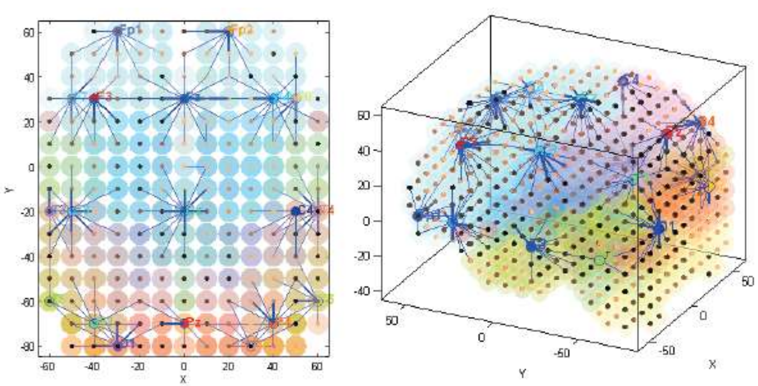
Predicting micro-sleeps (in seconds)
(with R.Jones, U Canterbury)



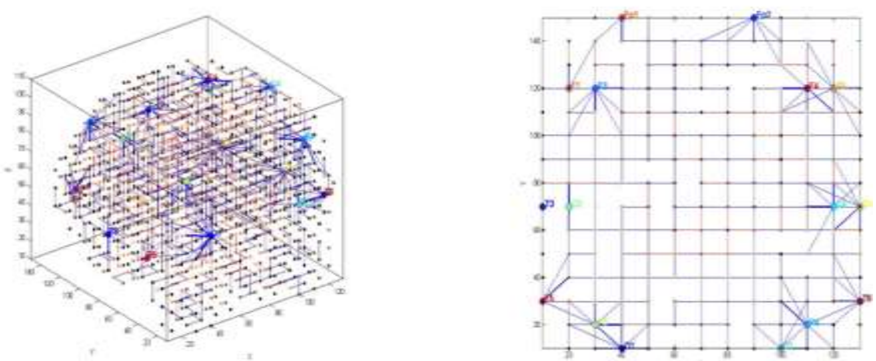
(a) EEG signal collected at $t_0$.



a)SNNcube connectivity based on pre-responsive event



(b) EEG signal collected at $t_1$.

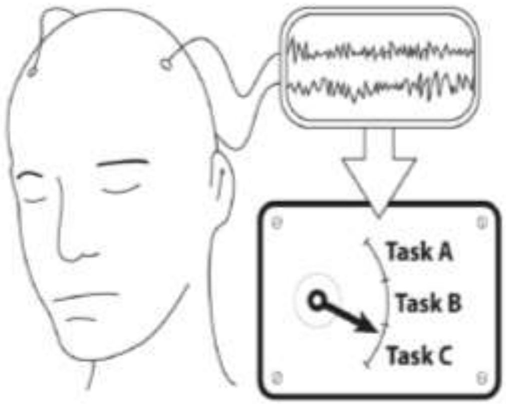


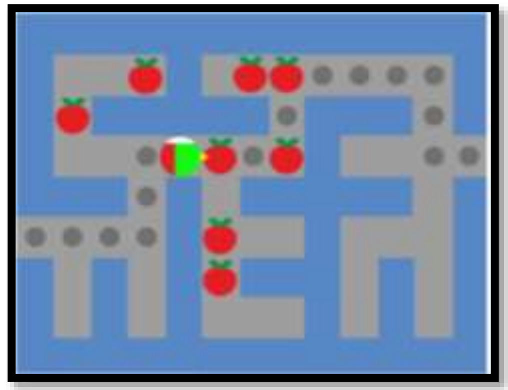
b)SNNcube connectivity based on pre-micro sleep event

nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

# Brain Computer Interfaces (BCI)

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

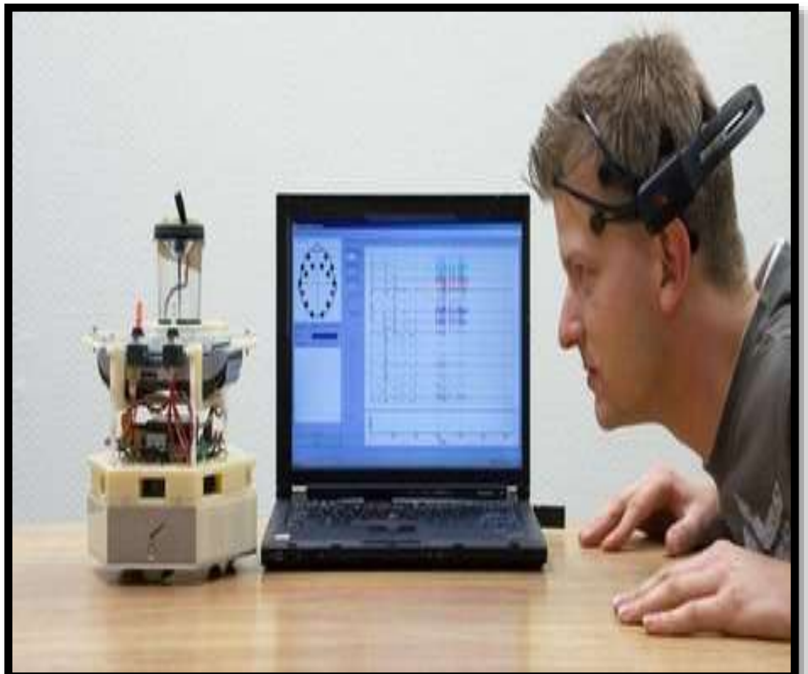


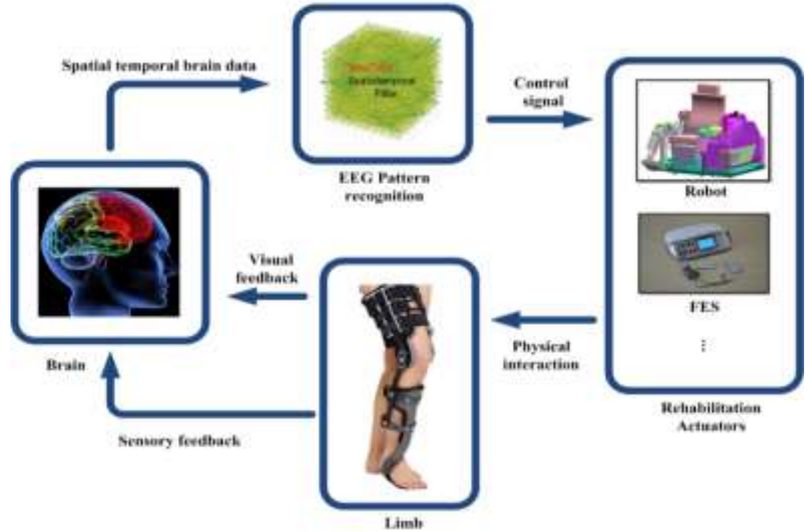
http://computer.howstuffworks.com

95% 125mSec **(Kronegg ,2007)**

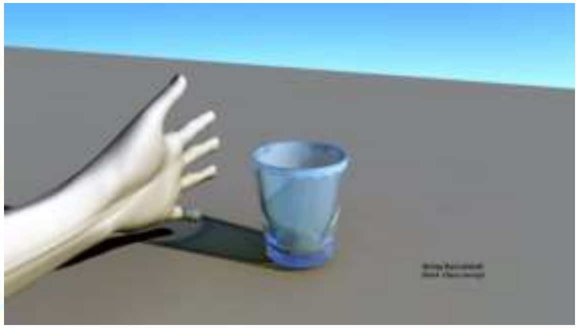
# BCI for robot control and neurorehabilitation
(D.Taylor, CASIA China)



http://www.nzherald.co.nz

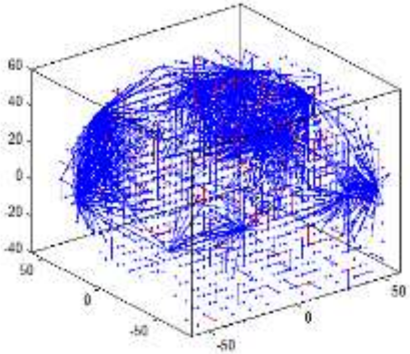



# BCI for interactive assistive devices and cognitive games



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.



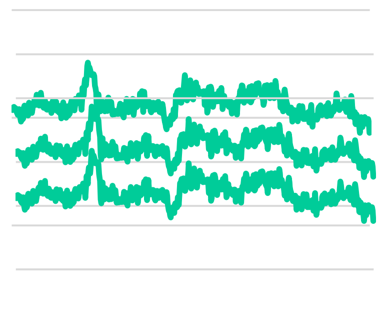
A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG signals.

# AI for recognition of emotional face expression

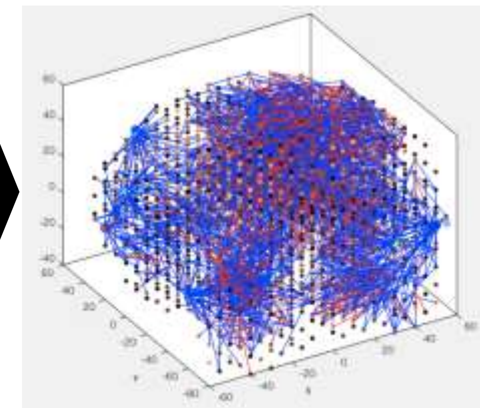
(with H.Kawano KIT Japan, Z.Doborjeh, ICONIP, Kyoto, 2016)

## Facial Expression Perception Task


14ch EEG



94.3 %



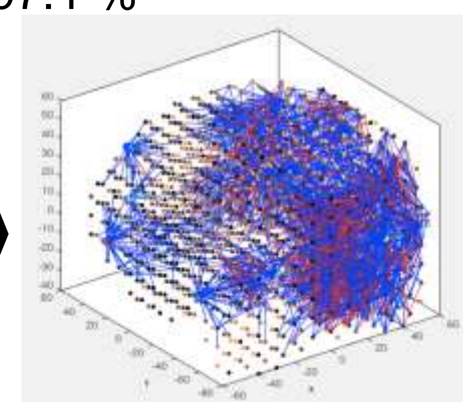
## Face Expression Production Task


14ch EEG



97.1 %

NeuCube

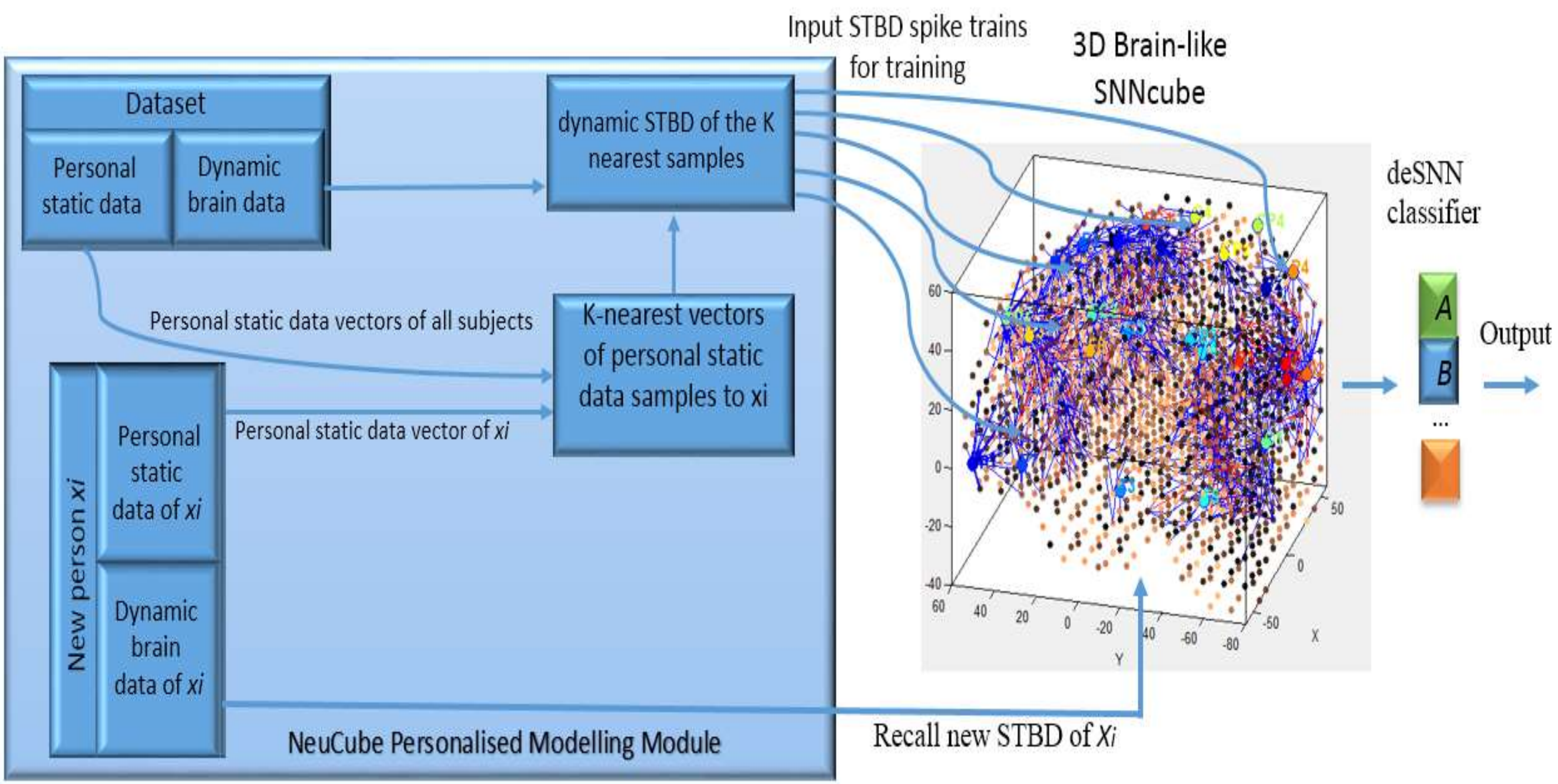


# Emotional (affective) computing

- Computer systems that can learn and express attitude/emotions.
- A motivation for the research is the ability to simulate empathy. The machine should interpret the emotional state of humans and adapt its behaviour to them, giving an appropriate response for those emotions.
- Computer systems with a human face as an interface.
- Mark Sagar – ABI/UoA, uses a baby face - the Baby X

# Precision medicine and precision health

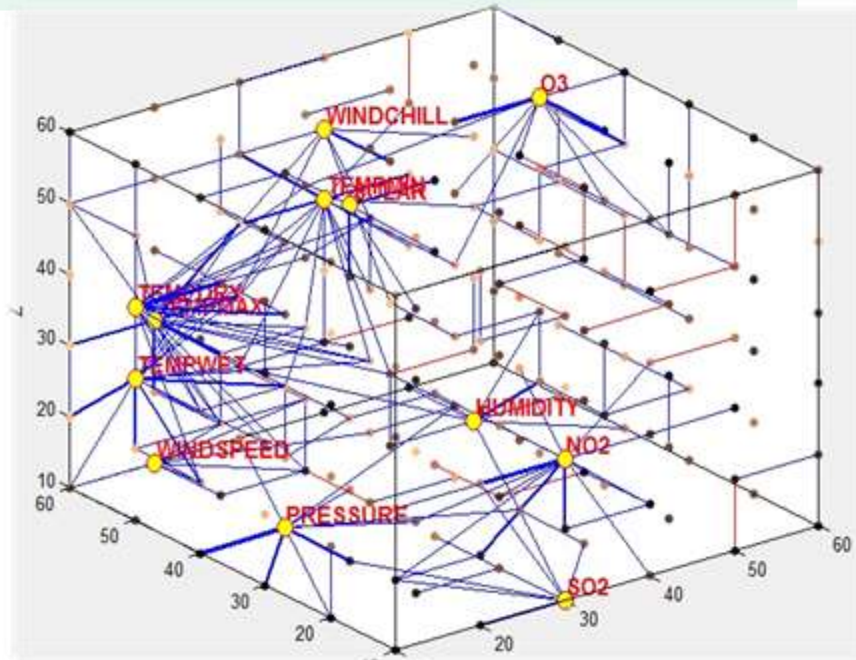
Building an optimal individual model from personal data and data from many persons to best predict outcome for the person

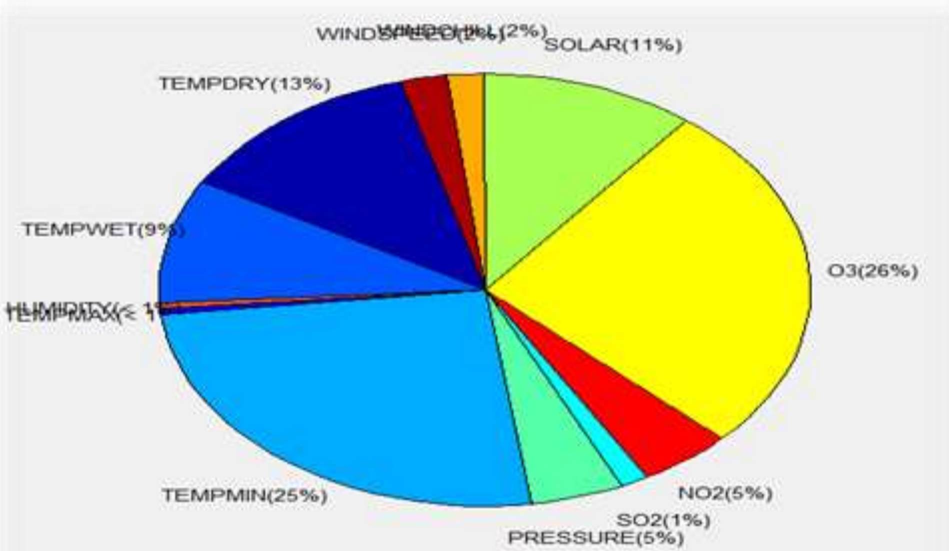


# Mobile devices to predict individual risk of events
## (Stroke risk prediction from 1 to 11 days ahead, KEDRI and NISAN)

(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)*** |



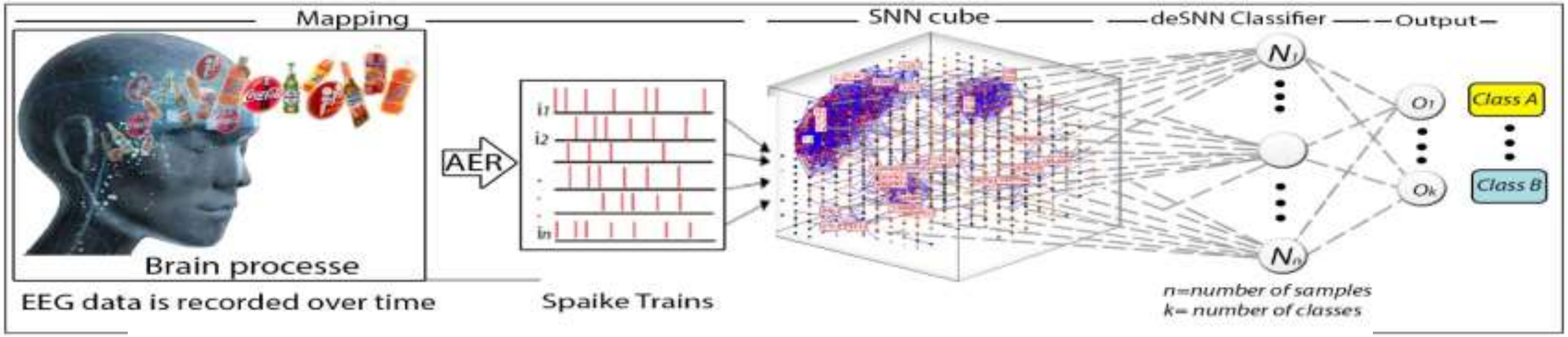



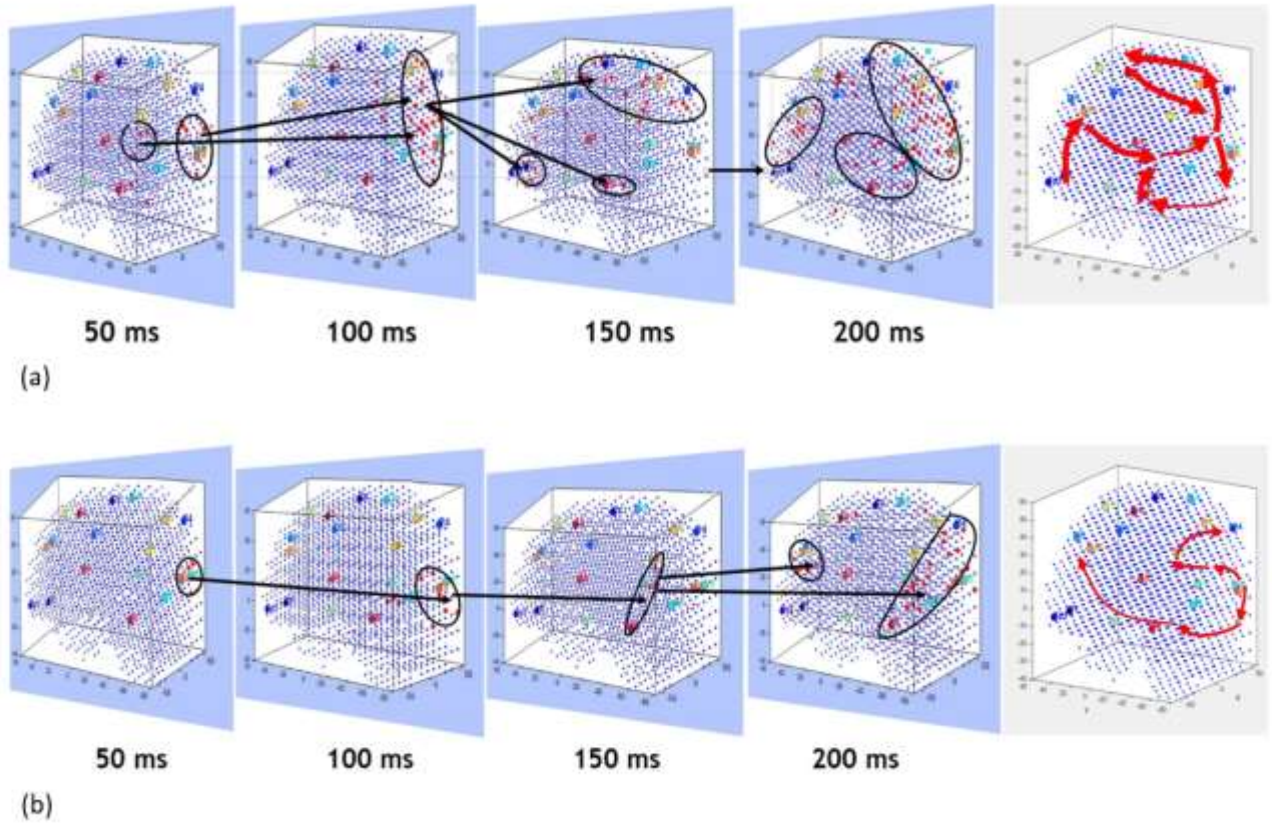

*(d) Neuron proportion based on spike transmission*

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

# Understanding human decision making

## Modelling brain activities in Neuromarketing: Familiar (a) vs unfamiliar (b) object perception

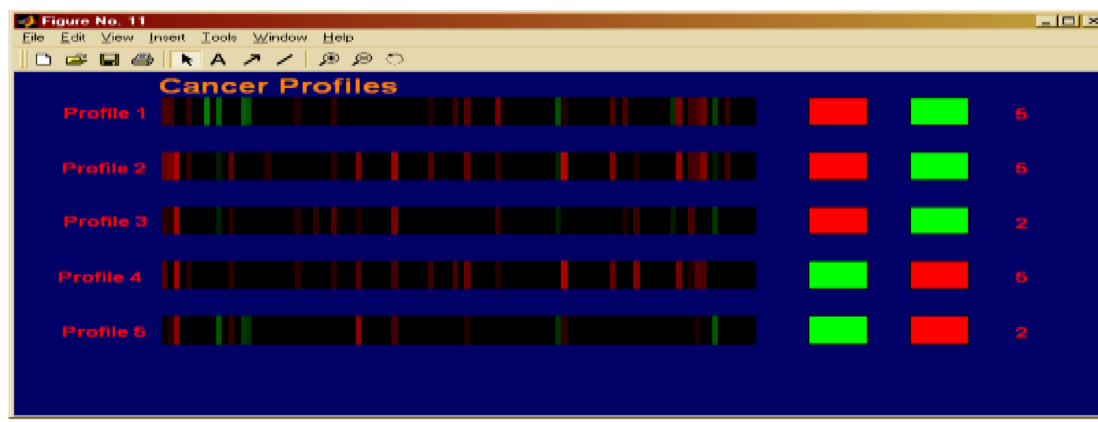


# AI in Bioinformatics: Detecting gene expression patterns

- DNA, gene and protein data analysis:
  - large data bases;
  - data always being added and modified;
  - different sources of information
- Extracting patterns of gene activity from data that discriminate outcomes
- Cancer Ontology-Based DSS
- Markers and drug discoveries

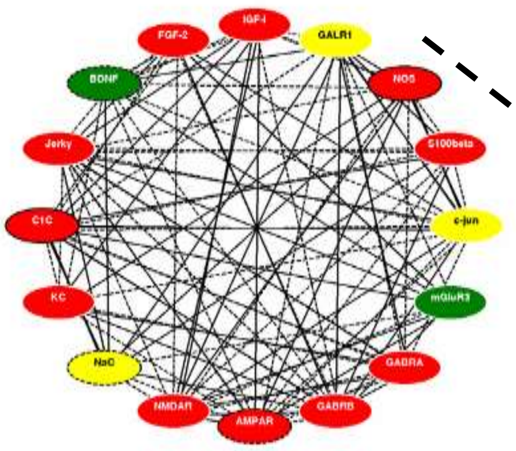
- PEBL: www.peblnz.com



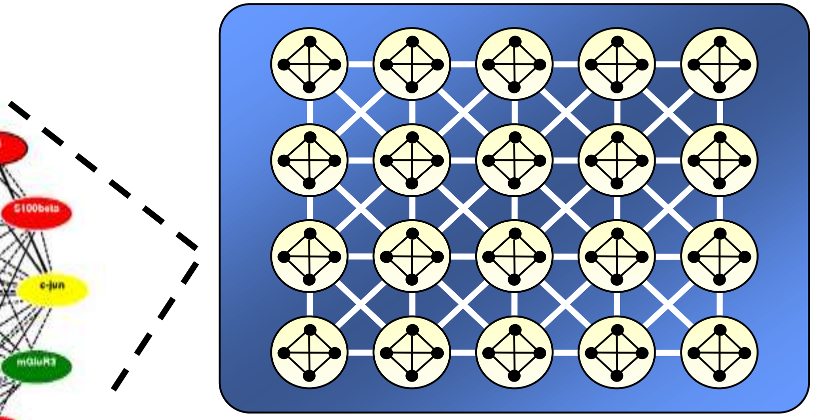
# Computational Neurogenetic Modelling

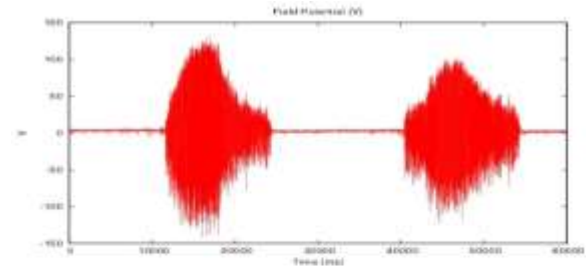
## Modelling dynamics of genes as part a brain computational model

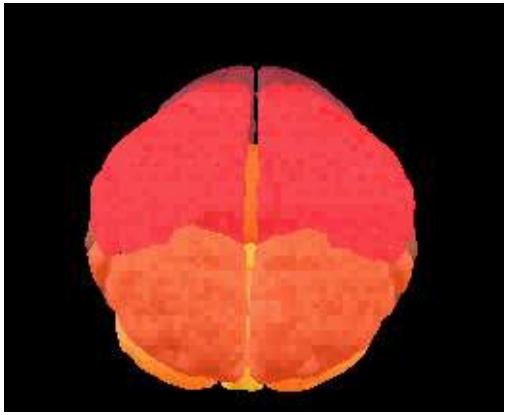
### GRN

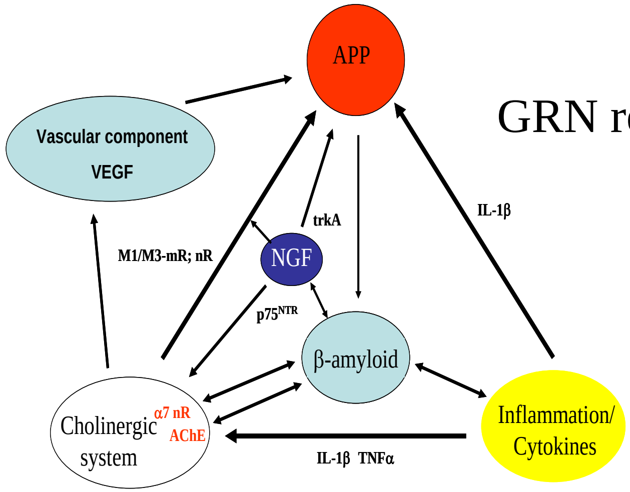



### CNGM as a SNN







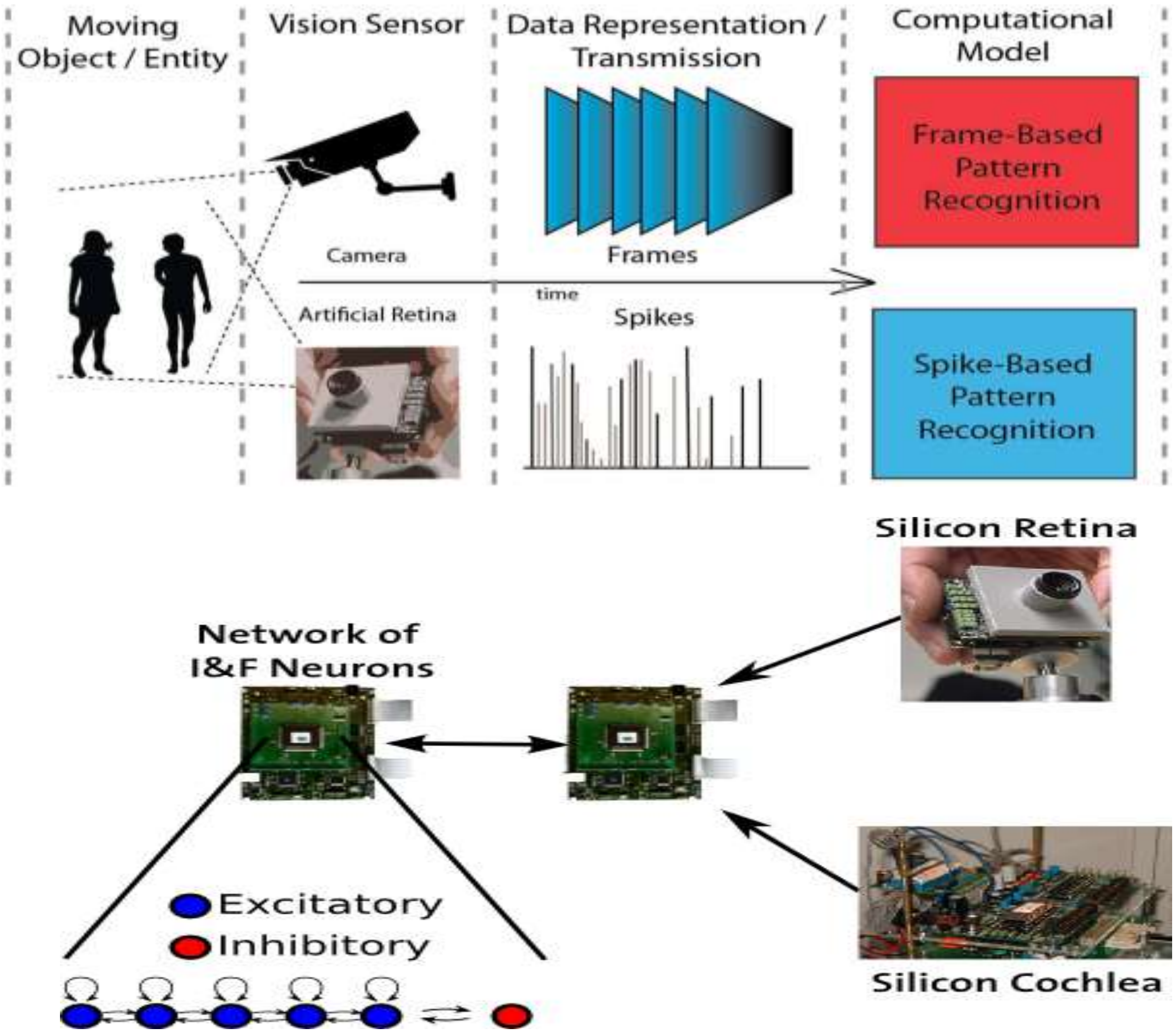



### GRN related to AD

nkasabov@aut.ac.nz

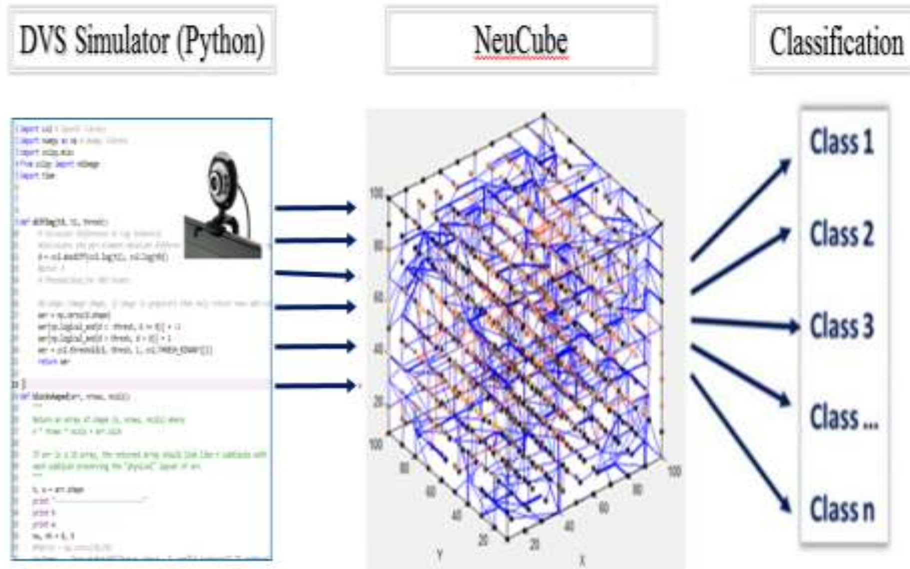
# AI for audio-/visual information processing

## Frame-based or spike-based approaches



# Fast moving object recognition

- Autonomous vehicles
- Surveillance systems
- Cybersecurity
- Military applications

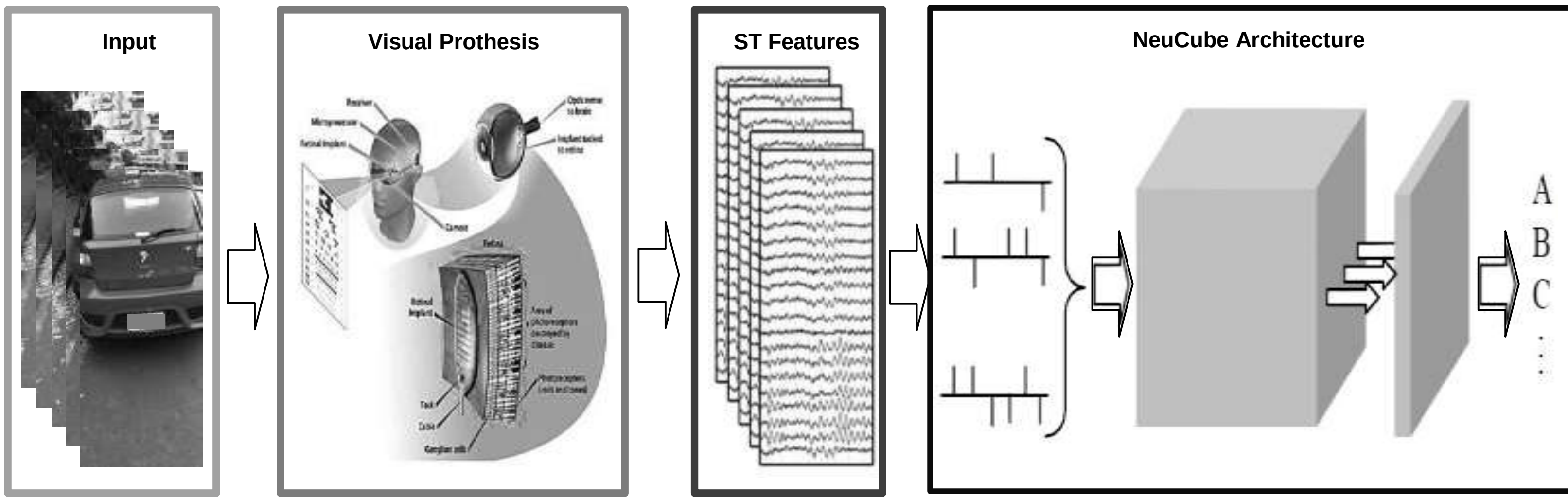



Overall Accuracy: 90.00%
-Class 1 Accuracy: 100.00%
-Class 2 Accuracy: 100.00%
-Class 3 Accuracy: 80.00%
-Class 4 Accuracy: 80.00%

# Enhancing human prosthetics

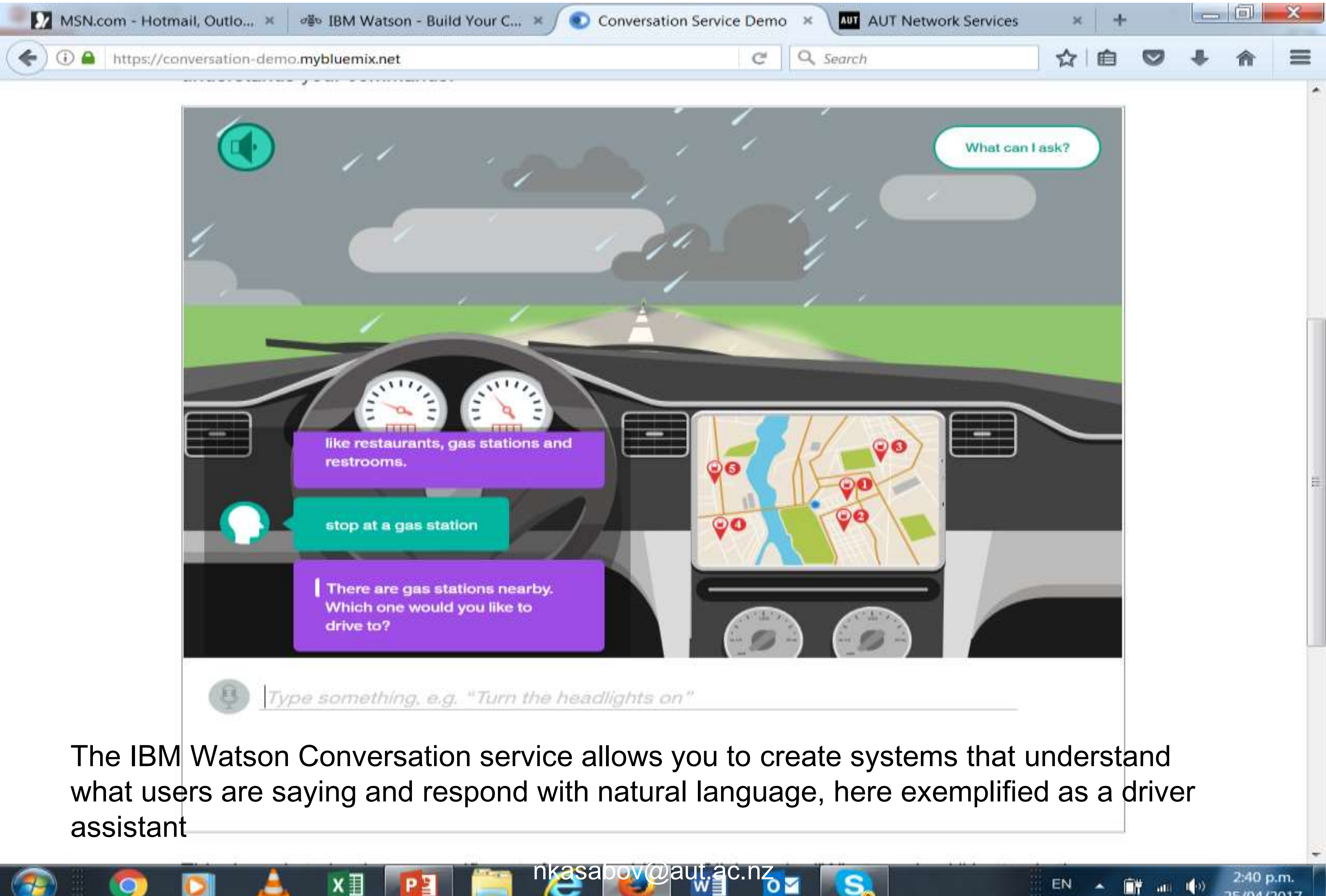
## Example: Enhancing visual prosthesis with description of obstacles and environment recognised through the NeuCube SNN AI

(Chenjie Ge, N.Kasabov, Jie Yang – Shanghai JiaoTong U, Information Sciences, 2017)



# Autonomous robots

# Driver assistance



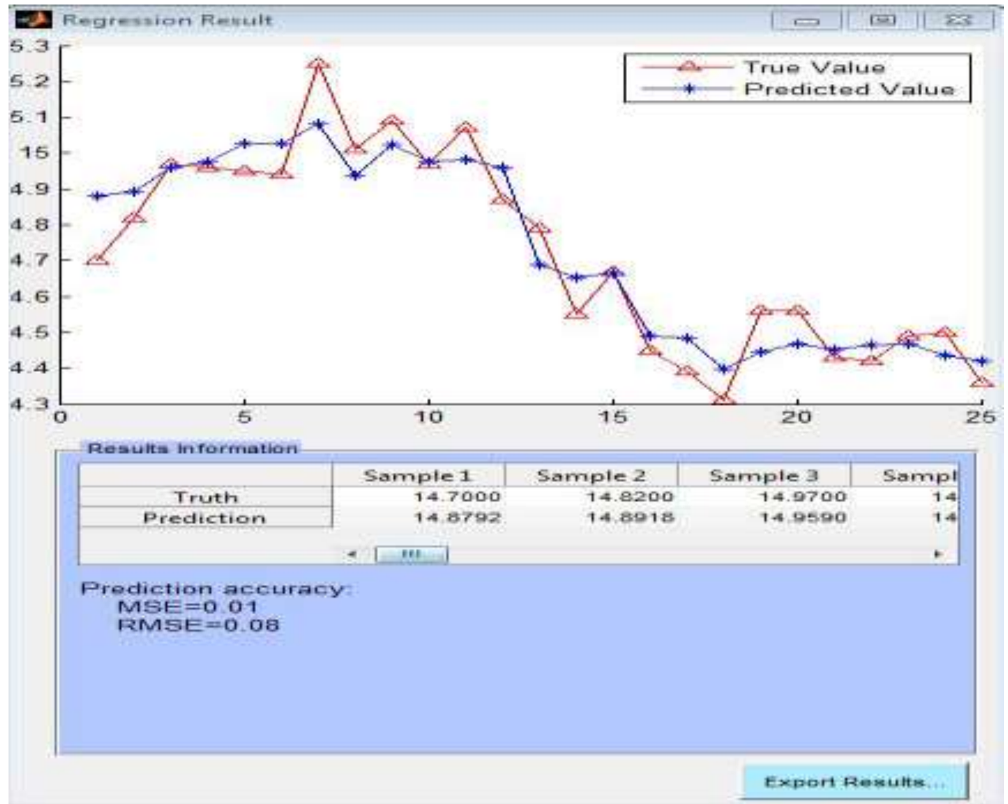

The IBM Watson Conversation service allows you to create systems that understand what users are saying and respond with natural language, here exemplified as a driver assistant

# AI in Finance

## Automated trading systems (autonomous robots on the Internet)

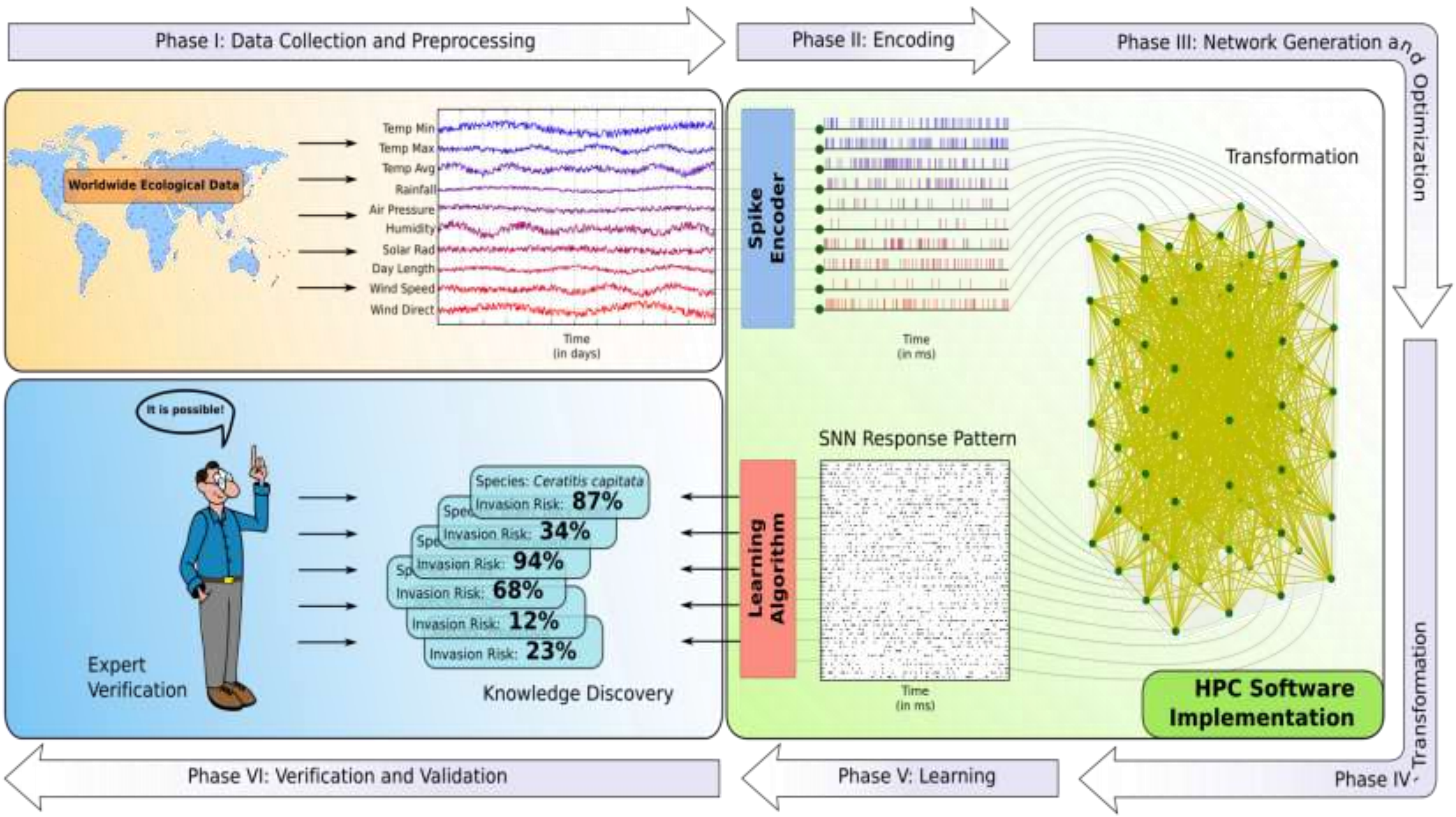
- Each sample consists of 100 timed sequences of daily closing price of 6 different stocks (Appel, Google, Intel; Microsoft, Yahoo, NASDAQ)
- The target values are the closing price of NASDAQ at the next day.
- See demo on:

http://www.kedri.aut.ac.nz/neucube/



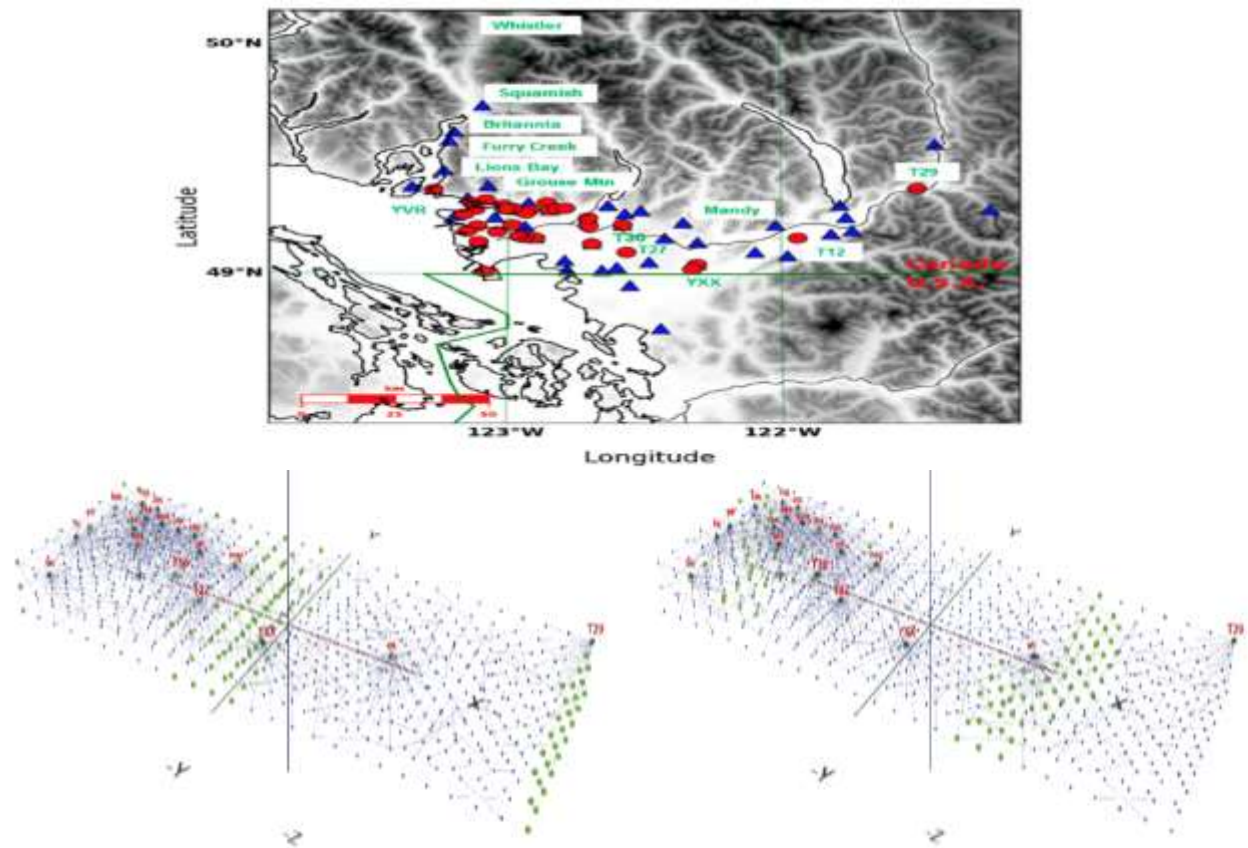
# AI for ecological data modelling and event prediction

Example: Predicting the establishment of harmful species based on temporal climate data streams and SNN (with U Lincoln)



# AI for environmental multisensory streaming data modelling and event prediction

## (Air pollution modelling, with UoA D.Williams and team)

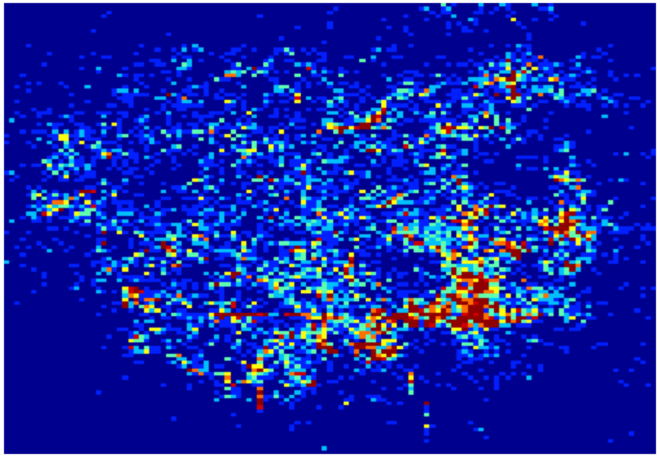


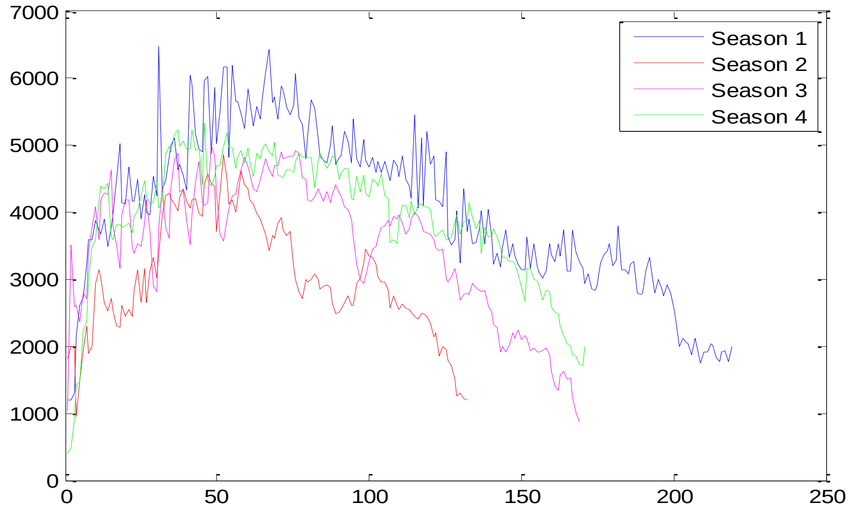

*NeuCube 3D spiking neural network map of southwestern British Columbia showing the Lower Fraser Valley network of monitors with regional and government fixed monitors (dark green circles). Spatio-temporal relationships (lines) and activity (light green circles) of ozone ($O_3$) (left cube) and carbon monoxide ($CO$) (right cube) concentrations can be analysed simultaneously.*

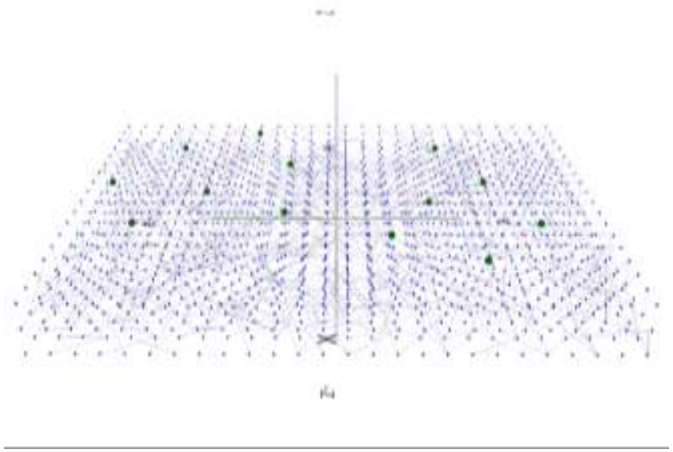
nkasabov@aut.ac.nz

# AI for predictive modelling on streaming data in telecommunication, energy and primary sectors

(a) Mobile calls prediction (TELECOM)
(b) Milk volume prediction (FONTERRA)
(c ) Wind energy prediction (project with DIT Ireland)

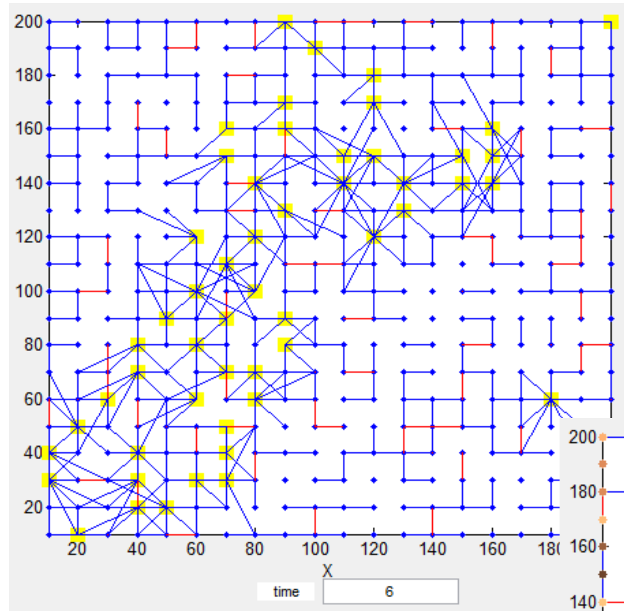


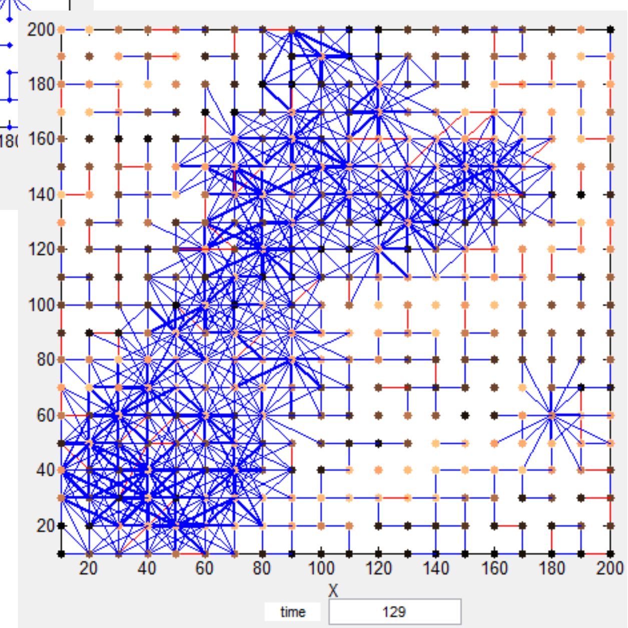


# AI for seismic data modelling. Can we predict earthquakes?

(with GNS M.Gerstenberger)


| 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?

# 4. AI in New Zealand: Research

- Rule based systems and associative memories for robotics:
  - John Andrea (1927-)
    - PURR-PUSS (Purposeful Unprimed Real-world Robot with Predictors Using Short Segments)

    J. Andreae: Thinking with the Teachable Machine, Academic Press, 1977; also Imper. College Press,1998.
- Human-computer interfaces
  - Mark Apperley (Massey and Waikato Universities)
- Neural networks, fuzzy systems and knowledge engineering
  - N Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996
  - N.Kasabov, Evolving connectionist systems, Springer 2003 and 2007
- Machine learning software (WEKA):
  - Ian Witten et al at Waikato

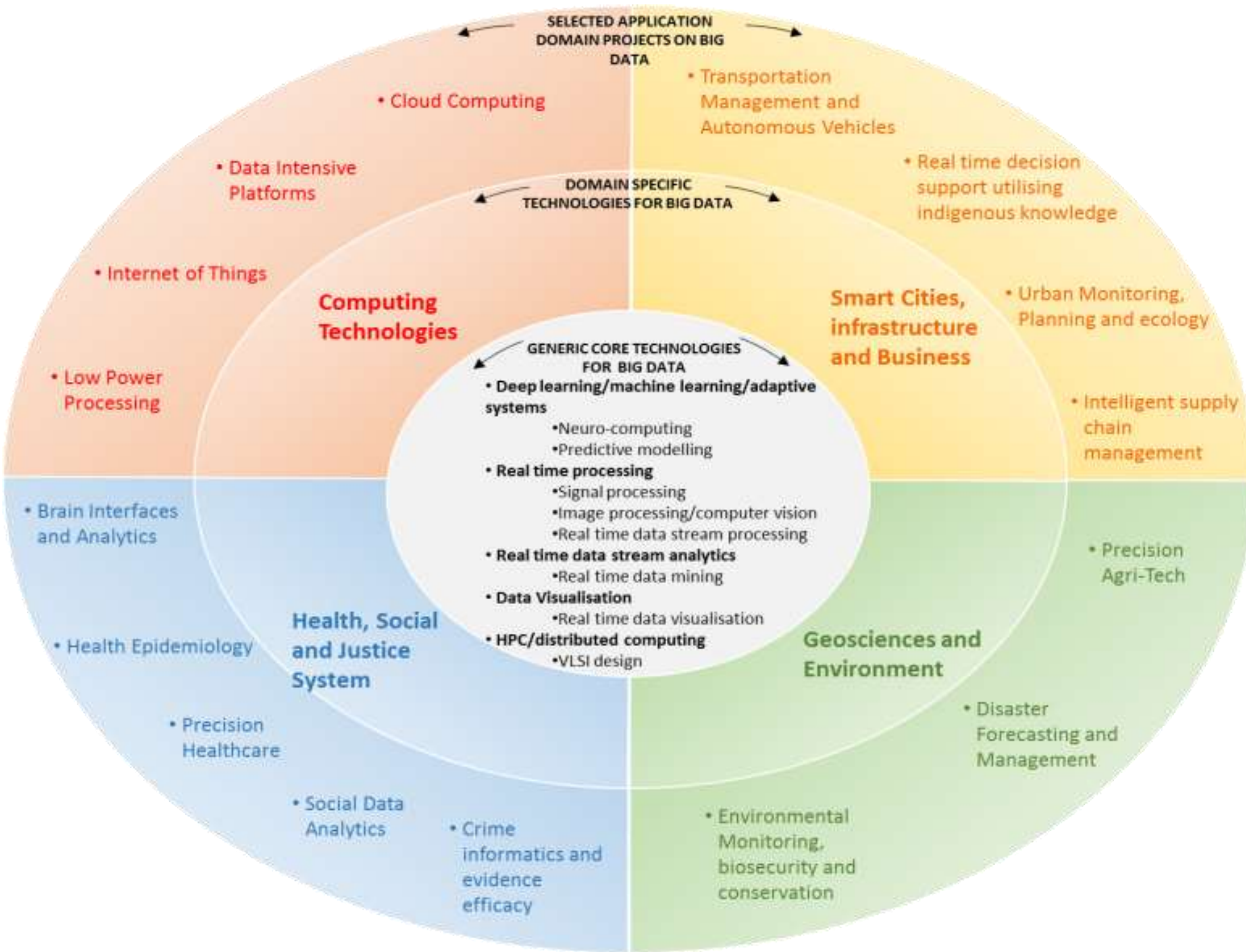
  M Hall, I Witten, E Frank, Data mining: Practical machine learning tools and techniques, Kaufmann, 2011.
- Computer vision (AUT, Massey)
- Natural language processing (Otago)
- Evolutionary computation (Victoria)
- Robotics (UoA, AUT, Massey)
- Emotional computing (ABI/UoA)
- Distributed AI: UoA.

- General computer and information sciences: B.Cox and P.Sallis (Otago), B.Doran (Auckland), T.Clear (AUT) and many others.

# AI in New Zealand: Some Applications

Brain data imaging and modelling: CBR/UoA (R.Faull), Otago.
Medical devices: ABI/UoA (P.Hunter).
Bioinformatics: Otago, UoA.
Neuroinformatics: AUT.
Cancer diagnostics: PEBL/Otago.
Healthcare - Personalised health risk prediction: Orion Health, AUT.
Weather forecast: NIWA, MetOceanSolutions.
Transportation and logistics: TRANZIT, Auckland Transport, RushDigital.
Precision agriculture – using drones: Massey, AUT, AgResearch.
Primary industry – milk volume prediction and transportation: Fonterra.
Finance - automated trading systems: EverEdge.
Neuromarketing – brick and mortar stores: AUT, UoA, Warehouse.
The Internet of Things: UoA, AUT.
Home robotics: UoA, Massey, AUT.
Neurorehabilitation – exoskeletons: RexBionix, ExSurgo Rehab, AUT.
Environmental hazards - predicting earthquakes: GNS, AUT.
Ecological hazards - predicting establishment of harmful species: Lincoln.
Autonomous vehicles: Canterbury, AUT.
Air quality modelling: UoA, BECA, Opus, Qrious, AeroQual, Air Quality.
Horticulture – fruit ripeness and market prediction: Zespri.
Aquaculture- fisheries: Aotearoa New Zealand, AUT, UoA.
Law: Goats Venture NZ.
AI Forum New Zealand. ai forum NEW ZEALAND

# INTERACT: AI for Big Data Technologies in New Zealand




nkasabov@aut.ac.nz

# 5. 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.
- Or, a tremendous technological progress:
  - Early disease diagnosis and disease prevention
  - Robots for homes and for elderly (see Lecture 2 by Prof Hans Guesgen)
  - Improved productivity
  - Improved human intelligence and creativity
  - Improved lives and longevity
- 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…"

The future is in the 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 (Ethics of AI, Lecture 4 by Ian Watson)

# .. and we can achieve this symbiosis through our HI

## Questions to address:

- Would improved AI help to improve our HI?
- Will reading books improve our IQ? (Jim Flynn)
- Will mindfulness help?
- Will brain prosthetics help?

- Or we need to listen more often to Mozart's music?

Why Mozart's Music is considered to stimulate creativity? The answer may be found through spectral analysis:


*W.Verrusio et al, The Mozart Effect: A quantitative EEG study, Consciousness and Cognition 35 (2015) 150–155*

# The Knowledge Engineering and Discovery Research Institute (KEDRI), Auckland University of Technology, New Zealand


AUT

MARIE CURIE ACTIONS

ROYAL ACADEMY OF ENGINEERING

THE UNIVERSITY OF AUCKLAND NEW ZEALAND

IT Professionals NEW ZEALAND

MINISTRY OF BUSINESS, INNOVATION & EMPLOYMENT
HĪKINA WHAKATUTUKI

AUT KNOWLEDGE ENGINEERING & DISCOVERY RESEARCH INSTITUTE

# 6. Selected references


Daniel Dennett: *From Bacteria to Bach and Back. The Evolution of Minds.* W. W. Norton & Co. 2017.

Stuart Russell and Peter Norvig *Artificial Intelligence: A Modern Approach* (3rd ed, Upper Saddle River, NJ, Prentice Hall, 2009).

Nils J Nilsson *The Quest for Artificial Intelligence: A History of Ideas and Achievements* (Cambridge, UK, Cambridge University Press, 2010).

Pamela McCorduck *Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence* (2nd ed, Natick, MA, 2004).

Nick Bostrom and Vincent C Millar “Future Progress in Artificial Intelligence: A survey of expert opinion” in Vincent C Muller (ed) *Fundamental Issues of Artificial Intelligence* (Synthese Library, Berlin, Springer, 2016) at 553.

John H. Andreae (ed.): *Man-Machine Studies,* ISSN 0110 1188, nos. UC-DSE/4 and 5. 1974.

John H. Andreae: *Thinking with the Teachable Machine,* Academic Press, 1977.

Richard S. Sutton & Andrew G. Barto: *Reinforcement Learning,* MIT Press, 1998.

Andy Clark: *Surfing Uncertainty,* Oxford University Press, 2016.

Google TensorFlow: www.tensorflow.org.

N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996

N.Kasabov, Evolving connectionist systems, Springer 2003 and 2007

Furber, S. et al (2012) Overview of the SpiNNaker system architecture, IEEE Trans. Computers, 99.

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

Benuskova, L., N.Kasabov (2007) Computational Neurogenetic Modelling, Springer, New York

EU Marie Curie EvoSpike Project (Kasabov, Indiveri): http://ncs.ethz.ch/projects/EvoSpike/

Indiveri, G. et al, Neuromorphic silicon neuron circuits, Frontiers in Neuroscience, 5, 2011.

Kasabov, N. (2014) NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, 52, 62-76.

Kasabov, N., et al. (2014). Evolving Spiking Neural Networks for Personalised Modelling of Spatio-Temporal Data and Early Prediction of Events: A Case Study on Stroke. Neurocomputing, 2014.

Kasabov (2010) To spike or not to spike: A probabilistic spiking neural model, Neural Networks, v.23,1, 16-19

Kasabov, N. (ed) (2014) The Springer Handbook of Bio- and Neuroinformatics, Springer.

Kasabov, N. (2007) Evolving Connectionist Systems: The Knowledge Engineering Approach, Springer, (first edition 2002)

Merolla, P.A., J.V. Arhur, R. Alvarez-Icaza, A.S.Cassidy, J.Sawada, F.Akopyan 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.

NeuCube: http://www.kedri.aut.ac.nz/neucube/

Wysoski, S., L.Benuskova, N.Kasabov (2007) Evolving Spiking Neural Networks for Audio-Visual Information Processing, Neural Networks, vol 23, issue 7, pp 819-835.