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Neuroinformatics, Neural Networks and Neurocomputers for Computational Intelligence

Prof Nikola K Kasabov

Life Fellow IEEE, Fellow RSNZ, Fellow INNS College of Fellows

Doctor Honoris Causa, Obuda University, Budapest

Founding Director, KEDRI and Professor of Knowledge Engineering

Auckland University of Technology, Auckland, New Zealand

Guest Professor, IICT Bulgarian Academy of Sciences

George Moore Chair Professor of Data Analytics, Ulster University, the UK

Invited Professor, Peking University and Dalian University China

Honorary Professor, Teesside University UK, The University of Auckland NZ

Director, Knowledge Engineering Ltd.; https://knowledgeengineering.ai

nkasabov@aut.ac.nz https://academics.aut.ac.nz/nkasabov

Abstract & Content

"Neuroinformatics, Neural networks and Neurocomputers " – the *N3* (group) of science and technology

Neuroinformatics offer a tremendous amount of data and knowledge about how the human brain and the nervous system work.

Many brain information processing principles can be now implemented in novel **Neural network** computational models.

The latter ones have inspired the development of neuromorphic hardware chips and N**eurocomputers,** characterised by much low power consumption, massive parallelism and fast processing.

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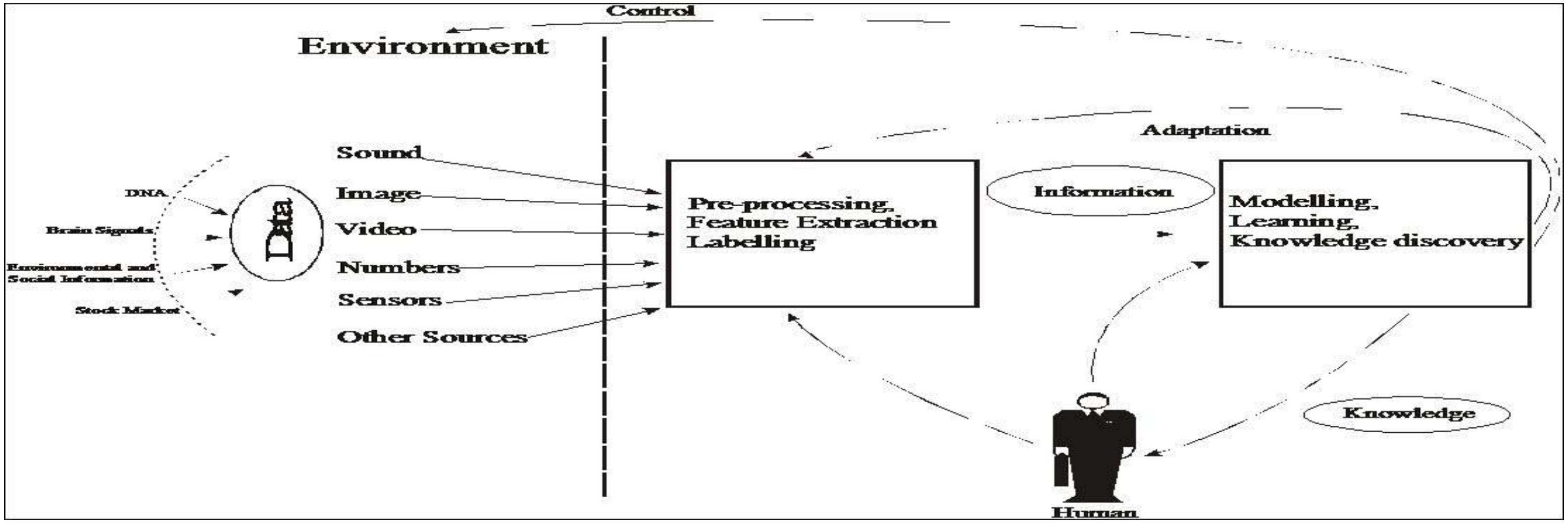
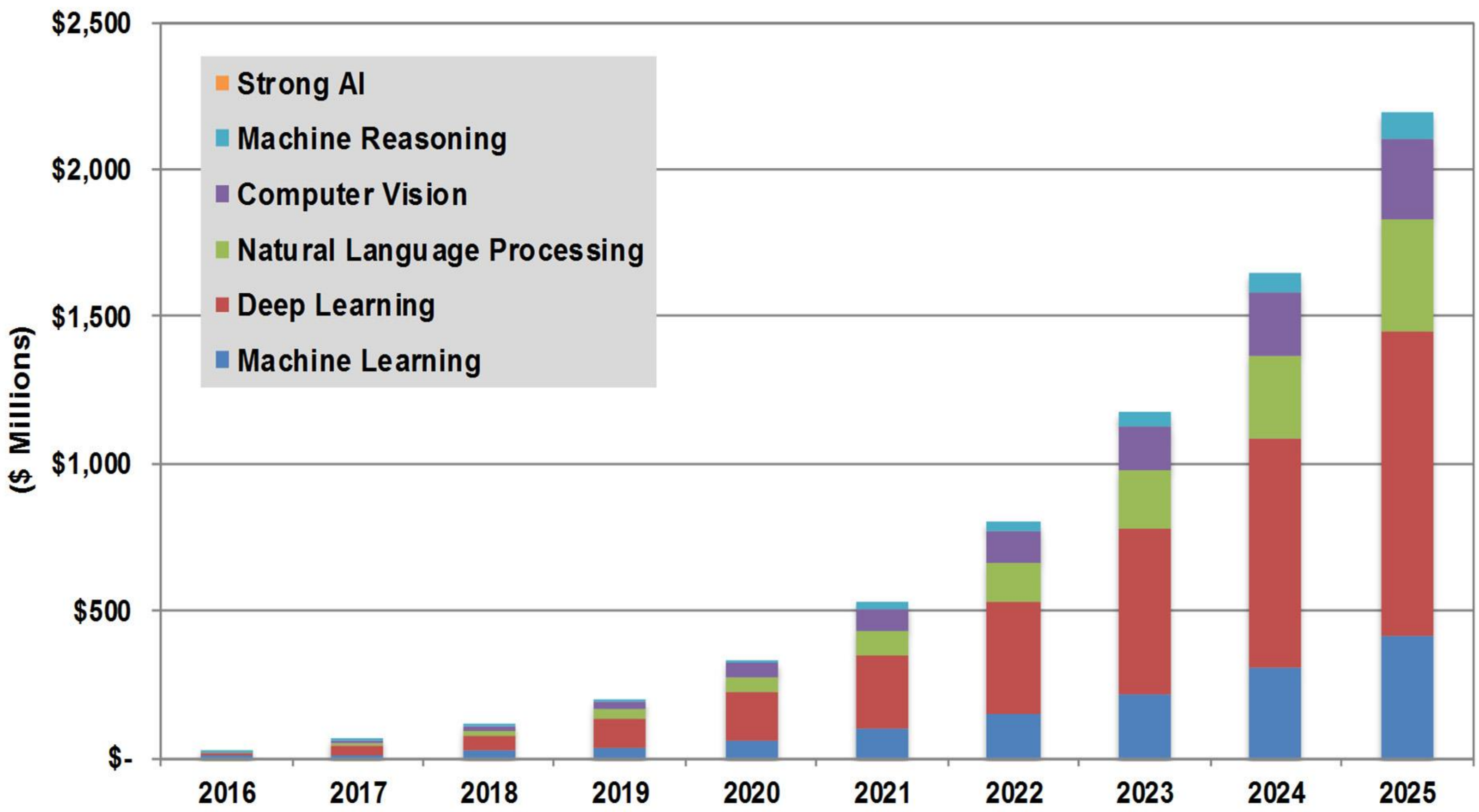
1. Seven challenges in data science and CI and the role of neural networks
2. Future opportunities for new technologies and systems based on *N3*.

1. Seven challenges in Data Sciences and CI and the role of neural networks



1. Learning from (big) data -> neural networks and deep NN
2. Explainability (extracting rules, associations) (explainable AI) → fuzzy logic/ neuro-fuzzy systems
3. Evolvability → evolving connectionist systems (ECOS) and brain-inspired SNN (NeuCube).
4. Precision health → personalised modelling with ECOS and NeuCube
5. Multiple modality of data (e.g. images, genetic, clinical, longitudinal, etc.) → NeuCube.
6. Reduced power consumption/sustainability → neuromorphic (brain-inspired) computers
7. Human-machine symbiosis -> new human-machine interfaces, BMI

The dominant role of neurocomputation technologies (Deep Learning) in CI

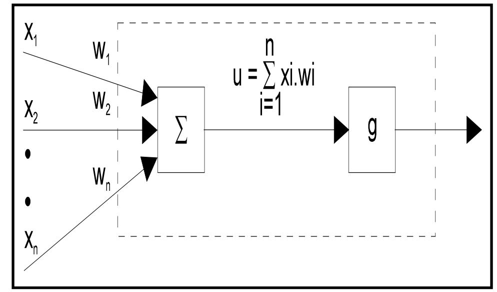


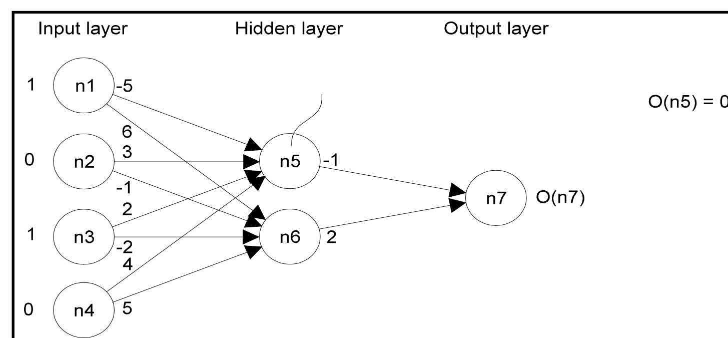
Tractica, White paper, 2017

Challenge No.1: Learning from (BIG) data → artificial neural networks and deep NN

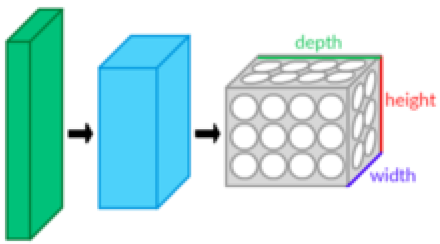
- ANN are computational models that mimic the nervous system in its main function of adaptive learning and *generalisation.*
- ANN are *universal computational models*
- 1943, McCulloch and Pitts neuron
- 1962, Rosenblatt - Perceptron
- 1971- 1986, Amari, Rumelhart, Werbos: Multilayer perceptron
- Many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

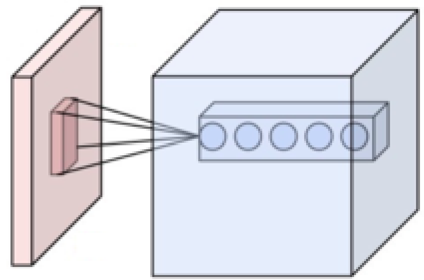
- Early NN were 'black boxes' and also - once trained, difficult to adapt to new data without much 'forgetting'.

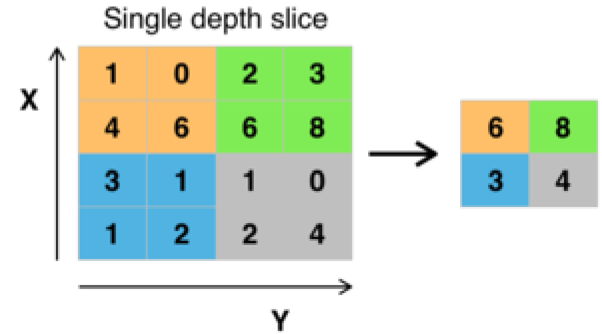


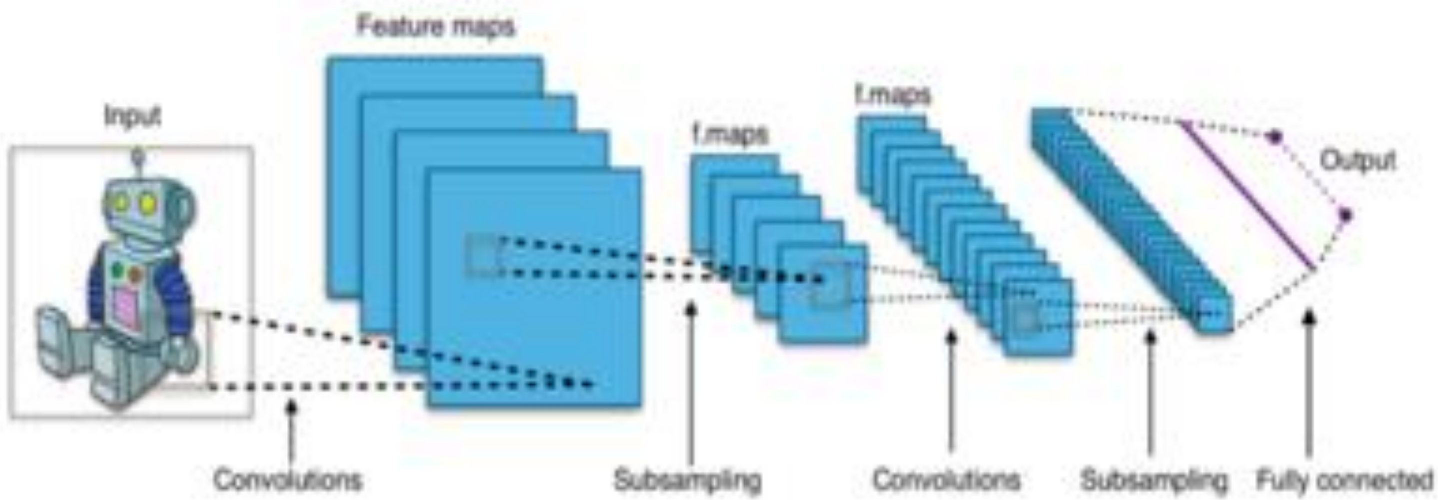


The BIG data challenge: Deep Convolutional Neural Networks









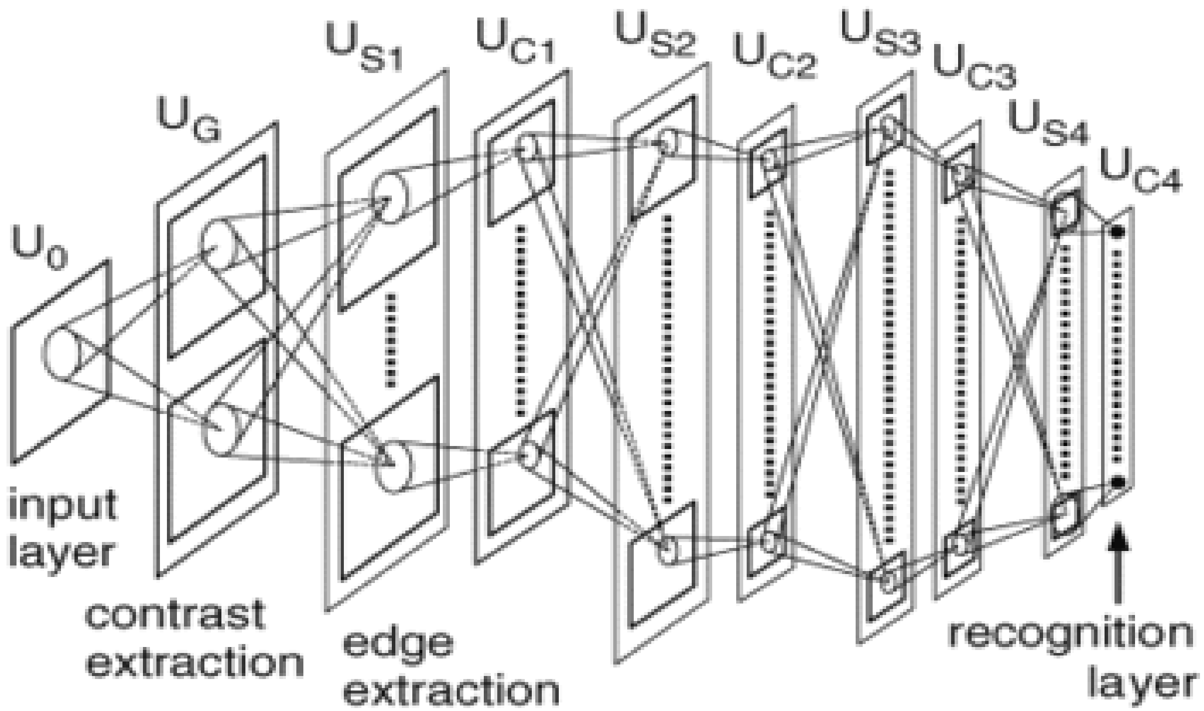
Deep NN are excellent for vector, frame- based data (e.g. image recognition), but not for time-space data and for knowledge extraction.

nkasabov@aut.ac.nz

Early deep convolutional NN in computer vision inspired by the brain

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

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



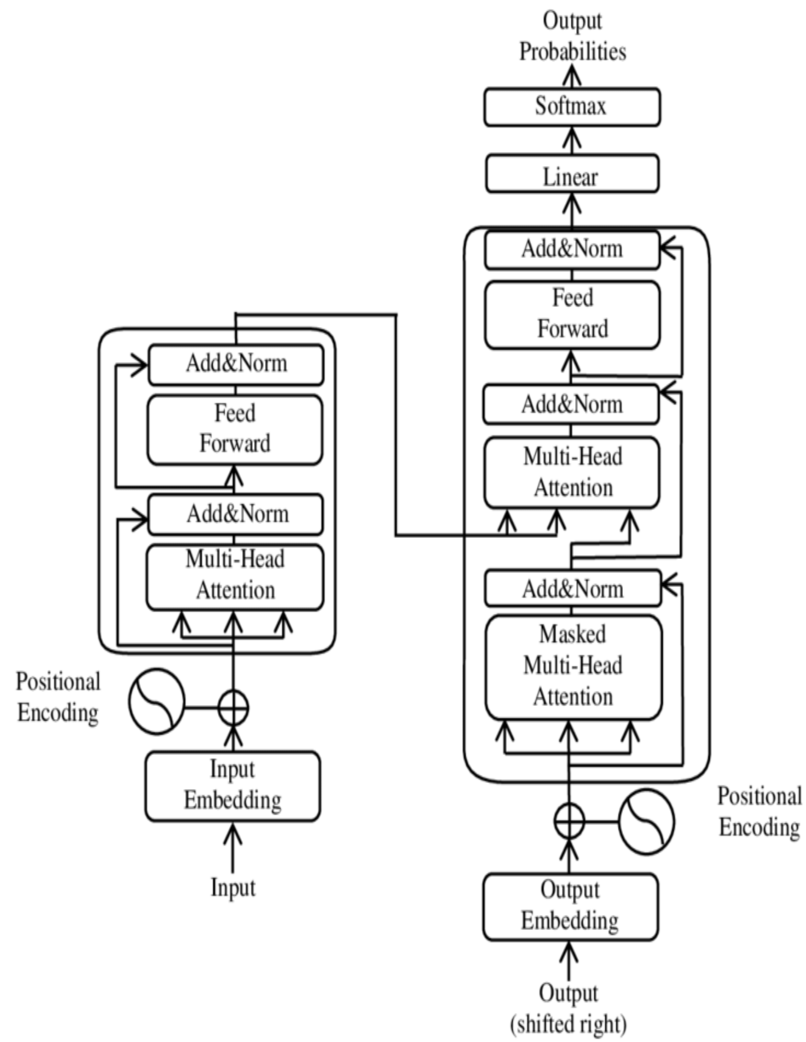
Latest DNN: Transformers and ChatGPT

Transformers are designed to process sequential input data, such as natural language, with applications towards tasks such as translation and text summarization.

Transformers process the entire input all at once. The attention mechanism provides context for any position in the input sequence.

Transformers allow training on larger datasets. This led to the development of pretrained systems such as GPT (Generative Pre-trained Transformer), which were trained with large language datasets, such as the Wikipedia Corpus and Common Crawl, and can be fine-tuned for specific tasks.

Transformers are NOT suitable for explanation of the solution or for on-line adaptation of new data. They are not suitable for spatio-temporal data either.



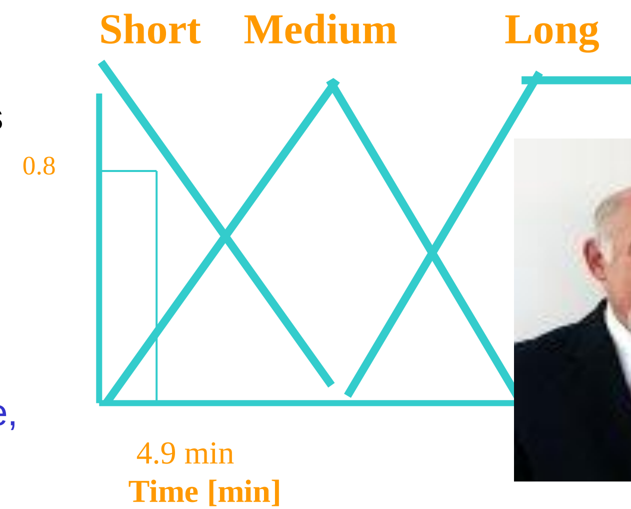
Challenge No.2: Explainability

→ Fuzzy logic and neuro-fuzzy systems

- Fuzzy logic (1965) represents information uncertainties and tolerance in a linguistic form (Lotfi Zadeh (1920-2018)
  - 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, Imre 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.

Lotfi Zadeh (1920-2018)



Challenge No.3: **Evolvability (**+ explainability)

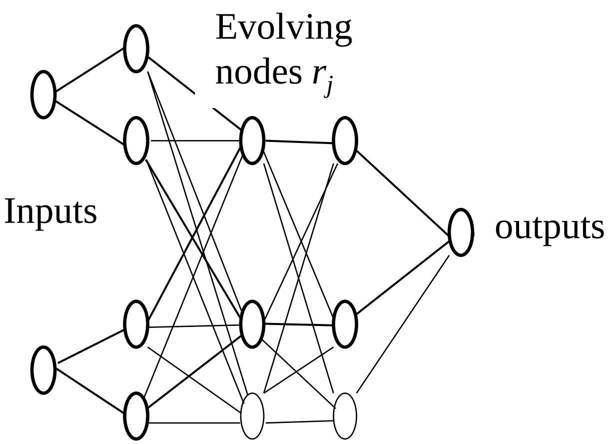
→ Evolving connectionist systems (ECOS)

- Neuro-fuzzy systems that evolve (develop) their structure and functionality from data

- Rules (knowledge) can be extracted from the models, e.g.
  IF Input 1 is High and Input 2 is Low
  THEN Output is Very High (static knowledge)

N. Kasabov, EFuNN, IEEE Tr SMC, 2001,

N.Kasabov, Evolving connectionist systems, Springer, 2007, (first edition 2003)



P.Angelov, D.Filev, N Kasabov
(co-editors)
Q1 (JSR), IF2.5

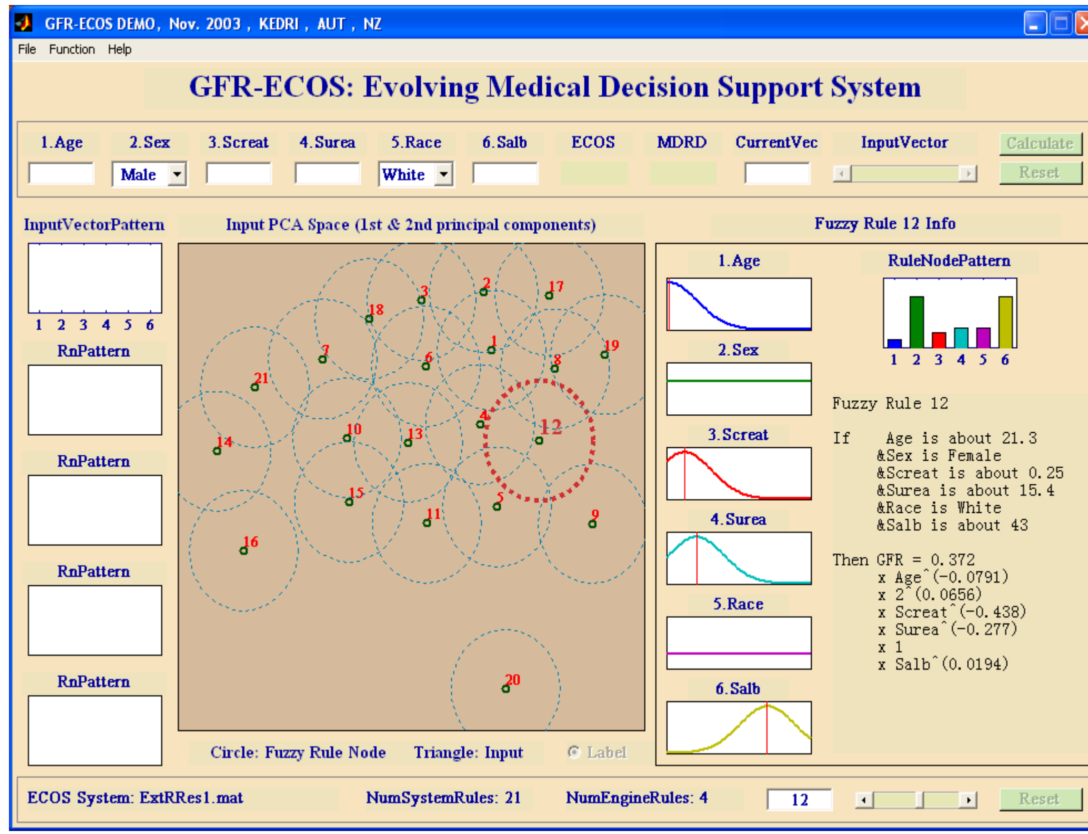
24 Centuries after Aristotle, now we can automate the process of rule extraction and knowledge discovery from data!

nkasabov@aut.ac.nz

Example: Local, adaptive renal function diagnostic system based on DENFIS

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

- A real data set from a medical institution is used here for experimental analysis (M. Marshal et al, 2005) The data set has 447 samples, collected at hospitals in New Zealand and Australia.
- Each of the records includes six variables (inputs):
  - age,
  - gender,
  - serum creatinine,
  - serum albumin,
  - race and
  - blood urea nitrogen concentrations,
  - output - the glomerular filtration rate value (GFR).

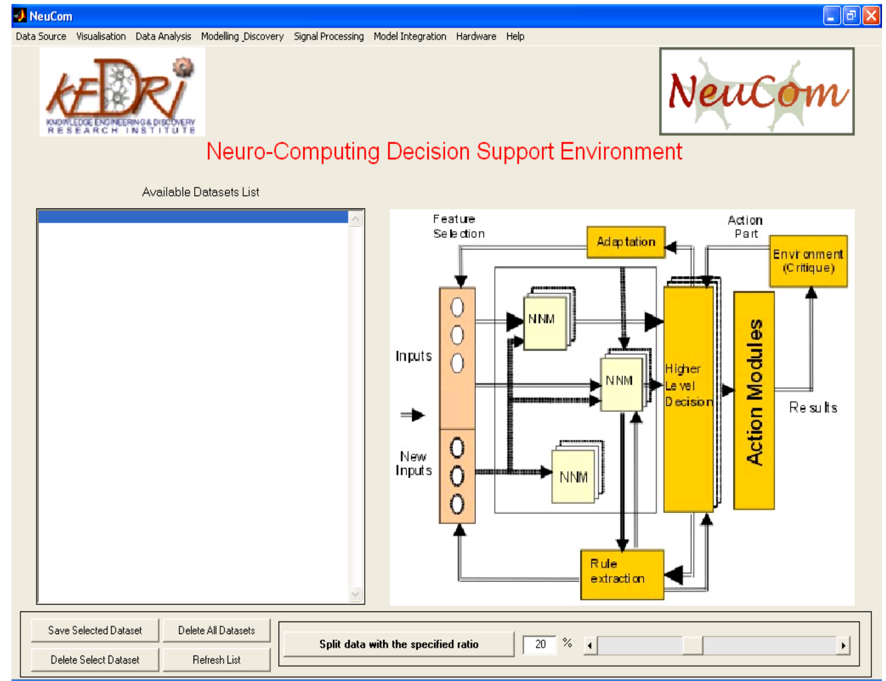


The NeuCom software environment (www.theneucom.com) including ECOS

- NeuCom is a generic environment, that incorporates 60 traditional and new techniques for intelligent data analysis and the creation of intelligent systems
- Methods for feature selection
- Methods for classification
- Methods for prediction
- Methods for knowledge extraction
- EFuNN and ECF
- DENFIS
- Fast data analysis and visualisation
- Fast model prototyping
- A free copy available for education and research from

  www.theneucom.com

ECOS methods are used in 2000+ specific methods and systems cross 50+ countries



Still challenge No.3: What about learning Time in the evolving models?

Modelling evolving processes in ***Time and Space***

Evolving processes in Nature:

- Evolutionary (population/generation) processes
- Brain cognitive processes
- System information processing (environment)
- Information processing in a cell
- Molecular information processing (genes, proteins)
- Quantum information processing

“ 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

Different types of time-space data (TSD)

- Temporal (e.g. climate, financial data, gene expression)
- Spatio-temporal with fixed spatial location, (e.g. brain data; seismic; GPS)
- Spatio-temporal with changing locations of the spatial variables (e.g. moving objects)
- Spectro-temporal data (e.g. radio-astronomy; audio; speech; music)

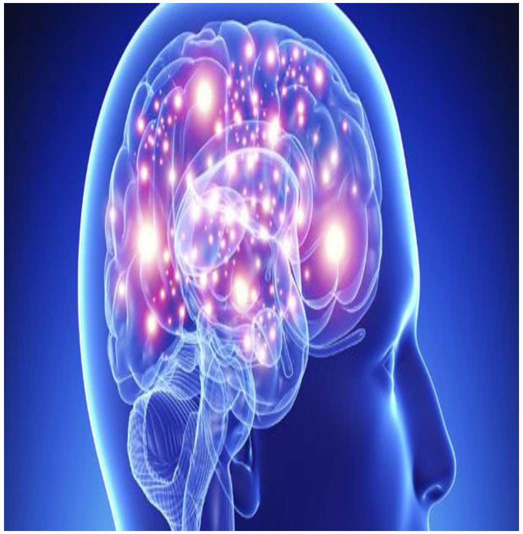
Different characteristics of TSD:

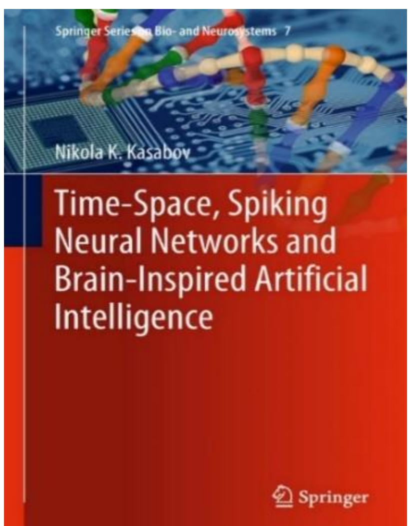
- Sparse features/low frequency (e.g. climate data; ecological data; multisensory data);
- Sparse features/high frequency (e.g. EEG brain signals; seismic data);
- Dense features/low frequency (e.g. fMRI; gene expression data);
- Dense features/high frequency (e.g. radio-astronomy data).

The challenge: To better analyse, model and understand *Time-Space* data and the processes that generate these data.

Inspiration from the brain --> brain-inspired SNN

Neuroinformatics provides knowledge about the human brain, the most sophisticated product of the evolution, a live-long learning system for knowledge representation.





The brain (80bln neurons, 100 trillions of connections, 200 mln years of evolution) is the ultimate learning 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:

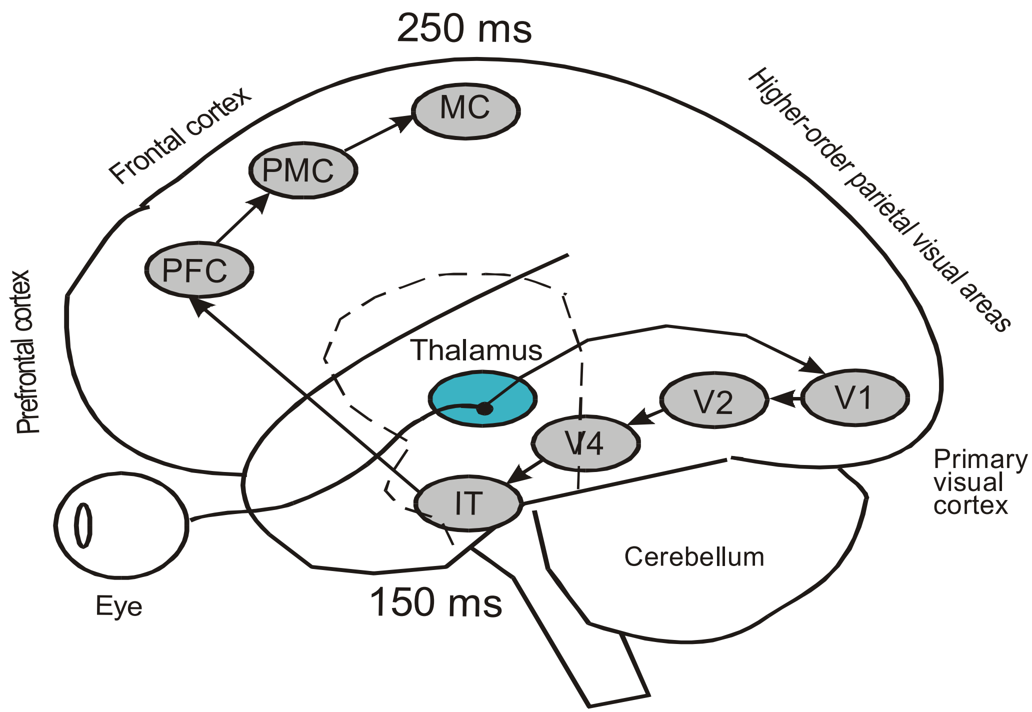
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

Knowledge is represented as deep **spatio-temporal patterns** that can evolve/adapt over time.

The brain "meets" all 7 data challenges, why not use it for brain-inspired AI !!

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

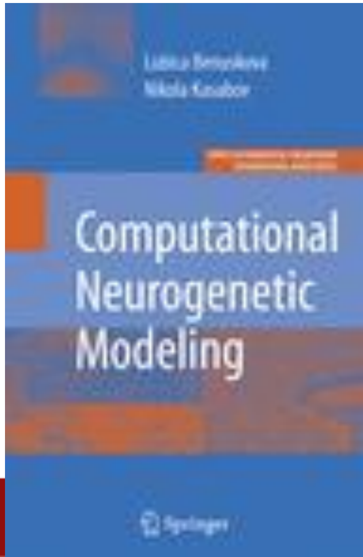
Knowledge of seeing an object and grasping it is learned incrementally as a deep **spatio-temporal trajectory** of connections between clusters of neurons in the brain



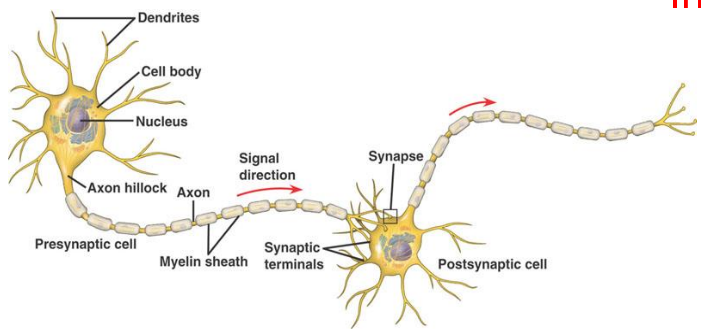
Deep serial processing of visual stimuli in humans for image classification and action.

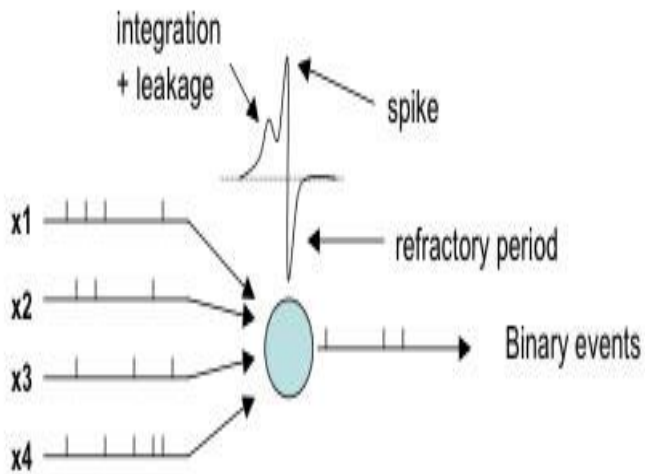
Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex.

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

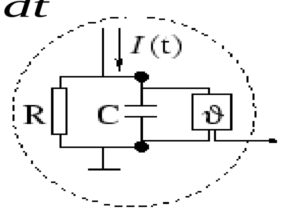


Spiking Neural Networks (SNN) capture time





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



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

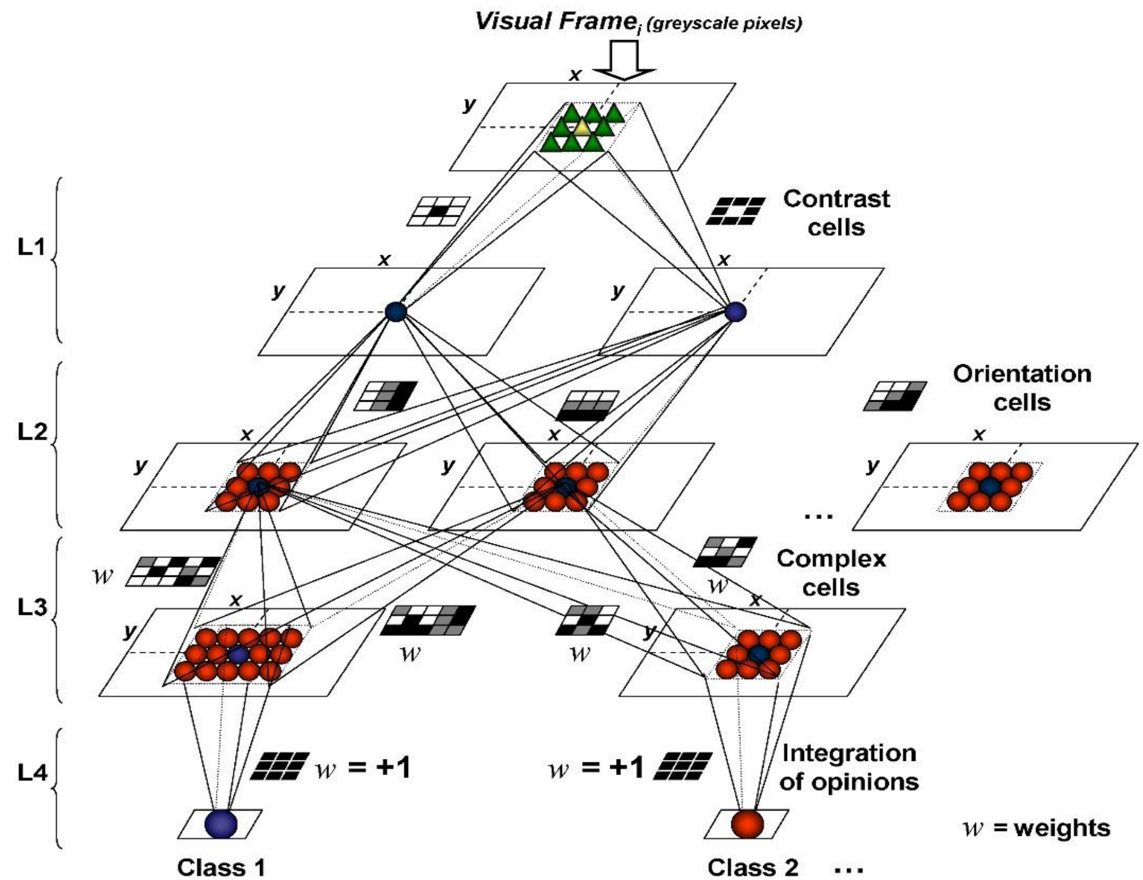
They offer the potential for:

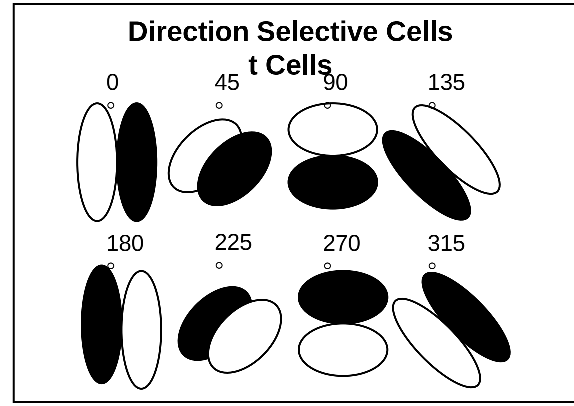
- Spatio-temporal data processing
- Bridging higher level functions and “lower” level genetics
- Integration of modalities

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,

Image Processing using evolving spiking neural networks and Gabor filters.

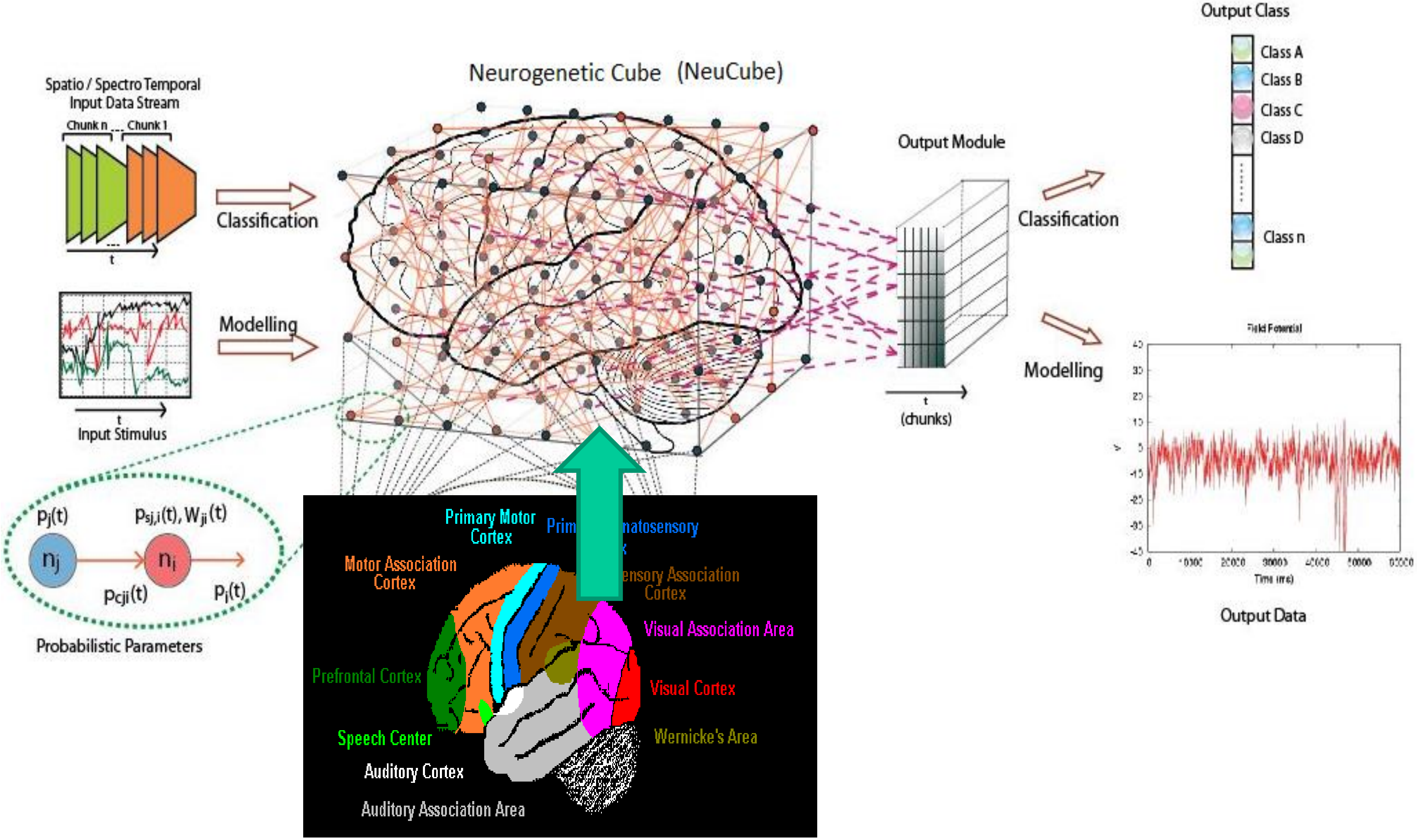




Dennis Gabor (1900-1979)

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

The NeuCube Architecture

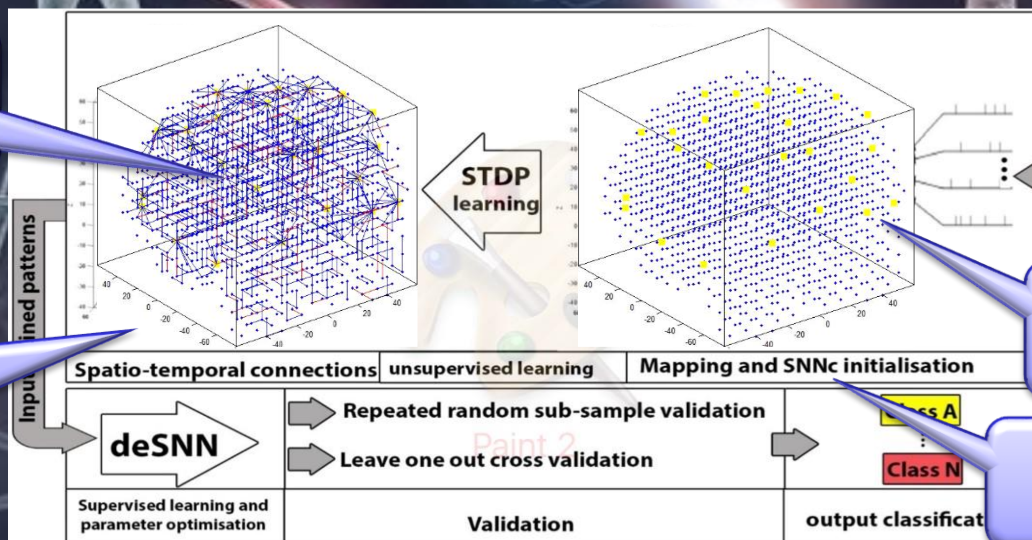


Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

Deep learning in NeuCube

Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created

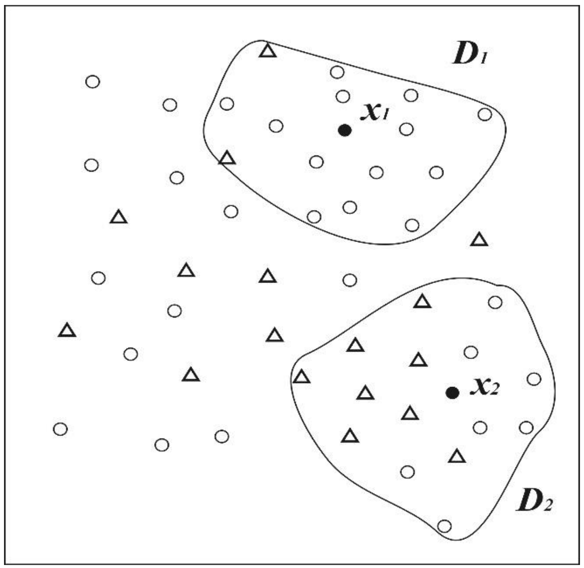


Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning

nkasabov@aut.ac.nz

Challenge No.4: Precision health -→ personalised modelling with NN



- A PM (transductive) model is created on a sub-set of neighbouring data to each input vector. A new data vector is situated at the centre of such a sub-set (here illustrated with two of them – x_1 and x_2), and is surrounded by a fixed number of nearest data samples selected from the training data *D* and generated from an existing model *M (Vapnjak)*
- The principle of "What is good for my neigbours is good for me"
- Problems:
    - **Which variables, weighted or not weighted ?**
    - **How many neighbours?**
    - **What distance measure?**
    - **Which model?**

Parameter and feature optimization.

PM based on ECOS and NeuCube result in a better diagnostic and prognostic accuracy and a better explanation

Example Applications	PM	Other AI methods accuracy
Schizophrenia Predicting formal diagnosis in next six months using gene expression measures from blood test	98%	92-97.5%
Mindfulness Treatment Predicting response to depression treatment using EEG data	73%	48.5-58.5%
Methadone Predicting treatment programme outcome using EEG data	91%	60-63%
Stroke Predicting stroke events using patient and environmental data	94%	67.5-87.5%
AD/MCI/normal Prediction 2 years ahead	91%	40% (LSTM)
Knee pain prediction 12 months after surgery using only pre-operative data	92%	66%

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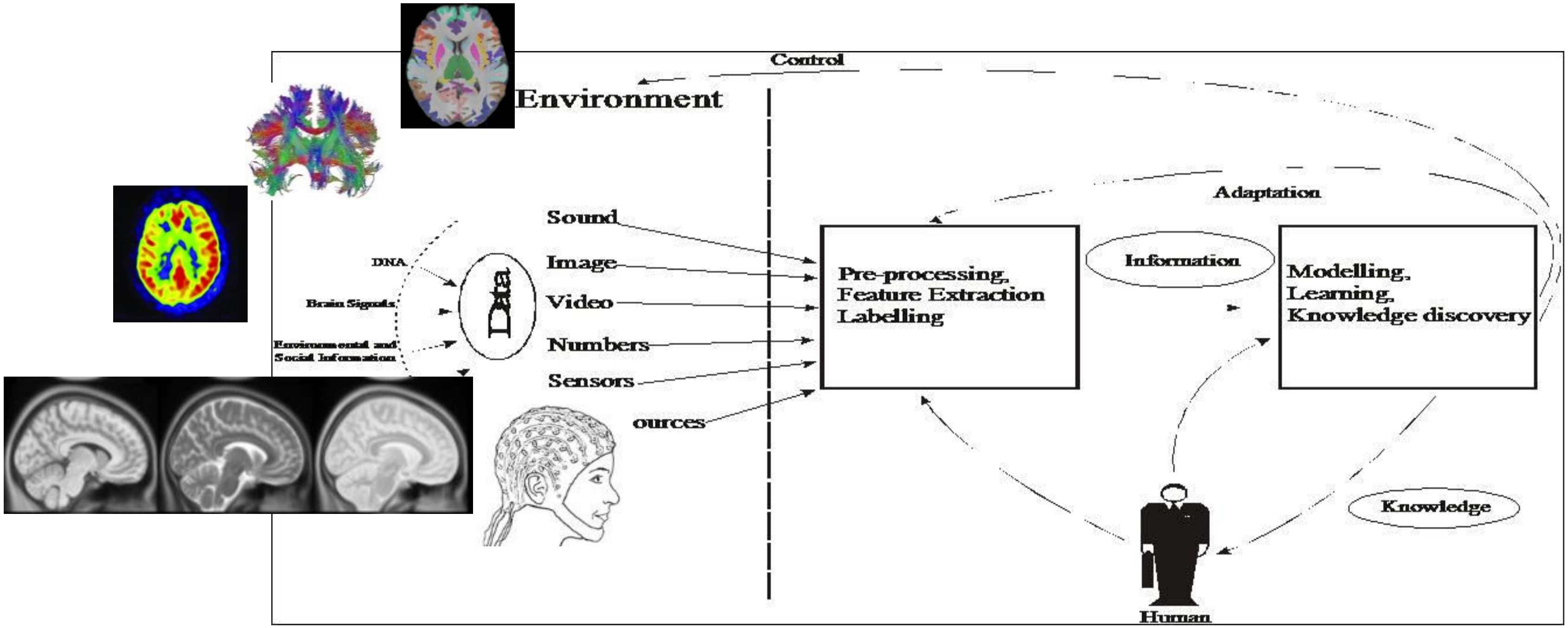
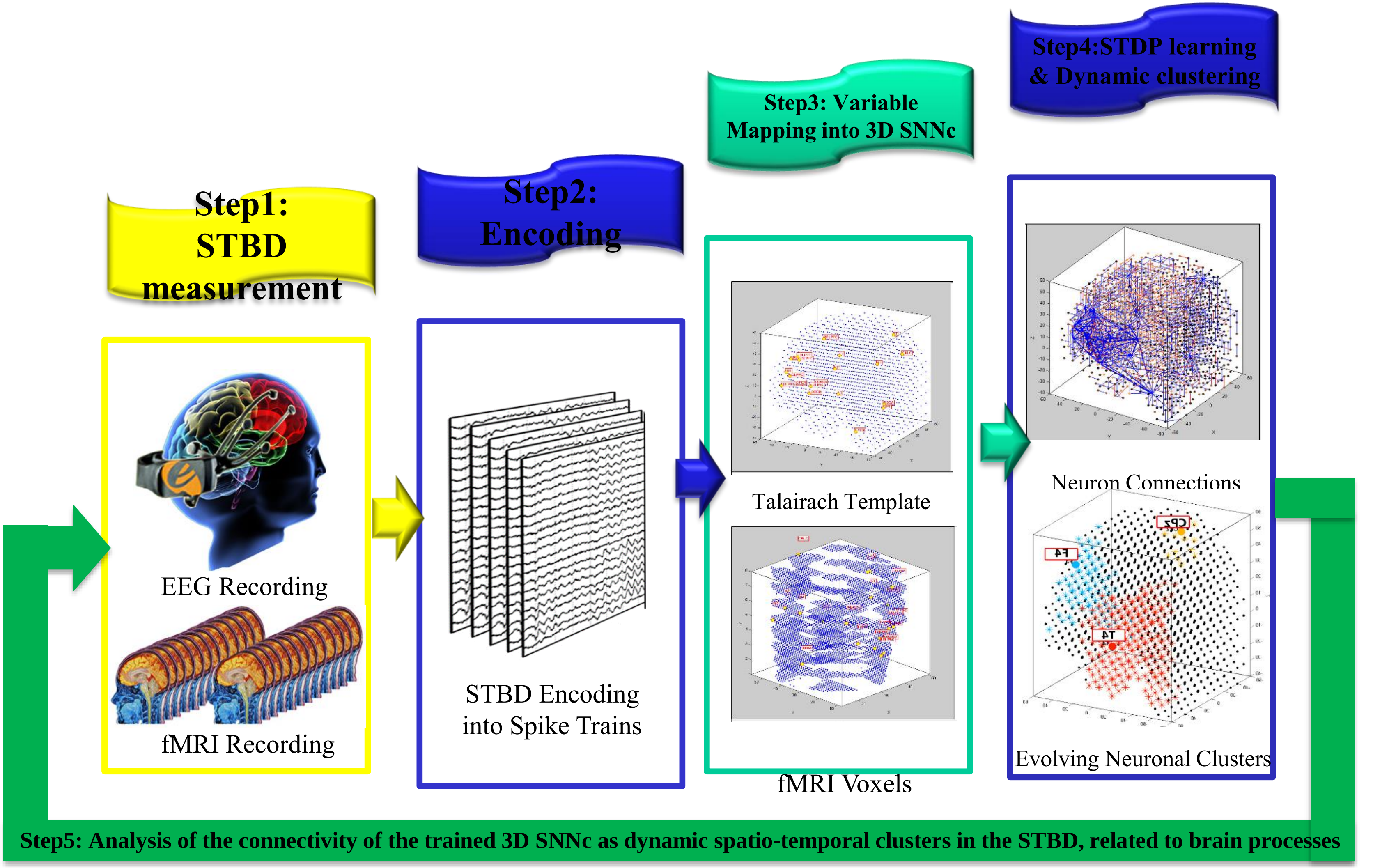
Challenge No.5: Multiple modalities → new methods are needed



nkasabov@aut.ac.nz

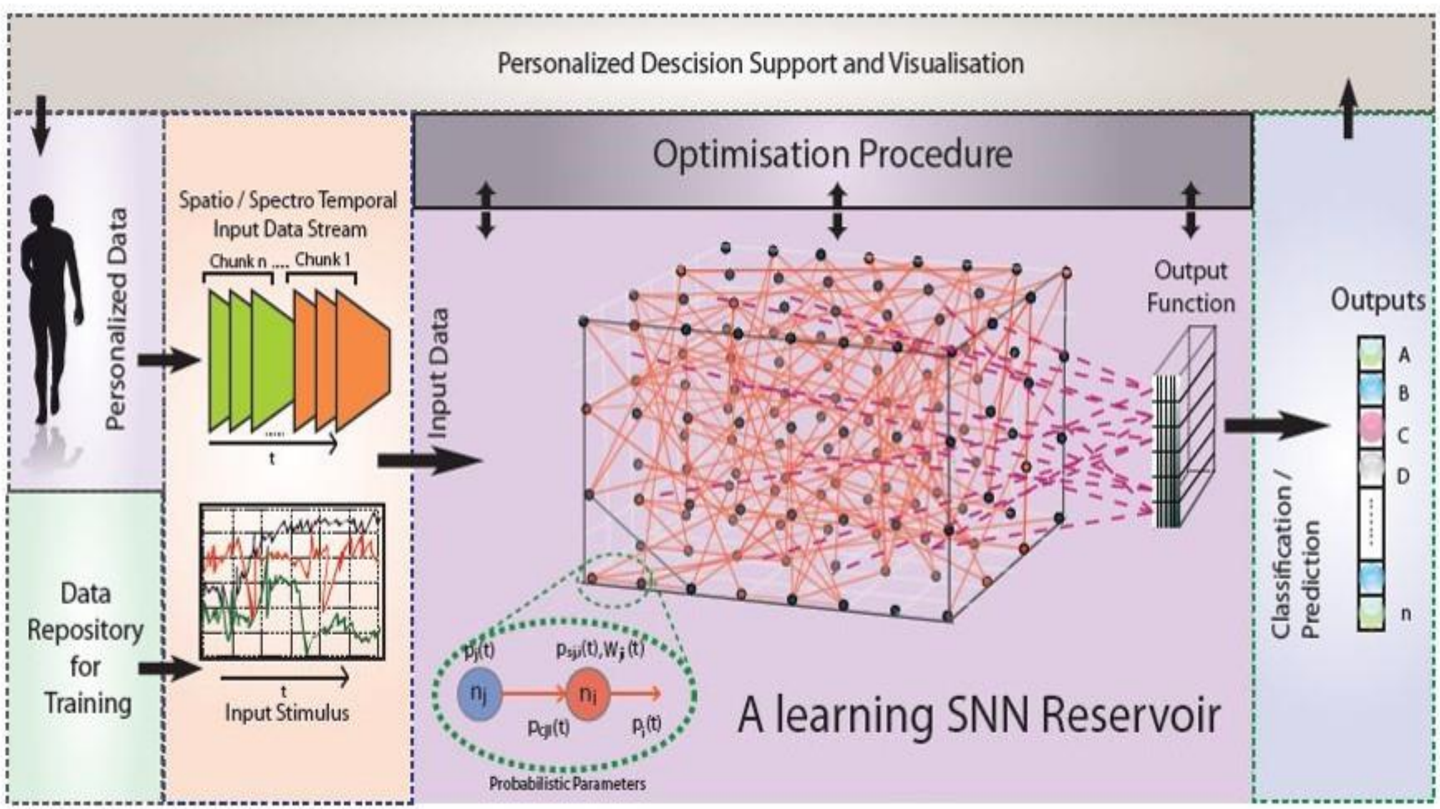
EEG and fMRI integrated modelling in NeuCube



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

Personalised modelling for integrated static and dynamic data using NeuCube

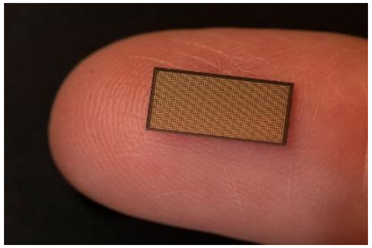
N.Kasabov, V.Feigin, Z.Hou, Y.Chen, Improved method and system for predicting outcomes based on spatio/spectro-temporal data, PCT patent WO2015/030606 A2, US2016/0210552 A1, Publication date: 21 July 2016.



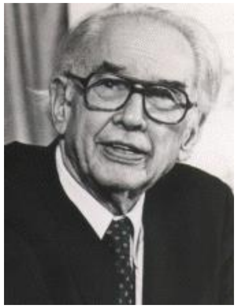
Challenge No.6: Reduced power consumption/sustainability

From von Neumann principles and Atanassov’s ABC to Neuromorphic Computers

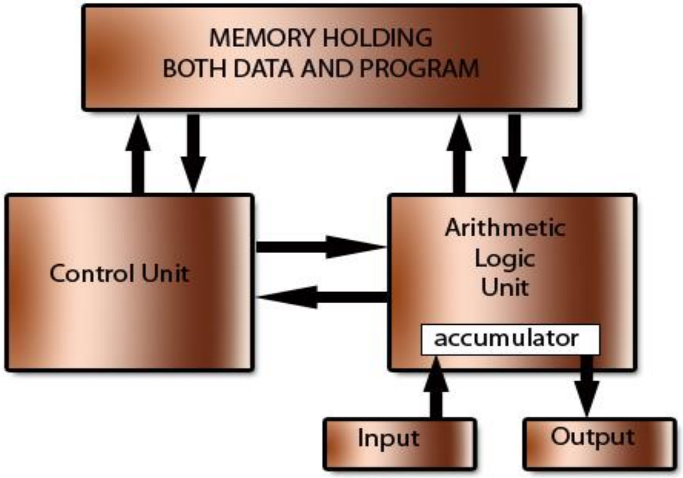
- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.
- A Neuromorphic architecture integrates the data, the programme and the computation in a SNN structure, similar to how the brain works; uses *spikes* (bits at times) (e.g. S.Furber SpiNNaker; IBM True North; Akira; ETH/EZH Indiveri)
- Intel Loihi:



- A quantum computer uses *q-bits* (bits in a superposition) (IBM D-Wave).



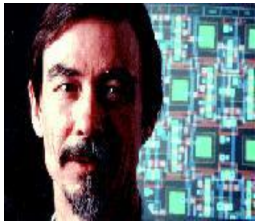
The Von Neumann or Stored Program architecture



(c) www.teach-ict.com

N. Sengupta et al, (2018), From von Neumann architecture and Atanasoffs ABC to Neuromorphic Computation and Kasabov’s NeuCube: Principles and Implementations, Chapter 1 in: Advances in Computational intelligence, Jotzov et al (eds) Springer 2018.

nkasabov@aut.ac.nz



Neuromorphic hardware

High speed and low power consumption. Energy and pollution sustainable!

Carver Mead (1989): A hardware model of an IF neuron: The Axon-Hillock circuit.

SpiNNaker (*Furber, S., To Build a Brain, I ctrum, vol.49, Number 8, 39-41, 2012).*

INI Zurich SNN chips (Giacomo Indiveri)

Silicon retina (the DVS) and silicon cochlea (ETH, Zurich, Toby Delbruck))

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

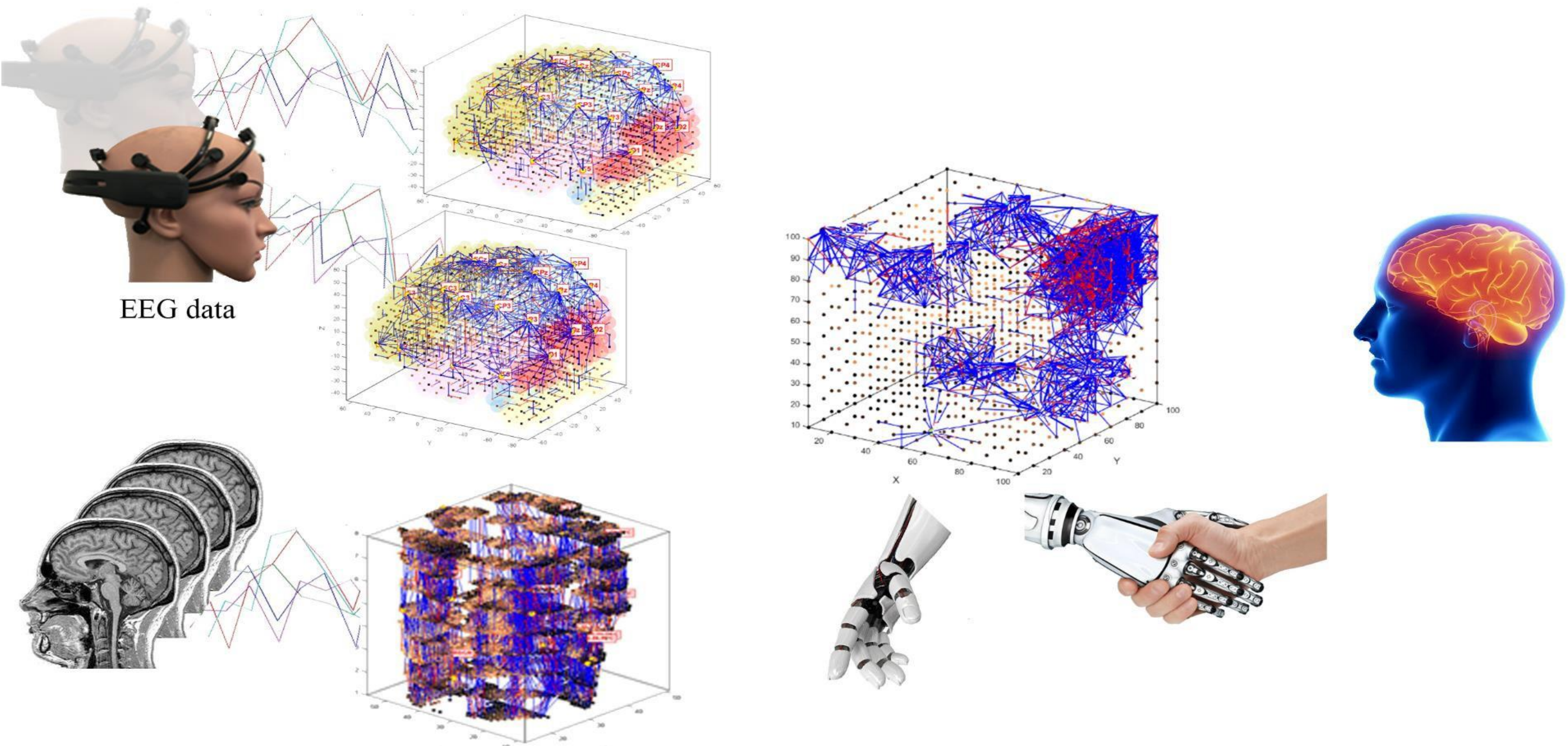
FPGA SNN realisations (McGinnity, Ulster and NTU)

Intel Loihi

NeuCube development environment for SNN system design

Challenge No.7: Human– Machine symbiosis
→ **new brain - machine interfaces (BMI)**

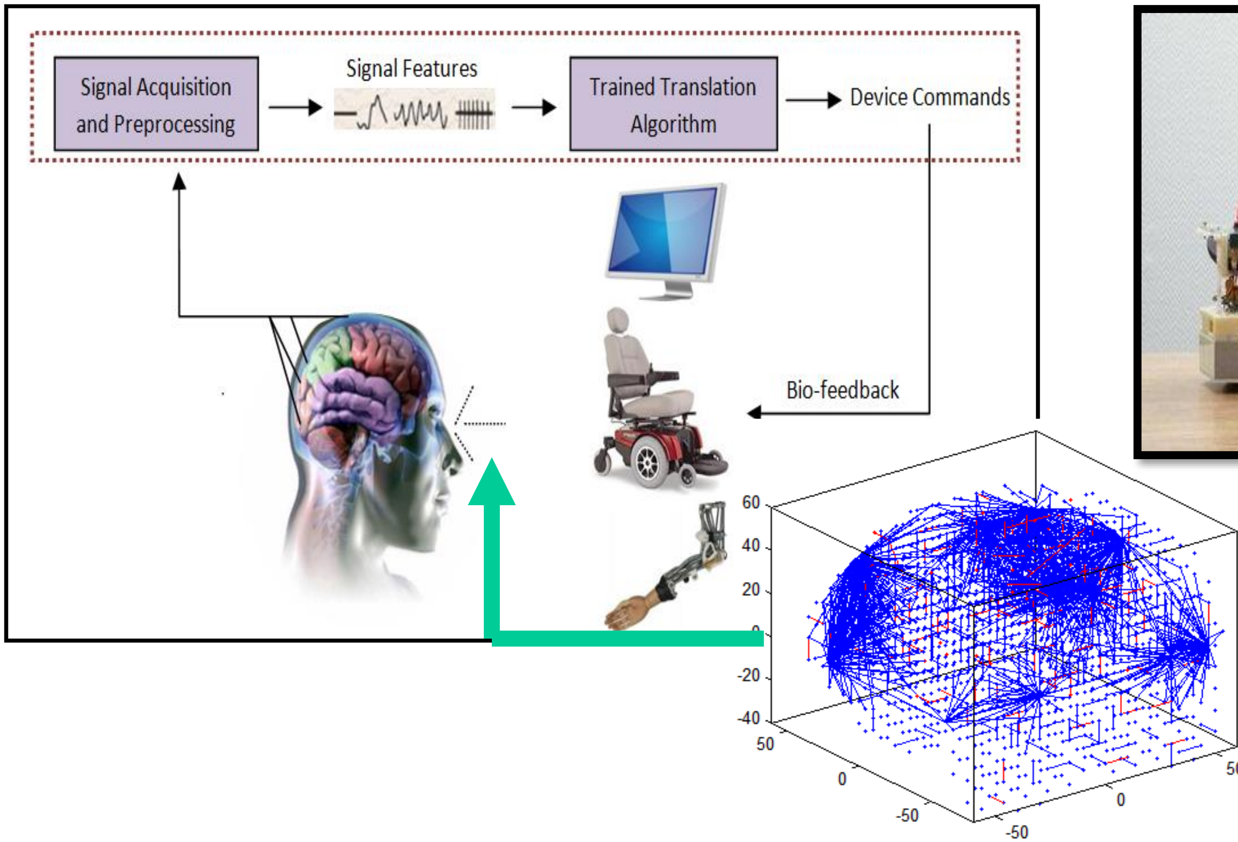
Knowledge-based human-machine interaction and symbiosis based on deep learning, knowledge representation and knowledge transfer with BI-SNN architectures (www.darpa.mil/program/explainable-artificial-intelligence)

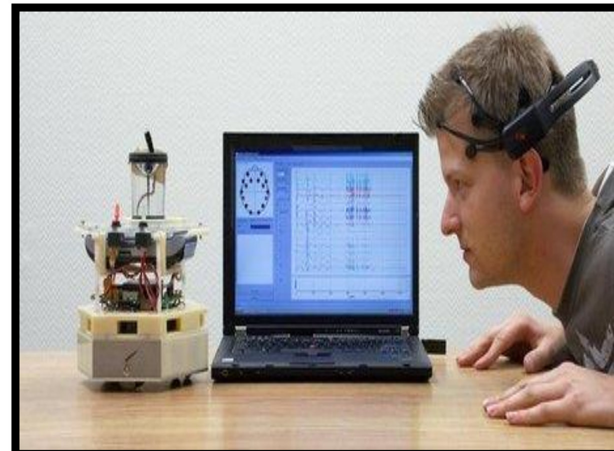


Brain Machine Interfaces using Brain-Inspired SNN

Brain-Computer Interfaces (BCIs) are systems trained on human brain data (e.g. EEG) for humans to communicate directly with computers or external devices through their brains

BI-BCI are designed using a brain template.





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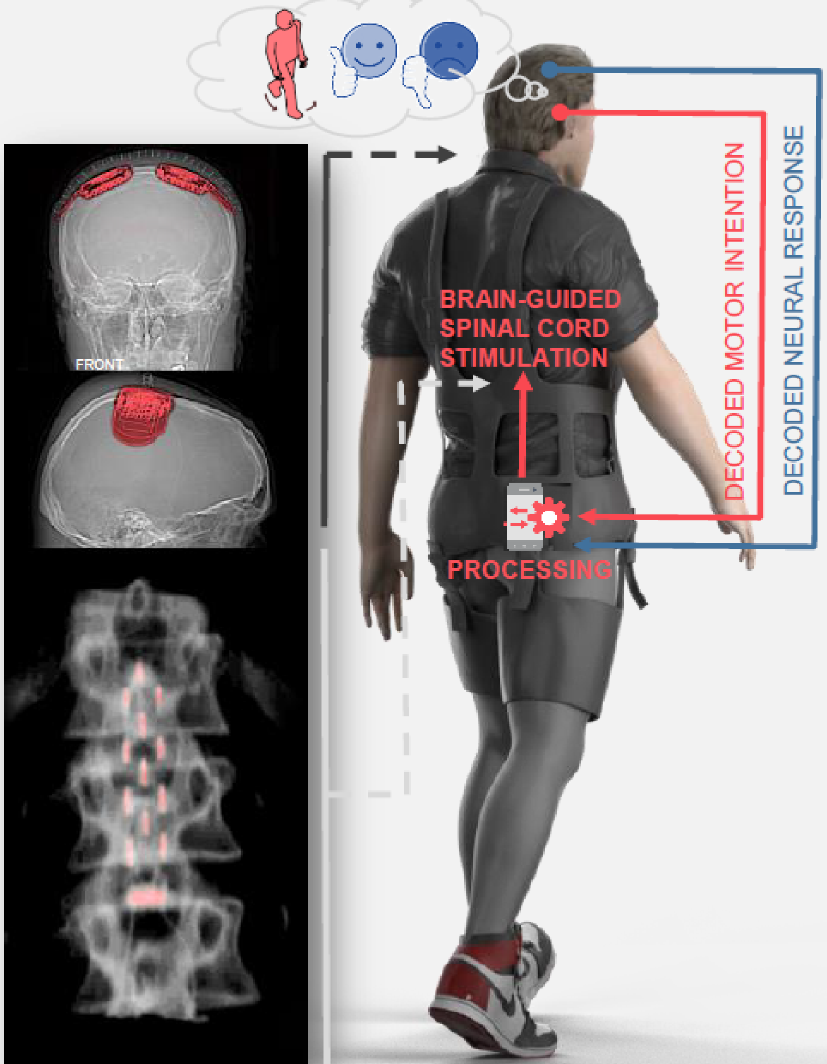
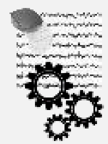
Fully embedded auto-adaptive Brain Machine Interface



Implantable measure – stimulation technology

- Chronic wireless brain recording WIMAGINE implant
- Spinal cord stimulation ONWARD implant
- 2 Clinical trials ongoing: brain machine interface proof of concept



Auto-adaptive motor BMI decoding

- Natural control based on patient's intention
- Multiple degrees of freedom control
- Decoding of neural response linked to intention/action coherence
- Real-time auto-adaptive decoder
- Assistance free
- Neuromorphic decoding algorithms

IICT- BAS

Brain-guided spinal cord Stimulation

- Epidural Electrical Targeted dynamic stimulation
- Auto-adaptative stimulation Patterns

Miniaturization of BMI technology

- Low power integrated circuit for accelerating the decoding algorithms
- High system level integration
- Portable battery-powered solution

NEMO-BMI using N3

Institute ICT
INSTITUTE OF INFORMATION AND COMMUNICATION TECHNOLOGIES

nemobmi

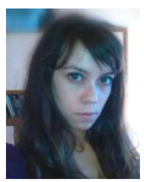
Our team

Team leaders

Prof. Petia Koprinkova-Hristova

Prof. Nikola Kasabov

Researchers

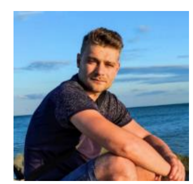


Assistant Simona Nedelcheva

MSc Eng. Alexandar Banderov

Programmers

Dimitar Penkov

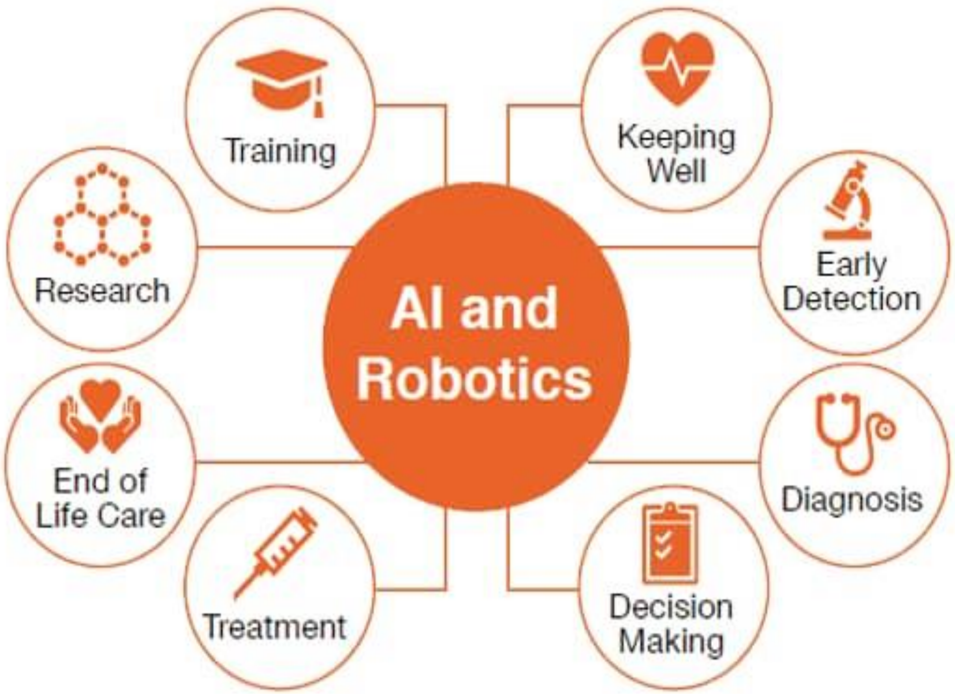


Svetlozar Yordanov

KEDRI

2. Future opportunities for new technologies and systems based on *N3*

AI in Medicine and Health
Molecular research: DNA and gene data analysis; vaccine designs; microbiology; …
Precision medicine : Machine learning for personalised predictive modelling
Global health data analysis: pandemics; population health.
Image analysis: brain images; EEG, fMRI, DTI,…
Robotics: - surgical robots; - patient care robots - Nano robots (drug delivery in the body) - Brain implants
Brain-machine interfaces (BMI) for neurorehabilitation
Many other



https://www.pwc.com/gx/en/industries/healthcare/publications/ai-robotics-new-health/transforming-healthcare.html

Future opportunities for new technologies and systems based on the N3

Brain data modelling

Deep learning and deep knowledge representation of EEG data
Brain Disease Diagnosis and prognosis based on EEG data
Deep learning and deep knowledge representation of fMRI data
Integrating time-,space and orientation .

Audio-visual data and brain computer interfaces

Audio and visual information processing in the brain and its modelling
Deep learning and modelling of audio and visual and multimodal audio-visual data in BI-SNN
Brain-computer interfaces (BCI) using BI-SNN

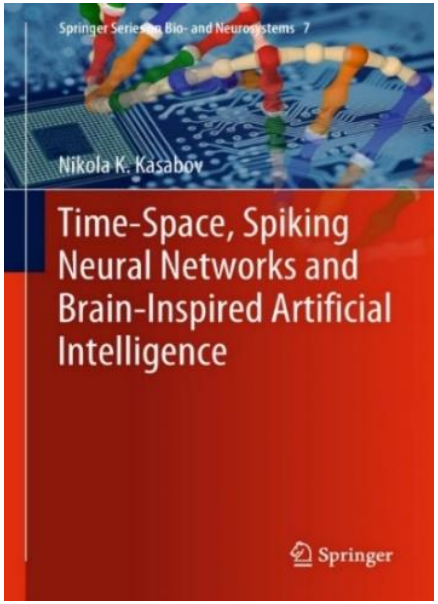
SNN in Bio- and Neuroinformatics

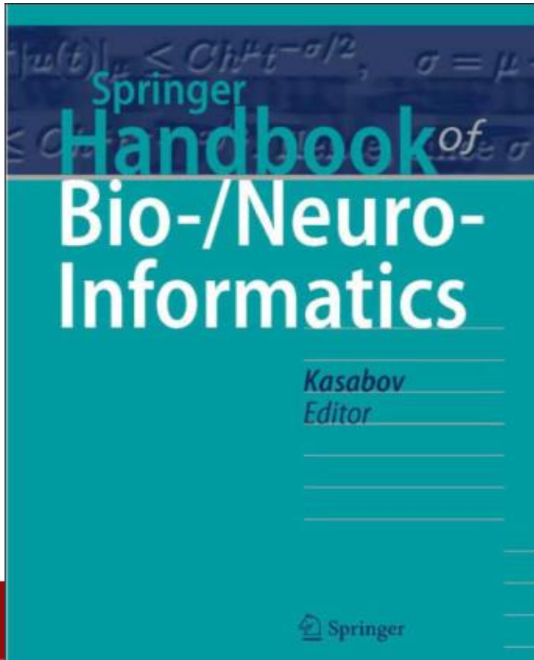
Computational modelling and pattern recognition in Bioinformatics
Computational neurogenetic modelling
Computational framework for personalised modelling. Applications in Bioinformatics.
Personalised modelling for integrated static and dynamic data.
Applications in neuroinformatics

Application for multisensory streaming data

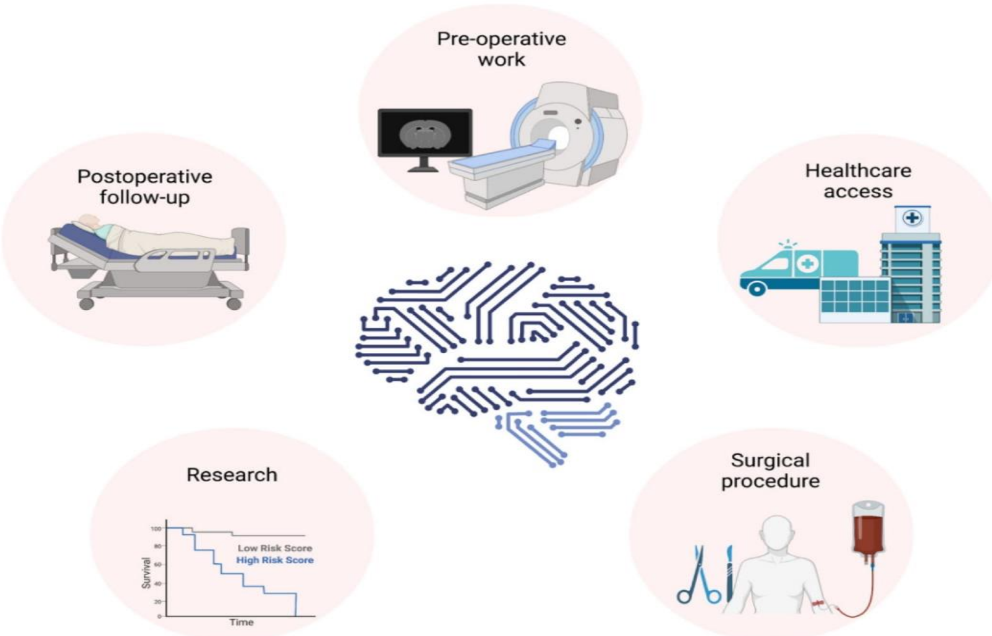
Cybersecurity
Environmental predictive modelling
Predicting earthquakes and nature disasters
Financial and economic data

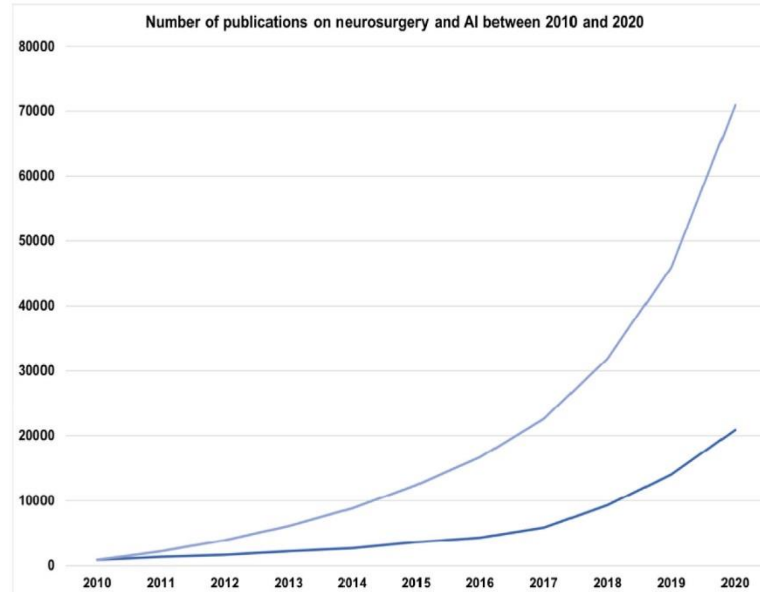
Software for neuromorphic computer systems





Example: N3 in Neurosurgery





Absolute and the cumulative number of publications involved neurosurgery and artificial intelligence

AI in Neurosurgery: https://doi.org/10.3934/Neuroscience.2021025)
AIMS Neuroscience, 8(4): 477–495.

THE EUROPEAN ASSOCIATION OF NEUROSURGICAL SOCIETIES

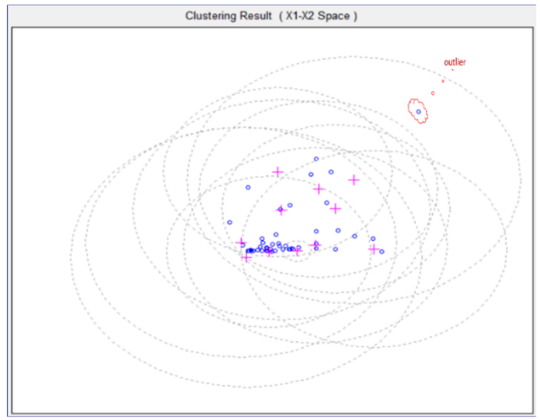
Emerging Technologies and Innovations in Neurosurgery
EANS ETIN Task Force

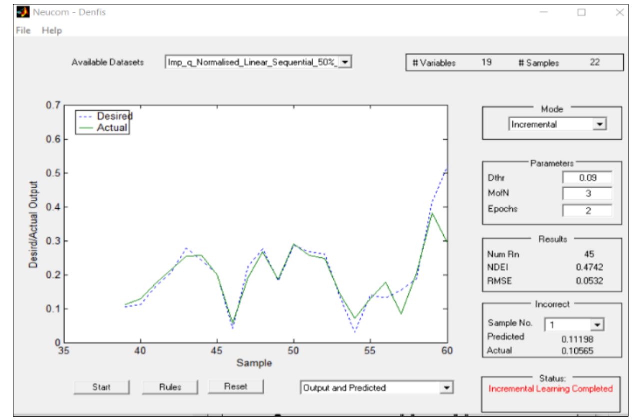
Prof. Nikolay Gabrovsky
Institute Pirogov Sofia and BAS

Knowledge Engineering
ai
Consulting
NNN
AI
NK

Example: N3 in Finance and Economics

Iman AbouHassan, N. Kasabov, G. Popov and R. Trifonov, "Why Use Evolving Neuro-Fuzzy and Spiking Neural Networks for incremental and explainable learning of time series? A case study on predictive modelling of trade imports and outlier detection," *2022 IEEE 11th International Conference on Intelligent Systems (IS)*, Warsaw, Poland, 2022, pp. 1-7, doi: 10.1109/IS57118.2022.10019673.



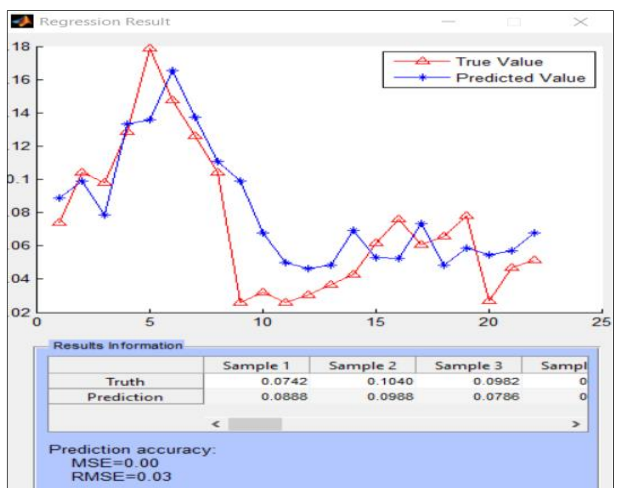


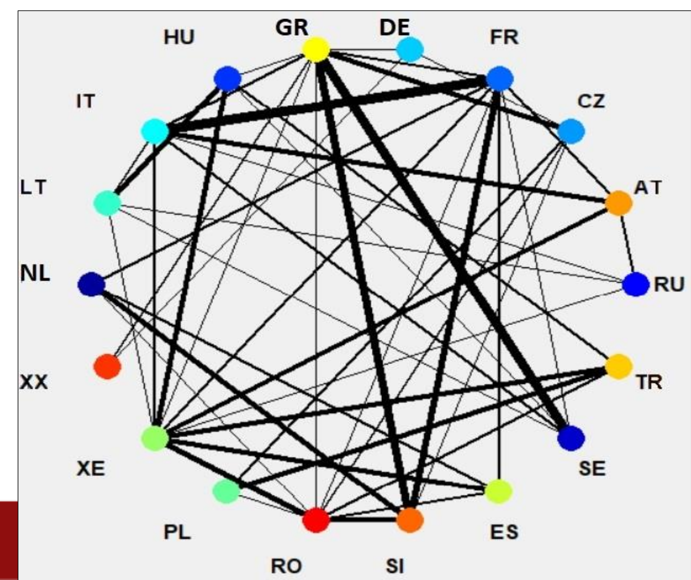
Evolving clustering for predictive modelling with DENFIS

Because:

1. Learning from (big) data
2. Explainability
3. Evolvability for life-long learning
4. Personalised modelling
5. Multiple modality of data
6. Much less power when
   on a neuromorphic hardware
7. New brain machine interfaces

Predictive modelling and dynamic interaction graph extraction from a NeuCube model →





iabouhassan@tu-sofia.bg

Quantum-inspired neurocomputation

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

- *Quantum bits (qu-bits)*

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

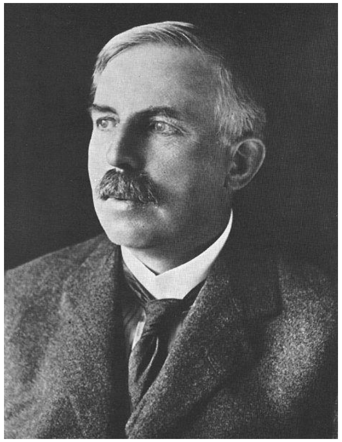
$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

- *Quantum vectors (qu-vectors)*

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

- *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)

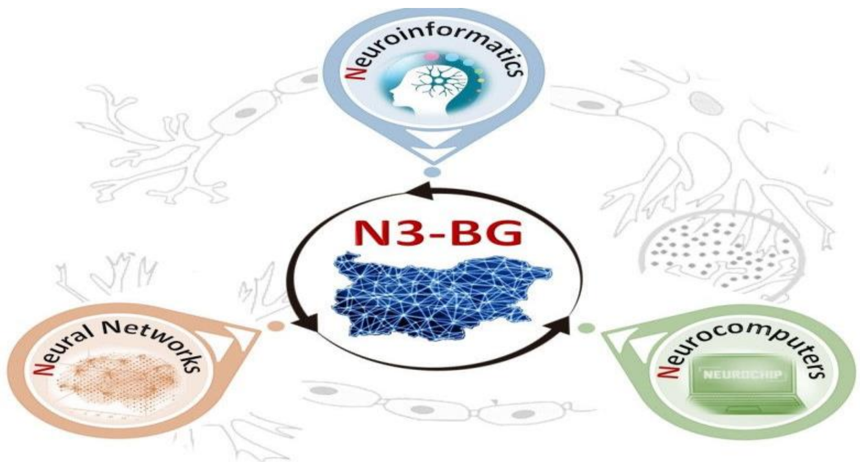
- **Applications:**
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), O($N^{1/2}$) vs O(N) complexity)
  - Quantum associative memories

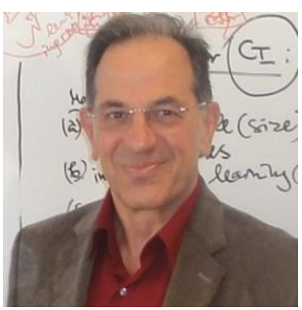
The N3-BG group (Neuroinformatics, Neural networks and Neurocomputers)

https://www.knowledgeengineering.ai/n3-bg

Established in 2022.

New members are welcome. It is free and informative !







Nikola Kasabov Roumen Trifonov, TU Petia Koprinkova, BAS Nikolay Gabrovsky Iman AbouHassan, TU

(Leading organisers)

For contacts: N.Kasabov (nkasabov@aut.ac.nz) or Ms Iman AbouHassan (iabouhassan@tu-sofia.bg)

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Óbuda University
Pro Scientia et Futuro

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17. KEDRI R&D Systems are available from: http://www.kedri.aut.ac.nz

Thank YOU!

nkasabov@aut.ac.nz https://academics.aut.ac.nz/nkasabov