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Neuromorphic Integration of Bio-and Neuroinformatics Methods and Data

Nikola Kasabov
FIEEE, FRSNZ, FINNS, DVF RAE UK
Professor of Knowledge Engineering and Founding Director KEDRI
Auckland University of Technology, NZ

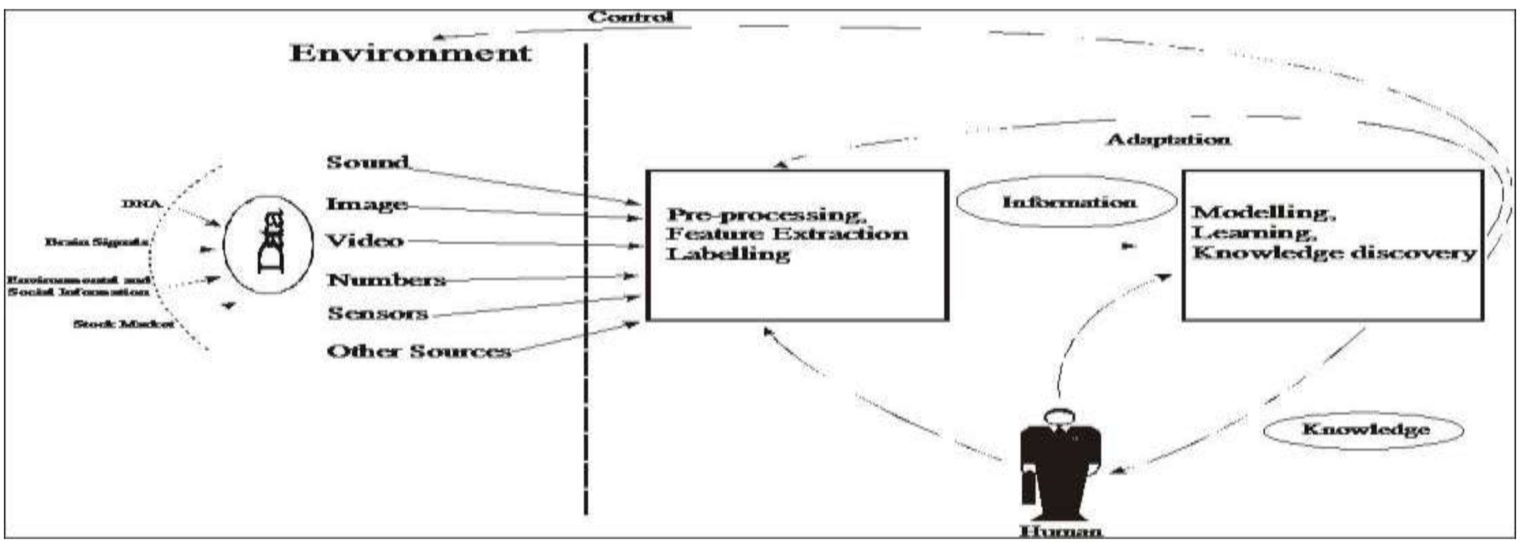
George Moore Professor of Data Analytics, Ulster University, UK

Honorary Academic/ Professor University of Auckland and
Teesside University UK
Doctor Honoris Causa Obuda University Budapest

Abstract

Integrating methods and data from bioinformatics and neuroinformatics related to same problems and tasks would result in a better accuracy of classification and prediction on multimodal data, better diagnosis, prognosis and prevention of disease and finally more efficient personalised treatment for the best individual outcome. The talk presents computational frameworks based on spiking neural network (SNN) and NeuCube as well as methods to achieve this goal. The talk is illustrated on problems and data related to neurological disorders and cognitive studies.

From *multimodal* data -> *Integrated* modelling > *Comprehensive* knowledge



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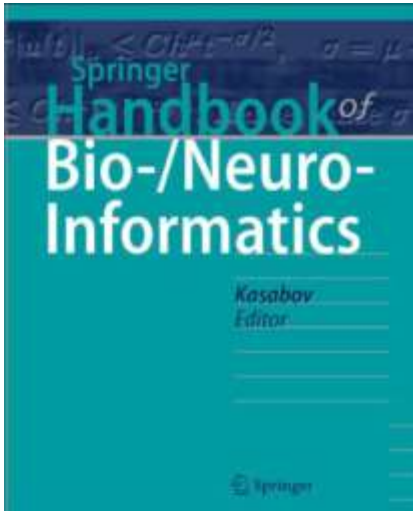


N.Kasabov (ed) The Springer Handbook of Bio- and Neuroinformatics, Springer (2014) 1230 p, https://www.springer.com/gp/book/9783642305733

1. The brain as a multimodal information processing system

The human brain, the most sophisticated product of the evolution, is a deep learning neurogenetic system

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).

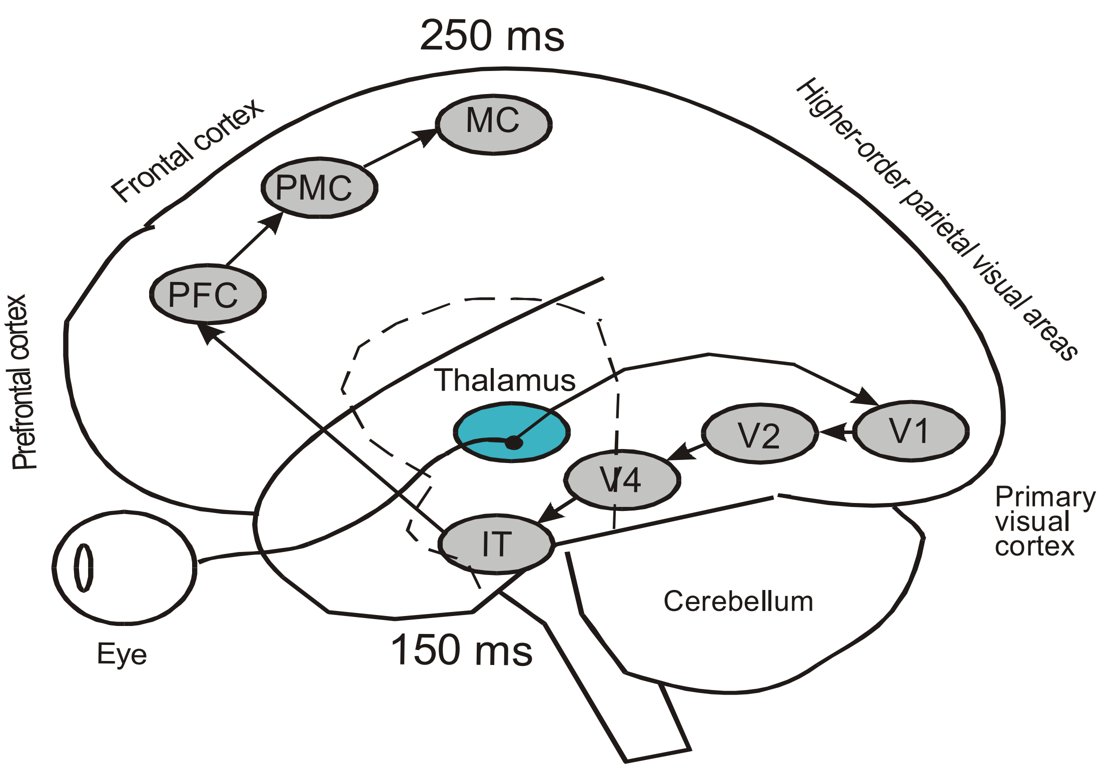
Temporal data at different time scales:

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

Spatially evolved structures with spatially allocated functions

Knowledge is represented as deep spatio-temporal patterns

Learning in the brain is in time and space: Image recognition

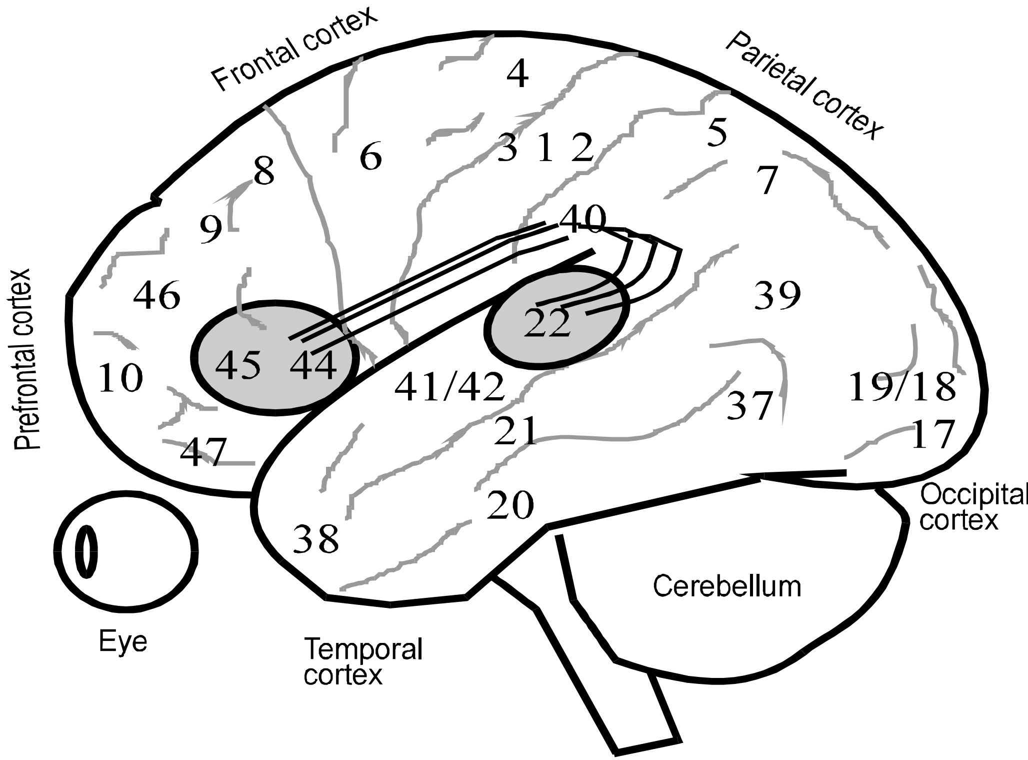


Deep serial processing of visual stimuli in humans for image classification and action.

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.

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

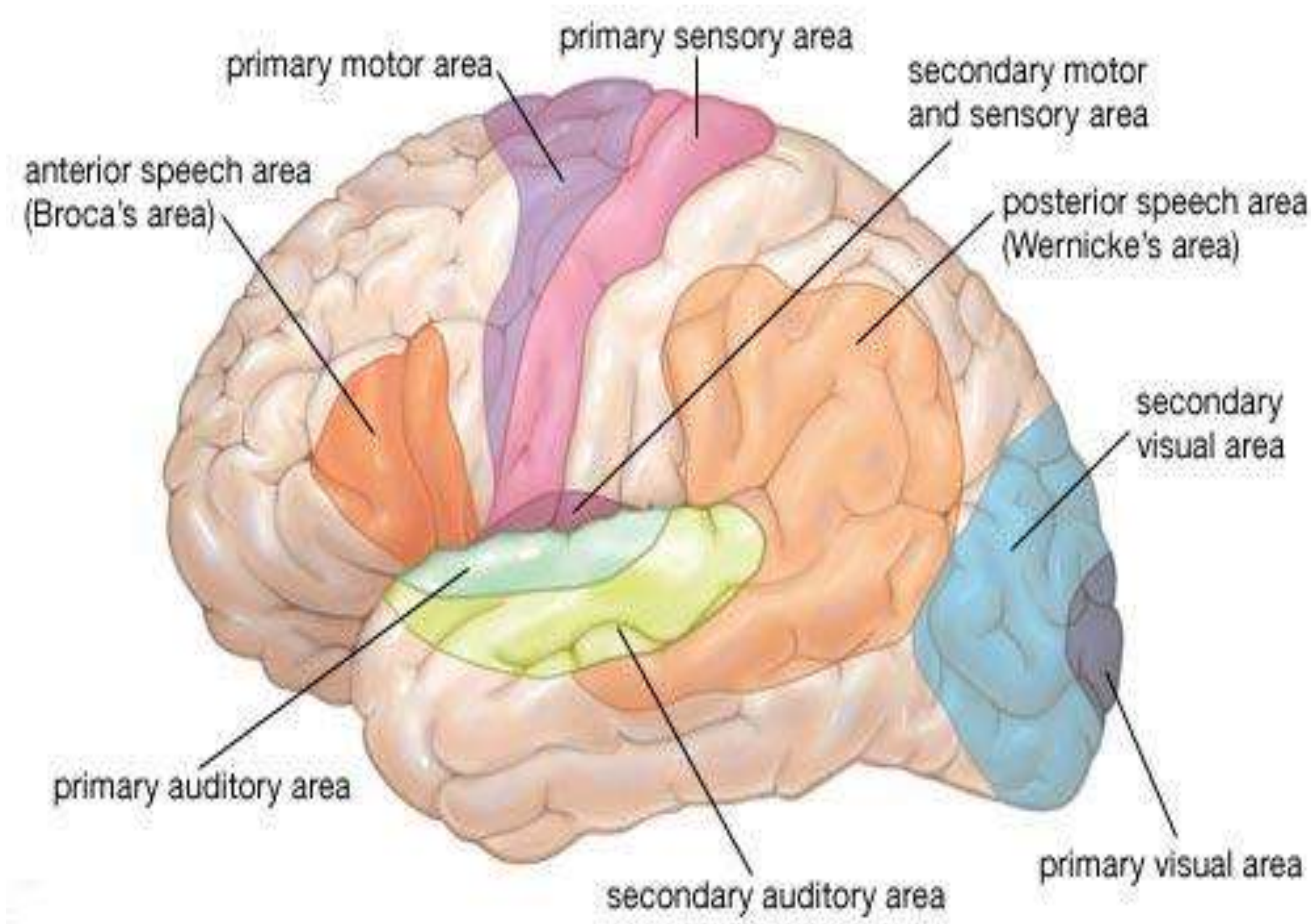
Language learning and processing in time-space



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

The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann's area 41), then to the higher-order auditory cortex (area 42), before it is relayed to the angular gyrus (area 39). From here, the information is projected to Wernicke's area (area 22) and then, by means of the *arcuate fasciculus*, to Broca's area (44, 45), where the perception of language is translated into the grammatical structure of a phrase and where the memory for word articulation is stored. This information about the sound pattern of the phrase is then relayed to the facial area of the motor cortex that controls articulation so that the word can be spoken.

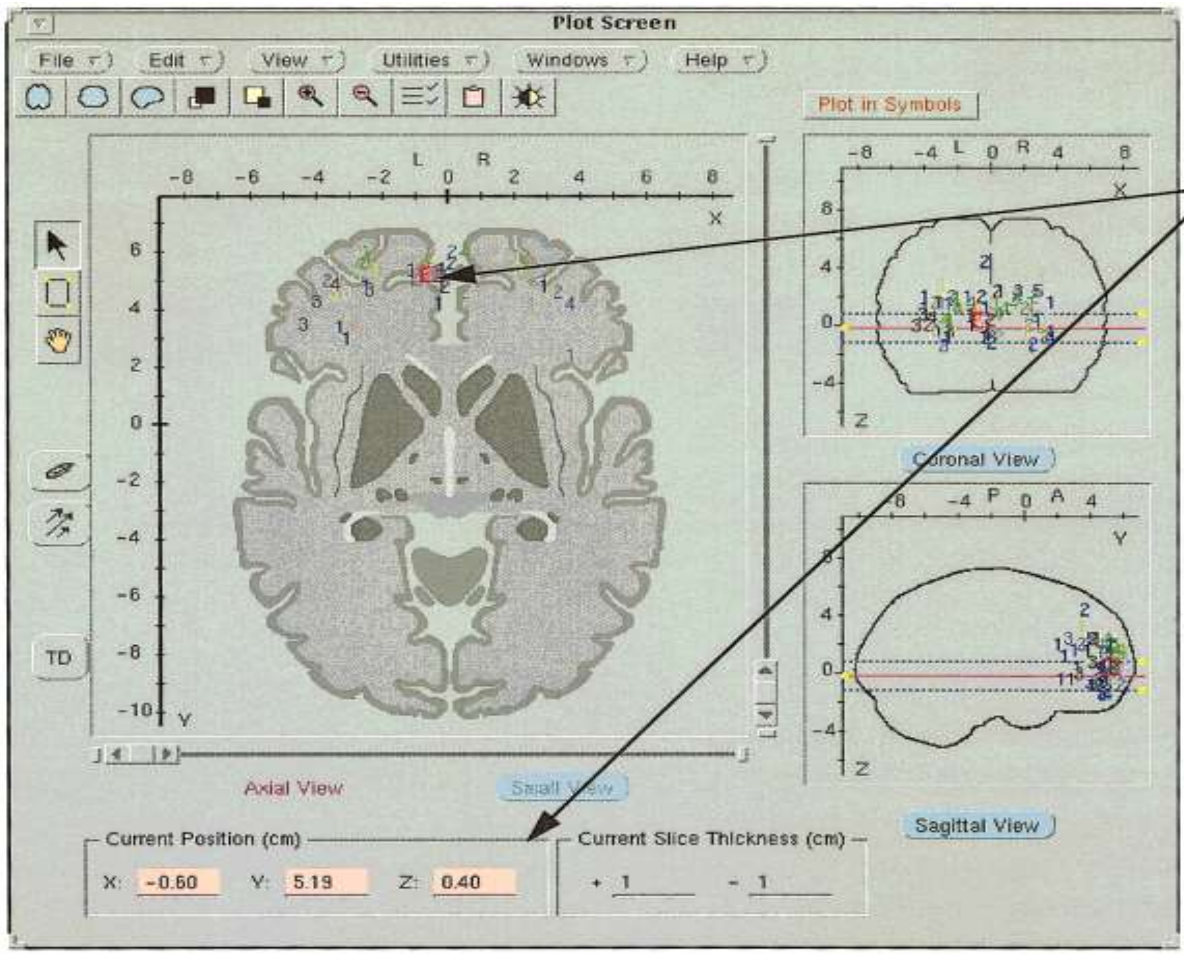
Different parts of the brain control different functions, define as space-time and genes



Brain Atlases: Brain spatial information

Talairach Atlas – Talairach Daemon

http://www.talairach.org/daemon.html



Talairach Label

Left Cerebrum
Frontal Lobe
Medial Frontal Gyrus
Gray Matter
Brodmann area 10

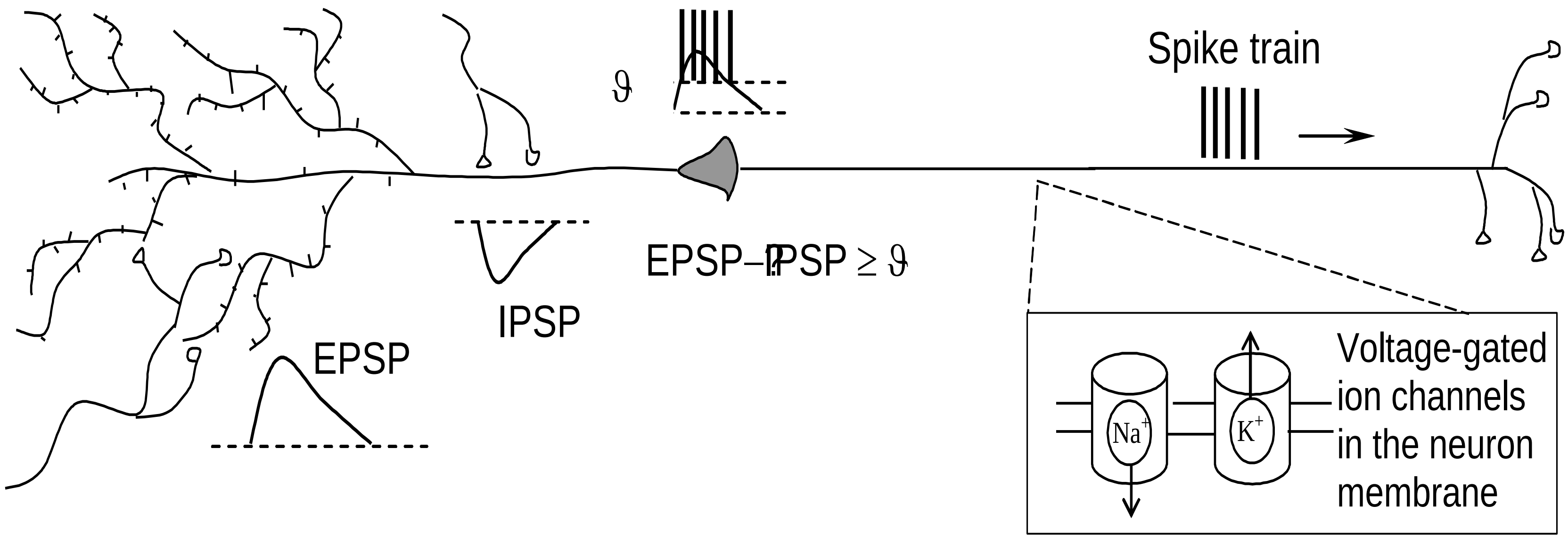
x = -6 mm
y = 52 mm
z = 4 mm

Query on Brodmann Area 10 yielded:

- **32 papers**
- **46 experiments**

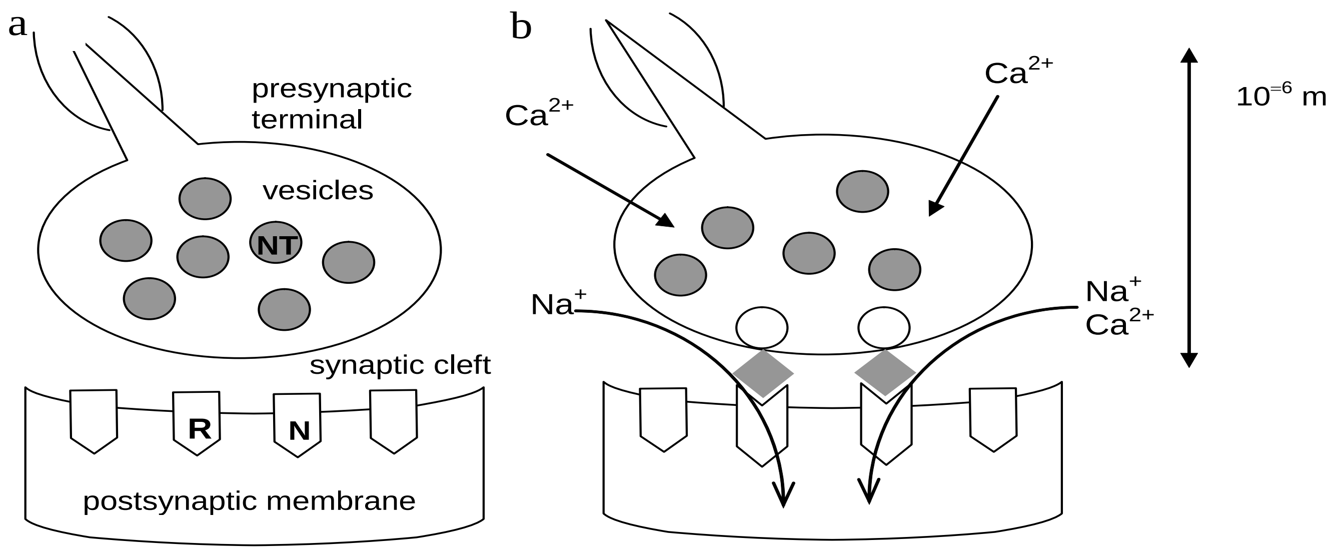
Spiking activities of neurons

Electric synaptic potentials and axonal ion channels responsible for spike generation and propagation: EPSP = excitatory postsynaptic potential, IPSP = inhibitory postsynaptic potential, ϑ = excitatory threshold for an output spike generation.



nkasabov@aut.ac.nz

Gene-based chemical processes in the synapses define spiking activity in neurons



Abbreviation:

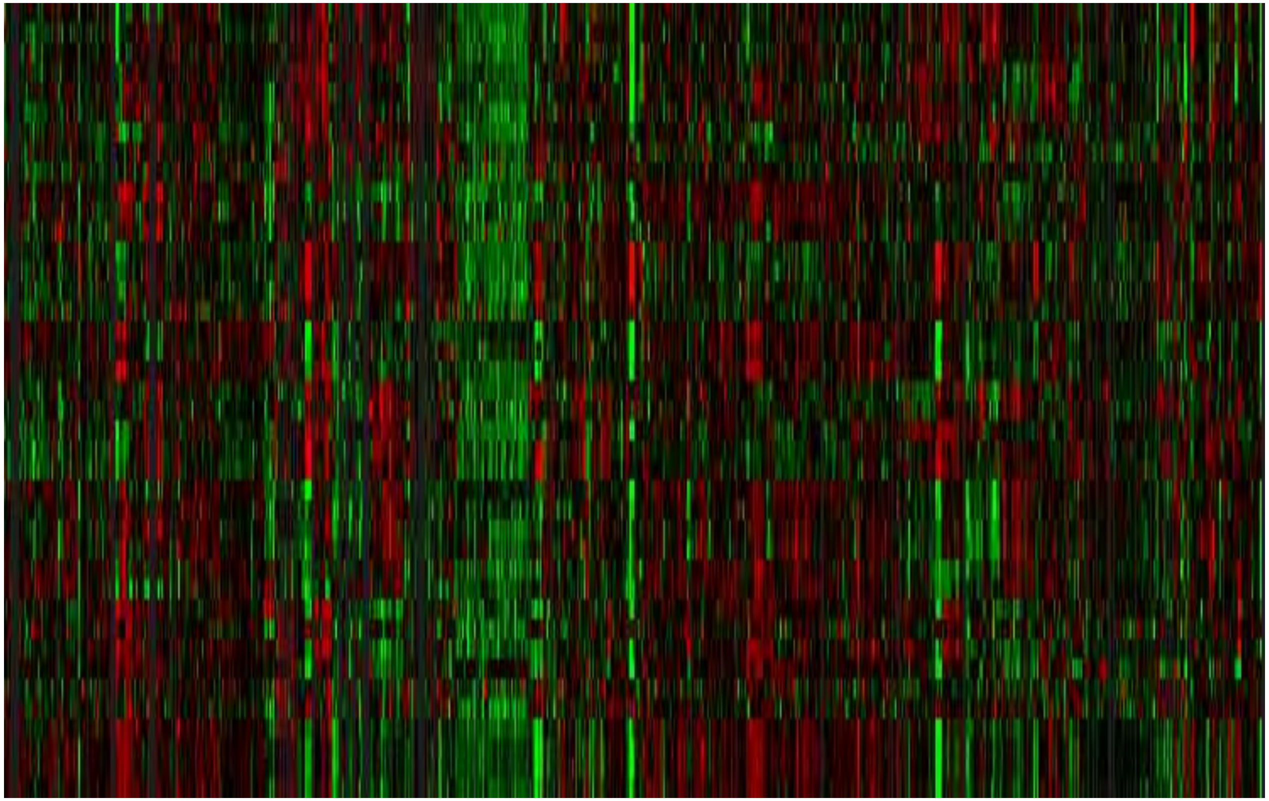
NT: neurotransmitter,

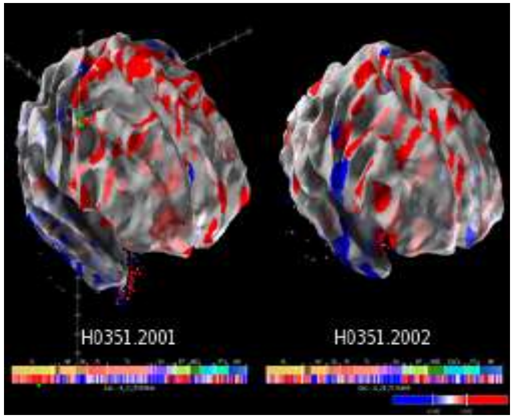
R : AMPA-receptor-gated ion channel for sodium,

N: NMDA-receptor-gated ion channel for sodium and calcium.

- Ion channels with quantum properties affect spiking activities in a stochastic way. “To spike or not to spike?” is a matter of *probability.*
- Transmission of electric signal in a chemical synapse upon arrival of action potential into the terminal is probabilistic
- Emission of a spike on the axon is also probabilistic
- Prior art on stochastic modelling of neuronal processes : D. Colguhoun, B. Sakmann, E. Neher, SShoman, SWang, DTank , JHopfield

Genes are expressed differently in different parts of the brain (http://www.brain-map.org)

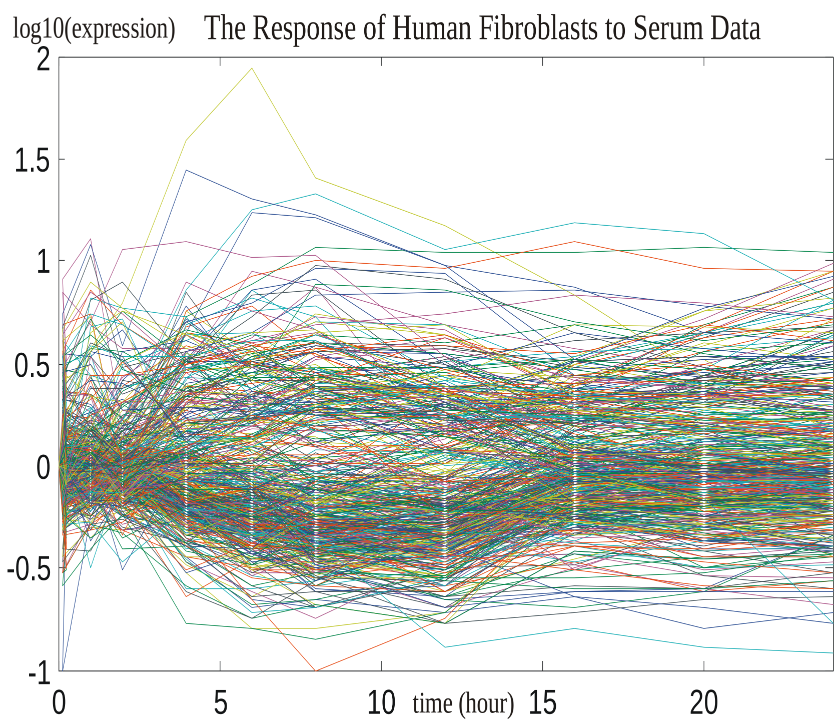


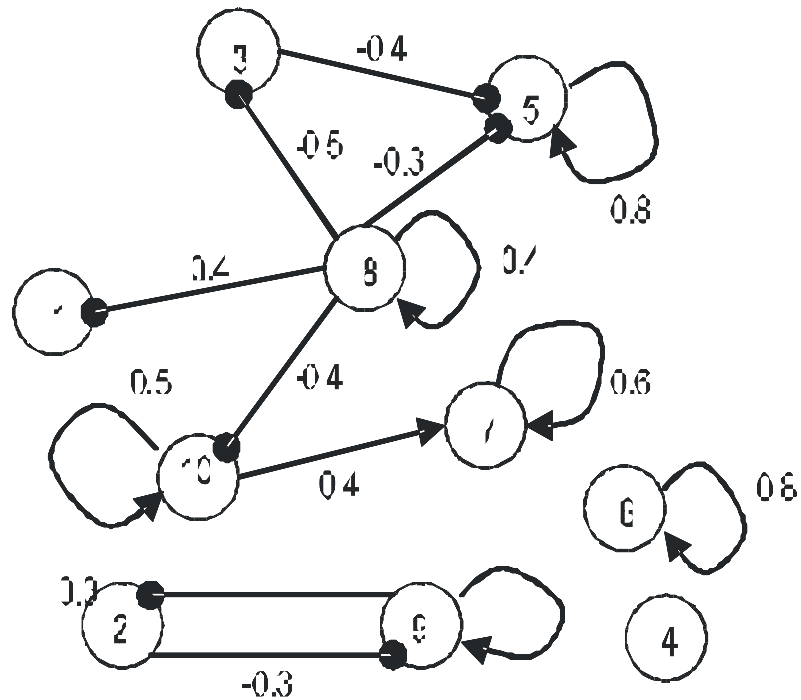


From the Brain Explorer: The Expression level of the genes (on the y-axis): ABAT A_23_P152505, ABAT A_24_P330684, ABAT CUST_52_PI416408490, ALDH5A1 A_24_P115007, ALDH5A1 A_24_P923353, ALDH5A1 A_24_P3761, AR A_23_P113111, AR CUST_16755_PI416261804, AR CUST_85_PI416408490, ARC A_23_P365738, ARC CUST_11672_PI416261804, ARC CUST_86_PI416408490, ARHGEF10 A_23_P216282, ARHGEF10 A_24_P283535, ARHGEF10 CUST_) at different slices of the brain (on the x-axis) (from www.brain-map.org) (http://www.alleninstitute.org)

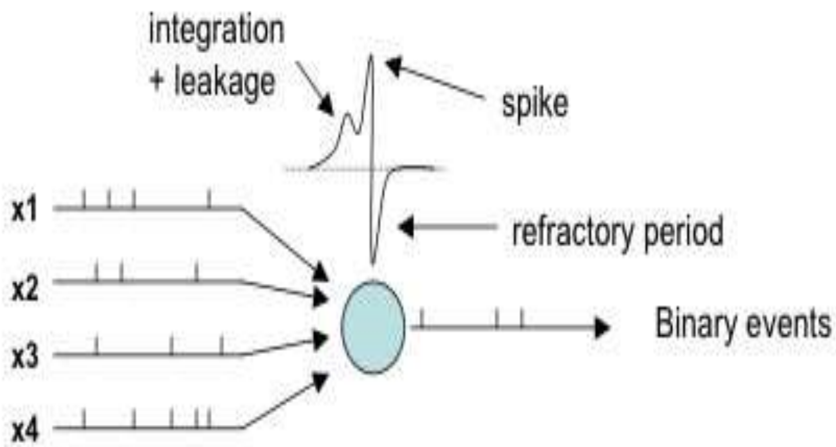
Gene Regulatory Networks as Dynamical Systems

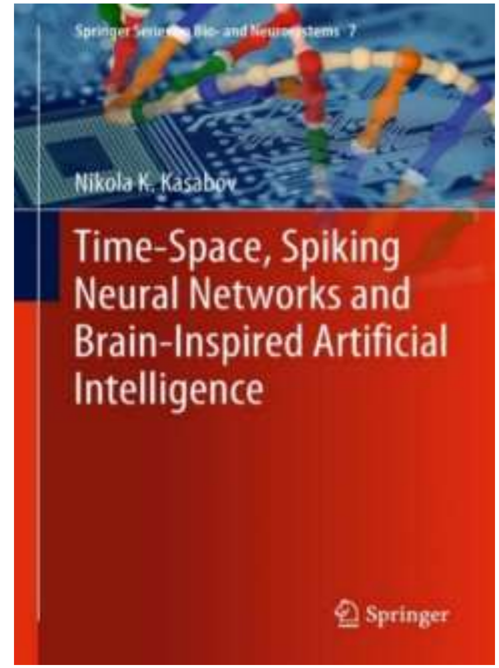
(Chan, Collins and Kasabov, JBCB, 2005)





2. Spiking neural networks and neuromorphic systems inspired by the brain



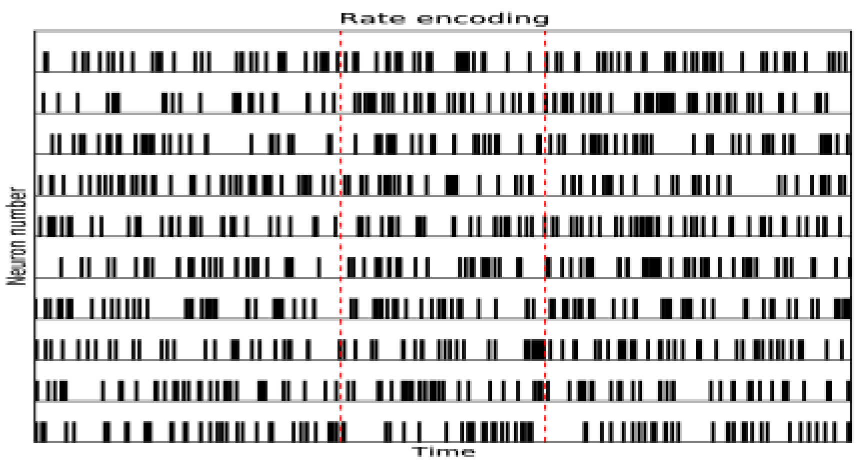


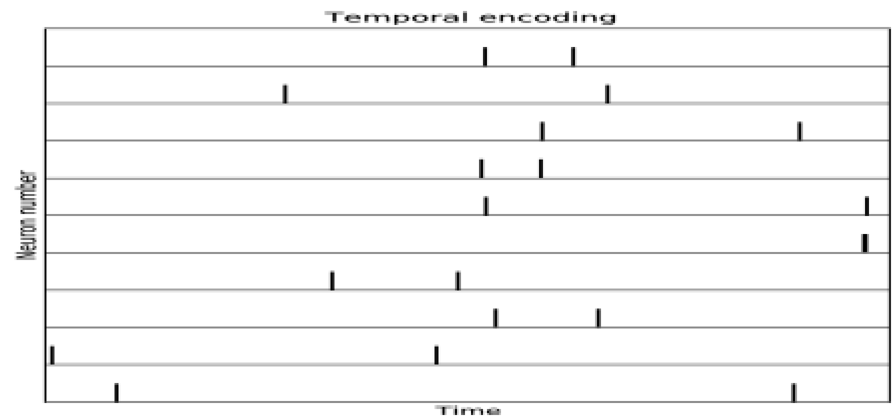
[N. Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019) 750p]

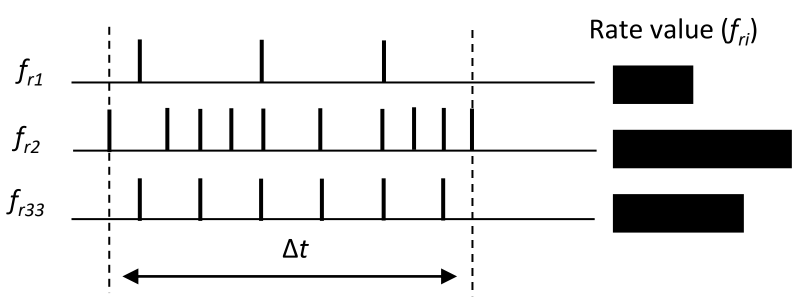
https://www.springer.com/gp/book/9783662577134

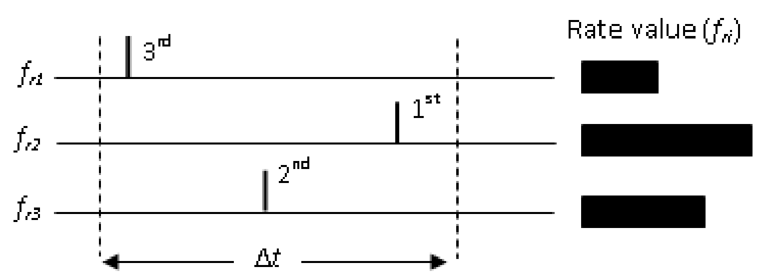
Spike encoding

- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.
- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters and its time - too!







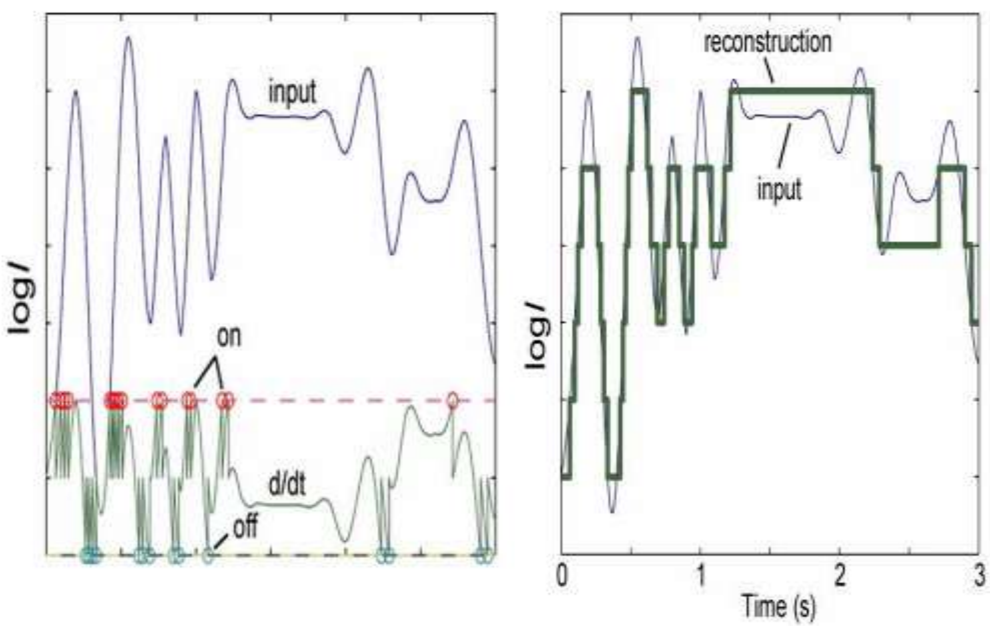


Spike encoding methods

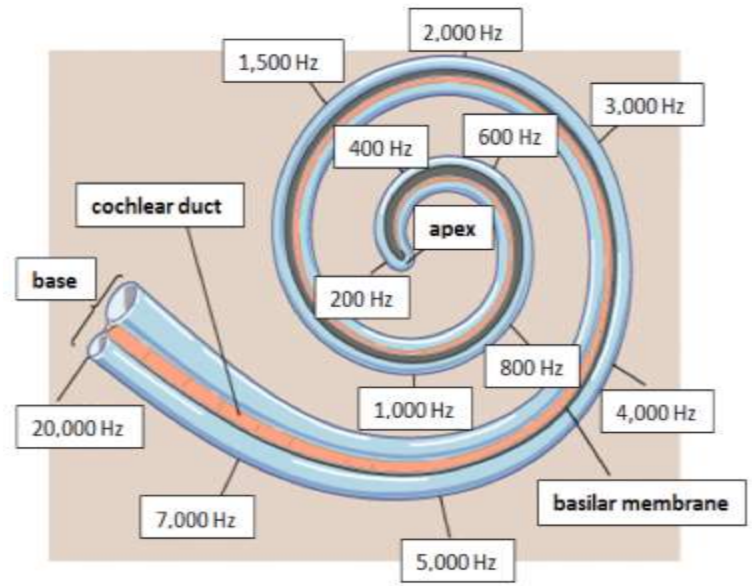
A spike is generated only if a change in the input data occurs beyond a threshold

Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128: Retinotopic

Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich): Tonotopic



Threshold-based encoding – retinotopic

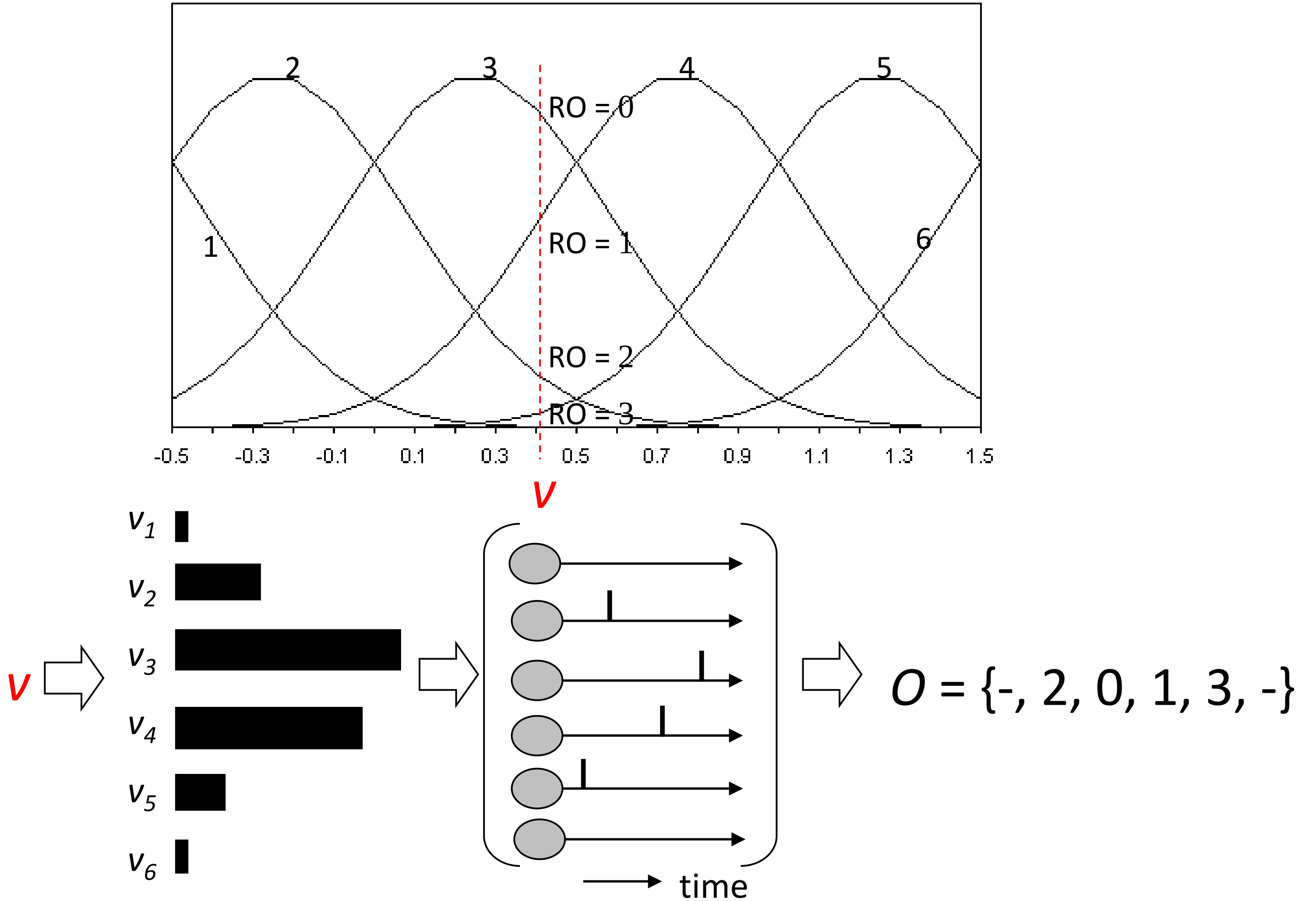


Tonotopic organization of the cochlea:
https://sites.google.com/site/jayanthinyswebite

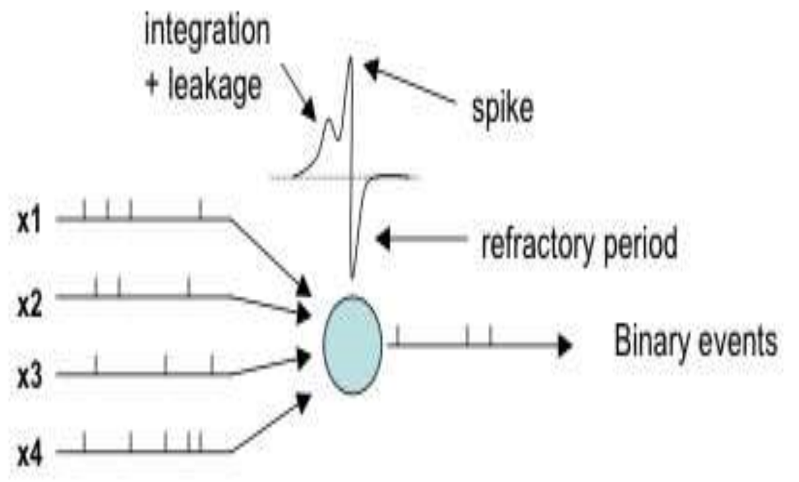
nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube

RO population coding(RO-POP C)

Distributes a single real input value V to multiple neurons and may cause the excitation and firing of several responding neurons depending on the membership to the receptive fields. Implementation based on Gaussian receptive fields introduced by Bothe *et al* . 2002



Spiking neuron models

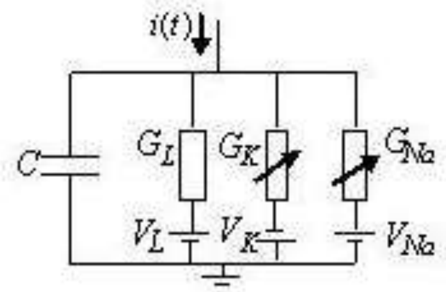


Models of a spiking neurons and SNN

- Hodgkin- Huxley
- Spike response model
- Integrate-and-fire
- Leaky integrator
- Izhikevich model
- Probabilistic and neurogenetic models

Hodgkin- Huxley Model

- A detailed description of the influences of the conductance of three ion channels on the spike activity of the giant axon of squid.
- Because of its biological relevance the model is commonly used by neuroscientists

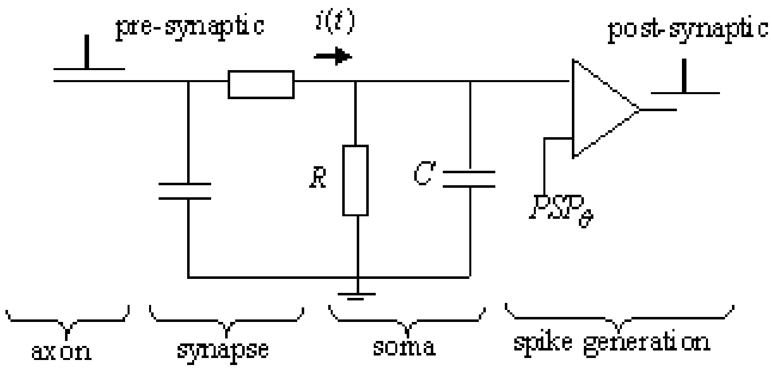


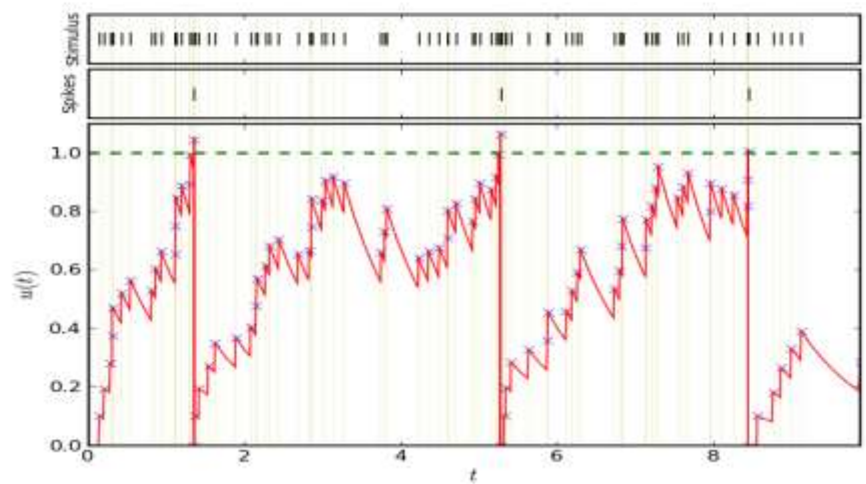
$$\sum_{ch} i_{ch}(t) = G_{Na} \times m^3 \times h \times (v_C - V_{Na}) +$$
$$G_K \times n^4 \times (v_C - V_K) + G_L \times (v_C - V_L)$$
$$\frac{dm}{dt} = \alpha_m(v_c) \times (1-m) - \beta_m(v_c) \times m$$
$$\frac{dn}{dt} = \alpha_n(v_c) \times (1-n) - \beta_n(v_c) \times n$$
$$\frac{dh}{dt} = \alpha_h(v_c) \times (1-h) - \beta_h(v_c) \times h$$

- G_{Na}, G_K and G_L - conductance of the sodium, potassium and leakage channels
- V_{Na}, V_K and V_L are constants called reverse potentials,
- m and n control the N_a channel and variable h controls the K channel
- α and β are empirical functions of v_c

Leaky Integrate-and-Fire Neuronal Model

- Model consists of capacitor *C* in parallel with resistor *R*, driven by a current $I(t) = I_R + I_{cap}$





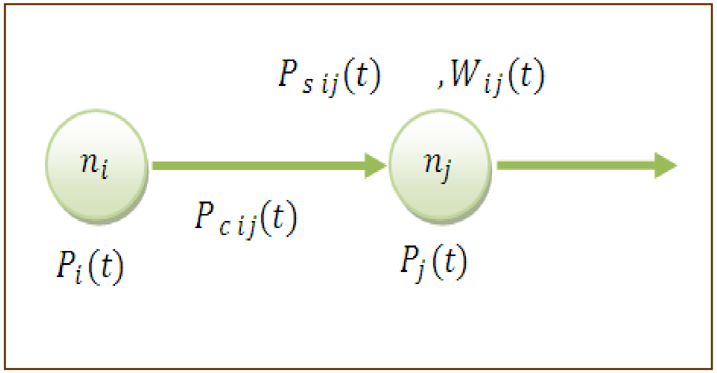
$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

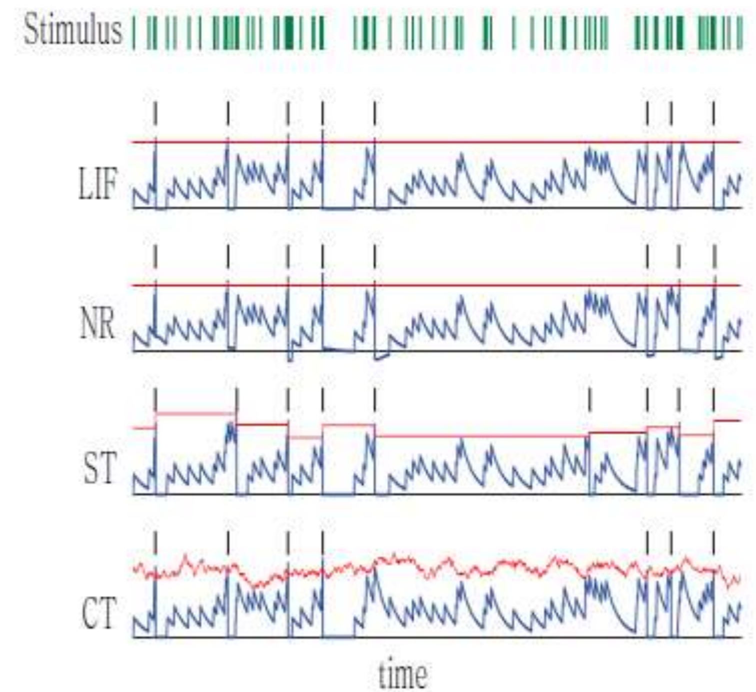
- $\tau_m = RC$ is the membrane time constant
- Shape of action potentials are not explicitly modeled
- Spikes are events characterized by a firing time $t^{(f)}$: $u(t^{(f)}) = \vartheta$
- After $t^{(f)}$ the potential is reset to a resting potential u_r
- In a more general form the LIF model can also include a refractory period, in which the dynamics are interrupted for an absolute time Δ^{abs}

nkasabov@aut.ac.nz

A probabilistic spiking neuron model

(N. Kasabov, To spike or not to spike: A probabilistic spiking neuron model, Neural Networks, Jan. 2010)





The information is represented as connection weights and probabilistic parameters.

The PSPi(t) is calculated using a formula:

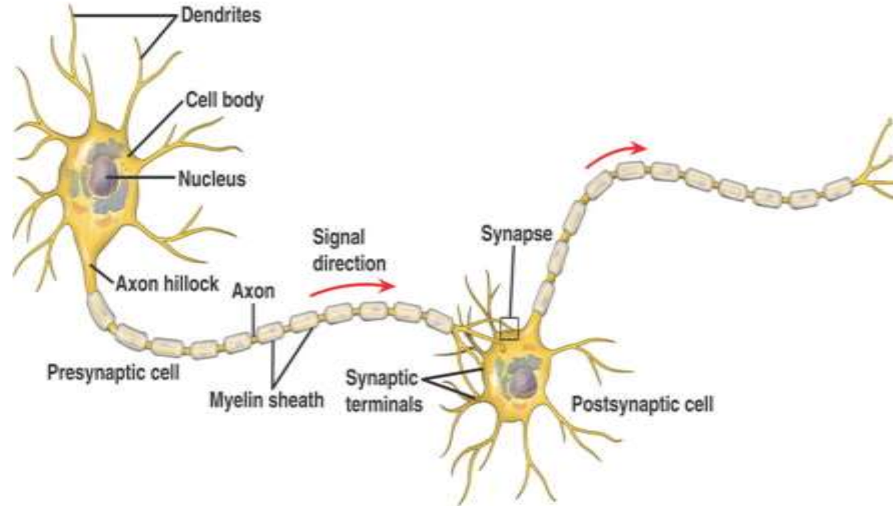
$$PSP_i(t) = p_i(t) \sum_{p=t_0,..,t} \; \sum_{j=1,..,m} e_j \, g(p_{cj,i}(t-p)) \, f(p_{sj,i}(t-p)) \, w_{j,i}(t) - \eta(t-t_0)$$

As a special case, when all probability parameters are "1", the model is reduced to LIF model.

Methods for unsupervised learning in SNN

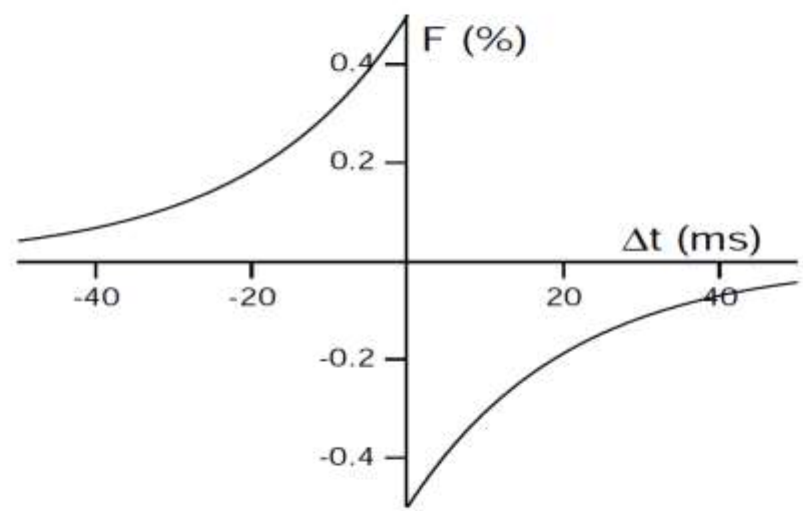
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from data.
- Variations of the STDP



Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

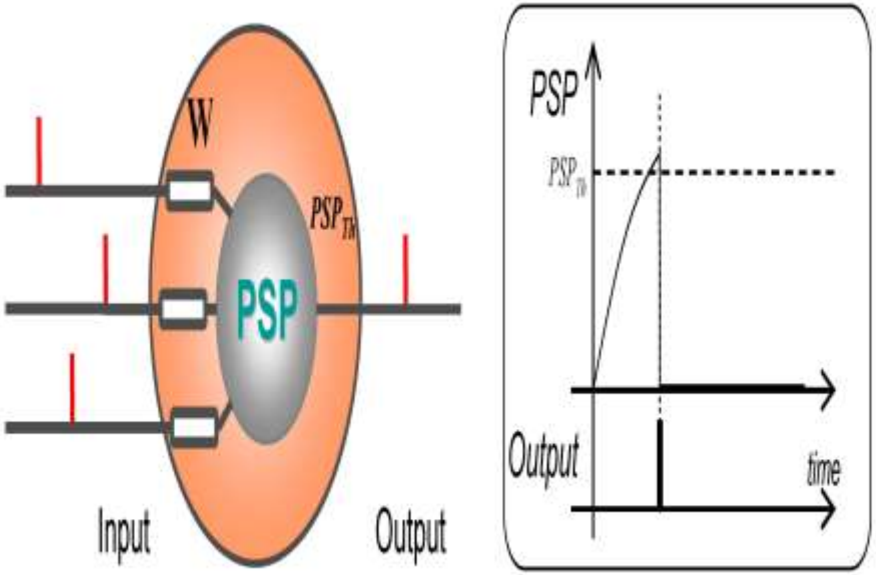
$\Delta t = tpre - tpost$



nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

Methods for supervised learning in SNN

Rank order (RO) learning rule (Thorpe et al, 1998)



$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

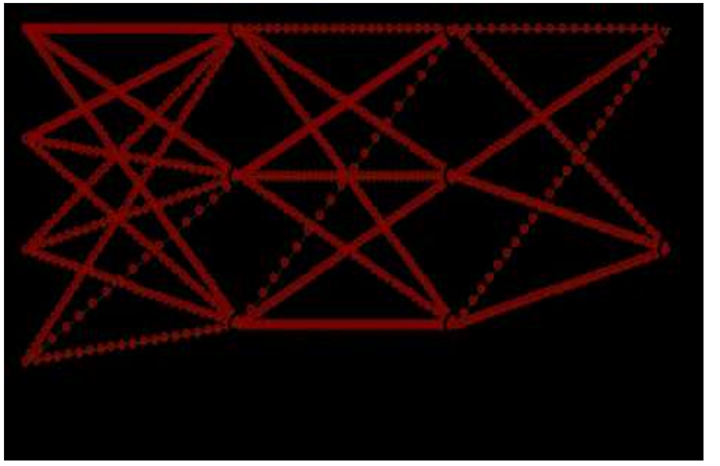
$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

PSP max (T) = SUM [($m^{\text{order}(j(t))}$) $w_{j,i}(t)$], for j=1,2.., k; t=1,2,...,T;

PSP_{Th}=C. PSPmax (T)

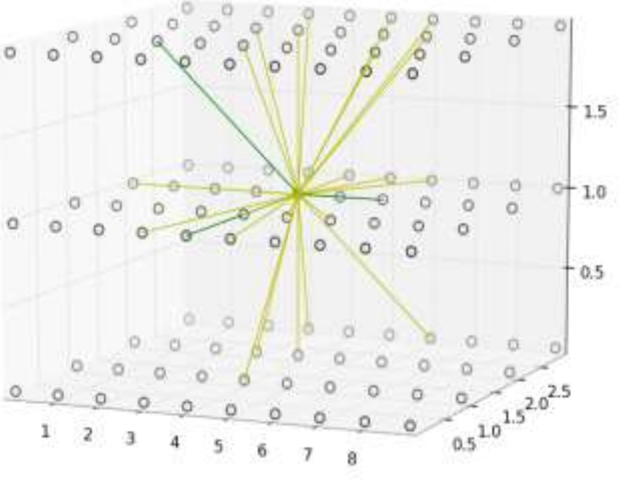
- Earlier coming spikes are more important (carry more information)
- Early spiking can be achieved, depending on the parameter C.

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



Generic SNN structures:

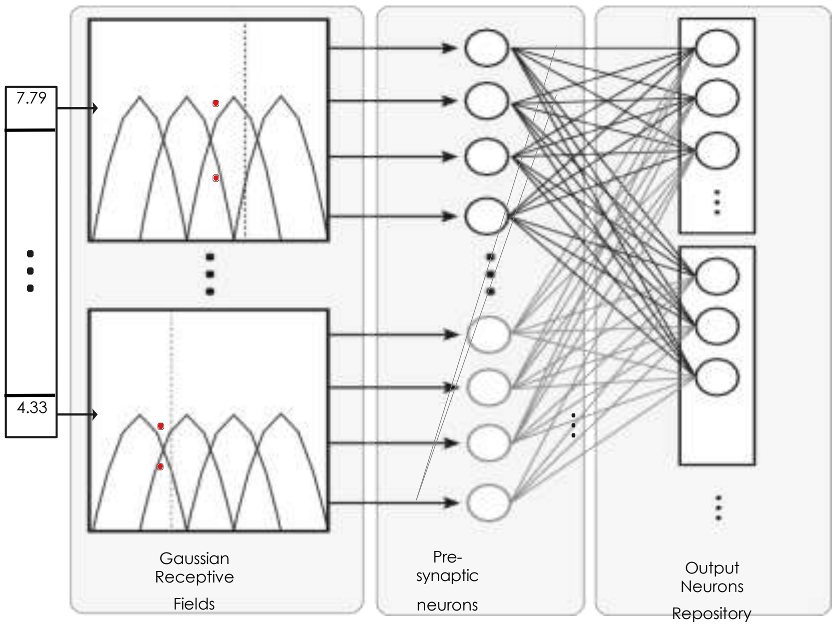
- Feedforward
- Recurrent
- Evolving
- Convolutional
- Reservoir
- Liquid sate-machines



Task oriented structures:

- Classification
- Regression
- Prediction

Evolving Spiking Neural Networks (eSNN)



Kasabov, Evolving connectionist systems, Springer, 2007

Kasabov, N. Evolving connectionist systems for adaptive learning and knowledge discovery: Trends and Directions, Knowledge Based Systems, 2015, (2015), http://dx.doi.org/10.1016/j.knosys.2014.12.032.

Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41, 188-201 (236 citations).

J. L. Lobo, J. Del Ser, A. Bifet, N. Kasabov, Spiking Neural Networks and online learning: An overview and perspectives, Neural Networks, 121 (2020), 88-110, https://doi.org/10.1016/j.neunet.2019.09.004

J. L. Lobo, I.Laña, J. Del Ser, M.N.Bilbao, N.Kasabov Evolving Spiking Neural Networks for online learning over drifting data streams, Neural Networks, 108, 1-19 (2018).

Jesus L. Lobo, Izaskun Oregi, Albert Bifet, Javier Del Sera, Exploiting the Stimuli Encoding Scheme of Evolving Spiking Neural Networks for Stream Learning, Neural Networks, 2019

nkasabov@aut.ac.nz

Evolving SNN (eSNN)

- ECOS: Evolving clusters as evolving neurons and functions (Kasabov,1998)
- eSNN: ~ for spiking neurons (Wysoski, Benuskova, Kasabov, 2006-2010);
- Uses the first spike principle (Thorpe et al.) for fast on-line training
- For each input vector

a) Create (evolve) a new output spiking neuron and its connections

b) Propagate the input vector into the network and train the newly created neuron

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\text{order}(j)} & \text{else} \end{cases}$$

$$\Delta w_{ji} = m^{\text{order}(j)}$$

Weights change based on the spike time arrival

c) : IF similarity between a new and old neurons > Threshold THEN merge neurons

$$W \Leftarrow \frac{W_{new} + NW}{1+N}$$

where N is the number of samples previously used to update the respective neuron.

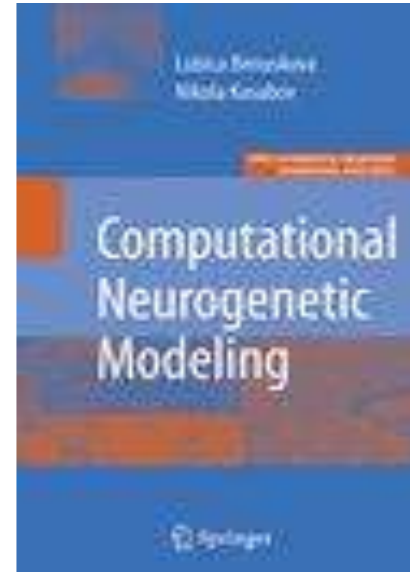
d) Update the corresponding threshold ϑ:

$$\vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

- Schliebs, S. and N.Kasabov, Evolving spiking neural networks: A Survey, *Evolving Systems*, Springer, 2013.

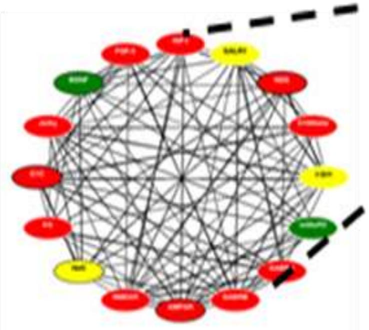
3. Computational Neuro-Genetic Modelling with SNN

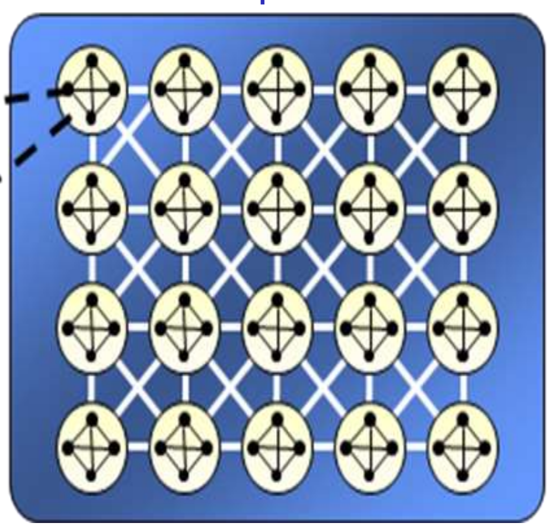
- Benuskova and Kasabov, Computational neurogenetic modelling, Springer, 2007.

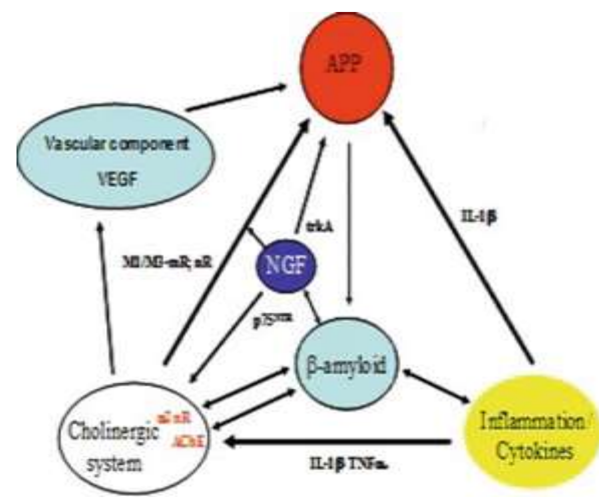


- SNN incorporate a gene regulatory network (GRN) as a dynamic parameter system to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model, e.g. GRN related to AD (R.Schliebs et al, SHBNI, 2014)

Challenge: The GRN and the SNN function at different time scales (minutes vs milliseconds) and different spatial locations.



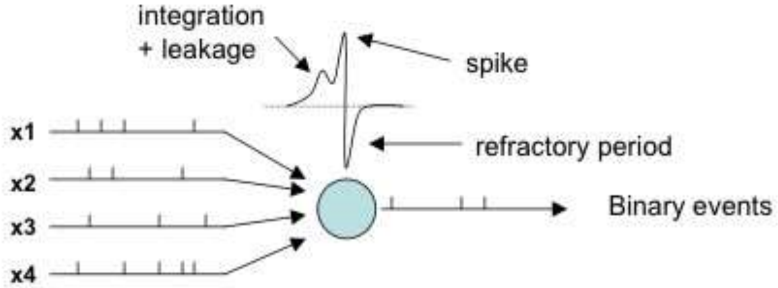




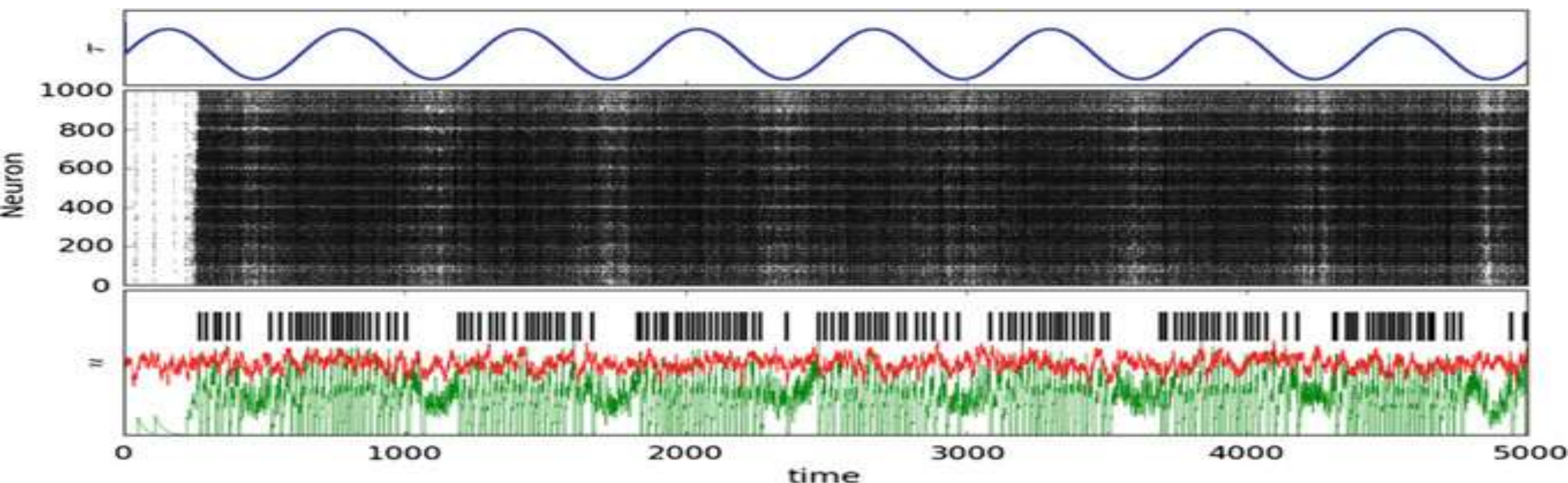
nkasabov@aut.ac.nz

A single gene expression level over time can affect the pattern of activity of a whole SNNr of 1000 neurons. The gene controls a parameter of all 1000 LIF neurons over a period of five seconds and changes in this parameter affect the spiking activity of the neurons

From: N.Kasabov, Time-space, spiking neural networks and brain-inspired artificial intelligence, 2019, Springer (Fig. 16.8)



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



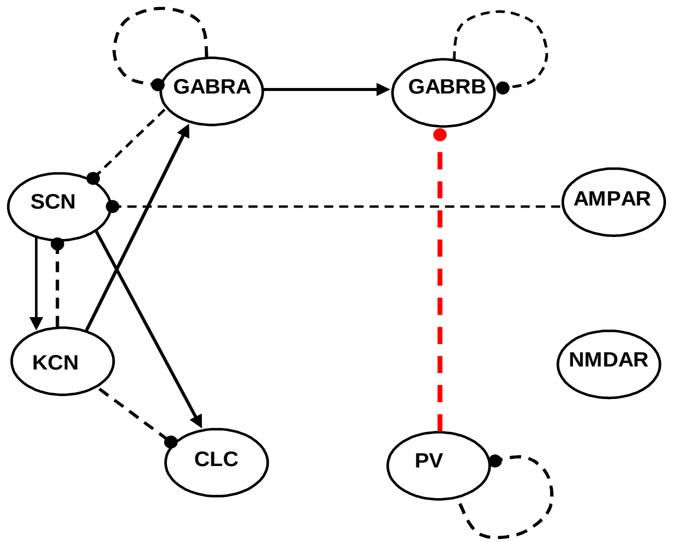
A neurogenetic model of a spiking neuron

(Kasabov, Benuskova, Wysoski, 2005)

- Four types of synapses: fast excitation; slow_excitation; fast_inhibition; slow_inhibition
- A Gene Regulatory Network (GRN) as a dynamical parameter system of the neuron

Table. Neuronal Parameters and Related Proteins

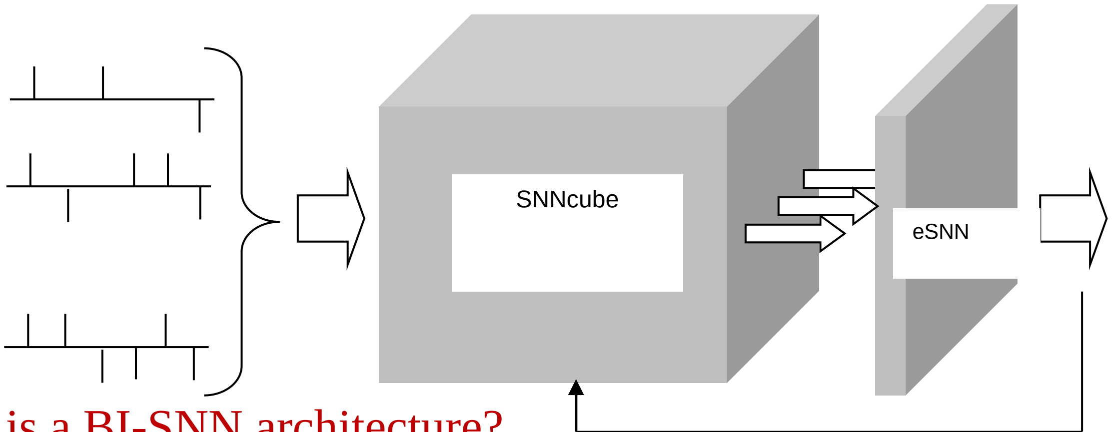
Neuronal parameter Amplitude and time constants of	Protein
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC
Late excitatory PSP through GABRA	PV

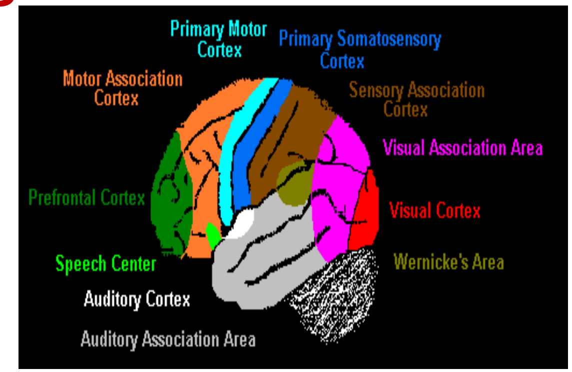


$$PSP_{ij}^{type}(t - t_j - \Delta_{ij}^{ax}) = A^{type}\left(\exp\left(-\frac{t - t_j - \Delta_{ij}^{ax}}{\tau_{decay}^{type}}\right) - \exp\left(-\frac{t - t_j - \Delta_{ij}^{ax}}{\tau_{rise}^{type}}\right)\right)$$

type = fast excitation; slow_excitation; fast_inhibition; slow_inhibition

4. Brain-inspired SNN NeuCube for computational neurogenetic modelling

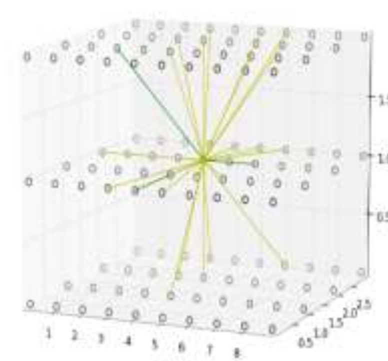




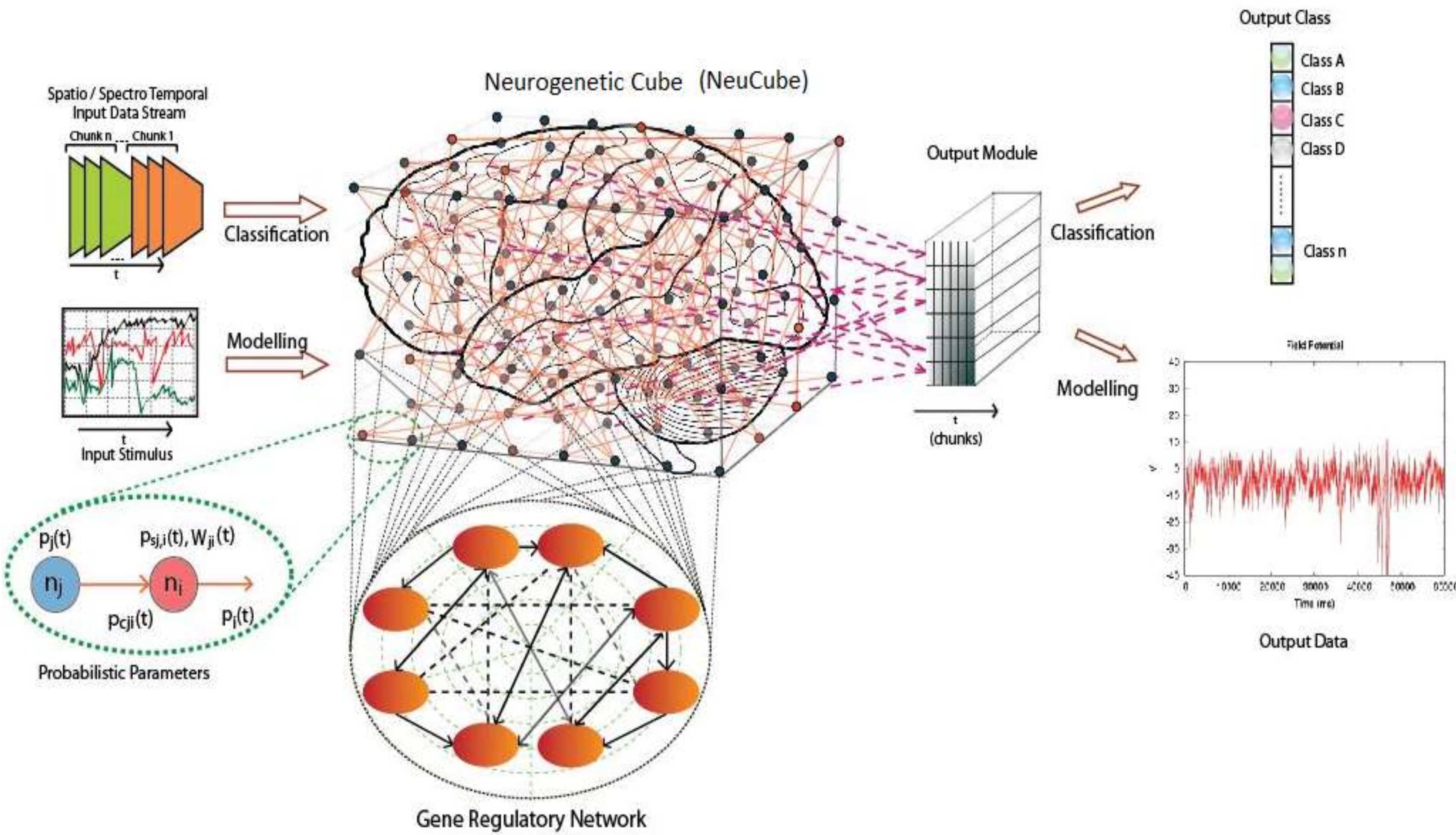
What is a BI-SNN architecture?

- Input data is encoded into spatio-temporal events as spike trains;
- A 3D SNN has spatially located neurons following a brain template, e.g Talairach, MNI etc. .
- Inputs are mapped spatially (brain-like) into the SNN, a 3D structure organised as a brain template.
- Unsupervised learning is spatio-temporal, adaptive and incremental resulting in evolved connectivity
- The structure is self-organising
- Supervised learning is evolving creating new output neurons
- Allows for knowledge representation as spatio-temporal patterns, interpreted as rules, graphs, associations, ….

$$p_{a,b} = C \times e^{-D^2_{a,b}/\lambda^2}$$



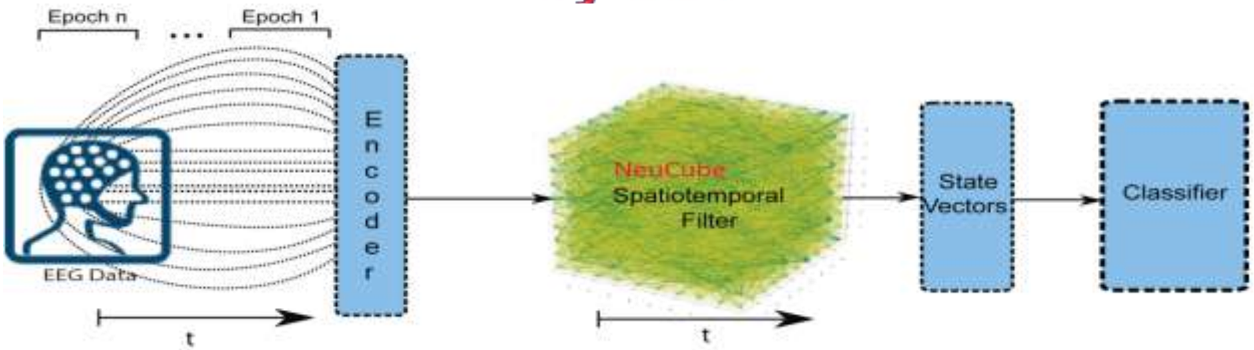
The NeuCube Architecture

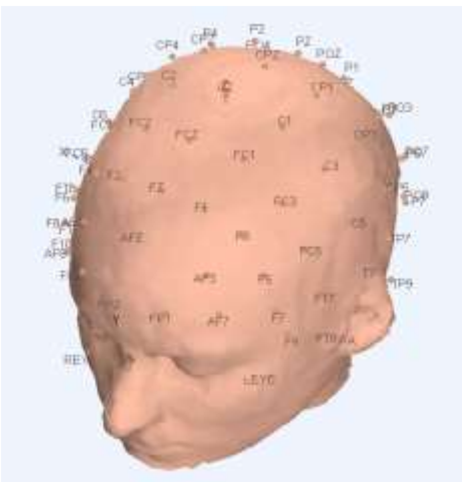


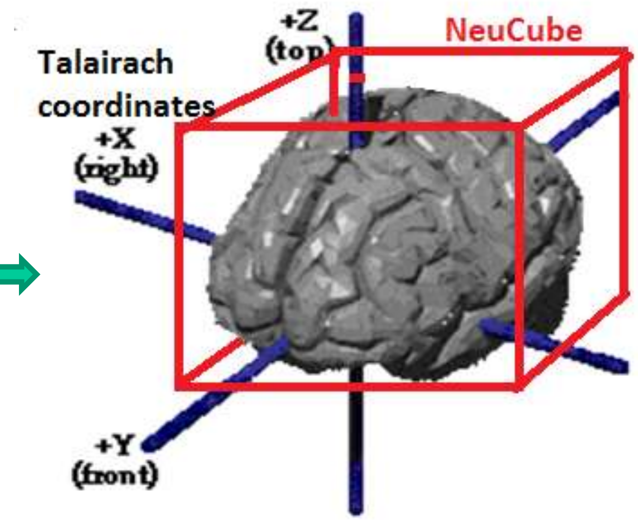
Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

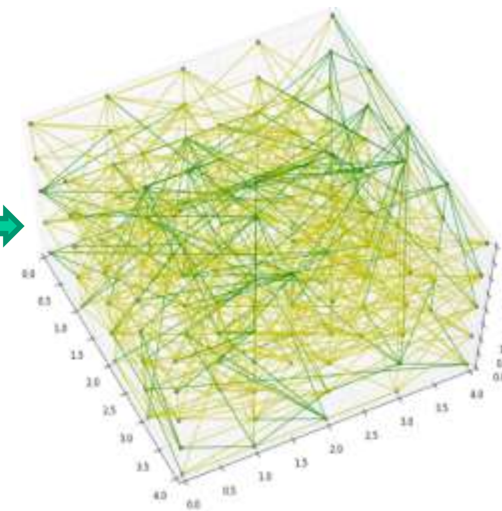
E. Tu, N. Kasabov, J. Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition and Predictive Modelling, IEEE Trans. on Neural Networks and Learning Systems, 28 (6), 1305-1317,, 2017 DOI: 10.1109/TNNLS.2016.2536742, 2017.

Mapping, learning and mining data in NeuCube exemplified by EEG



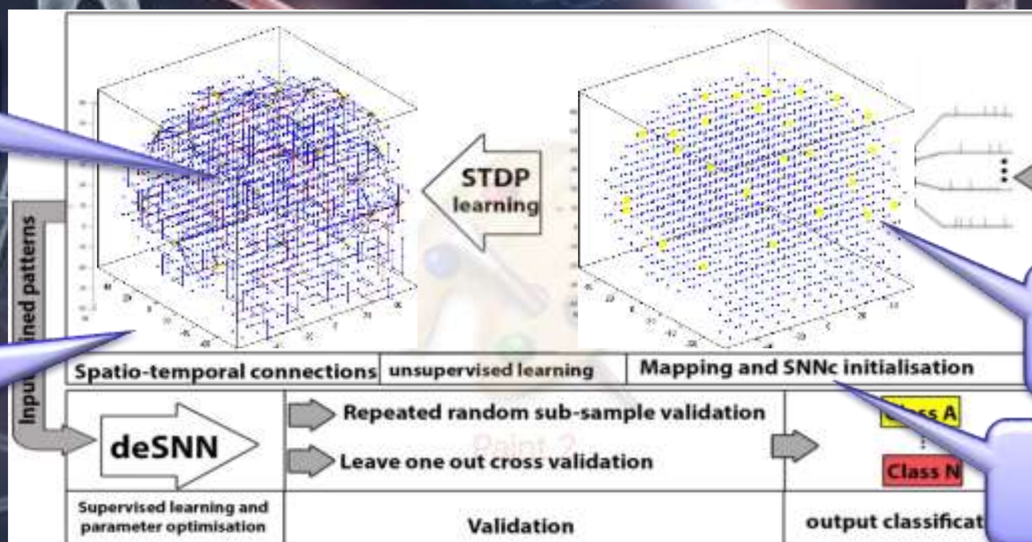






Same brain 3D coordinates (e.g. Talairach, MNI) are used for the allocated spiking neurons in the SNNc where the input data is mapped and the SNNc is analysed after training with the EEG data

Deep learning in NeuCube

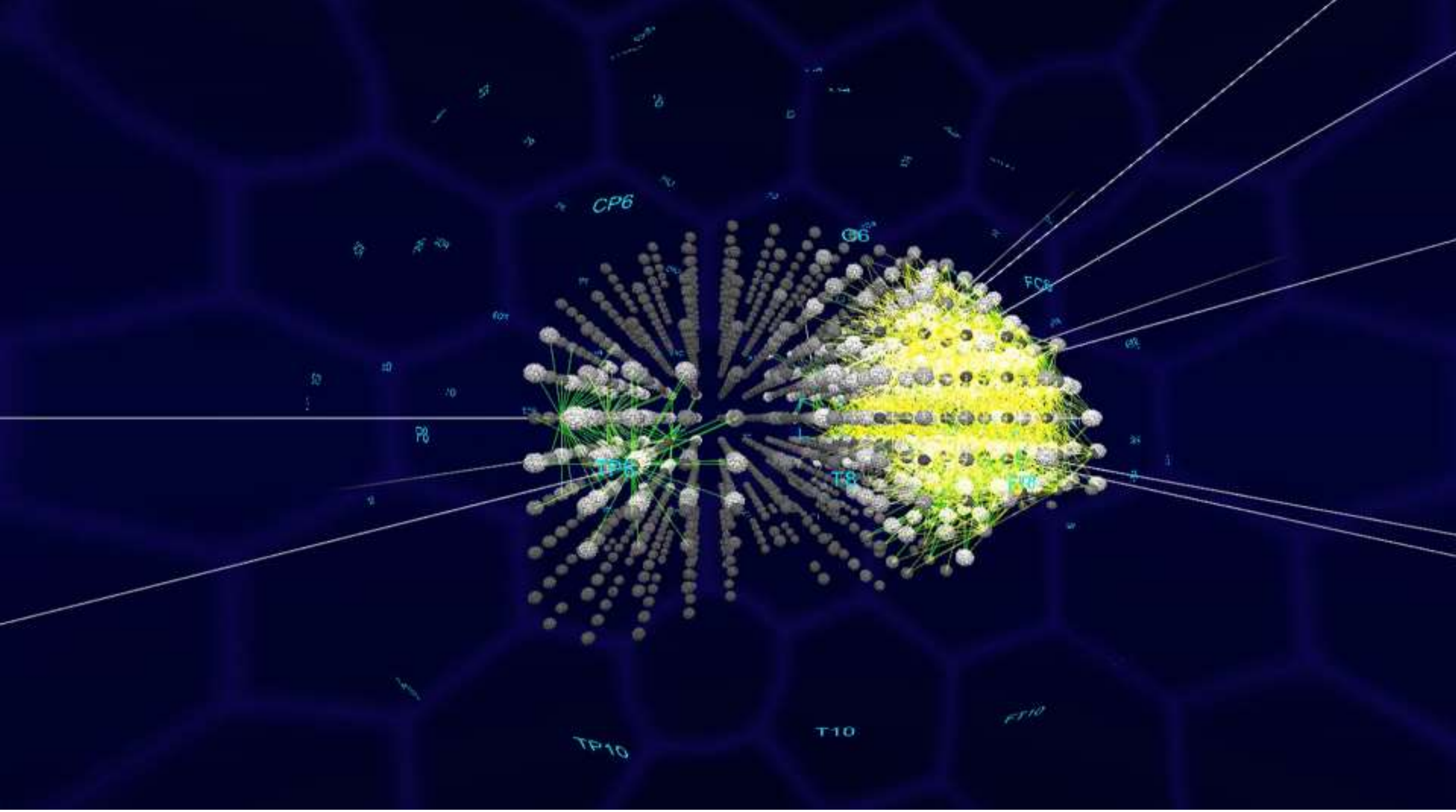


Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created

Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning



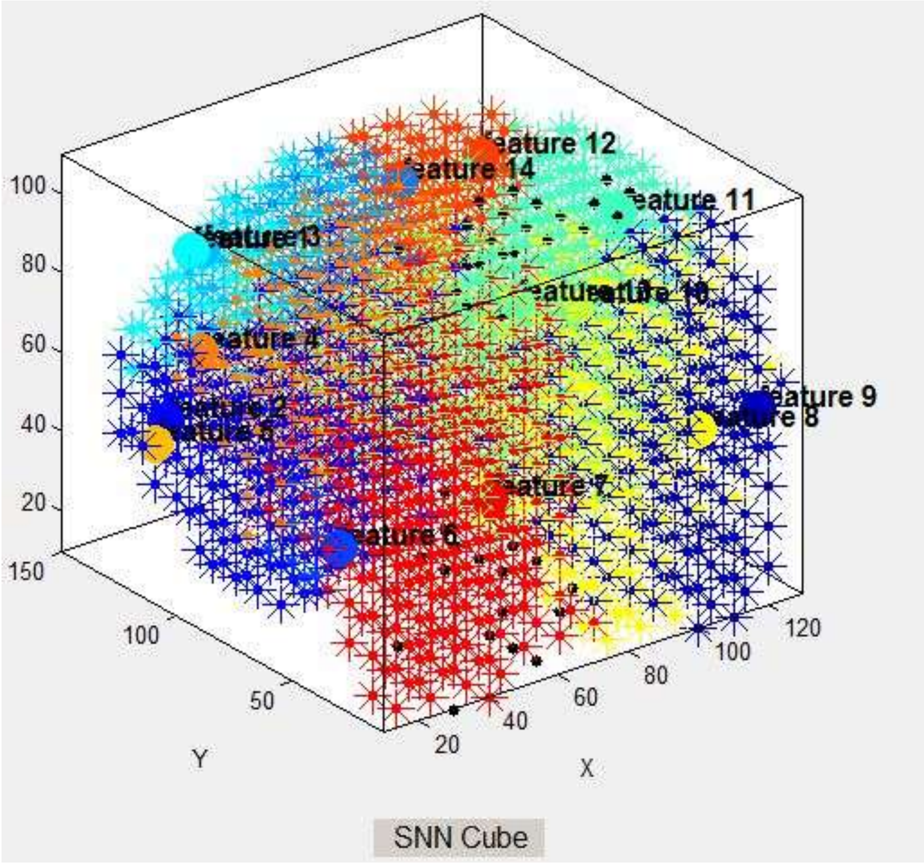
N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube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

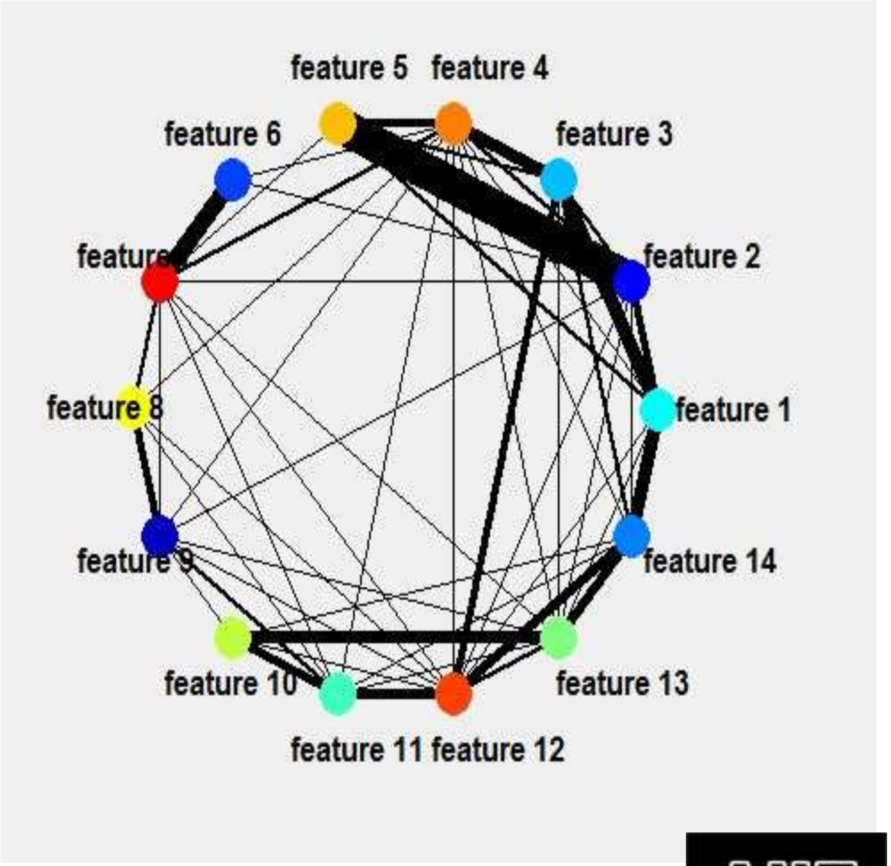
Capturing time-space knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

- Clusters of spiking activity spread from input neurons ;

- A graph of information exchange between spatially distributed clusters around the inputs





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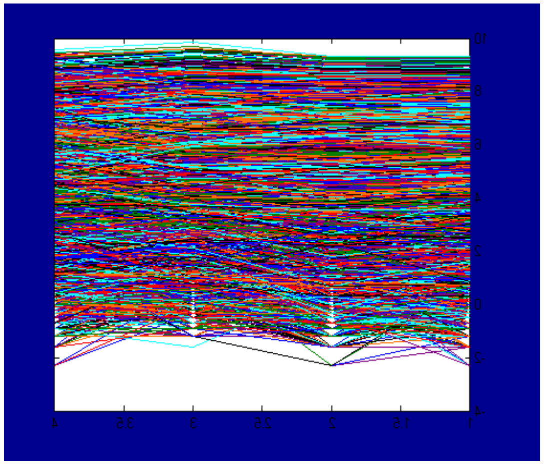
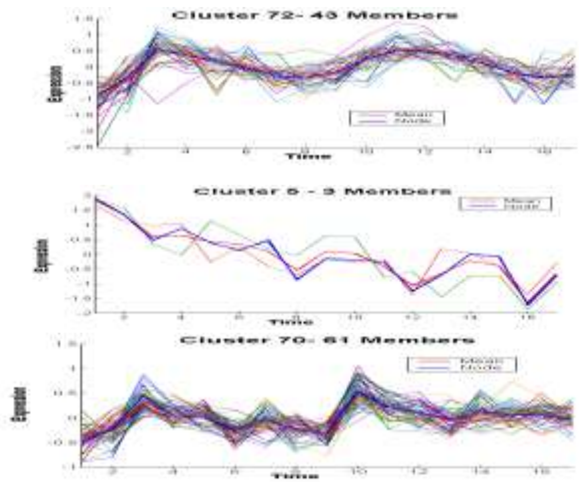
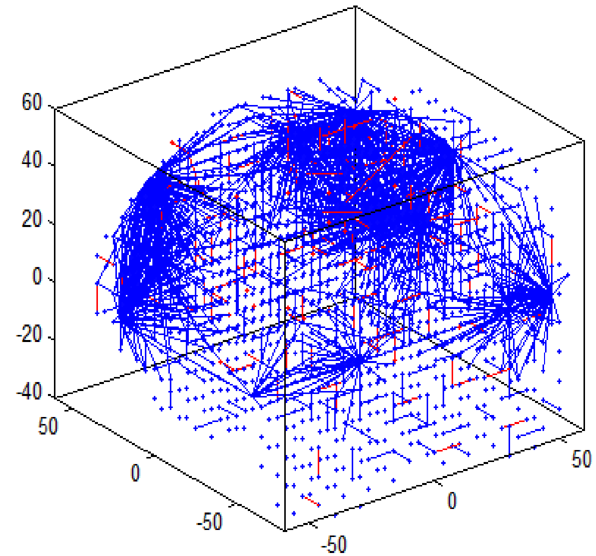
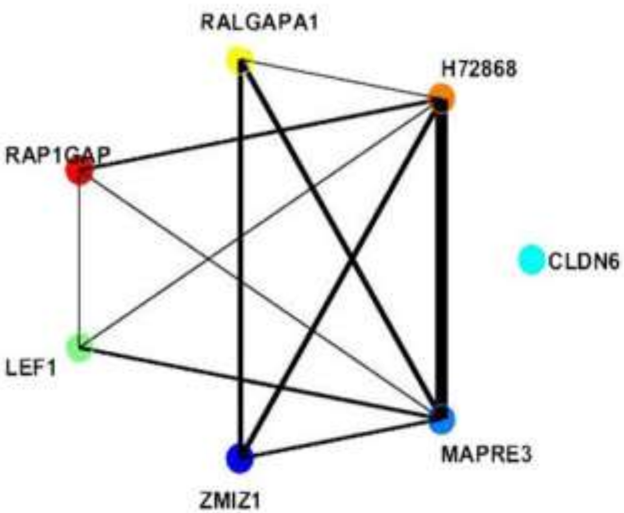
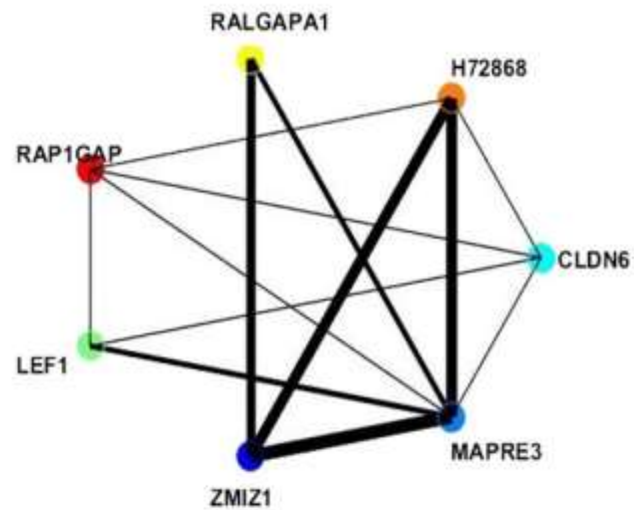
Using NeuCube to extract GRN from time series gene expression data







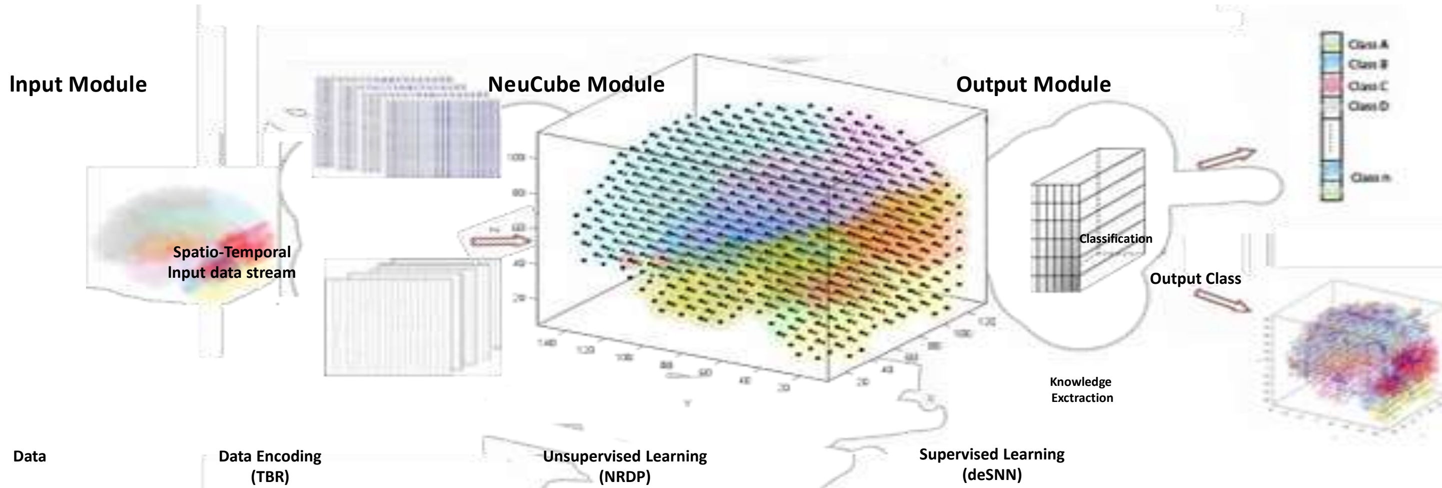




E.Capecci, J. L. Lobo, I.Lana, J. I. Espinosa Ramos, N.Kasabov, Modelling Gene Interaction Networks from Time-Series Gene Expression Data using Evolving Spiking Neural Networks, Evolving Systems, Springer, https://doi.org/10.1007/s12530-019-09269-6, 2019,

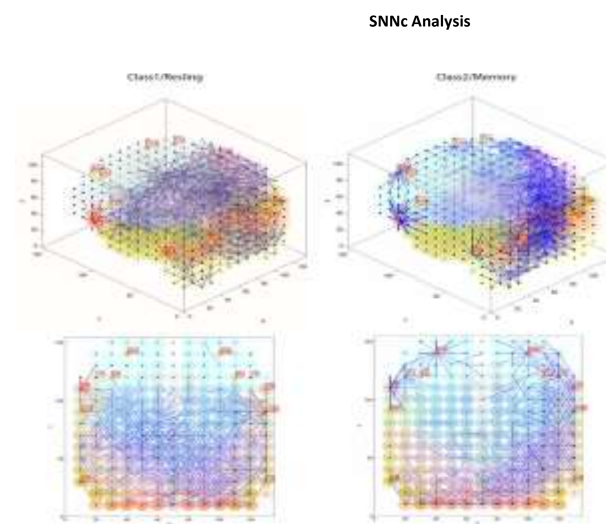
NeuroGenetic NeuCube

J.Espinosa-Ramos, E.Capecci, N.Kasabov, A Computational Model of Neuroreceptor-Dependent Plasticity (NRDP) Based on Spiking Neural Networks, IEEE Transactions on Cognitive and Developmental Systems, March, 2019, Vol. 11, Issue:1, 63-72, DOI: 10.1109/TCDS.2017.2776863



Neuroreceptors	Parameters	Values
AMPAR	θ_{A+}	0.901680
	k_A	0.542872
NMDAR	θ_{N+}	0.230013
	k_N	0.011660
GABA$_A$	θ_{Ga+}	0.755415
	k_{Ga}	0.385908
	P_{Ga}	0.7
GABA$_B$	θ_{Gb+}	0.795471
	k_{Gb}	0.110321
Inhibitory Rate	f_G	0.01

Table 1: NRDP learning rule parameters settings.



Design methodology for application oriented SNN

- Analysis of the type of data and possible solutions to the problem
- SNN reservoir design according to a template (brain template or other)
- Input data transformation into spike sequences;
- Mapping input variables into spiking neurons
- Deep unsupervised learning spatio-temporal spike sequences in a scalable 3D SNN reservoir;
- Supervised learning and classification of data over time;
- Dynamic parameter optimisation;
- Model visualisation
- Extracting deep knowledge from a trained SNN
- Adaptation on new data in an on-line/ real time mode;
- Extracting of modified knowledge
- Implementation of a SNN model: von Neumann vs neuromorphic hardware systems

NeuCube development environment for SNN system design for TSD

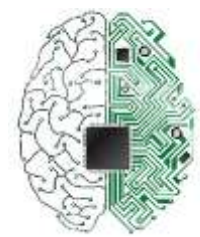
nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

NeuCube Implementations

Software versions:

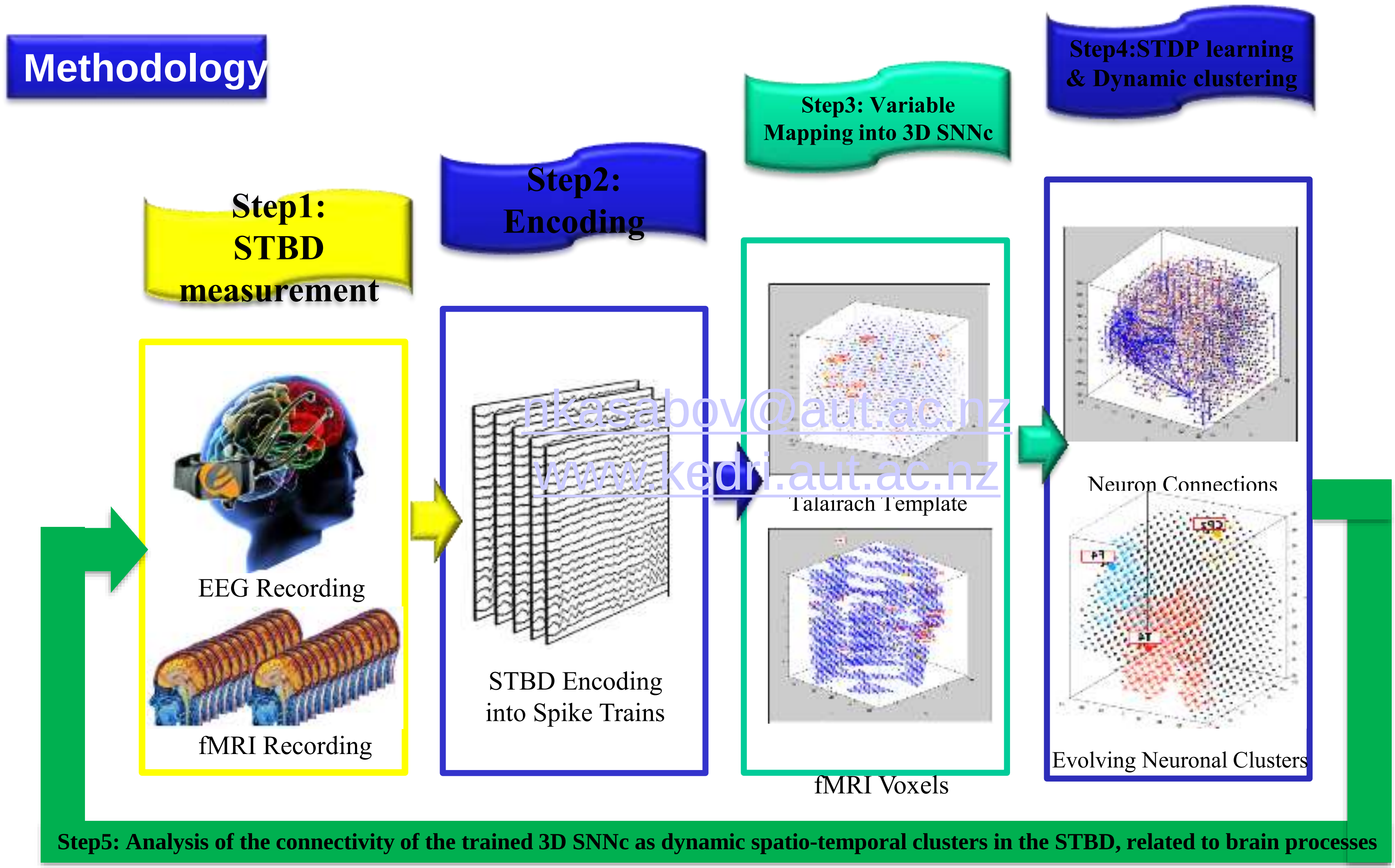
Cloud

Hardware-specific versions:



Future development: NeuCube chips for AI applications

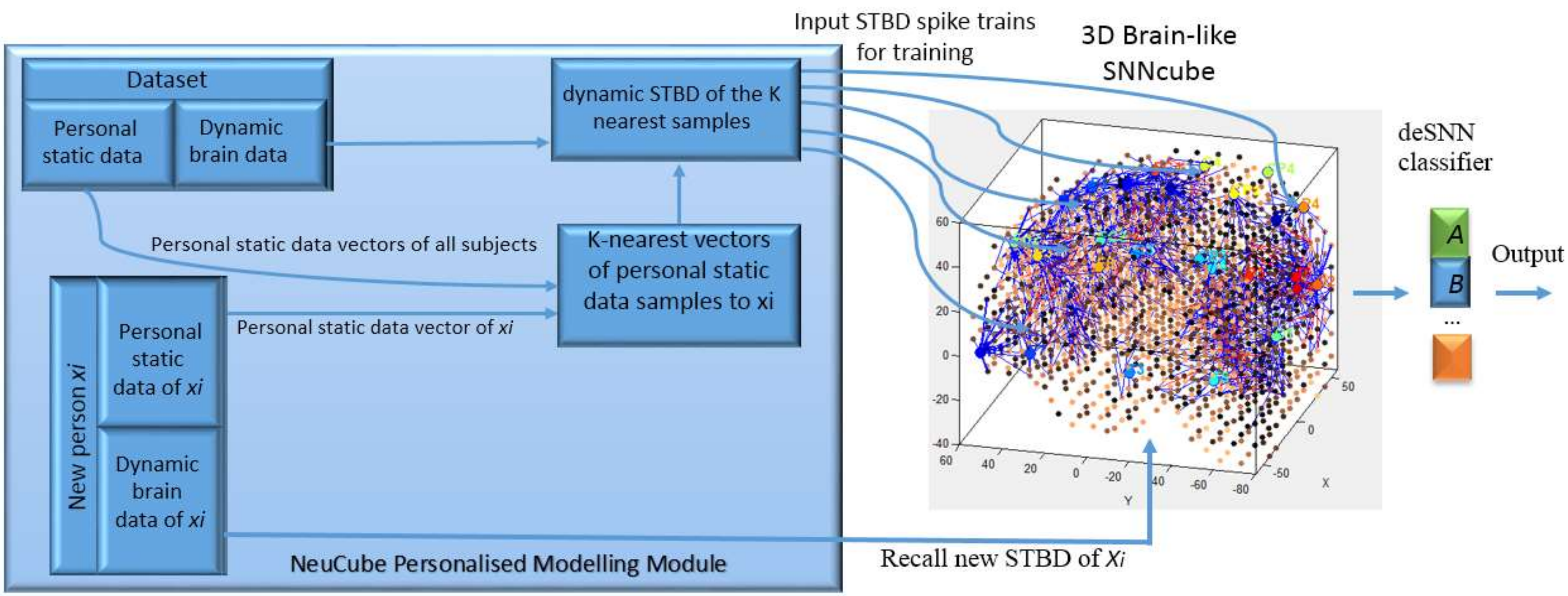
Spatio-temporal brain data (EEG, fMRI, integrated)



Personalised modelling for integrated static and dynamic data. Applications in neuroinformatics.

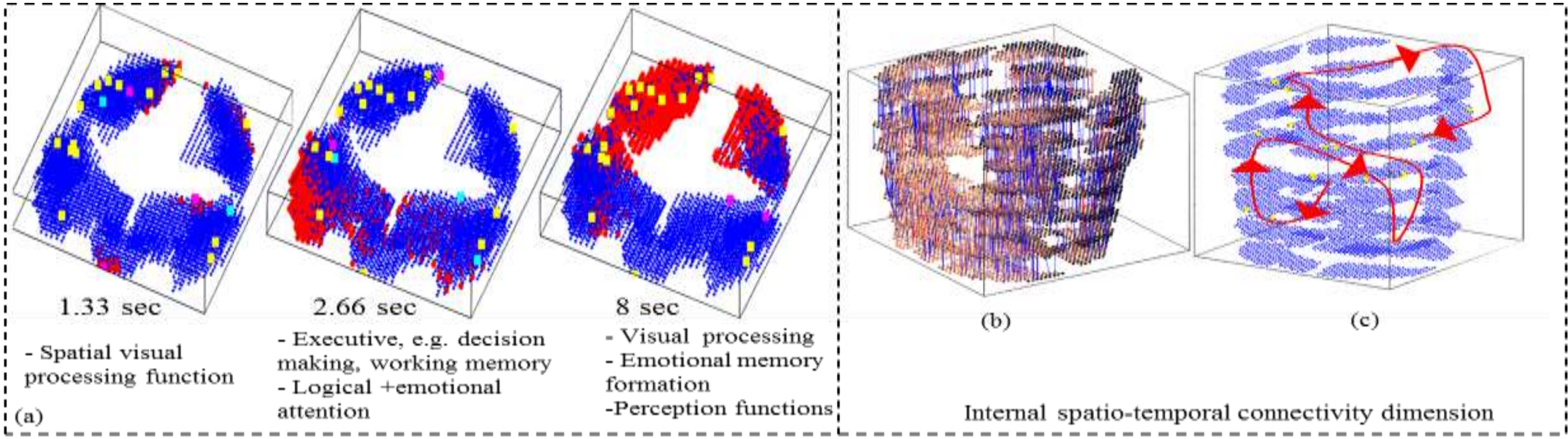
Doborjeh, M., and Kasabov, N., IEEE WCCI/IJCNN, 2016 (Response to treatment of drug addicts using clinical and EEG data)

M. Doborjeh, N. Kasabov, Z. Doborjeh, R. Enayatollahi, E. Tu, A. H. Gandomi, Personalised modelling with spiking neural networks integrating temporal and static information, Neural Networks, 119 (2019),162-177.



Methods	NeuCube-Personalised modelling	NeuCube- Global modelling
Classification accuracy of class M versus class OP in %	Averaged over 47 trained PSNN models: 93.61	One trained SNN model using all subjects and tested via leave-one-out method: 79.00

NeuCube for learning and knowledge representation of cognitive fMRI



Only three snapshots of learning of 8-second fMRI data in a NeuCube model when a subject is reading a negative sentence (time is in seconds) (the left 3 figures); Internal structural pattern represented as spatio-temporal connectivity in the SNN model trained with 8-second fMRI data stream; a functional pattern represented as a sequence of spiking activity of clusters of spiking neurons in a trained NeuCube model (the right most figure).

TSK representation extracted from a trained SNN model related to modelling fMRI data when a person is reading a negative sentence

IF (a person is reading a negative sentence)

THEN (the following events are triggered in space and time in a trained SNN model)

E1: Vision, in the Spatial Visual Processing area, at time T1,

AND E2: Decision making function, in the Decision making and working memory, at time T2,

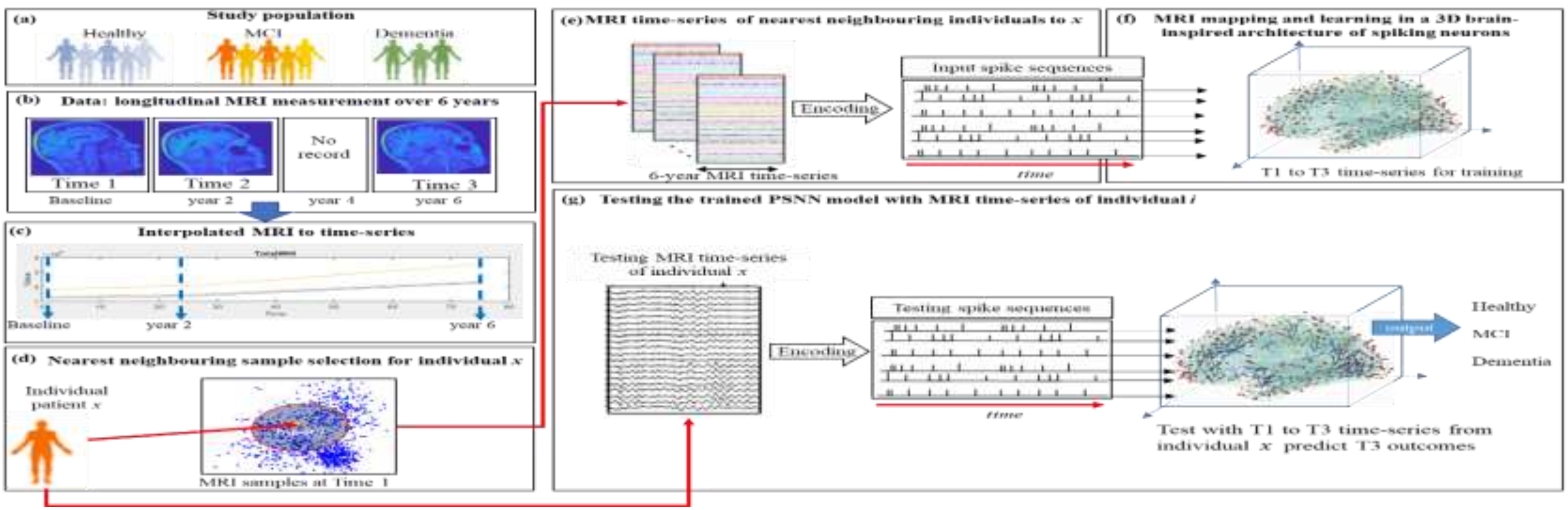
AND E3: Logical and Emotional Attention function, in the Attentional brain area, at time T3

AND E4: Emotional functions, in the Emotional brain area, at time T4

AND E5: Emotional memory formation function, in the Memory brain area, at time T5

AND E6: Perception function, Perception brain area, at time T6.

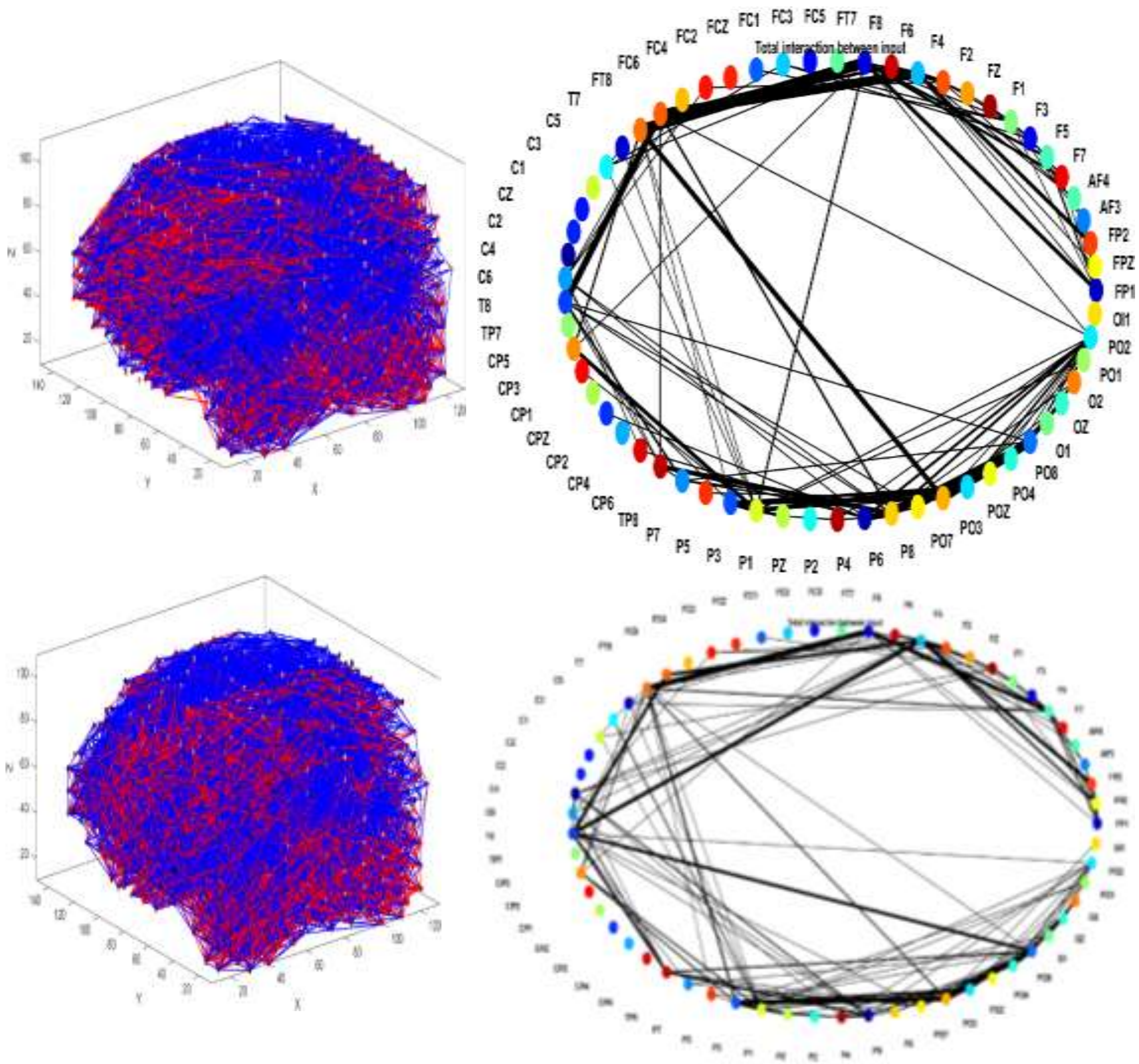
M. Doborjeh et al, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study of Dementia, Neural Networks, vol.144, Dec.2021, 522-539, https://doi.org/10.1016/j.neunet.2021.09.013,



Experiment	Predict	H	MCI	D	Accuracy	Sensitivity	Specificity	Total accuracy	F-score	Parameters
Classification	H	91	0	0	97%	100%	96%	95%	94%	Learning rate: 0.02 Mod: 0.5 Drift:0.22
	MCI	3	65	1	97%	97%	97%			
	D	0	2	13	93%	98%	92%			
Two-year ahead prediction	H	88	2	0	94%	93%	97%	91%	89%	Learning rate: 0.02 Mod:0.5 Drift:0.22
	MCI	4	63	2	94%	94%	94%			
	D	2	2	12	86%	86%	97%			
Four-year ahead prediction	H	73	11	1	78%	82%	78%	73%	67%	Learning rate: 0.01 Mod:0.4 Drift:0.25
	MCI	15	46	3	69%	82%	68%			
	D	6	10	10	71%	88%	76%			
	Sum	94	67	14						

Modelling brain data in NeuCube to better understand depression

D Shah, G Wang, M Doborjeh, Z Doborjeh, N Kasabov, ICONIP 2019, Sydney 12-15.12.2019 (submitted)



Visualization for eyes open state: (a) Depressed NeuCube connectivity and FIN; (b) Healthy connectivity and FIN

Different patterns of interactions are observed as TSK:

- A strong triangular connection between F4-T8-PO8 across the right hemisphere in the healthy group is absent in the depressed group (less interaction between PO8 and T8).
- There are more right frontal interactions in the depressed group[F4, F6, F8, FC4, FC6, and FC8 as compared to the healthy group indicating more negative stimuli in the brain. FC4 is totally inactive in the healthy group.
- Long-range interaction between FT8-PO7 and F8-P1 in the depressed group.

5. The NZ-Singapore project on neurogenetic modelling for diagnosis and prognosis in mental health

Multi-modal data of subjects of UHR of psychoses:
- genetic;
- gene pathways;
cognitive, clinical, MRI longitidinal

Dr Wilson Goh
School of Biological Sciences
Nanyang Technological University

Dr Jimmy Lee
Lee Kong Chian Medical School
Institute of Mental Health

Professor Limsoon Wong
School of Computing
National University of Singapore

Samuel Tan
PhD candidate
NTU

The NZ and NTU (UK) team

Professor Nikola Kasabov

Science Leader

Auckland University of Technology

AUT UNIVERSITY

Dr Maryam Doborjeh (PI)

Auckland University of Technology

AUT UNIVERSITY

Dr Zohreh Doborjeh (AI)

The University of Auckland

THE UNIVERSITY OF AUCKLAND NEW ZEALAND

Professor Edmund Lai (AI)

Auckland University of Technology

AUT UNIVERSITY

Dr Margaret Williams (AI and VM researcher)

Auckland University of Technology

AUT UNIVERSITY

Prof Alexander Sumich

Research consultant

NOTTINGHAM TRENT UNIVERSITY

Sugam Budhraja

PhD Candidate

AUT

Balkaran Singh

Research Associate

AUT

POUROTO NGAROPO

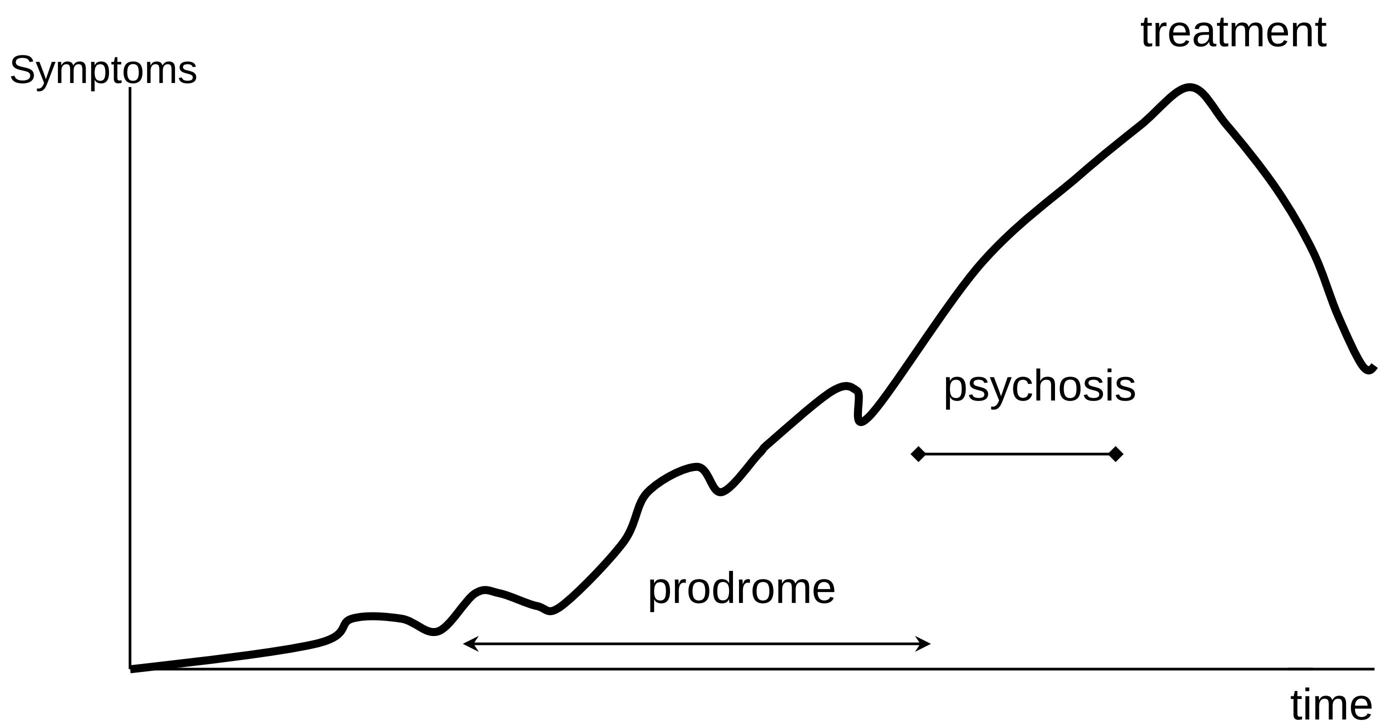
Māori PhD Candidate

AUT

KEDRI

CAN WE PREDICT PSYCHOSIS?

We know that psychotic disorders, such as schizophrenia, are almost always preceded by a prodromal phase. Can we detect this?



A "prodrome" is difficult to recognize because of its non-specific symptoms

6. Conclusion and future directions

Advantages of using SNN and neuromorphic systems:

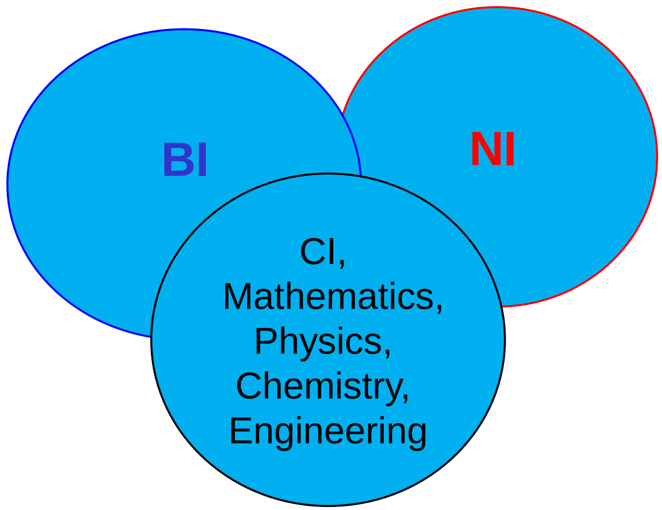
1. Self-organised, evolvable structure (no fixed number of layers/neurons, etc.)
2. *Event* based (asynchronous), fast, incremental, potentially “life-long” learning.
3. Temporal (spatio-temporal) associations learned.
4. Interpretability, e.g. TSK representation
5. Low computational power
6. Fault tolerance

Problems and limitations of SNN

- Sensitive to parameter values
- Large number of parameters to be optimised
- No rigid theory yet.

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

Future directions: Integration of Bioinformatics and Neuroinformatics knowledge, methods and data



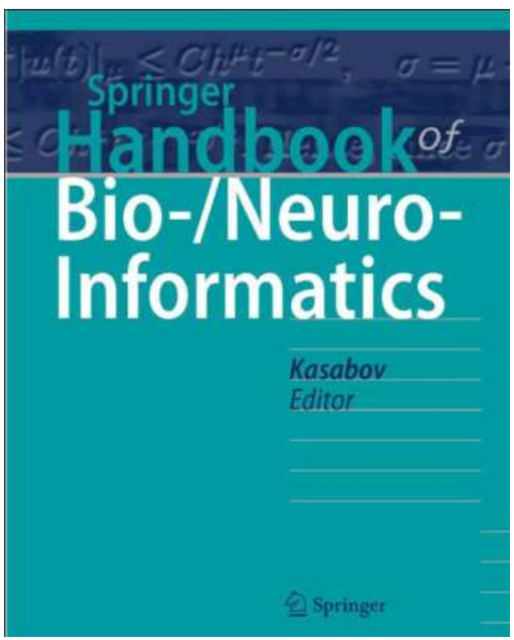
New BI-, and hybrid computational methods and systems

- Modelling emergence of symbolic representation
- Multimodal and multi-model SNN systems
- Quantum-inspired computation: Spikes as q-bits - in a superposition of 1/0
- www.mindthegap.ai
-

New Data Technologies

Transparent AI

- Real time event prediction systems
- Embedded systems
- Mental health evaluation systems
- Neurological prosthetics
- Brain-inspired SNN for quantum computation



nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

International BI-SNN community is growing

IEEE CIBCB 2021

Thank you and Questions?

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk https://academics.aut.ac.nz/nkasabov