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https://minisymp2026.uni-obuda.hu/en

Brain Inspired Computation for Generative-, Predictive-, Agentic AI and AGI: Methods, Systems, Applications

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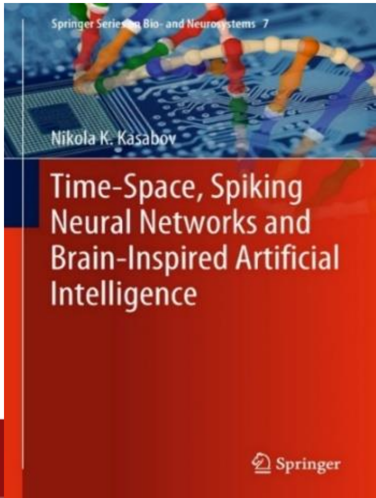
N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), https://www.springer.com/gp/book/9783662577134



1. Generative, predictive and agentic AI: All they need is neural networks and more specifically- brain-inspired neural network architectures

What are the current AI trends:

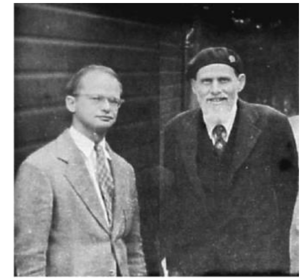
- *Generative AI*, such as LLM generate new information based on pretrained neural network models on stored data. Static data modelling.

- *Predictive AI* take into account most recent data to predict events in a future time. They are suitable for on-line personalized predictive modelling to predict an individual

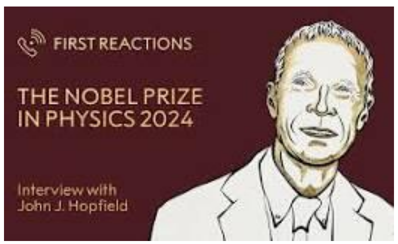
- A*gentic AI* relates to the design of AI agents that are autonomous entities, able to evolve itself from data, make decisions, take actions, adapt to the environment, communicate with other agents. They are also based on neural networks.

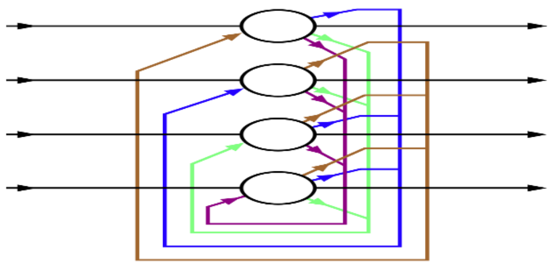
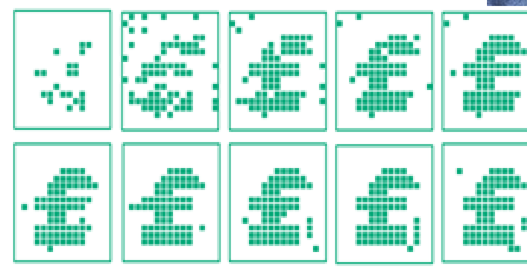
- *AGI* is an AI system with general, human-level intelligence that can learn and perform any intellectual task across domains.

2. What are the current NN trends and why brain-inspired computation?



A rich history of ANN:

- 1943, McCulloch and Pitts neuron (photo 1949)→
- 1962, Rosenblatt – Perceptron
- International Neural Network Society (INNS)
- 1971- 1986, **Amari, Rumelhart, Werbos, Hinton**: Multilayer perceptron; Self-organising maps (SOM) Kohonen; Adaptive resonance theory (Grossberg)
- Associative Memories: Amary, Hopfield,…
- 



- “*The Hopfield network provides a simple model of an associative memory in a neuronal structure. It is, however, based on highly artificial assumptions, especially the use of formal two-state neurons or graded-response neurons*”,
- International Neural Network Society (INNS)

Current NN trends

- *Transformers (not brain-inspired, yet….)*
- *Brain-inspired computation: Spiking Neural Networks*:
- *B*rain-inspired SNN architectures: e.g. N*euCube*

Why brain-inspired computation:

The human brain, the most sophisticated product of the evolution, is a live-long learning system for knowledge representation and knowledge transfer.

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).

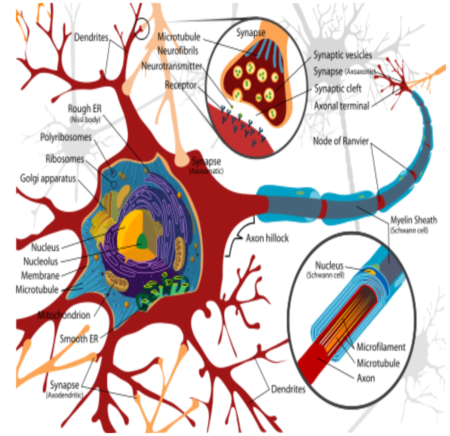
Temporal data at different time scales:

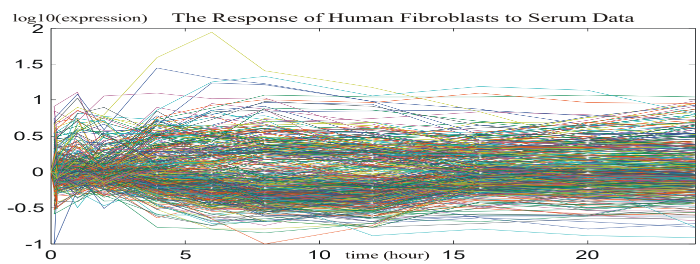
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

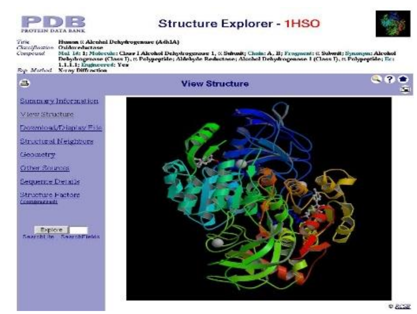
Knowledge is represented as deep spatio-temporal patterns that can evolve/adapt over time.

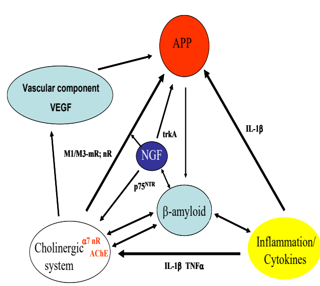
Many levels of rich information processing in the brain

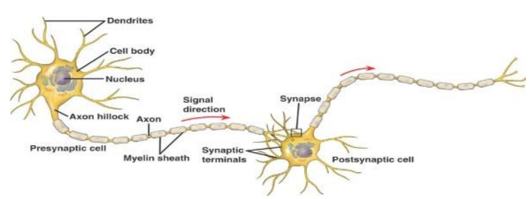
- Quantum
- Genetic
- Proteomic
- Neuronal
- Cognitive
- Consciousness
- Human social interaction

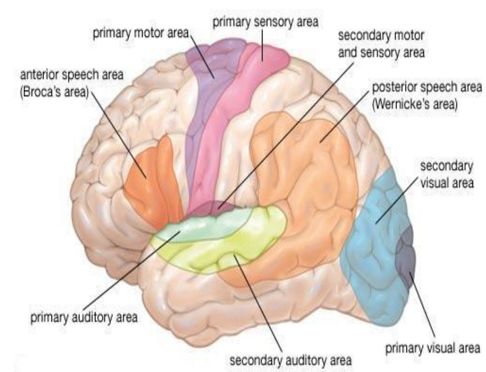




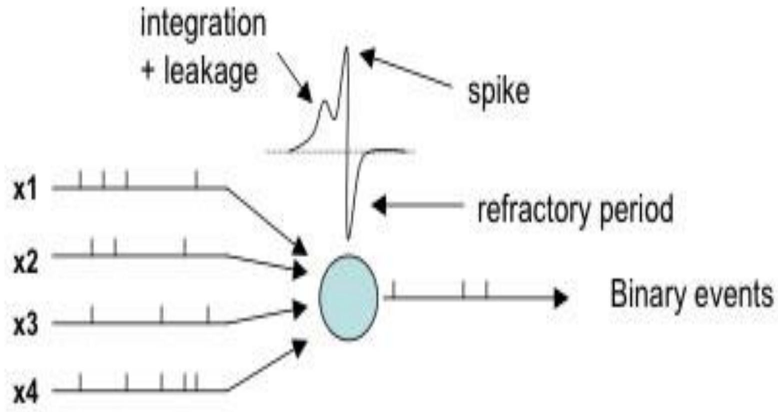


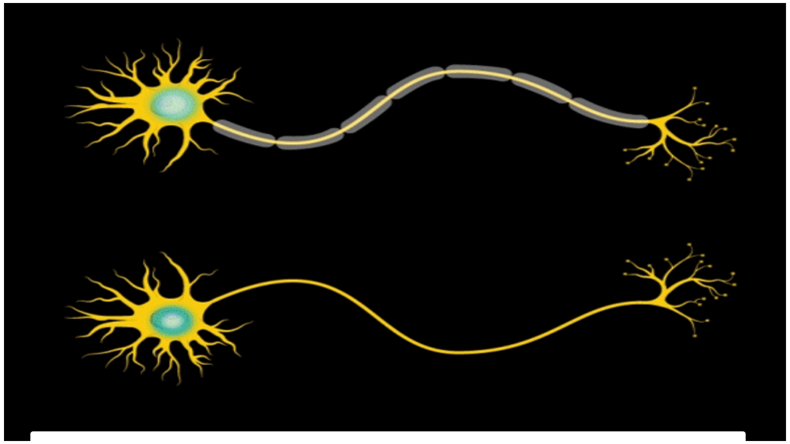


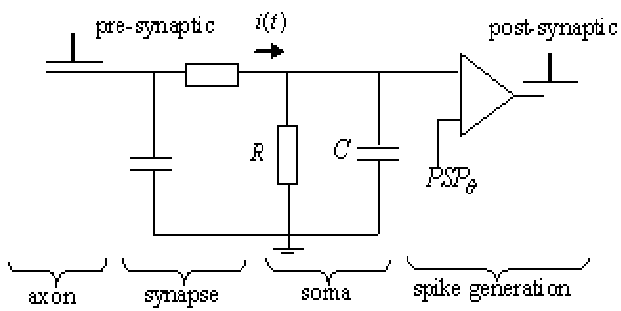


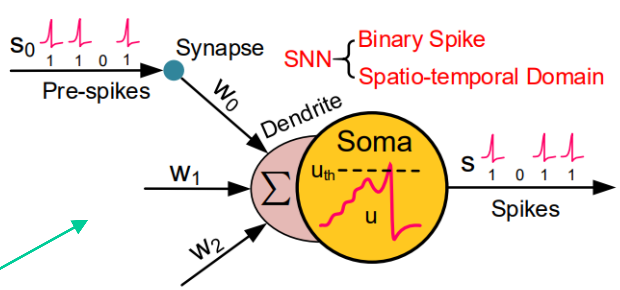


Spiking neural networks



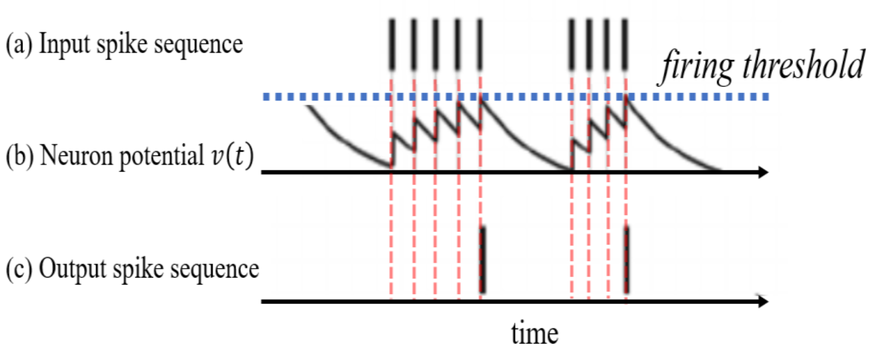






Models of a spiking neurons and SNN

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

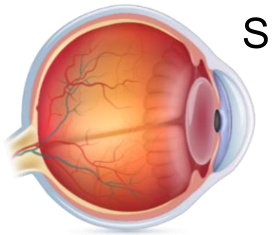


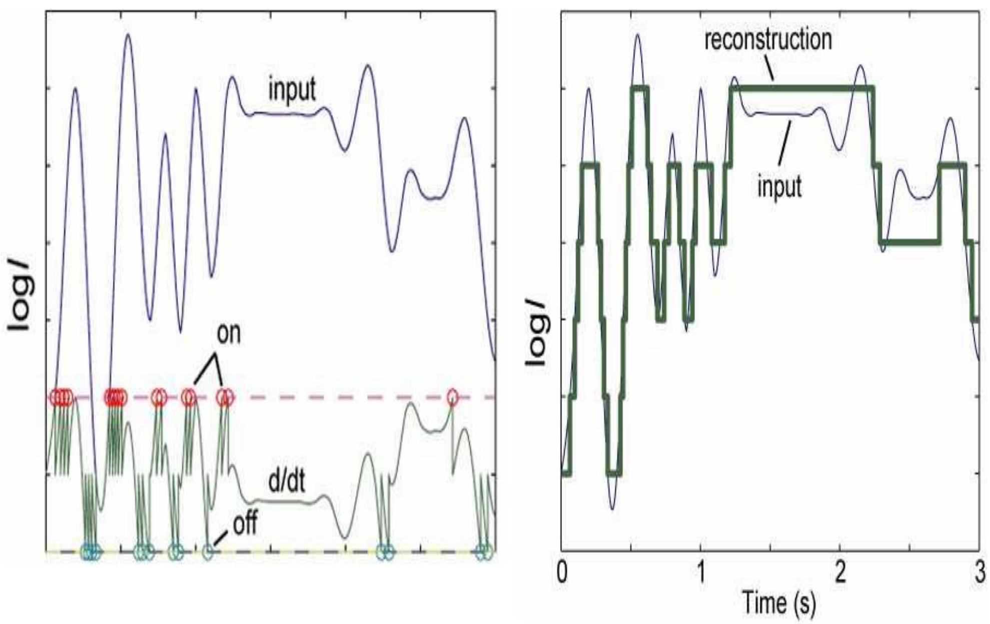
Spike encoding methods

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

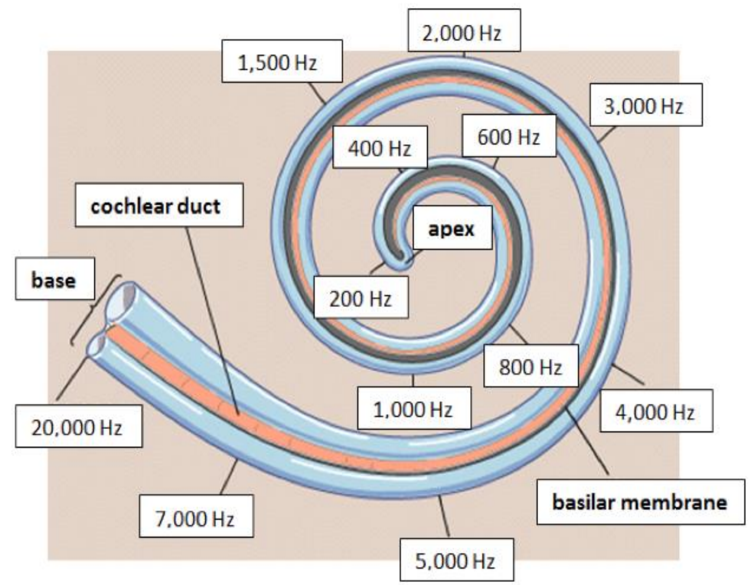
Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128: Retinotopic

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





Threshold-based encoding – retinotopic mapping for spatio-temporal data

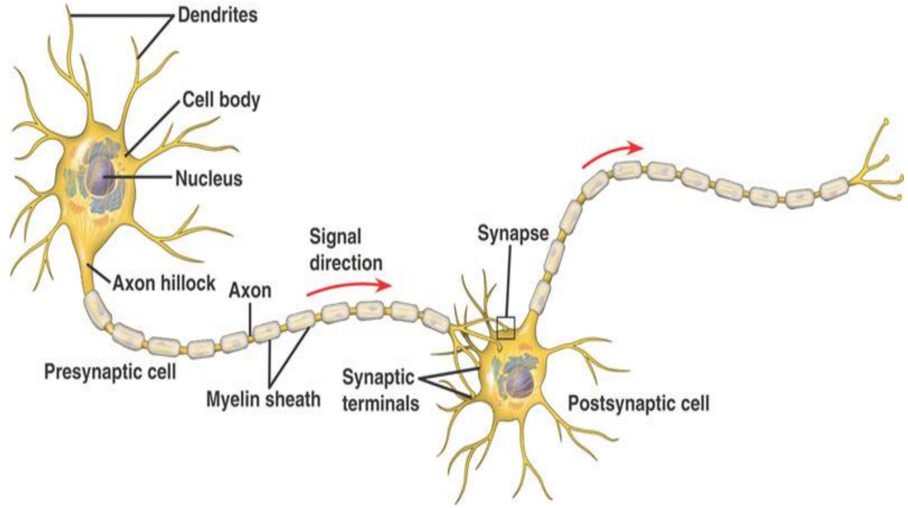


Tonotopic organization of the cochlea for spectro-temporal data

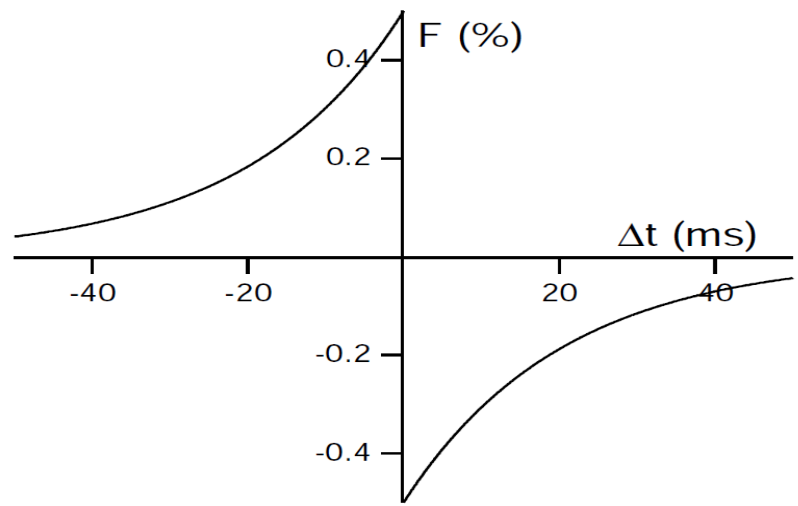
https://sites.google.com/site/jayanthinyswebite

Methods for unsupervised learning in SNN

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



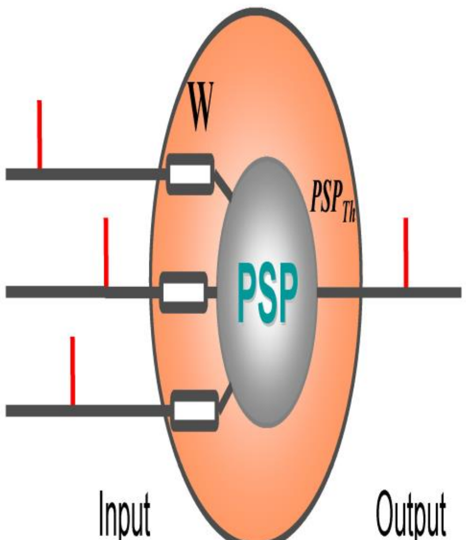
- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from data.
- Variations of the STDP
- Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD: $\Delta t = tpre - tpost$

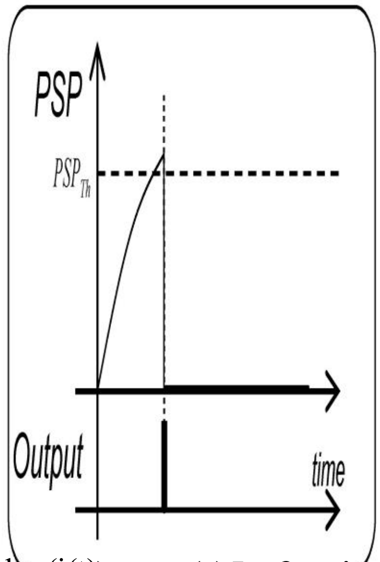


- Predictive coding !!!

Methods for supervised learning in SNN – predictive modelling

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





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

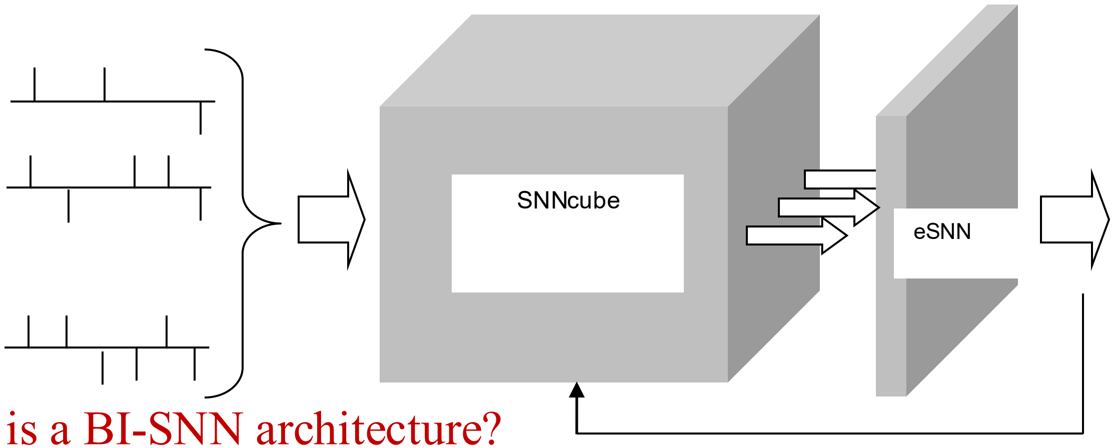
$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

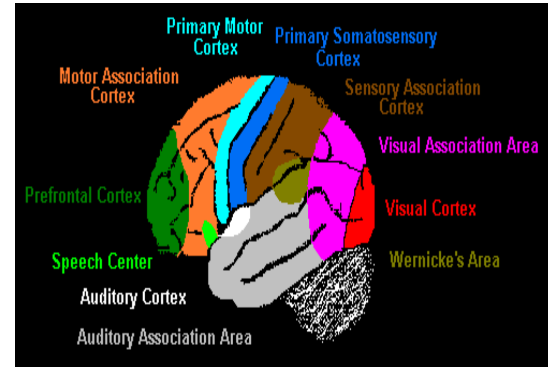
PSP max (T) = SUM [($m^{\mathrm{order}(j(t))}$) $w_{j,i}(t)$], for j=1,2.., k; t=1,2,...,T;

PSP_{Th}=C. PSPmax (T)

- Earlier incoming spikes are more important (carry more information)
- Early output spiking can be achieved, depending on the parameter C. , for predictive modelling

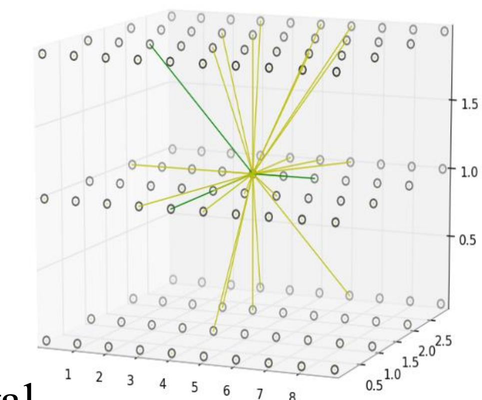
From SNN to brain-inspired SNN architectures





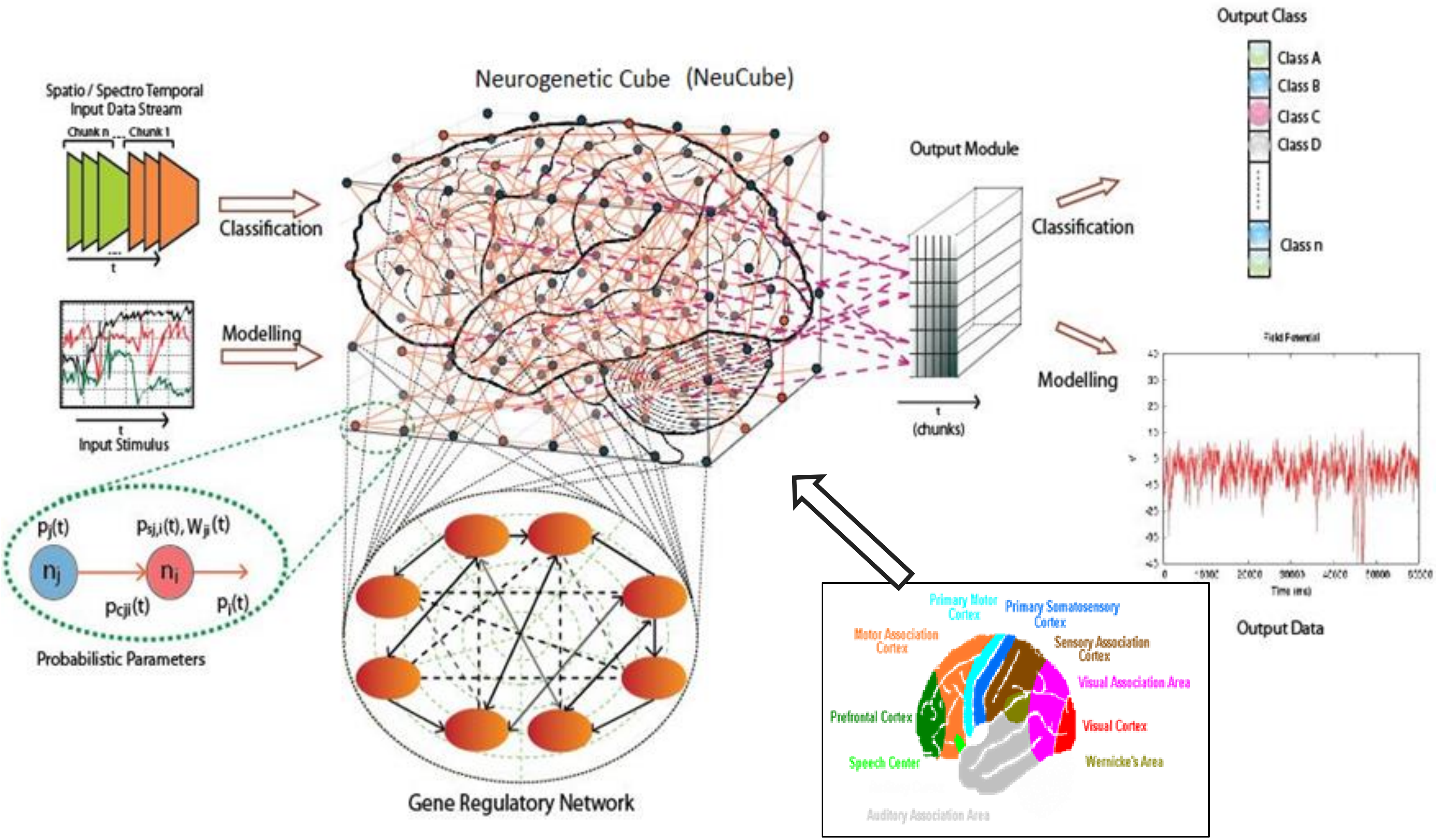
What is a BI-SNN architecture?

- 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 3D NeuCube BI-SNN Architecture

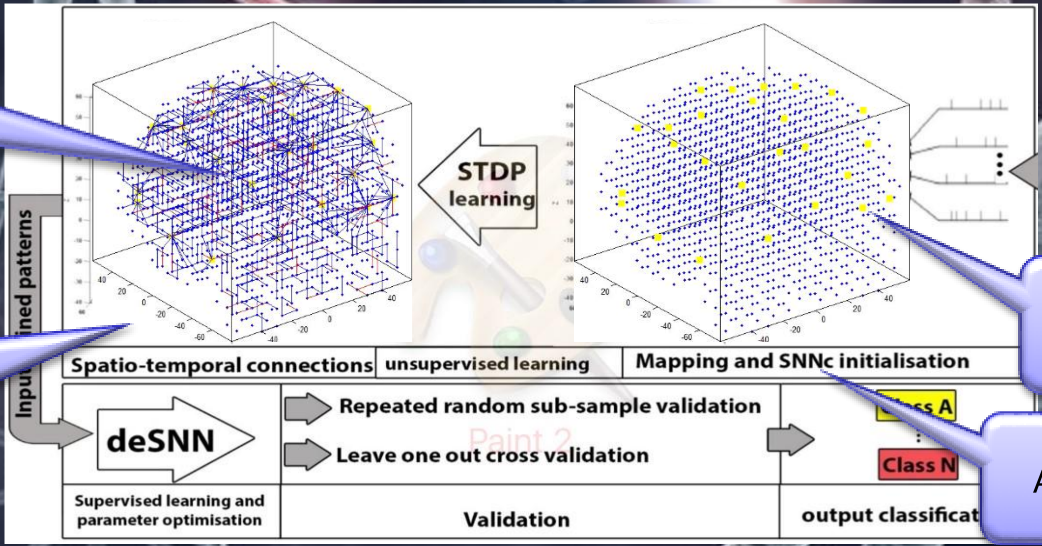


N. Kasabov, NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

Deep learning in NeuCube

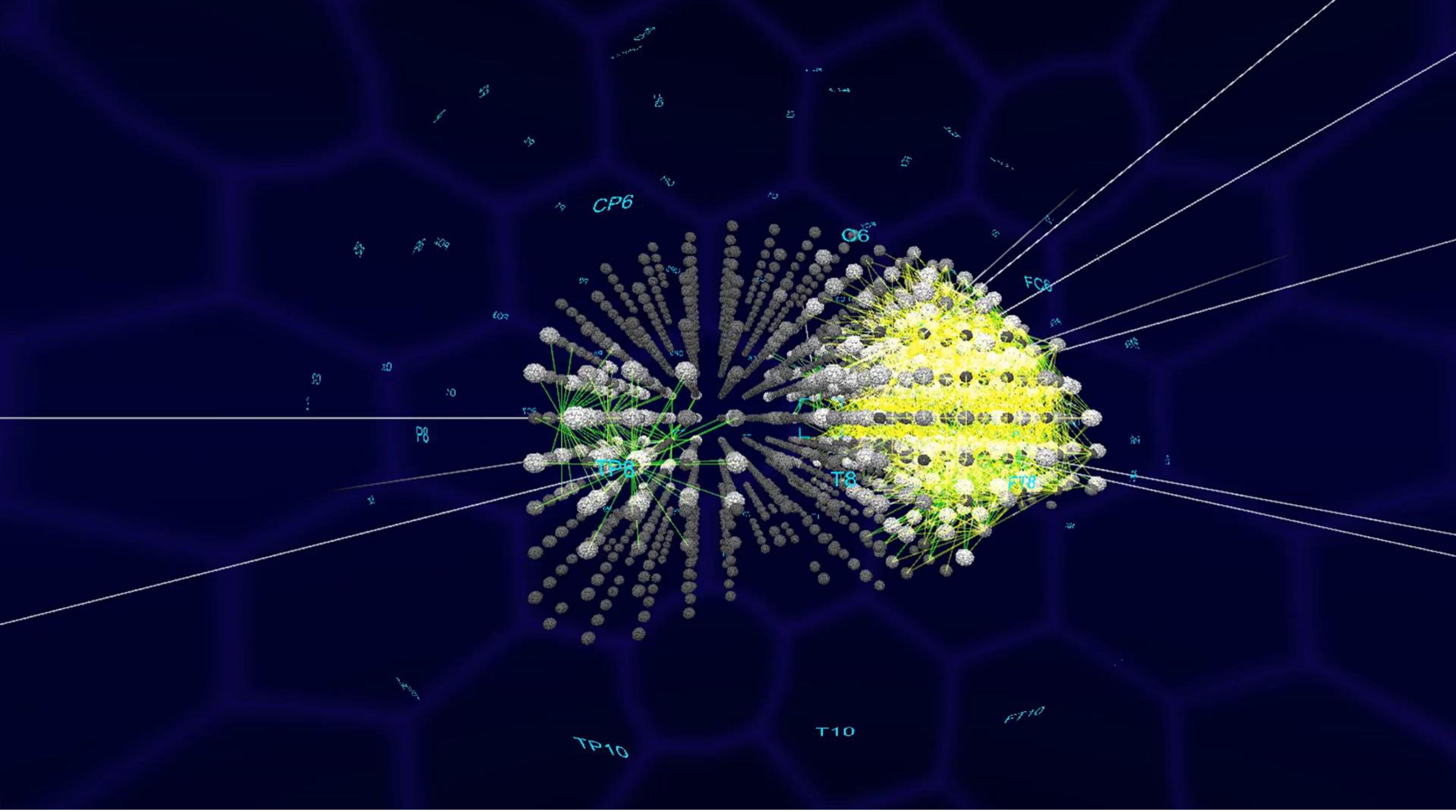
Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created



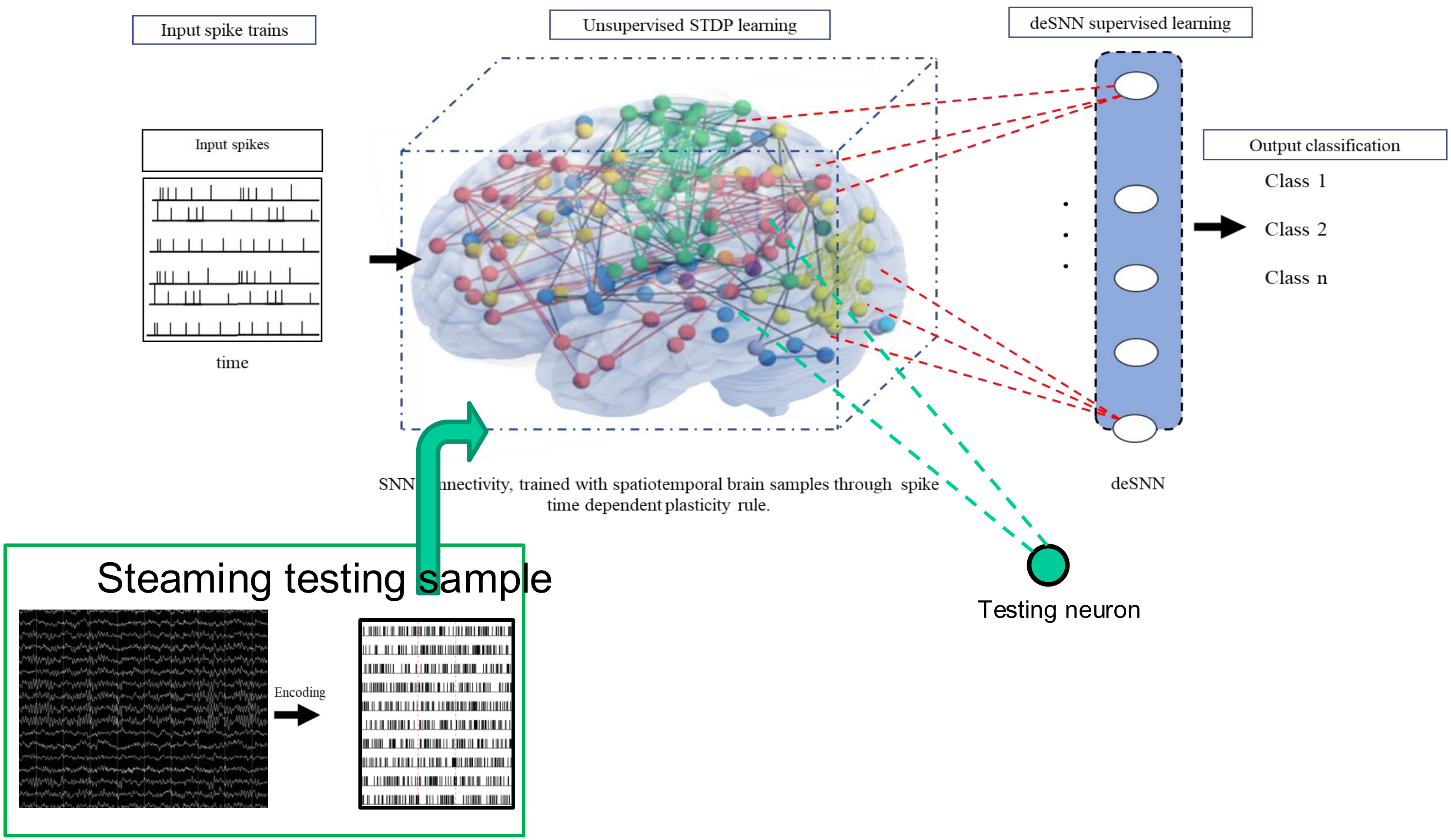
Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning



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.

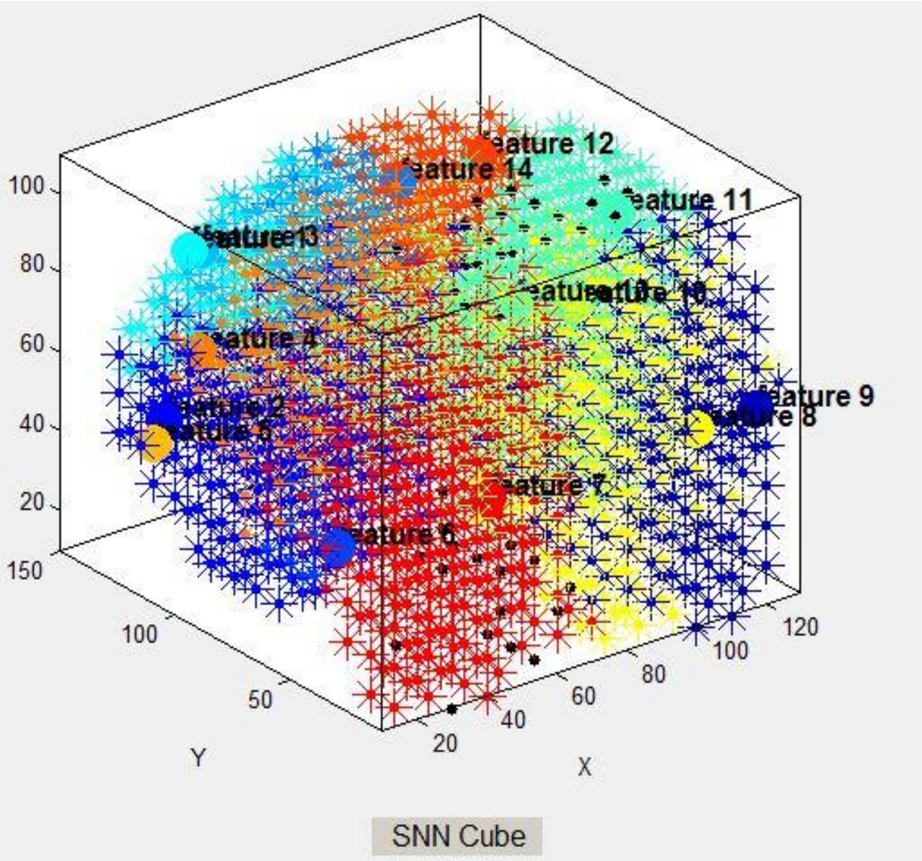
Supervised learning and classification of data over time

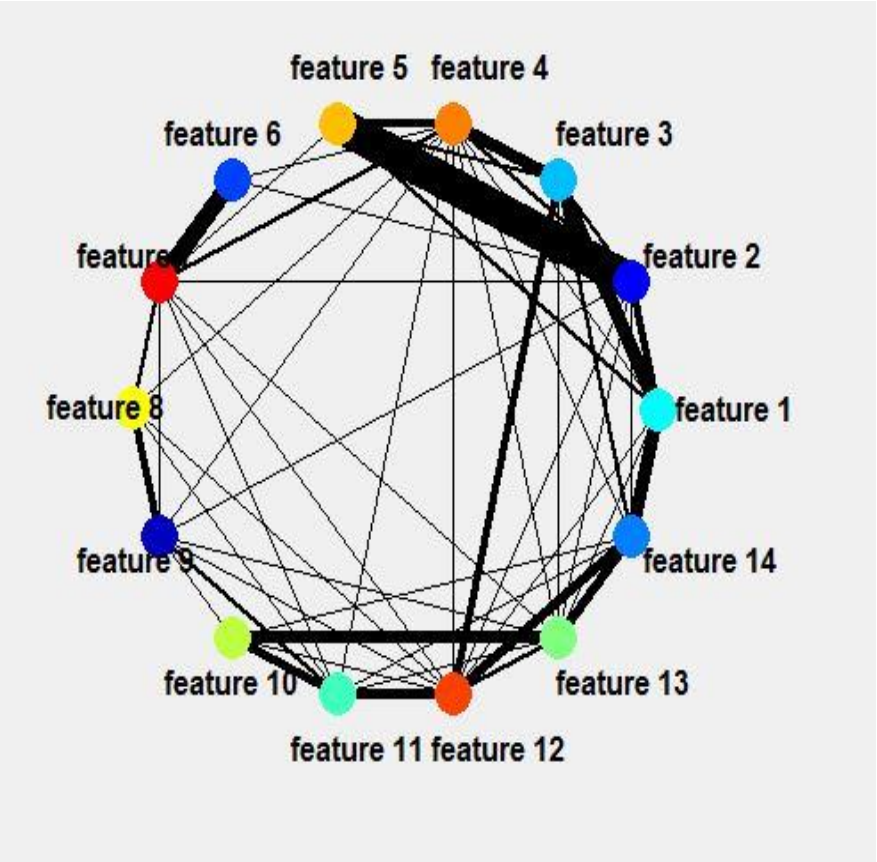


Explainability: Capturing time-space knowledge as evolving spatio-temporal associative memories (eSTAM)

- Clusters of highly connected neurons to input neurons;
- Clusters of spiking activity spread from input neurons ;

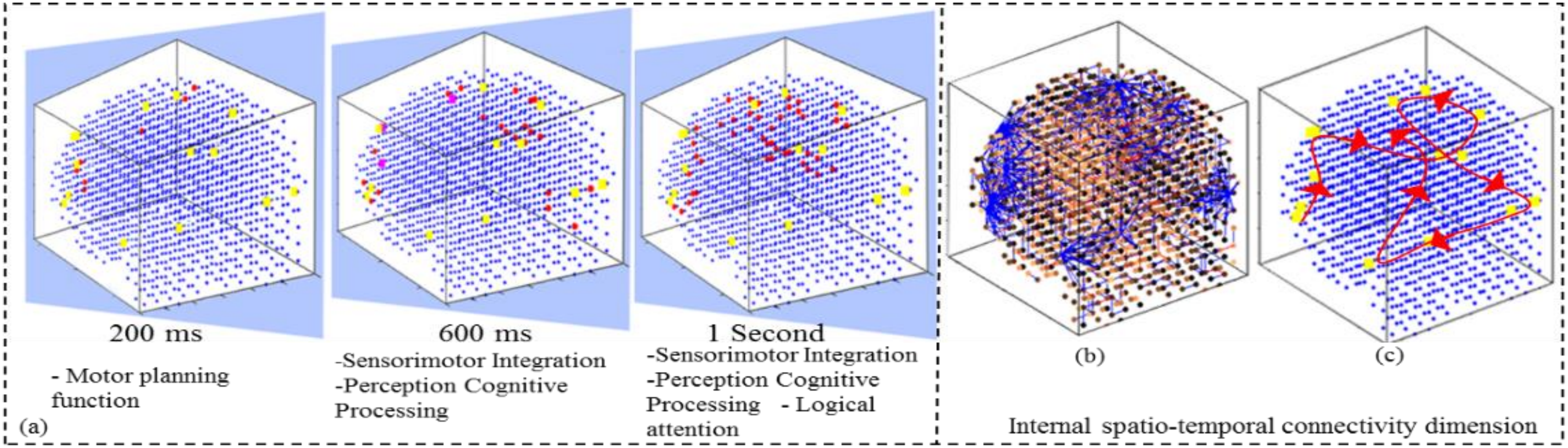
- A dynamic graph of information exchange between spatially distributed clusters around the inputs





BI-SNN can learn evolving spatio-temporal associative memories (eSTAM)

Example: A SNNcube that learns EEG data from 14 EEG channels when a person is moving a wrist. The sequence of connections of the trained SNNcube can be interpreted as TSR. The figure is showing only few aggregated events (out of 1000, one at each millisecond EEG data).



TSR representation of time and space aggregated events:

IF (a person is moving a hand up)

THEN (the following brain functions are activated in space and time):

E1: Planning, in the Motor Planning functional brain area, time T1,

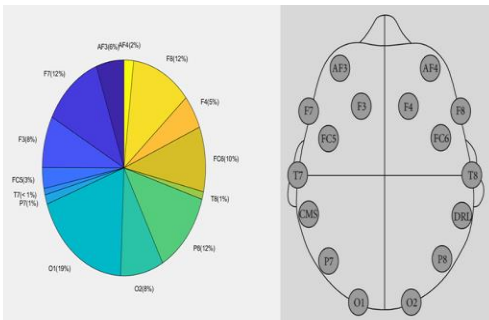
AND E2: Sensorimotor integration, in the Sensorimotor integration brain area, at time T2

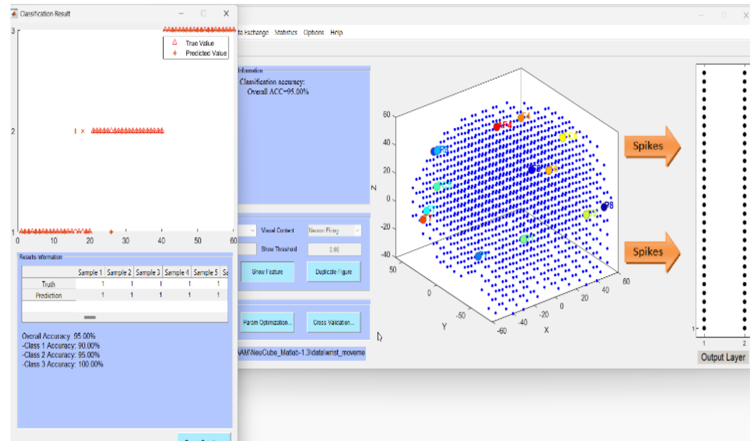
AND E3: Perception, in the Perception Cognitive brain area, time T3

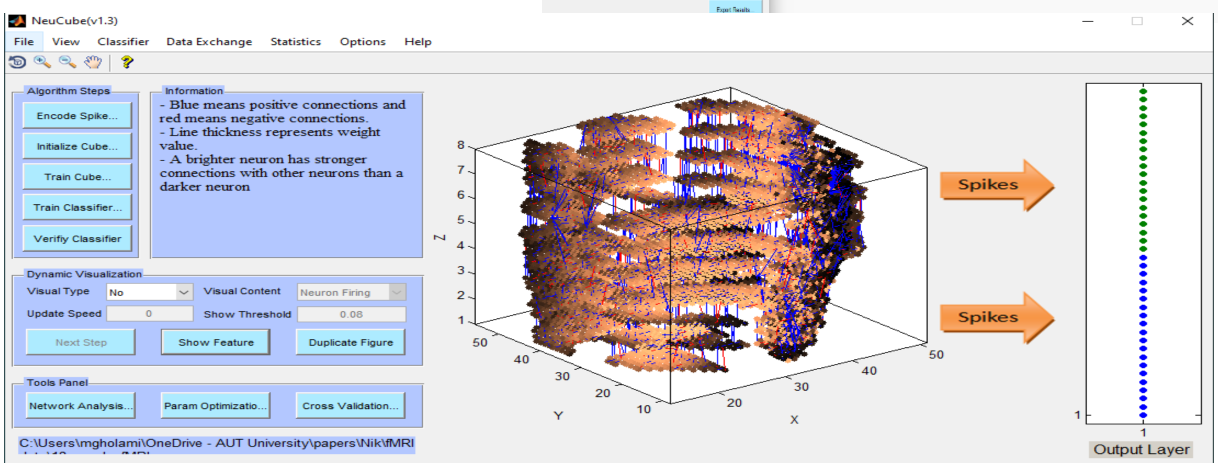
AND E4: Attention, in the Logical Attention brain area, time T4.

Predictive eSTAMs from neuroimaging data

N. Kasabov, H. Bahrami, M. Doborjeh, and A. Wang, "Brain inspired spatio-temporal associative memories for neuroimaging data: EEG and fMRI, *MDPI Bioengineering*, 2023, *10* (12), 1341
https://doi.org/10.3390/bioengineering10121341, www.mdpi.com/journal/bioengineering







Current work: Predictive systems trained on both modalities and recalled only on a single one.

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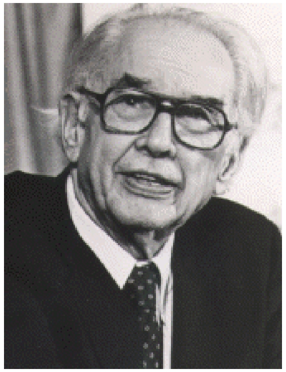
NeuCube development environment for neuromorphic AI

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

SNN Implementations



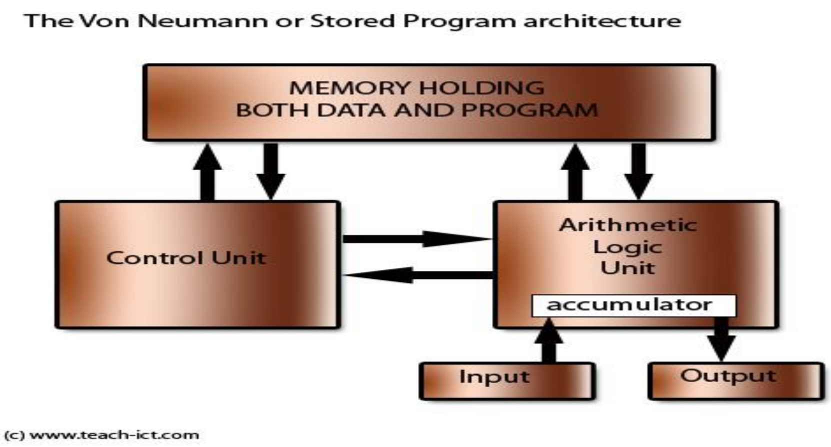
Flexible software/hardware implementations of SNN, that can use different platforms:

- von Neumann architectures, using bit information representation (first ABC machine by Atanassov and Berry)

- Neuromorphic architectures, using *spikes* (bits at times).

- Quantum computers, using *q-bits* (bits in a superposition).

- Hybrid implementation



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.

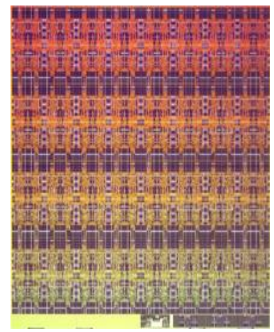
Neuromorphic platforms

SpiNNaker
Biologically Inspired Massively Parallel Architectures

IBM TrueNorth

intel Loihi

BrainScaleS



Biological realism

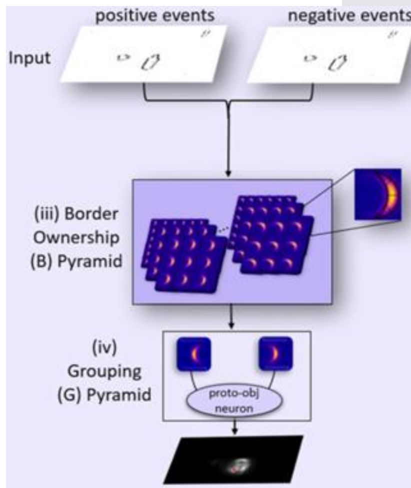
Ease of use

Many-core (ARM) architecture Optimized spike communication network Programmable local learning x0.01 real-time to x10 real-time	Full-custom-digital neural circuits No local learning (TrueNorth) Programmable local learning (Loihi) Exploit economy of scale x0.01 real-time to x100 real-time	Analog neural cores Digital spike communication Biological local learning Programmable local learning x10.000 to x1000 real-time

Adopted from: S. B. Furber, F. Galluppi, S. Temple, and L. A. Plana, “The spinnaker project,” Proceedings of the IEEE, vol. 102, no. 5, pp. 652–665, 2014.

Example1: Robot vision

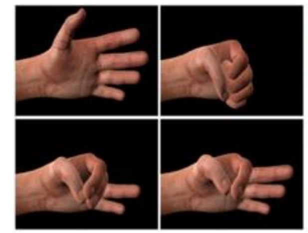
- Event-driven attentive system on iCub
  - SpiNNaker as neural substrate
- Event-driven vision sensors
- Produces saliency maps
- Average 16ms latency to produce a usable saliency map

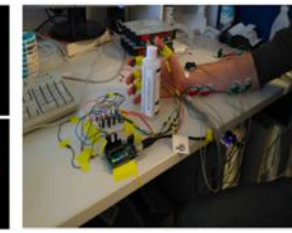


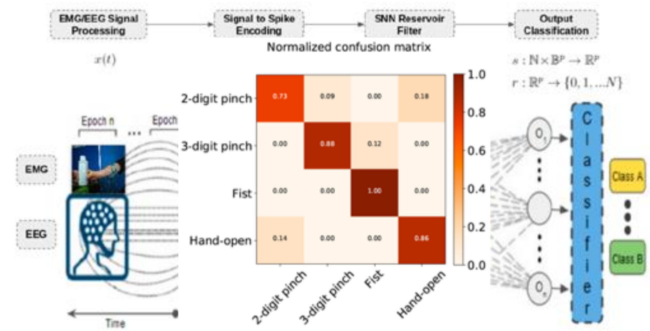
Adopted from: D'Angelo, G., Perrett, A., Iacono, M., Furber, S & Bartolozzi, C, *Event driven bio-inspired attentive system for the iCub humanoid robot on SpiNNaker.* IOP Neuromorphic Computing and Engineering 2 (2022).

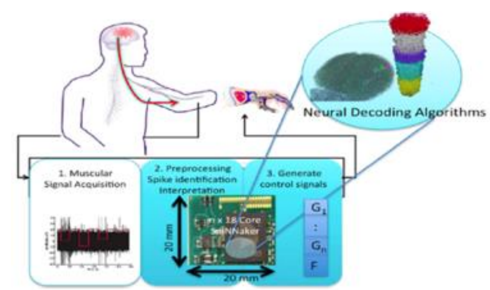
Example 2: NeuCube on SpiNNaker to predict hand movement of a prosthetic hand

- Classification of electrical signals
  - real-time control of active prosthetics
  - low power
- Record electrical activity of participants during prescribed hand movements
- Classification with reservoir of spiking neurons
  - encode signals into spikes
  - train network (unsupervised)
  - readout to classify









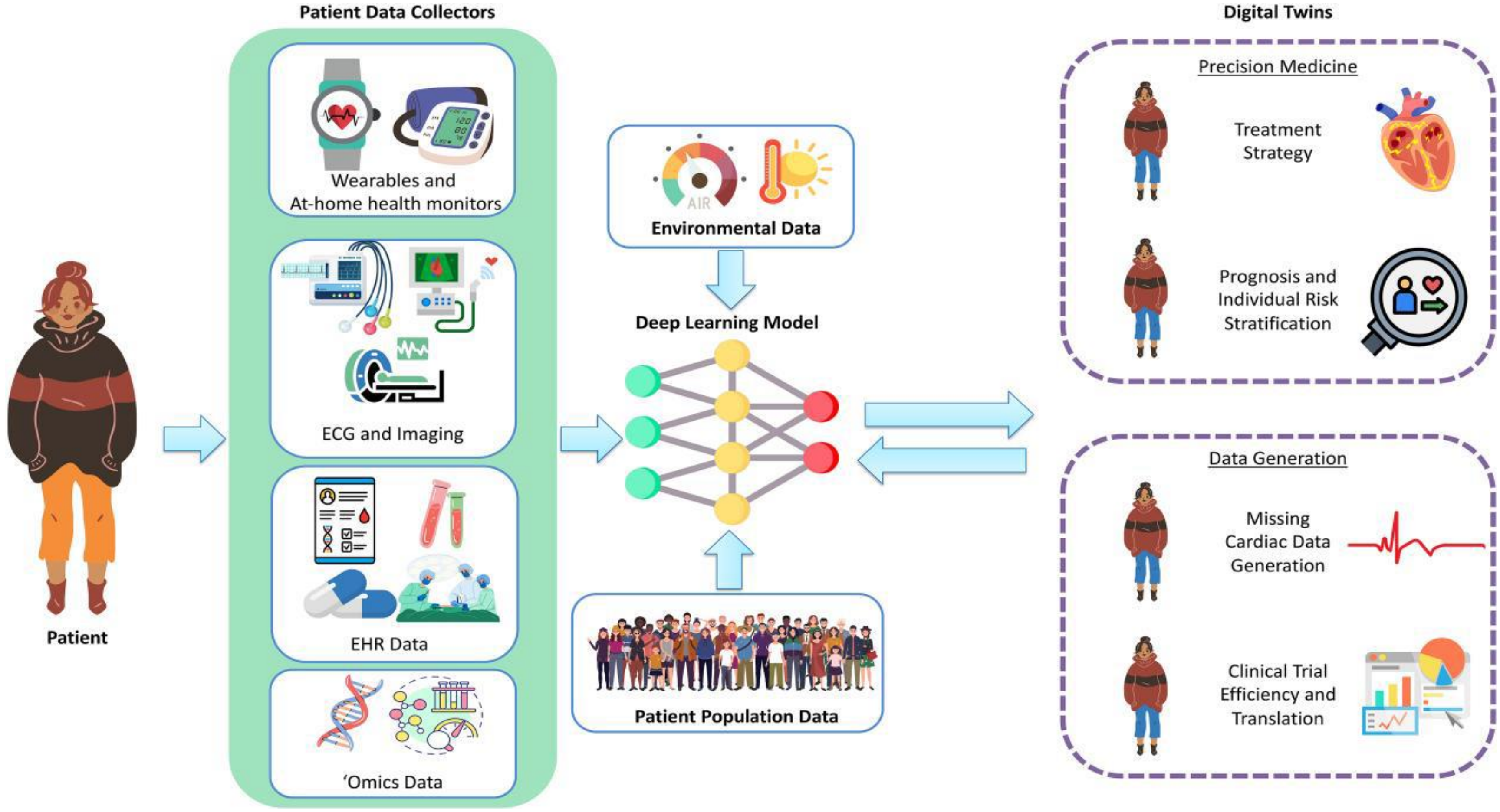
Behrenbeck, Z. Tayeb, C. Bhiri, C. Richter, O. Rhodes, N. Kasabov,- J. Espinosa-Ramos, S. Furber, G. Cheng, and J. Conradt, “Classification and regression of spatio-temporal signals using neucube and its realization on spinnaker neuromorphic hardware,” Journal of Neural Engineering, vol. 16, no. 2, 2019,

Overall, what benefits does brain-inspired computation offer to all AI systems?

- Improved Learning of Time and Space
- Highly Efficient and Scalable
- Low power consumption
- Robust and Flexible
- Event-based, predictive:
- Explainable: show spatio-temporal patterns of activity
- Higher accuracy, especially on spatio-spectro temporal streaming data classification or prediction tasks
- Creating evolving spatio-temporal associative memories, to recall on partial data in space and time
- Able to accommodate multimodal sound, image, gestures, smell and other stimulus
- Data compression and noise suppression
- Better understanding of our brains and better understanding and control of AI
- Towards machine consciousness

3. Spike-based LLM for Generative AI

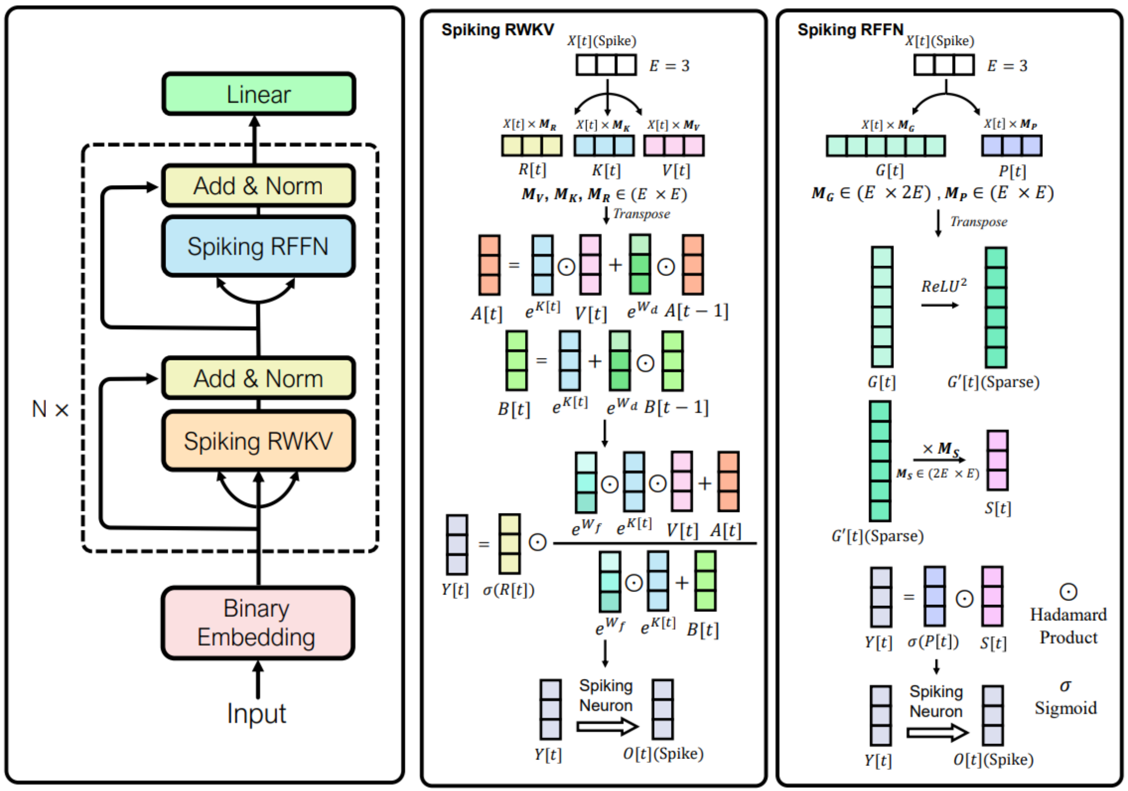
Example: Digital twins



Phyllis M. Thangaraj, Sean H. Benson, Evangelos K. Oikonomou, Folkert W. Asselbergs , and Rohan Khera, Cardiovascular care **with digital twin** technology in the era of generative artificial intelligence, European Heart Journal (2024) 00, 1–14 , https://doi.org/10.1093/eurheartj/ehae619

Spike-based Transformers for generative AI

SpikeGPT

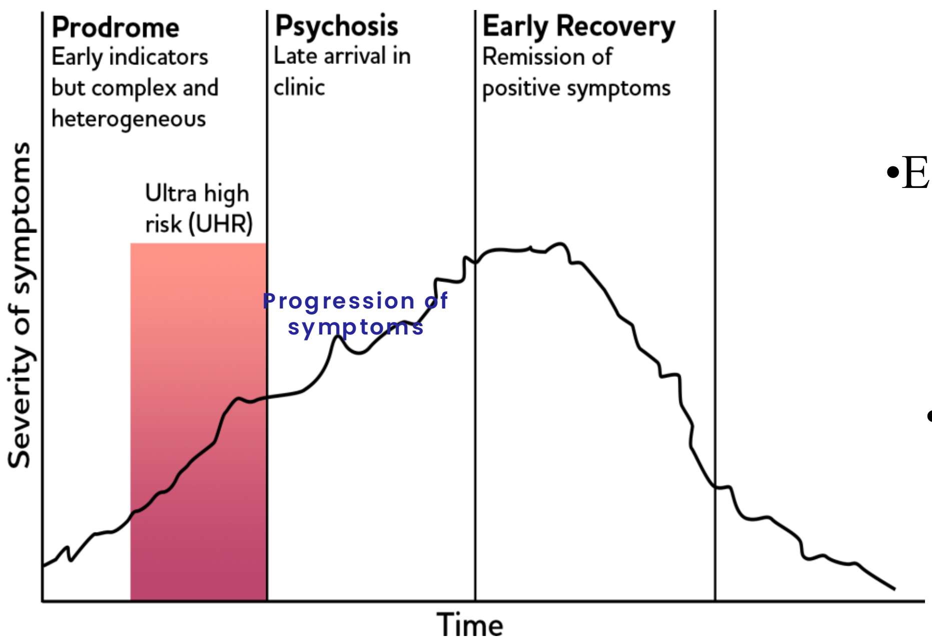


Zhu, R. J., Zhao, Q., Li, G., & Eshraghian, J. K. (2023). Spikegpt: Generative pre-trained language model with spiking neural networks. arXiv preprint arXiv:2302.13939.

4. Predictive AI

- Example: Early prediction of psychosis
- Psychosis is harmful
  - •Neurotoxic
  - •Suicide rate (18% to 55%)
  - •Depression rate > 40%

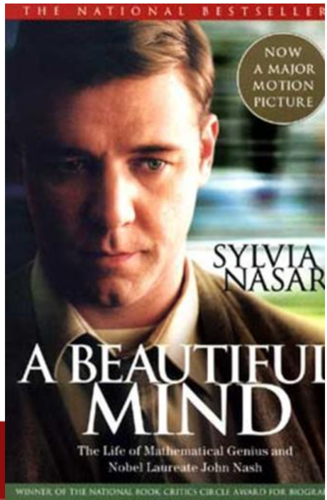
•Early treatment to reduce morbidity



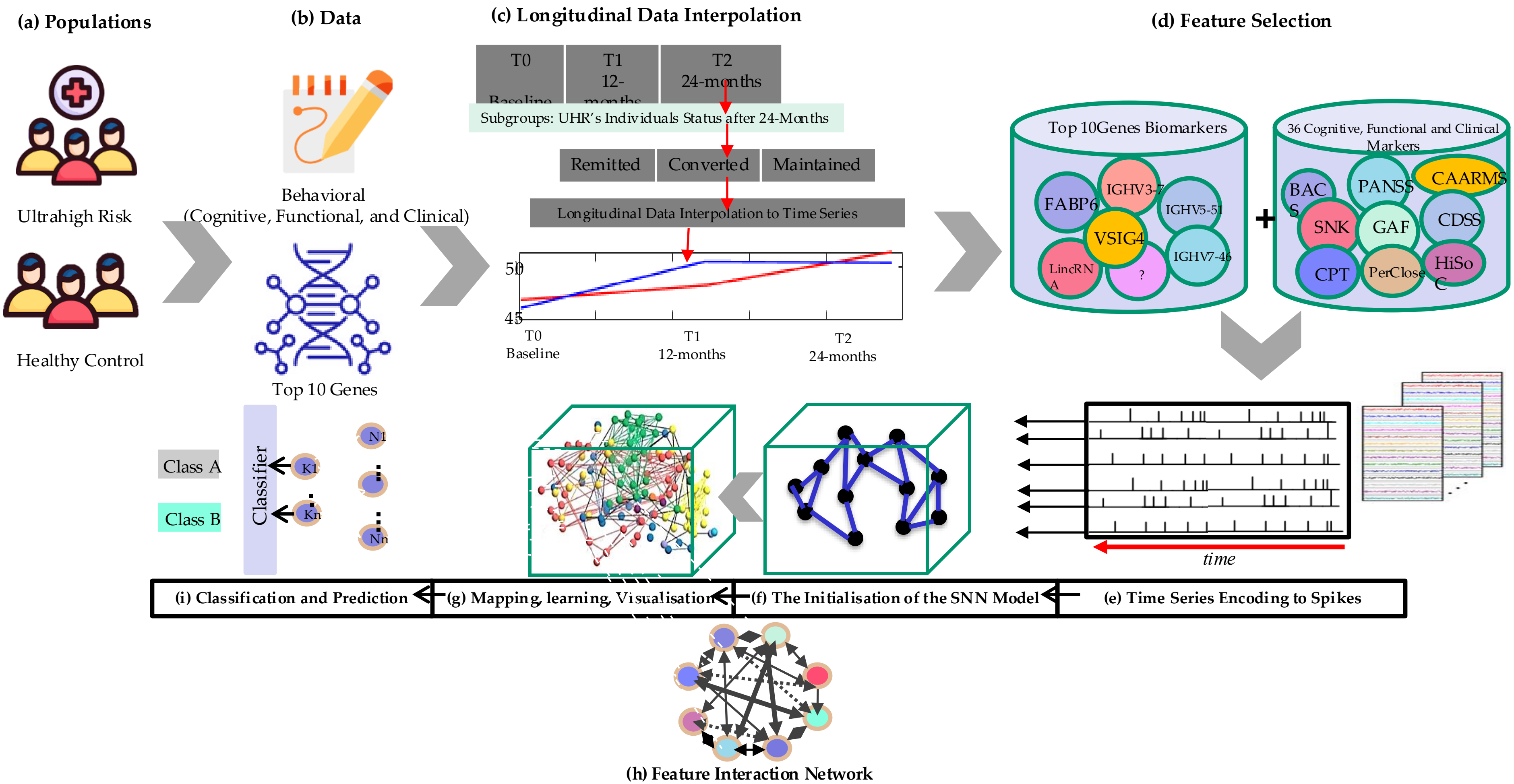
More than 50% of schizophrenia patients are diagnosed after 12 months of active symptoms

•Develop methods for:

- Biological marker identification
- Accurate prognosis
- Improved interpretability



Predicting personal onset of psychosis based on multimodal genetic, cognitive, functional and clinical variables



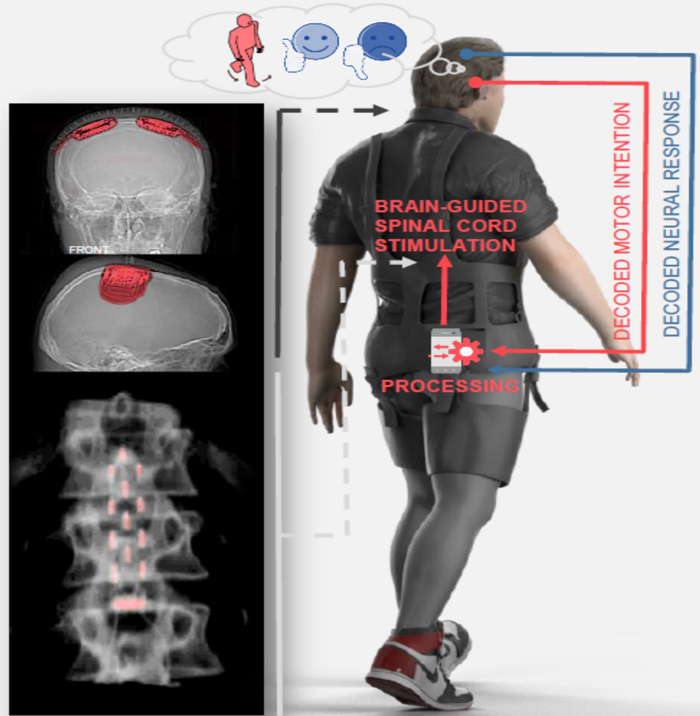
Zohreh Doborjeh, Oleg N. Medvedev, Maryam Doborjeh, Balkaran Singh, Alexander Sumich, Sugam Budhraja, Wilson Goh, Jimmy Lee, Margaret Williams, Edmund M-K Lai, and Nikola Kasabov, "A Generalisability Theory Approach to Quantifying Changes in Psychopathology Among Ultra-High-Risk Individuals for Psychosis", Nature Publisher, Schizophrenia (2024) 10:87 ; https://doi.org/10.1038/s41537-024-00503-y

Predictive Brain-Machine Interfaces (BMI)

EU Project: https://nemo-bmi.net

Auto-adaptive Neuromorphic Brain Machine Interface: toward fully embedded neuroprosthetics

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

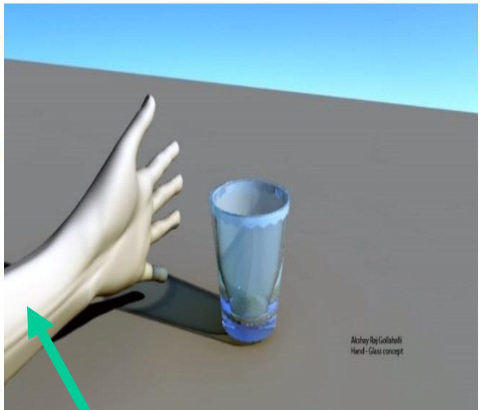
Miniaturization of BMI technology

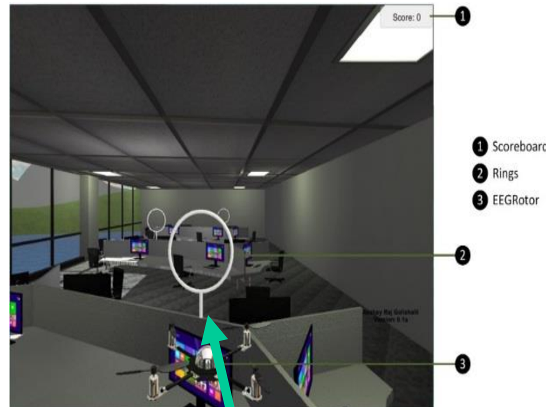
- Low power integrated circuit for accelerating the decoding algorithms
- High system level integration
- Portable battery-powered solution

1. Georgi Rusev, Svetlozar Yordanov, Simona Nedelcheva, Alexander Banderov, Fabien Sauter-Starace, Petia Koprinkova-Hristova *, Nikola Kasabov *, Decoding brain signals in a neuromorphic framework for a personalized adaptive control of human prosthetics, 2025, *Biomimetics* **2025**, *10*(3), 183

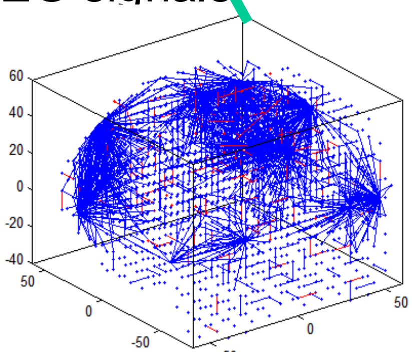
2. Rusev, G.; Yordanov, S.; Nedelcheva, S.; Banderov, A.; Lafaye de Micheaux, H.; Sauter-Starace, F.; Aksenova, T.; Koprinkova-Hristova, P.; Kasabov, N. NEuroMOrphic Neural-Response Decoding System for Adaptive and Personalized Neuro-Prosthetics' Control, Biomimetics **2025**, 10, 518, https://doi.org/10.3390/biomimetics10080518

Modelling brain EEG signals while working with a VR/AR during rehabilitation

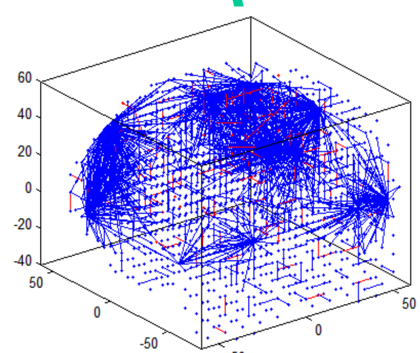




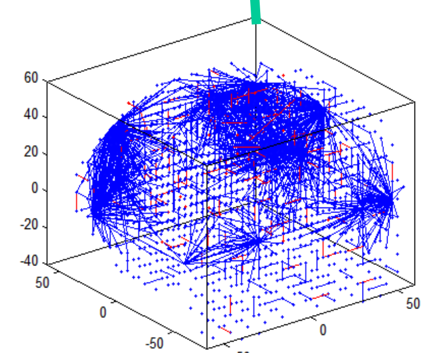
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.



A virtual environment to control a quadrotor using EEG signals.

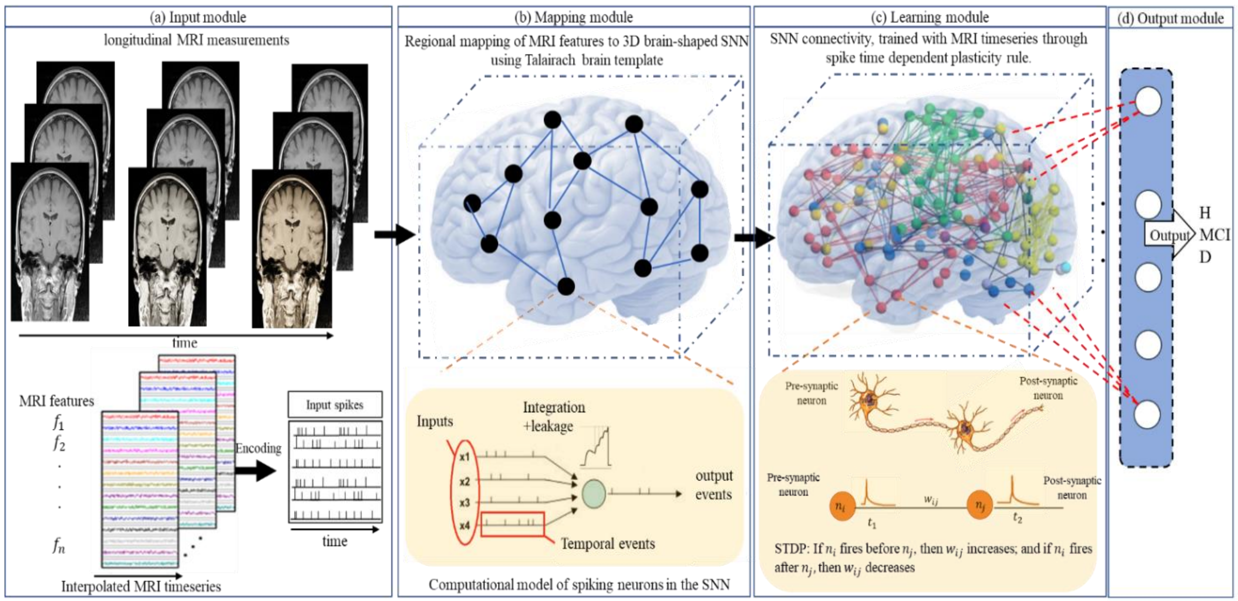


A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG.



Personalised prediction of dementia using longitudinal MRI data and NeuCube

M. Doborjeh, Z.Doborjeh, A.Merkin, H.Bahrami, A.Sumich, R.Krishnamurthi, O. Medvedev, M.Crook-Rumsey, C. Morgan, I.Kirk, P.Sachdev, H. Brodaty, K. Kang, W.Wen, V. Feigin, N. Kasabov, 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,



	BiLSTM Accuracy	BiLSTM F-Score	NeuCube Accuracy	NeuCube F-Score
Classification	43%	56%	95%	94%
2-year ahead prediction	40%	40%	91%	89%
4-year ahead prediction	41%	46%	73%	67%

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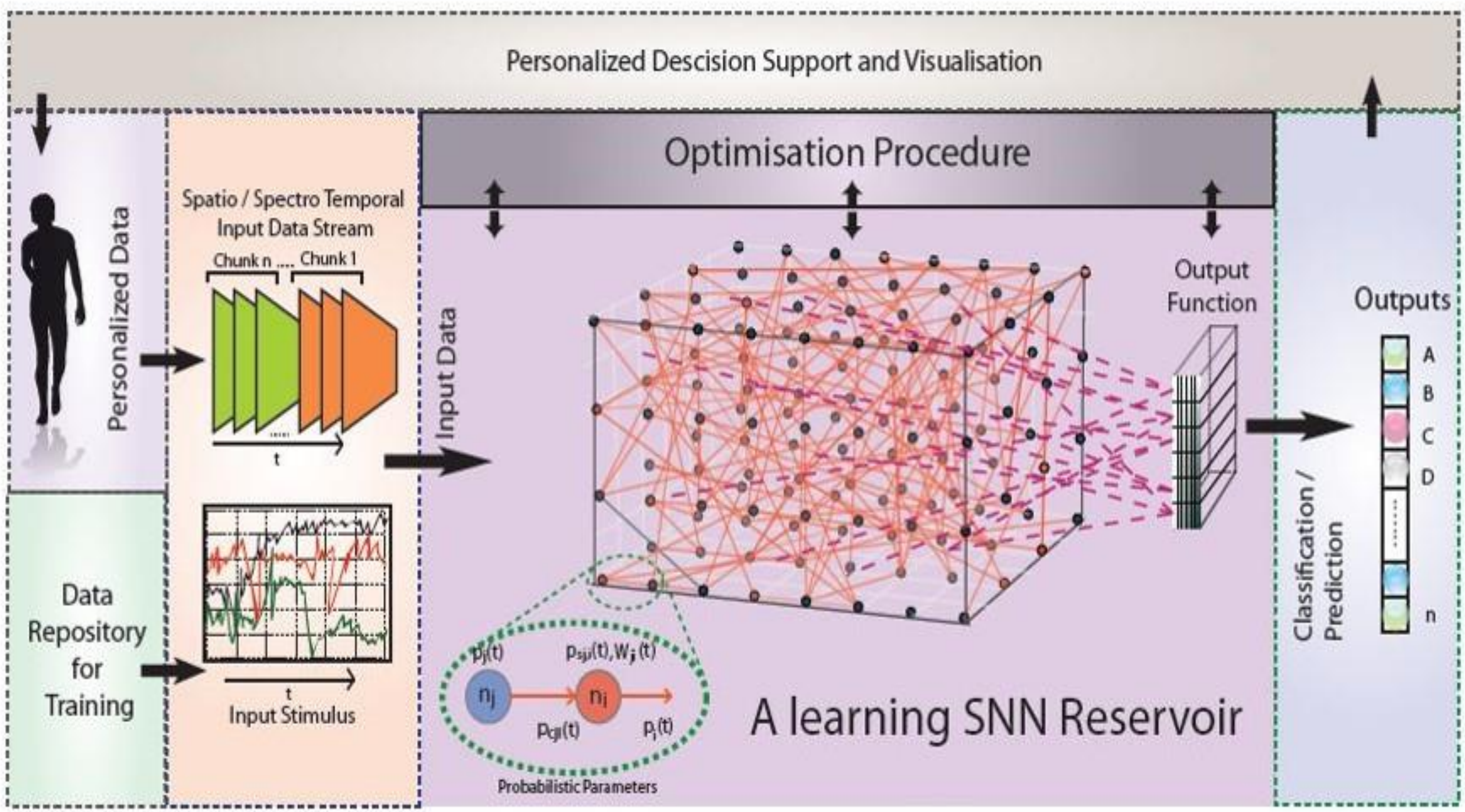
Personalised prediction of stoke on multimodal personal and temporal environment data

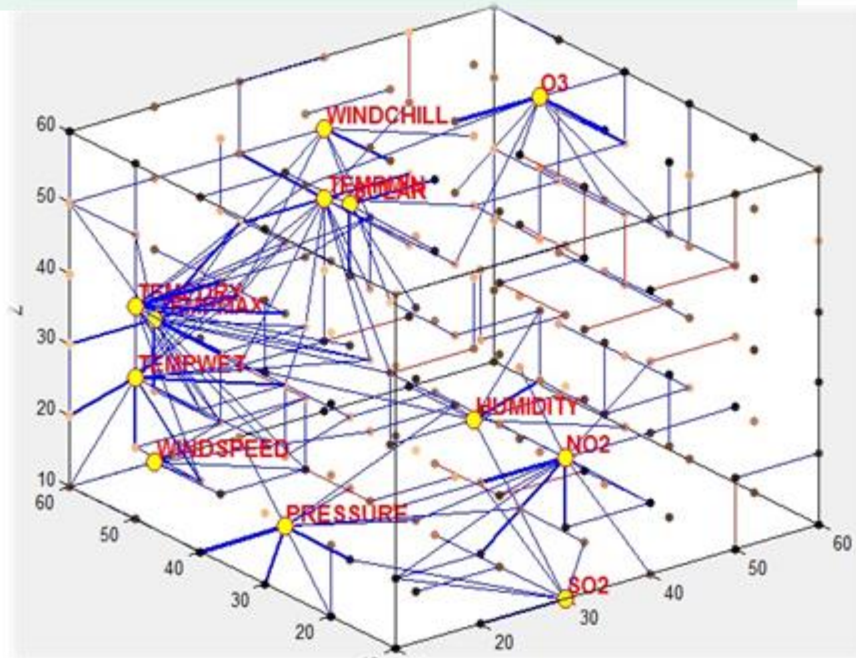
Case studies on stroke: N.Kasabov, V.Feigin, Z.Hou, Y.Chen, Improved method and system for predicting outcomes based on spatio/spectro-temporal data, PCT patent WO2015/030606 A2, US2016/0210552 A1, Publication date: 21 July 2016.

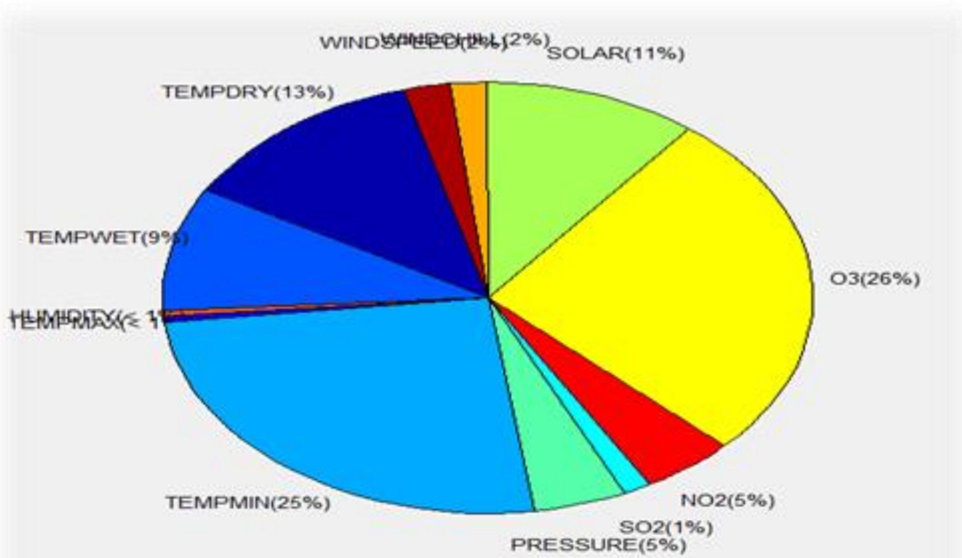


Personalised prediction of risk for stroke on ARCOS multimodal data

(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

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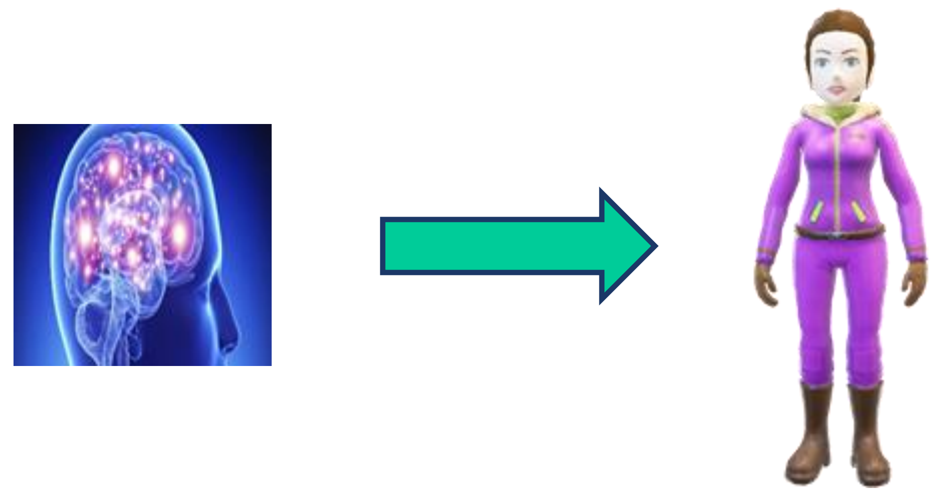
5. Agentic AI

- Autonomous behaviour
- Making decisions
- Pursuing goals
- Continuous learning
- Adapting to changing environment
- Performing a single task or a small number of tasks
- Many applications



EU Funded project on Agentic AI 2026-2029

COAGENT: COGNITIVE COMPUTING CONTINUUM FOR LARGE-SCALE DISTRIBUTED GENAI AGENTS

#@APP-FORM-HERIAIA@#

Participant No	Participant organisation name	Type	Country
1 (Coordinator)	University of Innsbruck (**UIBK**)	UNI	AT
2	SINTEF AS (**STF**)	RTO	NO
3	Consorzio Interuniversitario Nazionale per l'Informatica (**CINI**)	UNI	IT
4	Almaviva Group (**ALMA**)	LE	IT
5 (Affiliated)	AlmaWave (**AW**)		IT
6	Auckland University of Technology (**AUT**)	UNI	NZ
7	Yonsei University (**YSU**)	UNI	KR
8	Yonsei University Industry Foundation (**YSUIF**)		KR
9	CloudFerro (**CF**)	SME	PL
10	Neuromorphica (**NMBG**)	SME	BG
11	Nextworks (**NXW**)	SME	IT
12	Beawre Digital (**BAWD**)	SME	ES
13 (Affiliated)	Beawre Poland (**BAWP**)		PL
14	Onlim (**ONL**)	SME	AT
15	Indra Group (**IND**)	LE	ES
16	Philips Medical Systems Nederland BV (**PMSN**)	LE	NL
17 (Affiliated)	Philips Electronics Nederland BV (**PEN**)		
18	ETRA Investigación y Desarrollo S.A. (**ETRA**)	LE	ES
19	Telenor ASA (**TEL**)	LE	NO
20	Seoul National University (**SNU**)	UNI	KR
21 (Affiliated)	Seoul National University R&DB Foundation (**SNURF**)		
22	Municipality of Messina (**MOM**)	PUB	IT

Moving object recognition using DVS camera and NeuCube to predict movement of objects and take actions

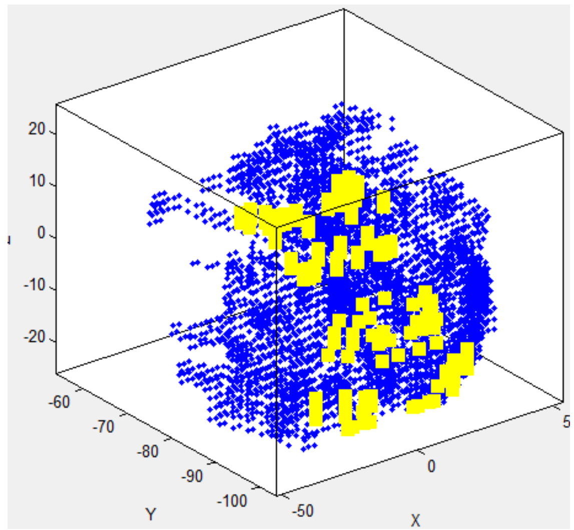
Applications:

- Transport : driverless cars, drones, roboits

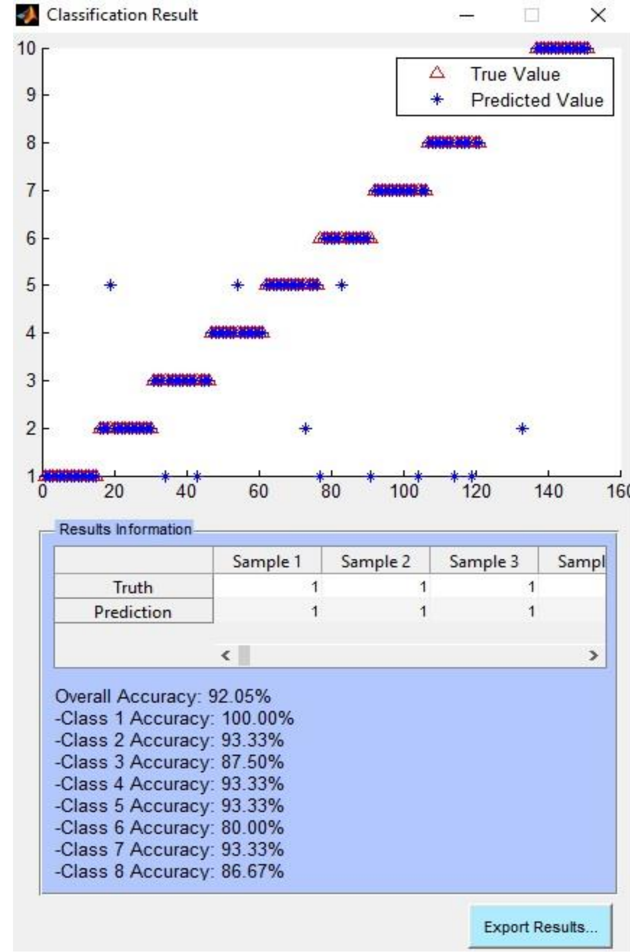
-- Defence industry

Deep learning and knowledge representation of moving objects using DVS and retinotopic mapping in NeuCube

30000 moving digits in 8 fonts and sizes from DVS MNIST



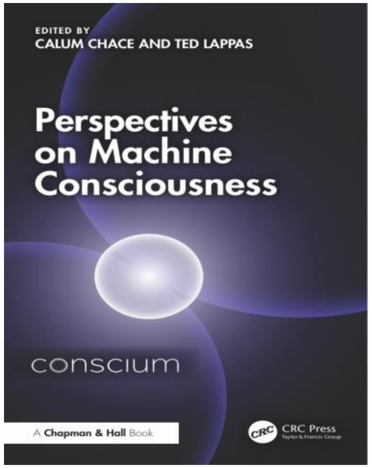
NeuCube with 4262 neurons from V1 and V2



L.Paulin, A.Abbott, N.Kasabov, A retinotopic spiking neural network system for accurate recognition of moving objects using NeuCube and dynamic vision sensors, Frontiers of Comp. Neuroscience, 2018, doi:10.3389/fncom.2018.00042.

6.Towards machine consciousness using the brain-inspired approach

- Explaining machine consciousness:



- Software tests for Ai and MC:

  https://conscium.com/verifyax/interactive-demo

  VerifyAX

The independent platform that tests your AI agents in simulated environments and tells you exactly how they perform.

- World Academy of Artificial Consciousness:

  https://www.waac.ac/academicians

- International company: Conscium Ltd UK (https://conscium.com)

- Forthcoming book:

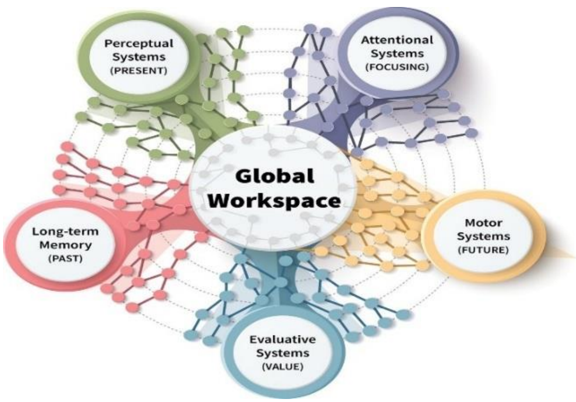
N.Kasabov, Evolving spatio-temporal associative memories: from the predictive brain to predictive AI and machine consciousness, Springer-Nature 2027.

Some theories of consciousness:

(1) Integration Information Theory (IIT)

C. of a system is defined by the following features: intrinsicality, information, integration, exclusion, composition

G.Tononi, An information integration theory of consciousness. BMC Neurosci. 5, 42 (2004).

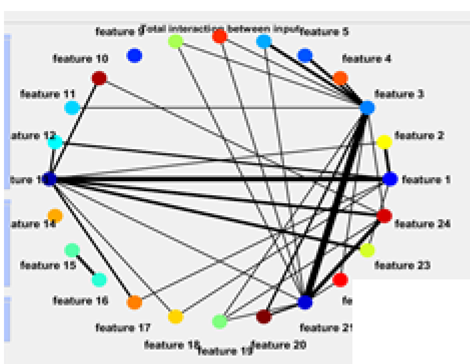


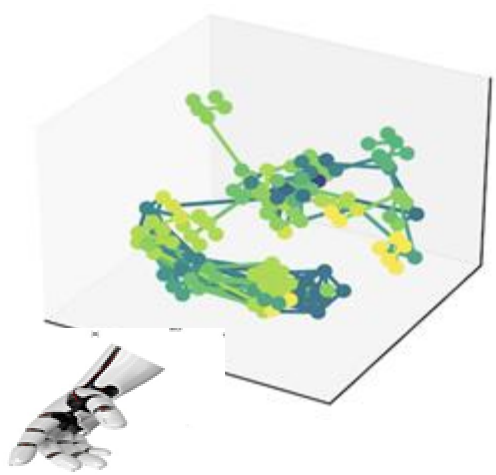
(2) Global Workspace Theory (GWT) and GNT

A central “blackboard” where multiple modules integrate and broadcast content brain-wide.

Baars, B. J. (2005). Global workspace theory of consciousness: toward a cognitive neuroscience of human experience. *Progress in brain research*, *150*, 45-53.

Dehaene S. Consciousness and the Brain: Deciphering How the Brain Codes Our Thoughts. New York: Penguin, 2014.





(3) Evolving spatio-temporal associative memory (eSTAM)

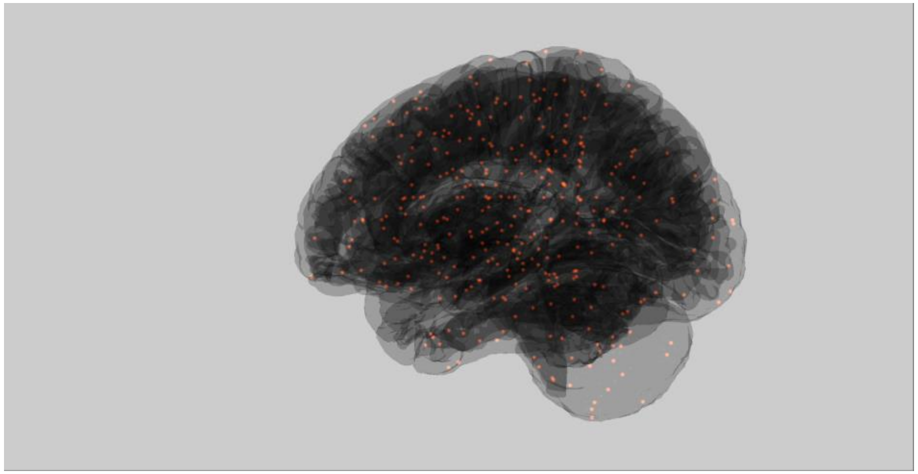
A theoretical and computational framework of dynamic models in natural or artificial systems that associates continuously related items, objects, processes of different modalities and scales, such as spatial and temporal scales, incorporating past-, present and future times and can be recalled with partial information.

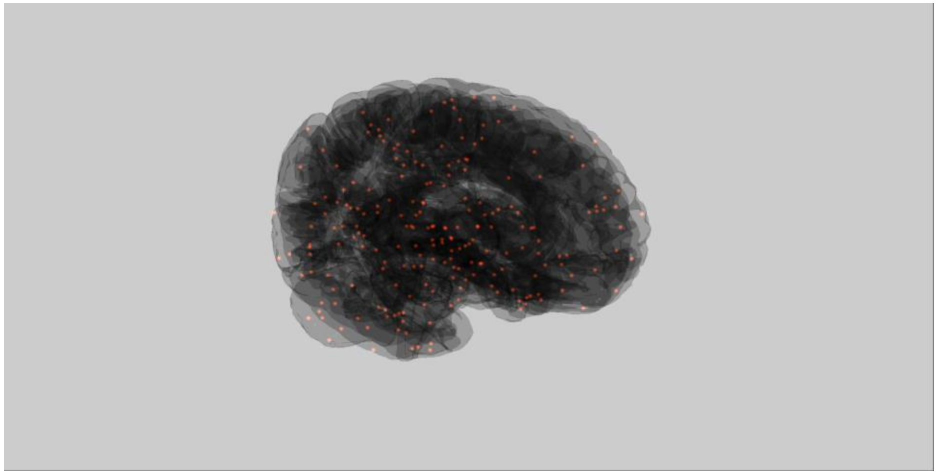
Kasabov, N (2023). STAM-SNN: Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.23723208.v1

Kasabov, N.K. (2024). STAM-SNN: Spatio-Temporal Associative Memory in Brain-Inspired Spiking Neural Networks: Concepts and Perspectives. In: **Kovács, L., Haidegger, T., Szakál, A.** (eds) Recent Advances in Intelligent Engineering. Topics in Intelligent Engineering and Informatics, vol 18. Springer, https://doi.org/10.1007/978-3-031-58257-8_1

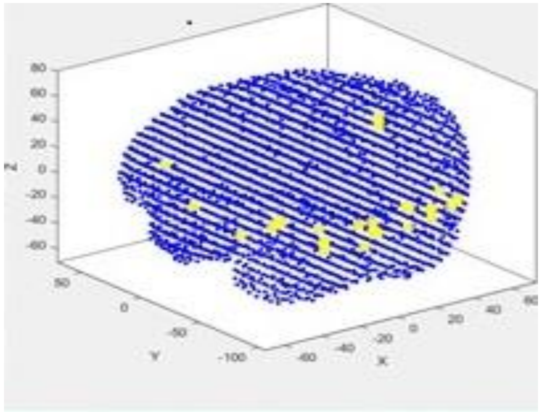
Example 1:

eXCube1: BI-SNN for learning eSTAM from fMRI data when people are perceiving consciously meaningful vs meaningless stimuli

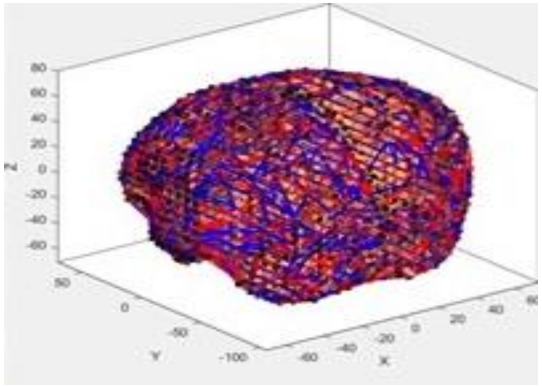




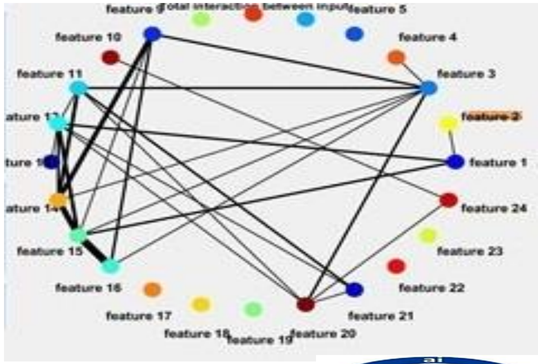
Feature Mapping



STDP Training



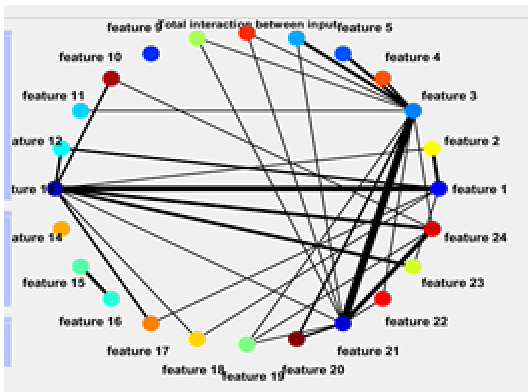
FIN as appr. of ESTAM

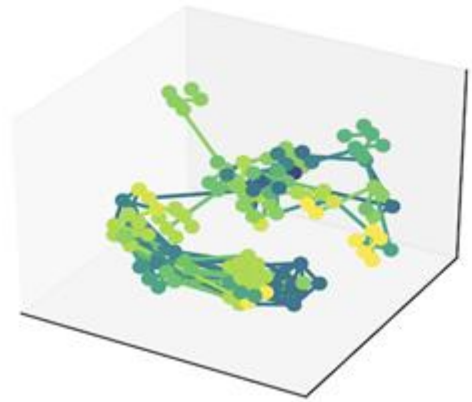


Tracing brain activity during a conscious perception of meaningful vs meaningless visual stimuli

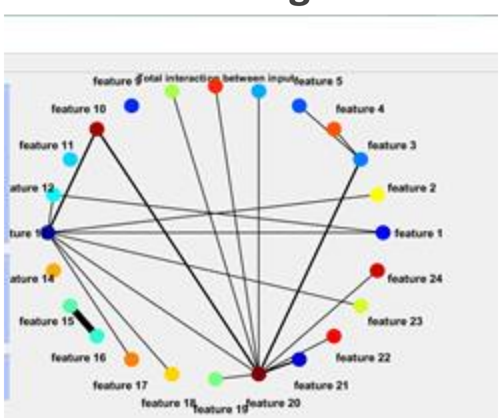
N.K. Kasabov, A. Yang, I. Abouhassan, A. Kassabova, C. Chace, T. Lappas, eXCube1: Explainable Brain-Inspired Spiking Neural Network Framework for Detecting Brain Patterns from fMRI Data of Conscious Perception of Meaningful vs Meaningless Audio and Visual Stimuli, Brain Sciences, MDPI, in submission, 2026.

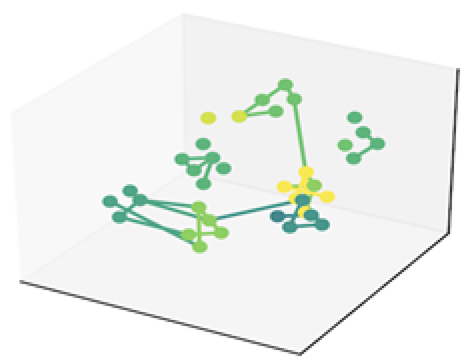
meaning*ful*





meaning*less*



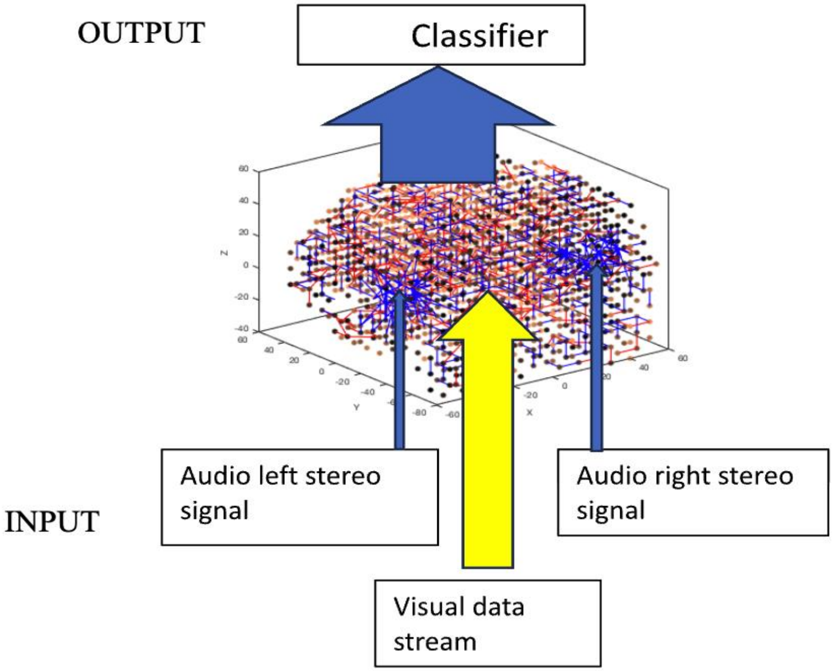


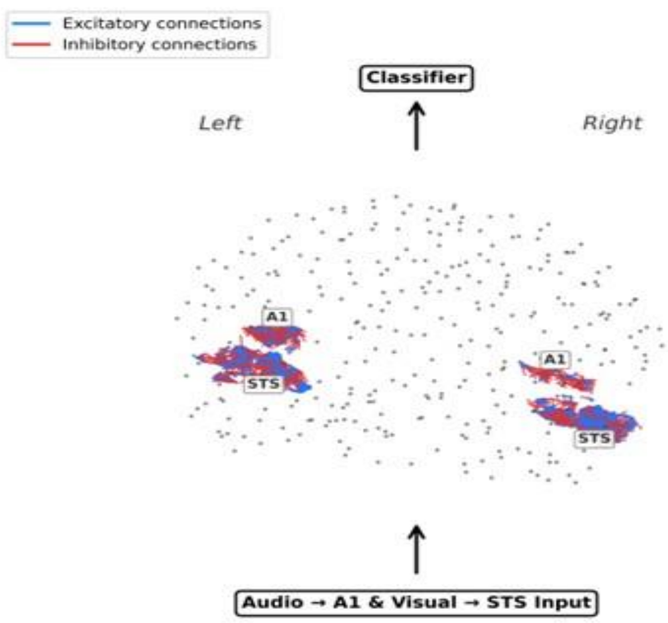
1: right middle occipital gyrus
7: left cuneus
17: right cuneus
16: right postcentral gyrus
13: right fusiform gyrus
14: left insula
15: right postcentral gyrus
16: right postcentral gyrus
12: right fusiform gyrus
9: left precentral gyrus
3: left middle temporal gyrus
15: right postcentral gyrus
14: left insula
12: right fusiform gyrus
9: left precentral gyrus
3: left middle temporal gyrus
23: right cuneus
21: left middle occipital gyrus
24: left lingual gyrus

Dominating dynamic features of information (spike) exchange for class 1 (meaningfulness of **visual stimuli**) : (1,24,23) -- 13; 21--3 ; voxel areas 1,3,13,21

Example 2: Recognising emotion of a person from audio-, visual- and audio-visual data as part of their conscious states

Kasabov, N.K.; Yang, A.; Wang, Z.; Abouhassan, I.; Kassabova, A.; Lappas, T. eXCube2: Explainable Brain-Inspired Spiking Neural Network Framework for Emotion Recognition from Audio, Visual and Multimodal Audio–Visual Data. *Biomimetics* **2026**, *11*, 208. https://doi.org/10.3390/biomimetics11030208





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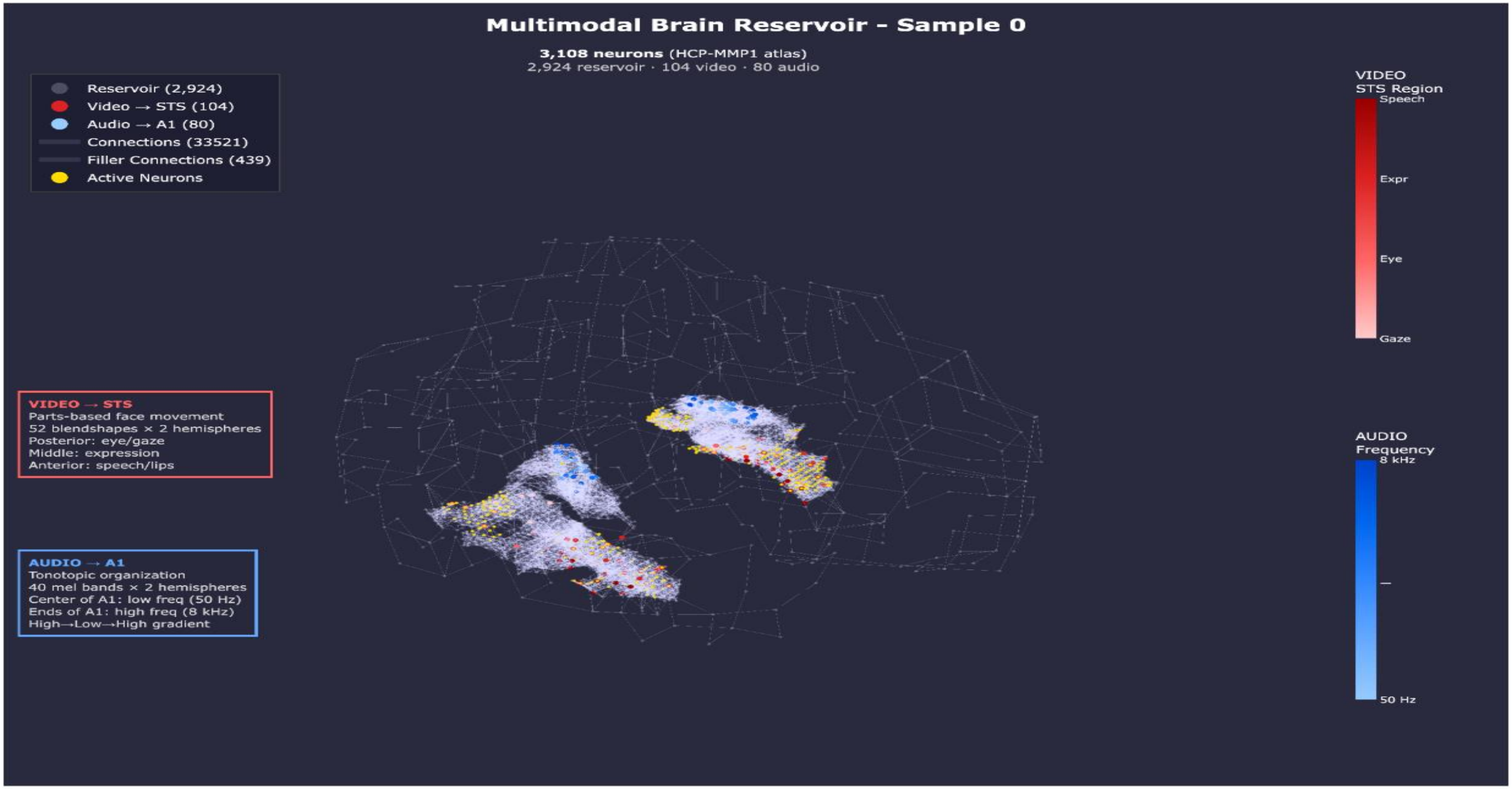
eXCube 2: A Neucube-based systems for emotion recognition from audio-, visual- and audio-visual data as part of conscious states

Kasabov, N.K.; Yang, A.; Wang, Z.; Abouhassan, I.; Kassabova, A.; Lappas, T. eXCube2: Explainable Brain-Inspired Spiking Neural Network Framework for Emotion Recognition from Audio, Visual and Multimodal Audio–Visual Data. *Biomimetics* **2026**, *11*, 208. https://doi.org/10.3390/biomimetics11030208



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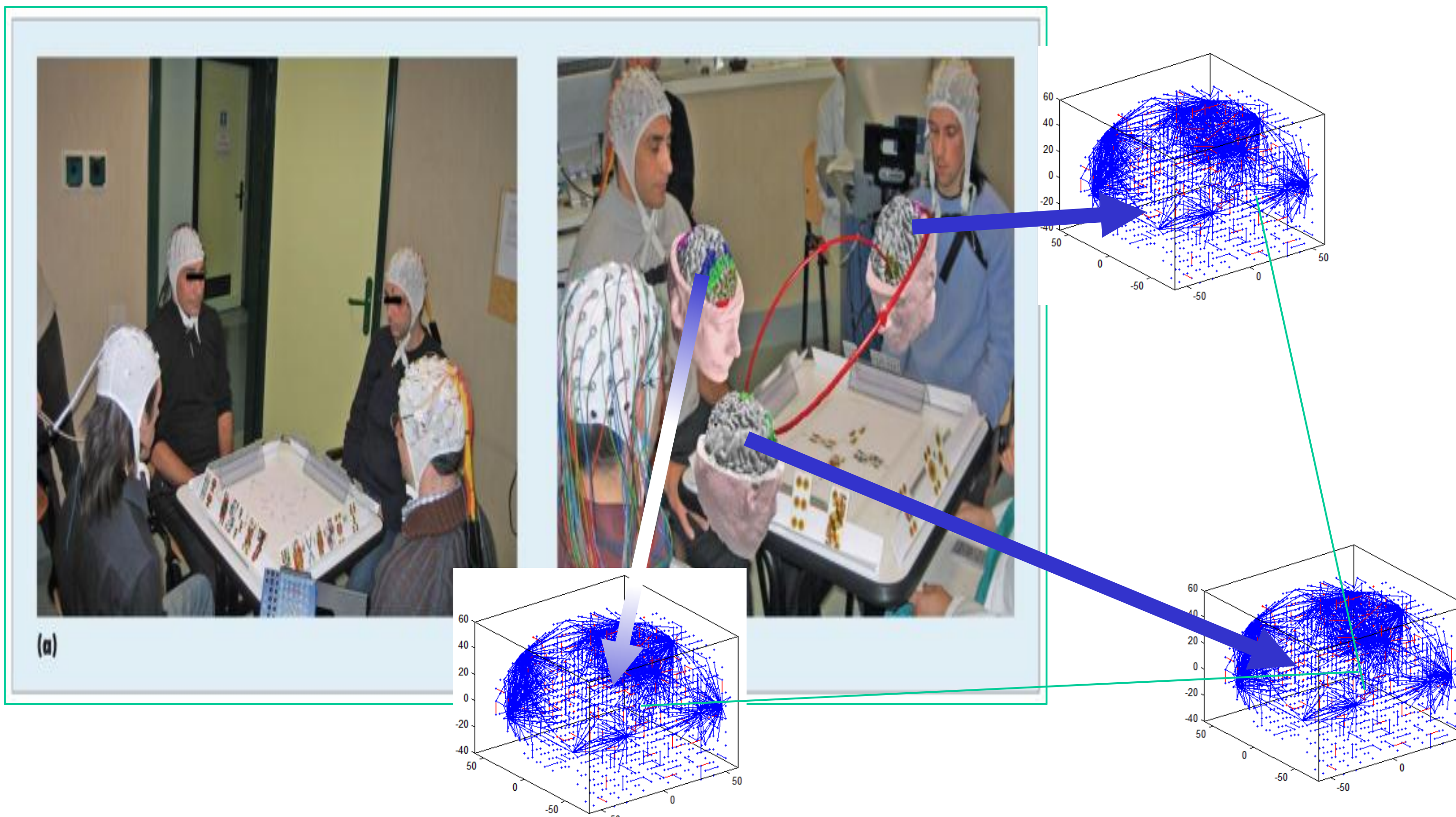
Example 3: BI-SNN can model human-to-human conscious interaction

B.Kelsen, A.Sumich, N.Kasabov, S.Liang, G.Wang, What has social neuroscience learned from hyperscanning studies of spoken communication? A systematic review. Neuroscience&Biobehavioural Reviews, 3 September 2020, https://doi.org/10.1016/j.neubiorev.2020.09.008;https://www.sciencedirect.com/science/article/abs/pii/S0149763420305650



LAstolfi, J Toppi, FDe Vico Fallani, G Vecchiato, F Cincotti, C. Wilke, HYuan, D Mattia, S Salinari, B He, and F Babiloni, I, **Imaging the Social Brain by Simultaneous Hyperscanning During Subject Interaction,** EEE Intell Syst. 2011 Oct; 26 (5): 38–45.

7. Conclusion and Future directions

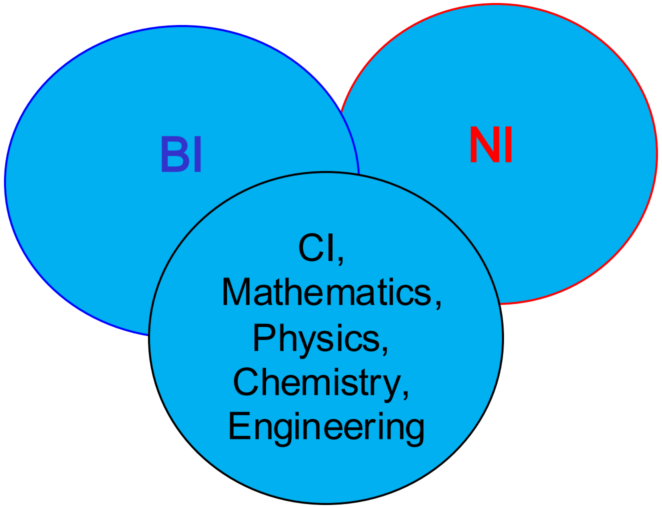
Advantages of BI-SNN:

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/spectro-temporal) associations learned.
4. Interpretability, e.g. rule representation
5. Low computational power
6. Fault tolerance

Problems and limitations of BI-SNN

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

What is next?



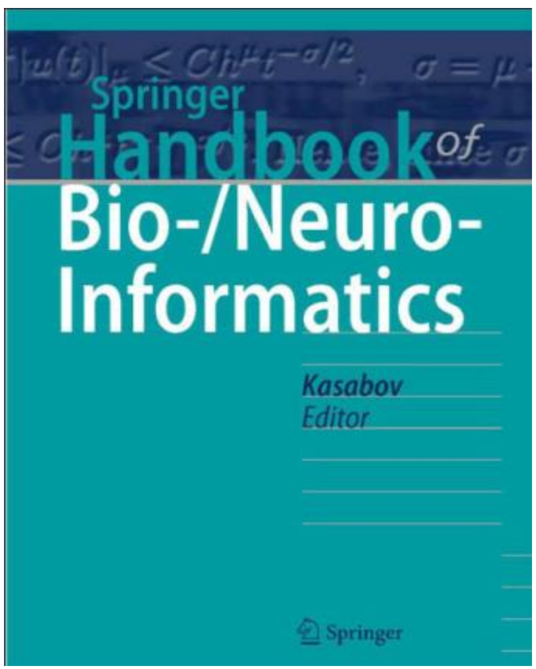
New BI-, and hybrid computational methods and systems

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

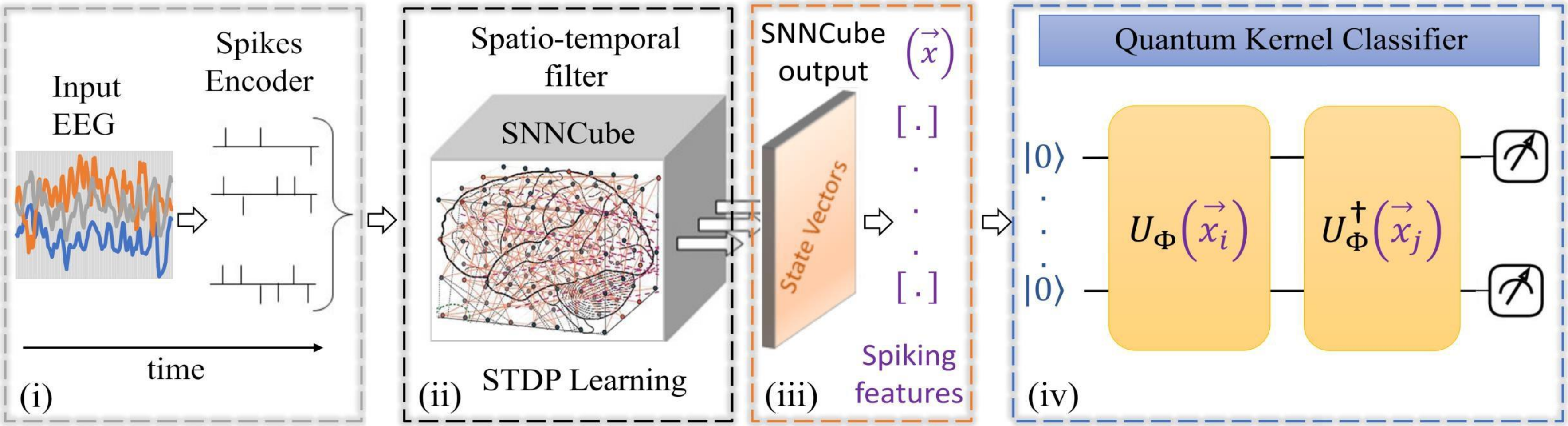
New Data Technologies

Transparent NAGI

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



A Hybrid SNN-QC Model



(i) input EEG signals are transformed into spike trains

(ii) spikes are mapped onto a spatiotemporal filter (SNNCube) using known locations (i.e. EEG channels locations) and learned synchronously

(iii) an output module provides trained spiking features in the form of spike frequency state vectors

(iv) these spiking features are used as input vectors to quantum kernel classifiers

Jha, N. Kasabov et al, Comparative Performance Analysis of Quantum Feature Maps for Quantum Kernel-based Machine Learning, Scientific Reports, February 2026, 16 (1), https://doi.org/10.1038/s41598-026-39392-9

Jha, R.K., Kasabov, N., Bhattacharyya, S. *et al.* A hybrid spiking neural network - quantum framework for spatio-data classification: a case study on EEG data. *EPJ Quantum Technol.* **12**, 130 (2025). https://doi.org/10.1140/ep 025-00443-1

The NeuCube world map, 2014- 2026

1. Algeria
2. Australia
3. Brazil
4. Bulgaria
5. Canada
6. Chile
7. China
8. Croatia
9. Czech Republic
10. Denmark
11. Egypt
12. Finland
13. France
14. Germany
15. Greece
16. Hungary
17. India
18. Indonesia
19. Iran
20. Ireland
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