Spiking Neural Networks

Energy Efficient Alternatives – MERCON 2025

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BRAIN LABS

Brain-Inspired AI & Neuroinformatics Research Group

Presentation Overview

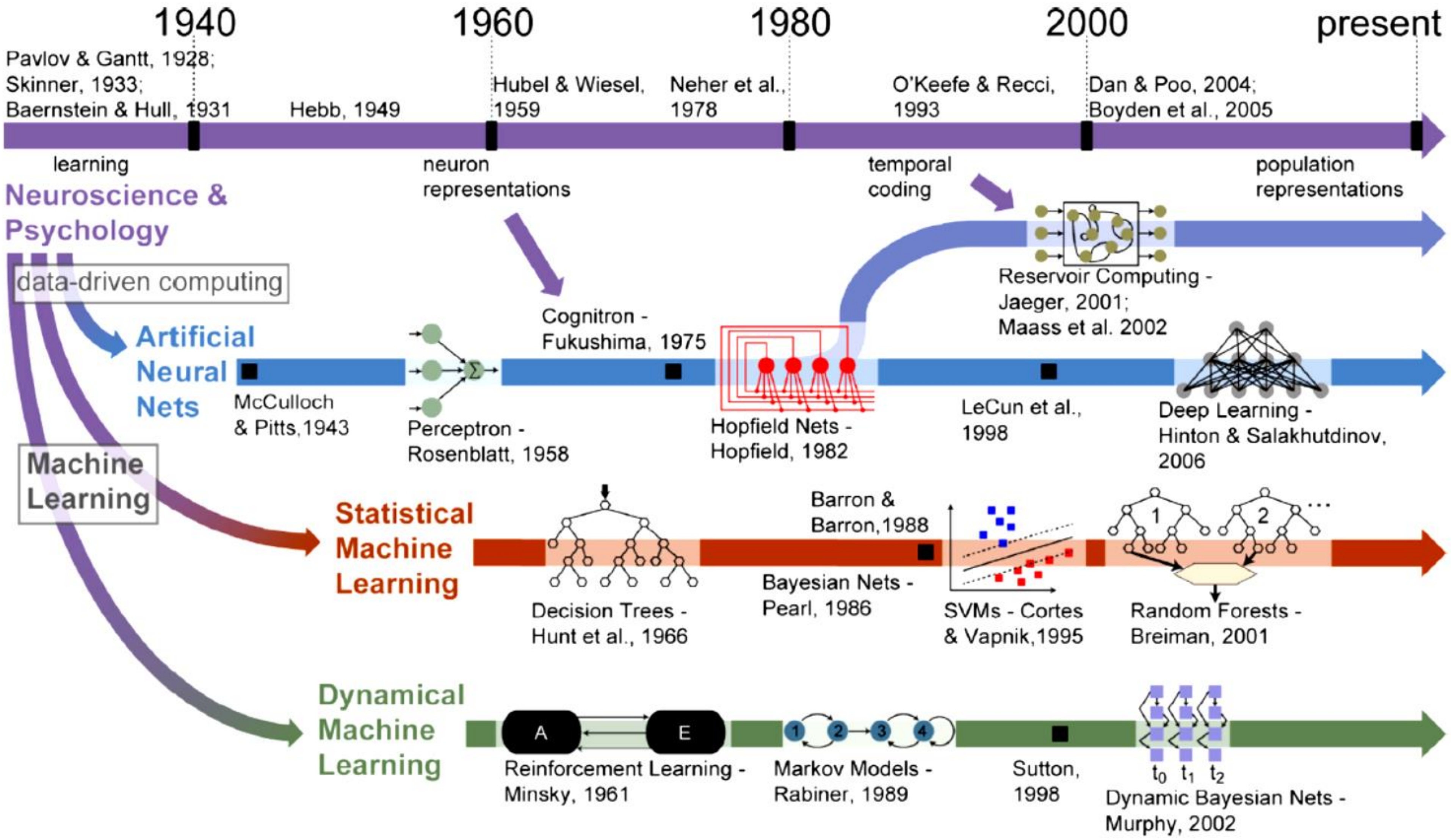
Presentation

1. ANNs & Computer Science
2. ANNs & the Brain
3. Artificial SNNs
4. Our research
5. Structural & Intrinsic Plasticity
6. Findings and Future

Development of AI

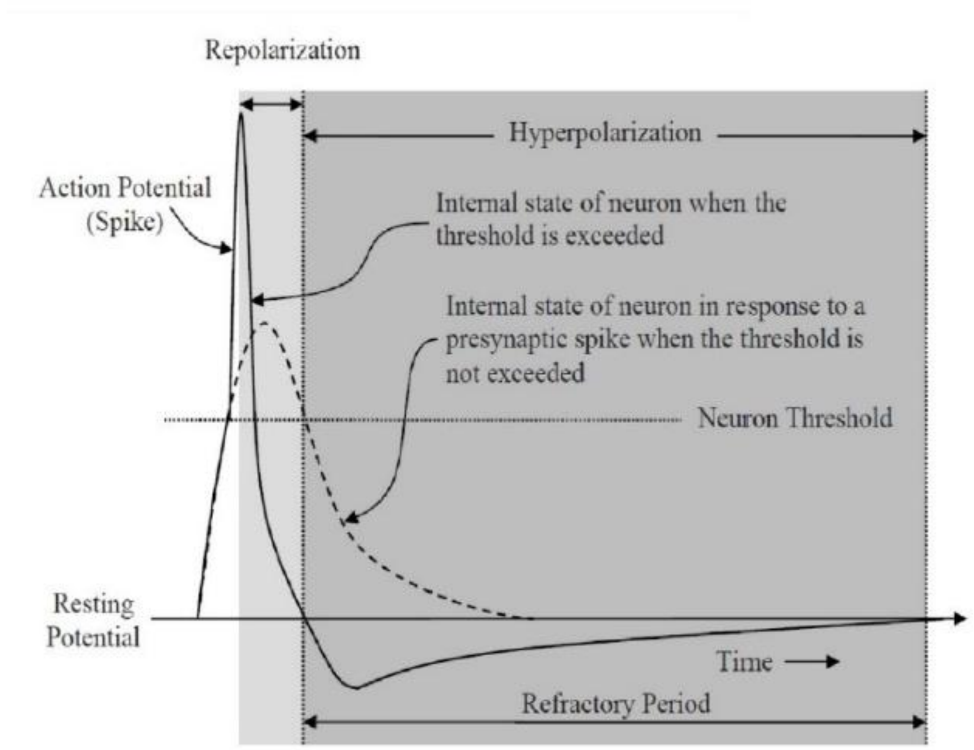
In 1943, neurophysiologist Warren McCulloch and mathematician Walter Pitts wrote a paper on how neurons might work. In order to describe how neurons in the brain might work, they modeled a simple neural network using electrical circuits.

[Stanford CS]



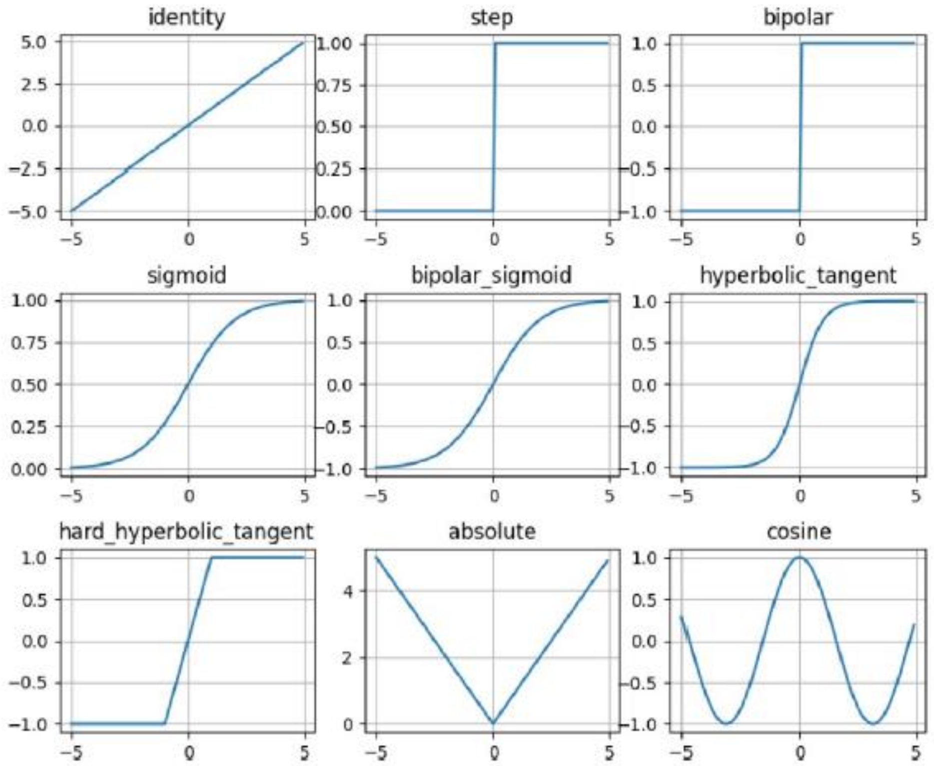
Brain vs ANNs

Transfer function of a biological neuron



From "Third Generation Neural Networks: Spiking Neural Networks" by Ghosh-Dastidar, S., & Adeli, H., 2009, Advances in Intelligent and Soft Computing, 61 AISC, 167–178, https://doi.org/10.1007/978-3-642-03156-4_17, Copyright 2009 by Springer, Berlin, Heidelberg.

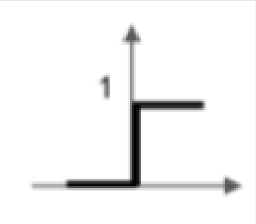
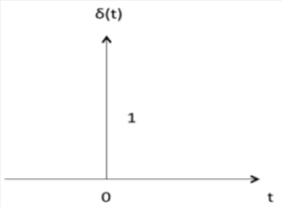
Transfer function of Artificial Neurons



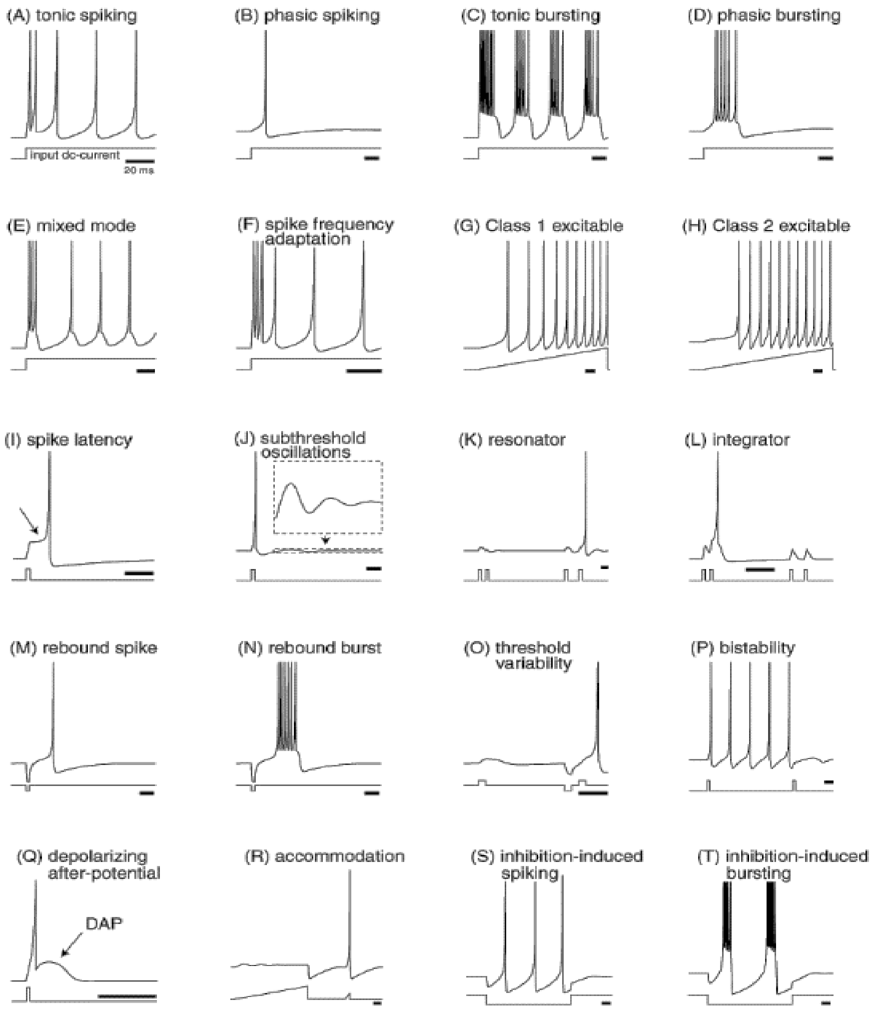
From "A survey on modern trainable activation functions. Neural Networks" by Apicella, A., Donnarumma, F., Isgrò, F., & Prevete, R., 2021, Neural Networks, 138, 14–32. https://doi.org/10.1016/j.neunet.2021.01.026, Copyright 2021 by Elsevier Ltd.

Computational Neurons

Comparison to other neurons

Neuron Type	Operational Description (Use examples)	Function representation
First Generation	Approximating any Boolean function (Perceptron, Hopfield network, Bidirectional Associative memory (BAM) and etc.)	
Second Generation	Approximating any real-valued function (Multi-layer Perceptron (MLP), Radial Basis Functions (RBF), Self Organizing Maps (SOM), Convolutional Neural Networks (CNN) and etc.)	
Third Generation	Approximating any temporal relations (Spiking Neural Networks)	

https://www.sciencedirect.com/science/article/pii/S0893608097000117



(Izhikevich, 2003)

Potential of SNNs in exploiting STD

"the use of SNN where computation is driven in a continuous time way naturally and driven only by the occurrence of spikes detecting certain spatio-temporal correlations can be much more advantageous" (Tavanaei et al., 2019).

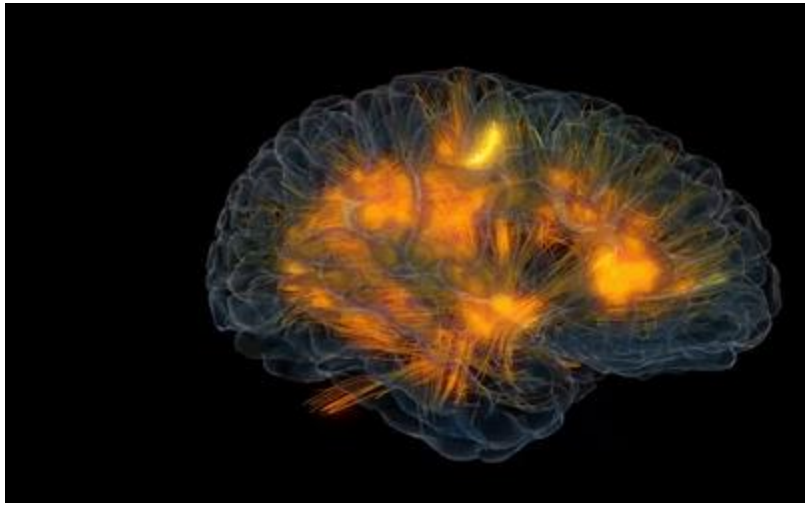
"the ultimate advantage of SNNs comes from their ability to fully exploit spatio-temporal event-based information" (Roy et al., 2019)

"SNNs are ideally suited for processing spatio-temporal event-based information from neuromorphic sensors" (Pfeiffer & Pfeil, 2018)

"SNNs are more biologically realistic than ANNs, and arguably the only viable option if one wants to understand how the brain computes" (Tavanaei, Ghodrati, Kheradpisheh, Masquelier, & Maida, 2019)

ANNs and the brain

GPT-3 training cost –
12 million USD



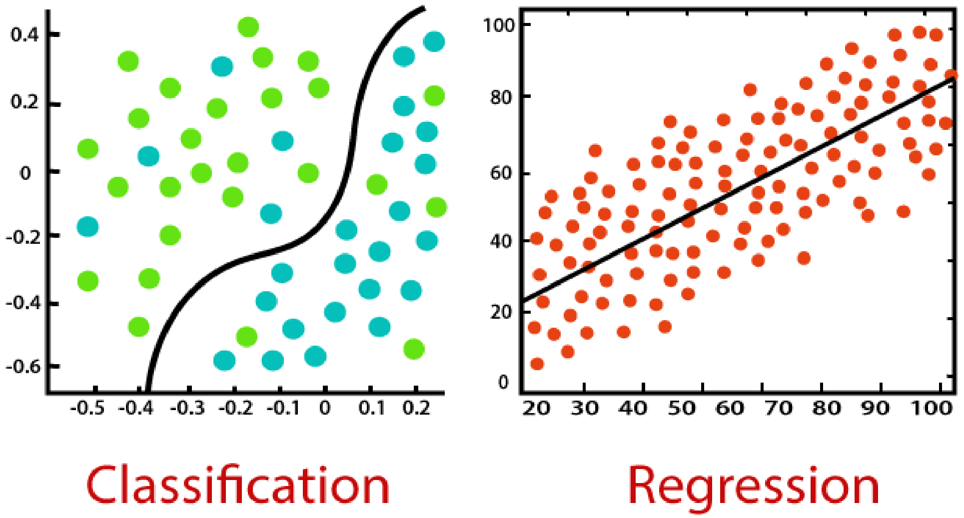
Brain needs ~ 20 W

Kyle Wiggers. "OpenAI's massive GPT-3 model is impressive, but size isn't everything" (2020). https://venturebeat.com/2020/06/01/ai-machine-learning-openai-gpt-3-size-isnt-everything/

Cox, D. D. & Dean, T. Neural networks and neuroscience-inspired computer vision. Curr. Biol. 24, R921–R929 (2014).

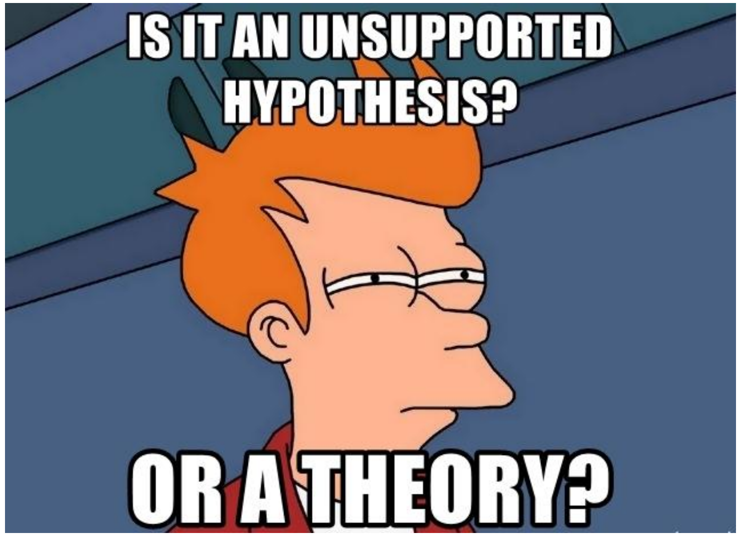
What can they do ?

Function approximation



("Regression vs Classification in Machine Learning - Javatpoint," 2021)

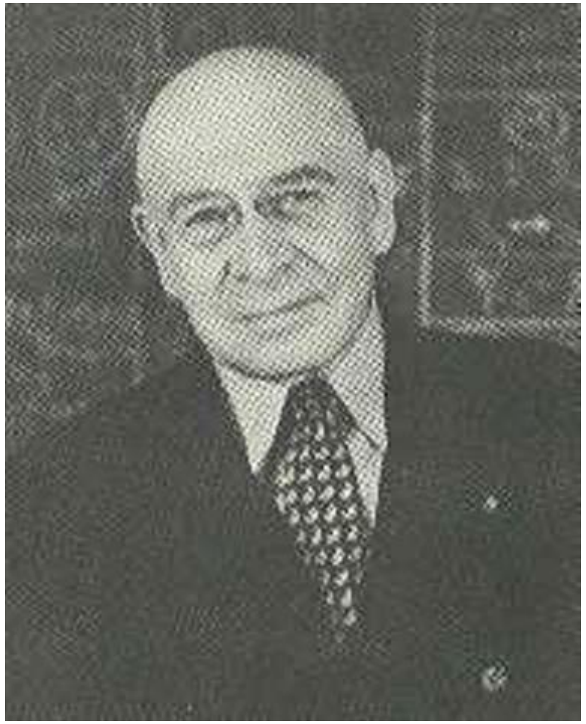
Hypothesis generator



("is it an unsupported hypothesis? or a theory? - Futurama Fry | Meme Generator," 2021)

Spiking ANNs the Brain

"The map is not the territory" and "the word is not the thing" ***Alfred Korzybski***



- Even though SNNs are claimed to be more biologically plausible, as the iterative change is done using "spikes" rather than continuous modelling there are some pretty big issues
    - Human Brains have 100 Billion Neurons – ANN's rarely go above 100's
    - Human brains have a complex structure at many different scales, ANN's tend to be homogeneous
    - ANN's generally act on structured data that is stored outside themselves.
- These are clearly big issues !

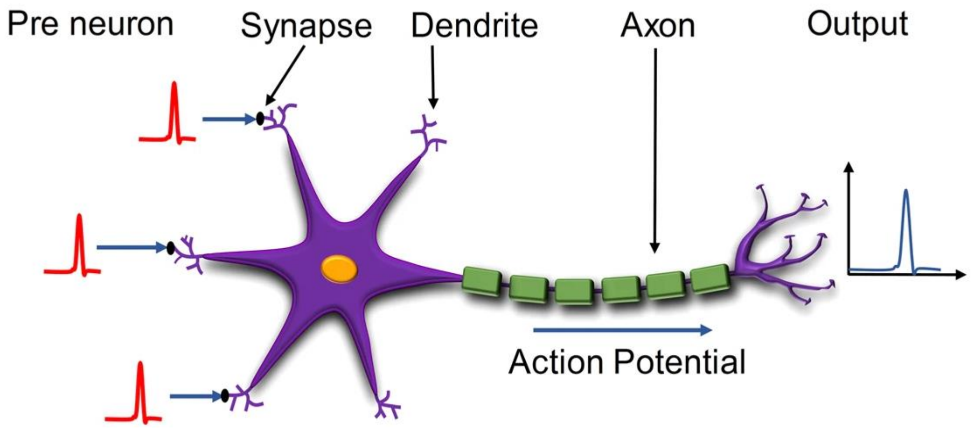
SNNs as a functional plausibility probe

- We can't build a brain (or even a bit of a brain) in a computer – we can model very simple organisms though http://openworm.org/
- Psychologists are very good at looking at relationships between stimulus and behaviour and the organism (and hence evolutionary) level
- Neuroscience can observe structural changes related to stimulus, and so give insights into what causes structural change and how it works.
- Linking these two levels is hard. MAYBE we can use results from ANN's to build models that link stimulus to behaviour, WHILE observing structural change or at least constraining structural change to biologically plausible mechanisms.

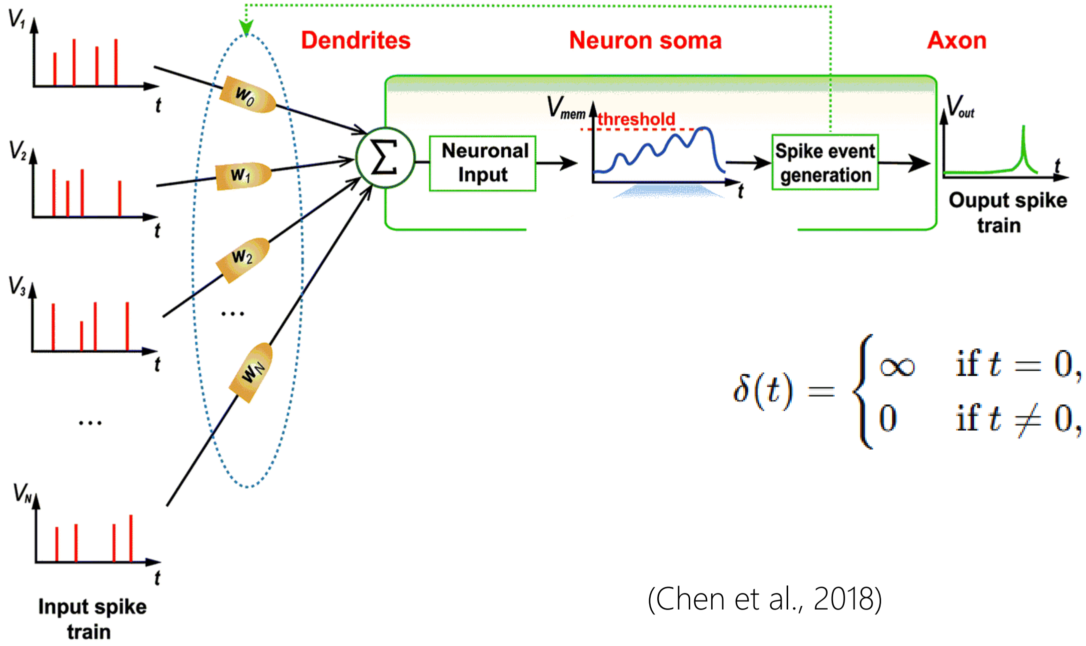
https://www.youtube.com/watch?v=1wj9nJZKlDk&ab_channel=OpenWorm

Spiking Neuron Function

What is a Spiking Neuron ?



(Kalita et al., 2019)



$$\delta(t) = \begin{cases} \infty & \text{if } t = 0, \\ 0 & \text{if } t \neq 0, \end{cases}$$

(Chen et al., 2018)

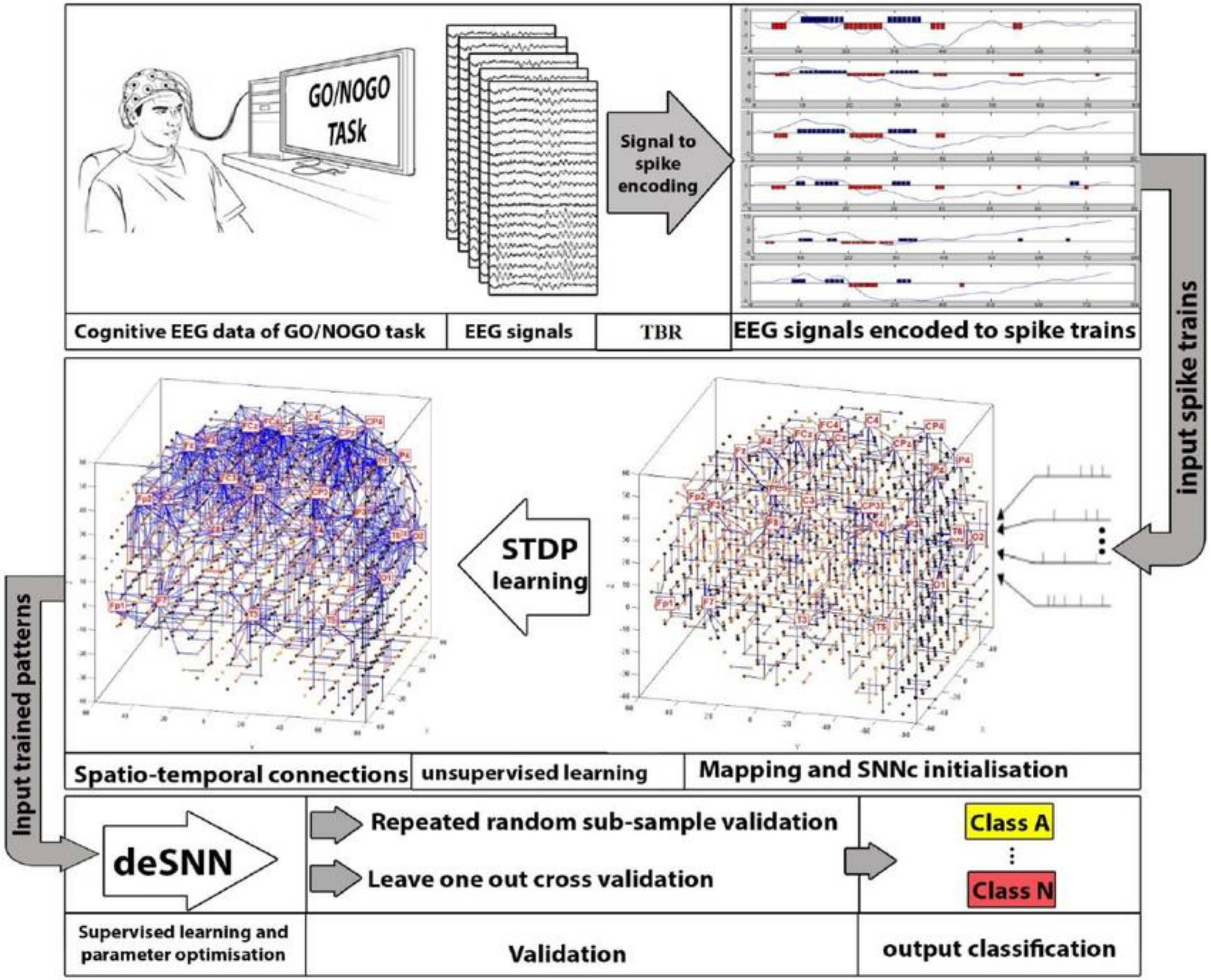
$$\tau_m \frac{dV(t)}{dt} = -\left(V(t) - V_{\text{rest}}\right) + R_m I(t)$$

Machine learning and deep learning models based on SNN	Supervised/ Unsupervised	Real-life Application
SpikeProp with a BP learning rule[97] / with Levenberg-Marquardt algorithm [98] / with multi-spike neurons [99]	Supervised	Non-linear classification tasks / classification of Poisson spike trains
SpikeProp with QuickProp or Rprop[100, 101]	Supervised	XOR and Fisher Iris data sets
Multi-SpikeProp[102]	Supervised	Epilepsy and seizure detection
Back-propagation with momentum[103]	Supervised	Wisconsin breast cancer classification
Spatio-temporal back propagation[104]	Supervised	MNIST / N-MNIST dataset
SuperSpike + Hebbian three-factor rule[105, 106]	Supervised	Randman, MNIST, SHD, RawHD
ReSuMe (Remote Supervised Method)[107]	Supervised	Learning spike trains
Chronotron with STDP[108]	Supervised	Precise spike trains
BP-STDP for multi-layer SNNs[109]	Supervised	XOR, Iris data, MNIST dataset
Supervised STDP (SSTDP) [110]	Supervised	CALTECH 101 / MNIST / CIFAR-10 datasets
Symmetric STDP[111]	Supervised	Fashion-MNIST dataset
SPAN (spike pattern association neuron)[112]	Supervised	Spike pattern classification
Spike train kernel learning (STKLR)[113, 114]	Supervised	LabelMe image dataset
STDP variants[115]	Unsupervised	Pattern recognition
Locally-connected SNN with STDP[116]	Unsupervised	Learning image features
Spiking CNN with STDP[117]	Unsupervised	MNIST digit dataset
Self-organizing SNN[21]	Unsupervised	Decision-making system
SpikeDyn[118]	Unsupervised	Image classification
SpiCNN (deep spiking CNN)[119]	Supervised	CALTECH / MNIST datasets
Deep spiking CNN using Tensorflow[120]	Supervised	MNIST and NM-NIST datasets
Deep residual learning SNN[121]	Supervised	ImageNet, DVS Gesture, CIFAR10-DVS
Spiking-Yolo[122]	Supervised	Object detection
Spiking recurrent NN[123]	Supervised	Cognitive tasks
Adaptive spiking RNN[124]	Supervised	Speech and gesture recognition
Spiking convolutional RNN[125]	Supervised	Hand gesture recognition
Spiking deep belief network (DBN)[126]	Supervised	MNIST handwritten digits
Spiking DBN on SpiNNaker[127, 128]	Supervised	MNIST handwritten digits
Spiking DBN with Siegert neuron model[129]	Supervised	Face recognition
Spiking DBN[130]	Supervised	Emotion analysis from electrodermal signals

Biologically plausible algorithms

https://www.sciencedirect.com/science/article/pii/S0893608019302680

(Paul et al., 2024)



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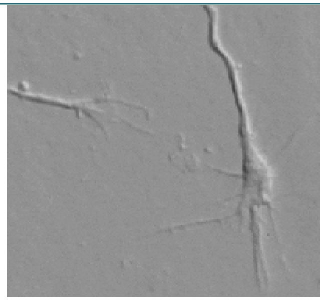
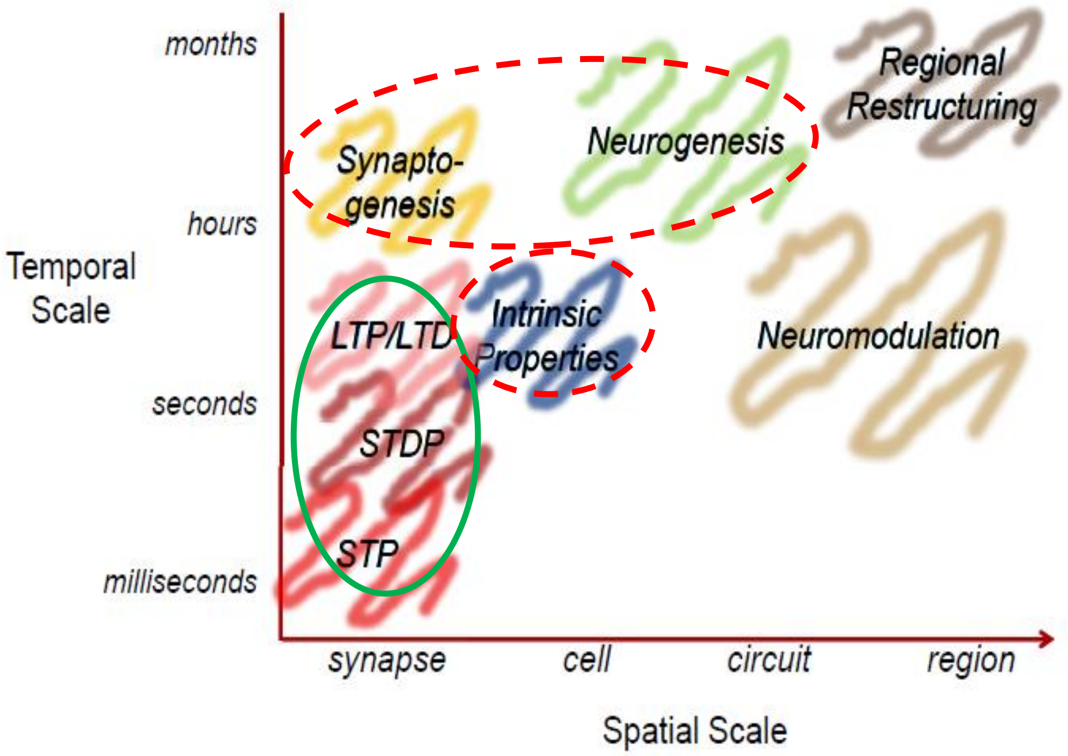
Plasticity in the Brain



Structural Adaptability in the Human Brain Circuits

Synaptogenesis , Synaptic Pruning, Neurogenesis and Apoptosis



(B. Aimone, 2011)

Proliferation followed by pruning

(Navlakha, Bar-Joseph, & Barth, 2018) (Peter R., 1979)

Adult neurogenesis enables pattern separation

(Aimone et al., 2014)

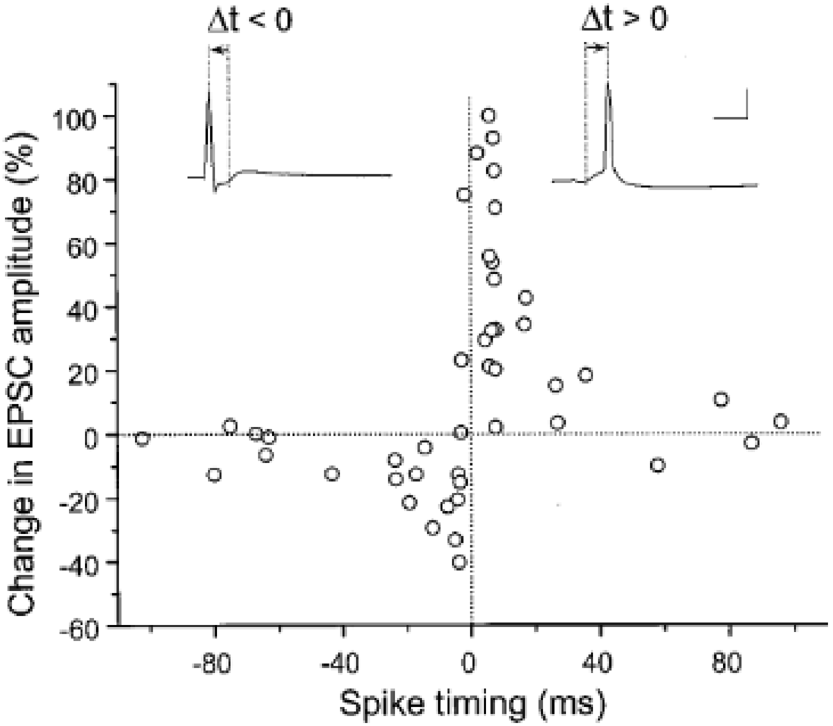
Network pruning and growing leading to network stability, efficiency and response denoising

(Iglesias & Villa, 2007) (Diehl, 2016) (Yuan et al., 2019)

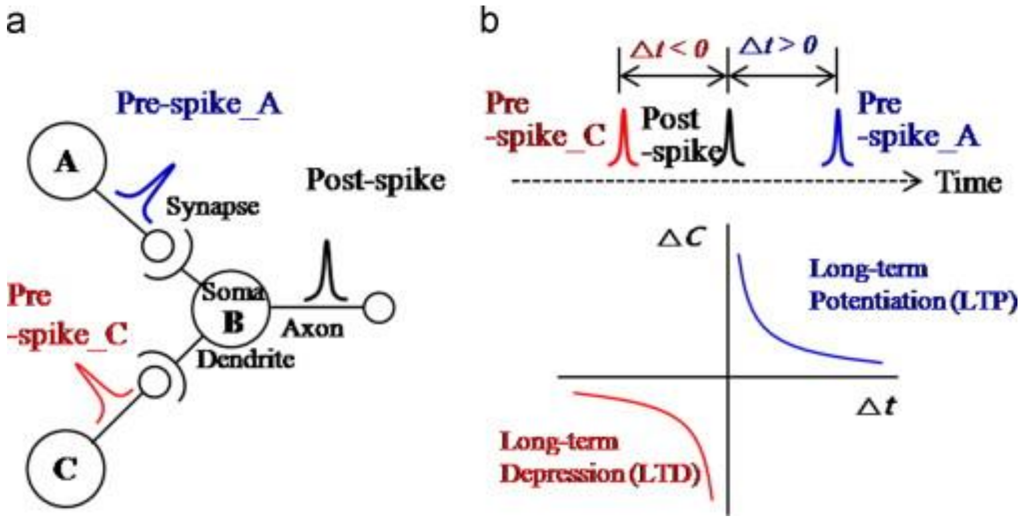
Learning in SNNs

How does SNNs learn?

Spike Time Dependent Plasticity (Bi & Poo, 1998) and/or its variations(Bill et al., 2015)(Brea, Senn, & Pfister, 2011) (Kappel, Nessler, & Maass, 2014) are biologically inspired unsupervised learning algorithms. **Plays a pivotal role in determining synaptic strength between neurons.**



(Kang, Jun, Ryoo, Jeong, & Sohn, 2015)



(Kang, Jun, Ryoo, Jeong, & Sohn, 2015)

Plasticity in the intrinsic excitability of cortical pyramidal neurons

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During learning and development, the level of synaptic input received by cortical neurons may change dramatically. Given a limited range of possible firing rates, how do neurons maintain responsiveness to both small and large synaptic inputs? We demonstrate that in response to changes in activity, cultured cortical pyramidal neurons regulate intrinsic excitability to promote stability in firing. Depriving pyramidal neurons of activity for two days increased sensitivity to current injection by selectively regulating voltage-dependent conductances. This suggests that one mechanism by which neurons maintain sensitivity to different levels of synaptic input is by altering the function relating current to firing rate.

Use it or lose it: How neurogenesis keeps the brain fit for learning

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Abstract

The presence of new neurons in the adult hippocampus indicates that this structure incorporates new neurons into its circuitry and uses them for some function related to learning and/or related thought processes. Their generation depends on a variety of factors ranging from age to aerobic exercise to sexual behavior to alcohol consumption. However, most of the cells will die unless the animal engages in some kind of effortful learning experience when the cells are about one week of age. If learning does occur, the new cells become incorporated into brain circuits used for learning. In turn, some processes of learning and mental activity appear to depend on their presence. In this review, we discuss the now rather extensive literature showing that new neurons are kept alive by effortful learning, a process that involves concentration in the present moment of experience over some extended period of time. As these thought processes occur, endogenous patterns of rhythmic electrophysiological activity engage the new cells with cell networks that already exist in the hippocampus and at efferent locations. Concurrent and synchronous activity provides a mechanism whereby the new neurons become integrated with the other neurons. This integration allows the present experience to become integrated with memories from the recent past in order to learn and predict when events will occur in the near future. In this way, neurogenesis and learning interact to maintain a fit brain.

Experiment Layout

Brain Computer Interface

Wrist Flexion (Taylor et al., 2014)

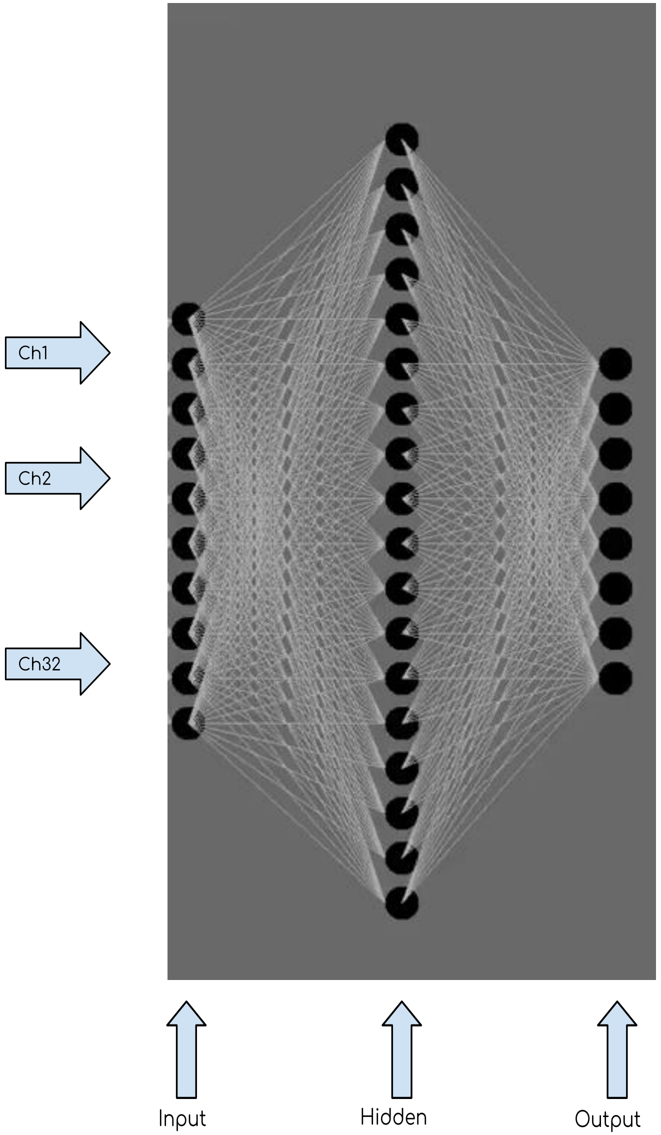
Affect Computing

DEAP-Emotional stress

(Koelstra et al., 2012)

Perceived mental stress

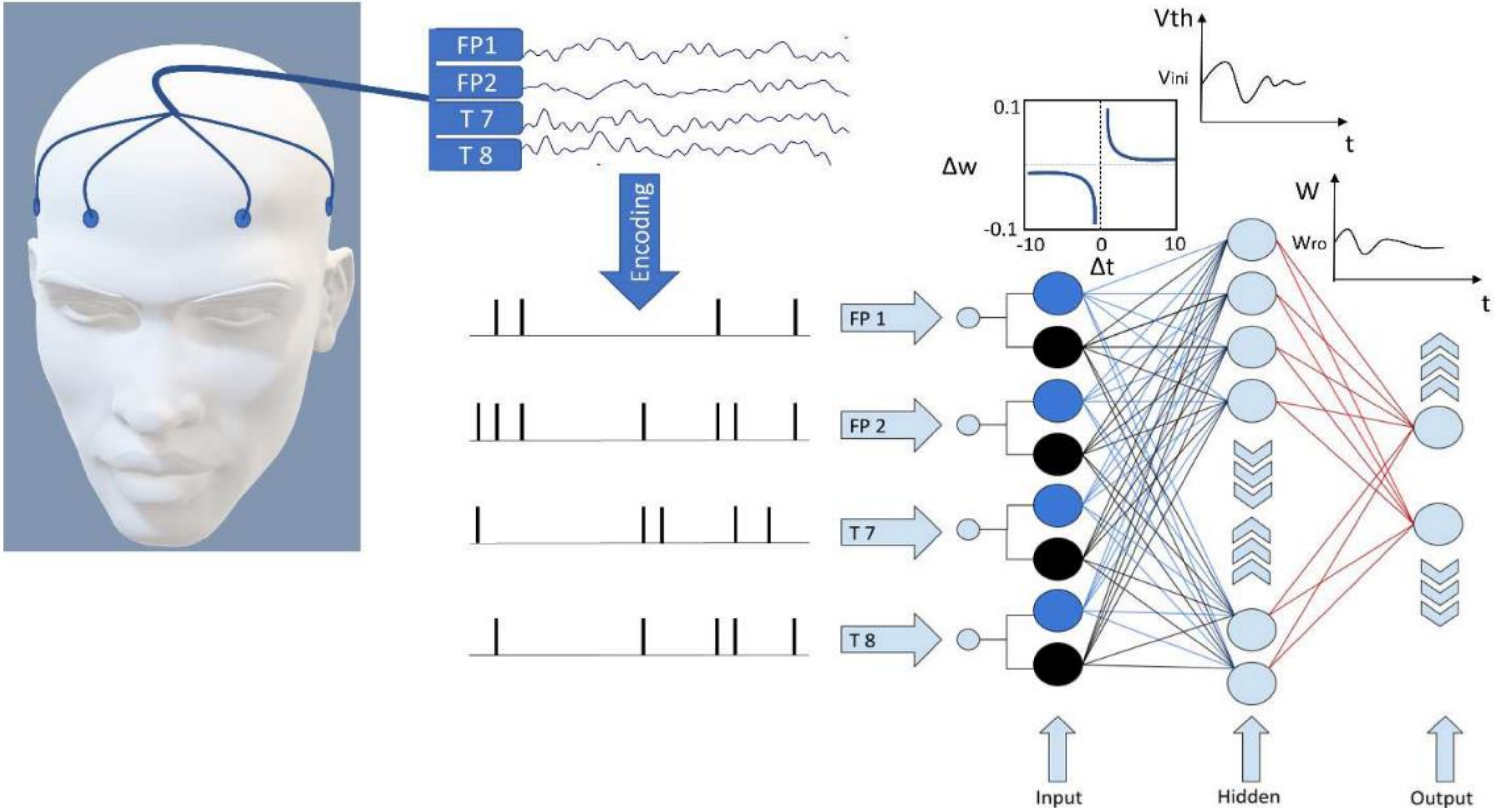
(AUT Dept. Psych.)



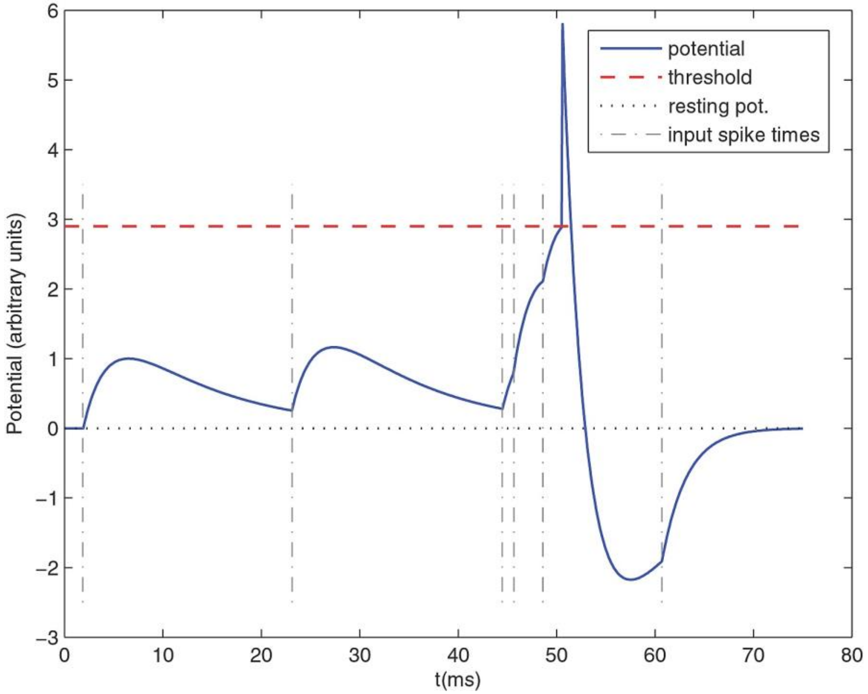
Learning capability
(Classification accuracy)

Hypothesis generation
(Network behavior)

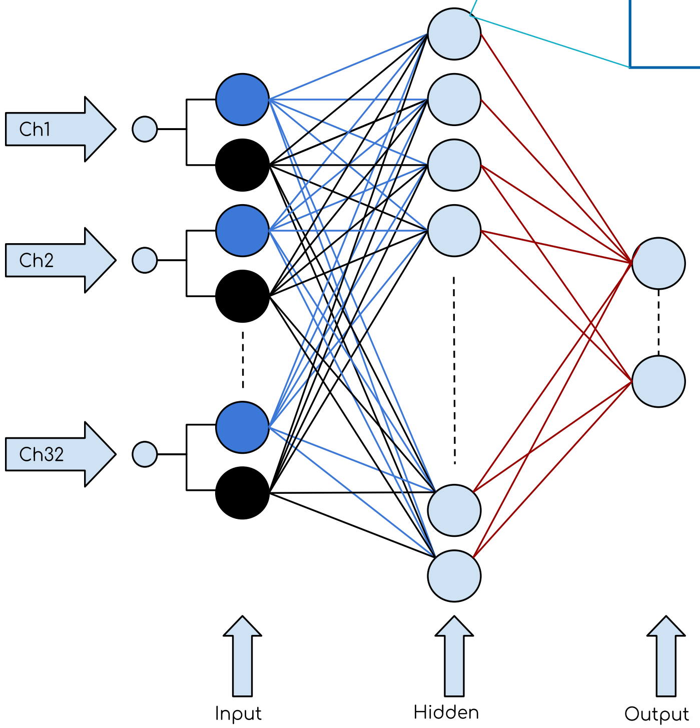
Neuroplasticity SNN



Intrinsic Plasticity SNN



("Leaky Integrate-and-Fire (LIF) neuron.," 2013)



Adaptive threshold

if fired

$$Th_{(t)} = Th_{(t-1)} + \theta_{pos}$$

else

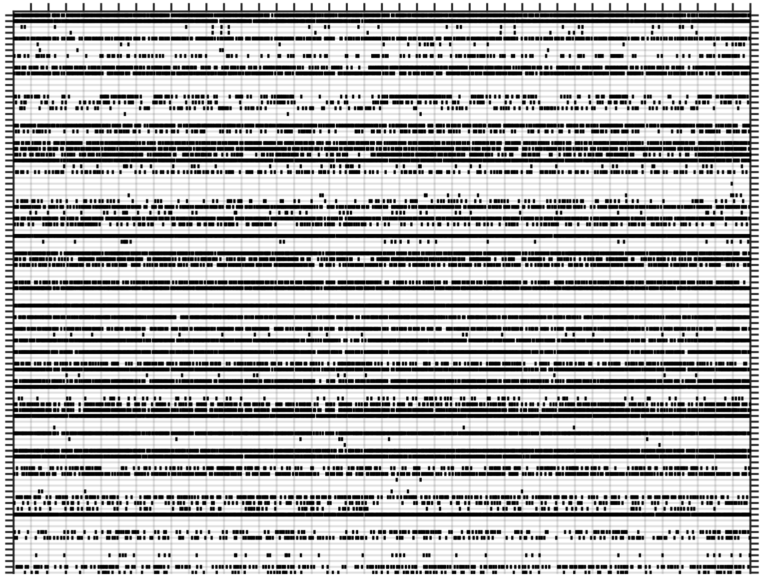
$$Th_{(t)} = Th_{(t-1)} - \theta_{neg}$$

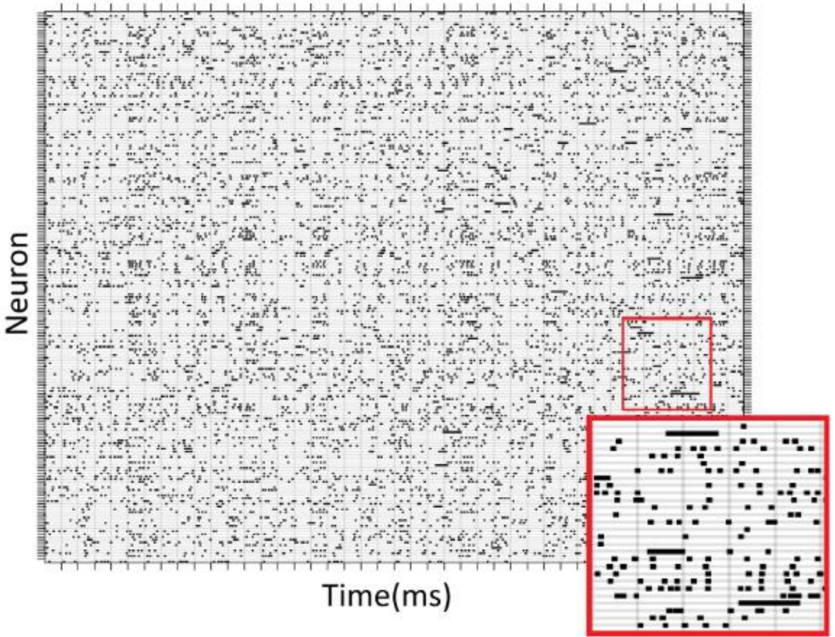
Intrinsic Plasticity SNN

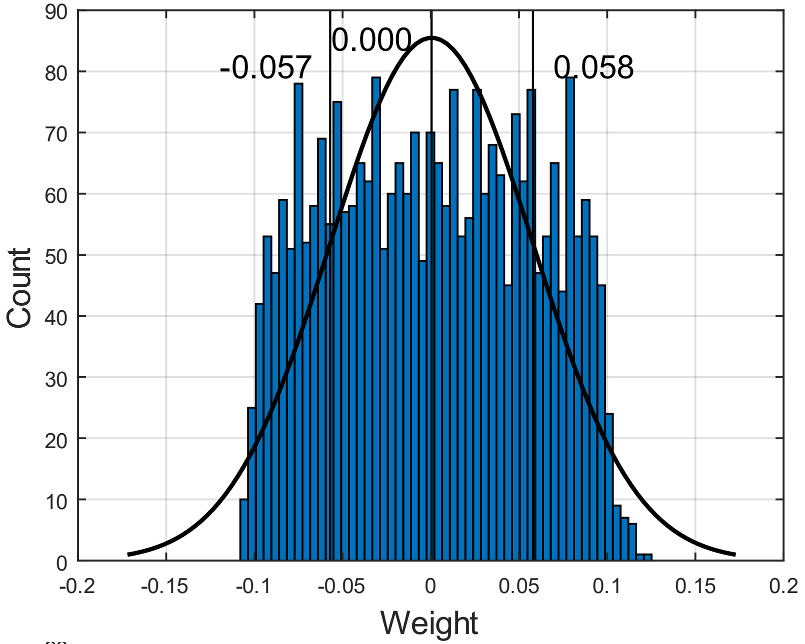
Without IP

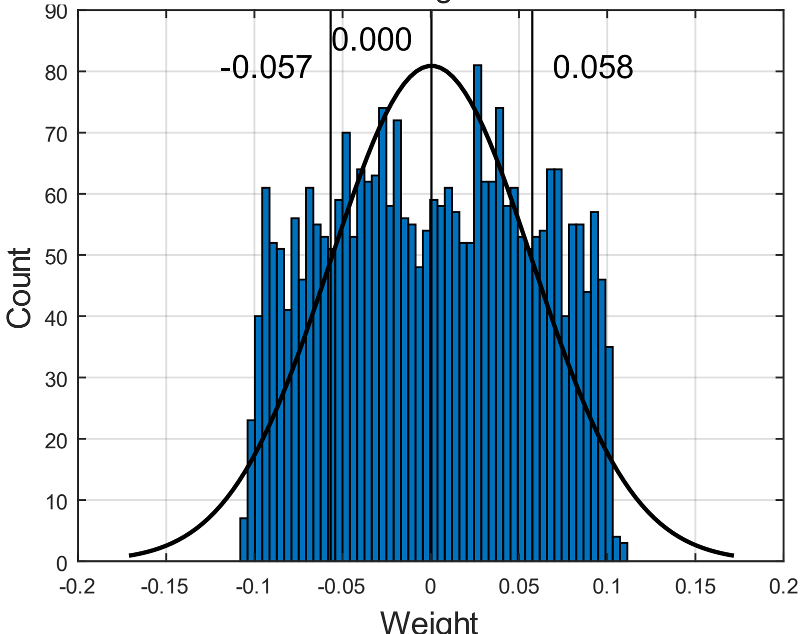
BCI Dataset

With IP



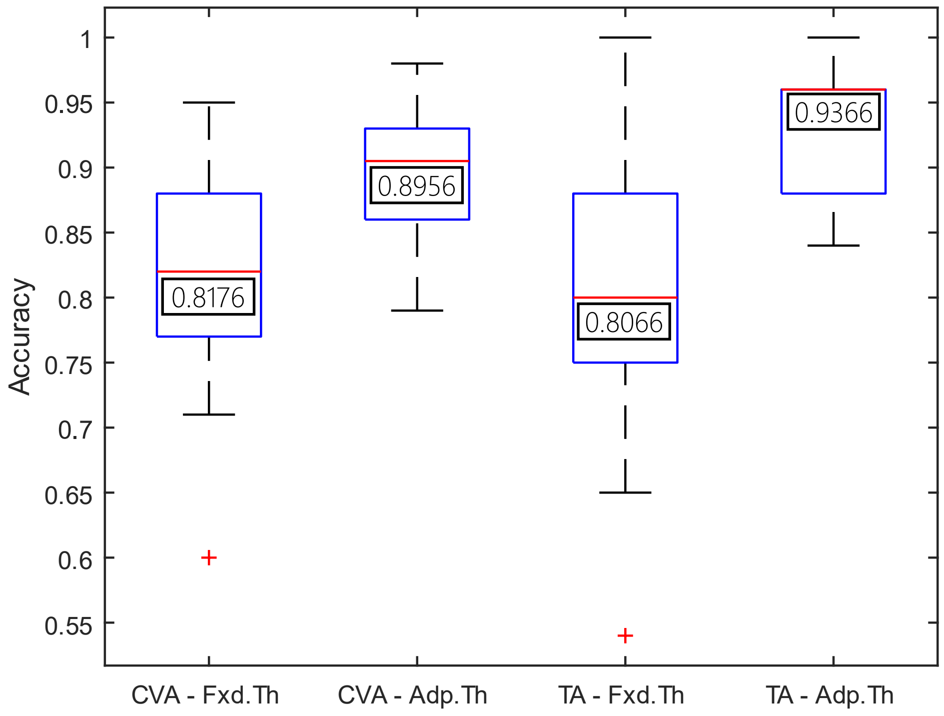




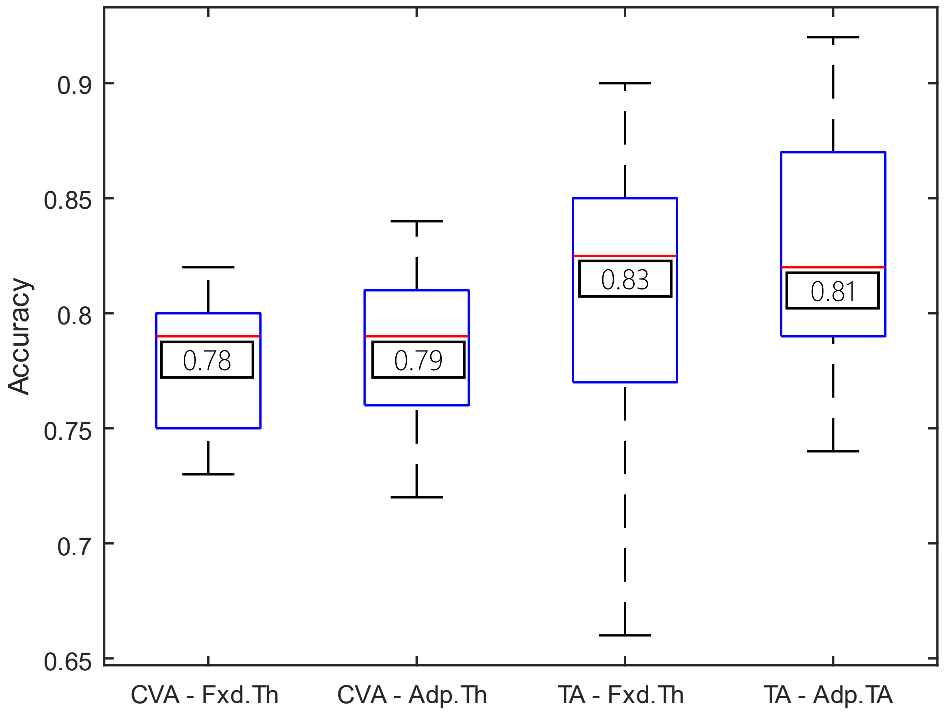


Intrinsic Plasticity SNN

BCI Dataset



Emotional Stress Dataset

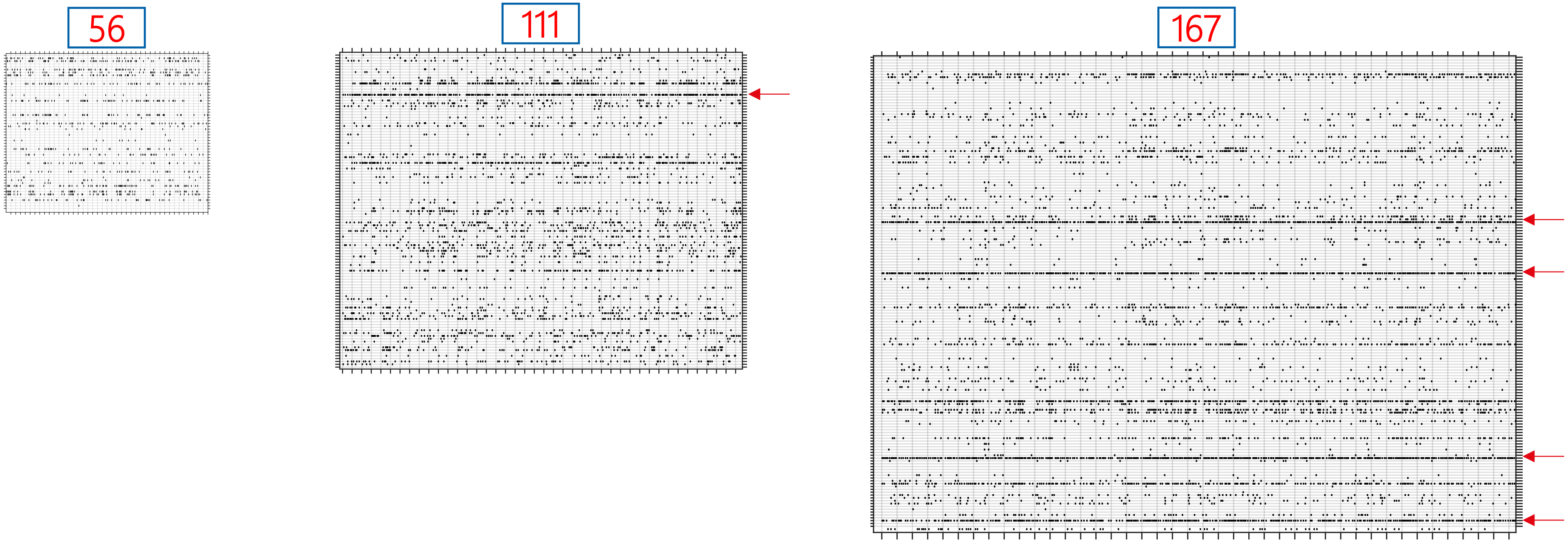


Average inactive neurons ~27 to 0

Average inactive neurons ~8 to 0

Structural Plasticity SNN

1. Why did optimized structure performed better in terms of accuracy and/or robustness?

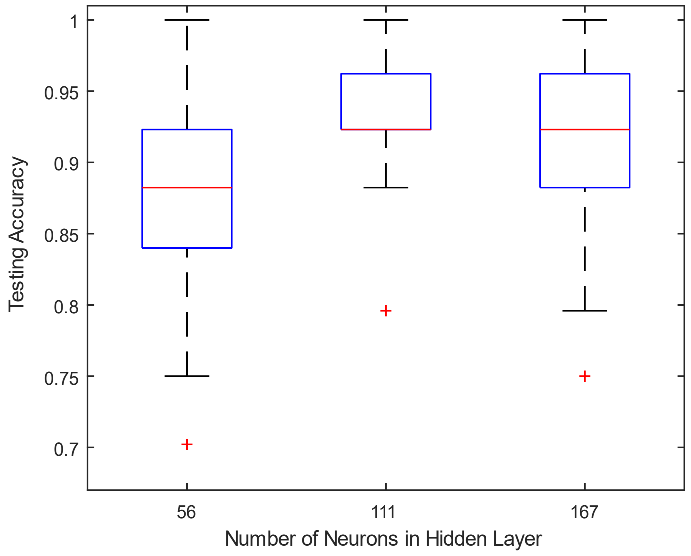


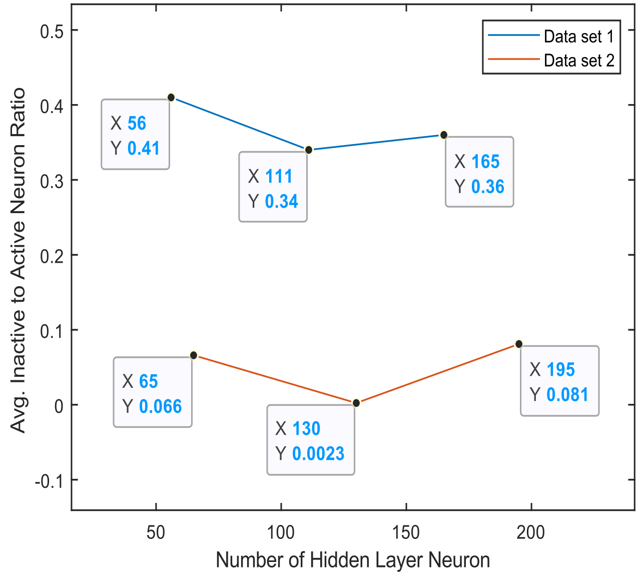
Redundant neurons getting activated during testing cycles

"*Rich getting richer*" (Too many hub neurons)

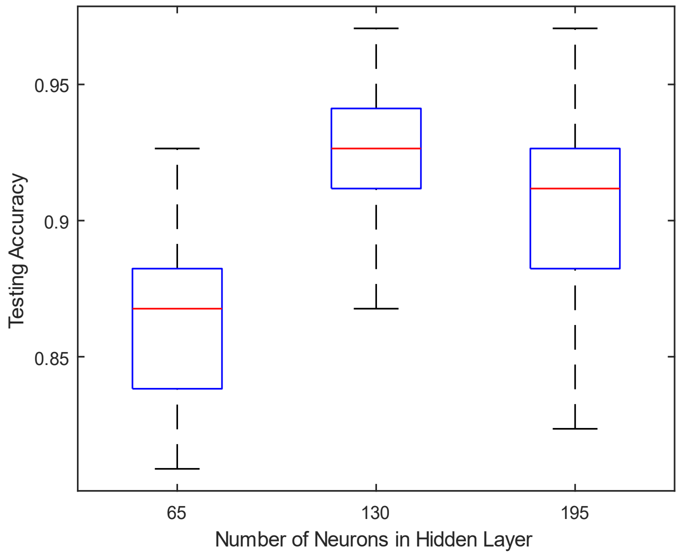
Structural Plasticity SNN

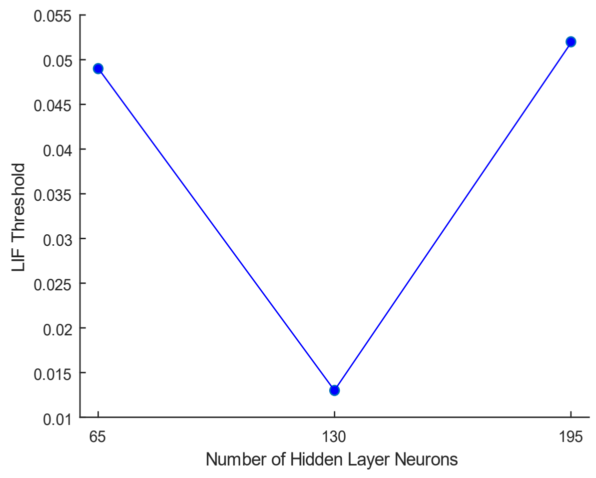
BCI Dataset
94% classification accuracy



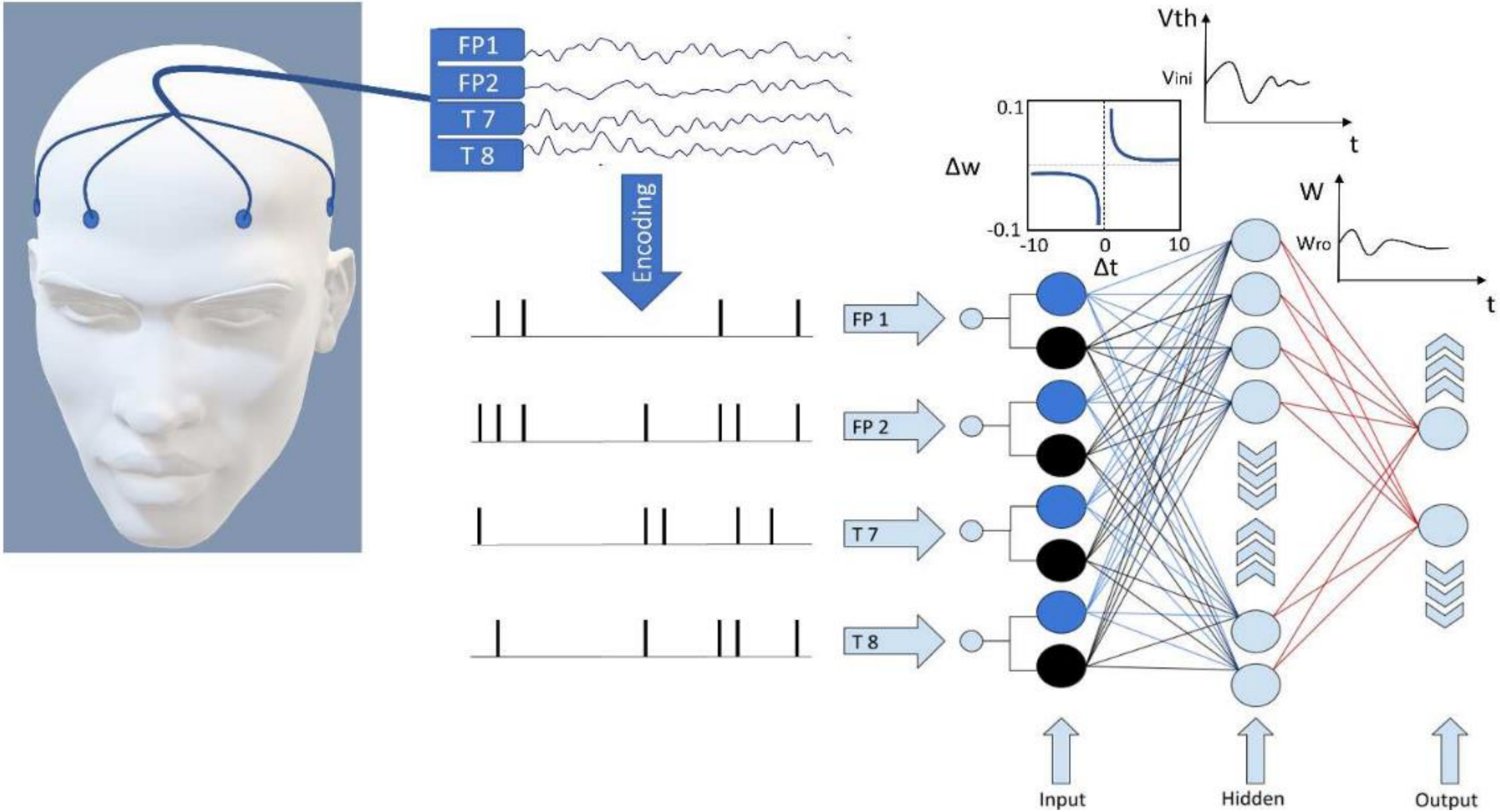


Emotional Stress Dataset
91% classification accuracy



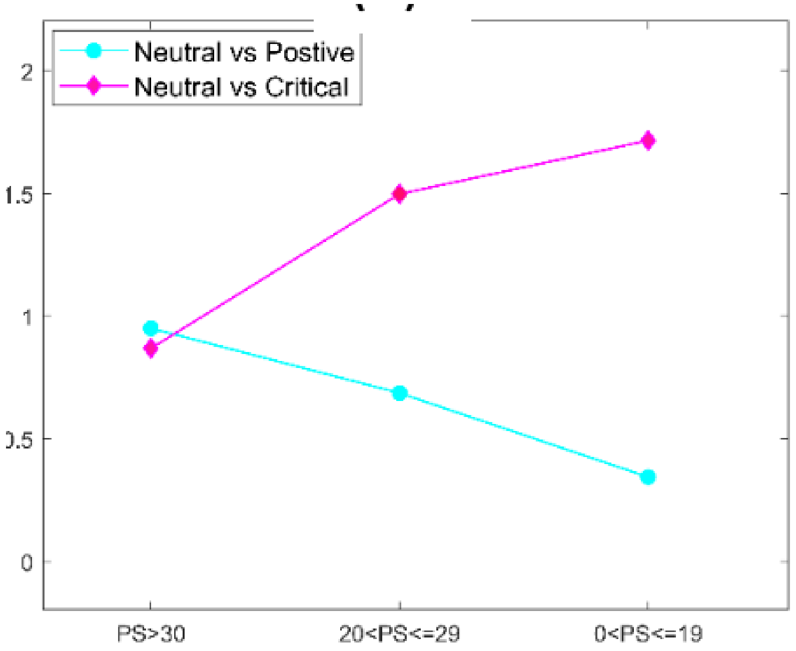


Neuroplasticity SNN



Findings

1. Accuracy of 90.76% in classifying between stress, neutral and positive audio stimuli
2. High Perceived Stress participants showed lower activation levels in prefrontal channels FP1 and FP2 compared to the LS group. This was observed during the synaptic weight analysis of individual models where the HS group had more inhibitory weights connected to FP1 and FP2 channels. The impairment of prefrontal activity during stressful events and, in individuals with high perceived stress have been reported previously.



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Way forward..

Discussion

1. Can ASNN is be power efficient? Yes. Given we use efficient learning algorithms running on Neuromorphic hardware
2. One way is to turn towards biology to find learning algorithms
3. Can ASNNs replace ANNs?
4. Can we use SNN network to better understand human brain ?

Ongoing work

1. Work on Intrinsic Plasticity
2. Applications on brain data modelling tasks (Attention, Depression)

Thank You

"Simplicity is the ultimate sophistication"
Leonardo da Vinci

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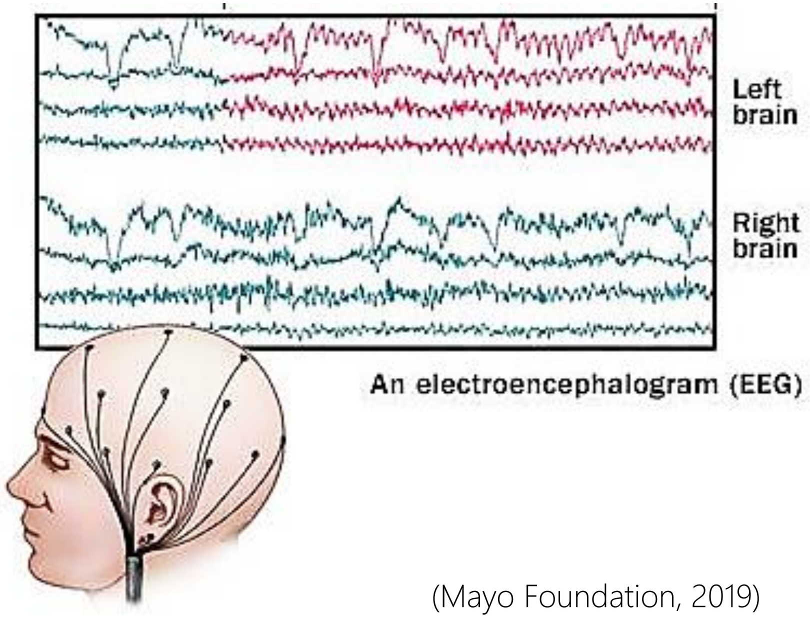
Spatiotemporal Data

Space and time are ubiquitous aspects of observations in a number of domains, including, climate science, neuroscience, social sciences, and Earth sciences, that are rapidly being transformed by the deluge of data. The real-world processes being studied in these domains are inherently spatiotemporal in nature. (Atluri, Karpatne, & Kumar, 2017)

Generic Properties

1. Autocorrelation
2. Heterogeneity



(Mayo Foundation, 2019)

SNN advantages in AI

Why SNNs for AI ?

Timing based

Increased information capacity

Event- Based

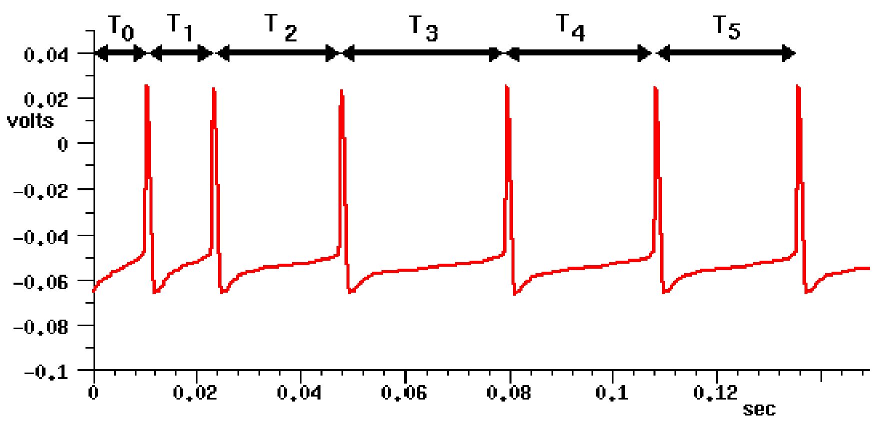
Power-efficient computing

Asynchronous data-driven

Fast propagation of salient information

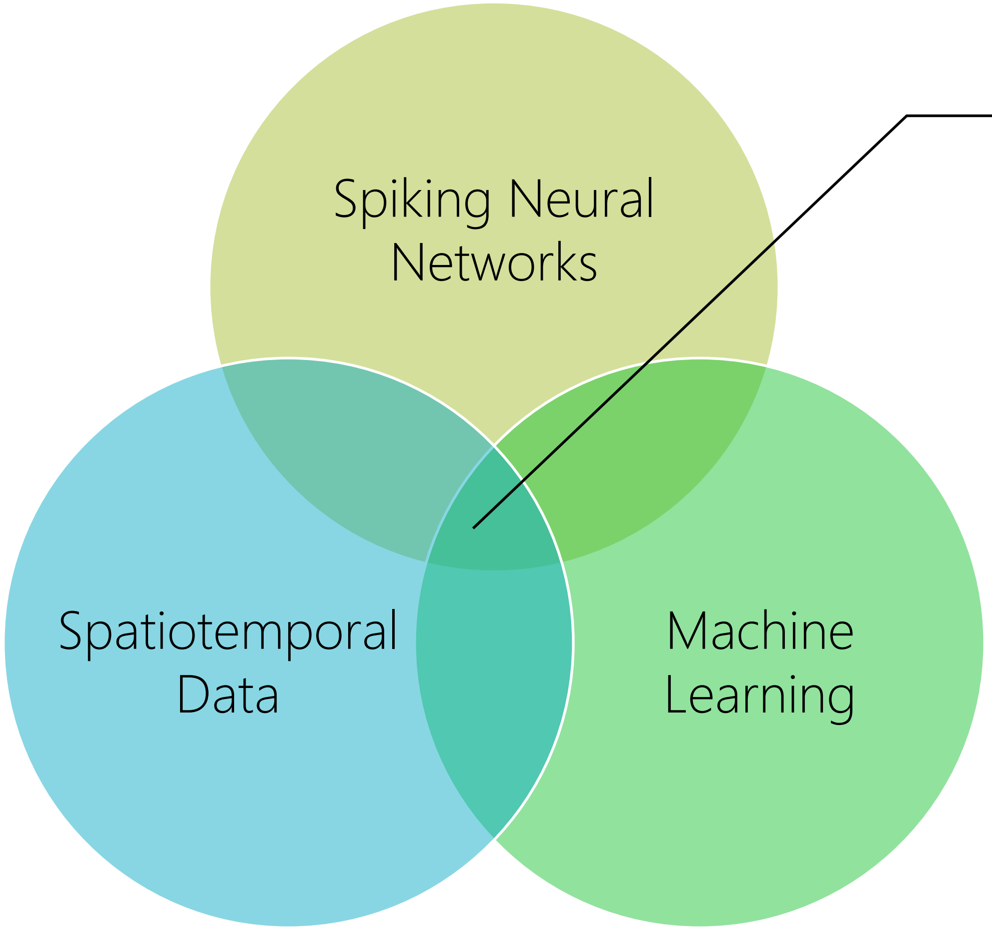
"SNNs on neuromorphic hardware exhibit favourable properties such as low power consumption, fast inference, and event-driven information"

(Pfeiffer & Pfeil, 2018)



(Dave Beeman, 2008)

Research Focus

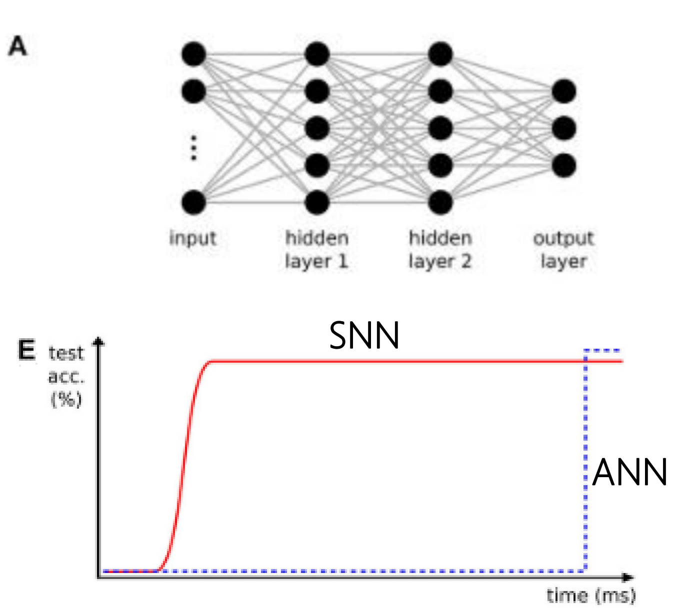


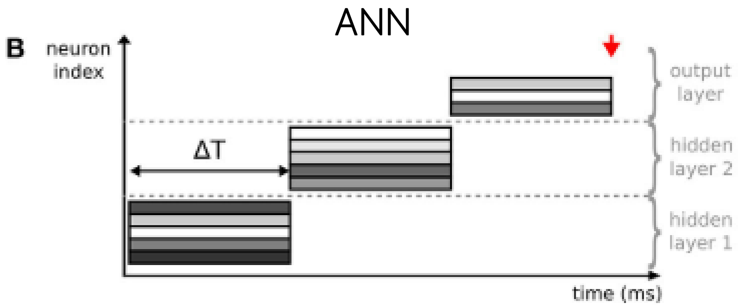
Exploring the impact of Structural Plasticity as a learning technique for modelling EEG data on Human Mental Stress using Spiking Neural Networks

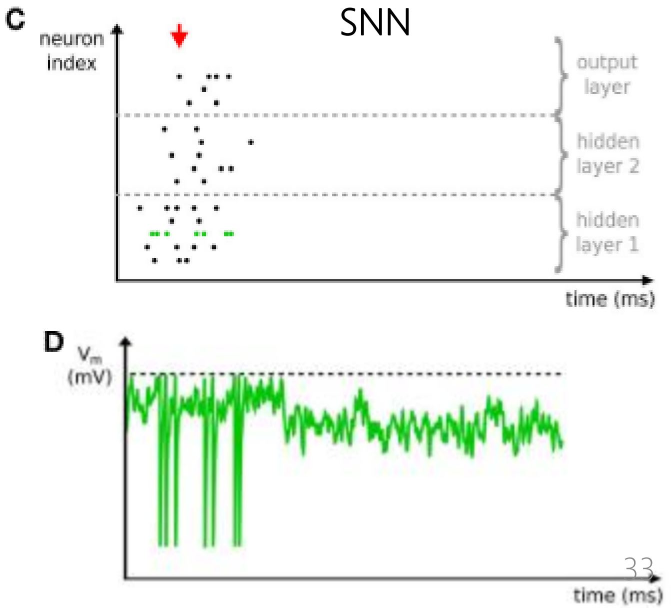
SNNs vs ANNs

Feature	ANN	SNN
Data processing Latency	Frame-based High	Spike-based Low(Pseudo-simultaneity)
Time resolution	Low	High Preserve spatio-temporal correlation
Time processing	Sampled	Continuous
Neuron model complexity	Low	High
Recognition accuracy	Higher	Lower
Recognition speed	Low	High
Power consumption	Depends on processor power and memory fetching	Depends on power per event processing

(Farabet et al., 2012)







(Pfeiffer & Pfeil, 2018)