Exploring Spiking Neural Networks

An exploration into Brain-Inspired Artificial Spiking Neural Networks
ICAC 2024

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Terminology alert !

Artificial Spiking Neural Networks - ASNNs | Spiking Neural Networks - SNNs
Artificial Spiking Neural Networks - ANNs
Spike Time Dependent Plasticity - STDP

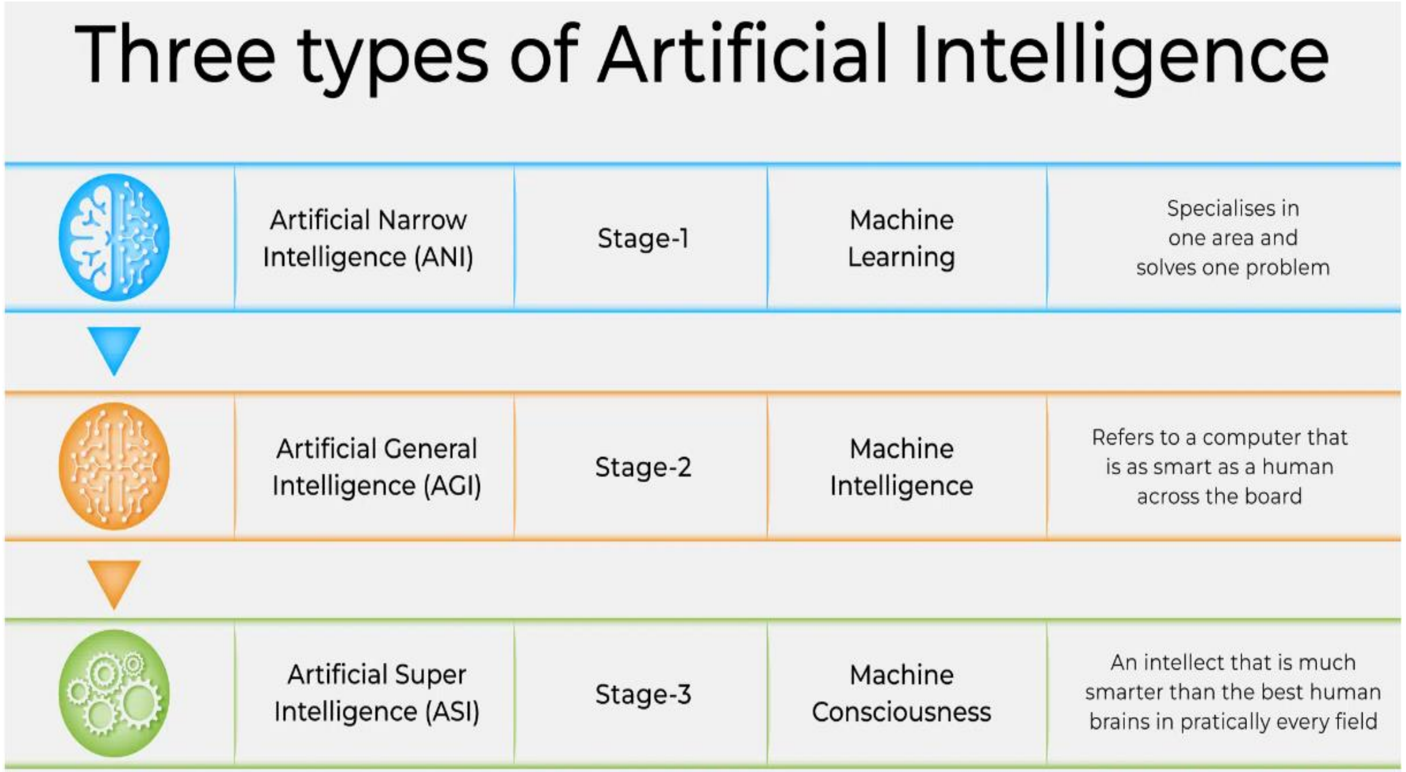
Presentation Overview

Presentation

1. What can SNNs do ?
2. Classification using SNNs
3. Why use SNNs ?
4. Different Neurons
5. How to use SNNs?
6. Building an SNN

What can SNNs do?

https://vedapuran.wordpress.com/the-deities-and-demigods/skanda/



Three types of Artificial Intelligence

Artificial Narrow Intelligence (ANI)	Stage-1	Machine Learning	Specialises in one area and solves one problem
Artificial General Intelligence (AGI)	Stage-2	Machine Intelligence	Refers to a computer that is as smart as a human across the board
Artificial Super Intelligence (ASI)	Stage-3	Machine Consciousness	An intellect that is much smarter than the best human brains in pratically every field

https://deltalogix.blog/en/2023/03/08/artificial-intelligence-a-look-at-its-three-types-and-their-possible-future-implications/

What is AI and where is it going?

What can SNNs do?

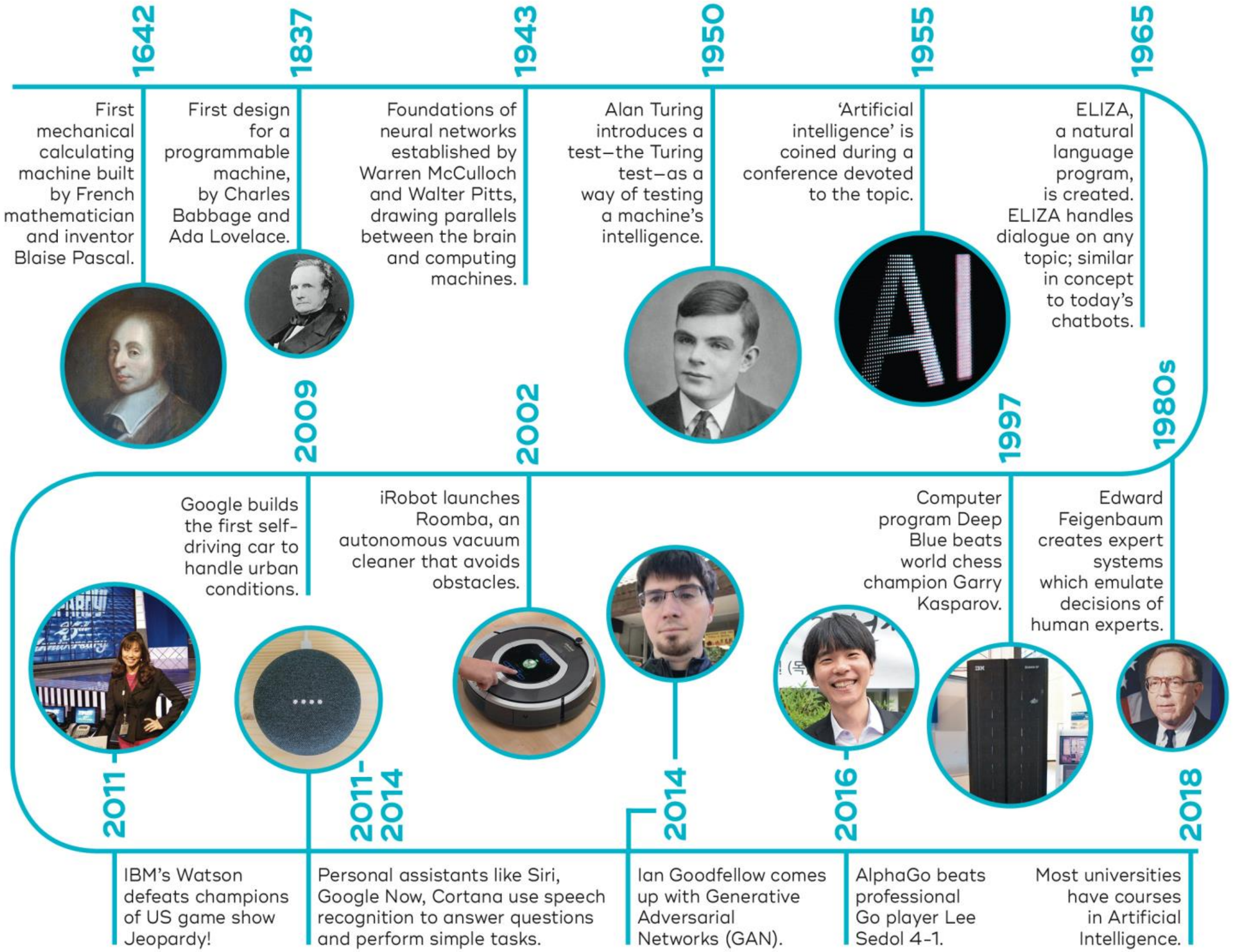
"What we want is a machine that can learn from experience" – Alan Turing

"Artificial intelligence is the science of making machines do things that would require intelligence if done by men" – Marvin Minsky

"Our ultimate objective is to make programs that learn from their experience as effectively as humans do" – John McCarthy

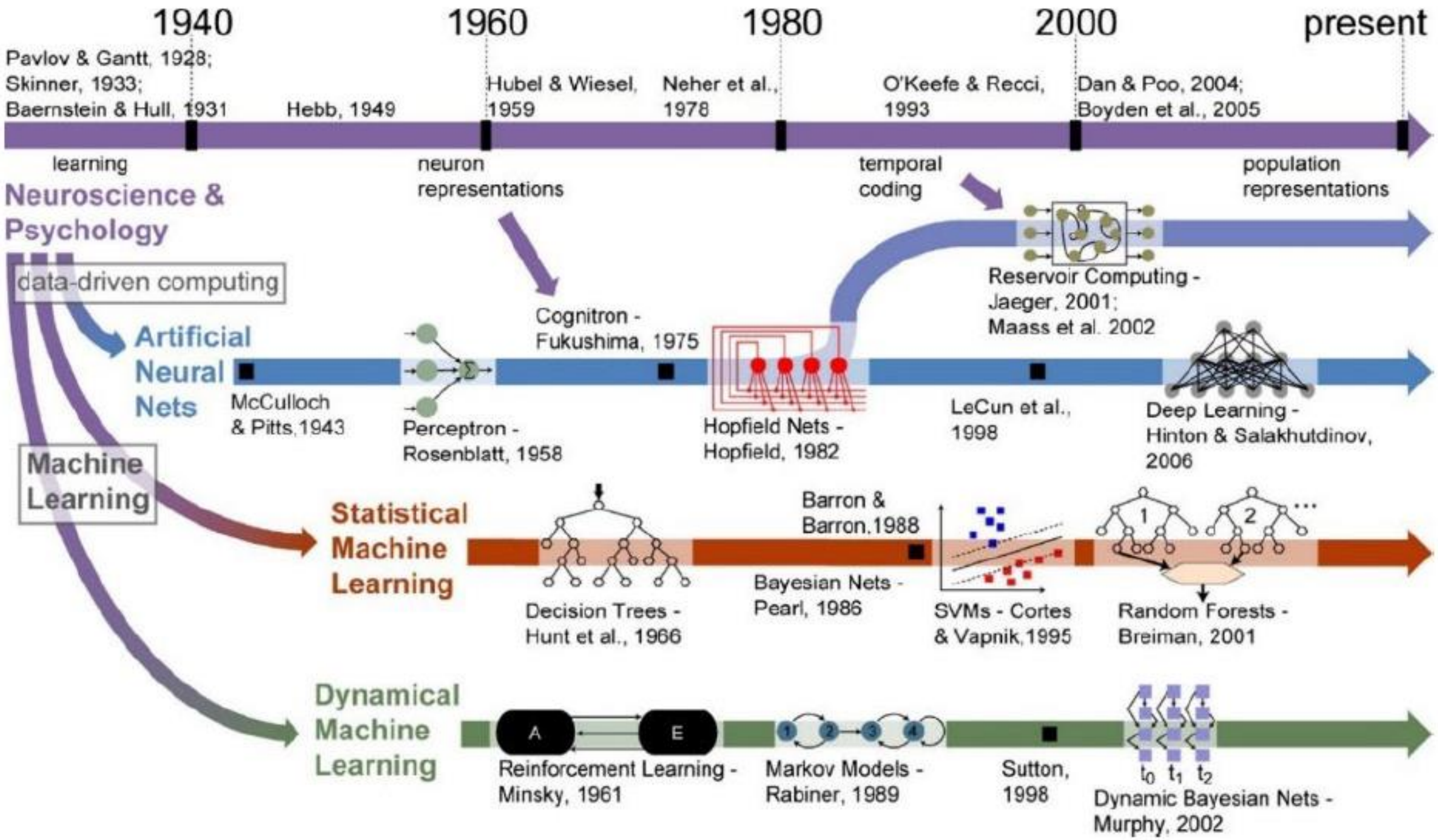
What is AI and where is it going?

Trajectory of AI Modern AI



https://qbi.uq.edu.au/brain/intelligent-machines/history-artificial-intelligence

Trajectory of AI Development



From "A historical survey of algorithms and hardware architectures for neural-inspired and neuromorphic computing applications", by James, C. D., Aimone, J. B., Miner, N. E., Vineyard, C. M., Rothganger, F. H., Carlson, K. D., Mulder, S. A., Draelos, T. J., Faust, A., Marinella, M. J., Naegle, J. H., & Plimpton, S. J., 2017, Biologically Inspired Cognitive Architectures, 19, 49–64. https://doi.org/10.1016/j.bica.2016.11.002, Copyright 2016 by Elsevier.

Two Schools of AI Development

Potential of SNNs

"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).

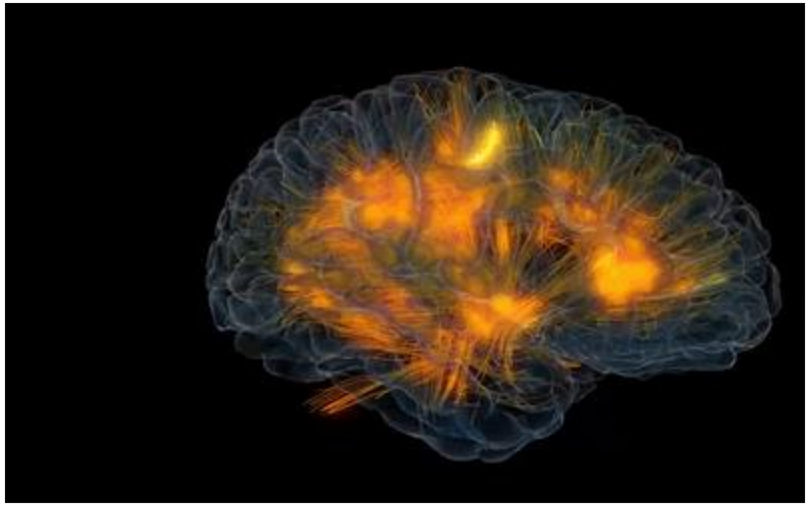
"the ultimate advantage of SNNs comes from their ability to fully exploit spatio-temporal event-based information" (Roy et al., 2019)

"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 vs the Brain

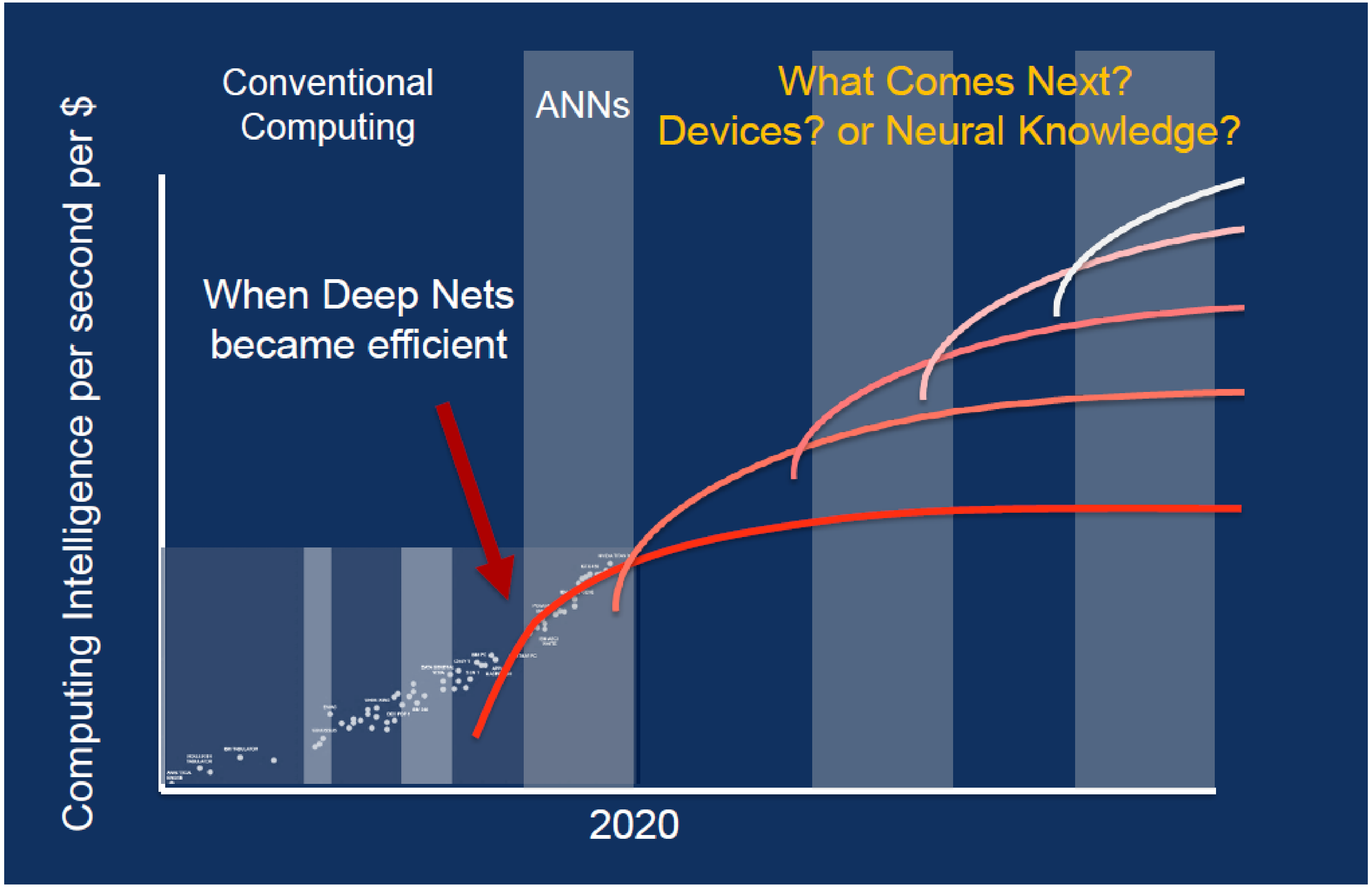
GPT-3 training cost –
12 million USD



Brain needs ~ 20 W

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

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/

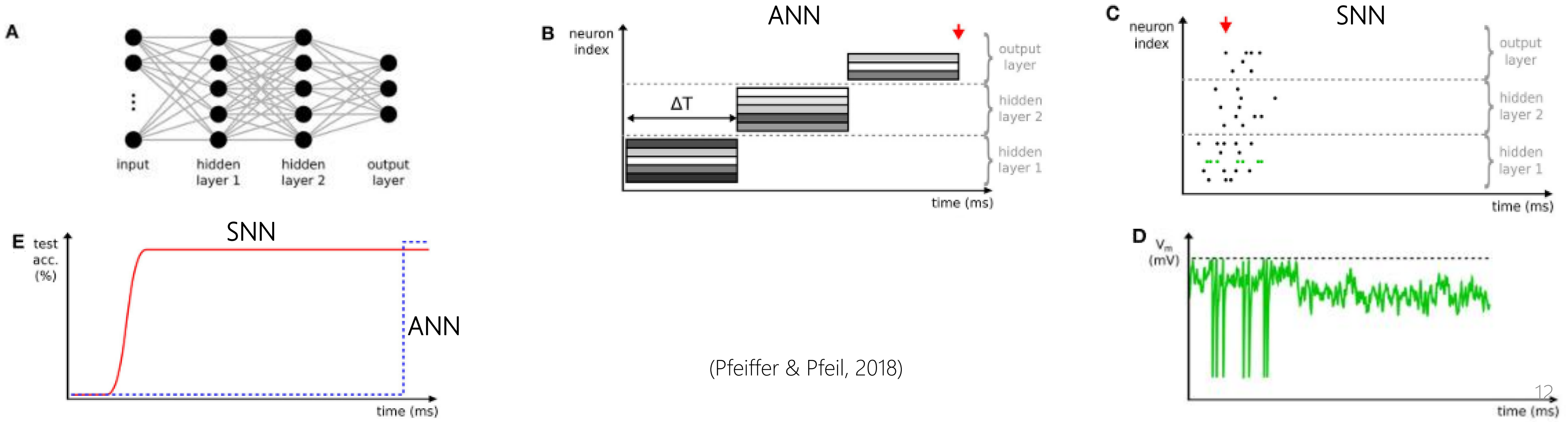


Aimone et al., 2020

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)

Session 1 Summary

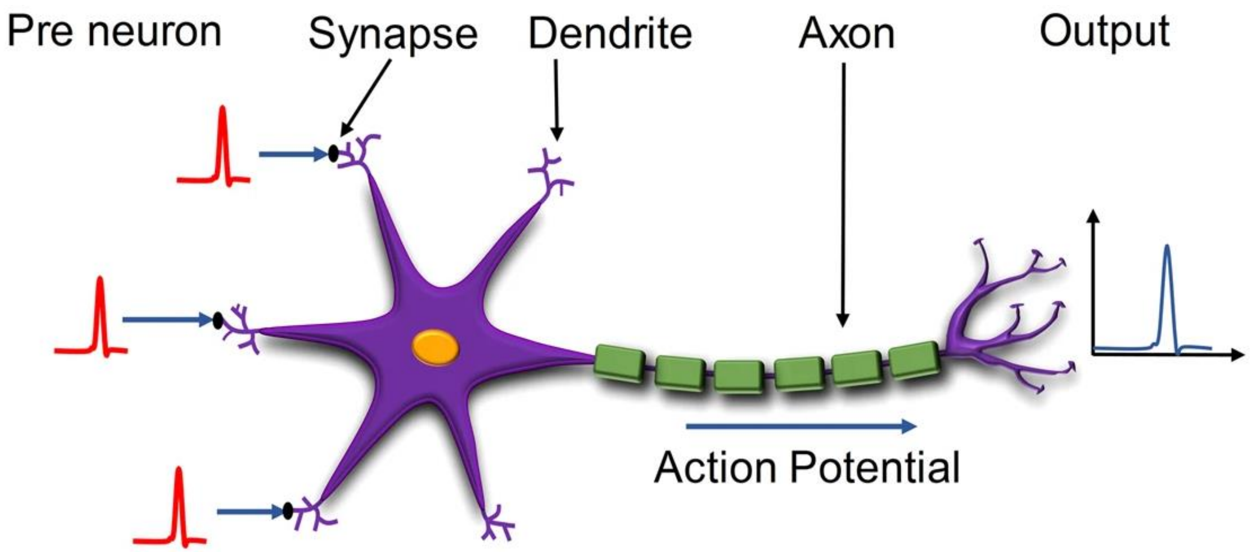
What can SNNs do?

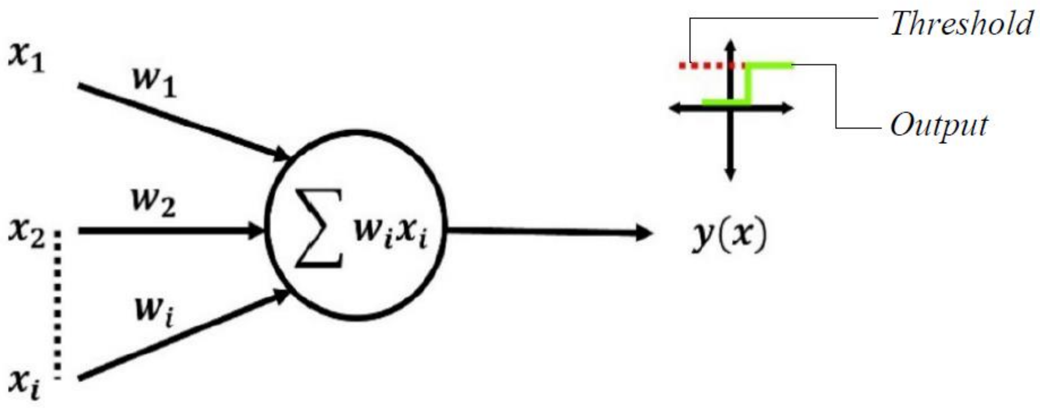
a. Build intelligence into machines
b. Help us understand brain computation better

Why SNNs for AI?

a. Train and infer faster*
b. Model Spatio-temporal data

Brain vs ANNs

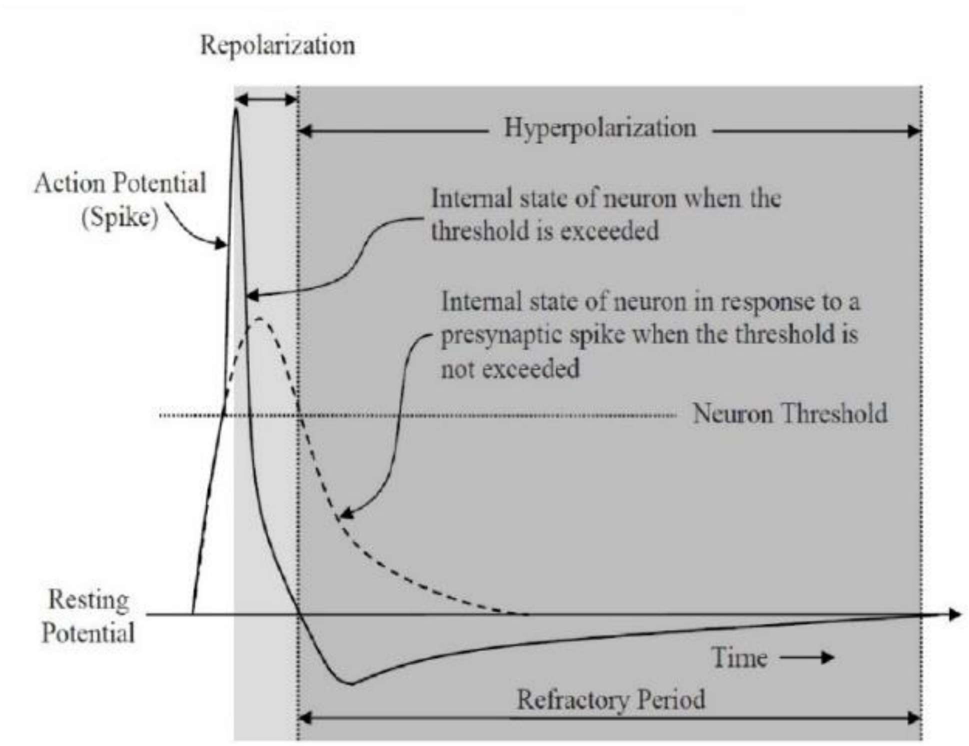




(Kalita et al., https://hal.archives-ouvertes.fr/tel-02429539%0Ahttps://hal.archives-ouvertes.fr/tel-02429539/document 2019)

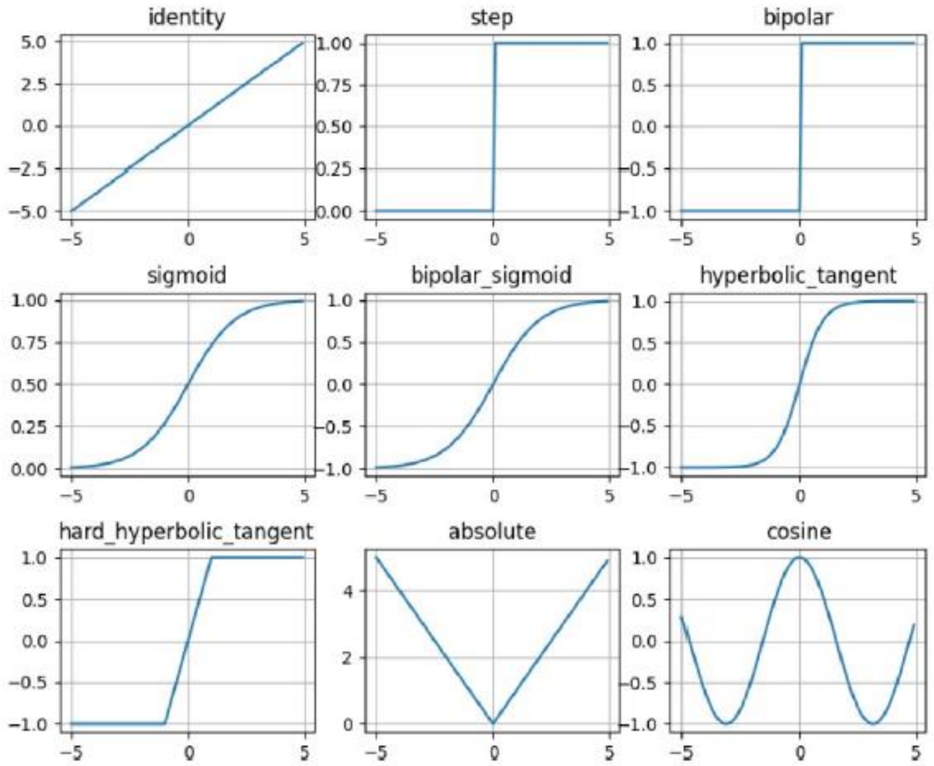
Brain vs ANNs

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.

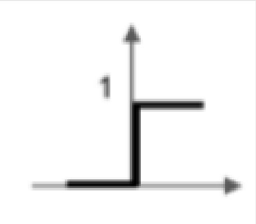
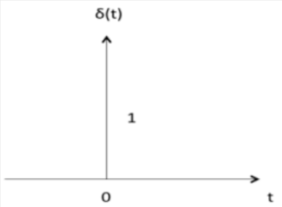
Transfer function of Artificial Neurons



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

Categories of Artificial Neurons in ANNs

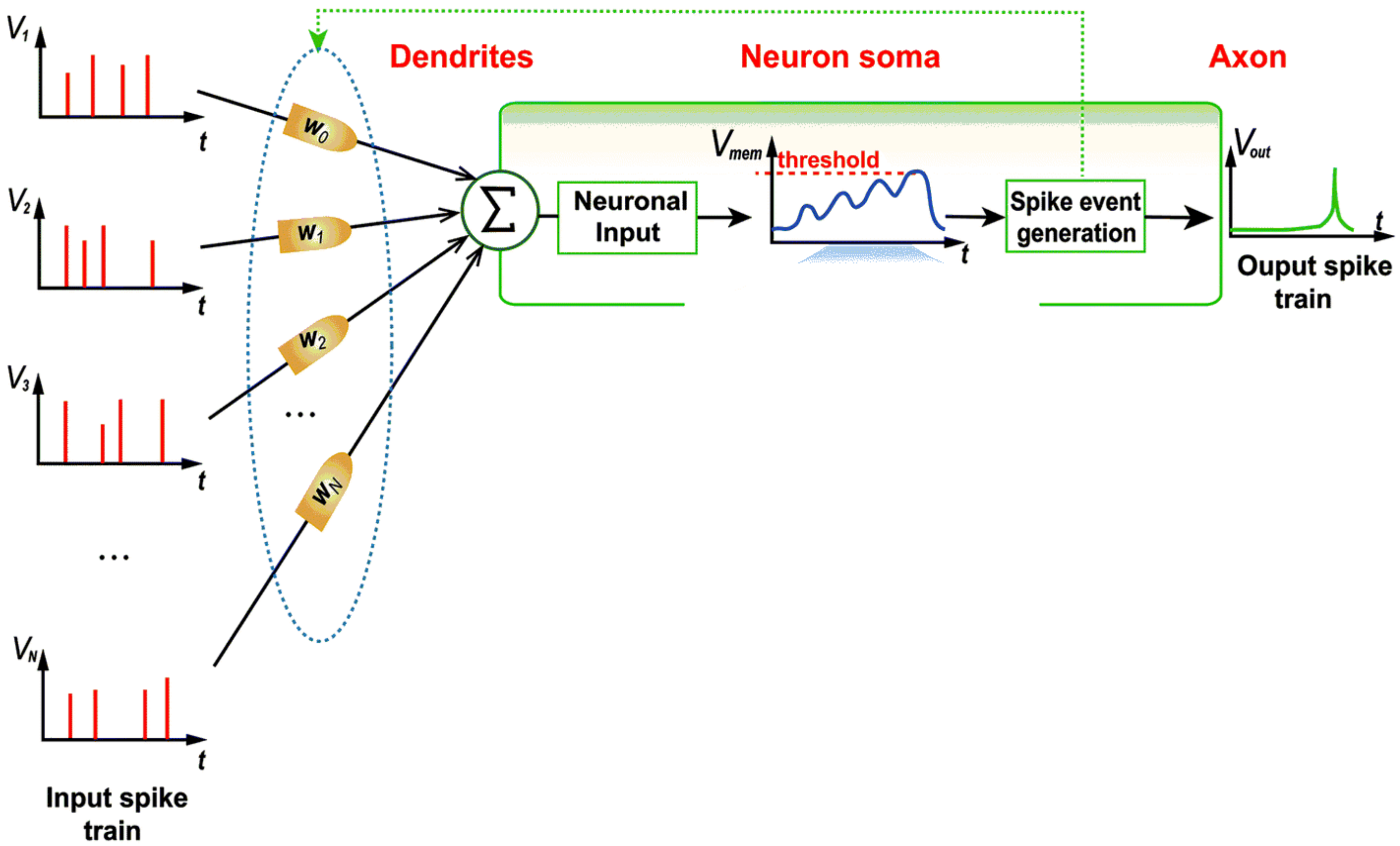
Neuron Type	Operational Description (Use examples)	Function representation
First Generation	**Approximating any Boolean function** (Perceptron, Hopfield network, Bidirectional Associative memory (BAM) and etc.)	
Second Generation	**Approximating any real-valued function** (Multi-layer Perceptron (MLP),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

"In particular it is shown that networks of spiking neurons are, with regard to the number of neurons that are needed, computationally more powerful than these other neural network models."

Networks of spiking neurons: The third generation of neural network models, W.Mass,1997

Artificial Spiking Neural Networks

Single spiking neuron representation



ASNN advantages in AI

Why ASNNs for AI ?

Timing based

Increased information capacity

Event- Based

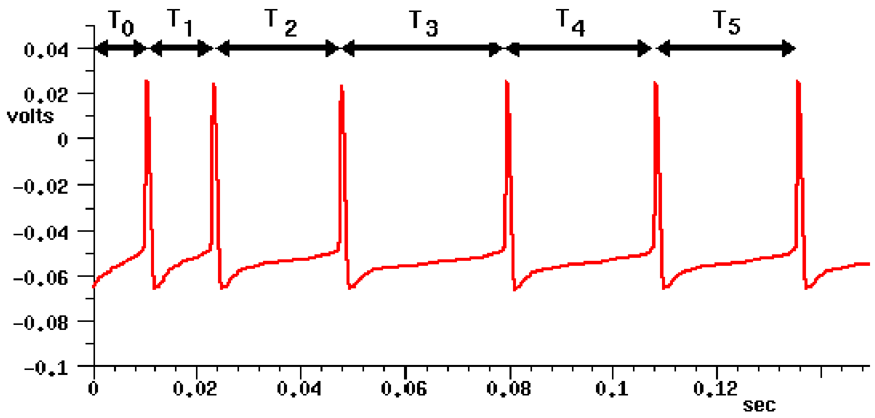
Power-efficient computing

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)

ASNN Experiment

Brain Computer Interface

Wrist Flexion (Taylor et al., 2014)

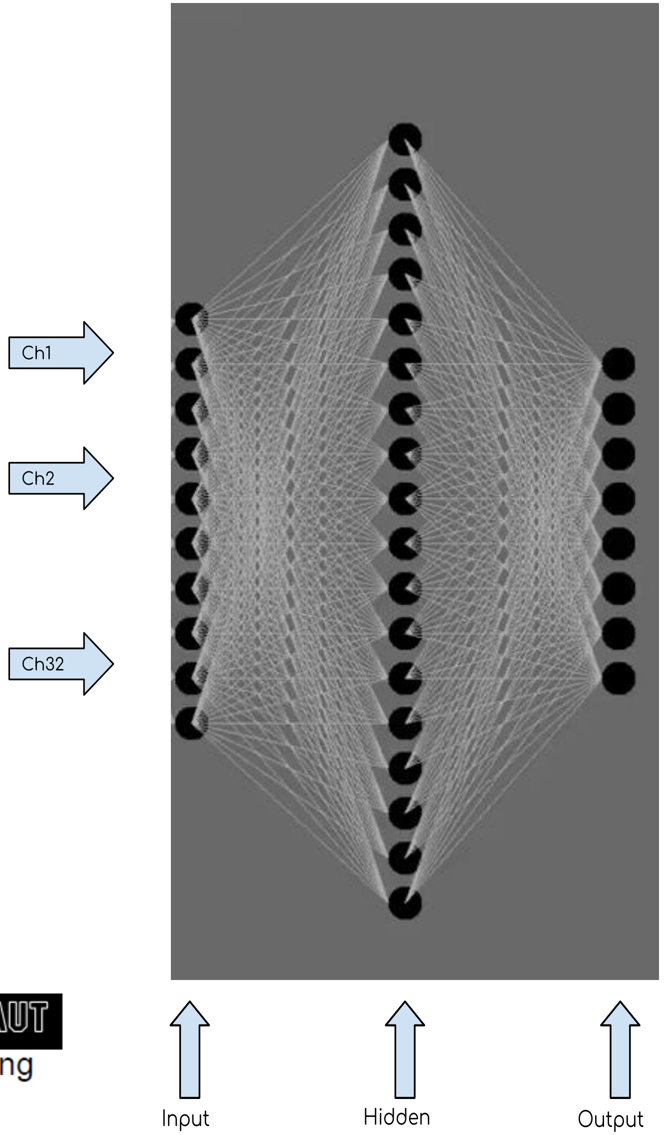
Affect Computing

DEAP-Emotional stress

(Koelstra et al., 2012)

Perceived mental stress

(AUT Dept. Psych.)



Learning capability (Classification accuracy)

Hypothesis generation (Network behavior)

AUT

Emotional Stress State Classification and Analysis using Spiking Neural Networks

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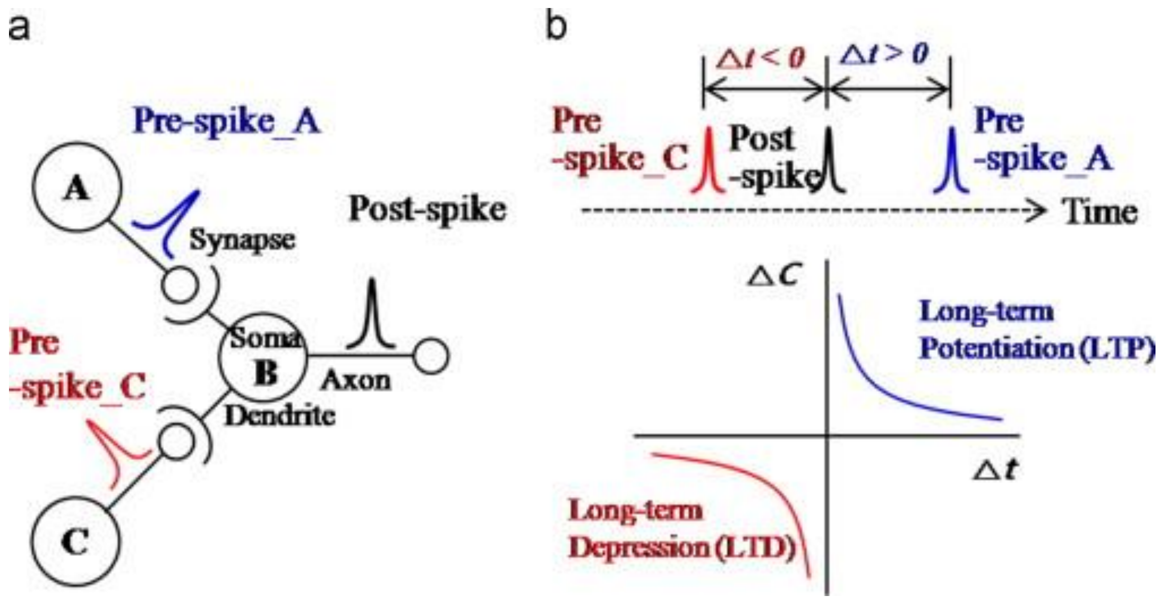
*dave.parry@aut.ac.nz

Learning in ASNNs

Having an efficient neuron is one thing, what about an efficient learning process ?

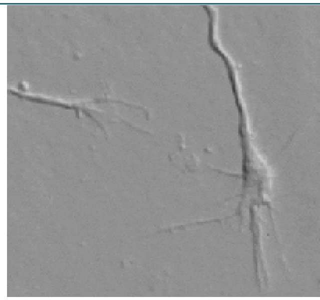
How does ASNNs learn?

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.**



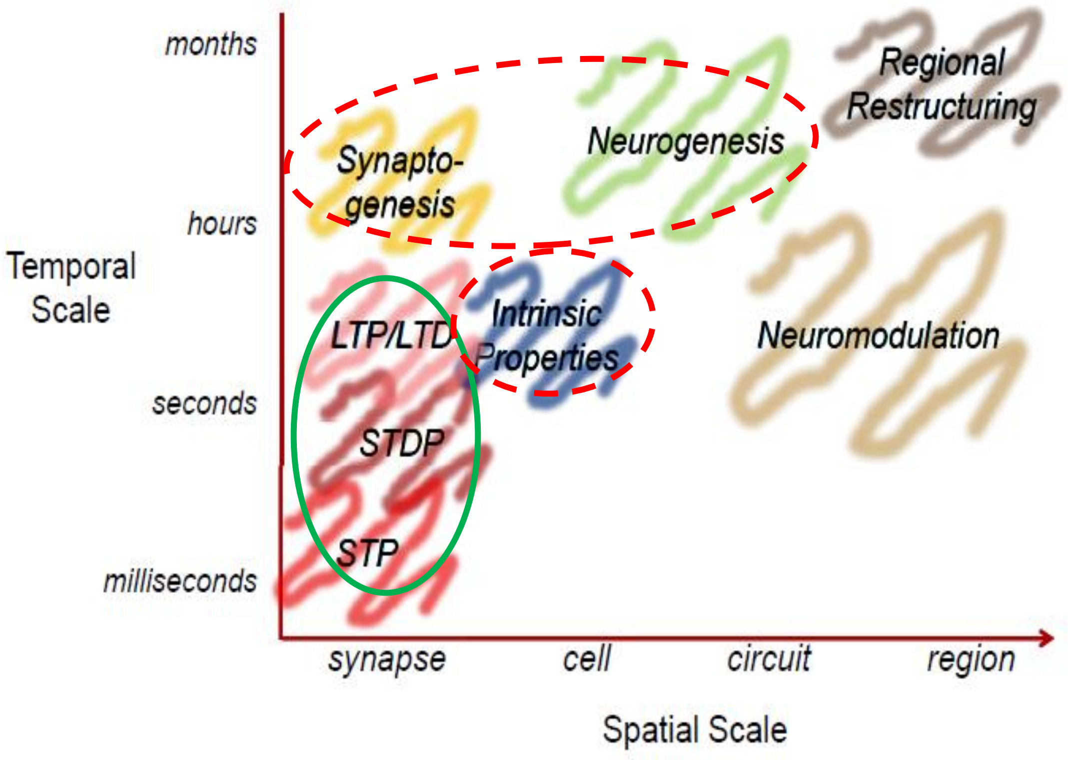
(Kang, Jun, Ryoo, Jeong, & Sohn, 2015)

Plasticity in the Brain



Structural Adaptability in the Human Brain Circuits

Synaptogenesis , Synaptic Pruning, Neurogenesis and Apoptosis



(A historical survey of algorithms and hardware architectures for neural-inspired and neuromorphic computing applications-C.James, 2017)

Proliferation followed by pruning

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

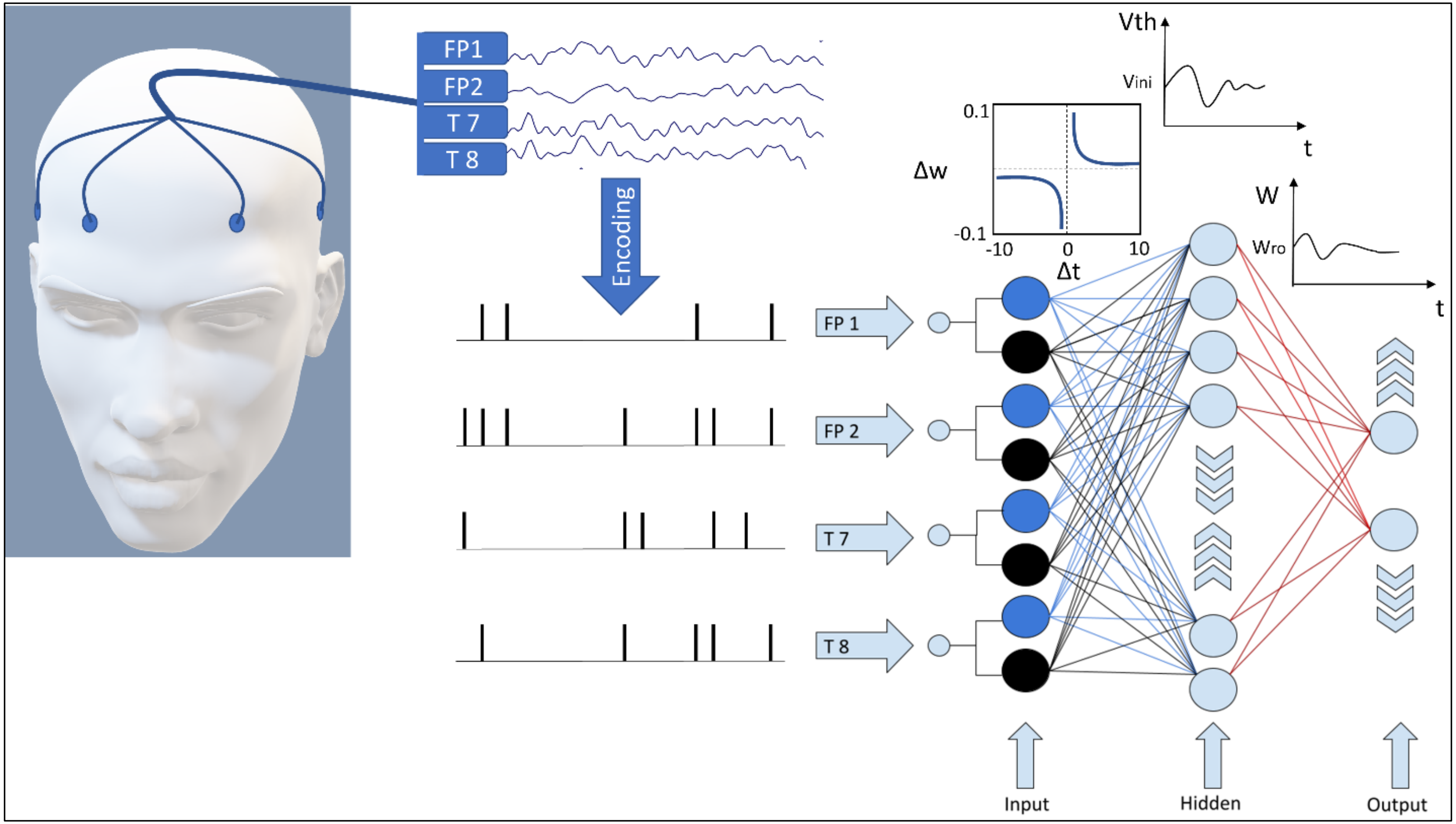
Adult neurogenesis enables pattern separation

(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)

Neuroplasticity ASNN



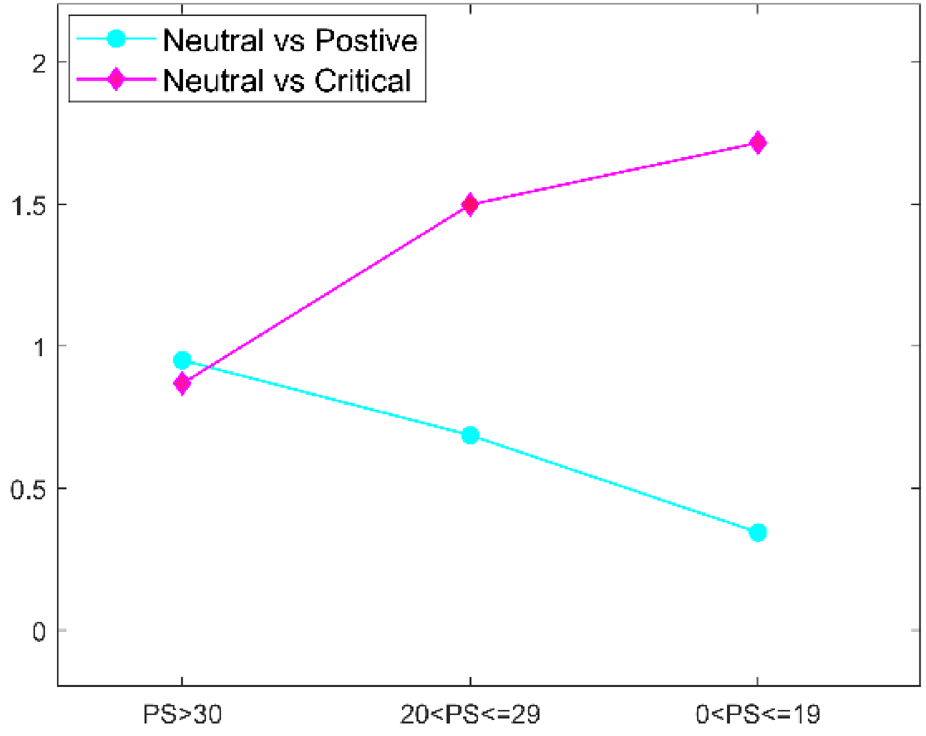
NSNN Results

Study	Method	Accuracy	Sensitivity
Bastos-Fiho et al.(Bastos-Filho et al., 2012)	K-NN (Batch mode)	0.70	-
Shon et al.(Shon et al., 2018)	K-NN (Batch mode)	0.72	
García-Martínez et al.(García-Martínez et al., 2017)	SVM (Batch mode)	0.81	-
Weerasinghe et al.(M. M. A. Weerasinghe et al., 2021b)	SNN (Batch mode)	0.92 ± 0.02	-
This study	NSNN (Online mode)	0.80 ± 0.05	0.79 ± 0.04

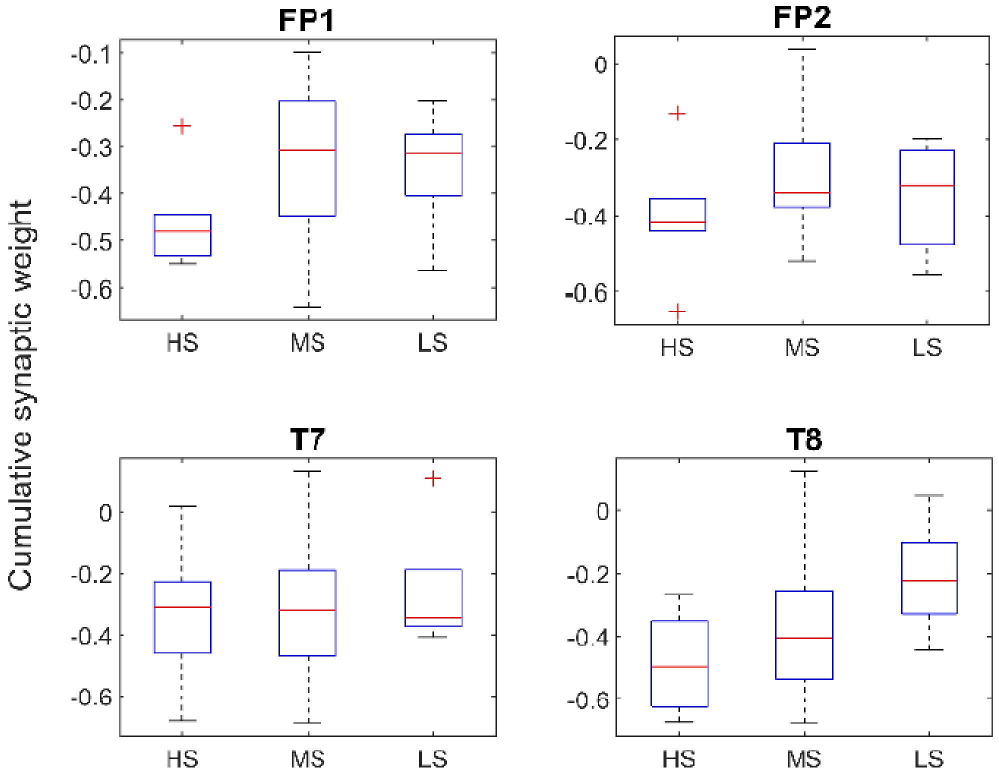
The efficiency of the NSNN in terms of the number of neurons used and spikes generated reduced drastically with the use of STDP+IP learning and self-pruning. Unlike continuous streams of spiking, these techniques enabled sparser spiking activity. When compared to STDP-only learning, STDP+IP was shown to have reduced the average spiking by 35 times (Student's t-test, $\alpha=0.05$, $p=0.008$)

NSNN Knowledge extraction

EEG pattern of generally stressed participants did not differ much regardless of the type of stimuli



While investigating this further by examining the input synaptic weights of the hidden layer, we found that the HS group had higher inhibition than the LS group in the FP1 and FP2 channels



Way forward..

Discussion

1. Can ASNN is be power efficient? Yes. Given we use efficient learning algorithms
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)

Weerasinghe, M. M. A., Wang, G., & Parry, D. (2022). Emotional stress classification using spiking neural networks. *Psychology & Neuroscience, 15*(4), 347–359. https://doi.org/10.1037/pne0000294

Mahima Weerasinghe, J. I. Espinosa-Ramos, G. Y. Wang and D. Parry, "Incorporating Structural Plasticity Approaches in Spiking Neural Networks for EEG Modelling," in IEEE Access, vol. 9, pp. 117338-117348, 2021, doi:10.1109/ACCESS.2021.3099492

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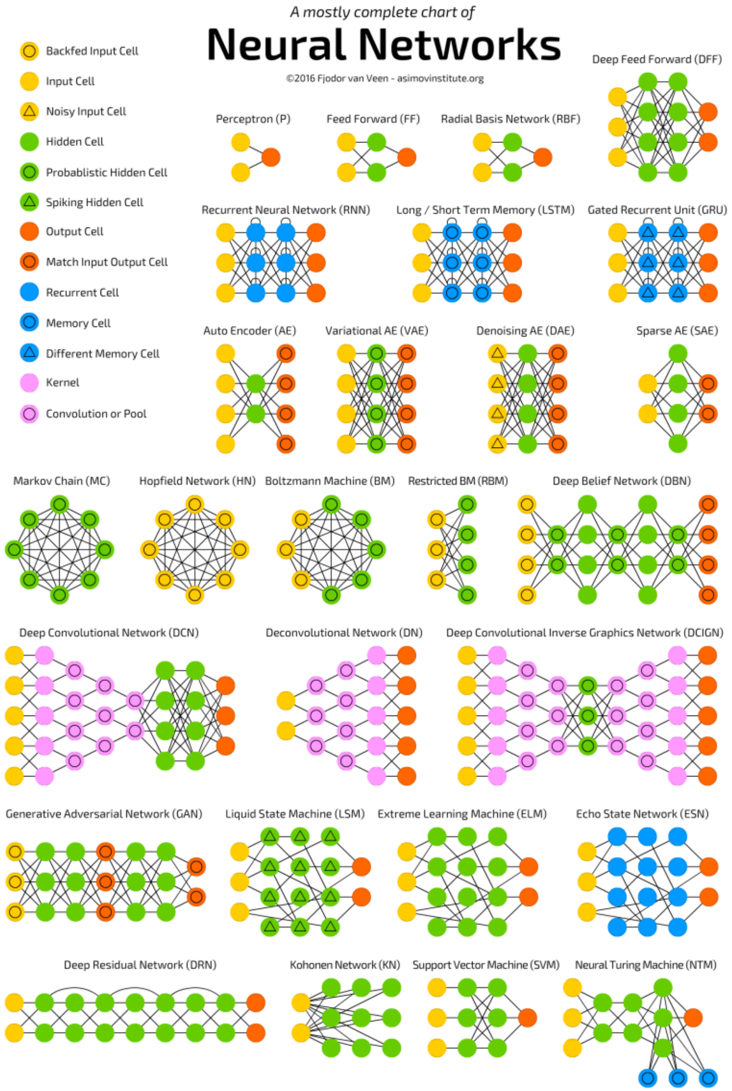
Thank You

Mahima, Prof. Parry, Dr.Wang, Prof.Kasabov

"Simplicity is the ultimate sophistication"
Leonardo da Vinci

Spiking Neural Networks

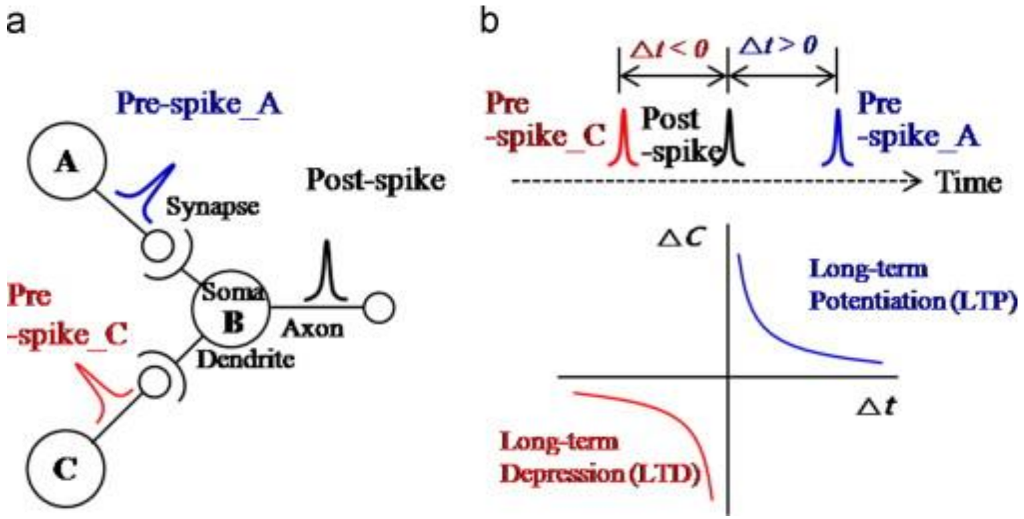
What are Neural Networks?



("The mostly complete chart of Neural Networks, explained | by Andrew Tch | Towards Data Science," 2017)

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)

Potential of SNNs in exploiting STD

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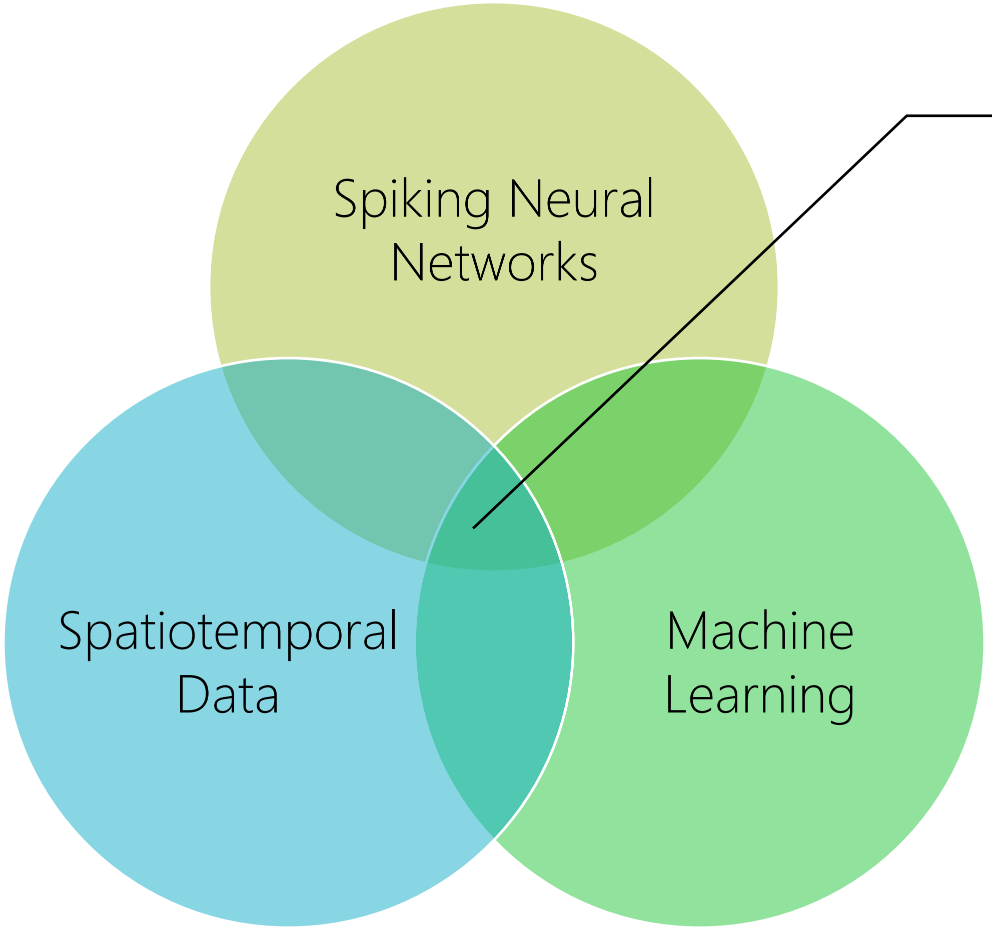
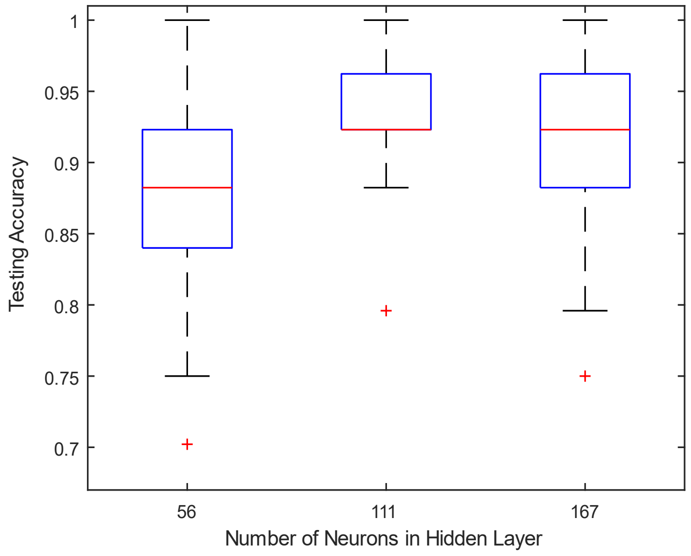
Research Focus

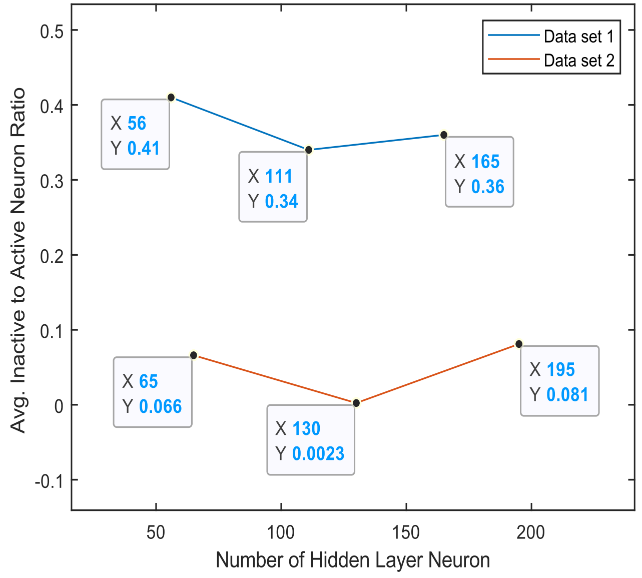


Exploring the impact of Structural Plasticity as a learning technique for modelling EEG data on Human Mental Stress using Spiking Neural Networks

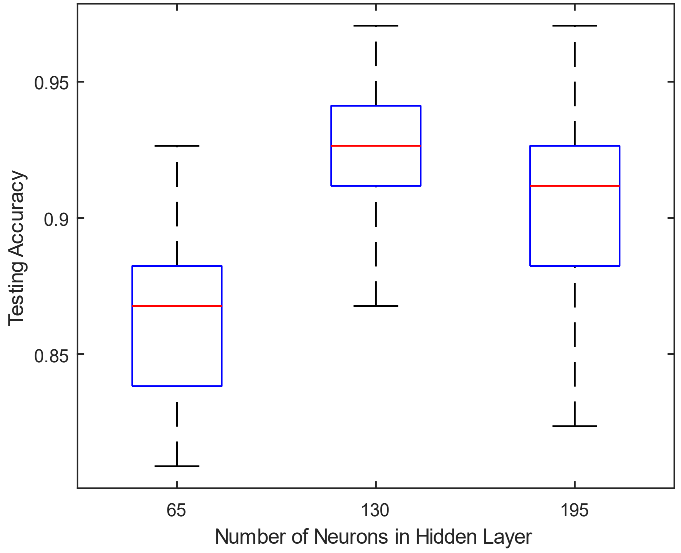
Structural Plasticity SNN

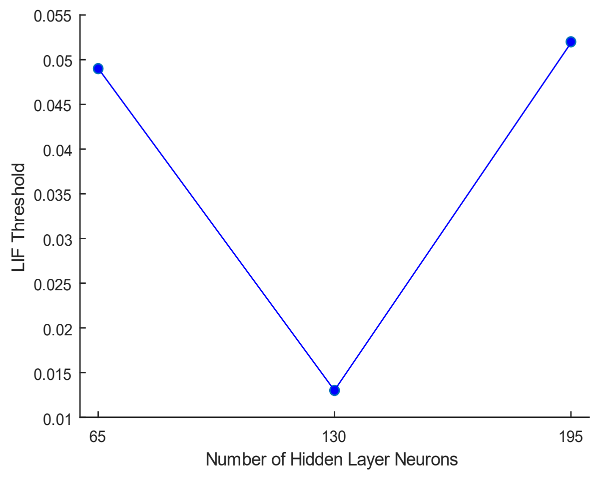
BCI Dataset
94% classification accuracy





Emotional Stress Dataset
91% classification accuracy





Structural Plasticity SNN

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

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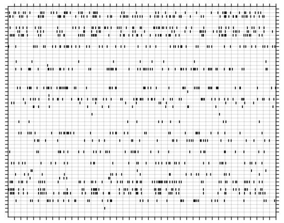

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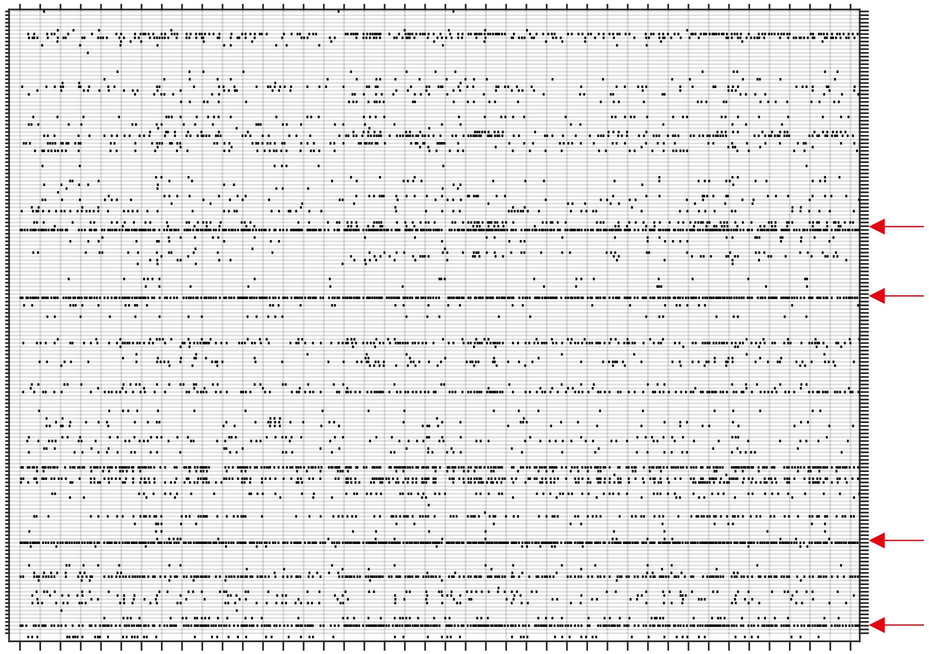
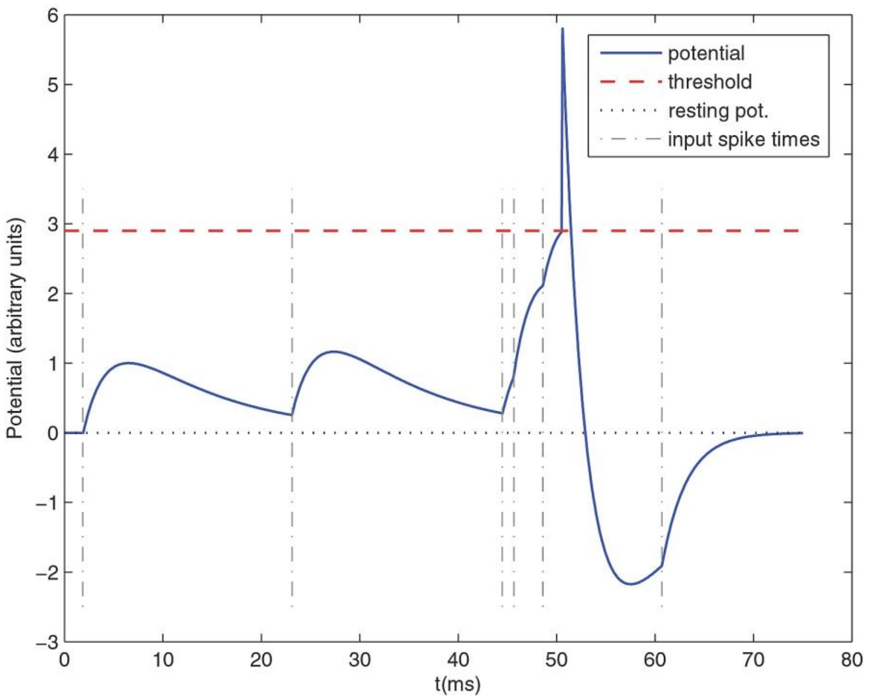


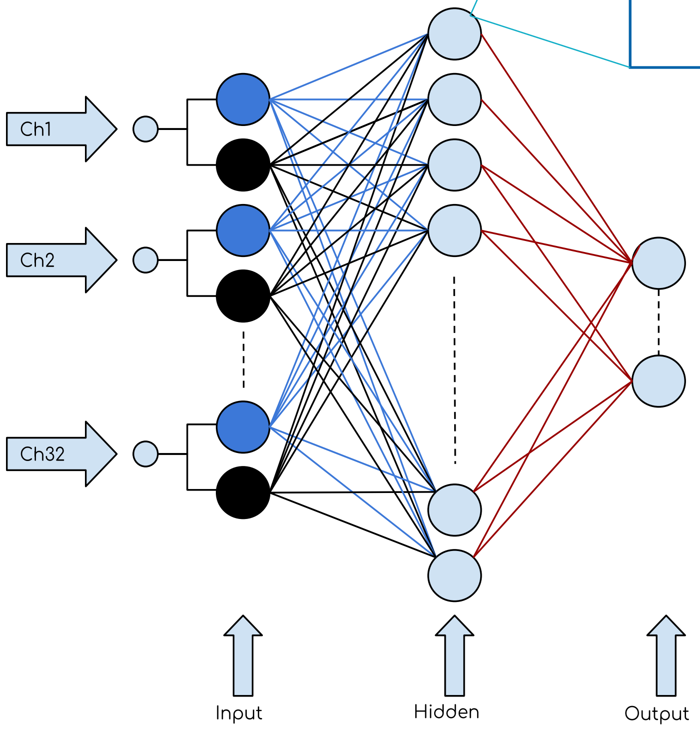
Redundant neurons getting activated during testing cycles

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

Intrinsic Plasticity SNN



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



Adaptive threshold

if fired

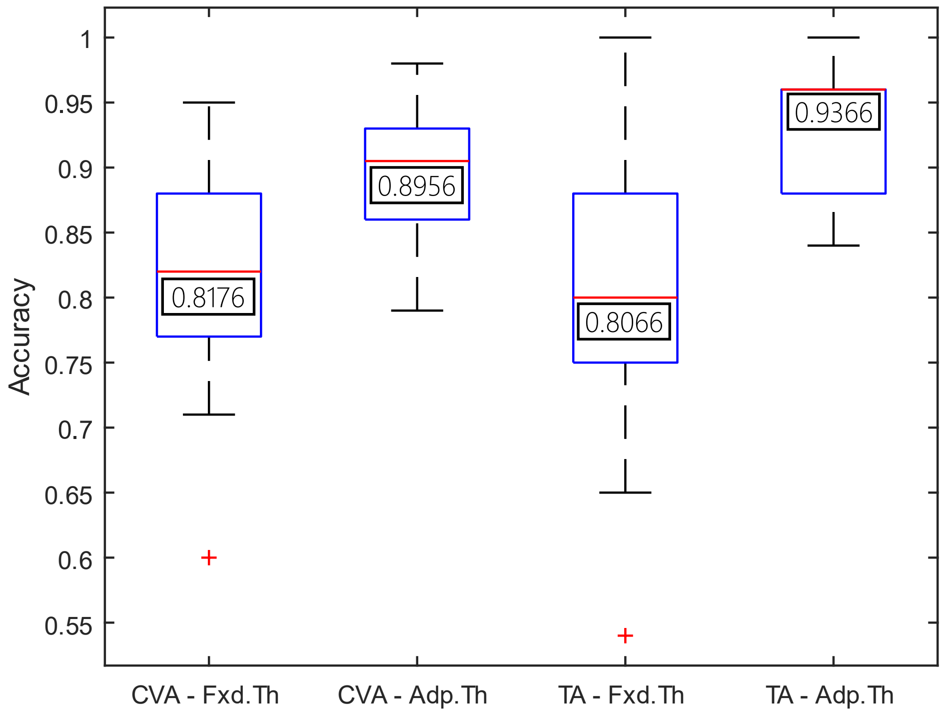
$$Th_{(t)} = Th_{(t-1)} + \theta_{pos}$$

else

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

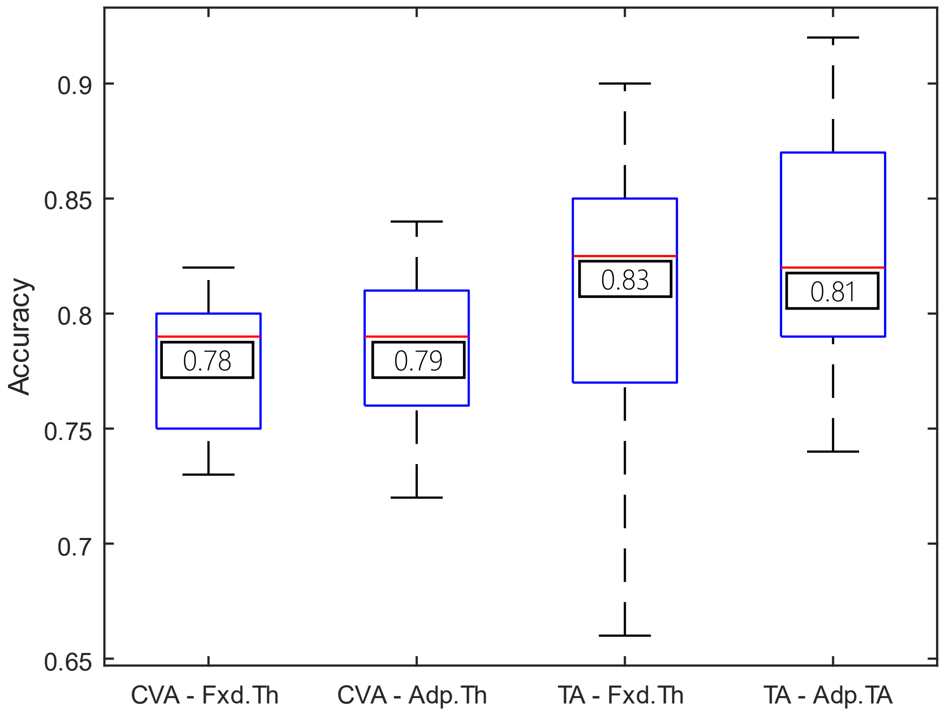
Intrinsic Plasticity SNN

BCI Dataset



Average inactive neurons ~27 to 0

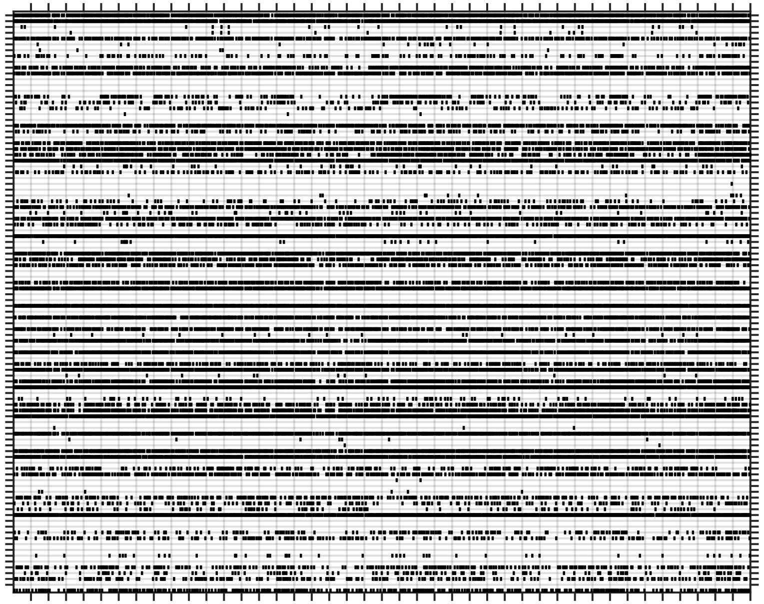
Emotional Stress Dataset

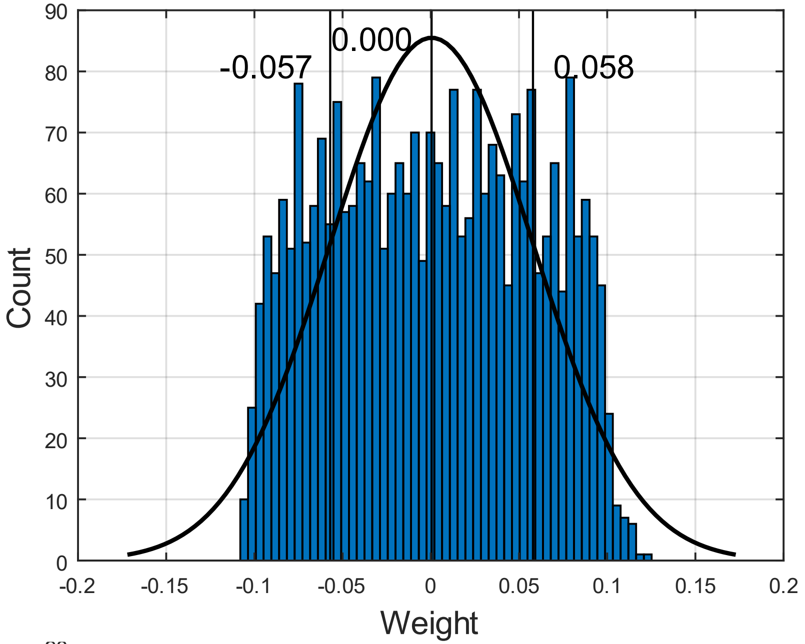


Average inactive neurons ~8 to 0

Intrinsic Plasticity SNN

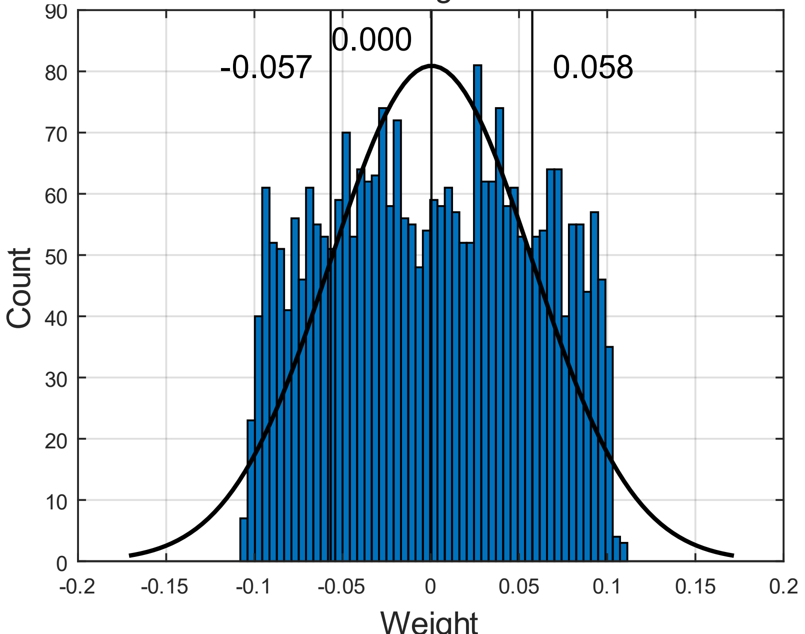
Without IP





BCI Dataset

With IP

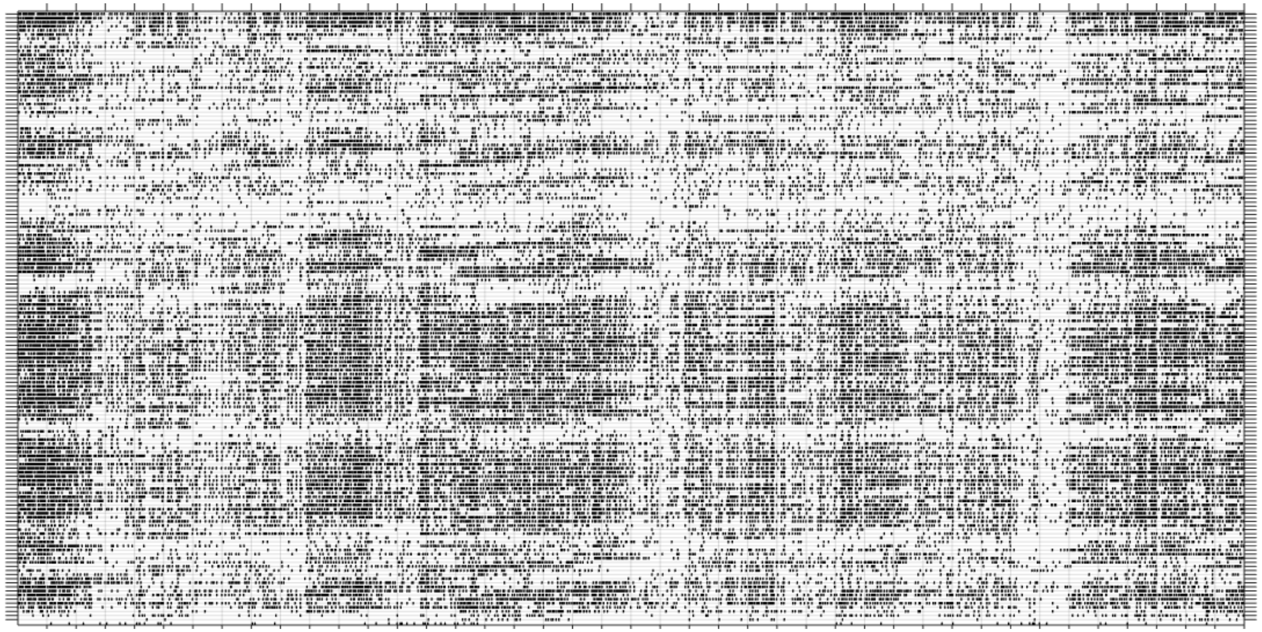


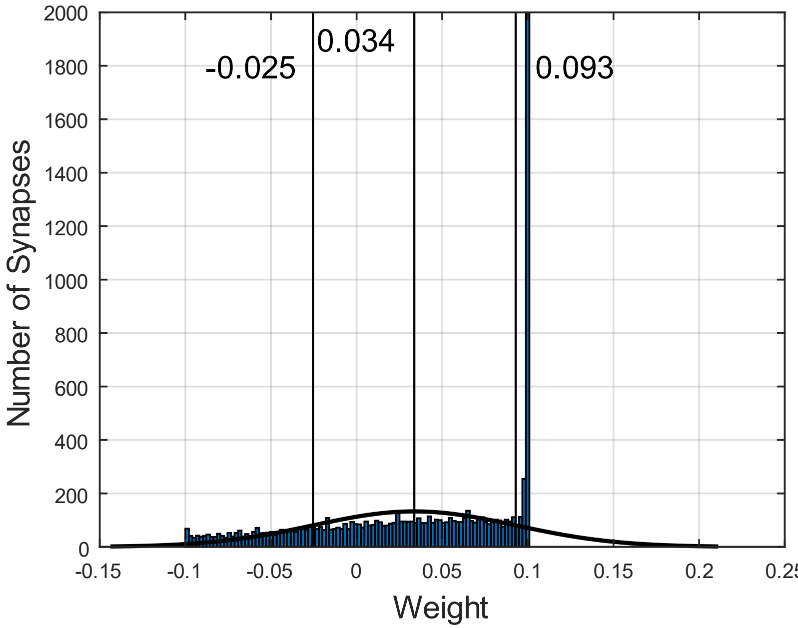
Intrinsic Plasticity SNN

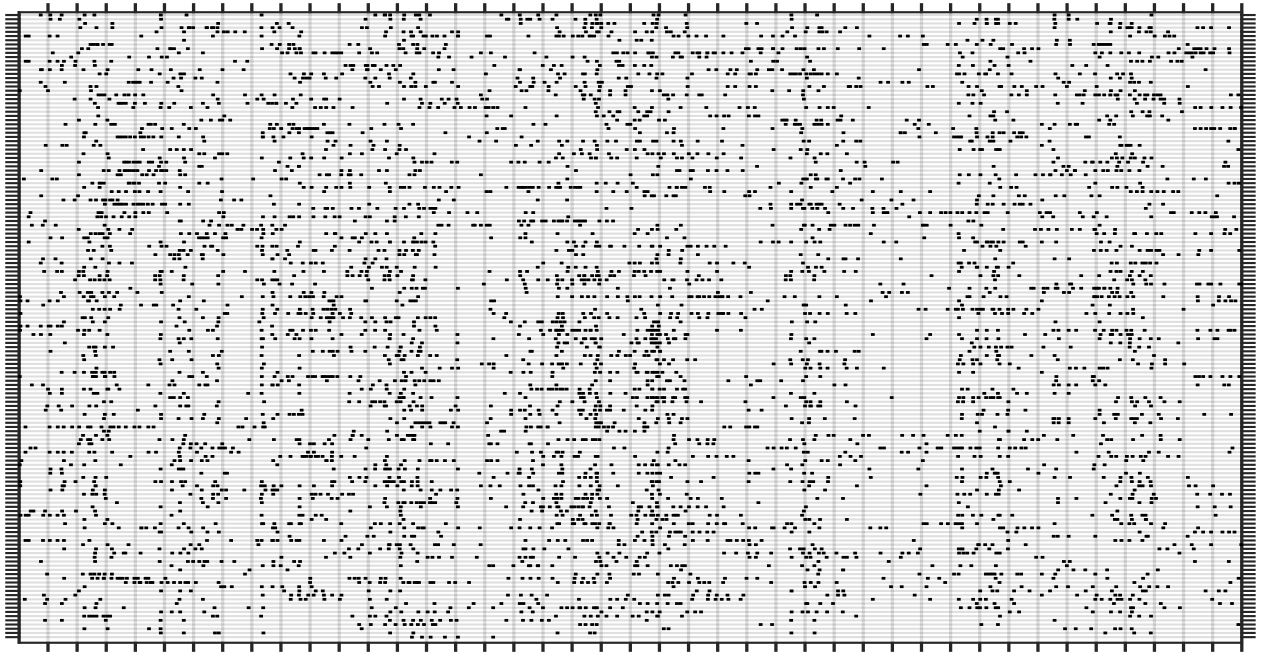
Without IP

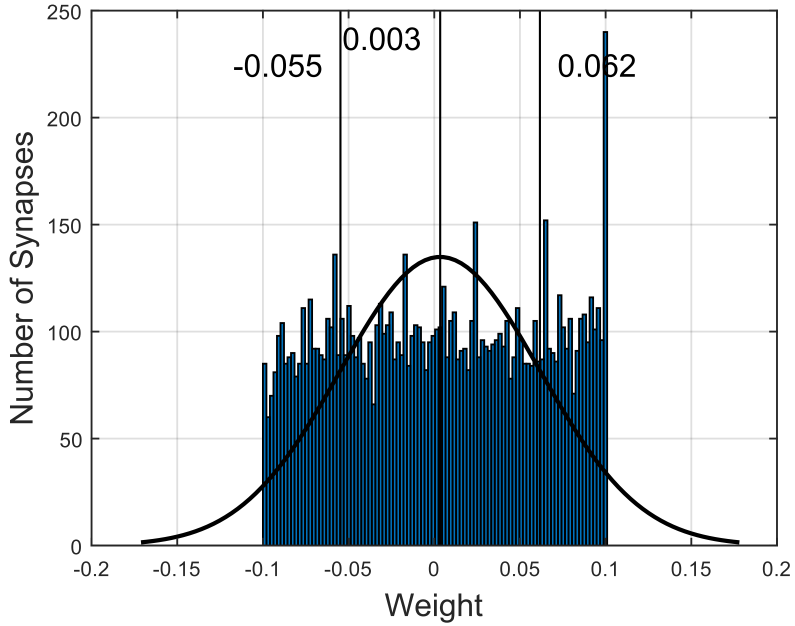
Emotional Stress Dataset

With IP









Observation recap

Structural Plasticity

1. Increase robustness, efficiency , adaptation
2. Reduces number of redundant neurons
3. Requires more firing but distributed (not many Hub neurons)

Intrinsic Plasticity

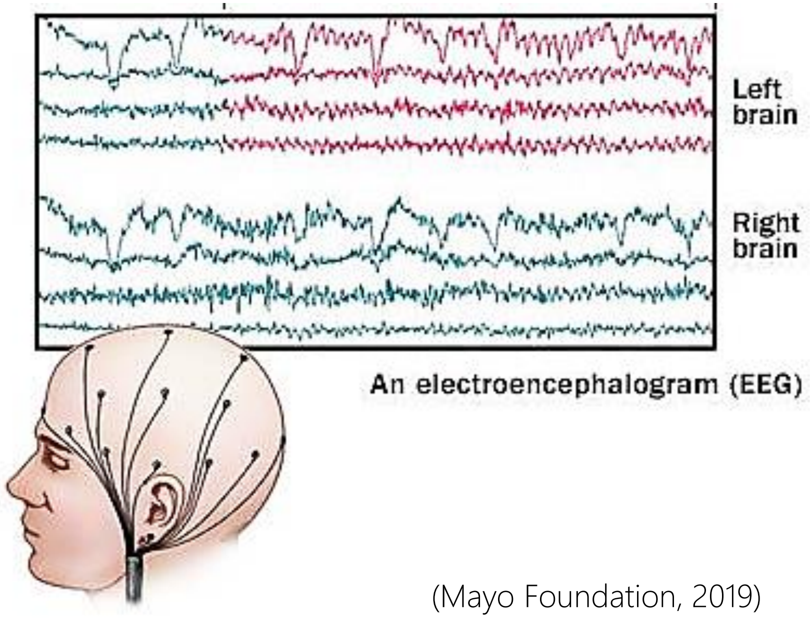
1. Higher efficiency(computation with less spikes)
2. Remedy for runaway synaptic potentiation
3. Robustness and adaptation capability ?

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)

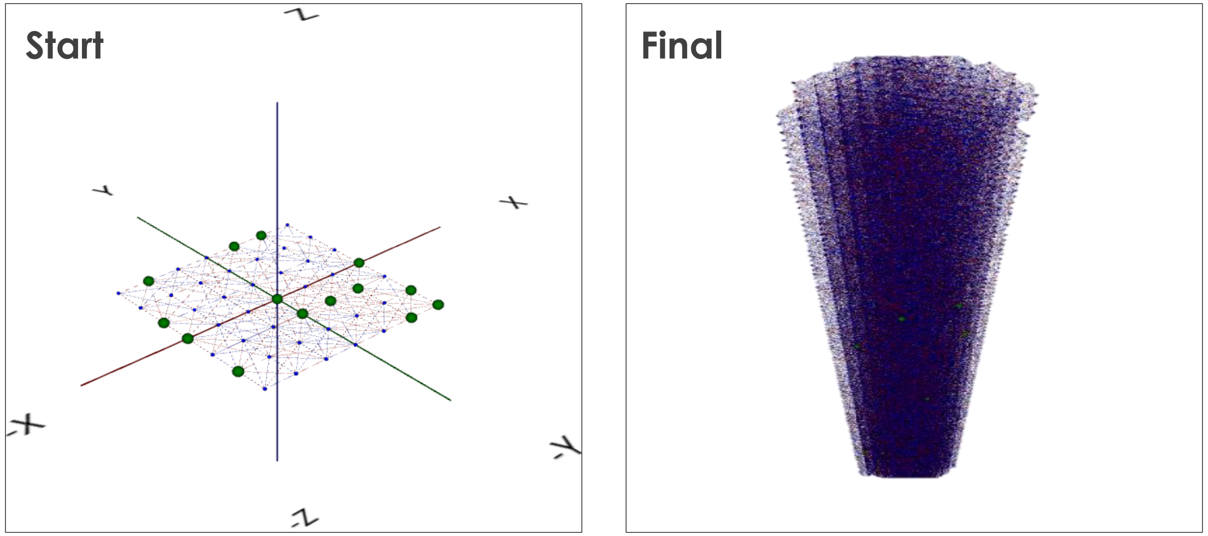
Generic Properties

1. Autocorrelation
2. Heterogeneity

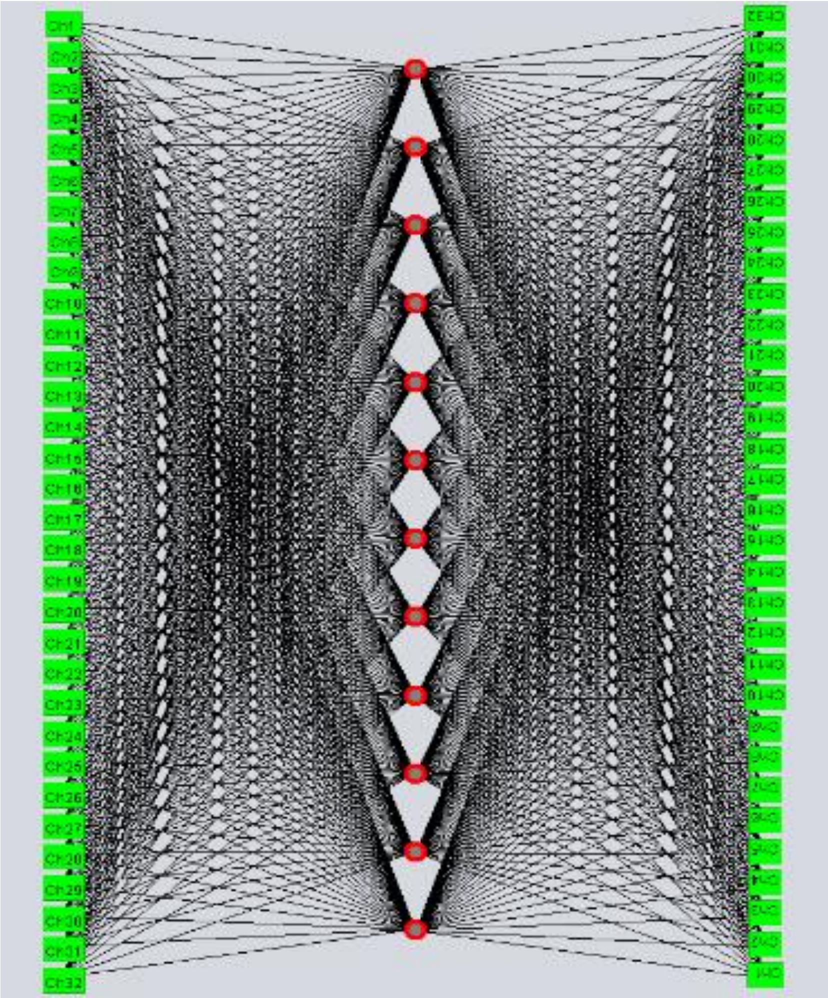


(Mayo Foundation, 2019)

Experiment Results

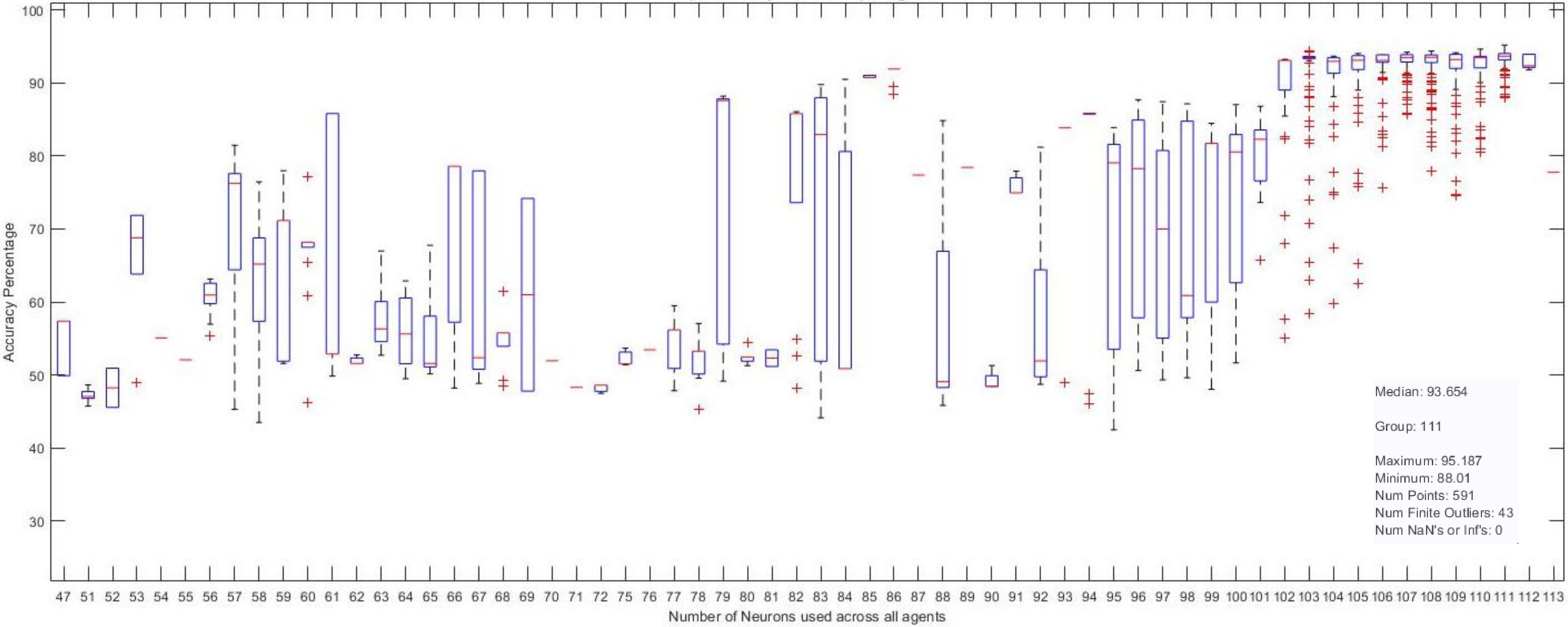


Structural Plasticity with increasing layers



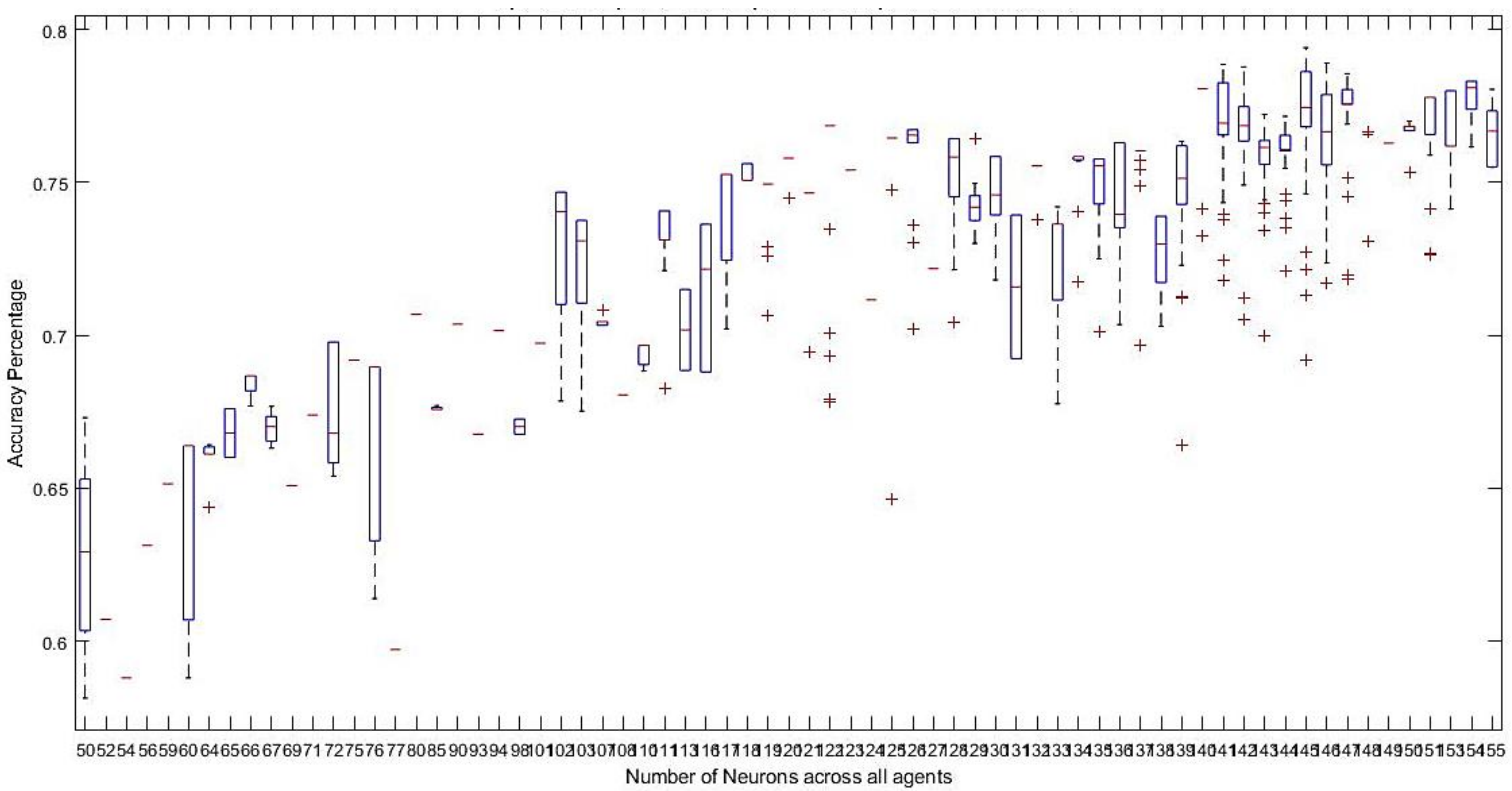
Structural Plasticity with increasing fully connected Neurons

Impact on accuracy with increasing fully connected neurons



average merit	average rank	attribute
0.75 +- 0.004	1 +- 0	8 Num_Neu
0.408 +- 0.007	2 +- 0	7 Knn
-0.114 +- 0.008	3.2 +- 0.4	2 LIF_Rr
-0.129 +- 0.006	3.8 +- 0.4	6 deSNN_D2
-0.346 +- 0.008	5 +- 0	5 deSNN_D1
-0.745 +- 0.002	6.3 +- 0.46	1 LIF_Th
-0.747 +- 0.004	6.7 +- 0.46	4 STDP_A2
-0.766 +- 0.005	8 +- 0	3 STDP_A1

Impact on accuracy with increasing fully connected neurons



Research Hypothesis

1. There exist a range of number of Neurons and Synapses in an SNN, that would enable best trade off between modelling accuracy and structural complexity. - RQ 1

2. Weight matrices produced using STDP unsupervised learning algorithm can enable implementation of Structural Plasticity techniques to produce an optimum network structure. – RQ2

3. Using the structural representations, firing activity and weight matrices, it is possible to extract further knowledge on Perceived Mental Stress and Alzheimer’s Disease. - RQ3

Research Contribution

	Developments	Knowledge
Computer Science	› Data modelling pipeline for EEG › Method to apply pruning techniques for EEG modelling using SNNs	› Concentration of knowledge related to 'Plasticity techniques in learning' from literature related to Neuromorphic SNNs and Computational Neuroscience
Applications	› Structurally adaptive prototype data models for Perceived Mental Stress	› Reporting knowledge extractions

Resources

Datasets

1. Effect of emotional comments on cortisol and frontal EEG asymmetry in healthy participants – Department of Psychology AUT

2. DEAP – Database for emotion analysis (Koelstra et al., 2012)

Developments and experiments

1. Matlab, Java, Python, R

2. NeuCube, WEKA

3. Intel core i7 processor with 16GB memory | Intel core i7 processor with 8GB memory

Stress & Alzheimer's

a. Human Mental Stress is considered as a precursor for a multitude of illnesses including cardiovascular diseases, neuropsychiatric diseases, gastrointestinal diseases, and cancers. (Pickering, 2001)

b. Alzheimer's Disease (AD) is an increasing neurodegenerative disease that has no cure. According to the World Health Organization(WHO) official website (World Health Organization, 2020), AD is the most common form of dementia which contributes to 60-70% of all dementia cases. Latest statistics reveal more than 50 million dementia patients with an expected escalation of cases to be 10 million each year.

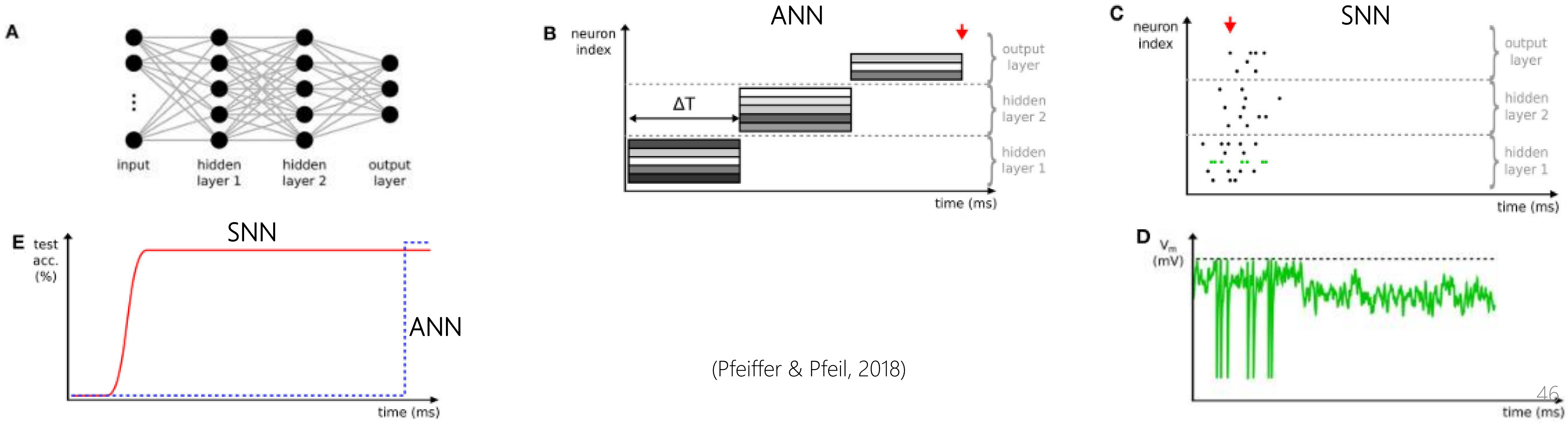
In current clinical setup, EEG is mainly observed by trained technicians to make inferences of these diseases/mental states

(Golmohammadi, Harati Nejad Torbati, Lopez de Diego, Obeid, & Picone, 2019).

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

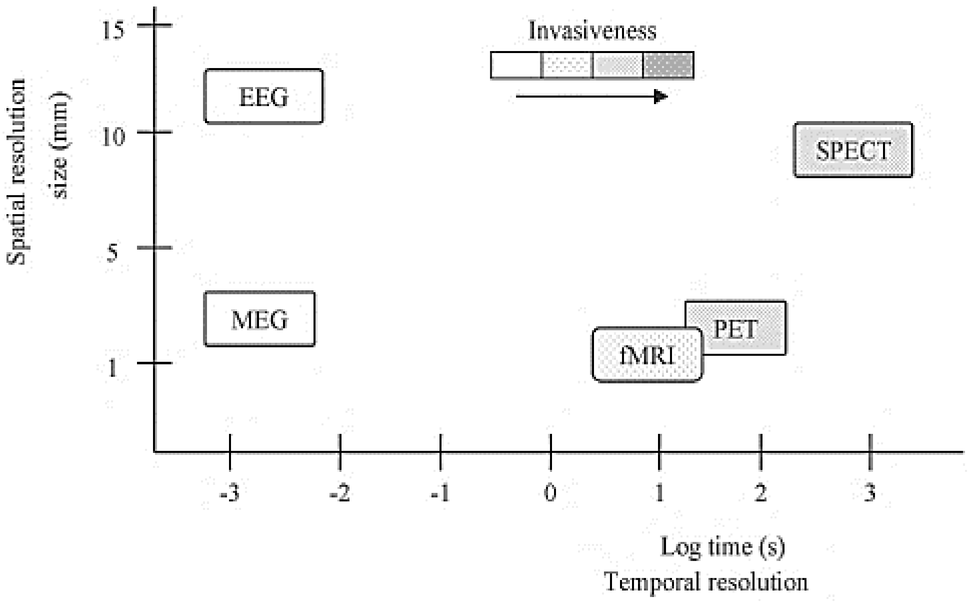
(Farabet et al., 2012)



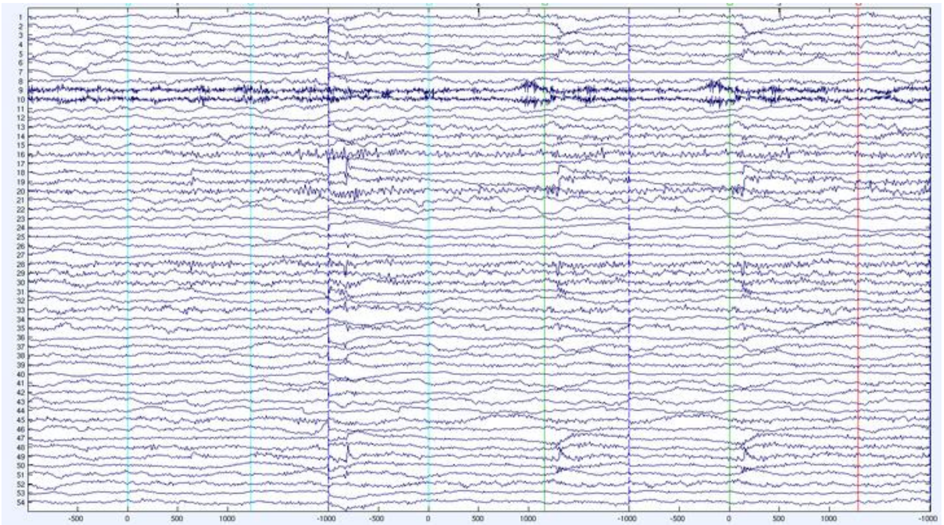
(Pfeiffer & Pfeil, 2018)

Electroencephalographic Data

	PET	SPECT	fMRI	EEG	MEG
Measure of neuronal activity	indirect	indirect	indirect	direct	direct
Biological process measured	Haemodynamic response	Haemodynamic response	Haemodynamic response	Neuroelectrical potentials	Neuromagnetic field
Invasiveness	invasive	invasive	non-invasive	non-invasive	non-invasive
Confined space	yes	yes	yes	no	yes
Radiation	yes (0.5–2.0 mSv)	yes (3.5–12.0 mSv)	none	none	none
Temporal resolution	poor (1–2 min)	poor (5–9 min)	reasonable (4–5 s)	excellent (<1 ms)	excellent (<1 ms)
Spatial resolution	good/excellent (4 mm)	good (6 mm)	excellent (2 mm)	reasonable/good (10 mm)	good/excellent (5 mm)



(Lystad et al., 2009)



("Makoto's preprocessing pipeline - SCCN," 2017)

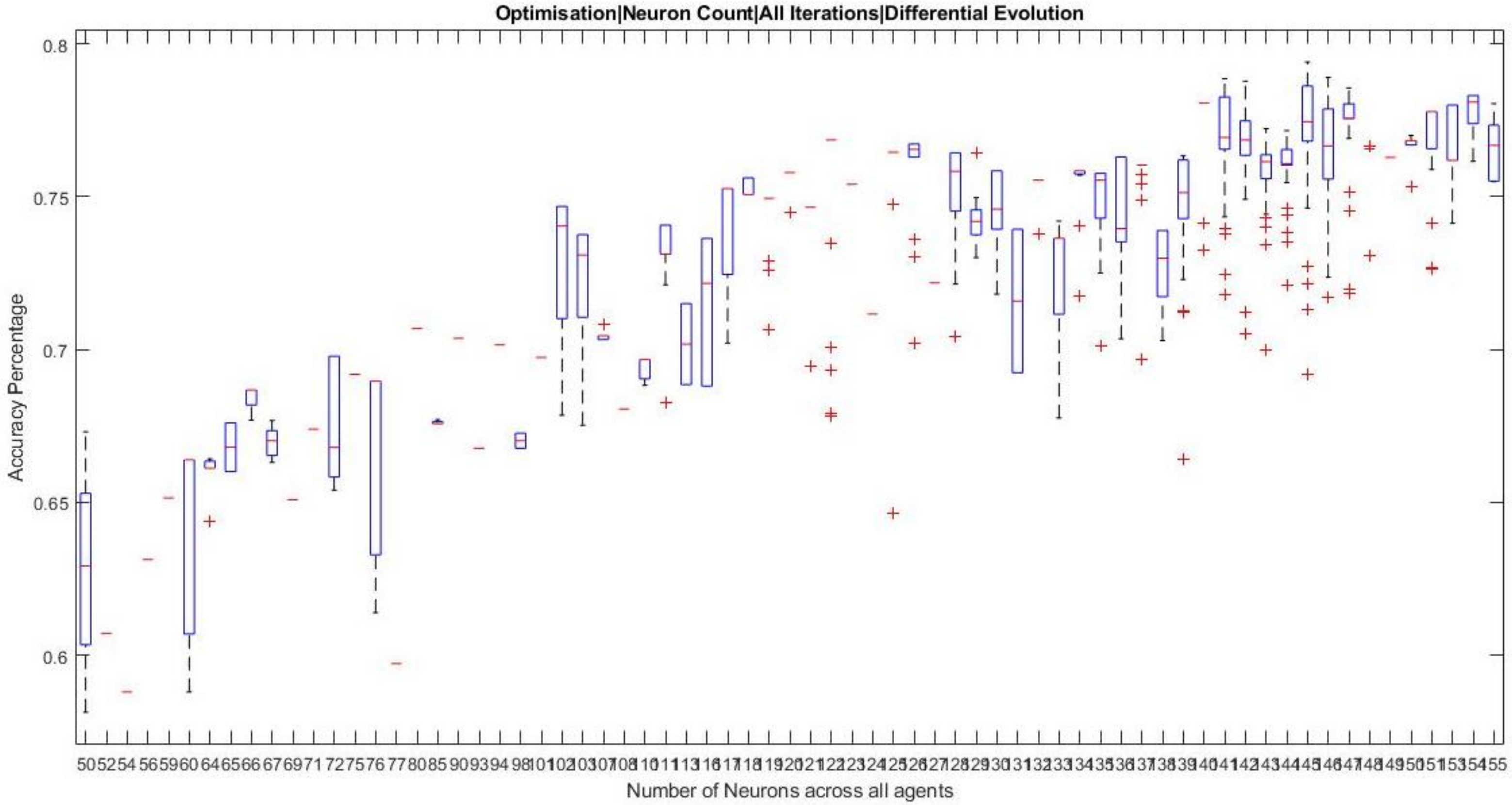
Significance

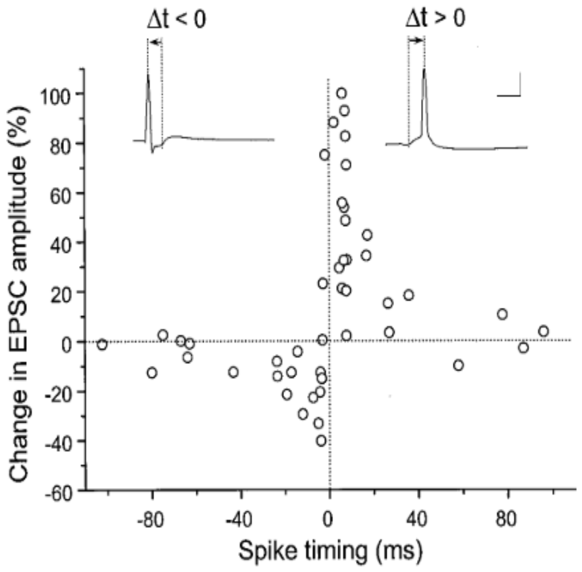
1. Exploration of brain-inspired structural plasticity techniques in data modelling using SNNs with an impact analysis on Accuracy and Hyperparameter optimization
2. Application of Structural Plasticity techniques in modelling EEG data related to Alzheimer's Disease
3. Application of SNNs in modelling EEG data related to Human Mental Stress

LIF parameters		STDP weight factors		deSNN weight factors		Structural Plasticity
Threshold	Refractory time	Positive modification	Negative modification	Positive modification	Negative modification	Neuron count

“Along with aging, another extrinsic factor negatively regulating hippocampal neurogenesis is stress” (Aimone et al., 2014)

“Alzheimer’s disease causes Neuronal Death in the brain causing memory failures and cognitive impairment.” (Brain Basics: The Life and Death of a Neuron | National Institute of Neurological Disorders and Stroke, 2019)





(Bi & Poo, 1998)

Rationale

Why Structural Adaptability for SNNs?

Interpretability & reproducibility of models

Transparency in parameter settings

(Grüning & Bohte, 2014)

Understanding mental health issues through modelling

Computational prototype models for Stress and Alzheimer's Disease

(Obeid & Picone, 2016) (Pickering, 2001)

(World Health Organization, 2020)

Accuracy

Increase computational Efficiency in Model Optimization. Denoising and ability to learn new features

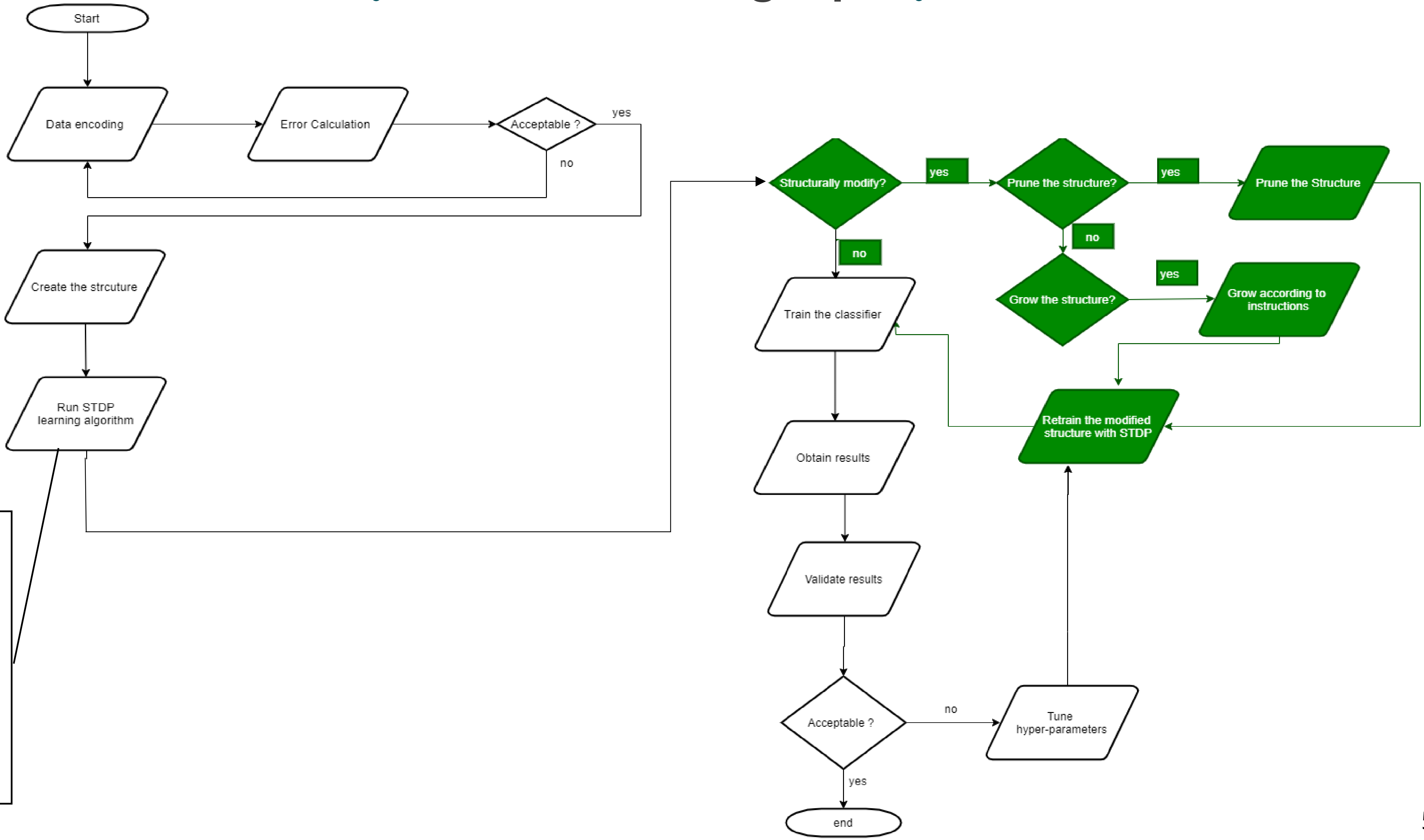
(Shi, Nguyen, Oh, Liu, & Kuzum, 2019)
(Yuan et al., 2019) (Diehl, 2016)

Insights towards novel research avenues

Data efficient learning, learning on the fly , life-long learning & knowledge extraction beyond classification

(Iglesias & Villa, 2007) (Wang, Belatreche, Maguire, & McGinnity, 2014)
(Draelos et al., 2017)

Idealized Modelling Pipeline



Note : The key idea is to Make the decision of structural changes based unsupervised learning