
Spike from brawl star (https://brawlstars.fandom.com/wiki/Spike)

Spiking Neural Networks

A path towards brain-inspired computing

Leow Cong Sheng, Ng Ho Chi

MACHINE LEARNING AND DATA ANALYTICS

How to participate?

WEB

1. Connect to www.wooclap.com/MLDASNN
2. You can participate

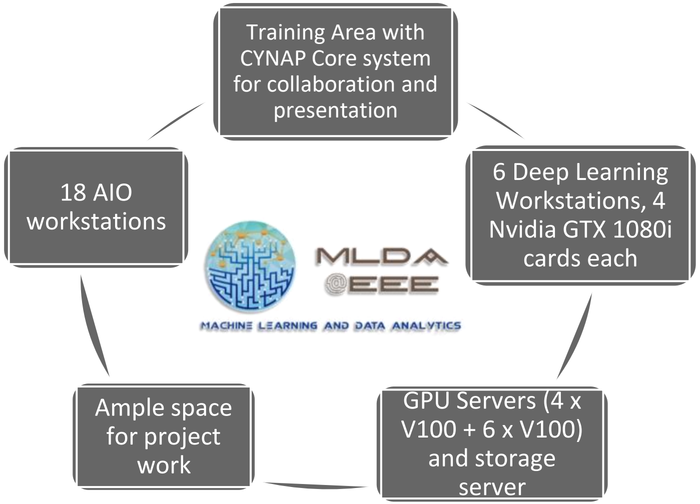
Your instructors

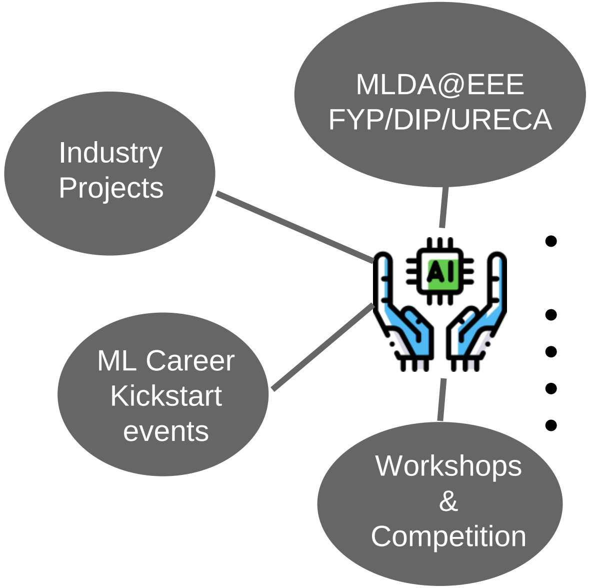
Ng Ho Chi
CSC Year 1

Leow Cong Sheng
EEE Year 4
[LinkedIn]

Our Mission

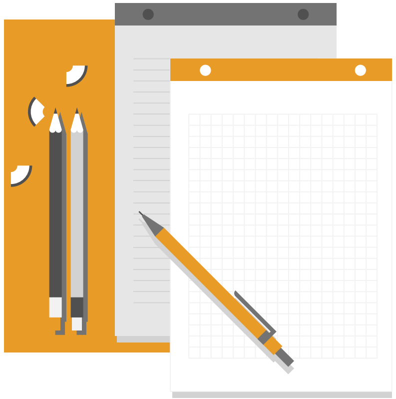
Provide an integrated platform for EEE/IEM students to learn and implement Machine Learning, Data Science & AI, as well as facilitate connections with the industry.





- >1000 Trained ML practitioners
- >10 Academic Projects
- >30 Industry projects
- >5 competition
- >15 Industry Partners

Outline of Workshop



01 Introduction to SNNs
History and motivation behind SNNs

02 Emulating the brain
About the biological nature of SNNs and their implementations

03 Future of SNNs
Applications, limitations, and research potential

04 Hands-on
Implement an image classifier with PyTorch (NN) and snnTorch (SNN)

05 Q&A
Ask any question you have about SNNs!

www.wooclap.com/MLDASNN

Spiking Neural Networks

Background

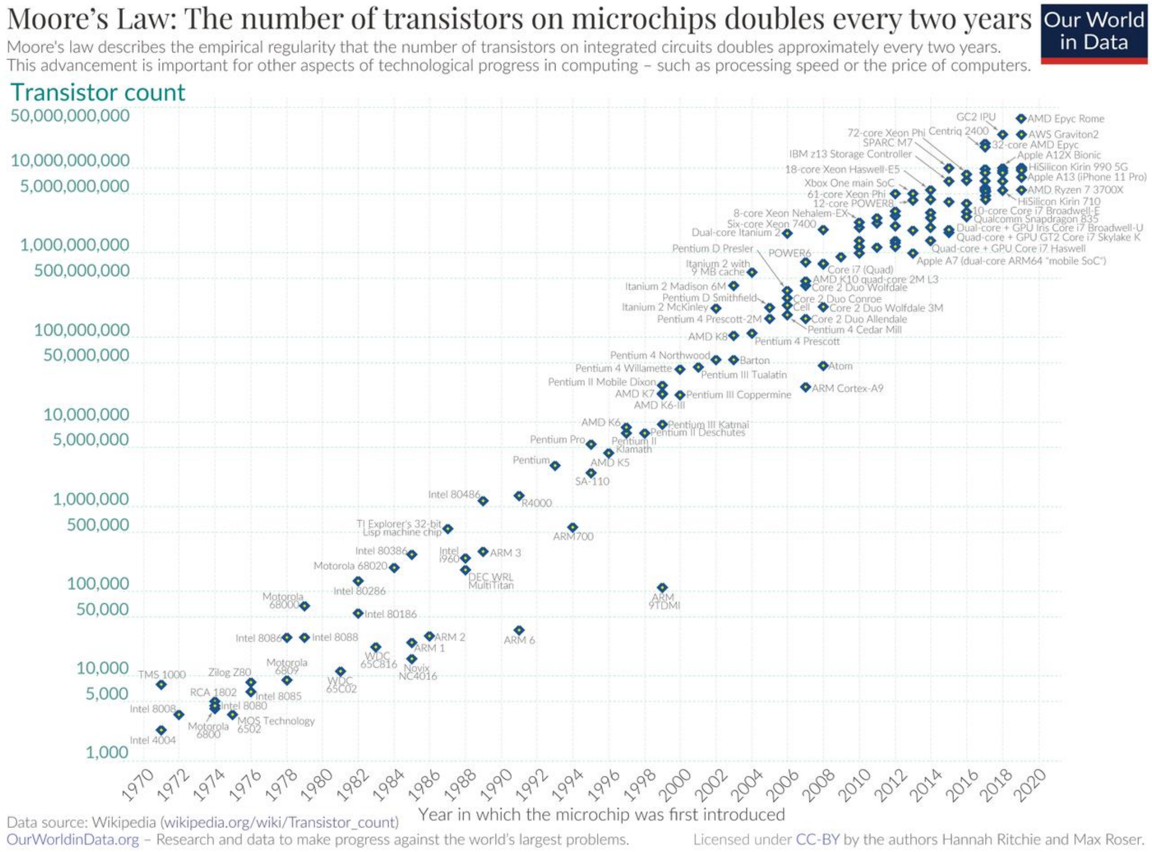
- Python programming knowledge
- Knowledge of neural networks and how neural networks work
- Basic idea of PyTorch or TensorFlow

Takeaways

- Understand the motivation behind SNNs and Neuromorphic Computing
- Identify differences between ANN and SNN
- Understand the concept behind spiking neurons, encoding and optimization
- Implement a SNN for image classification

Introduction to SNN

Moore’s Law



Moore’s Law: The number of transistors on microchips doubles every two years
Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years.
This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.
Our World in Data
Transistor count
Year in which the microchip was first introduced
Data source: Wikipedia (wikipedia.org/wiki/Transistor_count)
OurWorldinData.org – Research and data to make progress against the world’s largest problems.
Licensed under CC-BY by the authors Hannah Ritchie and Max Roser.

New computing paradigms

01

Quantum Computing

Utilises quantum states to perform calculations

02

Neuromorphic Computing

Mimicking neuro-biological architectures

Fig 1: Understanding about Cloud Computing (https://medium.com/@sourleangchhean/understanding-about-cloud-computing-76545af3b06a)

History

01 First Signs

Mead worked with Hopfield and Feynman to develop neuromorphic engineering among other fields.

02 Transition

Implementations of Neuromorphic Engineering transitioned from analog to VLSI (Very large scale integration)

03 Spiking Neural Networks (SNN)

Driven by booming popularity of AI, work on development of SNNs increase.

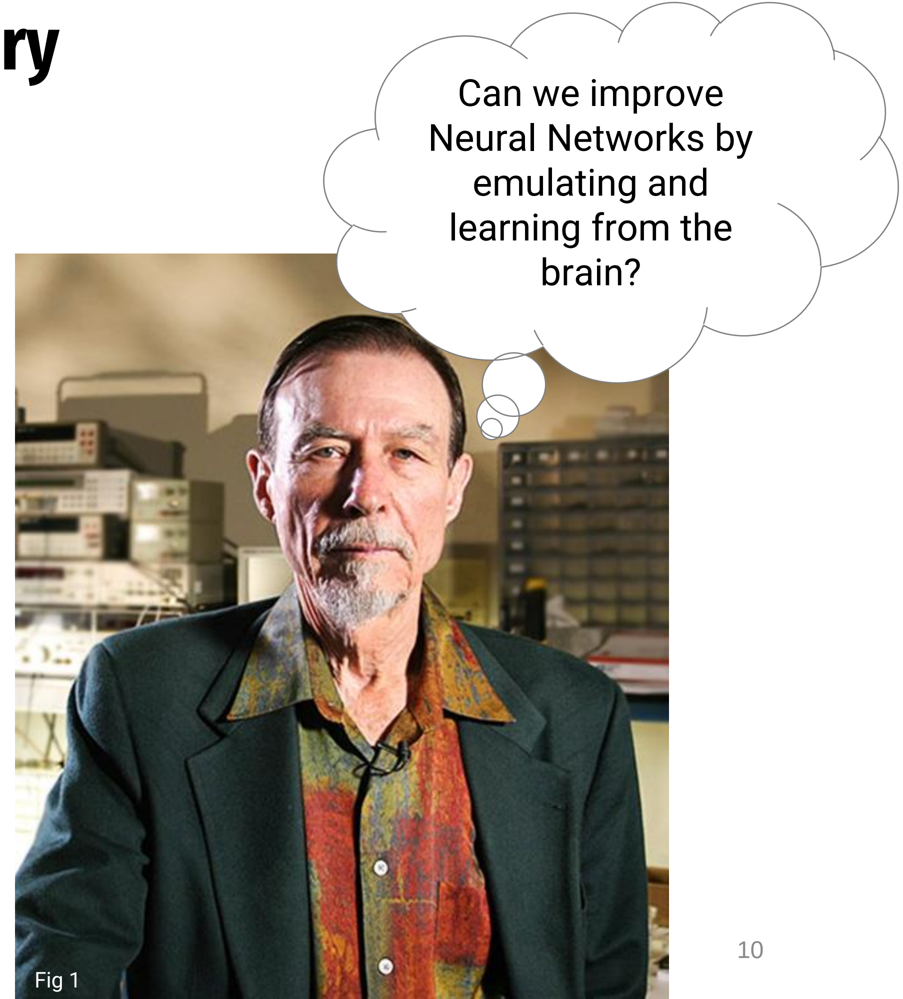


Fig 1

Fig 1: The father of Neuromorphic engineering, Carver Mead (https://www.frontiersofknowledgeawards-fbbva.es/galardonados/carver-a-mead-2/)

The three generations of Neural Networks

Perceptron

- Takes an input, applies a weight and bias, then produces an output.

Deep Learning

- Multilayer Perceptron, Convolutional Neural Networks.
- Able to process more dimensions of input.

Spiking Neural Networks

- Takes spikes as inputs, produces spikes as outputs.

The three generations of Neural Networks

Perceptron

- Takes an input, applies a weight and bias, then produces an output.

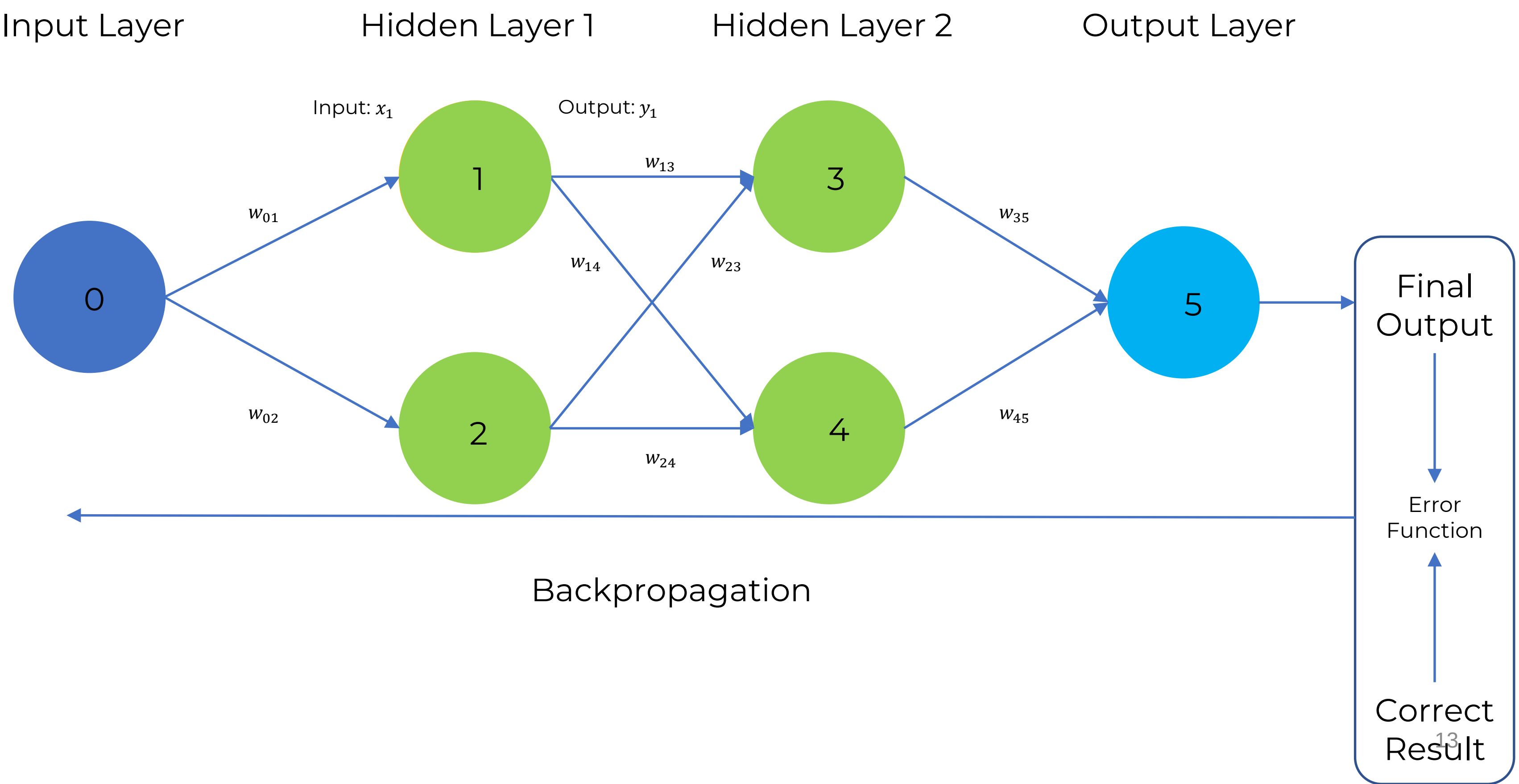
Deep Learning

- Multilayer Perceptron, Convolutional Neural Networks.
- Able to process more dimensions of input.

Spiking Neural Networks

- Takes spikes as inputs, produces spikes as outputs.

Multi-layer Perceptron



Deep Learning - Neurons

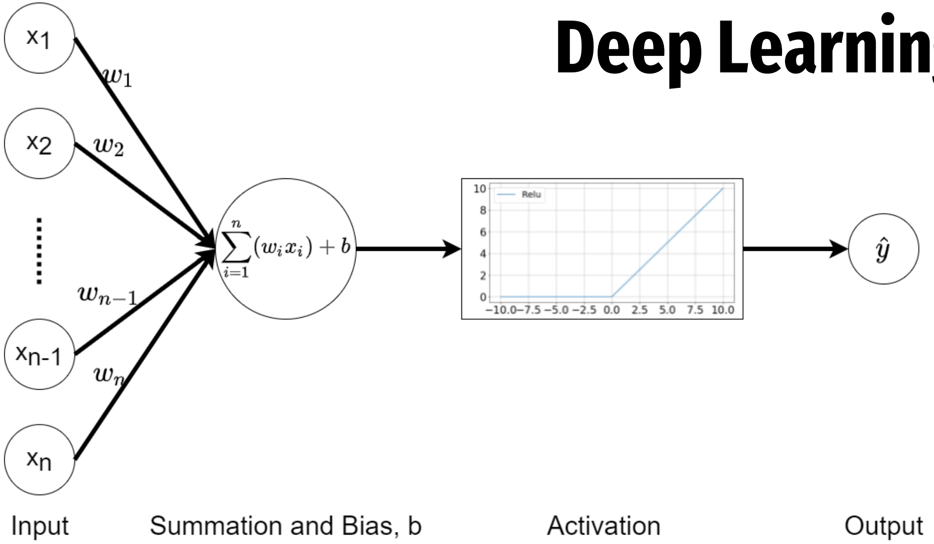


Fig 1

Artificial neural networks typically employ the use of activation functions to simulate how neurons propagate signals throughout the brain.
<u>However</u>, the typical activation functions are far from how the biological neurons actually work.

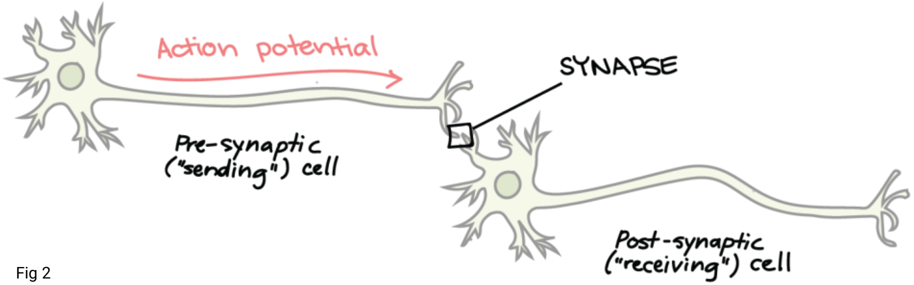


Fig 2

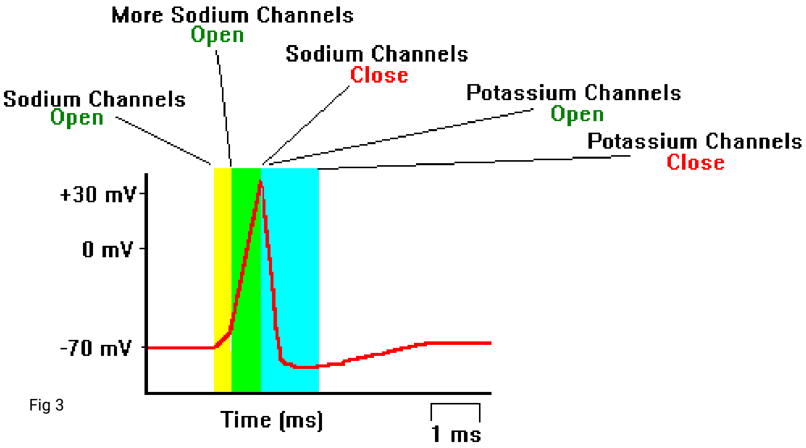


Fig 3

Fig 1: Activation function in traditional neural networks using a ReLU (rectified linear unit (Created by Leow Cong Sheng)
Fig 2: Pre- and post-synaptic neurons communication through synapses: (https://www.khanacademy.org/science/biology/human-biology/neuron-nervous-system/a/the-synapse)
Fig 3: Actual action potential of the neurons (http://faculty.washington.edu/chudler/ap.html)

The three generations of Neural Networks

Perceptron

- Takes an input, applies a weight and bias, then produces an output.

Deep Learning

- Multilayer Perceptron, Convolutional Neural Networks.
- Able to process more dimensions of input.

Spiking Neural Networks

- Takes spikes as inputs, produces spikes as outputs.


Gif 1

Gif 1: Hinata spiking in Haikyuu! (https://tenor.com/view/hinata-anime-haikyuu-spike-sports-anime-gif-17508602)

SNN - Neurons

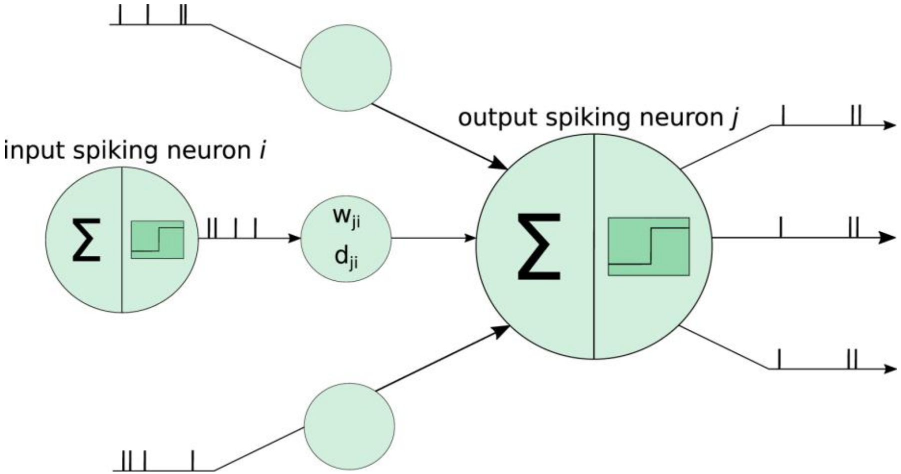


Fig 1

SNN uses mathematical models of the biological brain to encode data into spikes which are:

- Sparse
- Event-driven

01 **Hodgkin-Huxley Model**
Closest results to the biological neurons

02 **Izhikevich Model**
Efficient way to replicate spikes

03 **Leaky Integrate-and-fire Model**
Simple and most efficient

Simpler model, but more efficient!
Optimal for implementation

Fig 1: SNN Scheme (https://doi.org/10.1016/j.neunet.2019.09.004)

SNN – Leaky Integrate-and-Fire (LIF)

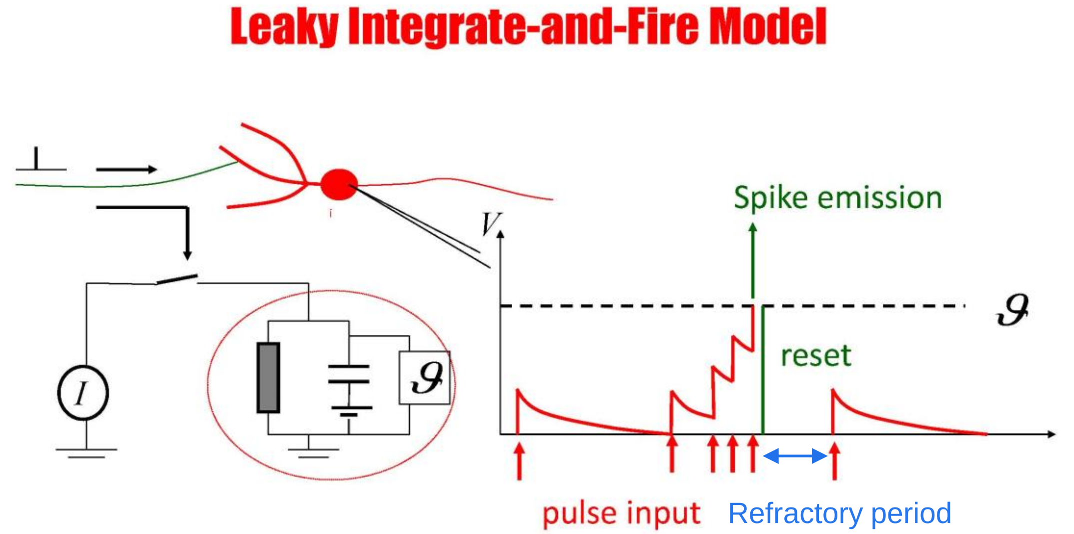


Fig 1

$$\tau_{mem}\frac{du}{dt} = -[u(t) - u_{rest}] + RI(t)$$

$$u(t) = u_{rest} + RI_0\left[1 - e^{\left(-\frac{t}{\tau_m}\right)}\right]$$

$By\ Newton's\ method,$

$$u(t) = u(t-1) + \frac{du}{dt}$$

$$I(t) = I_{syn} + I_{noise} + I_{inj}$$

τ_{mem}: *time constant of neuron*
$u(t)$: *membrane potential*
u_{rest}: *membrane resting potential*
R: *membrane resistance*
$I(t)$: *total current*
I_{syn}: *synaptic current*,
I_{noise}: *noise*,
I_{inj}: *injection current*

Fig 1: LIF model schematic and spikes (Wikipedia)

Common spike-encoding schemes

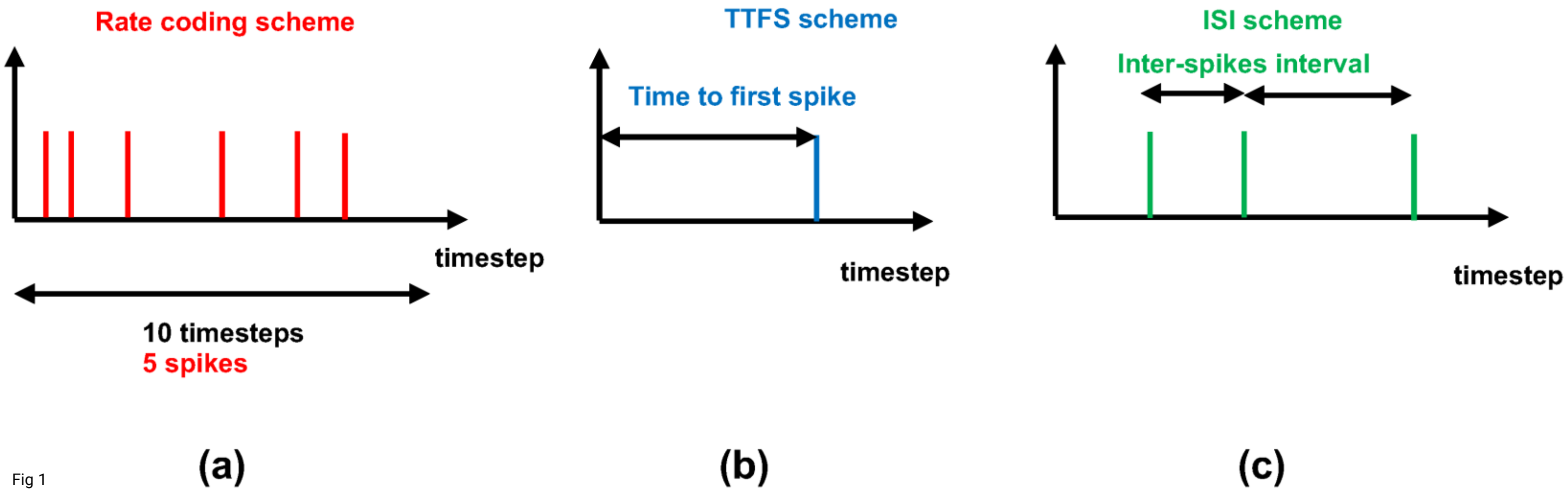


Fig 1

Fig 1: 3 Common spike-encoding schemes (https://doi.org/10.3390/jlpea11020023)

Optimization problem with SNN

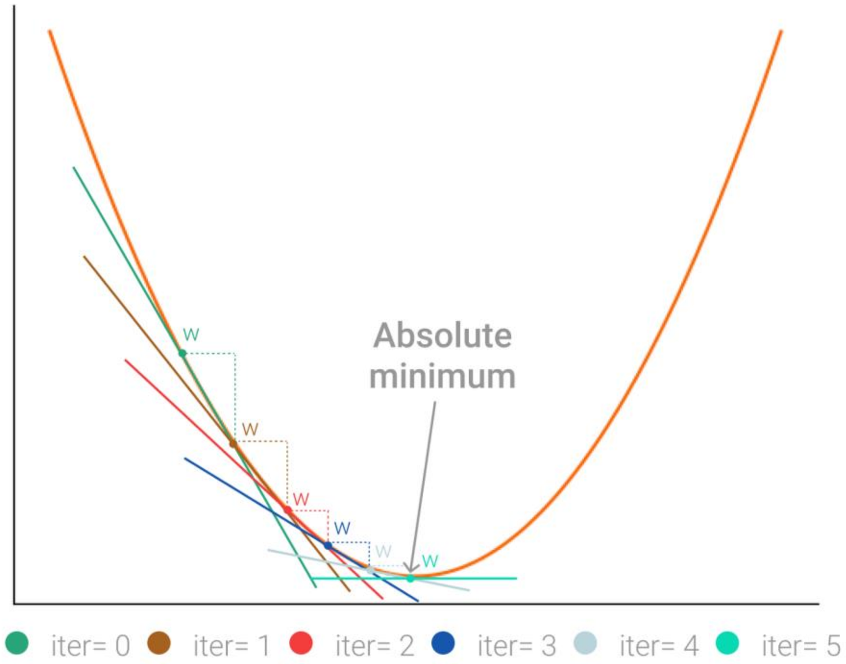


Fig 1

Stochastic gradient descent (SGD) with backpropagation used commonly for ANN to minimize loss. It requires the function to be:

1) Differentiable
2) Convex

However, spikes are discontinuous!

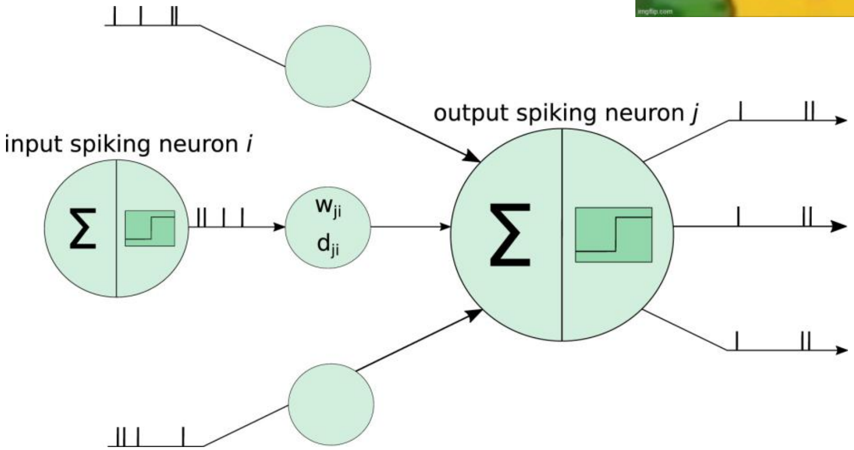


Fig 2

Fig 1: Multiple iterations through SGD to achieve minimum point (https://towardsdatascience.com/stochastic-gradient-descent-explained-in-real-life-predicting-your-pizzas-cooking-time-b7639d5e6a32)
Fig 2: SNN Scheme (https://doi.org/10.1016/j.neunet.2019.09.004)

Some potential solutions

Backpropagation Variants (Supervised)

Surrogate Gradient Learning

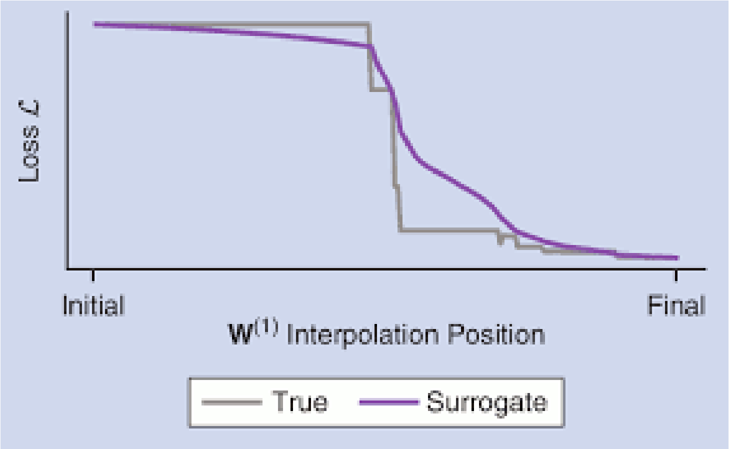


Fig 1

Unsupervised Approach

Spike-timing-dependent plasticity (STDP)

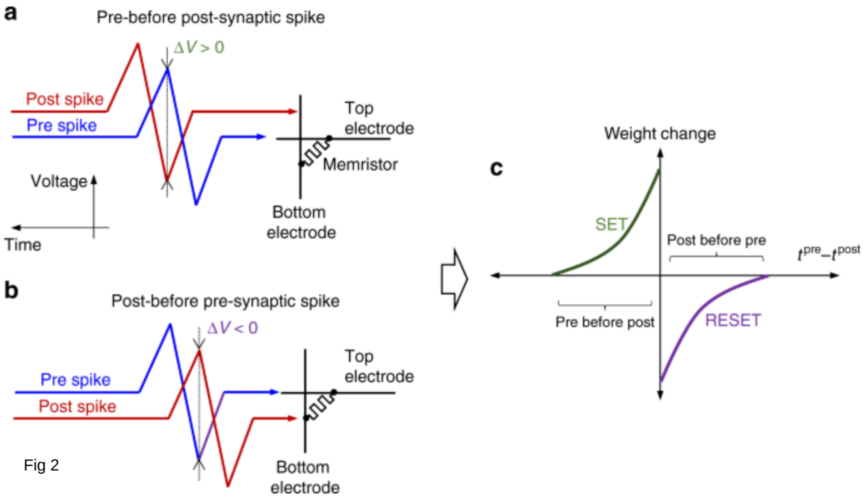


Fig 2

Some other approaches: Weight transfer, conversion, self-organising maps, and etc

Fig 1: Surrogate gradient approach to approximate discontinuous function (https://ieeexplore.ieee.org/document/8891809)
Fig 2:STDP for weight adjustments: https://www.nature.com/articles/s41467-018-07757-y

Current works of SNN

Applications

- Brain simulators
- Satellite image processing
- Bio-signal detections
- Automobile processing units
- Edge intelligence
- Prosthetic devices
- Brain-machine interfaces

Fig 1

Fig 2

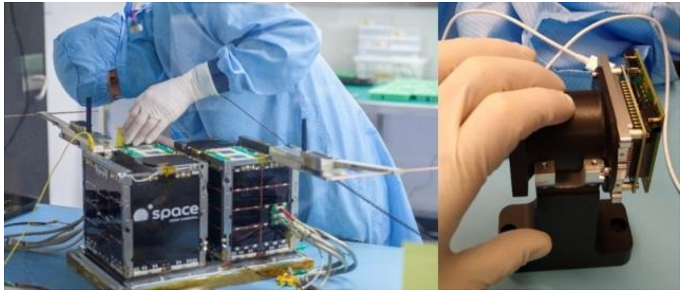


Fig 3

Players

intel

IBM

Qualcomm

Agency for Science, Technology and Research
SINGAPORE

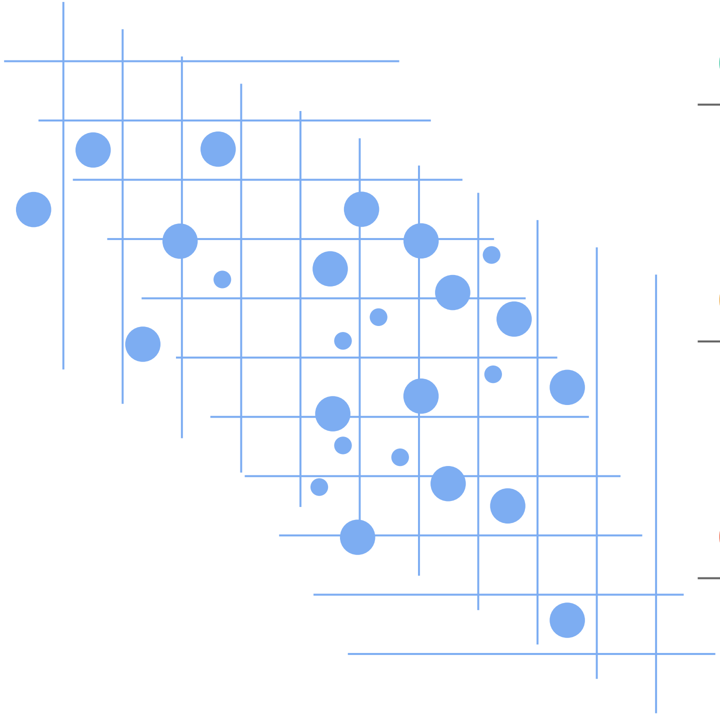
imec

Hewlett Packard Enterprise

Fig 4

Fig 1: Intel's new Loihi 2 chip (https://www.intel.com/content/www/us/en/newsroom/news/intel-unveils-neuromorphic-loihi-2-lava-software.html)
Fig 2: Akida Neural Processor (https://brainchipinc.com/technology/)
Fig 3:Custom neuromorphic camera payload launched into space in 2021 (UNSW Canberra Space, Western Sydney University)
Fig 4: A collection of some companies and institutions involved in Neuromorphic Engineering (Respective Wikipedia pages)

Future works of SNN



01 Algorithm

With comparatively lower performance than current deep learning opportunities, much research needs to be done in the algorithm (e.g., solution to address the optimization).

02 Architecture

Advancement in multiple disciplines such as neuroscience, cognitive science, and hardware will enable growth in neuromorphic computing and vice versa.

03 Application

New areas of application will determine the new requirements, and potential of SNNs.

Quiz Time!

To participate in the quiz:

https://www.wooclap.com/MLDASNN

Break Time!

Meanwhile, ask your questions here:

https://www.wooclap.com/MLDASNN

Hands On!

Save a copy of the template here:

https://bit.ly/3C0pmW3

Post Workshop Survey

https://bit.ly/3te5Npl

Ending off

Thank you for your participation in this workshop and hope you have enjoyed it.

Please fill in the workshop's feedback form for new and improved workshops in the future!

 Should you have any further questions or would like to voice out any errors in the materials, do feel free to reach out via cleow006 at e.ntu.edu.sg.

Appendix: Spike-encoding Schemes

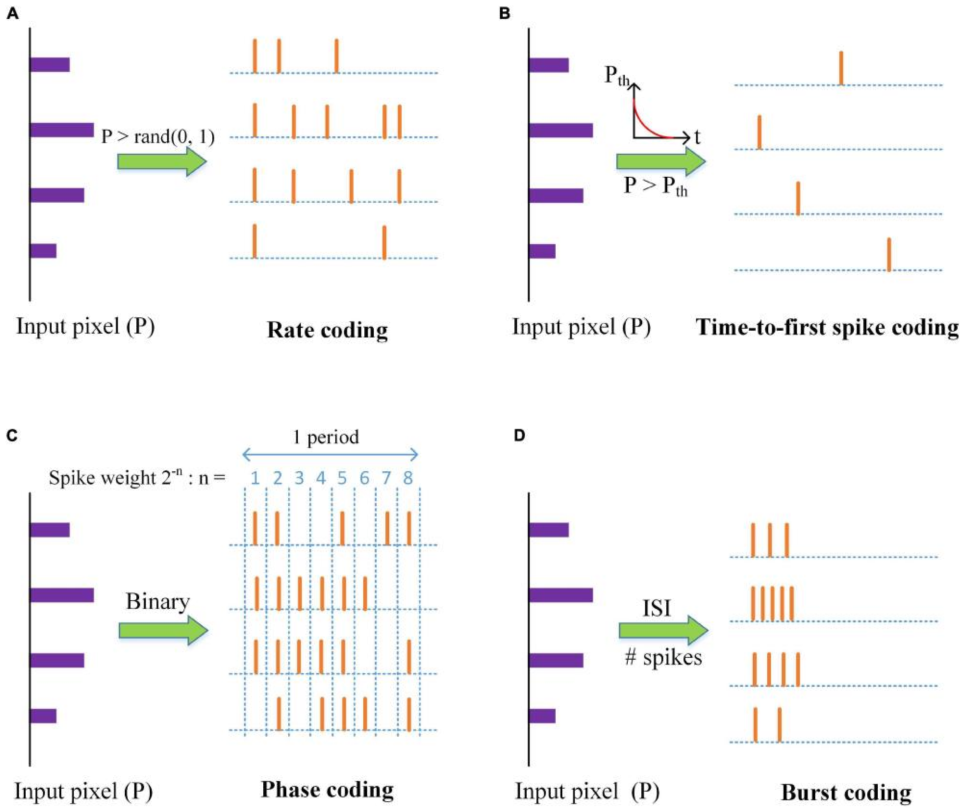


Fig A: Four different types of encoding schemes for SNN (https://doi.org/10.3389/fnins.2021.638474)