M02 Nervous Systems – From Spiking Neural Networks and Reservoir Computing to Neuromorphic Fault-tolerant Hardware

Date: Wednesday, 19 April 2023

Time: 16:30 CEST - 18:00 CEST

Location / Room: Okapi Room 0.8.2

Organisers:

Martin A. Trefzer, University of York, GB

Jim Harkin, Ulster University, GB

Speakers:

Martin A. Trefzer, University of York, GB

Jim Harkin, Ulster University, GB

Martin A. Trefzer, University of York, GB

Jim Harkin, Ulster University, GB

Presenters:

Shimeng Wu, University of York, GB

Andrew Walter, University of York, GB

Time	Label	Presentation Title Authors
16:30 CEST	M02.1.1	INTRODUCTION TO SNNS **Speaker**: Jim Harkin, Ulster University, GB
16:45 CEST	M02.1.2	NEUROMORPHIC HARDWARE OVERVIEW **Speaker**: Martin A. Trefzer, University of York, GB
17:00 CEST	M02.1.3	APPLICATIONS OF SNNS - NEUROMORPHIC EMBEDDED SENSORS AND NETWORKS FOR FAULT-TOLERANCE **Speaker**: Jim Harkin, Ulster University, GB
17:15 CEST	M02.1.4	NERVOUS SYSTEMS CONCEPT - MICROCIRCUITS AS BUILDING BLOCKS FOR NEUROMORPHIC ARCHITECTURES **Speaker**: Martin A. Trefzer, University of York, GB
17:30 CEST	M02.1.5	HANDS-ON SESSION: SNNS IN VHDL **Speaker**: Shimeng Wu, University of York, GB ***Abstract*** *Prerequisites for live participation is an installation of Xilinx Vivado 2022.1 (or later version).* *Tutorial resources are available from https://www-users.york.ac.uk/~mt540/nervous-systems/index.html#resources*
17:30 CEST	M02.1.6	HANDS-ON SESSION: SNNS WITH BRYAN2 & PYTHON **Speaker**: Andrew Walter, University of York, GB

Introduction to Spiking Neural Networks

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School of Physics, Engineering & Technology
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School of Computing, Engineering & Intelligent Systems
Ulster University

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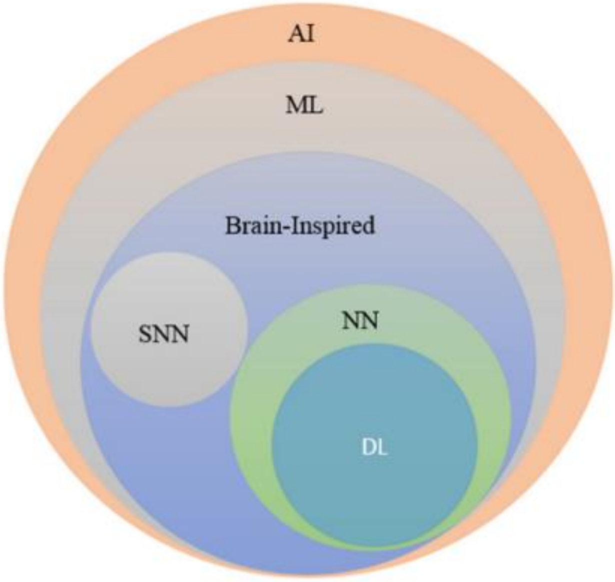
Artificial Intelligence

- Taxonomy of AI

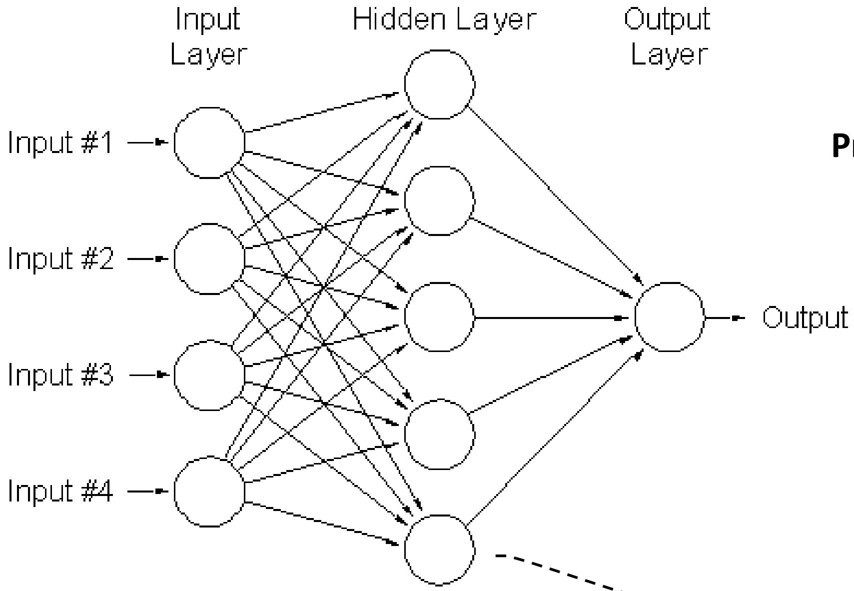


ML: Machine Learning
NN: Neural Networks
DL: Deep Learning
SNN: **Spiking Neural Networks**

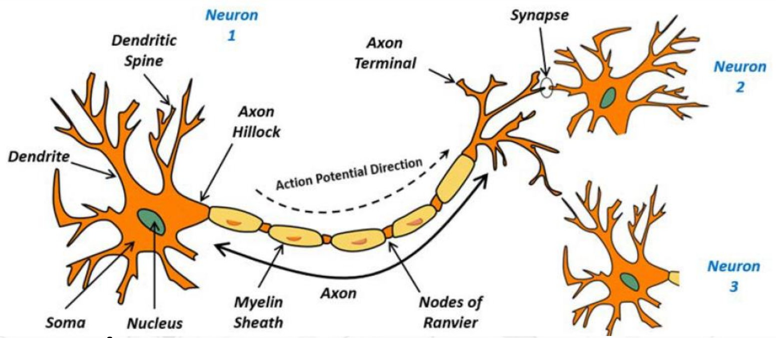
"A State-of-the-Art Survey on Deep Learning Theory and Architectures", Electronics, 8, 292 (2019)

Artificial Neural Networks

- Network of synapses and neurons

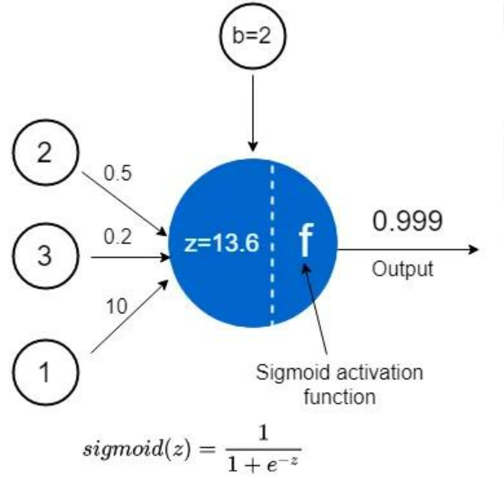


Biological neuron



Pre-synaptic

Post-synaptic

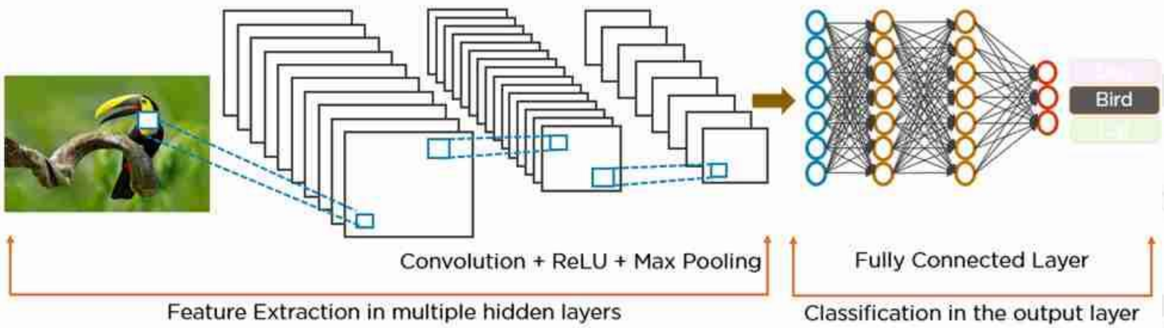


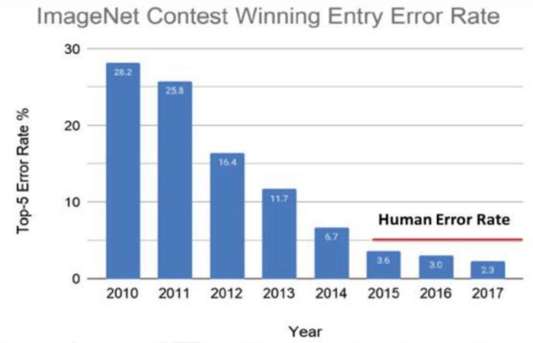
Source W. Gerstner et al.., Cambridge: Cambridge University Press, 2002.

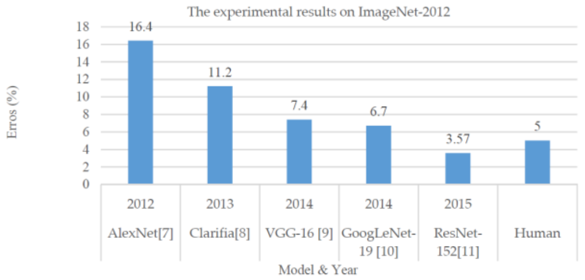
Source: R. Pramoditha, The Concept of Artificial Neurons (Perceptrons) in Neural Networks, 2021.

Artificial Neural Networks

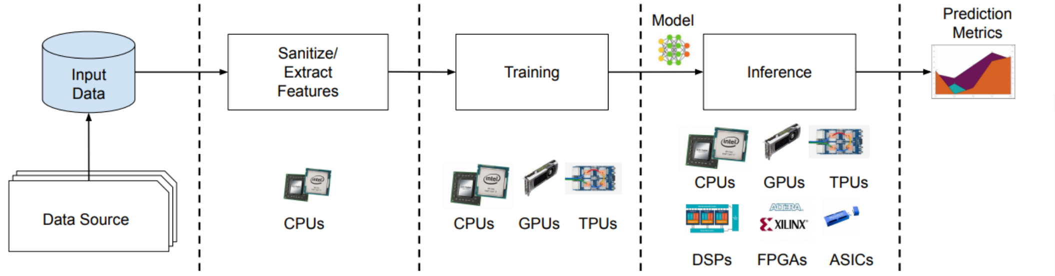
- CNN/DNN – popular in image recognition/speech processing, machine translation.







Md Zahangir Alom, Electronics, 2019 (doi:10.3390/electronics8030292)



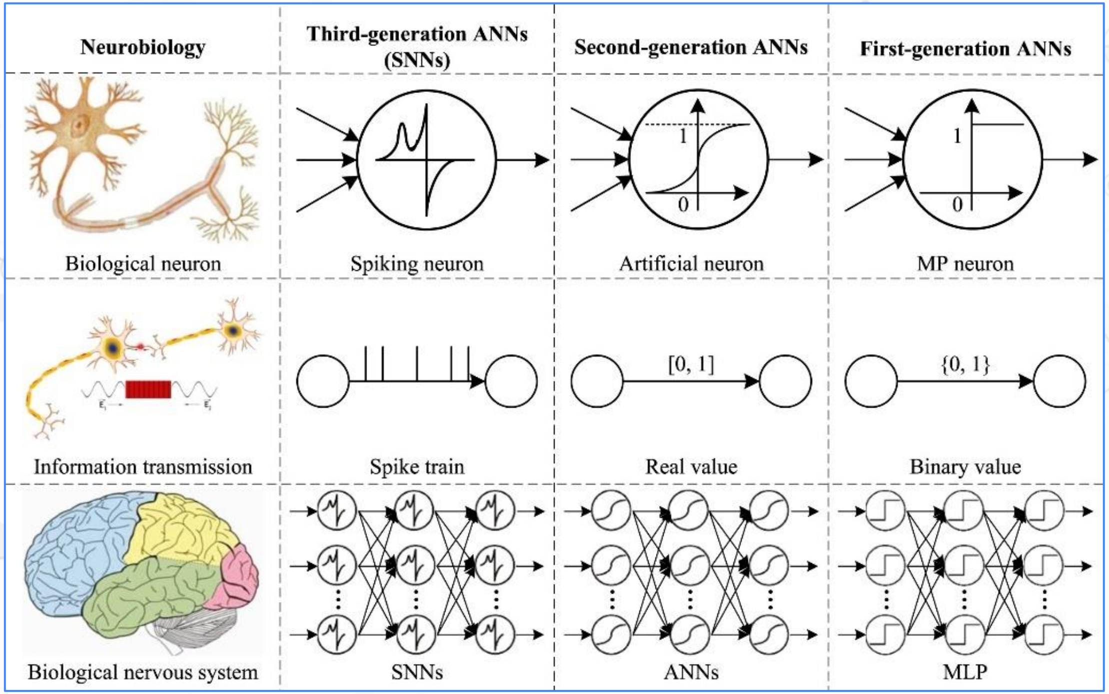
Source: "*Understanding Deep Learning: DNN, RNN, LSTM, CNN and R-CNN*" (2019)

*"The demands of AI neural networks, and of deep learning techniques… require thousands of petaflop-days to train…**strain on energy consumption**, and increasing **carbon dioxide emissions**."*

Source: *eFutures 2.0* Report, August 2021

Spiking Neural Networks

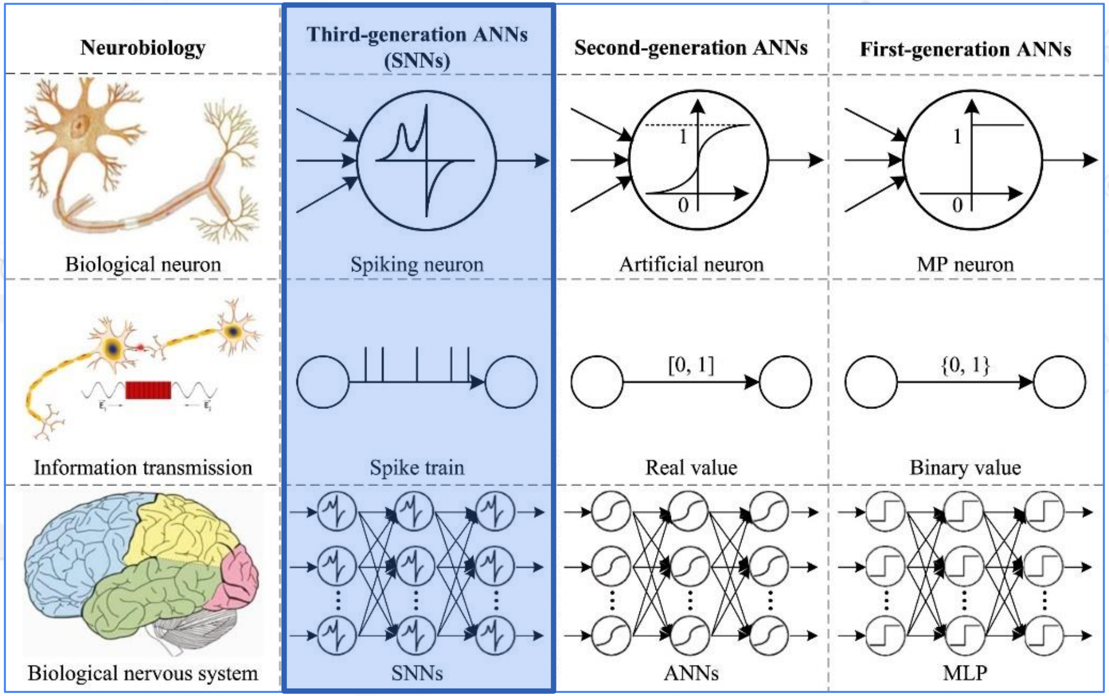
- Third generation of neural networks.



Source: X. Wang, Neural Networks, vol. 125, pp. 258-280, 2020

Spiking Neural Networks

- Third generation of neural networks.

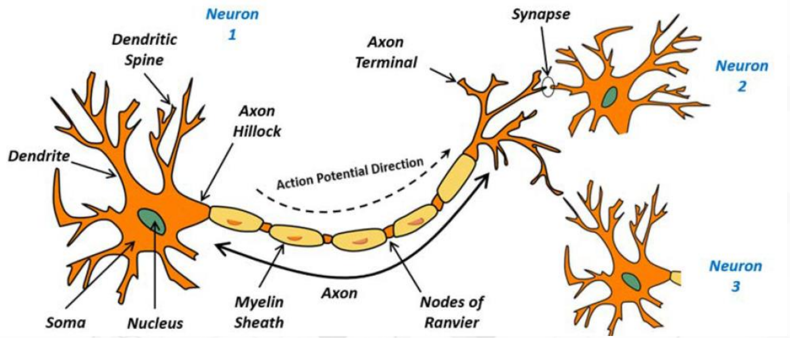


- More biologically-informed
- Temporal information
- Dynamical neurons

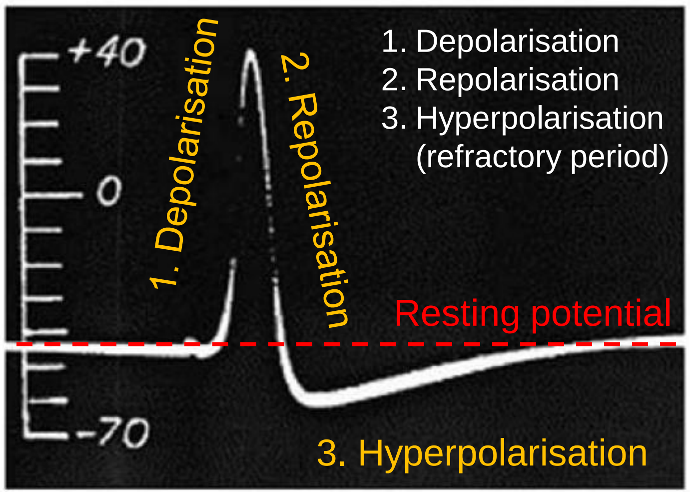
Source: X. Wang, Neural Networks, vol. 125, pp. 258-280, 2020

Spiking Neural Networks: Action Potential (Spike)

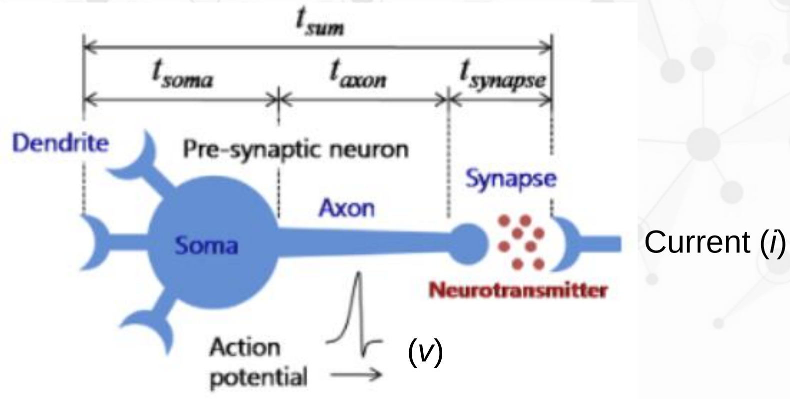
- Spiking Neural Networks (SNNs) **communicate via spikes** or action potentials (APs).
- Non-numeric values
- AP: distinct electrical spike produced by rapid depolarisation of the cell membrane followed by rapid repolarisation + brief period of hyperpolarisation.



Pre-synaptic **Post-synaptic**



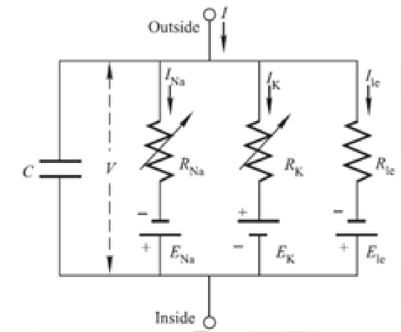
Intracellular AP recorded by Hodgkin and Huxley.



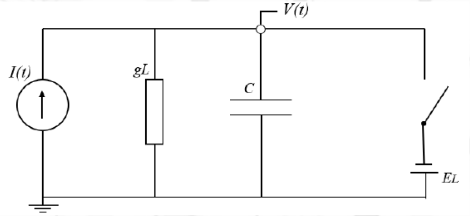
Source: Dae-Hwan Kang, Neurocomputing 155 (2015), 153-158

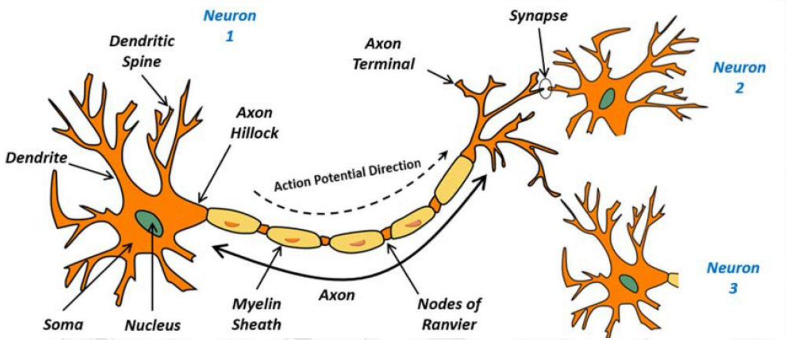
Spiking Neural Networks: Neurons

Electrical equivalent circuit of *Hodgkin and Huxley* (H&H) model



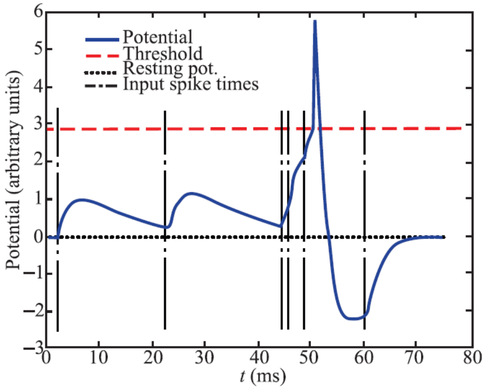
Electrical equivalent circuit of *Leaky-integrate & Fire* (LIF) model

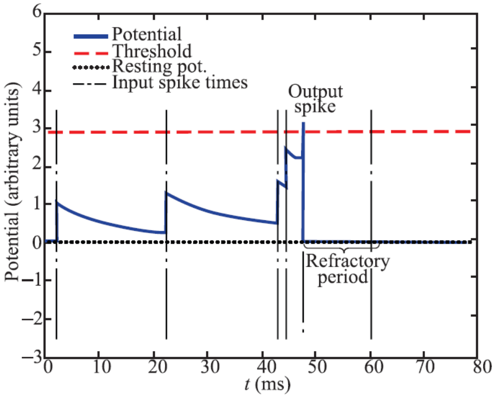


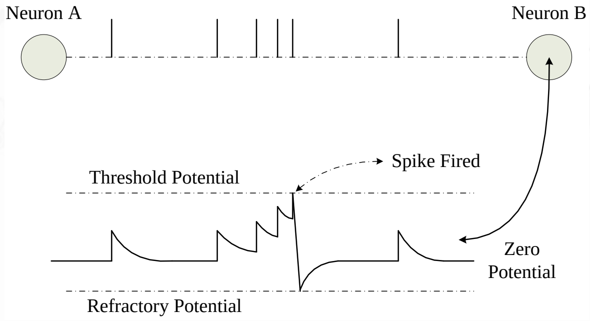


Pre-synaptic

Post-synaptic



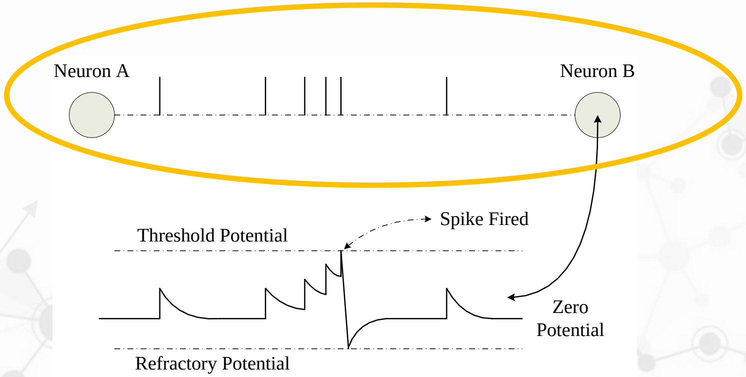




Brain-Inspired Data Processing

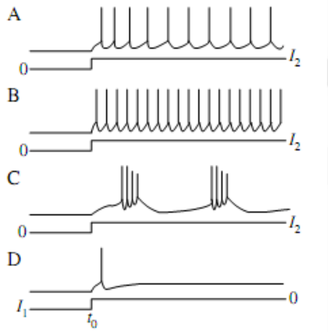
• **Spiking neural network (SNN)** a more biologically plausible model of the brain – a neural computing paradigm.

- Temporal nature utilised in data encoding
- Dynamics of neuron behaviour utilised.
- Asynchronous\event-based behaviour

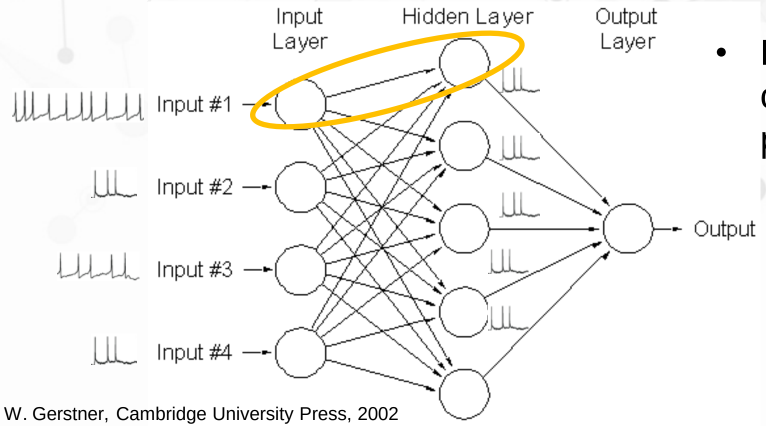


Spatiotemporal

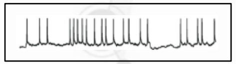
Data encoding



Input



- Reads I/P patterns and classifies with an O/P pattern

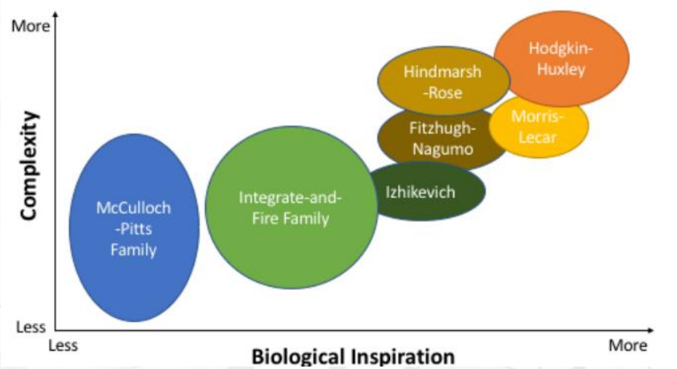


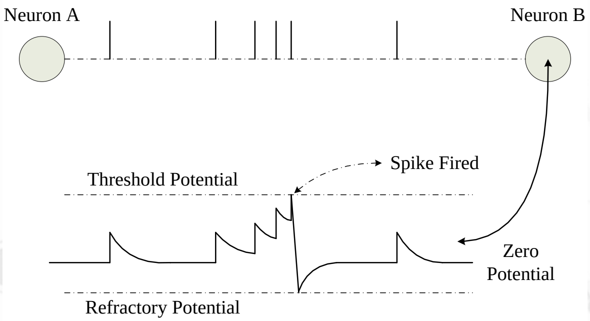
Output

Source: W. Gerstner, Cambridge University Press, 2002

Brain-Inspired Data Processing

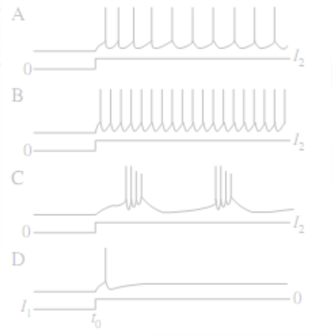
- **Spiking neural network (SNN)** a more biologically plausible model of the brain – a neural computing paradigm.



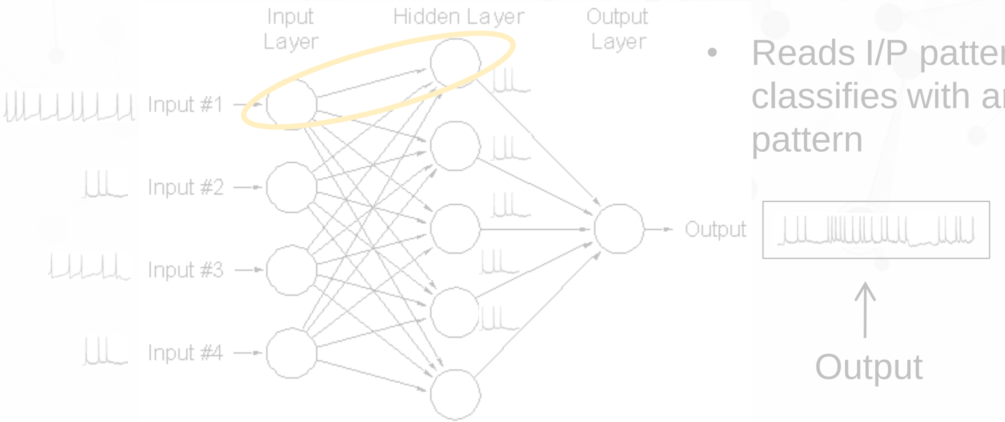


CD Schuman, "A survey of neuromorphic computing and neural networks in hardware", 2017

Data encoding



Input

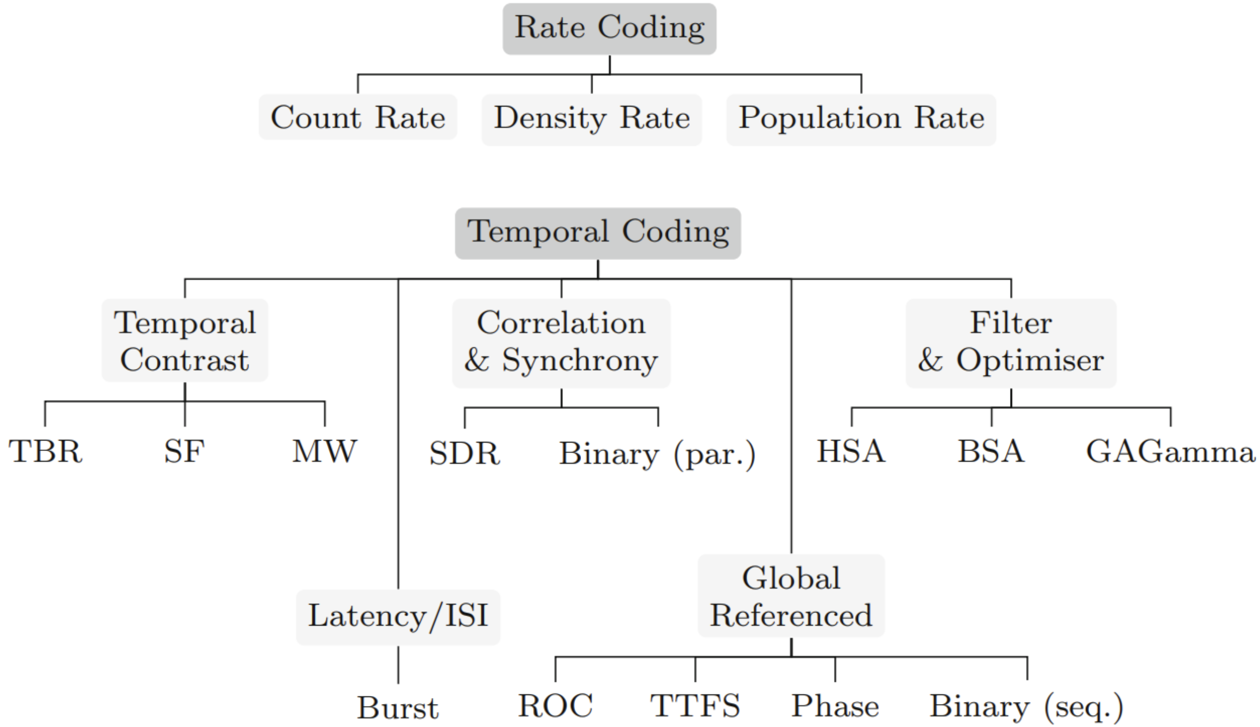


- Reads I/P patterns and classifies with an O/P pattern

Output

Data Encoding

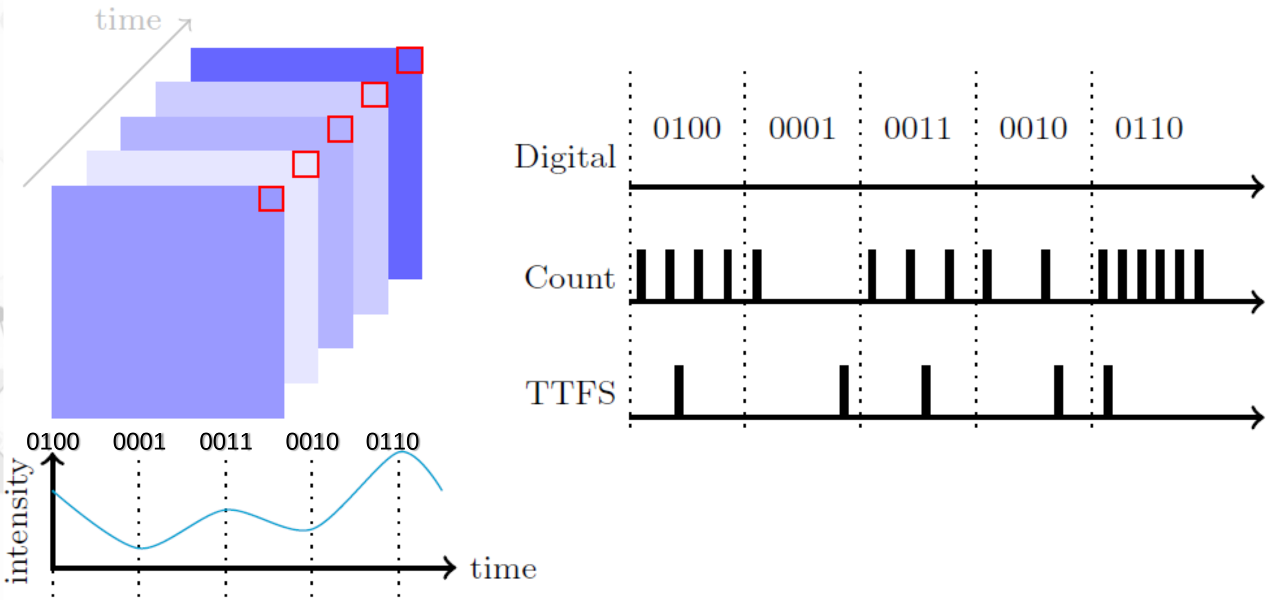
- How to encode analog and digital data as spike-based information.



D. Auge, Neural Processing Letters (2021) 53:4693–4710

Data Encoding

- How to convert analog and digital data into spikes



Rate Coding: e.g. '**Count rate**' - Intensity can be converted into the number of spikes generated within one frame.

Temporal Coding: e.g. Time-to-first-spike (**TTFS**) - High intensity pixel corresponds to a fast spike time.

The light intensity can directly be translated into spike times

D. Auge, Neural Processing Letters, 53, 4693–4710, 2021

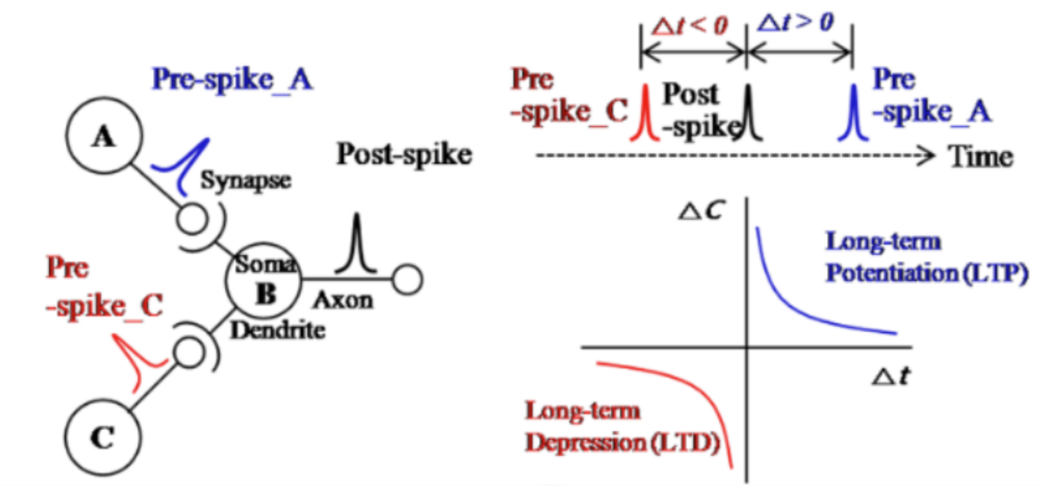
Learning Mechanisms

- **Unsupervised Learning**

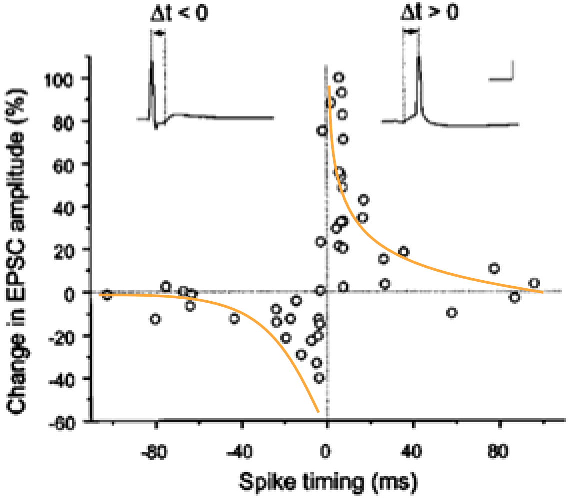
- Hebbian rule and STDP - *those who fire together, wire together (Hebbian rule); and those who fire out of sync, lose their link (STDP).*

STDP is a biological process that adjusts the strength of connections between neurons in the brain

$$\Delta W = A_+ e^{(t_{pre}-t_{post})/\tau_+} \quad \text{if} \quad t_{post} > t_{pre}$$
$$\Delta W = -A_- e^{-(t_{pre}-t_{post})/\tau_-} \quad \text{if} \quad t_{post} < t_{pre}$$



Source: Dae-Hwan Kang, Neurocomputing 155 (2015), 153-158

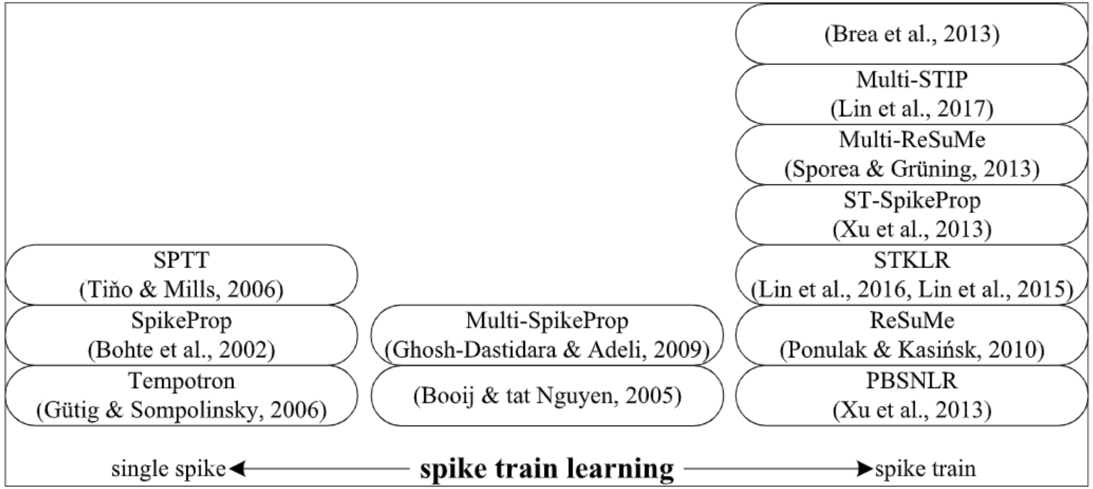


P. Rowcliffe, IEEE Transactions on Neural Networks, 19(9), 2008.

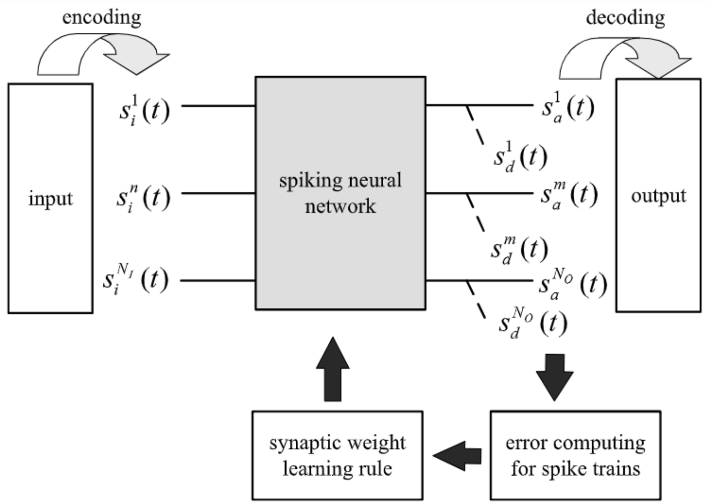
Learning Mechanisms

- **Supervised Learning**

- Modified Error-Backpropagation
- SpikeProp
- Synaptic weight association training (SWAT) algorithm
- Evolutionary algorithms approaches



Source: X. Wang et al.; Neural Networks 125, pp. 258–280, 2020



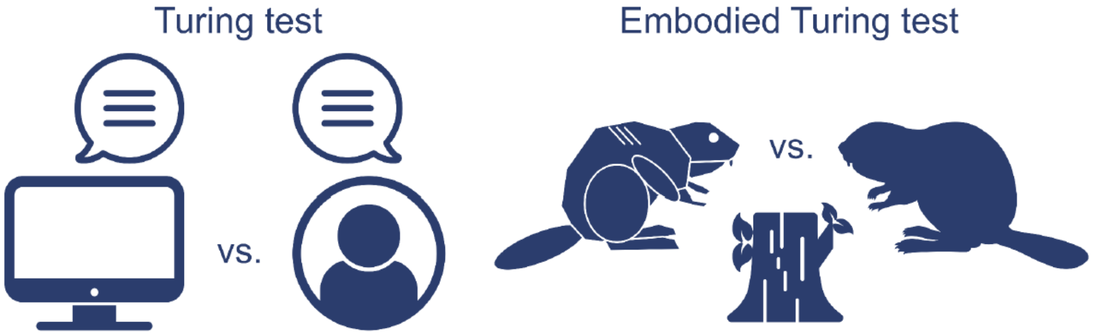
Source: X. Wang et al.; Neural Networks 125, pp. 258–280, 2020

- **Supervised learning** for SNNs is implemented through learning the **spatiotemporal** patterns of spike trains.

P. Rowcliffe, IEEE Transactions on Neural Networks, 19(9), 2008.
S. M. Bohte, Neurocomputing, 48(1-4), 2002
J. Wade, IEEE Transactions on Neural Networks, 21(11) 2010
A. Belatreche, Proc. IEEE Cybernetics Intelligence - Challenges and Advances, pp. 39-44, Sep. 2003

Motivation for SNNs

- SNN is a dynamic system → map well to speech and image recognition
- More energy efficient as it is asynchronous in operation
- Speed of computation improved due to event processing
- Challenges in ‘learning’ SNNs remain.
- Challenges in developing hardware mimics to exploit low energy, high-speeds



Source: A.Zador, Nature Communications, 14(1597), 2023

“An AI animal model – whether robotic or in simulation – passes the test if its behavior is indistinguishable from that of its living counterpart.”

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