Deep Spiking Neural Network, Deep Liquid State Machine e Deep Echo State Network

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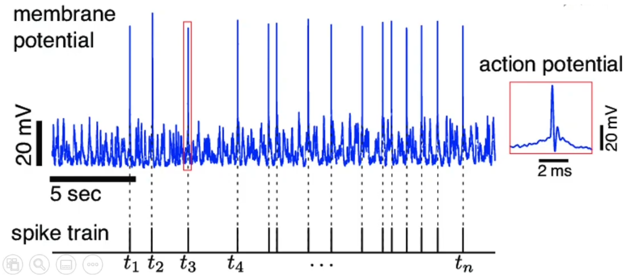
Rascunho

Spiking Neural Networks (SNN) mimic how the brain works i.e. works with action potential in opposition to the continuous values crossing the links between the neurons. So, the more we understand the SNNs the more we understand the brains iteself.
The "Spiking" comes from the behavior of the biological neuron which fires (action potential) from time to time creating voltage spikes when measured, these spikes represent the information (KASABOV, 2019). The figure 3 shows the spikes.



Rascunho II

Figura: Spikes from noisy signal. Source (GOODMAN et al., 2022)

Spiking Neural Networks (SNNs) exhibit several noteworthy characteristics that set them apart from traditional machine learning techniques, including classical neural networks. These distinctions encompass (KASABOV, 2019):

- Proficiency in modeling temporal, spatio-temporal, or spectro-temporal data.
- Effectiveness in capturing processes involving various time scales.
- Seamless integration of multiple modalities, such as sound and vision, into a unified system.
- Aptitude for predictive modeling and event prediction.
- Swift and highly parallel information processing capabilities.
- Streamlined information processing.

Rascunho III

- Scalability, accommodating structures ranging from a few tens to billions of spiking neurons.
- Minimal energy consumption when implemented on neuromorphic platforms.

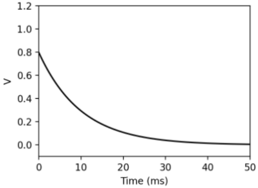
In order to mimic such behavior let's begin with a simple model: The "Leaky Integrate and Fire neuron"(LIF). LIF evolves the membrane potential according to the equations bellow.
Here we have the "leaking"equation which models the potencial losing across the time.

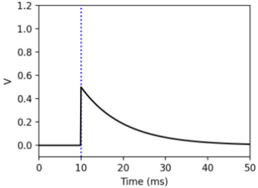
$$\tau.\frac{dV}{dt} = -V \tag{1}$$

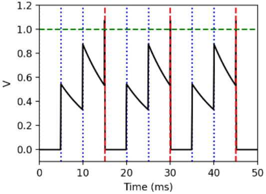
When a neuron receives a spike V increases according to a synaptic weight w.

$$V = V + w \tag{2}$$

Rascunho IV







tinuous dynamics!

Figura: Evolution of a Spike. Source (GOODMAN et al., 2022)

Like it can be seen in Figure 4 when a neuron reaches some threshold it resets ($V = 0$) and starts an refractory period.

Energy efficiency:

Spiking Neural Networks (SNNs) are often considered power-efficient for several reasons:

1. Event-Driven Processing: SNNs are inherently event-driven. Instead of constantly updating neuron activations and synapse weights as in traditional artificial neural networks (ANNs), SNNs only transmit spikes (action potentials) when a neuron's membrane potential reaches a certain threshold. This event-driven approach reduces the amount of computation required and can lead to significant energy savings.

Rascunho VI

2. Sparse Activity: SNNs tend to exhibit sparse activity, meaning that only a small percentage of neurons are active at any given time. This sparsity reduces the number of computations that need to be performed, which is especially beneficial for hardware implementations where most of the energy consumption comes from active components.
3. Low Precision: SNNs can often work with lower precision than ANNs. While ANNs typically use high-precision floating-point numbers for neuron activations and synaptic weights, SNNs can use lower precision fixed-point or binary representations. Lower precision computations require less energy to perform.
4. Neuromorphic Hardware: SNNs can be efficiently implemented on specialized neuromorphic hardware, which is designed to mimic the energy-efficient behavior of biological neural systems. These hardware platforms are optimized for the event-driven nature of SNNs, further reducing power consumption.

Rascunho VII

5. Energy-Aware Learning Rules: SNNs can employ learning rules that take into account energy efficiency. For example, some learning rules prioritize strengthening or weakening synapses based on their contribution to network activity, which can lead to more energy-efficient learning.
6. Spike Encoding: SNNs can encode information in the timing and frequency of spikes, which can be a highly efficient way to represent and process data, particularly for event-based sensors like vision sensors or auditory sensors.

Introdução

Estrutura da apresentação

Deep Spiking Neural Network

Rascunho I

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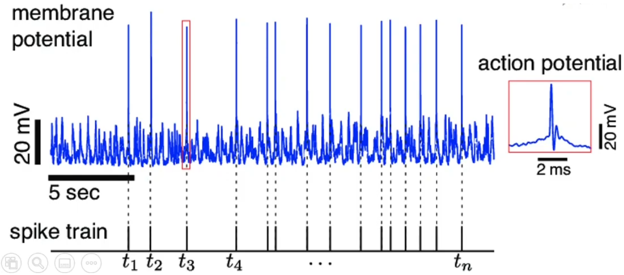

Rascunho II

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$$V = V + w \tag{4}$$

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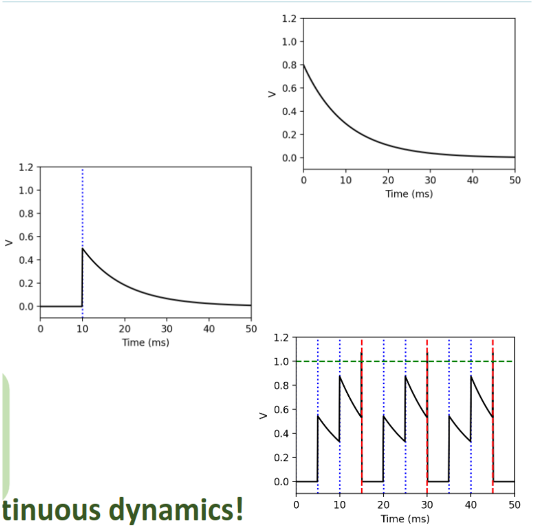
Rascunho IV



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Deep Liquid State Machine

Deep Echo State Network

Referências I

GOODMAN, D. et al. *Spiking Neural Network Models in Neuroscience - Cosyne Tutorial 2022*. Zenodo, 2022. Disponível em: ⟨https://doi.org/10.5281/zenodo.7044500⟩.

KASABOV, N. K. *Time-space, spiking neural networks and brain-inspired artificial intelligence*. [S.l.]: Springer, 2019.