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

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Rascunho

Rascunho I

Spiking Neural Networks (SNNs) mimic how the brain works by utilizing action potentials in contrast to continuous values transmitted between neurons.
The term "Spiking"originates from the behavior of biological neurons, which sporadically emit action potentials, creating voltage spikes that are measured; these spikes represent information (KASABOV, 2019). Figure 4 illustrates these spikes.
It is crucial to emphasize that an SNN **is not** a one-to-one simulation of neurons. Instead, it approximates certain computational capabilities of specific biological properties. Some studies explore the nonlinearity of dendrites and other neuron features (JONES; KORDING, 2020) yielding remarkable results in classification of the MNIST database.

Rascunho II

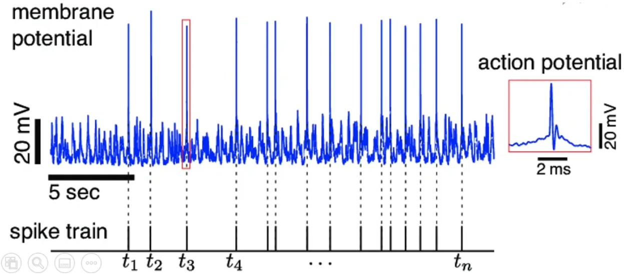


Figura: Spikes from a noisy signal. Source (GOODMAN et al., 2022)

SNNs possess several noteworthy characteristics that distinguish them from traditional machine learning techniques, including classical neural networks. These distinctions encompass (KASABOV, 2019):

- Proficiency in modeling temporal, spatial-temporal, or spectro-temporal data.
- Effectiveness in capturing processes involving various time scales.

Rascunho III

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

Rascunho IV

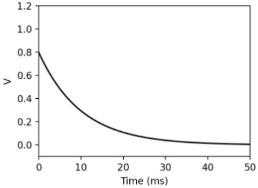
In order to emulate such behavior, let's begin with a simple model: The "Leaky Integrate and Fire neuron"(LIF). The LIF model describes the evolution of membrane potential as follows.
Here we have the "leaking"equation, which models the potential decay over time.

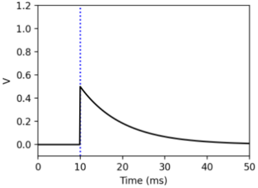
$$\tau \cdot \frac{dV}{dt} = -V \tag{1}$$

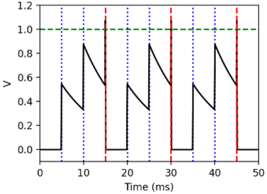
When a neuron receives a spike, the membrane potential V increases according to a synaptic weight w.

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

Rascunho V







tinuous dynamics!

Rascunho VI

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

As shown in Figure 5, when a neuron reaches a certain threshold, it resets ($V = 0$) and enters a 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 VII

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.

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.

How do SNNs get trained? Well, this is still an open question. An SNN neuron has an activation-function behavior that is more relatable to a **step-function**. Therefore, in principle, we can't use gradient descent-based solutions because this kind of function **is not** differentiable (KASABOV, 2019).
But there is some insigths out there that may put some light on this subject: While some *in vivo/ in vitro* observations shows that brains in general learns by strengthen/weaken and add/remove synapses or even by creating new neurons or other

Rascunho IX

cumbersome methods like RNA packets. There are some more acceptable ones like (KASABOV, 2019):

- Spike Timming Dependent Plasticity (STDP): The idea is that if there is a pre-synaptic neuron and it fires **before** the post-synaptic one there is a strengthening in connection but, if the post-synaptic fire before then we are going to have a weakening .
- Surrogate gradient descent: The technique **approximates** the step-function by using another mathematical function, which is differentiable (like sigmoid), in order train the network. These approximations are used only **in the backwards pass** keeping the steps function in forward pass (KASABOV, 2019).
- Evolving algorithms: Uses the selection of the fittest throughout many generations of networks.
- Reservoir computing: Echo state networks and Liquid state machines. Which will be discussed further in this presentation.

Rascunho X

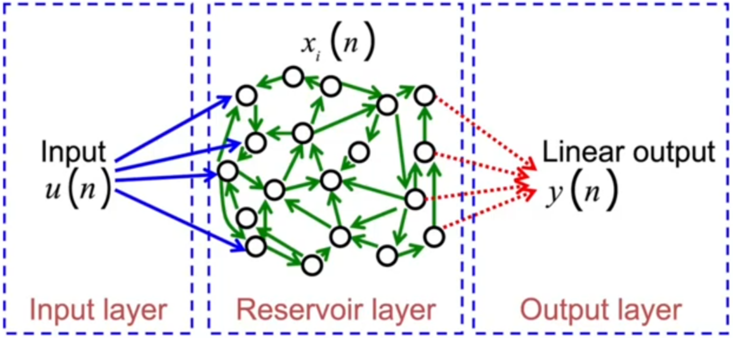


Figura: Reservoir computing: The reservoir layer is not trained. Intead just the weights between reservoir and output layer are ajusted. Source: (KASABOV, 2019)

Introdução

Estrutura da apresentação

Deep Spiking Neural Network

Rascunho I

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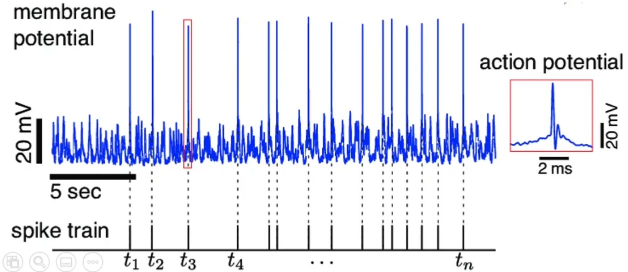

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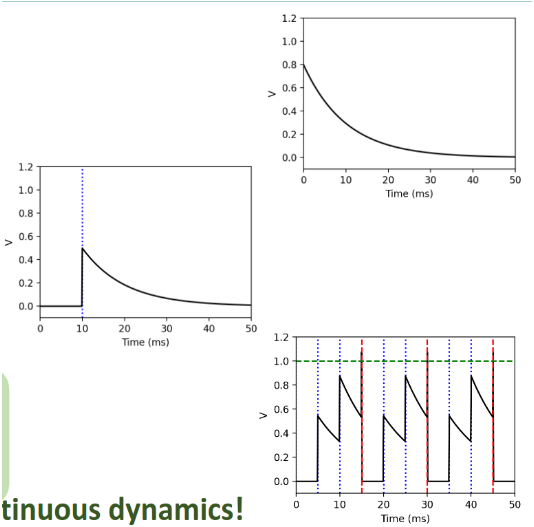

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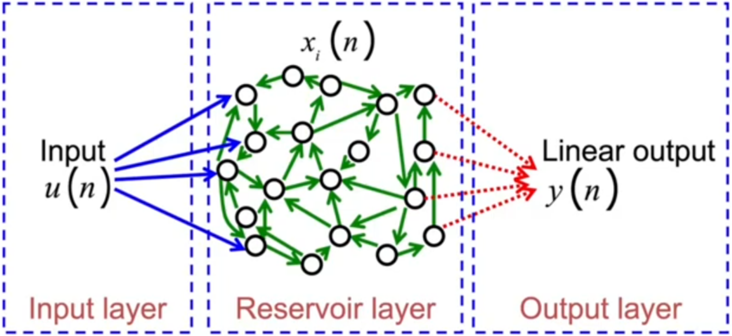


Figura: Reservoir computing: The reservoir layer is not trained. Intead just the weights between reservoir and output layer are ajusted. Source: (KASABOV, 2019)

Deep Liquid State Machine

The liquid state machine (LSM) has emerged as a computational model that is more suitable than Turing machines for describing neural networks. It is used to process continuous streams of data, typically in the form of spike trains, and it maps streams of inputs into streams of outputs. These outputs may depend on the previous states created by the streaming data (MAASS,).

LSM is model for adaptive computing systems. Considering that the training stage is the most expensive and sensible one, these kind of networks are trained only at the readouts. These readouts, usually, consists of only a single neuron which is called *"projection neuron"* that extracts information from a micro-circuit somewhere in the LSM. These structures can be used as inputs to another area of the neural network and can be modeled as a perceptron, linear gate, sigmoidal gate, spike neuron and others (MAASS,). The networks structure consists of several neurons randomly and recurrently connected forming the *"liquid part"* which is interpreted by the readouts. The word *"liquid"* can sometimes be take literally like in this work (FERNANDO; SOJAKKA, 2003) where a bucket of water has been taken the role of the liquid part of the network as can be seen in Figure 7.

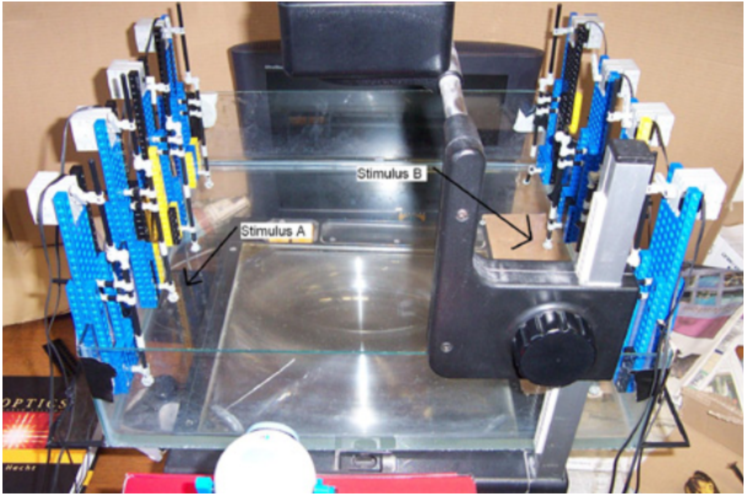
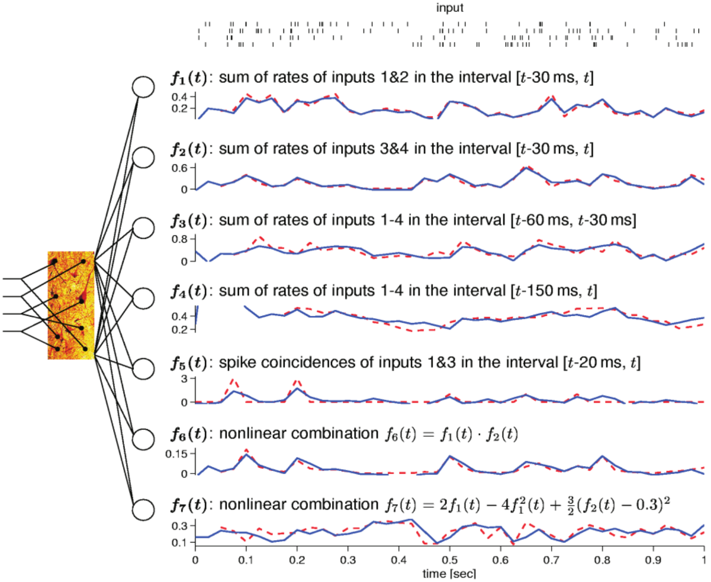


Figura: A liquid network. Source: (FERNANDO; SOJAKKA, 2003)

LSM can be adapted to multiple computation as the projection neurons can extract as many different characteristics one desires as can be seen in Figure 8.


input
$f_1(t)$: sum of rates of inputs 1&2 in the interval [t-30 ms, t]
$f_2(t)$: sum of rates of inputs 3&4 in the interval [t-30 ms, t]
$f_3(t)$: sum of rates of inputs 1-4 in the interval [t-60 ms, t-30 ms]
$f_4(t)$: sum of rates of inputs 1-4 in the interval [t-150 ms, t]
$f_5(t)$: spike coincidences of inputs 1&3 in the interval [t-20 ms, t]
$f_6(t)$: nonlinear combination $f_6(t) = f_1(t) \cdot f_2(t)$
$f_7(t)$: nonlinear combination $f_7(t) = 2f_1(t) - 4f_1^2(t) + \frac{3}{2}(f_2(t) - 0.3)^2$
time [sec]

Figura

More liquid

Also, according to (HASANI et al., 2020) the inspiration comes from the nervous system of the nematode *C. elegans* which, despite having just 302 neuron, have pretty complex behavior. In this model the networks parameter changes over time according to a set of nested differential equations **while it is already in use** i.e. **this model does not need a training phase in order to adapt**.

Conversely, LNNs introduce dynamic connectivity patterns, allowing information to flow and interact in a fluid manner.

Liquid Neural Networks, also known as Liquid State Machines (LSMs), were first introduced by Wolfgang Maass(MAASS; NATSCHLäGER; MARKRAM, 2002). The primary departure from traditional ANNs lies in their dynamic and recurrent architecture. While conventional ANNs consist of fixed layers of interconnected neurons, LNNs employ a vast collection of interconnected neurons that are constantly in a state of change. This dynamic behavior allows LNNs to process temporal data, sequential information, and streaming inputs with remarkable flexibility and efficiency.

- Adaptability: Their dynamic nature enables them to respond dynamically to varying data distributions, making them well-suited for tasks involving non-stationary data.

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- Robustness: LNNs have shown improved robustness against noise and input variations. The fluid-like behavior allows them to self-adjust and filter out irrelevant information, leading to enhanced generalization capabilities.
- Exploration of Solution Space: LNNs encourage solution space exploration by providing flexibility in the network's structure. The dynamic connectivity patterns enable the network to explore diverse pathways, potentially discovering novel solutions to complex problems.
- Reduced Overfitting: Due to their continuous learning capabilities, LNNs are less prone to overfitting, which often occurs in static networks, resulting in more accurate and generalizable models.

Being f the neural network, $I(t)$ its inputs, t current time, θ and A the hiperparameters and τ is time constant than the equation 5 represents the Liquid Time-Constant recurrent neural networks (LTC) hidden state's derivative (HASANI et al., 2020).

$$\frac{dx(t)}{dt} = -\left[\frac{1}{\tau} + f(x(t), I(t), t, \theta)\right] x(t) + f(x(t), I(t), t, \theta)A \quad . \tag{5}$$

To simplify a neuron in these kind of networks can be expressed like in the listing .

```python
import numpy as np
import matplotlib.pyplot as plt

class LiquidTimeConstantNeuron:
    def __init__(self):
        self.time_constant = 1.0

    def adjust_time_constant(self, input_data):
        # Adjust the time constant based on input data
        self.time_constant = 1.0 + input_data

    def update_state(self, state, time_step):
        # Update the state based on the time constant and time step
        return state - (state / self.time_constant) + np.sin(time_step)

# Create a Liquid Time-Constant Neuron
ltc_neuron = LiquidTimeConstantNeuron()

# Simulate over time
duration = 10.0
time = np.arange(0, duration, 0.1)
states = [0.0]

for t in time[1:]:
    input_data = np.sin(t)  # Simulated input data (can vary over time)
    ltc_neuron.adjust_time_constant(input_data)
    new_state = ltc_neuron.update_state(states[-1], t)
    states.append(new_state)

# Plot the results
plt.plot(time, states)
plt.xlabel("Time")
plt.ylabel("State")
```

```python
plt.title("Neuron with Adjustable Time Constant")
plt.show()
```

```python
import torch
import torch.nn as nn

class ESN(nn.Module):
def __init__(self, input_size, reservoir_size, output_size):
super(ESN, self).__init__()
self.reservoir_size = reservoir_size
self.W_in = nn.Linear(input_size, reservoir_size)
self.W_res = nn.Linear(reservoir_size, reservoir_size)
self.W_out = nn.Linear(reservoir_size, output_size)

def forward(self, input):
reservoir = torch.zeros((input.size(0), self.reservoir_size))
for i in range(input.size(1)):
input_t = input[:, i, :]
reservoir = torch.tanh(self.W_in(input_t) + self.W_res(reservoir))
output = self.W_out(reservoir)
return output

# Example usage
input_size = 10
reservoir_size = 100
output_size = 1

model = ESN(input_size, reservoir_size, output_size)
```

Deep Echo State Network

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