Optimization of Spiking Neural Networks

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The human brain is particularly good at pattern recognition requiring little power. Due to this fact, scientists are trying to improve their knowledge of the brain and build systems to model it. Since conventional *artificial neural network* (ANN) often use backpropagation and are thus, biologically implausible or require a lot of power to do computations, researchers have started focusing on implementing alternatives such as *spiking neural network* (SNN).

A SNN's neuron fires if its membrane potential exceeds a certain (adaptable) threshold. The membrane's potential is calculated by the sum of incoming spikes with respect to their timing. To improve this process' biological fidelity, the membrane potential decays exponentially. Synapses are modelled by the connections between neurons.

The influence of a synapse on the postsynaptic neuron is represented by the weight of the connection. This weight is altered during training to disconnect neurons from those that have little influence on their spiking activity. The usage of homoeostasis (i.e. adaptive membrane threshold and limiting the firing rate of neurons) prevents single neurons from firing all the time and enables the neurons to learn different input patterns.

Main focus of presentation:

1 Biology
2 Biology to SNN
3 ANN vs. SNN
4 Input encoding
5 Poisson model of spike generation
6 Spikes
7 Problem
8 Architecture
9 Synaptic plasticity
10 spike-timing-dependent plasticity (STDP)
11 Neuron model
12 Synapse model
13 Homoeostasis
14 Training & testing

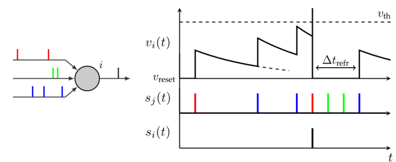


Figure 1: Multiple spikes $s_j(t)$ arrive at a neuron. The neuron's membrane potential $v_i(t)$ is calculated by the sum of incoming spikes with respect to their timing. The neuron fires, cf. $s_i(t)$, if $v_i(t) > v_{th}$, v_{th} being the threshold. There is a refractory period Δt_{refr} after a neuron has fired.

Synaptic plasticity: Activity-dependent modification of synaptic weights as shown in (1).

$$\Delta w = \begin{cases} \Delta w^{+} = A^{+} e^{\frac{-\Delta t}{\tau_{+}}}, & \text{if } \Delta t > 0 \\ \Delta w^{-} = -A^{-} e^{\frac{\Delta t}{\tau_{-}}}, & \text{if } \Delta t \leq 0 \end{cases} \tag{1}$$

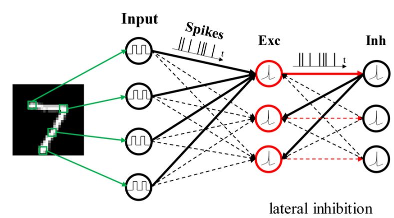
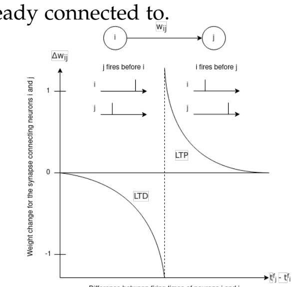


Figure 2: The architecture of the SNN consists of an input and a preprocessing layer. The input layer has $28x28$ neurons, i.e. one for each input pixel. All input neurons are connected to all excitatory neurons. Every excitatory neuron is connected to one inhibitory neuron. Every inhibitory neuron is connected to all but the one excitatory neuron it is already connected to.

goal of STDP: Strengthen synapses of pre- and postsynaptic neuron pairs, whose postsynaptic neuron reacts immediately after the presynaptic neuron fires.

Neuron model: A neuron fires if the membrane's potential V from (2) crosses the membrane's threshold v_{thresh}. After firing, the neuron's membrane potential is reset and within the next few milliseconds, i.e. the refractory period t_{ref}, the neuron cannot spike again.

$$\tau \frac{dV}{dt} = (E_{rest} - V) + g_e(E_{exc} - V) + g_i(E_{inh} - V) \tag{2}$$



Synapse model: The synapse's conductance g_e/g_i (e excitatory, i inhibitory) models the influence of a presynaptic neuron on another neuron. If a presynaptic spike arrives at the synapse the weight $w_{i,j}$ between neuron i and neuron j is added to g_e/g_i. Otherwise, g_e/g_i decays as displayed in (3).

$$\tau_{g_e} \frac{dg_e}{dt} = -g_e \tag{3}$$

Figure 3: Weight modification depending on the time difference $\Delta t = t_j^f - t_i^f$ between postsynaptic and presynaptic spikes. The weight change Δw is positive if the presynaptic spike precedes the postsynaptic one, i.e. $\Delta t > 0$, analogously for $\Delta t < 0$. The size of Δw depends on the size of Δt.