# SPIKE-TIMING-DEPENDENT PLASTICITY

**August 28, 2023**

Amin Zeinali
University of Tehran
Faculty of Mathematics, Statistics, and Computer Sciences

# 1 Abstract

This report details the implementation and results of a simulation of spike-timing-dependent plasticity (STDP) in a spiking neural network. The network consists of interconnected excitatory and inhibitory neuron populations. STDP learning rules are applied to the synapses between neuron groups. Input signals are provided to the excitatory population, and activity is analyzed in the output excitatory population. In order to make a competition between neurons for activation, The K-Winners-Take-All (KWTA) mechanism is also applied to the output neuron group. The goal is to demonstrate an unsupervised way of learning random signals via the STDP and KWTA mechanisms.

# 2 Introduction

Spike-timing-dependent plasticity (STDP) is a biological process that adjusts the strength of synaptic connections between neurons based on the relative timing of pre- and post-synaptic spikes [1]. It is widely believed to be a key mechanism for learning and information processing in the brain.

This report presents a simulation of STDP in a spiking neural network implemented in Python using the PyoNNtorch library [2]. The network consists of interconnected excitatory and inhibitory neuron populations with STDP applied to synapses between groups. The aim is to demonstrate how STDP and KWTA lead to synaptic weight changes in which neurons learn random signals in an unsupervised manner.

# 3 Methods

## 3.1 Network Structure

The network comprises three neuron groups - one inhibitory, one excitatory input, and one excitatory output. The excitatory and inhibitory neurons are modeled as leaky integrate-and-fire (LIF) units. The input group receives external stimulus signals generated from the Normal distribution, while the output group activity is analyzed.

The network is stimulated over multiple iterations. In each iteration, a signal is provided to the input group, followed by a rest period. Raster plots visualize spiking activity, and changes in output group activity over iterations demonstrate STDP effects alongside KWTA.

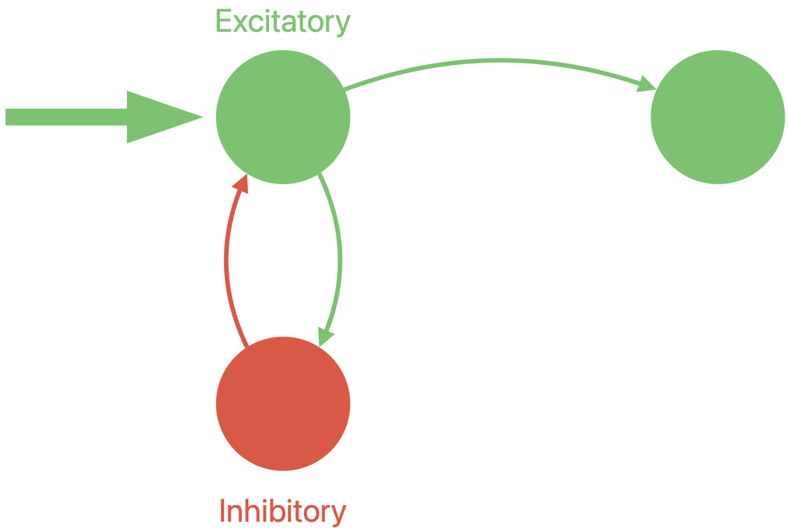


**Figure 1:** The structure of the network used in simulations.

## 3.2 STDP

STDP learning rules are applied to synapses between groups. The rules modulate synaptic weights based on the timing of pre- and post-synaptic spikes. The STDP curve has an asymmetric shape that potentiates synapses with pre- before post-spike pairings and depresses synapses with post- before pre-spike pairings. Soft and hard weight bounding and anti-Hebbian STDP are also implemented.

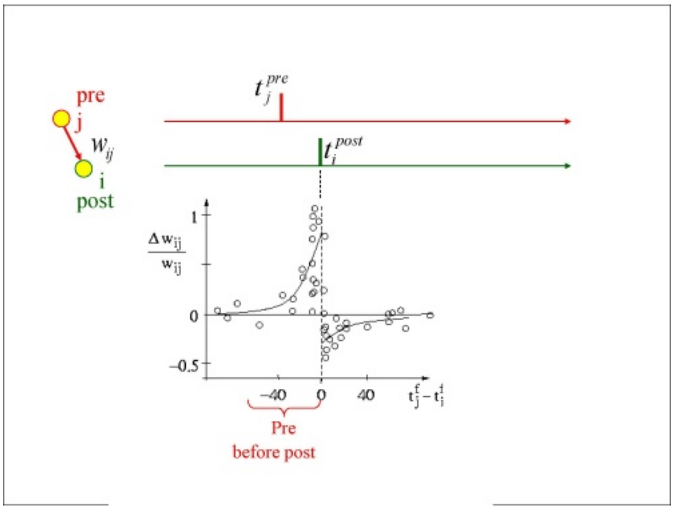


**Figure 2:** Spike-Timing Dependent Plasticity (schematic): The STDP function shows the change of synaptic connections as a function of the relative timing of pre- and post-synaptic spikes after 60 spike pairings

In order to calculate changes to each $W_{ij}$ (the weight from pre-synaptic neuron $j$ to post-synaptic neuron $i$), a synaptic trace $x_i$ is assigned for each neuron. $x_i$ increases with each spike $x_i \rightarrow x_i + 1$ and decays otherwise. following

$$\tau_{STDP} \frac{\mathrm{d}x_i}{\mathrm{d}t} = -x_i$$

The synaptic weight is updated for every pre- and post-synaptic event such that

$$\Delta W = \begin{cases} A_+ \exp\left(\frac{-\Delta t}{\tau_+}\right) & \Delta t \geq 0 \\ -A_- \exp\left(\frac{-\Delta t}{\tau_-}\right) & \Delta t < 0 \end{cases}$$

$$\Delta t = t_{post} - t_{pre}$$

The parameters $A_+$ and $A_-$ may depend on the current value of the synaptic weight. The time constants are on the order of $10ms$.

### 3.2.1 Weight dependence: soft bounds

For biological reasons, it is desirable to keep the synaptic weights in a range $w_{min} < w_{ij} < w_{max}$. This can be achieved by an appropriate choice of the functions $A_+(w_{ij})$ and $A_-(w_{ij})$. In the simulation, we have defined them using the following relations:

$$A_+(w_{ij}) = (w_{max} - w_{ij})\eta_+$$

$$A_-(w_{ij}) = (w_{ij} - w_{min})\eta_-$$

with positive constants $\eta_+$ and $\eta_-$ is called soft bounds.

## 3.3 K-Winners-Take-All

K-Winners-Take-All is a computational principle applied in computational models of neural networks by which neurons compete with each other for activation. In this mechanism, only $k$ neurons with the highest voltage activate while all other neurons are inhibited.

# 4 Results

We use raster plots to examine the activity of the output neuron group. The signals are illustrated in two different colors, orange and purple.

According to figure 3, in iterations 5, 6, and 7 the spikes of around 10 neurons have dominated the figure of the target neuron group. However, in the following iterations, their fire rate decreased significantly, while the other neurons started firing spikes in the last two iterations as a result of the changing signal given to the network.


**Figure 3:** Raster plots of neuron groups during the simulation.

# 5 Refrences

Jesper Sjöström, Wulfram Gerstner. "Spike-timing dependent plasticity." Scholarpedia. 2010.