## INHIBITORY PLASTICITY

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## 1 SIMULATIONS

### 1.1 Feedforward Inhibition

#### 1.1.1 Details

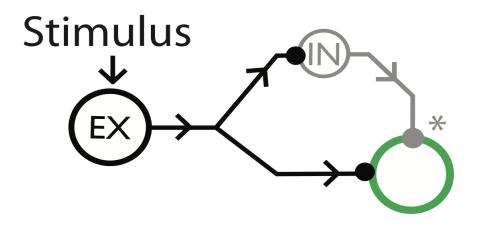


Figure 1: Network structure in Feedforward Inhibition

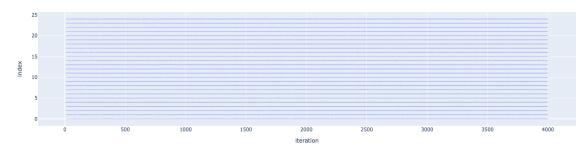
In Feedforward Inhibition, excitatory input reaches a target region through both direct excitation and indirect inhibition. (see figure 1) To investigate the effect of inhibitory synaptic plasticity in networks with feedforward inhibition, we simulated a single postsynaptic leaky-integrate-and-fire neuron receiving excitatory and inhibitory input signals. The cell received input through 125 synapses which were divided into two groups of 100 excitatory and 25 inhibitory synapses. To generate the stimulus that was given to the network, first, we generated an array of size 100 randomly from Normal Distribution with parameters  $\mu$ , $\sigma$  named I. After that to decide which neurons will get input we made an array of the same size as I from Uniform Distribution in the range [0,1] called mask. If  $mask_i > 0.5$  then the neuron with index i will get input of size  $I_i$ . Otherwise  $I_i = 0$ .

We used two learning rules for inhibitory synaptic plasticity(ISP), STDP, and iSTDP. You can compare their results in the following sub-section.

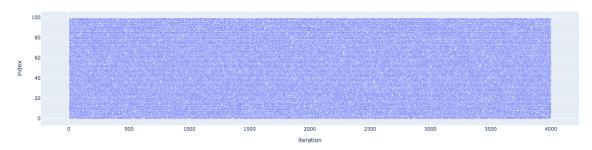
#### 1.1.2 Results

It is clear that in iSTDP, as the algorithm progresses, the total input of the target neuron decreases until it reaches its stable point. Thus, the neuron's fire rate is reduced significantly. In STDP, throughout the simulation total input of the target neuron fluctuates around 17. So the fire rate of the target neuron is stable during the simulation.

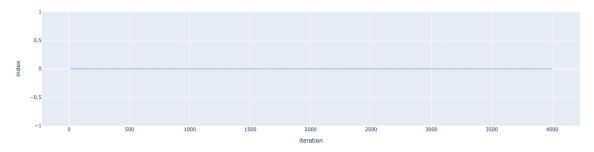




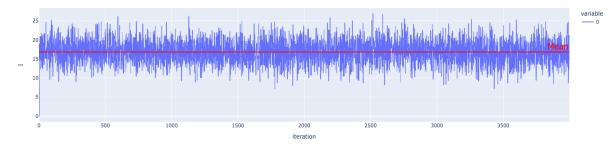
#### Raster Plot of Excitatory Population



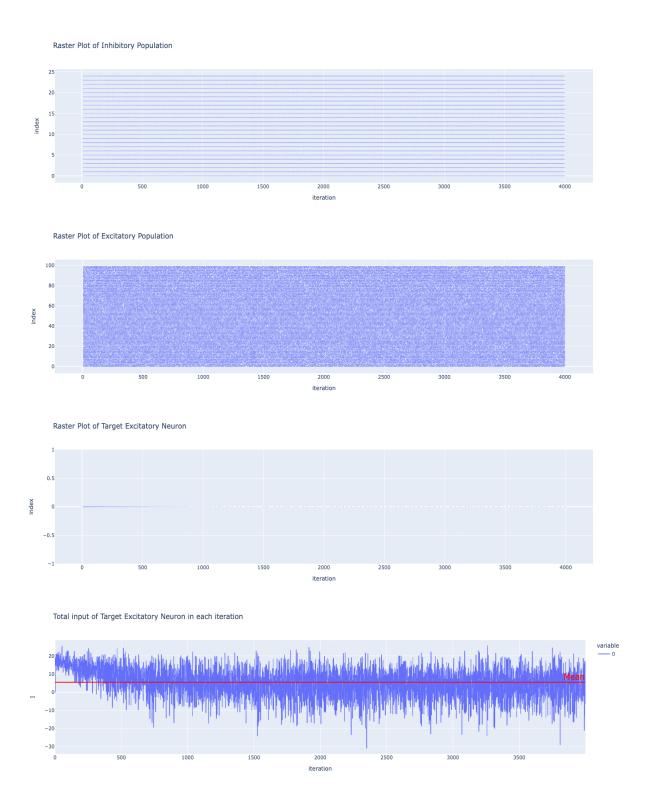
Raster Plot of Target Excitatory Neuron



Total input of Target Excitatory Neuron in each iteration



**Figure 2:** STDP learning rule with parameters :  $a_+ = 0.01$ ,  $a_- = 0.01$   $I: \mu = 60.0$ ,  $\sigma = 20.0$ 



**Figure 3:** iSTDP learning rule with parameters : lr = 0.01, frequency = 5.0  $I: \mu = 60.0, \sigma = 20.0$ 

## 1.2 Balanced Network

#### 1.2.1 Details

# **Excitatory Inhibitory**

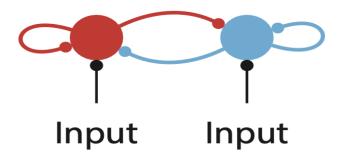


Figure 4: Balanced Network architecture

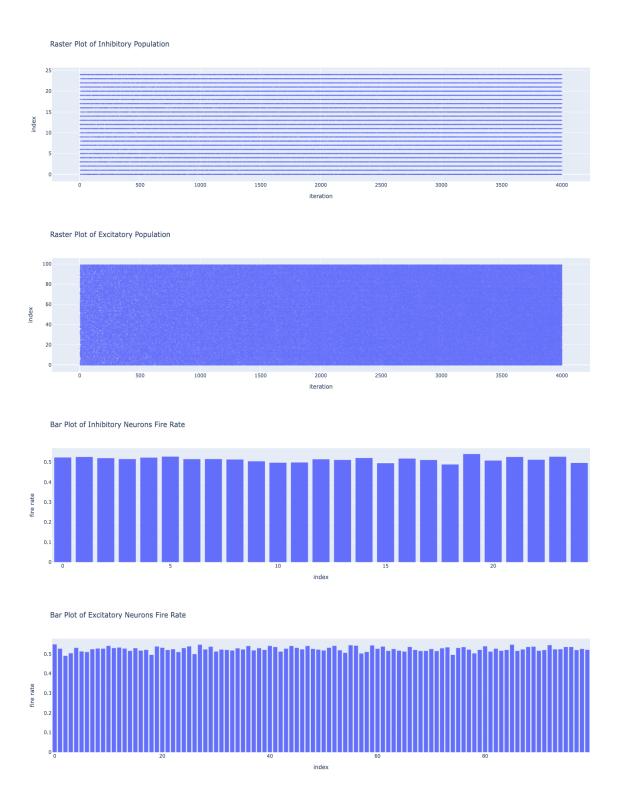
In Balanced Network, we have two populations of excitatory (red) and inhibitory (blue) neurons which are randomly and sparsely connected and receive external input. (see figure 4)

In our simulations, the excitatory population contains 100 neurons, whereas the inhibitory population consists of 25 neurons. The external input of the network is generated exactly like in the last section. You can see the results of the two learning algorithms in the following sub-section.

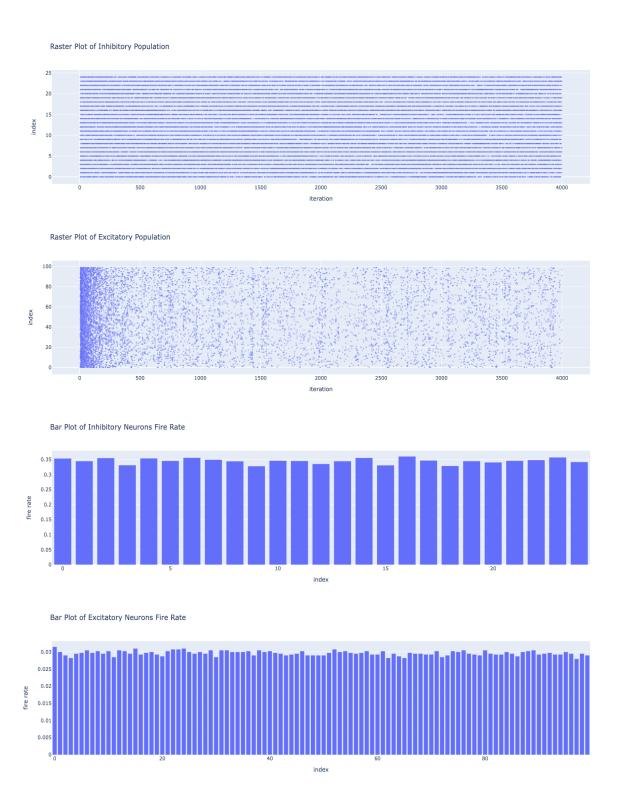
#### 1.2.2 Results

In STDP, the fire rate of excitatory neurons is about 0.5 which is very high and in addition, there isn't any particular pattern in their raster plot. On the other hand in iSTDP we can see an oscillation in the raster plot of excitatory neurons.

In iSTDP we also have more control over the fire rate of the excitatory population. In this case, it is approximately 0.03 which is much smaller than the fire rate for the STDP learning rule. Overall in iSTDP bigger value for lr leads to a smaller value for the fire rate.



**Figure 5:** STDP learning rule with parameters :  $a_+ = 0.01$ ,  $a_- = 0.01$   $I: \mu = 60.0$ ,  $\sigma = 20.0$ 



**Figure 6:** iSTDP learning rule with parameters : lr = 0.01, frequency = 5.0  $I: \mu = 60.0, \sigma = 20.0$ 

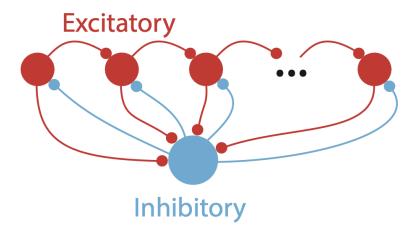


Figure 7: Network Architecture for Signal Learning

## 1.3 Signal Learning

#### 1.3.1 Details

In this section, the network architecture includes a feedforward chain of excitatory neurons with feedback inhibition. (see figure 7)

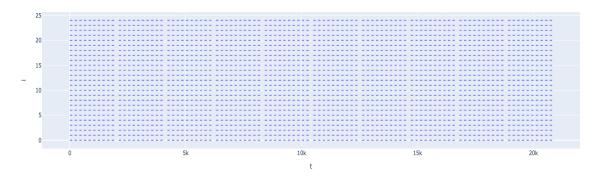
Three populations of neurons are made, two of them are excitatory populations and the other one is an inhibitory population and in addition, we have two distinct inputs. In this scenario, the larger excitatory population receives an external input and the goal is that neurons in the smaller population learn different patterns during the simulation.

First, we randomly choose an input then the chosen input was given to the network 10 times. After that, we choose another input in the same manner and repeat the remaining steps. We repeated this procedure 10 times.

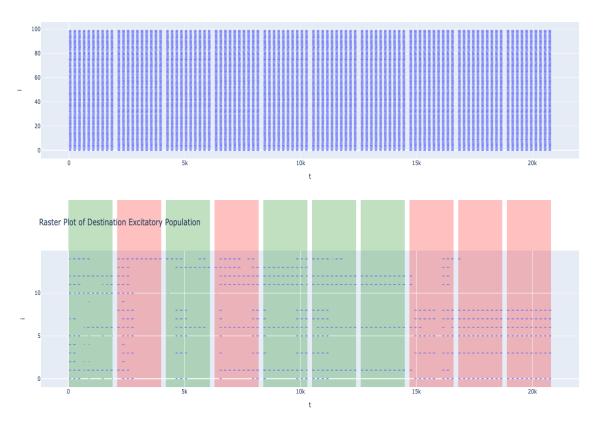
#### 1.3.2 Results

The raster plot of the smaller excitatory population contains two colors that demonstrate the input that was given to the network. We can see that in both of the learning rules, some neurons learned the input that was shown with green and some of the remaining neurons learned the other input.

Raster Plot of Inhibitory Population



Raster Plot of Source Excitatory Population



**Figure 8:** STDP learning rule with parameters :  $a_+ = 0.31, a_- = 0.301$   $I: \mu = 25.0, \sigma = 6.0$ 



**Figure 9:** iSTDP learning rule with parameters : lr = 0.000145, frequency = 8.0  $I: \mu = 25.0$ ,  $\sigma = 6.0$