INHIBITORY PLASTICITY

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1 Introduction

Inhibitory neurons play a key role in controlling the function of brain neural networks. Although few in number, they stabilize neural network activity against strong neural excitation and have an active presence in neural computations. Recent research indicates that balanced networks are very important in regulating brain function, but to achieve this in modeling it is necessary to precisely tune the inhibitory connections which is often very time-consuming. We are going to implement an unsupervised learning rule for them using PymoNNtorch. In the next step, we examine the role of this learning rule in balancing excitation and inhibition in neural networks.

2 Inhibitory Synaptic Plasticity

Experimental results show that inhibitory synapses can be modified by coincident pre- and postsynaptic activity with a coincidence time window δt. Additionally, sole presynaptic spikes lead to a reduction of synaptic efficacy. We model this behavior by a symmetric spike timing-dependent learning rule, which is implemented for inhibitory-to-excitatory synapses. In order to calculate the changes to each w_{ij}, 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

$$\tau_{iSTDP} \frac{\mathrm{d}x}{\mathrm{d}t} = -x$$

The synaptic weight w_{ij} is updated for every pre- or postsynaptic event such that

$$\begin{cases} w_{ij} = w_{ij} + \eta(x_i - \alpha) & for\, every\, presynaptic\, spike\, at\, time\, t_f^j \\ w_{ij} = w_{ij} + \eta x_j & for\, every\, postsynaptic\, spike\, at\, time\, t_f^i \end{cases}$$

where η is the learning rate and α is the depression factor.

$$\alpha = 2 * \rho_0 * \tau_{iSTDP}$$

The parameter ρ_0 is determined by the user and acts as a target firing rate. The learning rule thus implements a form of homeostatic plasticity that stabilizes the postsynaptic firing rate. This is reflected by the simulations, which show that the postsynaptic firing rate after convergence depends linearly on ρ_0.

3 Simulations

3.1 Balanced Network

In a Balanced Network, we have two populations of excitatory (red) and inhibitory (blue) neurons which are randomly and sparsely connected and may receive external input. We are going to investigate the effect of inhibitory synaptic plasticity on the population activity of an excitatory population. Two input signals with different noise levels were generated. The population activity of an excitatory network was examined in response to the inputs. Then, an inhibitory population was added and connected to the excitatory network to shape a balanced network. Inhibitory spike-timing dependent plasticity (iSTDP) was implemented from inhibitory to excitatory connections. Next, STDP was added to excitatory-to-inhibitory connections. Population activity was analyzed across these different network conditions.

3.1.1 Case 1: Excitatory Population only

The activity of a purely excitatory network was simulated in response to the inputs. The population is connected to itself with the STDP learning rule.

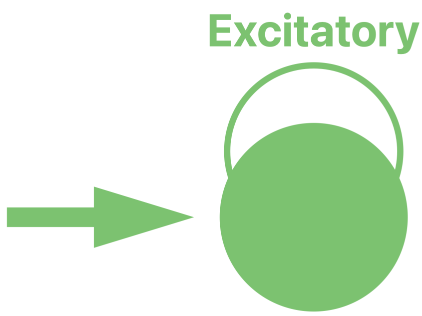


Figure 1: The Network Structure in Case 1

3.1.2 Case 2: Balanced Network with Constant Excitatory-to-Inhibitory Synapses

An inhibitory population was added and connected to the excitatory network to shape a balanced network. Similar to the excitatory population, there is a self-connection in the inhibitory population. iSTDP was implemented for inhibitory-to-excitatory connections. Whereas, excitatory-to-inhibitory connections are constant.

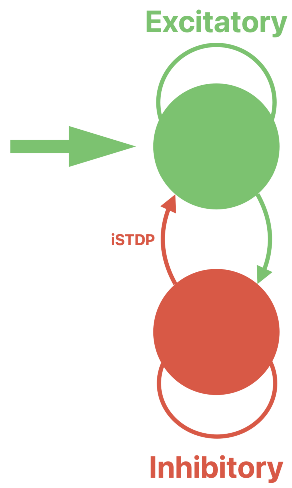


Figure 2: The Network Structure in Case 2

3.1.3 Case 3: Balanced Network with STDP on Excitatory-to-Inhibitory Synapses

This case is identical to case 2 except for one difference, STDP is applied for excitatory-to-inhibitory connections.

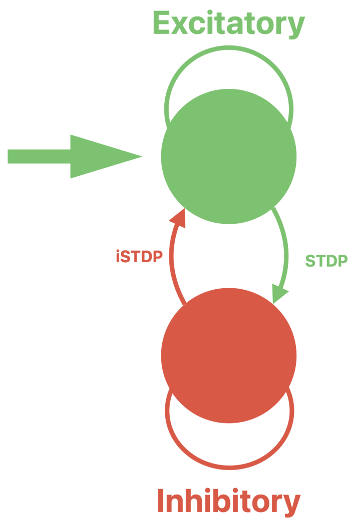


Figure 3: The Network Structure in Case 3

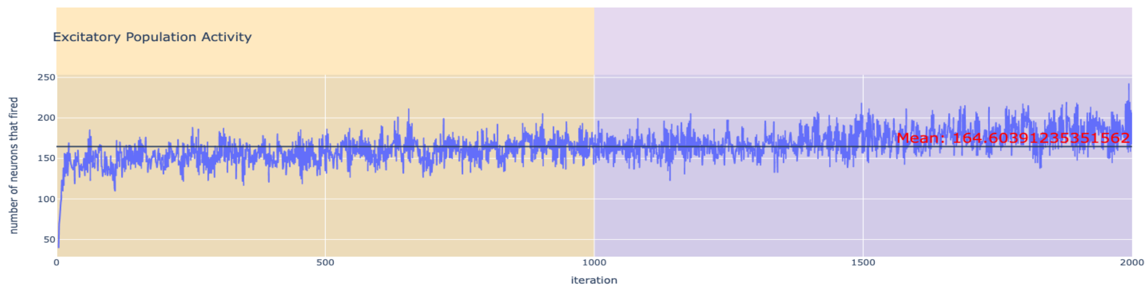
3.1.4 Results

In the following plots, the network response is illustrated through line plots of population activity in which the signals are demonstrated by two different colors, orange and purple.

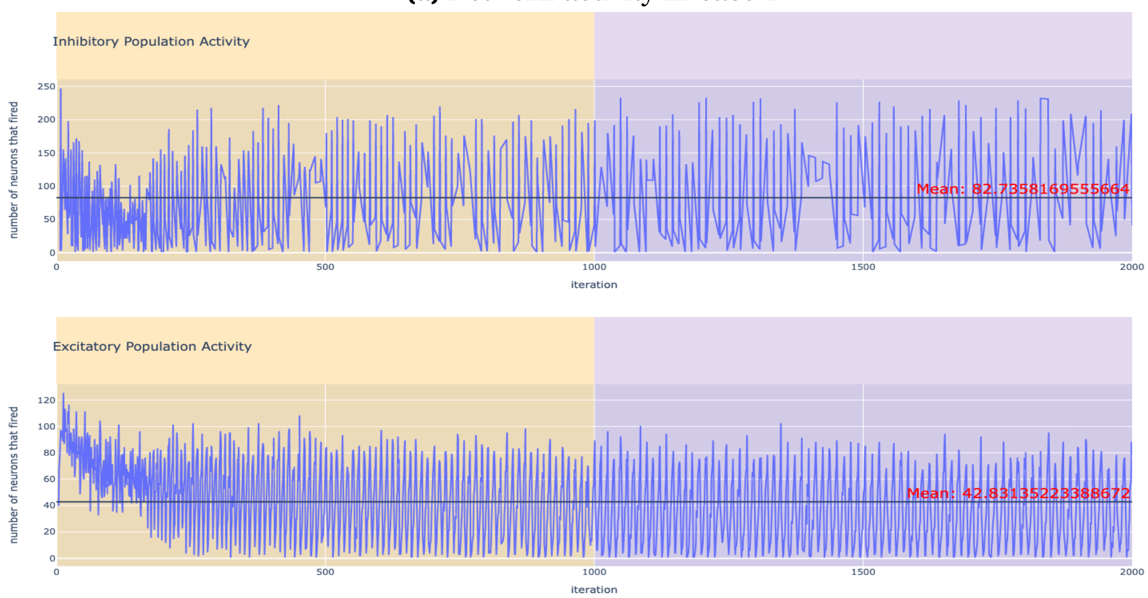
We connected the excitatory population to itself in two ways, sparse and dense. The results of these two situations are shown in figure 4 and 5 respectively.

In figure 4, as you can see, in case 1 around 164 neurons fired in each iteration. In addition, the population activity in the signal with larger noise was higher than the others. When we add the inhibitory population, this number decreases to 42. Furthermore, there is a clear and regular oscillation in the population activity of the excitatory population. A similar fluctuation happened for the inhibitory population.

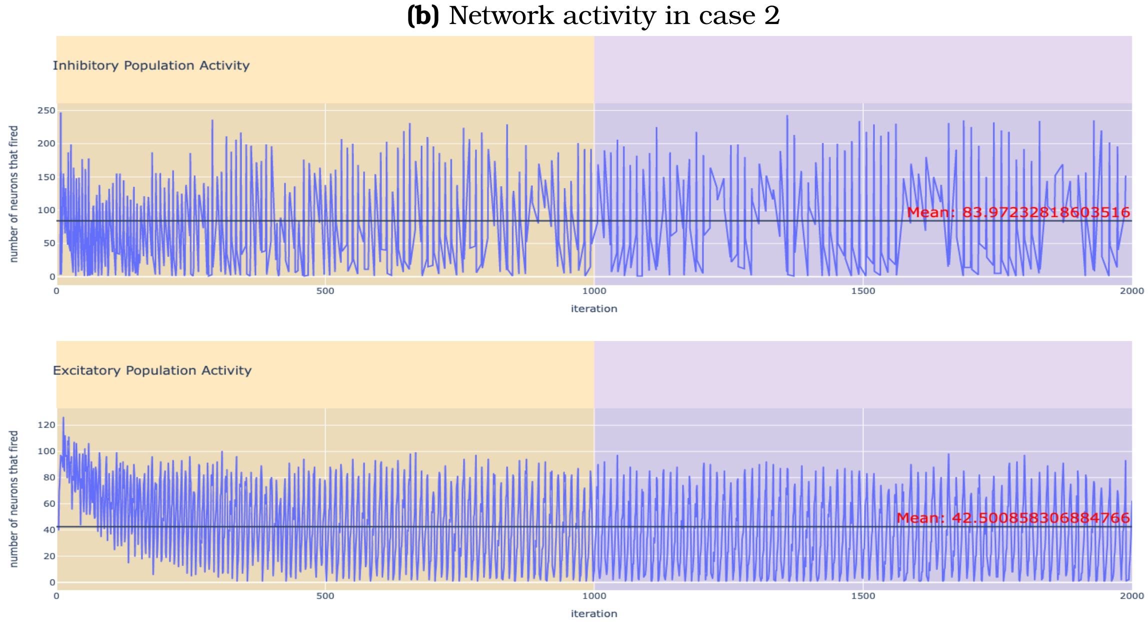
When the excitatory population is densely connected to itself, not only does the population activity rise, but the fluctuations also become larger and sharper. However, these changes don't affect the other cases. As you can see, main patterns of figure 4 are repeated in figure 5.



(a) Network activity in case 1

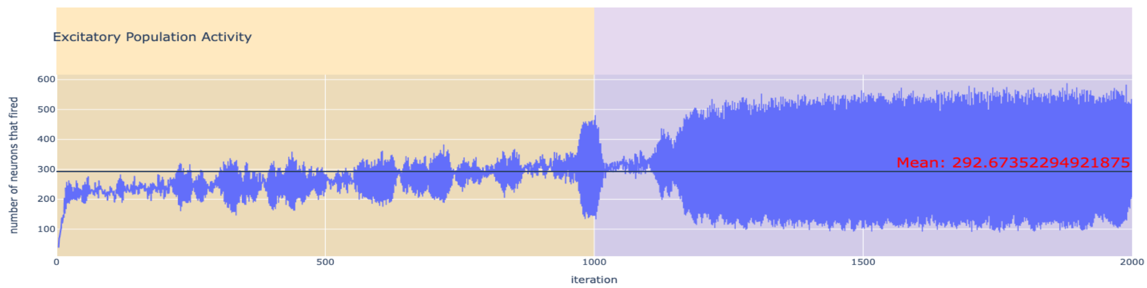


(b) Network activity in case 2

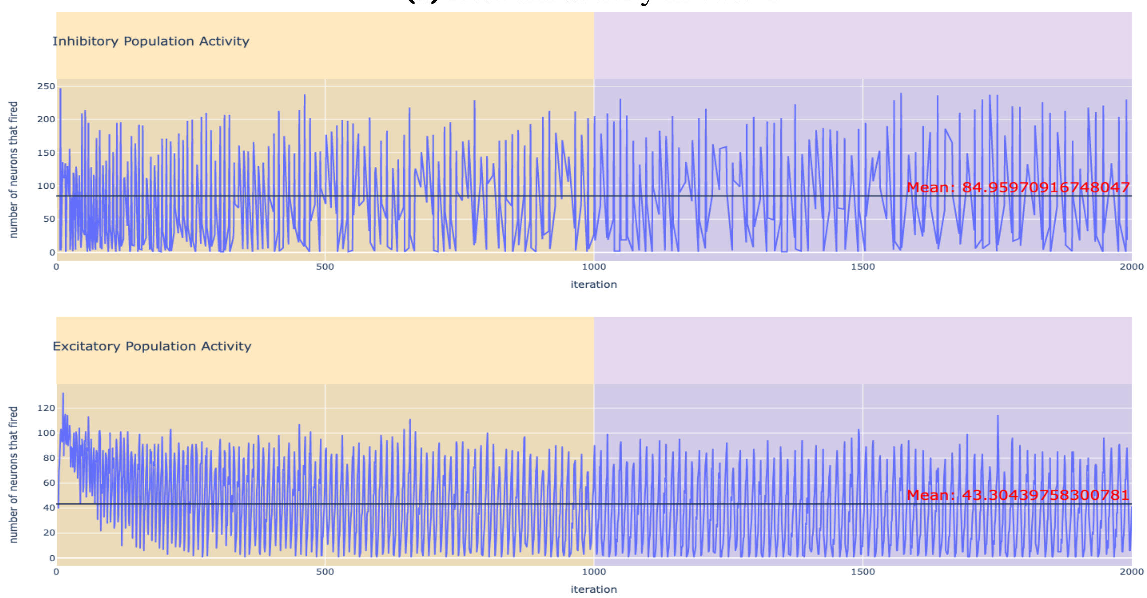


(c) Network activity in case 3

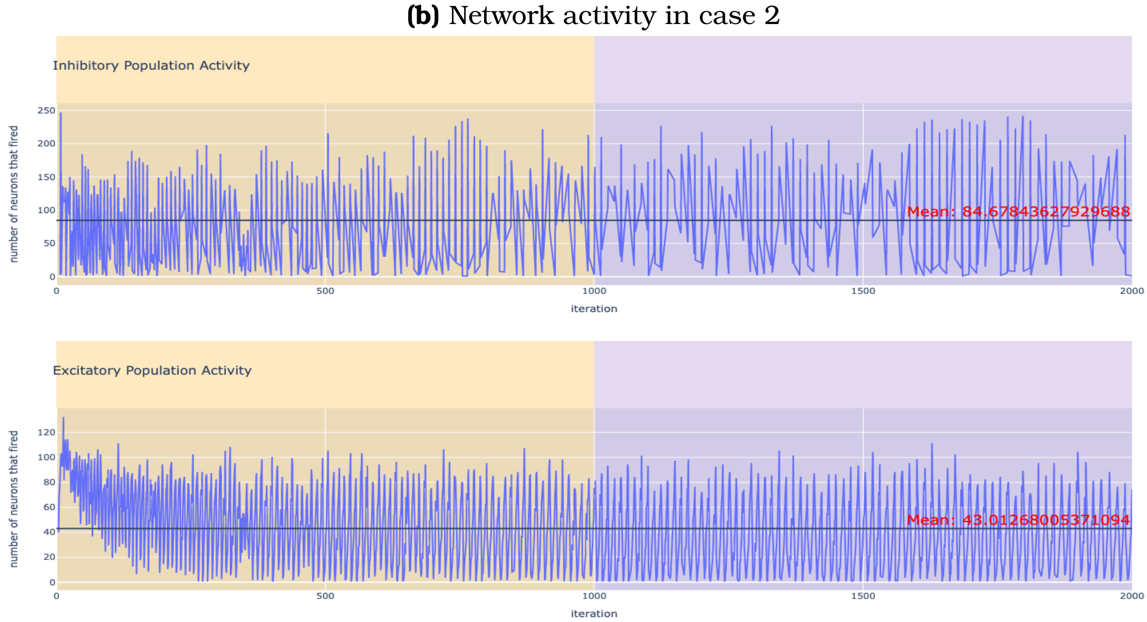
Figure 4: Network response in the three cases described when the self-connection in the excitatory population is sparse.



(a) Network activity in case 1



(b) Network activity in case 2



(c) Network activity in case 3

Figure 5: Network response in the three cases described when the self-connection in the excitatory population is dense.

3.2 Feedforward Inhibition

3.2.1 Details

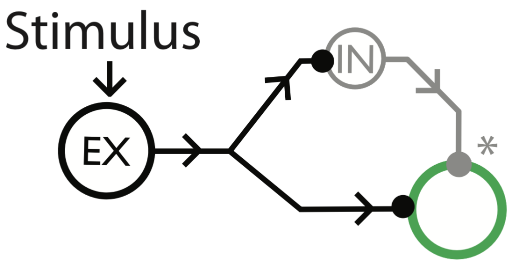


Figure 6: Network structure in Feedforward Inhibition

In Feedforward Inhibition, excitatory input reaches a target region through both direct excitation and indirect inhibition. (see figure 6) 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 μ, σ 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.

3.2.2 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.

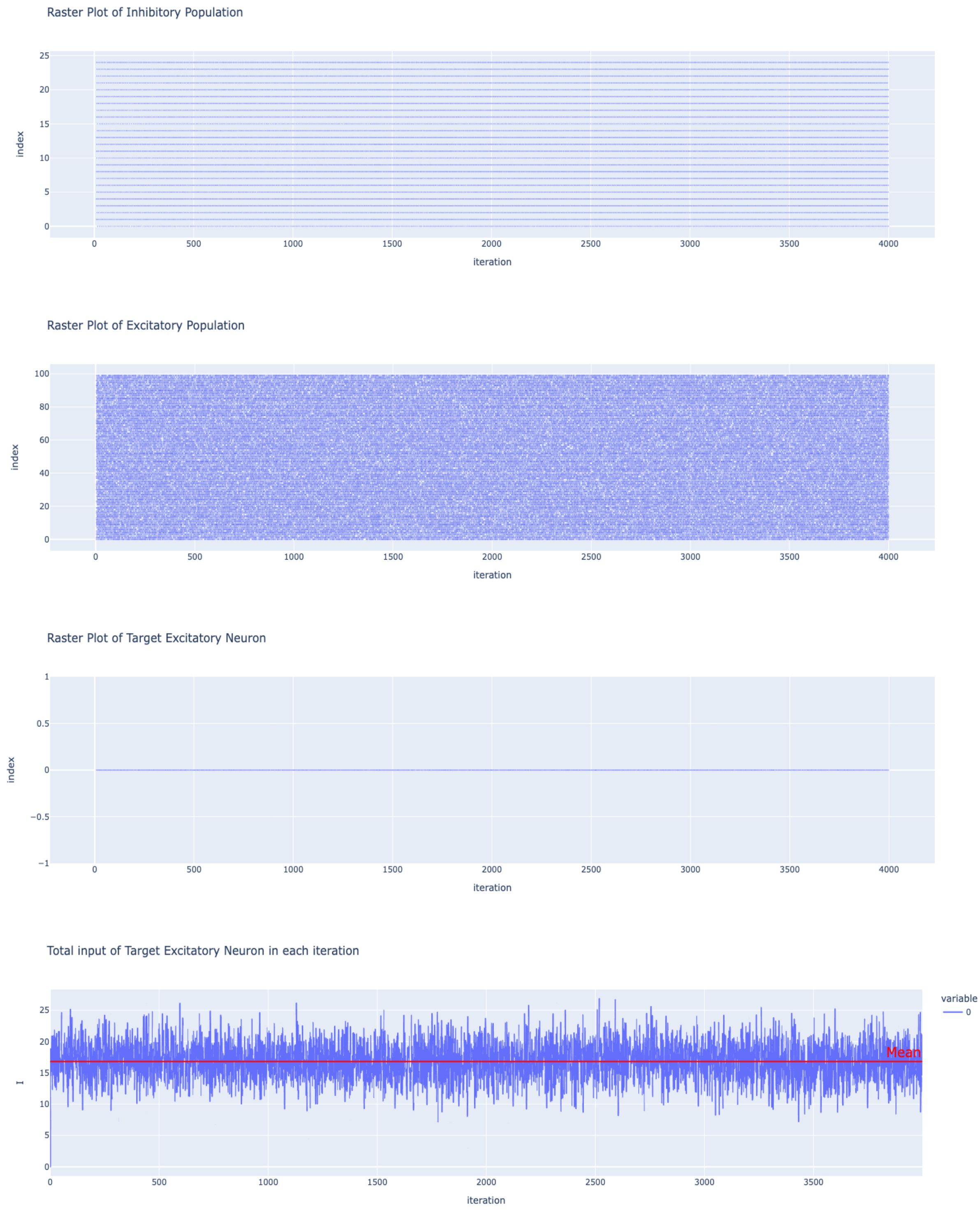


Figure 7: STDP learning rule with parameters : $a_+ = 0.01, a_- = 0.01$
$I : \mu = 60.0, \sigma = 20.0$

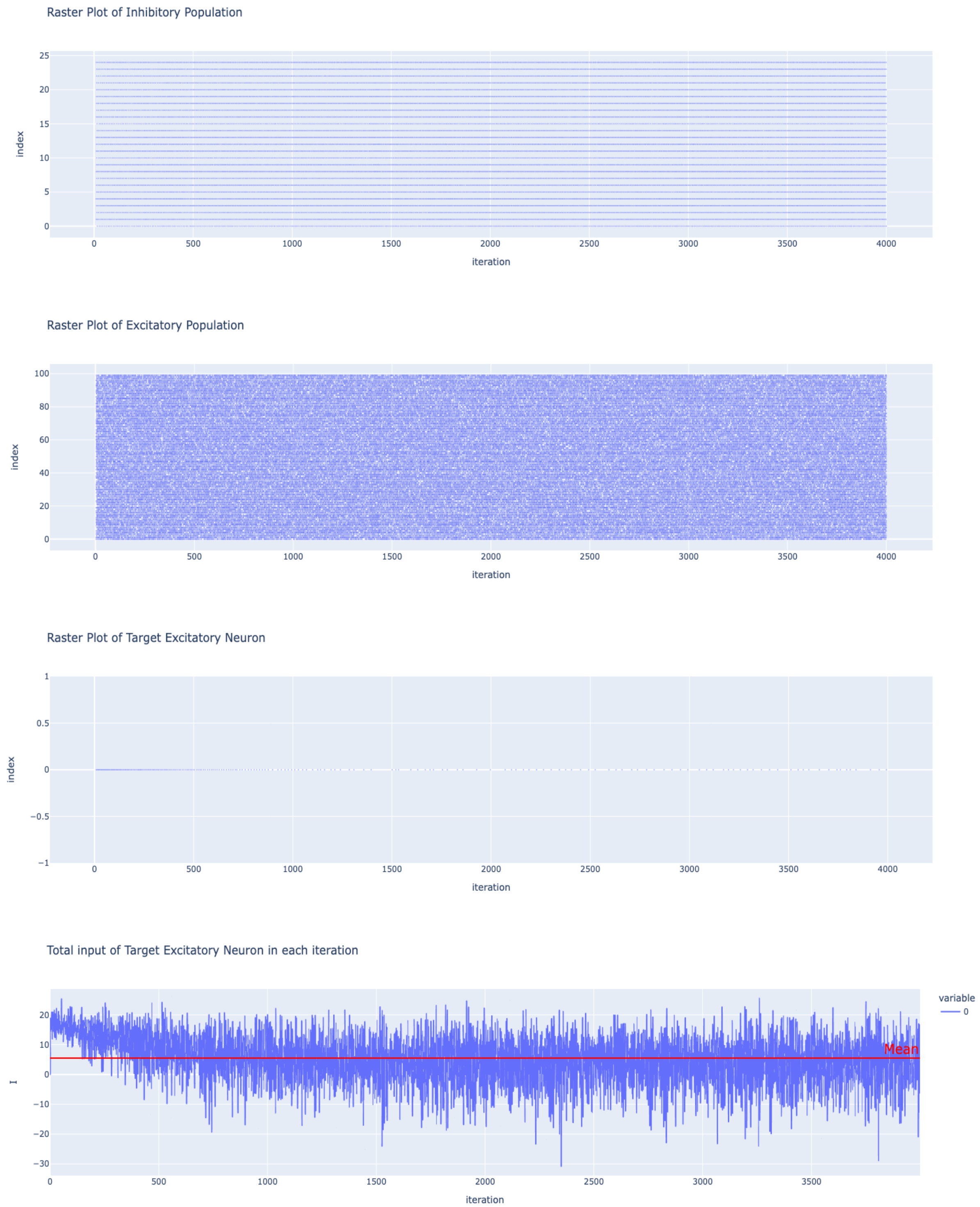


Figure 8: iSTDP learning rule with parameters : $lr = 0.01, frequency = 5.0$
$I : \mu = 60.0, \sigma = 20.0$

3.3 Signal Learning

Two distinct inputs are generated from the Normal distribution. 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 chose an input then the chosen input was given to the network 5 times. After that, we choose another input in the same manner and repeat the remaining steps. We repeated this procedure 10 times.

The raster plot of the smaller excitatory population contains two colors, orange and purple which demonstrate the input that was given to the network.

3.3.1 Unsupervised Learning + KWTA

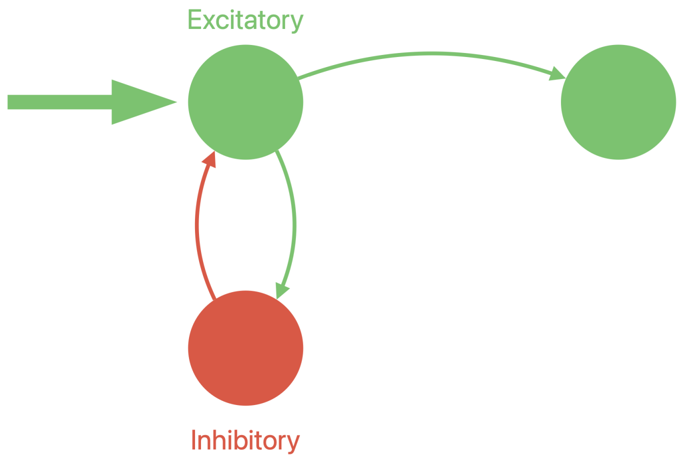


Figure 9: Network Architecture for Signal Learning in Unsupervised Learning + KWTA

As you can see in the figure above, in order to create competition between the neurons of the target population, the K-Winners-Take-All(KWTA) mechanism has been added to it.

KWTA has only one parameter, k that is determined by the user. In this mechanism, first, we select the neurons in which $v >= threshold$ then the selected neurons are sorted based on their voltage. After that, we allow the first k neurons to fire a spike. Finally, all other spiked neurons are inhibited.

You can check out the results in figure 10. It is clear that, after a while, we have two groups of neurons, each sensitive to a specific signal.

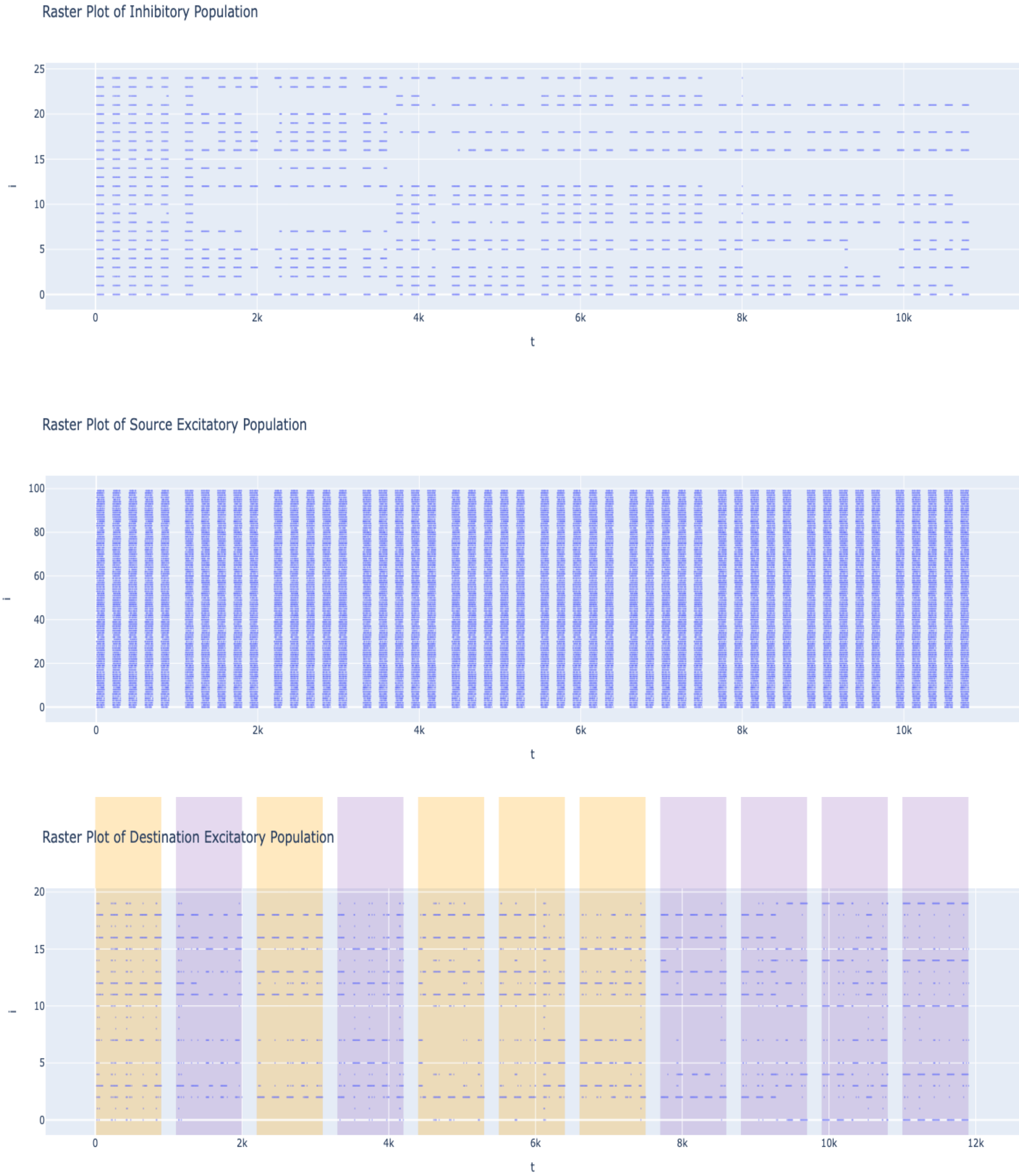


Figure 10: Network Response When we use iSTDP along with KWTA mechanism

3.3.2 Reinforcement Learning

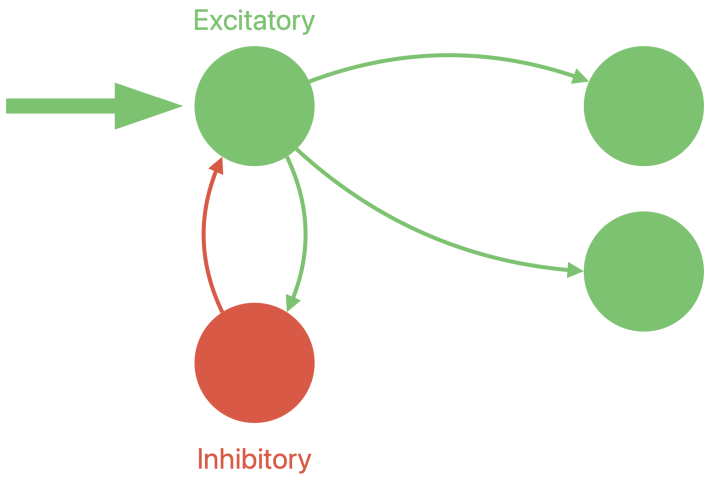


Figure 11: Network Architecture for Signal Learning in Reinforcement Learning

According to the figure above, in this section, we have two target excitatory populations. The goal is that each target excitatory population learns a specific signal which is determined by the user. If you are not familiar with this algorithm, see Computational Neuroscience repository.

Figure 12 displays the results for iSTDP. Each signal has been given to the network for 2500 iterations. Initially, neurons in both populations fire spikes, and the dopamine level fluctuates. However, after a while, the dopamine level increases and stabilizes, indicating that the network is behaving as we determined. This pattern repeats when we change signals.

Figure 12: $initial_{Dopamine} = 4.9, \tau_c = 1500, \tau_{Dopamine} = 10, \eta = 0.00004283, \rho_0 = 10.1$

Bibliography

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