Synaptic modeling, neural populations, and decision making

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1. Introduction

In this project we begin by discussing the synaptic modeling and translating spikes to synaptic currents. We then move on to neural populations and connectivity schemes between neuron populations, and finally we try to analyze the behavior of a model with three populations.

In all of these sections, we use LIF neurons to analyze the behavior of populations. Furthermore, The foundational parameters for the LIF model are given in the Table 1. We use these fixed parameters throughout the report. If needed, we will mention the changes in the parameters.

Parameter	Value	Description
u_{rest}	-80	resting potential
$threshold$	N(-55, 10)	threshold potential
u_{reset}	-90	reset potential
R	1	membrane resistance
τ	10	membrane time constant
$Time\ Resolution$	0.1	dt in euler's method
$Iterations$	1000	number of iterations
u_{init}	N(-80, 10)	initial potential

Table 1. *Base parameters for the LIF model. $N(\mu, \sigma)$ denotes a normal distribution with mean μ and standard deviation σ.*

2. Synaptic modeling

2.1. Dirac delta function

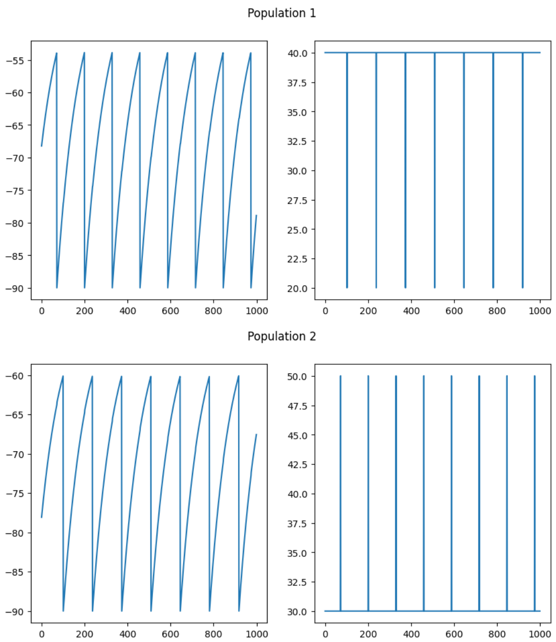

Figure 1. *Synaptic modeling with Dirac delta function.*

In this figure, we used two neuron populations with only 1 neuron each. The first population is excitatory and the other is inhibitory. The connectivity between the two populations is bidirectional. So they both have effects on each other as shown in the input current of each neuron. At the times where the excitatory neuron spikes, the inhibitory neuron receives a constant excitaion (J_0/N where N is the number of pre-synaptic neurons for some constant J_0) in addition to its own constant input current. Same goes for the inhibitory neuron.

The impact of the spikes on the other population, is only a short term effect which does not seem has much effect on the behavior of the post-synaptic neuron. In this figure,

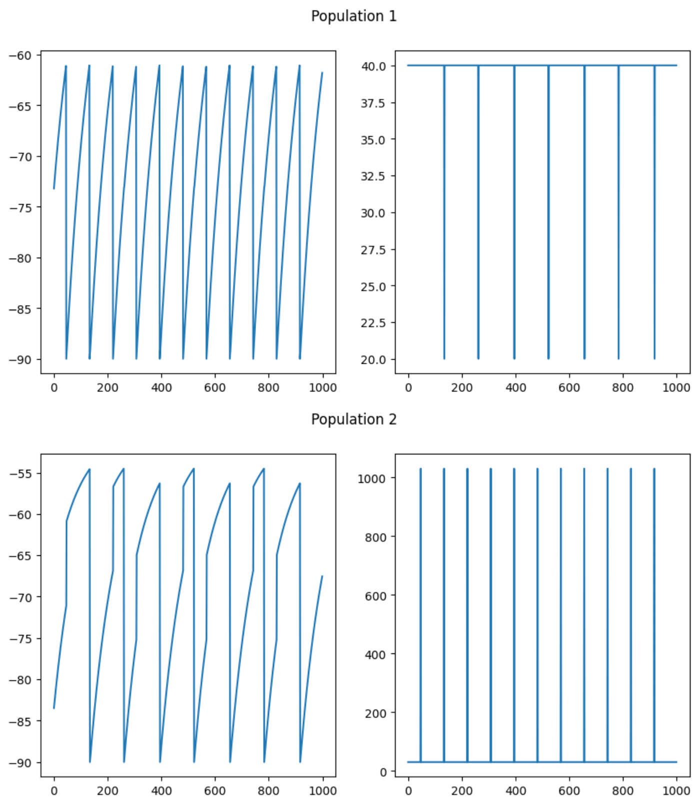

Figure 2. *Synaptic modeling with Dirac delta function.*

we increased the constant j_0 to be much more larger in the excitatory-to-inhibitory conncetion. As you can see, everytime that the excitatory neuron spikes, the input current of the inhibitory neuron increases significantly (1000 units in this example). But Still it doesn't seem to have a significant effect on the behavior of the inhibitory neuron. The reason is that the effect of the spike is only short term (only one time step).

Note that the synaptic weight of the inhibitory-to-excitatory connection is not too large since a negative input current does not make sense in this context.

In order to make a better impact on the post-synaptic neuron, we need to model the dynamics of the synapse.

2.2. Synaptic dynamics

This process (modeling the synaptic dynamics), can be done by assuming that the pre-synaptic neuron's spiking activity produces transient changes in the post-synaptic neuron's conductance ($g_{syn}(t)$). The equation that we use to reach this goal is as follows:

$$\frac{d}{dt}g_{syn}(t) = \bar{g}_{syn}\sum_{f}\delta(t-t^{f}) - \frac{g_{syn}(t)}{\tau_{syn}} \tag{1}$$

Where $\bar{g}_{syn}$ is the maximum conductance elicited by each incoming spike, τ_{syn} is the synaptic time constant.

Now we can write the equation for the synaptic current as follows:

$$I_{syn}(t) = g_{syn}(t)\cdot(u_{post}(t) - E_{syn}) \tag{2}$$

where the reversal potential E_{syn} determines the direction of current flow and the excitatory or inhibitory nature of the synapse.

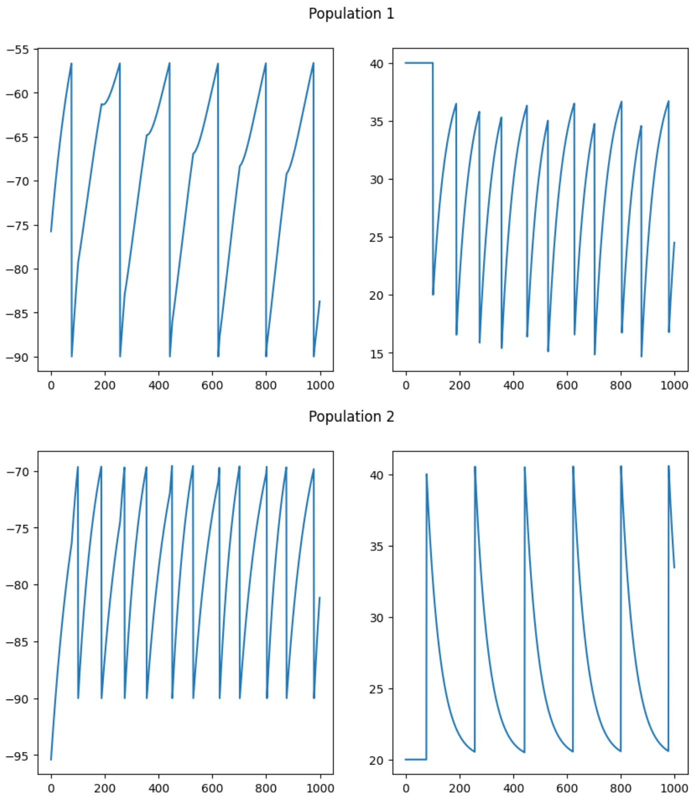

Figure 3. *Synaptic conductance dynamics*

Now it is obvios that the populations have impacts on each other. The excitatory neuron has a positive impact on the inhibitory neuron and vice versa. The impact of the spikes is not only short term anymore and the post-synaptic neuron's behavior is affected by the pre-synaptic neuron's spikes.

3. Connectivity schemes and Homogeneous populations

3.1. Full connection

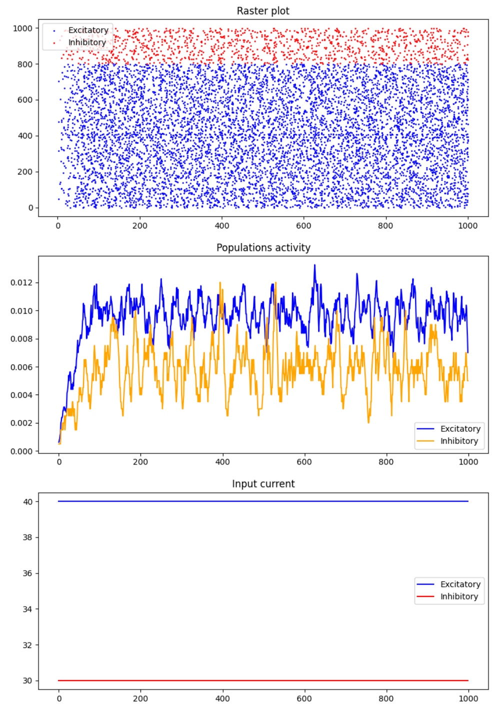

Figure 4

Here, in this figure, there is no connection between any of the neurons so the difference in the next plots be more clear.

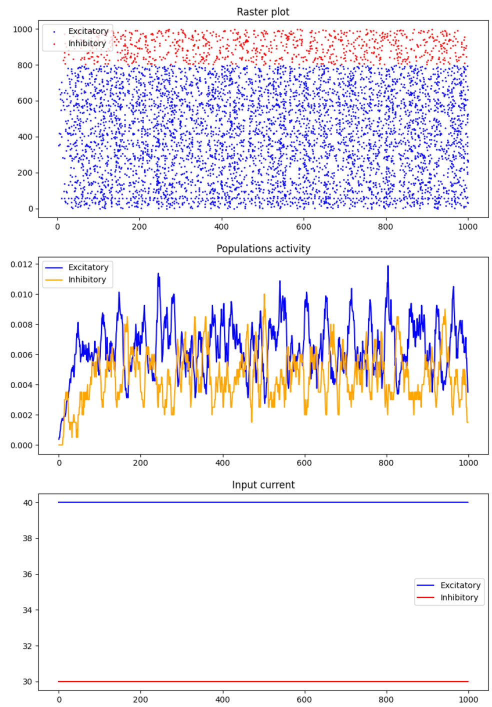

Figure 5

Here we established full connection from inhibitory neurons to excitatory ones. As you can see, the activity of the excitatory population is suppressed by the inhibitory population (It is more obvious from the raster plot rather than the activity plot because of the unsmoothness of the activity plot!).

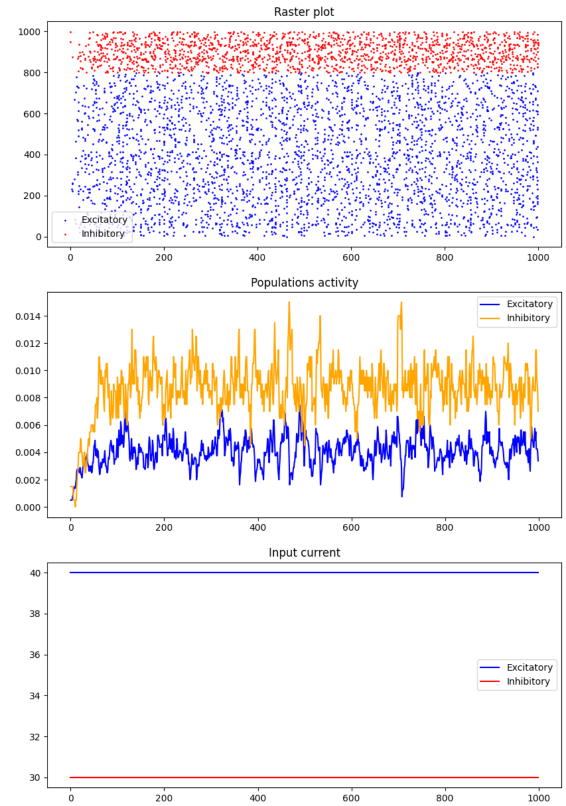

Figure 6

In these plots we fully connected the two populations in both directions. The activity of the excitatory population is suppressed by the inhibitory population, while the activity of the inhibitory population is increased by the excitatory population.

3.2. Fixed coupling probability

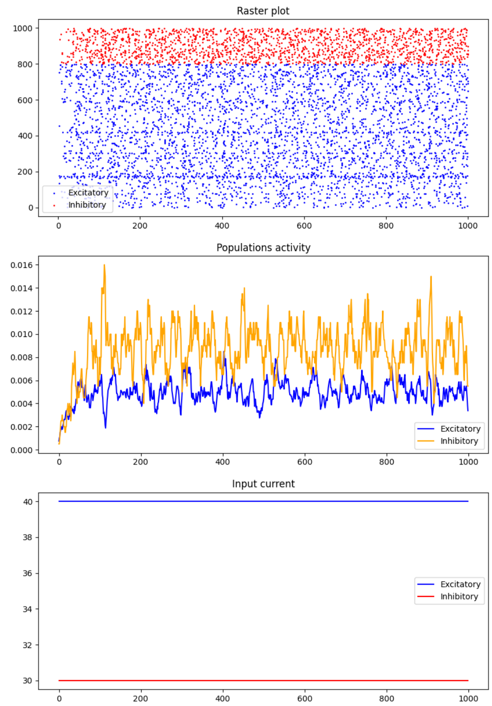

Figure 7. *Connection is bidirectional and the probability of connection is 0.1*

It is obvious from the raster plot that the activity of the populations is not changed significantly from the Figure-4 where there is not any connection between the populations.

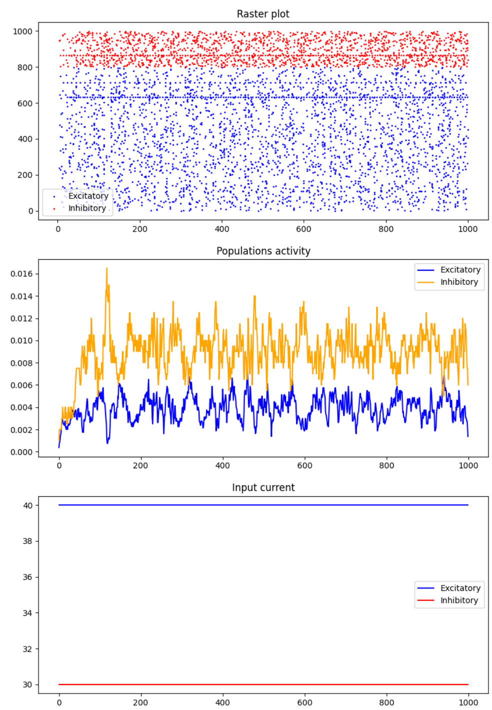

Figure 8. *Connection is bidirectional and the probability of connection is 0.9*

But here, where the probability of the connections is much higher, they affect each other.

3.3. Fixed number of pre-synaptic partners

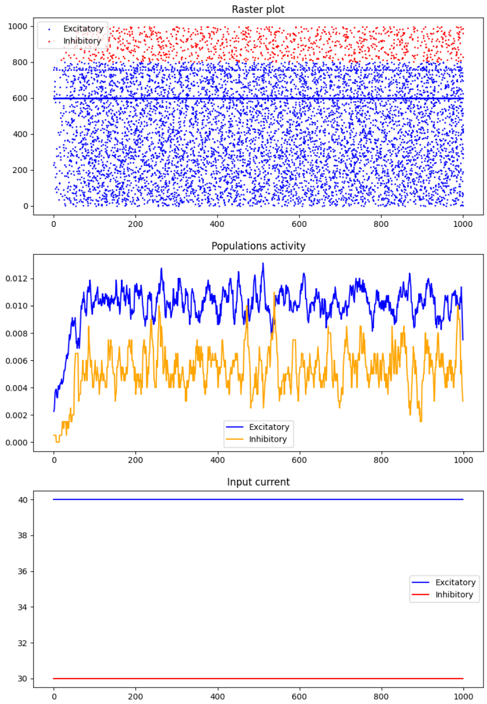

Figure 9. *$N = 10$ where N is the number of pre-synaptic partners*

As before in the fixed coupling probability, the activity of the populations is not changed significantly from the Figure-4 where there is not any connection between the populations.

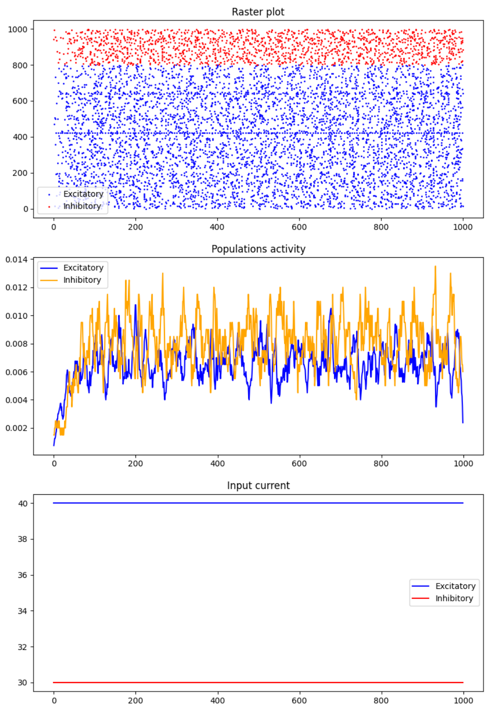

Figure 10. *$N = 150$ where N is the number of pre-synaptic partners*

Whereas the number of pre-synaptic partners increases, the activity of the populations is affected by each other.

Now turning into noisy input current for neurons, the following figure are exact same experiments as the previous ones but with noisy input currents.

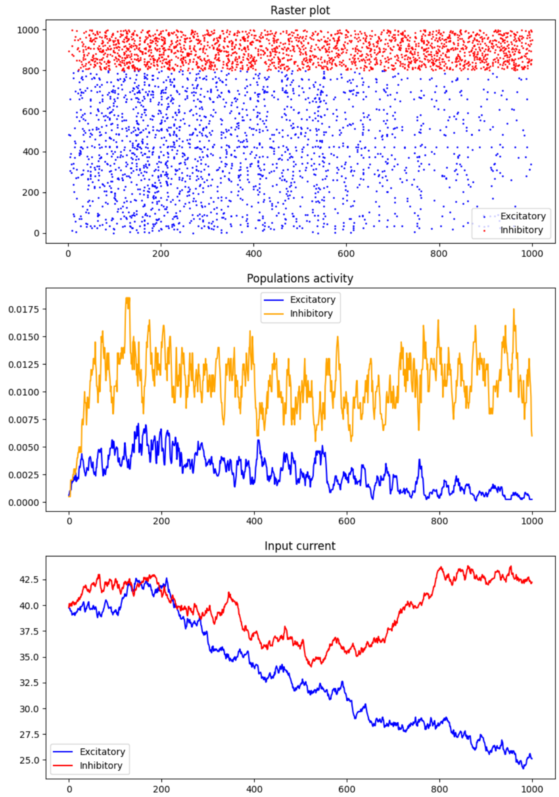

Figure 11. *Full and bidirectional connection*

Note in this figure that a rise to the inhibitory population's input together with a fall for the excitatory population's input, make the excitatory population's activity nealy zero.

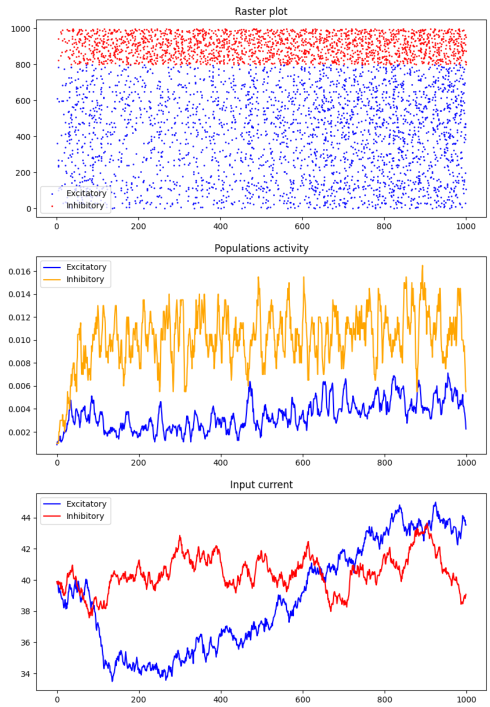

Figure 12. *Connection is bidirectional and the probability of connection is 0.1*

Here with the inhibitory being almost constant in activity, a rise to the excitatory population's input, makes its activity to rise. Not an important observaiton!

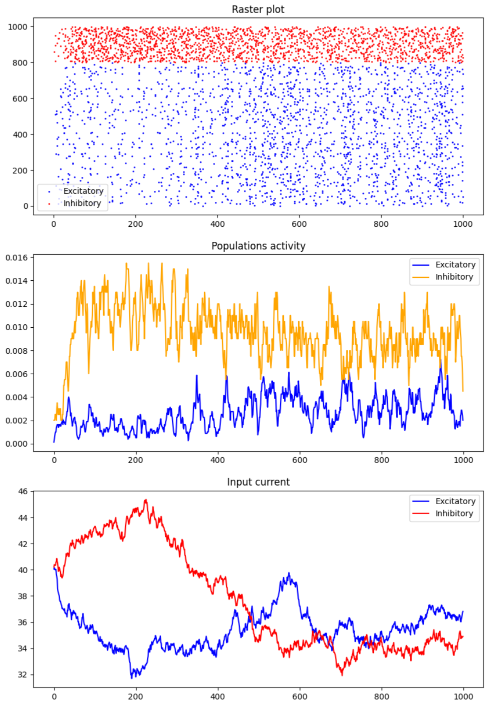

Figure 13. *Connection is bidirectional and the probability of connection is 0.9*

Here we can totally see the impact of the inhibitory population on the other one. The input of the excitatory population is almost in the same level in the second half of the iterations. But the inhibitory population's input experienced a fall and we can see that the excitatory population's activity lowers slightly.

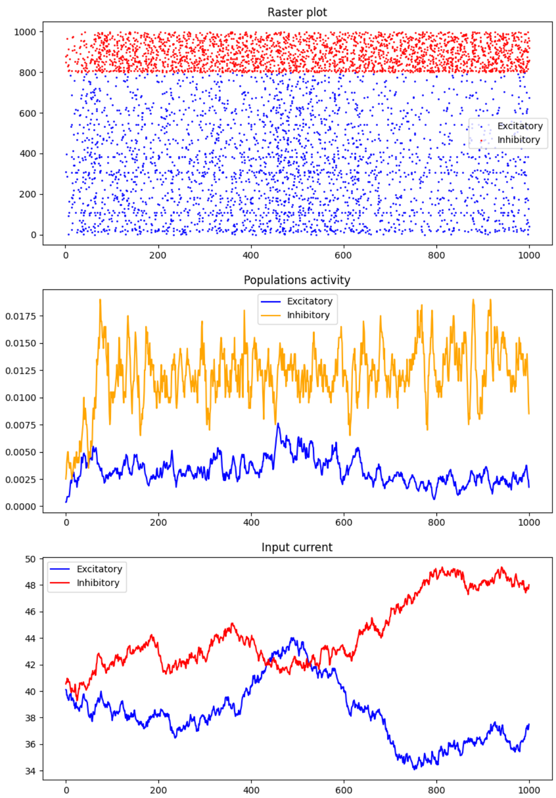

Figure 14. $N = 10$ *where N is the number of pre-synaptic partners*

Here although the activity of the excitatory population decreases, it is not the impact of the inhibitory population's activity where it increases. The reason is that the number of presynaptic partners are only 10 and this cannot have this much effect on the other population.

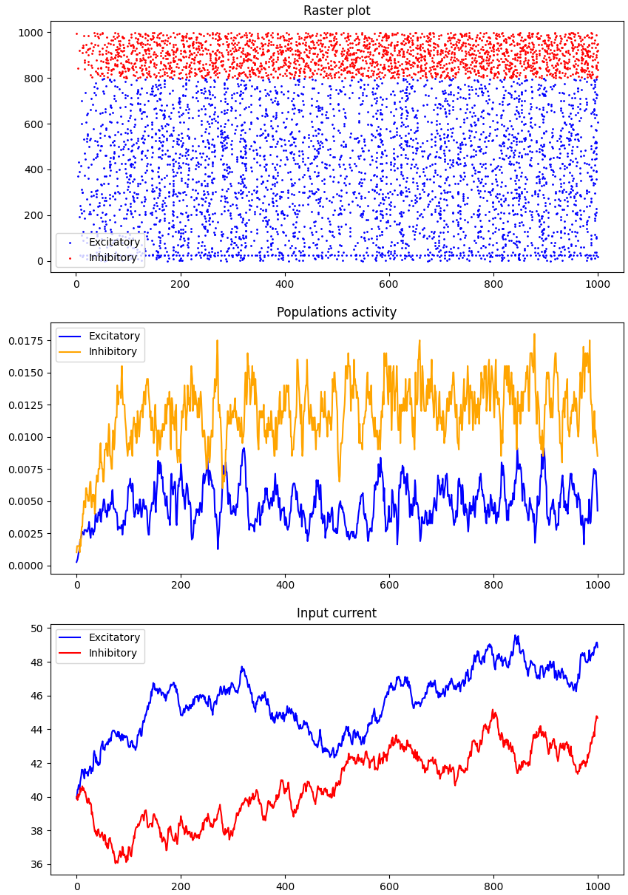

Figure 15. $N = 150$ *where N is the number of pre-synaptic partners*

4. Decision making

In the next few experiments, we try to analyze the behavior of a model with three populations in a decision making process.

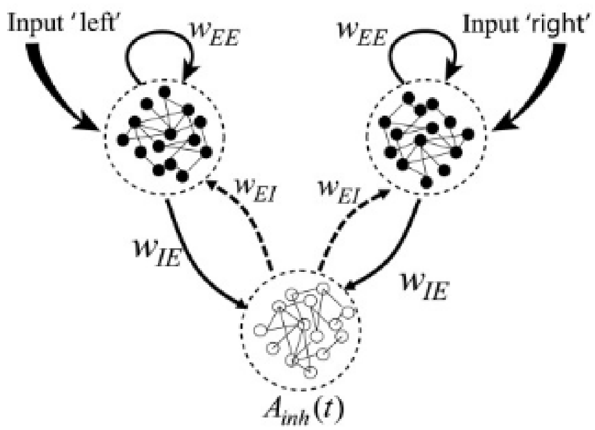

Figure 16. *A schematic picture of the model.*

Here in the following experiments, the connections *EE* are fixed coupling probability with $p = 0.7$, whereas the other connections are full. The number of neurons in each population is 500 as shown in the plots.

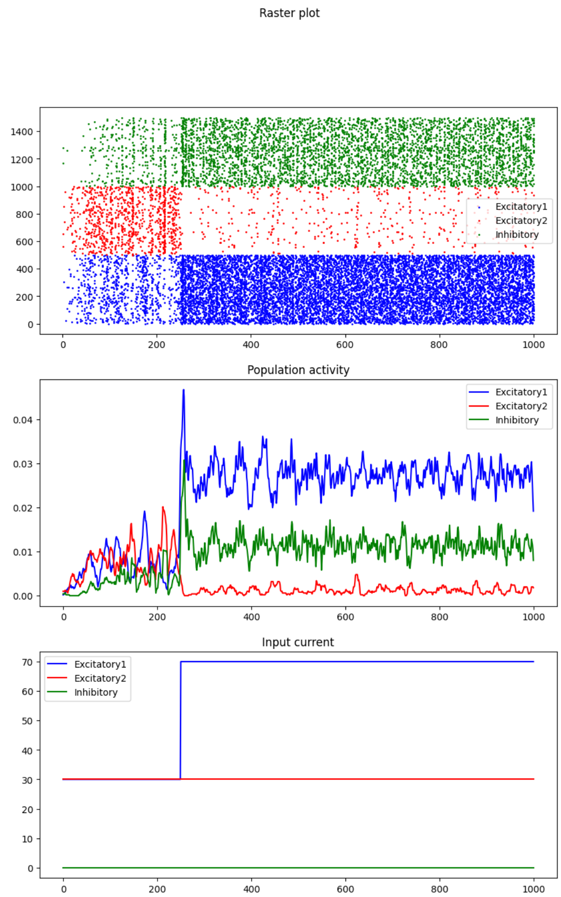

Figure 17

As you can see in these plots, the activity of the populations are stable before the stimulus is presented at iteration 250. After the input current of the first excitatory population rises, its activity along with the activity of the inhibitory population increases. In result, the activity of the second excitatory population decreases, and that, is the decision making process.

We conduct the same experiment with noisy input currents. Note that there is no significant difference between noisy and constant input current and the reason is that the parameters of the LIF neuron are set in a way such that a tiny difference in the input current, doesn't alter the behavior of the neurons significantly

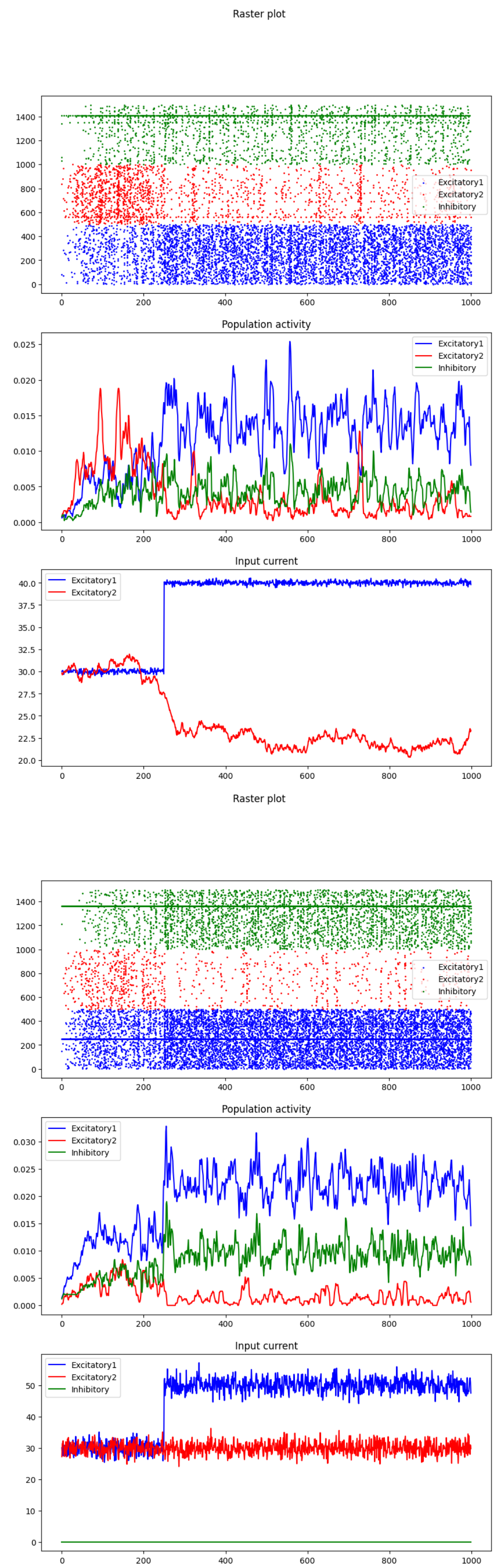

Figure 18. *Different noise inputs*