Spiking neurons

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Introduction

Thanks to Izhikevich, E. M. (2003), we can simulate and explore firing patterns of neurons. He designed a Simple Model of Spiking Neurons. Advantage of this model lies in its ability to manage the balance between biologically plausible scenario and simple computational approach.

We will be working with the differential equations:

$$v' = 0.04v^2 + 5v + 140 - u + I \qquad (1)$$
$$u' = a(bv - u) \qquad (2)$$

where:

v is membrane potential of the neuron,
a is time of the recovery variable u,
b is sensitivity of the recovery variable u,
c is after-spike reset value of the membrane potential v,
d is after-spike reset value of the recovery variable u,
I is step of dc-current.

These equations allow us to reduce many biophysically accurate Hodgin-Huxley-type of the neuronal models (Izhikevich, E. M., 2003).
These variables have their typical settings as follows:

a is typically set to 0.02,
b is typically set to 0.2,
c is typically set to -65 mV,
d is typically set to 2 and
I is typically set to 10.

For these equations to function properly, there is a need for after-spike resetting.

$$\text{if } v \geq 30 \text{ mV,} \qquad (3)$$
$$\text{then } v \leftarrow c; \ u \ \leftarrow u + d$$

Using (1) and (2), we will be calculating membrane potential and observe spiking patterns.

Spiking

Using different combinations of parameters, we are aiming for different neurons firing representation. They are shown in Figure 1 through Figure 8. We take a look at biologically known types of neurons using simulation.
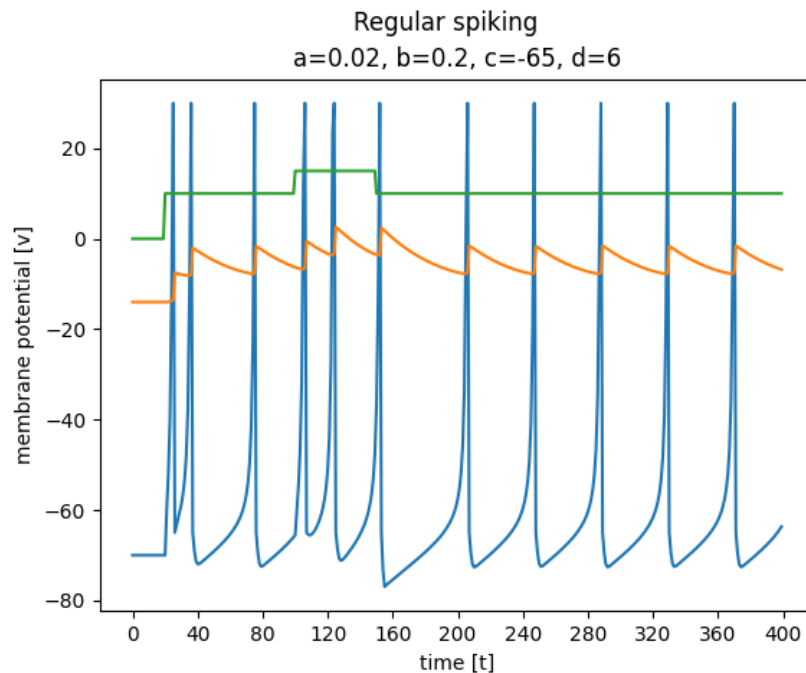
1 Regular spiking

Figure 1: Regular spiking, parameters: a = 0.02, b = 0.2, c = -65, d = 6, v0 = -70, I = 10

Figure 1 portraits regular spiking neurons, where we can observe firing or spiking after approximately 40ms. We are observing more regular firing at the beginning with a slow decrease. Note that we are observing excitatory cortical neurons.
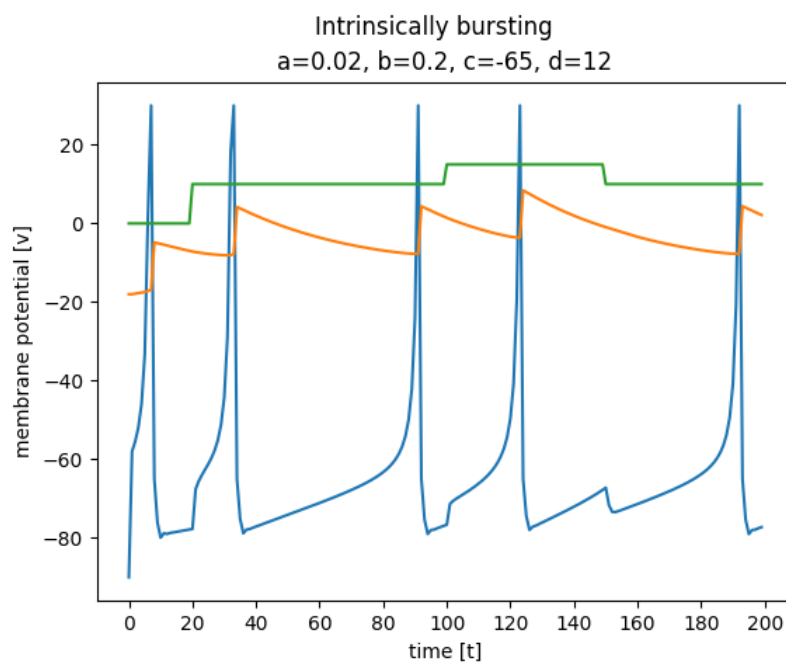
2 Intrinsically bursting

Figure 2: Intrinsically bursting neurons. Parameters: a = 0.02, b = 0.2, c = -65, d = 12, v0 = -90, I = 10

Observing excitatory cortical neurons in intrinsically bursting state, seen on Figure 2. Here, we see neuronal response in firing after applying the current. Afterwards, the neurons keep spiking.
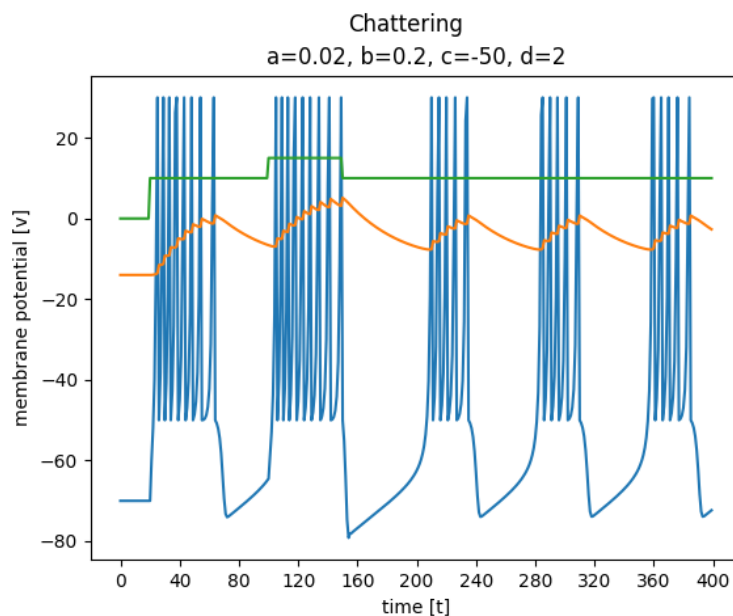
3 Chattering

Chattering
a=0.02, b=0.2, c=-50, d=2

Figure 3: Chattering. Parameters: a = 0.02, b = 0.2, c = -50, d = 2, v0 = -70, I = 10

Chattering (seen in Figure 3) is another pattern to observe in excitatory cortical neurons firing. It shows bursting of the neurons at high frequency followed by short resting period.
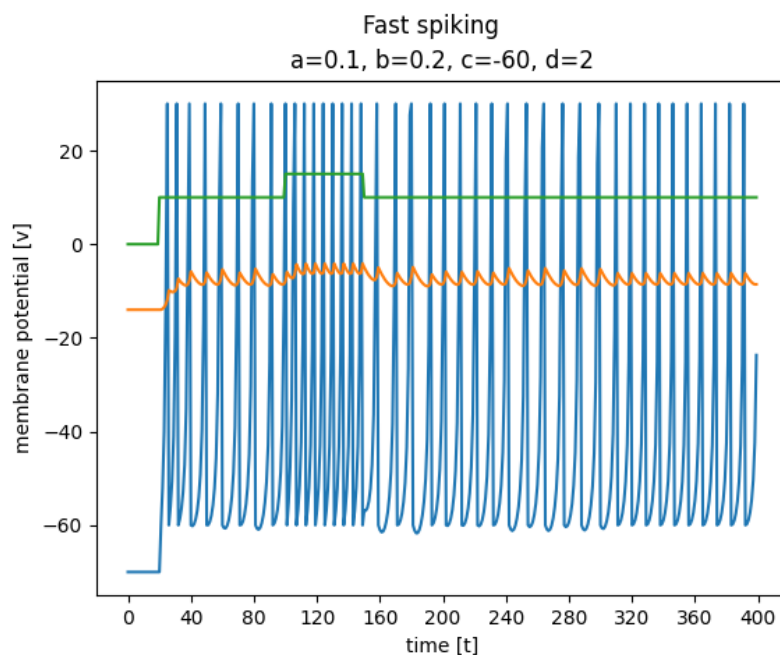
4 Fast spiking

Fast spiking
a=0.1, b=0.2, c=-60, d=2

Figure 4: Fast spiking. Parameters: a = 0.1, b = 0.2, c = -60, d = 2, v0 = -70, I = 10

From the name of the observed spiking, we can conclude and see on Figure 4, regular and high frequency spiking. This firing pattern can be seen in inhibitory cortical neurons. We are also observing decrease in frequency with time.
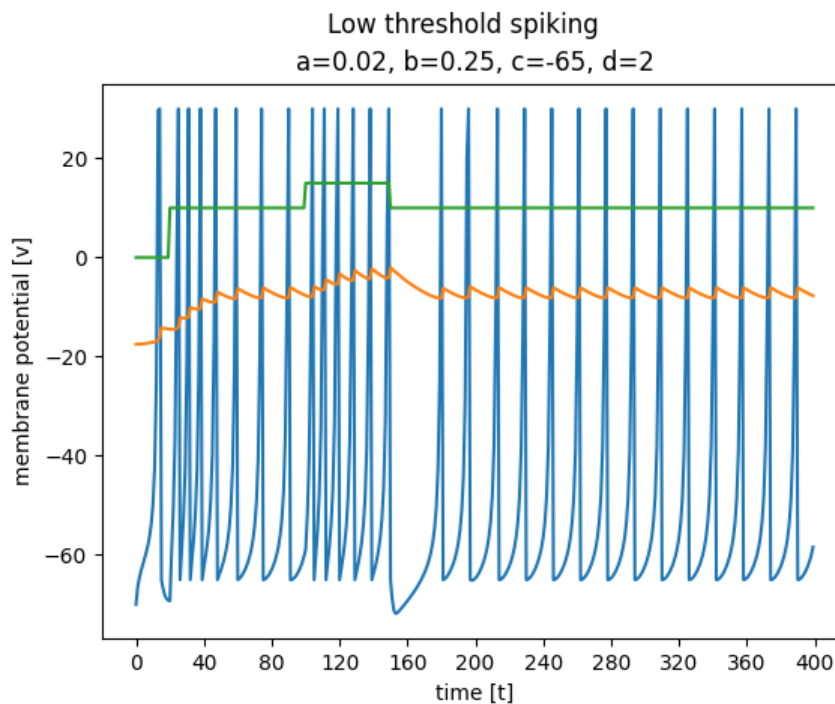
5 Low threshold spiking

Figure 5: Low threshold spiking. Parameters: a = 0.2, b = 0.25, c = -65, d = 2, I = 10

Low threshold spiking neurons (Figure 5) belong to the inhibitory cortical neurons part of the neurons. We can observe similar firing patters than in fast spiking neurons (Figure 4). Low threshold cortical neurons are also firing with high frequency. The difference between the two might be observable if we focus on time 160ms and later (Figure 5), where we observe lower frequency suggesting adaptation to the stimulus.
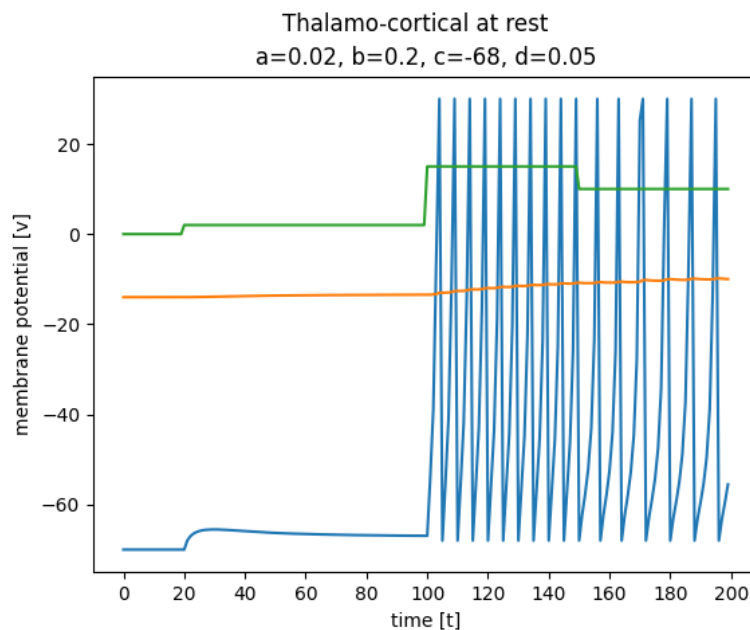
6 Thalamo-cortical spiking at rest

Figure 6: Thalamo-cortical neurons at rest. Parameters: a = 0.02, b = 0.2, c = -68, d = 0.05, v0 = -90, I = 10

Following firing (Figure 6) is caused by implying a negative current. We are observing resting state before the firing and firing is extensive and high frequency. Keep in mind that these are inhibitory cortical neurons.

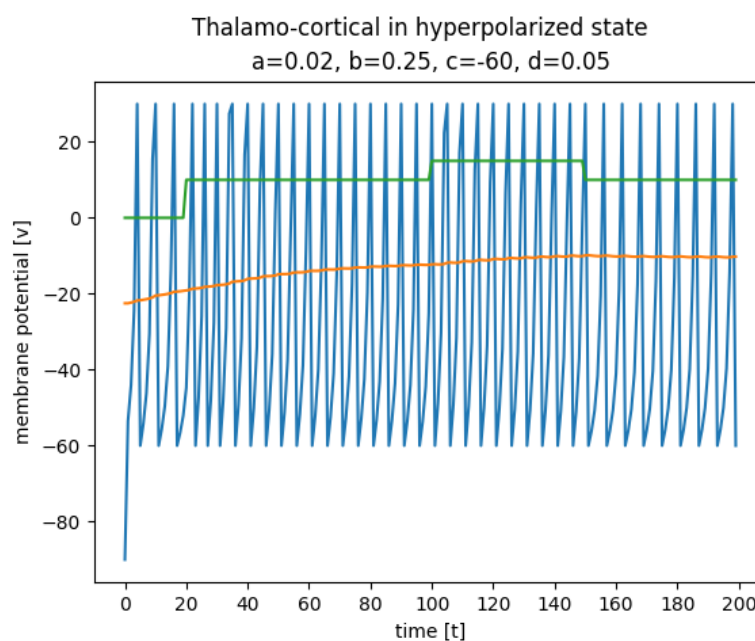## 7 Thalamo-cortical neurons in hyperpolarized state

Figure 7: Thalamo-cortical neurons in hyperpolarized state. Parameters: a = 0.02, b = 0.25, c = -60, d = 0.05, v0 = -90, I = 10

Comparing thalamo-cortical neurons in the resting state (Figure 6) and thalamo-cortical neurons in hyperpolarized state (Figure 7), we notice there are no oscillation before the fast spiking of the neurons. These types of neurons belong to inhibitory cortical neurons.
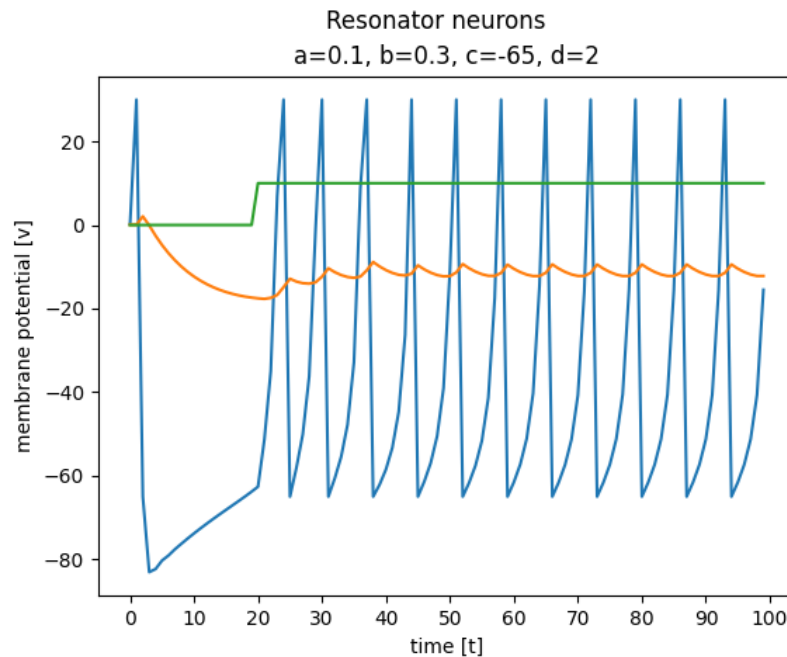
8 Resonator neurons

Figure 8: Resonator neurons. Parameters: a = 0.1, b = 0.3, c = -65, d = 2, I = 2

In the Figure 8, we may observe subthreshold oscillation until 20ms. This is achieved by creating an environment where neurons are sensitive to firing.

Network of neurons

1 Neural distribution

In this part of the assignment, we are exploring the ability of neurons to self-organize. We are observing different ratios of amount of excitatory and inhibitory neurons in order to determine .. and we are adjusting the thalamic noise to determine its involvement in the ability to self-organize and on the model.

Following, we can observe multiple graphs. On the x-axis, we are portraying time and we are portraying number of fired neurons on y-axis.

On Figure 9 we can observe the default amount of neurons, inspired by mammalian brain. Here, we can observe some self-organization forming.
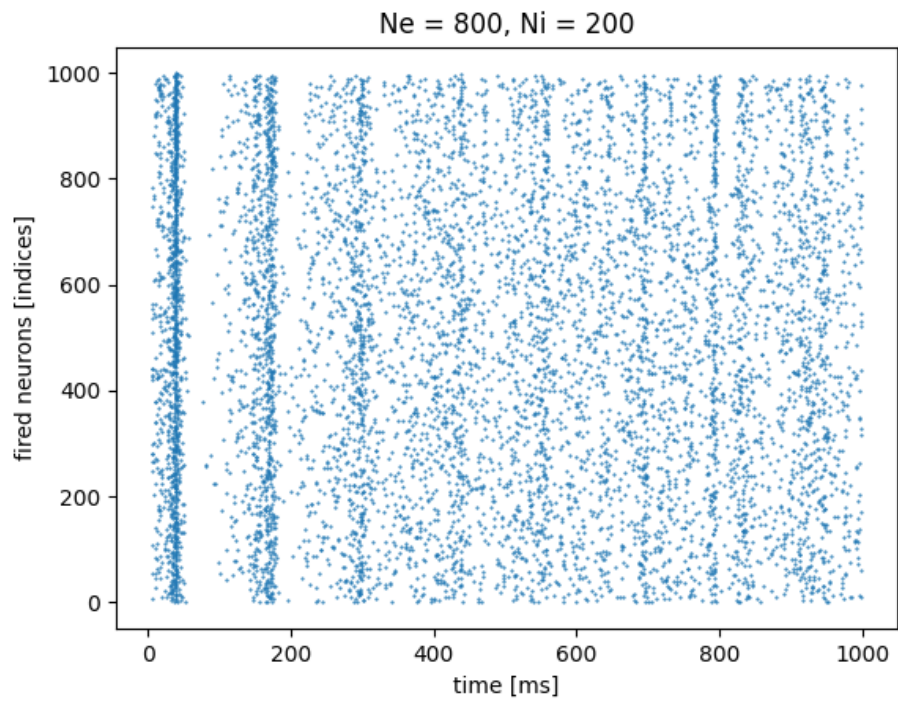
Figure 9: Default distribution of the neurons based on mammalian brain.
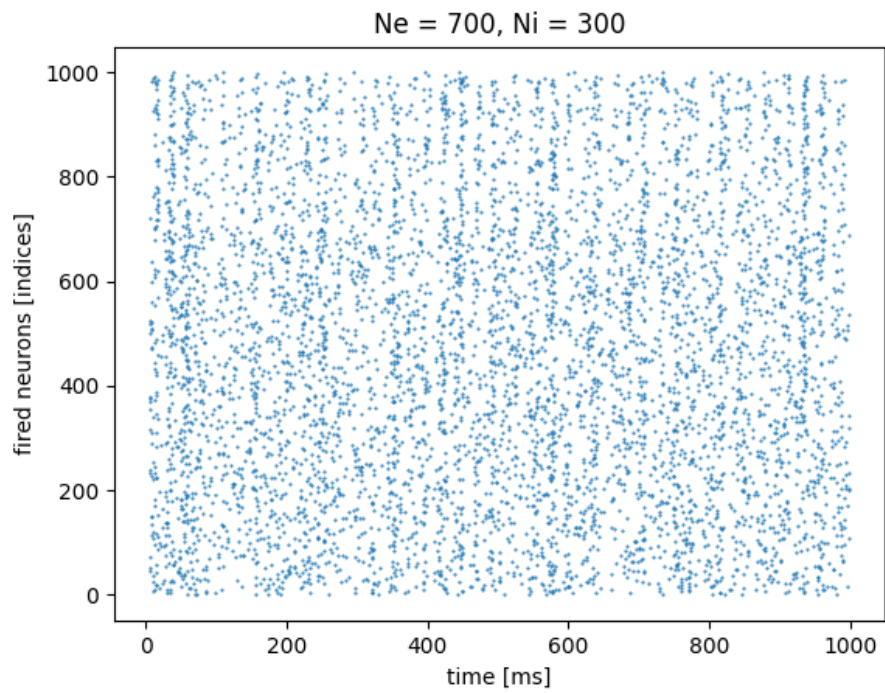

Figure 10: Increase in amount of inhibitory neurons causing dissolving of self-organization.
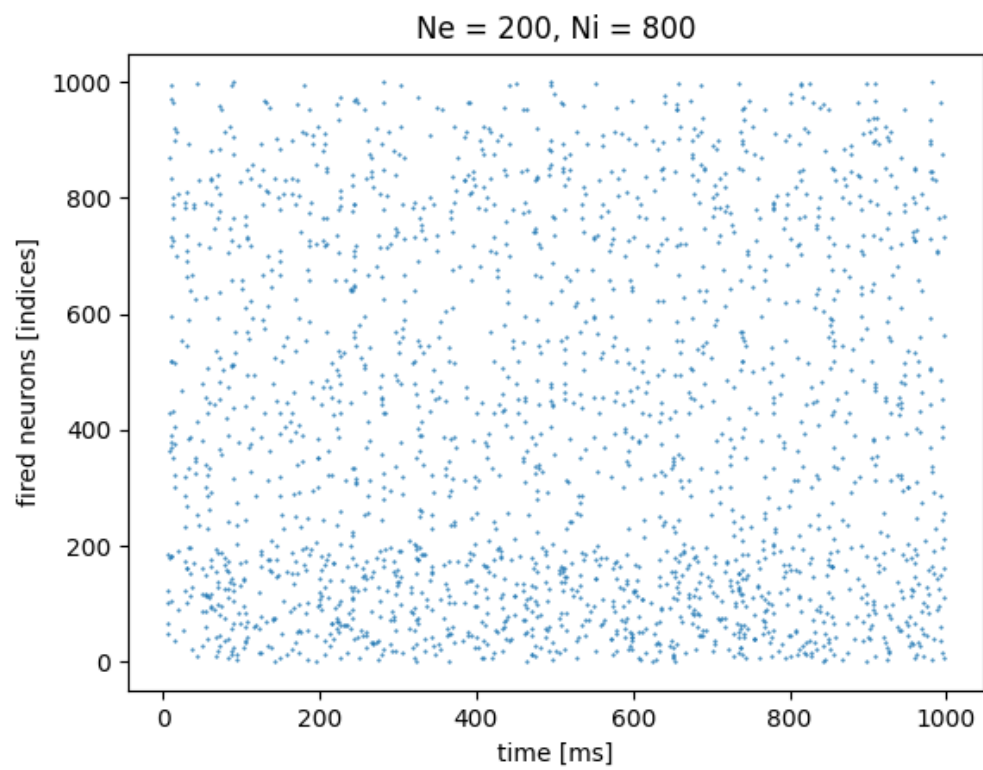
Figure 11: Majority of inhibitory neurons causing patterns to be lost and self-organization is not recognizable anymore.
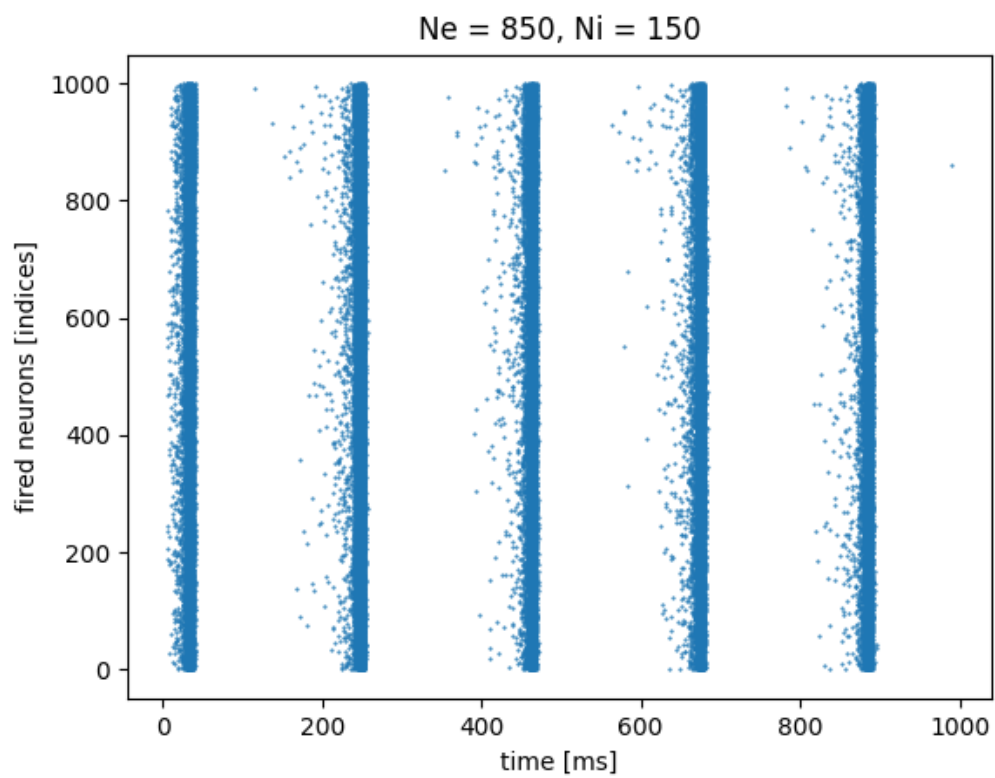
Figure 12: With slightly higher number of excitatory neurons, we observe better self-organization of the neurons. Note, that changes are small, yet we see clear pattern being created.
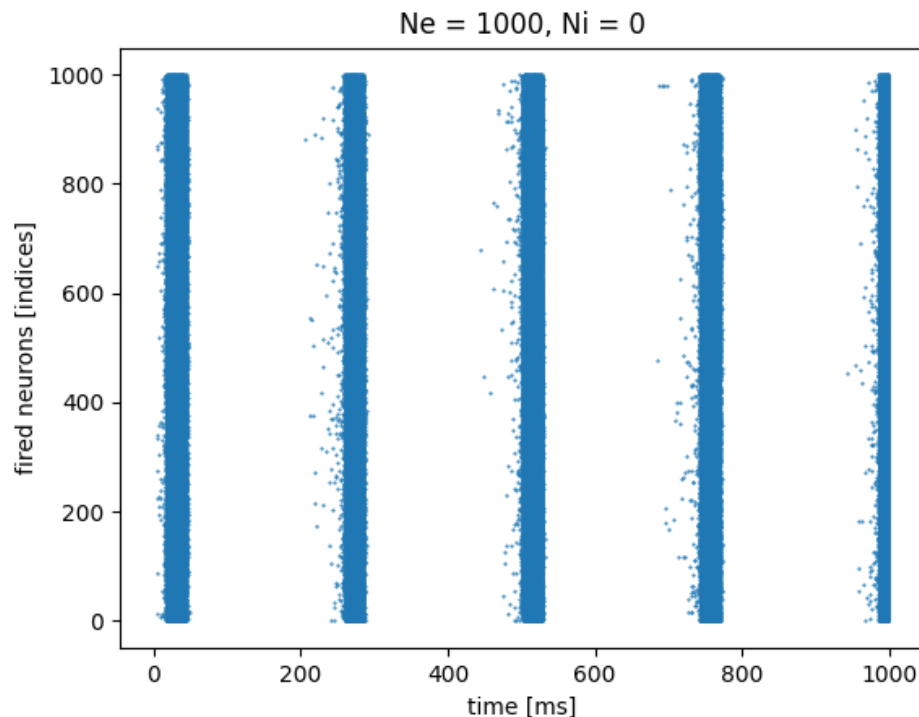

Figure 13: Complete absence of inhibitory neurons is causing decrease of the noise.

From the figures above (Figure 9 – Figure 13), we may observe that increasing amount of excitatory neurons results in better self-organization of the neurons and we are starting to see a clear patters. Even slight adjustment of the ratios can leave significant effect (Figure N, Figure N). On the other hand, if we take a look at Figure N, we can observe that neurons are randomly spread, without signs of organization. This happens when we increase the amount of inhibitory neurons (Figure N).

2 Thalamic noise

When dealing with thalamic noise, we have not been changing the ratio between excitatory and inhibitory neurons. We have tried to give neurons a constant values and enhance the noise on either side of the neurons – excitatory neurons and inhibitory, too. For Figure 14 and 15, we have used a constant value of thalamic noise. We have observed that thalamic noise around the value I = 2 (see Figure 15), neurons start to self-organize and we start to observe a structure.
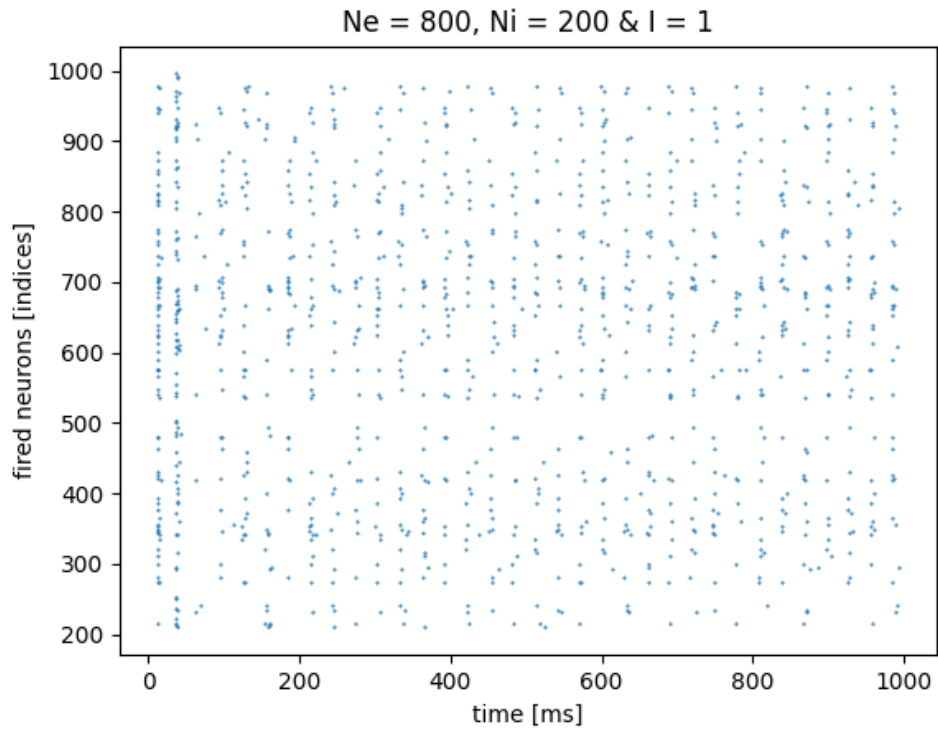
Figure 14: Default ratio of excitatory and inhibitory neurons according to mammalian brain with default value of thalamic noise set to 1.
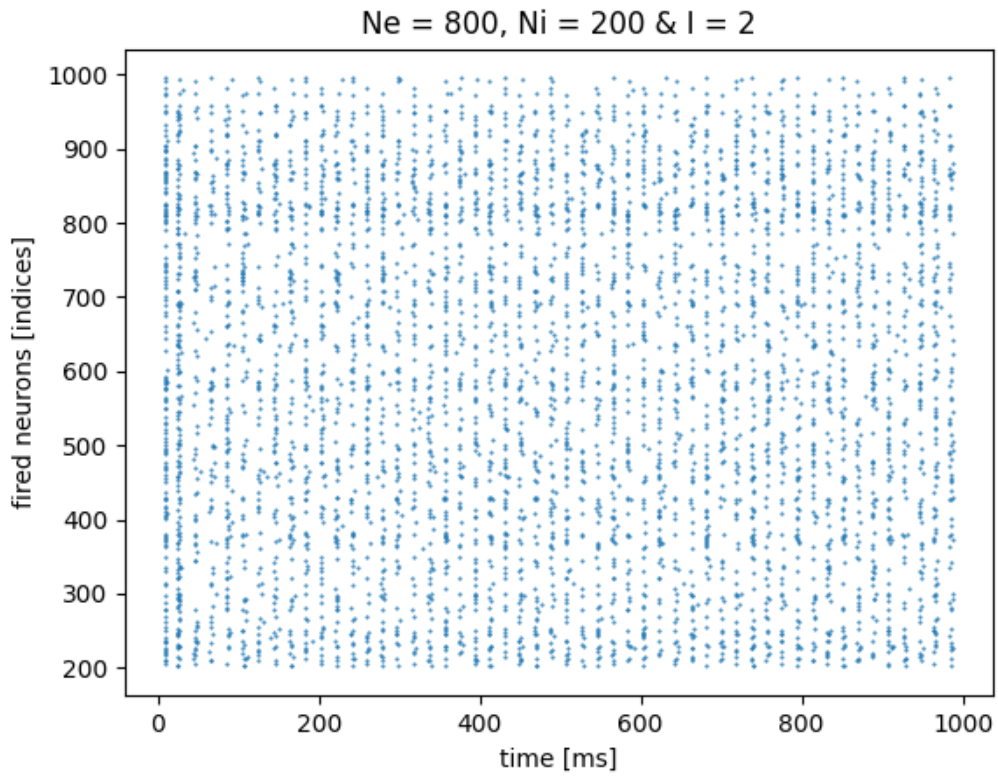

Figure 15: Default ratio of excitatory and inhibitory neurons according to mammalian brain with default value of thalamic noise set to 2. Note the structure being created.
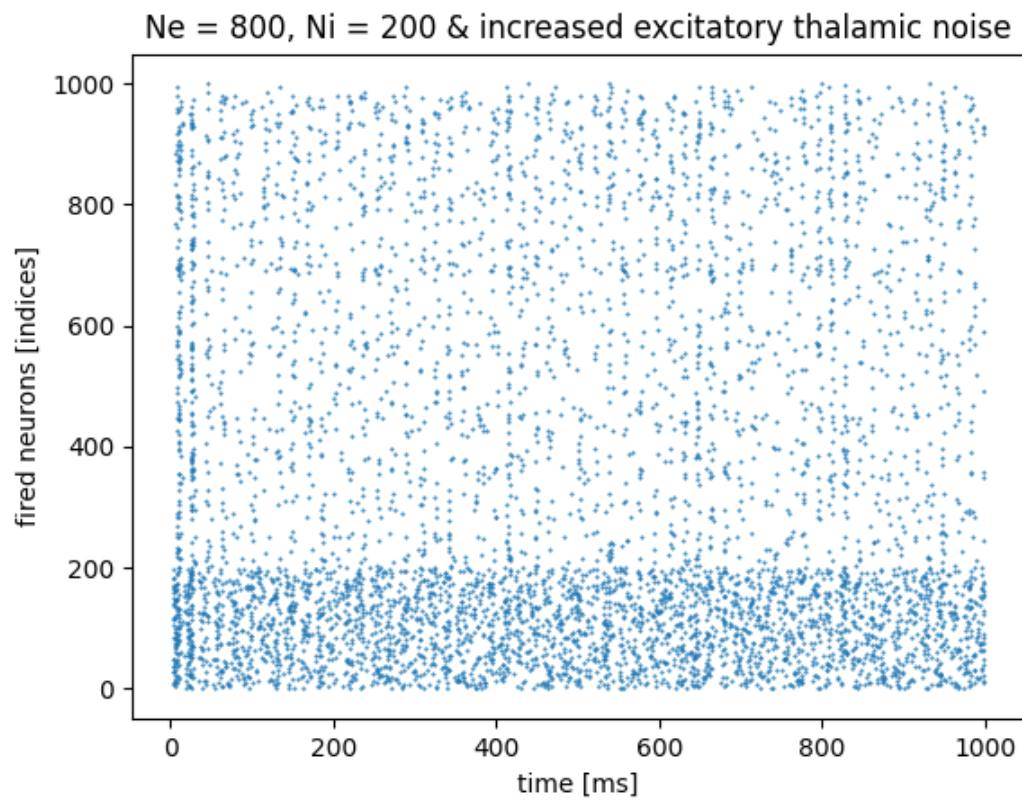
Figure 16: With increased excitatory thalamic noise, we can observe excitatory neurons forming into self-organized pattern. For purposes of this graph, we have doubled excitatory thalamic noise.
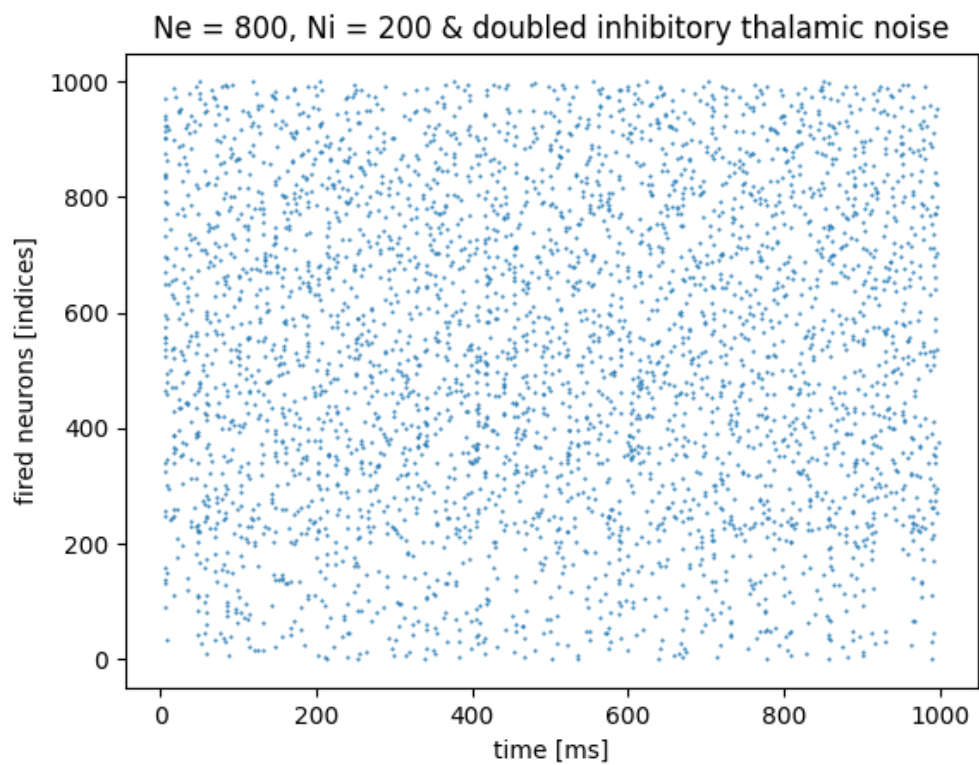
Figure 17: Doubling inhibitory thalamic noise results in creating disoriented patterns and disturbs the process of self-organization.

References

Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Transactions on neural networks*, *14*(6), 1569-1572.