project-3

April 23, 2021

In this project, we implement two types of connections, *DenseConnection* and *RandomConnection*. The *DenseConnection*'s weights are drawn from a normal distribution with $\mu = j_0/N$ and $\sigma = \sigma_0/N$. If a drawn weight from this distribution lie outside of $[w_{min}, w_{max}]$, it will be set to $\mu = j_0/N$.

Also, the scheme used for *RandomConnection* is **fixed number of pre-synaptic partners**, so we don't need to scale the weights. $w_{max} = 1$, and $w_{min} = 0$ is fixed for all the experiments. The weights in *RandomConnection* are set to $\frac{(w_{max} - w_{min})}{2}$, which by default is equal to 0.5. This value is fixed for all the experiments.

We use three connections:

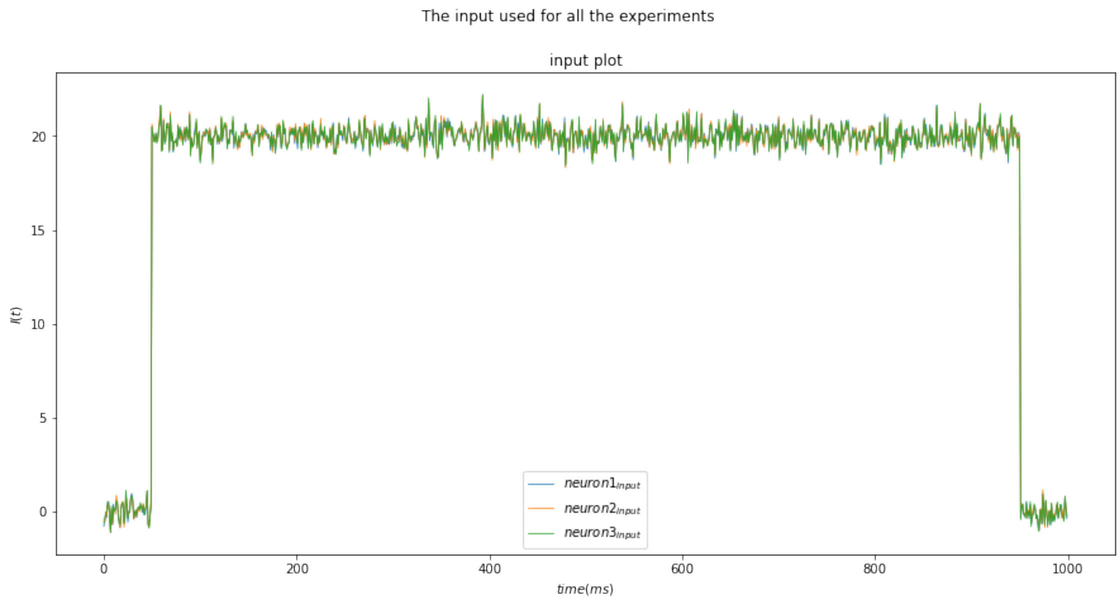
1. Excitatory population to itself
2. Excitatory population to inhibitory population
3. Inhibitory population to excitatory population

In all the experiments, the types of connections will be equal among the three connections, i.e., if one of the connections is dense, the other two are dense as well.

In each experiment, only one parameter will be changed compared to the previous parameter set to emphasise the effect of that specific parameter.

The input will be a pulse current with a mean value of 20, and a low amount of noise. Also, the inputs to the neurons (in one population) slightly differ from one another with a standard deviation of 0.25. This inter-neuron input noise is added to have some variation in each neuron's response. The time-noise standard deviation is set to 1.

For comparing the total activity of the populations during the simulation time, we calculate the area under the curve (AUC) of activity-plot. Higher AUC indicates higher total activation.



As you can see in the inputs' plot (maybe by zooming on the plot), the input each neuron receives is slightly different.

1 Dense Connection

The parameters of this connection is: J_0 and σ_0 for each connection, and the total number of neurons. J_0 directly controls the weights of the synapses and therefore the strength of that synapse. σ_0 controls the amount of variation in the synapses' weights.

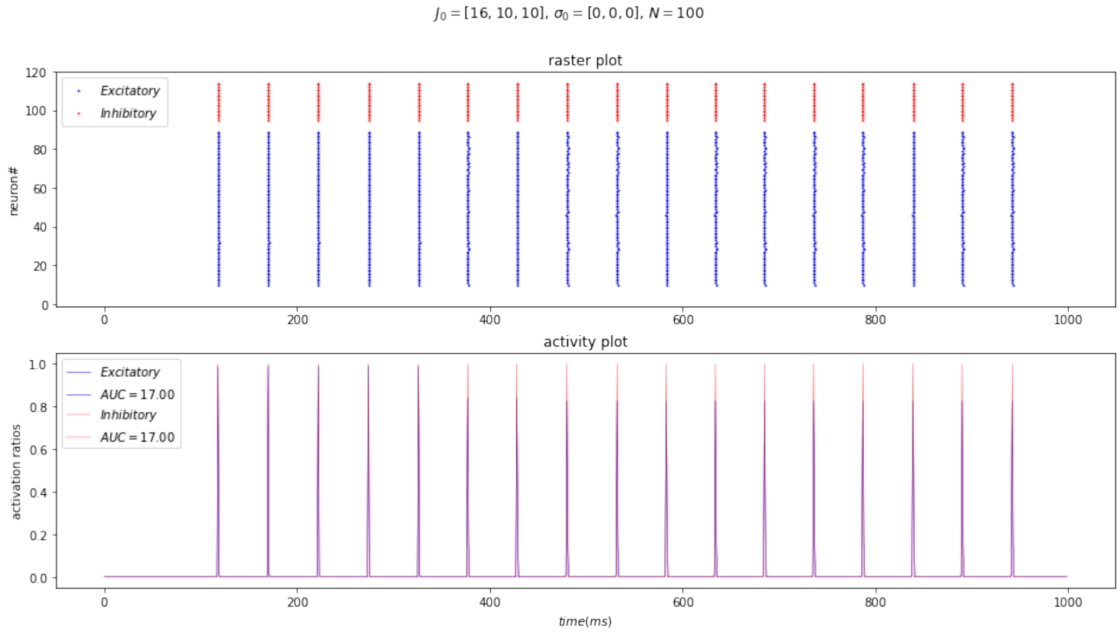
1.1 Parameter set 1:

$J_{EE} = 16$, $\sigma_{EE} = 0$,

$J_{EI} = 10$, $\sigma_{EI} = 0$,

$J_{IE} = 10$, $\sigma_{IE} = 0$,

$N = 100$



We see that both populations' AUC is equal, and by observing the plots we see that both of them, are showing activation in the same time, this means that we have a balanced connection between the two population.

1.2 Parameter set 2:

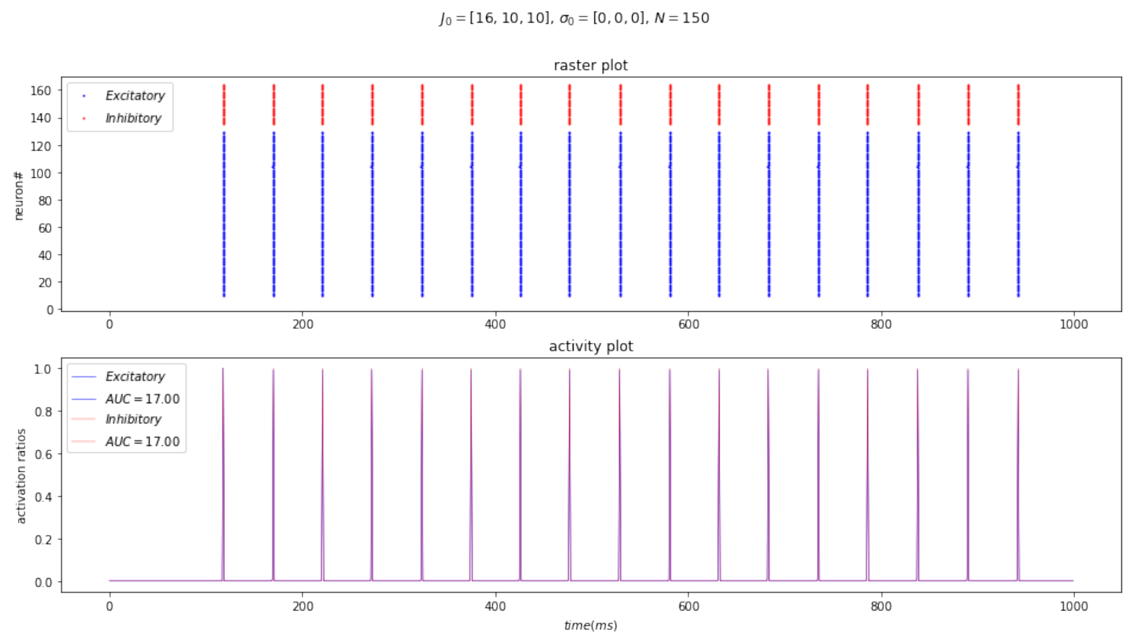
Testing N's effect

$J_{EE} = 16$, $\sigma_{EE} = 0$,

$J_{EI} = 10$, $\sigma_{EI} = 0$,

$J_{IE} = 10$, $\sigma_{IE} = 0$,

$N = 150$



1.3 Parameter set 3:

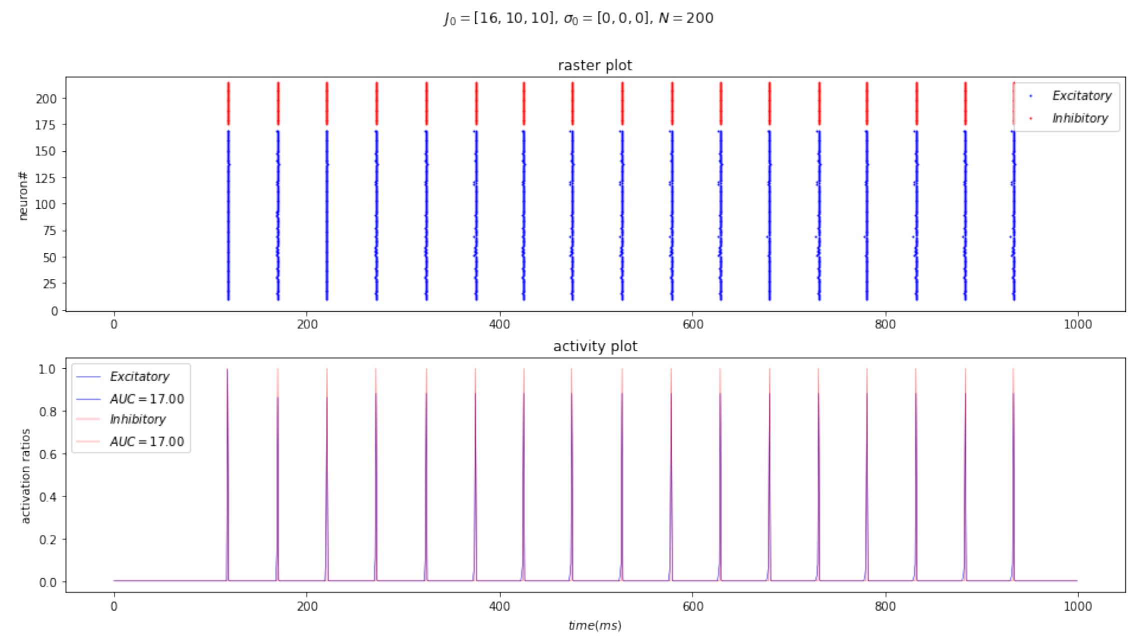
Testing N's effect

$J_{EE} = 16$, $\sigma_{EE} = 0$,

$J_{EI} = 10$, $\sigma_{EI} = 0$,

$J_{IE} = 10$, $\sigma_{IE} = 0$,

$N = 200$



from previous plots, we can conclude that total number of neurons in this setup, do not change the populations' activity trend.

1.4 Parameter set 4:

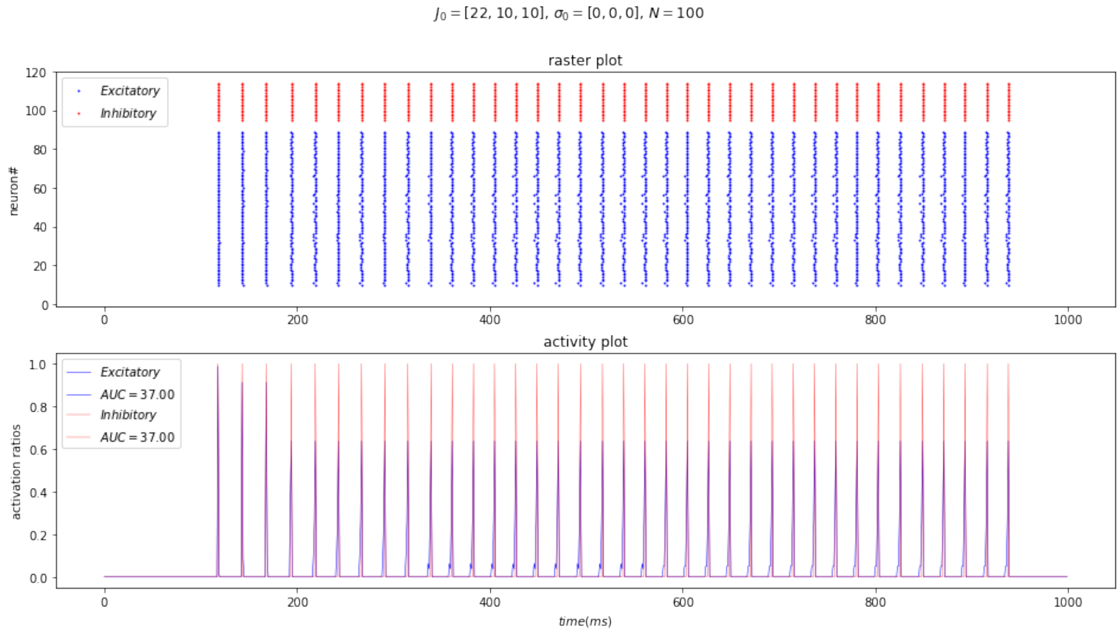
Testing J_{EE}'s effect

$J_{EE} = 22$, $\sigma_{EE} = 0$,

$J_{EI} = 10$, $\sigma_{EI} = 0$,

$J_{IE} = 10$, $\sigma_{IE} = 0$,

$N = 100$



By increasing J_{EE} (increasing the weights of the synapses in population E, in fact), the total activation of the populations will increase, since the excitatory populations' spikes will excite itself, and its activation will increase. Also, the increase in activation of the first population will excite the second population, so the second population's activity will increase as well.

1.5 Parameter set 5:

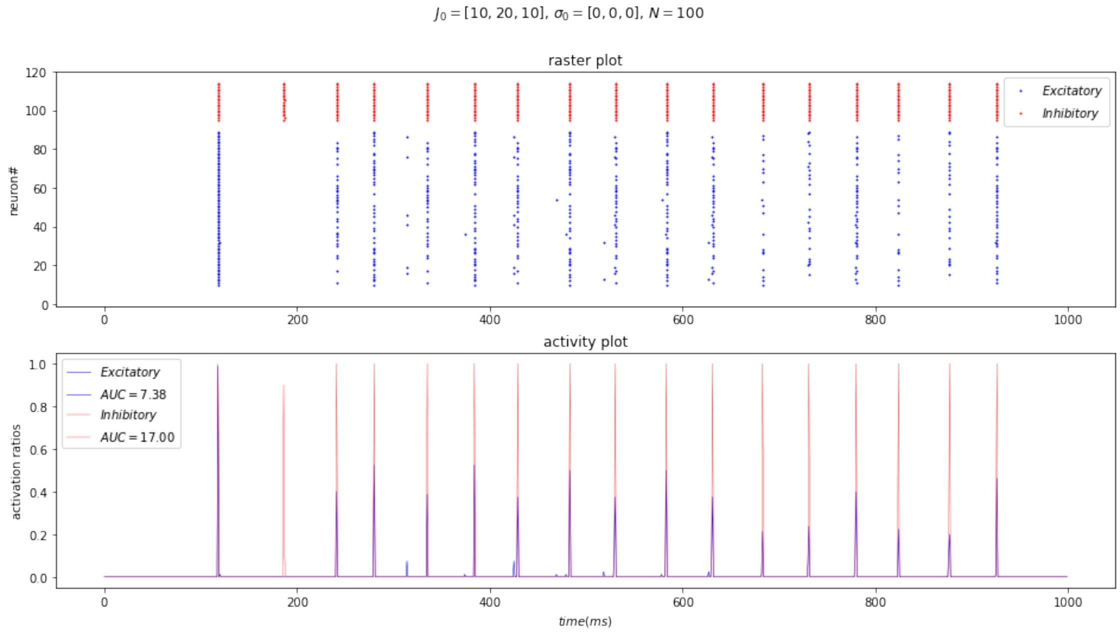
Testing J_{EI}'s effect

$J_{EE} = 10$, $\sigma_{EE} = 0$,

$J_{EI} = 20$, $\sigma_{EI} = 0$,

$J_{IE} = 10$, $\sigma_{IE} = 0$,

$N = 100$



Increasing the value of J_{EI} has an interesting effect; population I's activty will not increase, but the activation of population E will decrease. This observation could be explained as follows: By increasing J_{EI}, the population I will be more effected from population E's activity. This, eventually, reduce the activity of population E, but not much to significantly reduce the population I's activity. If we carefully observe the plot, we see that E's activity is vanished, and I's activity is decreased after the first interval of activation. The decrease in I's activity then let the E to be active in the next time steps. After that, they reach to a state of balance, and the cycles will go on. We could easily see that how the second population is controlling the activity of the first population.

1.6 Parameter set 6:

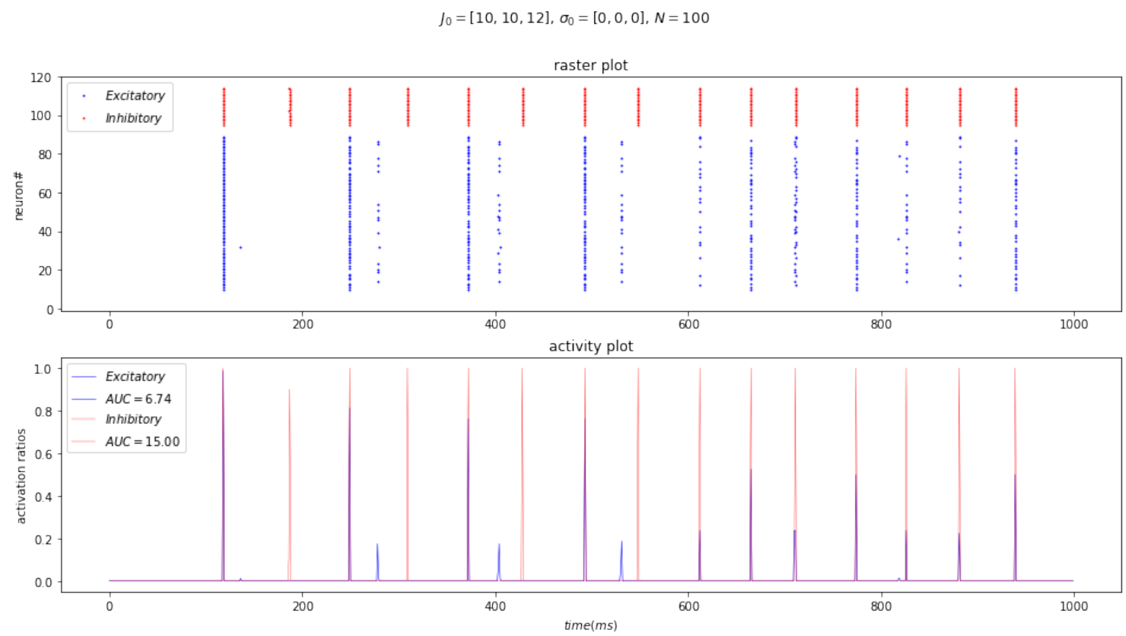
Testing J_{IE}'s effect

$J_{EE} = 10$, $\sigma_{EE} = 0$,

$J_{EI} = 10$, $\sigma_{EI} = 0$,

$J_{IE} = 20$, $\sigma_{IE} = 0$,

$N = 100$



Changing J_{IE} has a similar effect to changing J_{EI}, but its effect is more intense. It is because the IE connection is the one that directly inhibits population E's activity.

1.7 Parameter set 7:

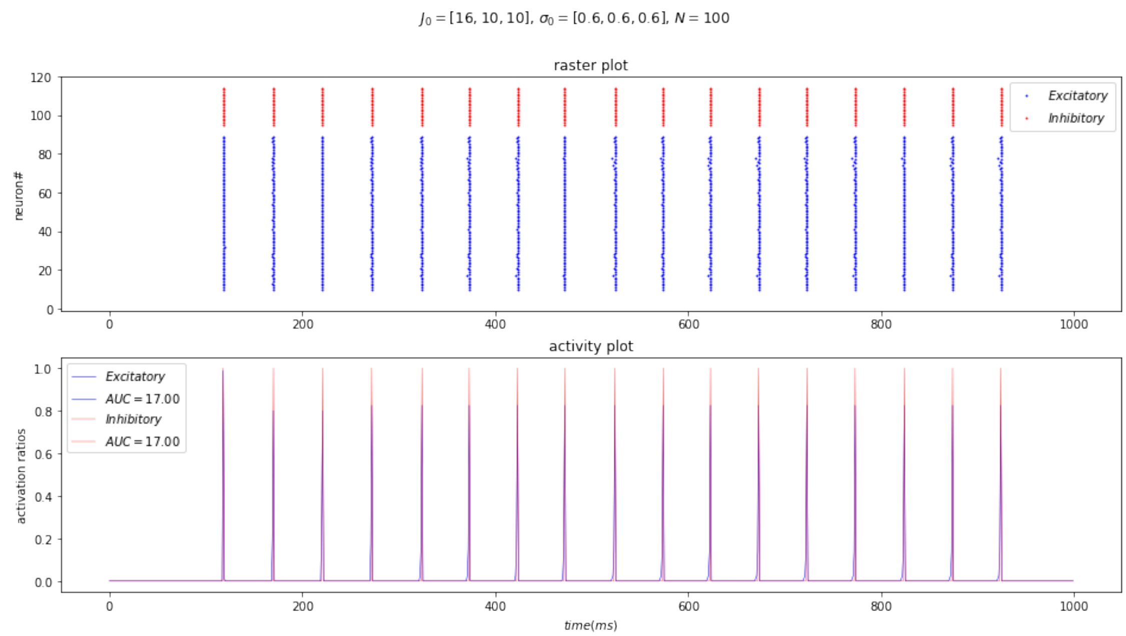
For the final parameter in DenseConnection, we explore the effect of changing the weights from equal in all synapses ($\sigma = 0$) to the case that we increase the sigma. We expect that it will produce a slightly more irregular output in both of the plots compared to the first parameter set plots.

$J_{EE} = 10$, $\sigma_{EE} = 0.1$,

$J_{EI} = 10$, $\sigma_{EI} = 0.1$,

$J_{IE} = 10$, $\sigma_{IE} = 0.1$,

$N = 100$



We observe a little amount of change in the populations' activity; however, it is negligible as expected. We should not have different results compared to uniform weight. It is due to the fact that weights' distribution is still normal around the same mean, and the expected activity of the populations' should be the same.

2 Random Connection

Since the random schema we implemented is the **fixed number of pre-synaptic partners**, the only parameters we have is number of pre-synaptic connections for each post-synaptic neuron. The weights for all the synapses are equal to 0.5 as explained in the top of this report. We also explore the effect of neurons' count.

2.1 Parameter set 1:

Testing the effect of n_{EE}

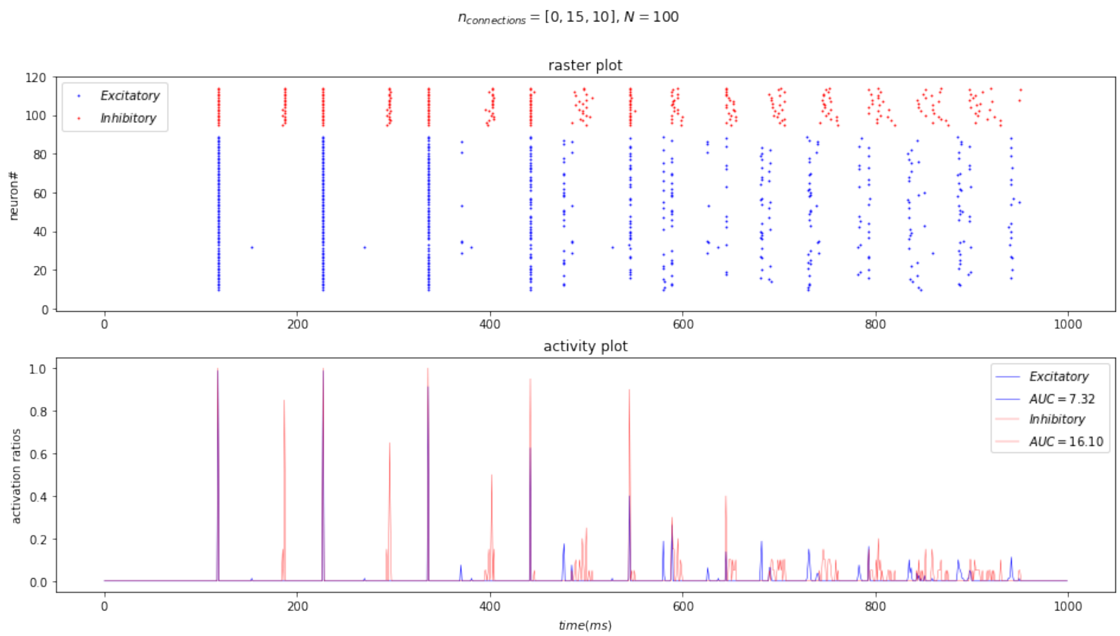
$n_{EE} : [0, 60]$

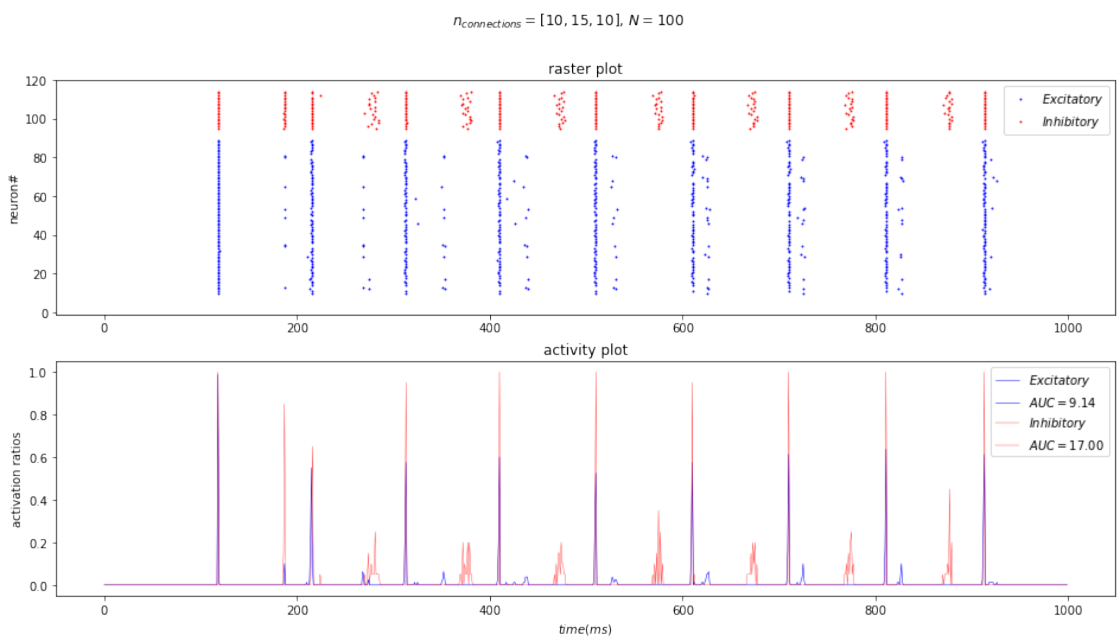
$n_{EI} = 20$

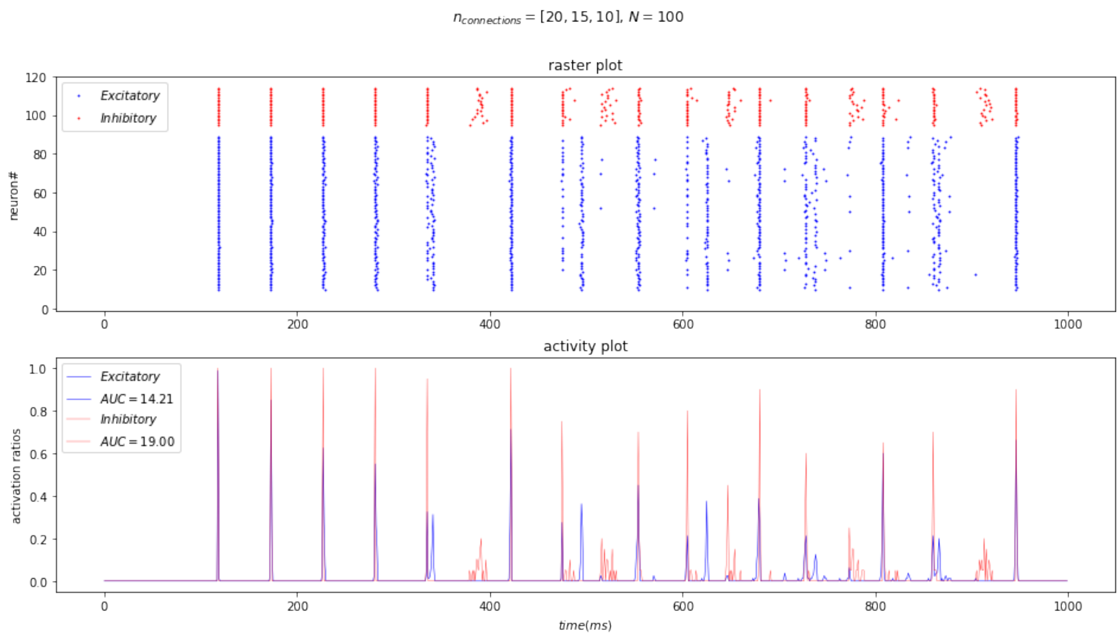
$n_{IE} = 10$

$N = 100$

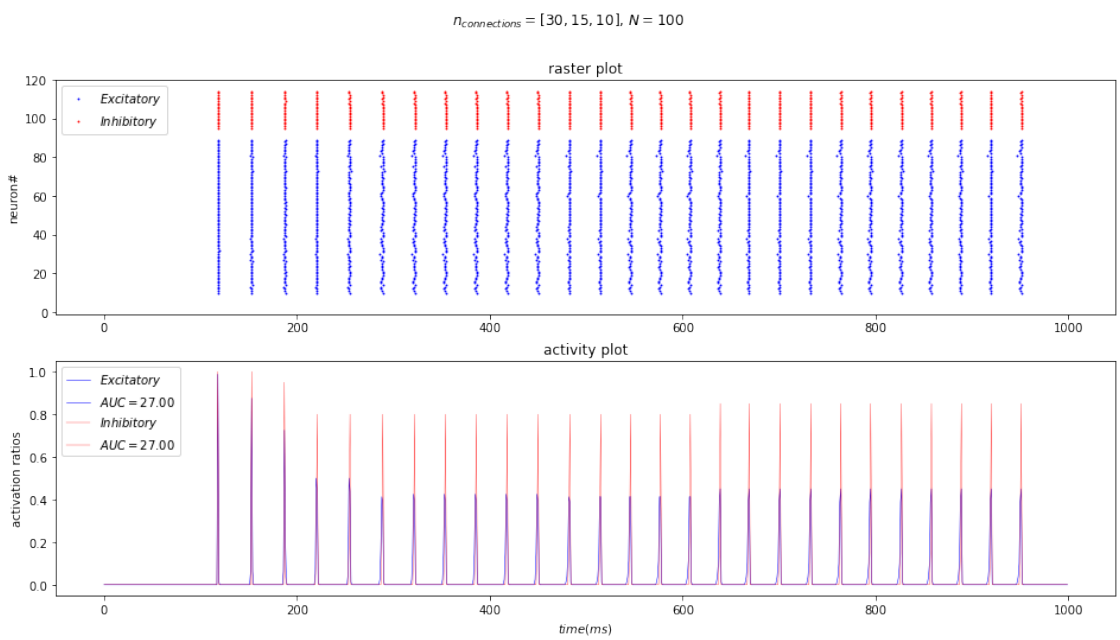
Note: $n_{EI} = 20$ means that each neuron in the population I, has 20 randomly sampled pre-synaptic connections to the population E from the set of all possible connections to population E.


$n_{connections} = [0, 15, 10], N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 7.32$
Inhibitory
$AUC = 16.10$
activation ratios
$time(ms)$

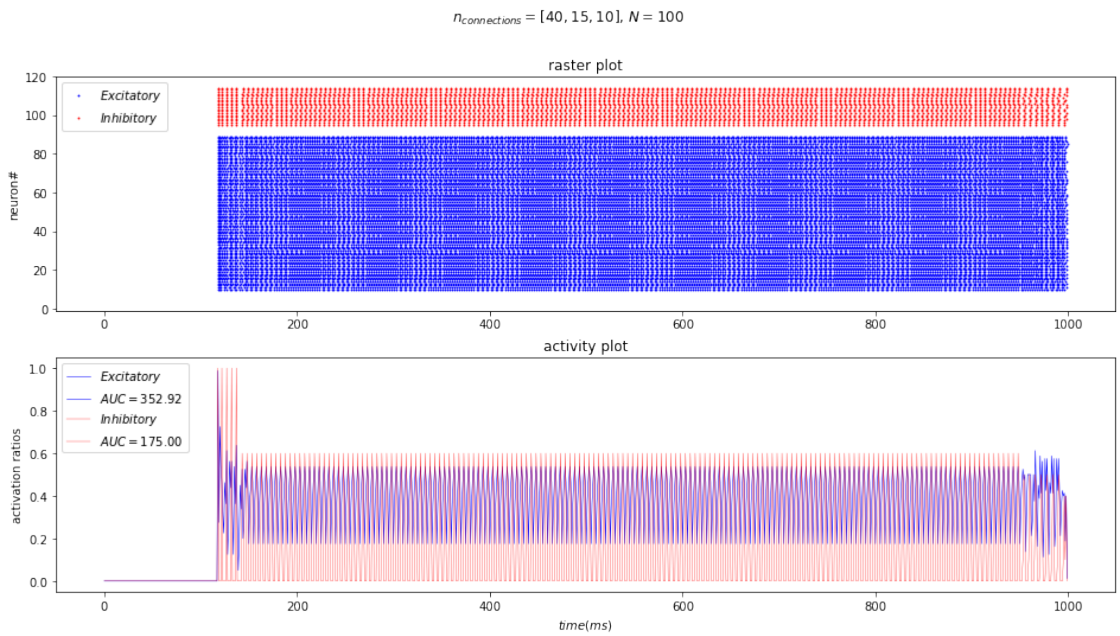

$n_{connections} = [10, 15, 10], N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 9.14$
Inhibitory
$AUC = 17.00$
activation ratios
$time(ms)$

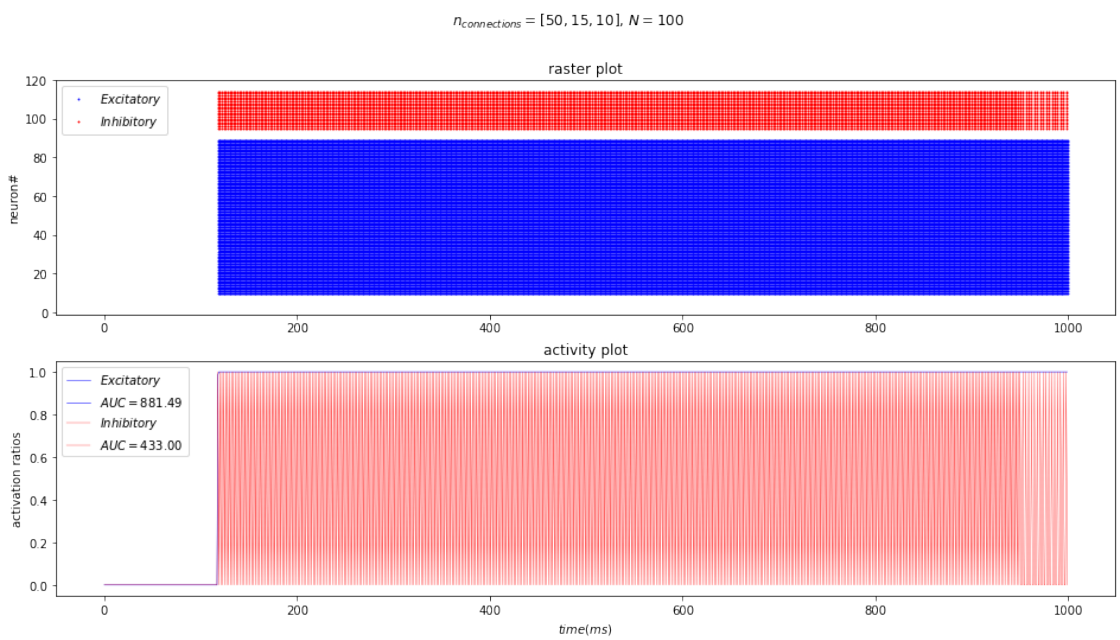


$n_{connections} = [20, 15, 10]$, $N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 14.21$
Inhibitory
$AUC = 19.00$
activation ratios
time(ms)



$n_{connections} = [30, 15, 10]$, $N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 27.00$
Inhibitory
$AUC = 27.00$
activation ratios
time(ms)





If n_{EE} is too low, the inhibitory population will prevent the normal activity of population E. By increasing it, we could achieve a balanced network where two populations work the same activity. If n_{EE} gets too high, population E activation will be saturated and population I cannot prevent this no matter how high its own activation is.

2.2 Parameter set 2:

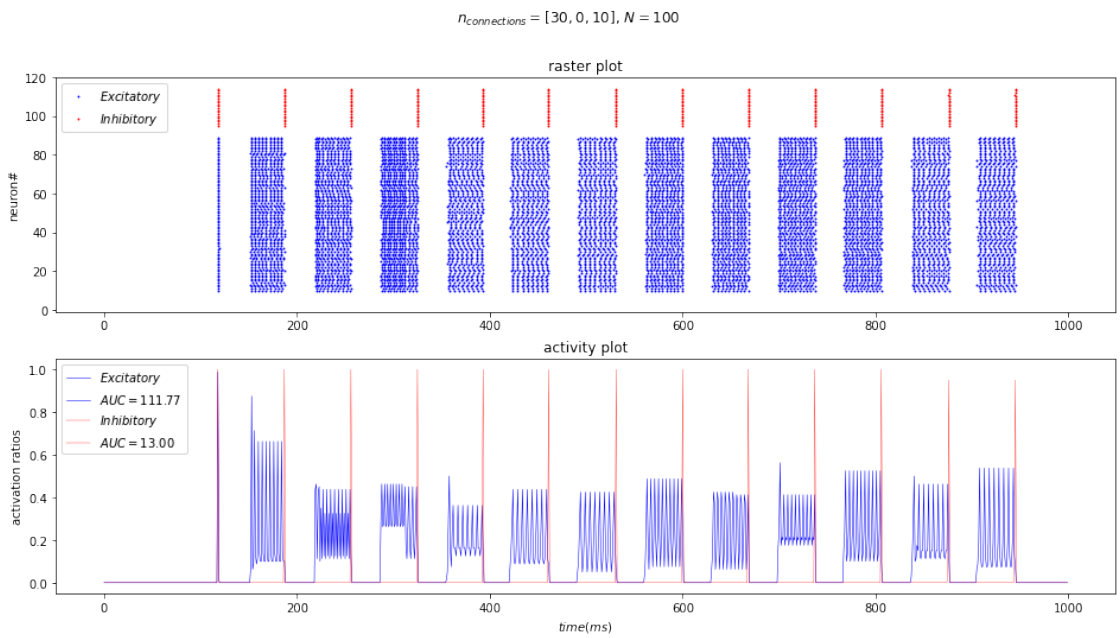
Testing the effect of n_{EI}

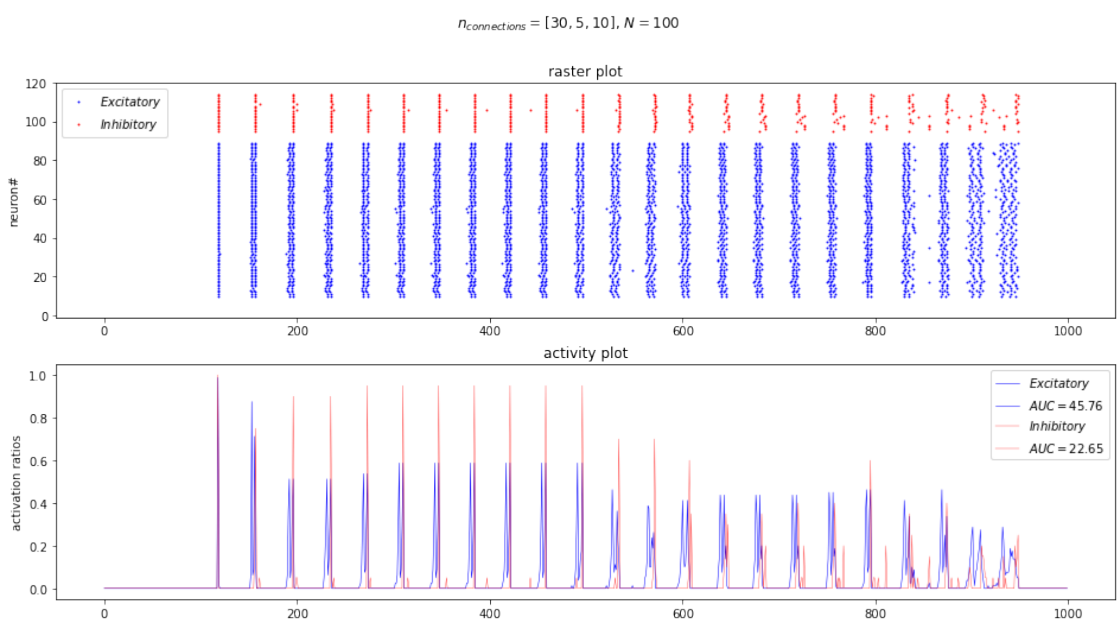
$n_{EE} = 30$

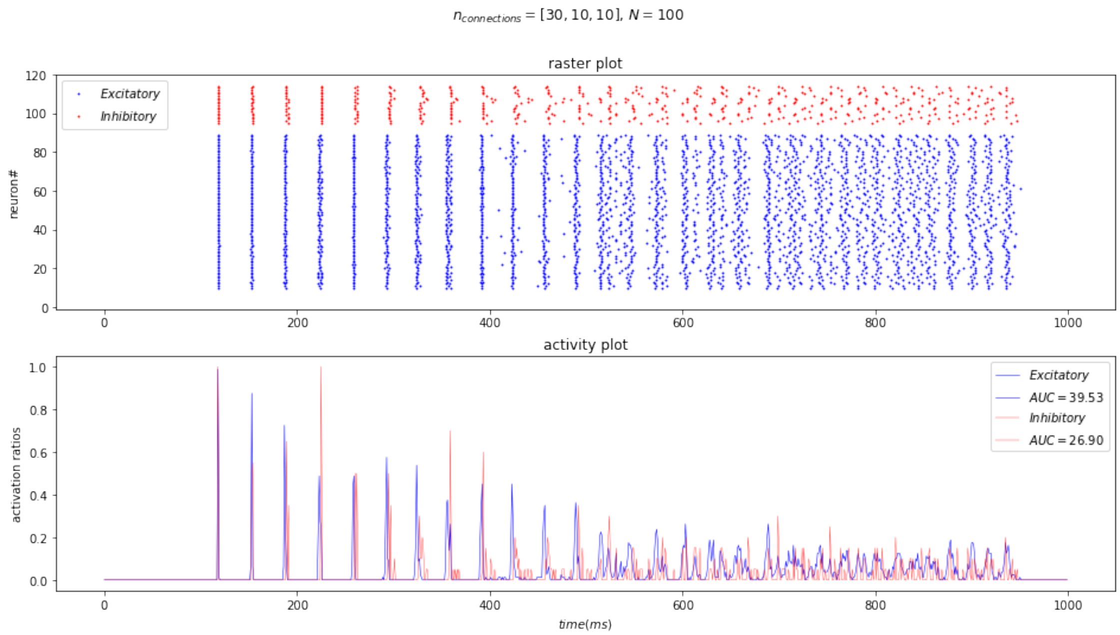
$n_{EI} : [0, 25]$

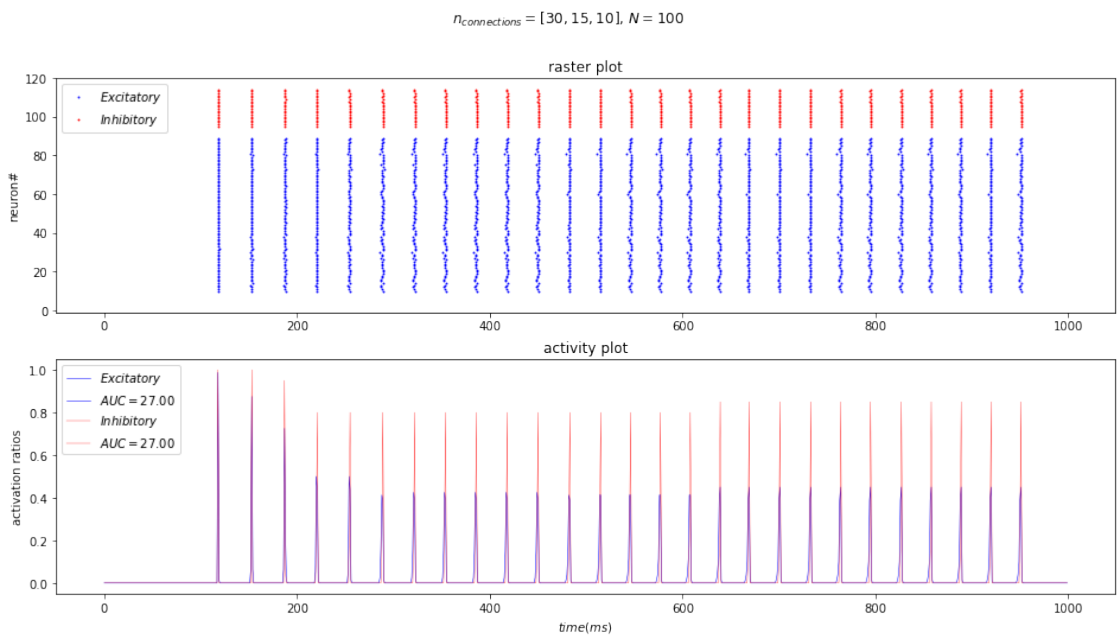
$n_{IE} = 10$

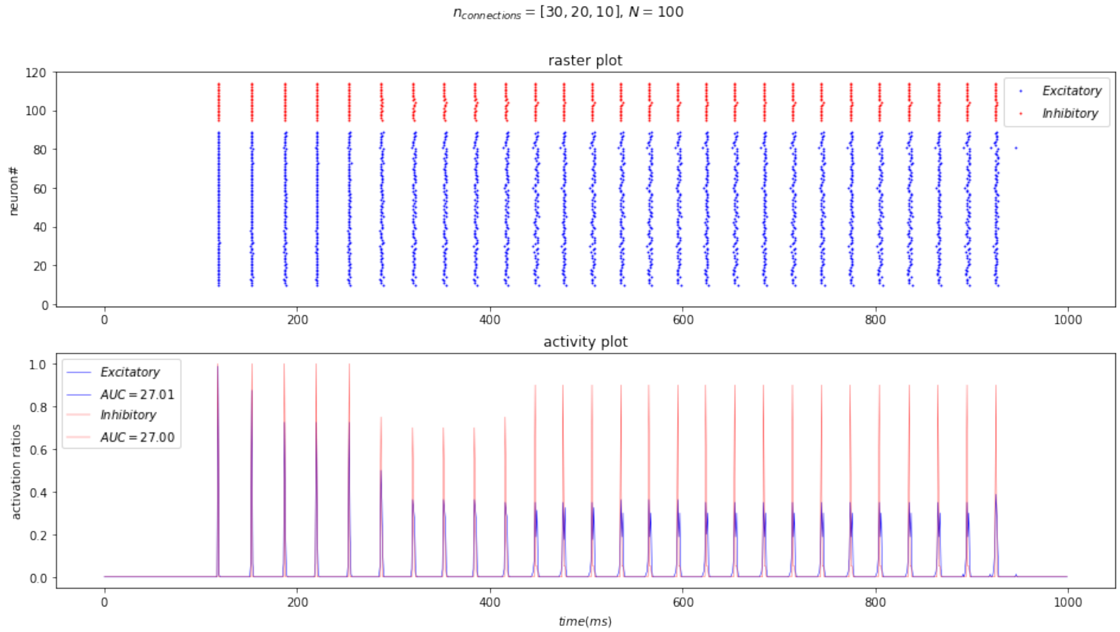
$N = 100$

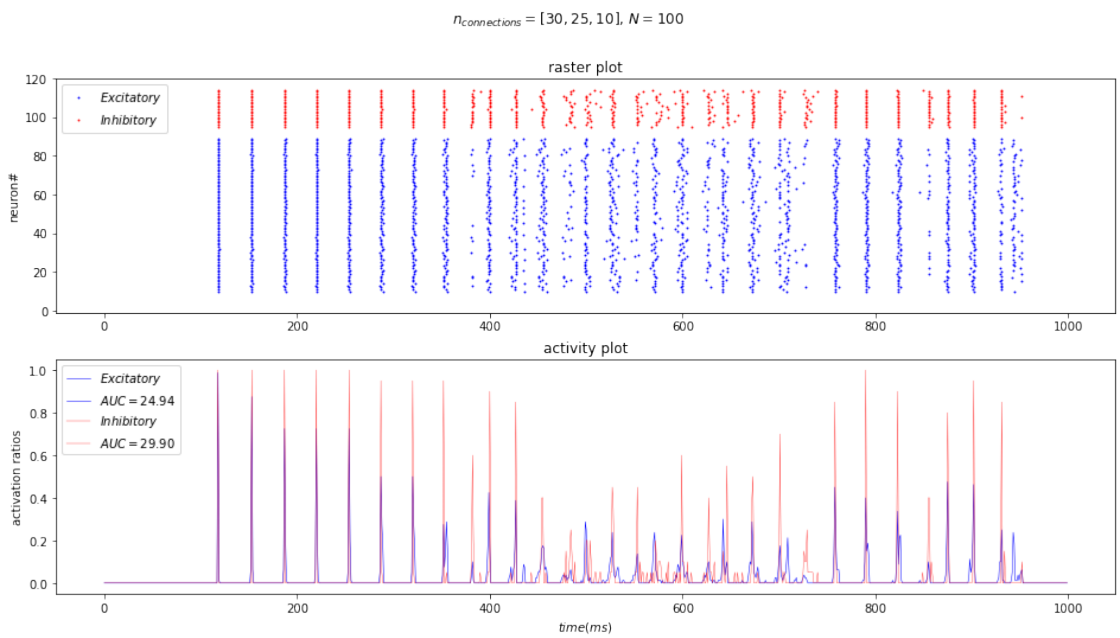





$n_{connections} = [30, 10, 10]$, $N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 39.53$
Inhibitory
$AUC = 26.90$
activation ratios
$time(ms)$


$n_{connections} = [30, 15, 10]$, $N = 100$
raster plot
Excitatory
Inhibitory
neuron#
activity plot
Excitatory
$AUC = 27.00$
Inhibitory
$AUC = 27.00$
activation ratios
$time(ms)$





From the above plots in which we only changed n_{IE} incrementally, the effect of n_{IE} is visible clearly. When n_{IE} is low, the activation of population E is more than the population I's activity. By increasing n_{IE}, we can reach a state the activations are equal. When n_{IE} becomes too high, the activation of population E tends to deteriorate.

2.3 Parameter set 3:

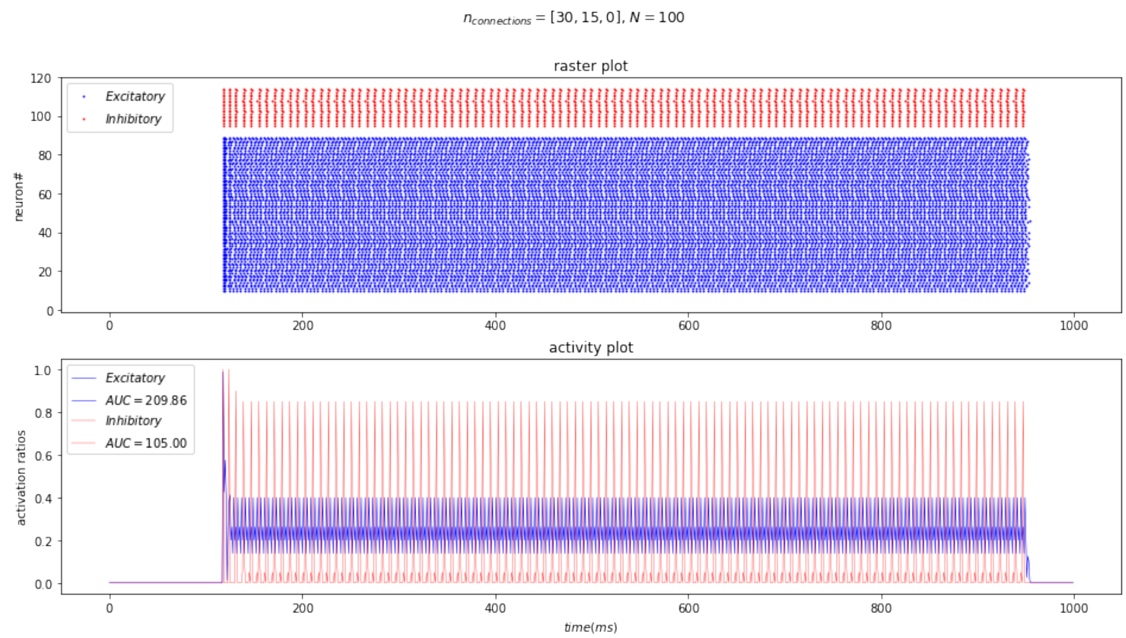
Testing the effect of n_{IE}

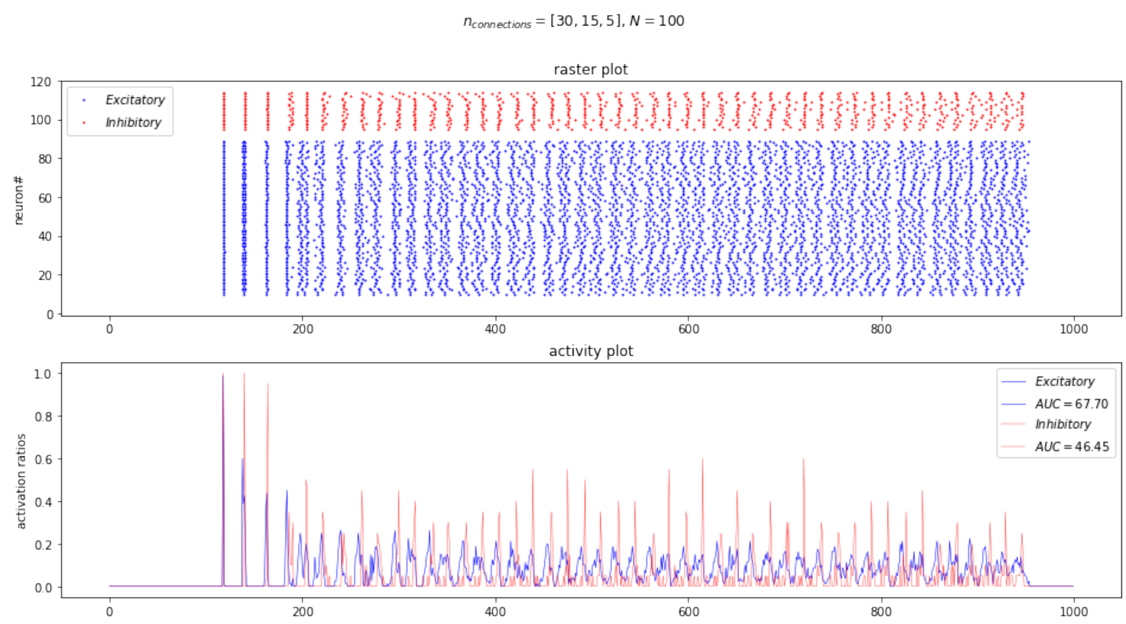
$n_{EE} = 30$

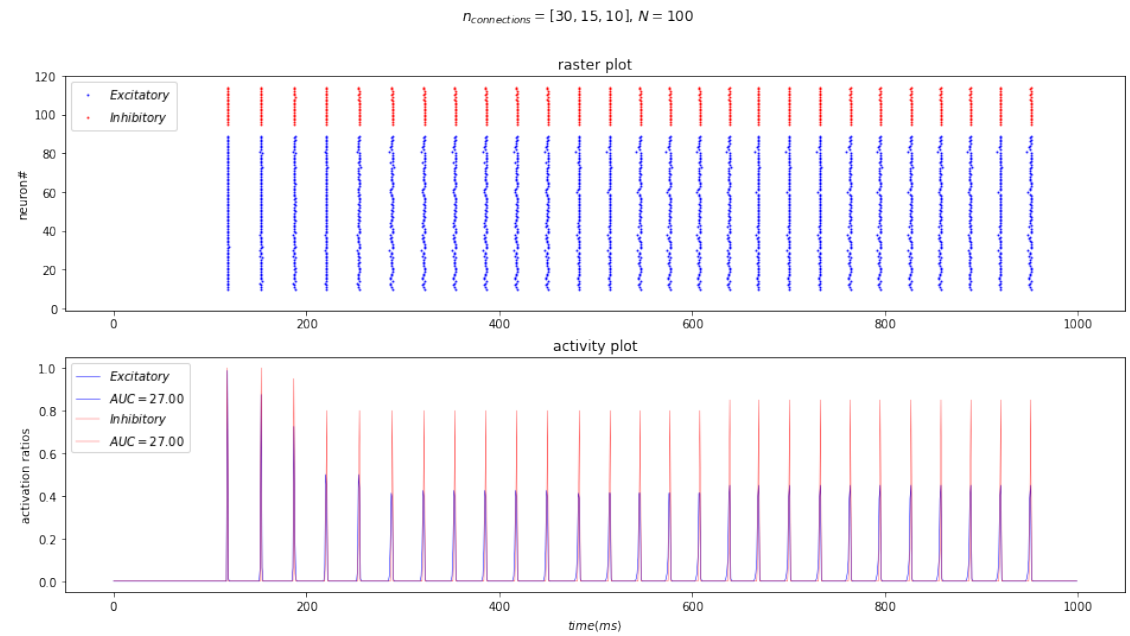
$n_{EI} = 15$

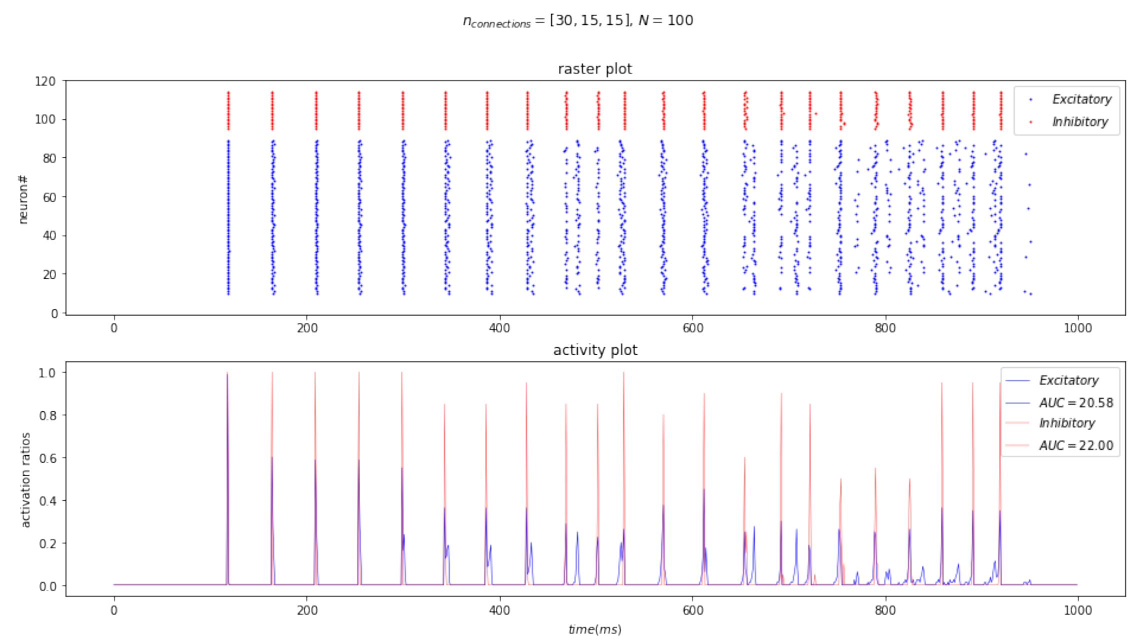
$n_{IE} : [2, 20]$

$N = 100$









We see that the effect of n_{IE} and n_{EI} is almost the same. The conclusion is that by tuning the number of connections in the random scheme, we could have a balanced network, which acts very similar to the balanced network we created using dense connections.

2.4 Parameter set 3:

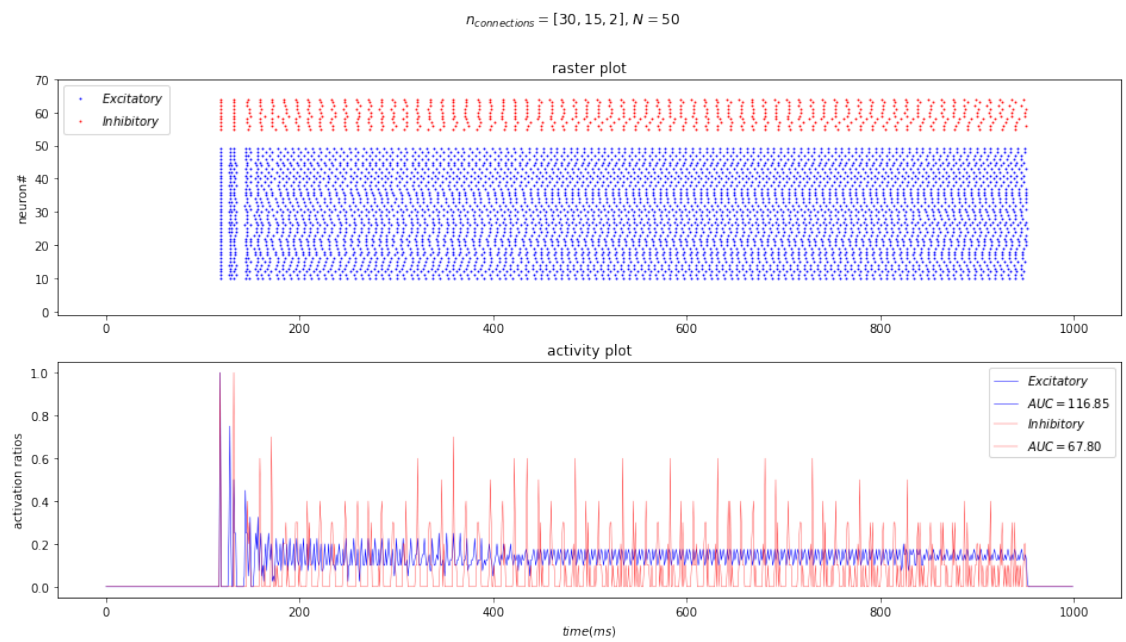
Testing the effect of N when two populations' activity are not equal.

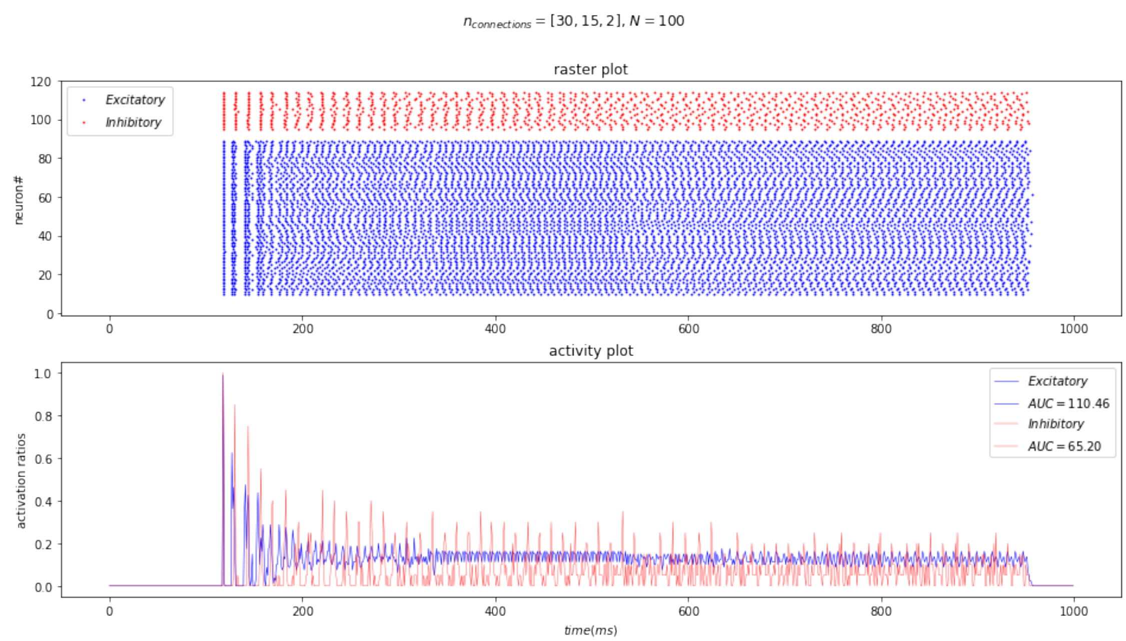
$n_{EE} = 30$

$n_{EI} = 15$

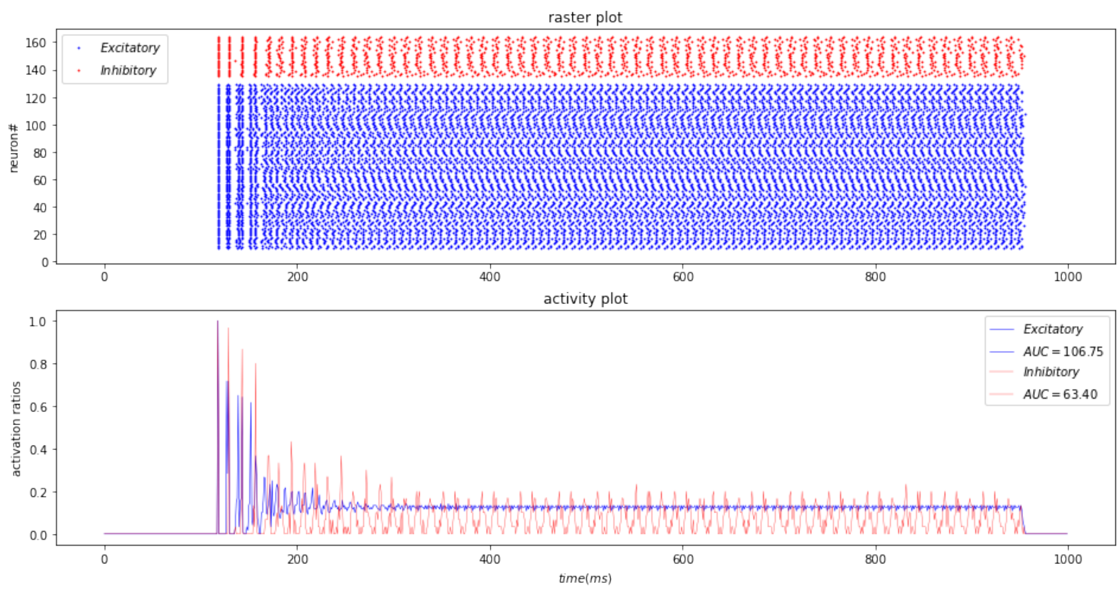
$n_{IE} = 2$

$N = [50, 300]$

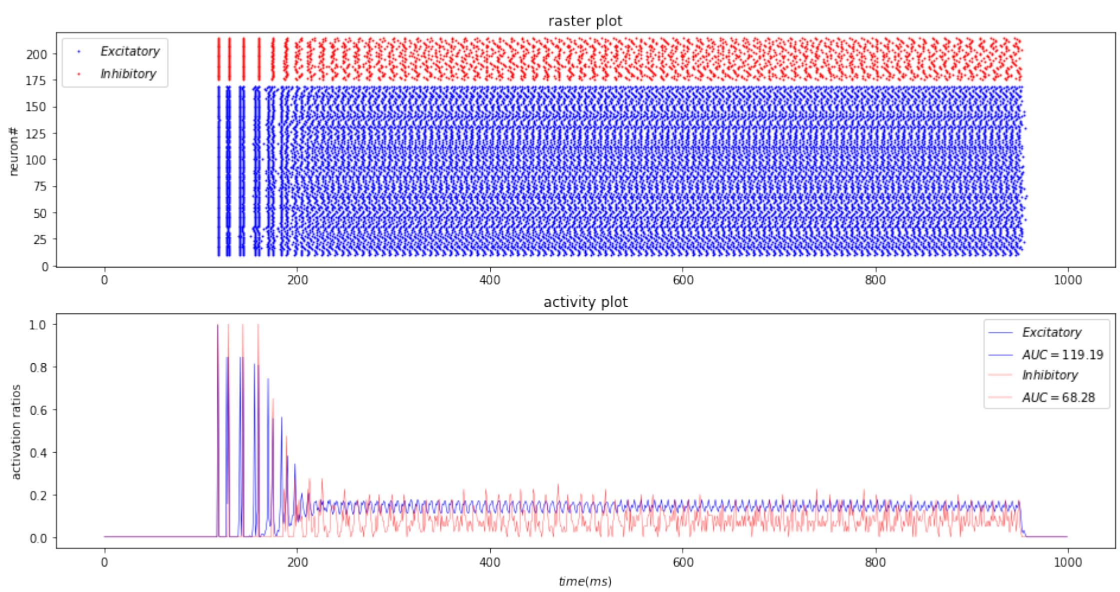


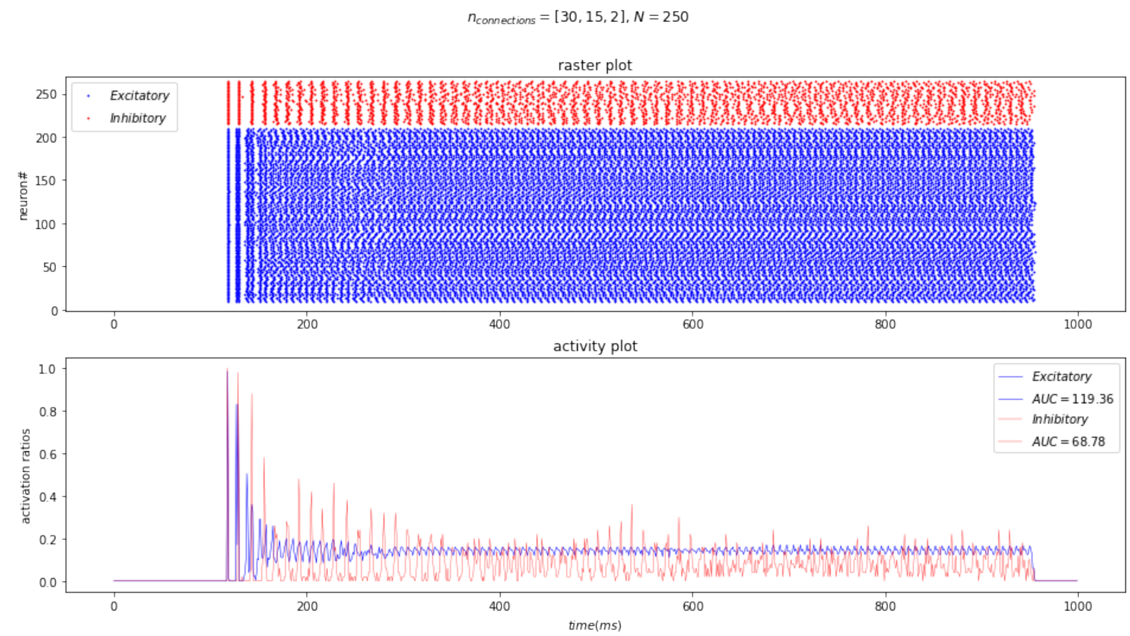


$n_{connections} = [30, 15, 2], N = 150$



$n_{connections} = [30, 15, 2], N = 200$





2.5 Parameter set 4:

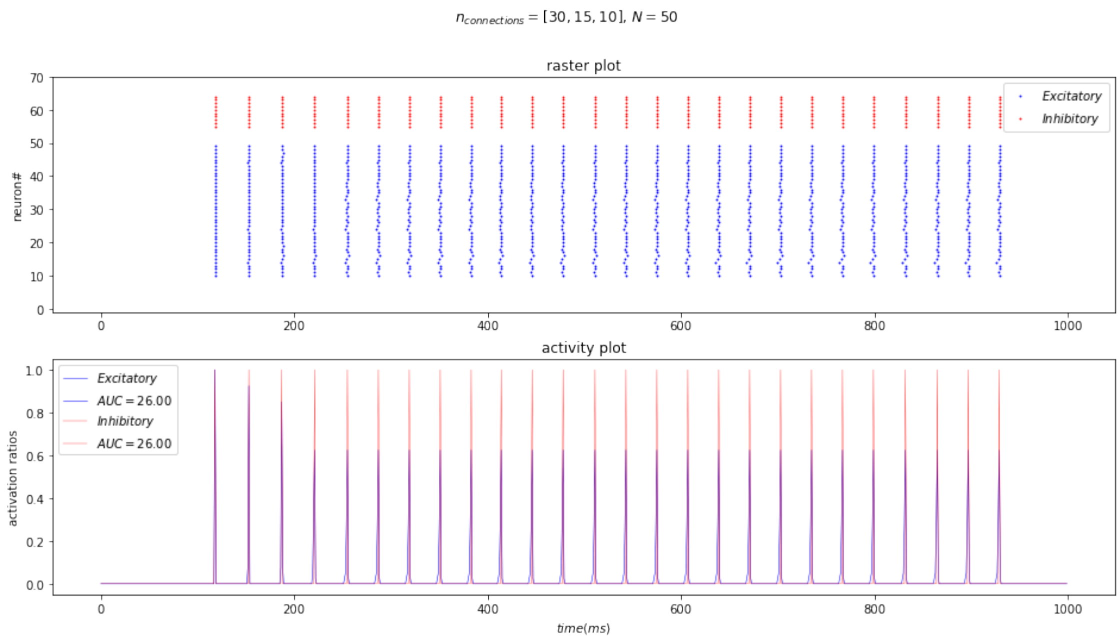
Testing the effect of N when two populations' activity are equal.

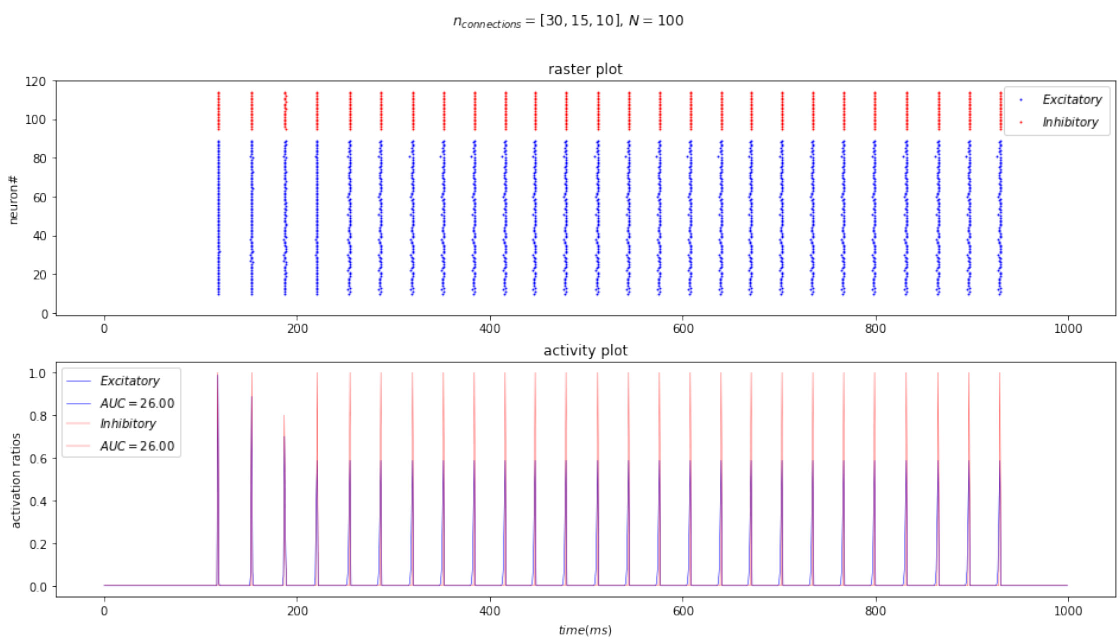
$n_{EE} = 30$

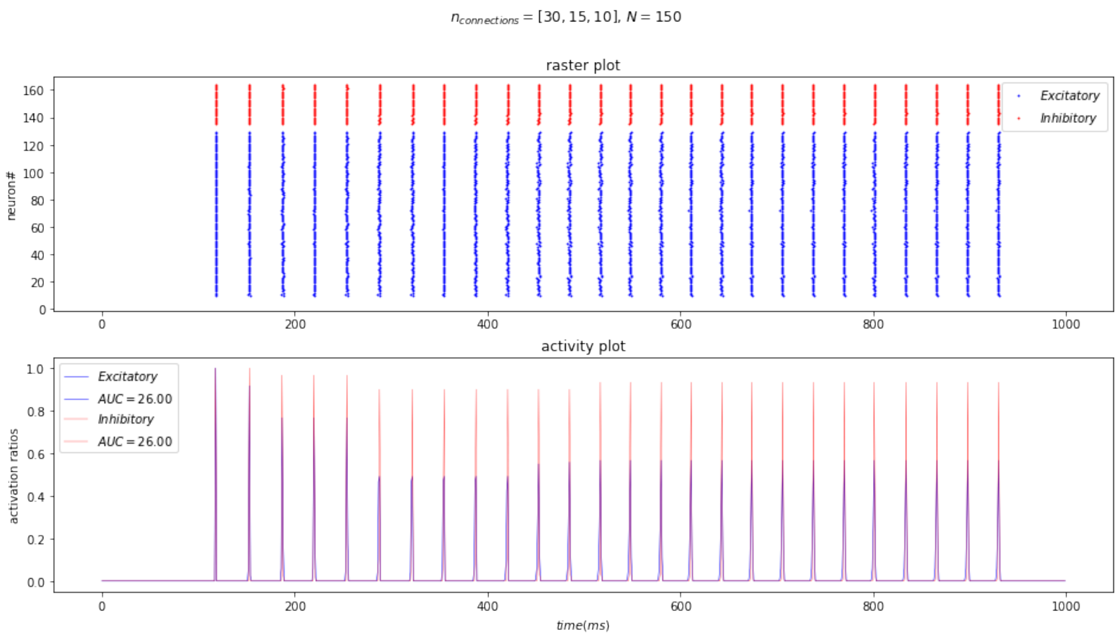
$n_{EI} = 15$

$n_{IE} = 10$

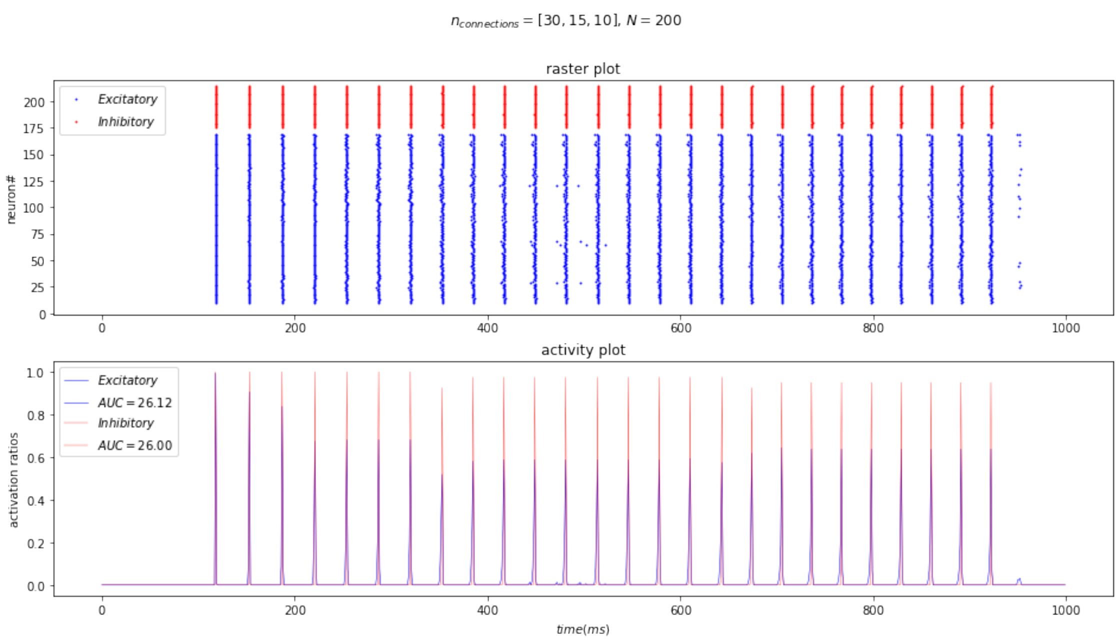
$N = [50, 300]$


$n_{connections} = [30, 15, 10]$, $N = 50$
raster plot
neuron#
Excitatory
Inhibitory
activity plot
activation ratios
Excitatory
$AUC = 26.00$
Inhibitory
$AUC = 26.00$
time(ms)

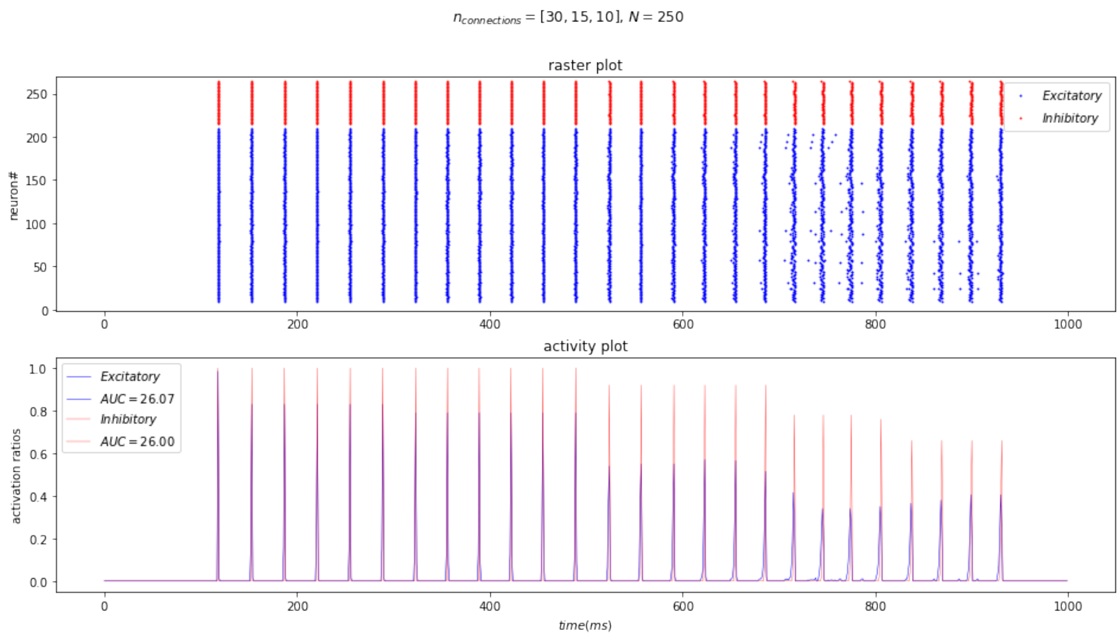

$n_{connections} = [30, 15, 10]$, $N = 100$
raster plot
neuron#
Excitatory
Inhibitory
activity plot
activation ratios
Excitatory
$AUC = 26.00$
Inhibitory
$AUC = 26.00$
time(ms)



$n_{connections} = [30, 15, 10]$, $N = 150$
raster plot
neuron#
Excitatory
Inhibitory
activity plot
activation ratios
Excitatory
$AUC = 26.00$
Inhibitory
$AUC = 26.00$
time(ms)



$n_{connections} = [30, 15, 10]$, $N = 200$
raster plot
neuron#
Excitatory
Inhibitory
activity plot
activation ratios
Excitatory
$AUC = 26.12$
Inhibitory
$AUC = 26.00$
time(ms)



In both of the cases (equal activity or not), the result is the same. The amount of activity of the populations do not change considerably when the number of neurons change. We achieved the same result with dense connections.

The small changes that happen is probably due to the randomness of the connections, and the inter-neuron input noise that we applied.

3 Summary

1. By comparing the result from DenseConnection and RandomConnection experiments, we see that the output of DenseConnections is more predictable in the sense that the populations' activities are regular and more periodic.
2. The effect of J_0s in DenseConnection and $num_{connections}s$ in RandomConnection is very similar.
3. The effect of strengthening EE connection is opposite to strengthening EI and IE connections. This observation is seen in both connection types.
4. Changing the total neuron's count do not change the populations' behaviour significantly.
5. The connection from the inhibitory population to the excitatory population (IE), affects the system more than the other two.
6. In both of the setups, with minimal parameter tuning we could create a balanced network.