Impact of Different Mechanisms on the Learning of Neurons

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1. Introduction

The following table is the set of parameters of the LIF neuron model in the output layer and it is fixed throughout the report. If any of them is changed in the next sectiones it will be mentioned.

Parameter	Value
u_{rest}	-60
u_{reset}	-65
u_{init}	N(-50, 10)
$threshold$	-47
R	8
τ	10
$Time\ Resolution$	0.1

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

2. Learning Process on Patterns

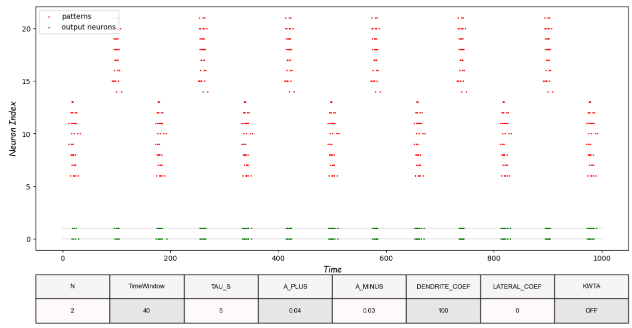


Figure 1

Without any extra mechanism, both of the output neurons learn both of the patterns if it can be called learning. Both of them become sensitive to both of the patterns and react when any of them is presented.

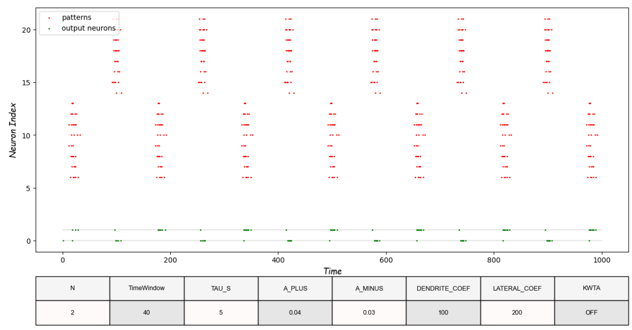


Figure 2

By adding the Lateral-Inhibition to the learning process, the output neurons become sensitive to only one of the patterns after some time (in this figure, after about 100 iterations). But there are some noises in the neurons' responses and they have some spikes when the other pattern is presented. This is because of the noise in the patterns and the parameters of the model. These noises can be seen only at the beginning of the time windows of the pattern presentation, and when the of that specific pattern is activated, it inhibites the other one and make it silent. This can be removed by parameter tuning.

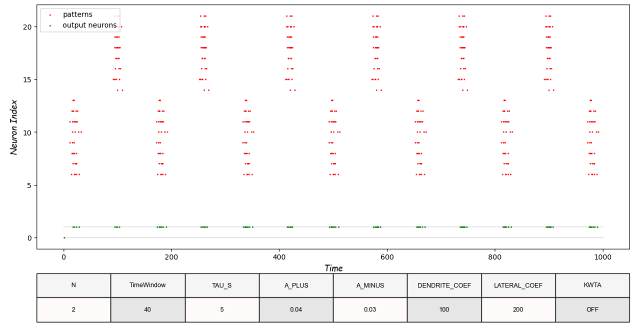


Figure 3

But this is not always the case with only the Lateral-Inhibition being on! As it can be seen in the figure 3, one neuron becomes sensitive to both of the patterns and inhibites the other.

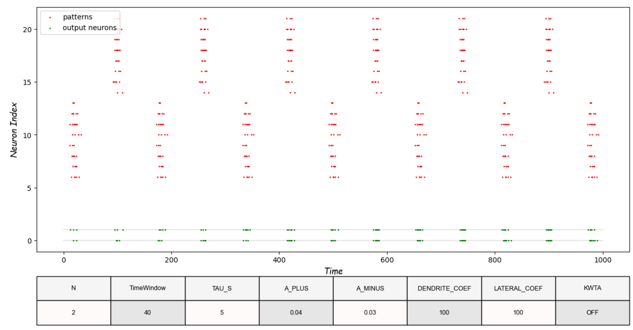
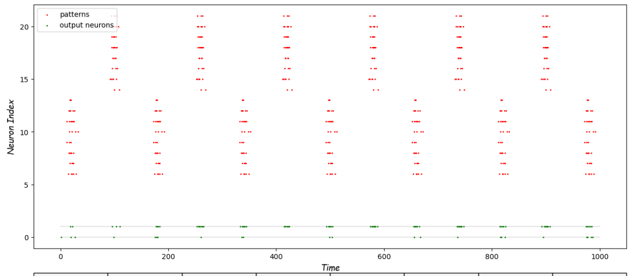


Figure 4

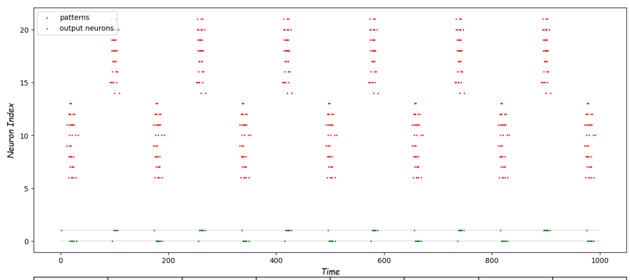
This is another case where it doesn't work as expected. the randomness in the initial values of the LIF neuron model parameters makes the Lateral-Inhibition mechanism seem effectless. This can be removed by increasing the threshold of the output neurons. If the threshold is increased, the neuron will need more input to be activated and when one of them is activated, the other will be inhibited. Becuase of the randomness I couldn't generate a figure for this case.



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	40	5	0.04	0.03	100	0	1

Figure 5

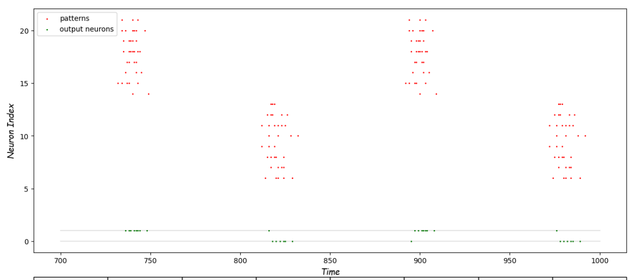
Here, with KWTA being on, and Lateral-Inhibition being off, the output neurons don't learn the patterns well because of the low density of the firing phase of the output. The low probability of the output neurons to fire simultaneously makes the learning process totally dependent on the initial values of the neurons and the randomness of the patterns. If the density of the spiking phase of the outputs is low, the KWTA mechanism alone is not effective.



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	40	5	0.04	0.03	100	200	1

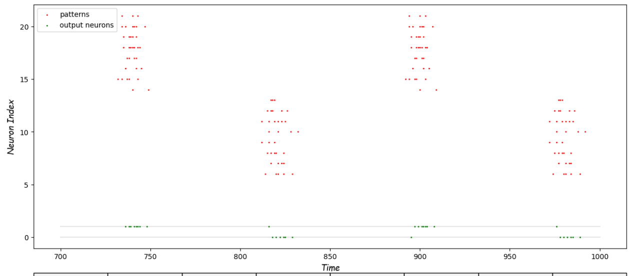
Figure 6

With both KWTA and Lateral-Inhibition, the output neurons learn the patterns well and become sensitive to only one of them. The KWTA mechanism makes the output neurons not to fire simultaneously and the fired one inhibits the other. In this case the probability of the output layer to learn the patterns well is high. But this also is not always the case. Only the probability of a good result is higher.



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	40	5	0.04	0.03	100	200	1

Figure 7. *Last 300 iterations of a good result with the parameters in the table.*



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	40	5	0.04	0.03	100	200	1

Figure 8. *Last 300 iterations of a good result with the parameters in the table.*

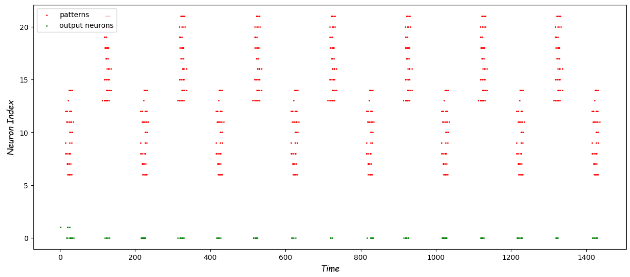
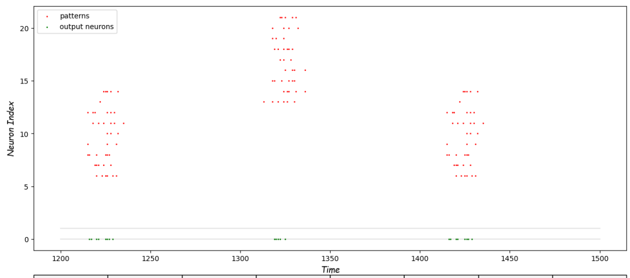


Figure 9. *intersection = 2 neurons*



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	50	5	0.4	0.4	200	500	OFF

Figure 10. *Last 300 iterations of the previous figure.*

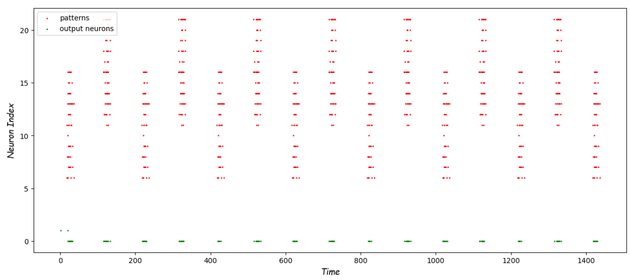


Figure 11. *intersection = 3 neurons*

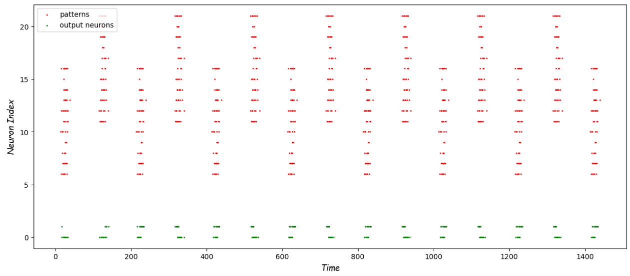


Figure 12. *intersection = 3 neurons*

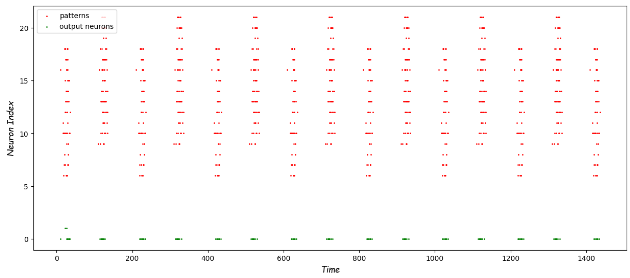
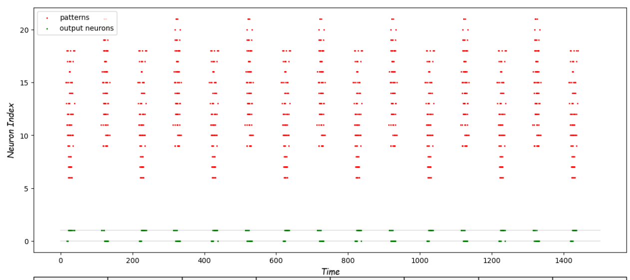


Figure 13. *intersection = 5 neurons*

Almost in all cases when patterns do have intersections, one of the neurons become sensitive to the first given pattern and inhibites the other. And when the next pattern is presented, the same neuron is activated since its synaptic weight is increased in the previous phase and inhibites the other neuron and this process continues.



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
2	50	5	0.4	0.4	200	OFF	1

Figure 14. *intersection = 5 neurons*

Here when there is only KWTA, without Lateral-Inhibition, both of them become sensitive to both patterns and the reason is obvious.

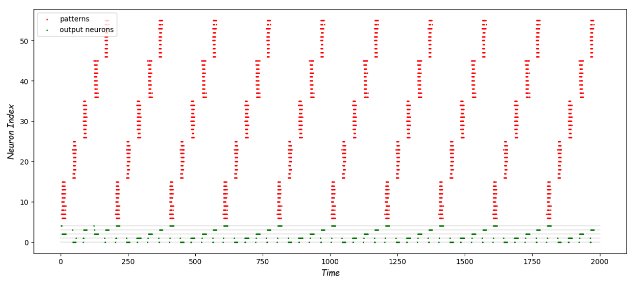


Figure 15

N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
10	20	5	30	20	1000	55	1

Figure 16. *Last 200 iterations of the previous figure.*

Here there are five different patterns and output neurons. In this process there is no homostasis mechanism and the neurons learn the patterns perfectly. At the beginning, neurons react randomly to different patterns. But after about 200 iterations, they become sensitive to only one of the patterns and the weight of the synapses is set perfectly in order to react to only one of the patterns.

But this is not always the case since the number of synaptic weight is high and the probability of the output neurons to learn the patterns well is low. In other words it totally depends on the initial values and the pattern itself since it has a random nature.

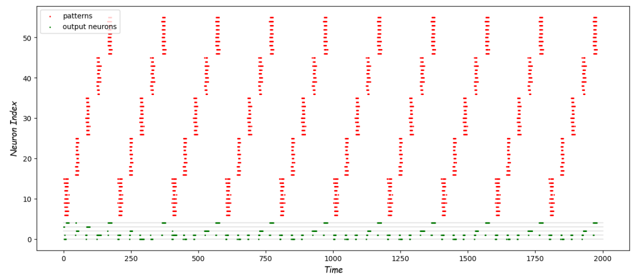


Figure 17

N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
10	20	5	30	20	1000	55	1

Figure 18. *Last 200 iterations of the previous figure.*

For instance, in this case, the second output neuron has become silent, and the last two neurons doesn't seem to be learn at all. This probability of not learning can be decreased by adding the homostasis mechanism which modifies the threshold of the output neurons and tries to keep the firing rate of the output neurons in a specific range.

In figure 16, it can be seen that in a perfect learning process, each output neuron fires about 10 times when its pattern is presented. So we set the activity rate of the homostasis to be 10.

The following figure is a typical result of the learning process with the three mechanisms combined.

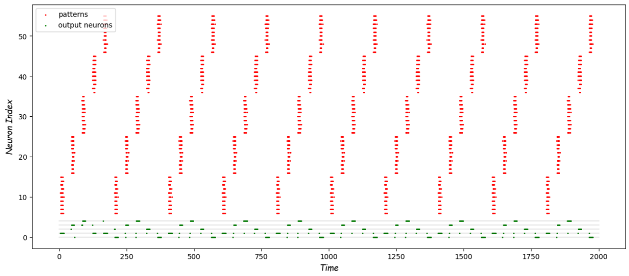
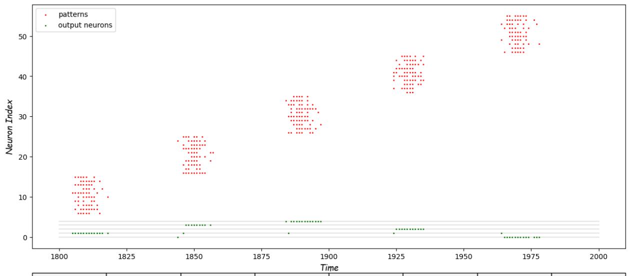


Figure 19



N	TimeWindow	TAU_S	A_PLUS	A_MINUS	DENDRITE_COEF	LATERAL_COEF	KWTA
10	20	5	30	20	1000	55	1

Figure 20. *Last 200 iterations of the previous figure.*

From now on, we keep the lateral inhibition, KWTA, STDP, and synaptic coefficient parameters fixed and analyze the impact of the homostasis parameters on the learning process.

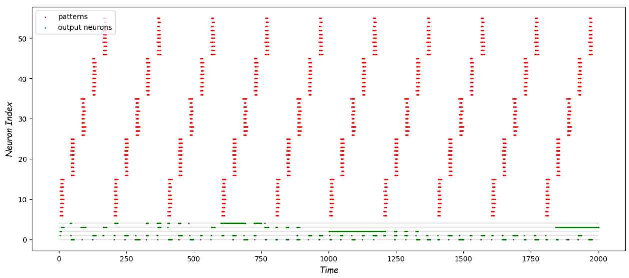
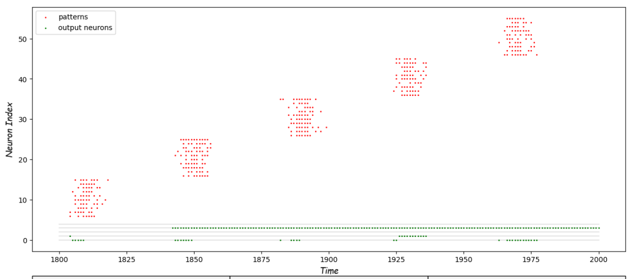


Figure 21



Activity rate	Updating rate	Decay rate
20	1	0.85

Figure 22. *Last 200 iterations of the previous figure.*

Here when we set the activity rate of the output neurons to be 20, which we know that it is not the case, the threshold of the neurons don't change properly and in result, they don't become sensitive to the patterns well. See the next figure.

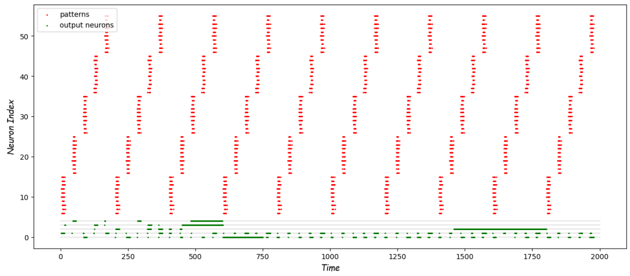


Figure 23

Activity rate	Updating rate	Decay rate
20	1	0.85

Figure 24. *Last 200 iterations of the previous figure.*

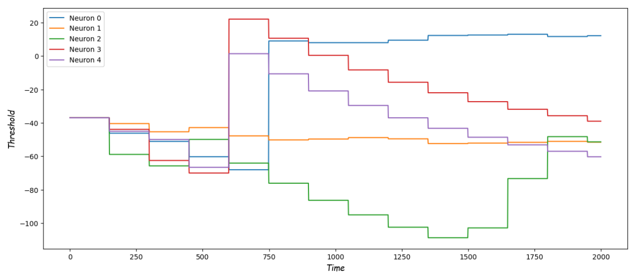


Figure 25

Here as it can be seen, the threshold of the Neuron2 is decrease significantly since it couldn't fire properly. And this, is because of the activity rate parameter is not realistic.

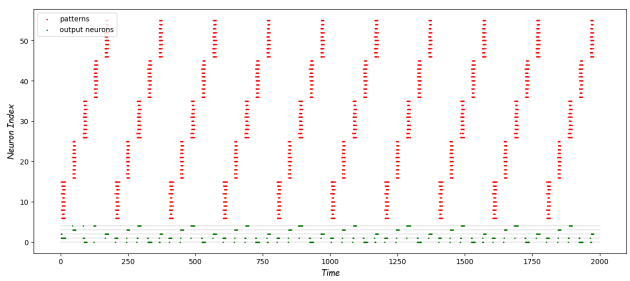
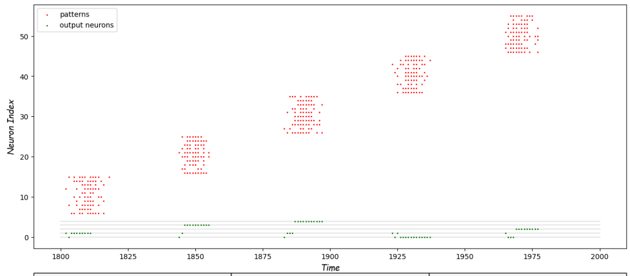


Figure 26



Activity rate	Updating rate	Decay rate
10	1	0.85

Figure 27. *Last 200 iterations of the previous figure.*

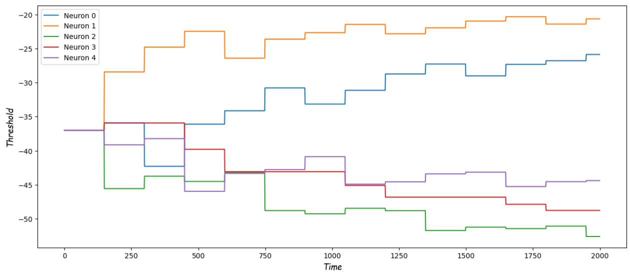


Figure 28

But this is a reasonable dynamic and change for the thresholds in a good learning process.

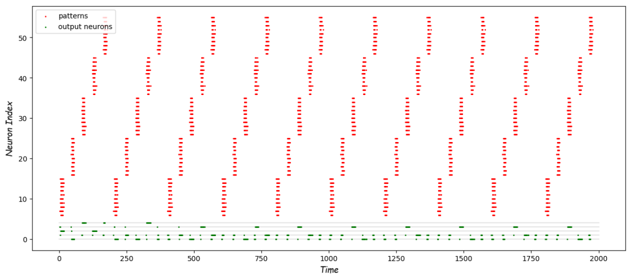


Figure 29

Activity rate	Updating rate	Decay rate
10	0.1	0.85

Figure 30. *Last 200 iterations of the previous figure.*

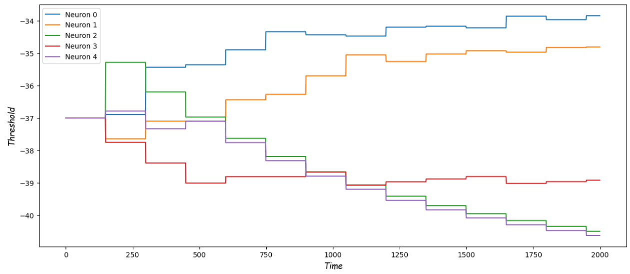


Figure 31

Setting the updating rate to be very low, makes the homostasis effectless as it is seen in the previous figure.

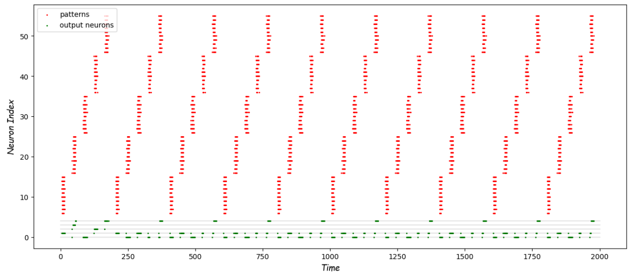


Figure 32

Activity rate	Updating rate	Decay rate
10	1	0.1

Figure 33. *Last 200 iterations of the previous figure.*

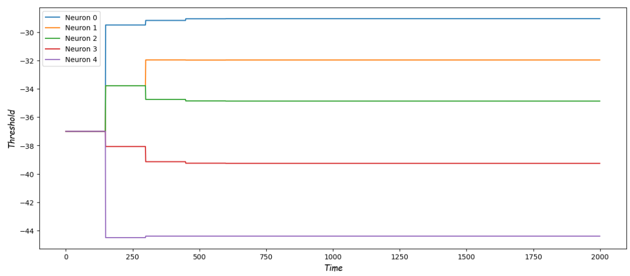
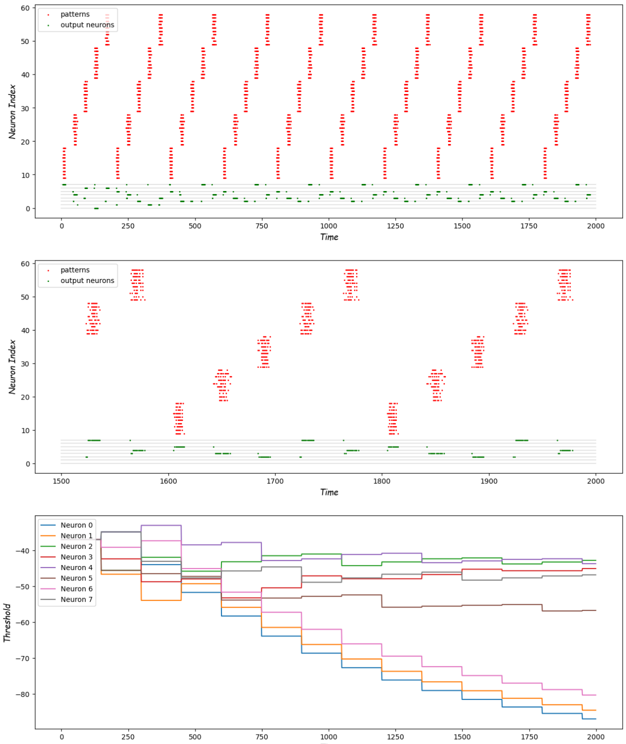


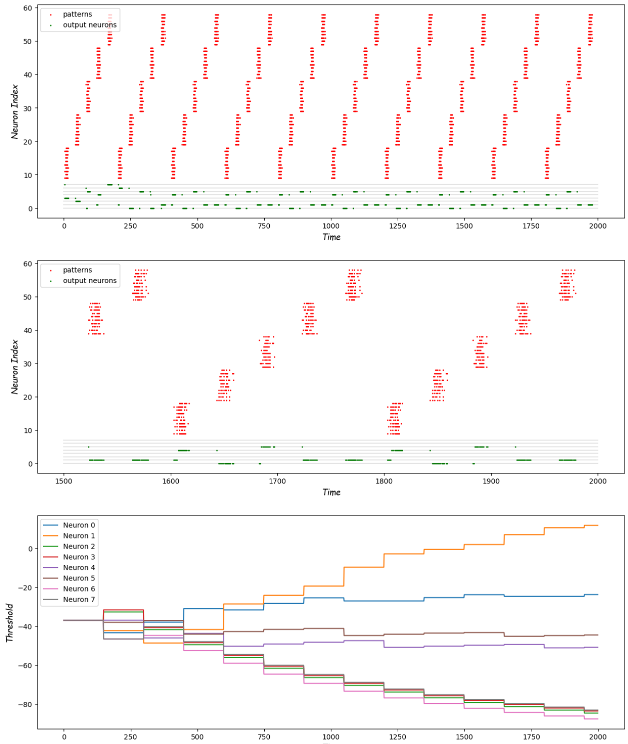
Figure 34

Also decreasing the decay rate, makes the updating rate to fall quickly and make the mechanism effectless similarly.



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
8	10	1	0.85	150	20	30	1	55	1000

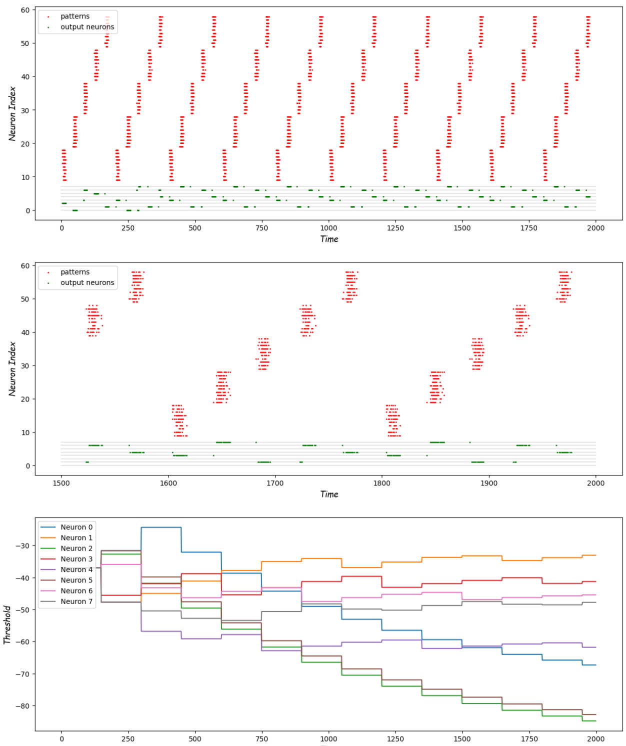
Figure 35



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
8	10	1	0.85	150	20	30	1	55	1000

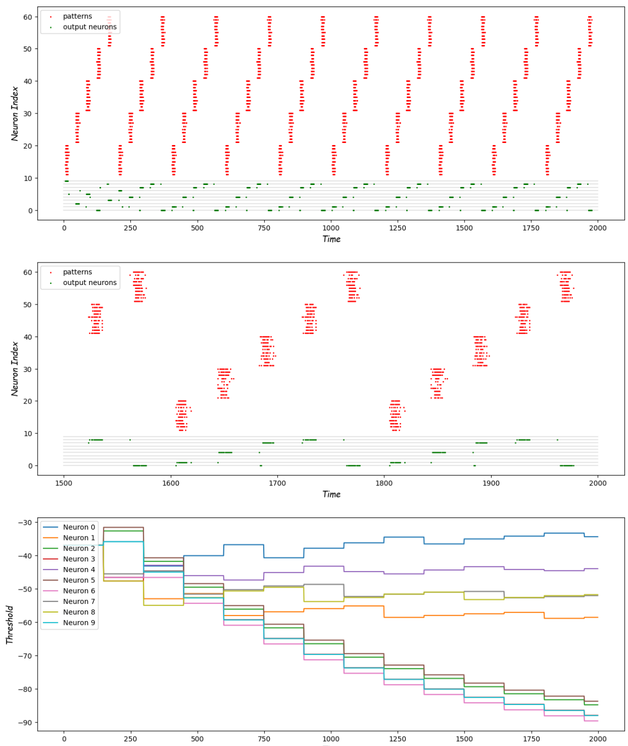
Figure 37

When the number of output neurons are greater than the number of patterns, almost always all patterns are learned by some neuron and sometimes some patterns are learned by more than one neuron and some neurons stay silent (previous figure and the next ones).



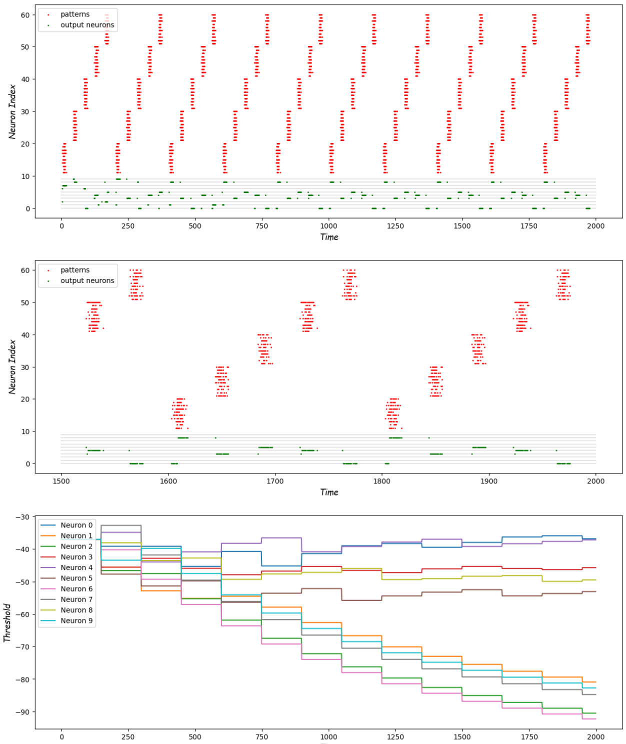
N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
8	10	1	0.85	150	20	30	1	55	1000

Figure 36



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
10	10	1	0.85	150	20	30	1	55	1000

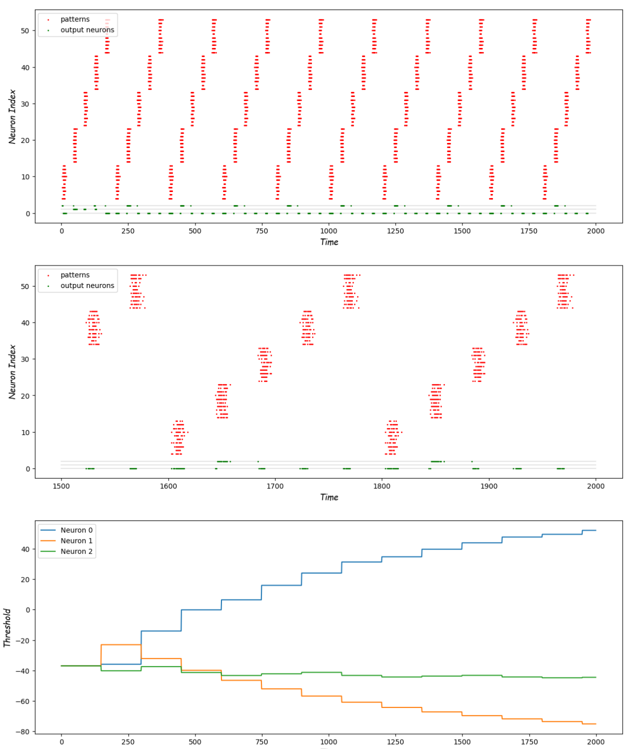
Figure 38



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
10	10	1	0.85	150	20	30	1	55	1000

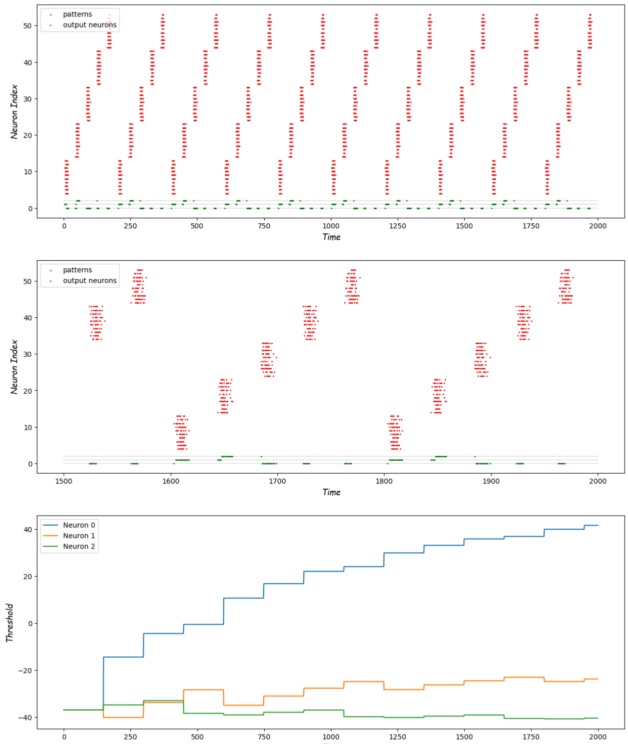
Figure 39

Now when the number of patterns is greater than the number of output neurons, the result can be same. Meaning that almost always all patterns are learned by some neuron and sometimes some patterns are learned by more than one neuron and some of them may stay silent.



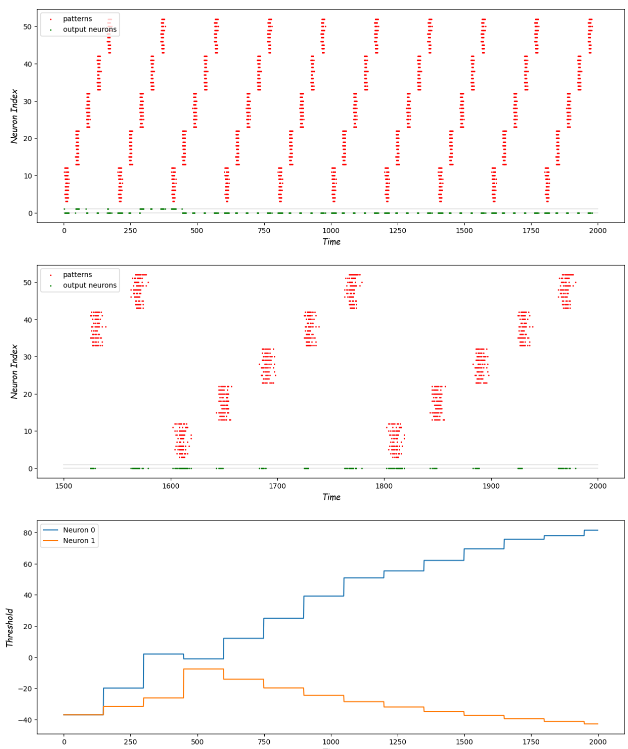
N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
3	10	1	0.85	150	20	30	1	55	1000

Figure 40



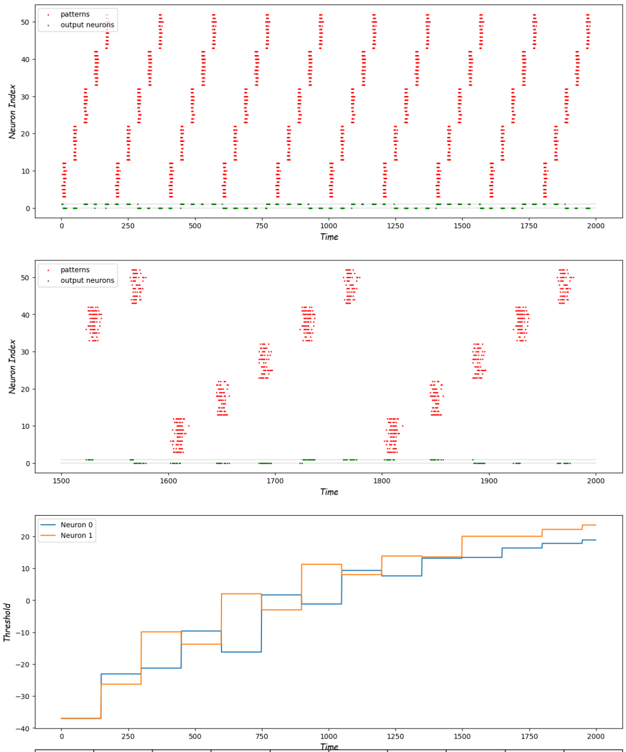
N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
3	10	1	0.85	150	20	30	1	55	1000

Figure 41



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
2	10	1	0.85	150	20	30	1	55	1000

Figure 42



N	Activity rate	Updating rate	Decay rate	Window size	A_MINUS	A_PLUS	K	Lat. coef	Syn. coef
2	10	1	0.85	150	20	30	1	55	1000

Figure 43