Practice 4

Exercise 3

Character recognition. Self-organizing network.

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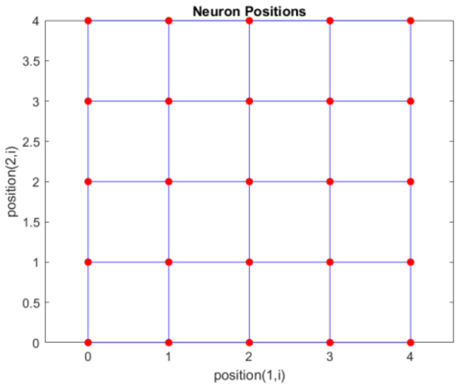
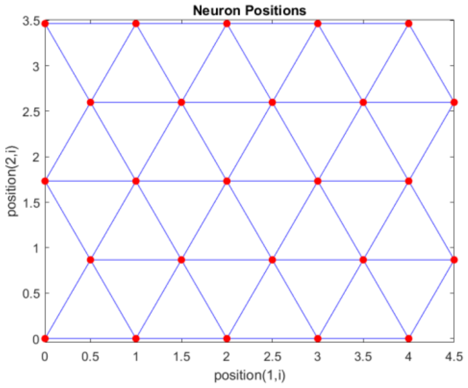
Parameters to explore

- Network topology

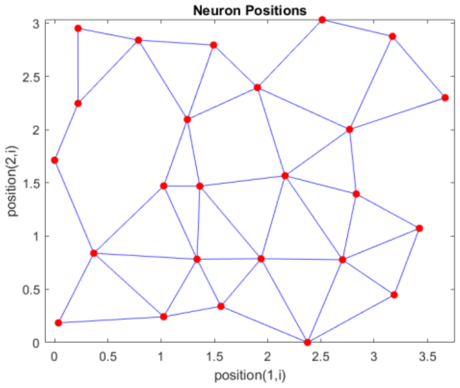
Gridtop



Hextop



Randtop



We will try 1D, 2D and 3D topologies (3D only for small numbers)

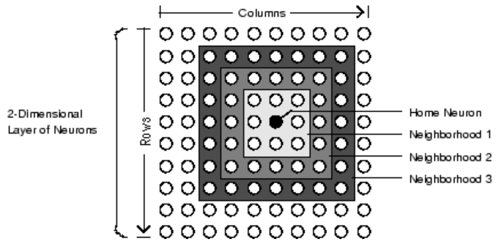
- Number of neurons

Parameters to explore

- Distance issues (depth of vicinity, distance calculation approach)

  dist: Euclidean distance

  linkdist: The *link distance* from one neuron is just the number of links, or steps, that must be taken to get to the neuron under consideration

  boxdist: 

  mandist: Manhattan distance

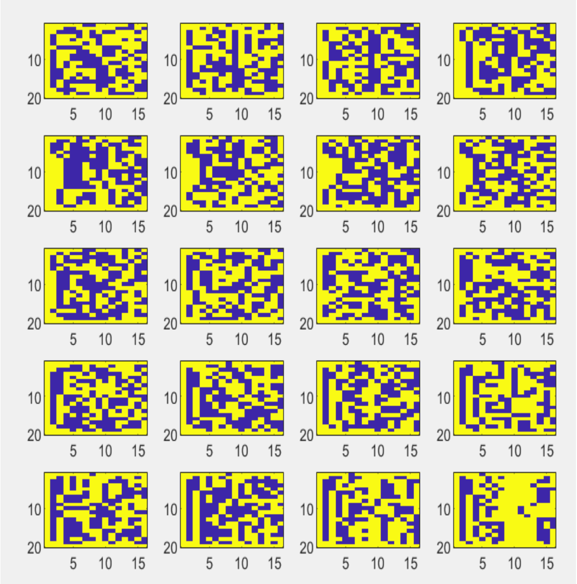
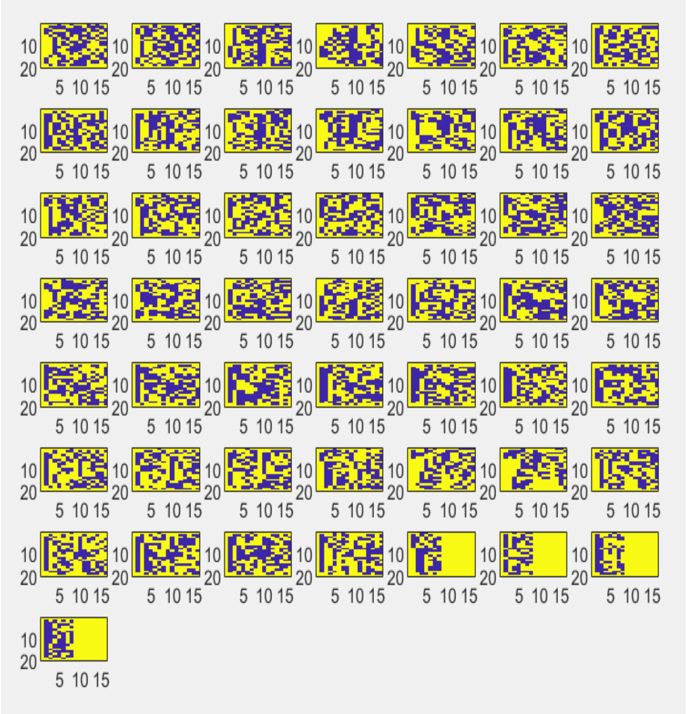
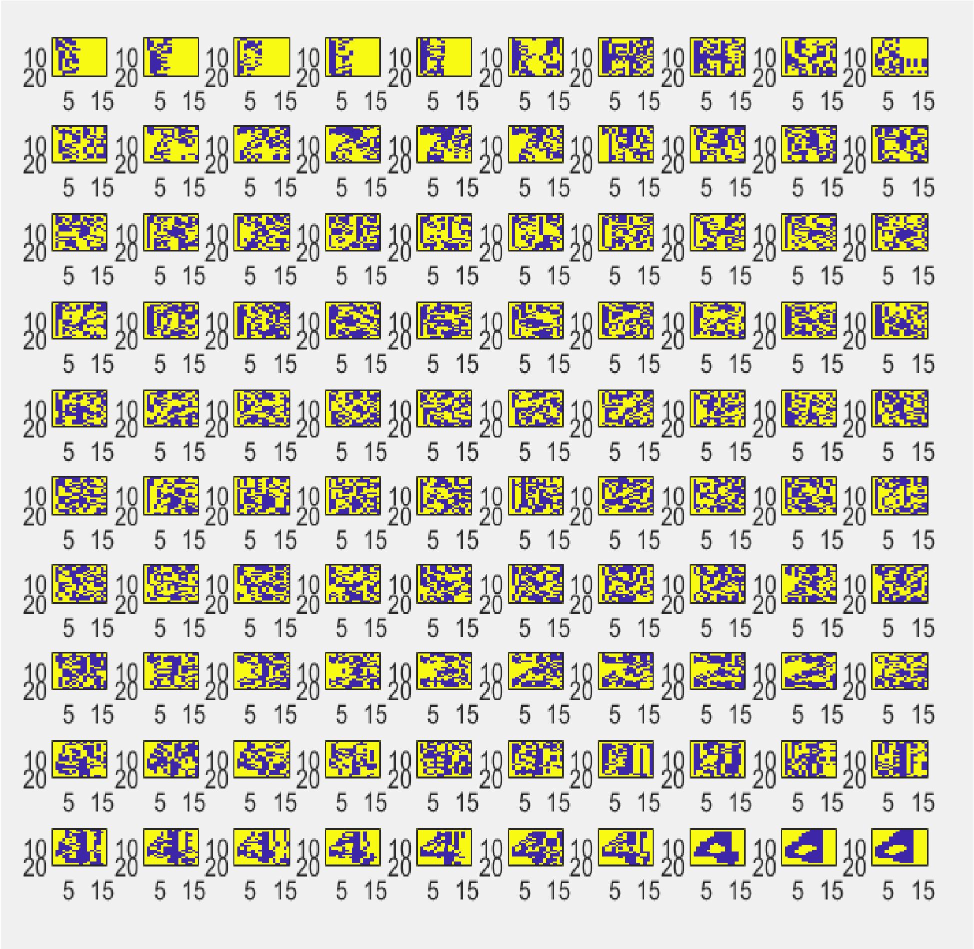
- Number of iterations

Behavior assessment

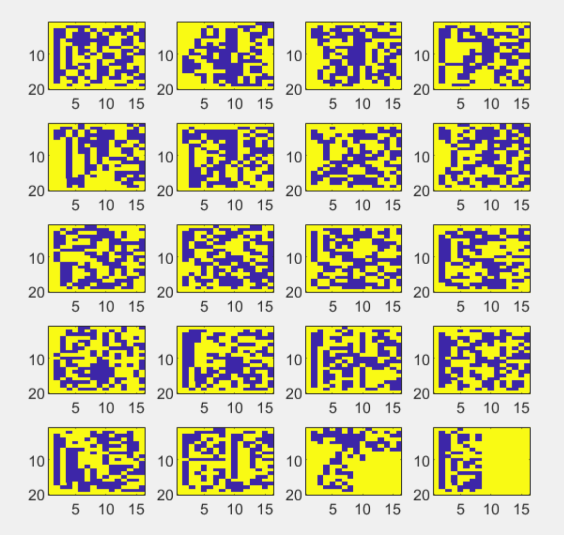
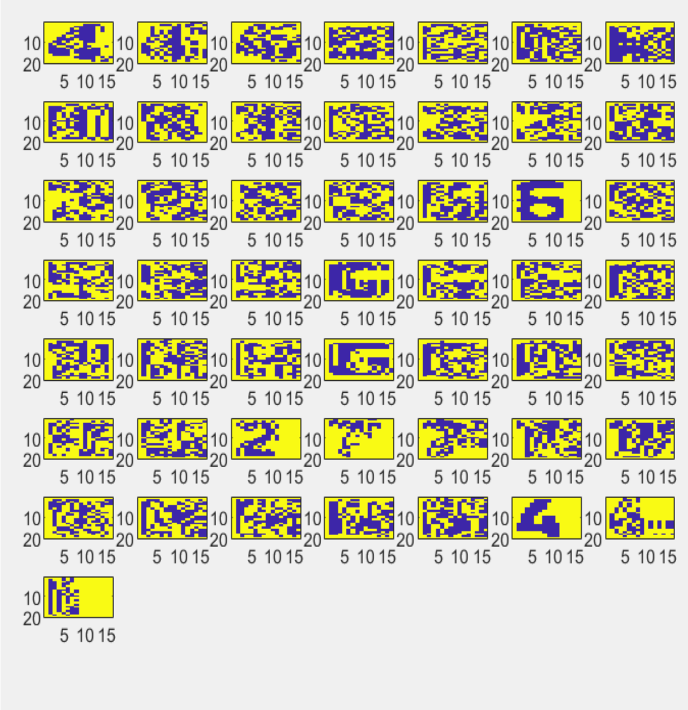
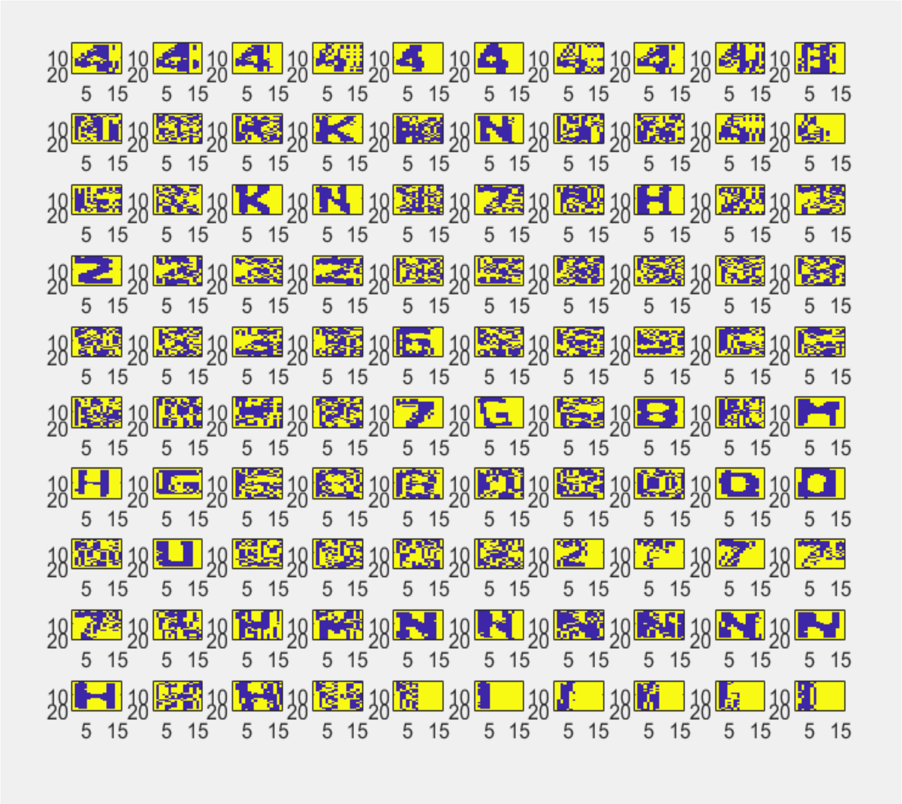
We will estimate how good or bad the system works from human point of view, e.g. we will count a number of “sufficiently recognizable symbols”, which is obviously quite a subjective measure.

1D topologies

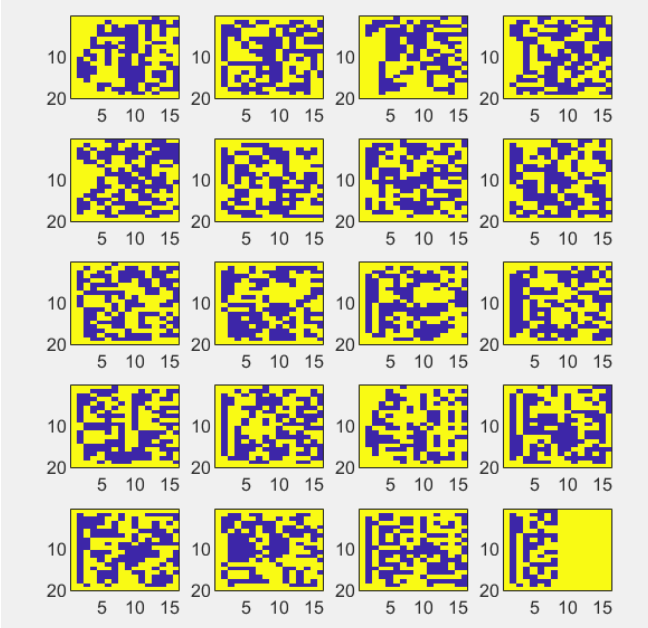
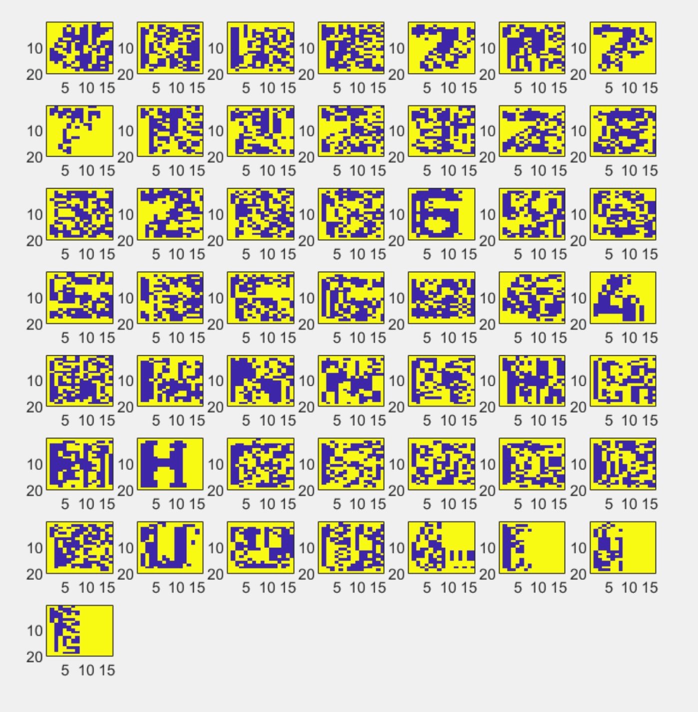
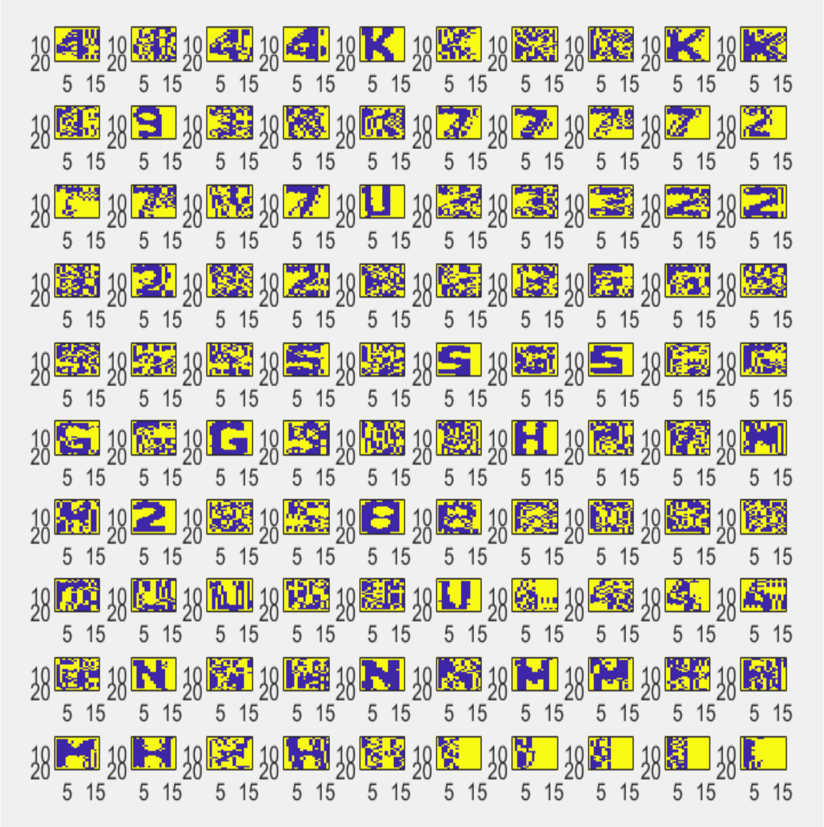
Neighbourhood size: 1

20 neurons	**50 neurons**	**100 neurons**
		
Sufficiently recognizable: 0 (0%)	Sufficiently recognizable: 4 (~8%) Most common outputs: "1"	Sufficiently recognizable: 21 (~21%) Most common outputs: "1", "4", "7", "2"

Neighbourhood size: 3

20 neurons	50 neurons	100 neurons
		
Sufficiently recognizable: 2 (~10%) Most common outputs: “1”, “7”	Sufficiently recognizable: 8 (~16%) Most common outputs: “4” – 2 “G” – 2	Sufficiently recognizable: 42 (~42%) Most common outputs: “1” – 6 “4” – 6 “7” – 6 “N” – 8

Neighbourhood size: 5

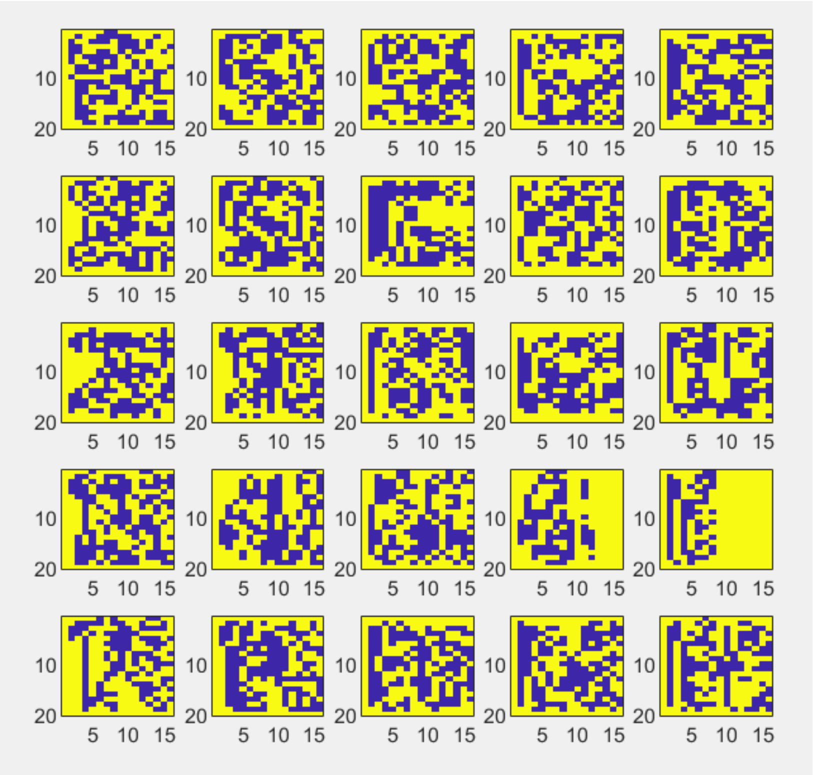
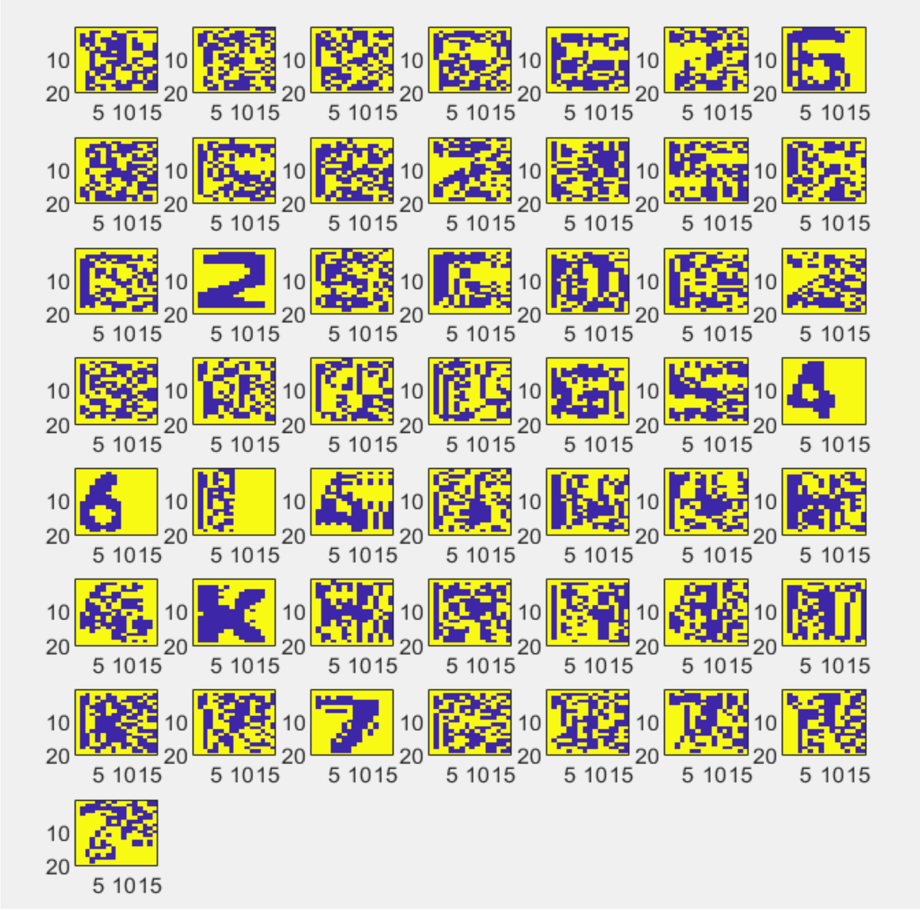
20 neurons	**50 neurons**	**100 neurons**
		
Sufficiently recognizable: 1 (~5%) Most common outputs: “1”	Sufficiently recognizable: 12 (~24%) Most common outputs: “7” – 3 “3” – 3 “4” – 2	Sufficiently recognizable: 54 (~54%) Most common outputs: “1” – 5 “4” – 6 “7” – 7 “K” – 5

Conclusion:

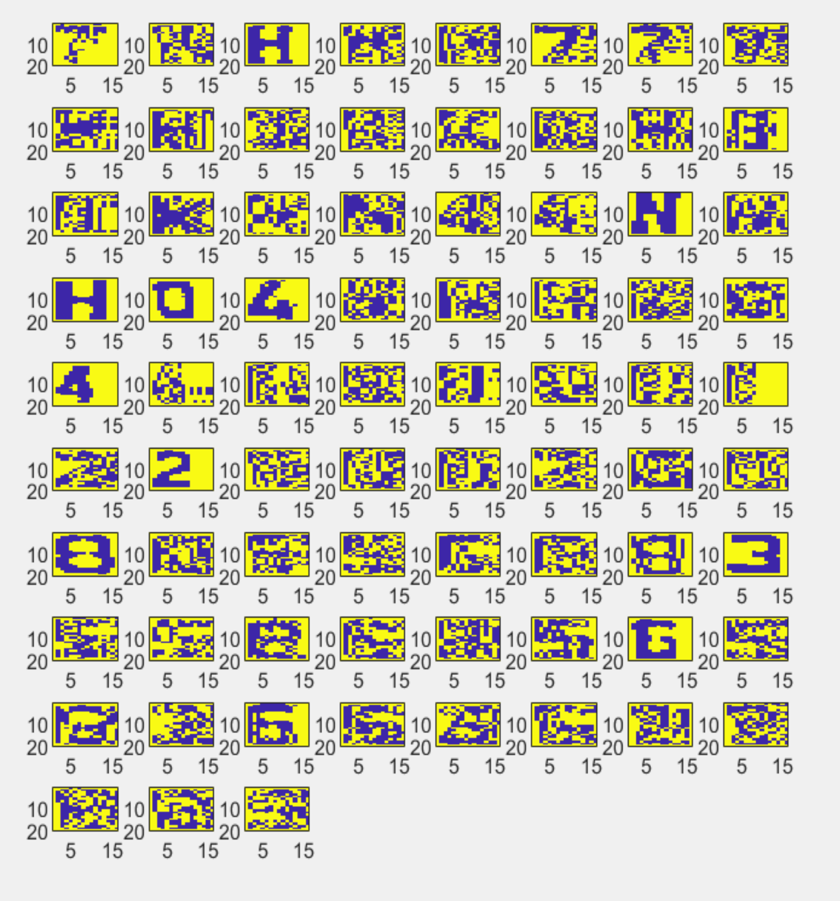
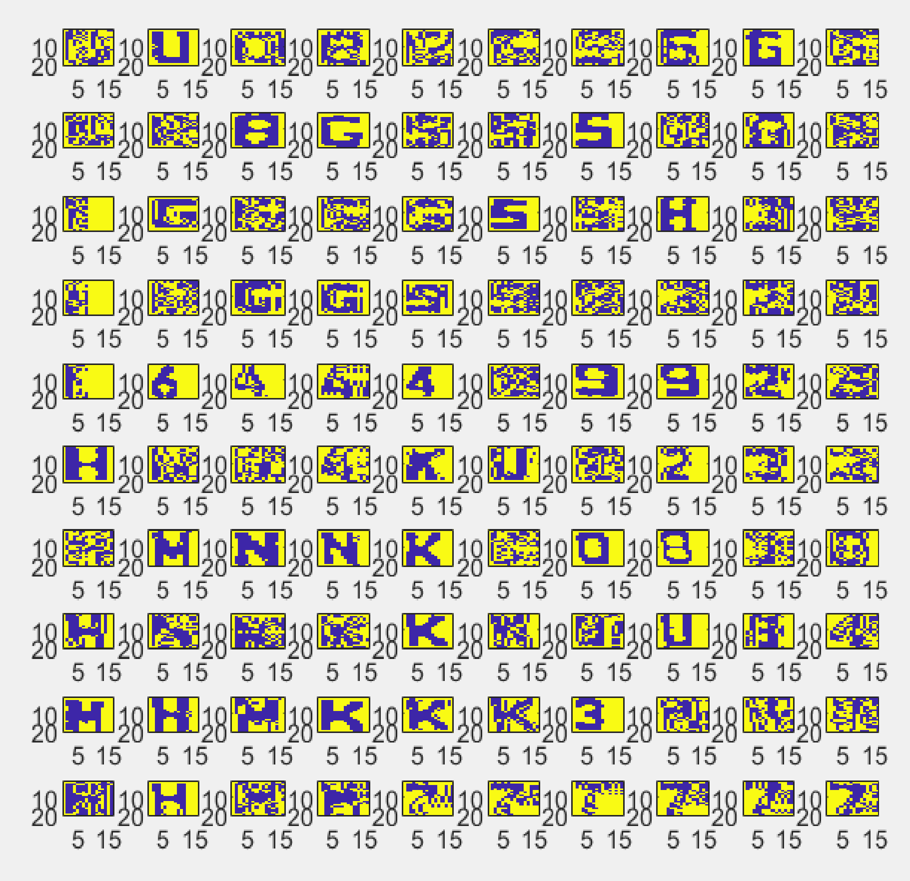
For 1D topology we obtained the best result (54% of sufficiently recognizable symbols) with 100 neurons and neighbourhood size 5. With neighborhood equal to 1 we’ve got very weak recognition ability, with 3 - rather good. We also noticed that the most recognizable outputs were “4”, “7”, “1”, “N”, “K”, “G”, “2”.

2D topologies

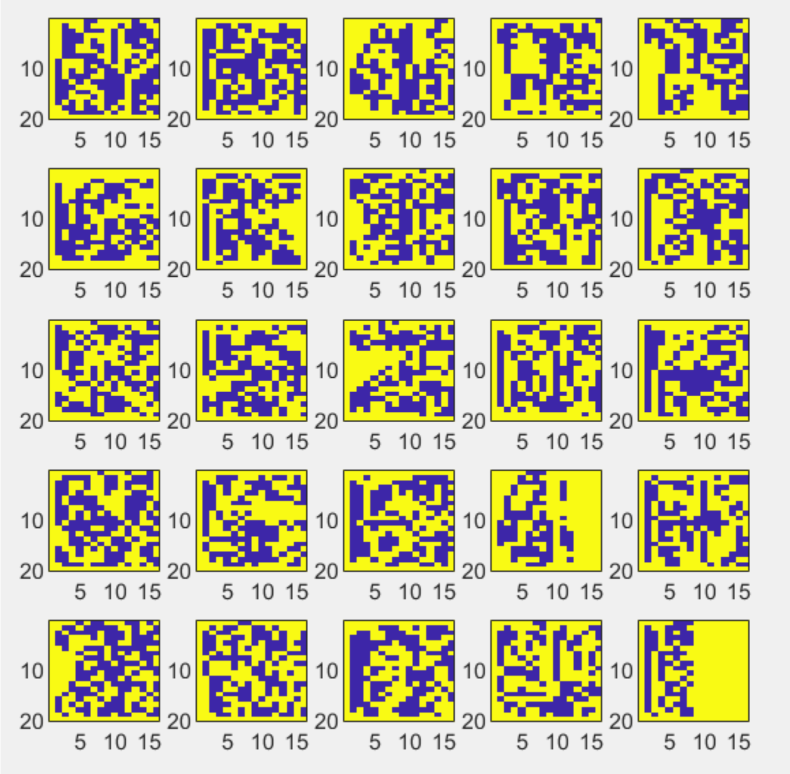
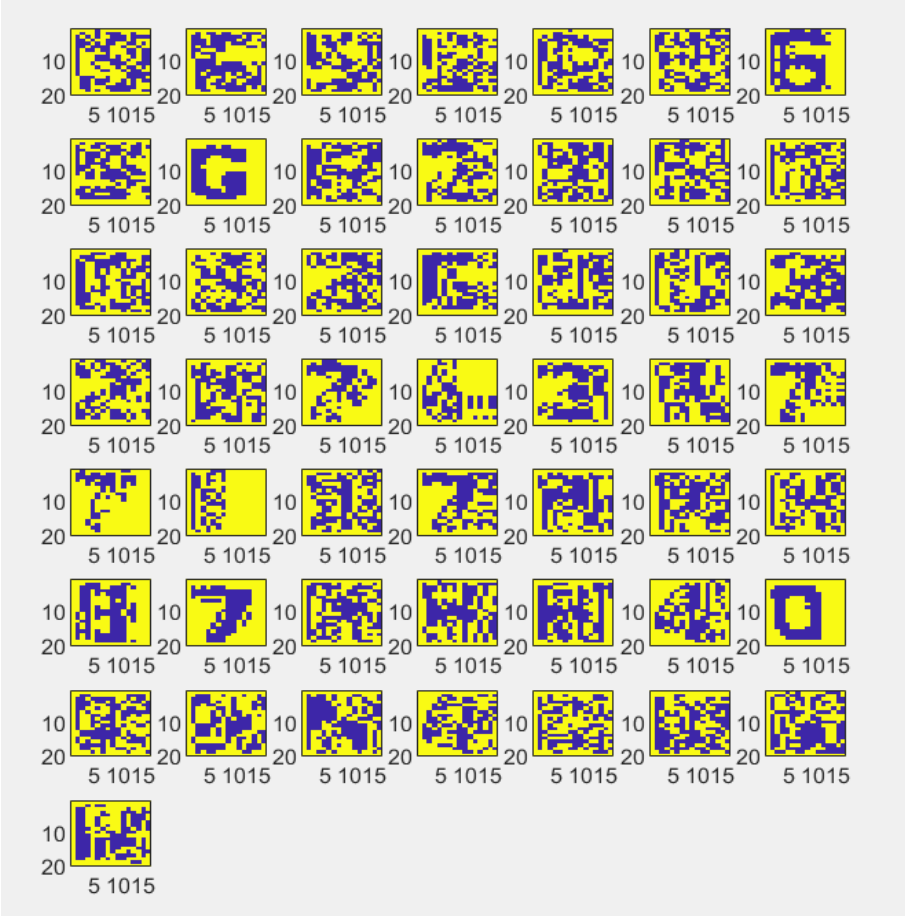
Neighbourhood size: 3

25 neurons (5*5)	50 neurons (5*10)
	
Sufficiently recognizable: 4 (~16%) Most common outputs: “1”, “G”, “K”, “4”	Sufficiently recognizable: 16 (~32%) Most common outputs: “4”, “6”, “K”, “7”, “2”

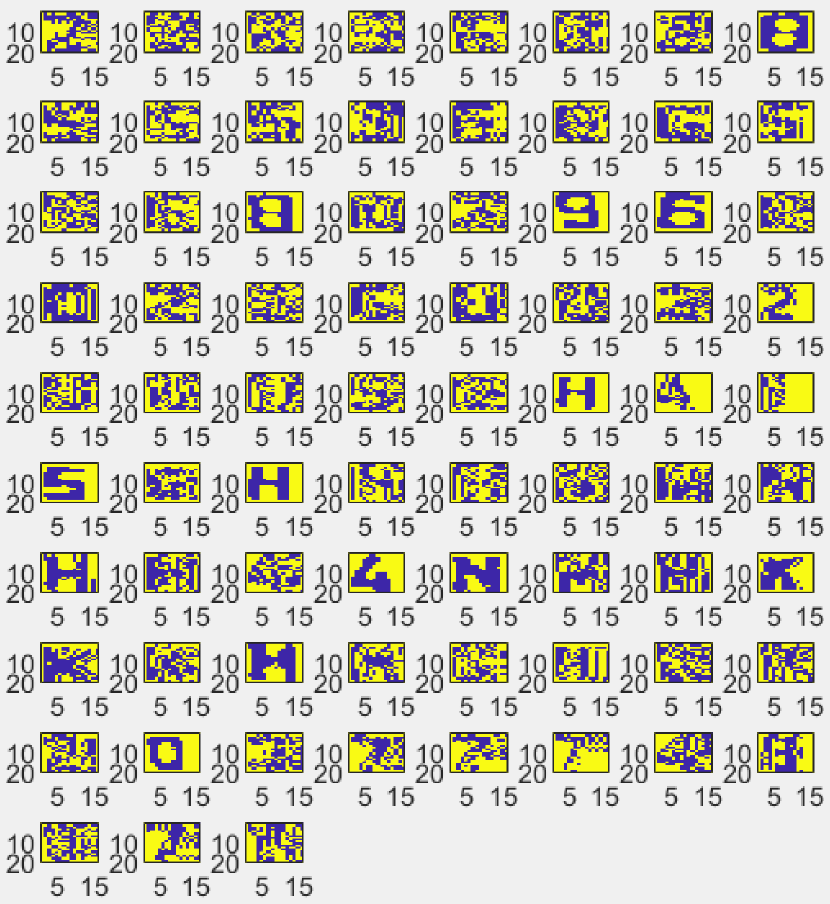
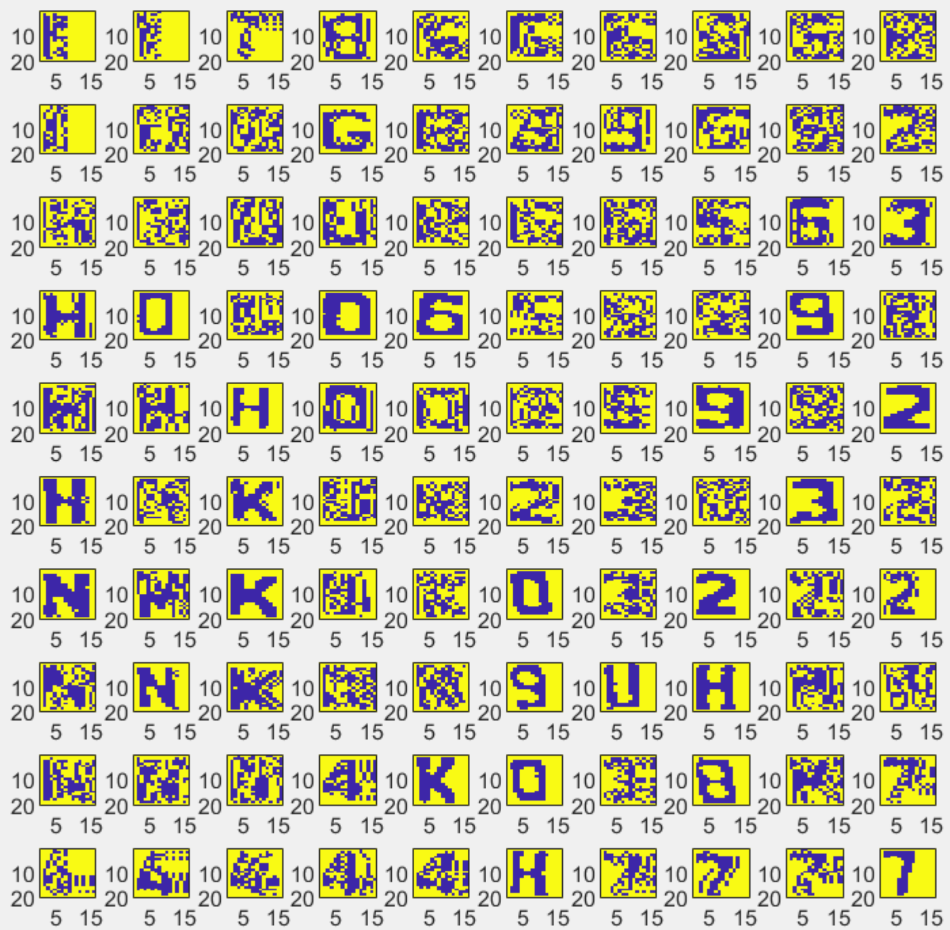
Neighbourhood size: 3

75 neurons (5*15)	100 neurons (10*10)
	
Sufficiently recognizable: 36 (~48%) Most common outputs: “7”, “G”, “6”, “4”, “H”, “2”, “0”	Sufficiently recognizable: 73 (~73%) Most common outputs:: “7”, “9”, “6”, “G”, “H”, “K”, “N”, “4”

Neighbourhood size: 5

25 neurons (5*5)	**50 neurons (5*10)**
	
Sufficiently recognizable: 4 (~16%) Most common outputs: “1”, “2”, “K”, “4”	Sufficiently recognizable: 21 (~42%) Most common outputs:“7”, “6”, “G”, “K”, “2”

Neighbourhood size: 5

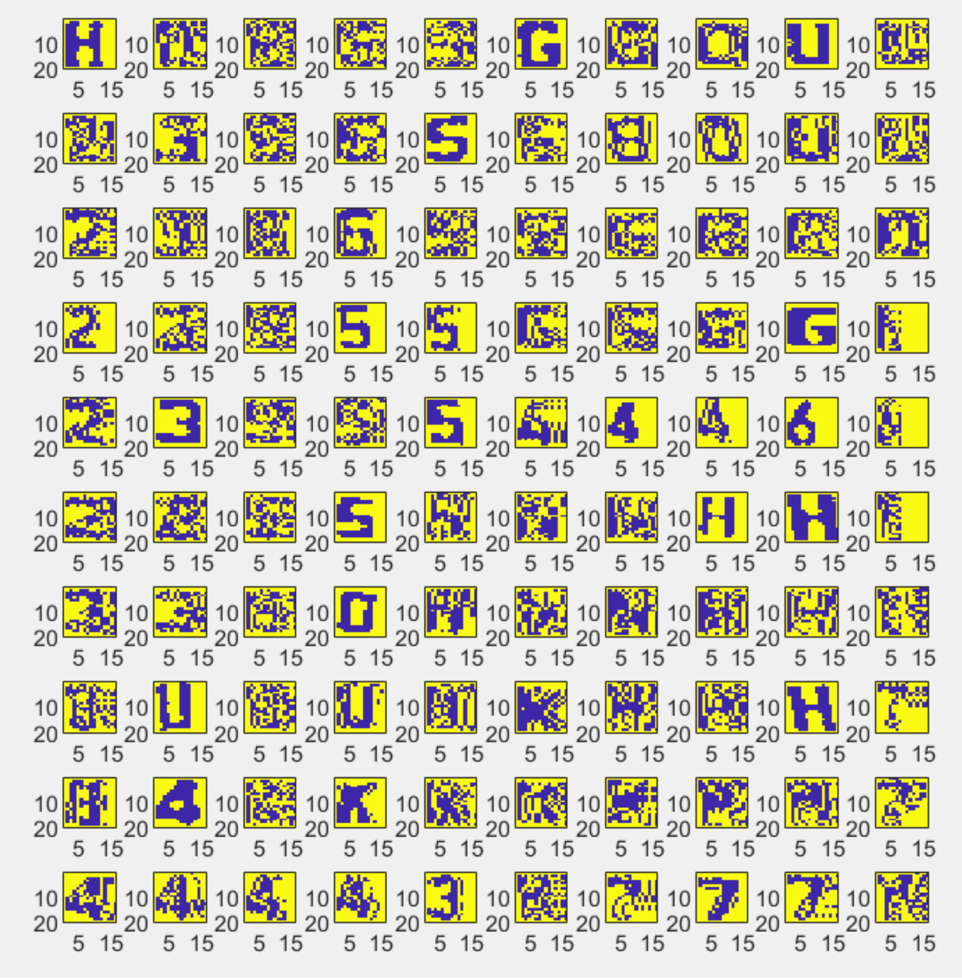
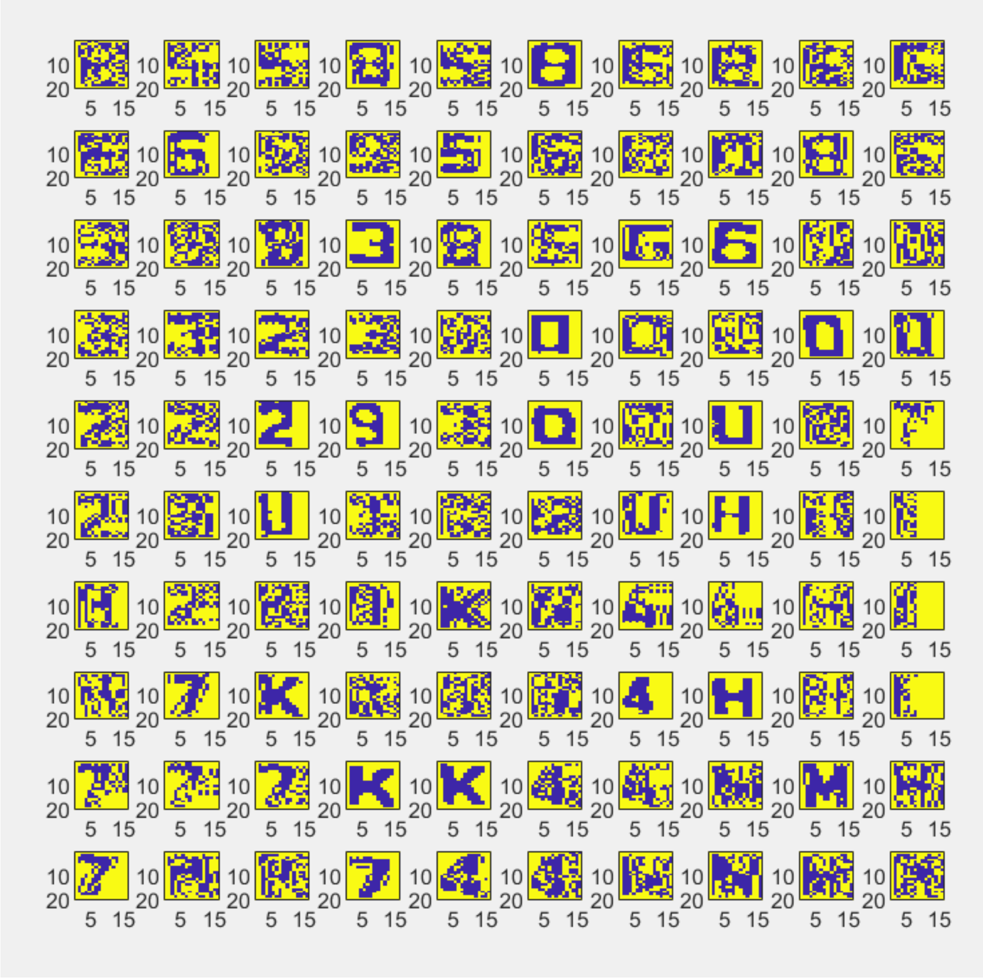
75 neurons (5*15)	**100 neurons (10*10)**
	
Sufficiently recognizable: 52 (~69%) Most common outputs: “0”, “2”, “K”, “N”, “7”, “H”, “8”, “G”, “6”, “5”	Sufficiently recognizable: 82 (~82%) Most common outputs: “H”, “K”, “0”, “7”, “2”, “3” , “8”, “9”, “6”

Conclusion:

For 2D topology we obtained the best result (82% of sufficiently recognizable symbols) with 100 neurons (10*10) and neighborhood size 5, which is much better than the result for 1D topology.

Concerning recognizable patterns, it is necessary to note that 2D topology is more likely to distinguish more different symbols and recognize probably more complicated shapes (symbols “3”, “9”, ”5”, “8”, “0”, “U”). The most recognizable outputs were “4”, “7”, “K”, “H”, “N”, “6”, “G”, “3”, “9”, “8”, “0”, “2”.

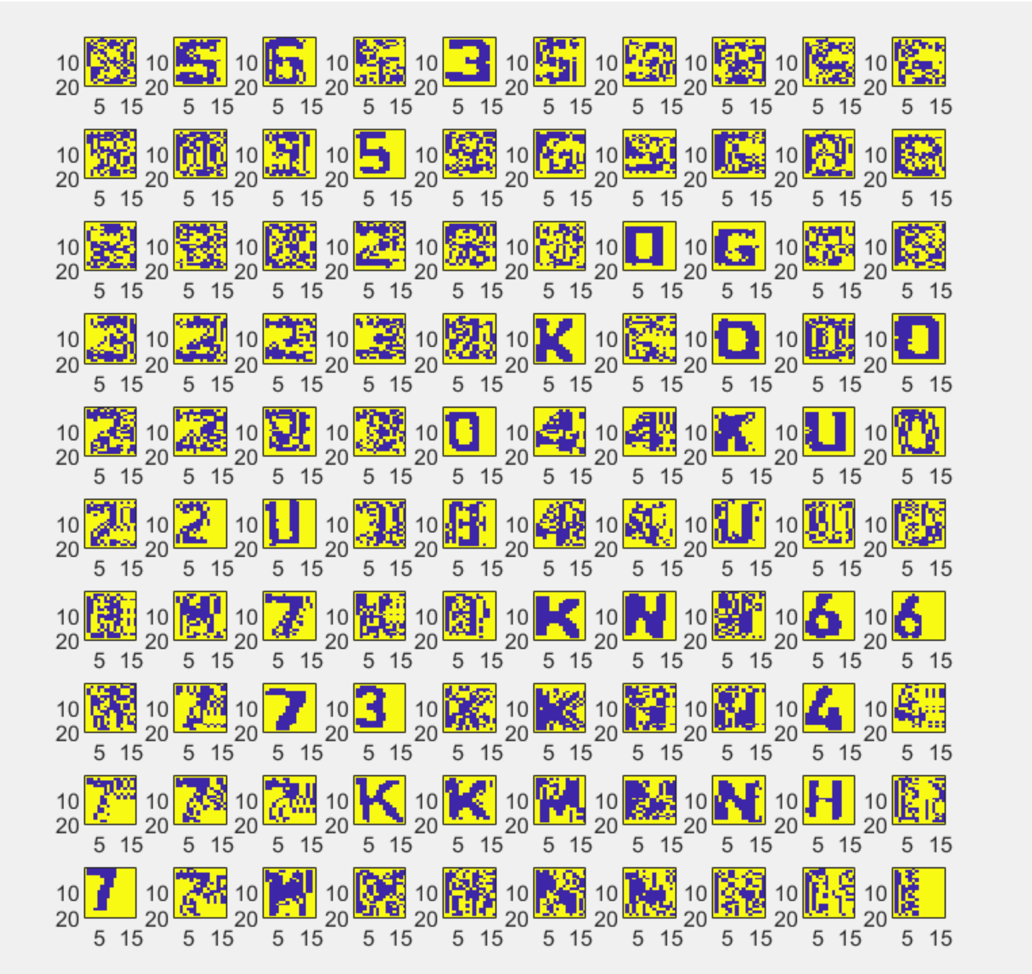
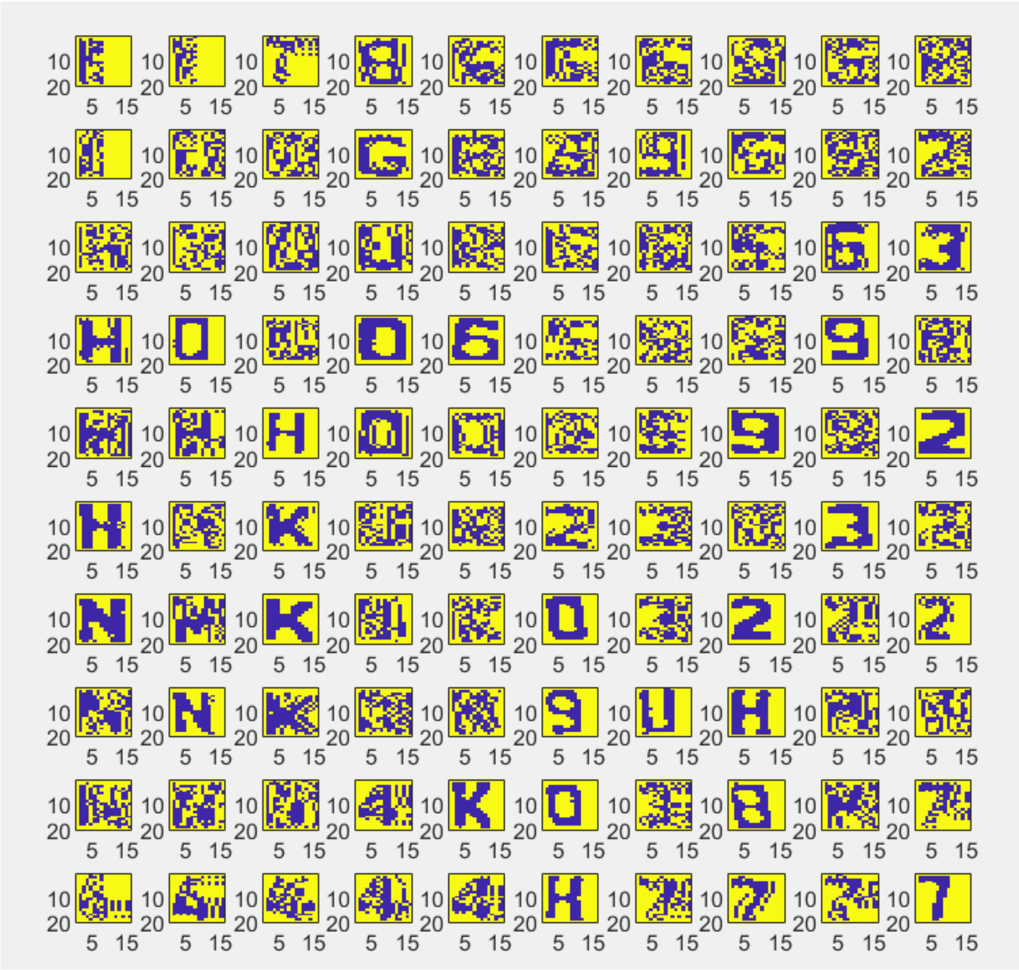
Neighbourhood size: 5; 100 neurons (10*10)

Gridtop	**Randtop**
	
Sufficiently recognizable: 72 (~72%) Most common outputs: “6”, “5”, “H”, “2”, “3”, “G”, “K”, “4”, “7”	Sufficiently recognizable: 77 (~77%) Most common outputs: “8”, “5”, “6”, “0”, “7”, “2” , “K”, “H”, “I”, “2”, “3”

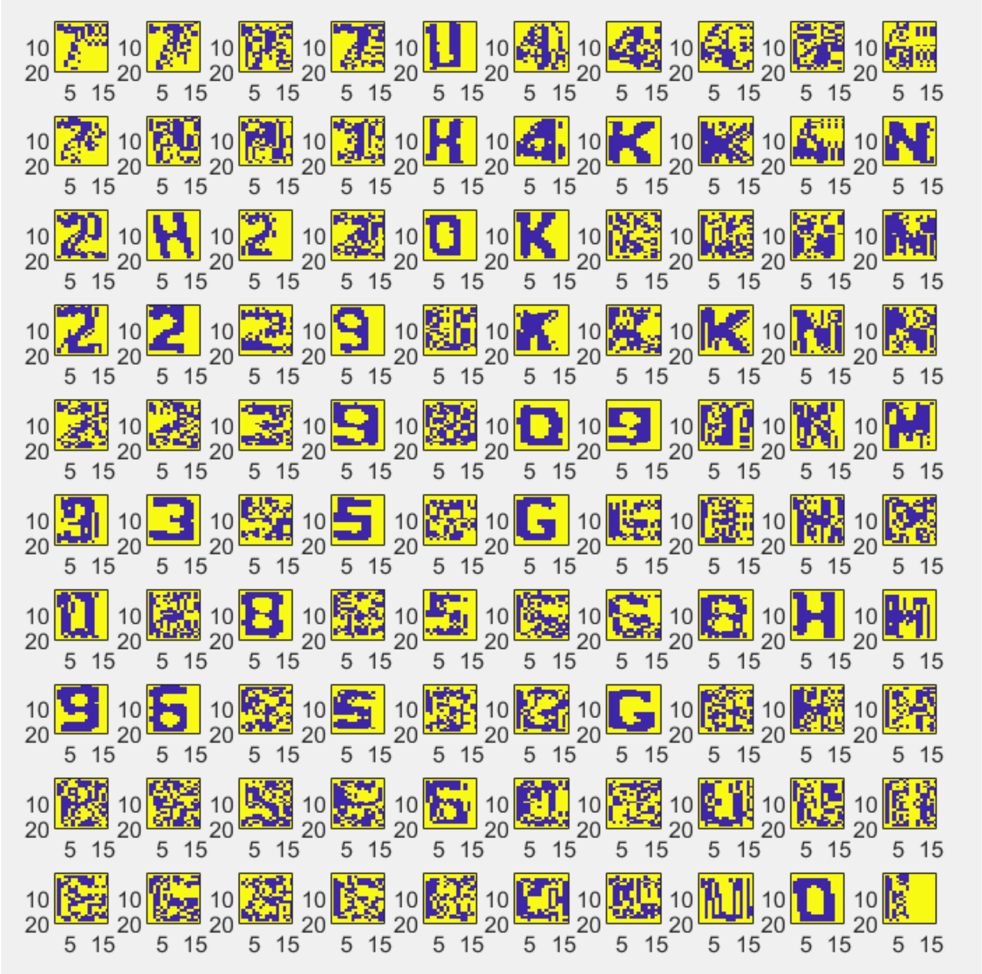
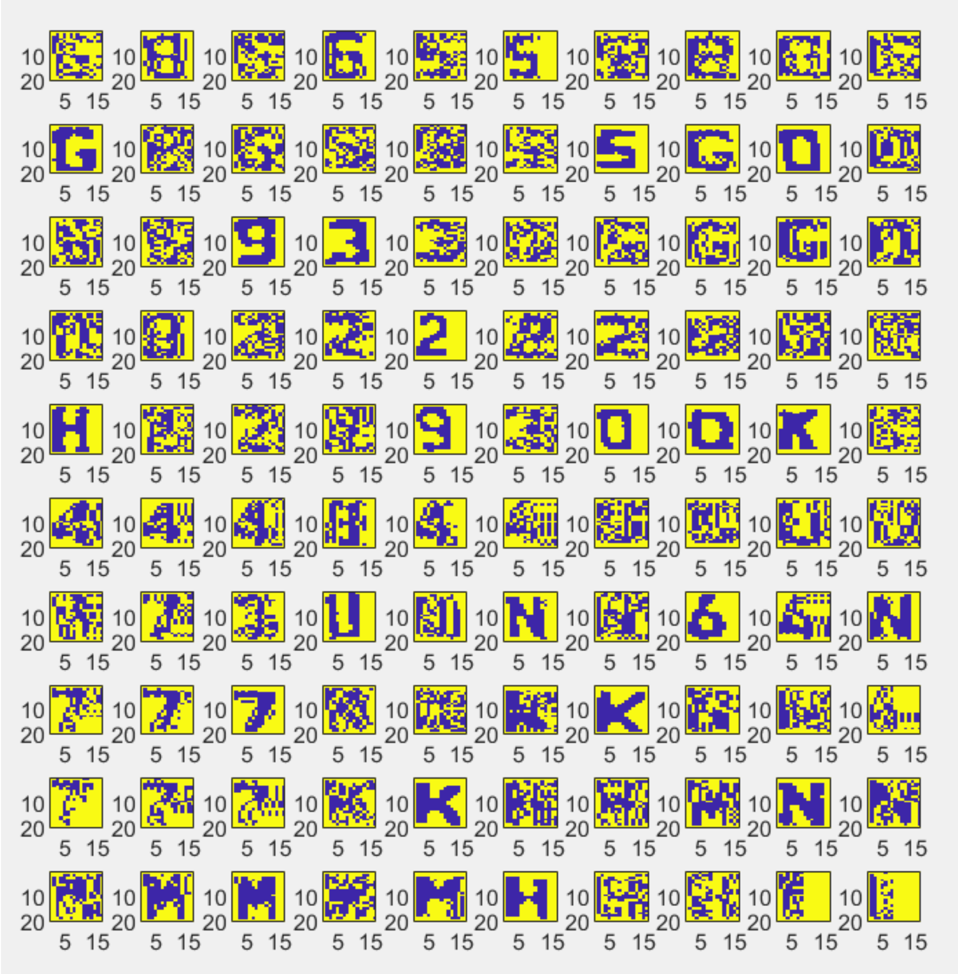
Conclusion:

We compared gridtop, randtop and hextop(default) for 2D topology of 100 neurons. Randtop and hextop have more or less the same quality, gridtop was a bit worse. They also have different "favourite" symbols. For example, gridtop is more likely to recognize "5", "6", "8", "H" but rarely differentiates "N" and "K". It also has more tendency to give either very clear image or very noisy ones, while hextop and randtop give more not so high-quality images, but total number of recognizable symbols seems to be higher. Nevertheless, it is not always the same, so we just analyze what we saw in this particular case.

Neighbourhood size: 5; 100 neurons (10*10), ‘hextop’ topology

dist	linkdist
	
Sufficiently recognizable: 66(~66%) Most common outputs: “0”, “2”, “3”, “4”, “5”, “7”, “K”, “N”, “6”	Sufficiently recognizable: 82 (~82%) Most common outputs: “H”, “K”, “0”, “7”, “2”, “3” , “8”, “9”, “6”

Neighbourhood size: 5; 100 neurons (10*10), ‘hextop’ topology

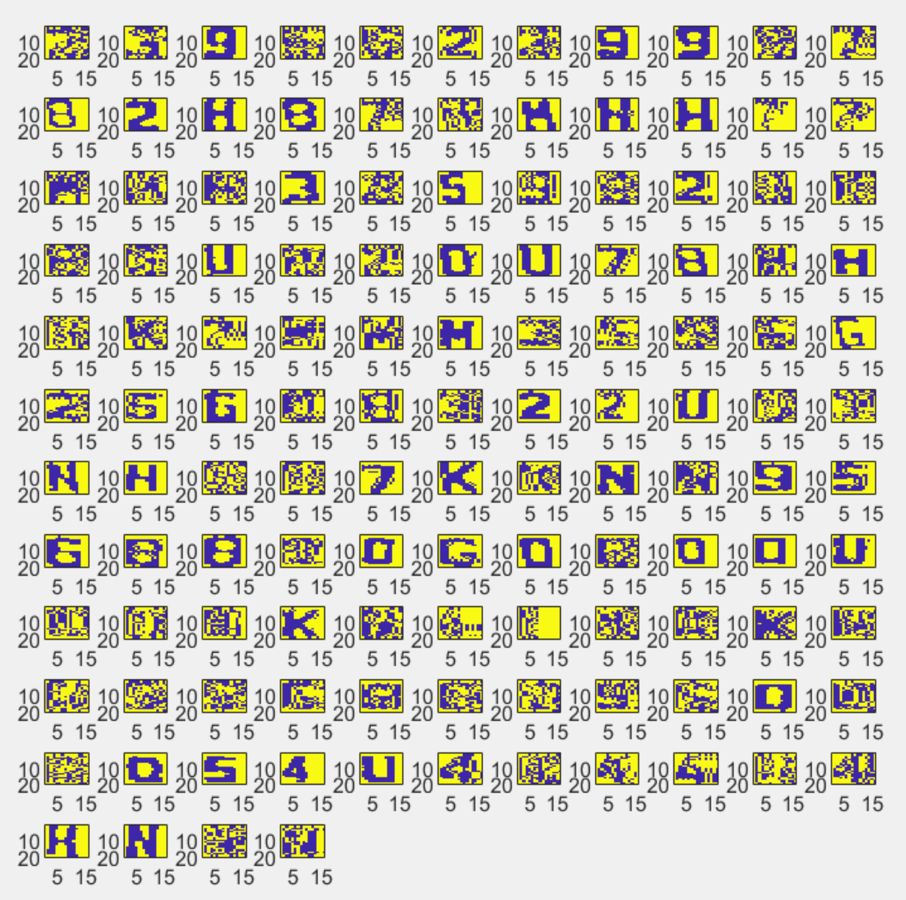
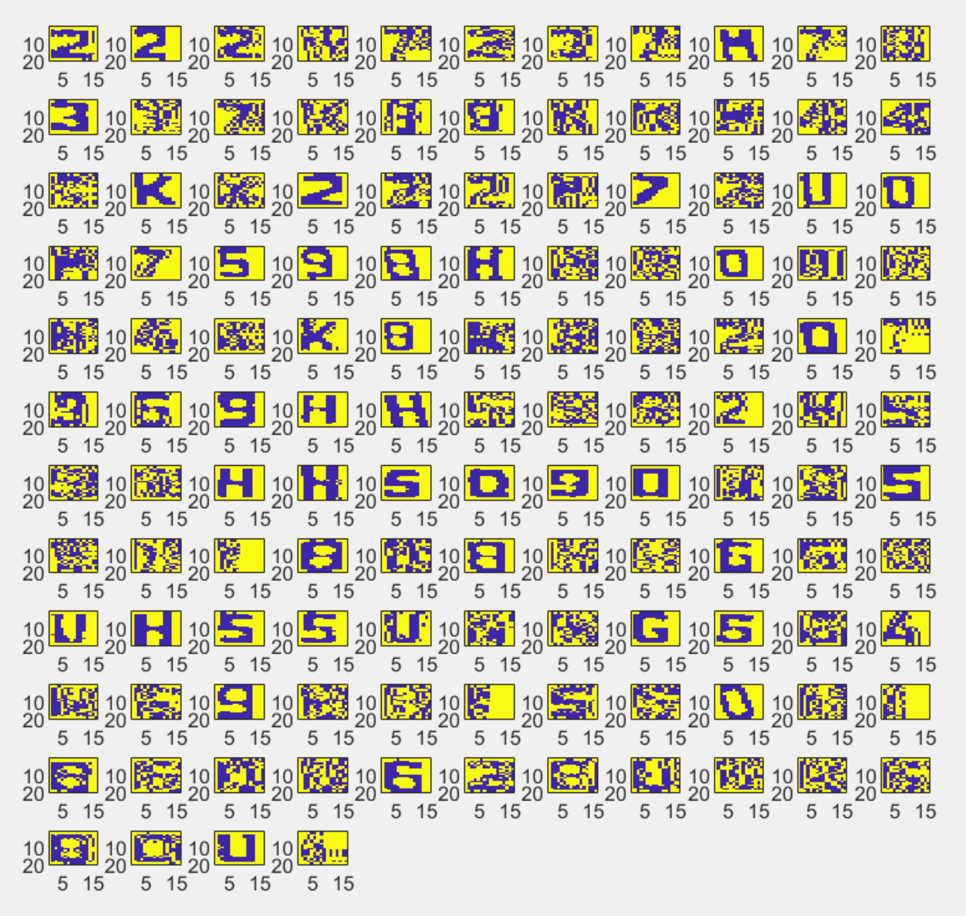
boxdist	**mandist**
	
Sufficiently recognizable: 78 (~78%) Most common outputs: “7”, “6”, “5”, “K”, “0”, “G”, “9”, “N”, “2”, “8”	Sufficiently recognizable: 77 (~77%) Most common outputs: “5”, “7”, “4”, “0”, “2”, “4”, “K”, “N” , “M”

Conclusion:

We compared the options ‘dist’, ‘linkdist’ (default), ‘boxdist’ and ‘mandist’. The best result was obtained with ‘linkdist’, but ‘boxdist’ and ‘mandist’ were also good enough. However, ‘dist’ shows much more poor results. What you can notice is that it is not likely to recognize “H”, creating too much noise around it. ‘Boxdist’ almost never recognizes “3”. ‘Mandist’ was surprisingly good at recognizing “M”.

3D topologies

125 neurons (5*5*5)

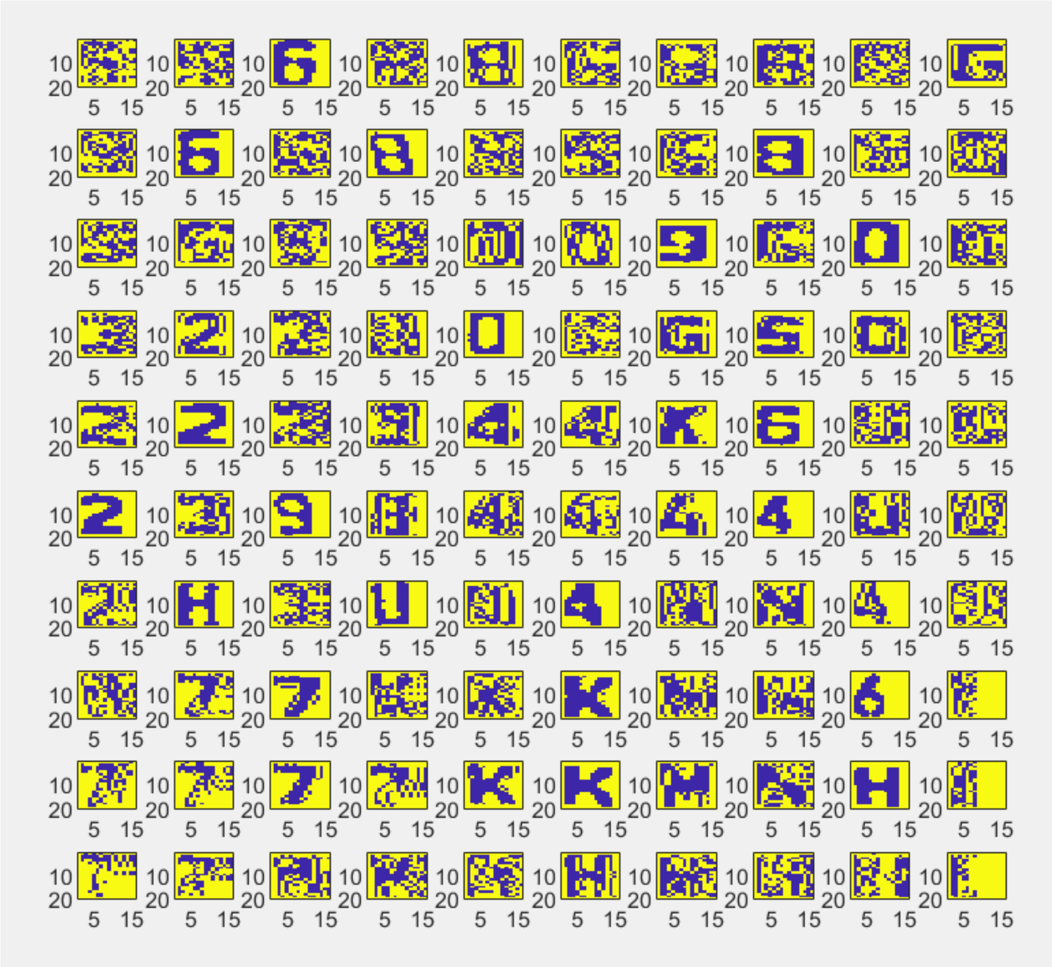
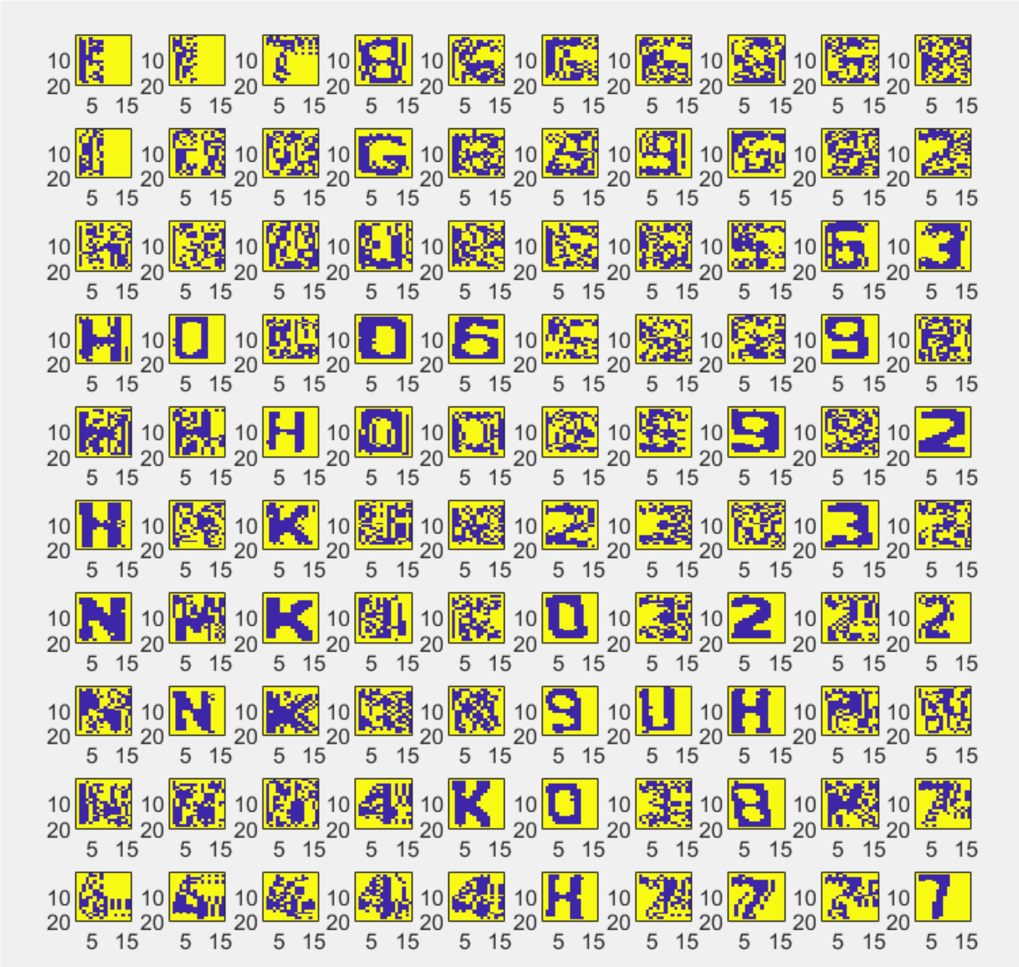
Neighbourhood size: 5	Neighbourhood size: 7
	
Sufficiently recognizable: 104(~83%) Most common outputs: “0”, “2”, “H”, “9”, “6”, “G”, “U”	Sufficiently recognizable: 95(~76%) Most common outputs: “H”, “5”, “2”, “7”, “K”, “6”, “8”

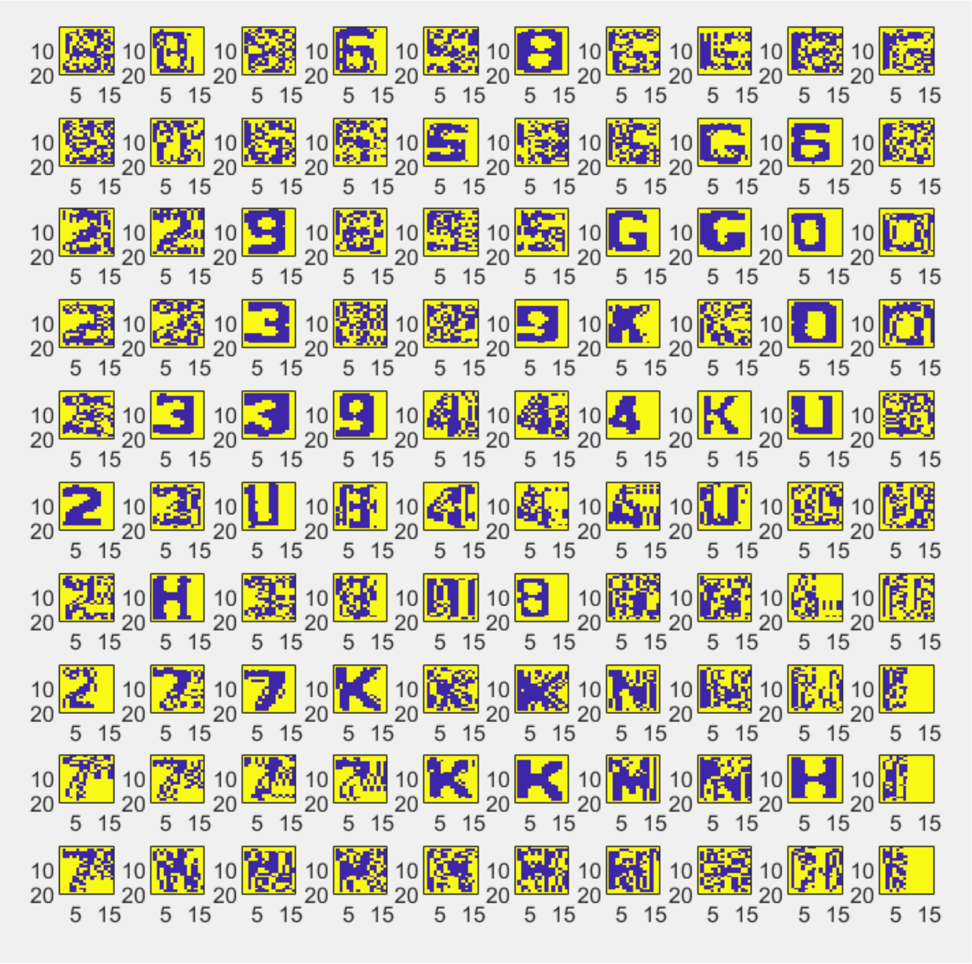
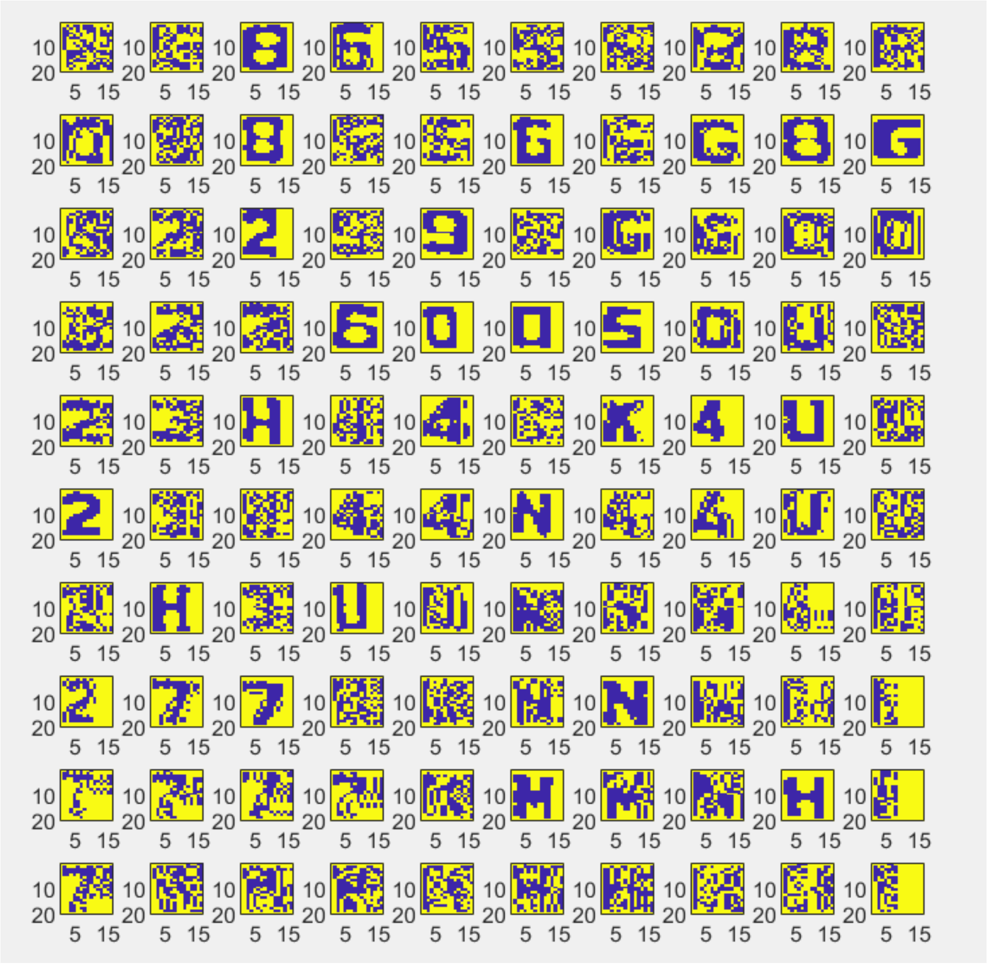
Conclusion:

For 3D topology with 125 neurons and neighbourhood size 5 we have almost the same accuracy as for 2D with 100 neurons (83% and 82%). But if we increase neighbourhood size to 7, the result becomes worse and we obtain a lot a of images with much noise.

After all these experiments we choose 2D ‘hextop’ ‘linkdist’ with 100 neurons(10x10) and neighbourhood size 5 as an optimal one and perform change of iterations number for this neural network.

Number of iterations

200 iterations	**400 iterations**
	
Sufficiently recognizable: 81(~81%) Most common outputs: “K”, “2”, “H”, “6”, “8”, “0”, “N”	Sufficiently recognizable: 82 (~82%) Most common outputs: “H”, “K”, “0”, “7”, “2”, “3” , “8”, “9”, “6”

600 iterations	800 iterations
	
Sufficiently recognizable: 89(~89%) Most common outputs: “K”, “7”, “1”, “H”, “5”, “8”, ”6”, “0”, “N”	Sufficiently recognizable: 82 (~82%) Most common outputs: “8”, “4”, “0”, “7”, “2”, “N” , “G”, “6”, “U”

Conclusion:

We have compared different numbers of learning cycles and found out that the result gradually improves with the increase of number of iterations, but between 600 and 800 iterations we noticed the decrease in number of recognizable symbols (however, some symbols were differentiated more clearly, but in others additional noise appeared). Thus, the best quality (89%) was obtained with 600 learning cycles.

Network is inclined to distinguish most accurately the following symbols: “2”, “4”, “5”, “6”, “7”, “8”, “0”, “G”, “K”, “N”, while symbols “1”, “3”, “9”, “H”, “M”, “U” appear not so frequently. Nevertheless, different topologies can invoke recognition of different patterns, for example 1D topologies usually recognized symbols “1”, “4”, “7” and “N”, while for 2D topologies “1” and “N” became not so prevailing ones.

Anyway, it is rather difficult to assess the behavior of the network, because we deal with unsupervised learning and it is hard to evaluate precisely how similar the generated image is to a real symbol image.