Assignment 6: Unsupervised Learning

NEUR503: Computational Neuroscience

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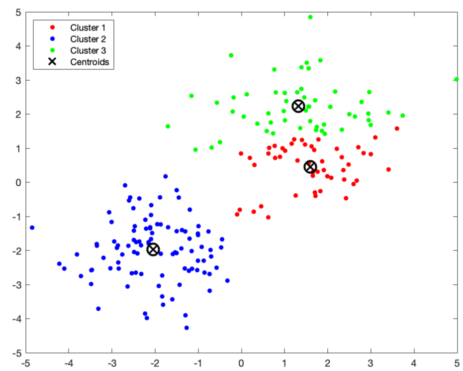
<u>Part I: Machine Learning - k-Means Clustering</u>

A. Two distributions with cluster k=3

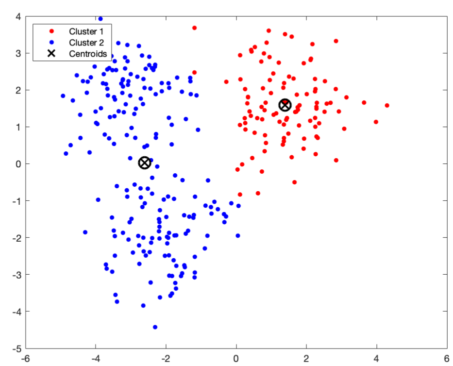
When k is set too high, the k-Means algorithm wrongly divides one of the distributions in two as illustrated in the following figure.



This figure illustrates that k-Means divided one of the distributions in 2 clusters, although it should be 1 cluster as illustrated by the green and red clusters.

B. Three distributions with cluster k=2

When k is set too low, the k-Means algorithm wrongly combines two distributions in one cluster as illustrated in the figure below.



In this figure, the blue distribution should had been divided into two clusters.

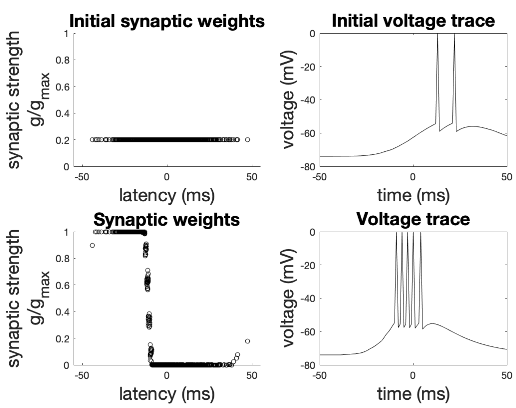
C. Three distributions with various k

Here, I used the evalclusters() function from MatLab with silhouette measure for values of k ranging from 2 to 5. The algorithm determined that k=3 was the optimal value of k.

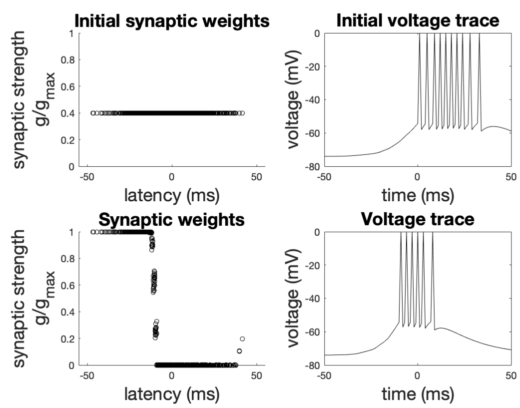
Part II: Learning in the Brain - STDP

A. Song et al say STDP reduces latencies and sharpens responses

The starting setting of the initial conductance was modified from 0.003 to 0.006. Below are the graphs comparing both initial conductances.



This figure shows the graphs for a conductance of 0.003



This figure shows that graphs for a conductance of 0.006

By comparing the two figures above, we notice a difference in the initial voltage trace when the conductance is doubled. The synapses' outputs are strong enough to drive the post-synaptic neuron to fire. Moreover, the voltage trace following STDP shows that the response has shifted temporally. It is now relatively earlier (reduced latency) and it is also shorter in duration (sharpened response).

B. STDP provides a degree of stability

The value of the initial conductance was changed to 0.01 (the same as g_max). As shown in the figure below, the initial voltage trace displays spurious behaviour as a consequence of an unreasonably large conductance. After STDP, post-synaptic activity is stabilized through LTD and high latency synaptic weights are brought to a value of 0.

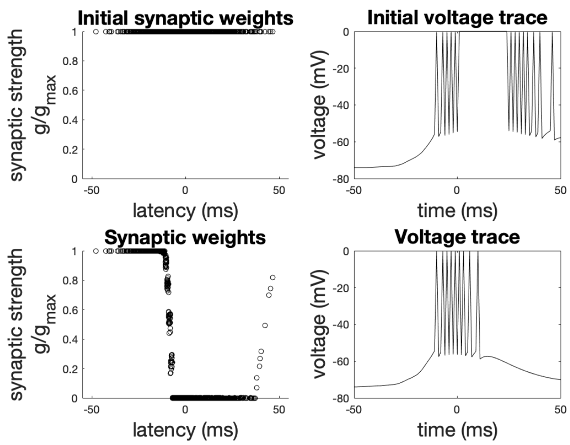


Figure showing the graphs for unreasonably high conductance (0.01).

C. Without instruction, STDP can pick up on correlations in inputs

STDP is a form of unsupervised learning and classification because the post-synaptic neuron learns to extract patterns and features from inputs without being provided any supervision on how it should respond to the inputs. As demonstrated in the figure below, the neuron responds randomly to uncorrelated inputs, will strengthen synapses that receive correlated inputs and will partition two types of correlated inputs by assigning opposing synaptic strengths to the inputs allowing for differential responses.

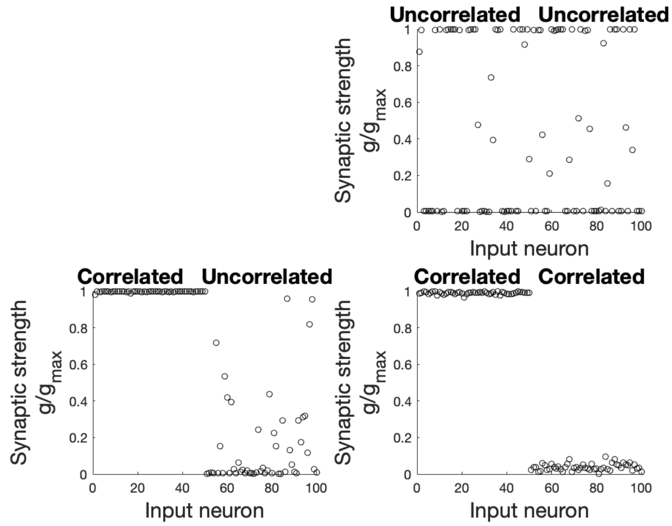
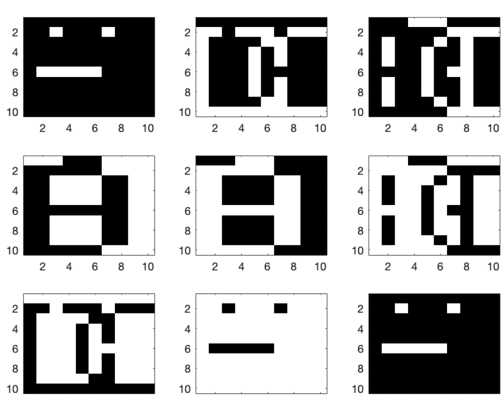


Figure reproducing the results from the Song et al 2001 paper.

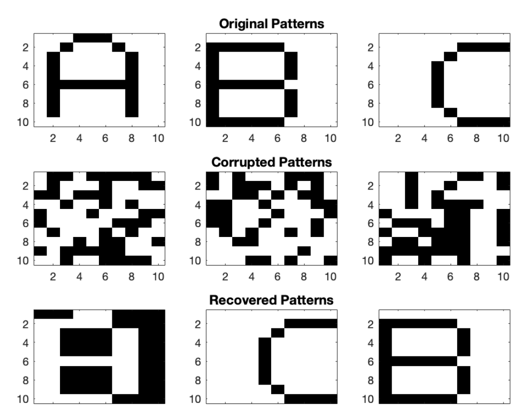
Part III: An Associative Memory - Hopfield Network

A. Experiment with noise levels to find local minima and ghost states

In the figure below, the Hopfield network function was called with noise levels of 50. The images being very corrupted by the noise, it was unable to converge to the correct memories. Instead, it converged to combination memories as illustrated in the figure which are local minima or to other attractor states.



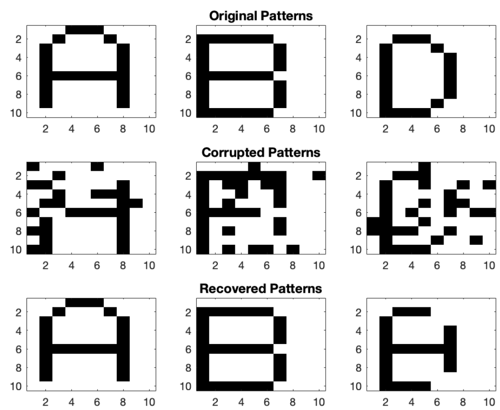
This figure illustrates all the potential combinations of memories.



In this figure, we can see that with high levels of noise, the network is unable to converge to the appropriate memories

B. Alter one memory

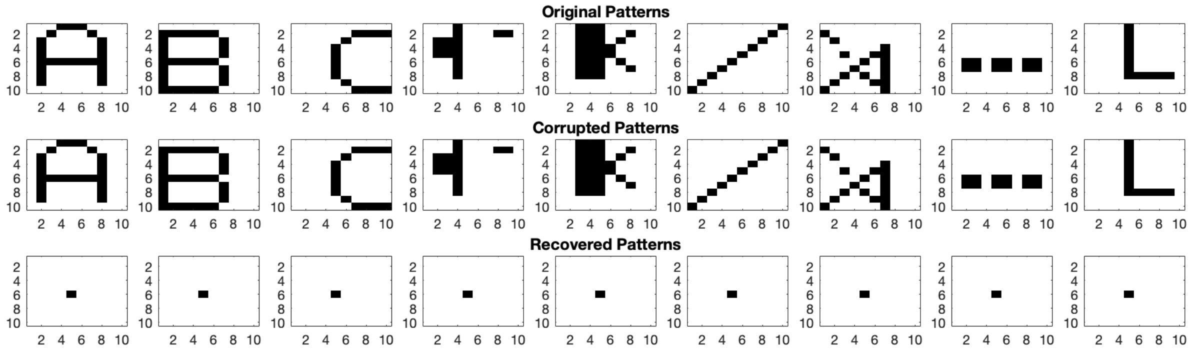
The third letter stored is a D which is similar to the two other letters. Even with low levels of noise, the network had difficulty converging to the appropriate memory. Instead, it converged to combinations of the other memories implying that the minima are close together thereby generating ghost memories.



This figure illustrates how the Hopfield networks behaves when stored memories are structurally similar.

C. The information storage limit of a Hopfield network

Nine memories were stored in the Hopfield network. Recall was attempted with no noise, yet the network was unable to recall any of the memories. It only recalled one ghost memory suggesting that it always converges to one attractor state and that even though the stored memories were different to the human eye, they are not mathematically different enough to generate minima that are sufficiently far apart. This relates to some of the shortcomings of Hopfield networks: they perform well when the stored memories are orthogonal to each other which is clearly not the case here.

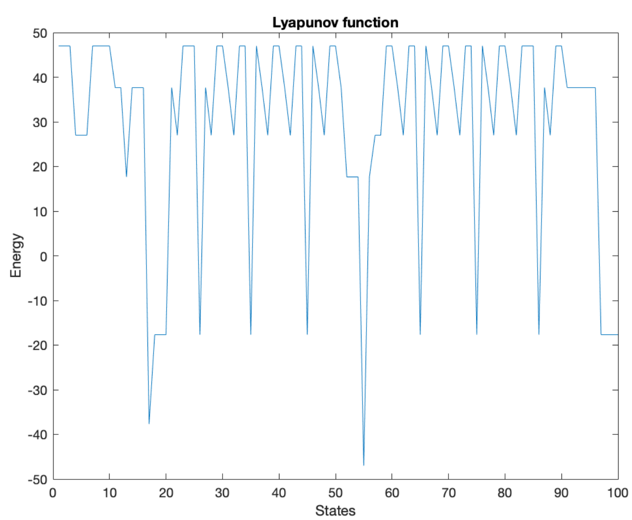


This figure shows the nine memories that were stored in the Hopfield network. It was unable to recall accurately any of them as it always converge to a global attractor state (ghost memory).

As seen in class, the theoretical information storage limit of a Hopfield network is defined by this equation: $p = \dfrac{N}{4logN} = \dfrac{100}{4log100} = 12.5$

D. Calculate numerically the network energy as it converges

As seen in the figure below, the network converges to a low energy at the 55th state. A Hopfield network can be used as a classifier since it learns the attractor states for different memories. When asked to recall a memory, it will converge to the attractor state closest to the presented input. In this way, the network



Lyapunov function for a Hopfield network of 100 nodes and trained on three different memories with a noise level of 20 at recall.

categorizes inputs according to their similarity to previously memorized inputs and clusters them depending on the attractor state to which they converge.