COSC 420: Biologically Inspired Computation

Project 3: Hopfield Net

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Introduction

The purpose of this experiment was, to create software that could be implemented to investigate the associative memory capacity of a Hopfield Network. In Gary William Flake's book, *The Computational Beauty of Nature* he describes a Hopfield network as a network that starts in a random initial state, where the weights and external inputs can be set in a way to solve a problem. In essence a Hopfield network can be used to find the optimal solution to a problem, and using this experiment is a general idea to see how they work.

Theory and Methods

To start this project, the first thing that needed to be done was to generate fifty vectors (patterns), each with one hundred elements (neurons), with either a positive or negative one value. Then looping through all the patterns some values needed to be calculated. First the patterns had to be imprinted onto the Hopfield network,

$$w_{ij} = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{k=1}^{p} s_i s_j & i = j \\ 0 & i \neq j \end{cases}$$

Figure 1. Weight Calculation

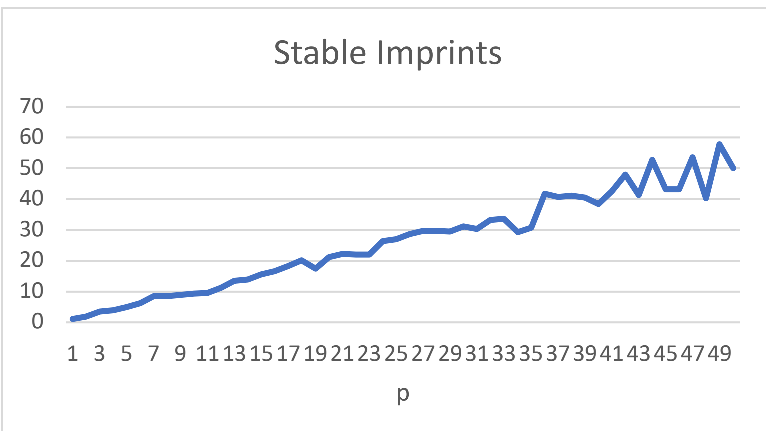
Next the imprinted patterns had to be tested for stability, to do this the neural network was set up to be equal to the pattern being imprinted, then for each of the neurons in the pattern its new state had to be calculated

$$h_i = \sum_{j=1}^{N} w_{ij} s_j$$

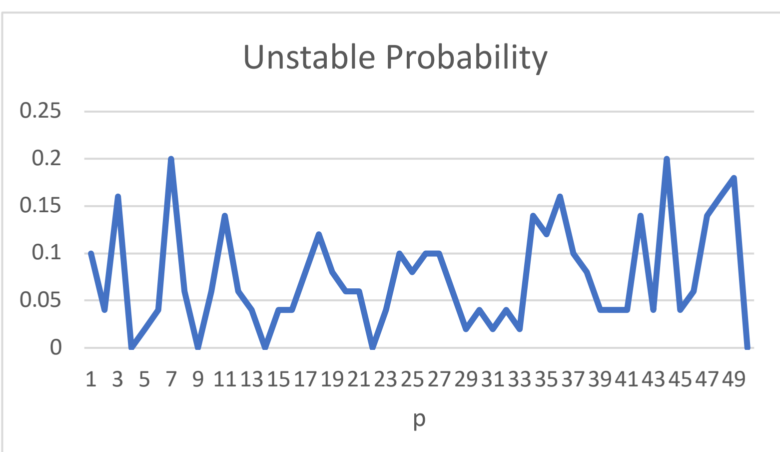
Figure 2. local field of neuron

Then after h was calculated the next state could be found using a sign function. Once that was completed the stable and unstable probabilities could be calculated.

Results



Graph 1. Number of stable imprints for p patterns



Graph 2. probability of unstable imprints for p patterns

Discussion and Conclusion

The results were, generally speaking, not what was expected. The graphs produced were not similar to the ones in the writeup. After the creation of the vectors, all was fine up until the counting of imprinted patterns. Hopfield networks are guaranteed to converge to a local minimum, but the graph 2 for unstable probability is chaotic with no clear pattern at all. Graph 1 shows the stable imprints as continually increasing throughout the fifty patterns, in theory the graph should look like a bell curve. The suspicion is somewhere within the calculation for the local field of the neuron is making it incorrect. However, this may not be the case. Another possible reason for inconsistencies is within the weights calculation, the Hebbian learning aspect of the experiment. Hebbian learning is meant to explain associative learning, as in the neurons that are connected tend to converge. In this experiment this was not the case, either the looping within code is wrong or either calculation mentioned earlier is the cause. Overall throughout the experiment much was learned about Hopfield networks, Hebbian learning, and artificial neural networks.