CS 420 Lab 3: Hopfield Networks

Introduction:

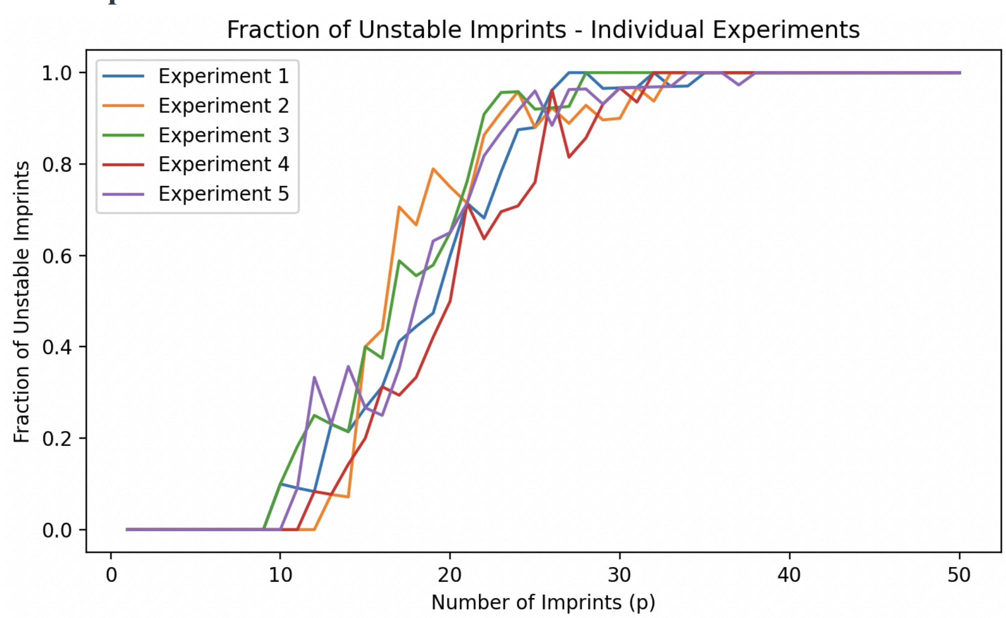
This lab is regarding Hopfield Networks. The Hopfield Networks are a type of recurrent artificial neural network that basically serves as models for associative memory. In The report below, I am investigating the associative memory capacity of a Hopfield network with 100 neurons and no self-coupling. The experiments that I performed involved imprinting a series of random bipolar vectors onto the network and testing their stability. I am also analyzing the results from the graphs to better understand the network's memory capacity and stability.

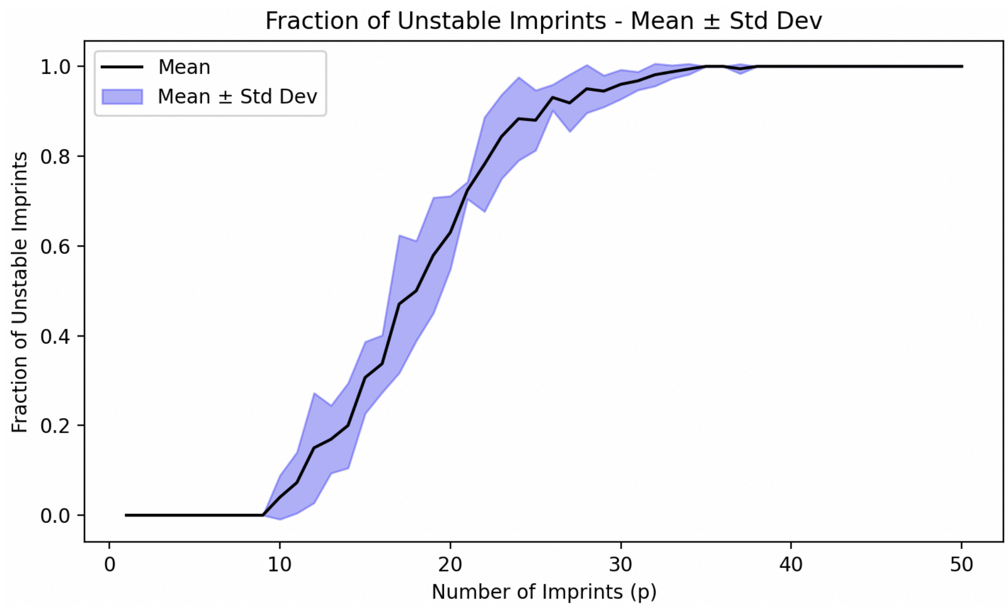
Experiment setup:

I conducted a series of experiments where each one of them involved the following steps:

1. Generate 50 random bipolar vectors.
2. Imprint the first p patterns onto the network.
3. Test the stability of the imprinted patterns.
4. Generate data for the two types of graphs:
    - Fraction of unstable imprints as a function of the number of imprints(p).
    - Number of stable imprints as a function of the number of imprints(p).

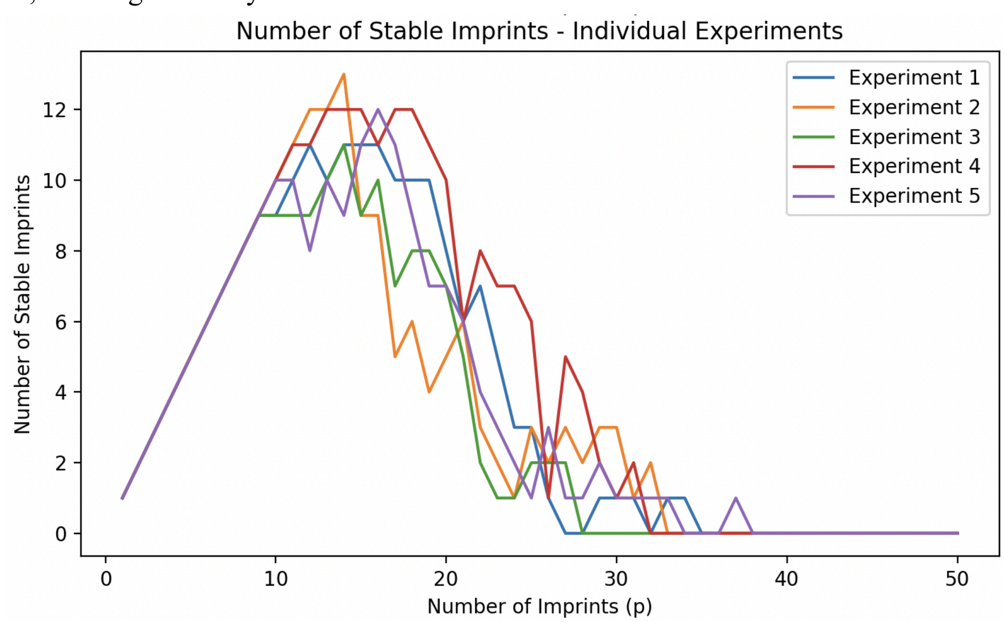
Results and Graphs:

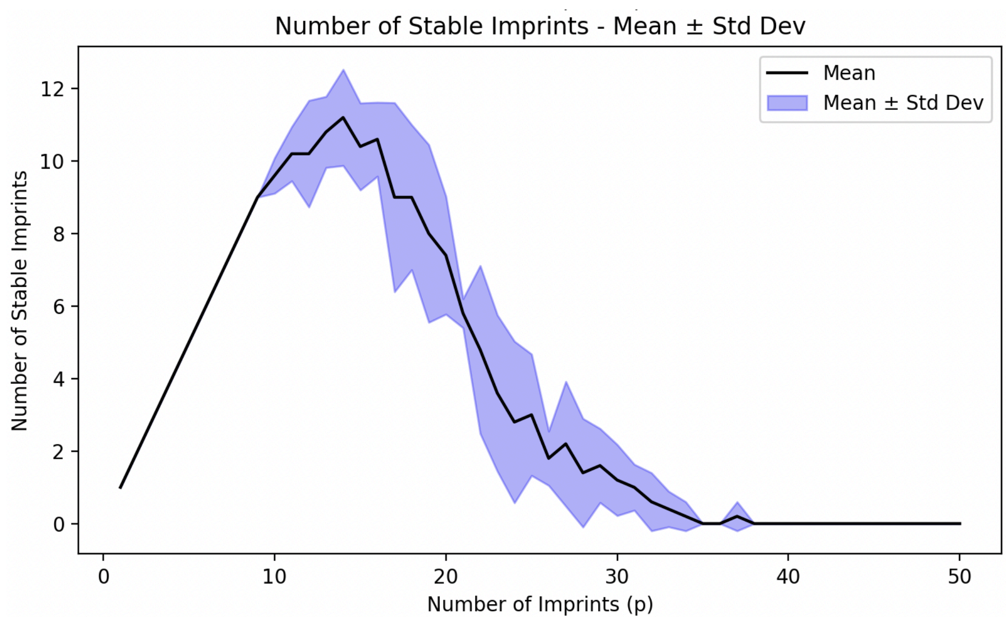




Fraction of Unstable Imprints:

The first set of graphs shows the fraction of unstable imprints. In the individual experiments, we observed that initially with a low number of imprints the fraction of the unstable imprints remained at 0. However, as the number of imprints increased, the fraction of unstable imprints rose sharply. They reached close to 1 as p approached 50. This tells us that the stability decreases as the network attempts to store more patterns. The second set of graphs represents the mean fraction of unstable imprints along with the standard deviation. I noticed a similar trend where the fraction of unstable imprints increased with the number of imprints. The mean curve shows a steady rise which indicates a consistent decrease in stability with increasing memory load. The standard deviation provides insight into the variability across experiments, showing relatively minor deviations from the mean.





Number of Stable Imprints:

In the individual experiments for stable imprints, the number of stable imprints initially increased linearly with the number of imprints. However, after a certain threshold, I saw that the number of stable imprints started to decline, which indicates that there is a saturation point in the network's memory capacity. This decline suggests that the network becomes increasingly prone to interference and overlaps between stored patterns as more patterns are added to the model. The mean number of stable imprints along with the standard deviation is like following a pretty similar pattern. The mean curve initially rises linearly but starts to decline after reaching a peak. Which indicates that it would be the network's maximum capacity. The standard deviation reflects the consistency of this read across experiments with minor variations.

Discussion:

Variation Across Experiments - Across the five experiments that I conducted, I observed slight variations in the capacity of the Hopfield network to store and access patterns. These variations are primarily displayed in the rate at which stability declined with an increasing number of ref imprints as well as the precise point at which the network reached its maximum capacity. Variations like these can arise due to factors like the random initialization of patterns, slight differences in the learning process, or sometimes it could be computational noise. Despite these variations, the overall trends remained pretty consistent, which indicates the robustness of the hop field network's associative memory capacity in different experimental runs that I did.

Maximum Capacity - The results that I got suggest the presence of a maximum capacity for the Hopfield network, beyond which the stability of stored patterns starts to go down. This maximum capacity occurs when the network reaches a peak in the number of stable imprints and also experiences a decrease as more patterns are added. This decline in stability can be attributed to the phenomenon of pattern interference, where the retrieval of one pattern becomes increasingly susceptible to interference from overlapping or conflicting information stored in the network. Understanding the mechanisms underlying this maximum capacity is crucial for optimizing the design and performance of the Hopefield networks in practical applications requiring efficient associative memory storage.

In conclusion, my experiments showed the associative memory capacity of Hopfield networks and it also provided insights into their stability and limitations. If I were to further investigate then I could explore the impact of different network architectures and learning rules on memory capacity and stability.

To run the python file:

- Have python installed on your device.
- Install numpy
- Install Matplotlib
- Run the file: python test.py