

(Brest State Technical University 2005 Spring Semester: Corse Practice)

# Associative Memory by Hopfield Neural Network

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## 1 Create your own patterns to be stored!

The first task of this practice is to create your own  $p$  patterns each of which is made up of  $N^2$  binary pixels. Examples are shown in Figure 1.

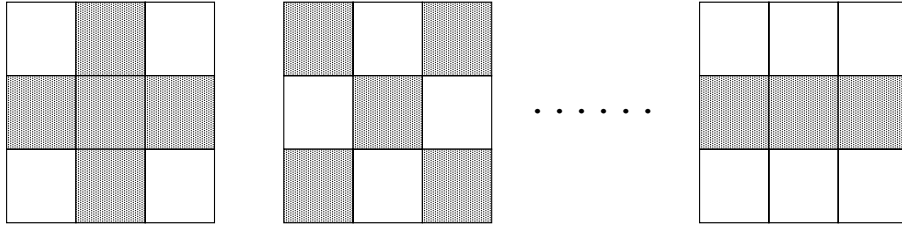


Figure 1: An example for  $N = 3$ . White pixel is represented by  $-1$  and white pixel is by  $+1$ . That is, patterns are represented with 9-bit *bipolar* vectors.

To be more formal, our  $p$  patterns are expressed as

$$(\xi_1^1, \xi_2^1, \dots, \xi_N^1), (\xi_1^2, \xi_2^2, \dots, \xi_N^2), (\xi_1^3, \xi_2^3, \dots, \xi_N^3), \dots, (\xi_1^p, \xi_2^p, \dots, \xi_N^p). \quad (1)$$

where  $\xi_i^\mu \in \{-1, 1\}$ ,  $\mu = 1, 2, \dots, p$  and  $i = 1, 2, \dots, N^2$ .

For example, the first example in the Figure 1 is

$$(-1, +1, -1, +1, +1, +1, -1, +1, -1)$$

**Excercise 1 (10 Patterns to be Stored)** Create your own 10 patterns each of which is made up of  $10 \times 10$  binary pixels.

## 2 Construct a Hopfield Neural Network to store your patterns!

Now Let's create a Hopfield Neural Network with  $N \times N$  neurons. All neurons are connected with each other via synapse.

Each of neurons are influenced by other  $(N \times N - 1)$  neurons. The strength of an influence from one neuron is according to the weight value of the synapse. Thus, state of neuron  $i$  at time  $t + 1$   $s_i(t + 1)$  is given as

$$s_i(t + 1) = \text{sgn} \left( \sum_{j \neq i}^N w_{ij} \cdot s_j(t) \right). \quad (2)$$

### 2.0.1 How we update state of neurons? — Synchronous and Asynchronous update

Now a question arise, how are neurons updated? Simultaneously-at-a-time or one-by-one? The former is called *Synchronous update* and the latter is *Asynchronous update*. In this practice course we use the asynchronous update.

In other words, at time  $t$ , neuron-1 is firstly updated, and, this new state will be used to update other neurons here after; next, neuron-2, neuron-3, and so on, until all the neurons are updated. Then this updated procedures are repeated at time  $t + 1$ , and on and on.<sup>1</sup>

## 2.1 An experiment with random weight values:

Now we have  $10^2$  synapses and each synapse has a strength called *weight*. The weight value from neuron- $j$  to neuron- $i$  is denoted here as  $w_{ij}$   $i, j = 1, 2, \dots, 100$ .

We must assign these 100 weight values appropriately to store our patterns. However, we start with a set of 100 random values each of which is in  $[-1, 1]$ , such as  $-0.534$ , are assigned.

**Excercise 2 (Observe the behaviours of your Hopfield Network.)** Give one of your patterns to your Hopfield Network with random weight values, and observe what will happen. That is, set  $S_i(0) = \xi_i^\mu$  for all  $i = 1, 2, \dots, N^2$  with a specific  $\mu$  you like. Then observe the pattern for  $t = 1, 2, \dots$ , namely, how the pattern changes as time proceeds.

## 3 Let's store your patterns!

### 3.1 Hebbian Learning

Here we calculate the weight according to the following equation, called Hebbian Learning.

$$w_{ij} = \frac{1}{N} \sum_{\mu=1}^p \xi_i^\mu \xi_j^\mu \quad (i \neq j), \quad w_{ii} = 0. \quad (3)$$

**Excercise 3 (Observe the behaviours of your Hopfield Network Part II.)** Repeat the previous excercise with the weights calculated with the above equation, instead of random values.

## 4 Let's observe how it is clever (or fool)!

Now if your work is successful Network recognize your patterns in the following way.

- (1) If you give one of your patterne as it is, then the initial state never be changed.<sup>2</sup>
- (2) If you give a noisy version of your pattern, then initial state changes several steps and converges to the original pattern.<sup>3</sup>
- (3) If you give a very different pattern from any of your patters, then network shows a *chaotic* behaviour, e.g., repeat a same cycle of patterns or changes forever in a random way.

Then you may test your Hopfield Network to know how it is clever or fool.by changing (i) the number of patterns stored and/or (2) number of noisy bit.

**Excercise 4 (Observe the behaviours of your Hopfield Network Part III.)** Starting with 1 pattern, test the capability of the Network by incrementing the number of noisy bits from zero, and observe when the Network become to be chaotic. Plot this critical number as a function of number of noise with a parameter of the number of patterns stored.

<sup>1</sup> We can update neurons in a random order different order at every time  $t$ , but here we update from the 1st neuron to the last neuron one by one.

<sup>2</sup> In this case the pattern is called *fixed point*.

<sup>3</sup> We call it "An initial state in the vasin of attraction is attracted to its fixed point."