UNIVERSITY OF TORONTO, DEPARTMENT OF ECE

ECE1512 - Project Report

Yang Wang
Student Number: 1001319227

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1 INTRODUCTION

Neural networks have received increasing usage in the areas of pattern recognition. One of the important applications is in character recognition. Character recognition has many practical interests, such as zip code recognition, document ananlysis. Many questions are usually involved, such as the choice of data representation, the design of classification algorithm and the selection of training data. In using neural net classifier, many resarchers were choosing the multi-layer feedforward model with backpropagation algorithms. In this report, we choose to investigate the handritten character(isolated digits) recognition project by using the discrete Hopfield network model as a pattern classifier. The data representation is based on image pixels. This type of representation is simple and straightforward.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements working in parallel to solve a specific problem. Neural networks learn by example. A neuron has many inputs and one output. The neuron has two modes of operation (i) the training mode and (ii) the using mode. In the training mode, the neuron can be trained for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the training rule is used. Neural network has many applications. The most likely applications for the neural networks are (1) Classification (2) Association and (3) Reasoning. An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern.

2 Background

2.1 Character Recognition

2.2 Hopfield Network

2.2.1 Hopfield Network Elements

Hopfield network consists of a set of interconnected neurons which update their activation values asynchronously. The activation values are binary, usually {-1,1}. The update of a unit depends on the other units of the network and on itself. A unit i will be influence by an other unit j with a certain weight w_{ij}, and have a threshold value.

So there is a constraint due to the other neurons and due the specific threshold of the unit.

The new activation value (state) of a neuron is compute, in discret time, by the function 2.1:

$$x_i(t+1) = sign(\sum_{j=1}^{n} x_j(t) w_{ij} - \theta_i) \tag{2.1}$$

or function 2.2

$$X = sign(XW - T) \tag{2.2}$$

Where X, W, T and the $sign$ function are:

- X is the activation value of the n units/neurons: $X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$
- W is the weight matrix: $W = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{bmatrix}$ where w_{ij} can be interpreted as the influence of neuron i over neuron j (and reciprocally).
- T is the threshold of each unit: $T = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{pmatrix}$

- the $sign$ function is define as function 2.3:

$$sign(x) = \begin{cases} +1 & \text{if } x \geq 0 \\ -1 & \text{otherwise} \end{cases} \tag{2.3}$$

Usually, an Hopfield Network has a weight matrix symmetrix, zero-diagonal(no loop, a unit does not influence on itself). We will only consider that case in our project.

2.2.2 Hebbian Learning

A simple model due to Donald Hebb captures the idea of associative memory. Imagine that the weights between neurons whose activities are positively correlated are increased:

$$\frac{dw_{ij}}{dt} \sim \text{Correlation}(x_i, x_j) \tag{2.4}$$

Now imagine that when stimulus m is present (for example, the smell of a banana), the activity of neuron m increases; and that neuron n is associated with another stimulus, n (for example, the sight of a yellow object). If these two stimuli: a yellow sight and a banana smell. co-occur in the environment, then the Hebbian learning rule (2.4) will increase the weights w_{nm} and w_{mn}. This means that when, on a later occasion, stimulus n occurs in isolation, making the activity x_n large, the positive weight from n to m will cause neuron m also to be activated. Thus the response to the sight of a yellow object is an automatic association with the smell of a banana. We could call this âĂŸpattern completionâĂŹ. No teacher is required for this associative memory to work. No signal is needed to indicate that a correlation has been detected or that an as- sociation should be made. The unsupervised, local learning algorithm and the unsupervised, local activity rule spontaneously produce associative memory.

This idea seems so simple and so effective that it must be relevant to how memories work in the brain.

2.2.3 Character recognition using Hopfield Network

3 Methodology

3.1 data set

3.2 preprocessing

3.3 Experiment Setup

4 Experiment Results

5 Conclustion and Discussion