

“ARTIFICIAL NEURAL NETWORKS ON HUMAN”

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ABSTRACT-This paper is an introduction to Artificial Neural Networks. Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras. Neural networks take a different approach to problem solving than that of conventional computers which has been explained in this paper. The various types of neural networks are explained and demonstrated, applications of neural networks like ANNs in medicine are described, and a detailed historical background is provided. The connection between the artificial and the real thing is also investigated and explained. Finally, the mathematical models involved are presented and demonstrated.

1. INTRODUCTION

1.1 What is a Neural Network?

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is **the novel structure of the information processing system**. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

1.2 Historical Background

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by **Minsky and Papert**. They published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis.

Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

The first artificial neuron was produced in **1943** by the neurophysiologist **Warren McCulloch and the logician Walter Pits**. But the technology available at that time did not allow them to do too much.

1.3 Why use neural networks?

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "whatif" questions.

Other advantages include:

1. **Adaptive learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. **Self-Organization:** An ANN can create its own organization or representation of the information it receives during learning time.

1.4 Neural networks versus conventional computers

Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the

problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

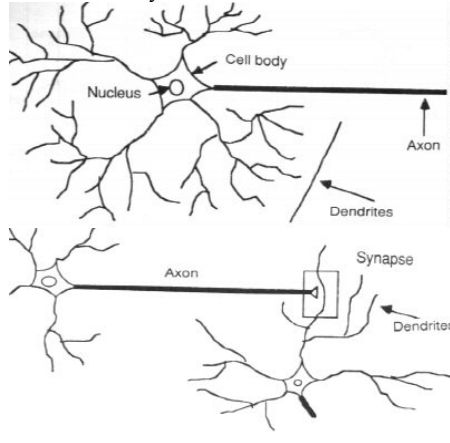
Neural networks and conventional algorithmic computers are not in competition but complement each other. **Neural networks do not perform miracles. But if used sensibly they can produce some amazing results.**

2. HUMAN AND ARTIFICIAL

NEURONS - Investigating the similarities

2.1 How the Human Brain Learns?

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a **typical neuron collects signals from others through a host of fine structures called dendrites**. The neuron sends out spikes of electrical activity through a long, thin strand known as an **axon**, which splits into thousands of branches. At the end of each branch, a structure called a **synapse** converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurons.

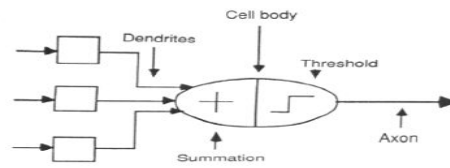


Components of a neuron

2.2 From Human Neurons to Artificial Neurons

We conduct these neural networks by first trying to deduce the essential features of neurons and their interconnections. We then typically program a computer to simulate these features. However because our knowledge of neurons is incomplete and our computing power is limited, our models are

necessarily gross idealizations of real networks of neurons.

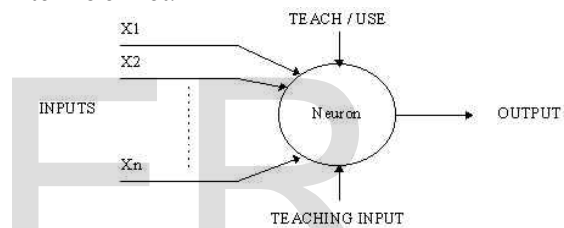


The neuron model

3. AN ENGINEERING APPROACH

3.1 A Simple Neuron

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), 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 firing rule is used to determine whether to fire or not.



A simple neuron

3.2 Firing rules

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained.

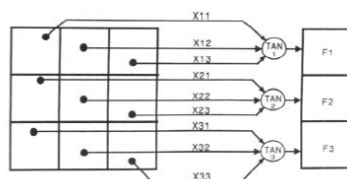
A simple firing rule can be implemented by using Hamming distance technique. The rule goes as follows:

Take a collection of training patterns for a node, some of which cause it to fire (the 1-taught set of patterns) and others which prevent it from doing so (the 0-taught set). Then the patterns not in the collection cause the node to fire if, on comparison, they have more input elements in common with the 'nearest' pattern in the 1-taught set than with the 'nearest' pattern in the 0-taught set. If there is a tie, then the pattern remains in the undefined state.

3.3 Pattern Recognition - An Example

An important application of neural networks is pattern recognition. Pattern recognition

can be implemented by using a feed-forward (figure 1) 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. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from



the given pattern.

3.4 A More Complicated Neuron

The previous neuron doesn't do anything that conventional computers don't do already. A more sophisticated neuron (figure 2) is the McCulloch and Pitts model (MCP). The difference from the previous model is that the inputs are 'weighted'; the effect that each input has at decision making is dependent on the weight of the particular input. The weight of an input is a number which when multiplied with the input gives the weighted input. These weighted inputs are then added together and if they exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.

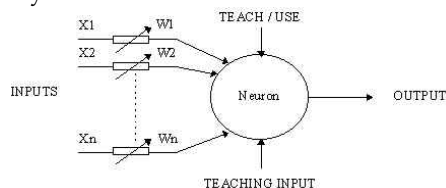


Figure 2. An MCP neuron

In mathematical terms, the neuron fires if and only if;

$$X1W1 + X2W2 + X3W3 + \dots > T$$

The addition of input weights and of the threshold makes this neuron a very flexible and powerful one. The MCP neuron has the ability to adapt to a particular situation by changing its weights and/or threshold. Various algorithms exist that cause the neuron to 'adapt'; the most used ones are the Delta rule and the back error propagation.

The former is used in feed-forward networks and the latter in feedback networks.

4 ARCHITECTURE OF NEURAL NETWORKS

4.1 Feed-Forward Networks

Feed-forward ANNs (figure 1) allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

4.2 Feed-Back Networks

Feedback networks (figure 1) can have signals traveling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

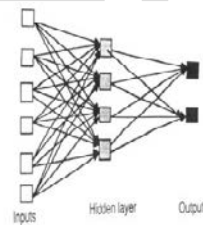


Figure 4.1 An example of a simple feed forward network

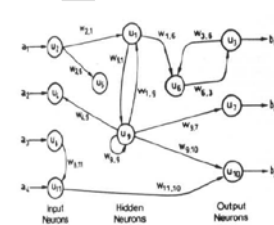


Figure 4.2 An example of a complicated network

4.3 Network Layers

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units as shown in Figure 4.1.

- The activity of the input units represents the raw information that is fed into the network.
- The activity of each hidden unit is determined by the activities of the input

units and the weights on the connections between the input and the hidden units.

The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

5. THE LEARNING PROCESS

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms:

Associative mapping in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units. The associative mapping can generally be broken down into two mechanisms:

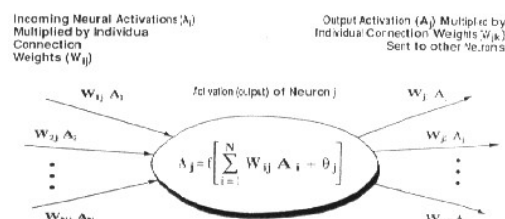
Auto-association: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern competition, i.e. to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.

Hetero-association: is related to two recall mechanisms:

Nearest-neighbour recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented, and

Interpolative recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant associative mapping is classification, ie when there is a fixed set of categories into which the input patterns are to be classified.

Regularity detection in which units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'. This type of learning mechanism is essential for feature discovery and knowledge representation.



Information is stored in the weight matrix W of a neural network. Learning is the determination of the weights. Following the way learning is performed, we can distinguish two major categories of neural networks:

Fixed networks in which the weights cannot be changed, i.e. $dW/dt=0$. In such networks, the weights are fixed a priori according to the problem to solve.

Adaptive networks which are able to change their weights, i.e. $dW/dt \neq 0$.

All learning methods used for adaptive neural networks can be classified into two major categories:

Supervised learning which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning. An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

Unsupervised learning uses no external teacher and is based upon only local information. It is also referred to as self-organisation, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

5.1 Transfer Function

The behaviour of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories:

● Linear (or ramp)

● Threshold

● Sigmoid

For **linear units**, the output activity is proportional to the total weighted output.

For **threshold units**, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurones than do linear or threshold units, but all three must be considered rough approximations.

We can teach a three-layer network to perform a particular task by using the following procedure:

1. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units.
2. We determine how closely the actual output of the network matches the desired output.
3. We change the weight of each connection so that the network produces a better approximation of the desired output.

5.2 An Example To Illustrate The Above Teaching Procedure:

Assume that we want a network to recognize hand-written digits. We might use an array of, say, 256 sensors, each recording the presence or absence of ink in a small area of a single digit. The network would therefore need 256 input units (one for each sensor), 10 output units (one for each kind of digit) and a number of hidden units.

For each kind of digit recorded by the sensors, the network should produce high activity in the appropriate output unit and low activity in the other output units.

5.3 The Back-Propagation Algorithm

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that

the neural network compute the error derivative of the weights (**EW**). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the **EW**.

6. APPLICATIONS OF NEURAL NETWORKS

6.1 Neural Networks in Practice

Given this description of neural networks and how they work, what real world applications are they suited for? Neural networks have broad applicability to real world business problems. In fact, they have already been successfully applied in many industries.

Since neural networks are best at identifying patterns or trends in data, they are well suited for prediction or forecasting needs including:

● Sales forecasting

● Industrial process control

● Customer research

● Data validation

● Risk management

● Target marketing

6.2 Neural Networks in Medicine

Artificial Neural Networks (ANN) are currently a 'hot' research area in medicine and it is believed that they will receive extensive application to biomedical systems in the next few years. At the moment, the research is mostly on modeling parts of the human body and recognizing diseases from various scans (e.g. cardiograms, CAT scans, ultrasonic scans, etc.).

The examples need to be selected very carefully if the system is to perform reliably and efficiently. Some of the areas in medicine where we use neural networks are...

- Modeling and Diagnosing the Cardiovascular System
- Electronic noses
- Instant Physician

6.3 Neural Networks in business

Business is a diverted field with several general areas of specialization such as accounting or financial analysis. Almost any neural network application would fit into one business area or financial analysis. There is some potential for using neural networks for business purposes, including resource

allocation and scheduling. There is also a strong potential for using neural networks for database mining that is, searching for patterns implicit within the explicitly stored information in databases. Most of the funded work in this area is classified as proprietary. Thus, it is not possible to report on the full extent of the work going on. Most work is applying neural networks, such as the Hopfield-Tank network for optimization and scheduling. Some of the areas in business where we use neural networks are...

- Marketing
- Credit Evaluation
- Forecasting the Demand and Sales

7. CONCLUSION

The computing world has a lot to gain from neural networks. Their ability to learn by example makes them very flexible and powerful. Furthermore there is no need to devise an algorithm in order to perform a specific task; i.e. there is no need to understand the internal mechanisms of that task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture.

Neural networks also contribute to other areas of research such as neurology and psychology. They are regularly used to model parts of living organisms and to investigate the internal mechanisms of the brain.

References:

1. An introduction to neural computing. Alexander, I. and Morton, H. 2nd edition.
2. Neural Networks at Pacific Northwest National Laboratory
Industrial Applications of Neural Networks (research reports Esprit, I.F.Croall, J.P.Mason).