

Artificial Neural Networks

ABSTRACT

Just as life attempts to understand itself better by modeling it, and in the process create something new, so Neural computing is an attempt at modeling the workings of a brain and this presentation is an attempt to understand the basic concept of artificial neural networks.

In this paper, a small but effective overall content of artificial neural networks is presented. First, the history of Neural Networks which deals with the comparative study of how vast the Neural Networks have developed over the years is presented. Next, having known what exactly is a neural network with the help of a MLP model, we proceed to next session: resemblance with brain where in the comparison between brain and neural networks as well as neurons and perceptrons are made with the help of figures. The most basic component of a neural network is the perceptron, which is called the artificial neuron, is studied and depicted in the Structure of a Neural Network section which is followed by architecture. The most important concept of the neural networks are its wide range of its applications, a few of which will be dealt in the consequent sections and then its limitations. The main question of interest to us would be “What will be the future of Neural Networks, Will it survive or will it rule us?”—This section leads us to a brief conclusion and we end the paper with the references.

1. Brief Historical background of 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. Many important advances have been boosted by the use of inexpensive computer emulations.

The earliest work in neural computing goes back to the 1940's when McCulloch and Pitts introduced the first neural network computing model. In the 1950's, Rosenblatt's work resulted in a two-layer network, the perceptron, which was capable of learning certain classifications by adjusting connection weights.

Although the perceptron was successful in classifying certain patterns, it had a number of limitations. The perceptron was not able to solve the classic XOR (exclusive or) problem. Such limitations led to the decline of the field of neural networks. However, the perceptron had laid foundations for later work in neural computing.

2. What exactly is a neural network?

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. In the broader sense, a neural network is a collection of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. It is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses.

To be more clear, let us study the model of a neural network with the help of figure.1. The most common neural network model is the multilayer perceptron (MLP). It is composed of

of hierarchical layers of neurons arranged so that information flows from the input layer to the output layer of the network. The goal of this type of network is to create a model that correctly

maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

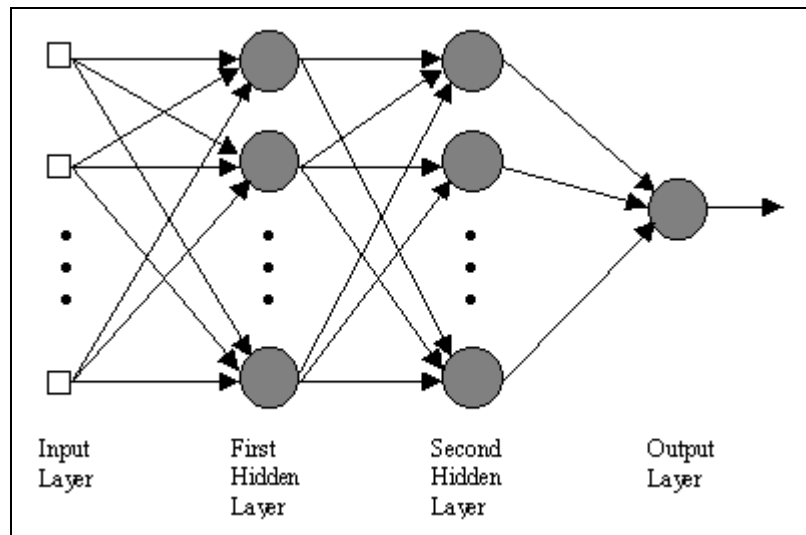


Figure 1. Graphical representation of MLP

3. Resemblance with brain

The brain is principally composed of about **10 billion neurons**, each connected to about 10,000 other neurons. Each neuron receives **electrochemical inputs** from other neurons at the dendrites. If the sum of these electrical inputs is sufficiently powerful to activate the neuron, it transmits an electrochemical signal along the axon, and passes this signal to the other neurons whose dendrites are attached at any of the axon terminals. These attached neurons may then fire.

So, our entire brain is composed of these interconnected electro-chemical transmitting neurons. From a very large number of extremely simple processing units (each

performing a weighted sum of its inputs, and then firing a binary signal if the total input exceeds a certain level) the brain manages to perform extremely complex tasks. This is the model on which artificial neural networks are based.

Neural network is a sequence of neuron layers. A neuron is a building block of a neural net. It is very loosely based on the brain's nerve cell. Neurons will receive inputs via weighted links from other neurons. This inputs will be processed according to the neurons *activation function*. Signals are then passed on to other neurons.

In a more practical way, neural networks are made up of interconnected processing elements called units which are equivalent to the brains counterpart ,the neurons.

Neural network can be considered as an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following ways:

1. A neural network acquires knowledge through learning.
2. A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.
3. Neural networks modify own topology just as neurons in the brain can die and new synaptic connections grow.

Graphically let us compare a artificial neuron and a neuron of a brain with the help of figures 2 and 3 given below

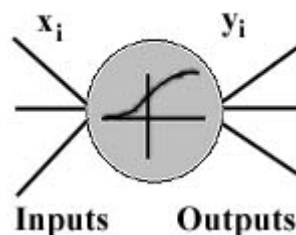


Figure2.Neuron of an artificial neural network

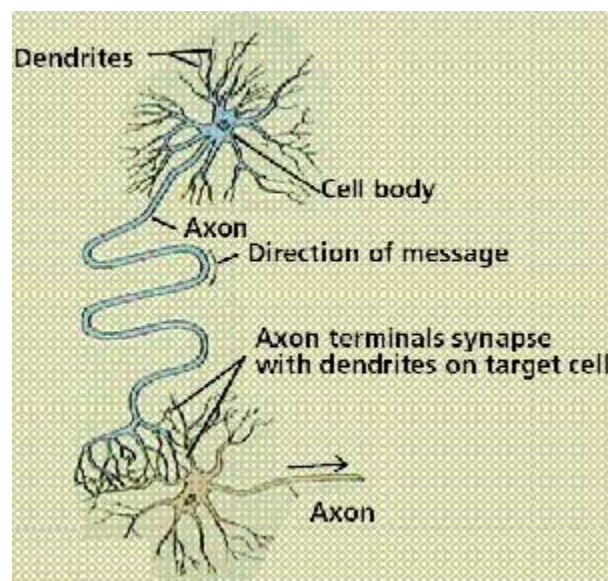


Figure3.Neuron of a brain

4.Structure of neural network

According to Frank Rosenblatt's theory in 1958 ,the basic element of a neural network is the perceptron, which in turn has 5 basic elements: an n-vector input, weights, summing function, threshold device, and an output. Outputs are in the form of -1 and/or +1. The threshold has a setting which governs the output based on the summation of input vectors. If the summation falls below the threshold setting, a -1 is the output. If the

summation exceeds the threshold setting, +1 is the output. Figure 4 depicts the structure of a basic perceptron which is also called artificial neuron.

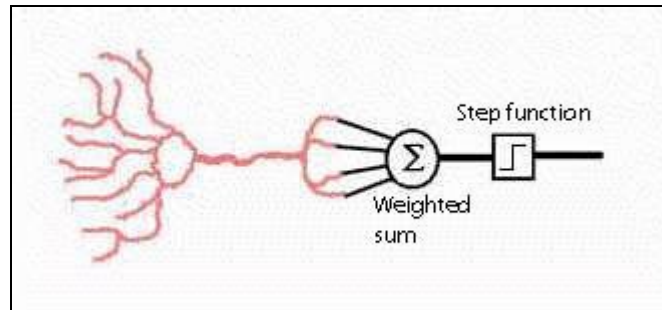


Figure 4. Artificial neuron(perceptron)

The perceptron can also be dealt as a mathematical model of a biological neuron. While in actual neurons the dendrite receives electrical signals from the axons of other neurons, in the perceptron these electrical signals are represented as numerical values.

A more technical investigation of a single neuron perceptron shows that it can have an input vector X of N dimensions (as illustrated in figure.5). These inputs go through a vector W of Weights of N dimension. Processed by the Summation Node, " a " is generated where " a " is the "dot product" of vectors X and W plus a Bias. " A " is then processed through an activation function which compares the value of " a " to a predefined Threshold. If " a " is below the Threshold, the perceptron will not fire. If it is above the Threshold, the perceptron will fire one pulse whose amplitude is predefined

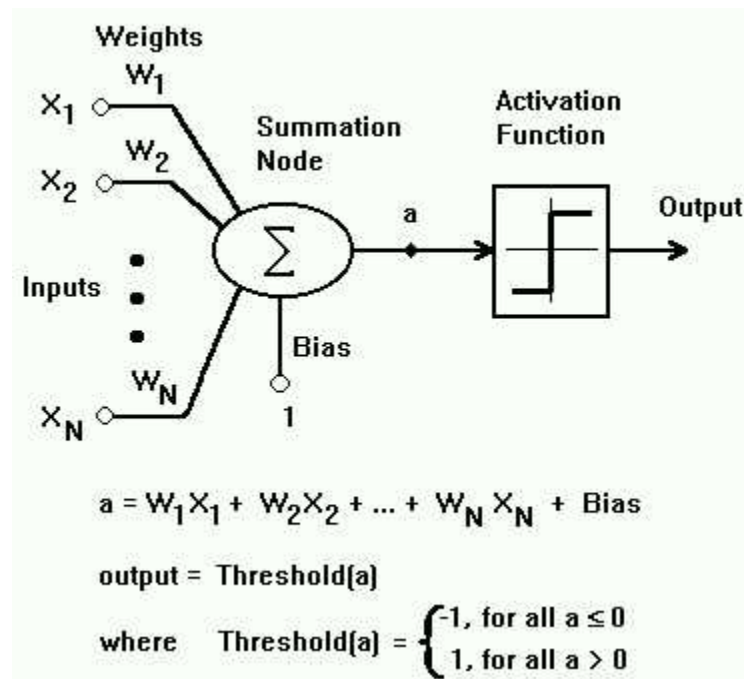


Figure 5. Mathematical model of a perceptron

5. Architecture of neural networks

1. Feed-forward networks

Feed-forward ANNs 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 organisation is also referred to as bottom-up or top-down.

2. Feedback networks

Feedback networks can have signals travelling 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 organisations.

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.

- 1.The activity of the input units represents the raw information that is fed into the network.
- 2.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.
- 3.The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organisation, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organisations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

6.Applications of neural networks

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 forecasting needs.

From the wide range of applications of neural networks,we deal with few of them as follows:

1.Character Recognition:

The idea of character recognition has become very important as handheld devices like the Palm Pilot are becoming increasingly popular. Neural networks can be used to recognize handwritten characters.

2.Image Compression:-

Neural networks can receive and process vast amounts of information at once, making them useful in image compression. With the Internet explosion and more sites using more images on their sites, using neural networks for image compression is worth a look.

3.Stock Market:-

The day-to-day business of the stock market is extremely complicated. Many factors weigh in whether a given stock will go up or down on any given day. Since neural networks can examine a lot of information quickly and sort it all out, they can be used to predict stock prices.

4.Food Processing:-

The food industry is perhaps the biggest practical market for electronic noses, assisting or replacing entirely humans. Inspection of food, grading quality of food, fish inspection, fermentation control, checking mayonnaise for rancidity, automated flavor control,

monitoring cheese ripening, verifying if orange juice is natural, beverage container inspection, and grading whisky.

5. Medicine:

One of the areas that has gained attention is in cardiopulmonary diagnostics. The ways neural networks work in this area or other areas of medical diagnosis is by the comparison of many different models. They assist doctors with their diagnosis by analyzing the reported symptoms and image data such as MRIs or X-rays.

6.Target Recognition:-

Neural networks also play an important part in the warfield , particularly in fighter jets and tanks.The tanks and planes are fitted with high resolution digital cameras hooked upto a computer which would continually scan the environment outside for possible threats.

7.Machine Diagnostics:-

Detect when a machine has failed so that the system can automatically shut down the machine when this occurs.

8.Signature Analysis:-

Neural nets can be used as a mechanism for comparing signatures made (e.g. in a bank) with those stored. This is one of the first large-scale applications of neural networks in the USA, and is also one of the first to use a neural network chip.

9.Monitoring:-

Networks have been used to monitor

- the state of aircraft engines. By monitoring vibration levels and sound, early warning of engine problems can be given.
- British Rail have also been testing a similar application monitoring diesel engines.

7. Limits to neural networks

The major issues of concern today are the scalability problem, testing, verification, and integration of neural network systems into the modern environment. Neural network programs sometimes become unstable when applied to larger problems. The defence, nuclear and space industries are concerned about the issue of testing and verification. The mathematical theories used to guarantee the performance of an applied neural network are still under development. The solution for the time being may be to train and test these intelligent systems much as we do for humans. Also there are some more practical problems like:

- the operational problem encountered when attempting to simulate the parallelism of neural networks. Since the majority of neural networks are simulated on sequential machines, giving rise to a very rapid increase in processing time requirements as size of the problem expands.

Solution: implement neural networks directly in hardware, but these need a lot of development still.

- instability to explain any results that they obtain. Networks function as "black boxes" whose rules of operation are completely unknown.

8.Future of neural networks

Neural networks are very good at a wide variety of problems, better suited than traditional computer architecture to problems that humans are naturally good at and which computers are traditionally bad at ! And researchers are continually constructing networks that are better at these problems. But will neural networks ever fully simulate the human brain? Will they be as complex and as functional? Will a machine ever be conscious of its own existence?

Of course, the whole future of neural networks does not reside in attempts to simulate consciousness. Indeed, that is of relatively small concern at the moment; more pressing are issues of how to improve the systems we have. All current neural network technologies will most likely be vastly improved upon in the future. Everything from handwriting and speech recognition to stock market prediction will become more sophisticated as researchers develop better training methods and network architectures.

Neural Networks might, in the future, allow:

- robots that can see, feel, and predict the world around them
- improved stock prediction
- common usage of self-driving cars
- composition of music
- handwritten documents to be automatically transformed into formatted word processing documents
- trends found in the human genome to aid in the understanding of the data compiled by the Human Genome Project
- self-diagnosis of medical problems using neural networks and much more.....

9. 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.

Perhaps the most exciting aspect of neural networks is the possibility that some day 'conscious' networks might be produced. There is a number of scientists arguing that consciousness is a 'mechanical' property and that 'conscious' neural networks are a realistic possibility.

Finally, I would like to state that even though neural networks have a huge potential we will only get the best of them when they are integrated with computing, AI, fuzzy logic and related subjects.

10.Bibliographic References:

WEBLINKS:

- <http://vv.carleton.ca/~neil/neural/tank.html>
- http://www.hse.gov.uk/research/crr_pdf/2001/crr01327.pdf
- www-cse.stanford.edu/classes/sophomore-cons/stocks.html
- www.lincoln.ac.nz
- www.crlpublishing.co.uk/neural.htm

- <http://www6.bcity.com/mj futures/>
- http://www.tradetrek.com/education/ai/ai_stock_trading03.asp
- www.fuzzytech.com
- <http://www.particle.kth.se/~lindsey/HardwareNNWCourse/>
- <http://www.geocities.com/SiliconValley/Lakes/6007/Neural.htm>
- <http://www.w3.org/TR/1998/REC-xml-19980210>.

BOOKS:

1. Bishop, C.M. Neural Networks for Pattern Recognition. Oxford: Oxford University Press. 1995.
2. Atencia, M.A., Joya and F. Sandoval. A formal model for definition and simulation of generic neural networks. Neural processing letters, Kluwer Academic Publishers.
3. D. Hamerstorm, Working with neural networks, spectrum, July 1993.