

Abstract

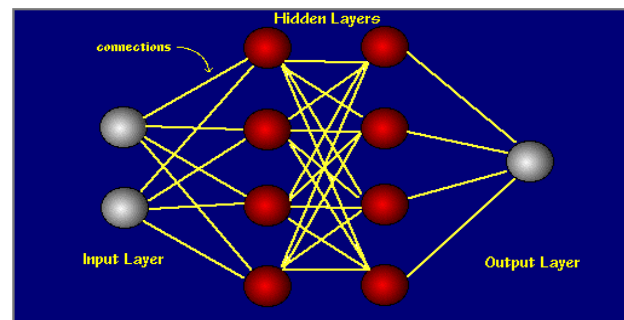
The basic idea behind a neural network is to simulate (copy in a simplified but reasonably faithful way) lots of densely interconnected brain cells inside a computer so you can get it to learn things, recognize patterns, and make decisions in a humanlike way. The amazing thing about a neural network is that you don't have to program it to learn explicitly: it learns all by itself, just like a brain! But it isn't a brain. It's important to note that neural networks are (generally) software simulations: they're made by programming very ordinary computers, working in a very traditional fashion with their ordinary transistors and serially connected logic gates, to behave as though they're built from billions of highly interconnected brain cells working in parallel. This paper is to propose that a neural network applied in engineering science that how a robots that can see, feel, and predict the world around them, improved stock prediction, common usage of self-driving car and much more!

Keywords: neural network simulation.

Introduction

This is a simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is provided by the inventor of one of the first neurocomputers. A neural network as: "...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. 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. Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers

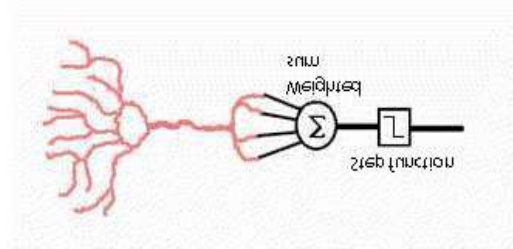
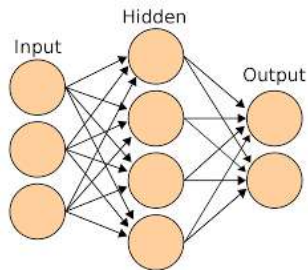
then link to an 'output layer' where the answer is output as shown in the graphic below



Architecture of neural network

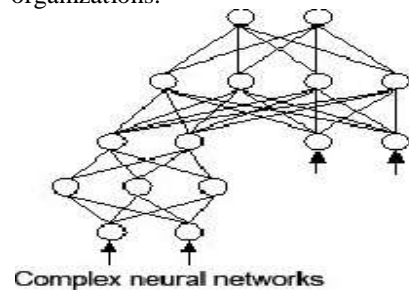
A. Feed-Forward Networks

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 organization is also referred to as bottom-up or top-down.



B. 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 connection in single-layer organizations.



C. 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. 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 represent.

D. Perceptron

The perceptron is 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.

Digital computer vs neural network

Digital computer

- 1) Parallelization difficult :sequential
- 2) processing of data
- 3) useless without software
- 4) rigid : modify one bit, disaster
- 5) conclusion: important differences
 -->new paradigm for information Processing

Neural network

- 1) parallelization easy parallel by definition cur brain
- 2) useless without training
- 3) choice of learning rule and examples crucial
- 4) robust against inaccuracies in data, defect neurons and error-correcting capability
 ->collective behavior cur brain

Neural network vs human brain

Neural network

- 1) low complexity : electronic VLSI chip : < few thousand neurons on 1 chip / simulations on computers : few 100.000 neurons
- 2) high processing speed : 30 to 200 million basic operations per sec on a computer or chip
- 3) energetic efficiency : best computers now consume 10**6 Joule per operation and per sec
- 4) conclusion : methodology for design and use of neural networks ≠ biologic neural networks

Human brain

- 1) high complexity : human brain 100.000.000.000 neurons --> gap cannot be bridged in a few decennia
- 2) Low processing speed: reaction time of biologic neural networks: 1 to 2 millisecond.
- 3) Energetic efficiency: biologic neural network much better. 10**16 Joule per operation and per sec
- 4) Conclusion: modesty with respect to the human brain.

Neural network software

Neural network software is used to simulate, research, develop and apply artificial neural networks, biological neural networks and, in some cases, a wider array of adaptive systems. such as artificial intelligence and machine learning.

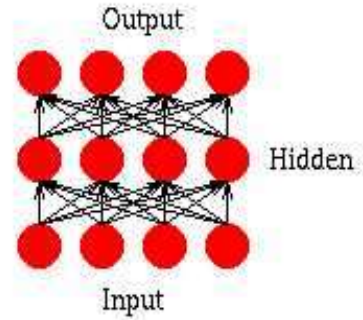


Properties of neural network and neurons

- 1) Nonlinearity. A neuron is basically a nonlinear device. Consequently, a neural network, made up of an interconnection of neurons, is itself nonlinear. Moreover, the nonlinearities of a special kind in the sense that it is distributed throughout the network.
- 2) Input-Output Mapping. A popular paradigm of learning called supervised learning involves the modification of the synaptic weights of a neural network by applying a set Of labeled training samples.
- 3) Adaptively. Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment.
- 4) Evidential Response. In the context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to select, but also about the confidence in the decision made.

Four different uses of neural networks that are of great significance

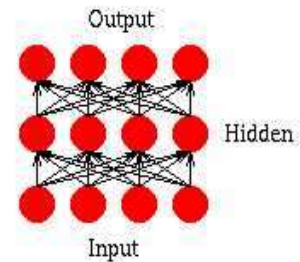
- 1) Classification. In a mathematical sense, this involves dividing an n-dimensional space into various regions, and given a point in the space one should tell which region to which it belongs. This idea is used in many real-world applications, for instance, in various pattern recognition programs. Each pattern is transformed into a multi-dimensional point, and is classified to a certain group, each of which represents a known pattern. Type of network used:



Feed forward network,

- 2) Prediction. A neural network can be trained to produce outputs that are expected given a particular input. If we have a network that fits well in modeling a known sequence of values, one can use it to predict future results. An obvious example is stock market prediction.

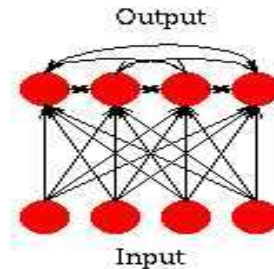
Type of network used:



Feed-forward networks

- 3) Clustering. Sometimes we have to analyze data that are so complicated there is no obvious way to classify them into different categories. Neural networks can be used to identify special features of these data and classify them into different categories without prior knowledge of the data.

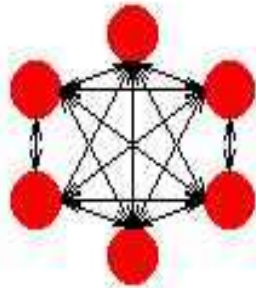
Type of network used:



Simple Competitive Networks, ART network, Adaptive Resonance Theory (ART) networks, Kohen Self-Organizing Maps (SOM)

- 4) Association. A neural network can be trained to "remember" a number of patterns, so that when a distorted version of a particular pattern is presented, the network associates it with the closest one in its memory and returns the original version of that particular pattern. This is useful for restoring noisy data.

Type of network used:



Hopfield network

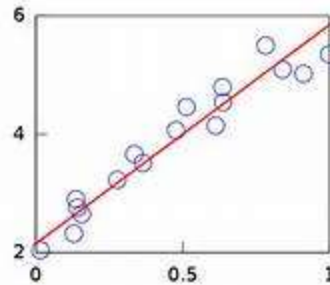
Example of neural network

Back propagation Nets: Back propagation nets are the most common kind of ANN. The basic topology is that layers of neurons are connected to each other. Patterns cause information to flow in one direction, then the errors "back propagate" in the other direction, changing the strength of the interconnections between layers. A very simple example of Neural Networks using back propagation this program is a simple example of Neural Networks using back propagation. My code has all basic functionalities like learning rate, load net, save net, etc. You can have as many layers as you can. The code here is extensible i.e. you can use my code in your programs to implement neural networks.

Hopfield Nets: John Hopfield, a Nobel Prize-winning physicist at California Institute of Technology (Caltech), invented Hopfield nets. The basic topology is that every artificial neuron is connected to every other artificial neuron.

Self-Organizing Maps: Finnish professor Teuvo Kohonen invented self-organizing maps, also known as Kohonen nets. The basic topology is that each artificial neuron is connected only to its neighbors. Kohonen nets reduce the complexity of data--especially experimentally obtained data.

Linear regression:



Applications of neural network

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.

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.

Stock Market Prediction - 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.

Traveling Salesman's Problem - Interestingly enough, neural networks can solve the traveling salesman problem, but only to a certain degree of approximation.

Medicine, Electronic Nose, Security, and Loan Applications - These are some applications that are in their proof-of-concept stage, with the accept ion of a neural network that will decide whether or not to grant a loan, something that has already been used more successfully than many humans.

Miscellaneous Applications - These are some very interesting (albeit at times a little absurd) applications of neural networks.

Where are neural network going?

A great deal of research is going on in neural networks worldwide. This ranges from basic research into new and more efficient learning algorithms, to networks which can respond to temporally varying patterns (both ongoing at Sterling), to techniques for

implementing neural networks directly in silicon. Already one chip commercially available exists, but it does not include adaptation. Edinburgh University have implemented a neural network chip, and are working on the learning problem. Production of a learning chip would allow the application of this technology to a whole range of problems where the price of a PC and software cannot be justified.

New Application areas: Pen PC's .PC's where one can write on a tablet, and the writing will be recognized and translated into (ASCII) text. Speech and Vision recognition systems not new, but Neural Networks are becoming increasingly part of such systems. They are used as a system component, in conjunction with traditional computers. White goods and toys. As Neural Network chips become available, the possibility of simple cheap systems which have learned to recognize simple entities.



Neural networks are based on complex interactions among processing elements.

Benefits of neural network

Problem Solving: Neural networks can help solve problems that are too complex for conventional technology that relies on finding an algorithmic solution. Real-world problems that require adaptable thinking include sales forecasting, industrial process control, customer research, risk management, target marketing and texture analysis. Neural networks help in these areas because of their ability to derive meaning from complicated and imprecise data.

Real-Time Operation: Unlike conventional serial computers, neural networks do not execute programmed instructions. Instead, they respond in parallel to the pattern of inputs presented to them. Neural networks create their own organization or representation of information fed into them during the learning time.

Fault Tolerance: If a neural network is partly destroyed, some areas will have a degradation of performance. Unlike traditional networks, however,

some capabilities of a neural network are maintained even with major damage.

Learning: Neural networks possess "learning rules" that allow them to learn by example. The most common is the delta rule used with back-propagation neural networks. Back-propagation refers to the backward propagation of error. Learning using the delta rule is a supervised process that happens every time the network is presented with a new input pattern. The network predicts what the pattern might be and then compares that estimate with what it is actually presented. It uses any difference to make adjustments to its connections.

Limitations of neural network

There are many advantages and limitations to neural network analysis and to discuss this subject properly we would have to look at each individual type of network, which isn't necessary for this general discussion. In reference to back propagation networks however, there are some specific issues potential users should be aware of: Back propagation neural networks (and many other types of networks) are in a sense the ultimate 'black boxes'. Apart from defining the general architecture of a network and perhaps initially seeding it with a random numbers, the user has no other role than to feed it input and watch it train and await the output. In fact, it has been said that with back propagation, "you almost don't know what you're doing". Some software freely available software packages (Ned Prop, by, Activation) do allow the user to sample the networks' progress' at regular time intervals, but the learning itself progresses on its own. The final product of this activity is a trained network that provides no equations or coefficients defining a relationship (as in regression) beyond its own internal mathematics. The network 'IS' the final equation of the relationship. Back propagation networks also tend to be slower to train than other types of networks and sometimes require thousands of epochs. If run on a truly parallel computer system this issue is not really a problem, but if the BPNN is being simulated on a standard serial machine (i.e. a single SPARC, Mac or PC) training can take some time. This is because the machines CPU must compute the function of each node and connection separately, which can be problematic in very large networks with a large amount of data. However, the speed of most current machines is such that this is typically not much of an issue.

Real and artificial neural networks

Before we go any further, it's also worth noting some jargon. Strictly speaking, neural networks produced

this way are called artificial neural networks (or ANNs) to differentiate them from the real neural networks (collections of interconnected brain cells) we find inside our brains. You might also see neural networks referred to by names like connectionist machines (the field is also called connectionism), parallel distributed processors (PDP), thinking machines, and so on—but in this article we're going to use the term "neural network" throughout and always use it to mean "artificial neural network."

What does a neural network consist of?

A typical neural network has anything from a few dozen to hundreds, thousands, or even millions of artificial neurons called units arranged in a series of layers, each of which connects to the layers on either side. Some of them, known as input units, are designed to receive various forms of information from the outside world that the network will attempt to learn about, recognize, or otherwise process. Other units sit on the opposite side of the network and signal how it responds to the information it's learned; those are known as output units. In between the input units and output units are one or more layers of hidden units, which, together, form the majority of the artificial brain. Most neural networks are fully connected, which means each hidden unit and each output unit is connected to every unit in the layers either side. The connections between one unit and another are represented by a number called a weight, which can be either positive (if one unit excites another) or negative (if one unit suppresses or inhibits another). The higher the weight, the more influence one unit has on another.

What are neural networks used for?

On the basis of this example, you can probably see lots of different applications for neural networks that involve recognizing patterns and making simple decisions about them. In airplanes, you might use a neural network as a basic autopilot, with input units reading signals from the various cockpit instruments and output units modifying the plane's controls appropriately to keep it safely on course. Inside a factory, you could use a neural network for quality control. Let's say you're producing clothes washing detergent in some giant, convoluted chemical process. You could measure the final detergent in various ways (its color, acidity, thickness, or whatever), feed those measurements into your neural network as inputs, and then have the network decide whether to accept or reject the batch.

Recent advances and future applications of neural networks include

Integration of fuzzy logic into neural networks: Fuzzy logic is a type of logic that recognizes more than simple true and false values, hence better simulating the real world. For example, the statement today is sunny might be 100% true if there are no clouds, 80% true if there are a few clouds, 50% true if it's hazy, and 0% true if rains all day. Hence, it takes into account concepts like -usually, somewhat, and sometimes. Fuzzy logic and neural networks have been integrated for uses as diverse as automotive engineering, applicant screening for jobs, the control of a crane, and the monitoring of glaucoma.

Pulsed neural networks: "Most practical applications of artificial neural networks are based on a computational model involving the propagation of continuous variables from one processing unit to the next. In recent years, data from neurobiological experiments have made it increasingly clear that biological neural networks, which communicate through pulses, use the timing of the pulses to transmit information and perform computation. This realization has stimulated significant research on pulsed neural networks, including theoretical analyses and model development, neurobiological modeling, and hardware implementation Hardware specialized for neural networks

Some networks have been hardcoded into chips or analog devices?

This technology will become more useful as the networks we use become more complex. The primary benefit of directly encoding neural networks onto chips or specialized analog devices is SPEED! NN hardware currently runs in a few niche areas, such as those areas where very high performance is required (e.g. high energy physics) and in embedded applications of simple, hardwired networks (e.g. voice recognition). Many NNs today use less than 100 neurons and only need occasional training. In these situations, software simulation is usually found sufficient When NN algorithms develop to the point where useful things can be done with 1000's of neurons and 10000's of synapses, high performance NN hardware will become essential for practical operation. Improvement of existing technologies All current NN 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.

NNs might, in the future, allow:

- 1) Robots that can see, feel, and predict the world around them
- 2) Improved stock prediction
- 3) Common usage of self-driving cars
- 4) Composition of music
- 5) Handwritten documents to be automatically transformed into formatted word processing documents
- 6) Trends found in the human genome to aid in the understanding of the data compiled by the Human Genome Project
- 7) Self-diagnosis of medical problems using neural network and much more!



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 someday '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. Neural networks are realistic alternatives for information problems (instead of tedious software development)not magic, but design is based on solid

mathematical methods neural networks are interesting whenever examples are abundant, and the problem cannot be captured in simple rules. superior for cognitive tasks and processing of sensorial data such as vision, image- and speech recognition, control, robotics, expert systems.

References

1. Neural Networks by Eric Davalo and Patrick Naima.
2. Prof. Leslie Smith Centre for Cognitive and Computational Neuroscience Department of Computing and Mathematics University of Stirling.
3. S. Haykin "Neural Networks: A Comprehensive Foundation (2nd Edition)", Prentice Hall, 1998.
4. From Wikipedia, the free encyclopedia.
5. Seattle Robotics: Back propagation Nets Wolfram: Hopfield Net Davis: Self Organizing Maps
6. Hassoun, Mohamad. Fundamentals of artificial neural networks. Boston, MA: MIT Press, 1994. Haykin, Simon. Neural Networks and Learning Machines. Englewood Cliffs, NJ: Prentice Hall, 2009. Chris Woodford.
7. By Christos Stergiou and Dimitrios Siganos
8. A web site created for Eric Roberts' Sophomore College 2000 class entitled "The Intellectual Excitement of Computer Science."