ARTIFICIAL NEURAL NETWORKS AND THEIR APPLICATIONS IN BUSINESS

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Abstract

In modern software implementations of artificial neural networks the approach inspired by biology has more or less been abandoned for a more practical approach based on statistics and signal processing. In some of these systems, neural networks, or parts of neural networks (such as artificial neurons), are used as components in larger systems that combine both adaptive and non-adaptive elements. There are many problems which are solved with neural networks, especially in business and economic domains.

Key words: neuron, neural networks, artificial intelligence, feed-forward neural networks, classification

Introduction

A biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Connections, called synapses, are usually formed from axons to dendrites, though dendrodendritic microcircuit and other connections are possible. Apart from the electrical signaling, there are other forms of signaling that arise from neurotransmitter diffusion, which have an effect on electrical signaling. As such, neural networks are extremely complex.

Artificial intelligence and cognitive modeling try to simulate some properties of neural networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems.

In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents (in computer and video games) or autonomous robots. Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimation, optimization and control theory.

Biological versus artificial neuron

Artificial neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943 (McCulloch & Pitts, 1943). These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks. The basic model of the neuron is founded upon the functionality of a biological neuron. "Neurons are the basic signaling units of the nervous

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system" and "each neuron is a discrete cell whose several processes arise from its cell body".

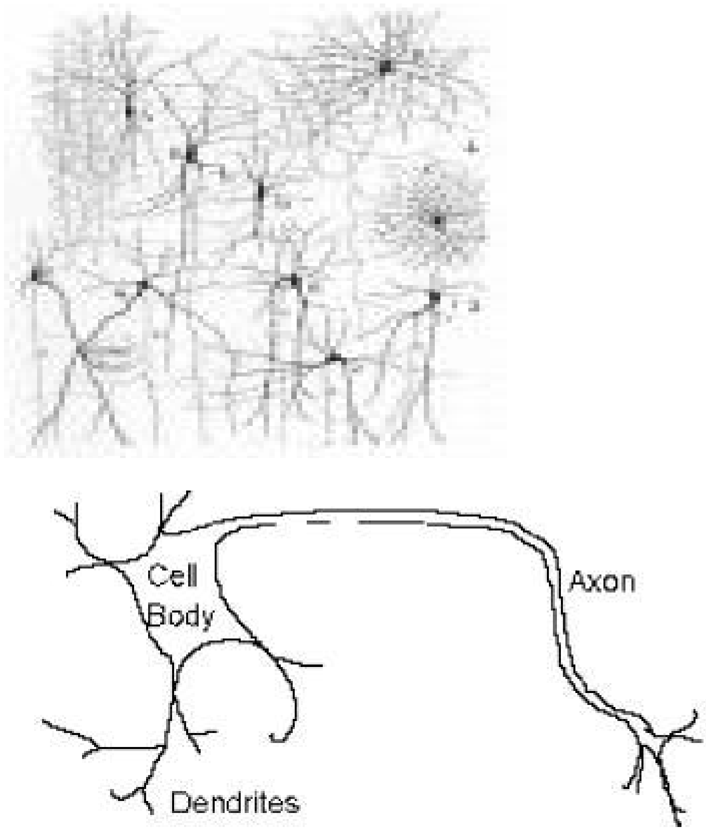

Figure 1. Biological neural network

In the figure 1 it is shown that the neuron has four main regions to its structure. The cell body, or soma, has two offshoots from it, the dendrites, and the axon, which end in presynaptic terminals. The cell body is the heart of the cell, containing the nucleus and maintaining protein synthesis. A neuron may have many dendrites, which branch out in a treelike structure, and receive signals from other neurons. A neuron usually only has one axon which grows out from a part of the cell body called the axon hillock. The axon conducts electric signals generated at the axon hillock down its length. These electric signals are called action potentials. The other end of the axon may split into several branches, which end in a presynaptic terminal. Action potentials are the electric signals that neurons use to convey information to the brain. All these signals are identical. Therefore, the brain determines what type of information is being received based on the path that the signal took. The brain analyzes the patterns of signals being sent and from that information it can interpret the type of information being received. Myelin is the fatty tissue that surrounds and insulates the axon. Often short axons do not need this insulation. There are uninsulated parts of the axon. These areas are called Nodes of Ranvier. At these nodes, the signal traveling down the axon is regenerated. This ensures that the signal traveling down the axon travels fast and remains constant. The synapse is the area of contact between two neurons. The neurons do not actually physically touch. They are separated by the synaptic cleft, and electric signals are sent through chemical 13 interaction. The neuron sending the signal is called the presynaptic cell and the neuron receiving the signal is called the postsynaptic cell. The signals are generated by the membrane potential, which is based on the differences in concentration of sodium and potassium ions inside and outside the cell membrane. Neurons can be classified by their number of processes (or appendages), or by their function. If they are classified by the number of processes, they fall into three categories. Unipolar neurons have a single process (dendrites and axon are located on the same stem), and are most common in invertebrates. In bipolar neurons, the dendrite and axon are the neuron's two separate processes. Bipolar neurons have a subclass called pseudo-bipolar neurons, which are used to send sensory information to the spinal cord. Finally, multipolar neurons are most common in mammals. Examples of these neurons are spinal motor neurons, pyramidal cells and Purkinje cells (in the cerebellum).

An **artificial neuron** is a mathematical function conceived as a crude model, or abstraction of biological neurons (figure 2). Artificial neurons are the constitutive units in an artificial neural network. Depending on the specific model used, it can receive different names, such as semi-linear unit, Nv neuron, binary neuron, linear threshold function or McCulloch–Pitts neuron. The artificial neuron receives one or more inputs (representing the one or more dendrites) and sums them to produce an output (synapse). Usually the sums of each node are weighted, and the sum is passed through a non-linear function known as an activation function or transfer function. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, piecewise linear functions, or step functions. They are also often monotonically increasing, continuous, differentiable and bounded.

For a given artificial neuron, let there be $m + 1$ inputs with signals x_0 through x_m and weights w_0 through w_m. Usually, the x_0 input is assigned the value +1, which makes it a *bias* input with $w_{k0} = b_k$. This leaves only m actual inputs to the neuron: from x_1 to x_m.
The output of kth neuron is:

$$y_k = \varphi\left(\sum_{j=0}^{m} w_{kj} x_j\right)$$

Where φ (phi) is the transfer function.

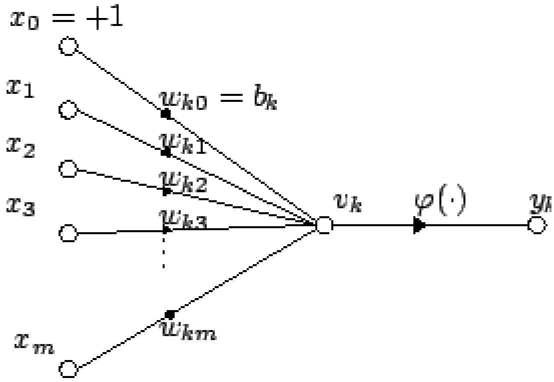

Figure 2 Artificial neuron

The output is analogous to the axon of a biological neuron, and its value propagates to input of the next layer, through a synapse. It may also exit the system, possibly as part of an output vector.

Artificial neural networks

An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. Although computing these days is truly advanced, there are certain tasks that a program made for a common microprocessor is unable to perform; even so a software implementation of a neural network can be made with their advantages and disadvantages.

Advantages of neural networks:

- A neural network can perform tasks that a linear program can not.
- When an element of the neural network fails, it can continue without any problem by their parallel nature.
- A neural network learns and does not need to be reprogrammed.
- It can be implemented in any application.
- It can be implemented without any problem.

Disadvantagesof neural networks:

- The neural network needs training to operate.
- The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated.
- Requires high processing time for large neural networks.

Another aspect of the artificial neural networks is that there are different architectures, which consequently requires different types of algorithms, but despite to be an apparently complex system, a neural network is relatively simple.

There are different types of neural networks, which can be distinguished on the basis of their structure and directions of signal flow. Each kind of neural network has its own method of training. Generally, neural networks may be differentiated as follows:

- ❖ feedforward networks
    - one-layer networks

        - multi-layer networks
- recurrent networks
- cellular networks

Feedforward neural networks, which typical example is one-layer perceptron, consist of neurons set in layers. The information flow has one direction. Neurons from a layer are connected only with the neurons from the preceding layer. The multi-layer networks usually consist of input, hidden (one or more), and output layers. Such system may be treated as non-linear function approximation block: $y = f(u)$.

Recurrent neural networks. Such networks have feedback loops (at least one) – output signals of a layer are connected to its inputs. It causes dynamic effects during network work. Input signals of layer consist of input and output states (from the previous step) of that layer.

Applications of natural and of artificial neural networks

The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations and also to use it. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

The tasks to which artificial neural networks are applied tend to fall within the following broad categories:

- Function approximation, or regression analysis, including time series prediction and modelling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Data processing, including filtering, clustering, blind signal separation and compression.

Application areas of artificial neural networks include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition, etc.), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications, data mining (or knowledge discovery in databases), visualization and e-mail spam filtering.

- Moreover, some brain diseases, e.g. Alzheimer, are apparently, and essentially, diseases of the brain's natural neural network by damaging necessary prerequisites for the functioning of the mutual interconnections between neurons and/or glia.
- Neural networks have broad applicability to real world business problems. In fact, they have already been successfully applied in many industries.

A few representative examples of problems to which neural network analysis has been applied successfully are:

- **Detection of medical phenomena.** A variety of health-related indices (e.g., a combination of heart rate, levels of various substances in the blood, respiration rate) can be monitored. The onset of a particular medical condition could be associated with a very complex (e.g., nonlinear and interactive) combination of changes on a subset of the variables being monitored. Neural networks have been used to recognize this predictive pattern so that the appropriate treatment can be prescribed.

- **Monitoring the condition of machinery.** Neural networks can be instrumental in cutting costs by bringing additional expertise to scheduling the preventive maintenance of machines. A neural network can be trained to distinguish between the sounds a machine makes when it is running normally ("false alarms") versus when it is on the verge of a problem. After this training period, the expertise of the network can be used to warn a technician of an upcoming breakdown, before it occurs and causes costly unforeseen "downtime."
- **Engine management.** Neural networks have been used to analyze the input of sensors from an engine. The neural network controls the various parameters within which the engine functions, in order to achieve a particular goal, such as minimizing fuel consumption.

But to give some more specific examples artificial neural networks are also used in the following specific paradigms:

- recognition of speakers in communications;
- diagnosis of hepatitis;
- recovery of telecommunications from faulty software;
- interpretation of multimeaning Chinese words;
- undersea mine detection;
- texture analysis;
- three-dimensional object recognition;
- hand-written word recognition;
- facial recognition.

Neural networks in business

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

Business is a diverted field with several general areas of specialisation 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.

There is a marketing application which has been integrated with a neural network system. The Airline Marketing Tactician (a trademark abbreviated as AMT) is a computer system made of various intelligent technologies including expert systems. A feedforward neural network is integrated with the AMT and was trained using back-propagation to assist the marketing control of airline seat allocations. The adaptive neural approach was amenable to rule expression. Additionaly, the application's environment changed rapidly and constantly, which required a continuously adaptive solution. The system is used to monitor and recommend booking advice for each departure. Such information has a direct impact on the profitability of an airline and can provide a technological advantage for users of the system.

While it is significant that neural networks have been applied to this problem, it is also important to see that this intelligent technology can be integrated with expert systems and other approaches to make a functional system. Neural networks were used to discover the influence of undefined interactions by the various variables. While these interactions were not defined, they were used by the neural system to develop useful conclusions. It is also noteworthy to see that neural networks can influence the bottom line.

Neural networks are applicable in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists, even when that relationship is very complex and not easy to articulate in the usual terms of "correlations" or "differences between groups."

Fluctuations of stock prices and stock indices are another example of a complex, multidimensional, but in some circumstances at least partially-deterministic phenomenon. Neural networks are being used by many technical analysts to make predictions about stock prices based upon a large number of factors such as past performance of other stocks and various economic indicators.

A variety of pieces of information are usually known about an applicant for a loan. For instance, the applicant's age, education, occupation, and many other facts may be available. After training a neural network on historical data, neural network analysis can identify the most relevant characteristics and use those to classify applicants as good or bad credit risks.

Prediction problems may be divided into two main categories: classification and regression.

In classification, the objective is to determine to which of a number of discrete classes a given input case belongs. Examples include credit assignment (is this person a good or bad credit risk), cancer detection (tumor, clear), signature recognition (forgery, true). In all these cases, the output required is clearly a single nominal variable. The most common classification tasks are (as above) two-state, although many-state tasks are also not unknown.

In regression, the objective is to predict the value of a (usually) continuous variable: tomorrow's stock price, the fuel consumption of a car, next year's profits. In this case, the output required is a single numeric variable.

Neural networks can actually perform a number of regression and/or classification tasks at once, although commonly each network performs only one. In the vast majority of cases, therefore, the network will have a single output variable, although in the case of many-state classification problems, this may correspond to a number of output units (the post-processing stage takes care of the mapping from output units to output variables). If you do define a single network with multiple output variables, it may suffer from cross-talk (the hidden neurons experience difficulty learning, as they are attempting to model at least two functions at once). The best solution is usually to train separate networks for each output, then to combine them into an ensemble so that they can be run as a unit.

Conclusion

Once a problem is solved by using neural networks, it needs to gather data for training purposes. The training data set includes a number of cases, each containing values for a range of input and output variables. The first decisions needed to be made are: which variables to use, and how many (and which) cases to gather.

The choice of variables (at least initially) is guided by intuition. The expertise in the problem domain should give some idea of which input variables are likely to be influential. As a first pass, it is needed to include any variables that could have an influence - part of the design process will be to whittle this set down.

Neural networks process numeric data in a fairly limited range. This presents a problem if data is in an unusual range, if there is missing data, or if data is non-numeric. Fortunately, there are methods to deal with each of these problems. Numeric data is scaled into an appropriate range for the network, and missing values can be substituted for using the mean value (or other statistic) of that variable across the other available training cases.

All neural networks take numeric input and produce numeric output. The transfer function of a unit is typically chosen so that it can accept input in any range, and produces output in a strictly limited range (it has a squashing effect). Although the input can be in any range, there is a saturation effect so that the unit is only sensitive to inputs within a fairly limited range.

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