1 Introduction

Objectives

As you read these words you are using a complex biological neural network. You have a highly interconnected set of some 10^{11} neurons to facilitate your reading, breathing, motion and thinking. Each of your biological neurons, a rich assembly of tissue and chemistry, has the complexity, if not the speed, of a microprocessor. Some of your neural structure was with you at birth. Other parts have been established by experience.

Scientists have only just begun to understand how biological neural networks operate. It is generally understood that all biological neural functions, including memory, are stored in the neurons and in the connections between them. Learning is viewed as the establishment of new connections between neurons or the modification of existing connections. This leads to the following question: Although we have only a rudimentary understanding of biological neural networks, is it possible to construct a small set of simple artificial "neurons" and perhaps train them to serve a useful function? The answer is "yes." This book, then, is about *artificial* neural networks.

The neurons that we consider here are not biological. They are extremely simple abstractions of biological neurons, realized as elements in a program or perhaps as circuits made of silicon. Networks of these artificial neurons do not have a fraction of the power of the human brain, but they can be trained to perform useful functions. This book is about such neurons, the networks that contain them and their training.

History

The history of artificial neural networks is filled with colorful, creative individuals from a variety of fields, many of whom struggled for decades to develop concepts that we now take for granted. This history has been documented by various authors. One particularly interesting book is *Neurocomputing: Foundations of Research* by John Anderson and Edward Rosenfeld. They have collected and edited a set of some 43 papers of special historical interest. Each paper is preceded by an introduction that puts the paper in historical perspective.

Histories of some of the main neural network contributors are included at the beginning of various chapters throughout this text and will not be repeated here. However, it seems appropriate to give a brief overview, a sample of the major developments.

At least two ingredients are necessary for the advancement of a technology: concept and implementation. First, one must have a concept, a way of thinking about a topic, some view of it that gives a clarity not there before. This may involve a simple idea, or it may be more specific and include a mathematical description. To illustrate this point, consider the history of the heart. It was thought to be, at various times, the center of the soul or a source of heat. In the 17th century medical practitioners finally began to view the heart as a pump, and they designed experiments to study its pumping action. These experiments revolutionized our view of the circulatory system. Without the pump concept, an understanding of the heart was out of grasp.

Concepts and their accompanying mathematics are not sufficient for a technology to mature unless there is some way to implement the system. For instance, the mathematics necessary for the reconstruction of images from computer-aided tomography (CAT) scans was known many years before the availability of high-speed computers and efficient algorithms finally made it practical to implement a useful CAT system.

The history of neural networks has progressed through both conceptual innovations and implementation developments. These advancements, however, seem to have occurred in fits and starts rather than by steady evolution.

Some of the background work for the field of neural networks occurred in the late 19th and early 20th centuries. This consisted primarily of interdisciplinary work in physics, psychology and neurophysiology by such scientists as Hermann von Helmholtz, Ernst Mach and Ivan Pavlov. This early work emphasized general theories of learning, vision, conditioning, etc., and did not include specific mathematical models of neuron operation.

The modern view of neural networks began in the 1940s with the work of Warren McCulloch and Walter Pitts [McPi43], who showed that networks of artificial neurons could, in principle, compute any arithmetic or logical function. Their work is often acknowledged as the origin of the neural network field.

McCulloch and Pitts were followed by Donald Hebb [Hebb49], who proposed that classical conditioning (as discovered by Pavlov) is present because of the properties of individual neurons. He proposed a mechanism for learning in biological neurons (see Chapter 7).

The first practical application of artificial neural networks came in the late 1950s, with the invention of the perceptron network and associated learning rule by Frank Rosenblatt [Rose58]. Rosenblatt and his colleagues built a perceptron network and demonstrated its ability to perform pattern recognition. This early success generated a great deal of interest in neural network research. Unfortunately, it was later shown that the basic perceptron network could solve only a limited class of problems. (See Chapter 4 for more on Rosenblatt and the perceptron learning rule.)

At about the same time, Bernard Widrow and Ted Hoff [WiHo60] introduced a new learning algorithm and used it to train adaptive linear neural networks, which were similar in structure and capability to Rosenblatt's perceptron. The Widrow-Hoff learning rule is still in use today. (See Chapter 10 for more on Widrow-Hoff learning.)

Unfortunately, both Rosenblatt's and Widrow's networks suffered from the same inherent limitations, which were widely publicized in a book by Marvin Minsky and Seymour Papert [MiPa69]. Rosenblatt and Widrow were aware of these limitations and proposed new networks that would overcome them. However, they were not able to successfully modify their learning algorithms to train the more complex networks.

Many people, influenced by Minsky and Papert, believed that further research on neural networks was a dead end. This, combined with the fact that there were no powerful digital computers on which to experiment, caused many researchers to leave the field. For a decade neural network research was largely suspended.

Some important work, however, did continue during the 1970s. In 1972 Teuvo Kohonen [Koho72] and James Anderson [Ande72] independently and separately developed new neural networks that could act as memories. (See Chapter 15 and Chapter 16 for more on Kohonen networks.) Stephen Grossberg [Gros76] was also very active during this period in the investigation of self-organizing networks. (See Chapter 18 and Chapter 19.)

Interest in neural networks had faltered during the late 1960s because of the lack of new ideas and powerful computers with which to experiment. During the 1980s both of these impediments were overcome, and research in neural networks increased dramatically. New personal computers and workstations, which rapidly grew in capability, became widely available. In addition, important new concepts were introduced.

Two new concepts were most responsible for the rebirth of neural networks. The first was the use of statistical mechanics to explain the operation of a certain class of recurrent network, which could be used as an associative memory. This was described in a seminal paper by physicist John Hopfield [Hopf82]. (Chapter 20 and Chapter 21 discuss these Hopfield networks.)

The second key development of the 1980s was the backpropagation algorithm for training multilayer perceptron networks, which was discovered independently by several different researchers. The most influential publication of the backpropagation algorithm was by David Rumelhart and James McClelland [RuMc86]. This algorithm was the answer to the criticisms Minsky and Papert had made in the 1960s. (See Chapter 11 for a development of the backpropagation algorithm.)

These new developments reinvigorated the field of neural networks. Since the 1980s, thousands of papers have been written, neural networks have found countless applications, and the field has been buzzing with new theoretical and practical work.

The brief historical account given above is not intended to identify all of the major contributors, but is simply to give the reader some feel for how knowledge in the neural network field has progressed. As one might note, the progress has not always been "slow but sure." There have been periods of dramatic progress and periods when relatively little has been accomplished.

Many of the advances in neural networks have had to do with new concepts, such as innovative architectures and training rules. Just as important has been the availability of powerful new computers on which to test these new concepts.

Well, so much for the history of neural networks to this date. The real question is, "What will happen in the future?" Neural networks have clearly taken a permanent place as important mathematical/engineering tools. They don't provide solutions to every problem, but they are essential tools to be used in appropriate situations. In addition, remember that we still know very little about how the brain works. The most important advances in neural networks almost certainly lie in the future.

The large number and wide variety of applications of this technology are very encouraging. The next section describes some of these applications.

Applications

A newspaper article described the use of neural networks in literature research by Aston University. It stated that “the network can be taught to recognize individual writing styles, and the researchers used it to compare works attributed to Shakespeare and his contemporaries.” A popular science television program documented the use of neural networks by an Italian research institute to test the purity of olive oil. Google uses neural networks for image tagging (automatically identifying an image and assigning keywords), and Microsoft has developed neural networks that can help convert spoken English speech into spoken Chinese speech. Researchers at Lund University and Skåne University Hospital in Sweden have used neural networks to improve long-term survival rates for heart transplant recipients by identifying optimal recipient and donor matches. These examples are indicative of the broad range of applications that can be found for neural networks. The applications are expanding because neural networks are good at solving problems, not just in engineering, science and mathematics, but in medicine, business, finance and literature as well. Their application to a wide variety of problems in many fields makes them very attractive. Also, faster computers and faster algorithms have made it possible to use neural networks to solve complex industrial problems that formerly required too much computation.

The following note and Table of Neural Network Applications are reproduced here from the *Neural Network Toolbox* for MATLAB with the permission of the MathWorks, Inc.

A 1988 DARPA Neural Network Study [DARP88] lists various neural network applications, beginning with the adaptive channel equalizer in about 1984. This device, which is an outstanding commercial success, is a single-neuron network used in long distance telephone systems to stabilize voice signals. The DARPA report goes on to list other commercial applications, including a small word recognizer, a process monitor, a sonar classifier and a risk analysis system.

Thousands of neural networks have been applied in hundreds of fields in the many years since the DARPA report was written. A list of some of those applications follows.

Aerospace

High performance aircraft autopilots, flight path simulations, aircraft control systems, autopilot enhancements, aircraft component simulations, aircraft component fault detectors

Automotive

Automobile automatic guidance systems, fuel injector control, automatic braking systems, misfire detection, virtual emission sensors, warranty activity analyzers

Banking

Check and other document readers, credit application evaluators, cash forecasting, firm classification, exchange rate forecasting, predicting loan recovery rates, measuring credit risk

Defense

Weapon steering, target tracking, object discrimination, facial recognition, new kinds of sensors, sonar, radar and image signal processing including data compression, feature extraction and noise suppression, signal/image identification

Electronics

Code sequence prediction, integrated circuit chip layout, process control, chip failure analysis, machine vision, voice synthesis, nonlinear modeling

Entertainment

Animation, special effects, market forecasting

Financial

Real estate appraisal, loan advisor, mortgage screening, corporate bond rating, credit line use analysis, portfolio trading program, corporate financial analysis, currency price prediction

Insurance

Policy application evaluation, product optimization

Manufacturing

Manufacturing process control, product design and analysis, process and machine diagnosis, real-time particle identification, visual quality inspection systems, beer testing, welding quality analysis, paper quality prediction, computer chip quality analysis, analysis of grinding operations, chemical product design analysis, machine maintenance analysis, project bidding, planning and management, dynamic modeling of chemical process systems

Medical

Breast cancer cell analysis, EEG and ECG analysis, prosthesis design, optimization of transplant times, hospital expense reduction, hospital quality improvement, emergency room test advisement

Oil and Gas

Exploration, smart sensors, reservoir modeling, well treatment decisions, seismic interpretation

Robotics

Trajectory control, forklift robot, manipulator controllers, vision systems, autonomous vehicles

Speech

Speech recognition, speech compression, vowel classification, text to speech synthesis

Securities

Market analysis, automatic bond rating, stock trading advisory systems

Telecommunications

Image and data compression, automated information services, real-time translation of spoken language, customer payment processing systems

Transportation

Truck brake diagnosis systems, vehicle scheduling, routing systems

Conclusion

The number of neural network applications, the money that has been invested in neural network software and hardware, and the depth and breadth of interest in these devices is enormous.

Biological Inspiration

The artificial neural networks discussed in this text are only remotely related to their biological counterparts. In this section we will briefly describe those characteristics of brain function that have inspired the development of artificial neural networks.

The brain consists of a large number (approximately 10^{11}) of highly connected elements (approximately 10^4 connections per element) called neurons. For our purposes these neurons have three principal components: the dendrites, the cell body and the axon. The dendrites are tree-like receptive networks of nerve fibers that carry electrical signals into the cell body. The cell body effectively sums and thresholds these incoming signals. The axon is a single long fiber that carries the signal from the cell body out to other neurons. The point of contact between an axon of one cell and a dendrite of another cell is called a synapse. It is the arrangement of neurons and the strengths of the individual synapses, determined by a complex chemical process, that establishes the function of the neural network. Figure 1.1 is a simplified schematic diagram of two biological neurons.

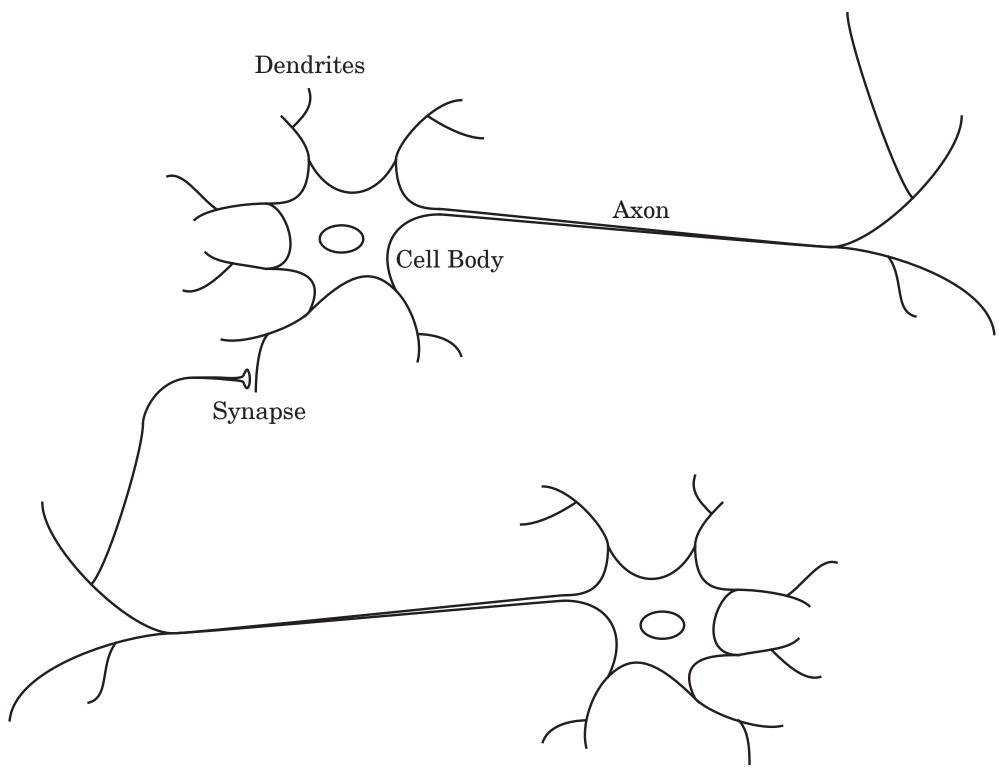

Figure 1.1 Schematic Drawing of Biological Neurons

Some of the neural structure is defined at birth. Other parts are developed through learning, as new connections are made and others waste away. This development is most noticeable in the early stages of life. For example, it has been shown that if a young cat is denied use of one eye during a critical window of time, it will never develop normal vision in that eye. Linguists have discovered that infants over six months of age can no longer discriminate certain speech sounds, unless they were exposed to them earlier in life [WeTe84].

Neural structures continue to change throughout life. These later changes tend to consist mainly of strengthening or weakening of synaptic junctions. For instance, it is believed that new memories are formed by modification of these synaptic strengths. Thus, the process of learning a new friend's face consists of altering various synapses. Neuroscientists have discovered [MaGa2000], for example, that the hippocampi of London taxi drivers are significantly larger than average. This is because they must memorize a large amount of navigational information—a process that takes more than two years.

Artificial neural networks do not approach the complexity of the brain. There are, however, two key similarities between biological and artificial neural networks. First, the building blocks of both networks are simple computational devices (although artificial neurons are much simpler than biological neurons) that are highly interconnected. Second, the connections between neurons determine the function of the network. The primary objective of this book will be to determine the appropriate connections to solve particular problems.

It is worth noting that even though biological neurons are very slow when compared to electrical circuits (10^{-3} s compared to 10^{-10} s), the brain is able to perform many tasks much faster than any conventional computer. This is in part because of the massively parallel structure of biological neural networks; all of the neurons are operating at the same time. Artificial neural networks share this parallel structure. Even though most artificial neural networks are currently implemented on conventional digital computers, their parallel structure makes them ideally suited to implementation using VLSI, optical devices and parallel processors.

In the following chapter we will introduce our basic artificial neuron and will explain how we can combine such neurons to form networks. This will provide a background for Chapter 3, where we take our first look at neural networks in action.

Further Reading

[Ande72] J. A. Anderson, "A simple neural network generating an interactive memory," *Mathematical Biosciences*, Vol. 14, pp. 197–220, 1972.

Anderson proposed a "linear associator" model for associative memory. The model was trained, using a generalization of the Hebb postulate, to learn an association between input and output vectors. The physiological plausibility of the network was emphasized. Kohonen published a closely related paper at the same time [Koho72], although the two researchers were working independently.

[AnRo88] J. A. Anderson and E. Rosenfeld, *Neurocomputing: Foundations of Research*, Cambridge, MA: MIT Press, 1989.

Neurocomputing is a fundamental reference book. It contains over forty of the most important neurocomputing writings. Each paper is accompanied by an introduction that summarizes its results and gives a perspective on the position of the paper in the history of the field.

[DARP88] *DARPA Neural Network Study*, Lexington, MA: MIT Lincoln Laboratory, 1988.

This study is a compendium of knowledge of neural networks as they were known to 1988. It presents the theoretical foundations of neural networks and discusses their current applications. It contains sections on associative memories, recurrent networks, vision, speech recognition, and robotics. Finally, it discusses simulation tools and implementation technology.

[Gros76] S. Grossberg, "Adaptive pattern classification and universal recoding: I. Parallel development and coding of neural feature detectors," *Biological Cybernetics*, Vol. 23, pp. 121–134, 1976.

Grossberg describes a self-organizing neural network based on the visual system. The network, which consists of short-term and long-term memory mechanisms, is a continuous-time competitive network. It forms a basis for the adaptive resonance theory (ART) networks.

[Gros80] S. Grossberg, "How does the brain build a cognitive code?" *Psychological Review*, Vol. 88, pp. 375–407, 1980.

Grossberg's 1980 paper proposes neural structures and mechanisms that can explain many physiological behaviors including spatial frequency adaptation, binocular rivalry, etc. His systems perform error correction by themselves, without outside help.

[Hebb 49] D. O. Hebb, *The Organization of Behavior*. New York: Wiley, 1949.

The main premise of this seminal book is that behavior can be explained by the action of neurons. In it, Hebb proposed one of the first learning laws, which postulated a mechanism for learning at the cellular level.

Hebb proposes that classical conditioning in biology is present because of the properties of individual neurons.

[Hopf82] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," *Proceedings of the National Academy of Sciences*, Vol. 79, pp. 2554–2558, 1982.

Hopfield describes a content-addressable neural network. He also presents a clear picture of how his neural network operates, and of what it can do.

[Koho72] T. Kohonen, "Correlation matrix memories," *IEEE Transactions on Computers*, vol. 21, pp. 353–359, 1972.

Kohonen proposed a correlation matrix model for associative memory. The model was trained, using the outer product rule (also known as the Hebb rule), to learn an association between input and output vectors. The mathematical structure of the network was emphasized. Anderson published a closely related paper at the same time [Ande72], although the two researchers were working independently.

[MaGa00] E. A. Maguire, D. G. Gadian, I. S. Johnsrude, C. D. Good, J. Ashburner, R. S. J. Frackowiak, and C. D. Frith, "Navigation-related structural change in the hippocampi of taxi drivers," Proceedings of the National Academy of Sciences, Vol. 97, No. 8, pp. 4398-4403, 2000.

Taxi drivers in London must undergo extensive training, learning how to navigate between thousands of places in the city. This training is colloquially known as "being on The Knowledge" and takes about 2 years to acquire on average. This study demonstrated that the posterior hippocampi of London taxi drivers were significantly larger relative to those of control subjects.

[McPi43] W. McCulloch and W. Pitts, “A logical calculus of the ideas immanent in nervous activity,” *Bulletin of Mathematical Biophysics.*, Vol. 5, pp. 115–133, 1943.

This article introduces the first mathematical model of a neuron, in which a weighted sum of input signals is compared to a threshold to determine whether or not the neuron fires. This was the first attempt to describe what the brain does, based on computing elements known at the time. It shows that simple neural networks can compute any arithmetic or logical function.

[MiPa69] M. Minsky and S. Papert, *Perceptrons*, Cambridge, MA: MIT Press, 1969.

A landmark book that contains the first rigorous study devoted to determining what a perceptron network is capable of learning. A formal treatment of the perceptron was needed both to explain the perceptron’s limitations and to indicate directions for overcoming them. Unfortunately, the book pessimistically predicted that the limitations of perceptrons indicated that the field of neural networks was a dead end. Although this was not true it temporarily cooled research and funding for research for several years.

[Rose58] F. Rosenblatt, “The perceptron: A probabilistic model for information storage and organization in the brain,” *Psychological Review*, Vol. 65, pp. 386–408, 1958.

Rosenblatt presents the first practical artificial neural network — the perceptron.

[RuMc86] D. E. Rumelhart and J. L. McClelland, eds., *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, Vol. 1, Cambridge, MA: MIT Press, 1986.

One of the two key influences in the resurgence of interest in the neural network field during the 1980s. Among other topics, it presents the backpropagation algorithm for training multilayer networks.

[WeTe84] J. F. Werker and R. C. Tees, “Cross-language speech perception: Evidence for perceptual reorganization during the first year of life,” Infant Behavior and Development, Vol. 7, pp. 49-63, 1984.

This work describes an experiment in which infants from the Interior Salish ethnic group in British Columbia, and other infants outside that group, were tested on their ability to discriminate two different sounds from the Thompson language, which is spoken by the Interior Salish. The researchers discovered that infants less than 6 or 8 months of age were generally able to distinguish the sounds, whether or not they were Interior Salish. By 10 to 12 months of age, only the Interior Salish children were able to distinguish the two sounds.

[WiHo60] B. Widrow and M. E. Hoff, “Adaptive switching circuits,” *1960 IRE WESCON Convention Record*, New York: IRE Part 4, pp. 96–104, 1960.

This seminal paper describes an adaptive perceptron-like network that can learn quickly and accurately. The authors assume that the system has inputs and a desired output classification for each input, and that the system can calculate the error between the actual and desired output. The weights are adjusted, using a gradient descent method, so as to minimize the mean square error. (Least Mean Square error or LMS algorithm.)

This paper is reprinted in [AnRo88].