

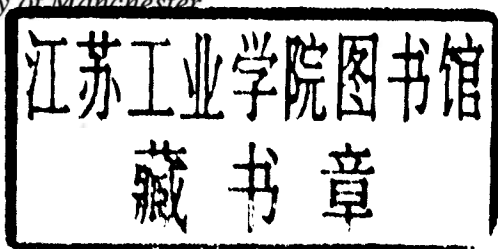
# Neural Networks

Eric Davalo and  
Patrick Naïm  
Translated by  
A. Rawsthorne

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# *Foreword*

The brain has a long history in the development of different species. It has evolved in size and in neurological complexity over many millions of years; from fish to amphibians, and from reptiles to the mammals, the story of vertebrates is that of a constant struggle to escape from the seas and conquer dry land. This long march, needing constant adaptation to a sometimes hostile environment, was made possible by the development of the brain, giving more precise sensory inputs, allowing coordination and even planning of future actions. At the same time, paradoxically, the brain has remained a mystery to man himself, and all the great thinkers since the Greeks have advanced their own theories to explain its operation.

Since the 1940s, it seems that a quiet revolution has taken place in this domain, made possible by the joint efforts of biology, cognitive studies and engineering. In the 1940s, one school of thought, following Von Neumann, Wiener, Turing and McCulloch, attempted to lay down the foundations of a science of self-organising systems. Wiener proposed the name 'Cybernetics' for this science. In 1943, McCullough and Pitts proposed a model for a nerve cell, or neuron, using a threshold device they called a 'formal neuron'. Some years later, Rosenblatt had the idea of arranging these devices into a network, conceiving the perceptron. This early system was capable of recognising simple shapes. Widrow designed the 'Adaline' machine, which was used for the recognition of speech. After having raised high hopes, this first direction of research was substantially abandoned following the work of Minsky and Papert, who brought the severe limitations of the perceptron to light. Workers in artificial intelligence then started a new school of thought, following Simon, Chomsky, Minsky and McCarthy, addressing the problem of symbolic manipulation, based on the hypothesis that thought processes could be modelled using a set of symbols and applying a set of logical transformation rules. Using computers as investigative tools, this approach had an enormous success, and started the development of artificial intelligence. This work was very fruitful, giving rise to important new concepts, and allowing expert systems to be applied in a number of different semantic domains, albeit in well-defined problem areas.

Nevertheless, this symbolic approach has a number of limitations. One is the speed of the sequential methods in use; it is difficult to parallelise them, and when the quantity of data increases, the methods may suffer a combinatorial explosion.

A second weakness concerns the representation of knowledge: this is localised, in the sense that one item of knowledge is represented by a precise object, perhaps a byte in memory, or a production rule. These two weaknesses simply do not appear in the neural network, or connectionist approach. In the first case, the fundamental operation of these networks is parallel, and secondly, knowledge representation is distributed: one fact may correspond to activity in a number of neurons. This non-localised means of representing information implies a certain resistance to damage.

A third weakness of the symbolic approach concerns learning. In spite of great efforts by many research teams, it seems difficult to simulate the learning process in a symbolic system. The connectionist approach exhibits learning very clearly. Learning a fact is carried out by reinforcing connections between the neurons which store that fact, and the network organises itself using the examples which are presented to it.

To summarise, the connectionist approach offers the following advantages over the symbolic approach:

- o parallel and real-time operation of many different components;
- o the distributed representation of knowledge;
- o learning by modifying connection weights.

These advantages drove the researchers of the 1980s to re-evaluate the connectionist approach. Neural networks became a useful topic again.

The two approaches are both currently being investigated, and the future will undoubtedly bring attempts to combine them, using connectionism to tackle low-level functions such as pattern recognition, and the symbolic methods to model, combine and supervise different areas of self-organisation, and carrying out syntheses at different levels of abstraction.

At the Ecole Centrale de Paris, the Applied Mathematics group and its associated laboratory have played a part in this story, having introduced an area of study into symbolic manipulation closely linked to the classical themes of applied mathematics. The weaknesses of the symbolic approach were recognised early, and in 1988 it was decided to create a research group into 'bionetworks and parallel computation'. In its initial conception, this group clearly shows the multidisciplinary nature of neural network study. The group has introduced lecturers such as M. Burnod, from the Institut Pasteur, and Mme. Fogelman, from the Ecole des Hautes Etudes en Informatique, for students studying both bioengineering and applied mathematics.

My thanks go to the two authors of this work, M. Davalo and M. Naïm, who have shared in the introduction of these courses, giving associated lectures and supervising practical work, essential to illustrate the concepts. The presentation of their book is lively, clearly showing the problem areas and describing the families of algorithms corresponding to actual solutions.

I think that anyone desiring to learn about the subject of neural networks will find this book a good introduction, showing how the increasingly abundant literature on the subject can be approached. Returning to the introductory phrases of this foreword, readers will be able to take part themselves in this great saga of the vertebrates, never fully satisfied with their actual position, always ready to escape to further horizons.

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# Preface

The term 'neural networks' is used to describe a number of different models intended to imitate some of the functions of the human brain, using certain of its basic structures. The historical origins of this study area are very diverse.

In 1943, McCulloch and Pitts studied a collection of model neurons and showed that they were capable of calculating certain logical functions. Hebb, in a psychophysiological study published in 1949, pointed out the importance of the connection between synapses to the process of learning.

Rosenblatt described the first operational model of neural networks in 1958, putting together the ideas of Hebb, McCulloch and Pitts. His perceptron, inspired by studies of the visual system, could *learn* to calculate logical functions by modifying the connections between its own synapses. This model stimulated a great deal of research at the time, and certainly gave rise to over-optimistic hopes.

When two mathematicians, Minsky and Papert, demonstrated the theoretical limits of the perceptron in 1969, the effect was dramatic: researchers lost interest in neural networks, and turned to the symbolic approach to artificial intelligence, which seemed much more promising at the time.

The recent resurgence of interest in neural networks is largely due to individual contributions such as that of Hopfield, who showed the analogy between neural networks and certain physical systems in a 1982 study, bringing a rich and well understood formalism to bear on these networks. More recently, since 1985, new mathematical models have enabled the original limits of the perceptron to be greatly extended.

Today, the first practical applications of neural networks are beginning to see the light of day, and the discipline is beginning to interest a larger and larger audience of students, researchers, engineers and industrialists.

However, as a result of the multi-disciplinary nature of the subject, it is very difficult to learn about neural networks in a coherent manner. Many thousands of papers have been published on the subject in journals covering biology, psychology, mathematics, physics and electronics, each approaching the problem from its own particular specialist direction.

This book is based upon the authors' own experience of these difficulties; its aim is to convey an intuitive and practical understanding of neural networks and to

provide the foundations necessary before undertaking further study. To this end, the first part of this book is devoted to a description of biological foundations. Biology is the source of study of neural networks and it seems probable that it will continue to provide a source of essential ideas. Following this introduction, a general model for neural networks is presented and a number of today's most important models are studied. Lastly, a number of real applications are discussed.

In conclusion, the authors hope that reading this book will enable readers to imagine a possible application for neural networks in their own area of interest, and to experiment further.



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# 1 *Biological Foundations*

The first part of this book begins by presenting a brief history of the study of the brain. Following this is a description of the principal components of the nervous system, with the aim of explaining the models introduced in later portions of the book, without pretending to be exhaustive. Lastly, the brain as a whole is considered, and we try to show how parts of its behaviour may follow from the description of its structure.

## 1.1 Background

### 1.1.1 *The History of the Study of the Brain*

#### *The Heart or the Brain*

The dispute which occupied the ancient Greeks over the respective roles of the heart and the brain took about 3,000 years before being resolved. Some philosophers thought the heart the place in which sentiment and intelligence resided. In their time, both Homer and Aristotle, the medieval thinkers and some as late as Descartes felt that the flow of blood from the heart to the brain served the purpose of producing 'animal spirits' which animated the body.

Not until the 18th century was the theory of the role of the brain as the central source of commands to the organism as a whole recognised in Europe. This theory was asserted by La Mettrie and Cabanis in a work called 'The Brain Secretes Thought as the Liver Secretes Bile'; this was after some centuries of obscurity during the medieval period (see [Chan]).

Democritus and then Plato were the first to explain this, but the first clinical observations were not carried out until the time of Hippocrates. Herophilus performed the first dissections in the third century BC.

Physiological studies of the brain date back to Galien, who demonstrated with the aid of animal experiments in the second century AD that the brain was definitely the central organ of command in the body.

Research work carried out since the 19th century has given rise to many theories about the operation of the brain.

### *Methods of Study*

Three comments can be made about the different methods of studying the brain.

The method which gave birth to neuro-psychology is based on the study of the relationships between anatomical features and aspects of behaviour. Broca started this work in the 19th century: he began the anatomic-pathological study of language, his work becoming the basis of modern neuro-psychology. Using his own experiences, Broca showed that the motor functions of the brain and its senses are precisely localised in its structure.

This localisation of function gives a good field of study for analytical methods. These methods, however, are criticised by some workers who favour a global approach. They consider them too simplistic to explain systems as complicated as living creatures. Nevertheless, analytical methods have been particularly useful in the study of the visual system, and they remain the basis of all scientific study of the brain today.

Lastly, the most recent area of study is the physical and chemical processes of brain functions. The operation of the brain can be explained in more and more detail, descending closer and closer to the molecular level. The study of the brain has passed from a classification of the parts of the brain responsible for function, to a study of the relationships between behaviour and electrical, then chemical properties.

#### **1.1.2 *The Evolution of the Brain***

The success of the work of Broca, who demolished the theories of the globalists, gave rise to maps of the brain which are used to describe its evolution in different animal species.

The very first brain on earth appeared in a fish. This brain represents a primitive stage in the evolution of vertebrates. It consisted of three areas, an anterior part, devoted to the sense of smell, a median part whose function was vision, and a posterior part for balance. This brain was incapable of fine nuances of responses or coordinating between its different parts. Each part performed a certain type of behaviour completely determined by responses to certain stimuli.

Species have evolved through a large number of stages from this original fish, before reaching *homo sapiens*. It is interesting to note that, in the evolutionary process, there is a link between the weight of the brain and the total body weight in each newly-evolved species. This is because the brain itself has developed. Firstly, the part of the brain devoted to smell developed in the first small mammals which hunted at night; the development continued with the growth of the cerebral cortex, the location of the higher activities of thought. One conclusion which can be drawn from this evolutionary process is that species with the highest ratio of brain weight to total body weight are best adapted to their environment and these species have progressively come to dominate.

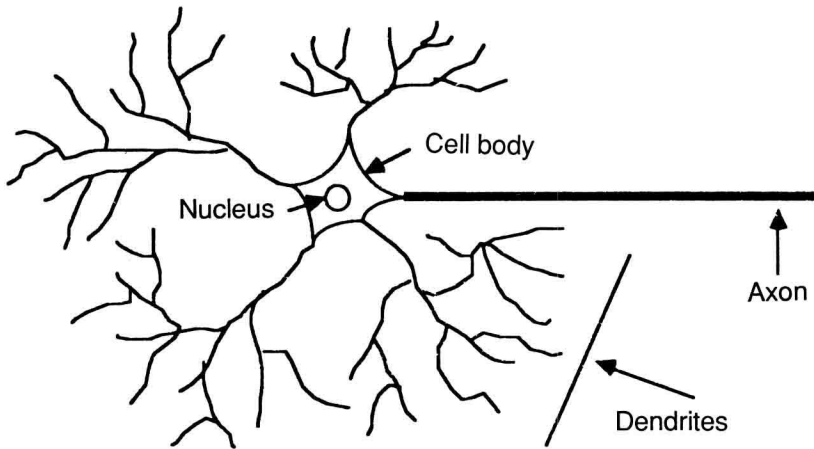


Figure 1.1 Components of a neuron

## 1.2 The Components of the Brain

### 1.2.1 The Neuron

Nerve cells, called neurons, are the fundamental elements of the central nervous system. The central nervous system is made up of about 5 billion neurons. Neurons possess a number of points in common with other cells in their general organisation and their biochemical systems, but they also possess a number of distinctive characteristics.

Neurons have five specialist functions: they receive signals coming from neighbouring neurons, they integrate these signals, they give rise to nerve pulses, they conduct these pulses, and they transmit them to other neurons which are capable of receiving them.

#### *Structure of Neurons*

A neuron is built up of three parts: the cell body, the dendrites, and the axon, as shown in figure 1.1.

The body of the cell contains the *nucleus* of the neuron and carries out the biochemical transformations necessary to synthesise enzymes and other molecules necessary to the life of the neuron. Its shape in most cases is a pyramid or a sphere. The shape often depends on its position in the brain, so most neurons in the neo-cortex have a pyramid shape. The cell body is some microns in diameter.

Each neuron has a hair-like structure of *dendrites* around it. These are fine tubular extensions some tenths of a micron across, tens of microns in length. They



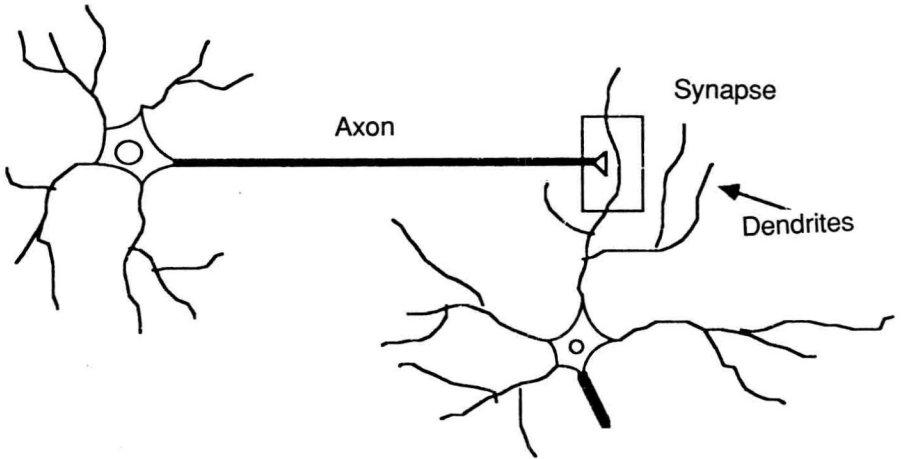


Figure 1.2 The synapse

branch out into a tree-like form around the the cell body. The dendrites are the principal receptors of the neuron and serve to connect its incoming signals.

The *axon* or nerve fibre is the outgoing connection for signals emitted by the neuron. It differs from dendrites in its shape and by the properties of its external membrane. The axon is longer than dendrites, in general, varying from a millimetre to more than a metre in length. It branches at its extremity where it communicates with other neurons, while the branching of dendrites takes place much closer to the cell body.

Neurons are connected one to another in a complex spatial arrangement to form the central nervous system. As shown in figure 1.2, the connection between two neurons takes place at *synapses*, where they are separated by a synaptic gap of the order of one-hundredth of a micron.

### Neuron Operation

The specific function performed by a neuron depends on the properties of its external membrane. This fulfils five functions: it serves to propagate electrical impulses along the length of the axon and of its dendrites, it releases transmitter substances at the extremity of the axon, it reacts with these transmitter substances in the dendrites at the cell body, it reacts to the electrical impulses which are transmitted from the dendrites and generates or fails to generate a new electrical pulse, and lastly, it enables the neuron to recognise which other neurons it should be connected to; during the development of the brain it permits the neuron to find those cells.