

*INTRODUCTION TO*

Neural  
& Cognitive  
Modeling

D.S. Levine

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# PREFACE

*How do you eat an elephant? One bite at a time.*

Beverly Johnson, after climbing the rock face of  
El Capitan, Yosemite National Park

Neural networks, which were relatively unknown to the educated public until the early 1980's, have recently catapulted into a major place in the consciousness of the scientific and technical community. There are at least two reasons for the sudden growth of interest in this field. One reason is the rapid progress both of neural network theory itself and of experimental neurobiology. Another reason is the increasing complexity of technical problems encountered in various industrial applications of knowledge-based computers, combined with some inadequacies found in traditional artificial intelligence approaches.

Yet after more than forty years of research, neural networks are still surrounded by mythology. Are these networks clever computers that can perform cognitive tasks with greater flexibility than expert systems? Or are they models of actual human or animal brains? Or are they abstract physical systems with certain interconnections, laws, and state transitions? In reality, all of these descriptions are partially valid but incomplete. The field of neural networks is now being investigated by researchers from as wide a range of disciplines as any field in the recent history of knowledge. These researchers include, in no particular order, biologists, psychologists, cognitive scientists, computer scientists, mathematicians, engineers, physicists, and even, at an early stage, a few social scientists and philosophers.

This book concentrates more on the theory of neural networks than on the applications. Some good reviews of neural network applications are found in Hecht-Nielsen (1986, 1988, 1990), Lippmann (1987), the DARPA study (1988), and Miller, Walker, and Ryan (1989). Theoretical principles, and their implementation in widely known models, are discussed here in a manner intended to be useful to a broad class of students, designers, and researchers. Neuroscientists can use these principles to move toward a stronger theoretical

foundation for brain science, including clinical neurology and psychiatry, and suggest further experiments. Modelers can use these principles to help provide a rational basis for building networks. Computer scientists and engineers can use them for inspiration in building devices. Mathematicians and physicists can find interesting theoretical problems in dynamical systems derived from neural or cognitive models. Psychologists and cognitive scientists can achieve more coherence in their understanding of interrelationships among cognitive phenomena. Social scientists can gain a better understanding of human decision processes, which should ultimately yield predictions relevant to their own disciplines (for a discussion, see Leven, 1988). Finally, philosophers can find insights into age-old epistemological issues, thereby adding scientific yet non-reductionistic bases to existing qualitative theories of the mind (see, *e.g.*, Maslow, 1968, 1972; Powers, 1973; Turner, 1981).

This book is aimed toward the varied audience of the neural network field, and is intended as a textbook for a graduate or advanced undergraduate course in the area. The focus will be on the common interest that all these researchers share, namely, the relationship between neural structure and cognitive function. The cognitive functions to be discussed include learning, perception, attention, memory, pattern recognition, categorization, and motor control, for examples. The neural structures will at times incorporate organizing principles such as competition, association, and opponent processing, principles which can be suggested either by the exigencies of modeling psychological data or by the description of known neuroanatomical structures. These principles will be developed in early chapters and will appear throughout the book.

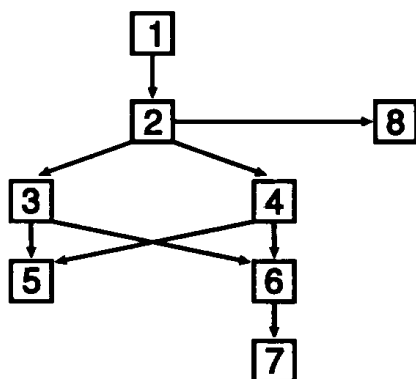
In keeping with the goal of accessibility to a varied audience, technical prerequisites in any one discipline are kept to a minimum. Recent advances in computing make the field accessible to many more people than before. Hence, for students, access to either a personal or mainframe computer is assumed. For those needing additional background in neurobiology or in mathematics, appendices in those fields are included; the appendices also list sources for more detailed coverage.

A word should be said here about equations. The last section of each chapter includes differential or difference equations for some of the networks discussed in that chapter, so that the reader can gain hands-on experience in computer simulation of the networks. On first reading, the student without mathematical background can skip these equations and follow the development of networks by means of the figures. On second reading, the same student can turn to Appendix 2 for explanations of how equations reflect the qualitative relationships in networks, and simple algorithms for simulating such equations. All but the last two sections of Appendix 2 are written so as not to require previous background in differential equations; notions needed from elementary

calculus are redefined and motivated in the context of neural network applications.

All chapters except the first and last contain both thought experiments and computer simulation exercises pertaining to various neural network models. The exercises herein are a small sampling of the possible questions that can be asked about the material discussed in the book, and the instructor is encouraged to supplement them as he or she sees fit. Many of the questions asked here do not have right and wrong answers, only a variety of better and worse answers. The reader should approach the field with at least as much intellectual flexibility and curiosity as possessed by the systems we model.

The following diagram illustrates how the understanding of each chapter depends on previous chapters:



After the introduction in Chapter 1 and the historical account in Chapter 2, Chapters 3 through 7 reflect a hierarchy from simpler to more complex neural and cognitive processes. Chapters 3 and 4 discuss various neural network rules for associative learning and for competition, respectively. Small networks incorporating some of these rules are then embedded in larger networks that model complex cognitive processes such as conditioning and attention (Chapter 5) and coding and categorization (Chapter 6). Chapter 7, building on earlier chapters, concludes this hierarchy with networks designed to deal with problems that are still largely open (such as optimization, control, decision making, and knowledge representation). Finally, Chapter 8 gives a brief survey of recent advances in both neurobiology and artificial neural systems.

The study of mind is a densely interconnected subject. Hence, the organization of topics in this book is not the only possible one, and the boundaries between classifications that I use are far from rigid. But if sense is to be made of the multiplicity of cognitive processes, and models of these

processes, it seems natural to try to isolate important sub-processes and thereby proceed from simpler to more complex cognitive functions.

I shall close by acknowledging and thanking the many people who helped make possible the undertaking of writing this book. The Editors from Lawrence Erlbaum Associates (LEA) at different stages, Julia Hough and Judi Amsel, both gave the book project enthusiastic support, and were tireless in working to smooth out administrative details. Major assistance was also provided by other members of the staff at LEA, in particular Lawrence Erlbaum, the company President; Joseph Petrowski, from the Publicity Department; and Arthur Lizza, from Production.

Wesley Elsberry provided months of technical assistance which allowed for delivery of camera-ready copy, expediting the book's production considerably. His expertise, and good humor, with computer software covered word processing, graphics, and the running of homework exercises. The text was done in WordPerfect 5.1 and the graphics in CorelDraw 1.21. The computer and printer on which the final copy was made are located at the Automation and Robotics Research Institute (ARRI) at the University of Texas at Arlington. Charles Lindahl, William Ford, and other staff members at ARRI provided generous assistance with their facilities. Raju Bapi, Nilendu Jani, and Carey Weathers also helped with graphics and with testing of homework exercises.

Several of my colleagues and former students made suggestions on earlier drafts of the book. Gregory Stone and Richard Golden reviewed the entire manuscript carefully and helped to shape the revisions. Others contributing valuable comments on sections of the manuscript included Manuel Aparicio, Raju Bapi, Daniel Bullock, Heather Cate, David Hestenes, Peter Killeen, Samuel Leven, Wing-Kwong Mak, Ennio Mingolla, Haluk Ogmen, David Olson, Alice O'Toole, Paul Prueitt, and David Stork. Their comments considerably improved the book's style and brought to it a variety of professional perspectives.

Finally, my wife, Lorraine Levine, lived patiently with the highs and the rebound lows associated with the book's composition. She combined an appreciation of the project's value with a warm sense of humor that kept me on course but helped me avoid the perils of overly grim determination.

Daniel S. Levine  
Arlington, Texas

## Some Technical Conventions Used in This Book

In figures, the following symbols are used for connections between nodes:

Filled semicircle for a modifiable connection;

Filled arrow for a non-modifiable connection;

"+" for an excitatory connection;

"-" for an inhibitory connection.

In equations, I have attempted to make the terminology as uniform as possible across different authors. Hence, node activities are generally denoted by "x" and "y," with subscripts, and connection weights by "w," with subscripts, regardless of what letters were used by the equation's originator. A few judicious violations of these conventions are explained in footnotes. Positive constants defined as system parameters are usually represented by other small Roman letters.

In exercises, I have not included answers in the back of the book. This is because most of the exercises are either thought experiments with no definite right or wrong answer (*e.g.*, "can the model of Anderson, 1968, be extended to a model of selective attention?") or computer simulations where the object is to come as close as possible to reproducing results that are described either in the text or the original source. In some cases, I have included expected results in the problem statement itself. More detail about the exercises will be contained in an accompanying instructor's manual. As for the symbols at the left margin of exercises, a single star (\*) means that the problem involves a relatively difficult computer simulation. A double star (\*\*) means that the problem requires a higher degree of mathematical knowledge than others. An open circle (O) means that the problem is an open-ended thought experiment or modeling exercise.

# Contents

<b>Preface</b>	ix
Some Technical Conventions Used in This Book	xiii
<b>Chapter 1</b>	
<b>Brain and Machine; the Same Principles?</b>	1
What are Neural Networks?	1
What are Some Principles of Neural Network Theory?	4
Methodological Considerations	8
<b>Chapter 2</b>	
<b>Historical Outline</b>	11
2.1. Digital Approaches	11
The McCulloch-Pitts Network	12
Early Approaches to Modeling Learning: Hull and Hebb	16
Rosenblatt's Perceptrons	19
Some Experiments with Perceptrons	21
The Divergence of Artificial Intelligence and Neural Modeling	24
2.2. Continuous and Random-net Approaches	
Rashevsky's Work	26
Early Random Net Models	30
Reconciling Randomness and Specificity	31
2.3. Definitions and Detailed Rules for Rosenblatt's Perceptrons	33
Exercises for Chapter 2	36
<b>Chapter 3</b>	
<b>Associative Learning and Synaptic Plasticity</b>	41
3.1. Physiological Bases for Learning	41

3.2. Rules for Associative Learning	43
Outstars and Other Early Models of Grossberg	44
Anderson's Connection Matrices	50
Kohonen's Work	54
3.3. Learning Rules Related to Changes in Node Activities	56
Klopf's Hedonistic Neurons and the Sutton-Barto Learning Rule	56
Error Correction and Back Propagation	57
The Differential Hebbian Idea	60
Gated Dipole Theory	62
3.4. Associative Learning of Patterns	66
Kohonen's Recent Work: Autoassociation and Heteroassociation	67
Kosko's Bidirectional Associative Memory	71
3.5. Equations and Some Physiological Details	74
Neurophysiological Principles	74
Equations for Grossberg's Outstar	75
Derivation of the Signal-to-noise Ratio for Anderson's Linear Filter	79
Equations for Sutton and Barto's Learning Network	80
Derivation of Rumelhart, Hinton, and Williams' Back Propagation Algorithm	81
Gated Dipole Equations Due to Grossberg	82
Kosko's Bidirectional Associative Memory (BAM)	83
Kohonen's Autoassociative Maps	84
Exercises for Chapter 3	86
<b>Chapter 4</b>	
<b>Competition, Lateral Inhibition, and Short-term Memory</b>	93
4.1. Early Studies and General Themes (Contrast Enhancement, Competition, and Normalization)	94

Hartline and Ratliff's Work, and Other Early Visual Models	99
Nonrecurrent Versus Recurrent Lateral Inhibition	101
4.2. Lateral Inhibition and Excitation Between Sensory Representations	104
Wilson and Cowan's Work	105
Work of Grossberg and Colleagues	107
Work of Amari and Colleagues	112
Energy Functions in the Cohen-Grossberg and Hopfield-Tank Models	114
The Implications of Approach to Equilibrium	117
4.3. Competition and Cooperation in Visual Pattern Recognition Models	118
Visual Illusions	118
Boundary Detection Versus Feature Detection	122
Binocular and Stereoscopic Vision	127
Comparison of Grossberg's and Marr's Approaches	131
4.4. Uses of Lateral Inhibition in Higher-level Processing	133
4.5. Equations for Various Competitive and Lateral Inhibition Models	135
Equations of Sperling and Sondhi	135
Equations of Wilson and Cowan	136
Equations of Grossberg and Co-workers: Analytical Results	137
Equations of Hopfield and Tank	140
Equations of Amari and Arbib	142
Exercises for Chapter 4	144

<b>Chapter 5</b>	
<b>Conditioning, Attention, and Reinforcement</b>	<b>151</b>
5.1. Network Models of Classical Conditioning	153
Early Work: Brindley and Uttley	153
Rescorla and Wagner's Psychological Model	158
Grossberg: Drive Representations and Synchronization	159
Aversive Conditioning and Extinction	163
Differential Hebbian Theory Versus Gated Dipole Theory	164
5.2. Attention and Short-Term Memory in Conditioning Models	166
Grossberg's Approach to Attention	168
Sutton and Barto's Approach to Blocking	170
Some Contrasts Between the Above Two Approaches	175
Further Connections with Invertebrate Neurophysiology	176
Gated Dipoles and Aversive Conditioning	181
5.3. Equations for Some Conditioning and Associative Learning Models	183
Klopf's Drive-reinforcement Model	183
Some Later Variations of the Sutton-Barto Model: Temporal Difference	184
The READ Circuit of Grossberg, Schmajuk, and Levine	185
The <i>Aplysia</i> Model of Gingrich and Byrne	187
Exercises for Chapter 5	190
<b>Chapter 6</b>	
<b>Coding and Categorization</b>	<b>195</b>
6.1. Interactions Between Short- and Long-term Memory in Code Development	198

## CONTENTS

v

Malsburg's Model with Synaptic Conservation	198
Grossberg's Model with Pattern Normalization	202
Mathematical Results of Grossberg and Amari	206
Feature Detection Models with Stochastic Elements	209
From Feature Coding to Categorization	210

### 6.2. Supervised Classification Models 212

The Back Propagation Network and its Variants	212
Some Models from the Anderson-Cooper School	219

### 6.3. Unsupervised Classification Models 228

The Rumelhart-Zipser Competitive Learning Algorithm	229
Adaptive Resonance Theory	232
Edelman and Neural Darwinism	239

### 6.4. Translation and Scale Invariance 241

### 6.5. Equations for Various Coding and Categorization Models 243

Malsburg's and Grossberg's Development of Feature Detectors	243
Error-correcting Rules and Linear Classification Algorithms	246
Some Implementation Issues for Back Propagation Equations	249
Brain-State-in-a-Box Equations	251
Rumelhart and Zipser's Competitive Learning Equations	252
Adaptive Resonance Equations	253

### Exercises for Chapter 6 255

## Chapter 7

### Optimization, Control, Decision, and Knowledge Representation 262

#### 7.1. Optimization and Control 264

Hopfield, Tank, and the Traveling Salesman Problem	265
Simulated Annealing and Boltzmann Machines	267
Motor Control: the Example of Eye Movements	269
Motor Control: Arm Movements	274
Speech Recognition and Synthesis	279
Robotic Control	284
<b>7.2. Decision Making and Knowledge Representation</b>	<b>284</b>
What, if Anything, do Biological Organisms Optimize?	284
Affect, Habit, and Novelty in Neural Network Theories	286
Neural Control Circuits, Neurochemical Modulation, and Mental Illness	288
Some Comments on Models of Specific Brain Areas	299
Knowledge Representation: Letters and Words	301
Knowledge Representation: Concepts and Inference	305
<b>7.3. Equations for a Few Neural Networks Performing Complex Tasks</b>	<b>310</b>
Hopfield and Tank's "Traveling Salesman" Network	310
The Boltzmann Machine	312
Grossberg and Kuperstein's Eye Movement Network	315
VITE and Passive Update of Position (PUP) for Arm Movement Control	316
Affective Balance and Decision Making Under Risk	317
<b>Exercises for Chapter 7</b>	<b>320</b>
<b>Chapter 8</b>	
<b>A Few Recent Technical Advances</b>	<b>325</b>
8.1. Some "Toy" and Real World Computing Applications	326
8.2. Some Neurobiological Discoveries	328

<b>Appendix 1: Basic Facts of Neurobiology</b>	<b>332</b>
The Neuron	332
Synapses, Transmitters, Messengers, and Modulators	337
Invertebrate and Vertebrate Nervous Systems	343
Functions of Vertebrate Subcortical Regions	343
Functions of the Mammalian Cerebral Cortex	350
<b>Appendix 2: Difference and Differential Equations in Neural Networks</b>	<b>355</b>
Example: the Sutton-Barto Difference Equations	355
Differential Versus Difference Equations	360
Outstar Equations: Network Interpretation and Numerical Implementation	363
The Chain Rule and Back Propagation	371
Dynamical Systems: Steady States, Limit Cycles, and Chaos	374
<b>References</b>	<b>378</b>
<b>Subject Index</b>	<b>414</b>
<b>Author Index</b>	<b>432</b>

# 1

## Brain and Machine: The Same Principles?

*My mind to me a kingdom is,  
Such perfect joy therein I find  
As far exceeds all earthly bliss  
That God or nature hath assigned.*

Edward Dyer

*What is mind? No matter. What is matter? Never mind.*

Thomas Hewitt Key (epigram in *Punch*)

### What Are Neural Networks?

The late 1980's and early 1990's are seeing what may be the start of a major intellectual revolution. The rapid development of neurobiology and of experimental psychology has led us closer to an understanding of biological cognitive functioning than most of us had thought possible a short time ago. At the same time, the expansion of cognitive or adaptive capabilities in

industrial applications of computers has proceeded even more rapidly. As the two fields of neurobiology and artificial intelligence develop further, it is natural to look for common organizing principles to both.

The belief that there are common quantitative foundations for both brain science and artificial intelligence has come and gone and come again. In the 1940's and 1950's, the notion that neurons are digital "on-off" switches (either firing or not firing), and thus that brains and the newly emerging digital computers had similar structural organizations, captured the imagination of scientists. Eventually, biologists discovered that the digital metaphor was an inadequate one for capturing what was known about neurobiology and psychology. It was found necessary to understand the graded (or analog, or gray scale) as well as the all-or-none (or digital) components of neuron responses (see, e.g., Thompson, 1967, Ch. 1). Concurrently, artificial intelligence moved in the direction of writing digital computer programs to perform narrowly specified cognitive tasks without much reference to how those same tasks are performed by humans or animals (see, e.g., Newell & Simon, 1972; Winston, 1977).

Recent years have seen a partial reunification of the two fields of neurobiological modeling and artificial intelligence. Designers of machines for performing cognitive functions have taken a renewed interest in learning how the brain performs those functions. Consequently, such machines have been built like simulated brain regions, with nodes corresponding to neurons or neuron populations, and connections between the nodes; at times, their designers have borrowed ideas from recent experimental results on the brain's analog responses. This development is often called *connectionism* (e.g., Feldman & Ballard, 1982; Rumelhart & McClelland, 1986; articles in Volume 9 of *Cognitive Science*); the industrial applications of connectionist theory are often called *artificial neural systems* (e.g., Hecht-Nielsen, 1986). Both of these terms are of recent coinage; the much older term *neural networks* is usually considered to encompass both theoretical and applied models. These models may or may not be designed as theories of actual brain organization, but always include nodes<sup>1</sup> and connections. The DARPA study (1988) gives a reasonable definition of the term:

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<sup>1</sup> The functional units in neural networks have alternatively been called "nodes," "units," "cells," and "populations." I prefer the first two terms because they do not commit the user to an assumption that units correspond to either single or multiple neurons. This book most often uses the term "node," but sometimes uses "unit" since that usage has been popularized by Rumelhart and McClelland (1986). In Section 2.1, the word "cells" or "neurons" is used for units in the network of McCulloch and Pitts (1943), for reasons explained in that section.

a neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes. ... Neural network architectures are inspired by the architecture of biological nervous systems, which use many simple processing elements operating in parallel to obtain high computation rates (p. 60).

Many factors have contributed to the recent renaissance of neural networks. First, in applied areas such as knowledge processing, robotic control, pattern classification, speech synthesis and recognition, and machine vision, computer engineers have encountered problems not easily amenable to the symbolic processing programs of mainstream artificial intelligence (for examples, see Hewitt, 1986; Minsky, 1986; Winograd & Flores, 1987). Second, neurobiological experimental methods and data analysis have advanced greatly. Techniques such as recording with electrodes from up to fifty neurons at once and taking tomographic scans of the entire brain have made neurophysiology more amenable to quantification. At the same time, advances in computing (running the gamut from personal computers to supercomputers) have made simulation of biological data easier and more practical. Third, a few publications, such as the article of Hopfield (1982) and the two-volume book edited by Rumelhart and McClelland (1986), have brought neural networks to the attention of mainstream scientists in such disciplines as physics and computer science.

The rapid surge in popularity of the neural network field conceals the field's maturity. The history of neural network models, which was summarized (up to 1983) in the review article of Levine (1983b) and is discussed further in Chapter 2, shows that most modern ideas in network design have much earlier antecedents. For example, the current distinction between input, hidden, and output units (Rumelhart & McClelland, 1986) owes much to the early work of Rosenblatt (1962) on networks with sensory, associative, and response units (though modern networks go far beyond Rosenblatt's perceptrons). Rosenblatt, in turn, combined extensions of the linear threshold law due to McCulloch and Pitts (1943) with extensions of the learning law due to Hebb (1949). Moreover, several current leaders in neural network research, such as Shun-ichi Amari, James Anderson, Walter Freeman, Stephen Grossberg, and Teuvo Kohonen, have been publishing in the field since the late 1960's or early 1970's. Many ideas that these investigators laid out in their early work remain fruitful today.