Book Reviews

Fundamentals of Artificial Neural Networks—Mohamad H. Hassoun. (Cambridge, MA: MIT Press, 1995, 544 pp., hardbound, \$60.00, ISBN 0-262-08239-X).
Reviewed by Payman Arabshahi.

There is no such thing as too much of a good thing—at least when it comes to well written and comprehensive graduate level texts in any technical field that has been growing as fast as neural computing. In recent years there has been a proliferation of neural network related textbooks that attempt to give a broad, mathematically rigorous introduction to the theory and applications of the field for an audience of either professional engineers, graduate students, or both. Among the most notable and recent perhaps are the excellent texts by Haykin [1], Zurada [2], Kung [3], and Hertz *et. al.* [4]. Add to this dozens of volumes of paper collections, and expositions from different perspectives (AI, physics, cognitive science, VLSI (very large scale integration), and parallel processing, etc.), as well as other textbooks, and you rapidly converge to the global minimum: so many books, so little time!

If you are interested in learning about the underlying theory of neural computation, however, then perhaps alongside your perusal of the above texts you should also look at yet another one. *Fundamentals of Artificial Neural Networks* emphasizes fundamental theoretical aspects of the computational capabilities and learning abilities of artificial neural networks (ANN's). The book is intended for either first year graduate students in electrical or computer science and engineering, or practicing engineers and researchers in the field. It has evolved from a series of lecture notes of two courses on ANN's taught by the author over the past six years at Wayne State University. Apart from the usual prerequisites of mathematical maturity (probability theory, differential equations, linear algebra, multivariate calculus), the reader is assumed to be familiar with system theory, the concept of a "state," as well as Boolean algebra and switching theory basics. The author himself is a well-established researcher in the field, with dozens of papers to his credit. The book is well organized and presented, and a delight to read. Exercises at the end of each chapter (some 200) complement the text, and range in difficulty level from the very basic to mathematically or numerically challenging. About 700 relevant references are also provided at the end of the book.

The book is centered on the idea of viewing ANN's as nonlinear adaptive parallel computational models of varying degrees of complexity. Accordingly, the author starts out in Chapter 1 by an exposition of the computational capabilities of the simplest models, namely linear and polynomial threshold gates. This is built upon basic concepts of switching theory. The discussion is then extended to the capacity and generalization ability of threshold gates via a proof of the function counting theorem. The treatment is coherent and mathematically rigorous

Chapter 2 picks up from the discussion in Chapter 1 by considering networks of linear threshold gates (LTG's) as well as neuronal units with nonlinear activation functions, and investigates their mapping capabilities. Important theoretical results on bounds on the number of functions realizable by a feedforward network of LTG's, as well as the size of such networks (two and three layer, as well as generally interconnected feedforward networks) are derived. A summary of some fundamental results on approximation capabilities of feedforward neural nets for continuous functions is presented next, based on a brief discussion of Kolmogorov's theorem. A more in-depth discussion of the later topic would have been valuable, even though the results are well established in the literature. Similarly the discussion on computational efficiency (especially algorithmic complexity) of neural networks at the end of the chapter is somewhat brief.

A very interesting and enlightening treatment of various learning rules for single unit nets is presented in Chapter 3. The exposition is unified in the sense that the learning process for each rule is viewed as a steepest-gradient-based search for a set of weights that optimize a specific objective function. In the case of supervised learning, the emphasis is on error-correction rules (perceptron and generalizations), and others such as the μ-LMS rule. Extending such rules to stochastic units, reinforcement learning is viewed and presented as a stochastic process that maximizes the average reinforcement. Hebbian learning is discussed under unsupervised algorithms. Finally simple single layer networks of multiply connected units are considered in the context of competitive learning, learning vector quantization, principal-component analysis, and self-organizing feature maps. And if you think you may be overwhelmed by the sheer volume of material covered in this chapter in one reading—do not fear. The author has put all of the major concepts in a nutshell in the form of a very useful, complete, and well organized seven-page table that gives a quick reference to the learning rules, their associated objective functions, appropriate parameter initializations, type of activation function employed, and remarks on convergence behavior and nature of the solution obtained.

A more detailed mathematical theory of the learning rules overviewed in Chapter 3 is presented next, in Chapter 4. This focuses mainly on the nature and stability of the asymptotic solutions obtained using these learning rules. The analysis is based on the same unifying framework introduced earlier. As such, a continuous time learning rule is viewed as a first-order continuous time stochastic dynamic system with a certain set of stable equilibria. Using approximation techniques, the author determines the nature of the asymptotic solutions of the stochastic system and shows that the stable equilibria minimize an average objective function which is part of an average learning equation. Conditions under which the equilibria can be taken as attractor states of the system are also discussed. Furthermore generalization capabilities of deterministic and stochastic networks are analyzed and results on the complexity of learning in neural networks are reviewed. Together with Chapter 3, this wraps up an excellent and relatively thorough discussion on the theory of learning in single unit/layer neural networks. The level of mathematical rigor is perhaps not that high and references are given throughout to some of the important results derived elsewhere. The author does, however, try (successfully) to provide insight and understanding from the mathematics and in the process puts together a coherent and well written exposition.

Chapters 5 and 6 cover adaptive multilayer neural networks. Chapter 5 is devoted exclusively to backpropagation, both static and dynamic. Apart from an explanation of the algorithm, several methods

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for improving the technique's speed, avoidance of local minima, and enhancing generalization are presented. Topics considered include weight initialization, learning parameter adjustments, addition of regularization terms to the error function, global-descent based backprop, and cross-validation. The Chapter continues with a brief look at a number of applications (NETtalk, handwritten zip code recognition, image compression, etc.). Extensions of backprop for temporal learning (time-delay neural networks, backpropagation through time, and recurrent networks) are also discussed. This discussion is well placed within the context of backprop learning. Overall, the chapter is well written. The practical suggestions on generalization and overview of the empirical results in backprop learning are especially useful.

Chapter 6 introduces additional adaptive multilayer structures that in general provide for faster training than backprop. The chapter starts with radial basis function (RBF) networks and the cerebellar model articulation controller (CMAC). RBF networks are motivated through a brief mention of the locally tuned response observed in biological nervous systems and earlier work in interpolation and estimation. A more detailed preliminary justification for the need for such networks is missing, however. Nonetheless a concise introduction to such networks is provided through the mathematical development, a brief comparison between RBF networks and backprop, and a discussion on variations on the RBF network. The CMAC network is then discussed in the same context of models utilizing localized receptive fields. Interesting relationships between this model and the classic perceptron and other models are summarized as well. The second class of networks considered in this Chapter employ resource allocation, enabling dynamic determination of the network size and providing for efficient training. Under this category the hyperspherical classifier and the cascade-correlation network are discussed. Finally, the ART 1 network and autoassociative clustering networks are presented as examples of unsupervised clustering techniques. Unfortunately, due to consideration of so many networks in the span of one chapter, sacrifices have been made on detail and mathematical rigor. References are provided throughout, however, for the reader interested in pursuing the topics further.

Chapter 7 presents a very nice discussion of Associative memories, both linear and dynamic. After an introduction to the workings of linear associative memories (LAM's), methods for improving their performance (such as multiple training and adding special associations to the training set) are also discussed. The bulk of the chapter however deals mainly with single layer dynamic (auto)associative memories (DAM's). The stability, capacity, and associative retrieval properties of these memories are characterized. This is done by viewing DAM's as nonlinear dynamic systems, and for instance in the case of stability analysis, defining appropriate Lyaponuv functions. Several projection recording DAM's are also analyzed and shown to have improved error correction and capacity. A variety of other DAM models (brain-state-in-a-box, nonmonotonic activations, hysteretic activations, exponential-capacity, etc.) are also introduced and briefly discussed.

The last chapter in the book (Chapter 8) considers global search methods for optimal learning and retrieval in multilayer neural networks. It covers the use of simulated annealing, mean-field annealing, and genetic algorithms for optimal learning. Simulated annealing is also discussed in the context of the Boltzmann machine, and a hybrid genetic algorithm/gradient-descent method for neural net training is presented and analyzed. Other optimization techniques such as random search are not covered, and overall, although the chapter is well written, it appears to be misplaced. Most if not all of the discussion about ocal versus global search and the global optimization techniques presented could have nicely been incorporated into the discussion in Chapters 5 and 6, where training of multilayer networks was presented. Nonetheless, the chapter discusses very important topics and does so very well.

Apart from such minor criticisms, Prof. Hassoun should be congratulated on writing an excellent overall textbook that covers, as advertised in its title, fundamental theoretical aspects of neural networks. The book covers a lot of material, and even though at times the level of mathematical rigor could have been higher, the sacrifice in math has certainly not detracted from its usefulness. If anything, it has added insight and understanding of the main theory to its intended audience of first-year graduate students or practicing engineers.

References

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