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BOOK REVIEW

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"Imitation of life: how biology is inspiring computing" by Nancy Forbes

This book surveys a fairly large number of research areas where biology has provided inspiration for the design of novel computational models and algorithms: artificial neural networks, evolutionary algorithms, cellular automata, artificial life, DNA computing, biomolecular self-assembly, amorphous computing, artificial immune systems, and biologically inspired hardware. A remarkable feature of the book is that it explains goals and results of these research areas in a very accessible and vivid style. It uses anecdotes and mini-portraits of researchers in order to avoid the account getting too dry. In addition, a number of figures are used to illustrate new concepts and discoveries. In this way the book manages to cover quite complex material without a single mathematical formula. This is very beneficial, since the topics discussed in this book are of interest for a diverse set of readers of widely varying age and educational background. In fact, the general public has a right to be informed about the research areas that are surveyed in this book since various government agencies have funded this research, with large special funding programs being created for these research areas not only in the US but also in Japan, Europe and many other countries. Therefore books of this type are clearly needed, and I hope that many other potential authors are encouraged by this fine example.

One research area not discussed in this book is machine learning, which is normally viewed as a sub-discipline of artificial intelligence, with strong tries to more analytically oriented disciplines such as statistic and theoretical computer science. If one compares the capabilities of artificial neural networks with those of "classical" methods from artificial intelligence or other areas of computer science, as Nancy Forbes does in Chap. 1 of her book, one cannot really avoid to compare their performance with that of competing methods from machine learning. If one decides to view machine learning as being part of "classical" artificial intelligence and computer science, then artificial neural networks have a hard time to win this competition (at least on the basis of all publications of which I am aware). This makes it difficult to agree with statements of the book such as (on p. 10): "…traditional digital computers can only solve problems we already know and understand how to solve… But if we can point to a number of examples of the kind of solution we require, or if we simply want to find a pattern in a mass of disorganized data, artificial neural nets are the best method."

But actually, machine learning can also be seen in a different light. Some of the currently best-performing methods of machine learning (kernel-based methods, also referred to as support vector machines [1, 2]) can be traced back to pioneering research on artificial neural networks in the 1950s [3]. Rosenblatt studied an artificial neural network model which consisted of a fixed nonlinear preprocessing device, followed by a single weighted sum with a decision threshold (i.e., a McCulloch–Pitts neuron), whose weights were adapted for each specific task by a suitable "learning rule". Obviously this architecture is closely related to that of support vector machines. Only the design of the fixed nonlinear preprocessing stage (the "kernel") and the learning process for the weights of the subsequent threshold gate use nowadays substantially more sophisticated tools, developed during several decades of intervening research. Hence one may argue that tools essential for our current use of digital computers, such as kernel-based methods in machine learning, were developed on the basis of earlier research on biologically inspired computing.

The other chapters of the book describe newer and more experimental ways of integrating biological ideas into novel computing devices, which go far beyond the goals of artificial neural networks. They discuss, for example, biologically inspired methods for self-assembly of devices, amorphous computing (for example with "smart paint"), and artificial immune systems.

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It would be nice if suggestions for further readings could be added to each chapter in a second edition of this book. In addition, the distinction between Turing machines and automata should be made clearer in Chap. 3 (perhaps the characteristic infinitely long work tape of the Turing machine should also be indicated in Fig. 3.1). I also think that speech production is not an example of a classification algorithm, as stated on p. 9; in fact the distinction between recognition algorithms and classification algorithms introduced on p. 8 is a bit unusual. In addition, historical comments should be checked. For example, John Hopfield did not "discover" recurrent neural networks as stated on p. 3; they had already been introduced over a decade earlier. But these are minor problems, which will distract most readers very little from this otherwise very enjoyable and inspiring book.

References

1. Vapnik VN (1998) Statistical learning theory. Wiley, New York
2. Schölkopf B, Smola AJ (2002) Learning with kernels. MIT Press, Cambridge
3. Rosenblatt JF (1962) Principles of neurodynamics. Spartan Books, New York