Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems

Every field of science relies on having its trusted sources of knowledge, the books that unite investigators with a common language and provide them with the basic toolbox for approaching problems. Physics, for instance, has its "Landau and Lifschitz"; electrical engineers routinely turn to "Horowitz and Hill"; and many a neuroscientist was brought up on "Kandel and Schwartz." Now, at last, the field of computational neuroscience has one of its own with the recent publication of Dayan and Abbott's *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems*.

The emergence of this book represents more than the usual feat of textbook publication. It is a significant development for the field as a whole, because up to now there has been no single book that unites the basic methods and models of computational neuroscience in one place. Those who teach courses on computational models have mostly hobbled along by copying papers and chapters from assorted journals and books, or by writing their own elaborate lecture notes. While there exist several excellent texts on neural networks—such as *Introduction to the Theory of Neural Computation* (Hertz, Krogh, & Palmer), *Neural Networks for Pattern Recognition* (Bishop), and *Neural Networks: A Comprehensive Foundation* (Haykin)—they are mostly written from the perspective of engineering, math, or physics, and so they do not make serious connections to neuroscience. Others that do address brain function are either tilted more towards cognitive science, emphasizing higher-level aspects of brain function—such as *Parallel Distributed Processing* (Mclelland & Rumelhart), *An Inroduction to Neural Networks* (Anderson), and *An Introduction to Natural Computation* (Ballard)—or else towards lower-level cellular models—as in *The Biophysics of Computation: Information Processing in Single Neurons* (Koch), and *Spikes: Exploring the Neural Code* (Rieke et al.).

What sets Dayan and Abbott's book apart is that it lands right smack in the center of computational neuroscience, spanning the entire range from models at the cellular level, such as ion channel kinetics, to those at the cognitive level, such as reinforcement learning. It also does a beautiful job explaining state-of-the-art techniques in neural coding, as well as recent advances in unsupervised learning models. And it does all of these with a level of depth and thoroughness that is impressive.

There tend to be two camps in the field of computational neuroscience, and they are probably best exemplified by how they use the term "computation." In one, mathematical models are constructed primarily to describe or characterize existing data, and computation is used mainly as a means to simulate or analyze the data, in rather the same way as computational chemistry or computational fluid dynamics. In the other camp, computation is applied in a more theoretical manner, as a metaphor for what the brain is actually doing.

The first six chapters of the book fall more in the first category, by using mathematical and computational techniques to characterize neural function. Some of these methods attempt to describe neural function in computational terms, but they are still primarily descriptive in nature. These include methods for characterizing spike statistics, reverse correlation techniques for measuring receptive field properties, methods for decoding information contained in neural spike trains, and information theoretic techniques for measuring information capacity of neurons and coding efficiency. There are also two chapters covering detailed electrical models of neurons, including channel kinetics, synapses, and cable properties. All of these techniques are covered with the kind of nuts-and-bolts detail that will allow readers to begin implementing and experimenting with them in computer simulations.

The last four chapters of the book fall into the second camp of computational neuroscience, presenting more abstract models that extrapolate beyond the available data. Experimentalists often recoil at the idea of entertaining such models, but they are every bit as essential as the descriptive models because they provide a theoretical framework for interpreting data and motivating future experiments. These chapters discuss recurrent network models with attractor dynamics, models of learning and adaptation, and theories of representation based on probabilistic models. Many of these topics are also covered in the more traditional books on neural networks, but the advantage of the presentation here is that it makes more direct contact with neuroscientific data. Also, by using terminology and mathematical notation that is consistent throughout the book, the authors

help to bring the two camps of computational neuroscience under one roof.

Of course, many will ask, ''will I need to know a lot of math to understand this book?'' Indeed, some pages are rife with equations and formulas, but this is unavoidable since mathematics provides the most compact and precise language for discussing the workings of a complex system such as the brain. At the same time, though, the authors have gone out of their way to make the book accessible to a wide audience, and there is very little here that requires more than first-year calculus or simple linear algebra to understand. Admirably, the text does not use the equations as a crutch, but rather strives to explain in words what is meant or implied by them without sacrificing mathematical rigor. The appendices also provide excellent tutorials and further background on topics such as linear algebra, statistics, and optimization.

In short, this is a book where students and grown scientists alike can turn to learn the main methods and ideas of computational neuroscience. It is a suitable text for graduate students in neuroscience and psychology, and it could probably be used for teaching advanced undergraduates as well. I have just finished using it for a graduate-level computational neuroscience course, and it went over quite well with students coming from diverse backgrounds. I predict that it will become the mainstay for courses on computational neuroscience for many years to come.

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