and its inevitable limitations. Some misunderstandings in cephalopod research mirror those in many other scientific fields, where ideas once thought to be fact later evolve or are overturned. That's not a failure; it's how science works. It's a process of continual refinement, not perfection. And though imperfect, science remains our most reliable tool for understanding the world and addressing the complex challenges we face.

Do you think that there is too much emphasis on 'big data'-gathering collaborations as opposed to hypothesis-driven research by small groups? I see value in both types of research approaches. On the one hand, the rise of big data has revolutionised the way we do science. Thanks to the decreasing costs of modern technologies, such as sequencing, microscopy and MRI, and the rapid advancement in computing power and AI-aided algorithms, big data collection and analyses are no longer a wishful dream. Large-scale data gathering and mining have become powerful tools for generating novel hypotheses and accelerating breakthrough discoveries.

At the same time, however, any proposed hypotheses — whether derived from big data or not — must be rigorously tested and validated through careful experimentation. I believe that finding a balance between these two approaches is an effective way by combining the broad, pattern-seeking power of big data with the depth and precision of hypothesis-driven experimentation.

What inspires you? Beyond the lab and the datasets, I also find immense inspiration in nature itself. Spending time in nature and learning from it offer invaluable insights. Evolution has shaped countless, elegant solutions over millions of years — many of which remain overlooked, waiting to inspire new scientific understanding and innovation.

DECLARATION OF INTERESTS

The author declares no competing interests.

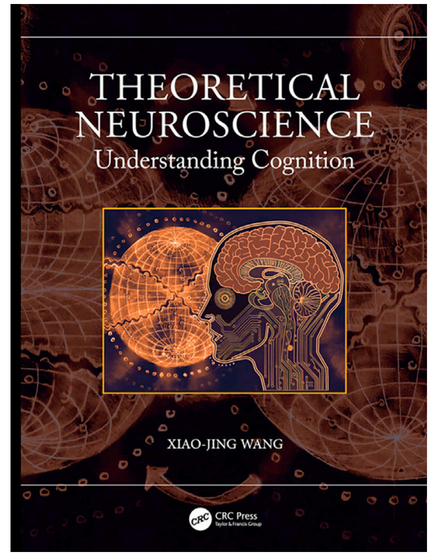
School of the Environment, Faculty of Science, The University of Queensland, St Lucia, QLD 4072, Australia.
E-mail: w.chung1@uq.edu.au

Book review

Brain computations

Stefano Panzeri

Theoretical Neuroscience: Understanding Cognition
Xiao-Jing Wang
(CRC Press, Boca Raton, FL; 2025)
ISBN: 978-1-032-60482-4



How does the brain compute? This is the central question driving Xiao-Jing Wang's *Theoretical Neuroscience: Understanding Cognition* — a masterful book that is timely, rigorous, engaging and profoundly interdisciplinary. Xiao-Jing Wang is one the most accomplished computational neuroscientists. As we read his book, we are invited not only to engage with neural network models of the brain computations underpinning cognition and with their biological mechanisms, but also to reflect deeply on epistemology, on the future of neuroscience, on computational psychiatry, on the influence of theoretical physics on the understanding of the brain, and on the relationship between natural and artificial intelligence.

Understanding the brain requires an appreciation of its organization on so many levels — from molecules to synapses to cell to small neural circuits to whole-brain networks. How to treat or even make sense of this complexity has puzzled scientists for more than a century. Early in the book, Wang lays out his vision for the epistemological grounding of computational neuroscience — the science of understanding the computations made by the brain. His starting point is a constructive critique of the framework of David Marr[1], whose three levels of analysis — first normative, then algorithmic and finally implementational at the neural level — have shaped for decades how theoretical neuroscientists have looked at how brain circuitry may implement these computations. Wang shifts Marr's notion proposing the central tenet that the brain is both a complex and a dynamical physical system. That the brain is a dynamical system implies that the evolution of neural activity over time is deeply informative of both the biological mechanisms and computations performed by the brain, something that Wang has masterfully exploited in his own research. The brain is a complex system, organized over many levels. This implies that to get insights on its workings we need to understand not only how each level works, but also how each affects the other levels. This leads Wang to propose the centerpiece concept of cross-level mechanistic theory, which amounts to inform the dynamical system describing the brain with plausible biological mechanisms. In other words, cross-level mechanistic theory seeks explanations of brain dynamics at scales that are both computationally meaningful and biologically grounded. Models should not merely reproduce behavior; they should account for how the behavior arises from specific circuit motifs, neural dynamics and plastic mechanisms. While Wang's approach is mechanistic, it is not reductionist because of its constant tension to see the brain from the point of view of emergent phenomena and systems-level principles. Because of this, the bottom-up reductionist effort to describe all high-level functions from mechanistic causes at a lower level is constantly complemented by the realization that high-level functions arising from large-scale dynamics can influence lower levels of biological organization.

The book's — and Wang's own — intellectual trajectory mirrors and captures the evolution of computational neuroscience as a field. Since its inception in the 20th century, it has benefitted from the influx of ideas — and people — from theoretical physics, especially inspired by seminal work of scientists such as John Hopfield[2] and

Geoffrey Hinton[3] and many others. One of the aims of theoretical physics is to understand complex systems by expressing interactions between their elements in mathematical terms and studying mathematically the behavior emerging from these interactions. The huge body of theoretical-physics-inspired computational neuroscience has not only contributed to make neuroscience a more mature science — building essential theoretical foundations to accompany the experimental ones — but has also led to genuine progress in the theoretical physics of complex systems, as witnessed by the award of the 2024 Nobel Prize for Physics to Hopfield and Hinton. Wang's own work is a prime example of what this approach, which permeates the book, has brought to neuroscience.

The book treats practical and epistemological questions of high relevance, which have challenged seasoned computational neuroscientists for years and keep challenging new generations of neuroscientists: What does it mean to understand the brain and its function? When can we claim that we have understood the biological brain mechanisms that causally explain behavior and cognition? Is it better to start our modelling of brain function with a specific focus or to look straight on for the grand general theory? Refreshingly for seasoned scientists and encouragingly for the new generations, the book argues that theoretical physics exemplifies the successful strategy of starting to crack specific problems and then going more general. For example, Max Planck's explanation of black-body radiation was central to developing the principles of quantum mechanics. The book reports several such success stories from computational neuroscience, with Wang's own model of persistent activity in the prefrontal cortex being a prime example[4]. This model has been instrumental in first establishing how attractor dynamics arise from well-defined biological mechanisms implemented in specific neural circuits, such as the prefrontal cortex, and then in showing how they can support specific cognitive computations, such as working memory and decision-making. Attractor dynamics have been eventually recognized as a computational primitive that occurs across cognitive domains and can even inform the understanding of large-scale models of brain dynamics, such as those described in later chapters that complement the initial cellular and circuit-level focus with forays into whole-brain modeling.

The final chapters discuss new directions and big challenges, such as computational psychiatry and artificial intelligence. Wang presents the recent success of computational models in advancing concepts in psychiatry, for example, the success in explaining working memory deficits in schizophrenia patients that may be due to the detrimental effect to attractor dynamics caused by an imbalance between D1 and D2 dopamine receptor activation[5]. He argues that the concept of cross-scale modelling is key to this recent success, as the correct inclusion of biological mechanisms by models is central to their power to not only reproduce observations of data but also to predict the consequences of perturbations of the brain and thus possibly design treatments. The closing discussion on the bidirectional relationship between neuroscience and artificial intelligence is also noteworthy. Wang elaborates how biologically inspired models can inform next-generation AI systems, while machine learning tools can, in turn, help make sense of increasingly complex neurobiological data.

The book is perhaps a little optimistic in describing the current opportunities for theory offered by the deluge of new big neural data that are coming in thanks to technological advances, such as connectomics or large-scale multi-unit recordings. The number of neurons that we are simultaneously able to record is increasing exponentially, and new datasets providing simultaneous measurements of different levels of organizations, such as synaptic matrices and functional activity of many neurons in specific circuits, are allowing theoreticians to formulate and validate better models[6,7]. However, many important gaps in data remain, and the acceleration of technological development that allows the collection of more data may somehow contrast with the slower progress in our conceptual understanding of the brain[8]. The topics treated in the book provide scientists with formal and conceptual tools that can help address these issues.

A primary goal of the book is to be an advanced teaching and training resource, reflecting Wang's commitment to training the next generation of scientists. The book offers detailed and deep mathematical and epistemological guidance on how to build and analyze biologically informed neural network models. For experimental neuroscientists, it helps understanding what kinds of data and measurements are most informative for building, ruling in or ruling out models and hypotheses. As a teaching resource, it covers extremely well how to build network models of cognitive functions informed by data step by step, and provides important elements for the analysis of data. *Theoretical Neuroscience: Understanding Cognition* is a remarkable and engaging book — one that will be essential reading for anyone interested in how the brain computes, and what it means to build a mathematical science of cognition grounded in biology.

DECLARATION OF INTERESTS

The author declares no competing interests.

REFERENCES

1. Marr, D. (1982). Vision (W.H. Freeman & Co.).
2. Hopfield, J.J. (1982). Neural networks and physical systems with emergent collective computational abilities. Proc. Natl. Acad. Sci. USA *79*, 2554–2558. https://doi.org/10.1073/pnas.79.8.2554.
3. Ackley, D.H., Hinton, G.E., and Sejnowski, T.J. (1985). A learning algorithm for boltzmann machines. Cogn. Sci. *9*, 147–169. https://doi.org/10.1016/S0364-0213(85)80012-4.
4. Wang, X.-J. (2002). Probabilistic decision making by slow reverberation in cortical circuits. Neuron *36*, 955–968. https://doi.org/10.1016/S0896-6273(02)01092-9.
5. Durstewitz, D., and Seamans, J.K. (2008). The dual-state theory of prefrontal cortex dopamine function with relevance to catechol-o-methyltransferase genotypes and schizophrenia. Biol. Psychiatry *64*, 739–749. https://doi.org/10.1016/j.biopsych.2008.05.015.
6. Kuan, A.T., Bondanelli, G., Driscoll, L.N., Han, J., Kim, M., Hildebrand, D.G.C., Graham, B.J., Wilson, D.E., Thomas, L.A., Panzeri, S., *et al*. (2024). Synaptic wiring motifs in posterior parietal cortex support decision-making. Nature *627*, 367–373. https://doi.org/10.1038/s41586-024-07088-7.
7. Wang, E.Y., Fahey, P.G., Ding, Z., Papadopoulos, S., Ponder, K., Weis, M.A., Chang, A., Muhammad, T., Patel, S., Ding, Z., *et al*. (2025). Foundation model of neural activity predicts response to new stimulus types. Nature *640*, 470–477. https://doi.org/10.1038/s41586-025-08829-y.
8. Fregnac, Y. (2017). Big data and the industrialization of neuroscience: A safe roadmap for understanding the brain? Science *358*, 470–477. https://doi.org/10.1126/science.aan8866.

Institute for Neural Information Processing, University Medical Center Hamburg-Eppendorf (UKE), 20251 Hamburg, Germany.
E-mail: s.panzeri@uke.de