# Neural networks in the future of neuroscience research

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Neural networks are increasingly seen to supersede neurons as fundamental units of complex brain function. In his Timeline article (From the neuron doctrine to neural networks. *Nat. Rev. Neurosci.* **16**, 487–497 (2015))[1], Yuste provides a timely overview of this process, but does not clearly differentiate between biological neural network models (broadly and imprecisely defined as empirically valid models of (embodied) neuronal or brain systems, which enable the emergence of complex brain function through distributed computation) and artificial neural network models (a relatively well-defined class of networks originally designed to model complex brain function[2] but now mainly viewed as a class of biologically inspired data-analysis algorithms useful in diverse scientific fields[3]).

A distinction between biological and artificial neural network models is important as the neuroscience network paradigm is mainly driven by the aim of uncovering biologically valid mechanisms of neural computation. Artificial neural networks were initially proposed as candidate models for such computation but, despite being enthusiastically researched at the end of the twentieth century, they have largely not bridged the gap between elegant theory and neuroscientific observation[4,5]. In this context, Yuste's emphasis on some classic artificial neural network models does not seem to be supported by the evidence of, or the promise for, the problem-solving capacity of these models in neuroscience[6].

What could be an alternative promising approach to biologically valid neural network modelling? At present we can only speculate, but the ongoing development of high-resolution high-throughput brain imaging technologies — including those being developed as part of the BRAIN Initiative[7] — and the consequent availability of increasingly large structural[8] and functional[9] imaging data sets, make it appealing to initially search for patterns in such data in less theory-bound and more data-driven ways[10,11], and to subsequently construct theories a priori constrained on these discovered patterns[12]. A famous example of this approach in biology is the formulation of the theory of evolution by natural selection; this theory arose from an initial aim to catalogue all living biological organisms on earth, and from a subsequent careful analysis of the obtained diverse biological data[13]. Interestingly, artificial neural networks may yet prove to be important in this quest but in the role of powerful tools for analysing complex imaging data sets[14], rather than as a theoretical foundation for how the brain computes.

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doi:10.1038/nrn4042
Published online 21 October 2015

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**Acknowledgements**
The author thanks C. Chang for helpful comments. The author has received funding from the NARSAD Young Investigator Award, the Isaac Newton Trust Research Grant and the Parke Davis Exchange Fellowship.

**Competing interests statement**
The author declares no competing interests.