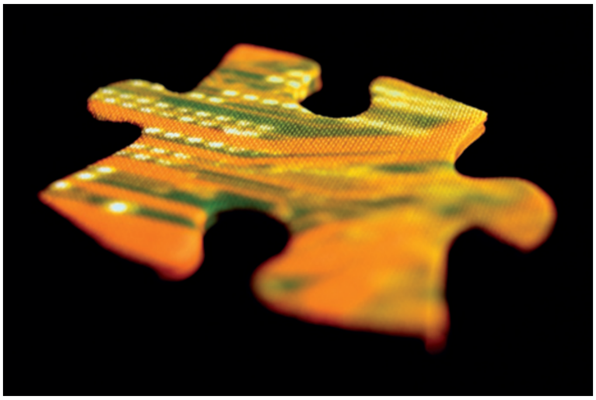
COMPUTATIONAL NEUROSCIENCE

# Modules of memory



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Computational neuroscience aims to understand how neural networks integrate the thousands of signals they receive from neighbouring cells, generate output signals and store, retrieve and manipulate information — processes that ultimately result in behaviour and cognition. Computer simulations of theoretical models that are based on data that have been produced experimentally aid the interpretation of complex datasets, the testing of hypotheses and the prediction of experimental outcomes. By using a combination of theoretical analyses and computer simulations, Roudi and Latham have shed new light on the brain's ability to form memories.

Experimental evidence supports 'attractor networks' as a theoretical mechanism of memory formation. In these networks, transient events trigger stable patterns of neuronal activity. These patterns remain active for some time after the events have passed, and so bear meaning to the organism. Although theoretical models of attractor networks have been around for decades, until now they have had difficulty explaining a feature of neuronal activity that is consistently observed experimentally: highly irregular neuronal firing. These models have also been unable to predict how many memories can be stored in a single, realistic network of spiking neurons. By analyzing networks using techniques borrowed from statistical physics, the authors uncovered a regime that guarantees irregular firing of foreground neurons (those that fire at a higher rate during the activation of a memory), and calculated a networks' storage capacity. Their model predicts that neurons fire irregularly if two conditions are satisfied: the number of neurons required to activate the memory is above a certain threshold, and the changes in synaptic strength between these neurons are much smaller than the weights between the background neurons (those that do not fire at a higher rate during the activation of a memory and that generate random and seemingly meaningless 'noise').

In the original models of attractor networks, the number of memories that can be stored in a network — memory capacity — was shown to be proportional to the number of neurons. More refined analyses, based on highly simplified models, indicated that this capacity scales with the number of connections per neuron. Roudi and Latham have now extended these results to realistic models. More importantly, they have shown that the scaling factor is small: even if each neuron makes 10,000 connections, only a few hundred memories can be stored, regardless of the number of neurons in the network. This not only implies that the memory capacity of individual neuronal networks might be smaller than we once thought but, more importantly, it offers some insight into how memory is implemented in neural systems: to store and retrieve large amounts of information, the brain must rely on multiple networks.

These predictions, which were verified using simulations with large networks of spiking neurons, might change the way we think about memory and help to explain the changes in memory capacity that are observed with aging, neurodegeneration and injury. Determining how multiple memory-storing modules are organized and coupled is likely to keep both theoretical and experimental neuroscientists busy for years to come.

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**ORIGINAL RESEARCH PAPER** Roudi, Y. and Latham, P. E. A balanced memory network. *PloS Comput. Biol.* **3**, e141 (2007)