Binary synapses: better than expected

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A longstanding hypothesis in neuroscience is that learning involves changes in synaptic efficacies. The flip side of this hypothesis is that learning one thing necessarily involves forgetting something else. The problem of forgetting is especially severe if synaptic efficacies take on a discrete set of values, something that has been suggested for theoretical reasons (e.g. [1]) and for which there is some experimental evidence [2]. For such discrete synapses, memories tend to fade exponentially fast, making it difficult to store information for long times.

The Cascade Model was suggested as a solution to the problem of fast forgetting [3]. In this model, synaptic efficacies still take on a discrete set of values, but each efficacy has associated with it many internal states. These internal states give the synapses multiple timescales, which can combine to produce power law, rather than exponential, decay of memories. Because power law decay is much slower than exponential, the Cascade Model has the potential to exhibit long memory lifetimes.

Here we show, somewhat counterintuitively, that these internal states – at least as implemented in the Cascade Model – do not exhibit memory lifetimes that are much longer than those of simple binary synapses. (We use ”simple” to mean no internal states). Moreover, for realistic coding levels (the coding level is the fraction of synapses modified during the formation of any one memory), simple binary synapses actually outperform the Cascade Model. Importantly, not only do they outperform it, they do well on an absolute scale: if the coding level scales as $N^{-1/3}$ where N is the number of synapses in the network, then an upper bound on the forgetting time scales as $N^{2/3}$. With this scaling, a cubic centimeter of cortex using simple binary synapses could store memories for about a year.

Our analysis suggests that there is no reason to use Cascade-like synapses for the sake of long memories. However, it is still possible, and even likely, that the range of timescales associated with the Cascade Model, and consequent power law forgetting, may play an important role in other aspects of memory formation, interaction and decay.

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References
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