Synaptic models for slow memory decay

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A longstanding hypothesis in neuroscience is that learning involves changes in synaptic efficacies. As synaptic efficacies are bounded, the flip side of this hypothesis is that learning one thing necessarily involves forgetting another. The problem of forgetting is especially severe if synaptic efficacies take on a discrete (or even binary) set of values, something that has been suggested for theoretical reasons (e.g. [1]) and for which there is some experimental evidence [2]. In this regime, past memories fade *exponentially* fast, and memory capacity is only logarithmic of the number of synapses.

Recently, a potential solution, using what is known as the **Cascade Model**, was proposed [3]. In this model, the synapse has many discrete internal states but only two efficacies. The synapse switches between the internal states in a stochastic fashion (assuming some Hebb-like learning rule), with switching rates that are different for different states. This mechanism results in *power-law* decay of the memory trace and, therefore, a much higher memory capacity.

In the work we report here, we have studied the family of such possible models. Our aims are: (1) analyze the performance of these models, and in particular determine if the internal states are used in an optimal way. And, (2) ask how likely these models are. In particular, can the original model be generalized into a broader class of models, and does the model demand fine tuning of its parameters, or is it robust to small parameter changes?

This work is divided into two parts. First we present an analytic solution for the original Cascade Model. Applying that analysis, we calculate the memory decay rate and the resulting memory capacity. Next, we introduce a framework for the analysis of generalized Cascade Models. Within this framework, we derive conditions for both power-law memory decay and its robustness to small changes in parameters, and describe several representative examples.

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References

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