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Efficient supervised learning in networks with binary synapses

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Recent experiments [1,2] have suggested single synapses could be similar to noisy binary switches. Binary synapses would have the advantage of robustness to noise and hence could preserve memory over longer time scales compared to analog systems. Learning in systems with discrete synapses is known to be a computationally hard problem. We developed and studied a neurobiologically plausible on-line learning algorithm that is derived from Belief Propagation algorithms. This algorithm performs remarkably well in a model neuron with N binary synapses, and a discrete number of 'hidden' states per synapse, that has to learn a random classification problem.

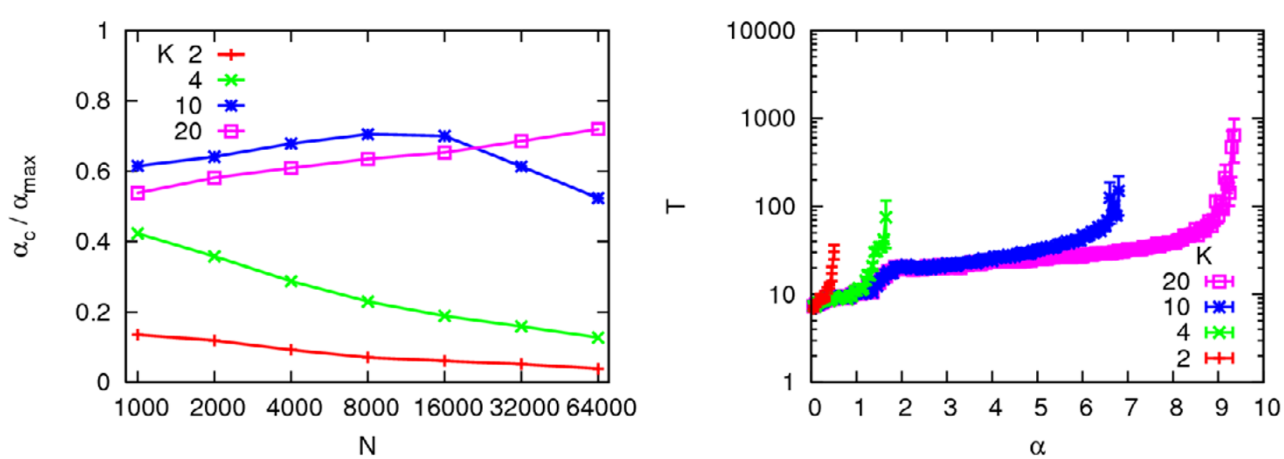

Figure 1

Learning capacity and learning time. (left) achieved capacity vs. the number of synapses N, with different numbers of hidden states, in the sparse coding case: the algorithm can achieve up to 70% of the maximal theoretical capacity at N ~10000 with 10 hidden states; **(right)** average learning time (number of presentations per pattern) versus number of patterns to be learned, for N = 64000: less than 100 presentations are required up to the critical point where learning fails.

Such a system is able to learn a number of associations which is close to the information theoretic limit, in a time which is sub-linear in system size, corresponding to very few presentations of each pattern. Furthermore, performance is optimal for a finite number of hidden states, that scales as $N^{1/2}$ for dense coding, but is much lower (~10) for sparse coding (see Figure 1). This is to our knowledge the first on-line algorithm that is able to achieve efficiently a finite capacity (number of patterns learned per synapse) with binary synapses.

The algorithm is similar to the standard 'perceptron' learning algorithm, but with an additional rule for synaptic transitions which occur only if a currently presented pattern is 'barely correct' (that is, a single synaptic flip would have caused an error). In this case, the synaptic changes are meta-plastic only (change in hidden states and not in actual synaptic state), and go towards stabilizing the synapse in its current state. This rule is crucial to the algorithm's performance, and we suggest that it is sufficiently simple to be easily implemented by neurobiological systems.

References

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