Adding a weak, stochastic, nonspecific reinforcement process to the clipped perceptron algorithm lets it efficiently solve the supervised learning problem in neuronal models 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 though. We developed and studied a neurobiologically plausible on-line learning algorithm that is originally derived from Belief Propagation algorithms, and further simplified by means of a mean-field analysis of the learning process.

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, or to learn a classification rule from a teacher. In the first case, 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. In the second case, perfect generalization is shown, from experiments and analytical calculations, to be achieved in finite (and short) time.

The algorithm is very similar to the clipped version of the standard `perceptron' learning algorithm, but with the addition of non-specific, purely meta-plastic reinforcement events, which occur with a given probability p_d at each learning step. The probability p_d has to be proportional to $N^{-1/2}$ and, in the classification task, is made dependent from the error rate for optimal performance. Both the simulations and the dynamical analysis show that without the additional process the learning time is exponential in N, in both learning protocols; therefore, since this process is so simple and effective, we suggest that neurobiological systems may implement it.

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