Effective Learning Requires Neuronal Remodeling of Hebbian Synapses

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Abstract

This paper revisits the classical neuroscience paradigm of Hebbian learning. We find that a necessary requirement for effective associative memory learning is that the efficacies of the incoming synapses should be uncorrelated. This requirement is difficult to achieve in a robust manner by Hebbian synaptic learning, since it depends on network level information. Effective learning can yet be obtained by a neuronal process that maintains a zero sum of the incoming synaptic efficacies. This normalization drastically improves the memory capacity of associative networks, from an essentially bounded capacity to one that linearly scales with the network's size. It also enables the effective storage of patterns with heterogeneous coding levels in a single network. Such neuronal normalization can be successfully carried out by activity-dependent homeostasis of the neuron's synaptic efficacies, which was recently observed in cortical tissue. Thus, our findings strongly suggest that effective associative learning with Hebbian synapses alone is biologically implausible and that Hebbian synapses must be continuously remodeled by neuronally-driven regulatory processes in the brain.

1 Introduction

Synapse-specific changes in synaptic efficacies, carried out by long-term potentiation (LTP) and depression (LTD) are thought to underlie cortical self-organization and learning in the brain. In accordance with the Hebbian paradigm, LTP and LTD modify synaptic efficacies as a function of the firing of pre and post synaptic neurons. This paper revisits the Hebbian paradigm showing that **synaptic learning alone cannot provide effective associative learning in a biologically plausible manner, and must be complemented with neuronally-driven synaptic remodeling.**

The importance of neuronally driven normalization processes has already been demonstrated in the context of self-organization of cortical maps [1, 2] and in continuous unsupervised learning as in principal-component-analysis networks [3]. In these scenarios normalization is necessary to prevent the excessive growth of synap-