Synaptic scaling enables extreme selectivity in high-dimensional neurons

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Abstract. A recent discovery of concept cells has revived the longstanding discussions on the role of individual cells in information processing. The theory of a high-dimensional (HD) brain has provided a foundation for their existence in the framework of an oversimplified mathematical model. In this work, we develop a biologically plausible model of concept cells, including spiking neurons, rate information coding, and homeostatic plasticity. Then, we provide analytical and numerical results illustrating the emergence of extreme selectivity in a neuronal aggregate to HD information patterns.

Introduction

In 1890 W. James proposed the hypothesis of a pontifical cell, which started a debate on the role of individual neurons in the brain. A recent discovery of concept cells has revived the longstanding discussion [1]. From the theoretical ground, the encoding of memories and high cognitive abilities require processing high-dimensional representations of the external environment [2]. Then, the recently introduced HD-brain concept has provided a mathematical foundation for these phenomena using formal neurons and an Oja-like learning rule [3, 4]. Its extension to brain neural networks requires biologically relevant models of neurons, information codding, and learning mechanisms. Here, we provide analytical and numerical results pushing further the HD-brain concept. In the long run, developing such models and relating them to electrophysiological data could shed light on the functional principles behind our intelligence.

Results and discussion

To simulate information processing in a neural network, we use the Izhikevich nonlinear model of a single neuron, which faithfully reproduces the spiking behaviors of cortical neurons [5]. We adopt the rate coding of complex information patterns received by HD neurons (with multiple synaptic inputs).

Earlier, on a simplified model, it has been shown that an aggregate of individual neurons can learn an arbitrary high number of unique patterns [6]. We then summarize and discuss the main theorems to develop an adequate nonlinear learning model for spiking neurons with similar properties. On this journey, an essential requisite is local adaptive learning. From one side, it could provide fast learning (by avoiding global optimization) and, from the other side, maintain an optimal spiking frequency.

Most mathematical models simulating learning in brain neural networks use Hebbian plasticity, which postulates an increase in the efficiency of synaptic transmission when the activity of the pre and postsynaptic neurons is correlated [7]. However, in its original form, the Hebbian rule has a severe drawback - it only describes the potentiation of synapses, which can lead to unbounded growth of synaptic weights. This problem can be solved using an ad hoc nonlinear mechanism, the so-called synaptic competition, which suppresses inactive or low-frequency synapses in accordance with experimental findings [8]. Although this approach is mathematically reasonable, its biological relevance remains unclear. We thus propose a nonlinear learning model that exploits homeostatic plasticity, which restores neuronal activity to a specific value after a disturbance. As a result, neurons can compensate for an increased or decreased overall synaptic input.

Using the developed models, we provide rigorous mathematical results and numerical simulations, which confirm that biological neurons can be highly selective to input patterns, as indirectly supported by experimental results [9].

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