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Review Article

Computational modeling of neural plasticity for self-organization of neural networks

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ABSTRACT

Self-organization in biological nervous systems during the lifetime is known to largely occur through a process of plasticity that is dependent upon the spike-timing activity in connected neurons. In the field of computational neuroscience, much effort has been dedicated to building up computational models of neural plasticity to replicate experimental data. Most recently, increasing attention has been paid to understanding the role of neural plasticity in functional and structural neural self-organization, as well as its influence on the learning performance of neural networks for accomplishing machine learning tasks such as classification and regression. Although many ideas and hypothesis have been suggested, the relationship between the structure, dynamics and learning performance of neural networks remains elusive. The purpose of this article is to review the most important computational models for neural plasticity and discuss various ideas about neural plasticity's role. Finally, we suggest a few promising research directions, in particular those along the line that combines findings in computational neuroscience and systems biology, and their synergetic roles in understanding learning, memory and cognition, thereby bridging the gap between computational neuroscience, systems biology and computational intelligence.

Contents

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1. Introduction

Understanding the principles behind the self-organization of biological nervous systems is the key to understanding cognition. Generally speaking, neural self-organization can be studied from the evolutionary and developmental perspectives. There were a number of major transitions or divergences in the evolution of nervous systems, for example, from the diffused nervous structure in cnidaria to the bilaterally symmetric one in flatworm (Ghysen, 2003). Computational models have been built up for co-evolving the development of the neural system and body plan of an animate based on primitive organisms such as hydra and flatworm and the results suggest that energy efficiency might be the most important constraint in neural self-organization (Jin et al., 2009; Jones et al., 2008). In addition, a strong coupling between the evolution of neural systems and body plan is also revealed (Jones et al., 2010; Schramm et al., 2012).

Meanwhile, increasing evidence has shown that adult brains undergo intensive rewiring (Holtmaat1 and Svoboda, 2009), which involves neural plasticity including the strengthening or weakening of existing connections, or even formation of new synapses and elimination existing ones. Seminal studies by Merzenich et al. (1983, 1984) demonstrated that once sensory nerves are severed, the cortical maps to which they projected are subsequently reorganized to accept nerves from surrounding nerves. This topographic adaptation can only be realized through neural plasticity and indicates the experience-dependent nature of plasticity and its central role in forming the basis of continual learning.

There has been a number of trend changes in the investigation of plasticity models. Initially, the focus was to provide a stable, self-regulated formulation of Hebbian learning (Hebb, 1949; Oja, 1982; Bienenstock et al., 1982). Then, a shift towards spiking neural networks had models of plasticity emerge that depended on the precise timing of spikes between connected neurons (Song et al., 2000). More recently, all of these models have been recognized as phenomenological approaches (Shouval et al., 2010), and more biological, molecular bases are being sought (Bush and Jin, 2012; Graupner and Brunel, 2012). Also, neuro-modulators are being included in spike-timing models that add reinforcement capabilities on top of the purely associative (Izhikevich, 2007; Legenstein et al., 2014).

While the high level functions of neuroplasticity – learning and memory – are taken for granted, the suggested roles of plasticity in formally defined neural network models are varied and often contradictory. In some cases, simply applying models of plasticity to existing paradigms, such as reservoir computing, has yielded improved results (Steil, 2007; Schrauwen et al., 2008; Joshi and Triesch, 2009; Xue et al., 2013). Other studies (Toyoizumi et al., 2005, 2007; Bohte and Mozer, 2007; Hennequin et al., 2014; Joshi and Triesch, 2009; Li and Li, 2014) link the role of plasticity with increasing the mutual information in the signals between connected neurons. Some claim that Hebbian plasticity thus increases the correlation between neurons in a reservoir (van Rossum and Turrigiano, 2001), while others suggest that the neural activity is decorrelated and that this is, in fact, a desirable property (Jaeger, 2005; Babinec and Pospichal, 2007). All of this is in addition to the classically proposed purpose of Hebbian learning as associative. Of course, there could be multiple roles that plasticity has to play in actual Human learning, each emerging in certain situations. Here we do not argue for one functional role in particular, but present a number of viewpoints.

The increasingly complex and self-regulated biological models of plasticity present a qualitatively different approach to the statistical optimization methods in machine learning. However, the success of these machine learning methods, particularly the recent advances made in deep learning (Hinton et al., 2006), cannot be ignored. Somehow, the new, biologically inspired findings in neuroscience must be systematically incorporated into applied methods in order to realize more advanced capabilities that it is clear many living beings possess.

This review focuses on the role of neural plasticity in dynamics, structure and functions rather than a detailed review of research on computational modeling of neural plasticity only. Related reviews can be found of spike-timing dependent plasticity (Markram et al., 2014) and plasticity dynamics in recurrent networks (Gilson et al., 2014). Reviews of the reservoir computing paradigm (Lukosevicius and Jaeger, 2009; Lukosevicius et al., 2012) are also relevant to much of the current practical application of computationally modeled plasticity.

The rest of the paper is organized as follows. Section 2 describes reservoir computing neural network models that have benefited from the application of neuro-plasticty, and deep neural networks that have the potential to. Section 3 outlines the early progression of formally defined and naturally inspired plasticity models. Section 4 focuses on some recent developments in plasticity that capture more details observed in more recent biological experiments. Section 5 explores the functional roles that have been suggested for plasticity models. Some important challenges for future research are raised and promising areas of potential in the field are discussed in Section 6.

2. Neural network models

Two recent neural network models are described in this section. In different ways, they take inspiration from neural structures observed in the mammalian cortex. However, while biologically motivated, both are also designed to work algorithmically with machine learning principles on data classification and prediction tasks. We propose in this review, that these models are prime candidates for being augmented with neural plasticity models in order to improve their performance.