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Biological context of Hebb learning in artificial neural networks, a review

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ABSTRACT

In 1949 Donald Olding Hebb formulated a hypothesis describing how neurons excite each other and how the efficiency of this excitation subsequently changes with time. In this paper we present a review of this idea. We evaluate its influences on the development of artificial neural networks and the way we describe biological neural networks. We explain how Hebb's hypothesis fits into the research both of that time and of present. We highlight how it has gone on to inspire many researchers working on artificial neural networks. The underlying biological principles that corroborate this hypothesis, that were discovered much later, are also discussed in addition to recent results in the field and further possible directions of synaptic learning research.

1. Introduction

In 2014 we commemorate 110 years since the birth of Donald Olding Hebb and 65 years since the first publication of his influential book *The Organization of Behavior* [1]. In the first half of the twentieth century, one of the most tantalizing questions in the field of mind and brain research was the problem of how the physiology of the brain correlates to high level behavior of mammals and especially humans. Pavlov proposed conditioned reflexes [2] as an explanation of how the neural excitation line connects the triggered target muscle to some external excitation along the way. In 1943, McCulloch and Pitts [3] used ideas coined almost a decade earlier by Turing [4] to formulate logical calculus as a framework of neural computation. A few examples of similar hypotheses include that of Jeffress, who during his sabbatical at California Institute of Technology in 1948 proposed a neural circuit for sound localization [5]. The proposed circuit was found in birds 40 years later [6]. Similarly, in 1947 Laufberger [7] proposed the idea of binary (all-or-none) representation and processing of information in the brain [8]. However this idea was not entirely new and its roots can be traced back to 1926, to a paper by Adrian and Zotterman [9]. The mid-twentieth century saw many researchers developing sophisticated hypotheses of how information might be processed by neuronal circuits in the brain. In 1948, Wiener's book [10] brought the perspectives of information theory and signal processing to the field.

During this time, Hebb was working on a theory that would explain complex psychological behaviors within the framework of neural physiology. The approach he adopted stemmed from the best practices used by behavioral psychologists in North America of the time, dating back some 40 years to William James [11]. To explain behavior using hypothetical neural computations, Hebb had to make a few novel assumptions, one of which has become the most cited sentence of his 1949 book [1]. It is the formulation of the general rule describing how changes in synaptic weights (also strengths, or efficiencies) control the way how neurons excite each other: "*When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.*"

Hebb's simplified formulation of the assumption was deliberate. Whilst the idea of increasing synaptic efficiency had been previously presented and the possible underlying chemical and biological processes already studied [12], their biological nature was not

Abbreviation: ANN, Artificial neural networks; AMPA, *α-Amino-3-hydroxy-5-Methyl-4-isoxazole-Propionic Acid*; BNN, Biological neural networks; BCM, Bienenstock, Cooper, and Munro; CA3, *Cornu Ammonis* no. 3 (area in the hippocampus); LTD, Long-term depression; LTP, Long-term potentiation; NMDA, *N-Methyl- D-Aspartate*; NO, Nitric oxide; STDP, Spike timing dependent plasticity

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yet known in detail [13]. Using the above postulate allowed Hebb to develop his theory further without discussing the processes involved in changing synaptic transmission. A further simplified and popular version of describing this assumption is "*Neurons that fire together, wire together*."

Today, the phenomena of neural adaptation, training, learning and working memory seems to be almost a trivial fact present in our everyday lives as we improve our cognitive skills. By applying this simple rule in the study of artificial neural networks (ANN) we can obtain powerful models of neural computation that might be close to the function of structures found in neural systems of many diverse species.

This review paper is divided into the following parts: after this initial introduction, the application of the Hebb rule in selected neural networks is outlined. This is succeeded by a brief review discussing how biological synapses, neurons and networks function, prior to the closing section, consisting of a summary and future directions. A commented list of relevant web links can be found in the appendix.

2. Models of neural networks

The above rule that Hebb proposed describes only the way in which synaptic efficiencies are changed in a dynamic system. Most artificial neural networks are characterized by two phases of synaptic change, learning and recall. First, in the *learning* phase there are outputs to train the network to achieve a desired response to a given input. Secondly, in the *recall* phase the synaptic efficiencies do not usually change and the network is only used to calculate the response to a given input, based on the synaptic efficiencies calculated previously.

Let us illustrate the two phases using the example of the Hopfield network [14–16]. In this network, the Hebb rule is used in the iterative learning phase to set up the weights of input patterns successively stored in the network. This is achieved by mixing the input and required output of all the neurons in the network with the first pattern. After this the next pattern is learned. The activity of the neurons approach the desired values by repeating the learning procedure. The Hebb rule is repeated in the network to set synaptic efficiencies accordingly, while the update algorithms may vary. Finally in the recall phase the weights are no longer adjusted and the memory retrieval of the network consist of the completed recall of partial inputs.

The type of learning whereby the required neuron output is used instead of the actual neuron output to change the synaptic weights is often called the *supervised learning rule*. In some cases, instead of using the neuron output directly, only the difference between the original and the required output is used during learning. This eliminates a change of weights if the neuron already yields the required output or if it is close to the output value. In contrast, applying only the changes in synaptic weights based on the actual neuron activity is called the *unsupervised learning rule*. In a strict sense, the Hebb rule in its original formulation did not include supervised learning as only one synapse from neuron A to neuron B is increasing its efficiency. In supervised learning there is a third factor C, which represents the additional input from another source of information, or the output of B. The efficiency here is the function of the activity of A, B and C (there are also supervised learning rules where the activity of B is ignored).

However, the Hebb rule can be utilized by supervised learning. For example, the idea behind contrastive Hebbian learning is to clamp output neurons to desired values and then use Hebbian learning rule to set the weights across the network [17]. Several other supervised learning rules use mathematical formulations similar to that of the Hebb rule, therefore we have incorporated them into this review in particular emphasis on those that have a biological counterpart.

In addition to the term *supervised learning*, the more general term of *reinforcement learning* is often used. From a psychological, or behavioral point of view, this is any learning whereby its process is facilitated (reinforced) either by (positively emotionally charged) reward or by (negatively emotionally charged) punishment [2]. Originating in the behaviorism, the term reinforcement was introduced into the ANN theories by several researchers between the years 1980 and 1986 [14,18,19]. Reinforcement in ANN means learning with the use of feedback input. This feedback is usually binary, signaling only that output is to be accepted or rejected. There is no information about desired output as in supervised learning.

The neural systems of all higher animals are hierarchically organized with many levels of connections between the neurons. Lower level circuits are typical for local, mostly inhibitory interneurons. Unsupervised learning is believed to be more likely present in these lower level biological cellular circuits and their mechanisms of learning since fewer conditions are imposed on its mechanism. Hebb's view on changes in synaptic efficiency considers only local factors acting on corresponding neurons and synapses. To implement the Hebb rule, there is no need for any supervision in learning. However, in biological neural networks (BNN) there exist multiple forms of reinforced feedback that affect learning and employ both local mechanisms in the circuit and global, longer range mechanisms. Many examples of biological feedback connections that change their synaptic weight are found in the visual pathway, specifically in the retina and visual cortex, which contain well described hierarchies of feedback connections. Global hierarchical reinforcement can be described as an abstract form. This higher level of description also bridges psychology with biology. From both a psychological and a biological perspective, we can look at emotions as an example of tagging and reinforcing memories [20].

2.1. Formulations of Hebb rule

One of the simpler formulations of the Hebb rule can be written as

$$\tau_w \frac{dw_i}{dt} = f(w_i) r^{\mathrm{out}} r_i^{\mathrm{in}}, \tag{1}$$

where weight w_i of the i-th input changes with time t and time constant τ_w. This constant includes both the change rate and the pre-set strength factor. According to the terminology of [21,22], τ_w^{-1} is a constant in the term correlating post- and pre-synaptic rates. The right side of this ordinary differential equation contains an unspecified function of weight $f(w_i)$. r^{out} and r_i^{in} are the respective output and input rates. Other equivalent formulations of the Hebb rule can be found in [21].

Several properties of the Hebb rule are important for its implementation in ANN. Six properties are summarized by Gerstner and Kistler [22]: (1) locality, meaning restricting the rule to input and output neurons of the given synapse (however some supervised learning rule variants are not local); (2) cooperativity, the requirement of simultaneous activity of both neurons; (3) boundedness of the weight values thereby preventing their divergence; (4) competition, that some synapses are strengthened at the expense of other synapses that are weakened; (5) long term stability, which is a natural requirement for the dynamic stability of the neural network system (this is however only one side of the dilemma of stability versus plasticity); (6) synaptic depression and facilitation, or weight decrease and increase, which is perhaps the most important property.

Synapses must be able to change in both directions, or, as is the case when extremal values occur in biological neurons, when new connections grow or existing links are disconnected. Obviously,