

## Learning from Dendrites: Improving the Point Neuron Model

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**Abstract :** The diversity in dendritic arborization, as first illustrated by Santiago Ramon y Cajal, has always suggested a role for dendrites in the functionality of neurons. In the past decades, thanks to new recording techniques and optical stimulation methods, it has become clear that dendrites are not merely passive electrical components. They are observed to integrate inputs in a non-linear fashion and actively participate in computations. Regardless, in simulations of neural networks dendritic structure and functionality are often overlooked. Especially in a machine learning context, when designing artificial neural networks, point neuron models such as the leaky-integrate-and-fire (LIF) model are dominant. These models mimic the integration of inputs at the neuron soma, and ignore the existence of dendrites. In this work, the LIF point neuron model is extended with a simple form of dendritic computation. This gives the LIF neuron increased capacity to discriminate spatiotemporal input sequences, a dendritic functionality as observed in another study. Simulations of the spiking neurons are performed using the Bindsnet framework. In the common LIF model, incoming synapses are independent. Here, we introduce a dependency between incoming synapses such that the post-synaptic impact of a spike is not only determined by the weight of the synapse, but also by the activity of other synapses. This is a form of short term plasticity where synapses are potentiated or depressed by the preceding activity of neighbouring synapses. This is a straightforward way to prevent inputs from simply summing linearly at the soma. To implement this, each pair of synapses on a neuron is assigned a variable, representing the synaptic relation. This variable determines the magnitude of the short term plasticity. These variables can be chosen randomly or, more interestingly, can be learned using a form of Hebbian learning. We use Spike-Time-Dependent-Plasticity (STDP), commonly used to learn synaptic strength magnitudes. If all neurons in a layer receive the same input, they tend to learn the same through STDP. Adding inhibitory connections between the neurons creates a winner-take-all (WTA) network. This causes the different neurons to learn different input sequences. To illustrate the impact of the proposed dendritic mechanism, even without learning, we attach five input neurons to two output neurons. One output neuron is a regular LIF neuron, the other output neuron is a LIF neuron with dendritic relationships. Then, the five input neurons are allowed to fire in a particular order. The membrane potentials are reset and subsequently the five input neurons are fired in the reversed order. As the regular LIF neuron linearly integrates its inputs at the soma, the membrane potential response to both sequences is similar in magnitude. In the other output neuron, due to the dendritic mechanism, the membrane potential response is different for both sequences. Hence, the dendritic mechanism improves the neuron's capacity for discriminating spa-tiotemporal sequences. Dendritic computations improve LIF neurons even if the relationships between synapses are established randomly. Ideally however, a learning rule is used to improve the dendritic relationships based on input data. It is possible to learn synaptic strength with STDP, to make a neuron more sensitive to its input. Similarly, it is possible to learn dendritic relationships with STDP, to make the neuron more sensitive to spatiotemporal input sequences. Feeding structured data to a WTA network with dendritic computation leads to a significantly higher number of discriminated input patterns. Without the dendritic computation, output neurons are less specific and may, for instance, be activated by a sequence in reverse order.

**Keywords :** dendritic computation, spiking neural networks, point neuron model

**Conference Title :** ICBICN 2020 : International Conference on Biologically Inspired Computing and Neurocomputing

**Conference Location :** Paris, France

**Conference Dates :** December 28-29, 2020