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On the applicability of spiking neural network models to solve the task of recognizing gender hidden in texts

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Abstract
Two approaches to utilize spiking neural networks, applicable for implementing in neuromorphic hardware with ultra-low power consumption, in the task of recognizing gender of a text author are analyzed. The first one is to obtain synaptic weights for the spiking network by training a formal network. We show the results obtained with this approach. The second one is a creation of a supervised learning algorithm for spiking networks that would be based on biologically plausible plasticity rules. We discuss possible ways to construct such algorithms.

Keywords: supervised learning, spike-timing-dependent plasticity, artificial neural networks, spiking neural networks

Introduction

For a few last years the interest to spiking neural networks has been growing greatly as the result of appearance of neuromorphic hardware capable of running such networks. It, in turn, gives rise to necessity to develop approaches that can be implemented on such hardware for solving practical tasks. Taking into account the fact that hardware with ultra-low power consumption gives a way to solve the mentioned tasks on autonomous devices, a problem of spiking neural network learning becomes particularly relevant. The task of predicting gender of a text author on base of linguistic parameters, that could be realised on these devices, is important, in particular, for security or conversational purposes.

There are generally two approaches to using spiking networks in a classification task. Since learning algorithms for artificial networks are developed more than those for spiking nets, the direct approach is to convert a trained formal network into a spiking one. In [1] each formal neuron is replaced with several spiking ones. They, along with the encoding and decoding

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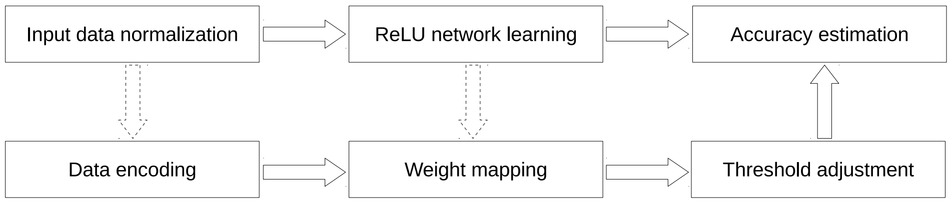

Figure 1: Algorithm steps

machinery, reproduce its activation function. Furthermore, one can simply transfer synaptic weights from a trained formal network to a spiking network of same topology [2]. We show in Section 1.2 that after such transfer the spiking network achieves higher accuracy than the formal one in the Fisher's Iris classification task, and in Section 1.3 apply this approach to the gender recognition task.

Another approach is to implement learning in spiking neuron networks by biologically inspired learning rules. There has been published a number of synaptic plasticity models suitable for supervised learning [3, 4, 5], but still none has been based only on the current knowledge of biological neural systems operating rules, namely, on the Hebb principle. As the biologically plausible long-term plasticity model we consider spike-timing-dependent plasticity (STDP) [6]. It was in [7] shown to be suitable for unsupervised learning, but a supervised learning protocol based on it has not yet been developed. In Section 2.2 the STDP parameters which allow to receive several different synaptic weight distributions are demonstrated. In Section 2.3 we show that any desired weight values can be reached in case of given proper value of correlation between input and output spike sequences. Based on this fact, in Section 2.4 we suggest a supervised learning algorithm suitable for classification of rate-coded binary vectors.

1 ANN to SNN mapping approach

1.1 Network parameters and learning algorithm

We here used, following [2], the combined learning algorithm, involving artificial (ANN) and spiking neural networks (SNN). It consists of the following steps (fig. 1):

1. *Training the artifical neural network using backpropagation.* The neurons' activation function was ReLU for hidden layers and Softmax for the output layer. Neuron biases were set to zero. Input data was normalized so that the L2 norm of each vector was 1.

2. *Transferring the synaptic weights to the spiking neural network.* Integrate-and-fire neuron model was chosen, in which the membrane potential V obeys $\frac{dV}{dt} = \sum_i \sum_{s \in S_i} w_i \delta(t-s)$, where S_i is the sequence of spikes (spike train) on i-th input synapse, and w_i is the synaptic weight. Whenever the potential exceeds the threshold Θ, it is reset to zero and the neuron fires a spike.

3. *Encoding input data to spike trains.* Input vector component x was encoded by a Poisson spike train with mean frequency $x \cdot \nu_{\max}$.

4. *Optimizing the spiking network parameters.* Besides $\nu_{\max}$ and Θ, simulation time T and simulation step Δt were adjusted. According to [2],