Bio-inspired sequence learning mechanisms and their implementation in a memristive neuromorphic hardware

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**. Same order*

Summary. We present a sequence learning model that explains how biological networks learn to predict upcoming elements, signal non-anticipated events, and recall sequences in response to a cue signal. The model accounts for anatomical and electrophysiological properties of cortical neuronal circuits and learns complex sequences in an unsupervised manner using known biological plasticity and homeostatic control mechanisms. We further investigate the feasibility of implementing the sequence learning model on dedicated hardware mimicking brain properties, specifically focusing on memristive crossbar arrays. Finally, we apply the model to sequence classification and anomaly detection in streams of real-world data, and discuss the role of dendritic branches for the sequence learning capacity.

Learning in an unsupervised manner using scarce data is a remarkable ability demonstrated by humans and animals. This is especially evident in infants, who are able to extract meaningful patterns from the limited information available in their environment. The neocortex and other brain areas receive and process this data in a sequential manner. This holds not only for sensory processing but also for high-level cognitive processes such as planning or reasoning. This data needs to be stored to form predictions of upcoming events or actions in a context specific manner, and to detect non-anticipated events. Understanding the neural mechanisms of these computations allows for the development of energy-efficient artificial intelligence systems with online learning capabilities.

Building on the ideas of Hawkins and Ahmad [2], we developed a biologically inspired sequence learning and prediction model (Figure 1). It learns to predict complex sequences in an unsupervised, continuous manner using biological, local learning rules. The model can also perform probabilistic sequential memory recall in response to ambiguous cues [3]. It strengthens the sequence learning mechanisms introduced in [2] and suggests new ones. In the following, we give a summary of these mechanisms:

- Learning and storage of sequences: sequences are represented by specific subnetworks embedded into the recurrent network. During the learning process, these subnetworks are carved out in an unsupervised manner by a form of structural Hebbian plasticity.
- Context specificity: learning of high-order sequences is enabled by a sparse, random potential connectivity, and by a homeostatic regulation of synaptic growth.
- Generation of predictions: neurons are equipped with a predictive state, implemented by a nonlinear synaptic integration mimicking the generation of dendritic action potentials (dAPs).
- Mismatch detection: only a few neurons become active if a prediction matches the stimulus. In our model, this sparsity is realized by winner-take-all (WTA) dynamics implemented in the form of inhibitory feedback. In the case of non-anticipated stimuli, the WTA dynamics cannot step in, thereby leading to a non-sparse activation of larger neuron populations.
- Sequence replay: an autonomous replay of learned sequences in response to a cue signal is enabled by increasing neuronal excitability.

In subsequent studies, we investigate whether it is possible to implement the sequence learning algorithm on neuromorphic hardware centered around memristive devices. Our investigations suggest that the model is robust towards the intrinsic potentiation and depression characteristics of memristive devices such as variability, limited precision, and synaptic failure, and shows that the memristive device can be operated either in a binary or gradual mode without a loss in performance [4]. We further devised an electronic circuit design of the hardware implementing the sequence learning model [5].

During the NNPC conference, we will give a summary of these findings and report on our progress in applying the sequence learning model to solve real-world tasks such as the classification and detection of patterns in spiking data and the role of dendritic branches in increasing the sequence learning capacity.

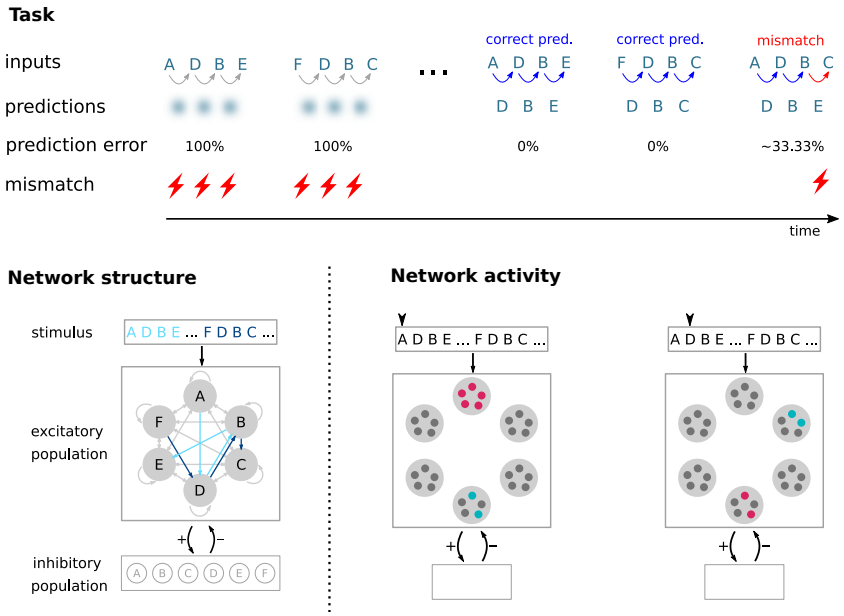

Figure 1: **Task:** The study describes a neuronal network model that is capable of learning and processing sequences of ordered discrete elements (such as characters, musical notes, numbers, or images). The model can predict subsequent elements in response to the presentation of other elements after repeated presentation of high-order sequences with overlapping characters, and it can detect unanticipated elements by generating a mismatch signal if the prediction is not met. **Network structure:** The architecture of the model consists of a recurrent network of excitatory and inhibitory neurons. The excitatory neuron population is divided into subpopulations with neurons that have identical stimulus preferences, and the connections within and between these subpopulations are random and sparse. The inhibitory neurons are mutually unconnected but each one is connected to a specific subpopulation of excitatory neurons in a recurrent manner. During learning, sequence specific, sparsely connected subnetworks with mature synapses are formed (light blue arrows: {'A', 'D', 'B', 'E'}, dark blue arrows: {'F', 'D', 'B', 'C'}). **Network activity:** Snapshots of network activity upon subsequent presentation of the sequence elements 'A' and 'D'. When the first element 'A' is presented, all neurons in the corresponding subpopulations fire. The activation of these neurons then triggers dAPs (predictions) in a subset of neurons that represent the subsequent element 'D'. When the next element 'D' is presented, only the neurons that made predictions become active, which in turn leads to predictions in the subpopulation that represents the subsequent subpopulation ('B'), and so on for subsequent elements. Adapted from [1].

References

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