## Sequence learning, prediction, and generation in networks of spiking neurons

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Sequence learning, prediction and generation has been proposed to be the universal computation performed by the neocortex. The Hierarchical Temporal Memory (HTM) algorithm [1] realizes this form of computation. It learns sequences in an unsupervised and continuous manner using local learning rules, permits a context-specific prediction of future sequence elements, and generates mismatch signals in case the predictions are not met. While the HTM algorithm accounts for a number of biological features such as topographic receptive fields, nonlinear dendritic processing, and sparse connectivity, it is based on abstract discrete-time neuron and synapse dynamics, as well as on plasticity mechanisms that can only partly be related to known biological mechanisms. Here, we devise a continuous-time implementation of the temporal-memory (TM) component of the HTM algorithm [2], implemented in NEST, which is based on a recurrent network of spiking neurons with biophysically interpretable variables and parameters. The model learns non-Markovian sequences by means of a structural Hebbian synaptic plasticity mechanism supplemented with a rate-based homeostatic control. In combination with nonlinear dendritic input integration and local inhibitory feedback, this type of plasticity leads to the dynamic self-organization of narrow sequence-specific feedforward subnetworks. These subnetworks provide the substrate for a faithful propagation of sparse, syn- chronous activity, and, thereby, for a robust, context-specific prediction of future sequence elements as well as for the autonomous replay of previously learned sequences. By strengthening the link to biology, our implementation facilitates the evaluation of the TM hypothesis based on experimentally accessible quantities. The continuous-time implementation of the TM algorithm permits, in particular, an investigation of the role of sequence timing for sequence learning, prediction and replay. We demonstrate this aspect by studying the effect of the sequence speed on the sequence learning performance and on the speed of autonomous sequence replay.

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## References

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