Scalable semi-online training of recurrent spiking and artificial neural networks with chunk-wise truncated backpropagation

Yeganeh Bahariasl(1), Simon Hitzginger(1), Robert Legenstein(1)

(1) Institute of Machine Learning and Neural Computation, Graz University of Technology, Graz, Austria

Recurrent neural networks support continuous signal processing through their recurrent dynamics, but using them for neuromorphic purposes requires training methods that enable efficient, online computation while maintaining accurate temporal credit assignment. Backward methods such as backpropagation through time (BPTT) compute accurate gradients but require storing the full temporal computation graph, making them unsuitable for long streams and neuromorphic on-chip learning. Truncated backpropagation through time(TBPTT) reduces memory by limiting the backward computation within sequence chunks, but loses long-range credit assignment. Forward online methods such as real-time recurrent learning (RTRL) [1] avoid backpropagation through time but require tracking high-dimensional state-parameter derivatives, making exact training impractical. This motivates approximate online algorithms. HYPR [2] for instance is an efficient online learning algorithm with sequence-length independent memory, which only considers neuron-internal recurrences and neglects gradient pathways through intra-layer recurrent connections.

We extend HYPR by combining forward propagation of long-term neuron-internal sensitivities across chunks with TBPTT inside short chunks to recover local intra-layer recurrent credit assignment. Across chunks, state sensitivities as used in HYPR, maintain long-term learning signals, while within each chunk TBPTT captures short-term dependencies through intra-layer recurrent connections ignored by HYPR. This yields a semi-online algorithm with chunk-wise updates, bounded memory, and no need to store the full temporal graph.

We formulate the proposed method for both spiking and artificial recurrent networks. For SNNs, we use oscillatory spiking neuron models[3] with surrogate gradients and for ANNs, we evaluate LSTM and GRU architectures. Results in Table 1 demonstrate consistent improvements over HYPR and TBPTT, supporting the effectiveness of separating neuron-internal recurrence for long-term memory from intra-layer recurrence for short-term dependencies in scalable semi-online learning.

Table 1: Comparison of methods on short- and long-term temporal credit assignment tasks. Results are reported of accuracy percentage on test set, and statistics (mean $\pm$ std. dev.) were performed over 5 random seeds.

Method	NeuroMorse (BRF)	Add Task (LSTM)
HYPR	2$\pm$ 0.00	88.15$\pm$ 0.36
TBPTT	56.66$\pm$ 1.45	31.39 $\pm$ 1.93
HYPR + TBPTT	**61.99 $\pm$ 0.87**	**96.65$\pm$ 0.57**
BPTT	71.99 $\pm$ 0.53	99.90$\pm$ 0.08

The Add task consists sequences of length 5000 which we divided into 500 chunks for TBPTT, stressing long-range credit assignment across many segment boundaries. For NeuroMorse[4], we used 10 chunks, introducing a moderate temporal horizon that requires linking learning signals across multiple segments. The proposed method exhibited superior performance in both scenarios as compared to HYPR and TBPTT, indicating that it was able to preserve long-range temporal information better across many chunks as well as under limited truncation.

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[4] Walters, B, et al. Neuromorph. Comput. Eng. 5.2, 2025.