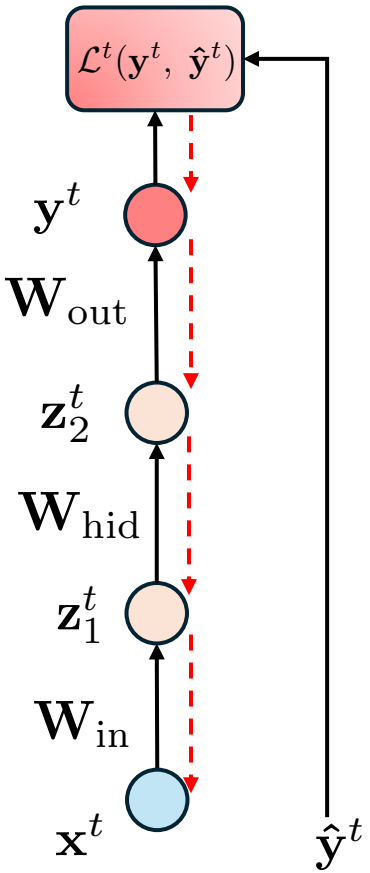
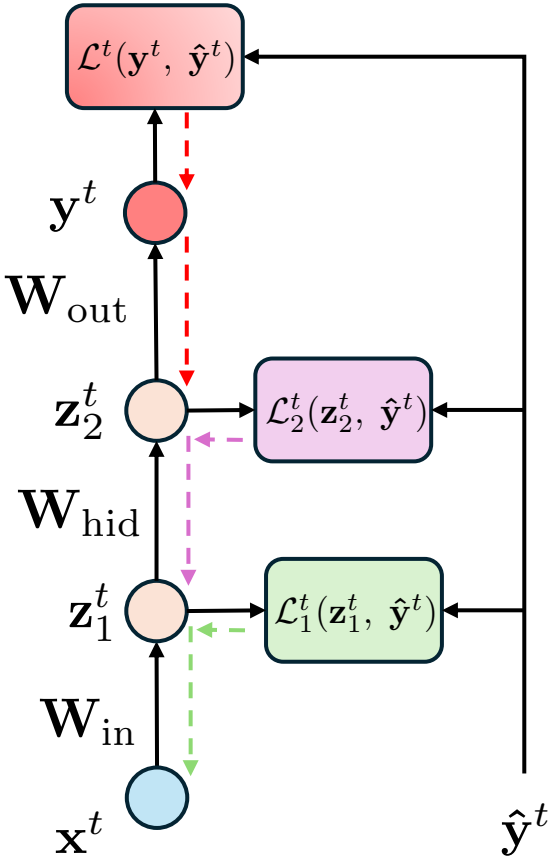
Introducing temporal and spatial locality to Spiking Neural Network training

BPTT / E-prop



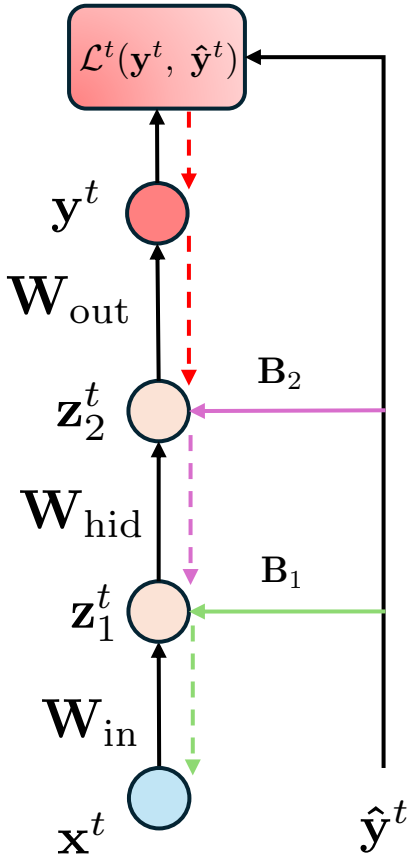
Single global loss function

DECOLLE



Global + local loss functions

Direct Random Target Projection (DRTP)



Global loss function + direct feedback to individual layers through random weight matrices

Learning Method	Temporal locality	Spatial locality
BPTT	❌	❌
E-prop [1]	✅	❌
DECOLLE [2]	✅	✅
DRTP [3]	❌	✅
ETLP [4]	✅	✅

Event-based Three factor local plasticity (ETLP) **combines eligibility traces and DRTP** to enable both temporally and spatially-local plasticity.

Temporal/Spatial locality impact on evaluation benchmarks

Based on experimental evaluation results reported in the literature for N-MNIST and Spiking Heidelberg Digits (SHD) datasets:

- ETLP and DECOLLE lead to **degradation** in test set top-1 accuracy when compared to BPTT and E-prop.
- ETLP underperforms E-prop by **-3.6 %** at N-MNIST and **-6.1%** at SHD.

Spatial locality comes with the **cost of decreased accuracy!**

We suspect that the use of either local loss functions or feedback from random weight matrices hurts the learning process by producing gradients which do not track the global optmization objective effectively.

Learning method	N-MNIST	SHD
BPTT	97.67	75.23
E-prop	**97.90**	**80.79**
DECOLLE	96.27	62.01
ETLP	94.30	74.59

Top-1 test set accuracies reported for BPTT, E-prop, DECOLLE and ETLP in [1]

Research problem/questions:

- Existing gradient-based learning rules that guarantee temporal and spatial locality for training Spiking Neural Networks cause degradation in evaluation benchmarks when compared to BPTT.
- What is the cause of this performance gap and how could it be bridged?

References

[1] Bellec, G., Scherr, F., Subramoney, A. *et al.* A solution to the learning dilemma for recurrent networks of spiking neurons. *Nat Commun* 11, 3625 (2020). https://doi.org/10.1038/s41467-020-17236-y

[2] Kaiser, J., Mostafa, H. and Neftci, E. Synaptic Plasticity Dynamics for Deep Continuous Local Learning (DECOLLE). *Front. Neurosci.* 14:424 (2020). https://doi.org/10.3389/fnins.2020.00424

[3] Frenkel, C., Lefebvre, M. and Bol, D. Learning Without Feedback: Fixed Random Learning Signals Allow for Feedforward Training of Deep Neural Networks. *Front. Neurosci.* 15:629892 (2021). https://doi.org/10.3389/fnins.2021.629892

[4] Quintana, F. M., Perez-Peña, F., Galindo, P. L., Neftci, E. O., Chicca, E. and Khacef, L. ETLP: event-based three-factor local plasticity for online learning with neuromorphic hardware. *Neuromorphic Computing and Engineering*, 4(3), 034006 (2024). https://www.doi.org/10.1088/2634-4386/ad6733