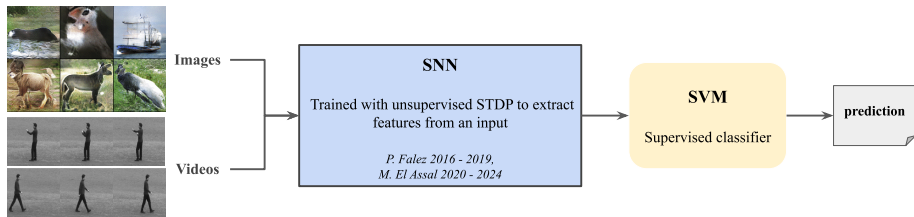


Paired Competing Neurons Improving STDP Supervised Local Learning In Spiking Neural Networks

Gaspard GOUPY, Ioan Marius BILASCO, Pierre TIRILLY

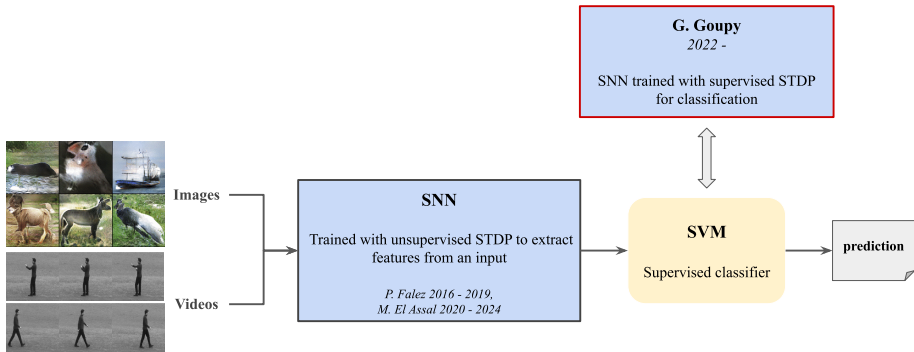
Univ. Lille, CNRS, Centrale Lille, UMR 9189 CRIStAL, F-59000 Lille, France





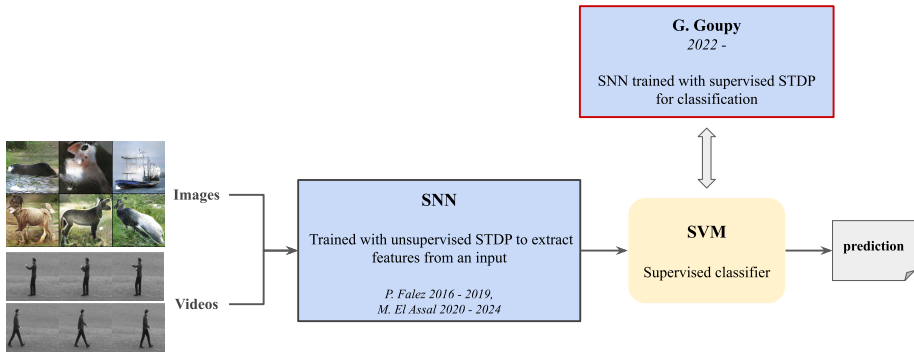
STDP: Spike-Timing Dependent Plasticity

SVM: Support Vector Machine



STDP: Spike-Timing Dependent Plasticity

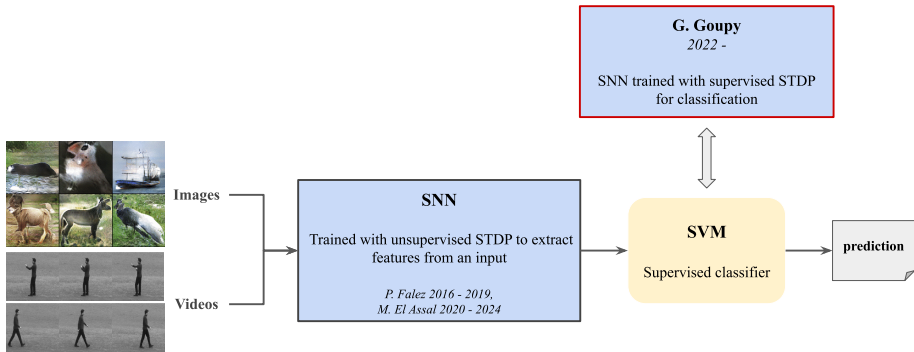
SVM: Support Vector Machine



→ **End-to-end SNN models that lessen the use of supervised learning**

STDP: Spike-Timing Dependent Plasticity

SVM: Support Vector Machine

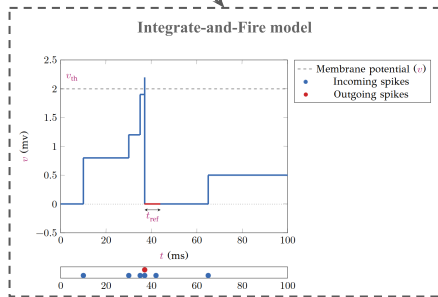
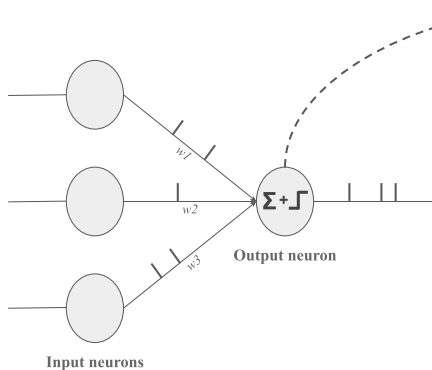


- End-to-end SNN models that lessen the use of supervised learning
- Supervised learning compatible with neuromorphic hardware

STDP: Spike-Timing Dependent Plasticity

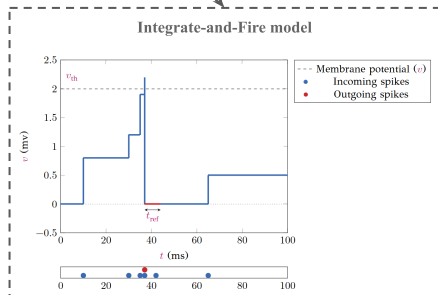
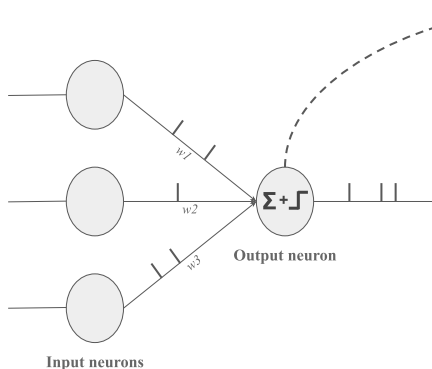
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Spiking Neural Networks (SNNs)



P. Falez, PhD thesis, Université de Lille, 2019

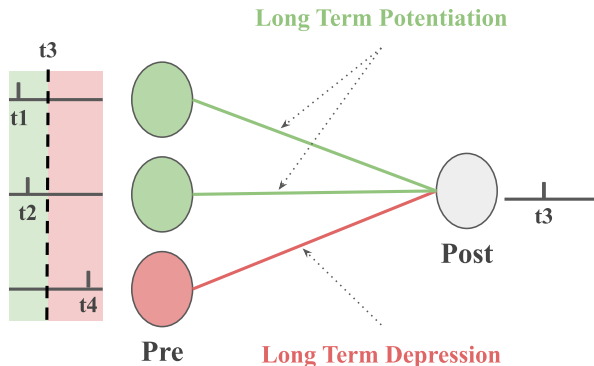
Spiking Neural Networks (SNNs)



P. Falez, PhD thesis, Université de Lille, 2019

→ In our models: one spike per neuron

Spike-Timing Dependent Plasticity (STDP)



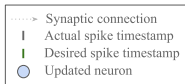
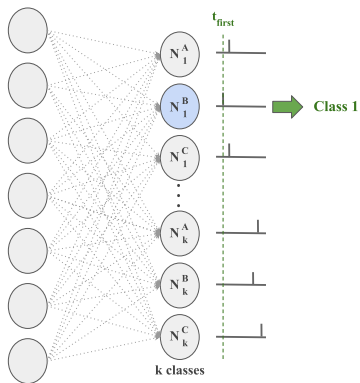
Supervised learning with STDP

State-of-the-art rules

Supervised learning with STDP

State-of-the-art rules

Input neurons



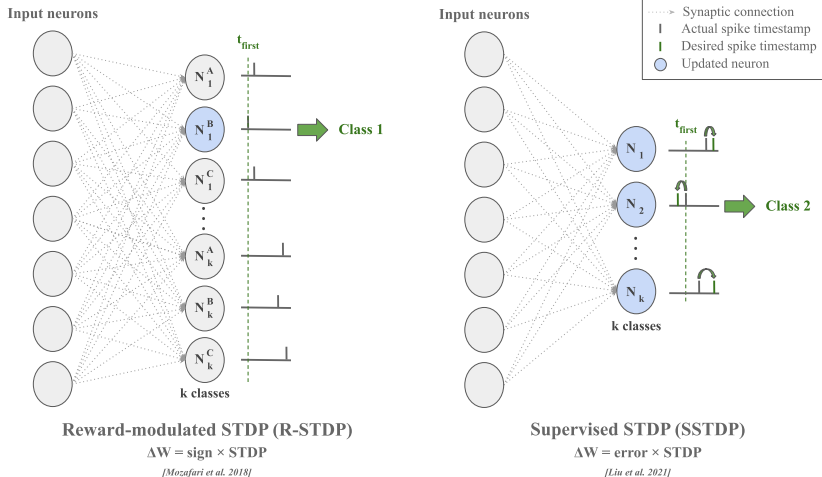
Reward-modulated STDP (R-STDP)

$$\Delta W = \text{sign} \times \text{STDP}$$

[Mozafari et al. 2018]

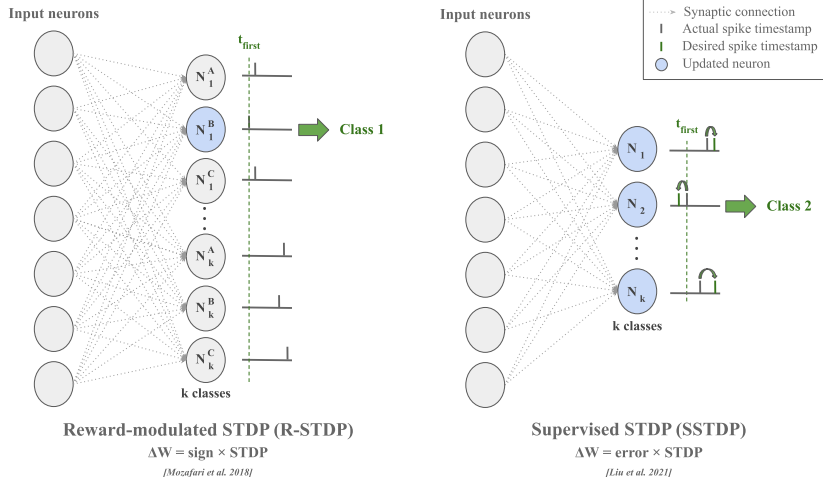
Supervised learning with STDP

State-of-the-art rules



Supervised learning with STDP

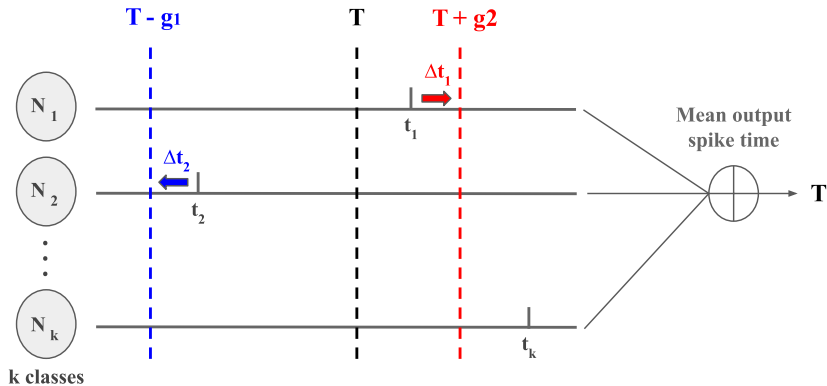
State-of-the-art rules



→ SSTDP: less neurons, more updates, more accurate

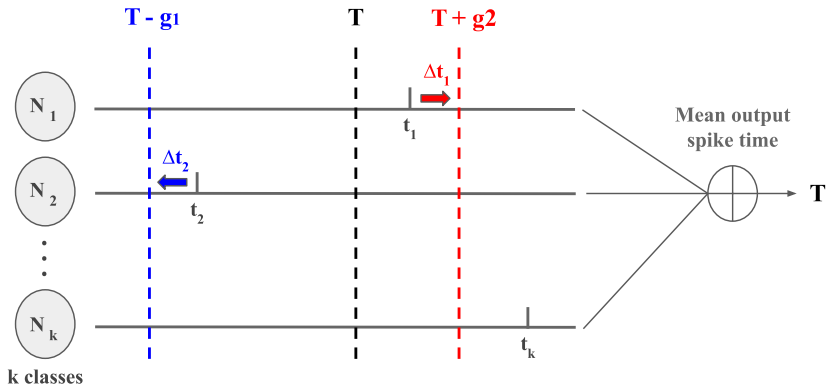
Supervised learning with STDP

Supervised STDP (SSTDP)



Supervised learning with STDP

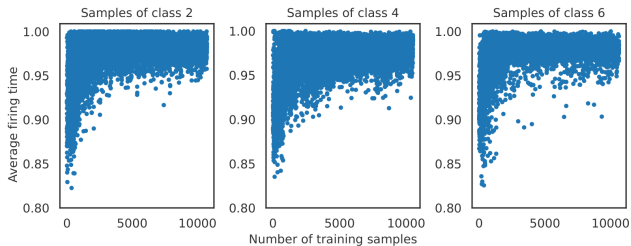
Supervised STDP (SSTDP)



→ Neurons that reach their target time range are not updated

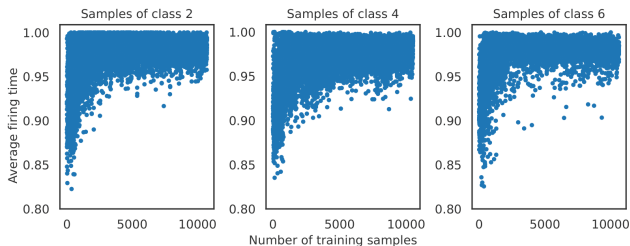
Supervised learning with STDP

Supervised STDP (SSTDP)



Supervised learning with STDP

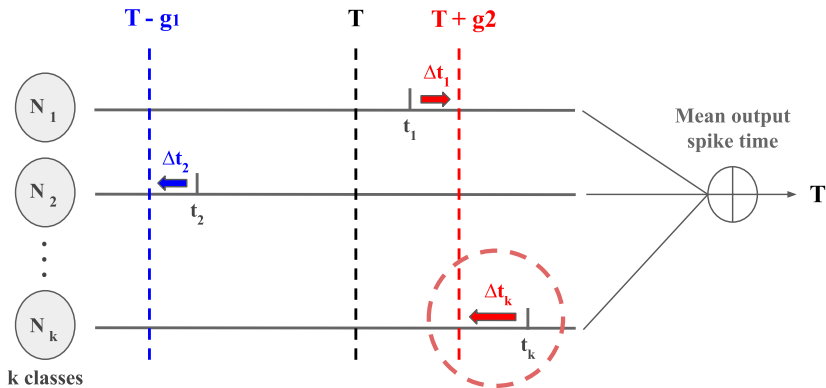
Supervised STDP (SSTDTP)



→ **Saturation of the firing timestamps toward the maximum time**

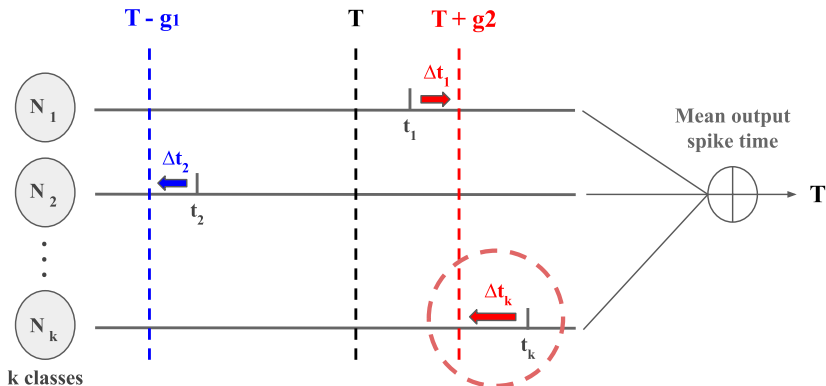
Contributions

Stabilized Supervised STDP (S2-STDP)



Contributions

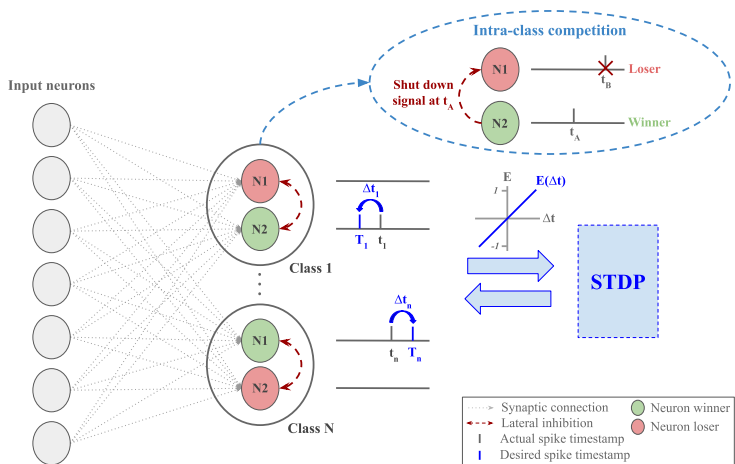
Stabilized Supervised STDP (S2-STDP)



→ Neurons are updated to reach the exact target time

Contributions

Paired Competing Neurons (PCN)



Contributions

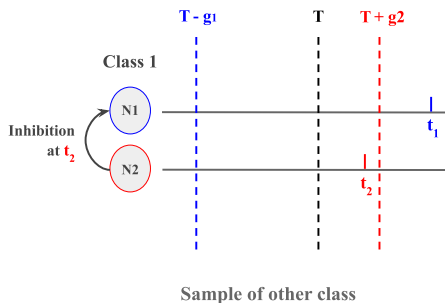
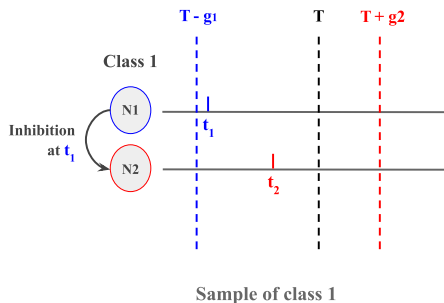
Paired Competing Neurons (PCN)

Goal: promote neuron specialization on target or non-target samples through intra-class competition

Contributions

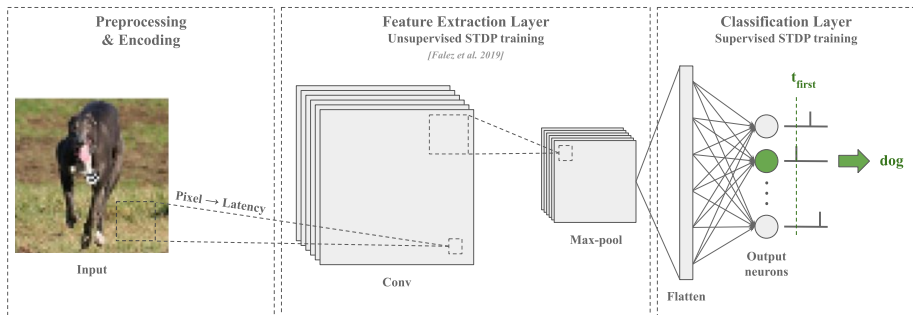
Paired Competing Neurons (PCN)

Goal: promote neuron specialization on target or non-target samples through intra-class competition



Results

Model



Results

Accuracy

Rule	MNIST	Fashion-MNIST	CIFAR-10
R-STDP (N=200)	97.88 \pm 0.13	83.26 \pm 0.22	65.56 \pm 0.38
R-STDP (N=20)	93.28 \pm 0.87	77.01 \pm 0.22	54.02 \pm 0.80
SSTDP	96.37 \pm 0.09	84.12 \pm 1.11	61.34 \pm 0.14
S2-STDP ¹	97.81 \pm 0.05	85.88 \pm 0.22	61.53 \pm 0.16
S2-STDP+PCN ¹	98.59 \pm 0.06	87.12 \pm 0.21	62.81 \pm 0.15
SVM	98.93 \pm 0.04	89.30 \pm 0.21	65.50 \pm 0.29

¹Our method

Results

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→ **S2-STDP outperforms SSTDP**

¹Our method

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→ **S2-STDP outperforms SSTDP**

→ **PCN further improves S2-STDP performance**

¹Our method

Results

Accuracy

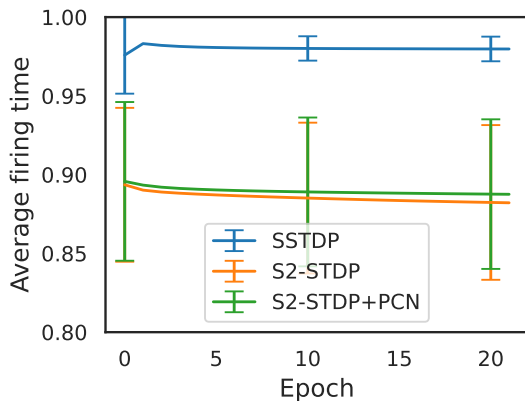
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- **S2-STDP outperforms SSTDP**
- **PCN further improves S2-STDP performance**
- **S2-STDP+PCN outperforms R-STDP for similar architectures**

¹Our method

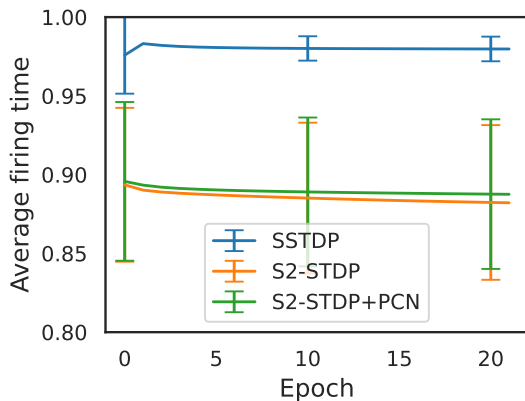
Results

Impact on the firing timestamps (MNIST)



Results

Impact on the firing timestamps (MNIST)



→ S2-STDP reduces the saturation effect

Objective

- Train a spiking classifier using a supervised adaptation of STDP

Contributions

- S2-STDP: a learning rule adapted from SSTDP that reduces the saturation effect
- PCN: a training architecture that improves the learning capabilities of our classifier

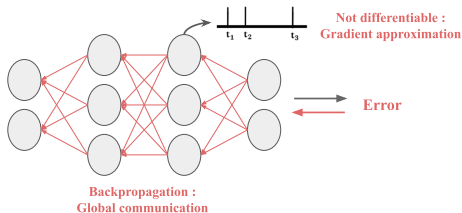
Perspectives

- Multi-layer local supervised learning with STDP
- Classification tasks with DVS data

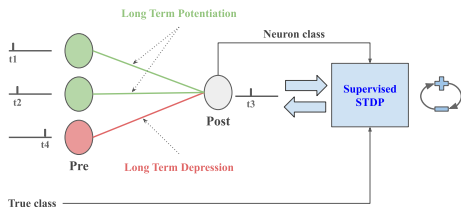
G. Goupy, P. Tirilly, I.M. Bilasco, *Paired Competing Neurons Improving STDP Supervised Local Learning In Spiking Neural Networks*, 2023.

<https://arxiv.org/abs/2308.02194>

Supervised learning in SNNs



BP-based

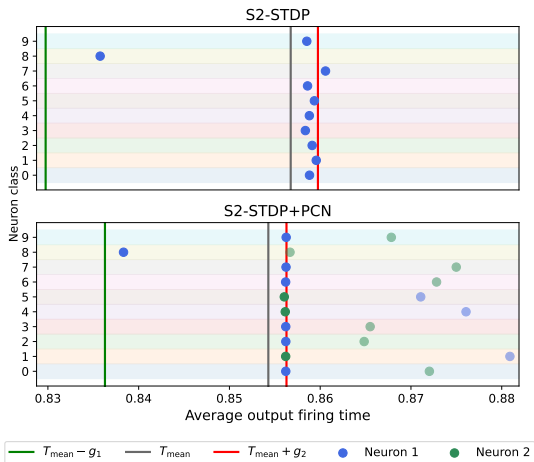


STDP-based

	BP-based	STDP-based
Good performance	✓	✗
Efficient computation/memory	✗	✓
No gradient approximation	✗	✓
Local communication	✗	✓
Easy switch to unsupervised learning	✗	✓

Results

Impact on the firing timestamps (MNIST)



→ PCN are better at reaching their targets