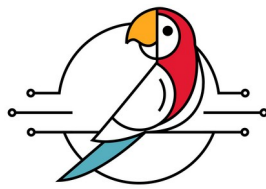




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Three Factor Delay Learning Rules For Spiking Neural Networks

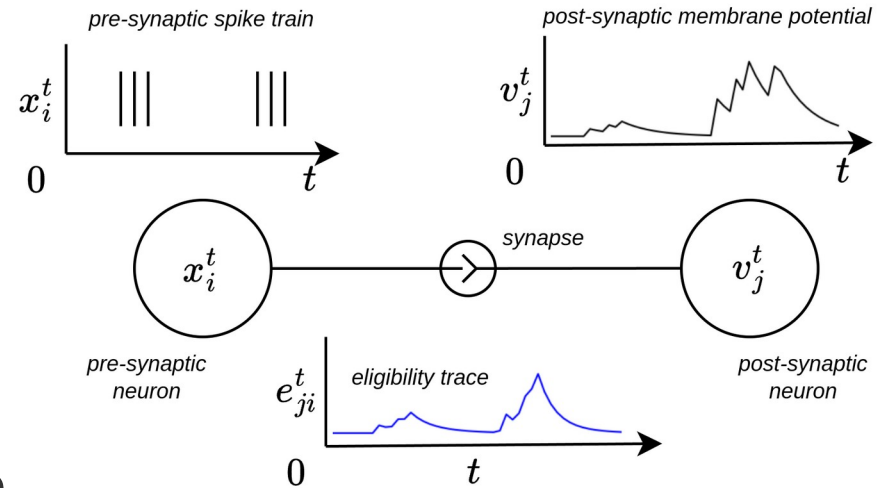
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Background & Motivation

Three factor learning rules

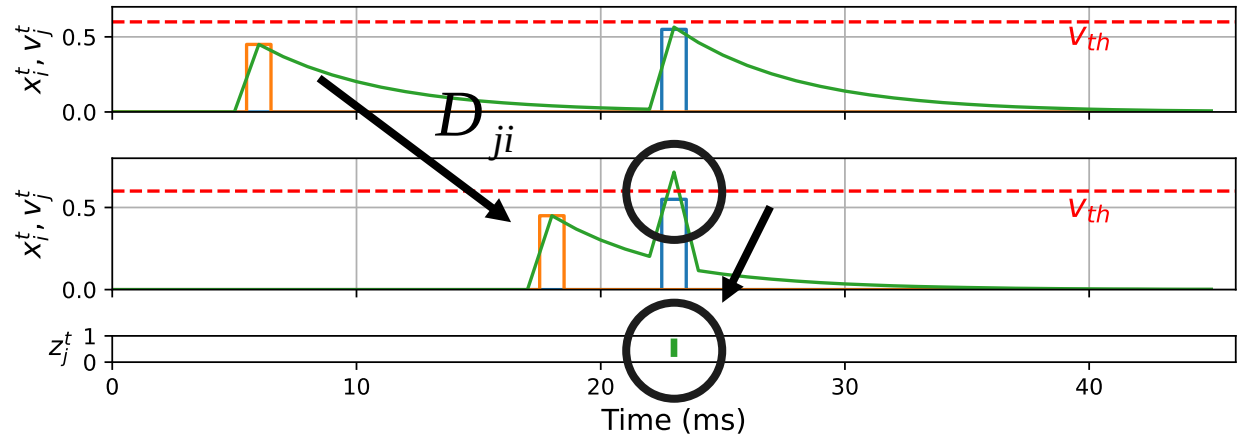
- Three factors
 - Pre-synaptic spike train
 - Post-synaptic membrane potential
 - Learning signal
- Offer some gradient equivalence
- Suitable for real-time / online implementation



Background & Motivation

Delay learning

- Exclusive parameter set for temporal features
- Can lead to significant accuracy improvement in temporal tasks
- Smaller model sizes



Method - Eligibility Propagation

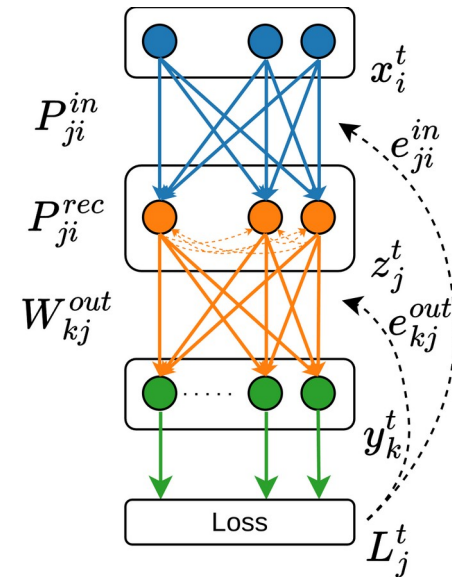
$$\tau_m \frac{dv_j}{dt} = -(v_j(t) - v_{reset}) + RI_j(t) \longrightarrow v_j^{t+1} = \alpha v_j^t + W_{ji}^{in} x_i^t - D_{ji}^{in}$$

$$\frac{dE}{dP_{ji}} = \frac{dE}{dz_j} \times \frac{dz_j}{dv_j} \times \frac{dv_j}{dP_{ji}}$$

$$\frac{dE}{dP_{ji}} = L_j^t e_{p,ji}^t$$

Learning Signal

Eligibility trace



$$P_{ji} \in \{W_{ji}, D_{ji}, D_i\}$$



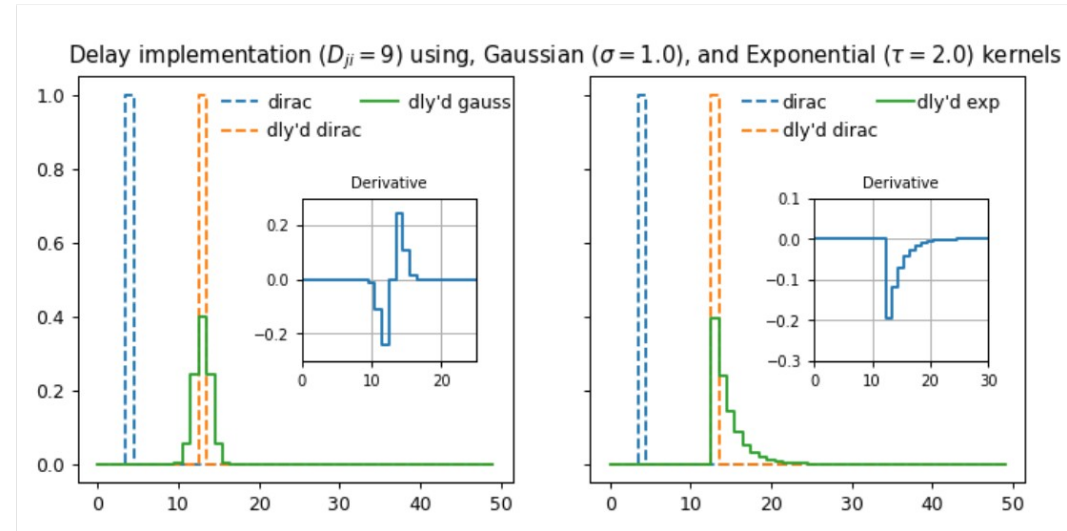
Method

Non-differentiable spikes

$$v_j^{t+1} = \alpha v_j^t + W_{ji}^{\text{in}} x_i^{t-D_{ji}^{\text{in}}}$$

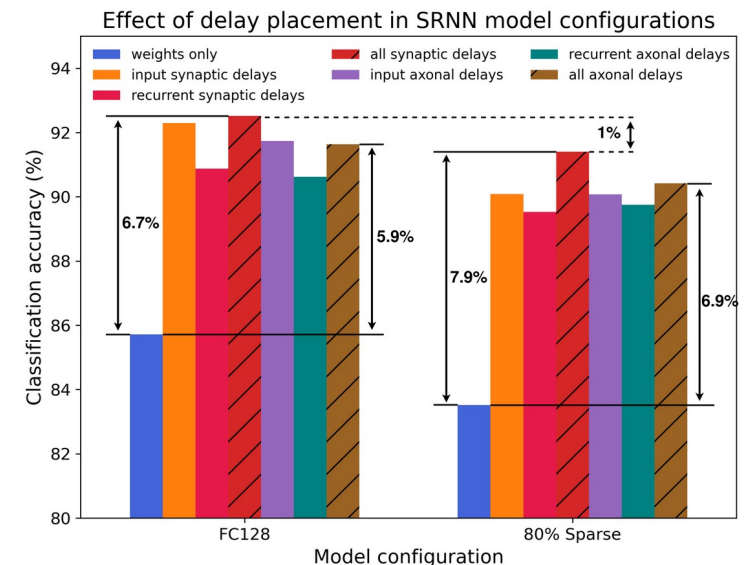
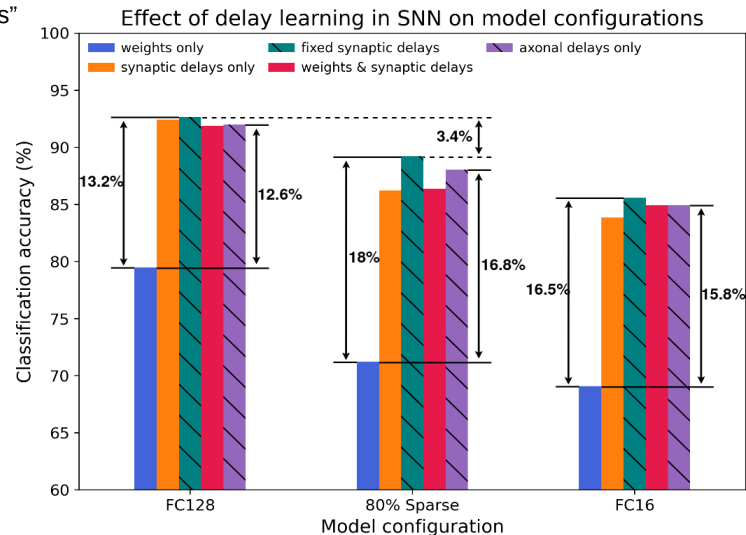
$$x_i^{t-D_{ji}} = \sum_k \delta(t - t_k - D_{ji})$$

$$x_i^{t-D_{ji}} \approx \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t-t_k-D_{ji})^2}{2\sigma^2}}$$



Results

- Synaptic and axonal delays
- Feedforward and recurrent SNNs
- Spiking Heidelberg Digits Dataset¹
- BPTT-based offline baseline²



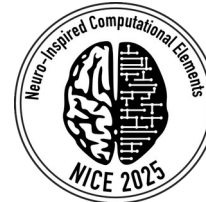
Conclusions

- Three factor learning rules for synaptic and axonal delays
- On audio classification tasks parameter heterogeneity enables:
 - Smaller models
 - Higher accuracy





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Thank you for your attention

Questions?