Eligibility propagation in multi-layer recurrent spiking neural networks.

Presentation 10: Evaluation meeting 2

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Introduction – context

- Biological inspiration to AI
- ANNs and backpropagation
- Deep learning

Introduction – relevance

- Deep learning is energy intensive
- Fundamental differences between DL and biological learning
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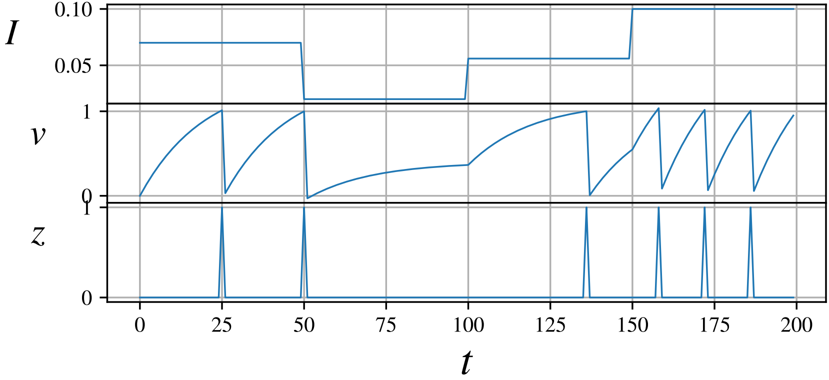
    - Continuous vs. binary communication
    - Backpropagation/BPTT vs. learning signals

Introduction – SNNs

- Binary spikes $\rightarrow$ no backpropagation
- Good performance, but not competitive with DL



Introduction – neuromorphic computing

- Physical embedding of neural network in an analog medium
- Colocalized memory and computation
  $\rightarrow$ no backpropagation
- SNNs as ideal biologically inspired NC paradigm for efficient computation
- Analog SNNs are extremely fast and energy efficient
- Problem: learning rule must be *local* and *online*
  $\rightarrow$ revalue biological learning

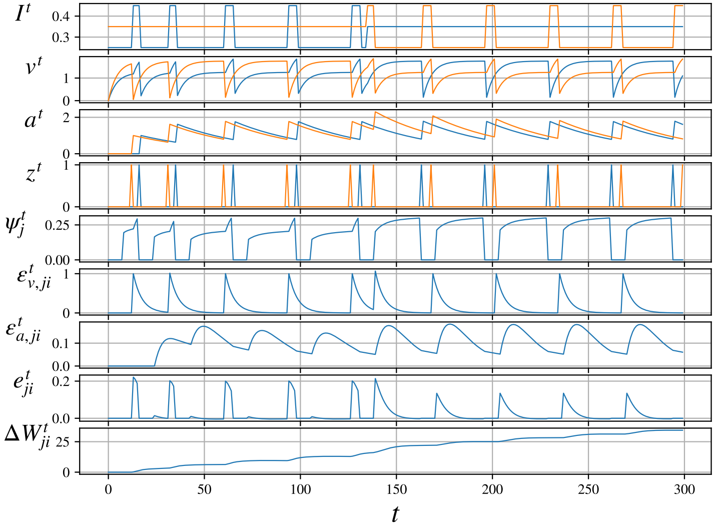
Introduction – biological learning

- Hebbian learning
  $\rightarrow$ runaway excitation
- STDP
  $\rightarrow$ how to teach?
- Learning signals: three-factor Hebbian learning, R-STDP
- Biological learning signals: neurotransmitters
  $\rightarrow$ credit assignment
- Eligibility traces

Introduction – eligibility propagation

- Mathematical approximation to BPTT
- Local learning signals and eligibility traces
- Applicable to any SNN topology and multiple neuron models
- Also applicable to neuromorphic VLSIs
- Competitive with LSTMs on phone classification

Introduction – eligibility propagation



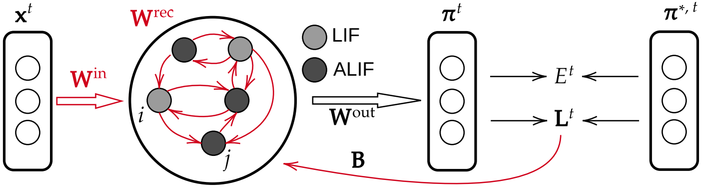
Introduction – eligibility propagation

- E-prop: only ALIF so far
- New research: STDP-LIF and Izhikevich neuron display STDP

Introduction – this research

- Reproduce results of original e-prop paper
  $\rightarrow$ explicitly instead of automatic differentiation
- Extend STDP-LIF to STDP-ALIF
- Experimentally verify the STDP-ALIF and Izhikevich neuron on phone classification task
- Examine effects of e-prop in multi-layer recurrent SNN

Methods – technical framework (e-prop)

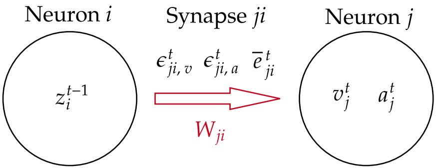


E-prop model $\mathcal{M} = \langle M, f \rangle$

$$\mathbf{h}_j^t = M\left(\mathbf{h}_j^{t-1}, \mathbf{z}^{t-1}, \mathbf{x}^t, \mathbf{W}_j\right) \tag{1}$$

$$z_j^t = f\left(\mathbf{h}_j^t\right) \tag{2}$$

Methods – the ALIF neuron model



Methods – the ALIF neuron model

$$z_j^t = H\left(v_j^t - v_{\mathsf{th}} - \beta a_j^t\right) \tag{3}$$

$$v_j^{t+1} = \alpha v_j^t + \sum_{i \neq j} W_{ji}^{\mathsf{rec}} z_i^t + \sum_i W_{ji}^{\mathsf{in}} x_i^{t+1} - z_j^t v_{\mathsf{th}} \tag{4}$$

$$a_j^{t+1} = \rho a_j^t + z_j^t \tag{5}$$

Methods – e-prop

$$\frac{dE}{dW_{ji}} = \sum_t L_j^t \; e_{ji}^t$$

$$\frac{dE}{dW_{ji}} = \sum_t \frac{dE}{dz_j^t} \underbrace{\frac{\partial z_j^t}{\partial \mathbf{h}_j^t} \underbrace{\sum_{t \geq t'} \frac{\partial \mathbf{h}_j^t}{\partial \mathbf{h}_j^{t-1}} \cdots \frac{\partial \mathbf{h}_j^{t+1}}{\partial \mathbf{h}_j^{t'}} \cdot \frac{\partial \mathbf{h}_j^{t'}}{\partial W_{ji}}}_{\epsilon_{ji}^t}}_{e_{ji}^t}$$

Methods – e-prop for ALIF

$$\frac{dE}{dW_{ji}} = \sum_t L_j^t \; e_{ji}^t$$

$$\mathbf{h}_j^t = \begin{pmatrix} v_j^t \\ a_j^t \end{pmatrix} \tag{6}$$

$$\psi_j^t = \gamma \max\left(0, 1 - \left|\frac{v_j^t - v_{\text{th}} - \beta a_j^t}{v_{\text{th}}}\right|\right) \tag{7}$$

$$\begin{pmatrix} \epsilon_{ji,v}^{t+1} \\ \epsilon_{ji,a}^{t+1} \end{pmatrix} = \begin{pmatrix} \alpha \cdot \epsilon_{ji,v}^t + z_i^{t-1} \\ \psi_j^t \epsilon_{ji,v}^t + \left(\rho - \psi_j^t \beta\right) \epsilon_{ji,a}^t \end{pmatrix} \tag{8}$$

$$e_{ji}^t = \psi_j^t \left(\epsilon_{ji,v}^t - \beta \epsilon_{ji,a}^t\right) \tag{9}$$

Methods – e-prop weight update

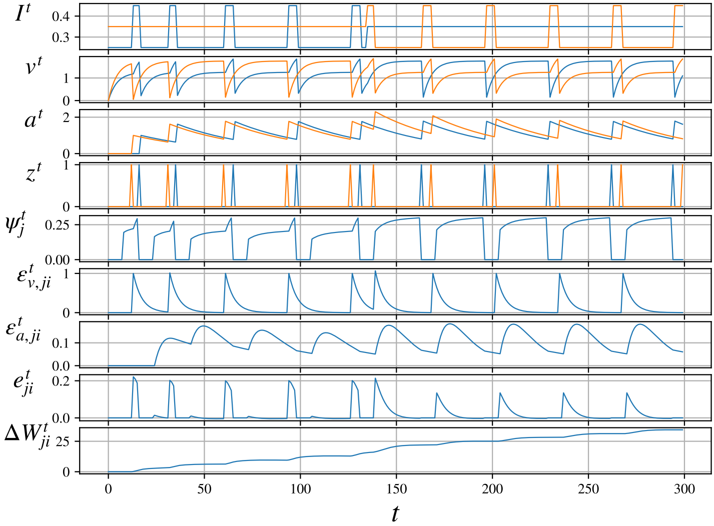
$$\Delta W_{ji} = -\eta \sum_t \underbrace{\sum_k B_{jk} \left(\pi_k^{t'} - \pi_k^{*,t}\right)}_{=L_j^t} \underbrace{\sum_{t' \leq t} \kappa^{t'-t} e_{ji}^{t'}}_{\overset{\text{def}}{=} \bar{e}_{ji}^t} \tag{10}$$

where $\pi_k^t = \sigma_k\left(y_1^t, \ldots, y_K^t\right)$.

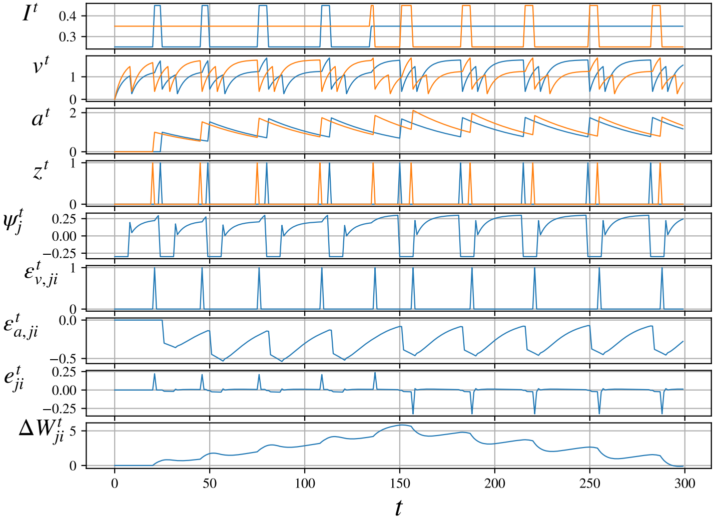
$$\Delta W_{kj}^{\text{out}} = -\eta \sum_t \left(\pi_k^t - \pi_k^{*,t}\right) \sum_{t' \leq t} \kappa^{t'-t} z_j^t \tag{11}$$

$$\Delta b_k = -\eta \sum_t \left(\pi_k^t - \pi_k^{*,t}\right). \tag{12}$$

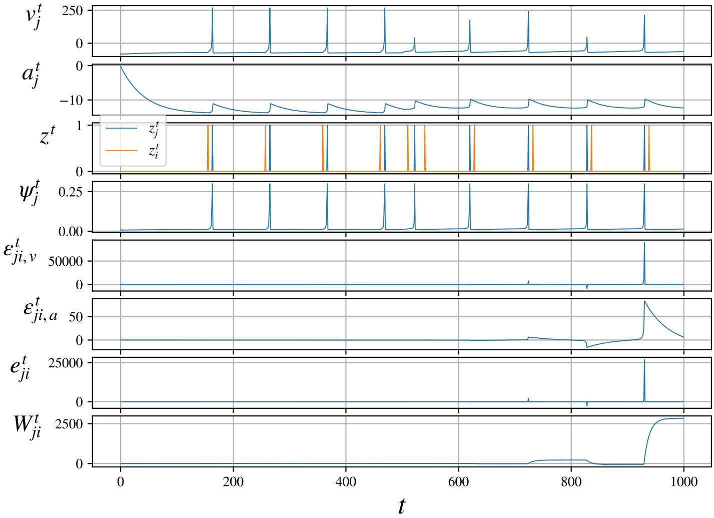
Methods – Visualizing the ALIF neuron



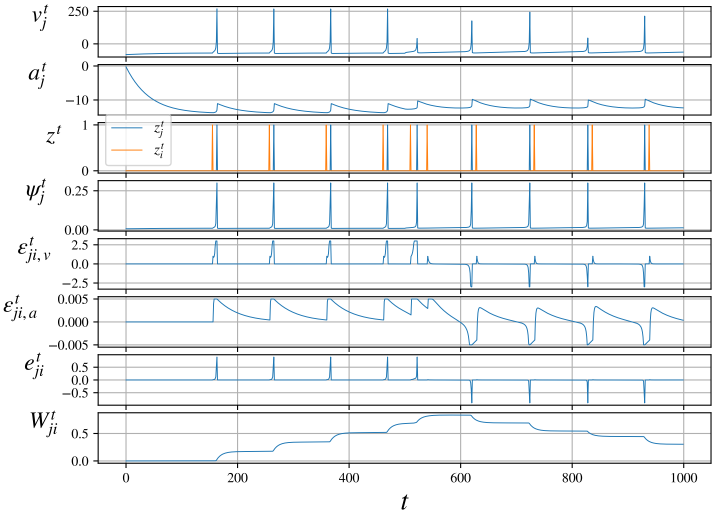
Methods – STDP-ALIF



Methods – Izhikevich



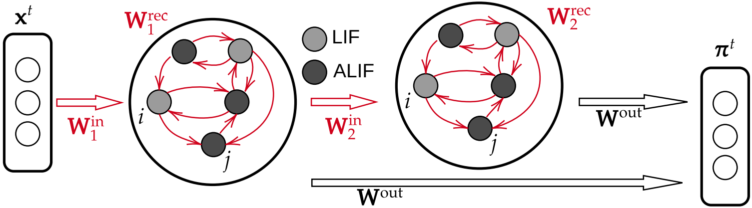
Methods – Izhikevich fixed



Methods – Multilayer

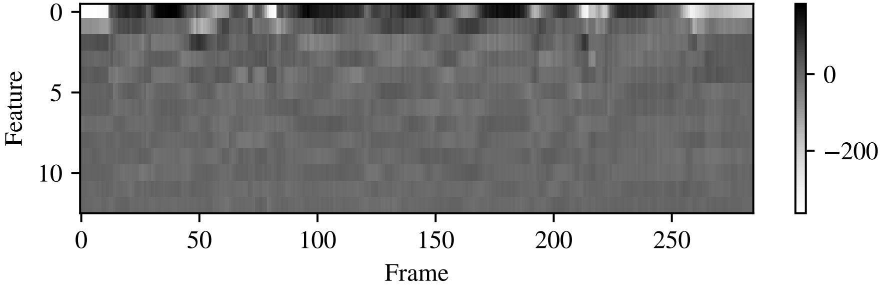
$$\mathbf{h}_{rj}^{t} = \begin{cases} M\left(\mathbf{h}_{rj}^{t-1}, \mathbf{z}_{r}^{t-1}, \mathbf{x}^{t}, \mathbf{W}_{rj}\right) & \text{if } r = 1 \\ M\left(\mathbf{h}_{rj}^{t-1}, \mathbf{z}_{r}^{t-1}, \mathbf{z}_{r-1}^{t}, \mathbf{W}_{rj}\right) & \text{otherwise,} \end{cases} \tag{13}$$

where $r \in [1 \mathinner{..} R]$.



Methods – Task

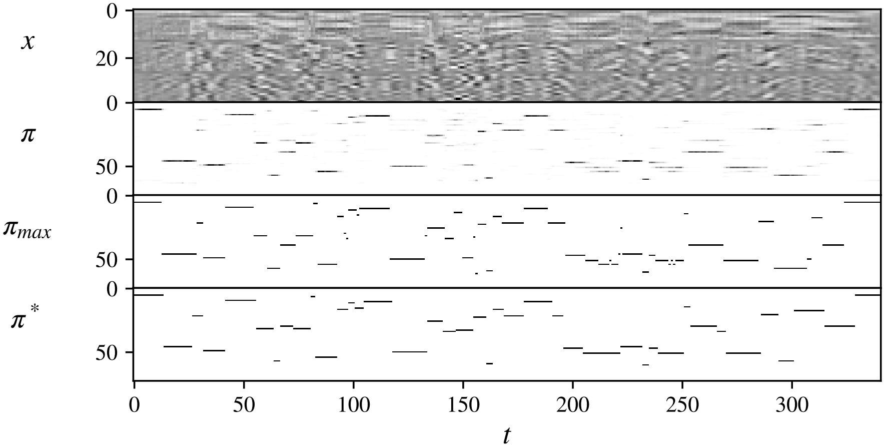
- Classify frame-wise phones from speech signals.
- There are 61 different class labels, and approximately 4000 speech sentences containing around 200-300 frames each.
- Speech is preprocessed into MFCCs (2–13) with their 1st and 2nd deltas, standardized per channel



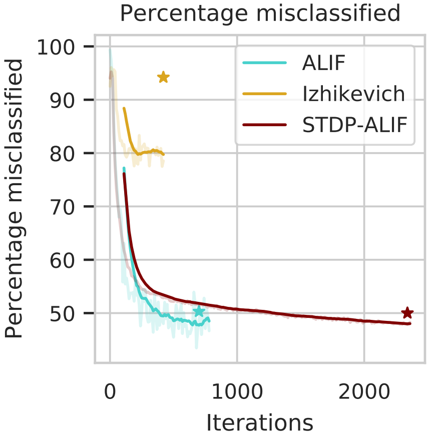
Methods – Other settings

- Adam optimizer for e-prop
- Firing rate regularization
- L2 regularization

Results – Example

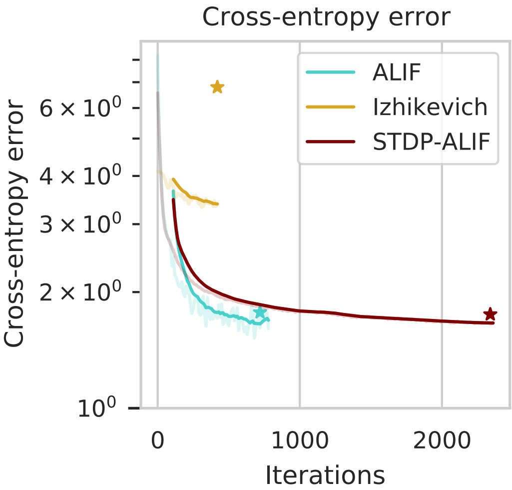


Results – Accuracy per neuron type

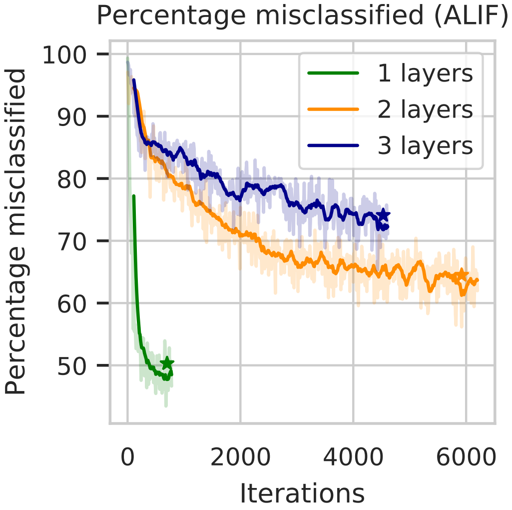


Test scores: ALIF = 50.3%, STDP-ALIF = 50%, Izhikevich = 94.2%

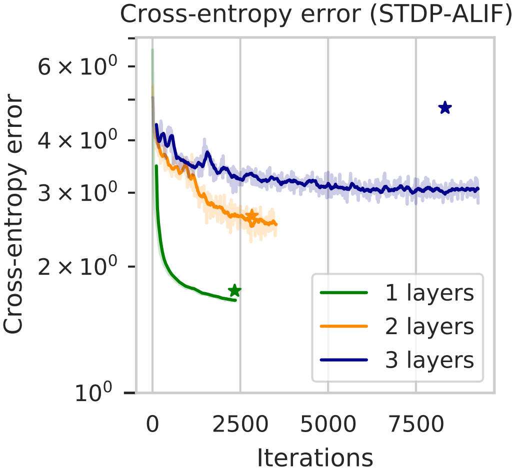
Results – Cross-entropy per neuron type



Results – Multi-layer effects



Results – Multi-layer effects



Discussion

- Izhikevich neuron unsuitable
- More layers = less efficient
- ALIF and STDP-ALIF contested
  $\rightarrow$ STDP inclusion slower but stabler and more accurate gradient descent

Discussion – future research

- Distributed parameters
- Custom connectivity graphs
- Dynamic pruning and growing
- Synaptic delay