Online learning in SNNs with e-prop and Neuromorphic Hardware

Adam Perrett
Sara Summerton
Andrew Gait
Oliver Rhodes
Overview

• Motivation
• Memory in neural networks
• E-prop
• SpiNNaker
• Wave form matching
• Temporal credit assignment
• Conclusions
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Motivation

• Online learning
  • No break between acting and learning
  • Local tailoring of a system

• Neuromorphic
  • Low power
  • Low latency
  • Event-based computing
  • Biologically inspired

• SpiNNaker
  • Real-time computing
  • Adaptable digital platform
  • Scale
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Recurrent models with working memory

• Common practice in machine learning is to use Long Short Term Memory (LSTM) units

• Very successful in temporal tasks such as language processing and video prediction
Back propagation through time (BPTT)

- Error is propagated backwards through the network and time

- Unravelling as another layer with shared weights for each time step

- All states must be recorded for all time steps you wish to learn over

- Not suited to neuromorphics

Working memory in spiking neurons

• The firing threshold $A_j(t)$ of a leaky integrate-and-fire (LIF) neuron $j$ contains a time-varying component $a_j(t)$

• It’s temporarily increased by each spike $z_j(t)$ of the neuron:

\[ A_j^t = v_{th} + \beta a_j^t \]

\[ a_j^{t+1} = \rho a_j^t + z_j^t \]

• Performance comparable with LSTMs when trained with BPTT!

Spiking neural network learning (LIF)

• Inherently recurrent as future states are influenced by past ones

• Non differentiable activation function

• Requires pseudo-derivative
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Eligibility propagation (e-prop)

• Eligibility captures the history of behaviour

• It is lowpass filtered through time

• The error is broadcast along random feedback weights\(^1\) creating the learning signal

• Eligibility and the learning signal create the weight updates

Neuron model - (A)LIF

- Membrane voltage leaks
- Integrates spikes from the inputs and recurrent connections
- Reset by subtraction after spiking
- Produce a spike if above threshold
- The adaptive threshold increases following a spike then decays back down

\[
v_{j}^{t+1} = \alpha v_{j}^{t} + \sum_{i \neq j} W_{ji}^{\text{rec}} z_{i}^{t} + \sum_{i} W_{ji}^{\text{in}} x_{i}^{t+1} - z_{j}^{t} A_{j}^{t}
\]

\[
z_{j}^{t} = \begin{cases} 
1, & \text{if } (v_{j}^{t} - A_{j}^{t}) > 0 \\
0, & \text{otherwise}
\end{cases}
\]

\[
A_{j}^{t} = v_{\text{th}} + \beta a_{j}^{t}
\]

\[
a_{j}^{t+1} = \rho a_{j}^{t} + z_{j}^{t}
\]
Weight updates

• Eligibility of a neuron is the product of the pseudo derivative and the incoming spike trace

• Weight updates are the product of the eligibility trace and the learning signal

\[ \psi_j^t = \frac{1}{v_{th \; base}} \gamma_{pd} \max \left( 0, 1 - \left| \frac{v_j^t - A_j^t}{v_{th \; base}} \right| \right) \]

\[ e_{ji}^t = \psi_j^t \left( z_i^{t-1} - \beta e_{ji,a}^t \right) \]

\[ \Delta W_{ji} = -\eta \sum_t \left( \sum_k B_{jk}(y_k^t - y_{k,*}^t) e_{ji}^t \right) \]

\[ = E^t \]

\[ = L_j^t \]
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spiNNaker

- Memory constraints
  - 96 kB TCM per core (32kB ITCM, 64kB DTCM)
  - 128 MB SDRAM per chip
  - 18 cores/chip

- Real-time/online

- Weight precision (16-bit fixed point)

- Programmable
SpiNNaker implementation

- 8 neurons/core
- 250 synapses/neuron
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Waveform matching

• Proof of concept to test matching a target output

• A repeated Poisson spike source is injected into a network

• A target waveform is compared with the output neuron’s membrane potential to produce an error

• The learning signal is broadcast to the network to reduce the error
Waveform matching architecture

Repeating Poisson spike train

Hidden population
n=100
Only LIF
No adaptive threshold

Readout neuron compares desired output with $V_{\text{mem}}$

Learning signal
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Temporal credit assignment

• Left and right signals are presented to a mouse as it walks down a hallway

• At the end of the hallway it should select the direction which presented the most cues
Temporal credit assignment

- input 0 = left cue
- input 1 = right cue
- input 2 = prompt signal
- input 3 = 10Hz noise
- ON = 100Hz
- OFF = 0Hz
- output 0 = right decision
- output 1 = left decision
Temporal credit assignment

• Receives left and right cues

• After presentation there is 1s delay

• Prompt signal indicates to the network that a decision must be made

• A learning signal is only broadcast during the duration of the prompt

• Curriculum learning increases the number of cues after threshold performance (1, 3, 5, 7)

Temporal credit assignment architecture

Variable Poisson spike train

Hidden population
n=100
ALIF – adaptive threshold

Readout neurons compare softmax of 2 neurons $V_{mem}$

Poisson rate control

Learning signal
Temporal credit assignment
Typical result for temporal credit assignment

- Significant learning takes place during the first stage
- Eventually the task becomes difficult enough to degrade performance requiring substantial retraining
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Challenges:
• Neuromorphic restrictions
• Firing rate regularisation

Future work:
• Move to multi-core model
• Recurrent connections
• Reinforcement learning tasks (eg Pong)
Questions?