

Efficient GPU training of LSNNs using eProp

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ABSTRACT

Taking inspiration from machine learning libraries – where techniques such as parallel batch training minimise latency and maximise GPU occupancy – as well as our previous research on efficiently simulating Spiking Neural Networks (SNNs) on GPUs for computational neuroscience, we have extended our GeNN SNN simulator to enable spike-based machine learning research on general purpose hardware. We demonstrate that SNN classifiers implemented using GeNN and trained using the eProp learning rule can provide comparable performance to those trained using Back Propagation Through Time and show that the latency and energy usage of our SNN classifiers is up to $7\times$ lower than an LSTM running on the same GPU hardware.

CCS CONCEPTS

• **Computing methodologies** → *Bio-inspired approaches; Supervised learning; Vector / streaming algorithms.*

KEYWORDS

datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

In recent years, several new techniques for directly training spiking neural networks (SNNs) have been developed. One approach is to replace the non-differentiable ‘transfer function’ of a spiking neuron with a differentiable surrogate function [3, 5, 25], allowing SNNs to be trained with the same algorithms used to train rate-based Recurrent Neural Network (RNNs) such as Back Propagation Through Time (BPTT). While BPTT is computationally efficient – because it requires gradients to be stored during the forward pass in order for them to be applied during a backward pass – it has a memory requirement which grows with time preventing it from being applied to long input sequences or used online. RTRL [20] is an alternative ‘forward mode’ algorithm for training

RNNs but, in its general form, it is too computationally expensive to be practical. However, if the gradients flowing through the ‘explicit’ recurrent connections are ignored and only those flowing through the ‘implicit’ recurrence represented by the dynamics of individual neurons is considered, much more computationally tractable learning rules can be derived [24]. Learning rules of this sort include SuperSpike [23], eProp [3] and Decolte [15]. **(TODO: SOME BACKGROUND ON SPIKE-TIME BASED LEARNING)** However, in order to apply new spike-based machine learning techniques to larger models and data-sets as well as prototyping algorithms for neuromorphic hardware [1, 8, 11], new tools are required which can efficiently simulate SNNs on existing hardware. The development of efficient SNN simulators has been a key area of computational neuroscience research for several decades [2, 6, 12, 13, 21] but, these simulators **(TODO: MORE)**, making them ill-suited for spike-based machine learning research. As such, many ML researchers have chosen to build libraries [9, 10, 14, 18] on top of more familiar tools such as PyTorch. However, while libraries like PyTorch are highly-optimised for rate-based models, they does not take advantage of the spatio-temporal sparsity of SNNs which have the potential to enable massive computational savings over rate-based networks [22].

While our GeNN simulator [16, 17, 21] was originally developed for Computational Neuroscience research, its longstanding focus on flexibility and its targeting of GPU accelerators make it well-suited to the needs of spike-based ML. **(TODO: TALK ABOUT ADDITIONS TO GENN)** Here we demonstrate this by training SNN classifiers on the Spiking Heidelberg Digits [7] and the Spiking Sequential MNIST [19] datasets. In section 2.1 we compare the trained performance of these classifiers to those trained using BPTT, in section 2.2 we compare the time taken to train these models and in section 2.3 we compare the latency and energy usage of our SNN classifiers to LSTMs running on the same GPU hardware.

2 RESULTS

We trained LSNNs of various sizes with feedforward and recurrent connectivity on the Spiking Heidelberg Digits (SHD) [7] and spiking sequential MNIST [19] datasets using eProp with the default parameters employed by Bellec et al. [4].

2.1 Accuracy

In figure 2 we compare the performance of our models trained on the SHD dataset with results obtained by Zenke and Vogels [25] using BPTT. There is no significant **(TODO: SUITABLE SIGNIFICANCE TEST?)** difference between the performance of the 256 neuron models and, because the reduced memory requirement of eProp allow larger models to be trained, we show that the performance can be significantly improved by increasing the number of neurons to 512.

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Figure 1: 1907 Franklin Model D roadster. Photograph by Harris & Ewing, Inc. [Public domain], via Wikimedia Commons. (<https://goo.gl/VLCRBB>).

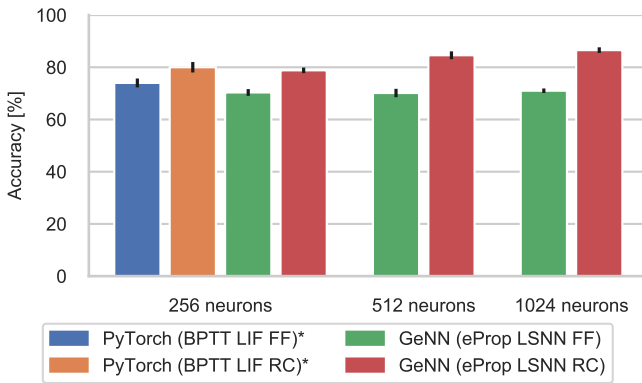


Figure 2: Comparison of performance on Spiking Heidelberg Digits dataset of LSNNs trained with eProp using GeNN and SNNs trained with BPTT using PyTorch [25]. Bars signify the mean and error bars the standard deviation over 5 (GeNN) and 10 (PyTorch) simulations.

2.2 Training time

While being able to train networks with high classification accuracy is important, training also needs to be fast. In figure 3 we compare the time taken to train recurrent LSNNs using eProp with GeNN against recurrent LIF networks training using BPTT with PyTorch. (**TODO: ANALYSIS**)

2.3 Inference time

In figure 1, we compare the inference time and energy delay products (**TODO: CITE**) of LSNNs simulated using GeNN against LSTM models running on the same hardware [19] as well as LSNNs running on the Loihi neuromorphic system [8]. On the same Titan V GPU, LSNNs are faster than LSTMs and have a lower EDP across all batch sizes. Compared to inference using LSTMs, LSNN inference has a much lower arithmetic intensity meaning that, at batch size

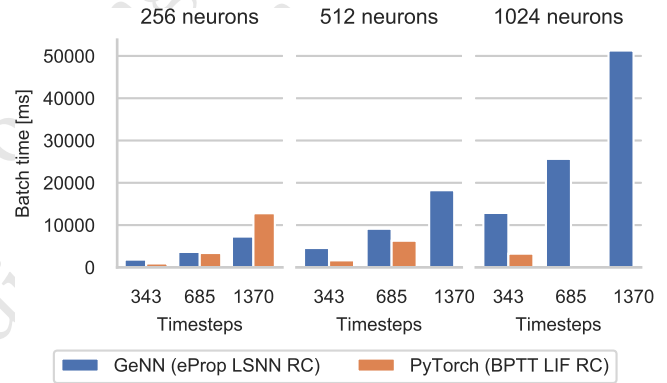


Figure 3: Comparison of training times on Spiking Heidelberg Digits dataset of LSNNs trained with eProp using GeNN and SNNs trained with BPTT using PyTorch. All experiments are performed on a 12GB Titan V GPU. The input spike trains are binned into different numbers of timesteps. Missing bars indicate that GPU had insufficient memory for experiment.

1, not only is the CPU code generated by GeNN faster than TensorFlow running on CPU but it is also faster than GeNN running on GPU. Finally, although LSNN inference on Loihi has a much lower Energy-Delay Product, inference on both GPU and CPU using GeNN has lower latency.

3 FUTURE WORK

(**TODO: EVENTPROP, CONVOLUTIONAL NETWORKS, DEEPER NETWORKS**)

4 CONCLUSIONS

By adding additional functionality aimed at accelerating spike-based machine learning workflows to our GeNN simulator, we

have demonstrated that training using ‘forward-mode’ learning rules like eProp can not only result in competitive accuracy in classification tasks but also allow larger models to be trained on longer input sequences than is possible when using BPTT. Finally we demonstrate that, by exploiting temporal sparsity, standard CPU and GPU hardware can perform inference faster and with less energy using LSNNs than it can using standard LSTM models.

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