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× lower than an LSTM running on the same GPU hardware.

CCS CONCEPTS

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

KEYWORDS

spiking neural networks, efficient simulation, GPU

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1 INTRODUCTION

In recent years, several new techniques for directly training spiking neural networks (SNNs) using gradient-based approaches have been developed. The discontinuity of spiking neuron's membrane potentials when they emit a spike is problematic when deriving gradients. One approach to work around this problem is to replace the derivative of the membrane potential with a 'surrogate gradient' [3, 5, 27], 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 [21] 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 are considered, much more computationally tractable learning rules can be derived [26]. Learning rules of this sort include SuperSpike [25], eProp [4] and Decolle [15]. However, in order to apply these new spike-based machine learning techniques to larger models and data-sets as well as prototyping algorithms for neuromorphic hardware [8, 11, 18], 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 [1, 6, 12, 13, 23] but, these simulators are not well-suited to the types of model and the workflows required for spike-based machine learning research. As such, many ML researchers have chosen to build libraries [9, 10, 14, 19] 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 [24].

While our GeNN simulator [16, 17, 23] was originally developed for Computational Neuroscience research, its longstanding focus on flexibility and its targeting of GPU accelerators has made it easily adaptable to the needs of spike-based ML. Specifically, we have added support for parallel batch simulation of models which allows multiple copies of the model to be run simultaneously to maximise GPU occupancy. We have also added support for user-defined "custom update" operations which can be used to implement a wide range of functionality including gradient-based optimizers, efficient matrix transpose operations and the reduction of variables across batches. In this paper we demonstrate how these new extensions can be used to efficiently implement and train SNN classifiers using eProp [4] on the Spiking Heidelberg Digits [7] and the Spiking Sequential MNIST [20] datasets.

2 RESULTS

We trained LSNNs of various sizes with feedforward and recurrent connectivity on the Spiking Heidelberg Digits (SHD) [7] and spiking sequential MNIST [20] datasets using eProp with the default parameters [4]. When comparing the performance of models trained with eProp on the SHD dataset with results obtained using BPTT [27] we found no considerable differences for the 256 neuron models (figure 1). However, because the reduced memory requirement of eProp allows training larger models, we were able to discover that the performance can be significantly improved by increasing the number of neurons to 512.

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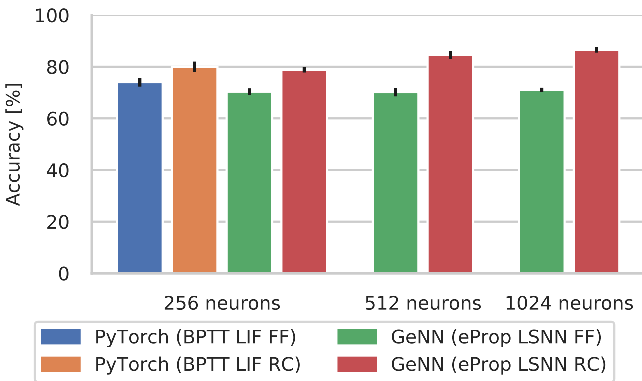

Figure 1: Performance comparison of LSNNs trained with eProp using GeNN and SNNs trained with BPTT using PyTorch [27] on Spiking Heidelberg Digits dataset. Bars signify the mean and error bars the standard deviation over 5 (GeNN) and 10 (PyTorch) simulations.

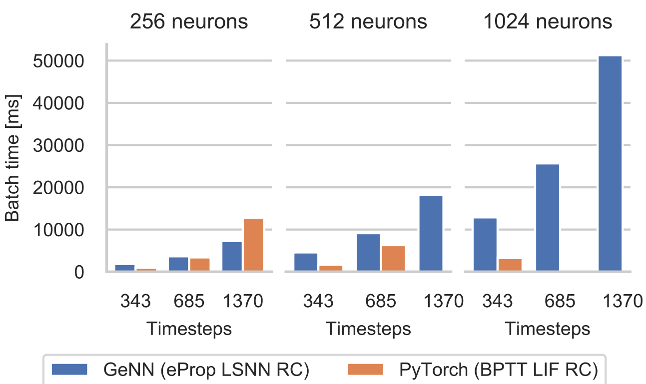

Figure 2: Training time comparison of LSNNs trained with eProp using GeNN and SNNs trained with BPTT using PyTorch on Spiking Heidelberg Digits dataset. A 12 GB Titan V GPU and a batch size of 512 are used for all experiments. Input spike trains are binned to achieve different numbers of timesteps. Missing bars indicate insufficient memory for experiment.

While being able to train networks with high classification accuracy is important, training also needs to be fast. Figure 2 shows how the time taken to train recurrent LSNNs using eProp with GeNN compares against training recurrent LIF networks using BPTT with PyTorch code from Zenke and Vogels [27]. For short input sequences, training using GeNN is slower but, the runtime of GeNN simulations increases slower with sequence length and, because BPTT requires the state of the model to be recorded every time step, the memory requirements are such that PyTorch is unable to train models larger than 256 neurons on 1370 timestep input sequences with our chosen batch size of 512.

Figure 3 compares the inference time and energy delay products (EDPs) of LSNNs simulated with GeNN against LSTM models running on the same hardware [20] as well as LSNNs running on

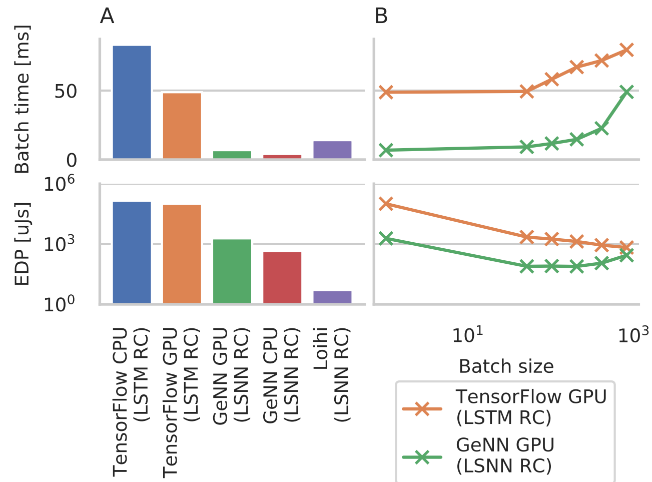

Figure 3: Inference time and energy delay product comparison of LSNNs and LSTMs trained on Sequential MNIST [20]. (A) Batch size 1 with Loihi data from Plank et al. [20]. (B) Across batch sizes.

the Loihi neuromorphic chip [8]. On the same Titan V GPU, LSNNs are faster than LSTMs and have a lower EDP across all batch sizes. Compared to using LSTMs, LSNN inference has a much lower arithmetic intensity meaning that, at batch size 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 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. 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. However, the eProp learning rule requires time-driven updates which dominate the time taken to *train* these models. Therefore, we are working to implement the fully event-driven EventProp [22] learning rule in GeNN which will allow training times to also benefit from temporal sparsity. Finally, the models presented in this paper are all densely connected so are not taking advantage of connection sparsity. We are working in parallel to address this by combining these learning rules with the Deep-R [2] rewiring rule, enabling SNN classifiers to take advantage of GeNN's support for efficient sparse connectivity [17].

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