

Easy and efficient spike-based Machine Learning with mlGeNN

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ABSTRACT

To demonstrate the value of mlGeNN in this space, we present the results of an exploration of shallow classifier architectures for the classification of the DVS gesture dataset.

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

The development of efficient spiking neural network (SNN) simulators has been a key area of computational neuroscience research for several decades [1, 5, 9, 10, 24]. However, the prevalent SNN simulators are not well-suited to the types of models and the workflows required for spike-based machine learning (ML). Consequently, many ML researchers have chosen to build libraries [7, 8, 11, 20] (**TODO: CITE NEKO**) on top of frameworks such as PyTorch [19] and TensorFlow [6] which allow defining SNNs in an environment that is familiar to ML researchers. In these libraries, the activity of a population of neurons is typically represented as a vector of activations and, for an SNN, this vector is populated with ones for neurons that are spiking and zeros for quiescent neurons. This representation allows using the existing infrastructure of the underlying ML library for SNNs but, as real neurons often spike at comparatively low rates, propagating the activity of inactive neurons through the network leads to many unnecessary computations. Additionally, the connections between populations of neurons can be sparse, in particular in biologically inspired SNNs. In standard ML libraries, sparse connections are typically implemented as a weight matrix containing many zeros.

To avoid these inefficiencies we have developed mlGeNN – a new library for spike-based ML built on the GPU-optimised sparse

data structures and algorithms provided by our GeNN simulator [13, 14, 24]. We previously presented an initial version of mlGeNN [22] which provided workflows for converting ANNs trained using TensorFlow [6] into SNNs that could be simulated using GeNN. However, while we found that performing inference using our converted SNNs was faster than with competing libraries, SNNs are inherently at a disadvantage for static image classification as by their nature they turn a single inference step in an ANN library into SNN dynamics across several, often numerous, timesteps. In this paper we introduce a second module of mlGeNN focused on training SNNs from scratch. This allows tackling ML problems that are inherently more suitable for SNNs because they contain a temporal dimension, for instance.

2 MLGENN

While fully describing the functionality of mlGeNN is beyond the scope of this paper, in the following sections we present an overview of some of our design decisions and the current feature set of mlGeNN. For more information about mlGeNN, we invite readers to visit github and explore our online documentation (**TODO: cite**).

2.1 Describing models

Machine learning frameworks such as PyTorch [19] and TensorFlow [6] are designed to efficiently process directed and acyclical computational graphs. In order to express recurrent connectivity within an otherwise directed acyclical graph, special recurrent layers are required to ‘hide’ the cyclical nature of the recurrent connectivity. However, when beginning to consider more brain-like models with highly recurrent connectivity, the whole model is likely to become one big recurrent layer which is not likely to be an efficient representation.

By contrast, mlGeNN allows Spiking Neural Networks (SNNs) with arbitrary topologies to be defined in terms of homogenous groups of neurons described by **Population** objects connected together with **Connection** objects. While this type of model description is common amongst SNN simulators used for computational neuroscience, the key difference in mlGeNN is that – like in ML frameworks – the model description is totally agnostic to how it is going to be trained. **Connection** objects don’t need to provide a model of how it’s weights will be trained and additional learning-rule specific structure such as feedback connections do not need to be added by hand.

All populations and connections are owned by a **Network** object which acts as a context manager. A network with two populations of neurons could be simply created like:

```
from ml_genn import (Connection, Population,
                     Network)
```

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```

network = Network()
with network:
    a = Population("poisson_input", 100)
    b = Population("integrate_fire", 100,
                   readout="spike_count")

    Connection(a, b, Dense(1.0))

```

For simplicity, in this example, built in neuron models with default parameters are specified using strings. However, if you wish to override some of the default model parameters, use a model that does not have default parameters or use a model not built into mlGeNN, you can also specify a neuron model using a `Neuron` class instance. For example, if we wished for the poisson population to emit positive and negative spikes for positive and negative input values and for the integrate-and-fire neuron to have a higher firing threshold we could instantiate `PoissonInput` and `IntegrateFire` objects ourselves like:

```

from ml_genn import (Connection, Population,
                    Network)
from ml_genn.neurons import (PoissonInput,
                             IntegrateFire)

network = Network()
with network:
    a = Population(
        PoissonInput(signed_spikes=True), 100)
    b = Population(
        IntegrateFire(v_thresh=2.0), 100,
        readout="spike_count")

    Connection(a, b, Dense(1.0))

```

By default, `Connection` objects use a ‘delta’ synapse model where the accumulated weight of incoming spikes is directly injected into neurons. However, if you wish to use a somewhat more realistic model where inputs are *shaped* to mimic the dynamics of real ion channels, this can be swapped

While the flexibility to create networks with any topology is very useful, mlGeNN also provides a `SequentialNetwork` wrapper class – inspired by `Sequential` models in Keras – for specifying common feedforward model more tersely:

```

from ml_genn import (InputLayer, Layer,
                    SequentialNetwork)

network = SequentialNetwork()
with network:
    a = InputLayer("poisson_input", 100)
    b = Layer(Dense(1.0), "integrate_fire", 100,
              readout="spike_count")

```

Finally, in the same way that Keras can easily be extended by subclassing built in classes and implementing new functionality using TensorFlow constructs, mlGeNN can be extended by subclassing built in classes and providing PyGeNN model descriptions. A full description of the model description syntax is beyond the

scope of this work but, is described in more detail in our documentation ([TODO: cite](#)) and previous work [13]. Nonetheless, the following example illustrates how a minimal Integrate-and-Fire neuron model could be defined for use in mlGeNN:

```

from ml_genn.neuron import Neuron
from ml_genn.utils.model import NeuronModel
from ml_genn.utils.value import ValueDescriptor

genn_model = {
    "var_name_types": [("V", "scalar")],
    "sim_code": "$ (V) += $(Isyn);",
    "threshold_condition_code": "$ (V) >= 1.0",
    "reset_code": "$ (V) = 0.0;",
    "is_auto_refractory_required": False}

class IntegrateFire(Neuron):
    v = ValueDescriptor("V")

    def __init__(self, v = 0.0, softmax = False,
                 readout=None):
        super(IntegrateFire, self).__init__(
            softmax, readout)
        self.v = v

    def get_model(self, population, dt):
        return NeuronModel.from_val_descriptors(
            genn_model, "V", self, dt)

```

2.2 Using models for training and inference

Once a network structure has been defined, mlGeNN provides a range of *compilers* to produce GeNN models which can then be used for training or inference. The simplest compiler is the `InferenceCompiler` which builds a GeNN model with static weights and parallel batching support for efficiently performing inference on an SNN model:

```

compiler = InferenceCompiler(
    evaluate_timesteps=1500, batch_size=512)

compiled_net = compiler.compile(network)

```

The resulting `compiled_net` object can then be used to evaluate the network on a dataset:

```

metrics, _ = compiled_net.evaluate(
    {input: spikes}, {output: labels})

```

By default, the evaluation method calculates sparse categorical accuracy against the provided labels but mlGeNN also provides alternative metrics for regression tasks and custom metrics can be easily implemented. As well as supporting the conversion of trained ANN models to SNNs as described in our previous work [22], mlGeNN now provides an e-prop compiler which enables models to be trained using the e-prop learning rule [4]. This compiler checks the validity of the model and automatically adds the appropriate learning rules to its connections as well as feedback connections and error signal calculation logic:

```

compiler = EPropCompiler(

```

```
example_timesteps=1500,
losses="sparse_categorical_crossentropy",
optimiser="adam", batch_size=512)
```

```
compiled_net = compiler.compile(network)
```

Note that here again, loss functions and optimisers with default parameters are specified using strings but these are also fully customisable. After compiling with the `EPropCompiler`, the `compiled_net` object can then be used to train the network on a dataset:

```
metrics, _ = compiled_net.train(
    {input: spikes}, {output: labels},
    num_epochs=args.num_epochs, shuffle=True)
```

We are also working on an EventProp compiler based on the recent work by Nowotny et al. [18].

2.3 Recording and debugging

One of the challenges of working with SNNs, compared to standard ANNs, is that neurons are stateful and the ability to efficiently record from in machine learning workflows, where models may be trained for millions of timesteps

3 RESULTS

In order to demonstrate the value of mlGeNN for spike-based ML research, here we present the results of a small exploration of SNN architectures, trained using e-prop [4] on the DVS gesture dataset [2] which has been recently used to evaluate the EGRU [21] and FPTT [25] learning rules. This dataset consists of 1342 recordings of 11 different hand and arm gestures, collected from 29 subjects under three different lighting condition using a DVS 128 event-based camera [17]. Here we used the Tonic library [16] to access the dataset and spatially downsample the events to 32×32 . While mlGeNN does not depend on Tonic, it includes a `preprocess_tonic_spikes` helper function which converts spike trains from Tonic datasets into mlGeNN's internal format.

3.1 Accuracy

Figure 1 shows the accuracy of a wide selection of one and two layer classifier models trained with e-prop. These include configurations with and without recurrent connections and using both Adaptive and standard Leaky Integrate-and-Fire (LIF and ALIF) neuron models. Of the single layer classifiers, the variant with a single layer of 512 recurrently connected ALIF neurons performs the best, achieving a mean accuracy of 89.55 % on the test set. Although this model only has a single hidden layer and around 1.3×10^6 parameters, it out-performs a two layer EGRU model [21] with over 4× as many parameters which achieved 88.02 % accuracy.

Models using ALIF neurons also perform better than those using simpler LIF neurons in all of the two layer configurations. However, interestingly, the best performing model (mean accuracy on test set of 91.29 %) had a feedforward first layer followed by a recurrent second layer – similar to the architecture employed by Yin et al. [25] – rather than having two recurrently connected layers.

- FPTT shallow recurrent (91.89 ± 0.16) % 512 neuron encoder for each channel, feeding into recurrent population of 512 neurons

- Take best architecture and explore sparsity

3.2 Performance

- Training time - compare to FPTT 400 ms per frame with batch size 64 on some sort of 24 GB GPU
- Inference time CPU and GPU - compare to real-time
- Show effect of sparsity on performance

4 CONCLUSIONS

Using mlGeNN, the architecture exploration presented here was made much simpler and easier than our previous work using PyGeNN directly [15]. While it is by no means a precise measure, this is illustrated by the fact that the code used for all simulations was less than 300 lines whereas, our previous work involved one 900 line model for training as well as a separate 500 line model for inference.

Furthermore, the results we have presented in this paper demonstrate that the approximation nature of the e-prop learning rule does not necessarily prevent it offering competitive performance on relatively complex datasets. However, e-prop does have some significant issues. Unsurprisingly for a visual task, both the original work using the IBM True North system [2] and more recent work using the Decolte and FPTT learning rules [12, 25], demonstrated that in order to get significantly better performance on the DVS gesture dataset convolutional networks are required. Because the eligibility traces which drive e-prop weight updates are calculated from the product of pre and postsynaptic activity, they cannot be shared across all the synapses in each connection. Neither the FPPT [25] learning rule – where the additional Φ_t state variable only depends on past weights so can be shared – and EventProp [23] – which does not require any additional synaptic state – have these issues so we are currently working on adding compilers for each of these learning rules to mlGeNN.

Furthermore, the e-prop learning rule requires time-driven updates which dominate the time taken to train our current although, as we demonstrate, by using sparse connectivity, this can be reduced. Therefore, we are working to implement the fully event-driven EventProp [23] 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 [3] rewiring rule, enabling SNN classifiers to take advantage of GeNN's support for efficient sparse connectivity [14].

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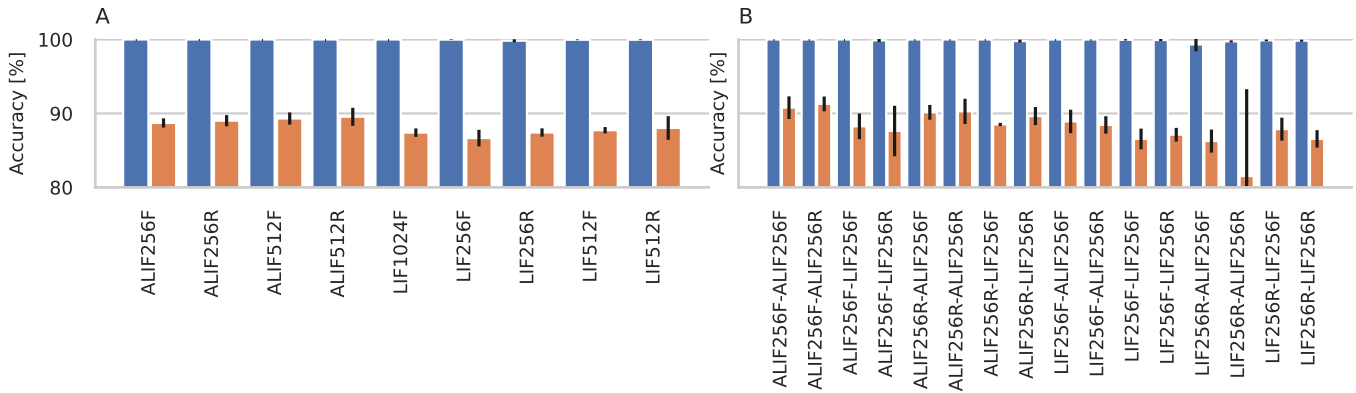


Figure 1: Accuracy on the testing and training set of the DVS gesture dataset [2] on one (A) and two (B) layer eProp classifiers. All models were trained for 100 epochs with a batch size of 512. (TODO: FINISH TRAINING 1024 NEURON MODELS) (TODO: INVESTIGATE GAPS) Bars signify the mean and error bars the standard deviation of 5 models trained with different seeds.

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