Leveraging PyTorch on BrainScaleS-2: Training a Real-World Application

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Introduction

The usability of novel neuromorphic hardware is dictated by software allowing non-expert users to describe experiments effortlessly [3]. Especially when approaching gradient-based optimization tasks with spiking neural networks (SNNs) on such hardware, support for model definition and automatic differentiation is indispensable.

- We discuss the abstraction of training on the accelerated mixed-signal neuromorphic hardware system BrainScaleS-2 (BSS-2) in our high-level PyTorch-based framework `hxtorch.snn` and motivate our design choices
- We demonstrate `hxtorch.snn` on a real-world application: The demapping of a nonlinearly impaired high-speed intensity modulation / direct detection (IM/DD) optical data link with SNNs on BSS-2 [1]

Methods

BrainScaleS-2 (BSS-2)

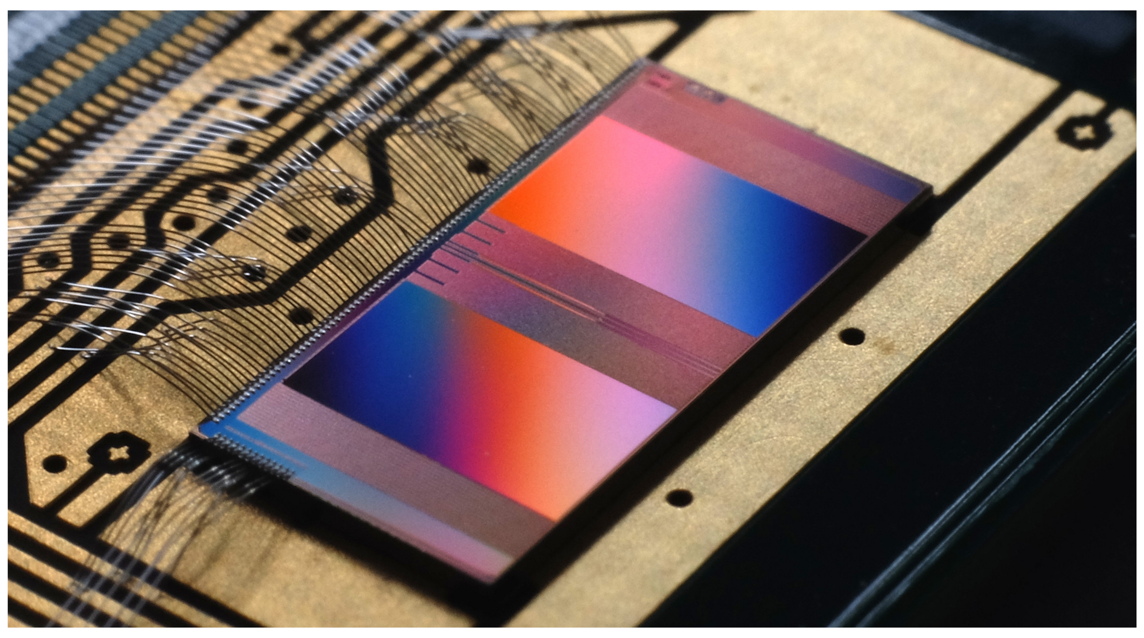


Figure 1. The BrainScaleS-2 analog neuromorphic system.

The mixed-signal neuromorphic BSS-2 system [6]:

- 512 spiking AdEx [2] neurons and 131k 6-bit plastic synapses in parallel analog circuits, emulated in continuous time
- Neural dynamics individually parameterized
- Support for arbitrary topologies
- Access to spike events and membrane potentials, sampled column-wise in parallel by analog-to-digital converters

Training SNNs with PyTorch

SNNs are studied for machine learning tasks using state-of-the-art software libraries typically deployed for artificial neural networks (ANNs), like PyTorch [5].

- The network model is described by a composition of PyTorch modules (layers)
- Easy computation of network gradient by the backpropagation through time algorithm
- Eager construction of a differentiable computational graph by executing all network operations successively and assigning a backward function to it → Gradient → Weight update

NOTE The non-differentiability of spiking neurons is often bypassed with surrogate gradients [4]

In-the-loop Learning on BSS-2

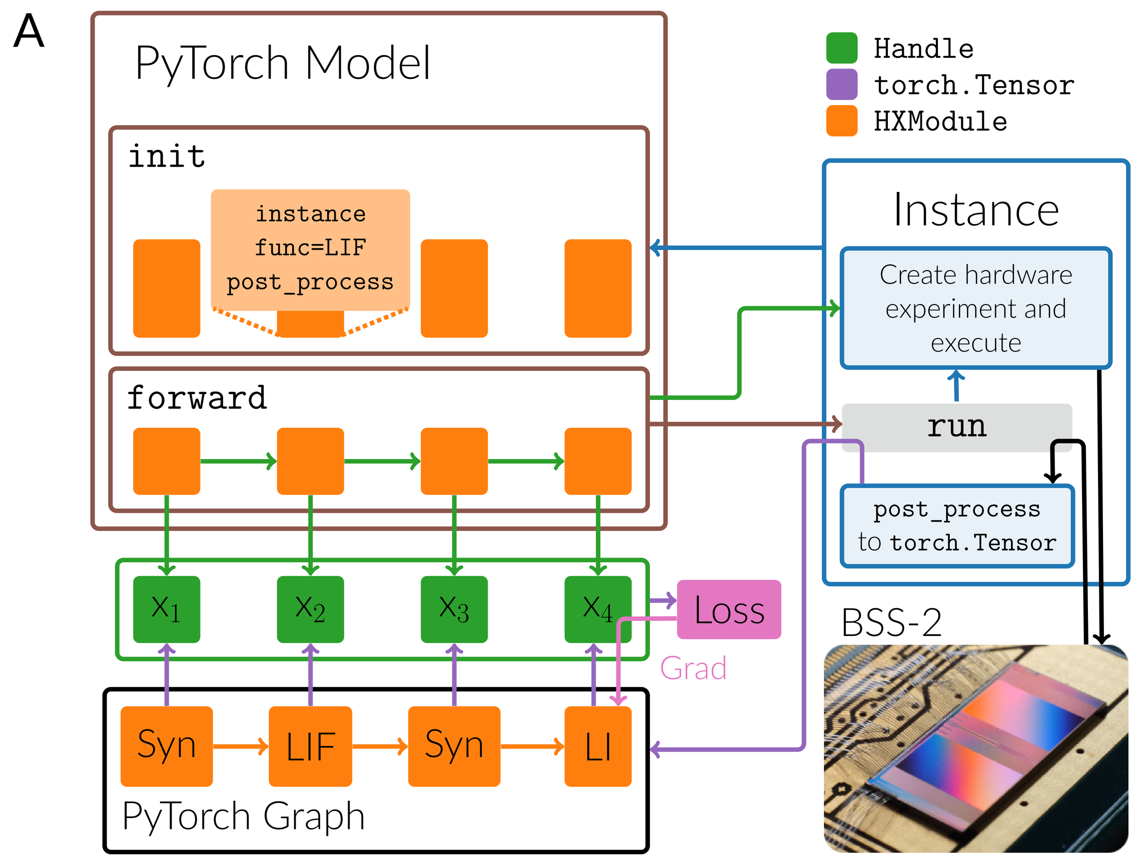
SNNs on BSS-2 can be trained in-the-loop within PyTorch's ecosystem:

1. Emulate the forward pass on BSS-2
2. Use the hardware observables to compute weight updates on the host computer

NOTE The SNN is executed on BSS-2 before the PyTorch graph is built to ensure that hardware data is present for the backward pass

`hxtorch.snn` Framework

A



B

```
ins = hxtorch.snn.Instance()

syn1 = hxtorch.snn.Synapse(ins, ...)
lif1 = hxtorch.snn.LIF(ins, ...)
syn2 = hxtorch.snn.Synapse(ins, ...)
li2 = hxtorch.snn.LI(ins, ...)

x1 = syn1(Handle(input))
x2 = lif1(x1)
x3 = syn2(x2)
x4 = li2(x3)

hxtorch.snn.run(ins, ...)

loss = f(x4)
loss.backward()
```

Figure 2. **A)** Schmeantic of `hxtorch.snn` framework. **B)** Code example of an feed-forward SNN. Both taken from [7].

- SNNs are defined as in PyTorch
- Modules are derived from a base-class `HXModule` representing entities on BSS-2, e.g., neuron populations `LIF` and `LI`, and projections `Syn`
- Modules hold a PyTorch-differentiable function `func(...)`, defining the backward pass
- Modules get `Handle`-typed inputs and return a `Handle`-typed output → References to data available after hardware execution
- Modules share an `Instance` (experiment on BSS-2) object in which they register themselves

Calling `run` → `Instance` extracts and executes the hardware experiment on BSS-2 → Hardware observables are `post_process`ed to `torch.Tensors` → The PyTorch graph is constructed by calling the modules' `func`tions, utilizing and returning the data tensors → Tensors are assigned to the modules' handles → PyTorch `backward` pass estimates the gradient of the SNN on BSS-2

NOTE For model development, `hxtorch.snn` also supports a simulation mode

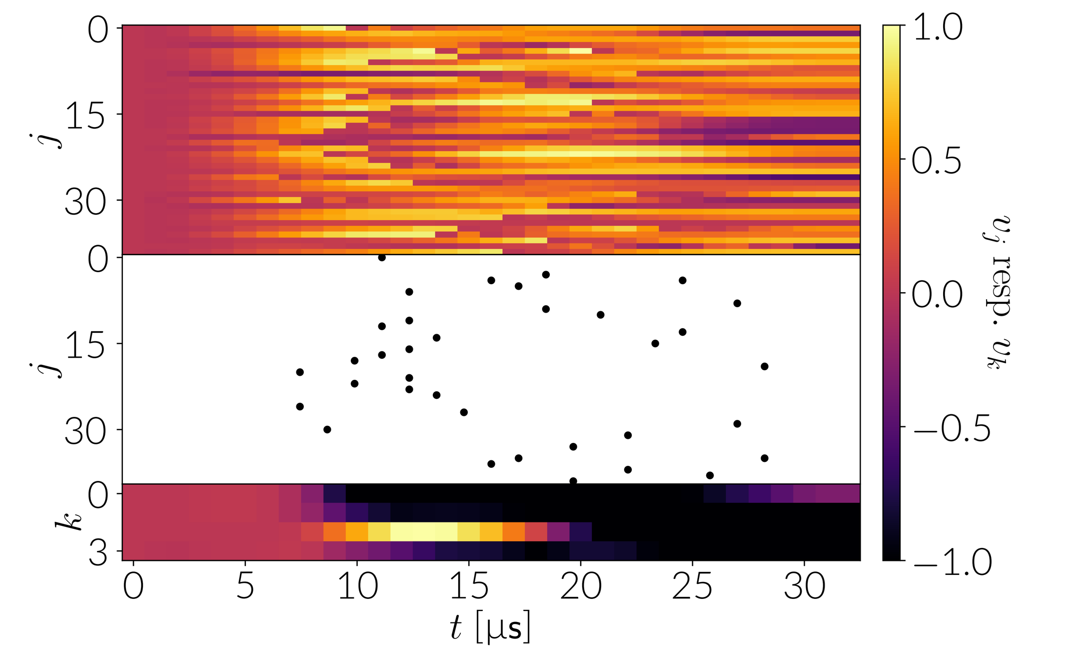


Figure 5. BSS-2 observables of the LIF (Upper: membrane, middle: spikes) and LIF (lower: membrane) layer while demapping two bits.

Example: Demapping an IM/DD Optical Link on BSS-2

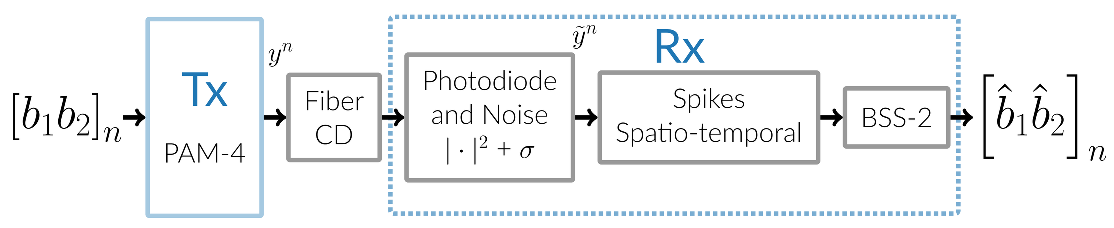


Figure 3. Demapping a simualted IM/DD link on BSS-2.

For demonstration, we train an SNN on BSS-2 to demap a simulated IM/DD link [1], see fig. 3. A bit sequence $[b_1 b_2]_n$ is modulated to a signal y^n, optically transmitted through a fiber, and measured at the receiver by a photodiode (PD). The resulting sequence $\tilde{y}^n$ is impaired by linear chromatic dispersion, the nonlinear PD, and noise (σ). The SNN equalizes and demaps $\tilde{y}^n$, translated into spikes, to the received bits $[\hat{b}_1 \hat{b}_2]_n$. The SNN, consisting of a hidden leaky-integrate and fire (LIF) and a leaky-integrator (LI) output layer, is trained to minimize the bit error rate (BER).

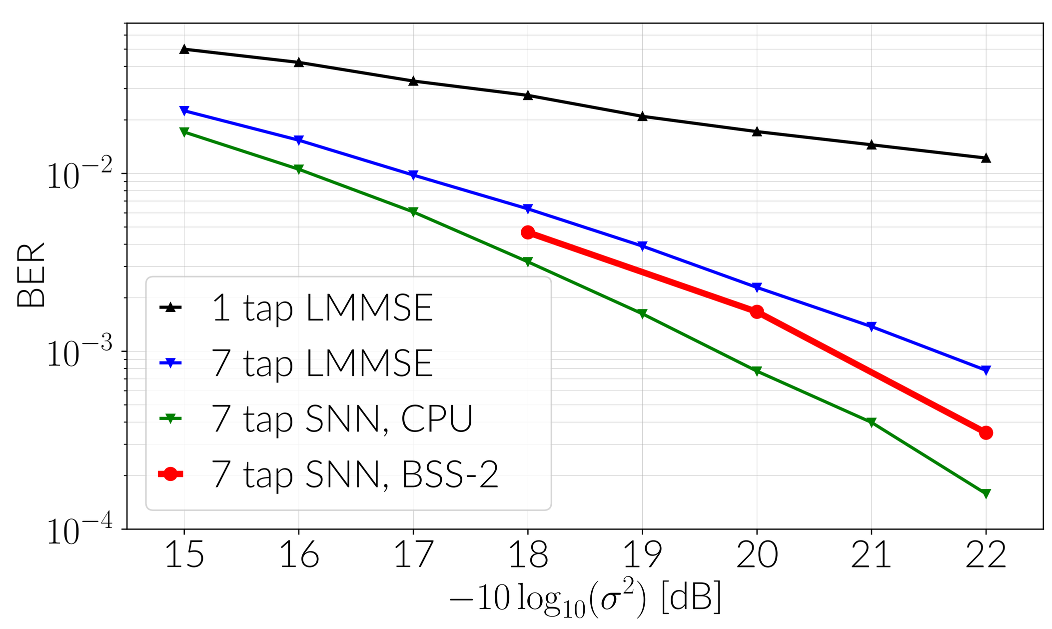


Figure 4. BER over noise in the IM/DD link.

In fig. 4, the BER is depicted over noise σ in the link. The simulated SNN and the SNN emulated on BSS-2 achieve lower BERs than the linear LMMSE equalizer. Figure 5 shows the LIF neurons' membrane voltages and their spikes together with the LI output traces are shown → The output neuron producing the highest voltage dictates the demapped bits.

Conclusion

- `hxtorch.snn` allows descriptions of high-level SNN models in PyTorch and their emulation on BSS-2
- By utilizing PyTorch data types, we can leverage its auto-differentiation mechanism and thus make learning on BSS-2 effortless
- API supports the definition of arbitrary networks (incl. feedback connections), the different neuron types on BSS-2 and different backward functions
- Integrated into the EBRAINS platform

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