Towards On-Chip Bayesian Neuromorphic Learning

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Figure 1: A mouse learns to associate a visual signal at the beginning of the experiment with the location of the reward at the end, a task an artificial Spiking Neural Network can solve as well. This article introduces a method to allow the learning agent to express confusion when presented with a novel situation, such as both visual signals being triggered.

ABSTRACT

If edge devices are to be deployed to critical applications where their decisions could have serious financial, political, or public-health consequences, they will need a way to signal when they are not sure how to react to their environment. For instance, a lost delivery drone could make its way back to a distribution center or contact the client if it is confused about how exactly to make its delivery, rather than taking the action which is “most likely” correct. This issue is compounded for health care or military applications. However, the brain-realistic temporal credit assignment problem neuromorphic computing algorithms have to solve is difficult. The double role weights play in backpropagation-based-learning, dictating how the network reacts to both input and feedback, needs to be decoupled. e-prop 1 is a promising learning algorithm that tackles this with Broadcast Alignment (a technique where network weights are replaced with random weights during feedback) and accumulated local information. We investigate under what conditions the Bayesian loss term can be expressed in a similar fashion, proposing an algorithm that can be computed with only local information as well and which is thus no more difficult to implement on hardware. This algorithm is exhibited on a store-recall problem, which suggests that it can learn good uncertainty on decisions to be made over time.

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CCS CONCEPTS

• Computing methodologies → Machine learning algorithms;
• Hardware → Neural systems;
• Mathematics of computing → Variational methods.

KEYWORDS

spiking neural networks, variational inference, bayesian statistics, neuromorphic computing

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1 INTRODUCTION

AI algorithms have made ridiculous progress in recent years at solving well-defined problems with high accuracy, but are generally not capable of determining whether a particular problem is solvable with the data they have been given. Classical AI algorithms will heroically “solve” problems which they are completely unequipped to handle without complaint. One popular solution for Uncertainty Quantification (UQ) is Bayesian inference, a procedure applicable to any statistical AI model.

Another of AI’s major challenges is a two-for-one: portability and energy consumption, a pair of problems to which neuromorphic computing offers a solution. Progress has been made in the transfer of classical artificial neural network weights to a spiking neural network (SNN), so that a relationship learned offline can be deployed on the edge. However, in order for an edge device to be adaptive, it would have to learn while under operation. It is therefore important to partition neuromorphic algorithms into two...
groups: those which can learn on-chip, and those which can only be deployed on-chip.

AI applications for which portability is essential have even greater need for UQ than most, as by definition a human may not be available to monitor the process. Indeed, as we describe in Section 5, previous research has developed neuromorphic Bayesian algorithms. However, to the best of our knowledge, an algorithm for Bayesian neuromorphic learning on-chip has not been described in the academic literature.

To address this gap, we formulate a pseudo-gradient based algorithm which performs Variational Bayesian Inference, building on e-prop 1 [2], a recently developed algorithm for on-chip learning. This endeavor presents several important challenges. First, we cannot introduce any additional need for information that is not local to each neuron. Crucially, as we show in Section 3, for a certain class of prior distributions, this is indeed the case. Second, Broadcast Alignment, the information locality method employed by e-prop 1, has little in the way of theoretical guarantees, and has been found to be unsuitable for certain applications [1]. We find that it still enables learning in a store-recall experiment (Section 4.2), but with less efficiency than when full weight transport is enabled. Fortunately, it still displays useful UQ behavior, showing high uncertainty when presented with a previously unseen situation.

2 BACKGROUND

2.1 Neuromorphic Learning on Chip

This article builds on a framework for neuromorphic learning described in [2] called e-prop 1, which purports to be deployable for on-chip learning. It employs Broadcast Alignment (BA) [14], a variant of Feedback Alignment [9, 12], to overcome the weight transport problem [7] and develops a reinforcement-learning-like eligibility trace to avoid the future errors problem [10].

Intuitively, e-prop 1 doesn't explicitly consider future contributions to the error, but does so implicitly by storing information about past interactions in its eligibility trace. As demonstrated in [2] and reproduced in Section 4.1, this is sufficient to solve problems with delayed reward.

A neuron's eligibility trace is characterized by its activity discounted over time. This information, encoding past behavior, is stored in the eligibility trace. As demonstrated in [2] and reproduced in Section 4.1, this is sufficient to solve problems with delayed reward.

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2.2 From Classical to Variational Inference

In classical neural network inference, we find a set of weights, \( \theta \), that minimizes loss, perhaps subject to regularization. In the standard variational approach, we no longer are optimizing individual weights; instead, each weight \( \theta_{i,j} \) has a mean parameter \( \lambda_{i,j} \) and variance parameter \( \psi_{i,j} \). These variational parameters are optimized, just as the weights themselves would be, to minimize a trade-off between data misfit and regularization. Specifically, whereas a particular set of weights maps to a well defined loss on a particular dataset, a particular set of variational parameters leads to a distribution on losses. We thus minimize the expected loss. Regularization of the variational distribution, denoted \( q_{\lambda, \psi}(\theta) \), is achieved by penalizing its KL distance from a given prior, denoted by \( p(\theta|\psi) \). Our variational cost is therefore:

\[
l(\lambda, \psi) = - \mathbb{E}_{q_{\lambda, \psi}}[\log p(\theta|X)] + KL(q_{\lambda, \psi}(\theta)||p(\theta|\psi)) \tag{2}
\]

Though the KL divergence between two multivariate Gaussian distributions is available in closed form, the expected loss term in Equation 2 is not. However, notice that the expectation is with respect to the variational distribution, which is easy to sample from. Thus, we can form a Monte-Carlo estimate of our variational loss:

\[
l(\lambda, \psi) \approx \frac{1}{V} \sum_{v=1}^{V} \left[ - \log L(y|\theta_{v}, X) \right] + KL(q_{\lambda, \psi}(\theta)||p(\theta|\psi)) \tag{3}
\]

\[
= \frac{1}{V} \sum_{v=1}^{V} \left[ - \log L(y|\theta_{v}, X) \right] + \frac{1}{2} \left[ \sum_{i,j} \frac{\phi_{i,j}^2}{\theta} + \sum_{i,j} \frac{\psi_{i,j}}{\psi} + \sum_{i,j} \frac{\lambda_{i,j}^2}{\lambda} \right] \tag{4}
\]

Here, \( \psi \) is the prior variance hyperparameter, which plays the role of the \( \ell_2 \) regularization coefficient in classical machine learning.

3 METHODS

e-prop 1 provides us with a way of estimating the gradient of each individual log \( L(y|\theta_{v}, X) \) term, which can be averaged to give an estimate of the overall loss gradient. This mean loss gradient is combined with the prior-KL gradient. For the variational mean, this is given by:

\[
\frac{\partial KL(q_{\lambda, \psi}(\theta)||p(\theta))}{\partial \lambda_{i,j}} = \frac{\lambda_{i,j}}{\phi_{i,j}} \tag{5}
\]

and that for the variational signed standard deviation by:

\[
\frac{\partial KL(q_{\lambda, \psi}(\theta)||p(\theta))}{\partial \psi_{i,j}} = \frac{\psi_{i,j}}{\phi_{i,j}} \tag{6}
\]

However, as shown in [3], this estimate is not unbiased. It is likely that we could do better by incorporating the changes suggested in that article. This task is left as future work.

Most authors parameterize the variational variance in log space, so that no positivity constraints are required. We elect to use a standard deviation parameterization instead, where possible negatives disappear after squaring.
\[
\frac{\partial KL(q_{\lambda}, \phi(\theta) \mid \mid P(\theta))}{\partial \phi_{i,j}} = \phi_{i,j} \left( 1 - \frac{1}{\phi_{i,j}} \right)
\]

Notably, the prior gradients for the variational parameters on the weight between \(i,j\) do not depend on those for any other \(i,k\) pair. Thus, the gradient for the entire posterior-KL term may be expressed as a sum of gradients involving only local information, and thus is local itself. This demonstrates that the algorithm presented here does not aggravate the locality issue.

4 EXPERIMENT

4.1 Experimental Setup

In this section, we will evaluate our algorithm on a simplified version of the temporal credit assignment task considered using SNNs in [2] and model mice in [4, 11]. Our virtual mouse "perceives light" through 20 input spike channels, ten for up and ten for down. When a light is turned on, each of the input neurons associated with it fire. Then, there is a break period, with no input, and, finally, a "cue" signal, during which an additional 10 channels fire, telling the virtual mouse it needs to make a decision: is the cheese Up or Down? That the SNN has to make a decision based on past events makes this problem interesting, and even impossible for certain neural network architectures, such as non-recurrent classical neural networks or simple Leaky Integrate and Fire (LIF) SNNs.

As such, following [2], we will use LIF neurons with an adaptive threshold: the potential required to generate a spike increases immediately after an action potential, and then decays exponentially back to the baseline \(^3\). We used gradient descent with a learning rate of 5e-4, a mini-batch size of 20, 5 variational samples \((V = 5)\), and 5000 epochs. Our SNN had \(H = 100\) neurons featuring all-to-all connectivity but no connections allowed between a neuron and itself. The simulation is run using time steps of 50 ms, which is also the duration of the input signal. Consequently, all input channels fire at once, on the second time step. The period between the input signal and the cue is sampled randomly and uniformly between 500 ms and 1500 ms, at which point the cue period begins, which lasts 150 ms. All 10 cue neurons fire at random during one and only one of these time steps. We set the prior variance \(\psi\) to \(\frac{1}{2\pi} = 0.01\).

4.2 Results

As shown in Figure 2, the Bayesian SNN learns to classify Up versus Down input channels over the course of the training whether weight transport is allowed or not. However, the KL cost does not decrease as reliably when BA is used, and the training set performance, as measured by the probability of giving the correct direction, is also worse when BA is employed.

Figure 3 demonstrates that the Bayesian SNN learns to remember which of Up or Down was signalled, a task the vanilla e-prop 1 algorithm can tackle as well. The Bayesian SNN, however, also gracefully handles the case where both input signals are simultaneously presented (a situation not present in any of the training cases) by giving high uncertainty as to whether the cheese is Up or Down.

4.3 Limitations

We have used minibatching in order to reduce gradient variance. This is not compatible with online learning, so smaller learning rates or variance reduction techniques will be required. Similar issues accompany our sampling and evaluating \(V = 5\) weights from the variational distribution for each element of the minibatch.

5 RELATED WORK

Variational inference in the context of classical neural networks has received significant attention [3, 6, 8]. It has also been studied in the context of spiking neural networks. [13] examined how Variational Inference could be used to infer states of unobserved neurons given some set of observed neurons for which spike trains are known. They also showed that the STDP learning rule could be derived from that model, though left discussion of biological plausibility (and, hence, we would argue, neuromorphic plausibility) as future work. In order for neuromorphic hardware to carry out the algorithm we

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\(^3\) (broadly following [2]): The membrane potential decay constant is 20 ms and the threshold decay constant is 2000 ms for all neurons. Each neuron triggers an action potential when its membrane potential crosses 1, and each spike increases the threshold by 2 (before exponentially decaying back to 1).
Some neuromorphic chips, such as Loihi, have the ability to simulate more complicated neuron models, such as those with multiple compartments. Potentially, this hardware could be enlisted to instead perform side-by-side simulation of the same network with different samples of its weights, a "multi-channel minibatching", lifting our requirement that $V = 1$.

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