Normalization Hyperparameter Search for Converted Spiking Neural Networks

Etienne Mueller [1], Daniel Auge [1], Alois Knoll [1]

1. Informatics, TU Munich, Boltzmannstr. 3(5607)/III 85748 Garching, Germany

Spiking neural networks (SNNs) offer high potential for energy reduction when used on neuromorphic hardware, as they are only active when information is being transmitted [1]. Their training algorithms, however, generally result in inferior performance compared to today's common analog neural networks (ANNs) trained with backpropagation. The best performing SNNs can be obtained by training ANNs and mapping the weights to a spiking network.

This approach works well because both the ReLU activation function in ANNs and the firing rate of spiking neurons increase linearly with their input. Unlike ReLU, spiking neurons have an upper limit determined by their maximum firing rate. To fit the activation into the spike range, the weights need to be normalized before conversion [2]. As single outliers with high activation would result in the majority of the neurons spiking far below their maximum rate, commonly robust normalization is used, where only the p-th percentile is normalized [3].

This additional hyperparameter p sets the trade-off between inference speed and accuracy. High values result in near lossless conversions but with slow convergence, whereas small values clip the higher activations, thus showing a large decrease in accuracy between the original ANNs and the converted SNNs but with fast convergence.

We propose a method to computationally discover the value for p that balances this speed/accuracy trade-off. When feeding uniformly distributed noise into a trained ANN, the resulting predictions will be completely random. As the result is very vulnerable to tiny changes in the network, this data can be used to evaluate how closely the converted SNN represents the original network. A conversion with poor choices for the normalization parameter will show bad performance on a synthetic dataset created this way (see fig. 1). Small values of p show even larger loss on the synthetic set than the test set, whereas for large values the network converges too slowly so that single spikes are not averaged out in the individual time steps, also resulting in large losses. By minimizing the conversion loss on the synthetic dataset, the determined value for p yields to the fastest converging SNN with the highest accuracy at that speed. The evaluation of this approach on networks with different sizes, performance, and random seeds, shows that it can be reliably implemented by using only a small synthetic dataset of only 1% the size of the original test set.

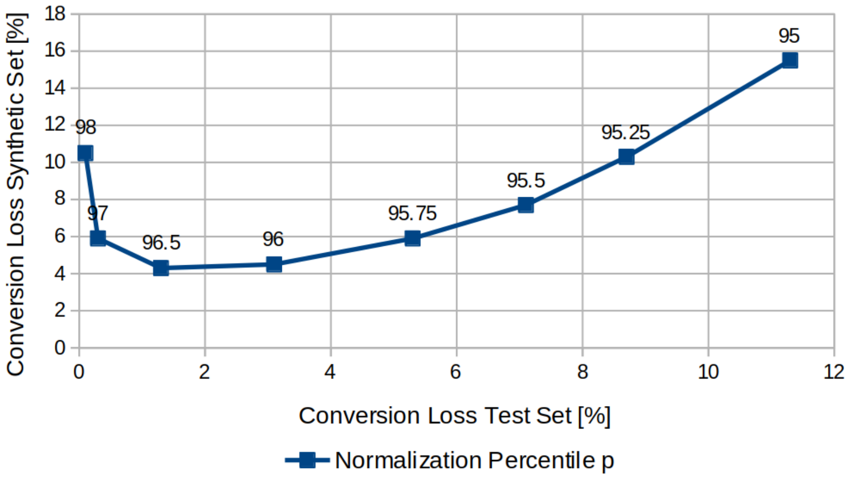

Figure 1: Relation between the conversion loss of test set and synthetic set of an exemplary 3 layer fully connected converted spiking network for different normalization percentiles. The determined value of 96.5 converges at twice as fast as the higher values while showing a reasonable loss of only 1.2%.

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References

1. Chi-Sang Poon and Kuan Zhou. Neuromorphic Silicon Neurons and Large-Scale Neural Networks: Challenges and Opportunities.Frontiers in Neuro-science, 5, 2011 (https://www.frontiersin.org/articles/10.3389/fnins.2011.00108/full), 10.3389/fnins.2011.00108 (http://dx.doi.org/10.3389/fnins.2011.00108)
2. Peter U. Diehl, D. Neil, J. Binas, Matthew Cook, S. Liu, and Michael Pfeif-fer. Fast-classifying, high-accuracy spiking deep networks through weightand threshold balancing. In2015 International Joint Conference on NeuralNetworks (IJCNN), pages 1–8, 2015. (https://ieeexplore.ieee.org/abstract/document/7280696), 10.1109/IJCNN.2015.7280696 (http://dx.doi.org/10.1109/IJCNN.2015.7280696)
3. Bodo Rueckauer, Iulia-Alexandra Lungu, Yuhuang Hu, Michael Pfeiffer, andShih-Chii Liu. Conversion of Continuous-Valued Deep Networks to EfficientEvent-Driven Networks for Image Classification.Frontiers in Neuroscience,11, 2017. (https://internal-journal.frontiersin.org/articles/10.3389/fnins.2017.00682/full), 10.3389/fnins.2017.00682 (http://dx.doi.org/10.3389/fnins.2017.00682)

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