Exploring the Potential of Spiking Neural Networks through Efficient Architecture **Design and Applications**

Authors

Hadjer Benmeziane, Amine Ziad Ounnoughene, Imane Hamzaoui, Younes Bouhadjar.

INTRODUCTION

Spiking Neural Networks (SNNs) are a type of artificial neural network that aims to mimic the behavior of biological neurons by using a spiking neuron model. In SNNs, information is processed and communicated in the form of discrete electrical impulses called spikes or action potentials. SNNs use discrete-time updates and event-driven computations. Besides robustness and their real-time processing on analog and digital devices, SNNs

2) HYPERPARAMETER OPTIMIZATION

Given an initial ANN topology, the optimization aims at finding the right number, position, and type of skip connections that minimize the drop between ANN accuracy and its SNN counterpart. The overall optimization process comprises two steps:

• (1) we begin by constructing the search space of all possible adjacency matrices. Each block is extracted from the given topology and the number of layers in each block as well as the initial adjacency matrices are defined.

• (2) We use Bayesian Optimization (BO) to optimize the accuracy drop. Our results show that our method outperforms the random search strategy in less iterations and with a more stable search.



Figure 2: Overview of the hyperparameters optimization process.

have the following main advantages:

- Energy Efficiency: SNNs are highly energy-efficient as they operate on the principle of spikes and consume less power compared to traditional neural networks.
- **Biological Plausibility:** SNNs are inspired by the functioning of the human brain, making them more biologically plausible. They can model the behavior of neurons and their interactions more closely than traditional neural networks.

MOTIVATION

SNN architecture design and training are still in their early phases. An important scientific question is to what extent architecture characteristics (e.g., operations, skip connections) are compliant with the spatial and temporal constraints in SNN

OBJECTIVE

We aim to apply SNNs to diverse projects that can benefit from their advantages in handling temporal data or achieving superior energy efficiency. As a first step towards this goal, we conducted an analysis of the impact of skip connections on network dynamics and training



Figure 3: Comparison of our methodology to random search on CIFAR-10-DVS.

Key observation

Optimizing skip-connections can significantly improve the accuracy of SNN and reduce the accuracy drop induced by converting ANN to SNN.

METHODOLOGY

Our methodology involves two steps:

1) Skip-connection importance in SNN: We first analyzed the importance of the skip connections and their various types, illustrated in Figure 1. This analysis helps us understand why skip-connections are important.

2) Skip-connections Optimization: We then optimize for different models the skipconnections types and numbers to achieve high accuracy. The hyperparameter optimization is based on Bayesian optimization.



Figure 1: Types of skip-connections

1) SKIP-CONNECTION IMPORTANCE IN SNN

We consider two types of skip-connections:

CONCLUSION

We present novel insights into the design and training of spiking neural networks (SNNs) and highlight the potential of skip connections as a promising tool for advancing SNN research. Our study evaluated both densenet-like and addition-type skip connections and found that both improved accuracy, with densenet-like connections being more energyefficient by slightly increasing the firing rate. Our comprehensive hyperparameter optimization process led to the discovery of the optimal ANN to SNN adaptation, resulting in an average accuracy improvement of 8% within approximately 5 minutes.

FUTURE WORKS

To continue our investigation on spiking neural network architectures and behavior, we are aiming now to explore their performance on neurological data for developing a brain-inspired, energy-efficient, and temporal neuromotor signal decoder.

To achieve this, we plan to test and optimize SNNs on **Nonhuman Primate Reaching with Multichannel Sensorimotor Cortex Electrophysiology** recording [3]





Densenet-like Skip Connections (DSC) [1] concatenate previous layers' outputs. A direct mathematical relation is then created between the weights of the previous layer and the output current layer, which enhances backward gradient computation. However, adding these connections enlarges the input tensor which augments the number of multiplies accumulates operations (MAC).

Addition-type Skip Connections (ASC) [2] perform element-wise summation of the outputs of previous layers. The result is the input to the current layer. This type is usually used in resnet-like architectures.

Key observation

Both skip-connection types increase the layer's firing rate. Addition-type skip connections result in a higher firing rate and a higher accuracy. However, this may significantly increase the energy consumption.

REFERENCES

[1] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in CVPR. IEEE Computer Society, 2017, pp. 2261–2269. [2] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in CVPR. IEEE Computer Society, 2016, pp. 770–778. [3] O'Doherty, Joseph E., Cardoso, Mariana M. B., Makin, Joseph G., & Sabes, Philip N. (2020). Nonhuman Primate Reaching with Multichannel Sensorimotor Cortex Electrophysiology. [4] N. Ahmadi, T. Adiono, A. Purwarianti, T. G. Constandinou and C. –S. Bouganis, "Improved Spike-Based Brain-Machine Interface Using Bayesian Adaptive Kernel Smoother and Deep Learning," in IEEE Access, vol. 10, pp. 29341–29356, 2022, doi: 10.1109/ACCESS.2022.3159225. [5] Benmeziane H, Ounnoughene AZ, Hamzaoui I, Bouhadjar Y. Skip Connections in Spiking Neural Networks: An Analysis of Their Effect on Network Training. arXiv preprint

arXiv:2303.13563.2023.

This work was done during School of AI Algiers reading session. This research is published in IPDPS Workshop "Scalable Deep Learning" 2023 [5]

