ETH zürich

Master / Semester Thesis

Bioplausible Machine Learning on Emulated Hardware

The structure of Artificial Neural Networks (NNs) is inspired by the way neurons are connected in the brain. However, NNs are typically trained using backpropagation, which does not have a direct biological counterpart. This fact makes it difficult to establish realistic comparisons between the two systems.

The difference between artificial- and biological-NNs has led to the development of 'bioplausible' learning frameworks that attempt to replace backpropagation with short-range approximations, similar to those which exist between real neurons. The motivation behind developing such frameworks is the potential of accelerating their training and inference with specialized hardware - the same factors which make 'bioplausible' NN models more likely to work with 'biological hardware' also enable artificial NNs to run on 'neuromorphic' hardware accelerators.

One such backpropagation-free training paradigm is Equilibrium Propagation (EP). It is based on the principle of the Hopfield Network, associated with the recent 2024 Nobel Prize in Physics. In this framework, neurons are updated using local contrastive Hebbian update rules which approximate the computation of gradients. Since the conceptualization of EP by Scellier & Bengio in 2017 [1], more recent advances have relaxed key theoretical architectural constraints [2] and enabled demonstrations on Quantum hardware [3].

This project will explore emulated hardware implementation of EP-trained networks. The student will be free to choose which architectures to explore, and investigate their performance. Hardware components for this project, such as (electronic) memristive devices and (optical) Mach-Zehnder interferometers, can be emulated in software using existing Python libraries which account for non-idealities unique to their physical operating principles.

If you are interested in exploring the intersection of software and hardware in Machine Learning, please refer to the contact details below.

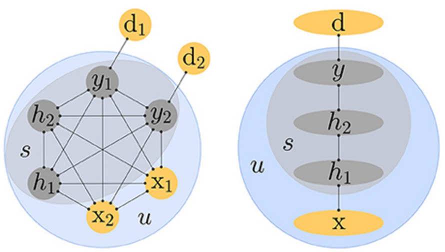

Fig 1: Examples of fully-connected and feed-forward architectures, both of which can be trained using EP [1]

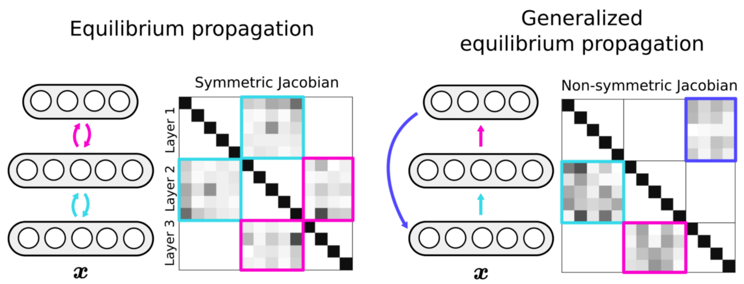

Fig 2: Layered structure of the weight connections in typical EP (left) and generalization to non-symmetric weights (right) [2]

Prerequisites

- Good coding skills, experience setting up models in PyTorch (through coursework or projects)
- Familiar with the principles of Neural Networks and how they are trained, and can in theory implement backpropagation for a simple neural network in Python
- (*Optional*) A familiarity with neuromorphic computing devices and simulations of them

Interested candidates please contact: Manasa Kaniselvan → mkaniselvan@iis.ee.ethz.ch
ETH Professor : Prof. Mathieu Luisier → mluisier@iis.ee.ethz.ch

References

[1] Benjamin Scellier and Yoshua Bengio. "Equilibrium Propagation: Bridging the Gap Between Energy-Based Models and Backpropagation", Frontiers in Computational Neuroscience, **2017**.
[2] Axel Laborieux and Friedemann Zenke. "Improving equilibrium propagation without weight symmetry through Jacobin homeostasis." ICLR **2024**.
[3] Jérémie Laydevant, Danijela Marković & Julie Grollier. "Training an Ising machine with equilibrium propagation." Nature Communications, **2024**

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