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Title: Promises and Challenges of Neuromorphic Computing

Abstract: Can one build a computers and algorithms that mimic the brain's performance, both in terms of computational power and energy consumption?
Neuromorphic engineering attempts to answer this question by designing dedicated circuits inspired by the brain's architecture and dynamics.
But simply replicating the building blocks of the brain, such as its neurons and synapses, is not sufficient. Even if given a perfect, fully programmable hardware brain, we wouldn't know how to program it to achieve brain-like cognition.

But isn't AI technology powered by neural networks and big data closer than ever to achieving general intelligence? The sobering fact is that these computers require kilowatts to run, and at least an order of magnitude more to train them, while our brains consume less than a hundred watts to achieve both. Current AI technology is unlikely to scale up to a level at which it can achieve cognition.

A key reason for this is that computer algorithms, including neural networks, are developed largely independently of the physics of the devices that support them. They are designed to run efficiently on fully programmable and general-purpose computation properties of the hardware. For example, deep learning algorithms powering current state-of-the-art AI are largely developed for vector processors, such as graphical processing units. But the speed of conventional computers is limited by the realities of the device physics.

One way to break this limit is to design algorithms more closely to the devices. Rather than using the "physics that is built into transistors, mashing it down to 1 or a 0, and painfully building [multiplication] back up with [logic] gates to reinvent multiply" (Mead, 1990), we can leverage the physics of the devices. Because every device has its properties and limitations, we need to innovate new algorithms dedicated to such devices. This approach is often called the algorithm-hardware co-design and is a distinguishing aspect of neuromorphic computing. There, the devices are materials and circuits replicating the brain dynamics and the algorithms are devised by interdisciplinary researchers in neuroscience, computer science, and electrical engineering.

This does not mean that our understanding of machine learning and neural networks needs to be discarded. On the contrary, recent work demonstrated the networks of biological neurons can be viewed as a type of deep neural network. But this subtype of neural network is extremely inefficient to run and train on a conventional computer. If they can be instead implemented on neuromorphic hardware, we could potentially reap enormous energy and speed benefits, even compared to state-of-the-art AI.

This talk will highlight several open challenges that remain in this endeavor: Training the algorithms remains a highly specialized process that can still not be fully mapped onto our software and hardware synapse models. How can a model learn without clear targets - or labels ? Brains do not learn from scratch, they rely on prior knowledge acquired through evolution, development and plasticity to build new knowledge. How much plasticity should we then implement on our hardware to achieve the learning capabilities of the brain? These questions cannot be answered through algorithms, neuroscience or engineering alone, but through a combination of all these approaches.

Bio: Dr. Neftci received his MSc degree in physics from EPFL in Switzerland, and his Ph.D. in 2010 at the Institute of Neuroinformatics at the University of Zurich and ETH Zurich. He is currently an institute director at the Jülich Research Centre and Professor at RWTH Aachen. His current research explores the bridges between neuroscience and machine learning, with a focus on the theoretical and computational modeling of learning algorithms that are best suited to neuromorphic hardware and non-von Neumann computing architectures.