SYNC 1: Symposium: Advanced neuromorphic computing hardware: Towards efficient machine learning

Recently novel computational approaches such a neural networks are revolutionizing computation. At the same time, we experience that the performance growth of digital microchips is saturating and the energy consumption of classical digital electronic processors is becoming a serious issue. This impasse has re-invigorated learning from the brain with its amazing intelligence-per-watt ratio and the exploration of unconventional physical substrates and nonlinear phenomena.

Our symposium will present the recent progress and future perspectives of neuro-inspired computing based on solid-state systems and their relation to machine learning. This includes not only important aspects of novel computational architectures in unconventional substrates but also new theoretical concepts of computing in non-digital, "brain-like" physical substrates.

The chosen topic has highly interdisciplinary as we aim at bringing together researchers from material science, machine learning, computer engineering, nonlinear dynamics with exciting talks of renowned international experts in the field.

Organizers: Julie Grollier (CNRS/Thales Lab, Paris, France), Daniel Brunner (FEMTO-ST, Besançon, France), Stephan Reitzenstein (TU Berlin, Germany)

Time: Wednesday 10:00–12:45 Location: Audimax 1

Invited Talk SYNC 1.1 Wed 10:00 Audimax 1
Equilibrium Propagation: a Road for Physics-Based Learning — •Damien Querlioz — Université Paris-Saclay, CNRS, C2N, Palaiseau, France.

Neuromorphic computing takes inspiration from the brain to create highly energy-efficient hardware for information processing, capable of sophisticated tasks. The resulting systems are most often preprogrammed: training neuromorphic systems on-chip to perform new tasks remains a formidable challenge. The flagship algorithm for training neural networks, backpropagation, is indeed not hardware-friendly. It requires a mathematical procedure to compute gradients, external memories to store them, and an external dedicated circuit to change the neural network parameters according to these gradients. The brain, by contrast, does not learn this way. It learns intrinsically, and its synapses evolve directly through the spikes applied by the neurons they connect, using their biophysics. This technique is very advantageous in terms of energy efficiency and device density. In this talk, I will introduce our approach towards reproducing this brain strategy of intrinsic learning exploiting device physics. I will show through simulations how we take advantage of the physical roots of an algorithm called Equilibrium Propagation (1) to design dynamical circuits that learn intrinsically with high accuracy (2-4).

1. B. Scellier, Y. Bengio, Front. Comput. Neurosci. 11 (2017). 2. M. Ernoult, J. Grollier, D. Querlioz, Y. Bengio, B. Scellier, Proc. NeurIPS, pp. 7081 (2019). 3. A. Laborieux et al., Front. Neurosci. 15 (2021). 4. E. Martin et al., iScience. 24 (2021).

Invited Talk SYNC 1.2 Wed 10:30 Audimax 1
Machine Learning and Neuromorphic Computing: Why Physics and Complex Systems are Indispensable — •Ingo Fischer — Instituto de Física Interdisciplinar y Sistemas Complejos IFISC (UIB-CSIC), Campus UIB, 07122 Palma de Mallorca, Spain

Advances in Machine Learning have recently boosted neuromorphic computing and its implementation in analog hardware. We discuss why physics and complex systems science provide valuable perspectives and tools for understanding existing methods and developing novel transdisciplinary approaches and their hardware implementation.

Invited Talk SYNC 1.3 Wed 11:00 Audimax 1
Photonic Tensor Core Processor and Photonic Memristor for Machine Intelligence — •Volker Sorger — George Washington University, Washington DC, USA

Photonic technologies are at the forefront of the ongoing 4th industrial revolution of digitalization supporting applications such as 5G networks, virtual reality, autonomous vehicles, and electronic warfare. With Moores law and Dennard scaling now being limited by fundamental physics, the trend in processor heterogeneity suggests the possibility for special-purpose photonic processors such as neural networks or RF-signal & image filtering. Here unique opportunities exist, for example, given by algorithmic parallelism of analog and distributed non-van Neuman architectures enabling non-iterative O(1) processors with ps-short delay towards real-time decision making. Here, I will share our latest work on photonic information processors to include a photonic tensor core including multistate photonic nonvolatile random-access memory [Appl. Phys. Rev.], and a massively parallel Fourier-optics convolutional processor [Optica]. In summary, photonics connects the worlds of electronics and optics, thus enabling new concepts of efficient intelligence information processing via algorithm-hardware homomorphism empowered by the distinctive properties of light.

15 min. break.

Invited Talk SYNC 1.4 Wed 11:45 Audimax 1
Material learning with disordered dopant networks — •Wilfred van der Wiel — BRAINS Center for Brain-Inspired Nano Systems, MESA+ Institute for Nanotechnology, University of Twente, Enschede, The Netherlands

The implementation of machine learning in digital computers is intrinsically wasteful and one has started looking at natural information processing systems, in particular the brain, that operate much more efficiently. Whereas the brain utilizes wet, soft tissue for information processing, one could in principle exploit any material and its physical properties to solve a problem. Here we give examples of how nanomaterial networks can be trained using the principle of Material Learning to take full advantage of the computational power of matter.

We have shown that a designless network of gold nanoparticles can be configured into Boolean logic gates using artificial evolution. We further demonstrated that this principle is generic and can be transferred to other material systems. By exploiting the nonlinearity of a nanoscale network of boron dopants in silicon, we can significantly facilitate classification. Using a convolutional neural network approach, it becomes possible to use our device for handwritten digit recognition. An alternative Material Learning is approach is followed by first mapping our Si:B network on a deep neural network model, which allows for applying standard Machine Learning techniques in finding functionality. Finally, we show that the widely applied machine learning technique of gradient descent can be directly applied in materio, opening up the pathway for autonomously learning hardware systems.

Invited Talk SYNC 1.5 Wed 12:15 Audimax 1
In-memory computing with non-volatile analog devices for machine learning applications — •John Paul Strachan — Peter Grünberg Institute (PGI-14), Forschungszentrum Jülich GmbH, Jülich, Germany — RWTH Aachen University, Aachen, Germany

I describe our work to build non-von Neumann computing systems for machine learning and other computing applications. We are able to improve speed and power by leveraging emerging non-volatile and analog devices (e.g., memristors) and combining with mature CMOS technology, enabling the construction of novel circuits and architectures. We describe the acceleration of linear algebra operations and also complex pattern storage and retrieval, which are core operations in modern deep learning and broader machine learning workloads. We also build improved Content Addressable Memory (CAM) circuits that can be used in a variety of computing applications from network security, genomics, and many types of data classification. We forecast significant improvement over CPUs, GPUs, and custom ASICs using these new architectures. I will also describe work in addressing the types of errors often observed in analog systems, both in mitigating their effects as well as harnessing them productively.