Centre de Nanosciences et de Nanotechnologies

Soutenance de thèse

Le 30 juin 2020
16h00

Lien public : https://eu.bbcollab.com/guest/9369f70b256f4575863d1b1d29ca5446

Le nombre de personne pouvant accéder à l'amphithéâtre étant limité, veuillez me contacter (mail : ernoult.m@gmail.com) si vous souhaitez assister à la thèse en présentiel.

Maxence ERNOULT

"Rethinking biologically inspired learning algorithms towards better credit assignment for on-chip learning"

Membres de jury :

Timothée Masquelier (CERCO): reviewer
Blake Richards (Montreal Neurological Institute, Mc Gill): reviewer
Laurent Daudet (CTO LightOn): examiner
Teodora Petrisor (Thales TRT): examiner
Pierre Bessière (ISIR): examiner
Julie Grollier: thesis advisor
Damien Querlioz: thesis coadvisor (invited)

Abstract :

The deep learning approach to AI has taken upon the whole society thanks to the use of Graphical Computing Units (GPUs). Going beyond the capability of the GPUs for deep neural network training is the core motivation of this thesis. One possible approach is neuromorphic computing, which consists in rethinking the computer from scratch by mimicking brain features. In particular memristors, which can store weight values as conductance states, are promising artificial synapse candidates. An appealing approach to train memristor-based hardware neural networks would be on-chip learning: the chip could sustain inference, gradient computation and subsequent conductance update altogether. However, on-chip learning is extremely challenging for two reasons. First, the computation of the objective function gradient calls at first sight for backpropagation, which is hardware unfriendly. More hardware convenient approaches use learning heuristics that poorly scale to deeper architectures, probably because of their lack of theoretical guarantees. The second challenge of on-chip learning is the conductance update to be performed given a gradient value: memristors exhibit many imperfections which dramatically hamper on-chip learning.
In this thesis, we propose to disentangle these two aspects of on-chip learning. On the one hand, we study the effect of memristive device imperfections on the training of Restricted Boltzmann Machines and propose appropriate programming strategies. On the other hand, we build upon Equilibrium Propagation, a hardware friendly counterpart of backpropagation whose learning rule, computed by the physics of the system itself, is spatially local and mathematically grounded. This work, along with very recent results, strongly suggest that Equilibrium Propagation could be a compelling scalable approach for on-chip learning.

UMR9001 CNRS-UPSUD
10 boulevard Thomas Gobert
91120 Palaiseau