Polytech network form for PhD Research Grants from the China Scholarship Council

This document describes the PhD subject and supervisor proposed by the French Polytech network of 15 university engineering schools. Please contact the PhD supervisor by email or Skype for further information regarding your application.

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PhD information	
Title	Towards Spike-Based Machine Learning
Main topics regards to CSC list (3 topics at maximum)	I-1. Calcul scientifique à grande échelle (Large scale computation)

Required skills in science and engineering	Machine Learning, Mathematics, Statistics, Data science

Subject description (two pages maximum)

Convolutional Neural Networks (CNN) are a brain inspired technique in artificial intelligence. They find applications in numerous areas, including self-driving cars, data analysis, commercial recommender systems and many more. In less than a decade, deep CNN such as Inception and VGG-16 have successfully pulled state-of-the-art classification performances to new levels, especially on challenging computer vision benchmarks like ImageNet. The availability of both tremendous amounts of annotated data and huge computational resources have enabled remarkable progress. Therefore, this success comes with substantial human cost required for manually labeling data, and energy cost required for inference, despite most recent advances in parallel digital architectures. Namely, training deep CNN requires tremendous amounts of power. For instance, ResNet has been trained for 3 weeks on a 8-GPU server, which is equivalent to a power consumption of about 1 GWh. More generally, worldwide data centers in general require a power of about 1 PW, which is equivalent to 4% of GHG emissions, which is over air transportation. Forecasts plan that this figure will double every 4 years. Therefore, a paradigm change in information processing and machine learning is needed in order to face the ever-growing demand in large scale computation.

On the other hand, the human brain has the ability to perform cognitive tasks with unrivalled computational and energy efficiency. It is believed that one major factor of this efficiency is the fact that information is represented by action potentials (or spikes) at analog –not discrete– times, in a sparse way. Inspired from biology, Spiking Neural Networks (SNN) are a special class of artificial neural networks in that they can work continuously and function more like the brain [Maass, 1997] [Ponulak, 2011] [Paugam-Moisy, 2012]. Spiking neurons communicate by sequences of spikes. Contrary to formal neurons, spiking neurons do not fire at each propagation cycle, but rather fire only when their activation level (or membrane potential, an intrinsic quality of the neuron related to its membrane electrical charge) reaches a specific threshold value. When a neuron fires, it generates a non-binary signal that travels to other neurons, which in turn increases their potentials. The activation level either increases with incoming spikes, or decays over time. SNNs have been shown to be computationally more efficient than standard rate-coding networks. In particular, they are more energy efficient if implemented on neuromorphic hardware. Neuromorphic hardware implementing SNN can be built with CMOS technology, and typically uses low power (under the threshold voltage), enabling to reduce energy dissipation by several orders of magnitude, compared to standard digital architectures [Merolla, 2014] [Desbief, 2015]. Regarding inference, SNN does not rely on stochastic gradient descent and backpropagation. Instead, neurons are connected through synapses, that implement a learning mechanism inspired from biology: it rests upon the “Spike-Timing-Dependent Plasticity”, a rule that updates synaptic weights (strength of connections) according to causal links observed between presynaptic and postsynaptic spikes. This updating rule reinforces incoming connections that cause the neuron to fire. Therefore, the learning process is intrinsically not supervised, and can be successfully used detect patterns in data in an unsupervised manner [Bichler, 2012] [Beyeler, 2013]. SNN are little used, yet there is an increasing interest in using such type of neural network in machine learning. A number of open issues and questions need to be addressed, such as the design of an efficient SNN topology (convolutional? layered? recurrent?), the understanding and control of the learning process with parameter tuning, the right way to input supervision (during or after inference?), the input coding (convert input data values to spike trains) and output decoding (interpret the output spikes). Recent work shows that SNN are competitive with the state-of-the-art in computer vision on "easy" datasets such as MNIST (handwritten digits) [Diehl, 2015] [Kheradpisheh, 2018] [Falez, 2019].

SNN show many interesting features for the paradigm change addressed in this proposal [Verzi, 2018] [Pei, 2019] [Roy, 2019] [Taherkhani, 2020], such as their unsupervised training with Spike-Timing-Dependant Plasticity rules, and their implementation on ultra-low-power neuromorphic hardware. And yet, a number of challenges lie ahead before they become a realistic alternative to deep CNN. The objective this PhD proposal is to quantify the fundamental limits of computations in terms of energy and cost. We are interested in developing energy-efficient computational neuro-inspired models based on SNNs implemented in neuromorphic hardware. An in-depth understanding of the theoretical computational properties of SNNs will help to exhibit fundamental limits to SNNs and on developing novel training algorithms for SNNs. Understanding how spiking neurons process information and learn remains an essential challenge in order to unlock their potential, towards a paradigm change in large scale computation.

References:
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