Quantum Machine Learning Applications for the Physics of the Two Infinites

Andrea Sartirana (LLR), Frédéric Mangiette (LLR), Denis Lacroix (IJCLab), G. Hupin (IJCLab).
On behalf of the QC2I project

This prospective is part of the [QC2I project](#) objectives.

Abstract:

With the arrival of the first quantum computer demonstrators the field of quantum computing (QC) is rapidly gaining interest and visibility. Quantum computers are expected to be a disruptive technology allowing to perform computing task that are out of reach for classical machines (quantum supremacy). On the other hand, programming such devices is a formidable challenge that requires a radical paradigm change in IT science. Today Noisy Intermediate-Scale Quantum (NISQ) computers are still noisy, limited in number of qubits (qumodes) and coherence time, but they open the possibility to start testing QC algorithms for different problems, including real-world research applications.

One field of QC which has raised a lot of interest and is evolving very fast is quantum machine learning (QML). After the seminal work of Harrow, Hassidim and Lloyd (HHL) [1], this discipline has understandably raised a lot of enthusiasm since it promises to bring the potential advantages of QC to the wide range of application of machine learning (ML). HHL-like algorithms may not be so simple to exploit [2] and are basically out of reach for the NISQ era quantum hardware, therefore much of the work today is devoted to hybrid quantum-classical techniques [3-5] that allow to implement (almost) real-world ML applications on small noisy devices.

Within IN2P3 the QC2I project aims to explore applications of the QC algorithms to Particle and Nuclear Physics as well as Astrophysics and Cosmology. One of the main direction of activity is of course to explore QML applications. As a first step we aim to provide proof of principle applications in the domain of activity of IN2P3. For example: event classification or detector simulation for particle physics or nuclear many-body systems study. On a longer timescale the goal is to develop a strong expertize on the subject and to be able to readily exploit the benefits of quantum supremacy when it becomes reality.

Current situation in quantum computing and quantum machine learning:

Several research institutions as well as private companies (Google, Amazon, IBM, Microsoft, Rigetti, etc.) are today engaged in a race to "quantum supremacy". That is, the realization of a quantum computer with enough qubits, coherence time and gates fidelity to allow tackling problems which are beyond the reach of classical computers. This intense international competition is boosting both technological and fundamental research with parallel developments of new hardware and new programming methods.

Currently, quantum devices have entered the NISQ (Noisy Intermediate-Scale Quantum) era [6]. That is, QC is possible but noise and instability limit the size of quantum circuits that can be reliably executed. Despites these limitations, for the first time, potential users in academics and private companies have the real possibility to access ready to work quantum devices and test their algorithms and real-world applications. This, understandably, triggers a lot of excitement among scientists in different domains for the potentially revolutionary contribution that QC can bring to their disciplines.

Among the different applications of QC, Quantum Machine Learning is certainly one of those which are currently experiencing the fastest expansion. QML started in 2009 with the definition in a paper of Harrow, Hassidim and Lloyd [1] of an algorithm which allows, under certain conditions, to obtain some information about the solution of a linear system of size N with time complexity log(N). Adapted to Machine Learning (ML) applications, the HHL algorithm opened the intriguing possibility to have exponential speedup for a wide range of applications. Unfortunately, algorithms like HHL are far from being NISQ compliant. Thus at present much of the focus is on hybrid quantum/classical optimization algorithms, where a classical optimizer is coupled to a parametric quantum circuit which is iteratively trained to minimize some cost function. Most of the applications in our field fall in this category, for example: variational circuits for Nuclear Physics, quantum classifiers for Particle Physics analysis and quantum GAN for detectors simulation [7-9].

In this context, initiatives around the application of QC and QML techniques are flourishing all around the high energy and nuclear physics communities. One example is the CERN Quantum Technology Initiative forum [10] which has been created in Q2 2020 with the goal of assessing the potential and role of QC - QML in particular - in HEP workloads, to build expertise in the state-of-the-art of QC and QC-related software as well as encourage technical discussions and collaborations between CERN, the LHC experiments scientists and the broader quantum community. Similarly, the Quantum Simulation for Nuclear Physics (QS4NP) [11] initiative organizes a series of online seminars around the topic of QC and its applications to Nuclear Physics, and the "InQubator for Quantum Simulation" [12] initiative at Washington University focuses on the study of quantum information techniques for Nuclear Physics.

Study of the application of QML techniques for nuclear and particle physics within the QC2I project:

The QC2I IN2P3 project started in January 2020. Its goal is to explore the application of Quantum Computing for Particle and Nuclear Physics as well as Astrophysics and Cosmology and to prepare the technology transition which will be brought by quantum applications. Since the beginning, QML has been, of course, identified as one of the main axes of the project activity.

As we already pointed out, QC is nowadays a rapidly emerging and evolving technology. It attracts strong investments by private companies, including giants as IBM, Microsoft, Google, Amazon. One should therefore expect quantum computers with an increasing number of qubits to become available, that their stability will be improved in the near future and that their usage will become more and more widespread. At the same time new algorithms and innovative ideas on possible applications are appearing almost on daily basis. Therefore, this is an extremely timely and exciting period to explore QC and QML, one of the most important tasks in the short and medium term being to keep up with this accelerated evolution.

For this same reason it is not simple to draw a definitive roadmap but we can already identify some steps for our future activity:

(i) A first near term goal (~1 year) is to acquire strong expertise and an exhaustive view of the different techniques used in QML, e.g. HHL , Quantum Variational algorithms, Quantum Neural Networks, etc. With particular focus on the hybrid algorithms currently used on NISQ devices. At the same times we seek contacts and collaborations with analogues initiatives around our community, like, for example the CERN QTI forum. In parallel we work on the quantum computing formulation of specific nuclear and particle physics problems where QML can be applied and which are nowadays treated on classical computers. For example: the optimization of many-body states in ab-initio calculations, the exploration of complex energy landscape for systems with large numbers of degrees of freedom, the classification of particle physics events in high-resolution multi-detectors or making 4D (position, energy) - or even 5D(+timing) - detectors imaging of events in High Resolution detectors like CMS [2] This phase is basically ongoing, we are already exploring QML techniques, defining proof of concept applications and reaching out for contacts with QC experts and QML groups in our community.

(ii) on a longer timescale, once our expertise is built up and we will have identified a panel of target problems, we will proceed to provide a series of proof-of-concept - and possibly real-size - applications. We will try to identify cases where QML offers an advantage w.r.t. classical ML and possibly provide new ideas and solutions while adapting the algorithms to our problems.

(iii) when quantum supremacy will be available - for which we cannot define a timescale - the (quite ambitious) goal is to be ready to exploit it and provide some disruptive applications to our discipline.

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