Quantum Machine Learning as HEP-tool

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POR MI RAZA HABLARA EL ESPIRITU

Abstract

In this poster, I share an introduction of QML, concepts and tools that could be relevant for High Energy Physics in a phenomenological view. I am interested in implementing some algorithms coming from Artificial Intelligence and Quantum Computing, an ideal language of programming and frameworks to analyze or reproduce some HEP process and its features. This project is going on and I hope to report results soon.

Introduction

Recently, Machine Learning (ML) discipline has been implemented in different analysis: experimental, theoretical and phenomenological [7, 4]. Each of this papers has a particular aim, and reports relevant results for the new way to do science in particular in High Energy Physics.

In fact, Concepts and main ideas on ML has been implemented more than several years ago and HEP experimentalists have contributed to develop this area continuously; and recently phenomenologists and theoretists at CERN and other laboratories require researchers in this area in order to boost analysis and contribution in science development.

ML consider mathematics and computing to automatize process, which impacts in time decrease. On the other, Quantum Computing implement mathematics, physics and computing to reduce run times or storage, whose are Complex Theory resources.

Quantum Machine Learning is Quantum Computing and Machine Learning combination. One of the most important feature of QC is the exponentially faster that compared to a classical algorithms. However, some issues are associated to design a new quantum algorithm. By the other side, ML techniques have become powerful tools for data analysis, e.g.: finding patterns [1].

Then, we have the field of QML to devise quantum tools in order to improve classical computers, contribute to the enhancement of QCs, or as a tool in the science development. Recent work has produced quantum algorithms that could act as the building blocks of machine learning programs, but the hardware and software challenges are still considerable.

Nowadays, we have tools as: Python, algorithms (classical and quantum), and relevant results in HEP, and I consider meaningful the contribution of the community in this area. Other, tools and programming languages have been developed as high-level with a strong static type system for quantum computing [2].

Overview

Algorithms for ML are split:

- Supervised: predicts the label of instances after training on a sample of labeled examples.
- Unsupervised: the data labels are missing
- Semisupervised: use labeled and unlabeled examples to build a model.

There are more sort of learning but we will discuss in futures literature [5].
Some algorithms are: K-means (clustering), K nearest neighbors, gradient descent, Support Vector Machines and others (some can be found in fig. 1).
Some relevant problem (algorithms) for QC are,

Problem	Maps	Function
Deutsch	$f : \{0,1\} \to \{0,1\}$; where one bit to one bit	$f(x)$ balanced and constant
Deutsch-Jozsa	$f : \{0,1\}^n \to \{0,1\}$; where n bits to one bit.	Black box oracle function.
Bernstein-Vazirano	$f : \{0,1\}^n \to \{0,1\}$; where n bits to one bit.	$f(x) = a \cdot x$
Simon	$f : \{0,1\}^n \to \{0,1\}^n$; where n bits to one bit.	$f(x) = a \oplus x$

Some quantum algorithms, application, mapping and a brief function description.

In fact, an analogous SVM algorithm has been implemented in they present two methods with new class of tools for exploring the applications of noisy intermediate scale quantum computers to machine learning [3]. Approaches for QML are

Algorithm	Reference	Grover	Speedup	Quantum Data	Generalization Performance	Implementation
K-medians	Aïmeur et al. (2013)	Yes	Quadratic	No	No	No
Hierarchical clustering	Aïmeur et al. (2013)	Yes	Quadratic	No	No	No
K-means	Lloyd et al. (2013a)	Optional	Exponential	Yes	No	No
Principal components	Lloyd et al. (2013b)	No	Exponential	Yes	No	No
Associative memory	Ventura and Martinez (2000)	Yes		No	No	No
	Trugenberger (2001)	No		No	No	No
Neural networks	Narayanan and Menneer (2000)	Yes		No	Numerical	Yes
Support vector machines	Anguita et al. (2003)	Yes	Quadratic	No	Analytical	No
	Rebentrost et al. (2013)	No	Exponential	Yes	No	No
Nearest neighbors	Wiebe et al. (2014)	Yes	Quadratic	No	Numerical	No
Regression	Bisio et al. (2010)	No		Yes	No	No
Boosting	Neven et al. (2009)	No	Quadratic	No	Analytical	Yes

Figure 1: The column headed ”Algorithm” lists the classical learning method. The column headed ”Reference” lists the most important articles related to the quantum variant. The column headed ”Grover” indicates whether the algorithm uses Grover’s search or an extension thereof. The column headed ”Speedup” indicates how much faster the quantum variant is compared with the best known classical version. ”Quantum data” refers to whether the input, output, or both are quantum states, as opposed to states prepared from classical vectors. The column headed ”Generalization performance” states whether this quality of the learning algorithm was studied in the relevant articles. ”Implementation” refers to attempts to develop a physical realization. Source: [6].

All concepts mentioned before can be implemented, in a phenomenological and theoretical view, to figure out the High Energy Physics models and that might be interesting for the experimentalists.
We first of all want to analize some data available in ref. [8] with different models and implement differents kind of learnings, classical and quantum algorithms in a phenomenological and theoretical view.

References

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