Maastricht Science Programme

Research Proposal for Experimental Implementation of Quantum Machine Learning Algorithms

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Abstract

Mixtape tote bag quinoa, deep v ramps organic pabst. Cliche trust fund twee lo-fi, lumbersexual sustainable skateboard brunch keytar edison bulb. Try-hard blue bottle meggings fashion axe, gentrify freegan PBRB. Squid retro viral, shoreditch sriracha salvia kogi chia. Celiac tumblr thundercats, williamsburg literally etsy man braid franzen flannel chambray raw denim. Try-hard woke retro intelligentsia. Af actually synth coloring book hoodie tumeric, knausgaard paleo butcher.

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1 Introduction

The ability to understand spoken language, to recognize faces and to distinguish different types of fruit comes naturally to humans, even though these processes of pattern recognition and classification are inherently complex. Machine learning (ML), a subtopic of artificial intelligence, is concerned with the development of algorithms that mimic these mechanisms, thereby enabling computers to find and recognise patterns in data and classify unknown inputs based on previous training with labelled inputs. Such algorithms paved the way for e.g. human speech recognition, recommendation engines as used by Amazon and prediction algorithms that can predict heart disease from real-time electrocardiograms (Acharya et al., 2015).

According to IBM (2016), every day approximately 2.5 quintillion (10^{18}) bytes of digital data are created. This growing number implies that every area dealing with data will eventually require advanced algorithms that can make sense of data content, retrieve patterns and reveal correlations. However, most ML algorithms involve the execution of computationally expensive operations and doing so on large data sets inevitably takes a lot of time (REFERENCE?). Hence, it becomes increasingly important to find efficient ways of dealing with big data and/or reduce the computational complexity of the algorithms.

A promising solution is the use of quantum computation which has been researched intensively in the last decades. Quantum computers use quantum mechanical systems and their special properties to manipulate and process information in ways that are impossible to implement on classical computers. The quantum equivalent to a classical bit is called a quantum bit (or qubit) and additionally to being in either state they can be in a linear superposition of $|0\rangle$ and $|1\rangle$. This peculiar property gives rise to so called quantum parallelism, which enables the execution of certain operations on many quantum states at the same time. However, despite this obvious advantage the real difficulty in quantum computation lies in the retrieval of the computed solution since a measurement of a qubit collapses it into a single classical bit and thereby destroys information about its previous superposition. Several quantum algorithms have been proposed that provide exponential speed-ups when compared to their classical counterparts with Shor's prime factorization algorithm being the most famous (Shor, 1994). Hence, quantum computation bears the potential to vastly improve computational power, speed up the processing of big data and solve certain problems that are practically unsolvable on classical computers.

Considering these advantages, the combination of quantum computation and classical ML into the new field of quantum machine learning (QML) seems almost natural. However, since most ML algorithms rely on solving some system of linear equations a corresponding quantum algorithm is required for QML to become achievable. Harrow, Hassidim, and Lloyd (2009) were first to describe such an algorithm (referred to as HHL-algorithm) which since has become a subroutine in many QML algorithms. There are currently two main ideas on how to merge quantum computation with ML, namely a) running the classical algorithm on a classical computer and 'outsourcing' only the computationally intensive task to a quantum computer or b) executing the quantum version of the entire algorithm on a quantum computer. Current QML research mostly focusses on the latter by developing quantum algorithms that tab into the full potential of quantum parallelism.

1.1 Motivation

Classical ML is a very practical topic since it can be directly tested, verified and implemented on any commercial classical computer. So far, QML has been of almost entirely theoretical nature since the required computational resources are not in place yet. QML algorithms often require a relatively large number of error-corrected qubits and some sort of quantum data storage such as the proposed quantum random access memory (qRAM) (Giovannetti, Lloyd, & Maccone, 2008). However, to date the maximum number of superconducting qubits reportedly used for calculation is nine, the D-Wave II quantum annealing device delivers 1152 qubits but can only solve a narrow class of problems and a qRAM has not been developed yet (D-Wave, 2015; O'Malley et al., 2016). Furthermore, qubit error-correction is still a very active research field and most of the described preliminary quantum computers deal with non error-corrected qubits with short lifetimes and are, thus, impractical for large QML implementations.

Until now there has been only three experimental verifications of QML algorithms that provide proof-of-principle. Li, Liu, Xu, and Du (2015) successfully distinguished a handwritten six from a nine using a Quantum Support Vector Machine on a four-qubit nuclear magnetic resonance test bench. In addition, Cai et al. (2015) were first to experimentally demonstrate quantum machine learning on a photonic quantum computer and showed that the distance between and the inner product of two vectors can indeed be computed quantum mechanically. Lastly, Ristè et al. (2015) solved a learning parity problem with five superconducting qubits and found that a quantum advantage can already be observed in non error-corrected systems. Consequently, considering the large gap between the number of proposed QML algorithms and experimental realisations of scaled-down QML problems, it remains important to find QML problems which can already be implemented on currently available quantum technology. This can ultimately be seen as an attempt to shift QML from a purely theoretical research area to a more applied field such as classical ML. Furthermore, this can also lead to verification or falsification of the claims and assumptions made in the field of QML. Successful proof-of-principle studies are also crucial for further research to be funded and supported since it shows that an upscaling of quantum computational power will eventually lead to at best exponential speed ups compared to classical ML and hence has the potential to revolutionize the handling of big data.

1.2 Research Question

Is it possible to already implement and solve a small ML problem on IBMs publicly available QC?

1.3 Research Objectives

Essentially: find a QAlg + a downscaled ML problem + a dataset and implement the circuit in a quantum system (ideally on a real QC otherwise simulate it in Liquid)

classification problems such as classifying handwritten digits/colours or fitting functions onto small datasets could be scaled down and executed on 5 Qbits

many QML algorithms assume the data to already be prepared in some particular quantum data format and also assume all kind of other things

This includes a) the preprocessing of data, b) the preparation of a suitable quantum state containing the training data and the to be classified data, c) the execution of a quantum circuit and finally d) the retrieval of the solution to the problem.

2 Research Methods

¿¿ how are you going to approach the problem? what tools do you wanna use?

shortly introduce the IBM QC and what Liquid is

3 Timeline

insert a nicely designed timescheme here!

4 Outlook & Conclusion

axidermy edison bulb plaid, chia swag organic roof party shabby chic raw denim tilde waistcoat. Swag everyday carry iPhone, pitchfork pop-up ethical blog small batch la croix before they sold out chartreuse chia gastropub craft beer crucifix. Occupy mustache organic tumblr, scenester cred listicle kombucha lumbersexual. Crucifix tumeric bushwick, organic unicorn ugh food truck 90's echo park freegan mumblecore chia shabby chic. Keytar actually intelligentsia mumblecore, ugh selvage schlitz tousled iPhone cray paleo wayfarers snackwave viral humblebrag. Subway tile pop-up squid church-key craft beer. Church-key la croix cornhole kitsch 8-bit gluten-free.

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