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Quantum perceptron over a field and neural network architecture selection in a quantum computer

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ABSTRACT

In this work, we propose a quantum neural network named quantum perceptron over a field (QPF). Quantum computers are not yet a reality and the models and algorithms proposed in this work cannot be simulated in actual (or classical) computers. QPF is a direct generalization of a classical perceptron and solves some drawbacks found in previous models of quantum perceptrons. We also present a learning algorithm named Superposition based Architecture Learning algorithm (SAL) that optimizes the neural network weights and architectures. SAL searches for the best architecture in a finite set of neural network architectures with linear time over the number of patterns in the training set. SAL is the first learning algorithm to determine neural network architectures in polynomial time. This speedup is obtained by the use of quantum parallelism and a non-linear quantum operator.

1. Introduction

The size of computer components reduces each year and quantum effects have to be eventually considered in computation with future hardware. The theoretical possibility of quantum computing initiated with Benioff (1980) and Feynman (1982) and the formalization of the first quantum computing model was proposed by Deutsch (1985). The main advantage of quantum computing over classical computing is the use of a principle called superposition which allied with the linearity of the operators allows for a powerful form of parallelism to develop algorithms more efficient than the known classical ones. For instance, the Grover's search algorithm (Grover, 1997) and Shor's factoring algorithm (Shor, 1997) overcome any known classical algorithm.

Quantum computing has recently been used in the development of new machine learning techniques as quantum decision trees (Farhi & Gutmann, 1998), artificial neural networks (da Silva, de Oliveira, & Ludermir, 2012; Narayanan & Menneer, 2000; Panella & Martinelli, 2011), associative memory (Trugenberger, 2001; Ventura & Martinez, 2000), and inspired the development of novel evolutionary algorithms for continuous optimization problems (Duan, Xu, & Xing, 2010; Hsu, 2013). There is an increasing interest in quantum machine learning and in the quantum neural network area (Schuld, Sinayskiy, & Petruccione, 2014b). This paper proposes a quantum neural network named Quantum Perceptron over a Field (QPF) and investigates the use of quantum computing techniques to design a learning algorithm for neural networks. Empirical evaluation of QPF and its learning algorithm needs of a quantum computer with thousands of qubits. Such quantum computer is not available nowadays and an empirical analysis of the QPF and its learning algorithm is not possible with current technology.

Artificial neural networks are a universal model of computation (Cabessa & Siegelmann, 2014) and have several applications in real life problems. For instance, in the solution of combinatorial optimization problems (Zhang, Rong, Neri, & Pérez-Jiménez, 2014), pattern recognition (González, Dominguez, Rodríguez, & Sánchez, 2014), but have some problems as the lack of an algorithm to determine optimal architectures (Yamazaki & Ludermir, 2003), memory capacity and high cost learning algorithms (Beigy & Meybodi, 2001).

Notions of Quantum Neural Networks have been put forward since the nineties (Kak, 1995), but a precise definition of what is a quantum neural network that integrates neural computation and quantum computation is a non-trivial open problem (Schuld et al., 2014b). To date, the proposed models in the literature are really just quantum inspired in the sense that despite using a quantum representation of data and quantum operators, in a way or another some quantum principles are violated usually during

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training. Weights adjustments need measurements (observation) and updates.

Research in quantum neural computing is unrelated, as stated in Schuld et al. (2014b):

> "QNN research remains an exotic conglomeration of different ideas under the umbrella of quantum information"

and there is no consensus of what are the components of a quantum neural network. Several models of quantum neural networks have been proposed and they present different conceptual models. In some models a quantum neural network is described as a physical device (Narayanan & Menneer, 2000); as a model only inspired in quantum computing (Kouda, Matsui, Nishimura, & Peper, 2005); or as a mathematical model that explores quantum computing principles (da Silva et al., 2012; Panella & Martinelli, 2011; Schuld, Sinayskiy, & Petruccione, 2014a; Zhou & Ding, 2007). We follow the last approach and assume that our quantum neural network model would be implemented in a quantum computer that follows the quantum principles as *e.g.* described in Nielsen and Chuang (2000). We assume that our models are implemented in the quantum circuit model of Quantum Computing (Nielsen & Chuang, 2000).

Some advantages of quantum neural models over the classical models are the exponential gain in memory capacity (Trugenberger, 2002), quantum neurons can solve nonlinearly separable problems (Zhou & Ding, 2007), and a nonlinear quantum learning algorithm with polynomial time over the number of patterns in the dataset is presented in Panella and Martinelli (2011). However, these quantum neural models cannot be viewed as a direct generalization of a classical neural network and have some limitations presented in Section 4. Quantum computing simulation has exponential cost in relation to the number of qubits. Experiments with benchmarks and real problems are not possible because of the number of qubits necessary to simulate a quantum neural network.

The use of artificial neural networks to solve a problem requires considerable time for choosing parameters and neural network architecture (Almeida & Ludermir, 2010). The architecture design is extremely important in neural network applications because a neural network with a simple architecture may not be capable of performing the task. On the other hand, a complex architecture can overfit the training data (Yamazaki & Ludermir, 2003). The definition of an algorithm to determine (in a finite set of architectures) the best neural network architecture (minimal architecture for a given learning task that can learn the training dataset) efficiently is an open problem. The objective of this paper is to show that with the supposition of non-linear quantum computing (Abrams & Lloyd, 1998; Panella & Martinelli, 2009, 2011) we can determine an architecture that can learn the training data in linear time with relation to the number of patterns in the training set. To achieve this objective, we propose a quantum neural network that respect the principles of quantum computation, neural computing and generalizes the classical perceptron. The proposed neuron works as a classical perceptron when the weights are in the computational basis, but as quantum perceptron when the weights are in superposition. We propose a neural network learning algorithm which uses a non-linear quantum operator (Abrams & Lloyd, 1998; Panella & Martinelli, 2011) to perform a global search in the space of weights and architecture of a neural network. The proposed learning algorithm is the first quantum algorithm performing this kind of optimization in polynomial time and presents a framework to develop linear quantum learning algorithms to find near optimal neural network architectures.

The remainder of this paper is divided into 6 Sections. In Section 2 we describe models that are out of the scope of this work. In Section 3 we present preliminary concepts of quantum computing necessary to understand this work. In Section 4 we present related works. Section 5 presents main results of this paper. We define the new model of a quantum neuron named quantum perceptron over a field that respect principles of quantum and neural computing. Also in Section 5 we propose a quantum learning algorithm for neural networks that determines a neural network architecture that can learn the train set with some desired accuracy. Section 6 presents a discussion. Finally, Section 7 is the conclusion.

2. Out of scope

Quantum computing and neural networks are multidisciplinary research fields. In this way, the quantum neural computing research is also multidisciplinary and concepts from physics, mathematics and computer science are used. Probably because of this multidisciplinary characteristic there are completely different concepts named quantum neural networks. In this section, we point some models that are out of the scope of this work.

2.1. Quantum inspired neural networks

Neural networks whose definition is based on quantum computation, but that works in a classical computer as in Kouda et al. (2005), Li et al. (2013) and Zhou, Qin, and Jiang (2006) are named in this work as Quantum Inspired Neural Networks. Quantum inspired neural networks are not real quantum models. Quantum inspired models are classical neural networks that are inspired in quantum computing exactly as there are combinatorial optimization methods inspired in ant colony or bird swarm.

In Kouda et al. (2005) a complex neural network named qubit neural network whose neurons act in the phase of the input values is proposed. The qubit neural network has its functionality based in quantum operation, but it is a classical model and can be efficiently simulated in a classical computer.

Another quantum inspired model is defined in Zhou, Gan, Krzyżak, and Suen (1999) where the activation function is a linear combination of sigmoid functions. This linear combination of activation functions is inspired in the concept of quantum superposition, but these models can be efficiently simulated by a classical computer.

Quantum inspiration can bring useful new ideas and techniques for neural network models and learning algorithms design. However, quantum inspired neural networks are out of the scope of this work.

2.2. Physical device quantum neural networks

Devices that implement a quantum neural network are proposed in Behrman, Nash, Steck, Chandrashekar, and Skinner (2000) and Narayanan and Menneer (2000). In this work, these models are named physical device quantum neural network. The main problem of this kind of proposal is the hardware dependence. Scalable quantum computers are not yet a reality and when someone build a quantum computer we do not know which hardware will be used.

In Narayanan and Menneer (2000) a quantum neural network is represented by the architecture of a double slit experiment where input patterns are represented by photons, neurons are represented by slits, weights are represented by waves and screen represents output neurons. In Behrman et al. (2000) a quantum neural network is represented by a quantum dot molecule evolving in real time. Neurons are represented by states of molecules, weights are the number of excitations that are optically controlled, inputs are the initial state of the quantum dot molecules and outputs are the final state of the dot molecules.

Physical device quantum neural networks are real quantum models. This kind of quantum neural networks needs of specific hardware and is out of the scope of this work.