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Neural Networks through Quantum Perspective

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Abstract - *Artificial neural networks, usually just called neural networks, computing systems indefinitely inspired by the biological neural networks and they are extensive in both research as well as industry. It is critical to design quantum Neural Networks for complete quantum learning tasks. In this project, we suggest a computational neural network model based on principles of quantum mechanics which form a quantum feed-forward neural network proficient in universal quantum computation.*

The expert training of the quantum neural network utilizing the fidelity as a cost function, providing an efficient quantum implementation.

Use of methods that enable quick optimization with reduced memory requirements.

Benchmarking our proposal for the quantum task of learning an unknown unitary and find extraordinary generality and a remarkable sturdiness to noisy training data.

***Key Words*: Artificial Neural Networks, Quantum Computation, Optimization Algorithm.**

1. INTRODUCTION

The concept of artificial neural networks has been proposed around the 1950s mainly to mimic the different activities of the human brain. An artificial neural network (ANN) Over the ages, quantum computing has witnessed outstanding development which has a great impact on accelerated computing. Related to the artificial neural network (ANN), an unprecedented, beneficial, and applicable concept has been intimated which is known as a quantum neural network (QNN)[20][5]

QNN has been realised combining the rudiments of ANN with a quantum computation standard which is superior to the traditional ANN.[8] Quantum computers assure notable advantages over classical computers for several different applications. A quantum computer harnesses some of the mystical marvels of quantum mechanics to achieve gigantic bounds forward in processing power. Quantum machines guarantee to outstrip even the most capable of today—and tomorrow—supercomputers. Machine learning (ML), especially applied to deep neural networks via the backpropagation algorithm, has permitted a wide range of innovative applications extending from the social to the scientific.

Quantum computing is based on quantum bits (or qubits) following the rules of quantum physics as opposed to the traditional bits of today that are based on traditional physics. [7] Since Moore's law meets its demise, two brand-new computing paradigms have been found, neuromorphic and quantum computers. Note that in physics the term classical/traditional is used to determine non-quantum and we obtain use of this nomenclature throughout Quantum machine learning strives to find an improvement in employing quantum computing in machine learning. The current study into QML falls into one of two classes.[7] Some quantum algorithms promise innovation in machine learning in theory but contain many gaps in their implementation in practice. In contradiction, others are more realistic in their method, but scuffle to prove a place amongst the well-established techniques of machine learning.

In this proposal, it is explained that a quantum computer can output a quantum state that incorporates the entire cost landscape for a given neural network[7]. The method is shown to be adaptable and has some remarkable properties, as the ability to generalize from very small data sets and a remarkable resiliency to noisy training data.[10]

2. Literature Review

To explain a variety of ideas, ranging from quantum computers imitate exact computations of neural nets, to general trainable quantum that bear only little resemblance with the multi-layer perceptron structure.

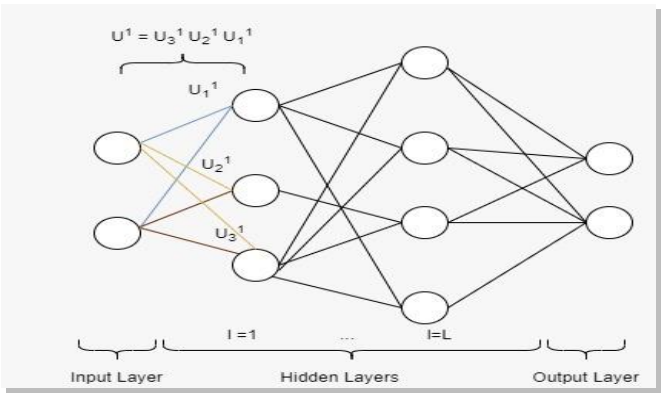

Fig -1: Multi Layer Feed Forward NN

Already in the 1990s, quantum scientists have tried to arise with different quantum versions of recurrent and feed-forward neural networks.

The models were attempts to change the modular edifice and also the nonlinear activation ideas of neural networks into the language of quantum algorithms. However, one could claim that series of linear and nonlinear calculations are rather “unnatural” for quantum computers.[10] More recent research has tackled this dilemma, special estimation designs or changes of the neural nets that make them more responsive to quantum computing, but the advantages of these designs for machine training are still not conclusively established.[2]

As a preparation method, it has important changes as it is landscape-independent, has a quadratic speedup above a regular search of same kind, and would be able to discover statistically vague problems such as parity problems

3. Aim & Objective

We have introduced a quantum analogue from formal neurons, which provide a quantum feedforward neural network skilled in universal quantum estimation.[21] Calculating fidelity as a cost function which is employed by both the traditional and efficient quantum implementations.[15]Memory requirements are significantly reduced and our proposal offers more accelerated optimization: the number of qubits needed scales with only the width, conceding deep-network optimization.[7][4] given neural network We measure the efficiency of our proposal for the quantum task of learning an undiagnosed unitary and find excellent generalization behavior and striking resiliency to noisy training data.

To build a completely quantum extensive neural network competent in universal quantum computation we have found it important to change the existing proposals.[7][21]co A quantum perceptron to be a common unitary executive acting on the corresponding input and output qubits has been defined by us, whose parameters incorporate the weights and biases of past proposals in a complex way. Moreover, we introduce a practice algorithm for this quantum neural network that is effective in a way that it only relies on the breadth of the individual layers and not on the depth of the network.[10][15] We notice that the proposed network has some remarkable properties, as the capability to generalize from very small data sets and a remarkable susceptibility to noisy training data.

4. Scope & Overview

A series of barriers faced by the author of a QML algorithm for quantum data includes obtaining the right quantum generalization of the perceptron, (deep) neural network structure, optimization algorithm, and loss function. In this paper, we face these difficulties and offer a natural quantum perceptron that, when combined into a quantum neural network (QNN), is proficient of carrying out the universal quantum computation [10]

By utilizing completely the positive layer transition maps our QNN design allows for a quantum analog of the standard backpropagation algorithm . We employ our QNN to the task of studying an unfamiliar unitary, both including and excluding errors. Our classical simulation results are very promising and urge the practicability of our system for noisy intermediate scale (NISQ) quantum devices[23]

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5. Implementation

It is an essential consideration that there is no aspect of exponentially disappearing gradients insufficiently expressive parametrized quantum circuits.. In the cost function landscape.[10] We find that the proposed network has some exceptional properties, as the ability to hypothesize from very small data sets and a remarkable understanding to noisy training data sets[17]

5.1 Design Details

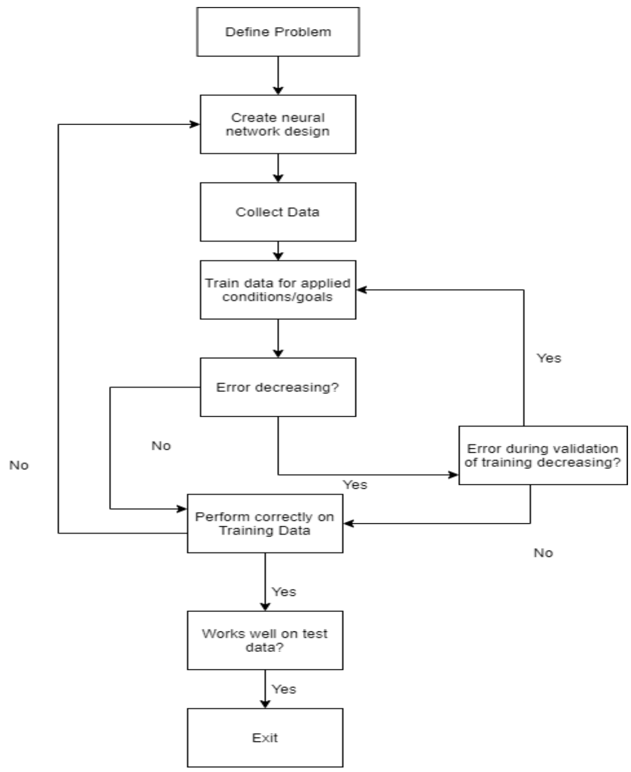

Fig -2: Flowchart

5.2 Network Architecture

The most modest structure block of a quantum neural network is the quantum perceptron, the quantum analog of perceptron used in traditional machine learning. In our proposal, a quantum perceptron is an imperious unitary executive with m input qubits and n allowing qubits. Our perceptron is then readily an imperative unitary suited to the m + n input and output qubits which depend on (2m+n)2−1(2m+n)2−1 parameters. The input qubits are initialized in a likely unknown mixed state ρin and the output qubits in a fiducial output state |0⋯0⟩out|0⋯0⟩out (note that this scheme can easily be progressed to qubits).

For clearness in the following, we focus on the matter wherever our perceptrons act on m input qubits and one output qubit, i.e., they are (m + 1)-qubit unitaries

Now we have a quantum neuron that can express our quantum neural network architecture. With the formal case and sequential operational plans we propose that a QNN is a quantum pathway of quantum perceptrons organized into L hidden layers of qubits, obeying on an initial state of the input qubits, and producing an, in customary diverse state for the output qubits according to

Pout ≡ trin,hid (μ(P ⊗ |0⋯0⟩hid,out <0⋯0|)μ†

Where ,

U≡U out ULUL−1⋯U1 is the QNN quantum circuit,

Ul is the layer unitaries, comprised of a product of quantum perceptron acting on the qubits in layers l − 1 and l. It is essential to note that, because our perceptron are arbitrary unitary operators, they don't usually commute, so that the order of operations is meaningful.

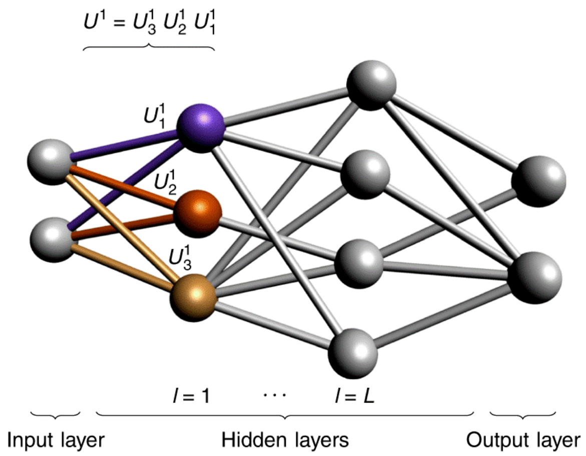

Fig -3: **Feed Forward QNN**

5.3 Simulation

To assess the performance of our algorithm we have thus been reduced to QNNs with small widths.

It's pointless to simulate and Train deep QNN learning algorithms for more than a handful of qubits Carrying out pilot simulations for I/O spaces of m = 2 and 3 qubits and have examined the behavior of the QML gradient descent algorithm for the task of learning a random unitary. We focused on two separate tasks: In the first task, we studied the ability of a QNN to generalize from a confined set of random training pairs (|∣ϕinx⟩, V|∣ϕinx⟩)(|ϕxin⟩, V|ϕxin⟩), with x = 1,…, N, where N was smaller than the Hilbert space dimension. the results are displayed. Here we have outlined the cost function as a general estimate of the optimal cost function which exploits all the available learning (for where n is the number of training pairs, N the number of test pairs, and D the Hilbert[15]. The QNN meets the theoretical estimation and confirms the remarkable ability of our QNNs to generalize.[17]

A quantum neural network has input, output, and L hidden layers. We apply the perceptron unitaries layer-wise from top to bottom (indicated with colors for the first layer): first the violet unitary is applied, followed by the orange one, and finally the yellow one.

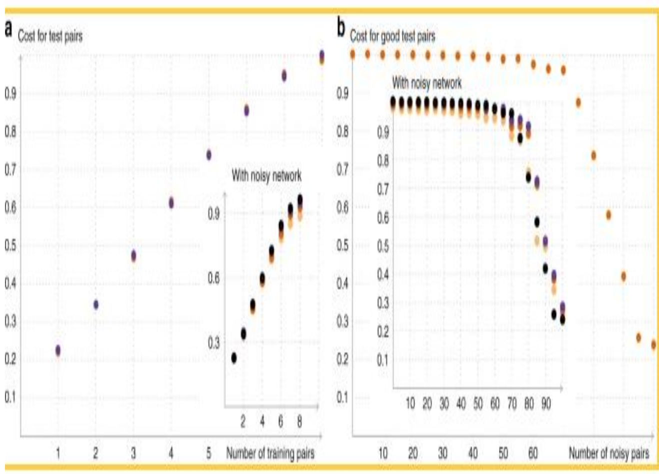

Fig -4: Simulation

5.4 Deliverables

The cost function takes a slightly more complicated form when the training data output states are not pure, which may occur if we were to train our network to learn a quantum channel. the cost function varies between 0 (worst) and 1 (best).

 Minimized cost function for QNN

 Achieved generalization of the quantum neural network against noisy (random) pairs and evaluate corresponding cost function for it.

 Once generalized, checking the robustness of QNN to noisy data

5.5 Assumptions

 A qubit cannot be copied like a classical bit

 The computer has high-performance GPU such as NVIDIA 1080TI

 The quantum computing library has density matrices and ket states for quantum operations.

 The computer has dedicated RAM for training the QNN.

Table -1: Requirements Table

Details of Hardware and Software	
Hardware Requirements	IBM Quantum Computer - 16 GB RAM
Software Requirements	Python-3x scipy,qupit,time,random, matplotlib.pyplot
Technology Used	NeuralNetwork,Quantum Computing

6. Conclusion

It's crucial to emphasize that it will probably be a long time before we have fault-tolerant quantum computers (having copies of qubit) for solving hard problems. Although, we can make important growth in the near term by improving more conventional methods and hardware for implementing quantum error emendation, guided by relatively small-scale experiments with quantum error-correcting codes.

In traditional neural networks arguably, the best-known disadvantage is their "black box" nature, example if we put an image of a dog it predicts it as a man so it becomes difficult to analyze what caused it to arrive at this Prediction.

The network architecture enables a Decrease in the number of intelligible qubits required to store the central states needed to evaluate a QNN. And to store several qubits compared with the width of the network. The network to estimate the derivative of the cost function

We have examined the fundamental quantum generalizations of perceptron and neural networks and thereby advancing an efficient quantum training algorithm. The resulting Quantum Machine Learning algorithm shows remarkable abilities, including, the ability to generalize, resistance to the noisy training data, and an absence of phenomenon of exponentially fading inclinations partly significant parametrized quantum circuits in the cost function landscape. [1]

As we know most of the algorithms are extremely sensitive to noise. Thus, Concluding the quantum perceptron and analyzing the effects of overfitting, and optimized implementation on the next span of NISQ devices.[23]

8. ACKNOWLEDGEMENT

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