Abstract: Reviewing Quantum Algorithms to replace a Feed Forward Neural Network

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A. Introduction

The neural network is a model that classifies data into accurate predictions. A feed-forward neural network (FFNN) is a variation with many applications [1] [2] [3], and it is defined by classical computation. An FFNN "trains" in sequential order by using: 1) Forward Propagation, 2) Cost Measurement, 3) Back Propagation, 4) Parameter Updating (Gradient Descent), and 5) Repeating (1-4) (Gradient Descent).

B. History of Quantum Neural Networks (QNNs)

Recent implementations of a full[4][5] and hybrid[6] QNN have yielded improved run-times. Full QNN improvements were made on small data sets, and each model was restricted by small quantum computers. Hybrid QNN improvements were made on large quantum computers. Benedetti et al. successfully created a hybrid Helmholtz machine to generate base-10 number images on a $2,000$ qubit quantum computer. However, the Helmholtz machine was unable to optimize the "correct" cost function.

C. Objectives & Methodology

Our objective is to replace an FFNN with the quantum approximate optimization algorithm (QAOA) QNN. The complexity of an FFNN scales poorly with large data[7][8], and researchers have not standardized the model of a QNN. We propose a QAOA-QNN with the foundations laid by [9]. We can create a QAOA-QNN by: 1)Encoding a Phase Hamiltonian, 2)Choosing a Mixing Hamiltonian, 3)Setting the initial state, 4) Creating a paremeterized quantum state, and 5) Employing gradient descent to optimize the parameterized quantum state. Further literature review is merited to derive a general-case phase Hamiltonian for the QAOA-QNN. Consider an FFNN once again; it computes the mapping:

$$X_m^{a_m} \rightarrow Y_m \quad (\textit{Classical Mapping})$$

where X are m examples of a_m features, and Y are m examples of one prediction. A FFNN makes this mapping sequentially. The proposed QNN with QAOA instead computes the ideal output by

$$|Y\rangle_m \rightarrow |Y'\rangle_m \quad (\textit{Quantum Mapping})$$

where Y is an initial state for m training examples and Y' are m examples of one prediction. The quantum circuit instead calculates in parallel, following the guidelines of parallelism & interference set by [10].

D. Future Direction

The implications of a QAOA-QNN are extreme; an FFNN with an exponential run-time improvement may classify high-dimensional data within seconds. There has been no application of a QAOA-QNN of the literature reviewed, and the QAOA algorithm shows long-term promise, as quantum hardware is expected to become larger in time. It may be possible to replace the FFNN for a reduced time complexity.

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