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Toward A Quantum Neural Network: Proposing the QAOA Algorithm to Replace a Feed Forward Neural Network

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Toward A Quantum Neural Network



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Introduction

A Feed-Forward Neural Network (FFNN) is used to solve an NP-complete problem[1], but an FFNN becomes inefficient for large input[2]. Over the past decade, researchers have developed a variety of quantum neural network (QNN) analogs. We propose to use the most promising algorithm, which has yet to be implemented by researchers: the quantum approximate optimization algorithm (QAOA).

Methods

$$X_m \rightarrow Y_m \quad (\text{Classical Mapping})$$

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

Figure 1: Mapping of an FFNN vs mapping of the proposed QNN. Given m training examples, the FFNN converts the input features X_m to a binary string of outputs Y_m . The QNN converts a superposition of predictions $|Y\rangle_m$ to a binary string of outputs $|Y'\rangle_m$. The quantum mapping is faster since it is executed in parallel.

Moving QNN toward QAOA

Given m training examples, an FFNN must compute the output for each example sequentially. This requires prodigious time computation, which is undesirable in solving for the ideal parameters, w and b . A QNN with QAOA can, in theory, create m predictions at after one iteration through the circuit, which is analogous to the FFNN model. The caveat is that the Phase Hamiltonian, H_C , becomes incredibly complex with more training examples m . We are left with the steps in the middle column to complete our QNN.

Discussion

The psuedo-quantum algorithm QAOA is the next step toward the implementation of an FFNN. Of the literature reviewed and cited, there has been no application of a quantum FFNN hybrid with QAOA. The only known issue is that QAOA may not scale well with an increased depth of the circuit, since the error of the quantum hardware increases. Since the reliability of quantum hardware is bound to increase over time, the QAOA algorithm shows promise in the long term. We believe it may be possible to apply this algorithm towards an FFNN for a reduced time complexity.

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References

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- 1 Derive the phase Hamiltonian H_C
- 2 Program a QNN on a quantum computer
- 3 Compare the QNN Vs. FFNN runtimes

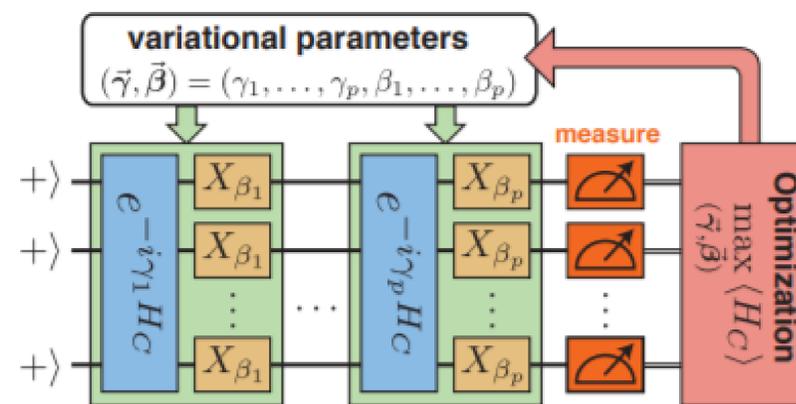


Figure 2: High-level QAOA model which encapsulates the classical and quantum portion (Source: [3]).

Results

After a thorough literature review, we learned that there were limitations of a complete quantum neural network analog, such as poor scaling for complex training examples[4], as well as current hybrid neural network analogs, which have trouble implementing a phase Hamiltonian[5] for unsupervised learning algorithms. Thus, our supervised FFNN will be ideal for the QAOA algorithm, and the phase Hamiltonian will not be impossible to derive.

$$|Y\rangle = \frac{1}{\sqrt{2^m}} |0\rangle_m + \dots + \frac{1}{\sqrt{m}} |2^m\rangle_m$$

Figure 3: Proposed initial state of QNN. The state is a superposition of predictions, which is then condensed into a final state $|Y'\rangle$ of size m .