Efficient Variational Quantum Classifier

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Problem Statement: In supervised setting, binary classifiers classify unknown data into two classes,$y \in [-1, 1]$ based on what they learn from training instances $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ where $y \in [-1, 1]$. First, we typically encode our data in machines and send them to the functions. We then measure the similarity between the actual labels and the classified labels. Finally we optimize our models by changing the hyper parameters of our function that approximates the classes or labels. The data which can be linearly separable is very straight forward and easy to classify. However, real life datas, such as- iris data set, pandas data sets etc, are not linearly separable. So, we apply kernel trick $(k(\vec{x_i}, x_j) =< f(x_i), f(x_j) >)$ to take the data to higher dimensional feature space. But when feature space is getting larger, kernel function estimation becomes very expensive. Quantum computer offers a solution to this problem. With controllable quantum phenomenon, like- entanglement, interference etc., there is a promise of achieving computational speed-ups through quantum algorithms. And one of the most incredible phenomenon is the similarity of the mathematical structure of kernel and quantum models. Quantum feature map takes feature vector $\vec{x}$ to the Hilbert space $|\phi(x)\rangle \langle\phi(x)|$ to enhance the solution. However, we are living in the Noisy Intermediate-Scale Quantum Technology era, where we have only less than 100 qubits. So, we have to find scalable solutions to the quantum machine learning problems. Hence, researchers and scientists of this field often take a hybrid quantum-classical architecture approach to come up with good solutions. This approach contains a variational quantum circuit with measurement operator and cost function. The variational quantum circuit are used to encode the data to the quantum circuit and tune the hyper parameters with rotation operator gates, R_x, R_y, R_z. The cost function measures the similarity between the resultant label of the circuit and actual label. It also updates the parameters of the circuit. This process of updating the circuit hyper parameters to train our circuit to recognize the correct label is often known as optimization. Our main goal is to avoid the local minima and to reach the global minima. Only then we can find the optimum hyper parameters for our circuit. Application of optimal hyper parameters will help us find the correct label to the unknown data similar to training model. With this in mind, we worked with iris data sets. We have found that a hybrid quantum-classical architecture approach is already taken to address the classification problem. However, the training and testing accuracy were very poor and unstable. So, we were assuming that the circuit and the optimizer are not giving the right hyper parameters or the existing approach gets stuck in local minima. That is why we were asking if we can take a different approach to avoid local minima and obtain a better outcome from variational Quantum Classifier.

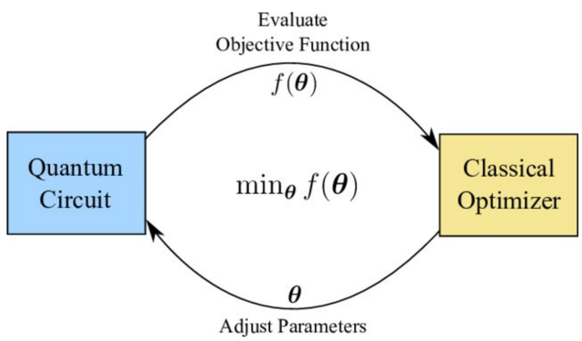

Figure 1: Hybrid quantum-classical Algorithms

Proposed Solution: We have taken an experimental approach to address this problem. First, we observe the way the system was developed. There were two major components. One was variational quantum circuit and another was classical optimizer. In the existing approach, the iris data sets were encoded with the technique known as amplitude encoding. The parameterized circuit has CNOT and R_y gates and measurement is performed on the first qubit. A gradient descent optimizer was used to optimize the hyper parameter of the parameterized circuit. So, with the depth of the circuit=1 and with the first order iterative optimizer, the accuracy were around 0.25-0.3 and unstable. The first problem of the existing solution is the data encoding technique. The existing method has applied such a technique which can be simulated by classical computers. So, there are no quantum advantages with this method. In our approach, we applied a higher order embedding technique proposed by Havlicek V., C´orcoles1 A.D., Temme K., Harrow A. W. Instead of applying $K(\vec{x_i}, \vec{x_j}) = |\langle\phi(\vec{x_i})|\, \phi(\vec{x_i})\rangle|^2$, we applied $U_\phi(\vec{x}) = U_{\phi(\vec{x})} H^{\otimes n} U_{\phi(\vec{x})} H^{\otimes n}$ where $U_{\phi(\vec{x})}$ is much complex operation. This higher order embedding technique is hard to simulate with classical computer. We then implement an ansatz as parameterized circuit with depth 2. The prepared quantum states with this ansatz have only real amplitudes. The complex part is 0 always. From our experiment, we have found that if we increase or decrease the depth of the parameterized circuit, the accuracy of the test result reduced drastically. Additionally, we have changed the cost function of our system. We measured all the qubit of our circuit instead of only the first one.The existing method has Mean Squared Error cost function where as we have found that sigmoid function along with hamming weight works better to estimate the labels. Finally, we tuned and tested the variational quantum circuit with various kind of optimizer. We used optimizers like- Analytic Quantum Gradient Descent (AQGD) with Epochs optimizer, Constrained Optimization By Linear Approximation optimizer, Simultaneous Perturbation Stochastic Approximation (SPSA) optimizer etc. However, Hessian-free optimization or Truncated Newton method improves our classifier and provides us better results.

Result: After applying better encoding technique, ansatz with depth 2, Changing measurement & cost function and testing with Truncated Newton optimizer, we are getting accuracy of 80% with 20% of iris test data.

References:

1. Preskill J., Quantum Computing in the NISQ era and beyond (https://arxiv.org/abs/1801.00862)

2.Schuld M., Supervised quantum machine learning models are kernel methods(https://arxiv.org/abs/2101.11020v2)

3.Havlicek V., C´orcoles1 A.D., Temme K., Harrow A. W.,Supervised learning with quantum enhanced feature spaces9https://arxiv.org/abs/1804.11326)

4. Ahmad S.F, Quantum Machine Learning with HQC Architectures using non-Classically Simulable Feature Maps (Published in IEEE Xplore, 2021)

4. Xiong Y., Chandra D., Xin Ng S., L. Hanzo L., Sampling Overhead Analysis of Quantum Error Mitigation: Uncoded vs. Coded Systems

5. $https : //github.com/qiskit-community/qiskit-community-tutorials/blob$ $/master/machine_learning/custom_feature_map.ipynb$

6. $https : //github.com/Qiskit - Challenge - India/2020/blob/master/Day$ $\%206\%2C\%207\%2C8/VQC_notebook.ipynb$

7.$https : //github.com/Qiskit-Challenge-India/2020/blob/master/Day\%205/Classical$ $\%20Support$

8.$https : //qiskit.org/documentation/stable/0.24/tutorials/machine_learning/03_vqc.html$

9. Lecture: Support Vector Machines, Instructor: Patrick Winston, MIT 6.034 Artificial Intelligence, Fall 2010

10. What is Quantum Machine Learning? - Quantum Computing Tutorial, Channel:Quantum Steve

11. $https : //qiskit.org/documentation/stubs/qiskit.circuit.library.RealAmplitudes.html$