An Approach to Work with Quantum Data in Federated Learning

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Abstract

Quantum Machine Learning (QML) is an emerging field and yet to be discovered. But there are some applications such as classification problems which can be done much more efficiently just by using quantum machine learning. Most of the QML problem is centralized which has some demerits. A better way to approach this problem is thinking about a decentralized way. Where quantum federated learning (QFL) can be a way for future quantum network architecture. This work shows how we can generate quantum data and then apply a hybrid computational model. Furthermore, it shows how our federated model can be trained by using this quantum data.

Introduction

Quantum Computations possess immense possibilities for the future. It excels its classical counterpart in different applications. But some of the applications are proven theoretically but not applied yet. Cause it requires a fault tolerant quantum computer. As scientists and engineers are working on this problem at the same time another way is being considered, which is hybrid computation. By using hybrid computation there is much progress than only using classical one. There are different types of applications where both quantum and classical computations being used. Recent works in quantum federated learning show a new way where we use quantum data and perform federated learning.

Quantum network which can gives us many advantages over the classical network. By using different phenomenon of quantum mechanics such as entanglement and superposition one can achieve supremacy in the communication sector. Although light is being used via optical fiber for communication so it can be a better way of communication if it can be implemented in our day-to-day life. In quantum federated learning users will use quantum data instead of classical one. Also, as we don't have a fully functional quantum network yet. So, then we can think of using a quantum classical or a hybrid network.

Methods and Data

In classical federated learning we check the available user and then send an initial model to them. After that they train that model with their own data on their device and all the parameters from user trained model get to the server and after using federated averaging, we get a new model, and this process continues. As we know quantum networks are not fully developed yet we can think of using a hybrid network architecture. We can generate quantum data on the user's device and then

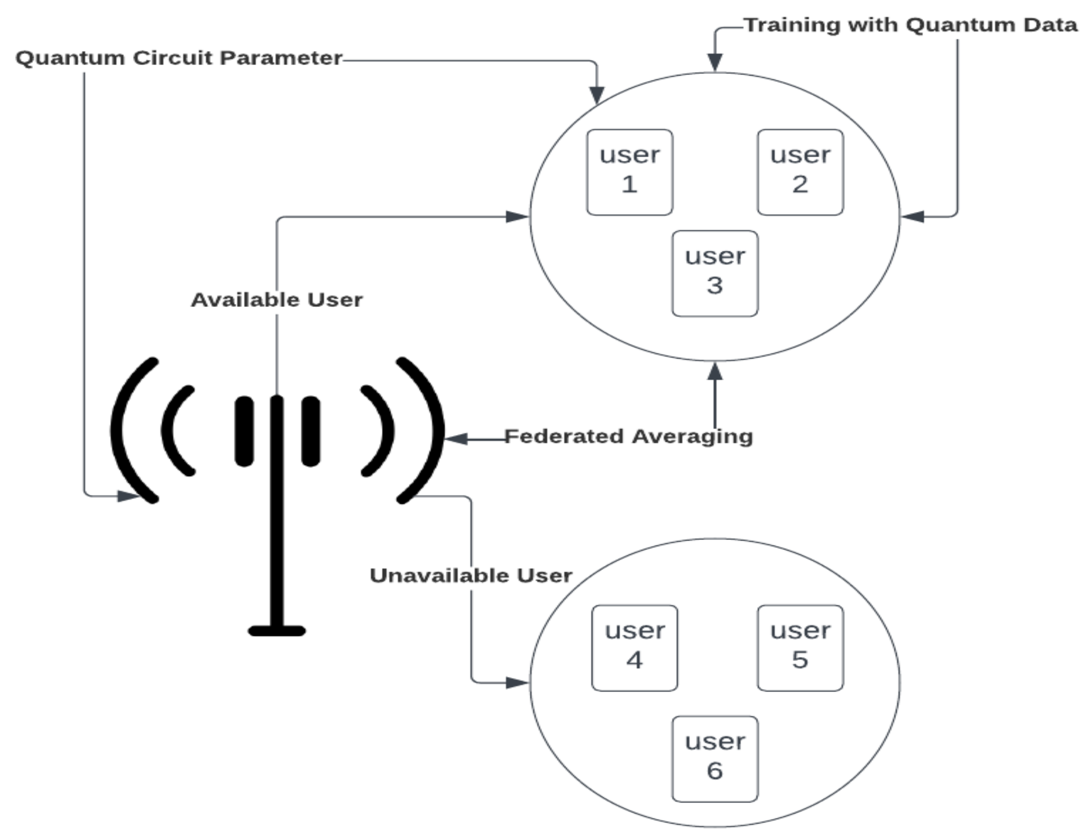

Figure-1: Hybrid Architecture for Federated Learning

train the model with that. After that we can use federated averaging on those quantum circuit parameters and then train our model.

So, for training one's own device with quantum data, first we need to generate a cluster of quantum data. This data set will consist of cluster states with excitation as label. This type of data is important for our network due to its ability to teleport quantum states between quantum clients. First, we will take a range between - Π to + Π and then apply those angles to the RX gate. In order to define the excitation of the quantum cluster state we observe most quantum gates operating on a single qubit can be described as rotation around the Bloch sphere. If the rotations are large enough, then the excitation for that is 1 and if it is not large enough then we are going to take 0 as the excitation which indicates not excited.

After generating quantum data, we are going to define a cluster state circuit which will return the cluster state qubits into bits. By using both H (Hadamard) and CZ gate we are going to do this. Then we will define the required unitary. After all of this we will define our quantum convolutional neural network (QCNN) and then train our model with that.

For the federated part once we get the data, we must make sure that this data can be used by federated learning. Here every data includes an id. Suppose we have 29 clients from $C_0, C_1, \dots \dots, C_{29}$

under this different client ids we will have our federated data. Then we will separate the data for training and testing. Then we will define a keras model based on our quantum cluster circuits so that it can work with quantum data. After all of this we will use federated averaging to train the initial model.

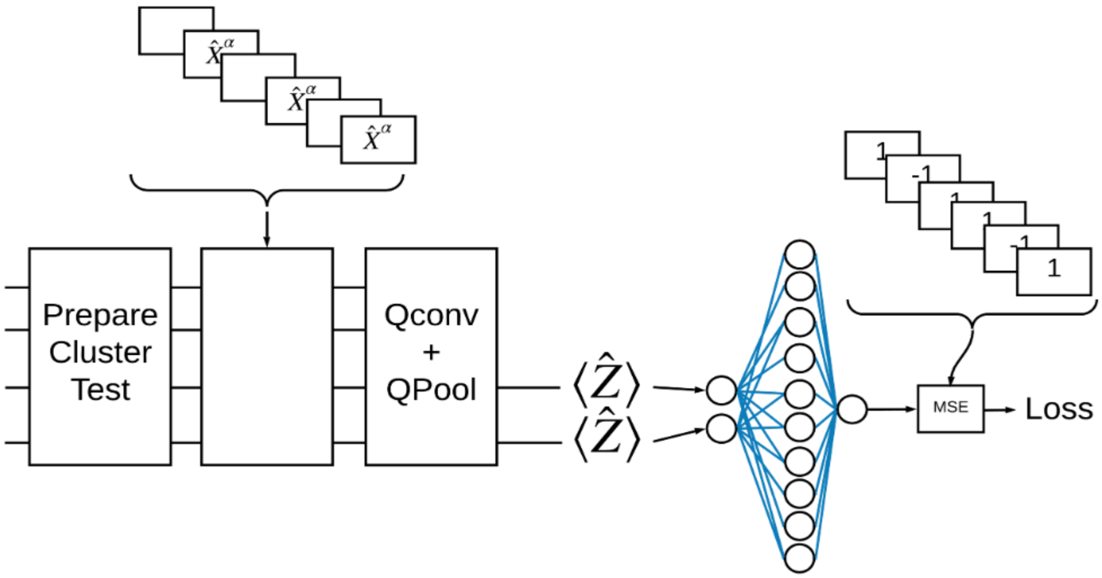

Figure-2: Hybrid model with a single quantum filter(https://www.tensorflow.org/quantum/tutorials/qcnn)

Result

We are going to use TensorFlow quantum to generate data and then make a keras model that connects TensorFlow quantum and federated with each other. However, there is no current version that can connect these three with each other. But we can generate quantum data and train our user device with that data and show validation per epoch. After the model being trained, we will use federated averaging for the quantum circuit parameter. Thus, we can see the result for federated learning with quantum data.

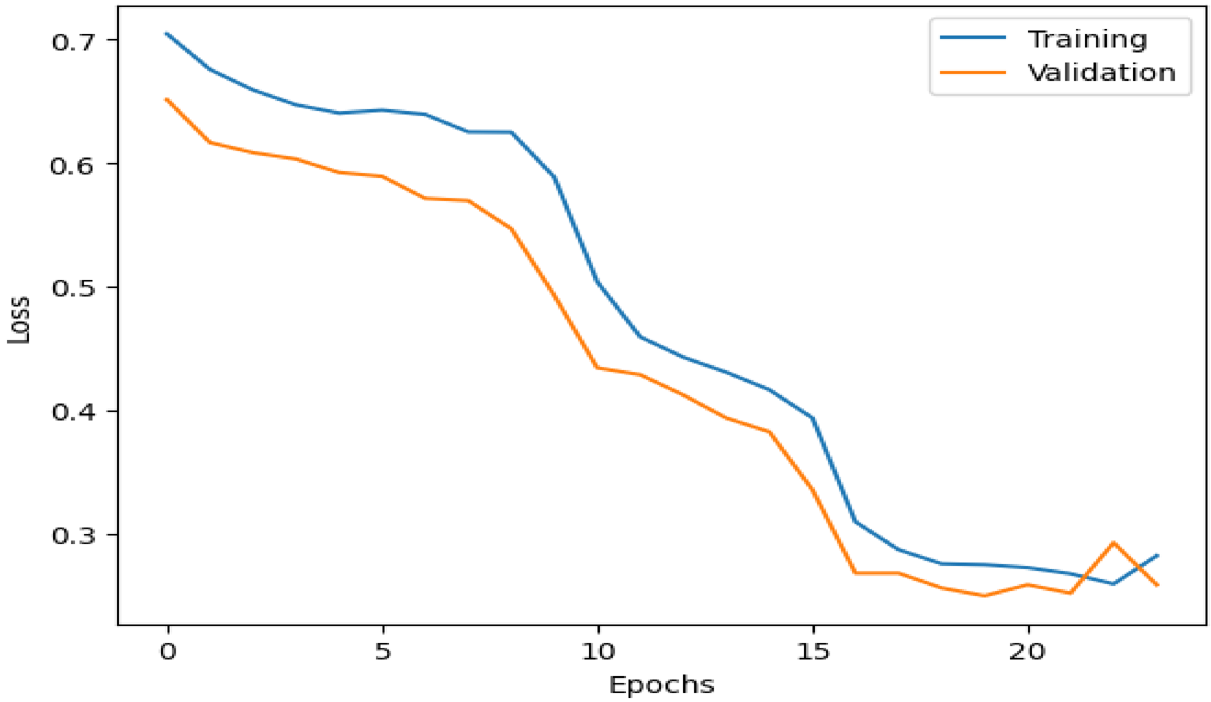

Figure-3: Training a Quantum CNN to Detect Excited Cluster State

Discussion

If we use hybrid architecture such as discussed above, then we will be able to use quantum classical neural network. Where we may have gotten a high accuracy rate. But there are some drawbacks such as generating quantum data for user devices. As we all know there is no quantum device that can be available for a user group. It has some limitations. But If in the future we were able to overcome those limitations then that will be another step towards our evolution. Though this project is not completed due to some version compatibility between TensorFlow, TensorFlow quantum and TensorFlow federated. But hopefully the issue will be noticed and will be solved. Until then this project will continue.

References

1. Chehimi, M. (2021). Quantum Federated Learning with Quantum Data. Quantum Physics (Quant-Ph); Machine Learning (cs.LG); Networking and Internet Architecture (cs.NI). https://doi.org/10.48550/arXiv.2106.00005

2. Zhao, H. Non-IID quantum federated learning with one-shot communication complexity. Quantum Mach. Intell. 5, 3 (2023). https://doi.org/10.1007/s42484-022-00091-z

3. Enrique Tomás Martínez Beltrán (2022). Decentralized Federated Learning: Fundamentals, State-of-the-art, Frameworks, Trends, and Challenges. Machine Learning (cs.LG); Cryptography and Security (cs.CR); Distributed, Parallel, and Cluster Computing (cs.DC); Networking and Internet Architecture (cs.NI). https://doi.org/10.48550/arXiv.2211.08413

4. Cong, I., Choi, S. & Lukin, M.D. Quantum convolutional neural networks. Nat. Phys.15,1273-1278 (2019). https://doi.org/10.1038/s41567-019-0648-8