Network sciEnce, Wireless, and Security Group

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Quantum Federated Learning with Quantum Data

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GOALS and OBJECTIVES

- Investigation of the **federated learning** setup for sharing a quantum machine learning (QML) task between quantum clients with purely-quantum data.
- Analysis of the potential to integrate existing classical communication networks instead of quantum networks in the quantum federated learning (QFL) setup.
- Addressing the practical implementation-related limitations rendering the wide-spread adoption of distributed quantum learning frameworks.
- Generating the first quantum federated dataset in the literature, which is necessary for future advances in the field.

CHALLENGES & MOTIVATION

- Prior work mainly focused on centralized QML models, not distributed learning.
- None of the existing works that consider FL scenarios with QML models rely on purely-quantum data, and there is not quantum federated dataset in the literature.
- Advances in quantum computing technologies happen at a much faster pace compared to advances in quantum communication networks, which are still lossy and unreliable for the transmission of quantum data.

QUANTUM MACHINE LEARNING

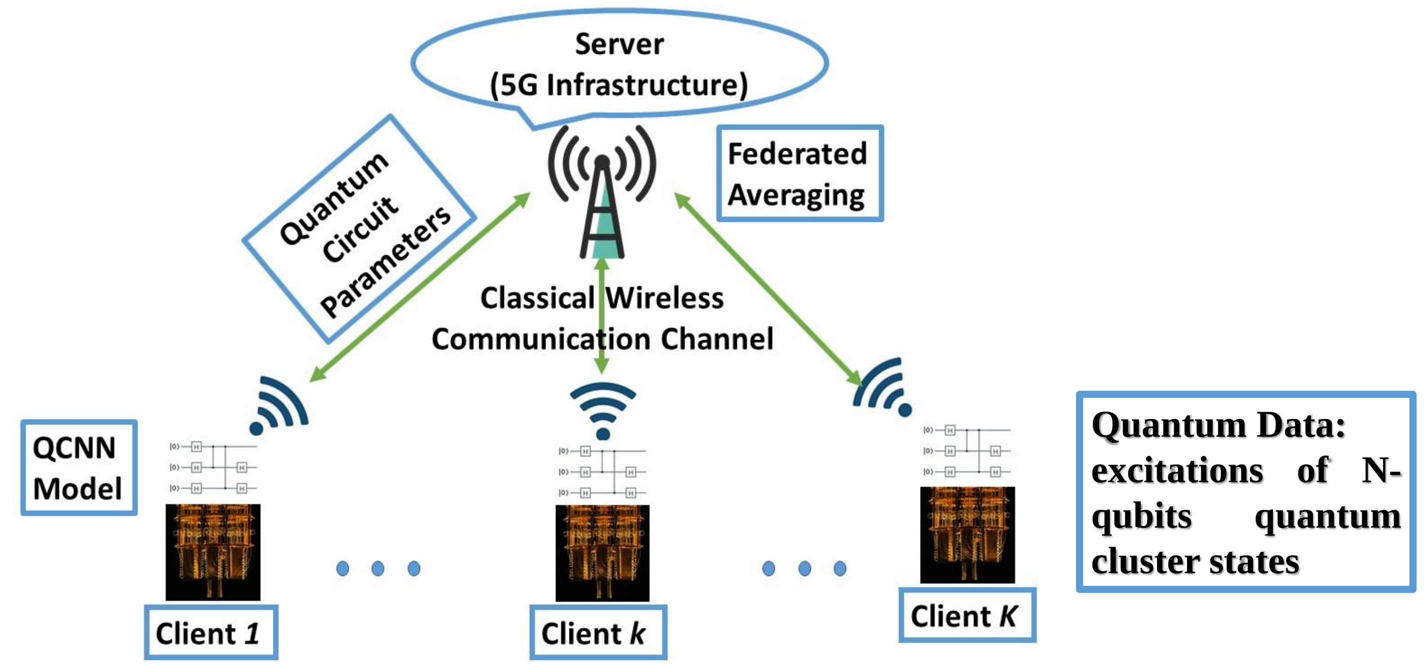
- Includes three major areas:
  - ❑ Quantum-assisted classical ML.
  - ❑ Hybrid quantum-classical ML.
  - ❑ **Purely-quantum QML.**
- Parametrized quantum circuits with tunable classical parameters.
- Purely-quantum QML models are necessary for **quantum many-body systems** that have a complex, exponentially large Hilbert spaces, which usually have intractable theoretical analysis.
- Quantum convolutional neural networks (QCNN) for classification tasks.
  - A sequence of quantum convolutional layers (unitary quantum gates), followed by quantum pooling layers (reduce size by quantum measurements), and end with a quantum fully-connected layer.

QFL Framework

- Each client has labeled input pairs $(|\psi_m\rangle, y_m)$: $m = 1,2,\dots,M$, where $|\psi_m\rangle$ is the m-th sample quantum state, y_m is the m-th binary label (cluster state excited or not), and M is the number of data samples.
- All K clients share the same QCNN model.
- The QCNN parameters $\boldsymbol{\theta}^k$ are classical values that can be sent using existing classical communication networks.
- Each client trains its QCNN model f by minimizing MSE loss function:

$$\arg\min_{\boldsymbol{\theta}^k} \mathfrak{I}(\boldsymbol{\theta}^k) := \frac{1}{2M}\sum_{m=1}^{M}\left(y_m - f_{\boldsymbol{\theta}^k}(|\psi_m\rangle)\right)^2$$

- Each round h of the server applies federated averaging to aggregate and update the parameters for all users.



SCIENTIFIC INSIGHTS and FUTURE OUTLOOK

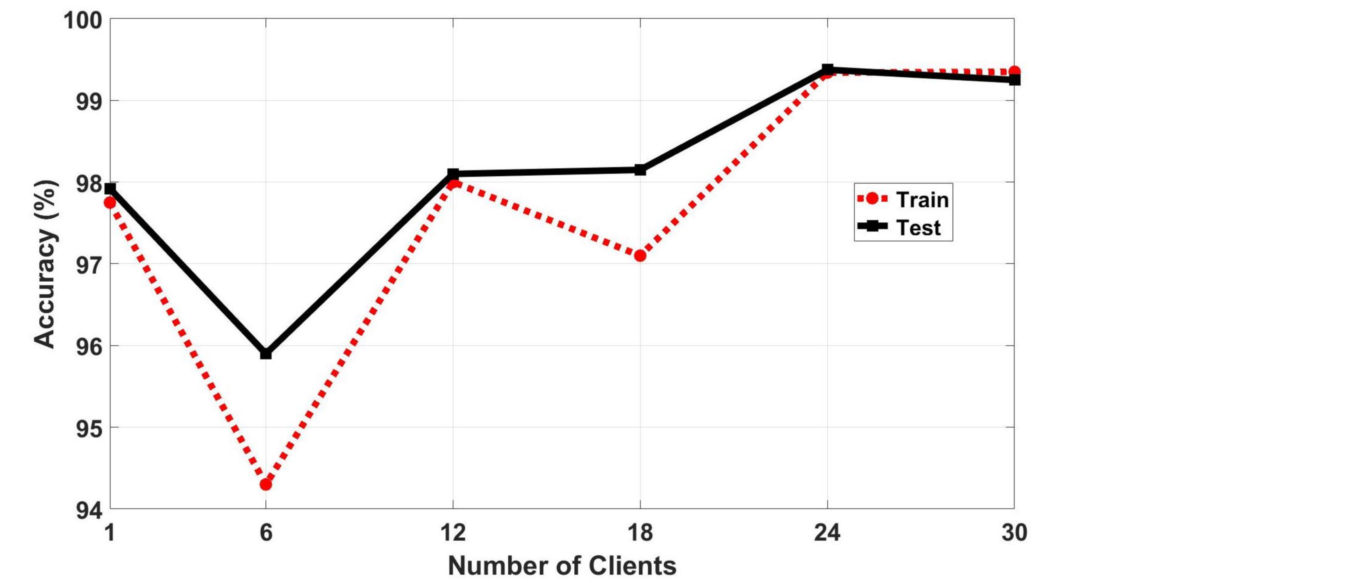
- A short-term solution to bridge the gap between advances in quantum computing and quantum communication networks by leveraging the existing classical networks.
- Lead to the development of hybrid networks with both classical users and quantum users with purely-quantum data.
- Quantum cryptographic techniques can be utilized to add an extra layer of security for the QFL setup, e.g., integration with quantum key distribution.
- Developing interfaces between different quantum technologies would advance the QFL framework towards incorporating both classical and quantum networks.

QUANTUM FEDERATED DATASET GENERATION

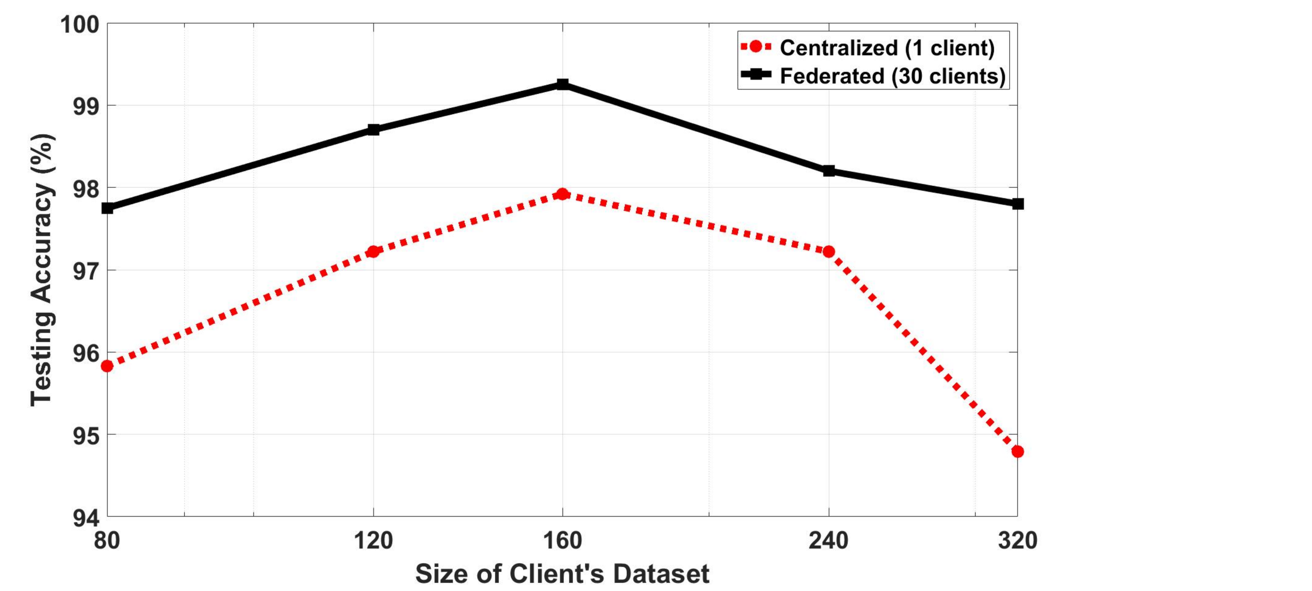
- Used TensorFlow Quantum (TFQ) and Google's quantum circuit programming: Cirq to generate single-client data.
- **Data: excitations of quantum cluster states represented by Rx rotations.**
  - If large-enough rotation is achieved ⟶ label = 1.
  - If rotation is not sufficiently large ⟶ label = 0.
- For each client, the inputs are quantum circuits.
- To store the data: transform into a tensor represented by strings.
- The strings represent an encoding of the serialized binary data of quantum circuits (TensorFlow data type: "1S5000").
- We generated a hierarchical data format version 5 (HDF5) federated dataset with different numbers of clients
- Each client has M labeled serialized binary data for a single feature.

SAMPLE RESULT: ENTANGLEMENT RATE OPTIMIZATION

- What is the impact of the number of clients on the achieved testing accuracy?



- What is the impact of the size of the datasets of the clients on the achieved testing accuracy?



SELECTED REFERENCES

1. M. Chehimi and W. Saad, "Entanglement rate optimization in heterogeneous quantum communication networks," in 2021 17th International Symposium on Wireless Communication Systems (ISWCS). IEEE, Sept. 2021, pp. 1–6.
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