Deakin's Quantum ML Research: Quantum Federated Learning with Simple Data Encoding and Aggregation

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ABSTRACT

Quantum computing provides unprecedented computational power, revolutionising fields such as healthcare, finance, and cybersecurity, particularly through advancements in machine learning [1]. Quantum Federated Learning (QFL) combines Federated Learning (FL) with quantum machine learning (QML) over distributed quantum networks, significantly enhancing computational efficiency and model performance while ensuring data privacy and security [2].

At Deakin University, we address the challenges of implementing QFL on cloud platforms by focusing on quantum complexities and constraints. Our innovative approach introduces a data-encoding-driven QFL, demonstrating its effectiveness with genomic datasets [3]. By deploying a QFL algorithm on cloud-based quantum platforms using IBM's Qiskit library, we aim to accelerate QFL adoption and facilitate efficient training models while ensuring local privacy.

The core innovation of our solution lies in the FL integration of novel quantum encoding and weighted aggregation techniques. These advancements enable us to capitalise on high-performing clients and reduce the influence of low-performing ones, ensuring robust model performance across diverse datasets. Our data-encoding-driven QFL employs amplitude encoding to streamline model training, utilising a fraction of the typically required qubits, which is particularly advantageous for complex genomic analysis [3].

Key novelties in our research include:

- *New Data Encoding Techniques*: Introduction of amplitude encoding to efficiently transform classical data into quantum states, enhancing computational efficiency and reducing qubit requirements.
- *Simple Weighted Aggregation Methods*: Development of three aggregation schemes—Simple Averaging, Weighted Averaging, and Best Pick—to effectively manage client updates and prioritise high-performing models [2].
- *Cloud-Based Implementation*: Utilisation of IBM's Qiskit library on cloud-based quantum platforms to ensure scalability and accessibility, facilitating widespread adoption of QFL [4].

Although QFL promises exponential speedups, it is currently limited by the nascent stage of quantum hardware development. Leading technology companies such as IBM, Amazon, and Microsoft strive to provide cloud-based access to quantum processors. IBM is at the forefront with its 433-qubit quantum processor, while Amazon and Microsoft provide access to third-party processors like IONQ's Harmony and Rigetti's Ankaa-1. Despite challenges in software standardisation and cloud-based access, IBM's Qiskit framework shows considerable potential [4]. Qiskit's quantum simulators are crucial for allowing developers to test algorithms on classical computers, facilitating rapid prototyping, and reducing the iterative refinement of algorithms while faithfully emulating actual quantum system behaviour [5].

Our QFL methodology includes several different realisations each consisting of local training, parameter sharing, aggregation, and global model updates, ensuring privacy while enabling collaborative model training. By adhering to FL principles and employing the Mean Squared Error (MSE) loss function via VQC, we ensure precise and reliable model performance.

We demonstrate the operationalisation of QFL via Qiskit, showcasing our innovative data encoding and weighted aggregation techniques. By employing genomic datasets, we train a decentralised QFL model crucial for understanding genomic sequences. This dataset, chosen for its ample sample size, holds significant potential for future QFL applications [3]. Demonstrated on the IBM Cloud platform, our algorithm employs multiple QML models, following essential steps such as data preparation, model training, and aggregation of updates from multiple clients [6].

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