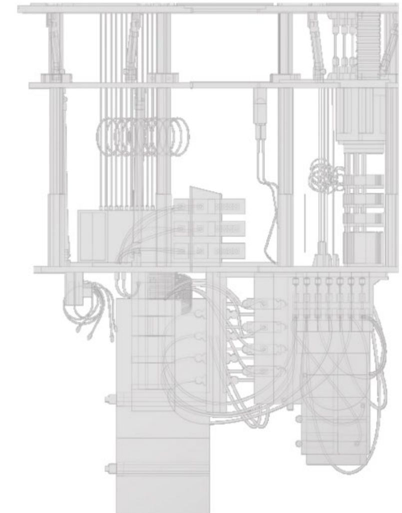

“Federated” Quantum Machine Learning in Health

Keeping data decentralized

Amandeep Singh Bhatia
Postdoctoral Research Associate,
Davidson School of Chemical Engineering,
Purdue University, IN, 47907

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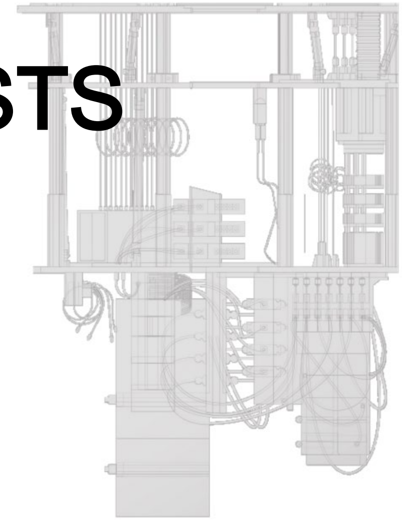
RESEARCH INTERESTS



Quantum computational models

Formal languages
quantum automata models, two-way multi-head models, quantum queue automata

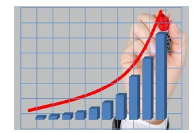
Applications of QC models

Biology & Chemistry
RNA, DNA formal languages & Chemical reactions

Tensor Network

MPS quantum circuit for classification
one-dimensional MPS for binary classification

Quantum optimization algorithms



IBMQ

Finance & WSNs

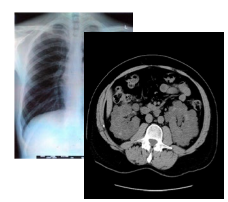
QAOA for Portfolio optimization problem, network coverage problem in WSN

Quantum machine learning

VQCs

Visualize the loss landscape of VQC for classification

Quantum federated learning

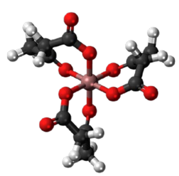


Google Quantum Virtual Machine

Healthcare

Hybrid quantum-classical and QCNN for medical imaging tasks

ChemInformatics



IBMQ & Pennylane

Chemistry

Control Blood-Brain penetration via quantum computers

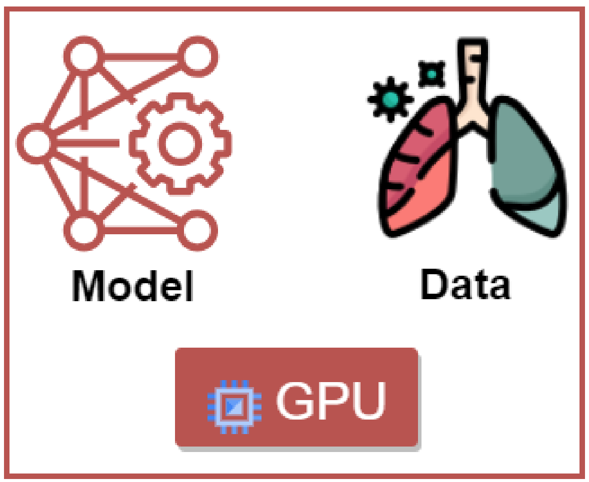
ROADMAP OF THE TALK

Federated Quantum Machine Learning

Federated Learning	Quantum Machine Learning	Quantum Federated Learning
- The reliance on data - Federated efforts - Deployment - Applications - Challenges	- QML models in AI - CNNs - QNNs - Applications - Challenges	- QC + FL - Data distribution - Deployment in Healthcare - Results - Challenges

DATA-DRIVEN MEDICINE

Data Governance and Privacy

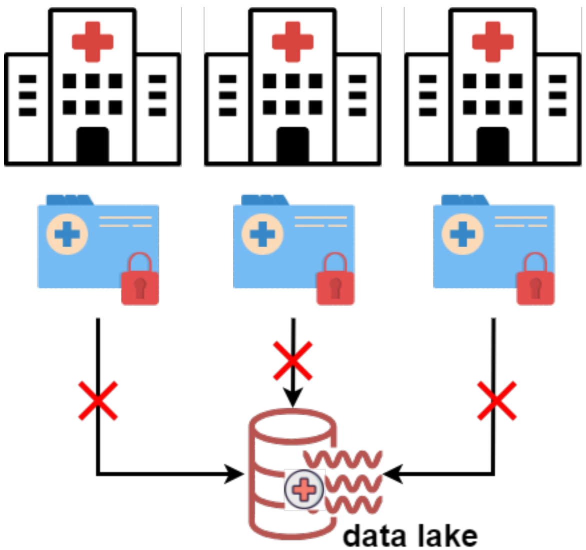


- Training of robust and accurate deep learning models requires large and diverse datasets.
- Research is driven by data lakes (centralized repository).
- Real-world data are not fully exploited by machine learning.

Demographic Bias / Healthcare in remote areas / Hindered Research?

THE RELIANCE ON DATA

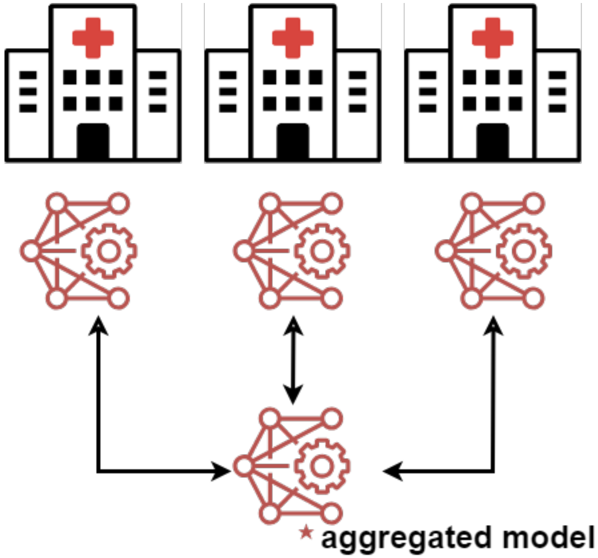
ROBUST MODELS, LARGE SCALE TRAINING



- Healthcare data is highly sensitive, subject to regulations, and cannot easily be shared.
- Biases where demographics or technical imbalances impact predictions.
- Adequate datasets are difficult to obtain:
  - Regulatory, ethical legal challenges
  - Technical challenges

THE PROMISE OF FEDERATED EFFO

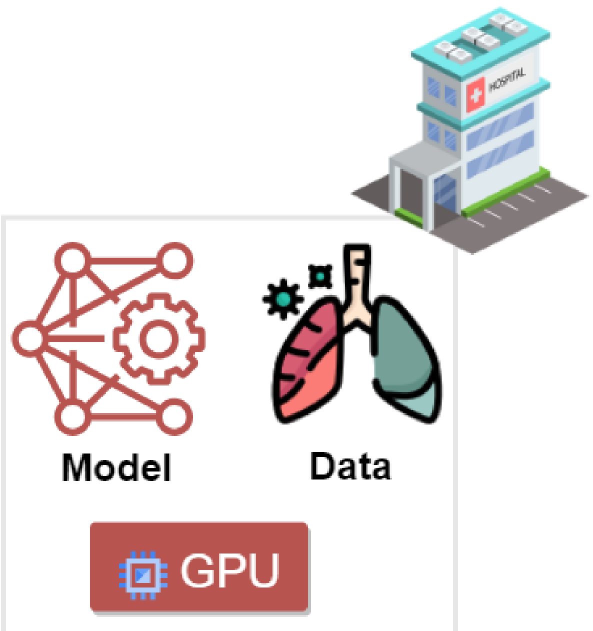
ROBUST MODELS, LARGE SCALE TRAINING



- Share **model updates**, not data
- Collaborative learning without centralizing data
- Address privacy and data governance challenges
- AI training occurs locally at each participant/client
- Participant controls data access and the ability to revoke it.

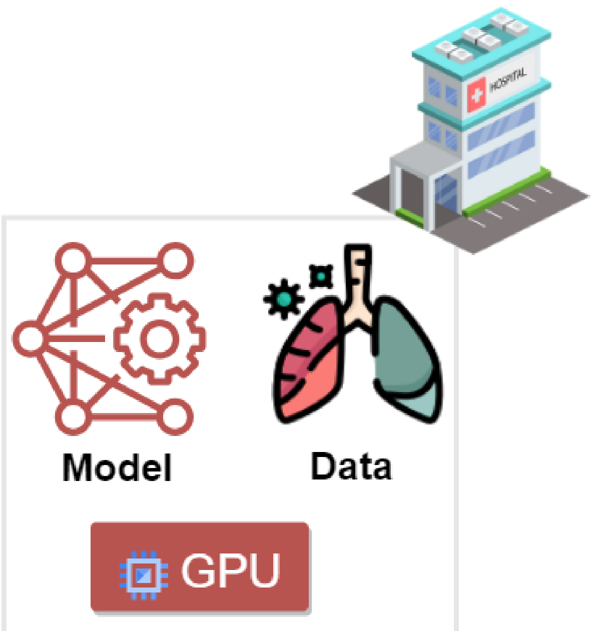
DATA-DRIVEN MEDICINE REQUIRES FEDERA

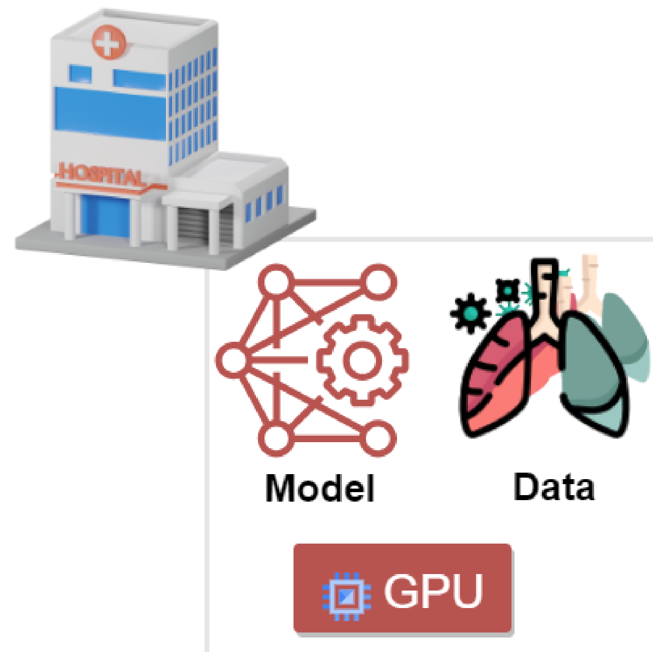
Federated Learning Solution



DATA-DRIVEN MEDICINE REQUIRES FEDERA

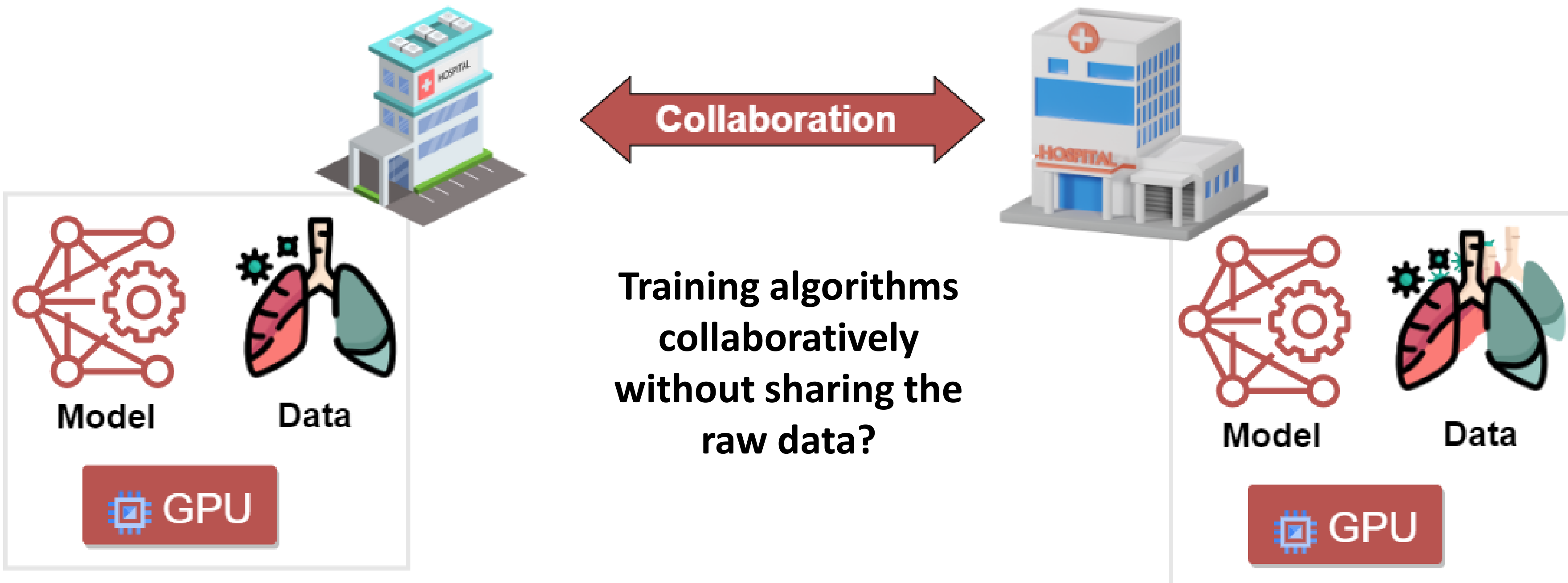
Federated Learning Solution





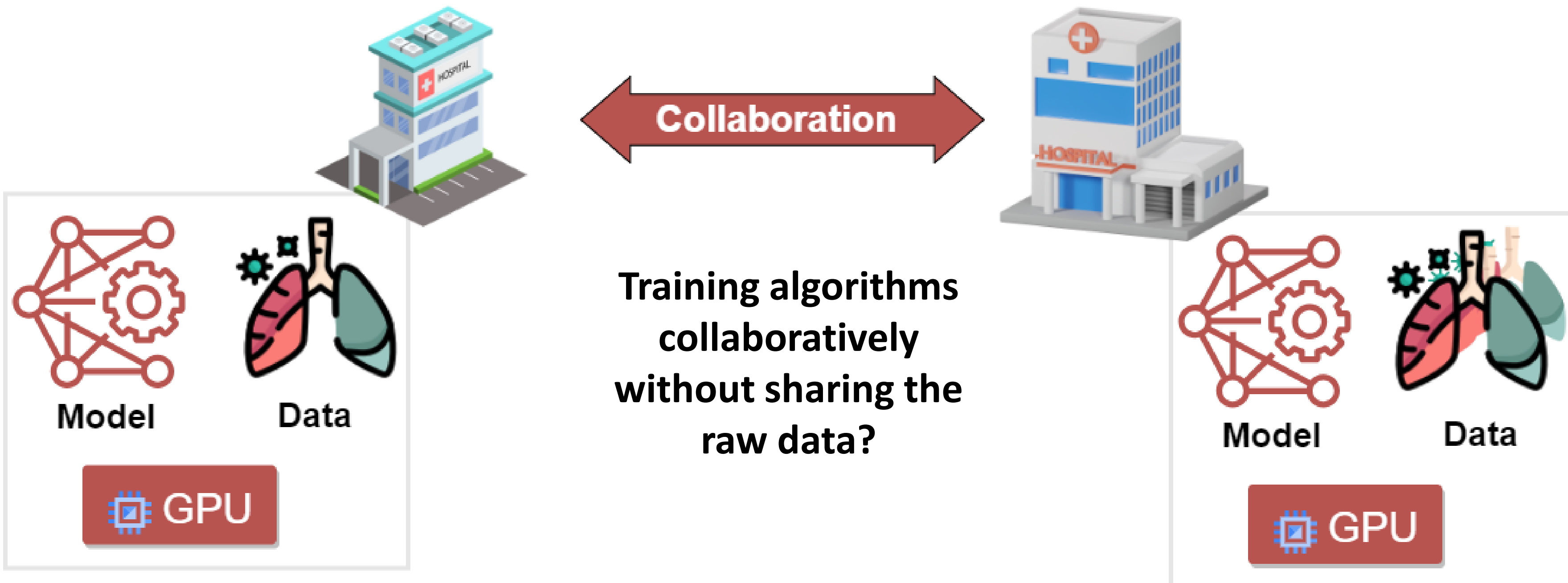
DATA-DRIVEN MEDICINE REQUIRES FEDERA

Federated Learning Solution



DATA-DRIVEN MEDICINE REQUIRES FEDERA

Federated Learning Solution

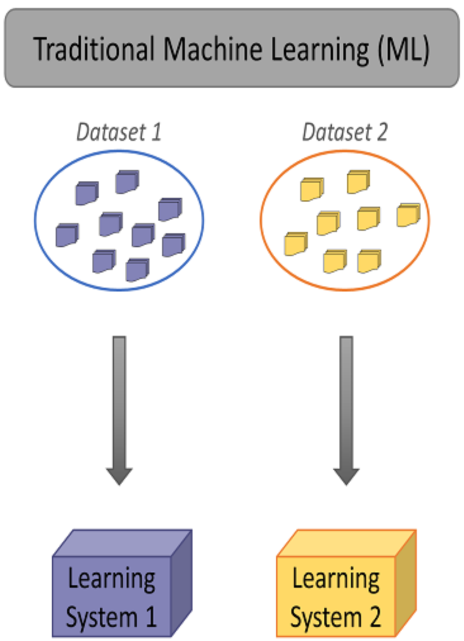


Possible Solution:

Federated Learning – allow algorithms to learn from non co-located data

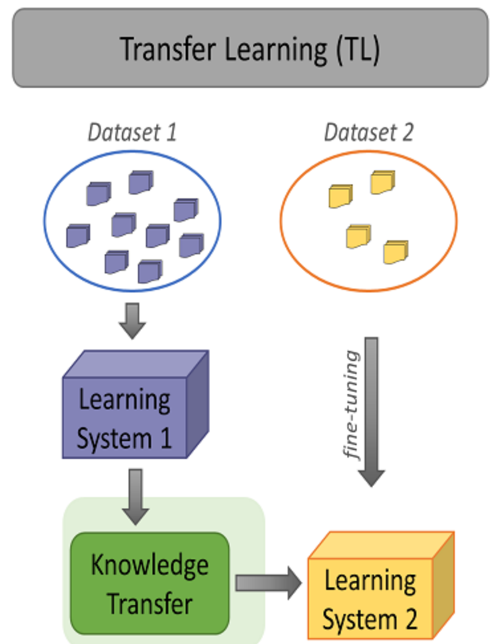
LEARNING PARADIGMS

A NEW WAY OF LEARNING



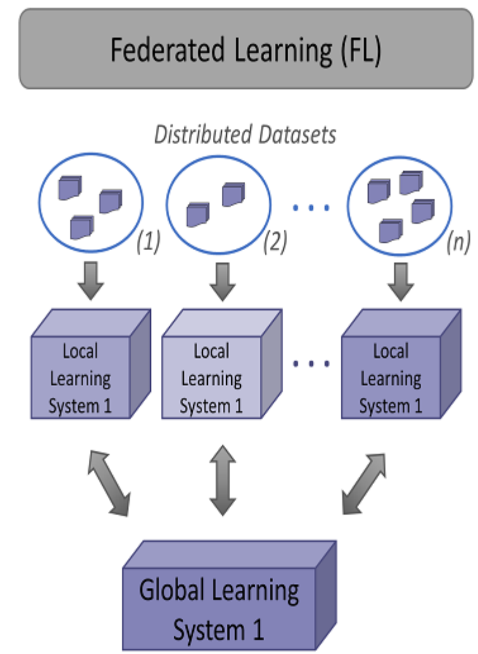
Dataset and Training in House

Local Training, Local Model



Finetune a pretrained Model

Local Training, Adept External Model



Collaborative Learning without sharing dataset

Local Training, Collaborate on Global Model

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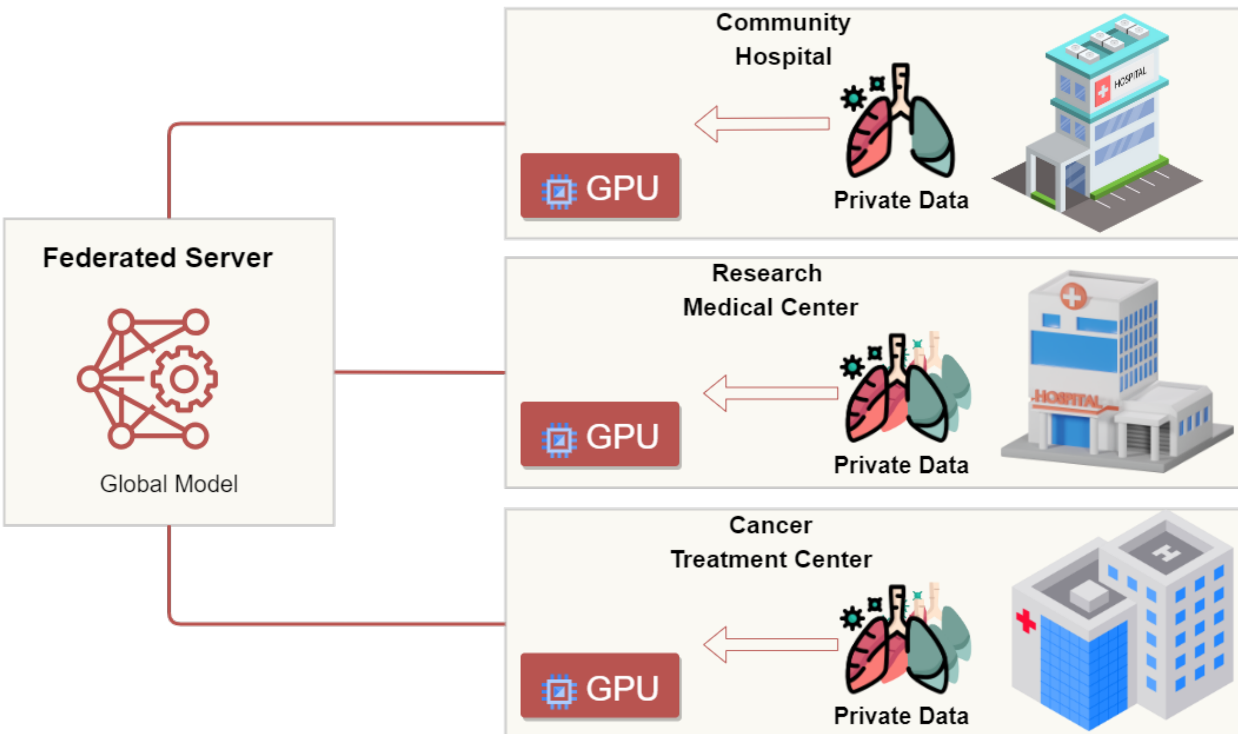
WHAT IS FEDERATED LEARNING

Changing the way AI algorithms are trained



WHAT IS FEDERATED LEARNING

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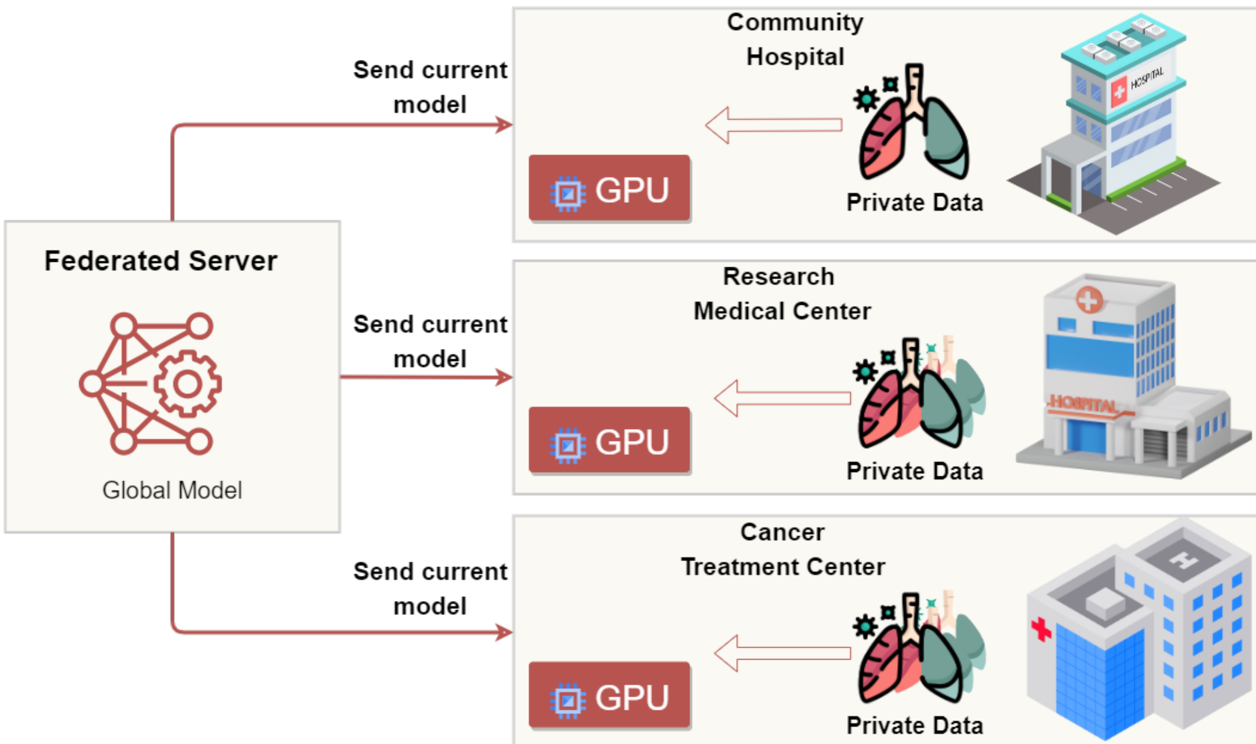

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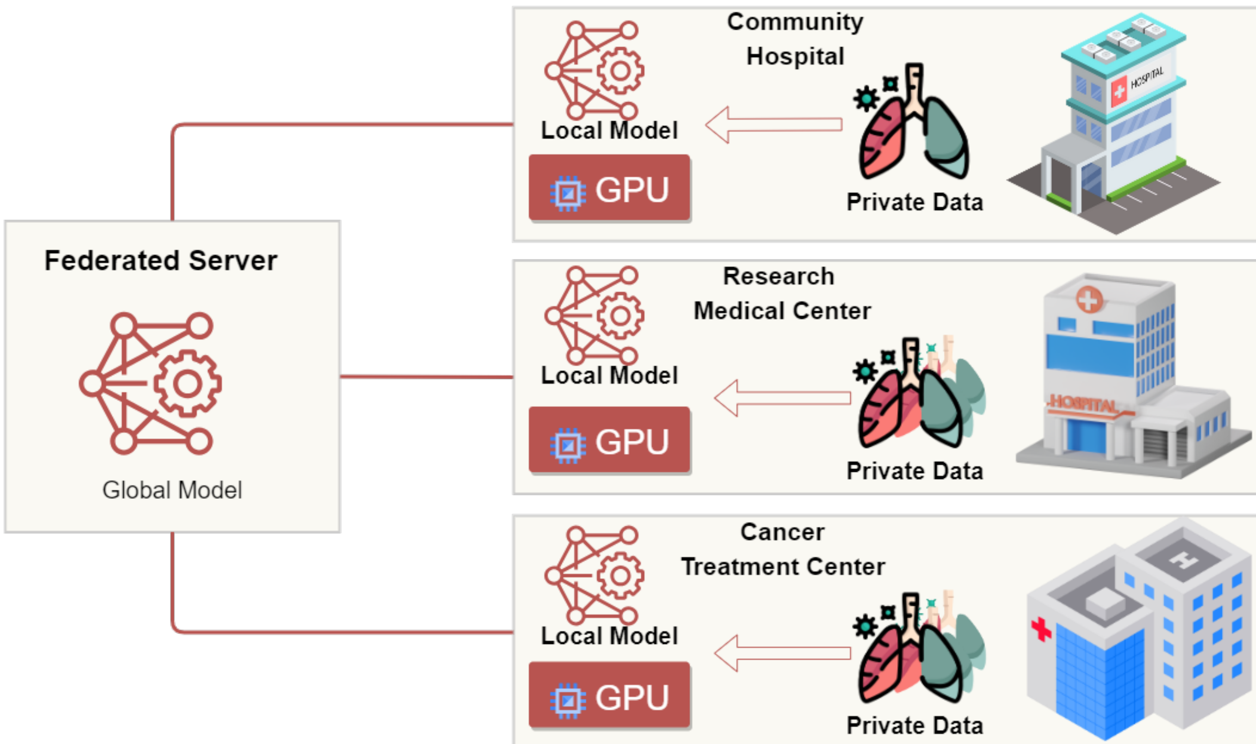

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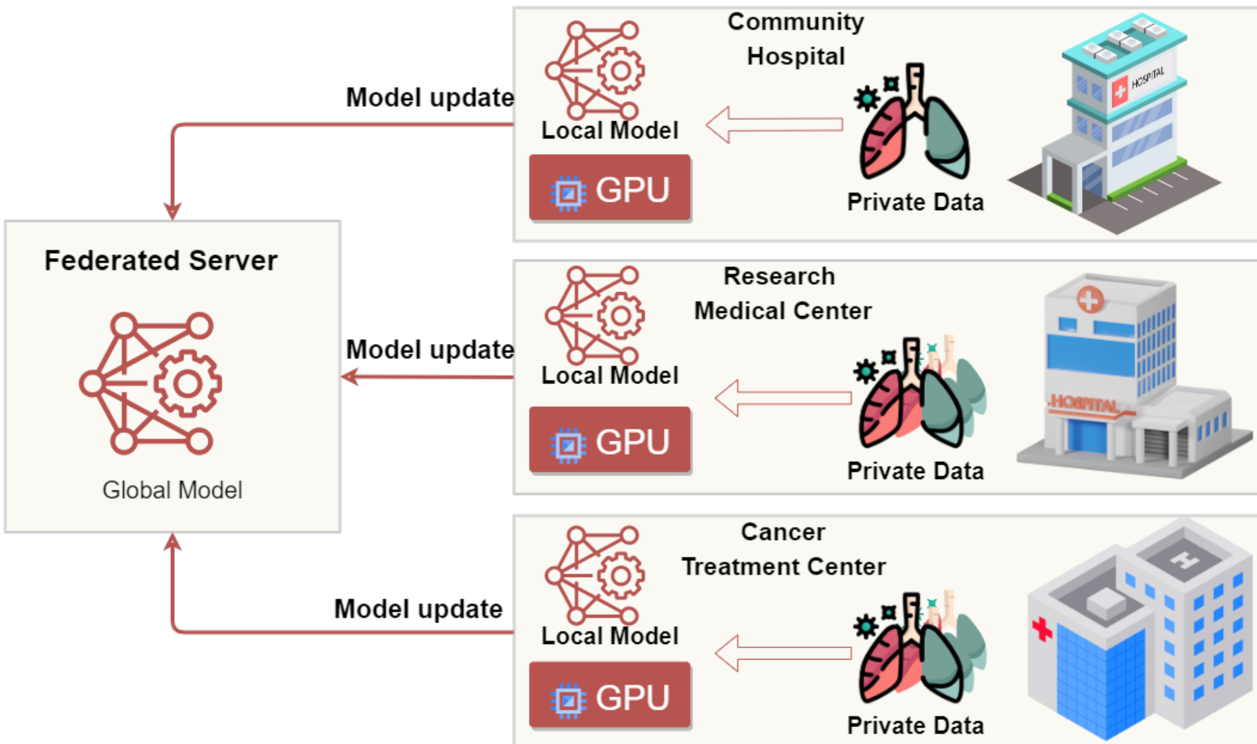
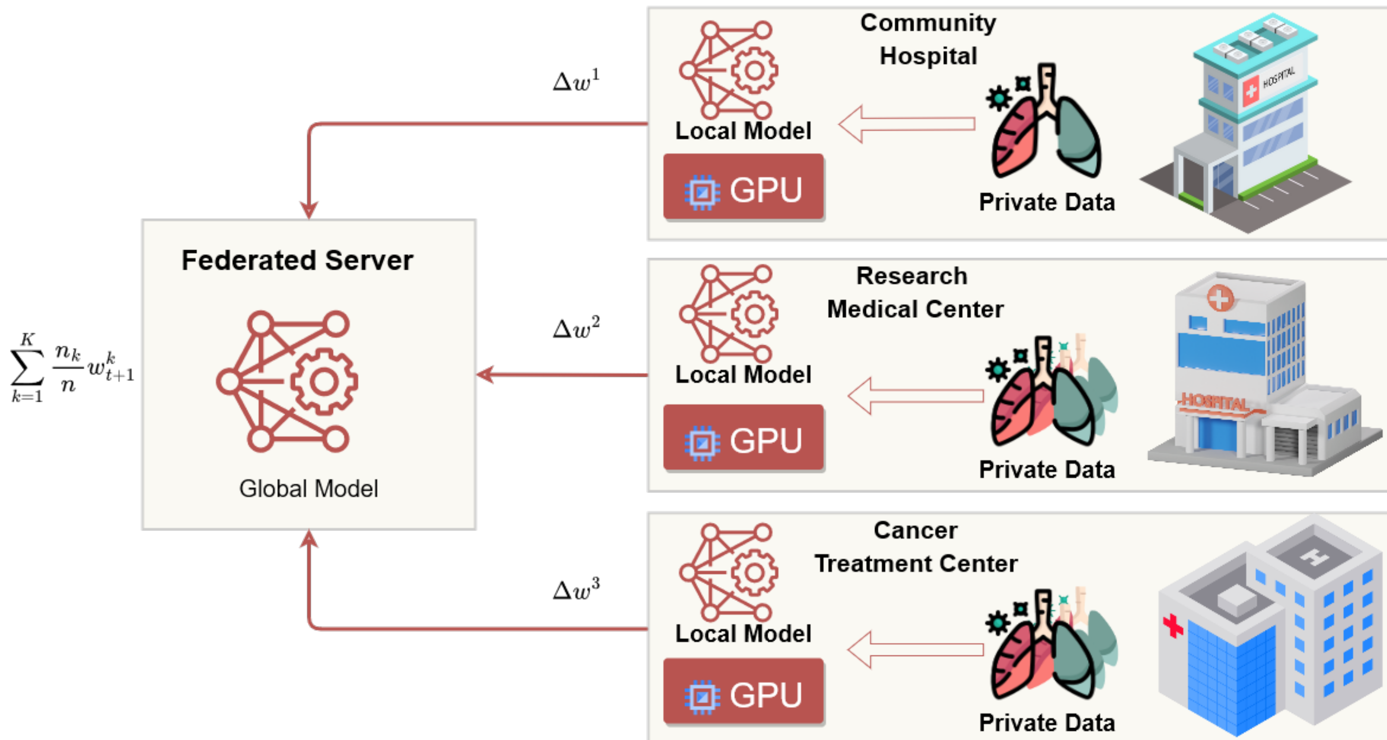


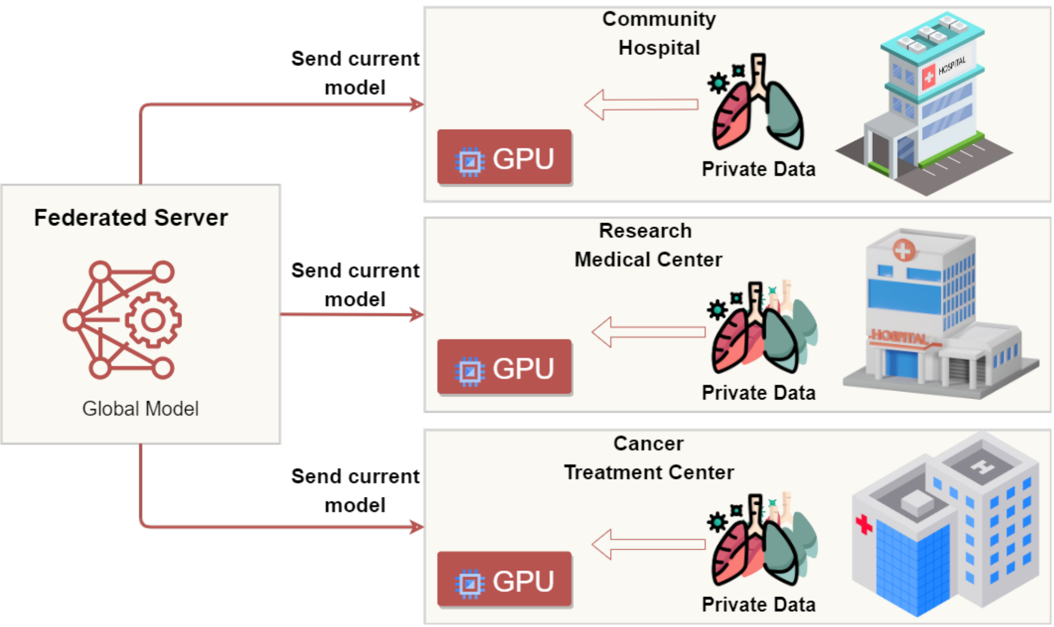
WHAT IS FEDERATED LEARNING

Changing the way AI algorithms are trained



FL APPLICATIONS & CHALLENGES

Changing the way AI algorithms are trained



Applications:

- Learning activities of mobile phone users (**in Google**), voice assistant Siri (**in Apple**)
- Adapting to pedestrian behavior in autonomous vehicles (**in Tesla**)
- Predicting health events like heart attack risk from wearable devices (**in Apple**)
- Predicting vehicles behavior due to varying weather, changing road conditions (**in BMW**)

Challenges:

Expensive Communication

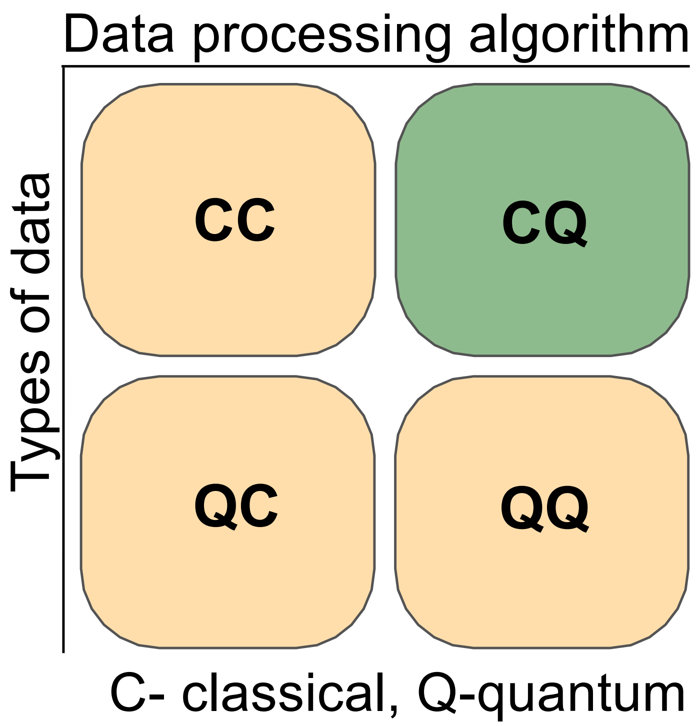
Systems Heterogeneity

Statistical Heterogeneity

Privacy Concerns

QUANTUM MACHINE LEARNING

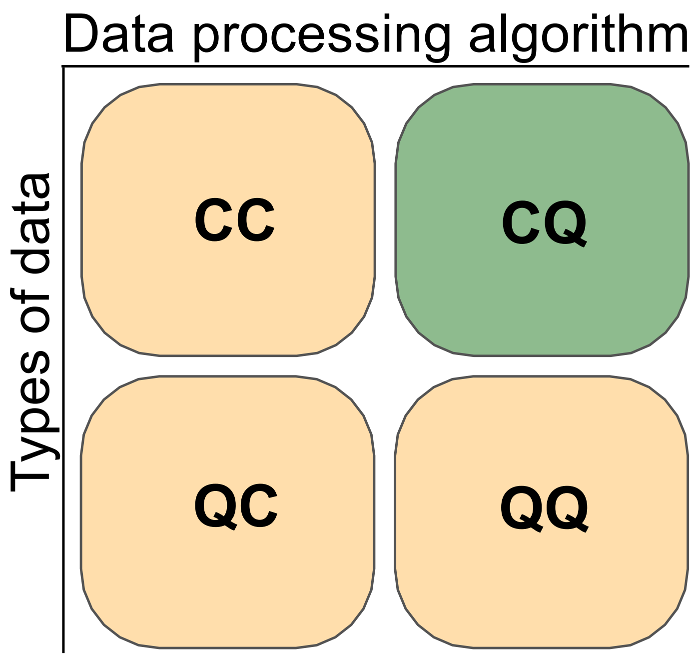
Combine Quantum Computing & Machine Learning



$$y = g(x)$$

QUANTUM MACHINE LEARNING

Combine Quantum Computing & Machine Learning



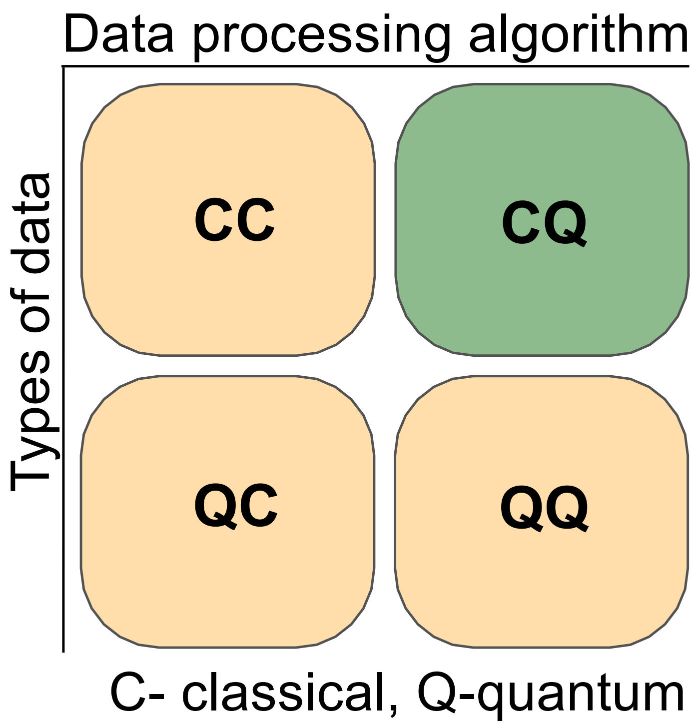
C- classical, Q-quantum

$$y = g(x)$$

$$y = f(x, \theta)$$

QUANTUM MACHINE LEARNING

Combine Quantum Computing & Machine Learning



$$|f(x, \boldsymbol{\theta})\rangle$$

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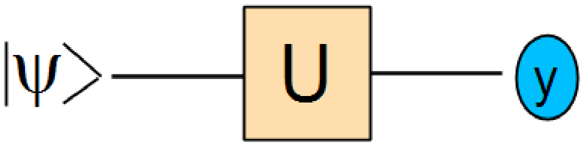
QUANTUM MODELS

Combine Quantum Computing & Machine Learning

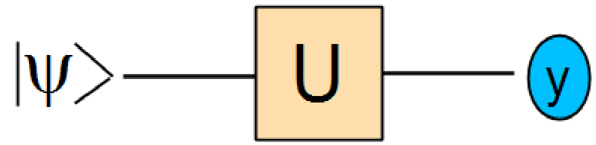
- **Deterministic quantum models**
  - Deutsch-Jozsa algorithm



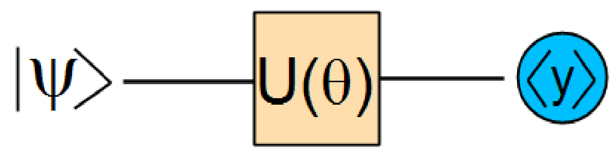
QUANTUM MODELS

Combine Quantum Computing & Machine Learning

- **Deterministic quantum models**
  - Deutsch-Jozsa algorithm



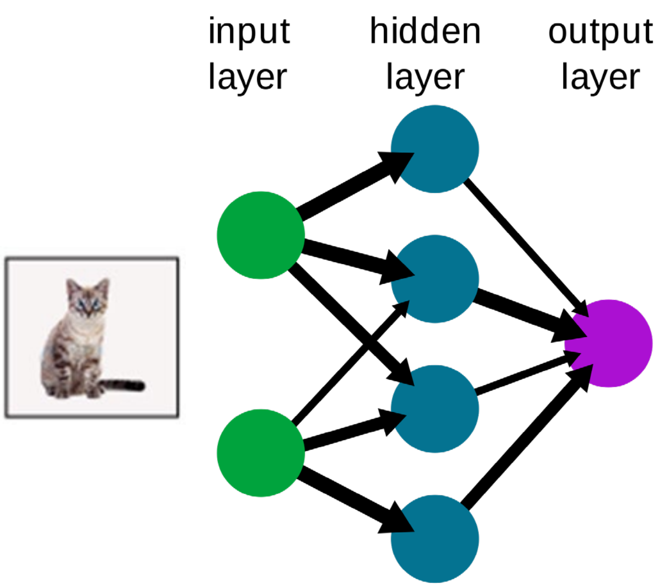
- **Variational quantum models**
  - Variational quantum eigensolver (VQE)
  - Variational quantum classifier (VQC)
  - Quantum support vector machine (QSVM)
  - Quantum neural networks (QNN)
  - Quantum convolutional neural networks (QCNN)
  - Quantum generative models (QGAN)



QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

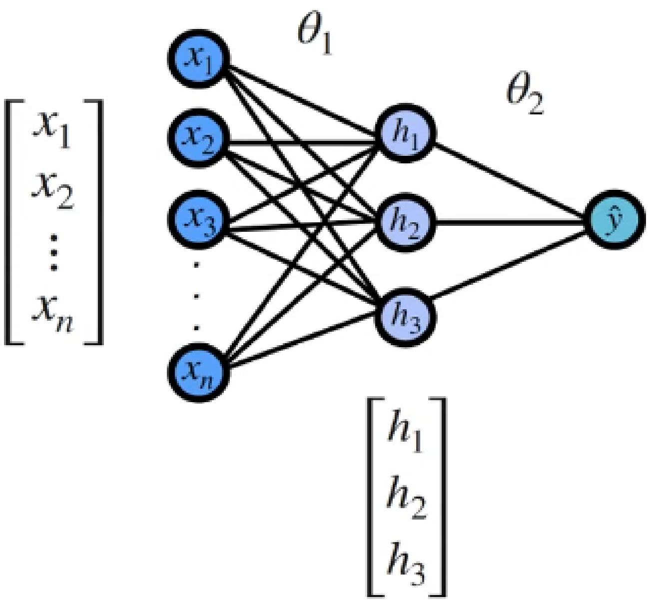
A simple neural network



QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

Classical Neural Network (CNN)



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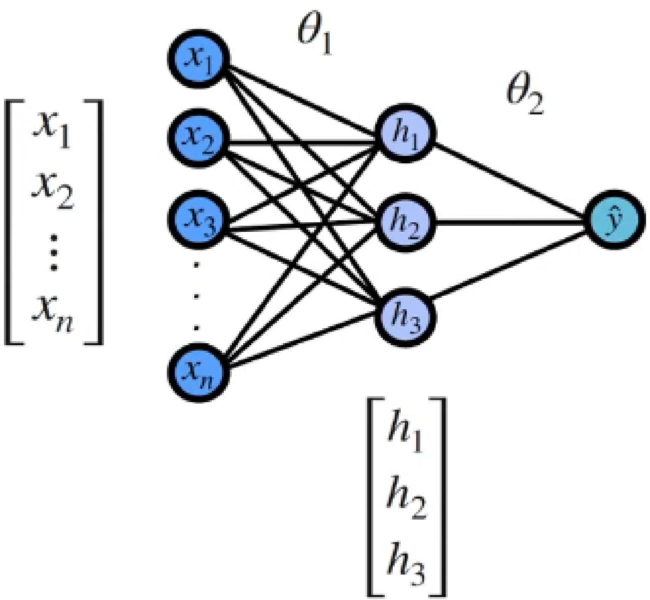
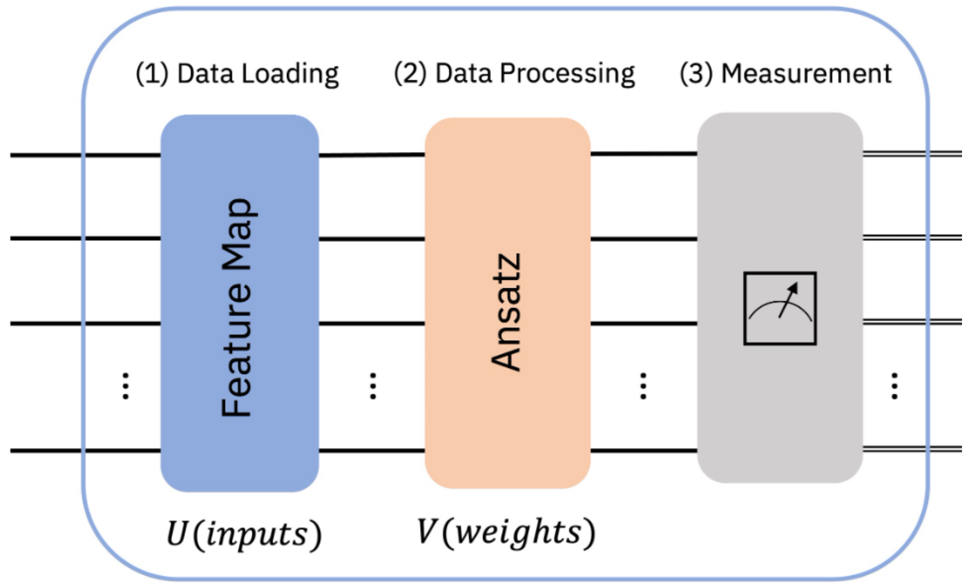
Based on parameterized quantum circuits

Classical Neural Network (CNN)



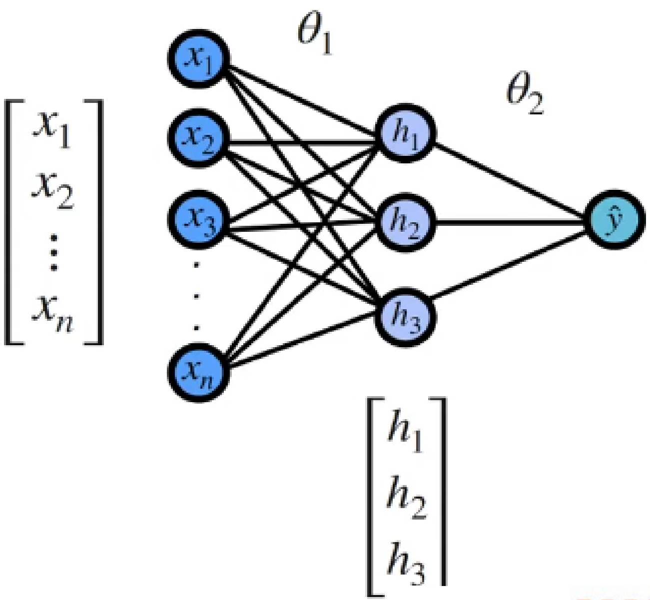
Quantum Neural Network (QNN)



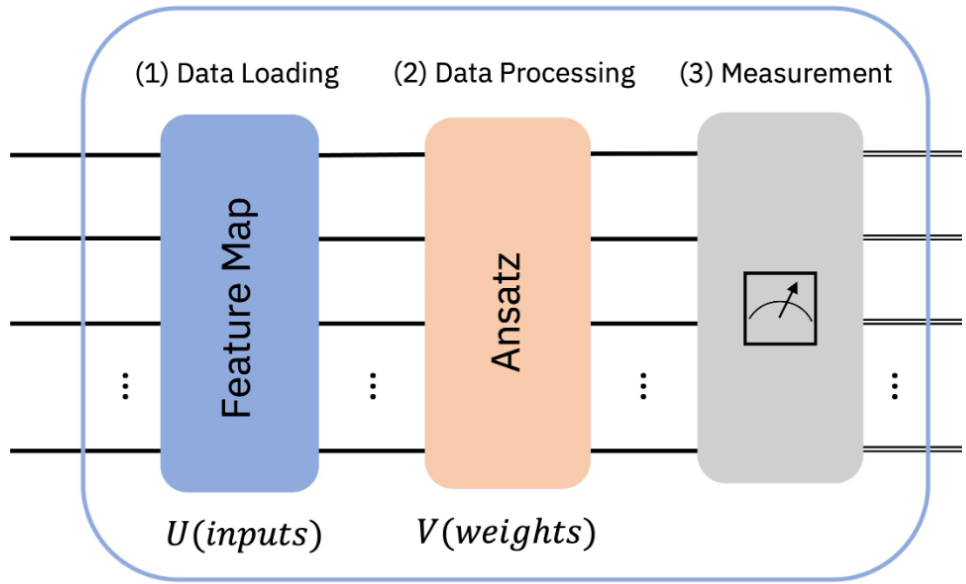
QUANTUM NEURAL NETWORKS

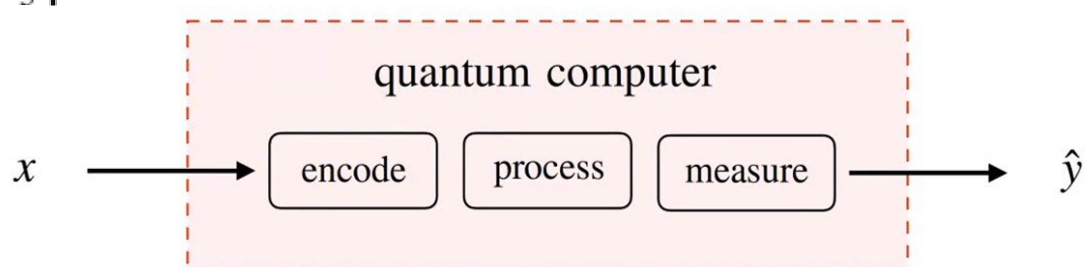
Based on parameterized quantum circuits

Classical Neural Network (CNN)



Quantum Neural Network (QNN)





QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

Feature Map

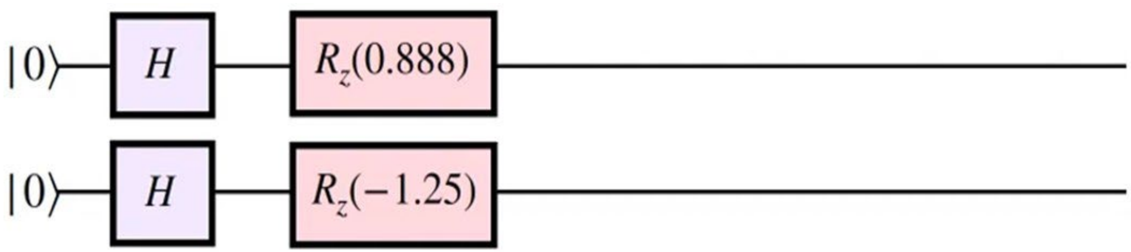
$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \end{bmatrix}$$

QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

Feature Map

$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \end{bmatrix}$$

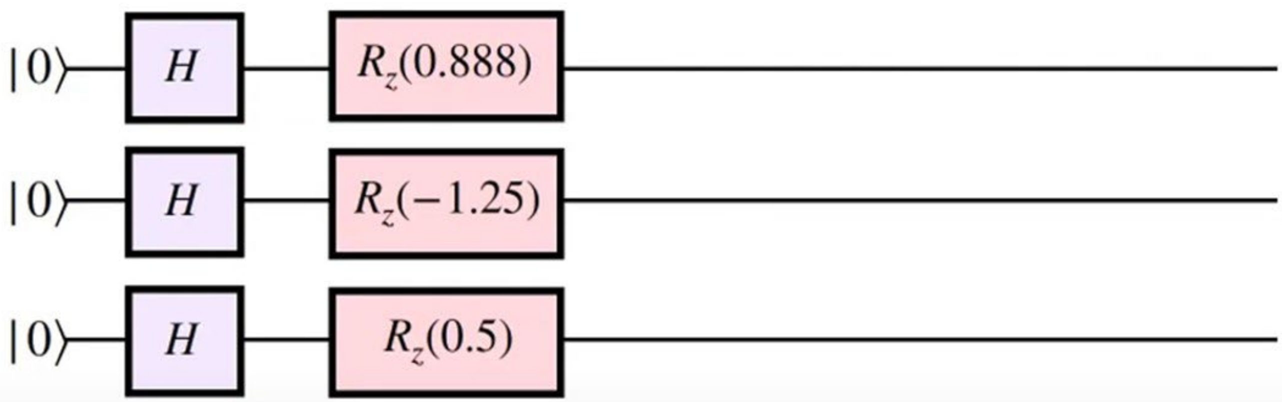


QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

Feature Map

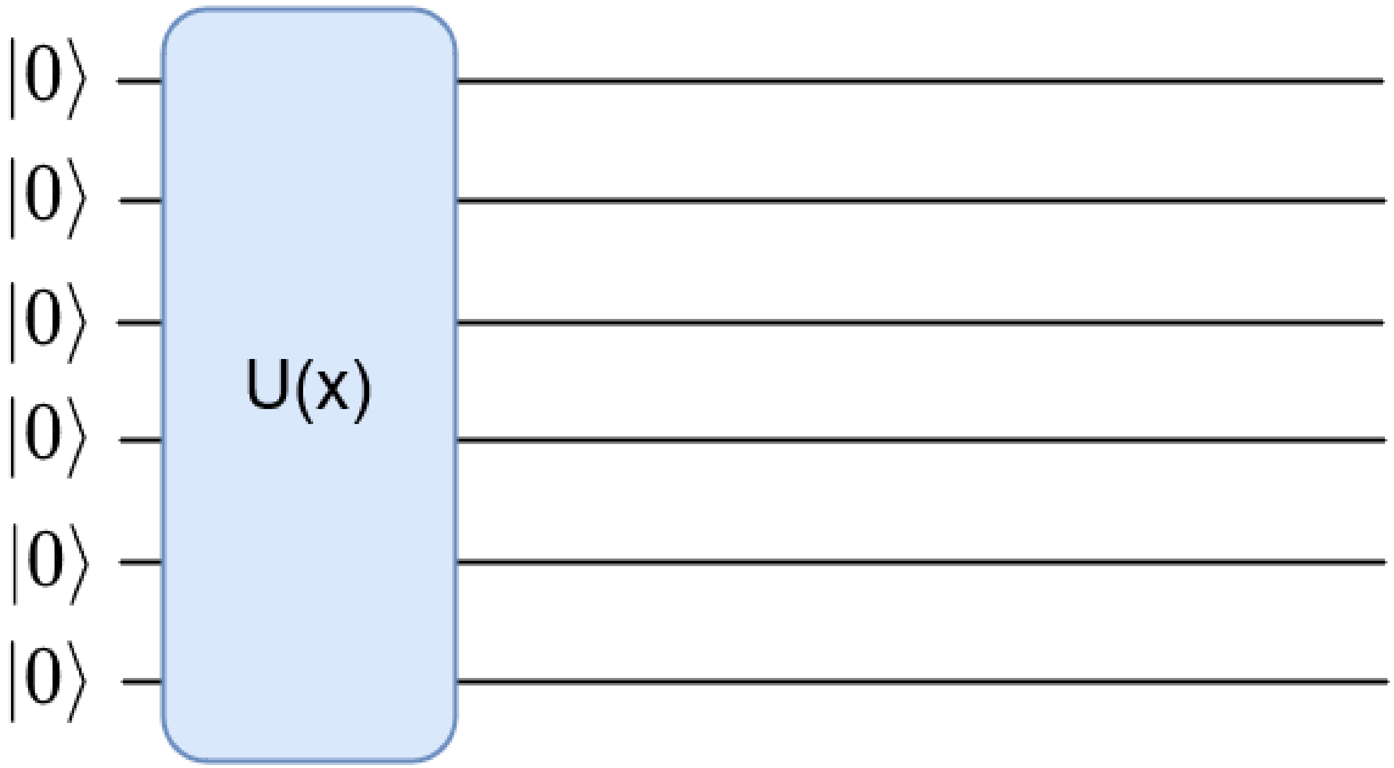
$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \\ 0.5 \end{bmatrix}$$



QUANTUM NEURAL NETWORKS

Based on parameterized quantum circuits

Angel Encoding



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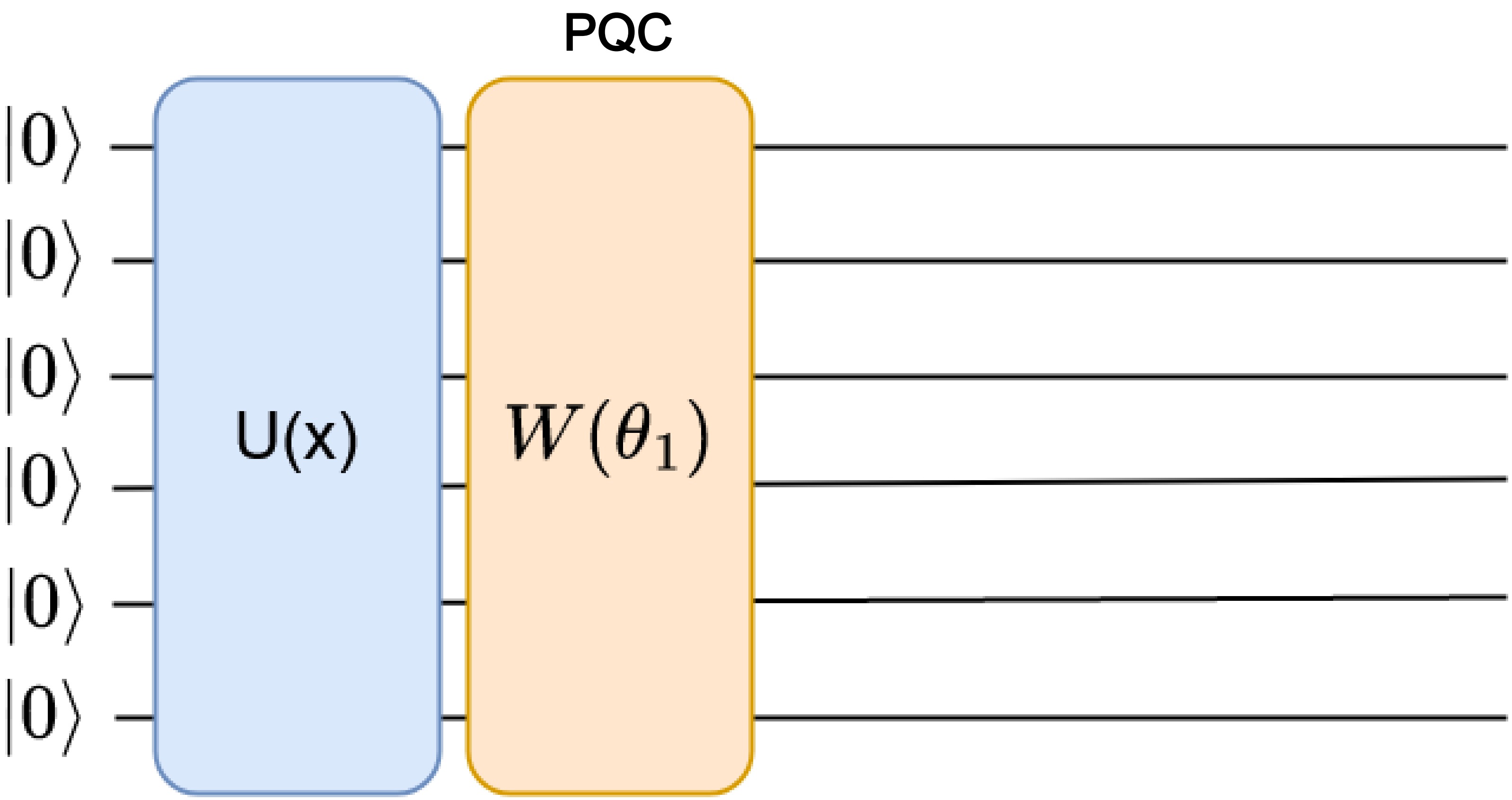

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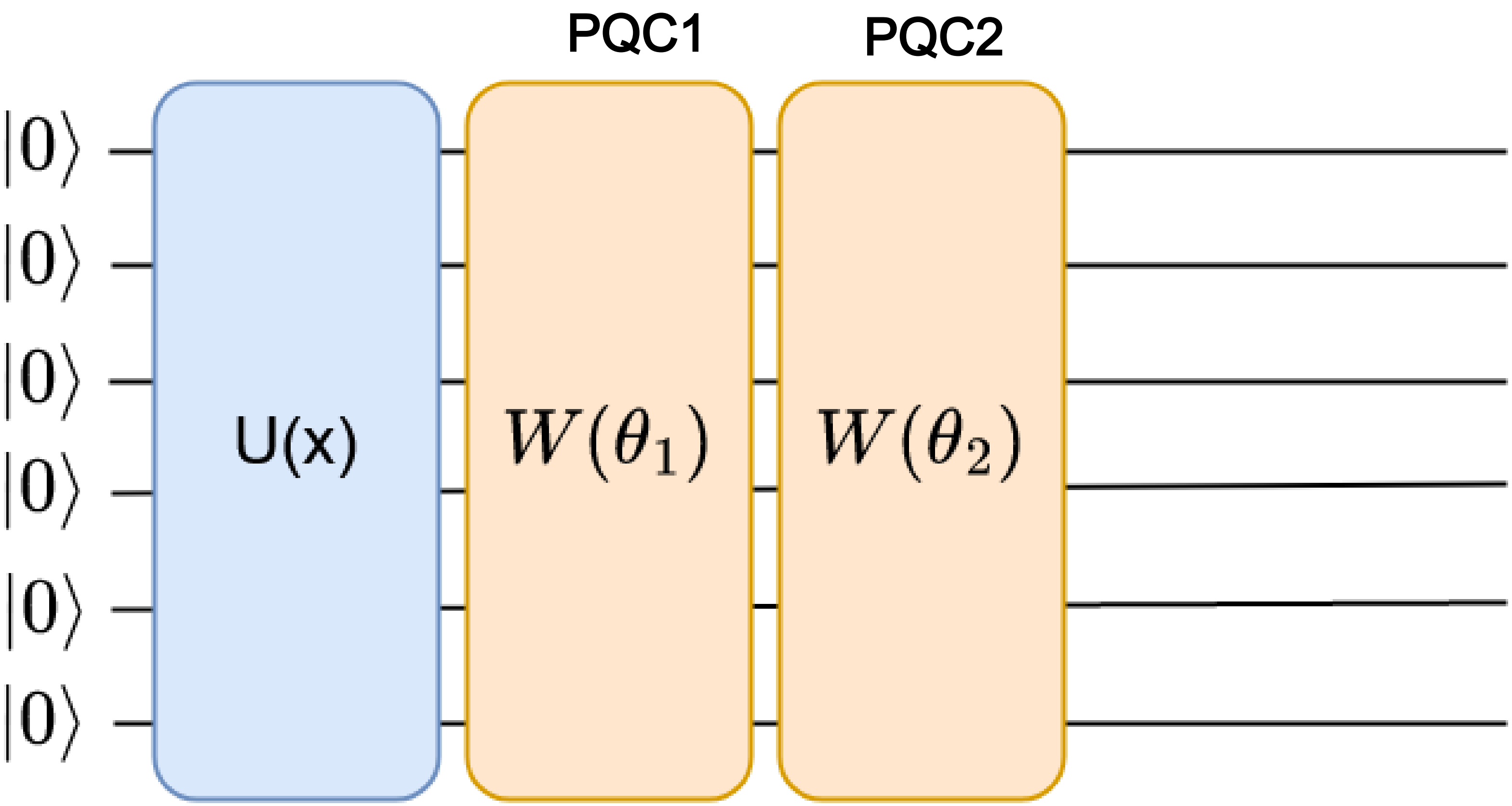

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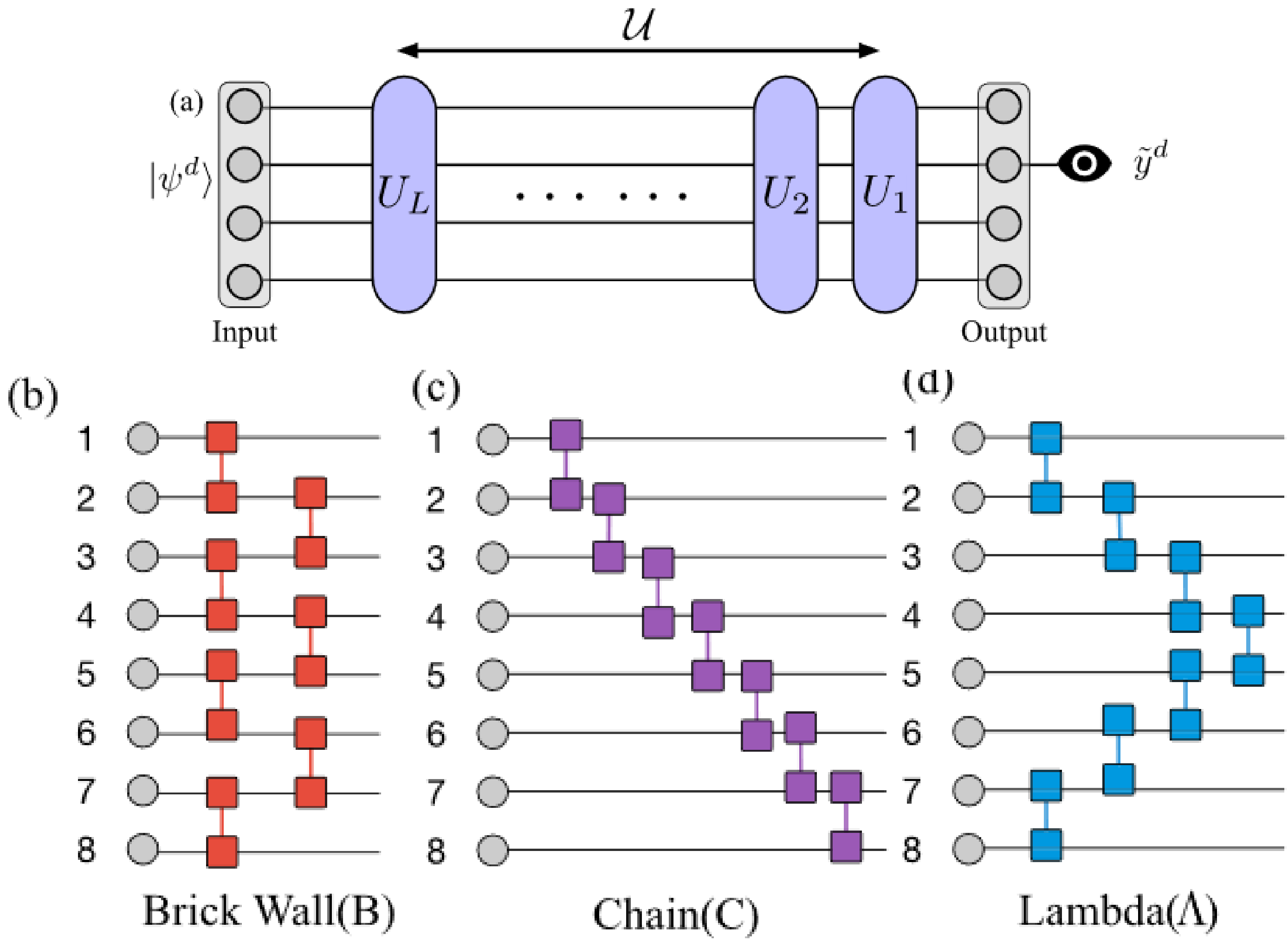

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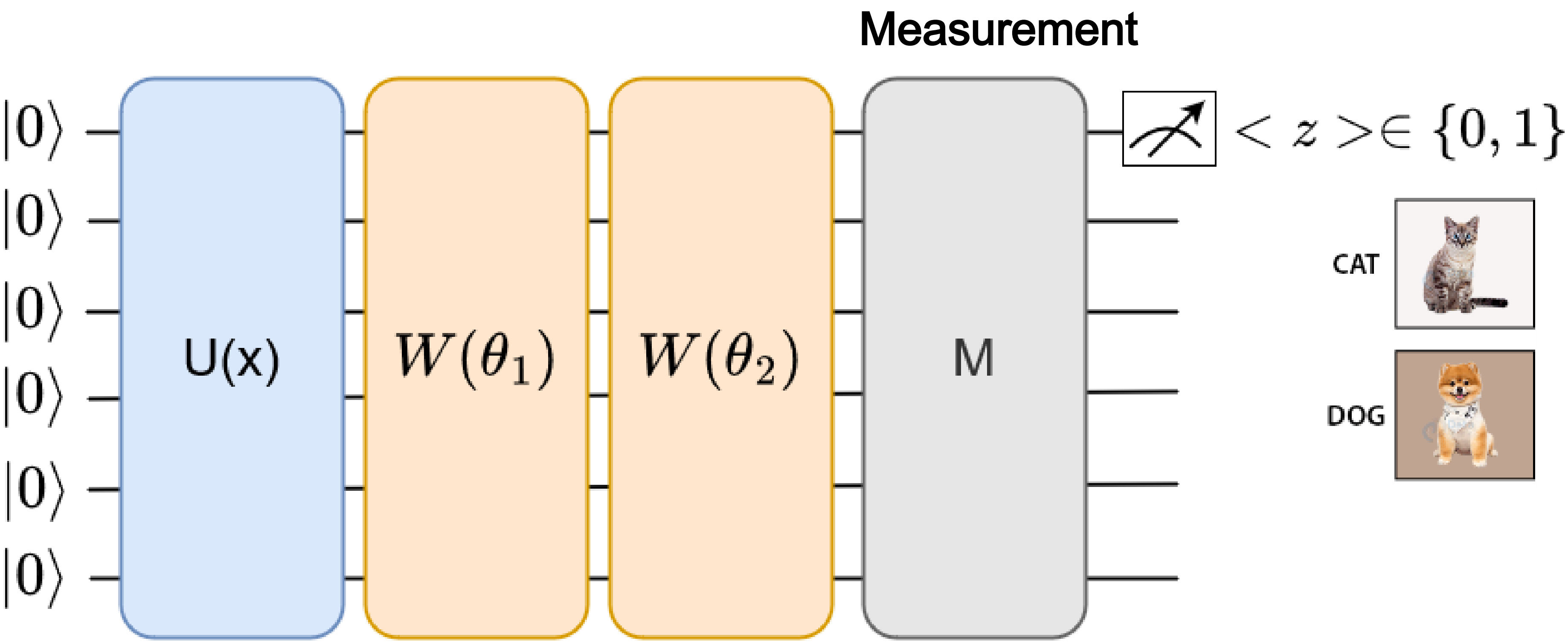
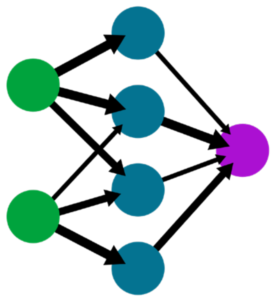


CHALLENGES

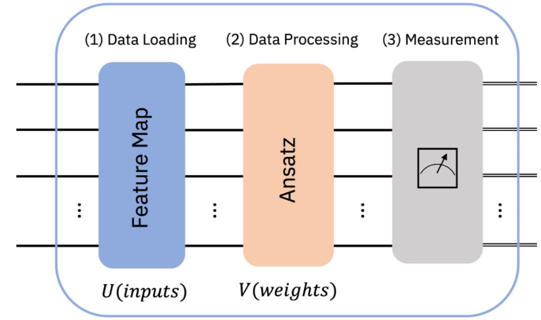
Quantum machine learning

There are still a lot of open problems:

- **Scalability**
- **Ansatz choice**
- **Training**
- **Scalable error correction**
- **Overcome barren plateaus problem**



- ❑ What architecture is best suited for a problem?
- ❑ What affects trainability?
- ❑ Generalization power?



“The question on whether quantum computers can really play a role in identifying practical ML application is still wide open, and it is unlikely to be decided by theoretical proofs or small-scale experiments”.

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SOFTWARE FRAMEWORKS

Quantum machine learning

Qiskit

SILQ
High-Level Quantum Programming

Cirq

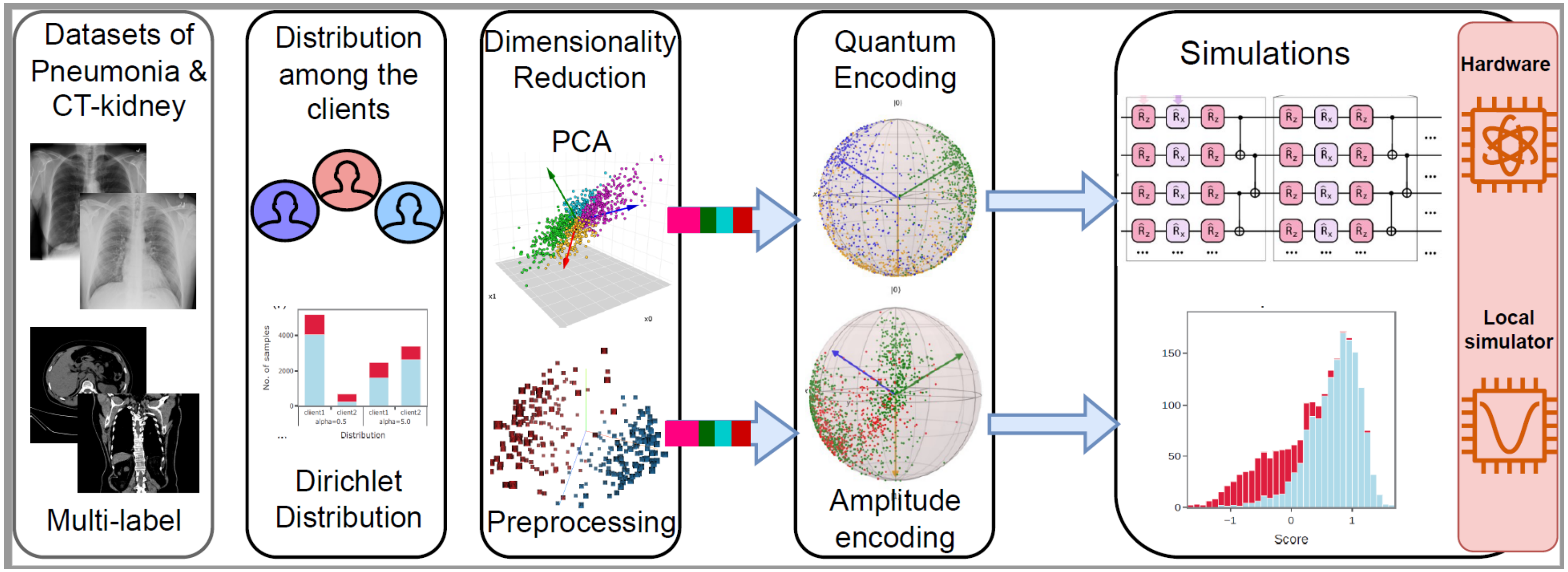
XANADU

Q#

rigetti

QUANTUM FEDERATED LEARNING

Quantum Federated Algorithm Workflow



Quantum Science and Technology

PAPER

Federated quanvolutional neural network: a new paradigm for collaborative quantum learning

Amandeep Singh Bhatia[1], Sabre Kais[1,2] and Muhammad Ashraful Alam[1,*]

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[2] Department of Chemistry, Purdue University, West Lafayette, IN, United States of America
[*] Author to whom any correspondence should be addressed.

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Keywords: quantum federated learning, quantum machine learning, quanvolutional neural network, federated learning, healthcare, collaborative learning

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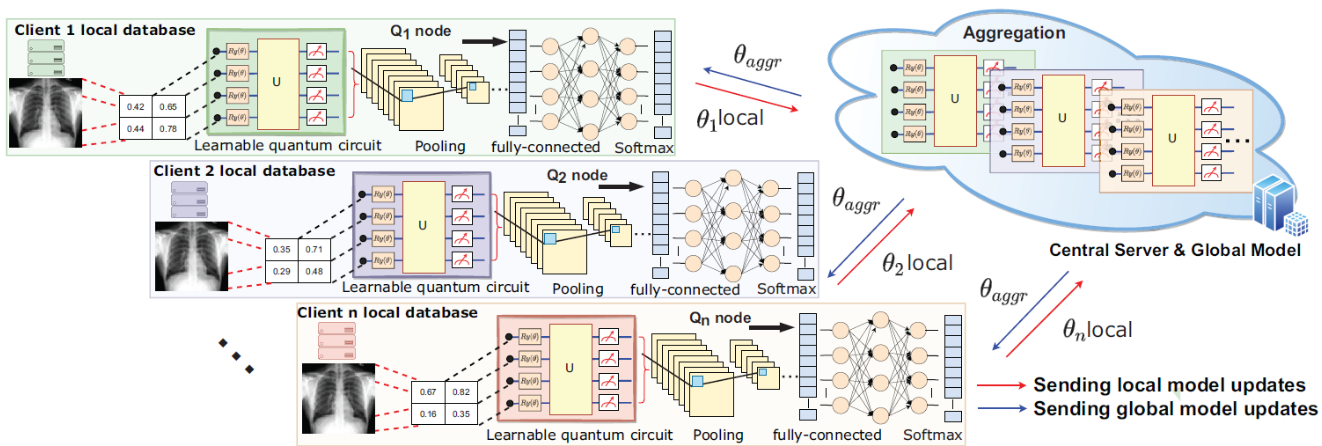
QUANTUM FEDERATED LEARNING

Combine Quantum Computing & Federated Learning

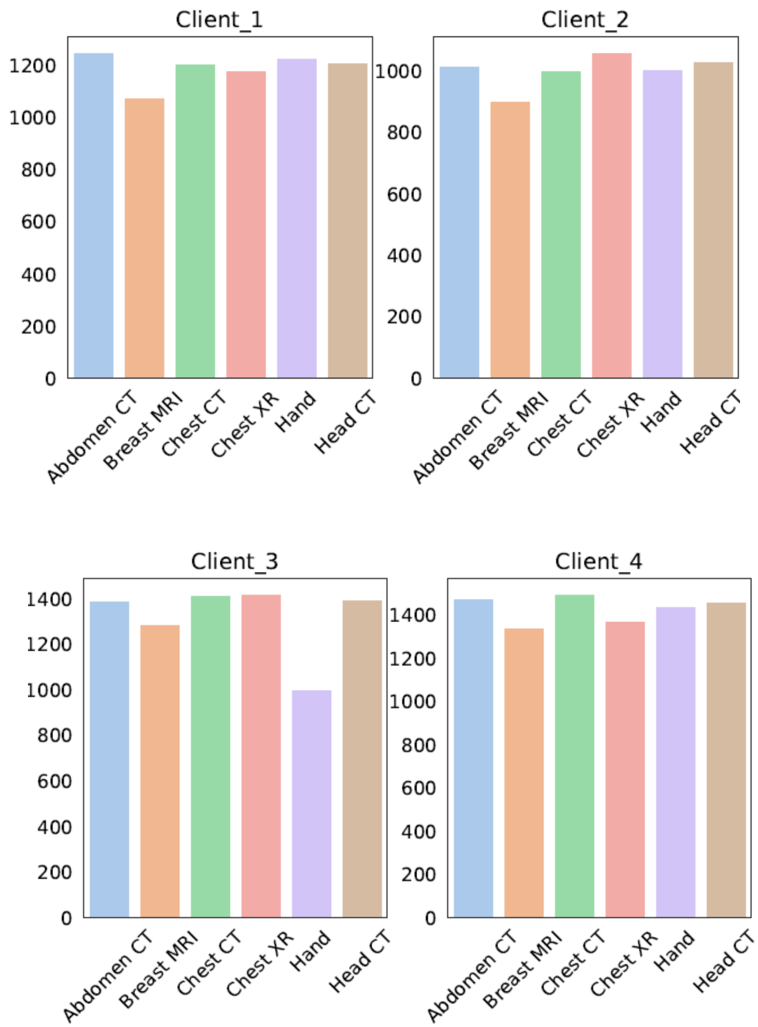
Algorithm 1 Quantum Federated Learning Averaging Algorithm

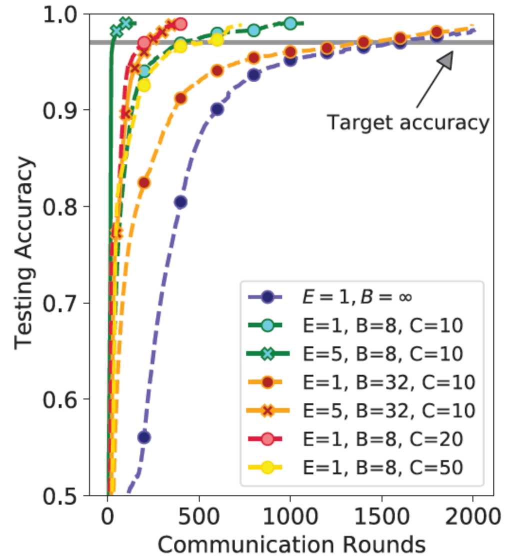
Input: D devices such that d=1, 2,..., D, n_d is the number of samples available with client, B represents batch-size, E is the number of local epochs, R denotes communication rounds, η_l, η_s are the learning rates of local client and global server, respectively.
LocalDevice(d, θ):
for i=1 to E **do**
  for $b \in B$ **do**
    $\theta^d \leftarrow \theta^d - \eta_l \nabla \mathcal{F}(\theta^d, b)$
  end for
end for
return θ^d to Server
GlobalServer:
Initialize θ_{1^s}
for r=0 to R-1 **do**
  Send θ_r global server parameters device.
  for each $d \in D$ **do**
    $\theta^d_{r+1^l} \leftarrow \text{LocalDevice}(d, \theta^d_{r^s})$,
  end for
  $\theta_{r+1^s} \leftarrow \theta^d_{r^l} - \eta_s \sum_{d=1}^{D} \frac{1}{n_d} \theta^d_{r+1^l}$
end for

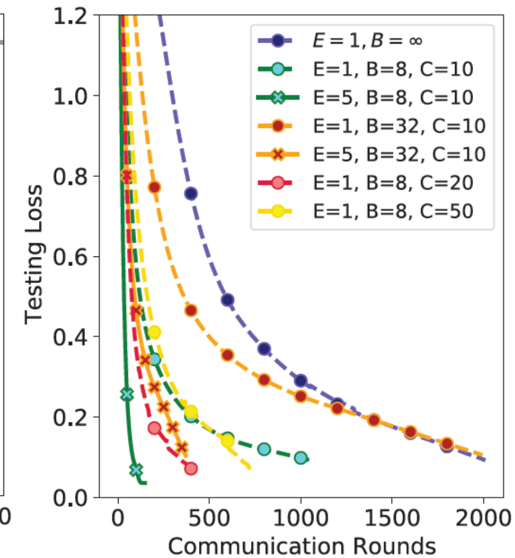
Objective: Develop a quantum federated learning (QFL) framework to tackle the optimization, security, and privacy challenges in the healthcare and clinical industries for medical imaging tasks.



QUANTUM FEDERATED LEARNING







MedNIST Non-IID1 dataset (97%)				
Fed	C	E	B	QCNN
FedSGD		1	∞	1950
FedAVG	10	1	8	626 (3.11×)
FedAVG	10	5	8	49 (39.7×)
FedAVG	10	1	32	1750 (1.11×)
FedAVG	10	5	32	289 (6.74×)
FedAVG	20	1	8	286 (6.81×)
FedAVG	50	1	8	646 (3.01×)

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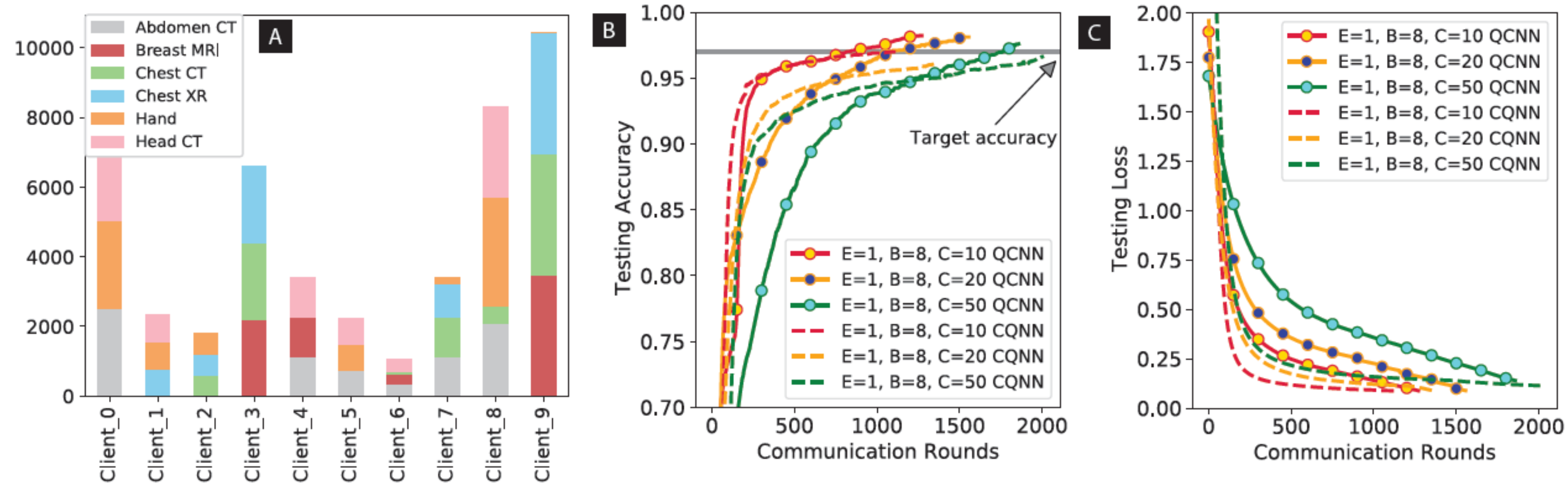
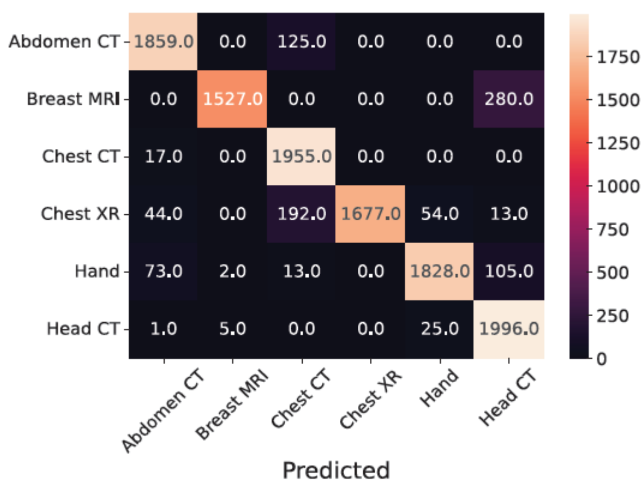
QUANTUM FEDERATED LEARNING





MedNIST dataset				
			Non-IID2 distribution	
C	E	B	QCNN	CQNN
10	1	8	1152 (1.69×)	1139 (1.72×)
20	1	8	1493 (1.30×)	1583 (1.23×)
50	1	8	1896 (1.02×)	>2000 (0.74×)
20	5	8	397 (4.91×)	927 (2.10×)
10	1	32	>2000 (0.64×)	>2000 (0.47×)
10	5	32	624 (3.12×)	959 (2.03×)

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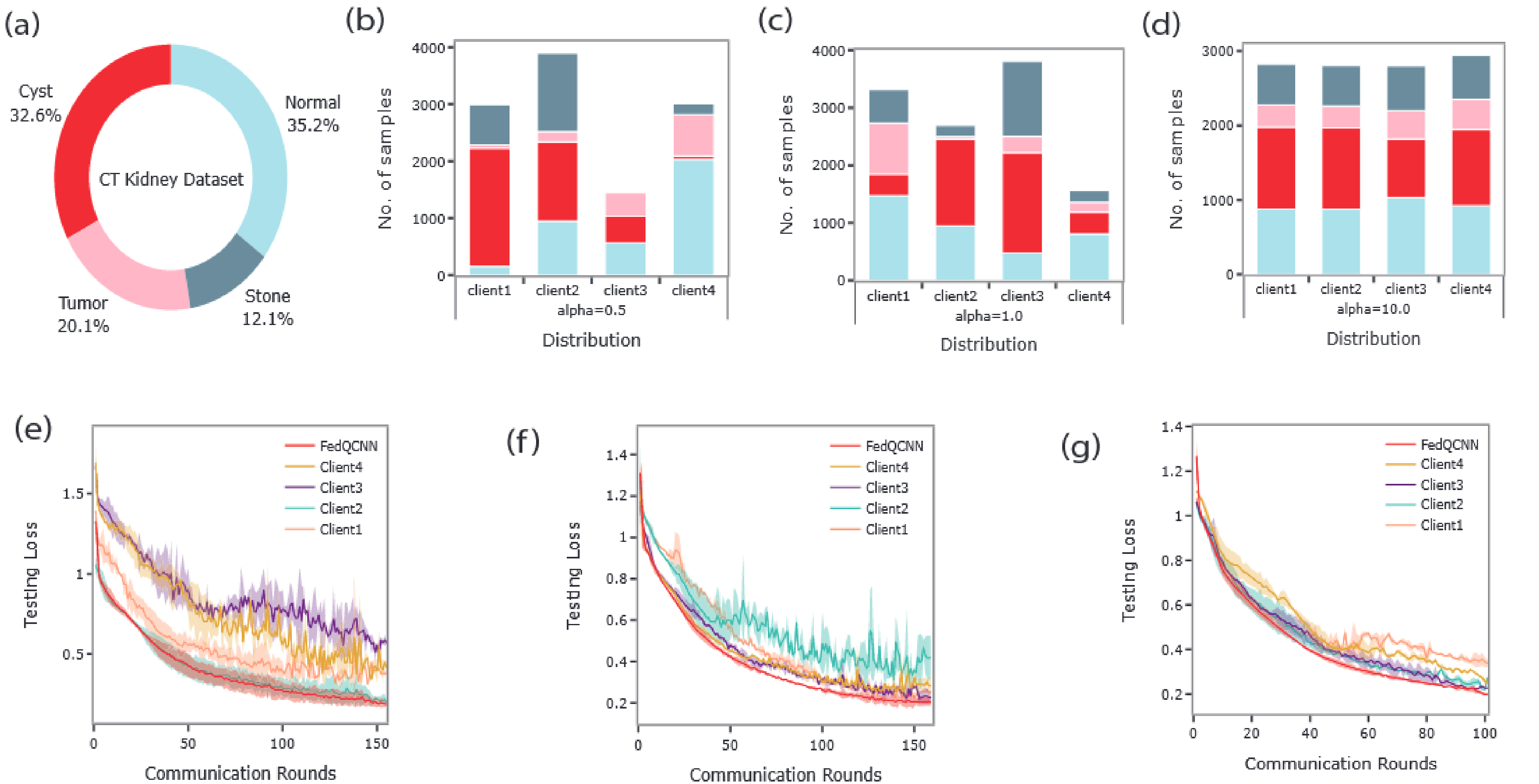
QUANTUM FEDERATED LEARNING

Quantum Convolutional Neural Networks (QCNNs) in Federated setti



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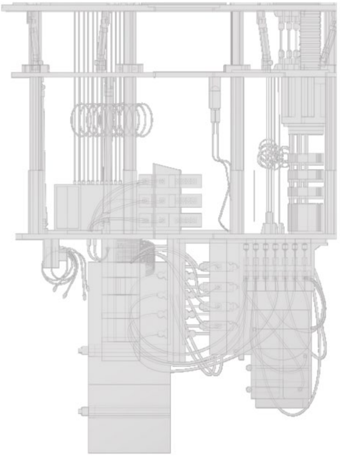
Conclusion

- Demonstrated the resilience and consistency of the federated hybrid models when confronted with **inadequate and unevenly distributed training data.**

- Federated quantum model **takes fewer rounds** for training on increasing the client fraction.

- The **tuning of a batch-size (B)** parameter is essential to maintain a balance between computational efficiency and convergence rate.

- On adding up the computation on the client side by **either increasing local epochs (E), decreasing batch size (B)**, or both to reduce the communication rounds in a quantum federated learning framework.



Thank you!

Questions?

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