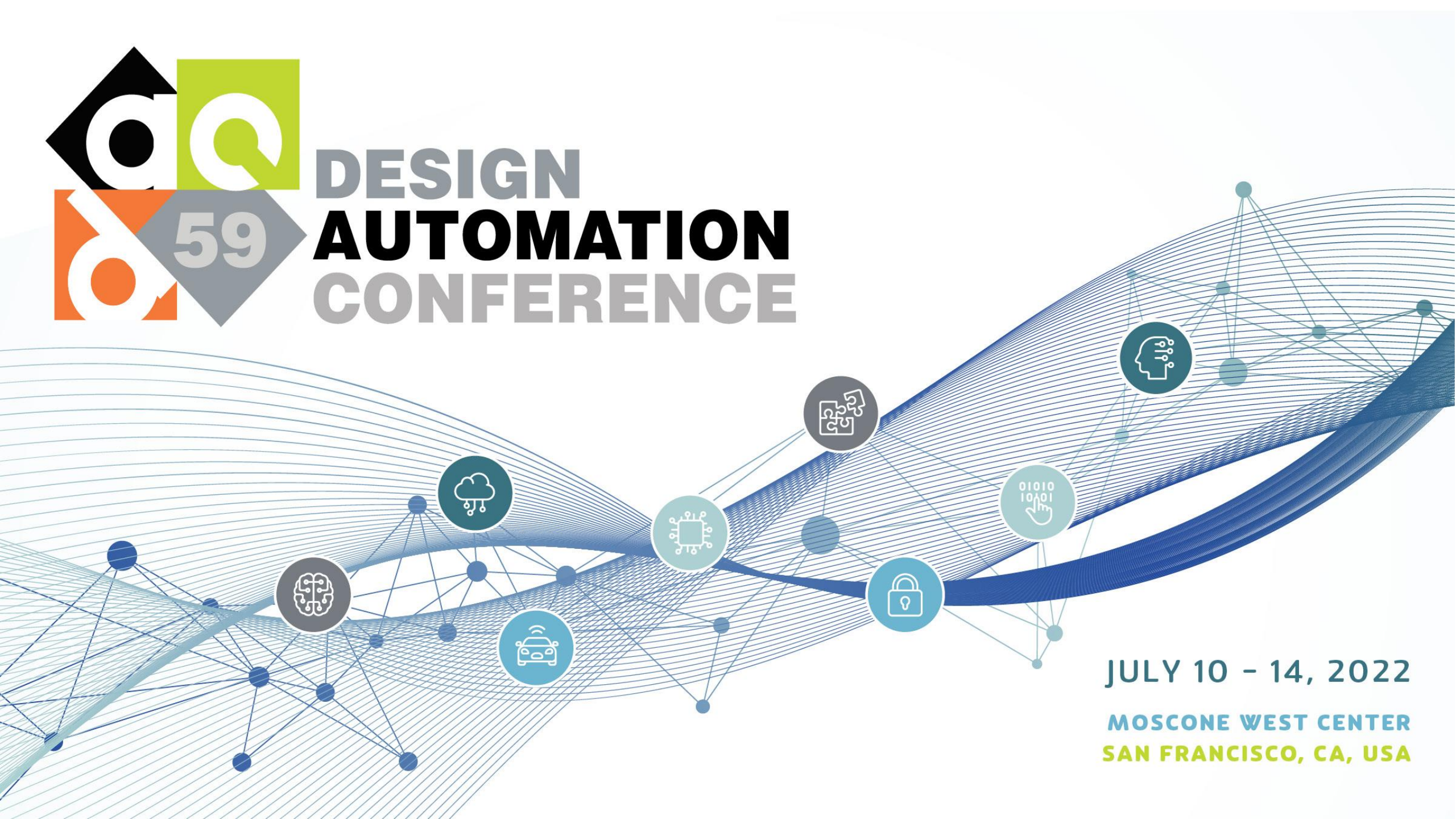
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DESIGN
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JULY 10 - 14, 2022
MOSCONE WEST CENTER
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Towards Quantum Learning Democratization

—— Start from Building a Quantum Neural Network Design Stack

Zhepeng Wang, Zhiding Liang, Yiyu Shi, Weiwen Jiang

07/11/2022

What is Classical AI Democratization & What is the Challenge?

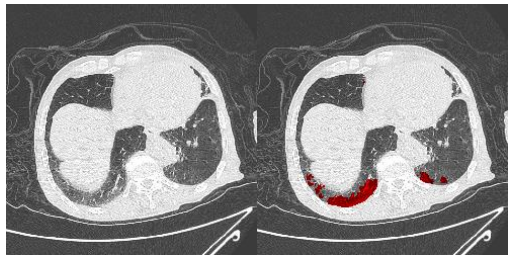
"It's here to collaborate, to augment, to enhance human lives and productivity and make everybody's life better. And related to that, is to **democratize A.I.** in a way that everybody gets benefit. Not just a few, or a selected group." **Fei-Fei Li, 2017**

Medical AI Scenario

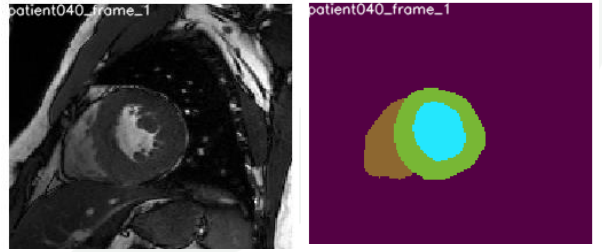
AR/VR in Surgery

Medical Diagnosis

AI Can Perform Medical Tasks



COVID CT Segmentation



Real-Time MRI Segmentation

Let Doctors Design Neural Networks?

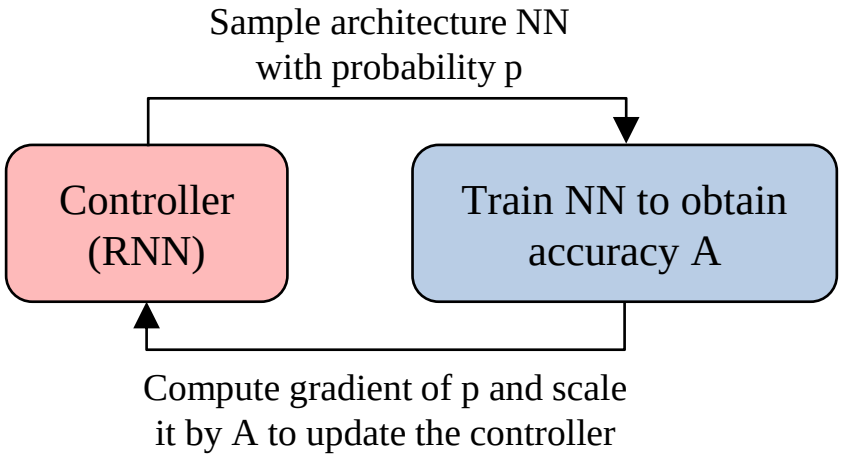
Progress of Classical AI Democratization

Google's Initial Contributions
(Neural Architecture Search)

Given: Dataset

Objective:
- Automated search for NN **(w/o human)**
- Maximize accuracy on the given dataset

Output: A neural network architecture



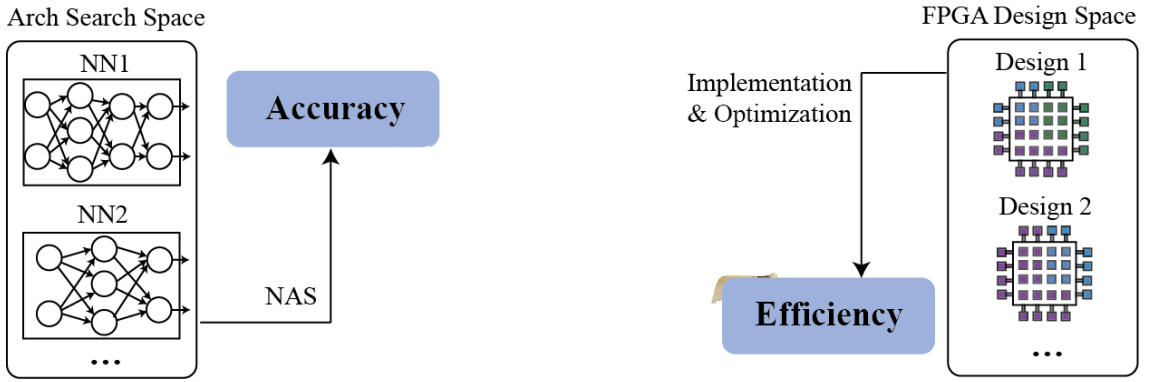
[ref] Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *ICLR 2017*

Our Contributions
(Network-Accelerator Co-Design)

Given: (1) Dataset; (2) Target hardware, e.g., FPGA.

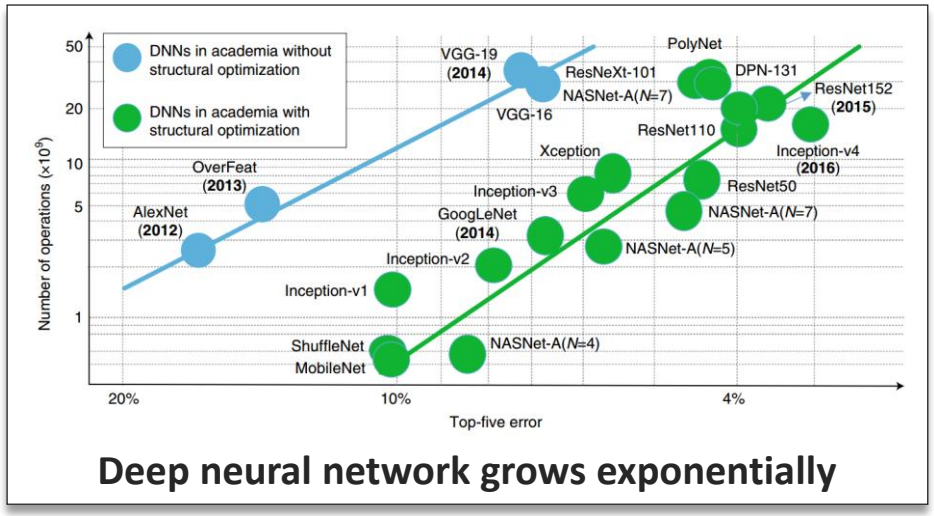
Objective:
- Automated search for NN and HW design
- Maximize accuracy on the given dataset
- Maximize hardware efficiency

Output: A pair of neural network and hardware design

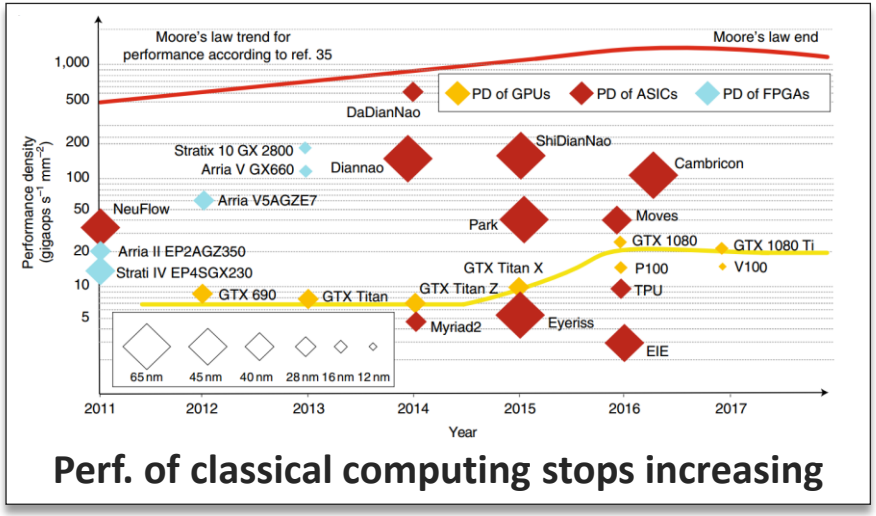


[ref] Jiang, Weiwen, et al. "Accuracy vs. efficiency: Achieving both through fpga-implementation aware neural architecture search." *DAC 2019*.

Bottlenecks in Classical Computing



Deep neural network grows exponentially



Perf. of classical computing stops increasing

Medical AI Scenario: (Input size exponentially grows from Radiology to Pathology Imaging)

Radiology Imaging

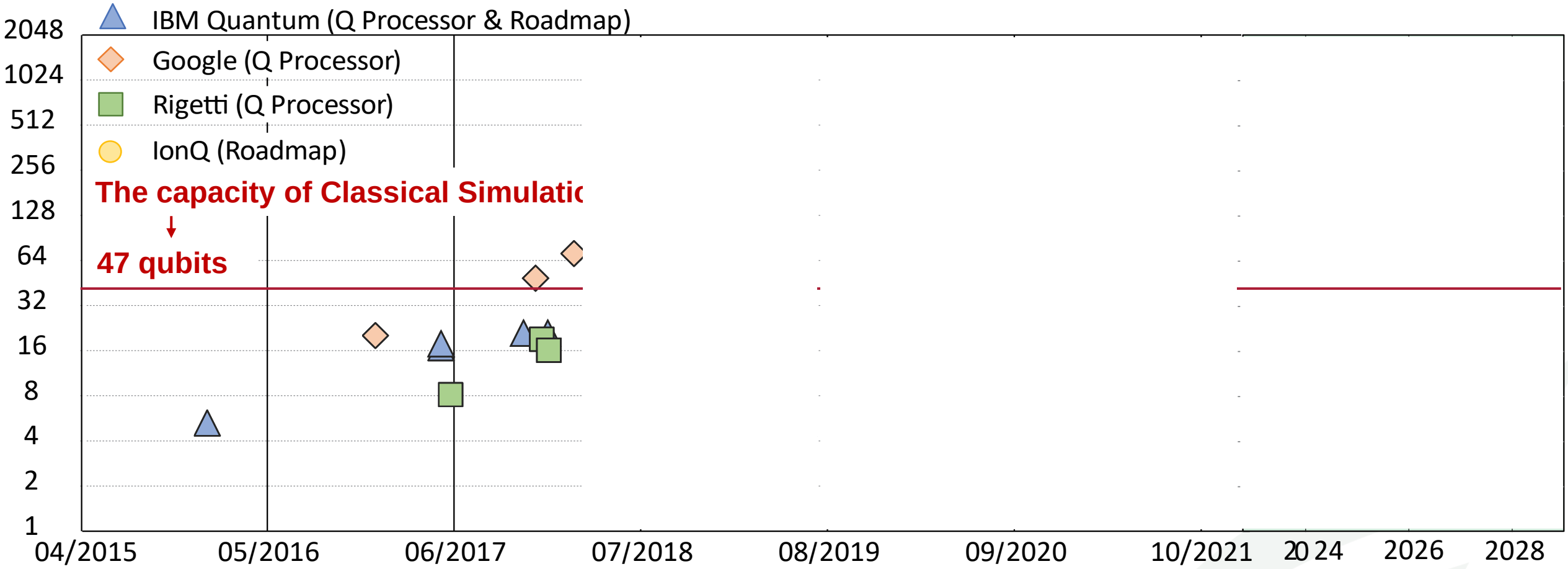
Radiology Modality	Avg. Size (MB)
CT Scan	153.4
MRI	98.6
X-ray angiography	157.5
Ultrasound	69.2
Breast imaging	38.8

Pathology Imaging

Biopsy Type	Compressed Size(MB)/Study	Original Size (GB)
Dermatopathology	1,392 (20x compression)	**27**
Head and neck	1,965 (20x compression)	**38**
Hematopathology	40,300 (40x compression)	**1574**
Neuropathology	1,872 (20x compression)	**37**
Thoracic pathology	3,240 (20x compression)	**63**

[ref] Lauro, Gonzalo Romero, et al. "Digital pathology consultations—a new era in digital imaging, challenges and practical applications." *Journal of digital imaging* 26.4 (2013).

Impossible in Classical But Possible in Quantum Computing



The maximum qubits that supercomputers can simulate for arbitrary circuits is less than 47 qubits.

(1) Summit w/ 2.8 PB memory for **47 qubits**; (2) Sierra w/ 1.38 PB memory for **46 qubits**;

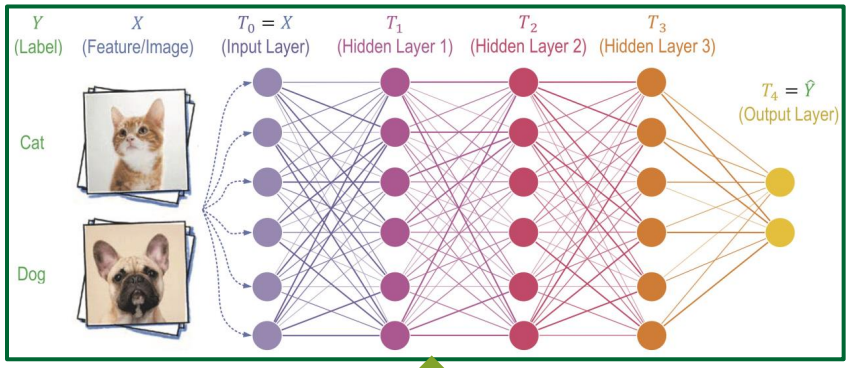
(3) Sunway TaihuLight w/ 1.31 PB memory for **46 qubits**; (4) Theta w/ 0.8 PB memory for **45 qubits**.

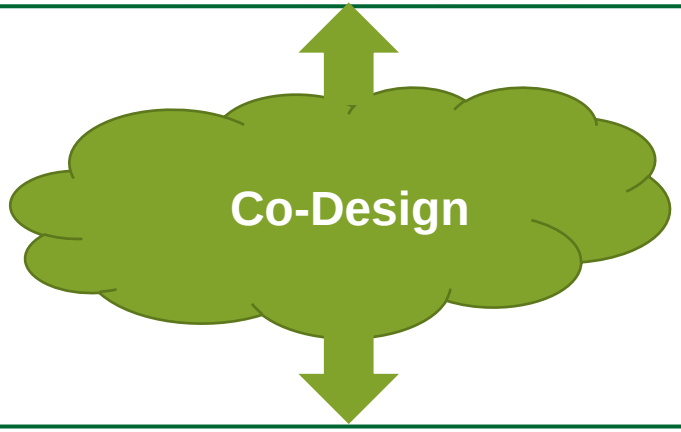
[ref] Wu, Xin-Chuan, et al. "Full-state quantum circuit simulation by using data compression." Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis. 2019.

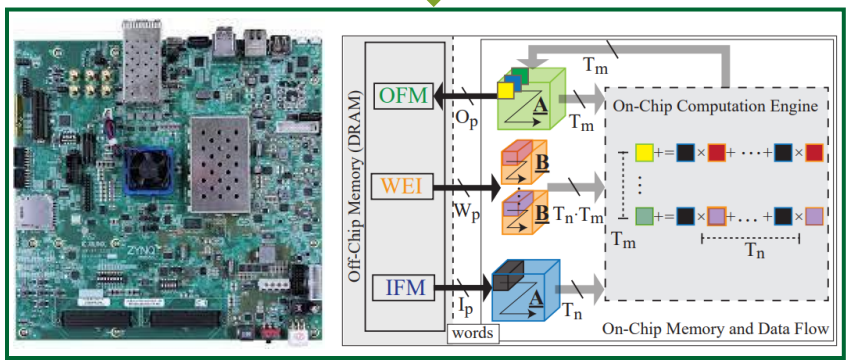
Outline

- Background
- Perspective: Co-Design --- from Classical to Quantum
- Built Design Stack
  - Quantum Neuron with Quantum Advantage: QuantumFlow
  - Quantum Neural Network Exploration: QF-Mixer
  - Quantum Neural Network Compression: CompVQC
  - Quantum Pluse: VQP
  - Quantum NN Library: QFNN
- Conclusion

My Previous Background: Co-Design of Neural "Architectures"





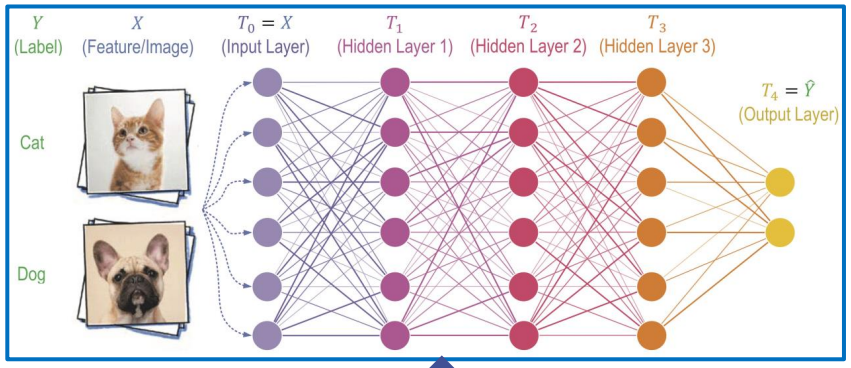


- What is the best **Neural Network Architecture** for FPGAs
- Model optimization (pruning and quantization)?
- Library

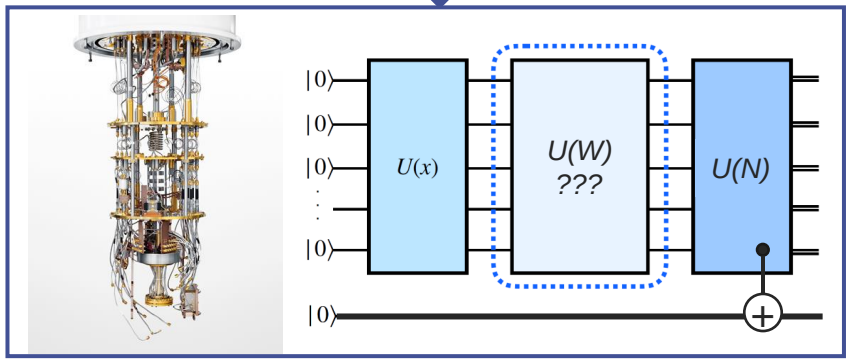
Co-Design Framework (e.g., Our FNAS)		
	Network exploration	NAS (Google)
	Network compression	Deep Comp (Stanford)
	Programming library	DNNBuilder (UIUC)
	Hardware accelerator	DNN on FPGA (UCLA)

- Mapping and scheduling?
- What is the best **FPGA Architecture** for neural networks

Our Works: Co-Design of Neural Networks and Quantum Circuit



Co-Design



- What is the best **Neural Network Architecture** for QC?
- Can we **compress** the quantum neural network?
- Library

Co-Design Framework QuantumFlow

Network exploration	QF-Mixer
Network compression	CompVQC
Programming library	QFNN
Device-level design	QPluse

- ……
- What is the best **QC design** for neural networks

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- Conclusion

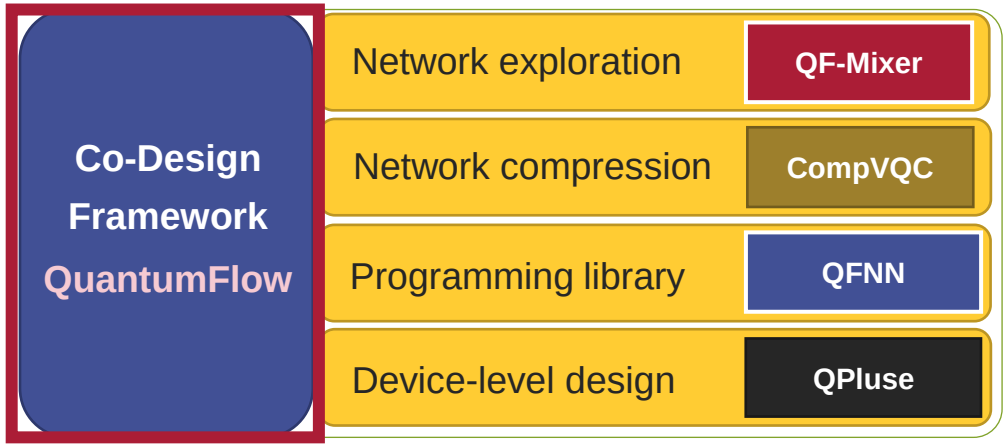
Quantum Neuron: QuantumFlow

A Co-Design Framework of Neural Networks and Quantum Circuits Towards Quantum Advantage

Published at Nature Communications 2021

nature COMMUNICATIONS

Presenter: Weiwen Jiang



Invited & Tutorial Talks:

IBM Quantum Summit September 15-17, 2020

IEEE QUANTUM WEEK

IEEE International Conference on Quantum Computing and Engineering — QCE21

58 DESIGN AUTOMATION CONFERENCE
FROM CHIPS TO SYSTEMS — LEARN TODAY, CREATE TOMORROW

EMBEDDED SYSTEMS WEEK

IEEE/ACM ICCAD 2021 INTERNATIONAL CONFERENCE ON COMPUTER-AIDED DESIGN 40th Edition

VILLANOVA UNIVERSITY

...

Classical Bit vs. Quantum Bit

Classical Bit

- 2 basic states — **0**, **1** (OFF or ON)
- Mutually exclusive

$$X = 0 \ \textit{or} \ 1$$

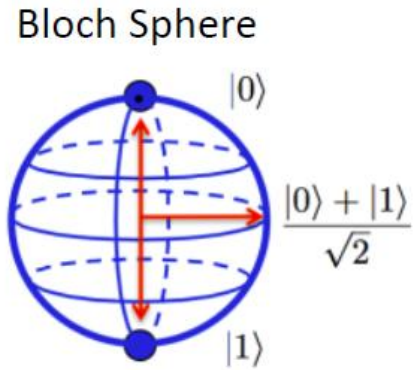
Classical Bit

Quantum Bit (Qubit)

- 2 basic states — $|0\rangle$, $|1\rangle$ (ket 0, ket 1)
- Uses **superposition** of both states with “quantum" effect store information.
- Thus, it represents both $|0\rangle$ and $|1\rangle$ at the same time.

$$|\psi\rangle = |0\rangle \ \textit{and} \ |1\rangle$$

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad \rightarrow \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$



Qubit

Multiple-Qubits System

2 Classical Bits

00 **or** 01 **or** 10 **or** 11

n bits for 1 value

$\boldsymbol{x \in [0, 2^n - 1]}$

2 Qubits

$c_{00}|00\rangle$ **and** $c_{01}|01\rangle$ **and** $c_{10}|10\rangle$ **and** $c_{11}|11\rangle$

n bits for 2^n values

$\boldsymbol{a_0, a_1, a_2, \cdots a_n}$

Qubits: q_0, q_1

$$|q_0\rangle = a_0|0\rangle + a_1|1\rangle$$

$$|q_1\rangle = b_0|0\rangle + b_1|1\rangle$$

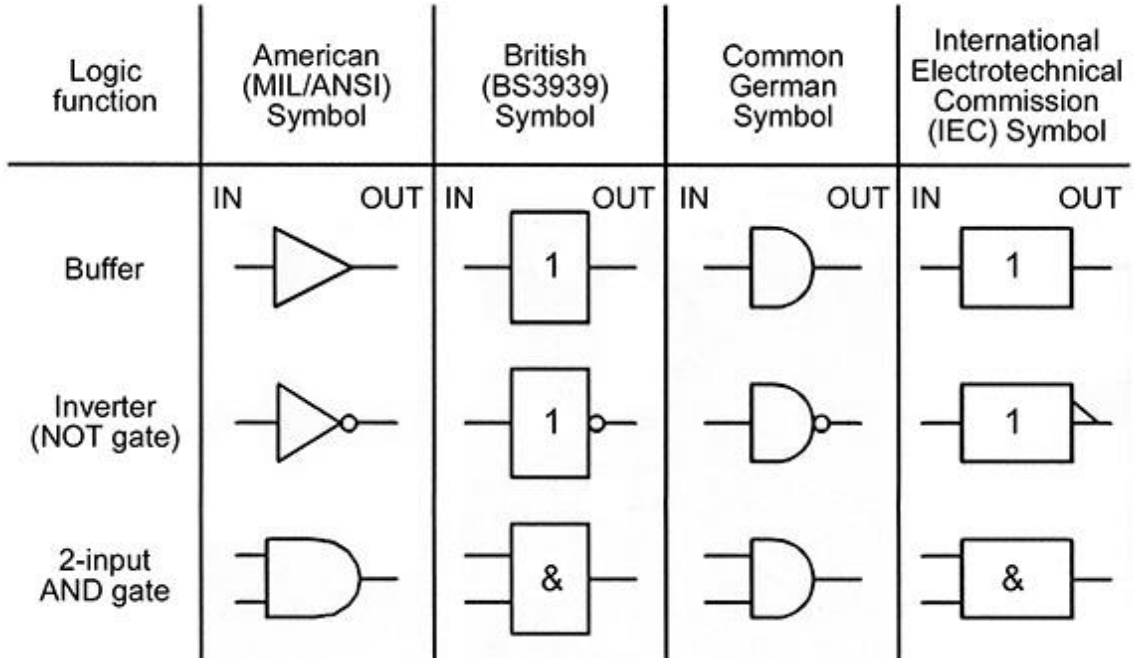
$$|q_0, q_1\rangle = |q_0\rangle \otimes |q_1\rangle$$

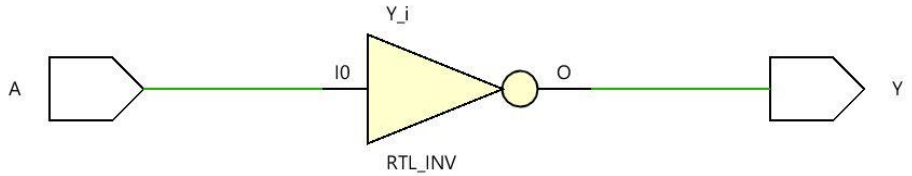
$$= c_{00}|00\rangle + c_{01}|01\rangle + c_{10}|10\rangle + c_{11}|11\rangle$$

$$|q_0, q_1\rangle = |q_0\rangle \otimes |q_1\rangle = \begin{pmatrix} a_0 \\ a_1 \end{pmatrix} \otimes \begin{pmatrix} b_0 \\ b_1 \end{pmatrix}$$

$$= \begin{pmatrix} a_0 \times \begin{pmatrix} b_0 \\ b_1 \end{pmatrix} \\ a_1 \times \begin{pmatrix} b_0 \\ b_1 \end{pmatrix} \end{pmatrix} = \begin{pmatrix} a_0 b_0 \\ a_0 b_1 \\ a_1 b_0 \\ a_1 b_1 \end{pmatrix} = \begin{pmatrix} c_{00} \\ c_{01} \\ c_{10} \\ c_{11} \end{pmatrix}$$

Computation: Logic Gates vs. Quantum Logic Gates

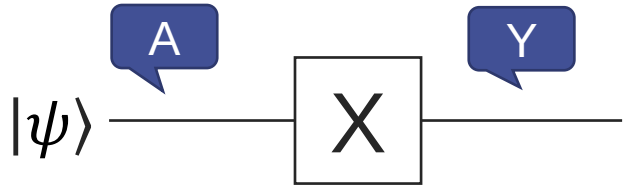




$$Y = \bar{A}$$

A	Y
0	1
1	0

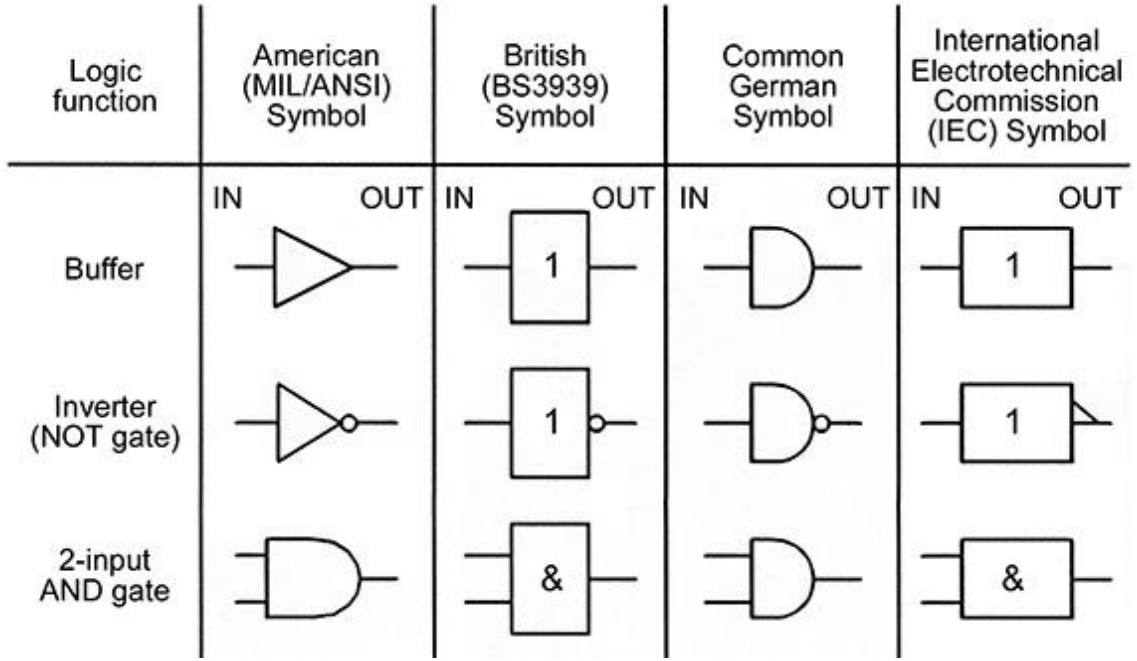
Operator	Gate(s)	Matrix
Pauli-X (X)	X	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$
Pauli-Y (Y)	Y	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$
Pauli-Z (Z)	Z	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Hadamard (H)	H	$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$
Phase (S, P)	S	$\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}$

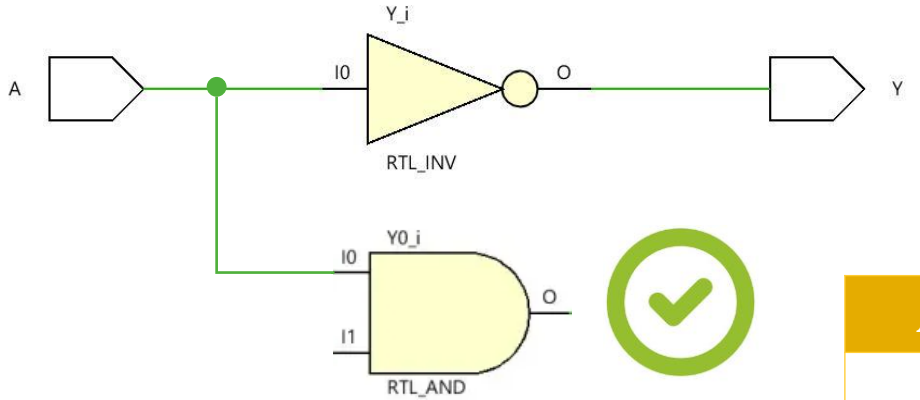


$$|Y\rangle = X \times |A\rangle$$

$$Y\begin{pmatrix} y_0 \\ y_1 \end{pmatrix} = X\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \times A\begin{pmatrix} a_0 \\ a_1 \end{pmatrix}$$

Computation: Logic Gates vs. Quantum Logic Gates





$$Y = \bar{A}$$

A	Y
0	1
1	0

Operator	Gate(s)	Matrix
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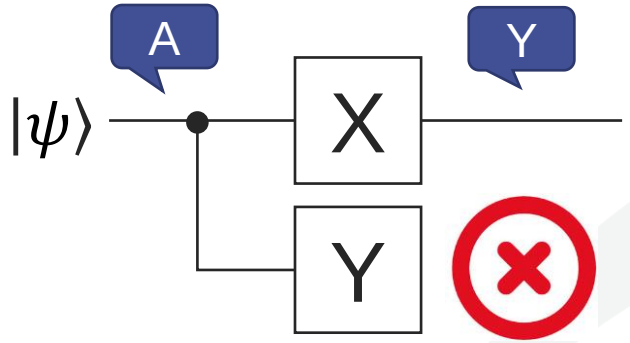
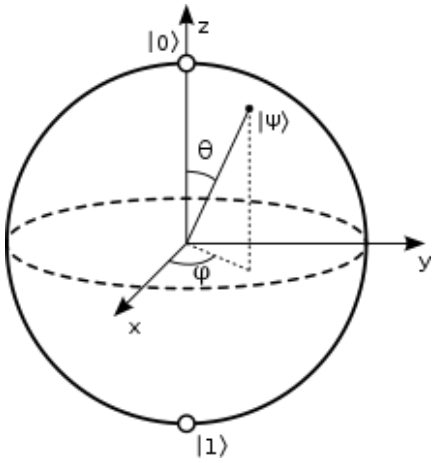
Pauli-Y (Y)	Y	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$
Pauli-Z (Z)	Z	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Hadamard (H)	H	$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$
Phase (S, P)	S	$\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}$



$$|Y\rangle = X \times |A\rangle$$

$$Y \begin{pmatrix} y_0 \\ y_1 \end{pmatrix} = X \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \times A \begin{pmatrix} a_0 \\ a_1 \end{pmatrix}$$

General U Gates



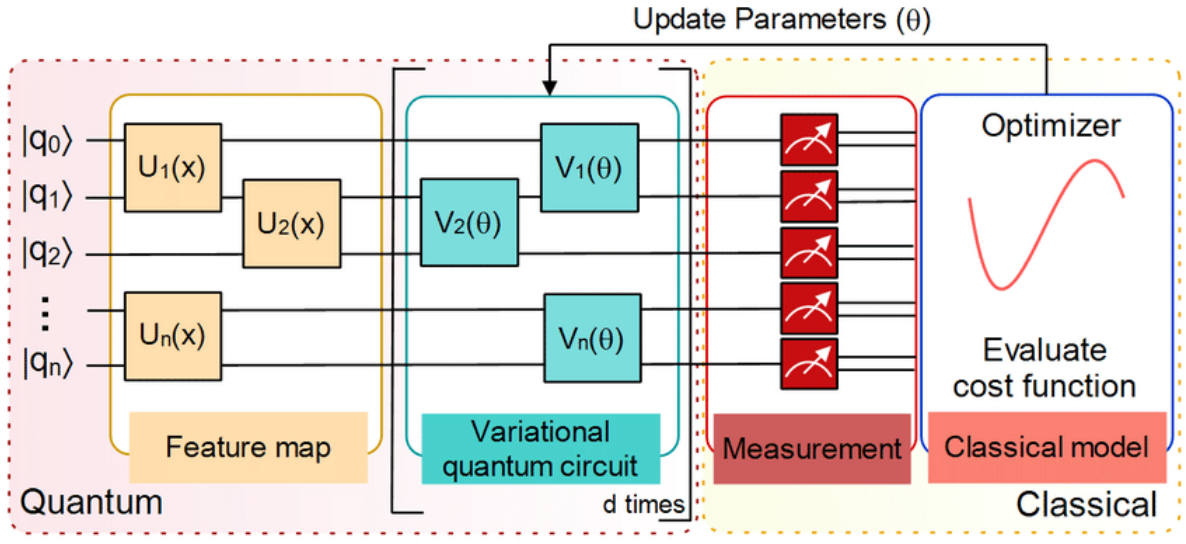
Single-Qubit Gates

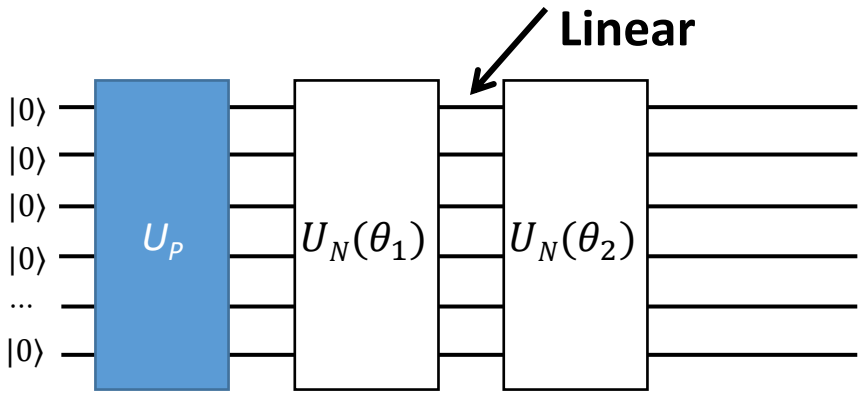
- Pauli operators: X, Y, Z Gates
- Hadamard gate: H Gate
- **General gate: U Gate**

$$\mathbf{U_3}(\theta, \phi, \lambda) = \begin{pmatrix} \cos(\theta/2) & -e^{i\lambda}\sin(\theta/2) \\ e^{i\phi}\sin(\theta/2) & e^{i(\lambda+\phi)}cos(\theta/2) \end{pmatrix}$$

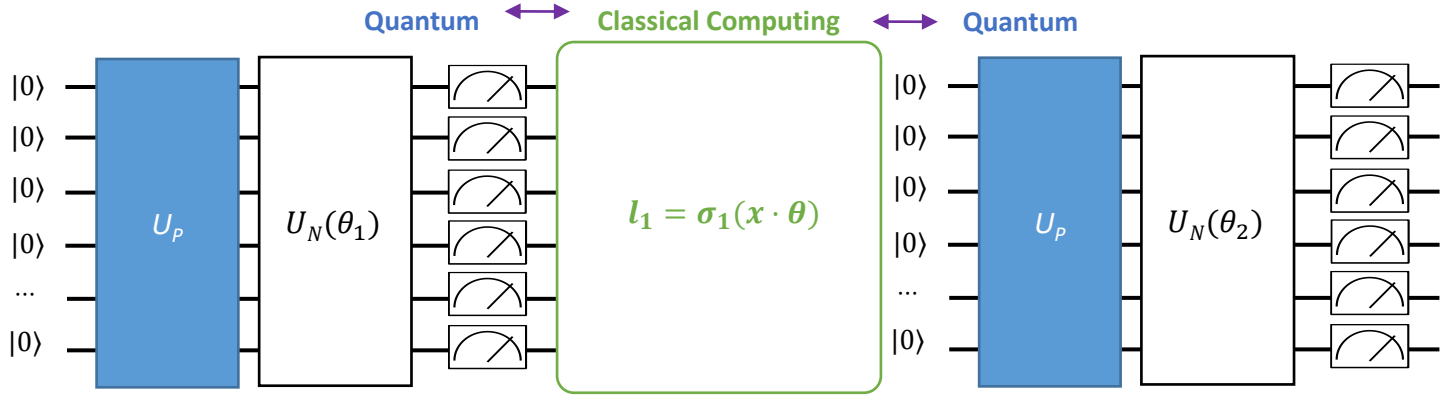
$$\mathbf{U_3}\,|\mathbf{0}\rangle = \begin{pmatrix} \cos(\theta/2) \\ e^{i\phi}\sin(\theta/2) \end{pmatrix} = \cos(\theta/\mathbf{2})\,|\mathbf{0}\rangle \;+\; \mathbf{e}^{\mathbf{i}\phi}\sin(\theta/\mathbf{2})\,|\mathbf{1}\rangle$$

Two Paths of Quantum Machine Learning: Path 1 --- VQC





[ref] Sen, P., Bhatia, A.S., Bhangu, K.S. and Elbeltagi, A., 2022. Variational quantum classifiers through the lens of the Hessian. Plos one, 17(1), p.e0262346.



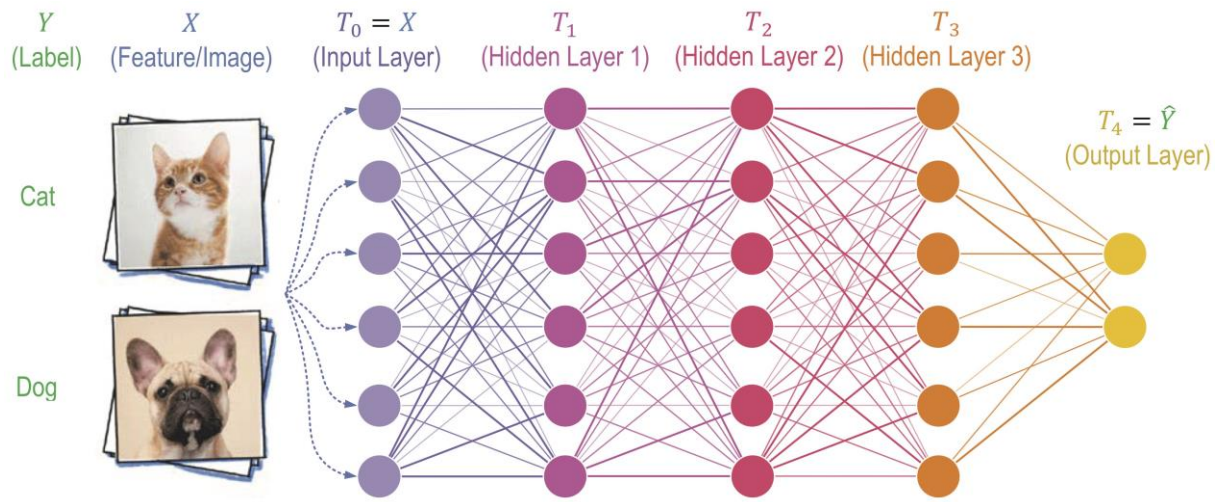
Pros:

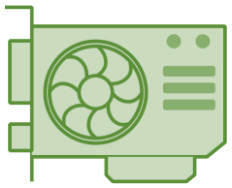
- Easy to **implement**

Cons:

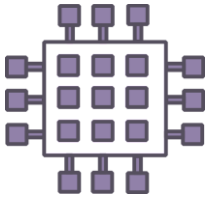
- On intermediate-scale quantum devices, no works show that **performance** of QML can beat classical ML, *so far*.
- Have no **non-linear** in the network
- Incur **heavy overhead** for **non-linearity**

Two Paths of Quantum Machine Learning: Path 2 --- Q Accelerator

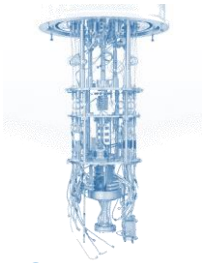




CPU/GPU Accelerator



FPGA/ASIC Accelerator



Quantum Accelerator

Pros:

- Same Performance as Classical ML

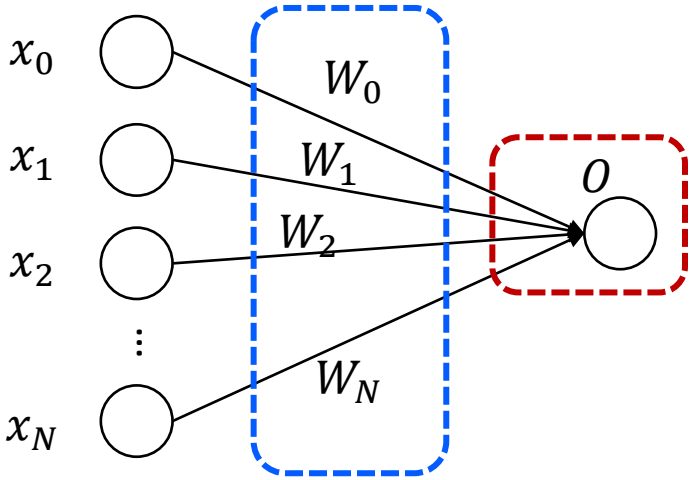
Questions:

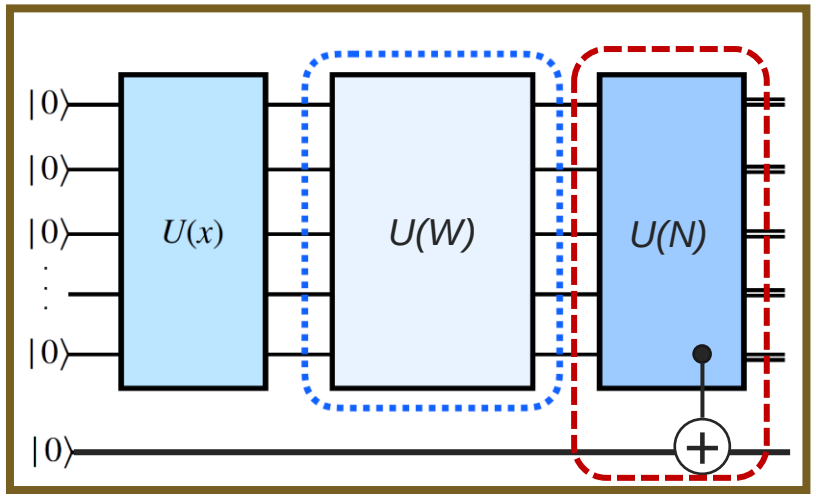
- How to design?
- Advantage?

QuantumFlow Answered Two Fundamental Questions

Fundamental questions:

- Can we use quantum gates to **correctly implement** neural functions?





- How to design quantum circuit to achieve **quantum advantage**?

$$O = \delta\left(\sum_{i\in[0,N)} x_i \times W_i\right)$$

where δ is a quadratic function

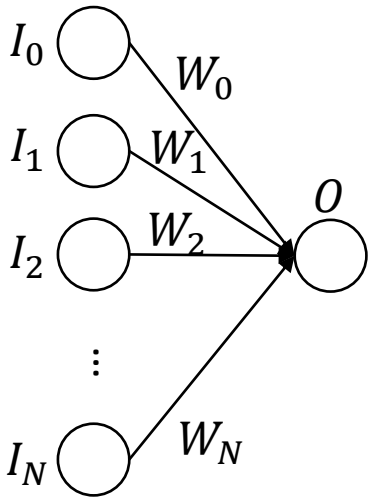
Classical Computing:

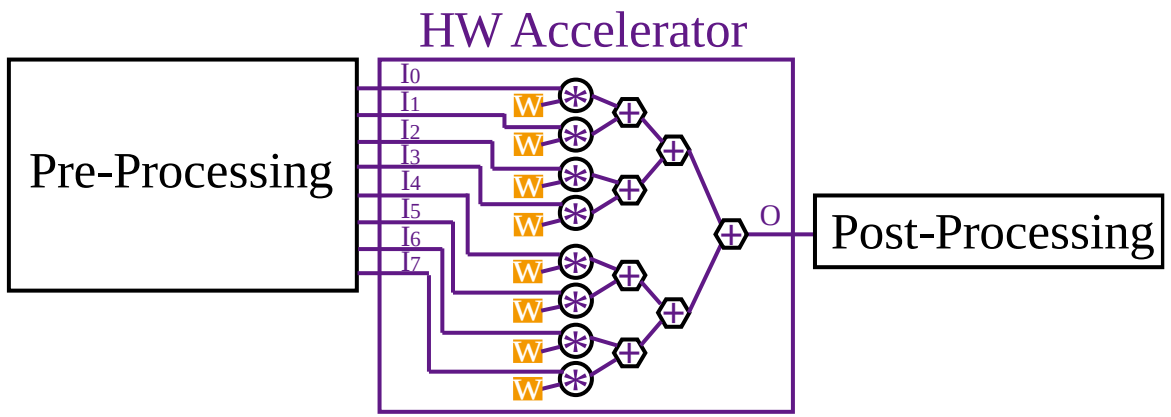
Complexity of $O(N)$

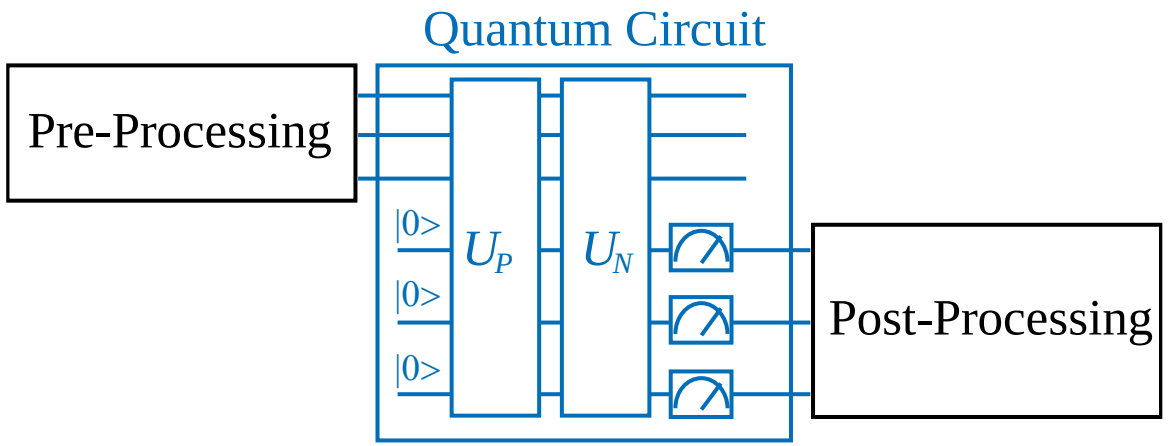
Quantum Computing:

Can we reduce complexity to $O(ploylogN)$, say $O(log^2 N)$?

Neural Network Accelerator Design from Classical to Quantum Computing







(1) Data Pre-Processing (*PreP*)

(2) HW Acceleration

(3) Data Post-Processing (*PostP*)

(1) Data Pre-Processing (*PreP*)

(2) HW/Quantum Acceleration

(2.1) U_p Quantum-State-Preparation

(2.2) U_N Quantum Neural Computation

(2.3) *M* Measurement

(3) Data Post-Processing (PostP)

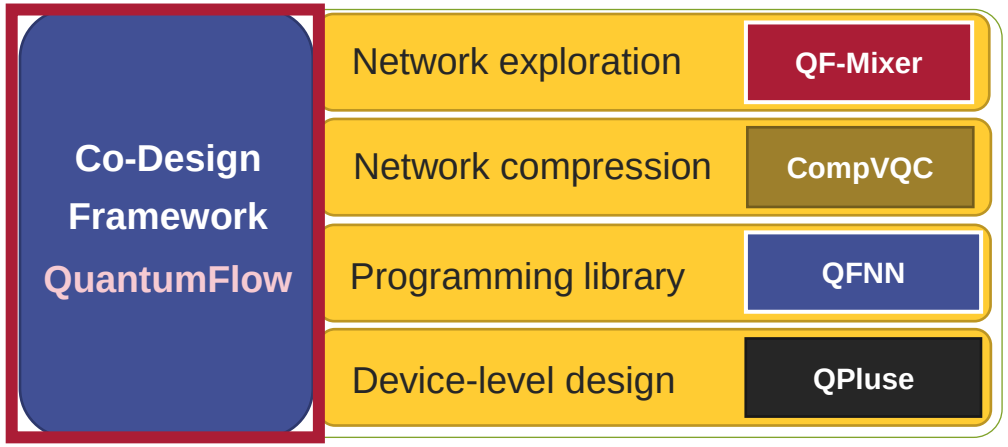
PreP + U_P + U_N + M + PostP

Hands-On: QuantumFlow

A Co-Design Framework of Neural Networks and Quantum Circuits Towards Quantum Advantage

Published at Nature Communications 2021

Presenter: Zhepeng Wang

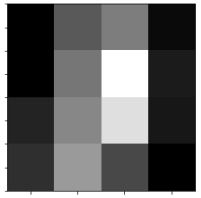


PreP + U_P + U_N + *M* + *PostP* : Data Pre-Processing

- **Given:** (1) 28×28 image, (2) the number of qubits to encode data (say Q=4 qubits in the example)
- **Do:** (1) downsampling from 28×28 to $2^Q = 16 = 4 \times 4$; (2) converting data to be the state vector in a unitary matrix
- **Output:** A unitary matrix, $M_{16\times16}$

Step 1: Downsampling

From 28×28 to 4×4



$$\begin{bmatrix} 0.0039 & 0.2118 & 0.2941 & 0.0275 \\ 0.0039 & 0.2784 & 0.5961 & 0.0667 \\ 0.0863 & 0.3176 & 0.5216 & 0.0588 \\ 0.1137 & 0.3608 & 0.1725 & 0.0039 \end{bmatrix}$$

$$\begin{bmatrix} 0.0039 & 0.2118 & 0.2941 & 0.0275 \\ 0.0039 & 0.2784 & 0.5961 & 0.0667 \\ 0.0863 & 0.3176 & 0.5216 & 0.0588 \\ 0.1137 & 0.3608 & 0.1725 & 0.0039 \end{bmatrix}$$

Step 2: Formulate Unitary Matrix

Applying SVD method
(See Listing 1 in ASP-DAC SS Paper)

Unitary matrix: $M_{16\times16}$

[SS] W. Jiang, et al. When Machine Learning Meets Quantum Computers: A Case Study, ASP-DAC'21

PreP + U_P + U_N + *M* + *PostP* --- Data Encoding / Quantum State Preparation

- **Given:** The unitary matrix provided by *PreP*, $M_{16\times16}$
- **Do:** Quantum-State-Preparation, encoding data to qubits
- **Verification:** Check the amplitude of states are consistent with the data in the unitary matrix, $M_{16\times16}$

Let's use a 2-qubit system as an example to encode a matrix $M_{4\times4}$

$$\begin{bmatrix} 0.3 & 0.5 \\ 0.7 & 0.9 \end{bmatrix} \xrightarrow{PreP} \text{data\_matrix} \begin{bmatrix} \mathbf{0.2343} & X & X & X \\ \mathbf{0.3904} & X & X & X \\ \mathbf{0.5466} & X & X & X \\ \mathbf{0.7028} & X & X & X \end{bmatrix} \xrightarrow{U_P}$$

State Transition:

data_matrix $|00\rangle$

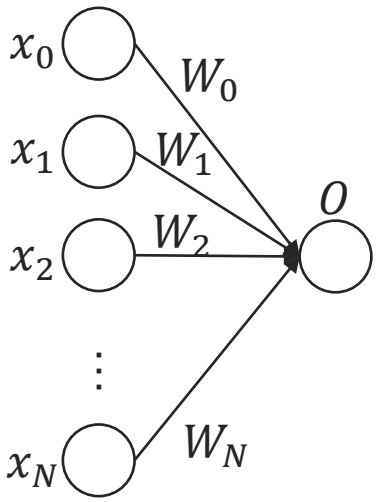
IBM Qiskit Implementation:

```
inp = QuantumRegister(4, ”in_qubit”)
circ = QuantumCircuit(inp)
iniG = UnitaryGate(data_matrix, label=”input”)
circ.append(iniG, inp[0:4])
```

Hands-On Tutorial (1)

PreP + U_P

PreP + U_P + U_N + M + PostP --- Neural Computation



- **Given:** (1) A circuit with encoded input data $\boldsymbol{x}$; (2) the trained binary weights $\boldsymbol{w}$ for one neural computation, which will be associated to each data.
- **Do:** Place quantum gates on the qubits, such that it performs $\frac{(\boldsymbol{x}*\boldsymbol{w})^2}{\|\boldsymbol{x}\|}$.
- **Verification:** Whether the output data of quantum circuit and the output computed using torch on classical computer are the same.

Target: $O = \left[\frac{\sum_i (x_i \times w_i)}{\sqrt{\|x\|}}\right]^2$

- **Assumption 1:** Parameters/weights (W_0 --- W_N) are binary weight, either +1 or -1
- **Assumption 2:** The weight $W_0 = +1$, otherwise we can use $-\boldsymbol{w}$ (quadratic func.)

Step 1: $m_i = x_i \times w_i$

Step 2: $n = \left[\frac{\sum_i (m_i)}{\sqrt{\|x\|}}\right]$

Step 3: $O = n^2$

Quantum Neuron Design: Step 1

Step 1: $m_i = x_i \times w_i$

EX: 4 input data on 2 qubits

$$\boldsymbol{x} = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{bmatrix} \qquad \boldsymbol{w} = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ w_3 \end{bmatrix} \qquad \begin{matrix} w_0 = 1 \\ w_1 = 1 \\ w_2 = 1 \\ w_3 = -1 \end{matrix} \Rightarrow m_3 = -1 \times a_3 = -a_3$$

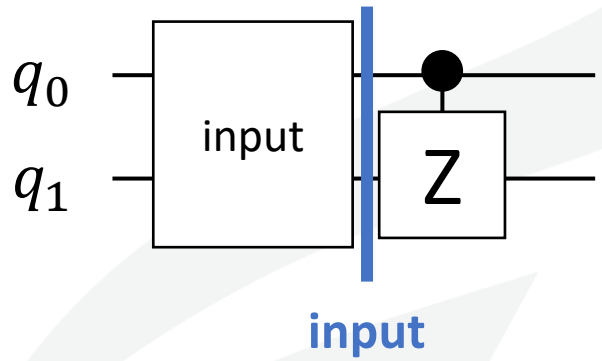
Output = **U** × **Input**

Output	
a_0	$\|00\rangle$
a_1	$\|01\rangle$
a_2	$\|10\rangle$
$m_3 = -a_3$	$\|11\rangle$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix} \times$$

Input	
a_0	$\|00\rangle$
a_1	$\|01\rangle$
a_2	$\|10\rangle$
a_3	$\|11\rangle$

Quantum Circuit



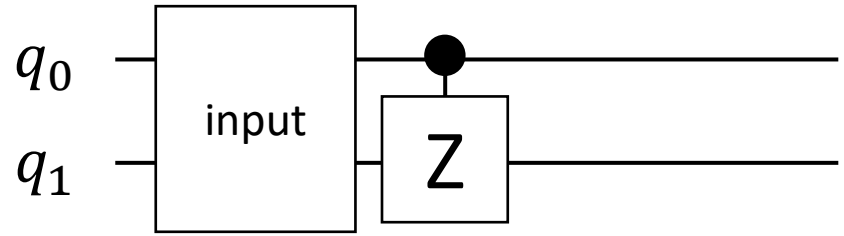
Quantum Neuron Design: Step 1

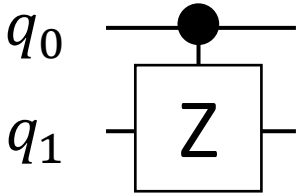
Step 1: $m_i = x_i \times w_i$

$$\boldsymbol{w} = \begin{bmatrix}+1\\+1\\+1\\-1\end{bmatrix} \text{or} \begin{bmatrix}+1\\+1\\-1\\-1\end{bmatrix} \text{or} \begin{bmatrix}+1\\-1\\-1\\-1\end{bmatrix} \text{or} \begin{bmatrix}+1\\+1\\-1\\+1\end{bmatrix} \text{or} \begin{bmatrix}+1\\-1\\-1\\+1\end{bmatrix} \text{or} \begin{bmatrix}+1\\-1\\+1\\+1\end{bmatrix}$$

EX: 4 input data on 2 qubits

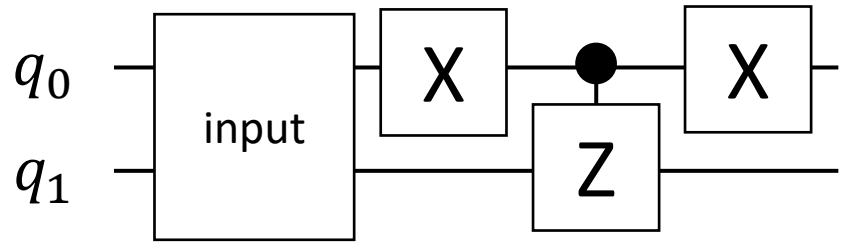
$\boldsymbol{w} = \begin{bmatrix}+1\\+1\\+1\\-1\end{bmatrix}$

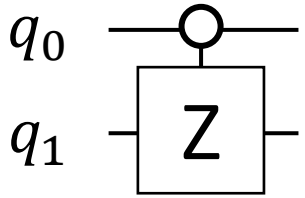




Flip the sign of $|11\rangle$

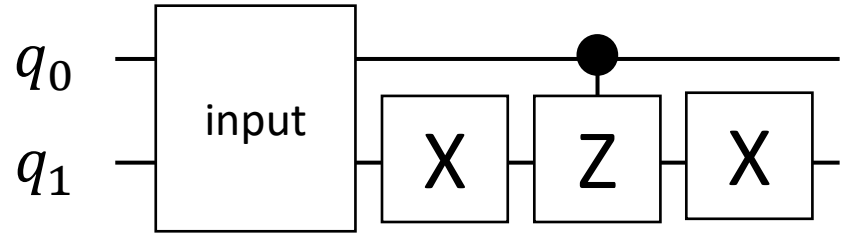
$\boldsymbol{w} = \begin{bmatrix}+1\\-1\\+1\\+1\end{bmatrix}$

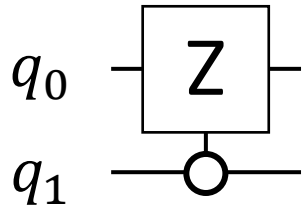




Flip the sign of $|01\rangle$

$\boldsymbol{w} = \begin{bmatrix}+1\\+1\\-1\\+1\end{bmatrix}$





Flip the sign of $|10\rangle$

Quantum Neuron Design: Step 2

Step 2: $n = \left[\frac{\sum_i (m_i)}{\sqrt{\|x\|}}\right]$

EX: 4 input data on 2 qubits

Output = **U** × **Input**

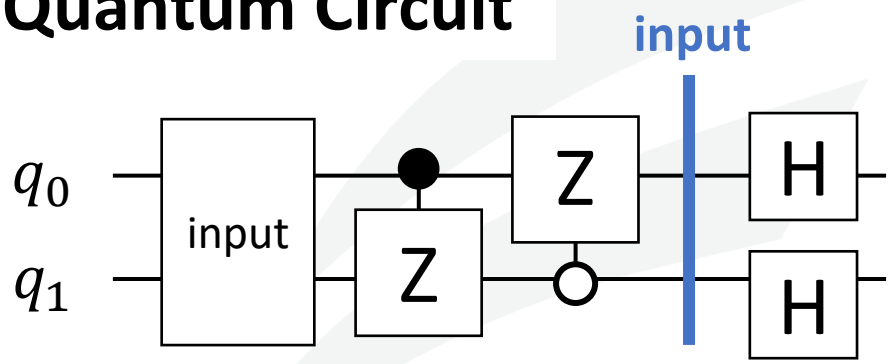
$\sum_i (m_i)/\sqrt{\|x\|}$	$\|00\rangle$
Do not care 1	$\|01\rangle$
Do not care 2	$\|10\rangle$
Do not care 3	$\|11\rangle$

$$= \frac{1}{\sqrt{\|x\|}} \begin{bmatrix} 1 & 1 & 1 & 1 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \times$$

m_0	$\|00\rangle$
m_1	$\|01\rangle$
m_2	$\|10\rangle$
m_3	$\|11\rangle$

note: $\|x\| = 2^N$

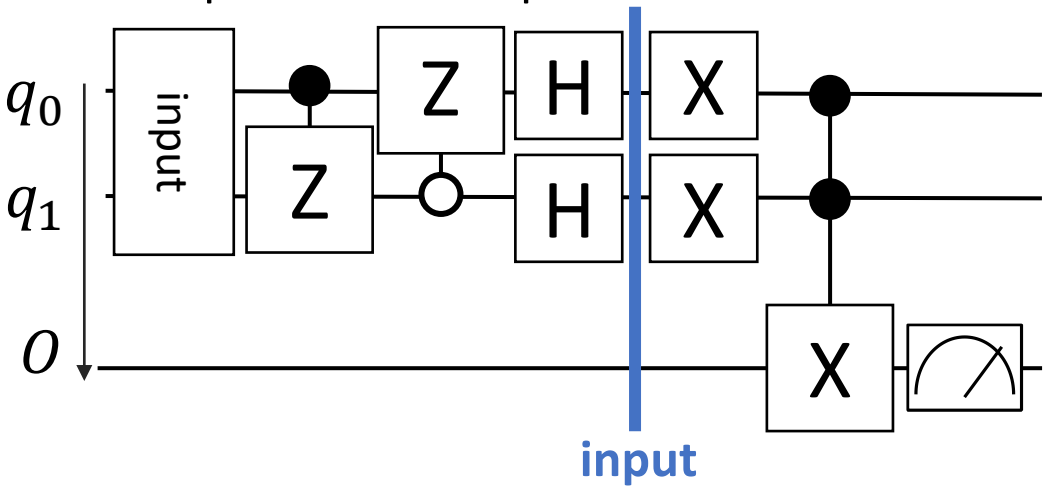
Quantum Circuit



Quantum Neuron Design: Step 3

Step 3: $O = n^2$

EX: 4 input data on 2 qubits



Input

$\sum_i (m_i)/\sqrt{\|\|x\|\|}$	$\|000\rangle$
0	$\|001\rangle$
Do not care 1	$\|010\rangle$
0	$\|011\rangle$
Do not care 2	$\|100\rangle$
0	$\|101\rangle$
Do not care 3	$\|110\rangle$
0	$\|111\rangle$

$X^{\otimes 2}$

Do not care 3	$\|000\rangle$
0	$\|001\rangle$
Do not care 2	$\|010\rangle$
0	$\|011\rangle$
Do not care 1	$\|100\rangle$
0	$\|101\rangle$
$\sum_i (m_i)/\sqrt{\|\|x\|\|}$	$\|110\rangle$
0	$\|111\rangle$

CCX

Do not care	$\|000\rangle$
0	$\|001\rangle$
Do not care	$\|010\rangle$
0	$\|011\rangle$
Do not care	$\|100\rangle$
0	$\|101\rangle$
0	$\|110\rangle$
$\sum_i (m_i)/\sqrt{\|\|x\|\|}$	$\|111\rangle$

Output

$$P\{O = |1\rangle\} = P\{|001\rangle\} + P\{|011\rangle\} + P\{|101\rangle\} + P\{|111\rangle\} = \left[\frac{\sum_i (m_i)}{\sqrt{\|\|x\|\|}}\right]^2$$

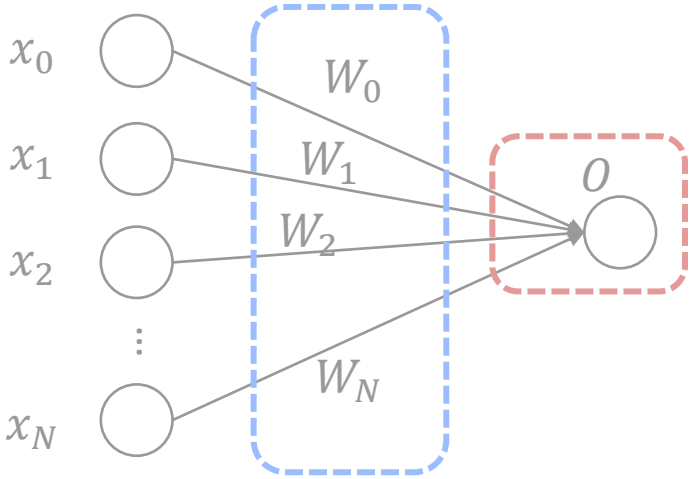
Hands-On Tutorial (2)

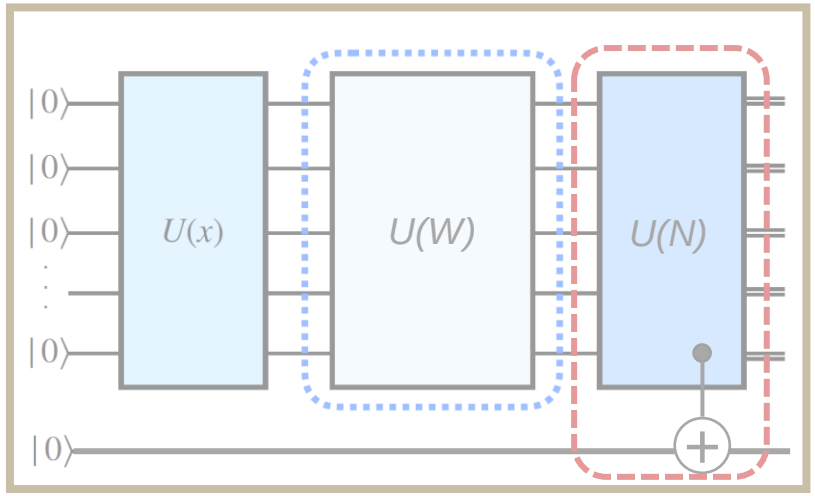
PreP + U_P + U_N

QuantumFlow Answered Two Fundamental Questions

Fundamental questions:

- Can we use quantum gates to **correctly implement** neural functions?





- How to design quantum circuit to achieve **quantum advantage**?

$$O = \delta\left(\sum_{i\in[0,N)} x_i \times W_i\right)$$

where δ is a quadratic function

Classical Computing:

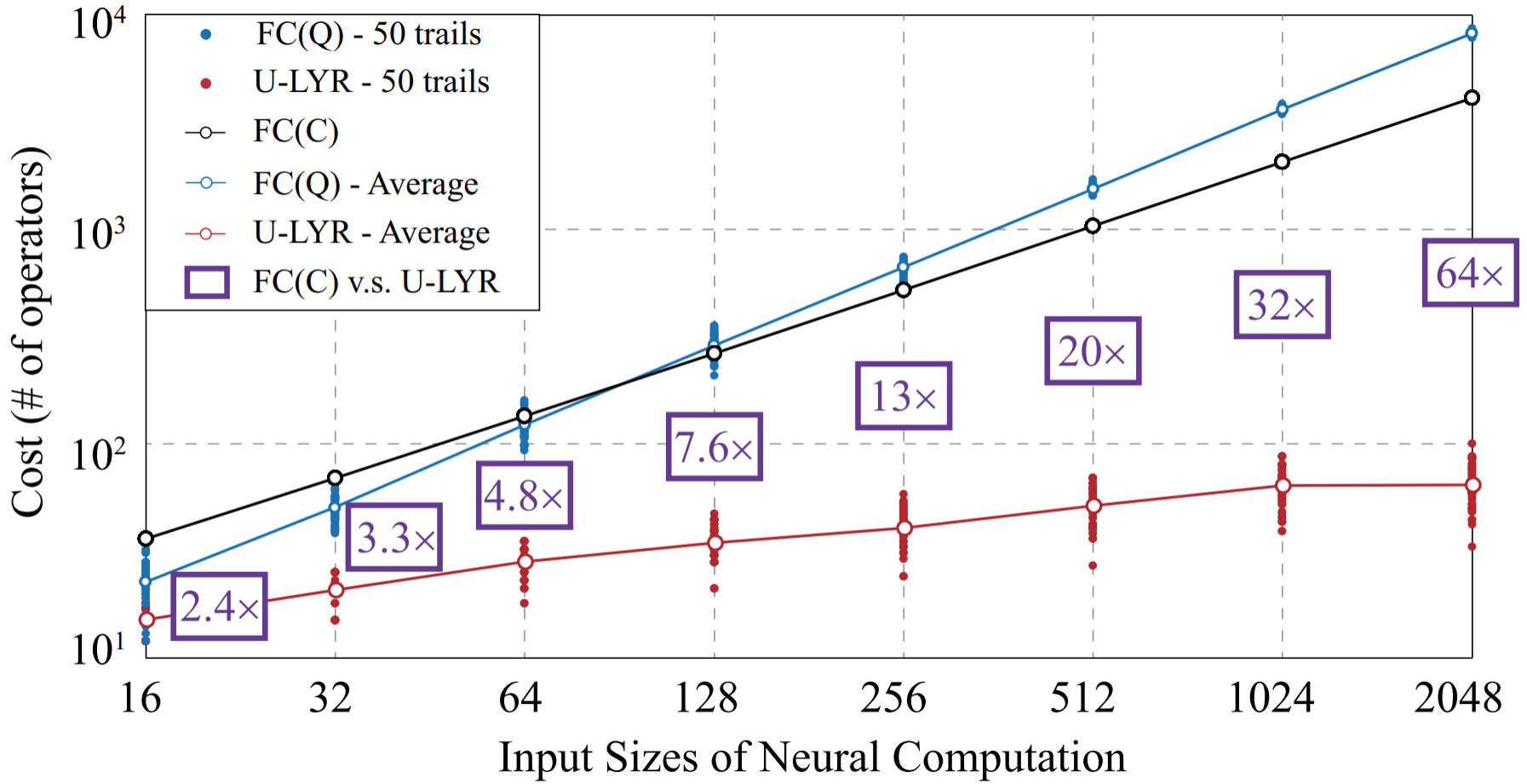
Complexity of $\boldsymbol{O(N)}$

Quantum Computing:

Can we reduce complexity to

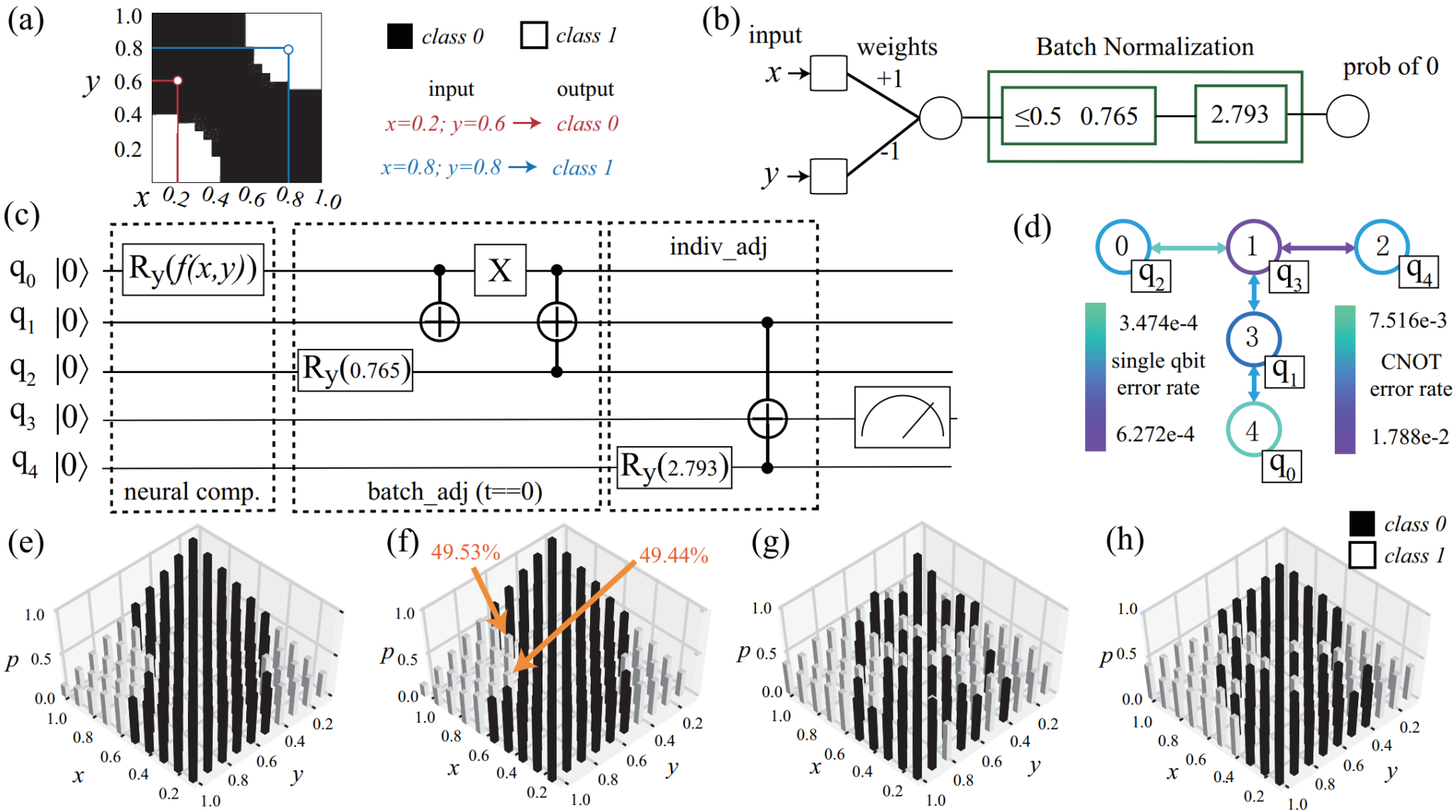
$\boldsymbol{O(ploylogN)}$, say $\boldsymbol{O(log^2 N)}$?

QuantumFlow Results



[ref] Tacchino, F., et al., 2019. An artificial neuron implemented on an actual quantum processor. *npj Quantum Information*, *5*(1), pp.1-8.

On Actual IBM "ibmq_essex" (retired) Quantum Processor

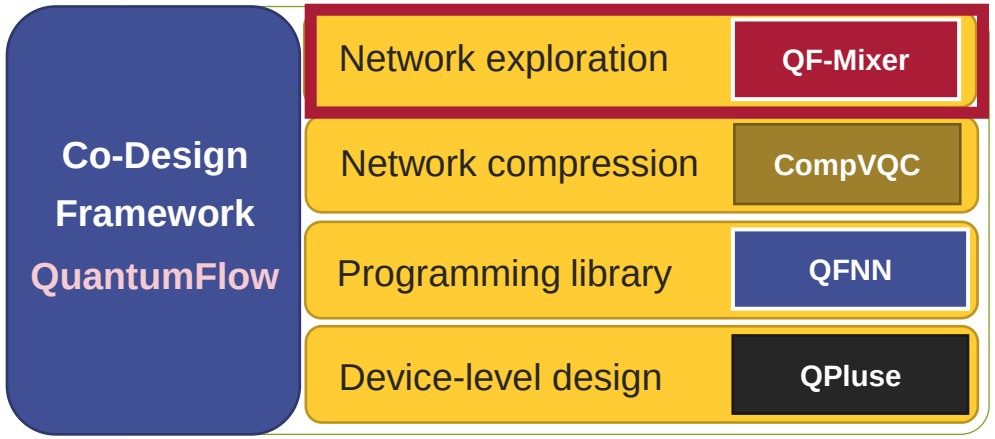


Quantum Neural Network: QF-Mixer

Exploration of Quantum Neural Architecture by Mixing Quantum Neuron Designs

Published at IEEE/ACM International Conference on Computer-Aided Design 2021

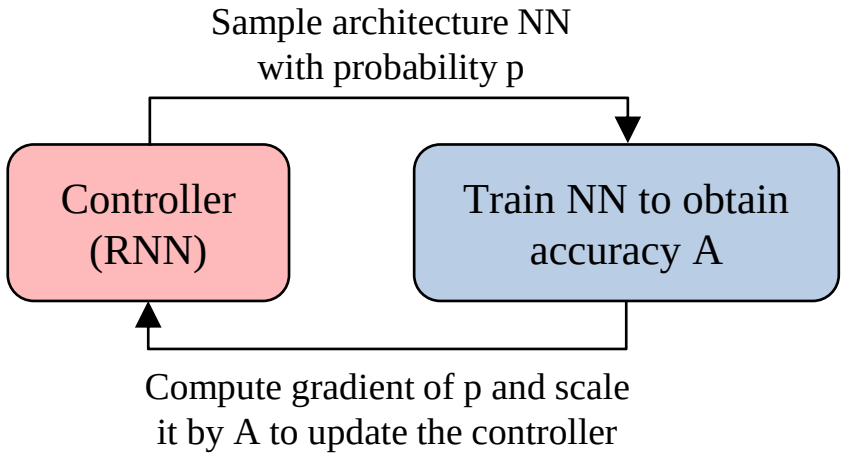
Presenter: Zhepeng Wang



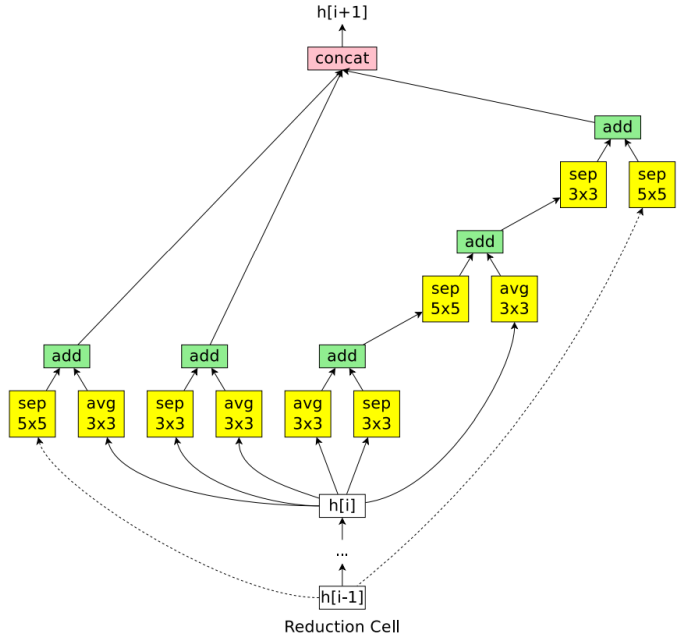
Towards the Automatic Design of Quantum Neural Networks

Further questions:

- What is the best quantum neural network for an application on NISQ computer?



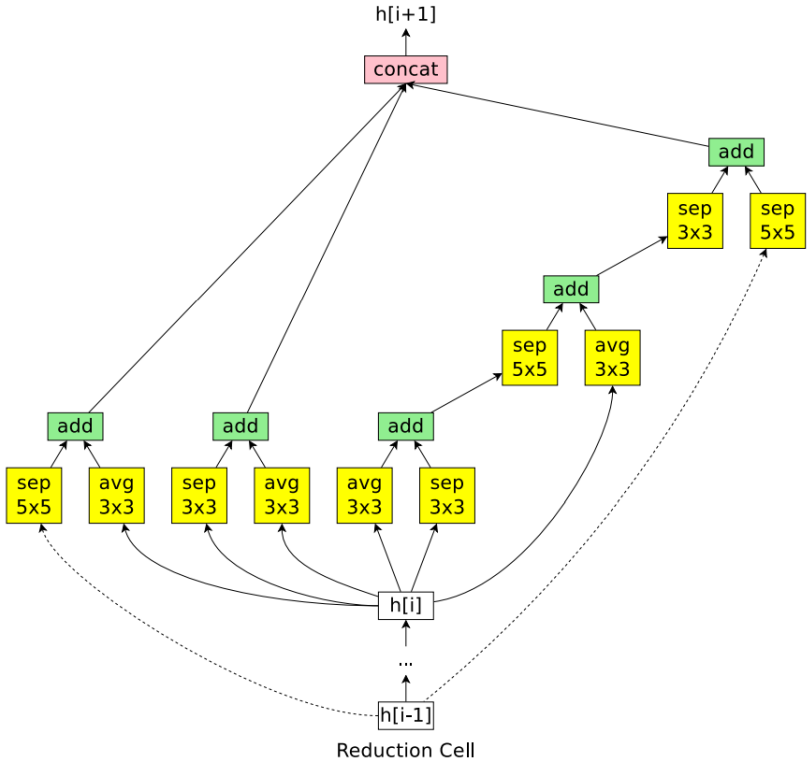
Google's Initial Contributions
(Neural Architecture Search)



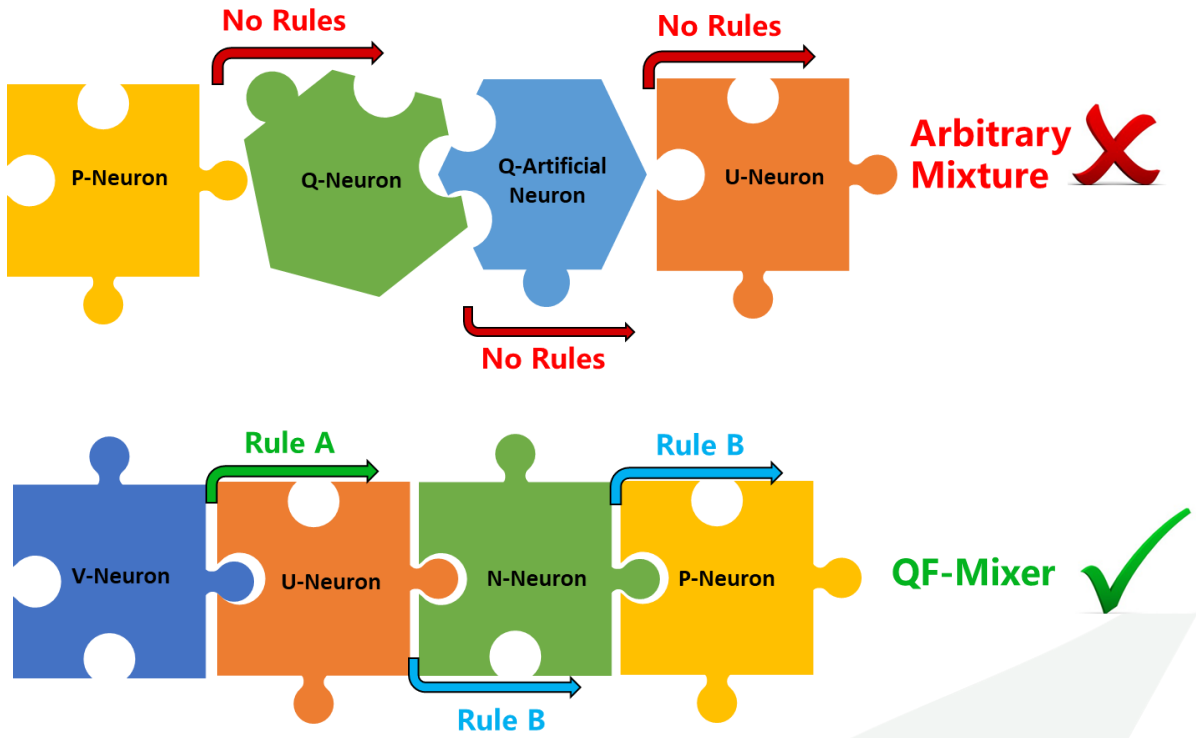
The "Architecture" of Different Artificial Neurons

[ref] Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *ICLR 2017*

Challenges



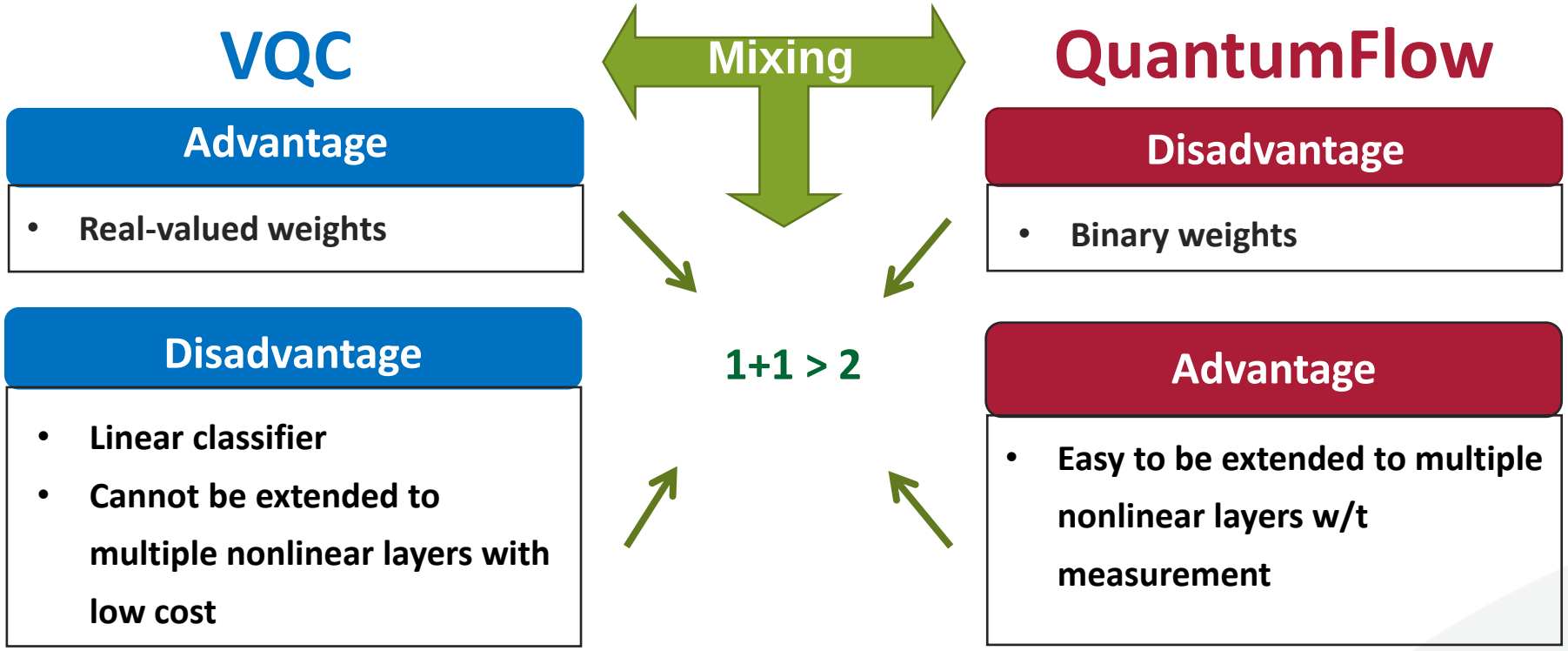
Different operators/neurons in classical computing can be connected seamlessly.

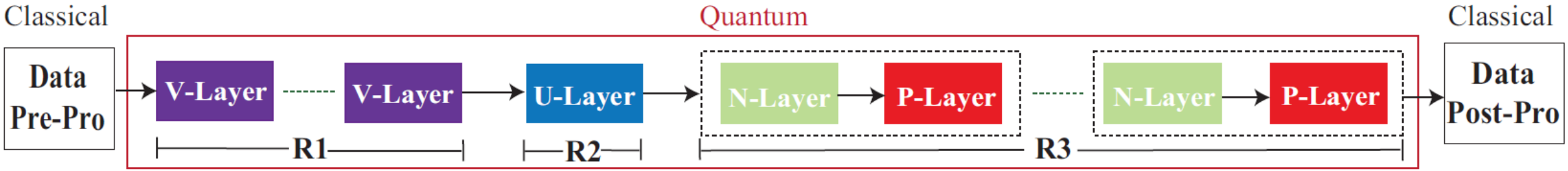


Connect different quantum neurons may incur high overhead; will not be seamless.

QF-MixNN

- Based on Design Principles, we found that VQC and QuantumFlow are complementary





QF-MixNN Achieves the Best Accuracy on MNIST

TABLE I
EVALUATION OF QNNS WITH DIFFERENT NEURAL ARCHITECTURE

Architecture		MNIST-2†	MNIST-3†	MNIST-4‡	MNIST-5‡	MNIST§
VQC (V×R1)		**97.91%**	90.09%	93.45%	91.35%	52.77%
QuantumFlow		95.63%	91.42%	94.26%	89.53%	69.92%
QF-MixNN	V+U	97.36%	**92.77%**	**94.41%**	**93.85%**	88.46%
	V+U+P	87.45%	82.9%	92.44%	91.56%	**90.62%**
	V+P	91.72%	76.93%	88.43%	85.02%	49.57%

Input resolutions: † 4 × 4; ‡ 8 × 8; § 16 × 16;

- **Non-linearity is important**. A linear decision boundary is not sufficient for complicated tasks.
- **Real-valued weight is helpful**. It increases the representation capability of QNN significantly.

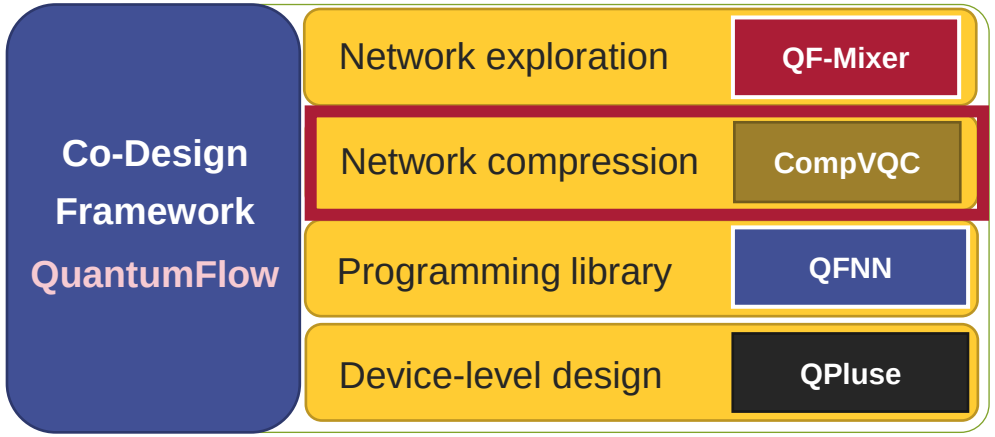
- **QF-MixNN** takes the advantage of both **VQC-based QNN** and **QF-Net** from Quantumflow.
- Achieve **highest accuracy** for full set of MNIST dataset

CompVQC

Quantum Neural Network Compression

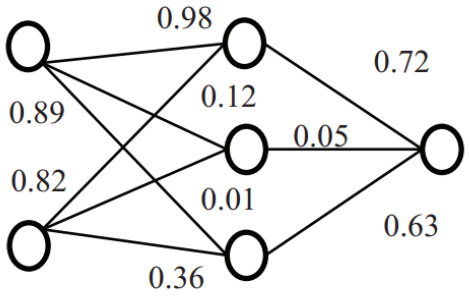
https://arxiv.org/pdf/2207.01578.pdf

Presenter: Weiwen Jiang

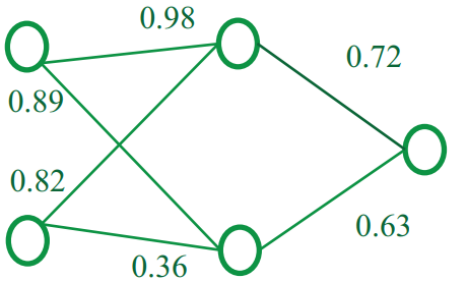


Compression: From Classical To Quantum

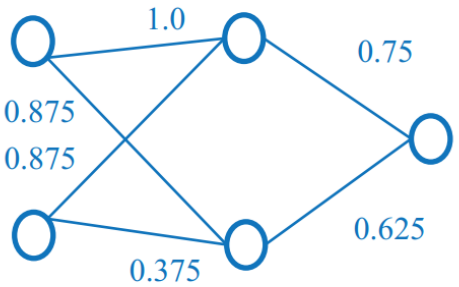
- Pruning and Quantization in Classical ML



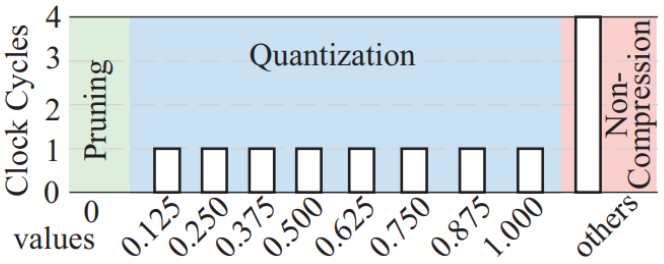
(a) Non-Compression Classical NN



(b) Classical NN with Pruning

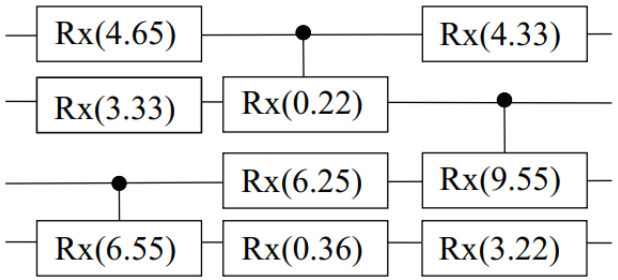


(c) Pruned NN with Quantization

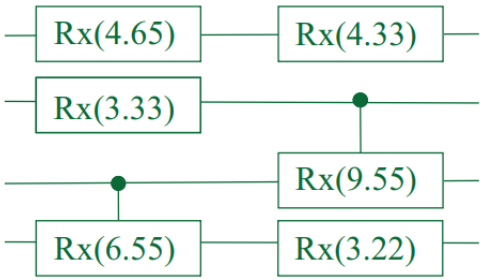


(d) Cost of Different Levels in Classical NN

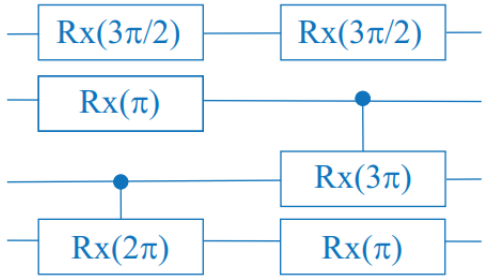
- Pruning and Quantization in Quantum ML



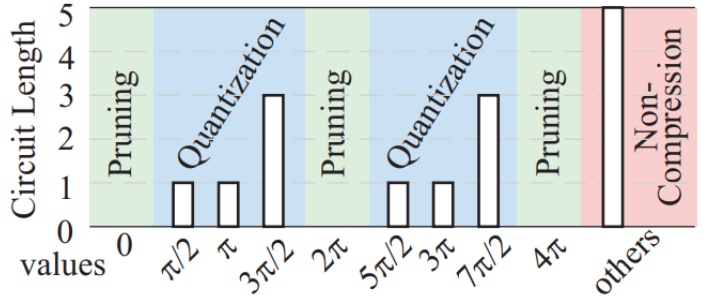
(e) Non-Compression QNN



(f) QNN with Pruning



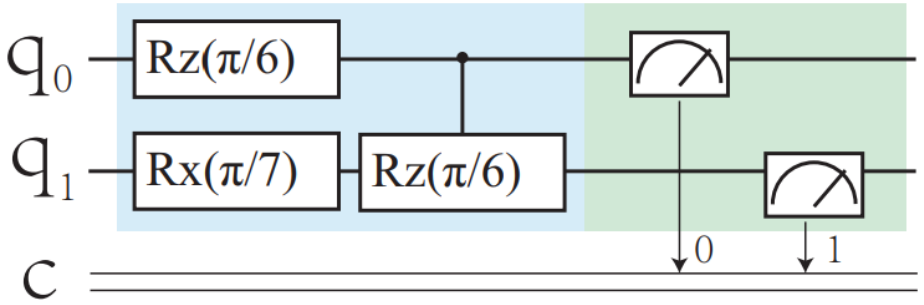
(g) Pruned QNN with Quantization



(h) Cost of Different Levels in RX Gate in QNN

- **Pruning:** Not only 0 can be pruned, but also 2pi, 4pi, etc.
- **Quantization:** Different quantization level may have different cost

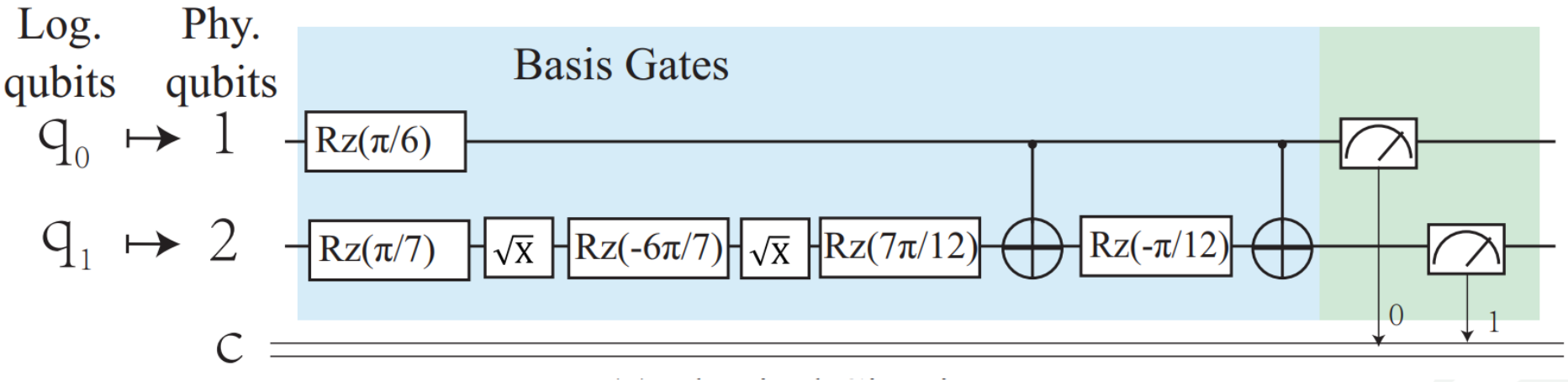
Quantum Compression is Compilation Aware



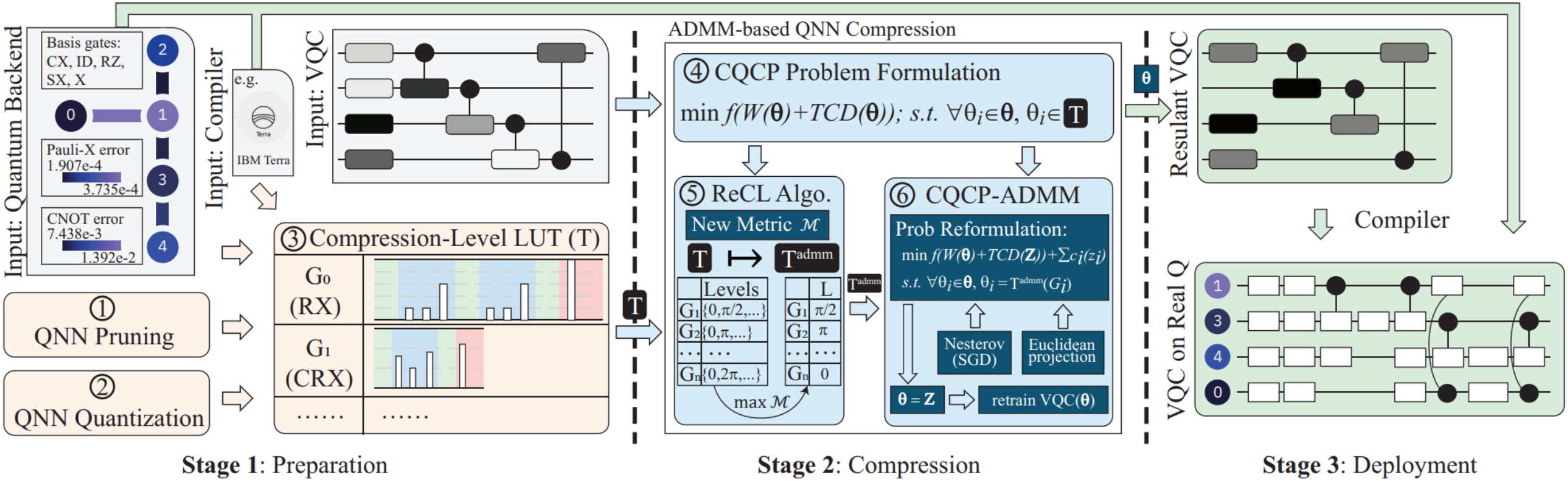
Compilation

Table 1: circuit depth of compiled quantum gates on IBM quantum processors; parameters are in the range of $[0, 4\pi]$

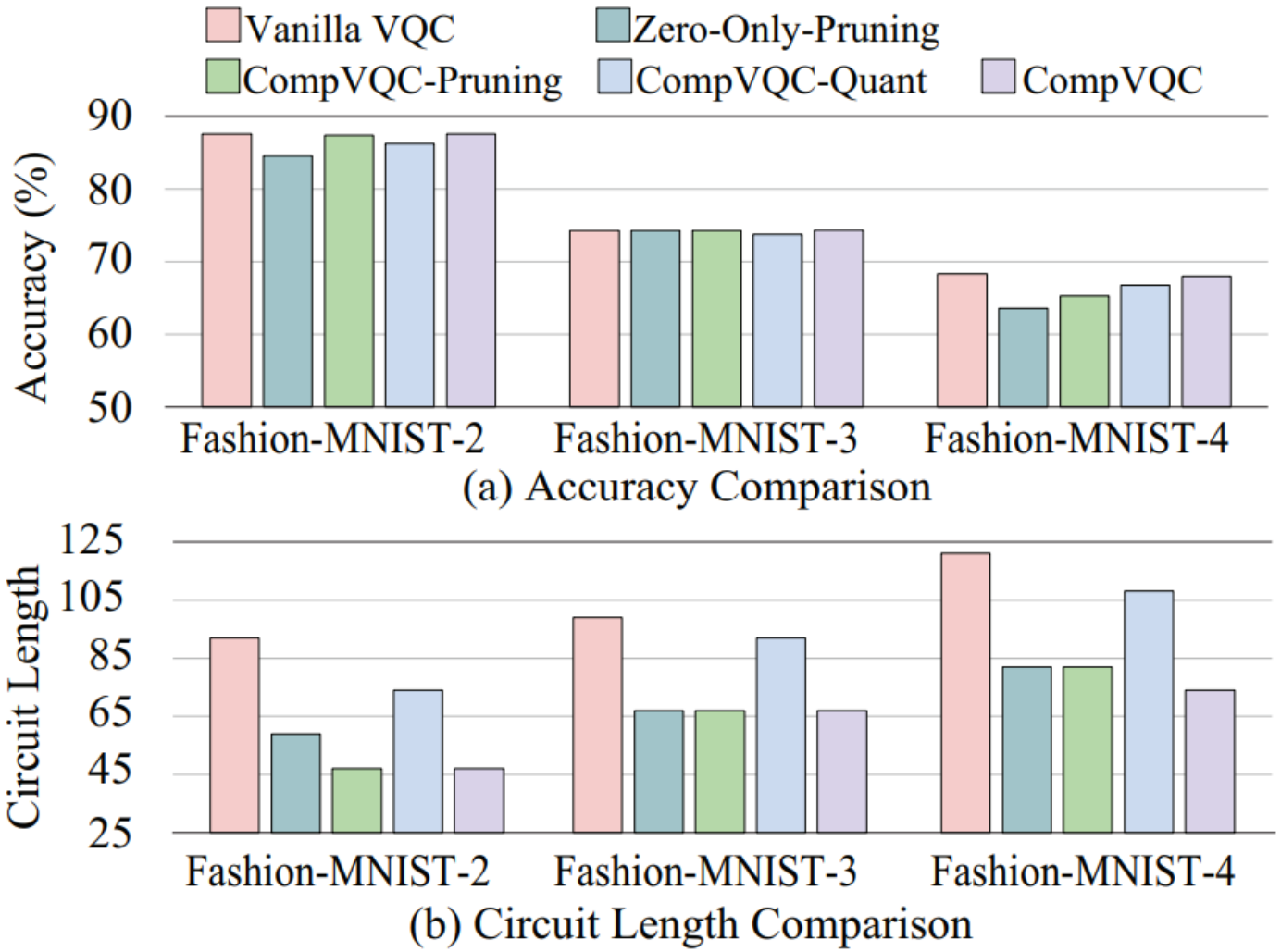
Gate	0	π	2π	3π	4π	$\pi/2$	$3\pi/2$	$5\pi/2$	$7\pi/2$	others
RX	0	1	0	1	0	1	3	1	3	5
RY	0	2	0	2	0	3	3	3	3	4
CRX	0	8	5	9	0	11	11	11	11	11
CRY	0	8	6	8	0	10	10	10	10	10



CompVQC Framework



Results



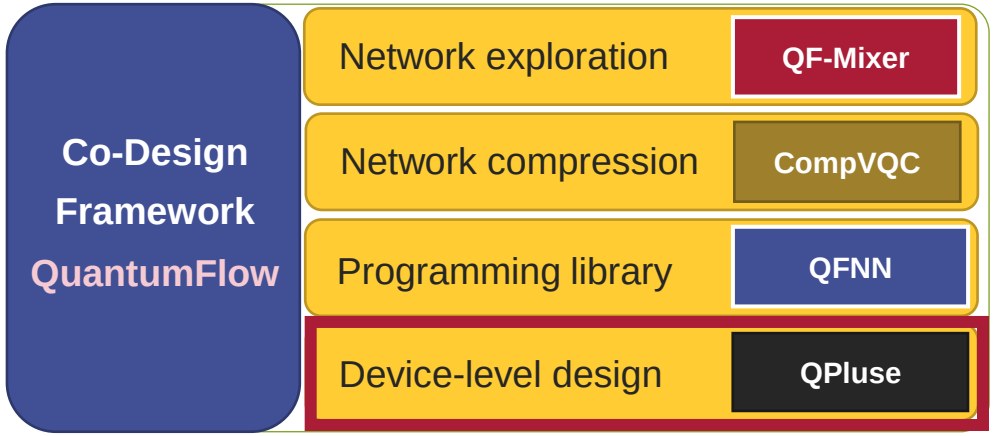
- CompVQC can maintain high accuracy with **<1% accuracy loss**
- CompVQC can reduce circuit length by **2.5X**

Quantum Pulse: VQP

Variational Quantum Pulse Learning

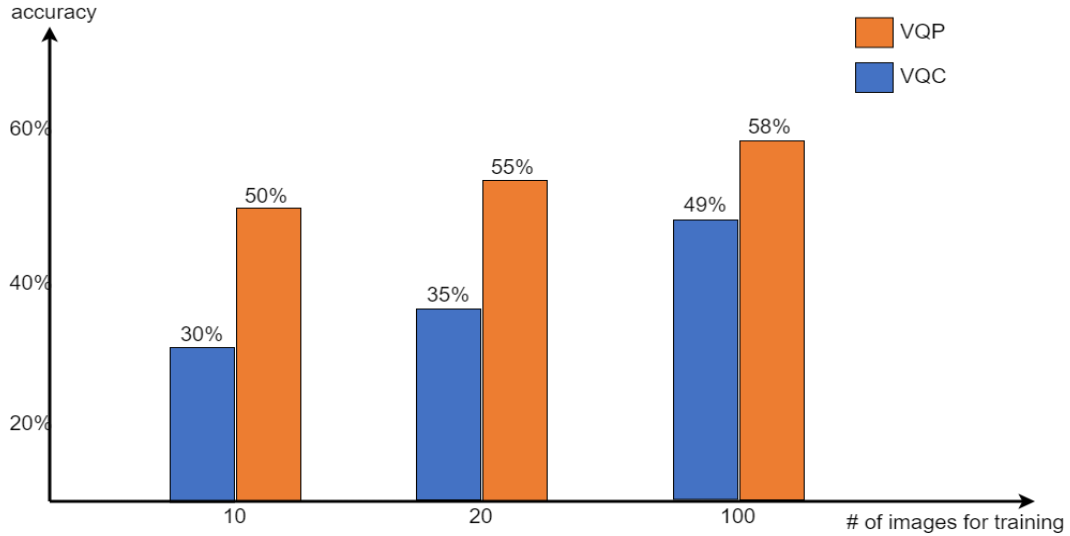
Published at IEEE Quantum Week 2022

Presenter: Zhiding Liang

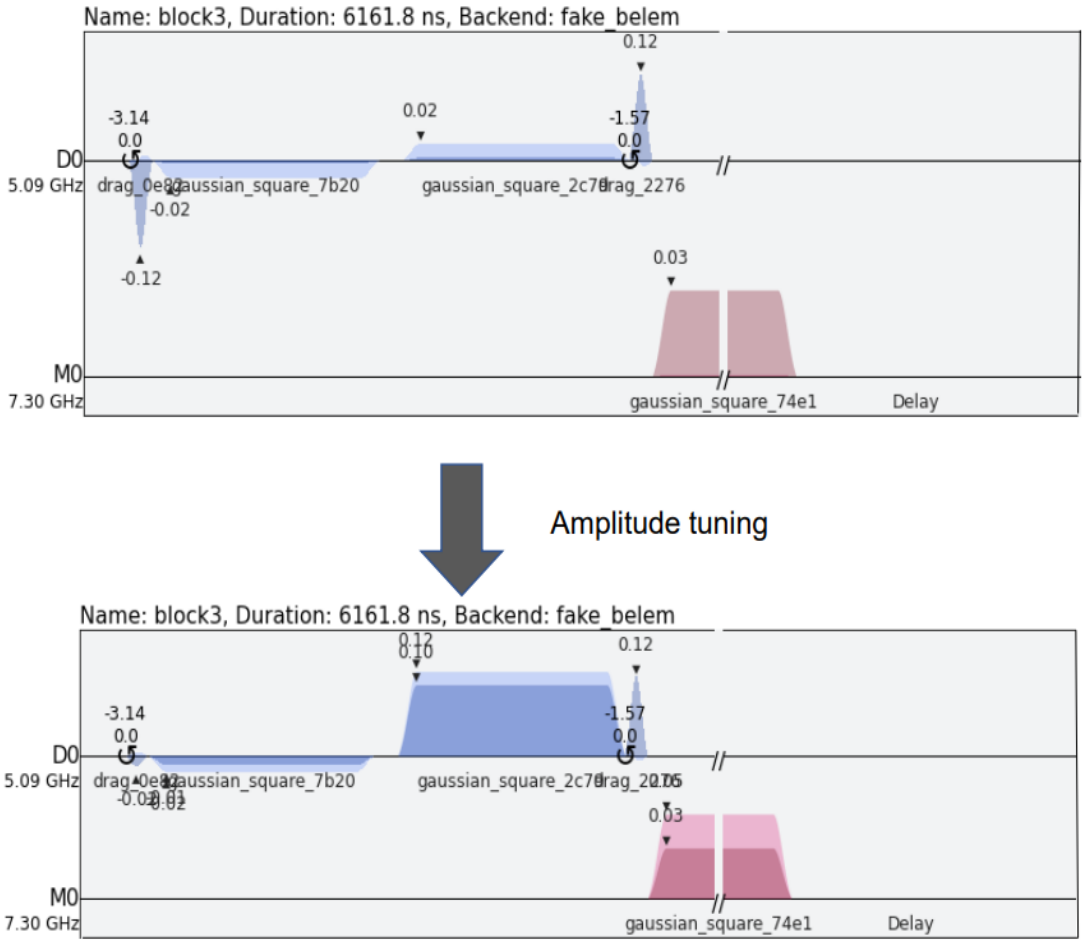


Why pulse learning?

- Variational quantum circuit (VQC) shows the potential on ML tasks on explore search space due to the property.
- Compared to the VQC, VQP has more parameters that learnable.
- Compared to the VQC, VQP avoid partial of noise from decoherence error.
- Compared to the VQC, VQP directly change the physical parameters on physical pulses. Thus, gain the flexible on the control.



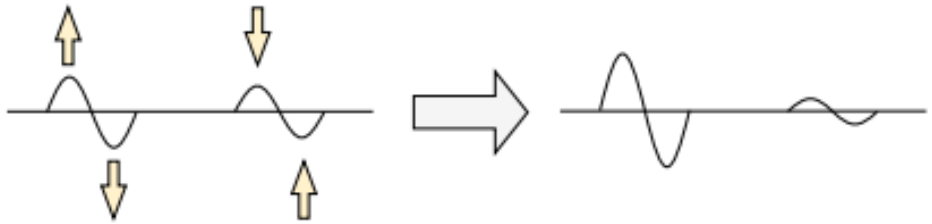
Why pulse learning?

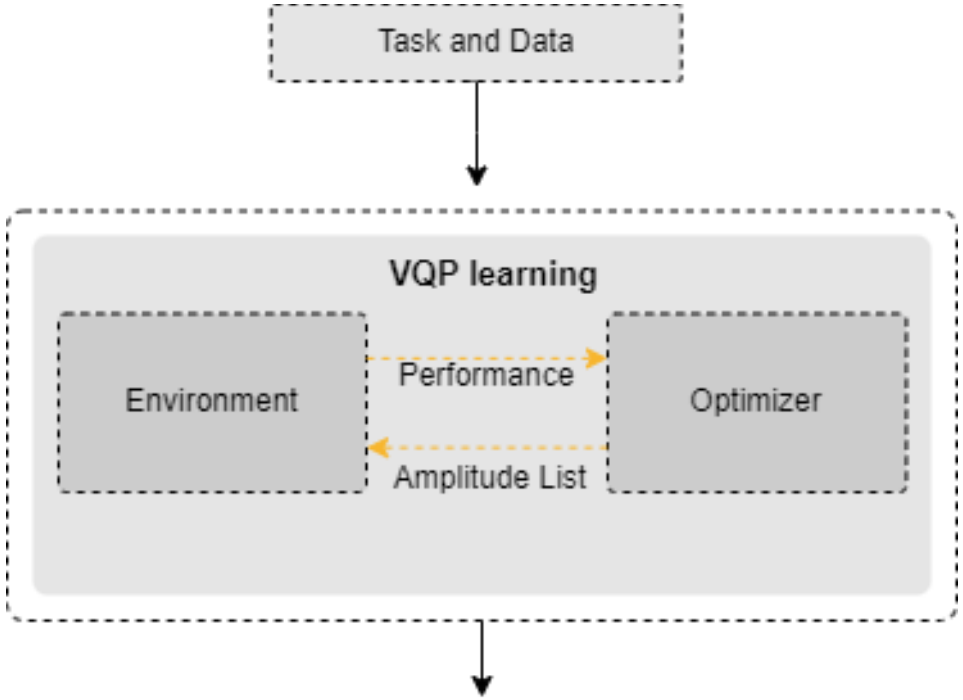


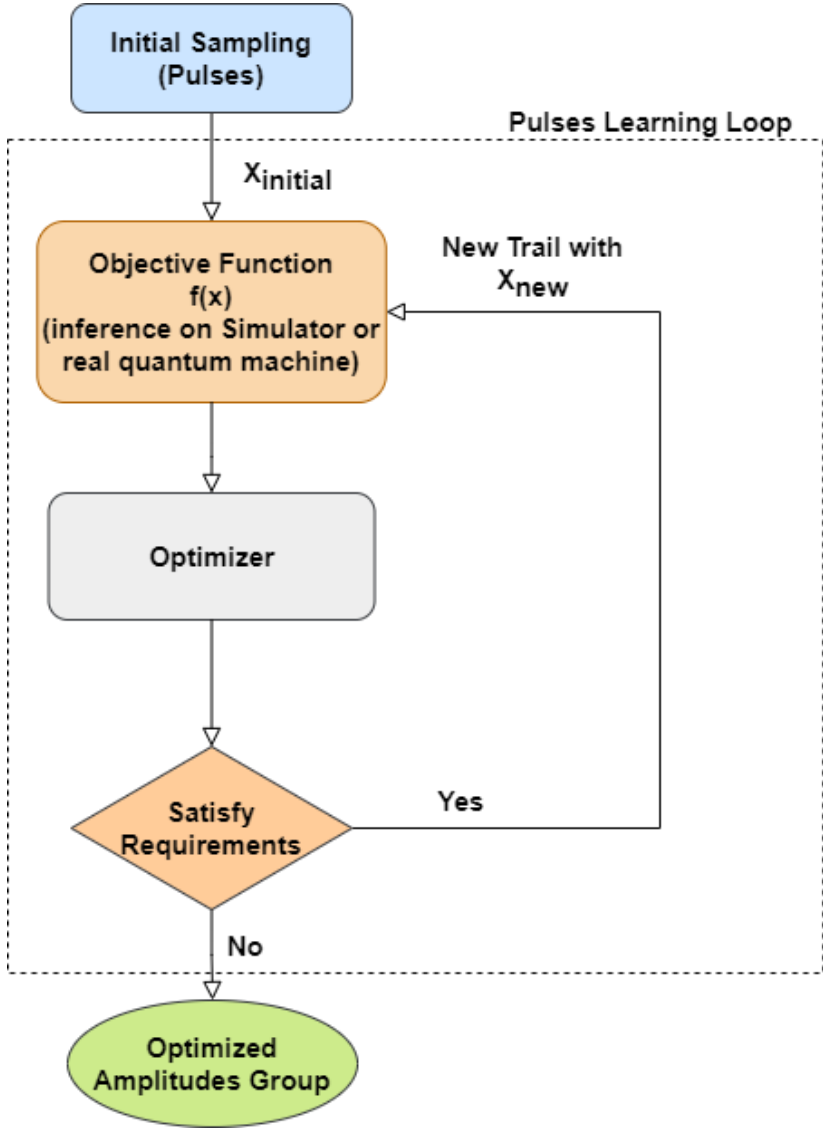
$$H = \sum_{i=0}^{1}(U_i(t) + D_i(t))\sigma_i^X + \sum_{i=0}^{1} 2\pi\nu_i(1-\sigma_i^Z)/2 + \omega_B a_B a_B^\dagger + \sum_{i=0}^{1} g_i\sigma_i^X(a_B + a_B^\dagger) \quad (1)$$

$$D_i(t) = Re(d_i(t)e^{iw_{d_i}t})$$
$$U_i(t) = Re[u_i(t)e^{i(w_{d_i} - w_{d_j})t})] \quad (2)$$

Optimization Framework?







Why pulse learning?

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Form of CX gate	Noise simulator (Quito)	Time Duration Noise simulator (Belem)	Noise simulator (Jakarta)
CRX(π) gate	26832.0dt	32016.0dt	26832.0dt
CX gate	25136.0dt	27728.0dt	25136.0dt

Advantage in specific gate

Model	# of Gate	Time Duration ibmq_jakarta	Noise simulator (Belem)
VQP	**9**	**40816.0dt**	**45168.0dt**
VQC*	12	58896.0dt	58768.0dt
VQP_transpiled	**11**	**32368.0dt**	**32816.0dt**
VQC*_transpiled	17	53008.0dt	46192.0dt

Advantage in general circuit

Experiment Result

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Model	Accuracy Noise simulator (Belem)	ibmq_jakarta
VQC learning 20	0.57	0.58
VQP learning 20	**0.6**	**0.69**
VQC learning 100	0.61	0.59
VQP learning 100	**0.63**	**0.64**
VQC learning MNIST 20	0.6	0.56
VQP learning MNIST 20	**0.66**	**0.62**
VQC learning MNIST 100	0.57	0.62
VQP learning MNIST 100	**0.61**	**0.71**

Achieves higher accuracy under same condition

Model	# of Gates	Accuracy
VQC_base	9	0.62
VQP	**9**	**0.71**
VQC*	12	0.68

VQC with more gates has similar performance in terms of accuracy

Challenge for Pulse Learning

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1. Non-gradient-based optimizer has randomness when parameter in high dimensional space.

2. Qiskit pulse simulator is not efficient, e.g., need around 3 mins to finish a 9-gate circuit.

Model	# of Gates	Accuracy
VQC_base	9	0.62
VQP	**9**	**0.71**
VQC*	12	0.68

Model	# of Gates	Accuracy
VQP	**9**	**0.71**
VQC with gradient	9	0.73
VQC* with gradient	12	0.77

This table shows the VQC with gradient-based algorithm and VQP with Bayesian optimization framework, both for same machine learning task.

Gradient based algorithm shows advantages than BO based.

Solution and future task:

1. Improvement on optimization process.
2. Developing an efficient and differentiable pulse simulator.

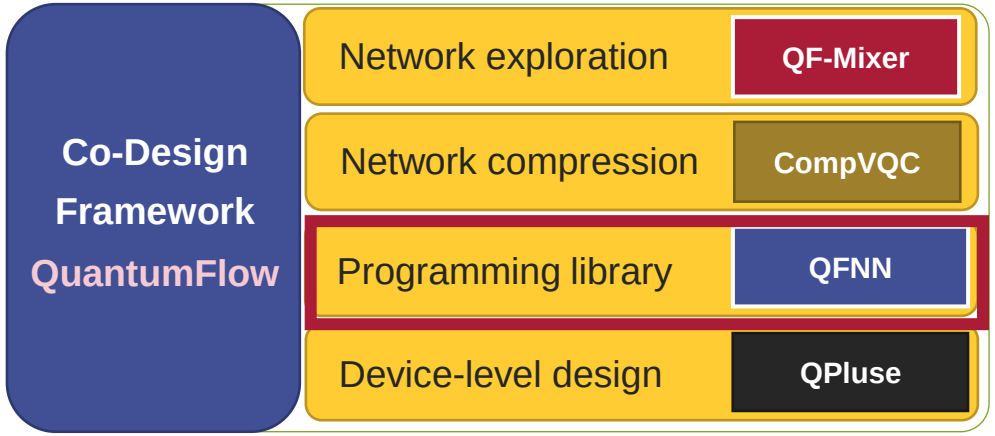
Quantum NN Library: QFNN

QuantumFlow Neural Network (QFNN) API

IEEE QUANTUM WEEK
IEEE International Conference on Quantum Computing and Engineering — QCE21

Released at IEEE International Conference on Quantum Computing and Engineering

Presenter: Weiwen Jiang



https://github.com/JQub/QuantumFlow_Tutorial
(Source Code of All Hands-On in Tutorial)

https://github.com/JQub/qfnn
(Source Code of QFNN API & Place to post Issues)

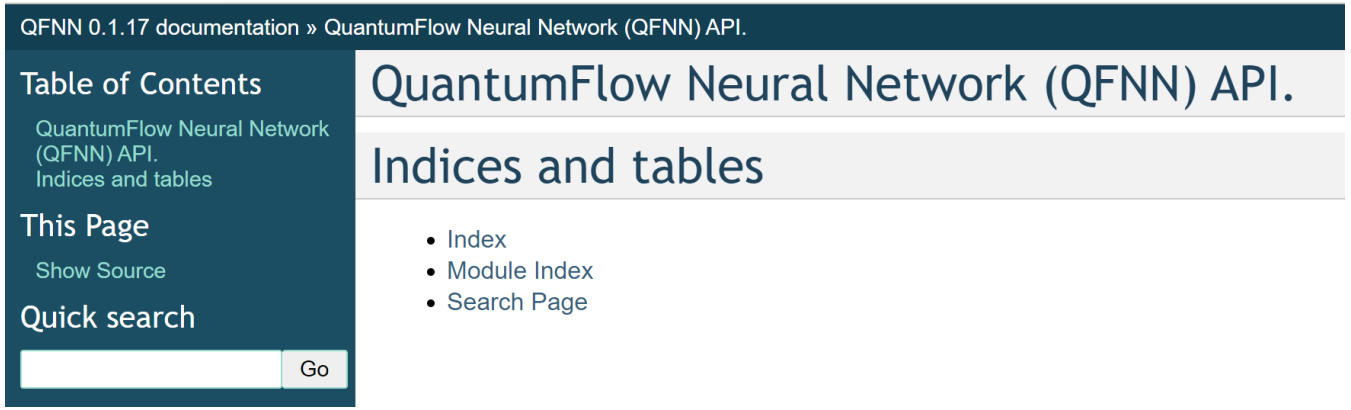
python Package Index

https://pypi.org/project/qfnn/
(Package of QFNN on PYPI)

https://libraries.io/pypi/qfnn/
(QFNN on Libraries.io)

Open-Source Quantum NN Library: QFNN

Qiskit + PyTorch + QuantumFlow



https://jqub.ece.gmu.edu/categories/QF/qfnn/index.html

https://github.com/jqub/qfnn

Example 1: QuantumFlow

Sub module of qfnn.qf_circ

- **Given:** (1) Number of input neural$2^{\mathcal{N}}$; (2) number of output neuron $\mathcal{M}$;

  (3) input $\mathcal{I}$; (4) weights $\mathcal{W}$; (5) an empty quantum circuit $\mathcal{C}$
- **Do:** (1) Encode inputs to the circuit; (2) embed weights to the circuit; (3) do accumulation and quadratic function
- **Output:** (1) Quantum circuit $\mathcal{C}$ with $\mathcal{M}$ output qubits

Algorithm 4: QF-Map: weight mapping algorithm

Input: (1) An integer $R \in (0, 2^{k-1}]$; (2) number of qbits k;
Output: A set of applied gate G

```
void recursive(G,R,k){
    if (R < 2^{k-2}){
        recursive(G,R,k − 1); // Case 1 in the third step
    }
    else if (R == 2^{k-1}){
        G.append(PG_{2^{k-1}}); // Case 2 in the third step
        return;
    }else{
        G.append(PG_{2^{k-1}});
        recursive(G,2^{k-1} − R,k − 1); // Case 3 in the third step
    }
}
// Entry of weight mapping algorithm
set main(R,k){
    Initialize empty set G;
    recursive(G,R,k);
    return G
}
```

$\mathcal{C}$

```
#create circuit
circuit = QuantumCircuit()
#init circuit, which is corresponding to a neuron with 4 qubits and 2 outputs
u_layer = U_LYR_Circ(4,2)

#create qubits to be invovled
inps = u_layer.add_input_qubits(circuit)
aux =u_layer.add_aux(circuit)
u_layer_out_qubits = u_layer.add_out_qubits(circuit)

#add u-layer to your circuit
u_layer.forward(circuit,binarize(weight_1),inps,u_layer_out_qubits,quantum_matrix,aux)

#show your circuit
circuit.draw('text',fold=300)
```

$\mathcal{N}$ for $2^{\mathcal{N}}$ data $\mathcal{M}$

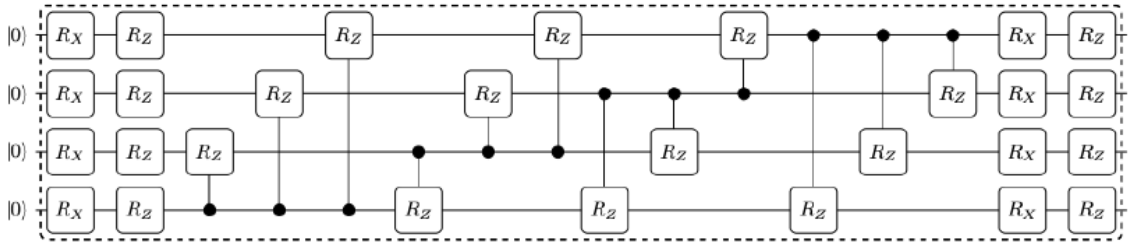
$\mathcal{W}$ $\mathcal{I}$

$\mathcal{C}$

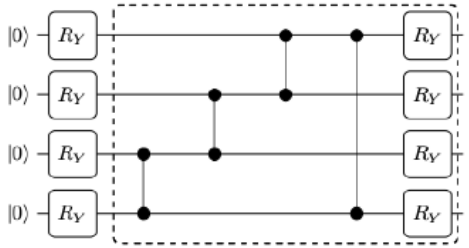
Example 2: Variational Quantum Circuits

Sub module of `qfnn.qf_circ`

- **Given:** (1) Number of input qubits $\mathcal{N}$; (2) weights $\mathcal{W}$; (3) a quantum circuit $\mathcal{C}$ with input data having been encoded
- **Do:** (1) embed weights $\mathcal{W}$ to the circuit;
- **Output:** (1) Quantum circuit $\mathcal{C}$ with measurements



Circuit 5

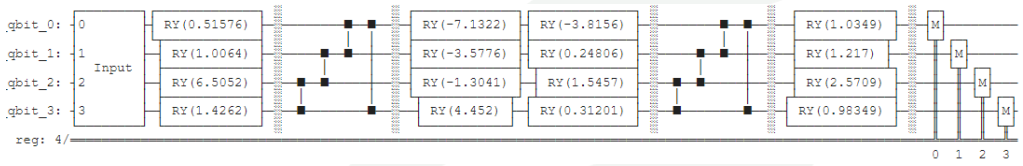


Circuit 10

```
#define your input qubits
vqc = V_LYR_Circ(4)
#add the first v-layer  to your circuit; We currently provide V10 and V5 only
vqc.forward(circuit,inputs,'v10',np.array(theta1,dtype=np.double))
#add the second v-layer  to your circuit
vqc.forward(circuit,inputs,'v10',np.array(theta2,dtype=np.double))

circuit.barrier()
#add measurement to your circuit if needed
add_measure(circuit,[inputs[0][0],inputs[0][1],inputs[0][2],inputs[0][3]],'reg')

circuit.draw('text',fold=300)
```

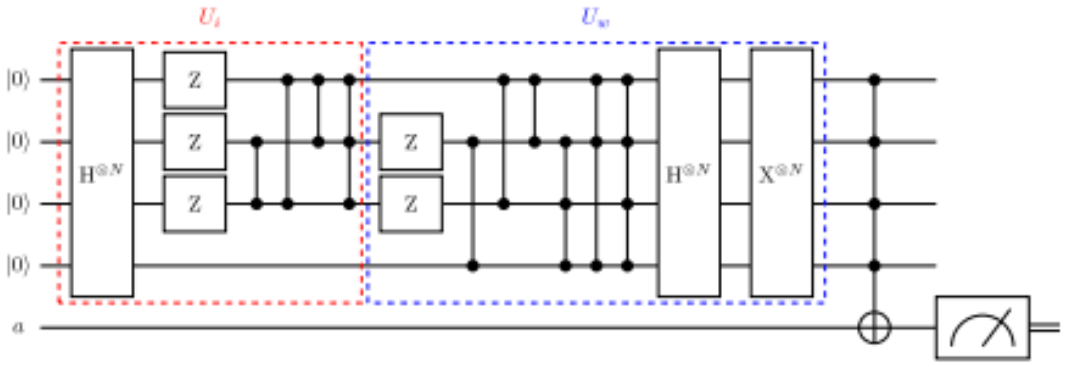


Example 3: An artificial neuron implemented on an actual quantum processor

Sub module of qfnn.qf_circ

- **Given:** (1) Number of input qubits $\mathcal{N}$; (2) number of output neuron $\mathcal{M}$;

  (3) a quantum circuit $\mathcal{C}$ with input data having been encoded
- **Do:** (1) embed weights to the circuit; (2) do accumulation and quadratic function
- **Output:** (1) Quantum circuit $\mathcal{C}$ with $\mathcal{M}$ output qubits




```
                    𝒩       ℳ
#define your input and repeat number
f_layer = F_LYR_Circ(4,2)

#add qubits to your circuit if needed
aux = f_layer.add_aux(circuit)
f_layer_out_qubits = f_layer.add_out_qubits(circuit)

#add f-layer to your 𝒞 circuit          𝒲
f_layer.forward(circuit,binarize(weight_1),inputs,f_layer_out_qubits,None,aux)

𝒞 circuit.barrier()
circuit.draw('text',fold=300)
```

Outline

- Background
- Perspective: Co-Design --- from Classical to Quantum
- Built Design Stack
  - Quantum Neuron with Quantum Advantage: QuantumFlow
  - Quantum NN Library: QFNN
  - Quantum Neural Network: QF-Mixer
  - Quantum Pluse: VQP
- **Conclusion**

Conclusion & Resources

- How to build up quantum circuit for **neural networks** from scratch
- **Co-design** can build a better *quantum neural network accelerator*
- Along with the development of quantum computers and quantum neural networks, we will see **real-world applications** in the NISQ Era

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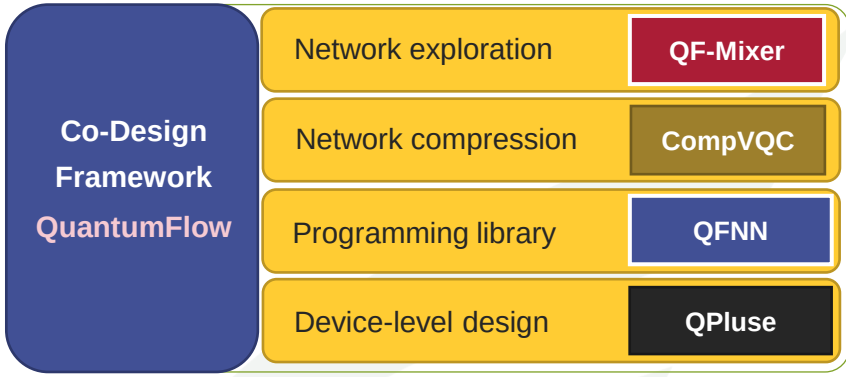
https://jqub.ece.gmu.edu (JQub Website)

https://jqub.ece.gmu.edu/categories/QF (News and **slides**)

https://jqub.ece.gmu.edu/categories/QF/qfnn/ (QFNN Documents)

https://www.nature.com/articles/s41467-020-20729-5



https://arxiv.org/pdf/2012.10360.pdf

https://arxiv.org/pdf/2109.03806.pdf

https://arxiv.org/pdf/2109.03430.pdf

Thank you!