Tools to Be Used in this Tutorial

Google CoLab

Github – Tutorial

Pytorch

Qiskit

https://jqub.ece.gmu.edu/categories/QFV/

Tutorial on QuantumFlow+VACSEN: A Visualization System for Quantum Neural Networks on Noisy Quantum Devices

Weiwen Jiang, Qiang Guan, Yong Wang

10/09/2022

Agenda

- **Session 1: Opening <u>(08:30 - 08:45)</u>**
- **Session 2: QuantumFlow Co-Design Framework <u>(08:45 - 09:45)</u>**
- **Session 3: Quantum Neural Network Compression <u>(10:00 - 10:40)</u>**
- **Session 4: VACSEN: A Visualization Tool for Noise in Quantum Computing <u>(10:45 - 12:00)</u>**

Tutorial on QuantumFlow+VACSEN: A Visualization System for Quantum Neural Networks on Noisy Quantum Devices

Session 1: Opening

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Our Goals on Quantum Learning

- For Quantum Neural Network Researchers

  Q: What's a practical way to approaching to quantum advantage?

  A: Algorithm-Compiler-Device Co-Design

- For Quantum Computer Users

  Q: How to make users be aware of the status of quantum devices?

  A: Visualization

- For Everyone

  Q: How to enable everyone can use quantum machine learning?

  A: Quantum learning demonization!

What is Classical AI Democratization & What is the Challenge?

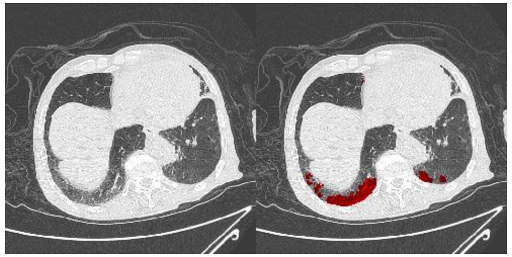
"It's here to collaborate, to augment, to <u>enhance human lives and productivity</u> and <u>make everybody's life better</u>. And related to that, is to **democratize A.I.** in a way that everybody gets benefit. Not just a few, or a selected group." **Fei-Fei Li, 2017**

Medical AI Scenario

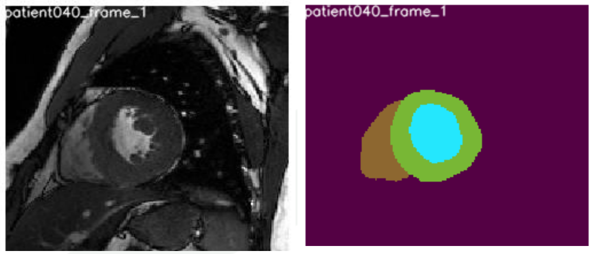
AR/VR in Surgery

Medical Diagnosis

AI Can Perform Medical Tasks



COVID CT Segmentation



Real-Time MRI Segmentation

Let Doctors Design Neural Networks?

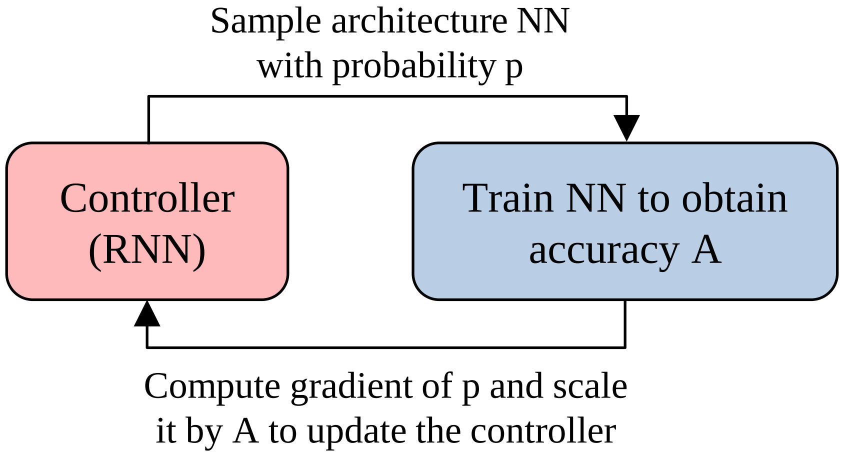
Progress of Classical AI Democratization

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



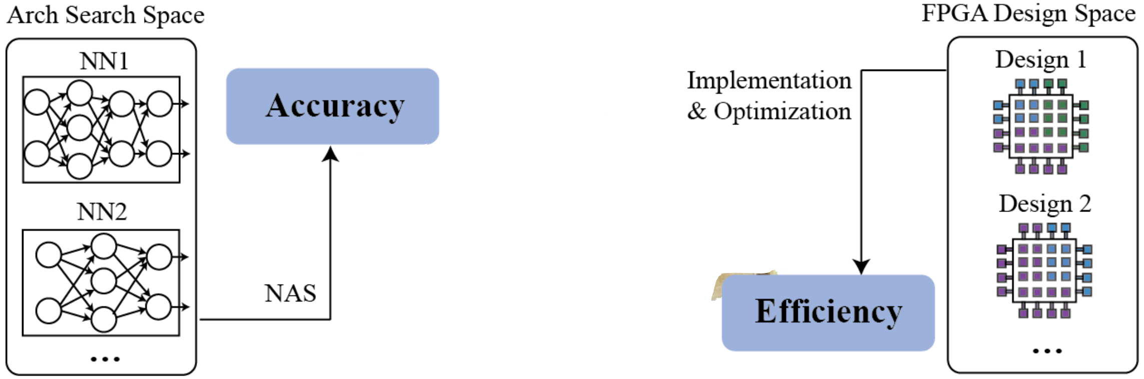
[ref] Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *ICLR 2017*

Our Contributions
(Network-Accelerator Co-Design)

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

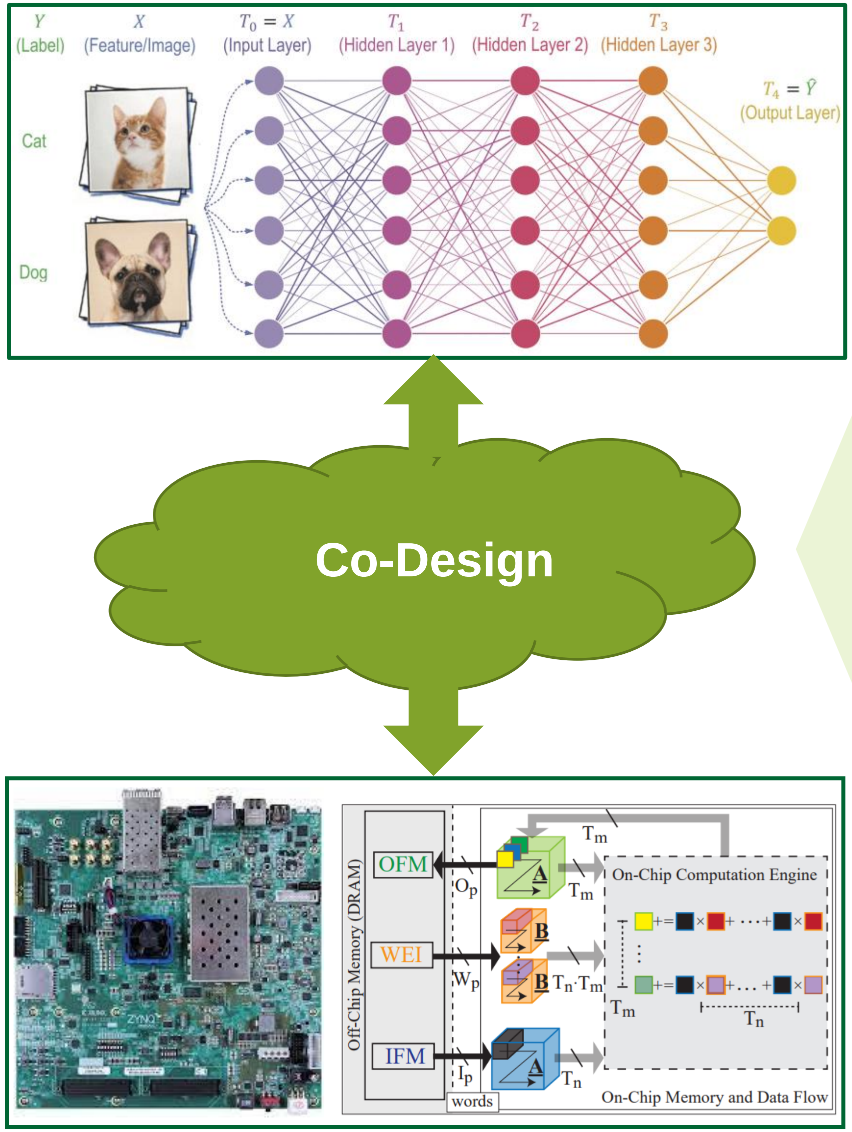
Objective:
- Automated search for NN and HW design
- Maximize accuracy on the given dataset
- Maximize hardware efficiency

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*. (BEST PAPER NOMINATION)
[ref] Jiang, Weiwen, et al. "Hardware/software co-exploration of neural architectures", TCAD 2020 (BEST PAPER AWARD)

Co-Design Stack of Neural “Architectures”

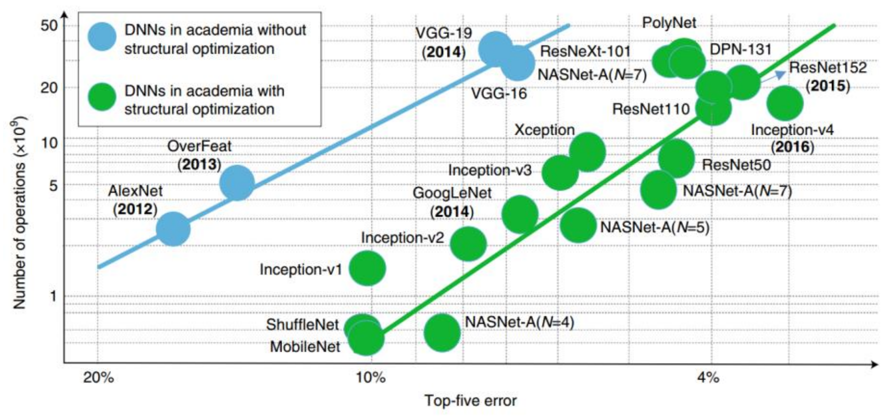


- What is the best **Neural Network Architecture** for FPGAs
- Model optimization (pruning and quantization)?
- Library

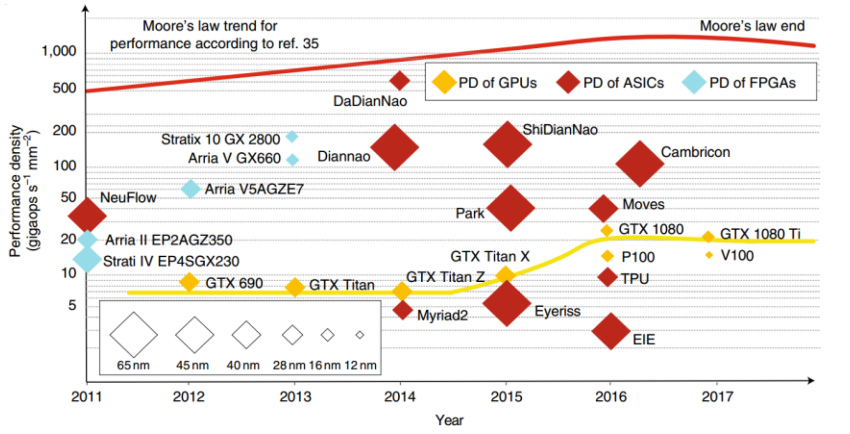
Co-Design Framework (e.g., Our FNAS)	Network exploration	NAS (Google)
	Network compression	Deep Comp (Stanford)
	Programming library	DNNBuilder (UIUC)
	Hardware accelerator	DNN on FPGA (UCLA)

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

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

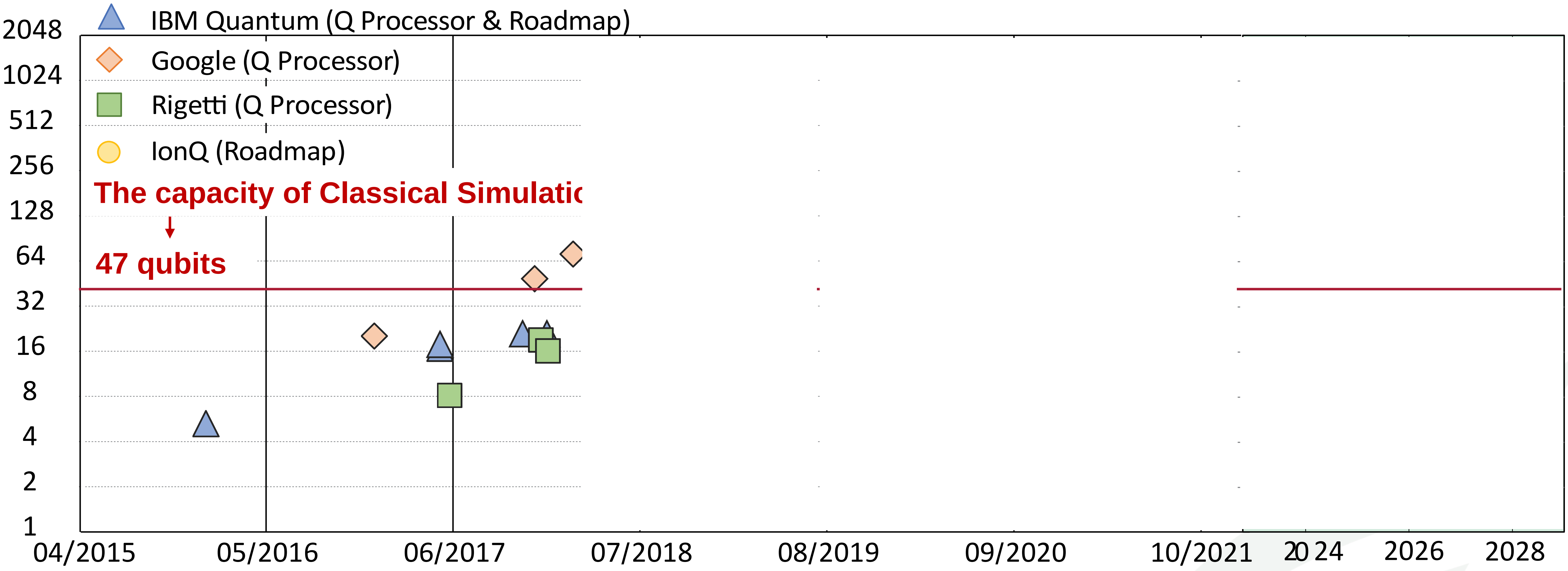
Radiology Modality	Avg. Size (MB)
CT Scan	153.4
MRI	98.6
X-ray angiography	157.5
Ultrasound	69.2
Breast imaging	38.8

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



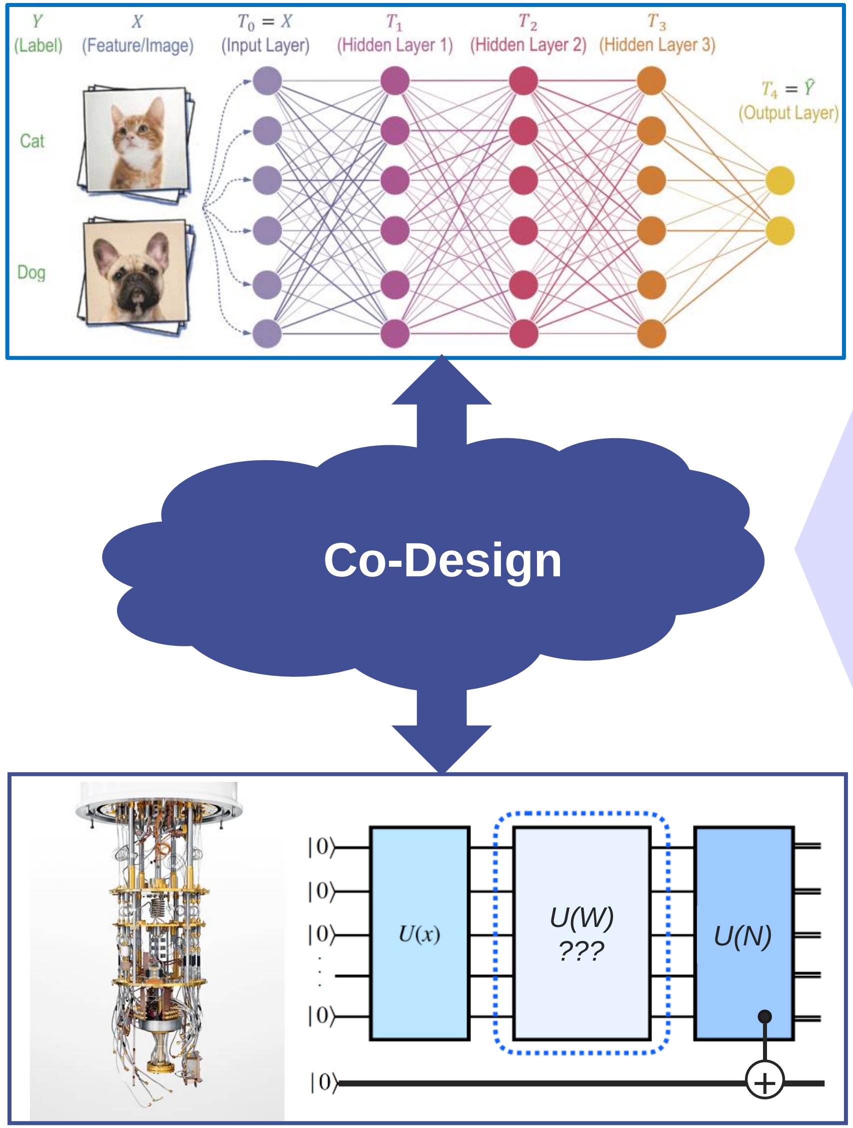
The maximum qubits that supercomputers can simulate for arbitrary circuits is less than 47 qubits.

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

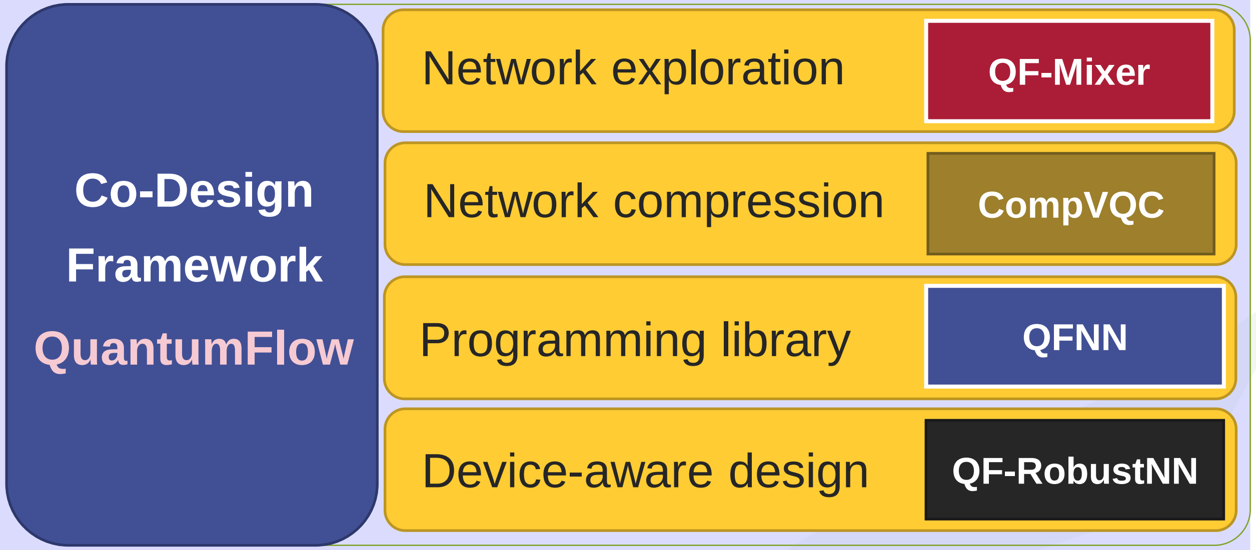
(3) Sunway TaihuLight w/ 1.31 PB memory for **46 qubits**; (4) Theta w/ 0.8 PB memory for **45 qubits**.

[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.

Co-Design of Neural Networks and Quantum Circuit

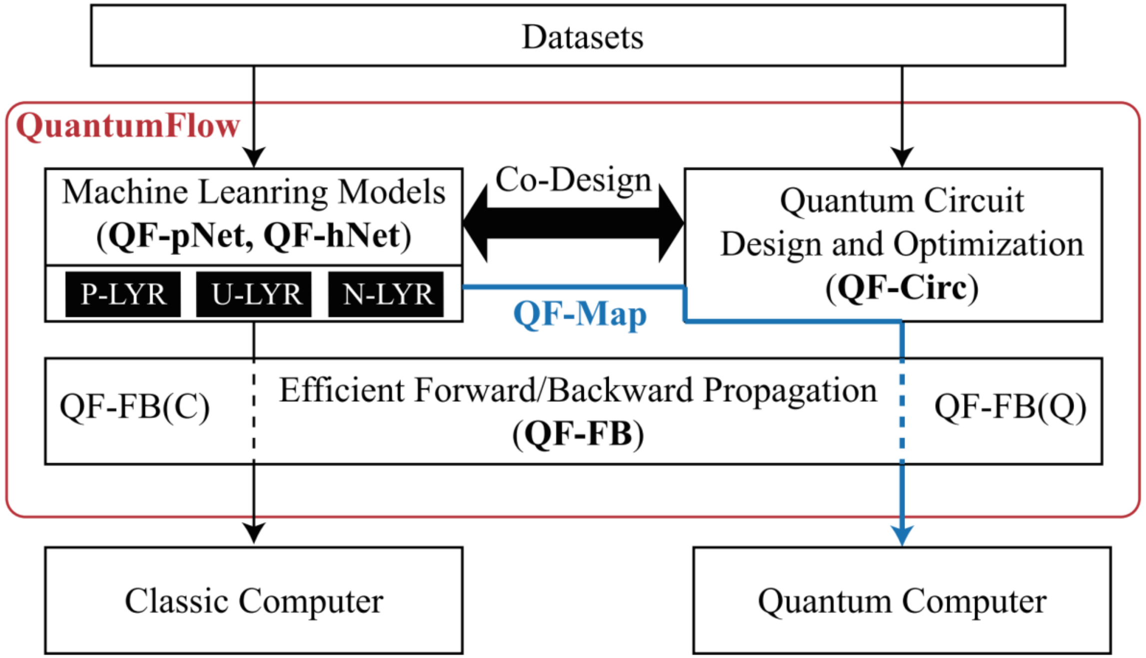


- What is the best **Neural Network Architecture** for QC?
- Can we **compress** the quantum neural network?
- **Library**



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

Session 2: QuantumFlow Co-Design Framework

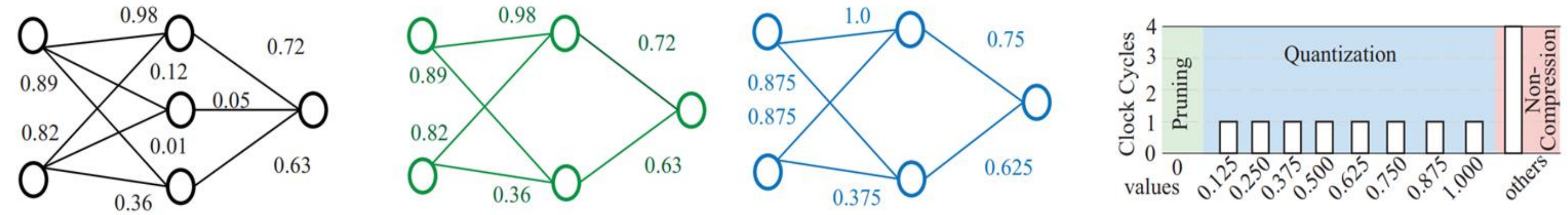


https://www.nature.com/articles/s41467-020-20729-5
https://github.com/JQub/QuantumFlow_Tutorial

- Correctly implement binary neuron on quantum computers.
- Reduce complexity from O(n) in classical computers to O(polylog(n)) in quantum computers.
- On MNIST, achieve same accuracy with a cost reduction of 10.85× over classical computers.

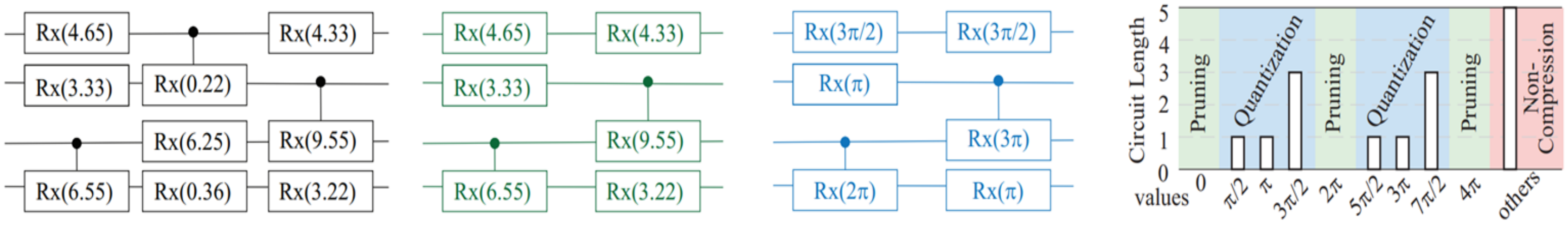
Session 3: Quantum Neural Network Compression

- 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

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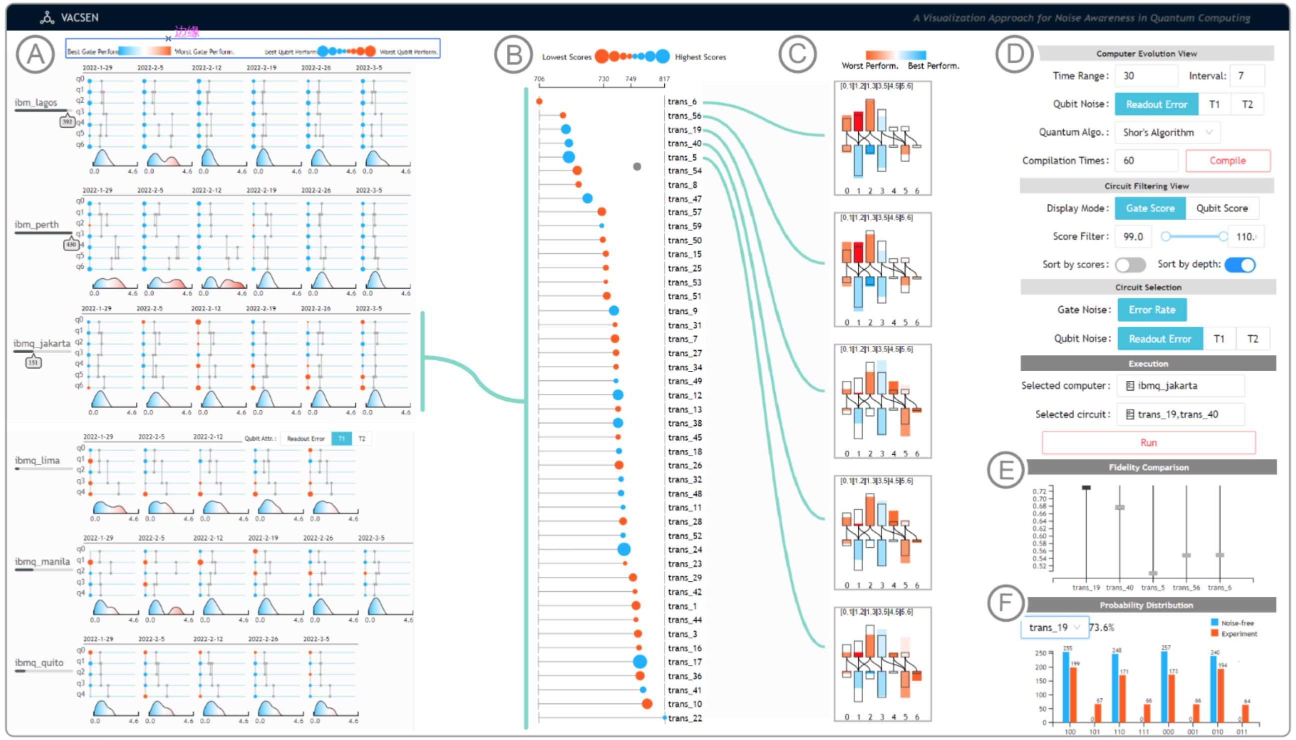
Reduction on the compiled circuit length for more than 2X with <1% accuracy loss.

Session 4: VACSEN: A Visualization Tool for Noise in Quantum Computing



October 16, 2022

VACSEN introduces a novel visualization technique to achieve noise-aware quantum computing, detailed comparison on the filtered compiled circuit view, and user-friendly interaction to achieve better fidelity.

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