

Tools to Be Used



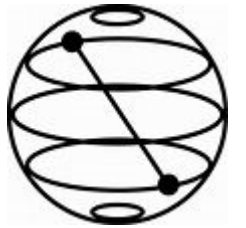
Google CoLab



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

Shaolun Ruan, Yong Wang, Betis Baheri, Qiang Guan, Zhepeng Wang, Weiwen Jiang

SMU | GUANS Lab @ KSU | JQub @ Mason

09/23/2022

Agenda

- **Session 1: Opening (10:00 - 10:15)**
- **Session 2: VACSEN: A Visualization Tool for Noise in Quantum Computing (10:15 - 11:30)**
- **Session 3: QuantumFlow Co-Design Framework (13:00 - 14:00)**
- **Session 4: Quantum Neural Network Compression (14:00 - 14:30)**



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

Session 1: Opening

Weiwen Jiang, Ph.D.

Assistant Professor

Electrical and Computer Engineering

George Mason University

wjiang8@gmu.edu

<https://jqub.ece.gmu.edu>

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 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

AI Can Perform Medical Tasks



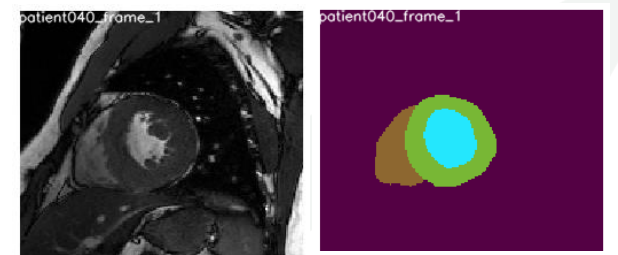
AR/VR in Surgery



Medical Diagnosis



COVID CT Segmentation



Real-Time MRI Segmentation

Let Doctors Design Neural Networks?



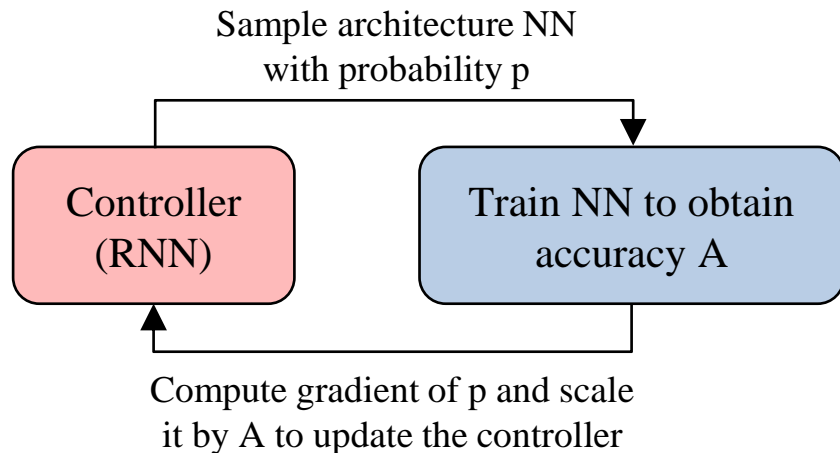
Progress of Classical AI Democratization

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



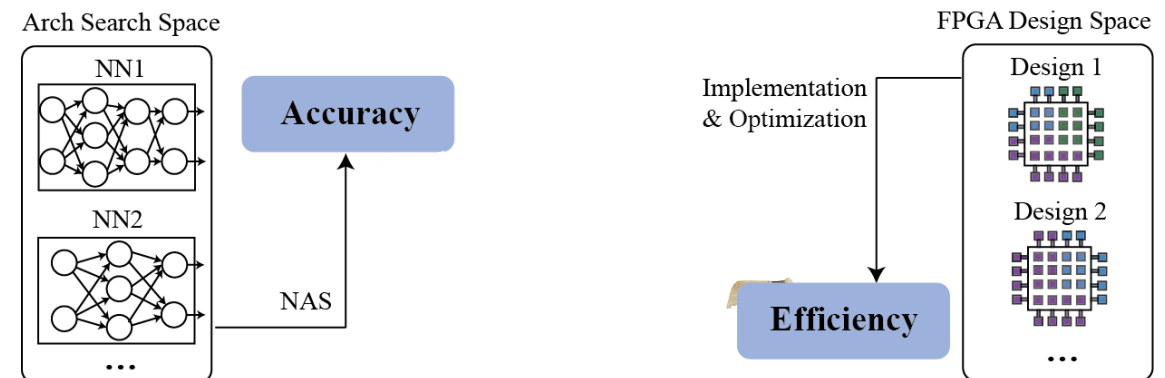
[ref] Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *ICLR 2017*

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

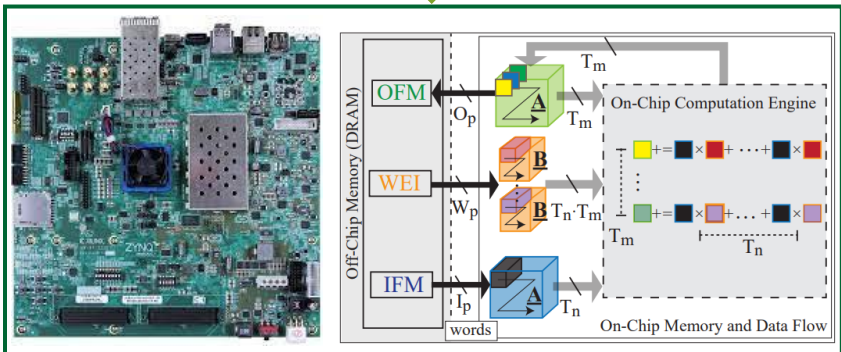
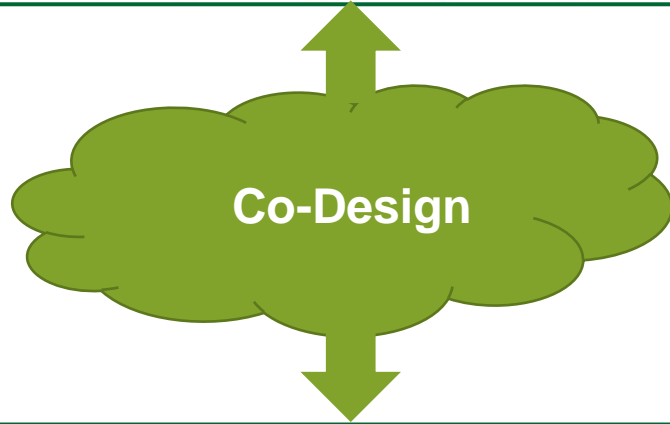
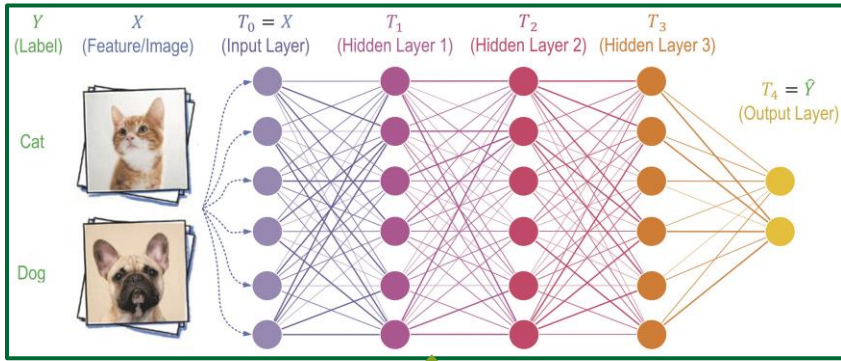
Output: A pair of neural network and hardware design



[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

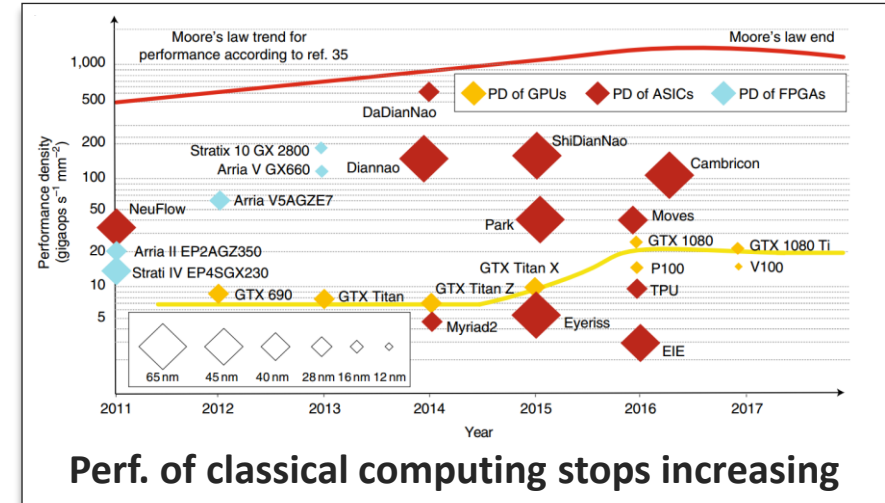
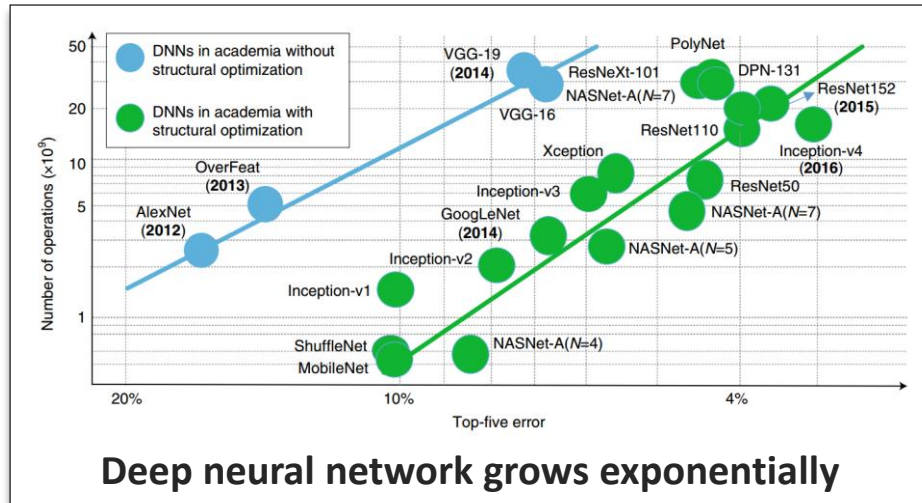
DNNBuilder
(UIUC)

Hardware accelerator

DNN on FPGA
(UCLA)

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

Bottlenecks in Classical Computing



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

Radiology Imaging

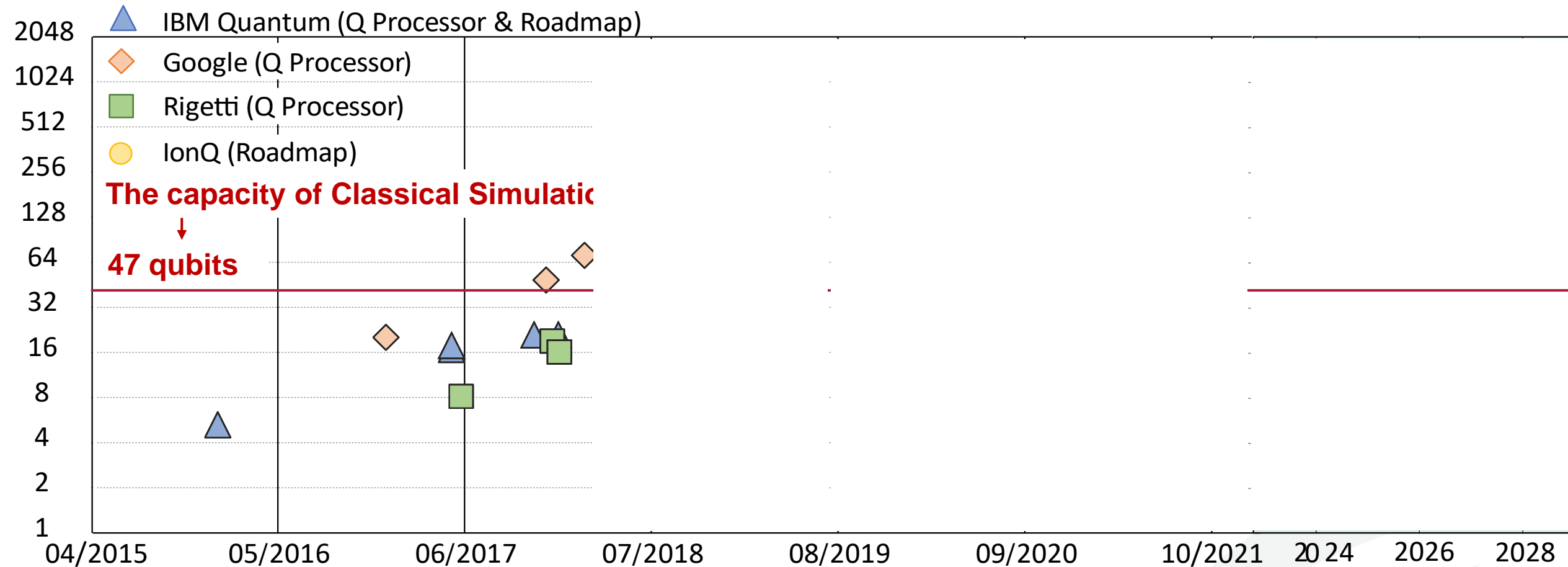
Radiology Modality	Avg. Size (MB)
CT Scan	153.4
MRI	98.6
X-ray angiography	157.5
Ultrasound	69.2
Breast imaging	38.8

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).

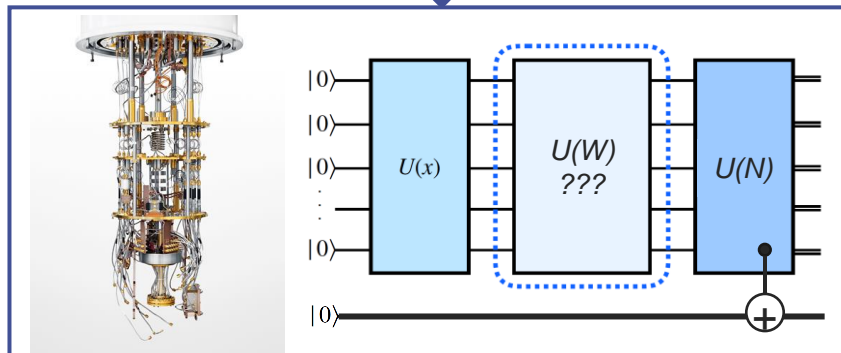
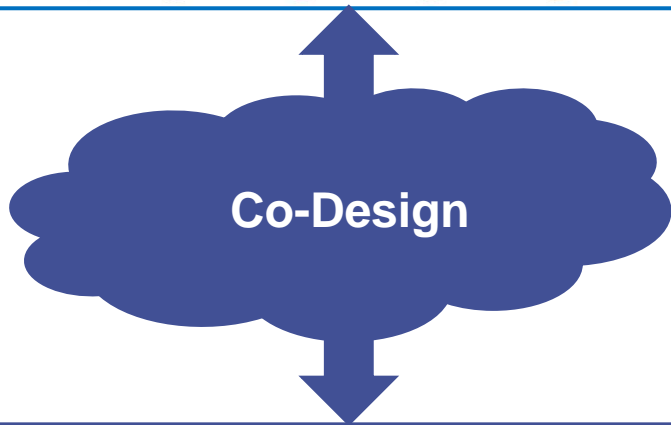
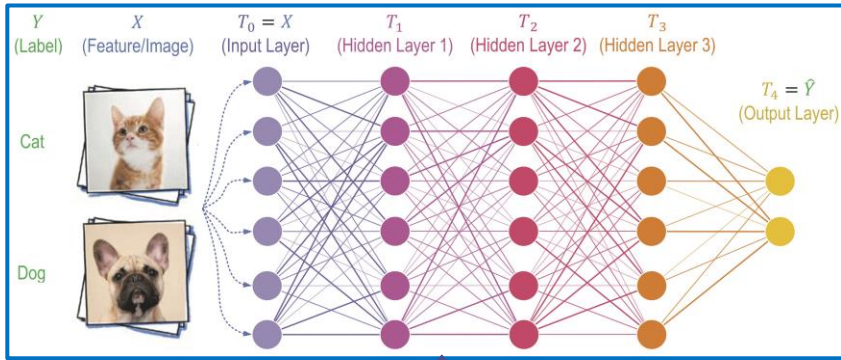
Impossible in Classical But Possible in Quantum Computing



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**.

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

Co-Design
Framework
QuantumFlow

Network exploration

QF-Mixer

Network compression

CompVQC

Programming library

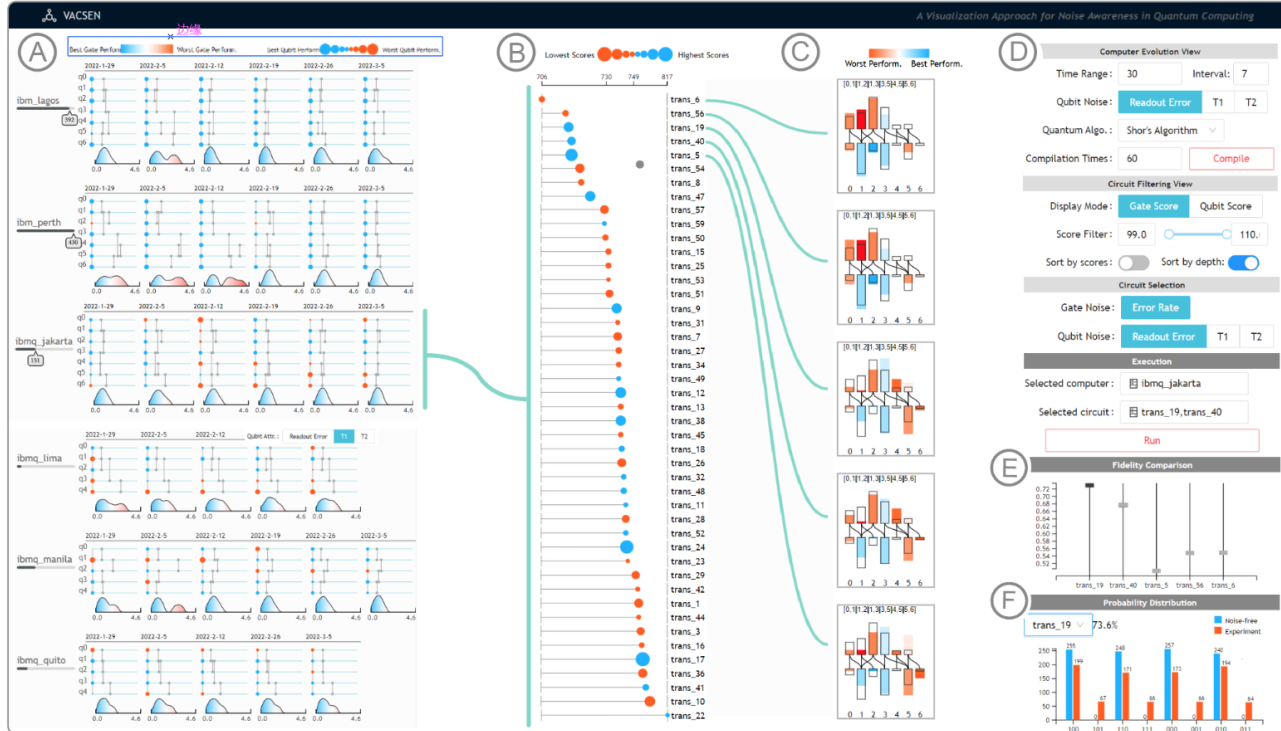
QFNN

Device-aware design

QF-RobustNN

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

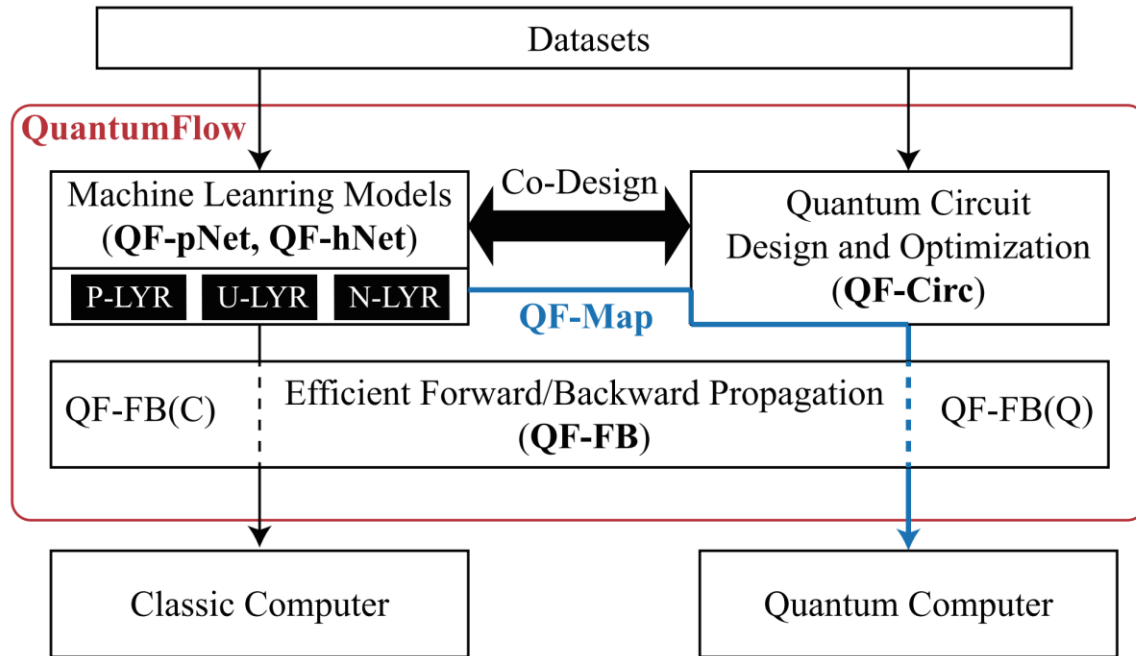
Session 2: VACSEN: A Visualization Tool for Noise in Quantum Computing



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.

Session 3: QuantumFlow Co-Design Framework

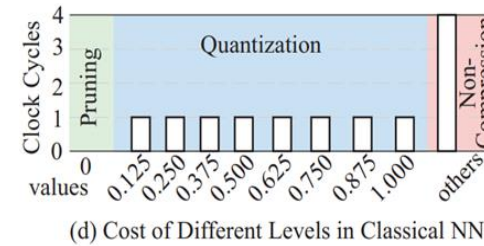
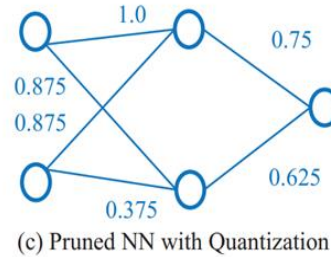
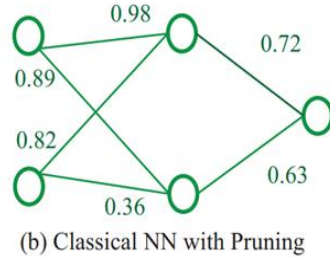
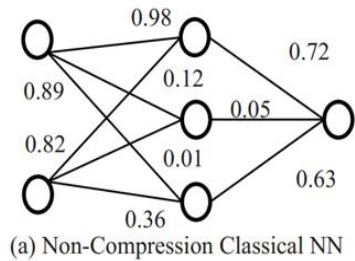


<https://www.nature.com/articles/s41467-020-20729-5>
https://github.com/JQub/QuantumFlow_Tutorial

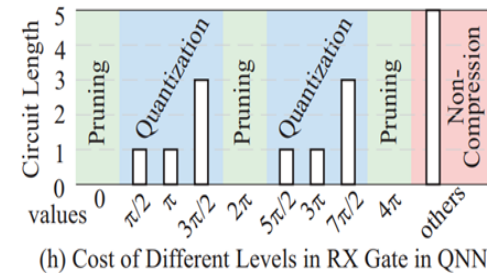
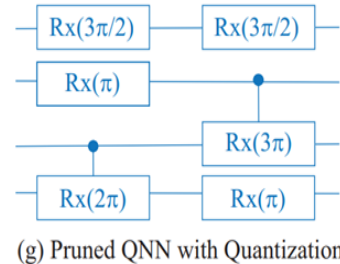
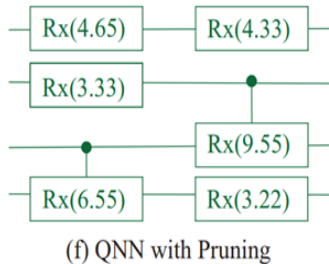
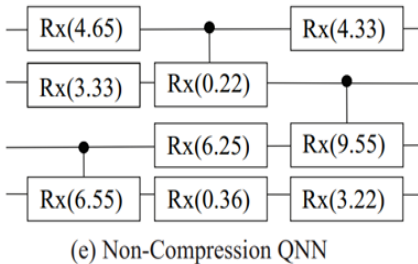
- Correctly implement binary neuron on quantum computers.
- Reduce complexity from $O(n)$ in classical computers to $O(\text{polylog}(n))$ in quantum computers.
- On MNIST, achieve same accuracy with a cost reduction of $10.85\times$ over classical computers.

Session 4: Quantum Neural Network Compression

- Pruning and Quantization in Classical ML



- Pruning and Quantization in Quantum ML



October 30, 2022

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



electronics
An open access journal by MDPI



Electronics (ISSN 2079-9292) is an international, peer-reviewed, open access journal on the science of electronics and its applications.

Editor-in-Chief

Prof. Dr. Flavio Canavero

Politecnico di Torino, Italy



First decision to author **16.6** days
Median Submission to Publication **35** days



Semi-Monthly Released



No Copyright Constraints



Electronics 2022 Best Paper Award
Electronics 2022 Young Investigator Award

More information can be found at
<https://www.mdpi.com/journal/electronics/awards>

- Email: electronics@mdpi.com
- www.mdpi.com/journal/electronics
- Twitter: @ElectronicsMDPI

Topics

- ☐ Microelectronics
- ☐ Optoelectronics
- ☐ Power Electronics
- ☐ Bioelectronics
- ☐ Microwave and Wireless Communications
- ☐ Computer Science & Engineering
- ☐ Networks
- ☐ Systems & Control Engineering
- ☐ Circuit and Signal Processing
- ☐ Semiconductor Devices
- ☐ Artificial Intelligence
- ☐ Electrical and Autonomous Vehicles
- ☐ Quantum Electronics
- ☐ Artificial Intelligence Circuits and Systems (AICAS)
- ☐ Industrial Electronics
- ☐ Flexible Electronics
- ☐ Electronic Multimedia
- ☐ Electronic Materials



Special Issue:

Quantum Machine Learning: Theory, Methods and Applications

Guest Editors:

Dr. Weiwen Jiang

George Mason University, Fairfax, VA 22030,
USA

Dr. Ying Mao

Fordham University, New York, NY 10458,
USA

Dr. Samuel Yen-Chi Chen

Computational Science Initiative, Brookhaven
National Laboratory, New York, NY 11973-5000,
USA

Deadline for manuscript submissions:
20 November 2022



Topics are welcome to contribute:

- Quantum machine learning
- Quantum neural network
- Quantum supervised learning
- Quantum unsupervised learning
- Quantum reinforcement learning
- Quantum learning theory
- Variational quantum circuits
- Noisy intermediate-scale quantum devices (NISQ)

https://www.mdpi.com/journal/electronics/special_issues/quantum_machine_learning