QuantumNAT: Quantum Noise-Aware Training with Noise Injection, Quantization and Normalization

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Outline

- Overview
- Background
- QuantumNAT Methodology
- Evaluation
- TorchQuantum Library
- Conclusion

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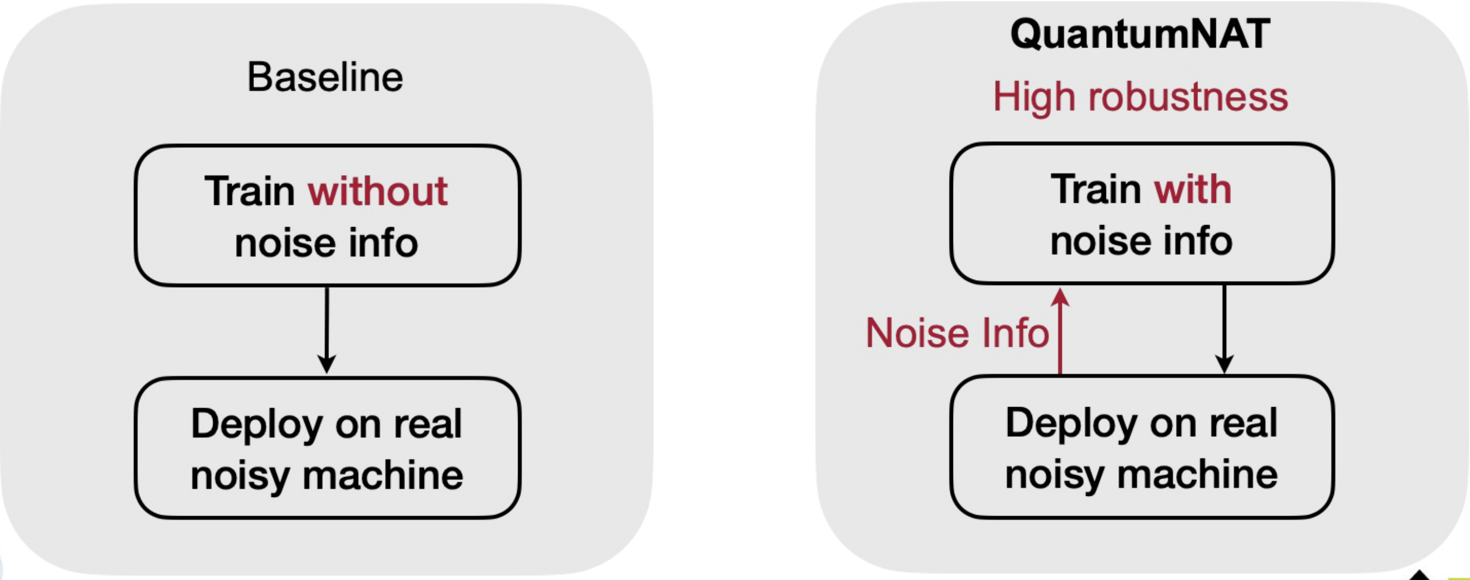
Overview: Noise-Aware Training

- Quantum circuits are noisy
  - Noise severely **degrades** the circuit performance

Overview: Noise-Aware Training

- Quantum circuits are noisy
  - Noise severely **degrades** the circuit performance
- Add real device noise during circuit training on classical simulator
  - Improve robustness on real quantum machines



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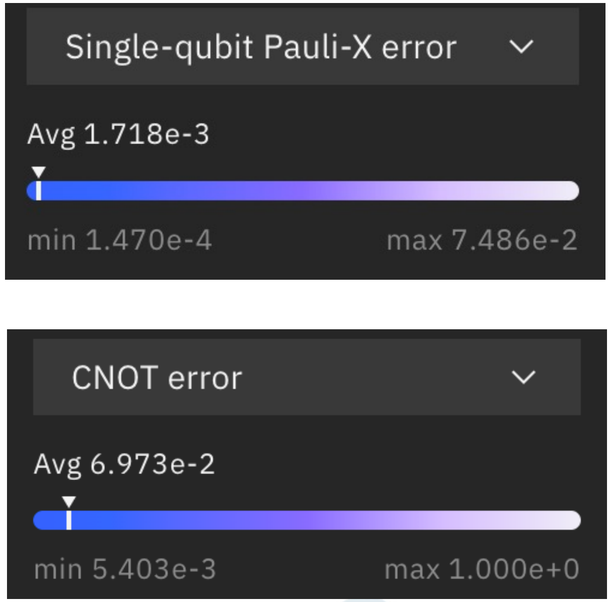
NISQ Era

- Noisy Intermediate-Scale Quantum (NISQ)
  - **Noisy**: qubits are sensitive to environment; quantum gates are unreliable

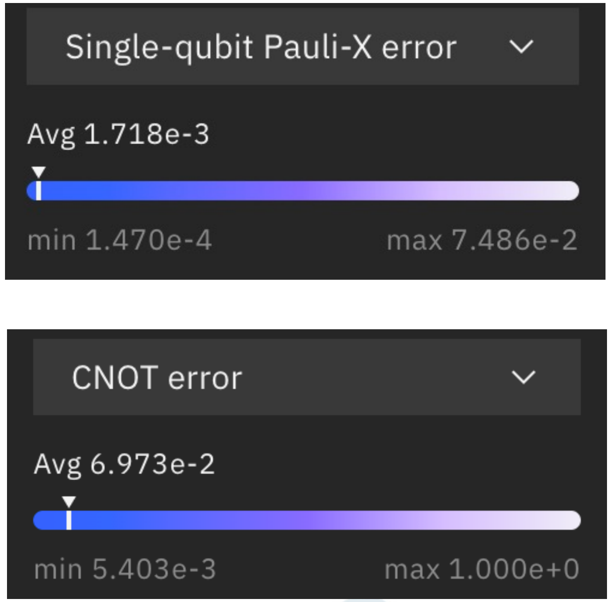


Gate Error Rate

https://quantum-computing.ibm.com/

NISQ Era

- Noisy Intermediate-Scale Quantum (NISQ)
  - **Noisy**: qubits are sensitive to environment; quantum gates are unreliable
  - **Limited number** of qubits: tens to hundreds of qubits



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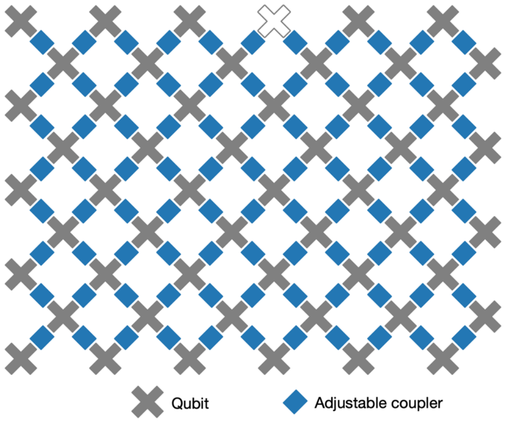
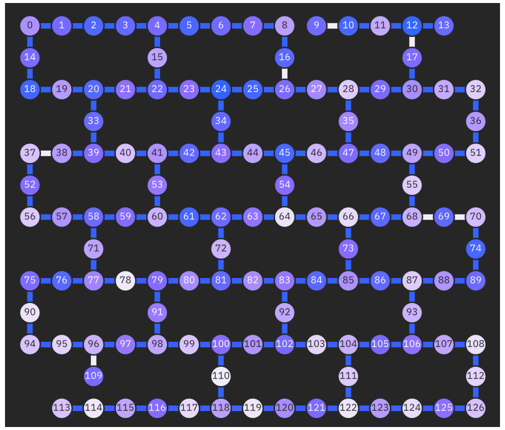


Google Sycamore
https://www.nature.com/articles/s41586-019-1666-5



IBM Washington
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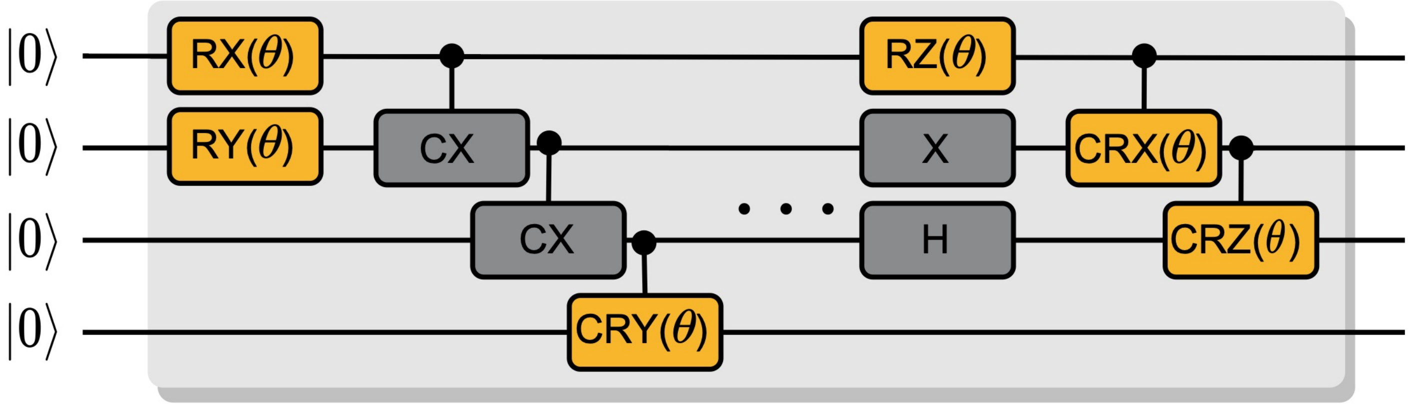
Parameterized Quantum Circuits (PQC)

- Parameterized Quantum Circuits (PQC)
- Quantum circuit with fixed gates and parameterized gates



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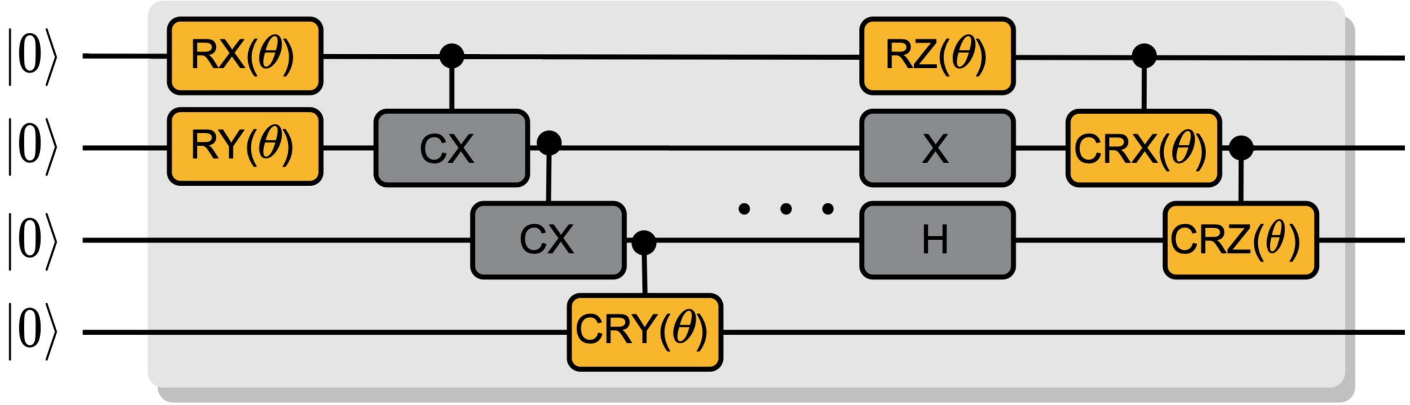
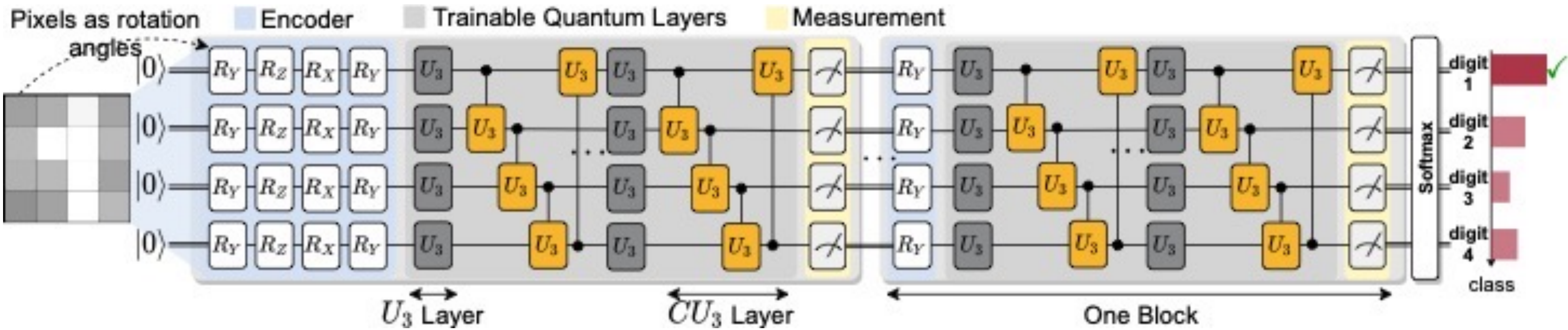


- PQCs are commonly used in **hybrid classical-quantum** models and show promises to achieve quantum advantage
  - Variational Quantum Eigensolver (VQE)
  - Quantum Neural Networks (QNN)
  - Quantum Approximate Optimization Algorithm (QAOA)

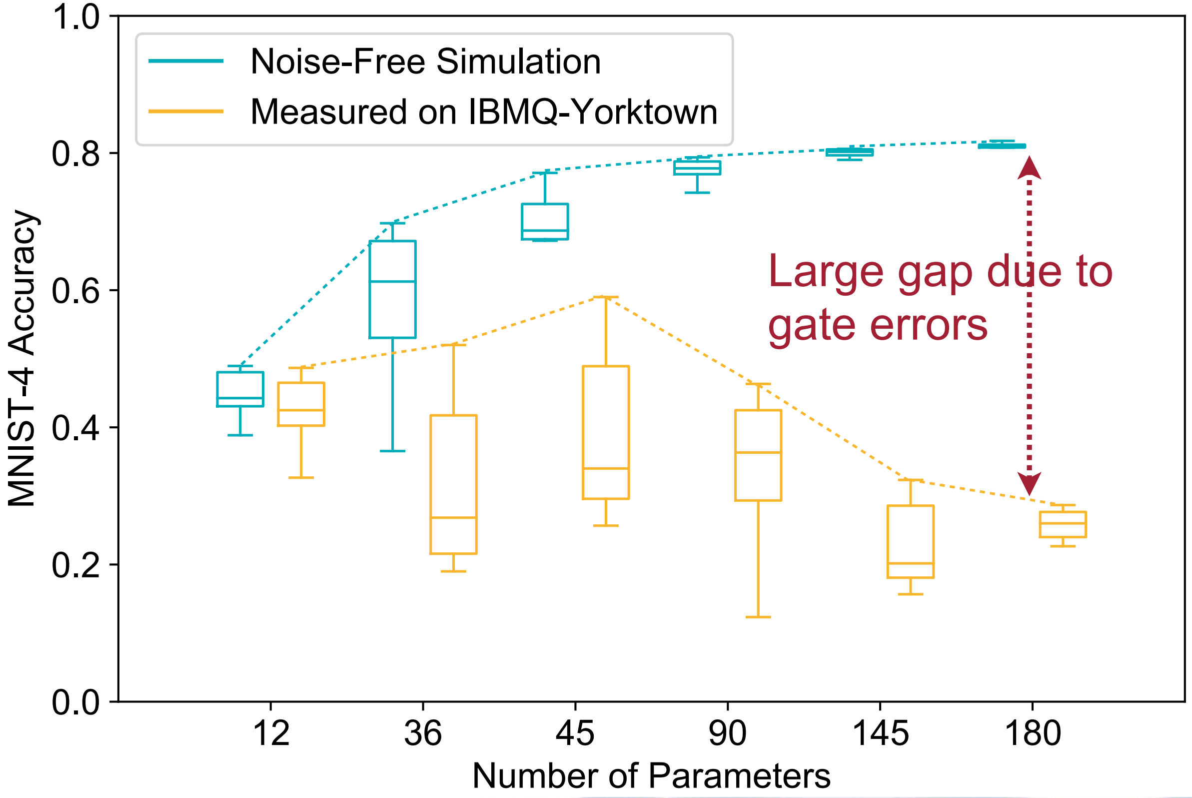
Quantum Neural Networks (QNN)

- QNN is one kind of PQC for machine learning tasks
  - Encoder
  - Trainable Quantum Layers
  - Measurements



Challenge of PQC: Noise

- Noise **degrades** the PQC reliability
  - Large **gap** between the noise-free simulation and real deployment



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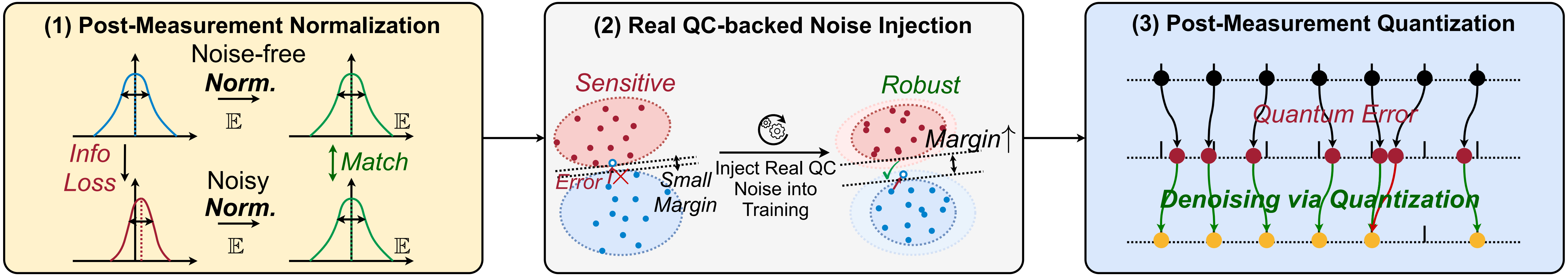
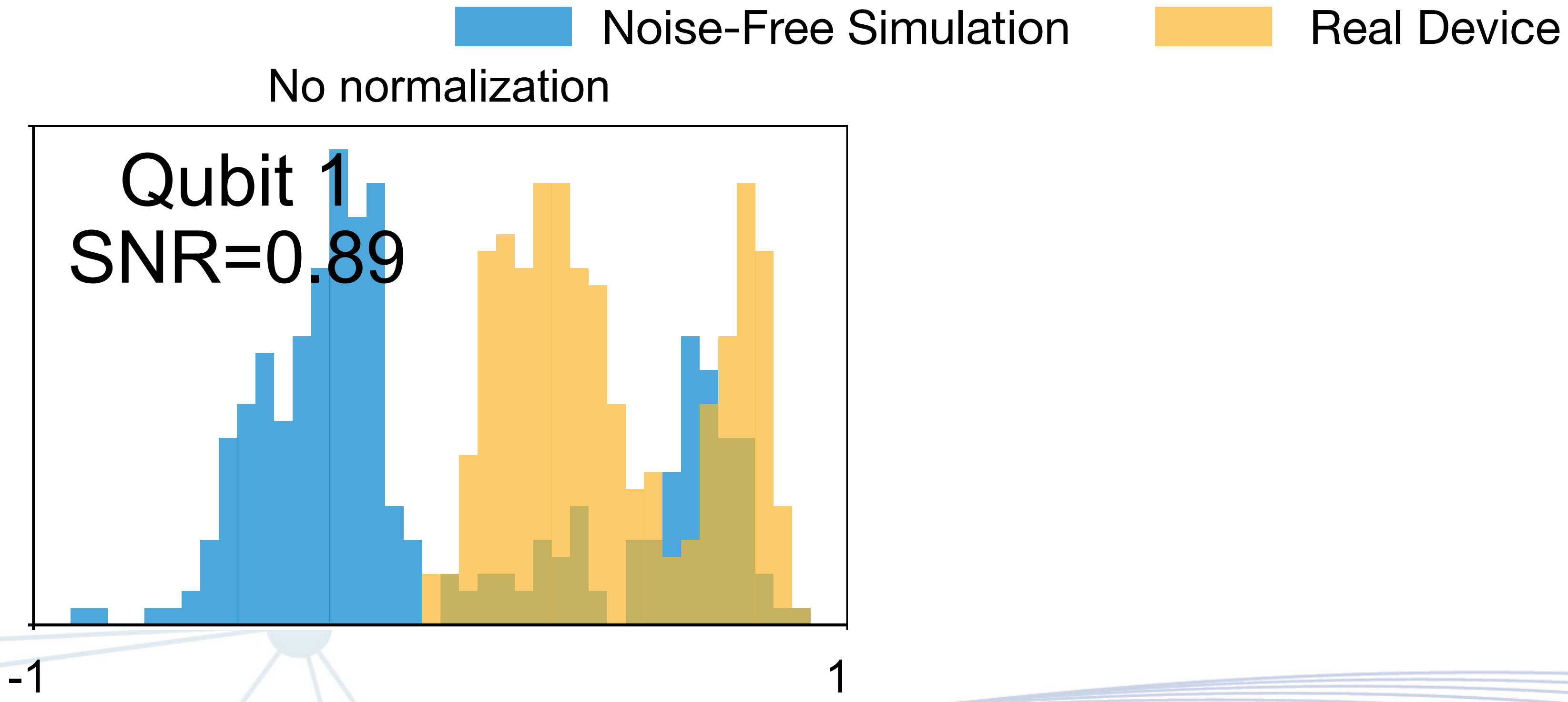
Three Techniques in QuantumNAT



Post-Measurement Normalization

- Normalize the measurement outcome (expectation value)
  - Along the **batch** dimension
- Measurement outcome distribution of 50 quantum circuits:



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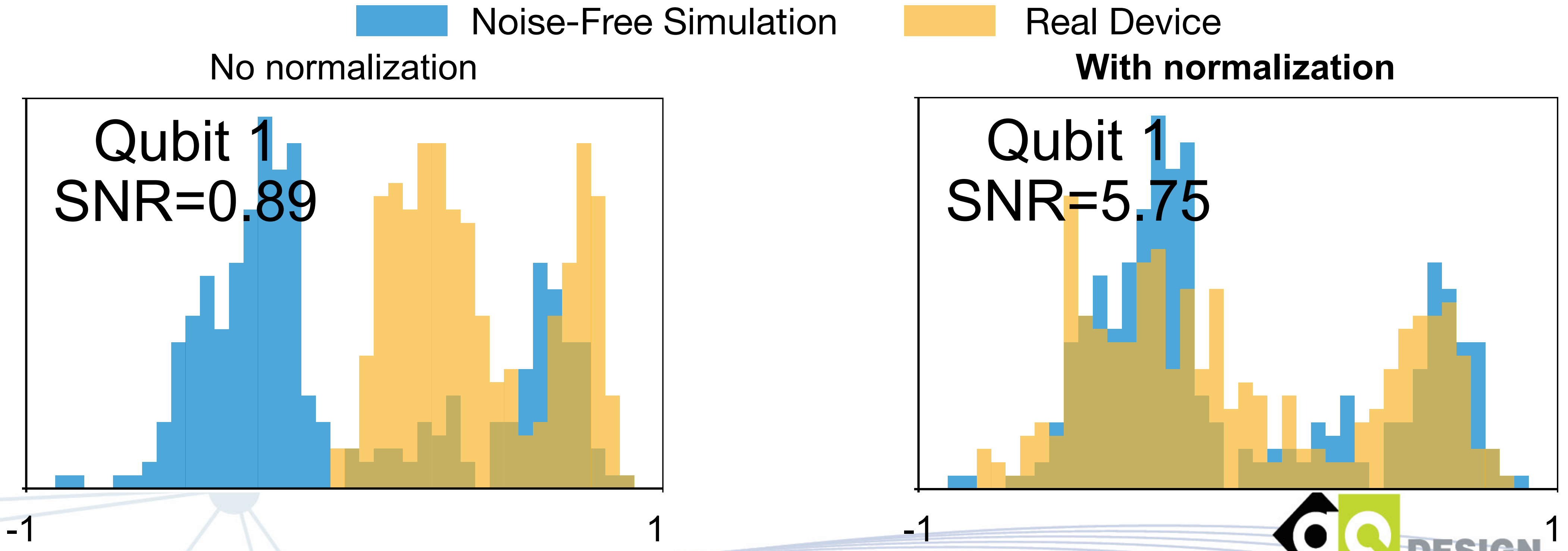
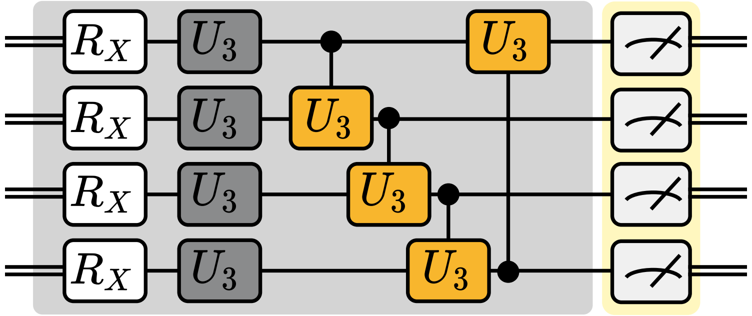


Noise Injection

- Inject noise during training on classical simulator
  - Pauli error
  - Readout error

Compiled Quantum Circuits
（Noise-free）



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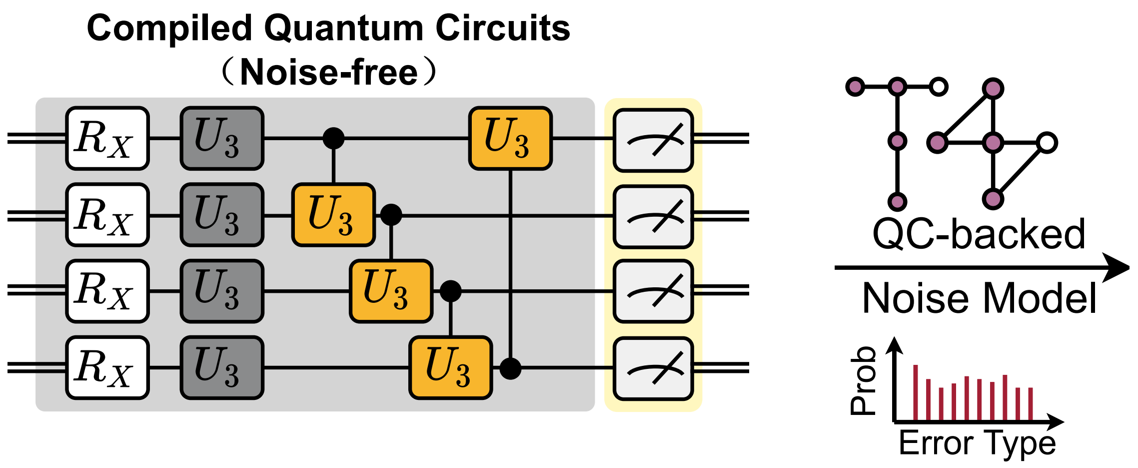

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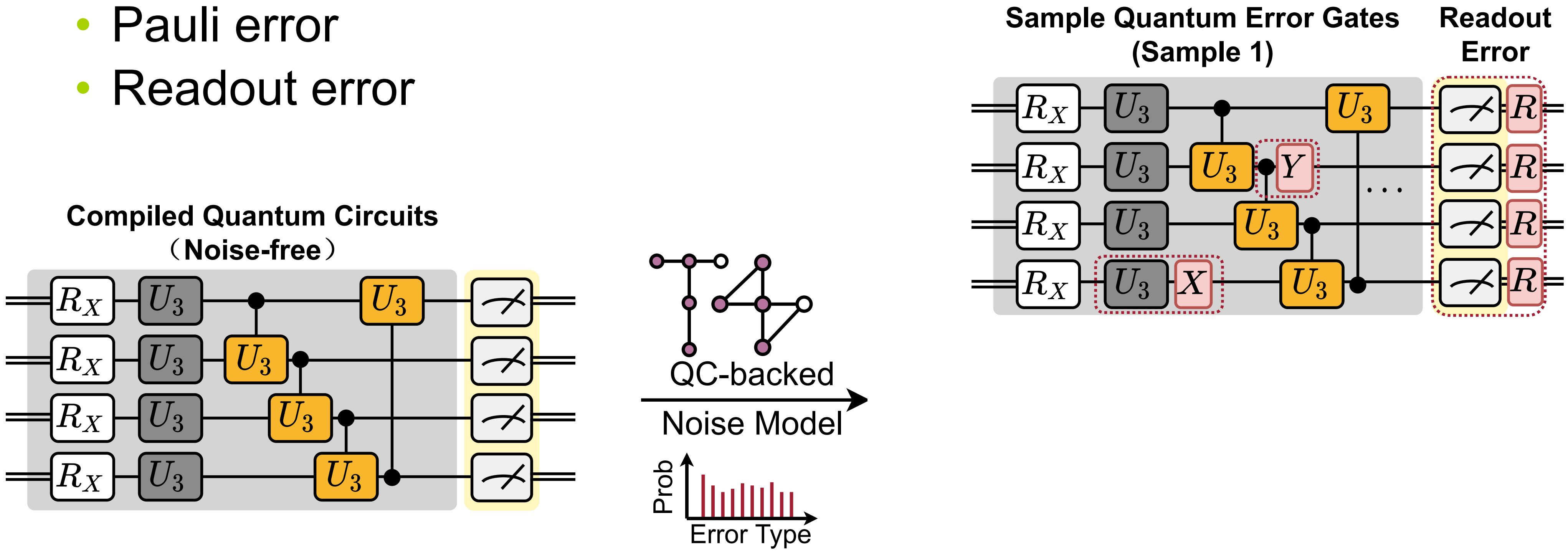

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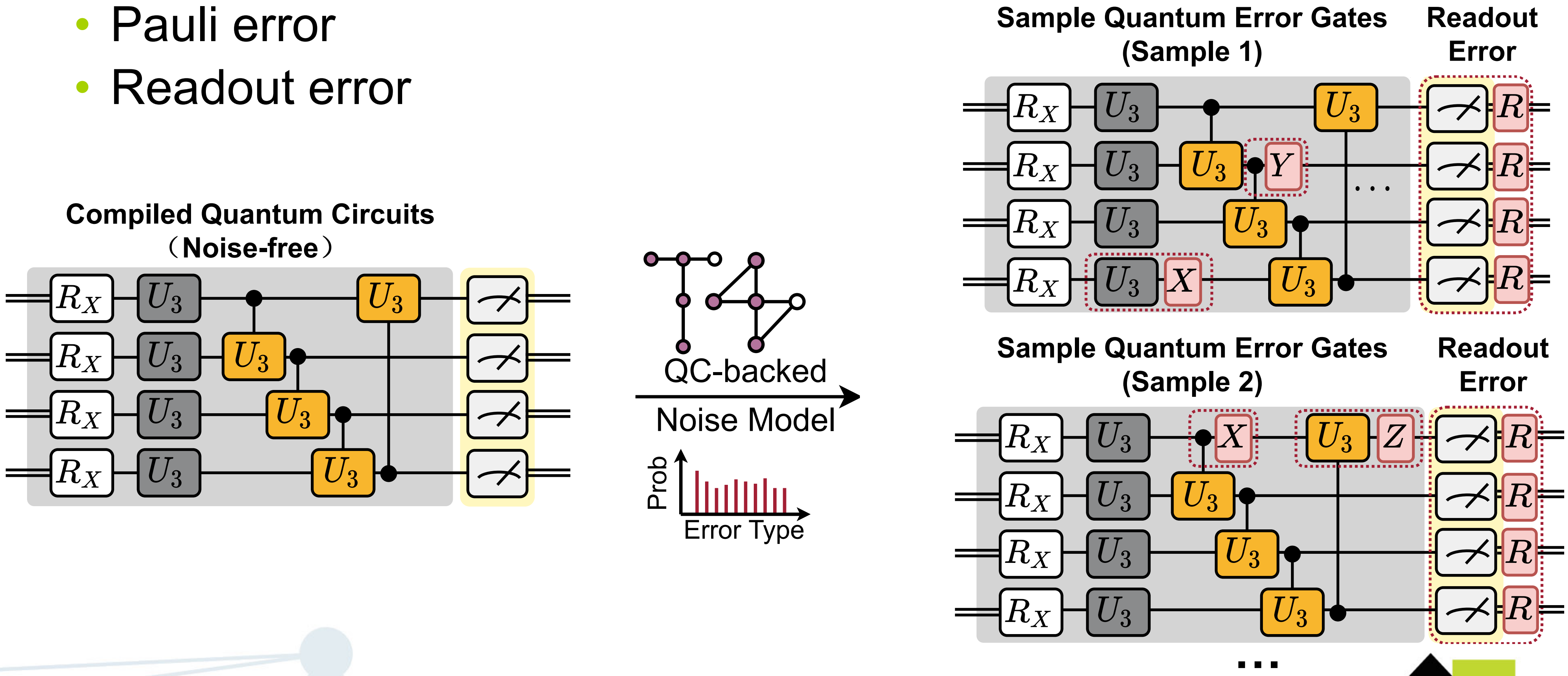
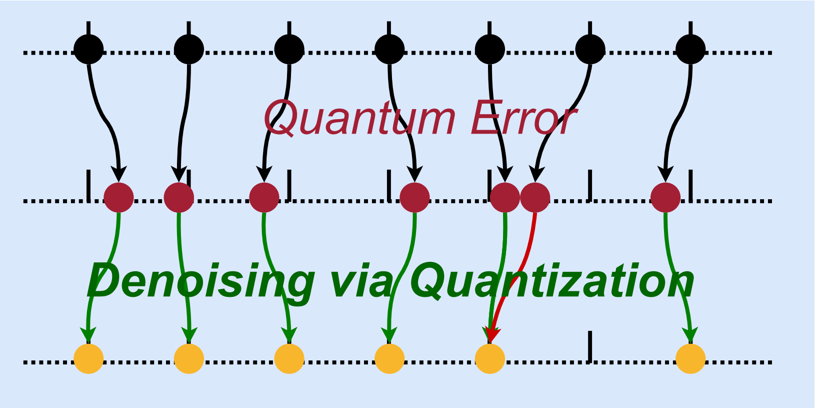


Post-Measurement Quantization

- Quantize measurement outcomes (expectation values)
  - Denoising effect
  - Small errors will be mitigated



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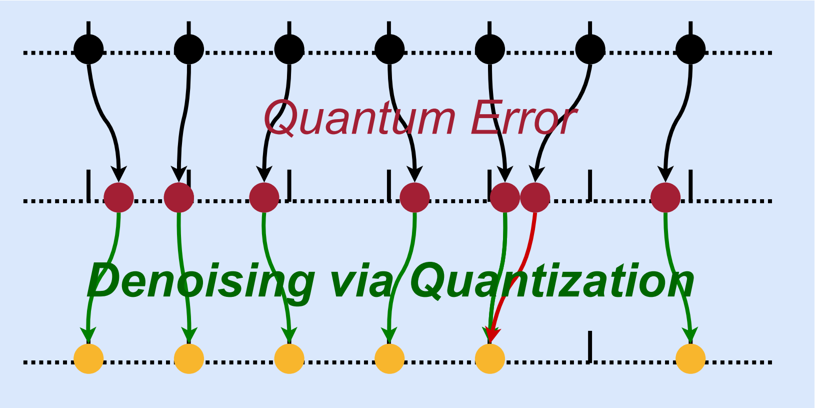
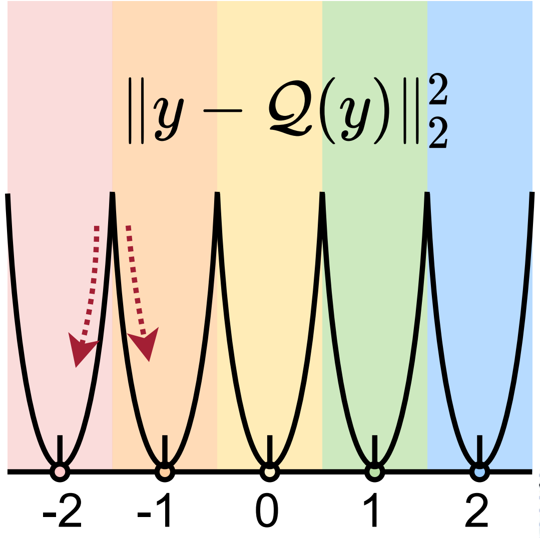
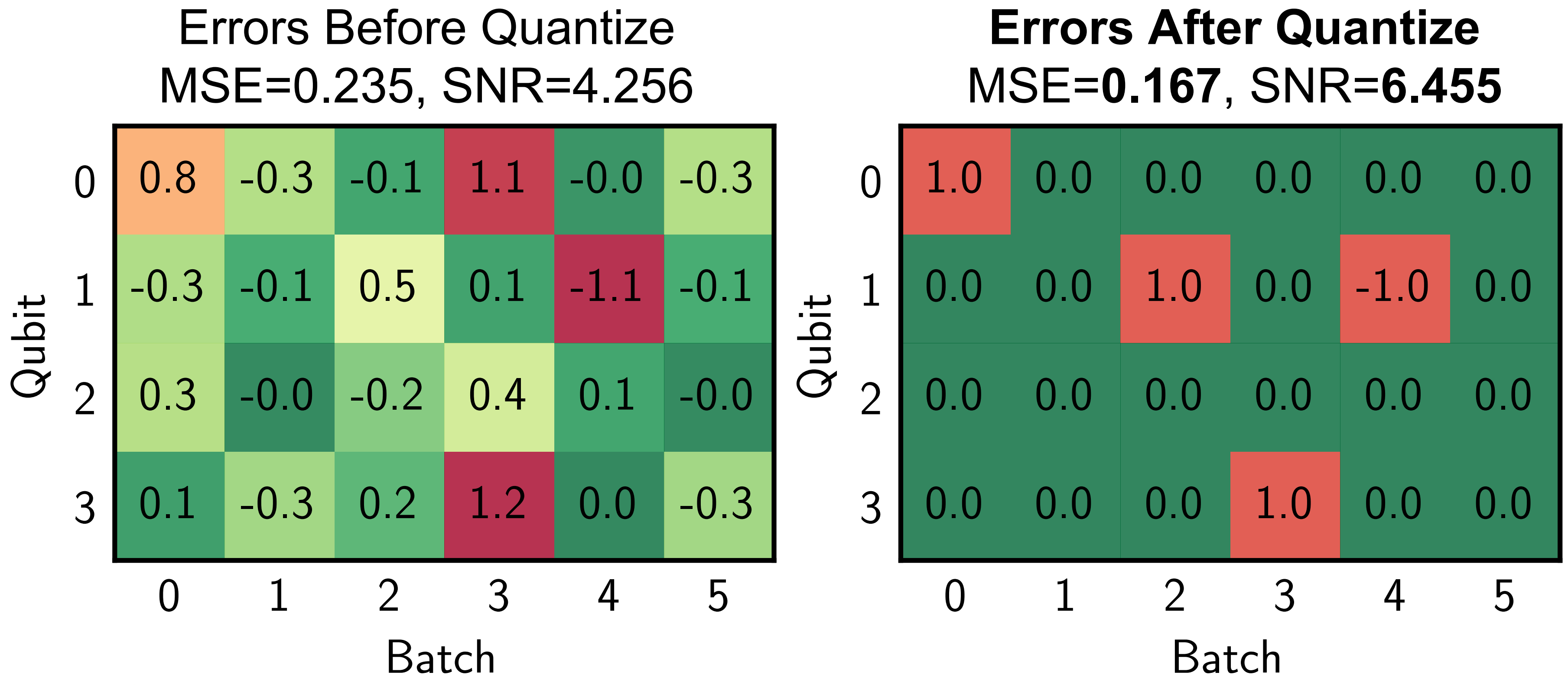


- **Loss** term to encourage measurement outcomes to be close to **centroids**



Post-Measurement Quantization

- Quantization reduces errors and improves SNR



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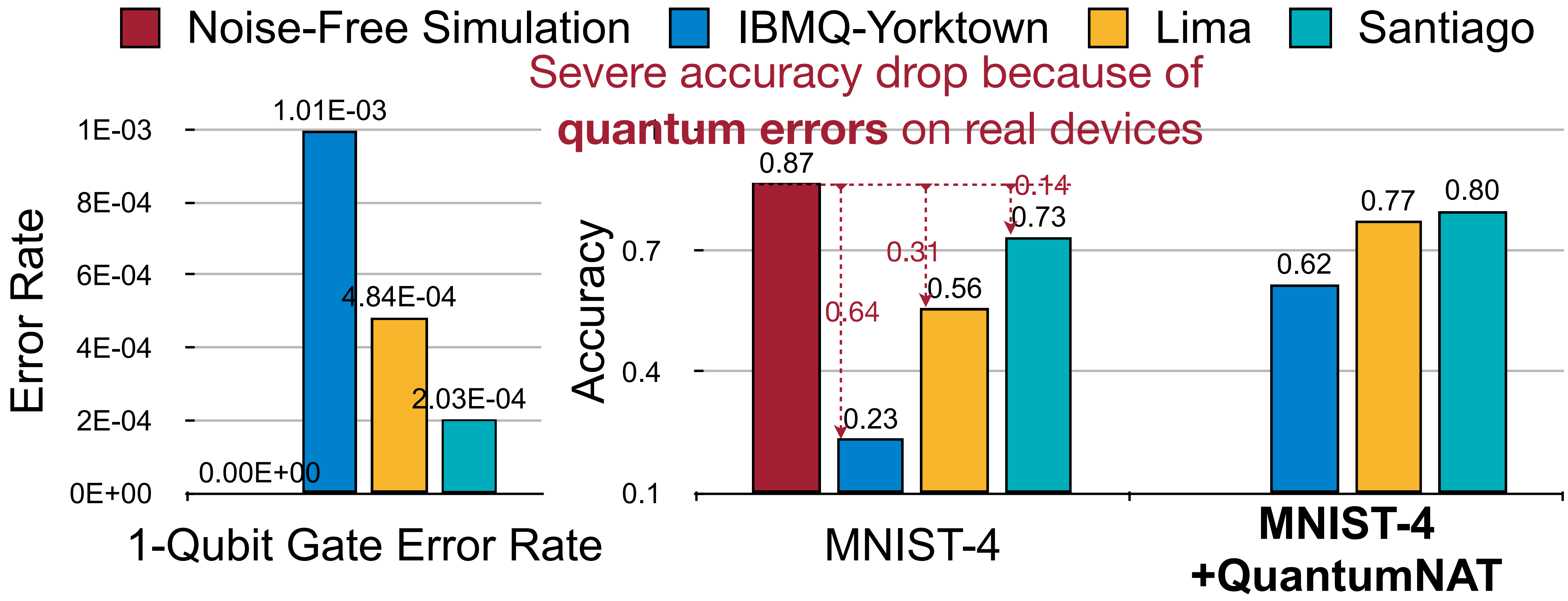
Evaluation

- Benchmarks
  - Quantum Machine Learning task: MNIST 10-class, 4-class, 2-class, Fashion MNIST 10-class, 4-class, 2-class, Vowel 4-class, Cifar-2 class
- Quantum Devices
  - IBMQ
  - #Qubits: 5 to 15
  - Quantum Volume: 8 to 32

Evaluation

- QuantumNAT significantly improves real measurement accuracy



Consistent Improvements on Various Benchmarks

- Different quantum devices
- Different models
- Different tasks

Model	Method	MNIST-4	Fash.-4	Vow.-4	MNIST-2	Fash.-2	Cifar-2
2B×12L Santiago	Baseline	0.30	0.32	0.28	0.84	0.78	0.51
	+ Post Norm.	0.41	0.61	0.29	0.87	0.68	0.56
	+ Gate Insert.	0.61	0.70	0.44	0.93	0.86	0.57
	+ Post Quant.	**0.68**	**0.75**	**0.48**	**0.94**	**0.88**	**0.59**
2B×2L Yorktown	Baseline	0.43	0.56	0.25	0.68	0.70	0.52
	+ Post Norm.	0.57	0.60	0.38	0.86	0.72	0.56
	+ Gate Insert.	0.58	0.60	**0.45**	0.91	0.85	0.57
	+ Post Quant.	**0.62**	**0.65**	0.44	**0.93**	**0.86**	**0.60**
2B×6L Belem	Baseline	0.28	0.26	0.20	0.46	0.52	0.50
	+ Post Norm.	0.52	0.57	0.33	0.81	0.62	0.51
	+ Gate Insert.	0.52	0.60	0.37	0.84	**0.82**	0.57
	+ Post Quant.	**0.58**	**0.62**	**0.41**	**0.88**	0.80	**0.61**
3B×10L Athens	Baseline	0.29	0.36	0.21	0.54	0.46	0.49
	+ Post Norm.	0.44	0.46	0.37	0.51	0.51	0.50
	+ Gate Insert.	-	-	-	-	-	-
	+ Post Quant.	**0.56**	**0.64**	**0.41**	**0.87**	**0.64**	**0.53**

Model	Method	MNIST-10	Fash.-10	Avg.-All
2B×2L Melbo.	Baseline	0.11	0.09	0.42
	+ Post Norm.	0.08	0.12	0.52
	+ Gate Insert.	0.25	0.24	0.61
	+ Post Quant.	**0.34**	**0.31**	**0.64**

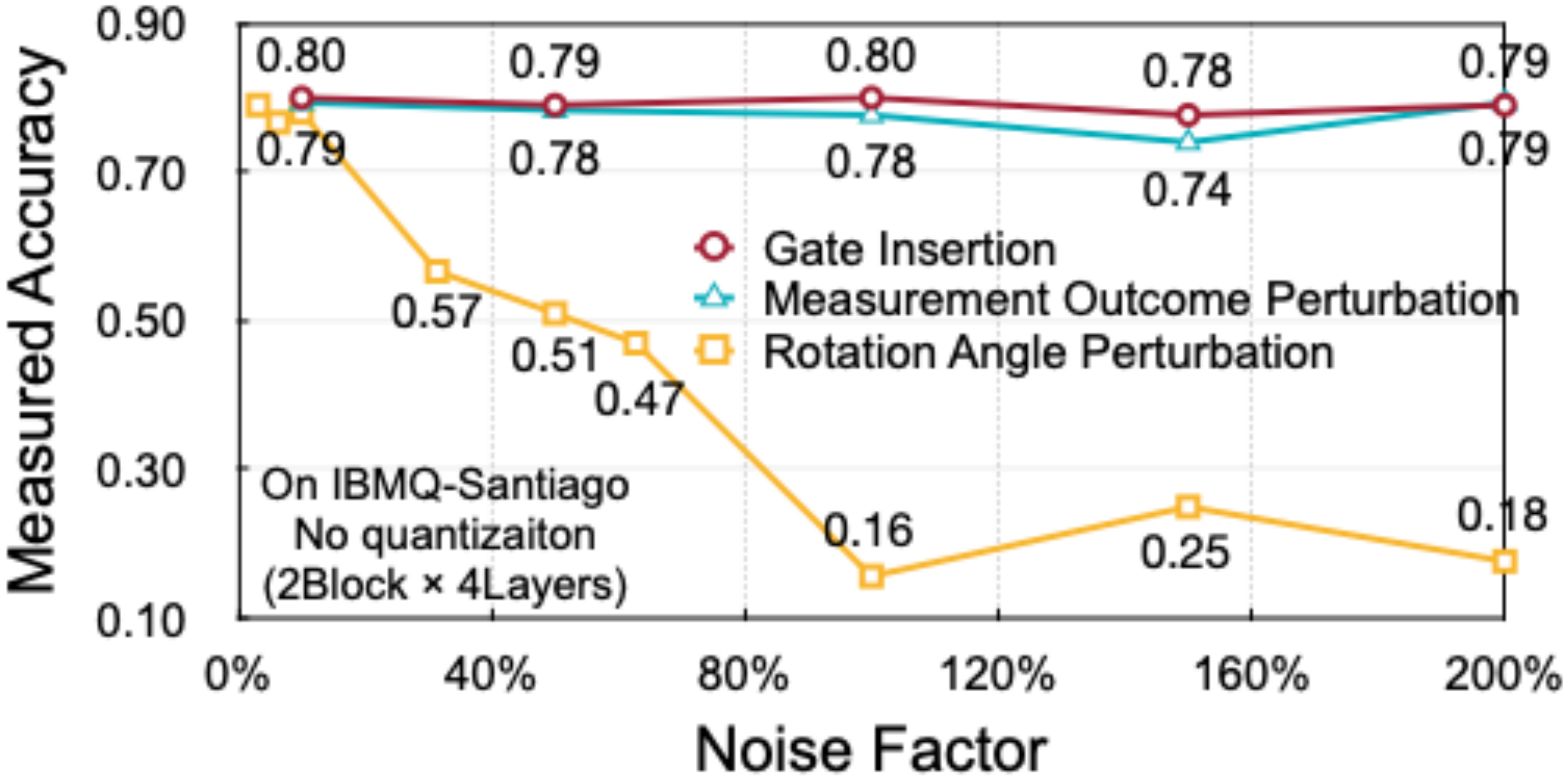
Consistent Improvements on Various Benchmarks

- Different gate set design spaces

Design Space	MNIST-4 Yorktown	MNIST-4 Santiago	Fashion-2 Yorktown	Fashion-2 Santiago
'ZZ+RY'	**0.43**	0.57	0.80	**0.91**
+QuantumNAT	0.34	**0.60**	**0.83**	0.86
'RXYZ'	0.57	0.61	0.88	0.89
+QuantumNAT	**0.61**	**0.70**	**0.92**	**0.91**
'ZX+XX'	0.29	0.51	**0.52**	0.61
+QuantumNAT	**0.38**	**0.64**	**0.52**	**0.89**
'RXYZ+U1+CU3'	0.28	**0.25**	0.48	0.50
+QuantumNAT	**0.33**	0.21	**0.53**	**0.52**

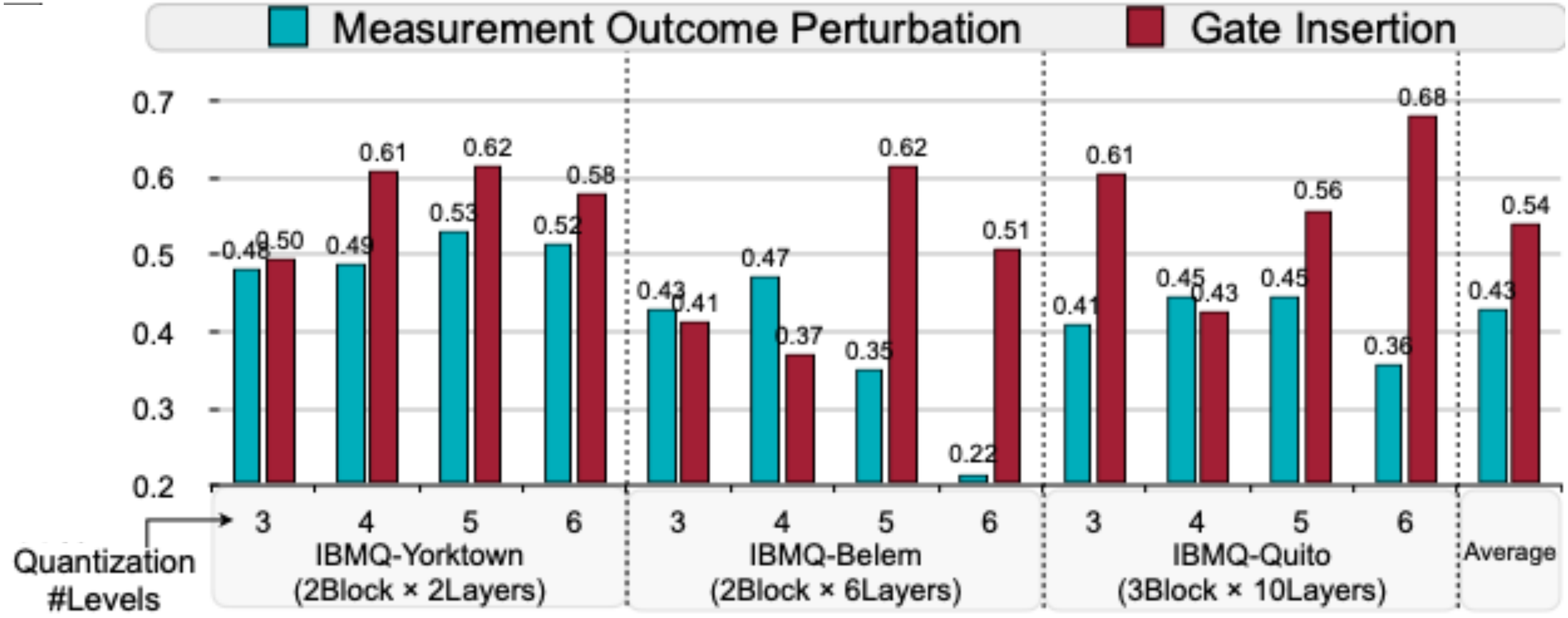
Ablation Study on Noise Injection Method

- Gate insertion is better than rotation angle perturbation



Ablation Study on Noise Injection Method

- Gate insertion is better than measurement outcome perturbation



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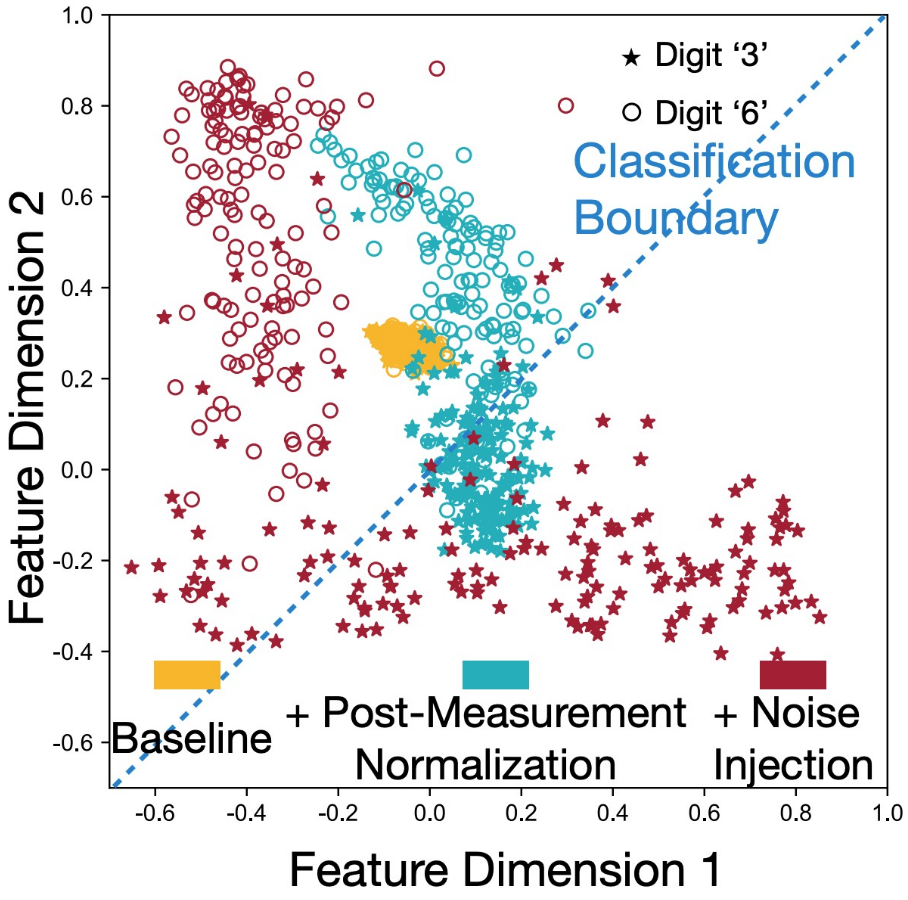
Visualization

- QuantumNAT stretches the distribution of features
  - MNIST-2 classification task



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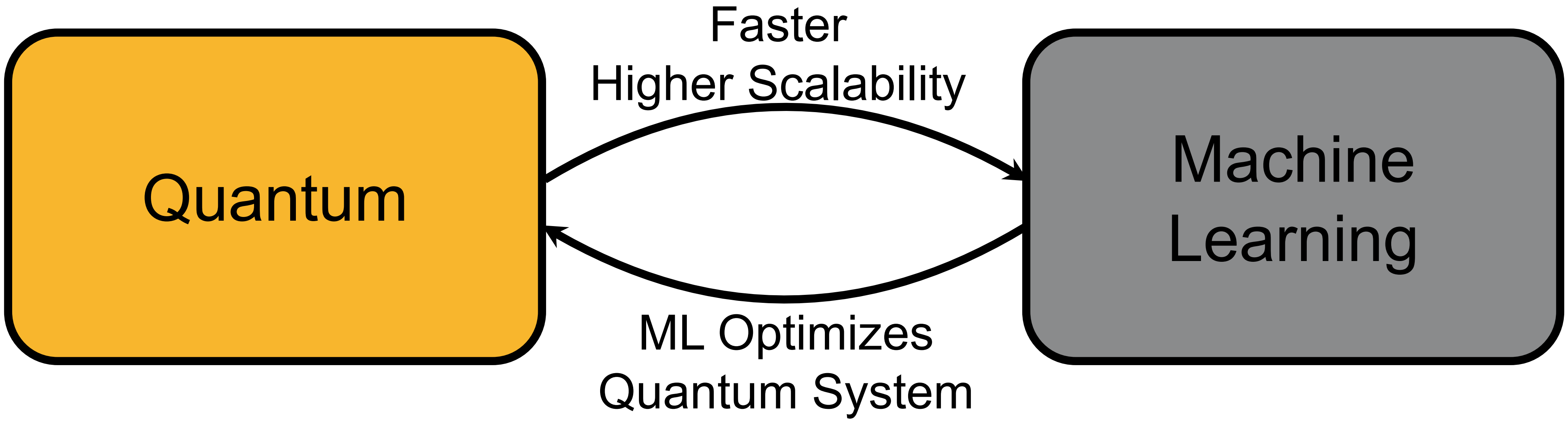
Torch Quantum

Open-source: TorchQuantum

- TorchQuantum — An open-source library for interdisciplinary research of quantum computing and machine learning
- https://github.com/mit-han-lab/torchquantum



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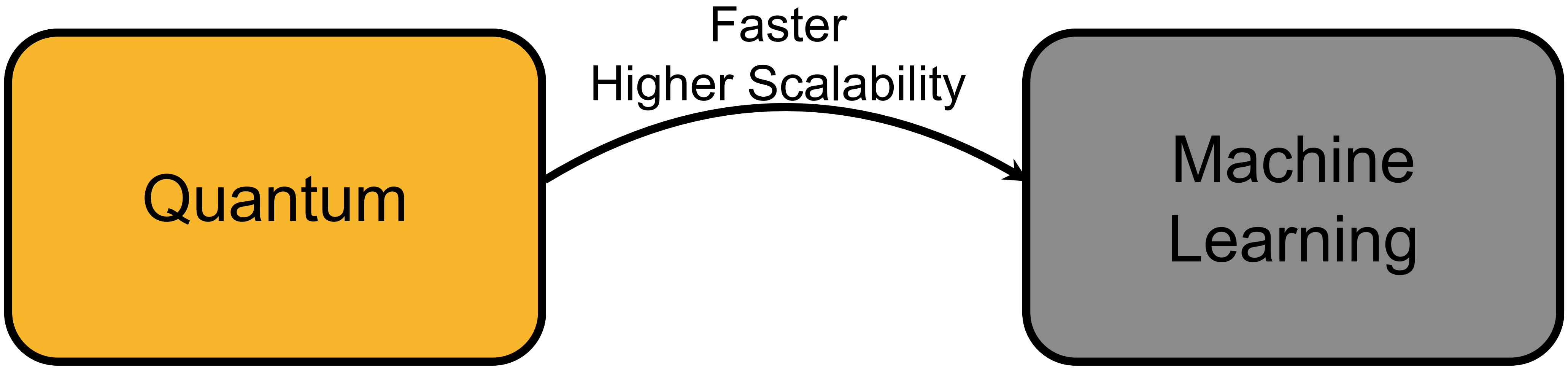

- Quantum ML
  - Quantum neural networks
  - Quantum kernel methods

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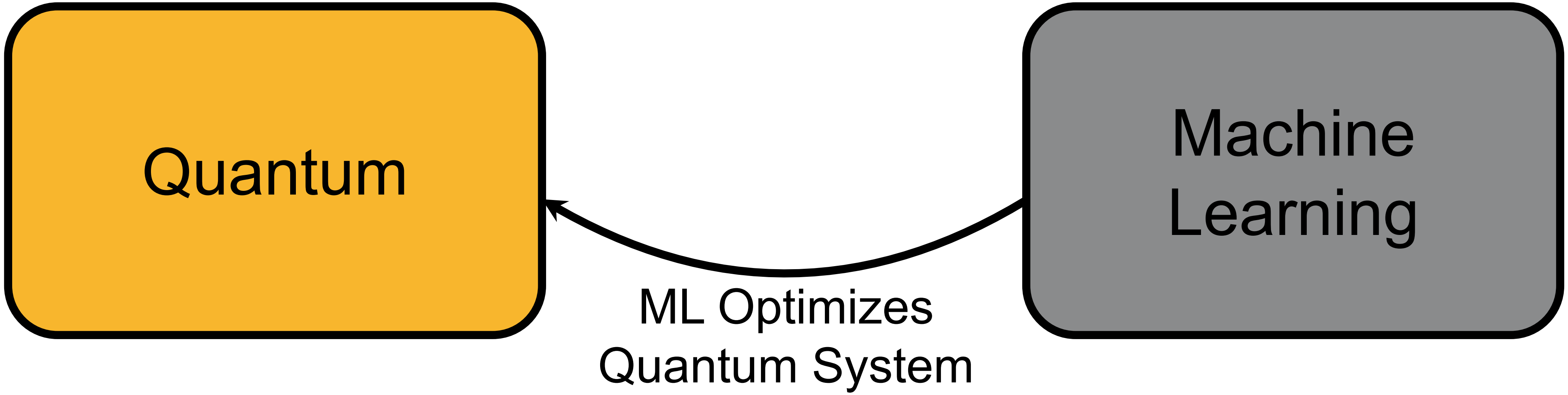

- ML for Quantum
  - ML optimizes quantum compilation

TorchQuantum Features

- Features
  - Easy construction of **parameterized quantum circuits** such as Quantum Neural Networks in PyTorch
  - Support **batch mode inference and training** on GPU/CPU, supports highly-parallelized training
  - Support **easy deployment** on real quantum devices such as IBMQ
  - Provide tutorials, videos and example projects of QML and using ML to optimize quantum computer system problems

TorchQuantum Examples & Tutorials

Torch Quantum

TorchQuantum Tutorials
Opening

Hanrui Wang
MIT HAN Lab

Torch Quantum

TorchQuantum Tutorials
Quanvolutional Neural Network

Zirui Li, Hanrui Wang
MIT HAN Lab

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Conclusion

- QuantumNAT: makes PQC **parameters** more noise-robust
  - Post-measurement Normalization
  - Noise injection
  - Post-measurement Quantization
- Achieve 94% 2-class and 34% 10-class classification accuracy
- Open-sourced **TorchQuantum** library for Quantum + ML research

Torch Quantum

qmlsys.mit.edu

https://github.com/mit-han-lab/torchquantum