ResilienQ: Boosting Fidelity of Quantum State Preparation via Noise-Aware Variational Training

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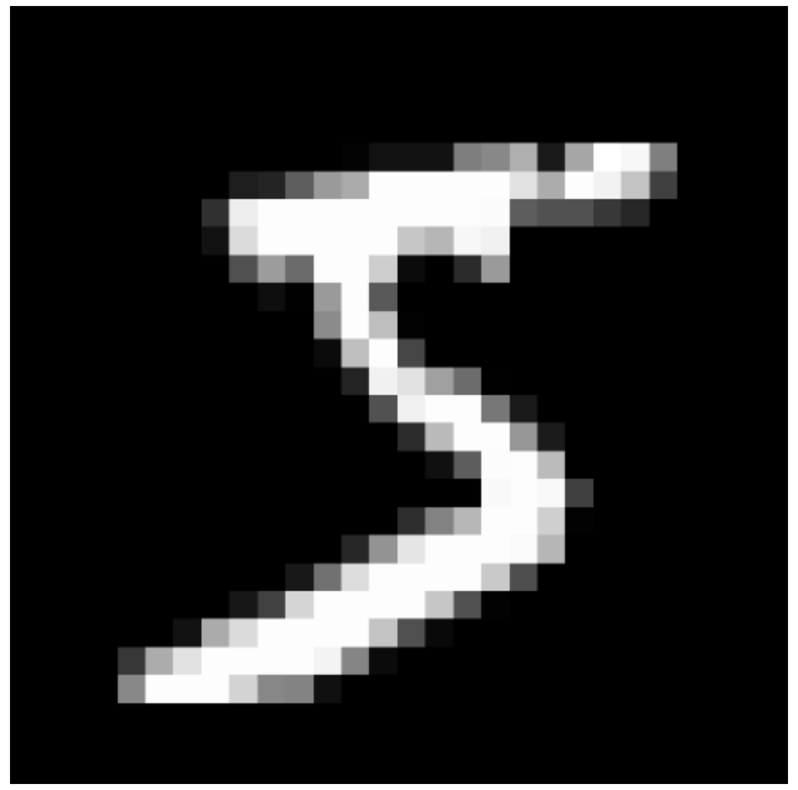
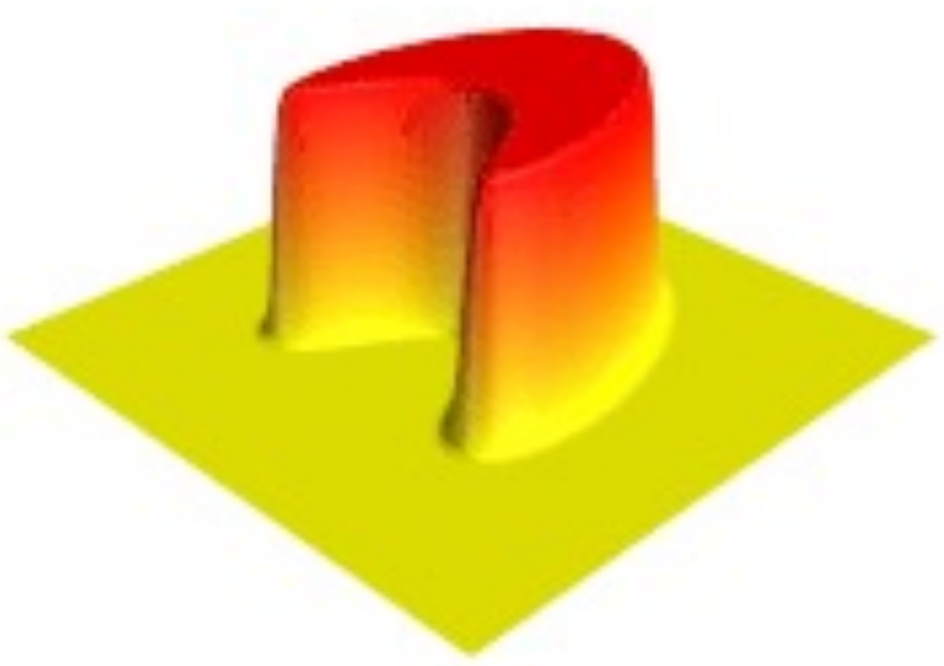
Quantum State Preparation

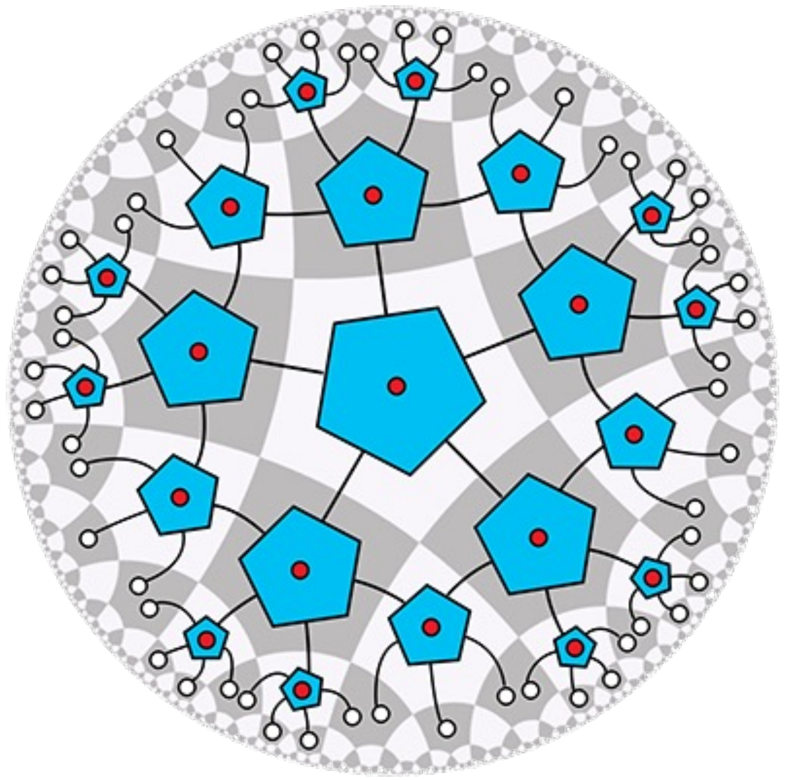
- Prepare the initial state of the quantum device



Amplitude Encoding in QML



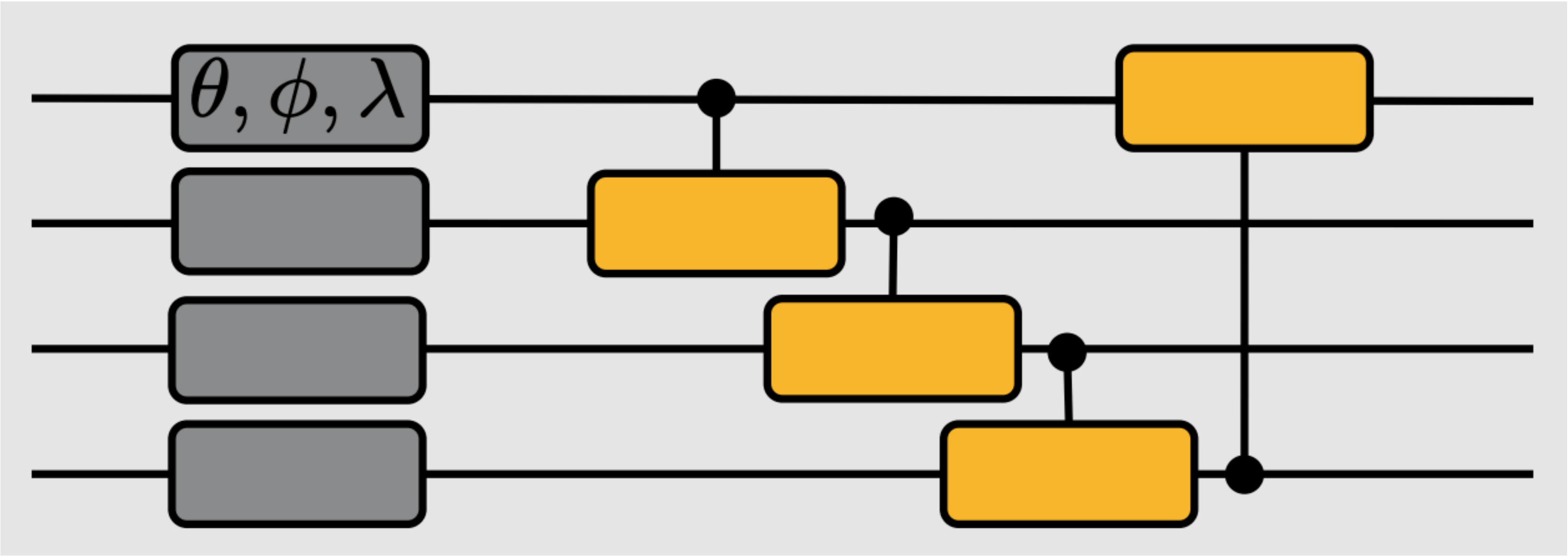
Initial States in PDE



Initial States in Quantum Error Correction

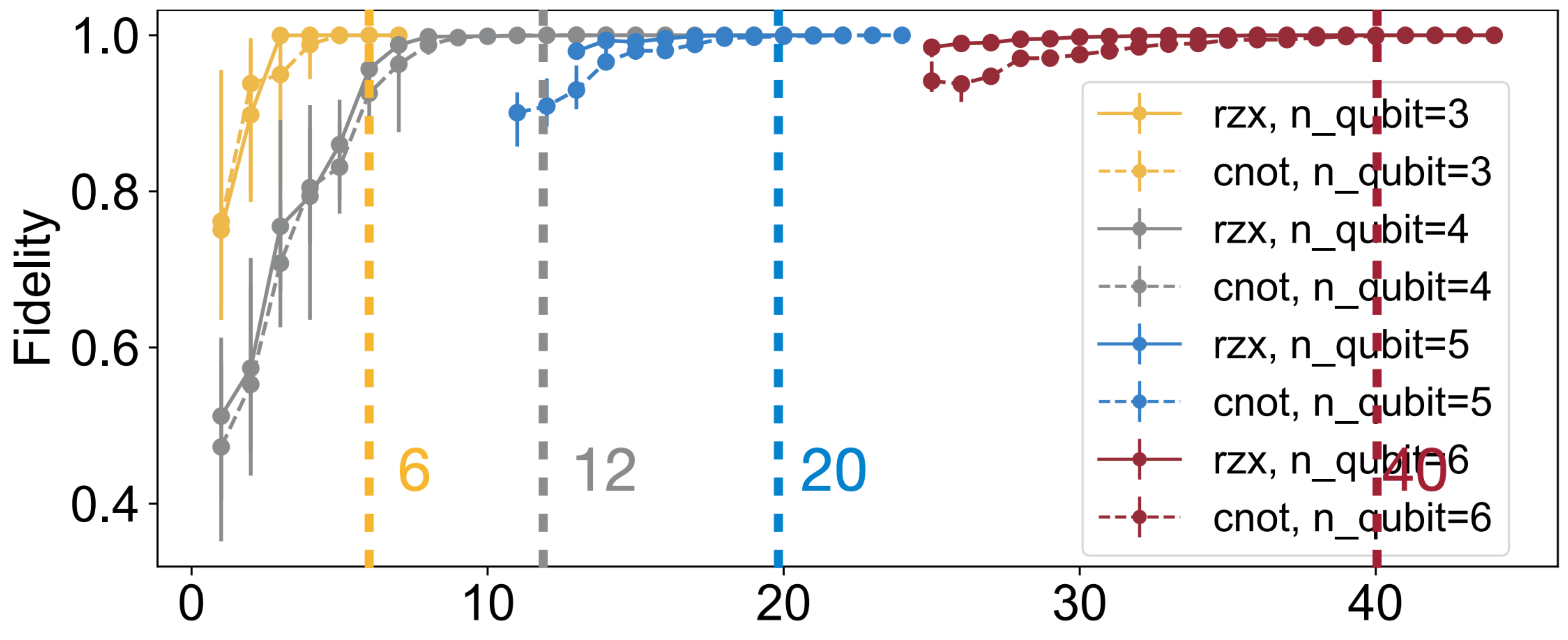
Quantum State Preparation

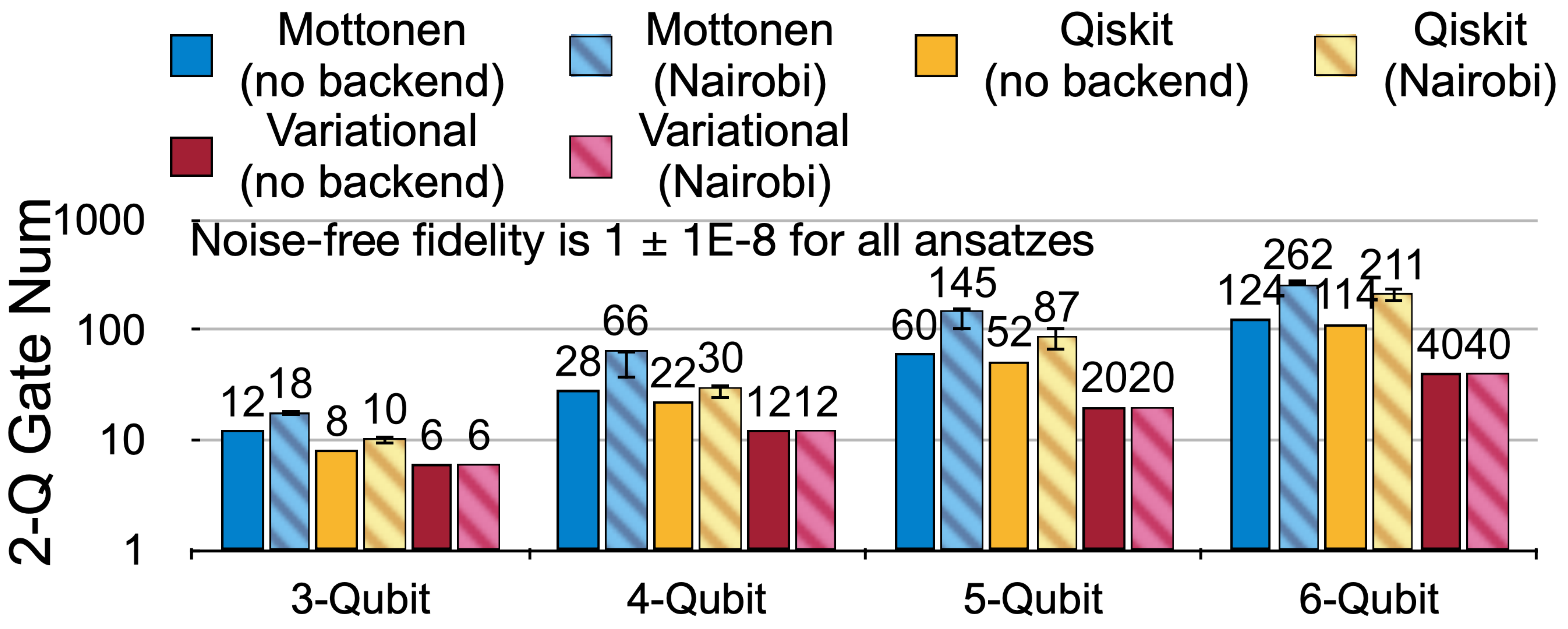
- Two ways for state preparation:
  - Arithmetic decomposition based
    - Shannon Decomposition
    - Mottonen Decomposition
  - Variational circuit based



Cost of Variational State Preparation

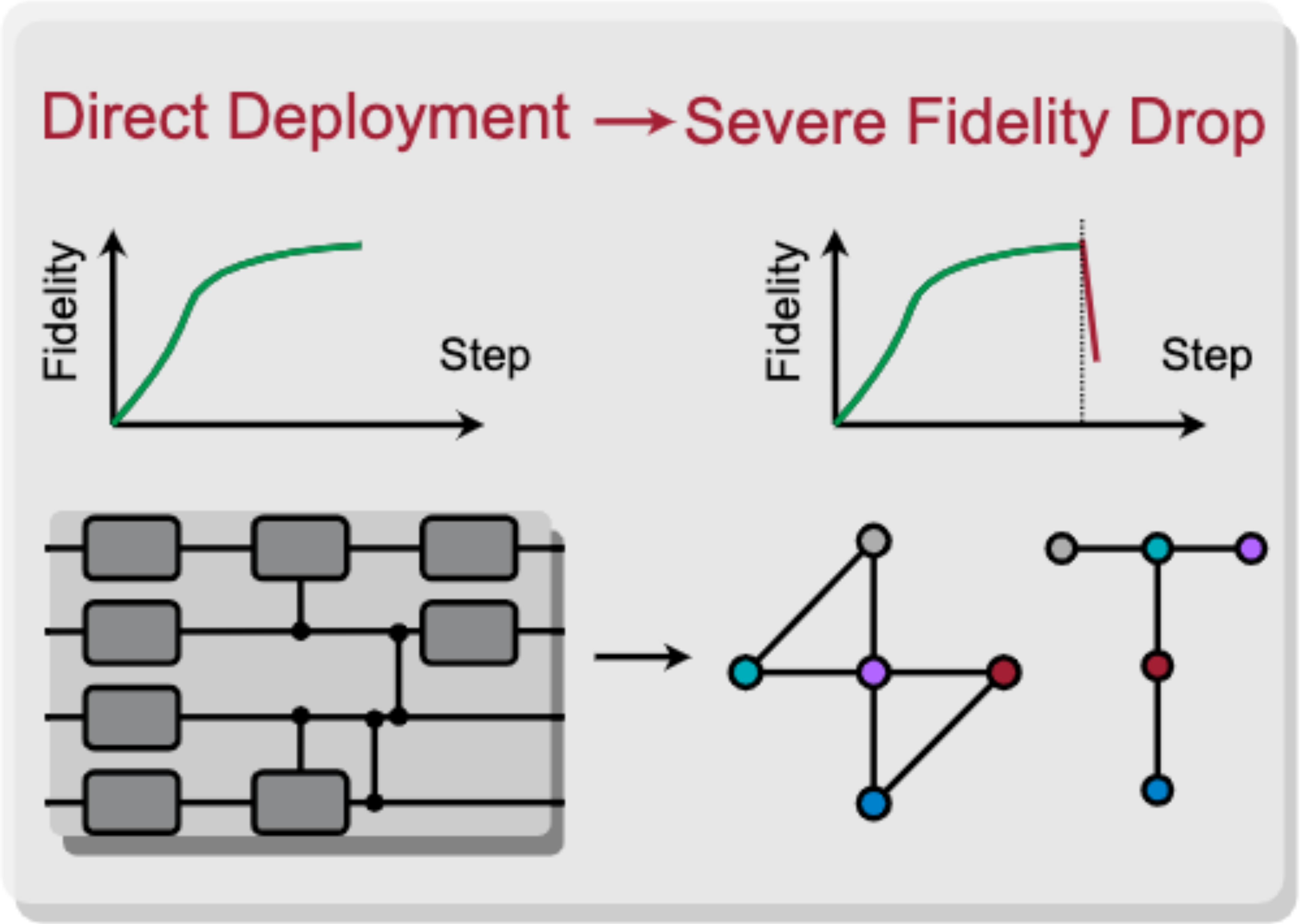
- Number of 2Q gate required is O(2^N)
- Variational State preparation requires fewer number of gates





Robust Variational State Preparation

- Noise degrades state prep fidelity

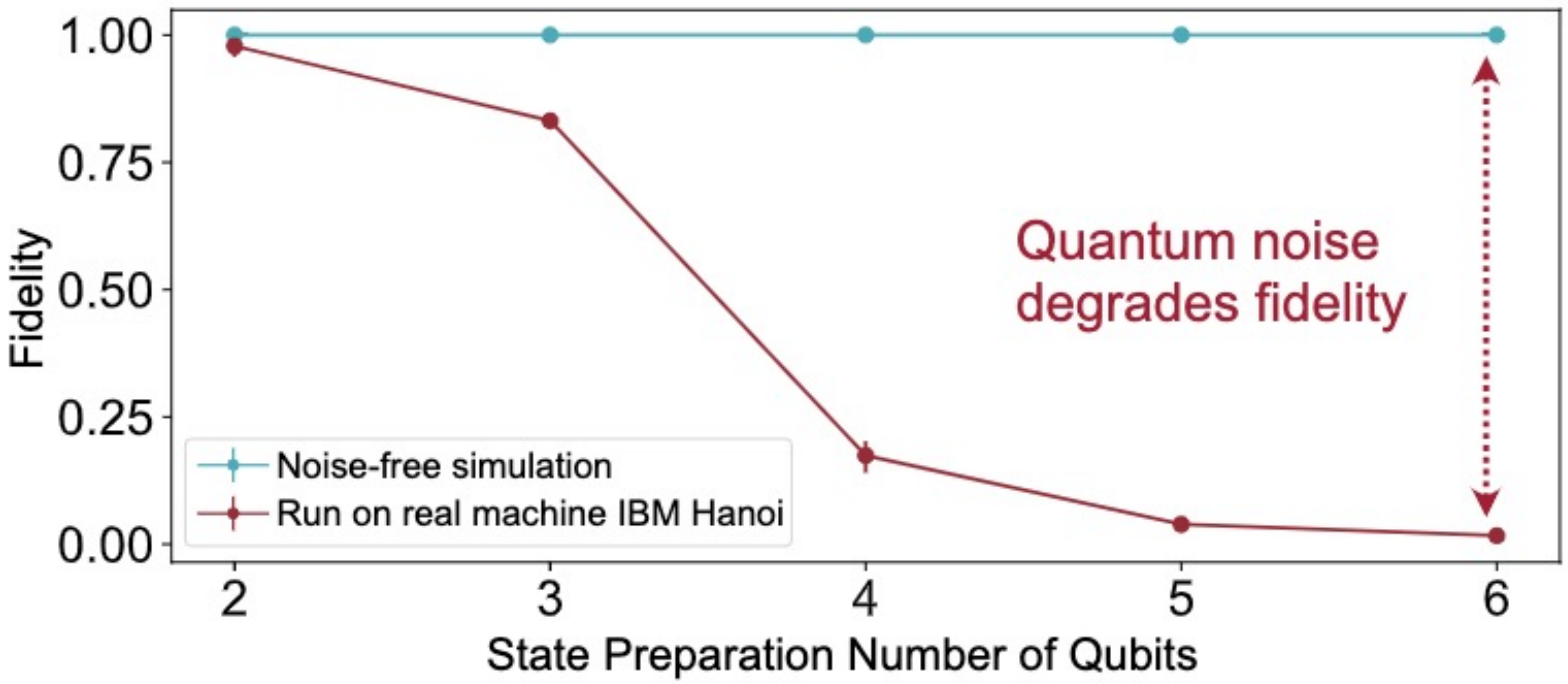


Classical Off-Chip Training Noise-Unaware

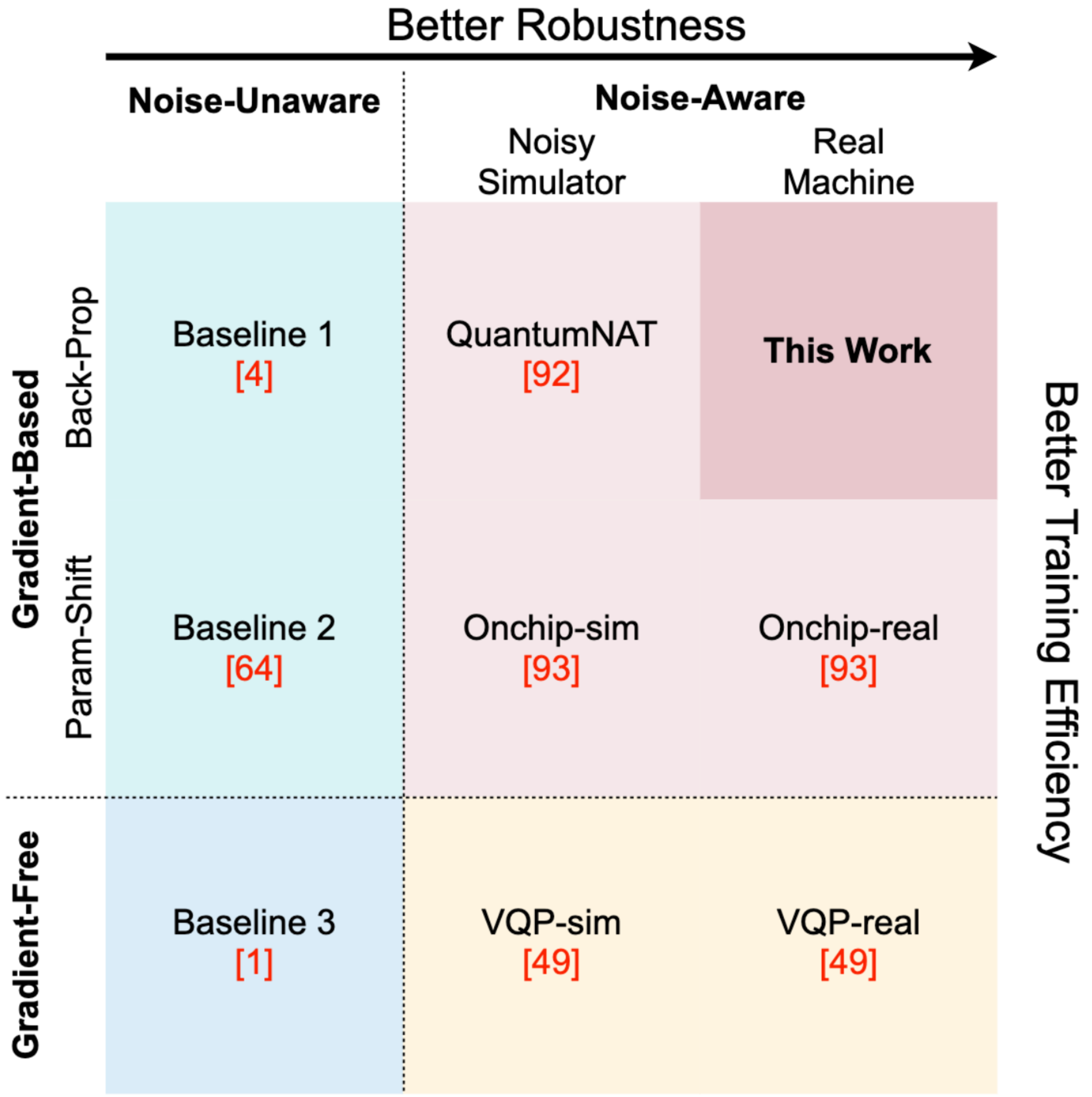
Conventional Offline Training

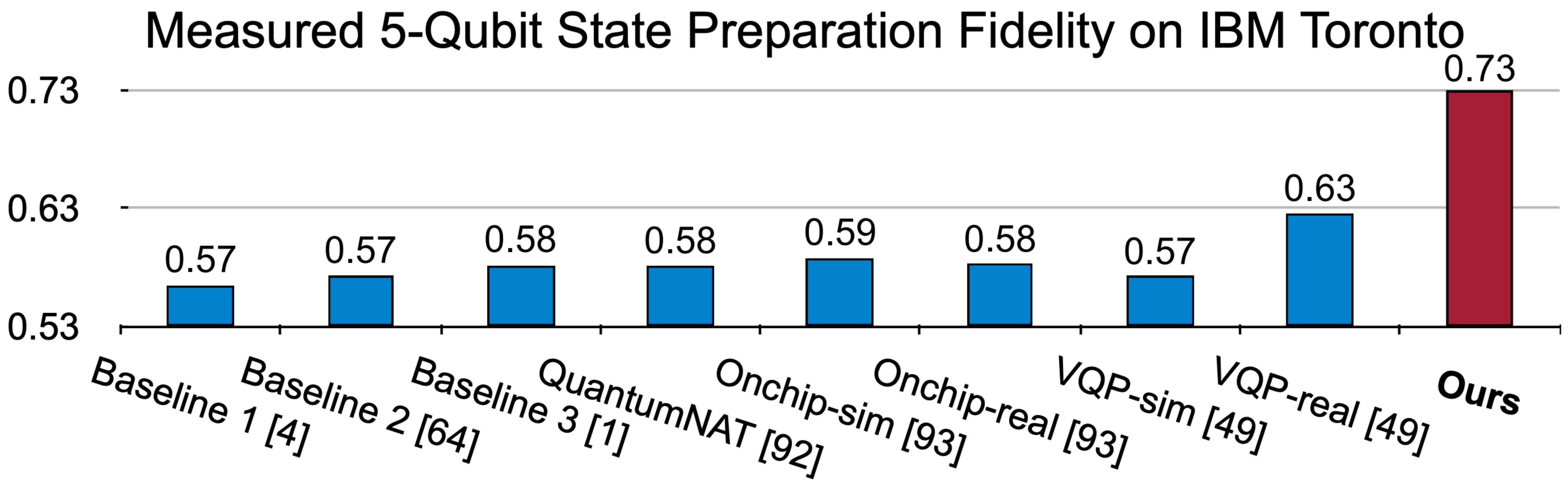
Quantum Noise Impact

- Noise degrades state prep fidelity



Prior Work for Robust Variational Circuit





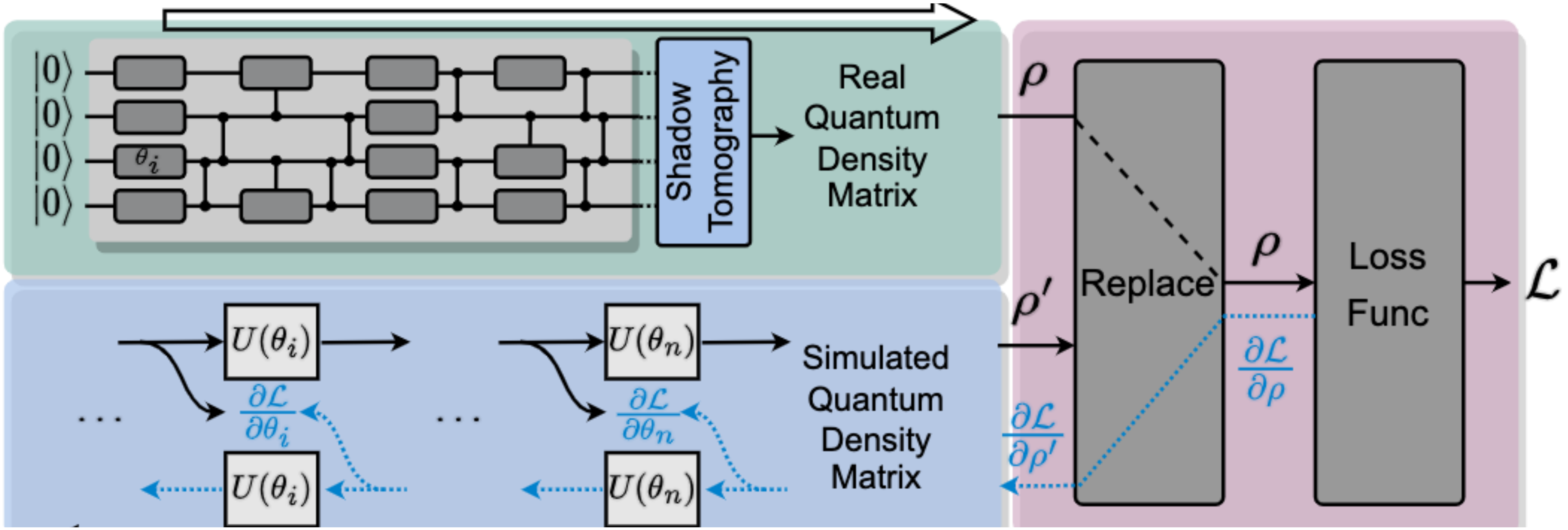
	Parameter-Shift	Gradient-Free	**Ours**
Scaling w.r.t. #Params	$\mathcal{O}(n)$	Unscalable	$\mathcal{O}(1)$
Gradient Guidance	✓	✗	✓

ResilienQ: Robust State Preparation

- Gradient Proxy
- Native Pulse
- Hardware Efficient Ansatz

Gradient Proxy: Forward on real device; backward on simulator

- Make the parameters aware of the real noise



Gradient Proxy: Forward on real device; backward on simulator

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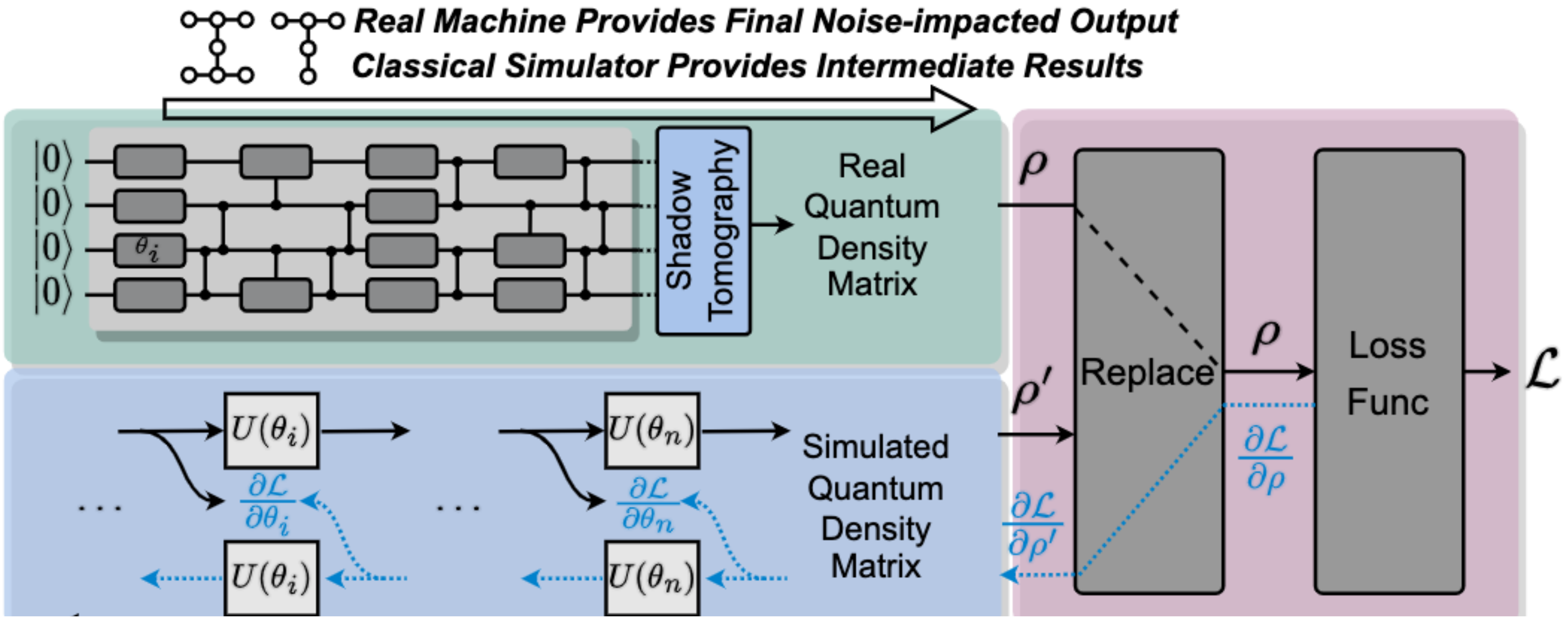

Gradient Proxy: Forward on real device; backward on simulator

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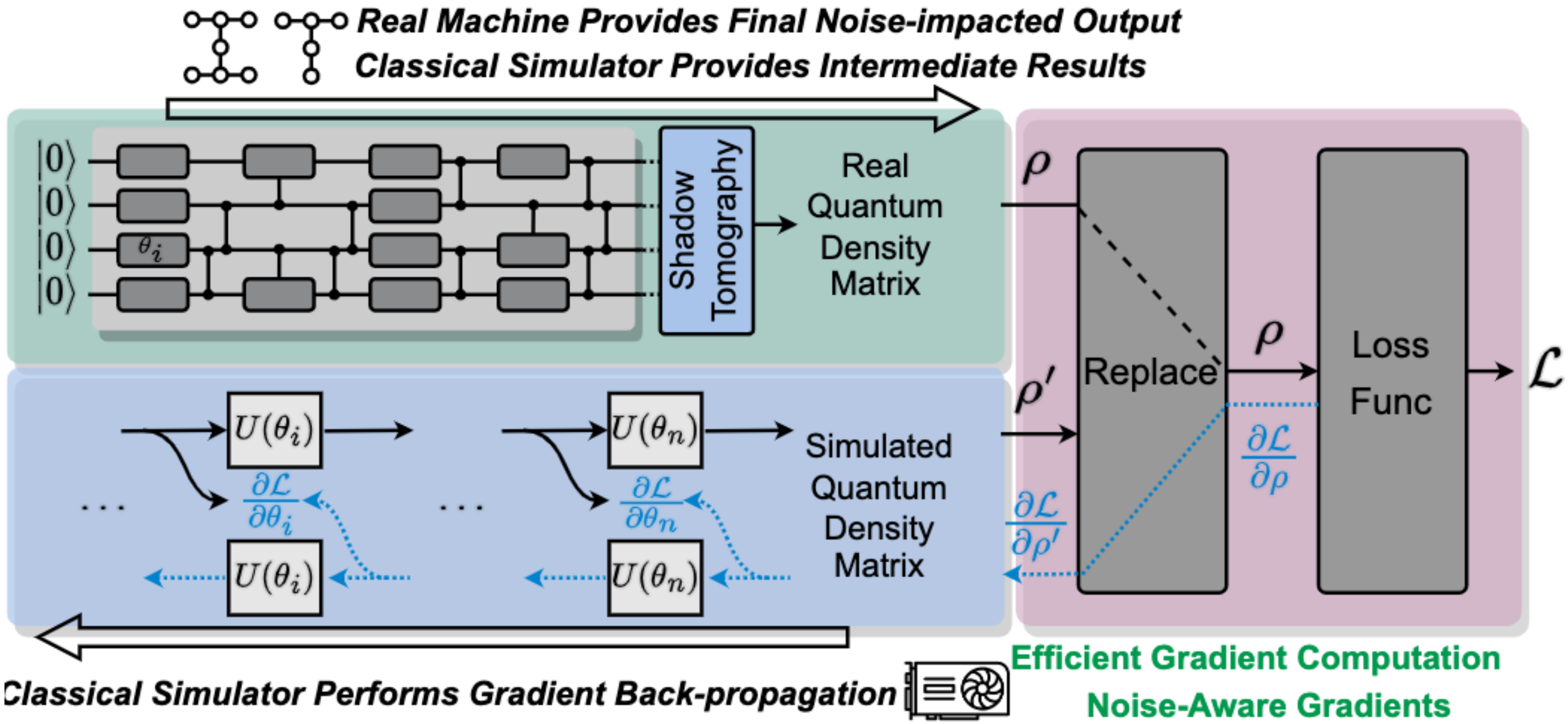

Proposed ResilienQ Training

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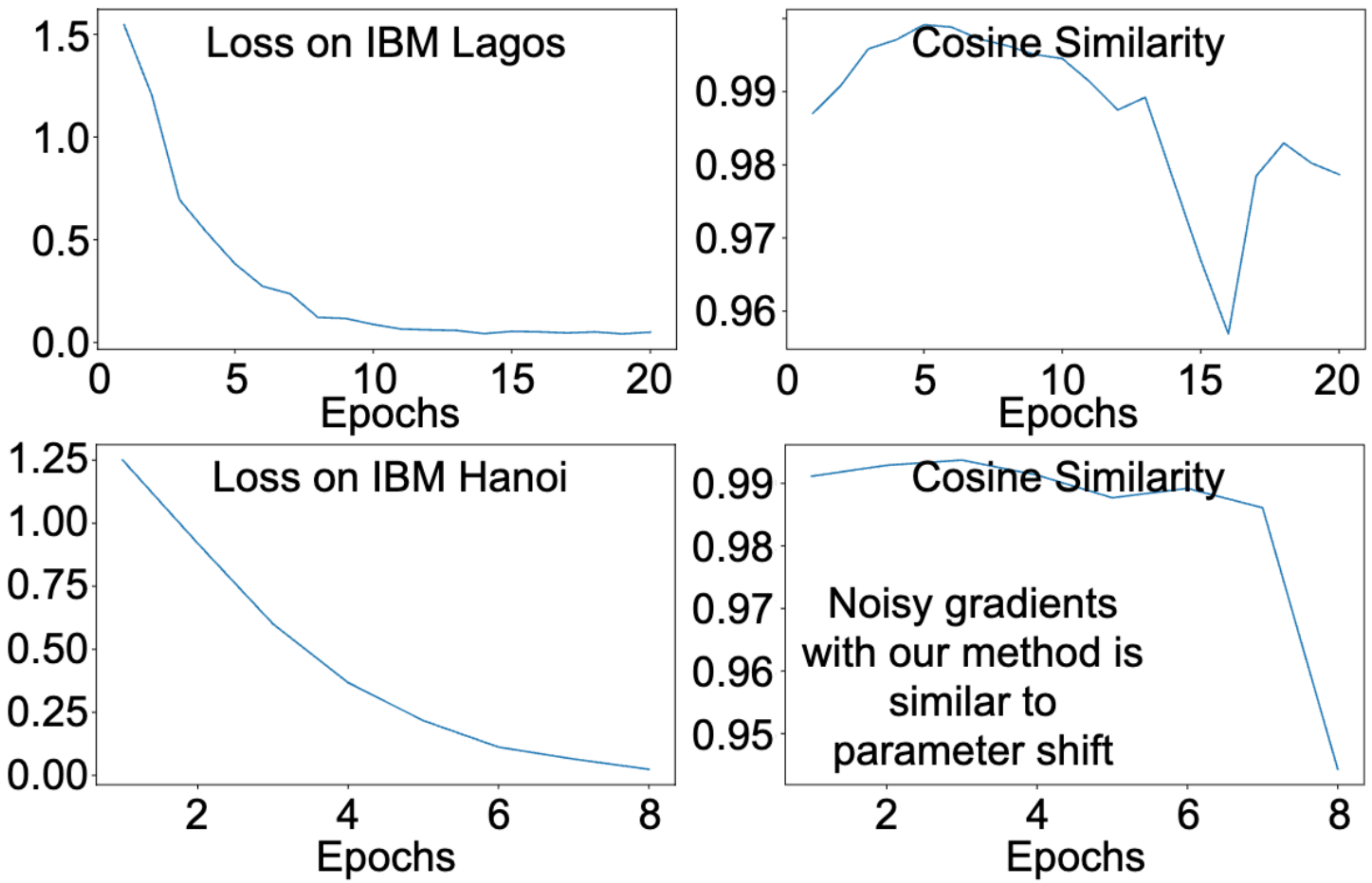
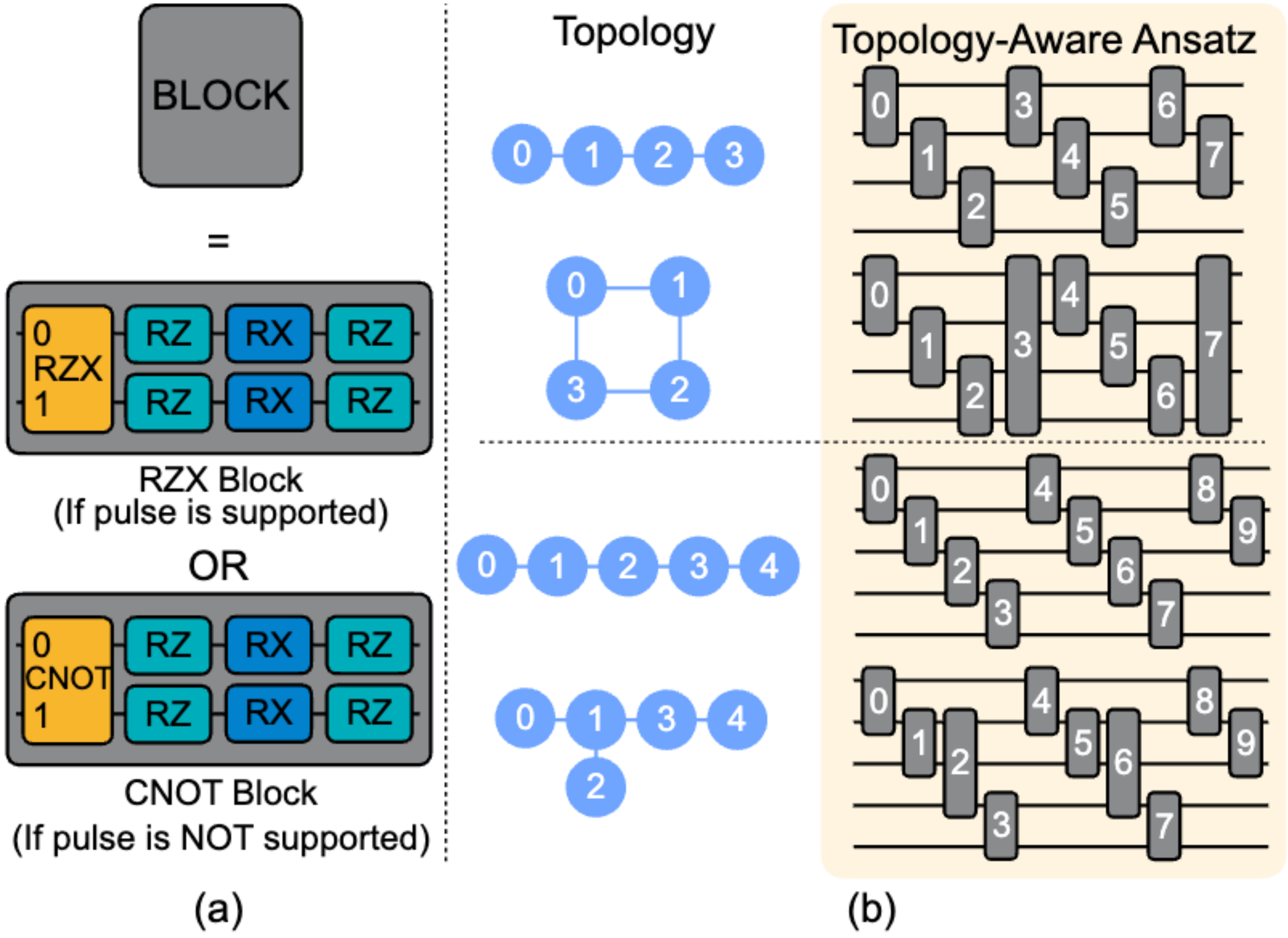
Is the estimated gradient accurate?

- Noise-aware gradients approximated with ResilienQ are close to the accurate ones computed with the parameter shift rule



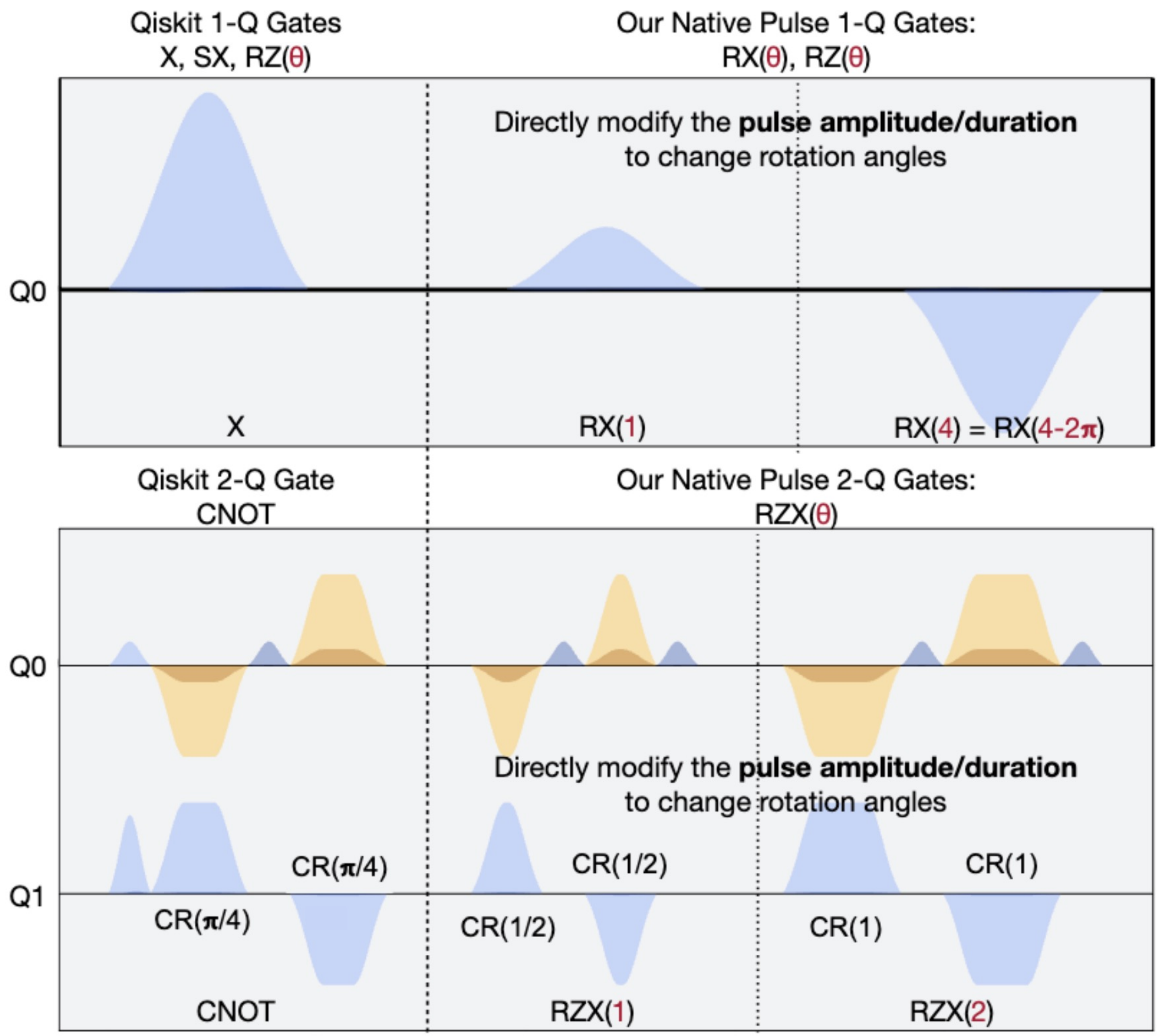
Hardware Efficient Ansatz

- Adapt to the hardware topology



Optimize on the Pulse level

- Scale the pulse magnitude according to the parameter.



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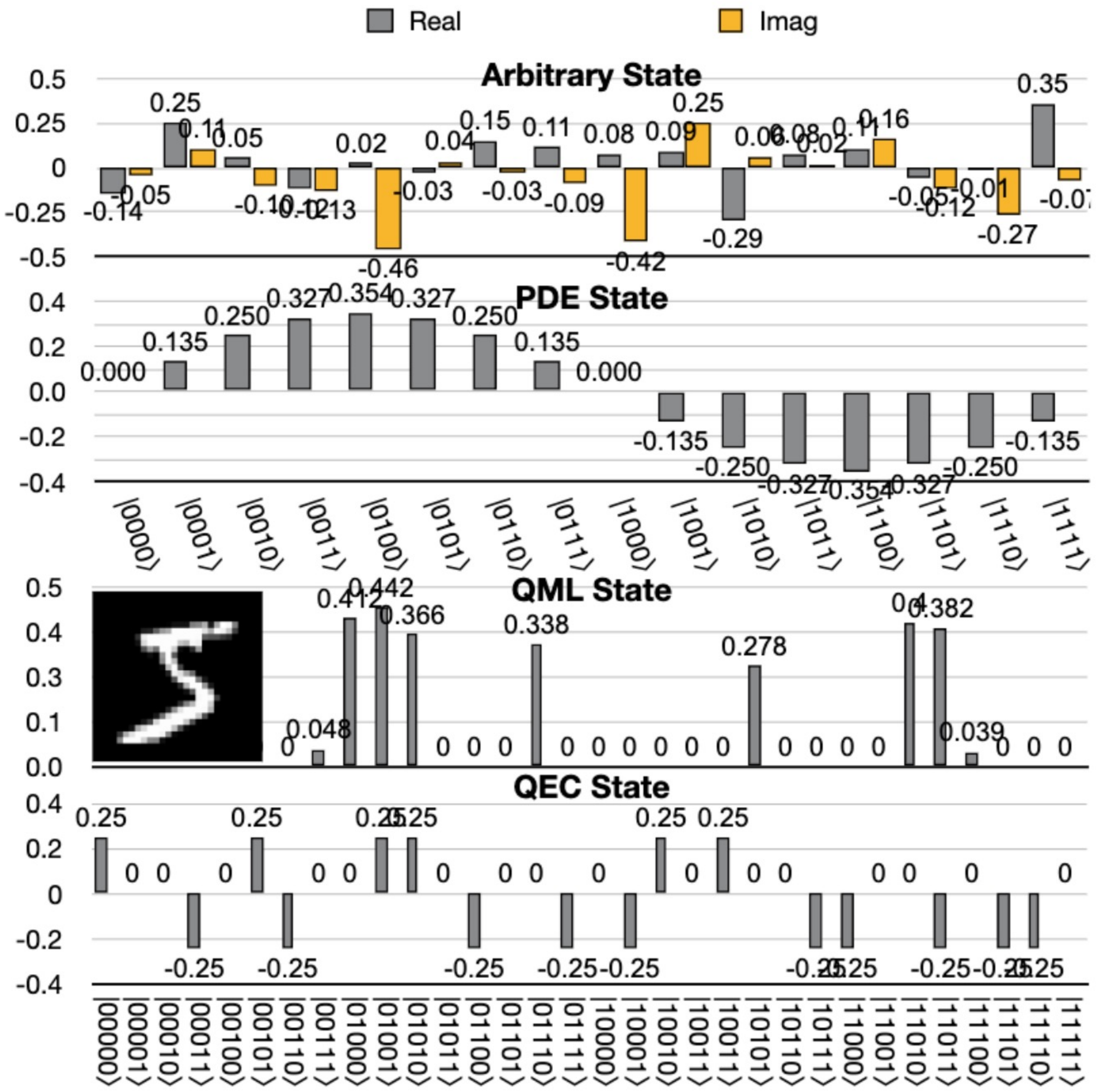
Evaluation

- Benchmarks



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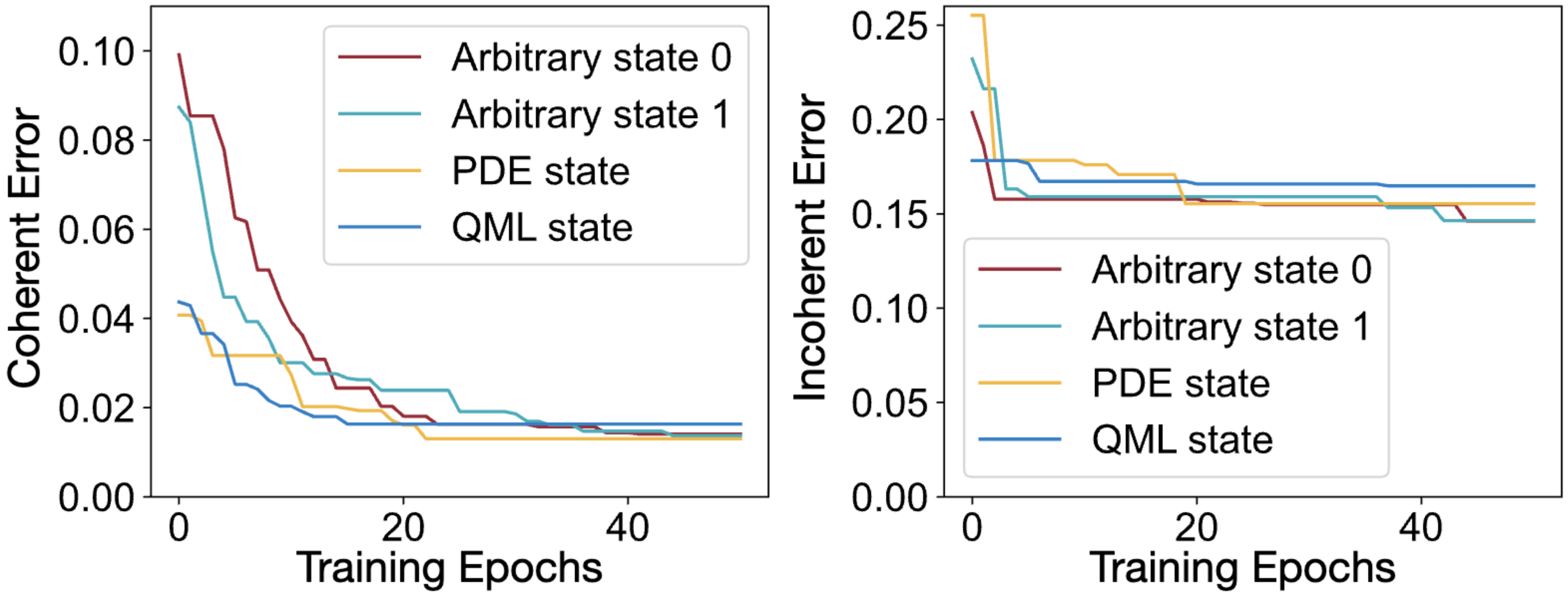
Reduction of Coherent Errors



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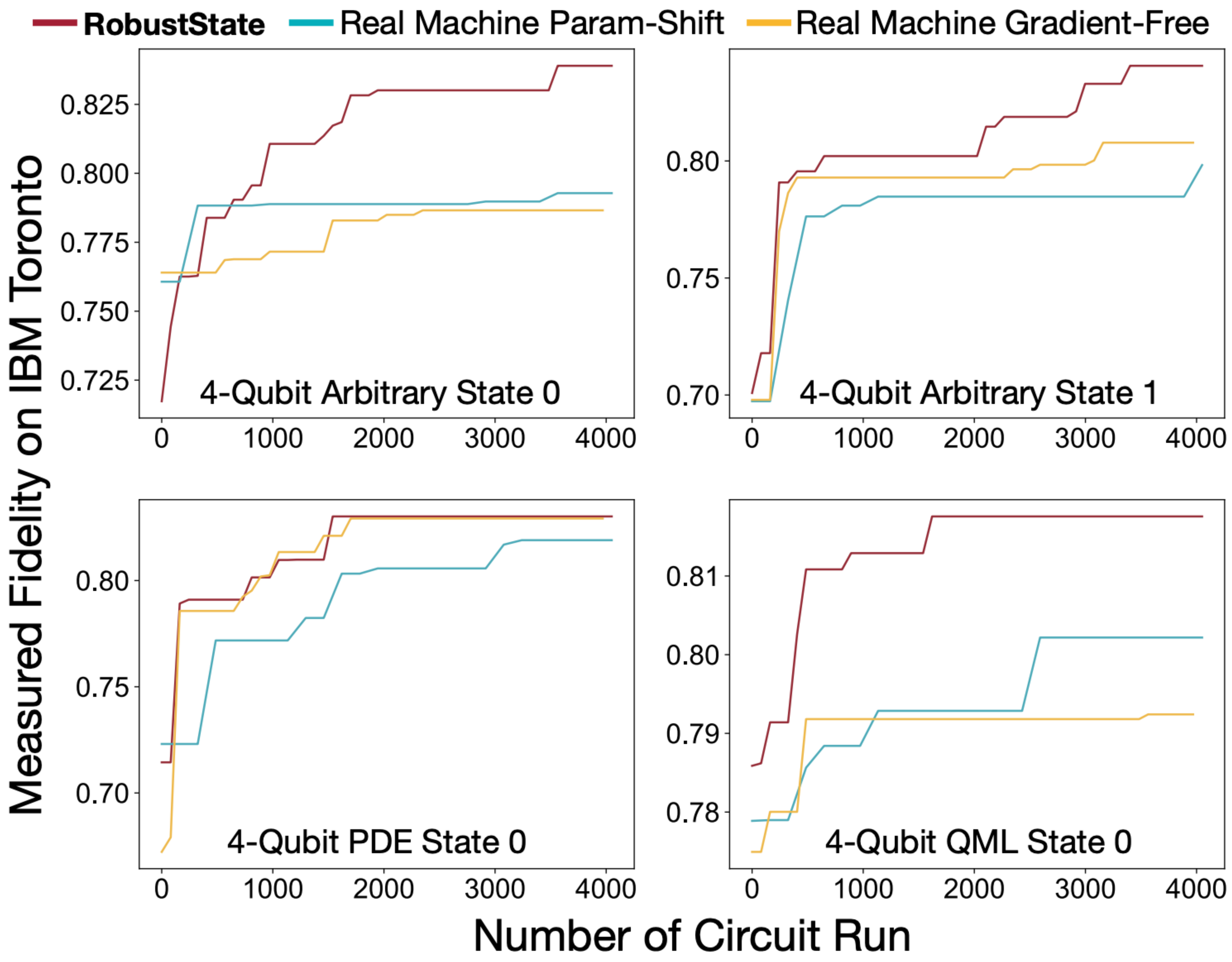
Efficiency over parameter shift

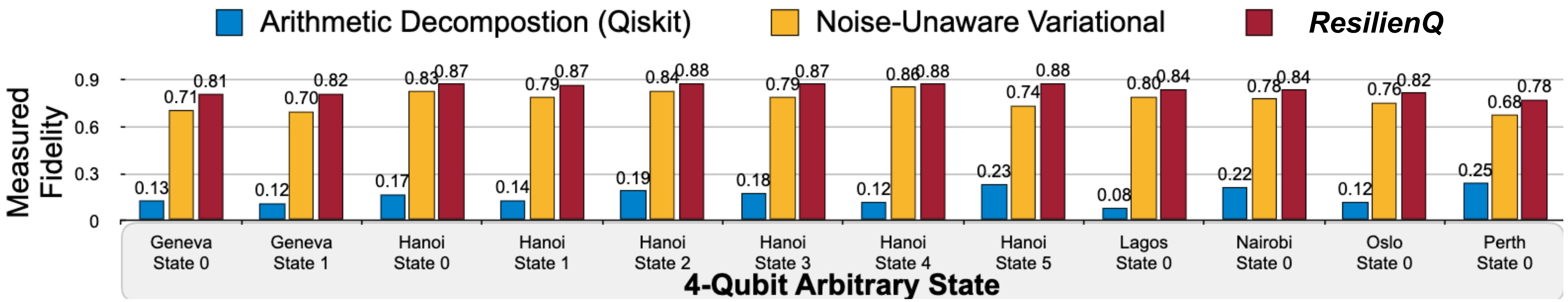


Comparison with arithmetic decomposition

Fidelity	Arbitrary	PDE	QML	Avg.
Mottonen [4], [66]	0.156	0.175	0.269	0.200
Mottonen+SABRE [4], [45], [66]	0.099	0.401	0.299	0.266
Qiskit [36]	0.176	0.277	0.481	0.311
Qiskit + SABRE [45]	0.262	0.266	0.626	0.385
Ours	**0.777**	**0.713**	**0.718**	**0.736**

Result on real quantum hardware

- On real quantum device



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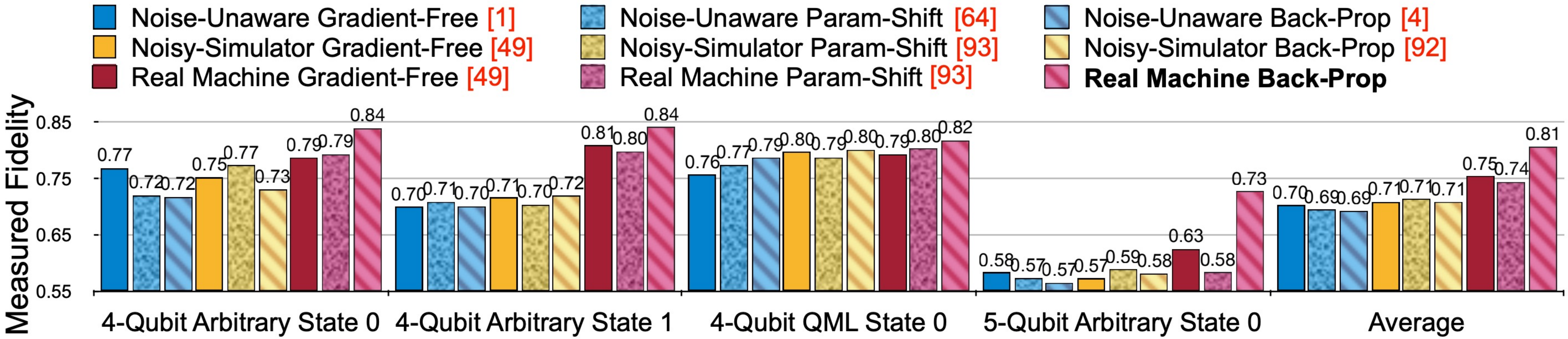
Comparison to other robust VQC training methods



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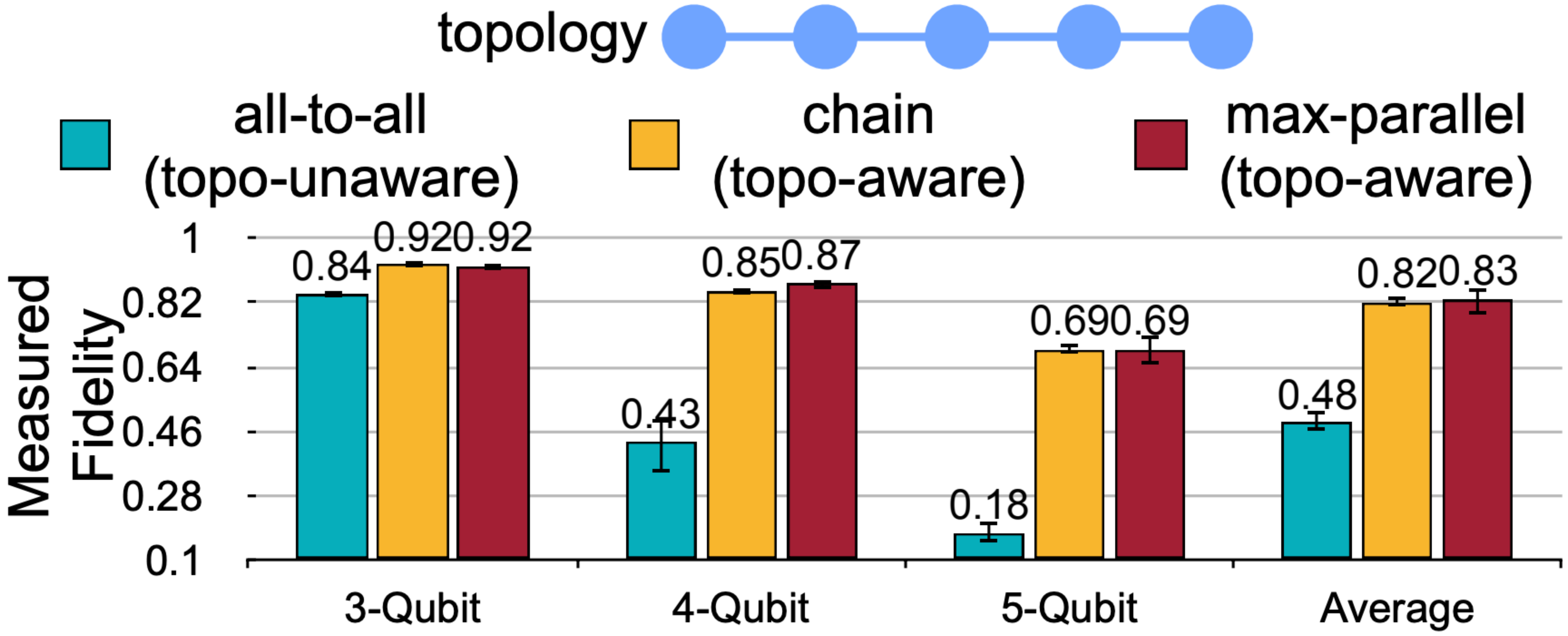
Effectiveness of hardware-efficient ansatz



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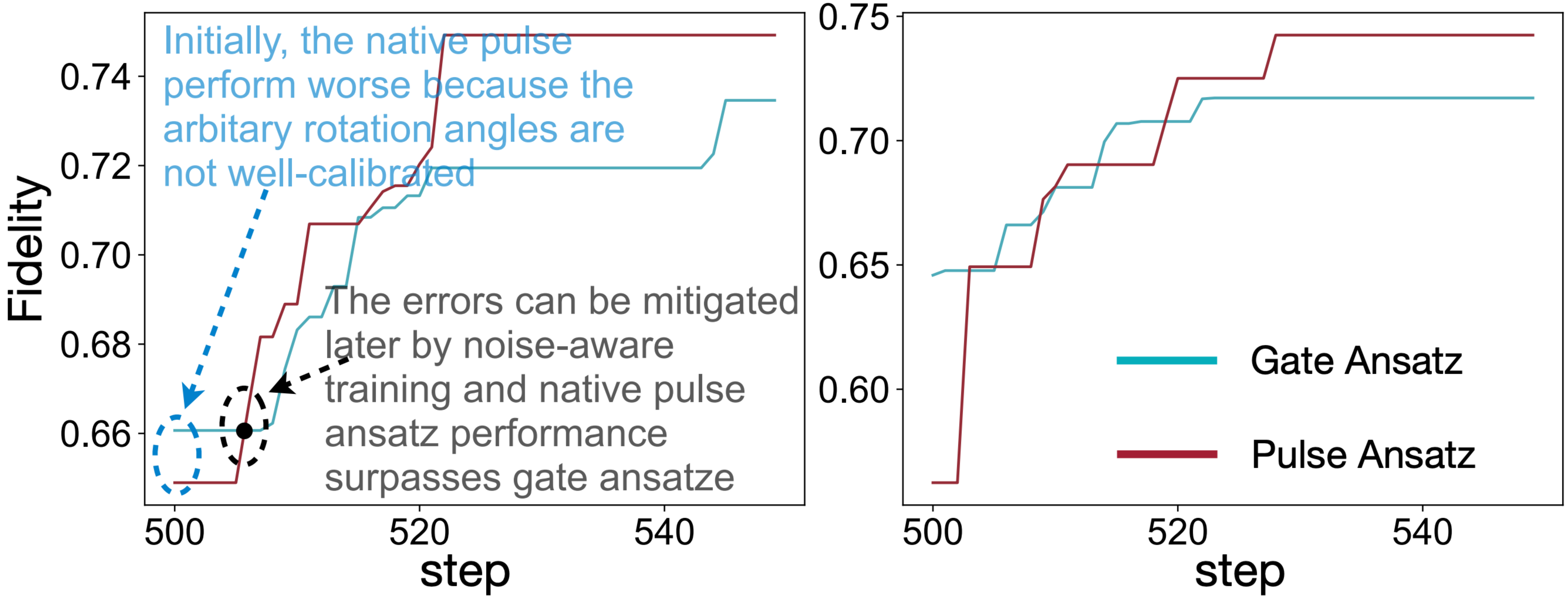
Pulse ansatz vs gate ansatz



Extension of gradient proxy to other tasks

- Unitary synthesis
- State regression

Task	Baseline	**Ours**
Unitary Synthesis Jakarta	0.845	**0.868**
Unitary Synthesis Toronto	0.858	**0.940**
Unitary Synthesis Perth (1)	0.817	**0.834**
Unitary Synthesis Perth (2)	0.798	**0.821**
Quantum State Regression (1) Loss	0.167	**0.147**
Quantum State Regression (2) Loss	0.163	**0.124**

Scalability

- Comparable to arithmetic decomposition, **much higher fidelity**
- Preparing **small to medium-sized** states with high fidelity is a crucial task in quantum computing e.g. the color code, surface code
- **Block-wise** unitary synthesis can benefit significantly from ResilienQ

Take Home

- **Forward on real device, backward on simulator** for noisy gradients
- **Pulse-level hardware-efficient** ansatz design
- Applicable to other tasks such as **unitary synthesis**

Thank you for listening!

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

qmlsys.mit.edu