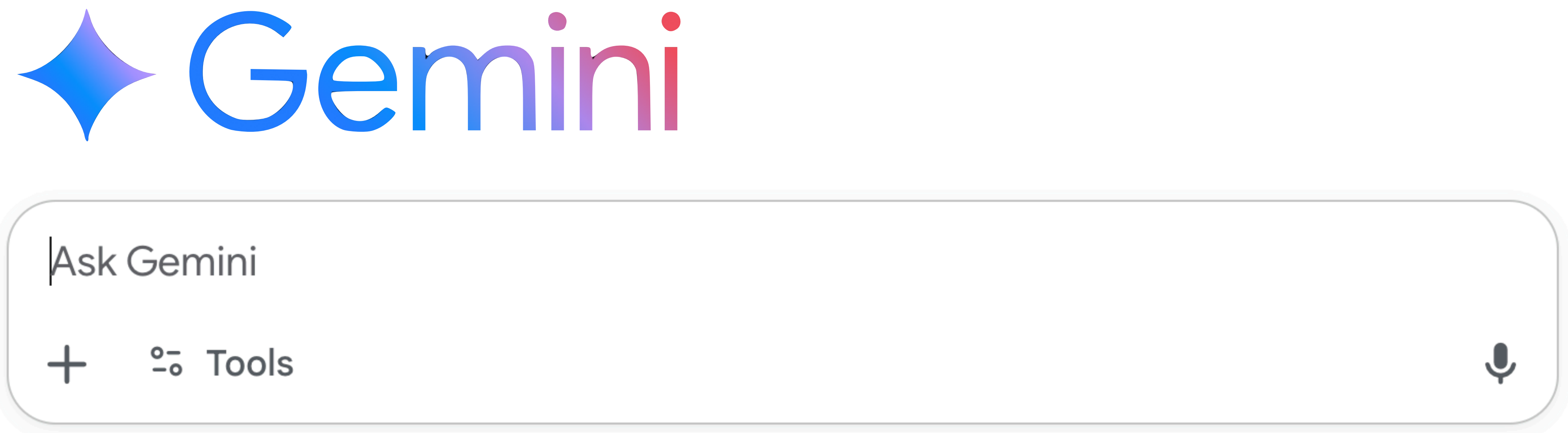
Ph 220: Lecture 12

Generative Quantum Advantage

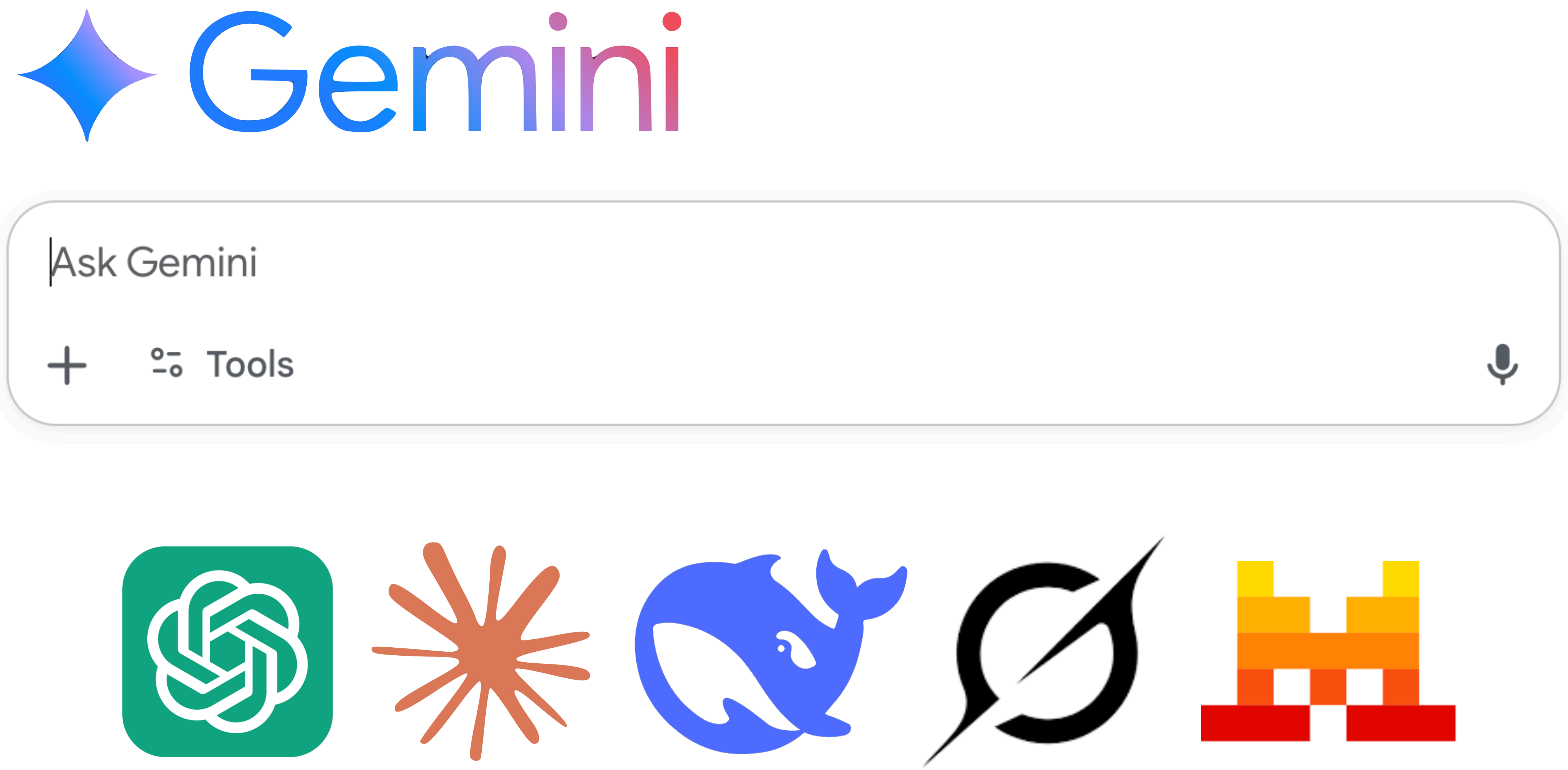
Generative Models

- **Definition (informal): Generative model** — A model that can learn to generate new outputs from some probability distribution.



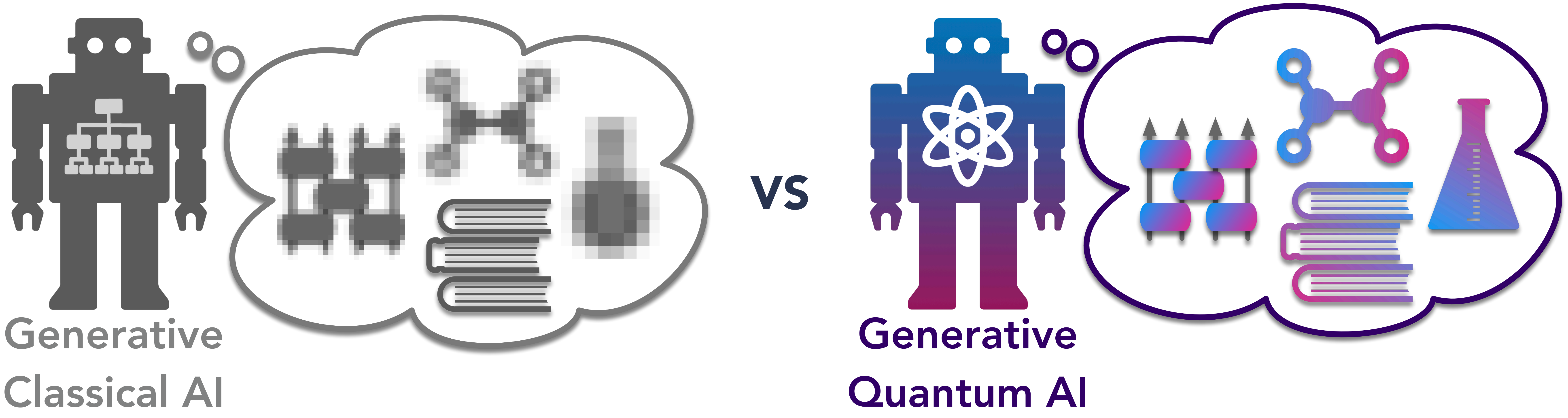
Generative Task

- **Definition:** Given a dataset of (x_i, y_i) sampled from unknown $p(y \mid x)$, learn to generate **new** y for **any given** x.



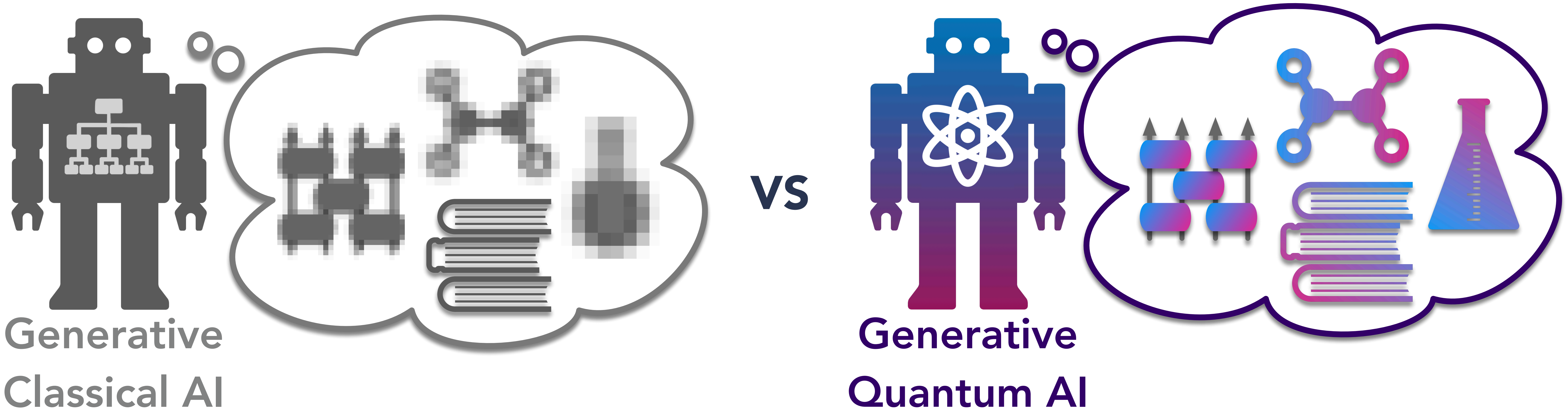
Generative Quantum Advantage

- **Definition (informal):** Generative quantum advantage — A quantum computer can learn to generate the desired outputs



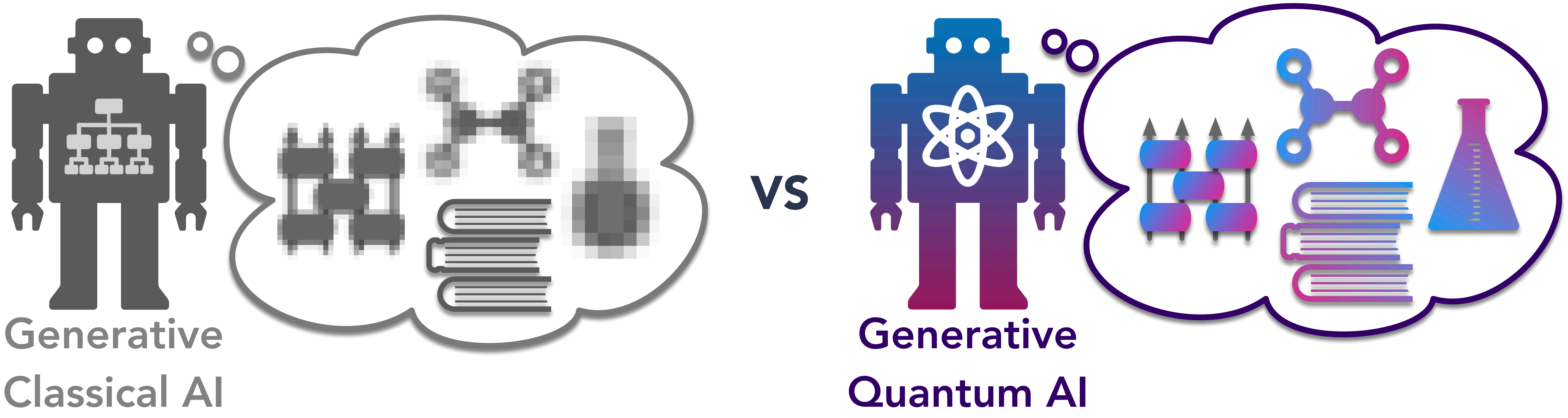
Generative Quantum Advantage

- **Definition (informal):** Generative quantum advantage — A quantum computer can learn to generate the desired outputs with reduced sample complexity



Generative Quantum Advantage

- **Definition (informal):** Generative quantum advantage — A quantum computer can learn to generate the desired outputs with reduced sample complexity, higher accuracy,



Generative Quantum Advantage

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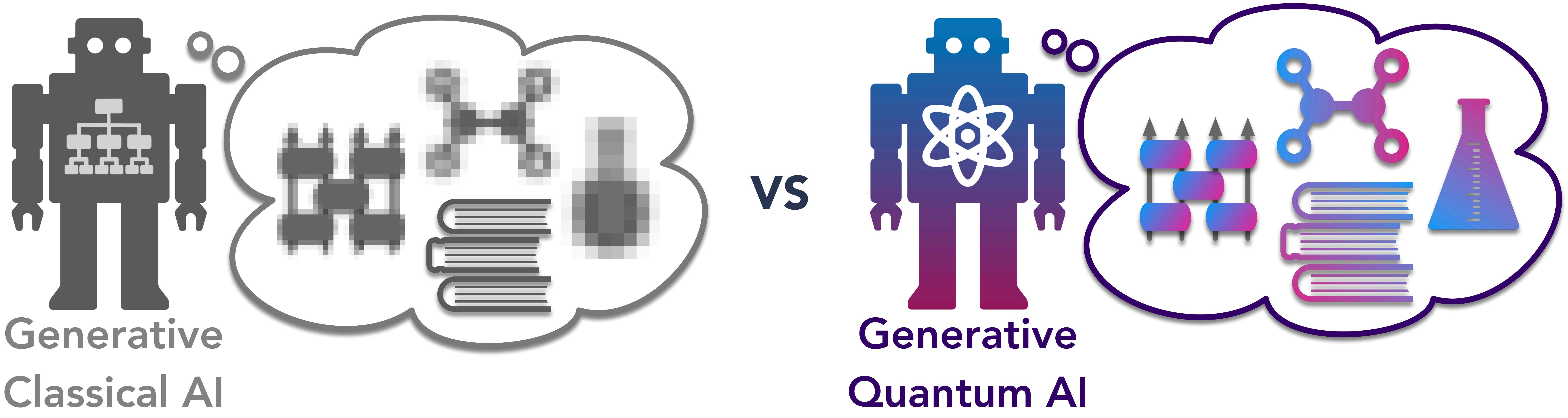
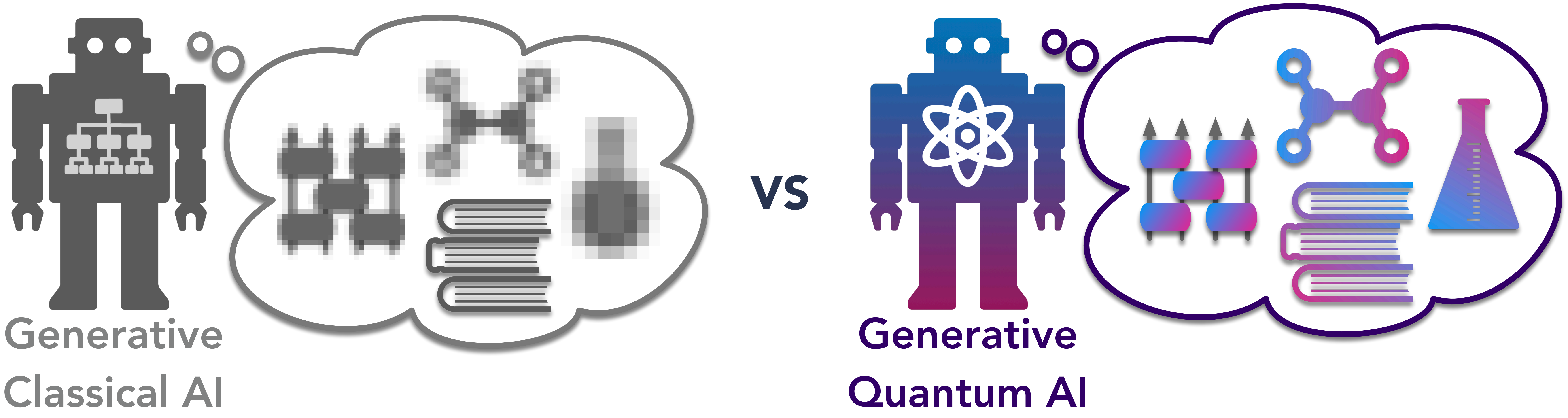


Generative Quantum Advantage

- **Definition (informal):** Generative quantum advantage — A quantum computer can learn to generate the desired outputs with reduced sample complexity, higher accuracy, faster learning and/or generation time, or outputs infeasible for classical computers.



Main Question

Are there families of unknown distributions $p(y \mid x)$ mapping classical inputs to classical outputs such that:

- Quantum computers can efficiently learn from few samples;
- Quantum computers can efficiently generate new outputs;
- Classical computers cannot efficiently generate new outputs?

Generative QNNs

- **Task:** Given a dataset of (x_i, y_i) sampled from unknown $p(y|x)$, learn to generate **new** y for **any given** x.

Generative QNNs

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- **Generative Quantum Neural Networks (QNNs):**
  1. Encode x into quantum state $|\psi_x\rangle$ and measurement basis M_x.
  2. Apply trainable quantum circuit C_β to the state $|\psi_x\rangle$.
  3. Measure $C_\beta|\psi_x\rangle$ in the basis M_x to sample y from $p(y \mid x; \beta)$.

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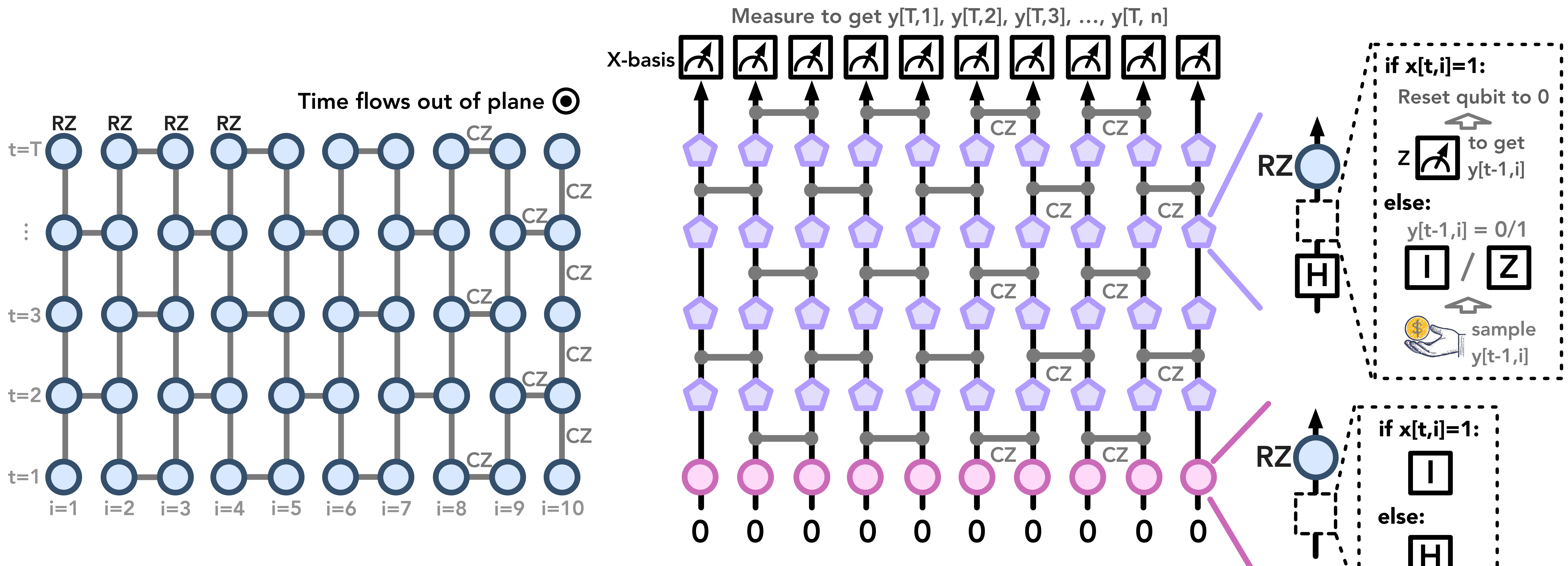
[1] Architectures for quantum simulation showing a quantum speedup, PRX
[2] Closing gaps of a quantum advantage with short-time Hamiltonian dynamics, PRL

Computational Power

- Under standard conjectures, there are shallow QNNs that can **generate** distributions no poly-time classical algorithm $\mathscr{A}$ can.



2D Shallow QNN

1D Deep QNN

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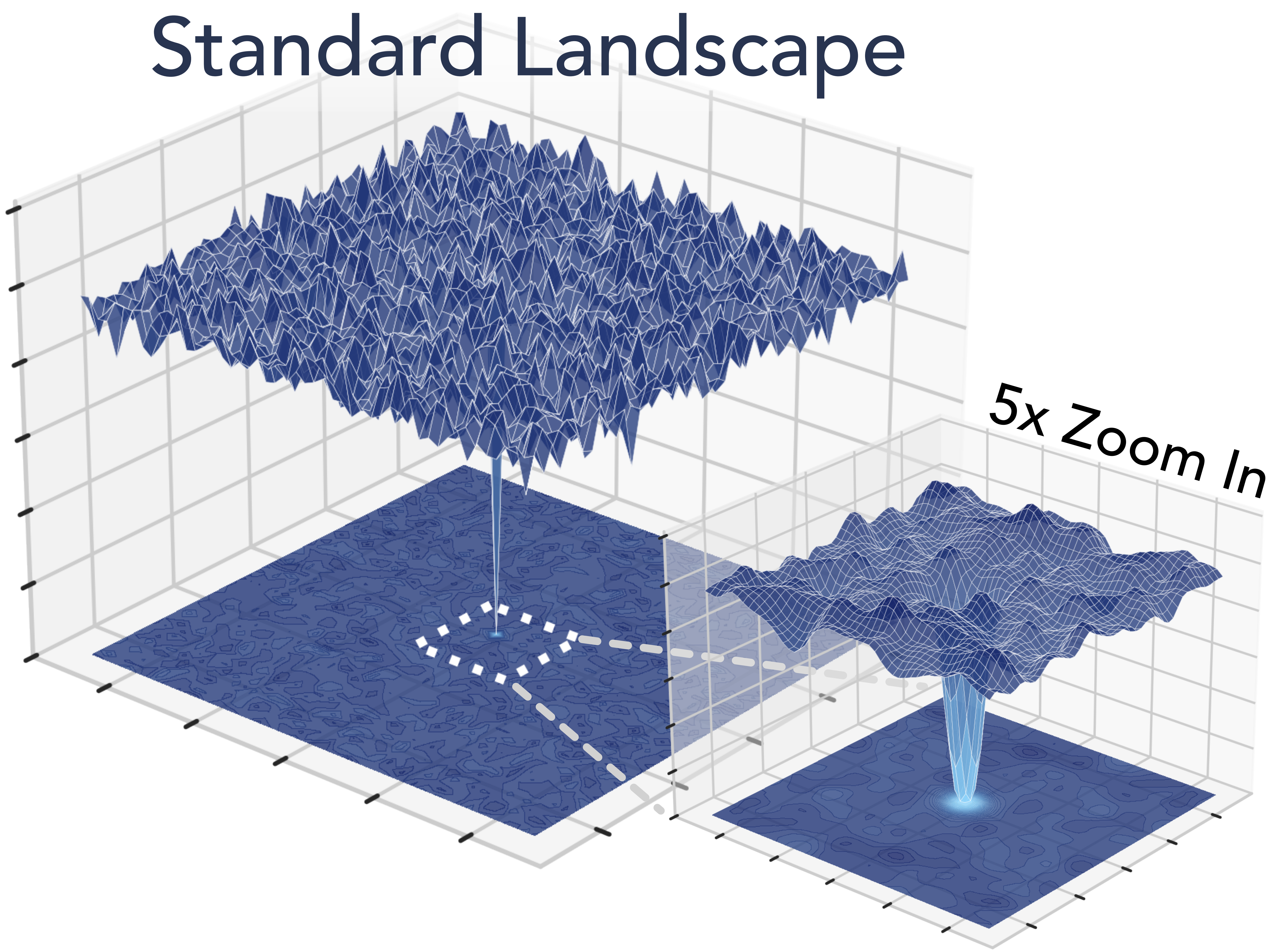
Bad Loss Landscape

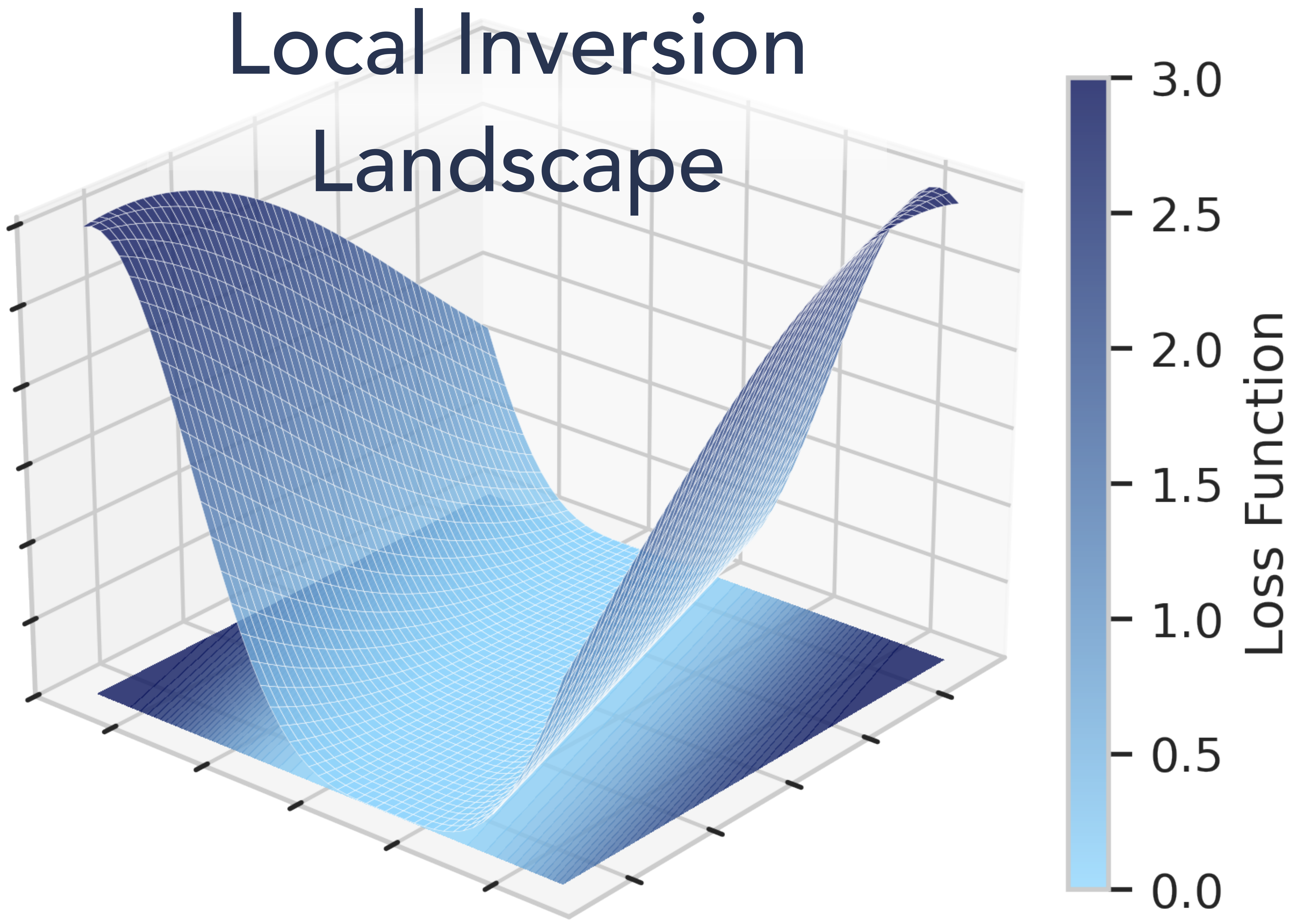
Shallow QNNs have **extremely bad** landscape.



Provably Efficient Learning

Theorem

Any n-qubit shallow QNN can be learned to ε error in **poly**$(n, 1/\varepsilon)$ **time**.



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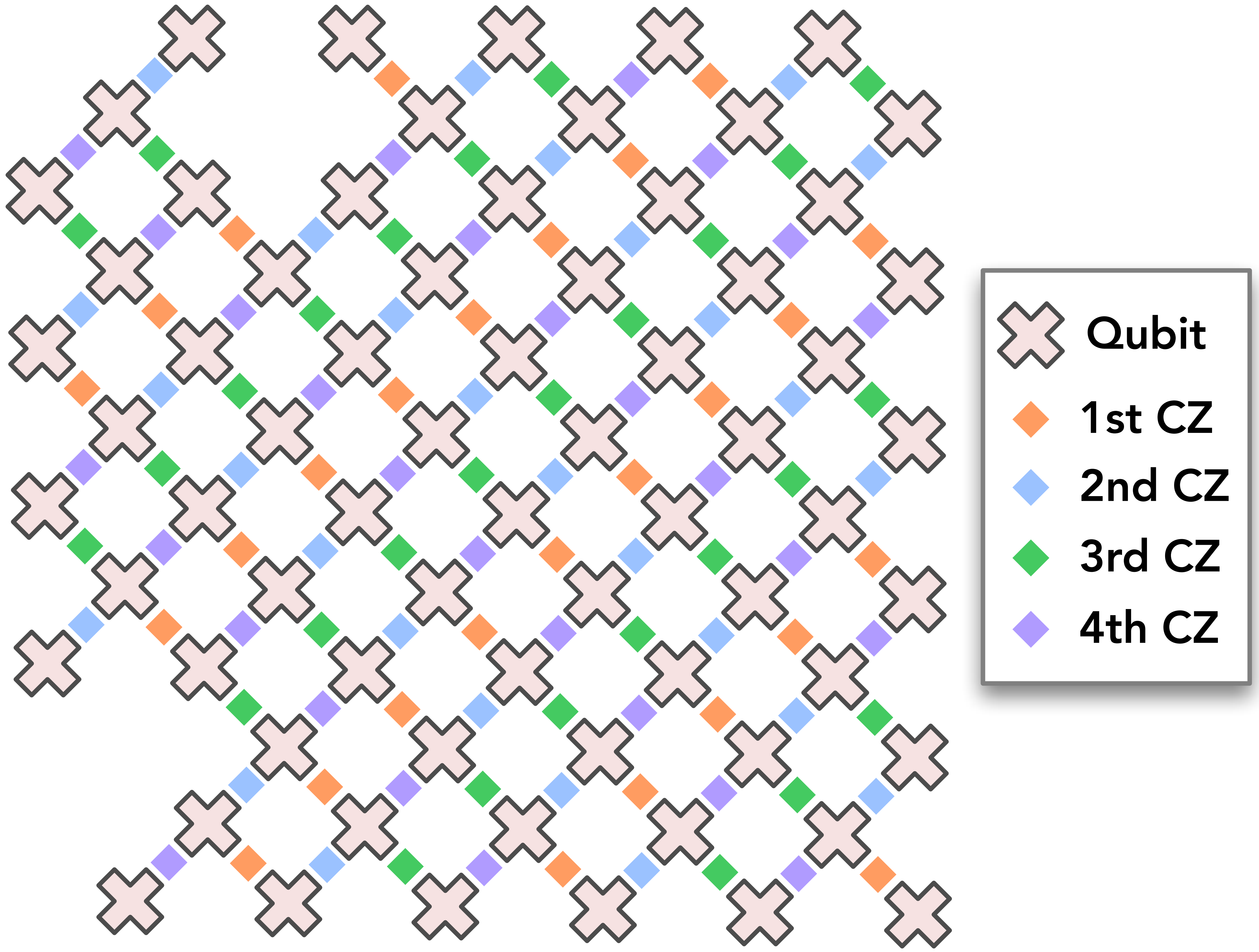
Experimental Demonstration

Device Layout



68 qubits on 2D geometry

- Train 3D shallow QNN.
- Map 3D shallow QNN to 2D deep QNN.
- Generate new output y using 2D deep QNN.

Experimental Demonstration

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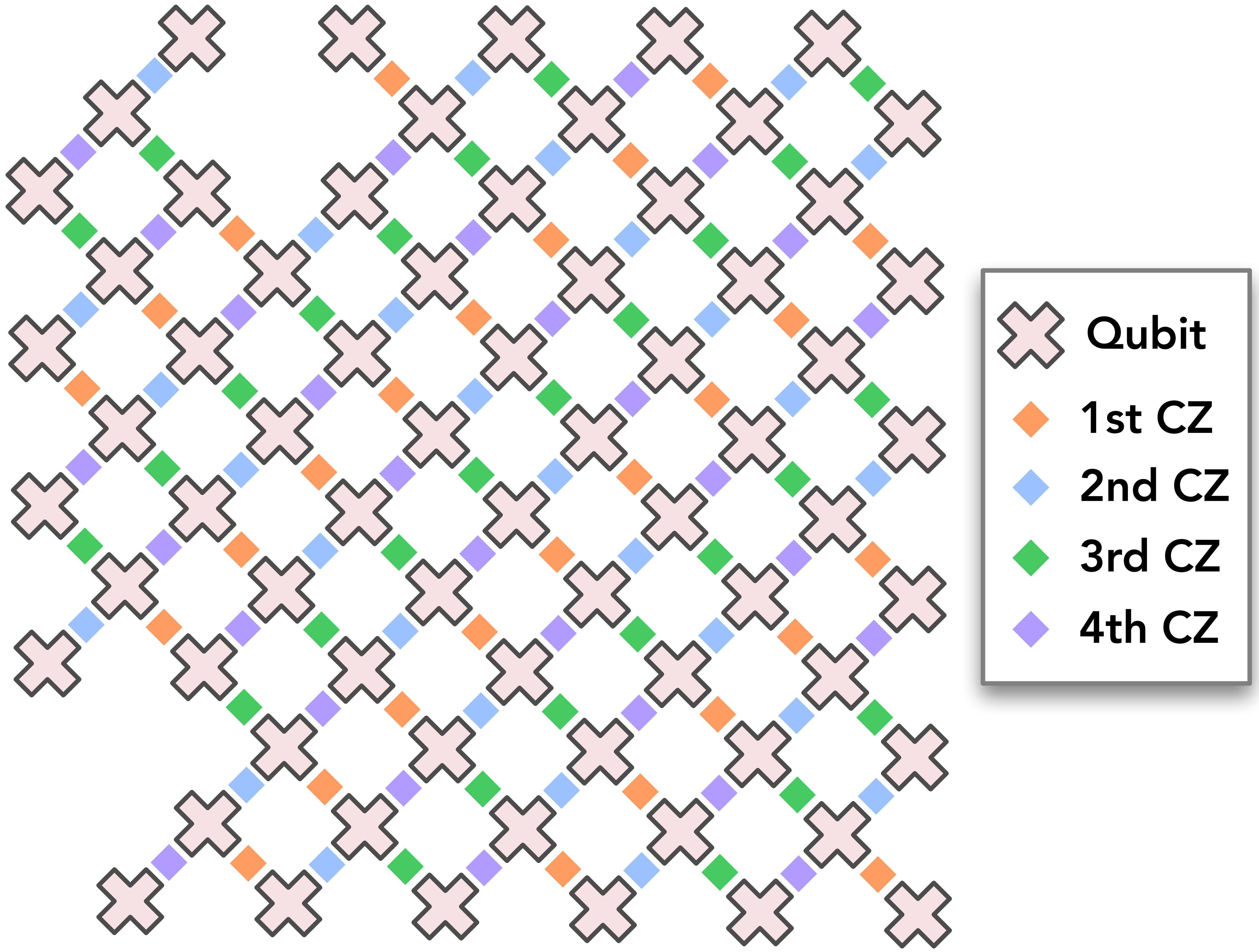

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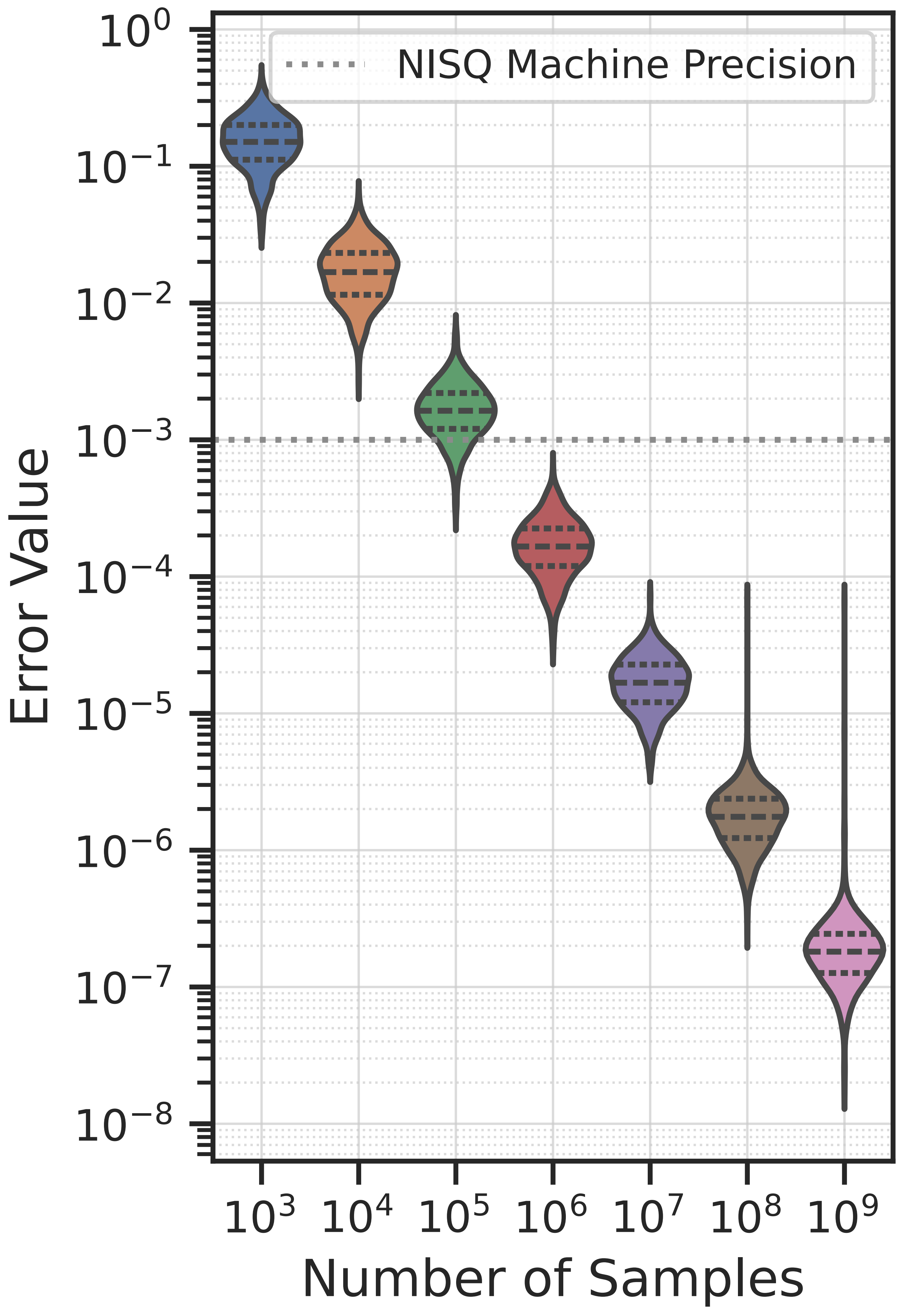

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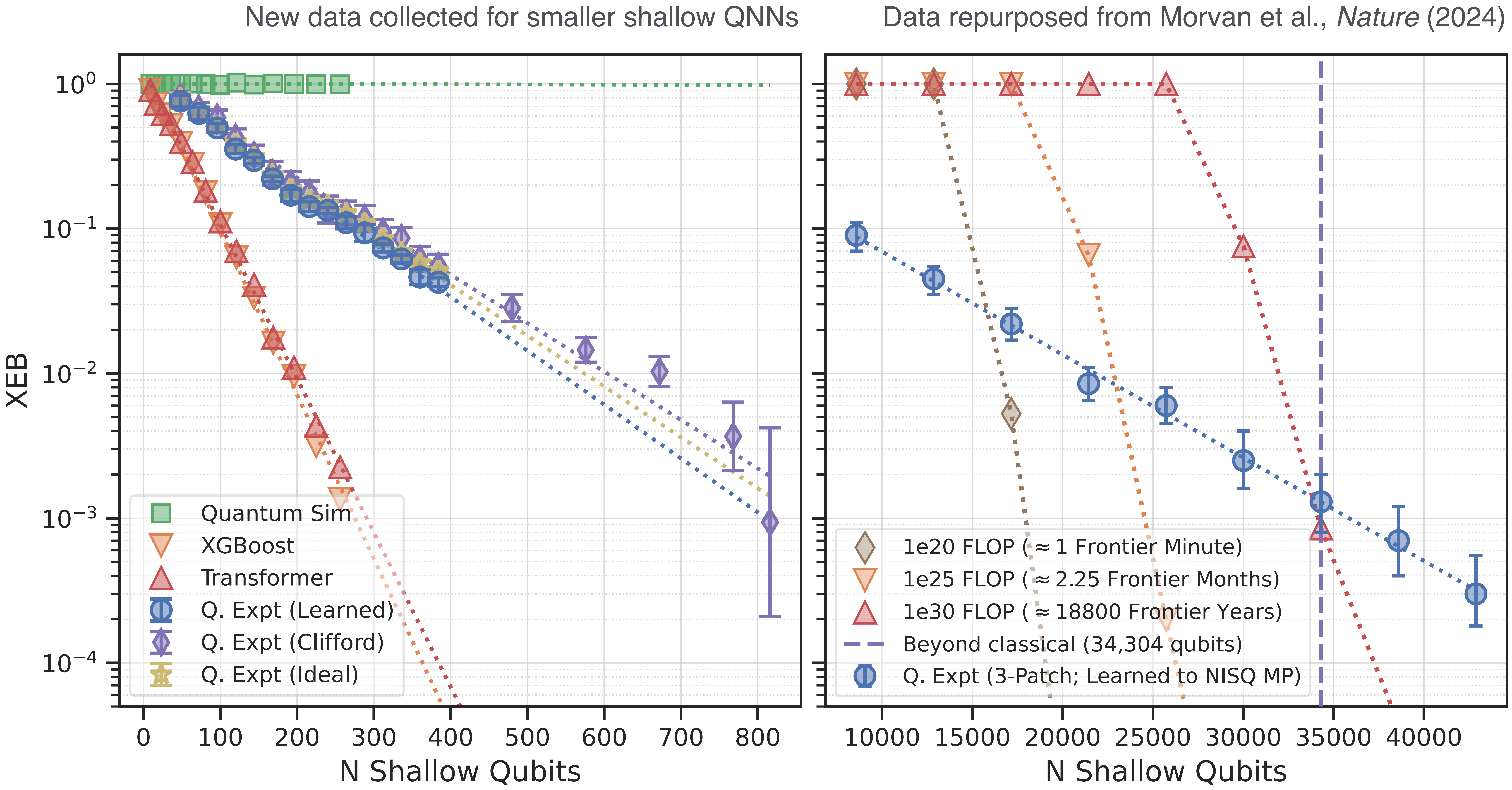
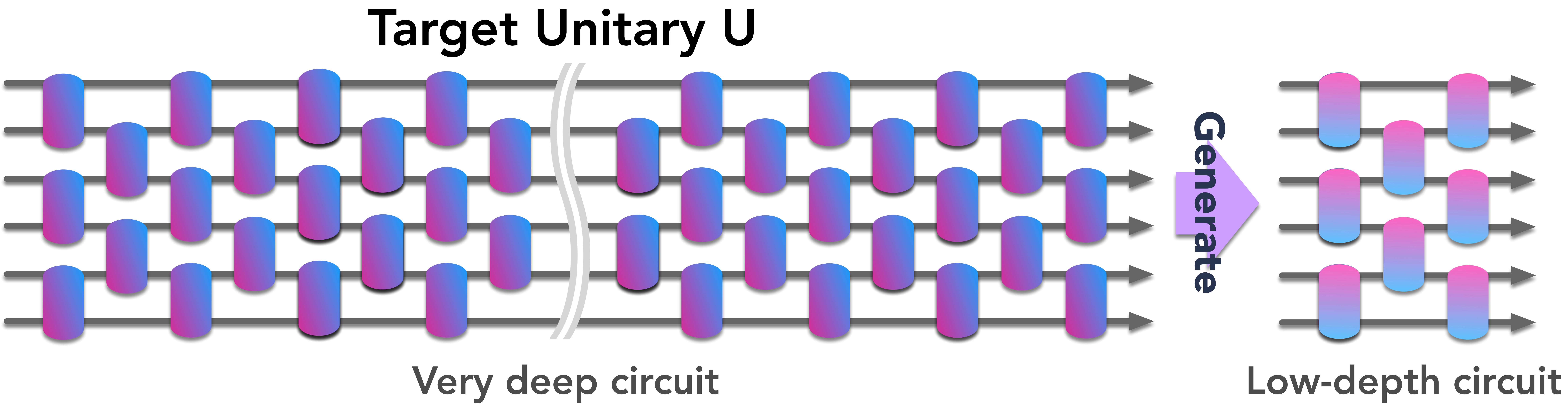
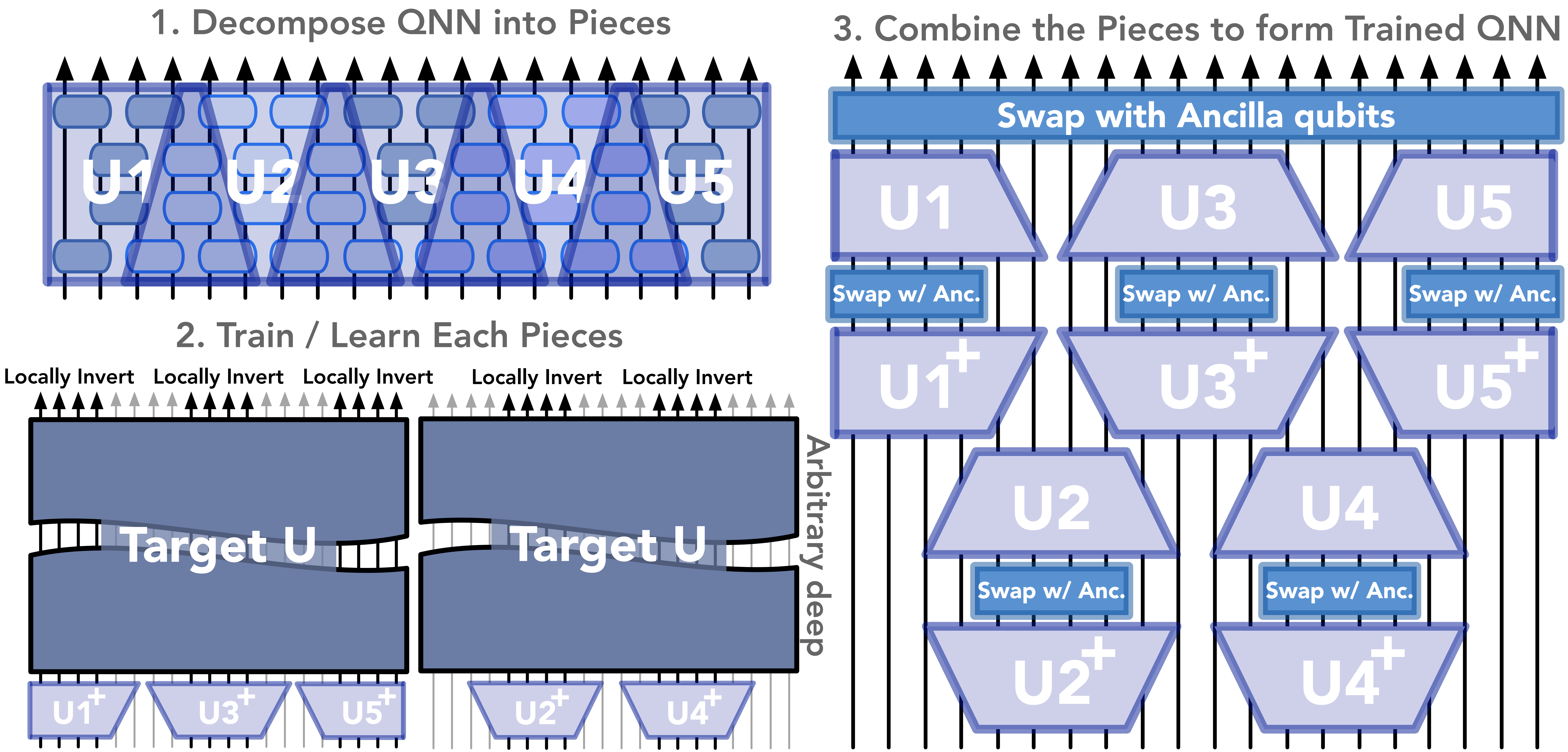


Application: Compressing Dynamics

- We also established generative quantum advantage for the task of compressing physical dynamics.



Application: Compressing Dynamics



Application: Compressing Dynamics