MIT HAN LAB

EfficientML.ai Lecture 23 Quantum Machine Learning

Part II

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Lecture Plan

Today we will:

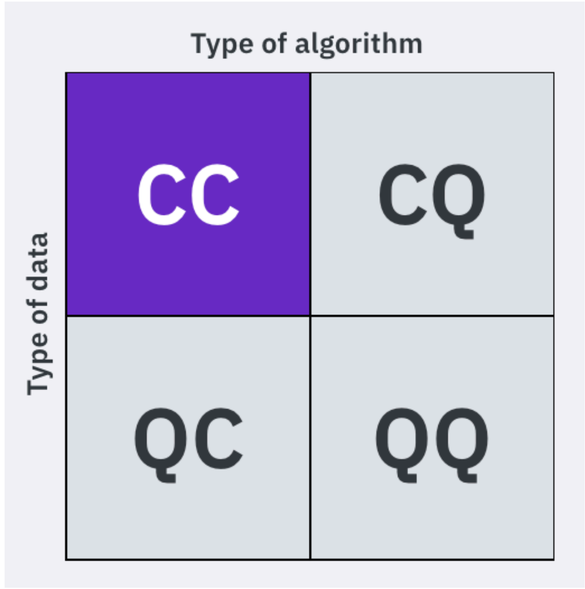
1. Introduce Parameterized Quantum Circuit (PQC)
2. Introduce PQC Training
3. Introduce Quantum Classifiers
4. Introduce Noise Aware On-Chip Training (QOC) of PQC
5. Introduce TorchQuantum Library for QML
6. Introduce Robust Quantum Architecture Search

Section 1

Parameterized Quantum Circuit

QML Approaches

- CC: Classical Data, Classical algorithm: what we have learned from previous lectures
- CQ: Classical Data, Quantum algorithm: what we are going to introduce
- QC: Quantum Data, Classical algorithm: qubit control, calibration, readout…
- QQ: Quantum Data, Quantum algorithm: process quantum info with quantum machine



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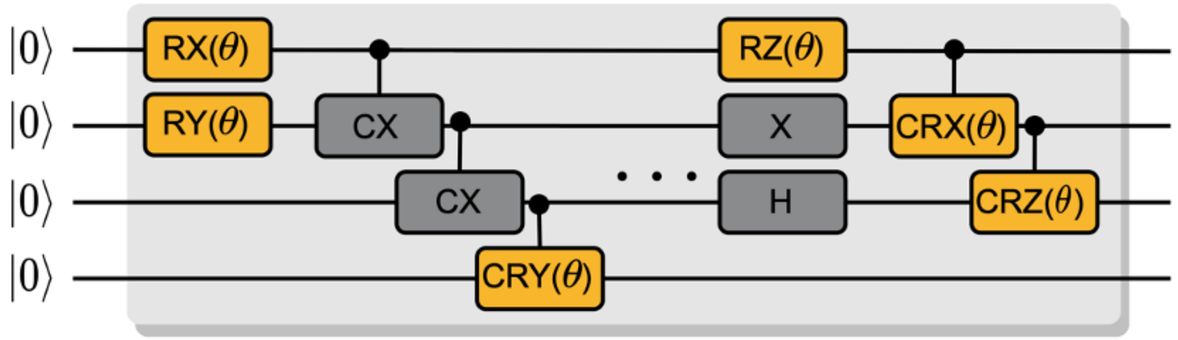
Parameterized Quantum Circuits

- Circuit that contains fixed gates and parameterized gates

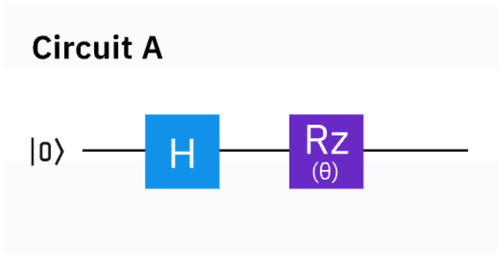


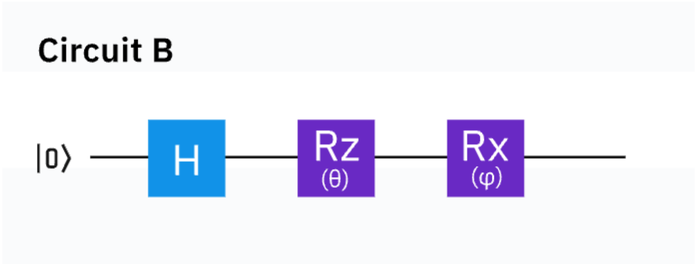
$$CNOT = \begin{array}{c} \\ \text{Input} \\ 00 \\ 01 \\ 10 \\ 11 \end{array} \begin{array}{c} \begin{array}{cccc} \text{Output} & & & \\ 00 & 01 & 10 & 11 \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$

$$CRX(\theta) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ 0 & 0 & -i\sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix}$$

Expressivity

- How the quantum circuit can cover the **Hilbert space**?
- The extent to which the states generated from the circuit deviate from the **uniform** distribution
- Which circuit has **better expressivity** below?





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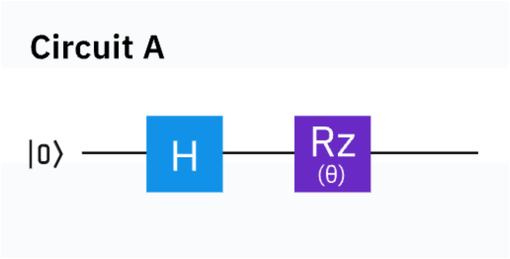
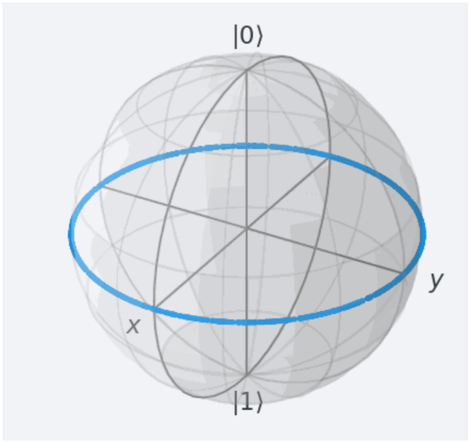
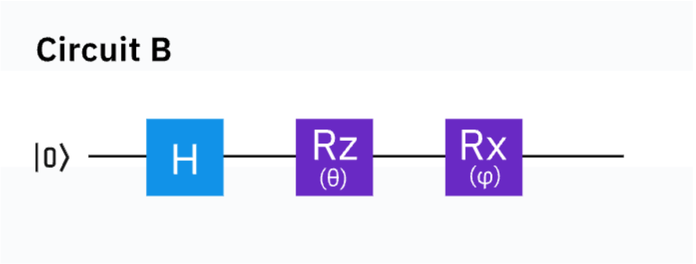
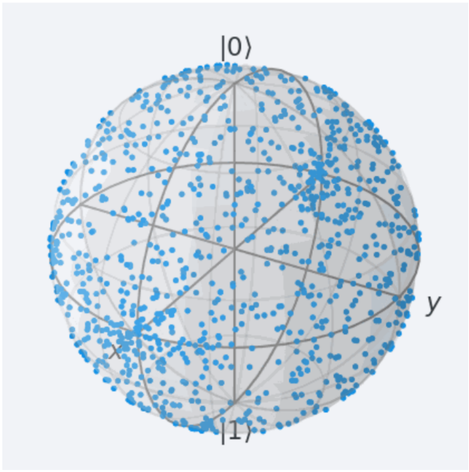
Expressivity

- Circuit B has better **coverage** of Hilbert Space









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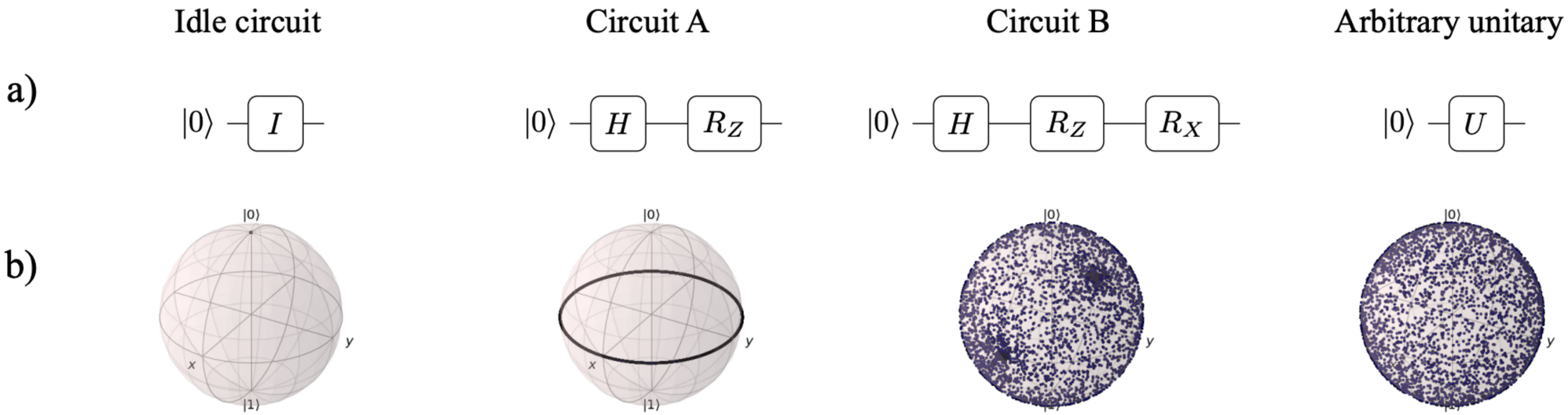
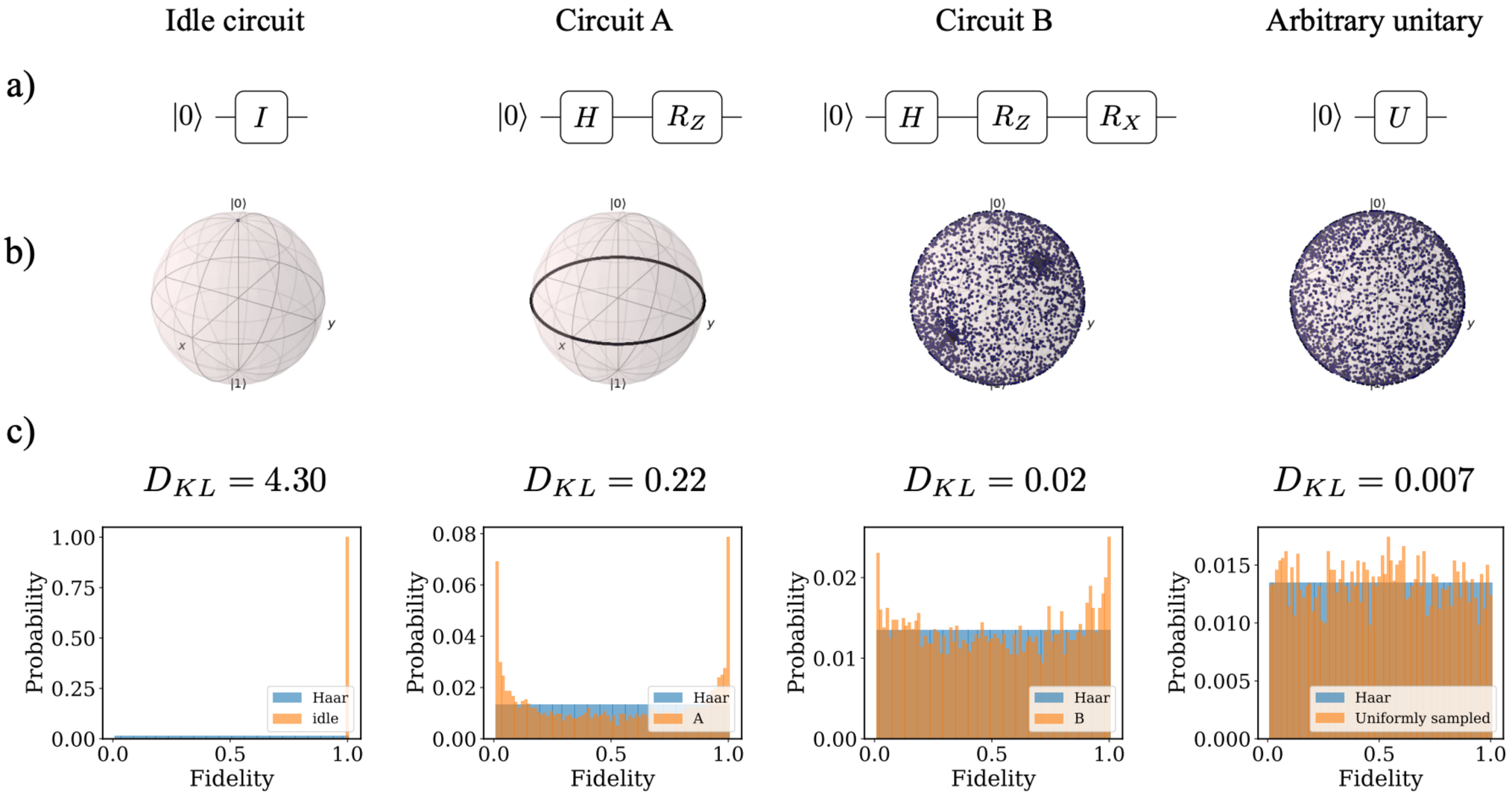
Expressivity



Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

Expressivity

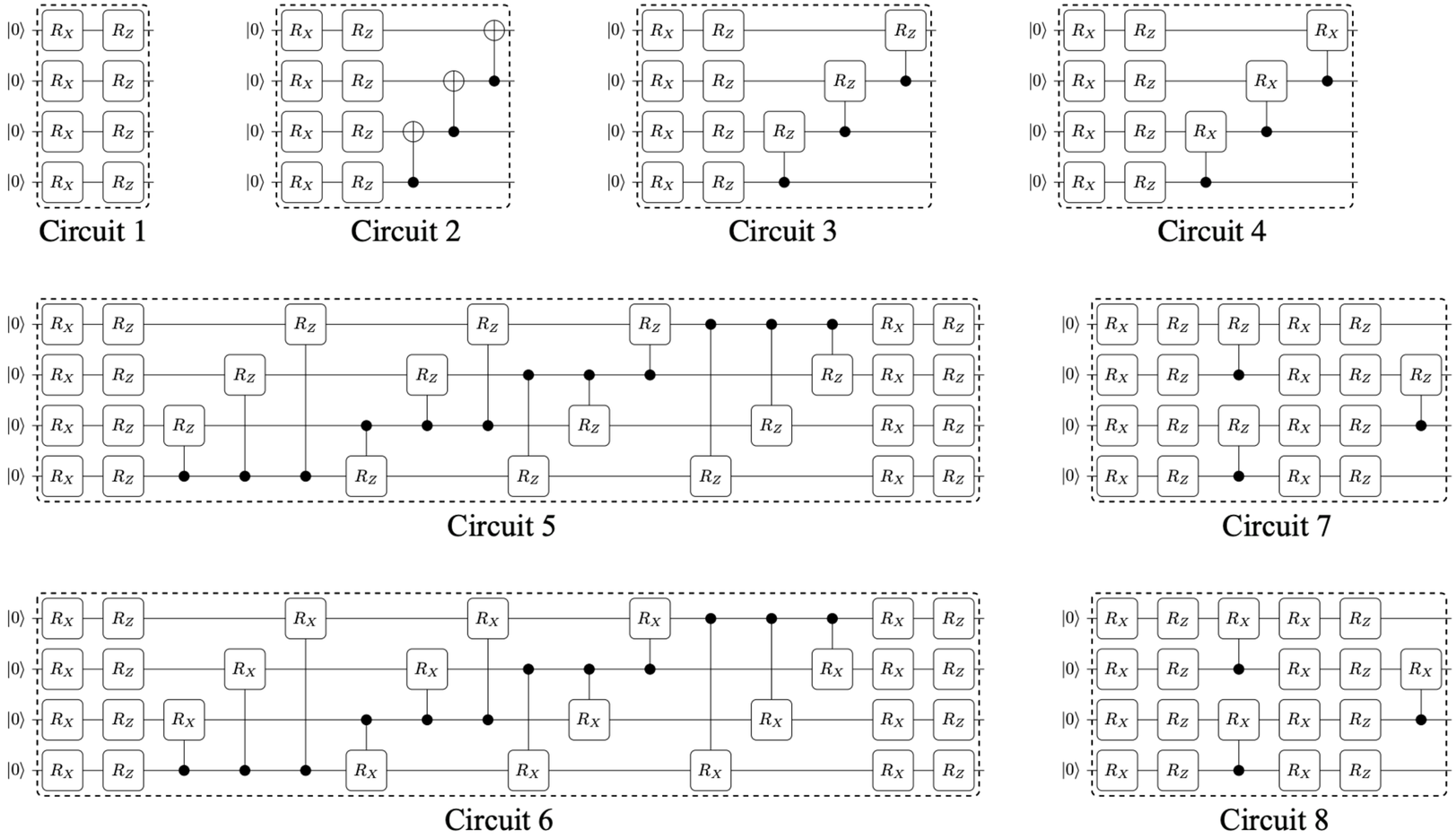


Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

Entanglement Capability

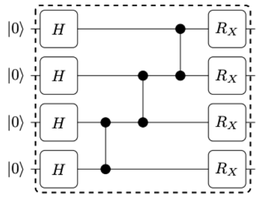
- The **Meyer-Wallach** measure tells how entangled a given state is; range [0, 1]
  - Unentangled state is 0
  - Full entangled state is 1
- We use **averaged MW** to measure the entanglement capability of circuit

Entanglement Capability

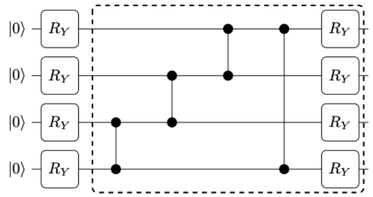


Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

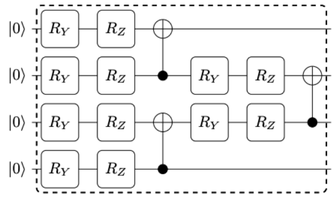
Entanglement Capability



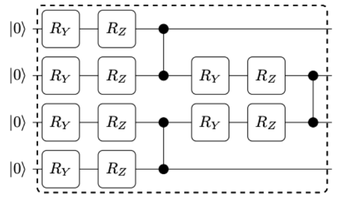
Circuit 9



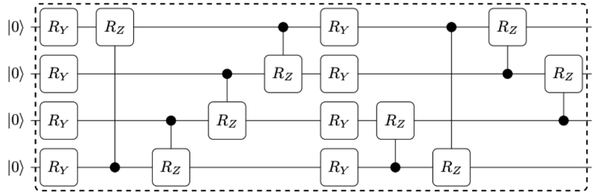
Circuit 10



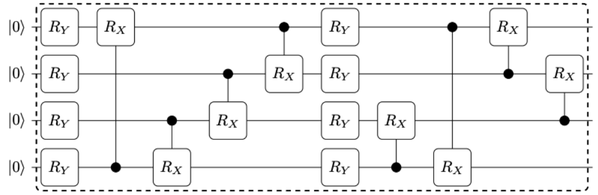
Circuit 11



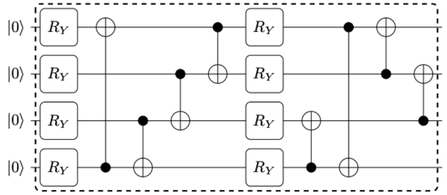
Circuit 12



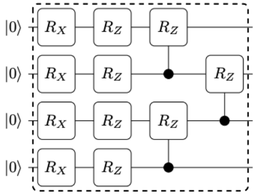
Circuit 13



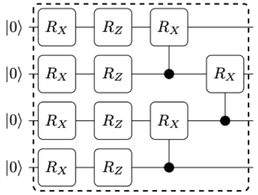
Circuit 14



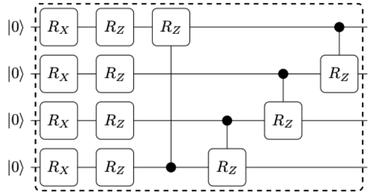
Circuit 15



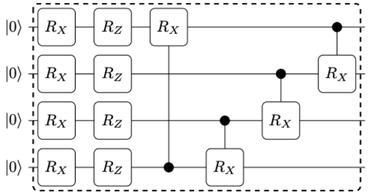
Circuit 16



Circuit 17



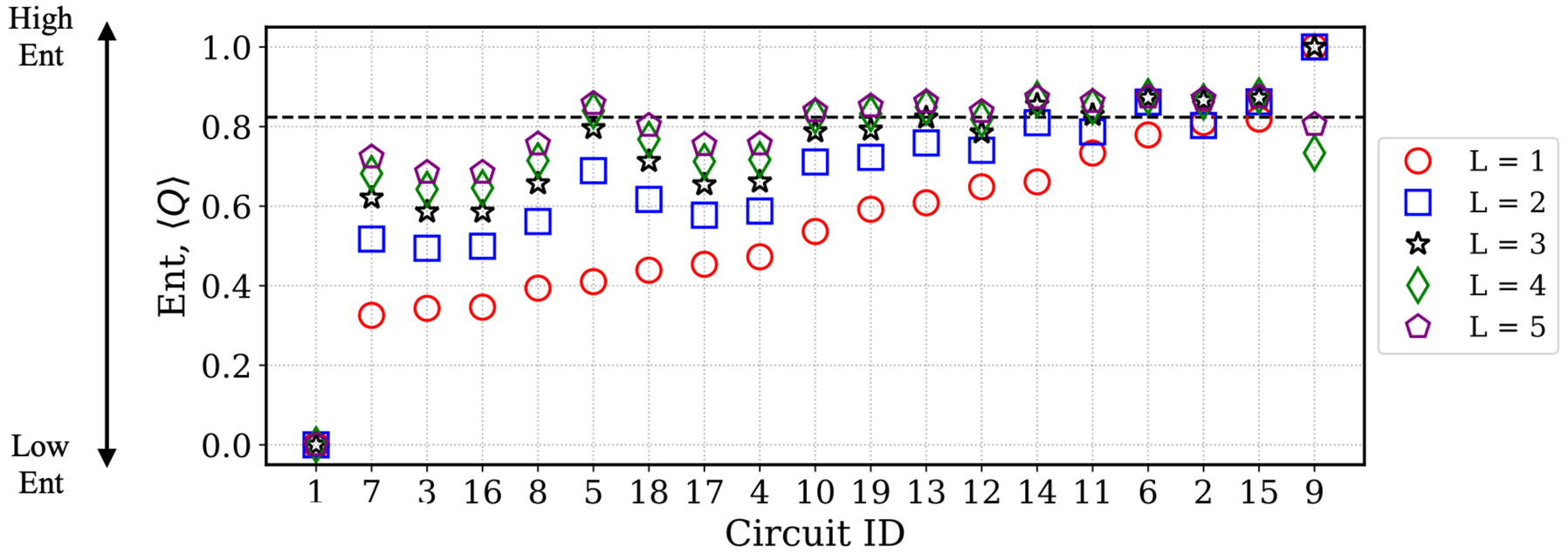
Circuit 18

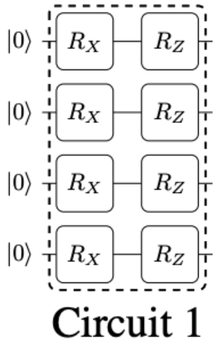


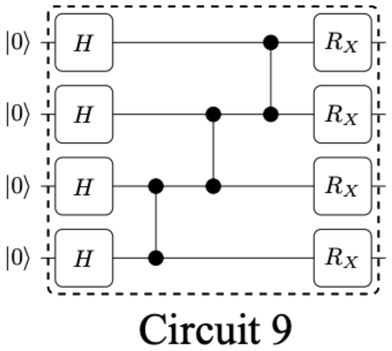
Circuit 19

Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

Entanglement Capability



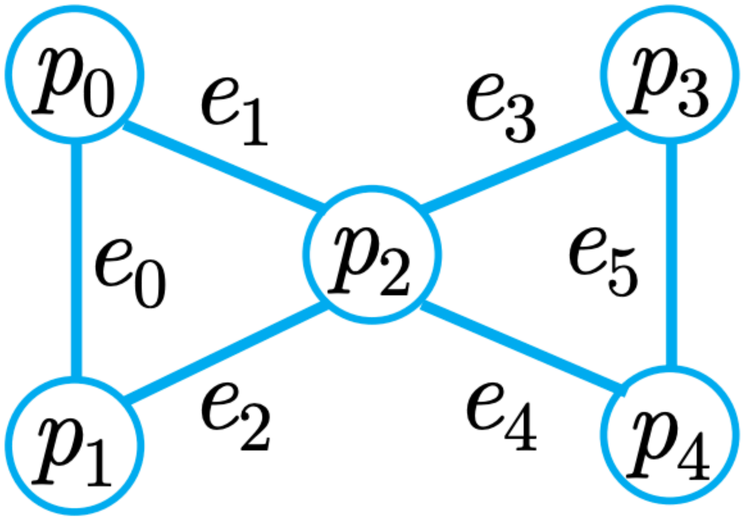




Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

Hardware Efficiency

- Whether the PQC design considers the qubit **connectivity**?
- Whether the gates are **native** gates?



Data Encoding

- Consider a classical data set X consisting of M samples each with N features

$$\mathscr{X} = \{x^{(1)}, \ldots, x^{(m)}, \ldots, x^{(M)}\}$$

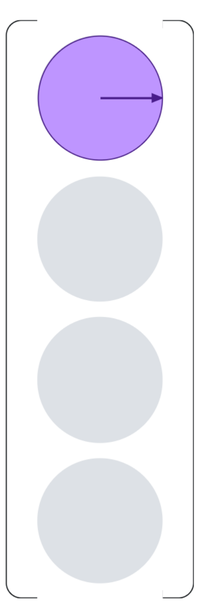
- **Encoding** methods:
  - Basis encoding
  - Amplitude encoding
  - Angle encoding
  - Arbitrary encoding

Basis Encoding

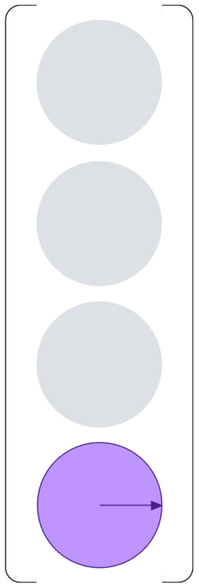
- Similar to the **binary** representation in the classical machine
- X = 2 -> binary “10”
- We create a quantum state with all energy on |10>

Basis Encoding

- Similar to the **binary** representation in the classical machine
- X = 2 -> binary “10”
- Not efficient for one data



x=0 (00)



x=3 (11)

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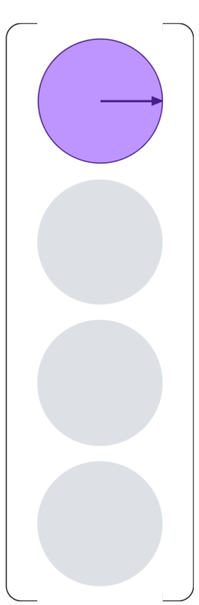
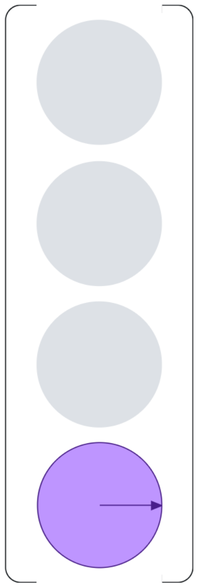
Basis Encoding

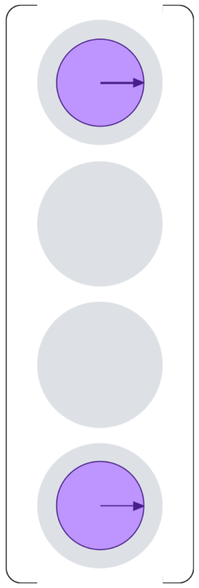
- Similar to the **binary** representation in the classical machine
- X = 2 -> 10
- Not efficient for one data but can be used to represent **multiple data simultaneously**



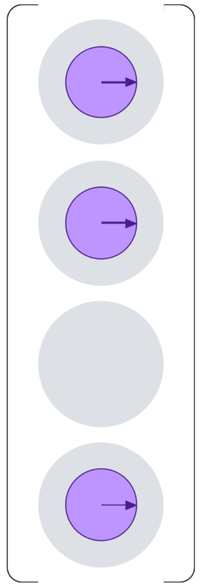
x=0 (00)



x=3 (11)



x=0 and 3 (00+11)

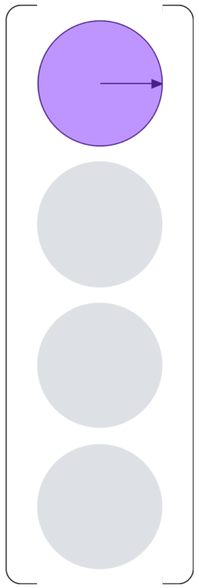


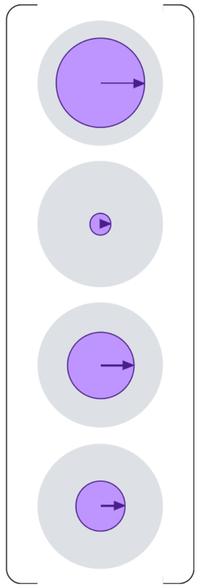
x=0 and 1 and 3 (00+ 01 +11)

Amplitude Encoding

- The numbers are encoded as the **statevector** of the qubits
- input vector = [1, 0, 0, 0]
- For N features, need **logN** qubits

input vector = [0.8, 0.2, 0.6, 0.45]





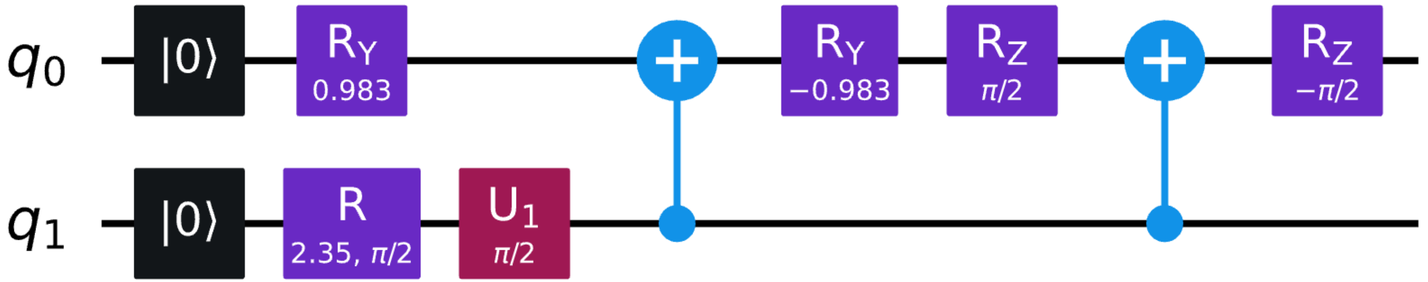
Amplitude Encoding

- Also able to encoder multiple data points together

$$\mathscr{X} = \{x^{(1)} = (1.5, 0), x^{(2)} = (-2, 3)\}$$

$$\alpha = \frac{1}{\sqrt{15.25}}(1.5, 0, -2, 3)$$

$$|\mathscr{X}\rangle = \frac{1}{\sqrt{15.25}}(1.5|00\rangle - 2|10\rangle + 3|11\rangle)$$



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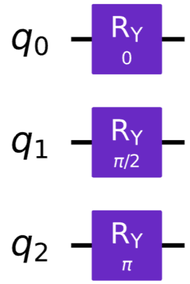
Angle Encoding

- Encode the data in the **rotation** angles of the qubit gates
- For vector [0, pi/2, pi]

$$|x\rangle = \bigotimes_{i=1}^{N} \cos(x_i)|0\rangle + \sin(x_i)|1\rangle$$

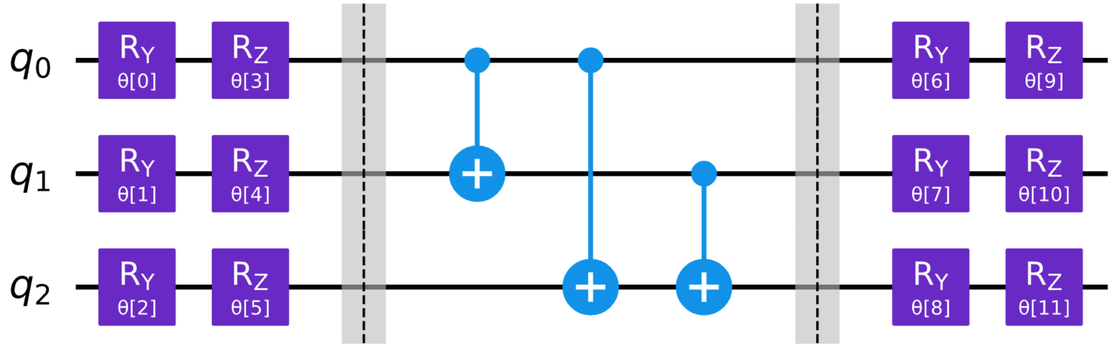
$$S_{x_j} = \bigotimes_{i=1}^{N} U(x_j^{(i)}) \qquad U(x_j^{(i)}) = \begin{bmatrix} \cos(x_j^{(i)}) & -\sin(x_j^{(i)}) \\ \sin(x_j^{(i)}) & \cos(x_j^{(i)}) \end{bmatrix}$$

$$RY(\theta) = \exp(-i\frac{\theta}{2}Y) = \begin{pmatrix} \cos\frac{\theta}{2} & -\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{pmatrix}$$

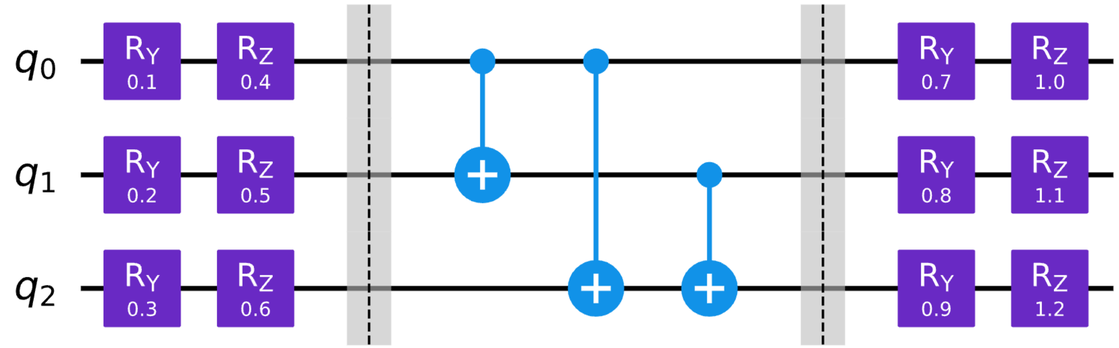


Arbitrary Encoding

- Design **arbitrary** parameterized quantum circuit and let input data as the rotation angles



$$x = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2]$$

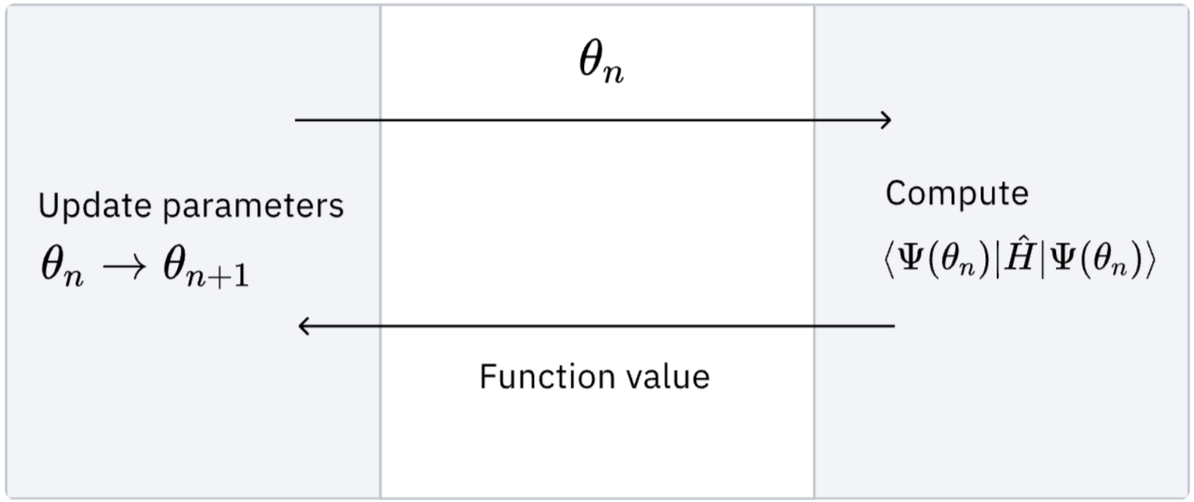


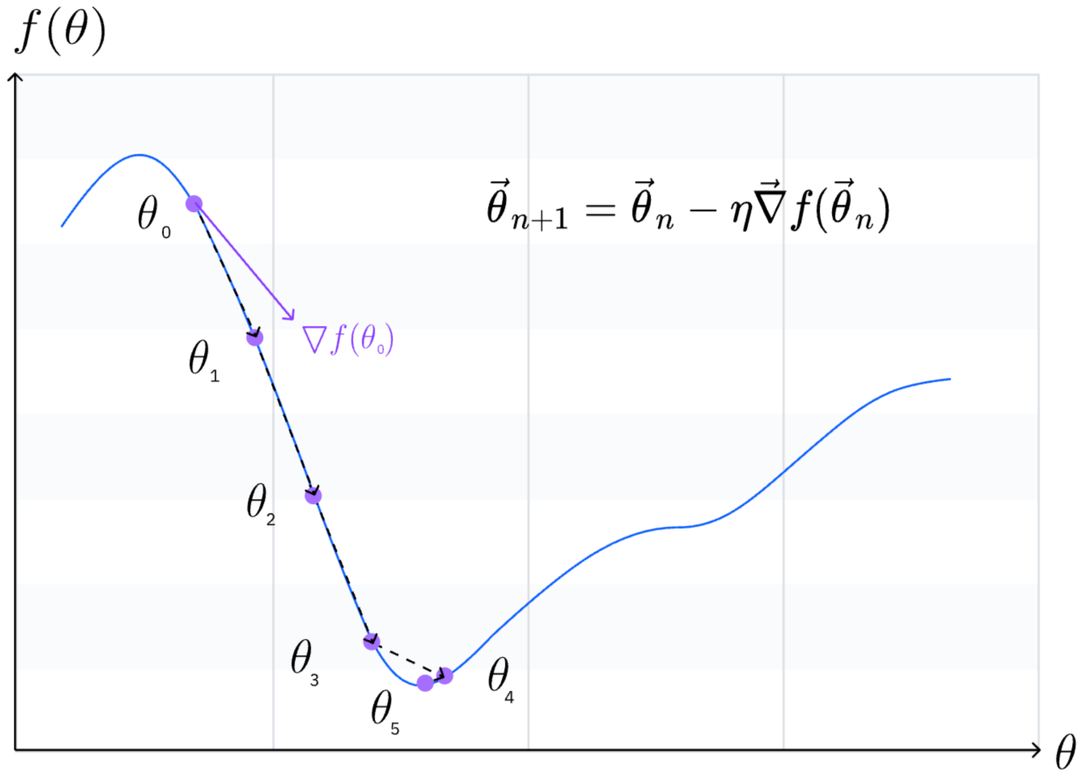
Section 2

PQC Training

PQC Training

- Train parameters in parameterized quantum circuit to perform **data-driven** tasks





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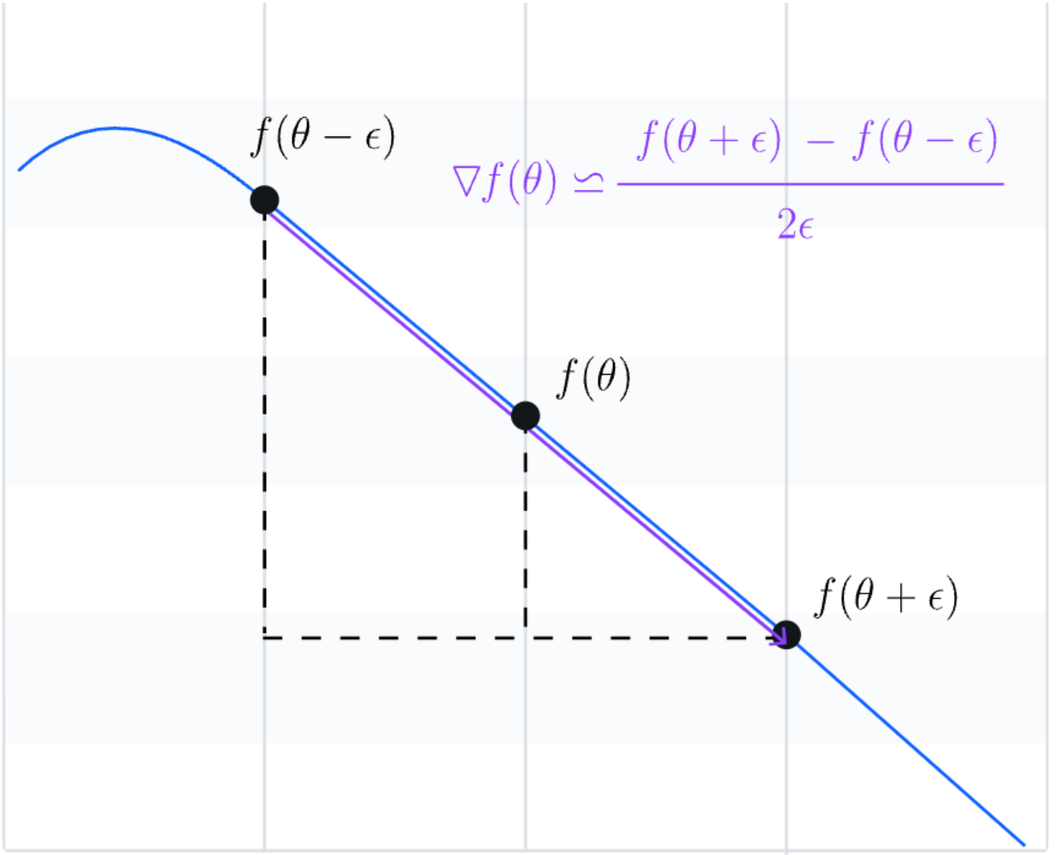
Finite Difference Gradients

- Works **independently** of function's structure

$$\vec{\nabla} f(\vec{\theta}) \approx \frac{1}{2\epsilon}\left(f(\vec{\theta}+\epsilon) - f(\vec{\theta}-\epsilon)\right)$$



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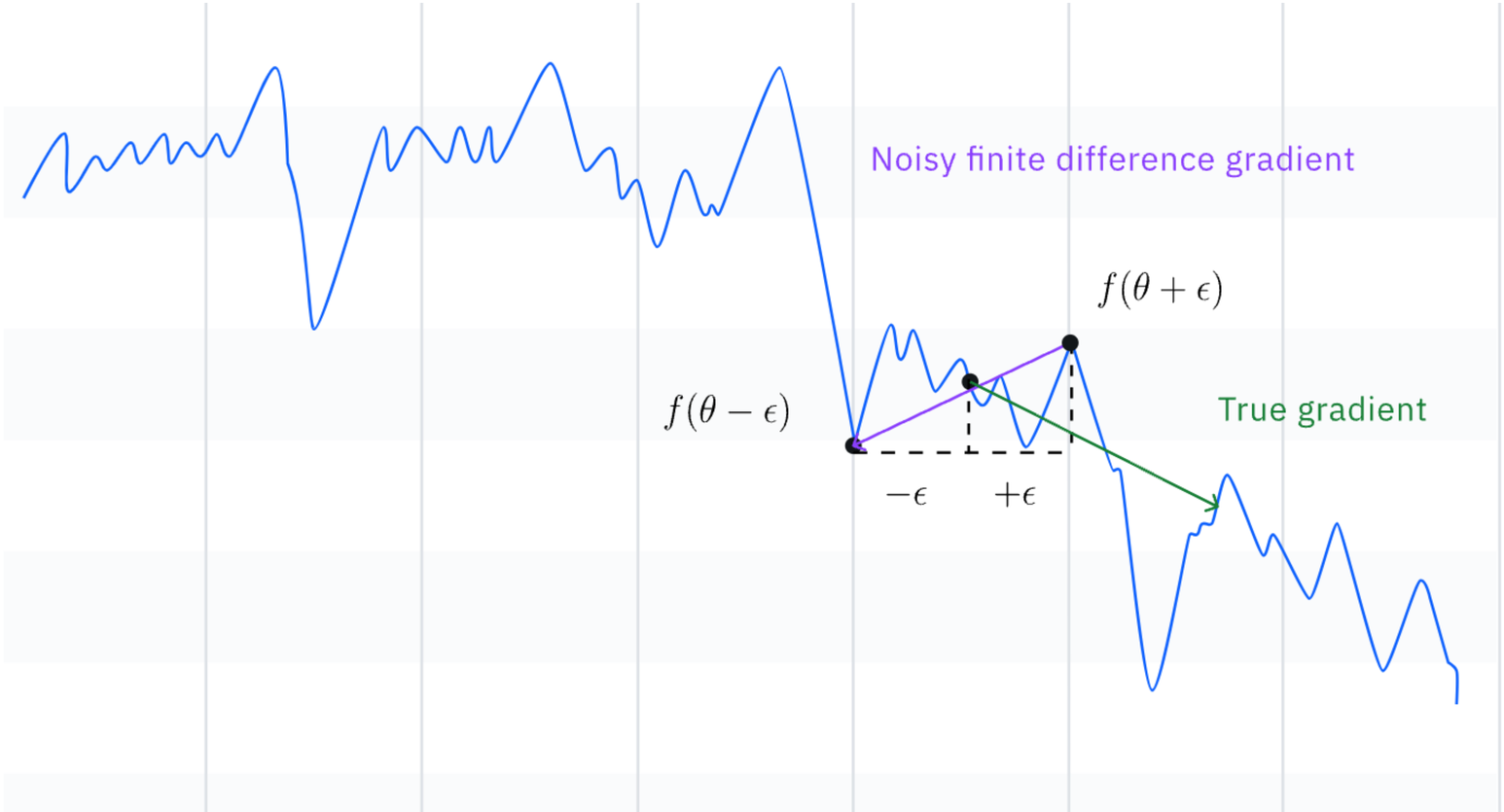
Finite Difference Gradients

- The accuracy depends on the epsilon



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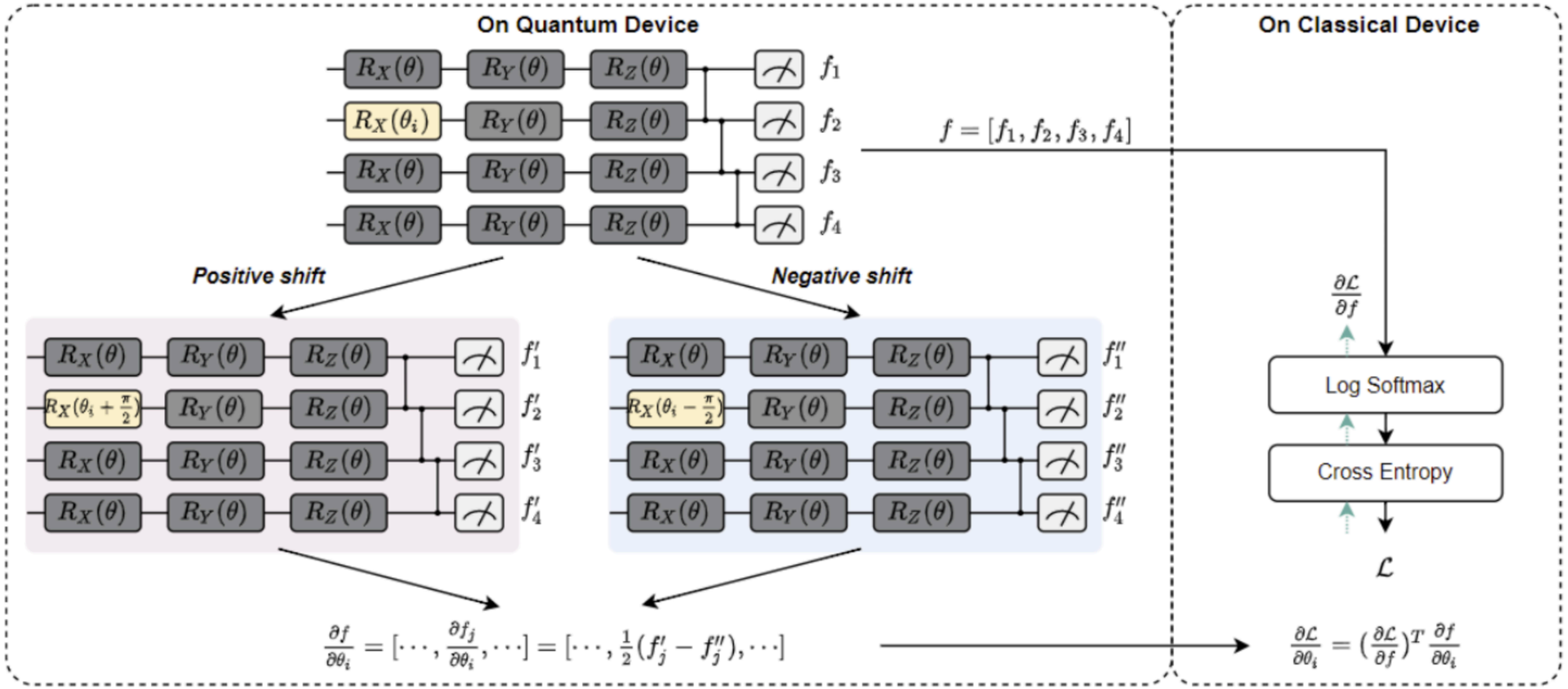
Parameter-Shift Gradients



Parameter shift

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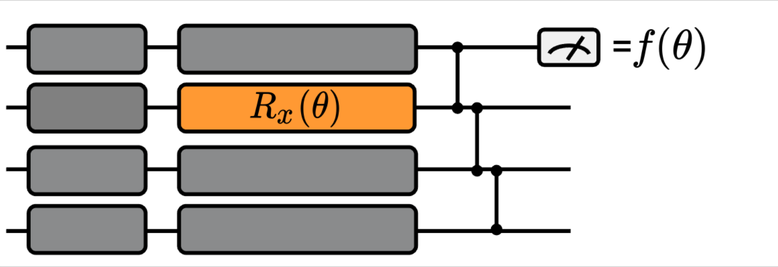
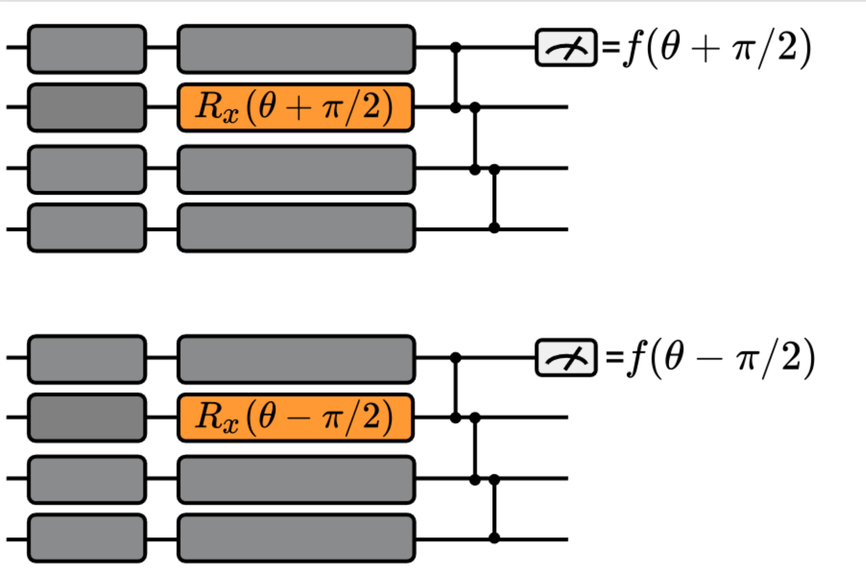
Parameter-Shift

- Calculate the gradient of theta w.r.t f(θ)



Parameter-Shift

- Shift θ twice



$$\frac{\partial}{\partial\theta}f(\theta) = \frac{1}{2}\left(f\left(\theta + \frac{\pi}{2}\right) - f\left(\theta - \frac{\pi}{2}\right)\right)$$

Proof of the parameter shift rule

- Convert to the exponential representation of gates and prove

Assume $U(\theta_i) = R_X(\theta_i)$, $R_X(\alpha) = e^{-\frac{i}{2}\alpha X}$, where X is the Pauli-X matrix.

Firstly, the RX gate is,

$$
\begin{aligned}
R_X(\alpha) = e^{-\frac{i}{2}\alpha X} &= \sum_{k=0}^{\infty} (-i\alpha/2)^k X^k / k! \\
&= \sum_{k=0}^{\infty} (-i\alpha/2)^{2k} X^{2k} / (2k)! + \sum_{k=0}^{\infty} (-i\alpha/2)^{2k+1} X^{2k+1} / (2k+1)! \\
&= \sum_{k=0}^{\infty} (-1)^k (\alpha/2)^{2k} I/(2k)! - i \sum_{k=0}^{\infty} (-1)^k (\alpha/2)^{2k+1} X/(2k+1)! \\
&= \cos(\alpha/2) I - i \sin(\alpha/2) X.
\end{aligned}
$$

Proof of the parameter shift rule

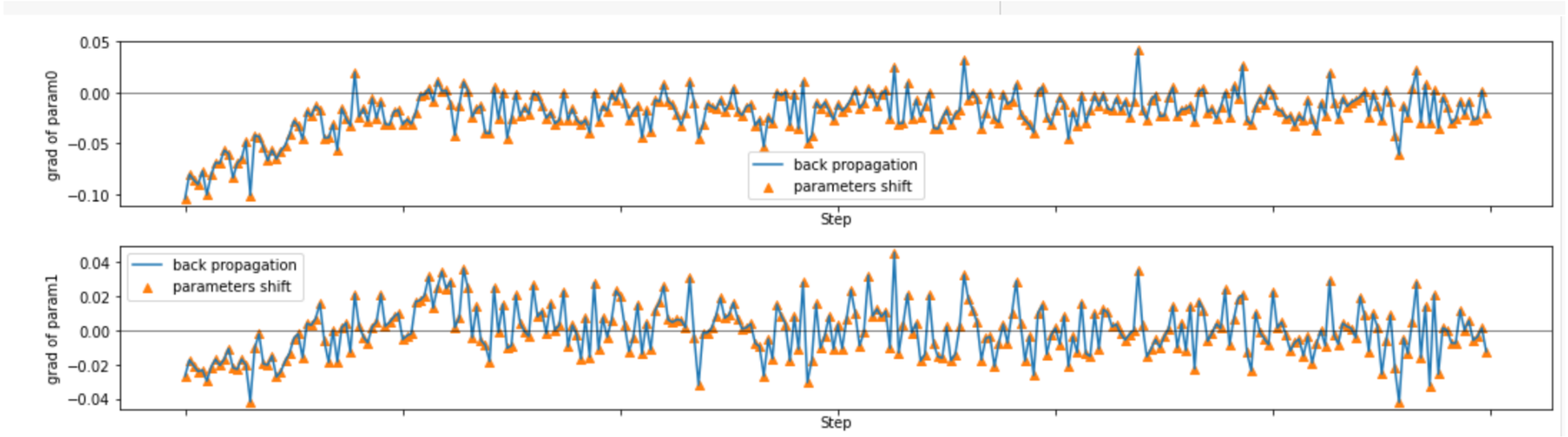
Let $\alpha = \frac{\pi}{2}$, $R_X(\pm\frac{\pi}{2}) = \frac{1}{\sqrt{2}}(I \mp iX)$.

As $f(\theta) = \langle\psi|R_X(\theta_i)^\dagger \widehat{Q} R_X(\theta_i)|\psi\rangle$, $R_X(\alpha)R_X(\beta) = R_X(\alpha+\beta)$, and $\frac{\partial}{\partial\alpha}R_X(\alpha) = -\frac{i}{2}XR_X(\alpha)$, we have

$$
\begin{aligned}
\frac{\partial f(\theta)}{\partial \theta_i} =& \langle\psi|R_X(\theta_i)^\dagger(-\frac{i}{2}X)^\dagger \widehat{Q} R_X(\theta_i)|\psi\rangle + \langle\psi|R_X(\theta_i)^\dagger \widehat{Q}(-\frac{i}{2}X)R_X(\theta_i)|\psi\rangle \\
=& \frac{1}{4}(\langle\psi|R_X(\theta_i)^\dagger(I-iX)^\dagger \widehat{Q}(I-iX)R_X(\theta_i)|\psi\rangle \\
& - \langle\psi|R_X(\theta_i)^\dagger(I+iX)^\dagger \widehat{Q}(I+iX)R_X(\theta_i)|\psi\rangle) \\
=& \frac{1}{2}(\langle\psi|R_X(\theta_i)^\dagger R_X(\frac{\pi}{2})^\dagger \widehat{Q} R_X(\frac{\pi}{2})R_X(\theta_i)|\psi\rangle \\
& - \langle\psi|R_X(\theta_i)^\dagger R_X(-\frac{\pi}{2})^\dagger \widehat{Q} R_X(-\frac{\pi}{2})R_X(\theta_i)|\psi\rangle) \\
=& \frac{1}{2}(f(\theta_+) - f(\theta_-)).
\end{aligned}
$$

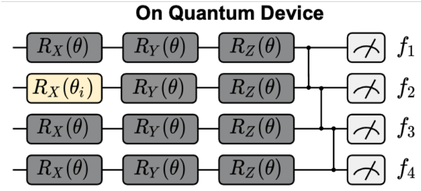
Back-Propagation

- The gradients can also be calculated with back-propagation
- Can only be used on **classical simulator**
- All computation are essentially differentiable linear algebra



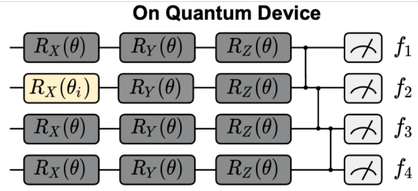
General Flow to calculate PQC gradients

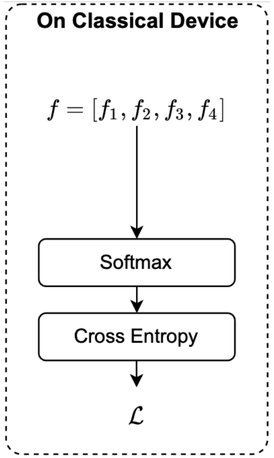
- Step 1: Run on QC without shift to obtain f



General Flow to calculate PQC gradients

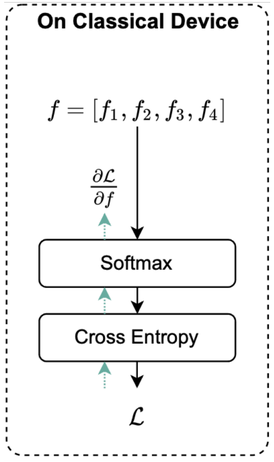
- Step 2: Further forward to get Loss





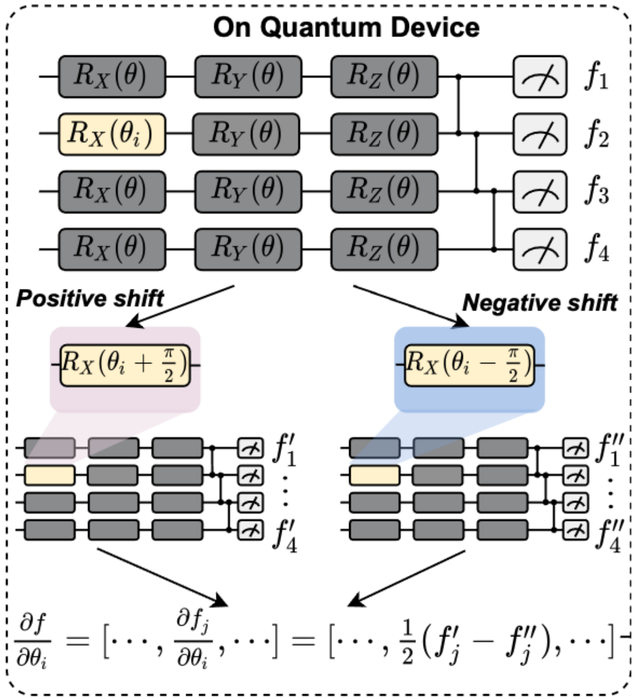
General Flow to calculate PQC gradients

- Step 3: Backpropagation to calculate ∂(Loss)/∂f(θ)



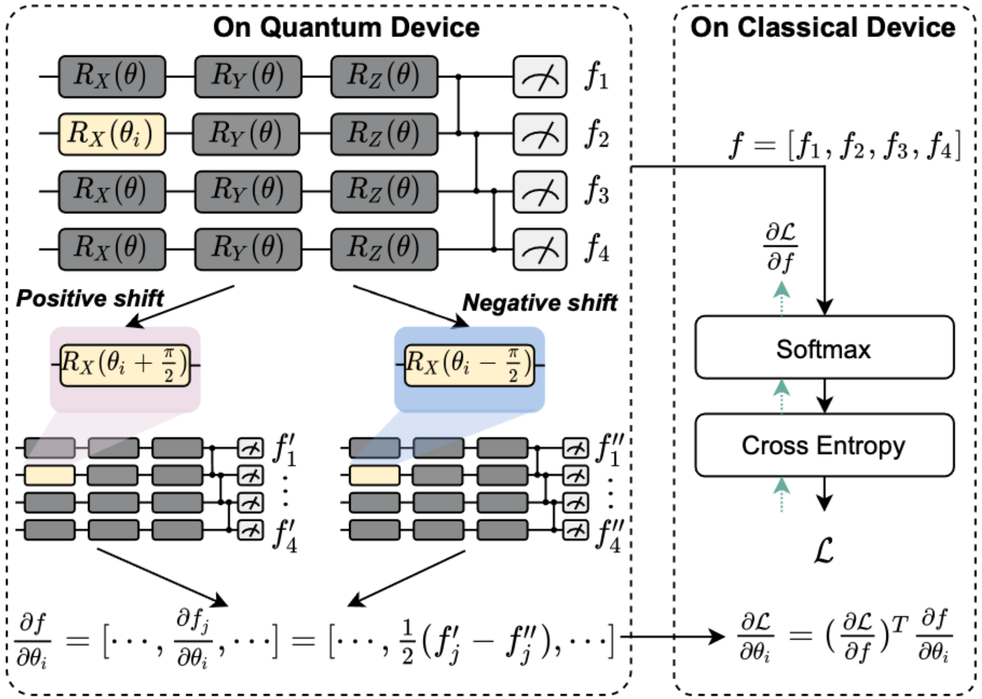
General Flow to calculate PQC gradients

- Step 4: Shift twice and run on QC to calculate (∂f(θ))/(∂θ_i)
  - Or use finite differentiate

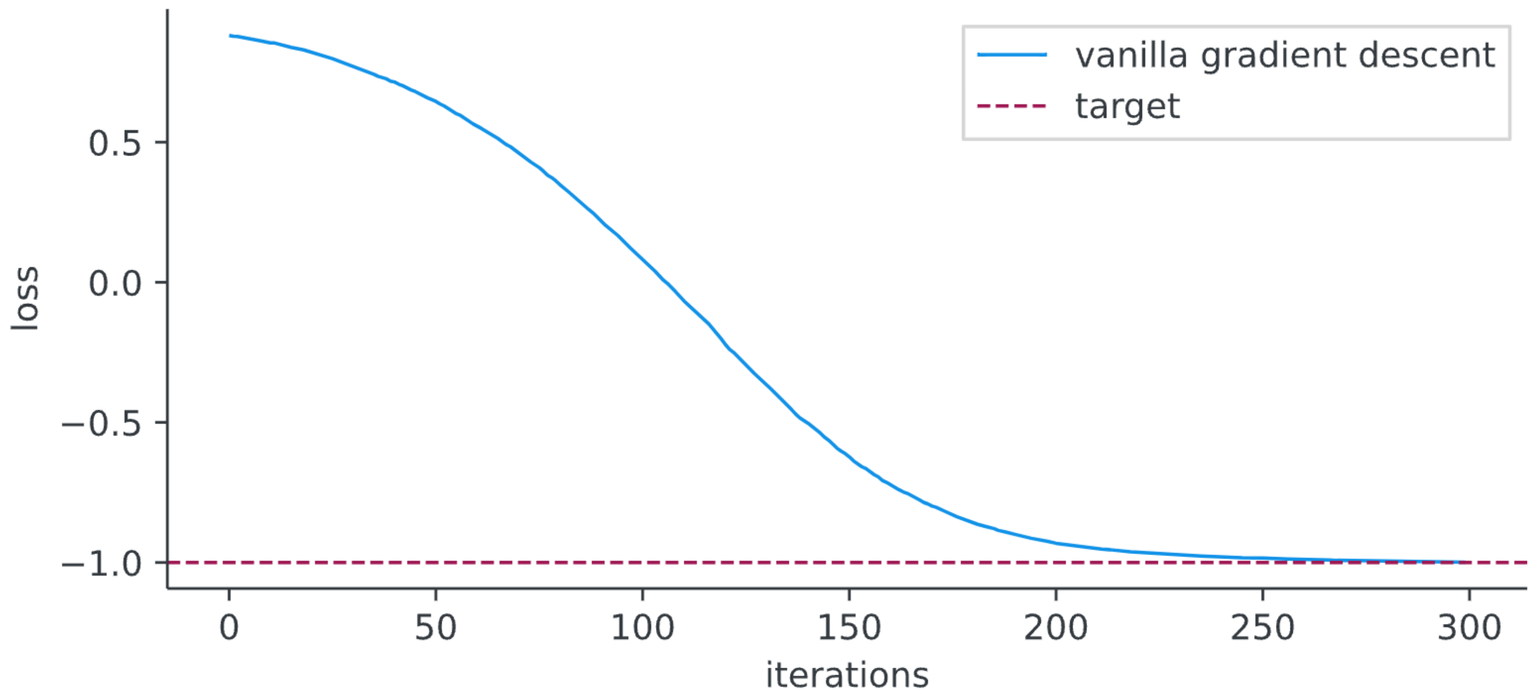


General Flow to calculate PQC gradients

- Step 5: By Chain Rule, sum over 4 passes (4 qubits)
- Only forward on quantum device



Training Techniques



Training Techniques

SPSA

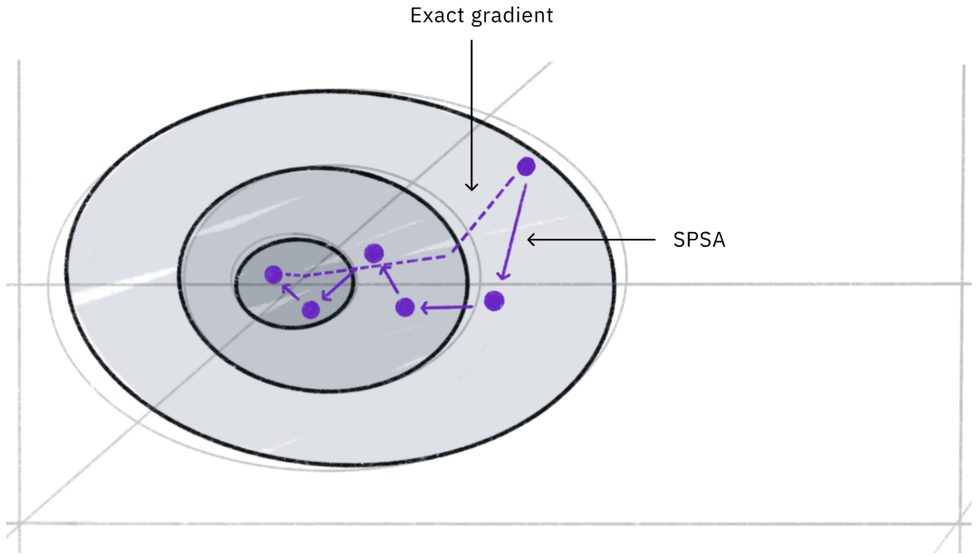
- Simultaneous Perturbation Stochastic Approximation
- How **many** circuit run for the original methods? 2N

Random perturbation $\vec{\Delta}\epsilon\{+1,-1\}^n$

$$\vec{\nabla} f(\vec{\theta}) = \begin{pmatrix} \frac{\partial f}{\partial \theta_1} \\ \vdots \\ \frac{\partial f}{\partial \theta_n} \end{pmatrix} \simeq \frac{1}{2\epsilon} \begin{pmatrix} f(\vec{\theta}+\epsilon\vec{e}_1) - f(\vec{\theta}-\epsilon\vec{e}_1) \\ \vdots \\ f(\vec{\theta}+\epsilon\vec{e}_n) - f(\vec{\theta}-\epsilon\vec{e}_n) \end{pmatrix} \simeq \frac{f(\vec{\theta}+\epsilon\vec{\Delta}) - f(\vec{\theta}-\epsilon\vec{\Delta})}{2\epsilon} \vec{\Delta}^{-1}$$

Finite difference:
Perturb each dim once

SPSA:
simultaneously
perturb all dims at once!



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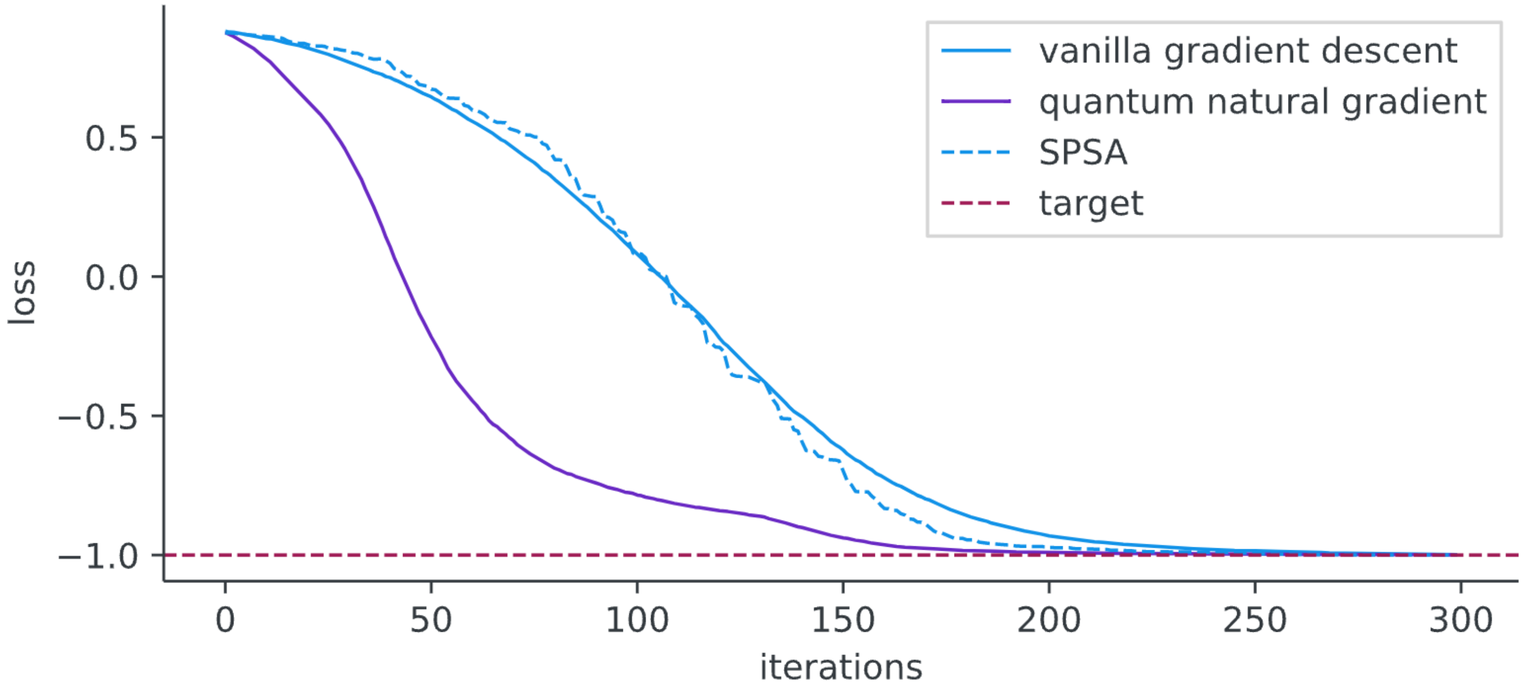
Training Techniques

SPSA

- The SPSA has similar convergence as the gradient descent



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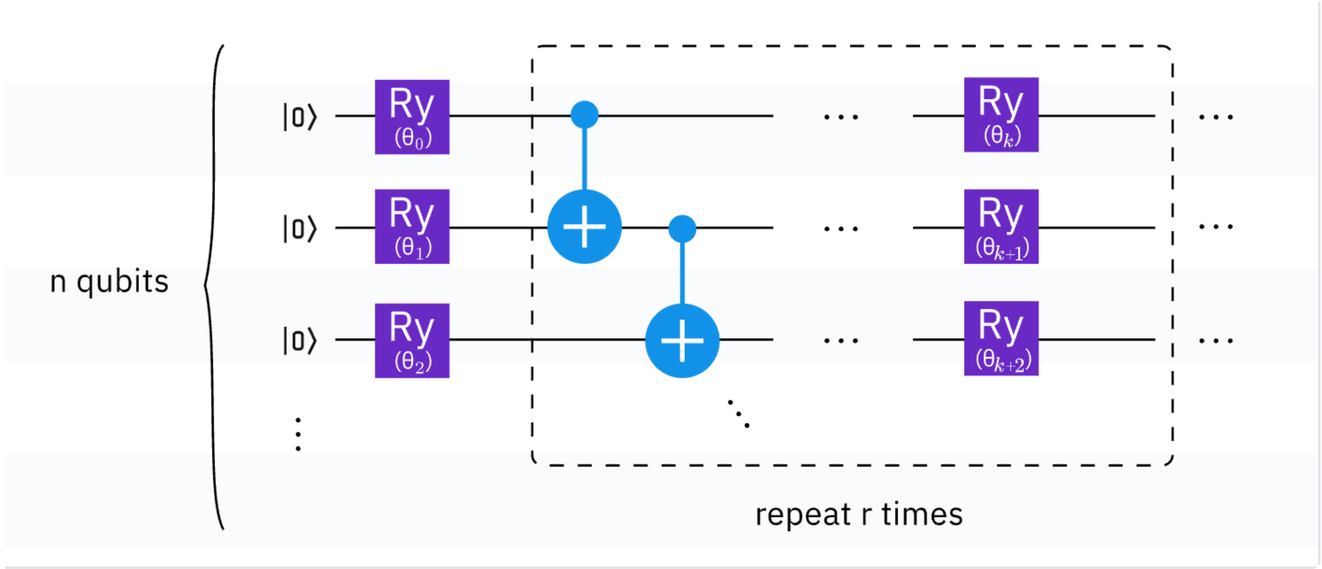
Barren Plateaus

- Vanishing Gradients problem when circuit goes larger



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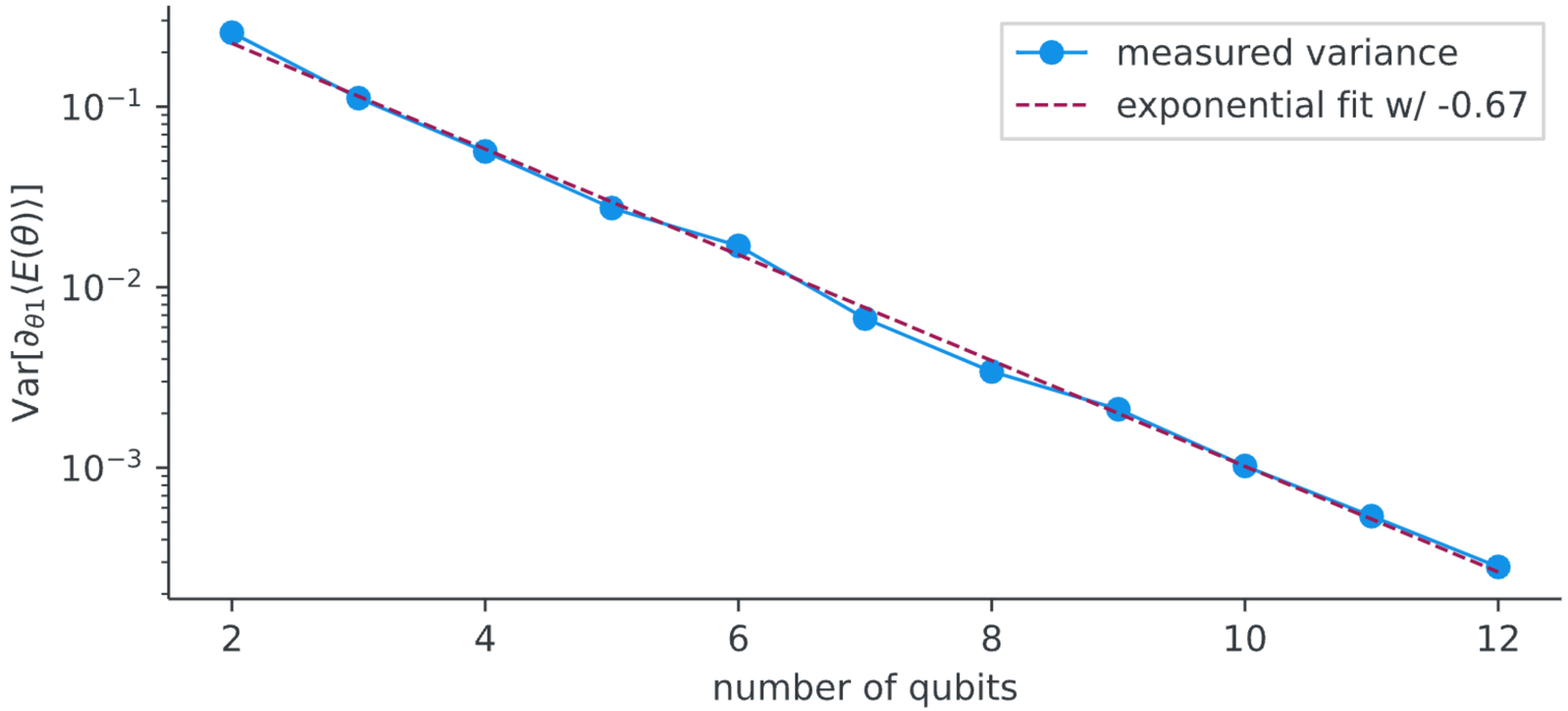
Barren Plateaus

- Gradient **variance** reduces drastically



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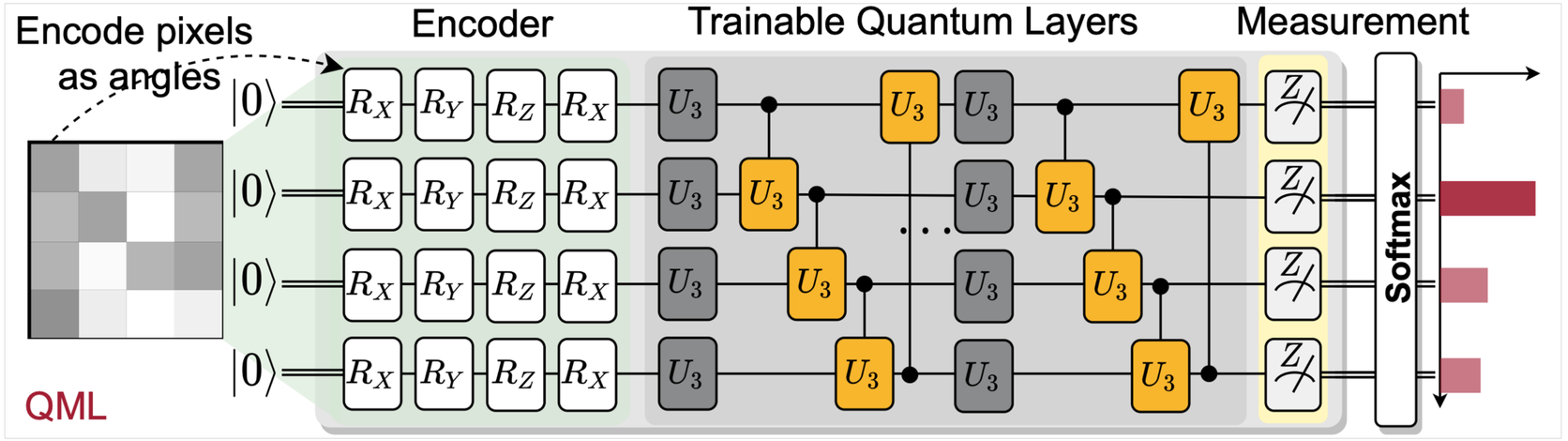
Section 3

Quantum Classifiers

Quantum Classifiers

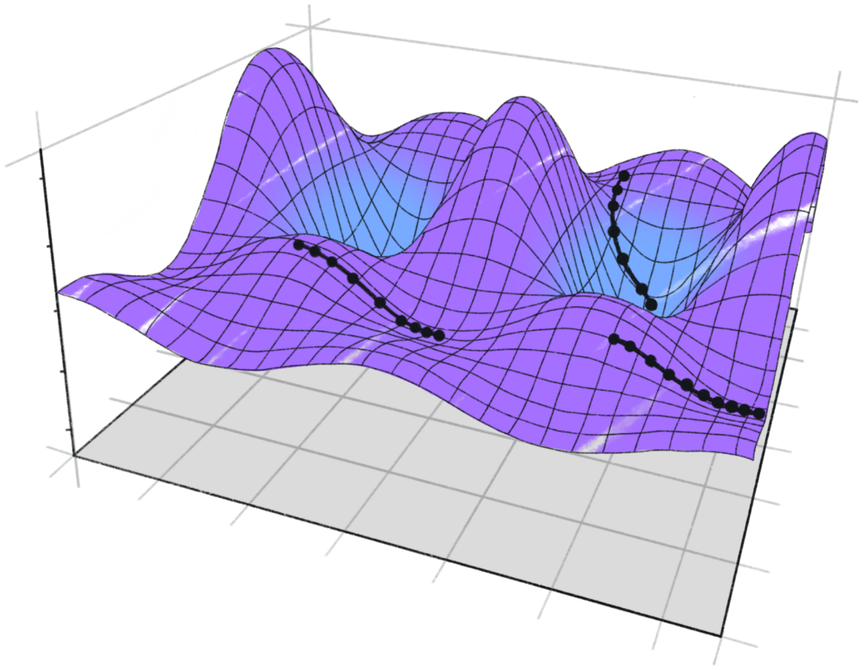
With Quantum Neural Networks

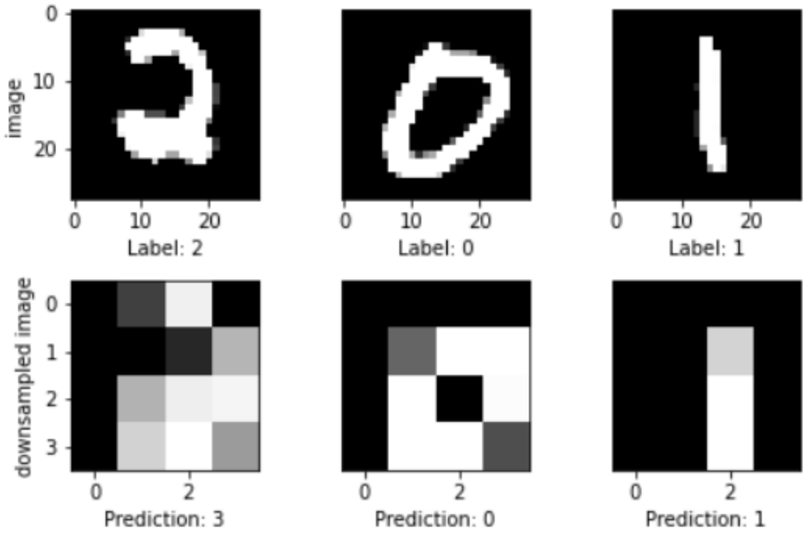


Quantum Classifiers

With Quantum Neural Networks

- Training



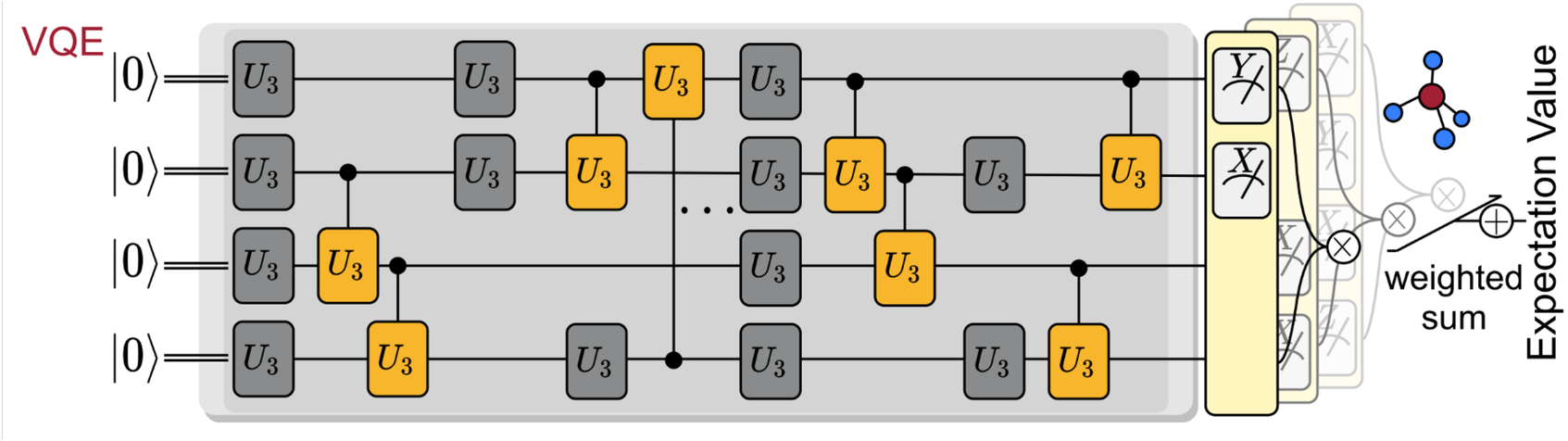


https://qiskit.org/learn/

PQC for Other tasks

VQE and QAOA

- Variational Quantum eigensolver
- Quantum Approximate Optimization Algorithm (QAOA)

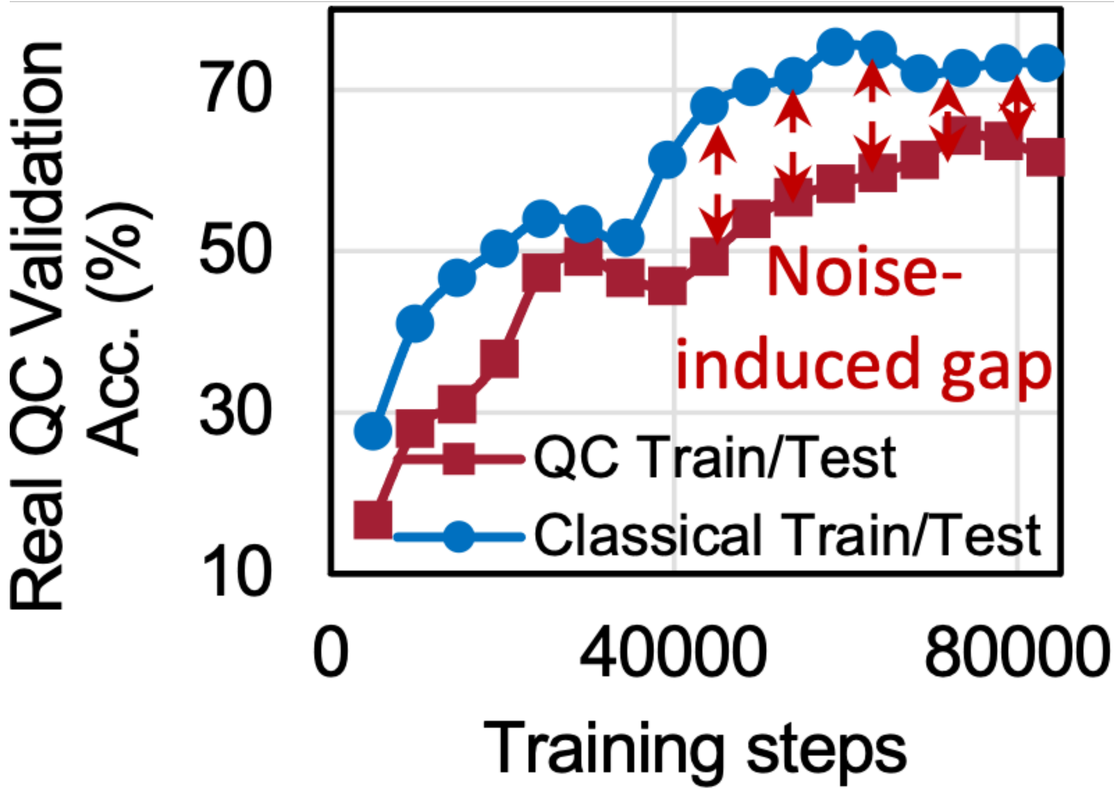


Section 4

Noise-Aware On-Chip Training (QOC)

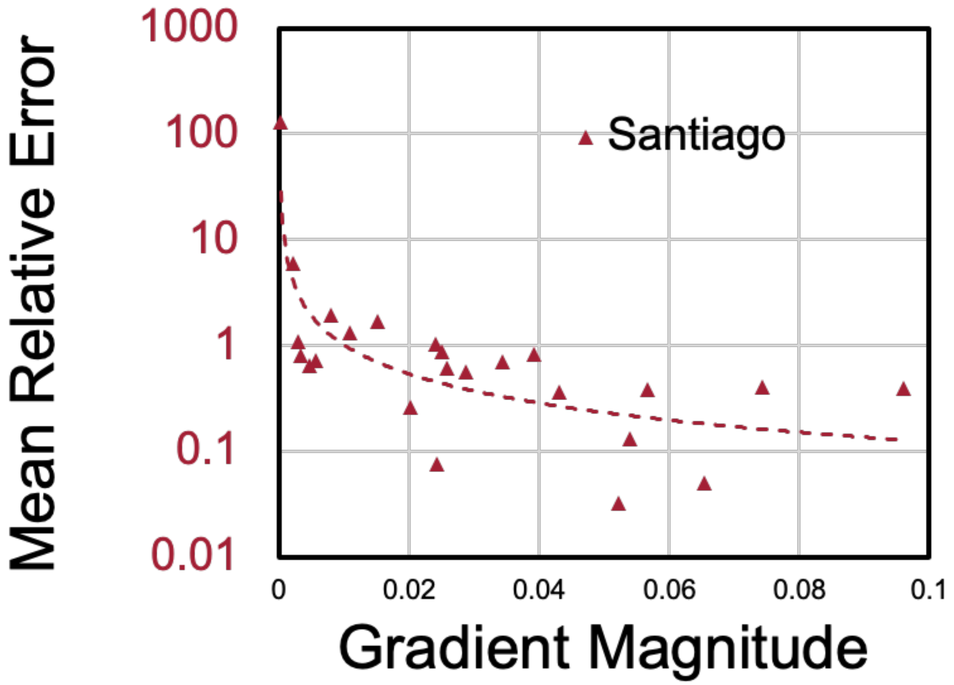
The impact of noise on gradient computation

- Noise reduces **reliability** of on-chip computed gradients



Noise Impact

- Noise reduces **reliability** of on-chip computed gradients
- **Small magnitude** gradients have large relative errors



Noise Impact

- Noise reduces **reliability** of on-chip computed gradients
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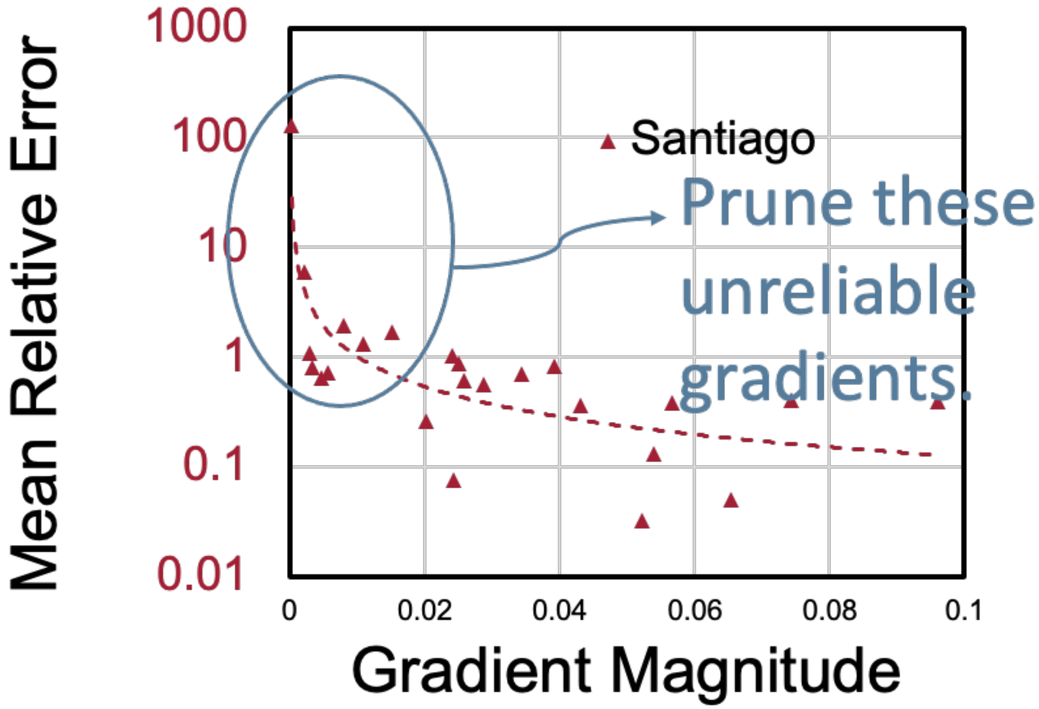
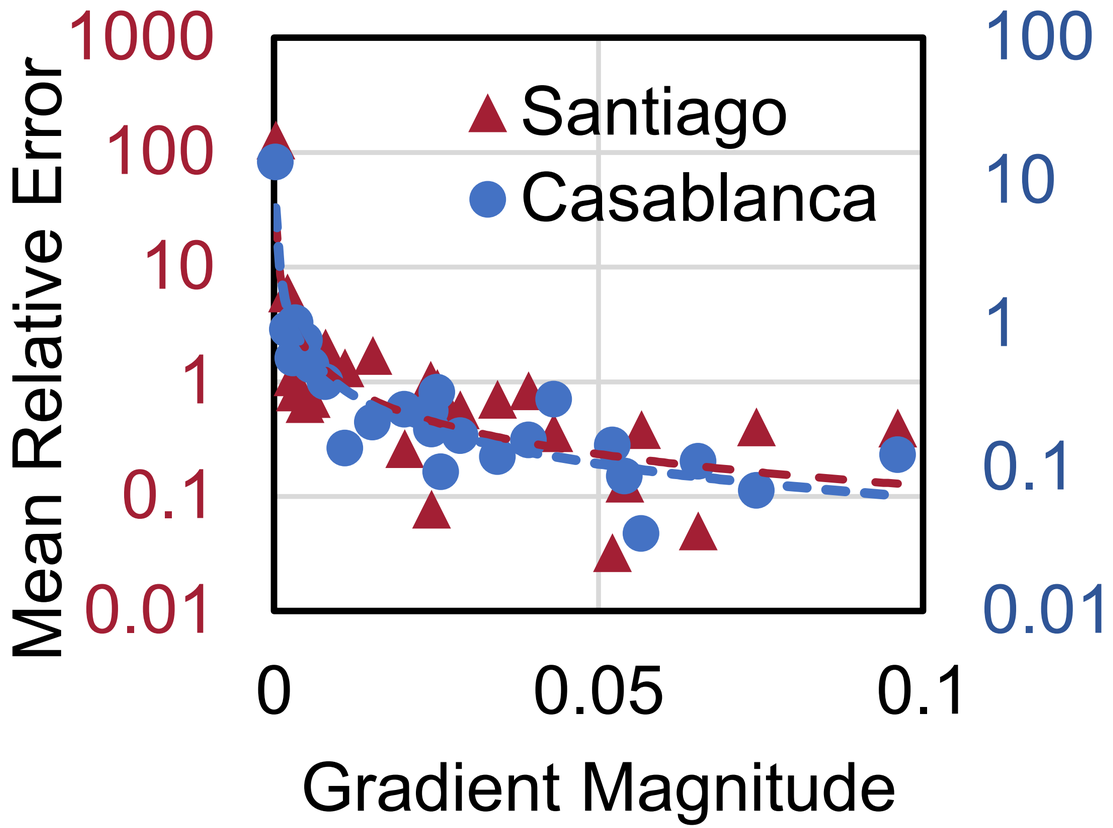


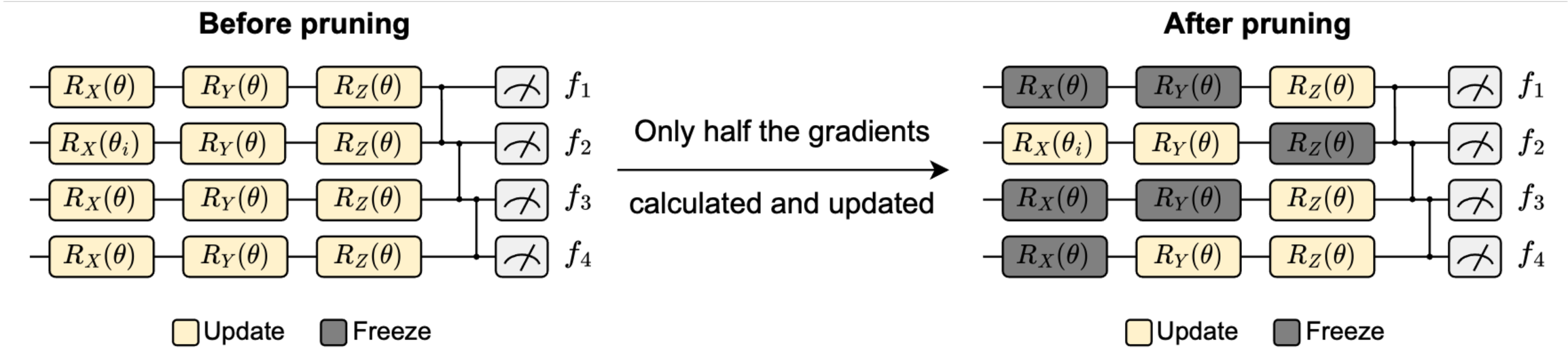
Probabilistic Gradient Pruning

- Small magnitude gradients have **large relative errors**



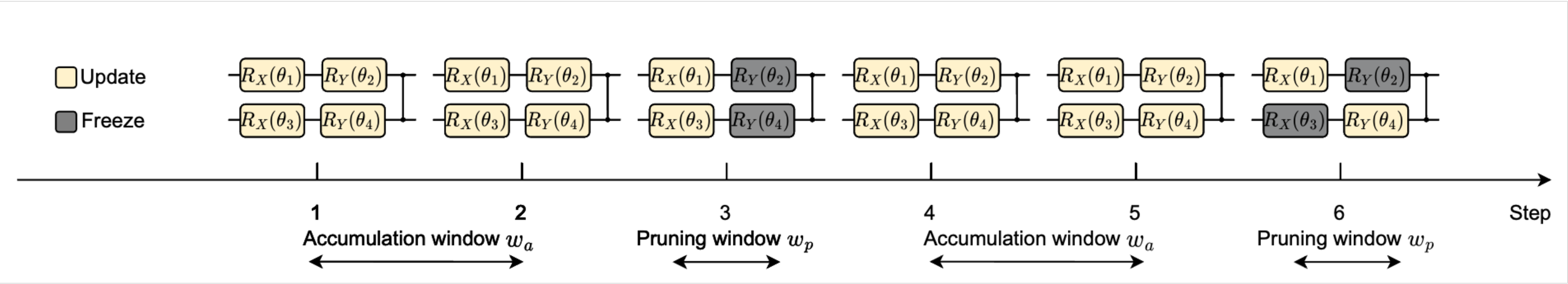
Probabilistic Gradient Pruning

- Small magnitude gradients have **large relative errors**



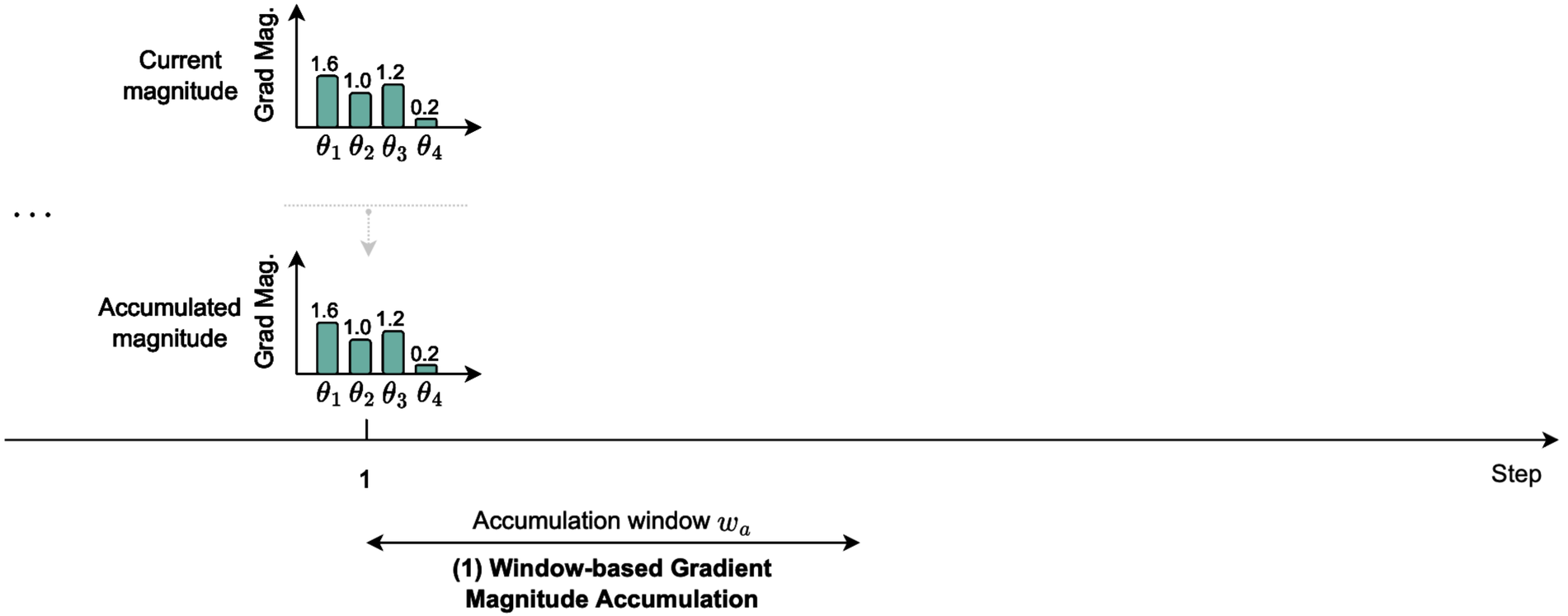
Probabilistic Gradient Pruning

- **Accumulation** Window followed by **Pruning** Window repeatedly



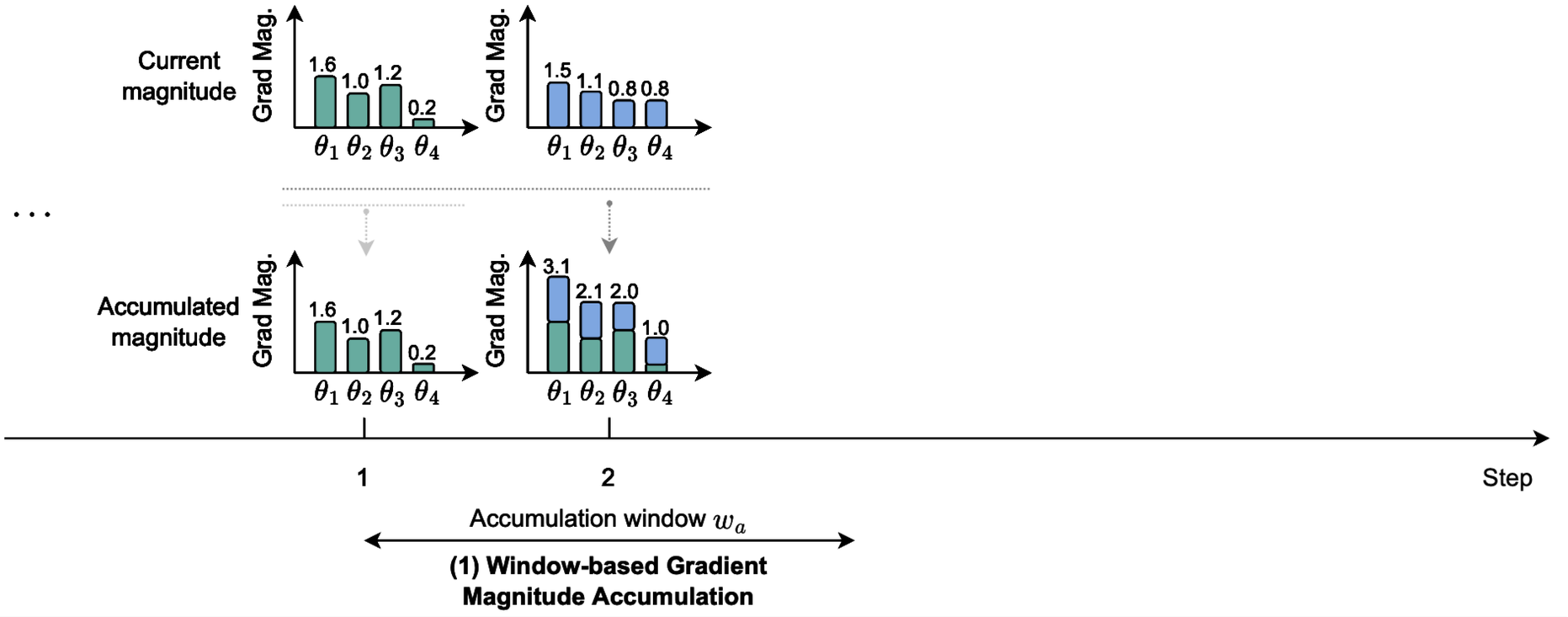
Accumulation Window

- Keep a **record** of accumulated gradient magnitude
-



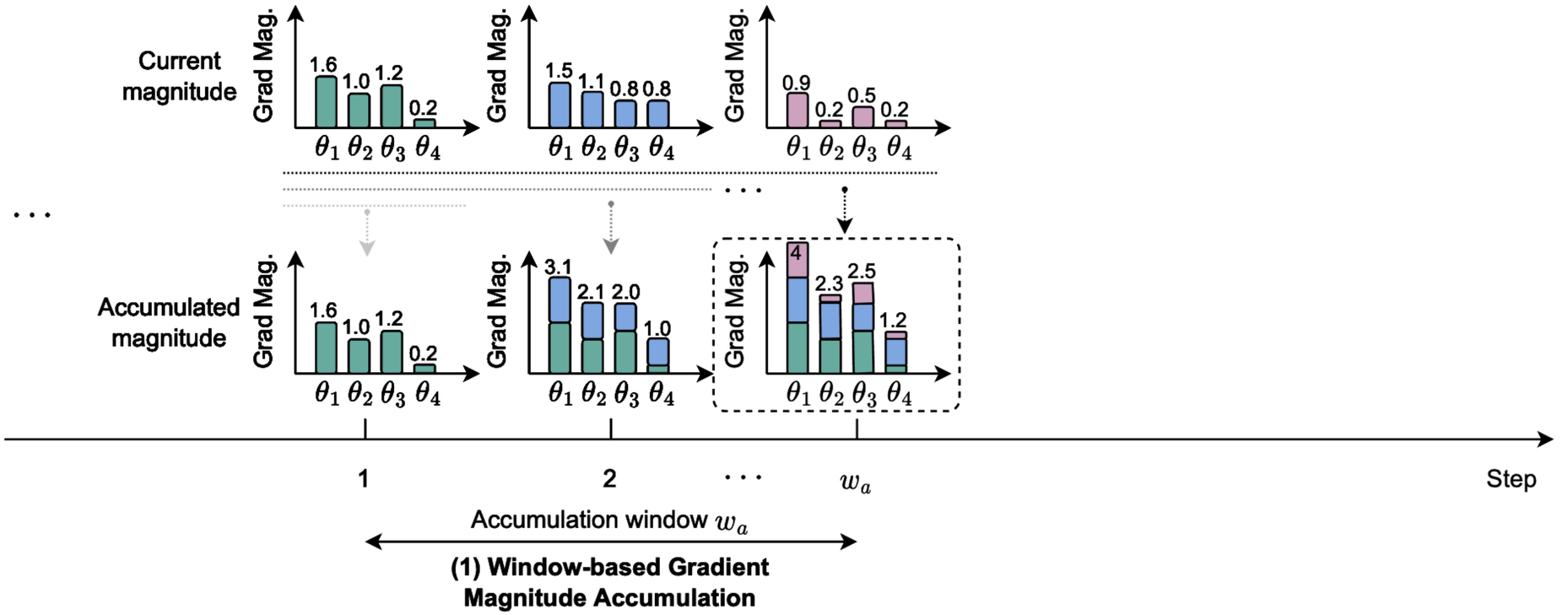
Accumulation Window

- Keep a **record** of accumulated gradient magnitude.



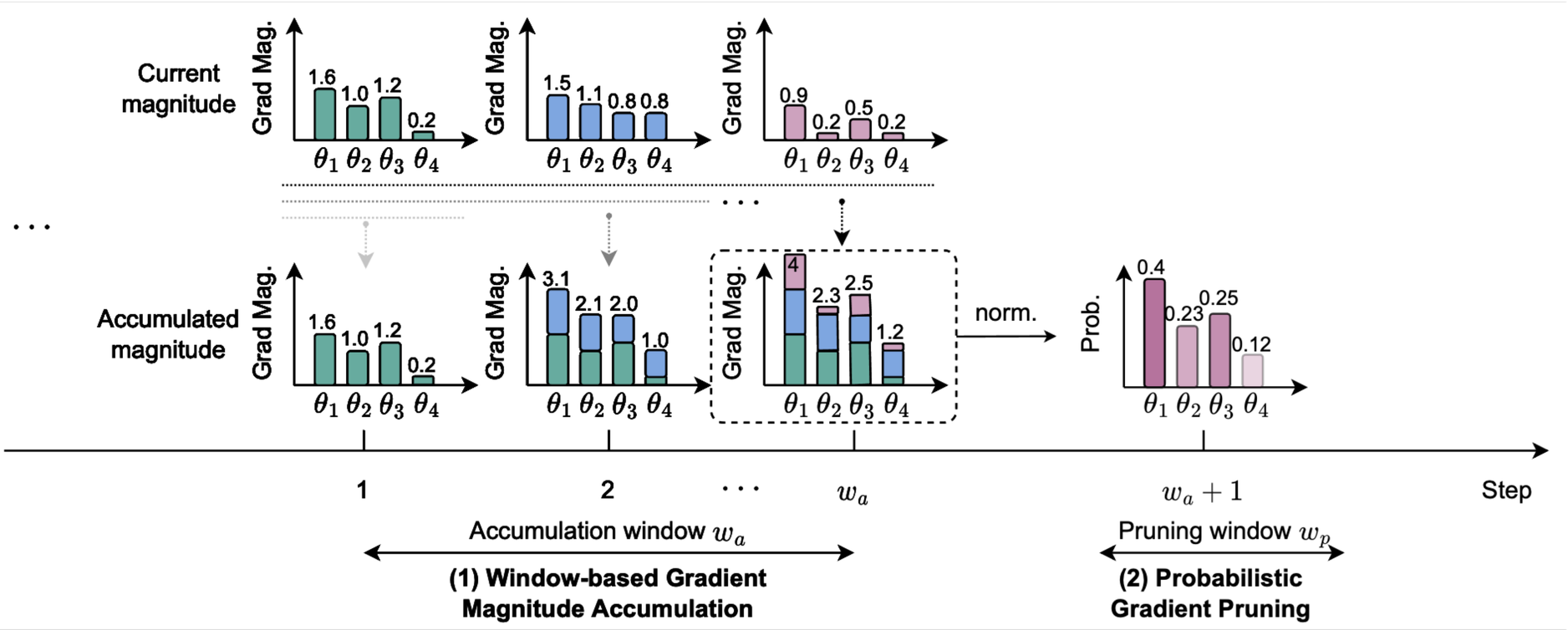
Accumulation Window

- Keep a **record** of accumulated gradient magnitude



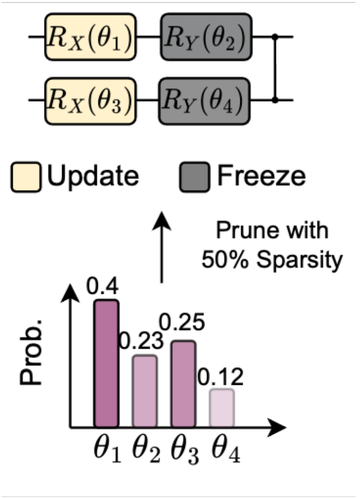
Pruning Window

- **Normalize** the accumulated gradient magnitude to a probability distribution



Pruning Window

- **Prune** the calculation of some gradients according to the probability distribution



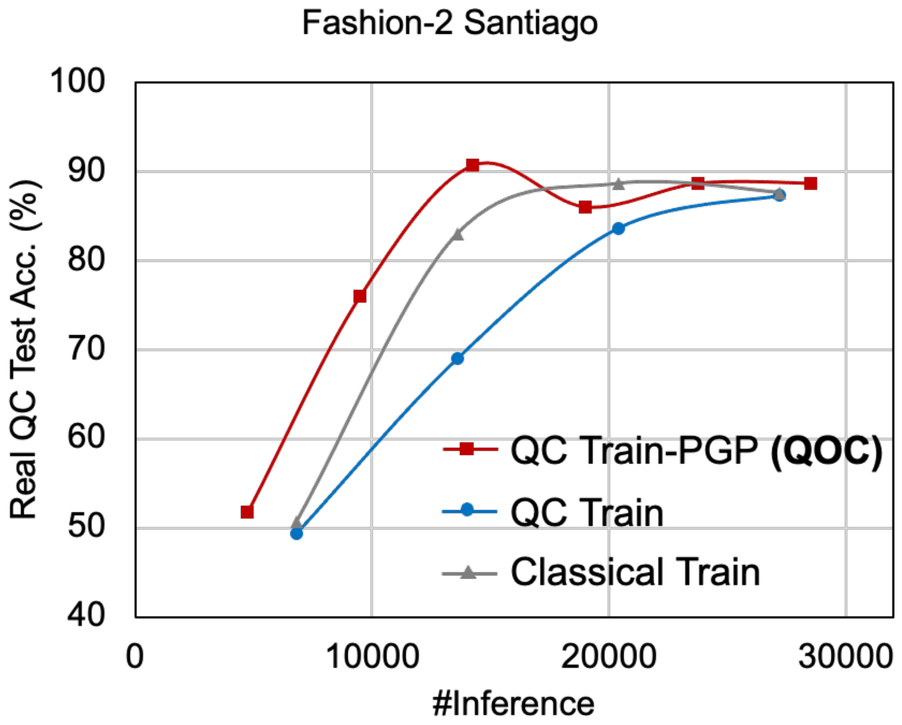
Classification Results

- Gradient achieves similar results to classical simulation

Method	Acc.	MNIST-4 Jarkata	MNIST-2 Jarkata	Fashion-4 Manila	Fashion-2 Santiago	Vowel-4 Lima
Classical-Train	Simu.	0.61	0.88	0.73	0.89	0.37
Classical-Train	QC	0.59	0.79	0.54	0.89	0.31
QC-Train		0.59	0.83	0.49	0.84	0.34
QC-Train-PGP		**0.64**	**0.86**	**0.57**	**0.91**	**0.36**

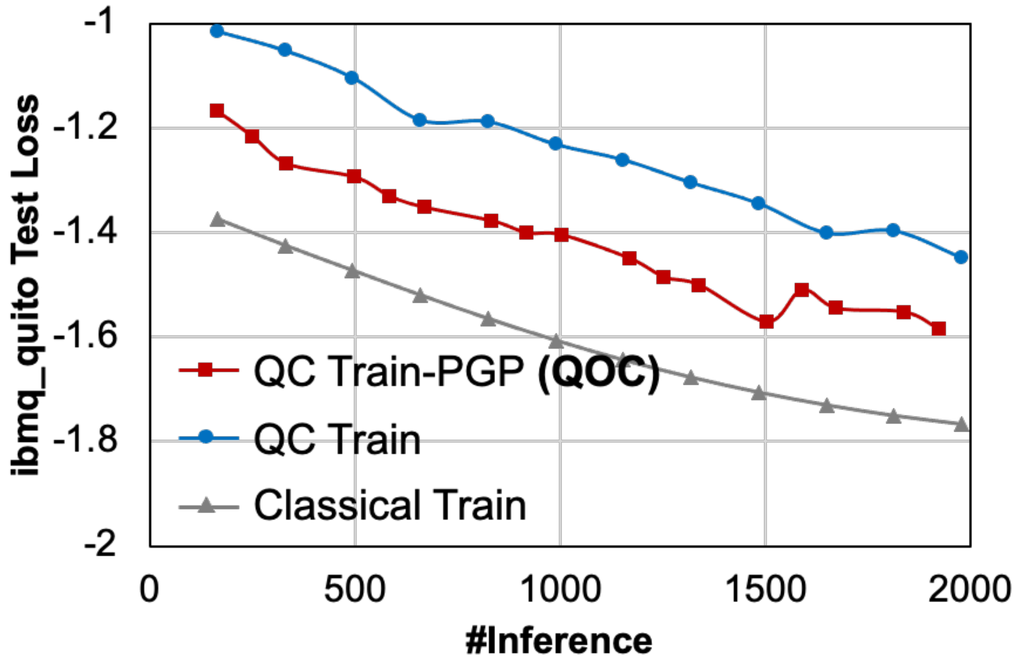
Classification Results

- Gradient pruning can brings **2%~4% accuracy** improvements
- Pruning accelerates convergence with 2x training time reduction



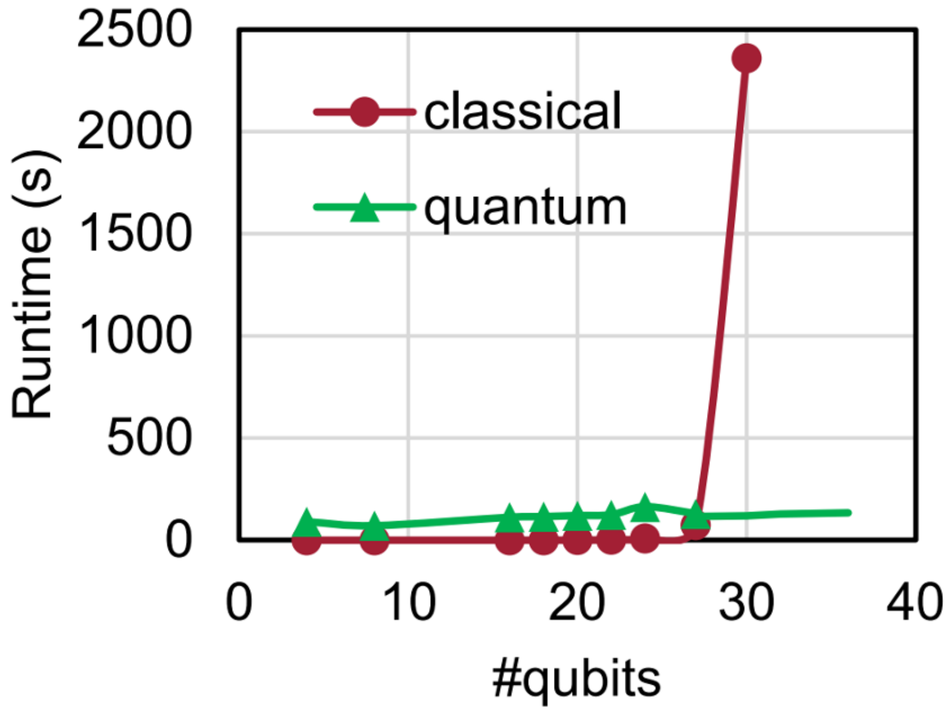
VQE Results

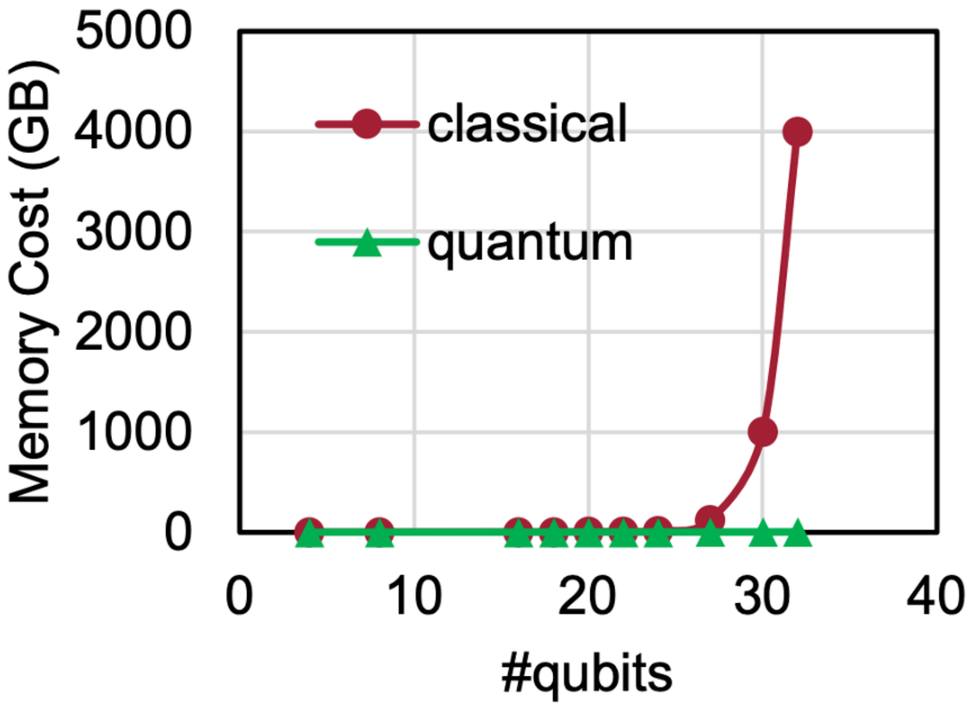
- Gradient pruning can **reduce the gap** between quantum and classical



Scalability

- On-chip Training is scalable





Probabilistic Pruning

- Probabilistic pruning can provide better results

Method	MNIST-4	MNIST-2	Fashion-4	Fashion-2
Deterministic	0.61	0.82	0.72	0.89
Probabilistic	**0.62**	**0.85**	**0.79**	**0.90**

Section 5

TorchQuantum Library for QML

TorchQuantum

Good Infrastructure is Critical

TorchQuantum

Good Infrastructure is Critical

- To enable ML-assisted hardware-aware quantum algorithm design
- Need a simulation framework on classical computer
  - Fast **speed**
  - **Convenience**: PyTorch native
  - **Portable** between different frameworks with common Quantum IR
  - Scalable
  - Analyze circuit behavior
  - Study noise impact
  - Develop ML model for quantum optimization

TorchQuantum

Good Infrastructure is Critical

- •A fast library for classical simulation of quantum circuit in **PyTorch**
  - Automatic gradient computation for training **parameterized quantum circuit**
  - **GPU-accelerated** tensor processing with batch mode support
  - **Density** matrix and state vector simulators
  - **Dynamic** computation graph for easy debugging
  - Easy construction of **hybrid** classical and quantum neural networks
  - **Gate** level and **pulse** level simulation support
  - **Converters** to other frameworks such as IBM Qiskit
  - And so on…

Construct a QNN with TorchQuantum

Initialize a quantum device

Specify encoder gates

Specify trainable gates

```python
import torch.nn as nn
import torch.nn.functional as F
import torchquantum as tq
import torchquantum.functional as tqf

class QFCModel(nn.Module):
  def __init__(self):
    super().__init__()
    self.n_wires = 4
    self.q_device = tq.QuantumDevice(n_wires=self.n_wires)
    self.measure = tq.MeasureAll(tq.PauliZ)

    self.encoder_gates = [tqf.rx] * 4 + [tqf.ry] * 4 + \
                         [tqf.rz] * 4 + [tqf.rx] * 4
    self.rx0 = tq.RX(has_params=True, trainable=True)
    self.ry0 = tq.RY(has_params=True, trainable=True)
    self.rz0 = tq.RZ(has_params=True, trainable=True)
    self.crx0 = tq.CRX(has_params=True, trainable=True)
```

Construct a QNN with TorchQuantum

Reset statevector

Encode classical pixels

Apply the trainable gates

Apply some non-trainable gates

Measure to get classical values

```
def forward(self, x):
  bsz = x.shape[0]
  # down-sample the image
  x = F.avg_pool2d(x, 6).view(bsz, 16)

  # reset qubit states
  self.q_device.reset_states(bsz)

  # encode the classical image to quantum domain
  for k, gate in enumerate(self.encoder_gates):
    gate(self.q_device, wires=k % self.n_wires, params=x[:, k])

  # add some trainable gates (need to instantiate ahead of time)
  self.rx0(self.q_device, wires=0)
  self.ry0(self.q_device, wires=1)
  self.rz0(self.q_device, wires=3)
  self.crx0(self.q_device, wires=[0, 2])

  # add some more non-parameterized gates (add on-the-fly)
  tqf.hadamard(self.q_device, wires=3)
  tqf.sx(self.q_device, wires=2)
  tqf.cnot(self.q_device, wires=[3, 0])
  tqf.qubitunitary(self.q_device0, wires=[1, 2], params=[[1, 0, 0, 0],
                                                         [0, 1, 0, 0],
                                                         [0, 0, 0, 1j],
                                                         [0, 0, -1j, 0]])

  # perform measurement to get expectations (back to classical domain)
  x = self.measure(self.q_device).reshape(bsz, 2, 2)

  # classification
  x = x.sum(-1).squeeze()
  x = F.log_softmax(x, dim=1)

  return x
```

TQ for Statevector simulation

- Performing matrix-vector multiplication between the gate matrix and statevector
  - The tq.QuantumDevice stores the statevectors
    - `q_dev = tq.QuantumDevice(n_wires=5)`
- Two ways of applying quantum gates: method 1:
  - `import torchquantum.functional as tqf`
  - `tqf.h(q_dev, wires=1)`

TQ for Statevector simulation

- Performing matrix-vector multiplication between the gate matrix and statevector
  - The tq.QuantumDevice stores the statevectors
    - `q_dev = tq.QuantumDevice(n_wires=5)`
- Two ways of applying quantum gates: method 1:
  - `import torchquantum.functional as tqf`
  - `tqf.h(q_dev, wires=1)`
- Two ways of applying quantum gates: method 2:
  - `h_gate = tq.H()`
  - `h_gate(q_dev, wires=3)`

TQ for Statevector simulation

- Performing matrix-vector multiplication between the gate matrix and statevector
- The tq.QuantumState class can also store the statevectors
  - `q_state = tq.QuantumState(n_wires=5)`
- Three ways of applying quantum gates
  - `import torchquantum.functional as tqf`
  - `tqf.h(q_state, wires=1)`
  - `h_gate = tq.H()`
  - `h_gate(q_state)`
  - `q_state.h()`
  - `q_state.rx(wires=1, params=0.2 * np.pi)`

TQ for Statevector simulation

- Performing matrix-vector multiplication between the gate matrix and statevector
- The implementation of statevector and quantum gates are using the native data structure in PyTorch

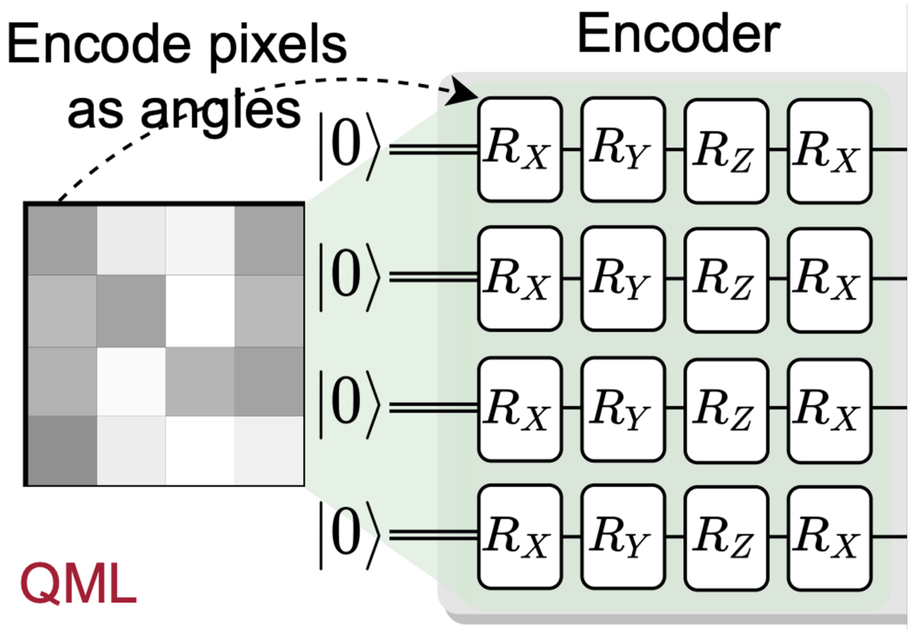
```
_state = torch.zeros(2 ** self.n_wires, dtype=C_DTYPE)
_state[0] = 1 + 0j
```

```
'cnot': torch.tensor([[1, 0, 0, 0],
                      [0, 1, 0, 0],
                      [0, 0, 0, 1],
                      [0, 0, 1, 0]], dtype=C_DTYPE),
```

Encoding Classical Data to Quantum

Various encoder support

- `tq.AmplitudeEncoder()` encodes the classical values to the amplitude of quantum statevector
- `tq.PhaseEncoder()` encodes the classical values using the rotation gates



Convert tq Model to Other Frameworks

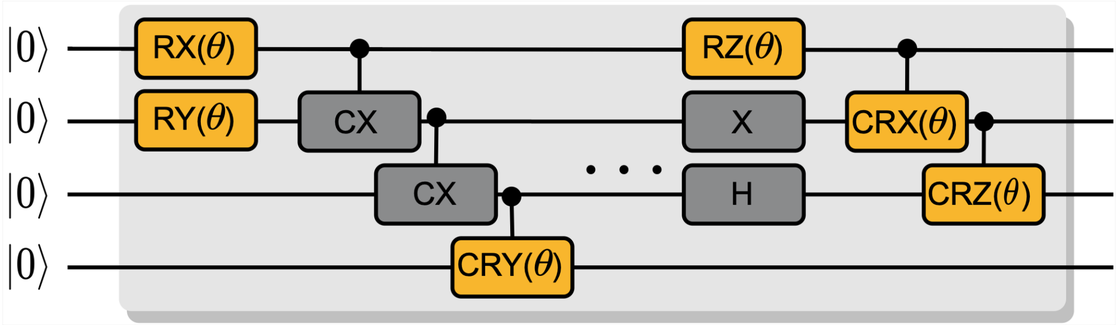
- Convert the `tq.QuantumModule` to other frameworks such as `Qiskit`
  - `from torchquantum.plugins.qiskit_plugin import tq2qiskit`
  - `circ = tq2qiskit(q_dev, q_model)`
  - `circ.draw('mpl')`

Section 6

Robust Quantum Circuit Architecture Search

Parameterized Quantum Circuits

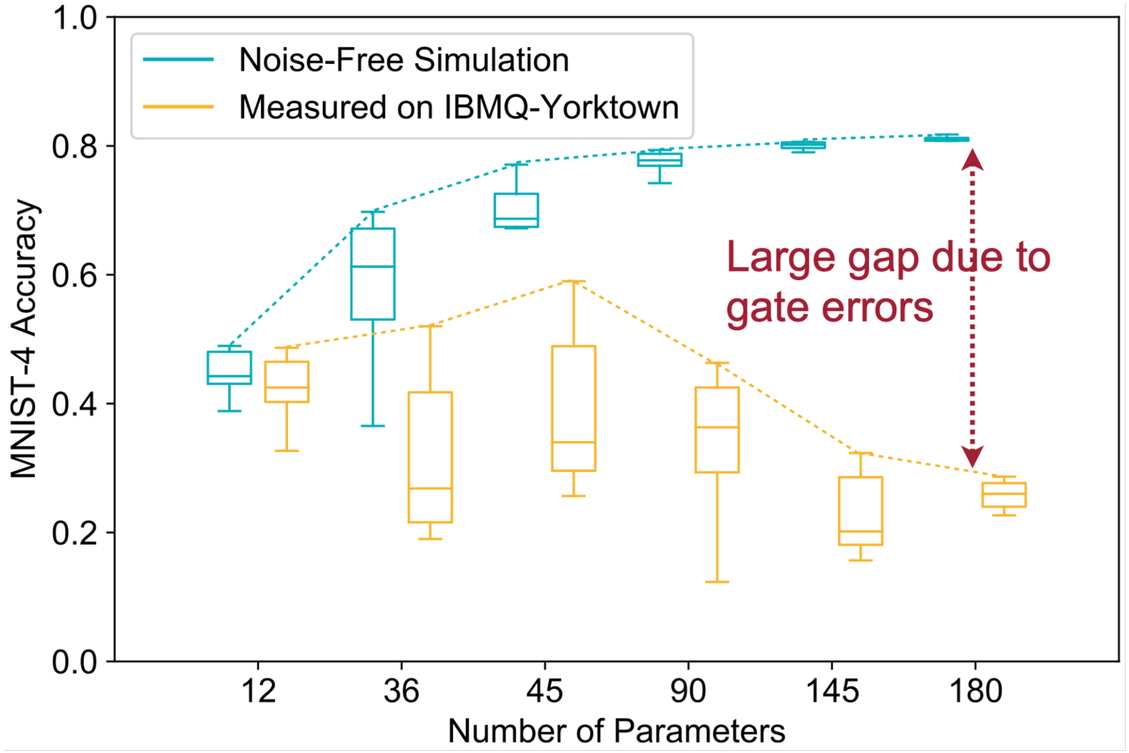
- Parameterized Quantum Circuits (PQC)
- Quantum circuit with fixed gates and parameterized gates



- 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)

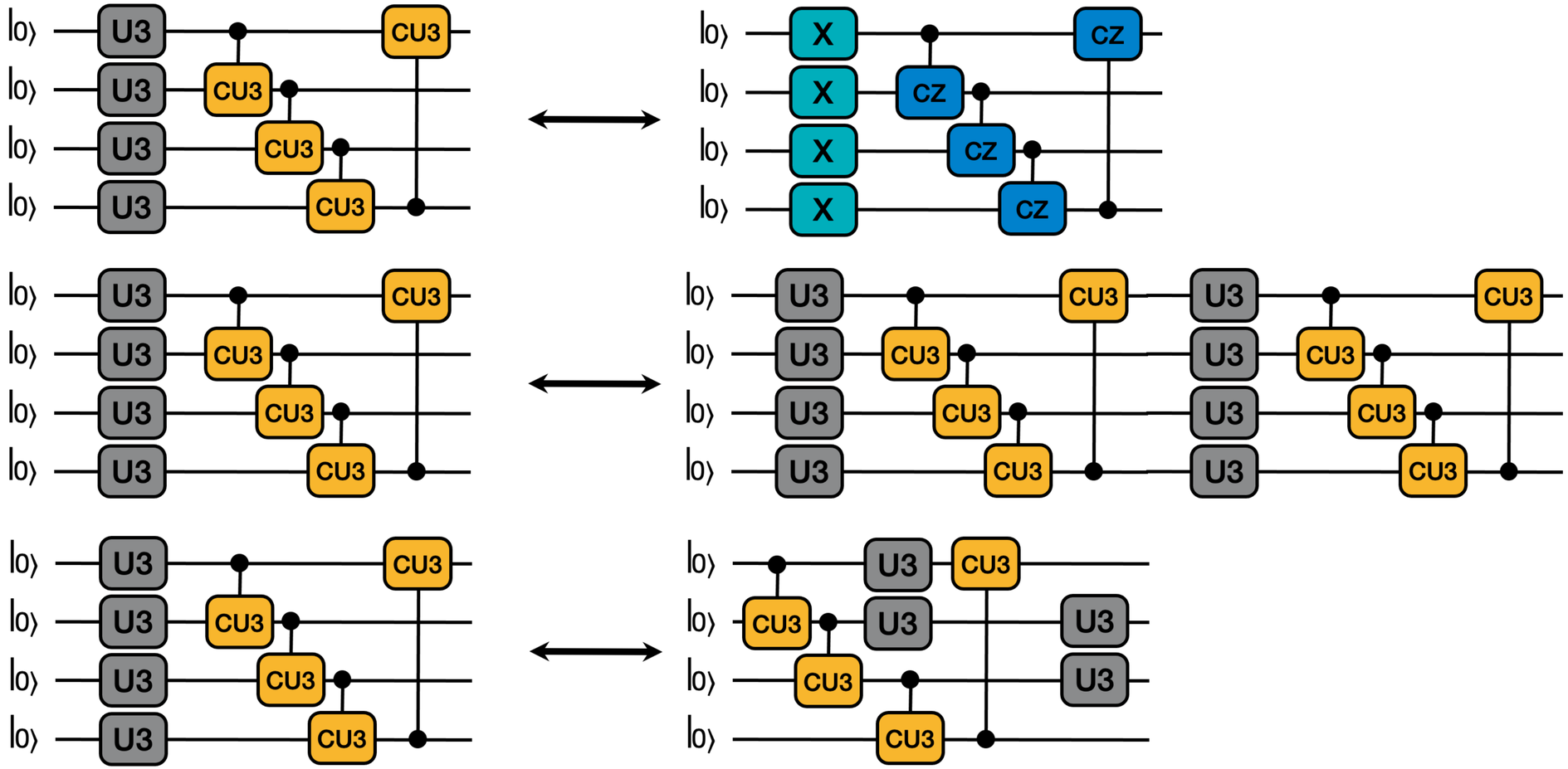
Challenges of PQC — Noise

- Noise **degrades** PQC reliability
- More parameters increase the noise-free accuracy but degrade the measured accuracy
- Therefore, circuit architecture is critical



Challenges of PQC — Large Design Space

- Large design space for circuit architecture
  - Type of gates
  - Number of gates
  - Position of gates



QuantumNAS Framework

Goal of QuantumNAS

Automatically & efficiently search for noise-robust quantum circuit

Train one “SuperCircuit”, providing parameters to many “SubCircuits”

Solve the challenge of large design space

(1) Quantum noise feedback in the search loop
(2) Co-search the circuit architecture and qubit mapping

Solve the challenge of large quantum noise

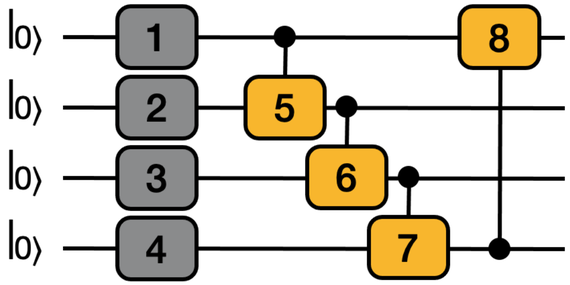
QuantumNAS Framework

Four Steps

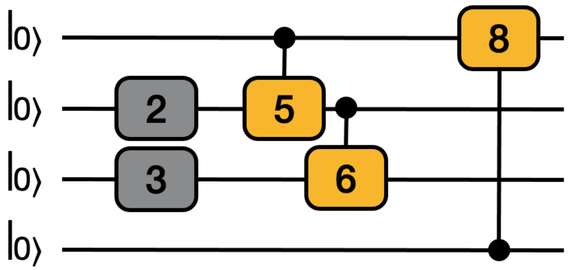
- SuperCircuit Construction and Training
- Noise-Adaptive Evolutionary Co-Search of SubCircuit and Qubit Mapping
- Train the Searched SubCircuit
- Iterative Quantum Gate Pruning

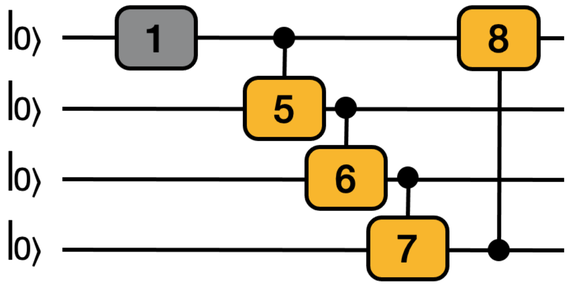
SuperCircuit & SubCircuit

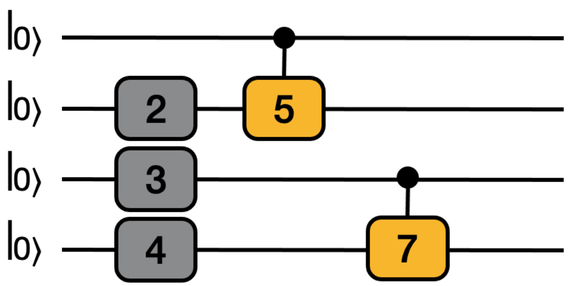
- Firstly construct a design space. For example, a design space of maximum 4 U3 in the first layer and 4 CU3 gates in the second layer
- SuperCircuit: the circuit with the **largest** number of gates in the design space
  - Example: SuperCircuit in U3+CU3 space



- Each candidate circuit in the design space (called SubCircuit) is a subset of the SuperCircuit







SuperCircuit Construction

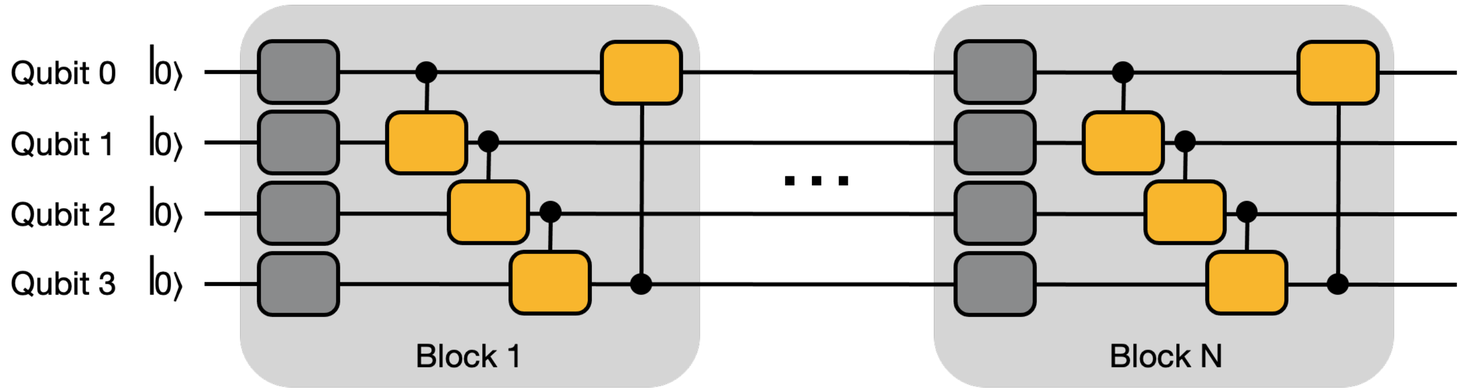
- Why use a SuperCircuit?
  - Enables **efficient** search of architecture candidates without training each
  - SubCircuit inherits parameters from SuperCircuit
  - With **inherited** parameters, we find some good SubCircuits, we find that they **are also good SubCircuits** with parameters **trained from-scratch** individually

SuperCircuit Training

- In one SuperCircuit Training step:
  - Sample a gate subset of SuperCircuit (a SubCircuit)
    - Front Sampling and Restricted Sampling
  - Only use the subset to perform the task and updates the parameters in the subset
  - Parameter updates are cumulative across steps

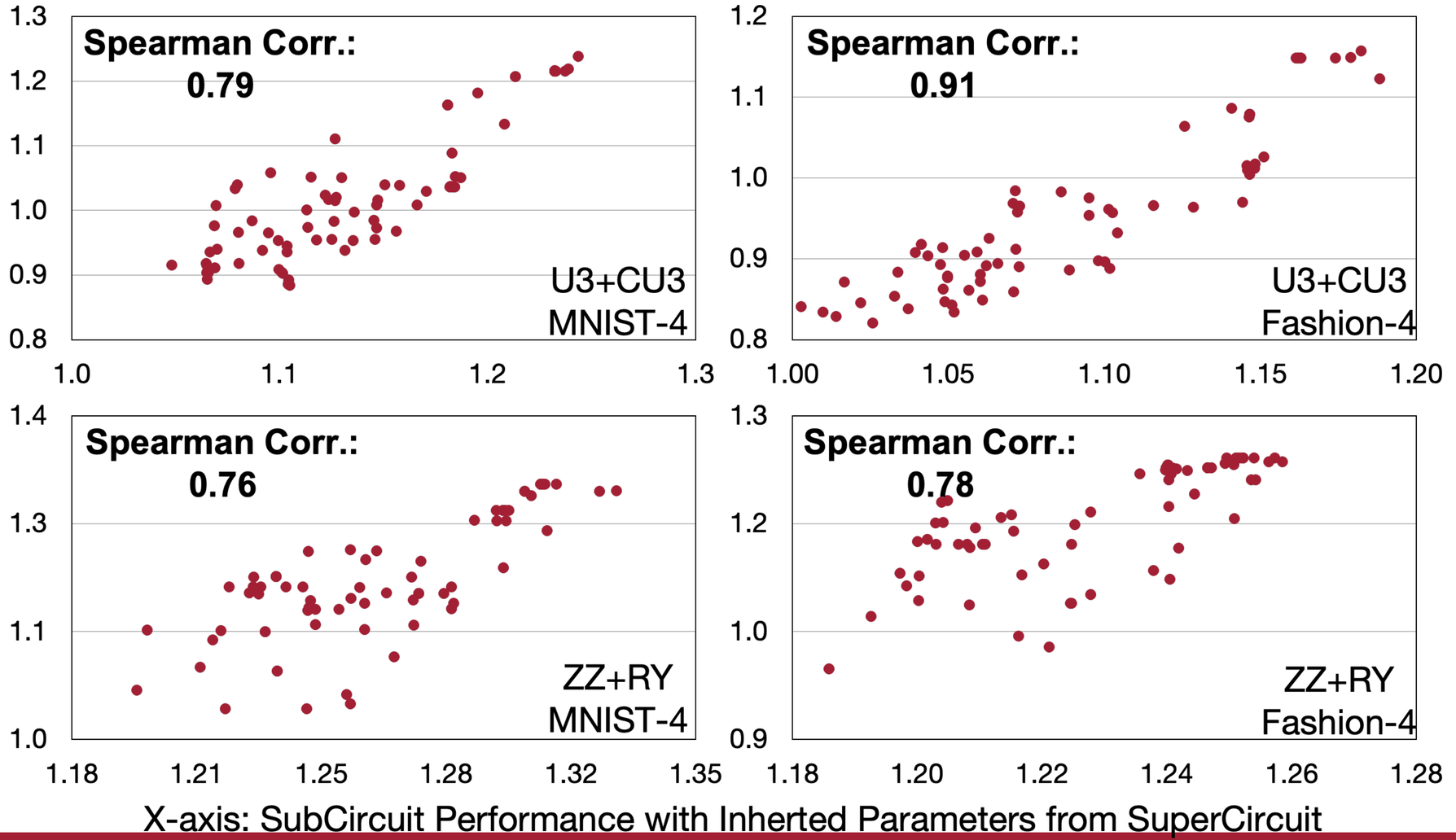
Train SuperCircuit for Multiple Steps

- In one SuperCircuit Training step: Sample and Train



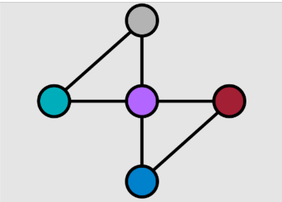
How Reliable is the SuperCircuit?

- Inherited parameters from SuperCircuit can provide accurate **relative performance**



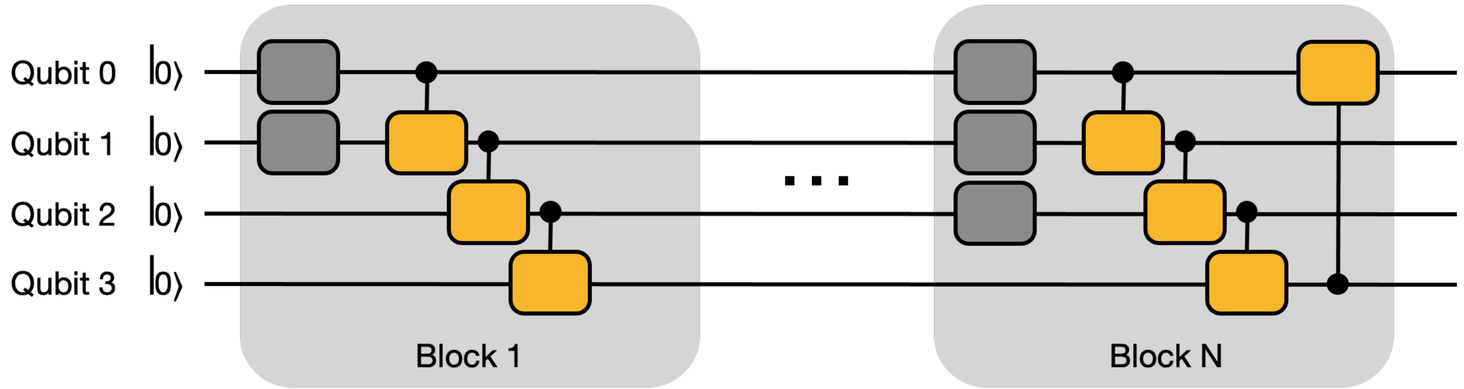
Noise-Adaptive Evolutionary Search

- Search the best SubCircuit and its qubit mapping on target device



Iterative Quantum Gate Pruning

- Some gates have parameters **close to 0**
  - Rotation gate with angle close to 0 has **small impact** on the results
- Iteratively prune small-magnitude gates and fine-tune the remaining parameters



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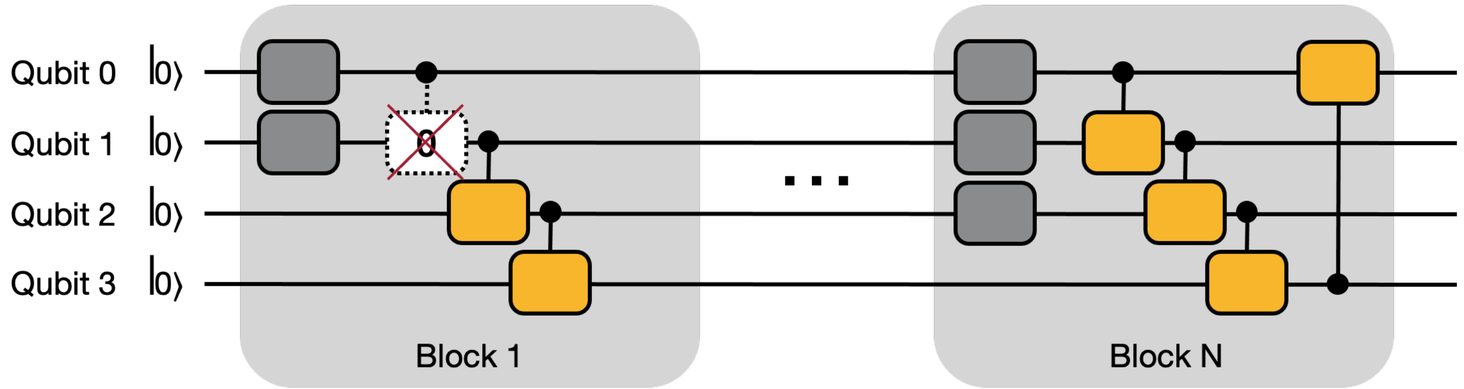

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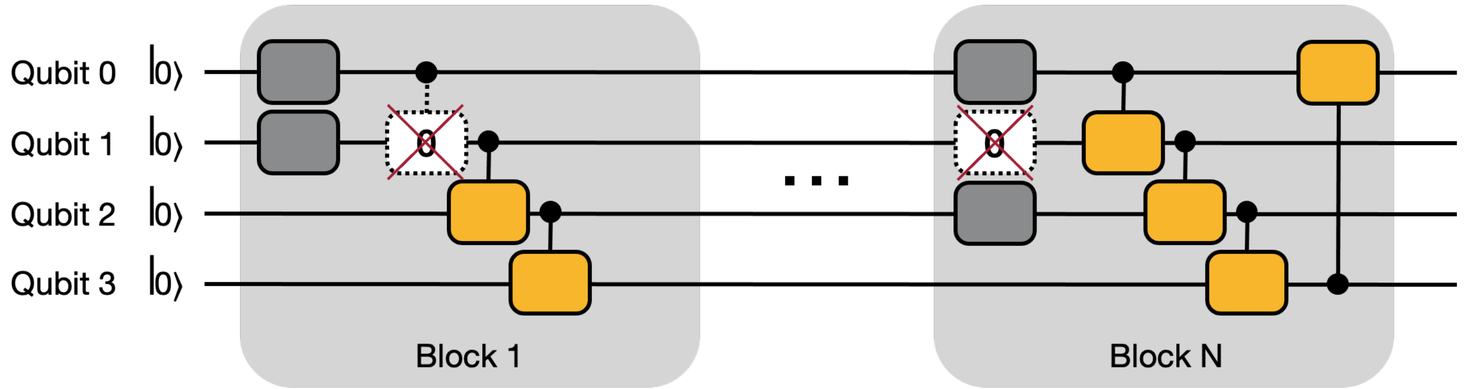

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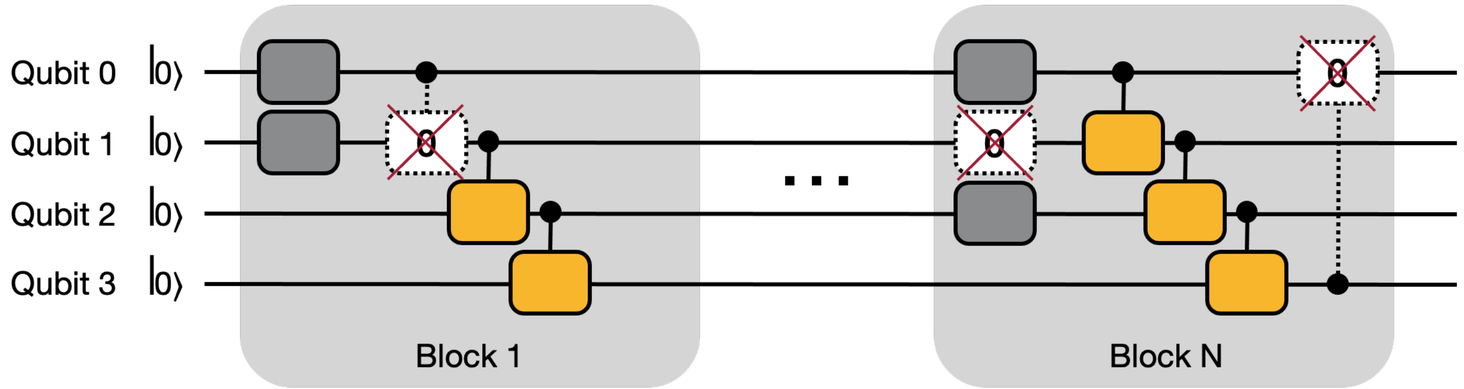

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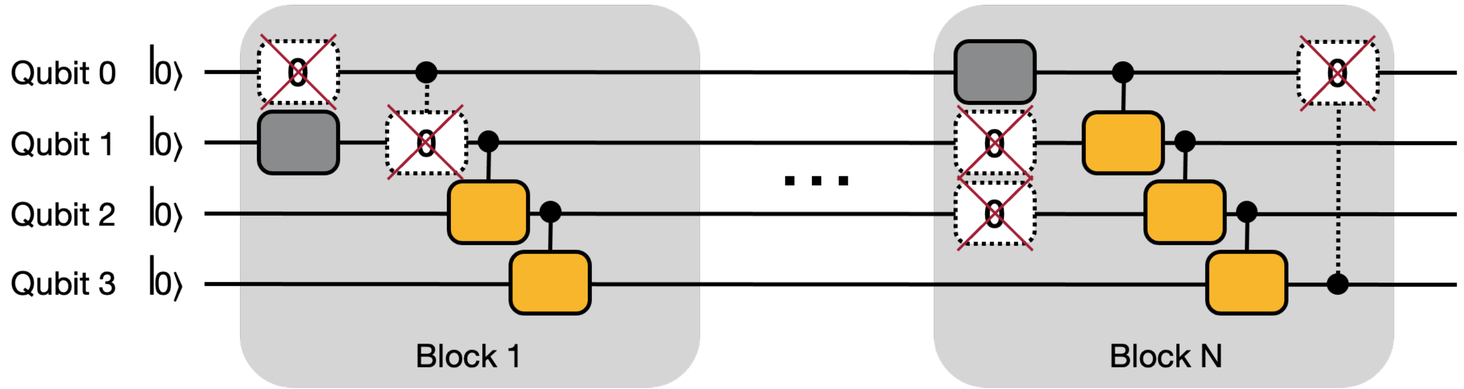
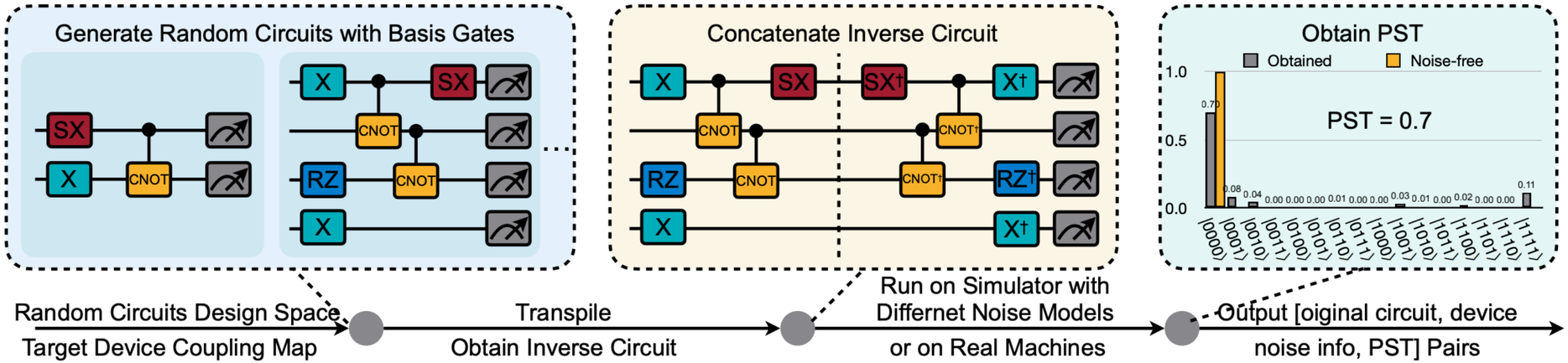


Other Search Frameworks

Faster method to evaluate real device performance

- Graph transformer for circuit fidelity estimation

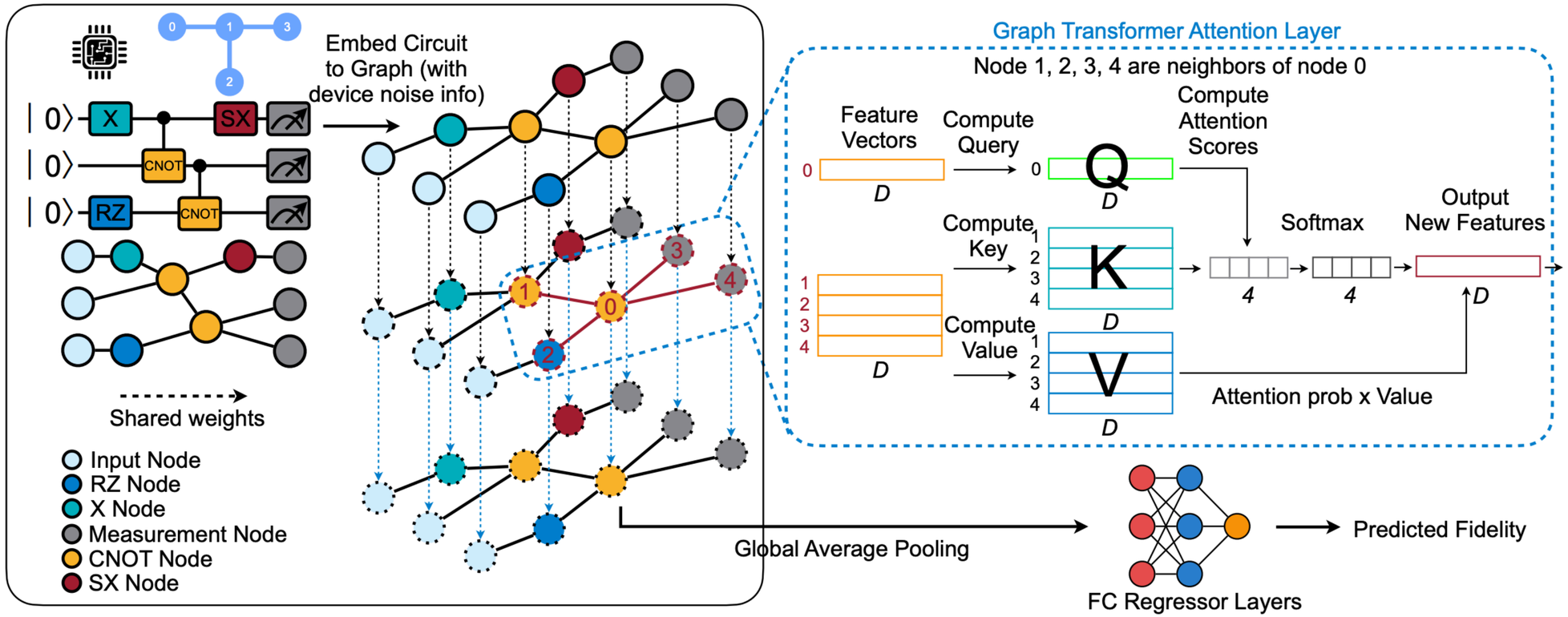


QuEst: Graph Transformer for Quantum Circuit Reliability Estimation

Other Search Frameworks

Faster method to evaluate real device performance

- Graph transformer for circuit fidelity estimation



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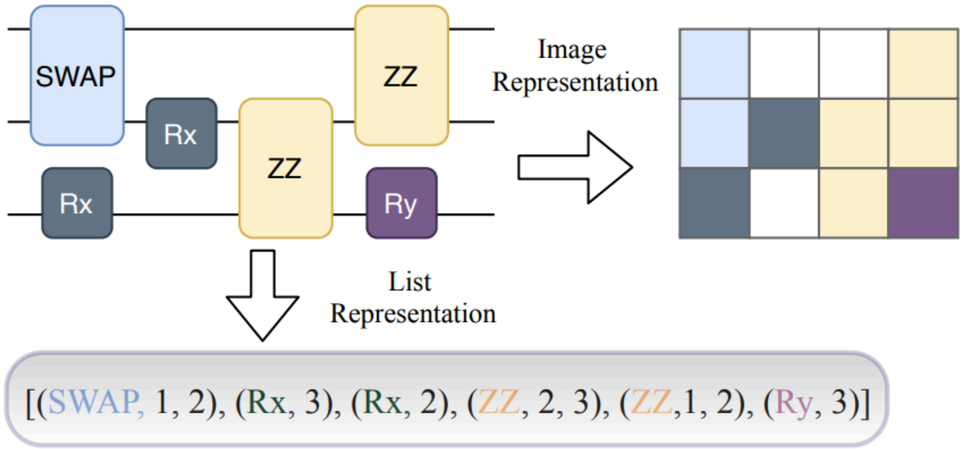
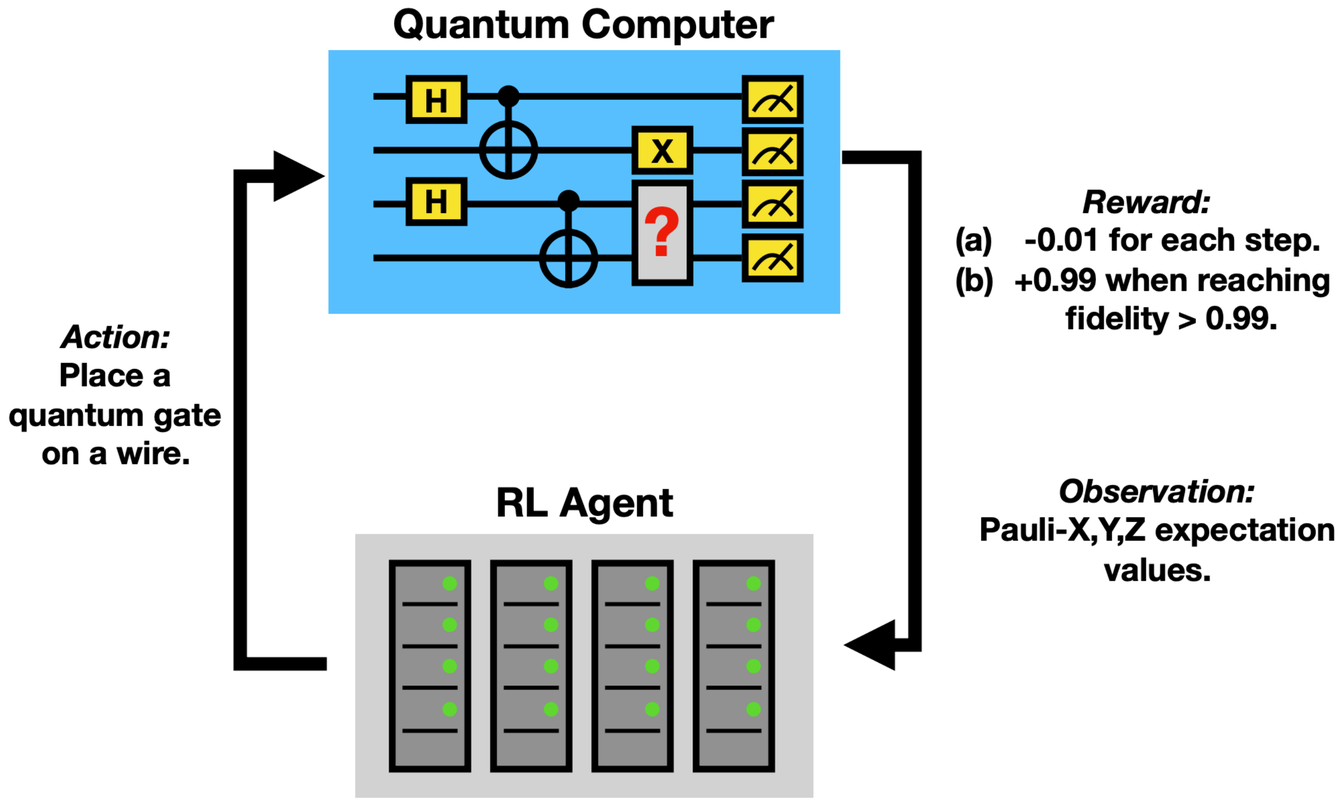


Neural Predictor based Quantum Architecture Search

Other Search Frameworks

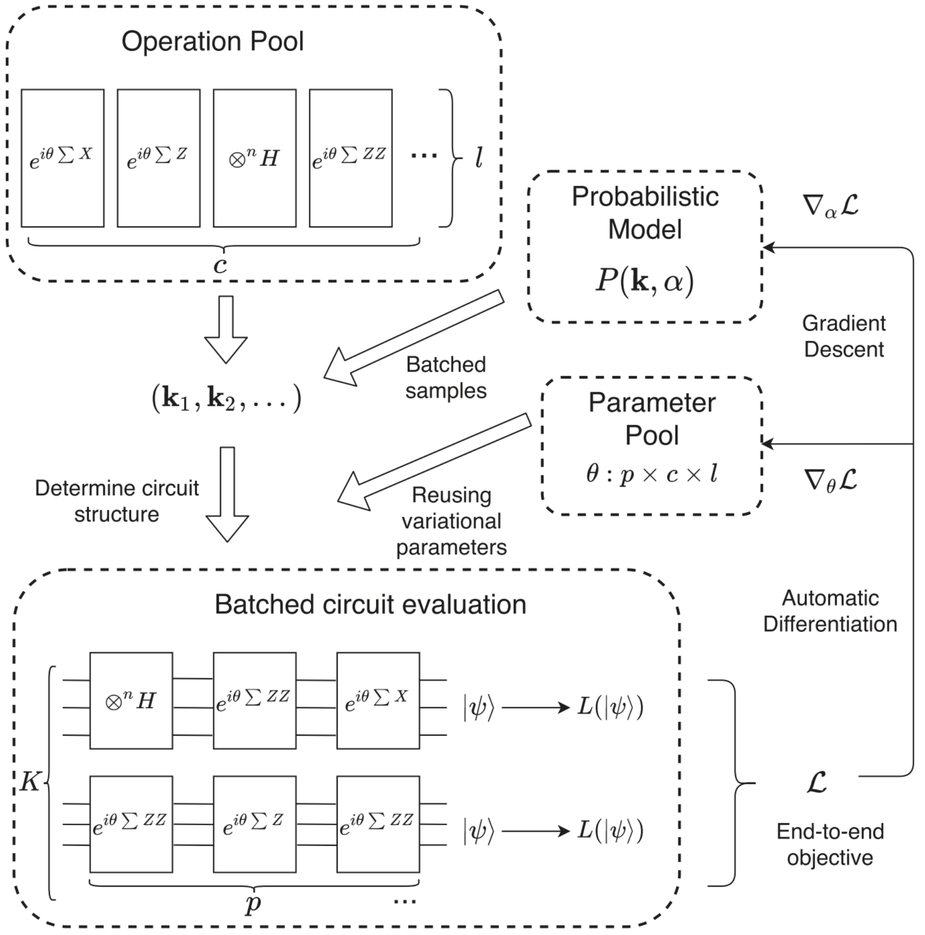
RL for Architecture Search



Quantum Architecture Search via Deep Reinforcement Learning

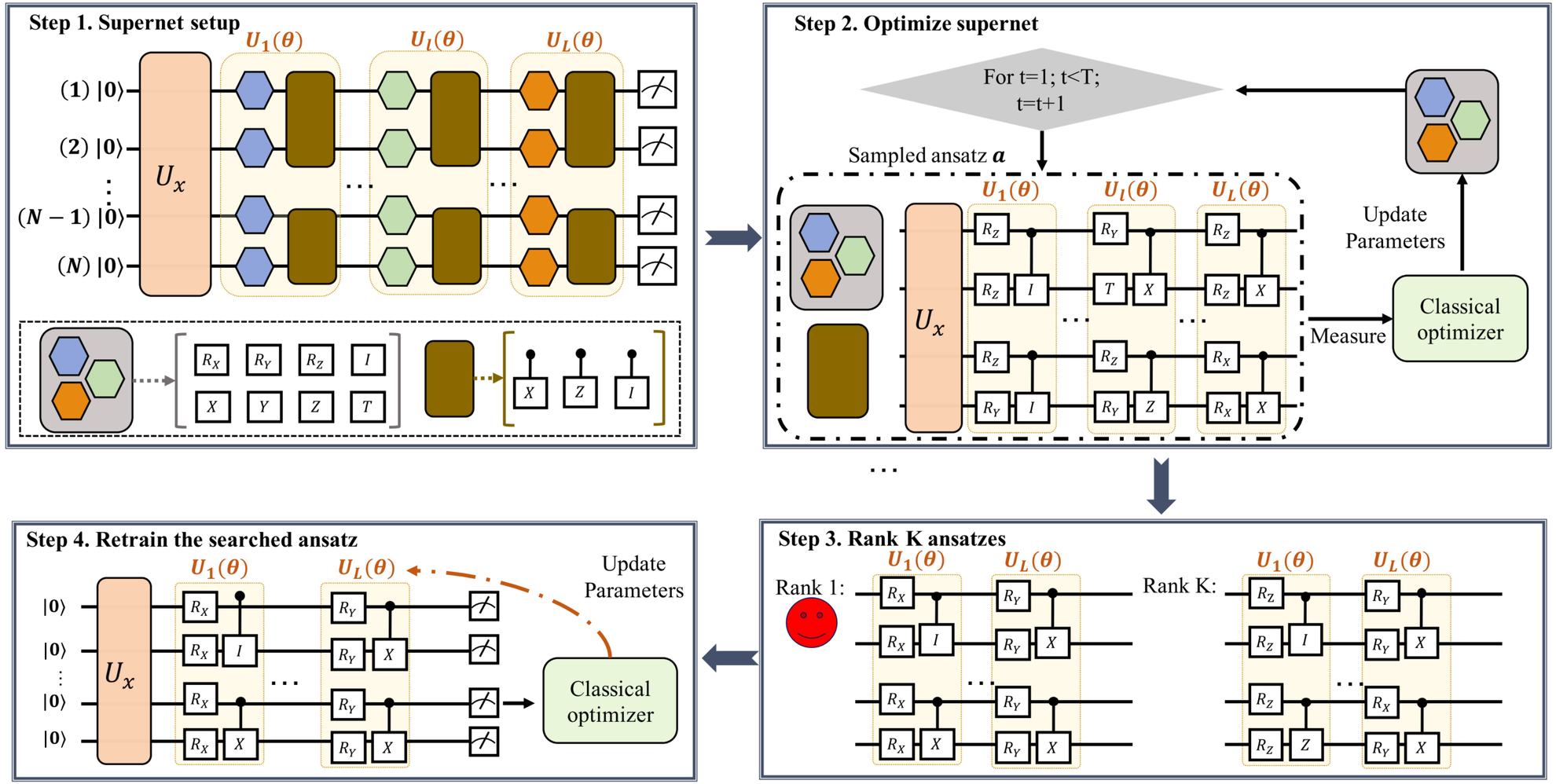
Other Search Frameworks

Differentiable Search



Differentiable quantum architecture search

Other Search Frameworks



Quantum circuit architecture search for variational quantum algorithms

Summary of Today's Lecture

- We learned
  - Parameterized Quantum Circuit (PQC)
  - PQC Training
  - Quantum Classifiers
  - Noise Aware On-Chip Training of PQC
  - TorchQuantum Library for QML
  - Robust Quantum Architecture Search