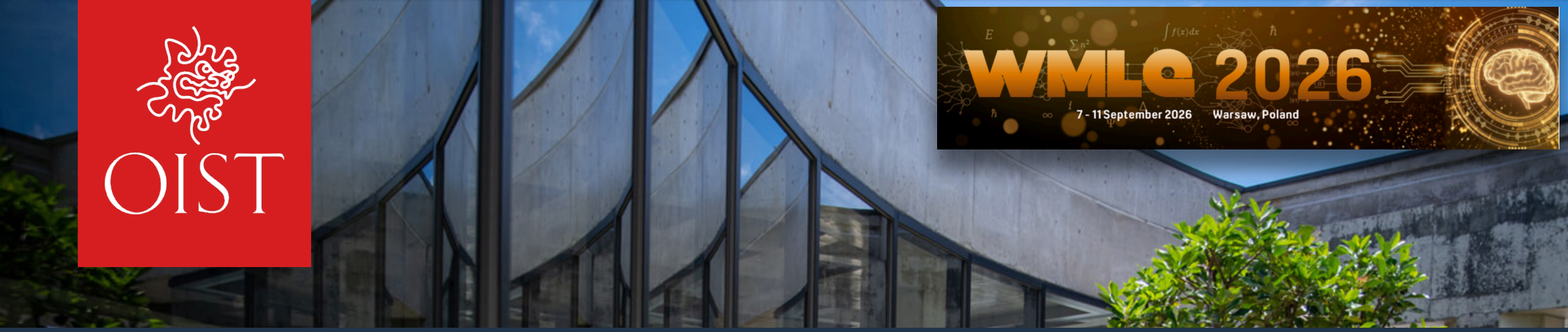
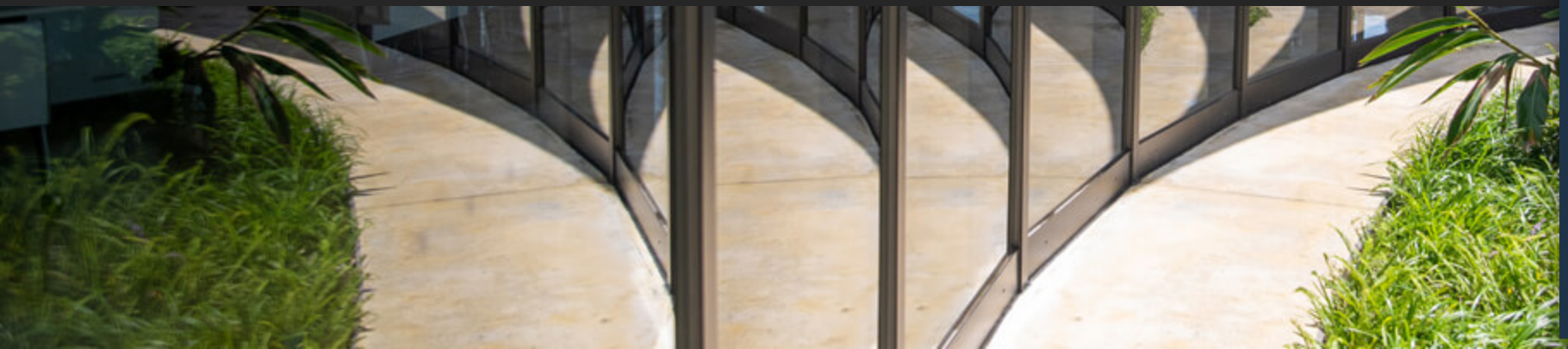


Simple quantum many-body dynamics reservoir for image classification

Akitada Sakurai

Okinawa Institue of Technology and Science (OIST), Japan





Overview of this talk

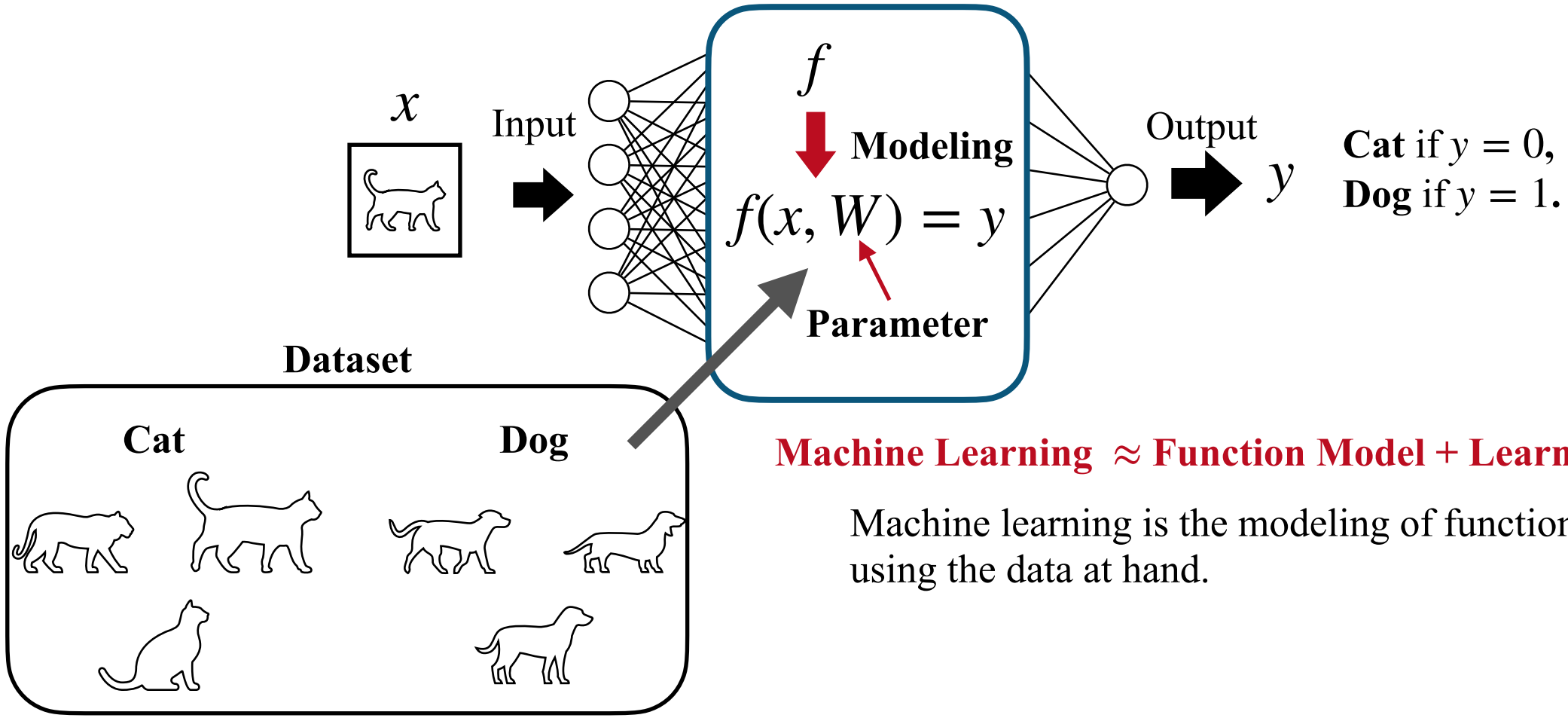
- Introduction
- Quantum Extreme Reservoir Computing
- How much complexity of dynamics is required for a quantum reservoir?
- Summary

Overview of this talk

- **Introduction**
- Quantum Extreme Reservoir Computing
- How much complexity of dynamics is required for a quantum reservoir?
- Summary

Classical machine learning

Before talking about our quantum model, let me share an image to help you understand machine learning and quantum machine learning.

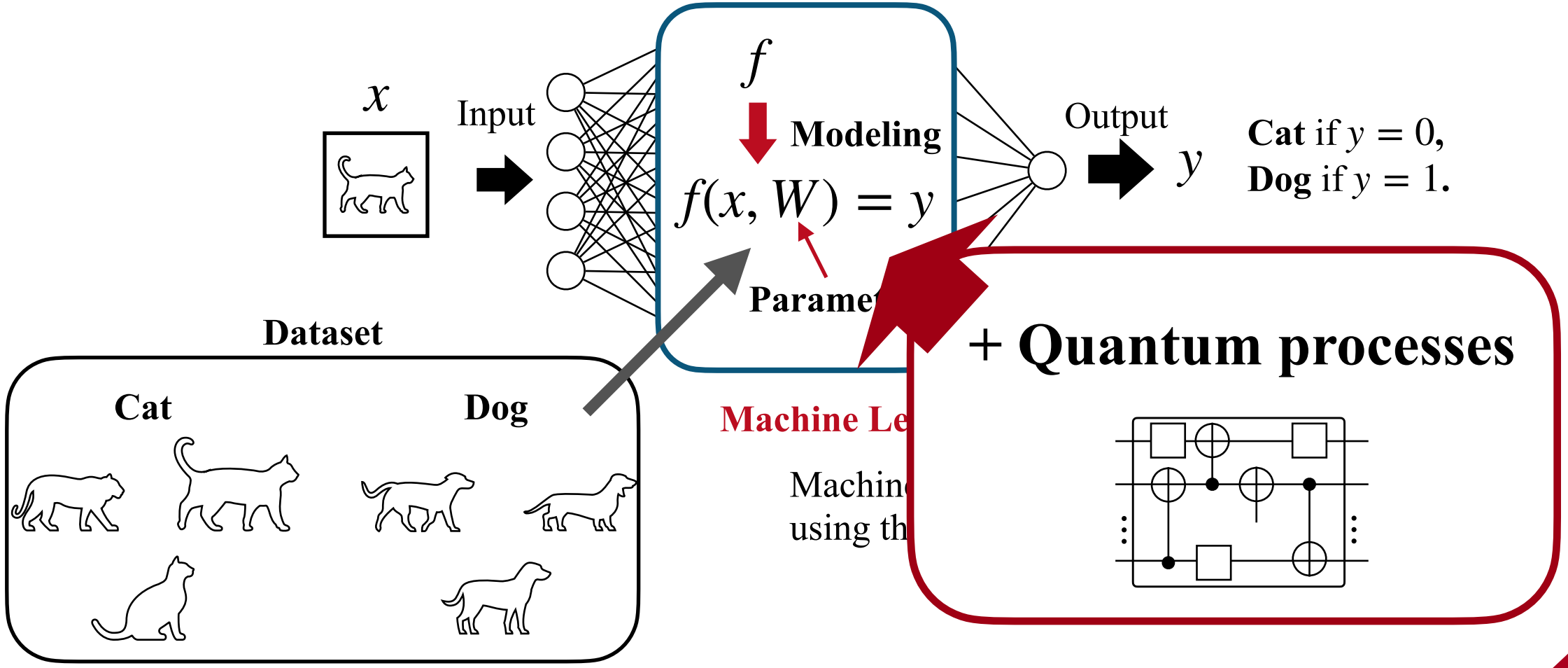


Machine Learning ≈ Function Model + Learning

Machine learning is the modeling of functions using the data at hand.

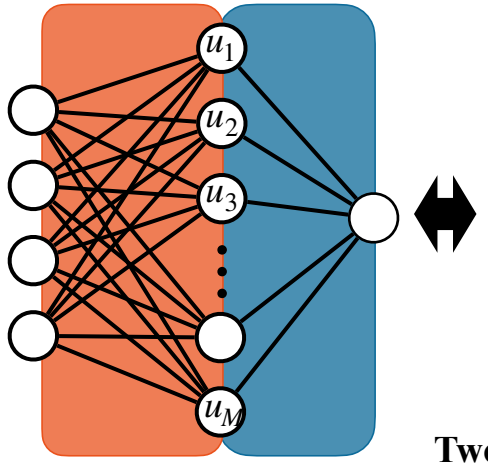
Classical machine learning

Before talking about our quantum model, let me share an image to help you understand machine learning and quantum machine learning.



What is a quantum model?

A famous universal ML model
Two-layer neural network



Feature map

$$f\left(\sum_j \alpha_j x_j\right) = \phi_i(\vec{x})$$

Decision function

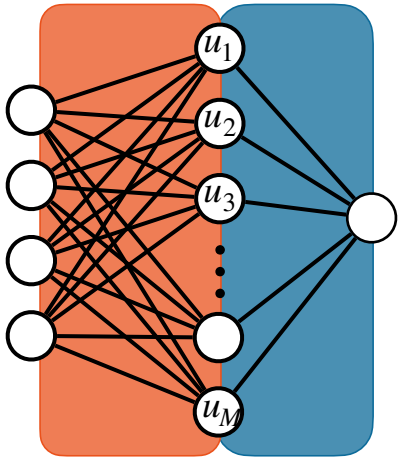
$$\sigma\left(\sum_i W_i \phi_i(\vec{x})\right) = y$$

Two-layer model: optimize both $\vec{\alpha}$ and $\vec{W}$

Random features: optimize $\vec{W}$ only

What is a quantum model?

A famous universal ML model
Two-layer neural network



Feature map | Decision function

Feature map

$$f\left(\sum_j \alpha_j x_j\right) = \phi_i(\vec{x})$$

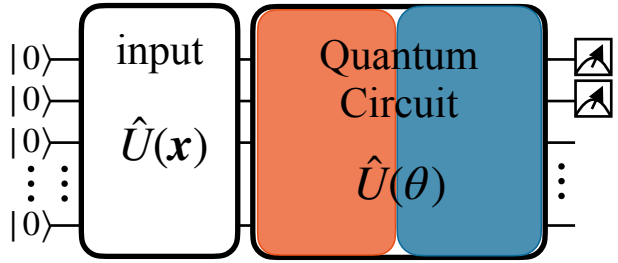
Decision function

$$\sigma\left(\sum_i W_i \phi_i(\vec{x})\right) = y$$

Two-layer model: optimize both $\vec{\alpha}$ and $\vec{W}$

Random features: optimize $\vec{W}$ only

Quantum Circuit Learning(QCL)

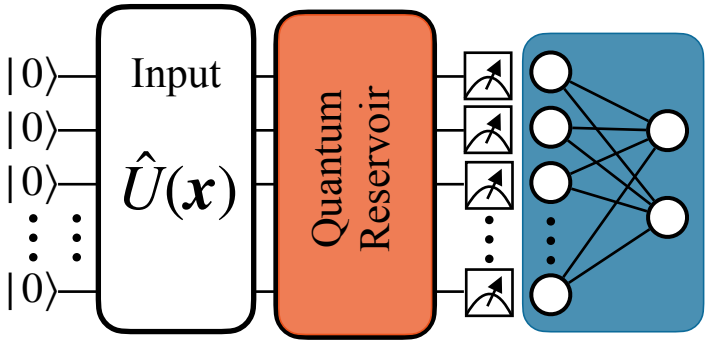


Both the feature map and the decision function run on a quantum processor.

Major bottleneck: Barren Plateau problem

Noise: Effects on training stability.

Quantum Reservoir Computing
& Quantum Extreme Learning Machine

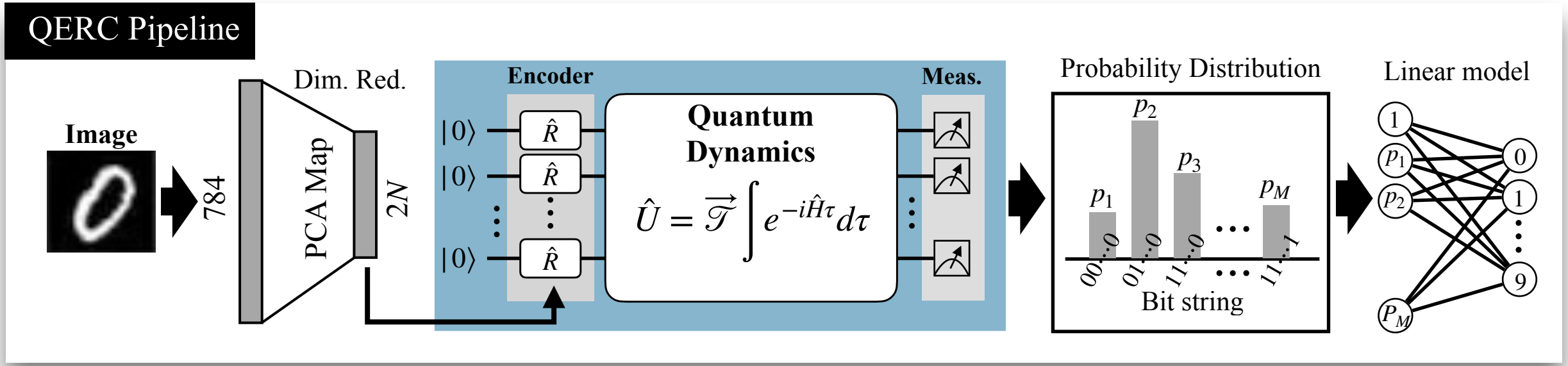


Use a quantum processor for the fixed feature map.

Overview of this talk

- Introduction
- **Quantum Extreme Reservoir Computing**
- How much complexity of dynamics is required for a quantum reservoir?
- Sampling cost in QERC
- Summary

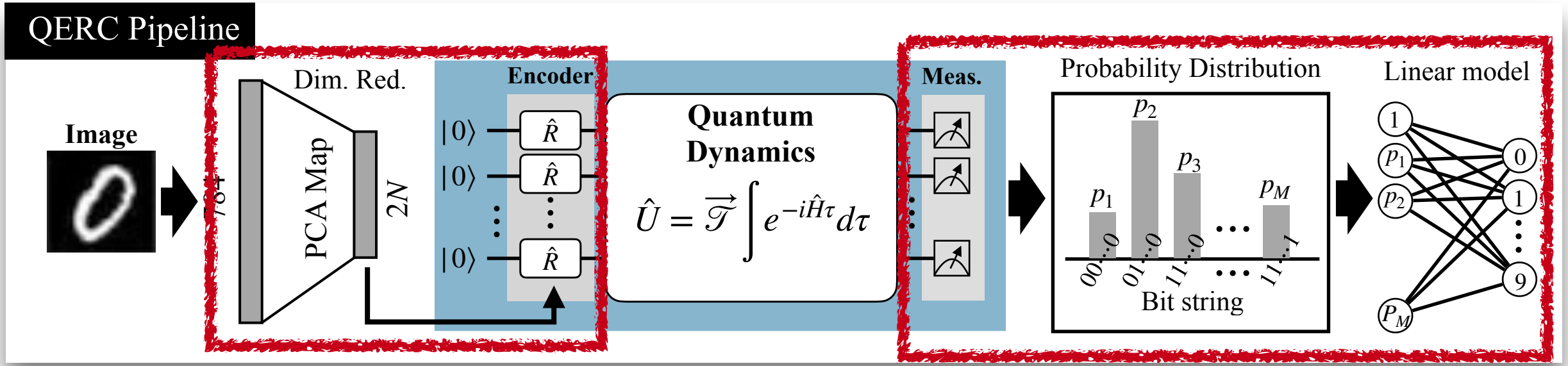
QERC: Quanum Exterem Reservoir Computation



	# of Qubits		# of Features
Quantum Processor:	N	⟶	2^N
Random feature:	$\log_2 M$	⟶	M

"Quantum Extreme Reservoir Computation Utilizing Scale-Free Networks", Phys. Rev. Applied **17**, 064044 (2022).

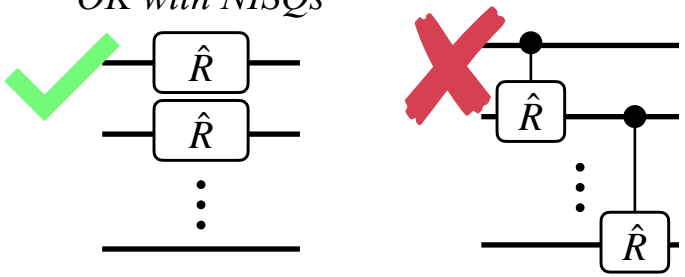
QERC: Quanum Exterem Reservoir Computation



Efficient Data Processing & Encoding

- **PCA** Preprocessing: Reduce dimensionality of large inputs (e.g., images).
- **Simplified Encoding:** Use rotation gates only.

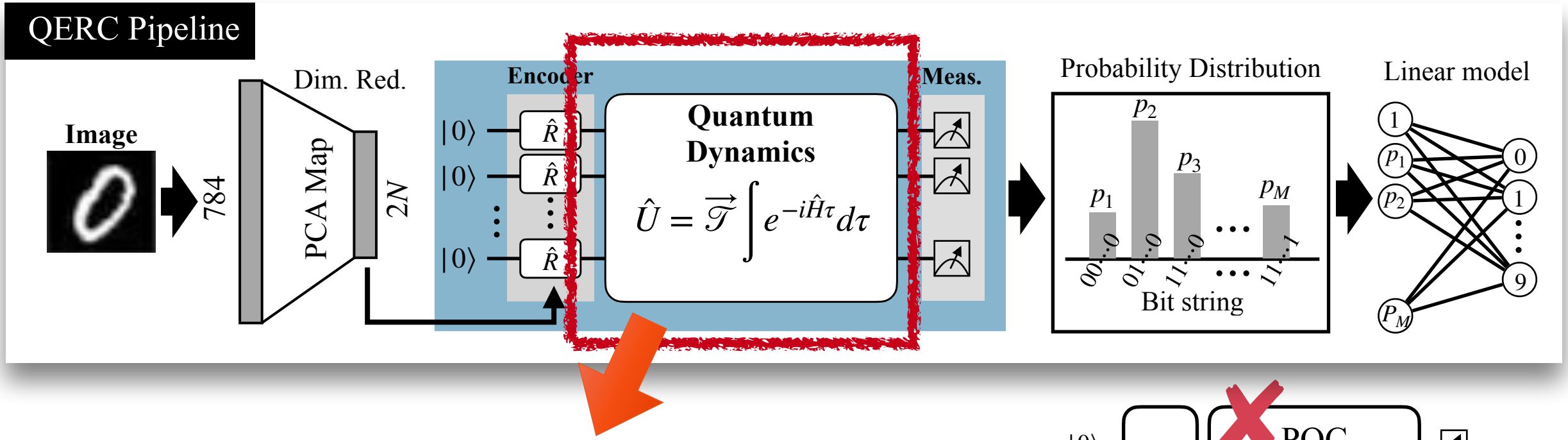
OK with NISQs



Reaout & Post-processing

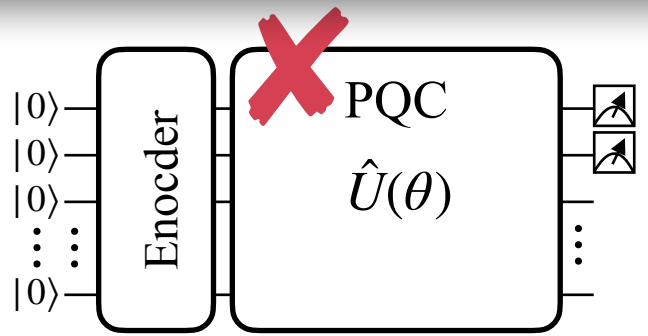
- **Measurement**: Probability distribution in computational basis.
- **Classical Labeling:** Map results via a simple classical model (Linear model).

QERC: Quanum Exterem Reservoir Computation



Use a given **quantum dynamics (processing)** without optimization

But what kind of quantum dynamics are good for ML?

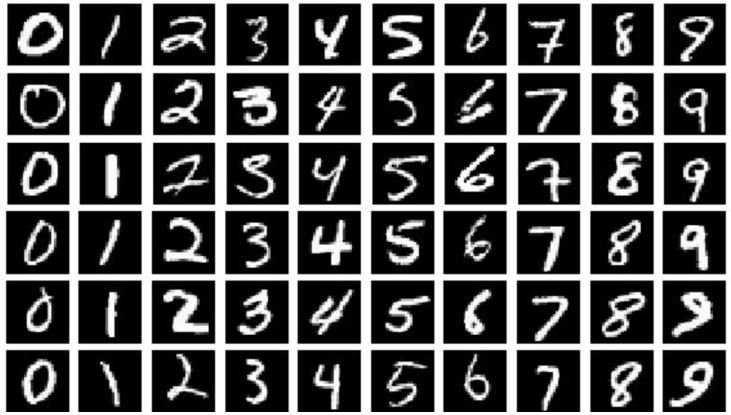


Optimization: Barren Plateau problem (Stop Traning)
Noise: Effects on training stability.

1. J. R. McClean et.al., Nat. Commun. **5** eid 4213 (2014)
2. Z. Holmes et al., PRX Quantum **3** 010313 (2022)

Experiment setup and baseline

Dataset: MNIST dataset



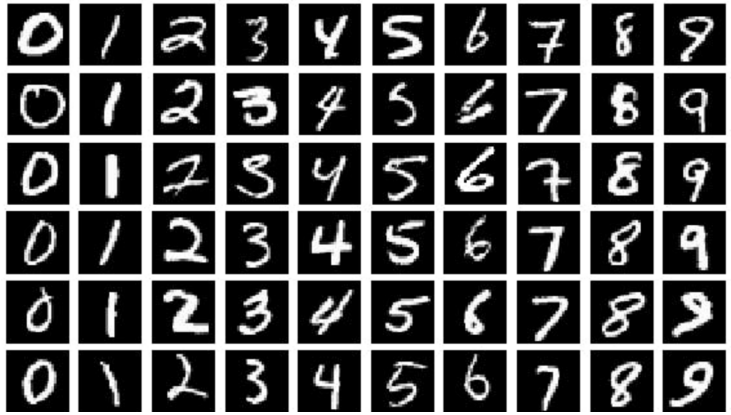
28  ~800 pixels

28

Total # of images: 70,000
For training: 60,000
For testing: 10,000

Experiment setup and baseline

Dataset: MNIST dataset

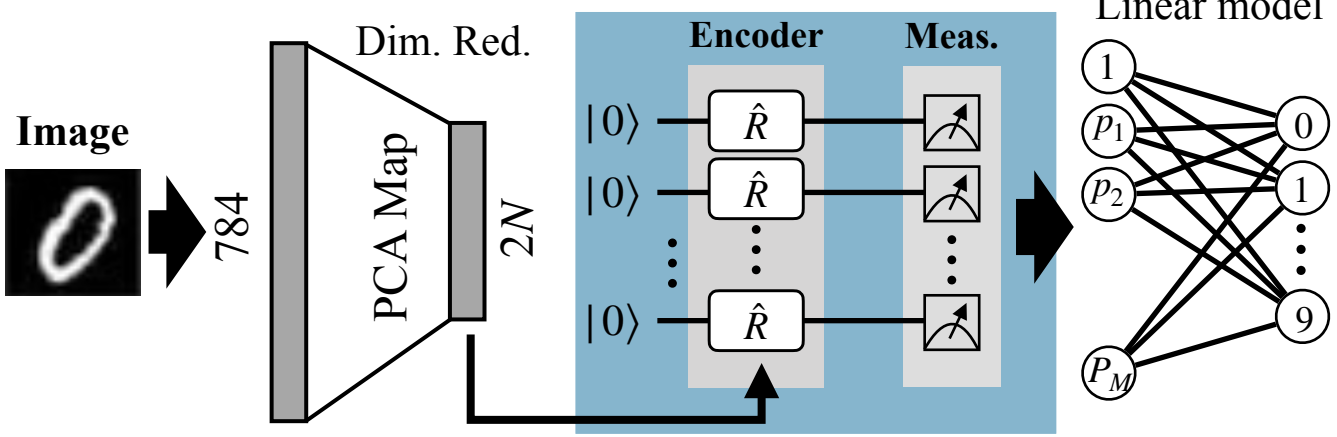


28  ~800 pixels

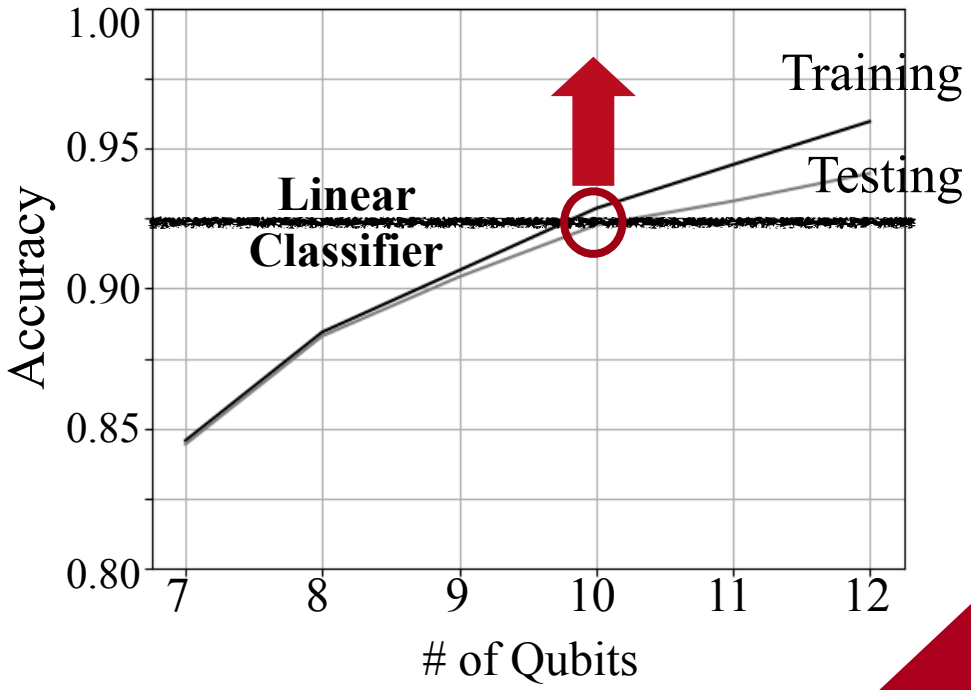
28

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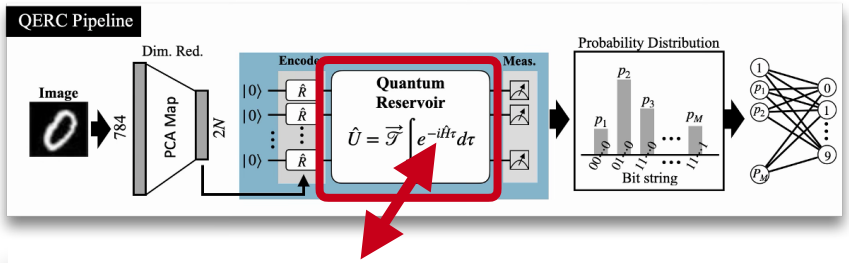
QERC without Quantum Dynamics



We expect gain from quantum dynamics



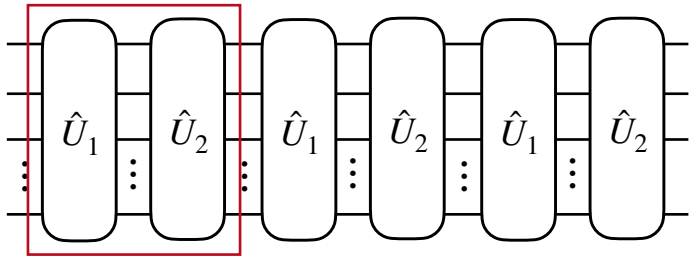
Our basemodel: Quantum Extreme Reservoir Computing (QERC)



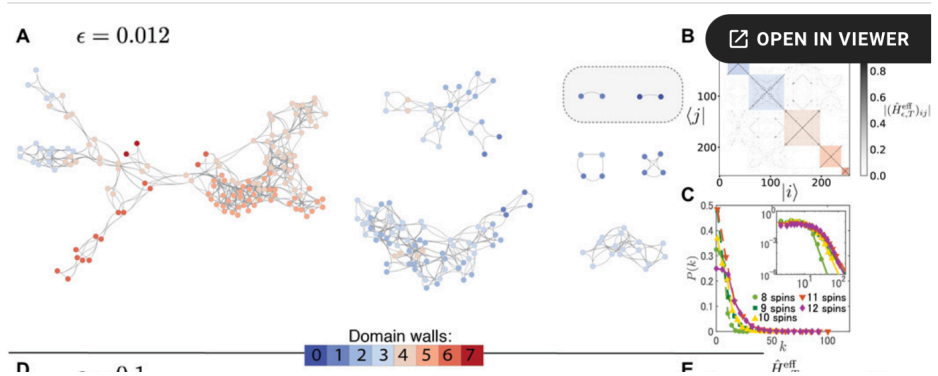
Quantum Dynamics：2T-Discret Time Crystal Model:

(Time-periodic Hamiltonian dynamics)

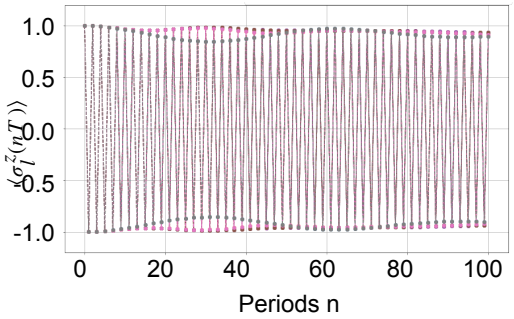
$$\hat{H}(t) = \begin{cases} \hat{H}_1 = \frac{\pi\hbar}{2T_1} \sum_l (1-\epsilon)\sigma_l^x & 0 \le t < T_1 \\ \hat{H}_2 = \hbar \sum_m \frac{J_0^z}{|l-m|^\alpha} \sigma_l^z \sigma_m^z & T_1 \le t < T_1 + T_2 \end{cases}.$$



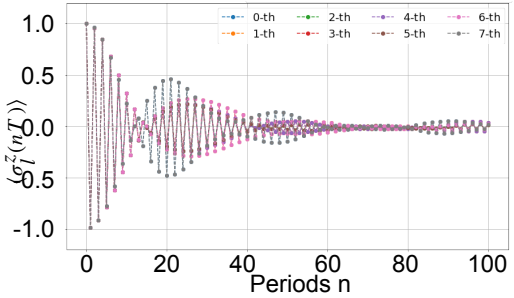
One period



$\epsilon = 0.01$



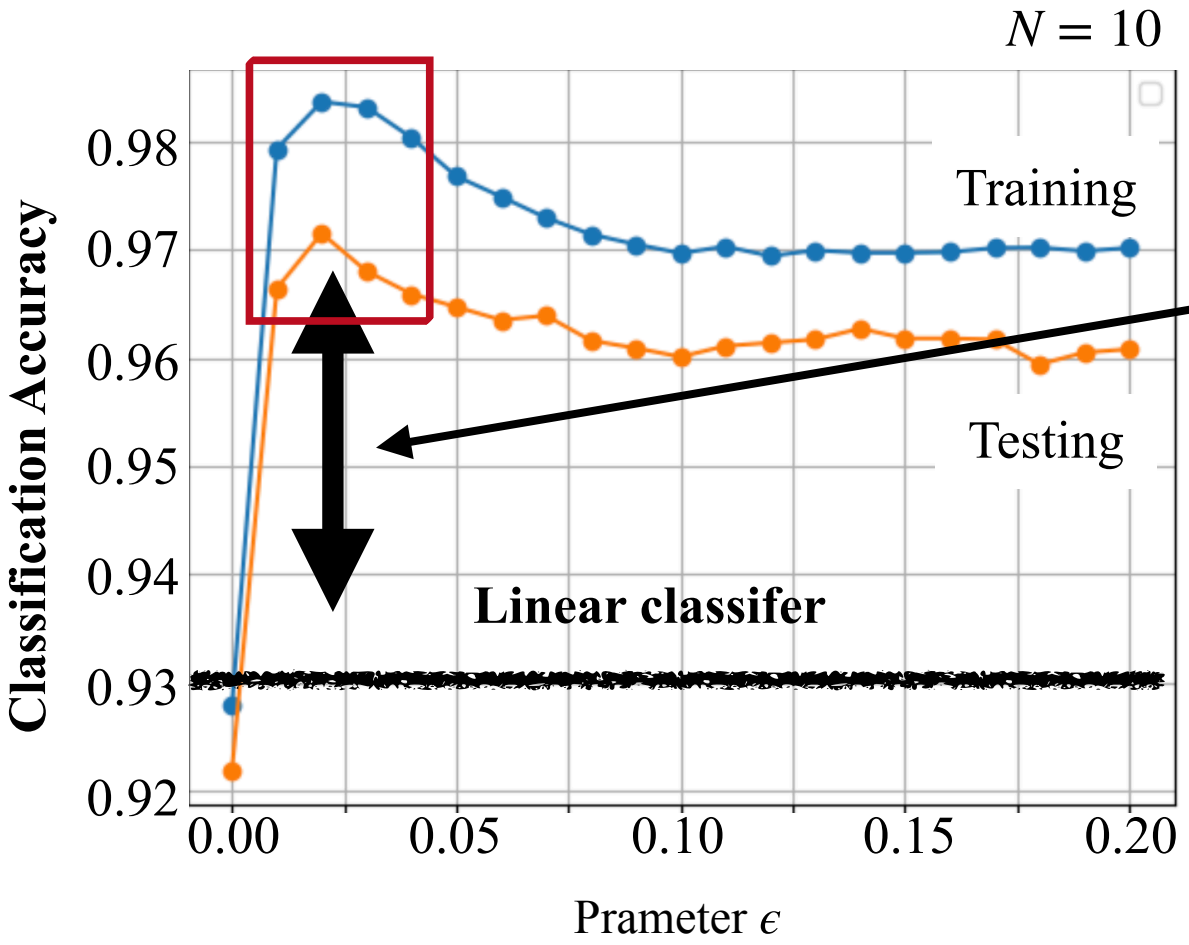
$\epsilon = 0.05$



- **Demonstration** has been achieved on NISQ devices.
- In 2019, a complex network space inside 2T-DTC was demonstrated, making it a candidate for a sufficiently complex reservoir.

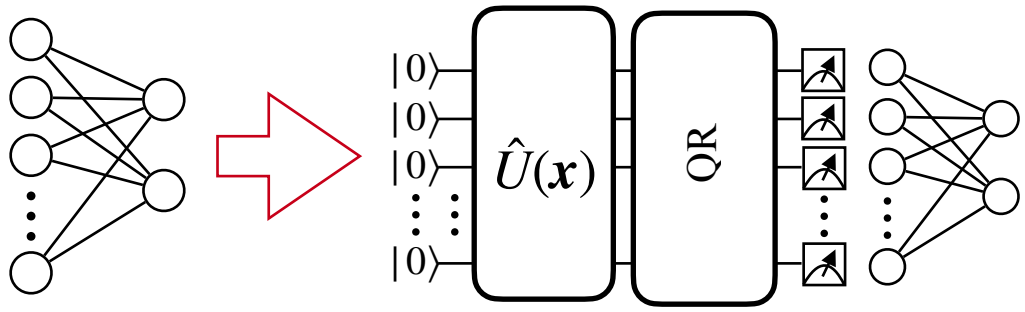
QERC: Benchmark Results

MNIST classification with 2-DTC



$J_0^z T = 0.06$, $\alpha = 1.51$ and $nT = 100$

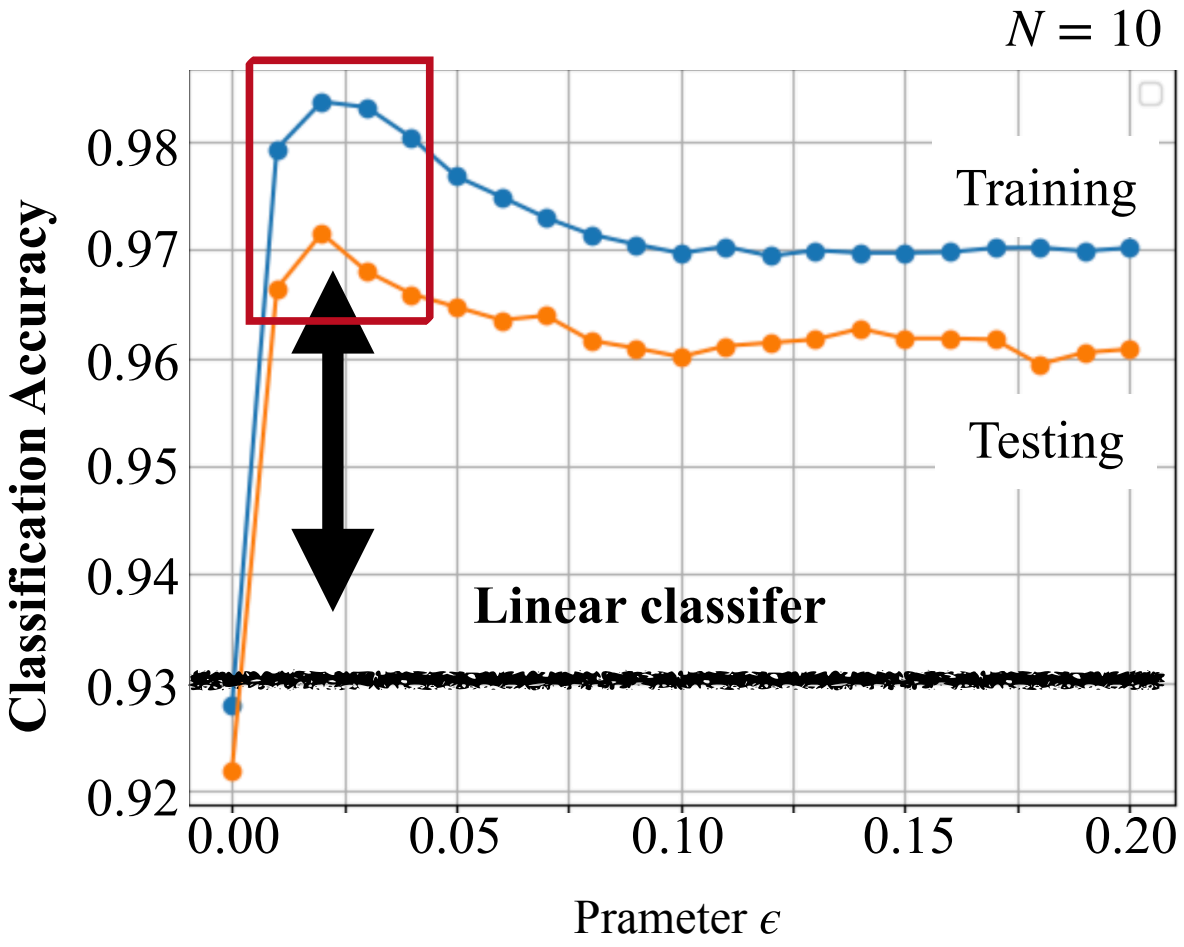
Quantum reservoirs have enhanced the performance of linear classifiers.



Test:~0.93 **Test:~0.97**

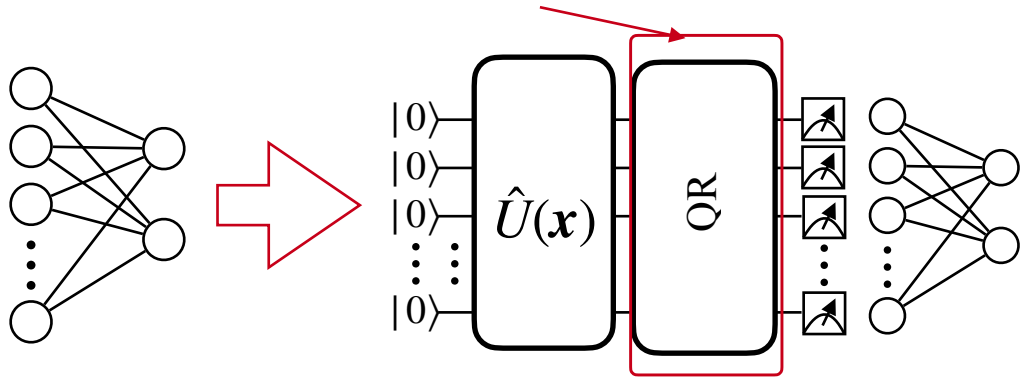
QERC: Benchmark Results

MNIST classification with 2-DTC



$J_0^z T = 0.06$, $\alpha = 1.51$ and $nT = 100$

Can more complex quantum systems achieve higher performance?



Test:~0.93 **Test:~0.97**

What quantum dynamics is required to achieve quantum advantages?

Overview of this talk

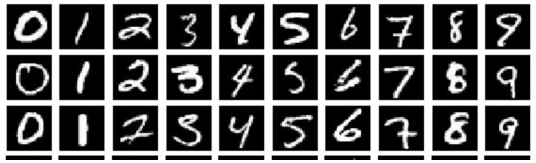
- Introduction
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The complexity required for quantum reservoirs

Base system (2T-DTC)

$$\hat{H}(t) = \begin{cases} \hat{H}_1 = \frac{\pi\hbar}{2T_1}\sum_l (1-\epsilon)\sigma_l^x & 0 \le t < T_1 \\ \hat{H}_2 = \hbar\sum_m \frac{J_0^z}{|l-m|^\alpha}\sigma_l^z\sigma_m^z & T_1 \le t < T_1 + T_2 \end{cases}.$$

The MNIST classification problem was fixed, and various reservoirs were tested.



Base system (2T-DTC)

Train: 0.99
Test: 0.97

More complex quantum systems

Random unitary: $\hat{U} \sim \mu_H$

OK, but DTC is enough!

Train: 0.99
Test: 0.97

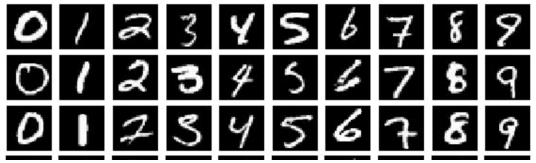
Haar's performance is comparable to DTC.

The complexity required for quantum reservoirs

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Test: 0.97

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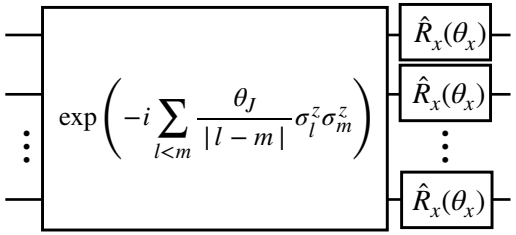
Train: 0.99
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Haar's performance is comparable to DTC.

Does a simple quantum dynamics work? *Works!*

Ising-model: $\hat{H} = \hbar\sum_{l,m}\frac{J_0}{|l-m|^\alpha}\sigma_l^z\sigma_m^z - \hbar g\sum_l \sigma_l^x$

ZZX-Model:



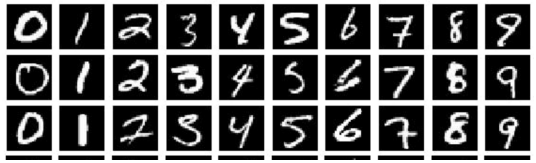
Train: 0.99
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The complexity required for quantum reservoirs

Base system (2T-DTC)

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The MNIST classification problem was fixed, and various reservoirs were tested.



Base system (2T-DTC)

Train: 0.99
Test: 0.97

More complex quantum systems

OK, but DTC is enough!

Random unitary: $\hat{U} \sim \mu_H$

Train: 0.99
Test: 0.97

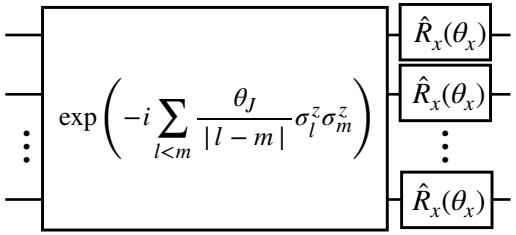
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ZZX-Model:



Train: 0.99
Test: 0.97

Can we further simplify the dynamics?

The complexity required for quantum reservoirs

Not classically simulatable (Requires a universal gate set)

More complex quantum systems *OK, but DTC is enough!*

Random unitary: $\hat{U} \sim \mu_H$

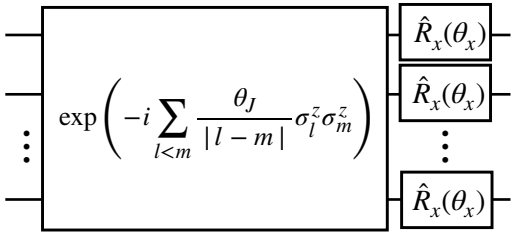
Train: 0.99
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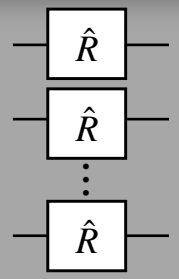
ZZX-Model:



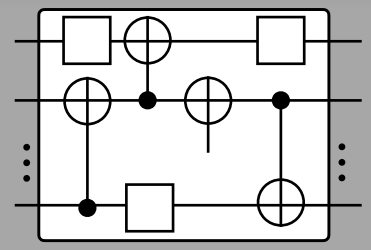
Train: 0.99
Test: 0.97

Efficiently classically simulatable

Random Rotation

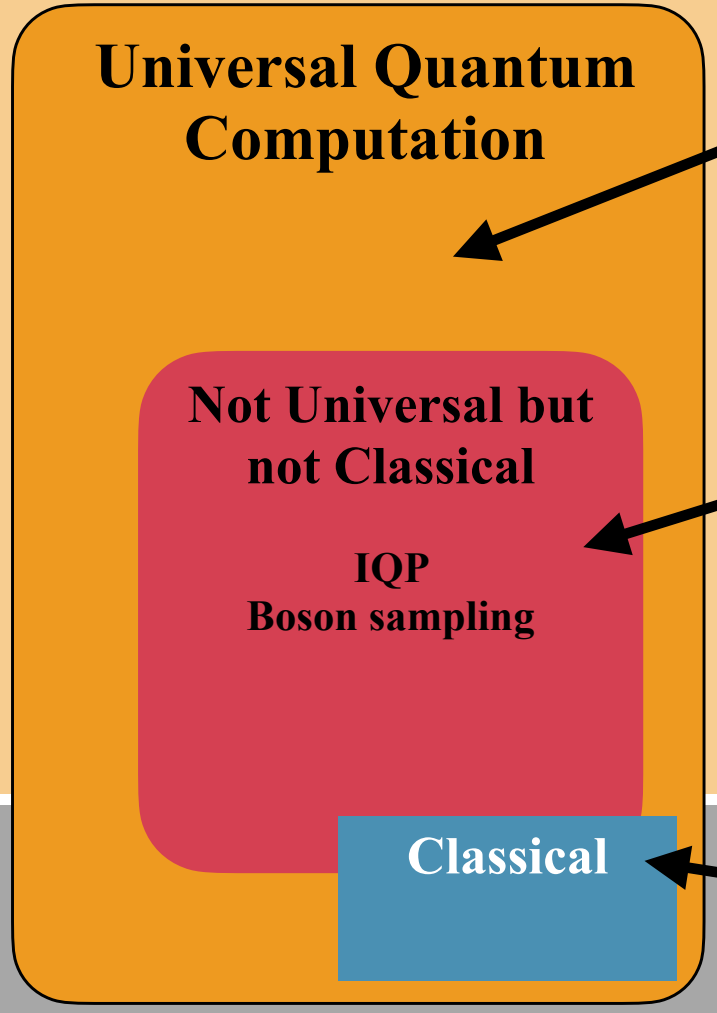


Random Clifford



Not!
Train: < 0.90
Test: < 0.80

The complexity required for quantum reservoirs



More complex quantum systems *OK, but DTC is enough!*

Random unitary: $\hat{U} \sim \mu_H$

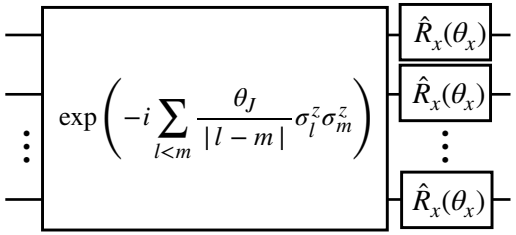
Train: 0.99
Test: 0.97

Haar's performance is comparable to DTC.

Does a simple quantum dynamics work? *Works!*

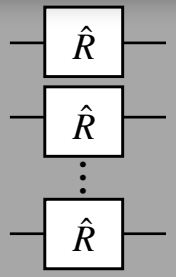
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ZZX-Model:

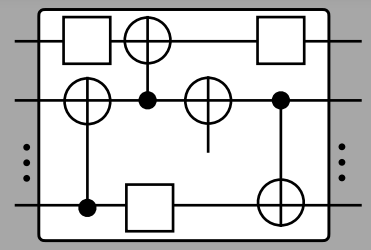


Train: 0.99
Test: 0.97

Random Rotation



Random Clifford



Not!
Train: < 0.90
Test: < 0.80

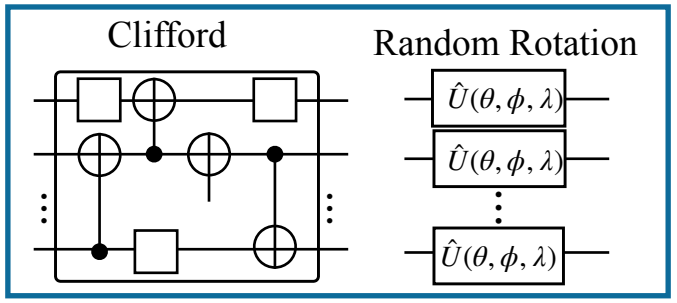
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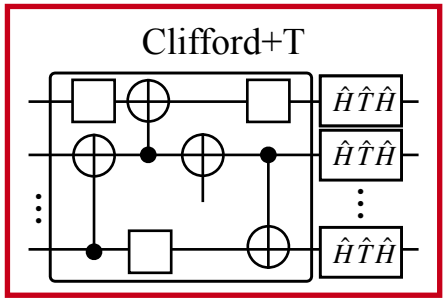
Conclusion: What is next?

- Even with a small number of qubits, it is possible to solve image classification problems.
- The model's performance is highly correlated with quantum complexity.

Why are these reservoirs not good?



Why is the single T-gate layer enough?



Train: 0.99
Test: 0.97

Why are both entangling gates and T-gates necessary, and why this order?

Remaining Challenges in QERC

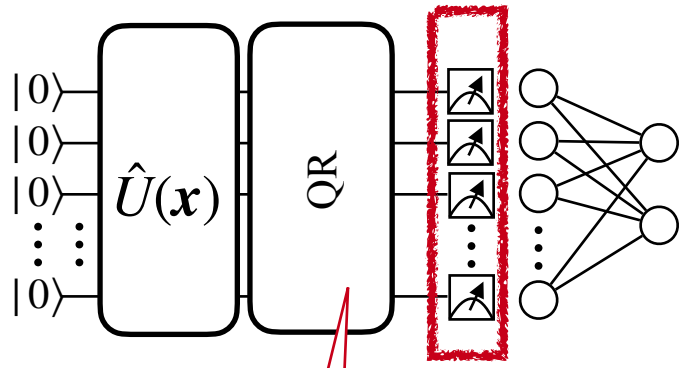
- **Sampling Cost Issues**:
  - **Can we improve the cost?** → Exploring Quantum Annealing.
- **Understanding Dynamics:**
  - What level of complexity is actually required?
  - **Why is a T-gate layer necessary?**

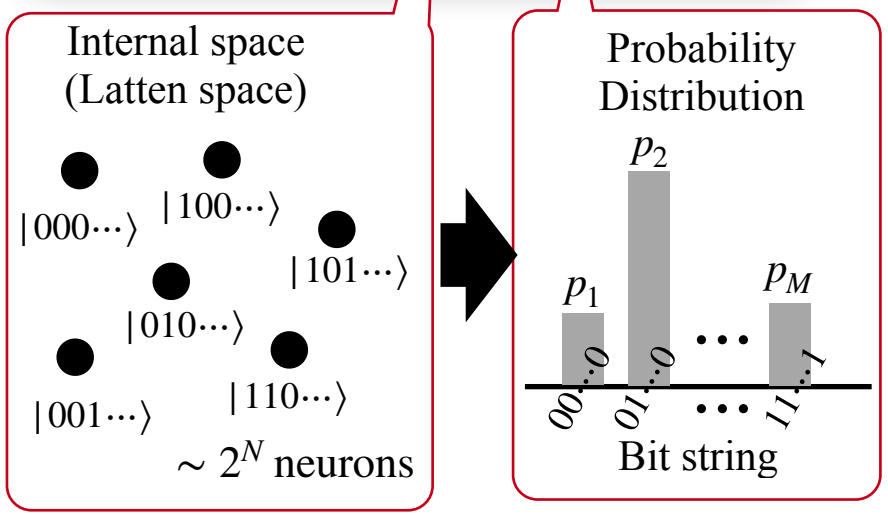


Thank you!

Measurement cost of QERC: Conventional thinking

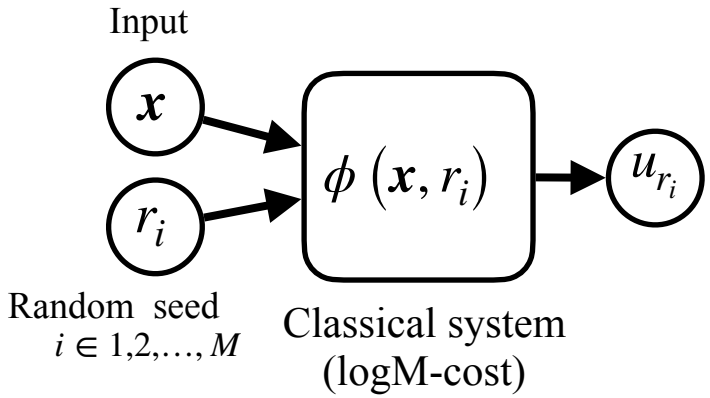
QERC Pipeline





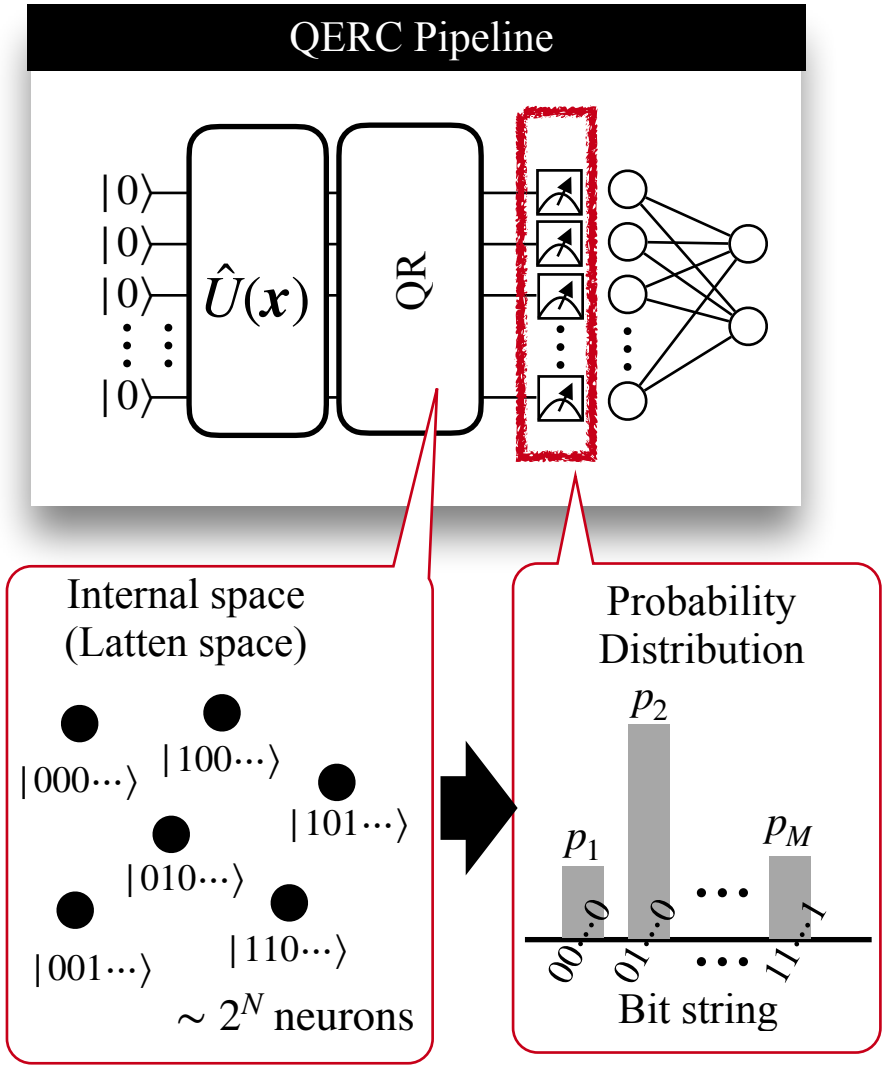
Q. Is the cost of measurement (readout) **exponential**?

Classical Implementation (Possibility)



Generate a mapping by applying the classical system M times

Measurement cost of QERC: Quadratic speedup



Q. Is the cost of measurement (readout) **exponential**?

What Machine Learning Models Essentially Need

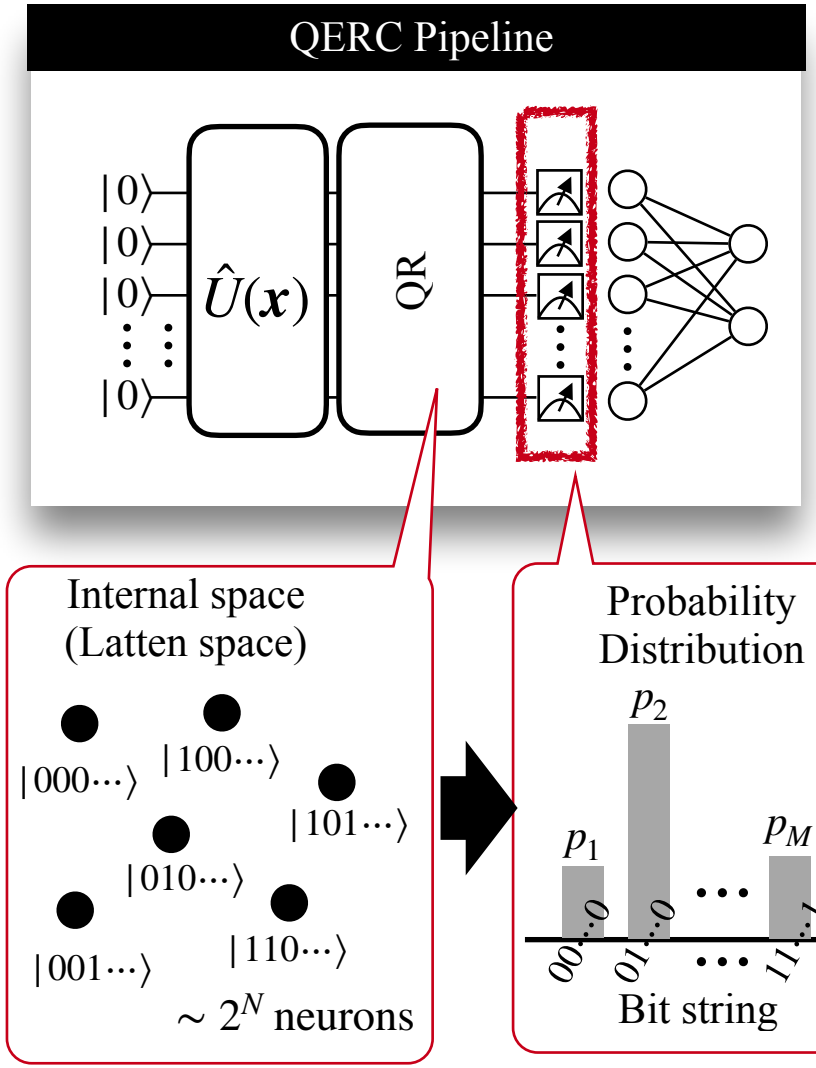
NOT: Estimating the entire probability distribution

BUT: Estimating **a specific scalar quantity** derived from it

Breaking the Measurement Cost Bottleneck

- Complete distribution estimation → its cost is about M.
- Target scalar estimation → its cost is about $\sqrt{M}$.

Measurement cost of QERC: Quadratic speedup



Q. Is the cost of measurement (readout) **exponential**?

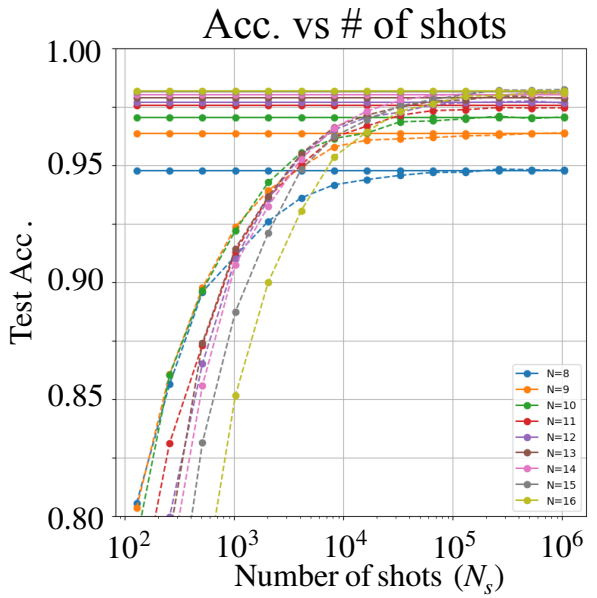
What Machine Learning Models Essentially Need

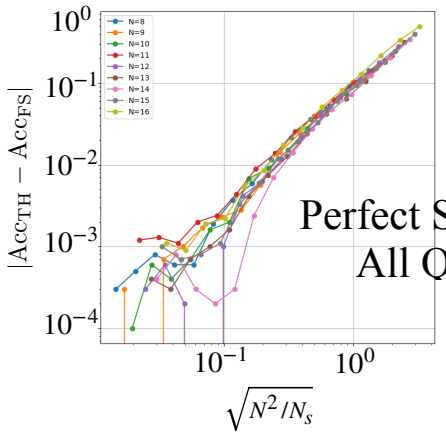
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Perfect Scaling Across All Qubit Sizes.

Promising a significant and drastic reduction in future measurement costs.