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Quantum Denoising Diffusion Probabilistic Models for Image Generation

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Outline

I. Introduction

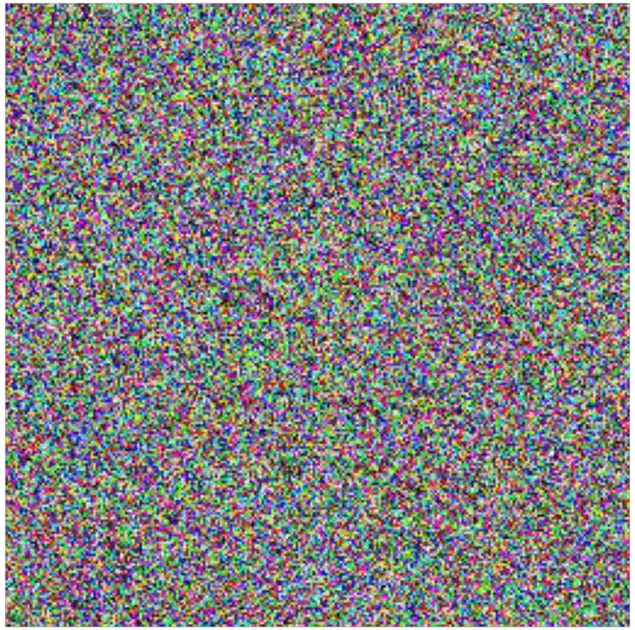
II. Preliminaries

III. Proposed Methods

IV. Experimental Setup and Results

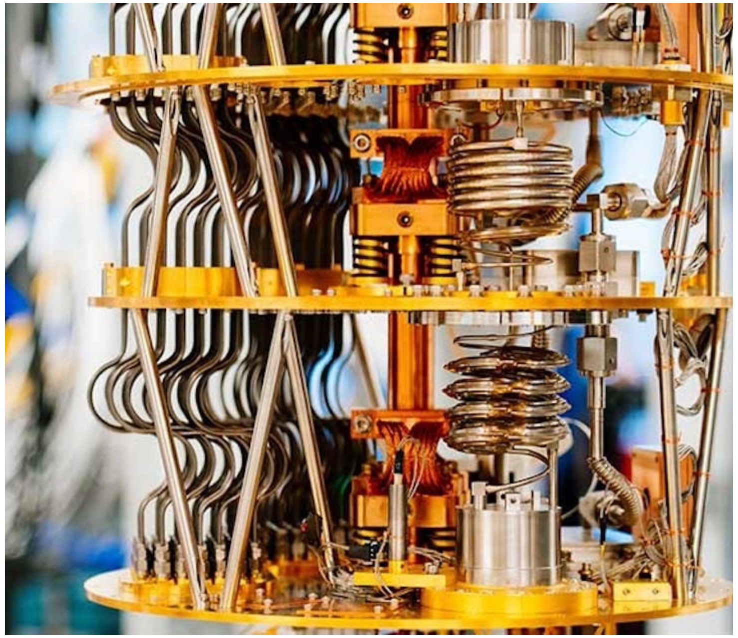
V. Conclusion

Quantum Diffusion Models



Animation of CIFAR-10 samples generated from noise by a diffusion model

+



Google's Quantum Computer

- Diffusion Models + Quantum Computing
  - To the best of our knowledge, this is the first attempt to apply quantum computing to diffusion model for image generation

I. Introduction

- **Quantum Computing**
- **Quantum Machine Learning**

Quantum Computing

- What is Quantum Computing?

Superposition

Classical physics

Heads or Tails
0 or 1

Quantum physics

Heads and Tails
0 and 1

Entanglement

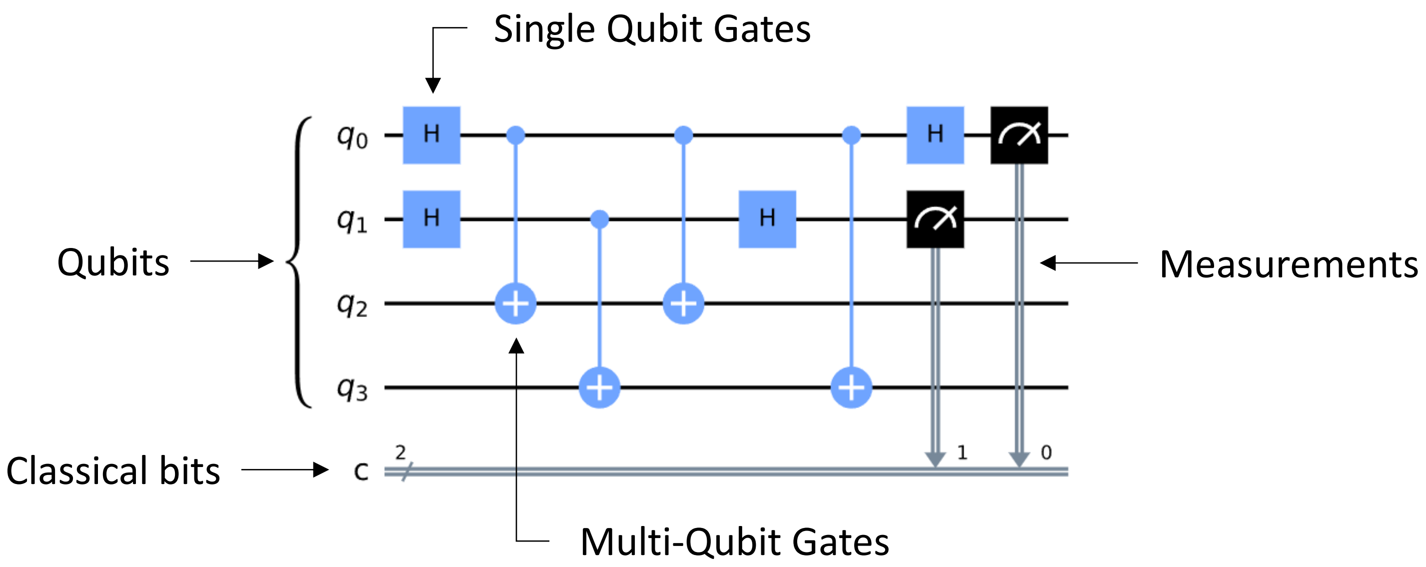
Quantum physics

The two qubits can no longer be treated separately

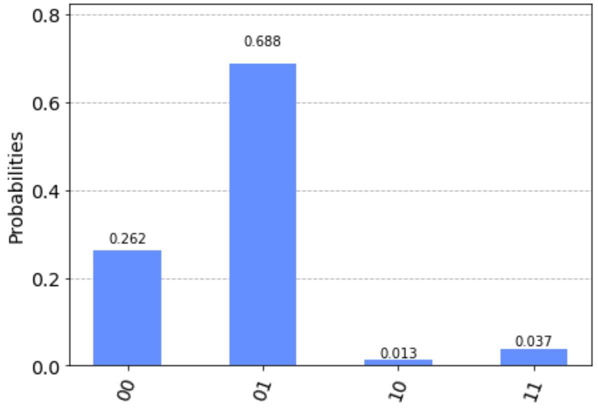
- Quantum Computing
  - Use quantum phenomena such as superposition and entanglement to perform computation
  - Can achieve exponential speed-ups for complex problems (e.g., Shor’s factoring algorithm)

Quantum Computing

- Quantum Circuits (≈ Quantum Algorithms)



Probability Distribution

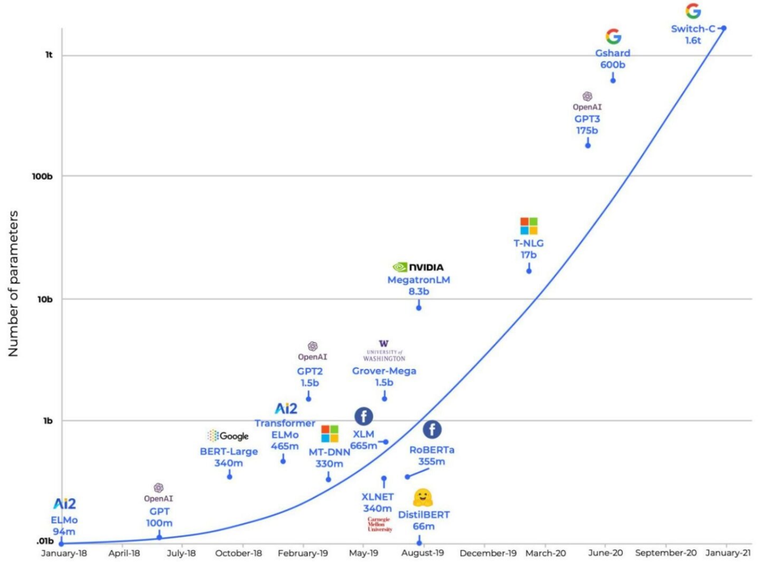


After the measurement, quantum state collapses to the basis state probabilistically

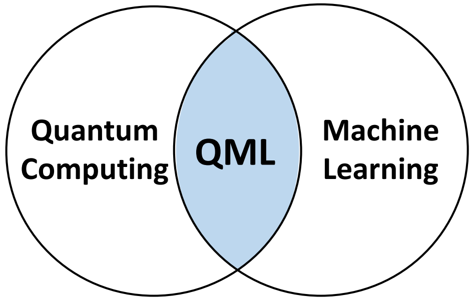
- Quantum Gate
  - Operators on qubits, analogous to logic gate in classical circuit
- Quantum Circuit
  - Sequence of quantum gates, measurements, initializations of qubits

Quantum Machine Learning

- Why Quantum for Machine Learning?

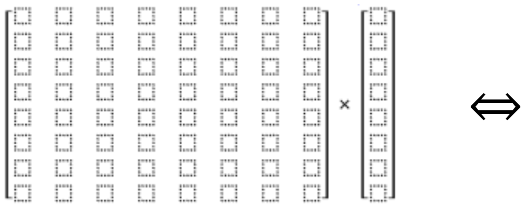


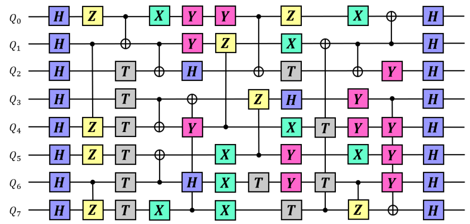
Exponential growth of number of parameters
in classical machine learning models



$2^N \times 2^N$ **Matrix Multiplication**

N-Qubit Quantum Circuit

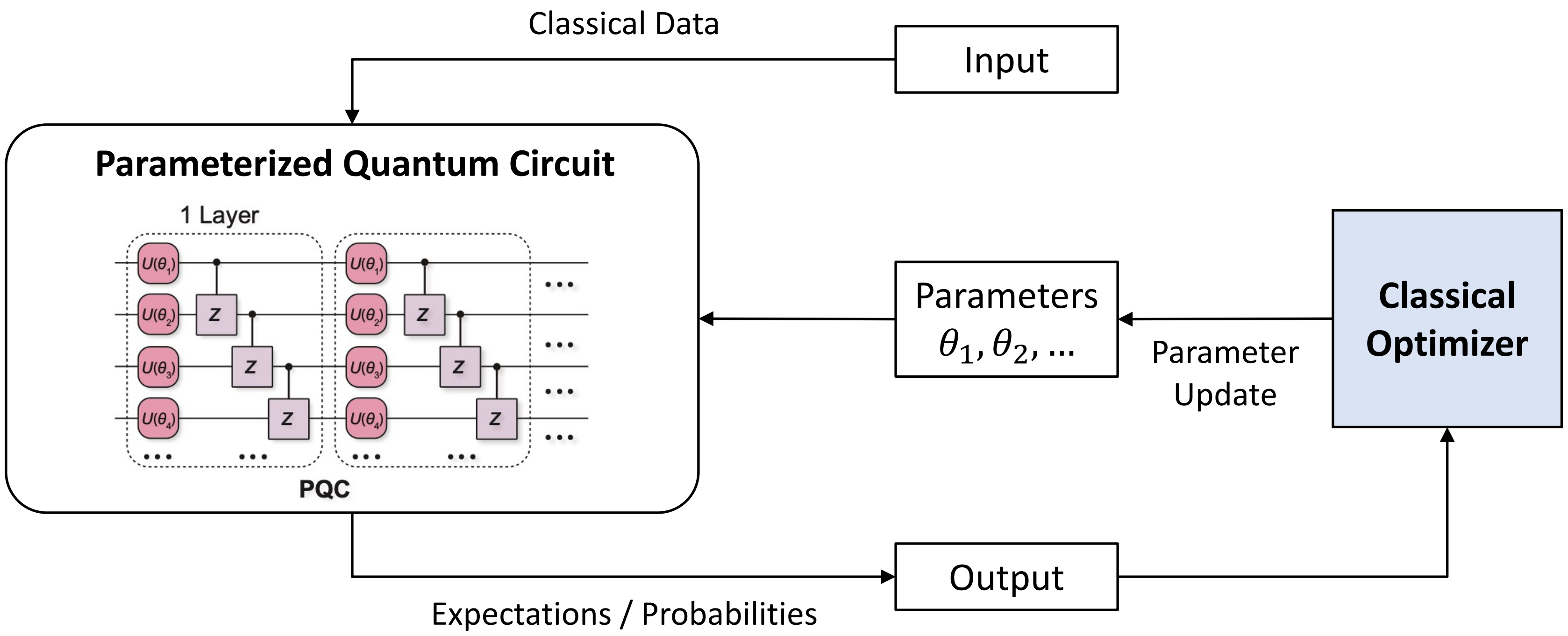




- Quantum Machine Learning
  - ➢ Using quantum algorithms to improve existing machine learning techniques
  - ➢ Offering potential advantages of enhanced performance and reduced computational resources

Quantum Machine Learning

- Parameterized Quantum Circuits



- Parameterized Quantum Circuits (PQCs)
  - ➢ Quantum circuits which contain the parameterized quantum gates
  - ➢ Parameters are trained by a classical optimization algorithms

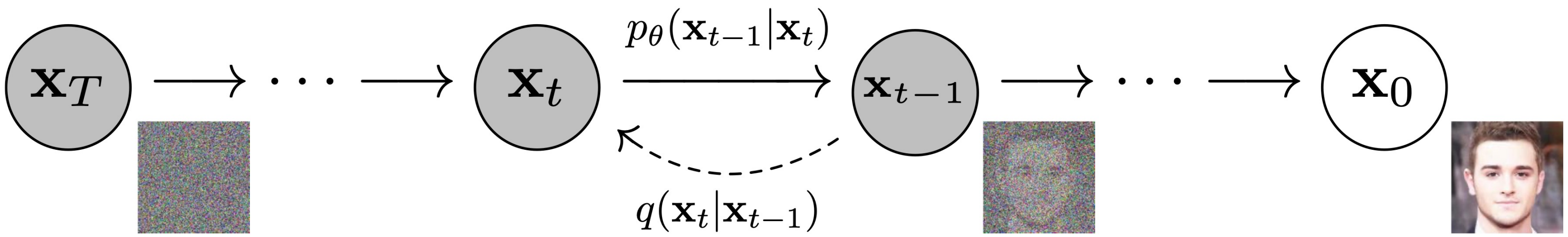
II. Preliminaries

- **Denoising Diffusion Probabilistic Models (Classical)**

Diffusion Models

- Denoising Diffusion Probabilistic Models (DDPM)

$p_\theta(\mathrm{x}_{t-1}|\mathrm{x}_t)$: Reverse process



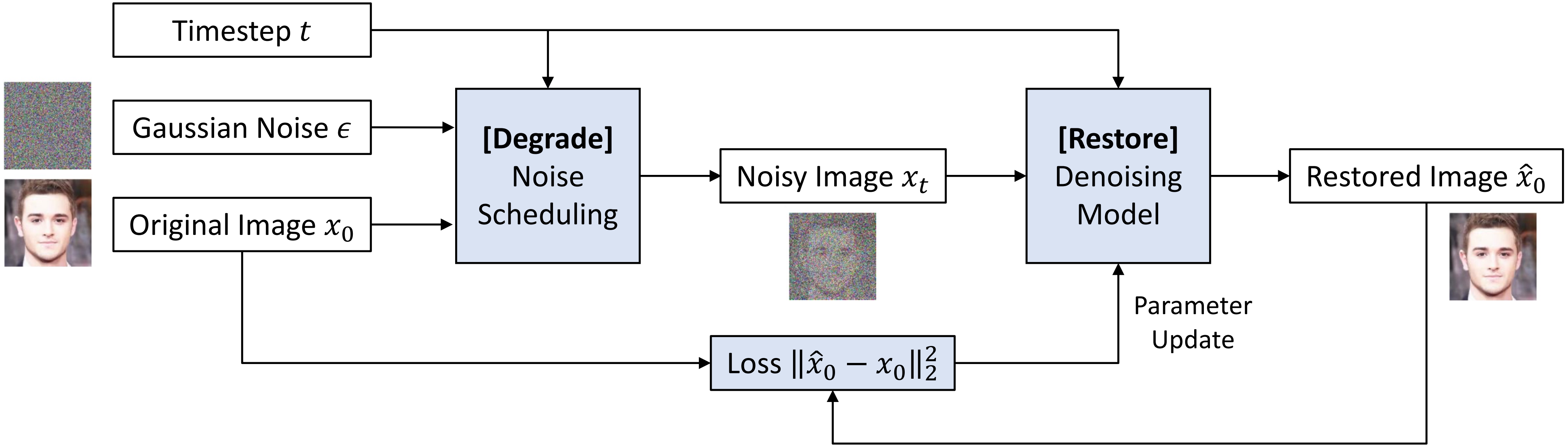
$q(\mathrm{x}_t|\mathrm{x}_{t-1})$: Forward process

- Forward Process (Degrade)
  - Add small amount of Gaussian noise to the sample
- Reverse Process (Restore)
  - Recreate the true sample from a Gaussian noise input

Denoising Diffusion Probabilistic Models, NeurIPS, 2020

Diffusion Models

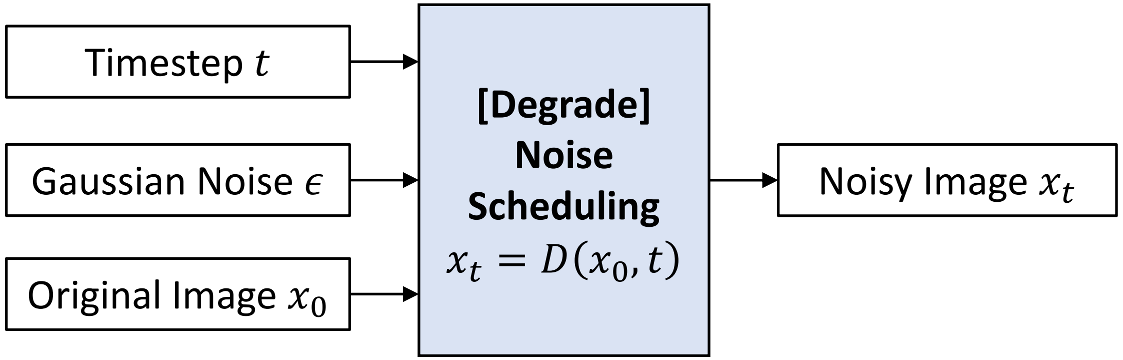
- Model Components and Training



- Forward Process (Degrade)
  - Add small amount of Gaussian noise to the sample
- Reverse Process (Restore)
  - Recreate the true sample from a Gaussian noise input

Diffusion Models

- Noise Scheduling (Degradation)



- Degrade function: $x_t = D(x_0, t)$

  Given beta scheduling: $\beta_1 < \beta_2 < \cdots < \beta_T$

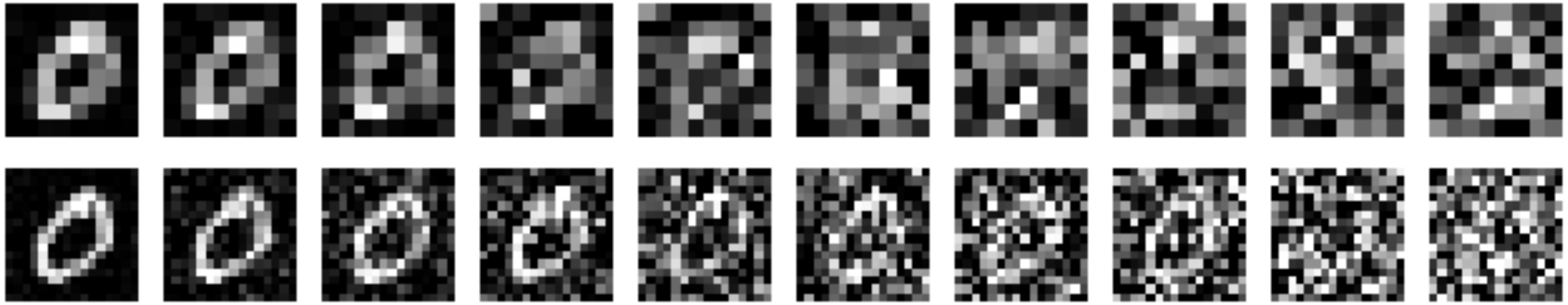
  Let $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{i=1}^{t} \alpha_i$

  Then, $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\boldsymbol{\epsilon}$

Example

8 x 8 image

16 x 16 image

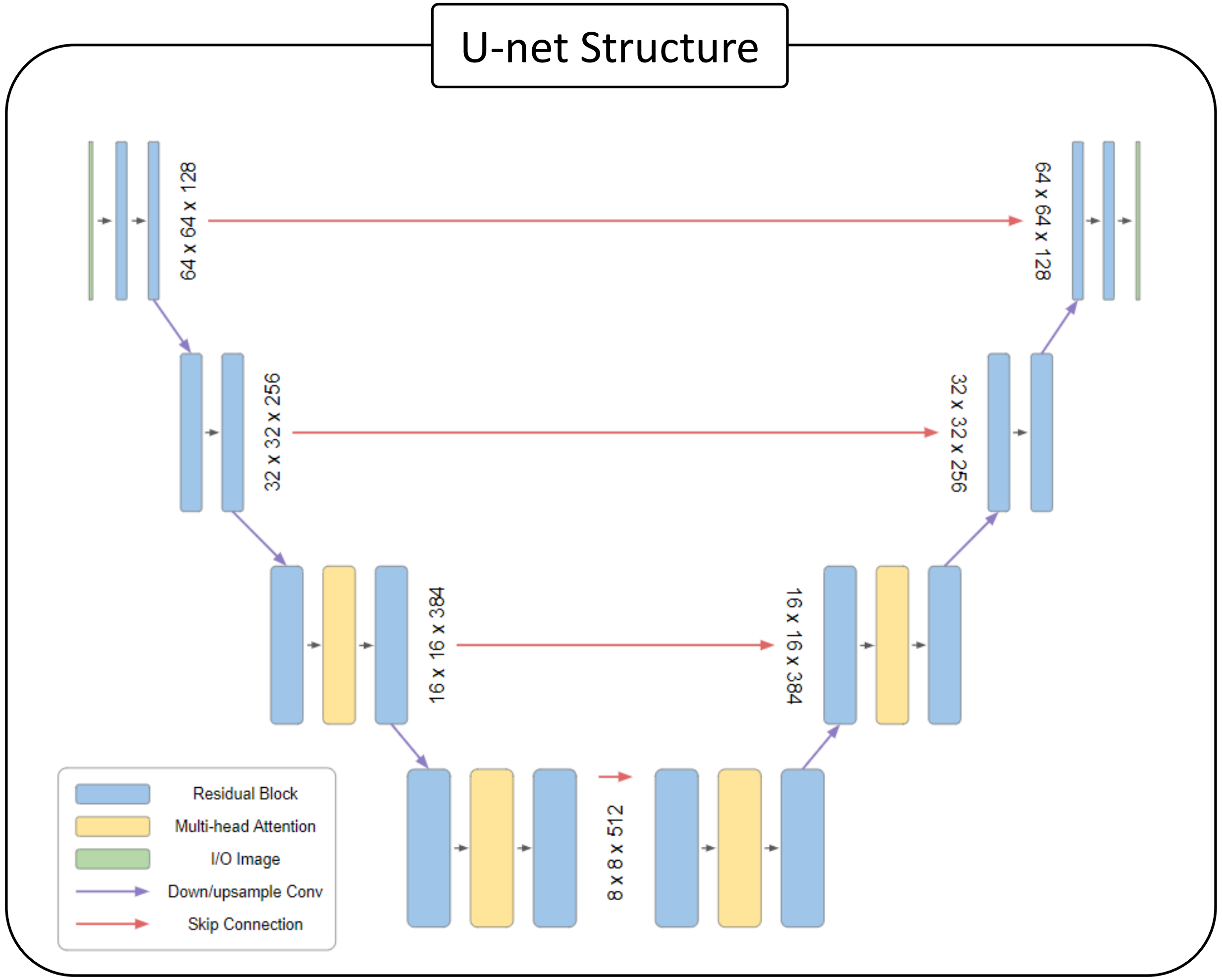


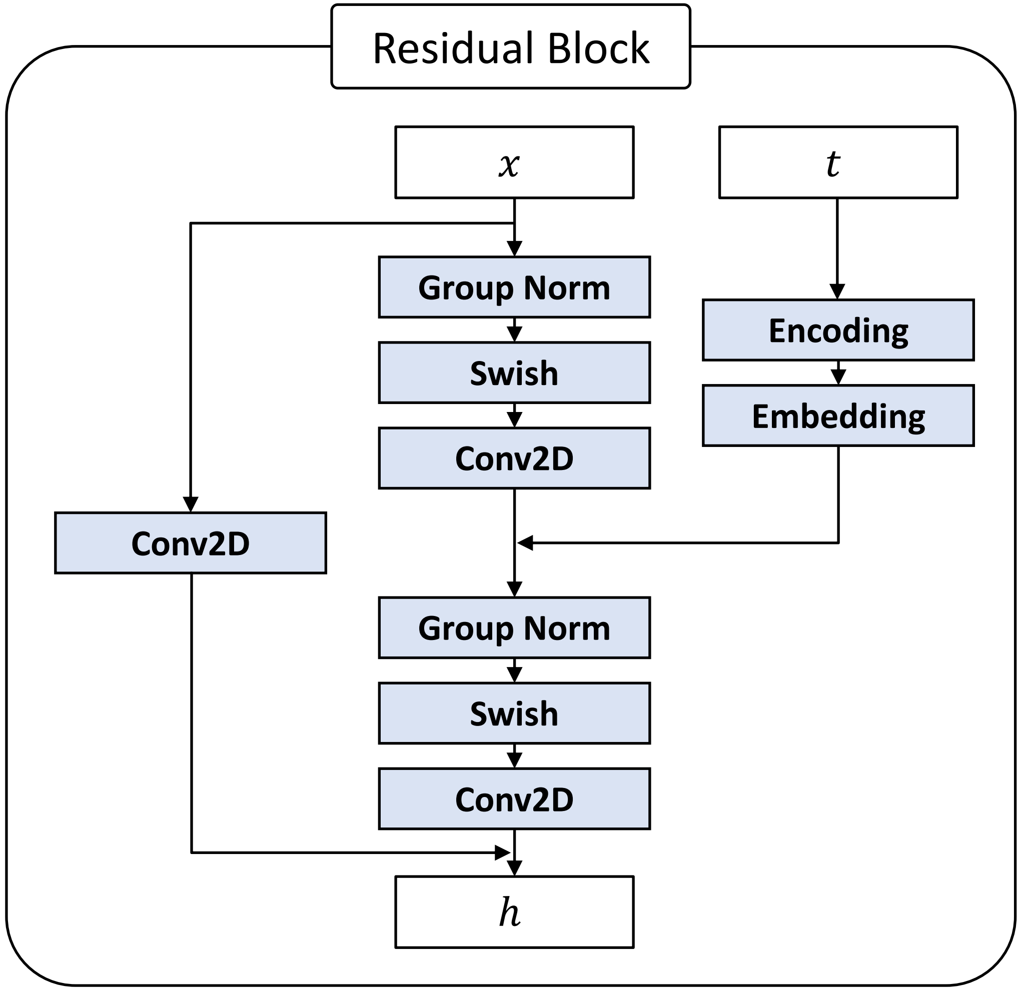
$t = 1$ Forward Diffusion Process $t = T$

Denoising Diffusion Probabilistic Models, NeurIPS, 2020

Diffusion Models

- Denoising Model (Restoration)



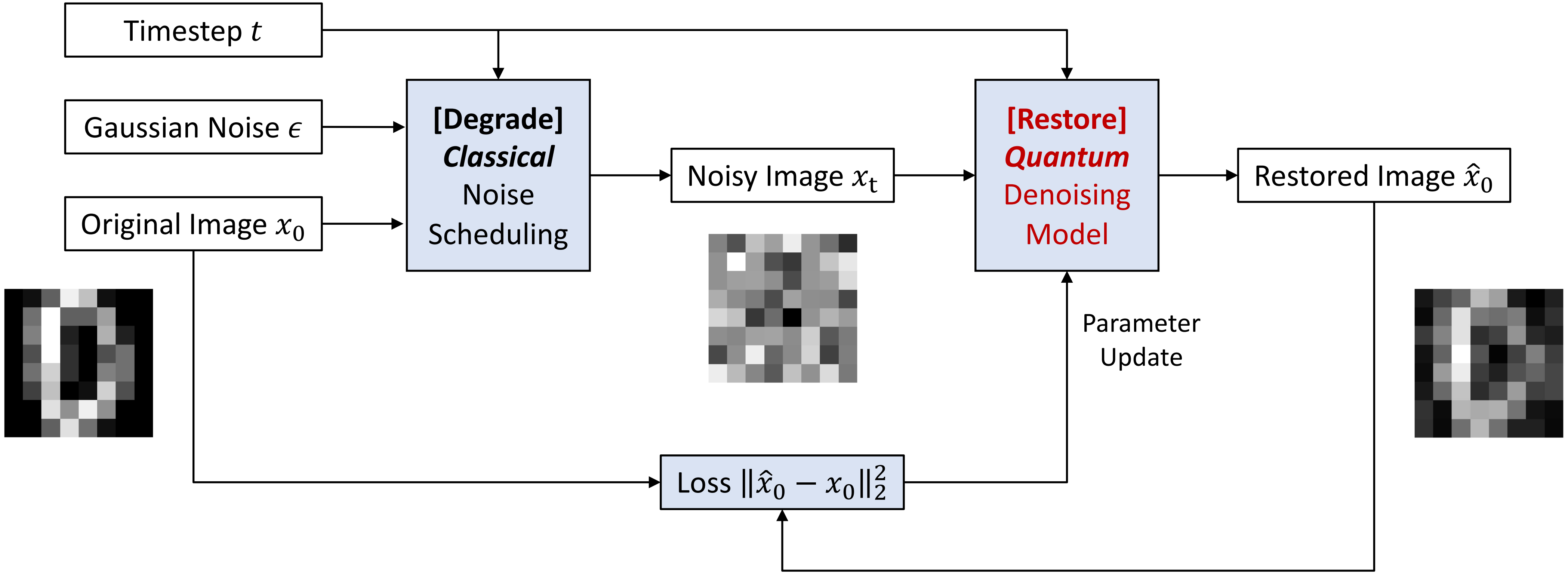


III. Proposed Methods

- **Quantum Denoising Diffusion Probabilistic Models**

Quantum Diffusion Models

- Model Components and Training

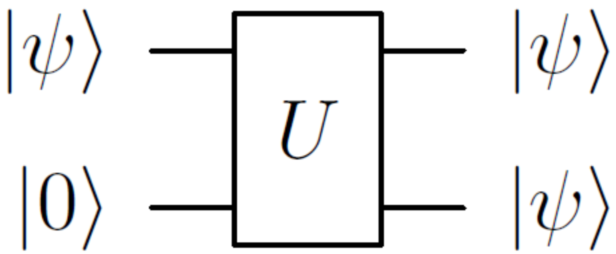


- Training objective of model
  - Minimization problem: $\min_{\theta} E\|\text{Restore}(\text{Degrade}(x_0, t), t) - x_0\|_2$

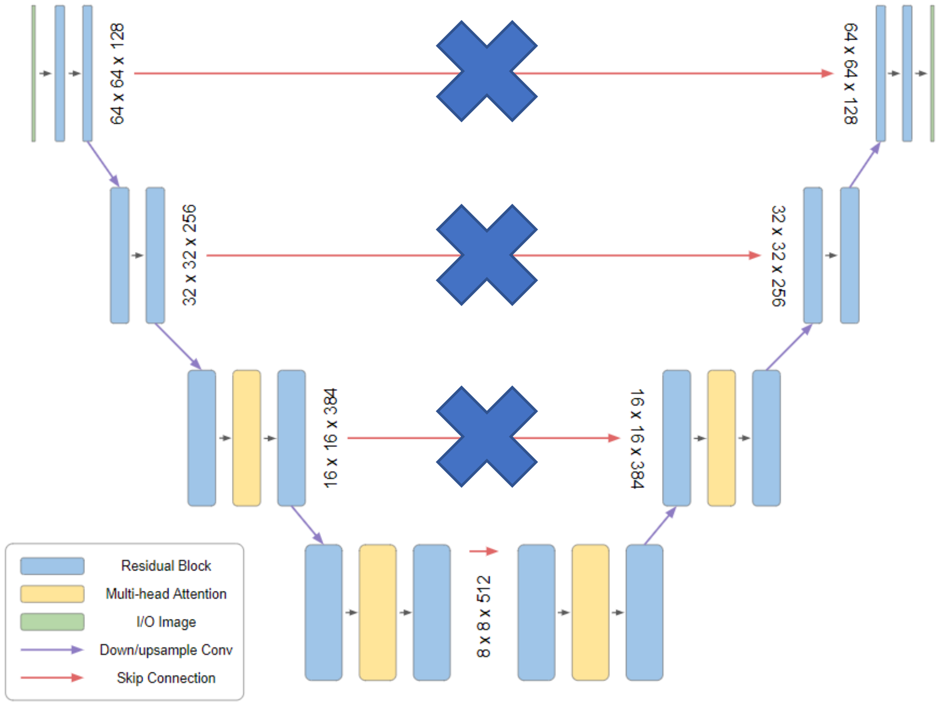
Quantum Diffusion Models

- Quantum Denoising Model (Restoration)

1. No-cloning Theorem



Such U does not exist

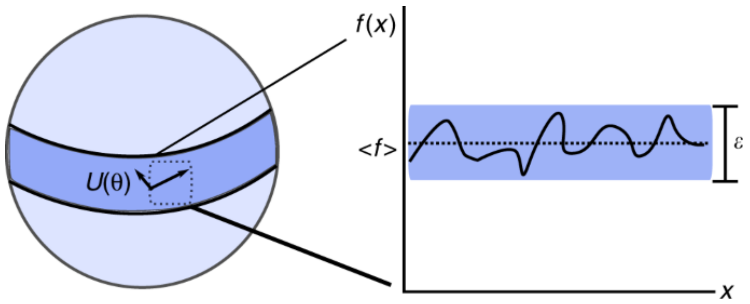


- Skip-connections are not feasible for quantum circuit
  - ➢ Quantum physics does not allow us to copy an arbitrary quantum state
  - ➢ New model architecture is required to design quantum denoising model

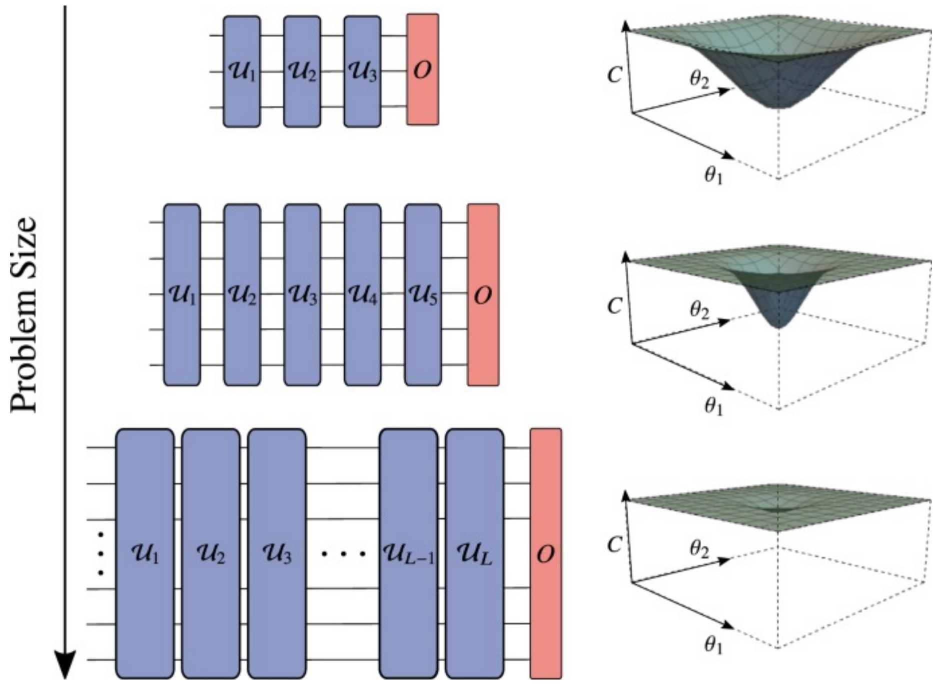
Quantum Diffusion Models

- Quantum Denoising Model (Restoration)

2. Barren Plateau



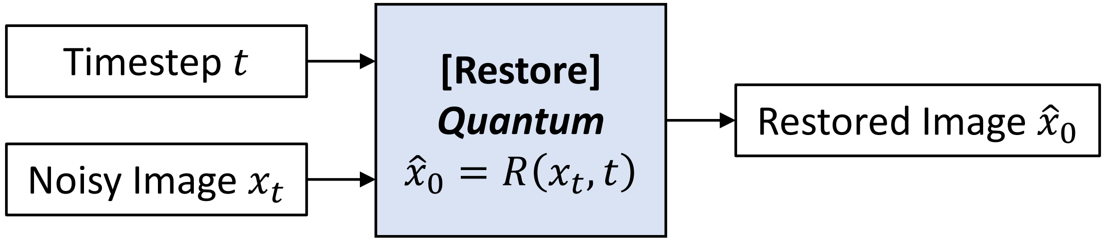
Gradients vanish exponentially according to the number of qubits



- Barren plateau: vanishing gradients in parameterized quantum circuits
  - ➢ Quantum circuit for the denoising model must be short-depth
  - ➢ New model architecture is required to design quantum denoising model

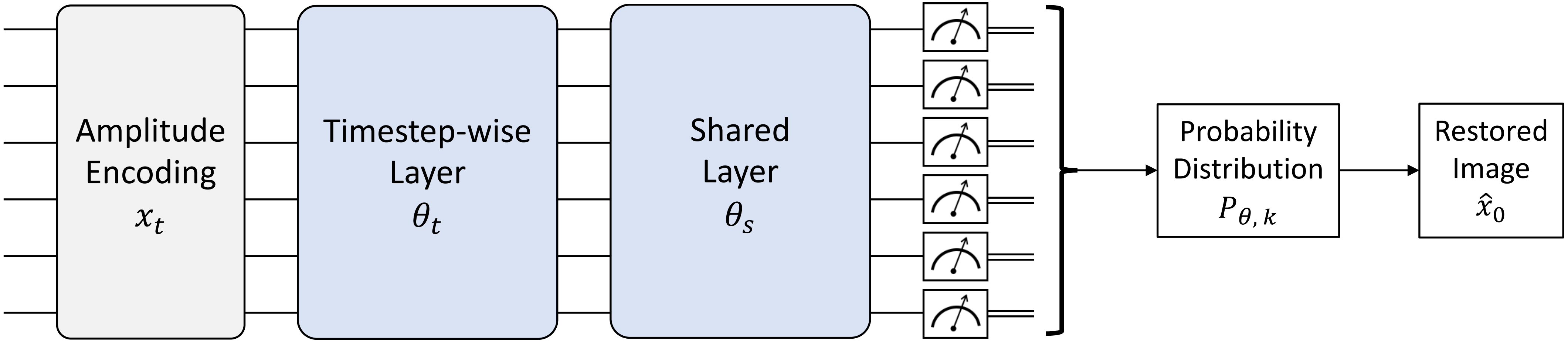
Quantum Diffusion Models

- Quantum Denoising Model (Restoration)



- Restore function: $\hat{x}_0 = R(x_t, t)$
  - Input:
    $|x_t\rangle = \frac{1}{\|x_t\|}\sum_k x_{t,k}|k\rangle, \; k = 0, \ldots, 2^{N-1}$
  - Parameters:
    θ_t: Timestep-wise parameters
    θ_s: Shared parameters

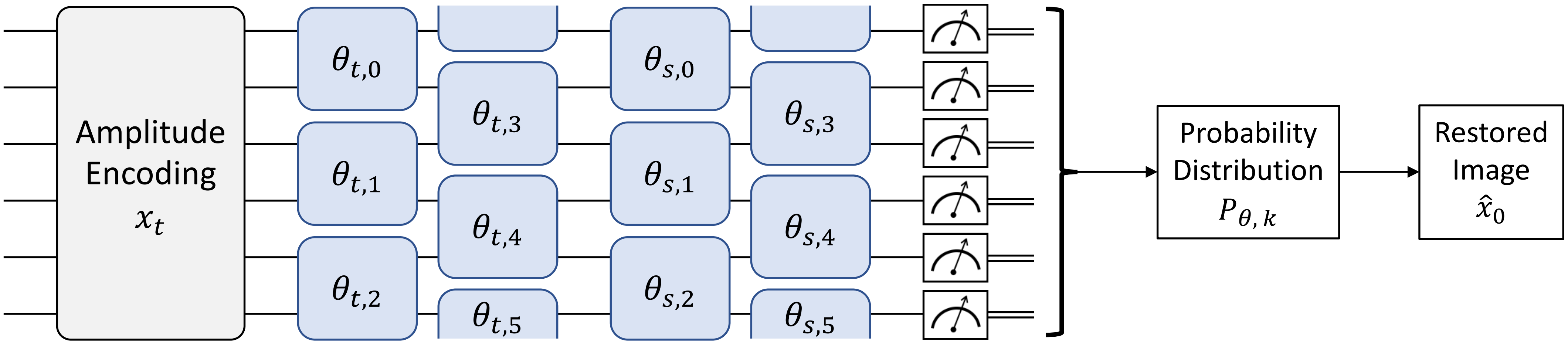
Parametric Quantum Circuit at timestep *t*



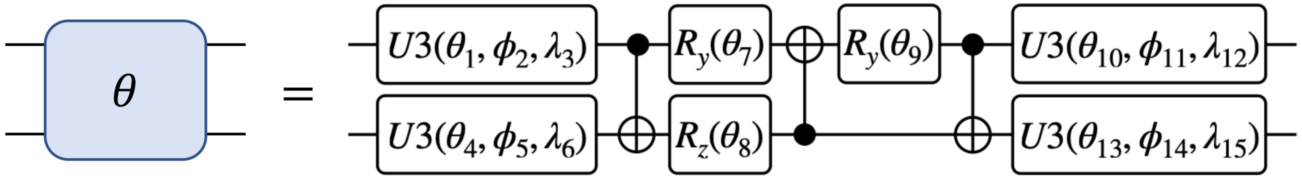
Quantum Diffusion Models

- Quantum Denoising Model (Restoration)

<u>Parametric Quantum Circuit at timestep *t*</u>



- Convolution Module: $SU(4)$ gate

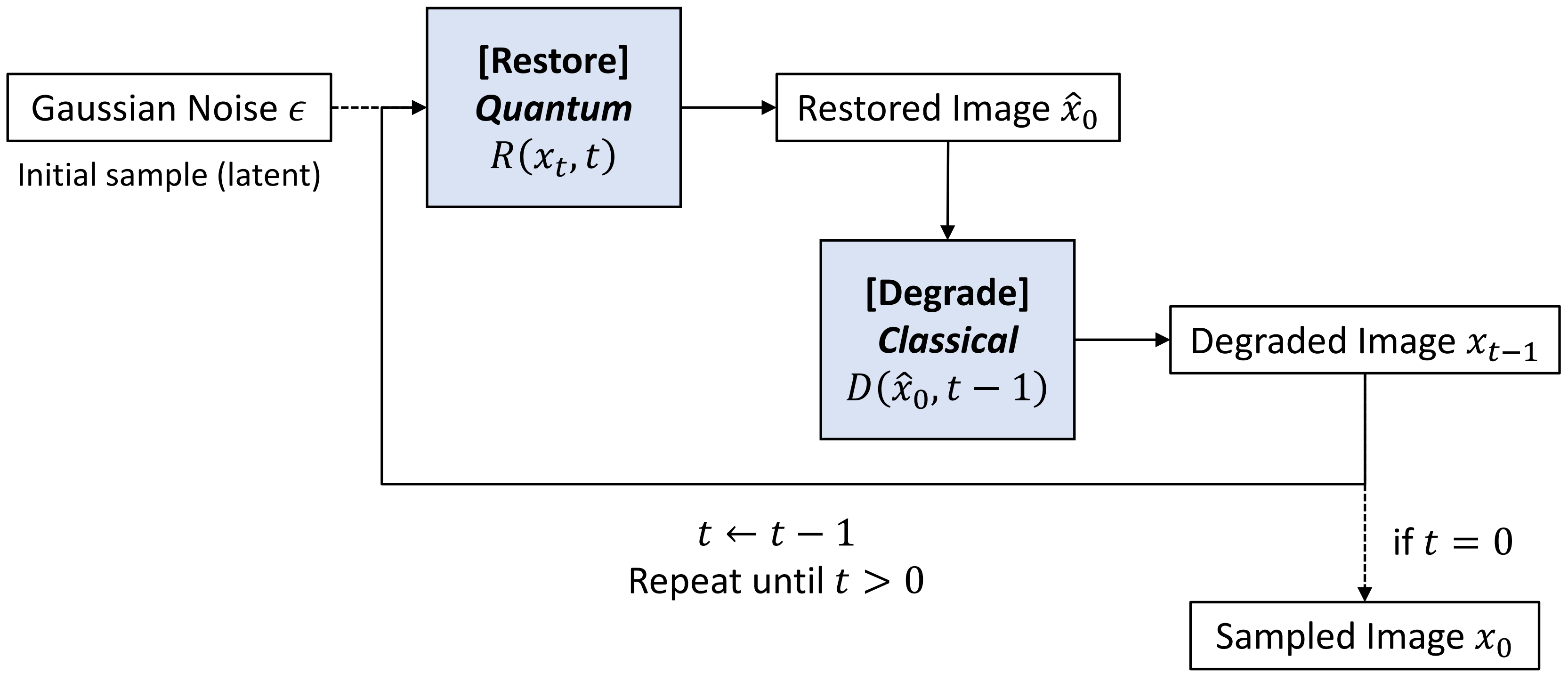


- Pixel arrangement (8 x 8 image)

$$x_t = \begin{bmatrix} x_{t,(000000)_2} & \cdots & x_{t,(000111)_2} \\ \vdots & \ddots & \vdots \\ x_{t,(111000)_2} & \cdots & x_{t,(111111)_2} \end{bmatrix}$$

Quantum Diffusion Models

- Sampling from gaussian noise



- Sampling (Image generation)
  - Iteratively applying the denoising operator and then adding noise back to the image, with the level of added noise decreasing over time

IV. Experimental Setup and Results

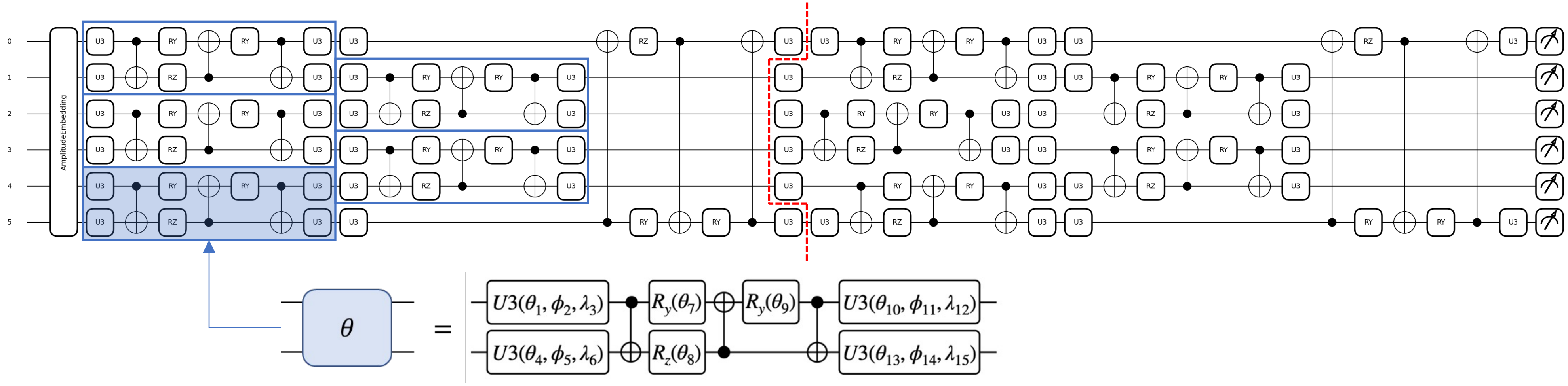
Experimental Result

- Implementation with PennyLane

<u>8 x 8 image</u>

→ 64 = 2^6 pixels

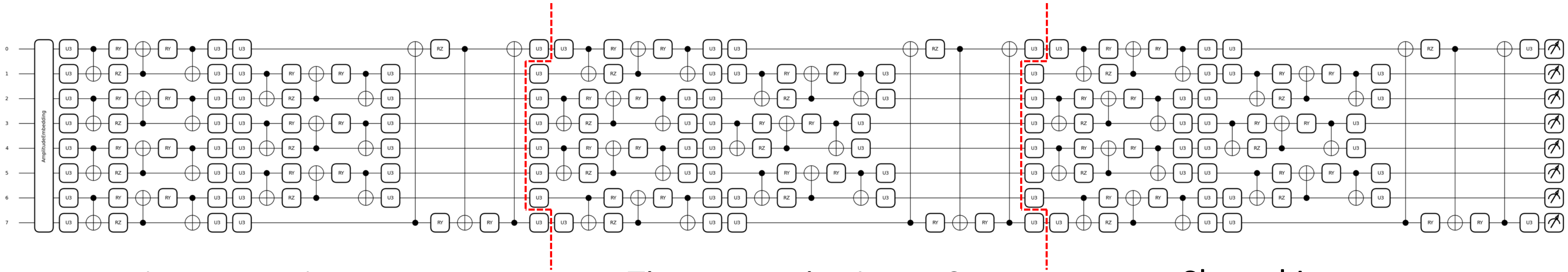
→ 6 qubit circuit



<u>16 x 16 image</u>

→ 256 = 2^8 pixels

→ 8 qubit circuit

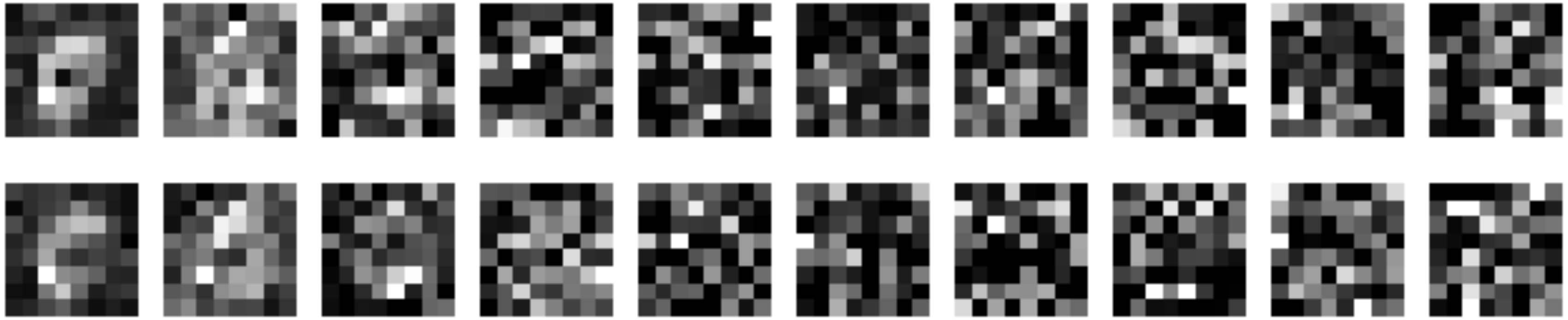


Timestep-wise Layer 1 Timestep-wise Layer 2 Shared Layer

Experimental Result

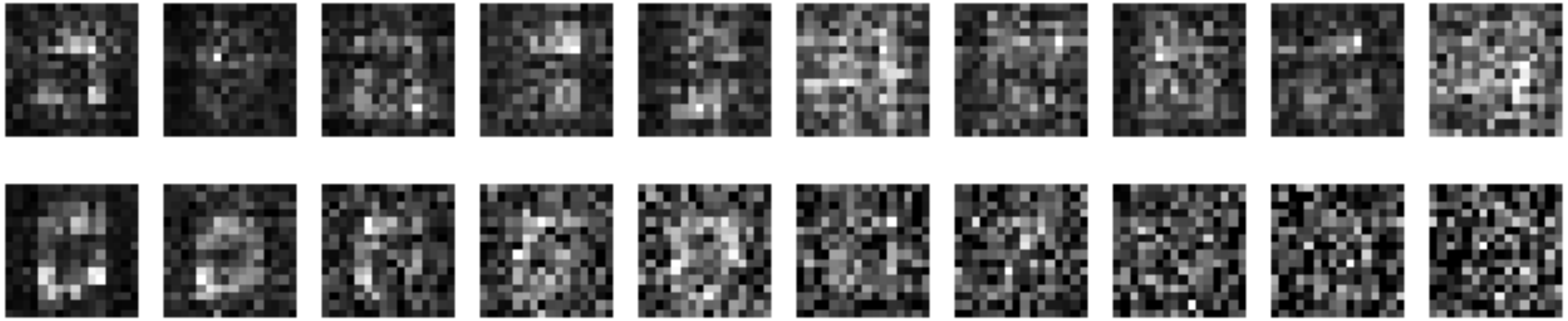
- Sampling from gaussian noise

8 x 8 image



$t = 1$ ← Reverse Process $t = 10$

16 x 16 image



$t = 1$ ← Reverse Process $t = 20$

V. Conclusion

Conclusion

Summary

- We showed the **feasibility of quantum diffusion models** in the image generation task
- The proposed quantum circuit has **better representation ability** for the amplitude-encoded 2D image compared to the general QNN structure
- Our image generation method is scalable and has a **logarithmic space/time complexity** according to the image size

Future Work

- We plan to further develop the quantum denoising model by designing the statistical realization of quantum U-net structure
- Also, we plan to conduct the experiments on the real quantum devices

THANK YOU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