# Quantum Denoising Diffusion Probabilistic Models for Image Generation

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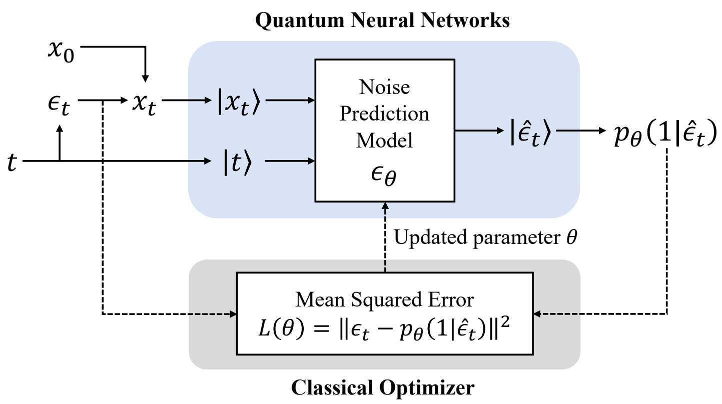
As the field of quantum computing grows rapidly, quantum algorithms for various applications are being developed. Among them, quantum machine learning algorithms are strong candidates expected to realize near-term quantum advantage. Quantum machine learning models are composed of variational quantum circuits which have modifiable parameters, and these parameters are updated with classical optimizers. In this work, we focus on quantum generative models for image generation. In the field of classical generative learning, the most common structure is Generative Adversarial Networks (GAN) [1]. GAN comprises two models, a generator, and a discriminator which are trained simultaneously. However, GAN architecture has fundamental limitations such as unstable training and mode collapse. Therefore, the Denoising Diffusion Probabilistic Models (DDPM) [2] are recently getting attention owing to their good training stability and mode coverage. We propose *Quantum Denoising Diffusion Probabilistic Models* (QDDPM) for image generation, leveraging the strength of the diffusion models and the quantum neural networks (Fig. 1). Since the key idea of DDPM is to predict the noise distribution of a specific timestep, the probabilistic nature of quantum circuit is well suited to the diffusion process. First, we sample a random noise for the given timestep $t$, $\epsilon_t$ with the Gaussian distribution, then create the noised image $x_t$ from the original image $x_0$ and noise $\epsilon_t$. The noised image $x_t$ is converted to the quantum state $|x_t\rangle$ with amplitude encoding. We create quantum embedding of the timestep $t$, $|t\rangle$ with positional sinusoidal encoding, followed by quantum neural network. For the noise prediction model $\epsilon_\theta$, we adapted the structure of patch-based quantum image generator [3]. The model $\epsilon_\theta$ takes $|t\rangle$ and $|x_t\rangle$ as input and generates the predicted probability distribution of noise at timestep $t$, $|\hat{\epsilon}_t\rangle = \epsilon_\theta|x_t\rangle|t\rangle$. The parameter of the $\epsilon_\theta$, $\theta$ is optimized with the loss function $L(\theta) = \|\epsilon_t - p_\theta(1|\hat{\epsilon}_t)\|^2$ where $p_\theta(1|\hat{\epsilon}_t) = \|\langle 1|\hat{\epsilon}_t\rangle\|^2$, which means the probability of measuring the state $|\hat{\epsilon}_t\rangle$ in the state $|1\rangle$. In our experiment on MNIST dataset, QDDPM successfully generated the image of digits.

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|---|---|
| $x_0$ | Original image |
| $t$ | Timestep |
| $\epsilon_t$ | Gaussian noise at timestep $t$ |
| $x_t$ | Noised image at timestep $t$ |
| $\|x_t\rangle$ | Quantum state embedding of $x_t$ |
| $\|t\rangle$ | Quantum state embedding of $t$ |
| $\|\hat{\epsilon}_t\rangle$ | Quantum state of predicted noise |
| $p_\theta(1\|\hat{\epsilon}_t)$ | Probability distribution of predicted noise |

Fig. 1: Overall architecture of the proposed Quantum Denoising Diffusion Probabilistic Model (QDDPM).

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**References** [1] Ian J. Goodfellow, et al., "Generative Adversarial Networks", arXiv:1406.2661, 2014. [2] Jonathan Ho, Ajay Jain, and Pieter Abbeel, "Denoising Diffusion Probabilistic Models", arXiv:2006.11239, 2020. [3] He-Liang Huang, et al., "Experimental Quantum Generative Adversarial Networks for Image Generation", Phys. Rev. Applied 16, 024051, 2021.