Editors' Suggestion

Experimental Quantum Generative Adversarial Networks for Image Generation

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Quantum machine learning is expected to be one of the first practical applications of near-term quantum devices. Pioneer theoretical works suggest that quantum generative adversarial networks (GANs) may exhibit a potential exponential advantage over classical GANs, thus attracting widespread attention. However, it remains elusive whether quantum GANs implemented on near-term quantum devices can actually solve real-world learning tasks. Here, we devise a flexible quantum GAN scheme to narrow this knowledge gap. In principle, this scheme has the ability to complete image generation with high-dimensional features and could harness quantum superposition to train multiple examples in parallel. We experimentally achieve the learning and generating of real-world handwritten digit images on a superconducting quantum processor. Moreover, we utilize a gray-scale bar dataset to exhibit competitive performance between quantum GANs and the classical GANs based on multilayer perceptron and convolutional neural network architectures, respectively, benchmarked by the Fréchet distance score. Our work provides guidance for developing advanced quantum generative models on near-term quantum devices and opens up an avenue for exploring quantum advantages in various GAN-related learning tasks.

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State-of-the-art quantum computing systems are now stepping into the era of *noisy intermediate-scale quantum* (NISQ) technology [1–4], which promises to address challenges in quantum computing and to deliver useful applications in specific scientific domains in the near term. The overlap between quantum information and machine learning has emerged as one of the most encouraging applications for quantum computing, namely, quantum machine learning [5]. Both theoretical and experimental evidences suggested that quantum computing may significantly improve machine-learning performance well beyond that achievable with their classical counterparts [5–14].

Generative adversarial networks (GANs) are at the forefront of the generative learning and have been widely used for image processing, video processing, and molecule development [15]. Although GANs have achieved wide success, the huge computational overhead makes them approach the limits of Moore's law. For example, BigGAN with 158 million parameters is trained to generate 512×512 pixel images using 14 million examples and 512 TPU for 2 days [16]. Recently, theoretical works show that quantum generative models may exhibit an exponential advantage over classical counterparts [17–19], arousing widespread research interest in theories and experiments of quantum GANs [17,20–24]. Previous experiments of quantum GANs on digital quantum computers, hurdled by algorithm development and accessible quantum resources, mainly focus on the single-qubit quantum-state generation and quantum-state loading [21,22], e.g., finding a quantum

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