Protocols for Trainable and Differentiable Quantum Generative Modelling

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Quantum generative modelling (QGM) aims to exploit trainable circuits that can prepare distributions as quantum states, for instance trying to match patterns from available data. Being a subject of the emerging field of quantum machine learning (QML), QGM utilizes the Born rule inherent to quantum mechanics. This is leads to the concept of quantum circuit Born machines (QCBM) as a generator of data samples from parametrized probability distribution [1]. QCBM offers a way to fast sampling, but is ultimately limited by its learning workflow based on binary variable representation. Importantly, QCBM circuit cannot be differentiated with respect to the encoded variable.

In the talk, I will describe an approach for learning probability distributions as differentiable quantum circuits (DQC) [2] that enable efficient quantum generative modelling (QGM) and synthetic data generation. Contrary to existing QGM approaches, we perform training of a DQC-based model, where data is encoded in a latent space with a phase feature map, followed by a variational quantum circuit. We then map the trained model to the bit basis using a fixed unitary transformation, coinciding with a quantum Fourier transform circuit in the simplest case. This allows fast sampling from parametrized distributions using a single-shot readout. Importantly, latent space training provides models that are automatically differentiable, and we show how samples from solutions of stochastic differential equations (SDEs) can be accessed by solving stationary and time-dependent Fokker-Planck equations with a quantum protocol [3]. Finally, our approach opens a route to multidimensional generative modelling with qubit registers explicitly correlated via a (fixed) entangling layer. In this case quantum computers can offer advantage as efficient samplers, which perform complex inverse transform sampling enabled by the fundamental laws of quantum mechanics. On a technical side the advances are multiple, as we introduce the phase feature map, analyze its properties, and develop frequency-taming techniques that include qubit-wise training and feature map sparsification.

References

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