An error-mitigated photonic quantum circuit Born machine

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In this work, we introduce a quantum circuit Born machine (QCBM) tailored to near-term photonic quantum computing, more specifically, to linear optical circuits. QCBMs are generative models based on parametrized quantum circuits, where data samples are obtained through measurements at the end of the circuit, thus using the Born rule [1,2].

The primary source of noise in photonic systems is photon loss. In related work [3], a quantum error mitigation technique was introduced to deal specifically with photon loss. It is called recycling mitigation and makes use of photonic output states that would normally be discarded in post-selection.

We apply this recycling mitigation technique to our QCBM, and we show that it greatly improves model training in realistic scenarios with photon loss -- both through numerical simulations and experiments. As shown in the example displayed in **Figure 1**, recycling mitigation can bring the value of the QCBM cost function close to the lossless one, while the lossy unmitigated case remains mostly untrainable.

We run our simulations using a software package for linear optical quantum computing introduced in [4] and we perform our experiments on a quantum processor made of a quantum-dot single-photon source supplying a universal linear optical network on a reconfigurable chip, similar to the one introduced in [5].

Additionally, we discuss the computational complexity implications of our model, with respect to classical simulability, hardness, and connections with boson sampling.

Our experiment is the first demonstration of an error mitigation technique specifically designed for photonic devices and successfully applied to an algorithm.

References

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Figures

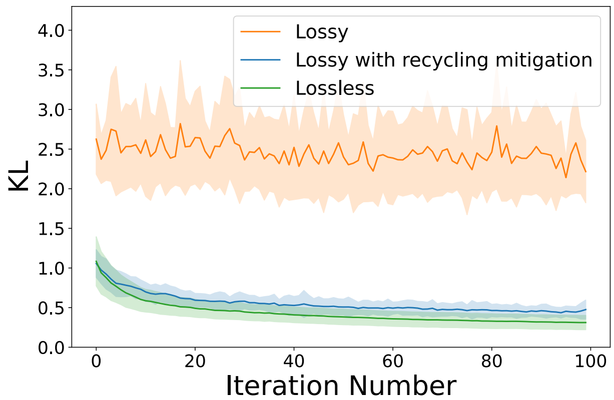

Figure 1: Evolution of the cost function (KL divergence) during the training of the QCBM for the problem of learning a bimodal Gaussian distribution. The circuit contains 4 photons and 12 modes, and the loss parameter is set to 0.8. The lossless case is compared to the lossy case with post-selection and the lossy case with recycling mitigation.