Variational Quantum Unsampling on a Programmable Nanophotonic Processor

Jacques Carolan[1*], Masoud Mosheni[2], Jonathan P. Olson[3], Mihika Prabhu[1], Changchen Chen[1], Darius Bunandar[1], Nicholas C. Harris[4], Franco N. C. Wong[1], Michael Hochberg[5], Seth Lloyd[6], Dirk Englund[1]

[1] *Research Laboratory of Electronics, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA*
[2] *Google Quantum AI Laboratory, Venice, CA 90291, USA*
[3] *Zapata Computing Inc., 501 Massachusetts Ave., Cambridge, MA, USA 02139*
[4] *Lightmatter, 61 Chatham St 5th floor, Boston, MA 02109*
[5] *Elenion Technologies, 171 Madison Avenue, Suite 1100, New York, New York 10016, USA*
[6] *Department of Mechanical Engineering, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139*
[*] *carolanj@mit.edu*

Abstract: We introduce the Variational Quantum Unsampling (VQU) protocol, a nonlinear quantum neural network approach for verification and inference of near-term quantum circuits outputs. We experimentally demonstrate this protocol on a quantum photonic processor.

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1. Introduction

While the construction of a fault tolerant quantum computer would enable an exponential advantage over the best classical computer in a variety of computational tasks, scaling these systems to a level required for large-scale computing is a major outstanding challenge [1]. Given this difficulty, there has emerged a significant effort towards algorithms for Noisy Intermediate-Scale Quantum (NISQ) processors, that can solve problems without the need for full-scale error correction [2]. Generally, algorithms for NISQ processors follow a similar structure, demonstrating that efficiently sampling from a distribution $p_U(x) \equiv |\langle x|\psi_{\rm out}\rangle|^2$ is classically intractable, with the quantum case giving a natural exponential advantage. Here $|\psi_{\rm out}\rangle = \hat{U}\,|\psi_{\rm in}\rangle$ is a quantum state generated by a quantum circuit $\hat{U}$ and initialization state $|\psi_{\rm in}\rangle$, and $\{|x\rangle\}$, for example, is the set of bit strings in the computational basis [3].

In this work, rather than first define a physical system and then determine the complexity of sampling, we ask the converse question: given direct access to the state $|\psi_{\rm out}\rangle$, what features of the physical system $\hat{U}$ can we efficiently learn? Inspired by neural network approaches to machine learning we develop the Variational Quantum Unsampling (VQU) protocol which performs optimization on $|\psi_{\rm out}\rangle$ using a sequence of auxiliary quantum circuits $\hat{V}(\vec{\phi})$ to find the time reversed condition $\hat{V}(\vec{\phi}) = \hat{U}^\dagger$ for a known input state. Our protocol uses a layer-by-layer training approach which has been shown to successfully train classes of deep-neural networks which otherwise get stuck in local optima [4]. We perform a proof-of-concept optical demonstration of this protocol with a state-of-the-art quantum photonic processor (QPP).

2. Variational Learning

The optical sampling protocol takes an n-photon initialization state of one photon per mode $|\psi_{\rm in}\rangle = |1_1 1_2 \dots 1_n\rangle$ (where $|i_j\rangle$ represents i photons in the $j^{\rm th}$ optical mode), and passes it through a m-dimensional linear optical circuit $\hat{U}_m$ [5] such that each amplitude of the output state $|\psi_{\rm out}\rangle = \hat{U}_m\,|\psi_{\rm in}\rangle$ is given by the permanent of a unique $n \times n$ submatrix of $\hat{U}_m$ [6]. The optical VQU protocol at each layer maximizes $\tilde{P}^1_j$, the probability of one and only one photon in a given optical mode j, effectively unentangling a photon from the remainder of the state. Formally, the $j^{\rm th}$ layer uses a $m-(j-1)$ mode circuit to minimize $L_j(\vec{\phi}) = 1 - \tilde{P}^1_j$, with $j \in [1,n]$.

3. Experimental Optical VQU

We implement a proof-of-concept demonstration of the optical VQU procedure on a state-of-the-art quantum photonic processor comprising three stages: (1) photon generation, (2) reprogrammable quantum circuitry and (3) single photon detection, all within an actively configured feedback loop for optimization [see Fig 1(a)]. Pairs of degenerate photons at 1582 nm are generated via spontaneous parametric down-conversion (SPDC) then delivered

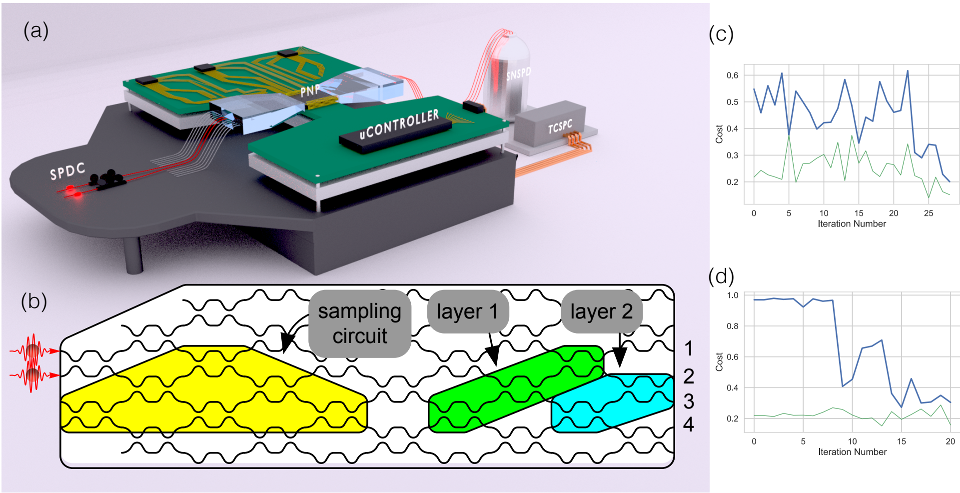

Fig. 1. (a) Schematic of the full experimental setup. (b) The structure of the full VQU protocol, with the optical sampling circuit (yellow) and the subsequent unsampling layers (green, blue). Experimental results for (c) the first layer of unsampling, and (d) the final layer of the protocol.

to a programable nanophotonic processor (PNP) [7] comprising 176 individually tuneable phase shifters across 26 optical modes. After passing through the PNP photons are out-coupled and delivered to four tungsten silicide superconducting nanowire single photon detectors (SNSPDs) for photon counting and temporal correlations are subsequently calculated.

The sampling circuit (Fig. 1(b), yellow) directly sets six MZIs (12 phases) to generate a four-mode random unitary according to the Haar measure. Two photons pass through the sampling circuit and the output state is fed into the first unsampling layer (Fig. 1(b), green); a four-mode circuit acting on modes $\{1,2,3,4\}$. The classical optimizer is programmed to find a single photon in optical mode 1 by minimizing $L_1(\vec{\phi}_4) = 1 - \tilde{P}_1^1(\vec{\phi}_4)$. The output state is then fed to the second unsampling layer; a three-mode circuit acting on modes $\{2,3,4\}$ (Fig. 1(b), blue). The optimizer is set to find a single photon in mode 2 by minimizing $L_2(\vec{\phi}_2) = 1 - \tilde{P}_2^1(\vec{\phi}_2)$. The evolution of the loss function at each layer is plotted in Fig. 1(c,d), reaching the noise floor of our experimental system.

4. Discussion

We have demonstrated a new nonlinear quantum neural network approach for verification and inference of near-term quantum circuits outputs: variational quantum unsampling. Our protocol uses ideas from machine learning and optimization and can be applied a broad range of phenomena; including quantum tomography, quantum verification and optimal quantum measurement.

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