In situ Training of Silicon Photonic Neural Networks: from Classical to Quantum

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Abstract: Photonic neural networks perform ultrafast inference operations but are trained on slow computers. We highlight on-chip network training enabled by silicon photonics. We introduce quantum photonic neural networks and discuss the role of weak nonlinearities.

Artificial intelligence (AI) powered by neural networks has enabled applications in many fields (medicine, finance, autonomous vehicles). Digital implementations of neural networks are limited in speed and energy efficiency. Neuromorphic photonics [1] aims to build processors that use light and photonic device physics to mimic neurons and synapses in the brain for distributed and parallel processing while offering sub-nanosecond latencies and extending the domain of AI and neuromorphic computing applications [2,3]. However, to date, most neuromorphic photonic processors are trained offline (to determine the synaptic weights and neuron biases) and only used for inference tasks that do not require synaptic weights to be updated, such as in machine acceleration (e.g., by performing fast matrix-vector multiplications) [4-8], nonlinear programming [9,10], intelligent signal processing [11,12], etc. The training algorithms, such as backpropagation [13], have high computation and memory costs that challenge the current hardware platforms executing them [14]. The substantial energy required to train large neural networks using standard von Neumann architectures presents a high financial and environmental cost [15]. Training large neural networks is an area of machine learning that would benefit from photonics' low power consumption and high information processing bandwidth.

We will discuss our recent work [16] on-chip training of photonic neural networks using the direct feedback alignment (DFA) training algorithm, which trains neural networks using error feedback rather than error backpropagation and can operate at speeds of trillions of multiply-accumulate (MAC) operations per second while consuming less than one picojoule per MAC operation. The photonic architecture exploits parallelized matrix-vector multiplications using arrays of microring resonators for processing multi-channel analog signals along single waveguide buses to calculate the gradient vector for each neural network layer in situ.

We will also briefly introduce quantum photonic neural networks (QPNNs) [17]. QPNNs are brain-inspired, reconfigurable quantum circuits that leverage the strengths of photonic platforms (for multiplexing, low latency, and low powers) and can be trained to implement high-fidelity quantum operations. We will discuss realistic QPNNs that suffer weak nonlinearities and fabrication imperfections leading to photon loss. We show that QPNNs can learn to overcome these errors and that an optimal network size balances imperfections versus the ability to compensate for lacking nonlinearities. With a sub-optimal nonlinearity, we show high unconditional fidelity (e.g., 0.891 for a Bell-state analyzer) and a near-perfect fidelity if it is possible to precondition success on detecting a photon in each logical photonic qubit.

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