Photonics × Machine Learning

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Abstract: We will present the recent progress of generative AI for the design of photonic devices, including variable autoencoders and diffusion models, and latent space optimization. We also review our non-traditional way of implementing optical neural networks using data re-uploading technique originally proposed for quantum computing.

1. Machine Learning for Photonics

1.1. Adversarial Variational Conditional AutoEncoder (A-CVAE)

In recent years, generative AI has made remarkable strides, enabling the creation of exceptional quality novel designs and images [1–4]. This study aims to enhance the performance of a conditional autoencoder, a type of generative deep learning framework.

Adversarial Variational Conditional AutoEncoder (A-CVAE) is a variant of CVAE, and the training enforces the latent variables to be centered around zero [5]. This makes device generation process and latent optimization process more efficient [6].

A Silicon-on-insulator (SOI) wavelength filter was optimized by A-CVAE as shown in Fig. 1 (a), and its transmission spectra are shown in Fig. 1 (b). Green dots in Fig. 1 (c) show the extinction ratio vs. center wavelength of the training data obtained by seven runs of the adjoint method, and red dots show the devices generated by A-CVAE by sweeping the target center wavelength [7]. This demonstrates that A-CVAE can fill the gap of the training data effectively. A-CVAE has also been applied to metasurface grating designs [8]

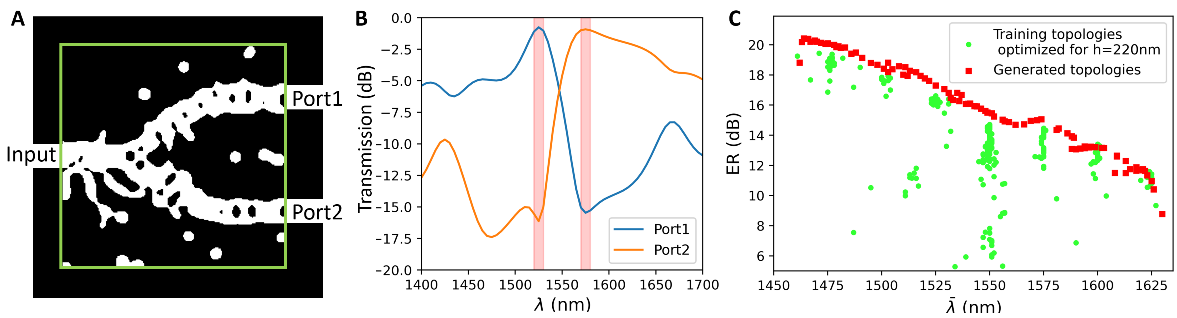

Fig. 1: (A) Optimized device topology (black: silicon oxide background, white: silicon waveguide, box: optimization area of $4.5 \times 4.5\ \mu\mathrm{m}^2$) and (B) transmission spectra of an example device generated by A-CVAE. (C) Performance of densely generated topologies (red squares) by A-CVAE trained with a sparse set of topologies optimized for 220 nm-thick devices (green dots).

1.2. Diffusion Model

The past few years have also seen an explosive increase in research on a novel generative deep learning method, called denoising diffusion probabilistic model (DDPM) [9], which has been applied to text-to-image generation services, including Dall-E and Stable Diffusion. Its first application to nanophotonics has only just been reported in 2023 [10]. We recently reported on the plasmonic metagratings optimized by the use of DDPM [11], yielding excellent results. DDPM is expected to play a larger role for photonics in the coming years.

2. Photonics for Machine Learning

Data re-uploading trick was originally proposed for universal quantum computing which achieves the universal approximation property [12] as shown in Fig. 2. The authors recently introduces the data re-uploading to realize universal non-quantum photonic computing with practical photonic integrated circuits (PIC) [13]. We discuss its advantages and PIC implementation options. Unlike the classical neural networks, the input data $\vec{x}$ are applied as rotation angles multiple times and nonlinear functions can be realized without using optical nonlinear components (Fig. 3).

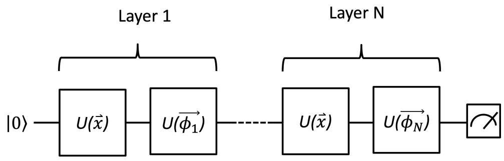

Fig. 2: The original data re-uploading view using a single qubit, where the input $\vec{x}$ are repeatedly applied.

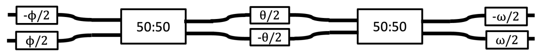

Fig. 3: Schematic of a PIC representing a rotation [13].

Data re-uploading demonstrates comparable accuracy without nonlinear optical components, to classical NNs with one hidden layer and ReLU nodes, when compared with the same number of phase shifters as shown in Fig. 4

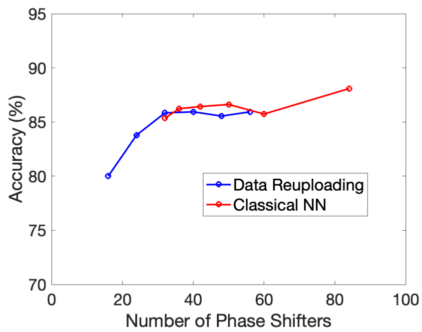

Fig. 4: Comparison of accuracy vs. number of phase shifters for the hypersphere (dim = 6) problem [13].

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