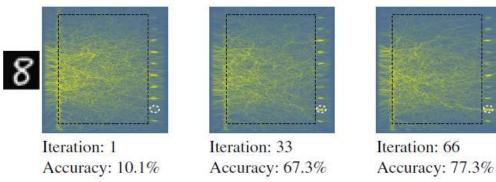
Deep Learning 调研

畅星兆, 2019.09.11

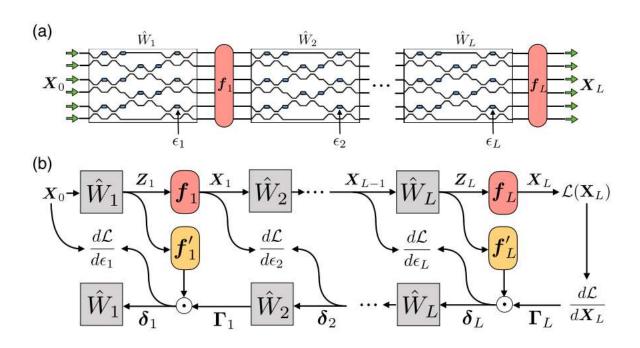
研究情况

- Yichen Shen (Lightelligence Inc.)
 - 1. Gated orthogonal recurrent units: On learning to forget
 - 2. Nanophotonic particle simulation and inverse design using artificial neural networks
 - 3. Tunable Efficient Unitary Neural Networks (EUNN) and their application to RNN
- Zongfu Yu (Wisconsin-Madison)
 - 有图
 - 深度学习指导光波导设计



- Nicholas C. (Lightelligence Inc.)
 - Linear programmable nanophotonic processors
- Shanhui Fan (Stanford)
 - Training of photonic neural networks through in situ backpropagation and gradient measurement
 - Wave Physics as an Analog Recurrent Neural Network(使用声波)

In situ backpropagation and gradient measurement



- in situ intensity measurements.
- requiring an integrated intensity detection scheme
- physically implementing adjoint variable method
- improved version of

Shen Yichen etal., Deep learning with coherent nanophotonic circuits, Nature Photonics, 2017

- (a) Schematic of the ANN architecture.
- (b) Illustration of operation and gradient computation in an ANN.

• ANN的实现

- input vector ---> output vector via matrices
- tuning matrix elements (weights) for minimized cost function
- tuning is implemented by "backpropagation algorithm"
- utilizing the chain rule from the output layer to the input layer

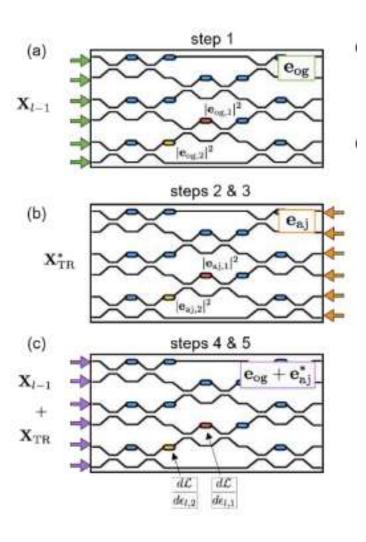
• 对原文献的评价:

• the training of the phase-shifter settings for this system was performed using a model implemented on a standard computer, which does not take into account experimental errors, and furthermore loses all the potential advantages in time and energy of the photonic implementation.

• 改进:

• The only additional component that is required is a means to measure the light intensity in the vicinity of each of the tunable phase shifters.

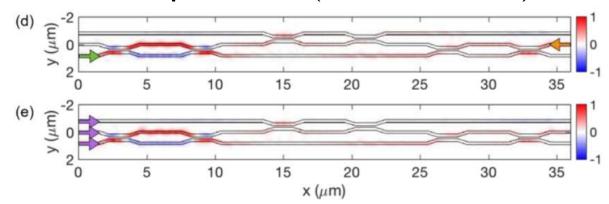
步骤



- 1. Send in the original field amplitude and measure and store the intensities at each phase shifter.
- 2. Send delta into the output ports and measure and store the intensities at each phase shifter.
- 3. Compute the time-reversed adjoint input field amplitudes.
- 4. Interfere the original and the timereversed adjoint fields in the device, measuring again the resulting intensities at each shifter.
- 5. Subtract the constant intensity terms from steps 1 and 2 and multiply by k square to recover the gradient.

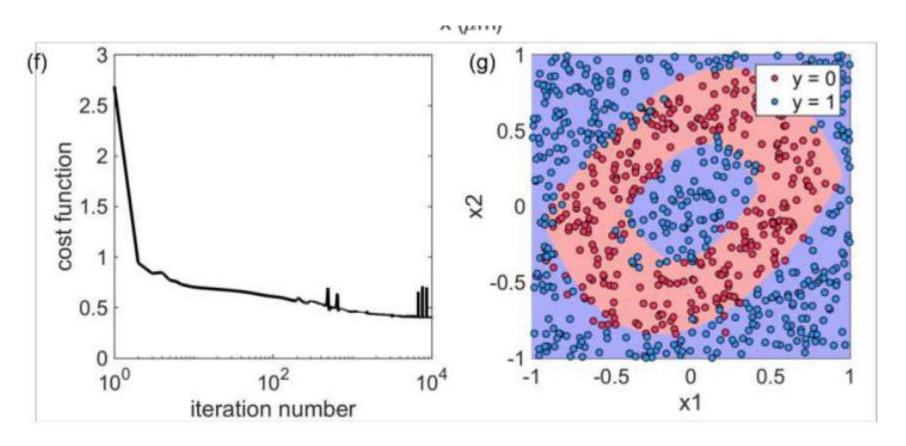
Restriction

- 1. Assuming linear, lossless, reciprocal, feed-forward propagation inside the OIU.
- 2. Mode-dependent loss limits the ability to accurately reconstruct the time-reversed adjoint field.
- 3. 40% of the light is lost due to back-scattering and radiation losses for 3 * 3 operation. (shown below)



Shanhui Fan et al., "In-situ Backpropagation in Photonic Neural Networks", Frontiers in Optics/ Laser Science, 2018.

Results



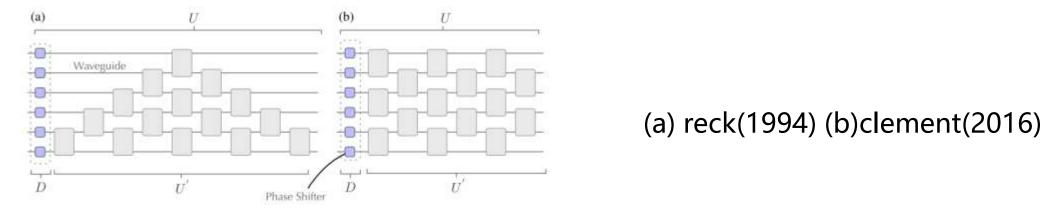
91% precision

Shanhui Fan et al., "In-situ Backpropagation in Photonic Neural Networks", Frontiers in Optics/ Laser Science, 2018.

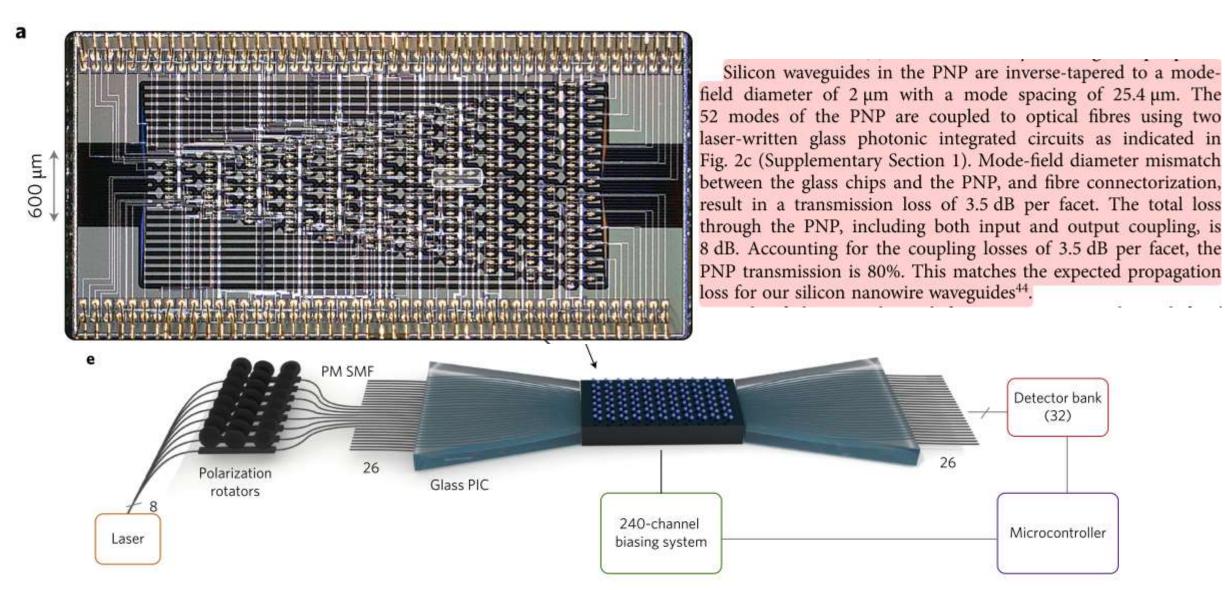
Linear programmable nanophotonic processors

(Nicholas C. let al., "Linear programmable nanophotonic processors", Optica, 2018.)

- N input to N output problem up into 2 x 2 mode transformers Mach-Zehnder interferometers(MZI).
- $\Sigma_n = N(N-1)/2$ MZI needed. For instance, n=6, $\Sigma_n = 15$.



- The SOI platform offers high index contrast of 3.4:1.5.
- Largest PNPs 88 MZIs connecting 26 optical modes(4.9 mm x 2.4 mm)



Processor composed of 88 MZIs, 26 input modes, 26 output modes and 176 phase shifters

(Nicholas C. let al., "Linear programmable nanophotonic processors", Optica, 2018.)