



Hardware-level simulations of nanophotonic neural networks

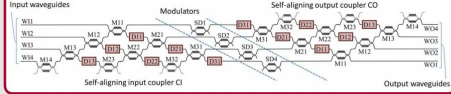
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Abstract

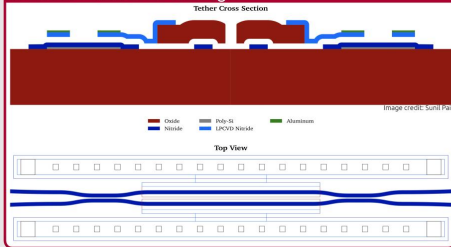
Modern computing hardware is inefficient at implementing neural networks, primarily because digital matrix multiplication is an $O(N^3)$ operation. We present a fully-optical architecture consisting of meshes of self-configuring nanophotonic interferometers which is capable of performing $O(1)$ matrix multiplication on an input vector of light intensities. Using detailed physical simulations of our interferometer design, we develop a theoretical control system for our architecture which generates the on-chip layout and applied voltages necessary to implement and train an arbitrarily specified feed-forward neural network.

Introduction

- Neural networks are computationally expensive to run, even once fully trained - $O(N^{2.37})$ best complexity
- Photonic devices can use interferometric effects for constant time matrix multiplication on input vector of light intensities
- Data throughput of ~100GHz and no theoretical energy cost!
- Phase-shifted Mach Zehnder Interferometer (MZI) can perform arbitrary $SU(2)$ transformation
- Blocks of MZIs can implement arbitrary unitary transformation
- Combine with attenuator layer to implement any matrix via SVD



Interferometer design



Interferometric matrix multiplication

Algorithm 1 $U(N) \rightarrow U(2)$ matrix decomposition

```

let  $U \in U(N)$  be an arbitrary unitary matrix and let  $\hat{U} = U$ 
for  $i = 1$  to  $N - 1$  do
  if  $i$  is odd then
    for  $j = 0$  to  $i - 1$  do
      find  $\theta, \phi$  such that  $T_{N-j+1, N-j+1}(\theta, \phi)$  nullifies element  $N - j, i - j$  of  $\hat{U}$ 
      update  $\hat{U} \leftarrow U T_{N-j+1, N-j+1}(\theta, \phi)$ 
    end for
  else
    for  $j = 1$  to  $i$  do
      find  $\theta, \phi$  such that  $T_{N-j+1, N-j+1}(\theta, \phi)$  nullifies element  $N + j - i, j$  of  $\hat{U}$ 
      update  $\hat{U} \leftarrow T_{N-j+1, N-j+1}(\theta, \phi) \hat{U}$ 
    end for
  end if
end for
return  $L = (T_{m,1}^{-1}), \hat{U}, R = (T_{m,n})$ 

```

Diagram illustrating the interferometric matrix multiplication process, showing the decomposition of a unitary matrix U into a product of unitary matrices $T_{N-j+1, N-j+1}(\theta, \phi)$ and $T_{N-j+1, N-j+1}(\theta, \phi)$.

neuroptical: a photonic neural network simulator

Diagram illustrating the neuroptical simulator architecture, showing the input waveguides, modulators, and output waveguides.

neuroptical components: PhotonicNeuralNetwork

- init_(self, layerSize, activation)
- forward_propagate(self, data)
- back_propagate(self, y_hat, y)
- update_params(self, dlw_list, dlb_list, learning_rate)
- compute_cost(self, y_hat, y)
- learn(self, data, y, learning_rate, num_iterations, plot = True, showProgress = True)
- classify(self, data)
- make_drawing(self, d = None, outputs = None)
- layers

neuroptical components: MZBlock

- init_(self, N)
- get_matrix(self)
- set_matrix(self, U)
- make_drawing(self, d = None, outputs = None)
- T_block
- D
- T_block
- N

neuroptical components: NetworkLayer

- init_(self, inputSize, outputSize, activation = "relu")
- initialize(self)
- get_w(self)
- set_w(self, newW)
- forward_pass(self, A_prev)
- activation(self, x)
- backward_pass(self, dA)
- linear_backward(self, dZ)
- activation_backward(self, dA)
- make_drawing(self, d = None, outputs = None)
- outputSize
- activationType
- cache
- inputSize
- bias
- clu

Voltage to phase shift response

Bridge Flexure to phase shift relation:

Voltage to bridge flexure relation:

- Model as Euler-Bernoulli beam: $\frac{d^2}{dx^2} \left(EI \frac{d^2 w(x)}{dx^2} \right) = q(x) = \frac{e_0 \Delta L^2 \epsilon_0}{216 L^3 j_2 \epsilon(x)}$
- Impose rigid boundary conditions: $w(-\frac{L}{2}) = w(\frac{L}{2}) = w'(-\frac{L}{2}) = w'(\frac{L}{2}) = 0$

Voltage to phase shift relation:

Future work

- Full on-chip backpropagation
- Extend fault tolerance of decomposition routine
- Efficient convolutional and recurrent architectures
- Include thermal tension from fabrication in bridge model
- Extend to low photon number regime for quantum information processing experiments

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