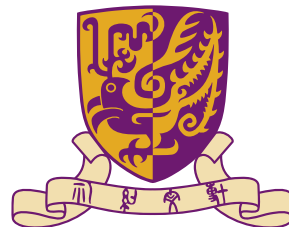


# Hardware-Software Co-design of Slimmed Optical Neural Networks

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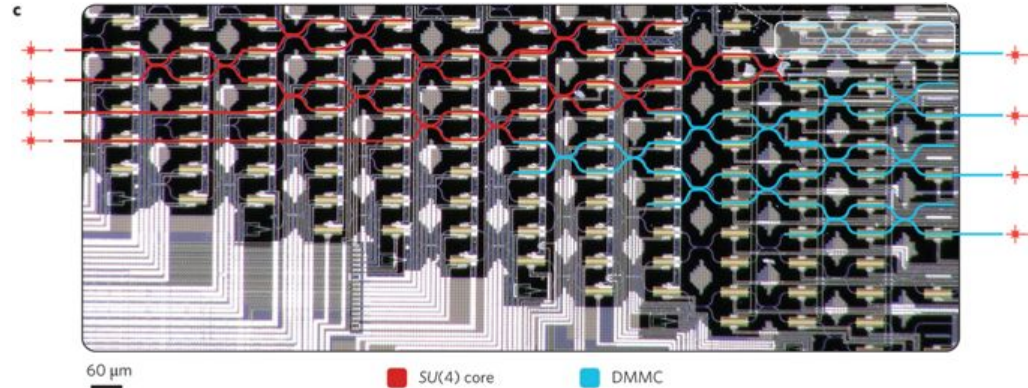
The University of Texas at Austin<sup>1</sup>

The Chinese University of Hong Kong<sup>2</sup>



# Introduction

- ◆ Emergence of dedicated AI accelerators
  - › Optical neural network processor: light in and light out
    - ›› Speed-of-light floating point matrix-vector multiplication
    - ›› >100GHz detection rate
    - ›› Ultra-low energy consumption if configured
  - › Great number of components, sensitivity to noise



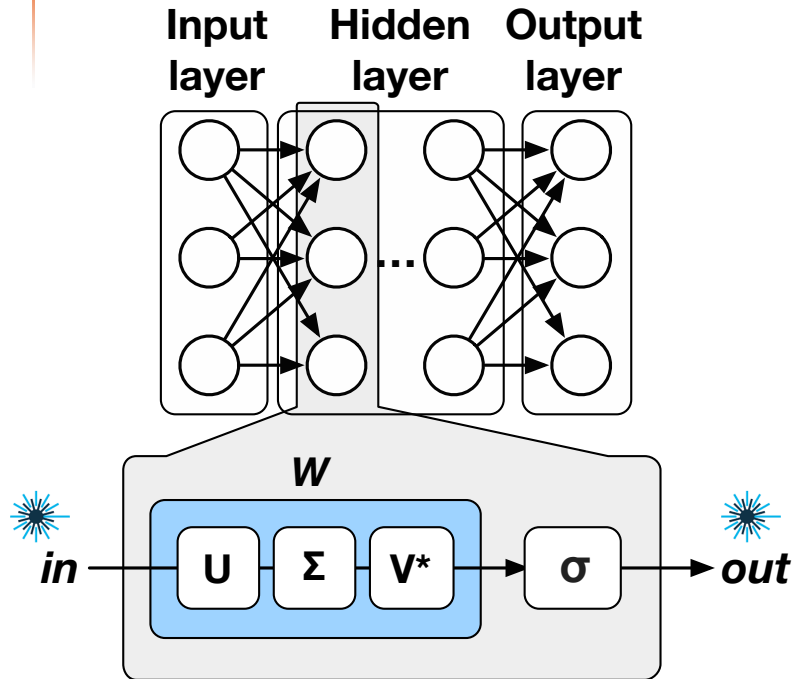
[Shen+, *Nature Photonics* 2017]



LIGHTELLIGENCE



# Previous Optical Neural Network (ONN)



[Shen+, *Nature Photonics* 2017]

◆ SVD decompose  $W = U \Sigma V^*$

◆  $U$  and  $V^*$  are unitary matrices

**Most area expensive**

◆  $\Sigma$  is a diagonal matrix

› Diagonal values are non-negative real

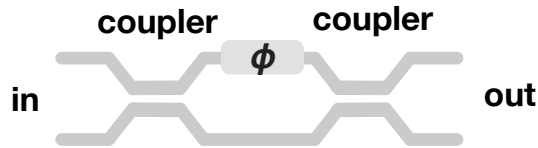
› Implemented by optical attenuators

◆  $\sigma$  is non-linear activation

› Implemented by saturable absorber

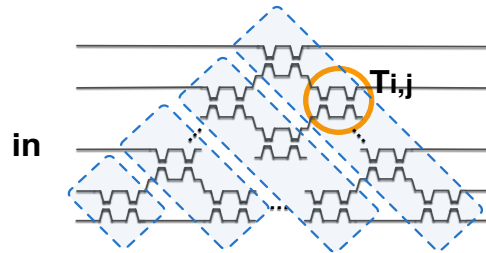
# Implementing Unitary $U$ and $V^*$

- ◆ Mach-Zehnder interferometers (MZI) for  $U$  and  $V^*$ 
  - › A single MZI implements a 2-dim unitary



$$\mathit{out} = \begin{pmatrix} \cos \phi & \sin \phi \\ -\sin \phi & \cos \phi \end{pmatrix} \cdot \mathit{in}$$

- › An array of  $n(n-1)/2$  MZIs implements an  $n$ -dim unitary



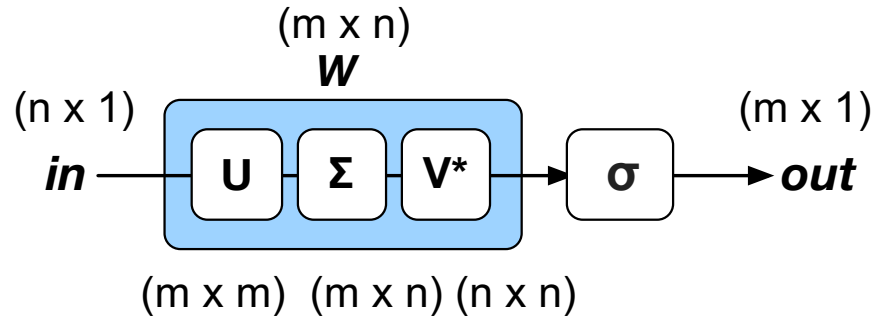
$$\mathit{out} \quad T_{i,j} = \begin{pmatrix} I & 0 & 0 & 0 & 0 \\ 0 & \cos \phi & 0 & \sin \phi & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & -\sin \phi & 0 & \cos \phi & 0 \\ 0 & 0 & 0 & 0 & I \end{pmatrix} \begin{matrix} \text{j}^{\text{th}} \text{ row} \\ \text{j}^{\text{th}} \text{ row} \end{matrix}$$

$\text{j}^{\text{th}} \text{ col.} \quad \text{j}^{\text{th}} \text{ col.}$

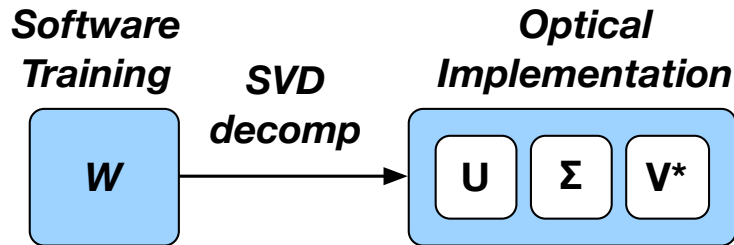
$$\mathit{out} = \prod_{i=n}^2 \prod_{j=1}^{i-1} T_{ij} \cdot \mathit{in}.$$

- ◆ Given an  $n$ -dim unitary,  $\phi$ 's can be uniquely computed

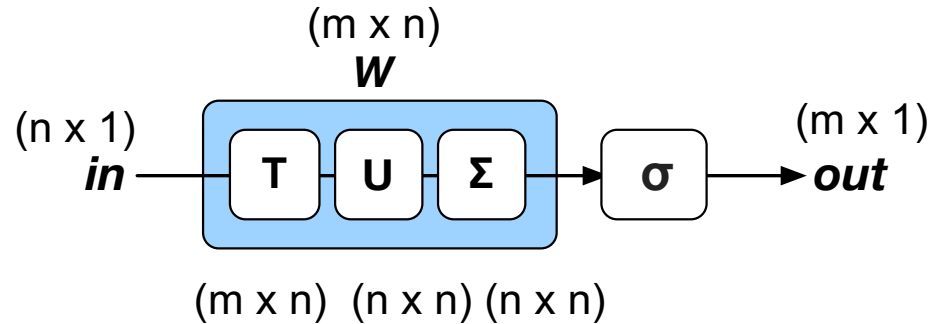
# Previous ONN overview



- ◆ Layer size measured by # of MZIs =  $m(m-1)/2 + n(n-1)/2$
- ◆ Software training and hardware implementation
  - › Train  $W$  directly in software  $\rightarrow$  SVD-decomp to obtain  $U, \Sigma, V^*$



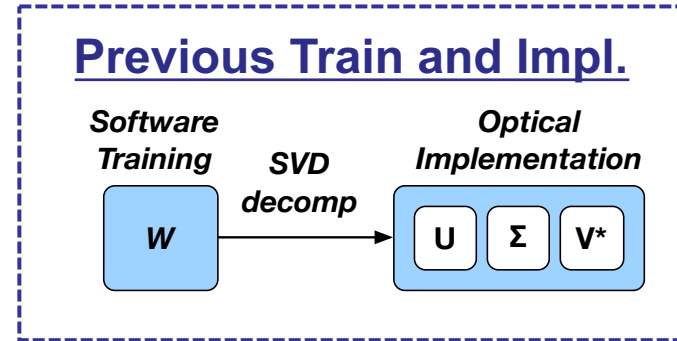
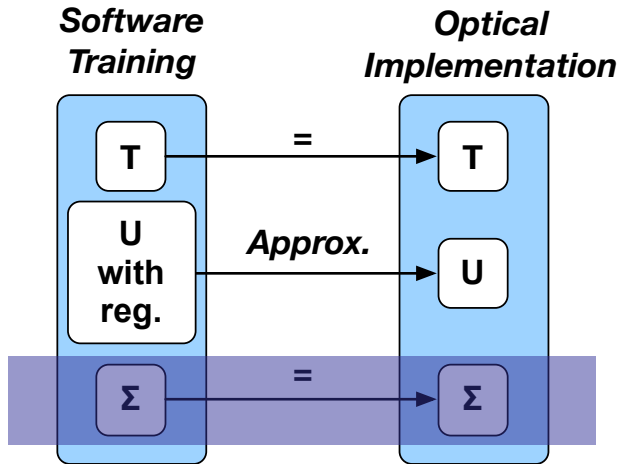
# Slimmed Architecture



- ◆ **T**: sparse tree network
- ◆ **U**: unitary network
- ◆  **$\Sigma$** : diagonal network } same constraints as the previous architecture
- ◆ Use less # of MZIs =  $n(n-1)/2$ 
  - › 1 unitary matrix to maintain the expressivity
  - › An area-efficient tree network to match the dimension

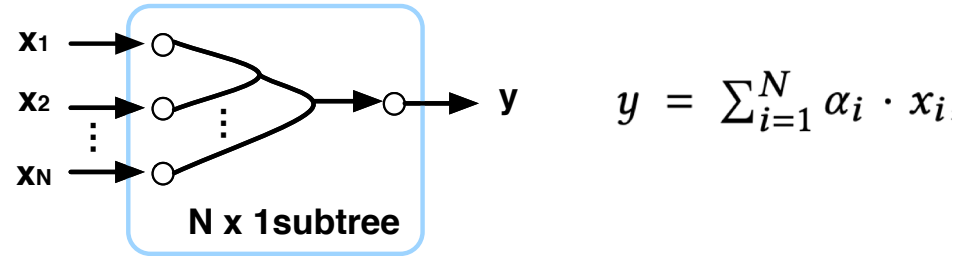
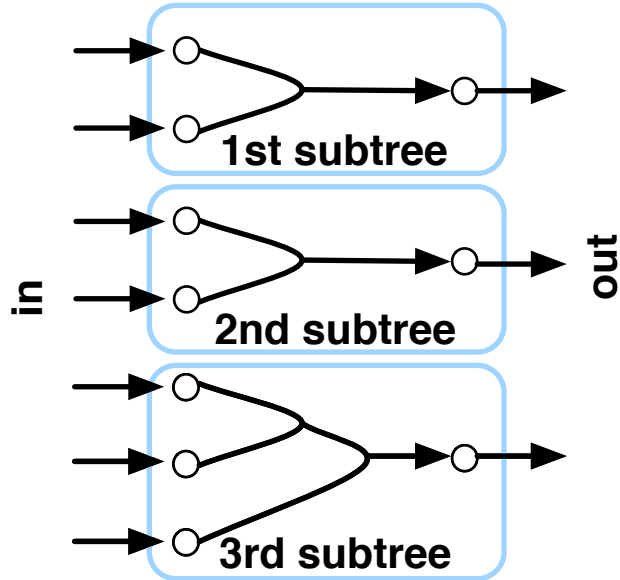
# Co-design Overview

- ◆ An arbitrary weight  $\mathbf{W}$  is **not TU $\Sigma$ -decomposable**
- ◆ Co-design solution: training and implementation are coupled
  - ›  $\mathbf{T}$  and  $\Sigma$ : Train the device parameters, constraints embedded
  - ›  $\mathbf{U}$ : Add unitary regularization then approximate with true unitary



# Sparse Tree Network

- ◆ Sparse Tree network (**T**) to match the different dimension
  - › Suppose in-dim > out-dim
  - ›  $\alpha$ : linear transfer coefficient

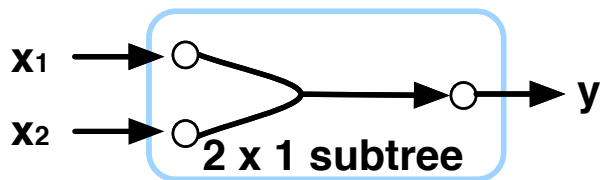


$$\mathit{out} = \begin{pmatrix} \alpha_{1,1} & \alpha_{1,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \alpha_{2,1} & \alpha_{2,2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \alpha_{3,1} & \alpha_{3,2} & \alpha_{3,3} \end{pmatrix} \cdot \mathit{in}.$$



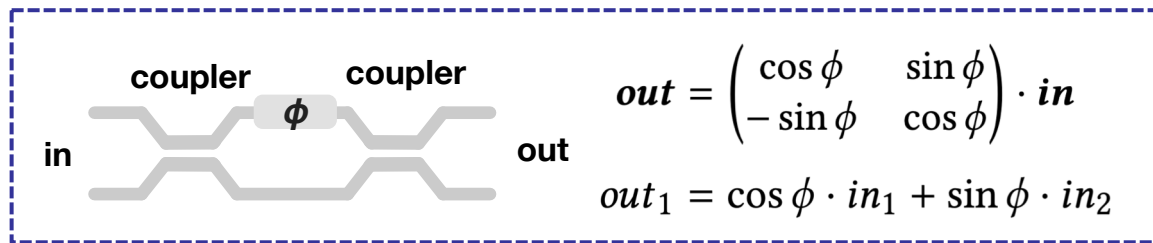
# Sparse Tree Network Implementation

- ◆ Implemented with MZIs or directional couplers
- ◆ A 2 x 1 subtree



$$y = \alpha_1 \cdot x_1 + \alpha_2 \cdot x_2$$

can be Implemented with a single-out MZI or directional coupler



$$\mathit{out} = \begin{pmatrix} \cos \phi & \sin \phi \\ -\sin \phi & \cos \phi \end{pmatrix} \cdot \mathit{in}$$
$$\mathit{out}_1 = \cos \phi \cdot \mathit{in}_1 + \sin \phi \cdot \mathit{in}_2$$

$$\alpha_1 = \cos \phi \text{ and } \alpha_2 = \sin \phi$$

$$\alpha_1^2 + \alpha_2^2 = 1 \text{ (energy conservation)}$$

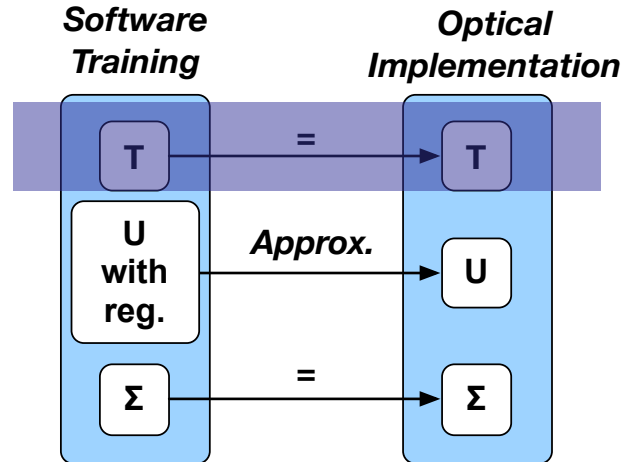
# Sparse Tree Network Implementation

- Any  $N$ -input subtree with arbitrary  $\alpha$ 's satisfying energy conservation

$$\sum_{i=1}^N \alpha_i^2 = 1, -1 \leq \alpha_i \leq 1, i = 1, \dots, N$$

can be implemented it by cascading  $(N-1)$  single-out MZIs.

- Energy conservation embedded in training



# Unitary Network in Training

- ◆ For unitary network  $\mathbf{U}$  satisfying  $\mathbf{U}\mathbf{U}^* = \mathbf{I}$ , add the regularization

$$\text{reg} = \|\mathbf{U}\mathbf{U}^* - \mathbf{I}\|_F$$

- ◆ Training loss function

$$\text{Loss} = \text{Data Loss} + \text{Regularization Loss}$$

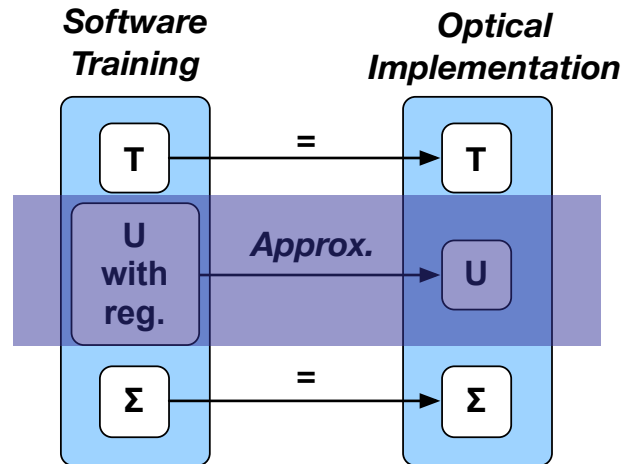
leading to a **near-implementable** ONN with high accuracy

- ◆ Trained  $\mathbf{U}_t \sim$  unitary but only true unitary is implementable by MZIs

# Unitary Network in Implementation

- ◆ Approximate  $\mathbf{U}_t$  by a true unitary  $\mathbf{U}_a$
- ◆ SVD-decompose  $\mathbf{U}_t = \mathbf{P}\mathbf{S}\mathbf{Q}^* \rightarrow \mathbf{U}_a = \mathbf{P}\mathbf{Q}^*$
- ◆ **Claim.** Minimize the regularization  $\Leftrightarrow$  find the best approximation

$$\text{Min. reg} \Leftrightarrow \text{Min. } \|\mathbf{U}_t - \mathbf{U}_a\|_F$$



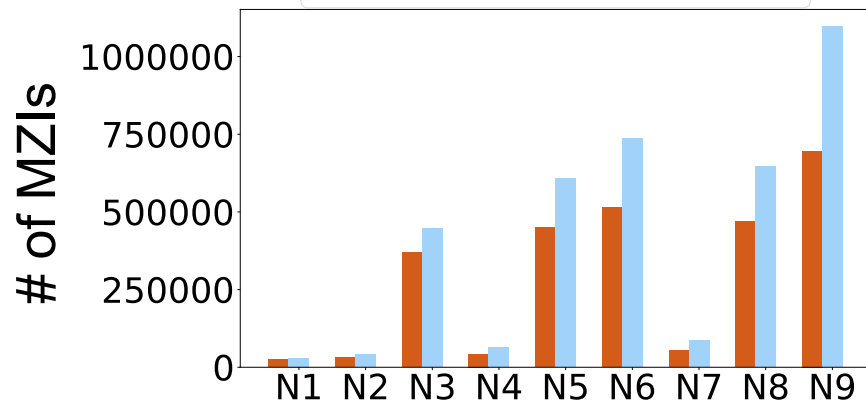
# Simulation Results

- ◆ Implemented in TensorFlow for various ONN setup

<b>N1:</b> (14 × 14)-100-10	<b>N4:</b> (14 × 14)-150-150-10	<b>N7:</b> (14 × 14)-150-150-150-10
<b>N2:</b> (14 × 14)-150-10	<b>N5:</b> (28 × 28)-400-400-10	<b>N8:</b> (28 × 28)-400-400-200-10
<b>N3:</b> (28 × 28)-400-10	<b>N6:</b> (28 × 28)-600-300-10	<b>N9:</b> (28 × 28)-600-600-300-10

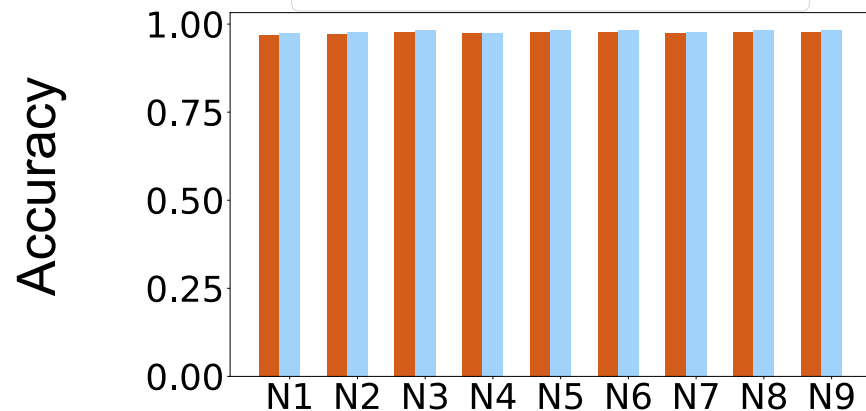
- ◆ Tested it on Intel Core i9-7900X CPU and an NVIDIA TitanXp GPU
- ◆ Performed on the handwritten digit dataset MNIST

# Simulation Results



prev. ours

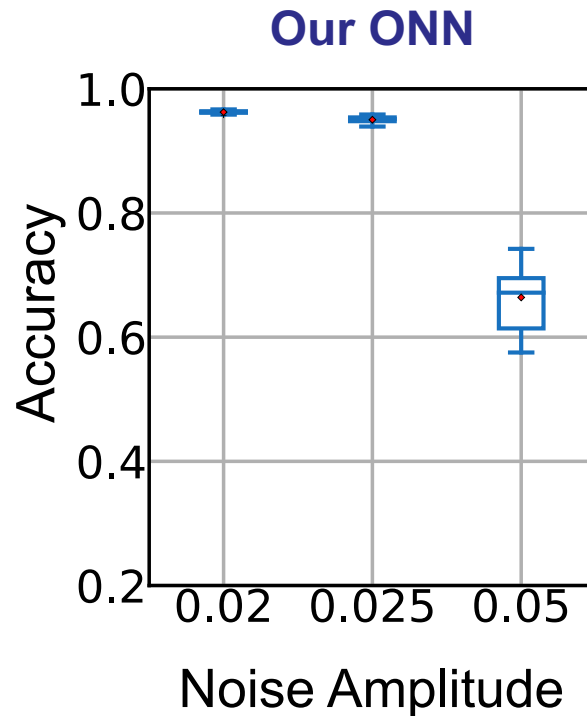
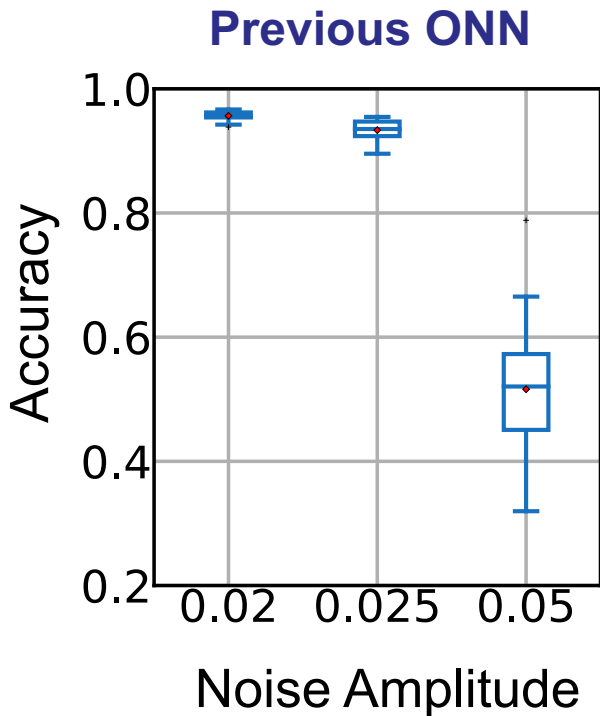
- N1~N9: network configurations
- Our architecture uses 15%-38% less MZIs



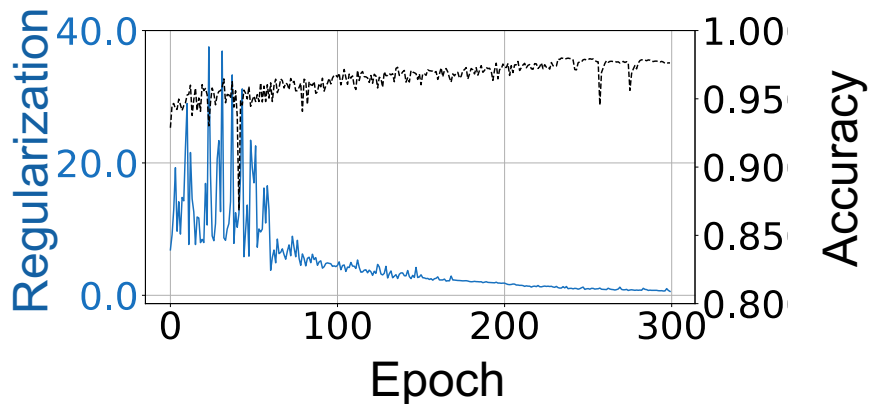
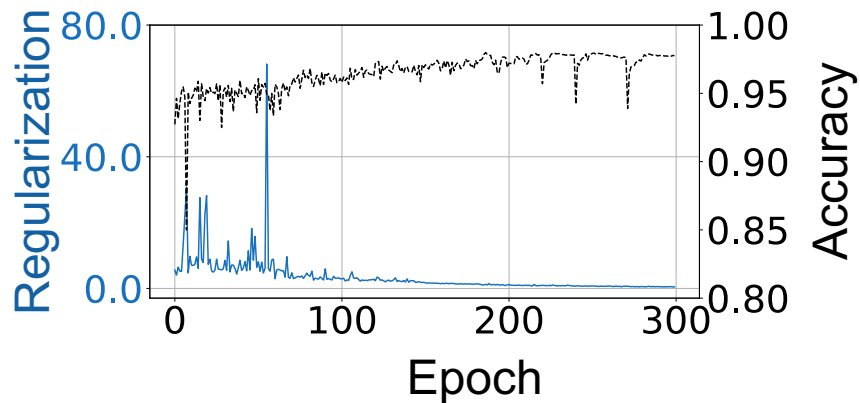
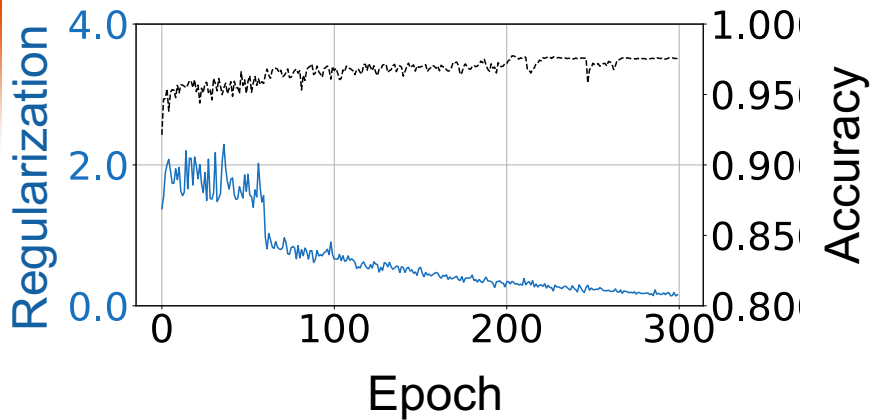
- Similar accuracy (~0 accuracy loss)
- Maximum loss is 0.0088
- Average is 0.0058

# Noise Robustness

- ◆ Better resilience due to less cascaded components



# Training Curve



- Converged in 300 epochs
- Balance of the accuracy and the unitary approximation



# Contributions of This Work

- ◆ An new architecture for ONN
  - › Area-efficiency
  - › ~0 accuracy loss
  - › Better robustness to noise
- ◆ Hardware and software co-design methodology
  - › Software-embedded hardware parameters
  - › Hardware constraints guaranteed by software

# Future Work

- ◆ Better MZI pruning methods
  - ›  $\sim 0$  phase MZI  $\rightarrow$  pruned + accuracy recover
  - › MZI-sparse unitary matrix
- ◆ Design for robustness
  - › Adjust noise distribution in training
- ◆ Online training
- ◆ ONN for other neural network architectures
  - › CNN, RNN, etc.

Thanks  
Q&A