



SqueezeLight: Towards Scalable Optical Neural Networks with Multi-Operand Ring Resonators

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AI Acceleration: Challenges

- ML models/dataset keep increasing -> more computations

- Low latency
- Low power
- High bandwidth



Autonomous Vehicle

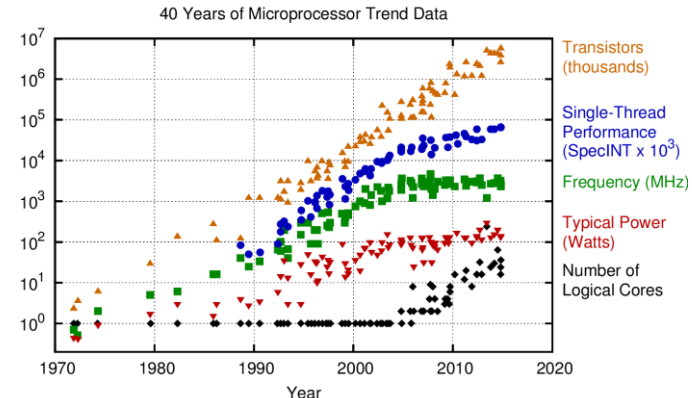
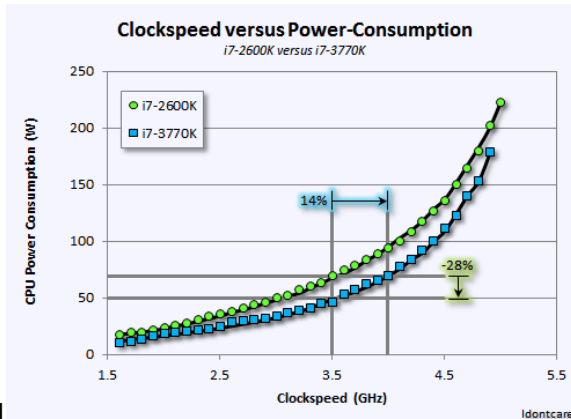


Data Center



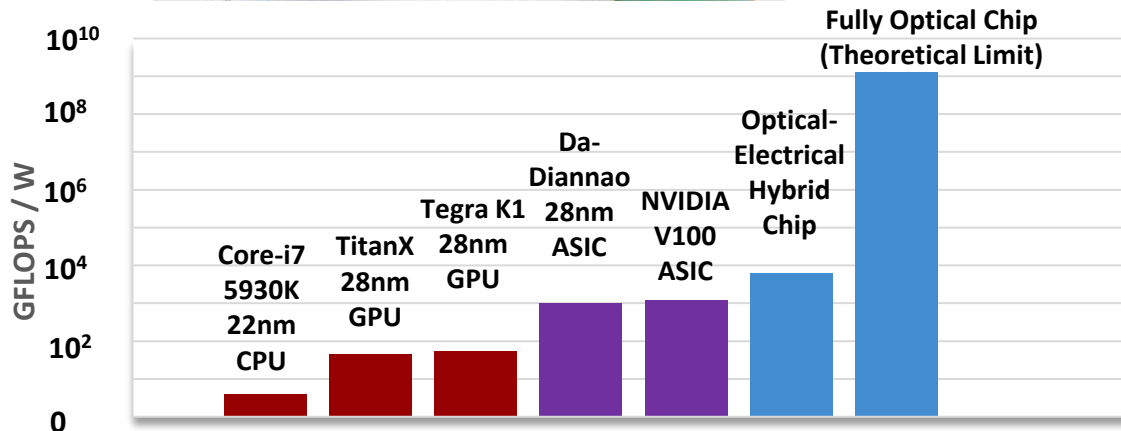
Edge Device

- Moore's law is approaching its physical limits



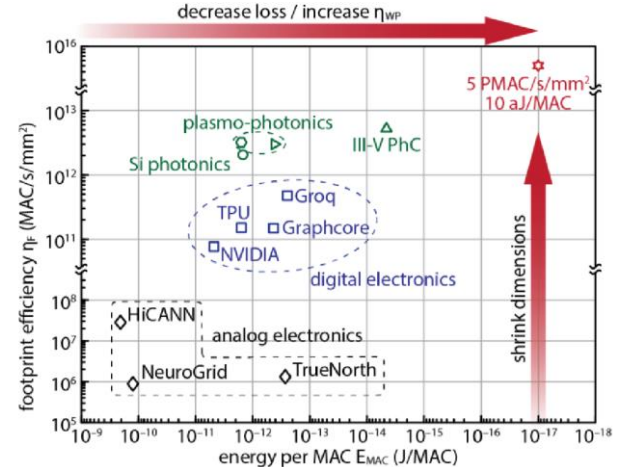
AI Acceleration: Opportunities

- Using light to continue Moore's Law
- Promising technology for next-generation AI accelerator



2 February 2021

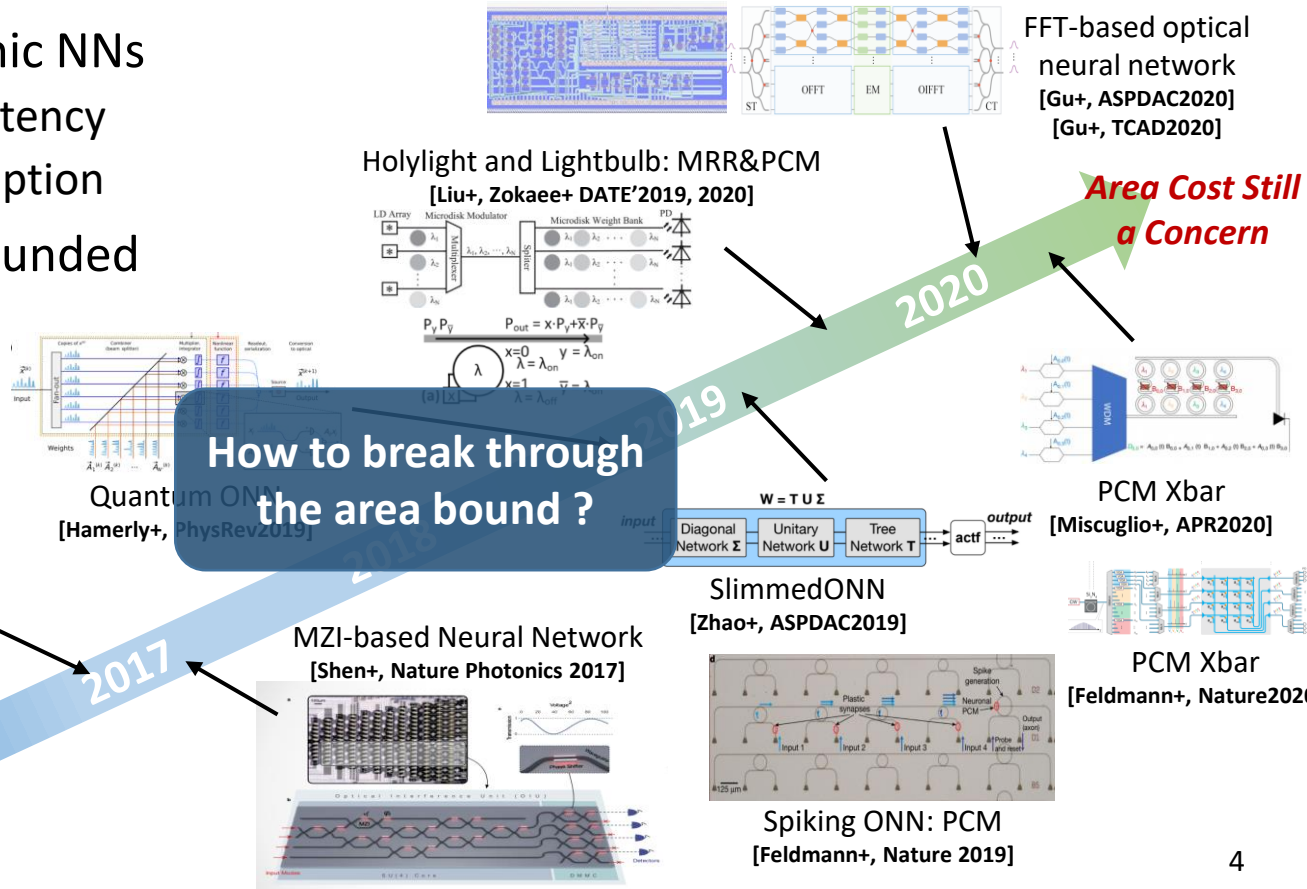
[Shen+, *Nature Photonics* 2017]



[Totovic+, *JSTQE* 2020]

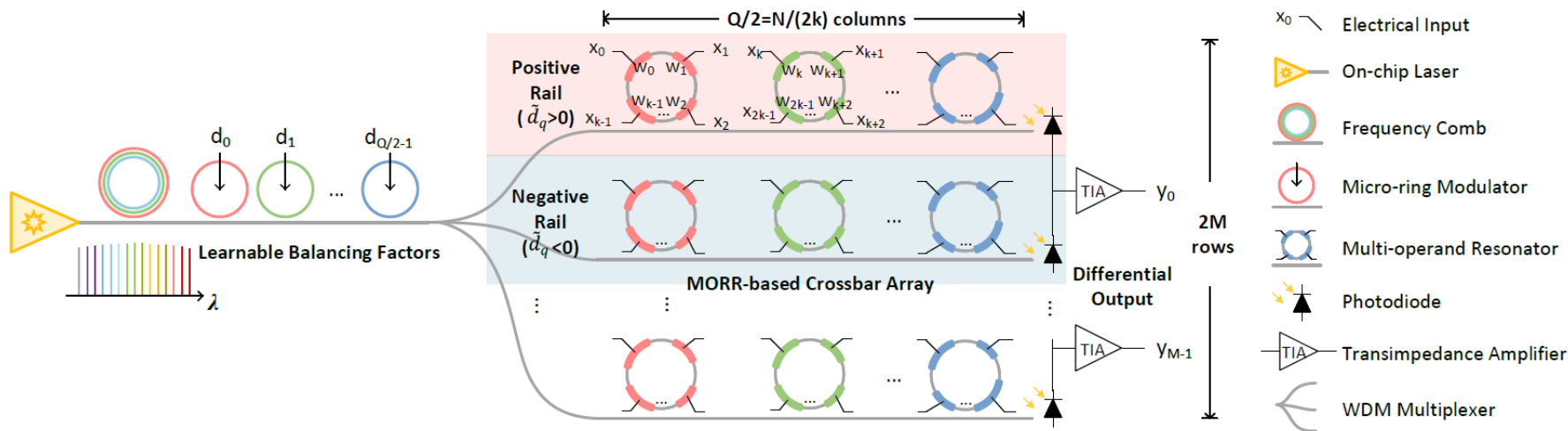
Optical Neural Networks (ONN)

- Emergence of photonic NNs
 - Ultra-low ps-level latency
 - Low energy consumption
- Compact design is bounded
 - 1 MAC per device



Proposed SqueezeLight

- SqueezeLight: ultra-compact MORR-ONN
 - **Scalability:** nonlinear neuron based on multi-operand ring resonators (MORR)
 - **Efficiency:** structured matrix with fined-grained structured pruning
 - **Robustness:** sensitivity-aware learning to overcome variations and crosstalk



Multi-Operand Ring Resonators

- MORR: k -segment controllers on one micro-ring
- Single-device vector dot-product

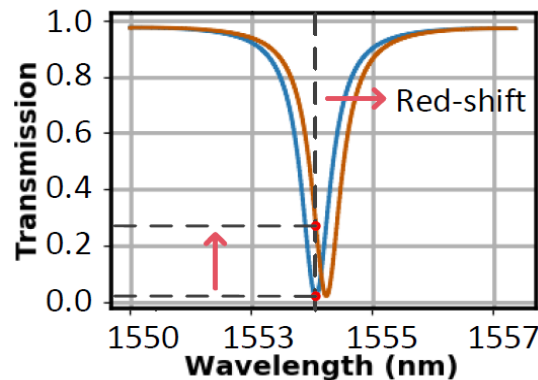
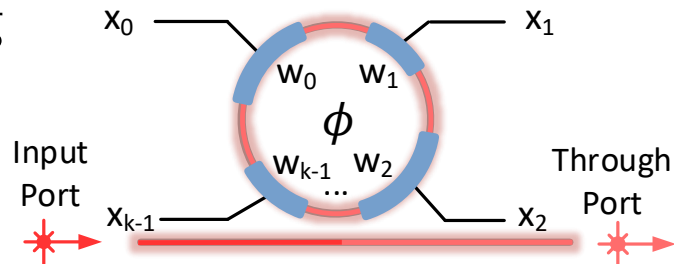
$$\text{Round-trip phase: } \phi \propto \sum_{i=0}^{k-1} w_i x_i^2$$

- Built-in nonlinearity
 - Half-Tanh-like nonlinear activation $f(\cdot) \in (0, 1)$
 - Tunable smoothness (r, a)

$$f(\phi) = \left| \frac{r - a e^{-j\phi}}{1 - ra e^{-j\phi}} \right|^2$$

$$OUT = f(\phi) \cdot in \propto f\left(\sum_{i=0}^{k-1} w_i x_i^2\right) \cdot IN$$

- No power consumption overhead
 - Same tuning range: half spectrum width, $\forall k$



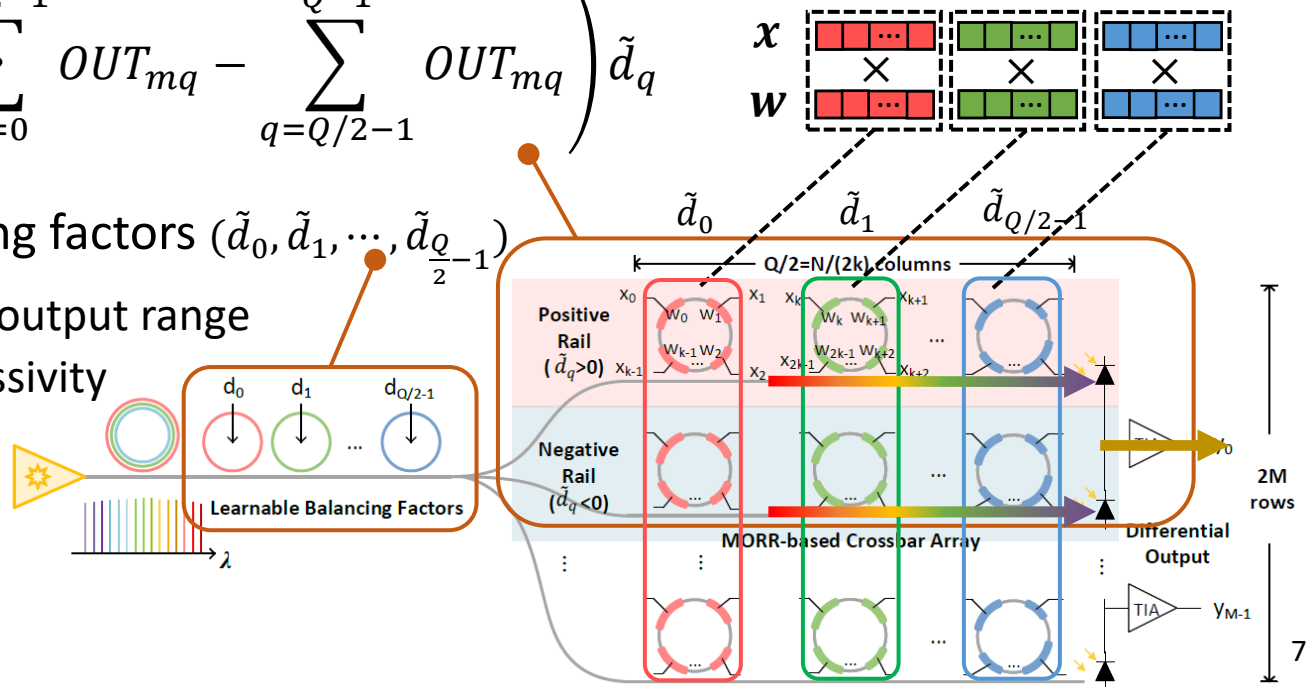
MORR-based ONN Architecture

- Nonlinear $M \times N$ MatMul in MORR crossbar array
- Differential rails support positive/negative neurons

$$y_m = \left(\sum_{q=0}^{Q/2-1} OUT_{mq} - \sum_{q=Q/2-1}^{Q-1} OUT_{mq} \right) \tilde{d}_q$$

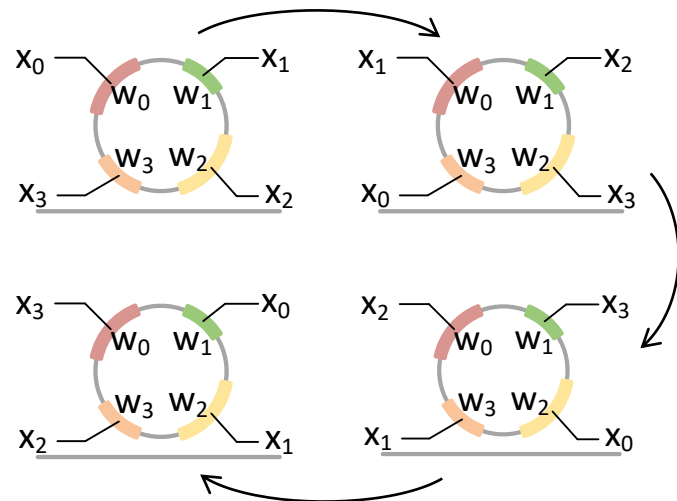
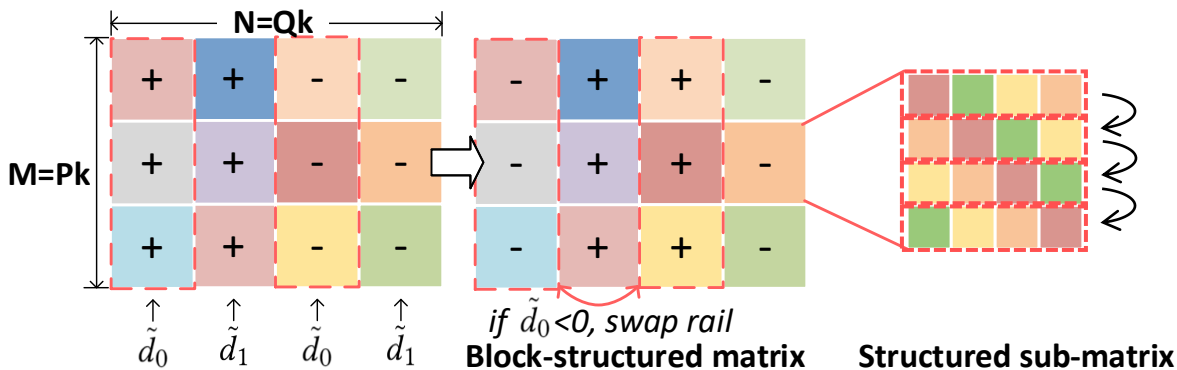
- Learnable balancing factors $(\tilde{d}_0, \tilde{d}_1, \dots, \tilde{d}_{\frac{Q}{2}-1})$

- Adaptive MORR output range
- Enhanced expressivity



Area Reduction: Block-Squeezing

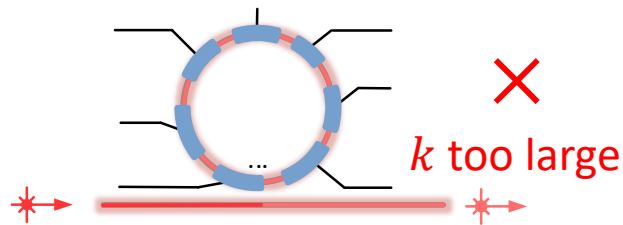
- Nonlinear $M \times N$ Block-structured MatMul in MORR crossbar array
- Squeeze a structured matrix into one MORR
 - Share weights in multiple rows \rightarrow share the same MORR
 - Saves $k^2 \times$ device usage via input rotation
 - $k \times$ less weight storage
 - $2k \times$ fewer wavelengths



Sparsity Exploration: Fined-Grained Pruning

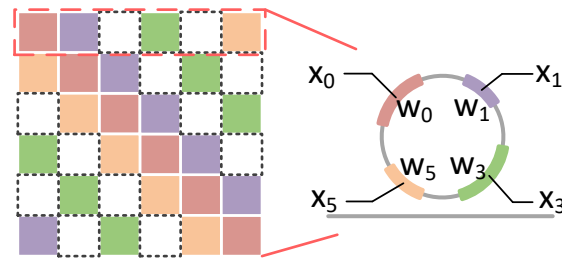
- How to squeeze larger block into one MORR?

- #Operand limit on one MORR
- Manufacturing, crosstalk, ...



- Sparsify blocks via fine-grained structured pruning

- 4-operand MORR \leftrightarrow 6×6 pruned block (33% sparsity)
- 4-operand MORR \leftrightarrow 8×8 pruned block (50% sparsity)
- Support larger blocks with small MORR
- Pruning-aware training



Sparse structured sub-matrix

Robustness Boost: Sensitivity Optimization

- Non-ideal effects of MORRs

- Individual phase drift

$$\Delta\phi \in \mathcal{N}(0, \sigma^2)$$

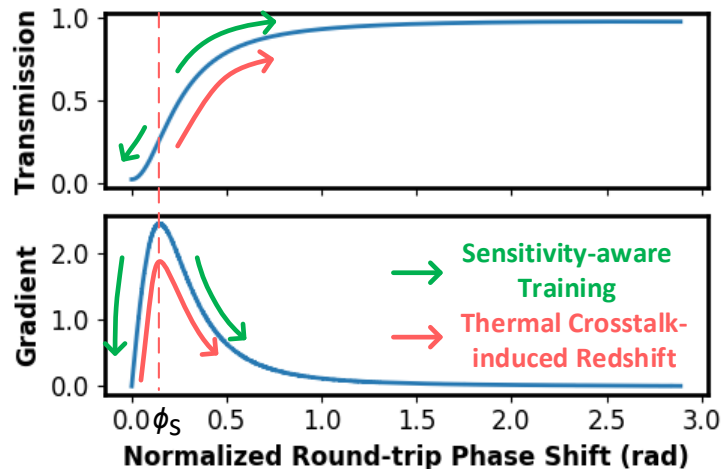
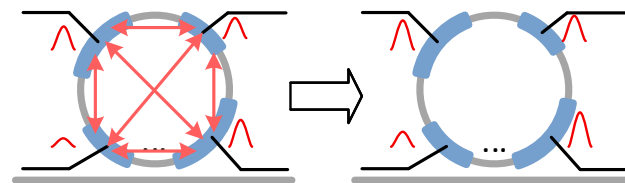
- Intra-MORR crosstalk

$$\begin{pmatrix} \gamma_{0,0} & \gamma_{0,1} & \cdots & \gamma_{0,k-1} \\ \gamma_{1,0} & \gamma_{1,1} & \cdots & \gamma_{1,k-1} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{k-1,0} & \gamma_{k-1,1} & \cdots & \gamma_{k-1,k-1} \end{pmatrix}$$

- Transmission sensitivity-aware regularization

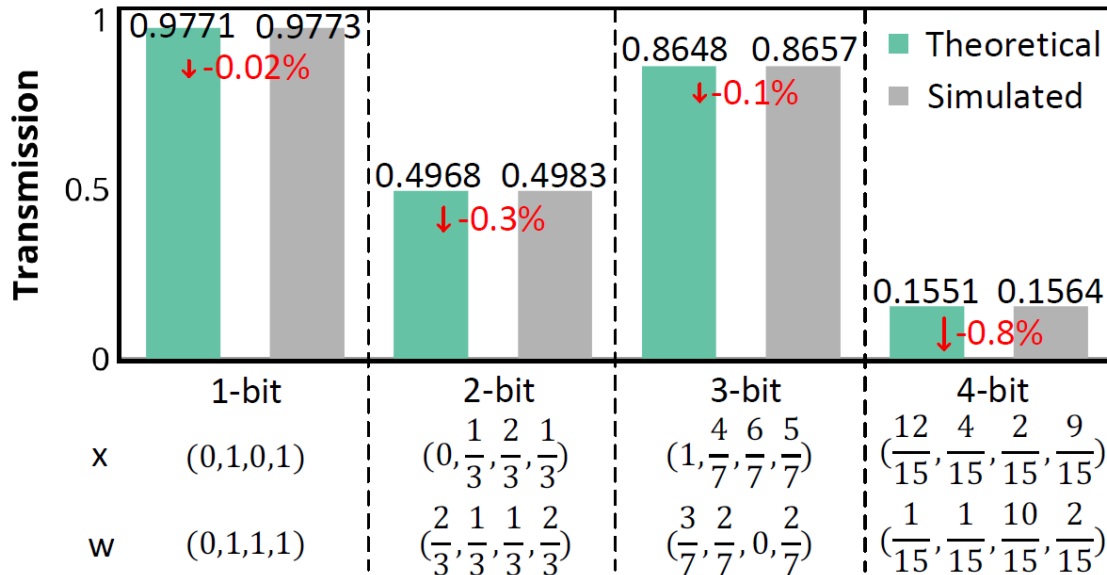
- Encourage phases with lower gradients

$$\mathcal{L} = \mathcal{L}_0(x; \mathbf{W}, \tilde{\mathbf{D}}, \mathbf{\Gamma}, \Delta\phi) + \alpha \sum_{l,m,q=0}^{L-1, M-1, Q-1} \nabla_{\phi} f(\hat{\phi}_{lmq} + \Delta\phi)$$



Fidelity Validation: Optical Simulation

- 1- to 4-bit MORR neuron
- Optical simulation with Lumerical INTERCONNECT
- <1% relative modeling error



Comparison: Accuracy, Scalability, Robustness

- Compare with SoTA MRR-ONNs on MNIST, FMNIST CIFAR-10

- MRR-ONN-1 [Liu+, DATE'2019]
- MRR-ONN-2 [Tait+, SciRep'2017]

- Comparable expressivity

- **23x-32x** less device usage

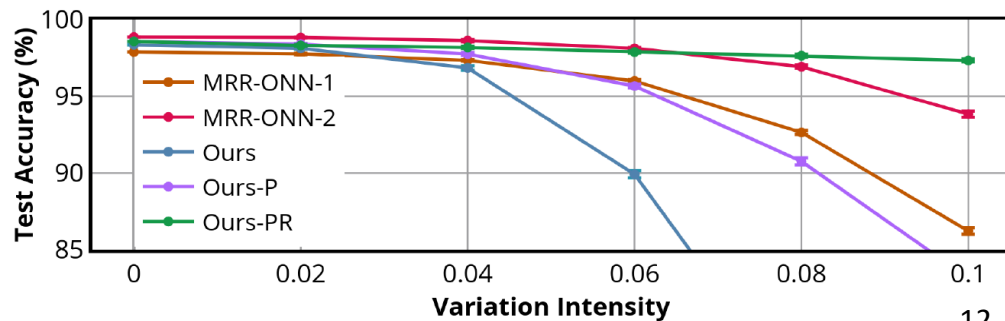
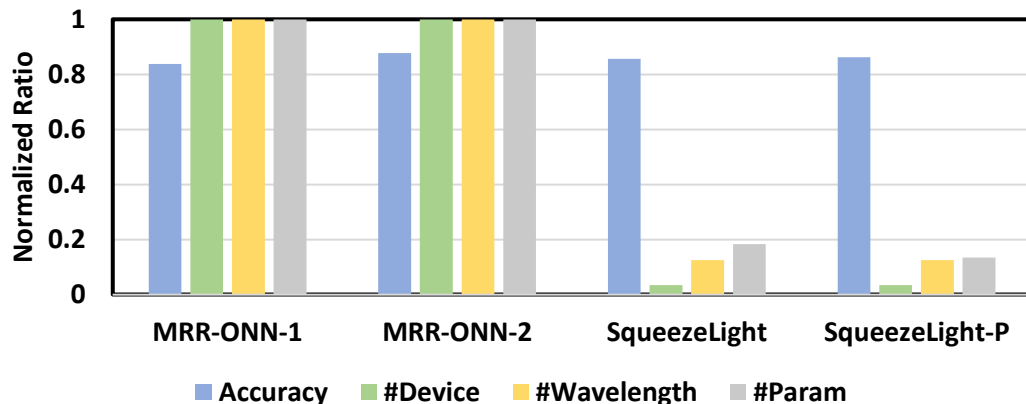
- **8x** fewer wavelength usage

- **>5x** fewer parameters

- 50% sparsity
- No accuracy drop

- Better noise-robustness

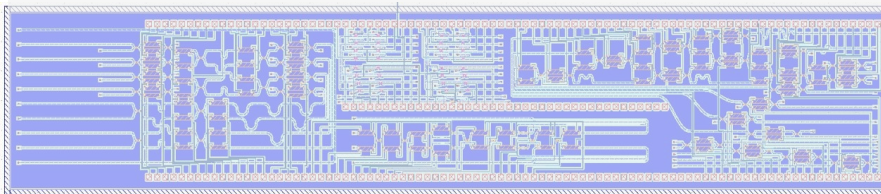
- Maintain > 97%



Conclusion and Future Work

- **New ONN Architecture:** Optical MORR-based neural architecture
- **Ultra-compact footprint:** $23\times\sim 32\times$ fewer device usage, built-in nonlinearity
- **Better scalability:** $8\times$ fewer wavelength usage
- **Better robustness:** $\sim 4\%$ higher accuracy under variations and crosstalk
- **Fewer parameters:** $>5\times$ fewer weight storage

- Future direction
 - Demonstrate more applications
 - Physical evaluation and testing on photonic neural chip tape-out



Thank You !
Q&A