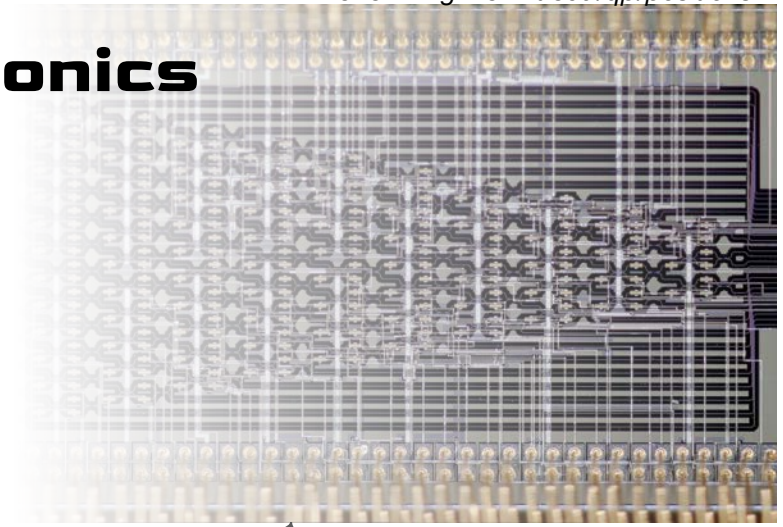
We're hiring! rle.mit.edu/qp/positions

Photonics for AI | AI for Photonics



MIT AI Hardware Program Spring Symposium

2025.03.31@MIT

Dirk Englund ∈ {RLE, MTL, EECS}@MIT

Quantum Computing & Networking

ML signal processing

We're hiring! rle.mit.edu/qp/positions

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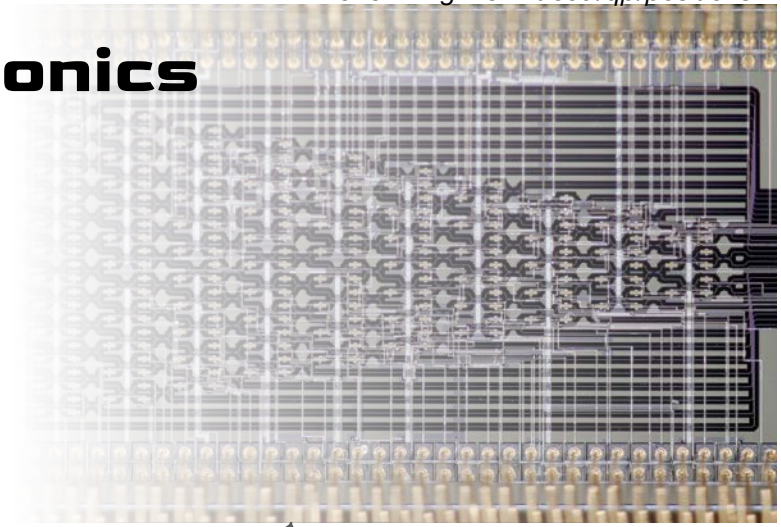

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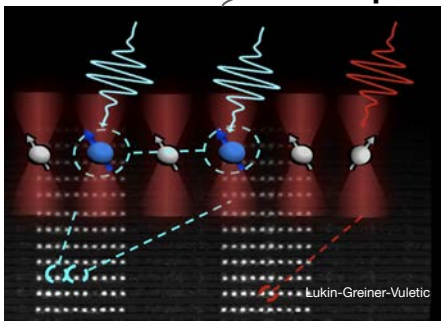
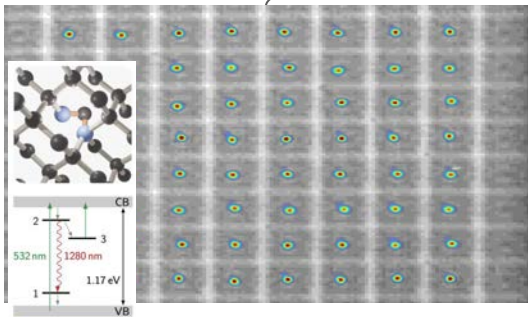


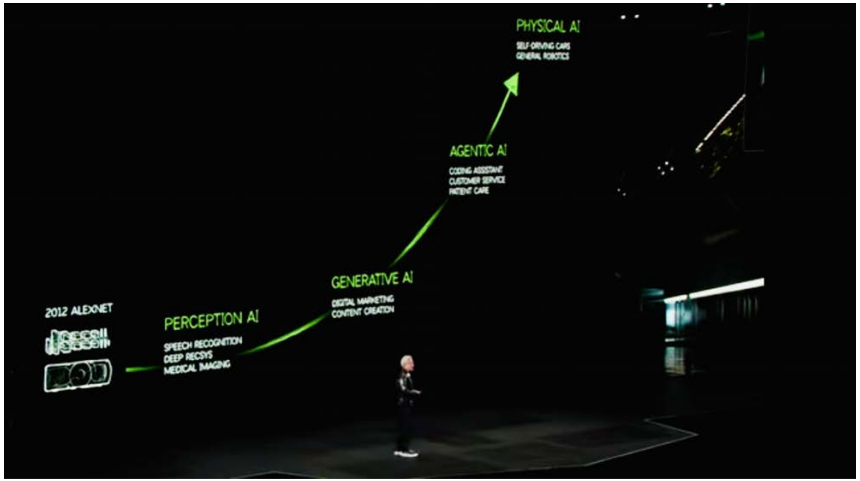


ML signal processing

The Renaissance in Computing

1. Quantum Computing

2. Machine learning & AI



Jensen Huang, NVIDIA CEO (Mar 12 2025)

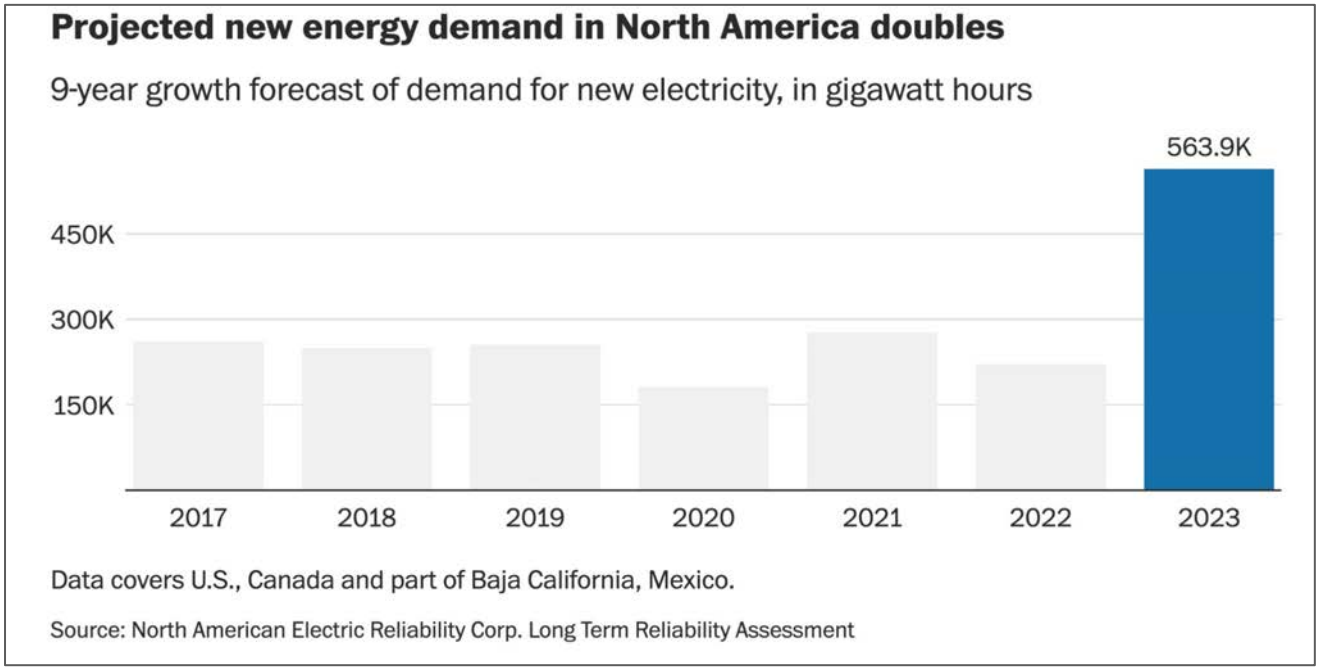
The Washington Post
Democracy Dies in Darkness

Amid explosive demand, America is running out of power

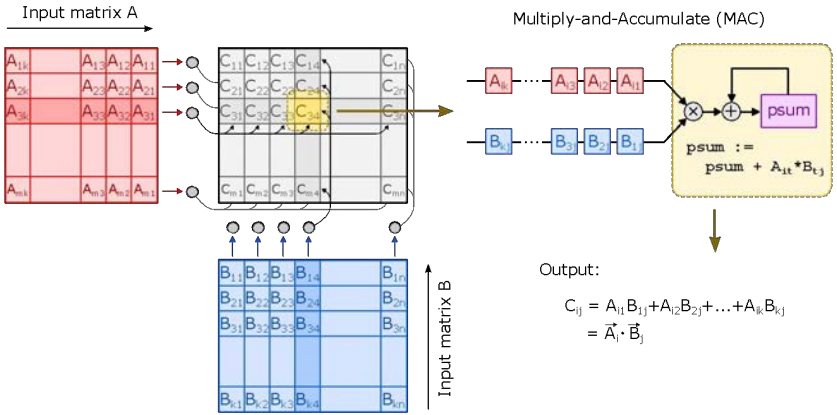
AI and the boom in clean-tech manufacturing are pushing America's power grid to the brink. Utilities can't keep up.

By Evan Halper

March 7, 2024 at 6:05 a.m. EST



Systolic Array architecture is optimized for general matrix multiplier

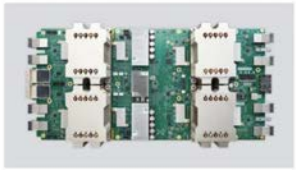


Google TPU cloud offerings:

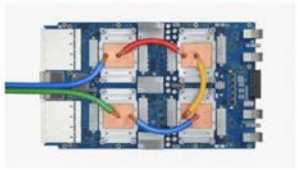
In-Datacenter Performance Analysis of a Tensor Processing Unit

.. Google team: >cs>arXiv:1704.04760

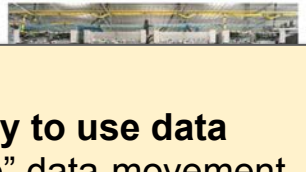
Cloud TPU offering

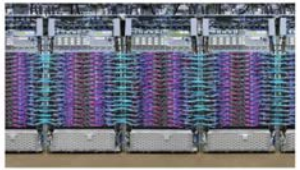


Cloud TPU v2
180 teraflops
64 GB High Bandwidth Memory (HBM)



Cloud TPU v3
420 teraflops
128 GB HBM



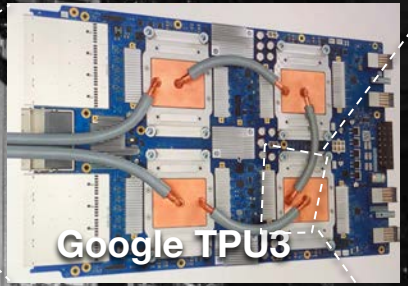


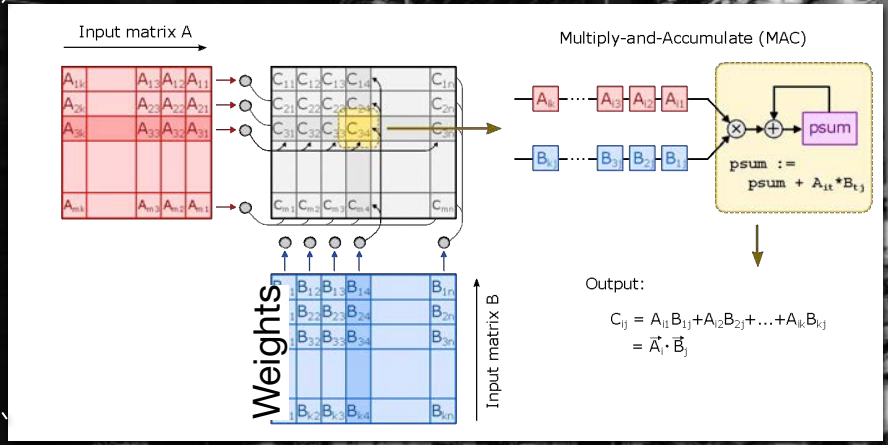
Cloud TPU v3 Pod
100+ petaflops
32 TB HBM
2-D toroidal mesh network

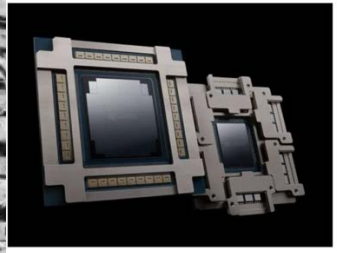
Despite all the optimizations, chips are dom
movement costs, not raw processing!

Key point #1: **Try to use data fan-out** for "free" data-movement

slide credit: R Hamerly







Nvidia looks to silicon photonics to cut datacentre AI power

Technology News | March 21, 2025

By Nick Flaherty

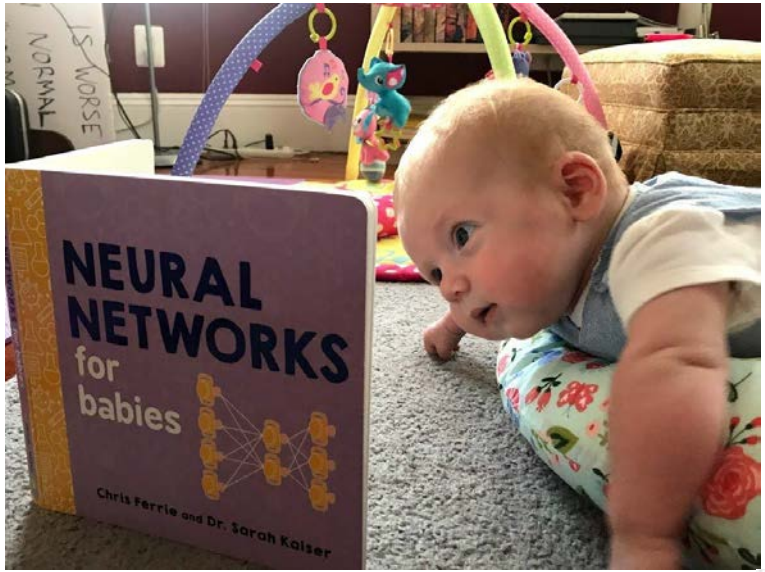
OPTOELECTRONICS AI POWER MANAGEMENT

Despite all the optimizations, chips are dominated by data movement costs, not raw processing!

Opportunity #1: **Try to use data fan-out** for “free” data-movement

* Google team: >cs>arXiv:1704.04760

Specialized information processing architectures

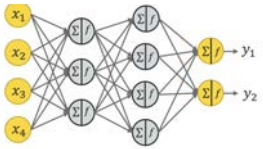


Non-boolean logic

Boolean

✅

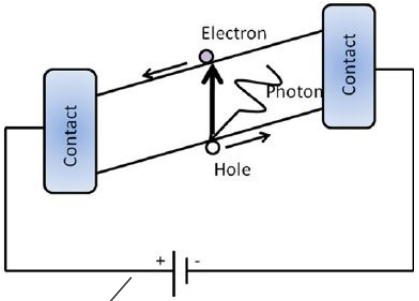
?



?

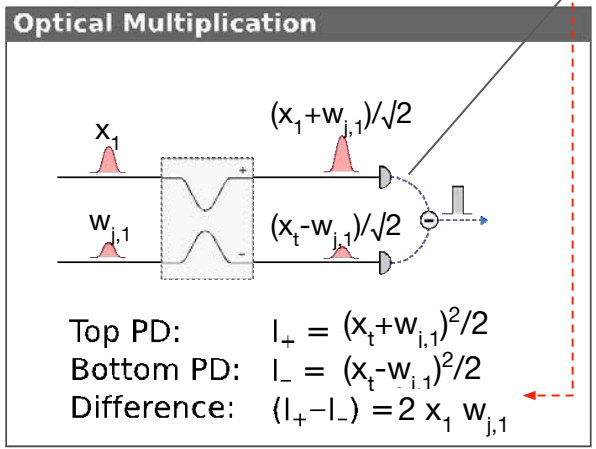
In-physics computing allows inner vector products with O(1) operations vs. O(N) for boolean logic

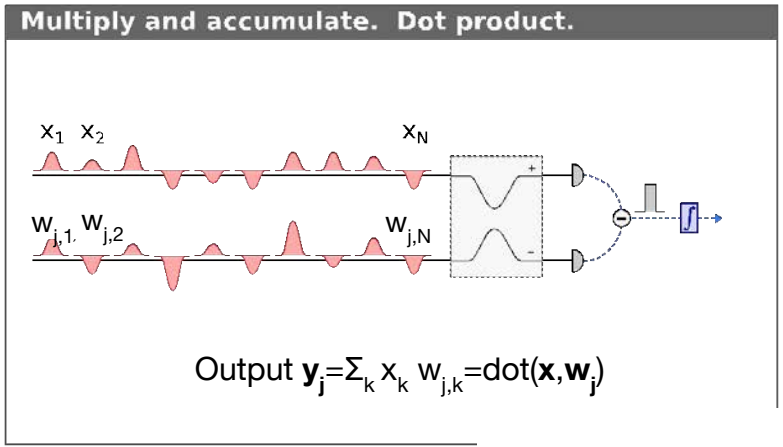
"Photoelectric multiplication"



The (quantum) process of photodetection has extreme photon-electron nonlinearity!

$$\langle \psi \mid E^{(-)}(\mathbf{r},t) \cdot E^{(+)}(\mathbf{r},t) \mid \psi \rangle$$





R Hamerly, A Sludds, L Bernstein, M Soljacic, DE, PRX **9** (2019)

Positions available in theory & experiment: https://qp.mit.edu/

Outline

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- A Renaissance in Physics of Computing & Sensing

Principles

- In-physics processing: vector products at O(1) effort vs O(N) effort
- EC in hardware compute, training: → "error-corrected physical system"

Y. Shen*, N Harris*, et al, N Phot. (2017)

Background: Nature **586** (2020); Nature **588** (2020)

R Hamerly et al, PRX **9** (2019)

S. Bandyopadhyay, Optica 8, 1247 (2021

Key point #3: Coherent error cancellation $\varepsilon \rightarrow \varepsilon^d$

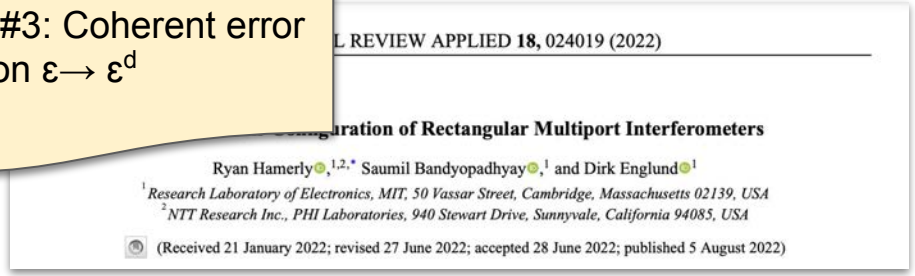
Applications


Article | Open Access | Published: 29 November 2022

Asymptotically fault-tolerant progra photonics

Ryan Hamerly, Saumil Bandyopadhyay & Dirk Englund

Nature Communications **13**, Article number: 6831 (2022) | Cite this article


L REVIEW APPLIED **18,** 024019 (2022)

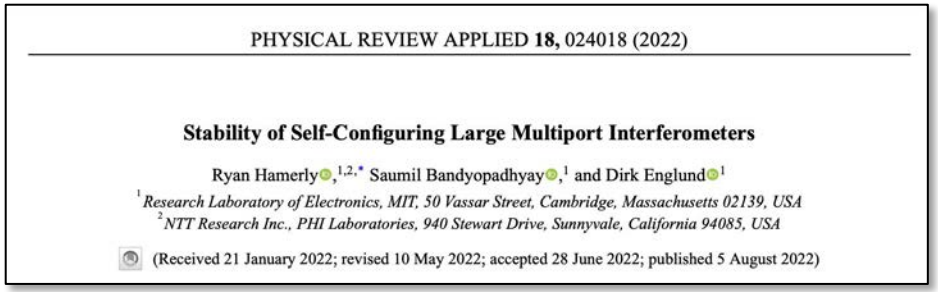
uration of Rectangular Multiport Interferometers

Ryan Hamerly[1,2,*] Saumil Bandyopadhyay[1] and Dirk Englund[1]

[1]*Research Laboratory of Electronics, MIT, 50 Vassar Street, Cambridge, Massachusetts 02139, USA*

[2]*NTT Research Inc., PHI Laboratories, 940 Stewart Drive, Sunnyvale, California 94085, USA*

(Received 21 January 2022; revised 27 June 2022; accepted 28 June 2022; published 5 August 2022)


PHYSICAL REVIEW APPLIED **18,** 024018 (2022)

Stability of Self-Configuring Large Multiport Interferometers

Ryan Hamerly[1,2,*] Saumil Bandyopadhyay[1] and Dirk Englund[1]

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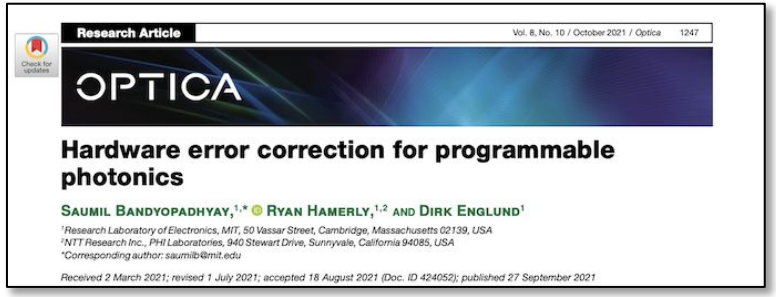
Research Article | Vol. 8, No. 10 / October 2021 / Optica 1247

OPTICA

Hardware error correction for programmable photonics

Saumil Bandyopadhyay,[1,*] Ryan Hamerly,[1,2] and Dirk Englund[1]

[1]*Research Laboratory of Electronics, MIT, 50 Vassar Street, Cambridge, Massachusetts 02139, USA*

[2]*NTT Research Inc., PHI Laboratories, 940 Stewart Drive, Sunnyvale, California 94085, USA*

**Corresponding author: saumilb@mit.edu*

Received 2 March 2021; revised 1 July 2021; accepted 18 August 2021 (Doc. ID 424052); published 27 September 2021

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S. Bandyopadhyay, Optica 8, 1247 (2021

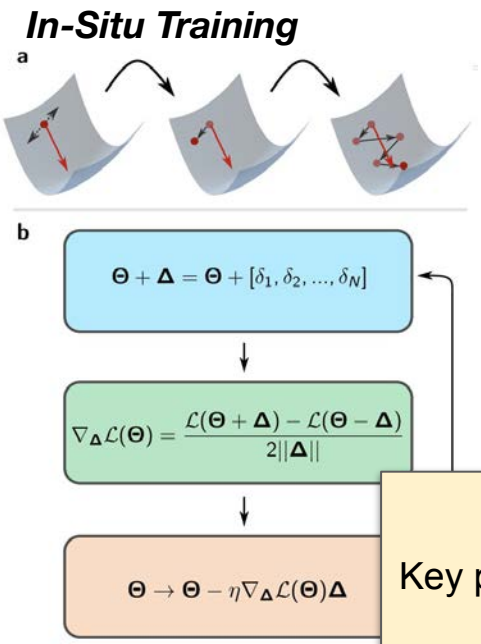
R Hamerly et al, Nature Comm. 13 (2023)

- In-situ training

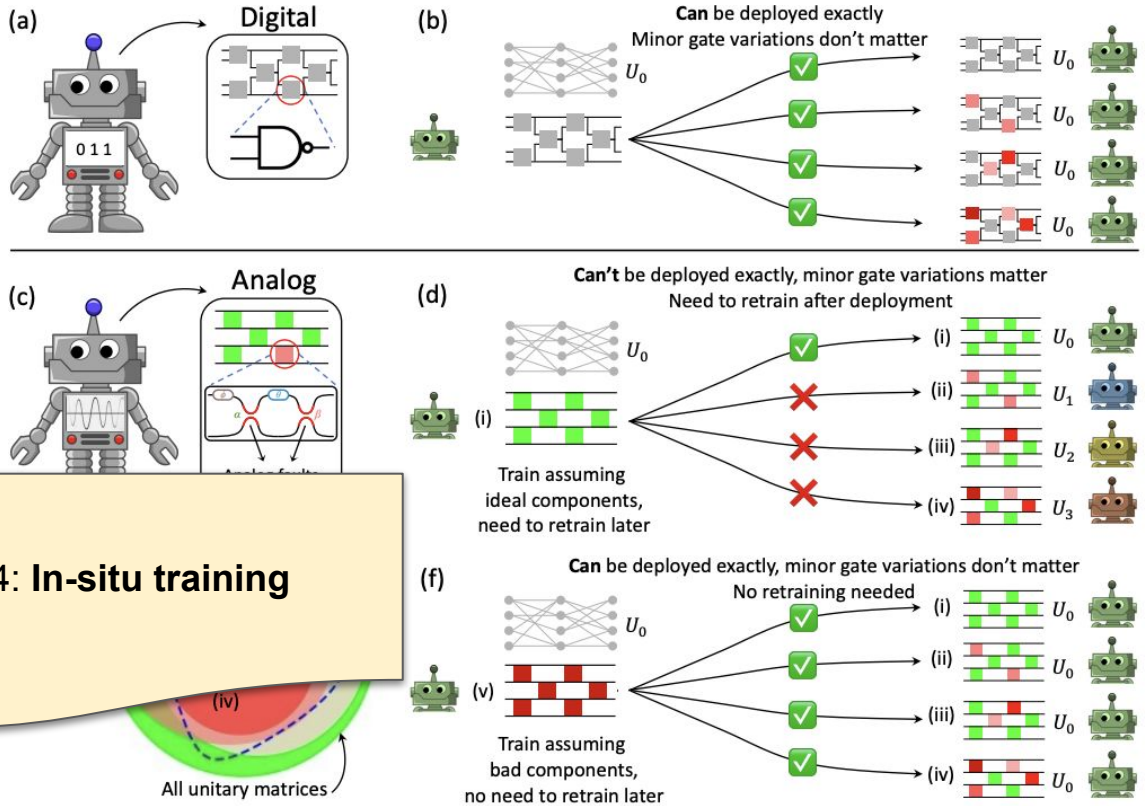
S Vadlamani, Science Advances (2022)
S. Bandyopadhyay, *Nature Photonics* (2024)

Applications

In-situ training: better .. and transferable



92.7% accuracy on a test set, which is the sam
the performance
(92.7%) obtained on a digital model with the sa
number of weights. Despite not having direct access
to gradients, our approach
produces a training curve similar to those produced
by standard gradient descent algorithms



Key point #4: **In-situ training**

S Bandyopadhyay et al, Nature Photonics (2025)

Sri K Vadlamani,DE, R Hamerly, ``Transferable Learning on Analog Hardware,'' Science Advances (2022)

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S Vadlamani, Science Advances (2022)
S. Bandyopadhyay, *Nature Photonics* (2024)

Computing Across the Internet's Edge: *Tops/sec @mW on edge devices*

A. Sludds et al, Science (2022)

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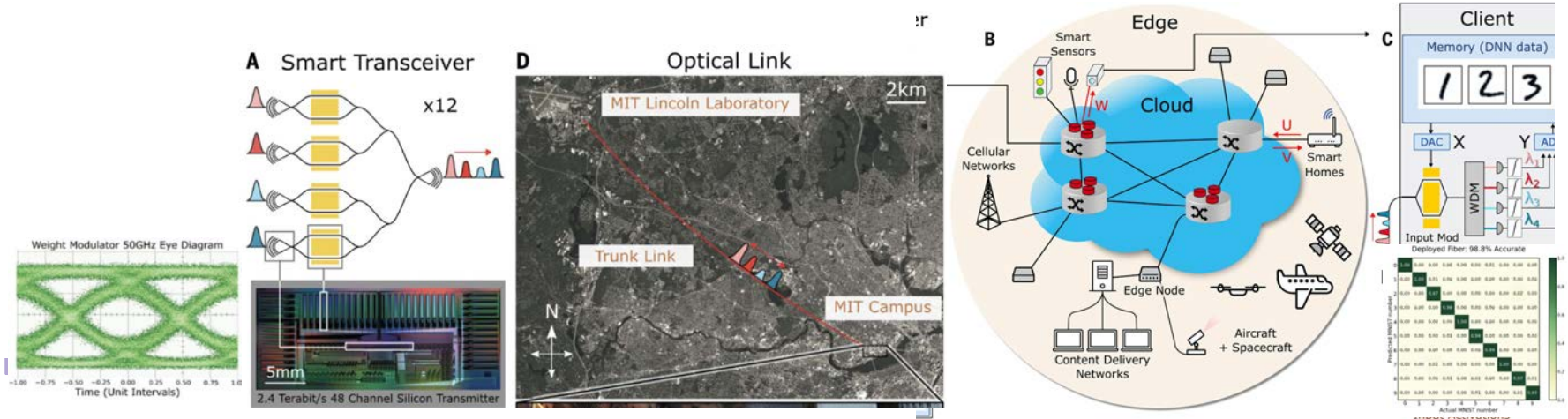

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A. Sludds et al, Science (2022)

- High compute density *~ fJ/OP and 25 TeraOP/(mm^2· s)*

Z. Chen et al, Nature Photonics

- Single-shot NNs: *20,000 MACs / 20 fs: Exascale computing*

L Bernstein et al, Science Advances (2023)

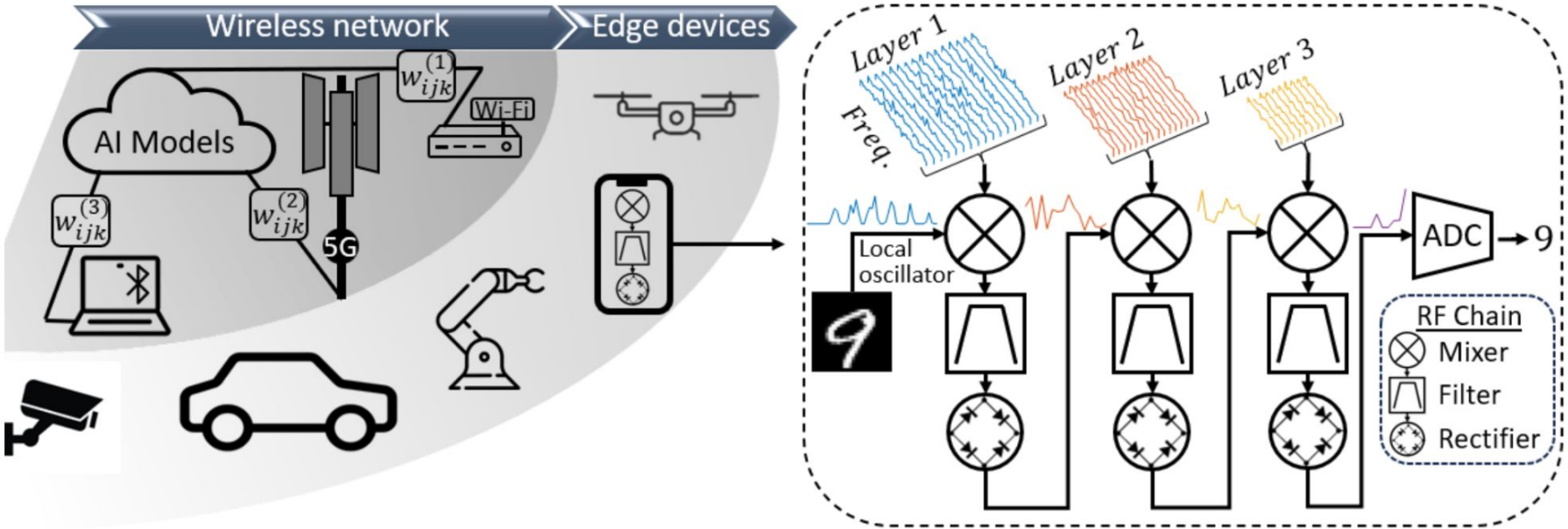
- RF-signal processing

C. Panuski et al, Nature Photonics (2023)

RF-Photonic Deep Learning Processor with Shannon-Limited Data Movement - Ronald Davis et al, under review (2025)
Deep Learning in Wireless Edge Networks - Zhihui Gao (with Prof T. Chen) - 2025
Deep Learning on Wireless Networks: Matching the Accuracy of Von Neumann Machines below Their Thermodynamic Limits - S Vadlamani et al - 2025
Marc Baqvanski, "OAMNet: Fast and Efficient Optical OAM Neural Networks", arXiv:2409.12305v (2024)

Perception at the network edge

- Perception moved into existing RF/analog chain of wireless signal processing
- “Smart-TRXs” eliminate or sharply reduce A/D and E/O conversions



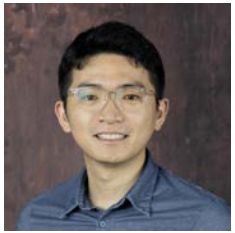
With Prof Tinjun Chen, Duke

Deep Learning on Wireless Networks: Matching the Accuracy of Von Neumann Machines below Their Thermodynamic Limits

Sri Krishna Vadlamani,[1,*] Kfir Sulimany,[1] Zhihui Gao,[2] Tingjun Chen,[2] and Dirk Englund[1]

[1] *Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA*
[2] *Department of Electrical and Computer Engineering, Duke University, Durham, North Carolina 27708, USA*

(Dated: November 20, 2024)



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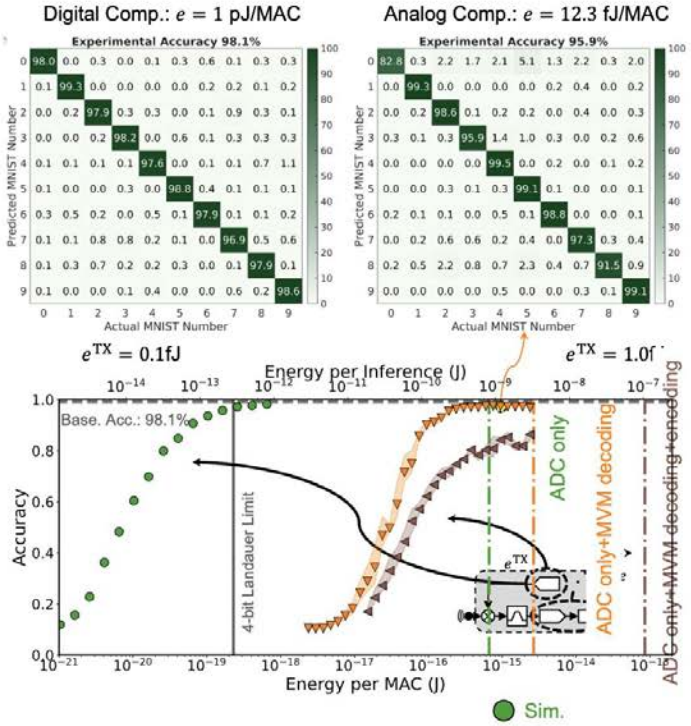
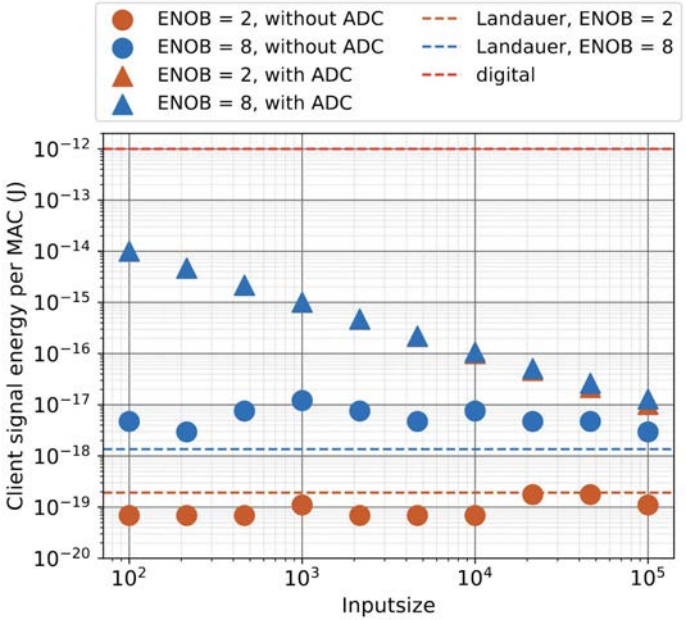




Quantum-limited perception on the edge

Micro-Ring Neural Sensors for High-Speed, Low-Power Radio-Frequency Signal Detection

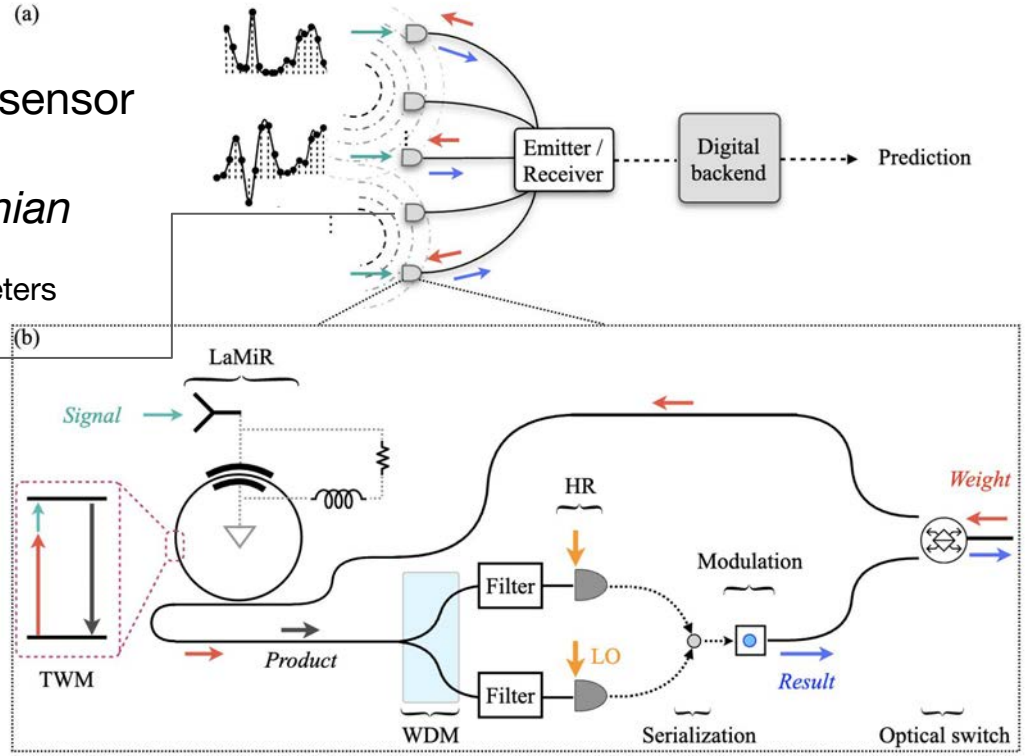
Bo-Han Wu[§,1,*] Shi-Yuan Ma[§,1,†] Sri Krishna Vadlamani,[1] Hyeongrak Choi,[1] and Dirk Englund[1,‡]
[1]*Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA*
(Dated: March 28, 2025)

- Perception moved into quantum-measurement process → optimal quantum control enables learned filters
- Convolutional layers in quantum sensor
- *RF-voltage transduction Hamiltonian*

streamed model parameters

$$\hat{\mathcal{E}}_j(t) = \hbar\mu\left(\hat{x}_j^\dagger(t) + \hat{x}_j(t)\right)\left(X_j(t) + \xi_B(t)\right)$$

RF field



Interested in RF ML technology transition?
Email
englund@mit.edu , tingjun.chen@duke.edu

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- RF-signal processing
- .. extensions to quantum networks

A. Sludds et al, Science (2022)

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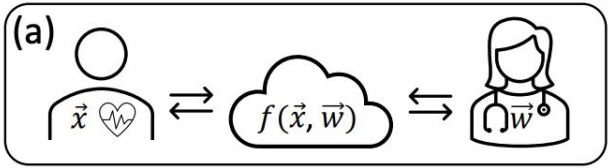
L Li et al, Nature (2025)
L Li et al, (with Kaiming He) "Dynamic Inhomogeneous Quantum Resource Scheduling with Reinforcement Learning" - 2025

Quantum-secure Deep Learning in multiparty deep learning frameworks.
Kfir Sulimanyar et al, ArXiv:2408.05629v1



Basic research

Industry, gov't partnerships

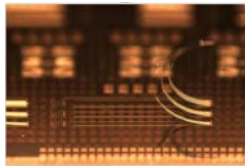
Technology transition

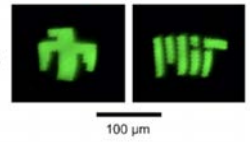
Startups

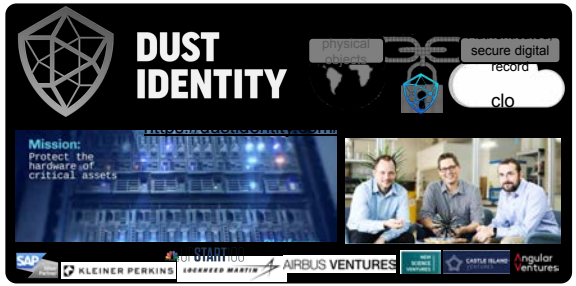
Quantum Network Technologies, Inc

Quantum communications, interconnects, memories

qunett.com







Now hiring in physics, mathematics, computer science, laboratory automation

Simulation vs. hallucination

Introduced ChatTutor Spring ’23 course 6.2410: Quantum Engineering Platforms

Open-source: https://github.com/ChatTutor

Sample quantum mechanics problem

Quantum Mechanics Exam: Optical Quantum Channel Problem

Consider an optical quantum channel through which a quantum state described as a superposition of number states is transmitted. The initial state before entering the channel is given by:

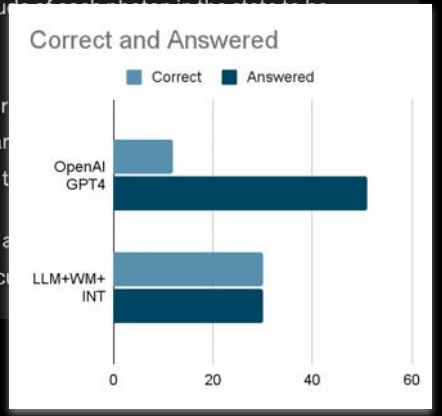
$$\Psi_{\text{initial}} = \frac{|n=3\rangle + |n=1\rangle}{\sqrt{2}}$$

where $|n = k\rangle$ represents a number state with k photons.

The optical quantum channel has a power transmission coefficient of 0.9. This coefficient represents the probability amplitu
transmitted through the channel.

Question: Calculate the probability of measur
has passed through the optical quantum char
change other than through the effects of the t

Provide your answer to three decimal places a
assumptions and equations used in your calcu



Axiomatic_AI

Team

- Began operations in 2024.
- Founding team track of entrepreneurs and recognized academics
- Global presence: Boston, Barcelona, Toronto
- 25+ Engineers and Scientists, 10+ PhDs

Founders

Dirk R Englund
CEO*, AX
Professor, MIT Electrical Engineering

Marin Soljačić
CTO, AX
Professor, MIT Physics

Frank Koppens
Partner + Advisor, AX
Professor, ICFO Physics

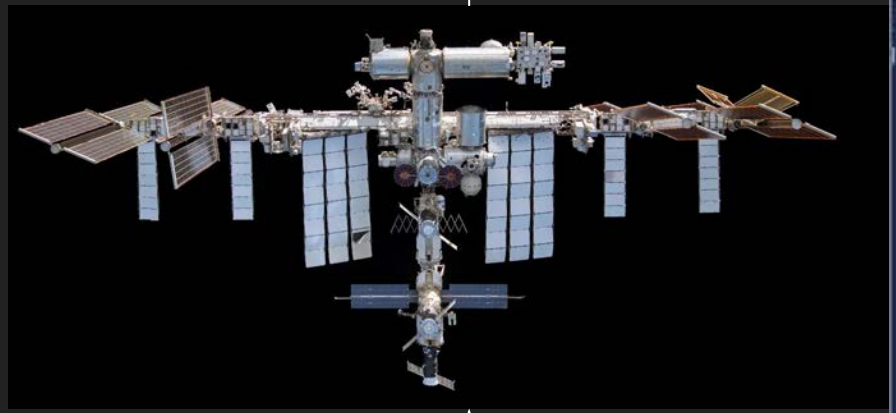
Joyce Poon
Partner + Advisor, AX
Director, Max Planck Institute
Professor, U of Toronto ECE

Alán Aspuru-Guzik
Professor, U of Toronto CS & Chemistry

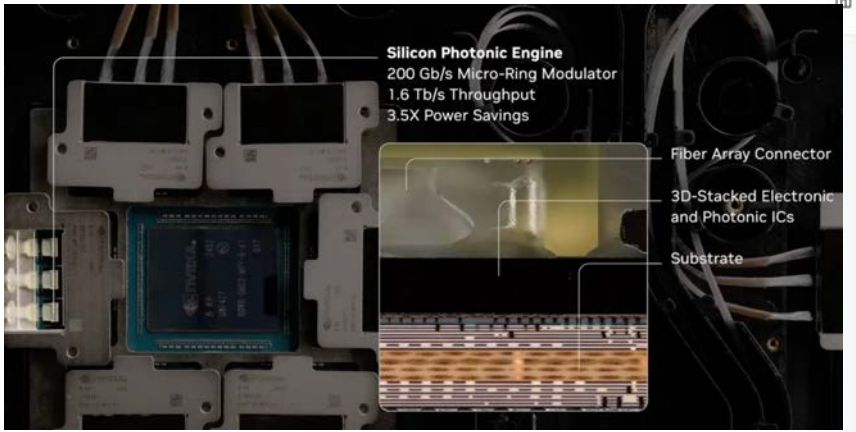
Amir Ghadimi
PhD EPFL
CEO Lightium

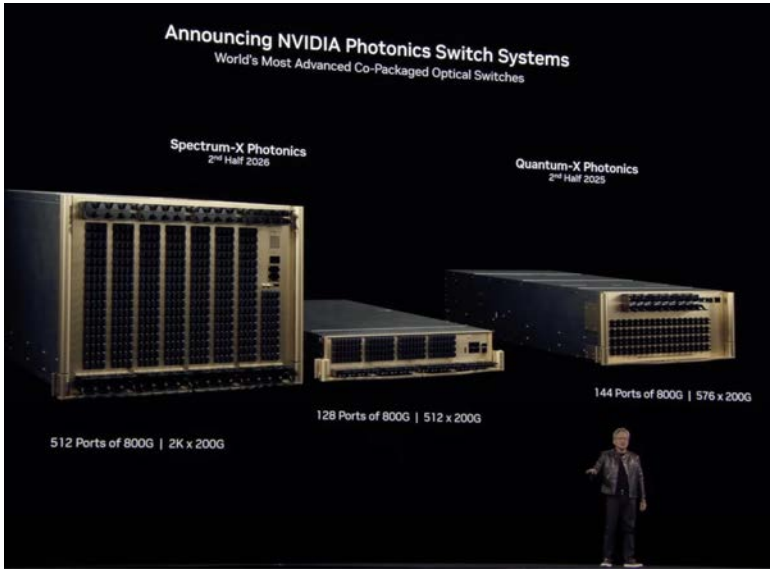
Digital Twins (DT)

understand, model



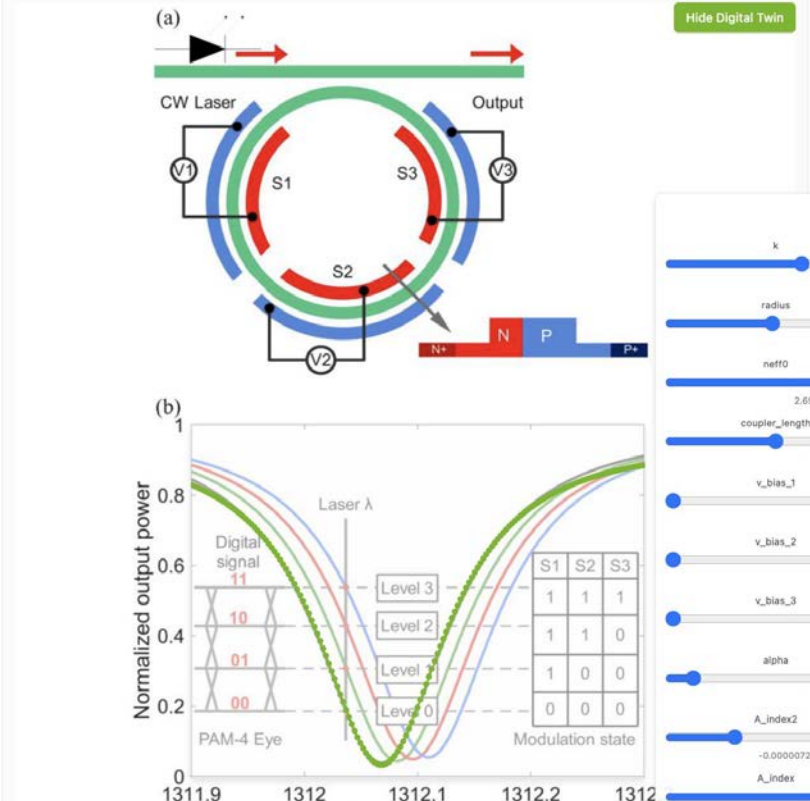
control, refine





A. Photonic Integrated Circuit Design

Fig. 5 shows the basic structure of the three-segment MRM. The MRM has a designed radius of $10\,\mu m$10 μm . We designed the proposed three-segment MRM based on the $220\,nm$SOI220 nm SOI platform. The waveguide has a width of $420\,nm$420 nm with a slab thickness of $70\,nm$70 nm . 60%60% of the ring's circumference is designated as the phase shifter region, employing a depletion-type PN junction, consisting of three segments of identical length. The remaining part of the ring is undoped, serving as an isolated region to minimize electric crosstalk during modulation. Due to fabrication errors, achieving critical coupling for optimal ER in the three-segment MRM is challenging. Hence, in our simulations, we slightly over-couple the MRM to mimic a more realistic scenario.



Formalizing physics

Problem addressed: Deriving verified analytical models for PIC components.

Approach: Mathematical framework to derive analytical models using formal methods.

- Input: Mathematical universe (variables and axioms).
- Procedure: Agents propose and verify truth of new statements with Lean.

Tools: Lean

Point of contact:
Ben Breen, PhD

Collaborators:
Leopoldo

Physics Universe in Lean: Maxwell's Equations

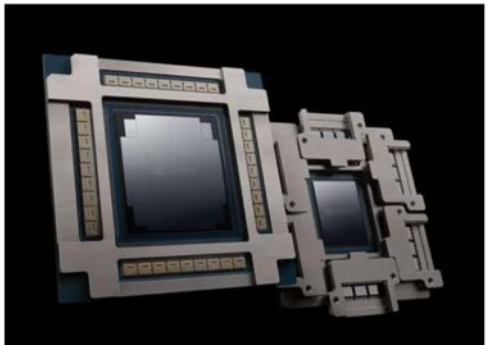
```
/- Universe -/
-- Variables
variable (ω k β N_eff : ℝ)
(ε₀ μ₀ ε n μ k : ℂ)
(E B J H : ℝ → ℝ³ → ℂ³)
(ρ : ℝ → ℝ³ → ℂ)
(Etilde Btilde : ℝ³ → ℂ³)

-- Axioms
axiom MaxwellEquation_1 : ∀ t x, ∇ • (E t) x = ρ t x / ε₀
axiom MaxwellEquation_2 : ∀ t x, ∇ • (B t) x = 0
axiom MaxwellEquation_3 : ∀ t x, ∇ × (E t) x = -∂ (λ t' => B t' x) t
axiom MaxwellEquation_4 : ∀ t x, ∇ × (B t) x = μ₀ • (J t x + ε₀ • ∂ (λ t' => E t' x) t)

-- Differentiable Axioms: C^∞
axiom hE : ∀ x, ContDiff ℝ ⊤ (λ t => E t x)
axiom hH : ∀ x, ContDiff ℝ ⊤ (λ t => H t x)
```

Helmholtz Equation: $\nabla^2 E = k^2 E$

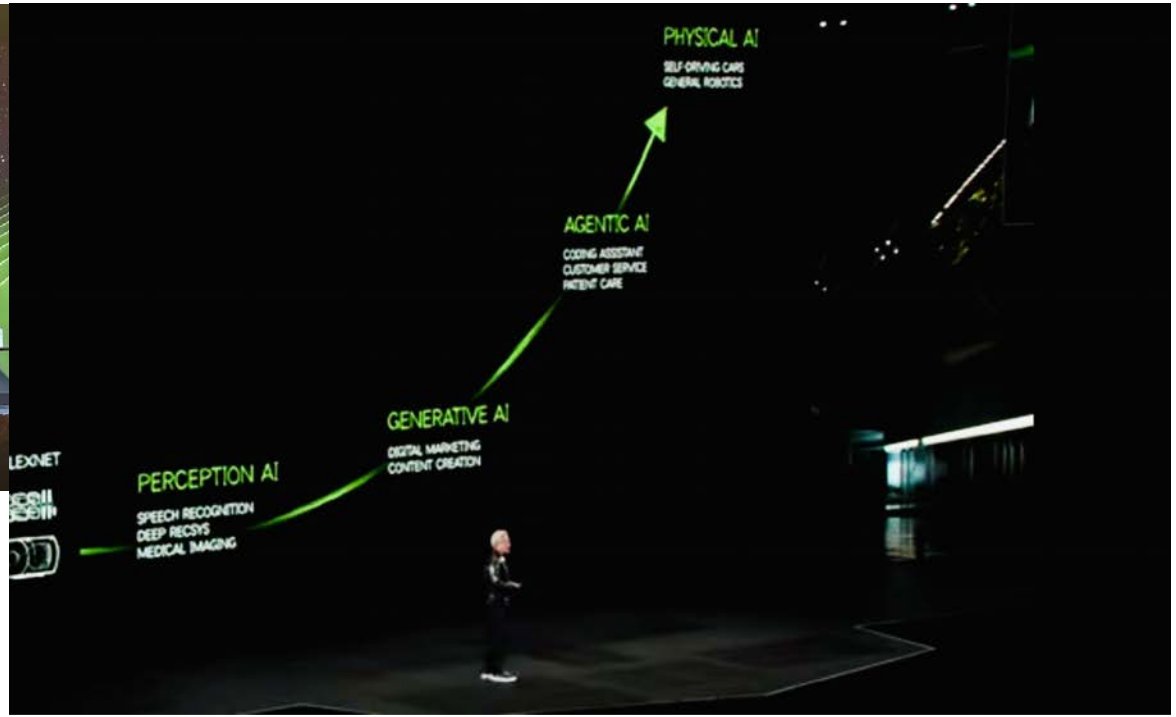
```
-- Helmholtz Equation: ∇² E = k² E
theorem HelmholtzEquation : ∇² (λ x => E t x) = k^2 • (λ x => E t x) := by
  rw [derivation_2 ε₀ μ₀ E B J ρ]
  have eq2 {x : ℝ³} : ∂ (λ t => E t x) = (λ t => (I * ω) • E t x) := by
    simp [derivation_3 ω E Etilde]
  simp [eq2]
  funext x
  rw [deriv_const_smul]
  simp_all only [Pi.neg_apply, Pi.smul_apply]
  ext1 i
  simp_all only [PiLp.smul_apply, smul_eq_mul, PiLp.neg_apply, Complex.real_smul,
  ring_nf
  simp_all only [Complex.I_sq, mul_neg, mul_one, neg_mul]
  rw [wave_equation ω μ₀ ε₀ k]
  simp_all only [smul_eq_mul, mul_neg, neg_inj]
  ring_nf
```

The next frontier: Physical AI

1. Quantum Computing



2. Machine learning & AI



Summary

Key point #1: **Try to use data fan-out** for “free” data-movement

Key point #2: **In-physics computing** (allows inner vector products with O(1) operations)

Key point #3: **Coherent error cancellation** possible in analog optical systems

Key point #4: **Compiling learning onto (quantum-)physical systems**

- single-shot $\mathbf{f}_{DNN}(\mathbf{x})$ evaluation → more general than back-prop
- transferable learning shown in some proof of concept cases

We need much better computable world models !

→ Physical AI to understand the world
→ Axiomatic_AI @SRIC/Toronto, Cambridge/MA, Barcelona/Spain