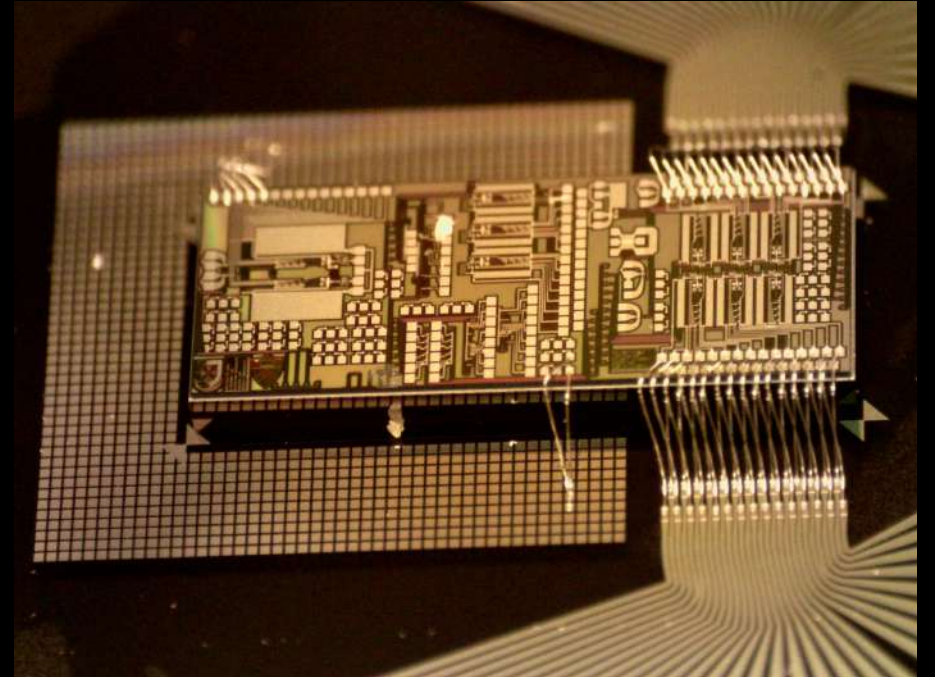


NEUROMORPHIC SILICON PHOTONICS: APPLICATIONS, CLASSICAL TO QUANTUM

Bhavin J. Shastri
Queen's University, Canada

Faculty Affiliate: Vector Institute
Visiting Faculty: Princeton University

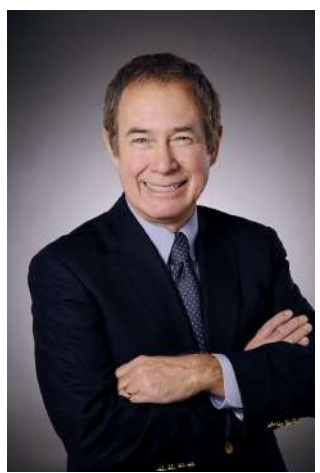


VECTOR
INSTITUTE



PRINCETON
UNIVERSITY

Collaborators



P. Prucnal
Princeton



L. Chrostowski
UBC



S. Shekhar
UBC



A. Tait
Queen's



C. Huang
CUHK



Volker Sorger
GWU



N. Rotenberg
Queen's



N. Youngblood
Pittsburgh

+ many others and co-authors

Fabrication Support



SiEPIC
FAB



Students and Postdocs



Credit: Ishana Gopaul

Shastri Lab (Queen's)

Researcher: B. Marquez

Current Graduate Students: Z. Guo; H. Morison; M. Tamura; M. Moridsadat; A. Khaled; J. Ewaniuk; A. Grace; A. McCaw; T. Austin; N. Al-Kayed; L. Rantz
+ former students



Prucnal Lightwave Lab (Princeton)

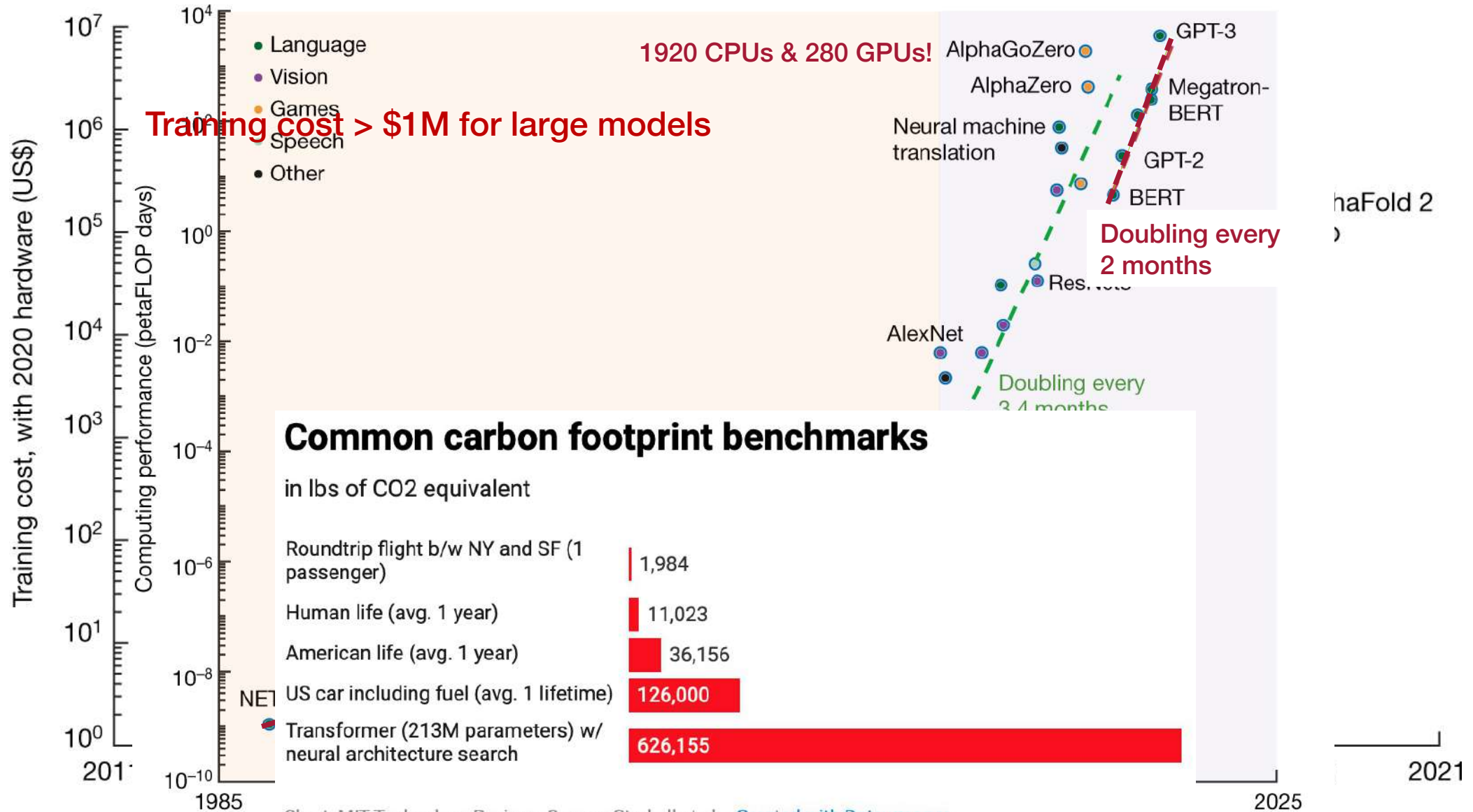
Researcher: T. Ferreira de Lima; Lei Xu

Graduate Students: E. Blow, A. Jha; S. Bilodeau; W. Zhang; J. Lederman; H-T. Peng
+ former students and postdocs

Outline

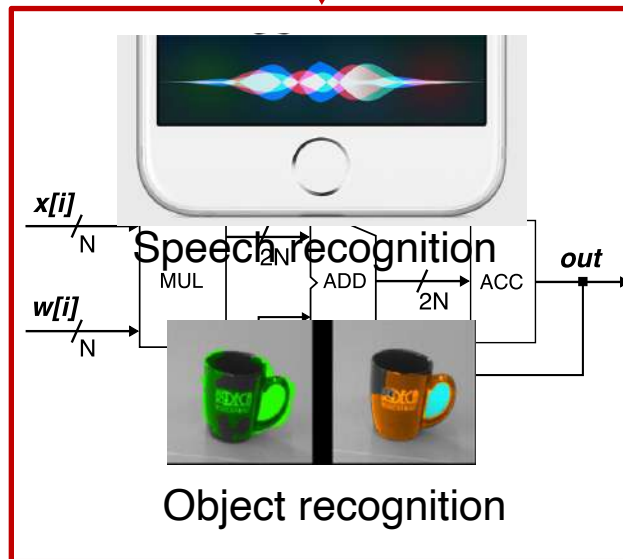
- ❑ Recent work in neuromorphic photonics
- ❑ Silicon photonic neural networks
 - weighted interconnects: synapses
 - nonlinearities: electro-optic & reconfigurable
- ❑ Neuromorphic photonics demonstrations
 - Highlight applications: wireless, fiber
 - Quantum photonic neural networks
- ❑ Roadmap for neuromorphic photonics

Compute Usage in AI Systems



Toward Neuromorphic (*neuron-isomorphic*) Hardware

Software neural networks
on digital hardware



Hz - kHz

Hardware neural networks
Neuromorphic Electronics

A silicon neuron *Nature* 354 (1991)

Misha Mahowald* & Rodney Douglas†‡

* Computation and Neural Systems Laboratory, California Institute of Technology, Pasadena, California 91125, USA

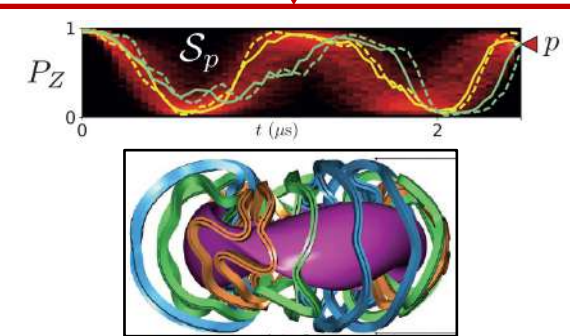
† MRC Anatomical Neuropharmacology Unit, University of Oxford, Oxford OX1 3TH, UK

By combining neurophysiological principles with silicon engineering, we have produced an analog integrated circuit with the functional characteristics of real nerve cells. Because the physics underlying the conductivity of silicon devices and biological membranes is similar, the 'silicon neuron' is able to emulate efficiently the ion currents that cause nerve impulses and control the dynamics of their discharge. It operates in real-time and consumes little power, and many 'neurons' can be fabricated on a single silicon chip. The silicon neuron represents a step towards constructing artificial nervous systems that use more realistic principles of neural computation than do existing electronic neural networks.

Bandwidth-complexity tradeoff!

- Bandwidth-complexity tradeoff!

Photonic neural networks
Neuromorphic Photonics



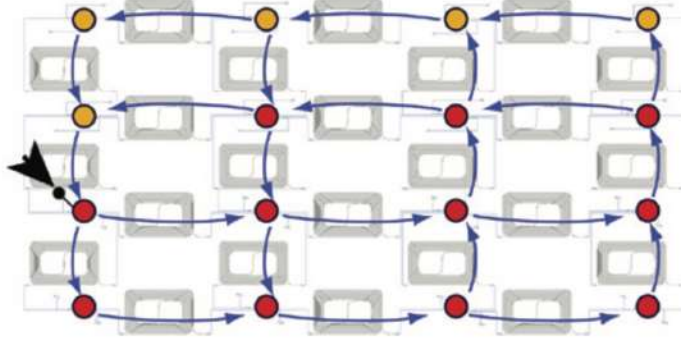
Nonlinear optimization
Ultrafast control
RF signal processing
Quantum tomography

GHz

Could enable new applications that are challenging to be achieved with electronics!

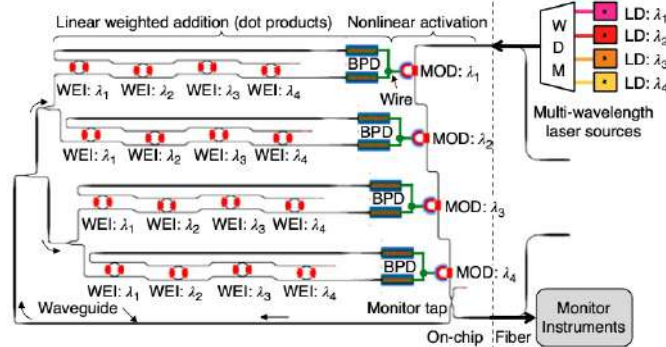
Recent Work on Neuromorphic Photonics

Reservoir computing (UIB, Ghent, Femto-St)



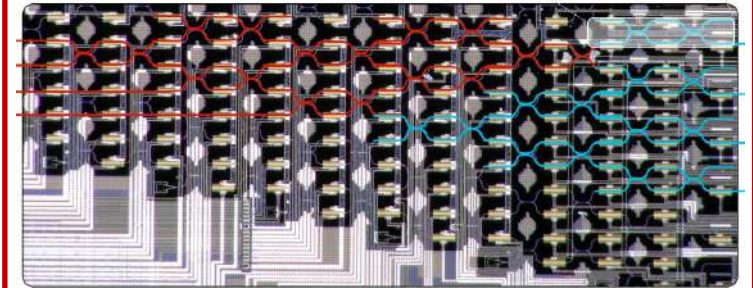
Brunner et al. *Nat. Commun.* 4 (2012)
Vandoorne et al. *Nat. Commun.* 5 (2014)

Multiwavelength Networks (Princeton, Queen's, GWU)



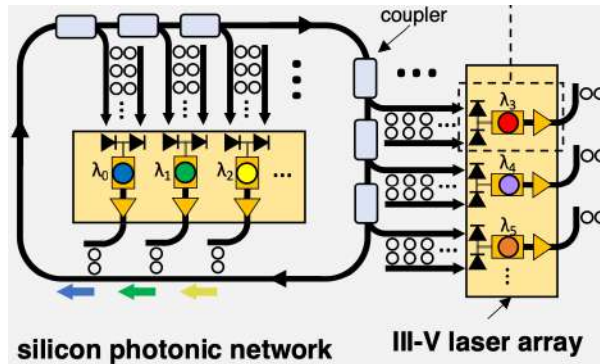
Huang et al. *Nature Electronics* 4 (2021)
Tait et al. *Sci. Rep.* 4 (2017)
Feldman et al. *Nature* 589 (2021)

Coherent networks (MIT, Stanford)



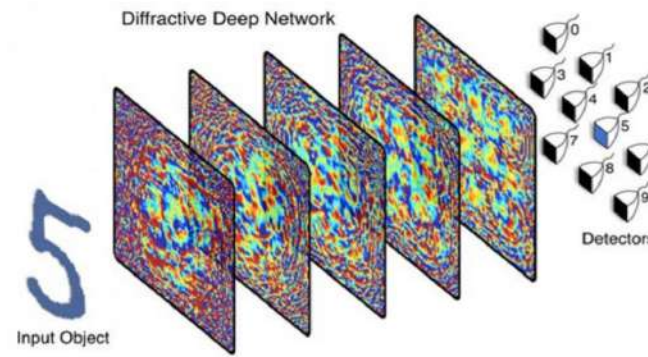
Shen et al. *Nat. Photon.* 11 (2017)
Hughes et al. *Optica* 5 (2018)

Spiking networks (Princeton, Oxford, Strathclyde)



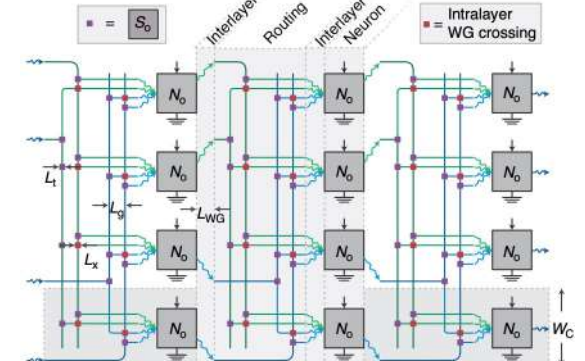
Shastri et al. *Sci. Rep.* 6 (2016)
Feldman et al. *Nature* 569 (2019)

Diffraction Optics (UCLA, Femto-St)



Bueno et al. *Optica* 5 (2018)
Lin et al. *Science* 361 (2019)

Superconducting (NIST)



Shainline et al. *Phys. Rev. Appl.* 7 (2017)

Applications for Neuromorphic Photonics

❑ Nonlinear programming

- Nonlinear optimization problems (robotics, predictive control, autonomous vehicles)
- Ordinary/partial differential equations

❑ High-performance computing and Machine Learning

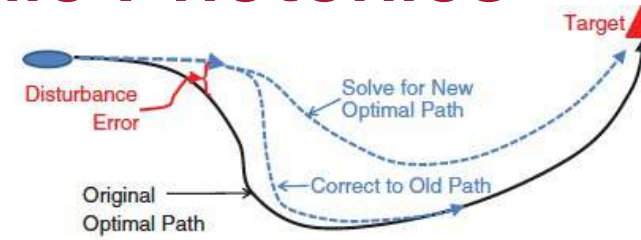
- Vector-matrix multiplications
- Deep learning inference
- Ultrafast and online learning

❑ Intelligent signal processing

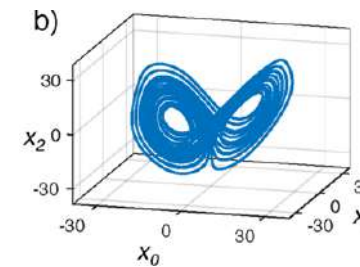
- Optical fiber communications
- mm-wave edge processing
- Spectral mining

❑ Quantum and high-energy physics

- Quantum neural networks
- High-energy particle collision experiments



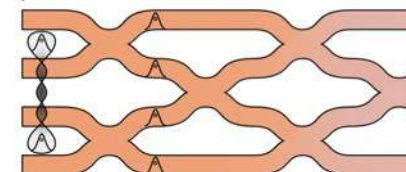
Tait, Shastri, Prucnal et al. Sci. Rep. (2017)
Lorenz attractor



Zhang, Shastri, Prucnal et al.
Nature Communications (2022)
Broadband cognitive radio



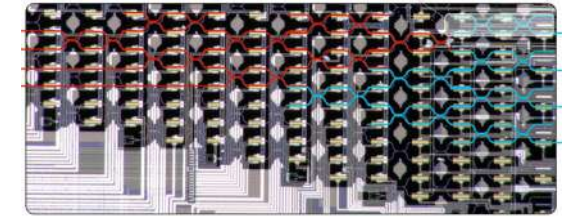
Ewaniuk, Rotenberg, Shastri et al.
Adv. Quantum Technol. (2023)
Quantum neural networks



Ferreira de Lima, Prucnal et al. JLT (2019)
Model predictive control



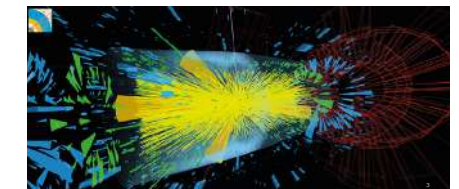
Shen et al. Nat. Photon. (2017)
Vector-matrix multiplier



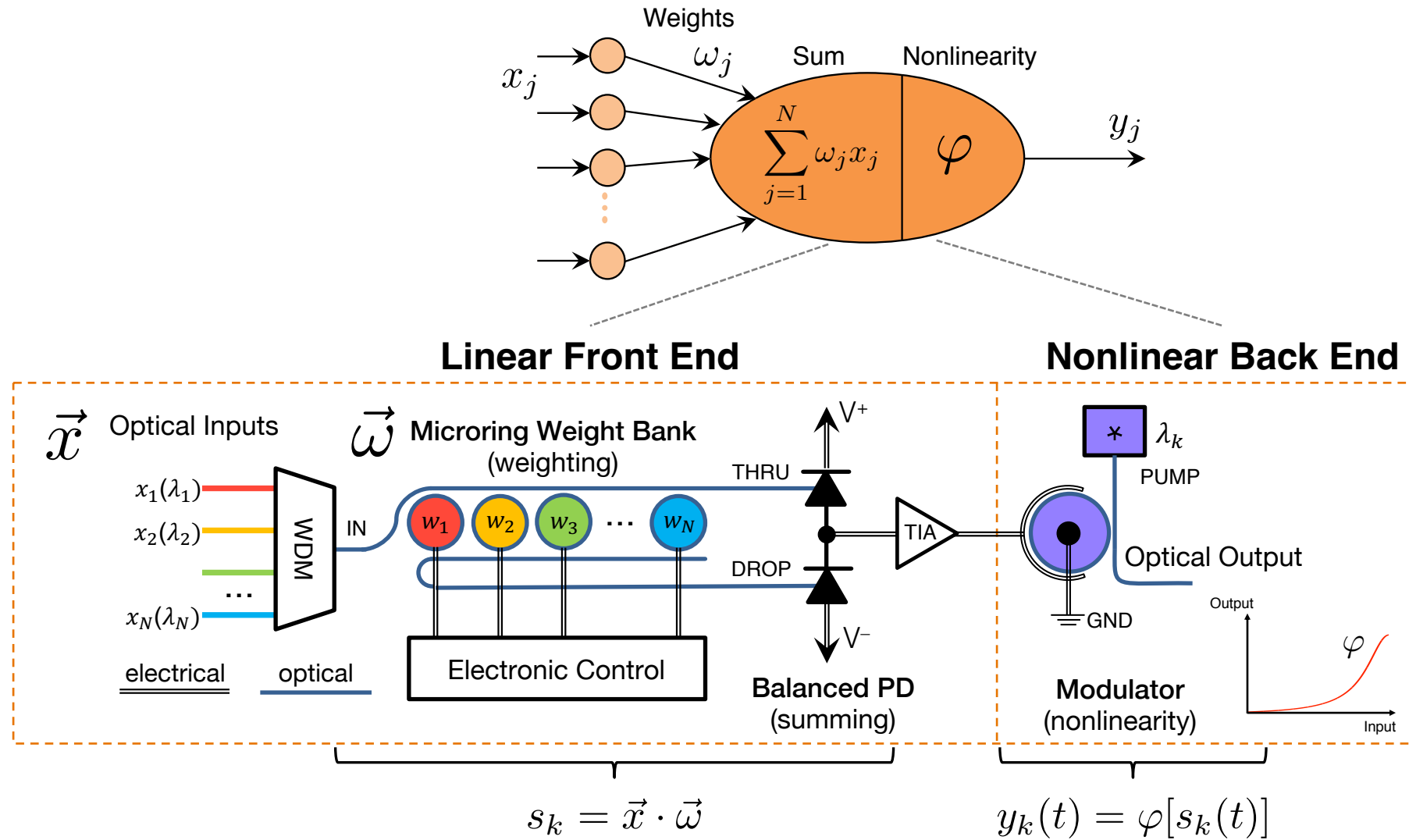
Huang, Shastri, Prucnal et al.
Nature Electronics (2021)
Fiber nonlinearity compensation



CMS detector at CERN

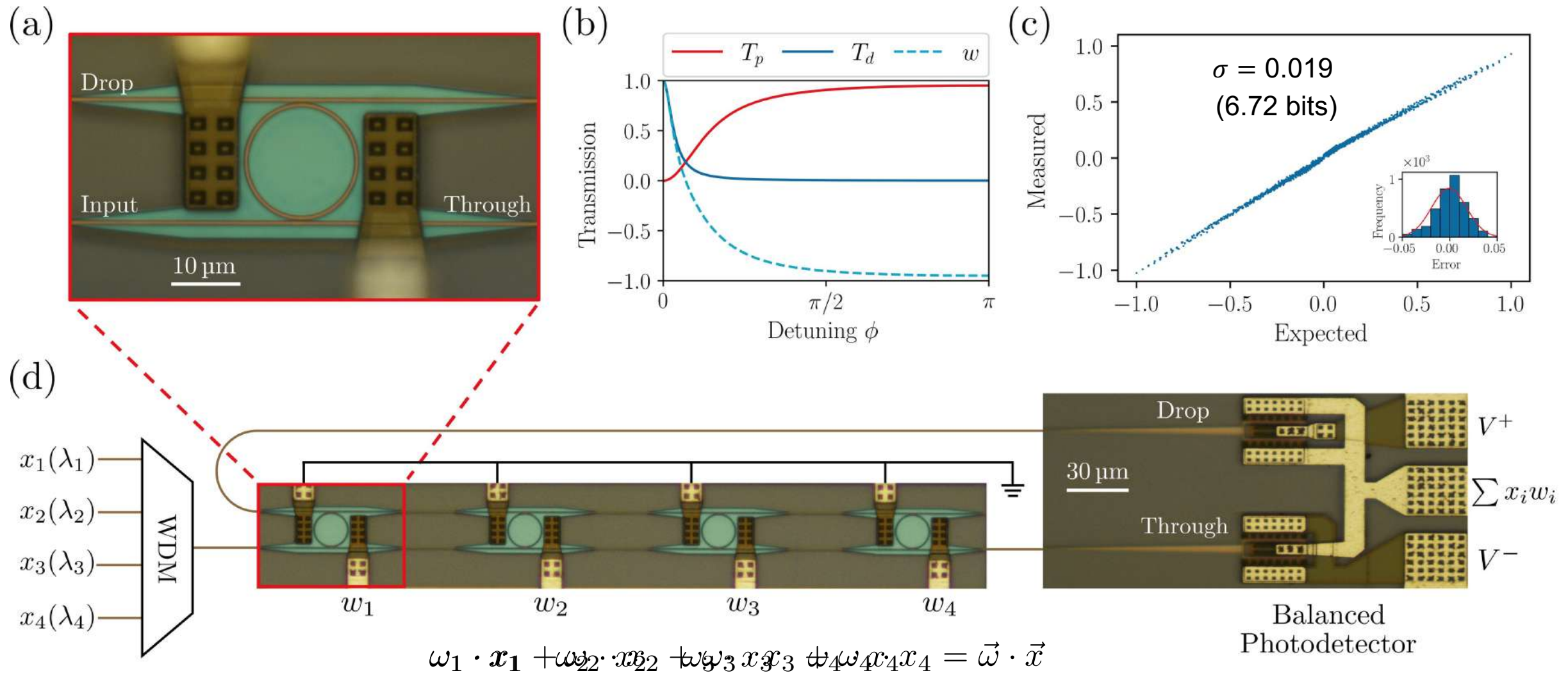


Multiwavelength Photonic Neuron

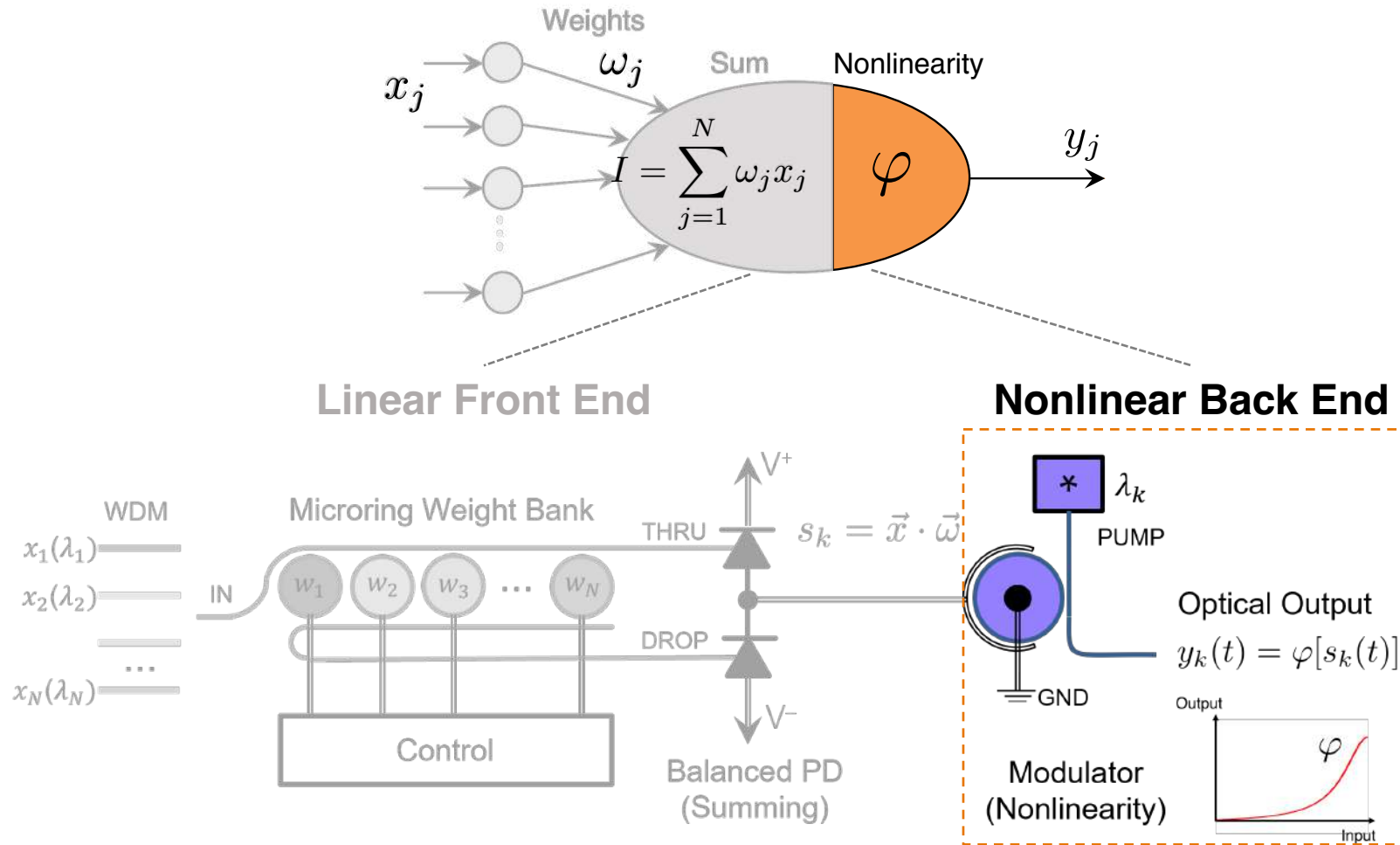


- ❑ All key functions are physically localized in each neuron, enabling distributed processing
- ❑ OEO enables gain, thresholding and cascability/recurrent operation

Silicon MRR and BPD = Dot Product

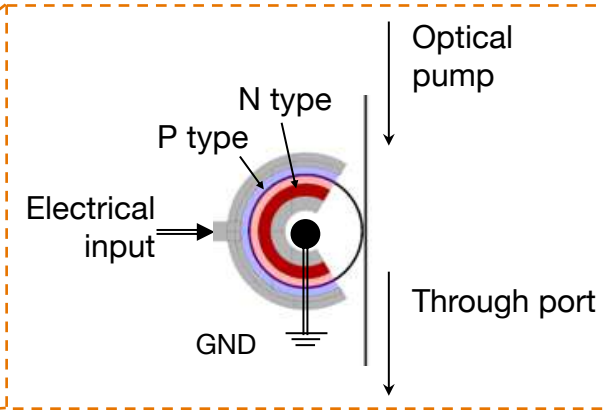
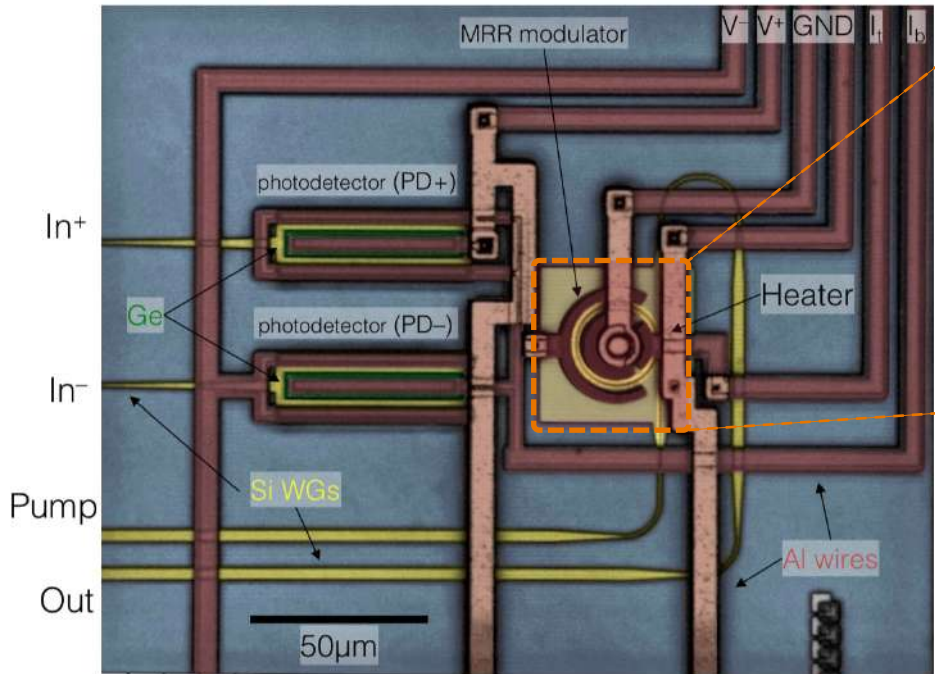


Multiwavelength Photonic Neuron

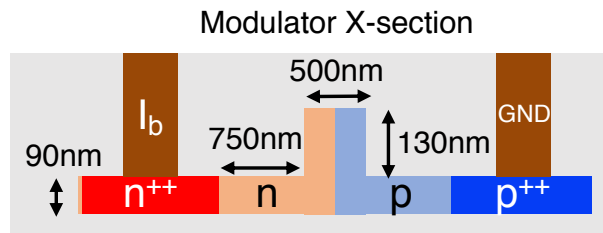


- ❑ All key functions are physically localized in each neuron, enabling distributed processing
- ❑ OEO enables gain, thresholding and cascability/recurrent operation

EO Nonlinearity: Reconfigurable Activation Functions



- Bias shifts the operating point on the resonance curve and changes its depth (see below)
- Drive signal modulates around the operating point



Experimental Nonlinear Modulation Curves (Power out vs. power in)

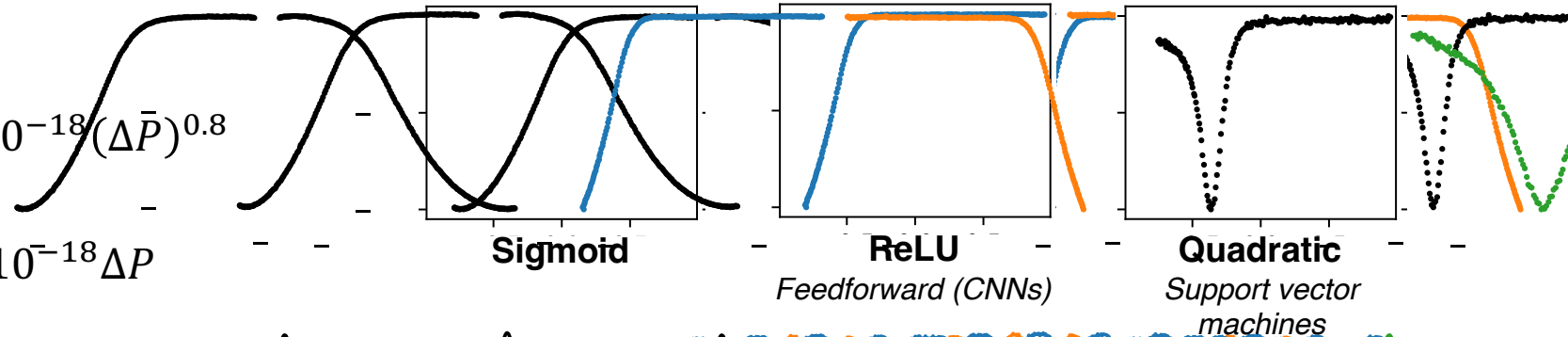
The Soref Equations

Index modulation

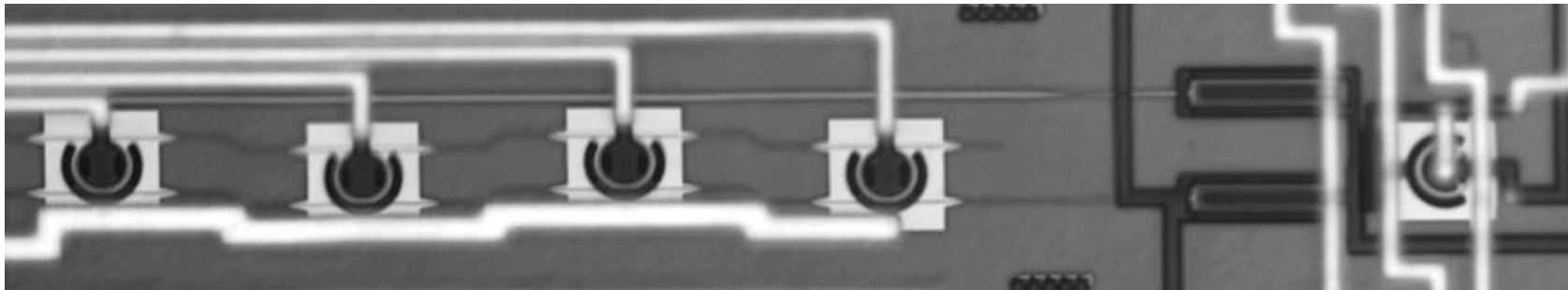
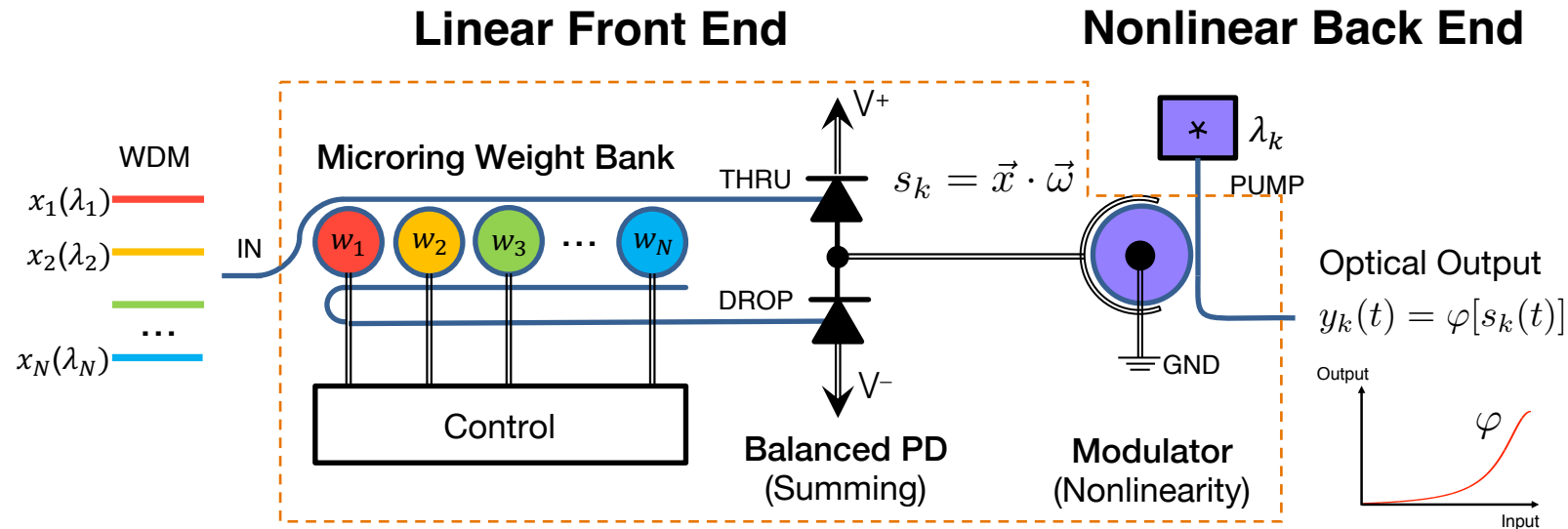
$$\Delta n_{FCD} = -8.8 \times 10^{-22} \Delta N - 8.5 \times 10^{-18} (\Delta \bar{P})^{0.8}$$

Loss modulation

$$\alpha_{FCA} = 8.5 \times 10^{-18} \Delta N - 6.0 \times 10^{-18} \Delta P$$



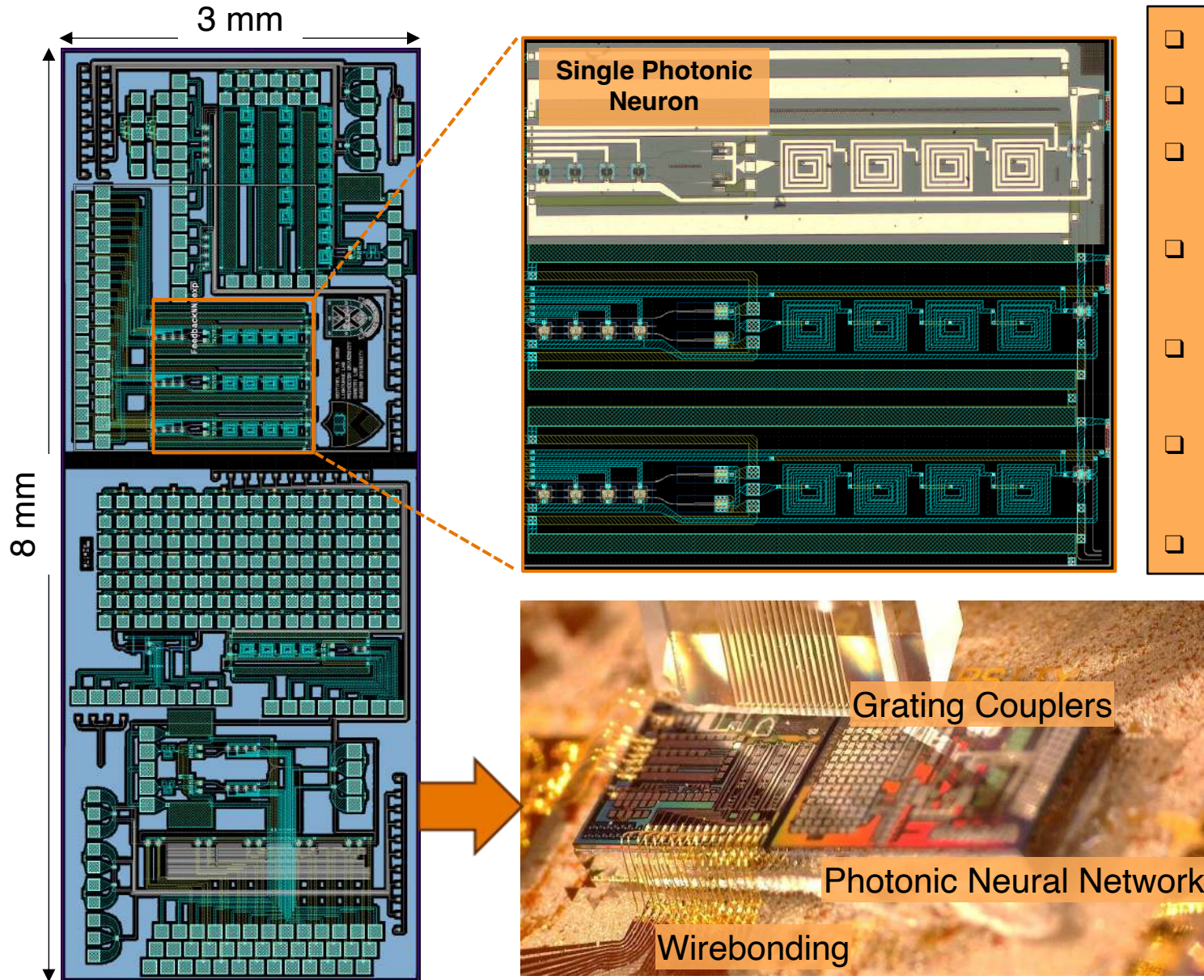
Monolithically-Integrated Photonic Neuron



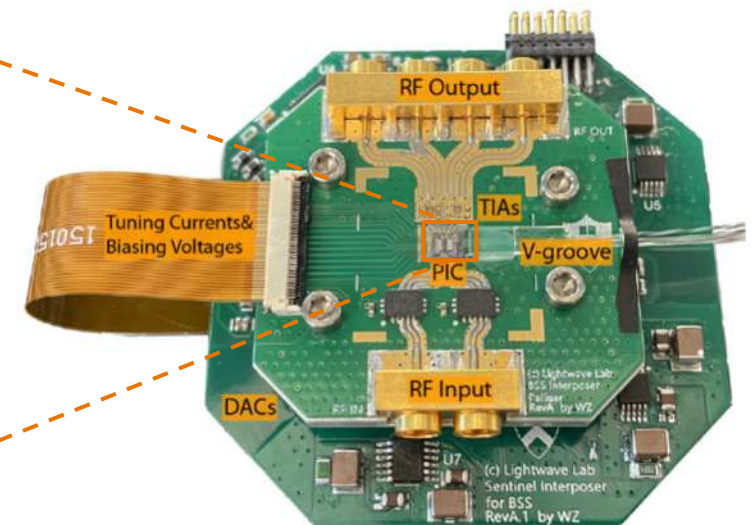
- ❑ Integrates both linear and nonlinear neuron functionality
- ❑ Energy efficiency today: 500fJ/MAC; foreseeable: 1.1 fJ/MAC*
- ❑ Operational speed: GHz

*Nozaki, K. *et al.*
Nat. Photonics **13**,
454–459 (2019)

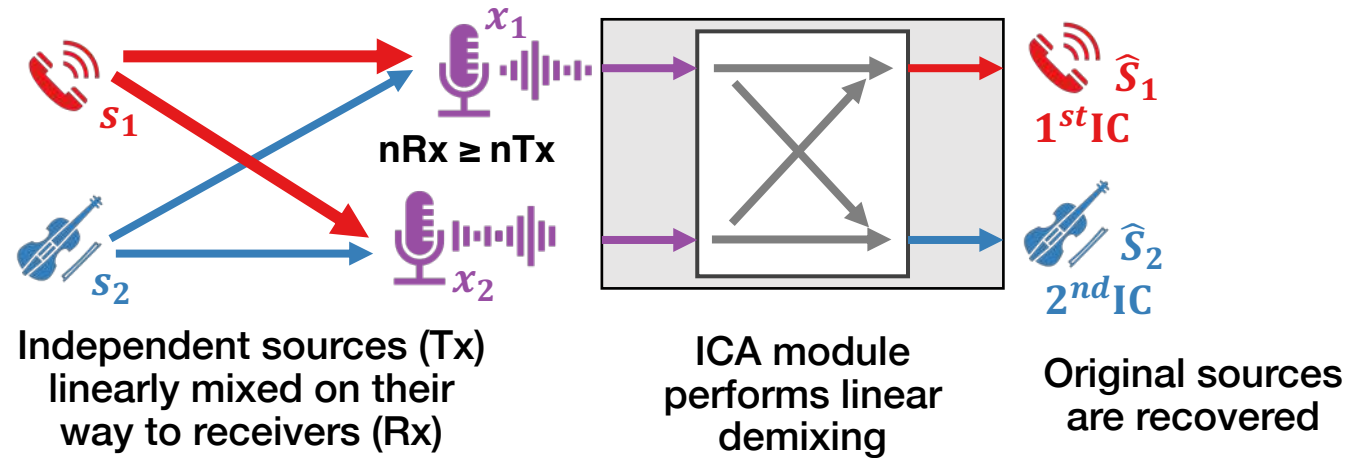
Silicon Photonic Neural Network Chips



- ❑ Operational speed: **10s GHz**
- ❑ Energy efficiency today: **500fJ/OP -> 1.1 fJ/OP**
- ❑ Demonstrated **complete system integration** and applications
- ❑ **Foundry compatible**; in-house optical and electrical packaging
- ❑ Utilizes open-source design tools created by our lab (<https://github.com/lightwave-lab>)
- ❑ Neural networks trained via mature software tools such as TensorFlow
- ❑ Experimentation is fully automated



Application: Cognitive Radio - Blind Source Separation (BSS)



Recovery of unknown signals from arbitrary mixtures using multiple receivers

- Employs independent component analysis (ICA), adjusting network weights to maximize kurtosis (metric describing Gaussianity)

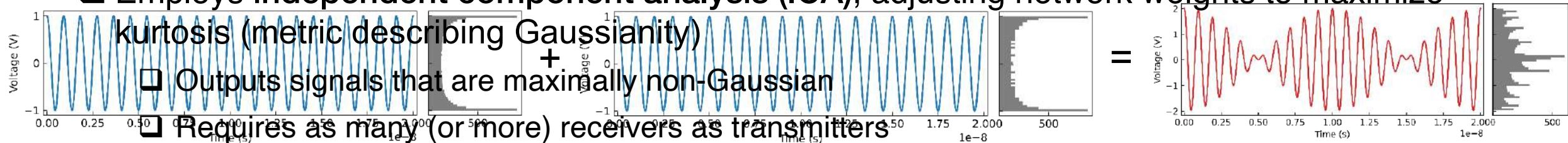
- Outputs signals that are maximally non-Gaussian

- Requires as many (or more) receivers as transmitters

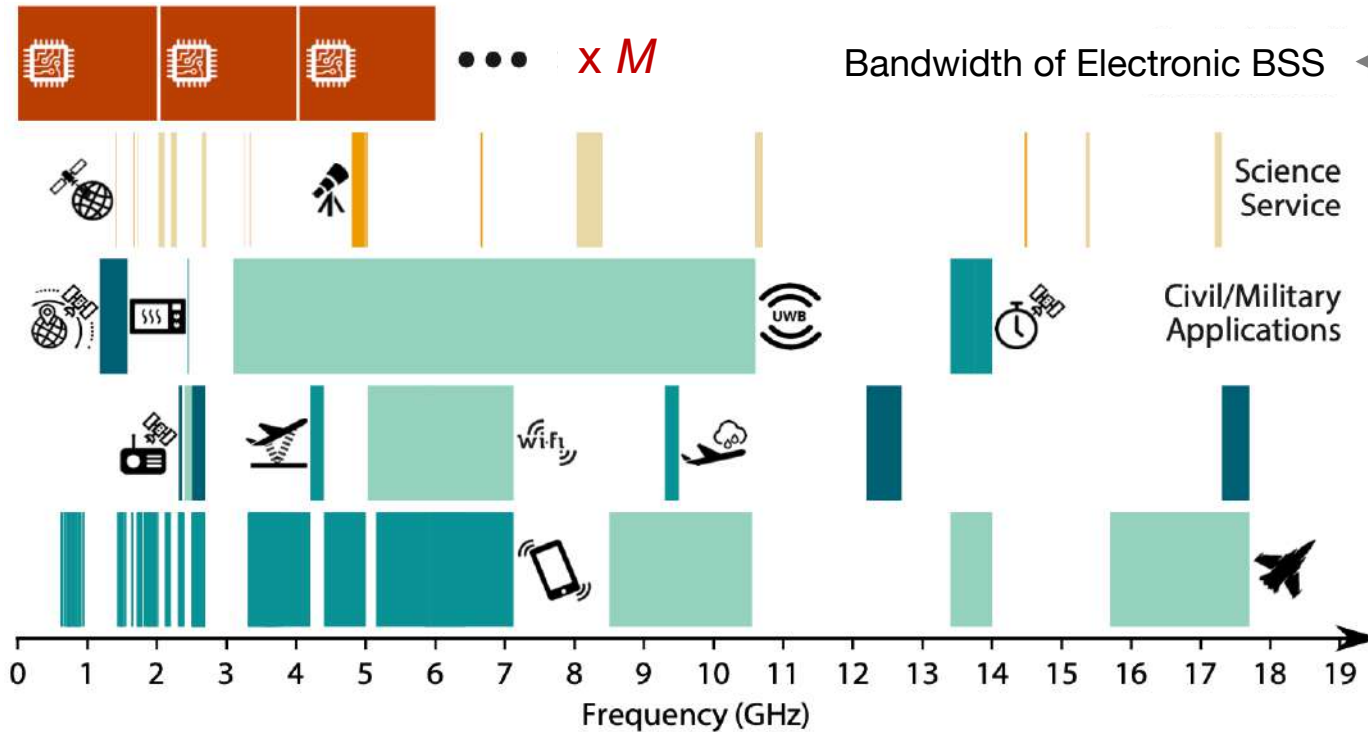
- Applications:

- Image denoising, object detection

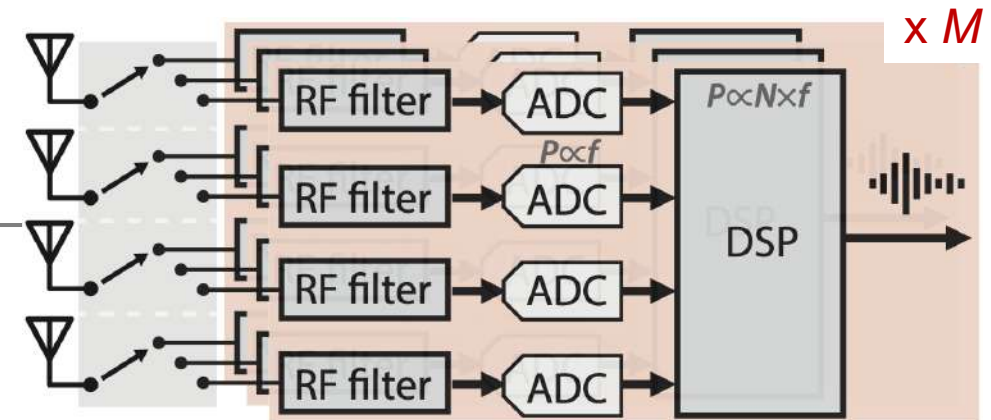
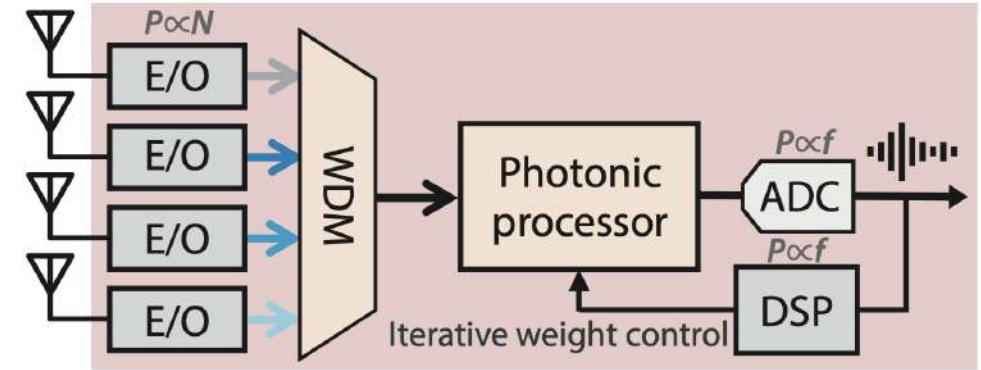
- RF signal separation, speech isolation



Application: Cognitive Radio - Blind Source Separation (BSS)

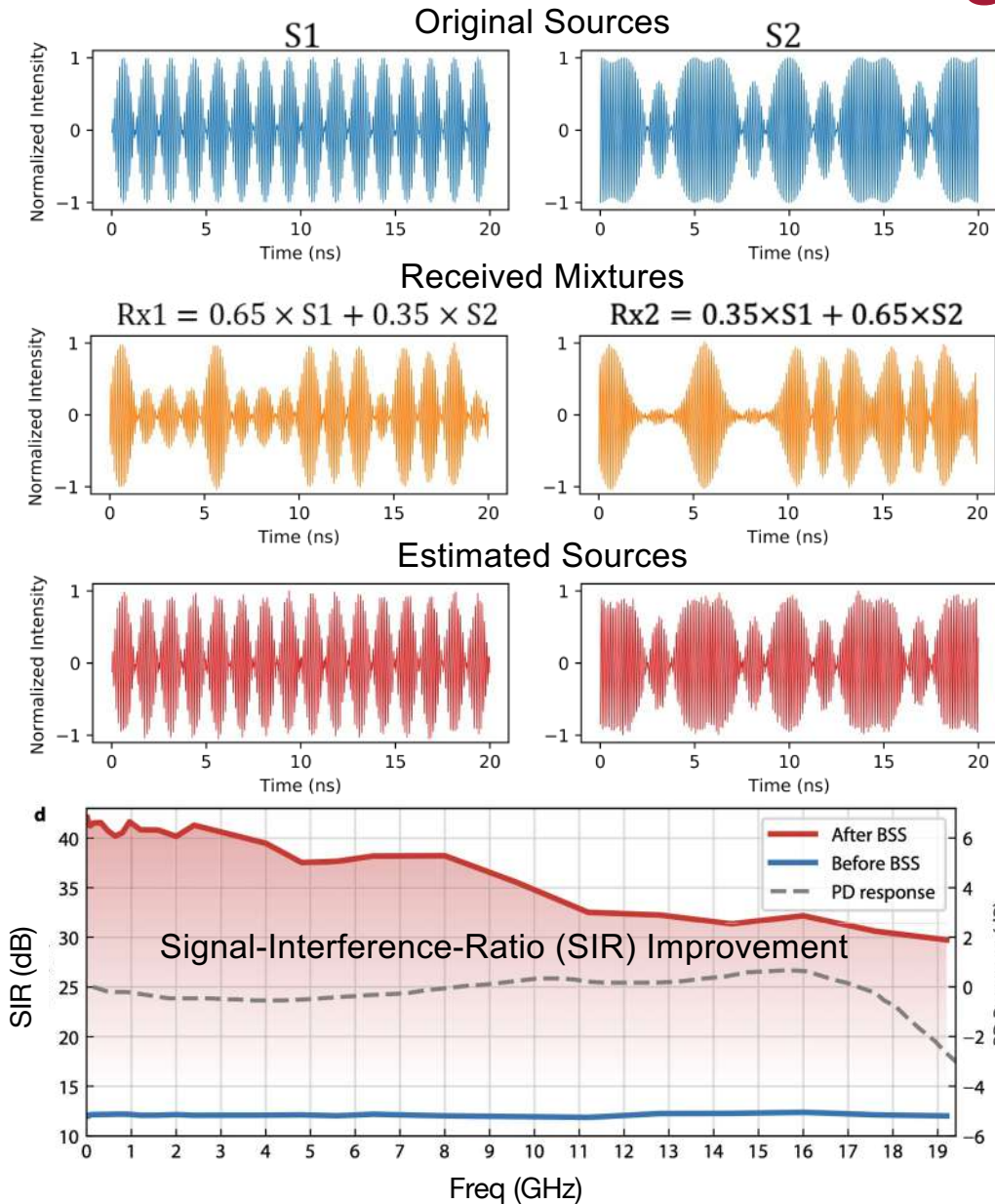


RF components are limited in bandwidth, requiring many different receivers to cover the RF spectrum

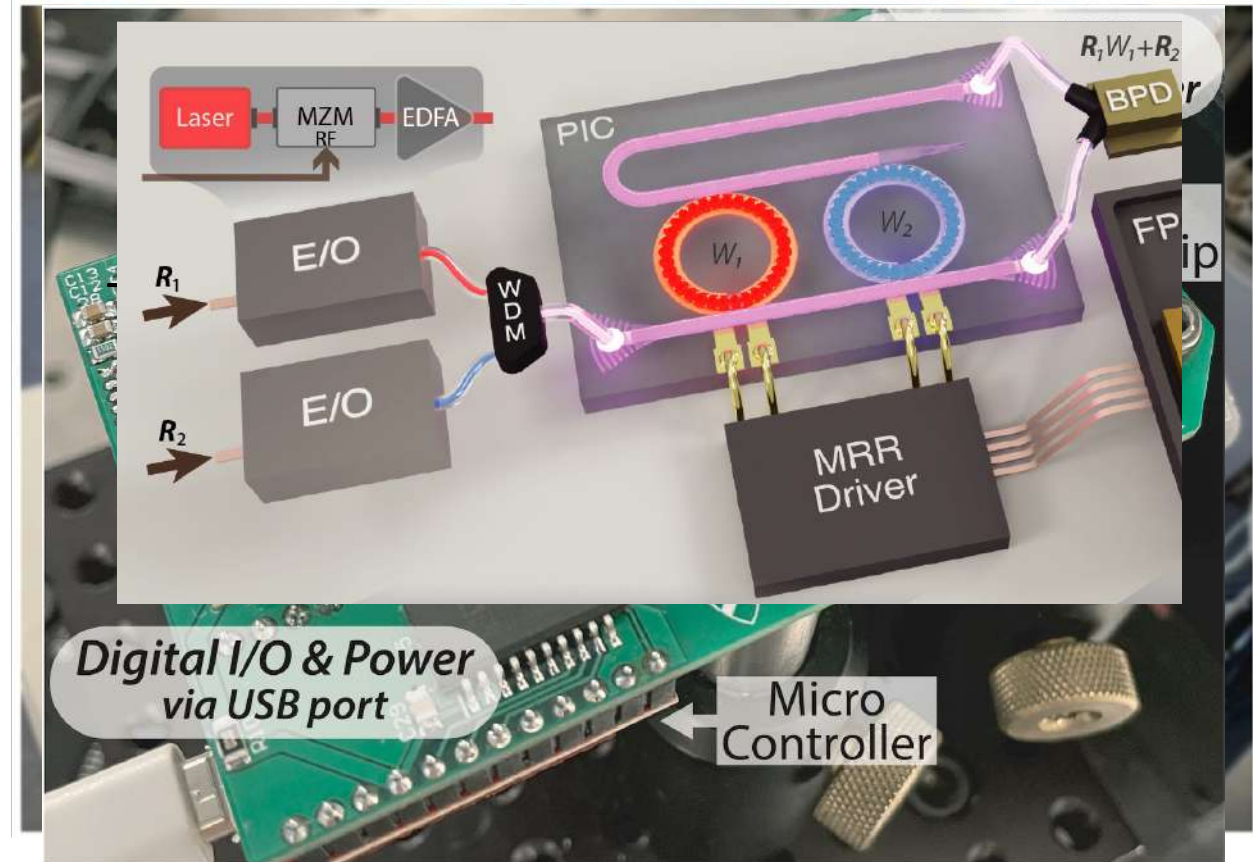


Linear photonic front-end allows ICA to be performed on the entire RF spectrum simultaneously (i.e., collective processing)

Broadband BSS with Single Photonic Chip

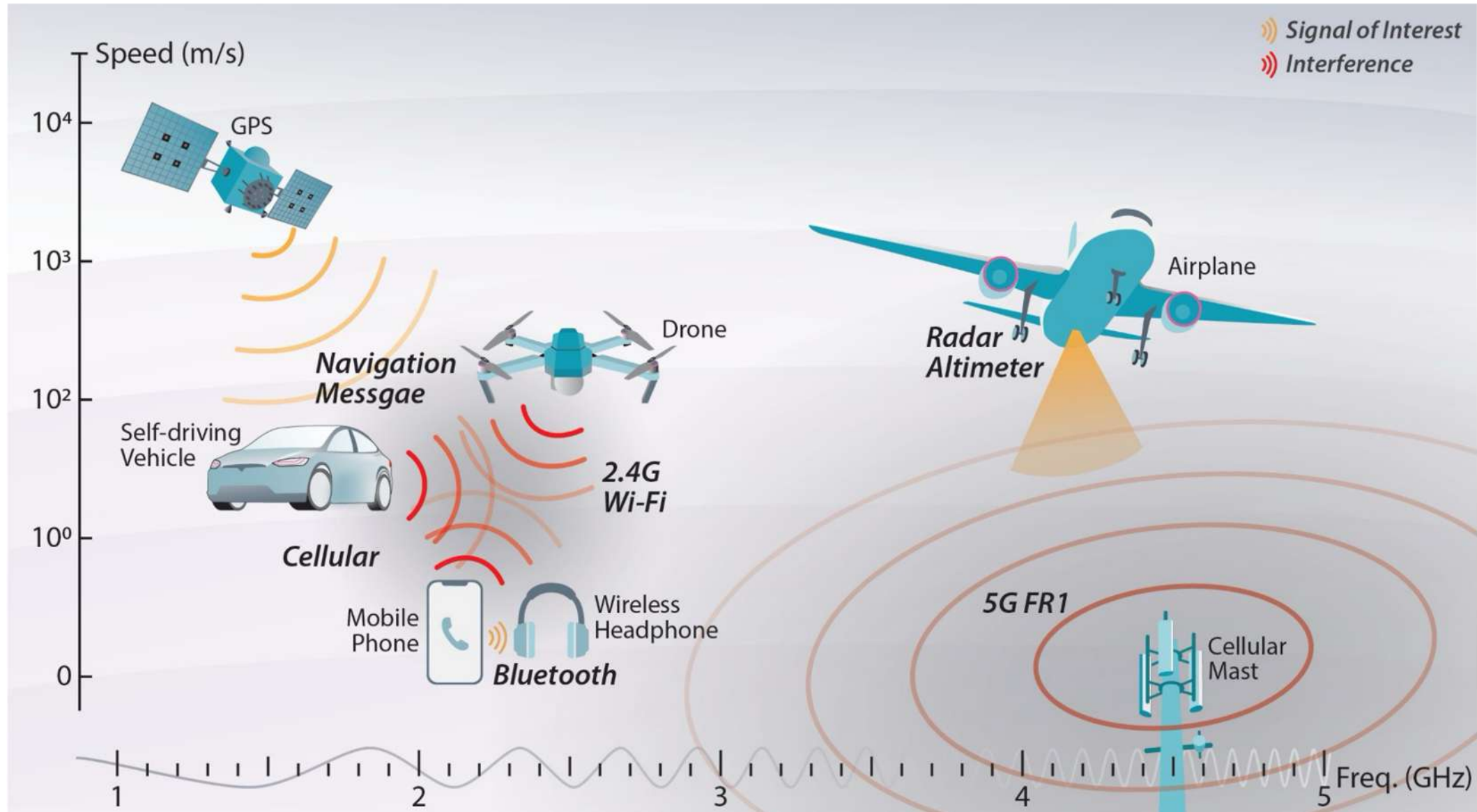


Experimental Setup

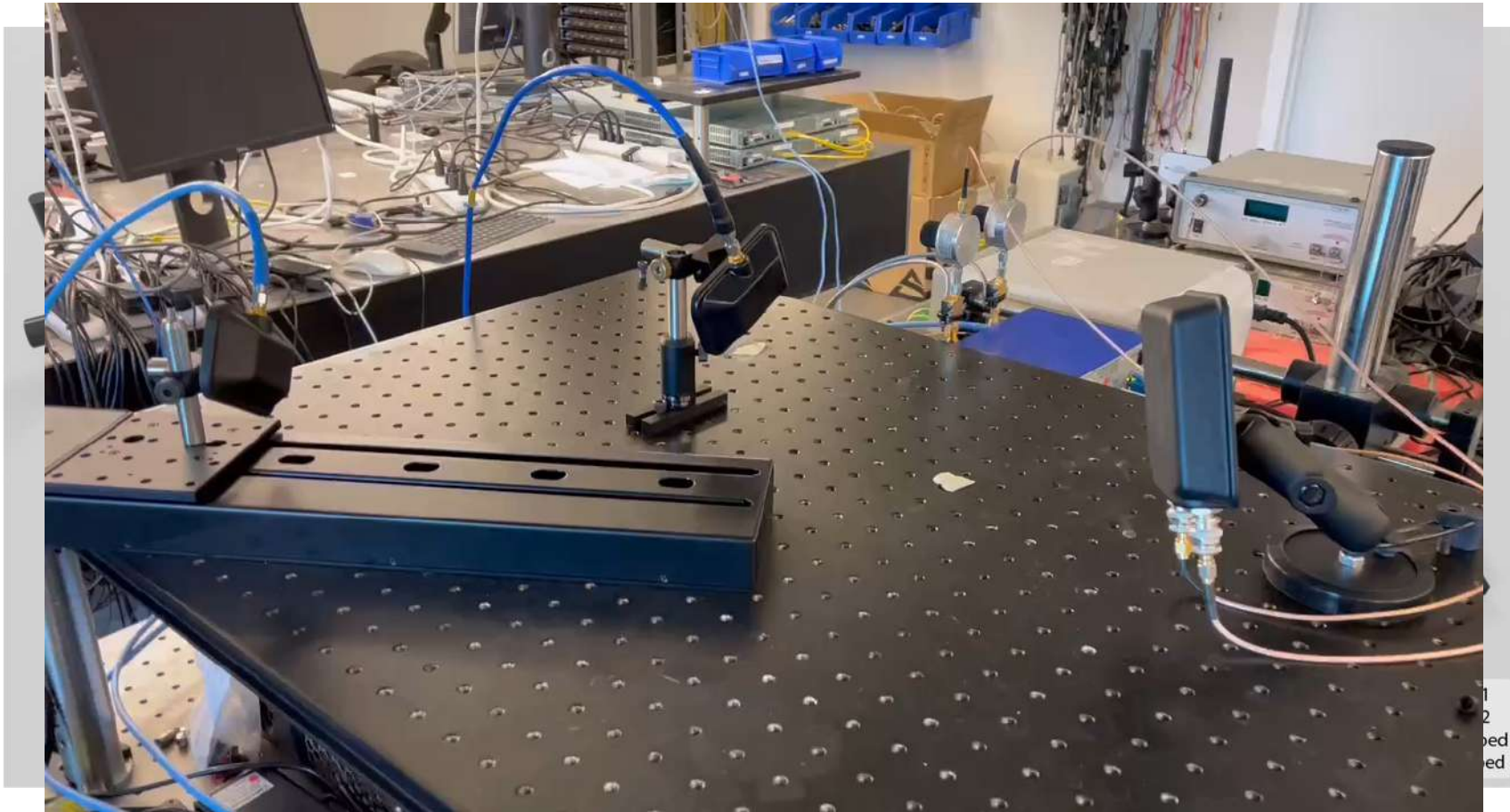


- Fully-integrated neuron used to demonstrate broadband BSS 20 MHz –19.2 GHz
- SIR improved >33 dB across entire operating bandwidth

Dynamical RF Interferences: 5G & Radar Altimeter

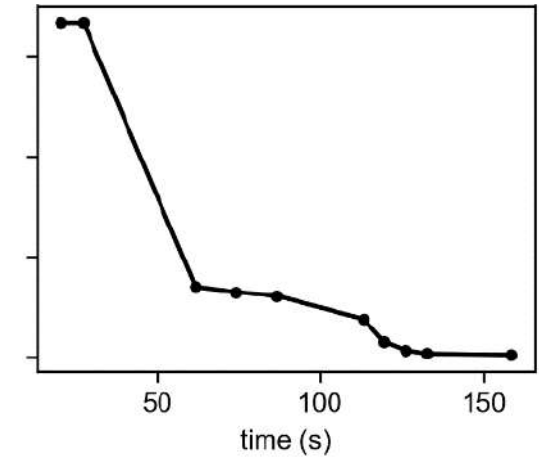


Dynamical and Real-Time BSS



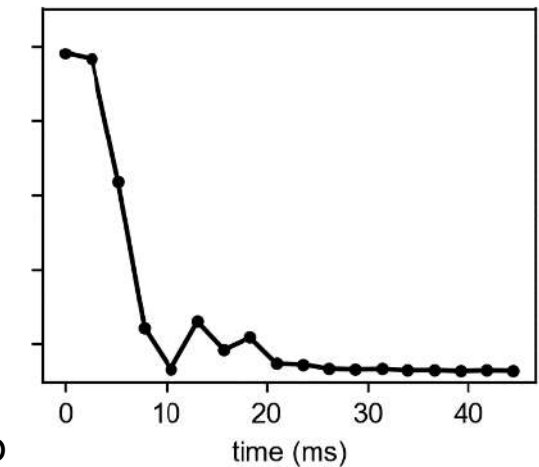
Previous

Convergence time (ICA)



w/FPGA

Convergence time (IC1)



❑ Wireless transceivers

❑ TXs: two directional antennas w/ single polarization

❑ Rx: one 2x2 MIMO antenna w/ two orthogonal polarization slots

❑ Dynamic mixing ratio

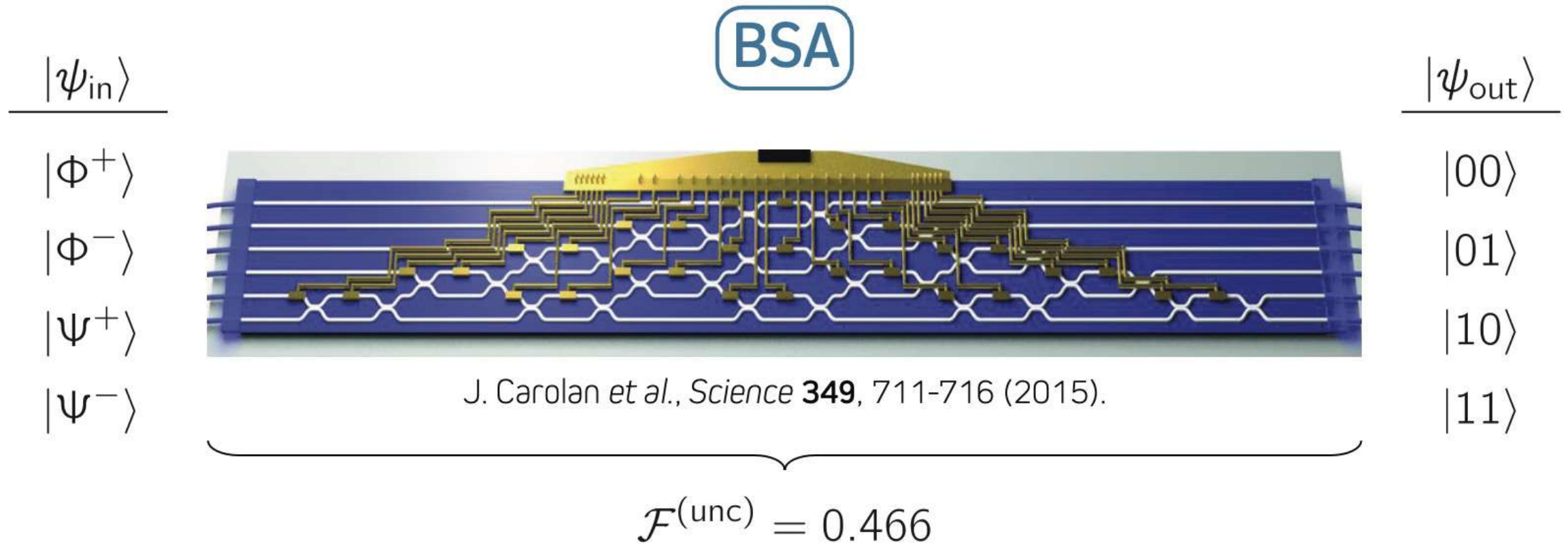
❑ One Tx mounted on a motorized translation stage

❑ 300 mm range, 50mm/s maximal speed

Zhang, Shastri, Prucnal et al. arXiv:2306.14727 (2023); forthcoming in **Light: Science and Applications**

Lederman, Shastri, Prucnal et al. arXiv:2305.05528 (2023); accepted in **Nature Communications**

Universal Linear Optics for Quantum Information Processing

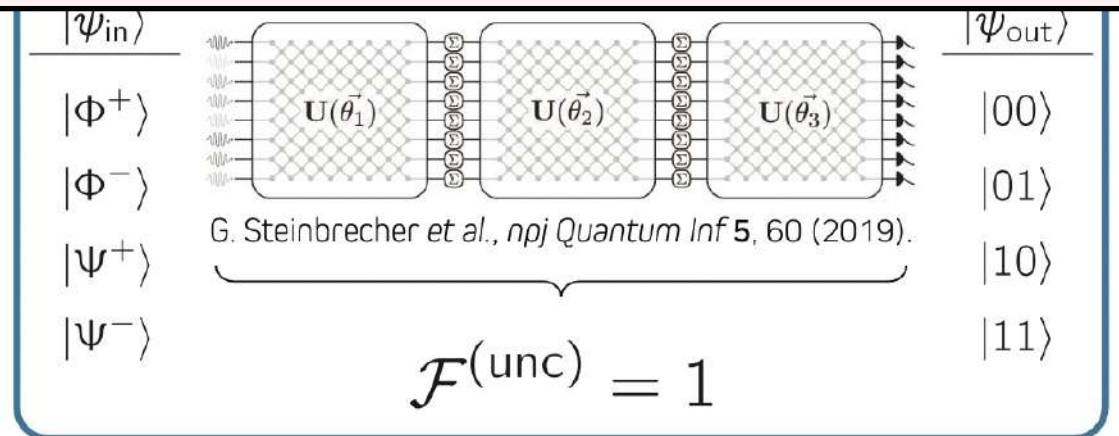
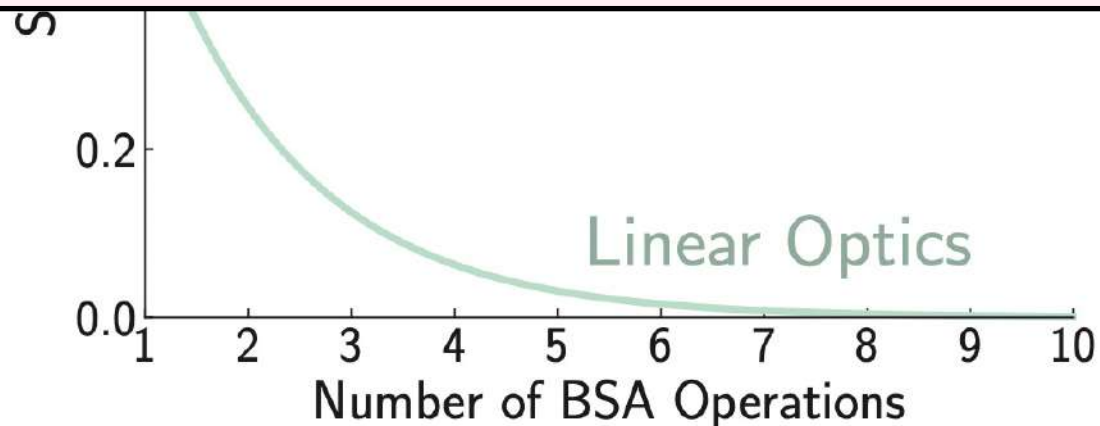


Even with a perfect circuit, linear optics is limited to $\mathcal{F}^{(\text{unc})} = 0.5$

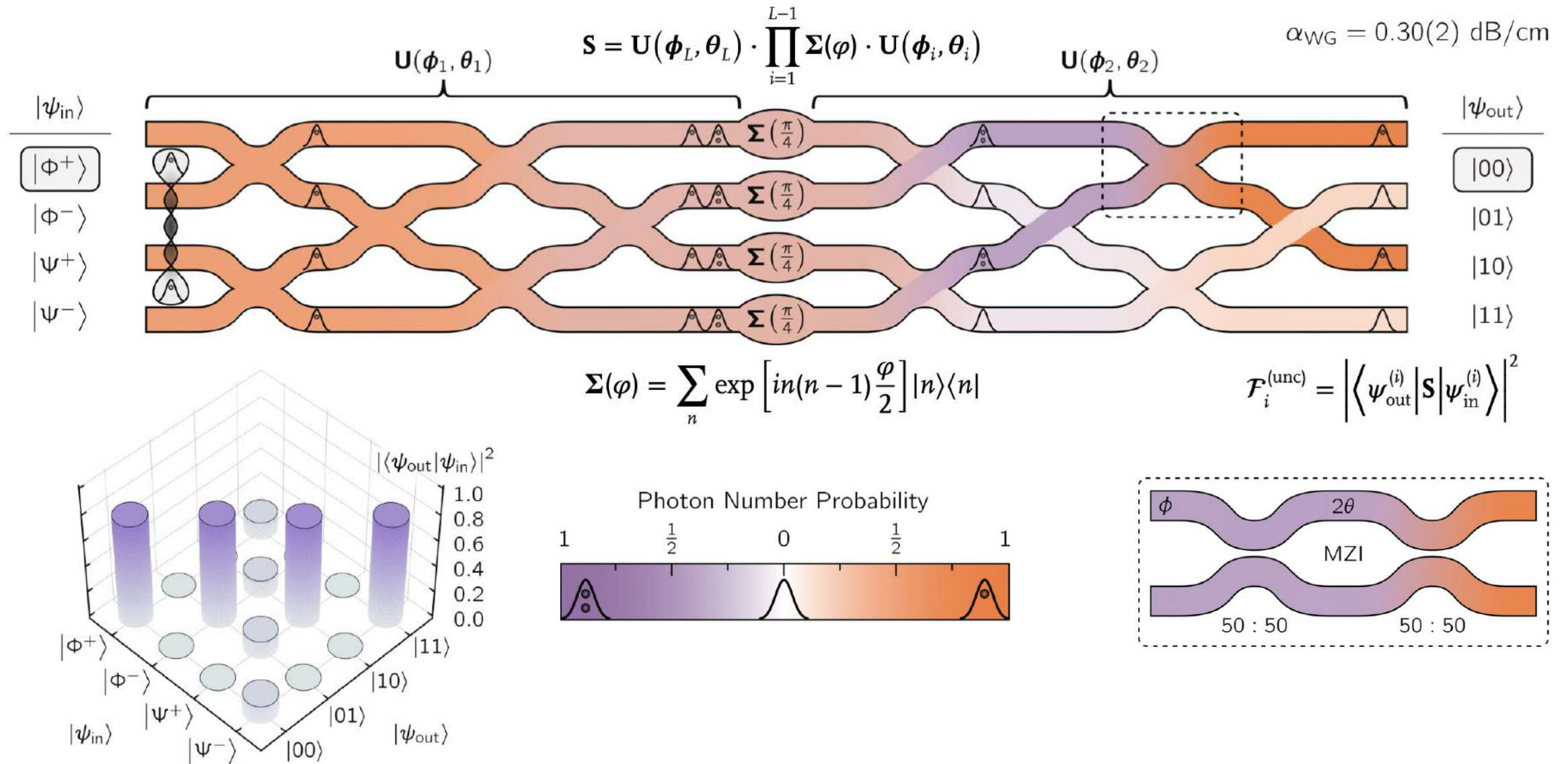
Quantum Photonic Neural Network



Can imperfect QPNNs achieve near-deterministic processing as required for emerging quantum technologies?

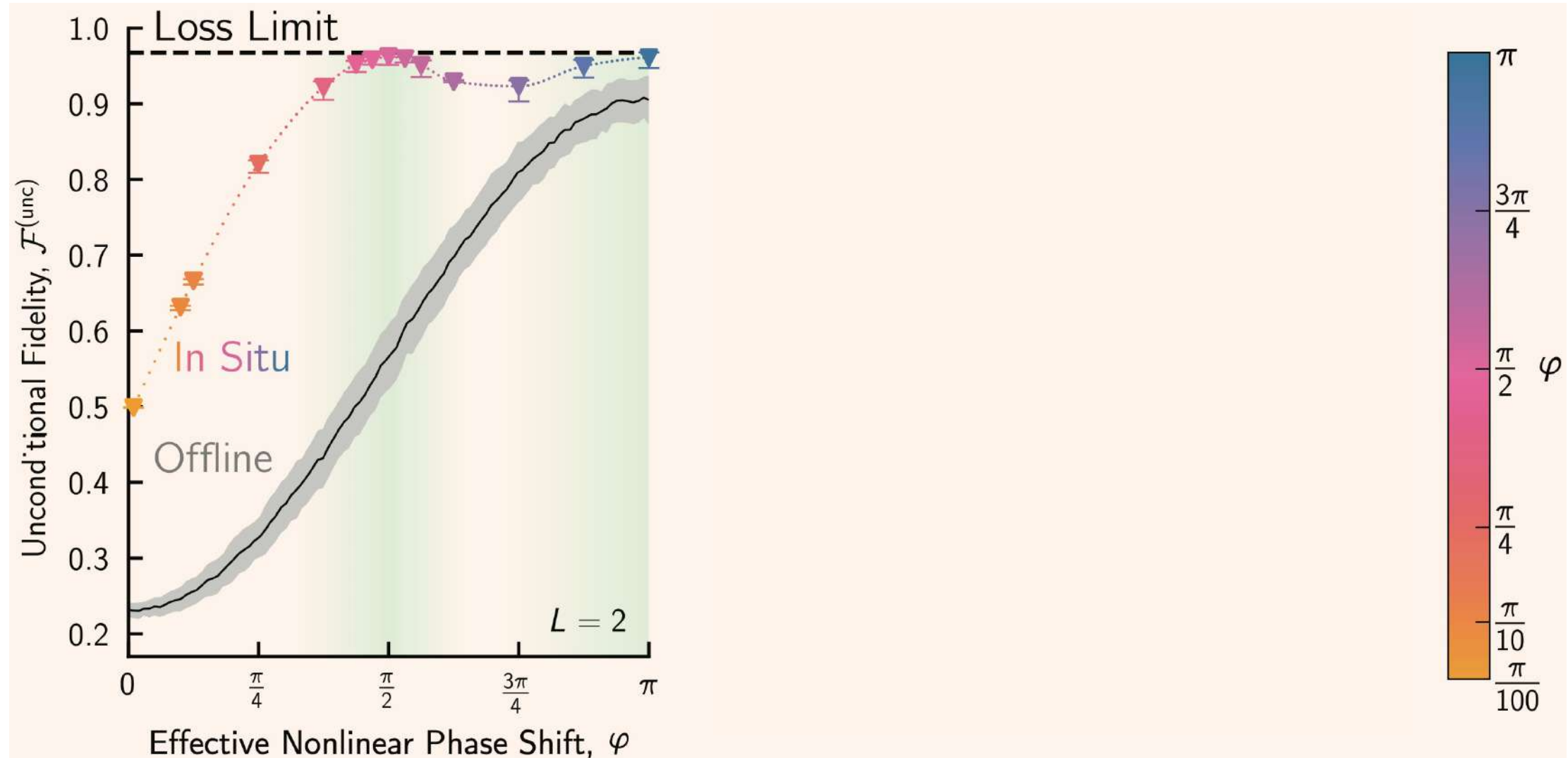


Imperfect Quantum Photonic Neural Network



Embracing Weak Nonlinearities

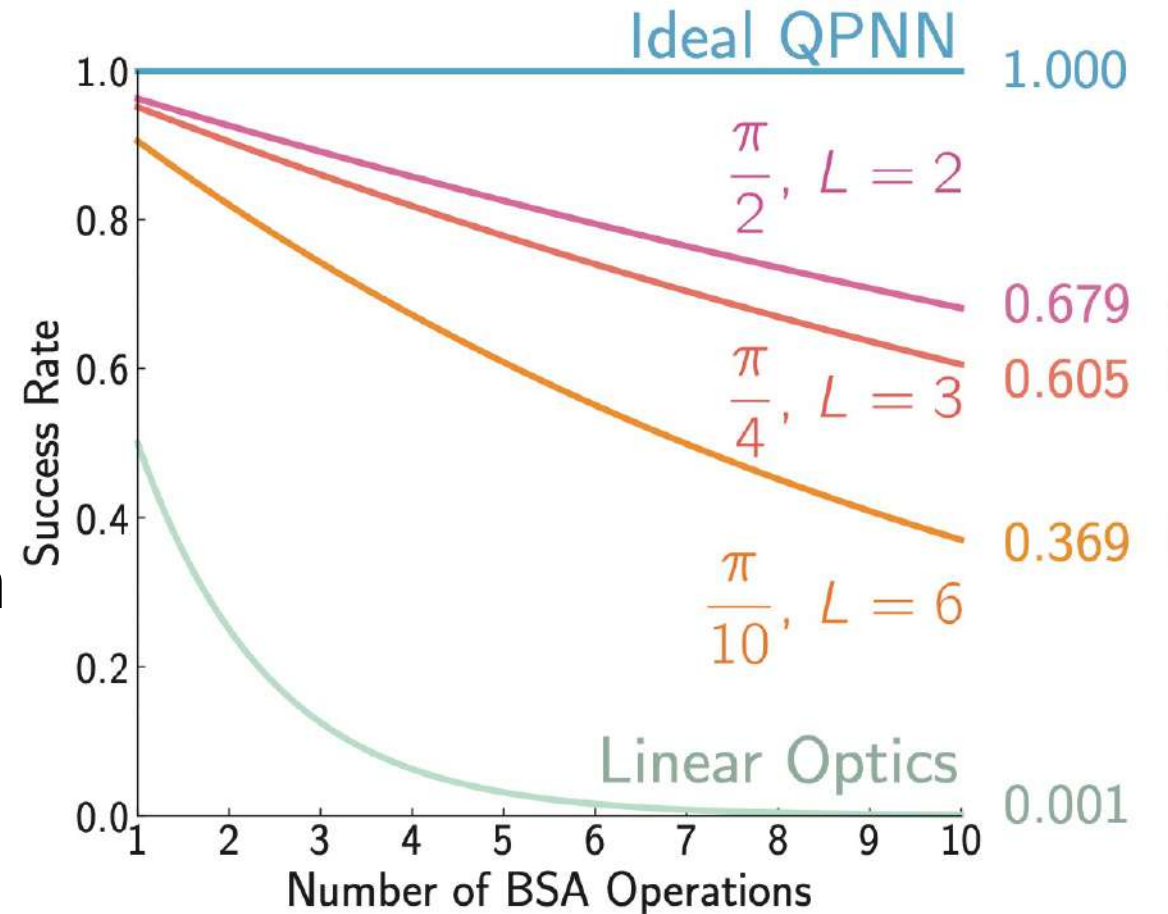
$$\alpha_{WG} = 0.3 \text{ dB/cm}$$



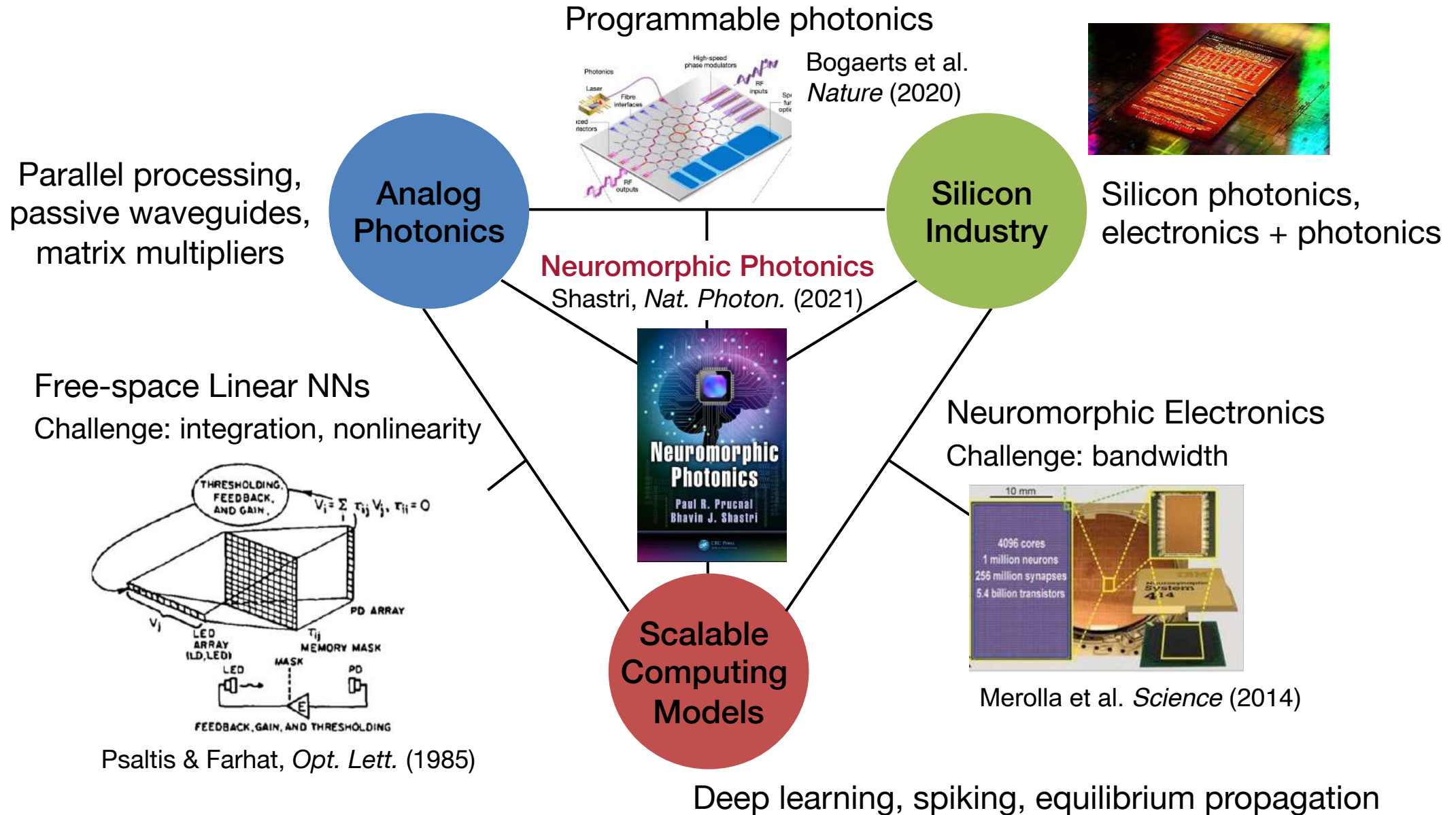
- ❑ When trained in situ, QPNNs learn to account for weak optical nonlinearities

Quantum Photonic Neural Network

- ❑ Perform near-deterministic quantum information processing
- ❑ Are reconfigurable and built on a mature photonics platform
- ❑ Learn to account for fabrication imperfections
- ❑ Optimize in the presence of weak nonlinearities



Photonics & Computing: A 2023 Perspective



Roadmap: Neuromorphic Photonics

REVIEW ARTICLE | FOCUS

<https://doi.org/10.1038/s41566-020-00754-y>

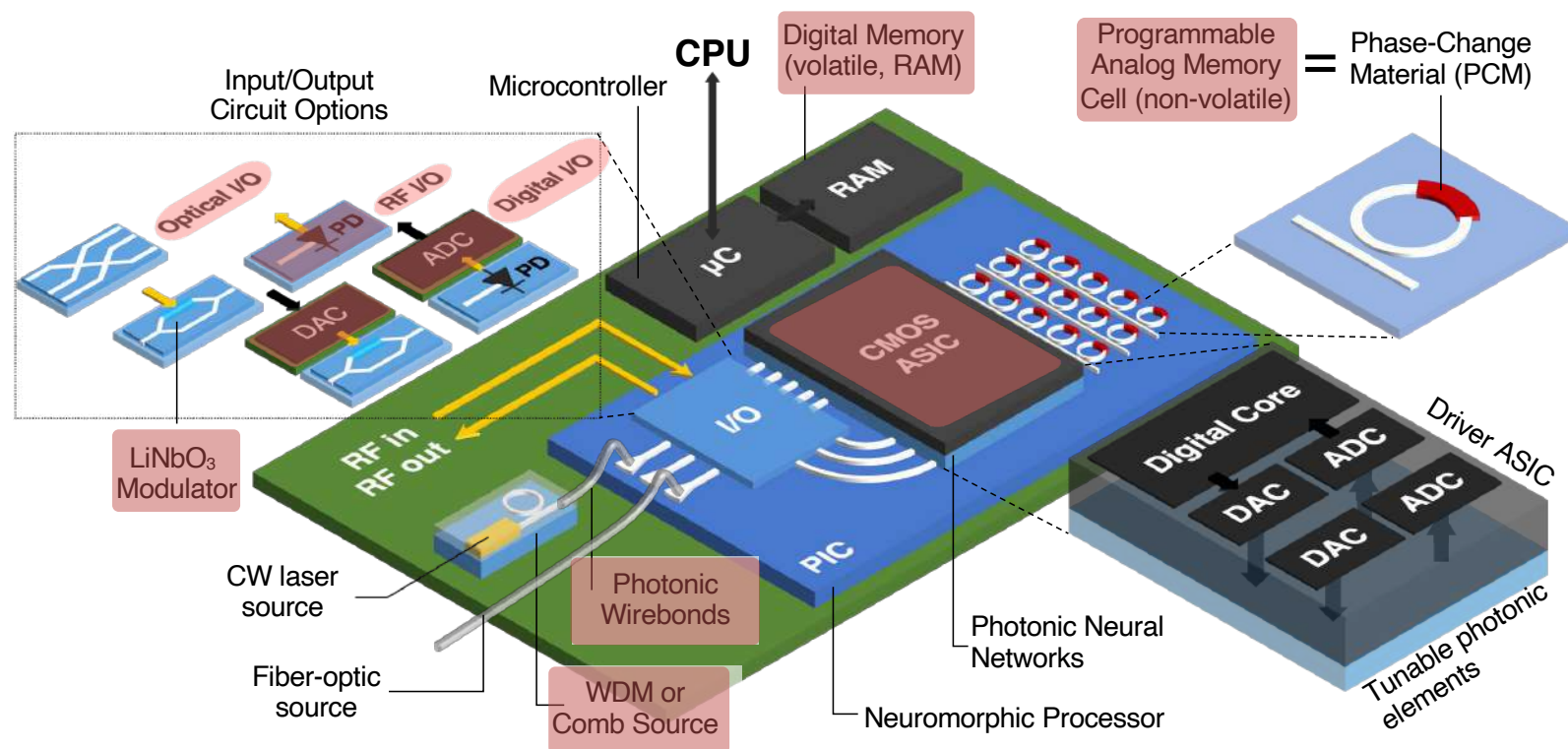
nature
photonics

Check for updates

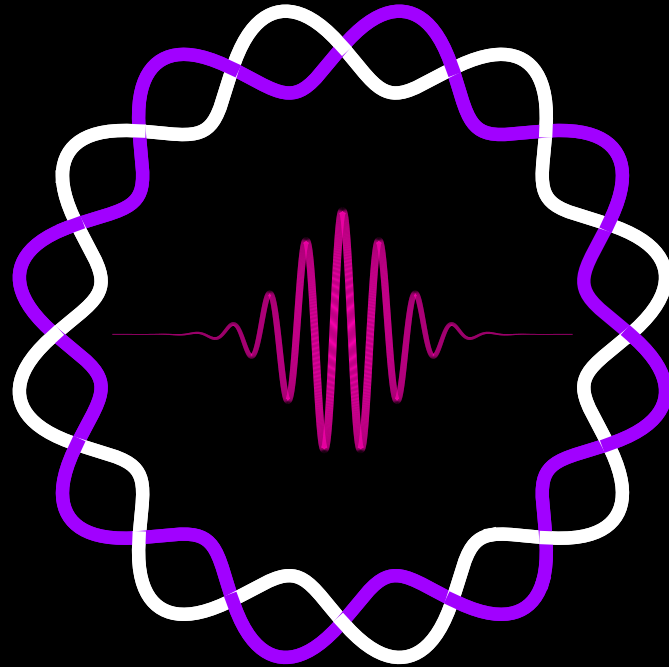
Photonics for artificial intelligence and neuromorphic computing

Bhavin J. Shastri^{1,2,7}✉, Alexander N. Tait^{2,3,7}✉, T. Ferreira de Lima², Wolfram H. P. Pernice⁴, Harish Bhaskaran⁵, C. D. Wright⁶ and Paul R. Prucnal²

- ❑ Laser integration
- ❑ WDM (frequency comb) sources
- ❑ Electronic co-integration
- ❑ Memory
- ❑ Lithium niobate-on-insulator modulators
- ❑ Trimming



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