Project Acronym: **Fun-COMP**

Project Title: **Functionally scaled computing technology:** From novel devices to non-von Neumann architectures and algorithms for a connected intelligent world

WP5

Integrated non-von Neumann computing primitives Project

(WP Leader UOXF)

Deliverable D5.8: Second cross-disciplinary training session and associated training webinars/videos

Deliverable ID: D5.8

Deliverable title: Second cross-disciplinary training session and associated training webinars/videos

Revision level: FINAL

Partner(s) responsible: UOXF

Contributors: UOXF (H Bhaskaran), UNEXE (C D Wright)

Dissemination level: PU[1]

[1] CO: Confidential, only for members of the Fun-COMP consortium (including the Commission Services); PU: Public.

Second cross-disciplinary training session and associated training webinars/videos

The Fun-COMP project brings together partners with expertise spanning a wide range of scientific and technical disciplines. To help ensure that such expertise is shared between partners, and to help to increase public awareness in the science and technology underpinning Fun-COMP, two cross-disciplinary training workshops will be held during the course of the project.

The first such training event was held at the University of Oxford on March 18th 2019 (note that this was formally delayed from month-9 - as in original DoW - to month-12 to make coincident with project progress meeting) and has been reported in Deliverable D5.7

The second training event was also held at the University of Oxford, on August 22nd 2019, and focused on integrated photonics systems. This event, which we entitled "Conversations on the Future of Integrated Photonics and Computing", consisted of two main sessions, as follows:

1) An invited tutorial presentation by Prof Paul Prucnal, MIT, on *Advances in Neuromorphic Silicon Photonics*

2) A panel session on *The Future of Photonic Computing*, in which Prof Prucnal, Fun-COMP WP leaders and the audience discussed key technical challenges facing the development of photonic computing technology.

The training session was attended by a wide-ranging audience including young PhD and post-doc scientists from partner laboratories, as well as editors of academic journals, representatives of EPSEC (UK funding council) and local (Oxford) PhD and post-doc researchers.

A copy of the presentation made by Prof Prucnal is attached to this deliverable report and currently available on the partner-only pages of the Fun-COMP website (www. fun-comp.org), but will be migrated to the private pages as soon as possible confidentiality issues have been addressed. See

https://fun-comp.org/research-contents/project-deliverables/

Advances in Neuromorphic Silicon Photonics

Paul R. Prucnal & Bhavin J. Shastri
Princeton & Queen's Universities

PRINCETON UNIVERSITY

Outline

Queen's UNIVERSITY

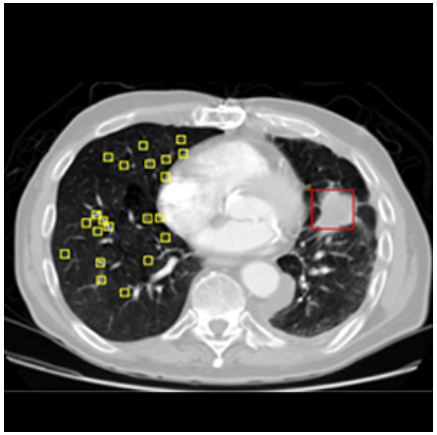
- Motivation
  - Artificial intelligence; neural networks
  - Recent work on photonic information processing
- Silicon Photonic Neural Networks
  - Micro-ring weight banks: vector multiplications
  - Micro-ring modulator nonlinearity
- Applications
  - Winner Take All Demonstration
  - Nonlinear Programming
  - Processing GHz RF Signals
- Conclusion
  - Challenges in Making This a Reality

Rise of Artificial Intelligence

- Natural language processing; Siri, Cortana, Alexa, Google
- Game playing (Go) and Chess; beating World Champions
- Face recognition
- YouTube, Netflix, Google Maps, Amazon
- Medicine and healthcare
- Autonomous vehicles
- Control and optimization

NETFLIX

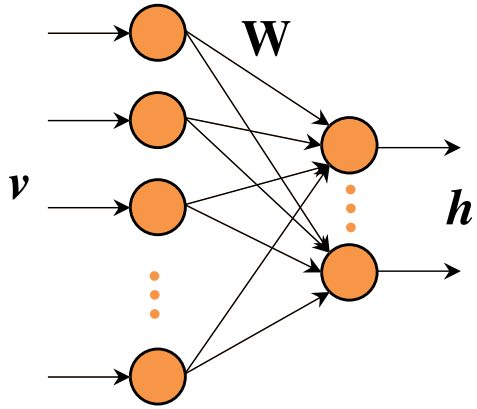
amazon



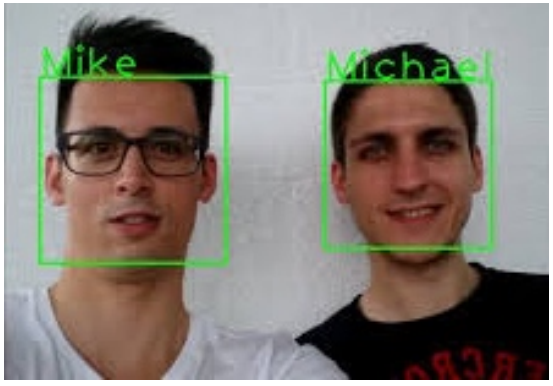
LeCun, Bengio, Hinton *Nature* **521** (2015)

Types and Functions of Neural Networks

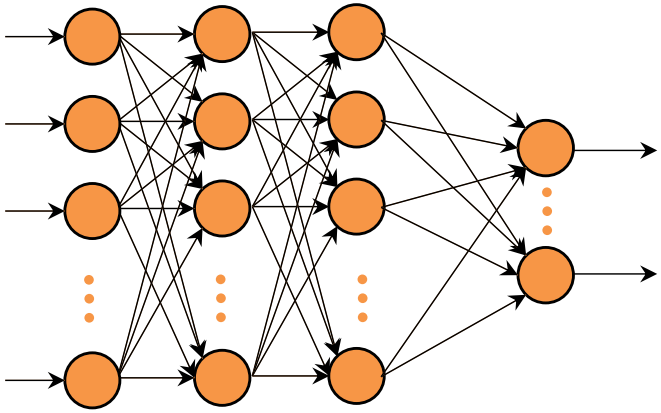
Feedforward



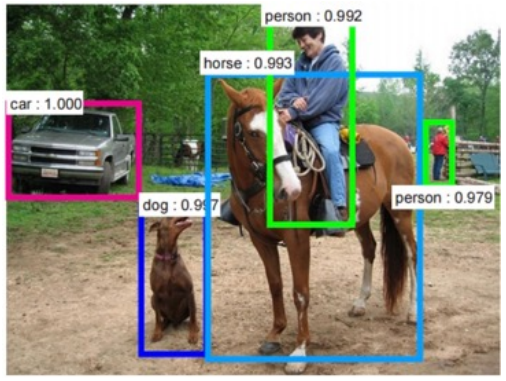
Train W (minimize error) for recognition tasks



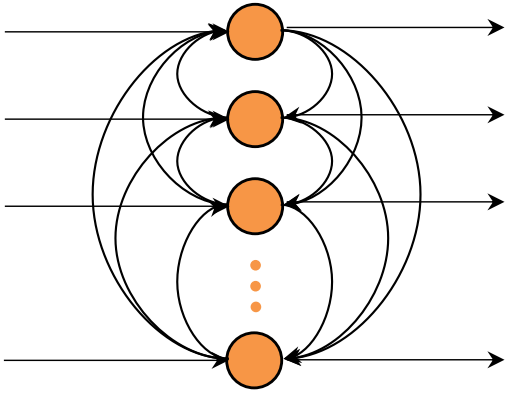
Multi-layered (deep) network



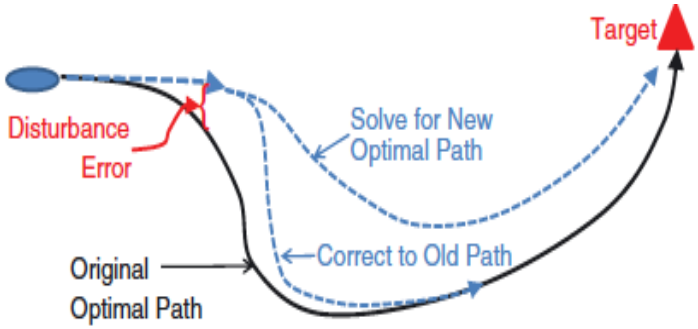
Feature extraction and classification



Recurrent

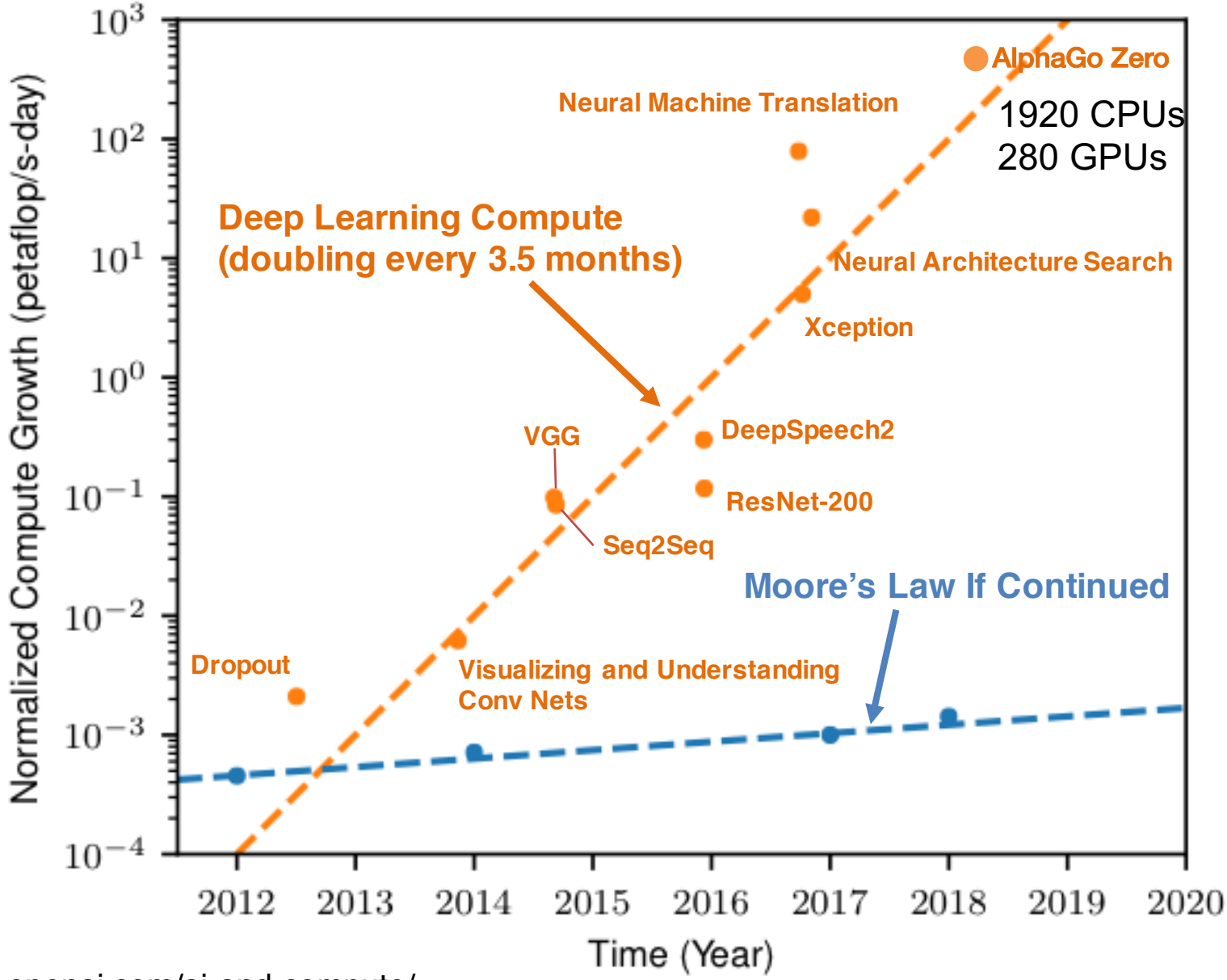


Learning, control & optimization



Computational Speed Limitations

Deep learning dominates HPC… exceeding the available compute capacity.



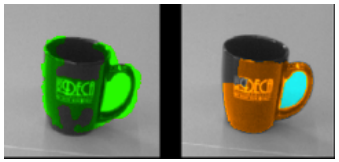
https://blog.openai.com/ai-and-compute/

Time Scales of Applications & Technologies

Time Scale

Hz-kHz

Speech recognition



Object recognition

Machine Learning with Computers (AI software)

kHz-MHz

Real-time (deep) surveillance

Neuromorphic Electronics (special purpose hardware)

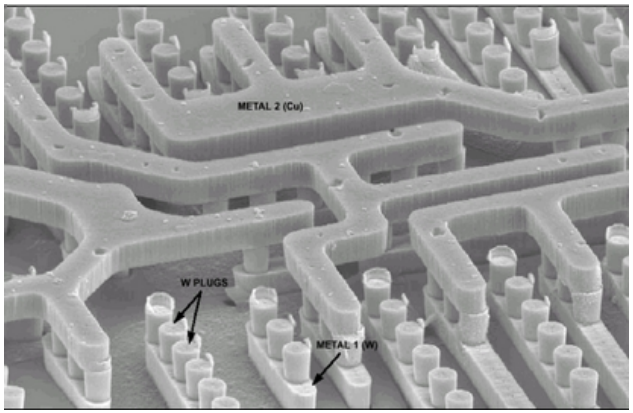
Prucnal, Shastri et al. *Adv. Opt. Photonics* **8** (2016)

Time Scales of Applications & Technologies

Time Scale

Hz-kHz

Tradeoff: challenge being fast and complex



kHz-MHz

Physical Limitations

- **Interconnection density**: capacitive loading, EMI, topological constraints
- **Bandwidth**: $\propto 1/N^2$ (N=wires)
- **Energy efficiency**: limited by electron tunneling (leakage) through gates

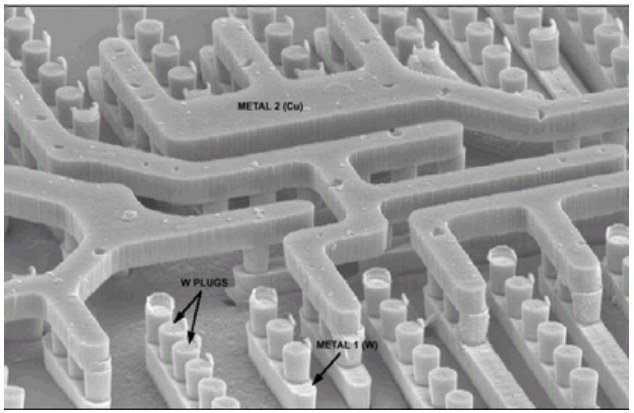
Prucnal, Shastri et al. *Adv. Opt. Photonics* **8** (2016)

Time Scales of Applications & Technologies

Time Scale

Tradeoff: challenge being fast and complex

Hz-kHz



Machine Learning with Computers (AI <u>software</u>)

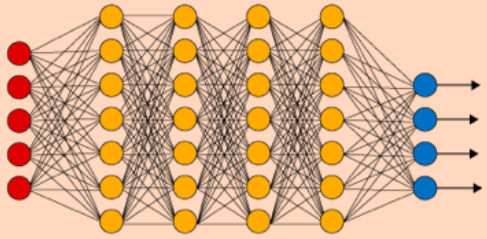
kHz-MHz

Physical Limitations

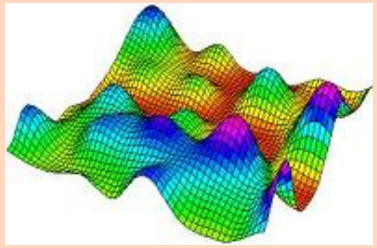
- **Interconnection density**: capacitive loading, EMI, topological constraints
- **Bandwidth:** $\propto 1/N^2$ (N=wires)
- **Energy efficiency:** limited by electron tunneling (leakage) through gates

Neuromorphic Electronics (special purpose <u>hardware</u>)

GHz



Deep Learning Acceleration



Nonlinear Optimization

Neuromorphic Photonics (hardware)

Enables new applications that can't be achieved with electronics, such as in RF.

Prucnal, Shastri et al. *Adv. Opt. Photonics* **8** (2016)

Optics & Computing--Why now?

Robert Keyes' main criticisms of digital optical computing in the 1980's: A 2019 perspective

Then: Problems	Now: Silicon Photonic Solutions
• Fan-out	WDM, Analog
• Physical cascadability • Logic level restoration • Input-output isolation • Large-signal gain	O/E/O signal pathway
• Large system integration • Cost relative to microelectronics • Footprint	Silicon photonic integration
• Fabrication precision • Stability/sensitivity • Individual adjustment	In-package CMOS control

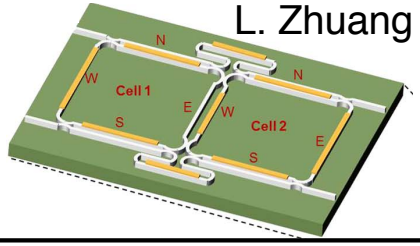
R. W. Keyes, Optical Logic: In the light of computer technology *Optica Acta*, **32** (5), 1985 (IBM)

R. W. Keyes, What makes a good computer device? *Science*, **230**, pp.138–144, 1985

Optics & Computing--Why now?

Integrated RF photonics
Challenge: programmability

L. Zhuang et al. (2015)



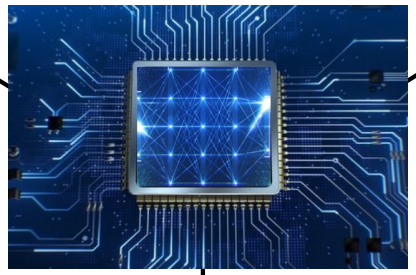
Microwave signal processing

Analog Photonics

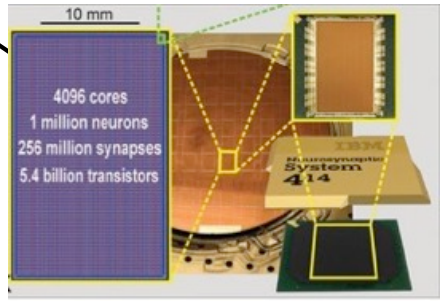
Silicon Industry

Silicon photonics, electronics+photonics

Neuromorphic Photonics

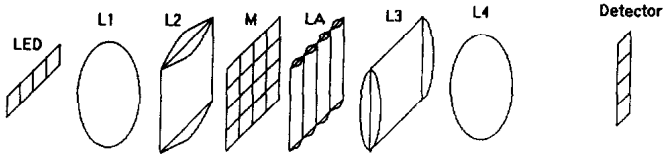


Neuromorphic Electronics
Challenge: bandwidth



P. Merolla et al. (2014)

Free-space Linear NNs
Challenge: integration, nonlinearity



J. Goodman et al. (1978)

Scalable Computing Models

Deep learning, spiking, machine learning

Prucnal & Shastri, ***Neuromorphic Photonics*** CRC Press (2017)

1) Photonic Reservoir Computing:

nature COMMUNICATIONS

Parallel photonic information processing at gigabyte per second data rates using transient states

Daniel Brunner[1], Miguel C. Soriano[1], Claudio R. Mirasso[1] & Ingo Fischer[1]

UIB, Spain

nature COMMUNICATIONS

Experimental demonstration of reservoir computing on a silicon photonics chip

Kristof Vandoorne[1,2], Pauline Mechet[1,2], Thomas Van Vaerenbergh[1,2], Martin Fiers[1,2], Geert Morthier[1,2], David Verstraeten[3], Benjamin Schrauwen[3], Joni Dambre[3] & Peter Bienstman[1,2]

Ghent

nature COMMUNICATIONS

Information processing using a single dynamical node as complex system

L. Appeltant[1], M.C. Soriano[2], G. Van der Sande[1], J. Danckaert[1], S. Massar[3], J. Dambre[4], B. Schrauwen[4], C.R. Mirasso[2] & I. Fischer[2]

Photonic information processing beyond Turing: an optoelectronic implementation of reservoir computing

L. Larger,[1] M. C. Soriano,[2] D. Brunner,[2,*] L. Appeltant,[3] J. M. Gutierrez,[4] L. Pesquera,[4] C. R. Mirasso,[2] and I. Fischer[2]

FEMTO-ST, France

2) Multiwavelength Neural Networks:

SCIENTIFIC REPORTS

Neuromorphic photonic networks using silicon photonic weight banks

Alexander N. Tait, Thomas Ferreira de Lima, Ellen Zhou, Allie X. Wu, Mitchell A. Nahmias, Bhavin J. Shastri & Paul R. Prucnal

Princeton

Optics EXPRESS

Neuromorphic photonics with electro-absorption modulators

JONATHAN K. GEORGE,[1] ARMIN MEHRABIAN,[1] RUBAB AMIN,[1] JIAWEI MENG,[1] THOMAS FERREIRA DE LIMA,[2] ALEXANDER N. TAIT,[2] BHAVIN J. SHASTRI,[2] TAREK EL-GHAZAWI,[1] PAUL R. PRUCNAL,[2] AND VOLKER J. SORGER[1,*]

Princeton & GWU

3) Coherent Optical Neural Networks:

nature photonics

ARTICLES

PUBLISHED ONLINE: 12 JUNE 2017 | DOI: 10.1038/NPHOTON.2017.93

Deep learning with coherent nanophotonic circuits

Yichen Shen[1*†], Nicholas C. Harris[1*†], Scott Skirlo[1], Mihika Prabhu[1], Tom Baehr-Jones[2], Michael Hochberg[2], Xin Sun[3], Shijie Zhao[4], Hugo Larochelle[5], Dirk Englund[1] and Marin Soljačić[1]

(Relinquished their claims at IEEE Summer Topical) MIT

Research Article Vol. 5, No. 7 / July 2018 / *Optica* 864

optica

Training of photonic neural networks through *in situ* backpropagation and gradient measurement

TYLER W. HUGHES,[1] MOMCHIL MINKOV,[2] YU SHI,[2] AND SHANHUI FAN[2,*]

Stanford

4) Photonic Spiking Neural Networks:

IEEE JOURNAL OF SELECTED TOPICS IN QUANTUM ELECTRONICS, VOL. 19, NO. 5, SEPTEMBER/OCTOBER 2013

A Leaky Integrate-and-Fire Laser Neuron for Ultrafast Cognitive Computing

Mitchell A. Nahmias, *Student Member, IEEE*, Bhavin J. Shastri, *Member, IEEE*, Alexander N. Tait, *Student Member, IEEE*, and Paul R. Prucnal, *Fellow, IEEE*

Princeton

SCIENTIFIC REPORTS

Spike processing with a graphene excitable laser

Bhavin J. Shastri*, Mitchell A. Nahmias*, Alexander N. Tait*, Alejandro W. Rodriguez, Ben Wu & Paul R. Prucnal

PRL **112,** 183902 (2014) PHYSICAL REVIEW LETTERS

Relative Refractory Period in an Excitable Semiconductor Laser

F. Selmi, R. Braive,* G. Beaudoin, I. Sagnes, R. Kuszelewicz, and S. Barbay†
Laboratoire de Photonique et de Nanostructures, LPN-CNRS UPR20, Route de Nozay, 91460 Marcoussis,

LPN-CNRS, France

SCIENTIFIC REPORTS

Regenerative memory in time-delayed neuromorphic photonic resonators

B. Romeira[1,*], R. Avó[1], José M. L. Figueiredo[1], S. Barland[2] & J. Javaloyes[3]

UIB, Spain & Université de Nice

IEEE JOURNAL OF SELECTED TOPICS IN QUANTUM ELECTRONICS, VOL. 24, NO. 6, NOVEMBER/DECEMBER 2018

Neuromorphic Photonic Integrated Circuits

Hsuan-Tung Peng, Mitchell A. Nahmias, Thomas Ferreira de Lima, Alexander N. Tait, Bhavin J. Shastri, *Member, IEEE*, and Paul R. Prucnal, *Fellow, IEEE*

Princeton

(Invited Paper)

APPLIED PHYSICS LETTERS **100**, 103703 (2012)

Investigation of vertical cavity surface emitting laser dynamics for neuromorphic photonic systems

A. Hurtado,[a] K. Schires, I. D. Henning, and M. J. Adams
School of Computer Science and Electronic Engineering, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, United Kingdom

Strathclyde & Essex

nature SUPPLEMENTARY INFORMATION
https://doi.org/10.1038/s41586-019-1157-8

In the format provided by the authors and unedited.

All-optical spiking neurosynaptic networks with self-learning capabilities

J. Feldmann[1], N. Youngblood[2], C. D. Wright[3], H. Bhaskaran[2] & W. H. P. Pernice[1]*

Exeter, Oxford, Munster

5) Diffractive Optics:

Science

UCLA

All-optical machine learning using diffractive deep neural networks

Xing Lin, Yair Rivenson, Nezih T. Yardimci, Muhammed Veli, Yi Luo, Mona Jarrahi and Aydogan Ozcan

optica

Reinforcement learning in a large-scale photonic recurrent neural network

J. Bueno,[1] S. Maktoobi,[2] L. Froehly,[2] I. Fischer,[1] M. Jacquot,[2] L. Larger,[2] and D. Brunner[2,*]

[1]Instituto de Física Interdisciplinar y Sistemas Complejos, IFISC (UIB-CSIC), Campus Universitat de les Illes Baleares, E-07122 Palma de Mallorca, Spain
[2]FEMTO-ST Institute/Optics Department, CNRS & University Bourgogne Franche-Comté, 15B avenue des Montboucons,

FEMTO-ST, France

6) Ising Machines:

nature photonics

LETTERS

PUBLISHED ONLINE: 26 OCTOBER 2014 | DOI: 10.1038/NPHOTON.2014.249

Network of time-multiplexed optical parametric oscillators as a coherent Ising machine

Alireza Marandi[1,2*], Zhe Wang[1], Kenta Takata[2,3], Robert L. Byer[1] and Yoshihisa Yamamoto[1,2,3]

Science

A fully programmable 100-spin coherent Ising machine with all-to-all connections

Peter L. McMahon, Alireza Marandi, Yoshitaka Haribara, Ryan Hamerly, Carsten Langrock, Shuhei Tamate, Takahiro Inagaki, Hiroki Takesue, Shoko Utsunomiya, Kazuyuki Aihara, Robert L. Byer, M. M. Fejer, Hideo Mabuchi and Yoshihisa Yamamoto

Stanford & NTT

7) Other Computing and Superconducting approaches:

Science

UPenn

Inverse-designed metastructures that solve equations

Nasim Mohammadi Estakhri, Brian Edwards and Nader Engheta

PHYSICAL REVIEW APPLIED **7,** 034013 (2017)

Superconducting Optoelectronic Circuits for Neuromorphic Computing

Jeffrey M. Shainline,* Sonia M. Buckley, Richard P. Mirin, and Sae Woo Nam

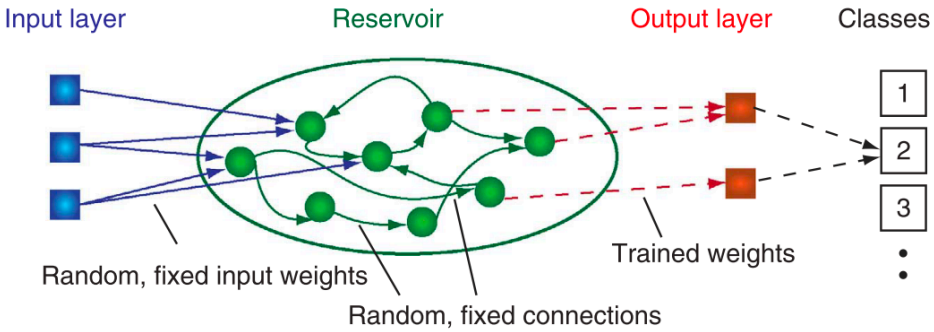
National Institute of Standards and Technology, 325 Broadway, Boulder 80305, Colorado, USA

NIST

1) Photonic Reservoir Computing

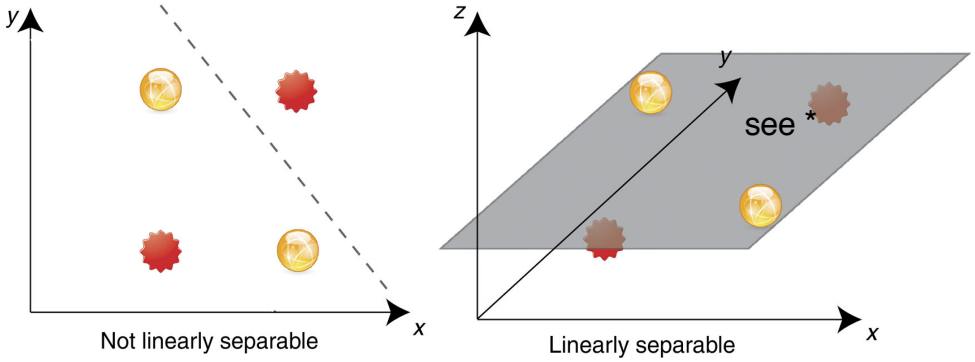
Echo State Network or Liquid State Machine

Jaeger, Haas *Science* **304** (2004)
Maass, et al, *Network: Comput.* **14** (2002)



Appeltant et al, *Nat. Commun.* **2** (2011)

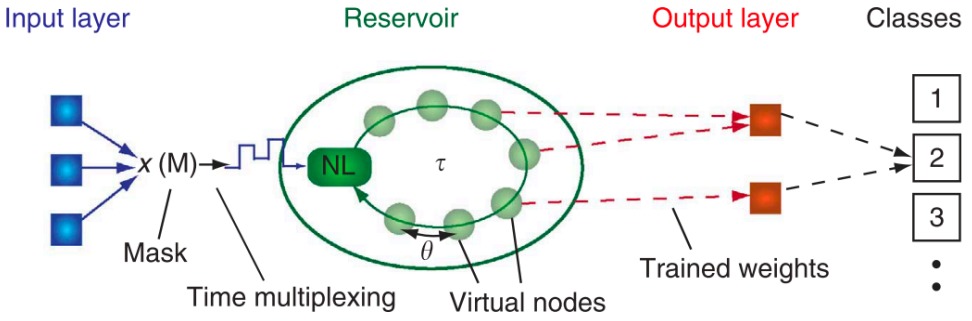
- Reservoir (random recurrent connections) increases number of dimensions
- Output layer trained to do linear classification



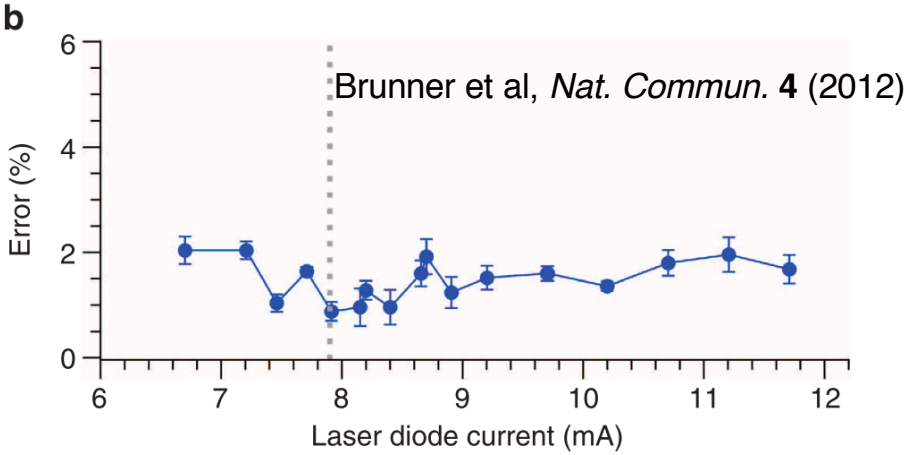
Increasing dimensions facilitates classification

Photonic implementation with delayed feedback

Larger et al. *Opt. Express* **20** (2012)
Appeltant et al, *Nat. Commun.* **2** (2011)

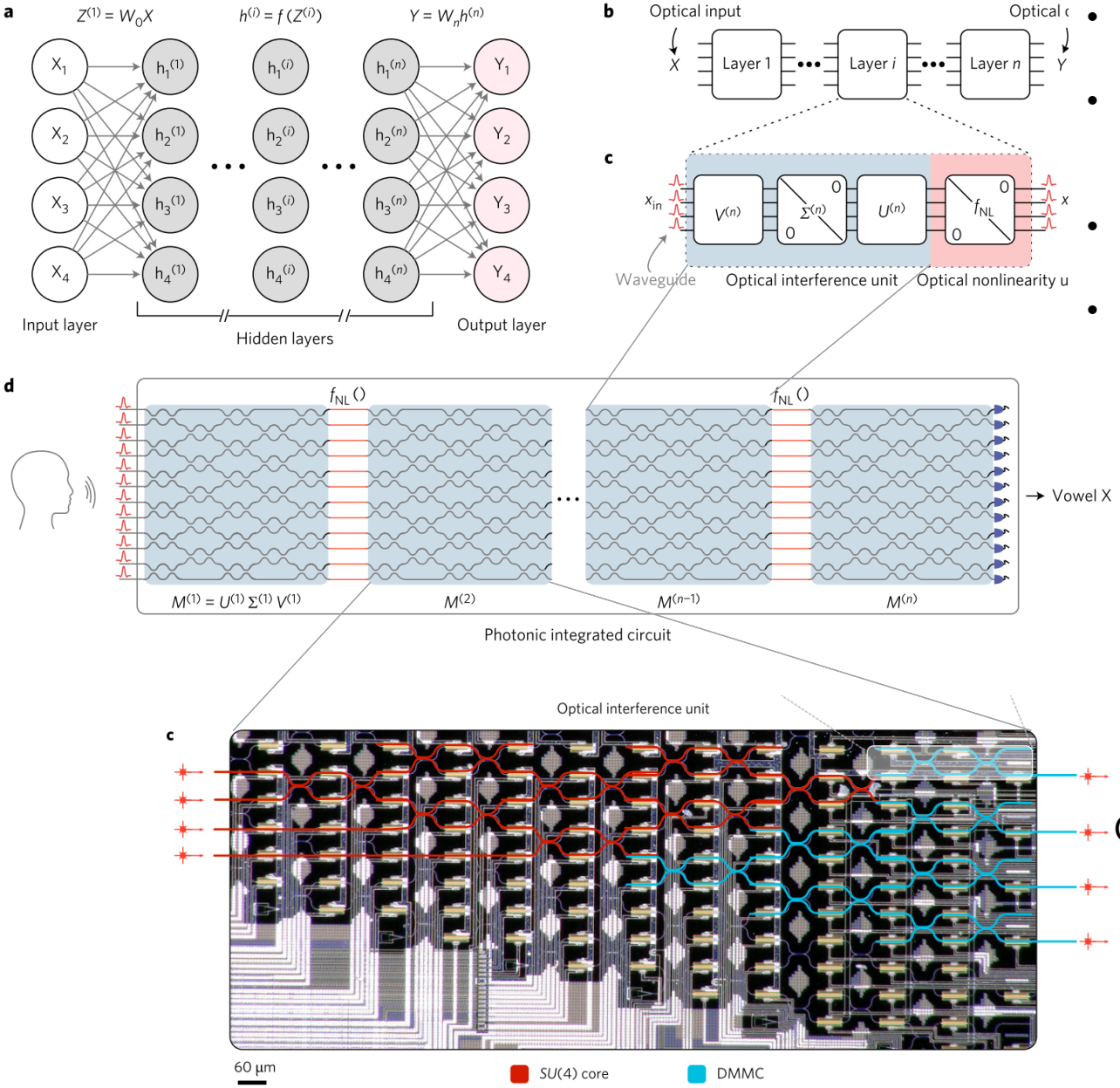


- Weights are time multiplexed
- Single nonlinear laser node (NL)
- Fiber loop creates recurrent network
- More nodes increases latency (with same NL)

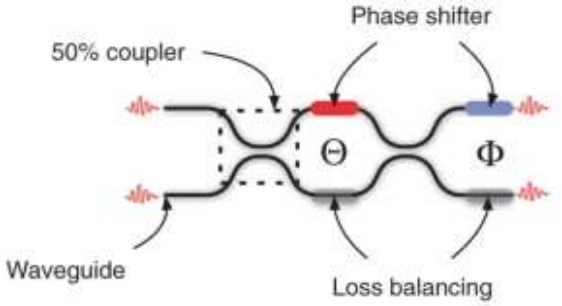


- Spoken digit (0, 1,…9) classification, 5 GHz bandwidth
- Lowest error near laser threshold current (highest nonlinearity)

2) Coherent Optical Neural Network



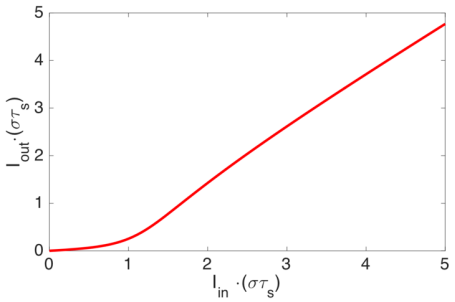
- This is a vector-matrix multiplier corresponding to a neuron front-end.
- Any matrix M can be represented by standard singular value decomposition: $M = U\Sigma \mathrm{V}^{\dagger}$ with U, $\mathrm{V}^{\dagger}$ unitary matrices.
- Implement U and $\mathrm{V}^{\dagger}$ with MZI, which has unitary Jones matrix (below)
- Diagonal weights Σ implemented with MZM.



$$U = \begin{pmatrix} e^{i\phi}\sin(\theta/2) & e^{i\phi}\cos(\theta/2) \\ \cos(\theta/2) & -\sin(\theta/2) \end{pmatrix}$$

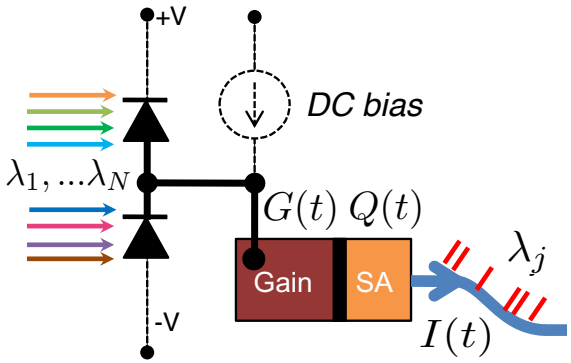
Optical nonlinearity was not implemented.

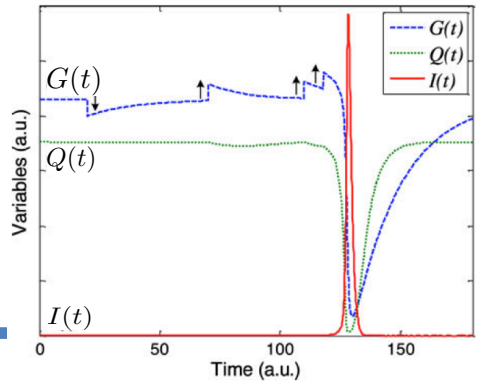
Simulated nonlinearity



Shen, Harris, Englund, Soljacic et al, *Nat. Photon.* **11** (2017)

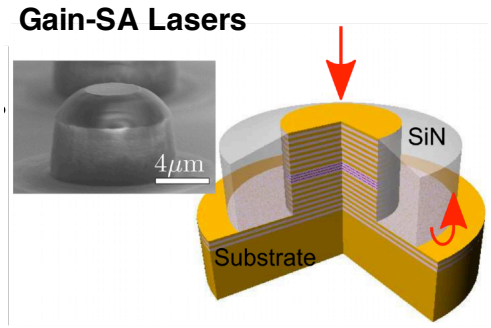
3) Photonic Spiking Neurons

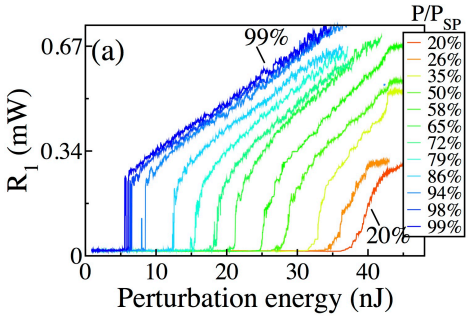




Nahmias, Shastri, Prucnal et al. *IEEE JSTQE* **19** (2013)

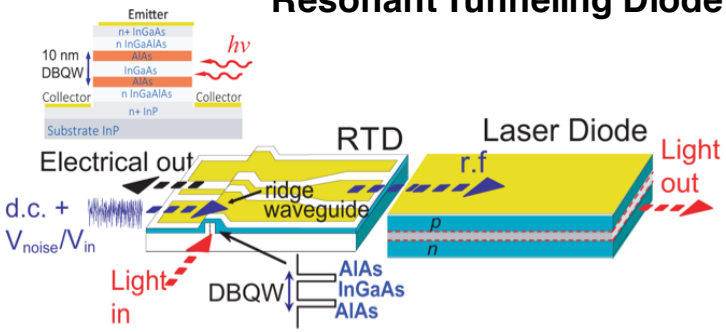
Gain-SA Lasers

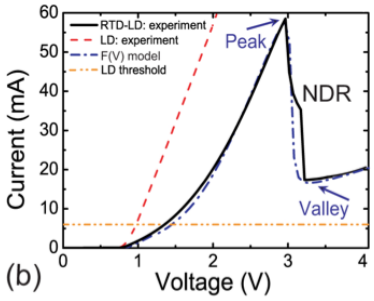




Selmi, Barbay *et al. Phy. Rev. Lett.* **112** (2014)

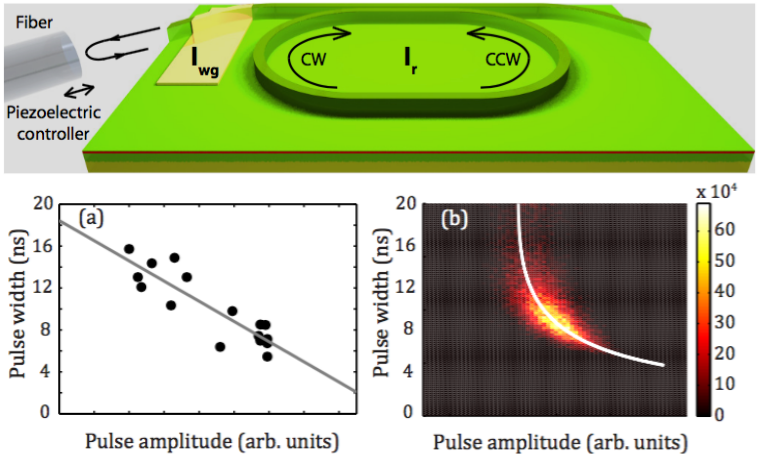
Resonant Tunneling Diode + LD





Romeira *et al. Sci. Rep.* (2016)

Semiconductor Ring & Microdisk Lasers

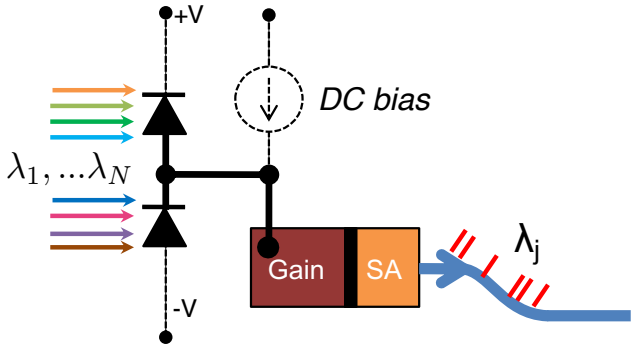


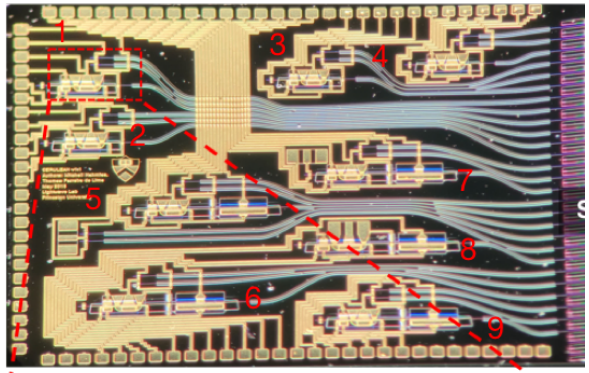
L. Gelens *et al. Phy. Rev. A.* **82** (2010)
Van Vaerenbergh *et al. Opt. Express* **21** (2013)

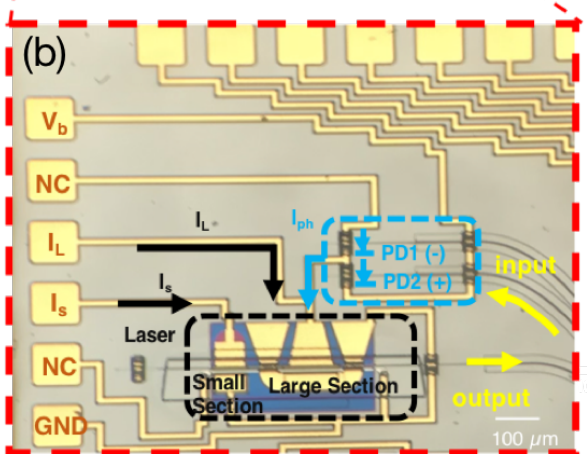
Some of these devices require optical injection, and are therefore not compatible with optical fan-in, an optical matched filter front-end, or WDM interconnects.

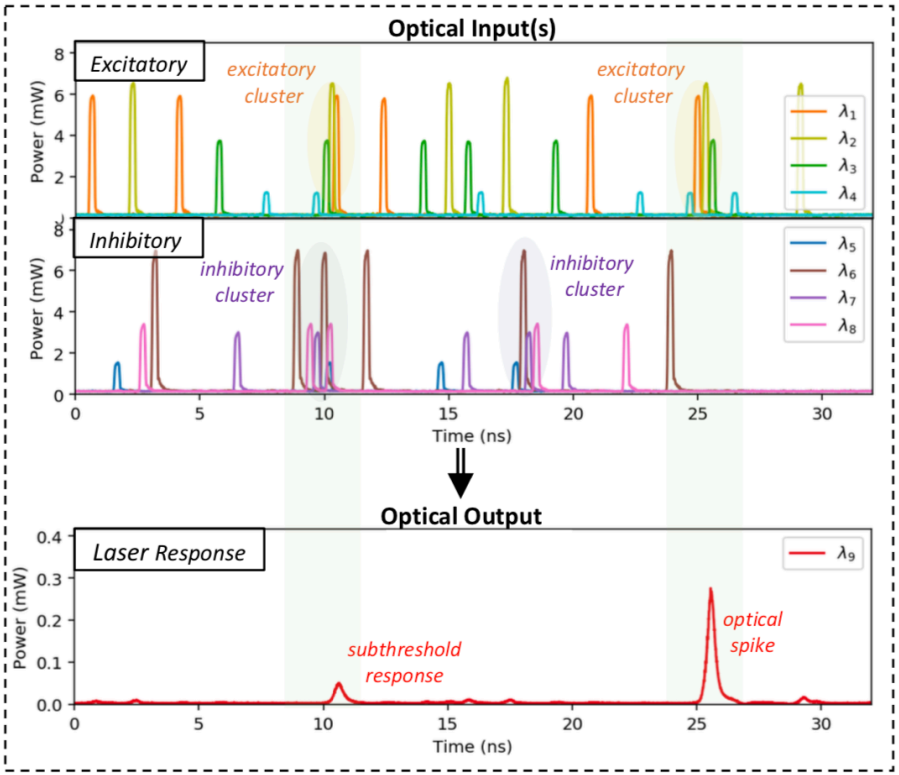
Prucnal, Shastri et al. *Adv. Opt. Photonics* **8** (2016)

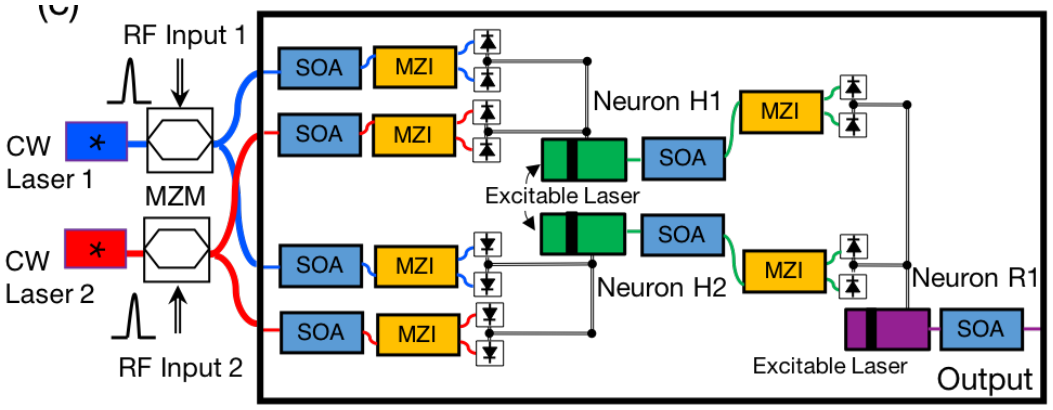
3) Photonic Spiking Neural Networks











Off-chip input signal generation

Spiking Neural Networks on Photonic Chip

Peng, Shastri, Prucnal et al. *IEEE JSTQE* **24** (2018)

PRINCETON UNIVERSITY

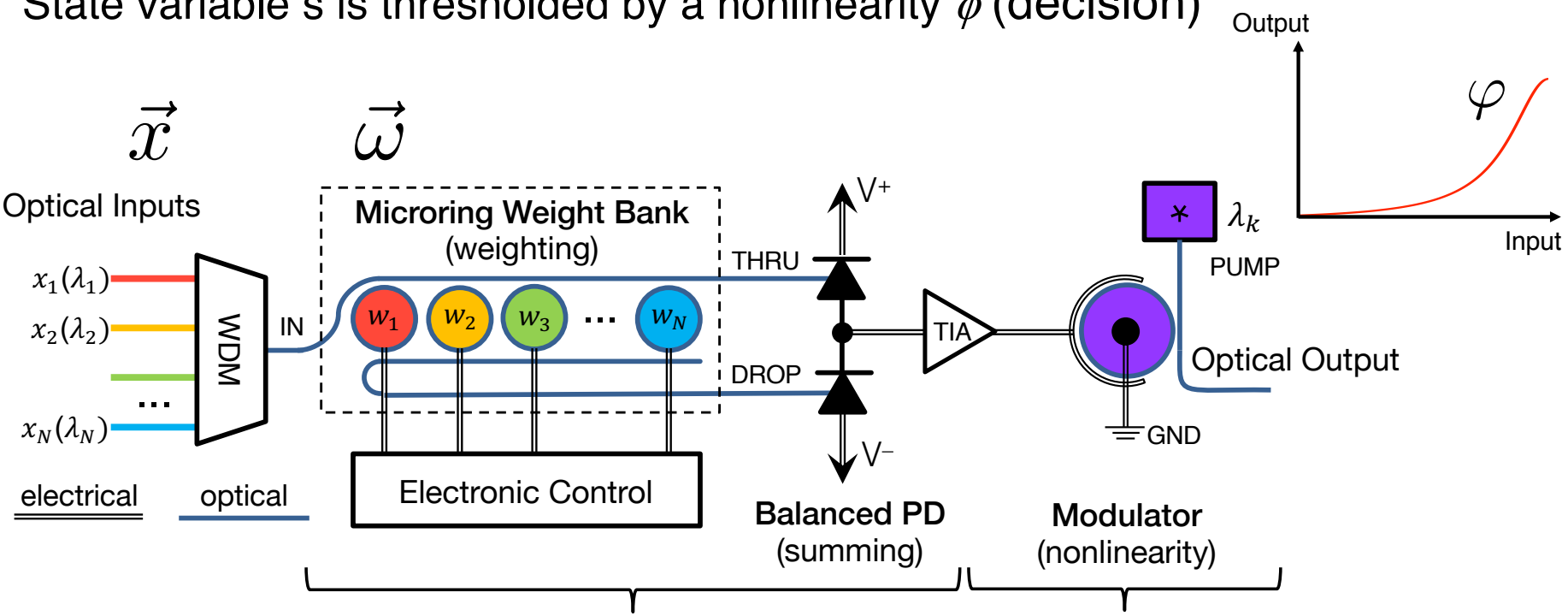
Outline

Queen's UNIVERSITY

- Motivation
  - Artificial intelligence; neural networks
  - Recent work on photonic information processing
- Silicon Photonic Neural Networks
  - Microring weight banks: vector multiplications
  - Microring modulator nonlinearity
- Applications
  - Winner Take All Demonstration
  - Nonlinear Programming
  - Processing GHz RF Signals
- Conclusion

Neuron Model and Photonic Implementation

- **Neuron operation:** 1) receive multiple inputs; 2) weight each by coefficient; 3) sum them; 4) perform a nonlinear process
- 1-3 is a weighted sum or **multiply & accumulate** (MAC)
- State variable s is thresholded by a nonlinearity ϕ (decision)

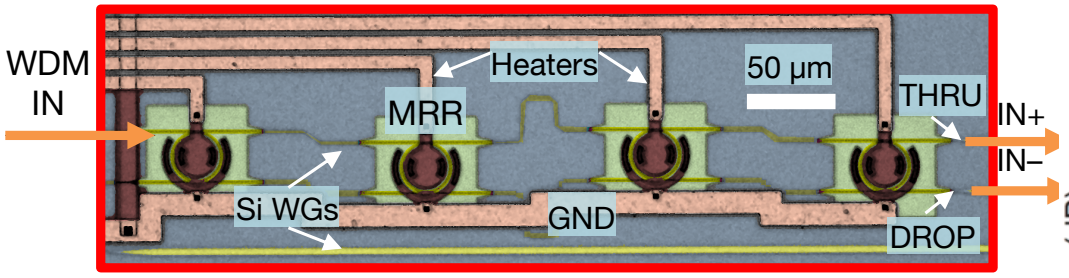


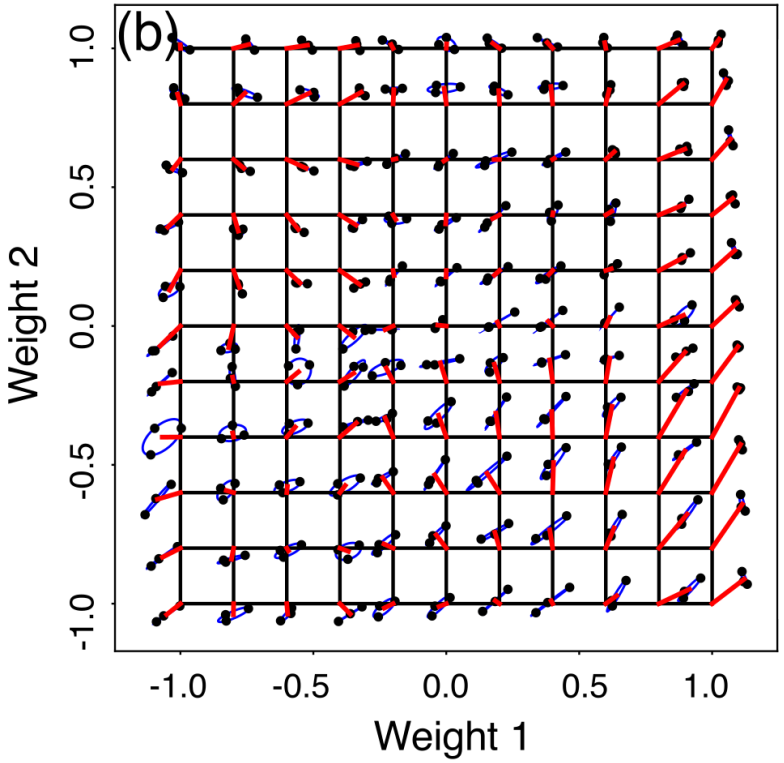
$$s_k(t) = \sum_{j=1}^{N} x_j(t) w_j$$

$$= \vec{x} \cdot \vec{\omega}$$

$$y_k(t) = \varphi[s_k(t)]$$

Multi-Channel Weighting & Control



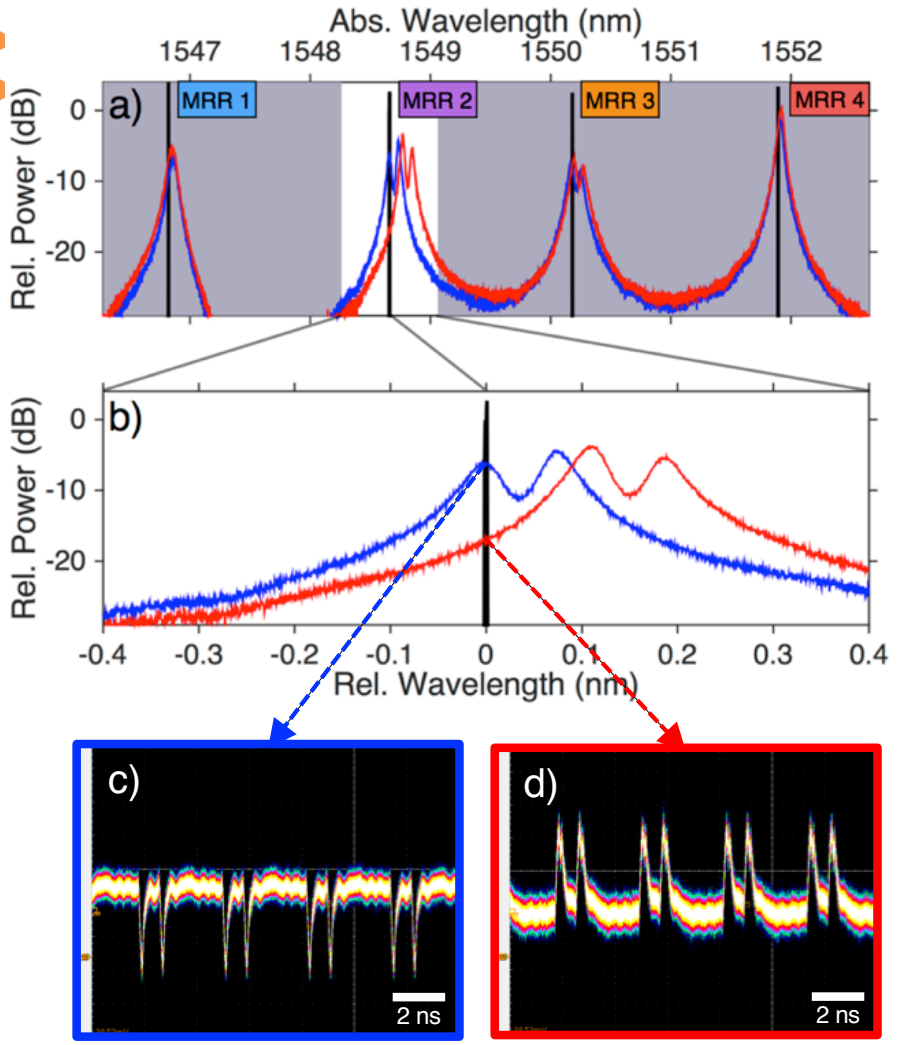


Red = mean error; Blue = std. dev.

Control precision: 7 bits + Sign bit

Tait, Shastri, Prucnal et al. *Opt. Express* **24** (2016)
Ma, Shastri, Prucnal et al. *Opt. Express* **27** (2019)

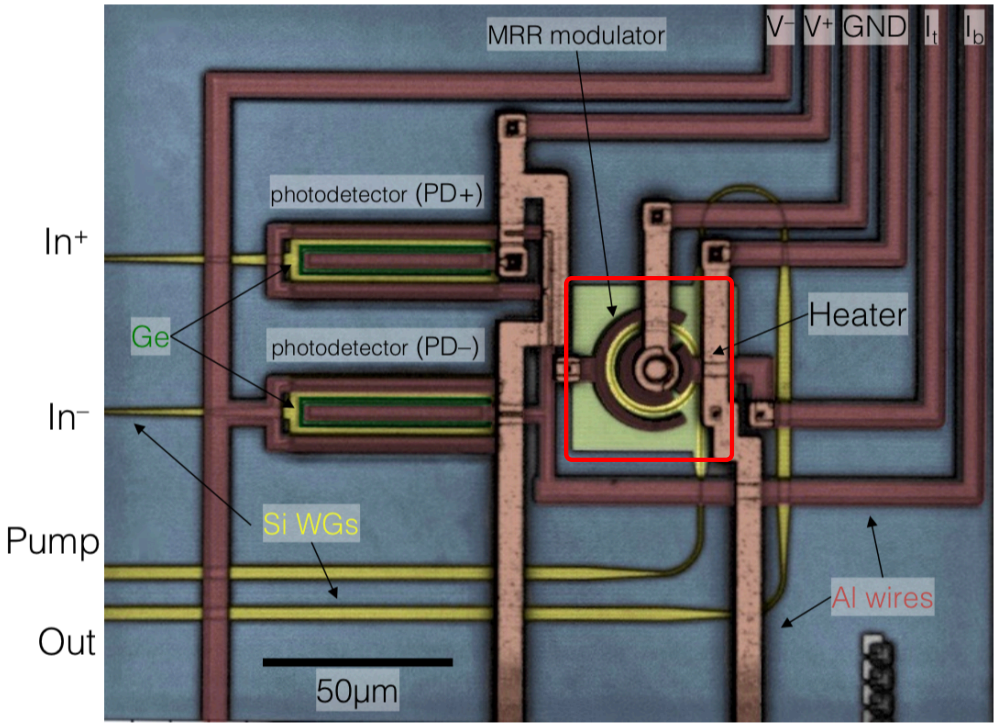
Measured Output of Drop Port

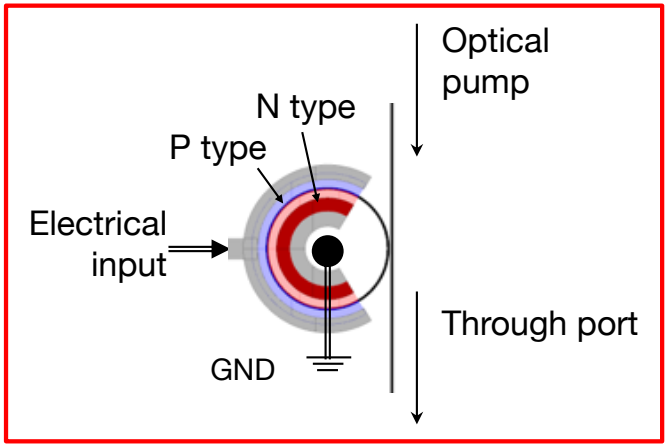


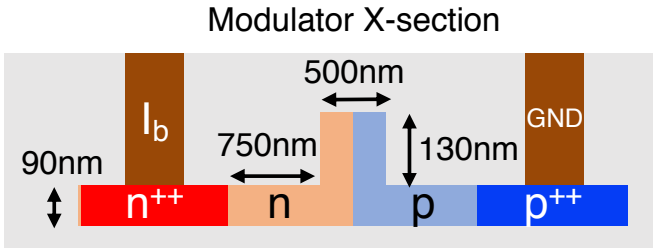
Balanced PD Output

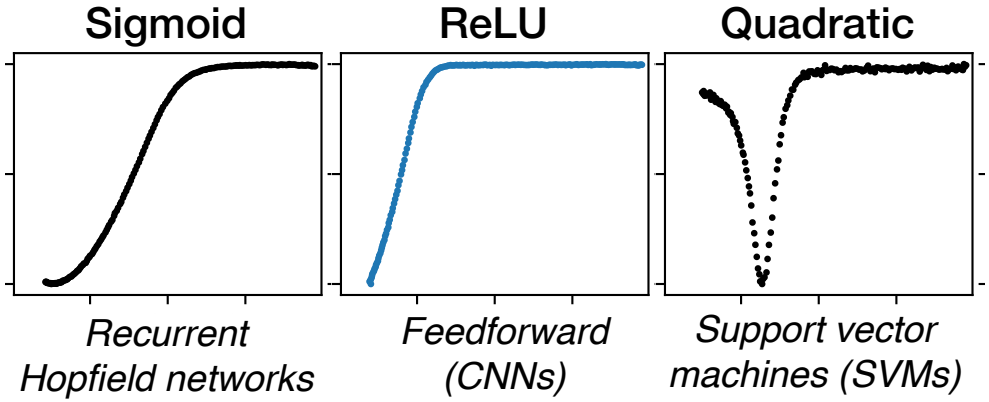
Photogenerated carriers change R; sense R to monitor light in ring.

Silicon Microring Modulator Nonlinearity







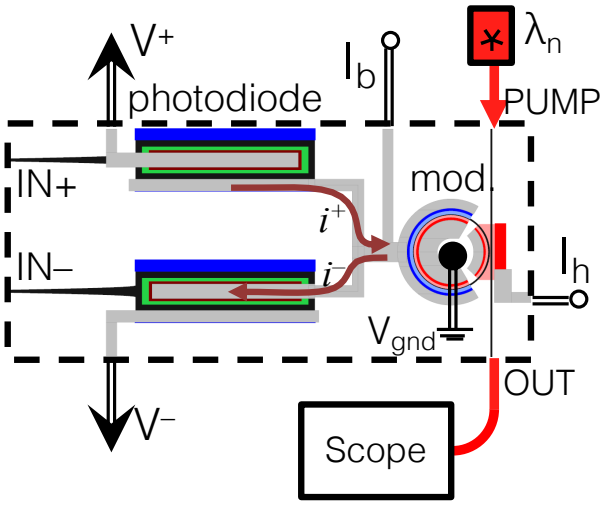


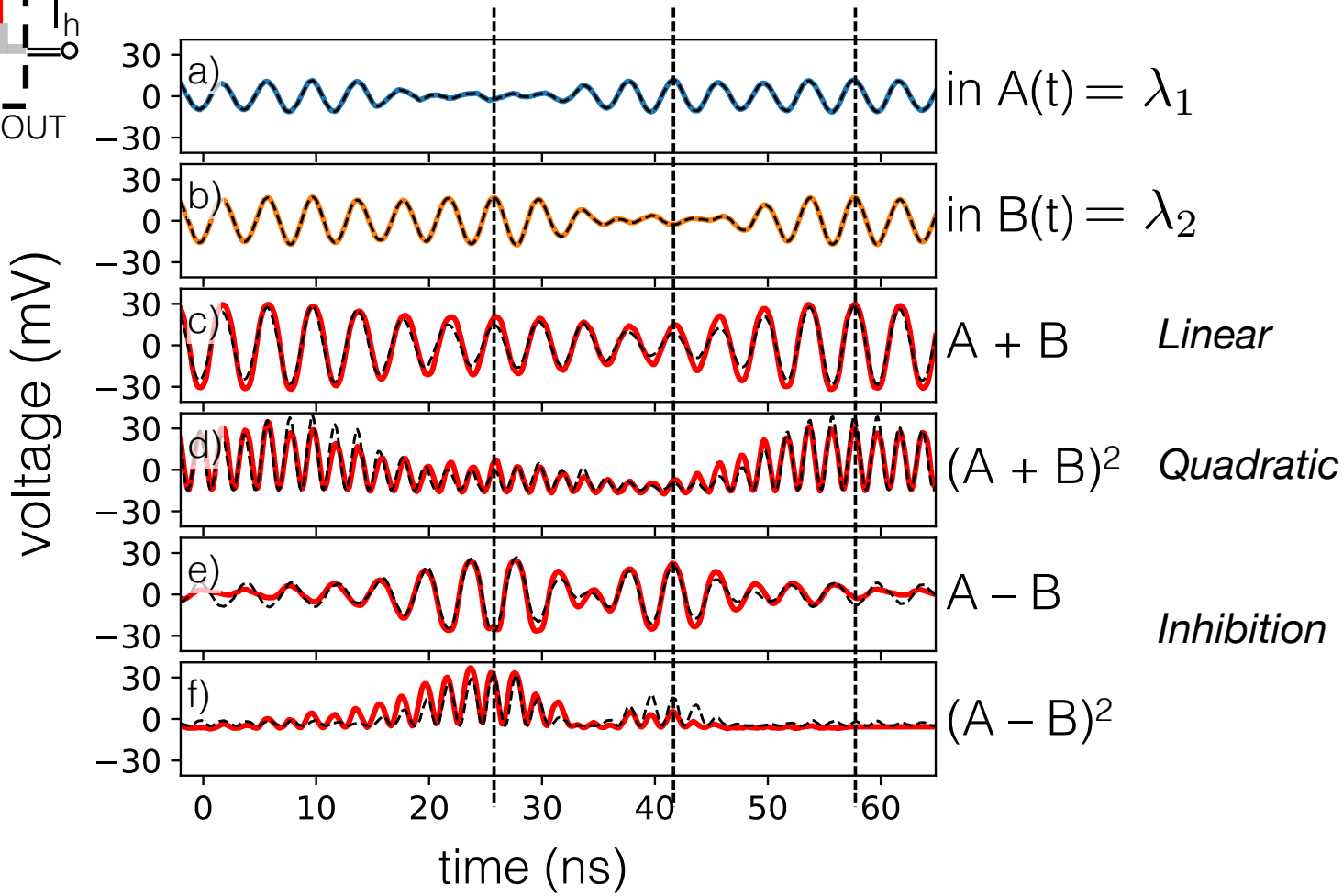
Plasma dispersion effect modulates index.
Free carriers can absorb light, leading to loss.

Bias current shifts the resonance and loss. Allows engineering the activation function

Tait, Shastri, Prucnal et al. *Phys. Rev. Appl.* **11** (2019)

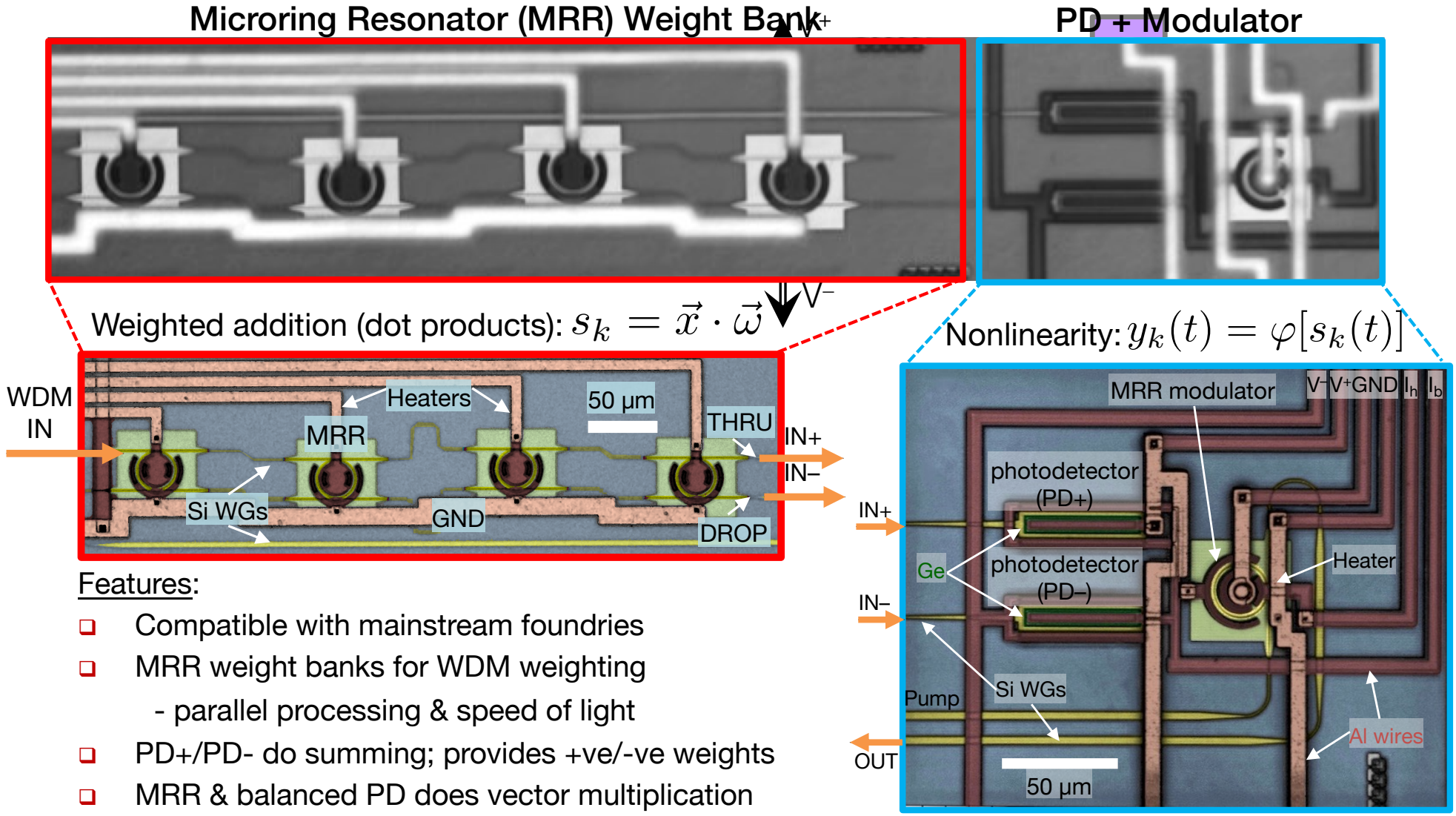
Tuning the Activation Function





Tait, Shastri, Prucnal et al. *Phys. Rev. Appl.* **11** (2019)

Multiwavelength Silicon Photonic Neuron



Features:

- Compatible with mainstream foundries
- MRR weight banks for WDM weighting
  - parallel processing & speed of light
- PD+/PD- do summing; provides +ve/-ve weights
- MRR & balanced PD does vector multiplication
- Modulator for fast electro-optic nonlinearity

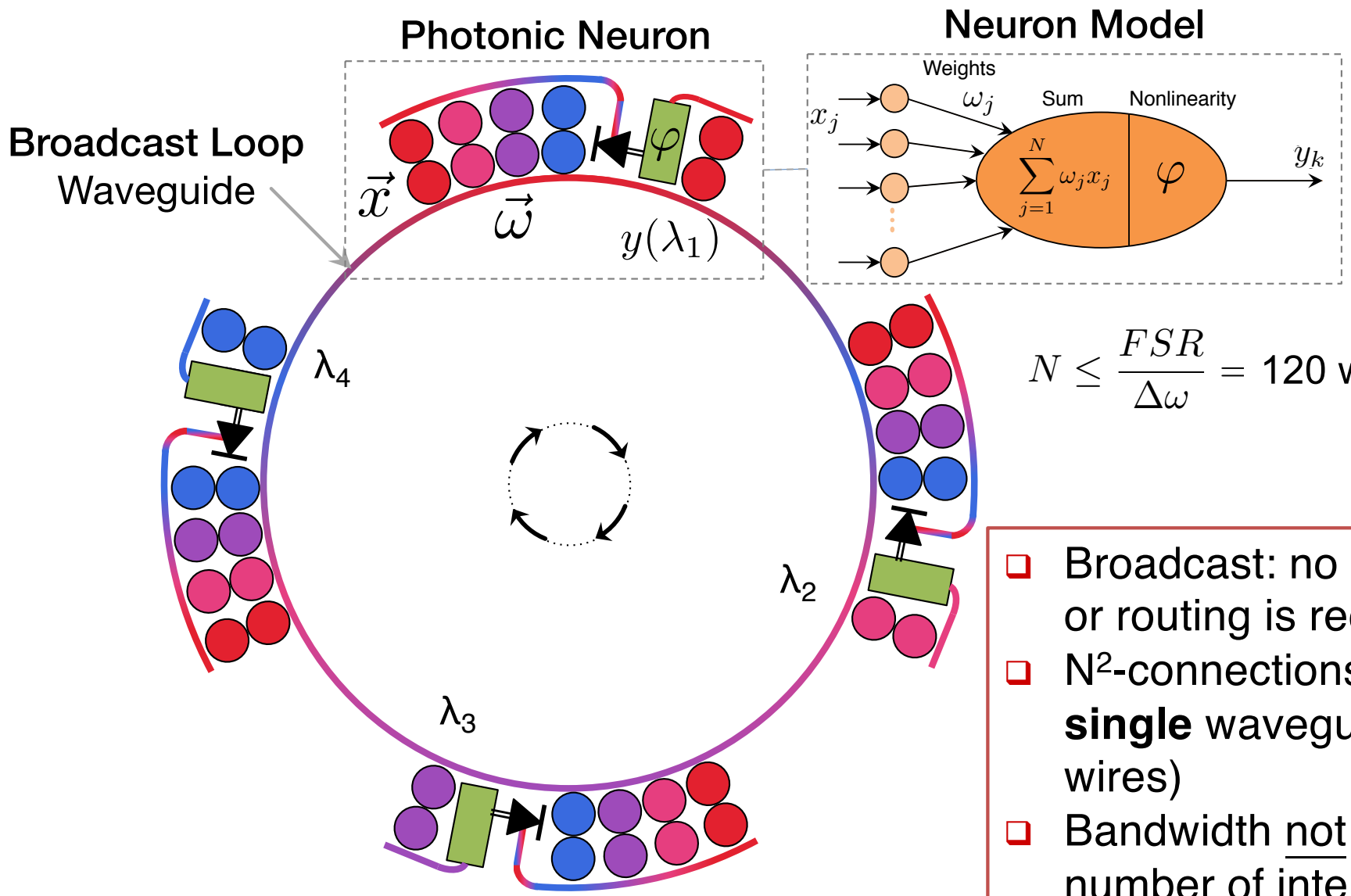
Metrics:

- Energy efficiency (today): 500fJ/MAC
- Efficiency (foreseeable tech.): 1.1 fJ/MAC
- Speed: 10-40 GHz operation

CMC MICROSYSTEMS amf ADVANCED MICRO FOUNDRY PRINCETON UNIVERSITY

Neural Network: Broadcast-and-Weight

Wavelength division multiplexing provides all-to-all interconnects



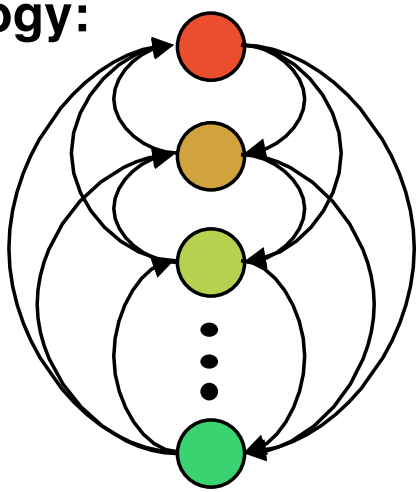
$$N \leq \frac{FSR}{\Delta\omega} = 120 \text{ wavelengths}$$

- Broadcast: no switching or routing is required
- N^2-connections with **single** waveguide (not N wires)
- Bandwidth not limited by number of interconnects (i.e fan-in)

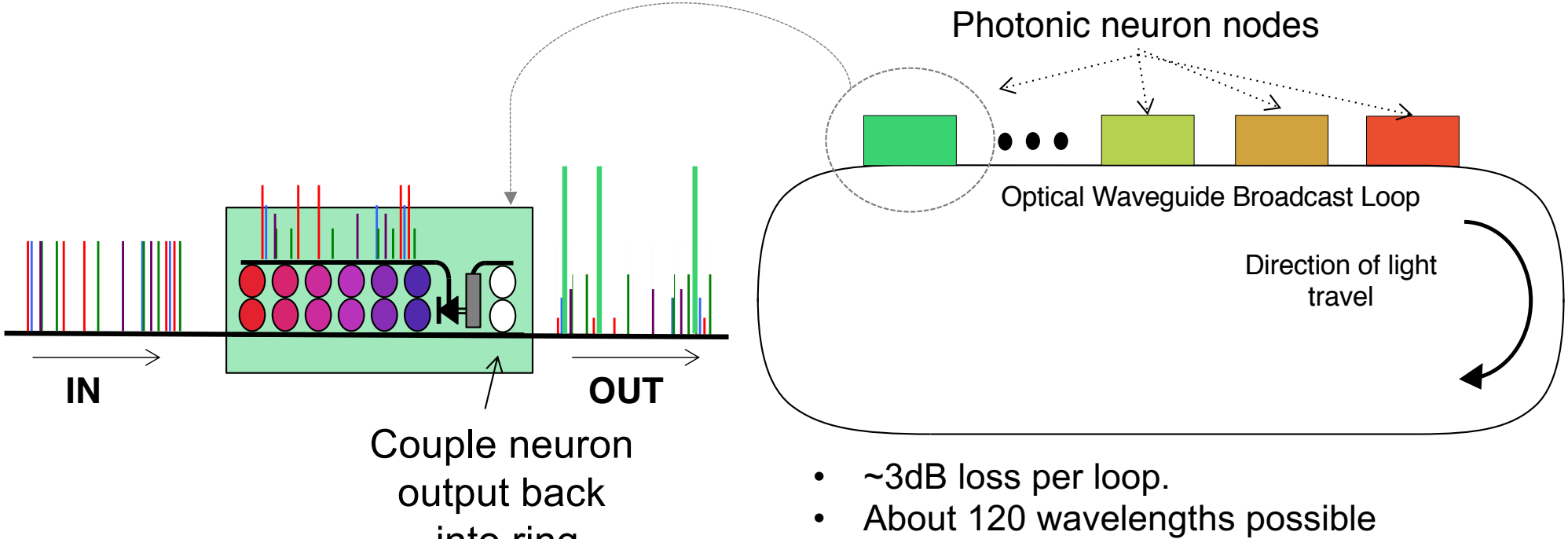
Prucnal and Shastri CRC Press 2017
Tait et al. *J. Lightw. Technol.* **32** (2014)

Recurrent Neural Networks

Logical topology:

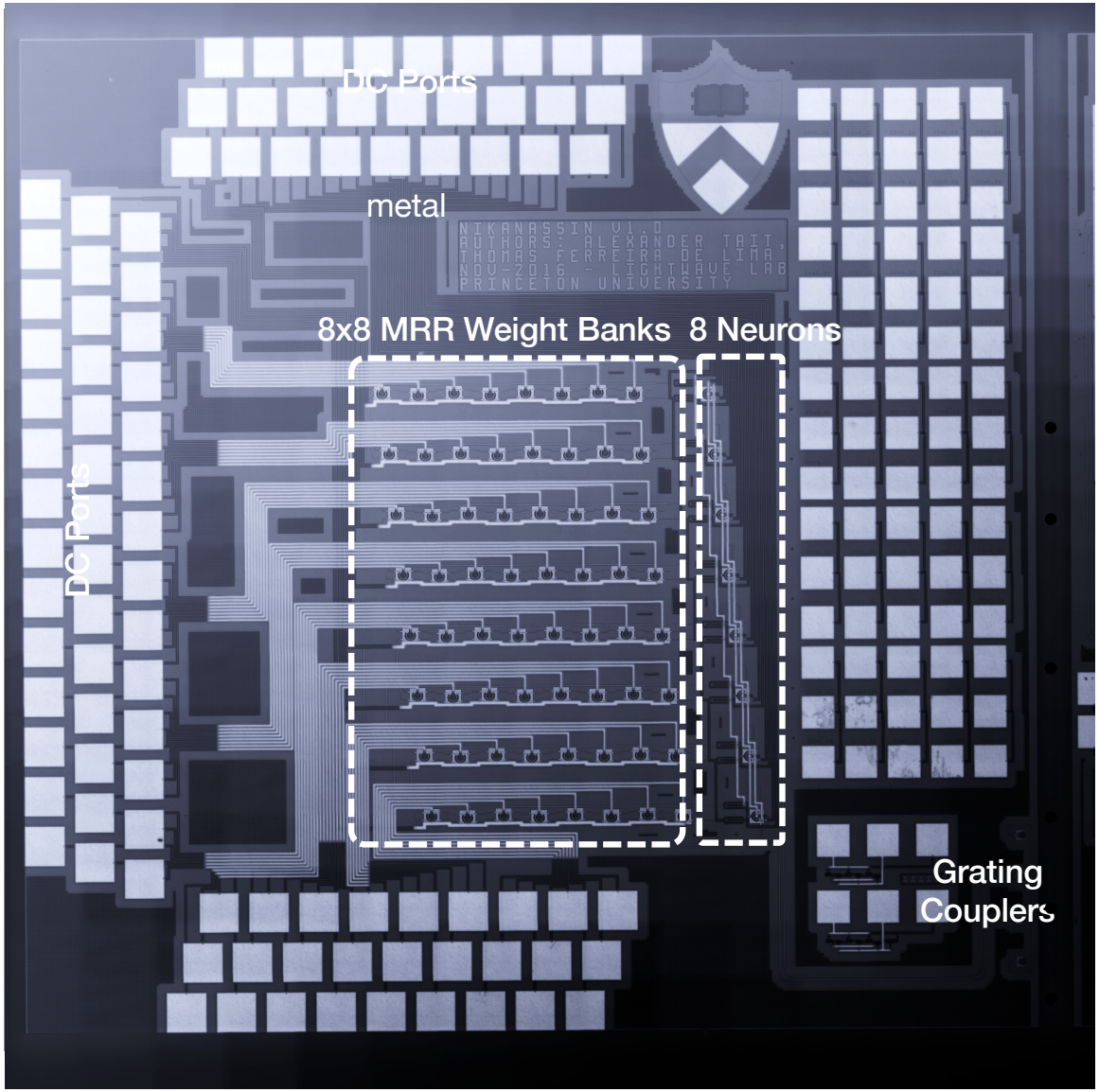


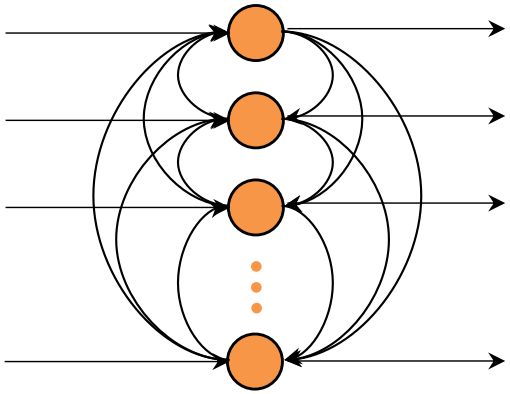
Photonic implementation:



- ~3dB loss per loop.
- About 120 wavelengths possible
- Can re-use wavelengths in other rings.

8×8 Silicon Photonic Recurrent Neural Network



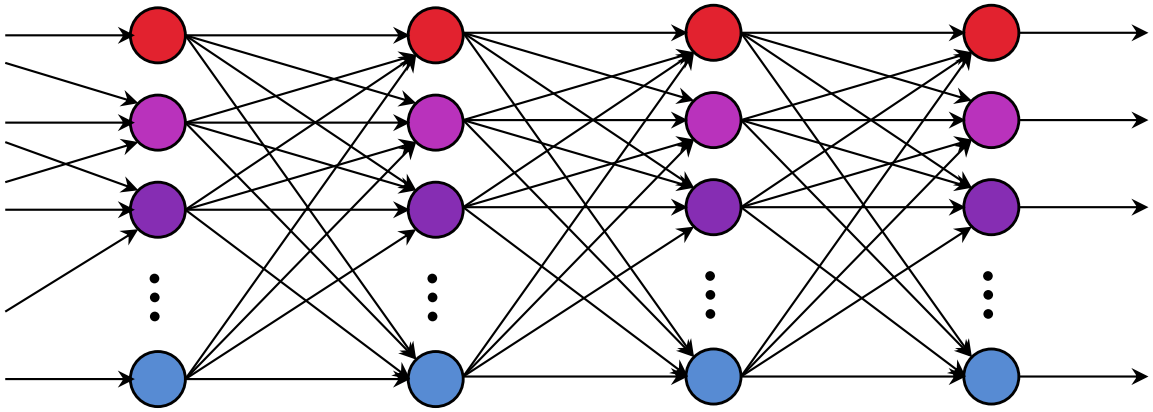


- Memory functionality
- Area: 64 MRRs weights:
  $64 \times 25\mu m \times 25\mu m = 0.04mm^2$
- 8 modulator neurons:
  $8 \times 30\mu m \times 30\mu m = 0.01mm^2$
- Static power: 64 x 5.2mW = 333mW
- Switching efficiency: 500 fJ/MAC
- Program with neural compiler (TensorFlow or Nengo)

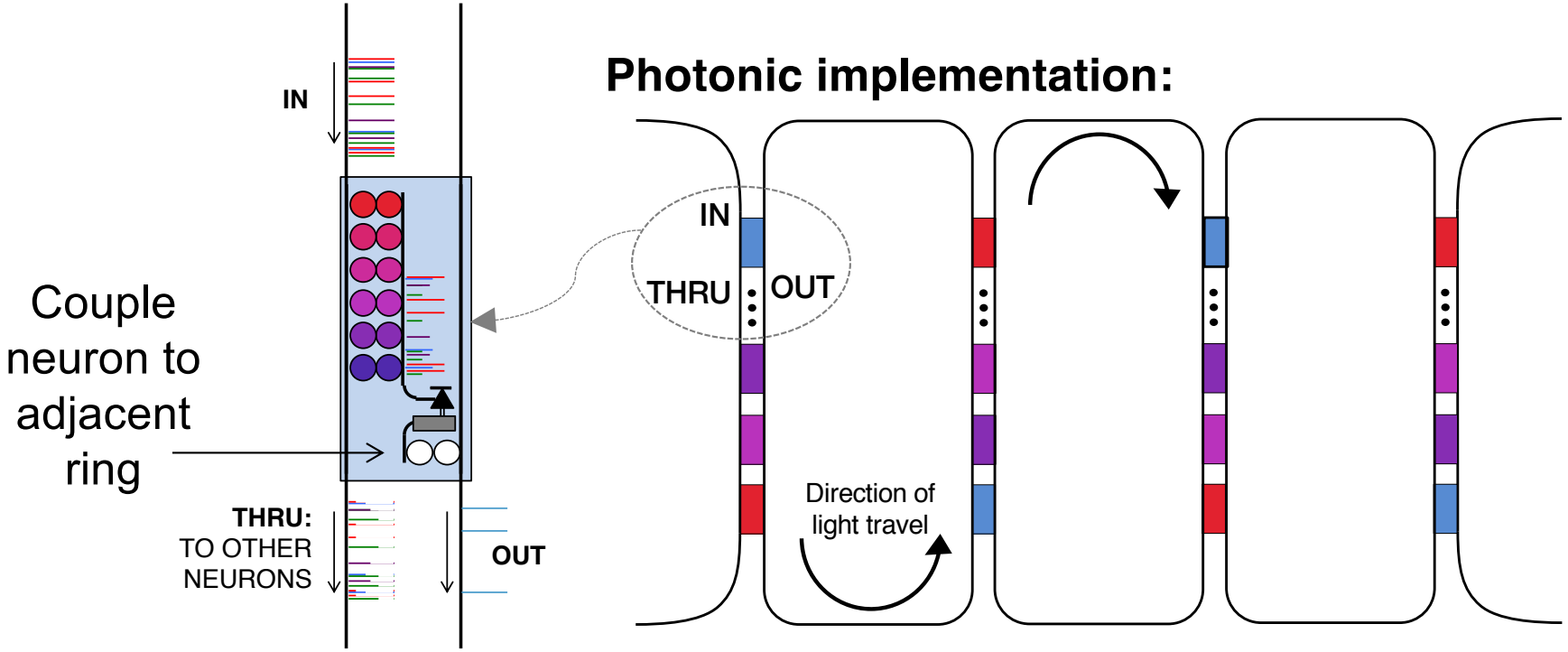
Work in progress

Feed-Forward Networks

Logical topology:

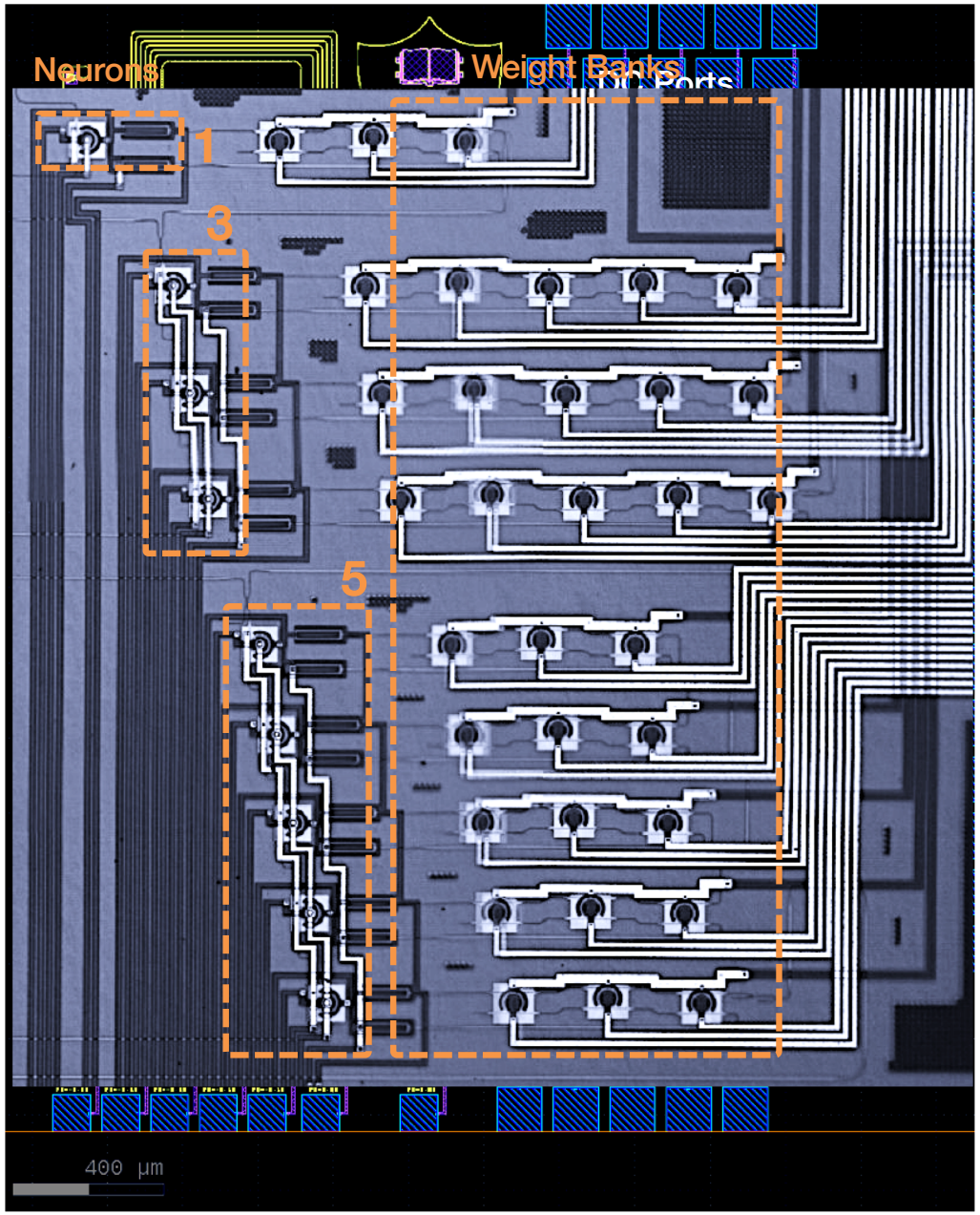


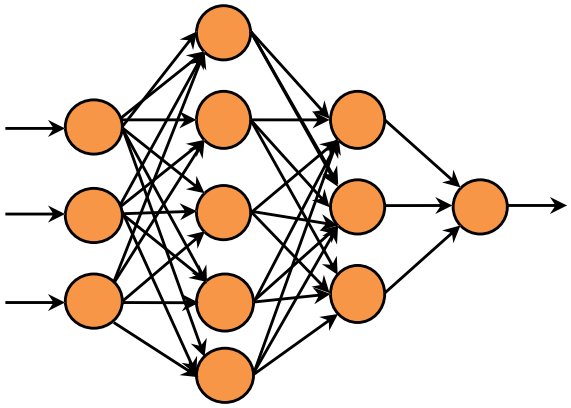
Photonic implementation:



Ferreira de Lima, Shastri, Prucnal et al. *Nanophotonics* **6** (2017)

3×5×3×1 Silicon Photonic Feedforward Networks





- Low-latency processing
- Spectral reuse between layers
- 3-layer network; 9 neurons and 33 weights

Work in progress

PRINCETON UNIVERSITY

Outline

Queen's UNIVERSITY

- Motivation
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  - Microring modulator nonlinearity
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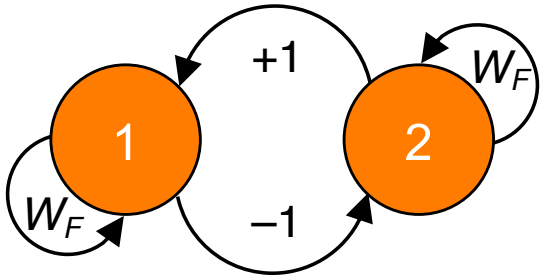
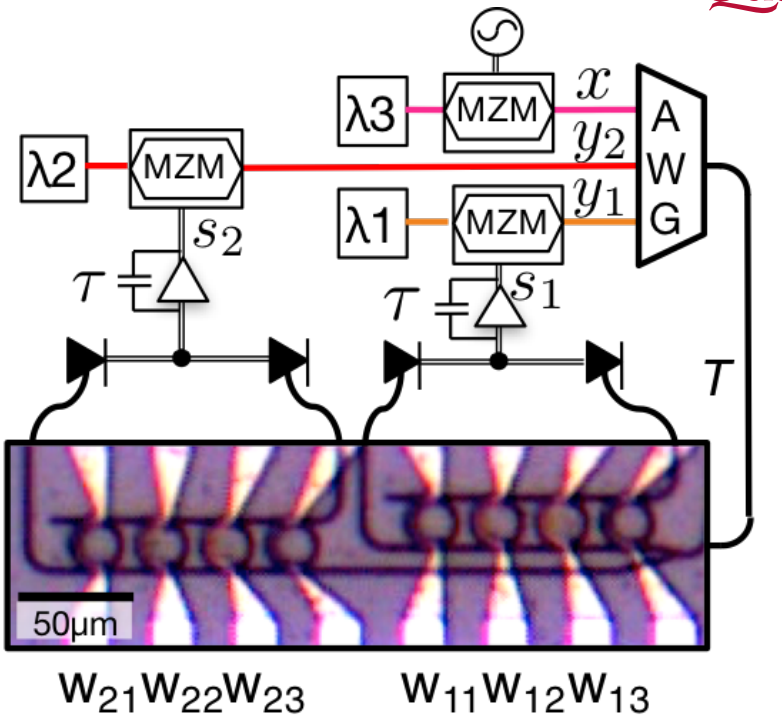
2x2 Photonic Winner-Takes-All Demonstration

Self-feedback and inhibition



$$[\mathbf{W} \mid w_{in}] = \left[\begin{array}{cc|c} W_F & -1 & 0 \\ 1 & W_F & 0 \end{array}\right]$$



Continuous-Time Recurrent Network Model

Weight matrix · State vector · Weighted input

$$\frac{d\vec{s}(t)}{dt} = \mathbf{W}\vec{y}(t) - \frac{\vec{s}(t)}{\tau} + \vec{w}_{in}x(t)$$

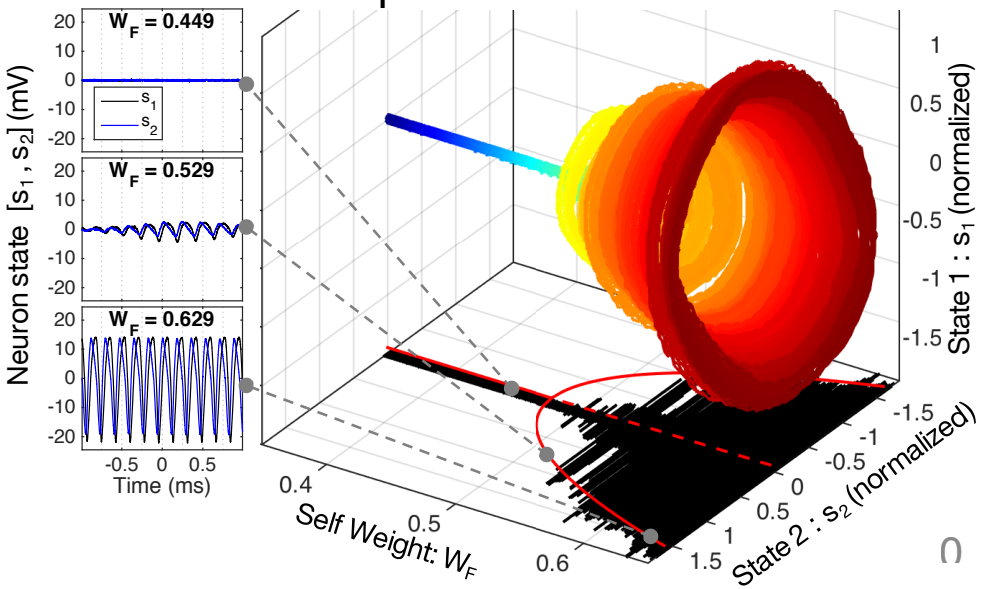
$$\vec{y}(t) = \sigma\left[\vec{s}(t)\right]$$

Time-constant

output · Nonlinear function

- Neurons compete for activation
- Strong self-feedback transitions from stable to oscillating (complex eignenvalues)

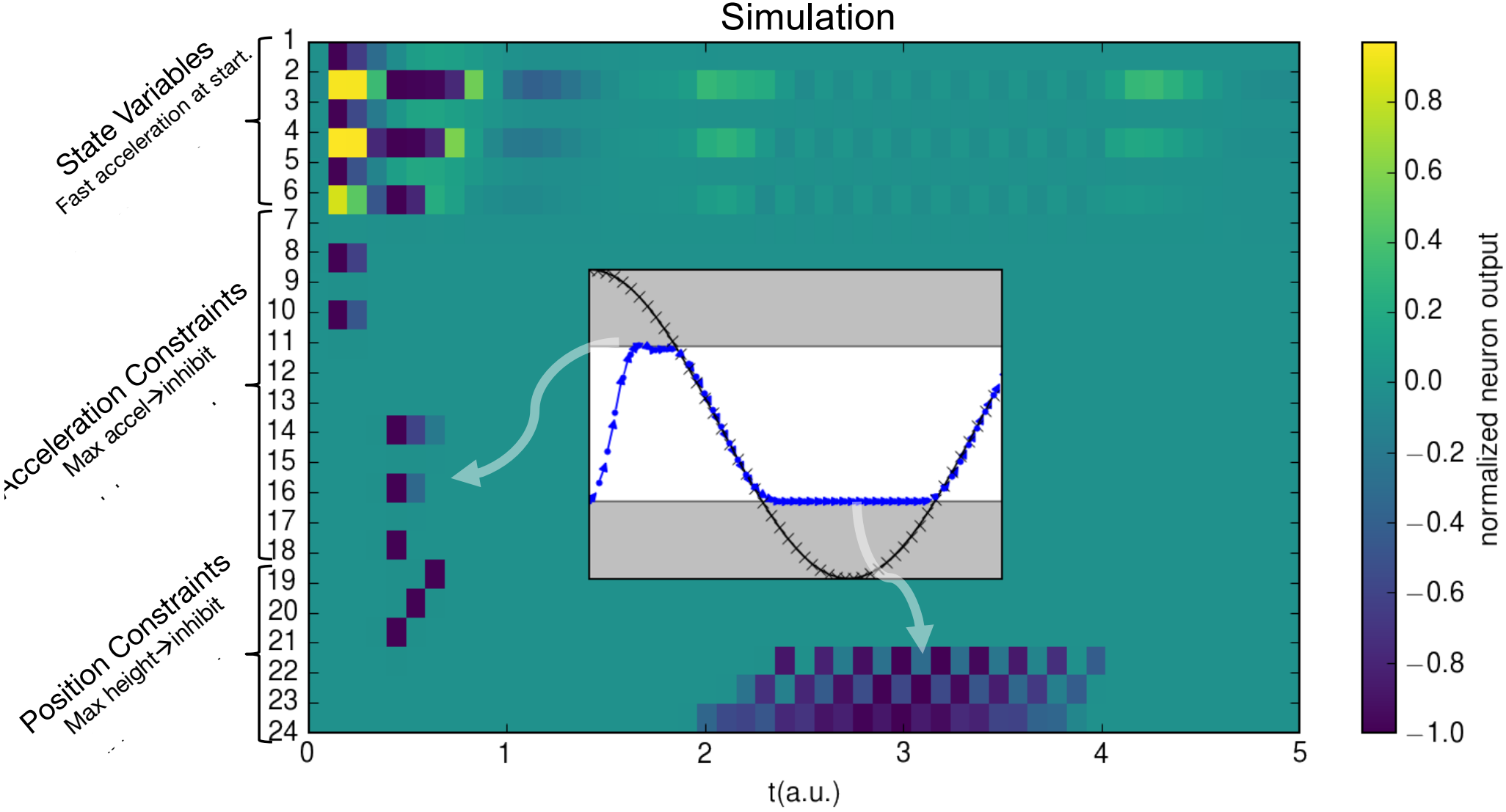
Experimental Data



Tait et al. *Scientific Reports* (2017)

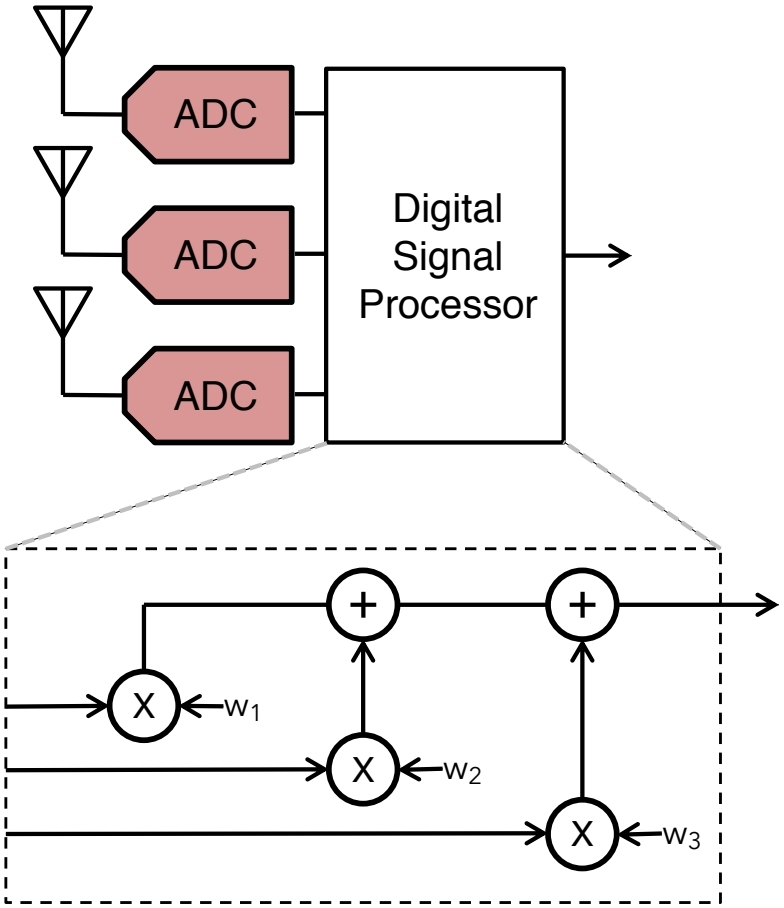
Photonic NN for Nonlinear Programming

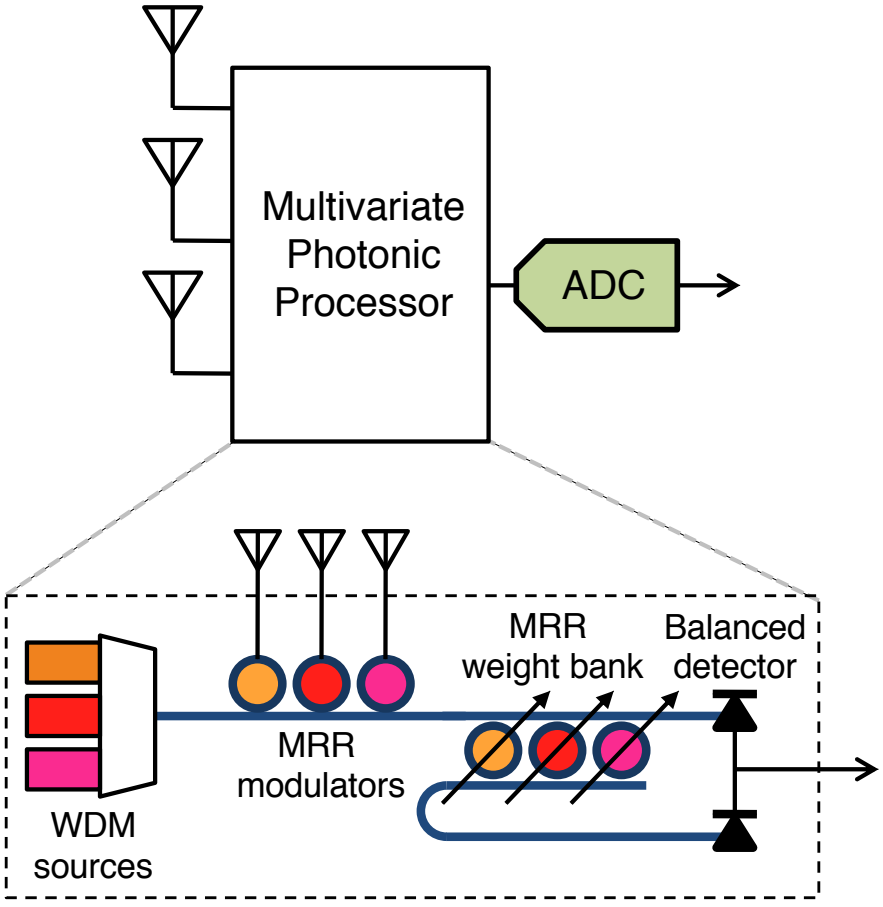
Constrained model predictive control problem: Intercept a moving target with matching speed while respecting constraints on acceleration and position.



Ferreira de Lima, Shastri, Prucnal et al. *J. Lightwav. Technol.* ***37*** (2019)

Principal Component Analysis of GHz RF Signals





- ADC bottleneck
- Weighted addition (MAC) in DSP
- Processing (dimension reduction) after DSP

- Analog wideband weighted
- Enables dimensionality reduction in wideband analog systems *before* digitizing
- No MACs, no DSP, only one ADC

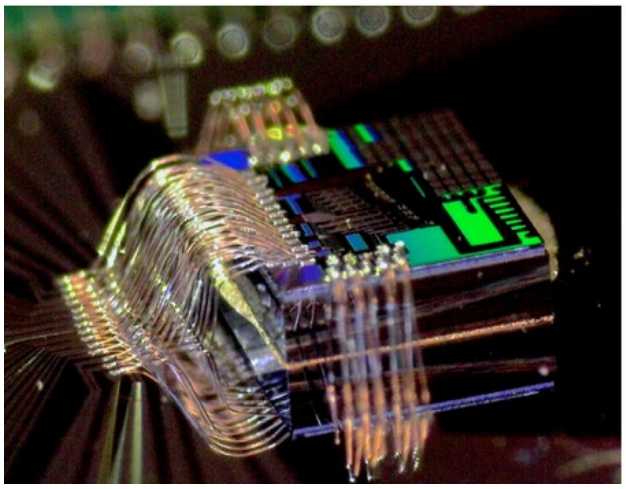
Tait, Shastri, Prucnal et al. arXiv:1903.03474 (2019)

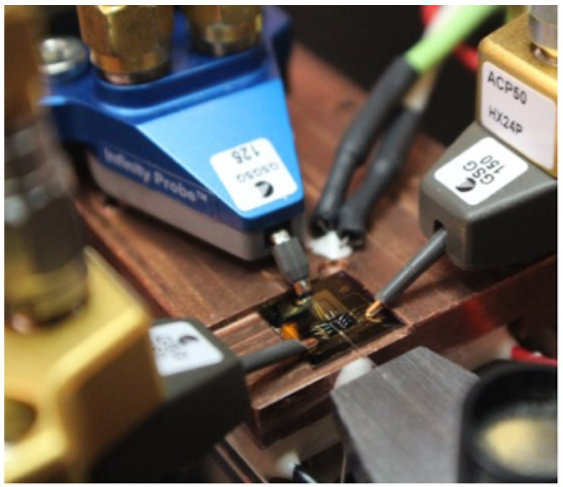
PRINCETON UNIVERSITY

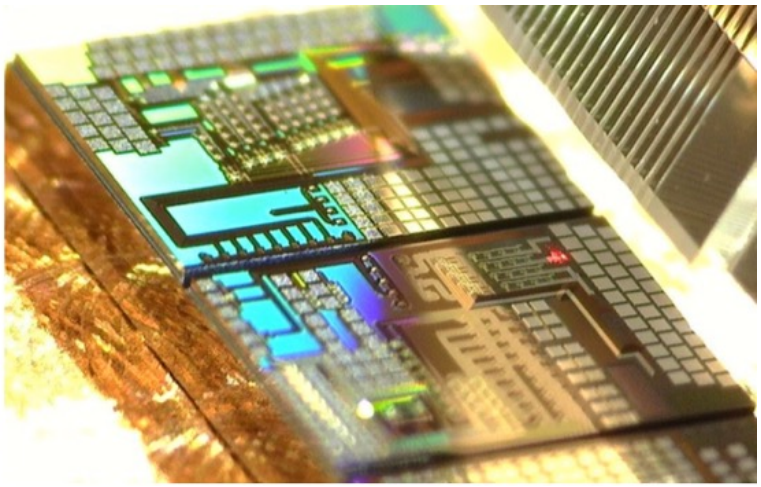
Conclusion

Queen's UNIVERSITY

- Neuromorphic photonics enabled by the maturing of three fields
  - Silicon photonics, RF analog photonics and scalable computing
  - It is compatible with commercial integration technology
- Wavelength-based networking provides massive interconnection
  - Overcomes the bandwidth limits of electronic fan-in & interconnection
- Carrier & photon dynamics allow very fast processing (ps v. ms)
- Applications include:
  - Winner takes all networks, nonlinear programming, analog processing of RF signals







Challenges in Making This a Reality

- Co-integration with CMOS
- Integration of laser sources
- Advances in packaging solutions
- New materials (memory) and device integration
- Development of a neural compiler and programming platform to interface the photonic hardware with applications.
- Target the right application: when does it make sense to use photonics over electronics?

Acknowledgements

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Zhimu Guo
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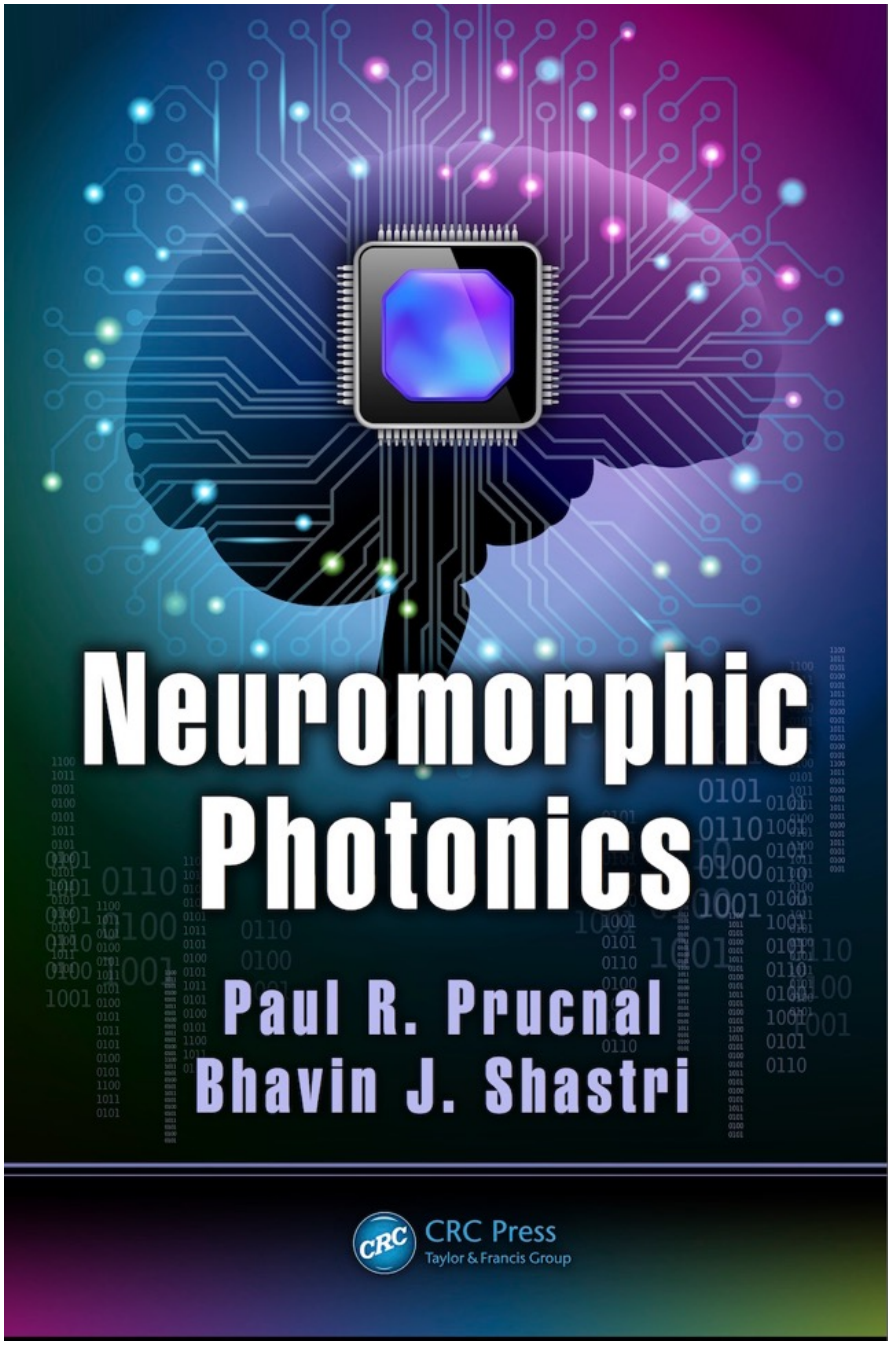
NSERC-CREATE Si-EPIC
Applied Nanotools (ANT), Canada

Book



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- Contributions:

  Tait, Ferreira de Lima, Nahmias

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