An integrated photonic neuromorphic interface for dimensionality expansion of optical signals

Alessio Lugnan, Alessandro Foradori, Stefano Biasi, Peter Bienstman and Lorenzo Pavesi.

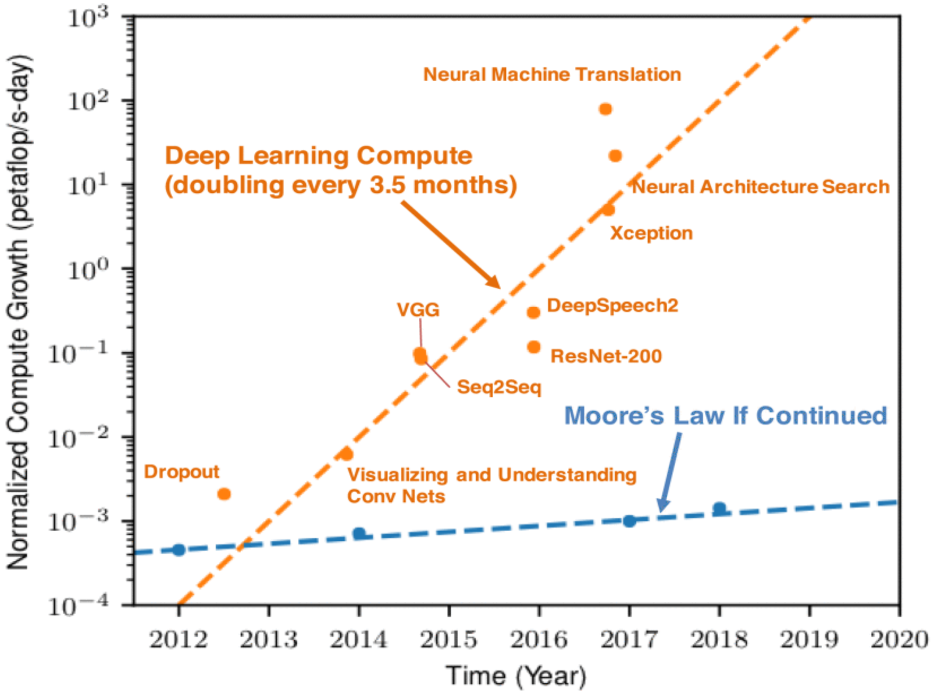
19 April 2024

Outline

- **Why** neuromorphic hardware/photonics?
- **Scalability** of training hardware ANNs
- **We propose** a A ‘plug & play’ neuromorphic interface
- **Why** silicon microring resonators (MRRs) as a building block?
- **Experimental results**: machine learning with photonic neural networks
- Conclusions

Why neuromorphic hardware?

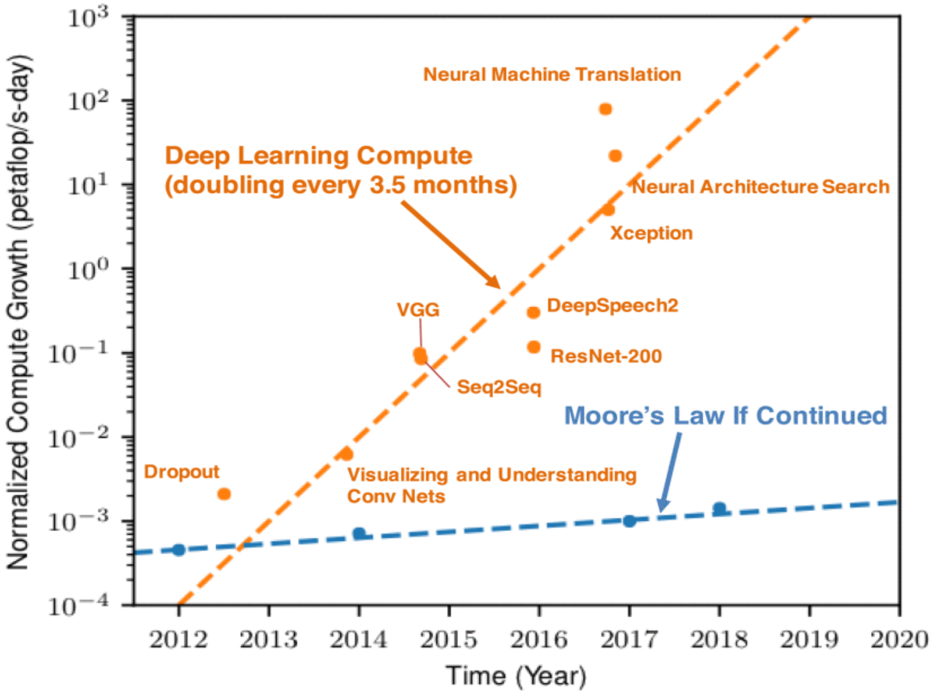
Deep learning is quickly saturating available computing growth



De Lima, Thomas Ferreira, et al. "Machine learning with neuromorphic photonics." Journal of Lightwave Technology 37.5 (2019)

Why neuromorphic hardware?

Deep learning is quickly saturating available computing growth



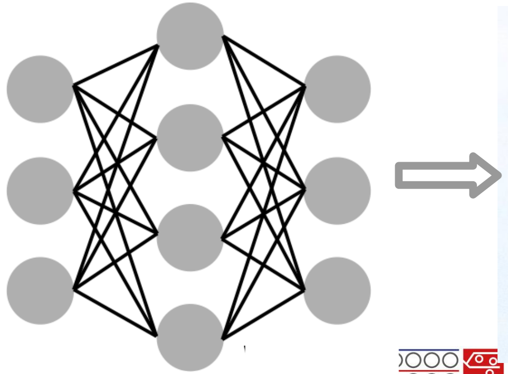
De Lima, Thomas Ferreira, et al. "Machine learning with neuromorphic photonics." Journal of Lightwave Technology 37.5 (2019)

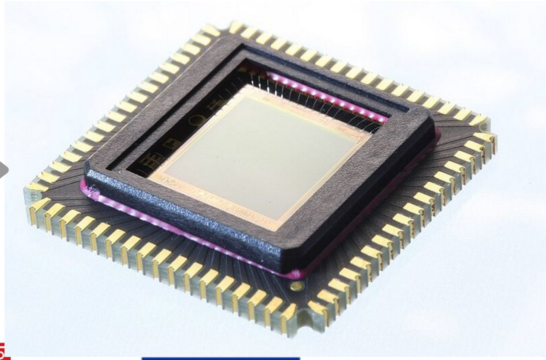
Projected contribution to global economy by 2030 from AI: **$15.7tr** (www.pwc.com)

Nowadays: AI is in data centres (cloud computing)

Current growth is far from sustainable

Solution: ~~Von Neuman architecture~~ → neuromorphic
- machine learning accelerators
- neuromorphic processors for edge computing





https://commons.wikimedia.org/wiki/File:PMD_Imager.jpg

UNIVERSITÀ DI TRENTO
NanoLab Department of Physics
Alessio Lugnan
19/04/2024, ECT* Workshop
ARIADNE
Funded by the European Union

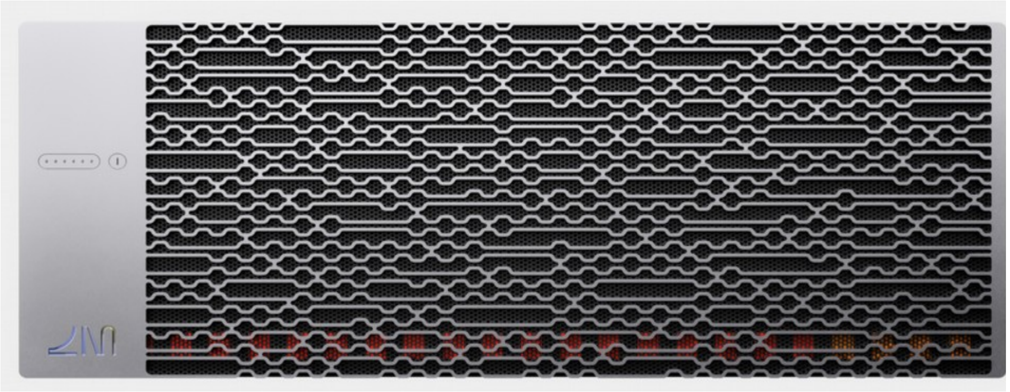
Why neuromorphic photonics?

Wavelength division multiplexing, low power dissipation,
no parasitic capacitance, ...
→ parallel, energy efficient, low-latency **linear operations**

High-tech industry is now interested in photonics

AI accelerators: perform general matrix multiplications

Sartup Lightmatter (>100M funding to accelerate ANNs)



Funded by the European Union

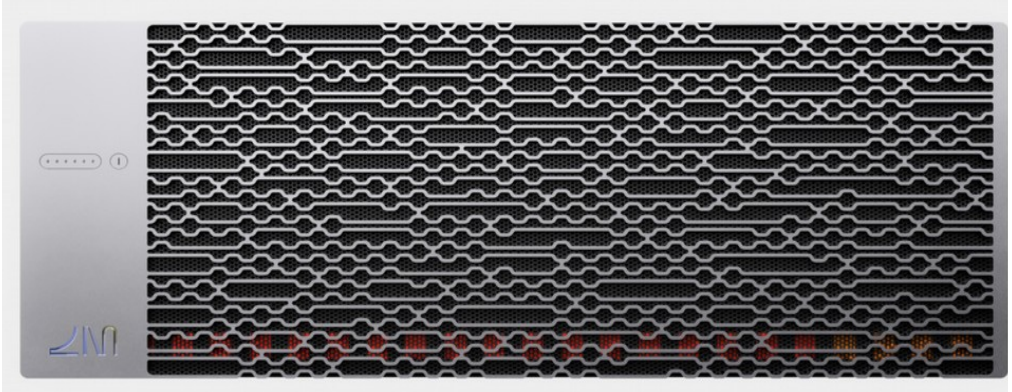
Why neuromorphic photonics?

Wavelength division multiplexing, low power dissipation, no parasitic capacitance, ...
→ parallel, energy efficient, low-latency **linear operations**

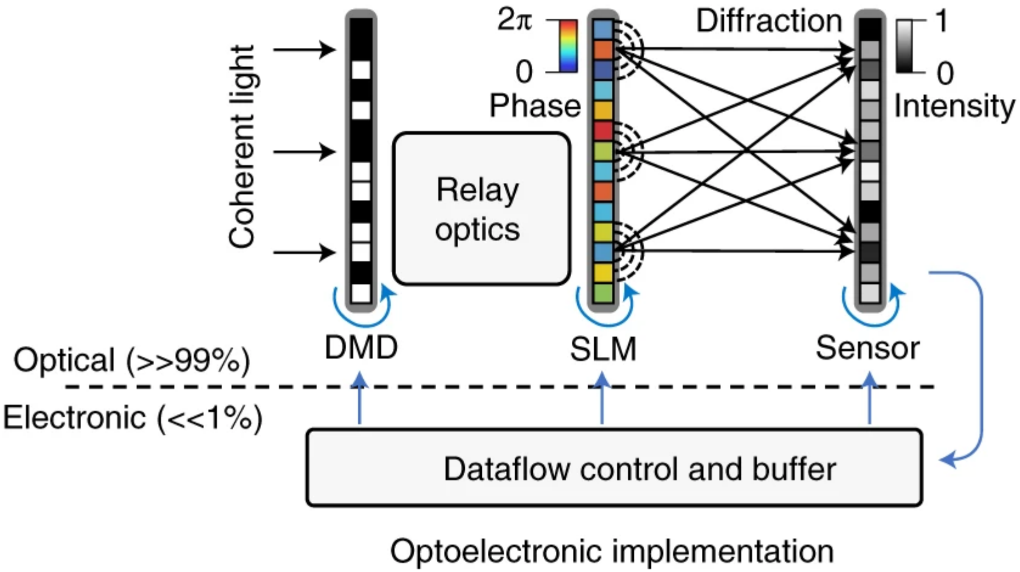
High-tech industry is now interested in photonics

AI accelerators: perform general matrix multiplications

Sartup Lightmatter (>100M funding to accelerate ANNs)



Photonics-based ANN outperforms cutting-edge electronics in energy efficiency and speed

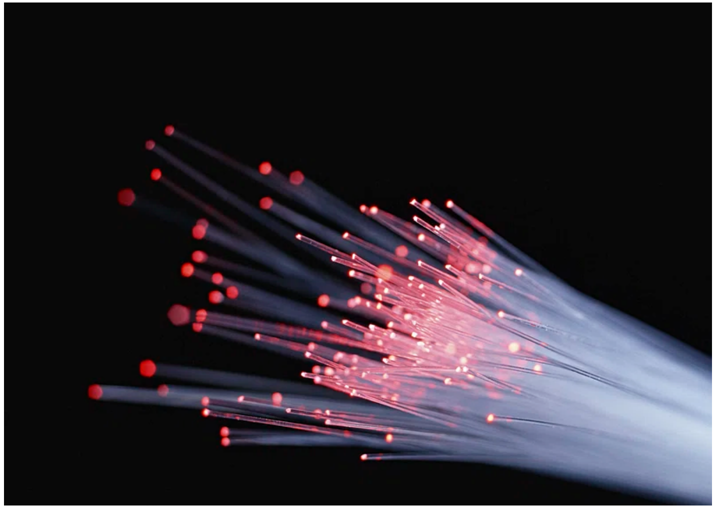


Zhou, Tiankuang, et al. "Large-scale neuromorphic optoelectronic computing with a reconfigurable diffractive processing unit." Nature Photonics 15.5 (2021)

Why neuromorphic photonics?

Advantage in processing **signals originally in the optical domain** → no Optical-Electrical conversion:

- internet data through optical fiber
- fiber sensing applications
- optics-based biomedical sensing
- ...



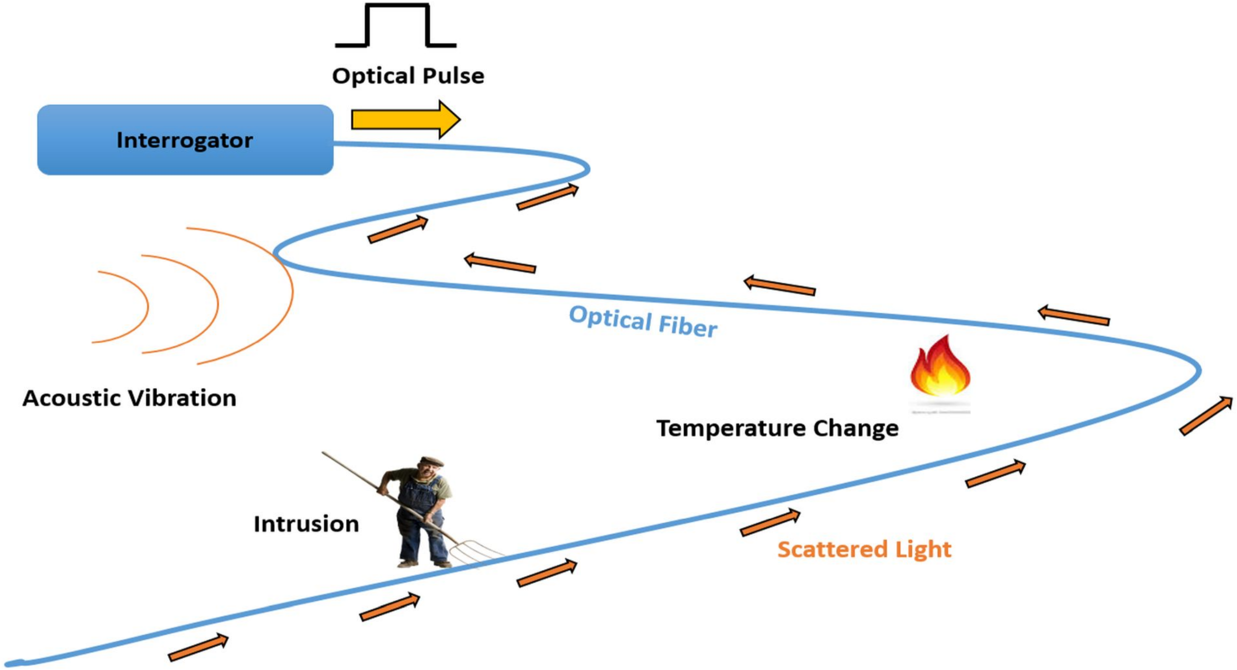


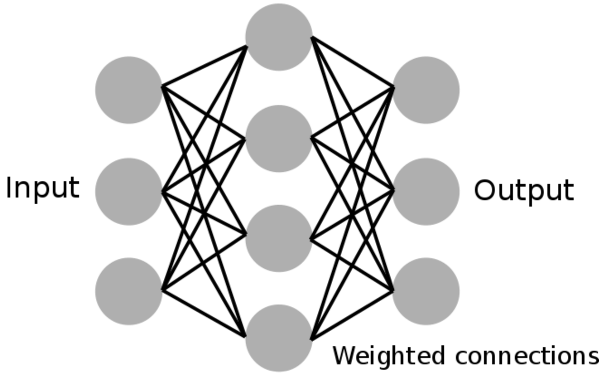
Image from website of Polytechnique Fédérale de Lausanne (EPFL, Switzerland)
https://www.epfl.ch/

Scalability of training hardware ANNs

Nowadays, neuromorphic computing systems are mainly **trained externally**, running **backpropagation** and **gradient descent** on a computer, requiring:

- control of parameters (weights)
- neuron states observability

↳ Not biologically plausible and **not scalable**!

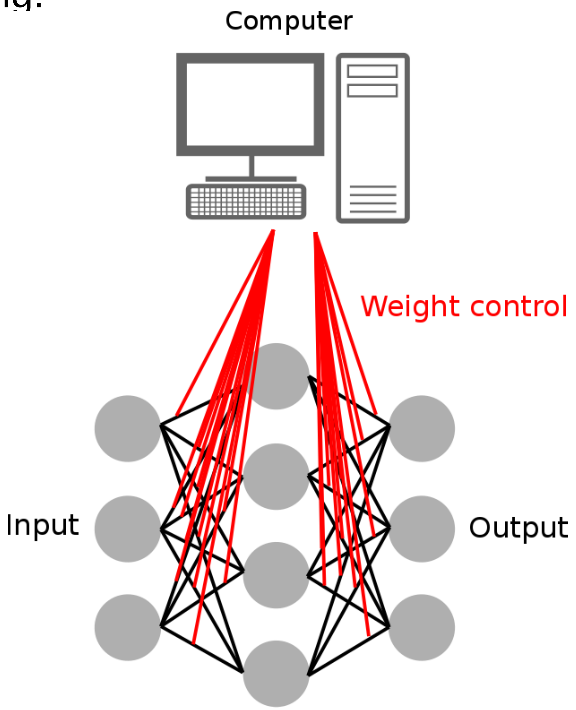


Scalability of training hardware ANNs

Nowadays, neuromorphic computing systems are mainly **trained externally**, running **backpropagation** and **gradient descent** on a computer, requiring:

- control of parameters (weights)
- neuron states observability

↳ Not biologically plausible and **not scalable**!

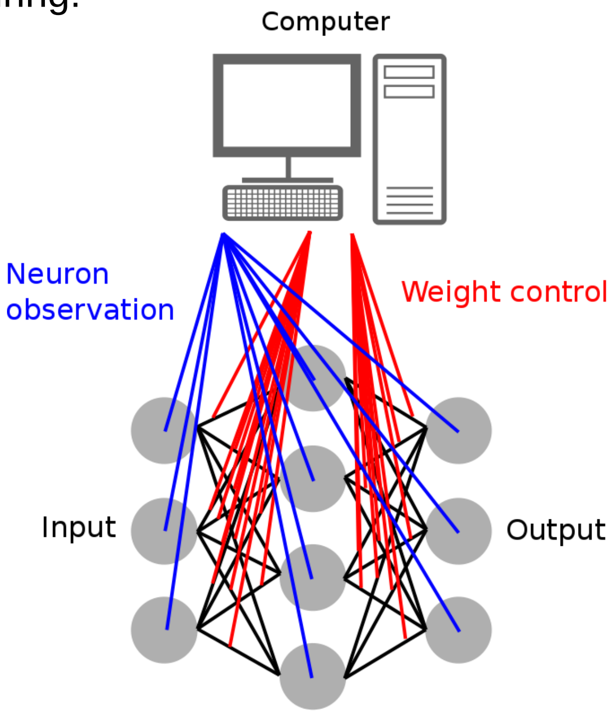


Scalability of training hardware ANNs

Nowadays, neuromorphic computing systems are mainly **trained externally**, running **backpropagation** and **gradient descent** on a computer, requiring:

- control of parameters (weights)
- neuron states observability

↳ Not biologically plausible and **not scalable**!

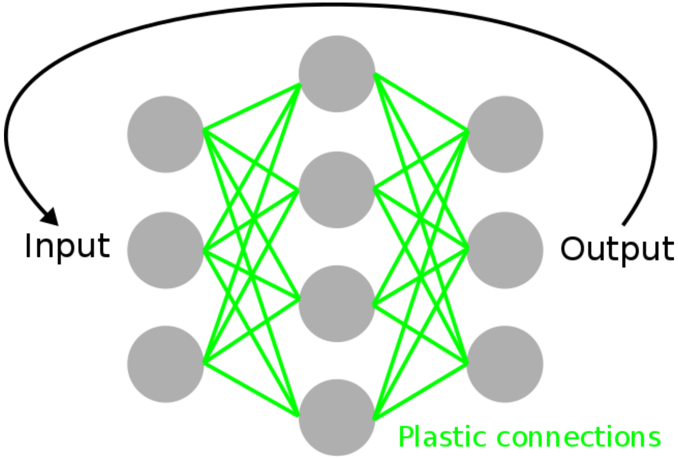


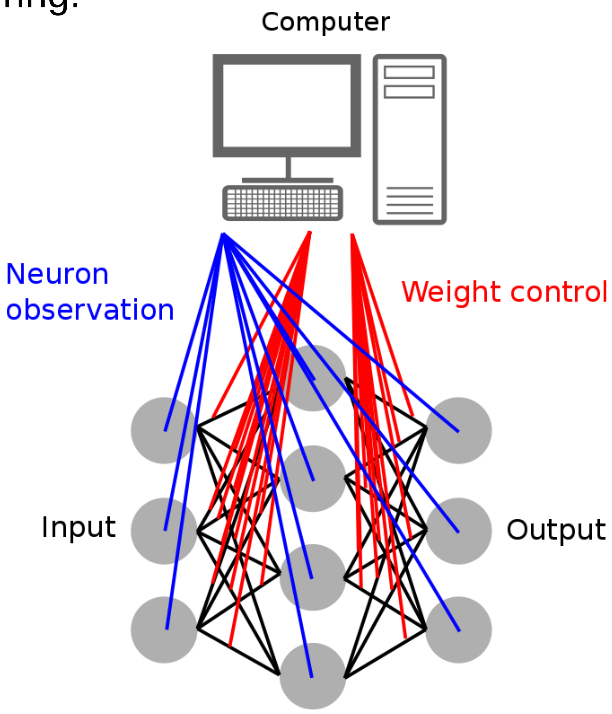
Scalability of training hardware ANNs

Nowadays, neuromorphic computing systems are mainly **trained externally**, running **backpropagation** and **gradient descent** on a computer, requiring:

- control of parameters (weights)
- neuron states observability

↳ Not biologically plausible and **not scalable**!





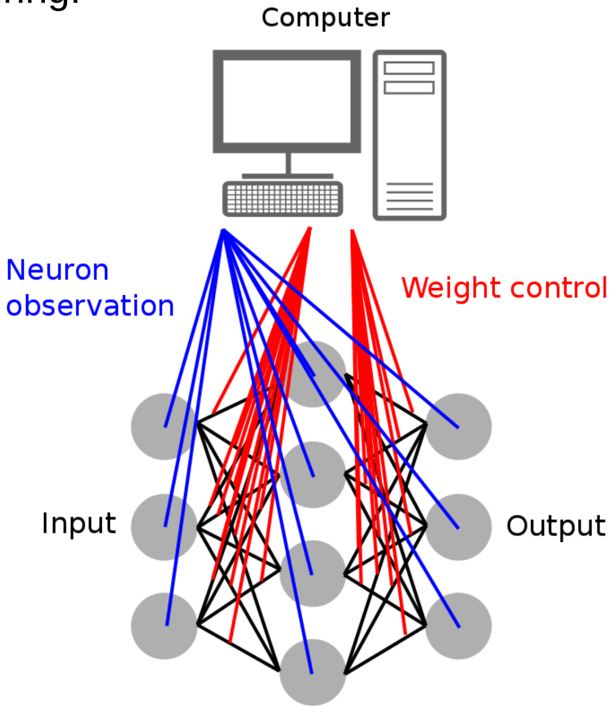
Learning via **self-adaptation** is the holy grail!

Scalability of training hardware ANNs

Nowadays, neuromorphic computing systems are mainly **trained externally**, running **backpropagation** and **gradient descent** on a computer, requiring:

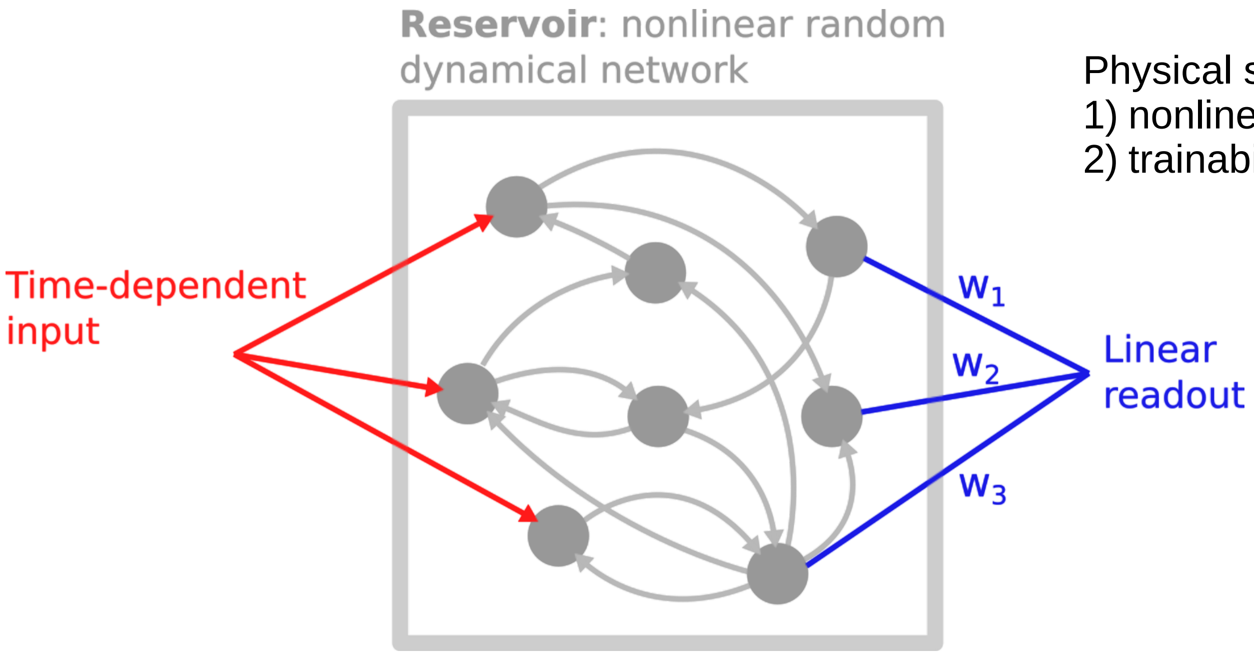
- control of parameters (weights)
- neuron states observability

↳ Not biologically plausible and **not scalable**!



Learning via **self-adaptation** is the holy grail!

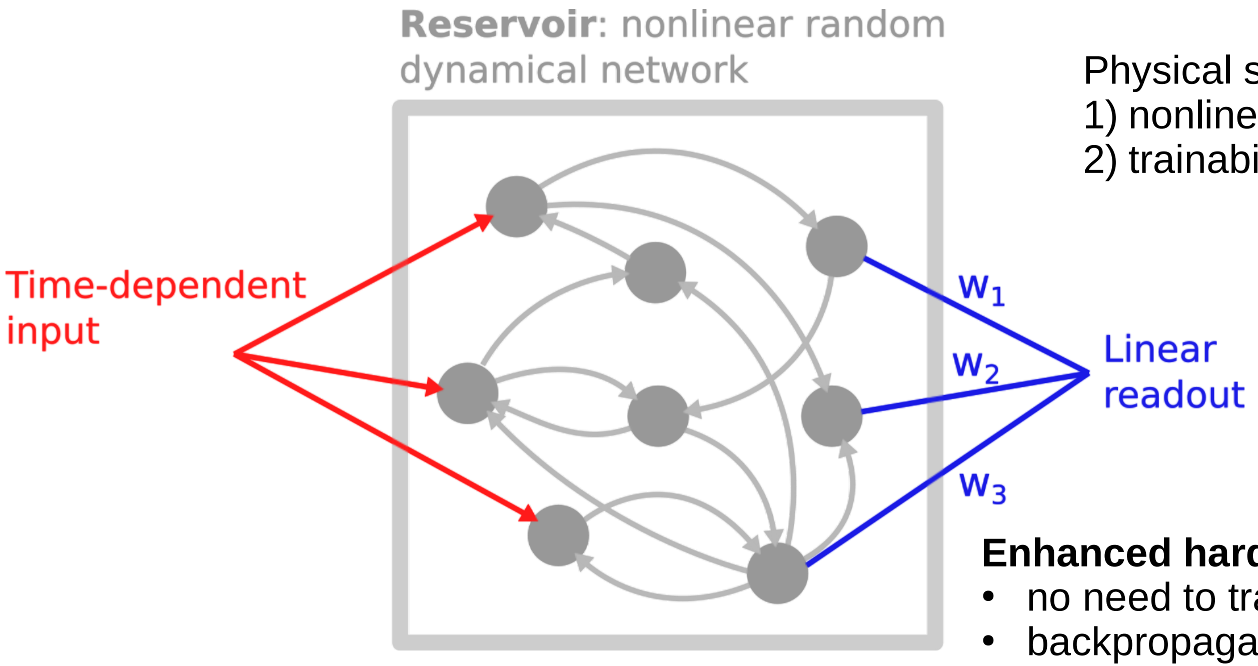
Reservoir computing: a hardware-friendly approach



Physical separation of ANN tasks:
1) nonlinearity + dynamics → reservoir (physical)
2) trainability → single-layer readout (software)

UNIVERSITÀ DI TRENTO
NanoLab Department of Physics
ARIADNE
Funded by the European Union

Reservoir computing: a hardware-friendly approach



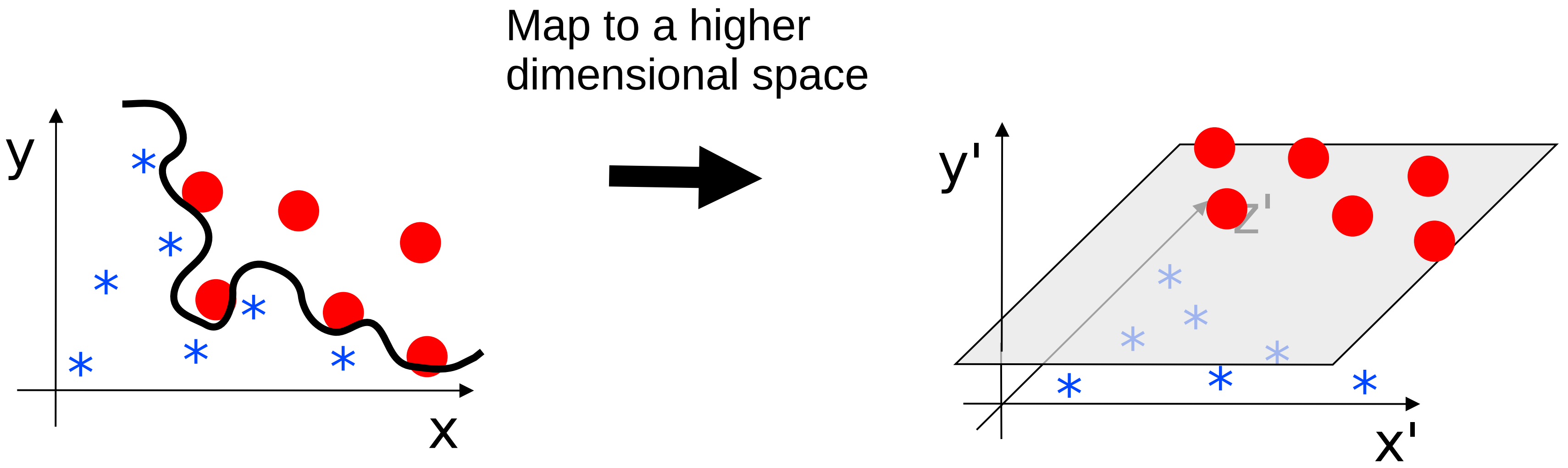
Physical separation of ANN tasks:
1) nonlinearity + dynamics → reservoir (physical)
2) trainability → single-layer readout (software)

Enhanced hardware scalability:
- no need to train the reservoir parameters
- backpropagation-free (no need to know error gradients)

… but limited computational power because of lack of learnable hierarchy

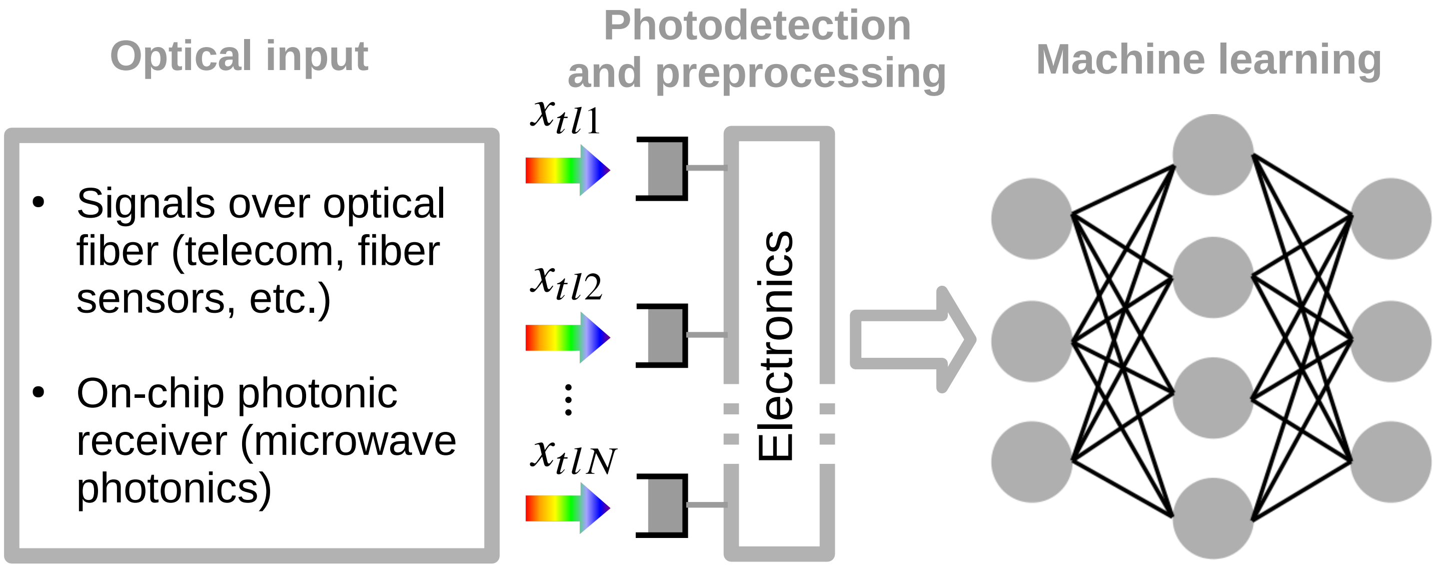
Reservoir computing: a hardware-friendly approach

How does it work?



A ‘plug & play’ neuromorphic interface

- Signals over optical fiber (telecom, fiber sensors, etc.)
- On-chip photonic receiver (microwave photonics)



A ‘plug & play’ neuromorphic interface

Optical input

- Signals over optical fiber (telecom, fiber sensors, etc.)
- On-chip photonic receiver (microwave photonics)

x_{tl1}

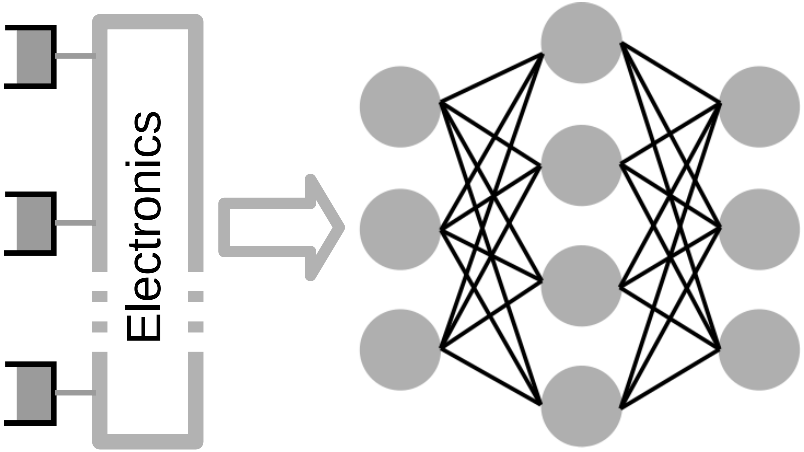
x_{tl2}

$\vdots$

x_{tlN}

Photodetection and preprocessing

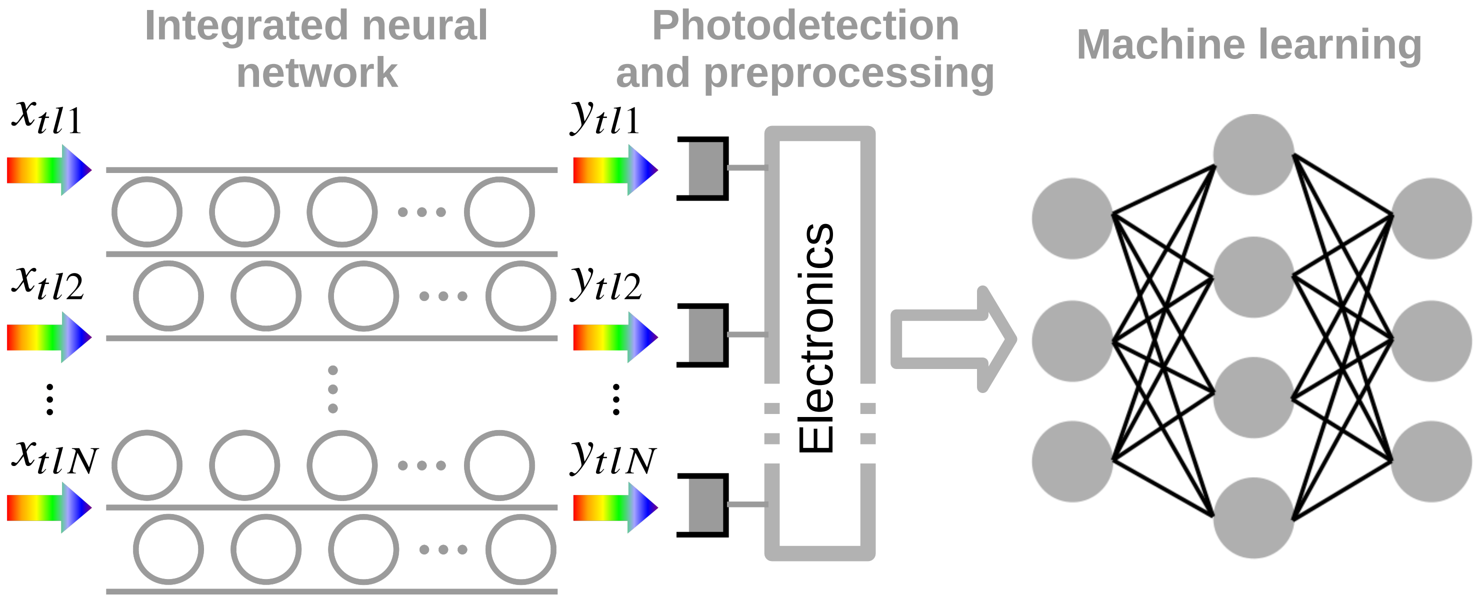
Machine learning



A ‘plug & play’ neuromorphic interface

Optical input

- Signals over optical fiber (telecom, fiber sensors, etc.)
- On-chip photonic receiver (microwave photonics)



- memory and interactions to couple spatial, temporal and frequency domains
- dimensionality expansion
- optical phase information
- preserved signal format (non-invasive)

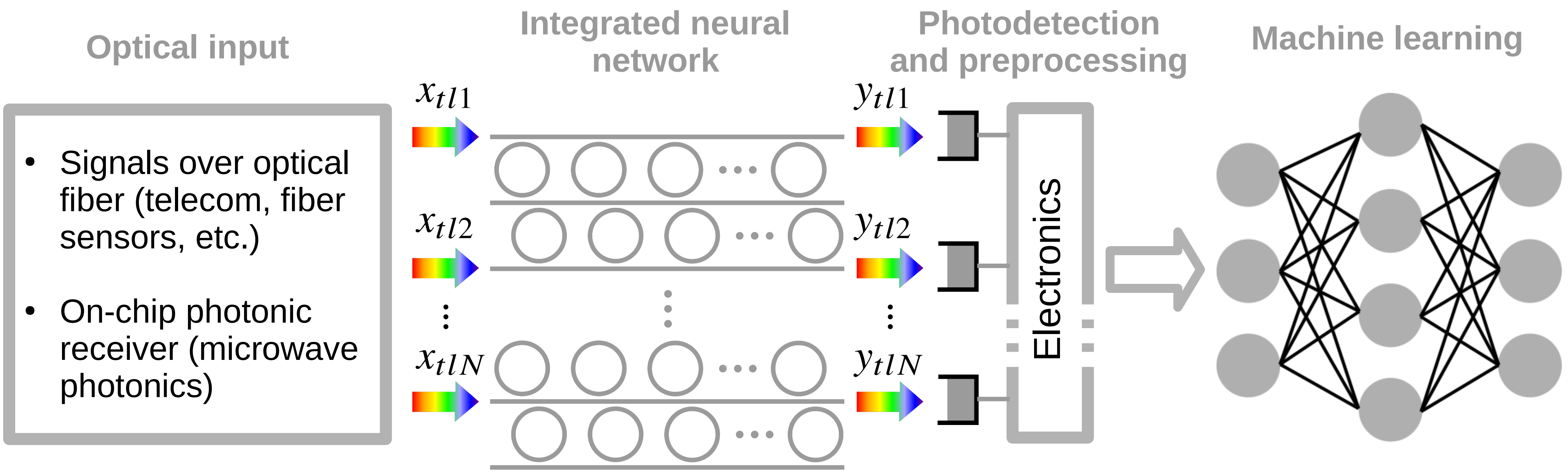
UNIVERSITÀ DI TRENTO

NanoLab Department of Physics

ARIADNE

Funded by the European Union

A ‘plug & play’ neuromorphic interface

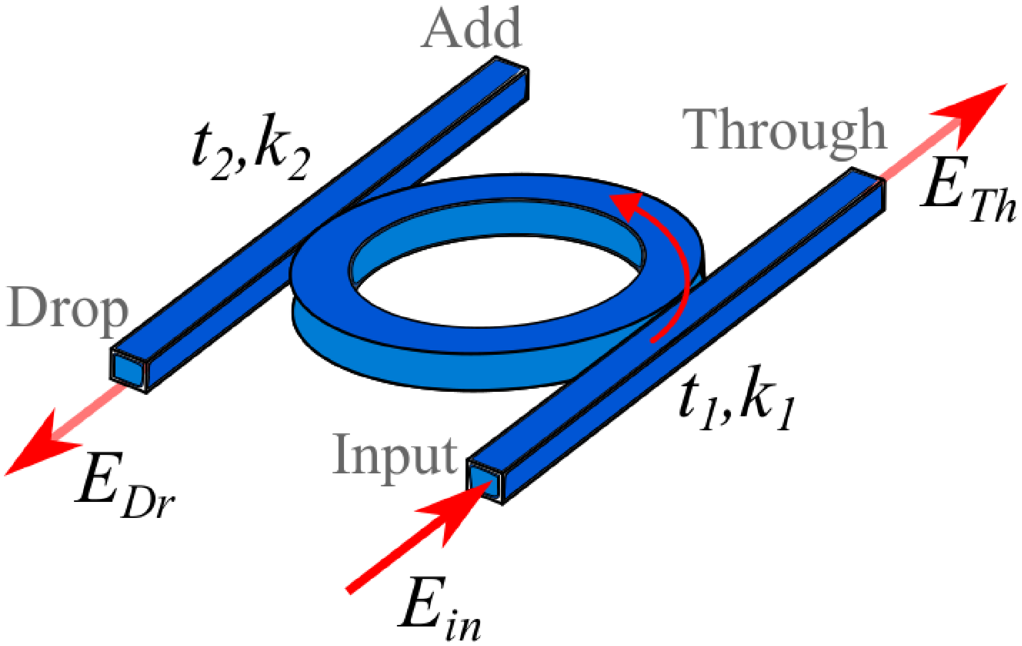


- memory and interactions to couple spatial, temporal and frequency domains
- dimensionality expansion
- optical phase information
- preserved signal format (non-invasive)

- more powerful ML (feature extraction/expansion)
- computationally cheaper model (fast re-training!)
- less high-speed preprocessing
- possibility for on-chip sensing

Why silicon microring resonators (MRRs)?

Infrared light (telecom wavelength: 1550 nm)



Optical resonance:

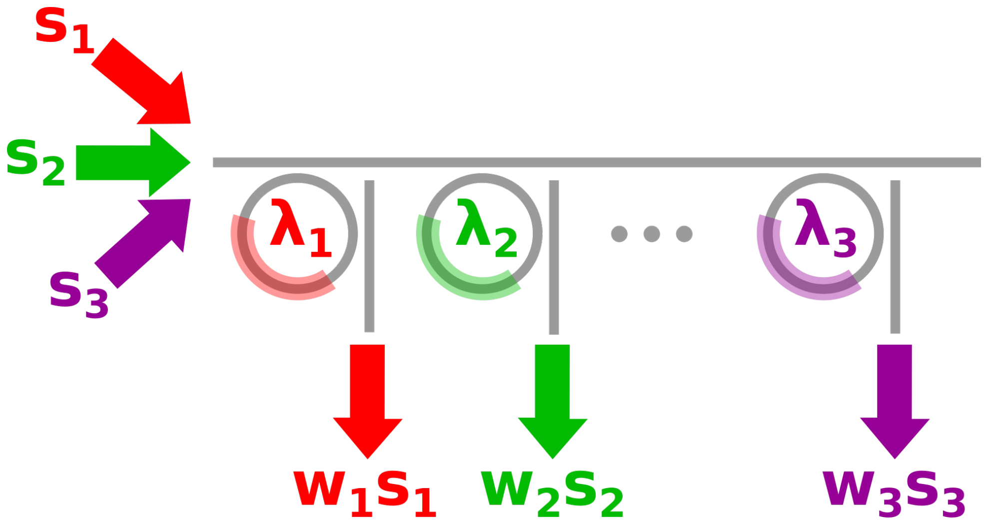
- only specific wavelengths enter the ring
- light power accumulates
- enhanced sensitivity to light path perturbations

Image from:
Biasi S, Donati G, Lugnan A, Mancinelli M, Staffoli E, Pavesi L., “Photonic neural networks based on integrated silicon microresonators.” arXiv preprint (2023)

Why silicon microring resonators (MRRs)?

MRRs can be tuned to **separate and weight multiple wavelengths** in the same channel (WDM, short for *wavelength division multiplexing*)

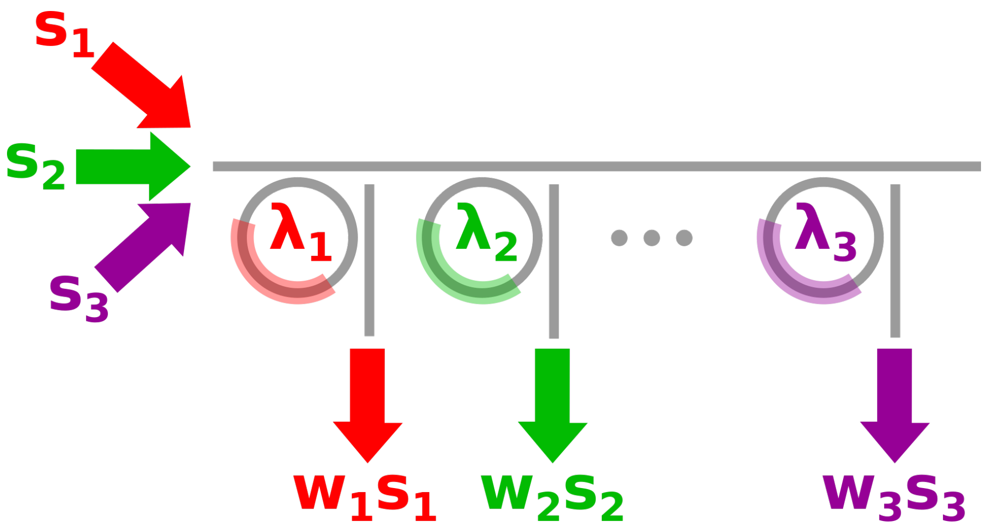
→ **artificial synapse**



Why silicon microring resonators (MRRs)?

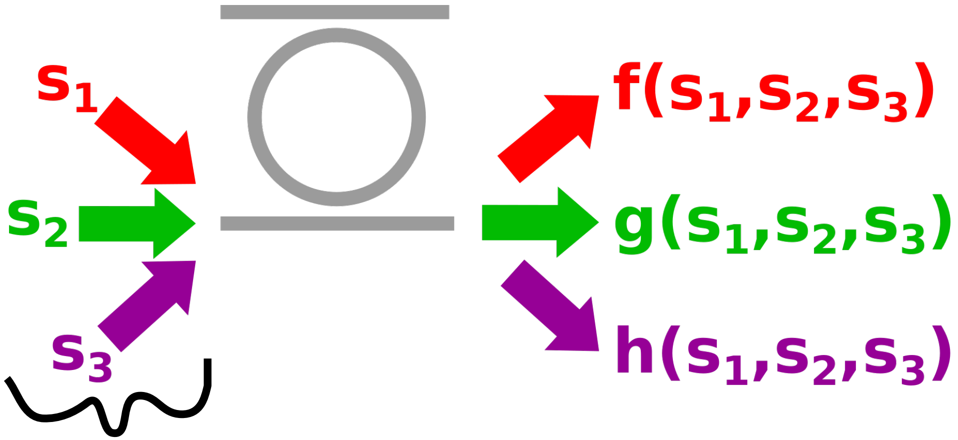
MRRs can be tuned to **separate and weight multiple wavelengths** in the same channel (WDM, short for *wavelength division multiplexing*)

→ **artificial synapse**



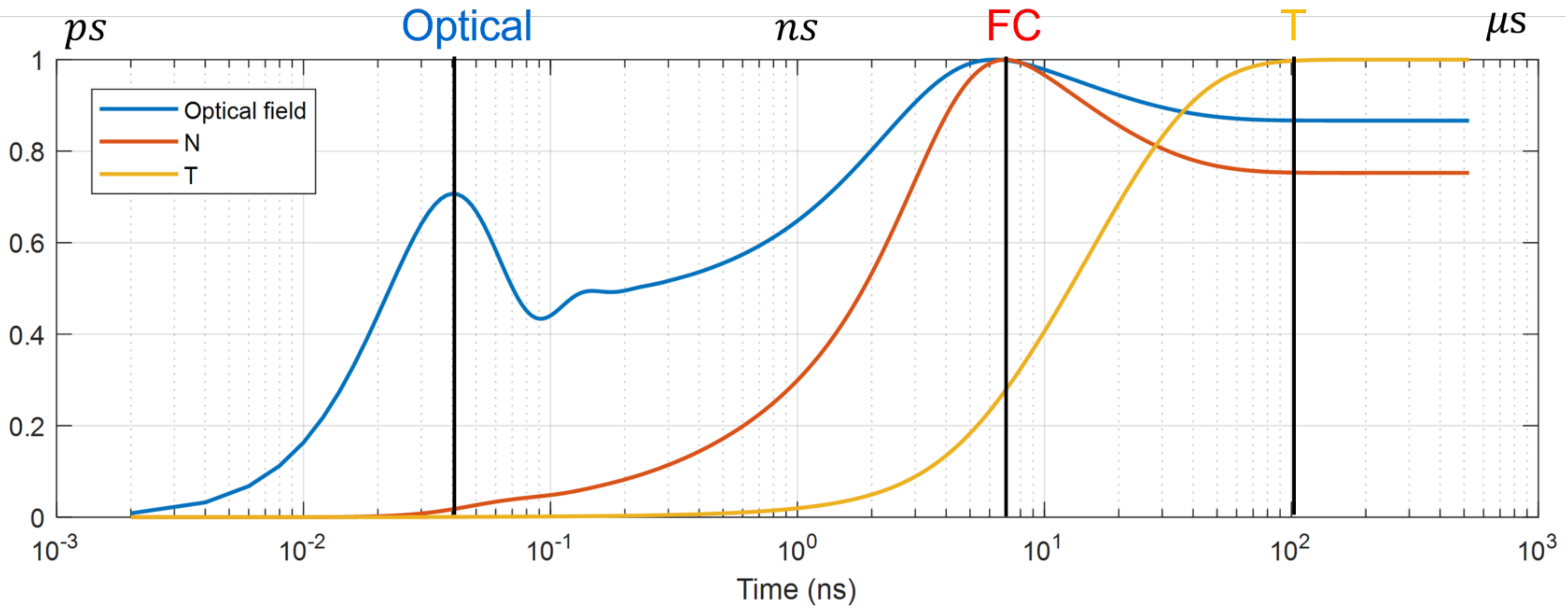
A MRR can **nonlinearly couple** multiple wavelengths

→ **artificial neuron**



Why silicon microring resonators (MRRs)?

Multiscale volatile memory → **short- and long- term plasticity**

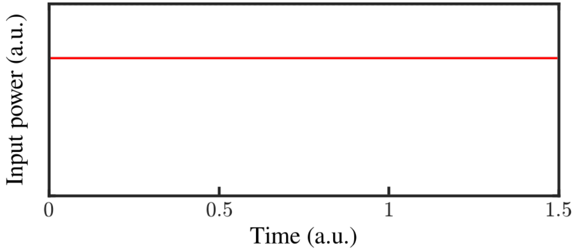


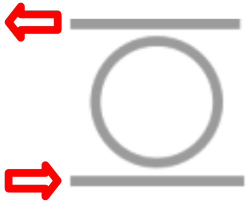
Biasi S, Donati G, Lugnan A, Mancinelli M, Staffoli E, Pavesi L., “Photonic neural networks based on integrated silicon microresonators.” arXiv preprint (2023)

Why MRRs?

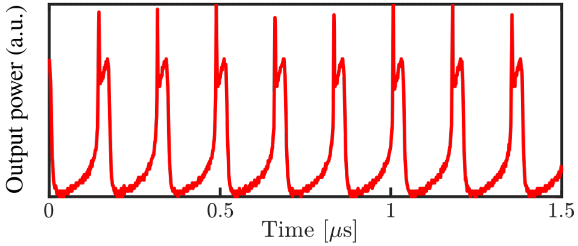
Spiking behaviour (self-pulsing)

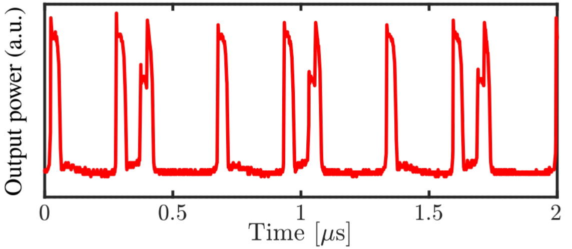
Input

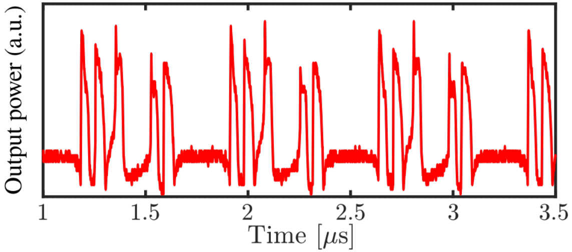




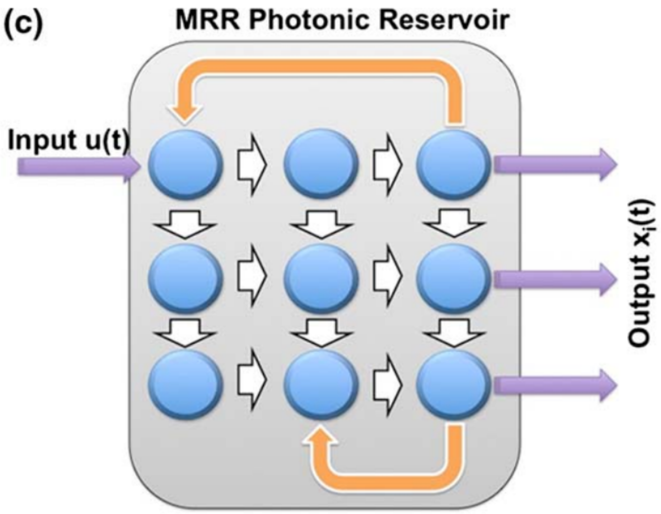
Output



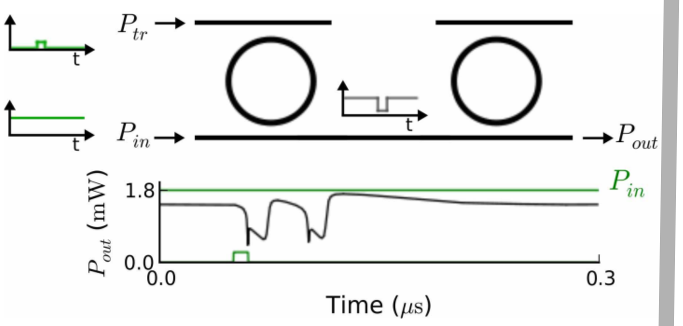




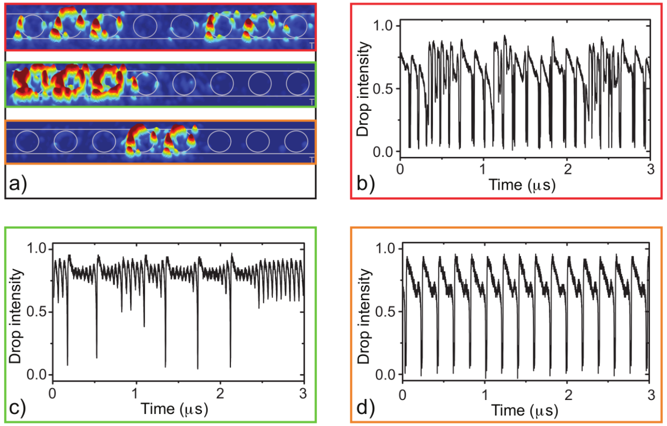
Coupled silicon microring resonators as neural networks



Mesaritakis, C., Papataxiarhis, V., & Syvridis, D. (2013). Micro ring resonators as building blocks for an all-optical high-speed reservoir-computing bit-pattern-recognition system. JOSA B, 30(11)

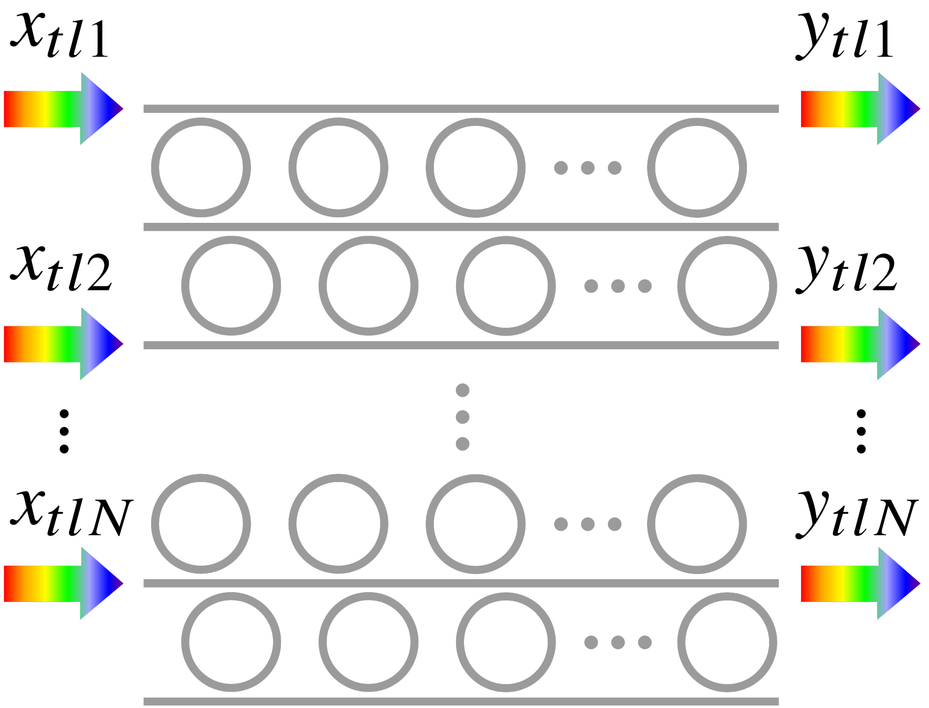


Van Vaerenbergh, T., Fiers, M., Mechet, P., Spuesens, T., Kumar, R., Morthier, G., ... & Bienstman, P. (2012). Cascadable excitability in microrings. Optics express, 20(18), 20292-20308.



Mancinelli, M., Borghi, M., Ramiro-Manzano, F., Fedeli, J. M., & Pavesi, L. (2014). Chaotic dynamics in coupled resonator sequences. Optics express, 22(12), 14505-14516.

Neural networks made of silicon MRRs



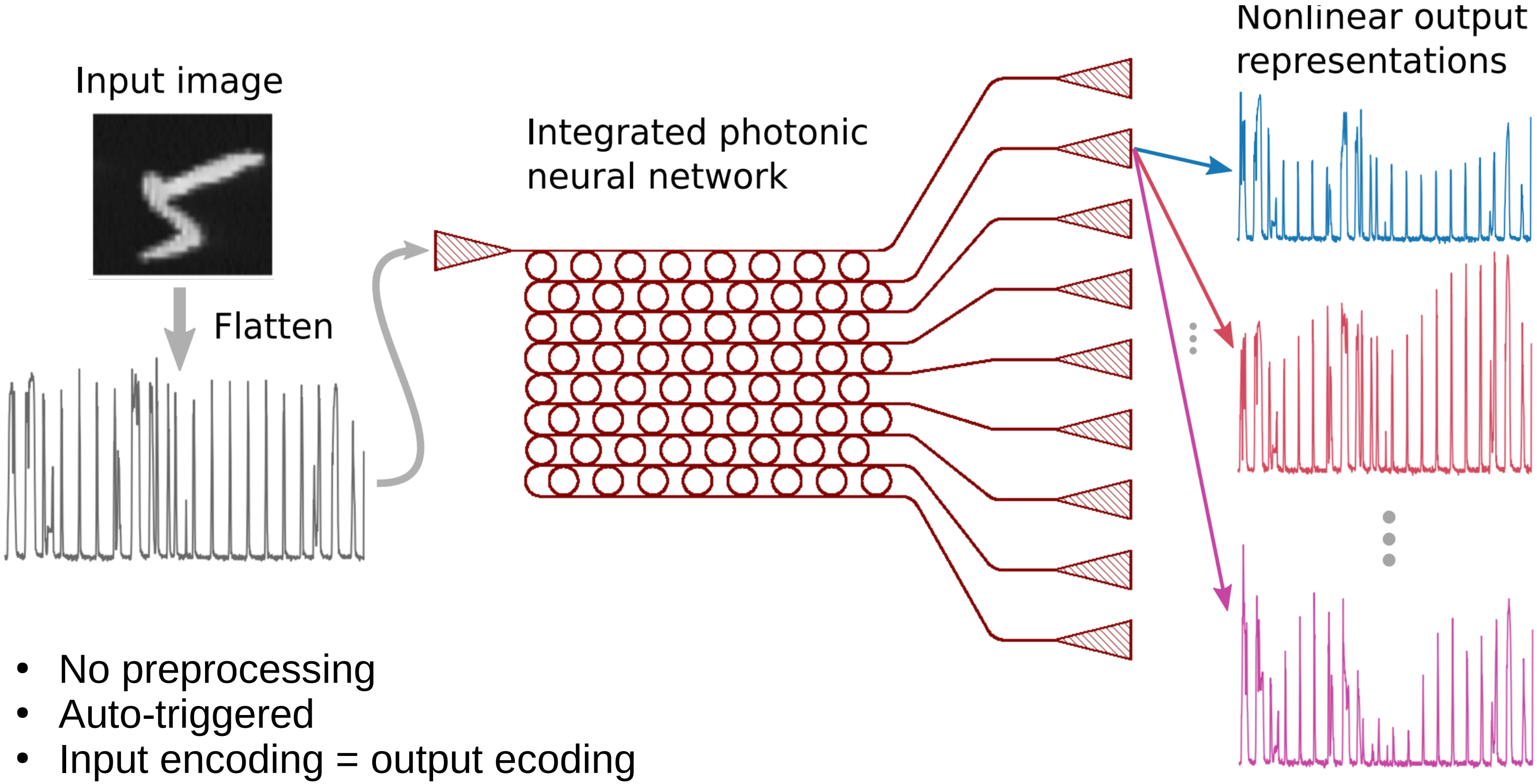
Input and output encoded and nonlinearly coupled in:

- **space** (physical network)
- **time** (nonlinear dynamics)
- **wavelength** (resonances of MRRs)

→ input-output neurons: ~ 10^4 x 10^4 per 100 ns per 0.5 mm^2 chip area (random operations)

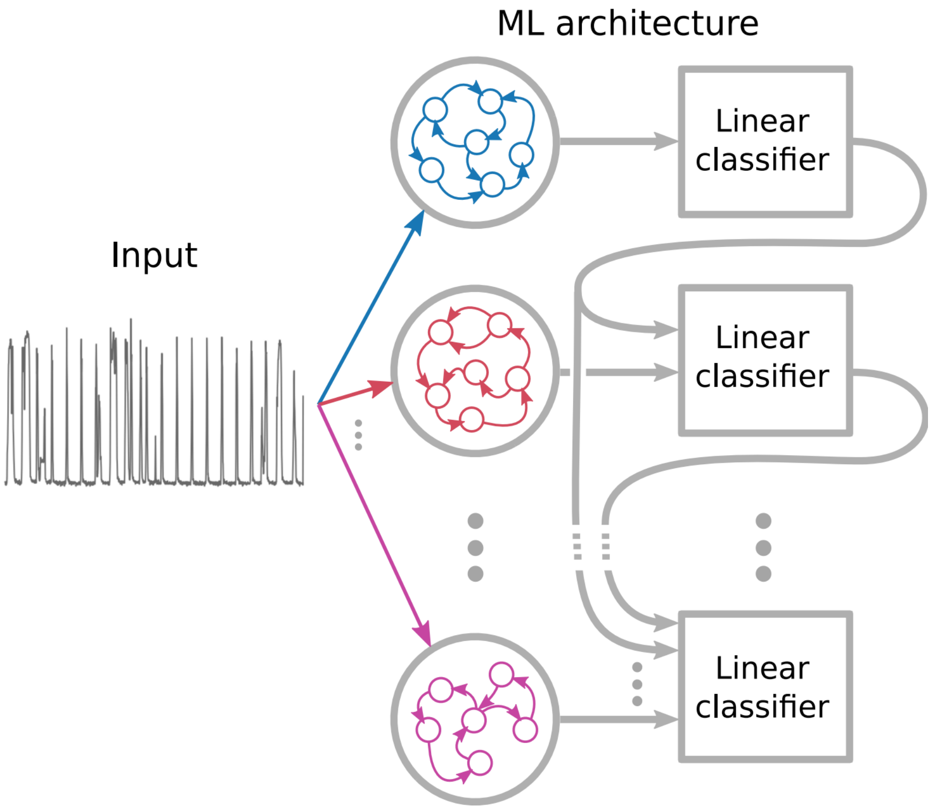
- throughput:
  10^{15} (MACs+NLOs)/s/mm^2
- energy efficiency:
  10^{16} (MACs+NLOs)/J

Proof of concept: handwritten digits classification



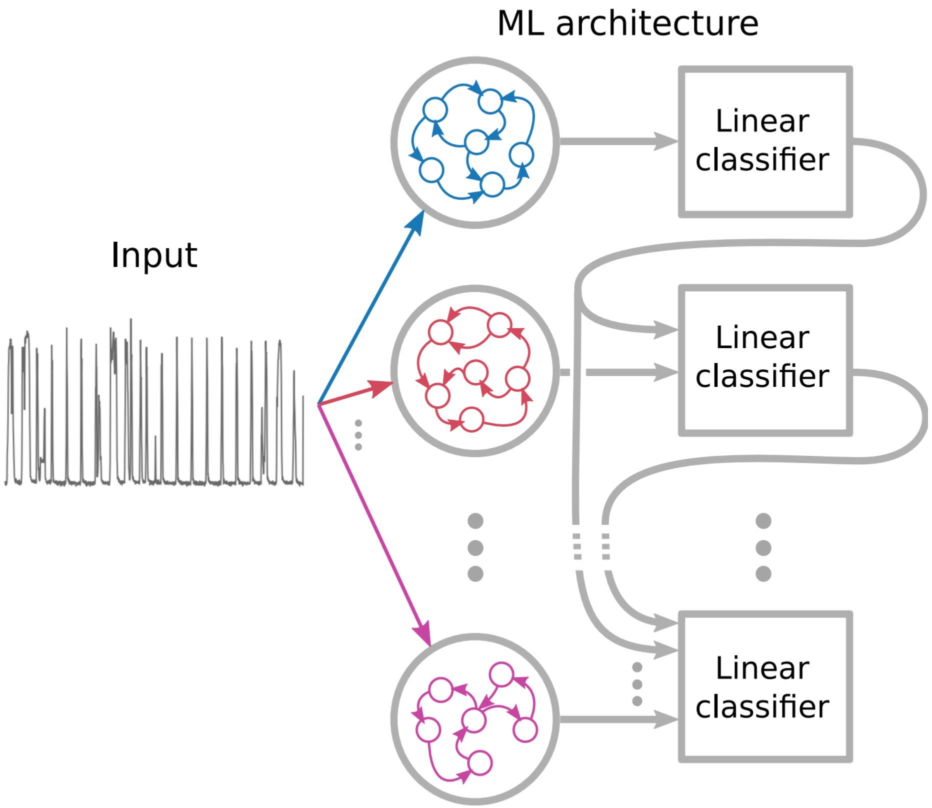
- No preprocessing
- Auto-triggered
- Input encoding = output ecoding
- 600 nonlinear representations

Proof of concept: handwritten digits classification

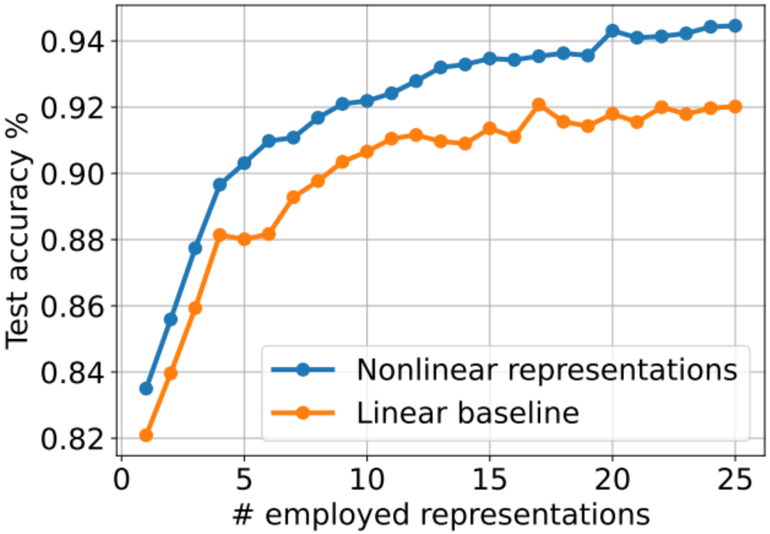


- *Ensemble* of reservoir computers
  Matthias Freiberger, *et al*. IEEE JSTQE, 26,1 (2019)
- Biologically plausible system and training (no backprop)
- Computationally cheap inference
- Easy and fast to train

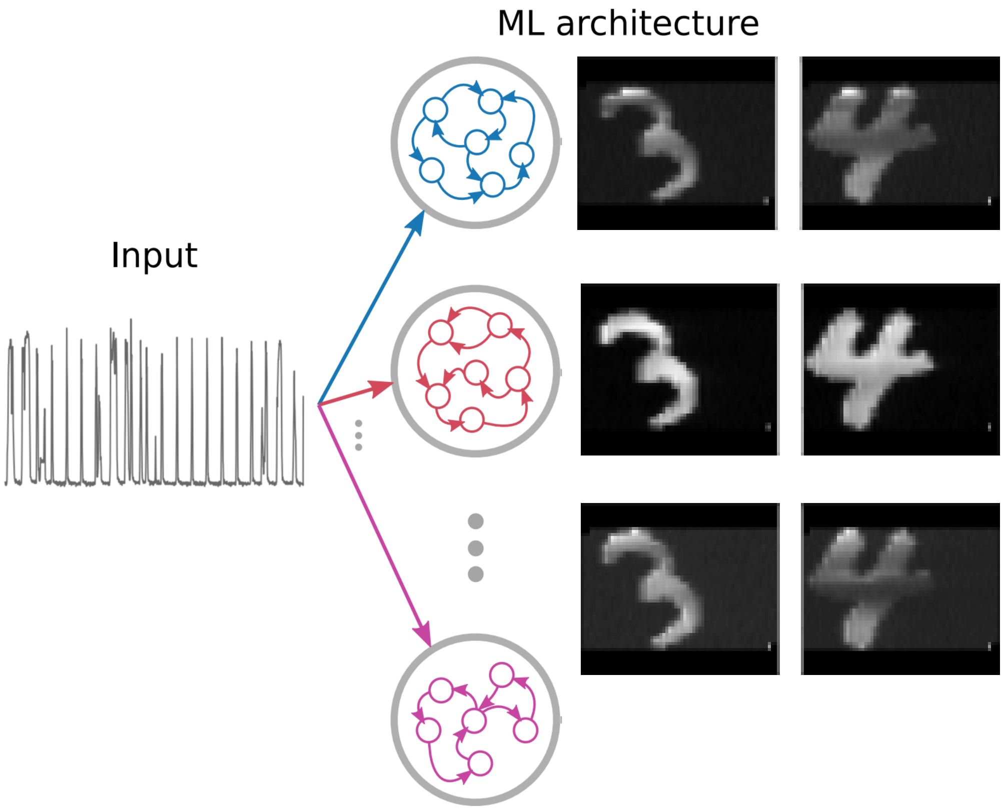
Proof of concept: handwritten digits classification



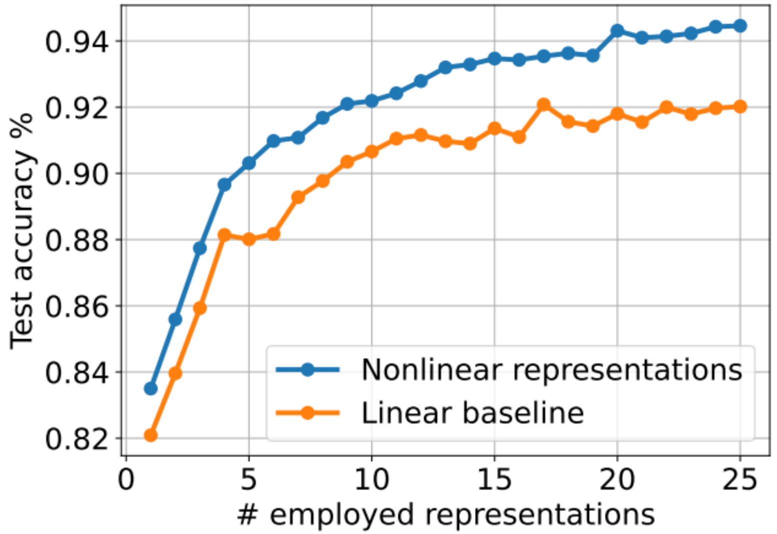
- *Ensemble* of reservoir computers
  Matthias Freiberger, *et al*. IEEE JSTQE, 26,1 (2019)
- Biologically plausible system and training (no backprop)
- Computationally cheap inference
- Easy and fast to train



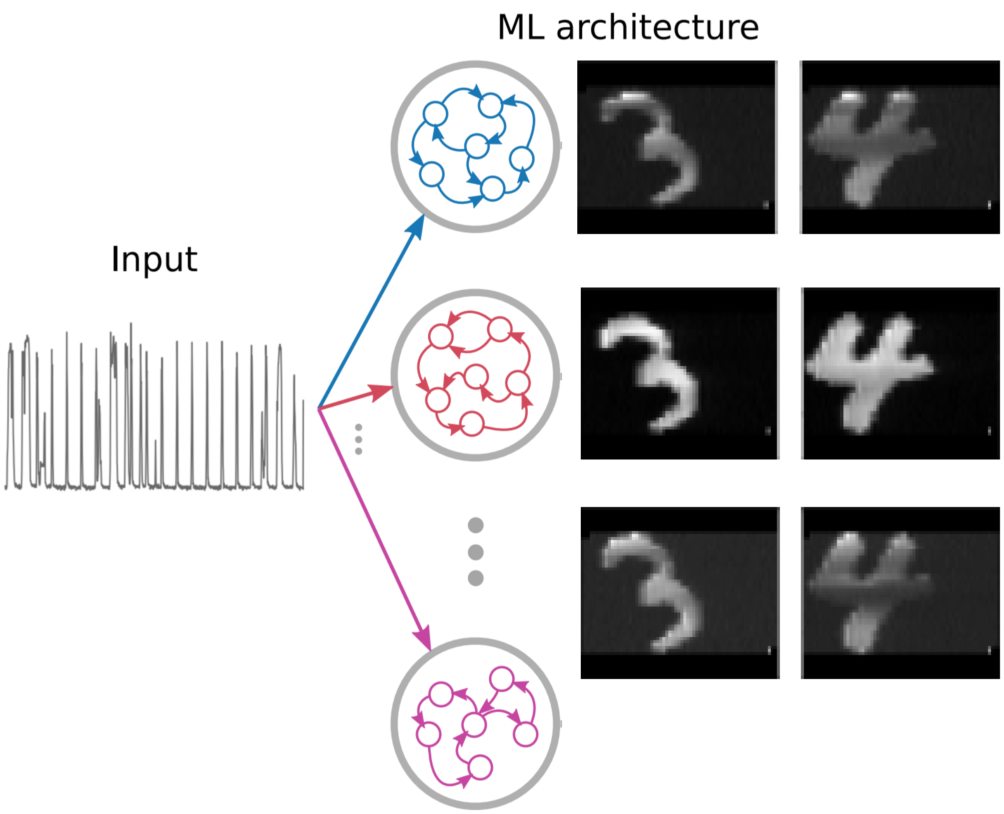
Proof of concept: handwritten digits classification



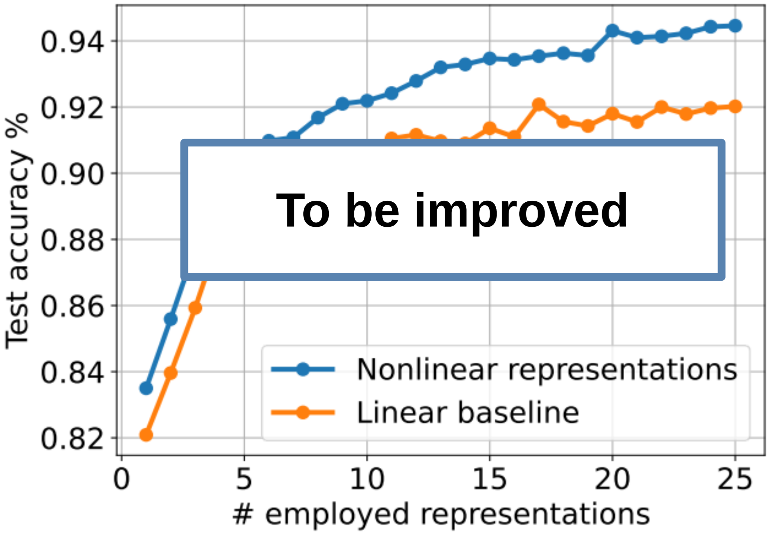
- *Ensemble* of reservoir computers
  Matthias Freiberger, *et al*. IEEE JSTQE, 26,1 (2019)
- Biologically plausible system and training (no backprop)
- Computationally cheap inference
- Easy and fast to train



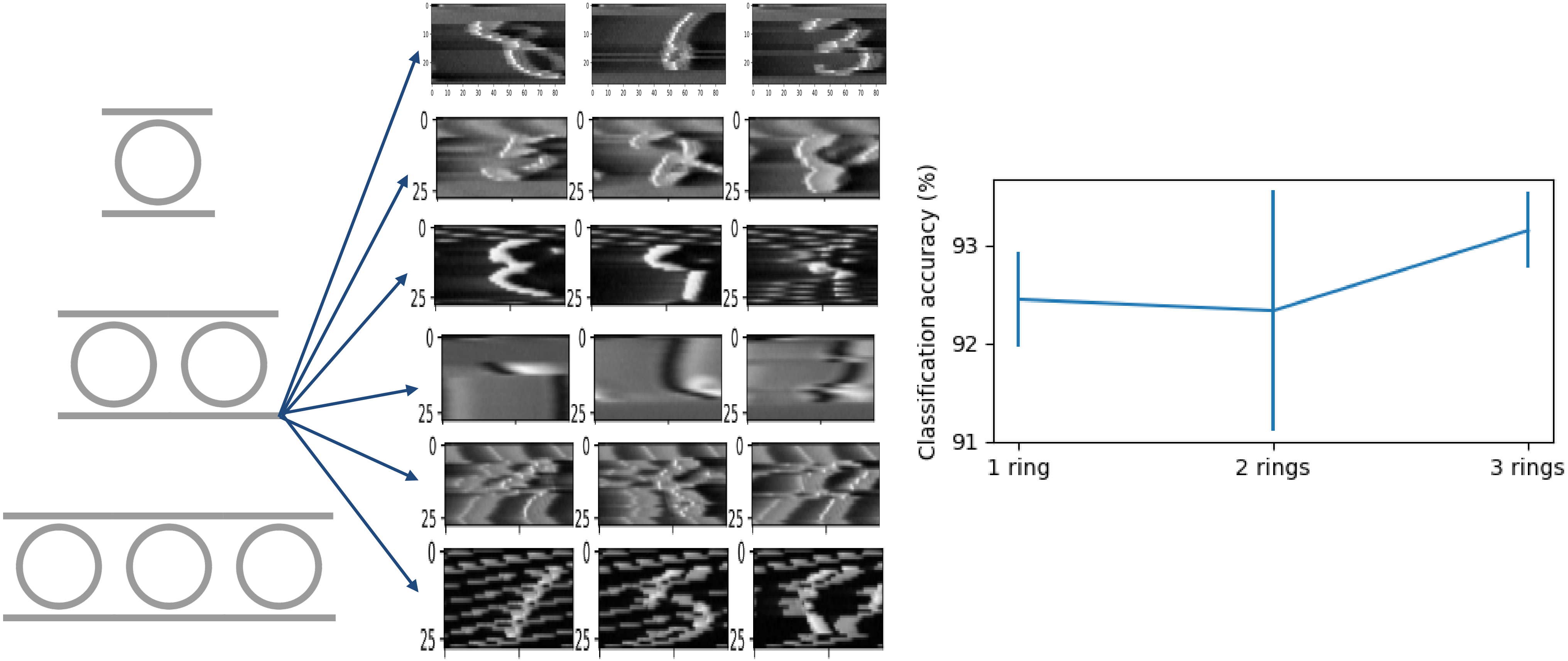
Proof of concept: handwritten digits classification



- *Ensemble* of reservoir computers
  Matthias Freiberger, *et al*. IEEE JSTQE, 26,1 (2019)
- Biologically plausible system and training (no backprop)
- Computationally cheap inference
- Easy and fast to train

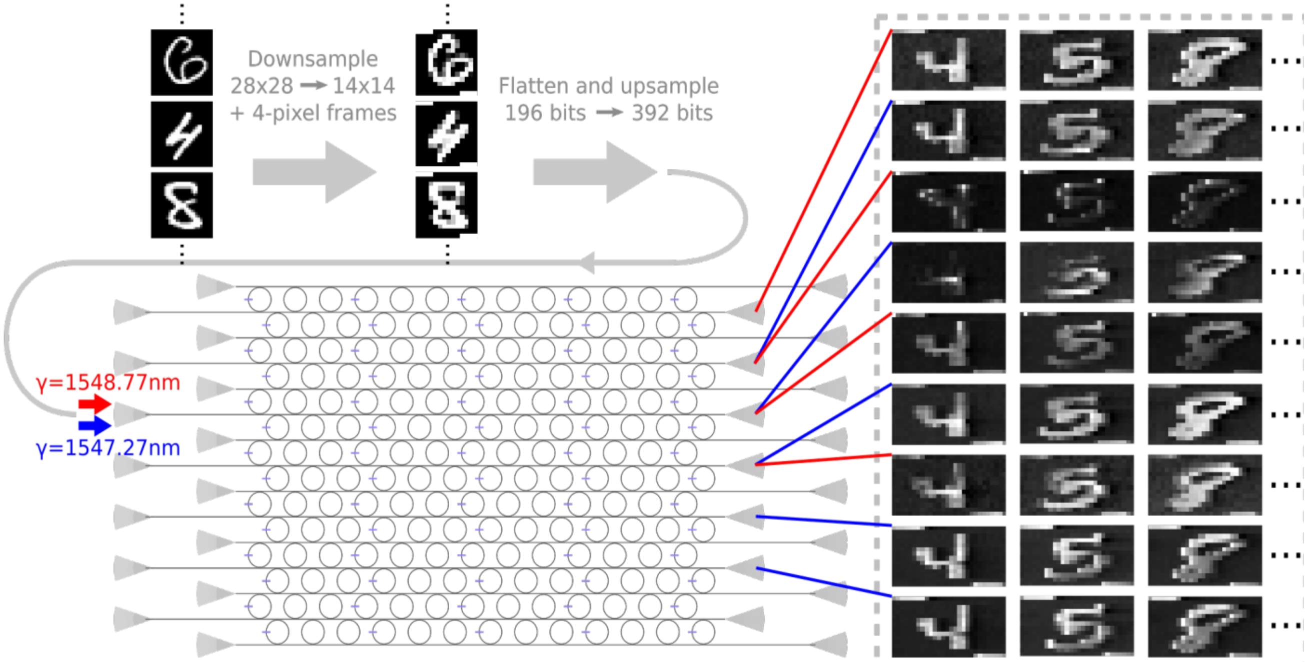


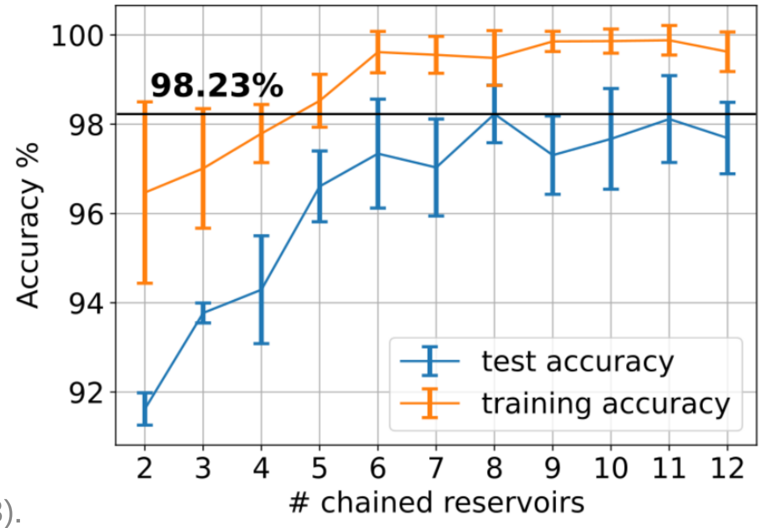
Increasing complexity with spiking behaviour



Non-volatile emergent plasticity with phase change material (GST)

- PCM adds non-volatile memory
- Better results: preprocessing, PCM, or better parameters?
- Self-adaptive neural network with **emergent plasticity**
- Final goal: self-learning





Lugnan, Alessio, Samarth Aggarwal, Frank Brückerhoff-Plückelmann, C. David Wright, Wolfram HP Pernice, Harish Bhaskaran, and Peter Bienstman. arXiv:2312.03802 (2023).

Conclusion

Silicon microring resonators are very **versatile** and promising components for efficient and **scalable** integrated photonic neural networks.

Scalability can be greatly enhanced by giving up training of parameters via external connections and computation (e.g. through reservoir computing).

Learning is in principle possible by self-adaptation of the network to its input (thanks to phase change materials).

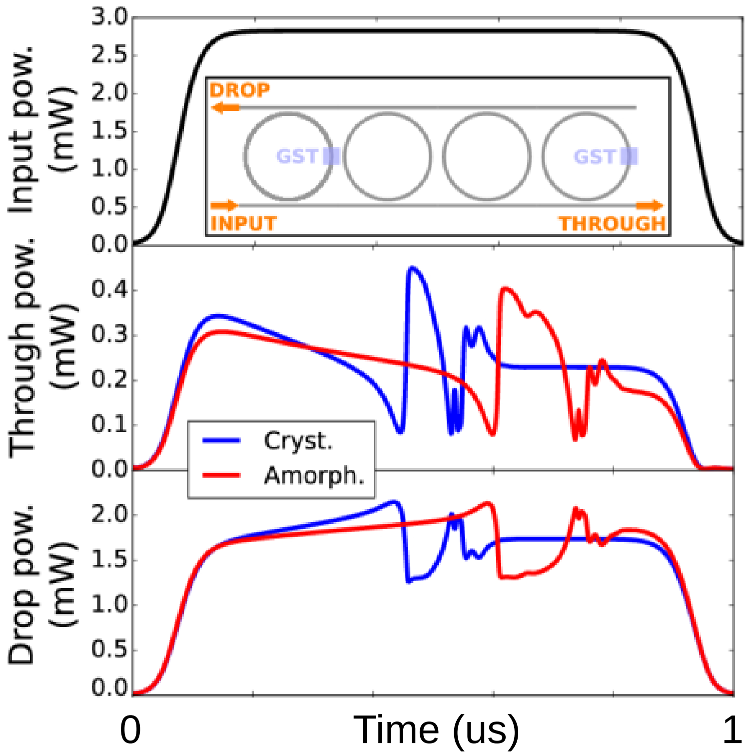
Funded by the European Union

Conclusion

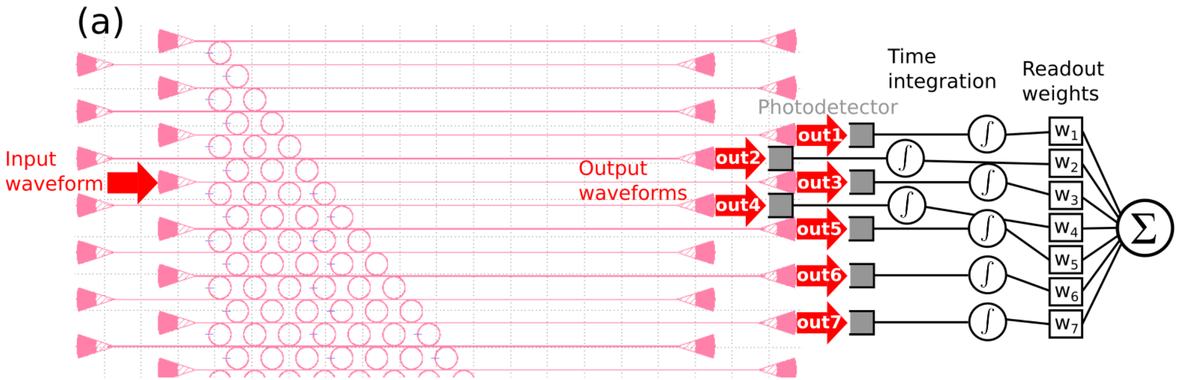
Silicon microring resonators are very **versatile** and promising components for efficient and **scalable** integrated photonic neural networks.

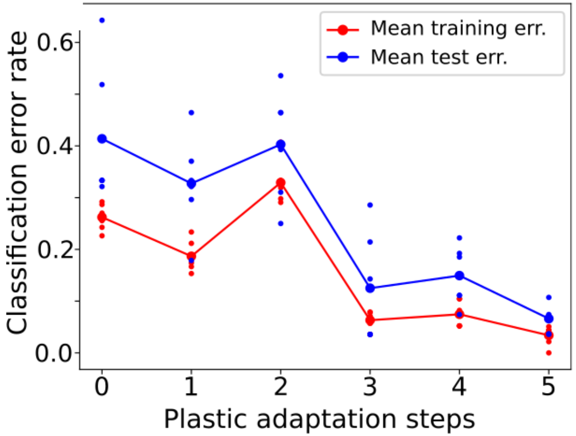
Thank you for your attention!

Self-adaptive plasticity with MRRs + PCMs



A. Lugnan, S. G.-C. Carrillo, C. D. Wright, and P. Bienstman, “Rigorous dynamic model of a silicon ring resonator with phase change material for a neuromorphic node,” Optics Express, (2022)



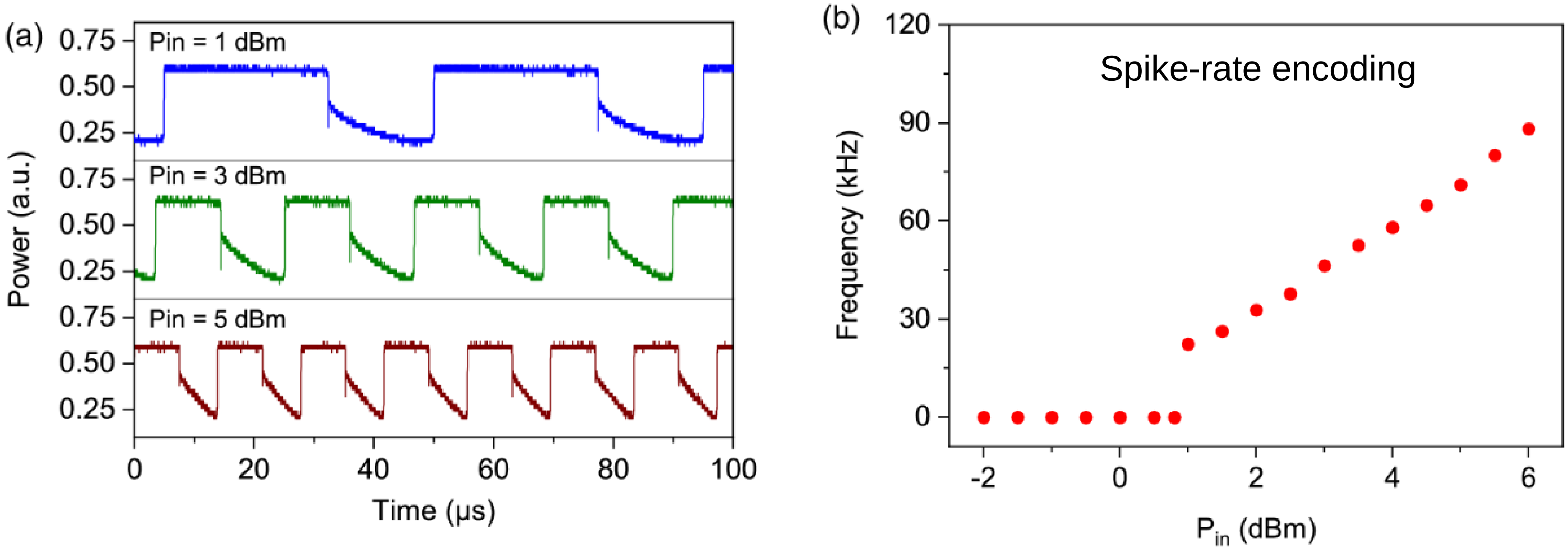


There is no suitable theory on self-learning based on plasticity, yet

Lugnan A, Aggarwal S, Brückerhoff-Plückelmann F, Pernice WH, Bhaskaran H, Bienstman P. “Performance enhancement via synaptic plasticity in an integrated photonic recurrent neural network with phase-change materials”. European Quantum Electronics Conference (2023).

MRR as a spiking neuron

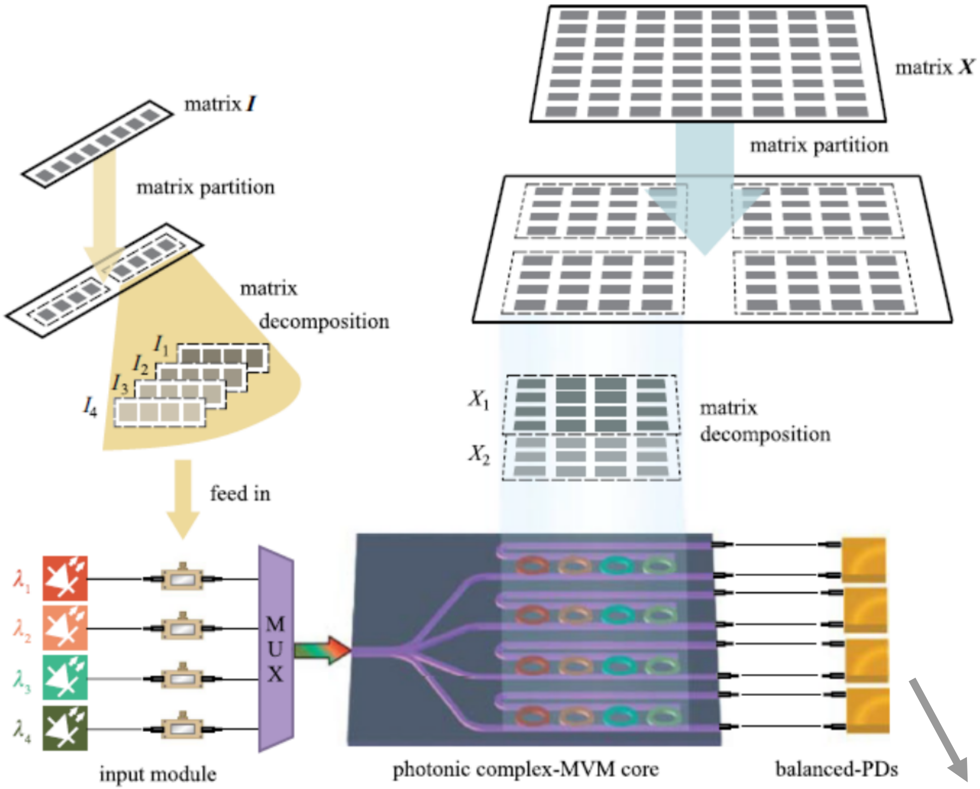
Self-pulsing regime: input constant power → output pulses (**spiking**)



Jinlong Xiang, Yujia Zhang, Yaotian Zhao, Xuhan Guo, and Yikai Su, "All-optical silicon microring spiking neuron," Photon. Res., (2022)

Applications: MMRs as synapses

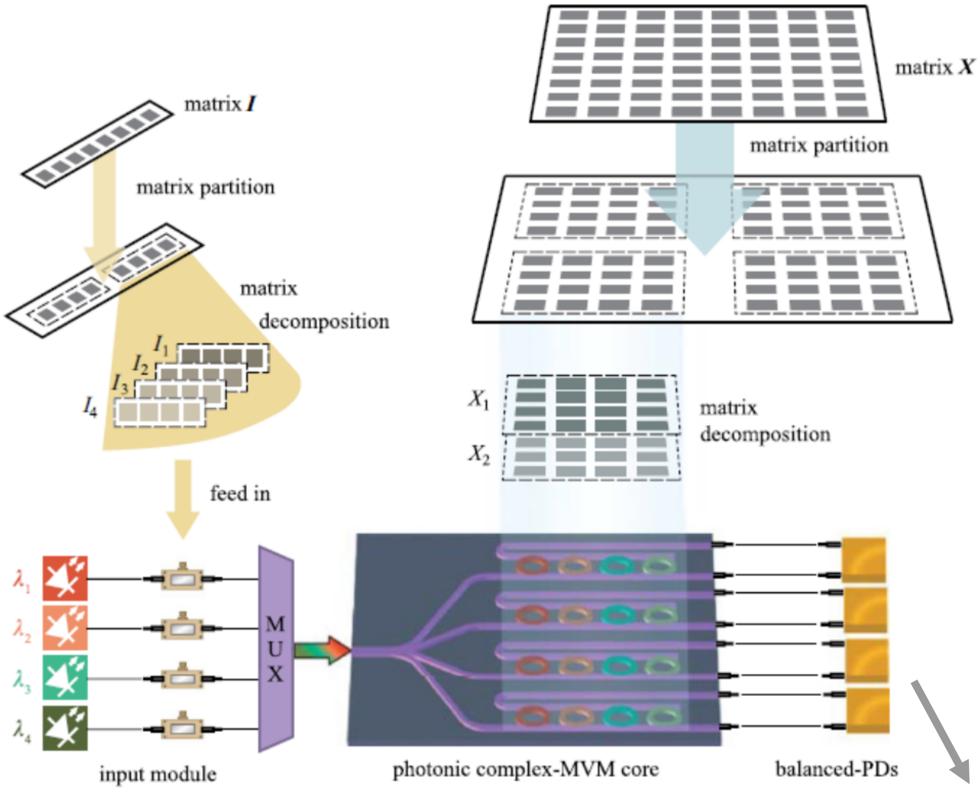
Hardware **accelerators** for large ANNs (like TPUs)
→ “only” linear **matrix-vector multiplications**



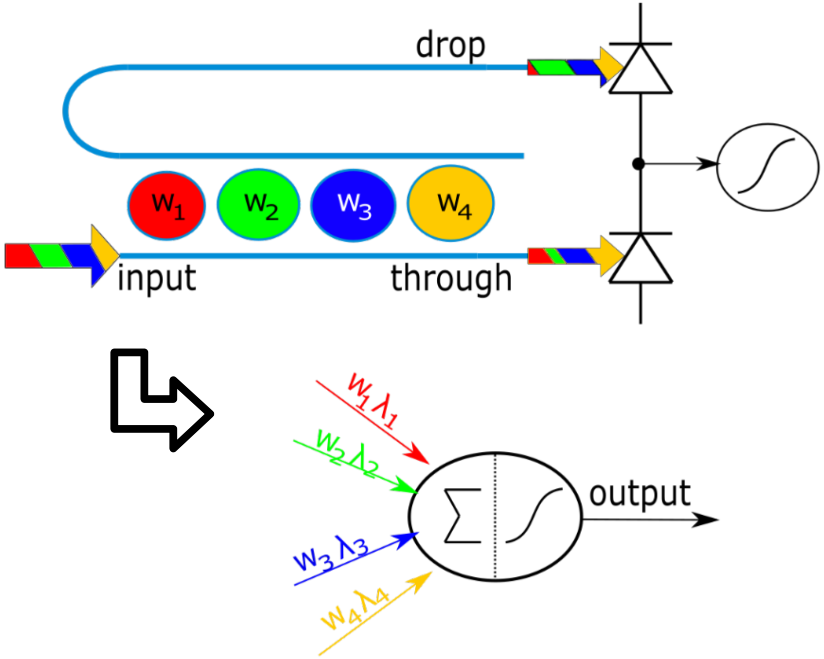
J. Cheng et al., “A small microring array that performs large complex-valued matrix-vector multiplication,” Frontiers of Optoelectronics, (2022).

Applications: MMRs as synapses

Hardware **accelerators** for large ANNs (like TPUs)
→ “only” linear **matrix-vector multiplications**



Photonic synapses + neuron



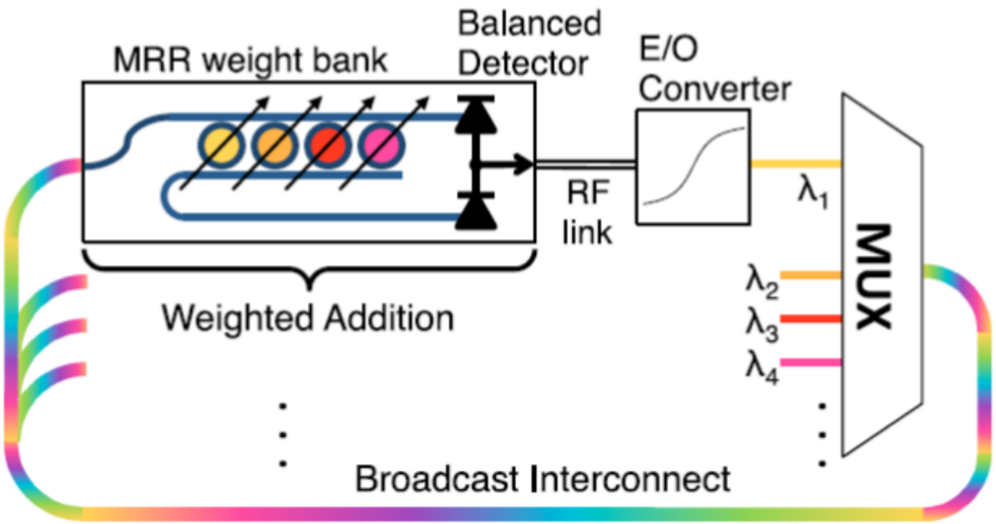
A. Tait et al., “Balanced wdm weight banks for analog optical processing and networking in silicon,” IEEE SUM, (2015)

J. Cheng et al., “A small microring array that performs large complex-valued matrix-vector multiplication,” Frontiers of Optoelectronics, (2022).

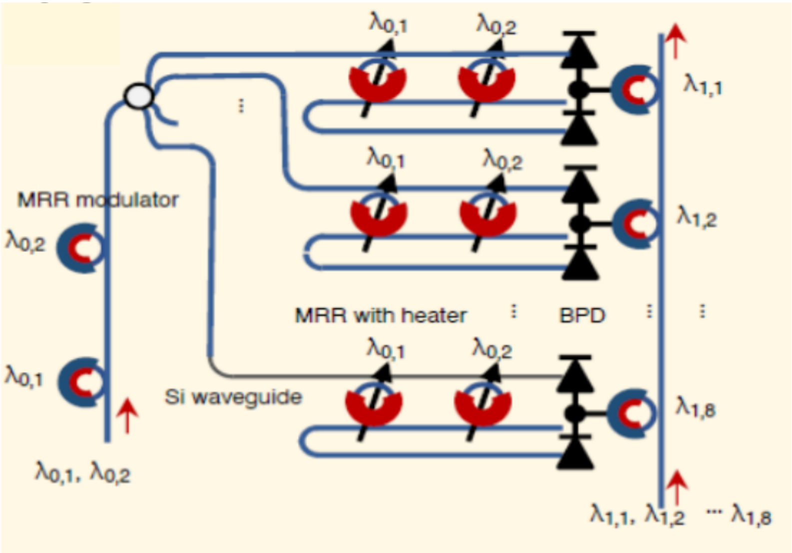
UNIVERSITÀ DI TRENTO
NanoLab Department of Physics
ARIADNE
Funded by the European Union

Applications: MMR-based ANNs

On-chip photonic neural network:
- high-speed processing
- multiple input and outputs in one waveguide
- potentially high energy efficiency



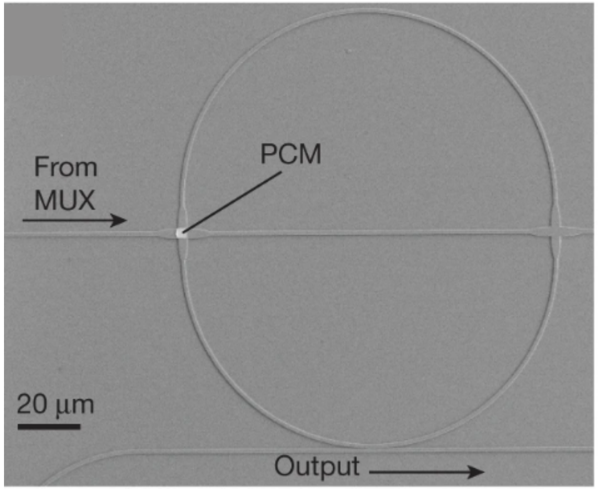
Tait, A. N., et al. "Microring weight banks." IEEE Journal of Selected Topics in Quantum Electronics, (2016).



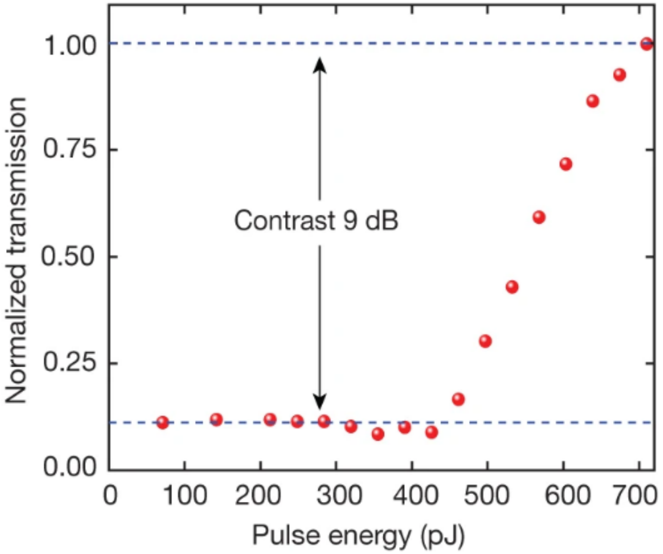
Huang, Chaoran, et al. "A silicon photonic–electronic neural network for fibre nonlinearity compensation." Nature Electronics, (2021).

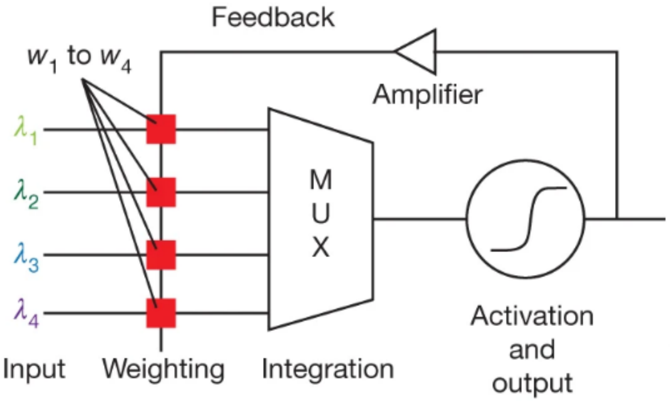
Applications: phase change materials (PCMs)

Tuning MRRs with PCMs: integrated **non-volatile photonic memory** instead of heaters
→ much higher energy efficiency
→ no thermal corss-talk



All-optical activation function





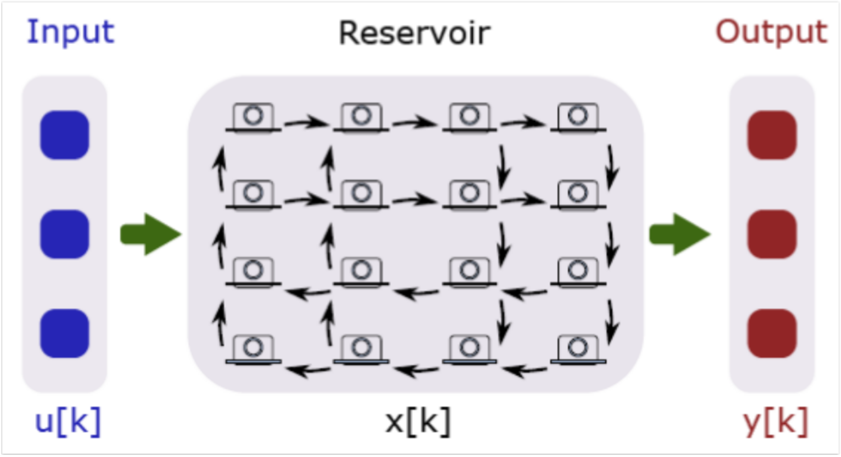
Feldmann, J., et al. "All-optical spiking neurosynaptic networks with self-learning capabilities." Nature, (2019).

Spike time dependent plasticity (**STDP**) for unsupervised on-chip self-learning

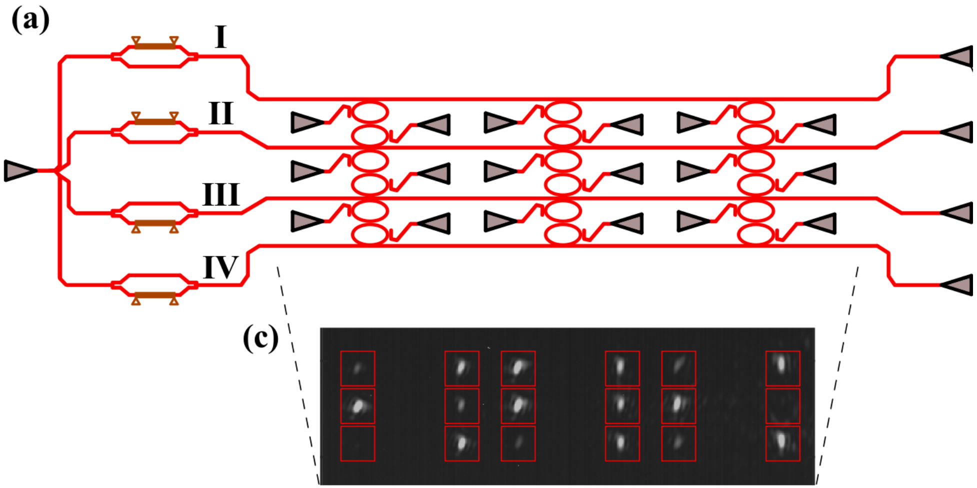
Still **difficult to scale up!**

Funded by the European Union

Applications: MRRs for reservoir computing

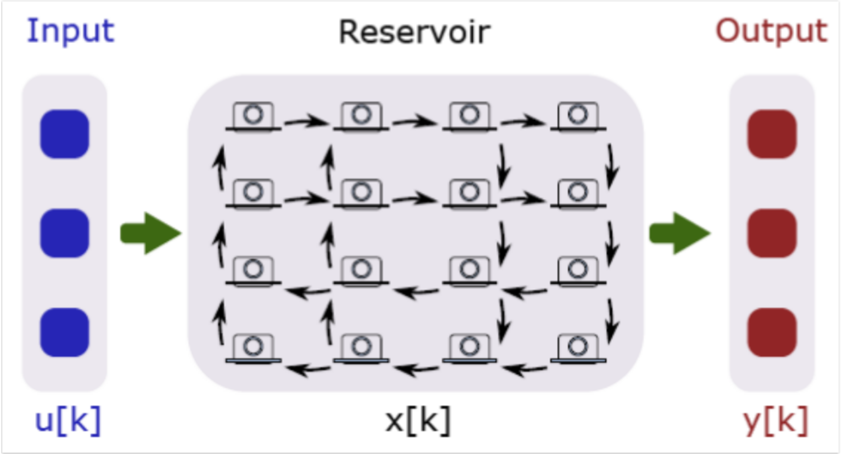


F. Denis-Le Coarer et al., “All-optical reservoir computing on a photonic chip using silicon-based ring resonators,” IEEE Journal of Selected Topics in Quantum Electronics, (2018)

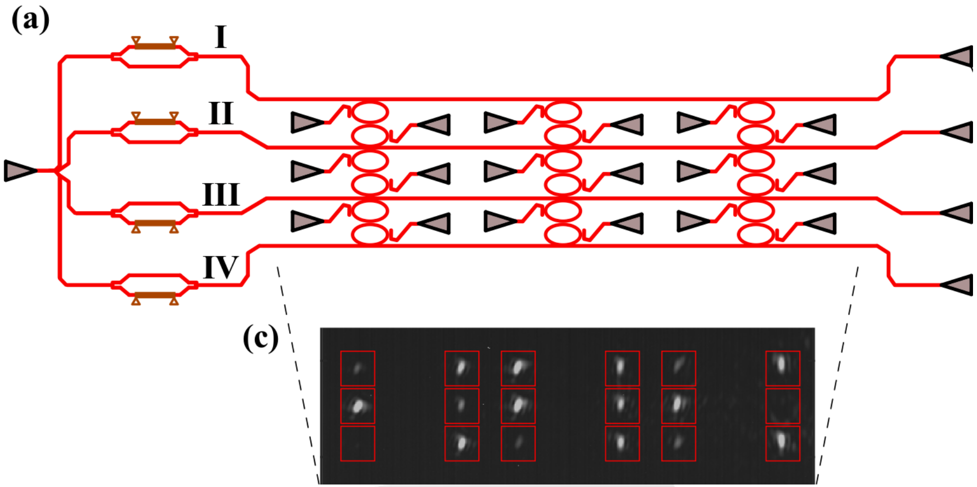


S. Biasi, R. Franchi, L. Cerini, L. Pavesi; “An array of microresonators as a photonic extreme learning machine”. APL Photonics, (2023).

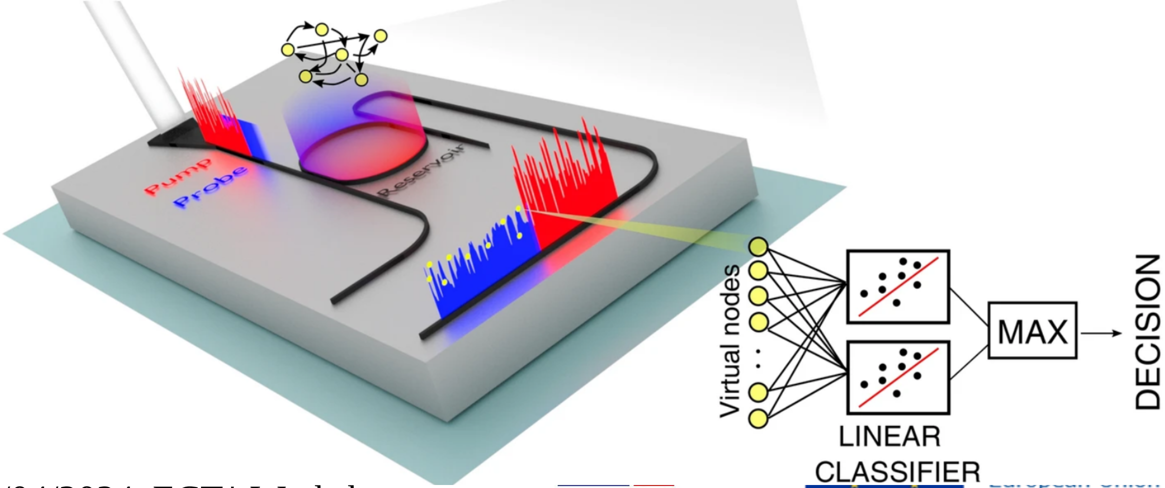
Applications: MRRs for reservoir computing



F. Denis-Le Coarer et al., "All-optical reservoir computing on a photonic chip using silicon-based ring resonators," IEEE Journal of Selected Topics in Quantum Electronics, (2018)



Still, relatively **small networks**



Borghi, M., Biasi, S., and Pavesi, L.. "Reservoir computing based on a silicon microring and time multiplexing for binary and analog operations." Scientific Reports, (2021).