Optical neural networks and integrated photonics: non-linear microresonators

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BACKUP
neuromorphic photonics and the brain

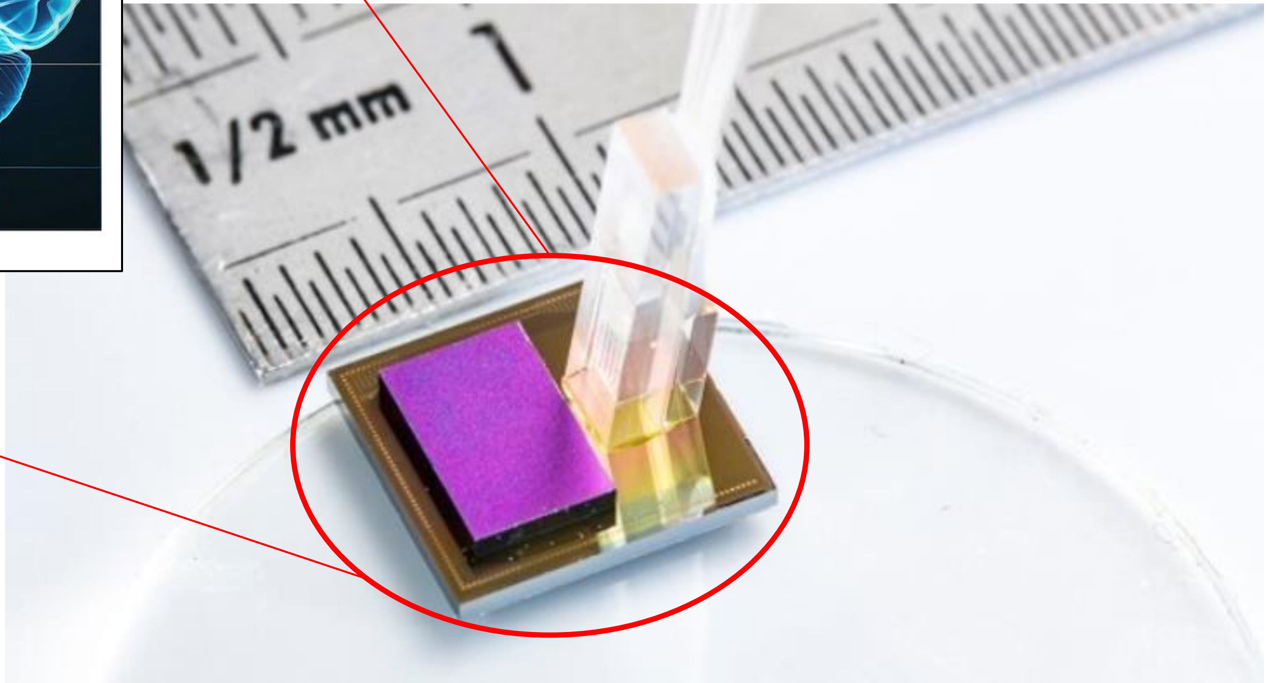
erc
European Research Council
Established by the European Commission

Outline

- Part 1: Introduction
  - Artifical Neural Network
  - Integrated photonics
  - Overview on neuromorphic photonics
  - Focus on non-linear microresonator dynamics
- Part 2: recent experimental results
  - Optical reservoir network based on uring
  - Optical complex perceptron
  - All optical signal recovery (ALPI project)

Artificial neural network

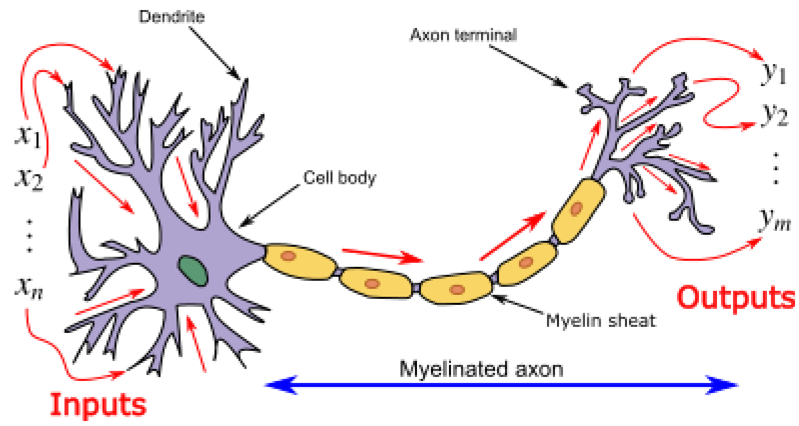
Picture Credit: Stanford University

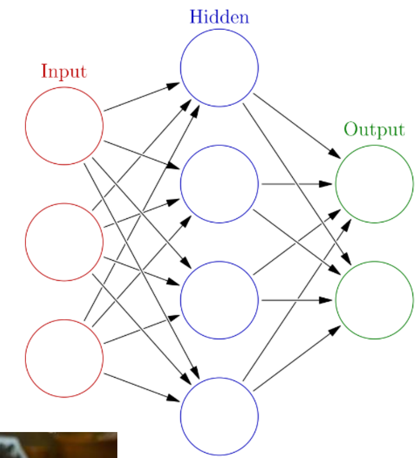


IRIS project: grid of 1000 resonators equipped with fully integrated CMOS eletronics (flip chip)

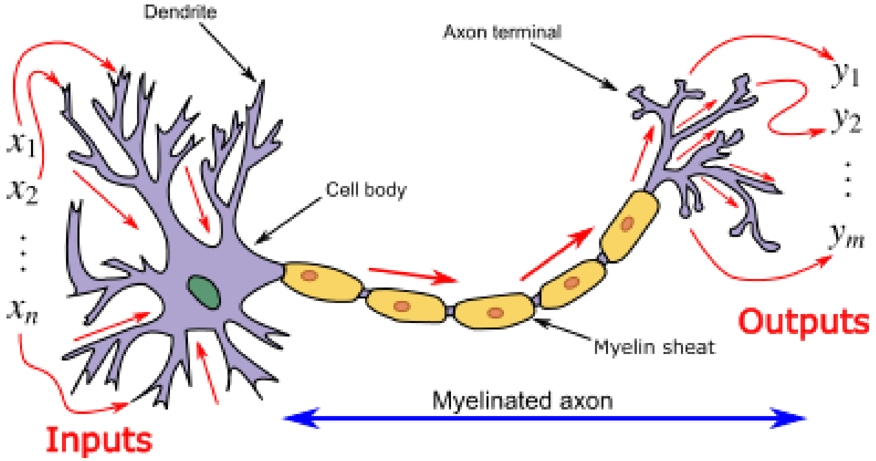
Artificial neural network

- Neurons
  - activation function
- Connections and weights
  - what is trained
- Propagation function
  - weigthed sum
- Organization
  - Network topology
- Learning
  - Network adaptation to a specific task
  - Neural networks learn by processing examples

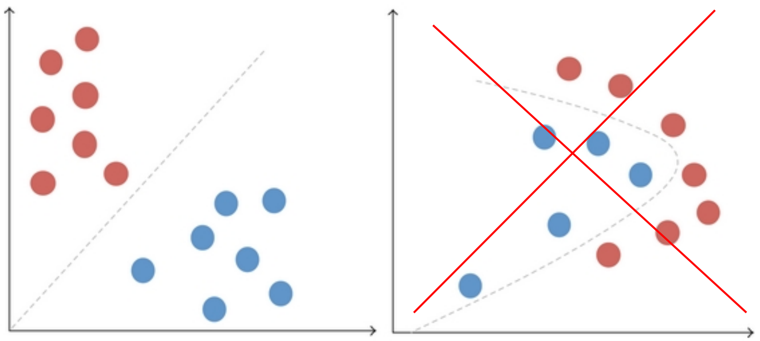


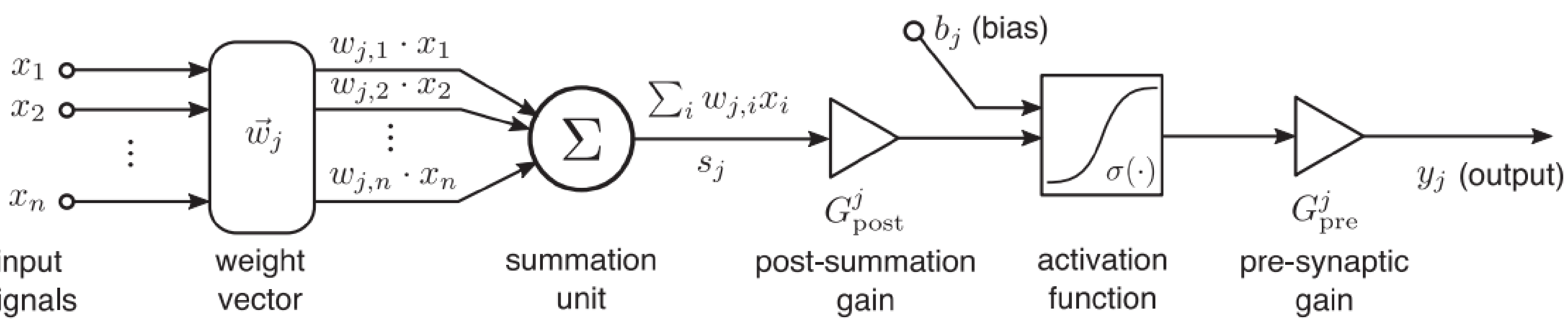


ANN: Perceptron



Linear classifier



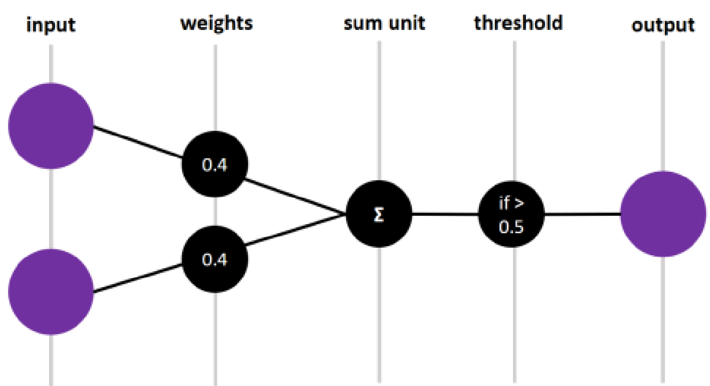


$$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0, \\ 0 & \text{otherwise} \end{cases}$$

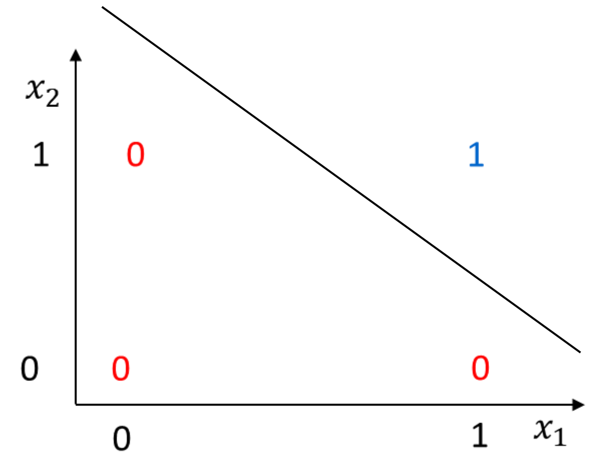
De Lima, Thomas Ferreira, et al. "Machine learning with neuromorphic photonics." *Journal of Lightwave Technology* 37.5 (2019): 1515-1534.

ANN: Perceptron

Linear binary problem: AND gate

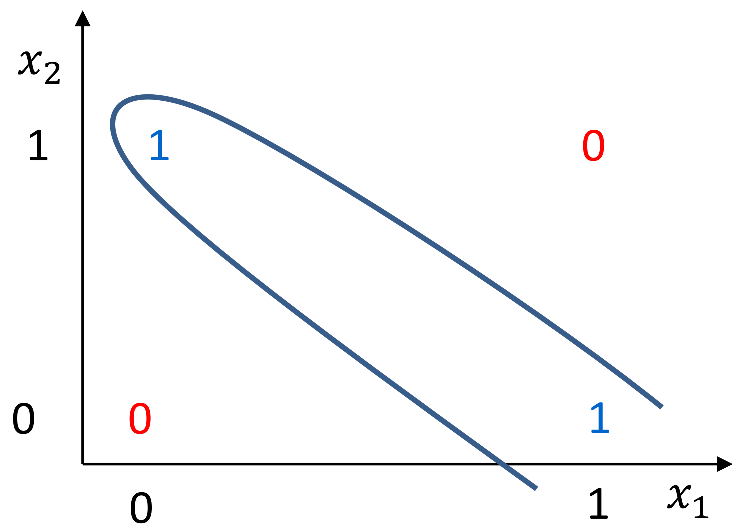


x_1	x_2	Out
0	0	0
0	1	0
1	0	0
1	1	1



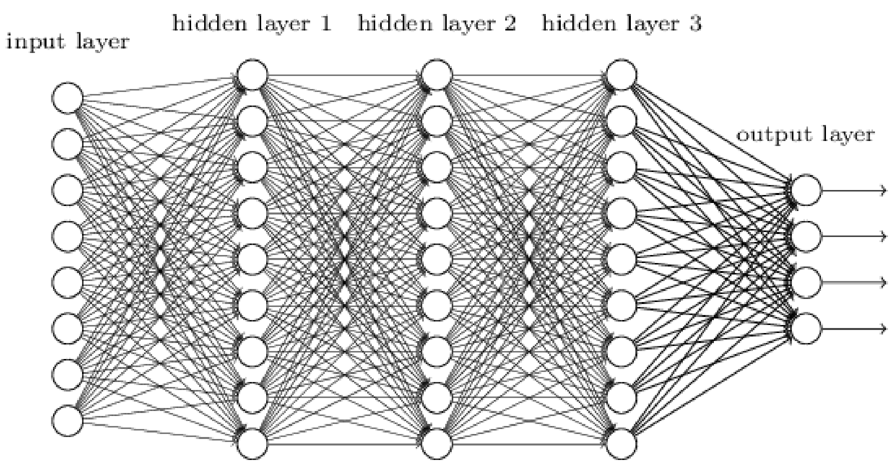
Non-linear binary problem: XOR gate

x_1	x_2	Out
0	0	0
0	1	1
1	0	1
1	1	0

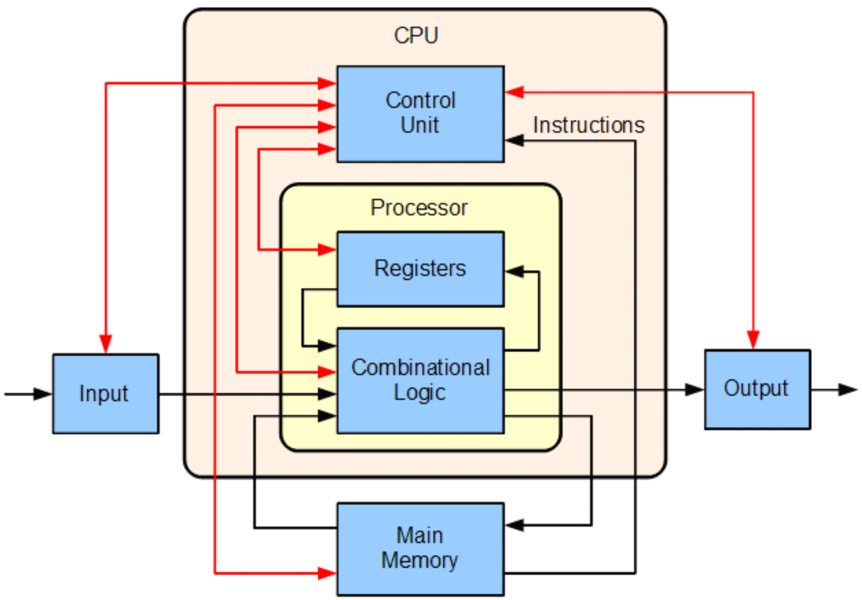


Artificial neural network

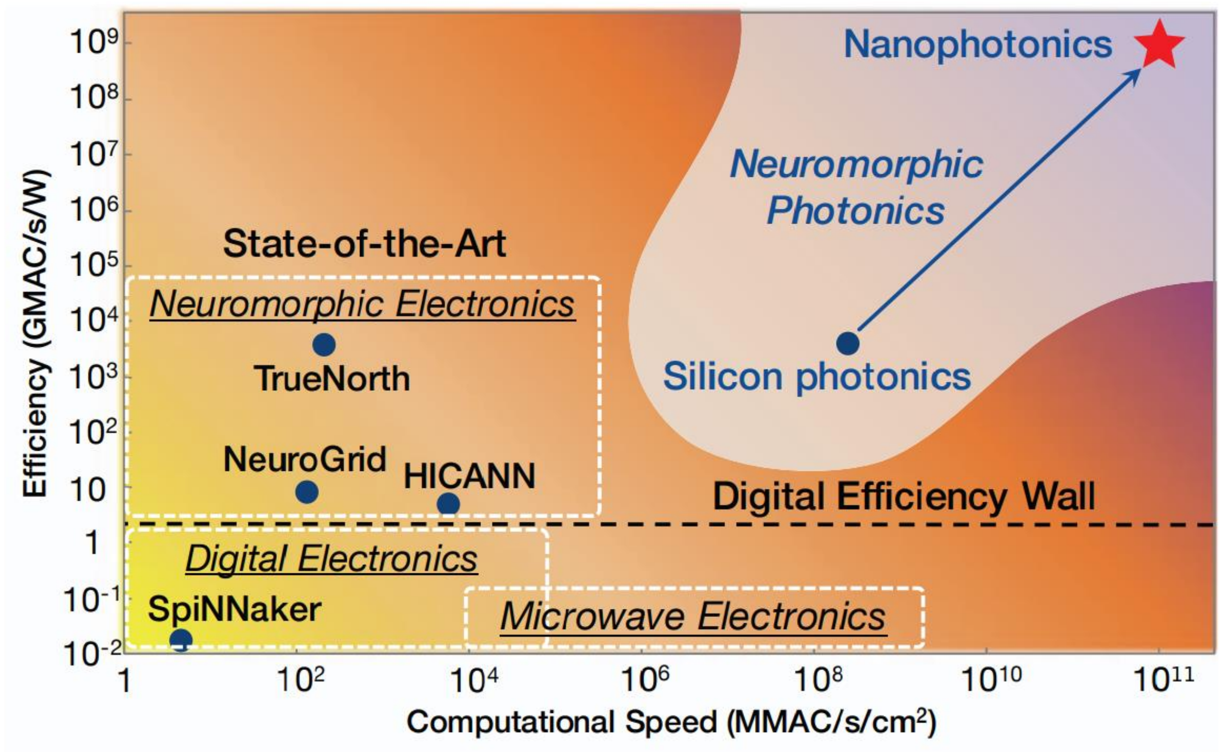
Artificial Neural Network



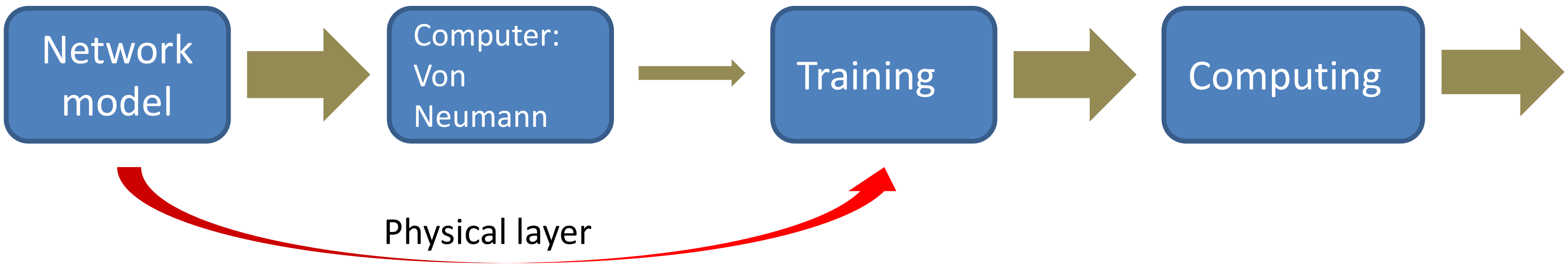
Von Neumann architecture



Neuromorphic photonics

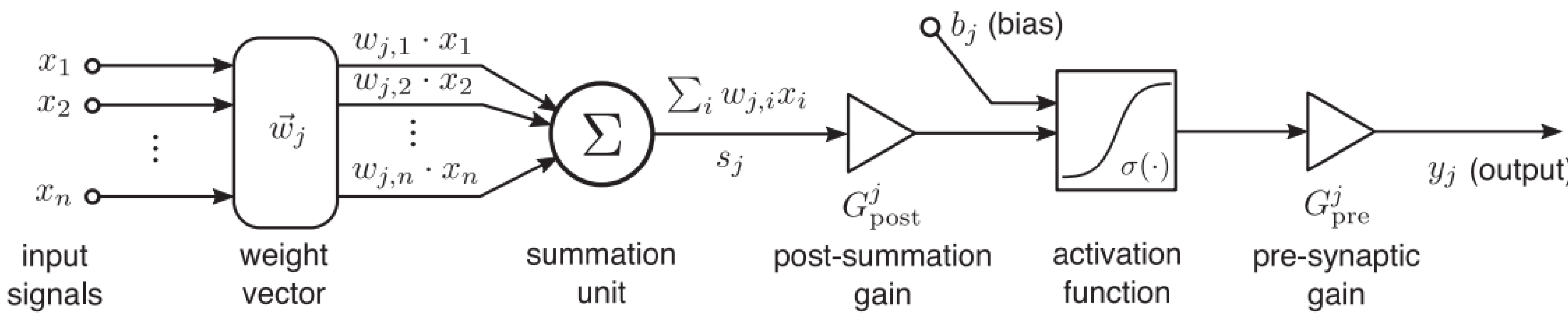


Prucnal, Paul R., and Bhavin J. Shastri. *Neuromorphic photonics*. CRC Press, 2017.



Neuromorphic photonics

Adapt the paradigm developed on software-based ANN to the law of optics



(Fading) Memory	Non-linearity	Inputs mixing/summing

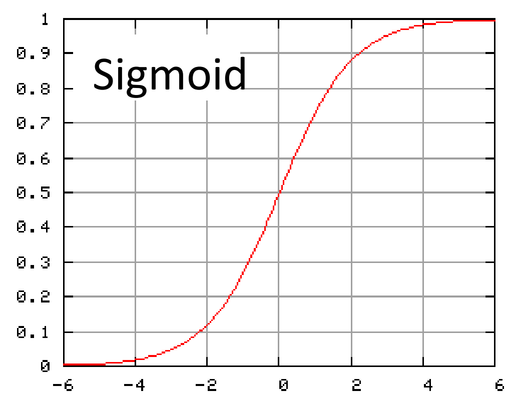
- Delay lines
- Spirals
- Group delay

Storing 10 bit @10 Gbps

1 ns

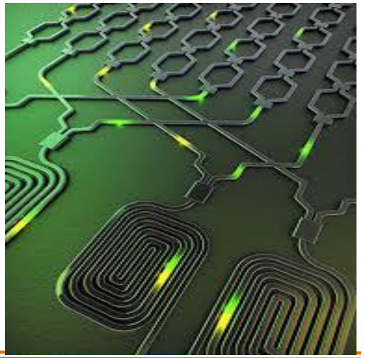
WG 7.5 cm

Loss 18.5 dB



If no gain

$0 < w_j < 1$

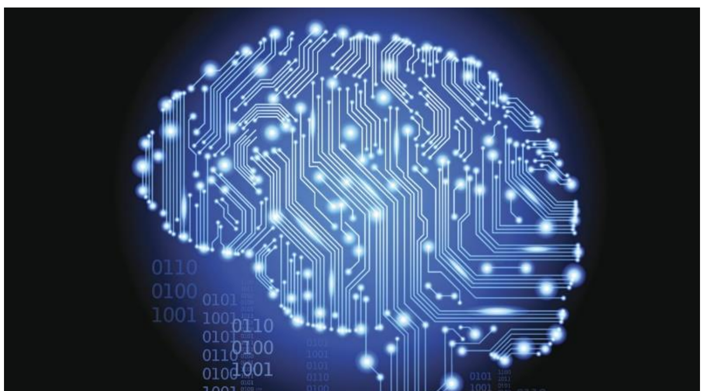


Why photonics?

- Ligth is fast!
  - Biological neuron timescale *ms*
  - Optical neurons timescale *ps*
  - Information processing at TBit/s
- Power efficient (hopefully)
- Parallelism (WDM)
- Passive interconnect BW 4 THz
- Fast optoelectronic devices

Factor of 10^9!!

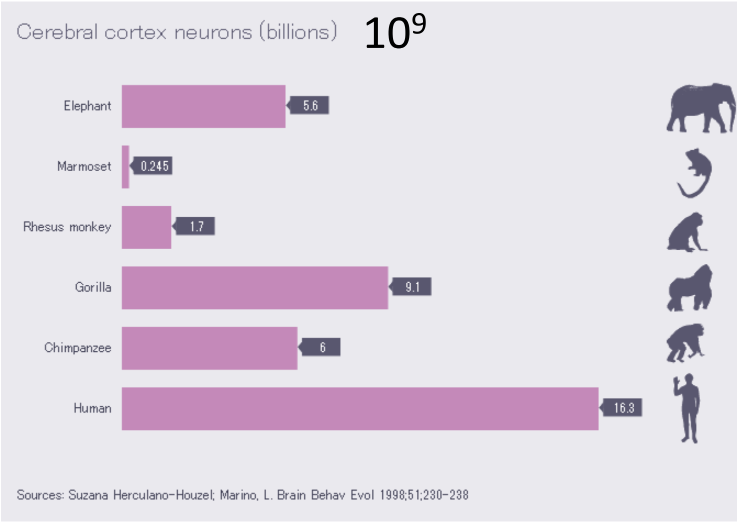
Brain learning process 15 years



Artificial optical brain 0.5 seconds

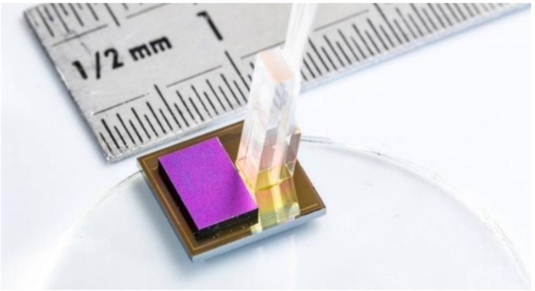
Integration is the key!

- Brain capabilities is related to neurons number
- Even a mouse has **milions** of neurons
- A lot of optical components are required to mimic biology



Bulk optics

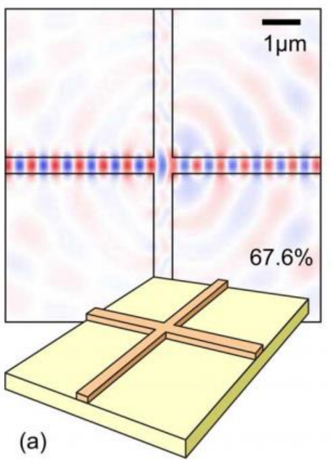
Integrated optics

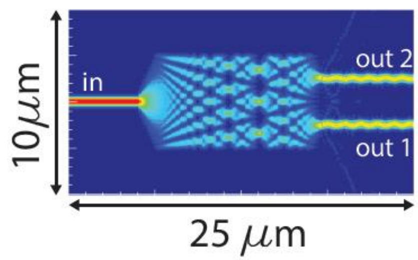


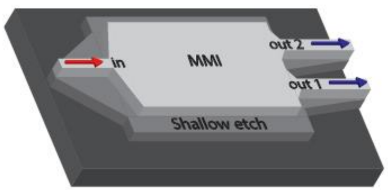
More than 1k optical components

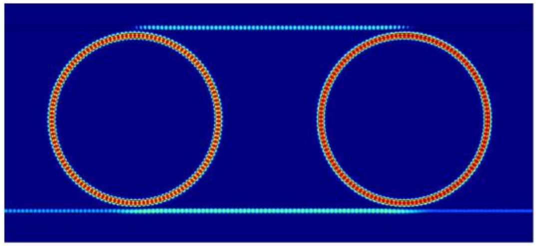
Devices example

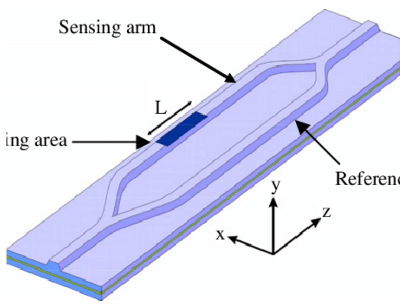
- Main building blocks of an optical integrated circuit
  - Grating coupler
  - Crossing
  - Power splitters (direction coupler, MMI)
  - Mach Zhender
  - Microresonator

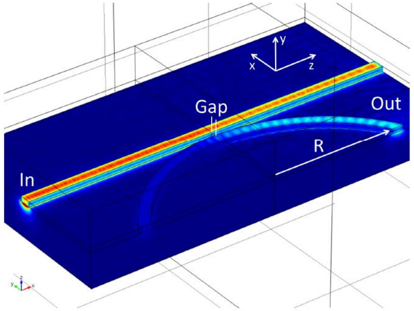


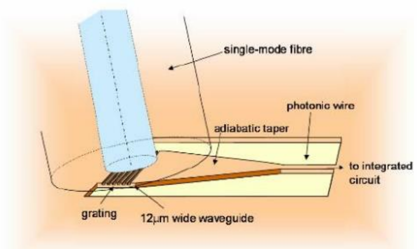






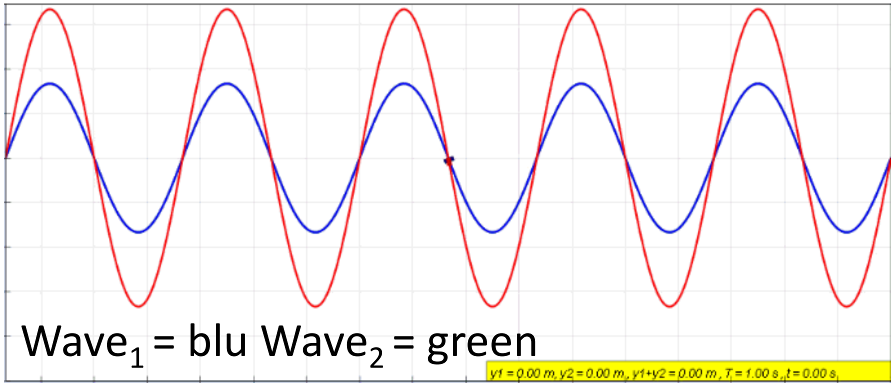


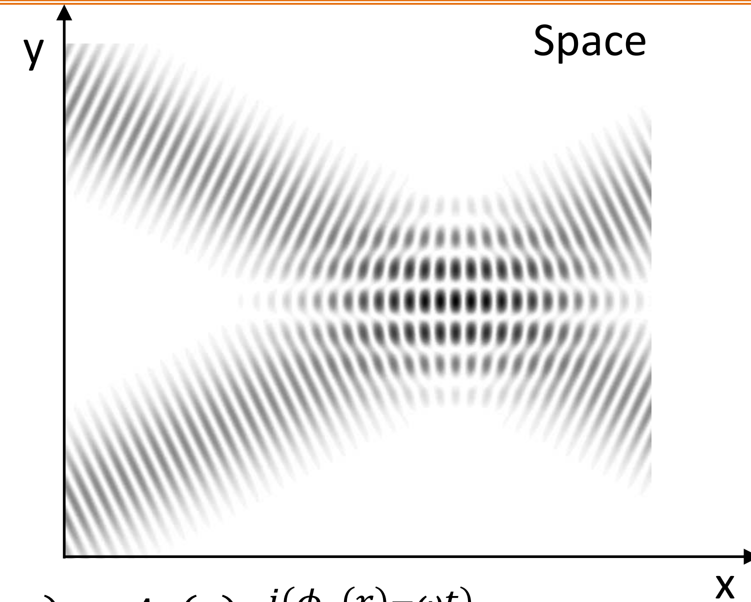




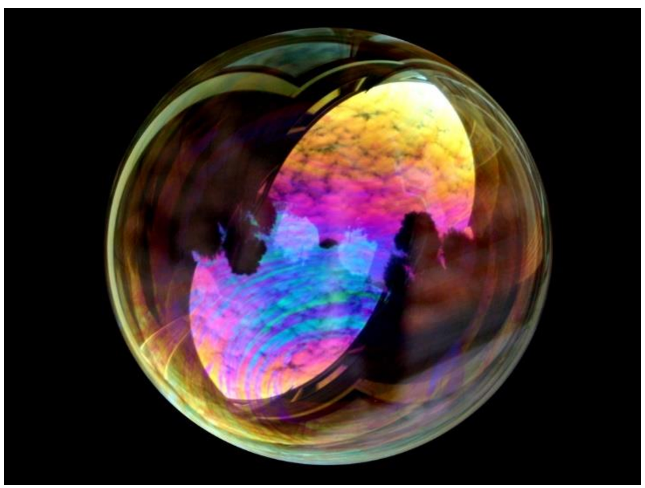
Ligth interference

Time





Thin film interference



$$U_1(r,t) = A_1(r)e^{i(\phi_1(r)-\omega t)}$$

$$U_2(r,t) = A_2(r)e^{i(\phi_2(r)-\omega t)}$$

$$U(r,t) = U_1(r,t) + U_2(r,t)$$

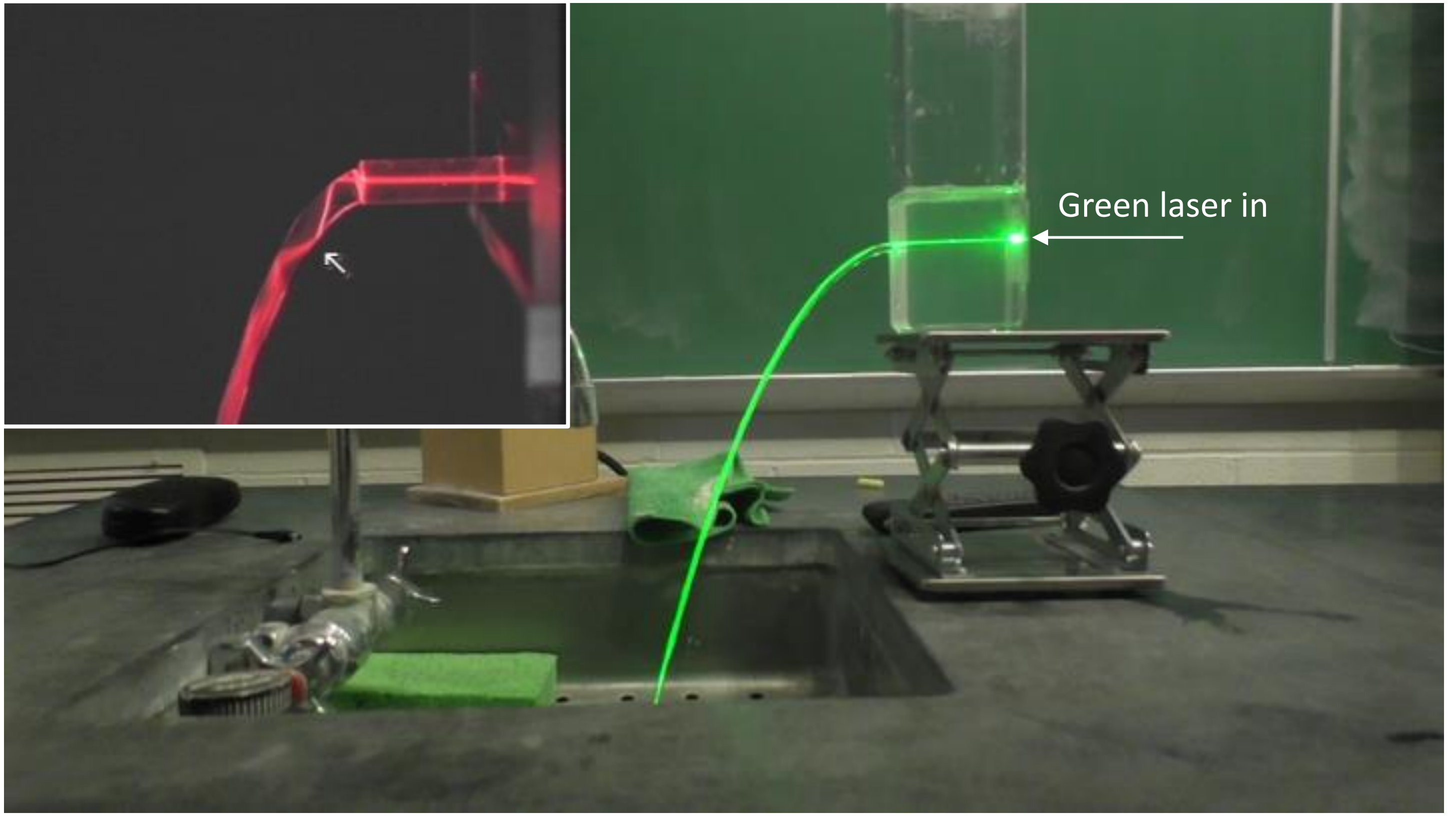
activation

$$I(r) = \int U(r,t)\, U^*(r,t) dt$$

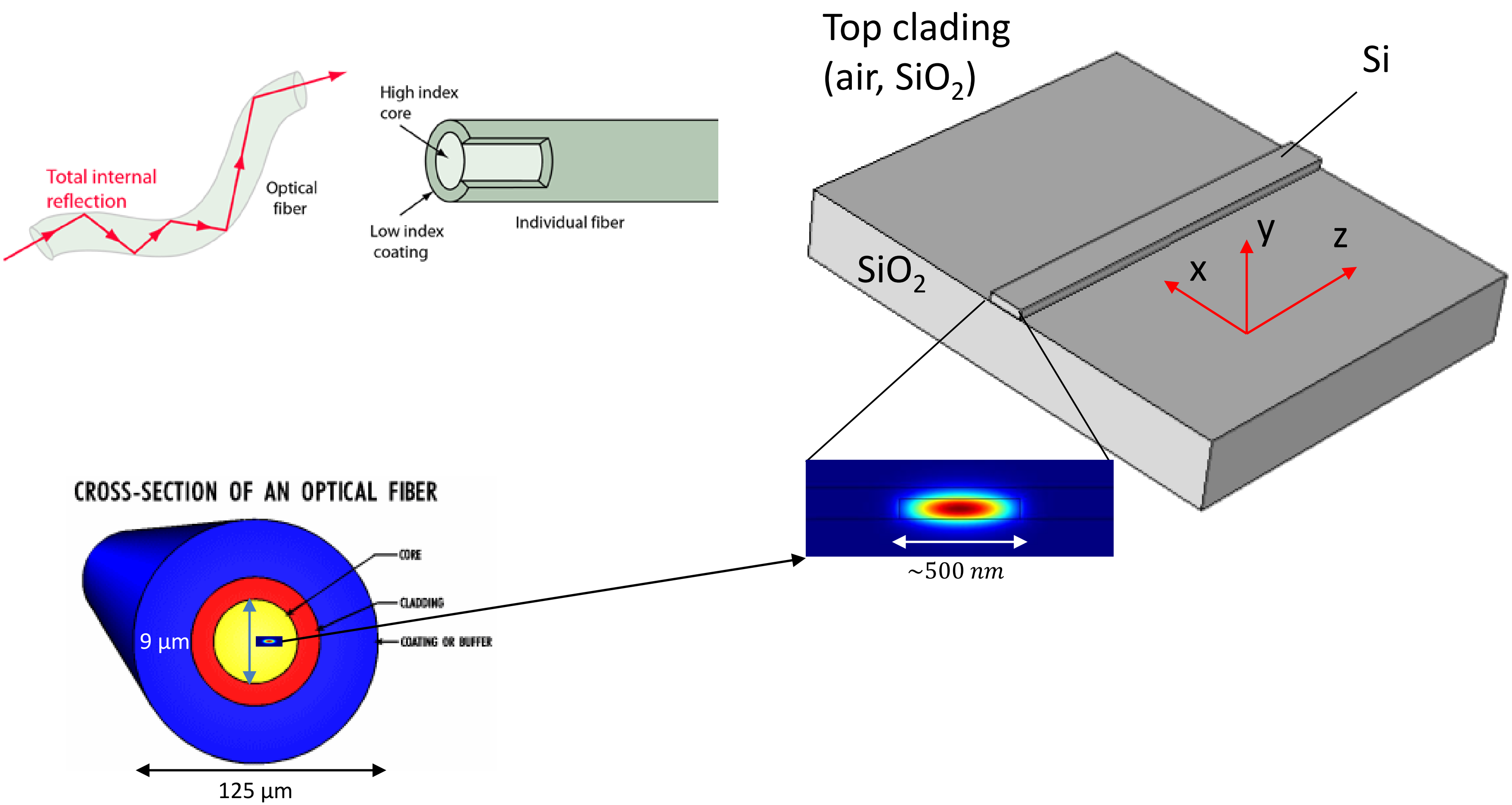
$$I(r) = I_1(r) + I_2(r) + 2\sqrt{I_1(r) I_2(r)} \cos(\phi_1(r) - \phi_2(r))$$

Optical waveguide principle

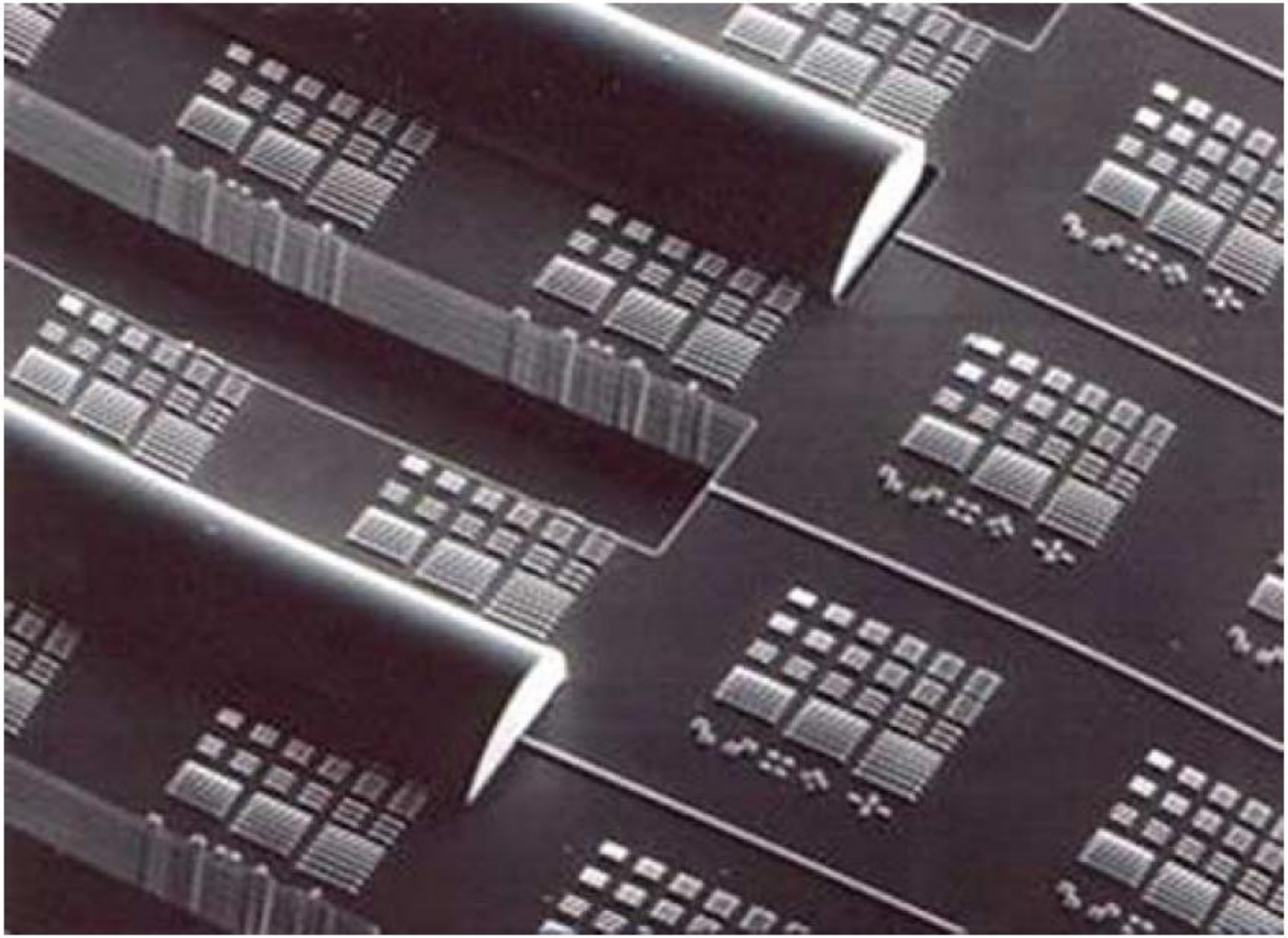
- Index contrast $n_{core} > n_{clad}$
- Total internal reflection



Optical waveguide: fiber vs wire

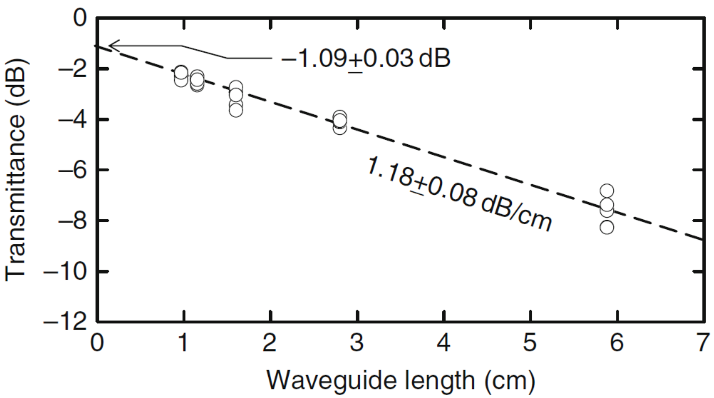


Optical waveguide: fiber vs wire

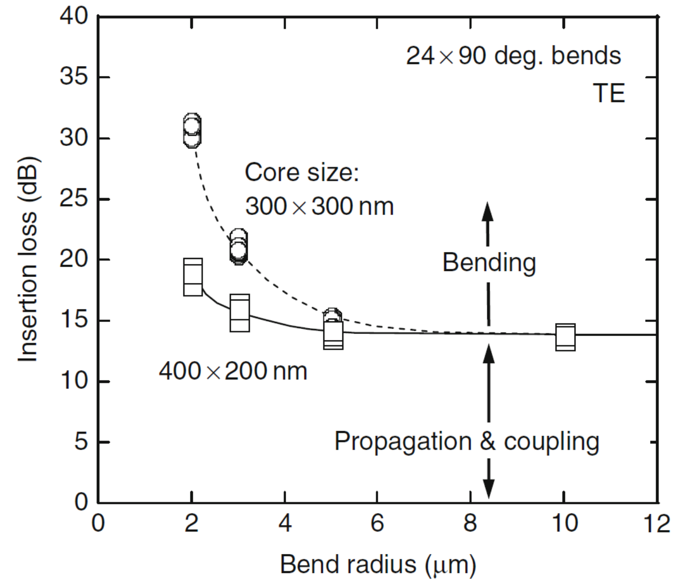


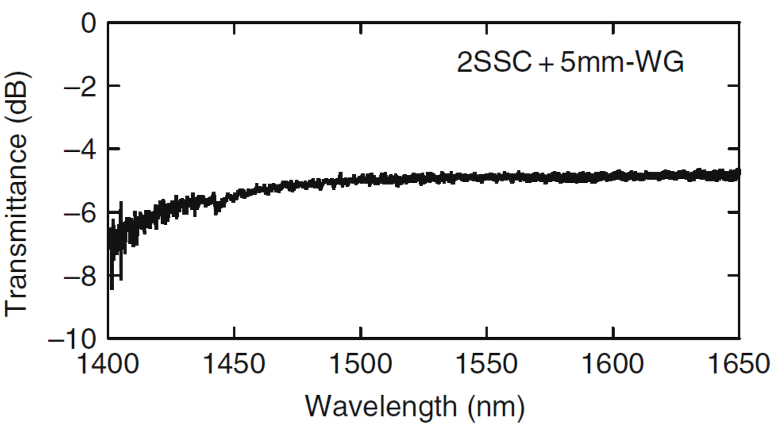
Optical waveguide performance

Propagation loss

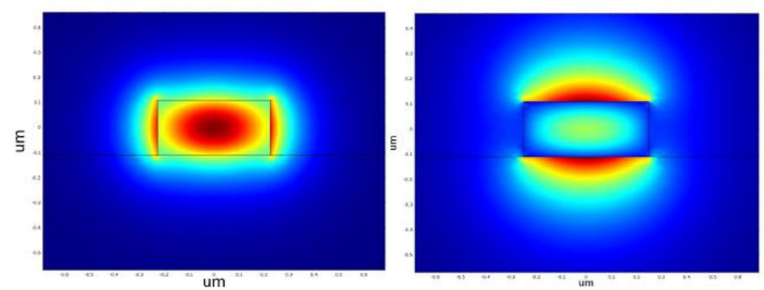


Bend loss

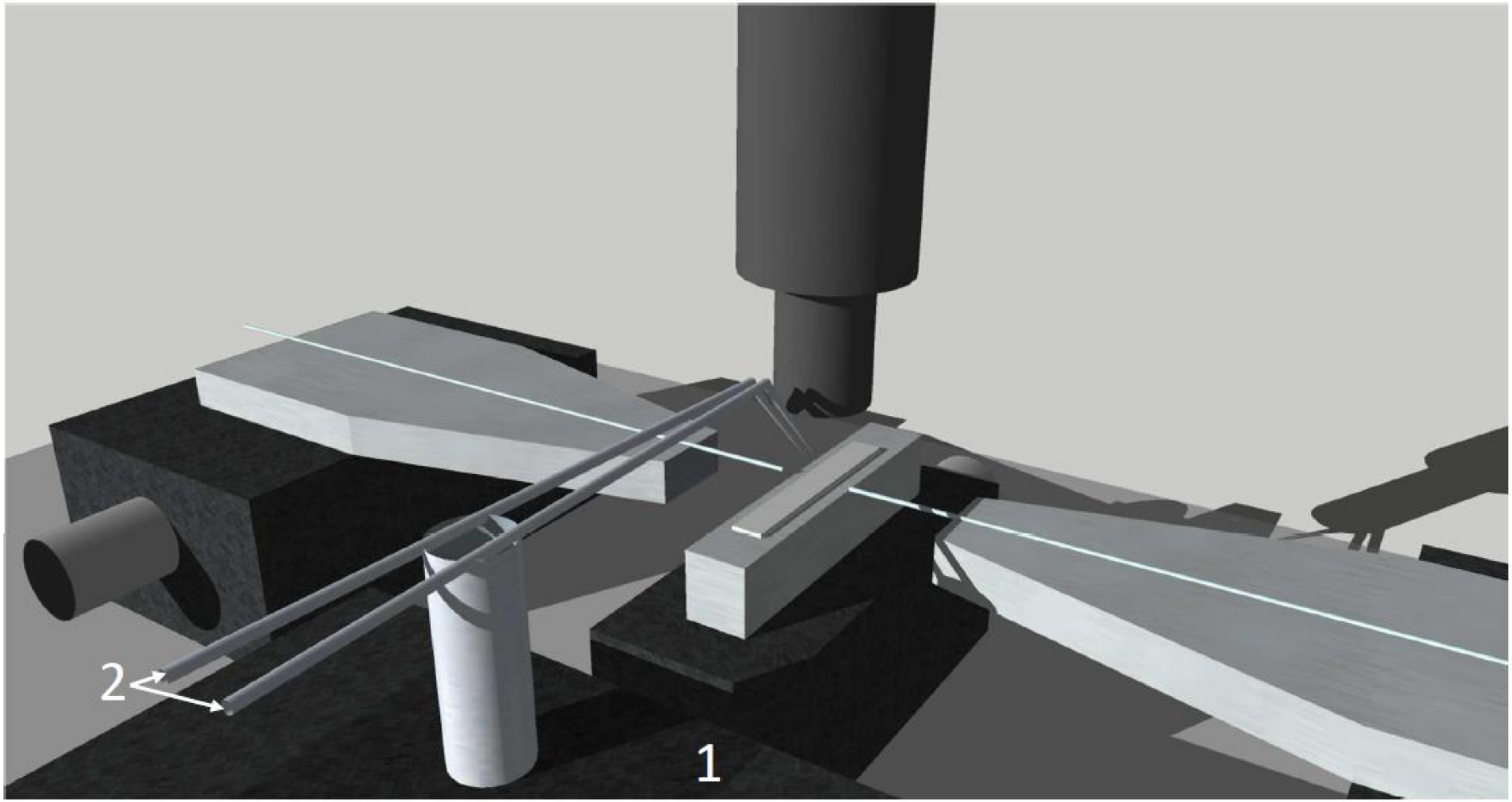




Bandwidth C-band (4 THz)

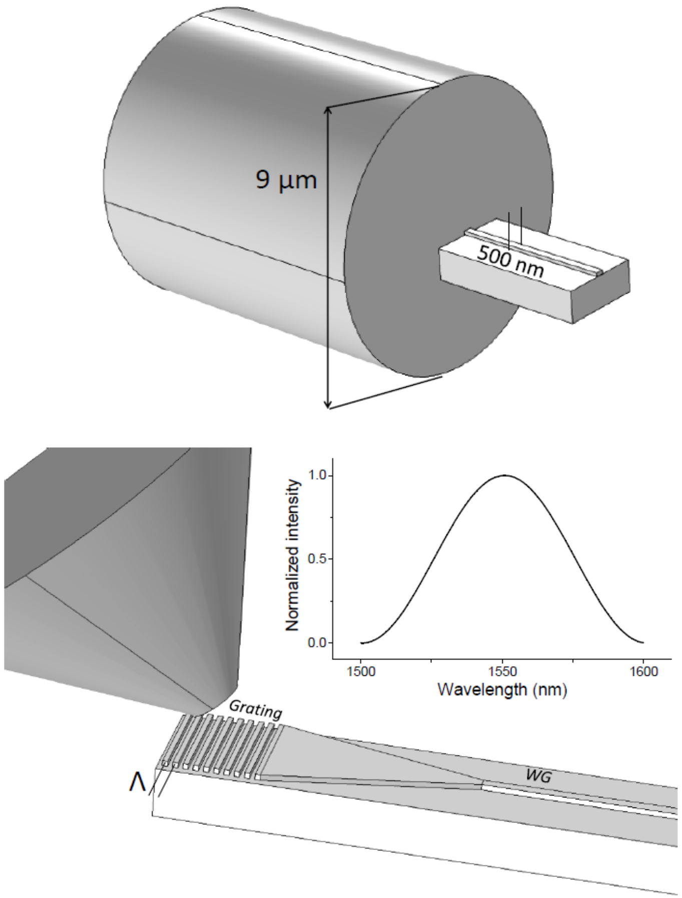


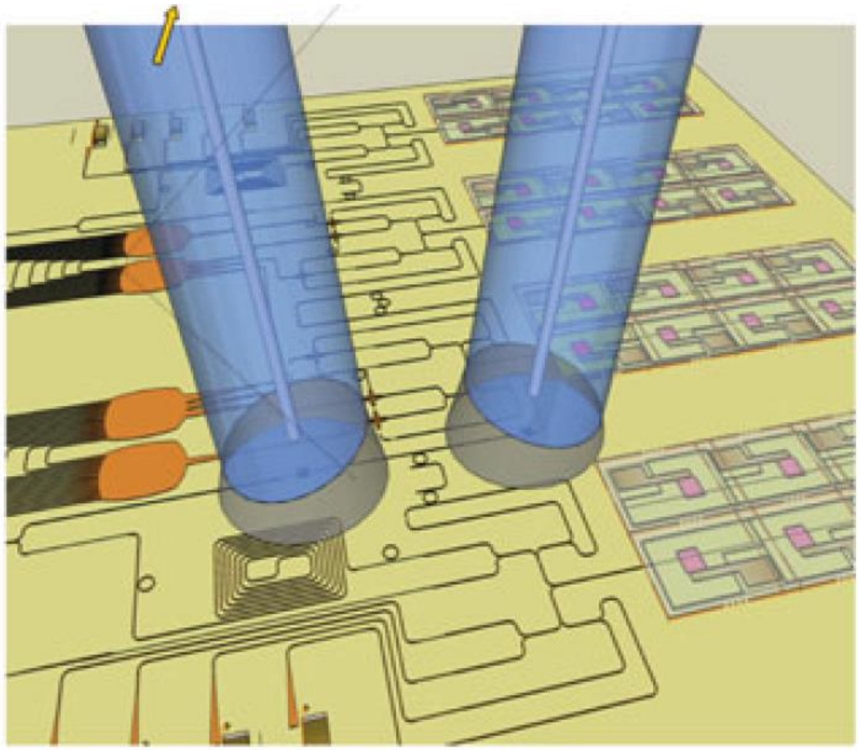
Fiber coupled setup for chip testing



Grating coupler

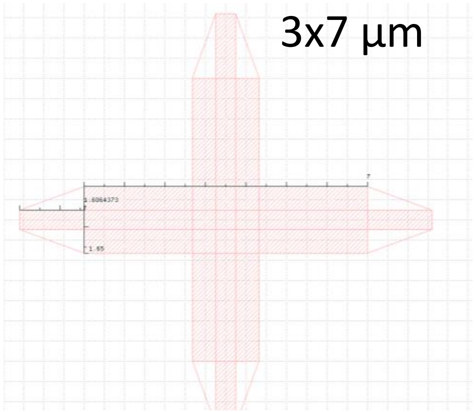
Coupling into and out-of the chip

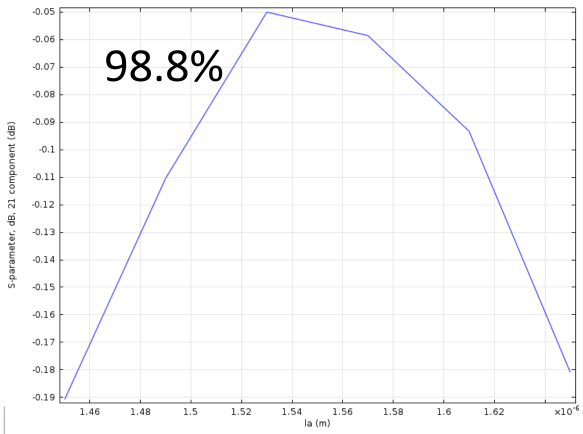


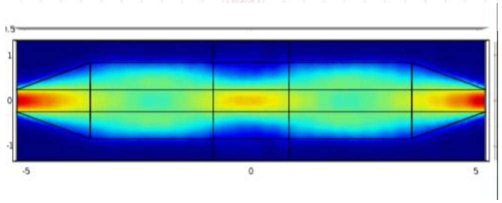


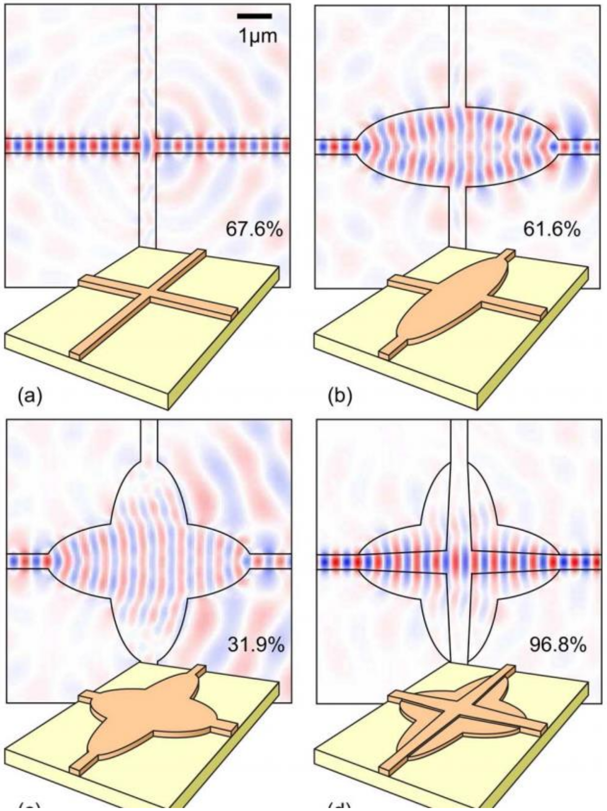
Crossing

- Cross of two waveguides
- Waveguide matrix



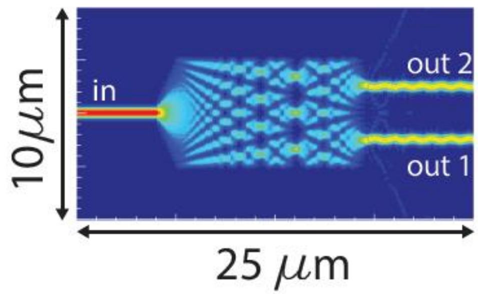


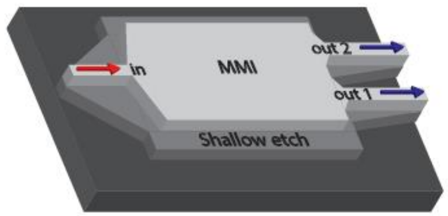


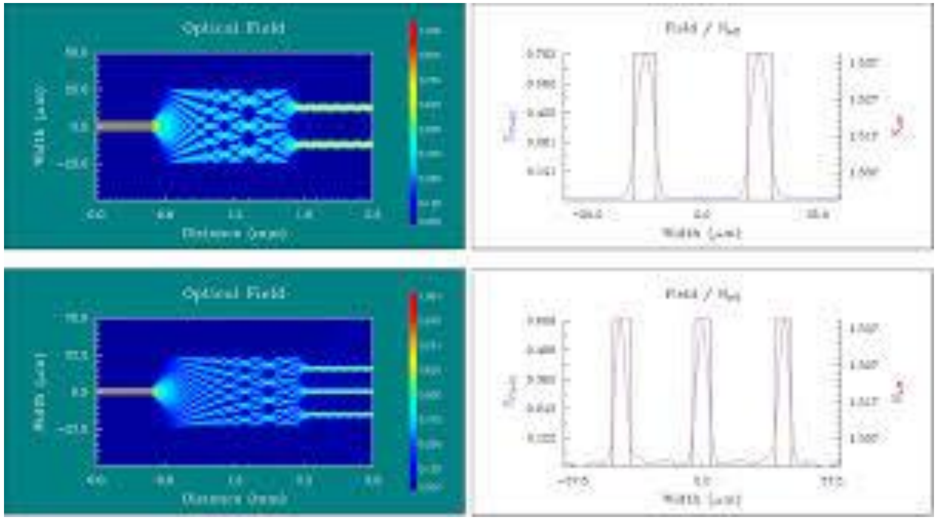


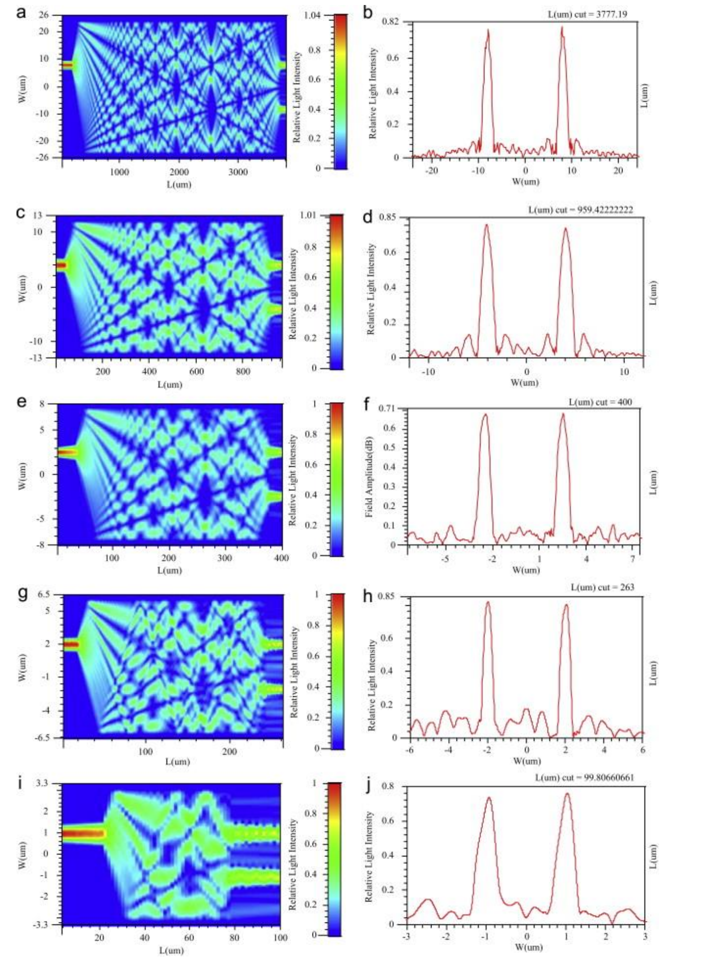
Power splitter: MMI

- Multimode Interference Waveguides
- Symmetric spatial interference (self-imaging)

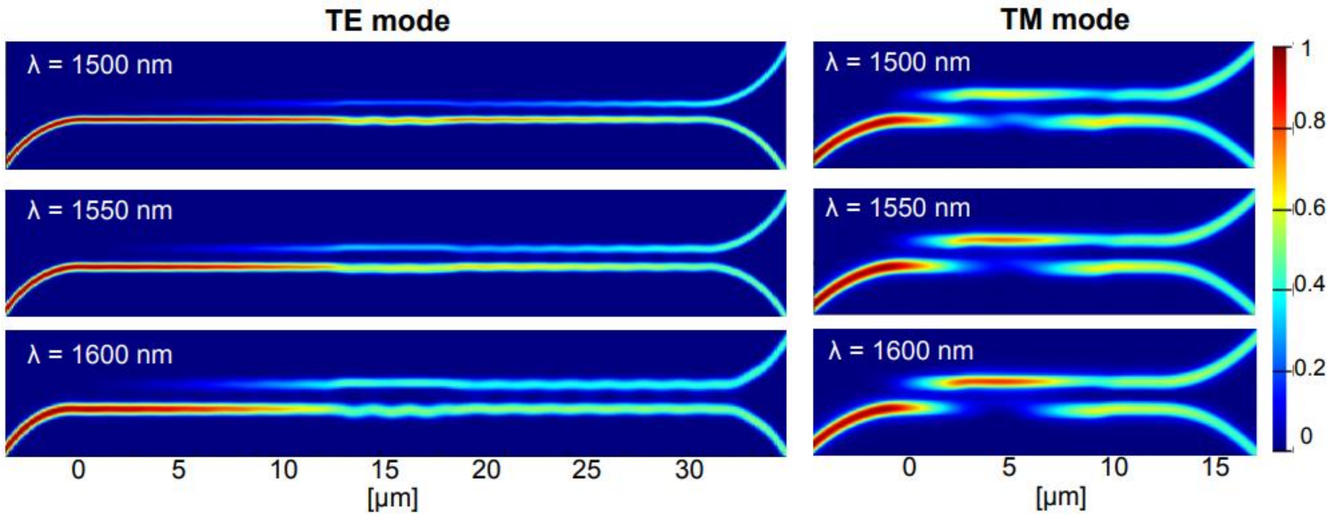






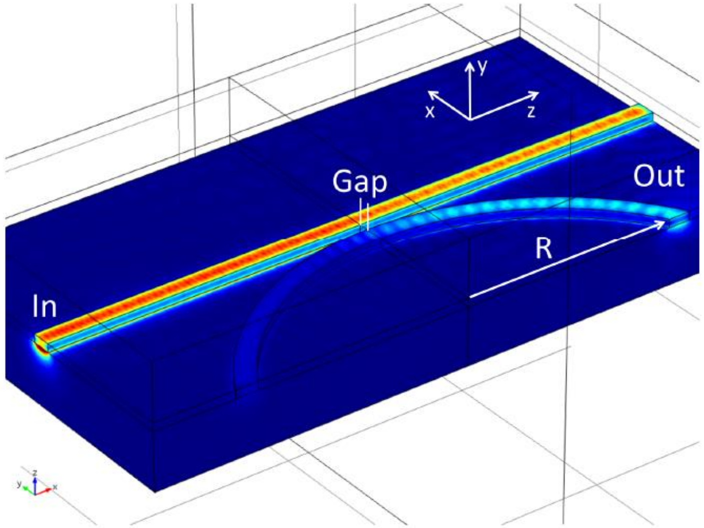


Power splitter: directional coupler



Straigth-Straigth

Straigth-bent



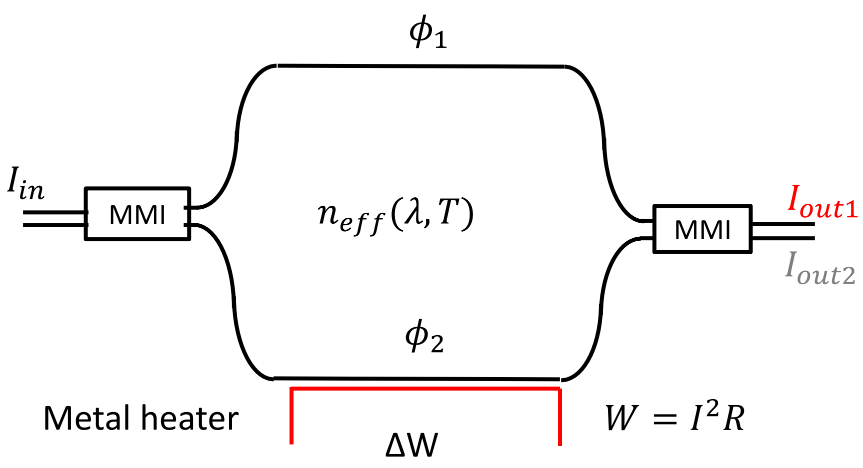
Mach Zehnder Interferometer

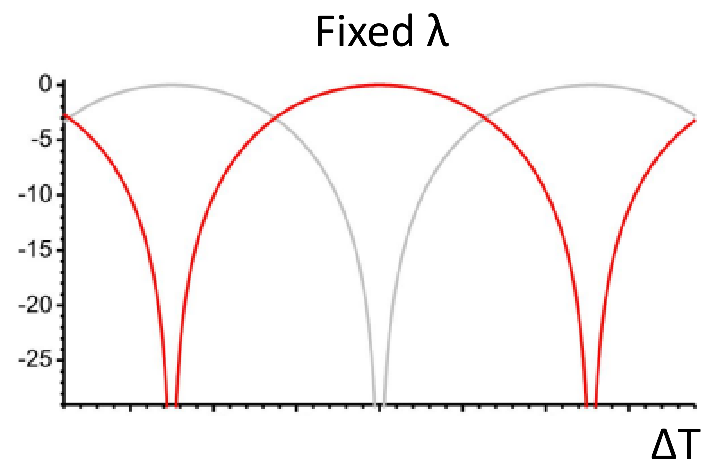
- Variable Optical Attenuator
- Unitary trasformation
- Signal mixing

$$I_{out1} = \frac{1}{2} I_{in}\,(1 + \cos(\Delta\phi))$$

$$I_{out2} = \frac{1}{2} I_{in}\,(1 - \cos(\Delta\phi))$$

$$\Delta\phi = \frac{2\pi}{\lambda}(n_{eff}L_1 - n_{eff}L_2)$$

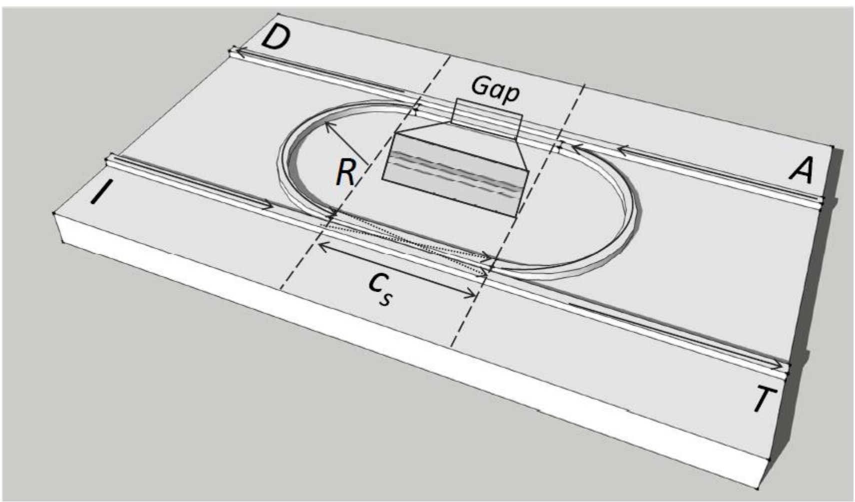


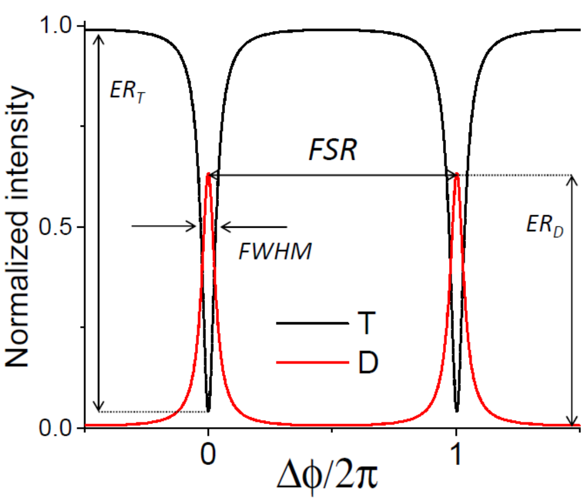


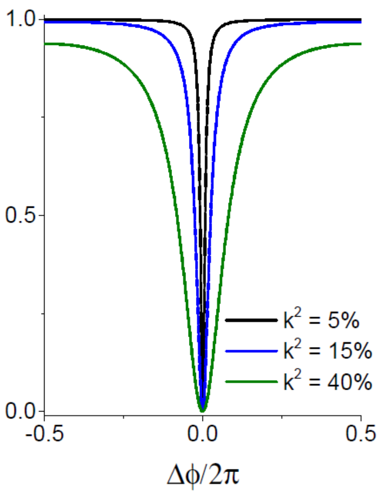
Micro-resonator

- Resonant fenomena
- Constructive interference for $m\lambda_0 = n_{eff}(\lambda, T)\, p \quad with\ p = 2\pi R + 2C_s$

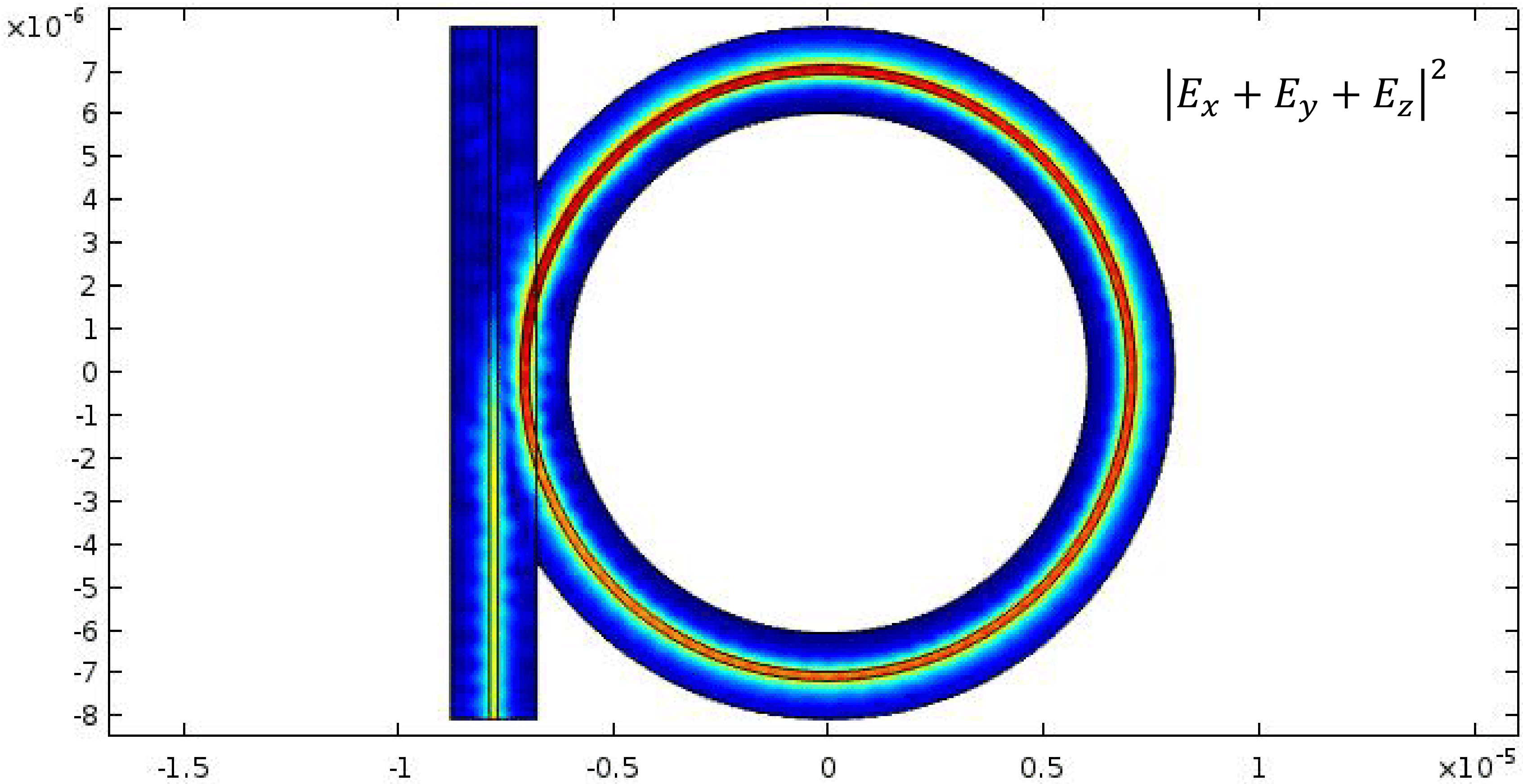
$n_{eff}(\lambda, T)$





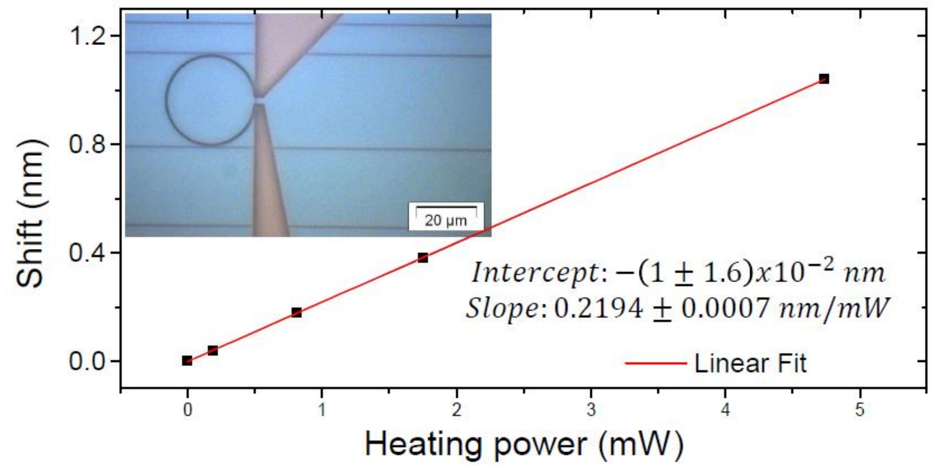


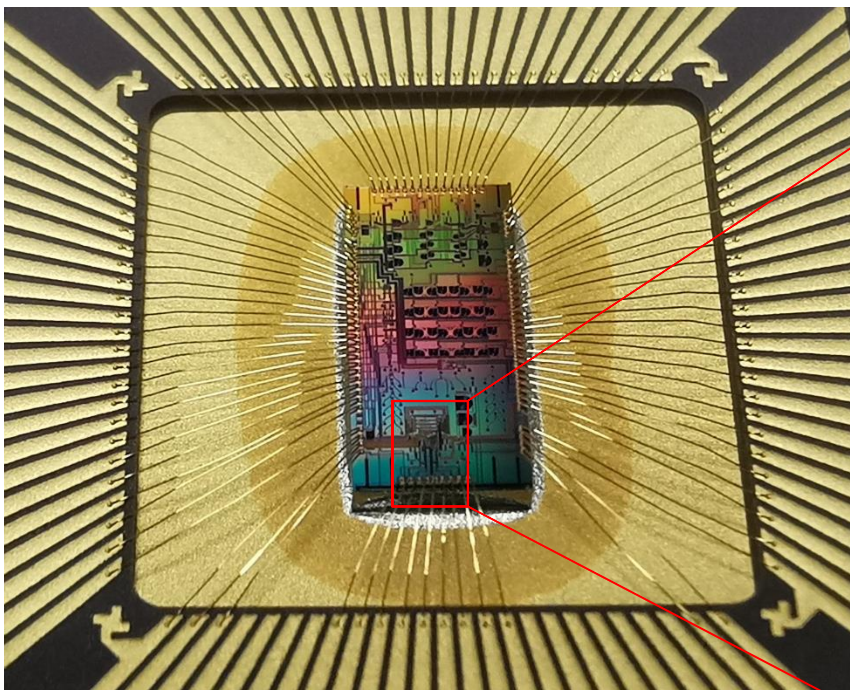
Micro-resonator: Enhancement factor

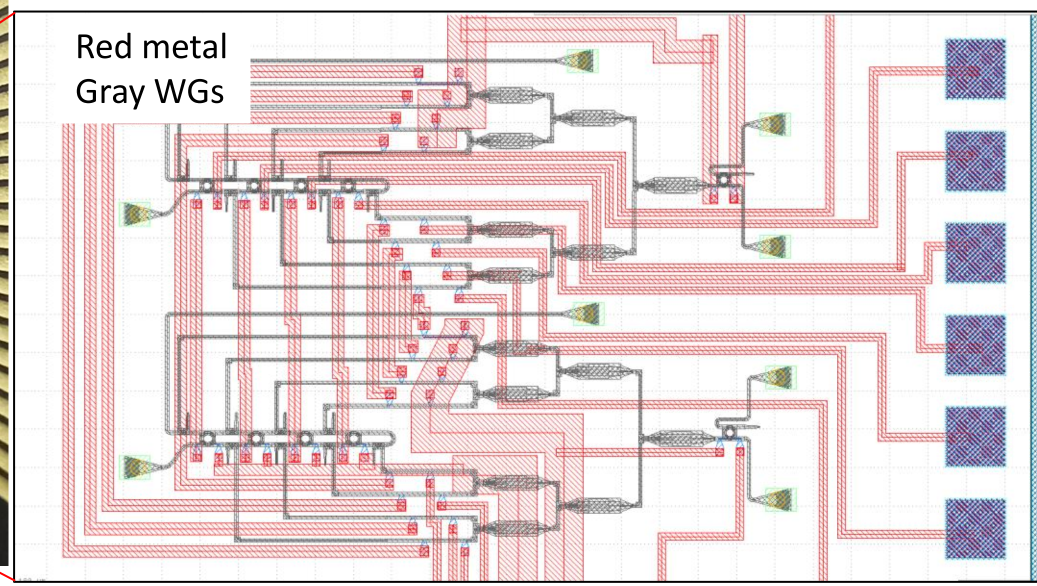


Micro-resonator tuning

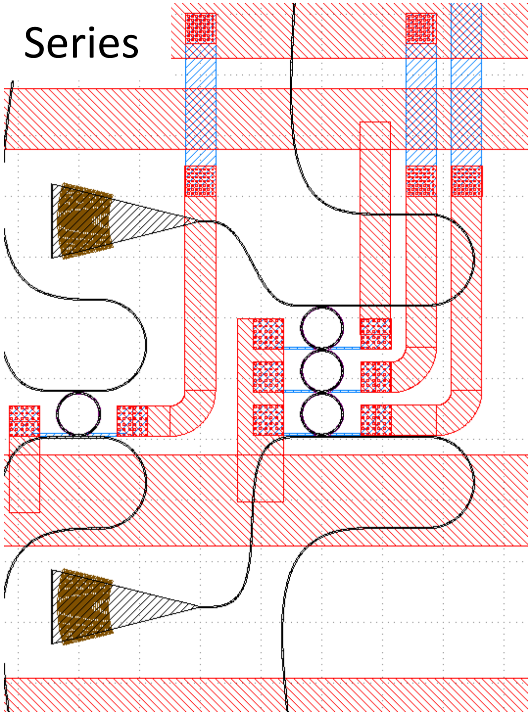
- Thermal tuning $m\lambda_0 = n_{eff}(\lambda, T)p$
- Carriers injection
- Strain induced by piezoelectric material
- Phase change material

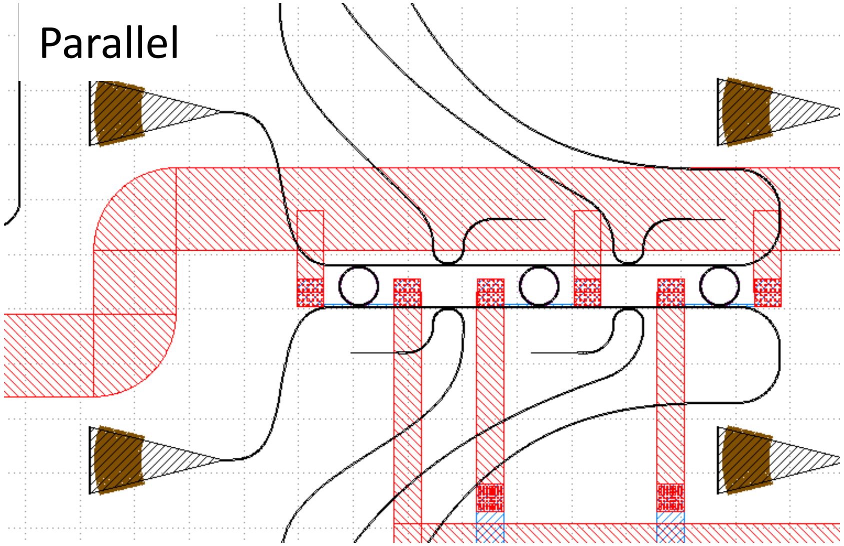


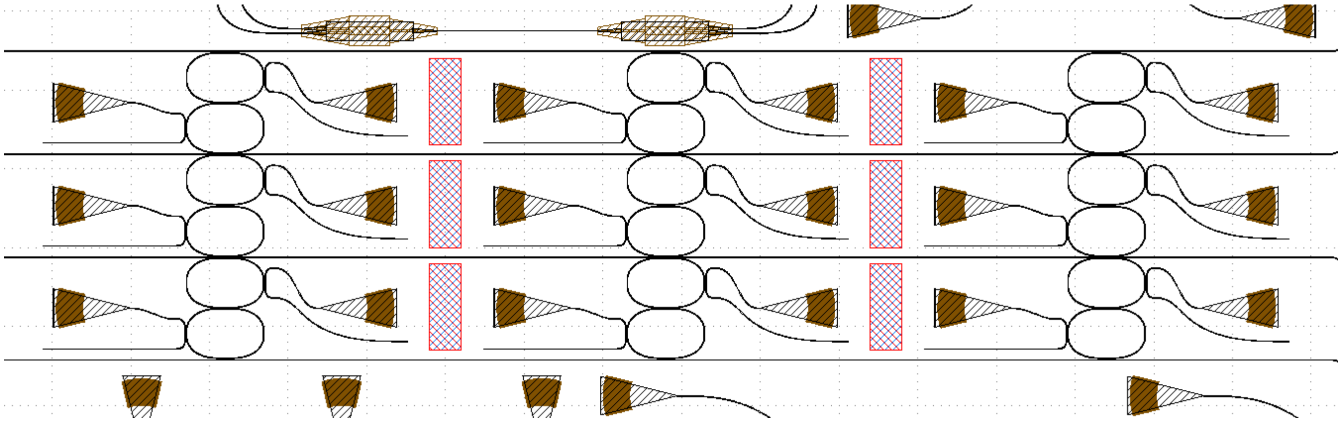




Multiple micro-resonators

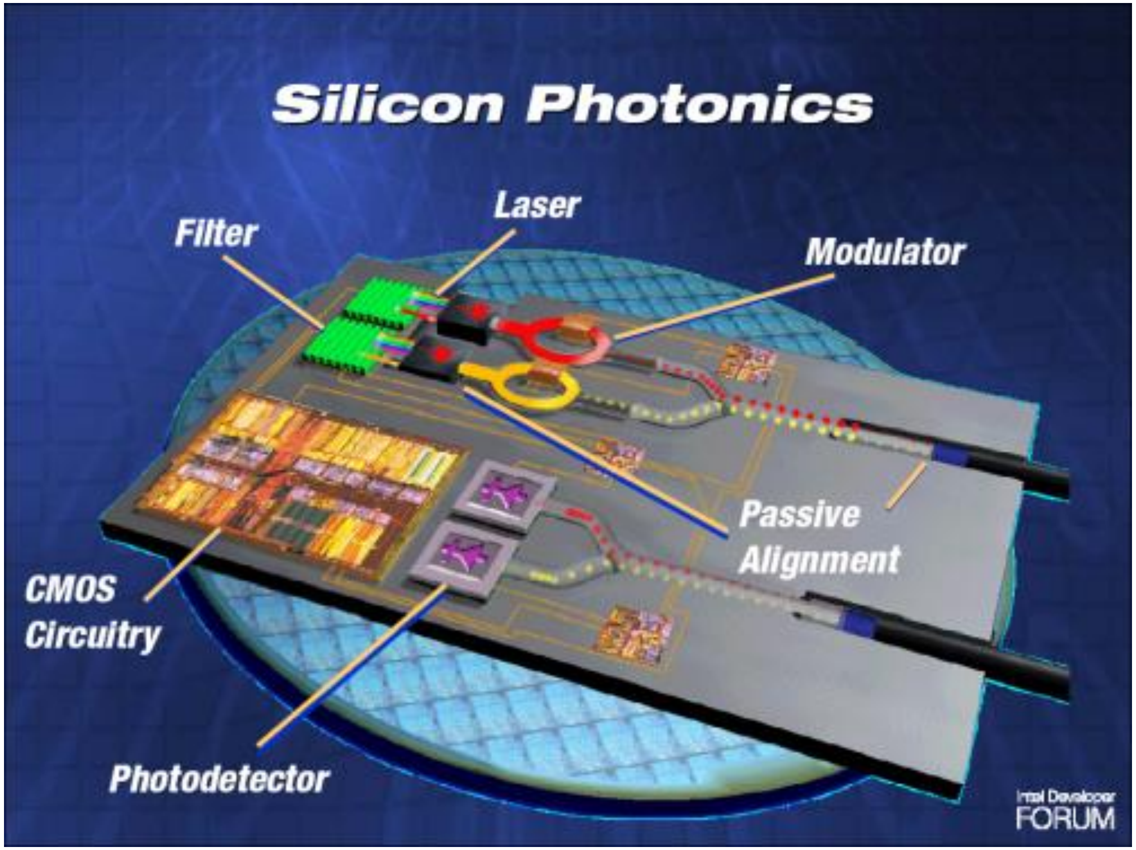


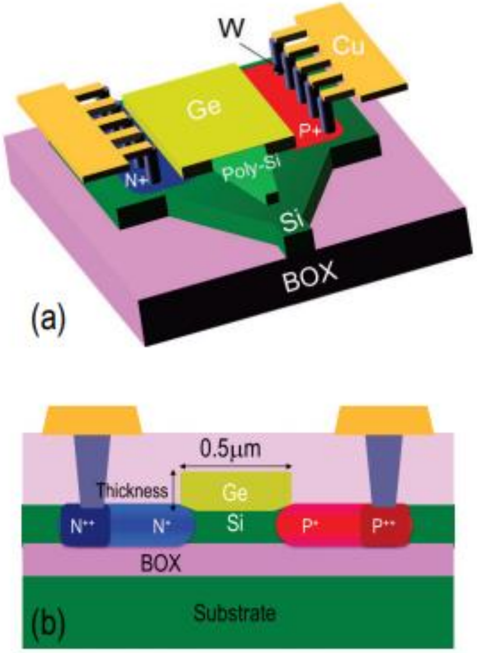




Integrated photodiode

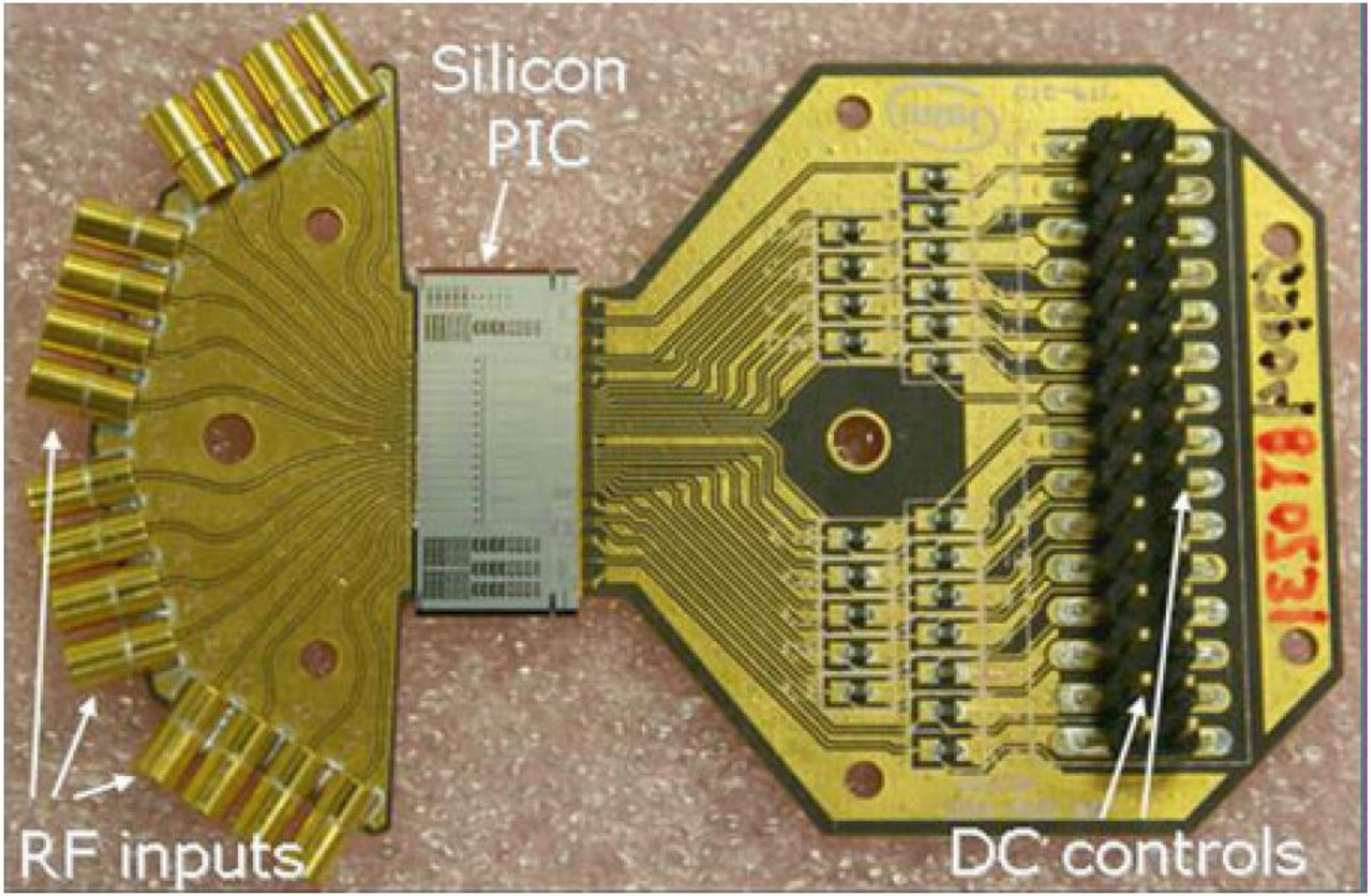
- Si-Ge photodiode
- Optical to electrical conversion → $|\cdot|^2$ (non linearity)
- Directily on chip, fast, TIA close to detector



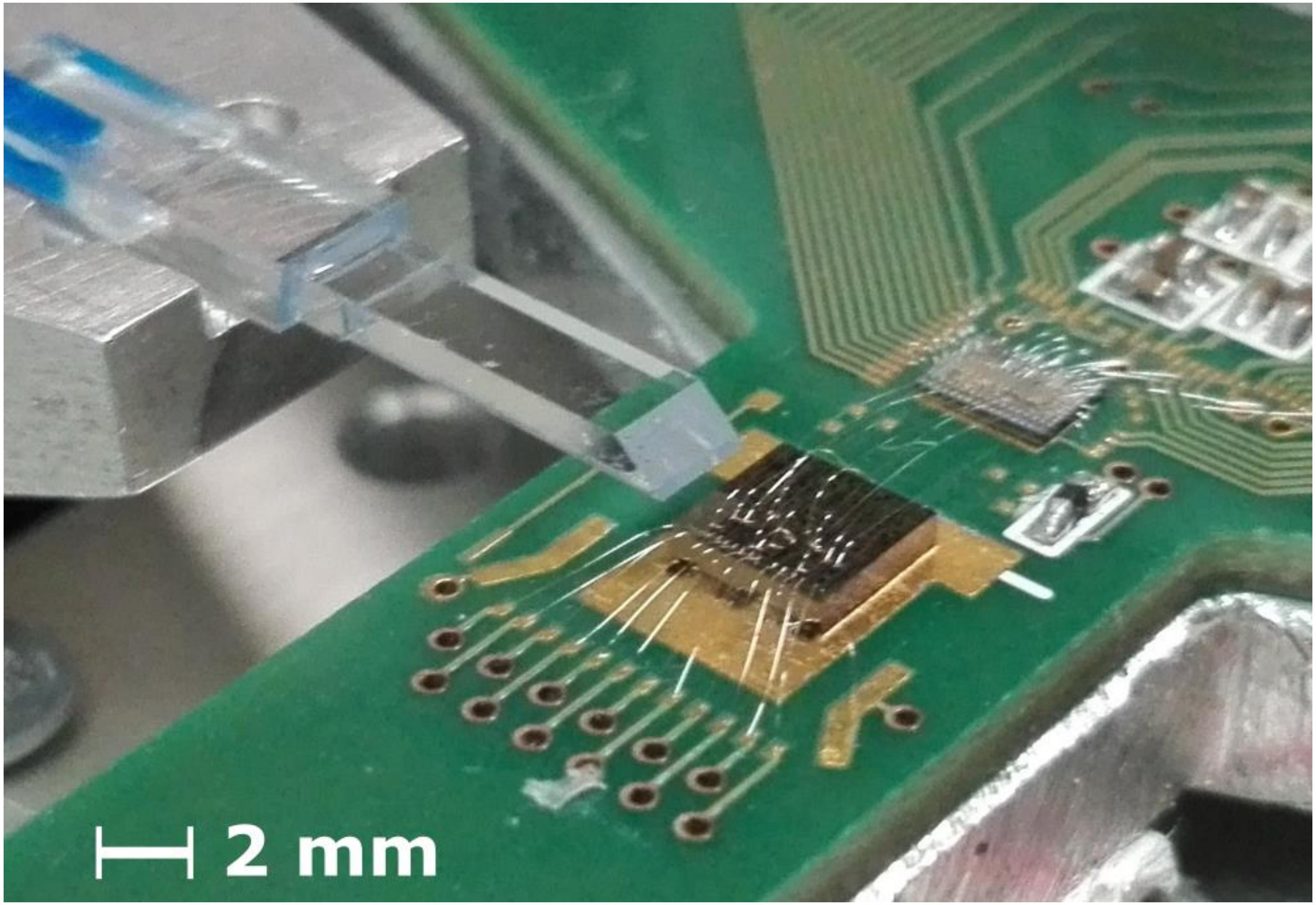


https://www.readkong.com/page/silicon-photonics-8907971

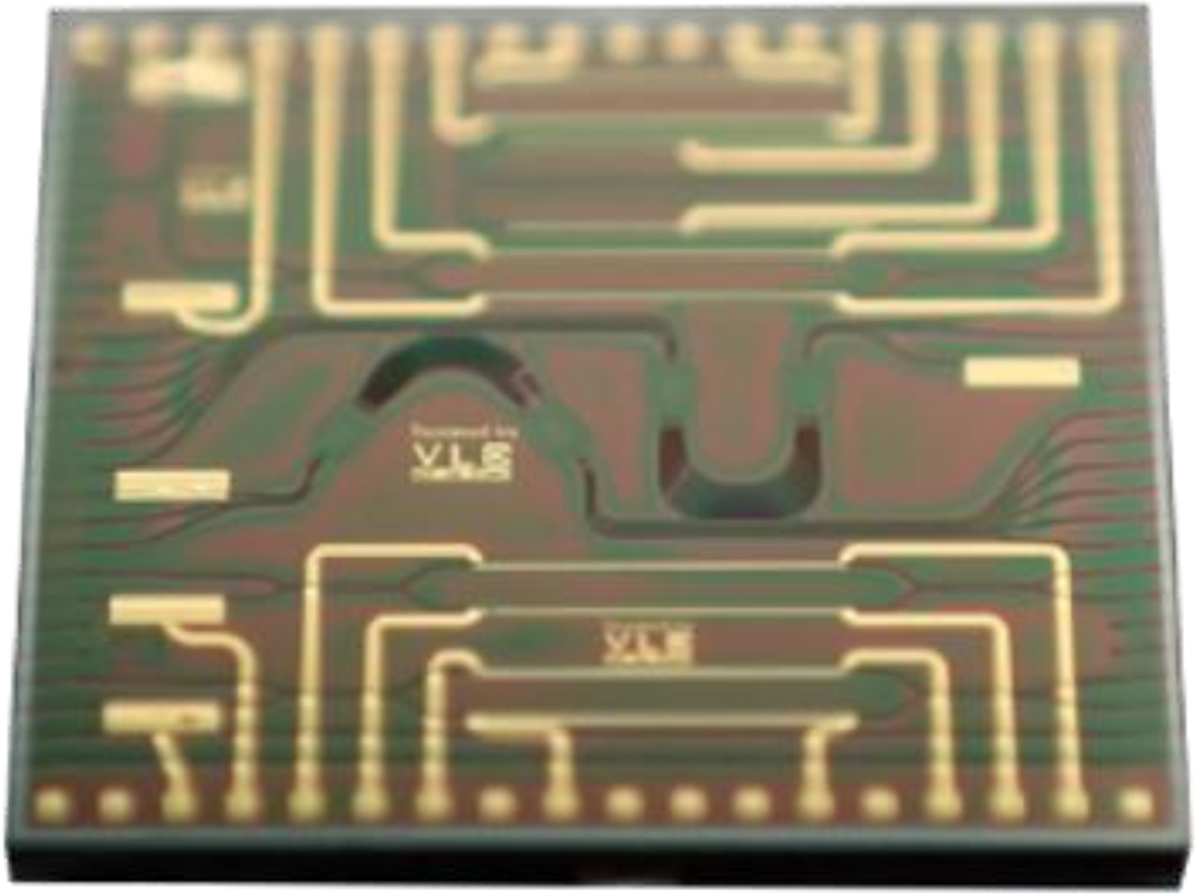
Packaging examples



Packaging examples

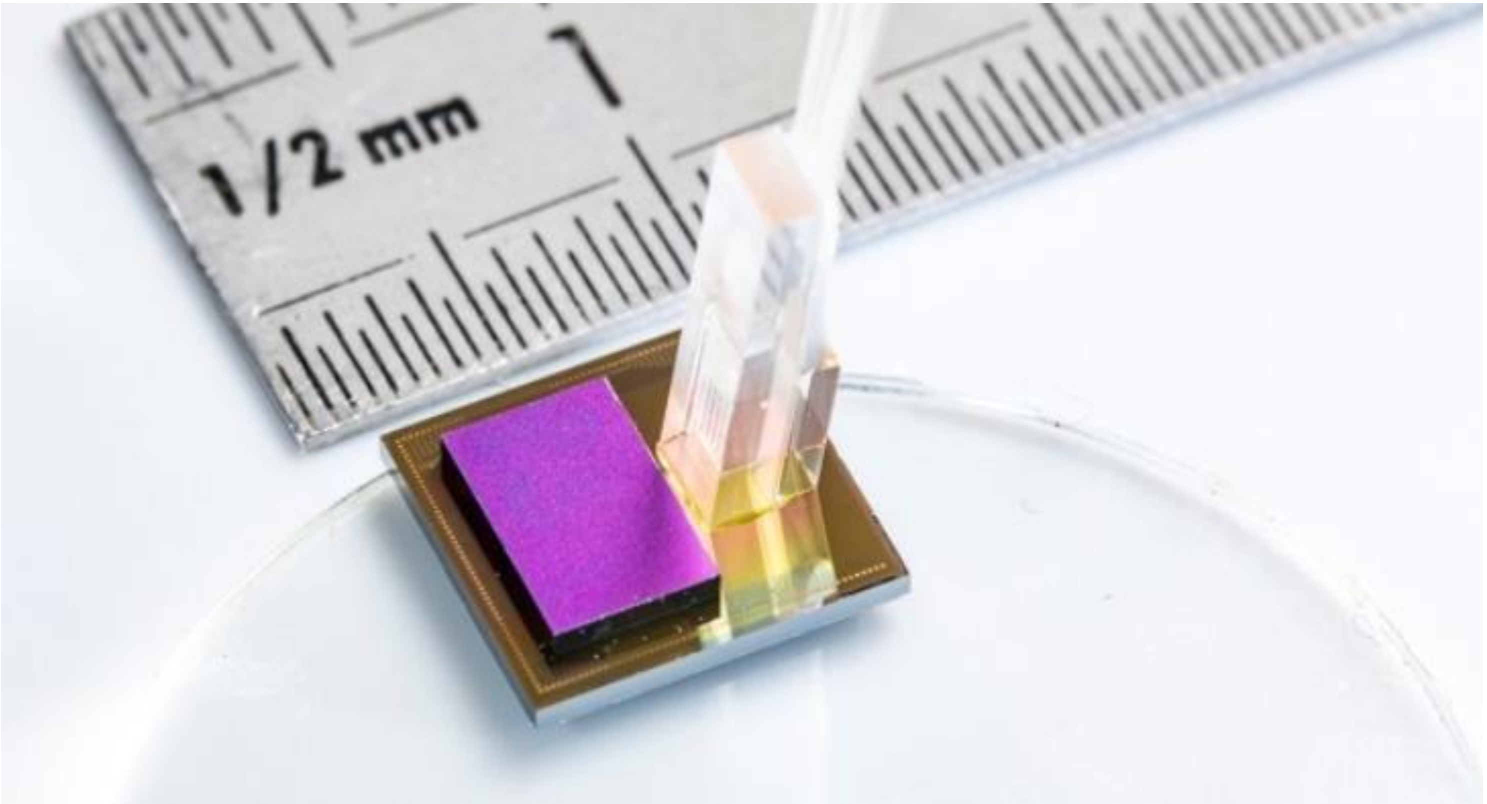


Chip + metal layer example



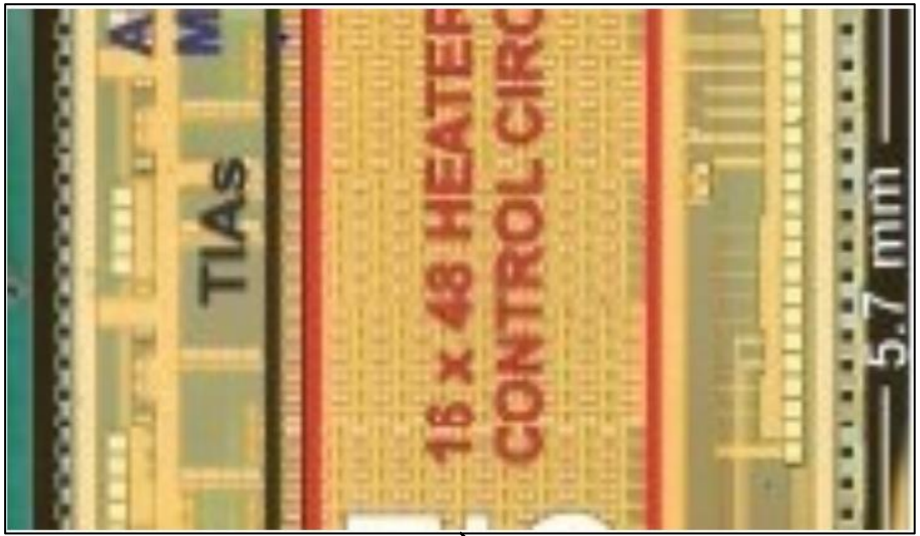
IRIS project (2017)

Full integration of optics and electronics

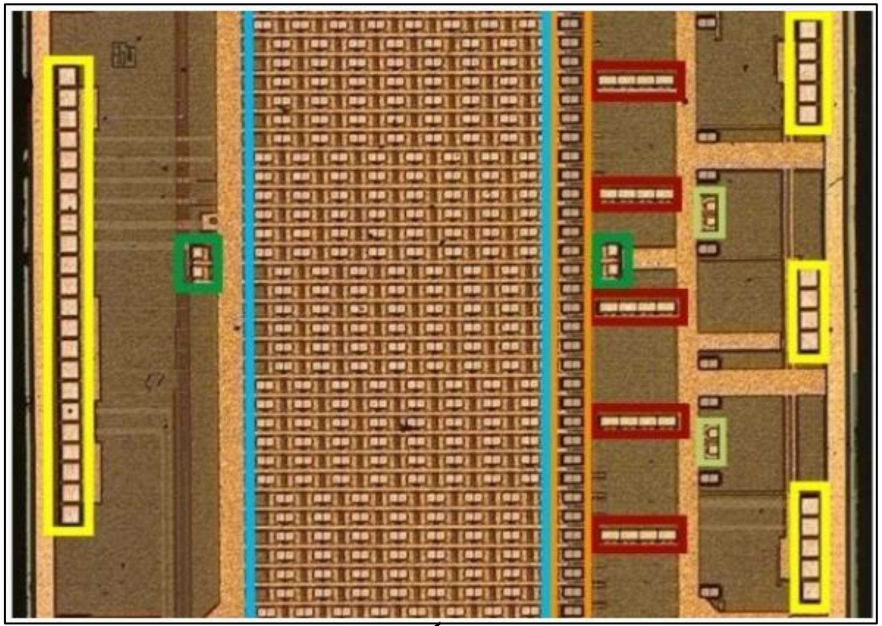


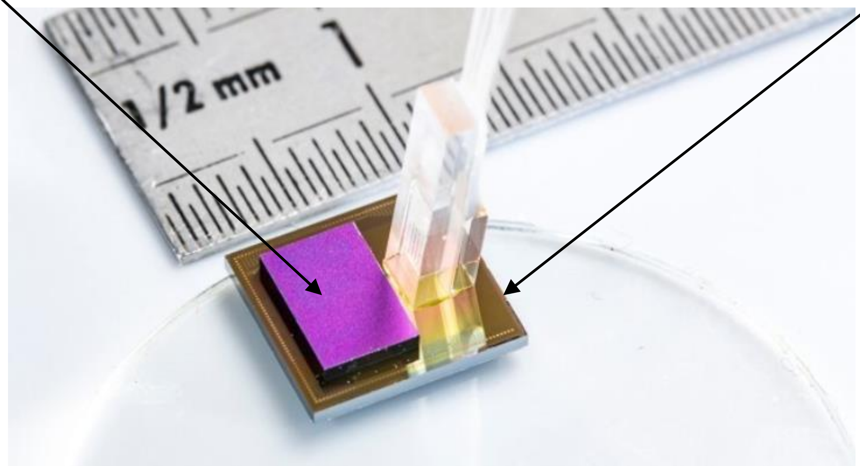
IRIS project (2017)

Electronics

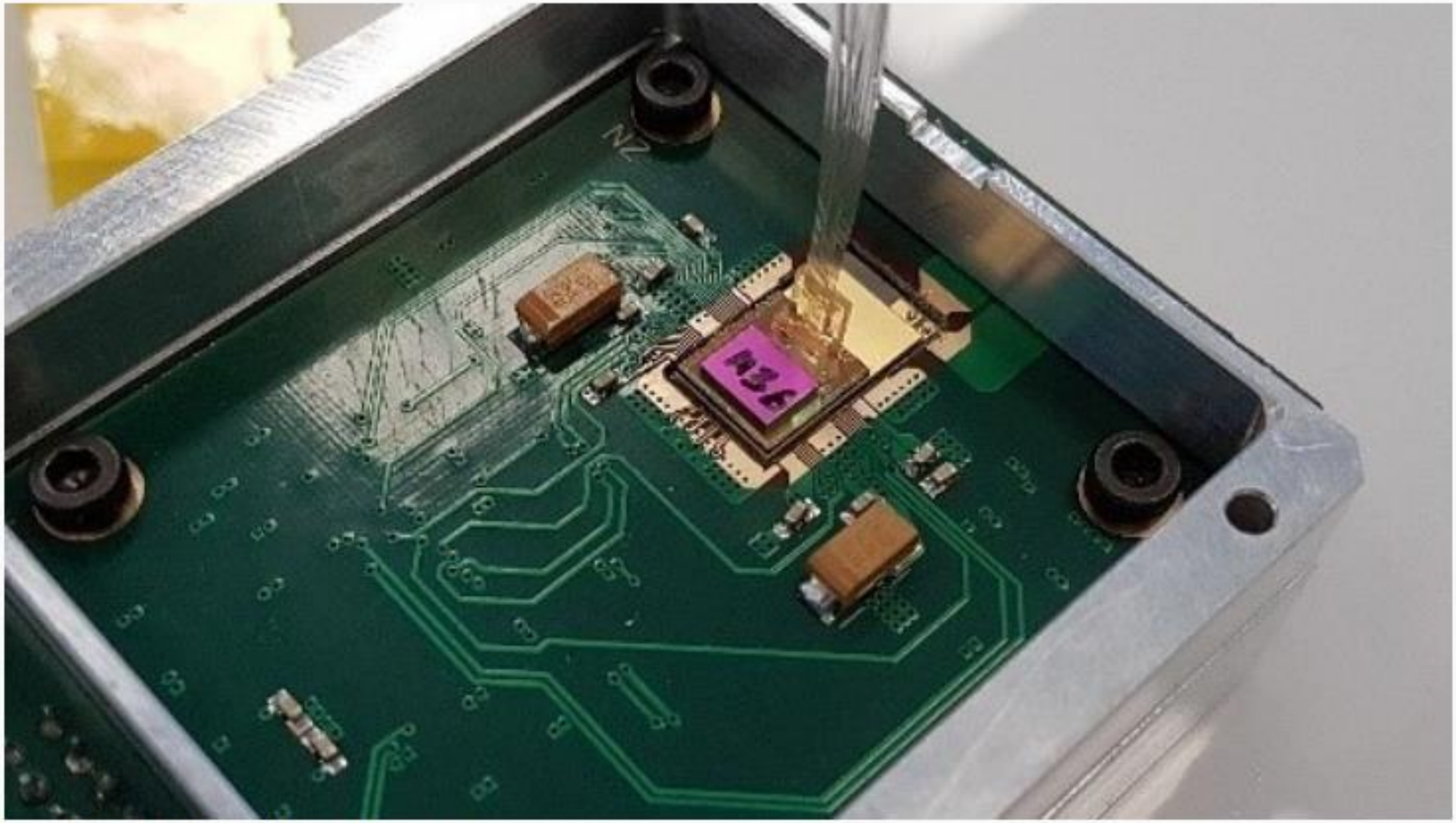


Optics





IRIS project



Photonics neural network

Feed Forward Network (FFN)

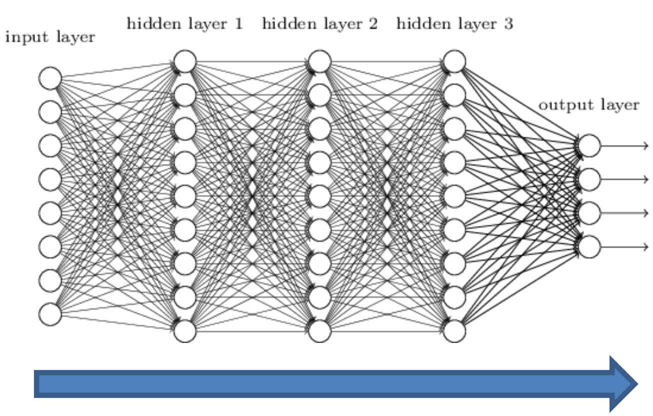
Recurrent Neural Network (RNN)

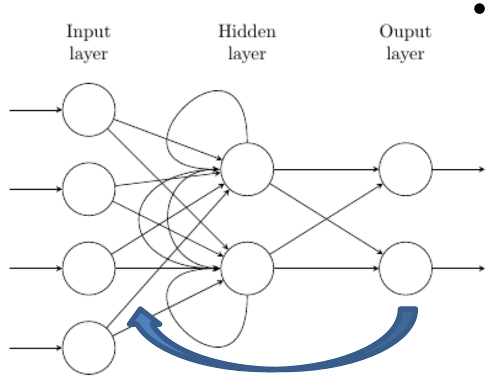
Convolution Neural Network (CCN)

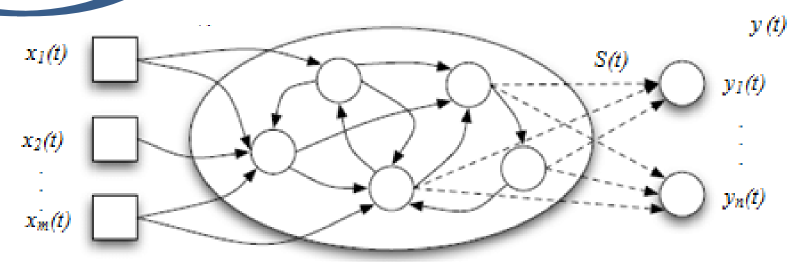
Reservoir computing Network (RCN)

- Output determined by actual input
- Classifier: Speech, image recognition ....
- Deep learning: back propagation
- All the weigths can be trained

- Time dependent signal
- Non linear time series prediction
- Memory of the past inputs
- Hard to be fully trained
- RC: only the readout is trained

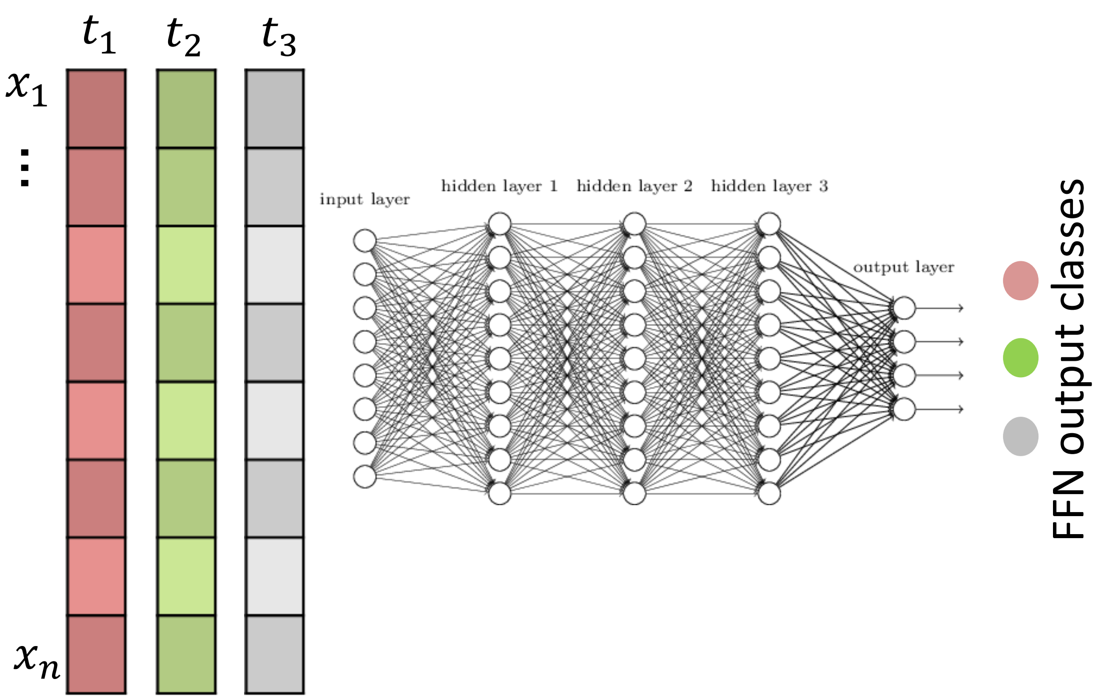




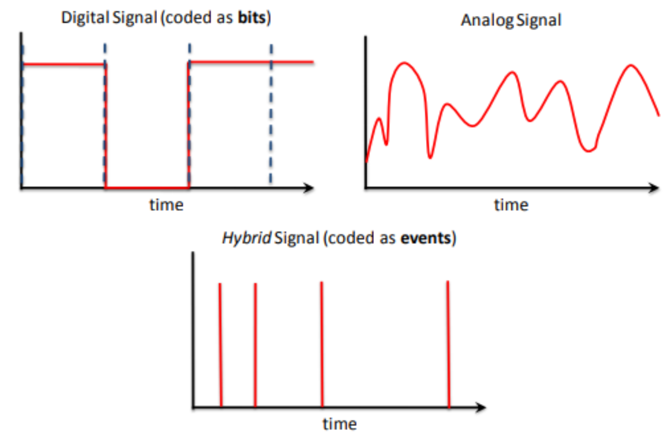


Photonics neural network

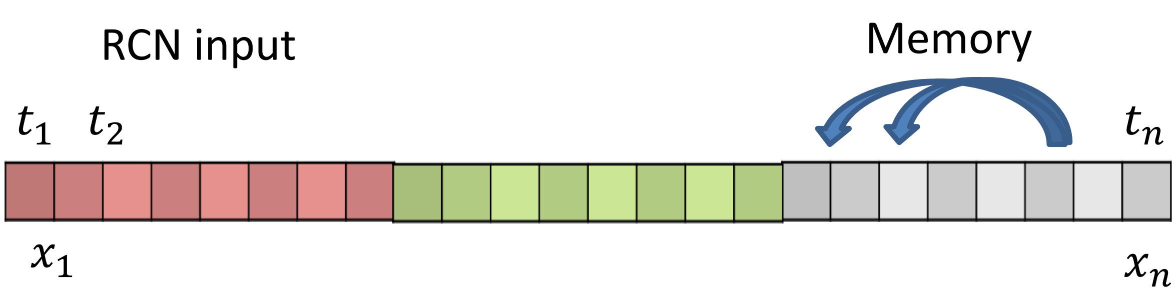
FFN input

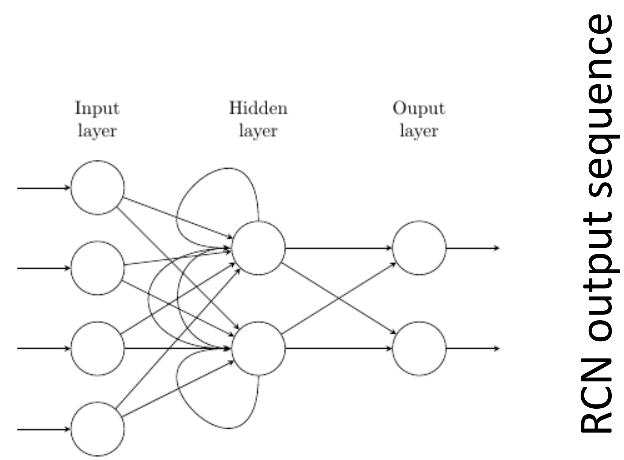


Input encoding



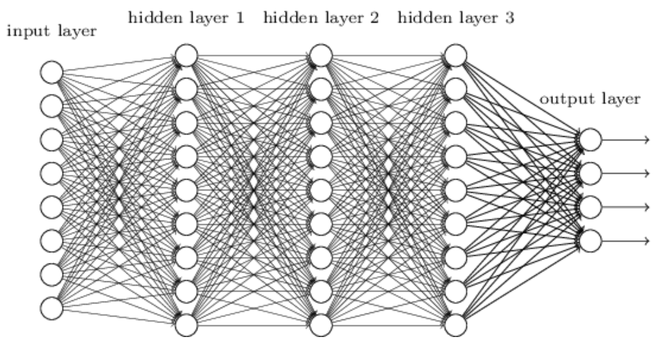
RCN input





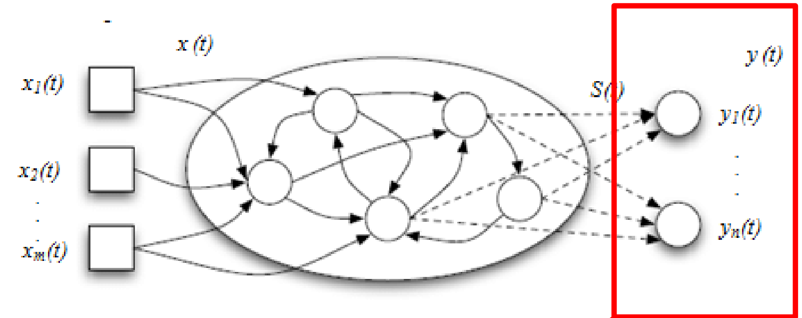
Photonics neural network

FFN



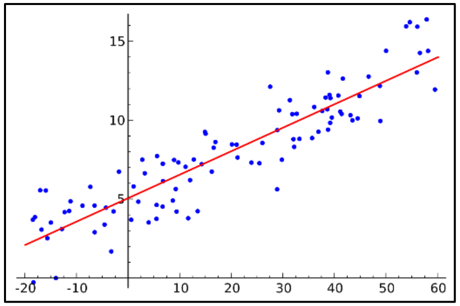
- Fully trained
- Backrpopagation
- Stochastic gradient descent

RCN



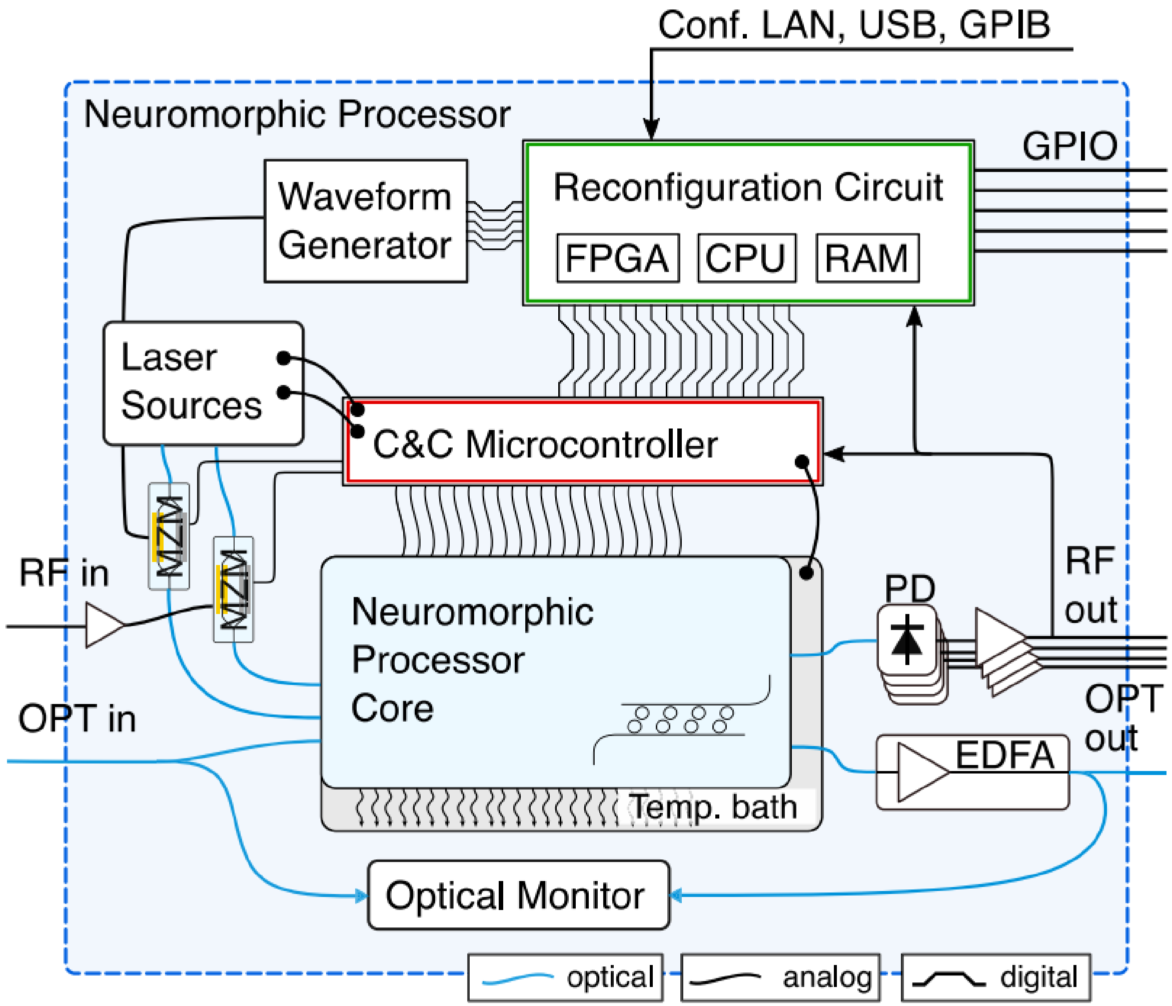
Only readout is trained
Linear regression

RCN states



out

Optoelectronic neural network



De Lima, Thomas Ferreira, et al. "Machine learning with neuromorphic photonics." *Journal of Lightwave Technology* 37.5 (2019): 1515-1534.

Photonic FFN

ARTICLE

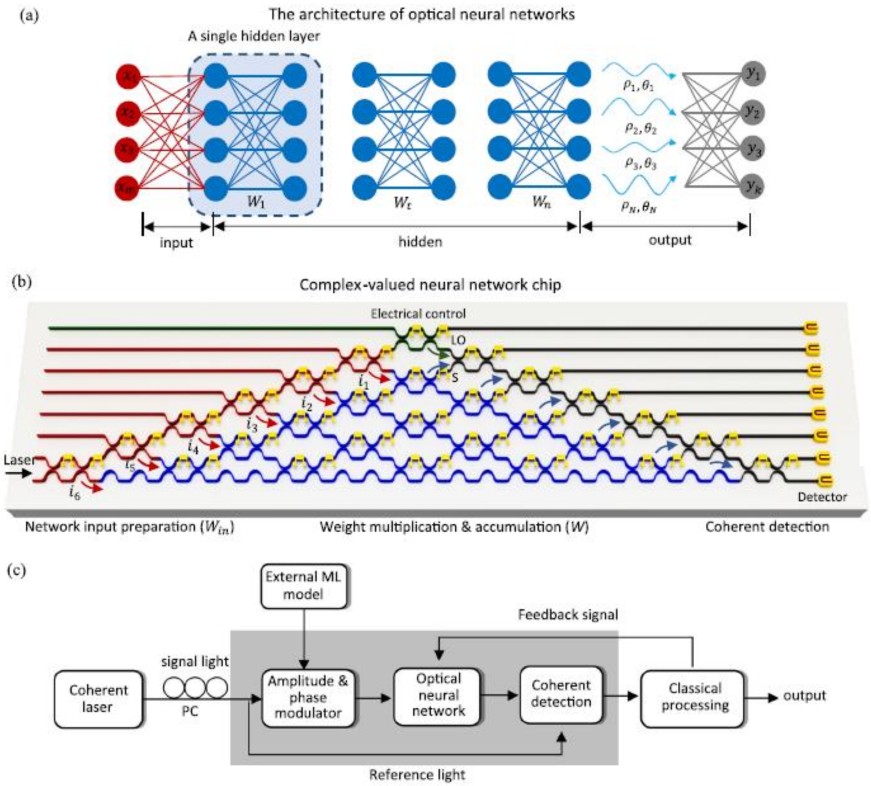
Check for updates

https://doi.org/10.1038/s41467-020-20719-7

OPEN

An optical neural chip for implementing complex-valued neural network

H. Zhang[1], M. Gu[2,3], X. D. Jiang[1], J. Thompson[3], H. Cai[4], S. Paesani[5], R. Santagati[5], A. Laing[5], Y. Zhang[1,6], M. H. Yung[7,8], Y. Z. Shi[1], F. K. Muhammad[1], G. Q. Lo[9], X. S. Luo[9], B. Dong[9], D. L. Kwong[4], L. C. Kwek[1,3,10] & A. Q. Liu[1]



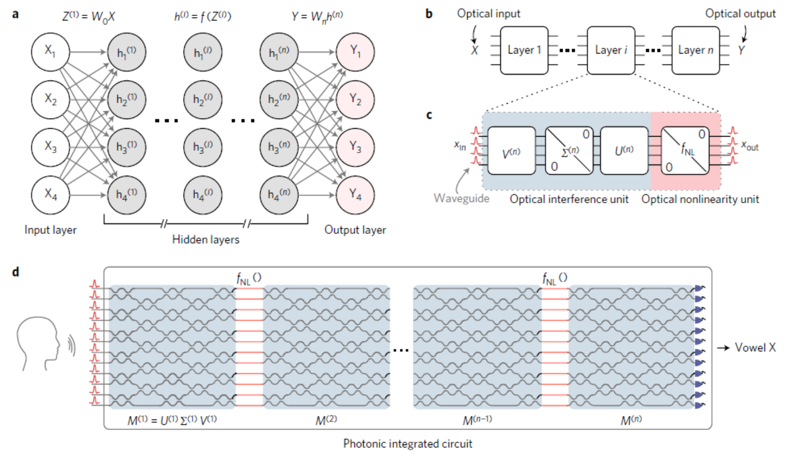
nature photonics

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]



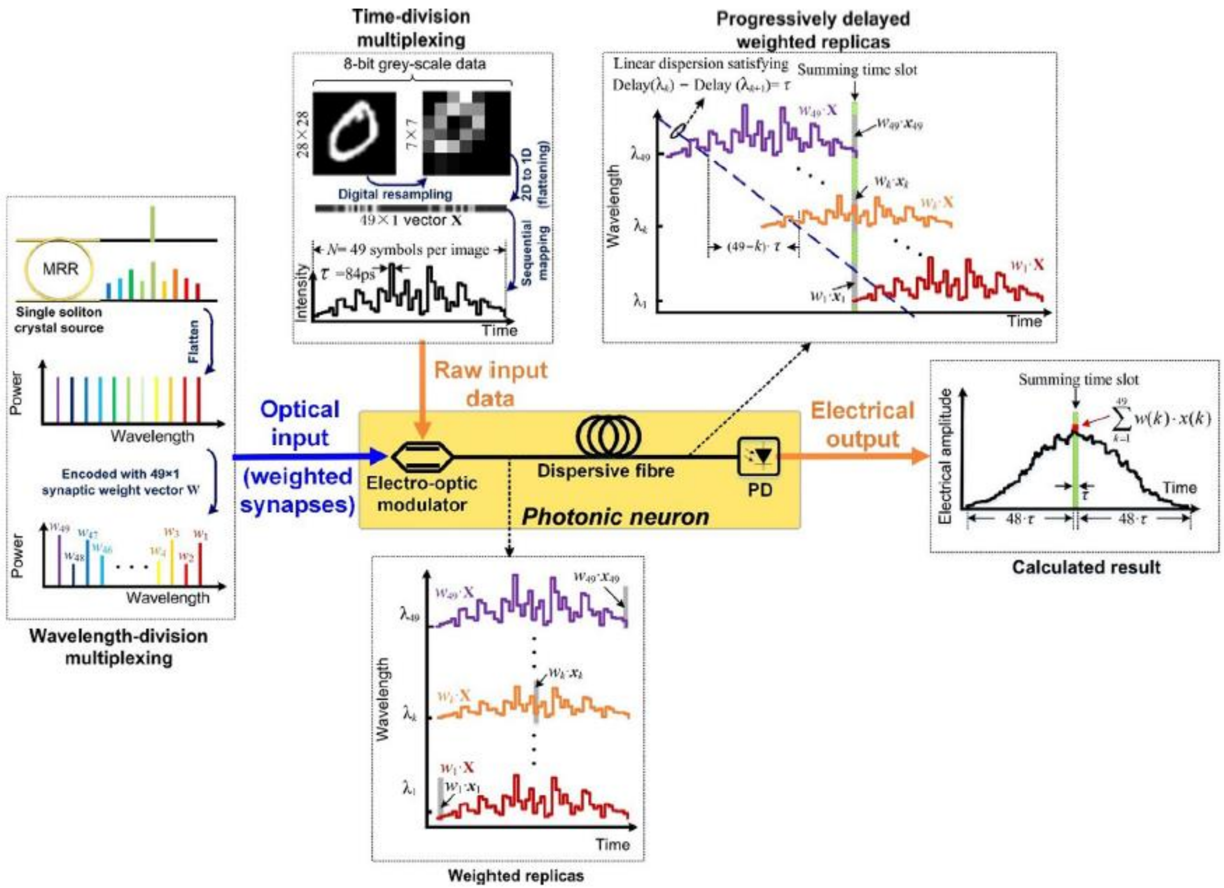
Coherent detection
Complex valued
Dectection based non-linearity
Integrated photonics

Photonic FFN

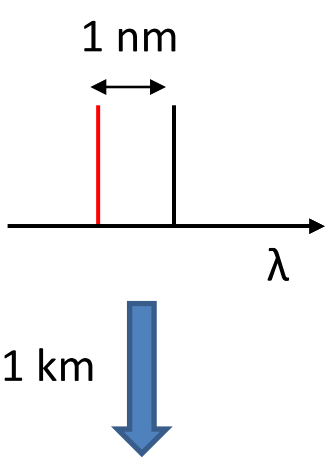
Photonic Perceptron Based on a Kerr Microcomb for High-Speed, Scalable, Optical Neural Networks

*Xingyuan Xu, Mengxi Tan, Bill Corcoran, Jiayang Wu, Thach G. Nguyen, Andreas Boes, Sai T. Chu, Brent E. Little, Roberto Morandotti, Arnan Mitchell, Damien G. Hicks, and David J. Moss**

Exploits WDM
Fiber dispersion as delay line
Fiber based



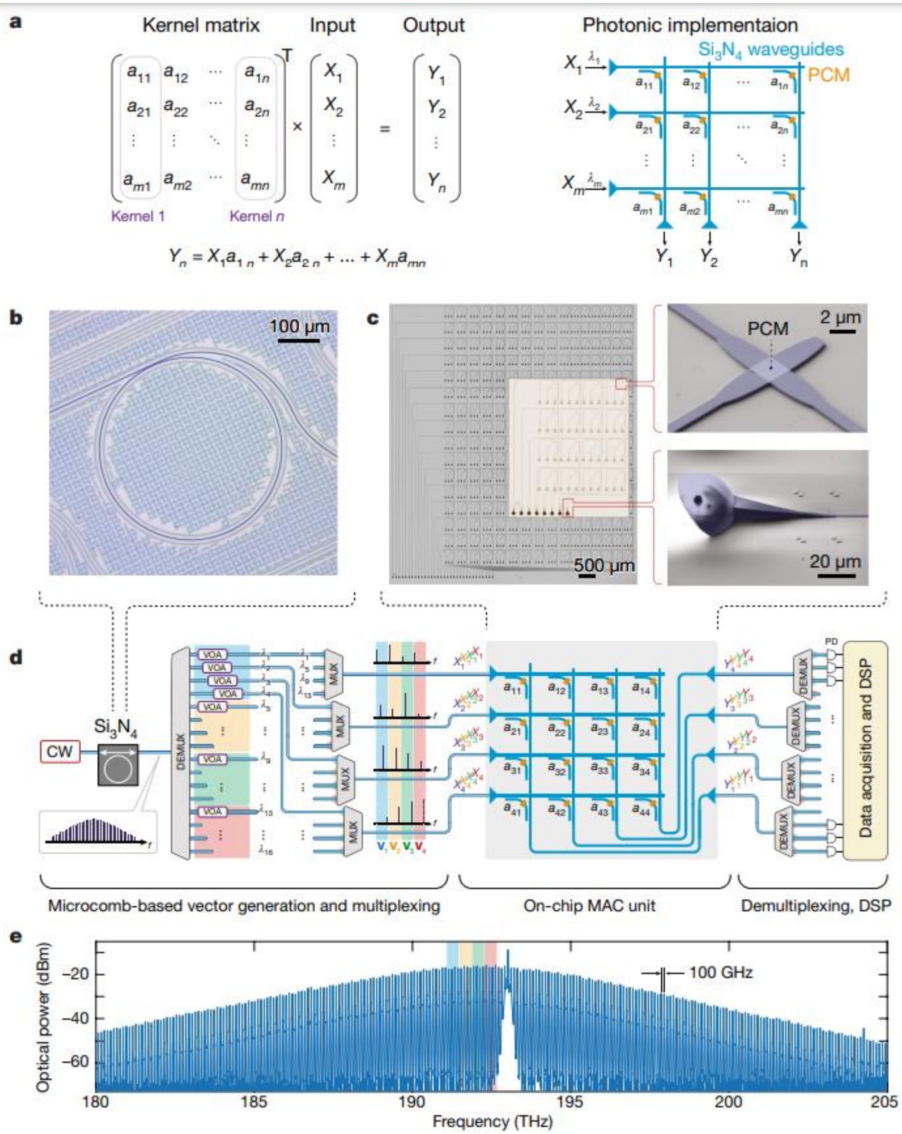
$$D \sim 17 \frac{ps}{nm\ km}$$



Delay of 17 ps

Photonic FFN: phase change material

Prof. Wolfram Pernice

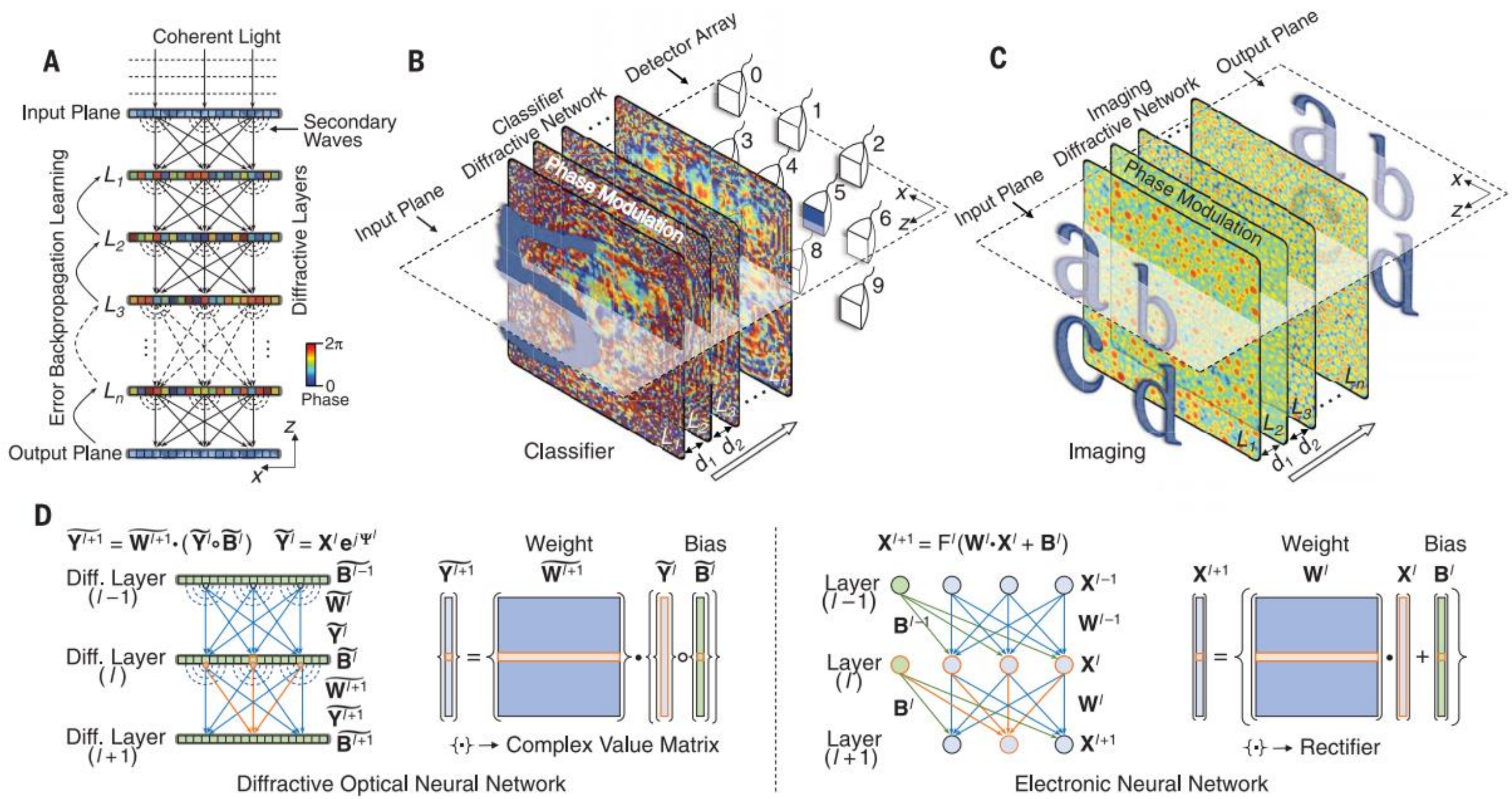


Photonic FFN

All-optical machine learning using diffractive deep neural networks

Xing Lin[1,2,3]*, Yair Rivenson[1,2,3]*, Nezih T. Yardimci[1,3], Muhammed Veli[1,2,3], Yi Luo[1,2,3], Mona Jarrahi[1,3], Aydogan Ozcan[1,2,3,4]†

Software base training
3D printed phase mask
Detection based non-linearity
Free space
Neurons number $0.4 \cdot 10^6$



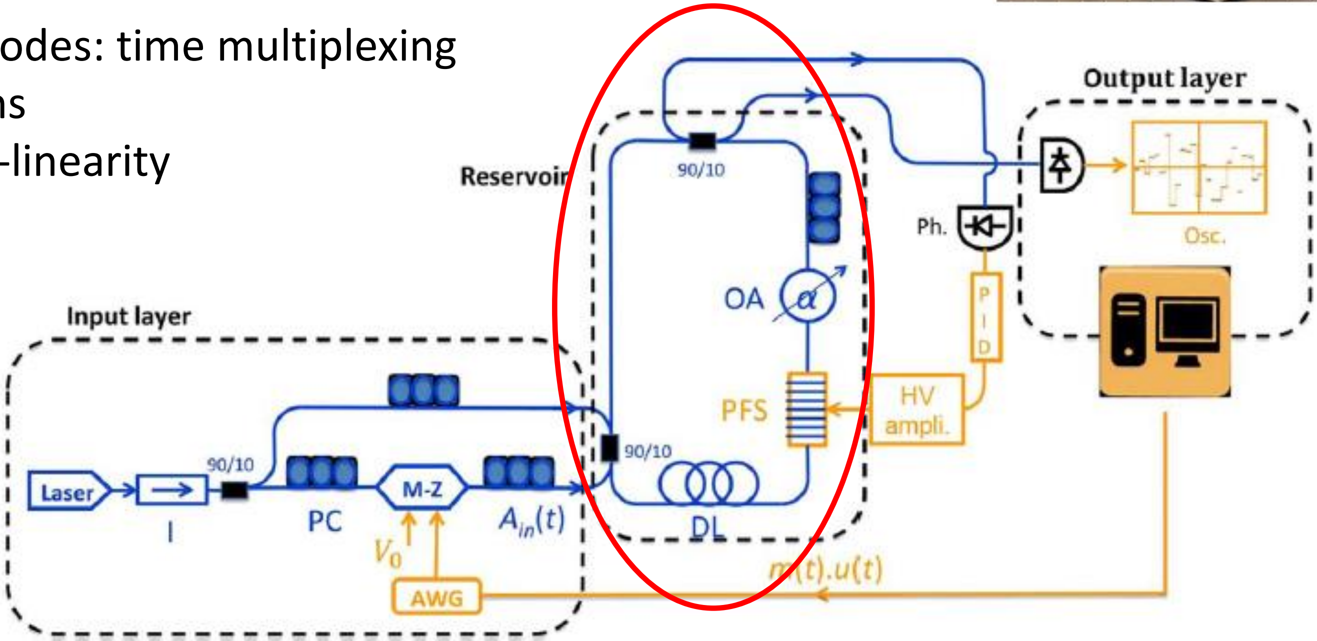
Photonic RCN

optica

High-performance photonic reservoir computer based on a coherently driven passive cavity

Quentin Vinckier,[1,*] François Duport,[1] Anteo Smerieri,[1] Kristof Vandoorne,[2] Peter Bienstman,[2] Marc Haelterman,[1] and Serge Massar[3]

Delay based virtual nodes: time multiplexing
MZM to apply weigths
Detection based non-linearity
Fiber based



Photonic RCN

SCIENTIFIC REPORTS

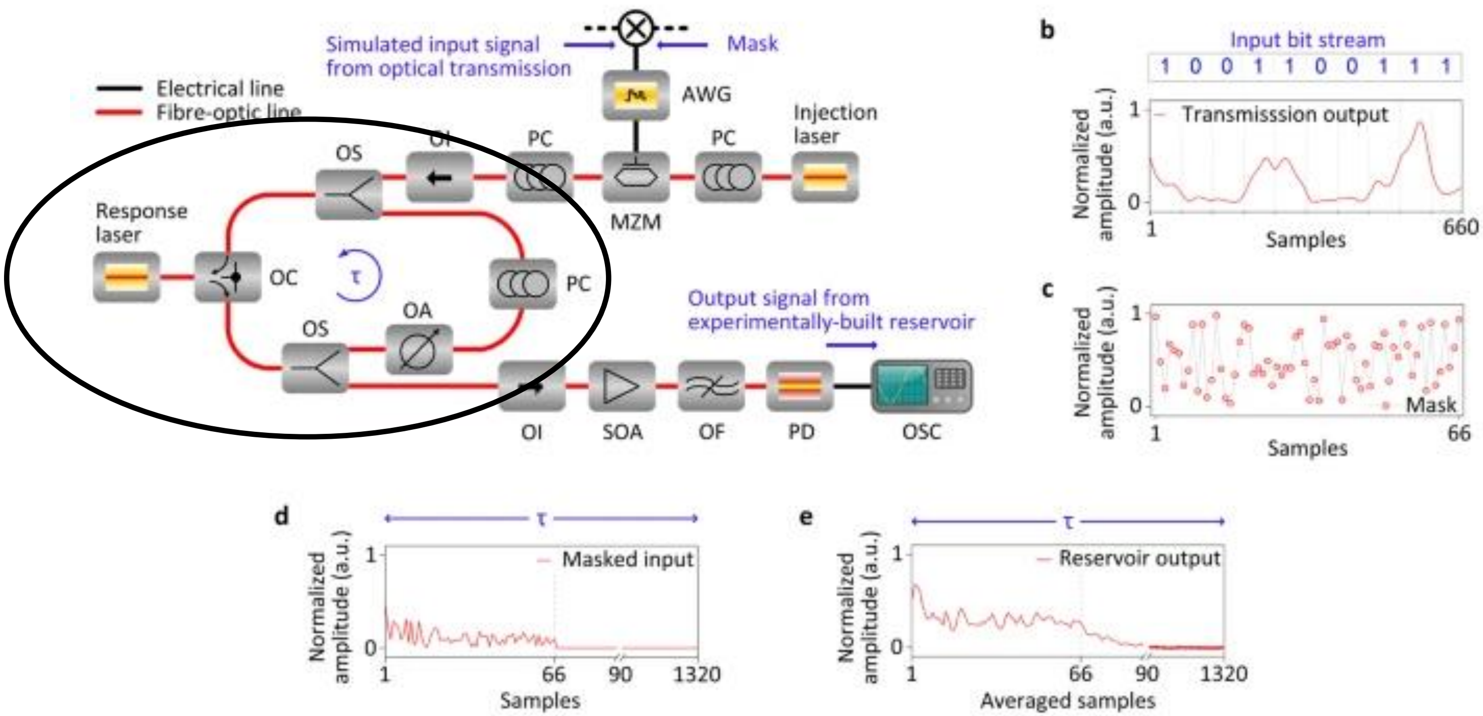
OPEN

Photonic machine learning implementation for signal recovery in optical communications

ed: 3 April 2018

Apostolos Argyris, Julián Bueno & Ingo Fischer

Delay based virtual nodes: time multiplexing
MZM to apply weigths
Laser non linearity
Fiber based



Photonic RCN

nature COMMUNICATIONS

ARTICLE

Received 13 Aug 2013 | Accepted 4 Mar 2014 | Published 24 Mar 2014

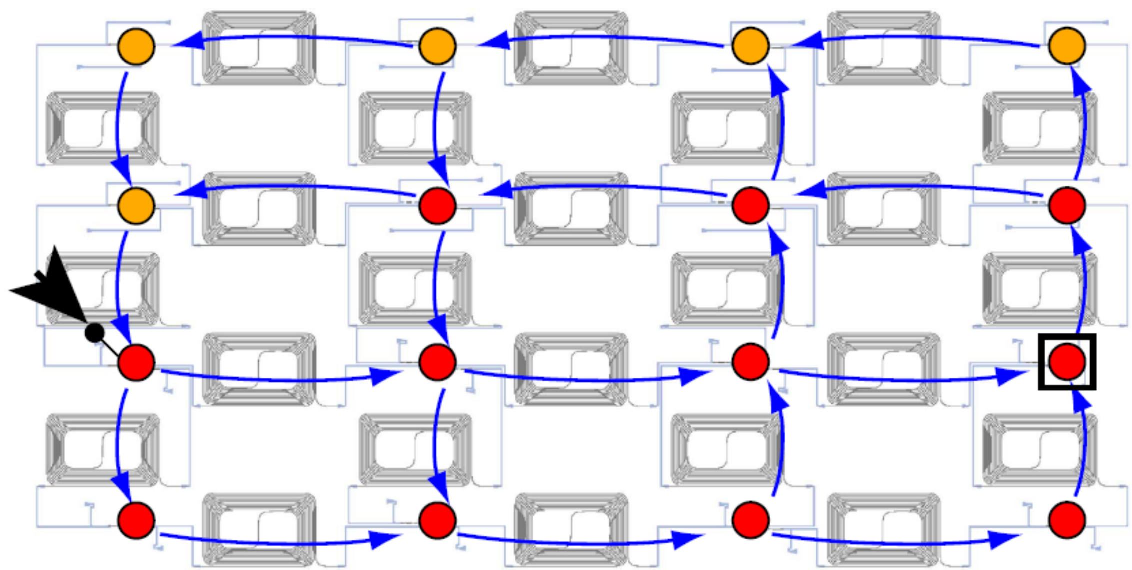
DOI: 10.1038/ncomms4541

OPEN

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]

Delay based nodes: spatial
Random connetions
Detection based non-linearity
Linear readout
Integrated photonics



Photonic RCN

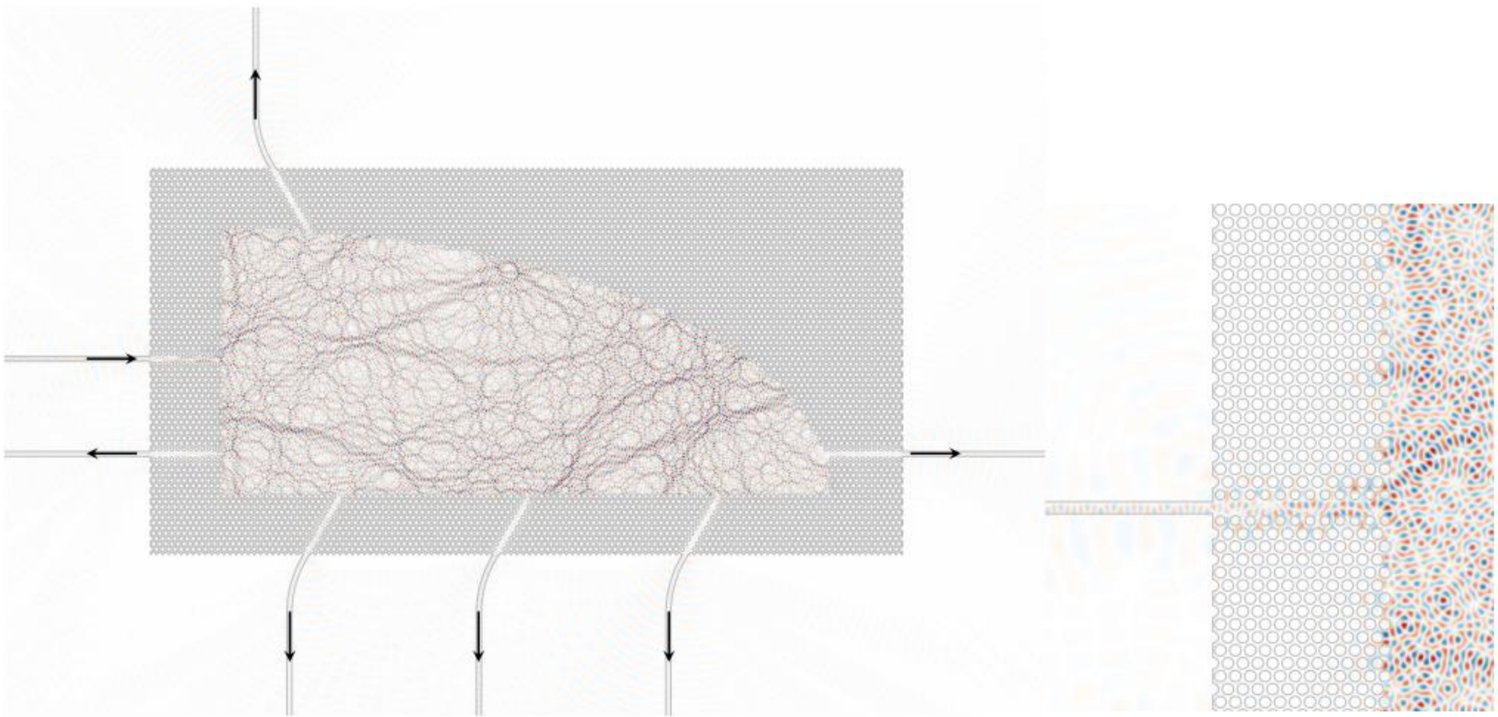
Research Article Vol. 26, No. 7 | 2 Apr 2018 | OPTICS EXPRESS 7955
Optics EXPRESS

Numerical demonstration of neuromorphic computing with photonic crystal cavities

FLORIS LAPORTE,[1,*] ANDREW KATUMBA,[1] JONI DAMBRE,[2] AND PETER BIENSTMAN[1]

[1] *Photonics Research Group, UGent-imec, Technologiepark-Zwijnaarde 15, 9052 Ghent, Belgium*
[2] *IDLab, UGent-imec, Technologiepark-Zwijnaarde 15, 9052 Ghent, Belgium*
[*] *floris.laporte@ugent.be*

Delay based nodes: multiple reflections
Random connetions
Detection based non-linearity
Linear readout
Integrated photonics

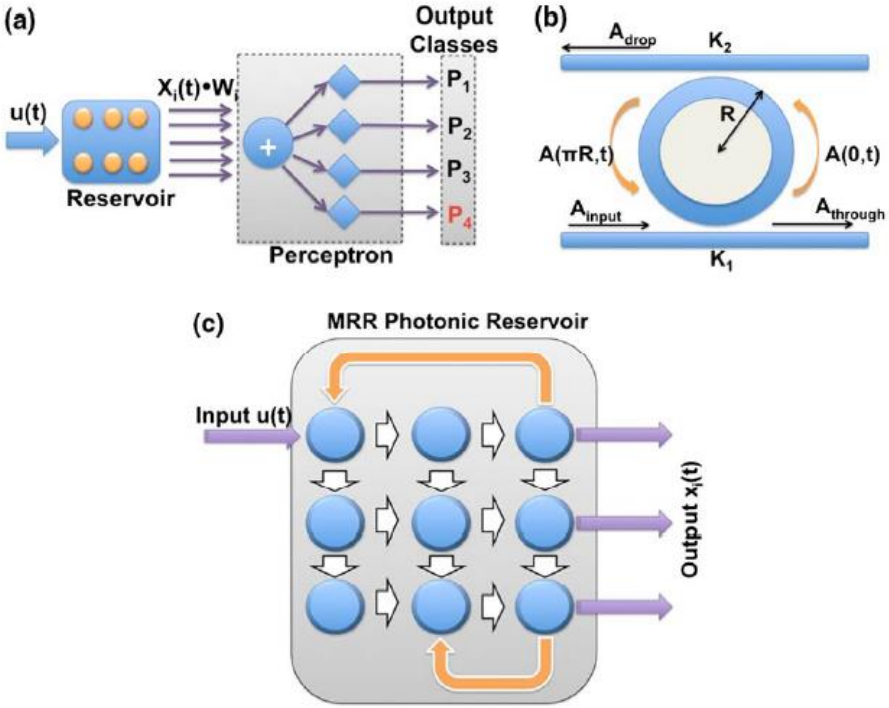


Photonic RCN

Micro ring resonators as building blocks for an all-optical high-speed reservoir-computing bit-pattern-recognition system

Charis Mesaritakis,* Vassilis Papataxiarhis, and Dimitris Syvridis

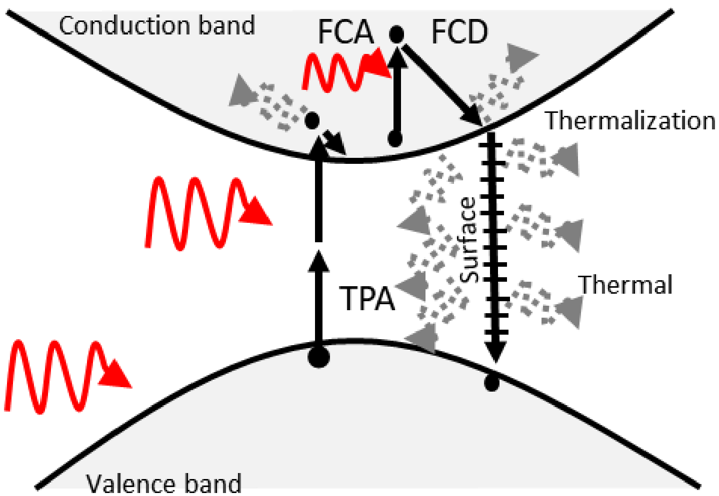
National and Kapodistrian University of Athens, Department of Informatics & Telecommunications, Panepistimiopolis Ilisia 15345, Athens, Greece
**Corresponding author: cmesar@di.uoa.gr*

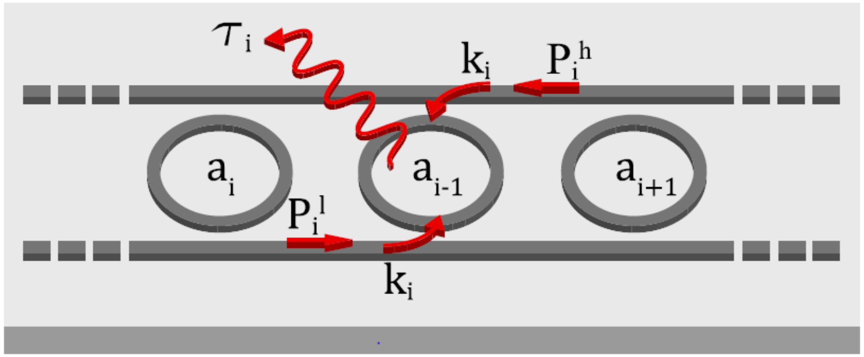


Theoretical investigation
Microring nodes
Random connetions
Non linear node: TPA and Kerr
Linear readout
Integrated photonics

Silicon platform non linearities

TOE: Thermo-optic effect $\Delta n > 0$ Red shift, timescale µs
FCD: Free carrier dispersion $\Delta n < 0$ Blue shift, timescale ns
TPA: change in the cavity decay rate, almost instantaneous
Kerr: $\Delta n > 0$ Red shift, almost instantaneous





4 degrees of freedom

Resonance shift

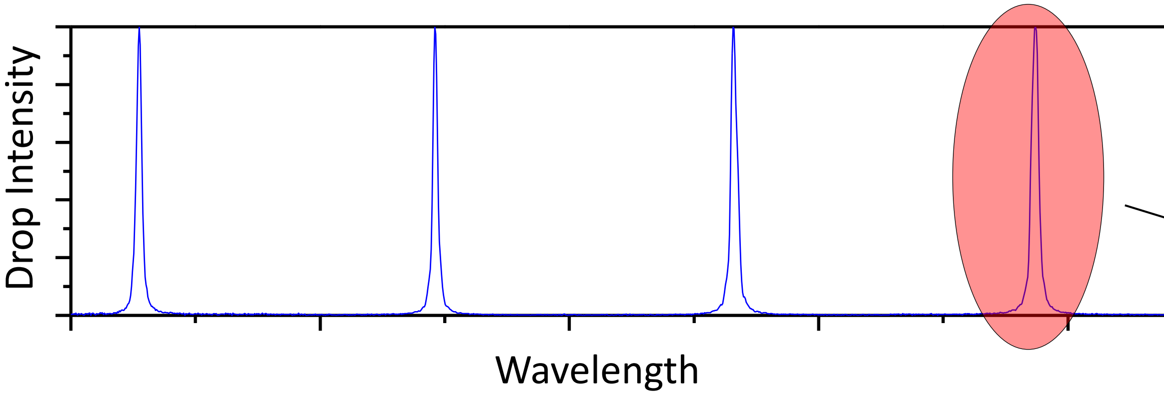
$$\frac{da_i(t)}{dt} = \left[-j(\omega_p - \omega_{0i}\left(1 + \Delta\omega\left(\Delta T_i(t)\right) + \Delta\omega\left(\Delta N_i(t)\right)\right) - \frac{1}{\tau_i(a_i(t))}\right] a_i(t) + j\sqrt{k_i}(P_i^l(t) + P_i^h(t))$$

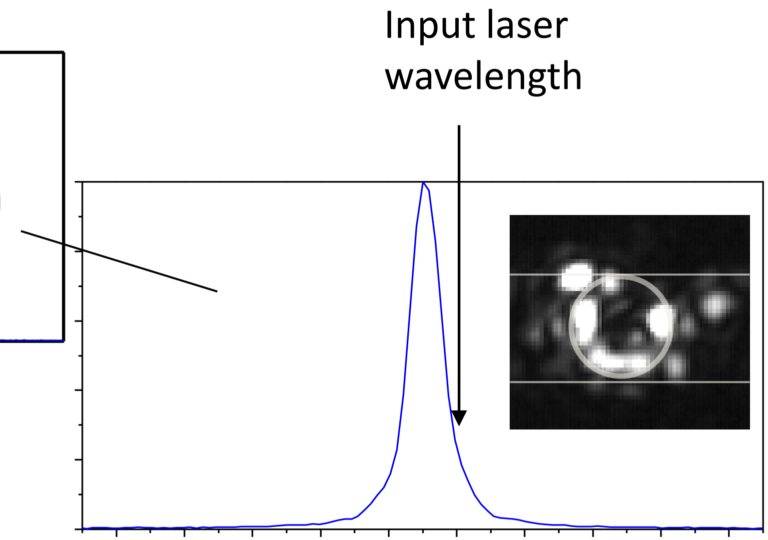
Decay time variations

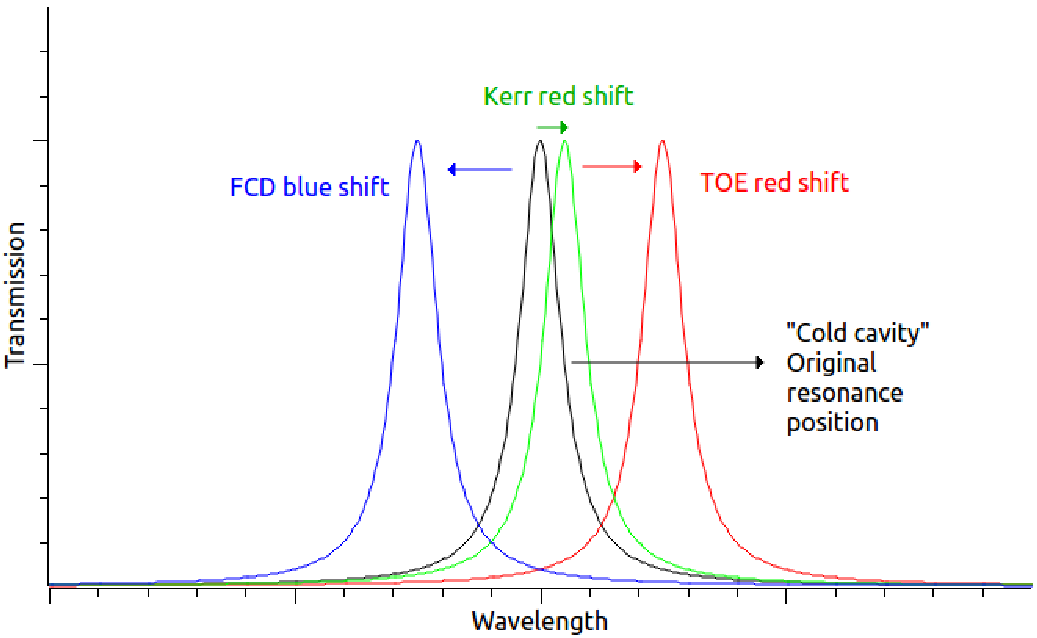
$$\frac{d\Delta T_i(t)}{dt} = -\gamma_{fh}\Delta T_i(t) + P_{abs,i}(a_i(t), \Delta N_i(t)) \rightarrow |a_i|^4$$

$$\frac{d\Delta N_i(t)}{dt} = -\gamma_{fc}\Delta N_i(t) + G_{TPA,i}(a_i(t)) \rightarrow |a_i|^4$$

Microrings non-linearity







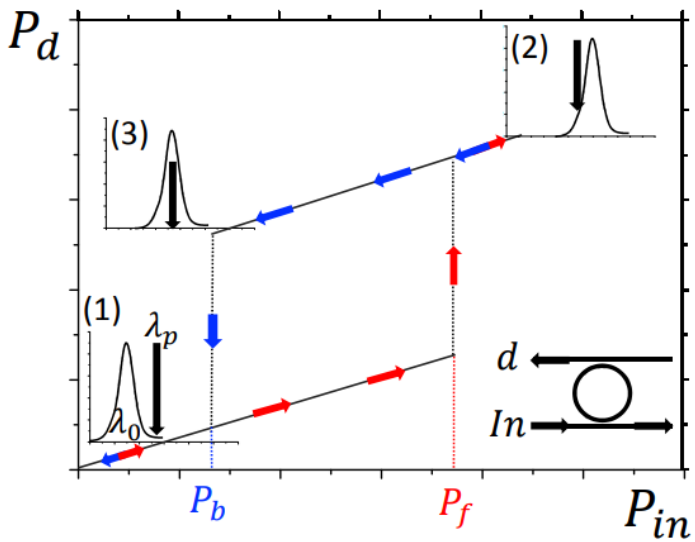
$$\Delta\lambda_{TOE} \approx \lambda_{cold} \cdot \Gamma \frac{dn_{Si}}{dT} \Delta T$$

$$\Delta\lambda_{FCD} \approx \lambda_{cold} \cdot \Gamma \frac{dn_{Si}}{dN_{e,h}} \Delta \mathrm{N_{e,h}}$$

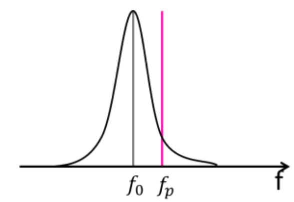
FCD : Free Carrier Dispersion

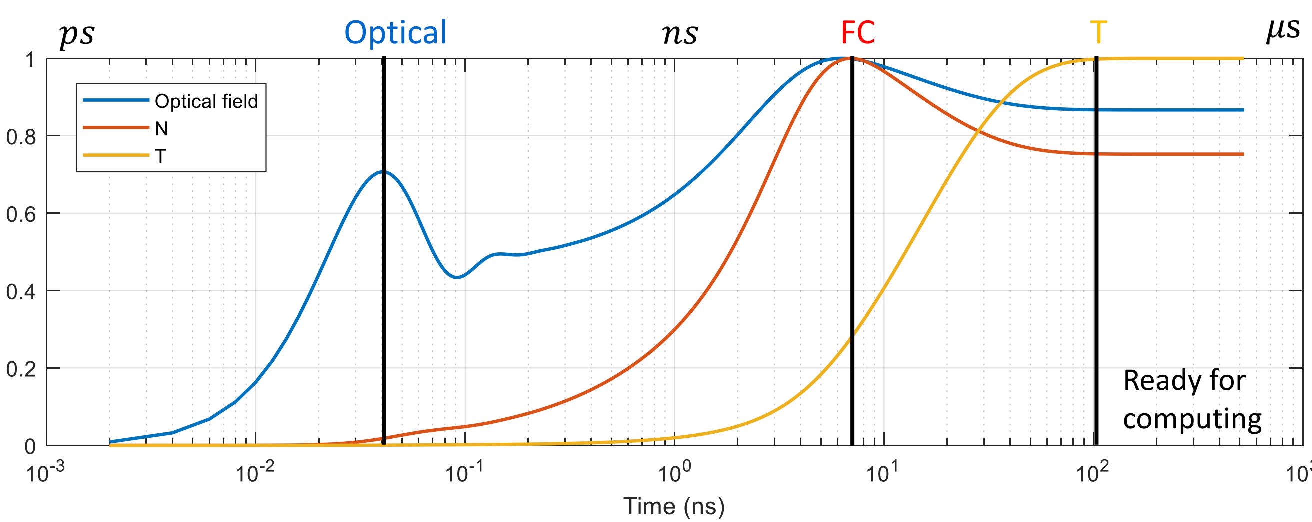
TOE : Thermo Optic Effect

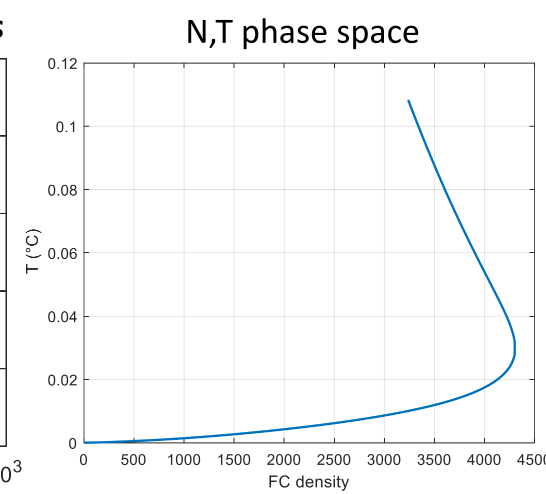
System dynamics: optical bistability



System dynamics spans over 3-4 order of magnitude







Input CW 5 mW, $k^2 = 2\%$, $df = +10\ GHz$, D port

UNIVERSITY OF TRENTO - Italy
Department of Physics

BACKUP neuromorphic photonics and the brain
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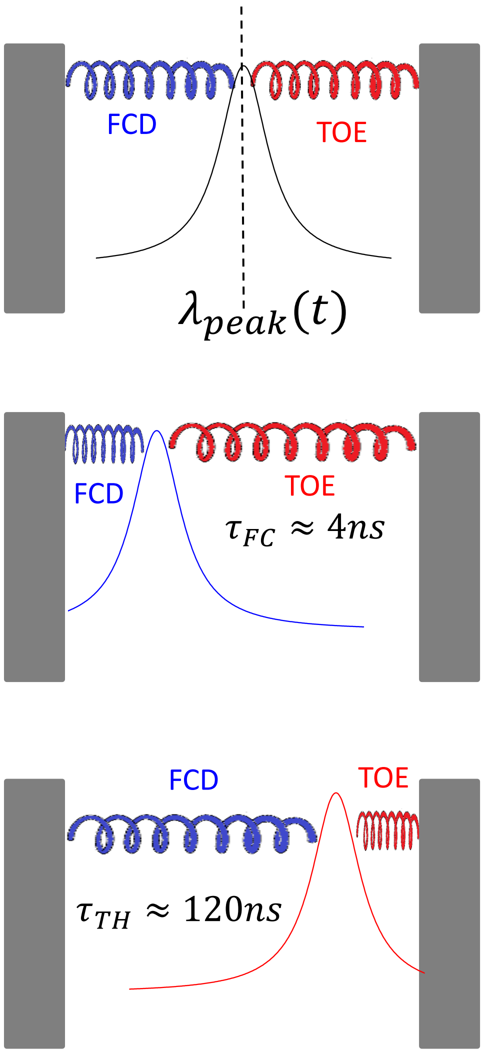
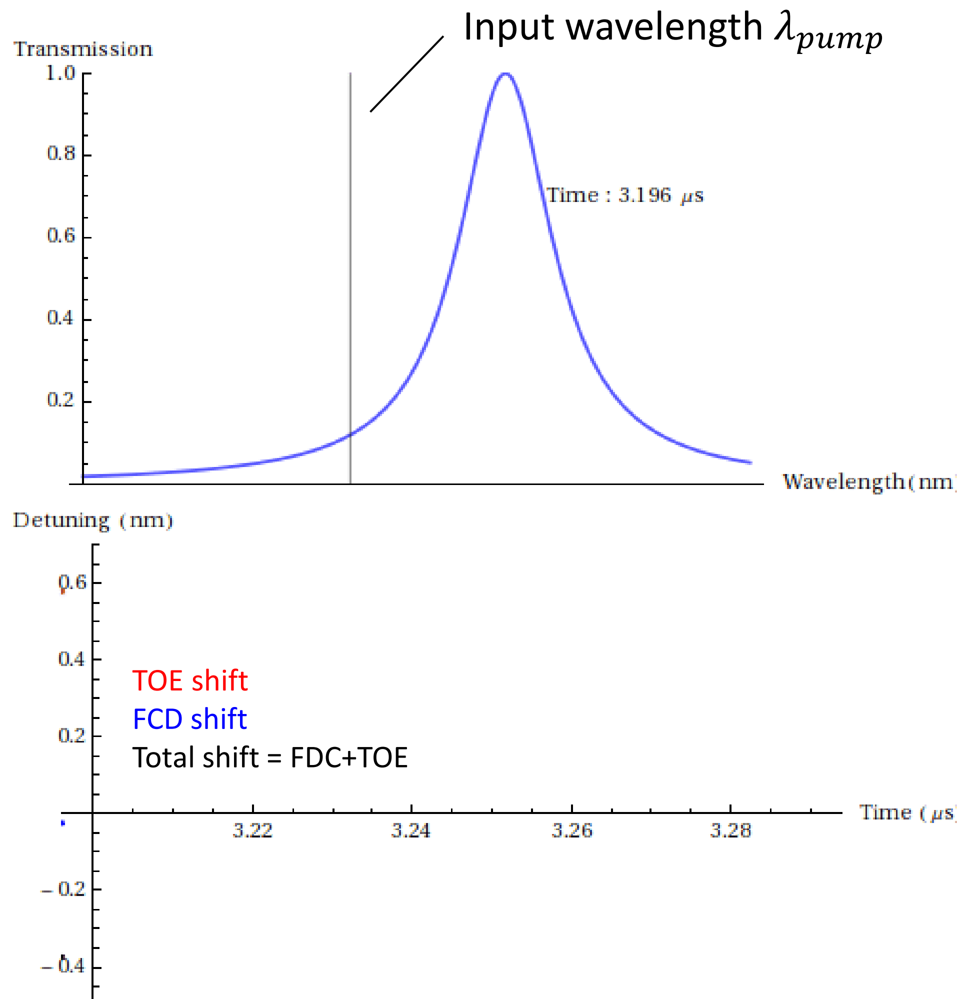
Self induced intensity modulation

Competing resonance shifts act as springs that pull the resonance in the opposite directions

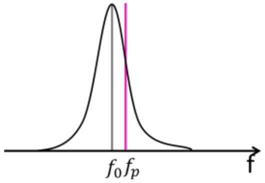




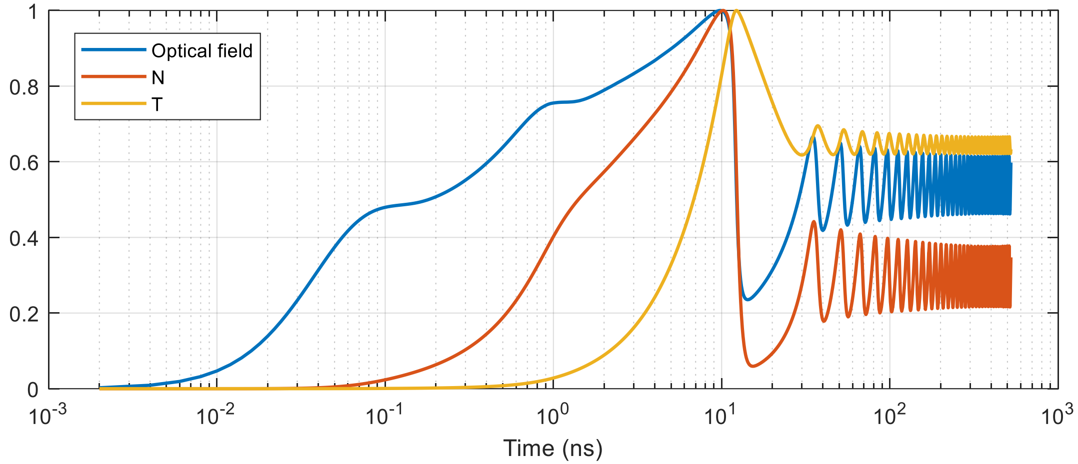
Detuning = $\lambda_{peak}(t) - \lambda_{pump}$

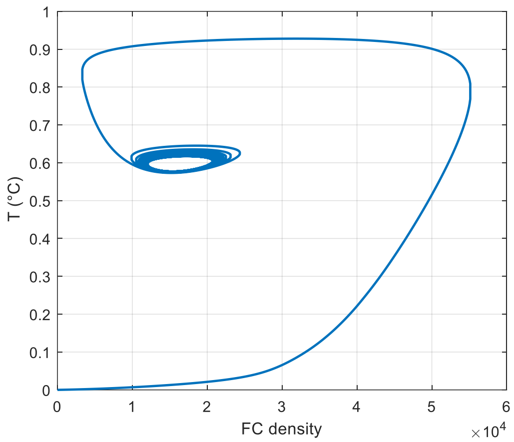
System dynamics: stable points

Self induced intensity modulation



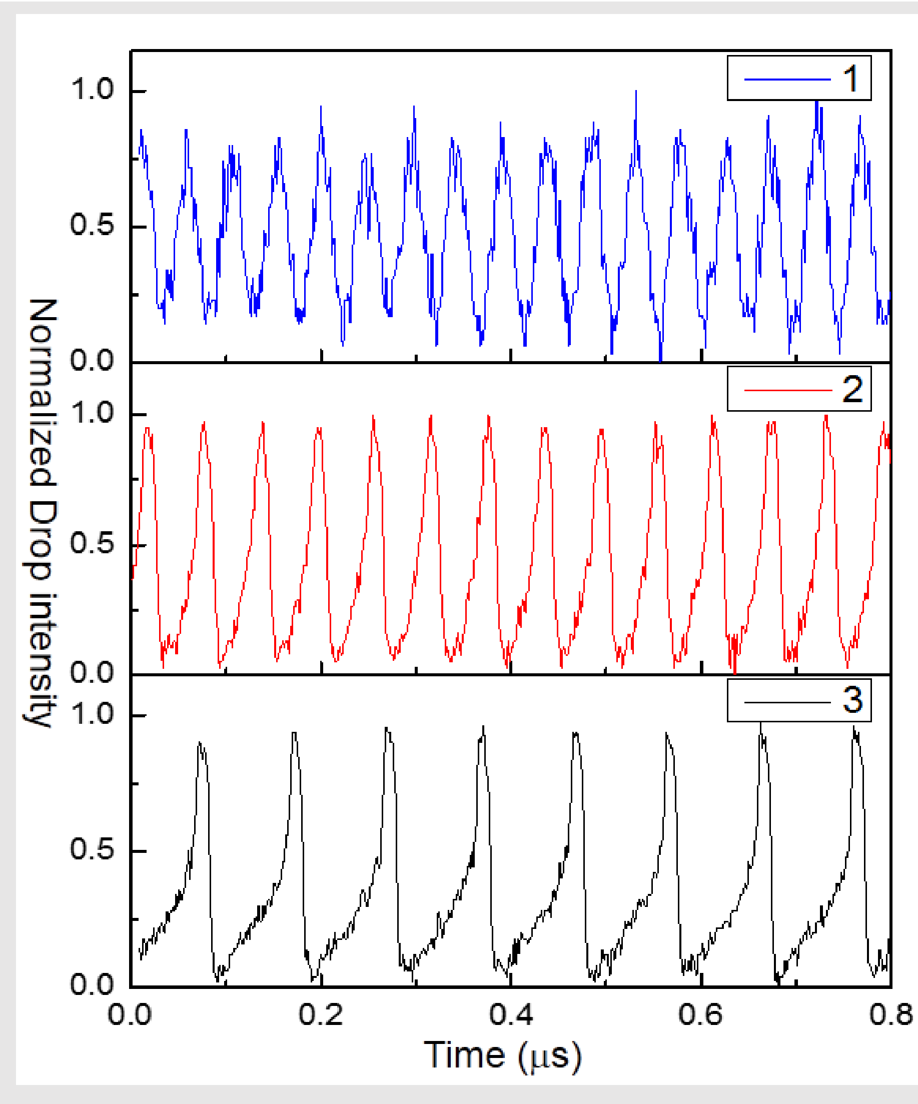
N,T phase space





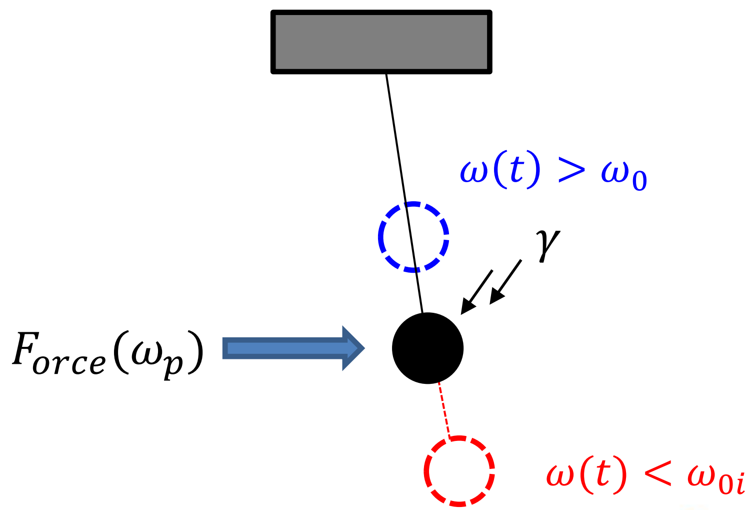
Input CW 5 mW, $k^2 = 2\%$, $df = +3\ GHz$, D port

Self induced intensity modulation

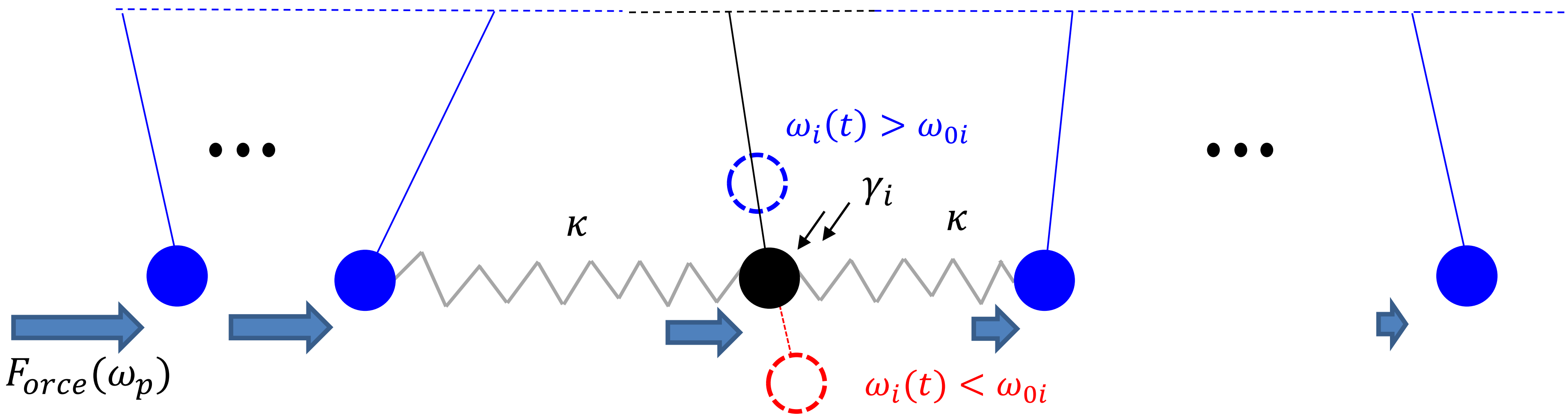


Pump scheme	Input wavelength	Input power (in wg)
1	1550 nm	2.3 mW
2	1550 nm	4.9 mW
3	1550 nm	6.0 mW
Low power resonance peak (λ_0) : $1549.66nm$ Q factor $\approx 10^5$		

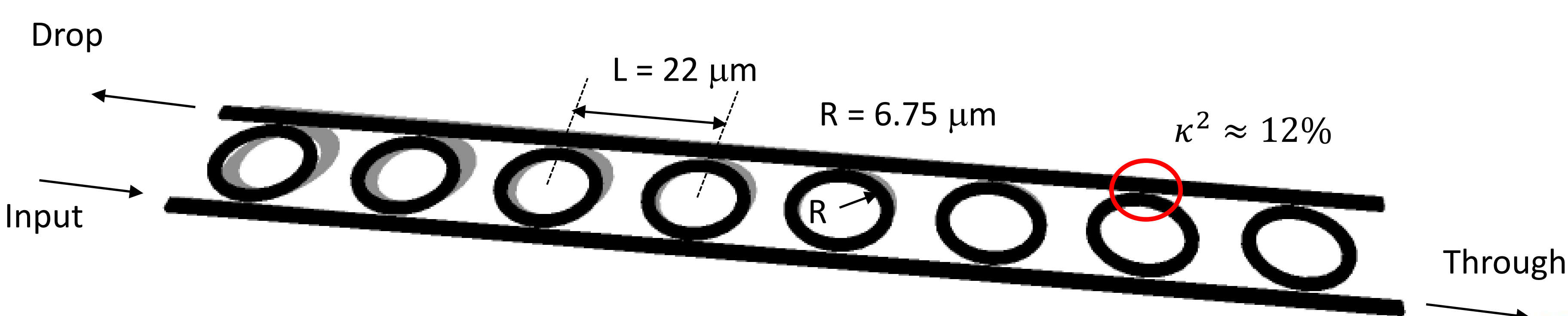
Mechanical equivalent



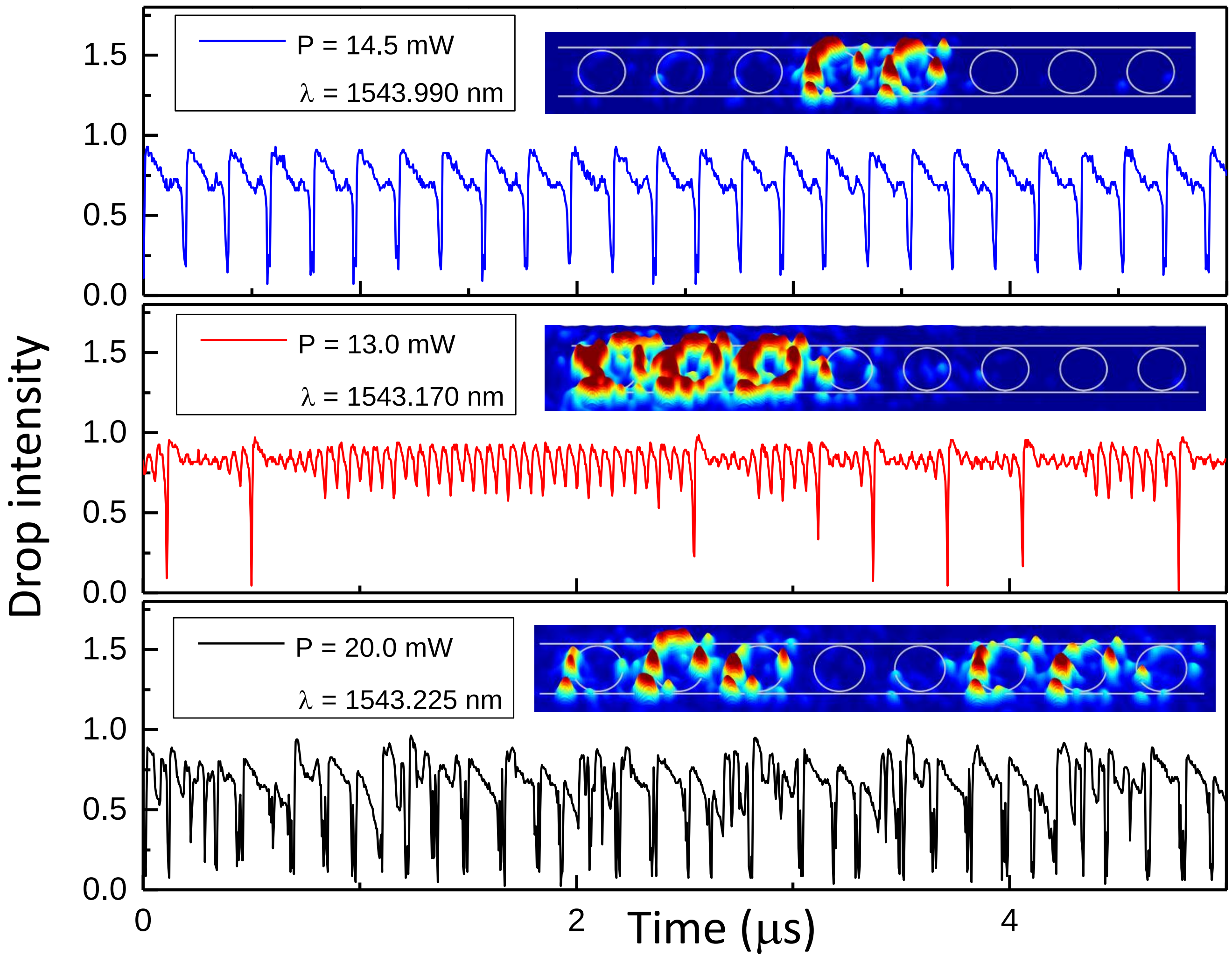
Coupled resonators

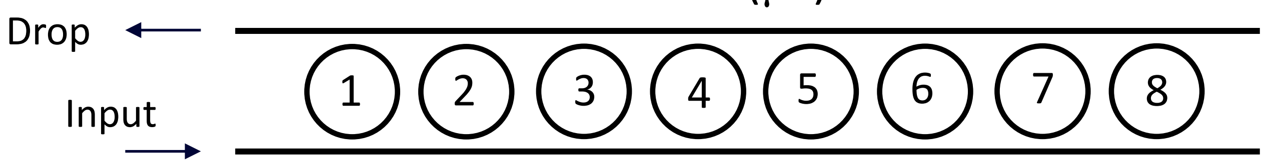


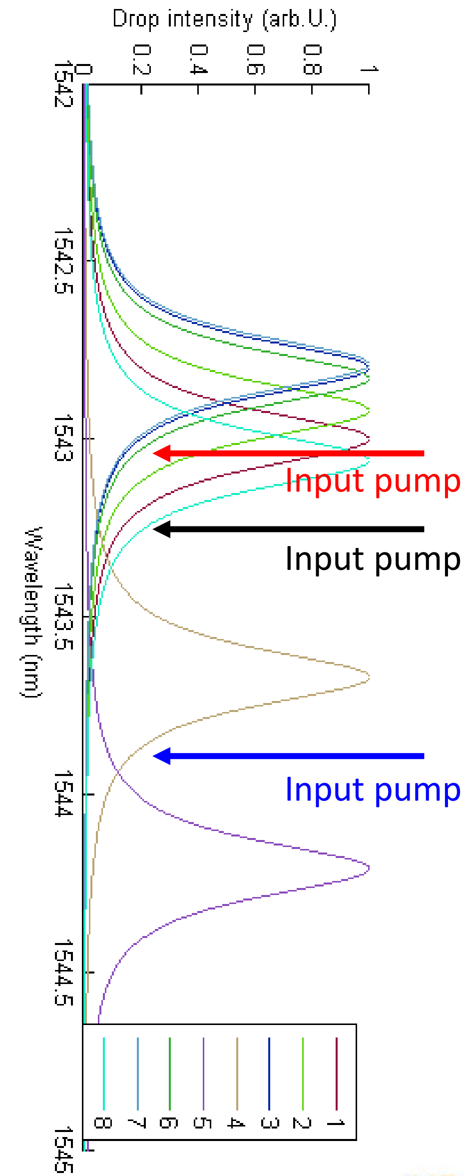
Side Coupled Integrated Spaced Sequence Of Resonators (SCISSOR) geometry



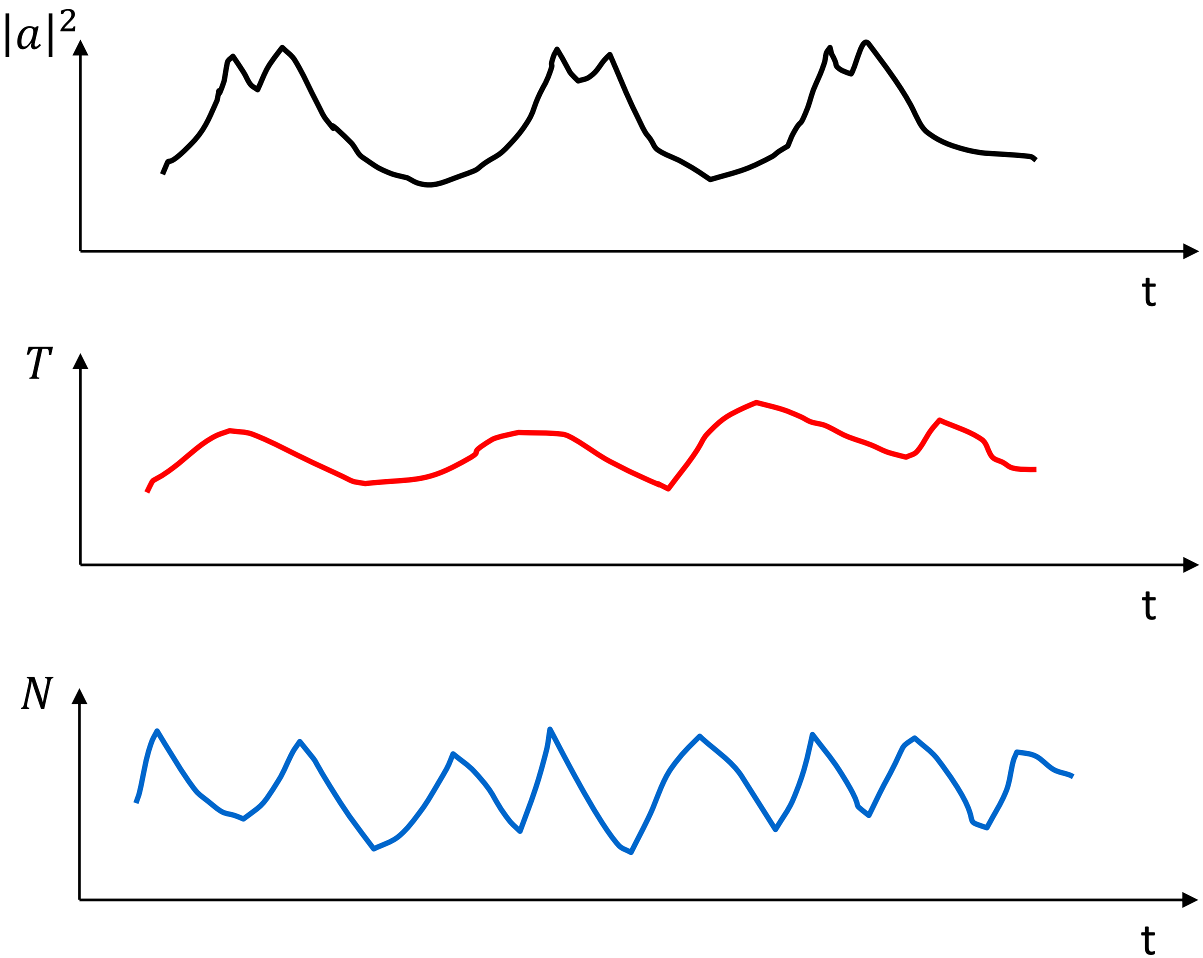
Coupled resonators dynamics

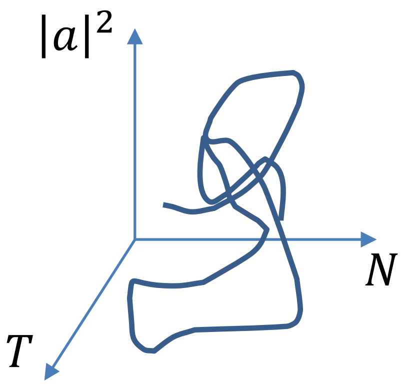






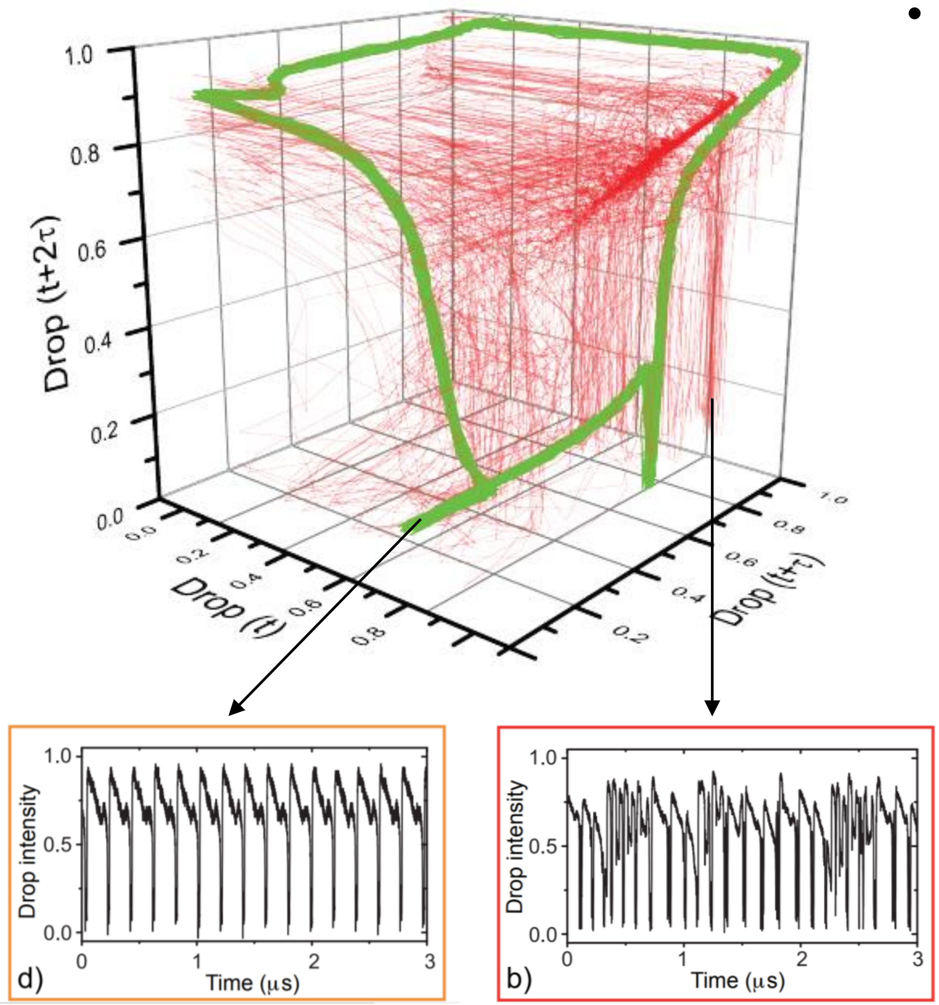
Coupled resonators dynamics



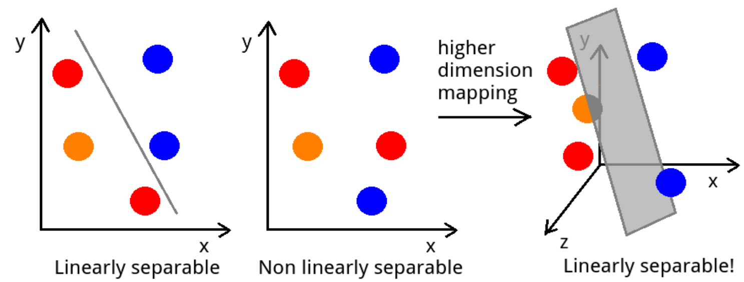


Coupled cavities dynamics

Reconstructed phase space



- 8 cavities for a total of 32 degree of freedom
  - Complex field of 8 cavities: 16 degrees
  - Resonator temperature: 8
  - Resonator free-carrier-density: 8



Tomorrow Pt2:
Using this system as resevoir