IA pour l'Optique, et Optique pour l'IA

Sylvain Gigan

AG du LabEx FIRST TF

Oct 2, 2026

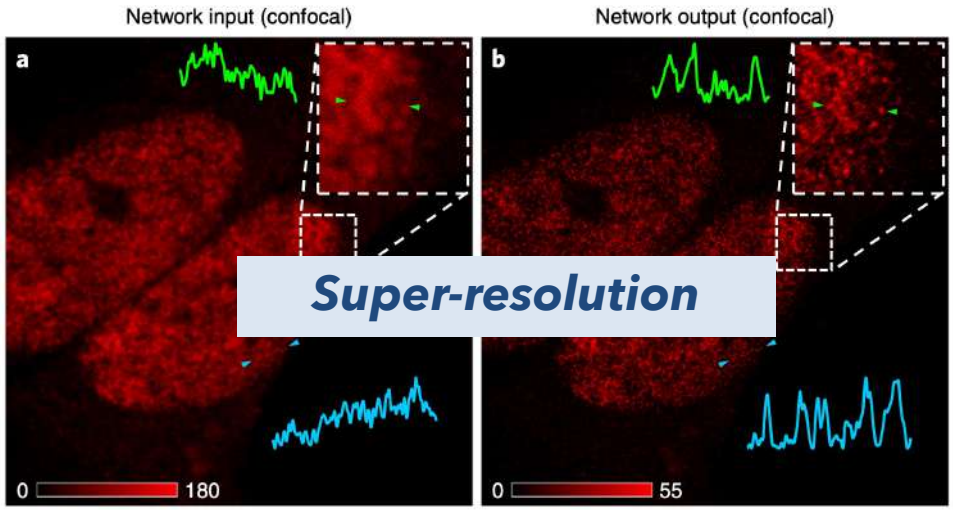
Laboratoire Kastler Brossel
Physique quantique et applications

ENS
SORBONNE UNIVERSITÉ
COLLÈGE DE FRANCE
cnrs

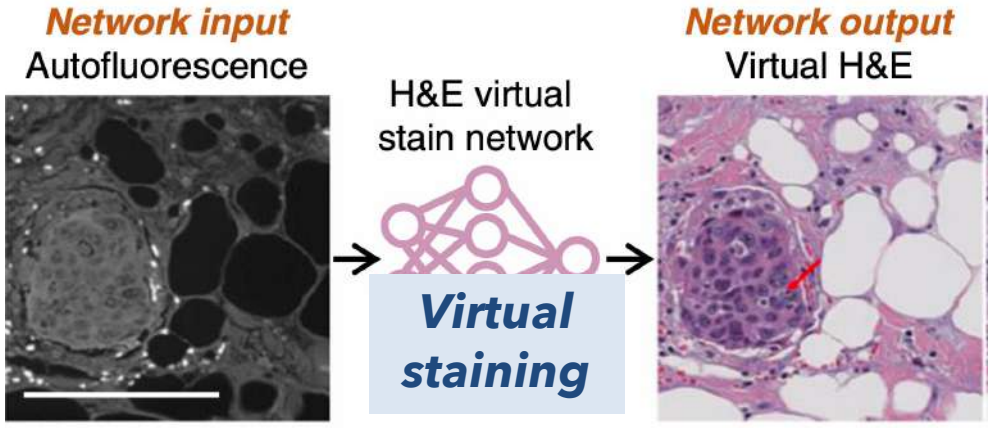

AI
ARTIFICIAL
INTELLIGENCE


AI
ARTIFICIAL
INTELLIGENCE
PHOTONICS

Deep learning for Microscopy

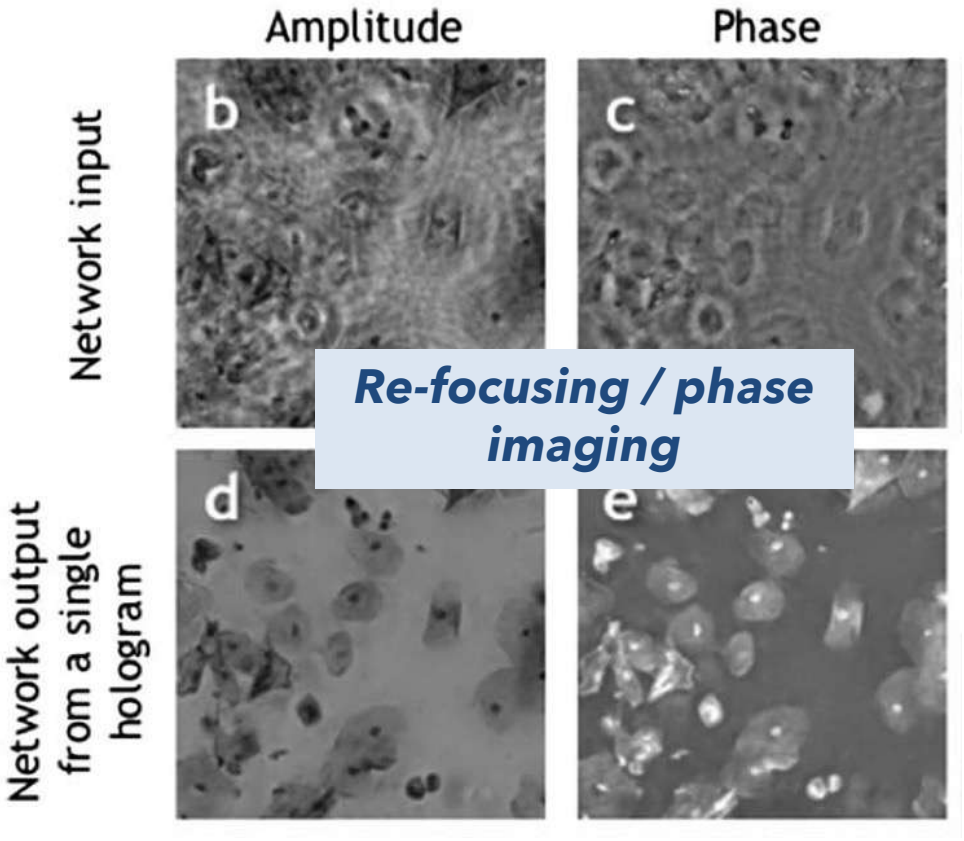


Super-resolution



Virtual staining

Bai et al. Light: Science & Applications (2023)



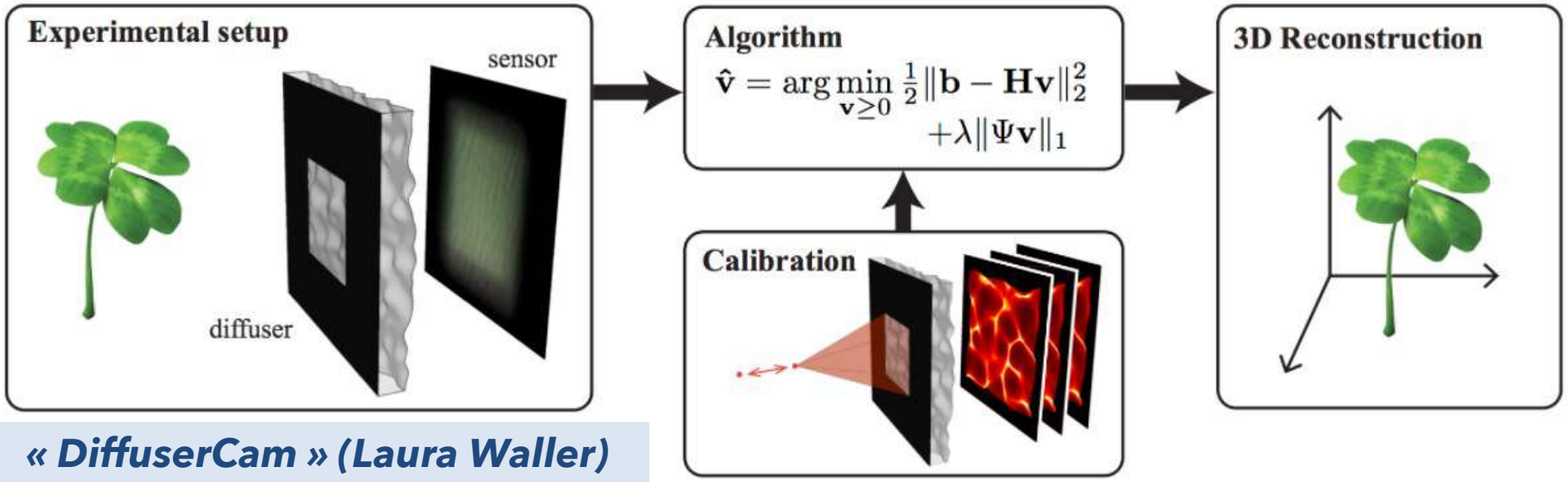
Re-focusing / phase imaging

+denoising etc…

In France : Sibarita (Bordeaux) J.C. Olivo Marin (Pasteur) etc…
France-BioImaging, GDR ImaBio, PRAIRIE.

Rivenson, Yair, et al. "Deep learning microscopy." *Optica* 4.11 (2017): 1437-1443.

Computational Imaging



« DiffuserCam » (Laura Waller)

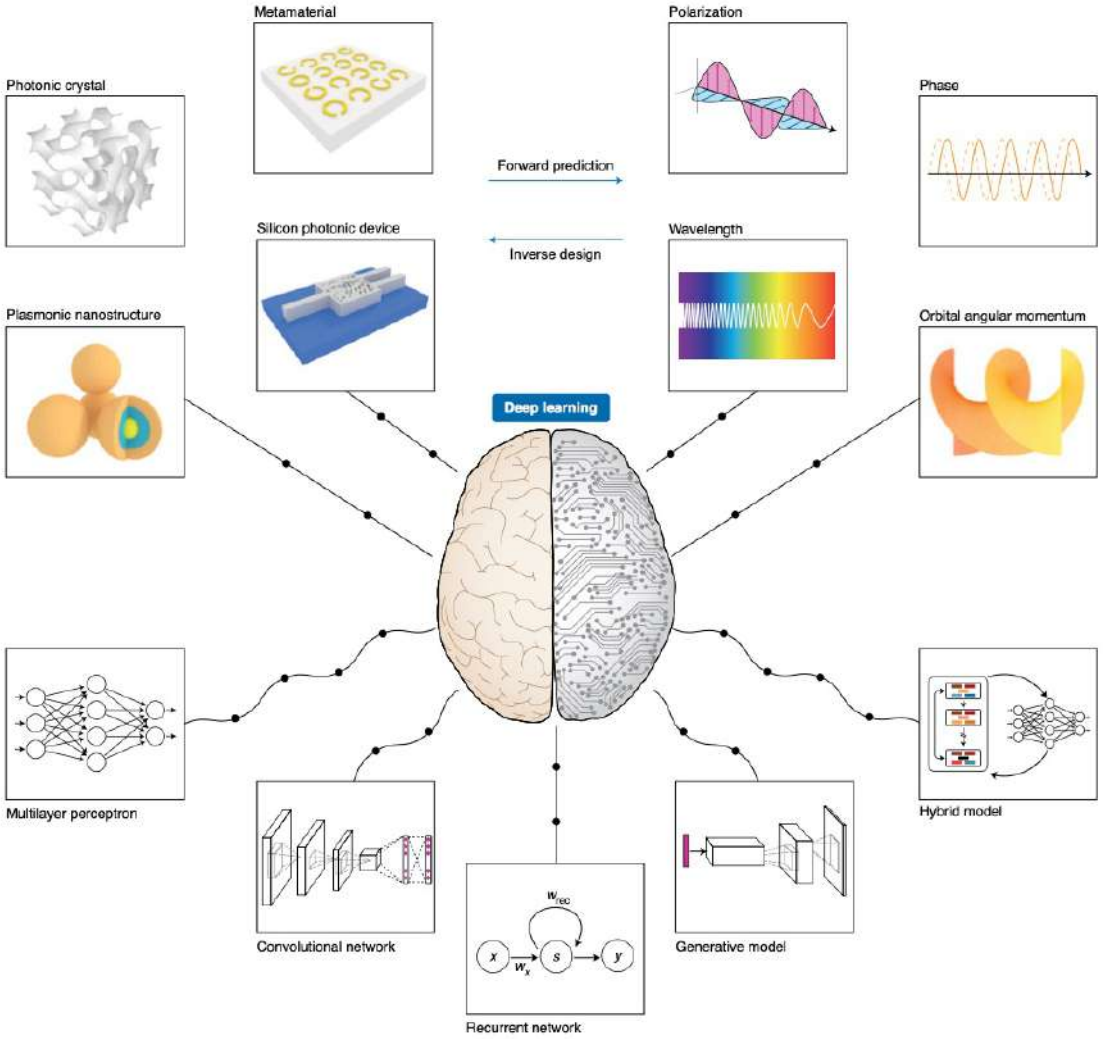
- Holography
- Inverse problems
- Hyperspectral Imaging
- Lensless imaging
- Ptychography
- Imaging in Complex Media
- …

In France :
- Anne Sentenac / Marc Allain (Marseille)
- Corinne Fournier (Saint Etienne)
- Laure Blanc-Féraud (Nice)

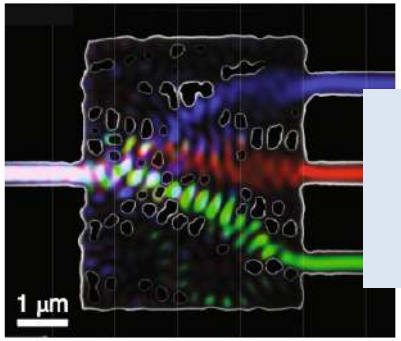
…

See talks of Vincent Favre-Nicollin and Nelly Pustelnik

Inverse design in nanophotonics

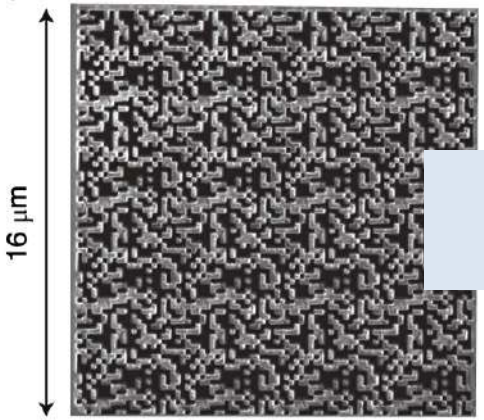


Ma, Wei, et al. "Deep learning for the design of photonic structures." *Nature photonics* 15.2 (2021): 77-90.



integrated wavelength demultiplexer

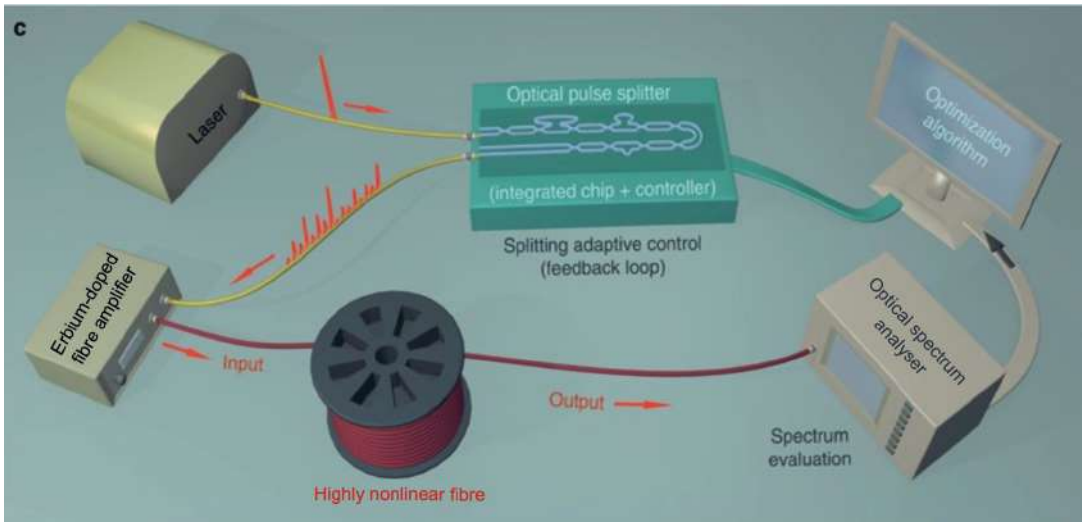
Molesky, Sean, et al. "Inverse design in nanophotonics." *Nature photonics* 12.1 (2018): 659-670.



Metasurface - polarizer

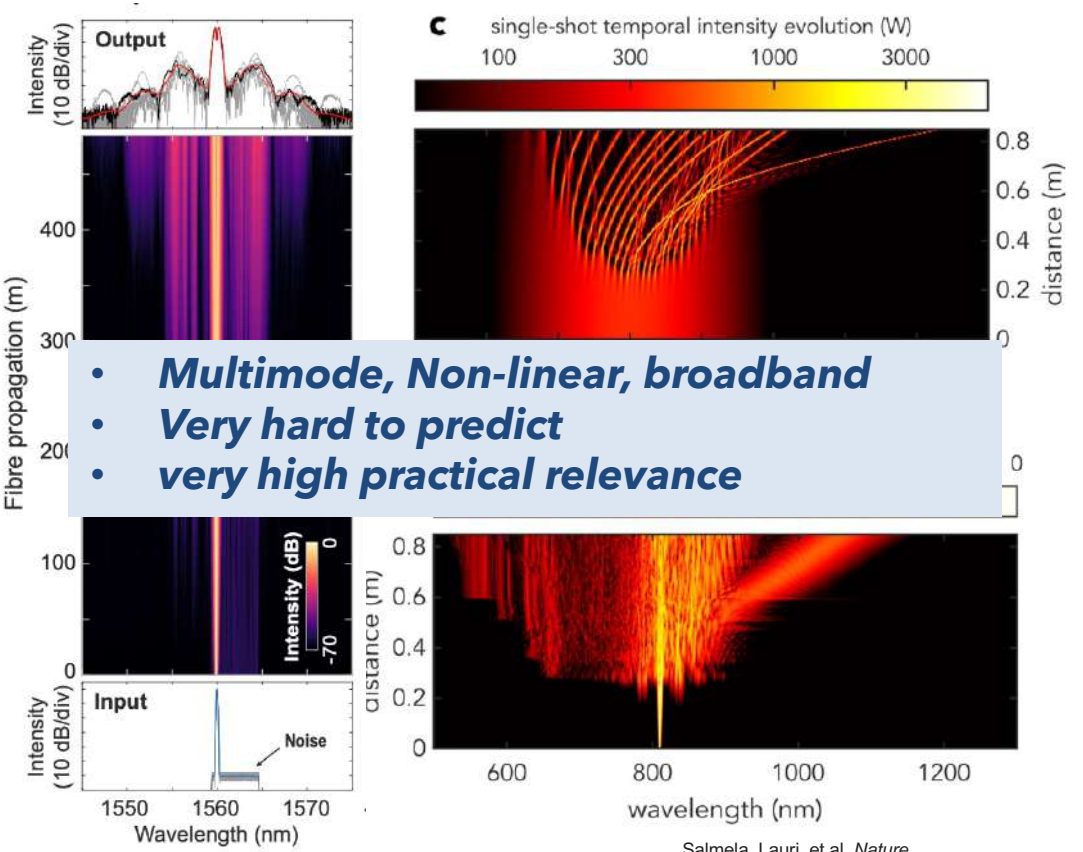
@CNRS: Philippe Lalanne (Bordeaux) Nicolas Bonod (Marseille) Peter Wiecha (Toulouse), etc…

Deep Learning for Non-Linear & Ultrafast Optics



Genty, G., Salmela, L., Dudley, J. M., Brunner, D., Kokhanovskiy, A., Kobtsev, S., & Turitsyn, S. K. (2021). Machine learning and applications in ultrafast photonics. *Nature Photonics*, *15*(2), 91-101.

- Mode locking of lasers
- Non-linear Dynamics
- Solitons / Rogue waves
- Ultrafast instabilities
- Supercontinuum generation
- Telecommunications …

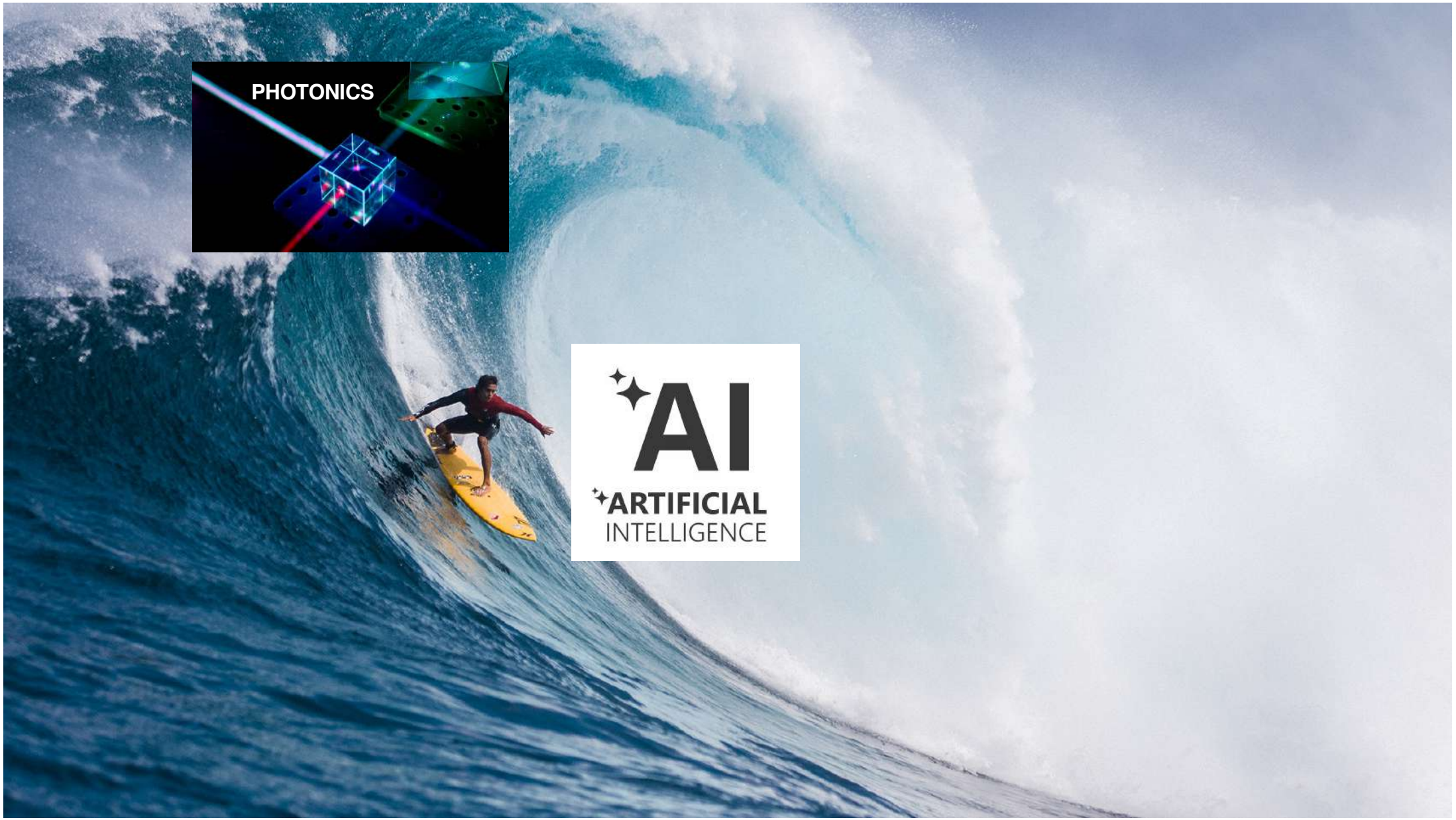


- ***Multimode, Non-linear, broadband***
- ***Very hard to predict***
- ***very high practical relevance***

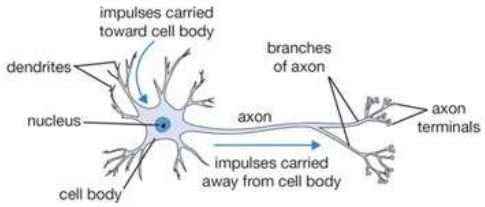
Boussafa, Yassin, et al. *Nature communications* 16.1 (2025): 7800.

Salmela, Lauri, et al. *Nature machine intelligence* 3.4 (2021): 344-354.

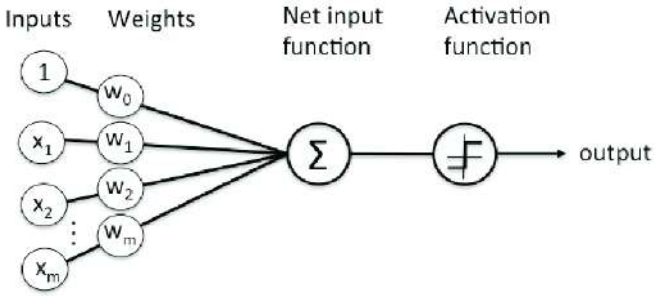
@CNRS: John Dudley, Daniel Brunner (Besancon) Benjamin Wetzel (XLIM) Christophe Finot (Dijon) A. Mussot (Lille) …


PHOTONICS
AI
ARTIFICIAL
INTELLIGENCE

Artificial neural networks (ANN) – the perceptron

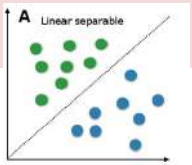


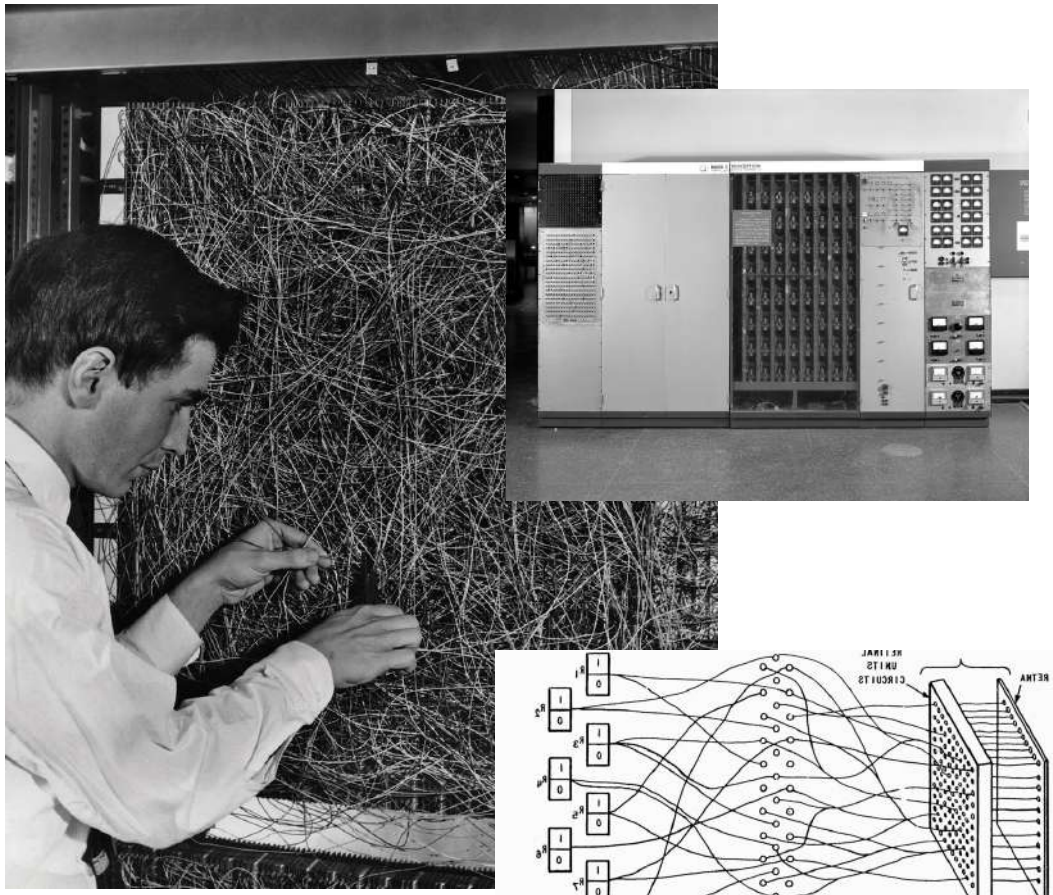
loosely inspired



$$y = \varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi(\mathbf{w}^T \mathbf{x} + b)$$

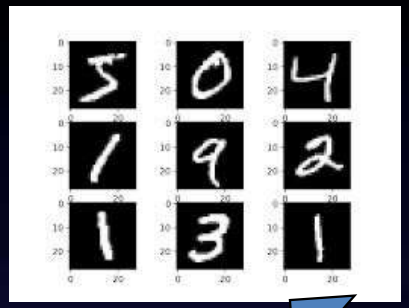
- Multiply-and-Accumulate (MAC)
- Tunable weights
- Non-linear activation function
  - ❖ Linear classifier





The Mark I perceptron
(Frank Rosenblatt – 1960')

The multi-layer perceptron

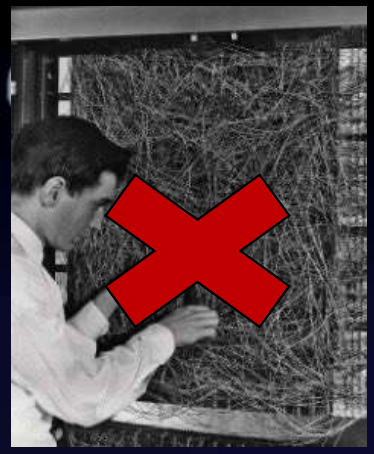


MNIST
50k examples
10 classes
~50MB

95% of analog computing papers

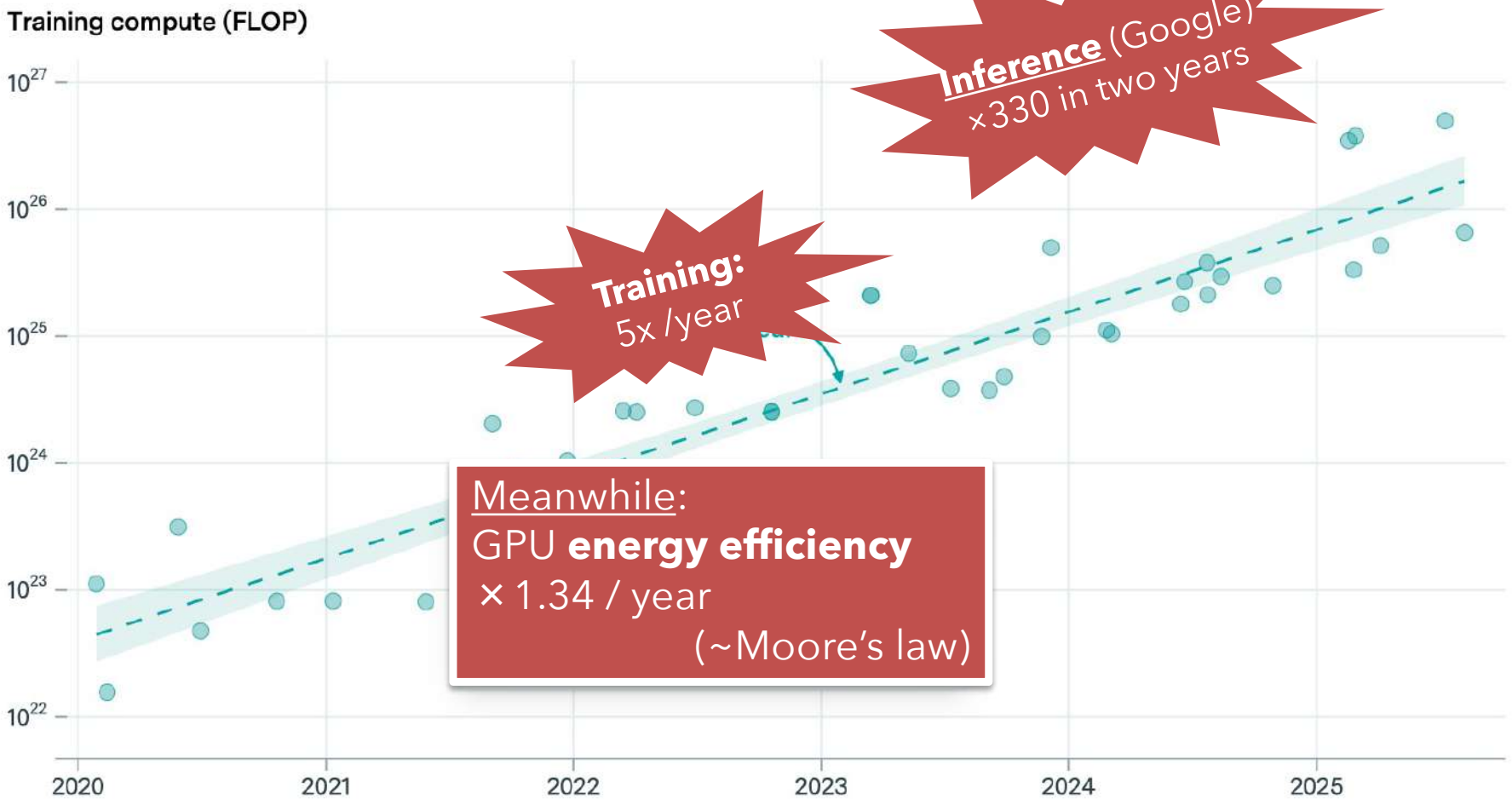
COMMON CRAWL

Text for training LLM
100 billions webpages
~8 PetaBytes
+ ~320 Terabytes / months



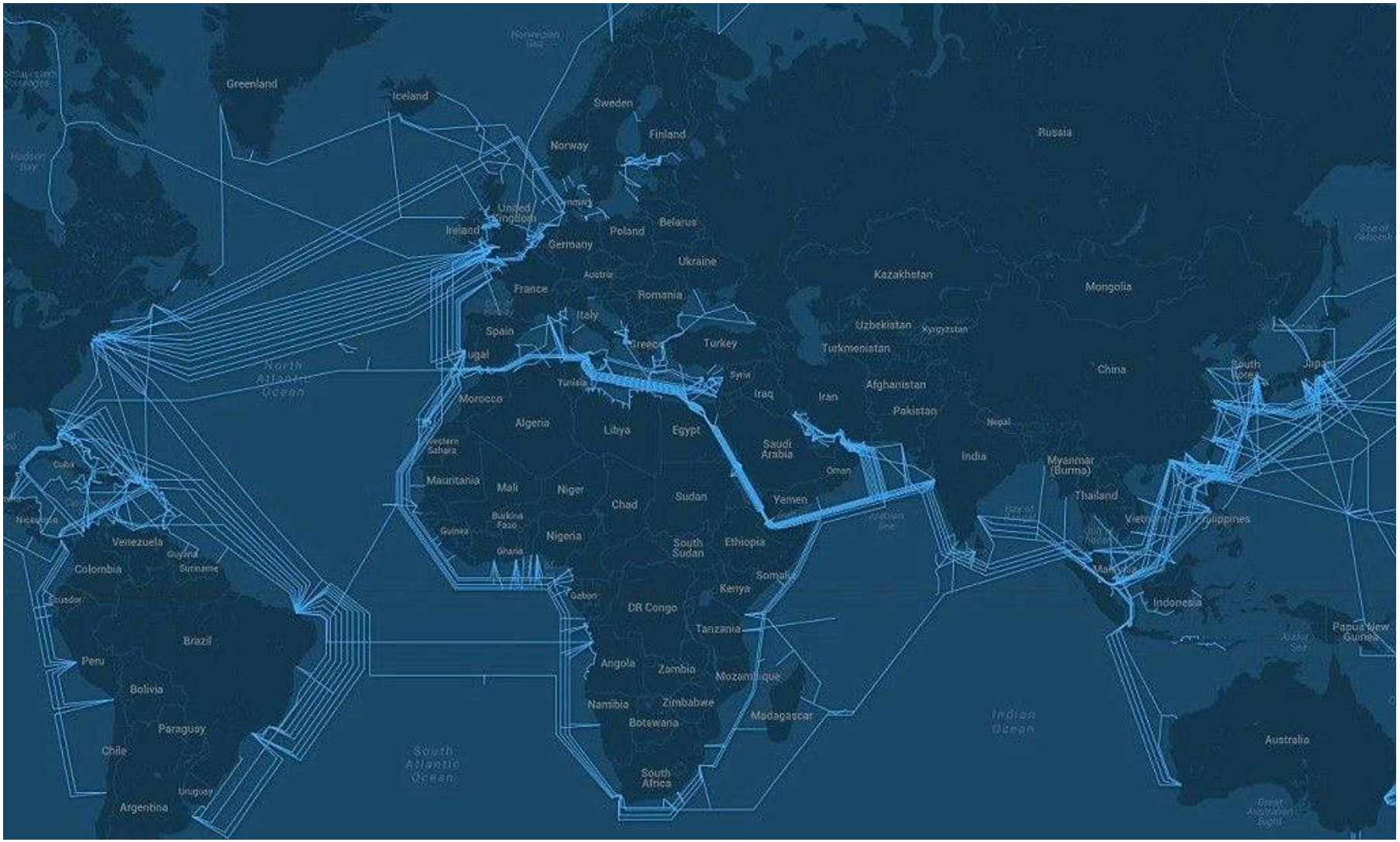
- All-to-all connectivity
- Adjustable weights
- Non-linear activation functions
- **Universal function approximator**

AI and Compute

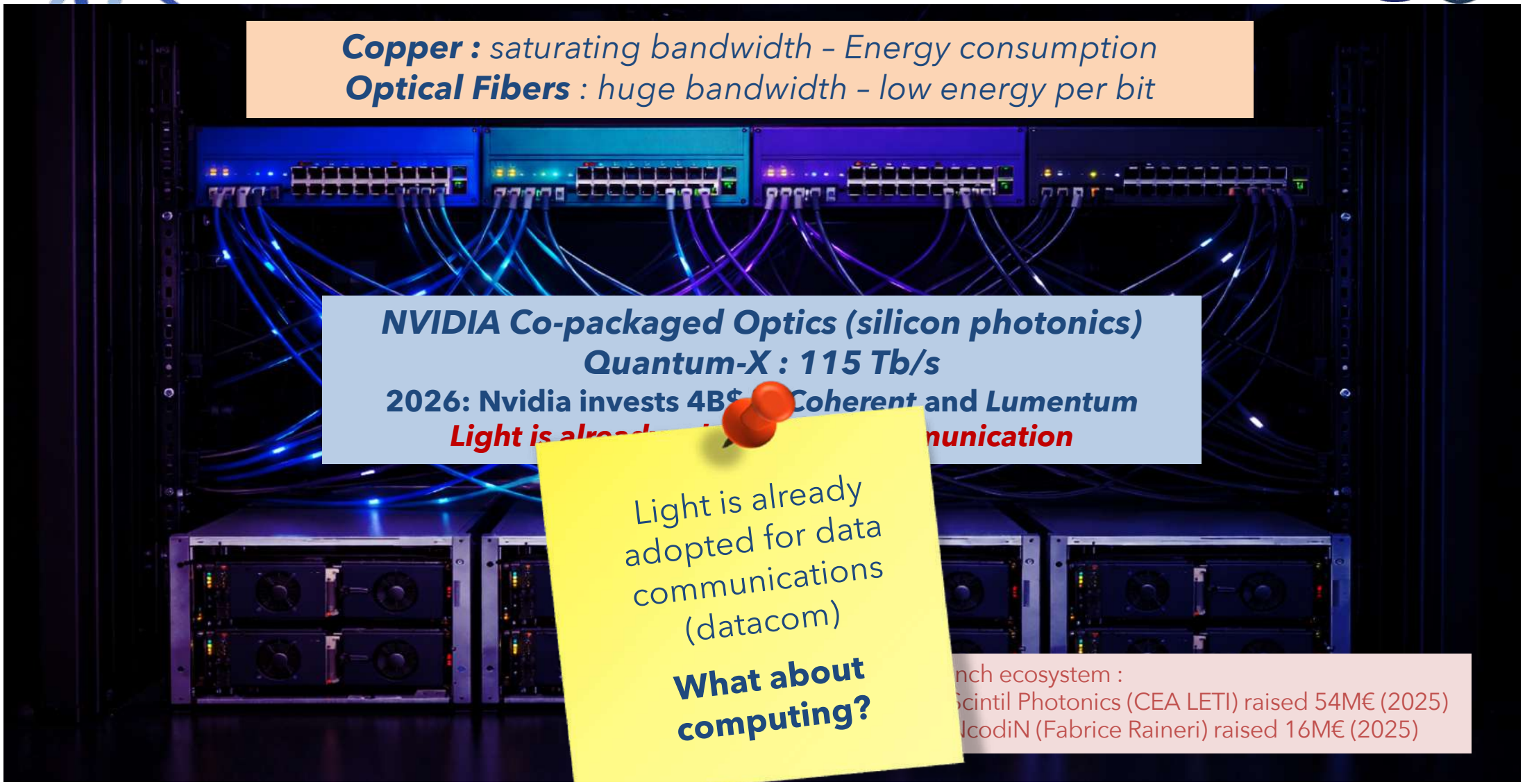


https://epoch.ai/trends

Light : moving information around the world



Light : moving AI's data with light within datacenters



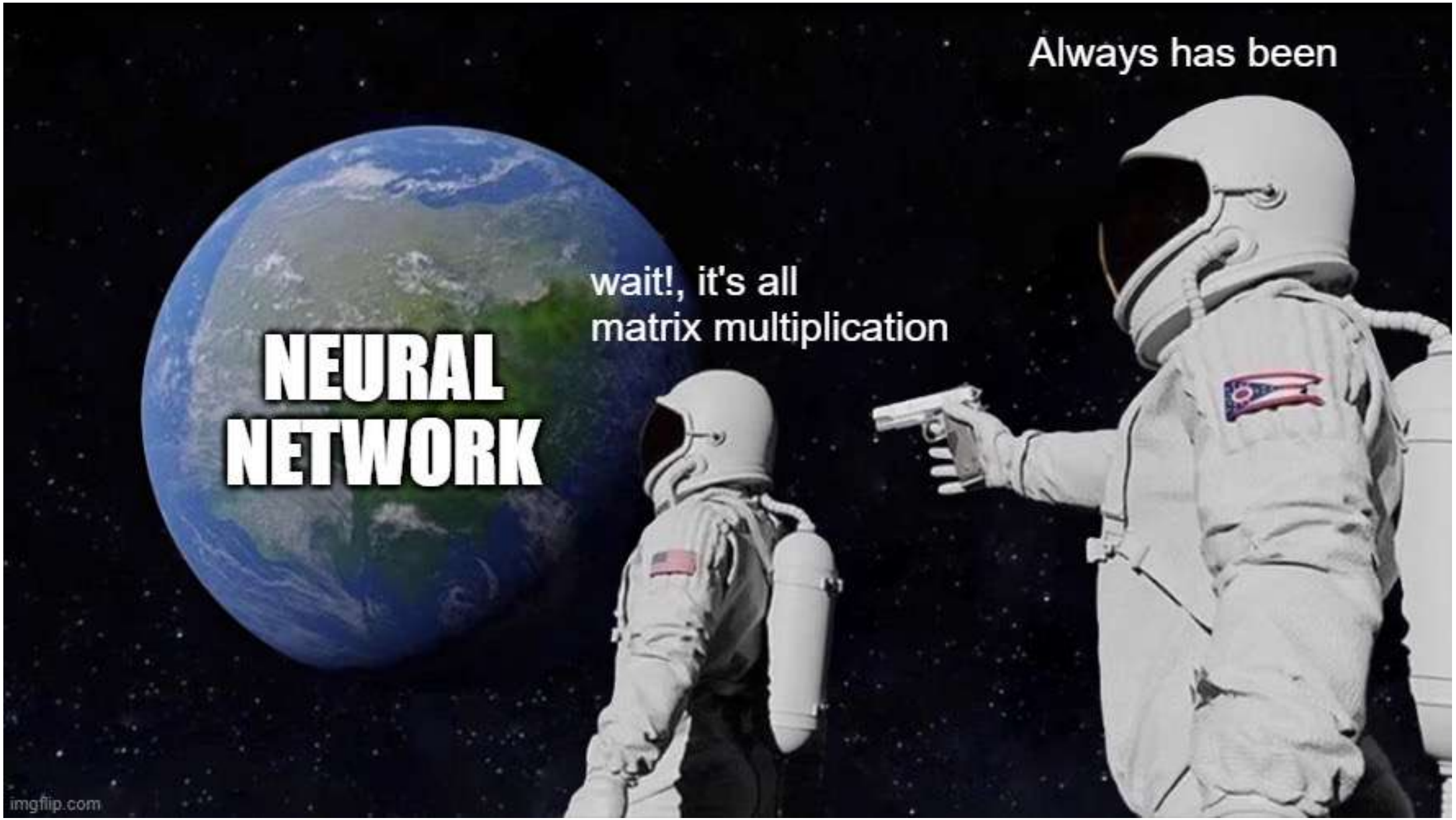
Copper : *saturating bandwidth – Energy consumption*
Optical Fibers *: huge bandwidth – low energy per bit*

NVIDIA Co-packaged Optics (silicon photonics)
Quantum-X : 115 Tb/s
2026: Nvidia invests 4B$ *Coherent* and *Lumentum*
Light is already adopted for data communication

Light is already adopted for data communications (datacom)

What about computing?

nch ecosystem :
Scintil Photonics (CEA LETI) raised 54M€ (2025)
NcodiN (Fabrice Raineri) raised 16M€ (2025)


Always has been
wait!, it's all
matrix multiplication
NEURAL
NETWORK
imgflip.com

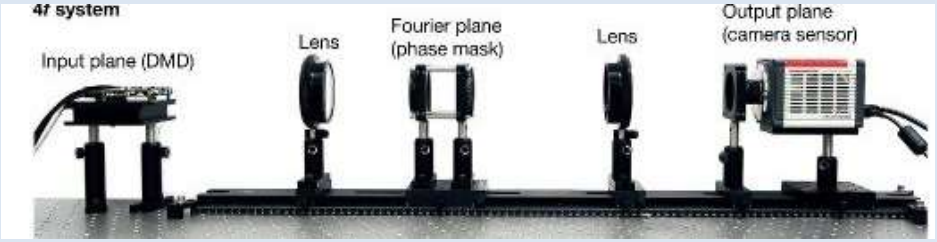
2015+ computing with light (redux)

Optics has distinct advantages…

- Low energy consumption
- Easy interconnect – Multiplexing
- Low latency + blazing speed

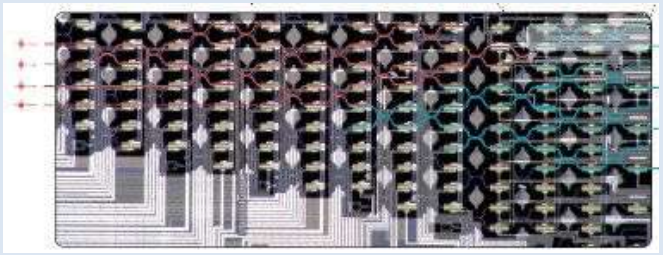
… and some disadvantages:

- Bulky
- Tricky non-linearities
- Storage



Sci. Rep. **8**, 12324 (2018).

Free space
vs
Integrated optics



Nature Photon **11,** 441–446 (2017)

Perspective | Published: 09 October 2023

The physics of optical computing

Peter L. McMahon

Nature Reviews Physics **5**, 717–734 (2023) | Cite this article

Comment | Published: 05 June 2026

The thin line for optical neural networks towards broad practical relevance

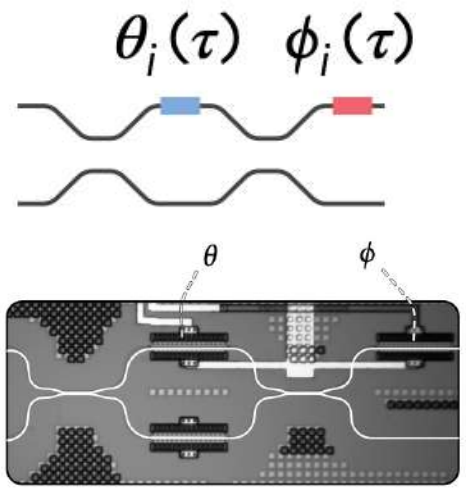
Anas Skalli & Daniel Brunner

Nature Photonics **20**, 601–604 (2026) | Cite this article

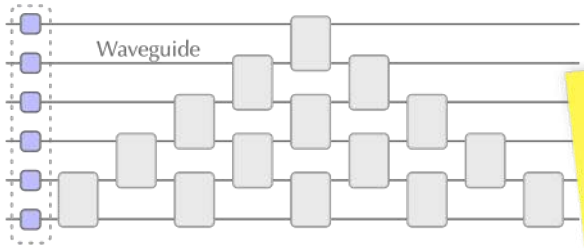
Integrated mach-Zehnder interferometers

Arbitrary Lossless 2x2 mixers

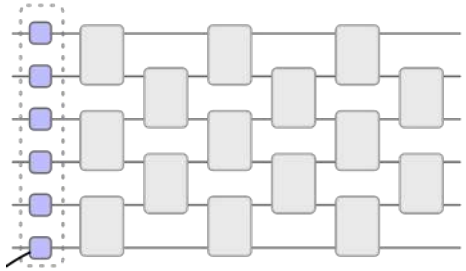
Slow (thermal) or fast (EOM) tuning



Nature Photon **11,** 447–452 (2017)



Unitary circuits



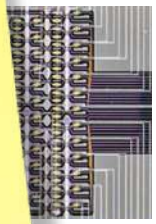
Integrated photonics

✅ GHz speed

✅ Fab compatibility

❌ In-out coupling

❌ Limited dimensions (few tens of modes)



Linear programmable nanophotonic processors (review) Optica 5, 1623-1631 (2018)

SoTA in Photonics integrated circuits

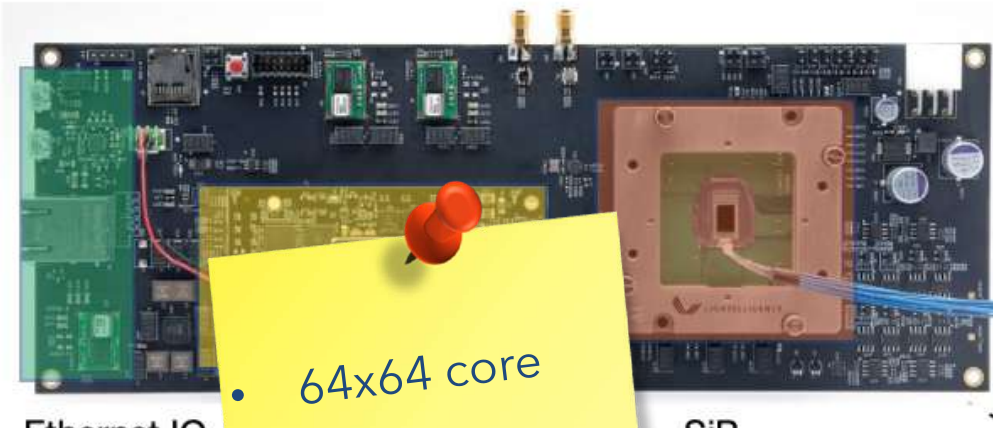
Article

An integrated large-scale photonic accelerator with ultralow latency

LIGHTELLIGENCE

https://doi.org/10.1038/s41586-025-08786-6
Received: 29 February 2024
Accepted: 13 February 2025
Published online: 9 April 2025

Shiyue Hua[1,3], Erwan Divita[1,3], Shanshan Yu[1], Bo Peng[1✉], Charles Roques-Carmes[2], Zhan Su[1], Zhang Chen[1], Yanfei Bai[1], Jinghui Zou[1], Yunpeng Zhu[1], Yelong Xu[1], Cheng-kuan Lu[1], Yuemiao Di[1], Hui Chen[1], Lushan Jiang[1], Lijie Wang[1], Longwu Ou[1], Chaohong Zhang[1], Junjie Chen[1], Wen Zhang[1], Hongyan Zhu[1], Weijun Kuang[1], Long Wang[1], Huaiyu Meng[1✉], Maurice Steinman[1] & Yichen Shen[1✉]



- 64x64 core
- 16000 components
- 1GHz

Article

Universal photonic artificial intelligence acceleration

LIGHTMATTER

https://doi.org/10.1038/s41586-025-08854-x
Received: 18 November 2024
Accepted: 3 March 2025
Published online: 9 April 2025
Check for updates

Sufi R. Ahmed[1], Reza Baghdadi[1], Mikhail Bernadskiy[1], Nate Bowman[1], Ryan Braid[1], Jim Carr[1], Chen Chen[1], Pietro Ciccarella[1], Matthew Cole[1], John Cooke[1], Kishor Desai[1], Carlos Dorta[1], Jonathan Elmhurst[1], Bryce Gardiner[1], Elliot Greenwald[1], Shashank Gupta[1], Parry Husbands[1], Brian Jones[1], Anthony Kopa[1], Ho John Lee[1], Arulselvan Madhavan[1], Adam Mendrela[1], Nicholas Moore[1], Lakshmi Nair[1], Aditya Om[1], Subie Patel[1], Rutayan Patro[1], Rob Pellowski[1], Esha Radhakrishnani[1], Sandeep Sane[1], Nicholas Sarkis[1], Joe Stadolnik[1], Mykhailo Tymchenko[1], Gongyu Wang[1], Kurt Winikka[1], Alexandra Wleklinski[1], Josh Zelman[1], Richard Ho[2], Ritesh Jain[1], Ayon Basumallik[1✉], Darius Bunandar[1✉] & Nicholas C. Harris[1✉]



- 128x128 cores
- 7-10 bits precision
- ~2GHz

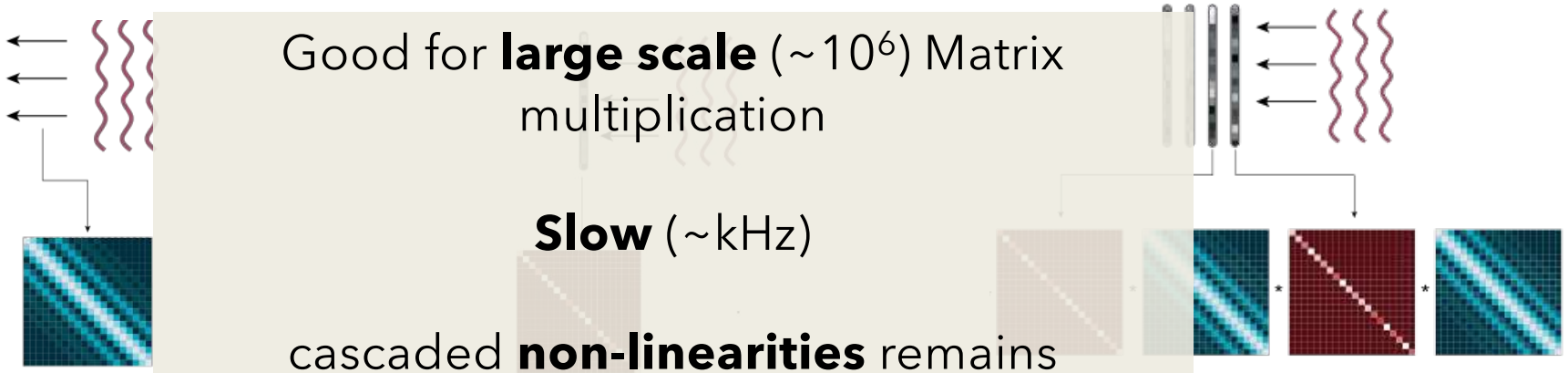
Matrix multiplication in free space optics

Basic building blocks:

Free space

Thin mask

layered scatterer



Good for **large scale** (~10^6) Matrix multiplication

Slow (~kHz)

cascaded **non-linearities** remains challenging

Diffractive ~~**deep**~~ neural networks

Training is hard

Advanced functions

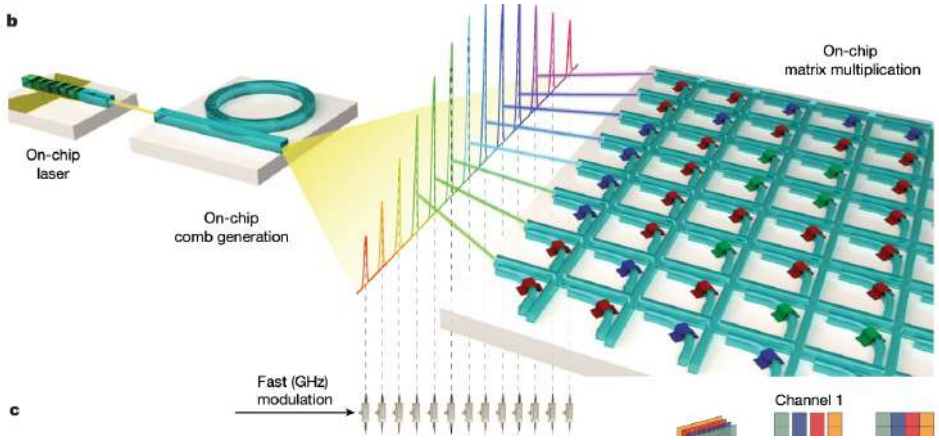


2D convolutions

1D vector-matrix multiplier

Adapted from *Nature 588, 39 (2020)*

The bandwidth and energy advantage



Feldmann, J., et al. "Parallel convolutional processing using an integrated photonic tensor core." *Nature* 589.7840 (2021): 52-58.

Frequency comb = N coherent lasers

✅ Same matrix multiplied N times in parallel

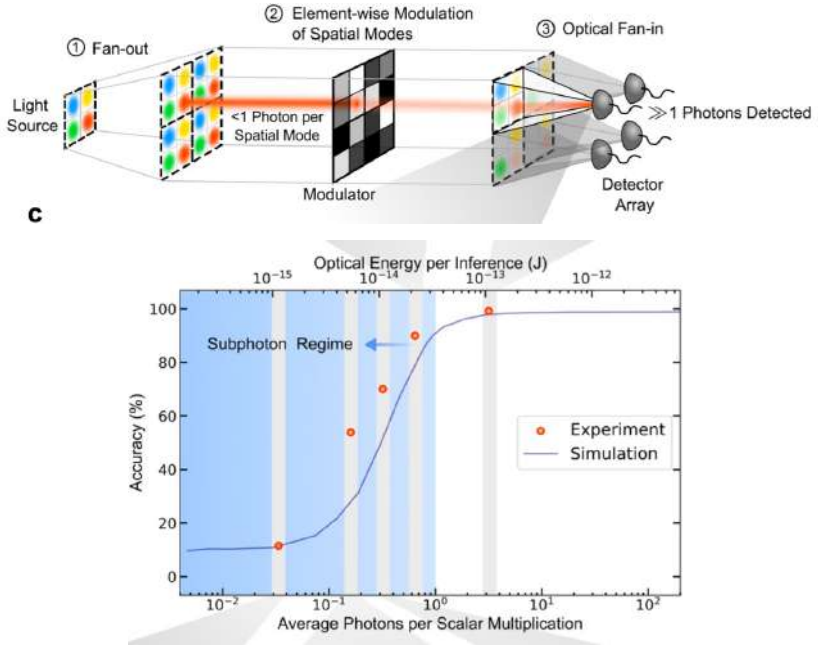
✅ Different inputs can be encoded on each comb line

❌ Need mux-demux at the input and output

https://doi.org/10.1038/s41467-021-27774-8 OPEN

An optical neural network using less than 1 photon per multiplication

Tianyu Wang[1✉], Shi-Yuan Ma[1], Logan G. Wright[1,2], Tatsuhiro Onodera[1,2], Brian C. Richard[3] & Peter L. McMahon[1✉]



Accuracy on MNIST:
90% with <1 (detected) photon/MAC

The PICo Lab

Photonics, Information and Complexity

ALUMNI

PhDs:
S.Popoff
M. Mounaix
D.Andreoli
B. Blochet
P.Bondareff
T. Sperber
T.Chaigne
J. Guilbert
H.Defienne
A. Boniface
S.Leedumrong-
J. Dong
L. Devaud
H. Wang
F. Mazzoncini
L. Delloye
M. Joly
B. Courme
L. Chibani

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P. Boucher
M. Dabrowski
D.Martina
C. Moretti
R. Savo
F. Soldevila
G. Volpe
L. Valzania
J.Bertolotti
J. Hu
O.Katz
C. Rimoli
T. Juffman
L. Valzania
R. Pandya
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C. Gentner
F. Xia

PIs:
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Dr. Shupeng ZHAO
Dr. Andrew VOITIV
Dr. Raouf AMARA
Dr. Zannatul FERDOUS
Dr. Yandong LI
Dr. Francois FIGLIOLIA
Dr. Morgan FACCHIN

PhD Students
Adrian MAKOWSKI
Ziao WANG
Hankun YANG
Amol MAHURKAR
Salim BENNANI
Haitao ZHOU
Baptiste PORTAIL
Thierry LAPOINTE-LECLERC
Ruotong FENG



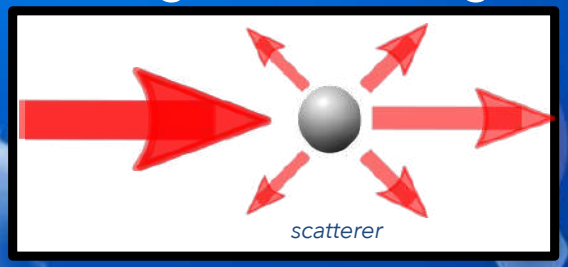
RECENT COLLABORATIONS

- J.M Tarascon
- P. Del Hougne
- H. Defienne
- E. Papagiokoumou
- L. Bourdieu, C. Ventalon
- P. Mounaix (CNRS)
- H. Defienne(CNRS)
- C. Conti (U. Sapienza)
- G. Volpe (UCL)
- R. Sapienza (Imperial)
- S. Rotter (TU Wien)
- F.Krzakala (EPFL)
- E. Charbon (EPFL)
- R. Grange (ETHz)
- Niao He (ETHz)
- R. Lapkiewicz (U. Warsaw)
- R. Fickler (U. Tampere)
- H. Cao (Yale)
- A.Vaziri (Rockefeller)
- Qiang Liu (Tsinghua)
- Puxiang Lai (PolyU)

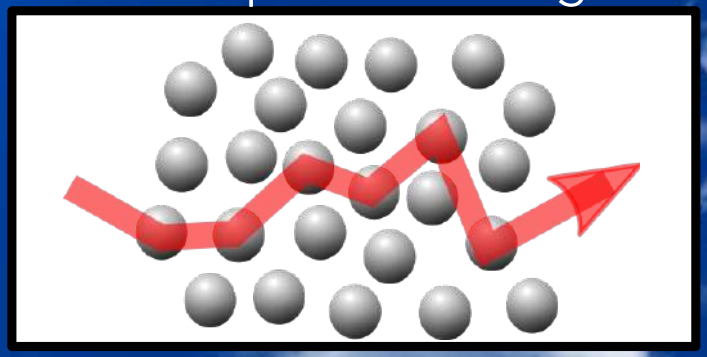
Scattering

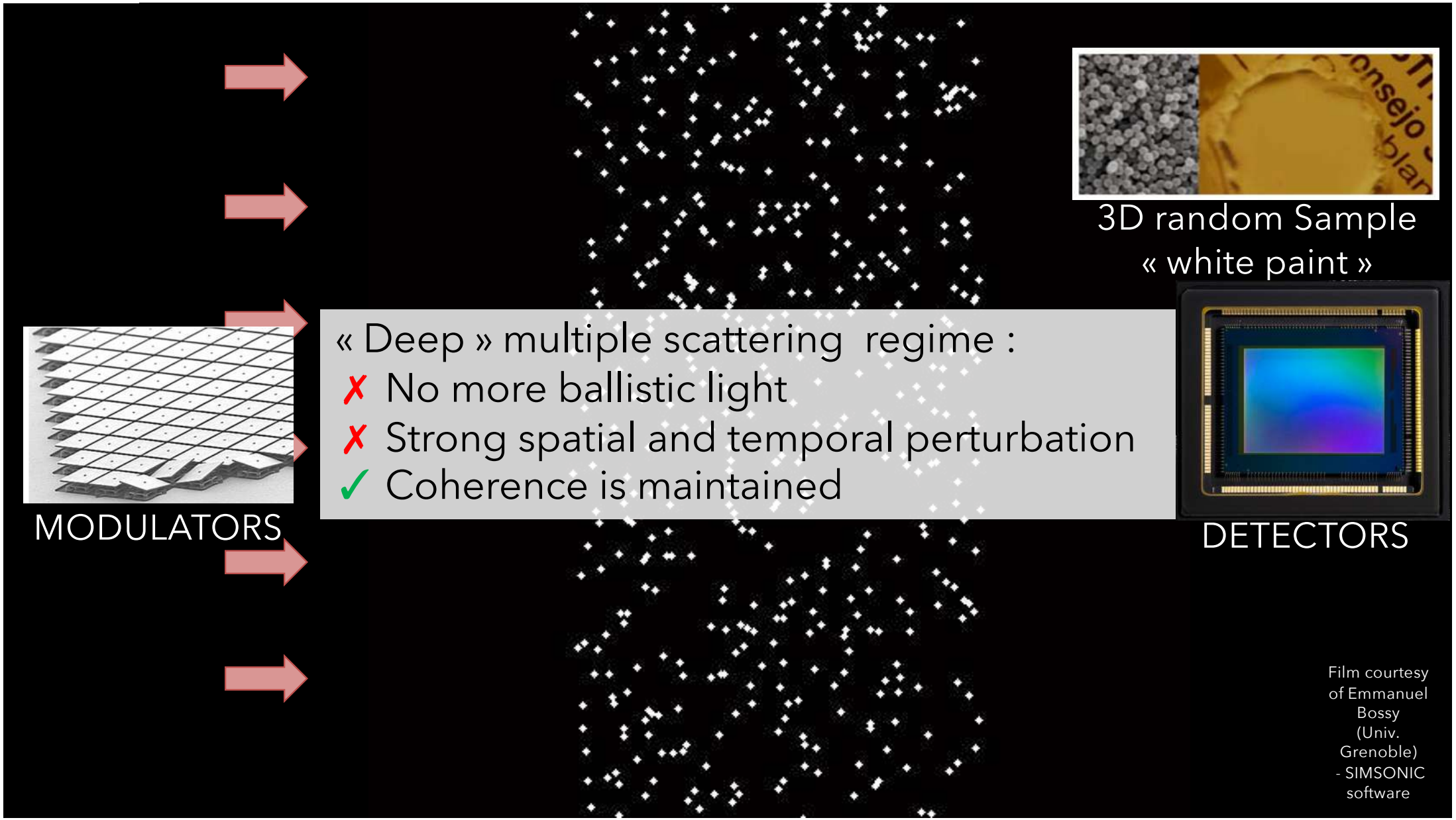
Ballistic Light

Single scattering



Multiple Scattering




3D random Sample
« white paint »
« Deep » multiple scattering regime :
✗ No more ballistic light
✗ Strong spatial and temporal perturbation
✓ Coherence is maintained
MODULATORS
DETECTORS
Film courtesy of Emmanuel Bossy (Univ. Grenoble) - SIMSONIC software

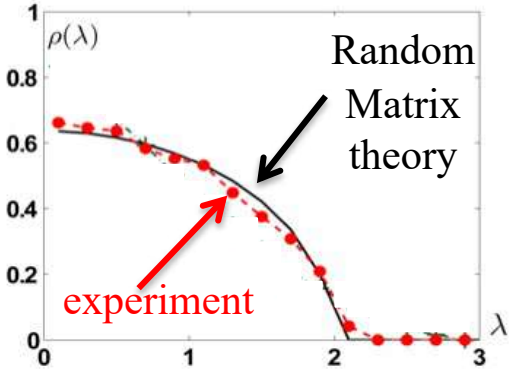
After a few minutes…

Transmission Matrix :

- Deterministic / stable
- Complex coefficients
- Potentially *very* large



Is it random ?

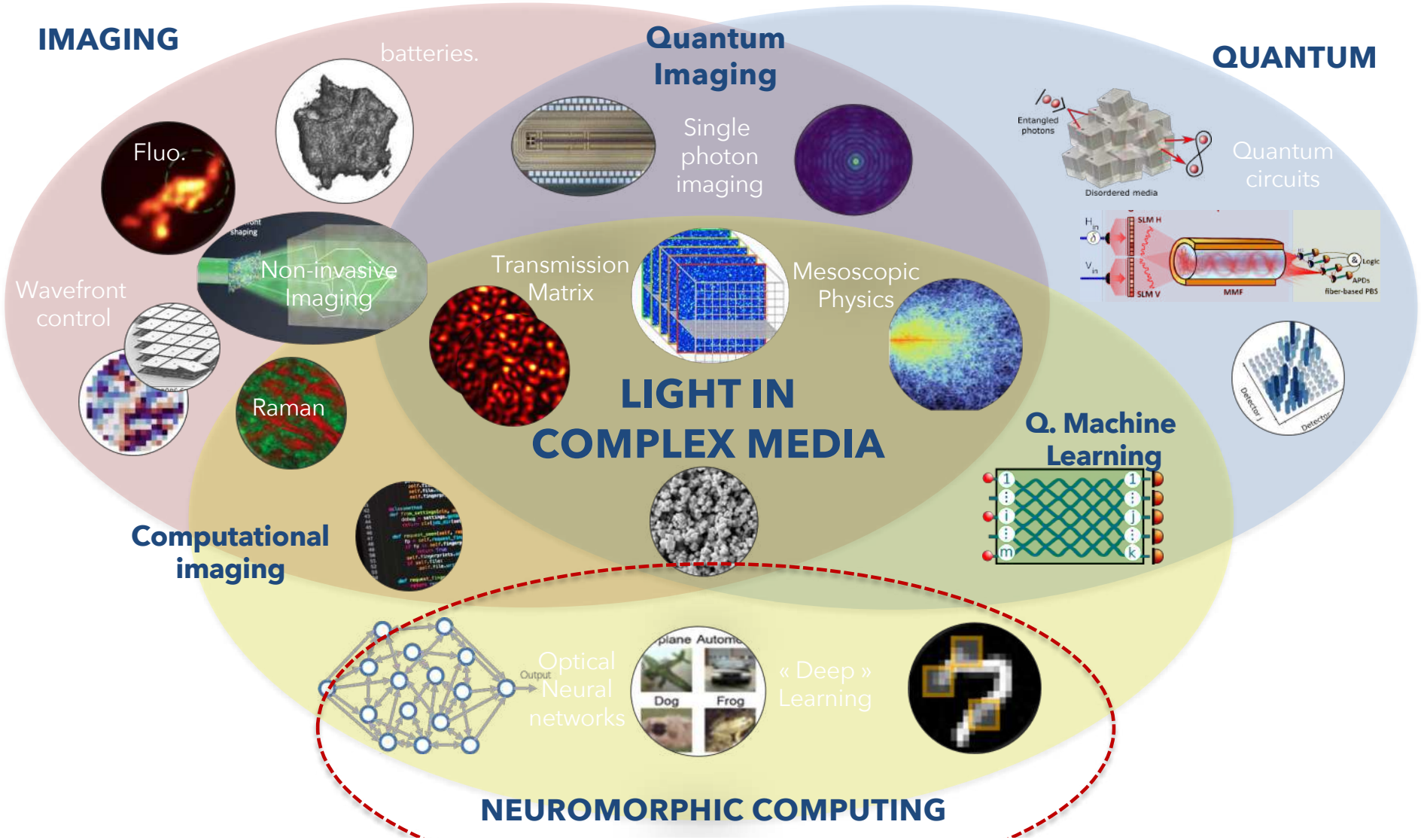


Singular value distribution

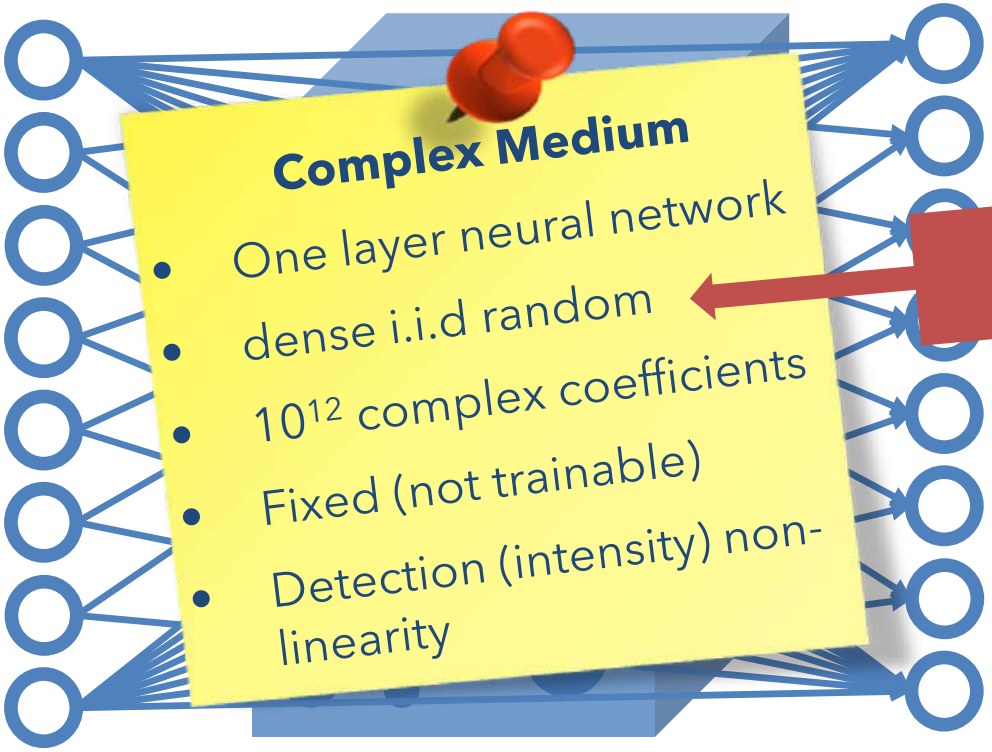
Disordered medium
= perfect mixer
i.i.d gaussian

+ Mesoscopic effects :
Rotter & Gigan, Rev. Modern. Physics (2017)

Our Goal : Understand and Harness light propagation in complex media



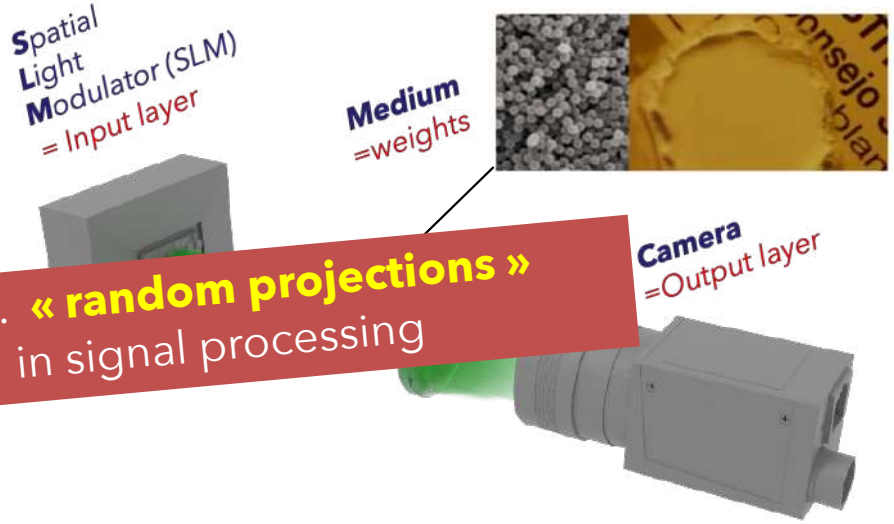
Optical computing with a complex medium ?

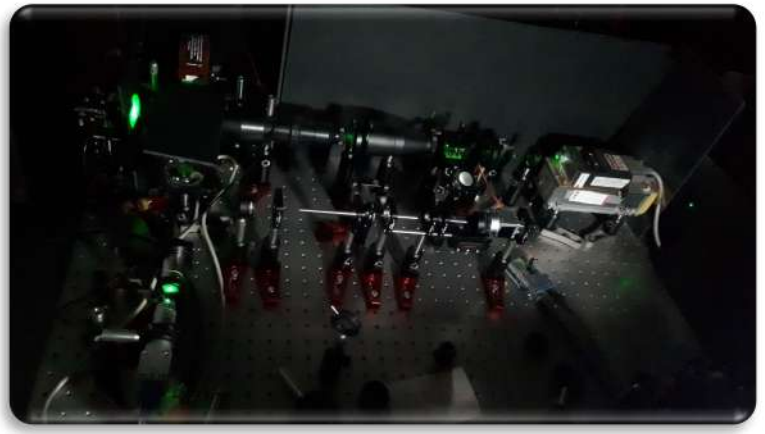


Complex Medium

- One layer neural network
- dense i.i.d random
- 10^{12} complex coefficients
- Fixed (not trainable)
- Detection (intensity) non-linearity

a.k.a. **« random projections »** in signal processing

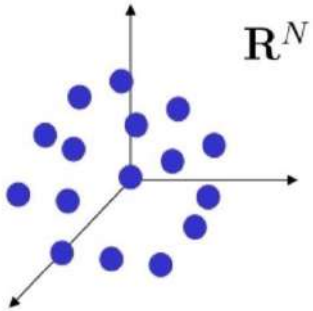


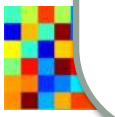


What are « random projections » good for?

Dimensional Reduction
« Johnson & Lindenstrauss »

Dimensional expansion
The "kernel Trick" « Rahimi & Recht »

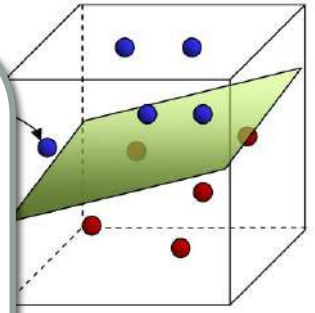




Key insight :

You don't need to know the matrix!

(you just need to know it is random)



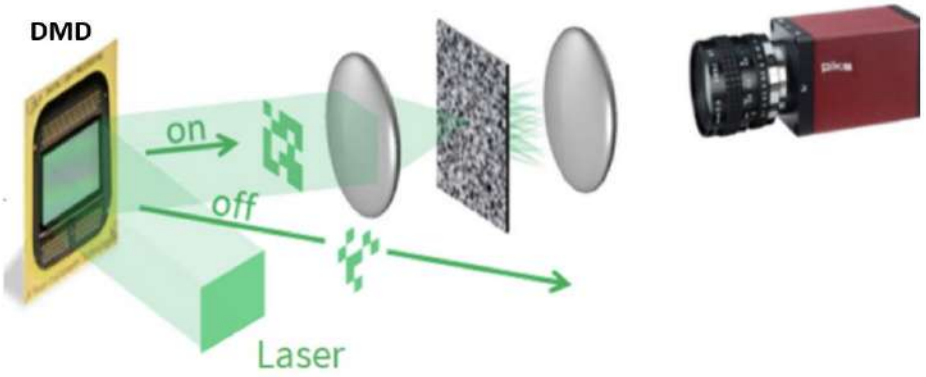
- Random matrix: dimension reduction
- **conserve distances** even for M<<N

- Make a **non-linear** regression problem **linear**
- Random projections are **efficient** and **universal**

Johnson, W. B., & Lindenstrauss, J. Extensions of Lipschitz mappings into a Hilbert space. *Contemporary mathematics*, 26,189(1984)
cited ~5000 times

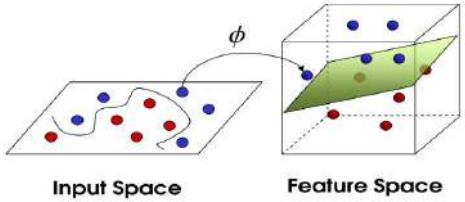
Rahimi, A., & Recht, B. (2007). Random features for large-scale kernel machines. In *Advances in neural information processing systems* (pp. 1177-1184).
cited >6000 times

Experimental Proof of Principle (2016)

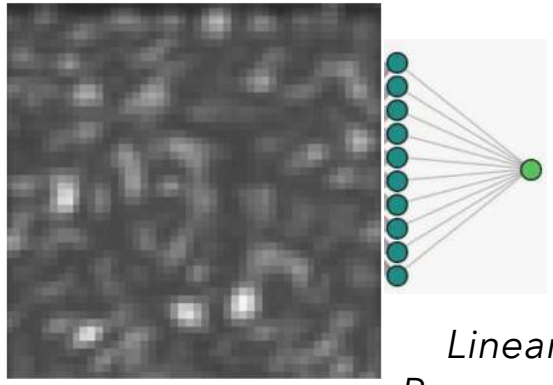


MNIST database





Random Optical projections

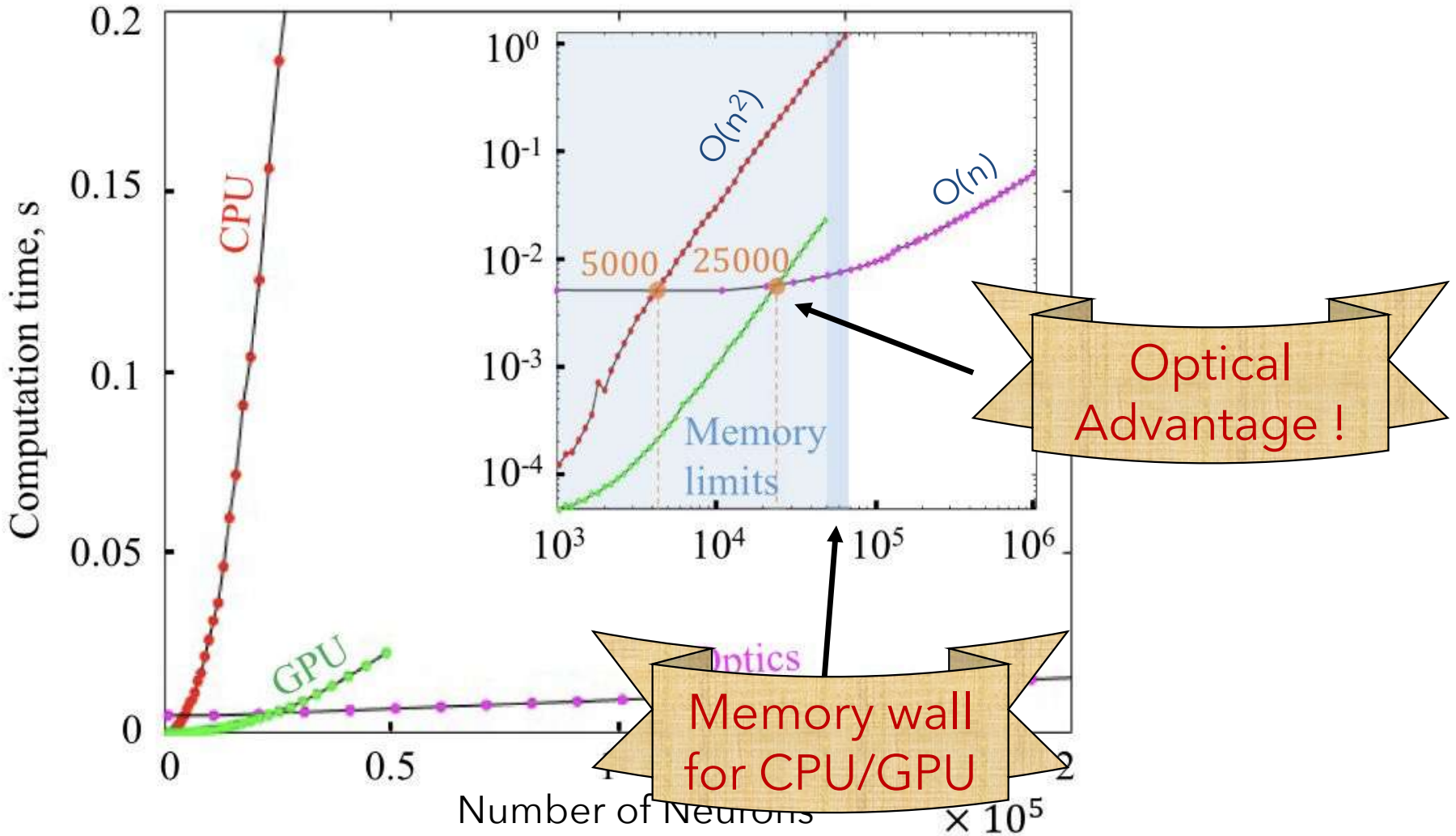


97% classification accuracy

Linear Regression (digital)

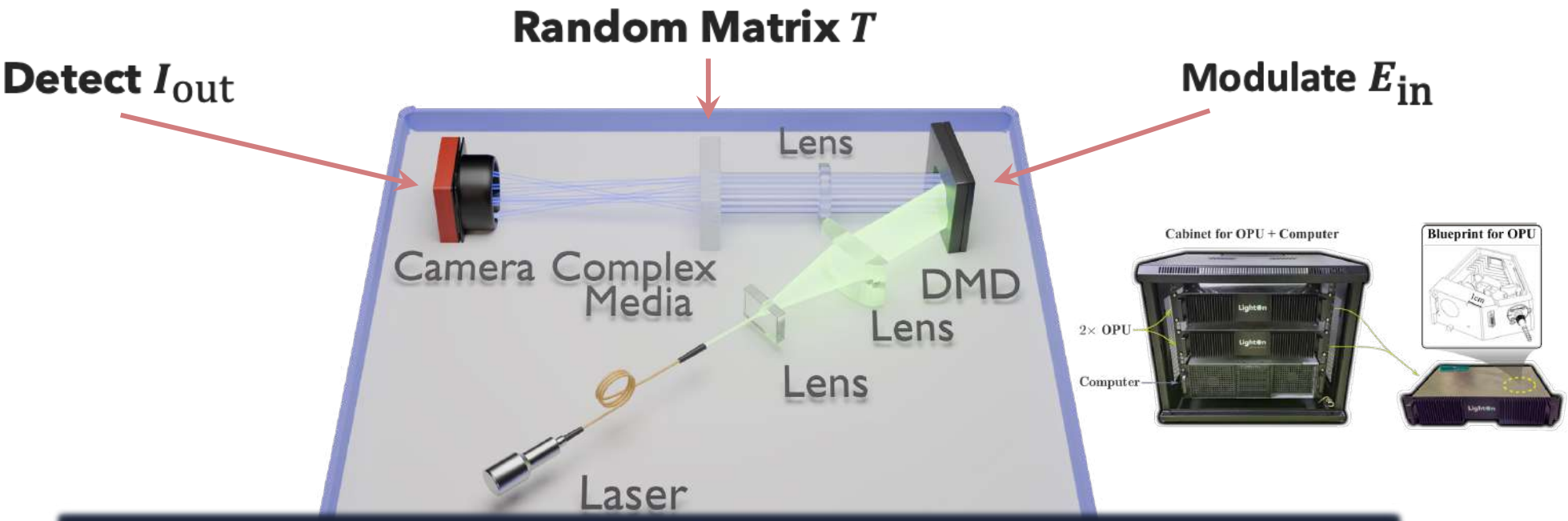
A. Saade, F. Caltagirone, I. Carron, L. Daudet, A. Drémeau, S. Gigan, F. Krzakala, ICCASP (2016)

Computation time vs. Matrix size



Rafayelyan, Dong, Tan, Krzakala, Gigan (2020). *Physical Review X*

Lighton's Optical Processing Unit



High Dimensional: $10^6 \times 10^6$
Fast: 1500Hz
~30W power consumption

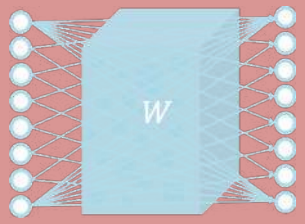
} ~1500 TeraOPS

} ~20 fJ/Ops

- **already at scale for modern machine learning ☺**
- **1st commercial optical co-processor (2018) ☺ in datacenter (2021) ☺**
- **Pivoted to pure GenAI (2023) ☹ but still very active in my lab ☺**

Computing with randomness – a 10 years journey

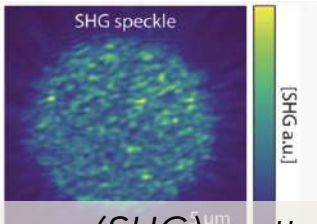
Optical Random Projections



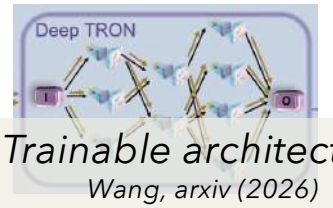
- Easy fabrication
- All-to-all connectivity
- Fixed weights
- Already at scale
- Low power consumption



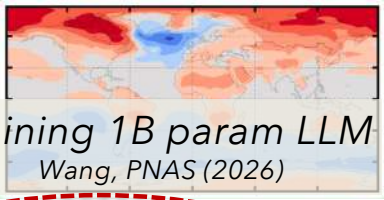
Physical information bottleneck
Wang, arxiv (2026)



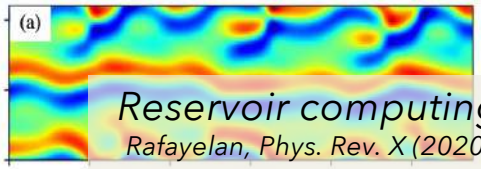
Nonlinear (SHG) scattering
Wang, Nat. Comp. Science (2024)



Trainable architecture
Wang, arxiv (2026)



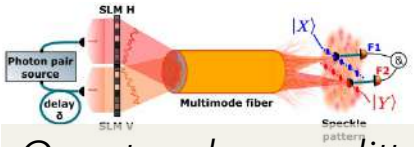
Training 1B param LLM
Wang, PNAS (2026)



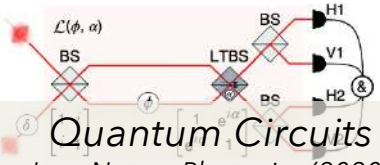
Reservoir computing
Rafayelan, Phys. Rev. X (2020)
Wang, LSA (2024)



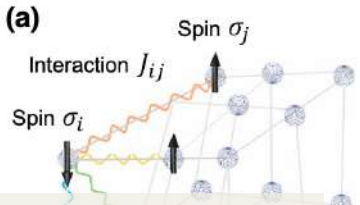
Classification
Saade, ICCASP (2016)



Quantum beamsplitter
Defienne, Science Advances (2016)



Quantum Circuits
Lee, Nature Photonics (2020)
Makowski, Optica (2024)



Ising Simulator
Pierangeli, Phys. Rev. Applied (2021) Jaccuci, Phys. Rev. A (2022) Delloye, Phys. Rev. A (2023)

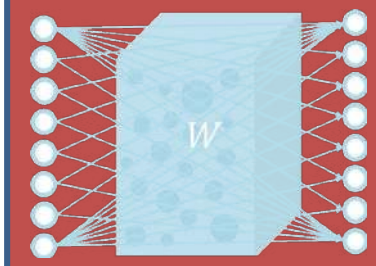


Structural non-linearity
Xia, Nature Photonics (2024)

2016 2018 2020 2022 2024 2026

Harnessing Optical complexity for AI ?

Optical Random Projections



- Easy fabrication
- All-to-all connectivity
- Fixed weights
- at scale
- passive

Many use cases:

- **Classification,**
- Reservoir computing,
- Direct feedback alignment
- Ising models
- Quantum circuits
- …

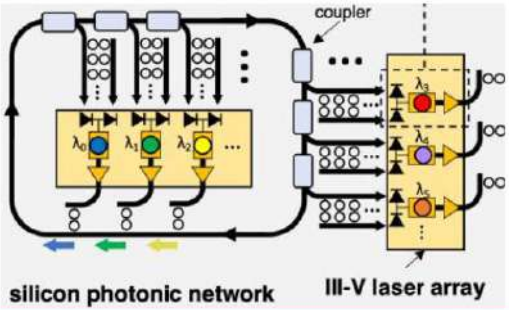
Beyond random projections:

- Adding tunability and trainability
- Including low-power non-linearity
- Passive non-linearities

Ability to tackle relatively large-scale/advanced AI tasks

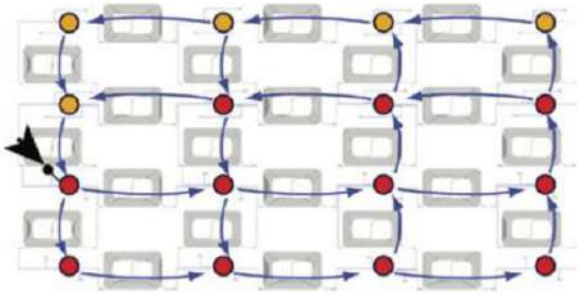
Many things I could not cover…

Spiking networks
(Princeton, Oxford, Strathclyde)



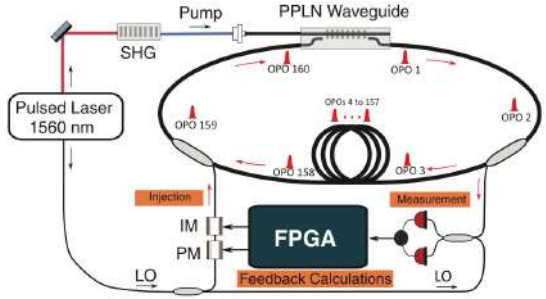
Shastri et al. *Sci. Rep.* 6 (2016)
Feldman et al. *Nature* 569 (2019)

Reservoir computing
(UIB, Ghent, Femto-St)



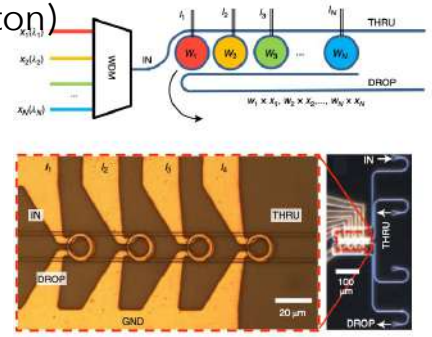
Brunner et al. *Nat. Commun.* 4 (2012)
Vandoorne et al. *Nat. Commun.* 5 (2014)

Coherent Ising Machines Optimizers…
(U Tokyo, U. Sapienza…)

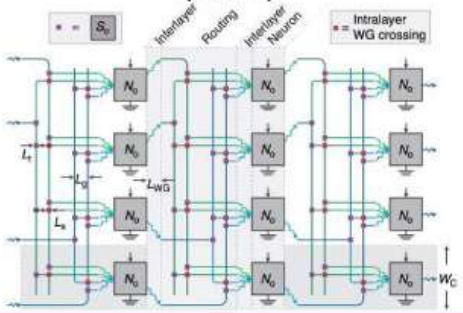


McMahon et al. Science (2016)
Pierangeli, PRL (2019)

Microrings weight banks
(Princeton)



Superconducting
(NIST)



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

…

Courtesy of B. Shastri

A thriving startup ecosystem (still deeptech!)

LKB

LIGHTELLIGENCE

LUMINOUS

COGNIFIBER
Pure Photonic Computing

Optalysys

AKHETONICS

celestial AI

neurophos

LIGHTMATTER

LUMAI

Microsoft Research

iPRONICS

SALIENCE LABS

LightSolver

arago

…and probably a few more !

Conclusion – AI and Photonics, a two-way street



AI for optics

•AI is a standard tool across optics: imaging, microscopy, inverse design, nonlinear and ultrafast optics

•AI solves ill-posed inverse problems and designs that we could not find by hand

•Strong French community



Optics for AI

Communication: already won. Optical interconnects are deployed, and industry is investing billions

Computation: Still maturing

- Mostly single layers with o-e-o connections
- Promising approaches to all-optical inference
- Incredible progress in integration
- Hard to keep up with fast-changing AI landscape

Perspectives – AI & Photonics



AI for optics

- End-to-end deep optics: co-design optics and algorithm
- Differentiable, physics-informed optics
- Generative inverse design at scale
- The real challenge: robustness and hallucination



Optics for AI

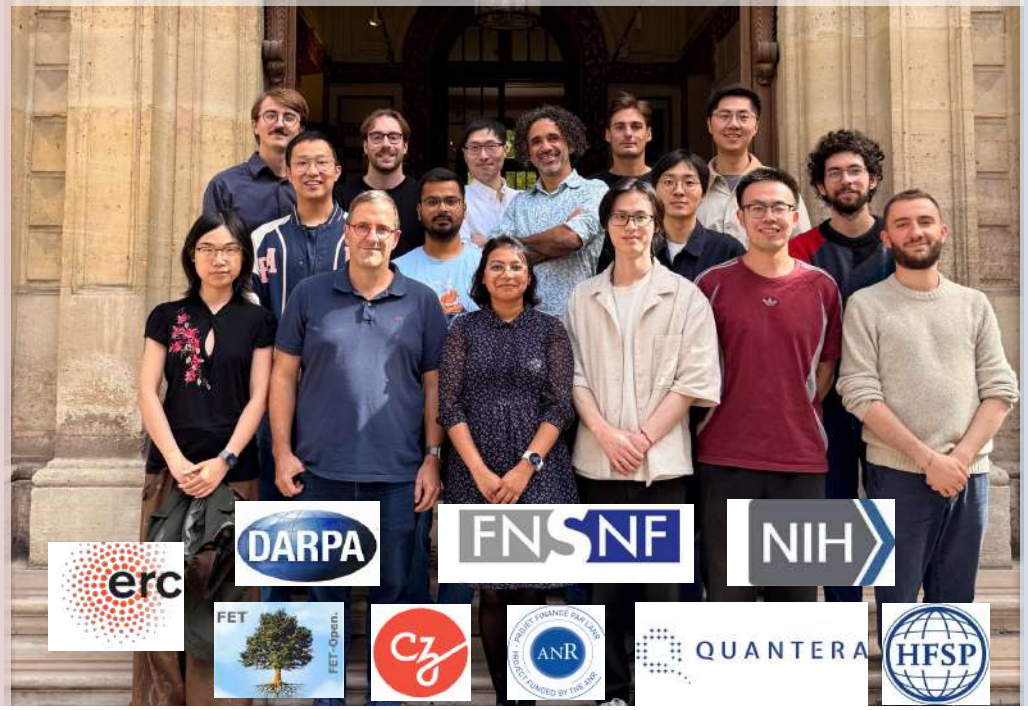
- Interconnects: co-packaged optics goes mainstream (2026+)
- Computation: nonlinearity, in-situ training, real advantage at scale
- Convergence: one photonic platform to communicate and compute
- Wild cards: quantum computing

The PICo Lab

Photonics, Information and Complexity

Thanks to my team
and my collaborators

Thank you for your attention !



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