Optical Computing redux:
Exploiting Light Scattering for Artificial Intelligence

Sylvain GIGAN

WICOM

June 11, 2025

Laboratoire Kastler Brossel
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Our Goal :
Understand and Harness
light propagation in complex media

Funding

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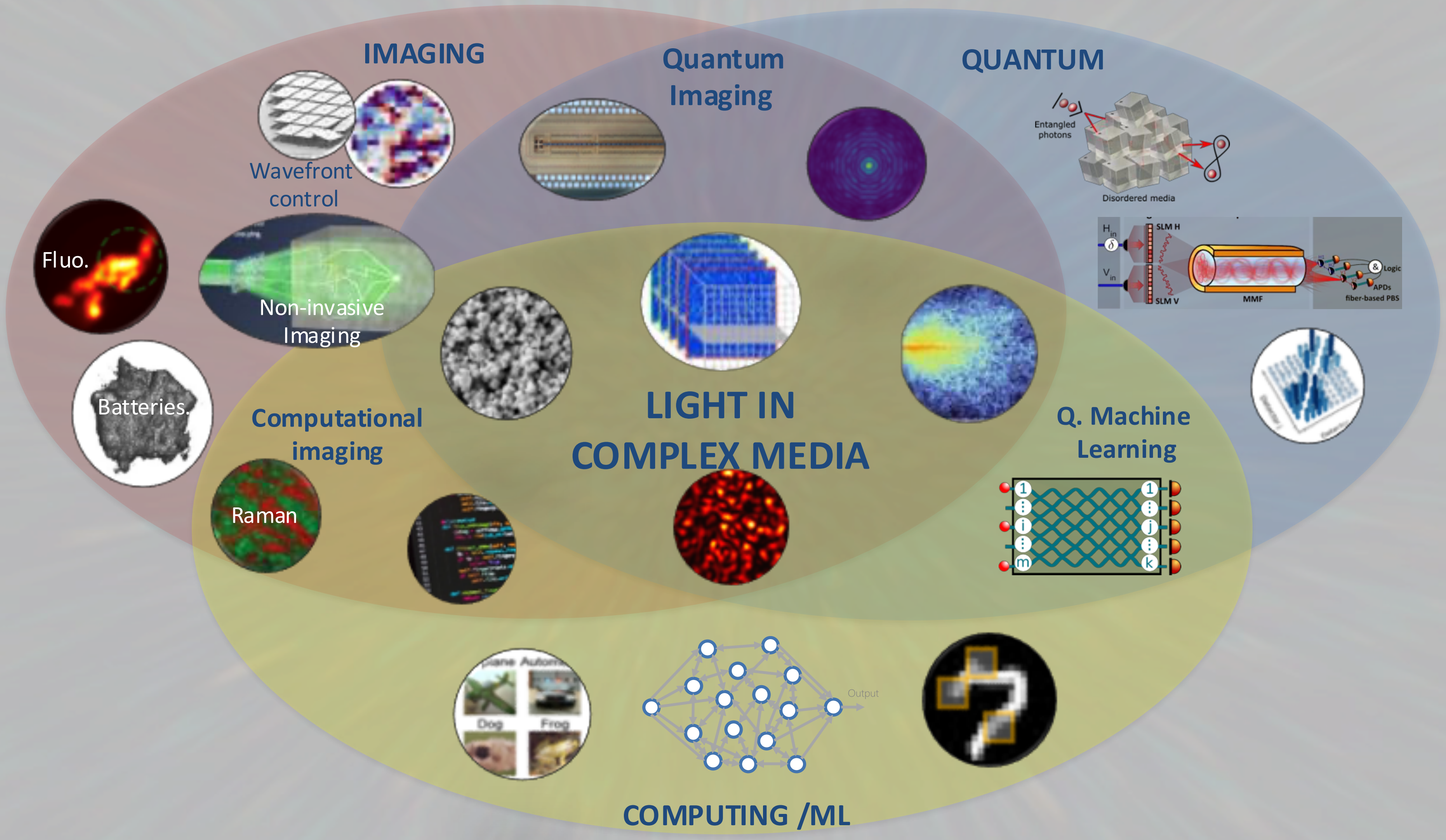
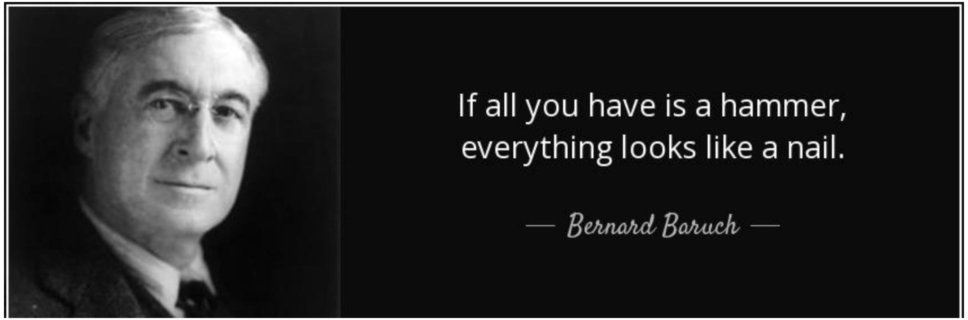
Our Goal : Understand and Harness light propagation in complex media



The « hardware lottery »



« …how hardware chooses which ideas succeed and which fail. »
(and vice-versa)

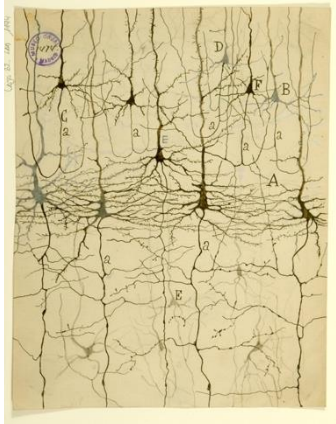
advocates for « (…) joint collaboration between hardware, software and machine learning communities. »

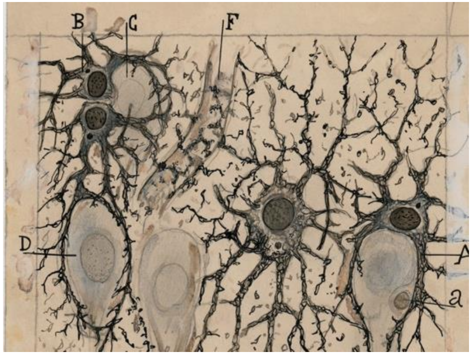
https://hardwarelottery.github.io
arXiv:2009.06489

why « neural » networks

The Human Brain

- 10^{11} neurons
- 10^{15} synapses
- 10^{4} synapses per neuron
- « Slow » millisecond timescale
  - ❖ 30 « Peta-Ops » per second
  - ❖ consume ~20 Watts
  - ❖ learns by itself

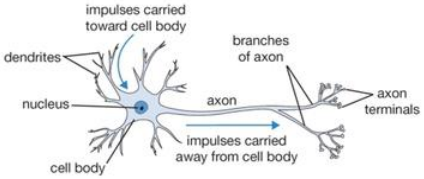




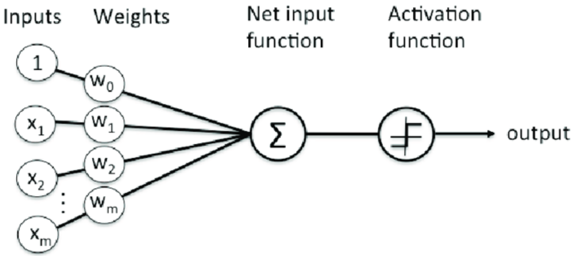
Ramon y Cajal (drawings)

Video: E. Beaurepaire team (LOB)

Artificial neural networks (ANN) – the perceptron

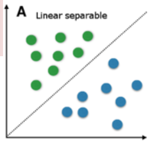


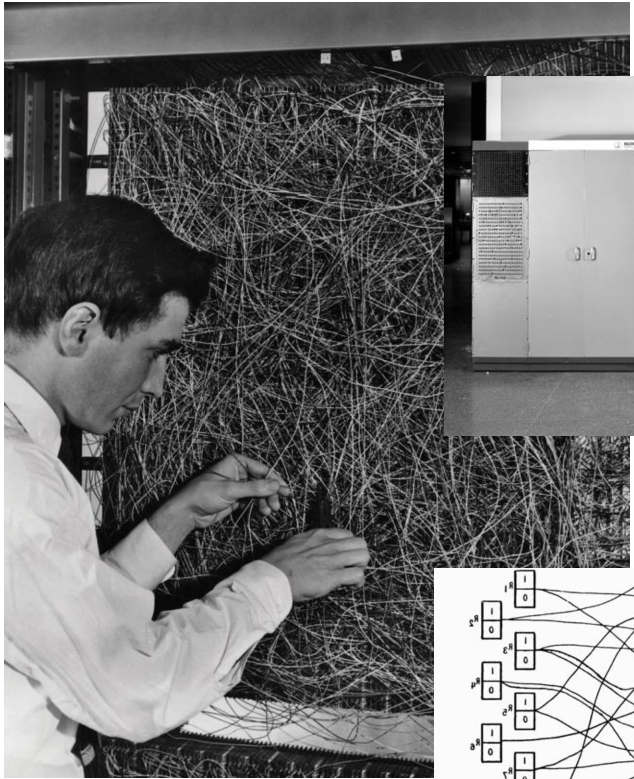
loosely inspired

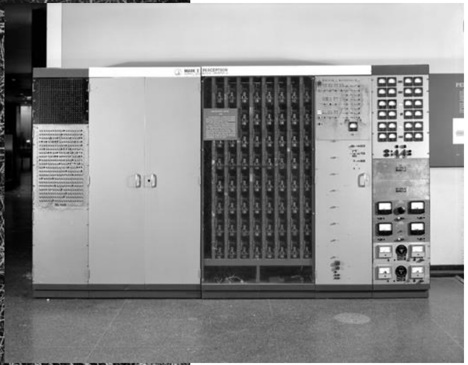


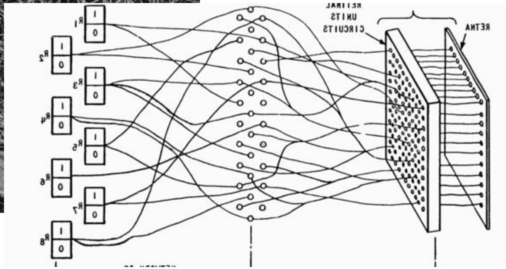
$$y = \varphi\left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi(\mathbf{w}^T \mathbf{x} + b)$$

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

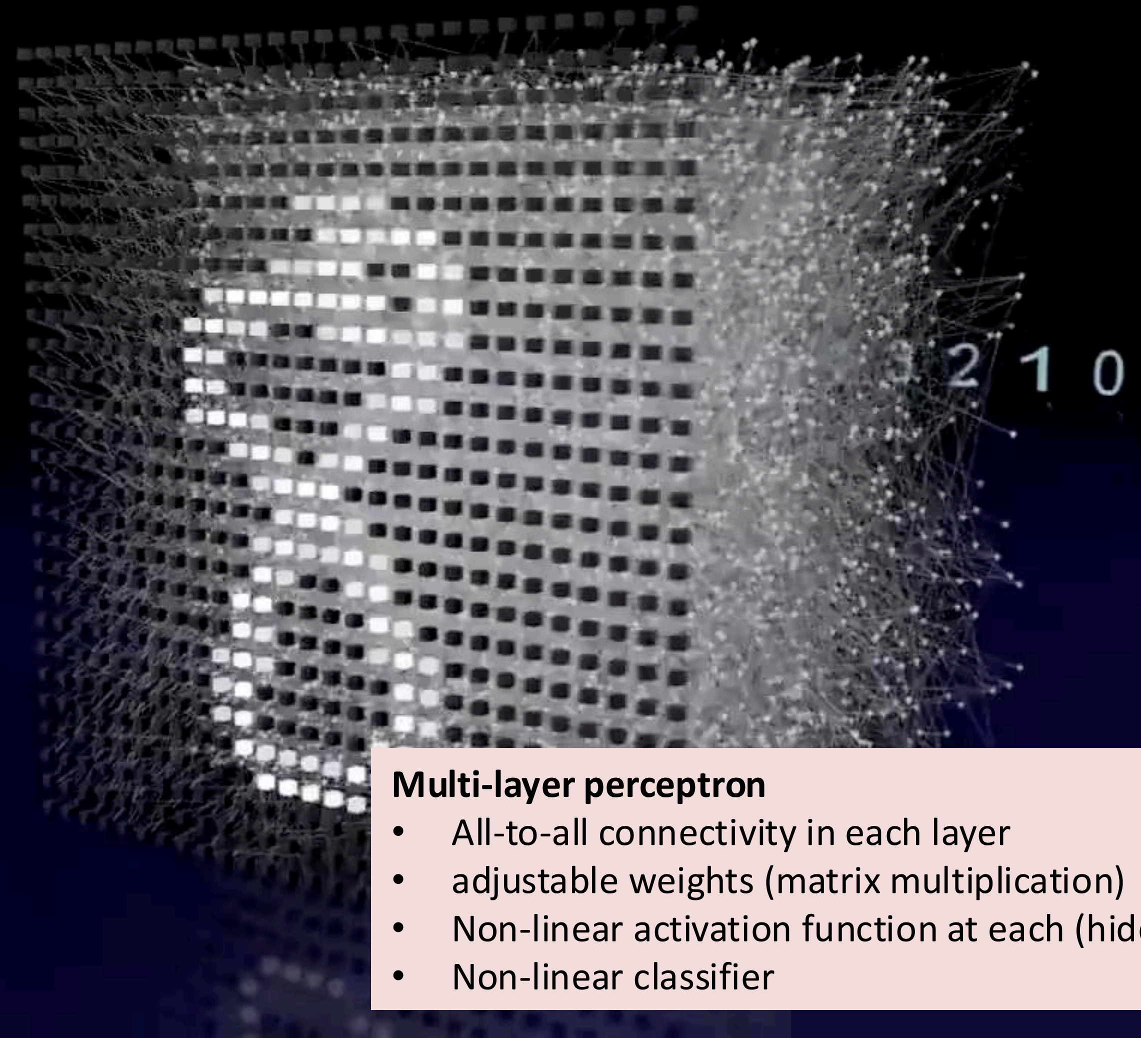








The Mark I perceptron
(Frank Rosenblatt – 1960’)

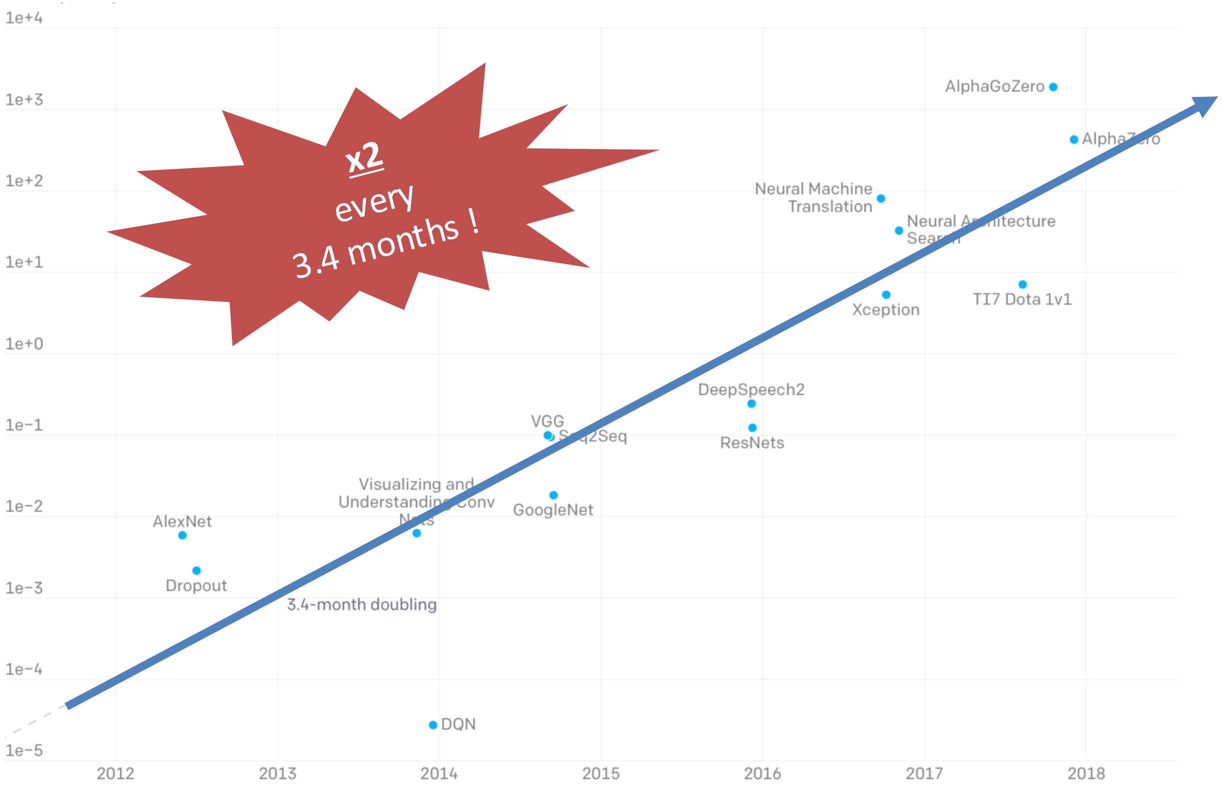


Multi-layer perceptron

- All-to-all connectivity in each layer
- adjustable weights (matrix multiplication)
- Non-linear activation function at each (hidden) layer
- Non-linear classifier

AI and Compute

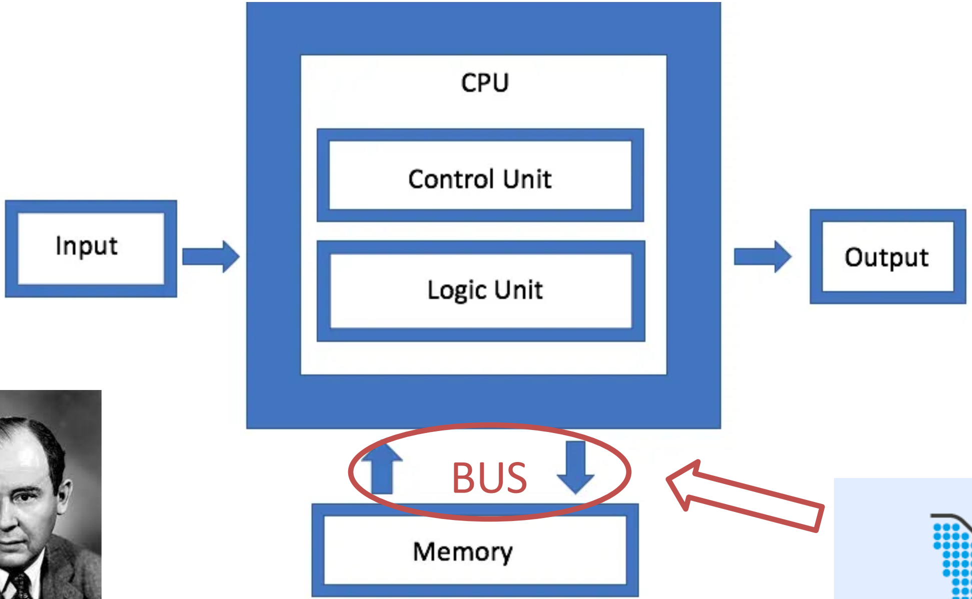
PetaFlop/s.days



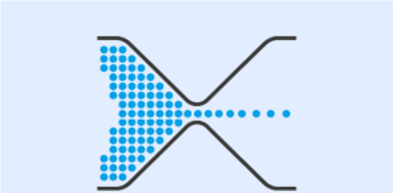
x300.000
(Moore: x7)

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

The Von Neumann architecture



John VON NEUMANN
(1903-1957)



Memory access:
The Von Neumann
bottleneck

CPU
Desktop PC
~100 GigaFLOPS
300W

GPU
NVIDIA A100
~10 TeraFLOPS
300W

TPU (Google)

~4 T-Ops
75W

Versatile .... *But not adapted for AI :* ***slow, power inefficient***

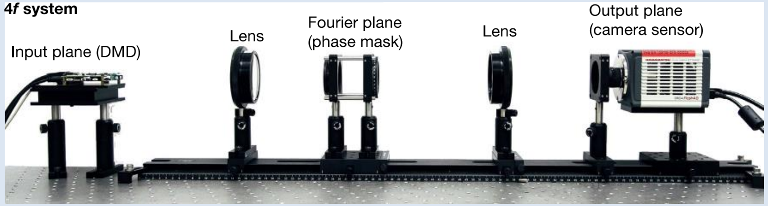
(neuromorphic) computing with light

Optics has distinct advantages…

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

… and some disadvantages:

- Bulky
- Tricky non-linearities
- Storage

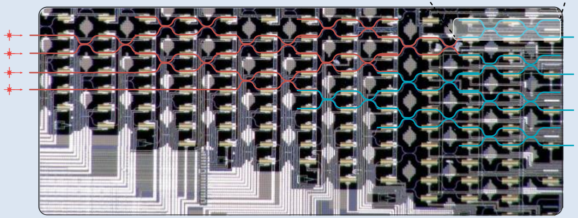


Sci. Rep. **8**, 12324 (2018).

Free space

vs

Integrated optics



Sci. Adv. **5**, eaay6946 (2019).

Nature Photonics 15, 10 (2021)

Photonics for artificial intelligence and neuromorphic computing

REVIEW ARTICLE | FOCUS
https://doi.org/10.1038/s41566-020-00754-y

Bhavin J. Shastri[1,2,7] ✉, Alexander N. Tait[2,3,7] ✉, T. Ferreira de Lima[2], Wolfram H. P. Pernice[4], Harish Bhaskaran[5], C. D. Wright[6] and Paul R. Prucnal[2]

Nature 588, 39 (2020)

Perspective

Inference in artificial intelligence with deep optics and photonics

https://doi.org/10.1038/s41586-020-2973-6

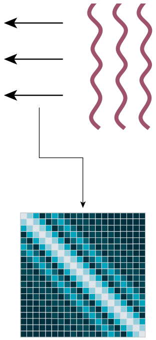
Received: 28 November 2019

Gordon Wetzstein[1] ✉, Aydogan Ozcan[2], Sylvain Gigan[3], Shanhui Fan[1], Dirk Englund[4], Marin Soljačić[4], Cornelia Denz[5], David A. B. Miller[1] & Demetri Psaltis[6]

Matrix multiplication in free space optics

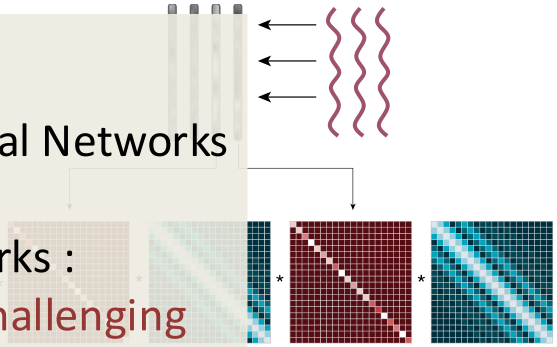
Basic building blocks:

Free space



Thin mask

layered scatterer

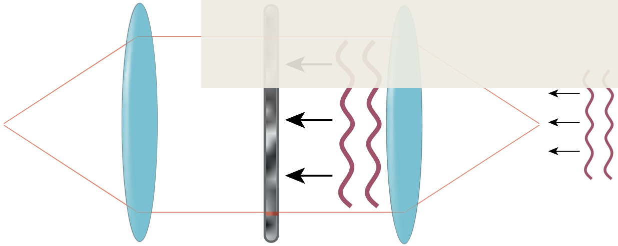


Good for **large scale** single-layer Neural Networks

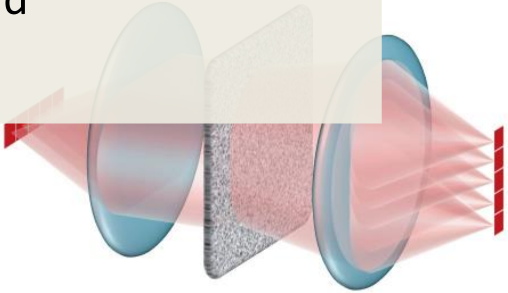
All-optical **deep** neural networks :
cascaded **non-linearities** remains challenging

Training is hard

Advanced functions



2D convolutions

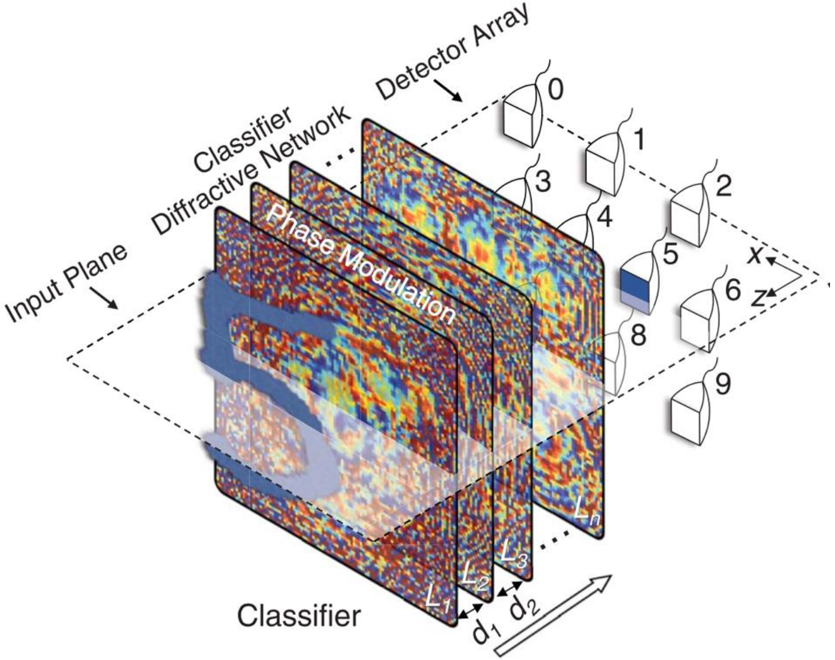


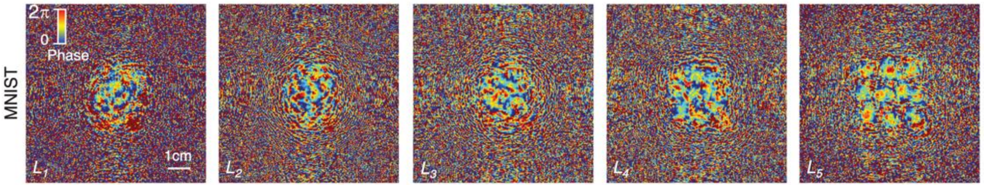
1D vector-matrix multiplier

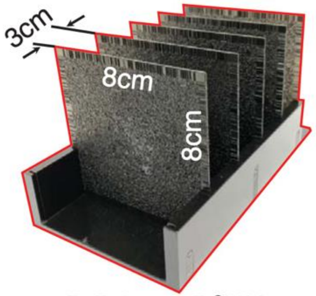
Adapted from *Nature* 588, 39 (2020)

Beyond convolutions : « Deep diffractive » networks

IDEA : fabricate and stack masks







3D Printed D²NN (Classifier)

THz realization

Multilayer : « **deep** »
no non-linearity between layers:
It's a just a dense single NN layer!
« **diffractive** »

Lin, Xing, et al. "All-optical machine learning using diffractive deep neural networks." Science 361.6406 (2018): 1004-1008

The energy advantage

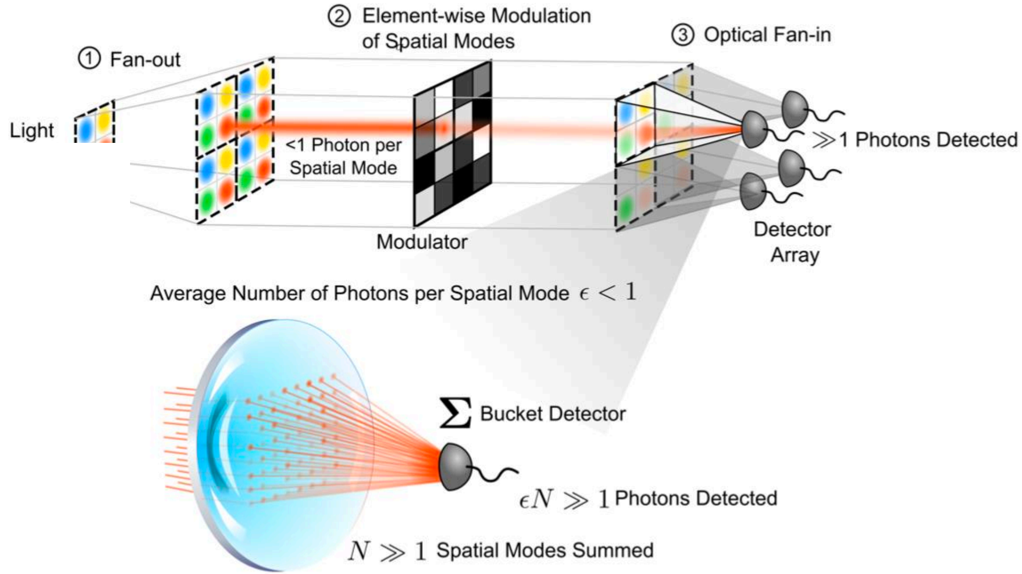
Article | Open Access | Published: 10 January 2022

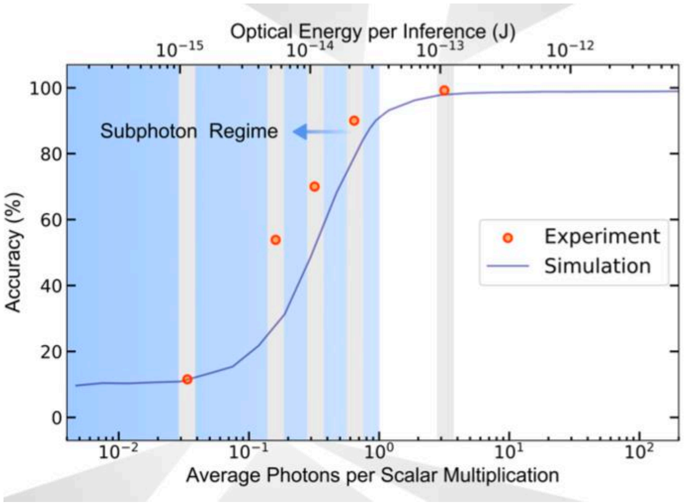
An optical neural network using less than 1 photon per multiplication

Tianyu Wang, Shi-Yuan Ma, Logan G. Wright, Tatsuhiro Onodera, Brian C. Richard & Peter L. McMahon

Nature Communications **13**, Article number: 123 (2022) | Cite this article

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





Review Article | Published: 08 September 2022

Shaping the propagation of light in complex media

Hui Cao, Allard Pieter Mosk & Stefan Rotter

Nature Physics **18**, 994–1007 (2022) | Cite this article

Review Article | Published: 08 September 2022

Physics of highly multimode nonlinear optical systems

Logan G. Wright, Fan O. Wu, Demetrios N. Christodoulides & Frank W. Wise

Perspective | Published: 08 September 2022

Quantum light in complex media and its applications

Ohad Lib & Yaron Bromberg

Nature Physics **18**, 986–993 (2022) | Cite this article

Comment | Published: 08 September 2022

Controlling random lasing action

Riccardo Sapienza

Nature Physics **18**, 976–979 (2022) | Cite this article

Review Article | Published: 08 September 2022

Imaging in complex media

Jacopo Bertolotti & Ori Katz

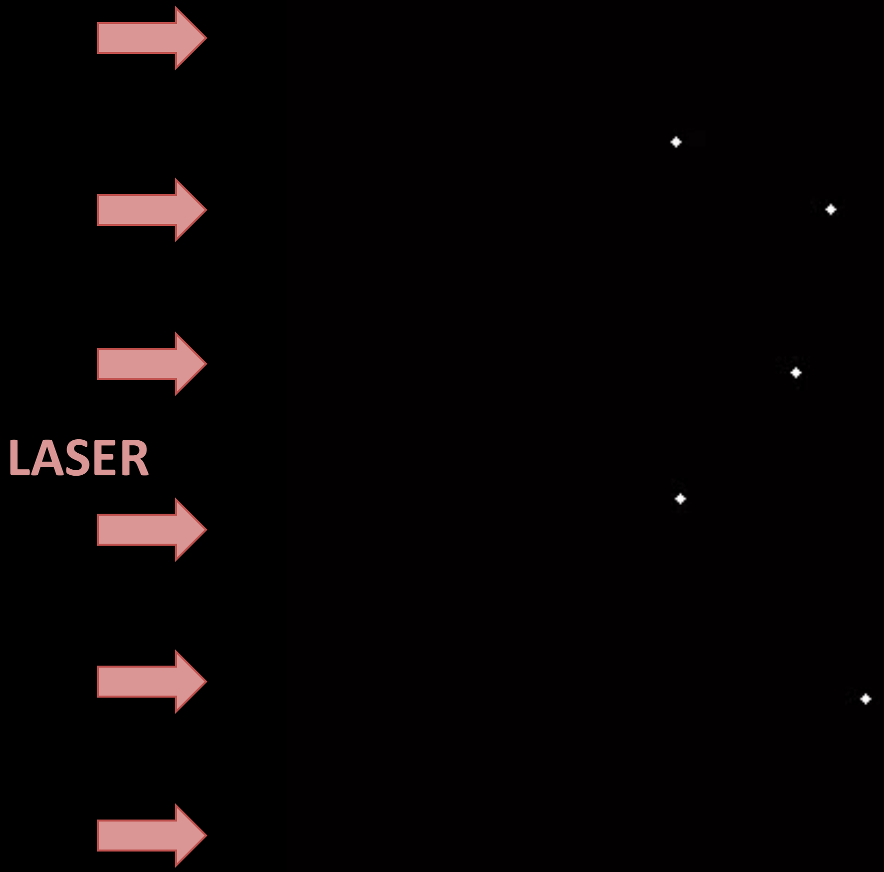
Nature Physics **18**, 1008–1017 (2022) | Cite this article

Perspective | Published: 08 September 2022

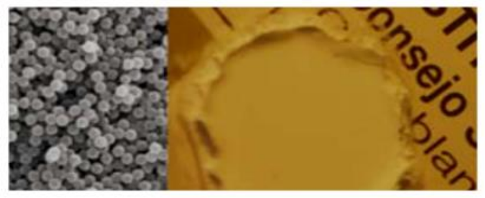
Imaging and computing with disorder

Sylvain Gigan

Nature Physics **18**, 980–985 (2022) | Cite this article

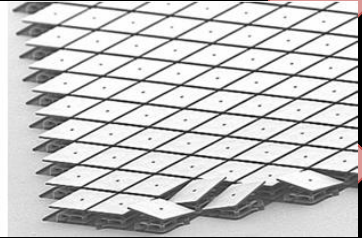


Film courtesy of
Emmanuel Bossy
(Univ. Grenoble)
- SIMSONIC
software



3D random Sample

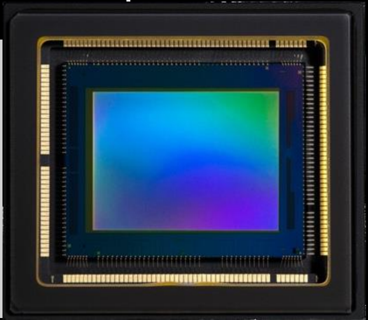
« white paint »



MODULATORS

« Deep » multiple scattering regime :

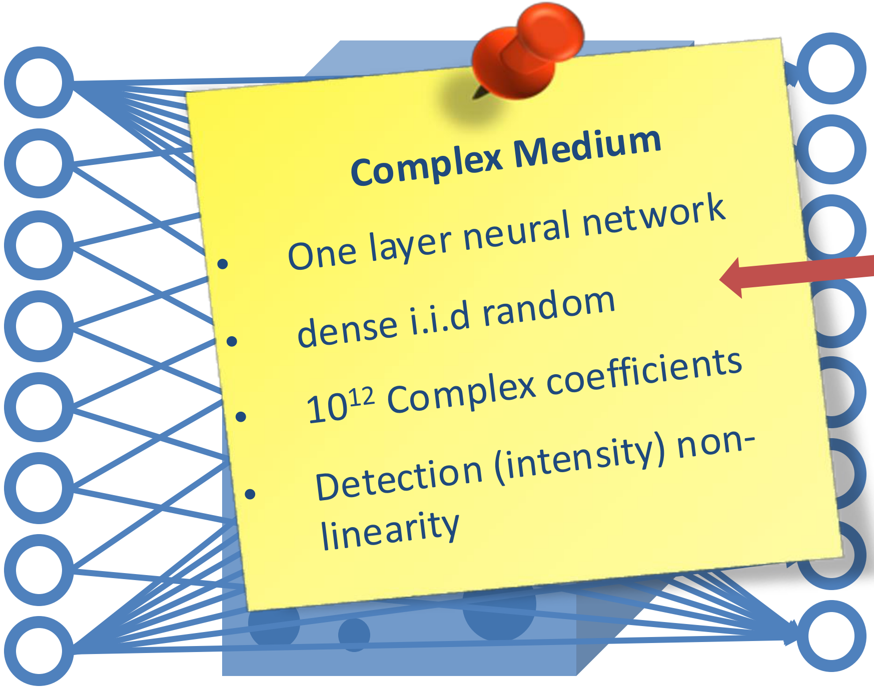
- ✗ No more ballistic light
- ✗ Strong spatial and temporal perturbation
- ✓ Coherence is maintained



DETECTORS

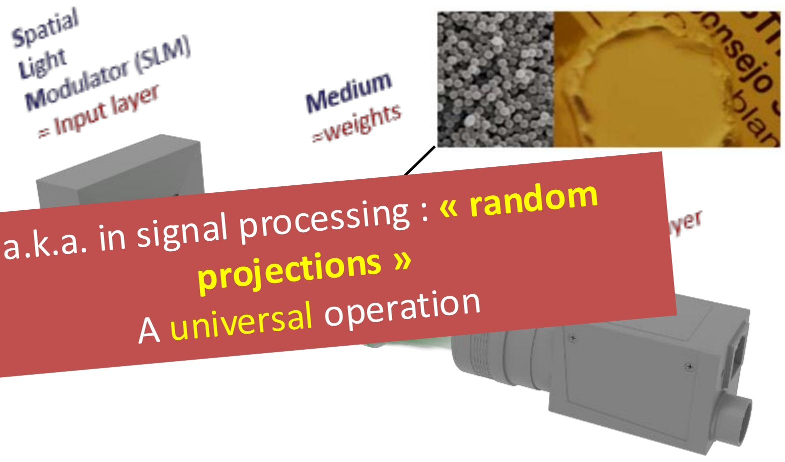
Film courtesy of Emmanuel Bossy (Univ. Grenoble) - SIMSONIC software

Optical computing with a complex medium ?



Complex Medium

- One layer neural network
- dense i.i.d random
- 10^{12} Complex coefficients
- Detection (intensity) non-linearity

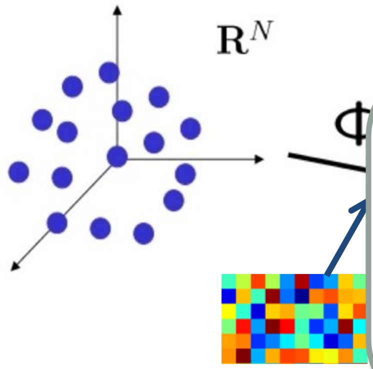


a.k.a. in signal processing : **« random projections »**
A universal operation

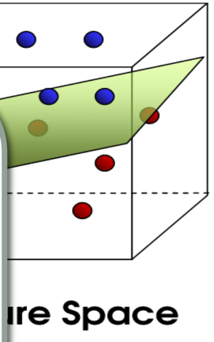
Using disorder for computation in Machine Learning?

What are « random projections » good for?

Dimensional Reduction
« Johnson & Lindenstrauss »



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



Optical pre-processing

You don't need to know the matrix!

(just know that it is random)

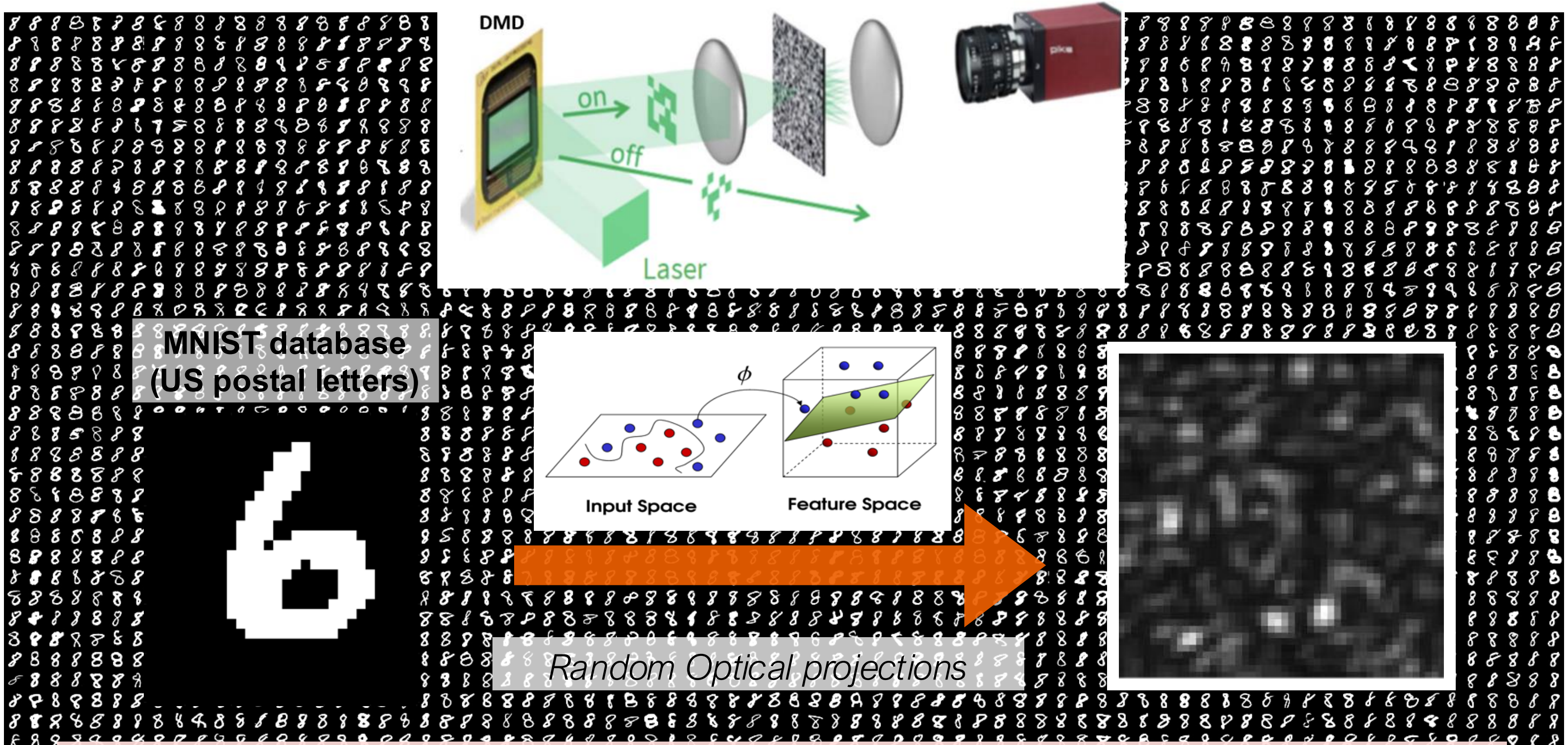
- Random matrix : reduction in dimension
- **conserve distances** even for M<<N

- 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 >3000 times

Rahimi, A., & Recht, B. (2007). Random features for large-scale kernel machines. In *Advances in neural information processing systems* (pp. 1177-1184).
cited >4000 times

Experimental Proof of Principle



A. Saade, F. Caltagirone, I. Carron, L. Daudet, A. Drémeau, S. Gigan, F. Krzakala, **Random projections through multiple optical scattering: approximating kernels at the speed of light**, ICCASP (2016)

Why is it interesting ?

EXTRA-LARGE & **SUPER-FAST**

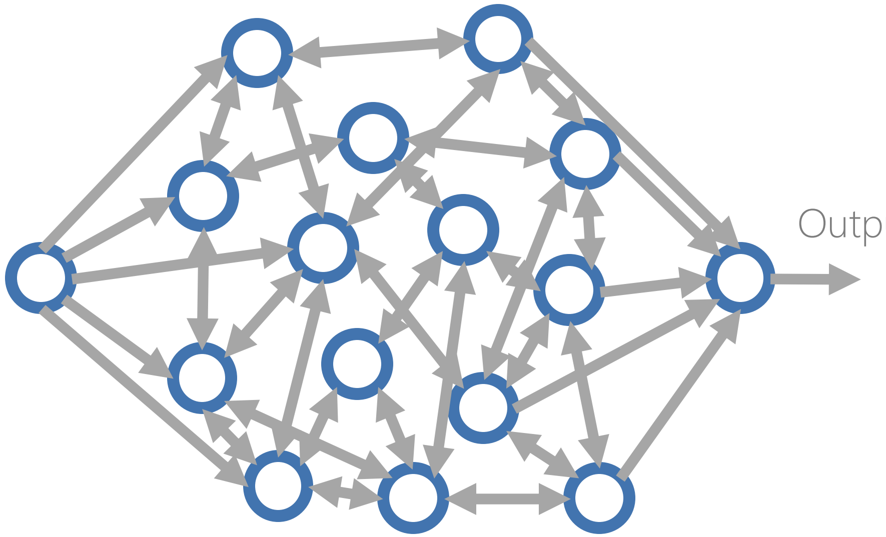
W of size higher than 10^6 x 10^6 (TBs of memory)

kHz operation
→10^3 such multiplies / s

Equivalent 10^{15} operations / s : You would need a *Peta-scale* computer to do the same !

(CoI disclosure: S.G. acknowledges financial interest in LightOn)

- **many, many use cases (inference, training, linear algebra…)** ☺
- **already at scale for modern machine learning** ☺
- **1st commercial optical co-processor** ☺
- **Recently moved away from optics** ☹

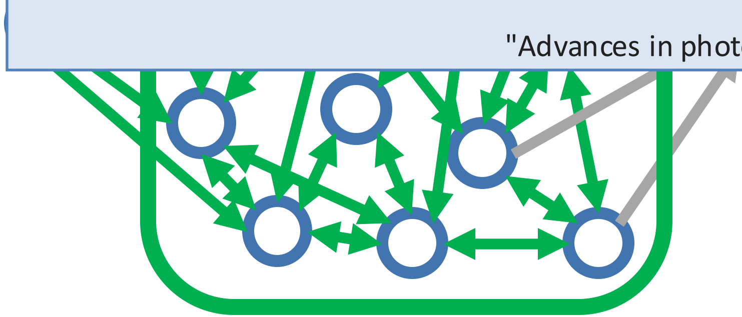


Recurrent Neural Networks are notoriously hard to train

Jaeger & Haas (2004). *Science*

« Reservoir » Computing

Input



Reservoir

s are
in
all
y

Particularly well suited for physical implementations

- Dedicated electronics
- Exotic architectures
- Integrated & free space photonics

Van der Sande, Guy, Daniel Brunner, and Miguel C. Soriano. "Advances in photonic reservoir computing." Nanophotonics 6.3 (2017): 561-576.

Only the output weights are trained

Random matrices

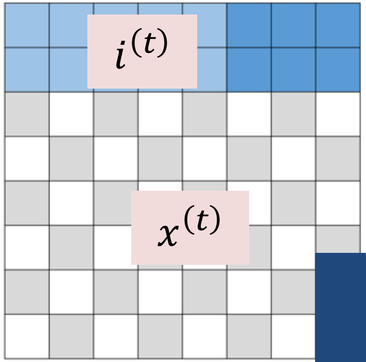
$$x^{(t+1)} = f\left(W_r\, x^{(t)} + W_i\, i^{(t)}\right)$$

next reservoir   current reservoir   current input

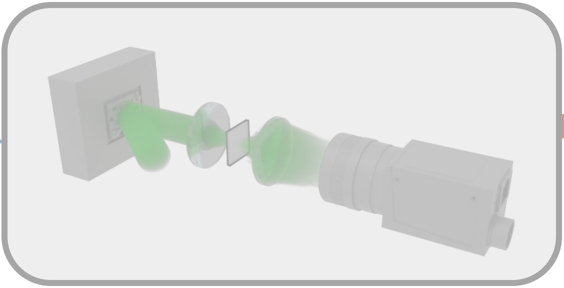
Jaeger & Haas (2004). *Science*

Reservoir computing with a complex medium ?

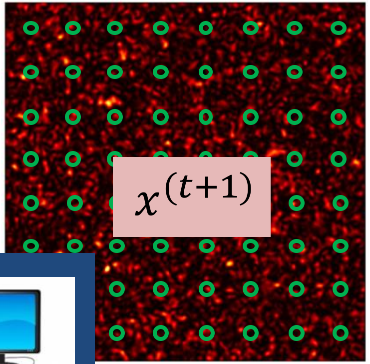
Input



Reservoir state



$$x^{(t+1)} = f\left(W_r\, x^{(t)} + W_i\, i^{(t)}\right)$$



utput speckle
ratic non-linearity)

$f = |.|^2$

Last stage / off-line

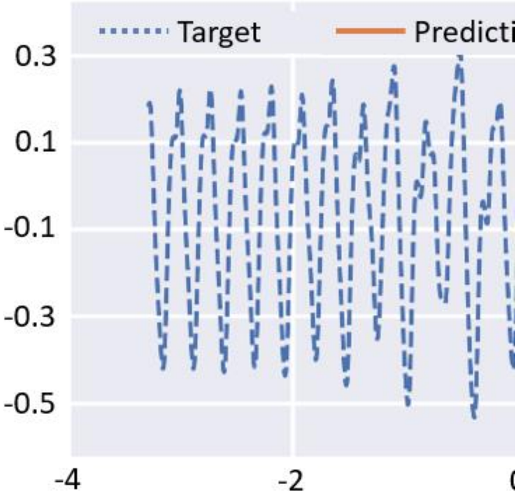
Predict output with a linear model

$$o^{(t)} = W_o x^{(t)}$$

(done on a CPU or GPU - Typically not the bottleneck)

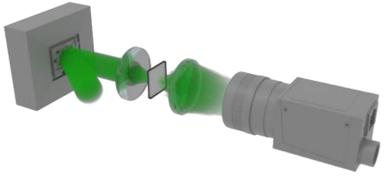
Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Mackey-Glass prediction (1D)



1. Compute the reservoir states

$$x^{(t+1)} = \frac{1}{\sqrt{N}} f\left(W_r\, x^{(t)} + W_i\, i^{(t)}\right)$$

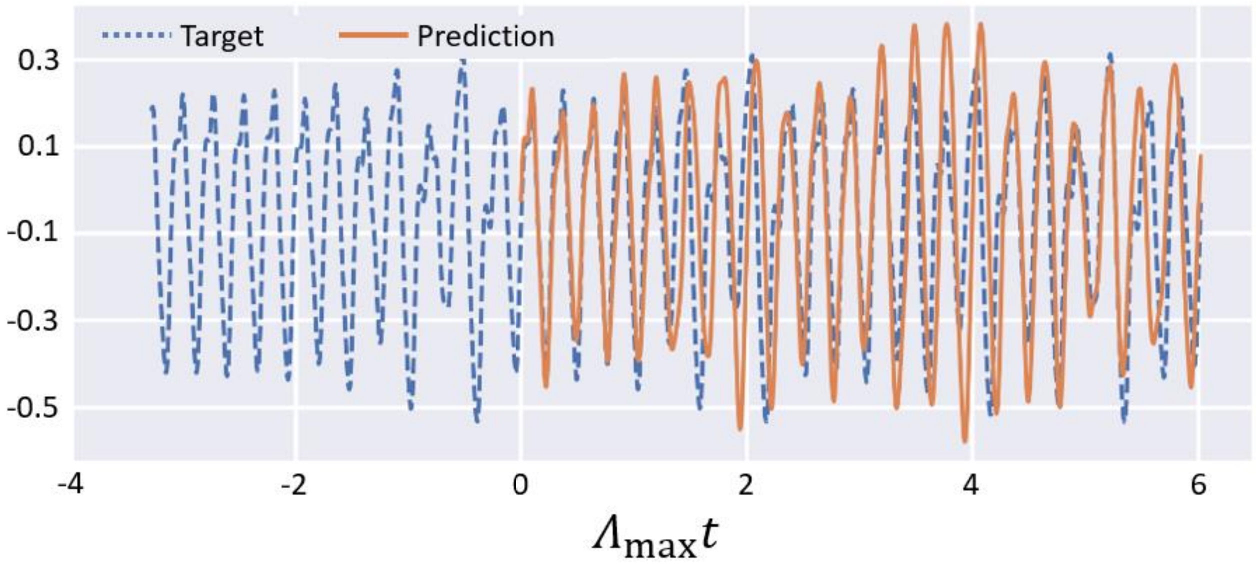


2. Output with a linear model

$$o^{(t)} = W_o x^{(t)}$$

Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Mackey-Glass prediction (1D)

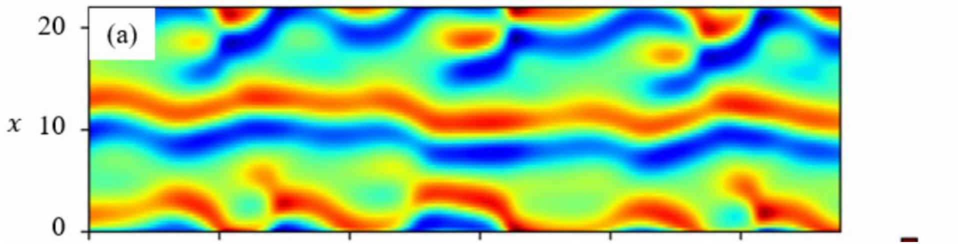


Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Kuramoto-Sivashinsky prediction - results

HARD

Ground truth



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

Optical computing efficiency

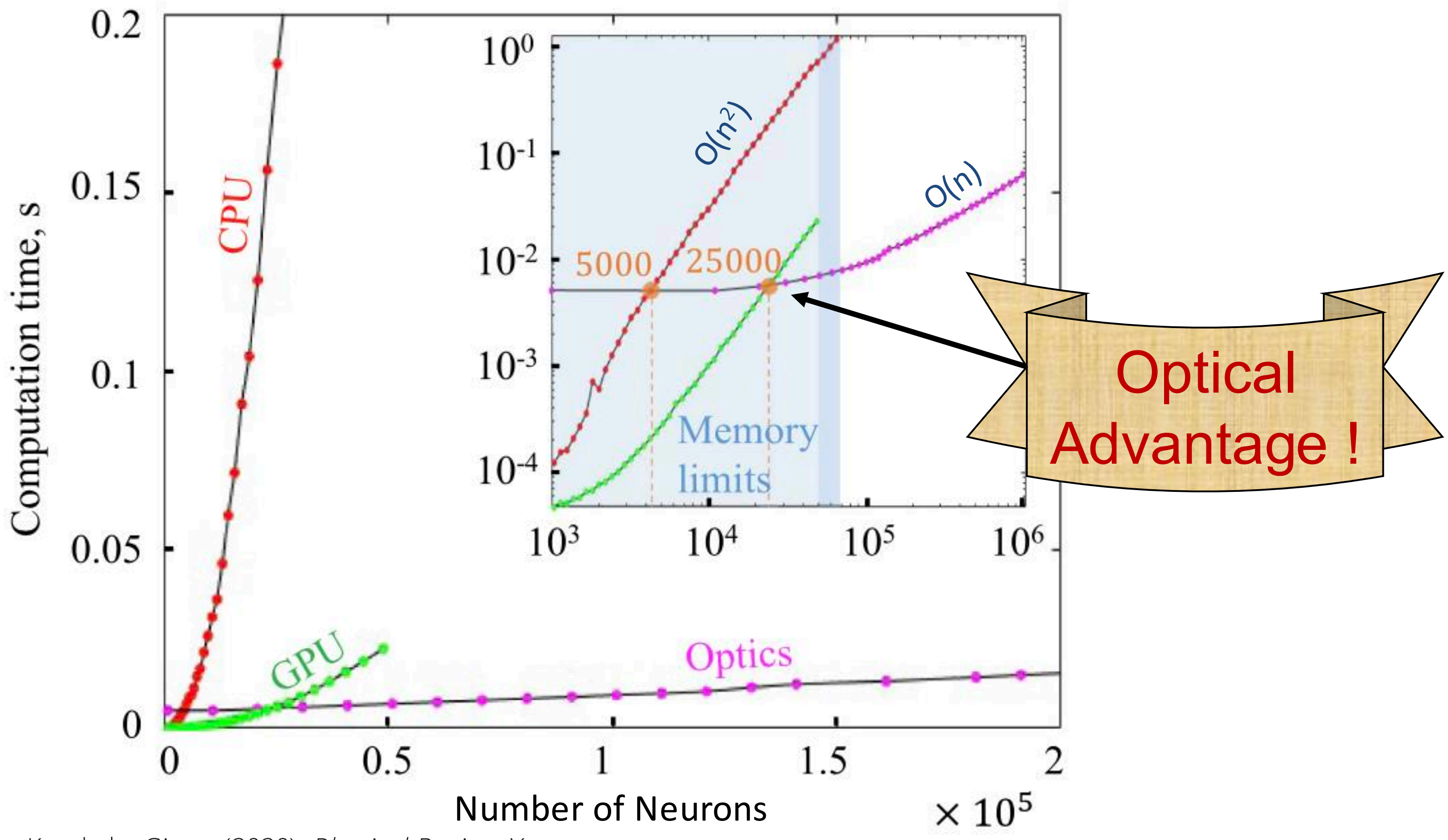
Speed

	Electronics	Optics
Speed	$\mathcal{O}(n^2)$	$\mathcal{O}(1)$
Energy efficiency	~150 W	~30 W
Dimensionality	Memory limit (~ GB)	Resolution limit (~ TB)

Energy efficiency

Dimensionality

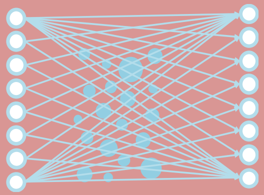
Computation time versus reservoir size (one iteration)



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

Fixed Random Projections – is that the end of the story?

Optical Random Projections



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

➢ **Proof of principle:** classification, reservoir computing, Ising models …

➢ **Drawbacks:**

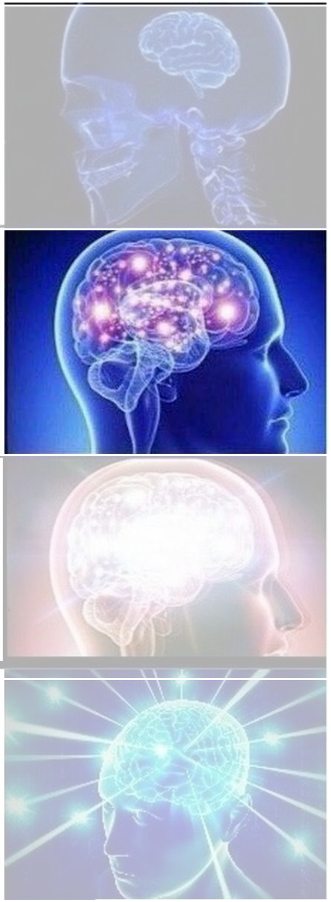
- ➢ **No possibility to train**
- ➢ **No non-linearity (single layer)**

Random Projections

Trainable Random Projections

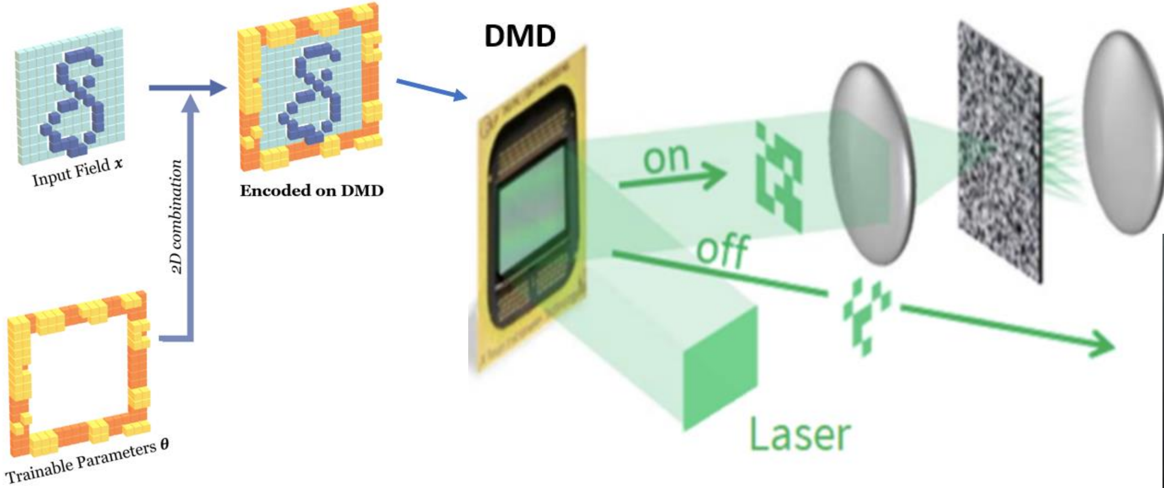
Non-Linear Random Projections

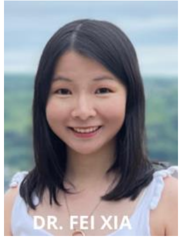
Passive Non-Linear Random Projections



Can we add a bit of tunability ?

- Tunable in weight by encoding on DMD





Laboratoire Kastler Brossel
Physique quantique et applications

Fei Xia, Ziao Wang, Jianqi Hu

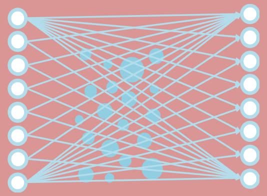
Peter McMahon

Cornell University

Collaboration with the Peter McMahon group
(Logan Wright, Tatsuhiro Onodera, Martin Stein)

Fixed Random Projections – is that the end of the story?

Optical Random Projections



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➢ **Proof of principle:** classification, reservoir computing, Ising models …

Random Projections

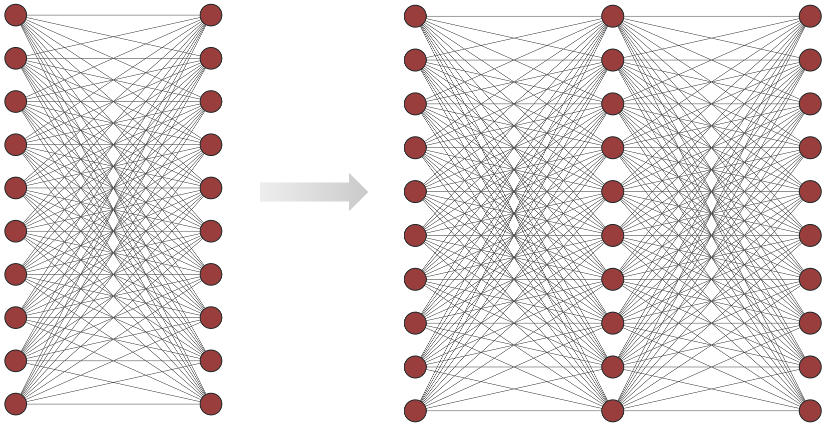
Trainable Random Projections

Non-Linear Random Projections

Passive Non-Linear Random Projections

Light scattering – a linear process

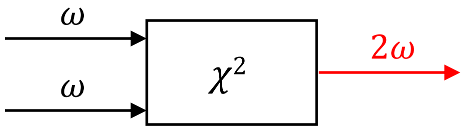
Nonlinearity is the prerequiste for deep neural networks and essential for good performance



Linear weights W1   Linear weights W1   Linear weights W2

- How to introduce nonlinearity into the optical scattering process ?

Second-harmonic generation



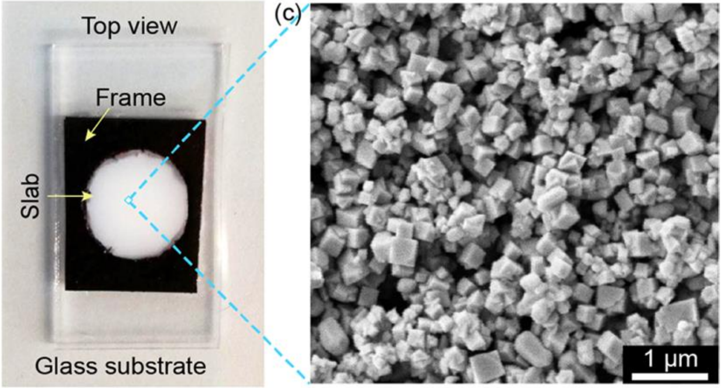
Other second or third-order nonlinear processes, photon-phonon prcesses (Raman, Brillouin), etc can be explored

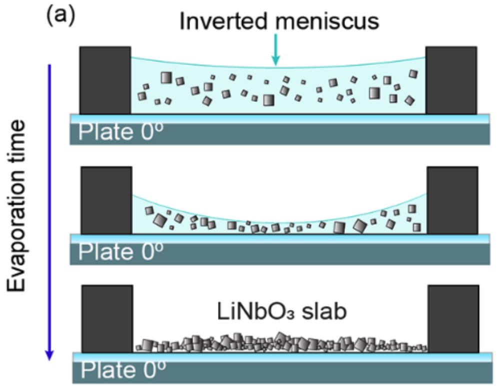
For instance:

<u>Third-order nonlinearity</u>: U. Tegin et al., Nat. Comput. Sci., 1, 542–549 (2021)
<u>O-E nonlinearity</u>: A. Farshid et al., Nature, 606, 501-506 (2022)
<u>O-E-O nonlinearity</u>: T. Wang et al., Nat. Photonics, 17, 408-415 (2023)
…

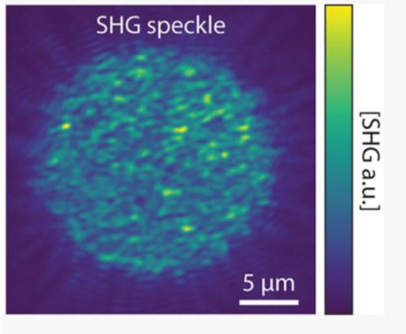
Nonlinear scattering media

Disordered lithium niobate (LN) nanocrystals



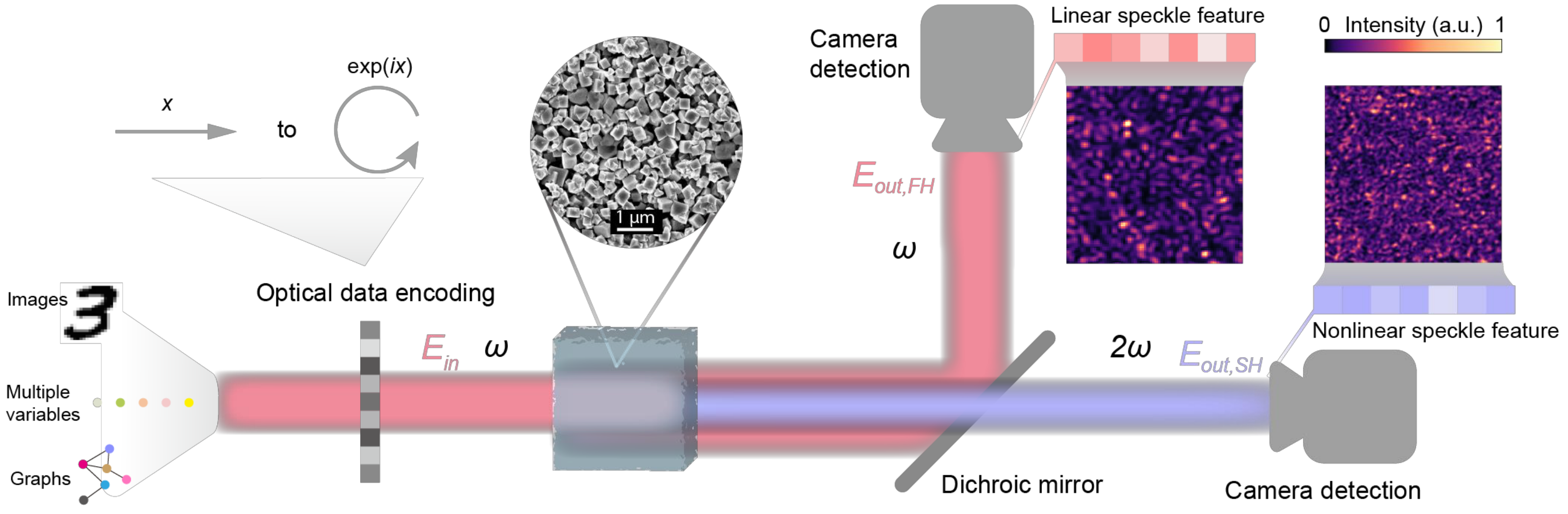


- Nanocrystal size: 100 – 400 nm
- Slab thickness: 5 um
- The LN slab is both nonlinear and random scattering
- SH speckle is generated by the chi-(2) nonlinearity of LN and random quasi-phase-matching



A. Morandi et al., ACS Photonics, 9, 1882-1888 (2022)

Experimental setup



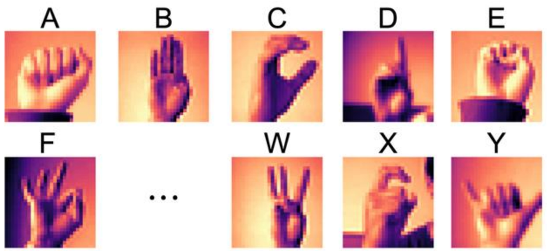
- Both fundamental-harmonic (FH, linear) and second-harmonic (SH, nonlinear) speckle features are generated
- Ridge regression for analytic readout layer (digital part)
- Focus on optical nonlinearity, with linear random projection as baseline

Hao Wang and Jianqi Hu (LKB) in collaboration A. Nardi, A. Morandi, R. Savo, R. Grange (ETH) arXiv:2310.07690 [physics.optics]
Nature Computational Science (in press)

Image classification – Results #1

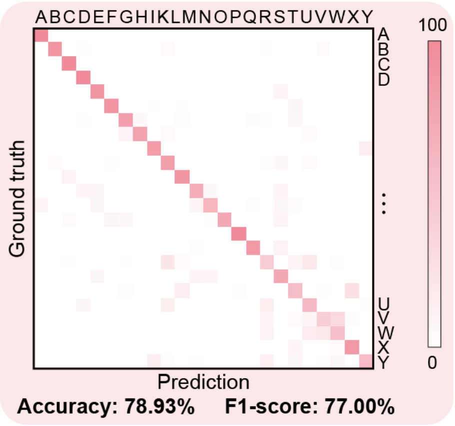
Classification of 24 sign language letters

- Training/ test size: 27,455/7,172
- Image size: 28×28

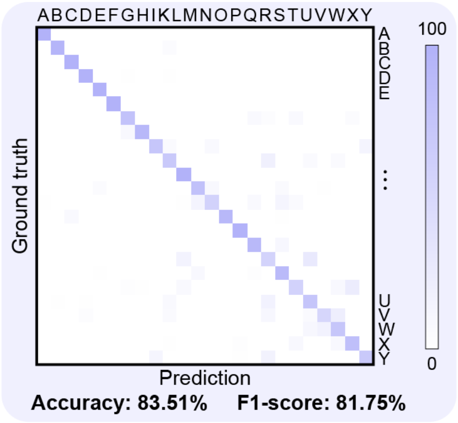


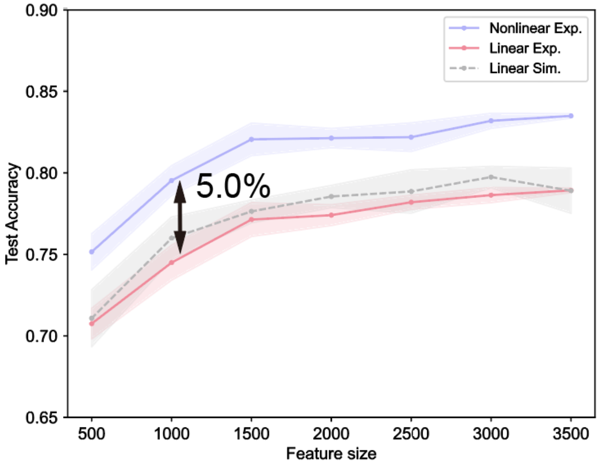
At the same feature size of 3,500:

Linear feature



Nonlinear feature



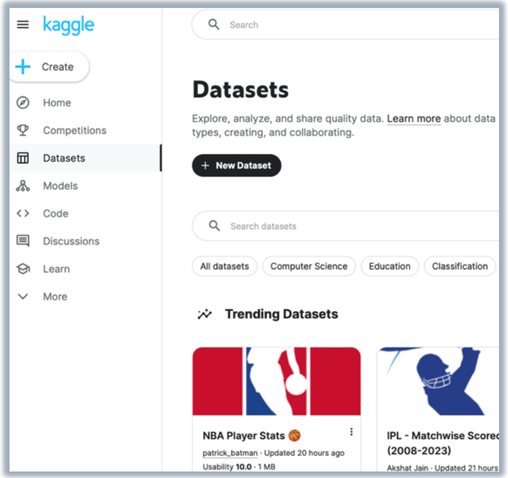


Hao Wang and Jianqi Hu (LKB) in collaboration A. Nardi, A. Morandi, R. Savo, R. Grange (ETH) [arXiv:2310.07690] [physics.optics]
Nature Computational Science (in press)

Summary of experimental results

Dataset	Task description	Training/test size	Sample dimension	Macro-pixel size	Average optical nonlinearity gain
SLD	Image classification (10 categories)	1,649/413	64×64	[illegible]5	[illegible]
ASL	Image classification (24 categories)	[illegible]	[illegible]	[illegible]	[illegible]
CIFAR-10	Image classification (10 categories)	50[illegible]	[illegible]	[illegible]	[illegible]
Sinc function	Interpolate the sinc function (univariate regression)	2[illegible]	[illegible]	[illegible]	[illegible]
UCI yacht hydrodynamics	Predict the residuary resistance of sailing yachts (multivariate regression)	2[illegible]	[illegible]	[illegible]	[illegible]
Concrete compressive strength	Predict the concrete compressive strength (multivariate regression)	92[illegible]	[illegible]	[illegible]	[illegible]
SBM-generated graph dataset	Graph classification (2 categories)	400/[illegible]	[illegible]	[illegible]	[illegible]
Reddit-binary graph dataset	Graph classification (2 categories)	1,800/[illegible]	[illegible]	[illegible]	[illegible]
MNIST	Image classification (10 categories)	60,000/1[illegible]	[illegible]	[illegible]	[illegible]
FashionMNIST	Image classification (10 categories)	60,000/10[illegible]	28×28	10×10	-0.2% ~ 0.9%
STL-10	Image classification (10 categories)	8,000/5,000	96×96×3	2×2	2.4% ~ 3.5%

- Combination of the nonlinear conversion and light scattering
- Large dimension given by megapixel SLM and camera
- Gain compared to linear random projections



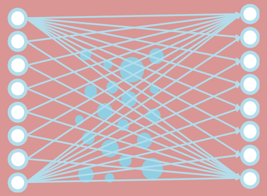
The nonlinear speckle features outperform their linear counterparts (and ideal linear random projection) for a large collection of datasets

Hao Wang and Jianqi Hu (LKB) in collaboration A. Nardi, A. Morandi, R. Savo, R. Grange (ETH) arXiv:2310.07690 [physics.optics]
Nature Computational Science (in press)

Fixed Random Projections – is that the end of the story?

LKB

Optical Random Projections



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

➢ **Proof of principle:** classification, reservoir computing, Ising models …

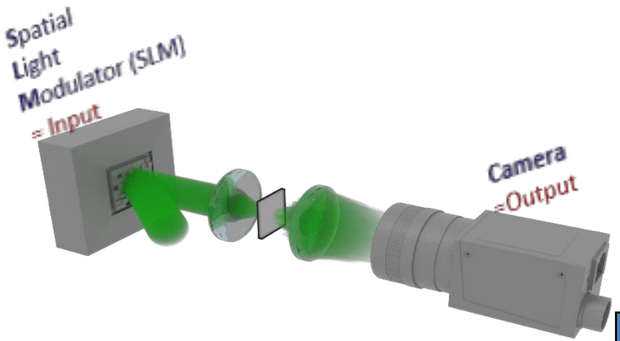
Random Projections

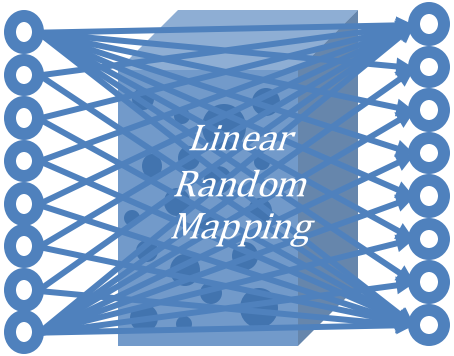
Trainable Random Projections

Non-Linear Random Projections

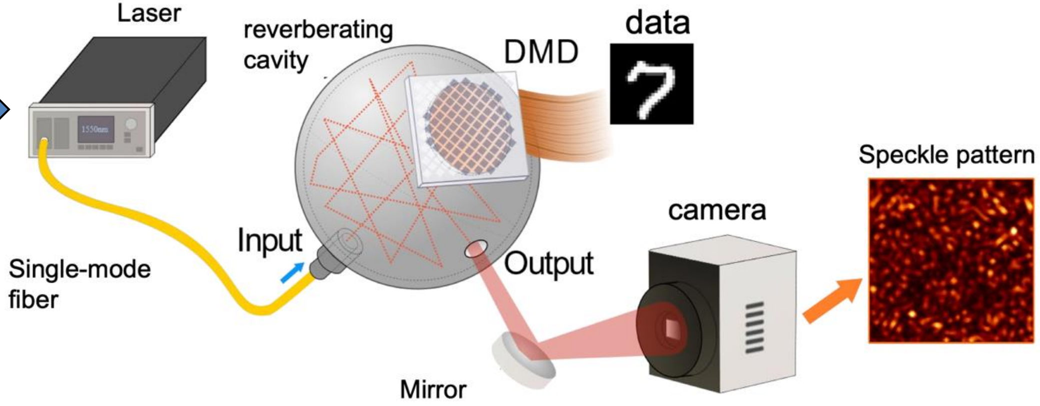
Passive Non-Linear Random Projections

Passive non-linear random projections ?





Idea : multiple bounces off the same spatial light modulator

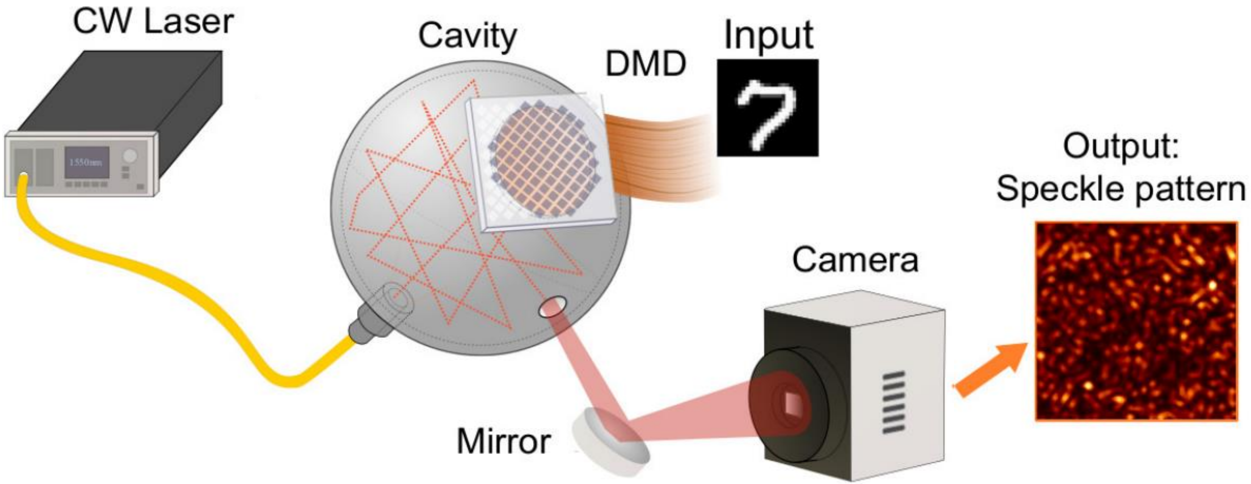


F. Xia, K. Kim, Y. Eliezer, L. Shaughnessy, S. Gigan, **Hui Cao (Yale)** Nature Photonics (2024)
See also : Yildirim et al. Nature Photonics (2024) (Chris Moser & Demetri Psaltis, EPFL)
See also Wanjura & Marquardt, Nature Physics (2024)

F

Key idea: encoding in scattering potential **V**

→ a nonlinear data encoder in the optical domain



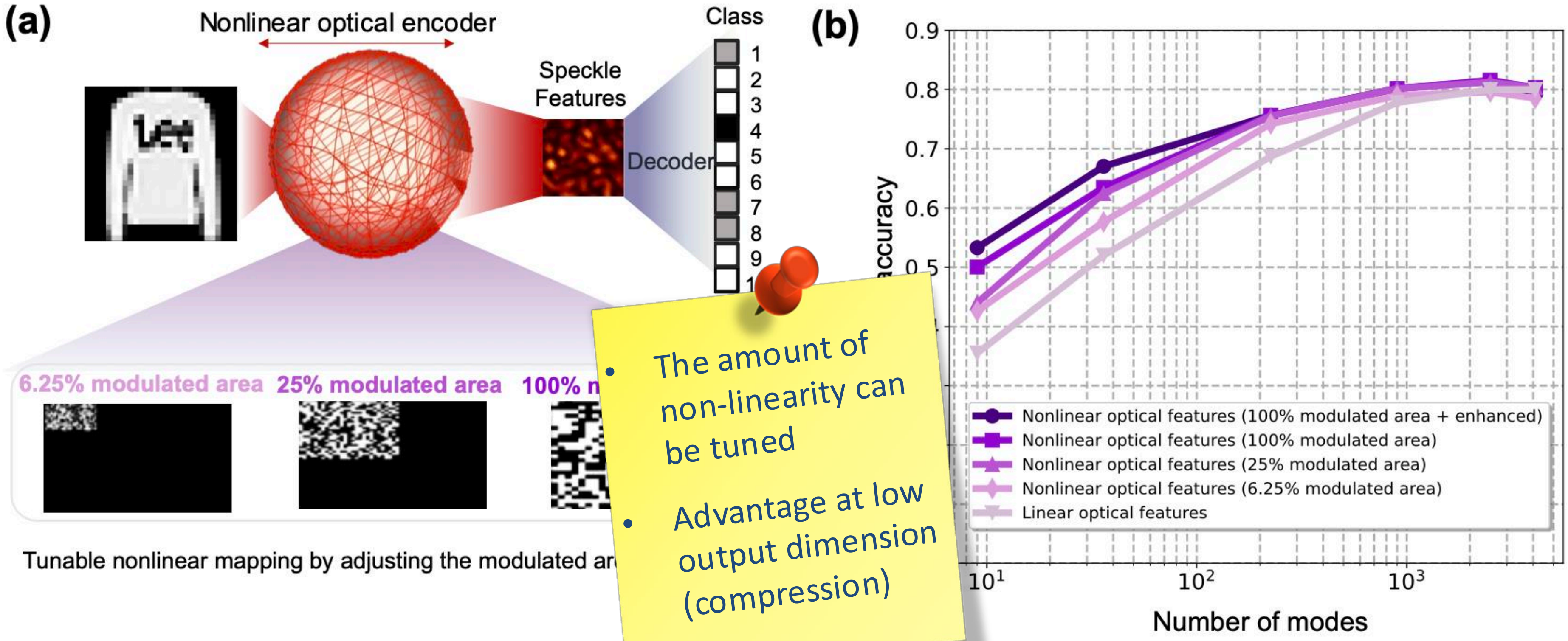
The input field E_{in} and output field E_{out} are related by:

$$E_{out} = \mathbf{W}E_{in} = (\mathbf{V} + \mathbf{V}(\mathbf{G}_o\mathbf{V}) + \mathbf{V}(\mathbf{G}_o\mathbf{V})^2 + \dots)\, E_{in}$$

Encoding in scattering potential V

where **W** is a complex transmission matrix, **V** is scattering potential, $\mathbf{G}_o$ represents the free-space Green's function

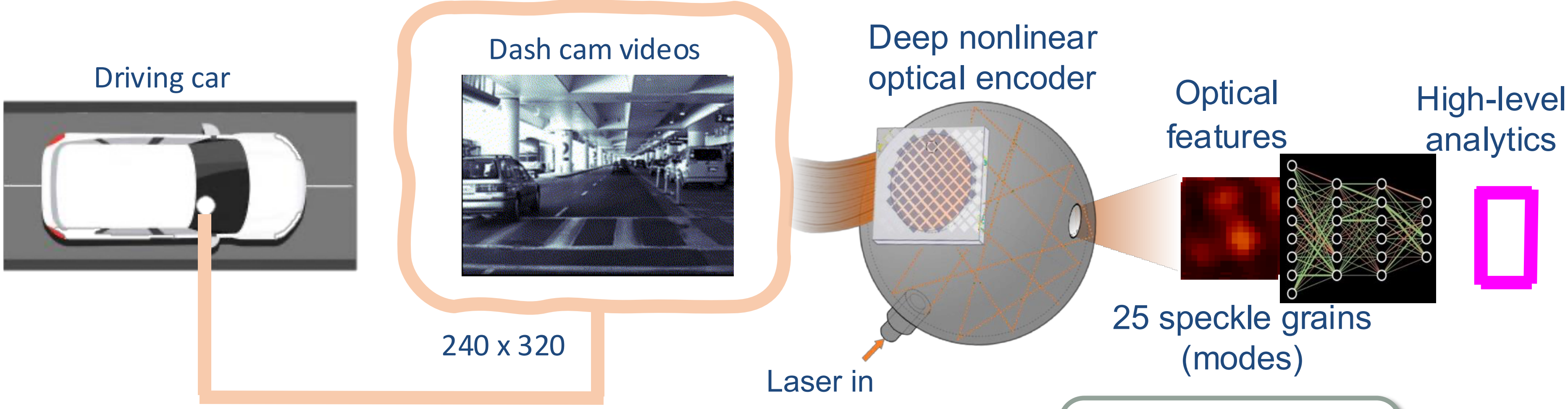
Tuning the non-linearity – classification results



- The amount of non-linearity can be tuned
- Advantage at low output dimension (compression)

F. Xia, K. Kim, Y. Eliezer, L. Shaughnessy, S. Gigan, H. Cao, Nature Photonics (2024)

Large scale task : self driving



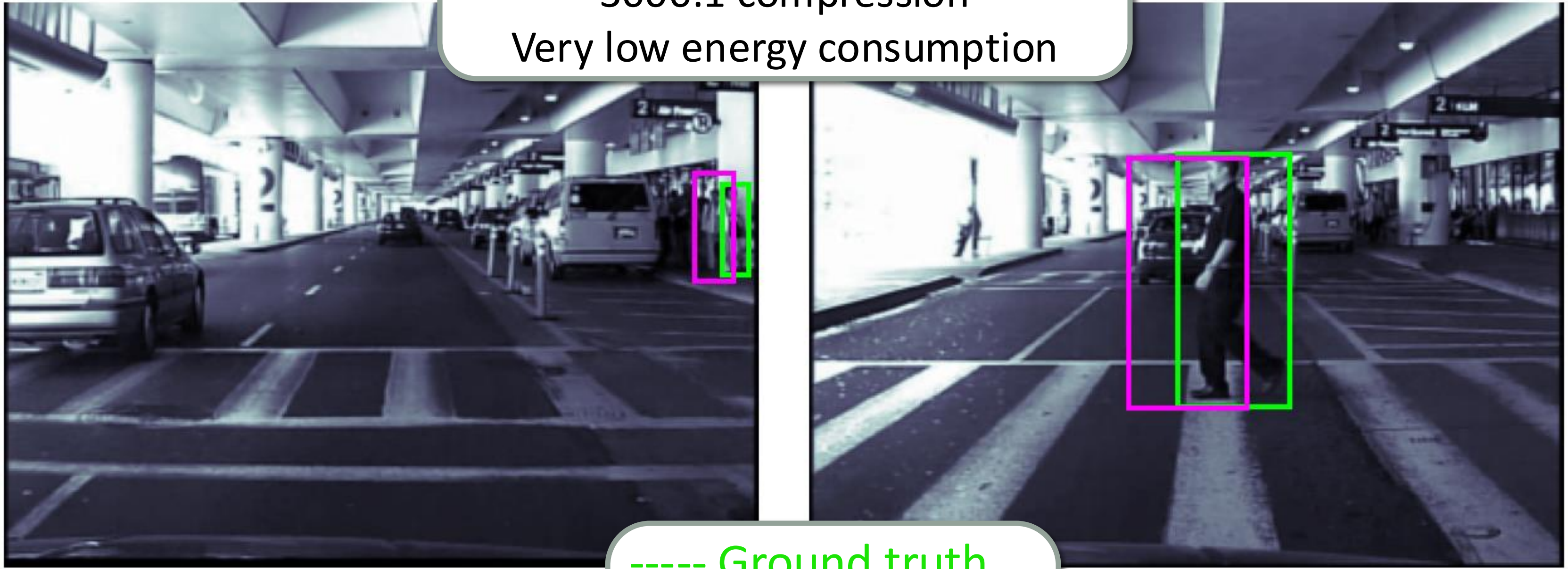
Compression
3000:1

Dataset: Caltech Pedestrian

F. Xia, K. Kim, Y. Eliezer, L. Shaughnessy, S. Gigan, H. Cao, Nature Photonics (2024)

Pedestrian detection at 30Hz

25 output pixels
3000:1 compression
Very low energy consumption



----- Ground truth
----- speckle
<2 px sdev error

F. Xia, K. Kim, Y. Eliezer, L. Shaughnessy, S. Gigan, H. Cao, Nature Photonics (2024)

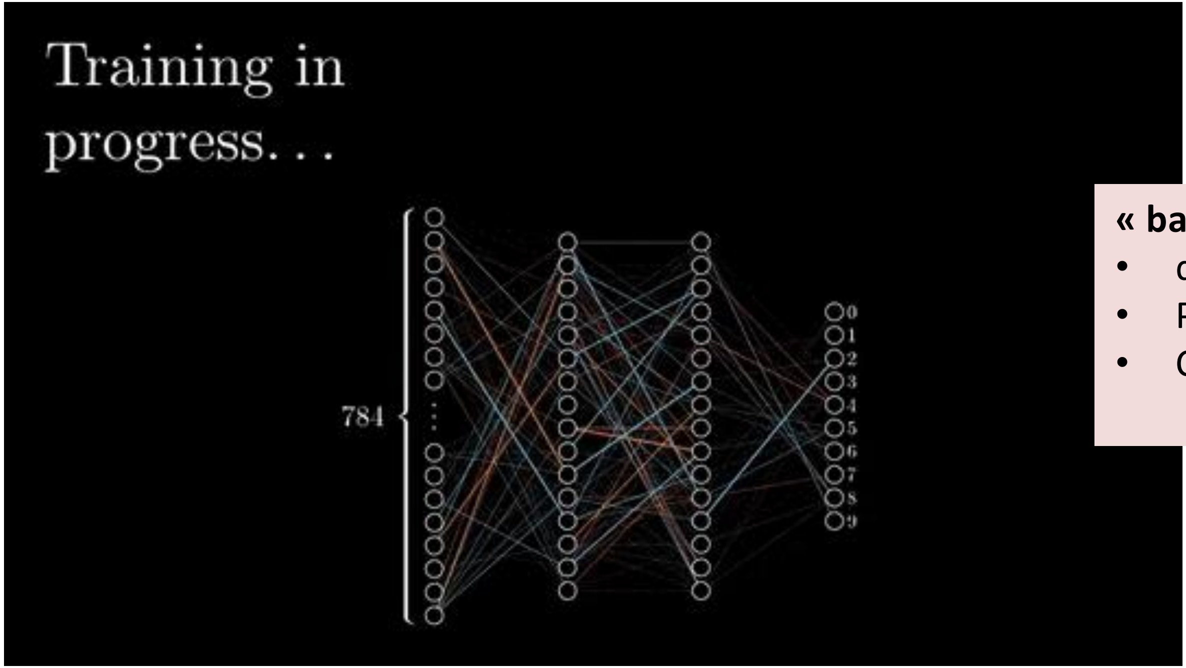
Can you use optics to train a (very) large digital model ?

Can we replace « backprop' » ?

Wang, Muller, et al., arXiv:2409.12965(2024)

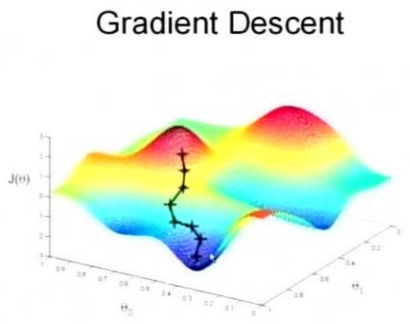
Training - Backpropagation

FORWARD : inference



« backprop' »

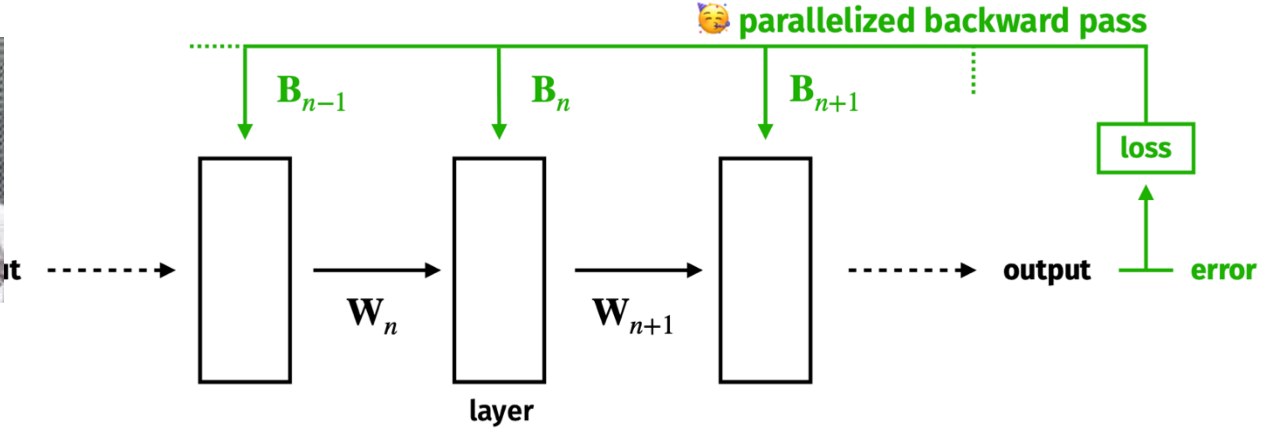
- de-facto standard for training
- Power-intensive
- Constraints to a layered NN architecture



BACKWARD : Error propagation and weight-tuning based on local gradients

Training a neural network with Direct Feedback Alignment (DFA)

🔁 Use **random weights** to **directly** deliver feedbacks from the global loss.

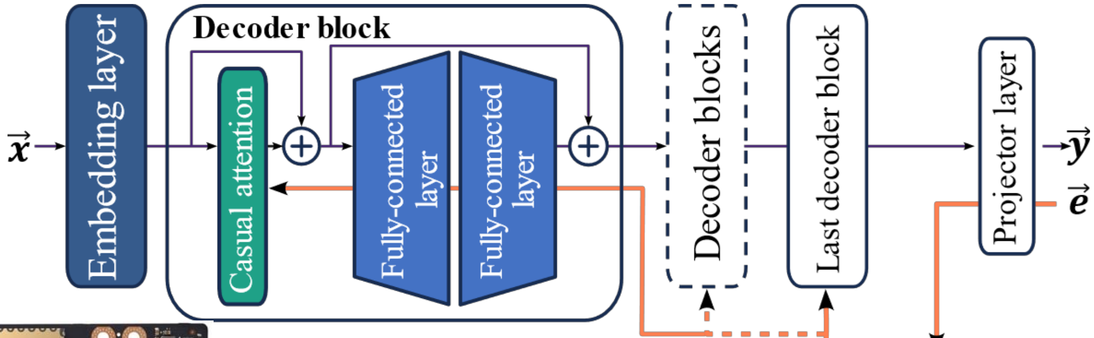


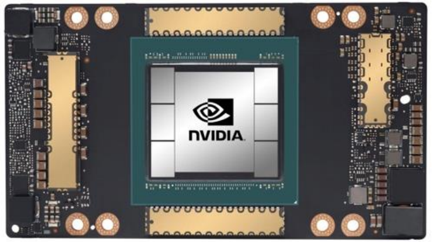
$$\delta \mathbf{W}_i^{BP} = -[\overbrace{(\mathbf{W}_{i+1}^T \delta \mathbf{a}_{i+1})}^{\text{gradient signal from layers above}} \odot f_i'(\mathbf{a}_i)]\mathbf{h}_{\mathbf{i-1}}^{\mathbf{T}} \longrightarrow \delta \mathbf{W}_i^{DFA} = -[\overbrace{(\mathbf{B}_i^T \mathbf{e})}^{\text{random projection of the loss gradient}} \odot f_i'(\mathbf{a}_i)]\mathbf{h}_{\mathbf{i-1}}^{\mathbf{T}}$$

General-purpose: agnostic to model architecture & scale well

Original paper : Arild Nøkland, NIPS 2016 arXiv:1609.01596

Can we train a transformer with 1 Billion Parameters ?

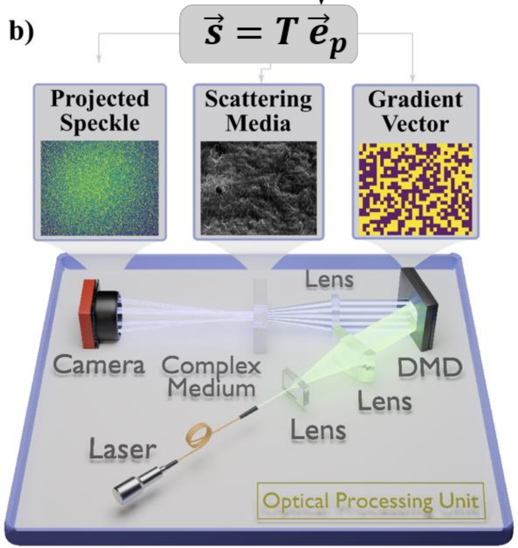




- 1B parameters GPT-like transformer
- 400M parameters directly receive optical signal

Cornell Movie-Dialogs Corpus
Example in the Dataset

- MILES: Back at you.
- JACK: Love you, man.
- MILES: Yeah.
- JACK: So I'll see you at the rehearsal.



Ziao Wang
(LKB)

Kilian Müller
(Lighton)

Wang, Muller, et al., arXiv:2409.12965(2024)

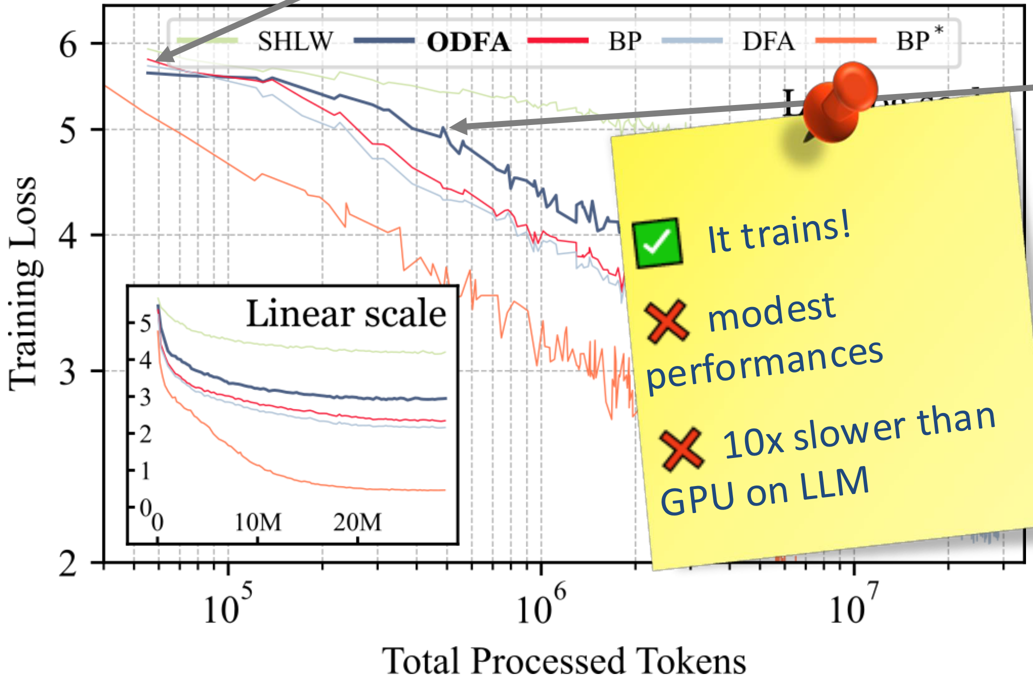
ODFA on Text Transformer: Performance

0% Training

aQ o do wantQain do do twoain o re[through show" happenQ start. 2lt JULIANNE JULIANNE

20% Training

JACKIE : Snkups to the brags, but I know that. ↵
CRAYC : It ' s just a concer. ↵



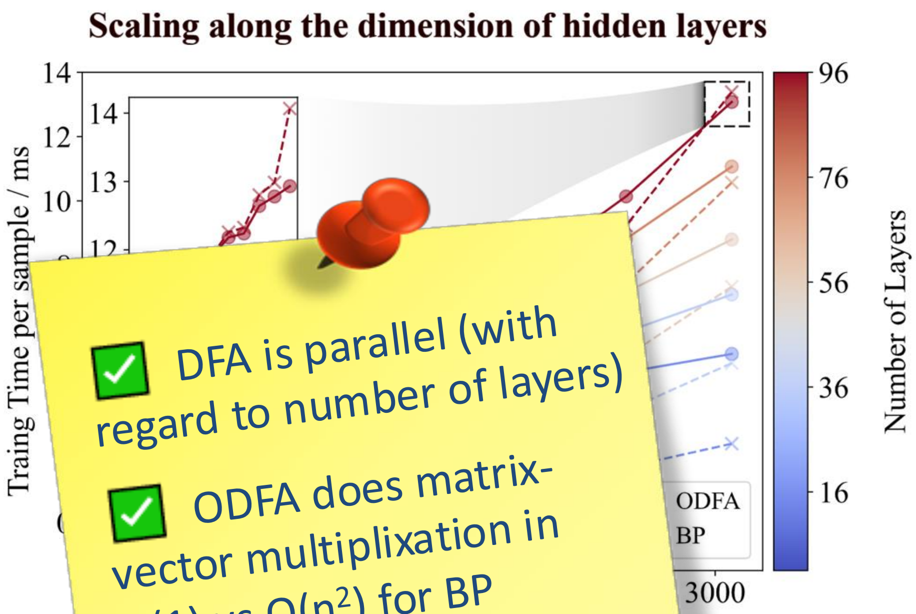
- ✅ It trains!
- ❌ modest performances
- ❌ 10x slower than GPU on LLM

100% Training

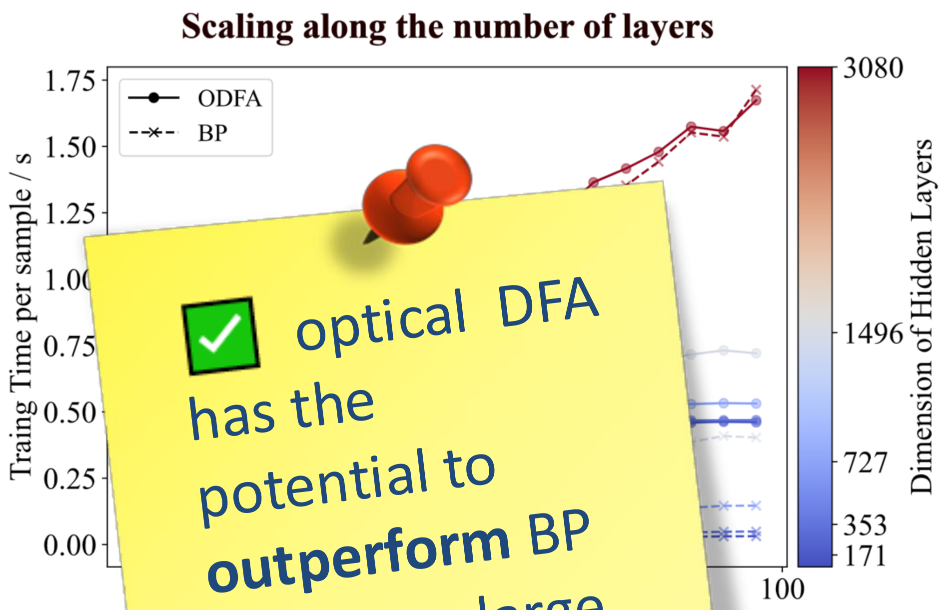
JOE : So what are you talking about? ↵
ED : I mean I'm sorry, you know how to know you are. ↵

Wang, Muller, et al., arXiv:2409.12965(2024)

Towards Extreme Scale: When will ODFA be faster than BP?



- ✅ DFA is parallel (with regard to number of layers)
- ✅ ODFA does matrix-vector multiplixation in $O(1)$ vs $O(n^2)$ for BP



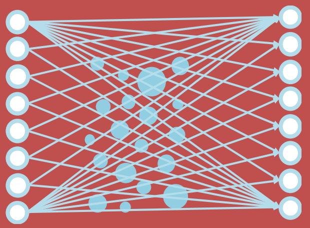
✅ optical DFA has the potential to **outperform** BP for future large models !

Wang, Muller, et al., arXiv:2409.12965(2024)

Take-home message

LKB

Optical Random Projections



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

Many proof of principles:

- Classification,
- Reservoir computing
- Image generation
- Ising models
- Quantum circuits
- …

Beyond random projections

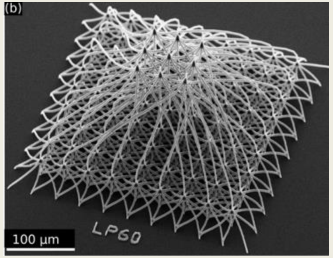
- Adding tunability and trainability
- Including low-power non-linearity
- « Reverberating » passive non-linearities

Ability to tackle relatively large-scale + advanced AI tasks

Perspectives for optical computing ?

Convergence between free space and integrated optics?

"Best of both worlds"



Optica 7, 640-646 (2020) (D. Brunner team – FEMTO-ST)

Convergence between algorithms & optics?

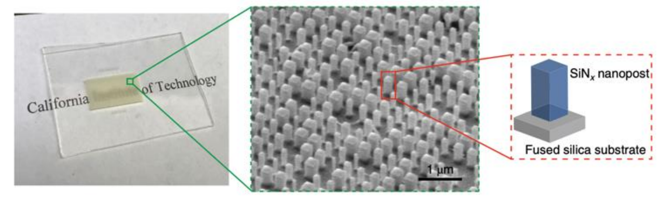
(Not just deep learning)

"the hardware lottery"

S. Hooker [arXiv:2009.06489]

Convergence between top-down and bottom-up

reproducibility / scalability / inverse design



Nature Photon **12**, 84–90 (2018) (C. Yang and A. Faraon, Caltech)

Thanks to my team and collaborators

Special mention to : Ziao Wang, Fei Xia, Jianqi Hu, Hao Wang




Thank you for your attention !

Don’t hesitate to ask for the slides

Mail : sylvain.gigan@lkb.ens.fr

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Gordon Wetzstein, Aydogan Ozcan, Sylvain Gigan, Shanhui Fan, Dirk Englund, Marin Soljačić, Cornelia Denz, David A. B. Miller & Demetri Psaltis

Nature **588**, 39–47(2020) | Cite this article

Perspective | Published: 08 September 2022

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Sylvain Gigan

Nature Physics **18**, 980–985 (2022) | Cite this article