Optical Computing with Disorder:

Spatiotemporal time-series prediction using scattering-based optical reservoir computing

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SwissPhotonics

Workshop on Optical Computing

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Laboratoire Kastler Brossel
Physique quantique et applications

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The team

Our Goal :
Understand and exploit the complexity of light propagation in complex media

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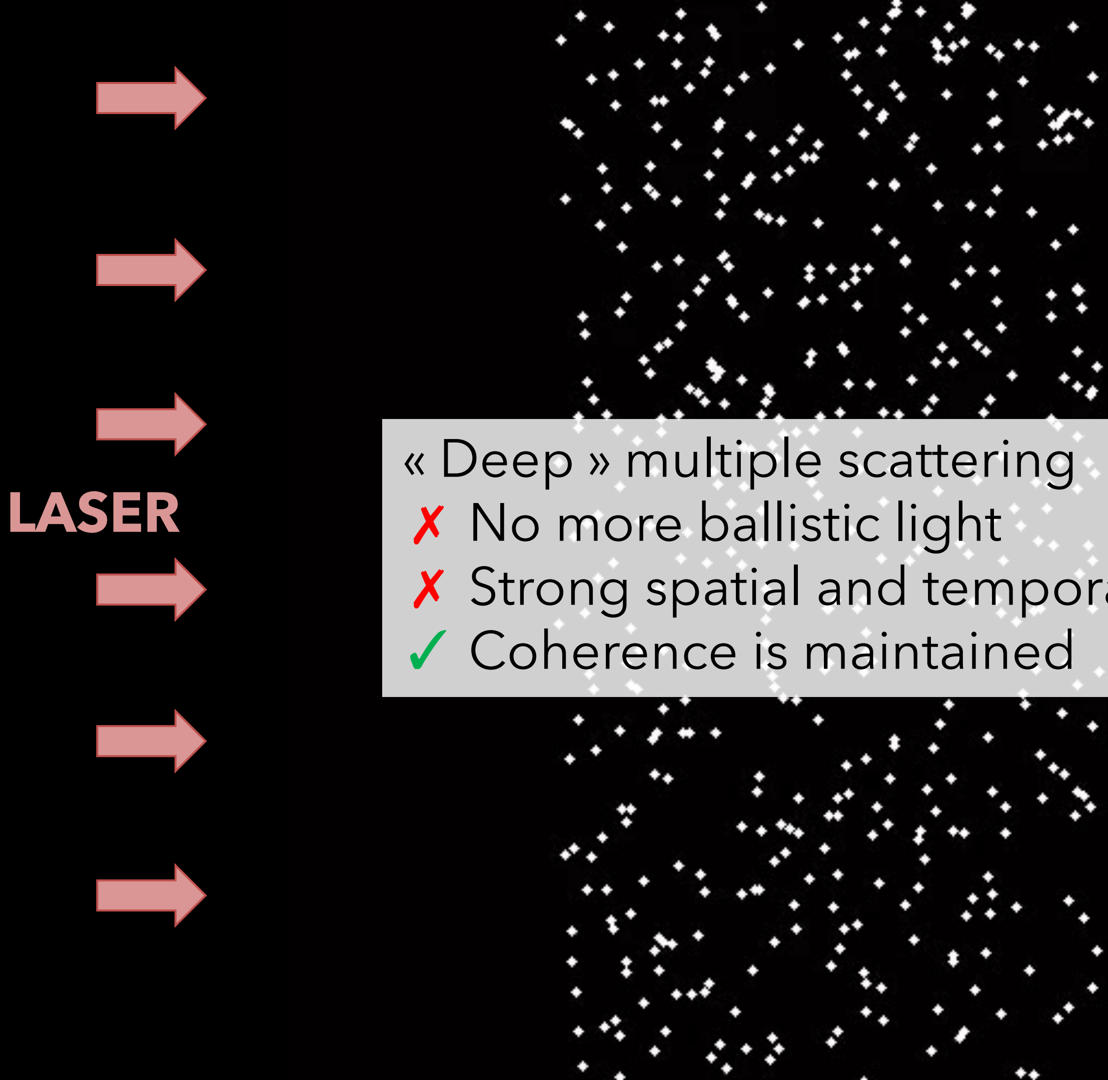


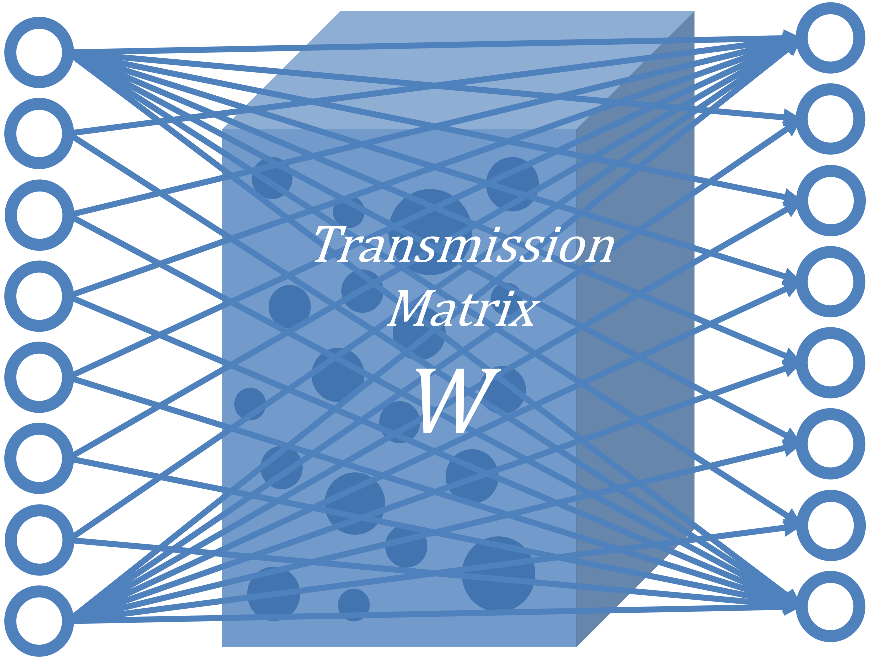
« Deep » multiple scattering regime :

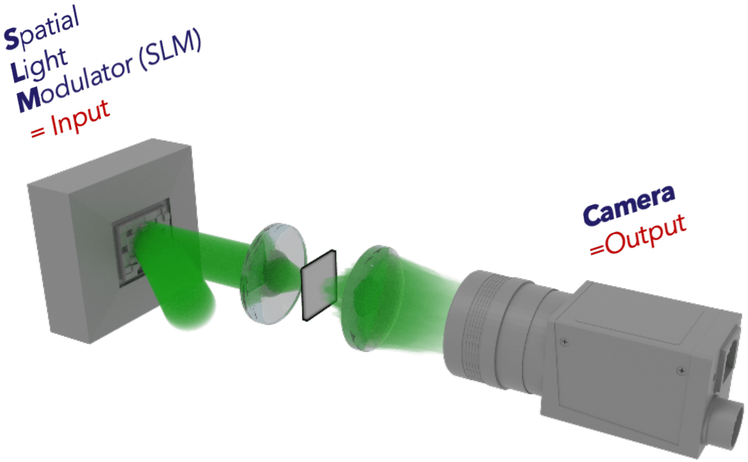
- ✗ No more ballistic light
- ✗ Strong spatial and temporal perturbation
- ✓ Coherence is maintained

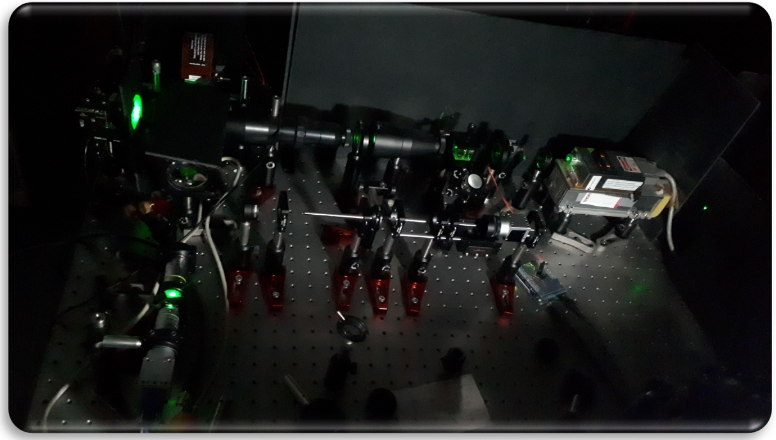
3D random Sample
« white paint »

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

Optical computing with a complex medium ?





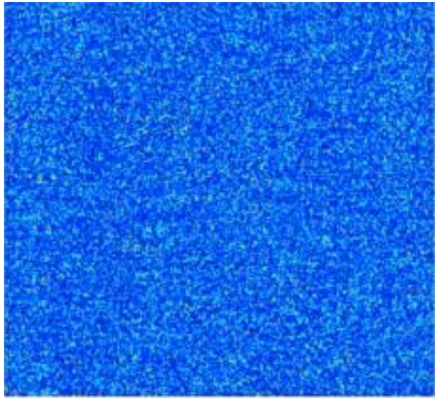


The Transmission Matrix

$$E^{out} = W E^{in}$$

Experimentally-measured Transmission Matrix (TM)

Out

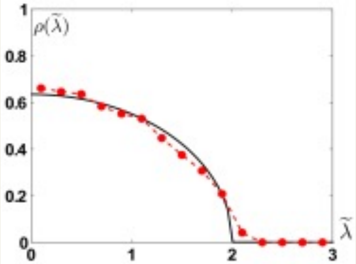


In

Popoff et al. Phys. Rev. Lett. 104,100601 (2010)

Random

Mesoscopic physics



« Quarter-circle law »

Large dimensional

Area $A \sim 1\ mm^2$

Wavelength $\lambda \sim 1\ \mu m$

$$N \sim A/\lambda^2$$

~ many million in/out modes

as in *Yu, Lee, & Park (2017)*

Propagation of light through a disordered medium

=

multiplication by a complex i.i.d. random matrix

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

A **universal** operation

optical computing revisited?

Why is it interesting ?

EXTRA-LARGE **&** **SUPER-FAST**

H of size higher than $10^6 \times 10^6$ (TBs of memory)

kHz operation $\rightarrow 10^3$ such multiplies / s

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

LightOn

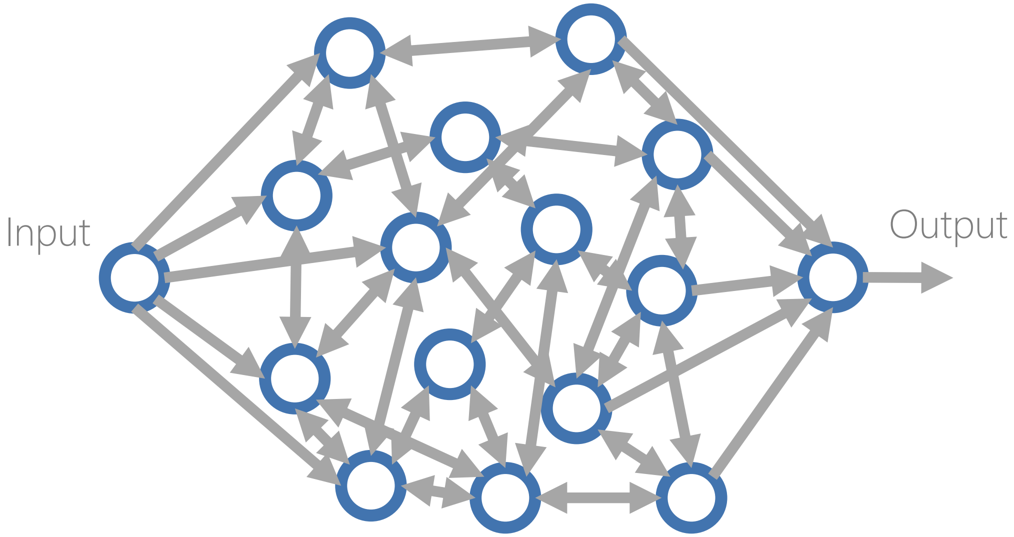
We bring Light to AI

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

See Laurent Daudet's talk later today :

- **Many, many use cases**
- **At scale for modern machine learning**
- **You can buy it already**

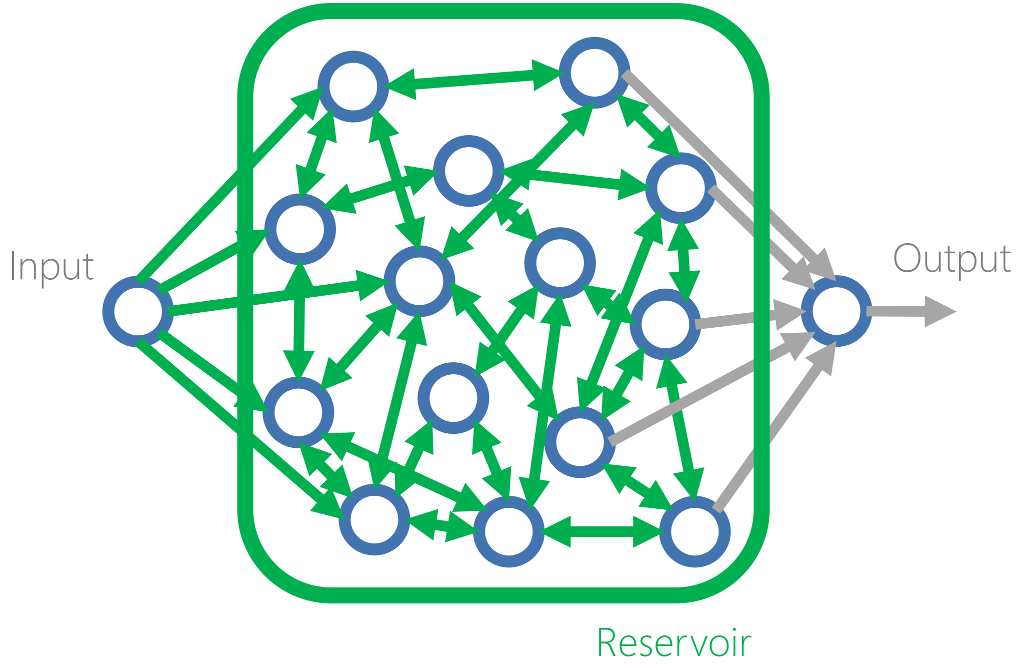
Reservoir Computing



Recurrent Neural Networks are notoriously hard to train

Jaeger & Haas (2004). *Science*

Reservoir Computing



Recurrent Neural Networks are notoriously hard to train

Reservoir Computing fixes all internal weights randomly

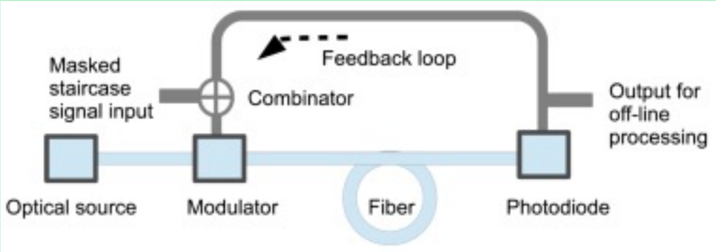
Jaeger & Haas (2004). *Science*

Recurrent Neural Networks

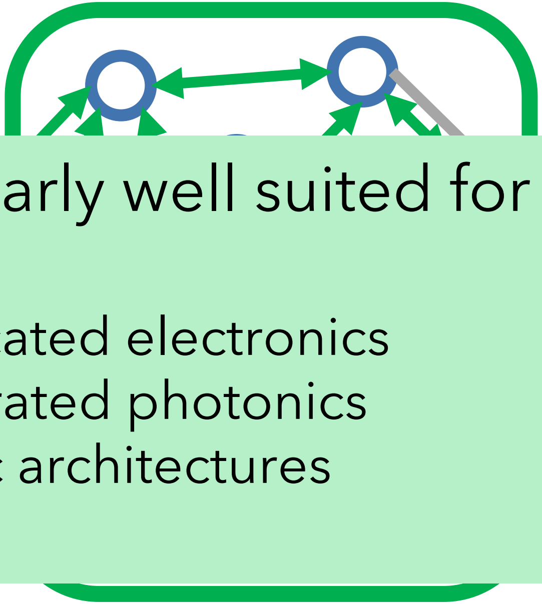
in

Particularly well suited for physical implementations

- Dedicated electronics
- Integrated photonics
- Exotic architectures



Tanaka, Gouhei, et al. "Recent advances in physical reservoir computing: A review." *Neural Networks* 115 (2019): 100-123



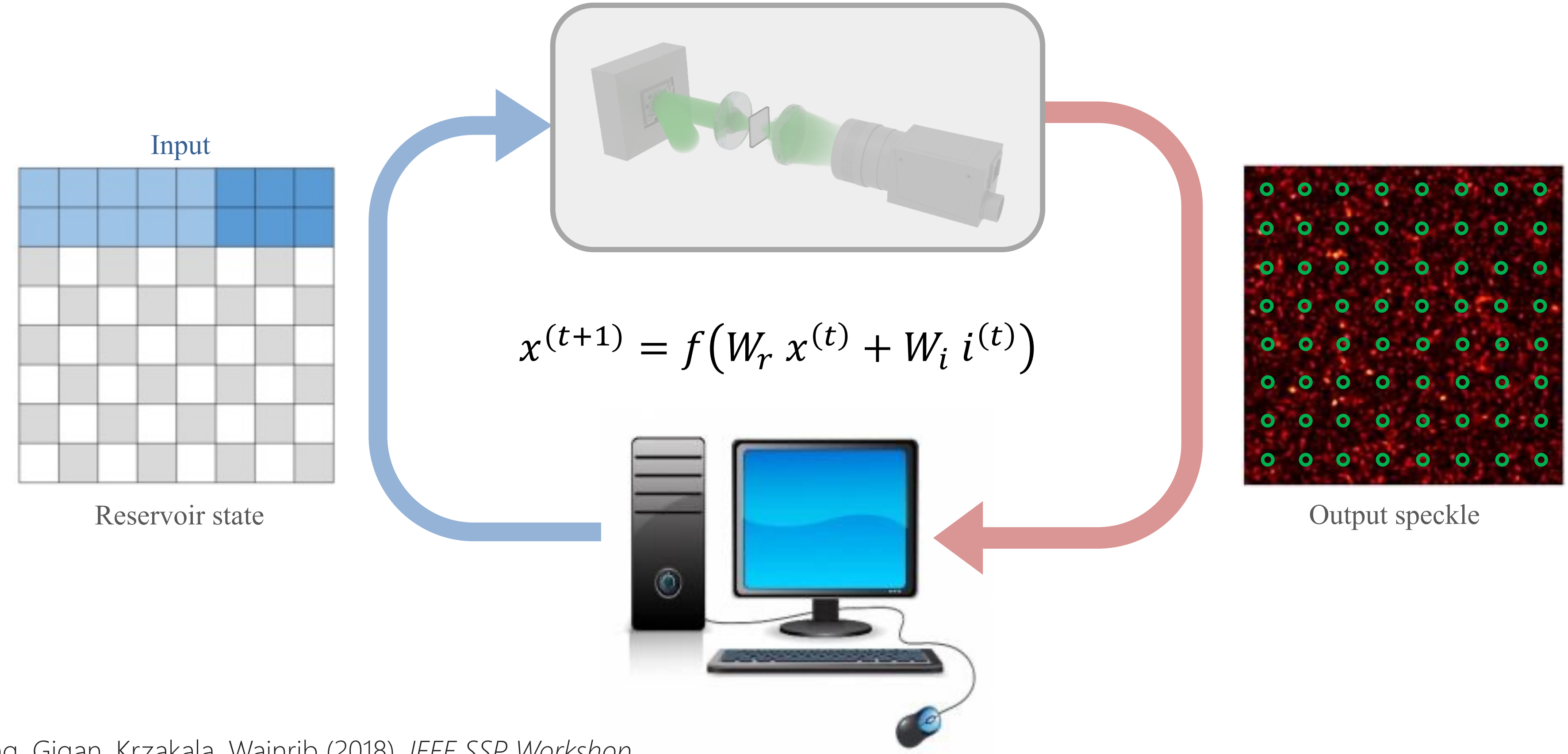
next reservoir

current reservoir

current input

Jaeger & Haas (2004). *Science*

Reservoir computing with a complex medium ?



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

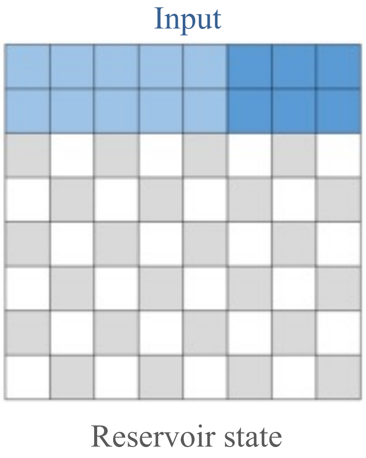
Dong, Gigan, Krzakala, Wainrib (2018). *IEEE SSP Workshop*

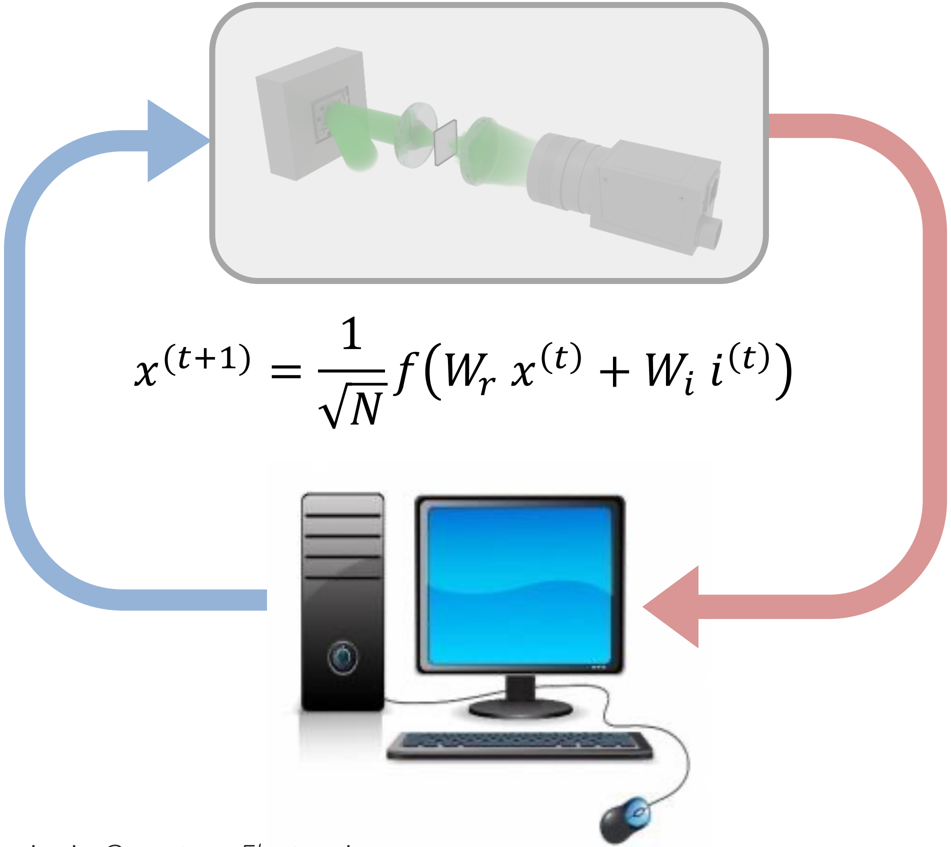
Reservoir computing with a complex medium ?

SLM encoding
Input $i^{(t)}$
and reservoir $x^{(t)}$

Important hyperparameter: relative areas of input and reservoir state

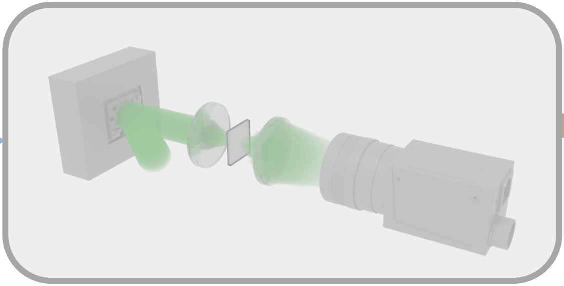
Comparison of different SLM technologies in [1]



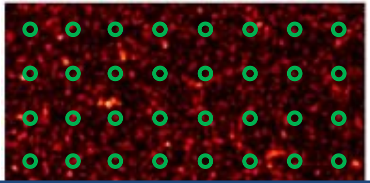


$$x^{(t+1)} = \frac{1}{\sqrt{N}} f\left(W_r\, x^{(t)} + W_i\, i^{(t)}\right)$$

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



$x^{(t+1)}$ … 1 … $f(W$ …



Camera readout

To get $x^{(t+1)}$

Modulus

…rity

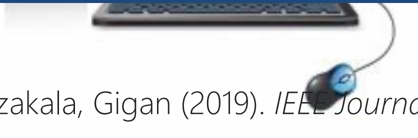
…a grid to
…ations

Last stage / a posteriori

Predict output with a linear model

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

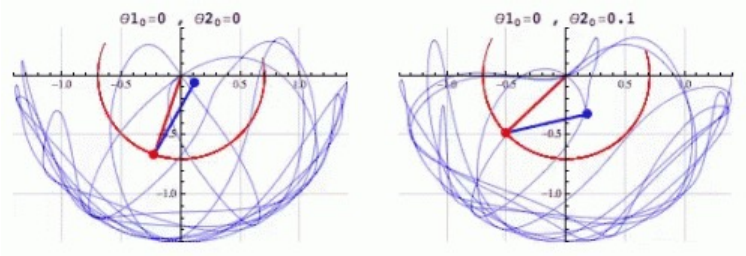
(done on a CPU or GPU - Typically not the bottleneck)



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

chaotic systems

Double-rod pendulum

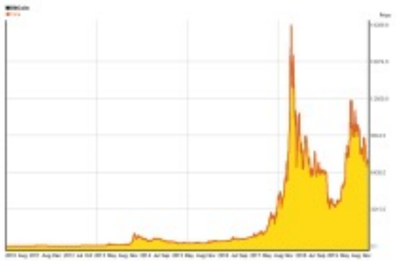


System becomes unpredictable a after characteristic time : the Lyapunov time

Turbulence

Weather and climate

Financial markets



…

Chaotic time series prediction

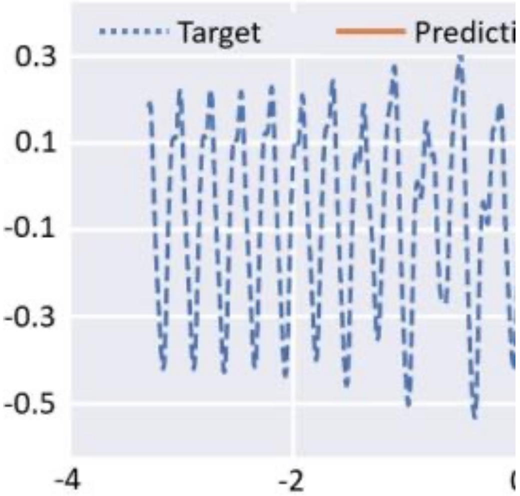
The Mackey-Glass equation (1D):

$$\frac{dx}{dt} = \frac{\beta x_\tau}{1 + x_\tau^n} - \gamma x$$

The Kuramoto-Sivashinsky equation (2D):

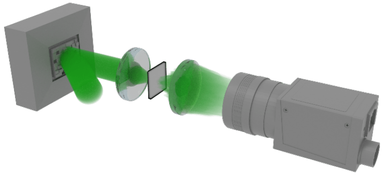
$$\frac{\partial u}{\partial t} + \nabla^4 u + \nabla^2 u + \frac{1}{2}|\nabla u|^2 = 0$$

Mackey-Glass prediction (1D)



1. Compute the reservoir states

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

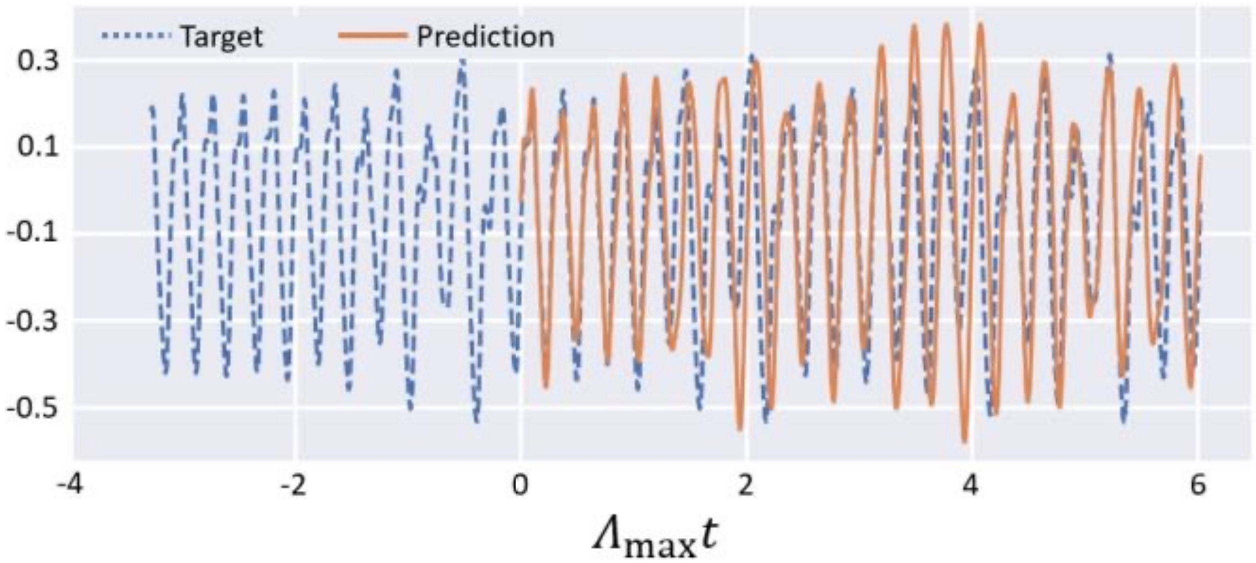


2. Output with a linear model

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

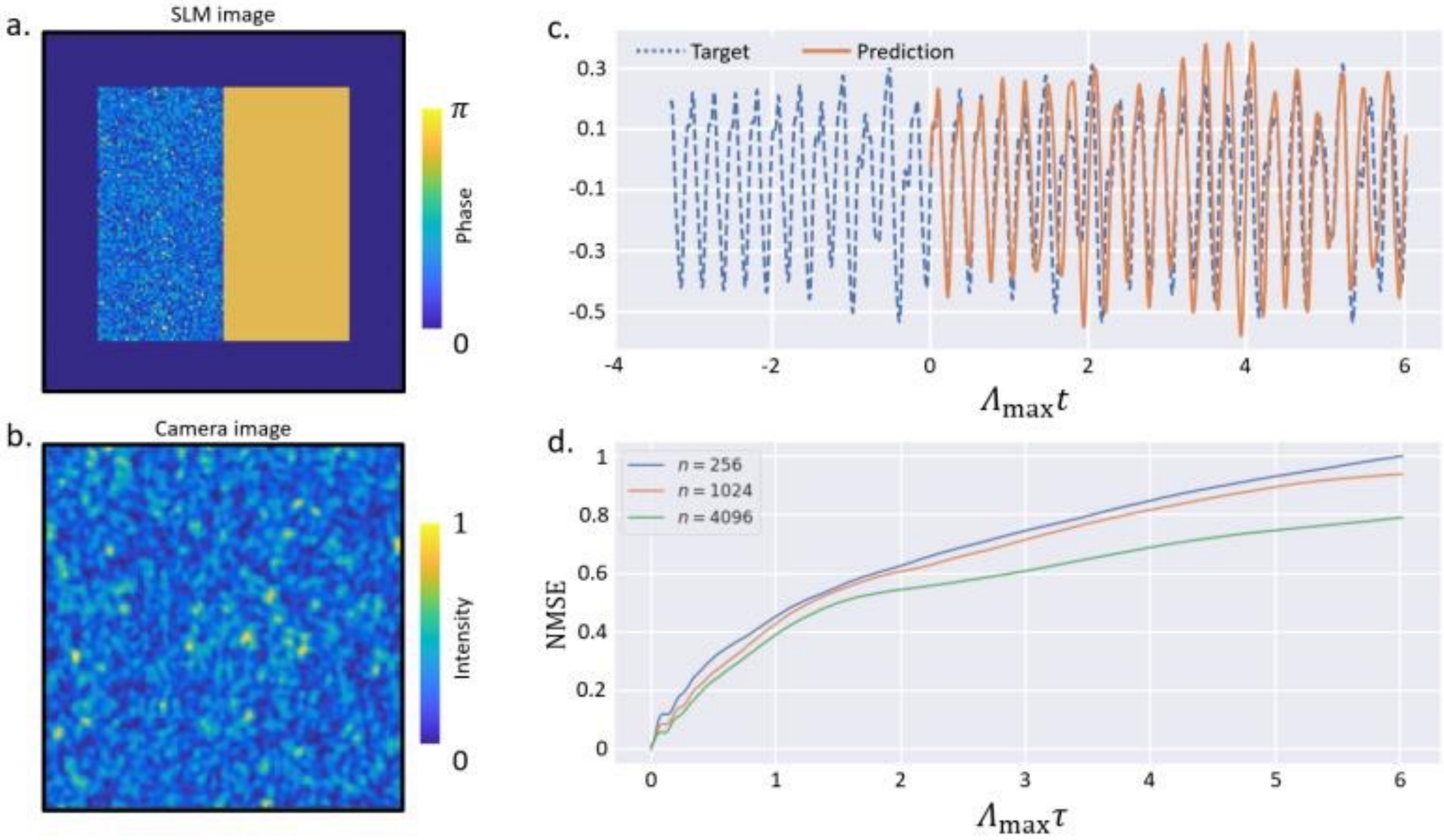
Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Mackey-Glass prediction (1D)



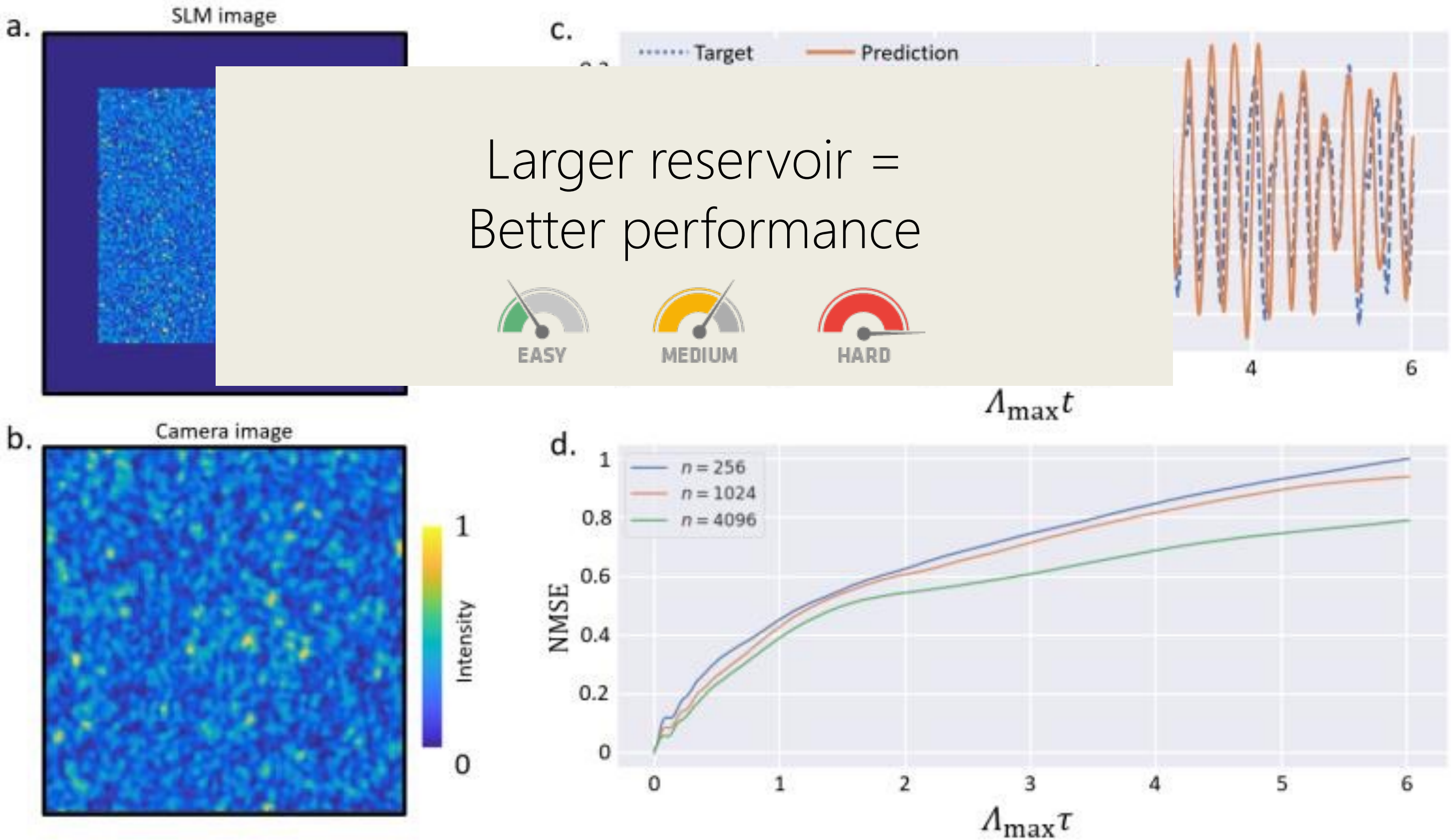
Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Mackey-Glass prediction (1D)



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

Mackey-Glass prediction (1D)



Larger reservoir =
Better performance

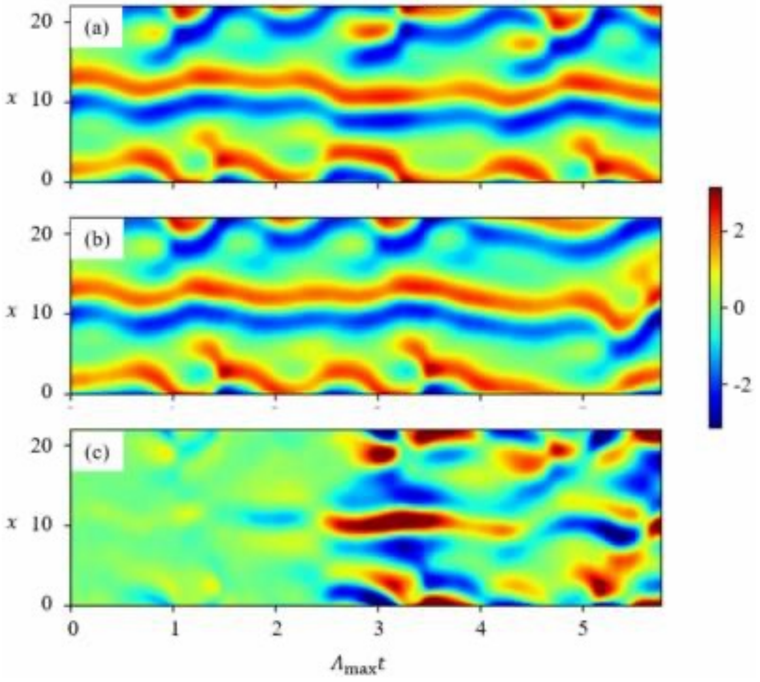
Dong, Rafayelyan, Krzakala, Gigan (2019). *IEEE Journal of Selected Topics in Quantum Electronics*

Kuramoto-Sivashinsky prediction - results

Ground truth

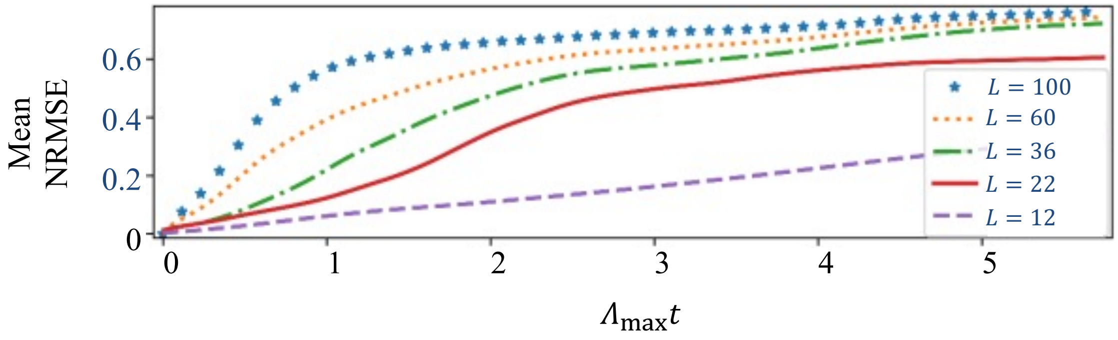
Prediction

Error =
Ground truth - Prediction

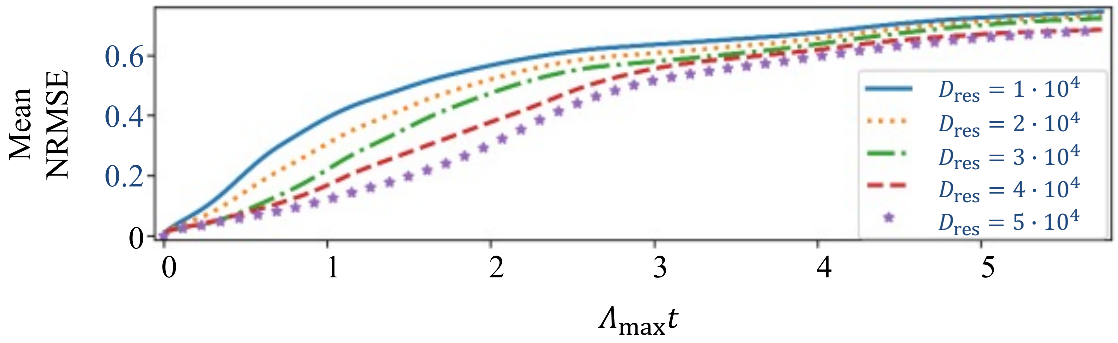


Rafayelyan, Dong, Tan, Krzakala, Gigan (2020). *Physical Review X*

Reservoir size is fixed, $D_{res} = 10000$



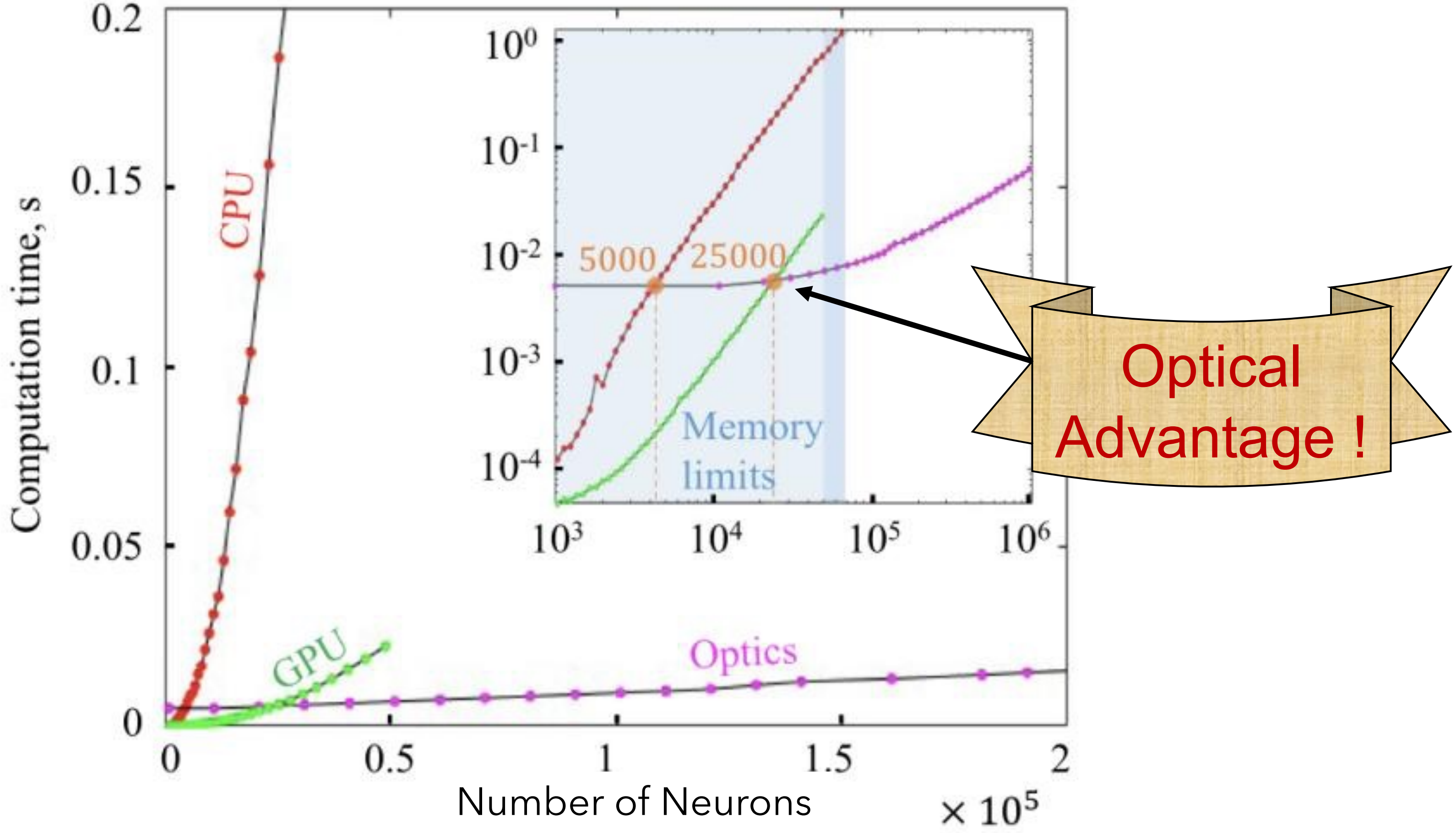
Spatial domain size is fixed, $L = 60$



Larger chaotic systems can be predicted by increasing the network size

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

Computation time versus reservoir size (one iteration)



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

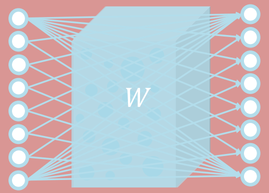
Conclusion and perspectives

Optical random projections for Reservoir Computing

- Efficient
- Large-dimensional
- Off-the-shelf components

- Noise
- Encoding on the SLM
- Only the random projection in optics

Classical optical computing



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

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

Perspective:

- Large scale problems
- New functions
- Interfacing with electronics
- « designed » matrix ?
- Adjustable weights?

Thanks to my coworkers and collaborators

Jonathan DONG, Mushegh RAFAYELAN, Florent KRZAKALA (EPFL)

Thank you for your attention !

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