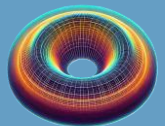
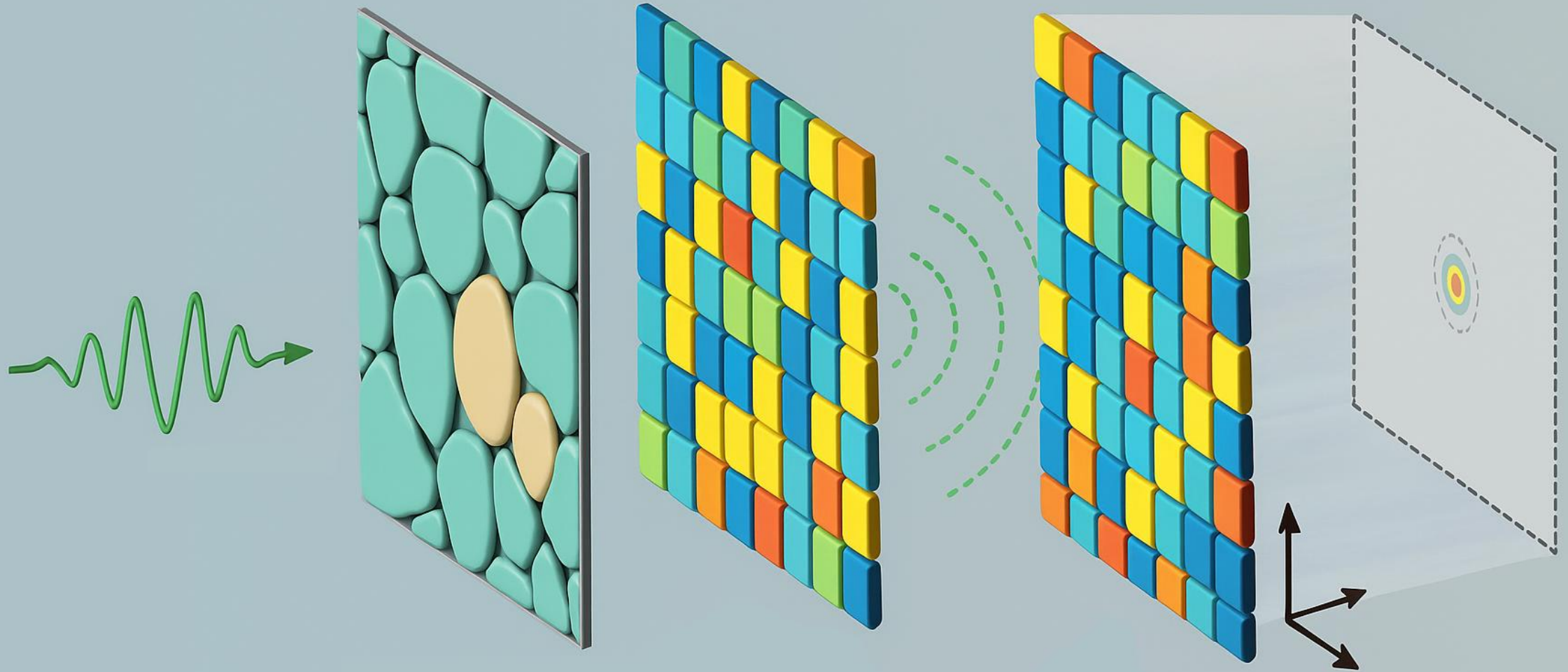


Optics that Learn



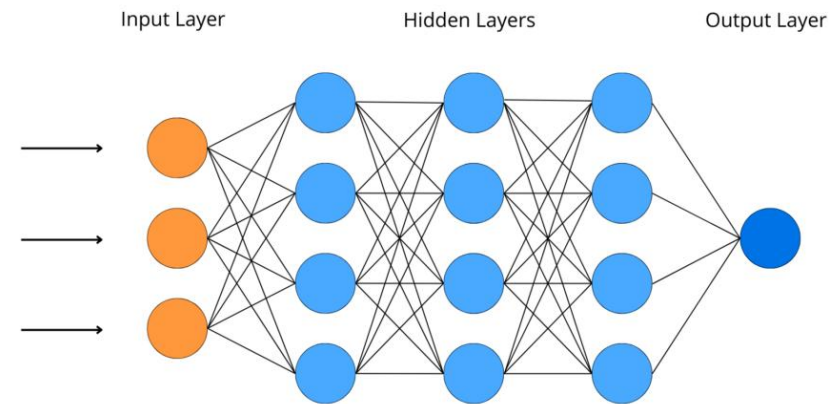
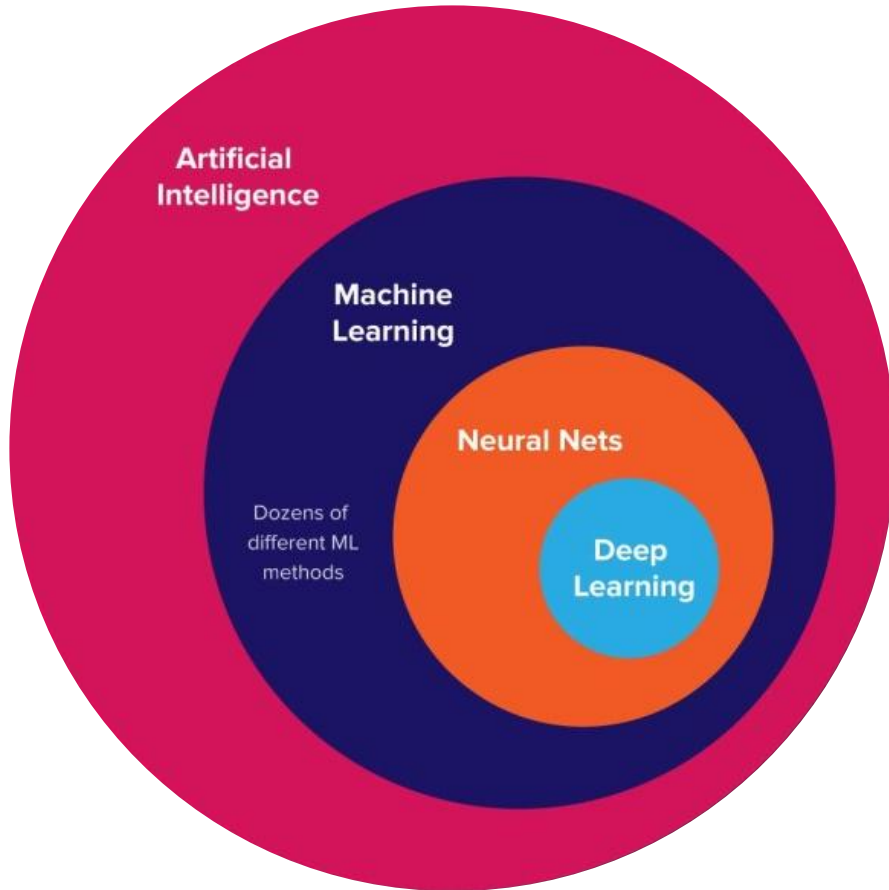
Marco Piccardo
Multimode Photonics Group



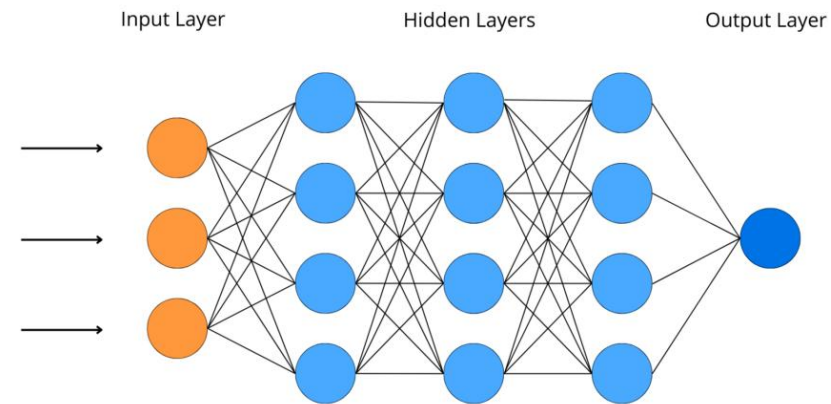
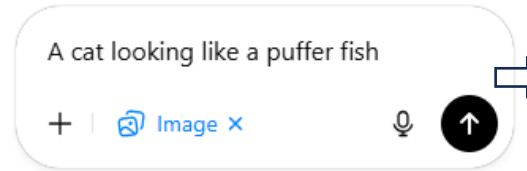
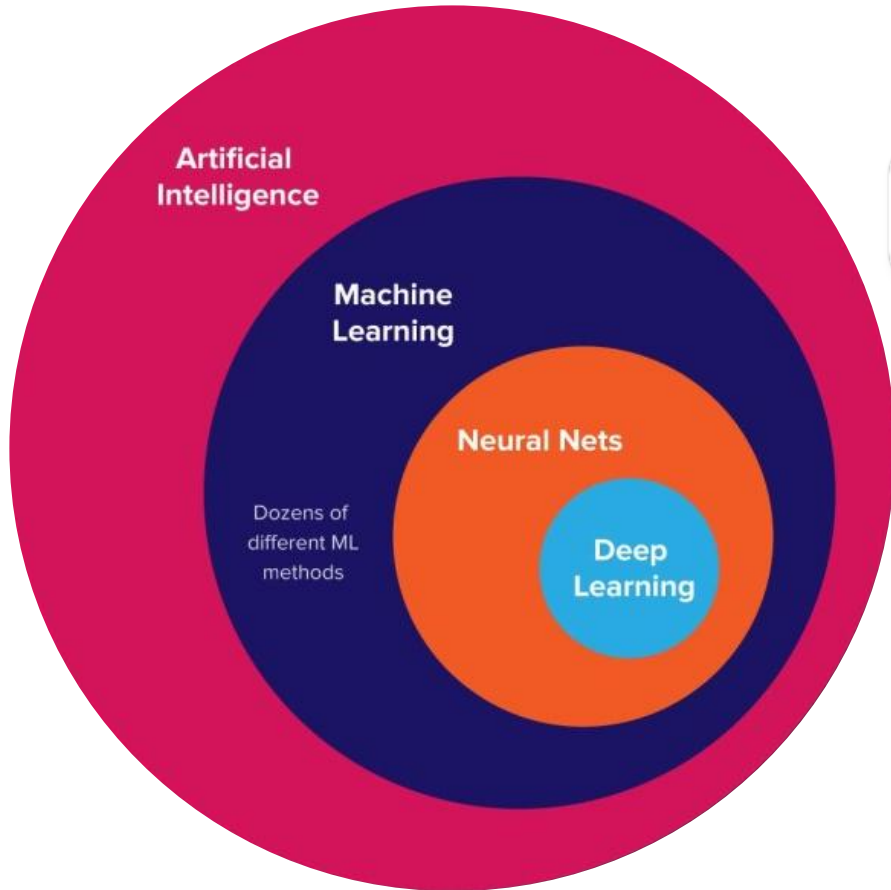
TÉCNICO
LISBOA



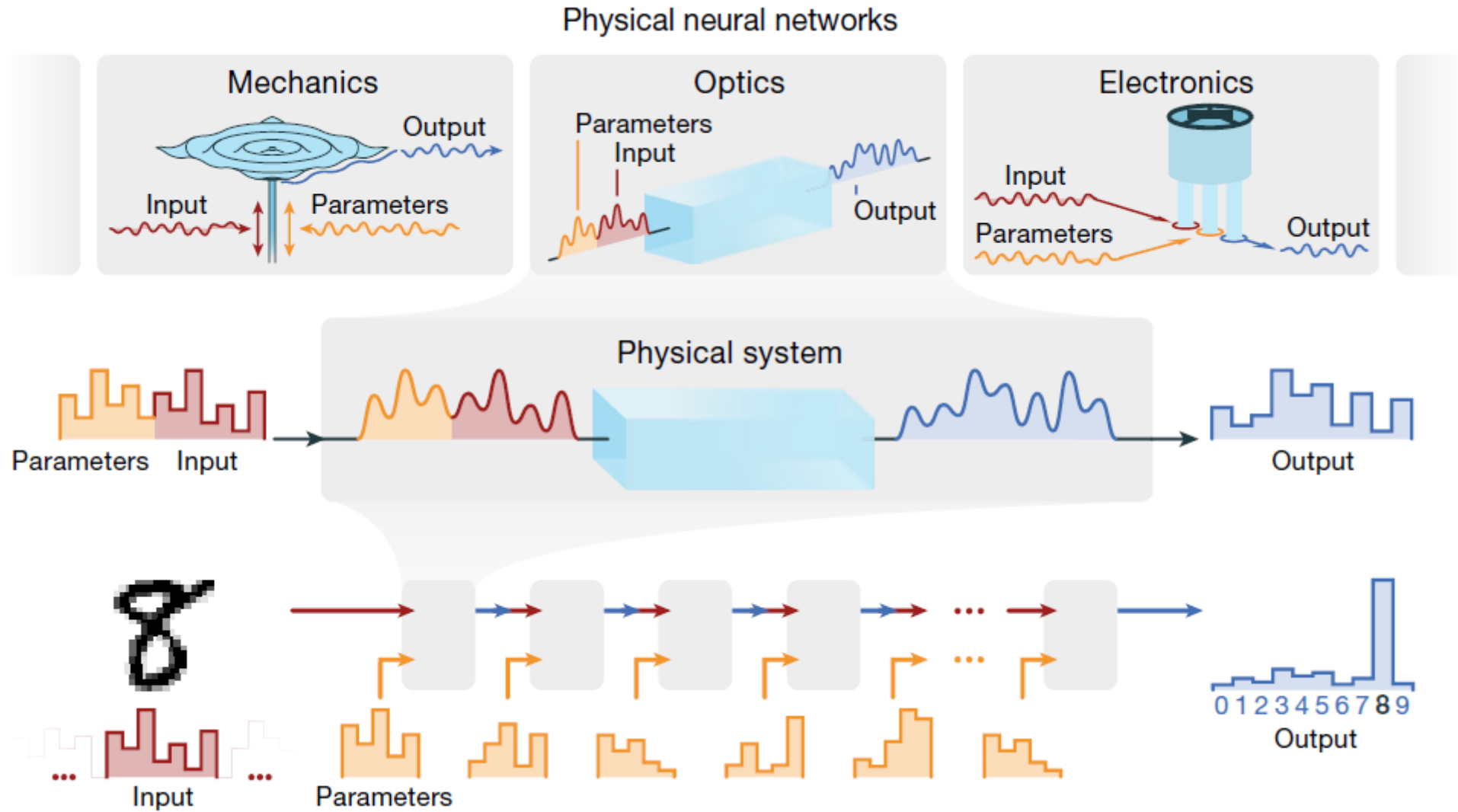
A key subset of Machine Learning: Artificial neural networks



A key subset of Machine Learning: Artificial neural networks



Physical neural networks



Optical neural networks

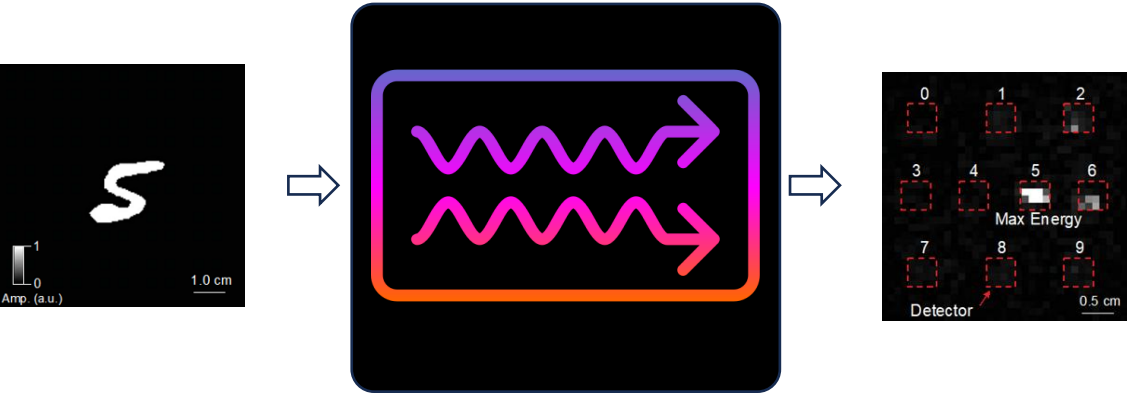
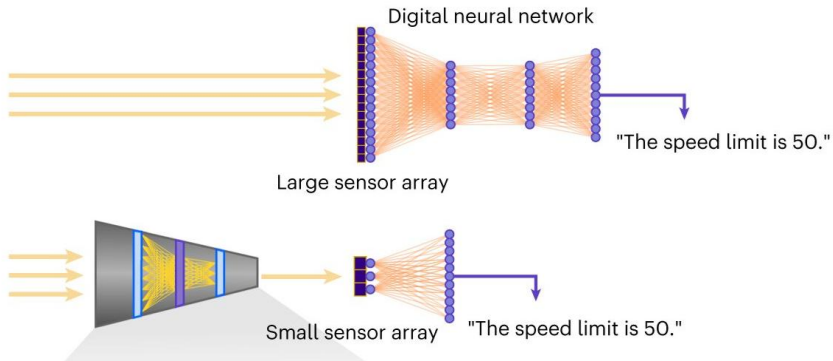


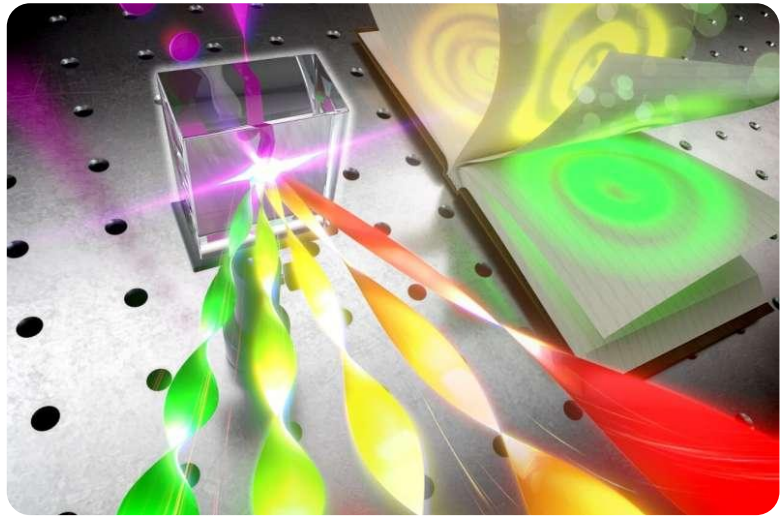
Image sensing via direct imaging



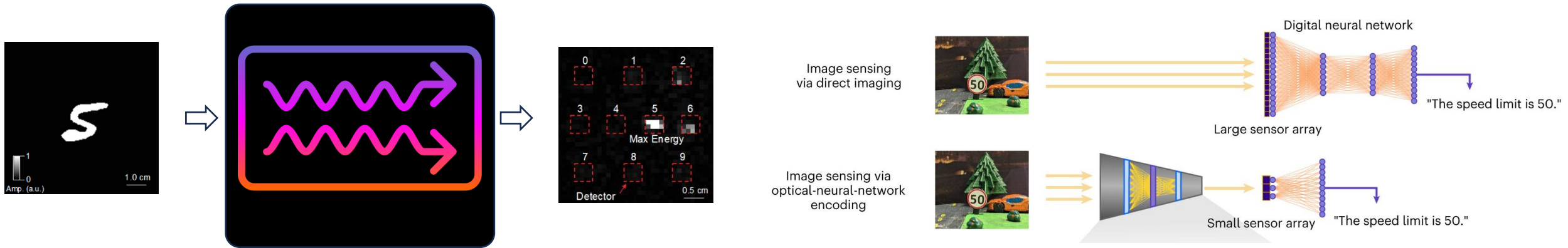
Image sensing via optical-neural-network encoding



Complex structured light transformations



Optical neural networks

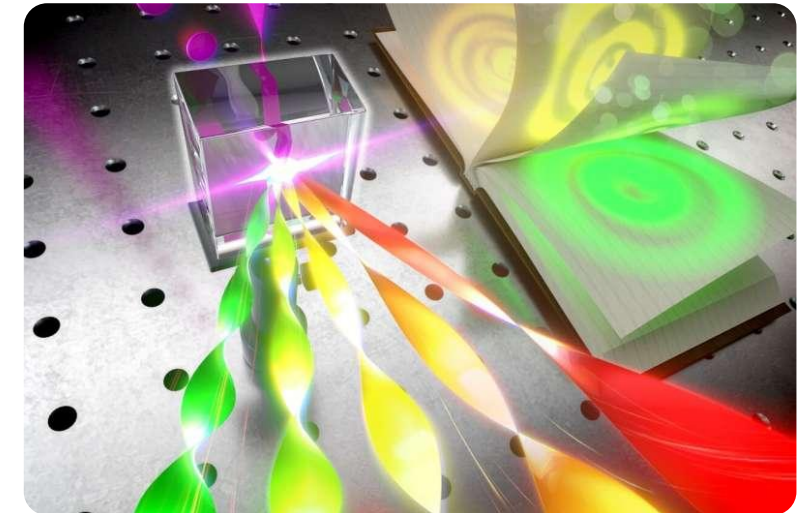
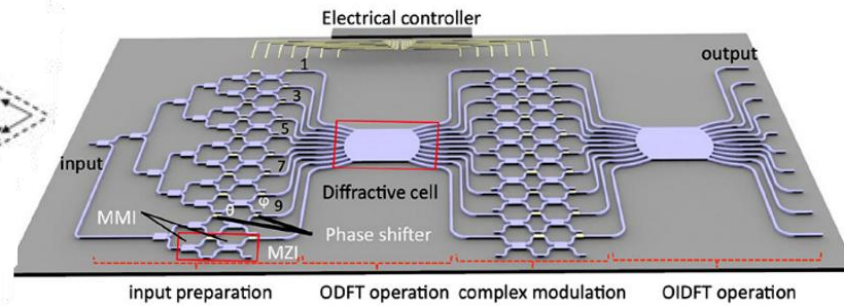
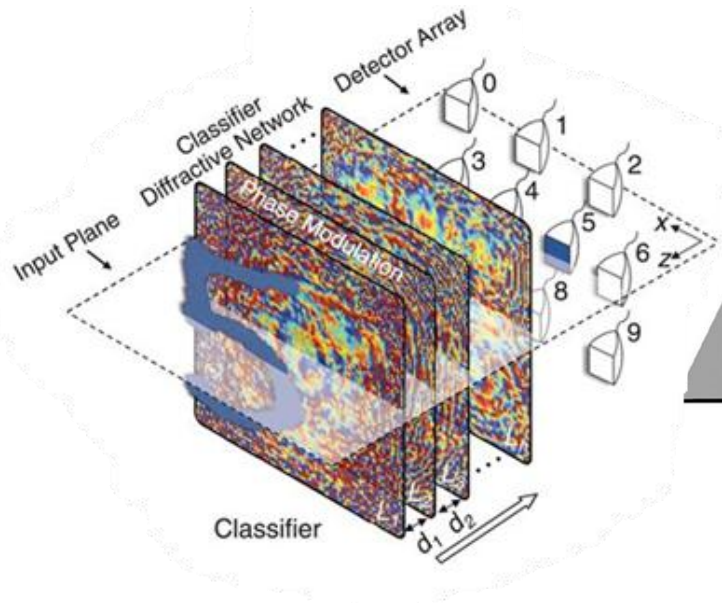


Free space and diffractive

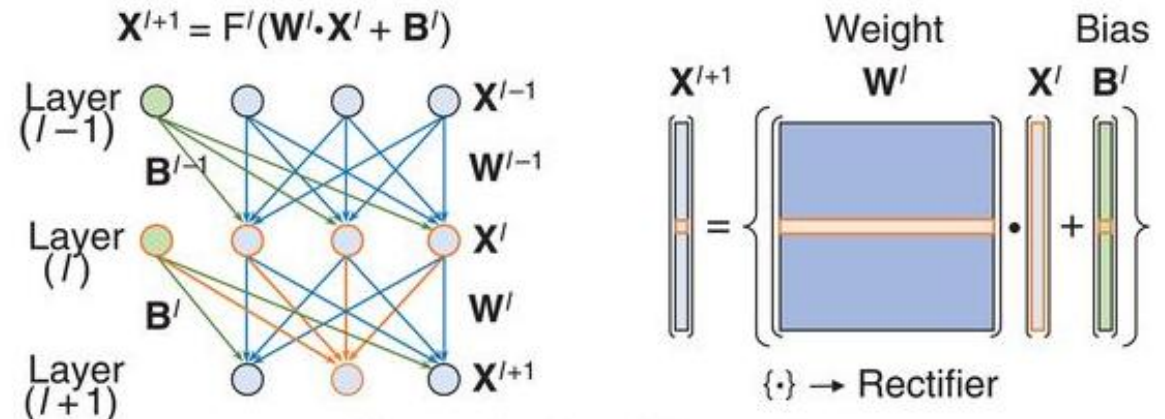
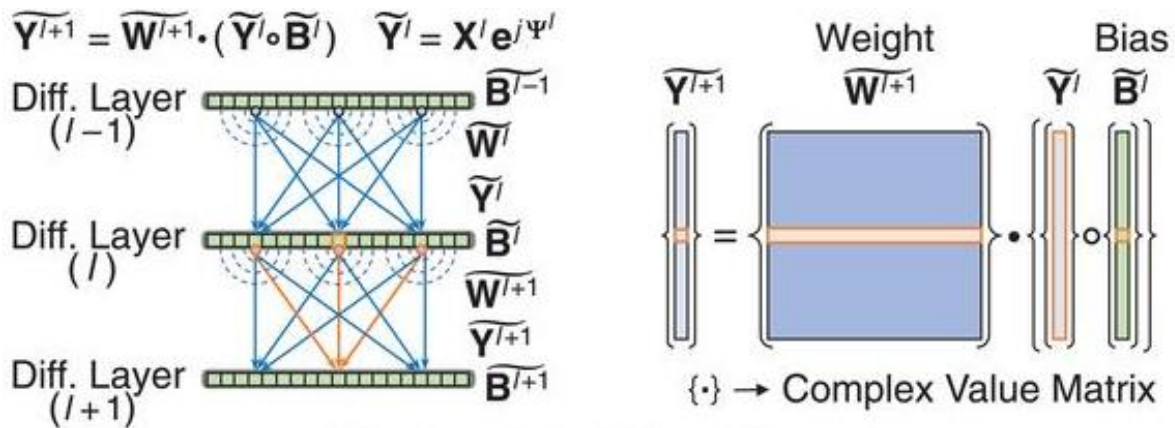
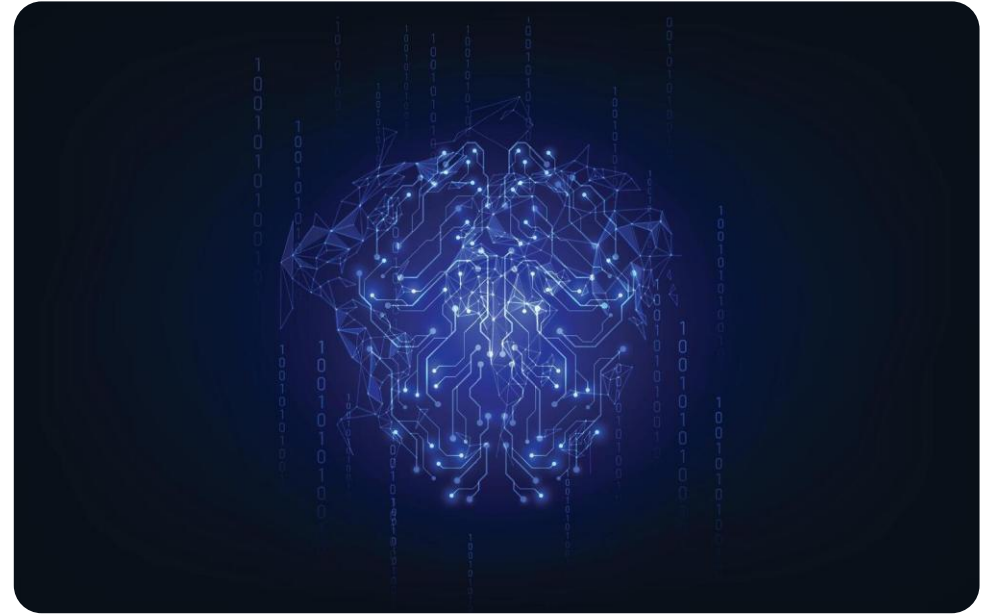
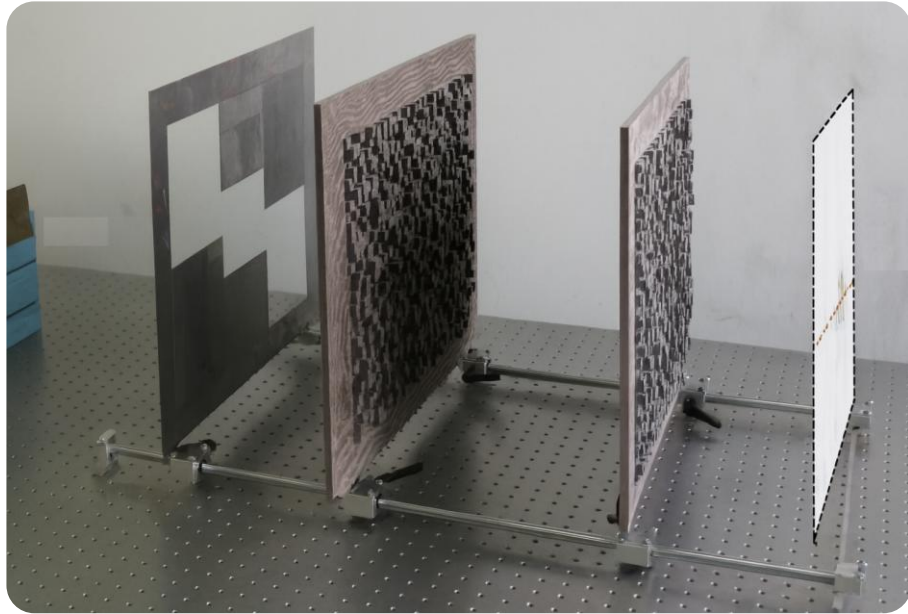
Integrated and interferometer-based

Complex structured light transformations

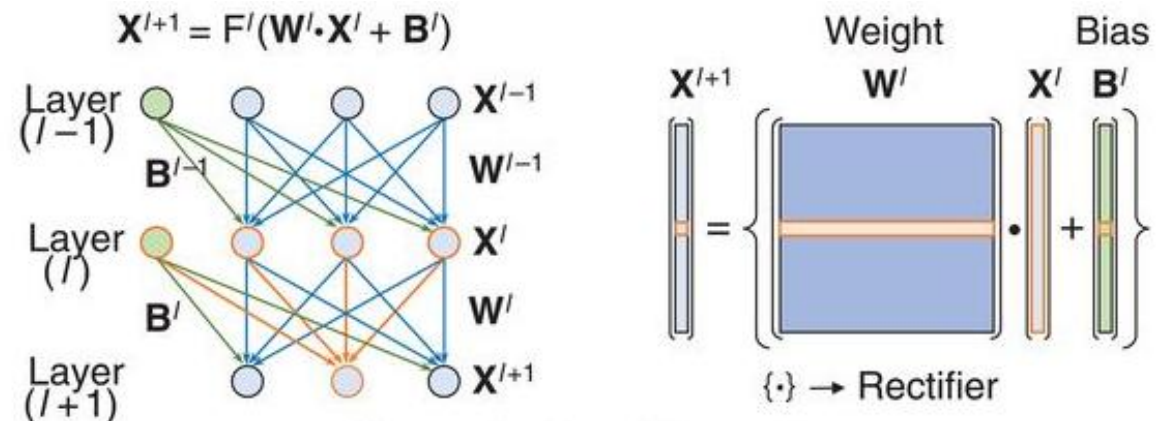
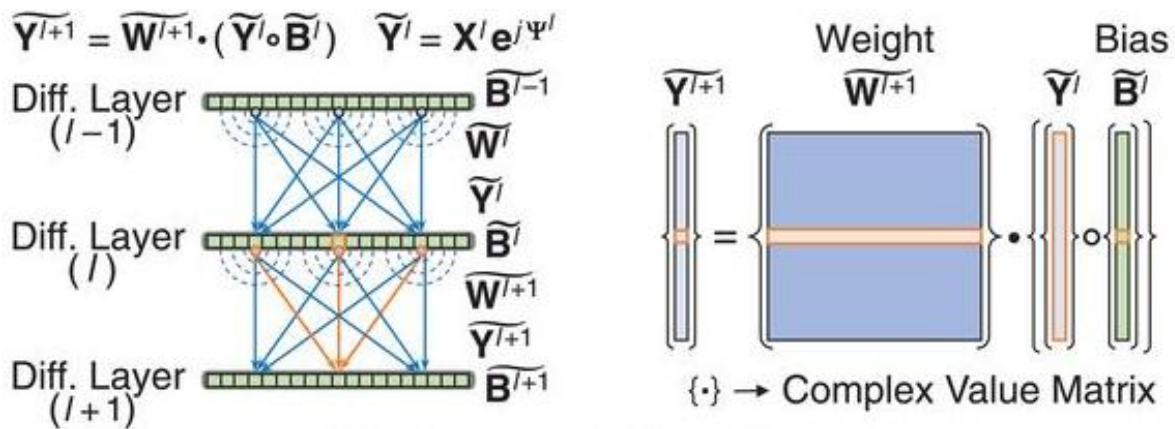
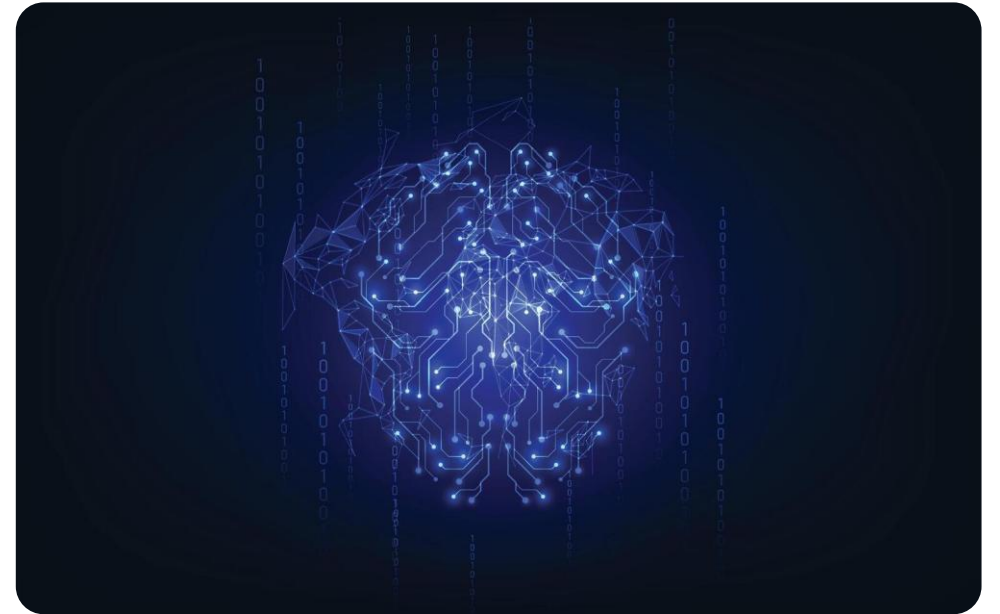
Architectures



Optical vs. artificial neural networks

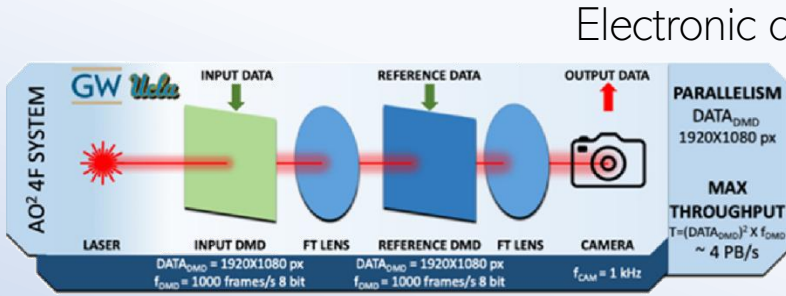


Optical vs. artificial neural networks



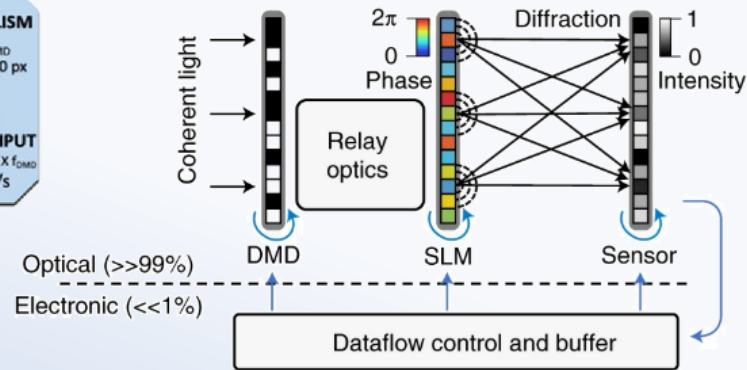
The issue of nonlinearity in optical neural nets

Optoelectronic hybrid NNs



M. Miscuglio et al., *Optica* 7, 1812 (2020)

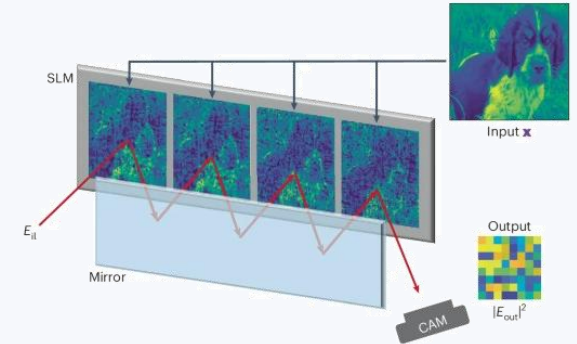
Electronic detection



Optoelectronic implementation

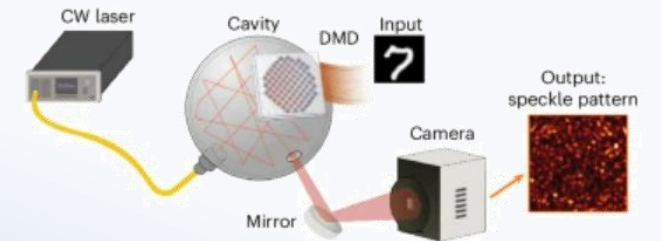
T. Zhou et al., *Nature Photonics* 15, 367 (2021)

Data repetition method



M. Yildirim et al., *Nature Photonics* 18, 1076 (2024)

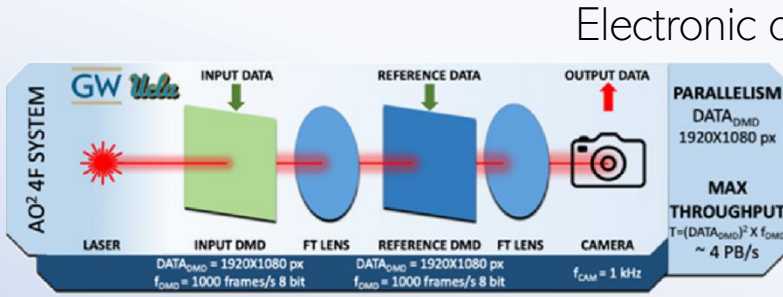
Nonlinear mapping with a multiple-scattering cavity



F. Xia et al., *Nature Photonics* 18, 1067 (2024)

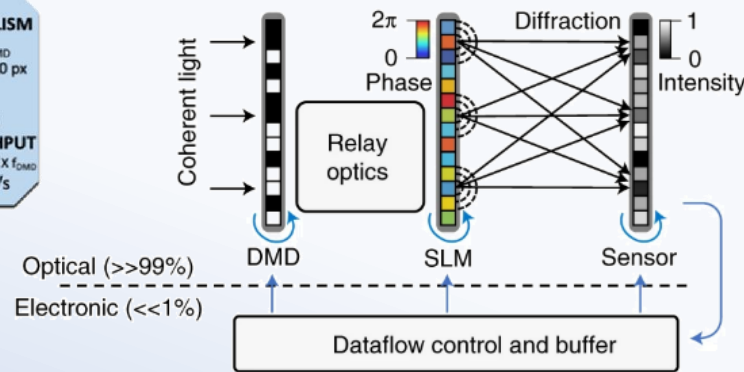
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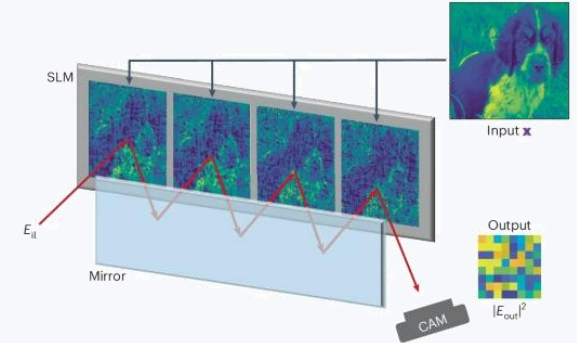
Electronic detection



Optoelectronic implementation

T. Zhou et al., *Nature Photonics* 15, 367 (2021)

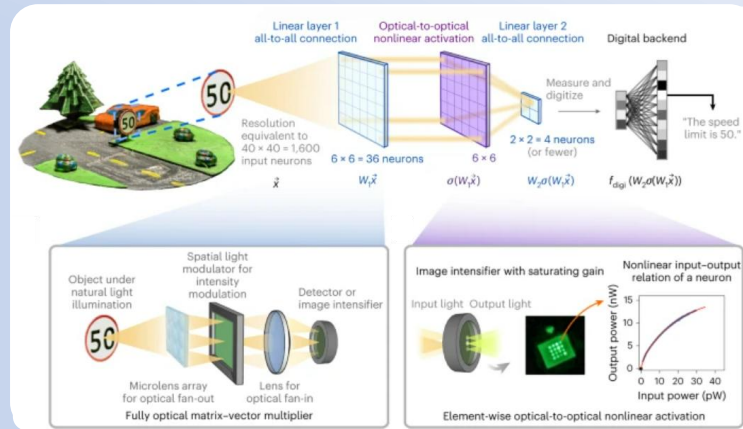
Data repetition method



M. Yildirim et al., *Nature Photonics* 18, 1076 (2024)

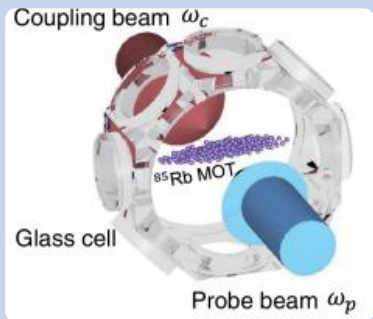
All-optical

Image intensifiers



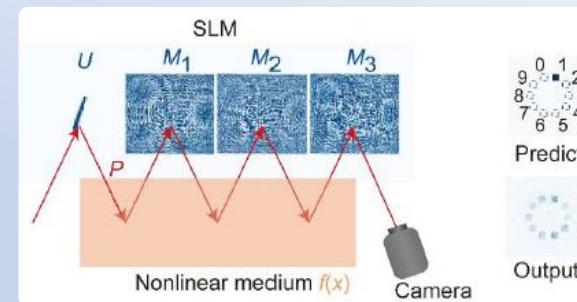
T. Wang et al., *Nature Photonics* 17, 408 (2023)

Atomic nonlinearity



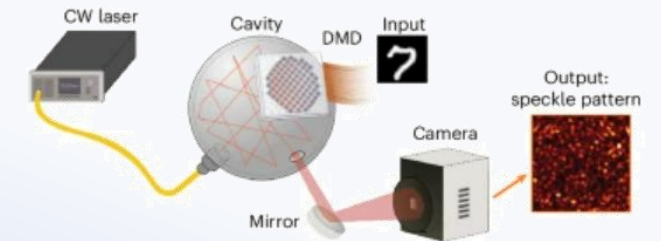
Y. Zuo et al., *Optica* 6, 1132 (2019)

Kerr nonlinearity



Y. Dong et al., arXiv:2504.13518 (2025)

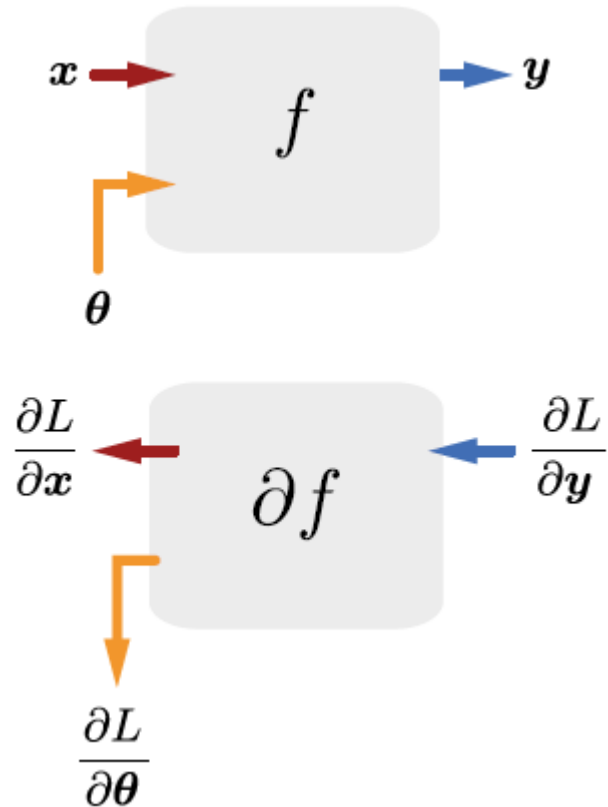
Nonlinear mapping with a multiple-scattering cavity



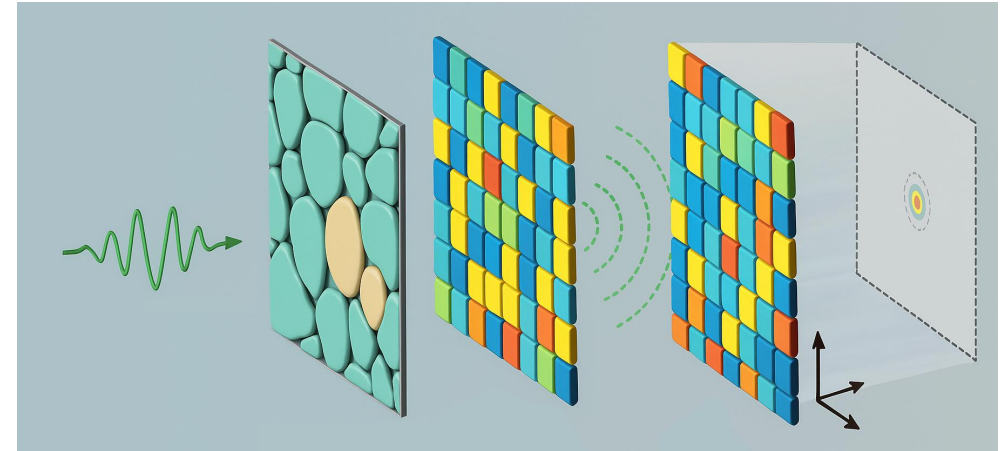
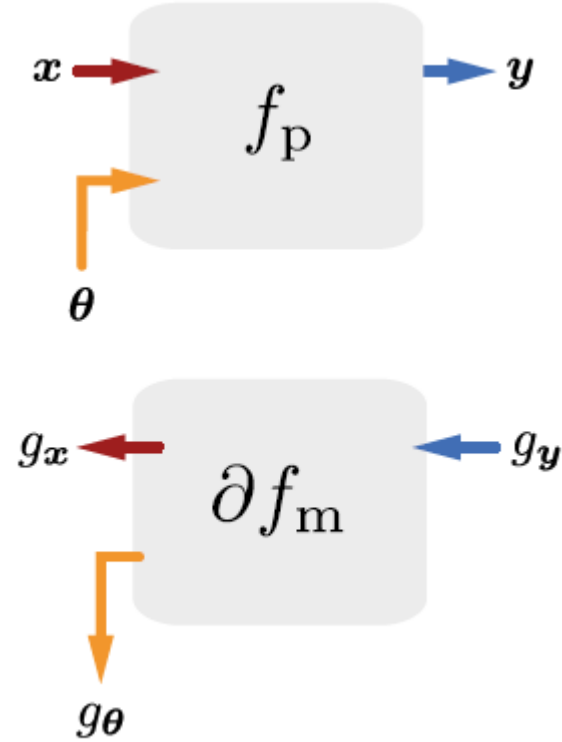
F. Xia et al., *Nature Photonics* 18, 1067 (2024)

How do optics learn?

Conventional back-propagation



Physics-aware training



Review

Training of physical neural networks

<https://doi.org/10.1038/s41586-025-09384-2>

Received: 25 January 2024

Accepted: 10 July 2025

Published online: 3 September 2025

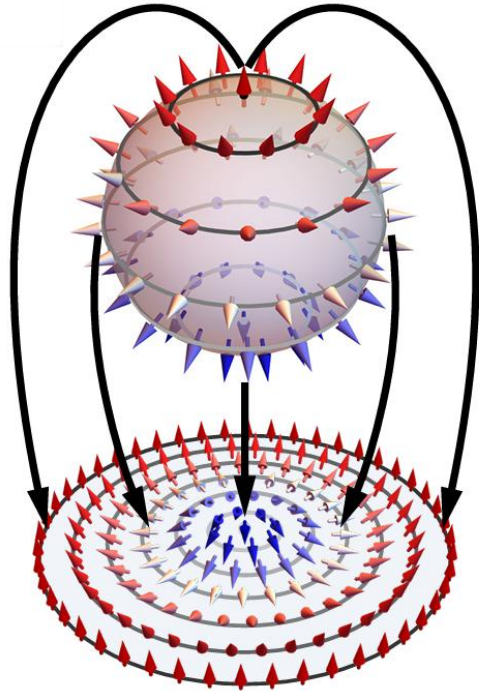
Check for updates

Ali Momeni¹, Babak Rahmani², Benjamin Scellier³, Logan G. Wright⁴, Peter L. McMahon⁵, Clara C. Wanjura⁶, Yuhang Li⁷, Anas Skalli⁸, Natalia G. Berloff⁹, Tatsuhiro Onodera^{5,10}, Ilker Oguz¹¹, Francesco Morichetti¹², Philipp del Hougne¹³, Manuel Le Gallo¹⁴, Abu Sebastian¹⁴, Azalia Mirhoseini^{15,16}, Cheng Zhang⁷, Danijela Marković¹⁷, Daniel Brunner⁸, Christophe Moser¹¹, Sylvain Gigan¹⁸, Florian Marquardt⁸, Aydogan Ozcan⁷, Julie Grollier¹⁹, Andrea J. Liu²⁰, Demetri Psaltis²¹, Andrea Alù^{22,23} & Romain Fleury^{12a}



Two optical neural nets for two big challenges in structured light

Giving texture to light



M. Ines Nunes



G. Vaz

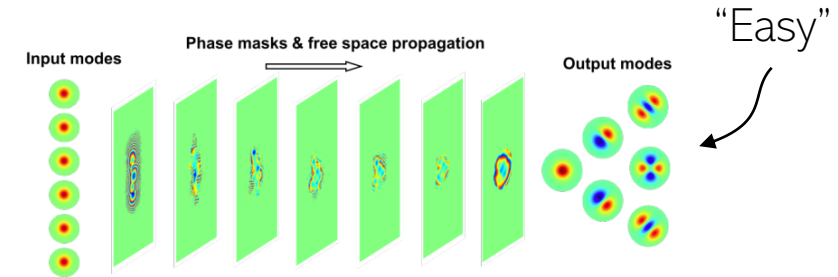
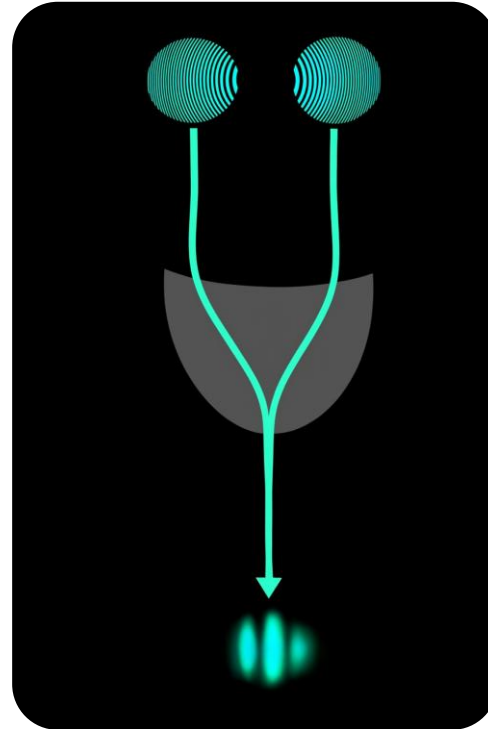


J. Bonito



J. Pimenta

Making an all-optical switch



Y. Zhang and N. K. Fontaine, arXiv:2304.11323 (2023)

Why Machine Learning?

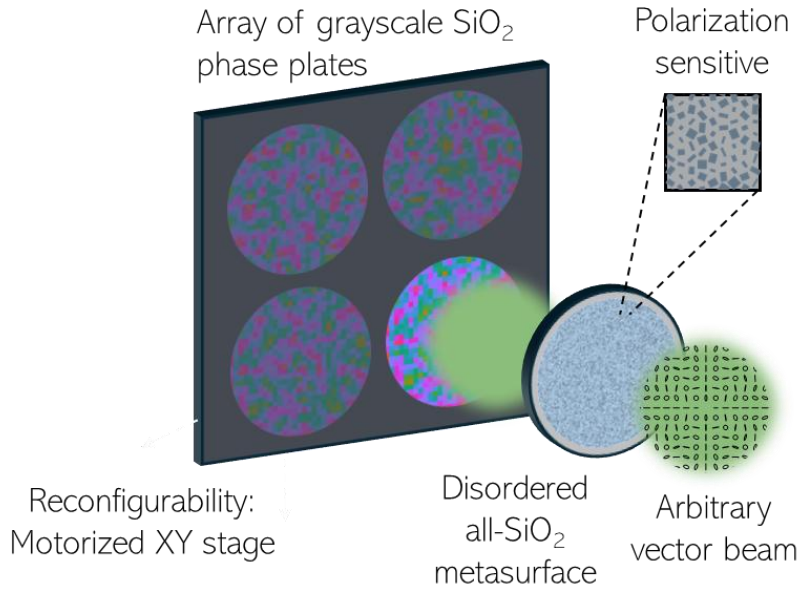
- Nonlinear optics
- Nonlinear loss

Multimode Photonics Group



Texturing light with a single metasurface

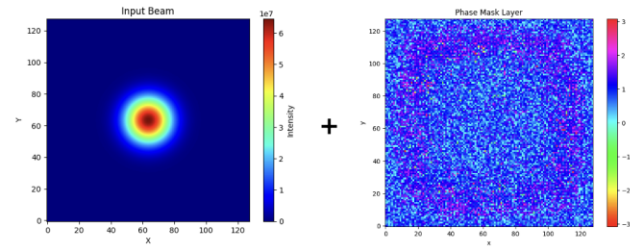
Our goal: Arbitrary **vectorial outputs** from a single disorder-engineered birefringent metasurface in combination with custom scalar phase plates



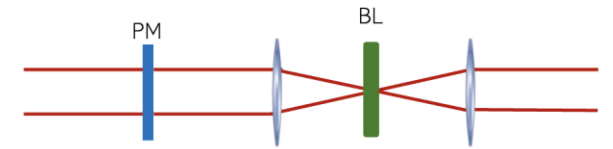
Machine Learning mask optimization:

our ML code designs an input mask for any arbitrary output vector beam

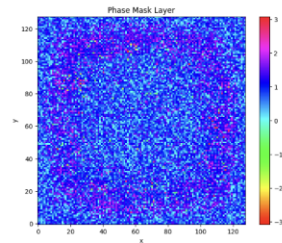
Apply learned mask



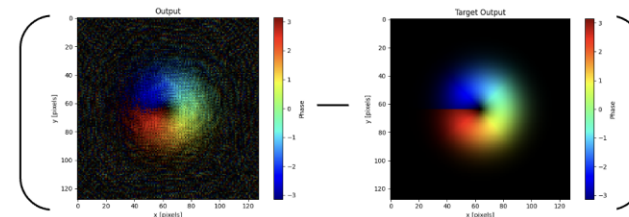
Propagate through the optical system



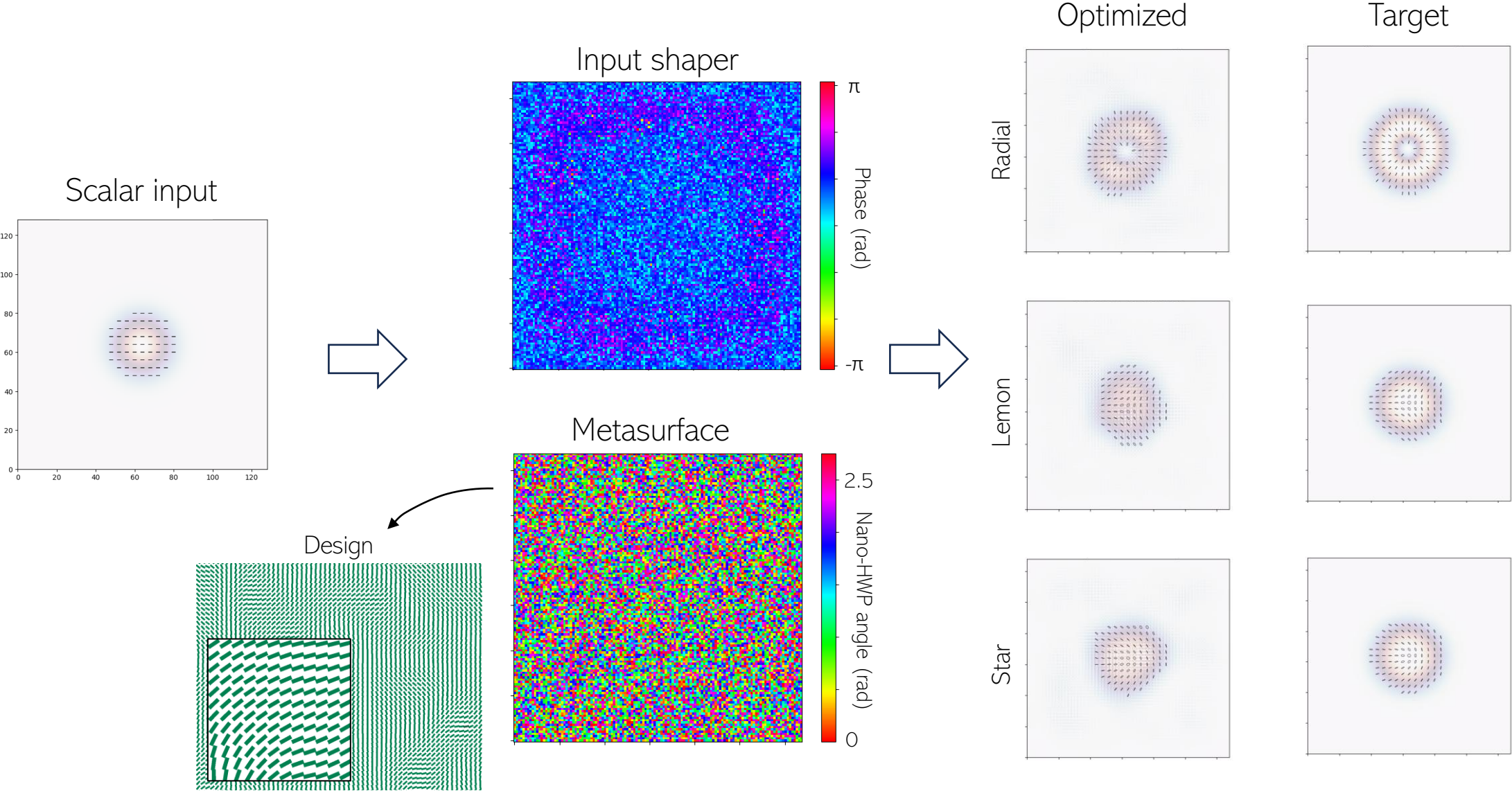
Update PM



Compute Loss

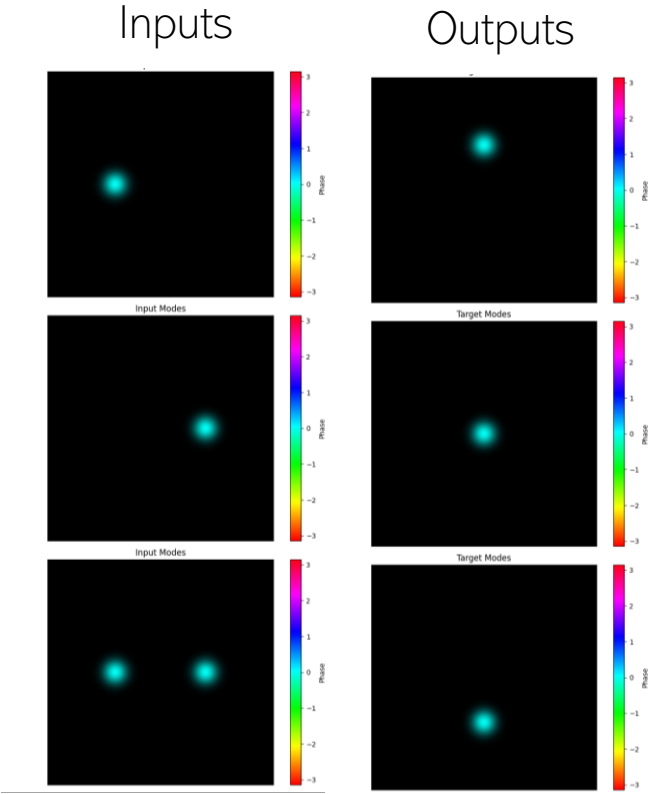


Scalar to vectorial mapping

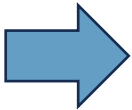


Chasing 3 dots: Analog logic gates of structured light

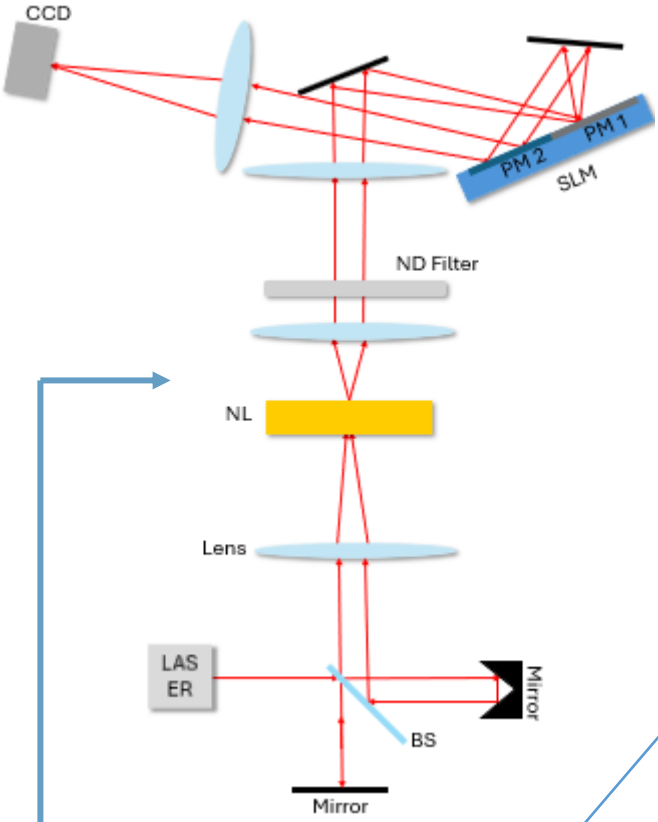
What if we had a Decoder but for light?



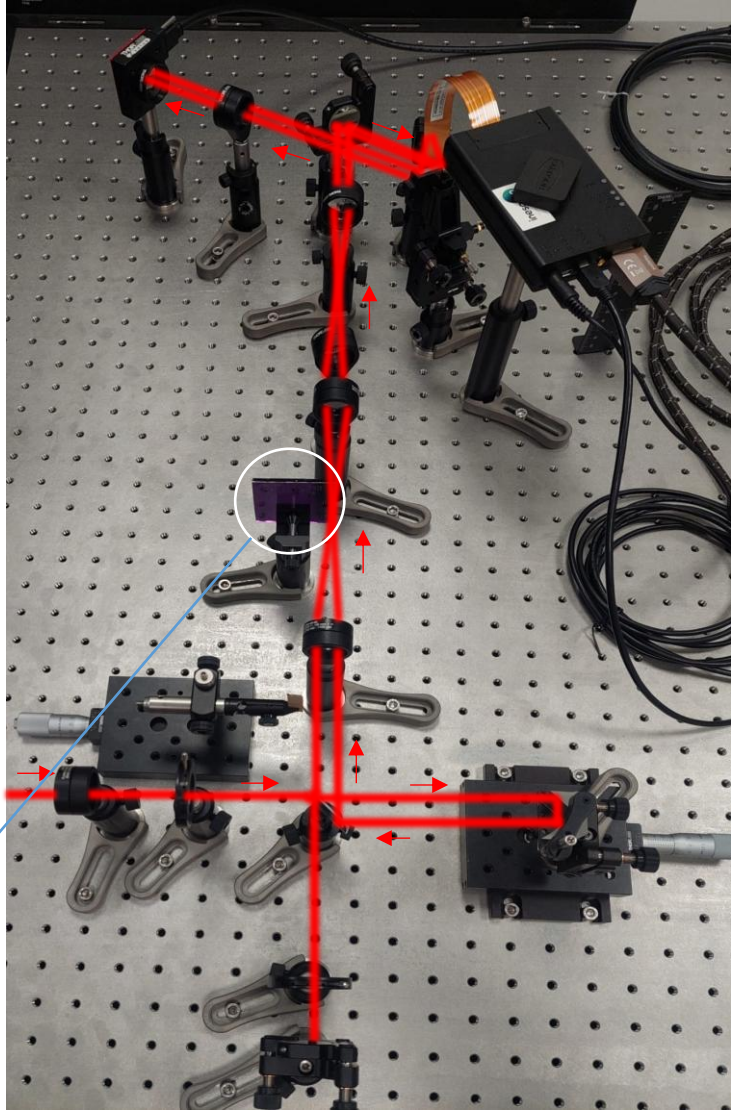
But how?



Using a Physical Neural Network!

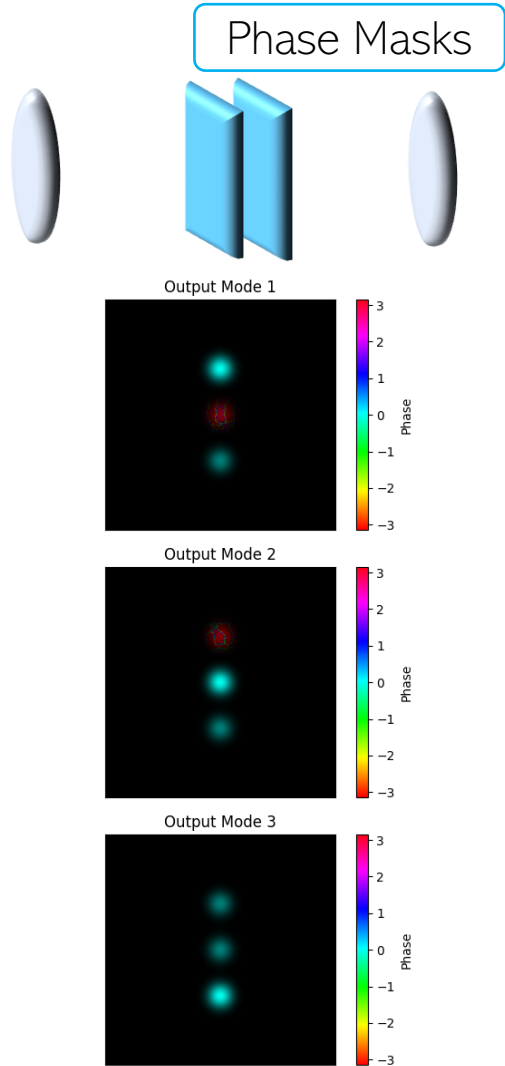


Nonlinear Layer!

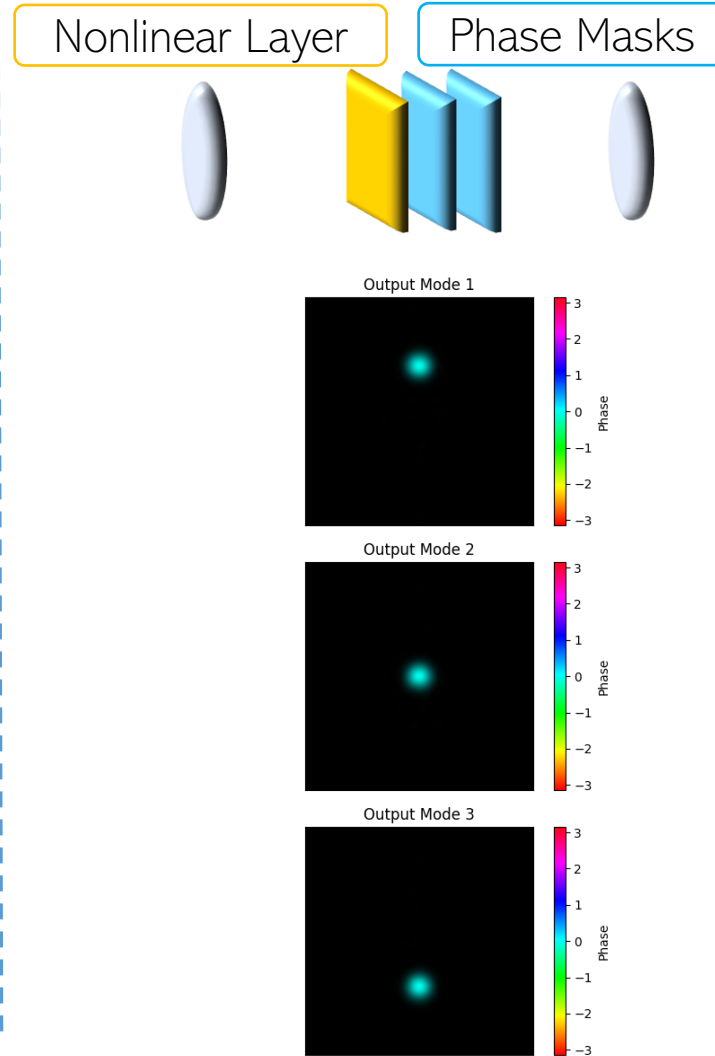


Why a Nonlinear Layer?

Without Nonlinear Layer

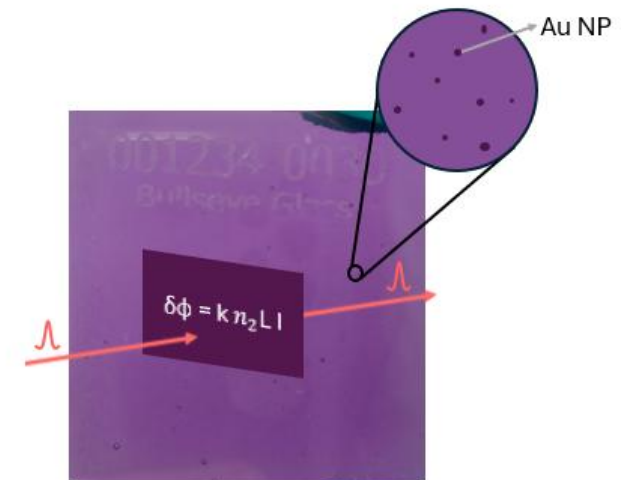


With Nonlinear Layer



Nonlinearity
enables the
switch!

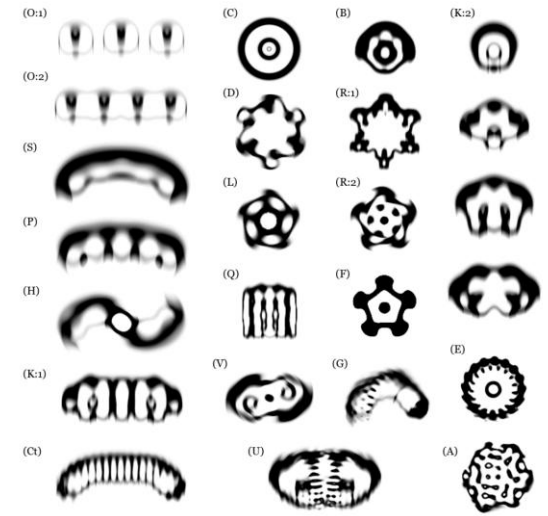
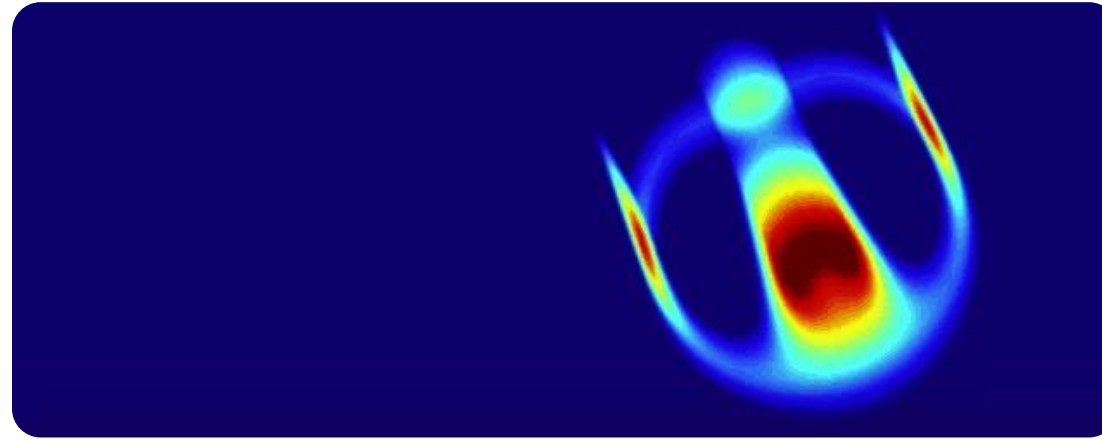
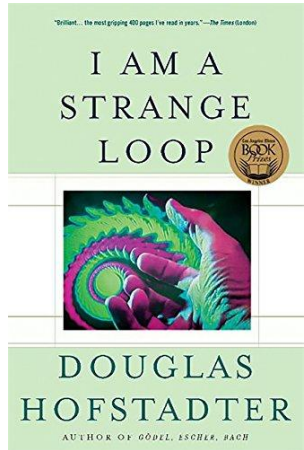
In our case, the nonlinearity comes from the **Kerr Effect**, a third order nonlinear effect



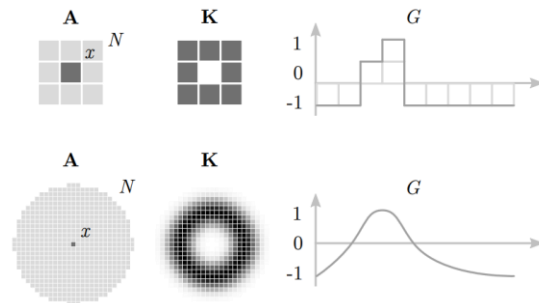
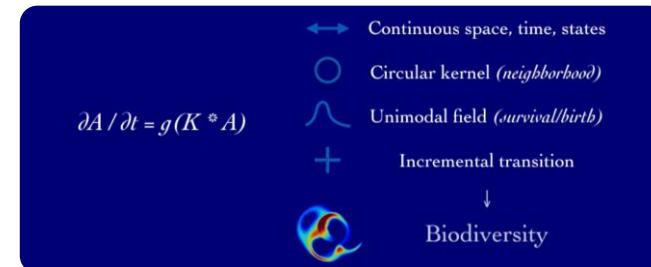
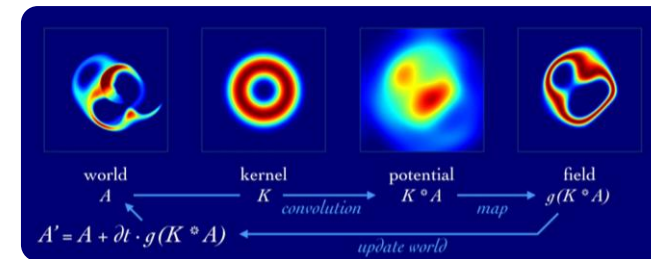
Vision: A path towards artificial photonic life

Lenia project @Google Brain

Loops are essential to move from useful processors to truly intelligent and aware systems



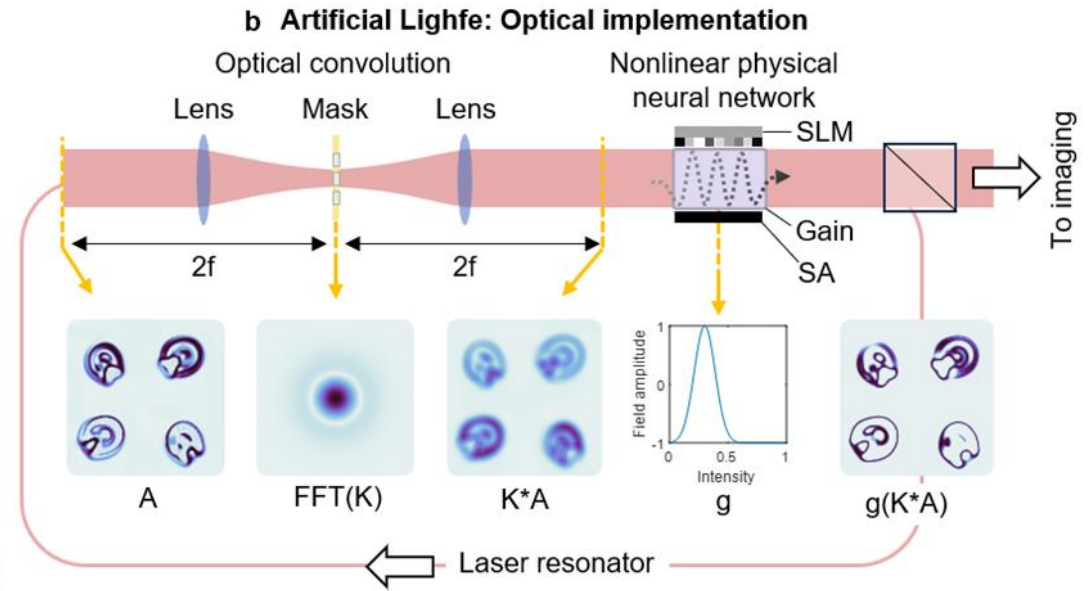
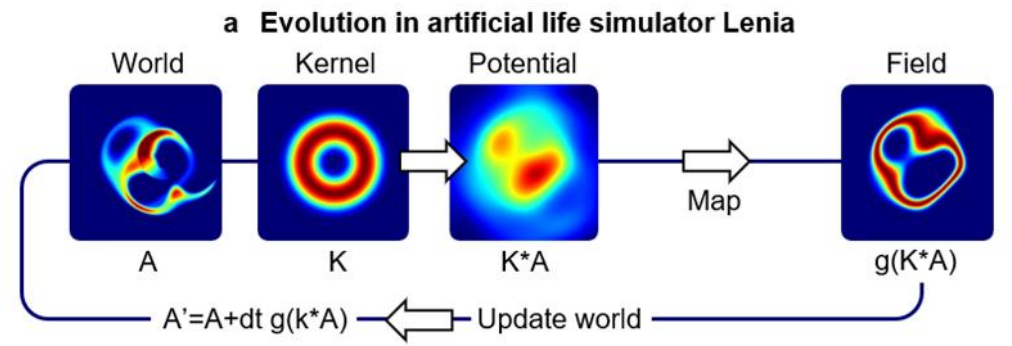
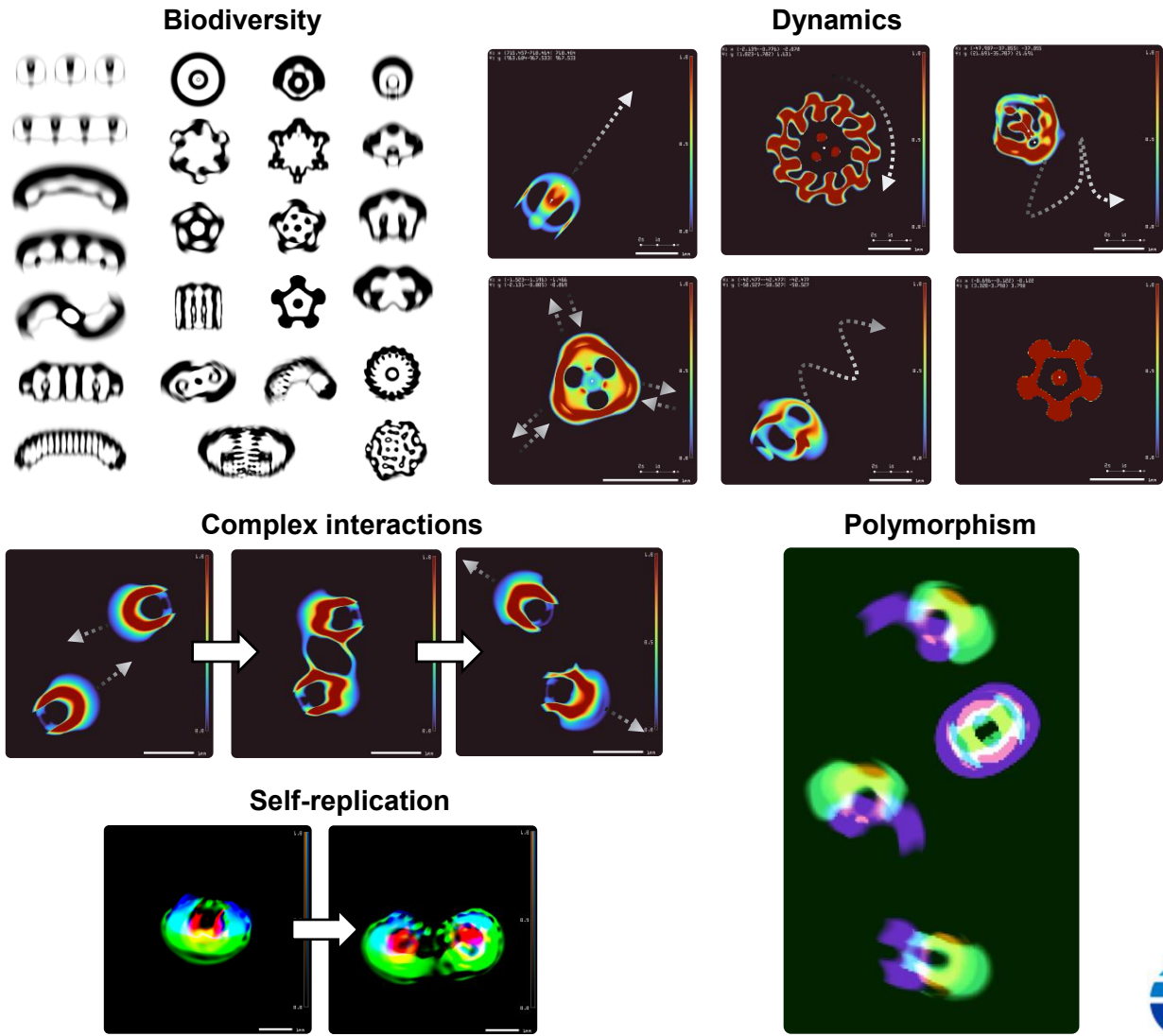
- Mathematical project based on continuous cellular automata
- Lifelike features like: self-organization, self-repair, bilateral and radial symmetries, locomotive dynamics, and sometimes chaotic nature
- From a smooth continuous version of Conway's Game of Life



14 open problems in Artificial Life:

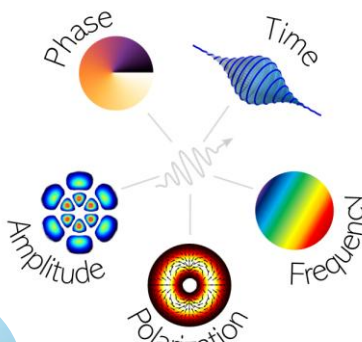
#3 Determine whether fundamentally novel living organizations can exist

Optical Lenia



J. Pimenta





Marco Piccardo



PhD

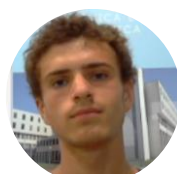
Gabrielle Vaz



Vitthal Mishra



Ines Silva
(with J.P. Conde)



Adrian Cabral
(with G. De Tomasi)



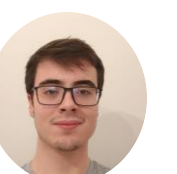
Bruno Semiao



Ines Nunes



Joana Bonito



Joaquim Pereira



Joana Pimenta



Sofia Simenta



Carlos Reis
(with D. Caetano)



Filipe Baptista



Miguel Martins

Reconfigurable Polarization Shaping with a Single Metasurface

Maria Inês Nunes^{1,2,3}, M. Piccardo^{1,2,*}

¹Instituto de Engenharia de Sistemas e Computadores para os Microsistemas e as Nanotecnologias, INESC-MN, Portugal
²Department of Physics, Instituto Superior Técnico, Universidade de Lisboa, Portugal
³Mestrado em Engenharia Física Tecnológica

*marco.piccardo@tecnico.ulisboa.pt

Motivation and Objectives

Metasurfaces are commonly used for beam structuring since they are made up of sub-wavelength resonators that offer control at the nano-scale of the form birefringence. This makes them the best option for polarization shaping. However, beam shaping techniques that rely on metasurfaces face a great challenge when structuring vectorial light at high power. To operate below the damage threshold of these materials, the beam is expanded, so large metasurfaces are required, as a result, fabrication costs become extremely high, imposing restraints on applications that rely on these beams, such as material processing and laser-induced nuclear fusion. For this reason, we aim to design a system that requires only one static birefringent metasurface capable of multifunctional vectorial shaping, drastically reducing production costs. To design this system, we use Machine Learning (ML) techniques described below.

Fundamentals

Light beams can be engineered to have arbitrary spatial distributions of their degrees of freedom. In the case of vectorial light, its polarization states are manipulated to have an anisotropic distribution. In this work, we tailor the beam's polarization using a single birefringent layer with a random profile. This is possible using a ML model that optimizes the phase profile of the scalar input beam that needs to be propagated through the optical system to get the target output. This way, we can get several vectorial beams by simply adjusting the phase mask in the system.

Methods

To obtain arbitrary vectorial outputs from a single disorder-engineered birefringent metasurface layer (BL) in combination with custom scalar phase plates, we designed a ML algorithm that optimizes the phase mask (PM) that needs to be placed in the system, so the output is the target vector beam.

Conclusions

Vector beams are crucial for many applications: optical trapping, imaging, optical communications, is vital that the generation of these beams is straightforward. With our system, we can perform a modulation using a simple scalar input and one disorder-engineered layer. Fabricating this metasurface layer, allows the generation of this beams for a wide use of these beams in the applica...

Simulation Results

Starting from a simple horizontally polarized Gaussian beam propagating in a Kerr Medium will result in a charge in the phase front and a phase shift that can be quantified. This phase shift will result in a non-linear effect.

Spatial Light Modulator and Holograms
To have a tunable OAM, a Spatial Light Modulator (SLM) is introduced. This device has the capability to modulate the phase of the incident light. By using Liquid Crystals and an applied voltage, it is possible to display any hologram. To know the holograms to display, a machine learning model needs to be trained to obtain the best phase masks.

Materials and Methods

2-Scan
The 2-Scan technique relies on the spatial distortion of a Gaussian beam and the self-focusing effect to study the nonlinear Kerr effect. The method uses the changes in the far-field intensity distributions to characterize the nonlinear layer.

Optical Decoder
The ML model was trained to simulate the optical decoder. Each component of the physical system is defined in a script on the simulation. The trainable parameters of the Neuron Network are the Phase Masks (PM). The goal of this ML model is to obtain the PM to input in the SLM.

Conclusions

In conclusion, with this work the aim is to experimentally perform a 2x4 Optical Decoder based on Optical Neuron Networks architecture. First, a study on local areas experimentally was performed on some samples, in order to choose the best one for the system. The choice was a purple glass with gold nanoparticles. The second part of the project consists of training a Machine Learning model that simulates the physical system, to obtain the holograms for the Spatial Light Modulator.

The future step of this project is to experimentally test the phase masks in the optical decoder setup. This project demonstrated how Machine Learning is applied to physics, not only in simulation and computational grounds, but in this case also the theoretical ideas in Neuron Networks are applied to the physical system.

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References

1. J. B. Pendry, L. V. Elezović, D. J. Taylor, and J. J. Mock, "Theory of metamaterials," *Journal of Physics: Condensed Matter*, vol. 15, pp. 1071-1102, 2003.

2. N. I. Zheludev and Y. S. Kivshin, "From metamaterials to metadevices," *Nature Reviews Materials*, vol. 1, pp. 191-210, 2016.

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Analog logic gates of structured light based on Optical Neural Networks

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Motivation and Objectives

Optical Neuron Networks (ONNs) have multiple applications, like information processing or image recognition. One of them can be Optical Logic Gates. This work aims to experimentally perform an AND using logic gates. Using an optical system based on nonlinear ONNs, an AND gate is the most basic nonlinear testbed, and so, once its realization is demonstrated, new functionalities with ONNs can be introduced. Hence, it will serve as a proof of concept of the potential of nonlinear ONNs. Even more, this work can lead to a new way of combining structured light.

The project will be carried out in two phases. The first phase is focused on studying optical nonlinearity, particularly in Kerr media, to introduce nonlinearity into the system. The second phase is the experimental realization of an Optical Decoder based on ONNs, which involves the training of a Machine Learning Model to obtain the holograms for the Physical Neuron Network, in the image on the right; the optical decoder 2x4 aimed is shown.

Fundamentals

Optical Kerr Effect
Change in the refractive index: $n = n_0 + n_2 I$

2-Scan and Kerr Medium
To choose the best material for the nonlinear layer, a scan was performed on some samples. The samples were of fused silica (SiO₂), and fused silica with gold (Au) nanoparticles (NP). The purpose was with Au NP was the one with bigger phase shift, hence it is the one chosen for the physical system.

Materials and Methods

2-Scan
The 2-Scan technique relies on the spatial distortion of a Gaussian beam and the self-focusing effect to study the nonlinear Kerr effect. The method uses the changes in the far-field intensity distributions to characterize the nonlinear layer.

Optical Decoder
The ML model was trained to simulate the optical decoder. Each component of the physical system is defined in a script on the simulation. The trainable parameters of the Neuron Network are the Phase Masks (PM). The goal of this ML model is to obtain the PM to input in the SLM.

Conclusions

In conclusion, with this work the aim is to experimentally perform a 2x4 Optical Decoder based on Optical Neuron Networks architecture. First, a study on local areas experimentally was performed on some samples, in order to choose the best one for the system. The choice was a purple glass with gold nanoparticles. The second part of the project consists of training a Machine Learning model that simulates the physical system, to obtain the holograms for the Spatial Light Modulator.

The future step of this project is to experimentally test the phase masks in the optical decoder setup. This project demonstrated how Machine Learning is applied to physics, not only in simulation and computational grounds, but in this case also the theoretical ideas in Neuron Networks are applied to the physical system.

References

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Simulation Results

The ML model was trained to simulate the optical decoder. Each component of the physical system is defined in a script on the simulation. The trainable parameters of the Neuron Network are the Phase Masks (PM). The goal of this ML model is to obtain the PM to input in the SLM.

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References

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