Machine learning for ultrafast nonlinear fibre photonics

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REGION BOURGOGNE FRANCHE COMTE
UNIVERSITÉ BOURGOGNE EUROPE
cnrs
EIPHI-BFC
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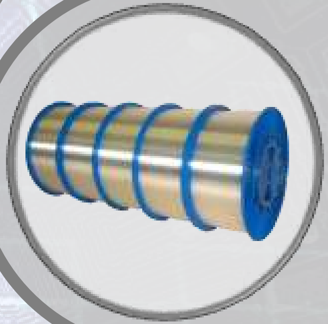
IUF

newcomers to the field
who have not yet had
the opportunity to delve into it

a few words
on
artificial intelligence

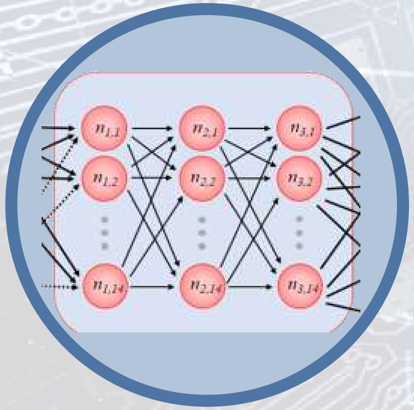
general reference

research article

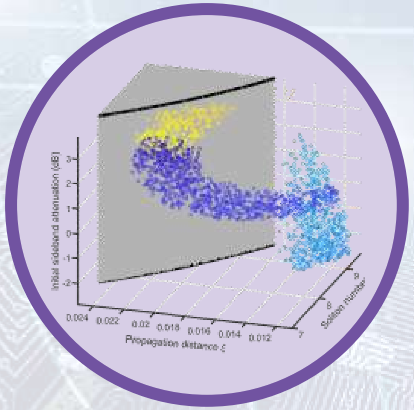


ultrafast
nonlinear
fiber
optics

Machine Learning for output predictions

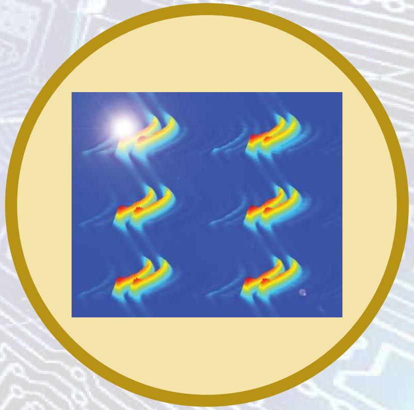


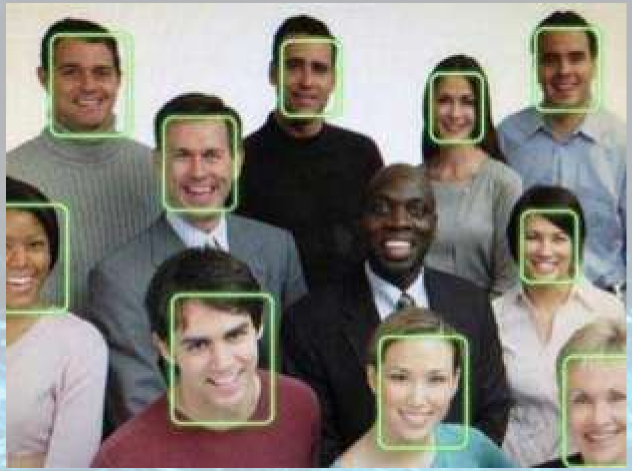
Machine Learning for inverse design



Machine Learning for physics insights

Artificial Intelligence for smart lasers





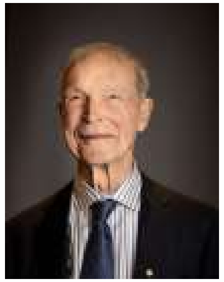
Google Microsoft facebook amazon

TensorFlow

python MATLAB julia

J.J. Hopfield
G. Hinton

2024



- plethora of MOOCs available
  Marquardt, *machine learning for physicists*
- Nielsen, *neural networks and deep learning*
- Goodfellow et al., *deep learning*
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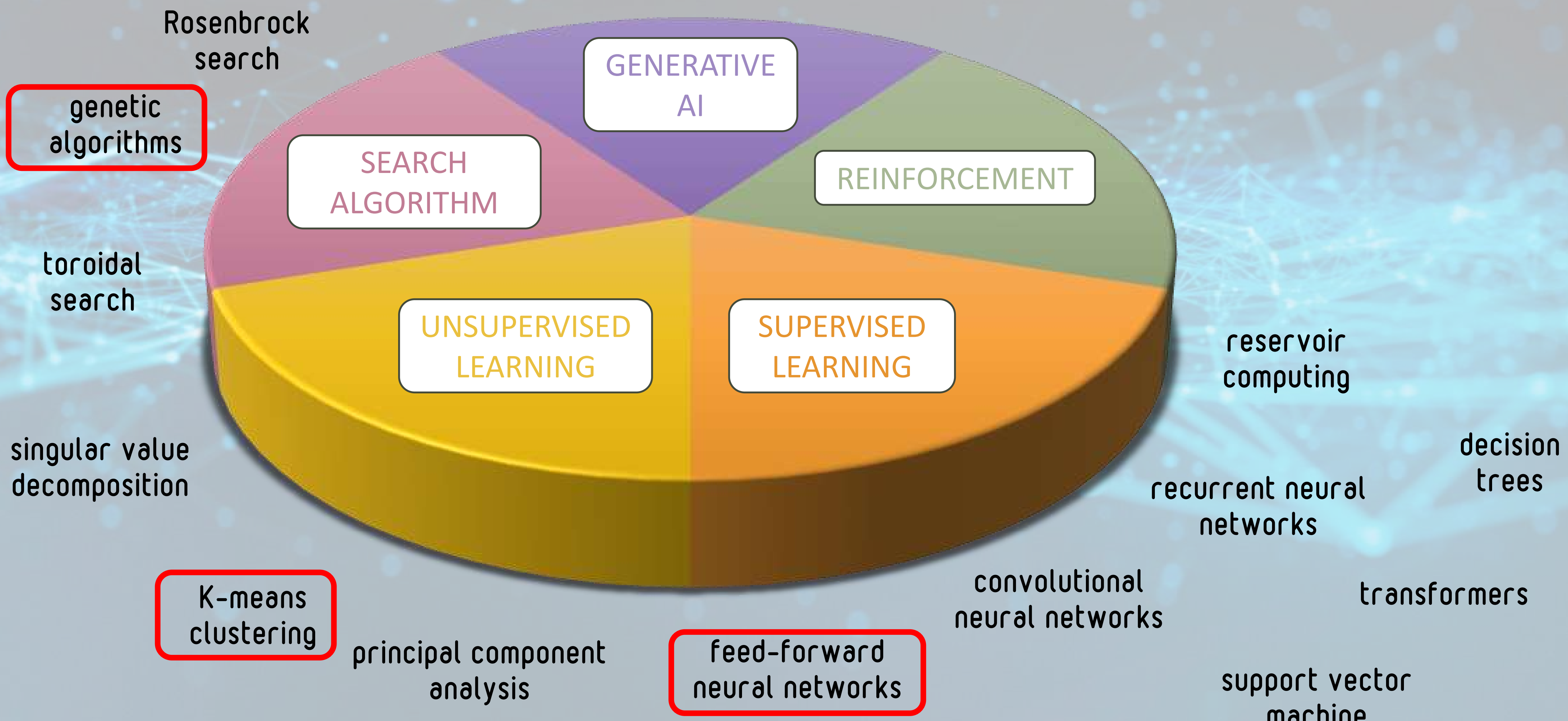

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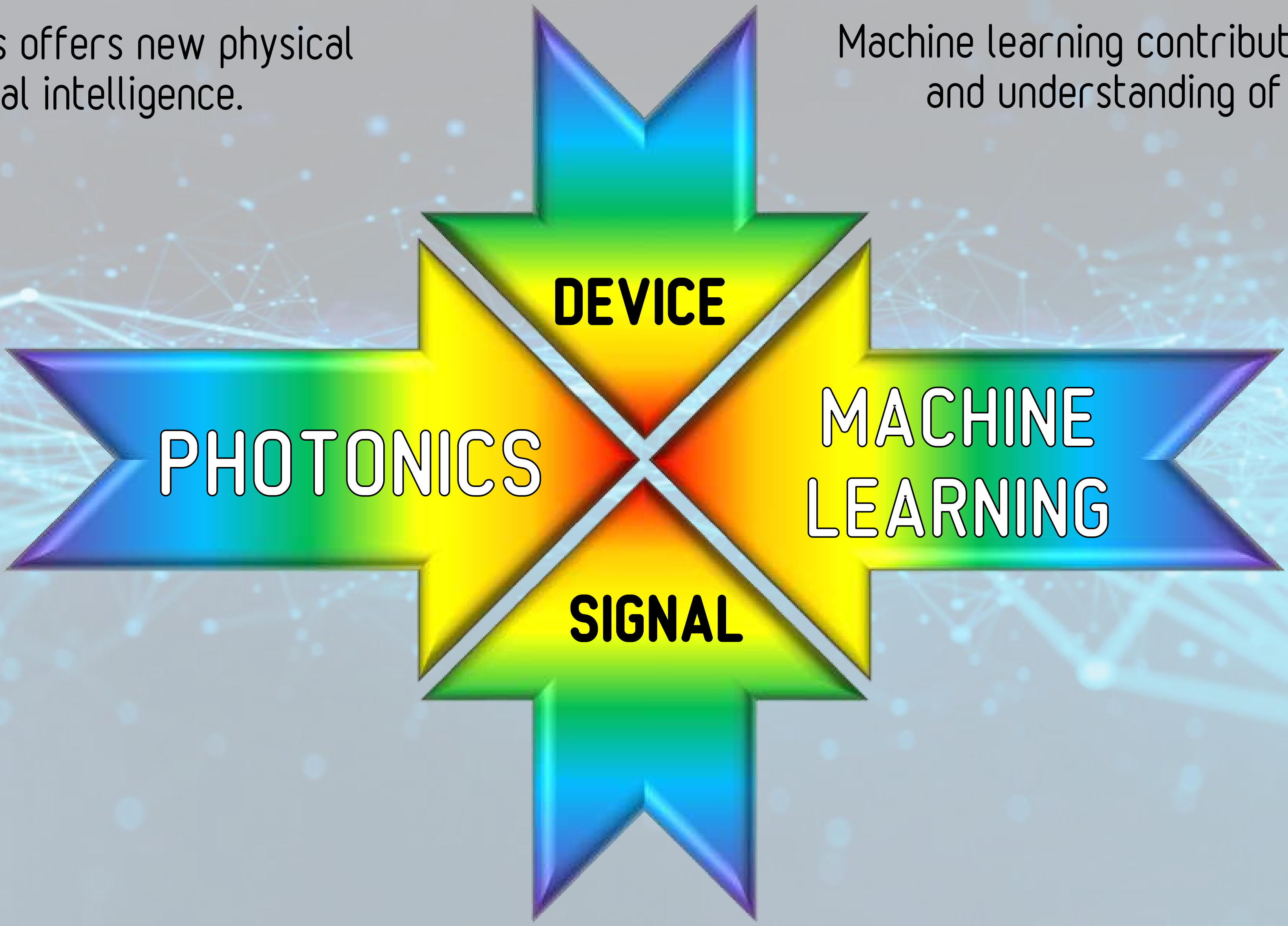
Guided wave optics offers new physical support for artificial intelligence.

Machine learning contributes to better designs and understanding of optical propagation.



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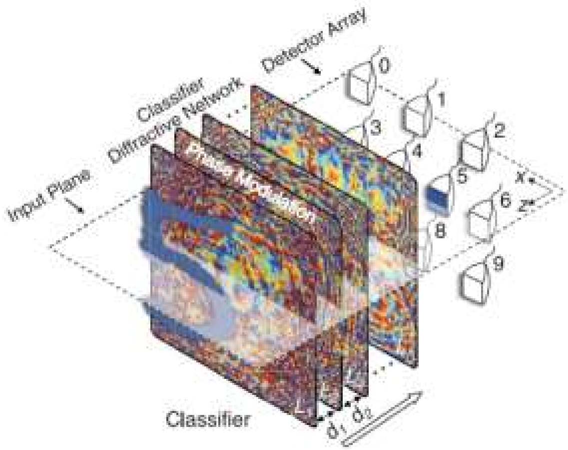

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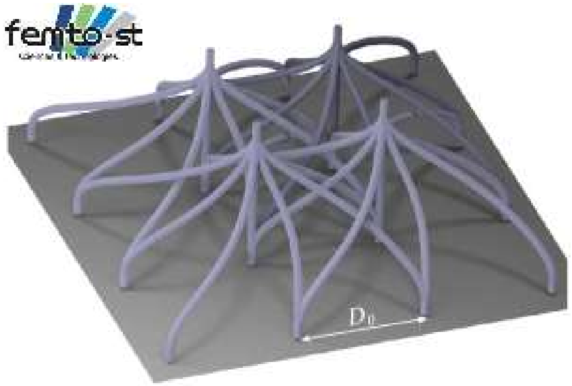

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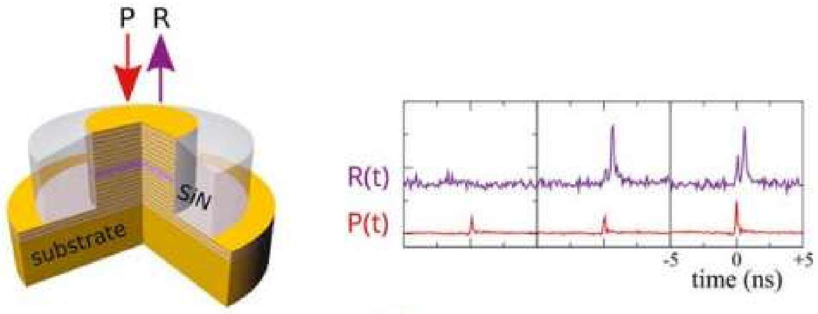

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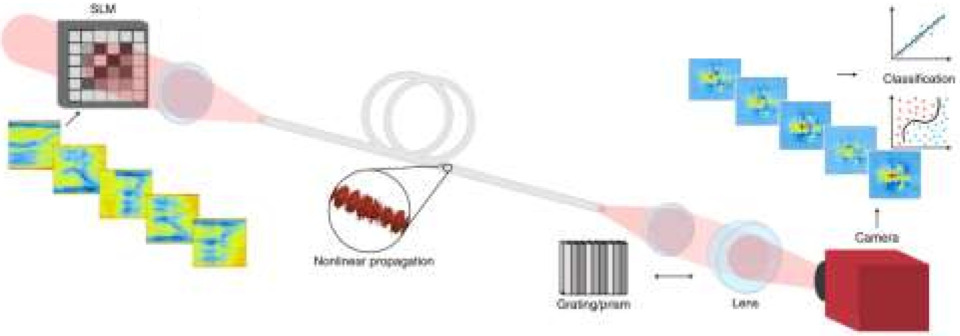

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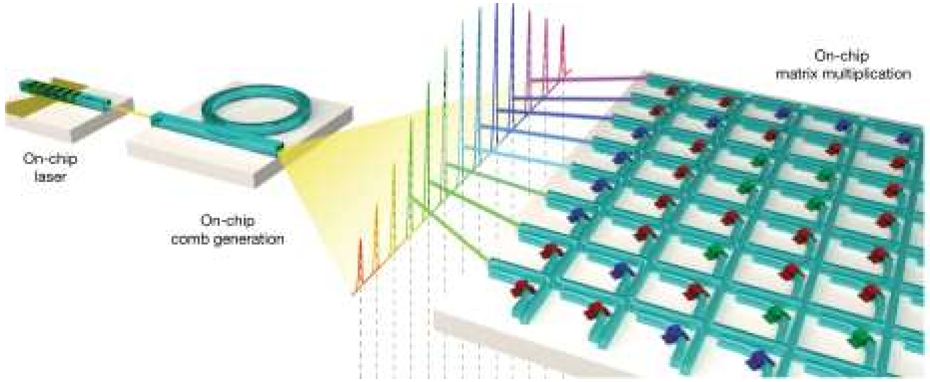

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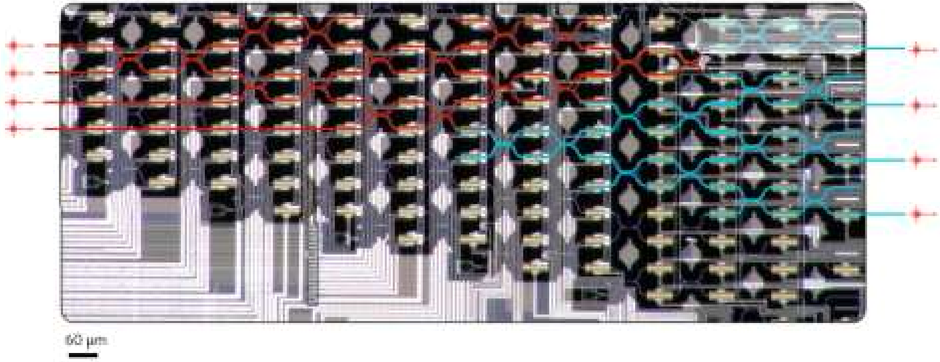

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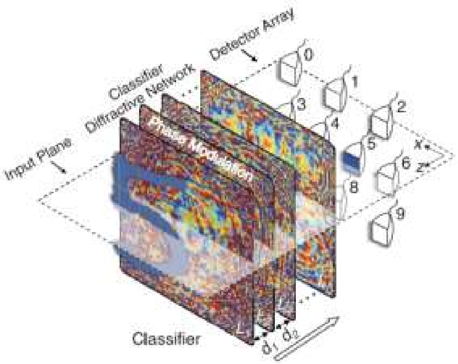

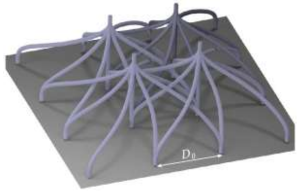

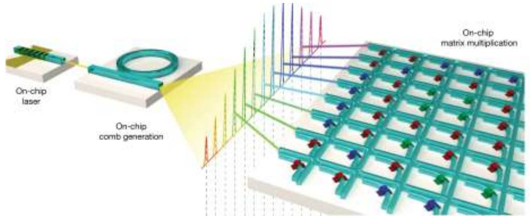

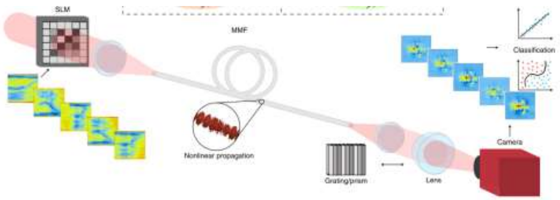

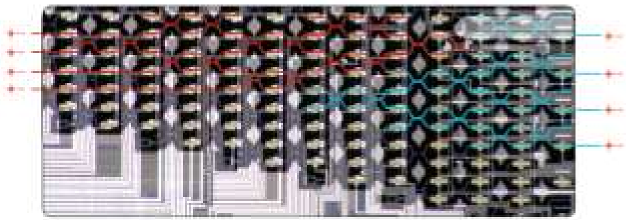

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speed and energy efficiency
reduced heat
high bandwidth
massive parrallelism

- J. W. Nevin et al. *Machine learning for optical fiber communication systems: An introduction and overview*. Apl Photonics 6.12 (2021)
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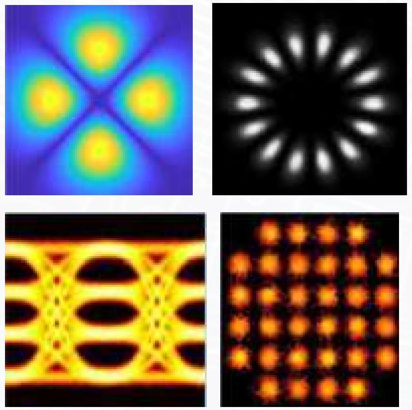
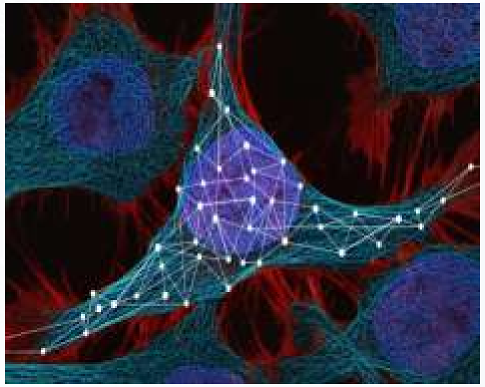
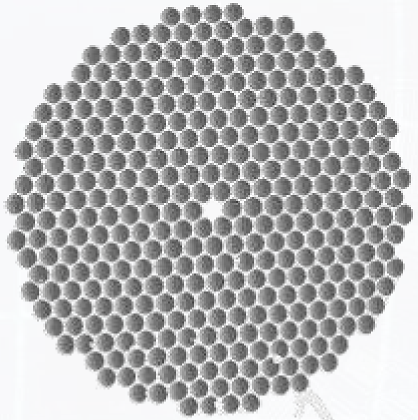


Optical Telecommunications

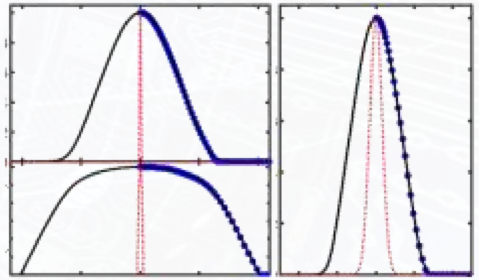


Imaging

Components design



Ultrafast optics



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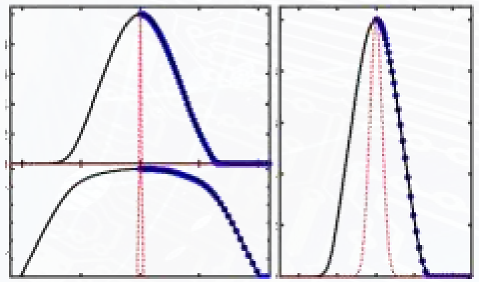
Optical Telecommunications

Imaging

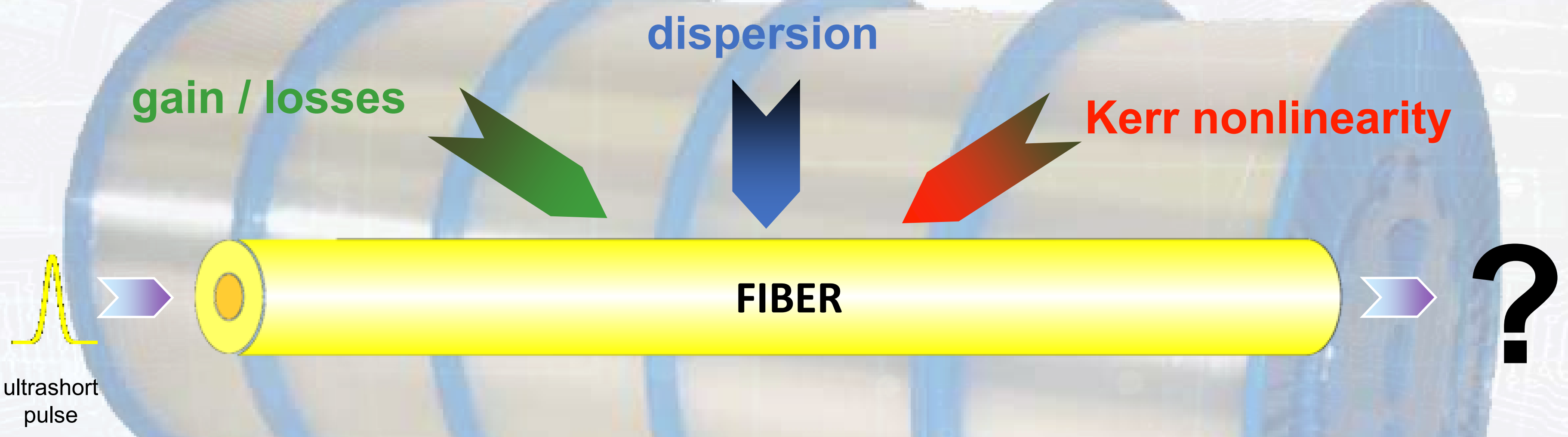
Components design

propagation
in an optical waveguide
with Kerr nonlinearity

Ultrafast optics



- Propagation in singlemode fiber (waveguides) is approximated by the **Nonlinear Schrödinger equation.**
- Usually solved by the split-step Fourier algorithm.



β_2 second order dispersion
γ non-linear coefficient
g constant gain

$$i\frac{\partial\psi}{\partial z} = \frac{\beta_2}{2}\frac{\partial^2\psi}{\partial T^2} - \gamma|\psi|^2\psi + i\frac{g}{2}\psi$$

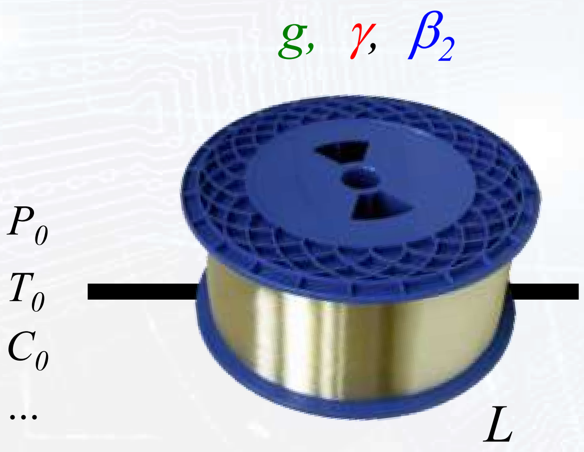
G. P. Agrawal, *Nonlinear Fiber Optics*

- NLSE should be solved numerically.

$$i\frac{\partial \psi}{\partial z} = \frac{\beta_2}{2}\frac{\partial^2 \psi}{\partial T^2} - \gamma |\psi|^2 \psi + i\frac{g}{2}\psi$$

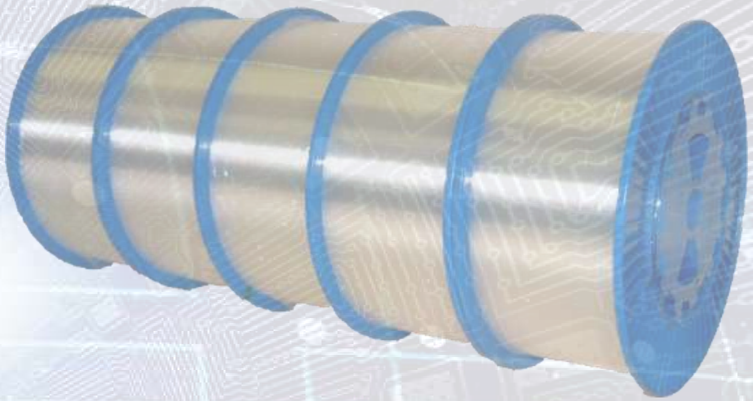
β_2 second order dispersion
γ non-linear coefficient
g constant gain/loss
L fiber length

P_0 input peak power
T_0 input pulse duration
C_0 input chirp
input pulse waveform

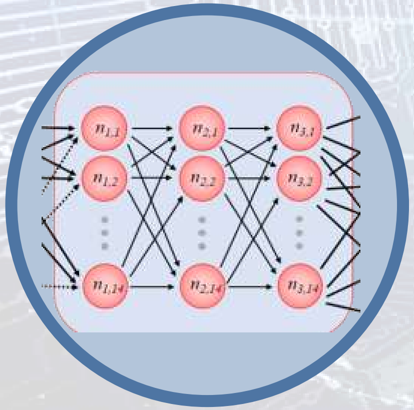


- Scaling rules can be used to reduce the number of parameters.

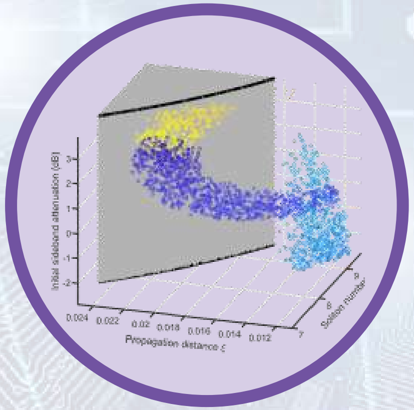
$$i\frac{\partial u}{\partial \xi} = \frac{1}{2}\frac{\partial^2 u}{\partial \tau^2} - N^2 |u|^2 u + i\frac{\delta}{2}u$$



Machine learning for output predictions

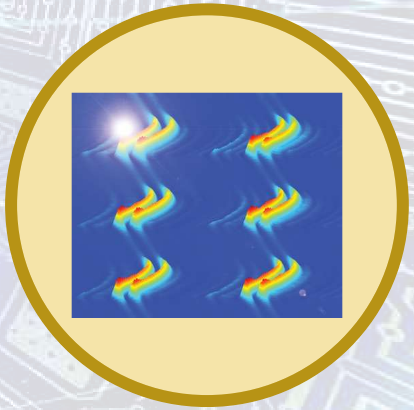


Machine learning for inverse design



Machine learning for physics insights

Machine learning for smart lasers



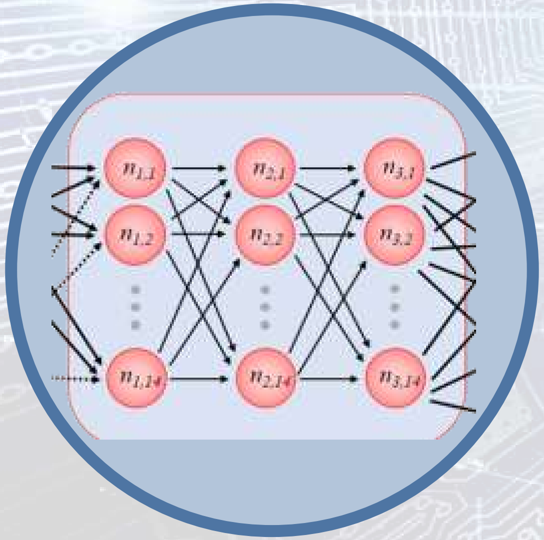
Machine learning for output predictions

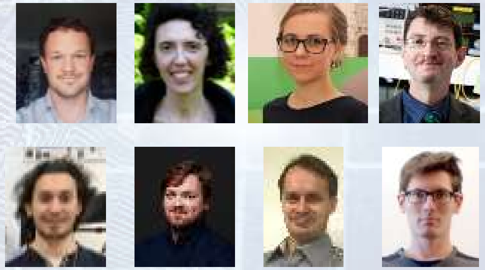
nonlinear reshaping

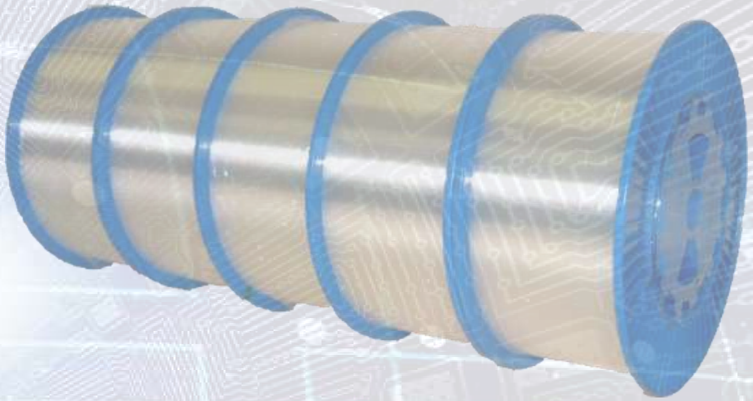
ideal four-wave mxing

frequency combs

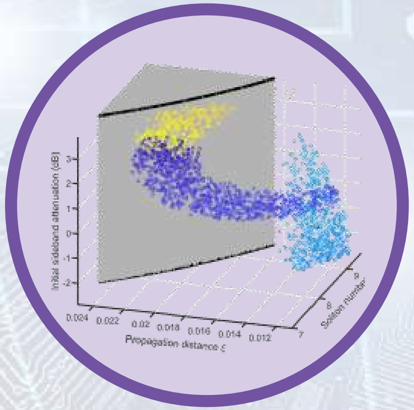
more complex systems





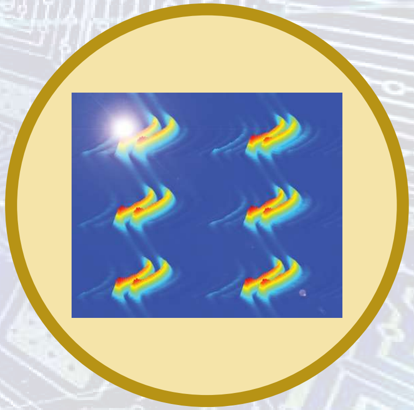


Machine learning for inverse design

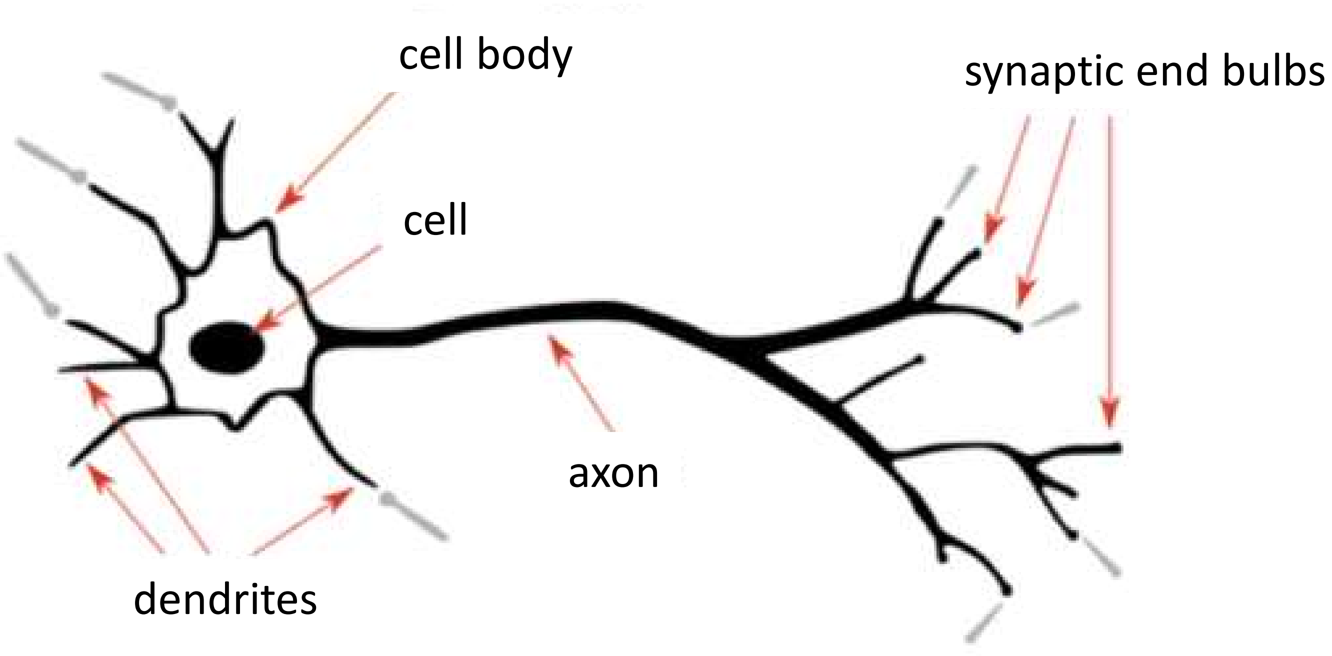


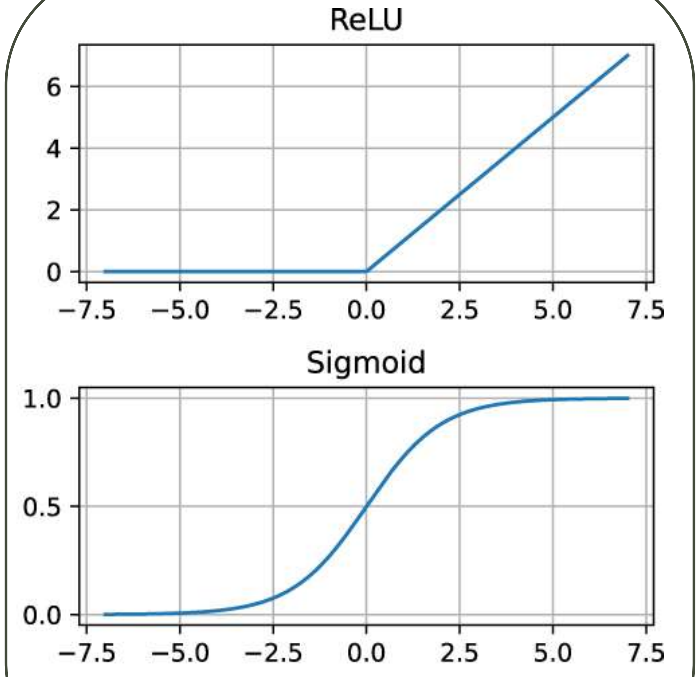
Machine learning for physics insights

Machine learning for smart lasers



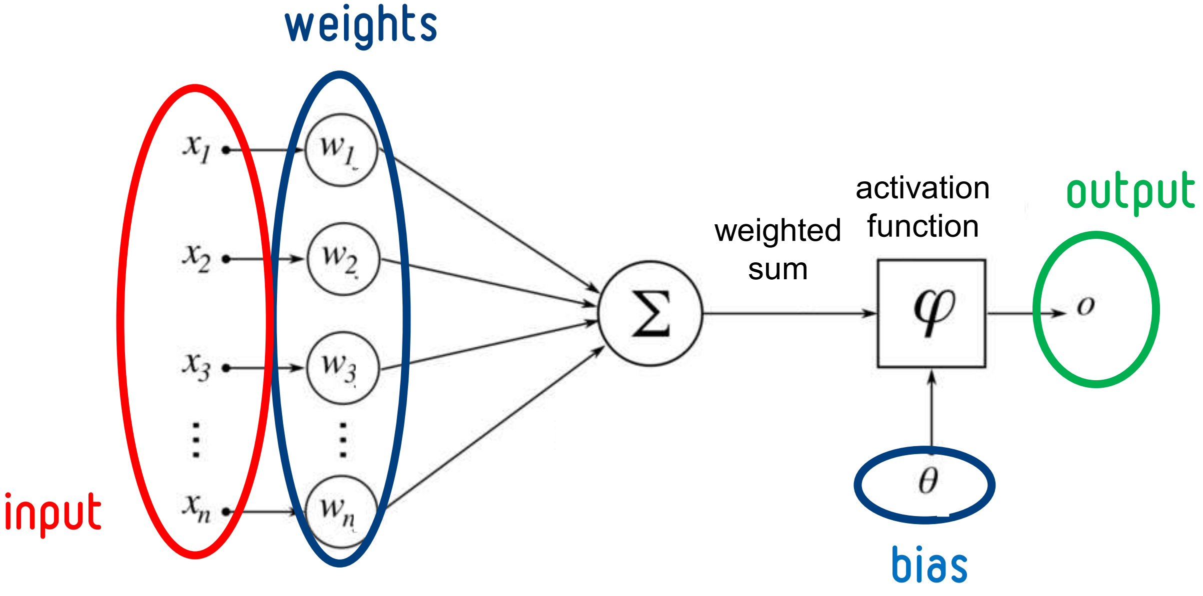
biological neuron





activation function φ

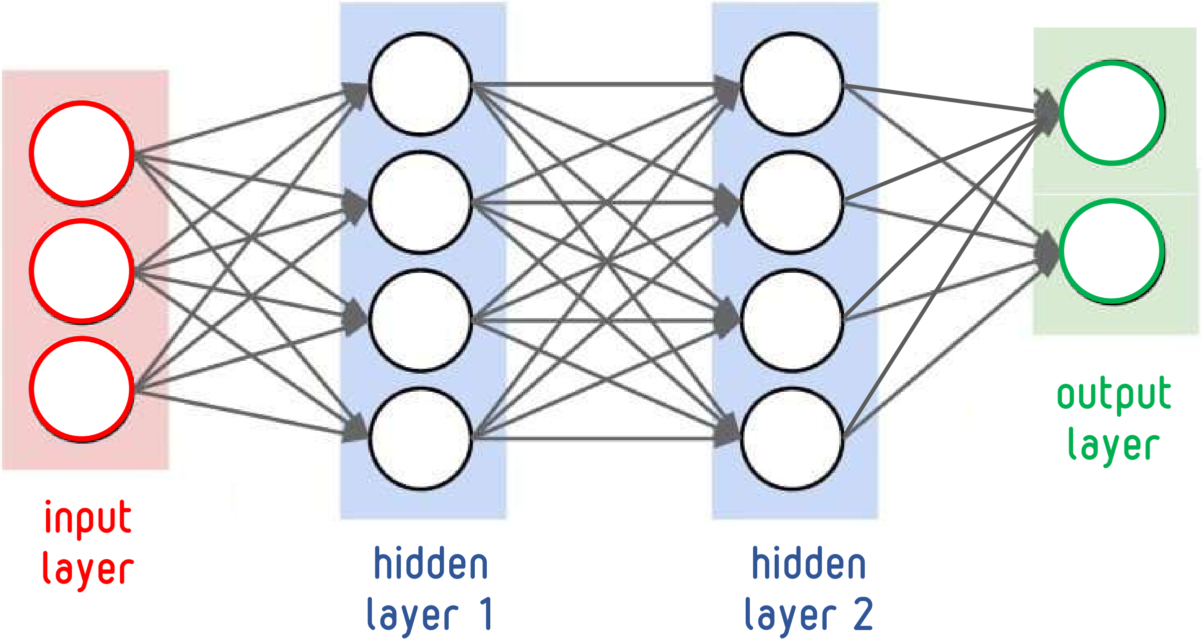
artificial neuron



$$o = \varphi\left(\sum_n w_n x_n + \theta\right)$$

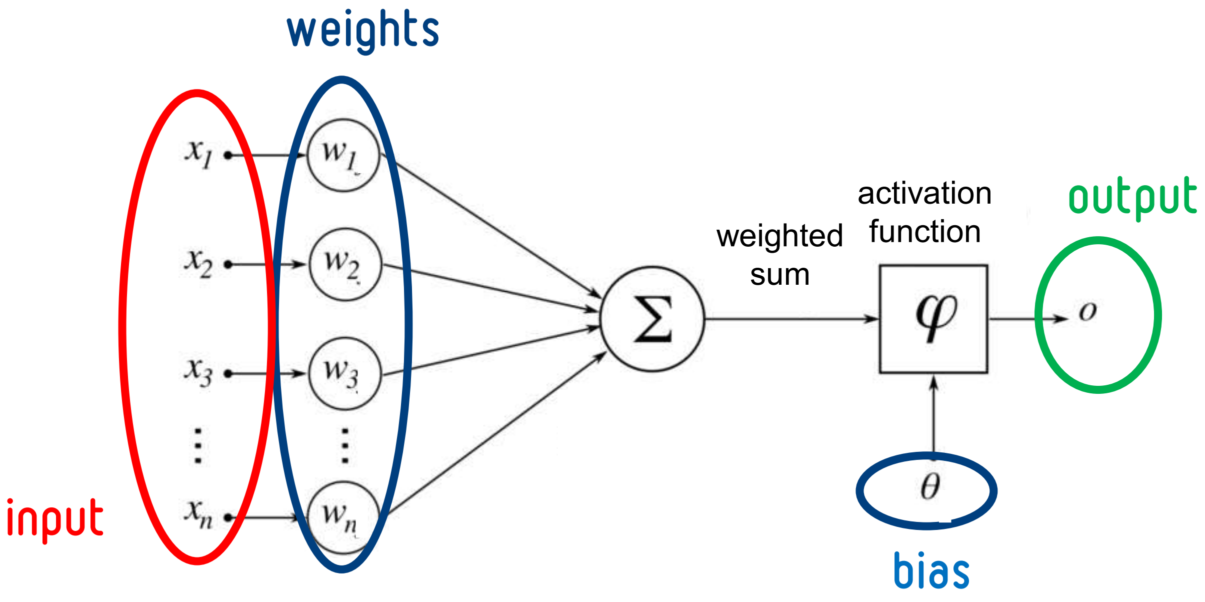
W. McCulloch & W. Pitts, *A Logical Calculus of the Ideas Immanent in Nervous Activity*, Bull. Math. Biophys. 5 115 (1943.)

artificial neural network (ANN)

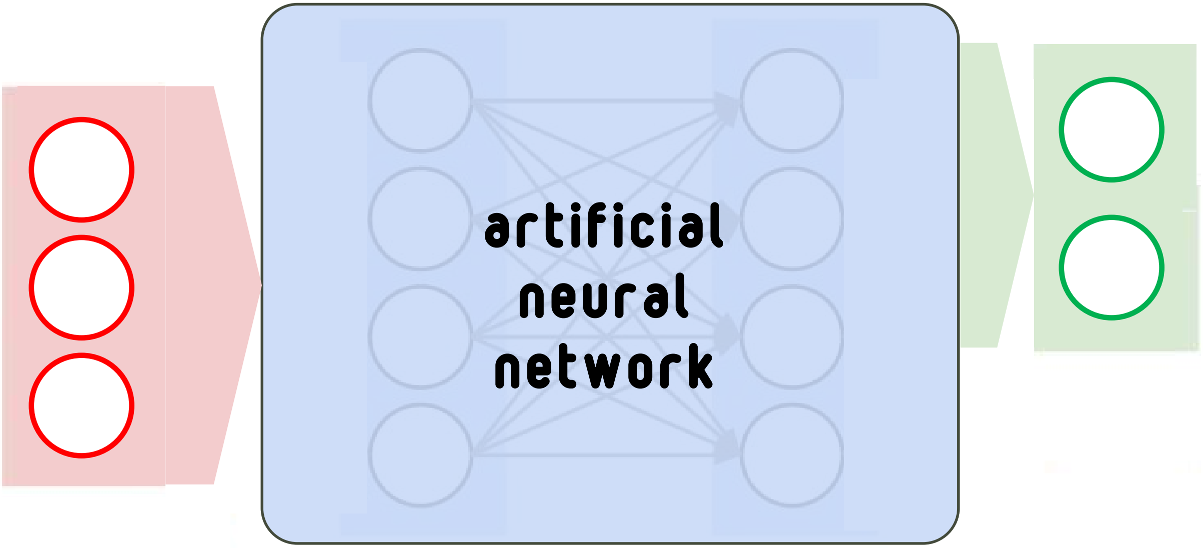


feed foward
fully connected

artificial neuron



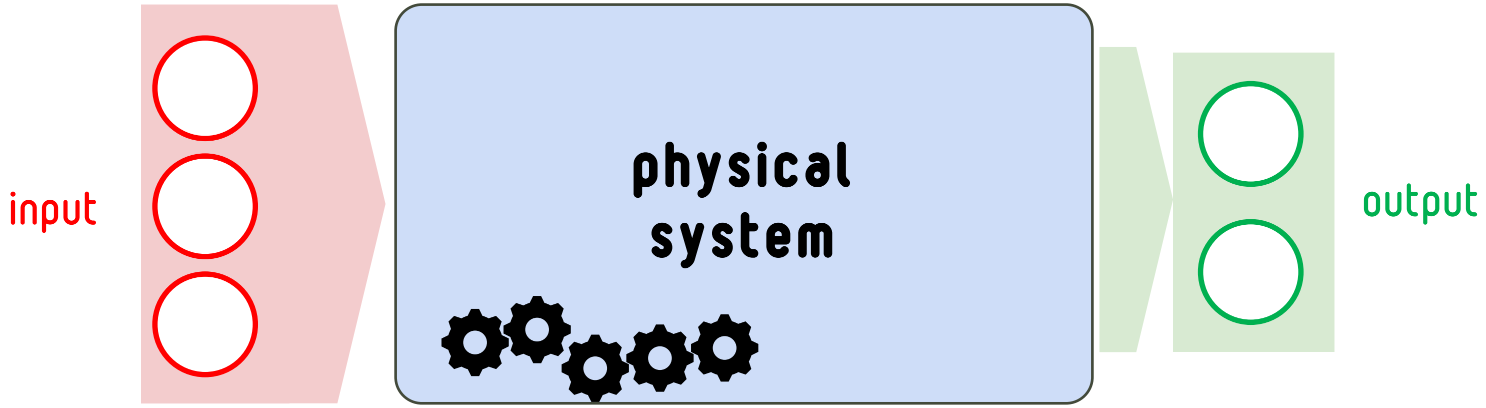
$$o = \varphi\left(\sum_n w_n x_n + \theta\right)$$

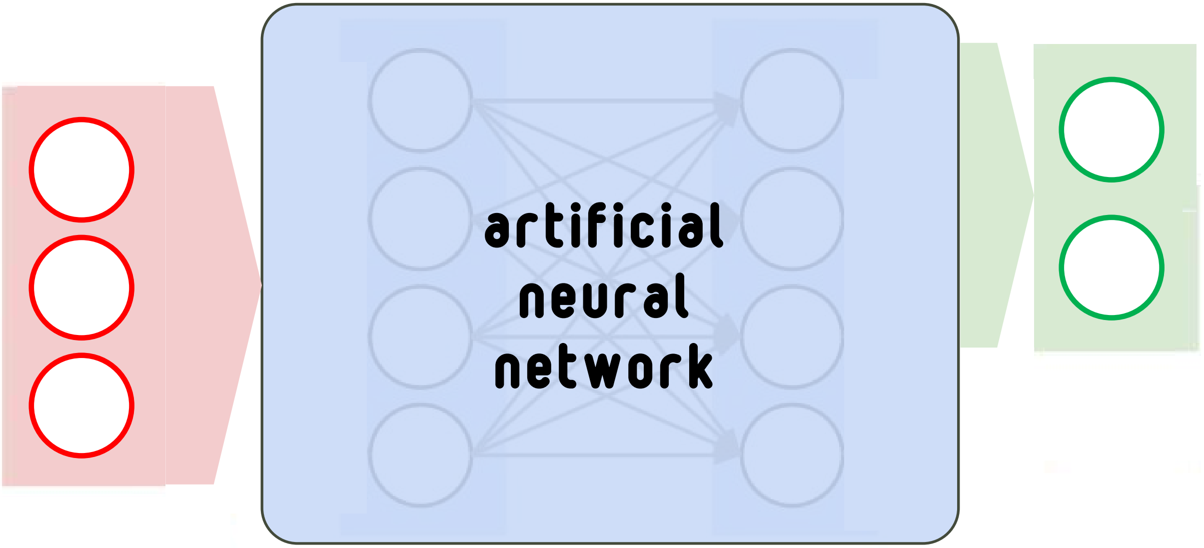


but first
you have to train the ANN

- The ANN mimics the response of the physical system : it is a **digital twin.**
- The ANN is a **universal interpolator**.

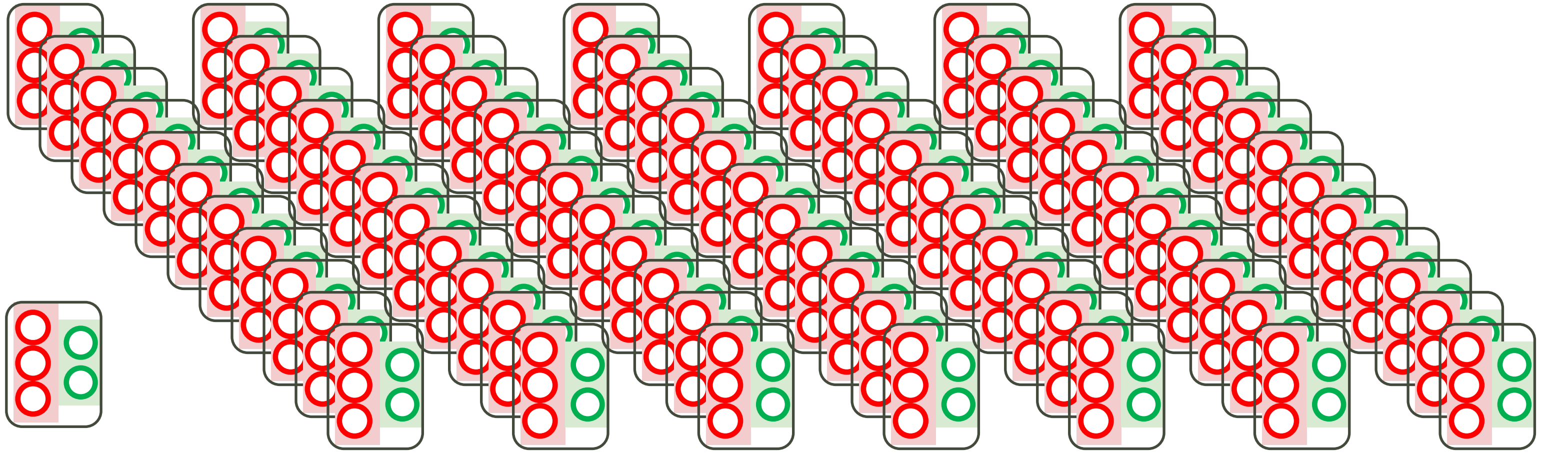
G. Cybenko, *Approximation by superpositions of a sigmoidal function.*" Math. Control Signals Syst. 2 303 (1989)





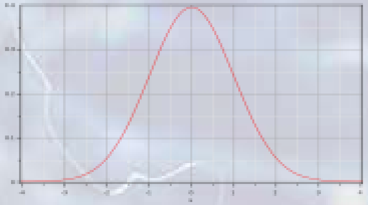
but first
you have to train the ANN

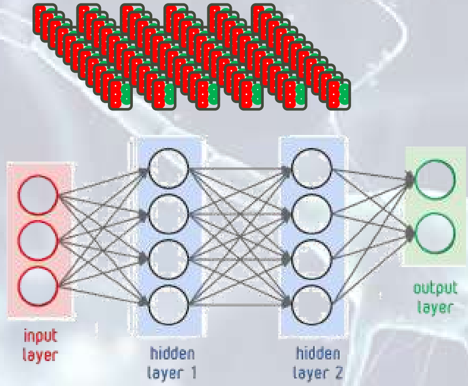
Data are needed ! A large dataset is required.

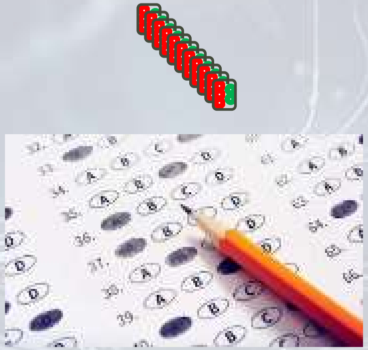


- The more data you have, the better..
- Data from experiments.
- Data from numerics.

SUPERVISED MACHINE LEARNING : PERFORMING A REGRESSION







DATA | **NORMALIZATION** | **TRAINING** | **VALIDATION** | **USE**

optimization algorithms :
backpropagation algorithm
stochastic gradient descent
Levenberg-Marquardt algorithm

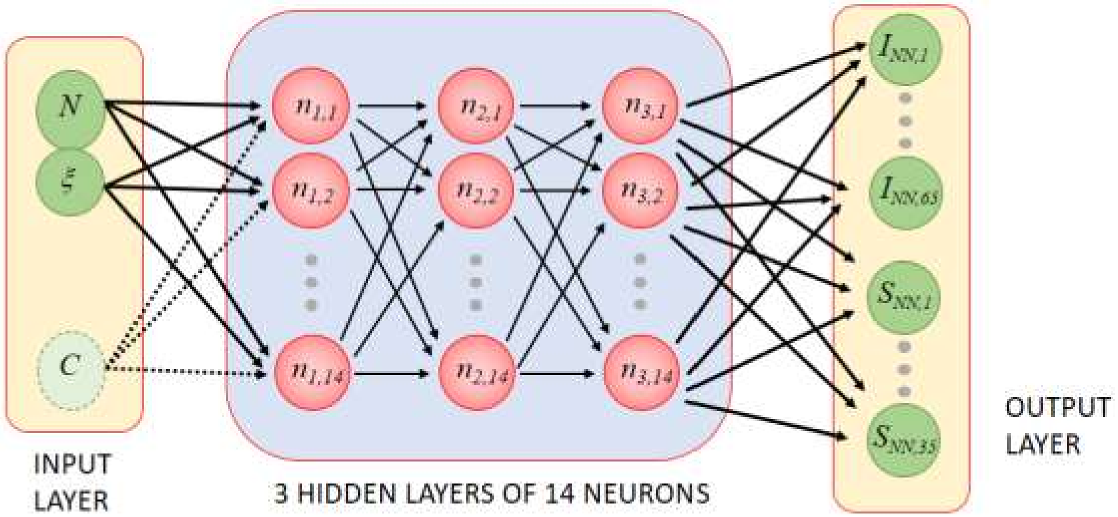
$w_1, w_2, w_3, \ldots , w_n, \theta$
for each neuron

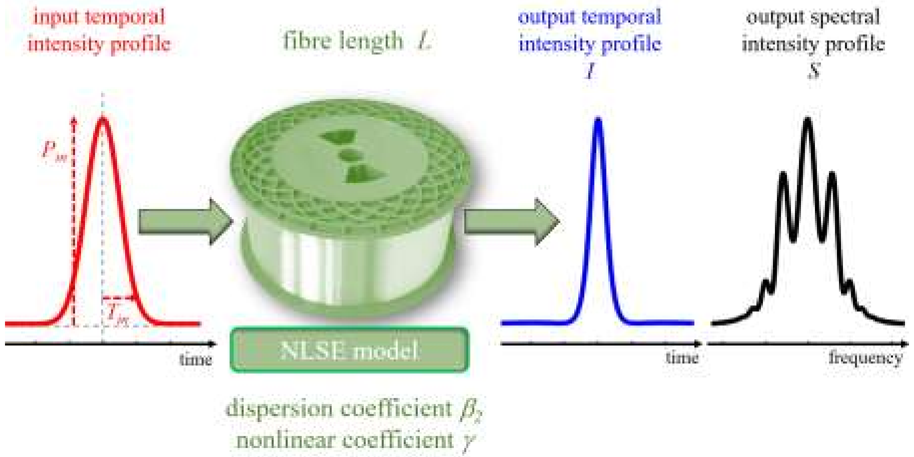
avoid overtraining

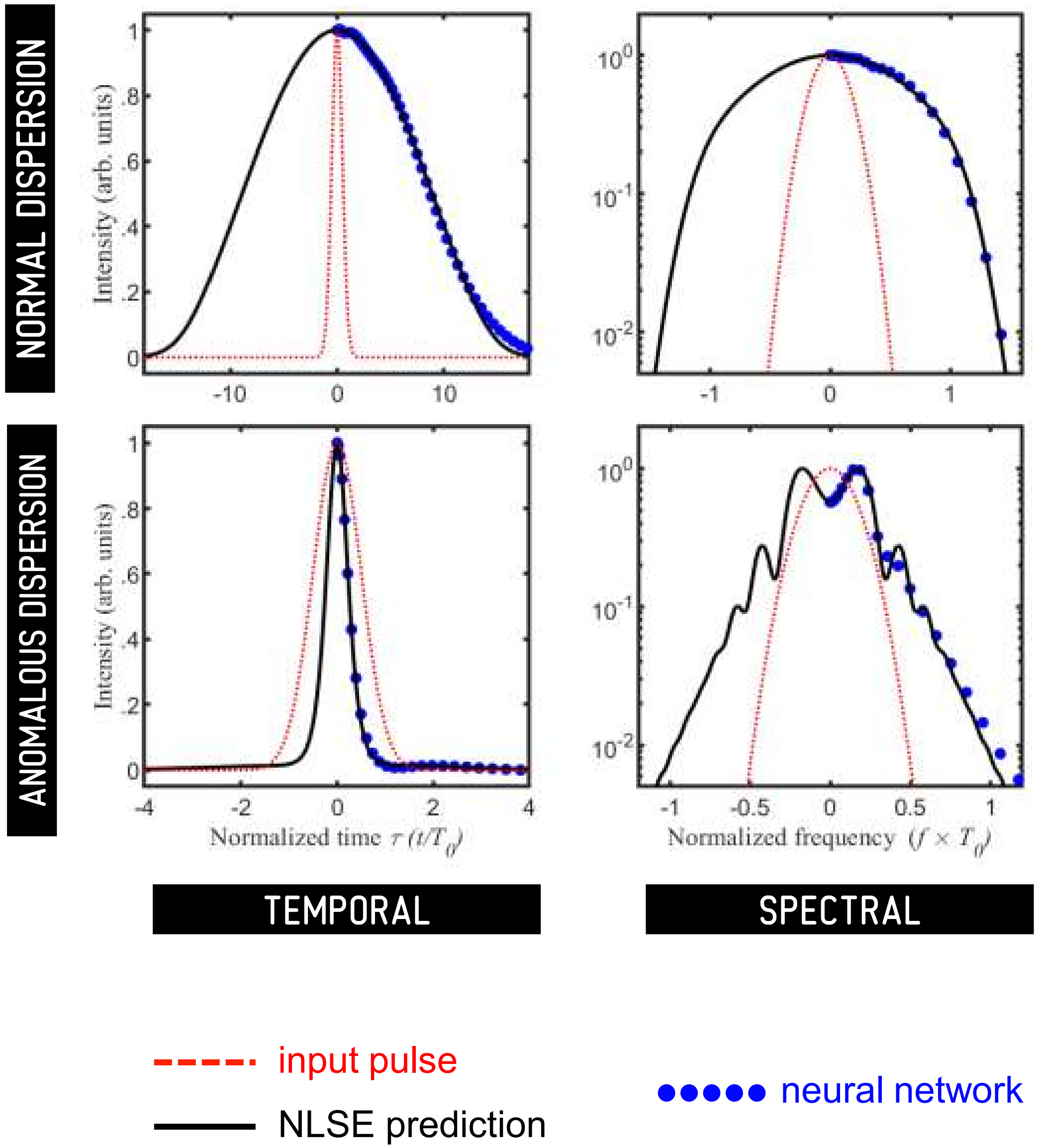
« black box »

define hyperparameters :
number of layers, number of neurons on each layer
learning rates, loss functions …

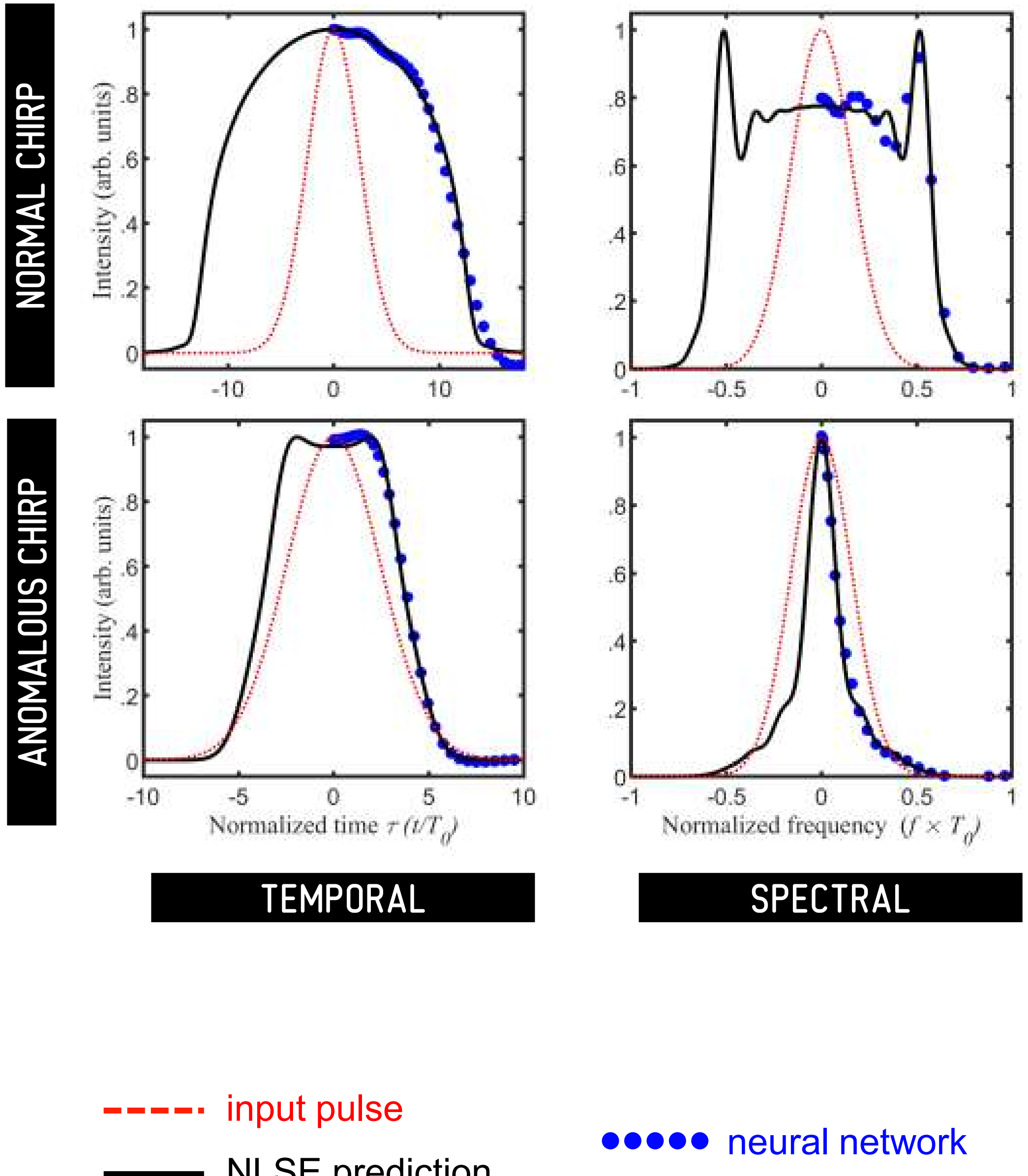
Rumelhart et al.
Learning representations by back-propagating errors.
Nature, 323, 533-536, (1986)

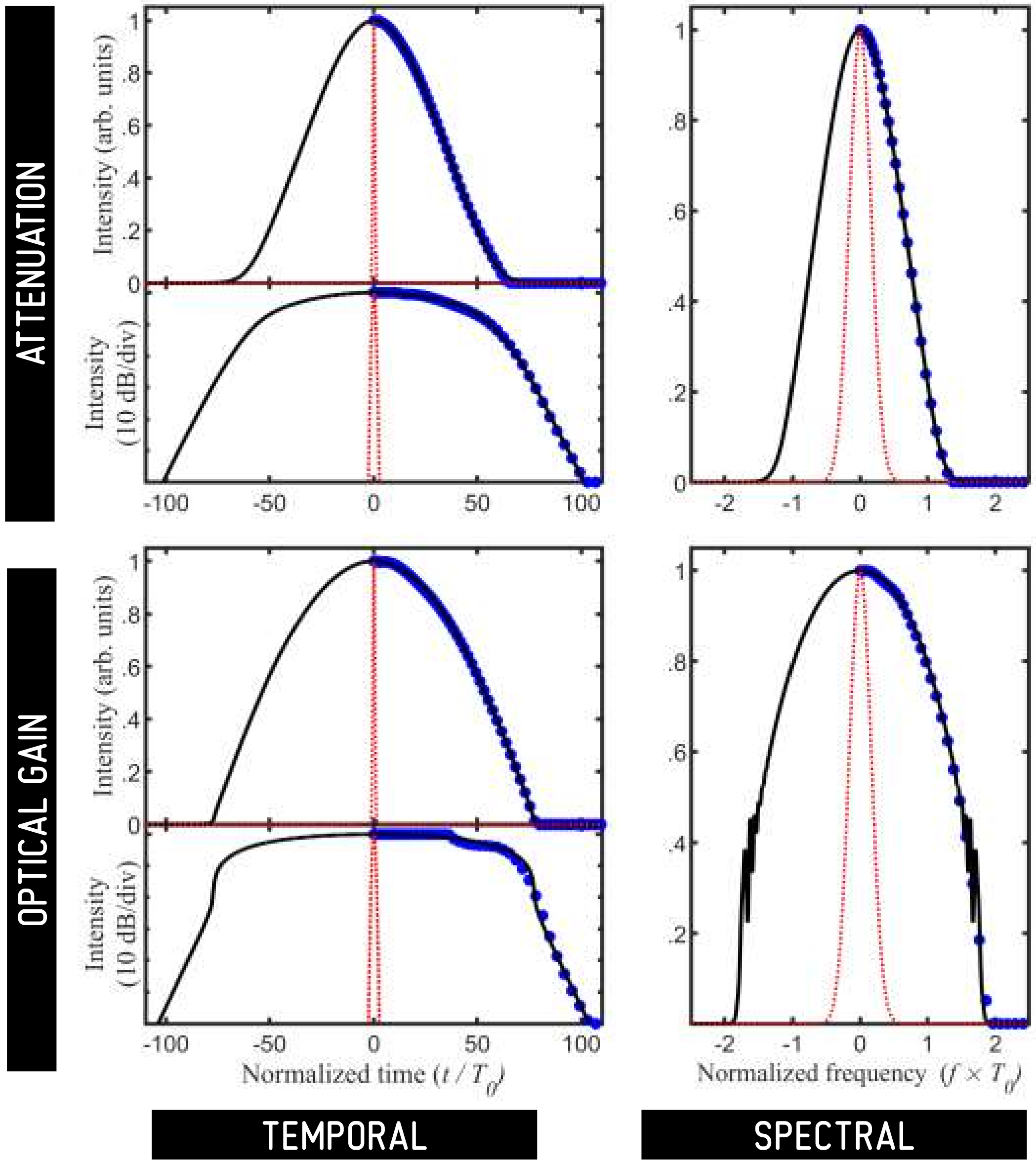






S Boscolo, C Finot, *Artificial neural networks for nonlinear pulse shaping in optical fibers*, Opt. Laser Technol. 131, 106439 (2020)

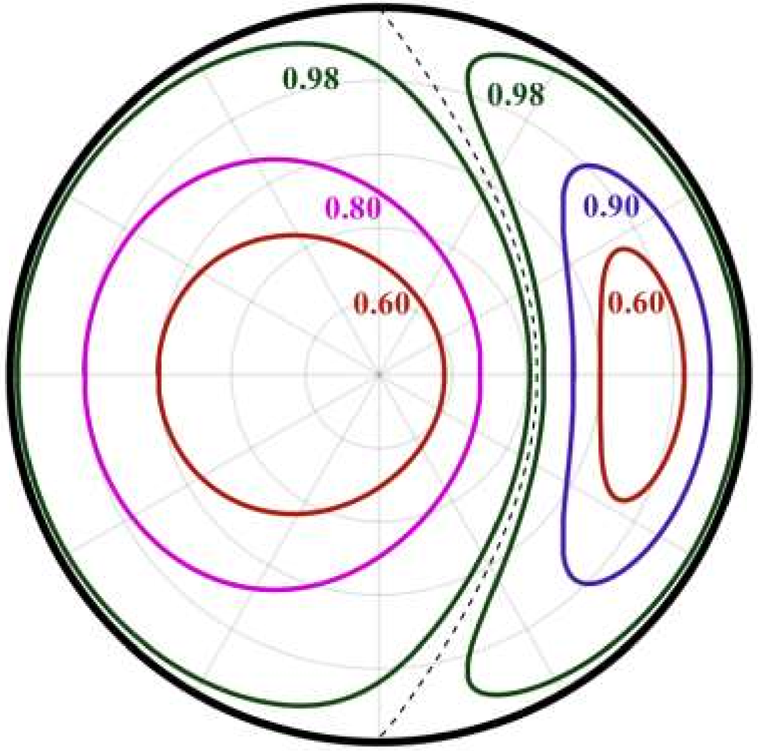

NORMAL CHIRP
ANOMALOUS CHIRP
Intensity (arb. units)
Normalized time τ (t/T0)
Normalized frequency (f × T0)
TEMPORAL
SPECTRAL
input pulse
NLSE prediction
neural network


ATTENUATION
OPTICAL GAIN
Intensity (arb. units)
Intensity (10 dB/div)
Normalized time (t / T0)
Normalized frequency (f × T0)
TEMPORAL
SPECTRAL

$$H = 2\eta\left(1-\eta\right)\cos\phi + \left(\Omega^2+1\right)\eta - \frac{3}{2}\eta^2$$

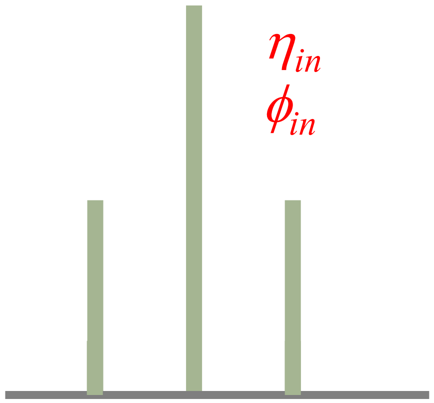
$$\frac{\partial \eta}{\partial \xi} = \frac{\partial H}{\partial \phi} \quad \text{and} \quad \frac{\partial \phi}{\partial \xi} = -\frac{\partial H}{\partial \eta}$$

$$\begin{cases} -i\dfrac{dA_0}{d\xi} = \left(|A_0|^2 + 2|A_{-1}|^2 + 2|A_1|^2\right)A_0 + 2\,A_{-1}A_1A_0^* \\ -i\dfrac{dA_{-1}}{d\xi} + \dfrac{1}{2}\Omega^2 A_{-1} = \left(|A_{-1}|^2 + 2|A_0|^2 + 2|A_1|^2\right)A_{-1} + A_1^*A_0^2 \\ -i\dfrac{dA_1}{d\xi} + \dfrac{1}{2}\Omega^2 A_1 = \left(|A_1|^2 + 2|A_0|^2 + 2|A_{-1}|^2\right)A_1 + A_{-1}^*A_0^2 \end{cases}$$



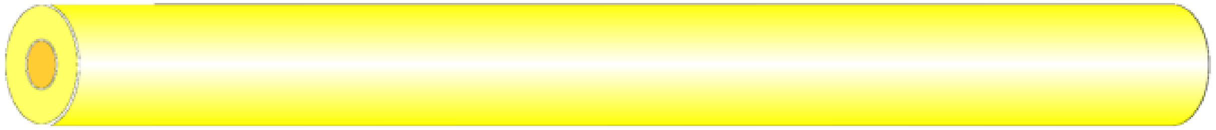
$$\frac{d\eta}{d\xi} = \dot{\eta} = 2\eta^2\sin\phi - 2\eta\sin\phi$$

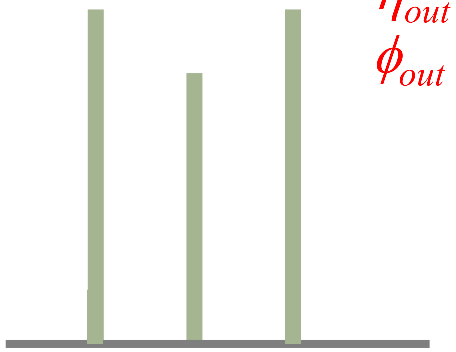
$$\frac{d\phi}{d\xi} = \dot{\phi} = -(\Omega^2+1) - 2\cos\phi + 3\eta + 4\eta\cos\phi$$



η_{in}

ϕ_{in}



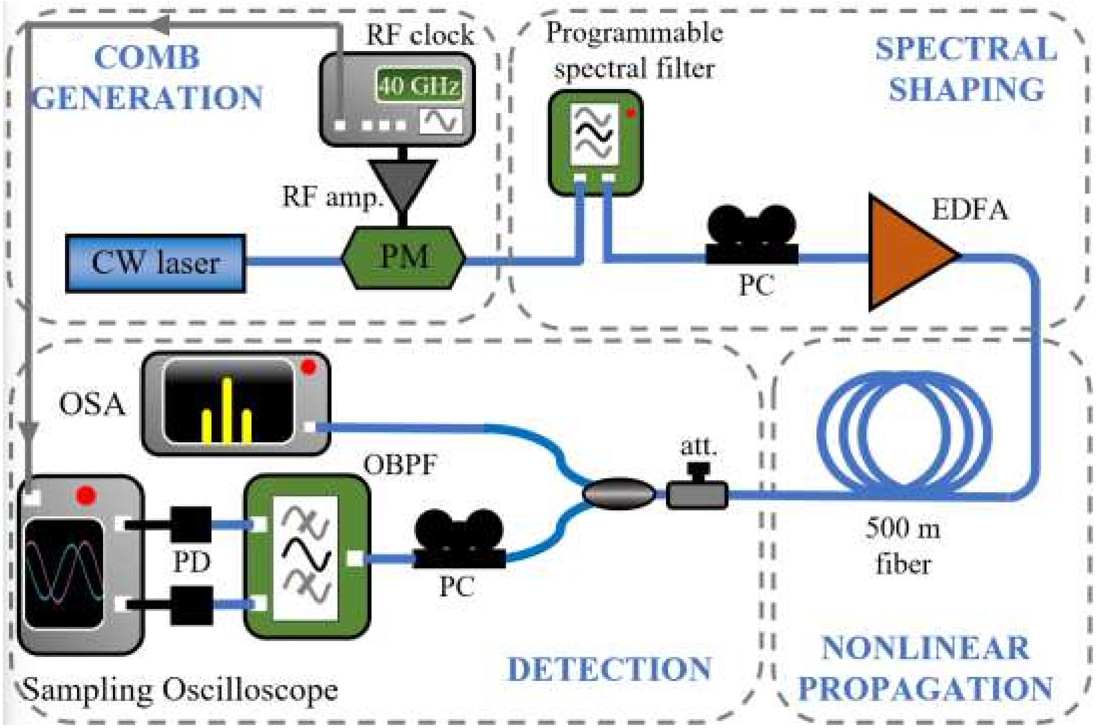


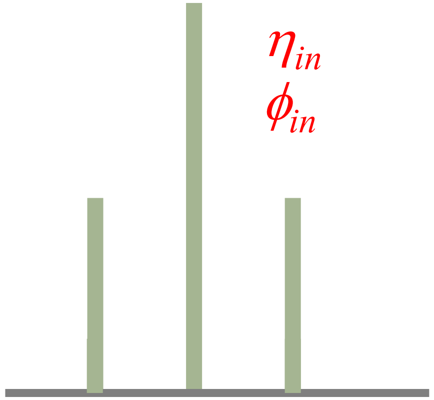
η_{out}

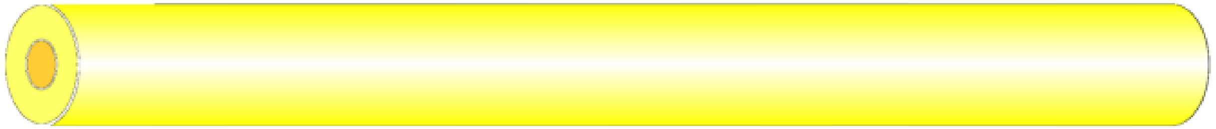
ϕ_{out}

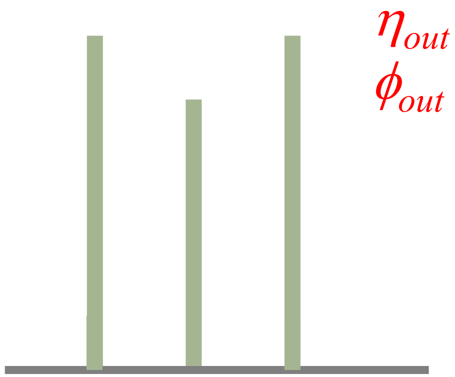
$$\begin{cases} \eta = |\psi_0|^2 / P_T \\ \phi = \varphi_1 + \varphi_{-1} - 2\,\varphi_0 \end{cases}$$

S. Trillo, S. Wabnitz, *Dynamics of the nonlinear modulational instability in optical fibers*, Opt. Lett., 16 986 (1991)

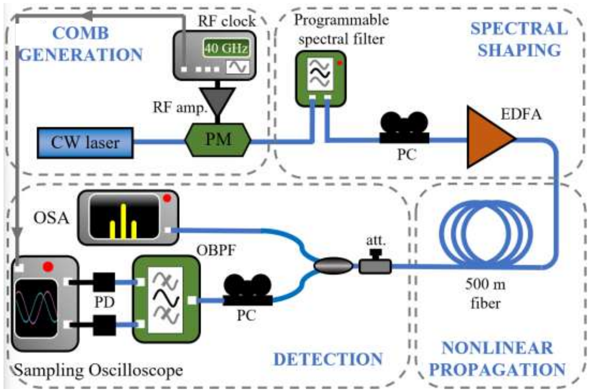




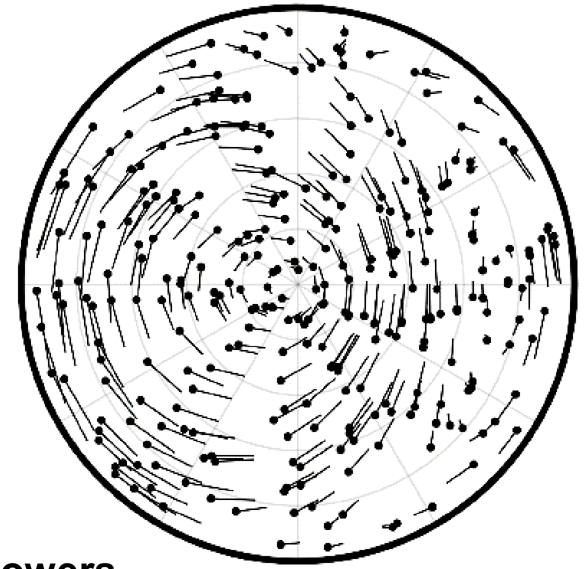




$$\begin{cases} \eta = |\psi_0|^2 / P_T \\ \phi = \varphi_1 + \varphi_{-1} - 2\,\varphi_0 \end{cases}$$

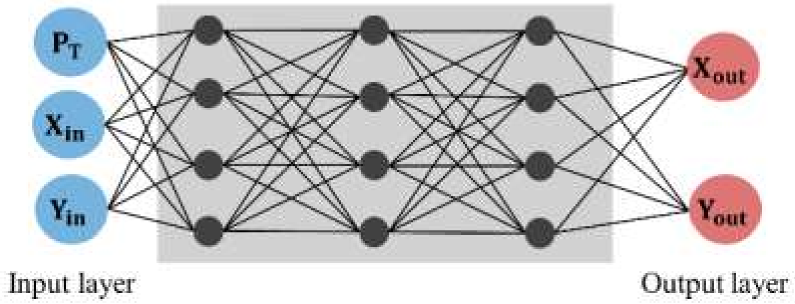


MEASURE

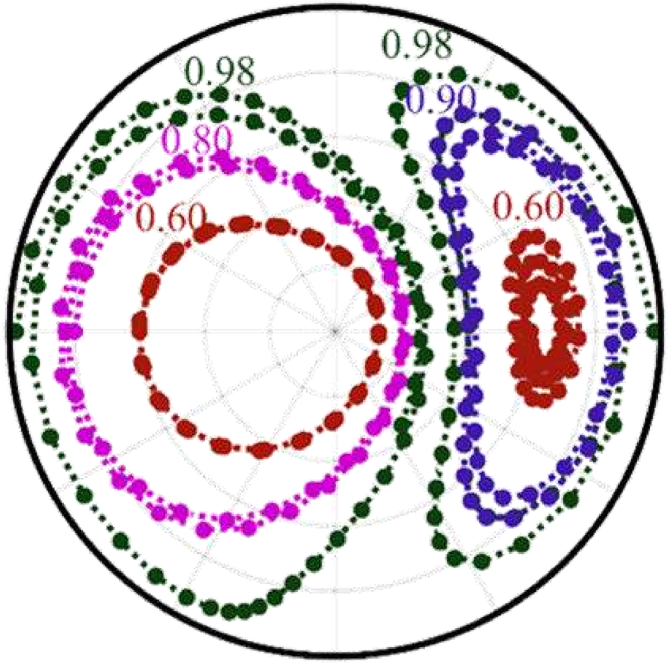


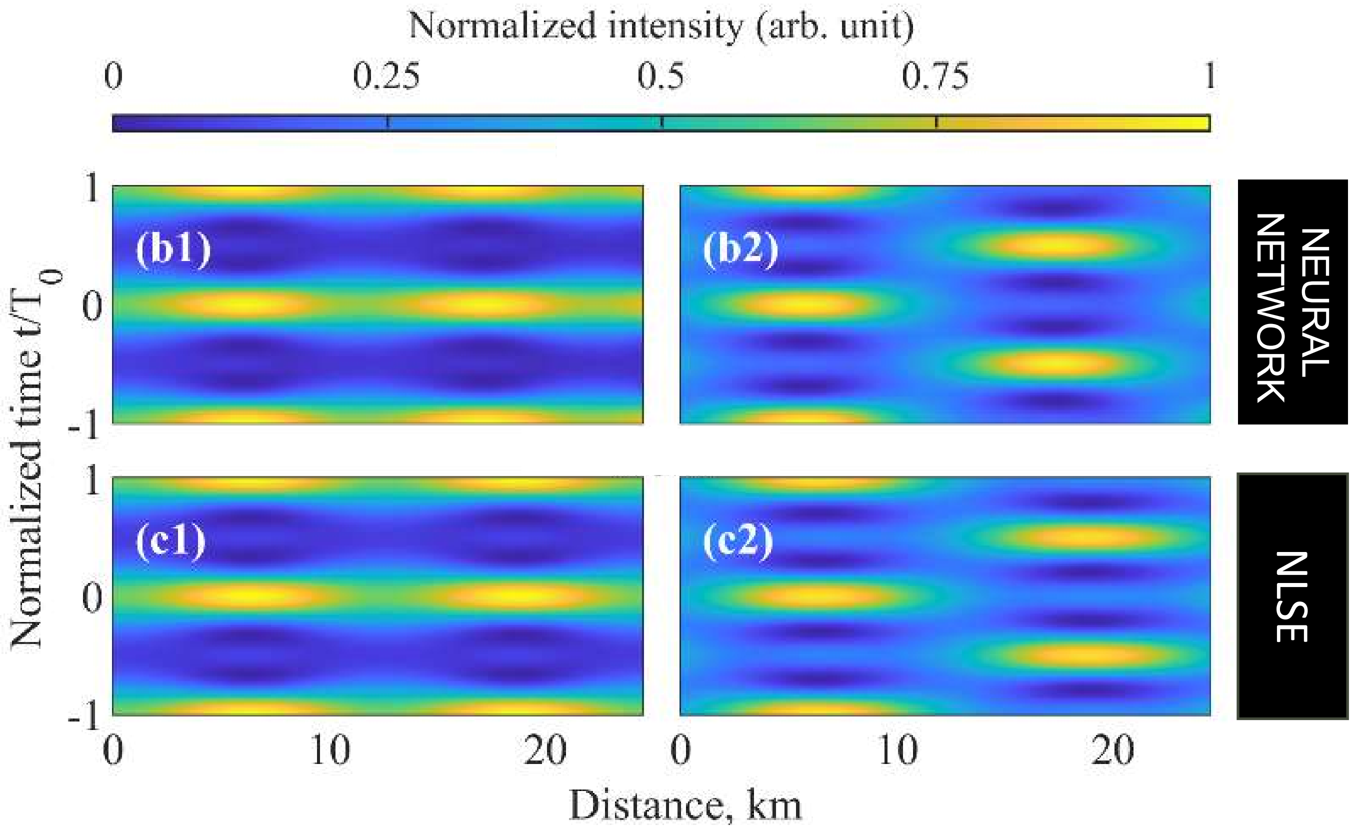
x 6 powers

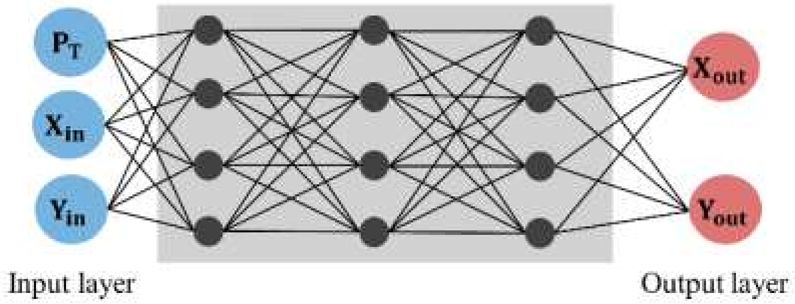
TRAIN

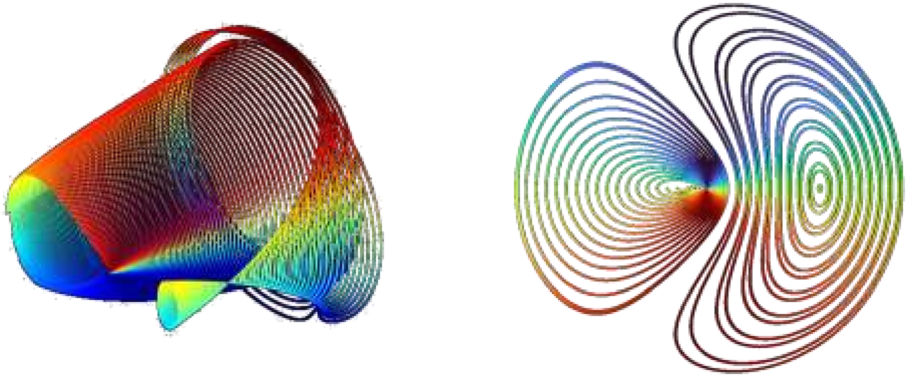


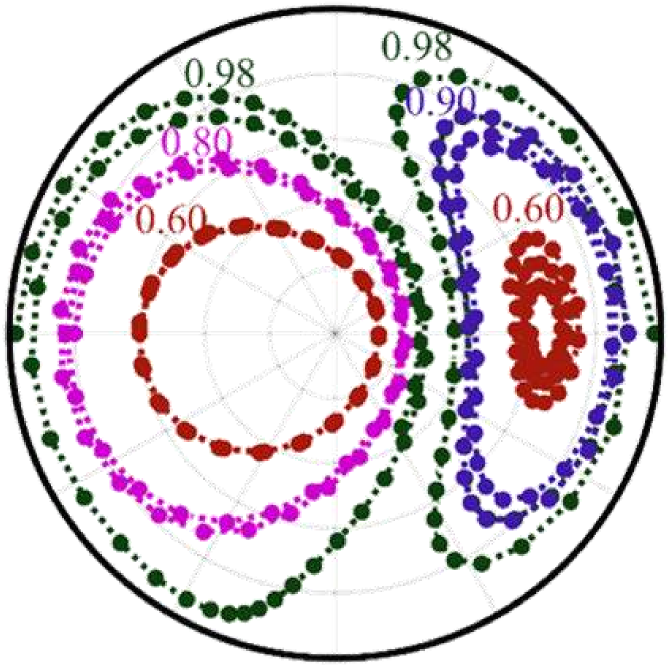
USE

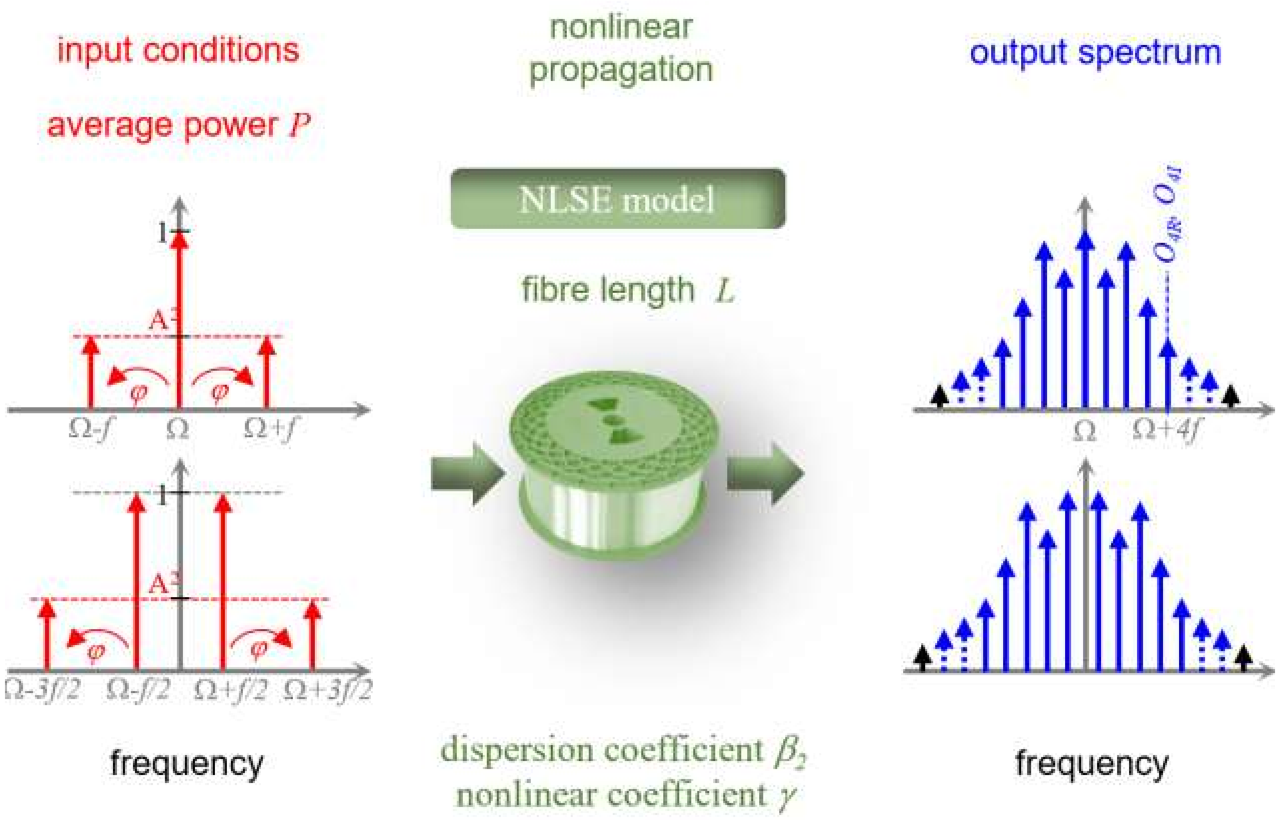


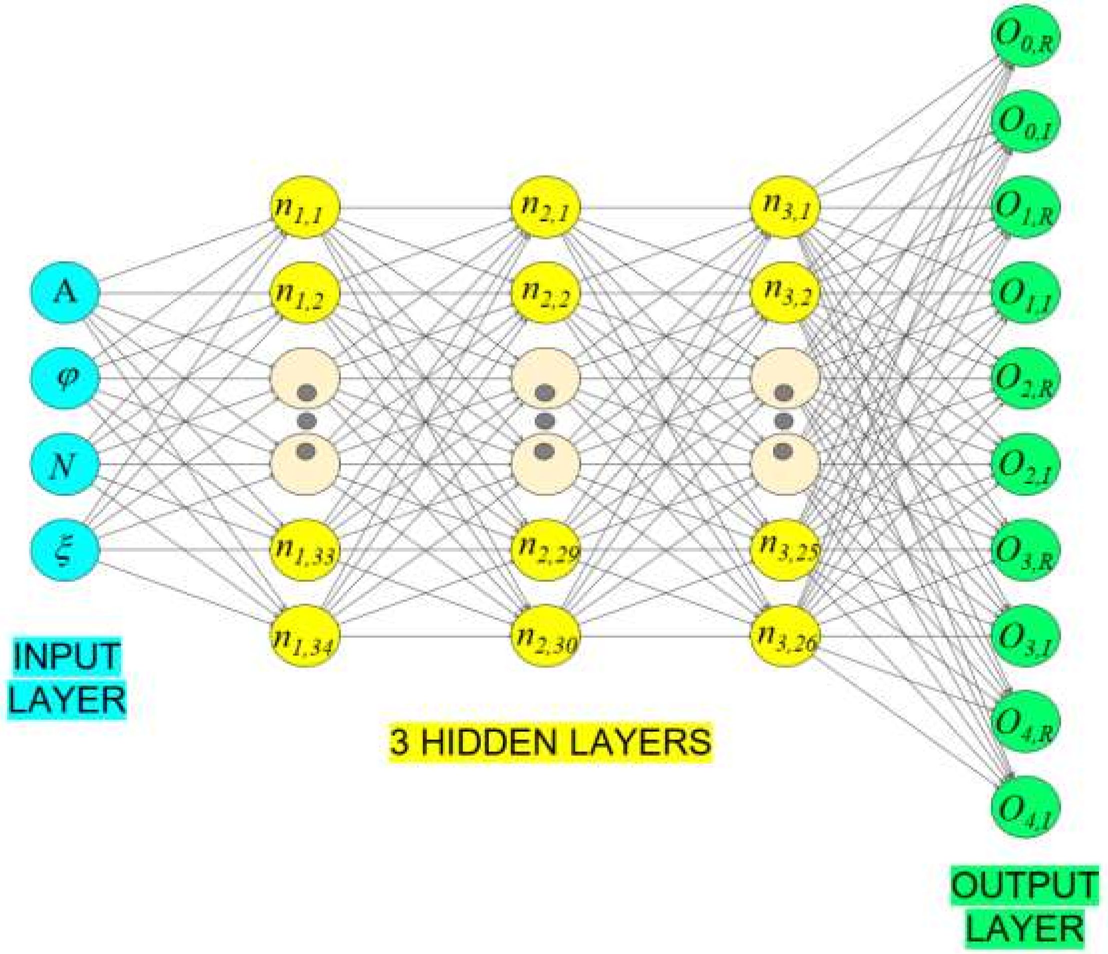

Normalized intensity (arb. unit)
0
0.25
0.5
0.75
1
Normalized time t/T0
(b1)
(b2)
(c1)
(c2)
NEURAL NETWORK
NLSE
Distance, km
0
10
20

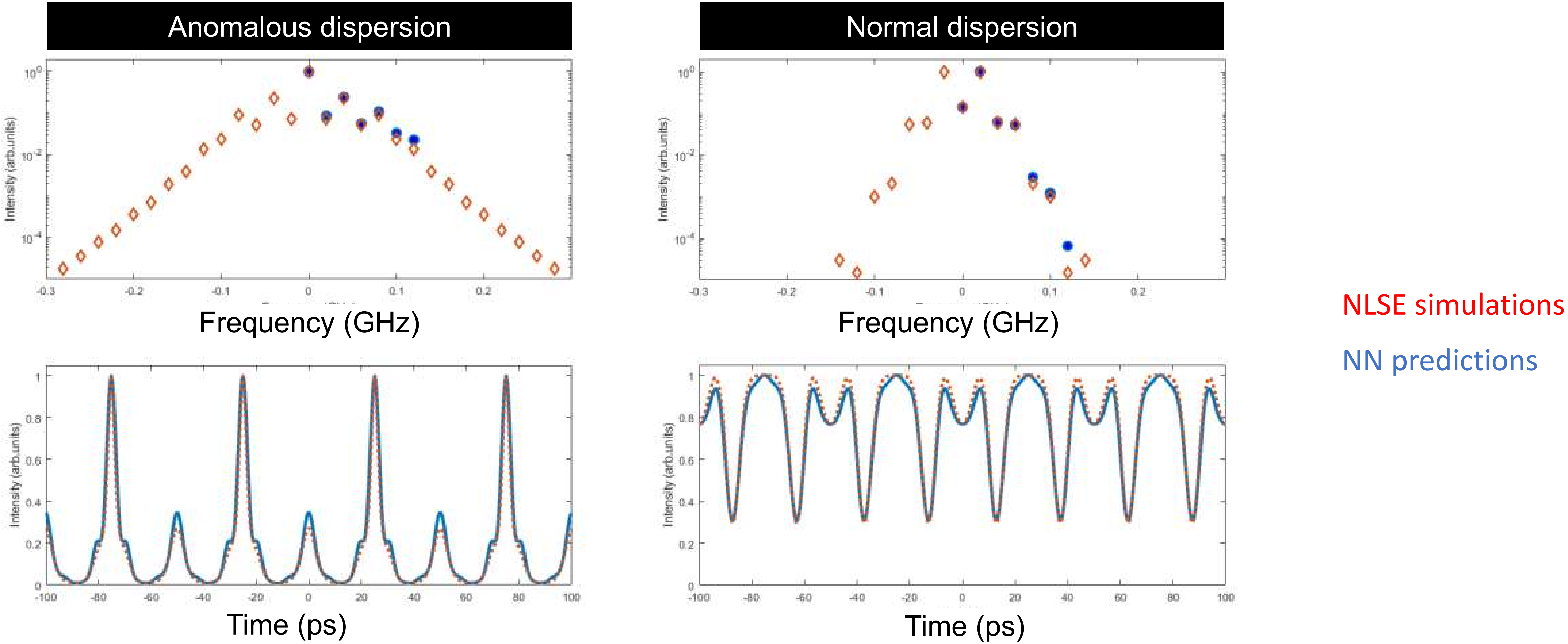

PT
Xin
Yin
Xout
Yout
Input layer
Output layer




0.98
0.98
0.90
0.80
0.60
0.60

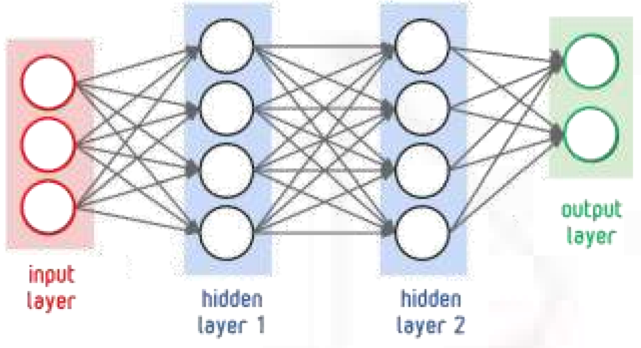

input conditions
average power P
nonlinear propagation
NLSE model
fibre length L
output spectrum
O_{4R}, O_{4I}
1
A^2
φ
Ω-f
Ω
Ω+f
Ω-3f/2
Ω-f/2
Ω+f/2
Ω+3f/2
Ω+4f
frequency
dispersion coefficient β_2
nonlinear coefficient γ
frequency

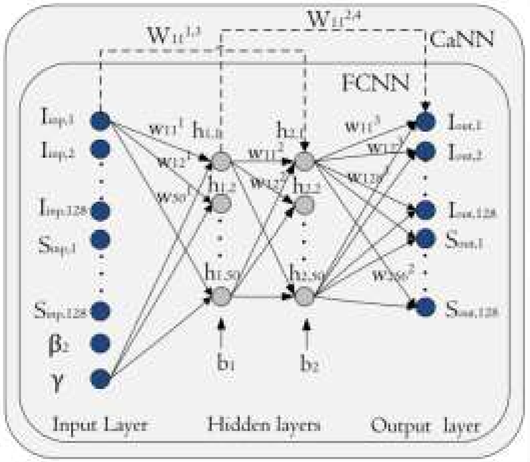

A
φ
N
ξ
INPUT LAYER
$n_{1,1}$
$n_{1,2}$
$n_{1,33}$
$n_{1,34}$
$n_{2,1}$
$n_{2,2}$
$n_{2,29}$
$n_{2,30}$
$n_{3,1}$
$n_{3,2}$
$n_{3,25}$
$n_{3,26}$
3 HIDDEN LAYERS
$O_{0,R}$
$O_{0,I}$
$O_{1,R}$
$O_{1,I}$
$O_{2,R}$
$O_{2,I}$
$O_{3,R}$
$O_{3,I}$
$O_{4,R}$
$O_{4,I}$
OUTPUT LAYER

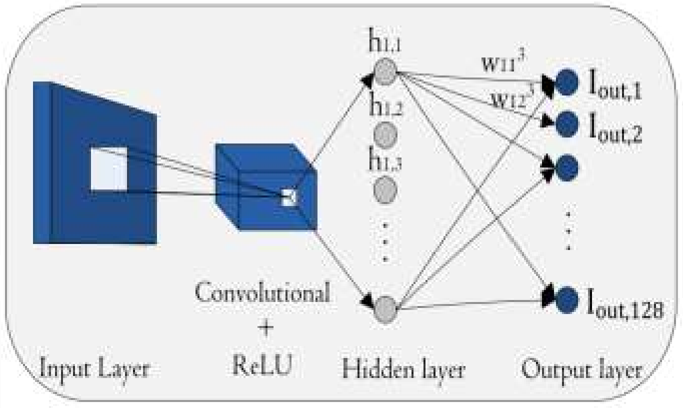


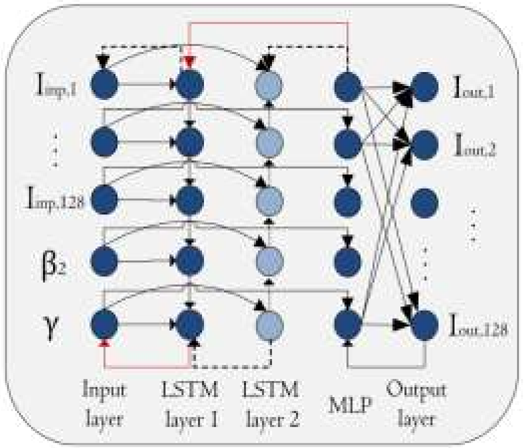
Prediction with very high accuracy of the temporal and spectral output profiles.

Many architectures of ANN exist : reccurent networks, convolutional networks (80s).









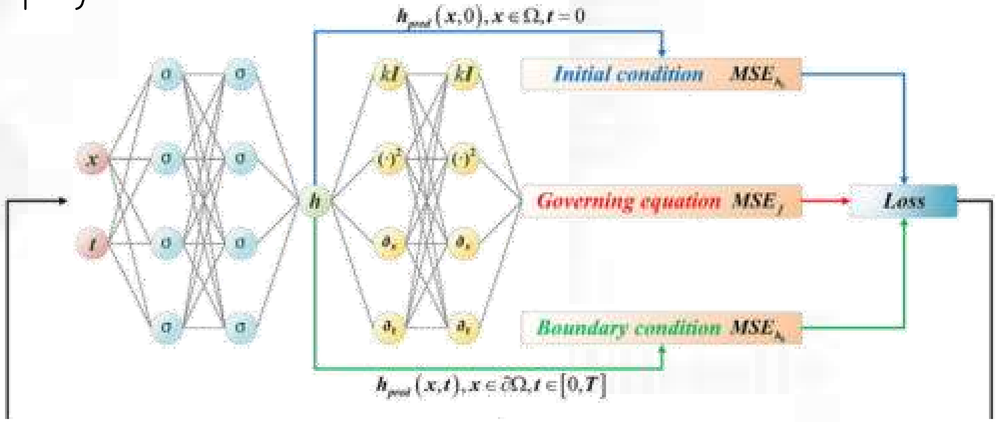
G., Naveenta, et al *Comparative study of neural network architectures for modelling nonlinear optical pulse propagation*, Opt. Fiber Technol. 102540 (2021)

Goodfellow et al., *Deep Learning*

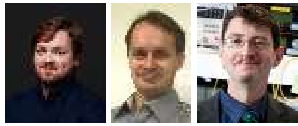
Freire, P. et al. *Artificial neural networks for photonic applications–from algorithms to implementation: tutorial*. Adv. Opt. Photonics 15 739 (2023)

Possibility to include some additionnal constraints linked to the physics

Physics-Informed Neural Networks



X. Jiang et al., *Physics-Informed Neural Network for Nonlinear Dynamics in Fiber Optics*, Laser & Photonics Rev. 16, 2100483 (2022).



And what about more complex dynamics such as supercontinuum generation ?

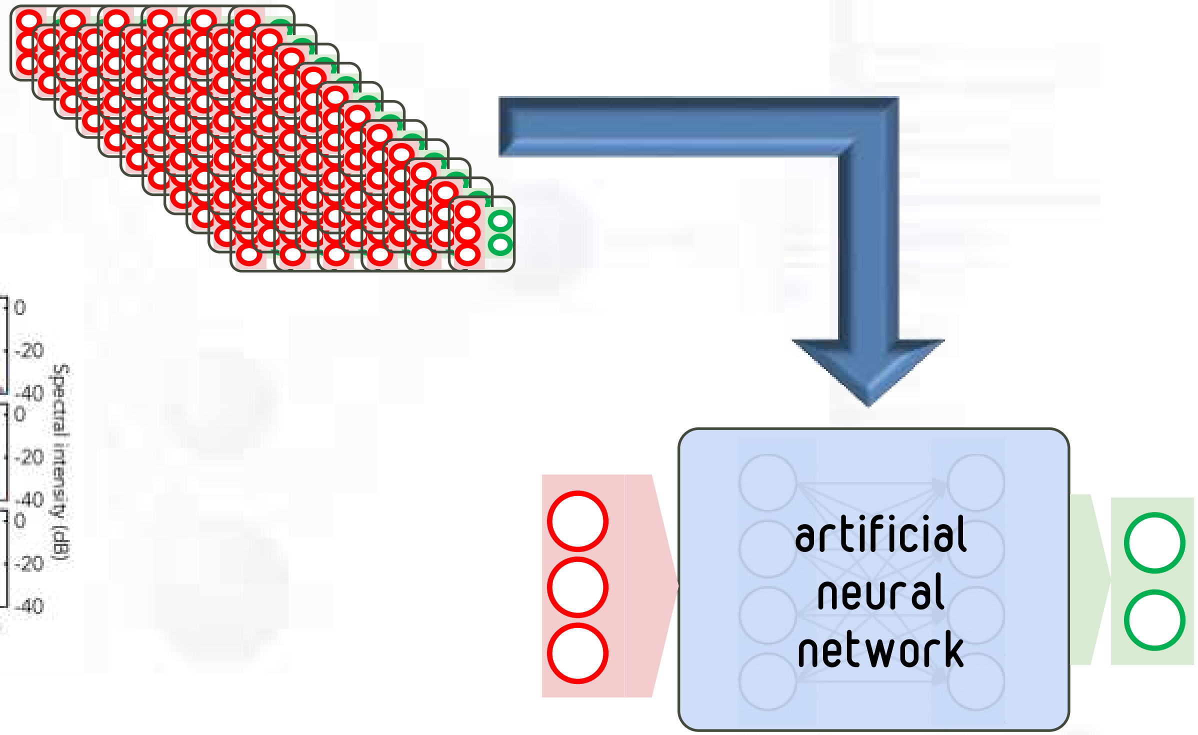
the physical model becomes the generalized nonlinear Schrödinger equation

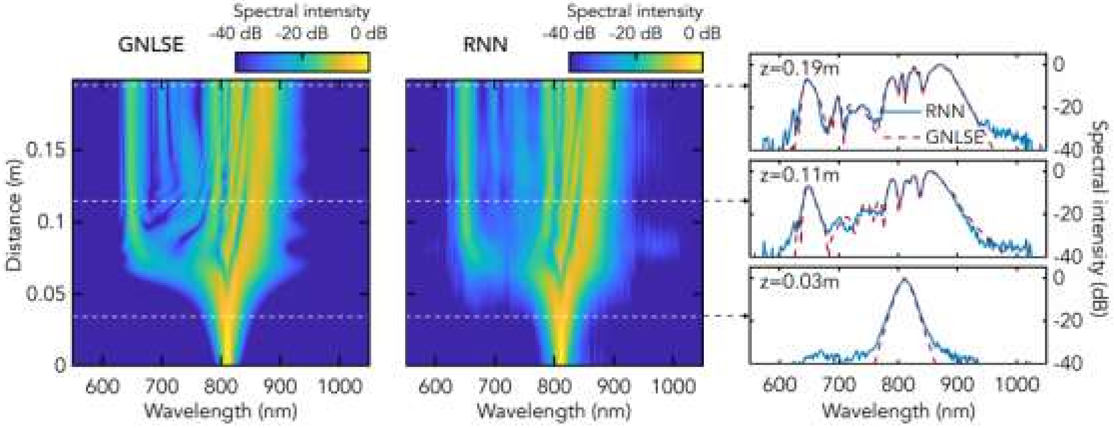
$$\frac{\partial A}{\partial z} + \beta_1 \frac{\partial A}{\partial t} + \frac{i\beta_2}{2!}\frac{\partial^2 A}{\partial t^2} - \frac{\beta_3}{3!}\frac{\partial^3 A}{\partial t^3} + \ldots = i\gamma\left(1+\frac{i}{\omega_0}\frac{\partial}{\partial t}\right)\left(A(z,t)\int_{-\infty}^{\infty} R(t')|A(z,t-t')|^2\, dt'\right)$$

new dataset from training

experimental data

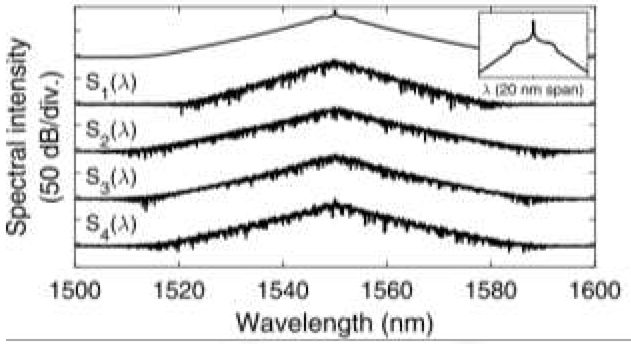
numerical simulations

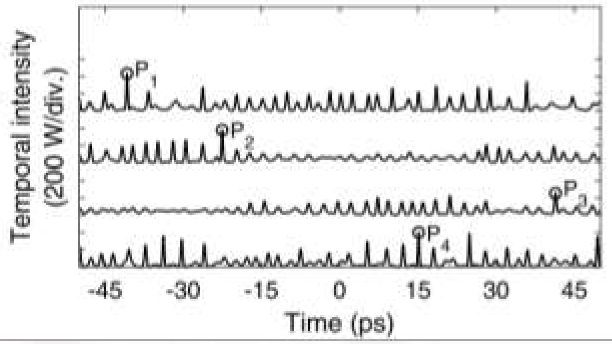


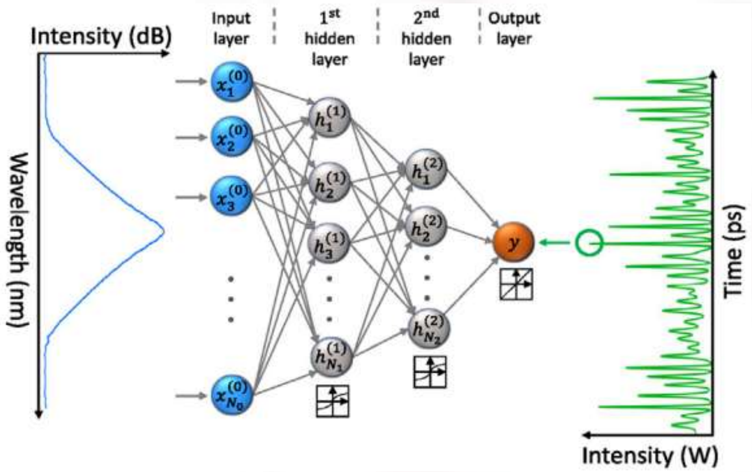


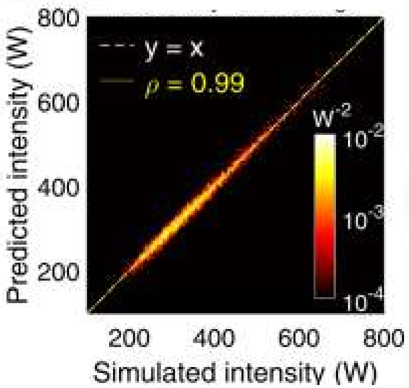
L. Salmela et al. *Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network*. Nat. Mach. Intell. 3, 344 (2021).

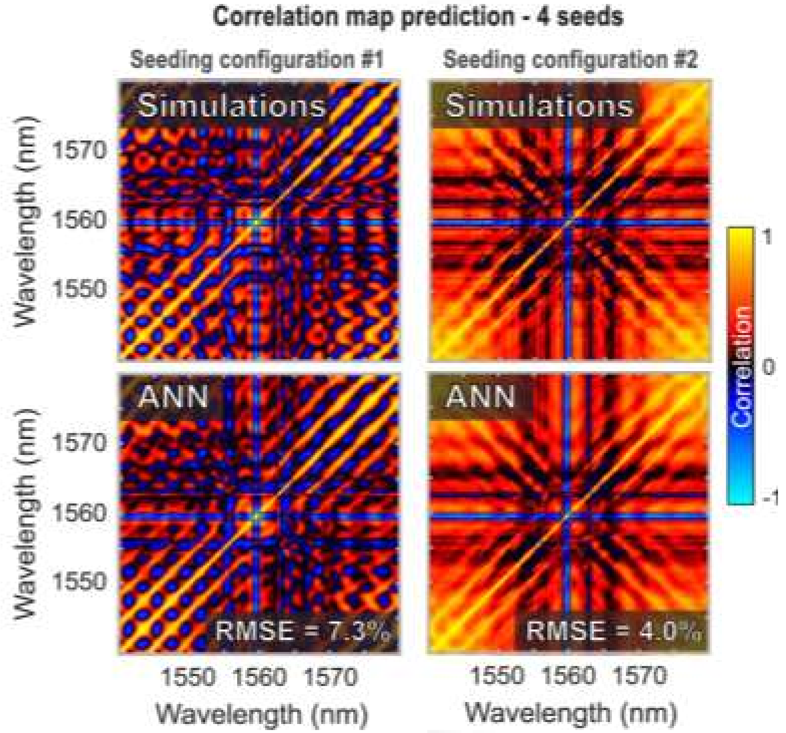
Neural networks are also relevant for rogue events analysis or coherence analysis.











M. Närhi et al. *Machine learning analysis of extreme events in optical fibre modulation instability*. Nat. Commun. 9, 4923 (2018)

M. Mabed et al. *Neural network analysis of unstable temporal intensity peaks in continuous wave modulation instability* Opt. Commun. 541, 129570 (2023)

Y. Boussafa et al. *Deep learning prediction of noise-driven nonlinear instabilities in fibre optics*. Nature Communications 16 7800 (2025)

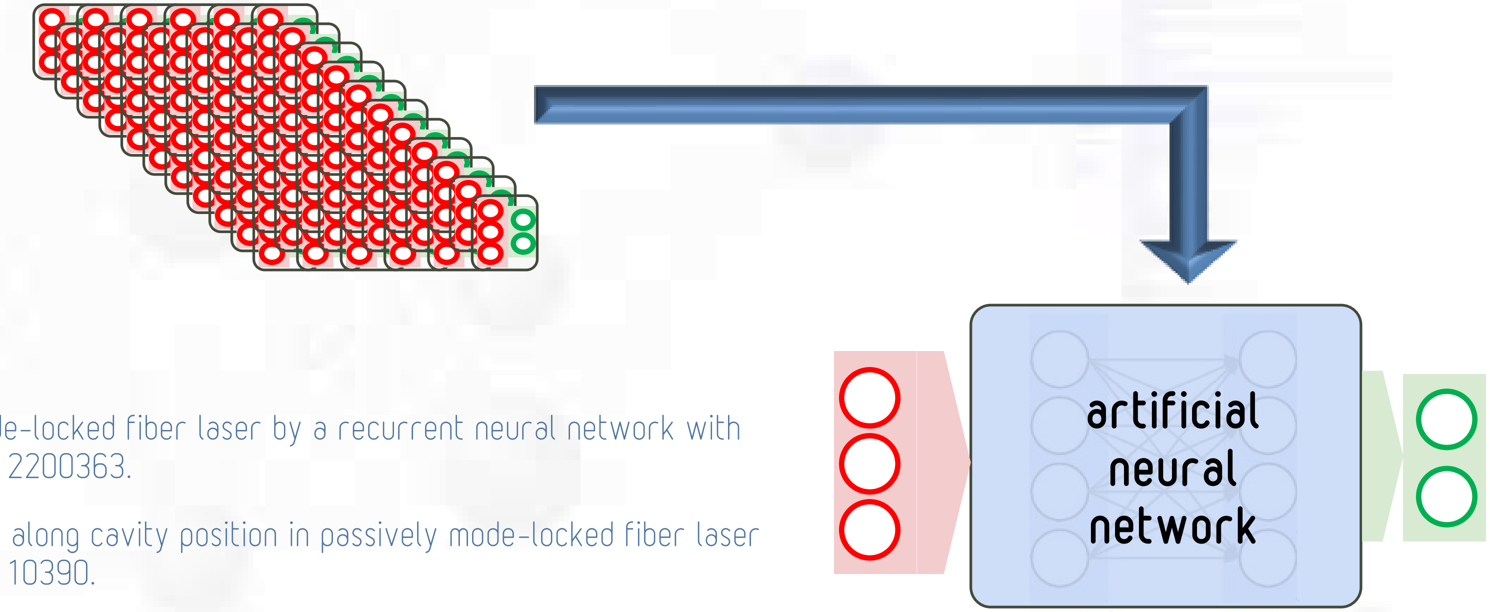
ANN are also suitable for lasers, cavities and resonators

physical models are the complex Ginzburg-Landau equation, the Luigiato-Lefever equation or lumped model

$$i\,\psi_{\xi} + \frac{D}{2}\psi_{\tau\tau} + |\psi|^2\,\psi + \eta|\psi|^4\,\psi = i\,\Theta\,\psi + i\,\epsilon|\psi|^2\,\psi + i\,\beta\,\psi_{\tau\tau} + i\mu|\psi|^4\,\psi$$

$$\frac{\partial\psi(t,\tau)}{\partial t} = -(1+i\Delta)\psi + i\,|\psi|^2\,\psi - i\frac{\partial^2\psi}{\partial\tau^2} + F$$

new dataset
for training

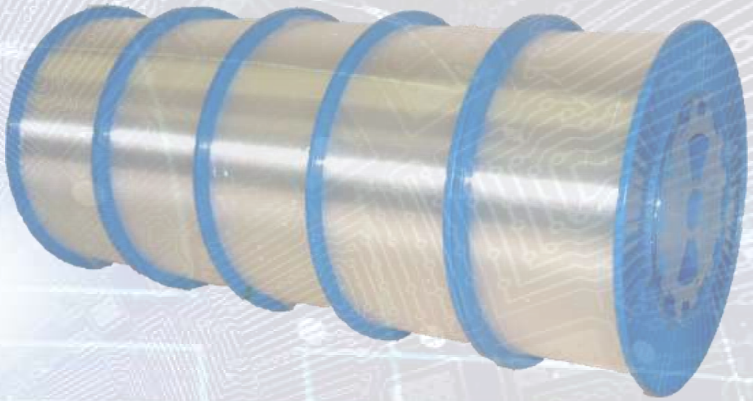


Pu, G. et al. "Fast predicting the complex nonlinear dynamics of mode-locked fiber laser by a recurrent neural network with prior information feeding." Laser & Photonics Reviews 17.6 (2023): 2200363.

Han, Dongdong, et al. "Predicting evolutions of pulse characteristics along cavity position in passively mode-locked fiber laser via SSA-LSTM approach." Optics & Laser Technology 171 (2024): 110390.

Huang, Ti, et al. "Rapid prediction of complex nonlinear dynamics in kerr resonators using the recurrent neural network." *Frontiers of Optoelectronics* 18.1 (2025): 19.

Machine learning for output predictions

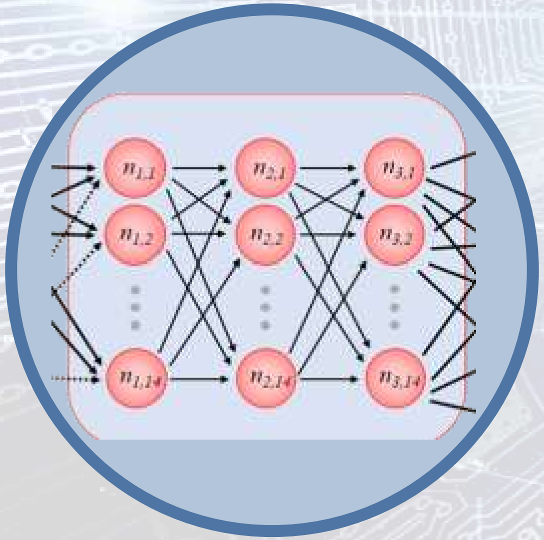


nonlinear reshaping

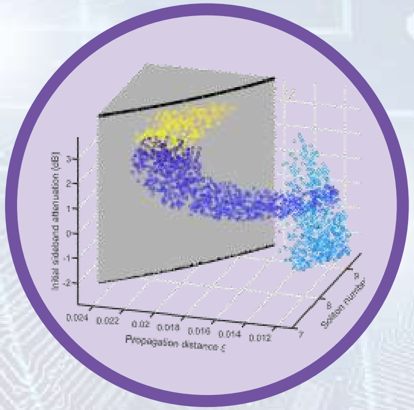
ideal four-wave mxing

frequency combs

more complex systems

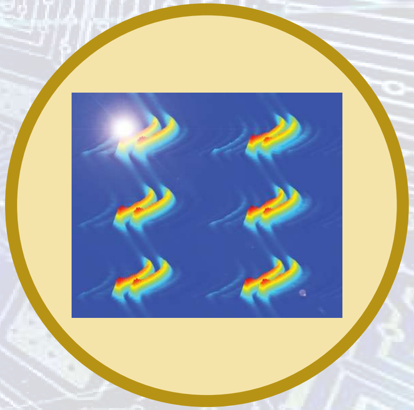


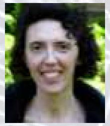
Machine learning for inverse design



Machine learning for physics insights

Machine learning for smart lasers

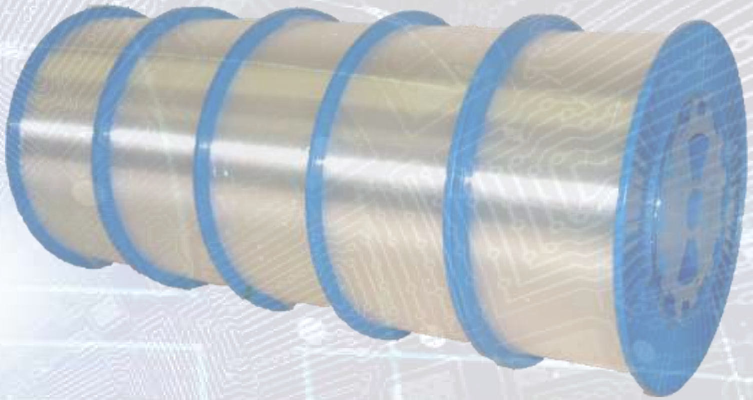


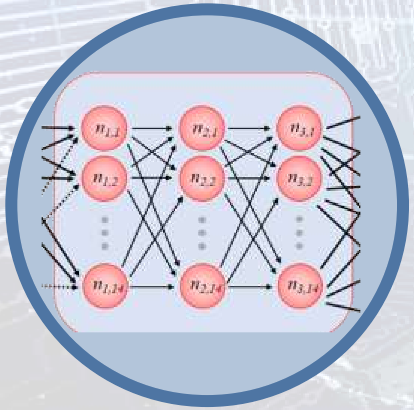

Machine learning for inverse design

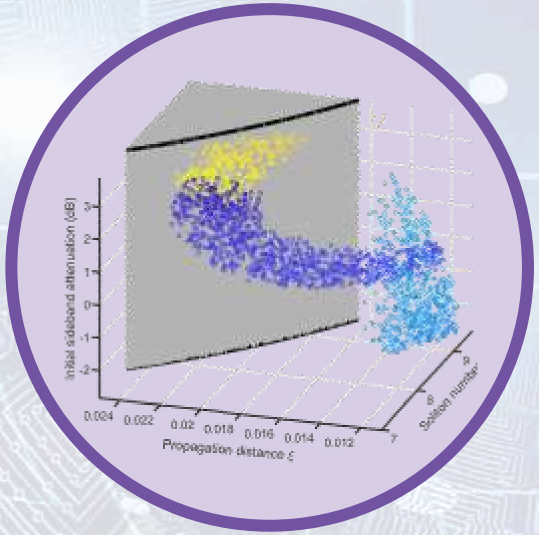
nonlinear reshaping

combs



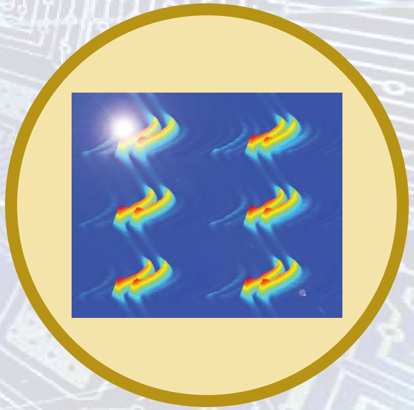
Machine learning for output predictions





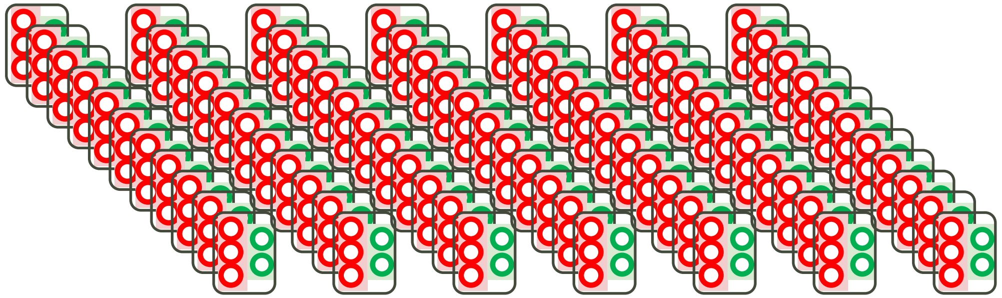
Machine learning for physics insights

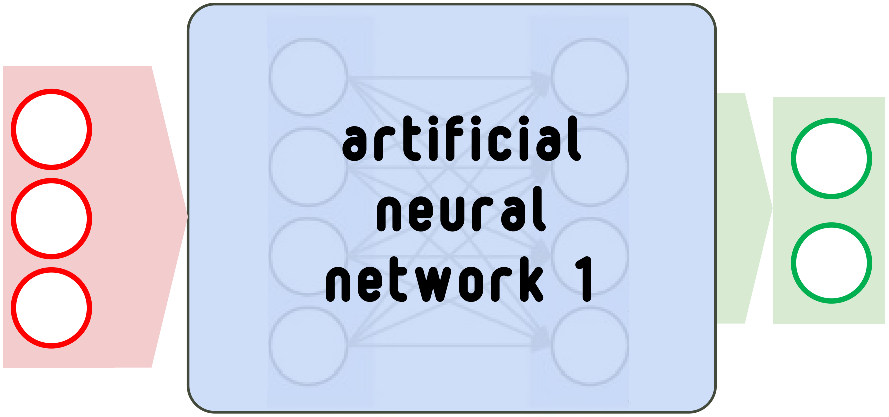
Machine learning for smart lasers

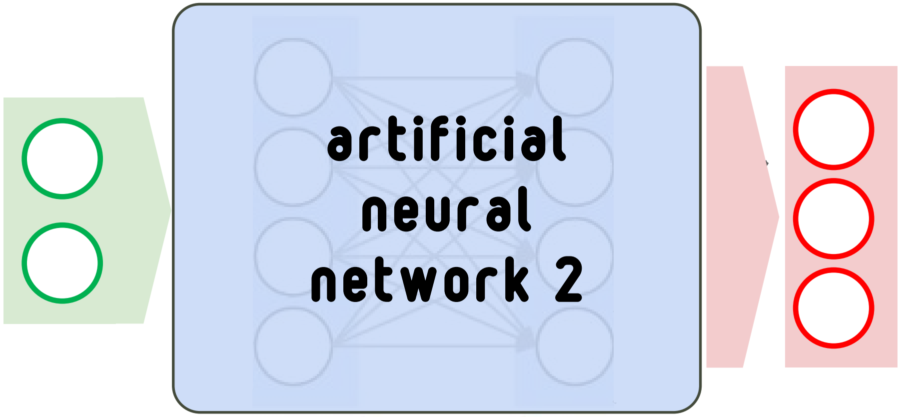


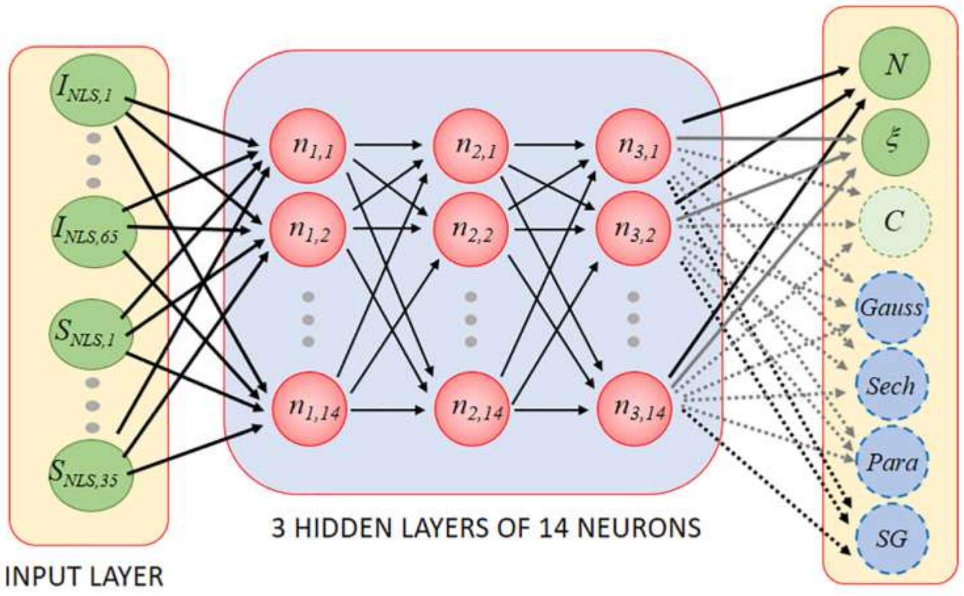
you want to find the parameters that provide you a given profile or given output properties.

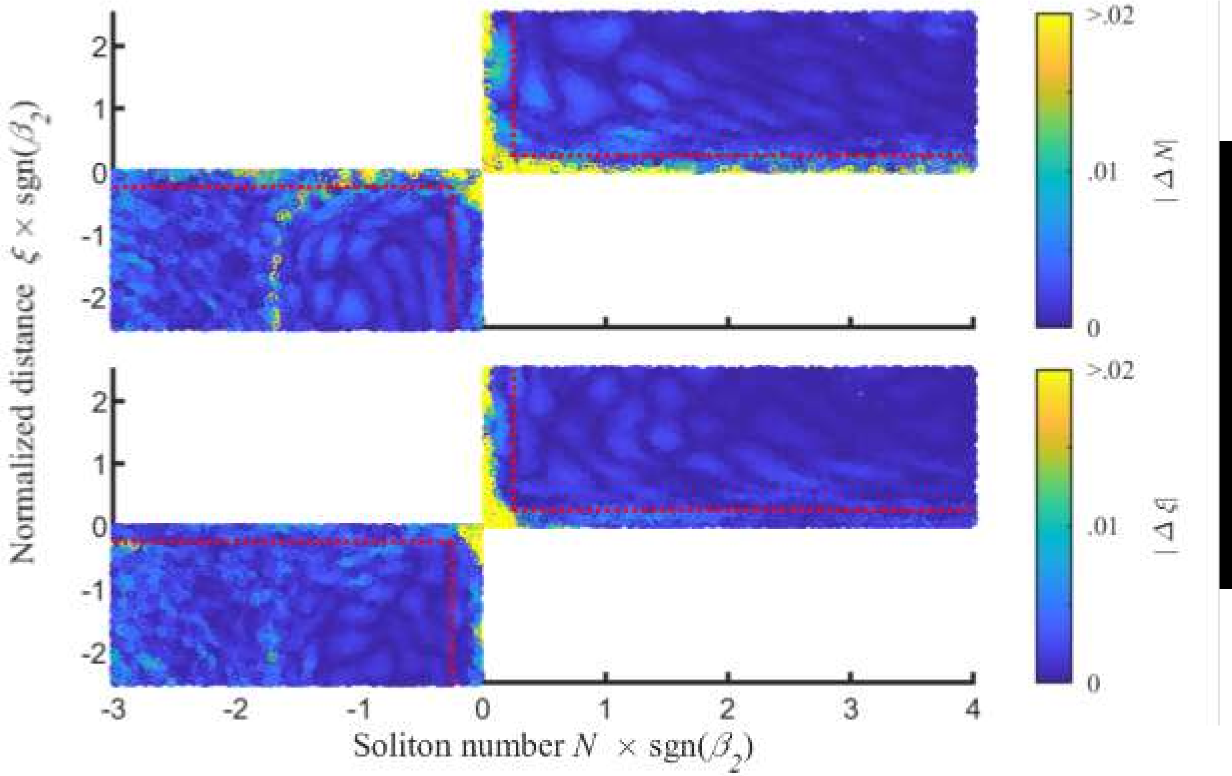
first strategy



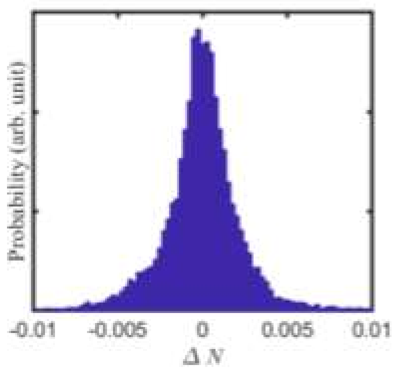








INPUT GAUSSIAN PULSE

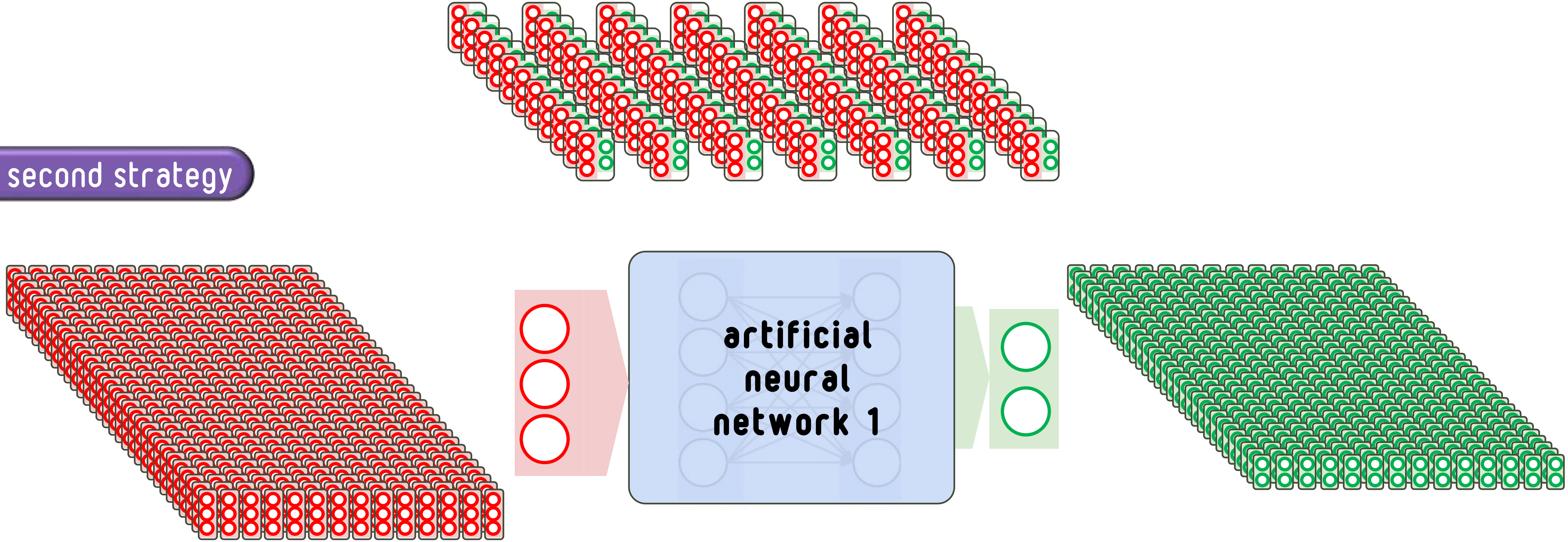


The neural network efficiently retrieves the input pulse properties from the knowledge of the output profile.

S Boscolo, C Finot, *Artificial neural networks for nonlinear pulse shaping in optical fibers*, Opt. Laser Technol. 131, 106439 (2020)

S. Boscolo, J. M. Dudley, and C. Finot, *Modelling self-similar parabolic pulses in optical fibres with a neural network*, Results in Optics, 100066 (2021).

second strategy



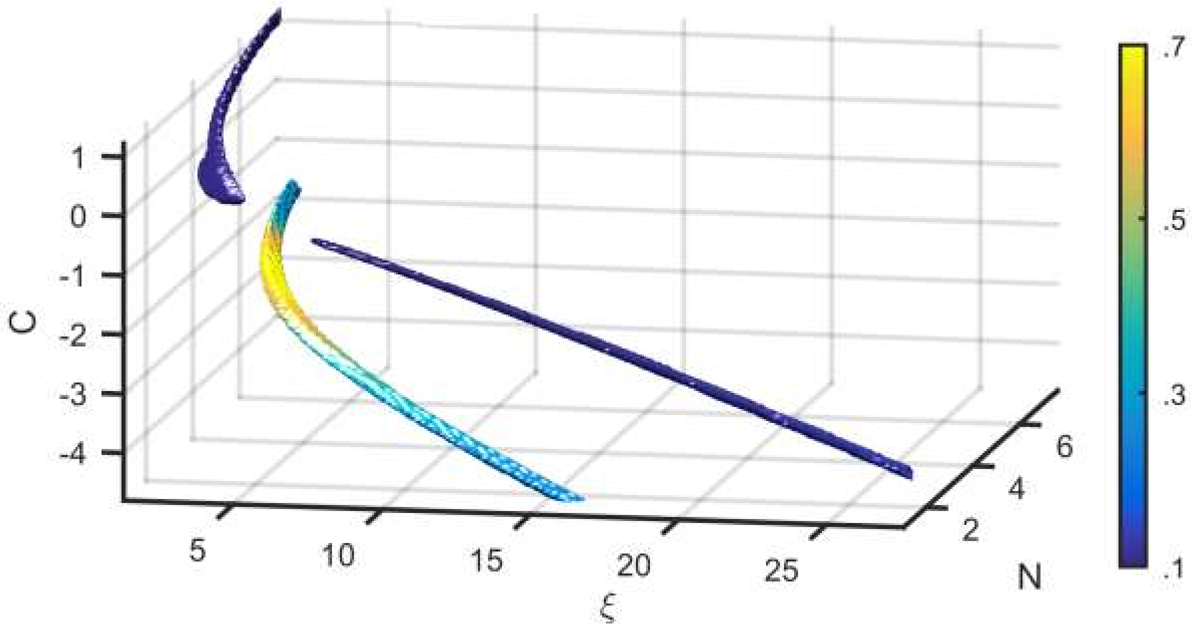
ANN are incredibily fast

million outputs in a few minutes

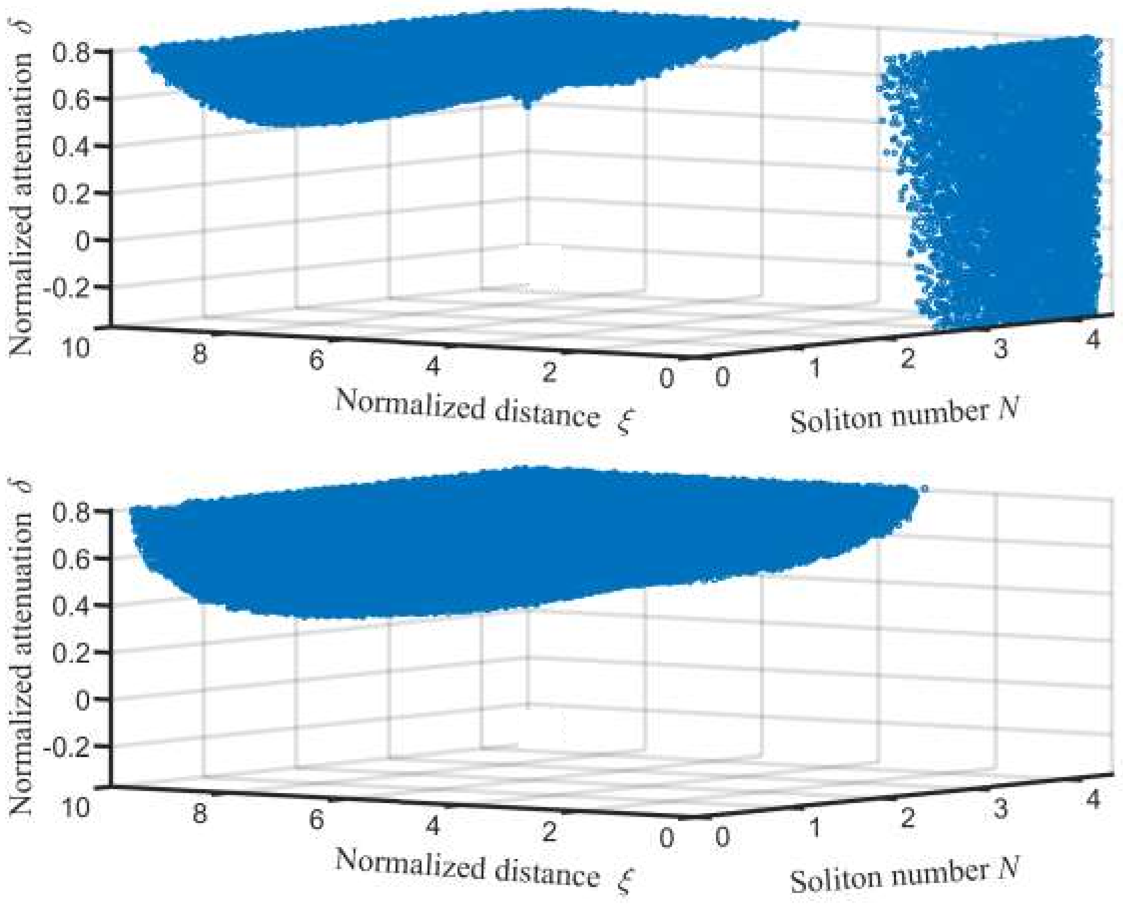
the space of parameters can be explored and a cost function evaluated in each point

the input parameters that fulfill the target can be isolated

mapping of the generation
ofchirp-free parabolic pulses with a given duration

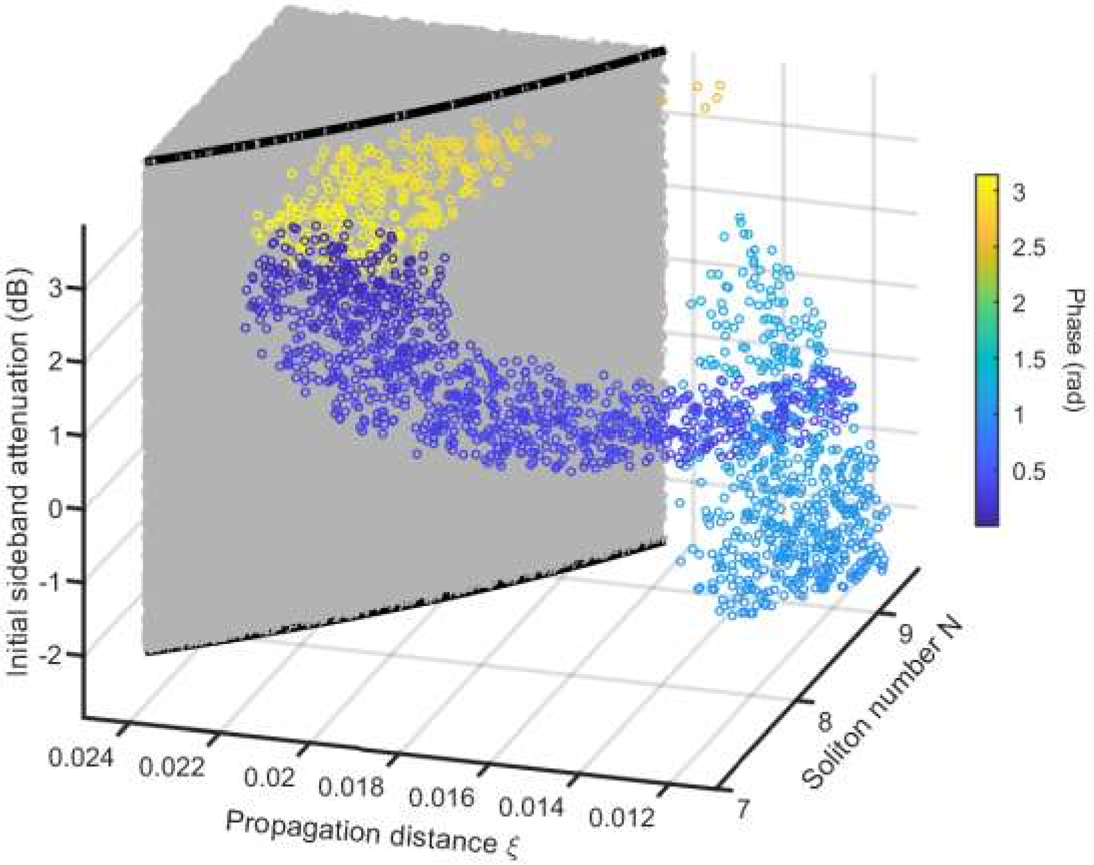


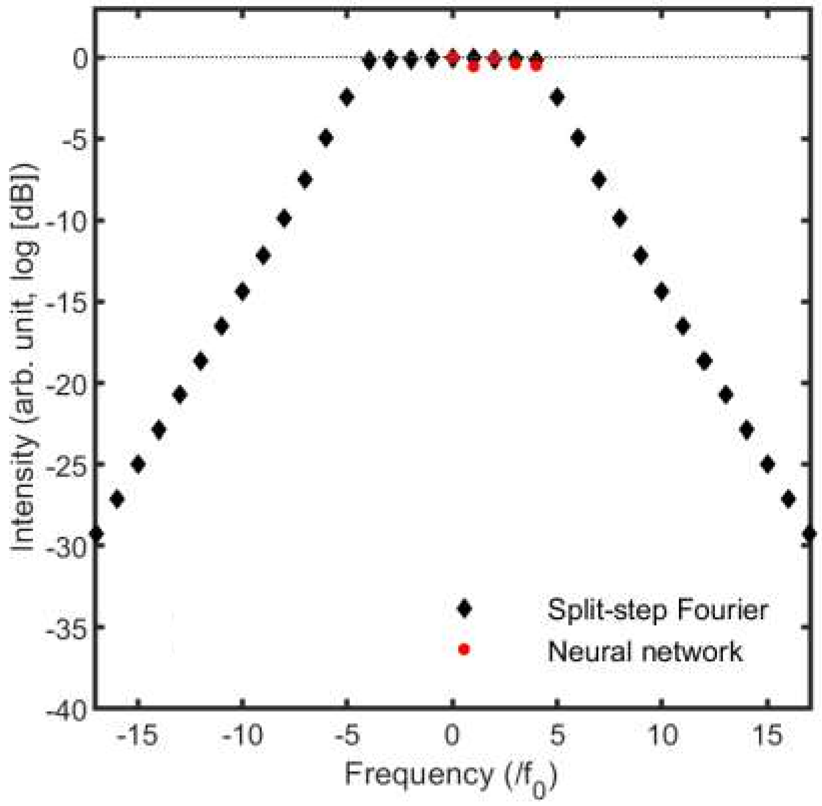
mapping of the generation
of self-similar parabolic pulses



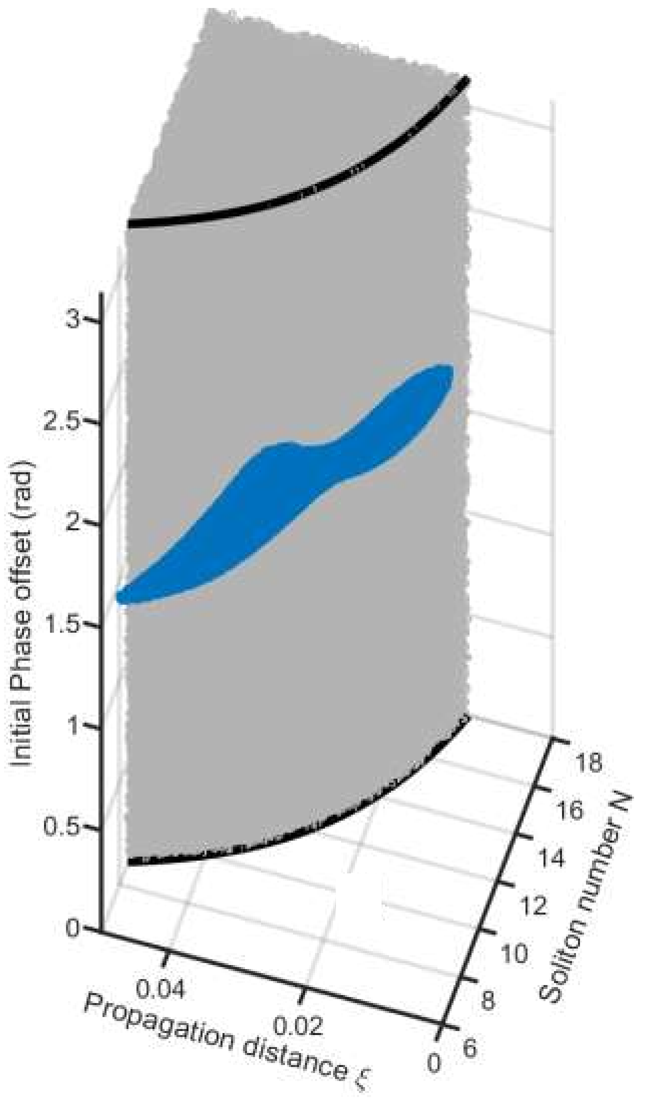
C. Finot, I. Gukov, K. Hammani, S. Boscolo. *Nonlinear sculpturing of optical pulses with normally dispersive fiber-based devices*. Opt. Fiber Technol. 45, 306 (2018)

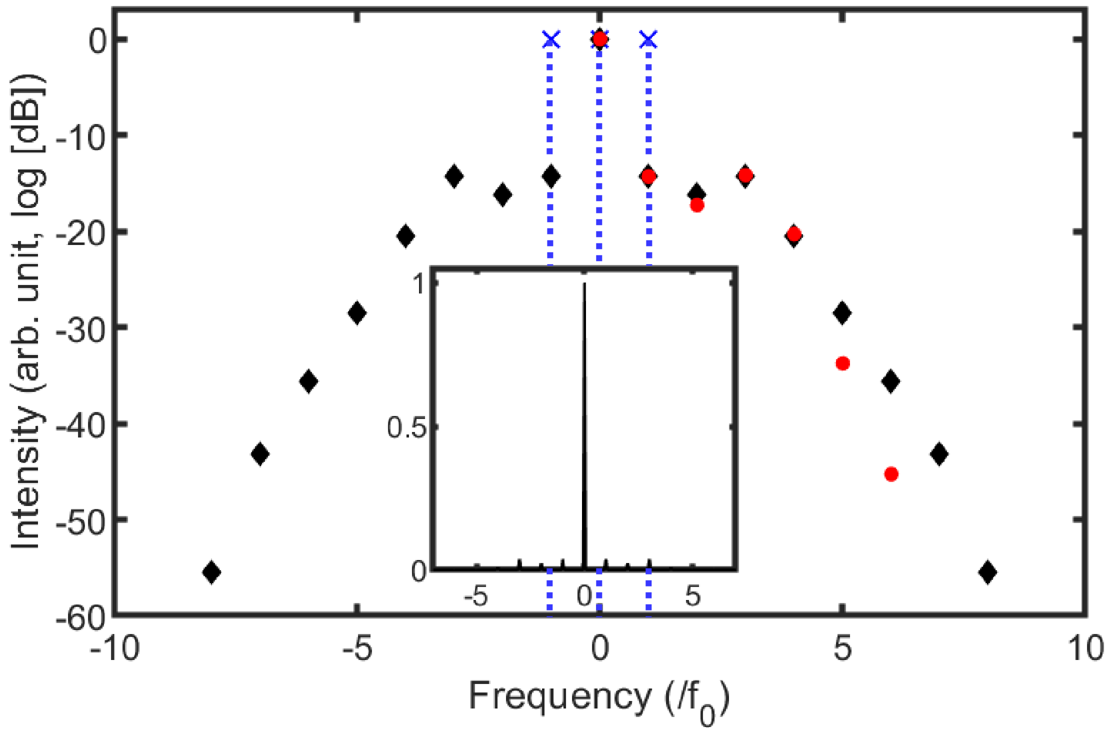
S. Boscolo, J. M. Dudley, and C. Finot. *Modelling self-similar parabolic pulses in optical fibres with a neural network*. Results in Optics, 100066 (2021)



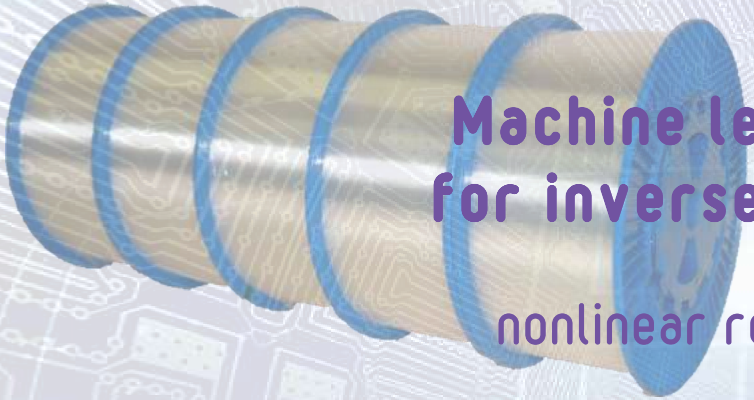


The full space of parameters can be covered very quickly.





Optimal conditions for inverse four-wave mixing can be found.

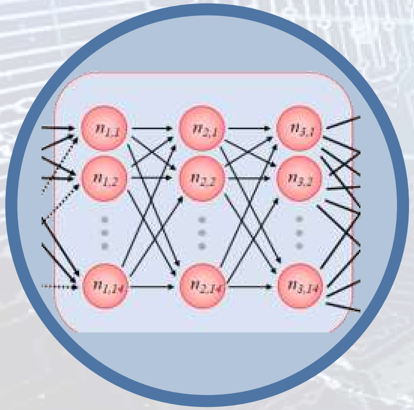


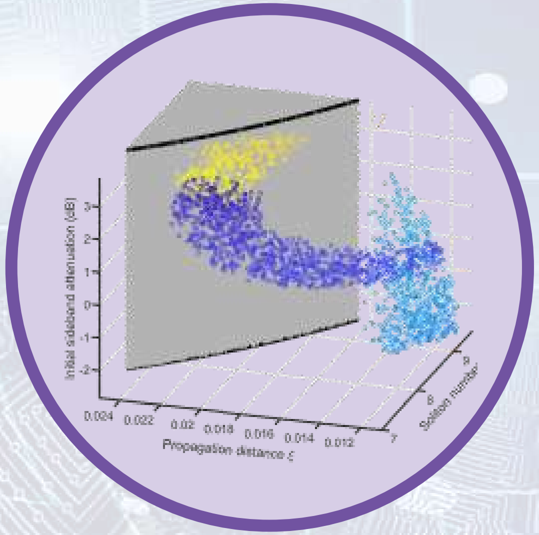
Machine learning for inverse design

nonlinear reshaping

combs

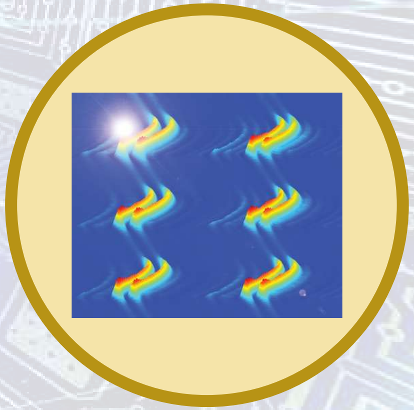
Machine learning for output predictions

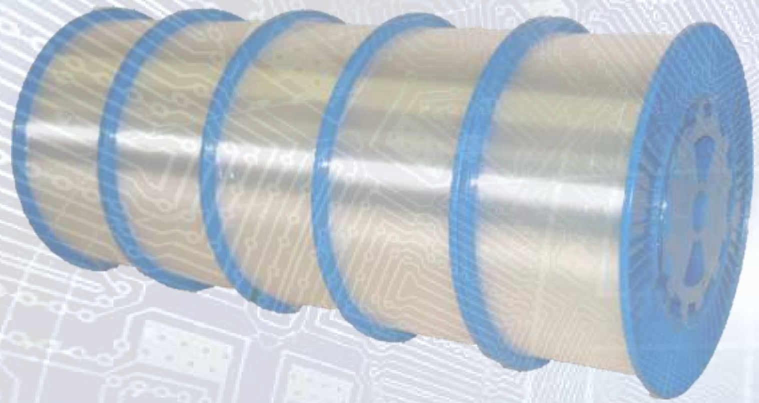




Machine learning for physics insights

Machine learning for smart lasers





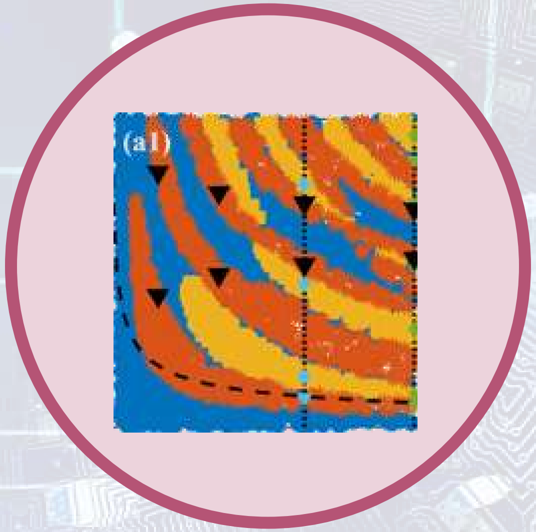
Machine learning for physics insights

data driven discovery

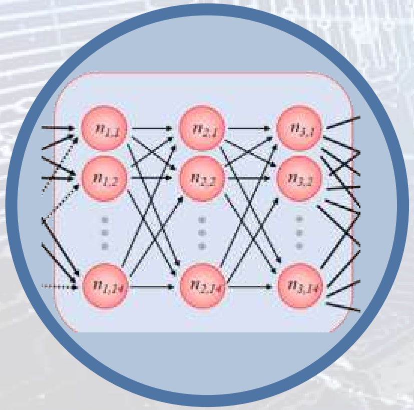
clustering

dominant balance

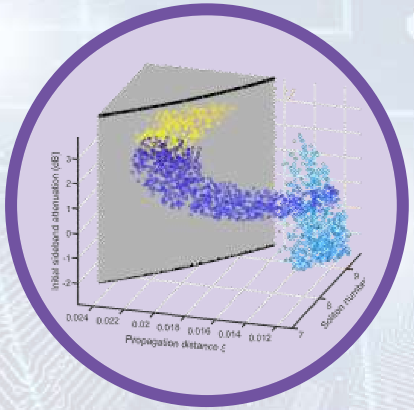
SINDY



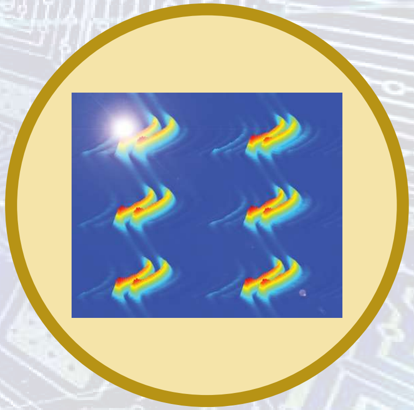
Machine learning for output predictions

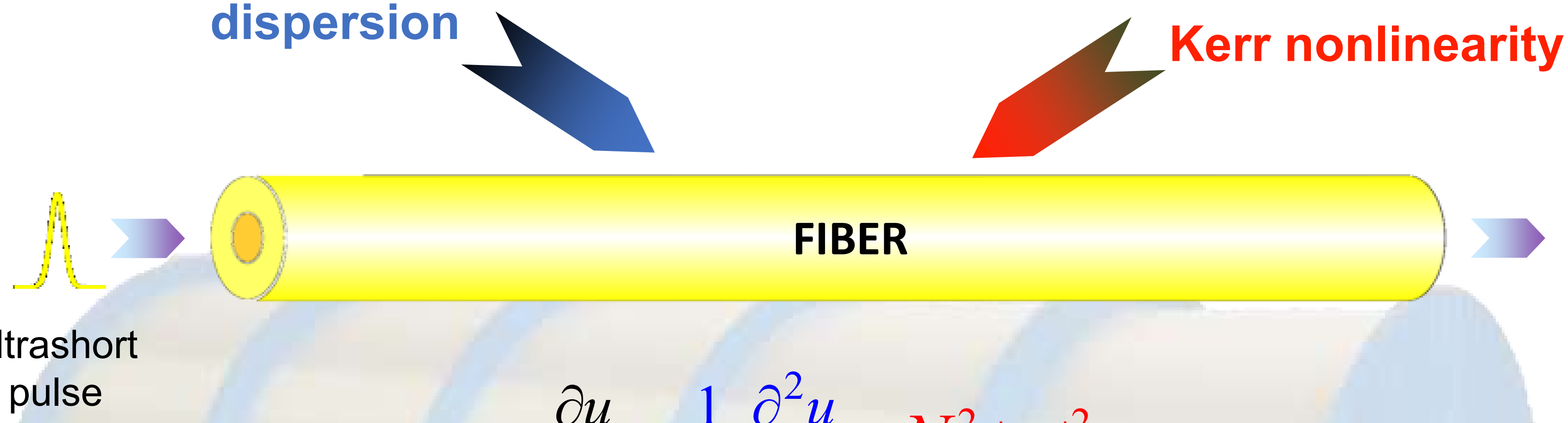


Machine learning for inverse design

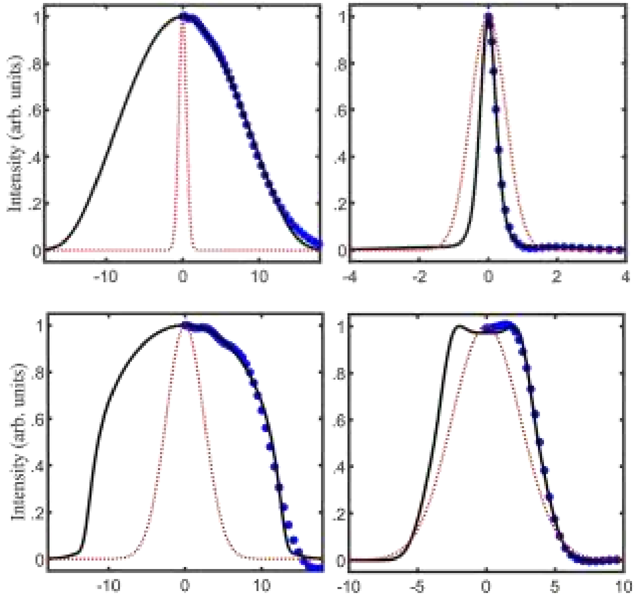


Machine learning for smart lasers





$$i\frac{\partial u}{\partial \xi} = \frac{1}{2}\frac{\partial^2 u}{\partial \tau^2} - N^2 |u|^2 u$$



many different output shapes are generated.

many different dynamics are experienced.

Can machine learning help to classify these shapes using unsupervised clustering ?

K-means algorithm

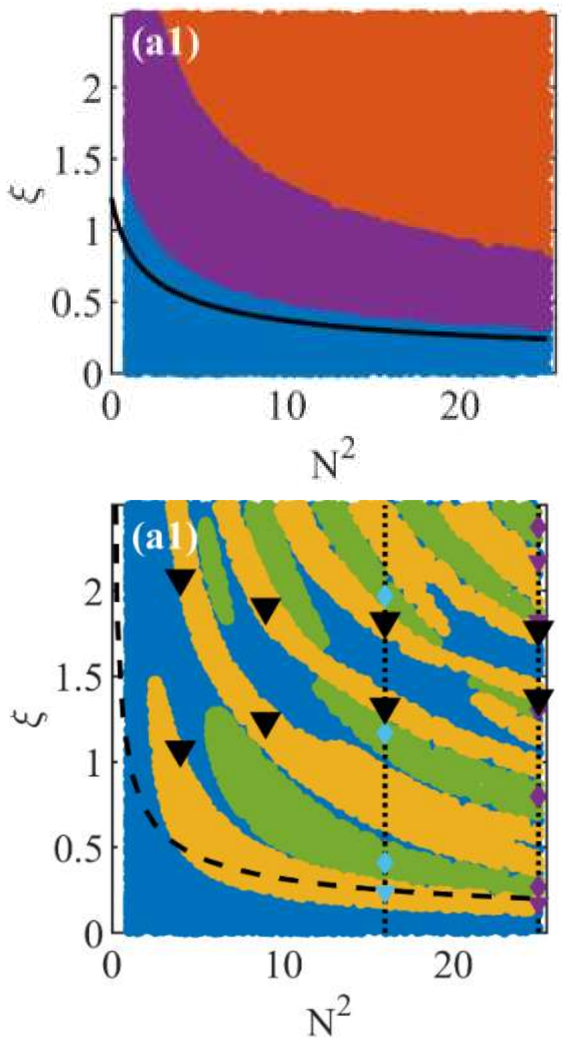
S. Lloyd *Least Squares Quantization in PCM.* IEEE Trans. Inf. Theory, 28 129 (1982)

Does it have a physical meaning ?

A. Sheveleva, A. V. Ermolaev, J. M. Dudley, and C. Finot, *Unsupervised classification of non-linear dynamics in optical fiber propagation using intensity clustering*. Physica D: Nonlinear Phenomena 472, 134502 (2025).

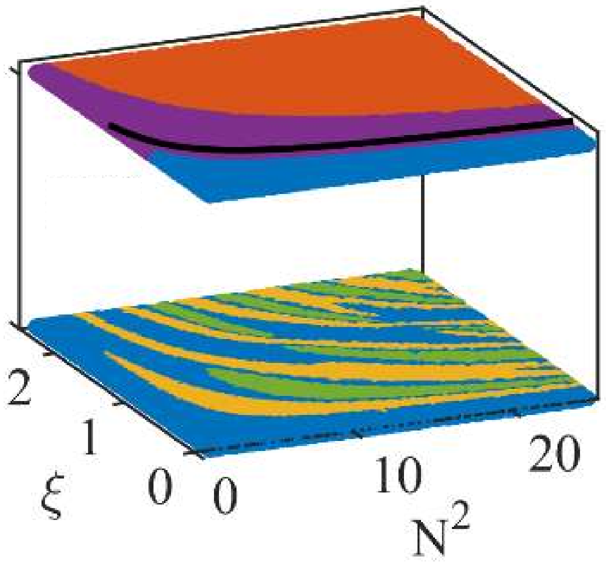
normal dispersion

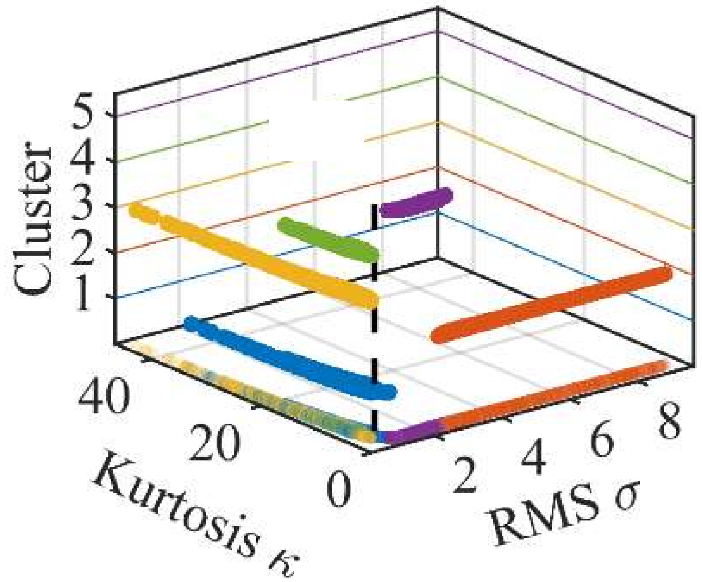
anomalous dispersion



normal dispersion

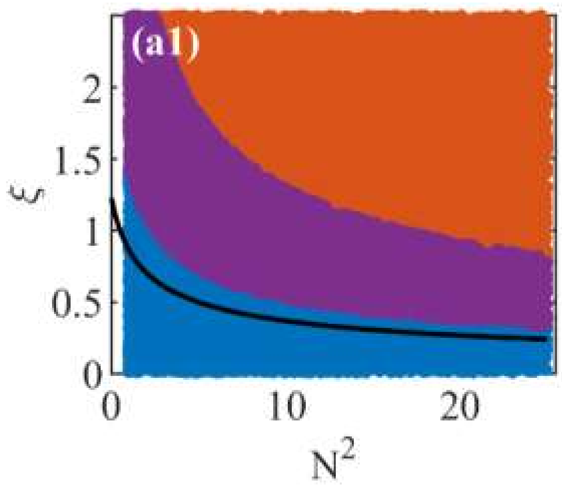
anomalous dispersion



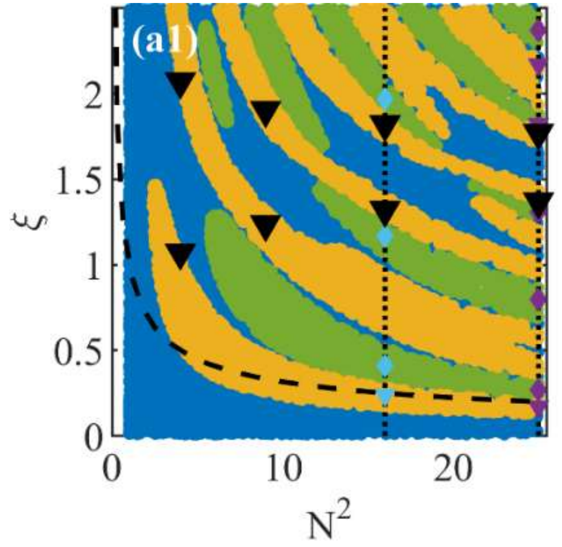


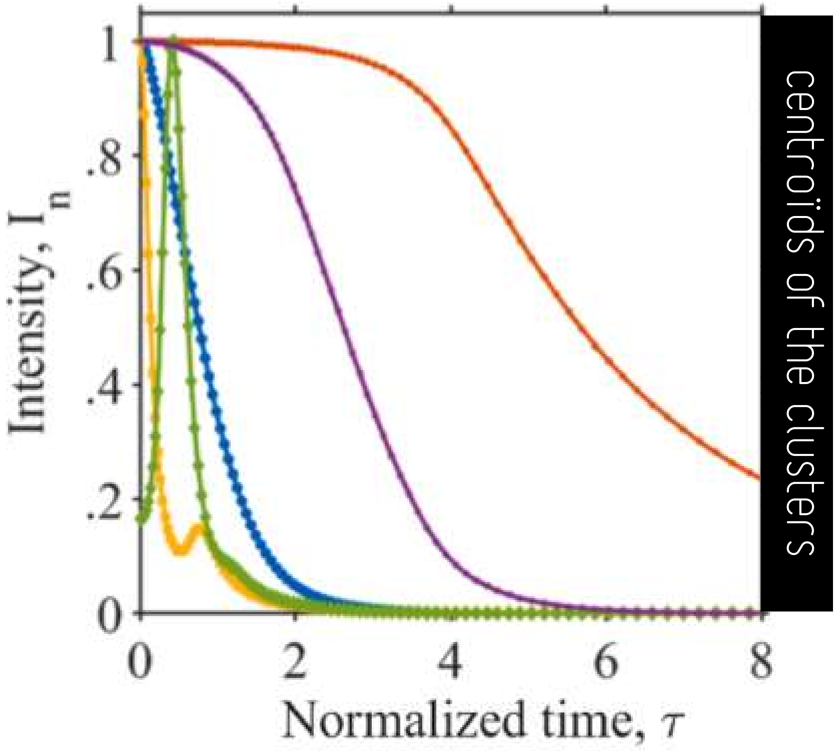
Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
no temporal change	spectronic regime	pulse compression	pulse splitting	wave-breaking stage

Unsupervised techniques based on classifications of the temporal intensity profiles only normal dispersion



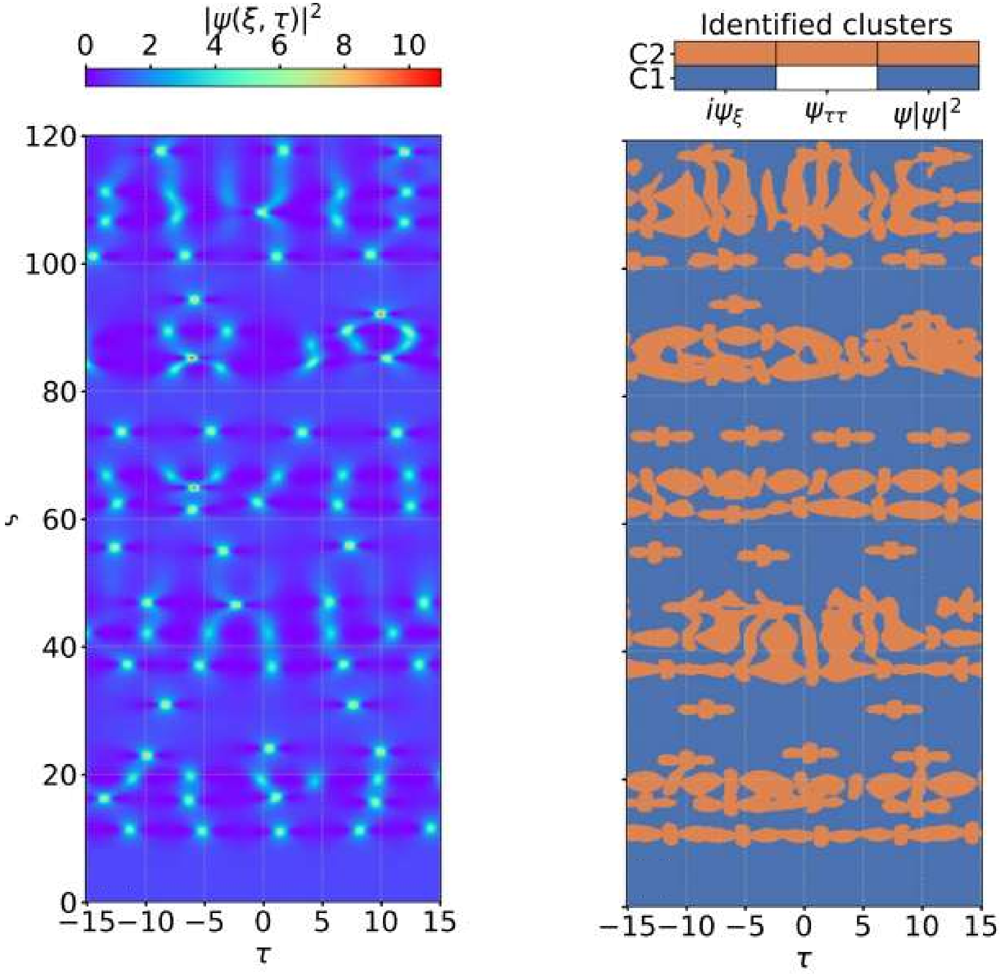
anomalous dispersion





Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
no temporal change	spectronic regime	pulse compression	pulse splitting	wave-breaking stage

Unsupervised techniques based on classifications of the temporal intensity profiles only.



The data-driven dominant balance locally highlights the main contribution to the modulation instability process.

Kerr nonlinearity is locally dominant

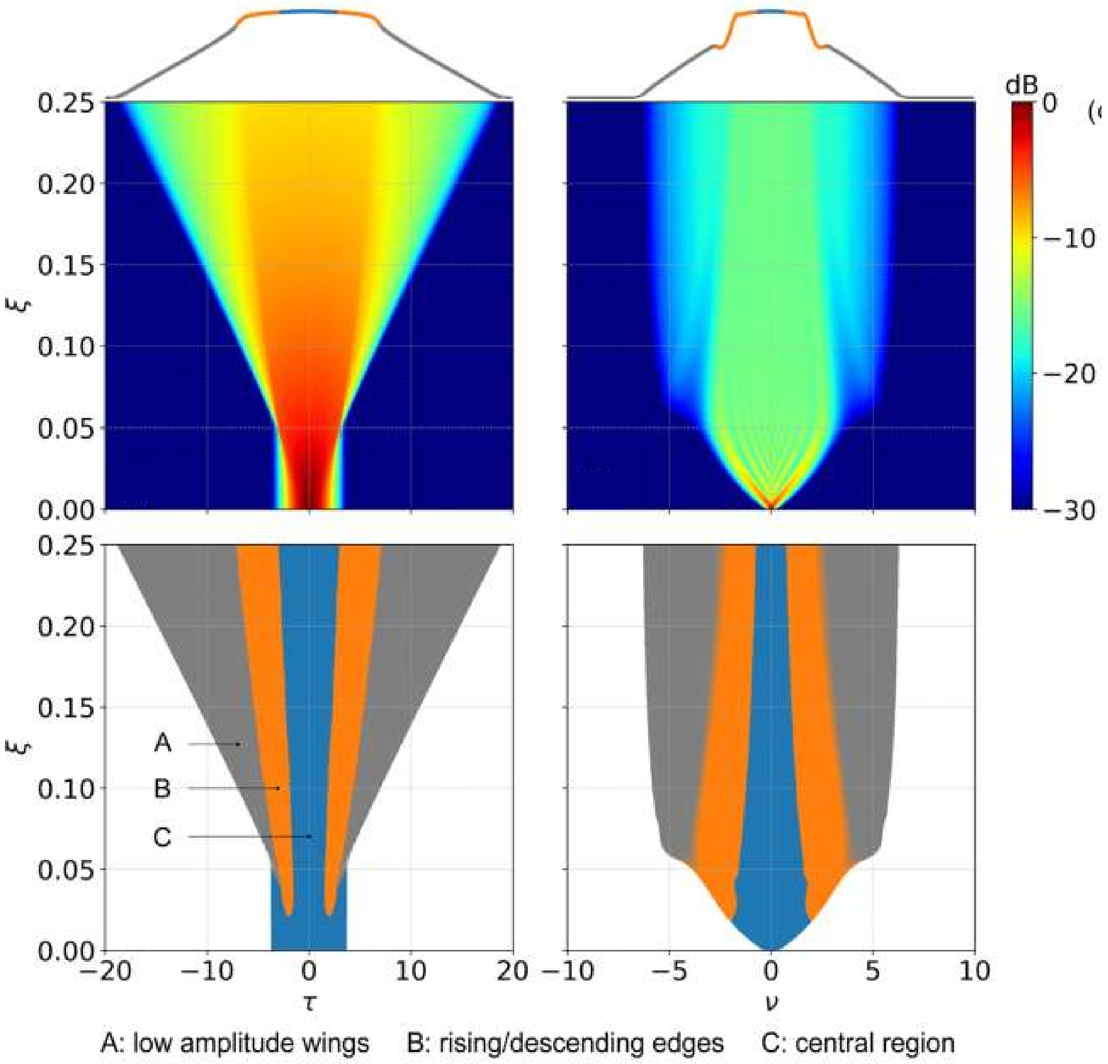
$$i\frac{\partial u}{\partial \xi} = \frac{1}{2}\frac{\partial^2 u}{\partial \tau^2} - N^2 |u|^2 u$$

Both effects are essential

A. V. Ermolaev, M. Mabed, C. Finot, G. Genty, and J. M. Dudley, *Analysis of interaction dynamics and rogue wave localization in modulation instability using data-driven dominant balance*, Sci. Rep. 13, 10462 (2023)

J. L. Callaham, J. V. Koch, B. W. Brunton, J. N. Kutz, and S. L. Brunton, *Learning dominant physical processes with data-driven balance models* Nat. Commun. 12, 1016 (2021)

The process can be extended to other regimes of dispersion and include higher-order terms.



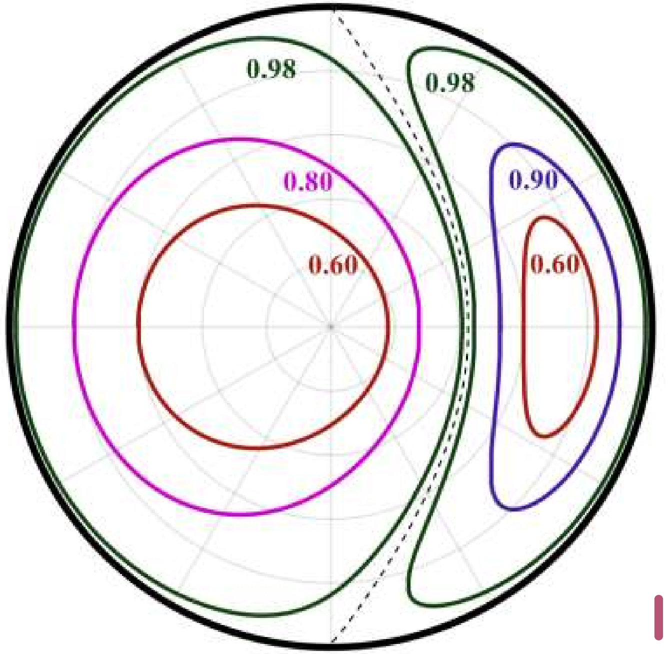
$$i\frac{\partial u}{\partial \xi} = \frac{1}{2}\frac{\partial^2 u}{\partial \tau^2} - N^2 |u|^2 u$$

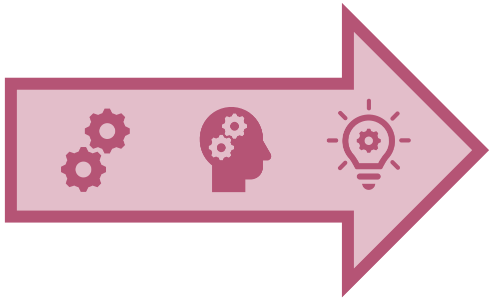
dispersion is locally dominant

Kerr nonlinearity is locally dominant

Both effects are essential

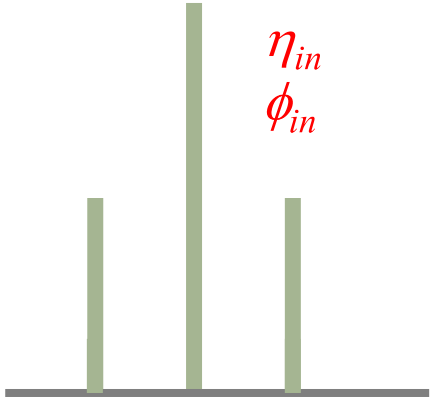
A. V. Ermolaev, C. Finot, G. Genty, and J. M. Dudley, *Automating physical intuition in nonlinear fiber optics with unsupervised dominant balance search*, Opt. Lett., 4202 (2024).





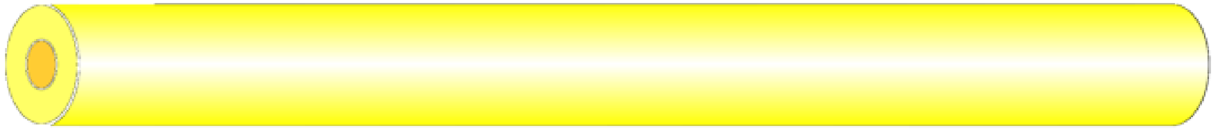
$$\begin{cases} \dfrac{d\eta}{d\xi} = \dot{\eta} = 2\,\eta^2 \sin\phi - 2\,\eta \sin\phi \\ \dfrac{d\phi}{d\xi} = \dot{\phi} = -3 - 2\cos\phi + 3\,\eta + 4\,\eta\cos\phi \end{cases}$$

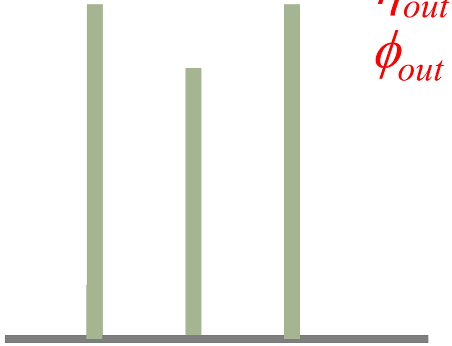
Is this possible to retrieve the underlying equations from the orbits ?



η_{in}
ϕ_{in}

$$\begin{cases} \eta = |\psi_0|^2 / P_T \\ \phi = \varphi_1 + \varphi_{-1} - 2\,\varphi_0 \end{cases}$$





η_{out}
ϕ_{out}

S. Trillo, S. Wabnitz, *Dynamics of the nonlinear modulational instability in optical fibers*, Opt. Lett., 16 986 (1991) what we want to retrieve

$$\begin{cases} \dot{\eta} = 2\,\eta^2 \sin\phi - 2\,\eta \sin\phi \\ \dot{\phi} = -3 - 2\cos\phi + 3\,\eta + 4\,\eta\cos\phi \end{cases}$$

what we know

$$\mathbf{X} = \begin{pmatrix} \eta(\xi_1) & \phi(\xi_1) \\ \eta(\xi_2) & \phi(\xi_2) \\ \vdots & \vdots \\ \eta(\xi_m) & \phi(\xi_m) \end{pmatrix}$$

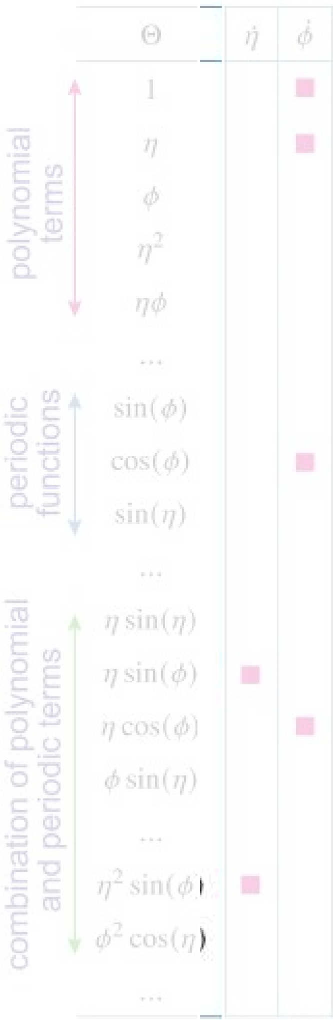
multiple trajectories

estimation of the derivative matrix

$$\dot{\mathbf{X}} = \begin{pmatrix} \dot{\eta}(\xi_1) & \dot{\phi}(\xi_1) \\ \dot{\eta}(\xi_2) & \dot{\phi}(\xi_2) \\ \vdots & \vdots \\ \dot{\eta}(\xi_m) & \dot{\phi}(\xi_m) \end{pmatrix}$$

multiple trajectories

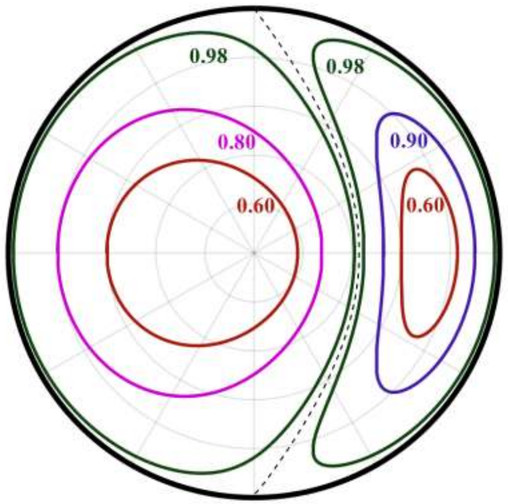
Library function



Sindy output

RHS candidates	x0'	x1'
1	0.000000000	-2.999999304
x0	0.000000000	2.999998855
x1	0.000000000	0.000000000
x0^2	0.000000000	0.000000000
x0x1	0.000000000	0.000000000
...		
sin(x1)	0.000000000	0.000000000
cos(x1)	0.000000000	-1.999997466
sin(x0)	0.000000000	0.000000000
...		
x0 sin(x0)	0.000000000	0.000000000
x0 sin(x1)	-1.999998381	0.000000000
x0 cos(x1)	0.000000000	3.999996344
x1 sin(x0)	0.000000000	0.000000000
...		
x0^2 sin(x1)	1.999998092	0.000000000
x1^2 cos(x0)	0.000000000	0.000000000
...		

sparse identification of nonlinear dynamics
SINDy

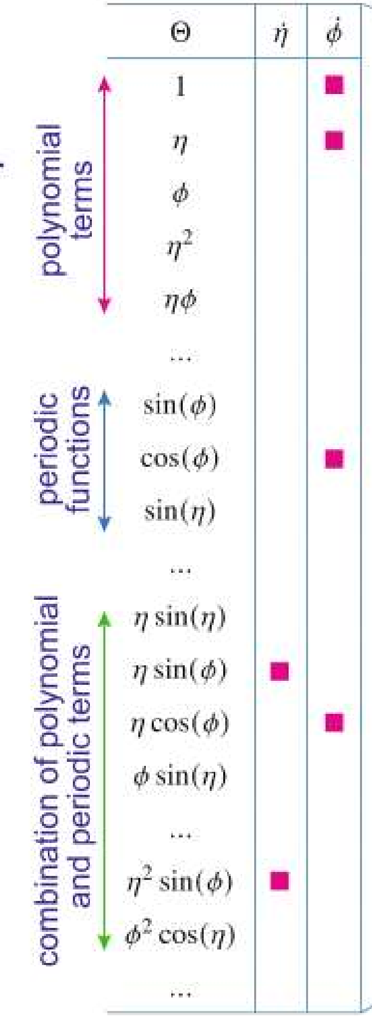


YouTube

S.L. Brunton, J. L., Proctor & J. N. Kutz, *Discovering governing equations from data by sparse identification of nonlinear dynamical systems*. Proc. Natl. Acad. Sci. 113, 3932-3937 (2016).

S.L. Brunton & J. N. Kutz *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*

$$\begin{cases} \dot{\eta} = \boxed{2}\,\eta^2 \sin\phi \boxed{-2}\,\eta \sin\phi \\ \dot{\phi} = \boxed{-3}\boxed{-2}\cos\phi + \boxed{3}\,\eta + \boxed{4}\,\eta\cos\phi \end{cases}$$



RHS candidates	x0'	x1'
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x0 sin(x0)	0.000000000	0.000000000
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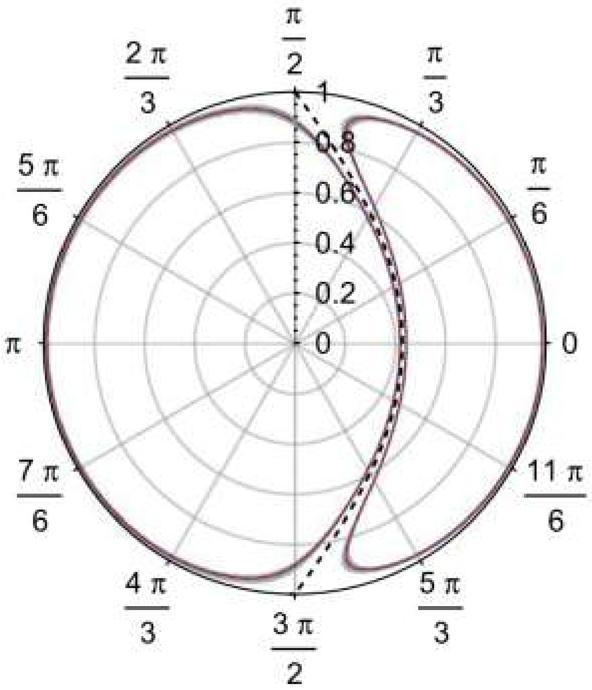
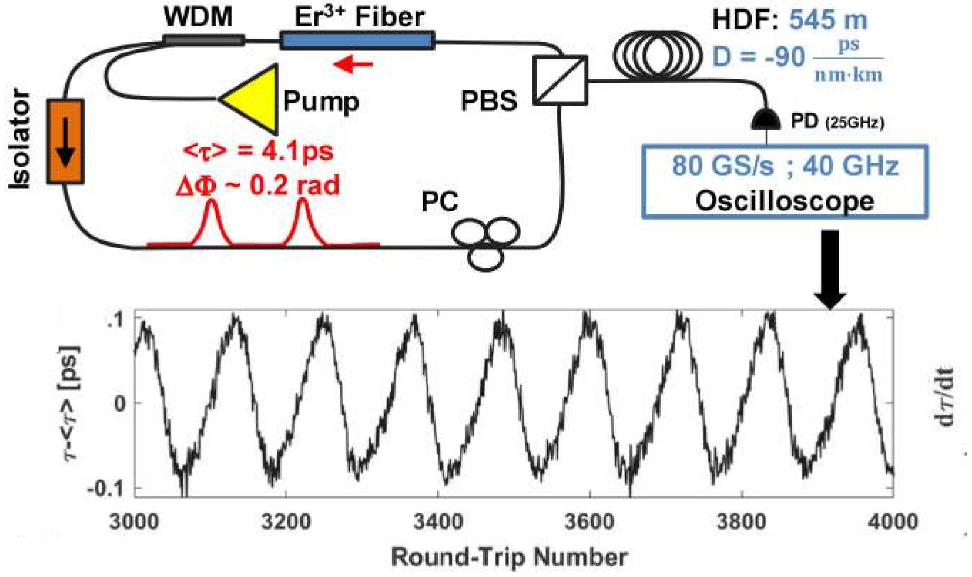
x1 sin(x0)	0.000000000	0.000000000
...		
x0^2 sin(x1)	1.999998092	0.000000000
x1^2 cos(x0)	0.000000000	0.000000000
...		

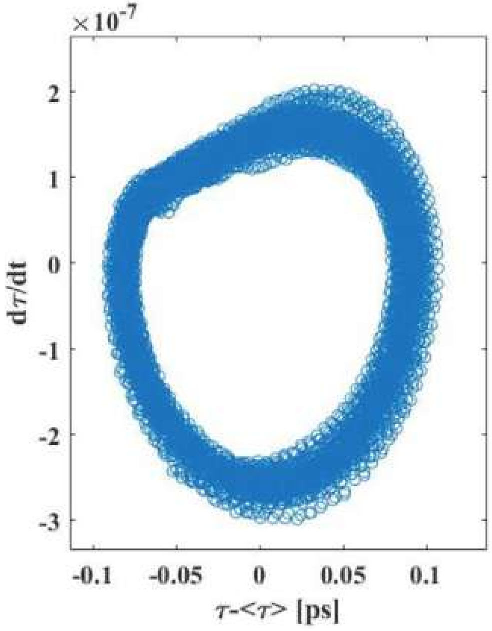


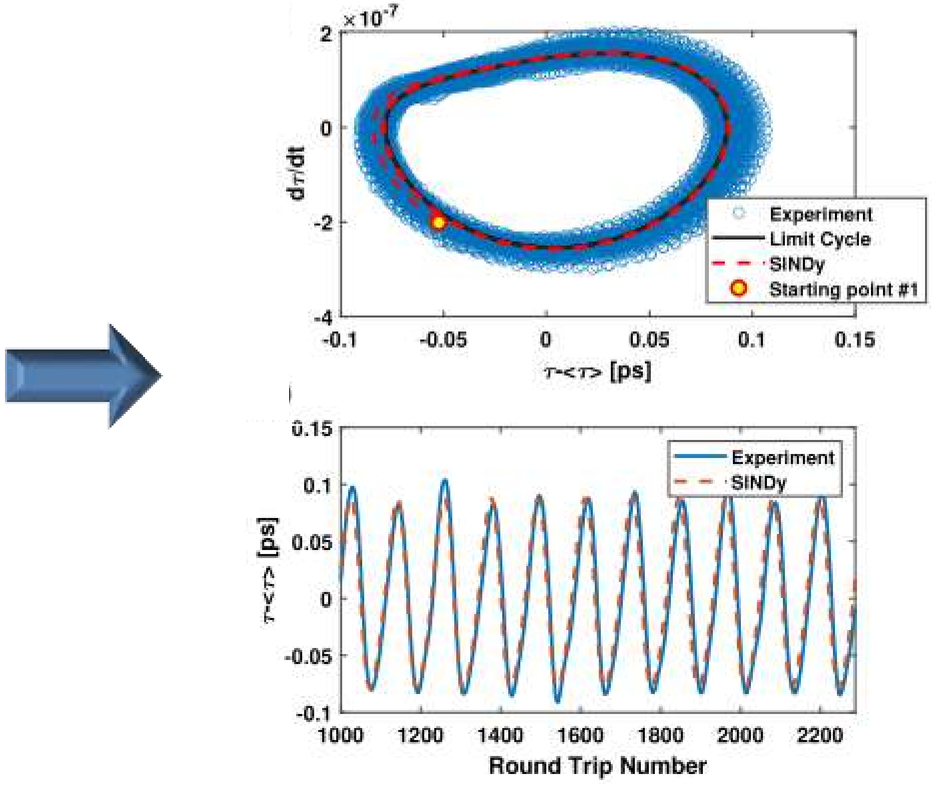
using noise free data

The process can be extended to noisy data.

A.V. Ermolaev, A. Sheveleva, G. Genty, C. Finot, J.M. Dudley, *Data-driven model discovery of ideal four-wave mixing in nonlinear fibre optics*, Scientific Reports 12 12711 (2022)

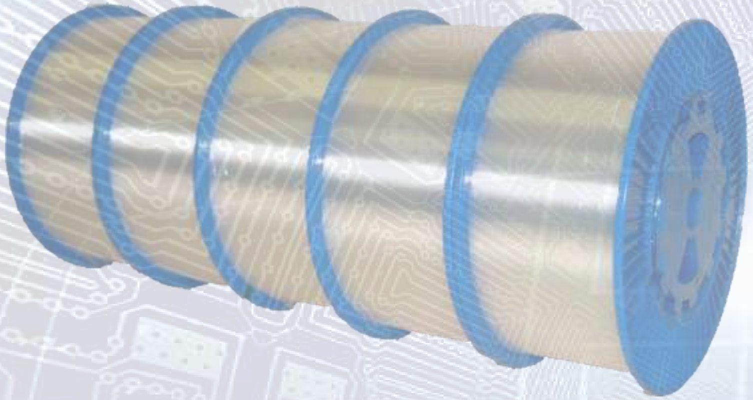






$$\frac{d^2u}{dt^2} = \xi_1 u + \xi_2 u^2 + \xi_3 u^5 + \dot{u}(\xi_4 u + \xi_5 u^2) + \dot{u}^2(\xi_6 u^2 + \xi_7 u^3)$$

A. Sheveleva, A. Coillet, C. Finot, and P. Colman, *Langevin's model for soliton molecules in ultrafast fiber ring laser cavity: Investigating experimentally the interplay between noise and inertia*, Chaos, Solitons & Fractals 197, 116472 (2025).



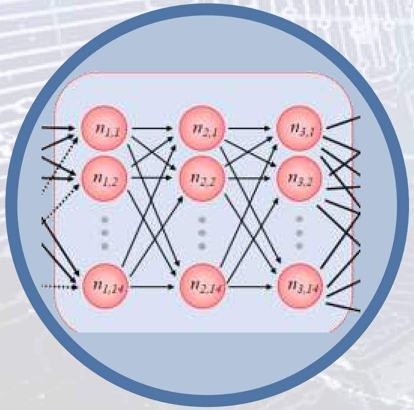
Machine learning for physics insights

clustering

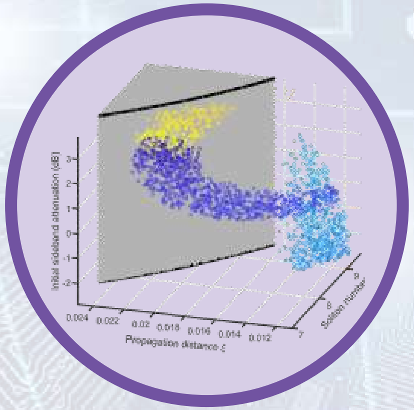
SINDY

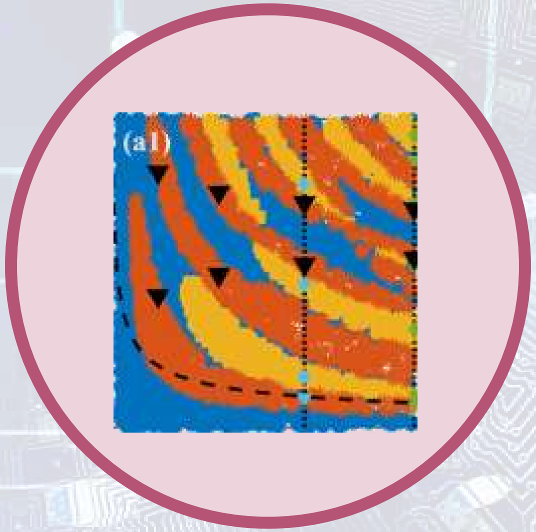
dominant balance

Machine learning for output predictions

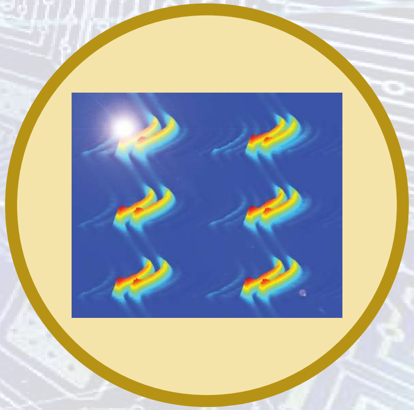


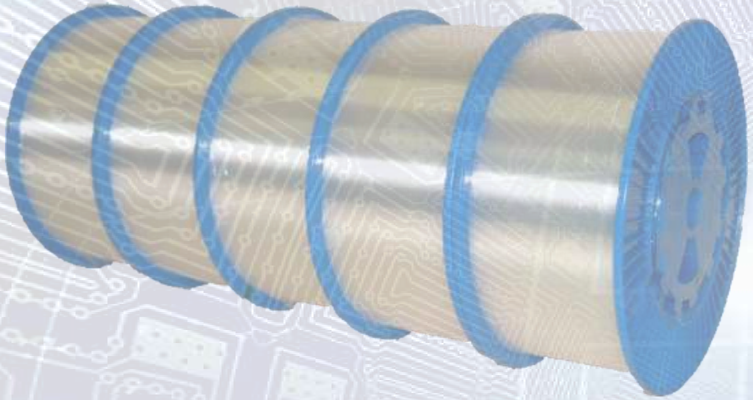
Machine learning for inverse design





Machine learning for smart lasers



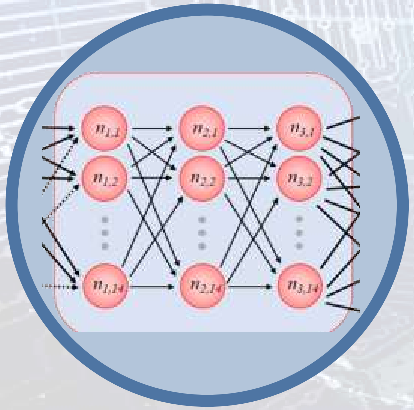


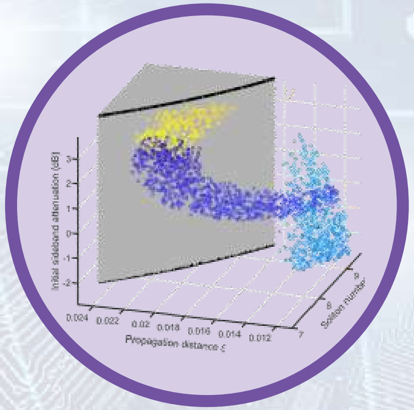
Machine learning for smart lasers

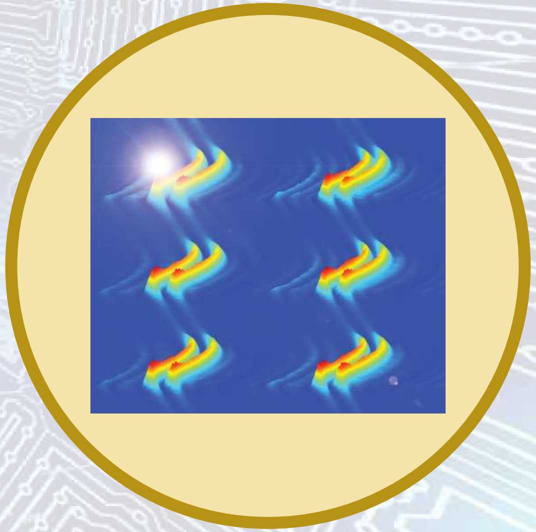
Machine learning for output predictions

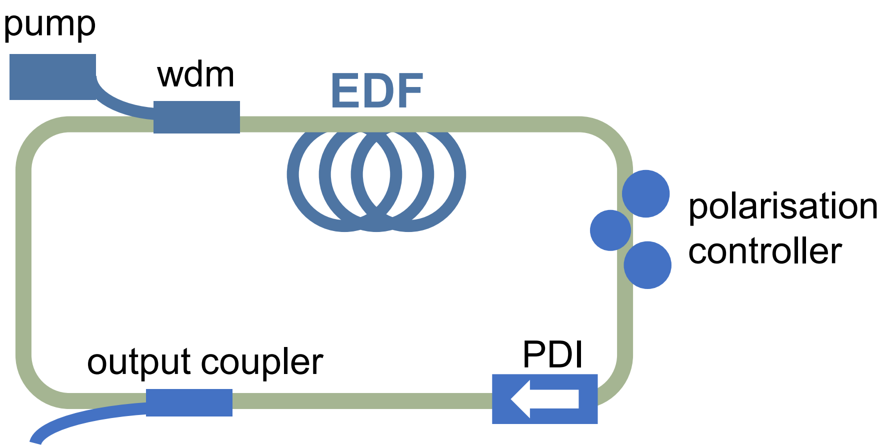
Machine learning for inverse design

Machine learning for physics insights







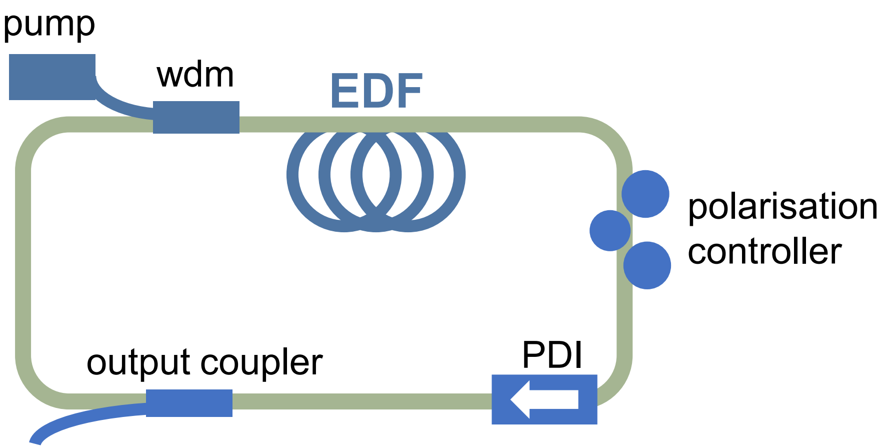


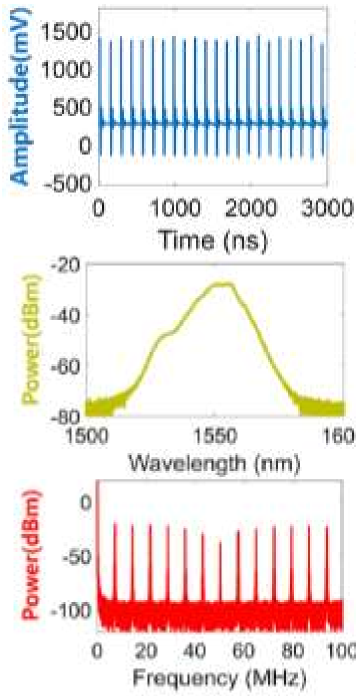
Ultrafast fiber lasers have enabled major progress in the field of laser thanks to their reduced cost, high stability, high power.

The nonlinear dynamics leading to dissipative solitons is a result of a balance between dispersion, Kerr nonlinearity, gain and losses.

Nonlinear polarization rotation is often used as a process achieve modeloncking. However, it requires manual and empirical adjustements of the waveplates.

The mode-locking of a fiber laser requires manual and empirical adjustements of the waveplates.





FML

pulses identical at each roundtrip — oscilloscope traces

spectrum identical at each roundtrip — optical spectra

RF spectral lines spaced by the repetition rate of the cavity — RF spectra


Letter — Vol. 2, No. 4 / April 2015 / Optica 279

optica

Fiber laser mode locked through an evolutionary algorithm

U. Andral,* R. Si Fodil, F. Amrani, F. Billard, E. Hertz, and P. Grelu


Research Article — Vol. 6, No. 3 / March 2019 / Optica 362

optica

Intelligent programmable mode-locked fiber laser with a human-like algorithm

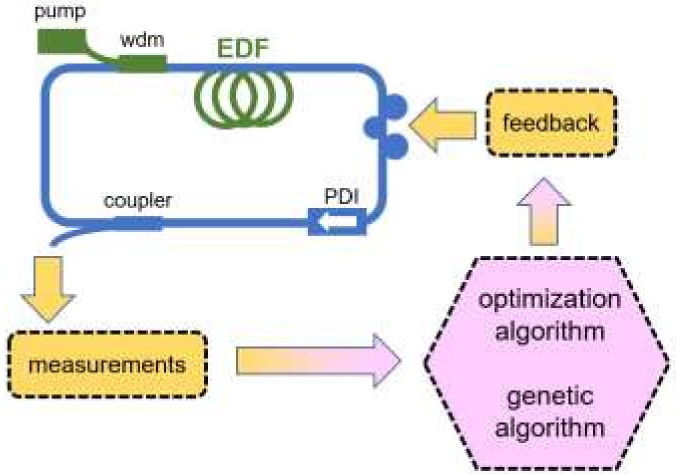
Guoqing Pu, Lilin Yi,* Li Zhang, and Weisheng Hu

M. Jiang et al. *Fiber laser development enabled by machine learning: review and prospect* PhotoniX 3 16 (2022): 16.

Q. Wu et al. *Advancements in ultrafast photonics: confluence of nonlinear optics and intelligent strategies*. Light Sci. Appl. 14 97 (2025)

J. H. Holland, *Adaptation in Natural and Artificial Systems.*

D. Simon, *Evolutionary Optimization Algorithms*



an individual

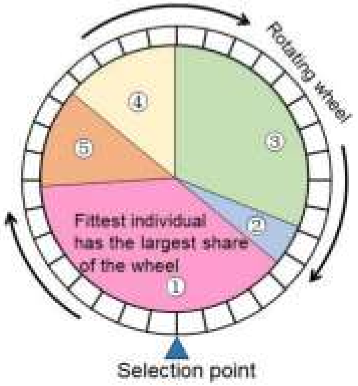
F_1	0.11	1.47	2.66	1.22
F_2	2.42	1.92	1.02	2.91
F_3	3.70	0.39	1.14	2.78
F_4	2.57	1.05	0.31	0.85

a gene

generate initial population → measurements → fitness function evaluation → termination condition satisfied ?

yes → 👍

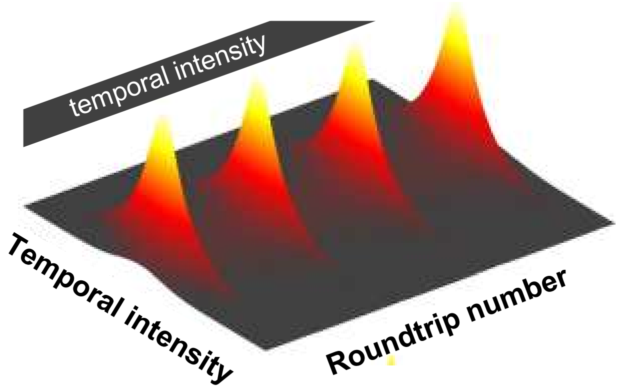
no → selection of the best individuals → crossover → mutation → new population → feedback → measurements



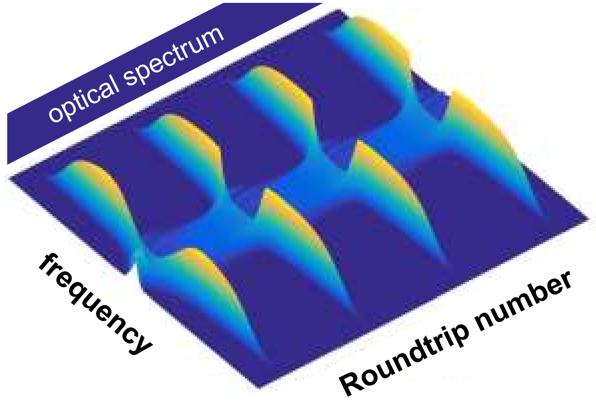
0.11	1.47	1.22
2.42	1.92	2.91
3.70	0.39	2.78
2.57	1.05	0.85

0.11	1.47
2.42	1.92
3.70	0.39
1.05	2.57

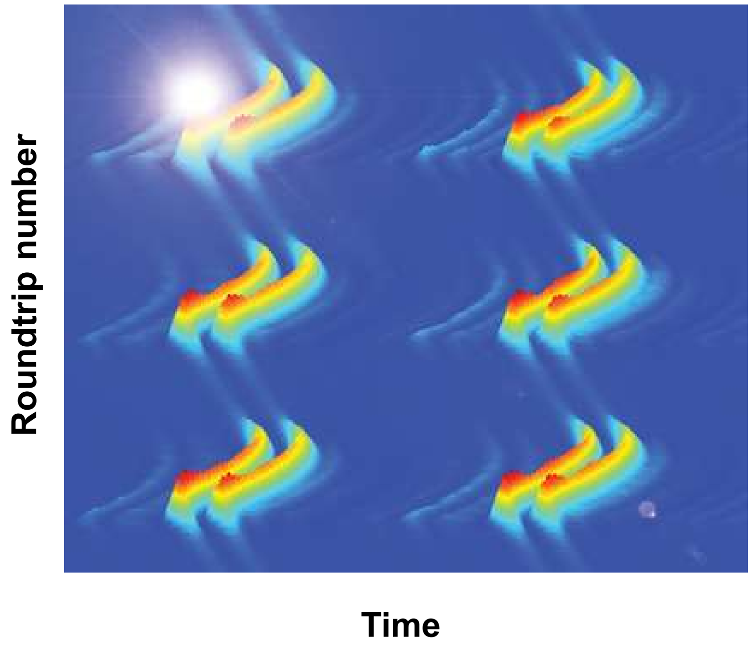
0.11		0.11
2.42	10111101011100	2.42
3.70	10110101011100	3.54
1.05		1.05

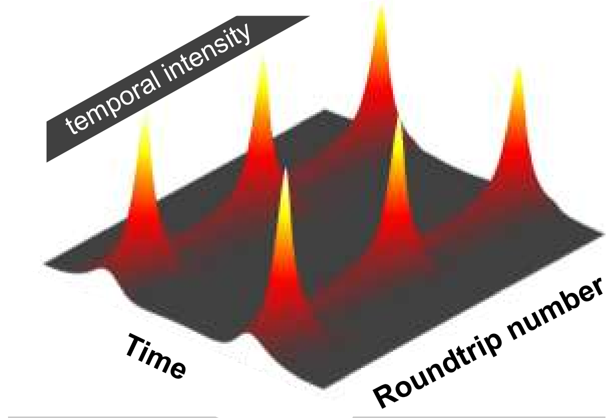


SINGLE BREATHER

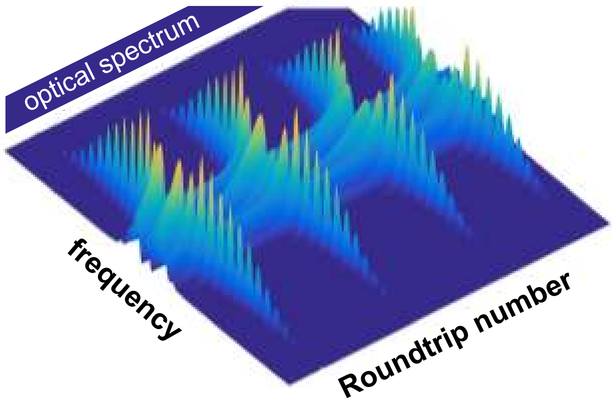


BREATHER MOLECULE

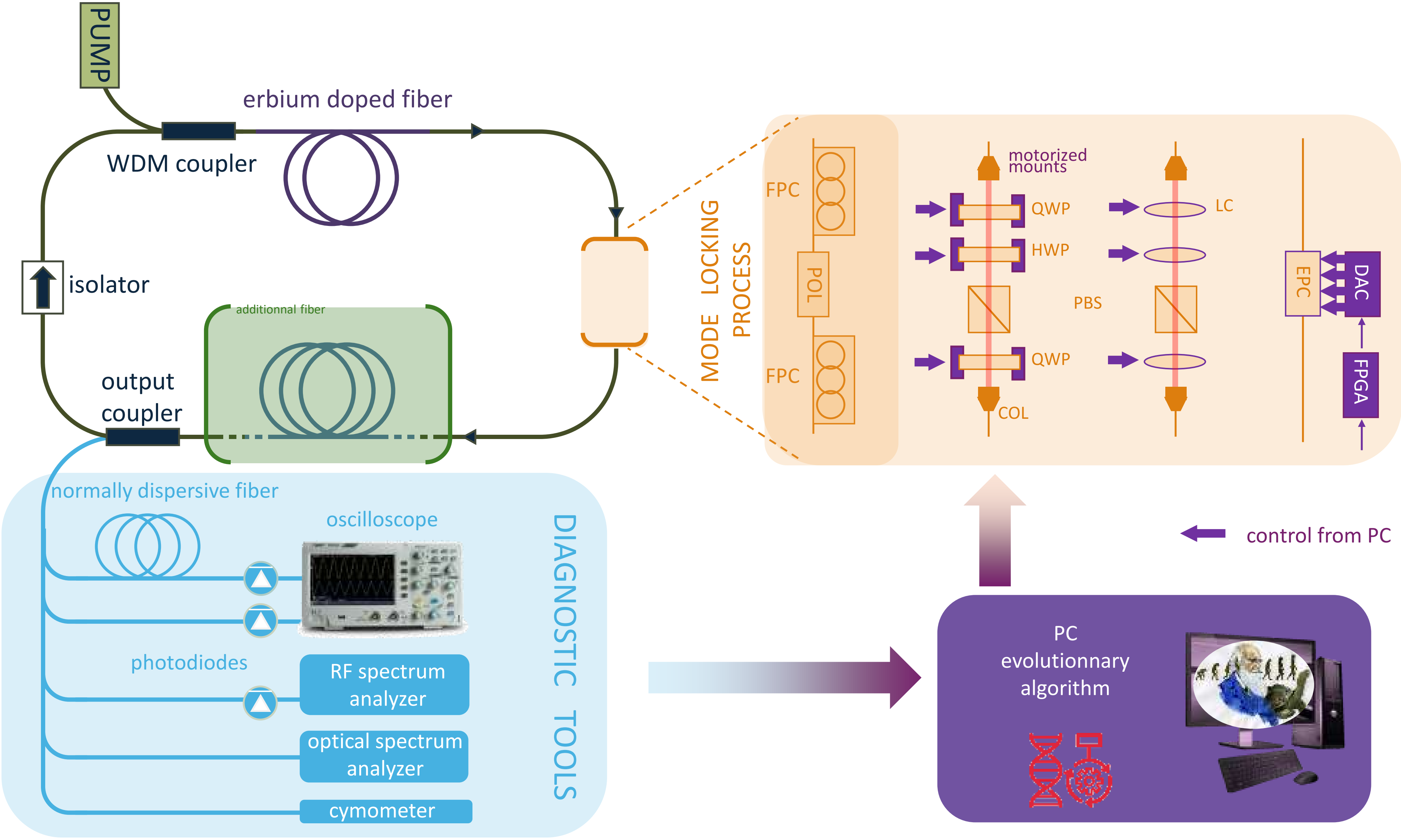




BREATHER PAIR



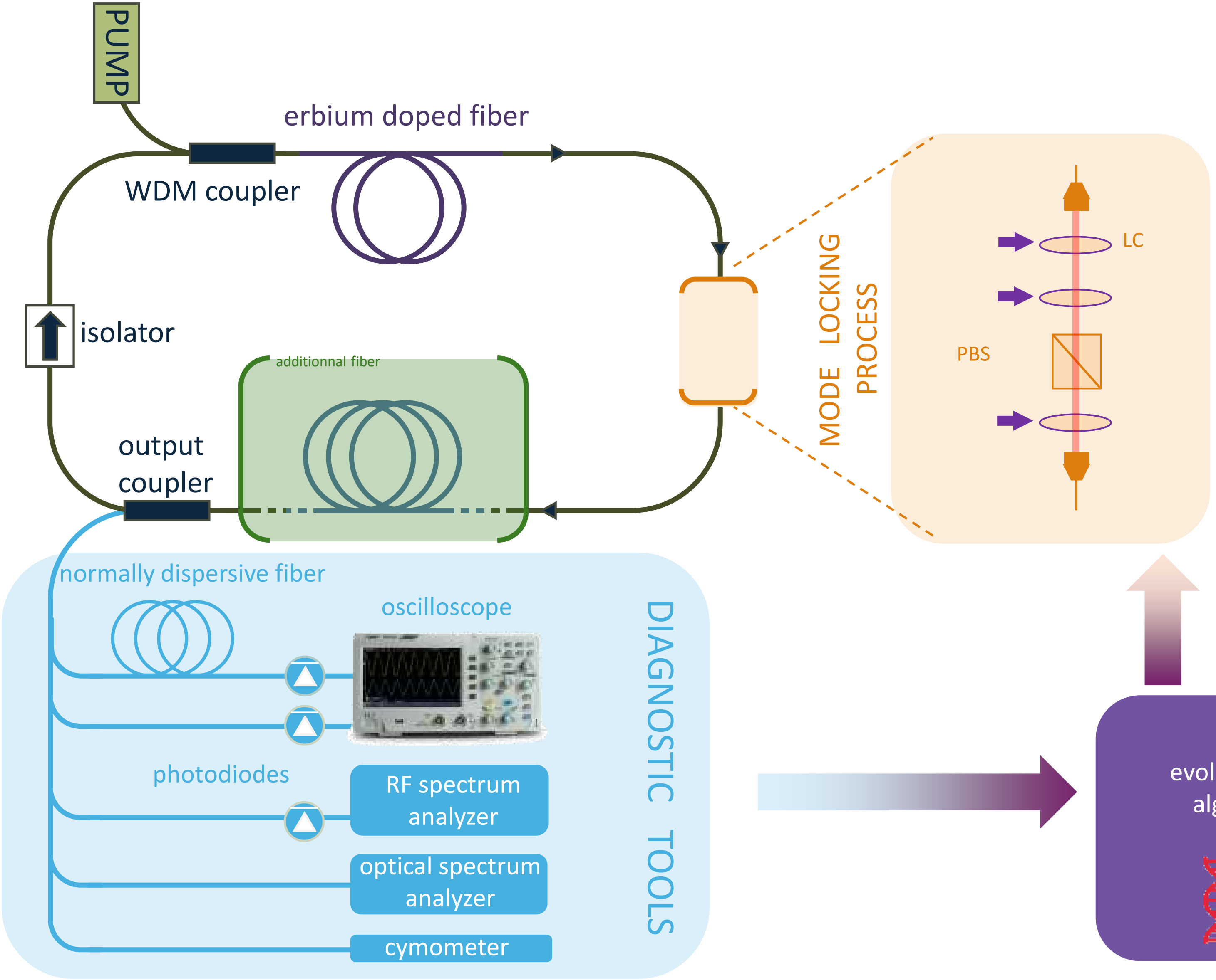
J Peng, X Wu, H Kang, A Zhou, Y Zhang, H Zeng, C Finot, S Boscolo.
Nonlinear dynamics in breathing-soliton lasers., Advances in Physics: X 10 2580628 (2025)

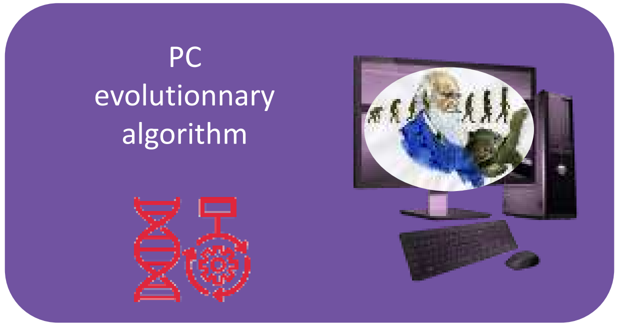


population : 30-50 individuals
evaluation of a population : 2.5 min

Xiuqi Wu

Ying Zhang





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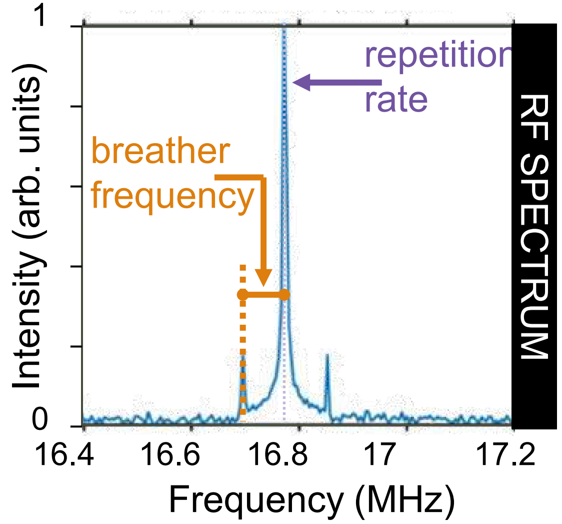
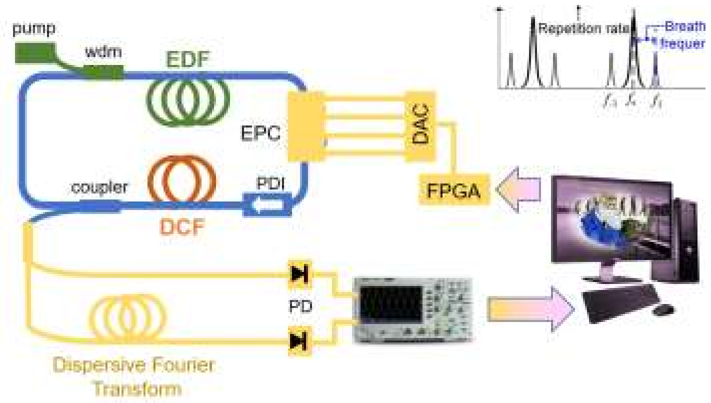
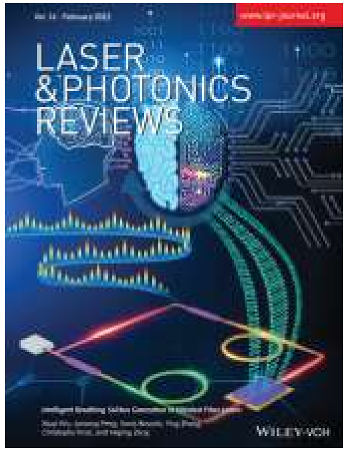


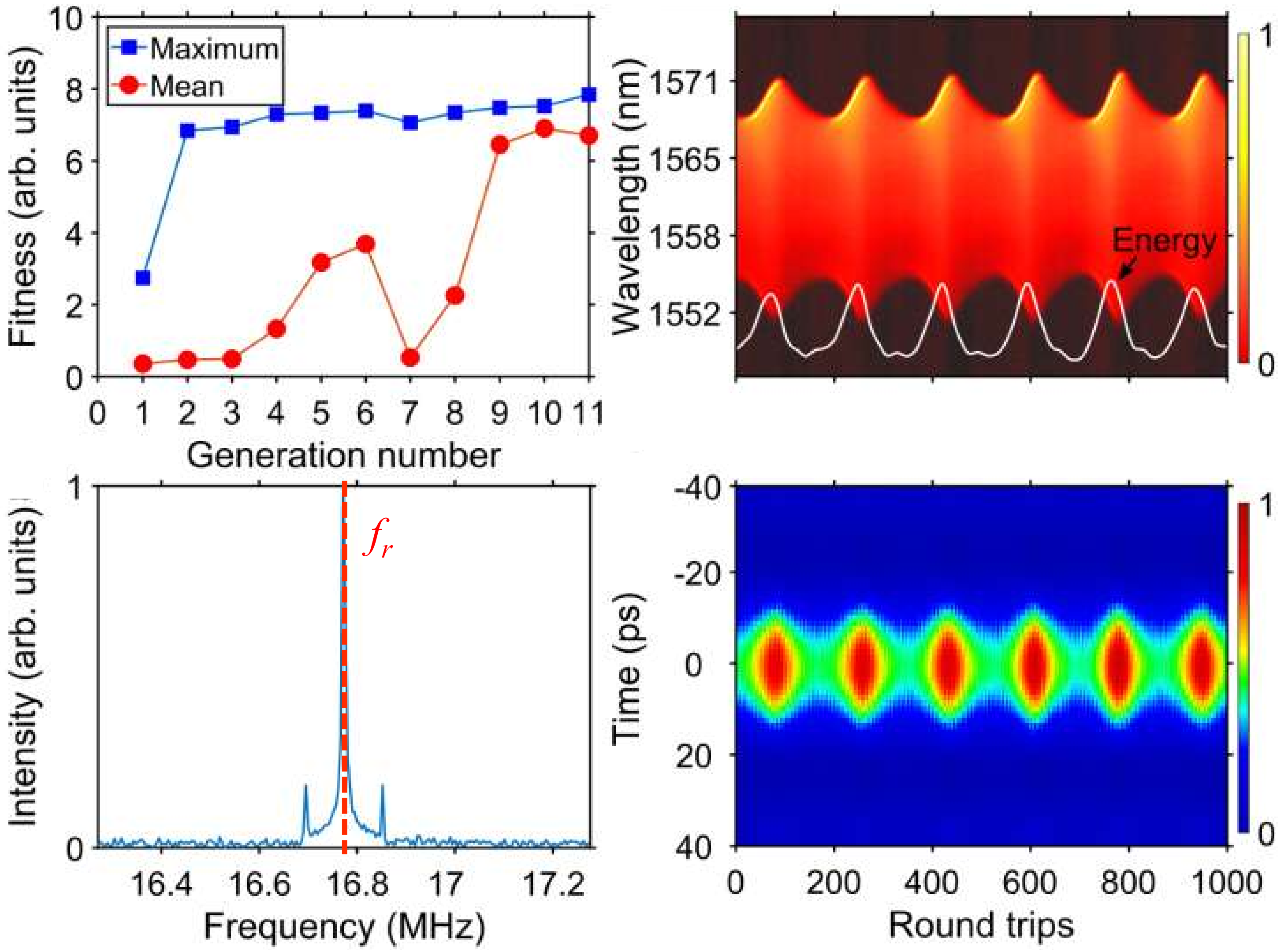
Xiuqi Wu

Ying Zhang



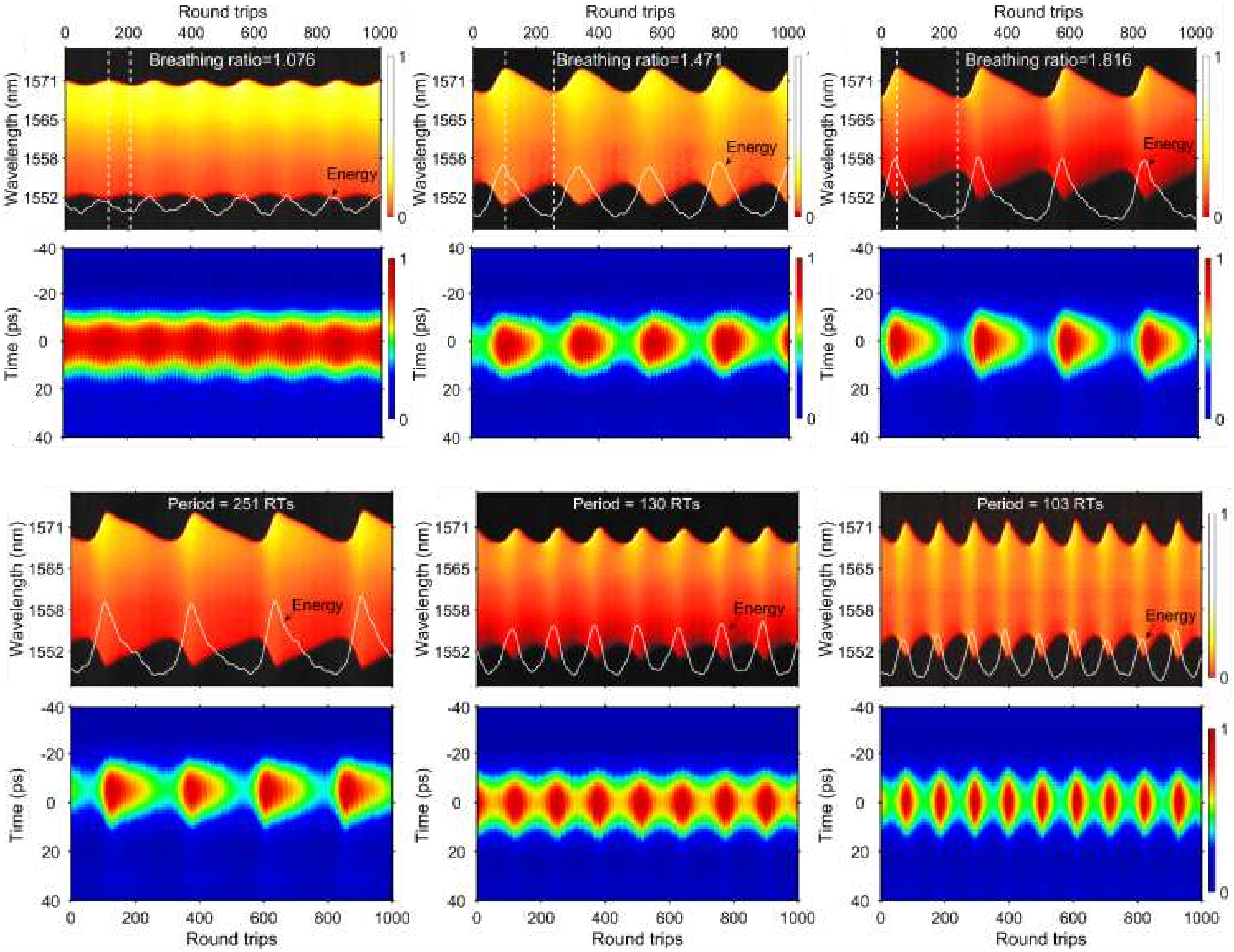


X Wu, J Peng, S Boscolo, Y Zhang, C Finot, H Zeng
Intelligent breathing soliton generation in ultrafast fiber lasers
Laser Photonics Rev. 16, 2100191 (2022)

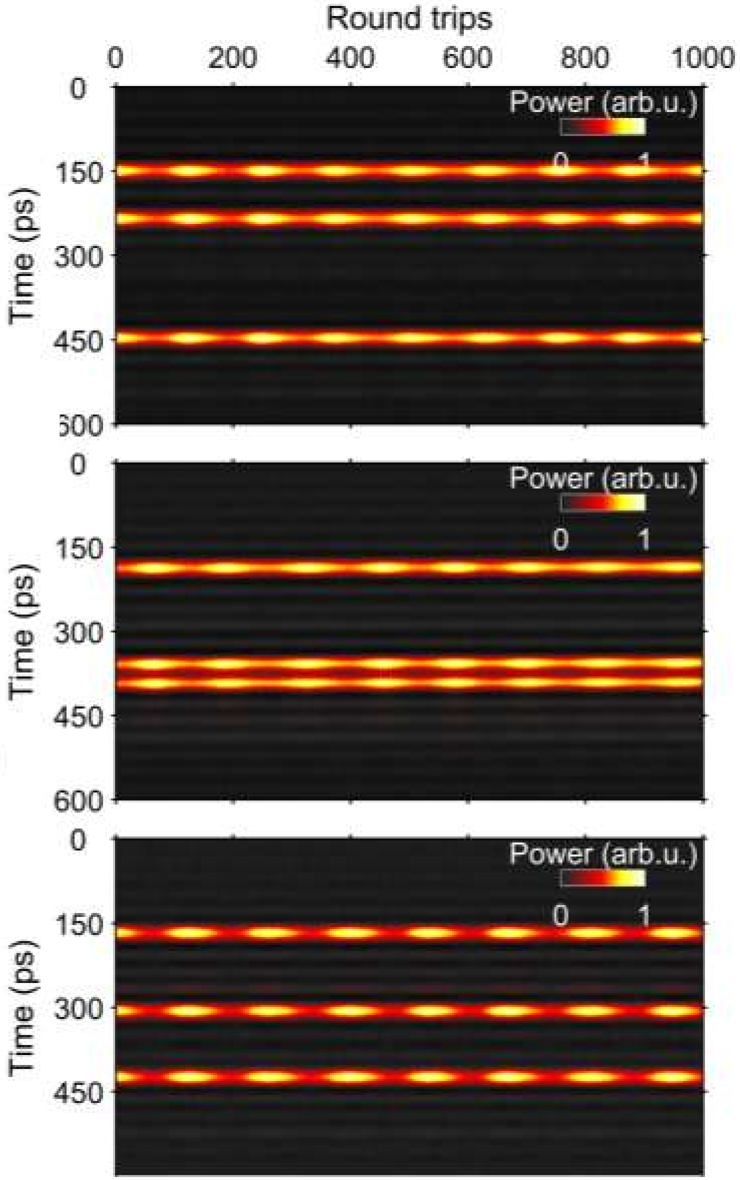


Auto-setting of optimized breather regime

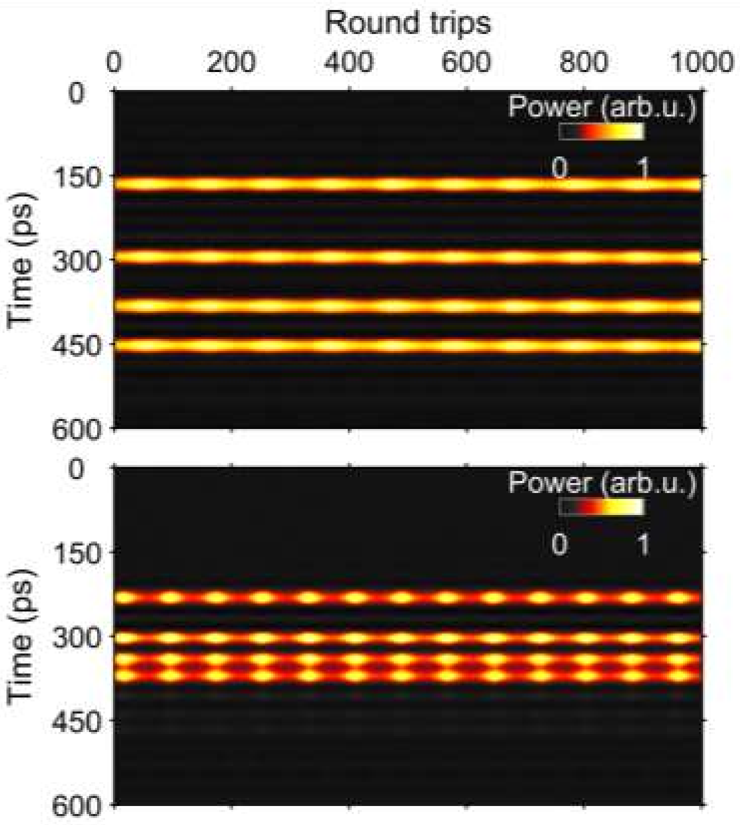
CONTROL
OF THE BREATHING RATIO



CONTROL
OF THE BREATHING PERIOD



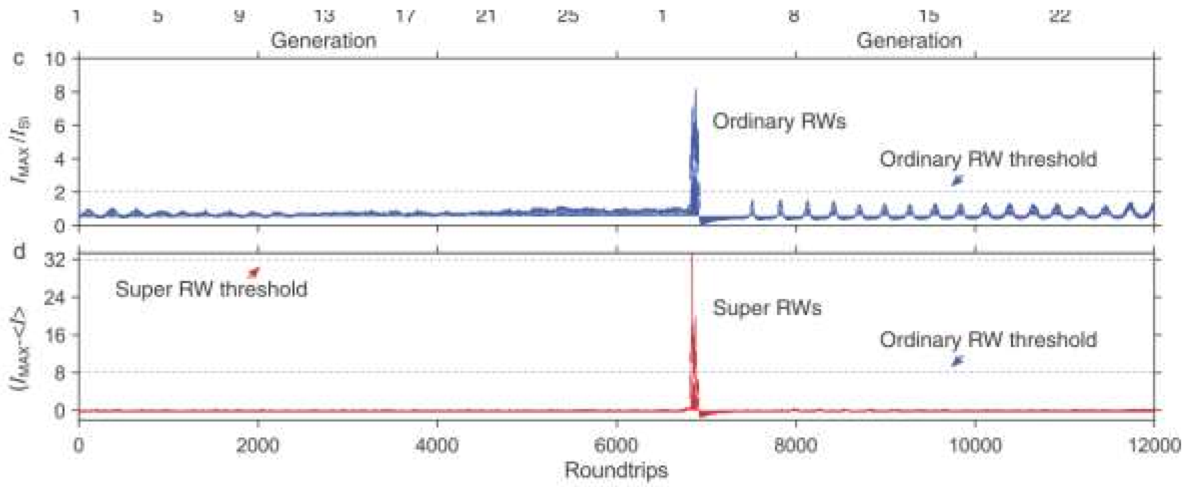
TRIPLETS OF PULSES

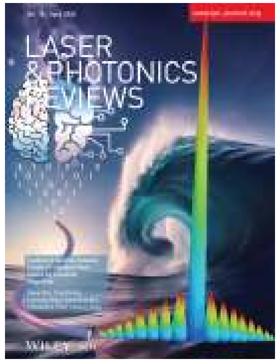


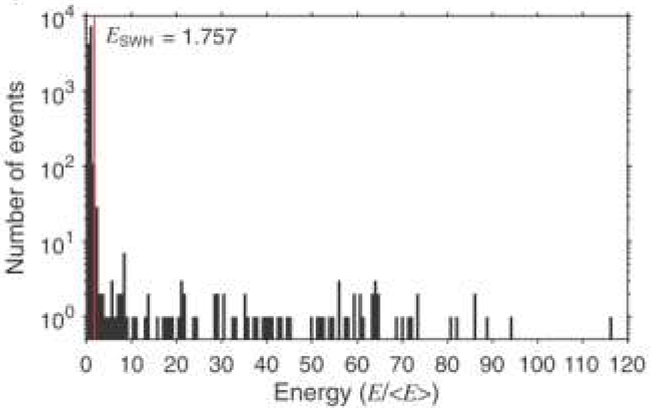
QUADRUPLETS OF PULSES

see also :
Wu, Xiuqi, et al. *Farey tree and devil's staircase of frequency-locked breathers in ultrafast lasers.* Nature Comm. 13 5784 (2022).

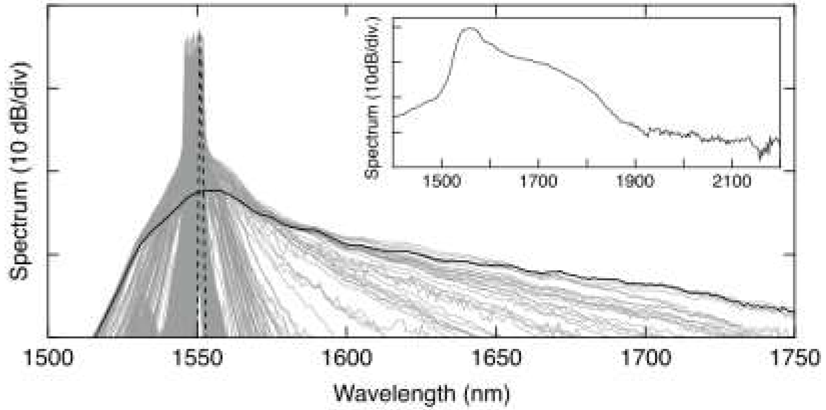
X. Wu, Y. Zhang, J. Peng, S. Boscolo, C. Finot, and H. Zeng,
Control of spectral extreme events in ultrafast fiber lasers by a genetic algorithm,
Laser Photonics Rev. 2200470 (2023).

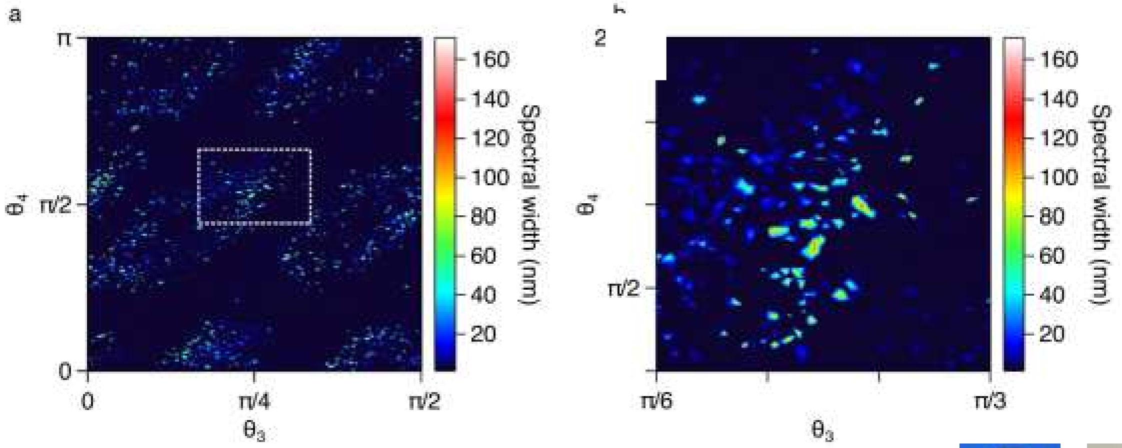


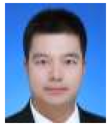




C. Lapre, F. Meng, M. Hary, C. Finot, G. Genty, and J. M. Dudley,
Genetic algorithm optimization of broadband operation in a noise-like pulse fiber laser
Sci. Rep. 13, 1865 (2023).





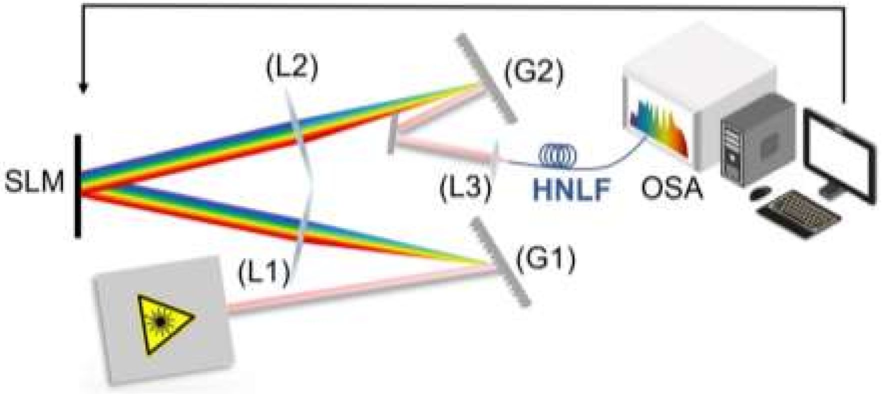


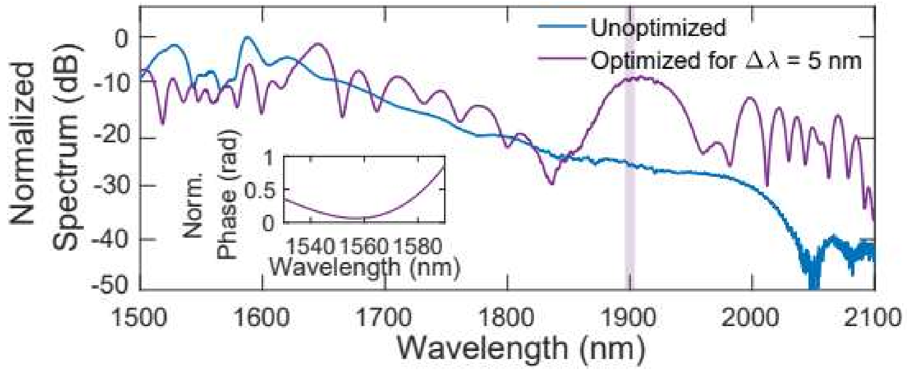
Control of extreme events

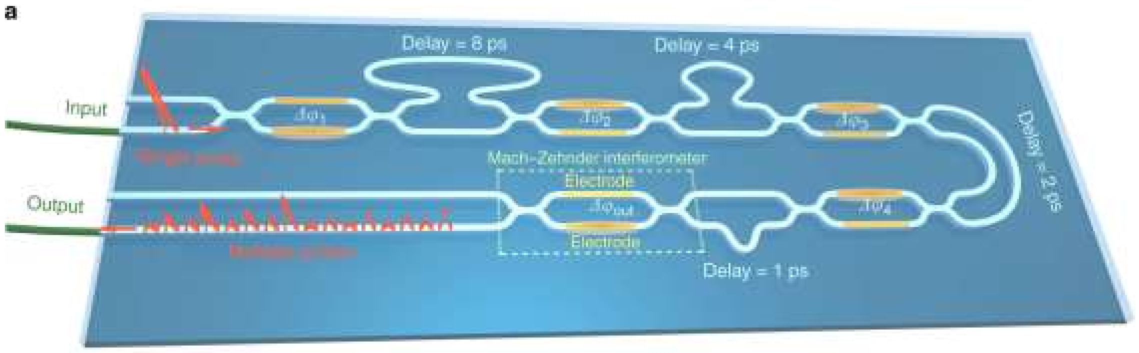
Broadband operation in noise-like laser

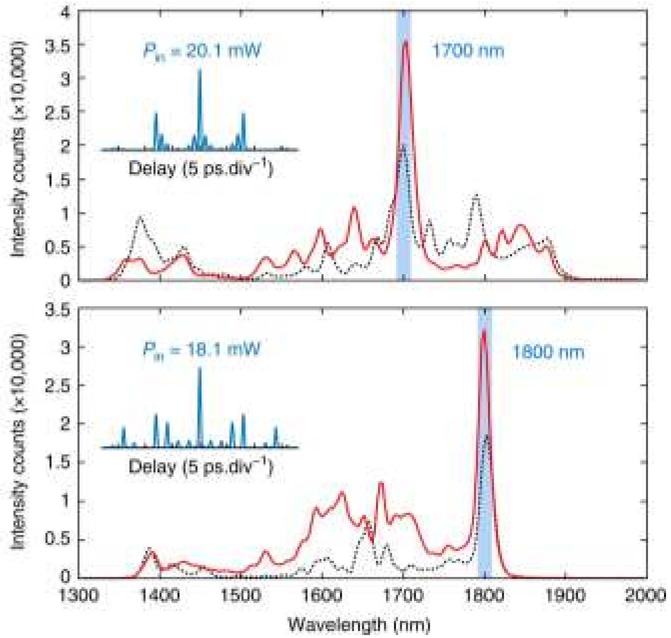
M. Hary et al., *Tailored supercontinuum generation using genetic algorithm optimized Fourier domain pulse shaping*. Optics Lett. 48 4512 (2023)

B. Wetzel et al., *Customizing supercontinuum generation via on-chip adaptive temporal pulse-splitting*. Nature Comm. 9 4884 (2018)





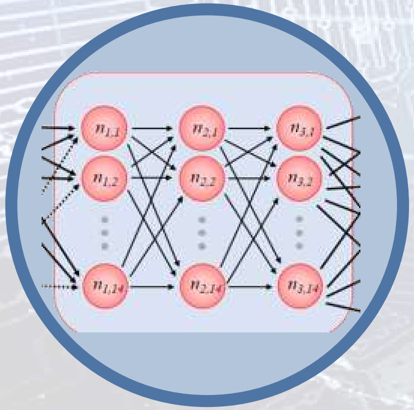




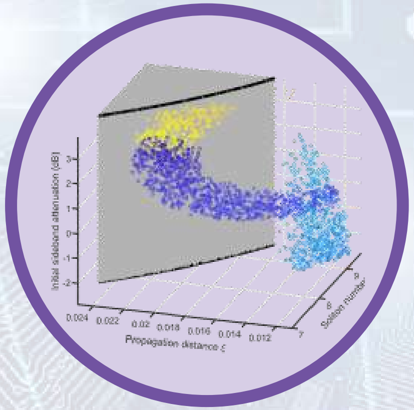
in HNLF with spectral phase shaping

on-chip with controled pulse splitting

Machine learning for output predictions

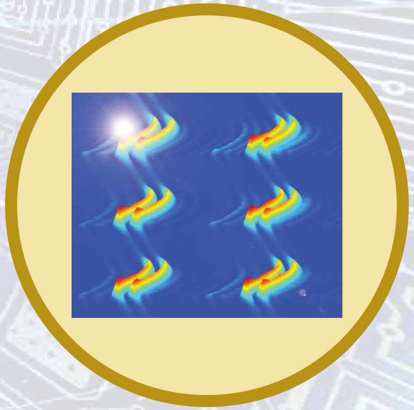


Machine learning for inverse design



Machine learning for physics insights

Machine learning for smart lasers

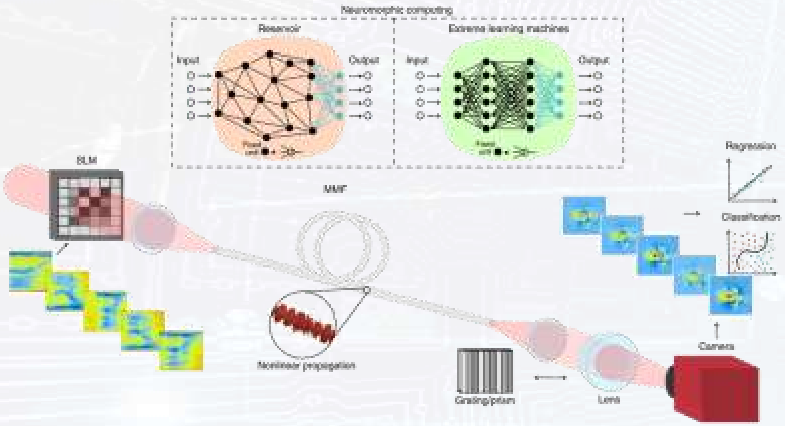


- Machine learning offers very different techniques to speed up the search of waveforms with given properties.
- Many approaches are possible, from the most simple ones to the most expert ones. You do not need to be an expert in computing science to use these tools.
- Both theoretical and experimental works in the field of ultrafast nonlinear optics can benefit from these new features.
- We are just at the beginning and there are still many things to be investigated.

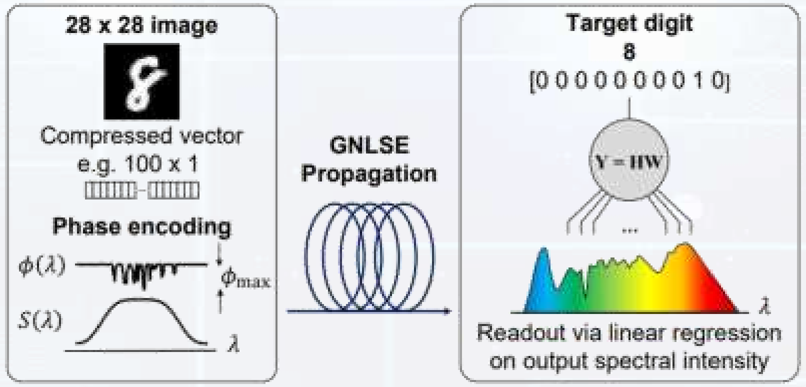
nonlinear multimode fibers

supercontinuum generation

frequency comb

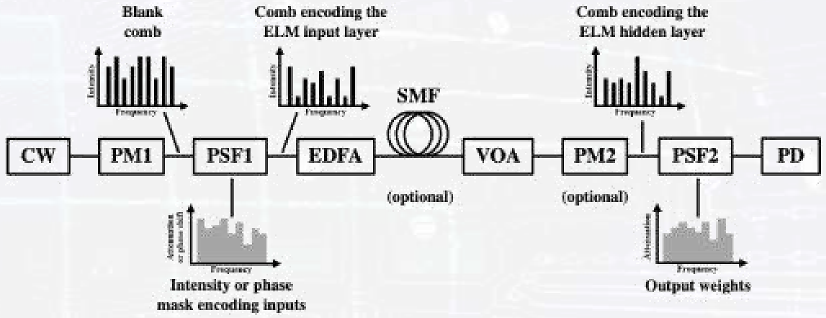


Y. Teğin et al. *Scalable optical learning operator.* Nature Computational Science 1 542 (2021)



$$i\frac{\partial A}{\partial z}-\frac{1}{2}\beta_2\frac{\partial^2 A}{\partial T^2}-\frac{i}{6}\beta_3\frac{\partial^3 A}{\partial T^3}+\frac{1}{24}\beta_4\frac{\partial^4 A}{\partial T^4}+\gamma\left(1+i\omega_0\frac{\partial}{\partial T}\right)\left(A\left[R*|A|^2\right]\right)=0$$

M. Hary, Mathilde, et al. *Principles and metrics of extreme learning machines using a highly nonlinear fiber*. Nanophotonics 14 (2025).



M. Zajnulina et al. *Weak Kerr nonlinearity boosts the performance of frequency-multiplexed photonic extreme learning machines: a multifaceted approach.* Opt. Express 33 7601 (2025)

the story between ultrafast nonlinear guided photonics and machine learning is also on the device side