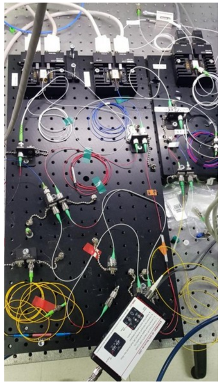
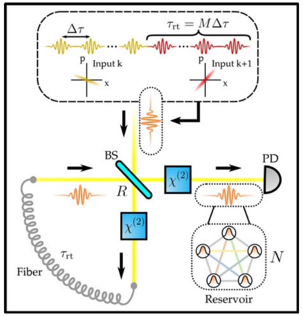
Unconventional Computing with Photonic Substrates

MIGUEL C. SORIANO





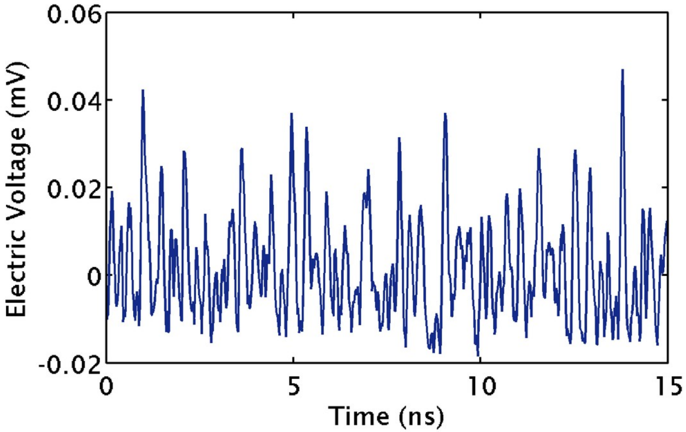
IFISC
AGENCIA ESTATAL DE INVESTIGACIÓN
EXCELENCIA MARÍA DE MAEZTU 2023 - 2027

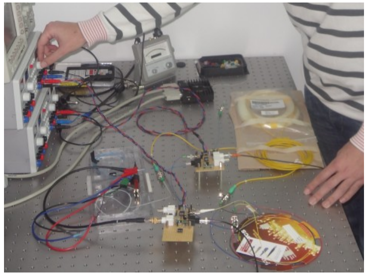
Workshop on Unconventional Computing
Erice, 6 – 12 July 2024

- IFISC: Institute for Cross-Disciplinary Physics and Complex Systems in Mallorca

- Joint research Institute of the University of the Balearic Islands (UIB) and the Spanish National Research Council (CSIC) created in 2007

Nonlinear Photonics Laboratory at IFISC has been operational since 2009



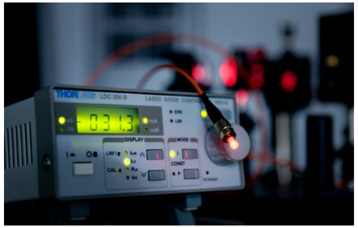


Experimental implementations + numerical simulations

Semiconductor lasers

$$\dot{E}(t) = \frac{1}{2}(1+i\alpha)\xi n(t)E(t) + \kappa E(t-\tau)e^{-\omega_o\tau} + F_E(t),$$

$$\dot{n}(t) = (p-1)\frac{I_{th}}{e} - \gamma_e n(t) - [\Gamma_o + \xi n(t)]|E(t)|^2 + F_N(t).$$



$$\frac{dx(t')}{dt'} = -x(t') + \beta\sin^2[x(t'-T)+\Phi]$$

M. C. Soriano, J. Garcia-Ojalvo, C. R. Mirasso, and I. Fischer, “Complex photonics: Dynamics and applications of delay-coupled semiconductors lasers”, Reviews of Modern Physics 85, 421-470 (2013).

Photonics for Unconventional Computing

Review Article | Published: 29 January 2021

Photonics for artificial intelligence and neuromorphic computing

Bhavin J. Shastri, Alexander N. Tait, T. Ferreira de Lima, Wolfram H. P. Pernice, Harish Bhaskaran, C. D. Wright & Paul R. Prucnal

Nature Photonics **15**, 102–114(2021) | Cite this article

Review Article | Open Access | Published: 03 February 2022

Photonic matrix multiplication lights up photonic accelerator and beyond

Hailong Zhou, Jianji Dong, Junwei Cheng, Wenchan Dong, Chaoran Huang, Yichen Shen, Qiming Zhang, Min Gu, Chao Qian, Hongsheng Chen, Zhichao Ruan & Xinliang Zhang

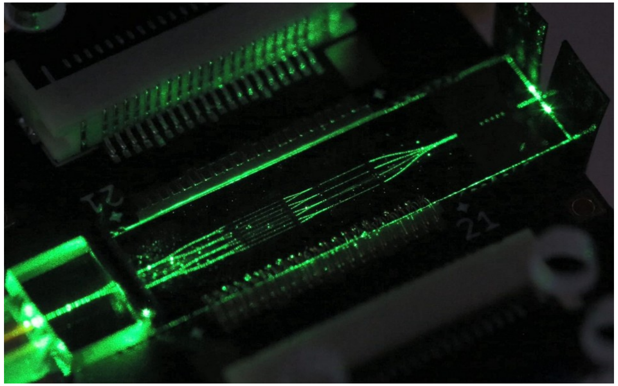
Light: Science & Applications **11**, Article number: 30 (2022) | Cite this article

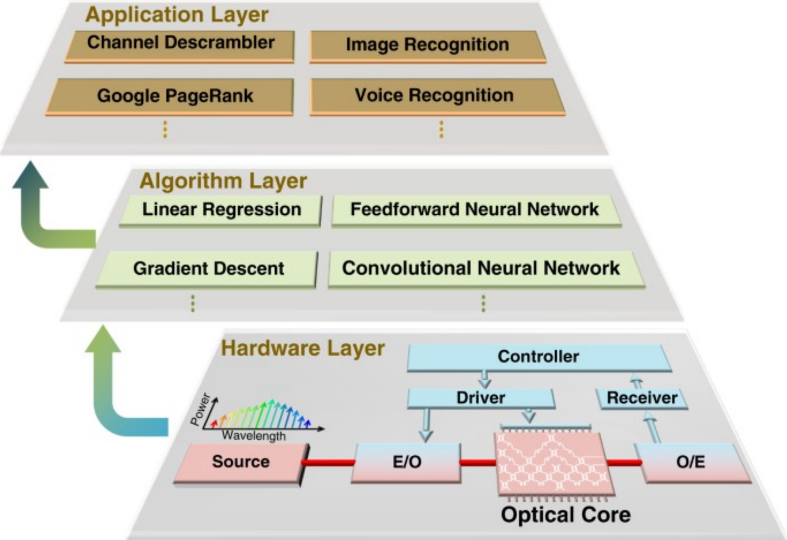
DE GRUYTER Nanophotonics 2023; 12(5): 773–775

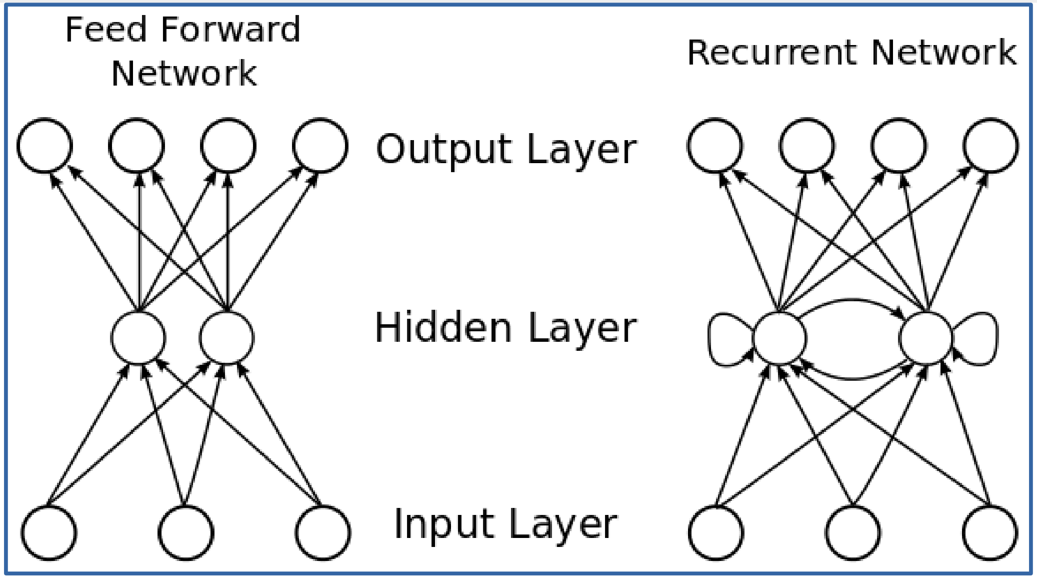
Editorial

Daniel Brunner*, Miguel C. Soriano and Shanhui Fan

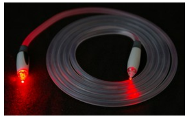
Neural network learning with photonics and for photonic circuit design







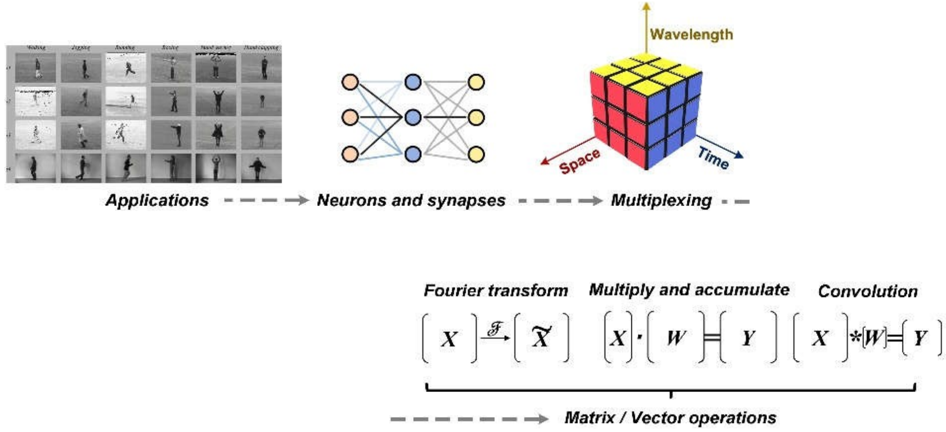
Optics and photonics:
- Parallelism
- Speed & bandwidth
- Energy efficiency
- Lossless transmission
- Nonlinear effects



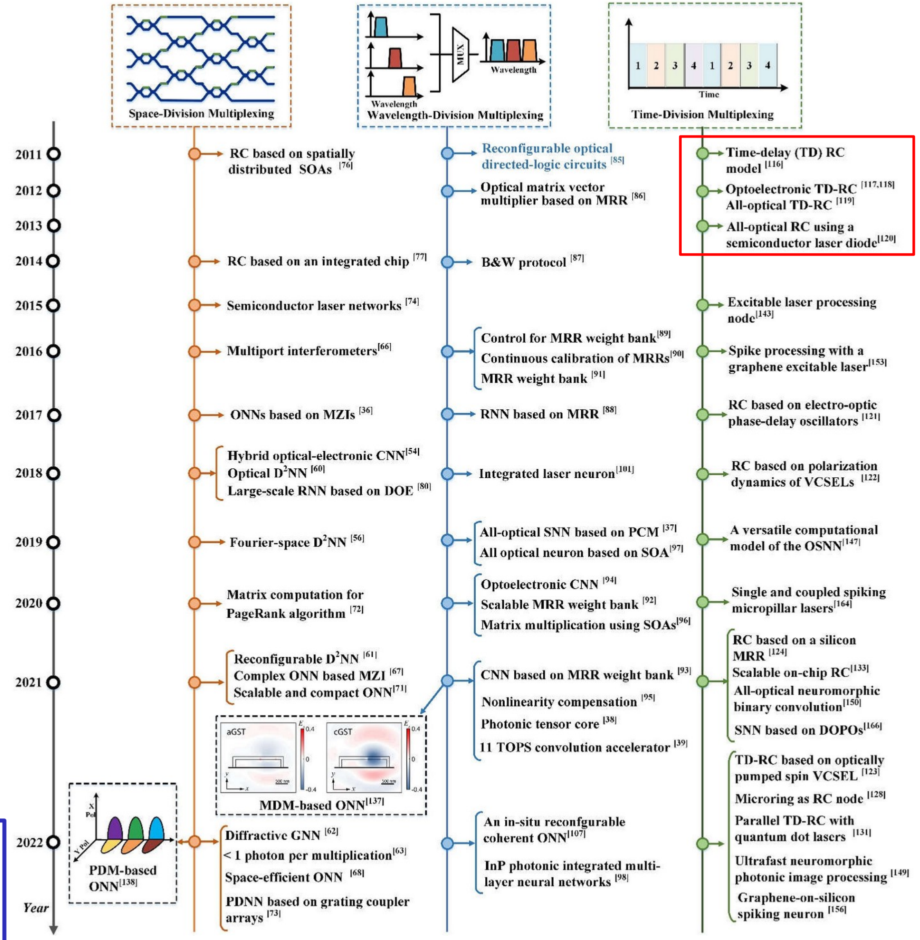
Feed Forward Neural Networks can approximate any continuous function (≥1 hidden layers + non-linear activations)

Recurrent Neural Networks can approximate a dynamical system

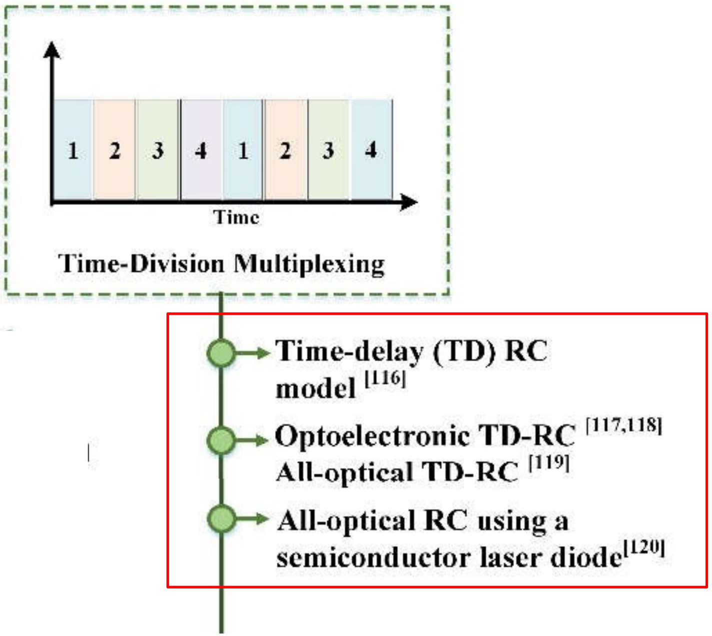
- Optical neural networks explored in the 1980s but interest in AI declines
- Renewed interest from 2010: Approaches to optical neural networks using different multiplexing techniques



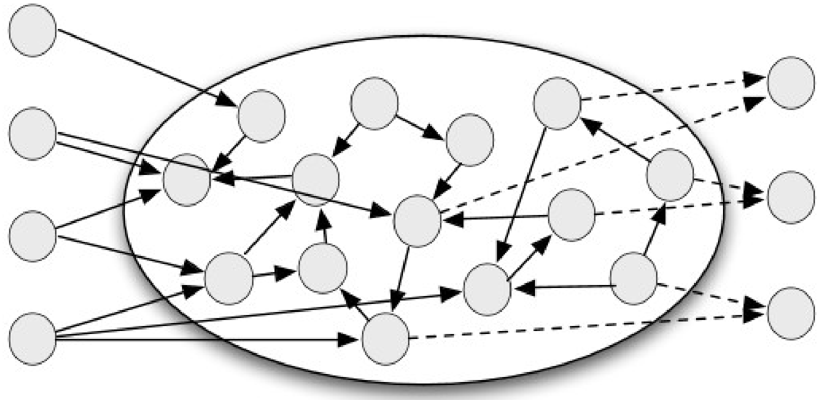
Ideal solution: combination of techniques



Y. Bai, X. Xu, M. Tan, Y. Sun, Y. Li, J. Wu, R. Morandotti, A. Mitchell, K. Xu, and D. Moss, “Photonic multiplexing techniques for neuromorphic computing”, Nanophotonics 12, 795-817 (2023)



- Reservoir Computing: RNN with random input and hidden layer connections



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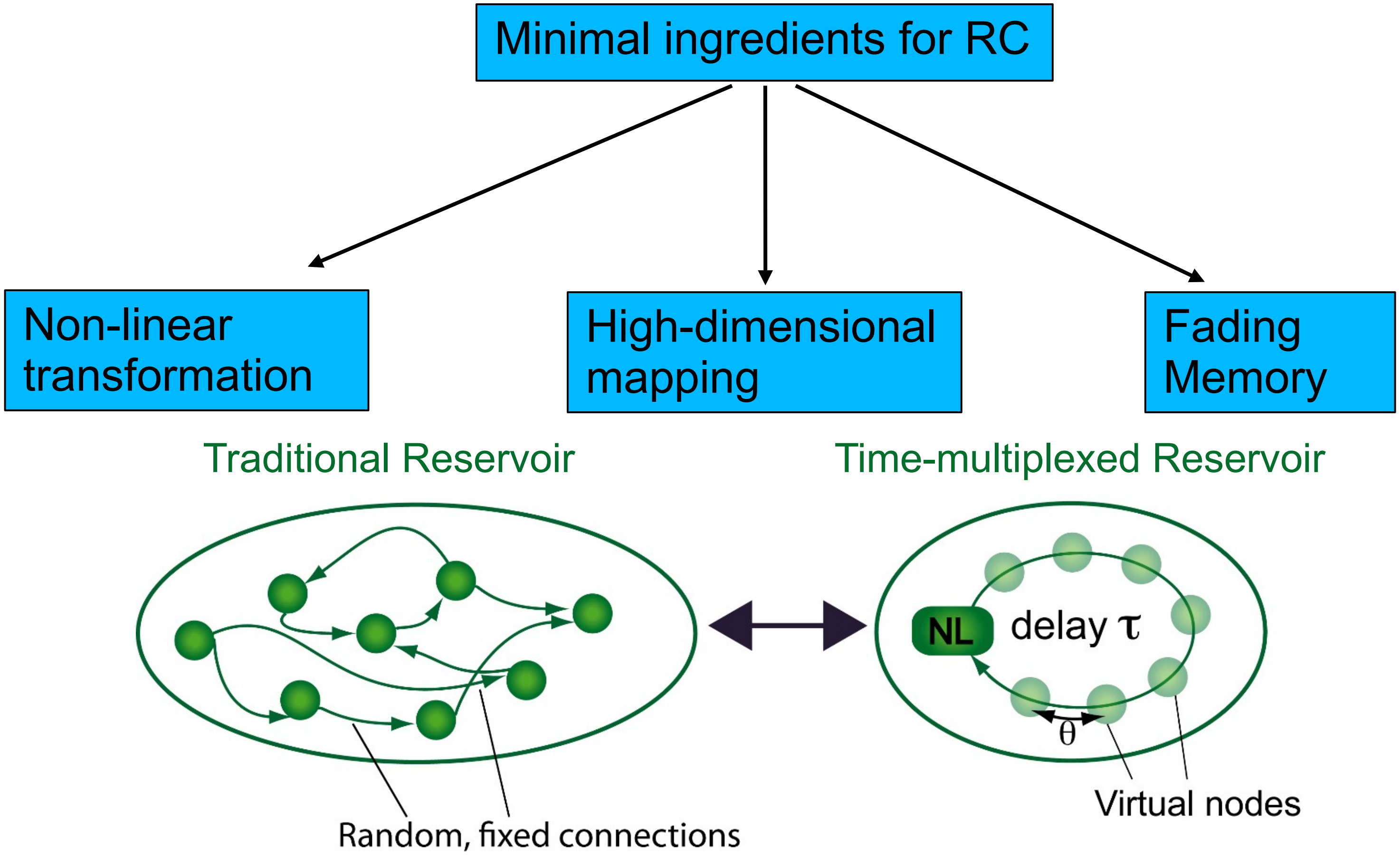
K. Vandoorne, et al., “Toward optical signal processing using Photonic Reservoir Computing”, Optics Express 16, 11182-11192 (2008).

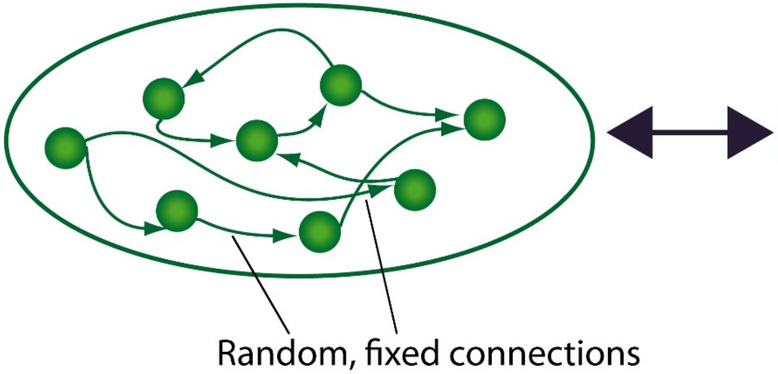


L. Appeltant, M. C. Soriano, G. Van der Sande, J. Danckaert, S. Massar, J. Dambre, B. Schrauwen, C. R. Mirasso, and I. Fischer, “Information processing using a single dynamical node as complex system”, Nature Communications 2, 468 (2011).

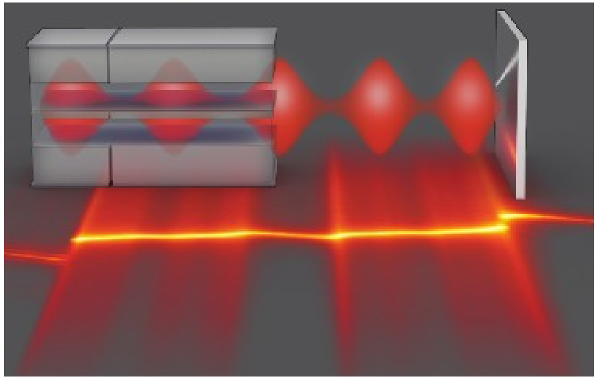
Minimal ingredients for RC

- Non-linear transformation
- High-dimensional mapping
- Fading Memory

Traditional Reservoir



Time-multiplexed Reservoir



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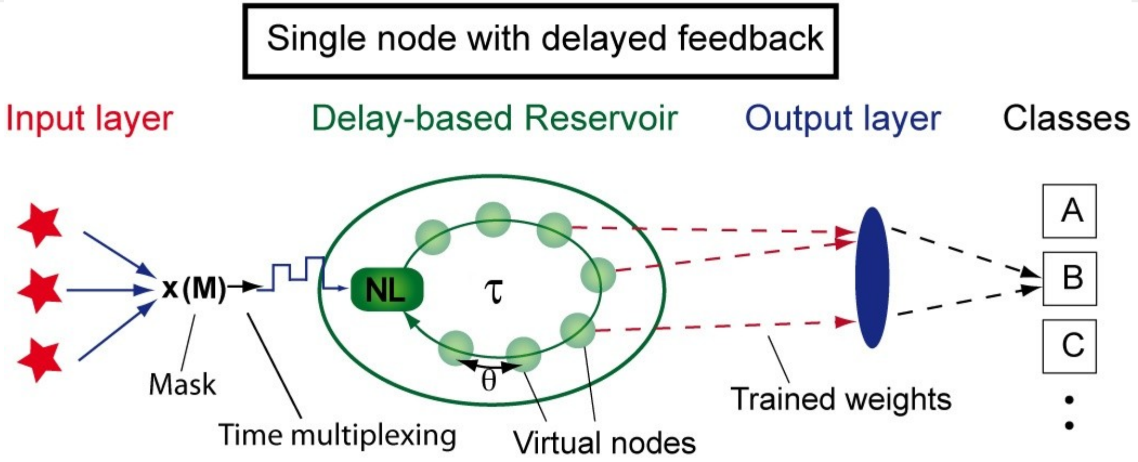
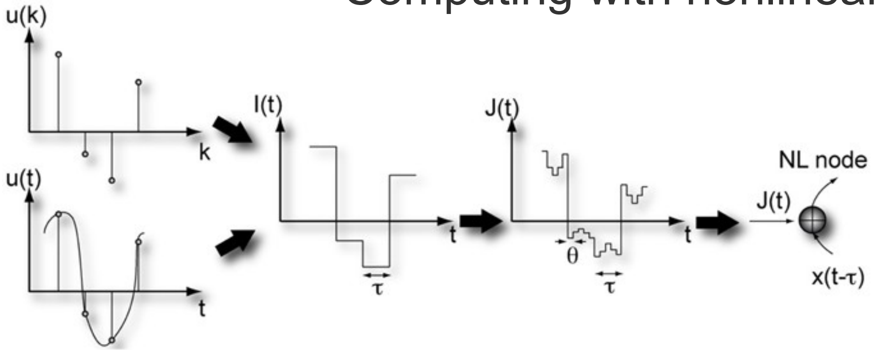
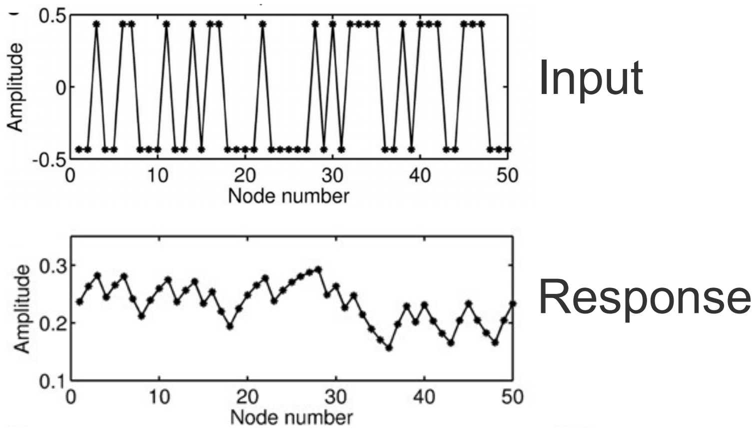


Output

$$\sum_{i=1}^{N} \mathbf{w}_i \cdot x\left(t - \frac{\tau}{N}(N-i)\right)$$

Computing with nonlinear transient dynamics





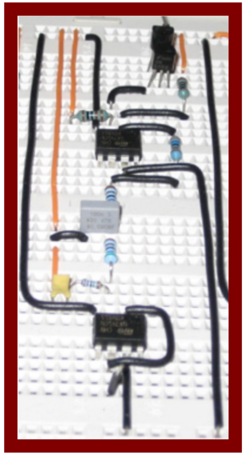
L. Appeltant et al., “Information processing using a single dynamical node as complex system”, Nature Communications 2, 468 (2011).

How it started:

phocus — towards a PHOtonic liquid state machine based on delay-CoUpled Systems
SEVENTH FRAMEWORK PROGRAMME
European Commission

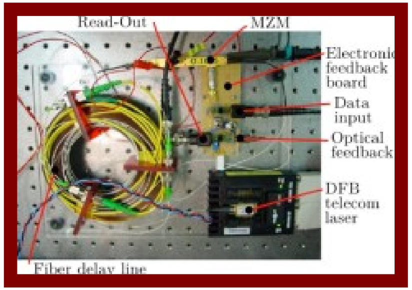
Electronic approach

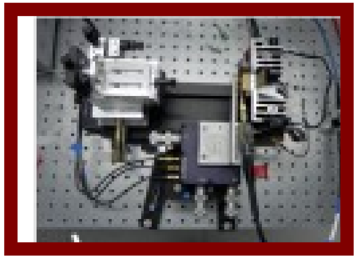
Nature Commun. 2, 468 (2011)



Optoelectronic approach

Optics Express 20, 3241 (2012)



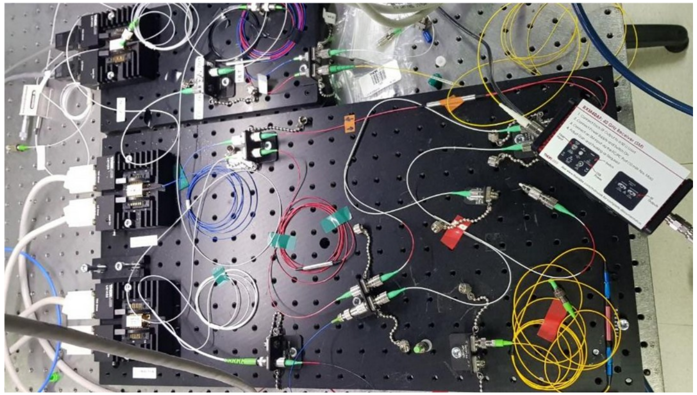


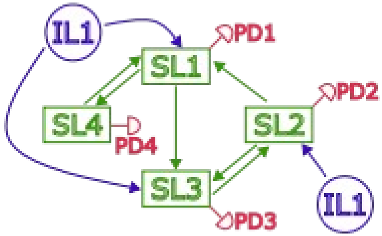
Optical approach

Nat. Commun. 4, 1364 (2013)

How it's going:

Telecom wavelengths / fiber based

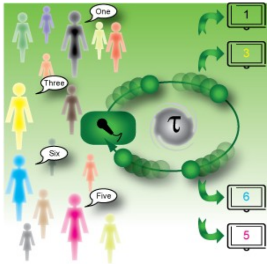


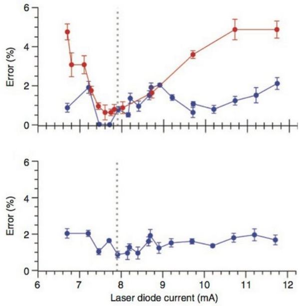


Laser networks

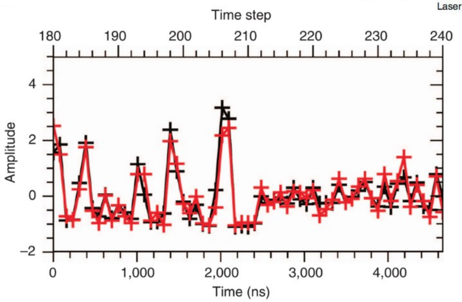
MINISTERIO DE CIENCIA, INNOVACIÓN Y UNIVERSIDADES
Cofinanciado por la Unión Europea
AGENCIA ESTATAL DE INVESTIGACIÓN

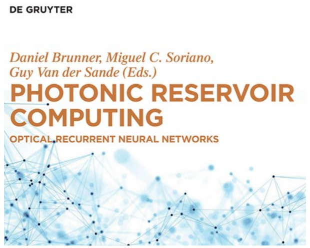
- Recognition of spoken digits
Error-free classification
~ 0.1 Million words / sec



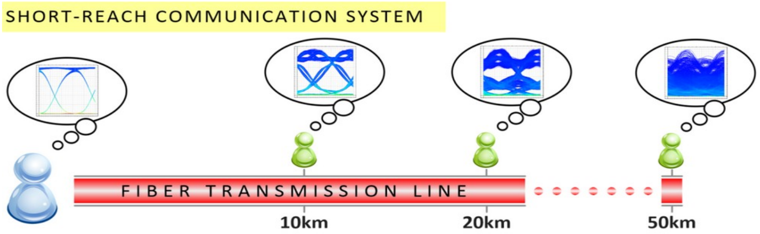


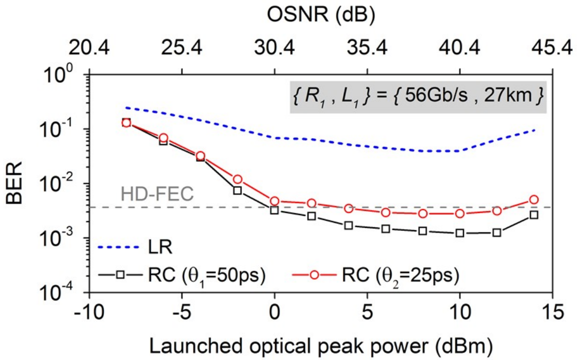
- Prediction of chaotic time series
Prediction errors <6%
~ 13 Million points / sec





- Approaching processing speeds of Gb/s for telecom tasks



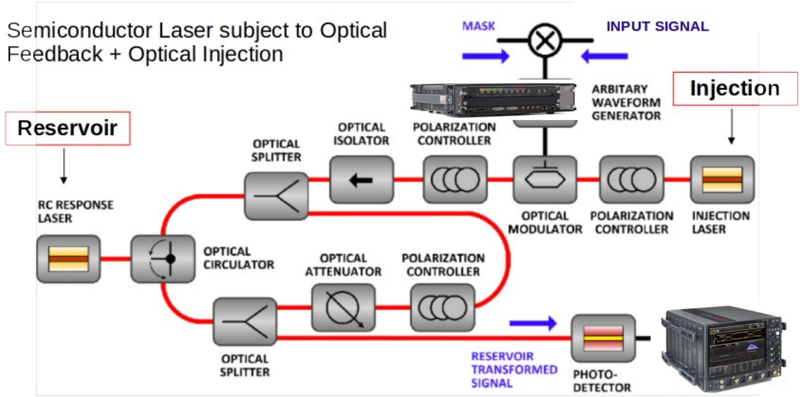


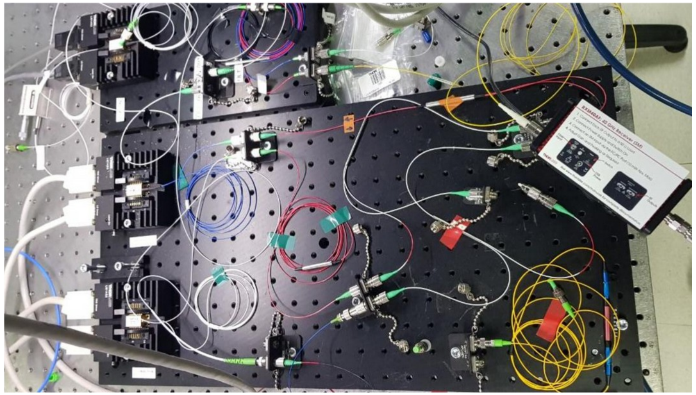
A. Argyris, Nanophotonics 11, 897-916 (2022)

- **Information processing with photonic systems and time-multiplexing**
  - **From Classical...**
    - Speeding up computation with semiconductor lasers
    - Integrated photonics
    - Training hardware systems
  - **To Quantum Reservoir Computing**
    - Proposal in a photonic substrate

Experimental Setup

Semiconductor Laser subject to Optical Feedback + Optical Injection





Reservoir: Response laser with feedback

- semiconductor laser @ 1545.5 nm
- biased around threshold 10.8mA
- single longitudinal mode
- delay loop with 24.5 ns (40MHz)

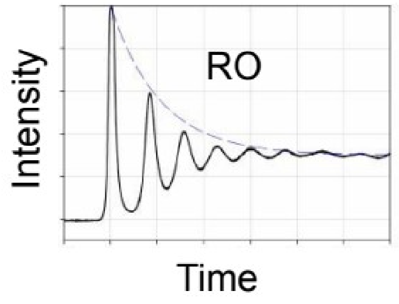
Input modulation

- Keysight AWG M8196A
  - intensity modulation @ max. **92 GSa/s**
  - analog bandwidth @ 32 GHz
- optical modulator (MZM) @ 40 GHz bandwidth

Output measurement

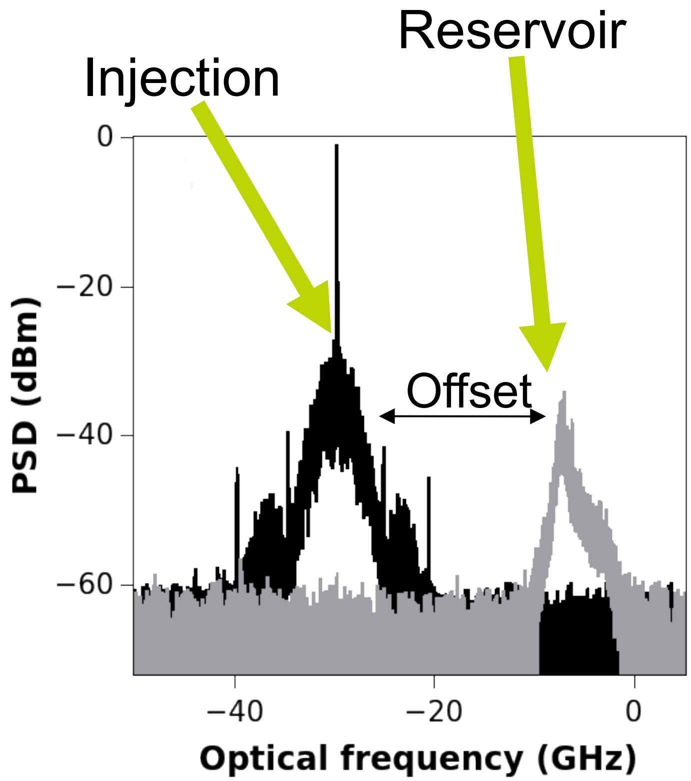
- photoreceiver @ 40 GHz bandwidth
- Keysight Oscilloscope UXR0404A
  - sampling intensity @ max. 256 GSa/s
    - 3 samples per input sample
  - analog bandwidth @ **40 GHz**

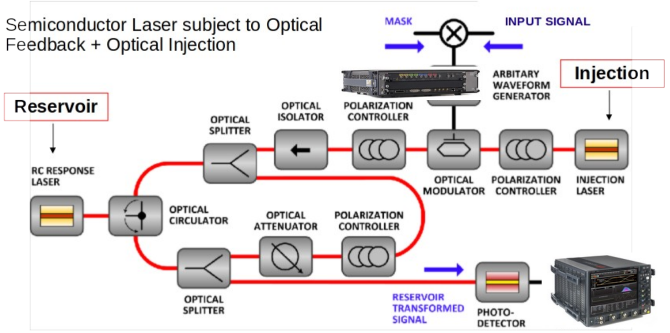
Optical injection as nonlinear mechanism to increase bandwidth

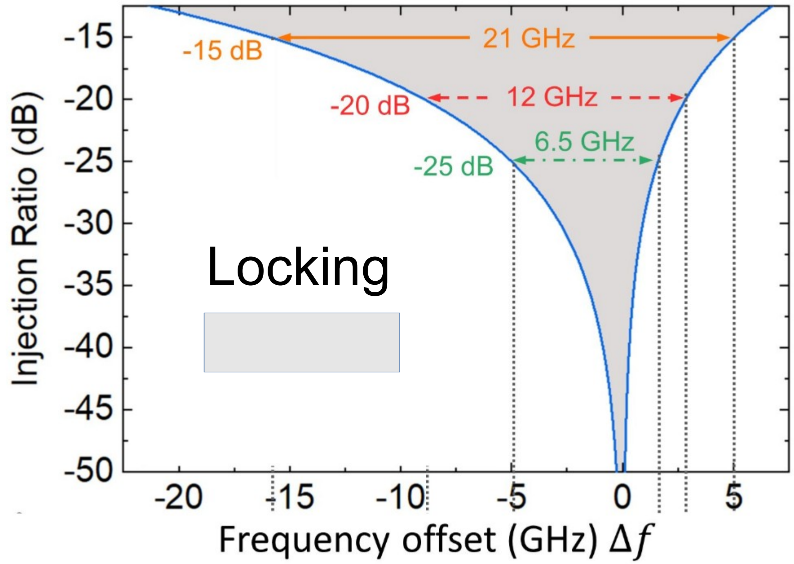


Relaxation Oscillation Frequency

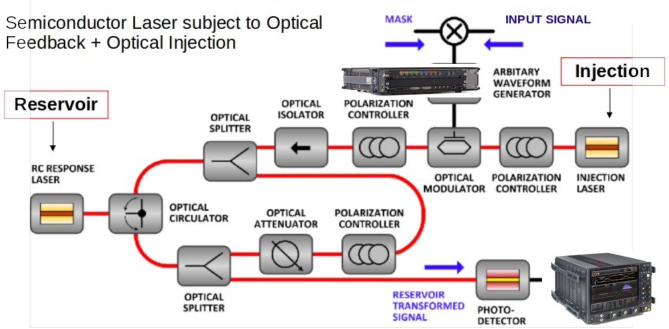
f_{RO} = 1-10 GHz

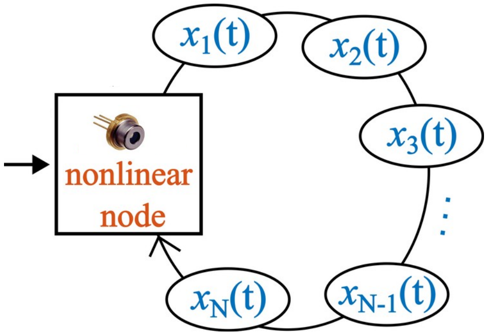






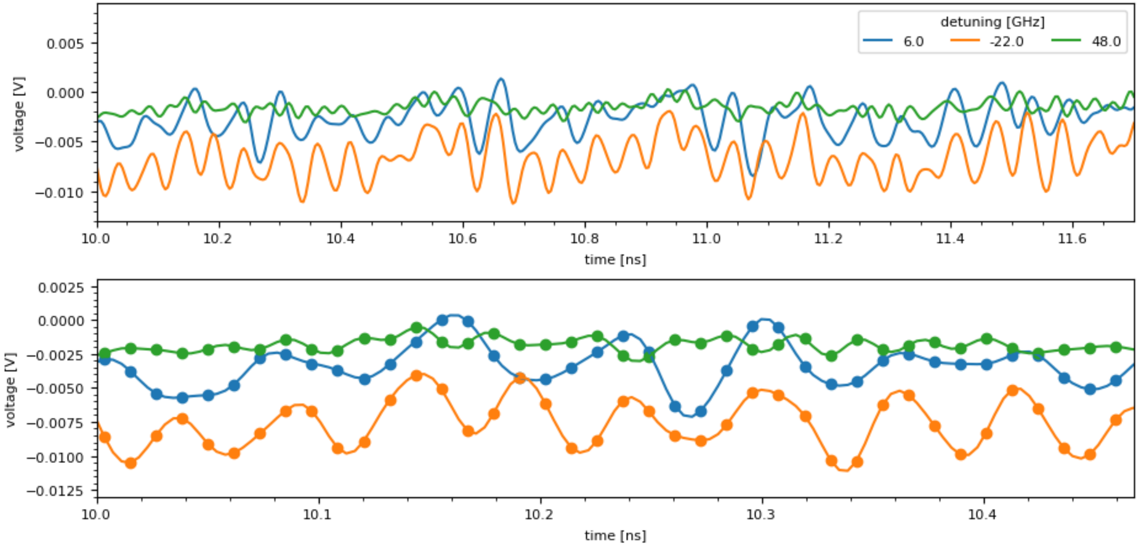
Optical injection as nonlinear mechanism to increase bandwidth → exploit fast dynamics





Possible to encode virtual neurons @ 11.7ps/85 GHz

- strong injection gain to exploit bandwidth enhancement
- varying detuning between injection and reservoir laser

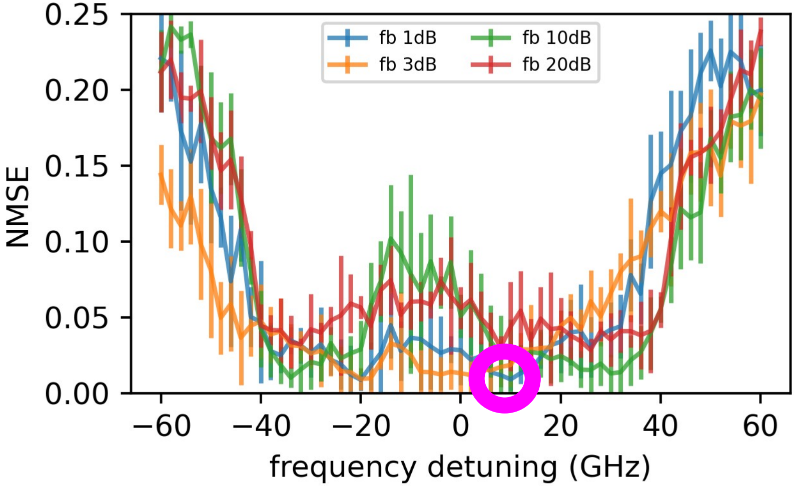


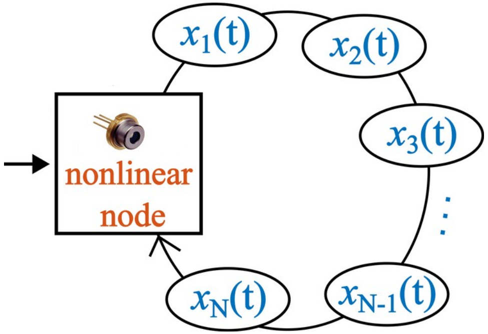
Time-series prediction

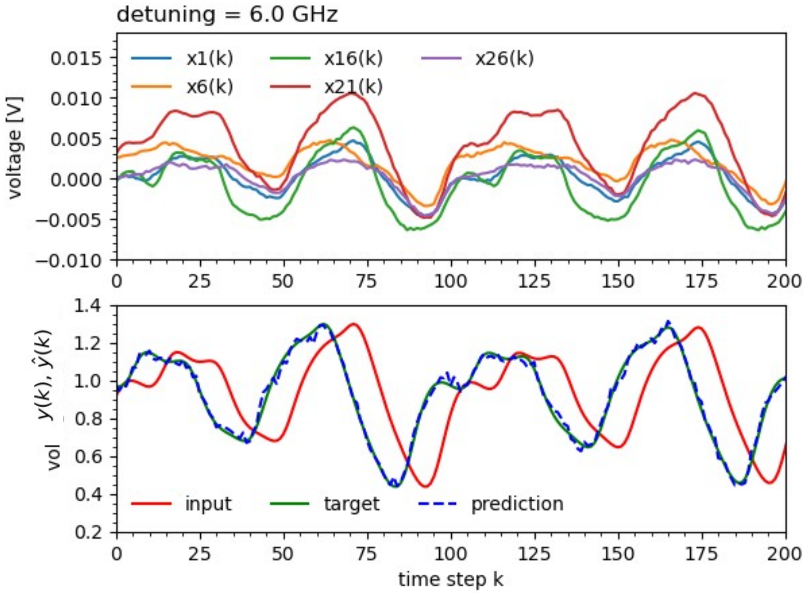
- 200 nodes @ 11.7ps → T ~ 2.4ns (~ 0.4GHz)

ultrafast RNN for time-series processing

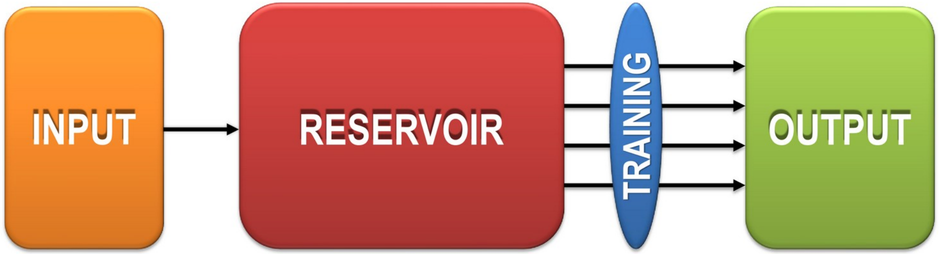
Gaining 10x effective speed up

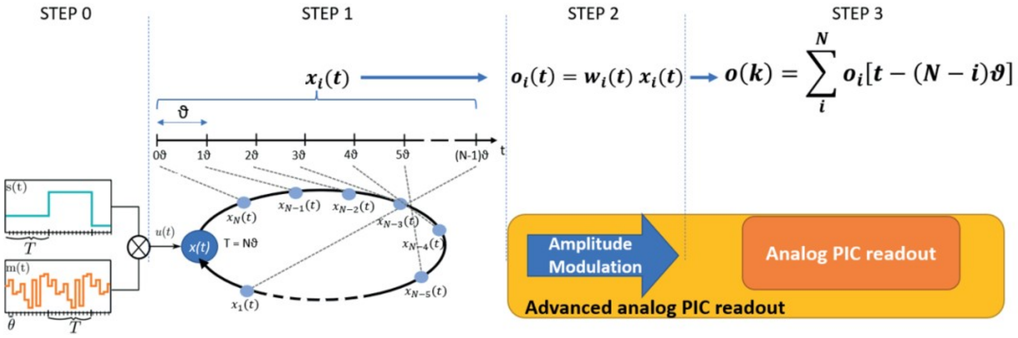






Towards a complete device for delayed RC:





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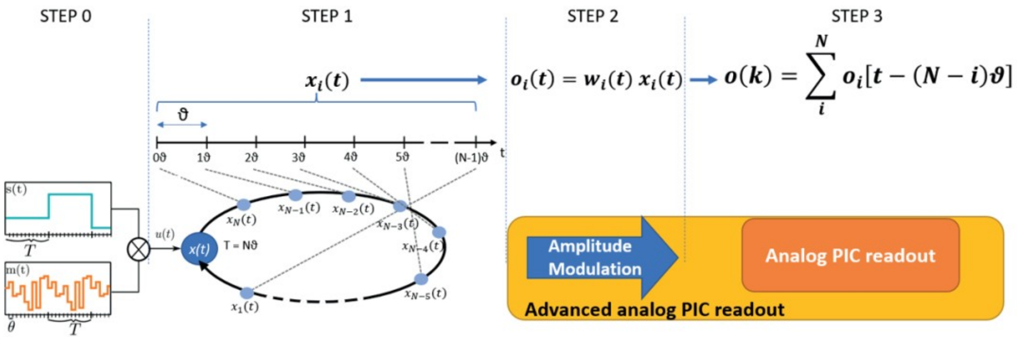
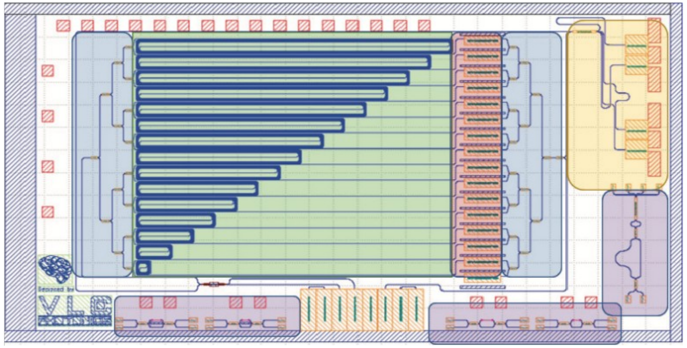
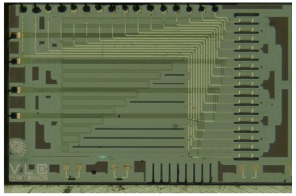
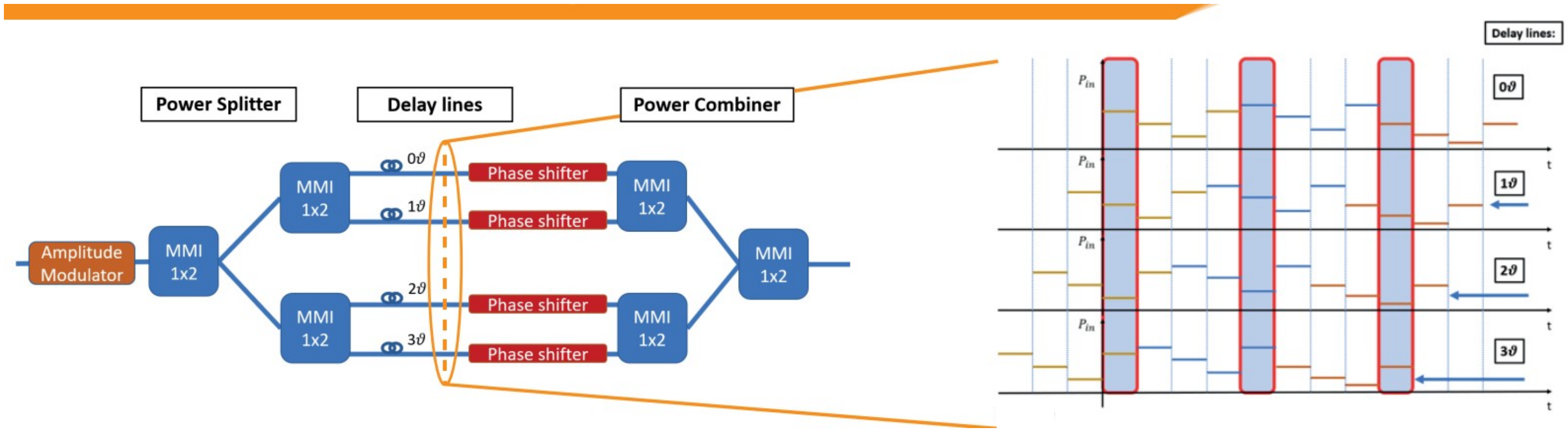


Circuit proposal:





Integrated solution for output layer:

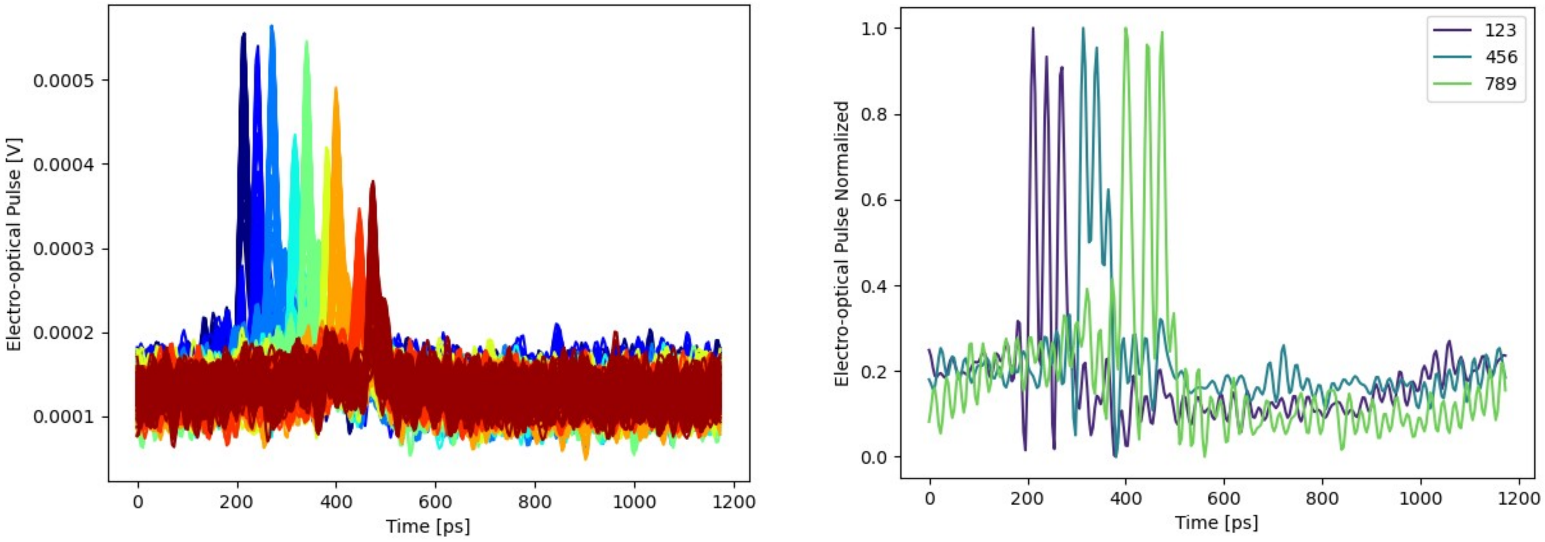


PhD thesis
T. Jonuzi

VLC PHOTONICS
A Hitachi Group Company

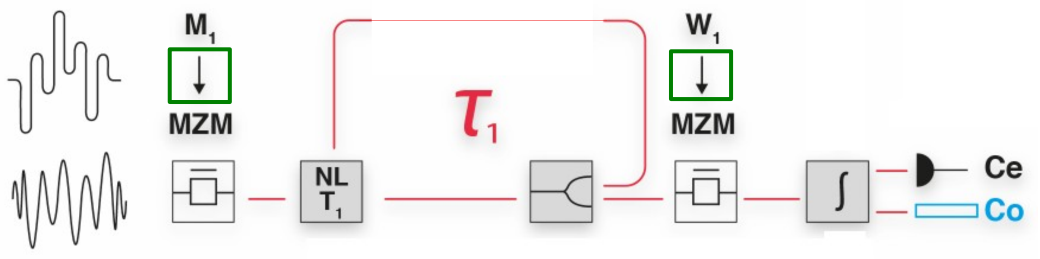
Preliminary results for a circuit with 9 paths of increasing delay ~ 33ps spacing

- Tuning of amplitudes (weights) with tunable heaters
- Injection of a single pulse at the input of the PIC



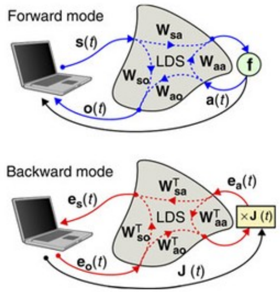
PhD thesis
T. Jonuzi

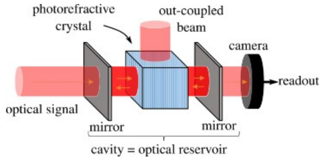
Hardware-based learning / Hardware and software co-design → better adaptation means higher resource efficiency



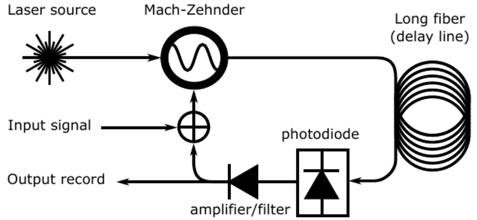
1) Training on model and transfer of parameters to experimental system
(include in the model the detailed characteristics of the experiment: component tolerance, signal to noise ratio, bandwidth, ...)

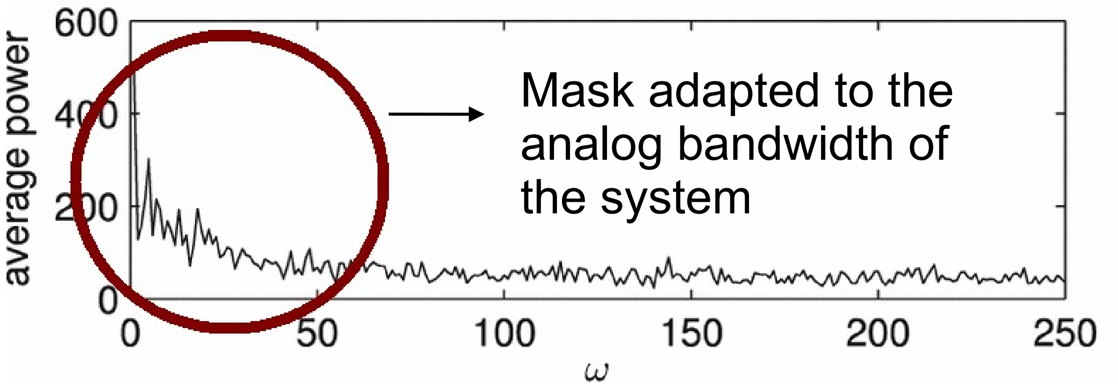
2) Training directly on experimental system
(with external feedback or autonomous)

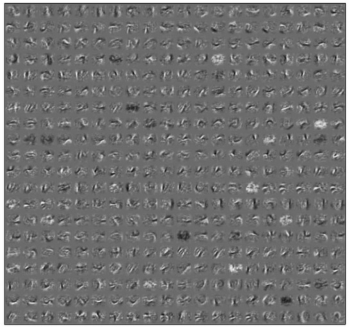




- From random mapping to full optimization
  - Back-propagation through time (BPTT)
  - Optimized mask for the system and the task



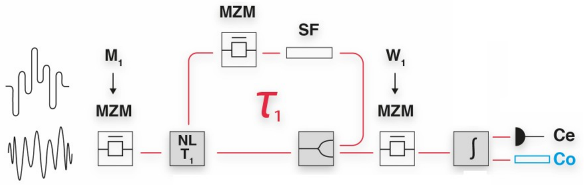




- Learning procedure improves results but increases complexity
  - For handwritten digit recognition task (MNIST) error for RC ~ 7% and BPTT ~ 1%
  - Training time for RC ~ minutes and BPTT ~ hours

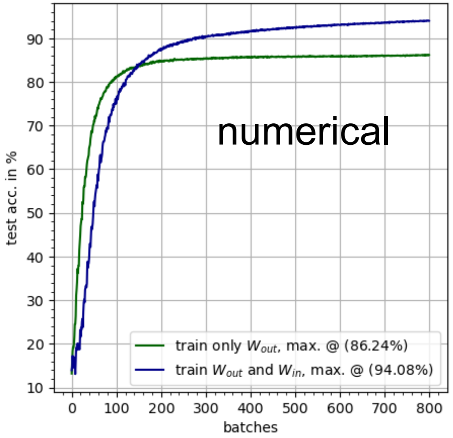
M. Hermans, M. C. Soriano, J. Dambre, P. Bienstman, and I. Fischer, "Photonic delay systems as machine learning implementations", Journal of Machine Learning Research 16, p. 2081-2097 , Oct 2015.

- Online learning strategies for optical neural networks
  - No mathematical model needed
  - Train input and output weights



- Extract the system's gradient and use it for learning
  - estimating the gradients via sampling (measuring) the error related to small changes in the weights

$$\hat{y} = F(u, W_k),\ e = y - \hat{y}$$
$$\hat{y_\delta} = F(u, W_k + \alpha\delta W),\ e_\delta = y - \hat{y_\delta}$$
$$W_{k+1} = W_k + \sum_i^N \eta(e - e_\delta) W_\Delta^i$$



PhD thesis
M. Goldmann

  - evolutionary strategies based on sampling adaptation: parameter exploring policy gradient (150 neurons with 10 bit weight resolution on MNIST)

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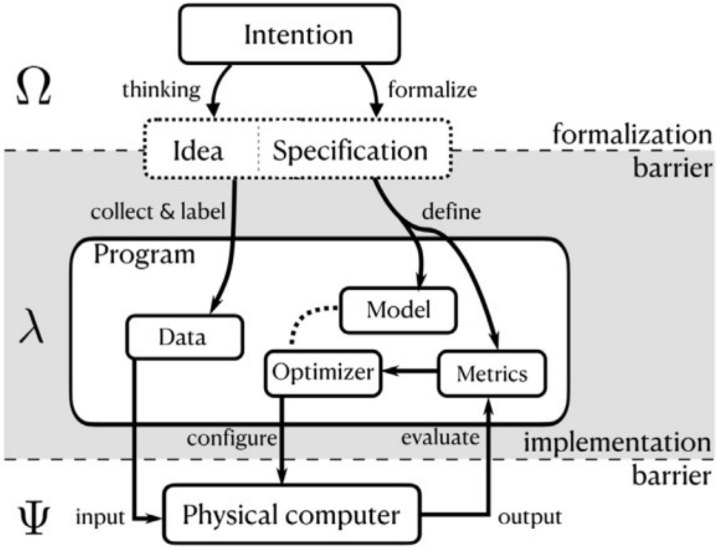
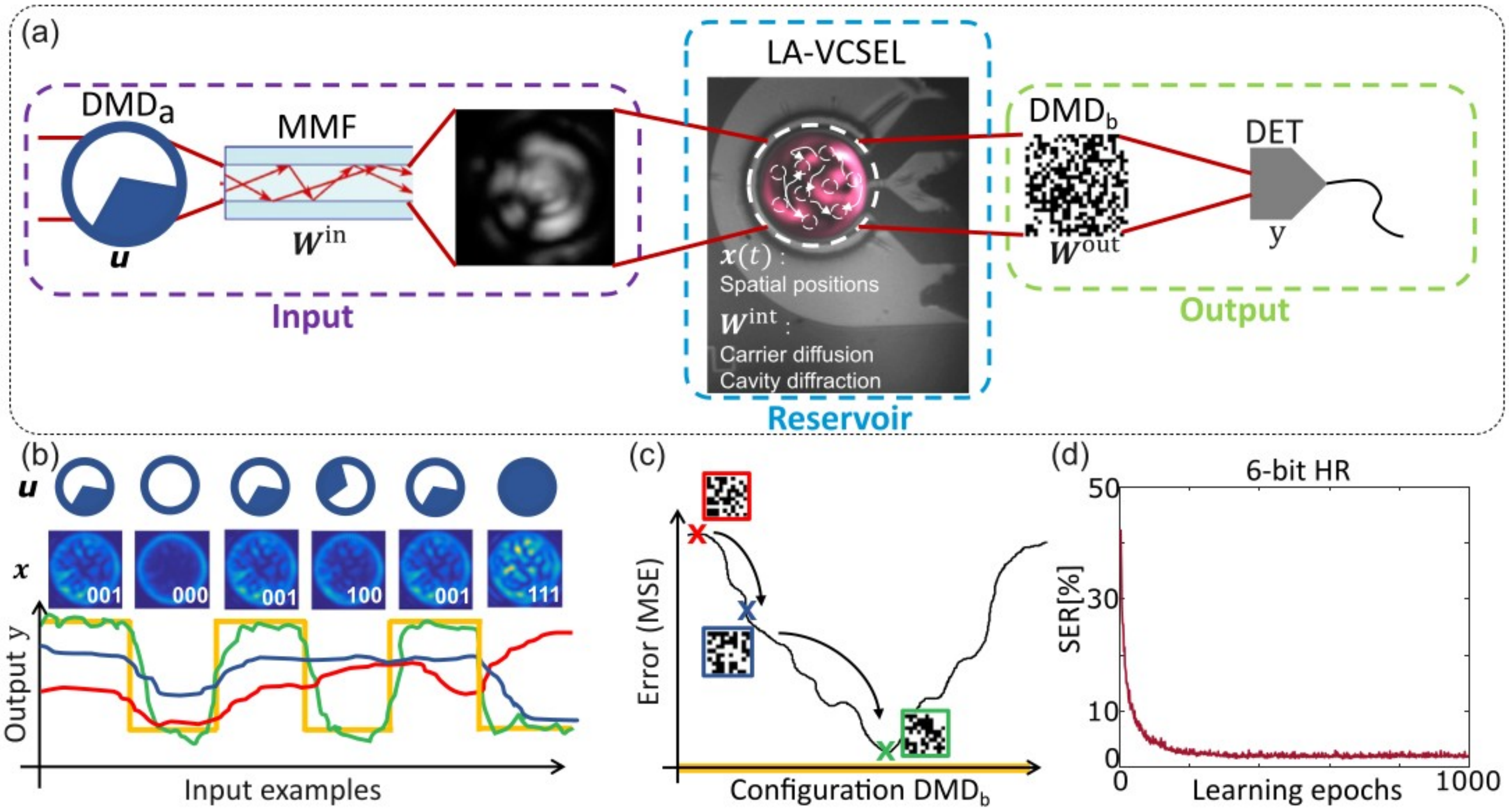
A photonics perspective on computing with physical substrates

S. Abreu [a], I. Boikov [b], M. Goldmann [c], T. Jonuzi [d], A. Lupo [e], S. Masaad [f], L. Nguyen [g], E. Picco [e], G. Pourcel [a], A. Skalli [h], L. Talandier [c], B. Vettelschoss [i], E.A. Vlieg [j], A. Argyris [c], P. Bienstman [f], D. Brunner [h], J. Dambre [i], L. Daudet [k], J.D. Domenech [d], I. Fischer [c], F. Horst [j], S. Massar [e], C.R. Mirasso [c], B.J. Offrein [j], A. Rossi [b], M.C. Soriano [c,*], S. Sygletos [g], S.K. Turitsyn [g]



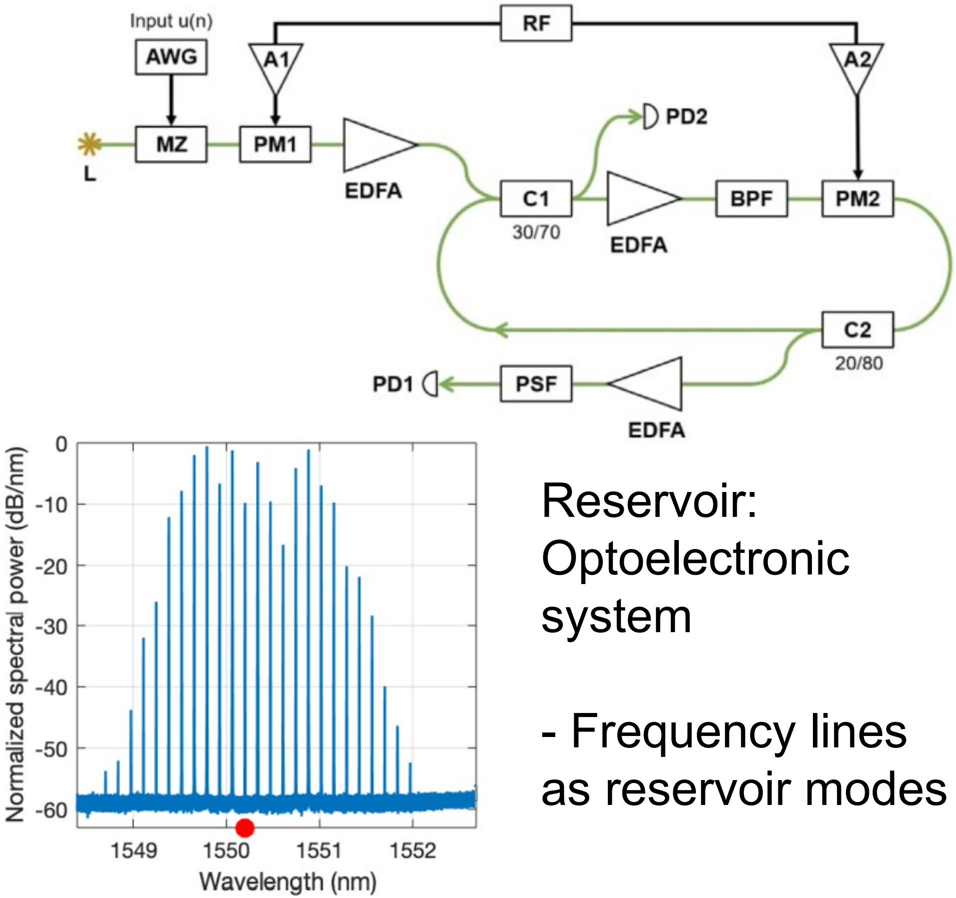


Reservoir: Large-area Vertical Cavity Surface Emitting Laser

- Different spatial locations as reservoir nodes

- Input and output layer also in hardware!

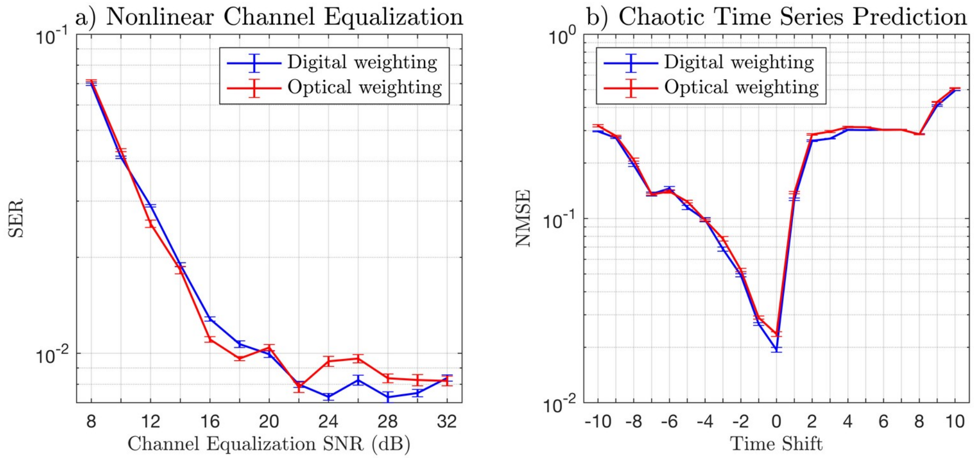
A. Skalli, J. Robertson, D. Owen-Newns, M. Hejda, X. Porte, S. Reitzenstein, A. Hurtado, D. Brunner, “Photonic neuromorphic computing using vertical cavity semiconductor lasers”, Optical Materials Express 12, 2395 (2022).



Reservoir: Optoelectronic system

- Frequency lines as reservoir modes

Demonstrated in benchmark tasks:
- Nonlinear channel equalization
- Chaotic time series prediction



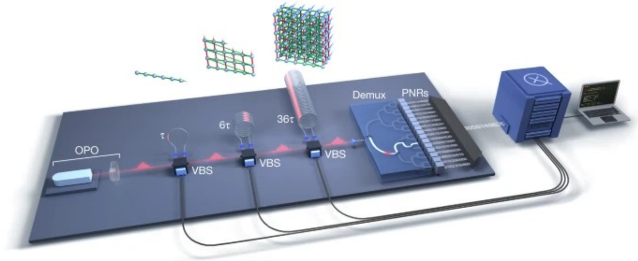
- Recent extension to deep reservoirs!

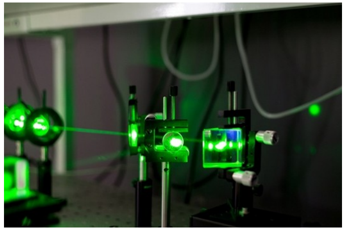
L. Butschek, A. Akrout, E. Dimitriadou, A. Lupo, M. Haelterman, S. Massar, “Photonic reservoir computer based on frequency multiplexing”, Optics Letters 47, 782 (2022).

- **Information processing with photonic systems and time-multiplexing**
  - **From Classical...**
    - Speeding up computation with semiconductor lasers
    - Integrated photonics
    - Training hardware systems
  - **To Quantum Reservoir Computing**
    - Proposal in a photonic substrate

Advantages of quantum photonics

- High transmission speed
- Long time quantum coherence
- Scalability (time/frequency multiplexing...)





QUANTUM COMPUTING

Quantum computational advantage using photons

Han-Sen Zhong[1,2]*, Hui Wang[1,2]*, Yu-Hao Deng[1,2]*, Ming-Cheng Chen[1,2]*, Li-Chao Peng[1,2], Yi-Han Luo[1,2], Jian Qin[1,2], Dian Wu[1,2], Xing Ding[1,2], Yi Hu[1,2], Peng Hu[3], Xiao-Yan Yang[3], Wei-Jun Zhang[3], Hao Li[3], Yuxuan Li[4], Xiao Jiang[1,2], Lin Gan[4], Guangwen Yang[4], Lixing You[3], Zhen Wang[3], Li Li[1,2], Nai-Le Liu[1,2], Chao-Yang Lu[1,2]†, Jian-Wei Pan[1,2]†

Quantum computers promise to perform certain tasks that are believed to be intractable to classical computers. Boson sampling is such a task and is considered a strong candidate to demonstrate the quantum computational advantage. We performed Gaussian boson sampling by sending 50 indistinguishable single-mode squeezed states into a 100-mode ultralow-loss interferometer with full connectivity and random matrix—the whole optical setup is phase-locked—and sampling the output using 100 high-efficiency single-photon detectors. The obtained samples were validated against plausible hypotheses exploiting thermal states, distinguishable photons, and uniform distribution. The photonic quantum computer, *Jiuzhang*, generates up to 76 output photon clicks, which yields an output state-space dimension of 10^{30} and a sampling rate that is faster than using the state-of-the-art simulation strategy and supercomputers by a factor of ~10^{14}.

Zhong *et al.*, *Science* **370**, 1460–1463 (2020)

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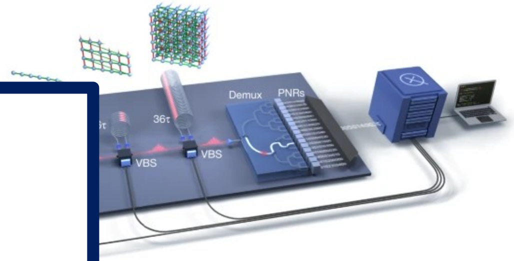
Quantum computational advantage with a programmable photonic processor

Lars S. Madsen, Fabian Laudenbach, Mohsen Falamarzi. Askarani, Fabien Rortais, Trevor Vincent, Jacob F. F. Bulmer, Filippo M. Miatto, Leonhard Neuhaus, Lukas G. Helt, Matthew J. Collins, Adriana E. Lita, Thomas Gerrits, Sae Woo Nam, Varun D. Vaidya, Matteo Menotti, Ish Dhand, Zachary Vernon, Nicolás Quesada & Jonathan Lavoie

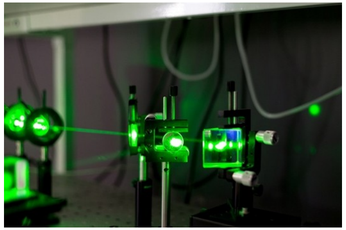
Nature **606**, 75–81 (2022) | Cite this article

Advantages of quantum photonics

- High transmission speed
- Long time quantum c
- Scalability (time/freq



- Fast-evolving field
- Relevant for a wide variety of applications (quantum computing, quantum simulation, quantum communications, etc)



QUANTUM COMP

Quantum co

Han-Sen Zhong[1,2*], Hu
Yi-Han Luo[1,2], Jian Qin
Hao Li[3], Yuxuan Li[4], Xi
Nai-Le Liu[1,2], Chao-Yan

Quantum computers p
computers. Boson sampling is such a task and is considered a strong candidate to demonstrate the quantum computational advantage. We performed Gaussian boson sampling by sending 50 indistinguishable single-mode squeezed states into a 100-mode ultralow-loss interferometer with full connectivity and random matrix—the whole optical setup is phase-locked—and sampling the output using 100 high-efficiency single-photon detectors. The obtained samples were validated against plausible hypotheses exploiting thermal states, distinguishable photons, and uniform distribution. The photonic quantum computer, *Jiuzhang*, generates up to 76 output photon clicks, which yields an output state-space dimension of 10^{30} and a sampling rate that is faster than using the state-of-the-art simulation strategy and supercomputers by a factor of ~10^{14}.

Zhong *et al.*, *Science* **370**, 1460–1463 (2020)

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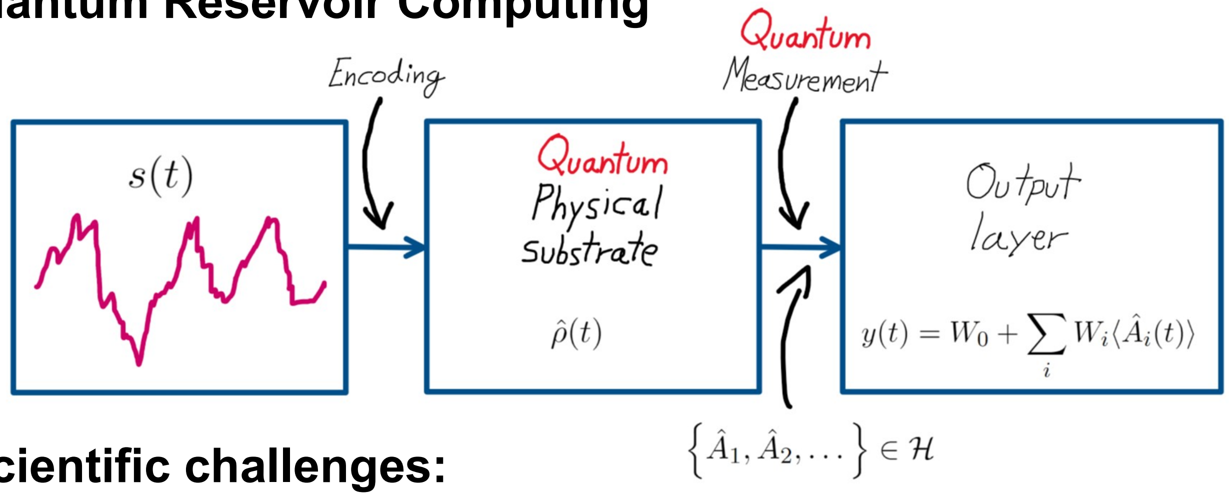
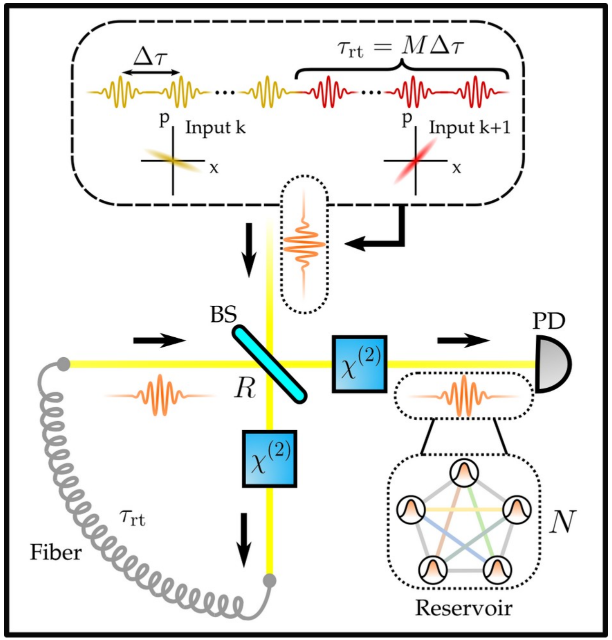
Lars S. Madsen, Fabian Laudenbach, Mohsen Falamarzi. Askarani, Fabien Rortais, Trevor Vincent, Jacob F. F. Bulmer, Filippo M. Miatto, Leonhard Neuhaus, Lukas G. Helt, Matthew J. Collins, Adriana E. Lita, Thomas Gerrits, Sae Woo Nam, Varun D. Vaidya, Matteo Menotti, Ish Dhand, Zachary Vernon, Nicolás Quesada & Jonathan Lavoie

Nature **606**, 75–81 (2022) | Cite this article

Quantum Reservoir Computing



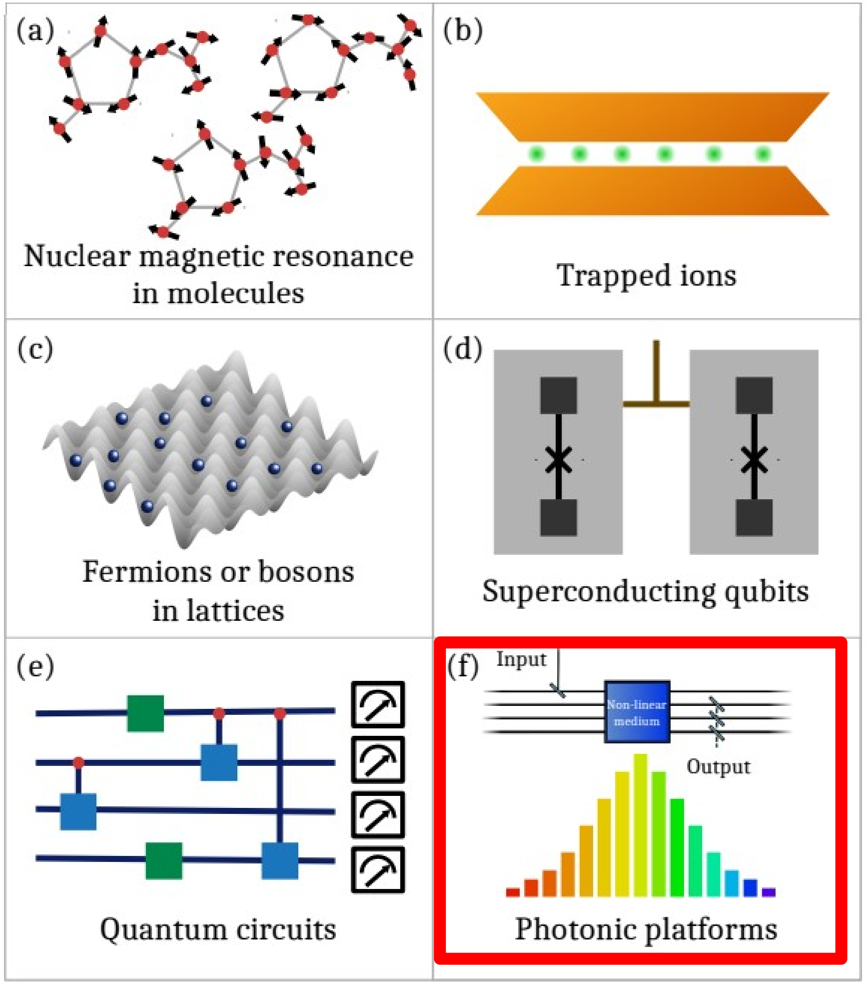
Proposal in photonics:

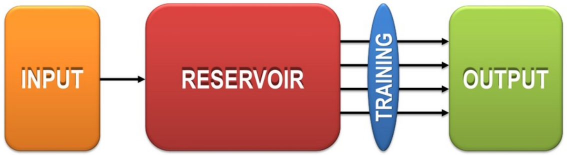


Scientific challenges:

- RC requires **memory**, **nonlinearity**, and **high dimensionality**
- Measurement alters quantum state → memory needs to be preserved
- Output layer over expected values → multiple measurements or multiple copies of the experiment are needed
- Strategies are needed for conducting experiments in **real time**

P. Mujal, R. Martínez-Peña, J. Nokkala, J. García-Beni, G. L. Giorgi, M. C. Soriano, and R. Zambrini. "Opportunities in Quantum Reservoir Computing and Extreme Learning Machines." Advanced Quantum Technologies, 2100027 (2021)

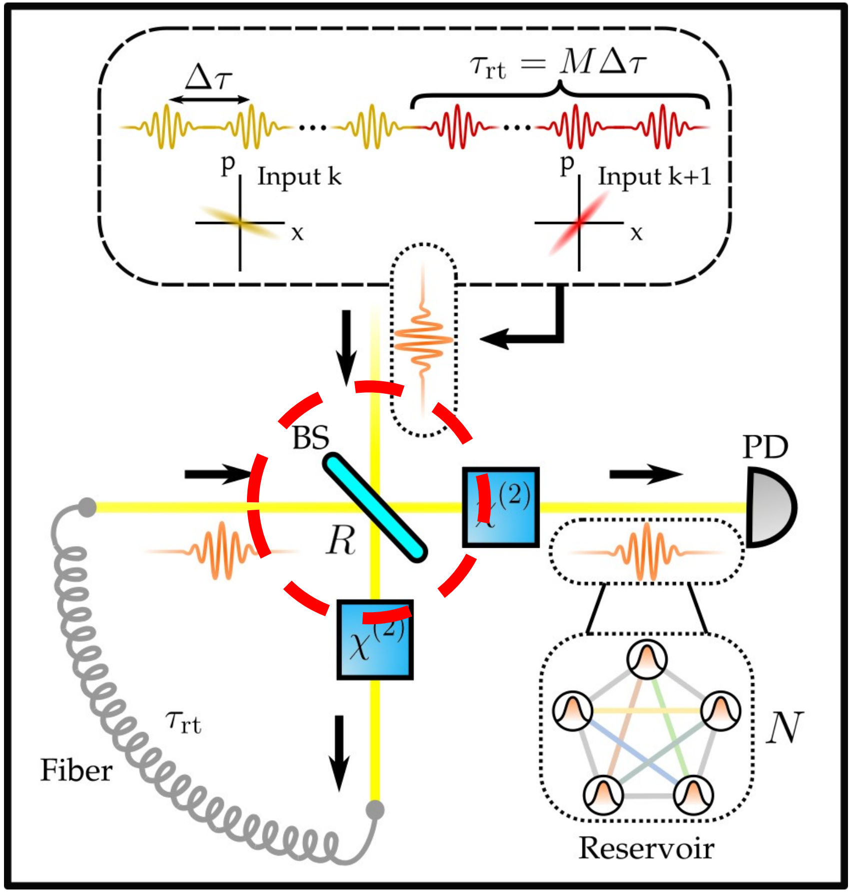




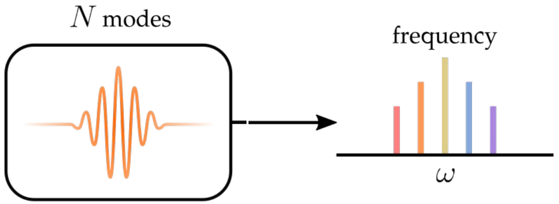
	Classical Substrate $\mathbf{x}_k$	Quantum Substrate ρ_S
Classical Input	**CCC** $\{s_k\}, \mathbf{x}_k^{\text{out}} \to T_C$ [21, 23, 54–60]	**CQC** $\{s_k\}, \{O_i^{\text{out}}\} \to T_C$ [33–41, 43, 44, 47, 52]
s_k	**CCQ** $\{s_k\}, \mathbf{x}_k^{\text{out}} \to T_Q$	**CQQ** $\{s_k\}, \{O_i^{\text{out}}\} \to T_Q$ [48, 49]
Quantum Input	**QCC** $\{\rho_k^{\text{in}}\}, \mathbf{x}_k^{\text{out}} \to T_C$	**QQC** $\{\rho_k^{\text{in}}\}, \{O_i^{\text{out}}\} \to T_C$
ρ_k^{in}	**QCQ** $\{\rho_k^{\text{in}}\}, \mathbf{x}_k^{\text{out}} \to T_Q$ [61]	**QQQ** $\{\rho_k^{\text{in}}\}, \{O_i^{\text{out}}\} \to T_Q$ [46, 50, 62, 63]

P. Mujal et al, (2021), *Opportunities in Quantum Reservoir Computing and Extreme Learning Machines*. Adv. Quantum Technol., 4: 2100027.

Platform scheme:



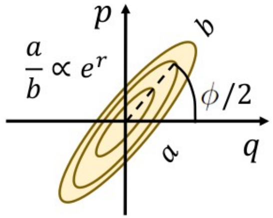
Information carrier: optical pulse



Input ancilla: squeezed vacuum state

Input encoding

$$\phi_k = f(s_k)$$



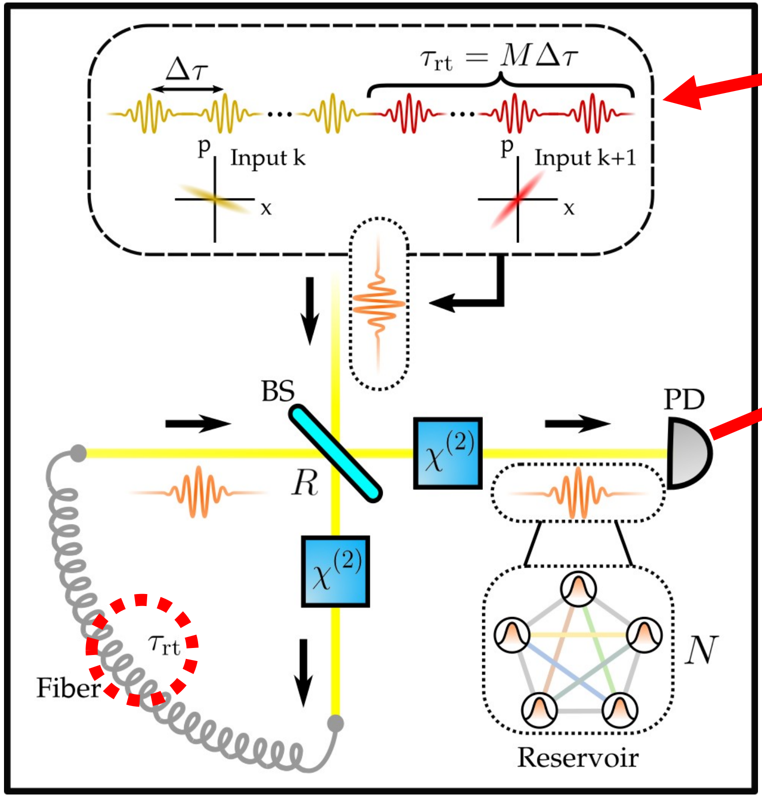
Non-linear crystals: mode coupling

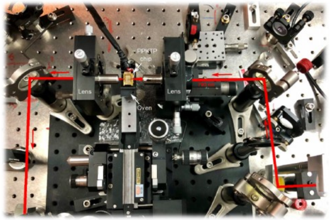
$$\hat{H}_{\chi^{(2)}} = \sum_{i=1}^{N} \omega_i \hat{a}_i^\dagger \hat{a}_i + \sum_{j>i} \left(g_{ij} \hat{a}_i^\dagger \hat{a}_j + i h_{ij} \hat{a}_i^\dagger \hat{a}_j^\dagger + \text{h.c.} \right)$$

Quantum measurement: photodetection

Homodyne detection of quadratures $\hat{x}_i = \frac{1}{\sqrt{2}} \left(\hat{a}_i + \hat{a}_i^\dagger \right) \quad i = 1, \ldots, N$

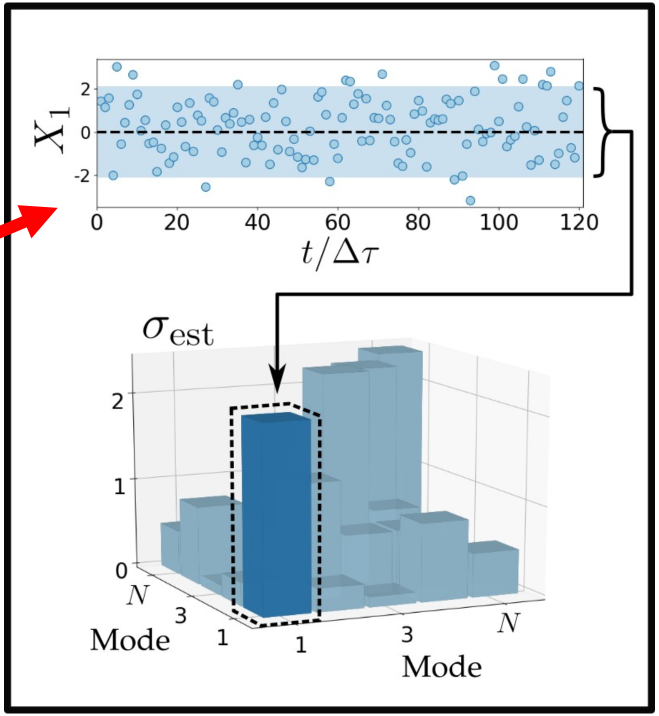
Platform scheme:





V. Parigi, LKB

Physical ensemble:



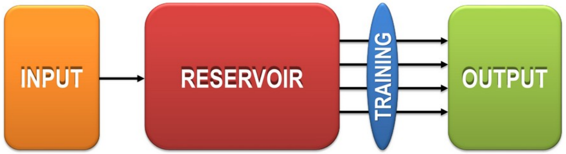
Readout observables:

$$\text{Input } s_k \longrightarrow \left[\sigma_{\text{est}}^{(k)}\right]_{ij} = \left\langle X_i^{(k)} X_j^{(k)} \right\rangle_M - \left\langle X_i^{(k)} \right\rangle_M \left\langle X_j^{(k)} \right\rangle_M$$

Size of the reservoir (covariance matrix): $N(N+1)/2$

- M denotes the number of pulses in the loop and the number of statistical samples for the ensemble

Benchmark tasks

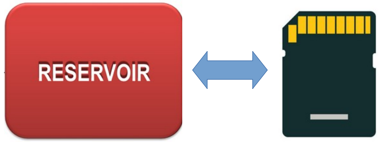


$$\text{Readout layer} \longrightarrow y_k = W_0 + \sum_{i=1}^{\#\,\text{obs.}} W_i O_i^{(k)}$$

$$\text{Target function} \longrightarrow \bar{y}_k \equiv \mathcal{F}(s_k, s_{k-1}, s_{k-2}, \dots)$$

Short-term memory

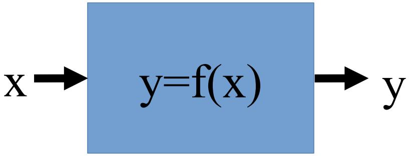
x(k)={3,4,2,9,6,1,8,5,2,3…}

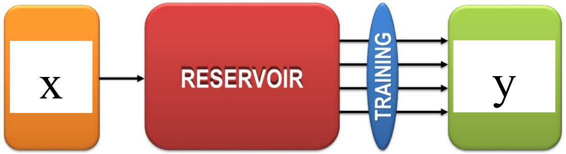


y=x(k-1)={4,2,9,6,1,8,…}

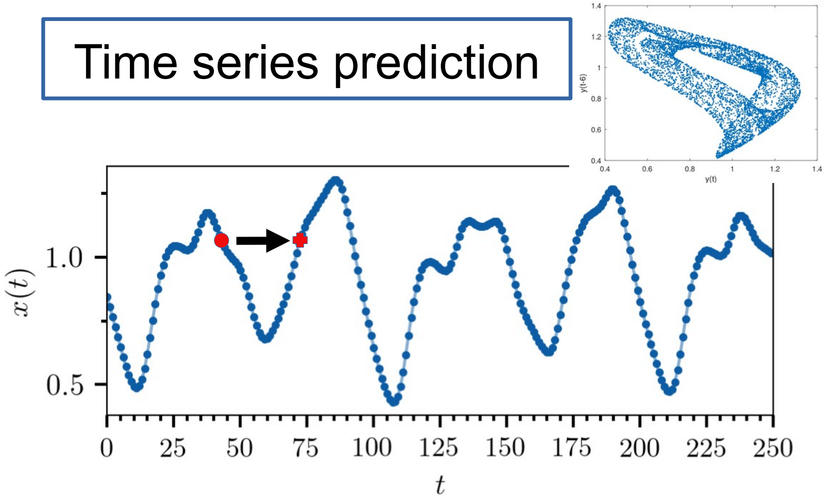
y'=x(k-3)={9,6,1,8,5,2,...}

System identification





Time series prediction

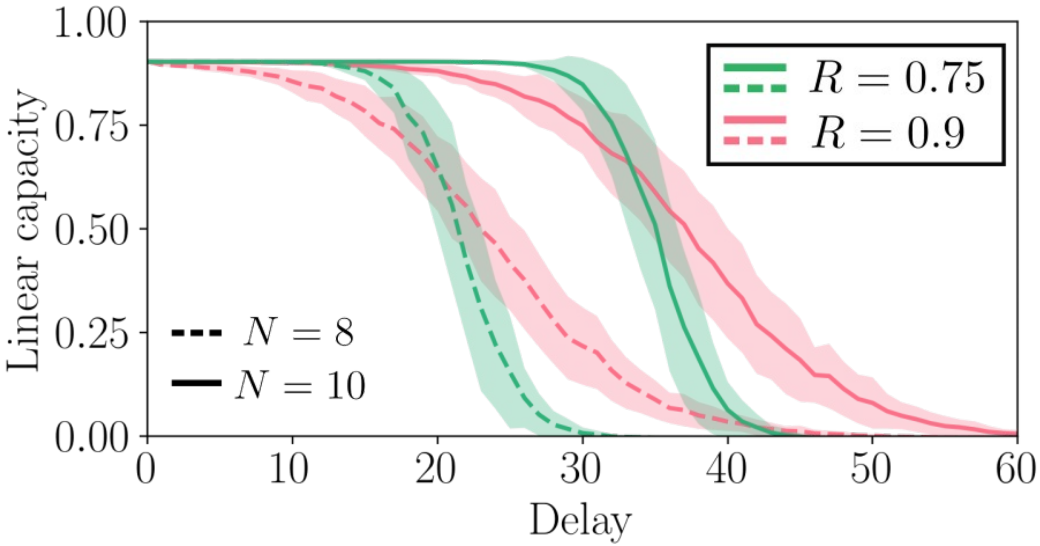


Performance metrics: $\mathrm{MSE}_L(\mathbf{y}, \bar{\mathbf{y}}) = \sum_{k=1}^{L} (y_k - \bar{y}_k)^2$

Capacity

$$\mathcal{C}_L(\mathbf{y}, \bar{\mathbf{y}}) = 1 - \mathrm{MSE}_L(\mathbf{y}, \bar{\mathbf{y}})$$

Linear memory capacity



Reconstruct linear functions of the inputs

$$\bar{y}_k(d) = s_{k-d}$$

Ideal case (infinite ensemble)

- Increasing N: more delay depth, same shape.
- Increasing R: more delay depth, different shape.

Photonic QRC platform has memory!

Simulation parameters

- **Input:** $\{s_k\} \in \mathcal{U}_{[-1,1]}$

$$r_k = 1$$

$$\phi_k = 3\pi s_k/4$$

- **Dynamics:**

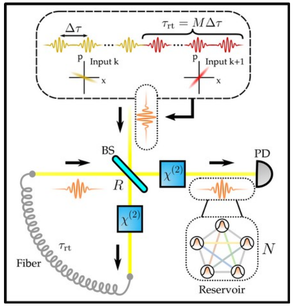
$$\omega_i = 1 \quad \forall i \qquad \Delta t = 1$$

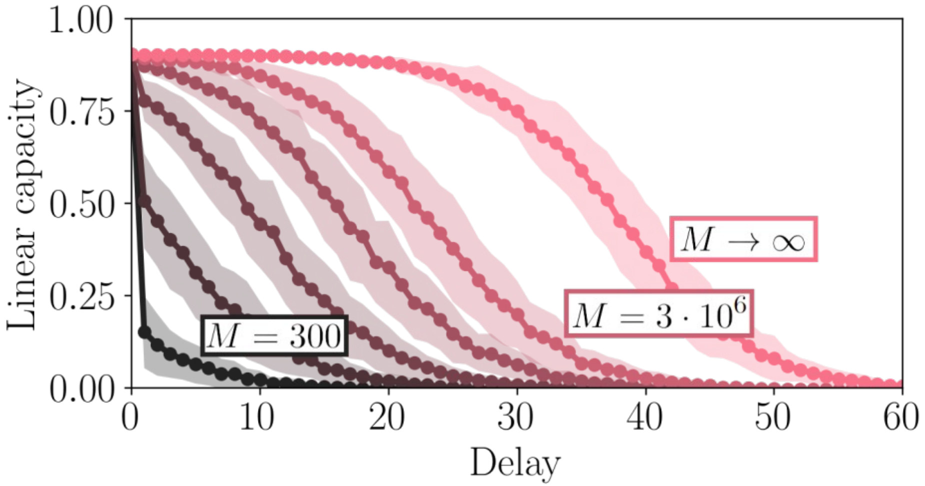
$$g_{ij} \in \mathcal{U}_{[\langle g\rangle - \Delta g, \langle g\rangle + \Delta g]}$$

$$h_{ij} \in \mathcal{U}_{[\langle h\rangle - \Delta h, \langle h\rangle + \Delta h]}$$

$$\left\{ \begin{array}{c} \langle g\rangle = 0.2\ ;\ \langle h\rangle = 0.3 \\ \Delta g = \Delta h = 0.1 \end{array} \right.$$

From ideal case to finite ensemble





Statistical fluctuations:

$$\sigma_{\text{est}}^{(k)} = \sigma_{\text{ideal}}^{(k)} + \xi_M^{(k)}$$

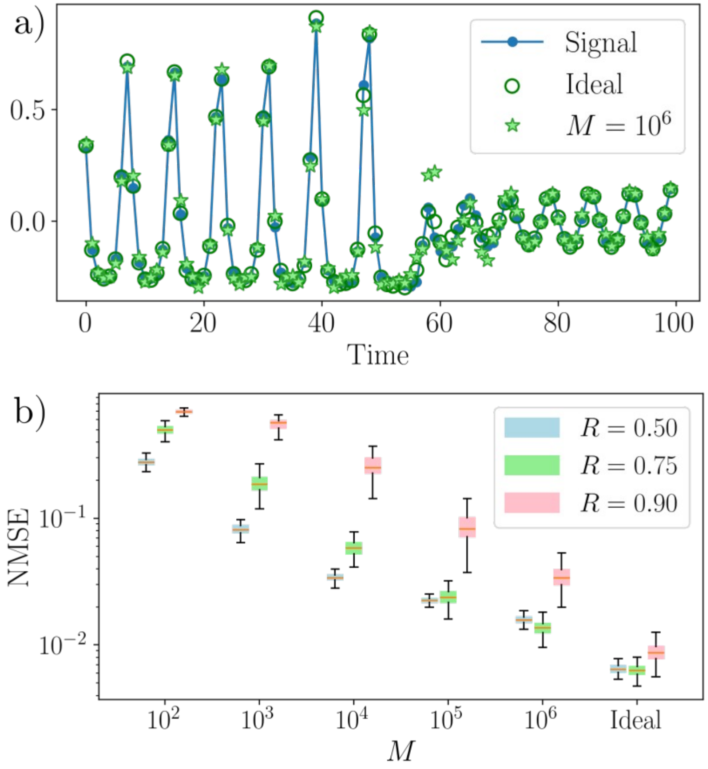
$$\langle |\xi_M| \rangle_{\text{real.}} \propto M^{-1/2}$$

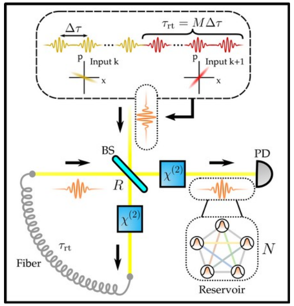
- Decomposition of ideal observables + statistical noise
- Statistical noise related to the number of pulses (size of the ensemble M)

- **Finite ensemble:** reduced memory
- Exponential factor increase of M needed to maintain quadratic scaling with N

* $M = 300, 3000, 30000, \ldots$

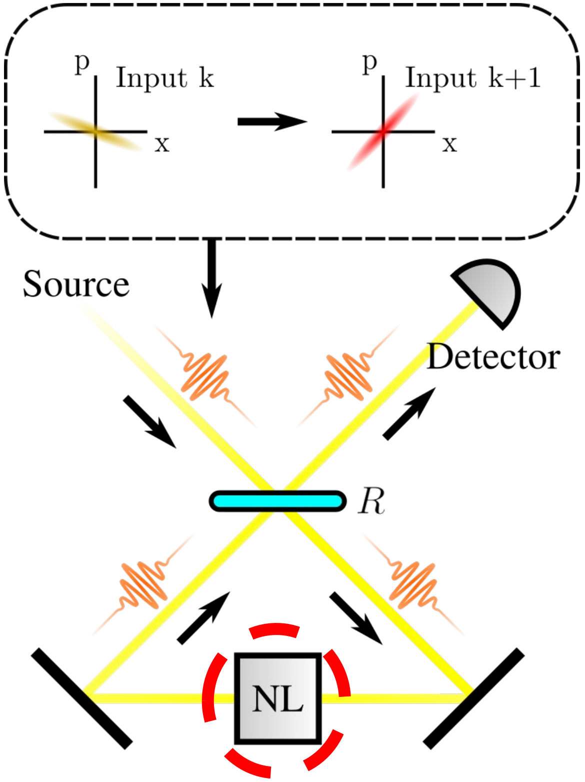
Time-series prediction





- With finite number of pulses, high performance for practical benchmarks is possible
- Strategy to improve size scalability and number of needed measurements M → balance between signal-to-noise ratio of observables and signal in the loop
- Photonic platform has nonlinearity and high-dimensionality

J. García-Beni, G. L. Giorgi, M. C. Soriano, and R. Zambrini. "Scalable photonic platform for real-time quantum reservoir computing." Physical Review Applied 20, 014051 (2023) / arXiv:2207.14031



Non-linear crystal:

Transformation applied to the quadrature vector:

$$\hat{\mathbf{R}}' = S_{\rm NL}\hat{\mathbf{R}}$$

Passive

$$S_{\rm NL} = U\Delta_{\mathbf{r}}V$$

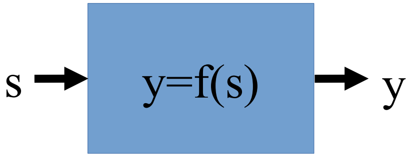
Active (squeezing)

$$\Delta_{\mathbf{r}} = \mathrm{diag}\left(e^{r_1/2}, e^{-r_1/2}, \ldots, e^{r_N/2}, e^{-r_N/2}\right)$$

Parameter r determines the squeezing per mode generated by the crystal.

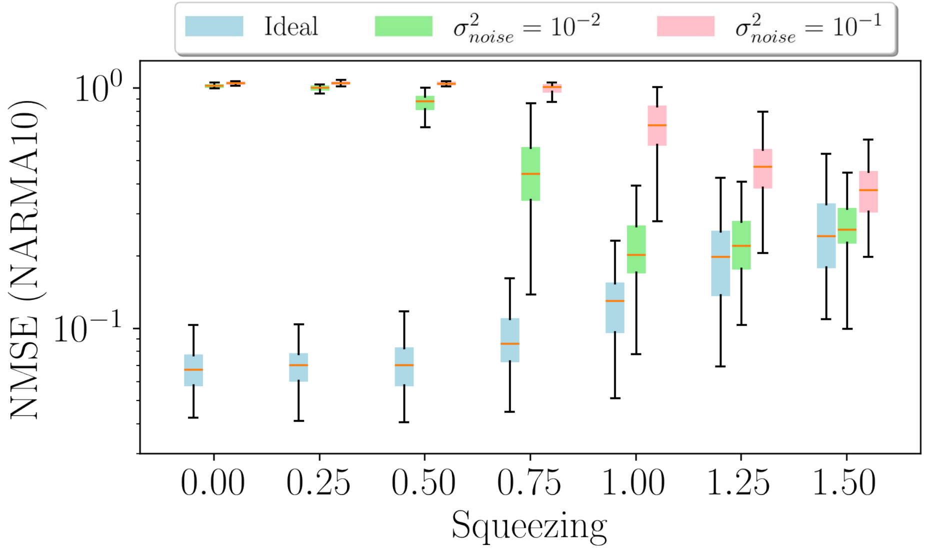
- **Active** transformation: generates squeezing
- **Passive** part: constant number of photons

Non-linear system identification task (NARMA10)



Target f: $$y_k = 0.3y_{k-1} + 0.05y_{k-1}\sum_{i=1}^{10} y_{k-i} + 0.06s_{k-1}s_{k-10} + 0.1$$

- Requires high linear and quadratic memory
- Quite sensitive to readout noise

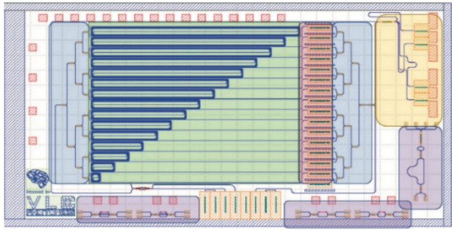


- Squeezing in active cavity improves the noise robustness of the quantum reservoir

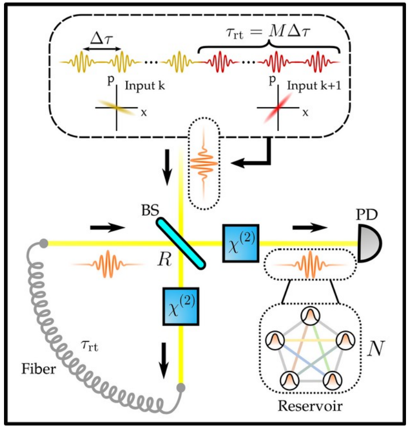
Readout noise

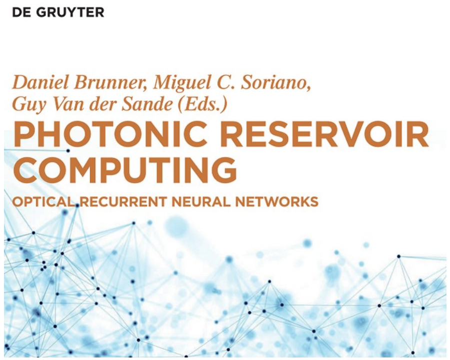
$$\mathbf{O}^{(k)}_{\text{meas}} = \mathbf{O}^{(k)}_{\text{ideal}} + \mathcal{E}^{(k)}(0, \sigma^2_{\text{noise}})$$

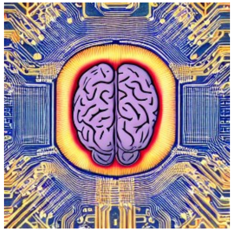
J. García-Beni, G. L. Giorgi, M. C. Soriano, and R. Zambrini, "Squeezing as a resource for time series processing in quantum reservoir computing", Optics Express 32, 6733-6747 (2024).

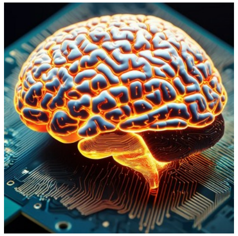


1. Cross-fertilization between complex photonics and information processing
    A. Opportunities for integrated photonic circuits
    B. Development of new learning concepts (hardware-aware)
    C. Practical implementations for quantum reservoir computing
2. Approaches based on Time-multiplexing
    A. Rapid prototyping
    B. Adaptability to task requirements









A human brain on top of a photonic integrated circuit

* Stable Diffusion (2022 / 2024)

Ingo Fischer

Apostolos Argyris

Mirko Goldmann

Claudio R. Mirasso

Tigers Jonuzi (VLC Photonics)

1. Cross-fertilization between complex photonics and information processing
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2. Approaches based on Time-multiplexing
   A. Rapid prototyping
   B. Adaptability to task requirements

THANK YOU

for your attention

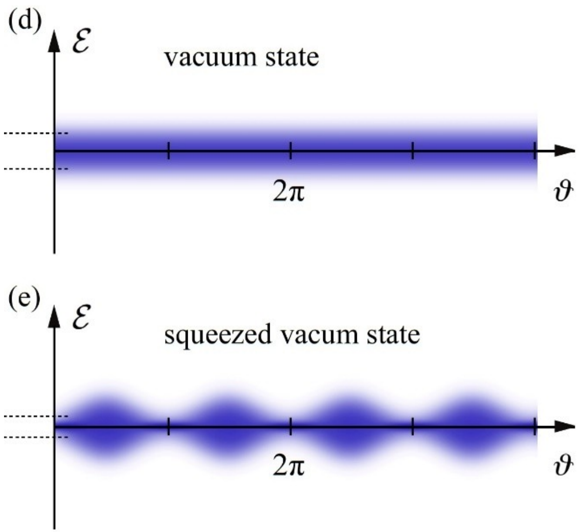
Roberta Zambrini

Gian Luca Giorgi

Jorge García Beni

Squeezing

- Quadrature (field operators) fluctuations below shot-noise limit.
- Resource for entanglement in CV quantum optics.
- Key to several quantum technologies.



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Enhanced sensitivity of the LIGO gravitational wave detector by using squeezed states of light

The LIGO Scientific Collaboration*

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Quantum computing with continuous-variable clusters

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