

Novel architectures for brain-inspired photonic computers

Nieuwe architecturen voor brein-geïnspireerde fotonische computers

Floris Laporte

2020.03.23

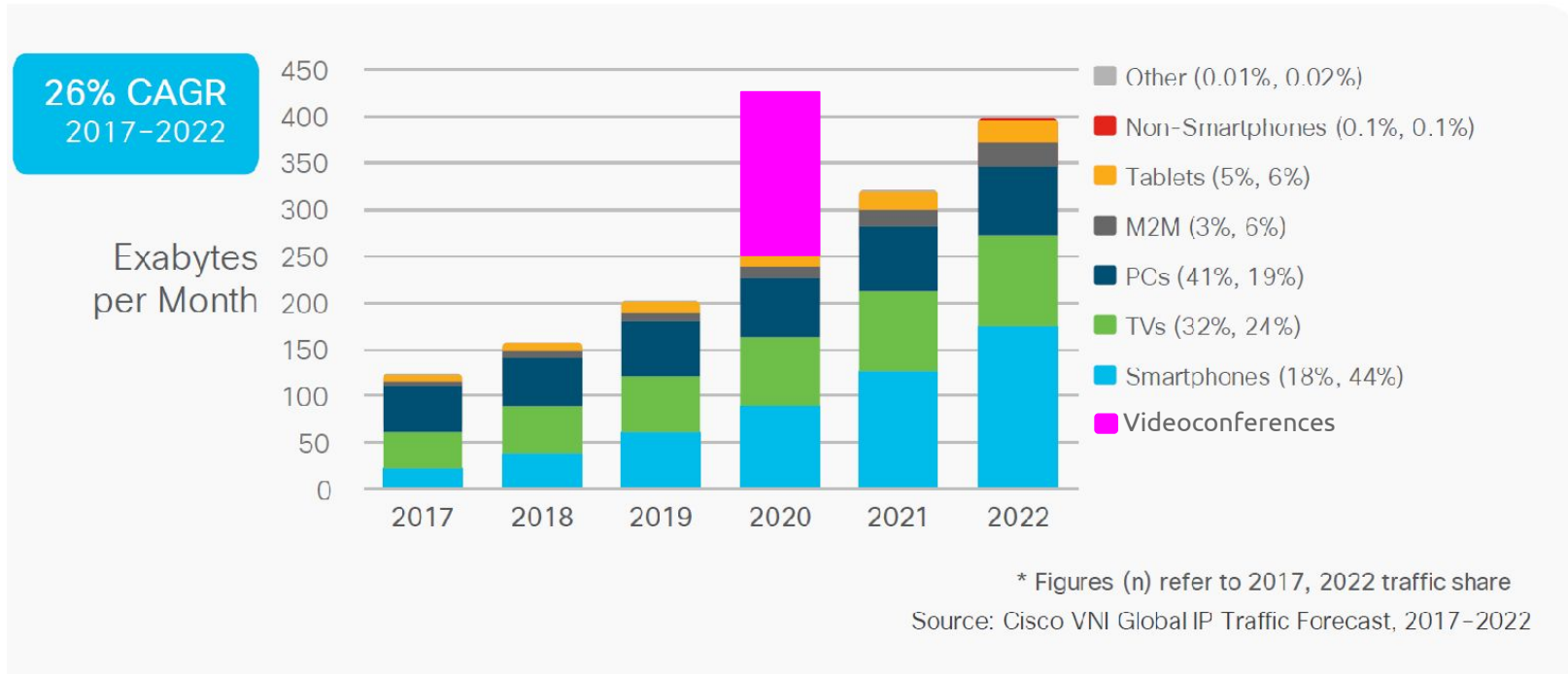
Examencommissie:

Prof. Dr. Ir. Filip De Turck (voorzitter)	Universiteit Gent, INTEC
Prof. Dr. Ir. Peter Bienstman (promotor)	Universiteit Gent, INTEC
Prof. Dr. Ir. Joni Dambre (promotor)	Universiteit Gent, IDLab
Prof. Dr. Ir. Francis wyffels	Universiteit Gent, IDLab
Prof. Dr. Ir. Dries Vande Ginste	Universiteit Gent, IDLab
Prof. Dr. Ir. Wim Bogaerts	Universiteit Gent, INTEC
Prof. Dr. Ir. Serge Massar	Université Libre de Bruxelles, LIQ
Dr. Ir. Martin Fiers	Luceda Photonics

Overview

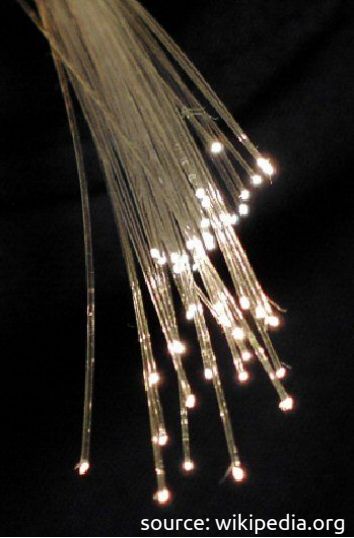
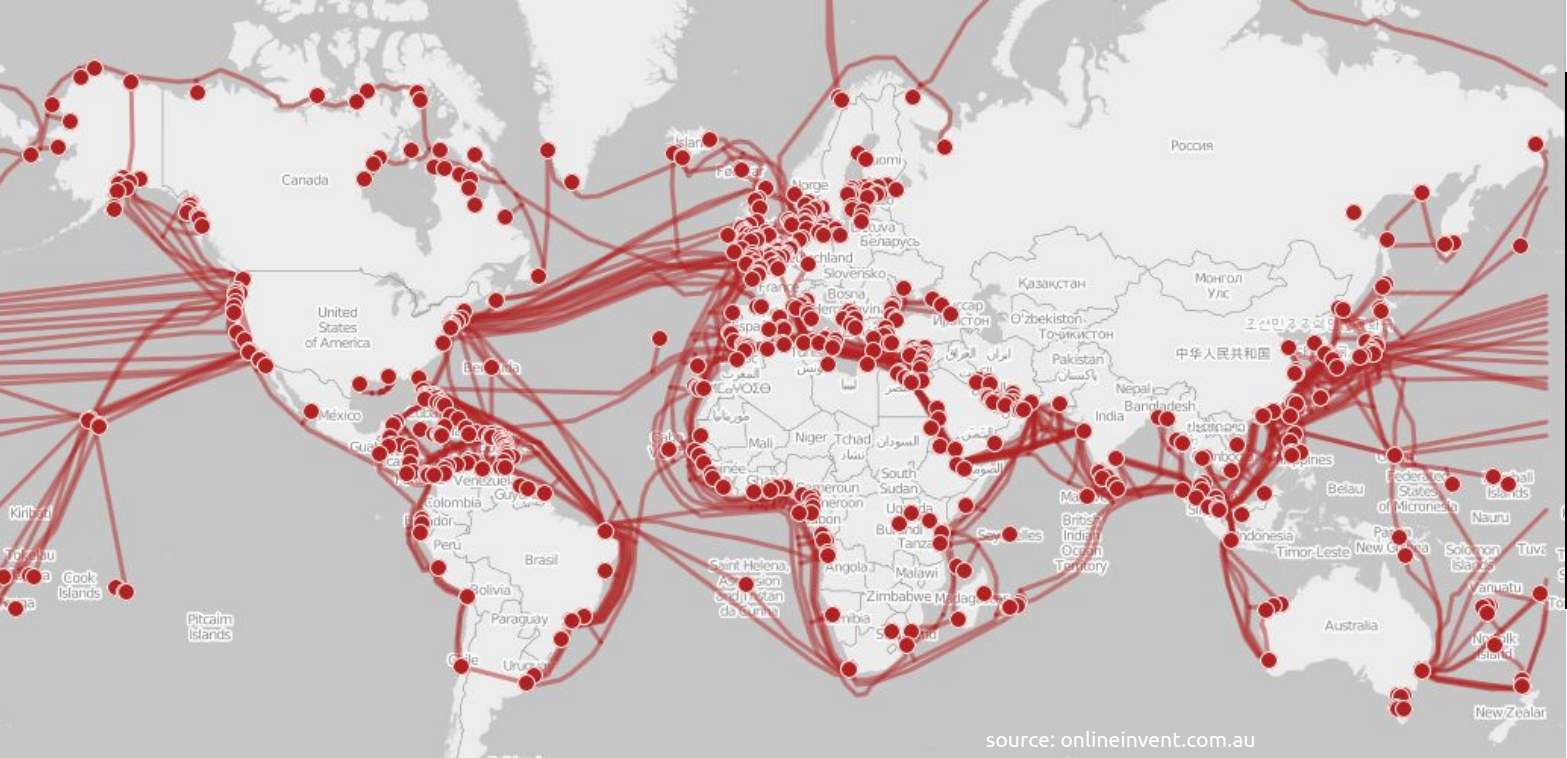
- **Background**
- Machine learning & Neuromorphic computing
- Reservoir computing with signal-mixing cavities
- Photontorch: optimizing photonic circuits
- Neuromorphic computing with photorefractive crystals

Internet usage



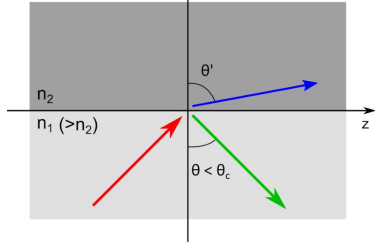
1 exabyte = 10^{18} bytes = 1 million terabytes

Data transmission is optical

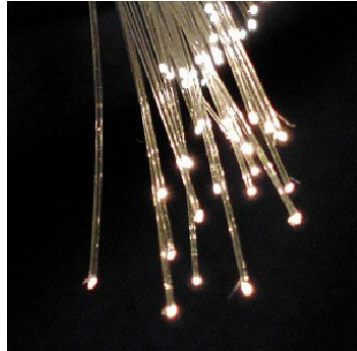
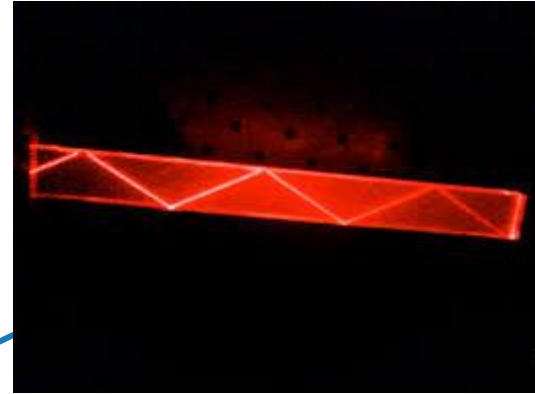
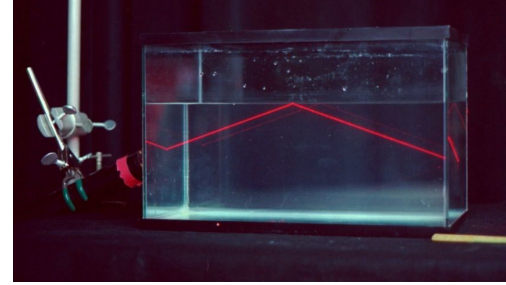
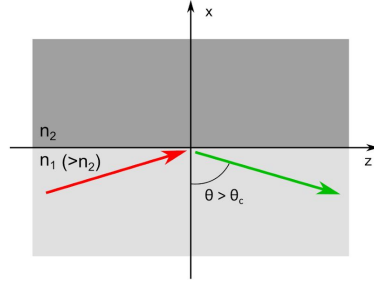


Data transmission is optical

Partial reflection
& refraction



Total internal reflection



Data **processing** is electrical

Digital Signal Processor (**DSP**):



Problem:

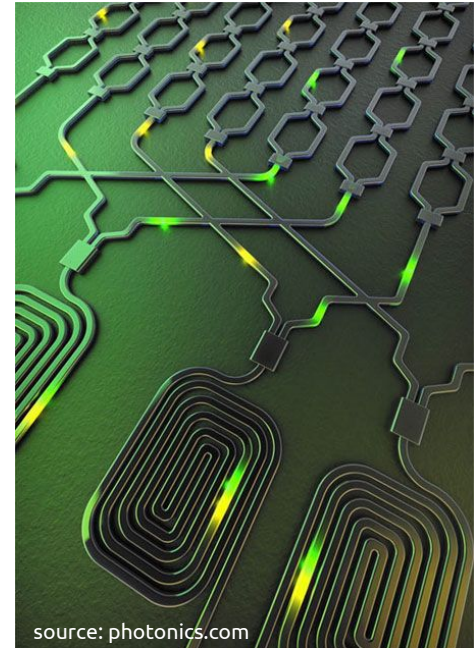
- Too costly
- Too power hungry

Main **challenge:**

- Increase bandwidth...
- ... while decreasing power consumption

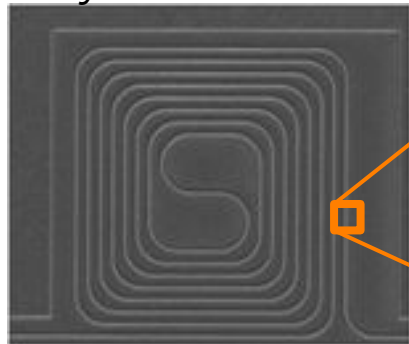
Optical signal processors?

- Very high bandwidth
- Low energy consumption
- Highly parallel execution

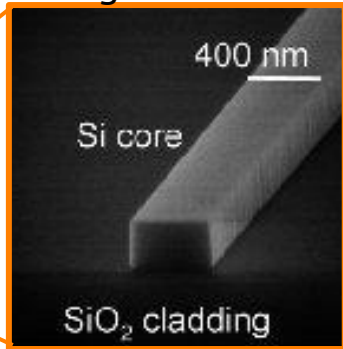


Silicon photonics

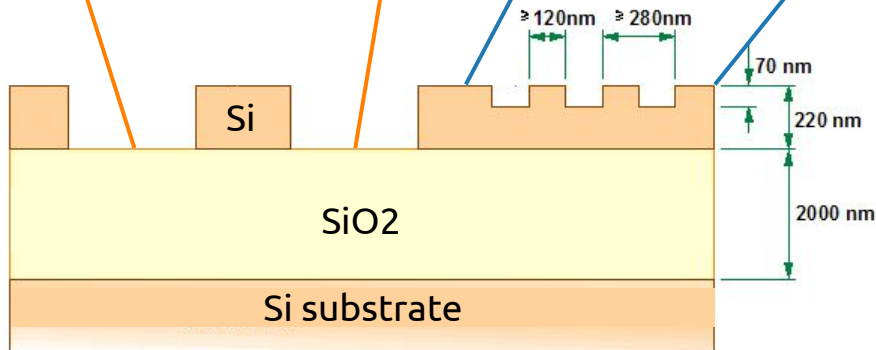
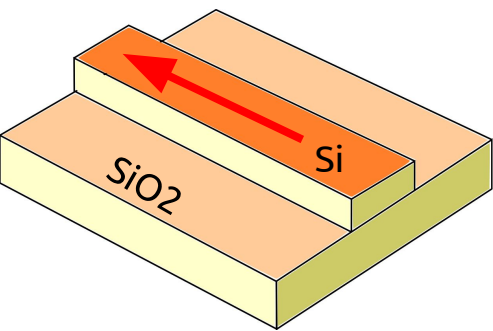
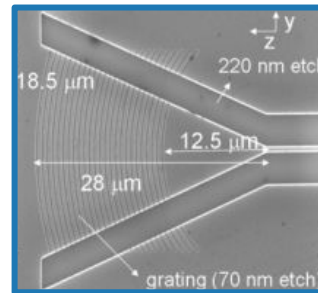
delay line



waveguide

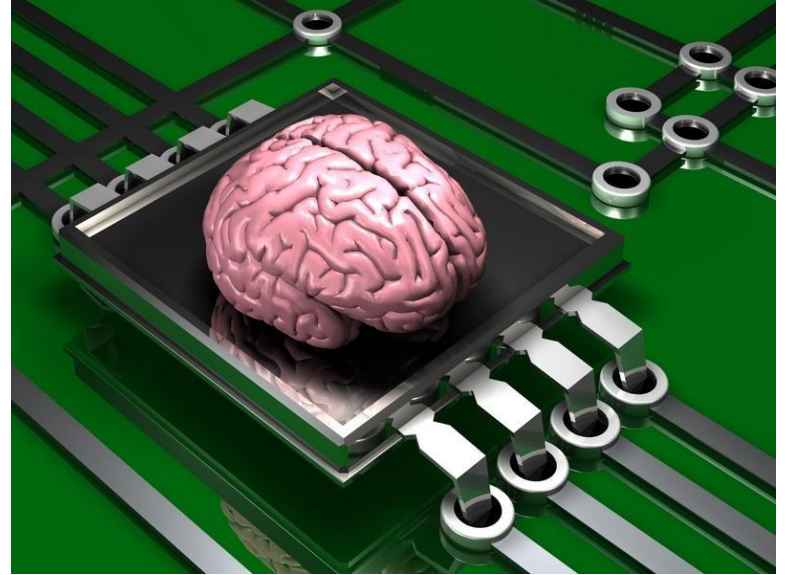
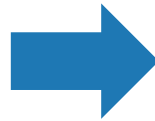


grating coupler (I/O)



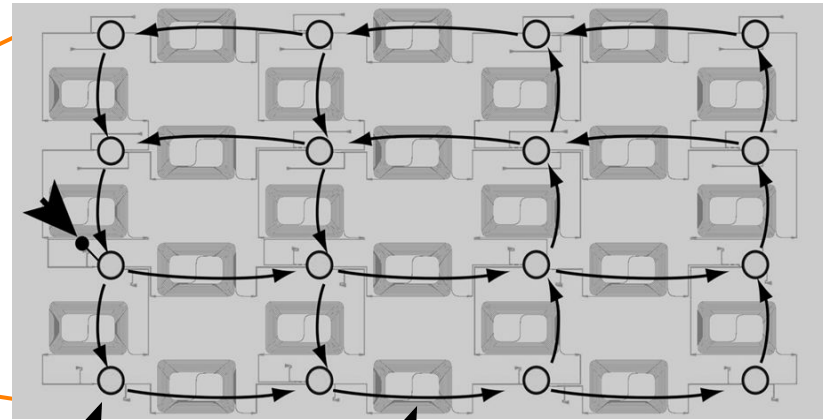
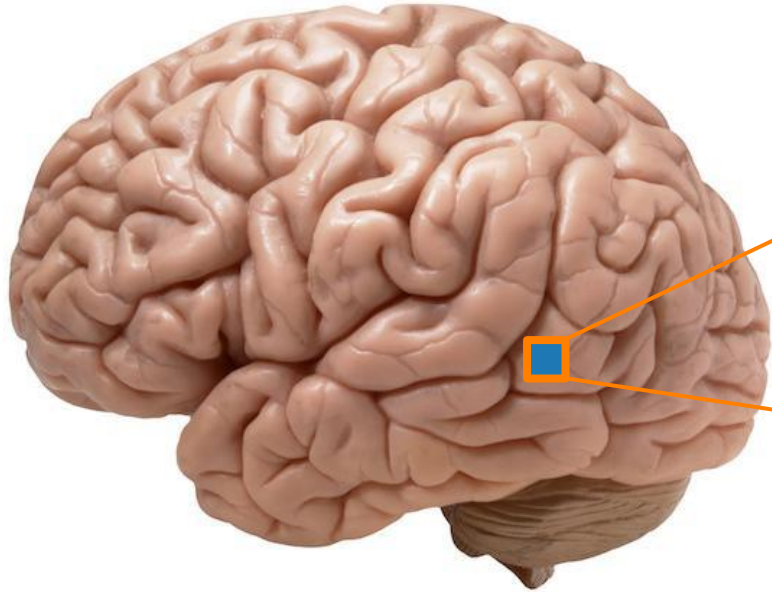
Neuromorphic computing

“brain-inspired”



Neuromorphic computing

“brain-inspired”



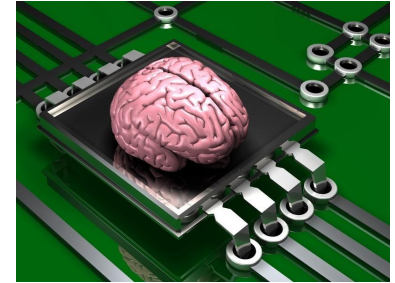
neuron

synapse

Goal

Solve **telecom** related tasks

- **Fast**
- **Efficiently**

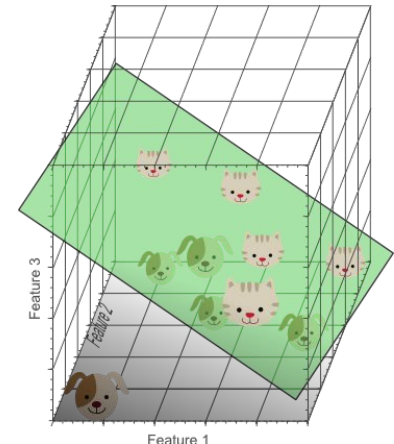
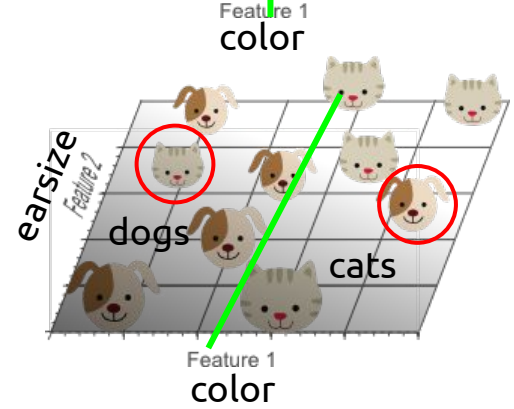


By using smart **neuromorphic** photonic architectures

Overview

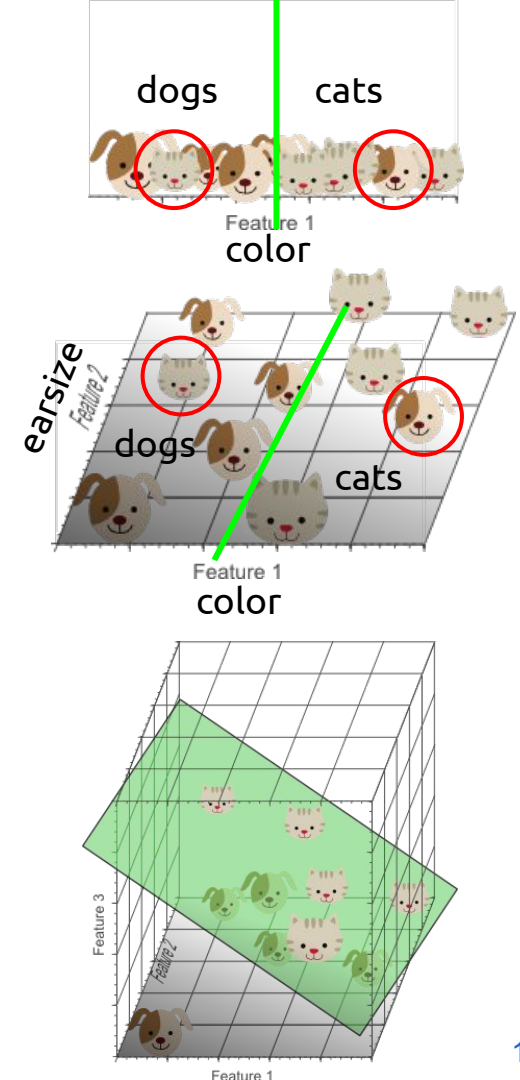
- Background
- **Machine learning & Neuromorphic computing**
- Reservoir computing with signal-mixing cavities
- Photontorch: optimizing photonic circuits
- Neuromorphic computing with photorefractive crystals

Learn from examples



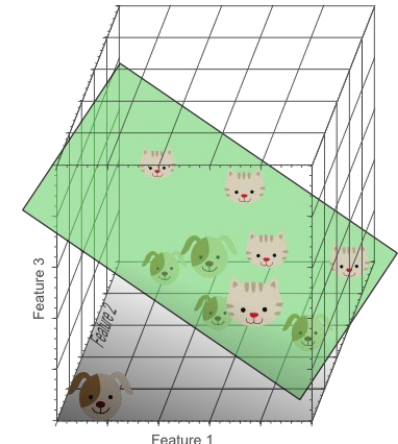
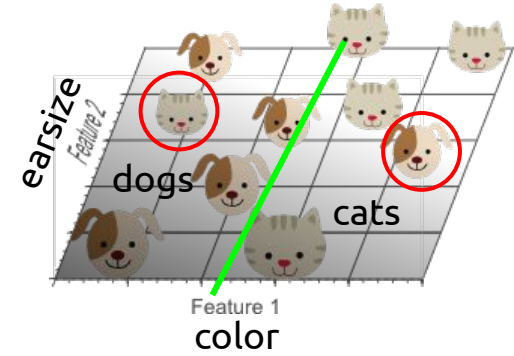
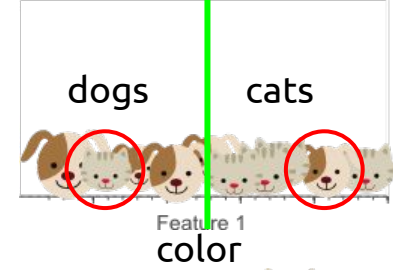
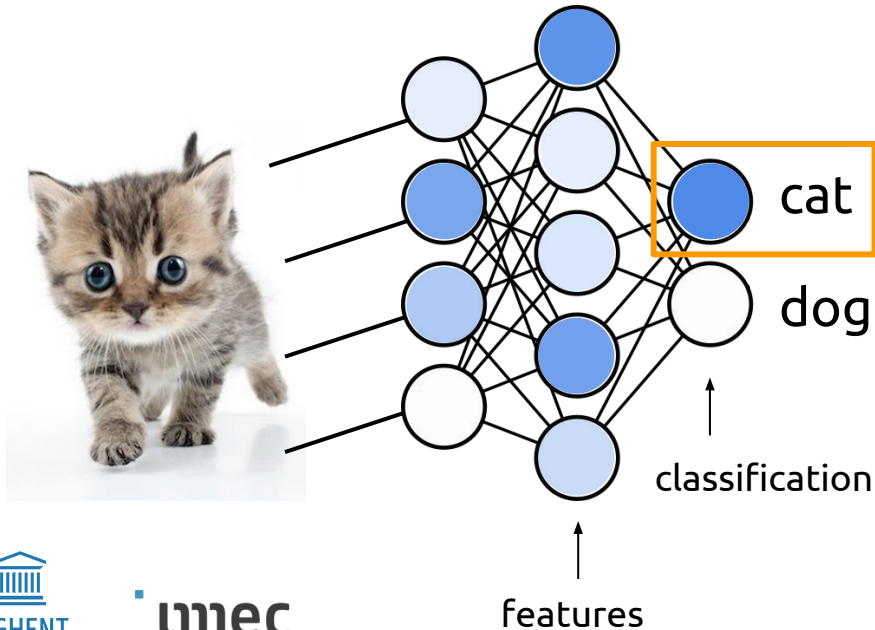
Machine learning

- Feature extraction
- Classification



Neural networks

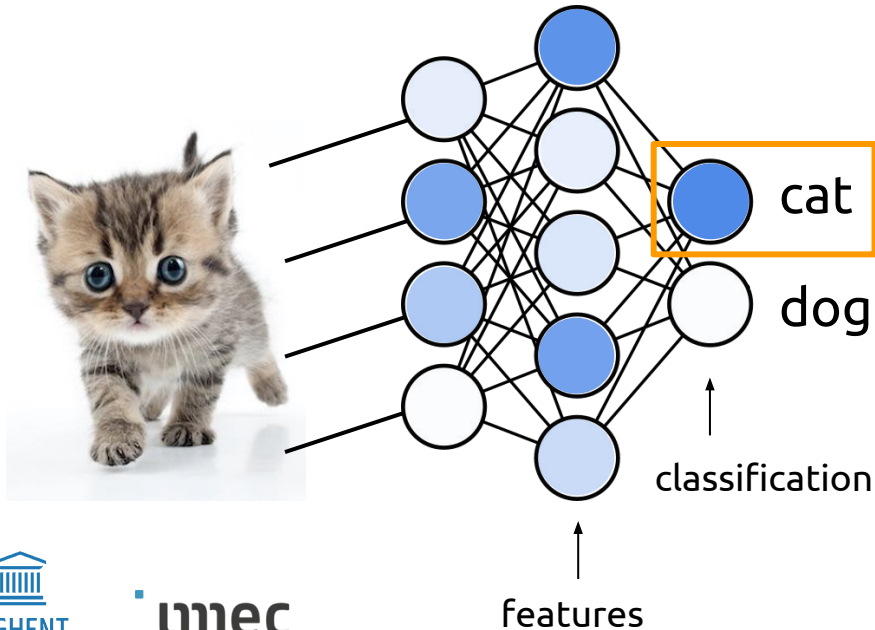
- Feature extraction
- Classification



Neural networks

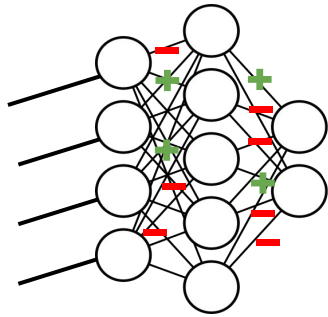
- Feature extraction
- Classification

- Image recognition
- Facial recognition
- ...



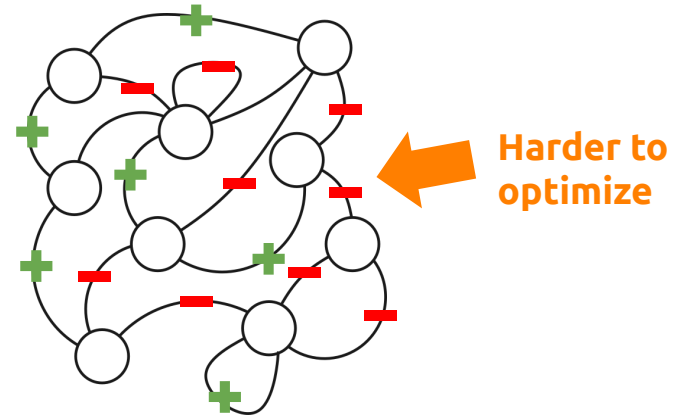
Neural networks

(Deep) Neural Network



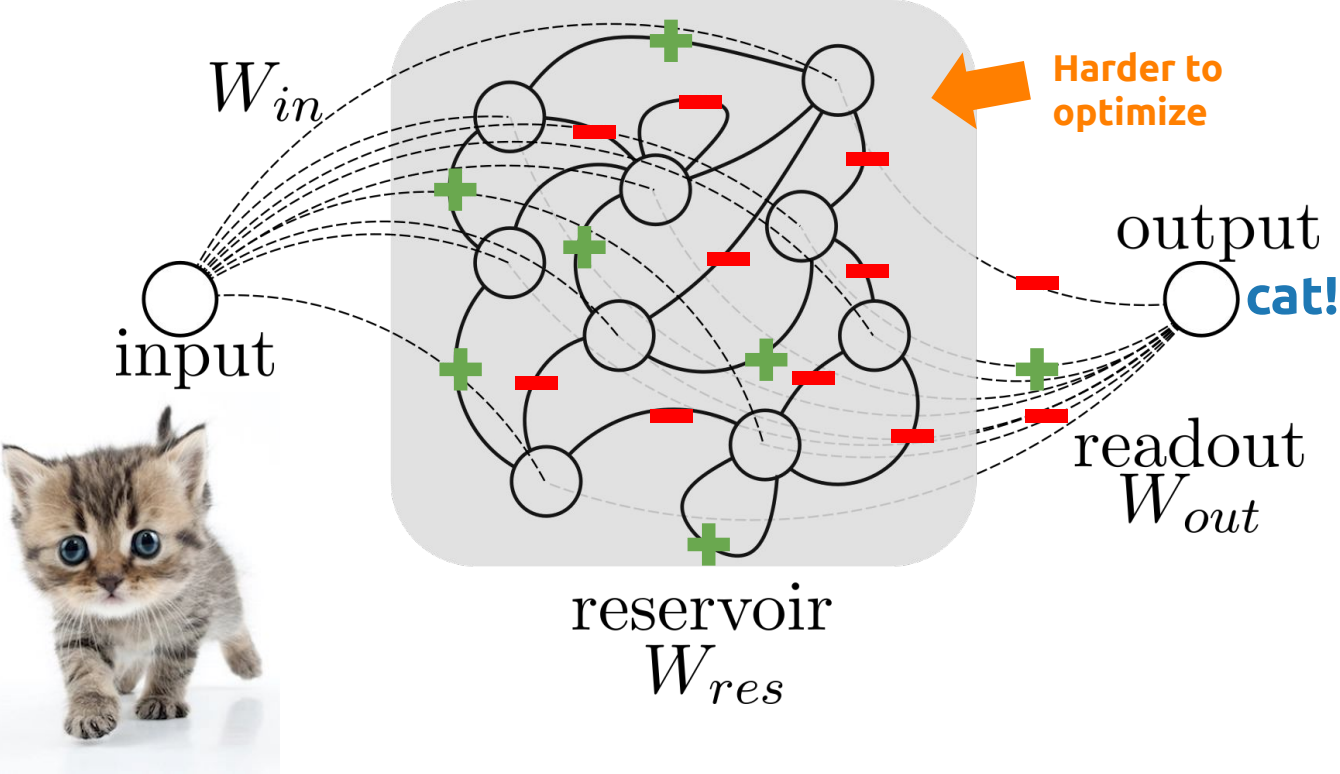
- Image recognition
- Facial recognition
- ...

Recurrent Neural Network

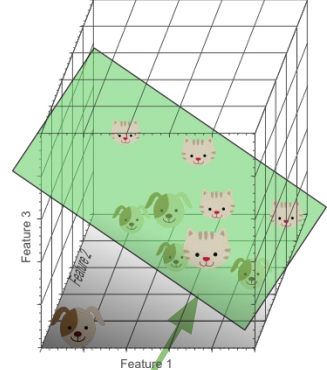
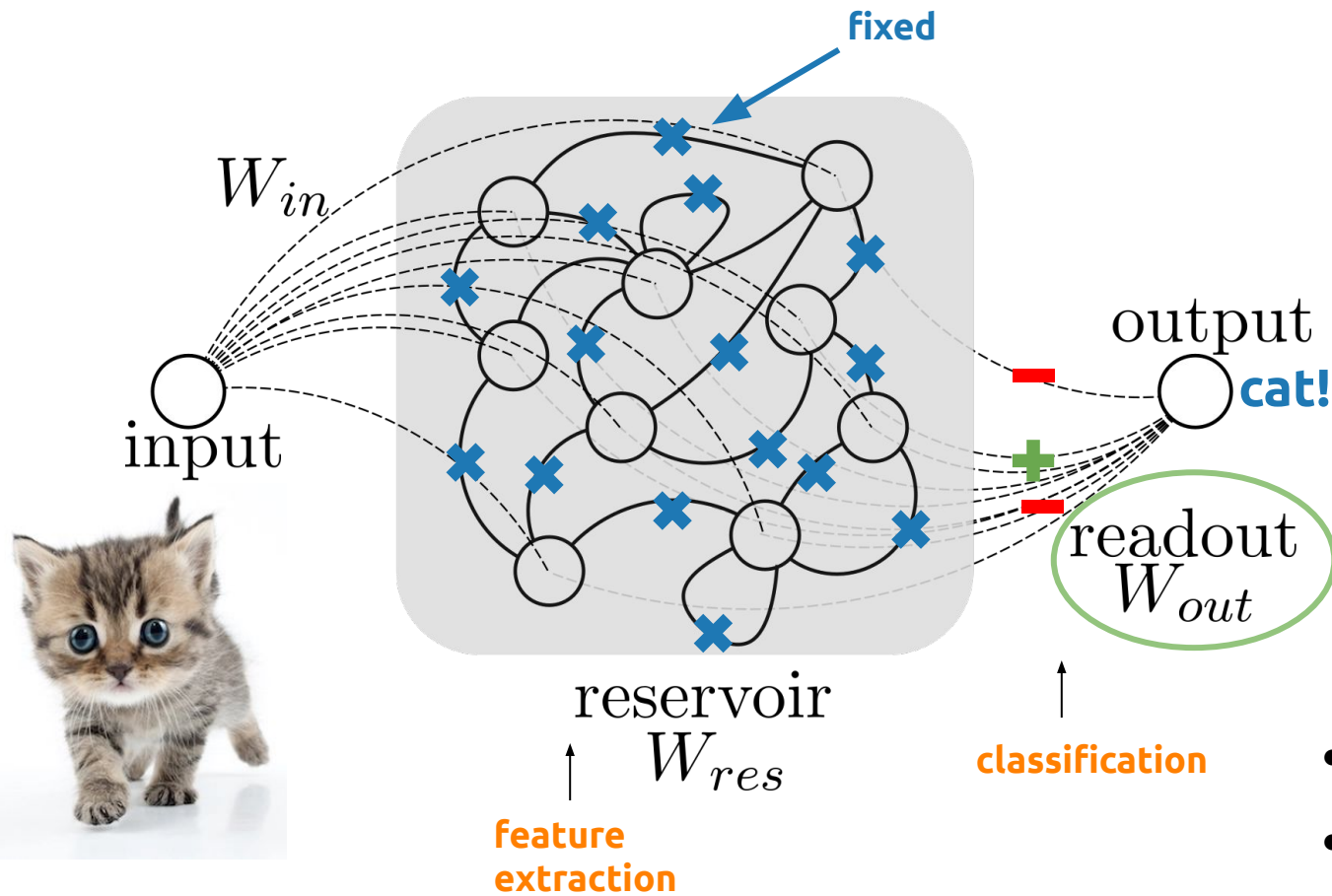


- Speech recognition
- Time series prediction
- Robot control
- ...

Recurrent Neural Network

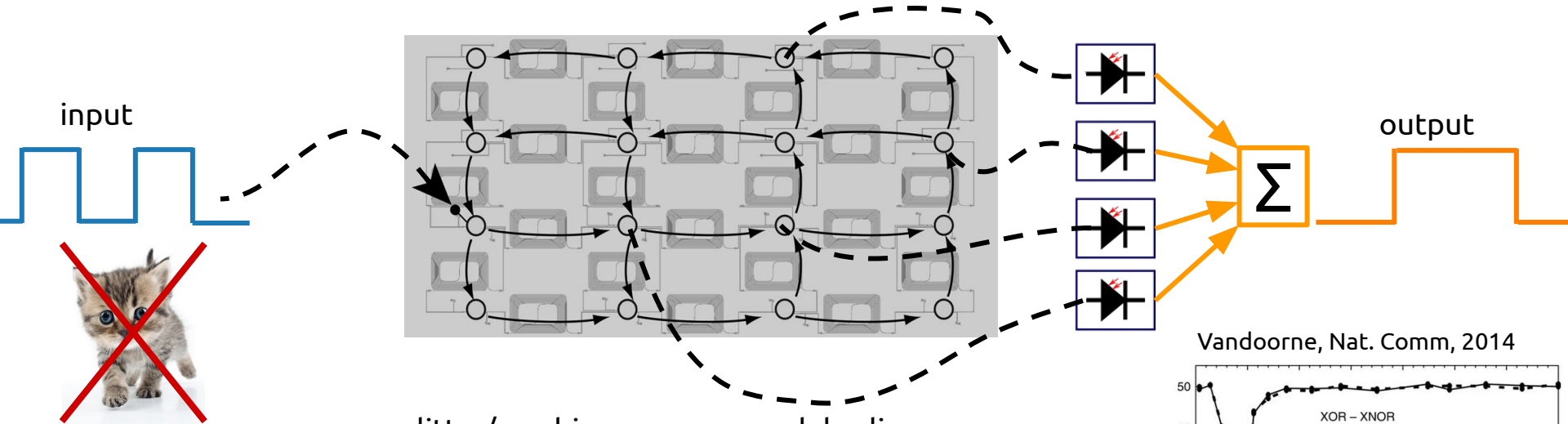


Reservoir computing

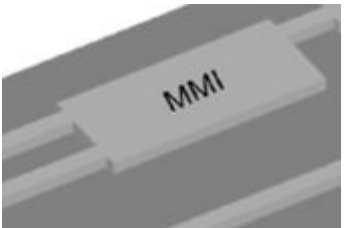


- Feature extraction
- Classification

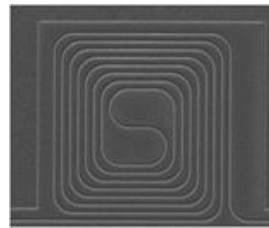
Photonic Reservoir Computing



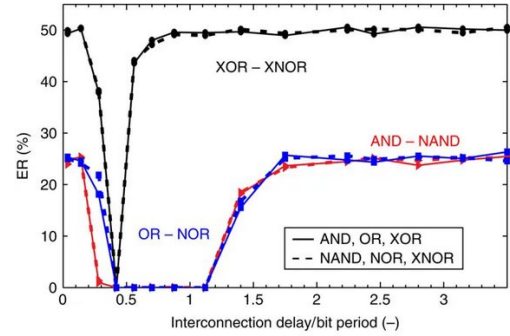
splitter/combiner



delay line

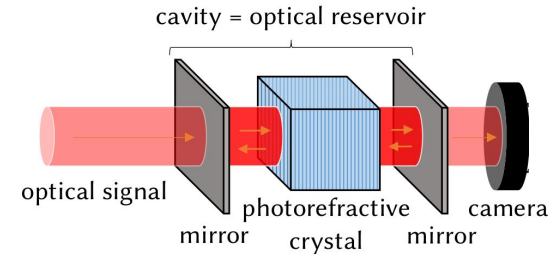
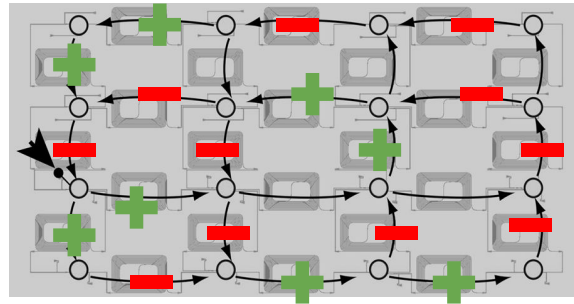
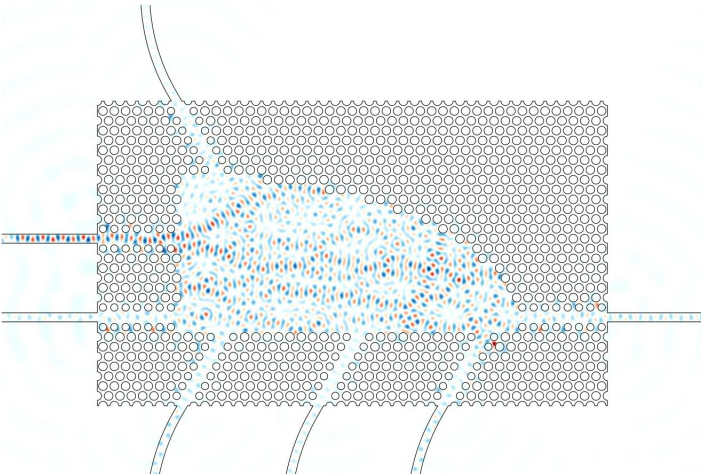


Vandoorne, Nat. Comm, 2014



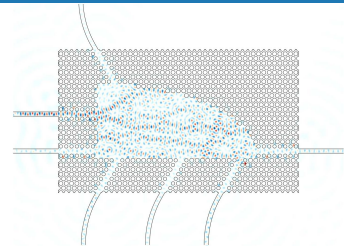
Novel architectures for brain-inspired photonic computers

- Reservoir Computing with **signal-mixing cavities**
- Transition to completely **optimizable photonic circuits**
- **Self-learning** with photorefractive crystals



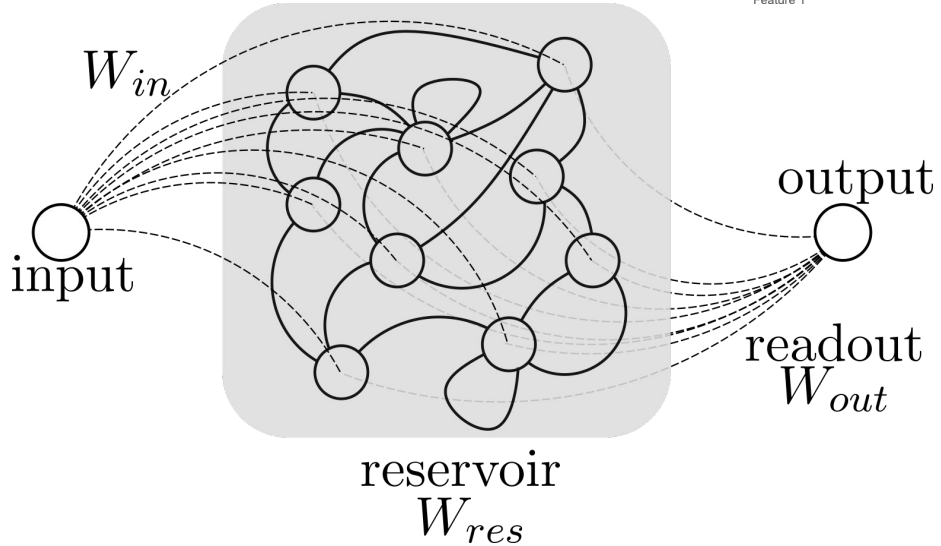
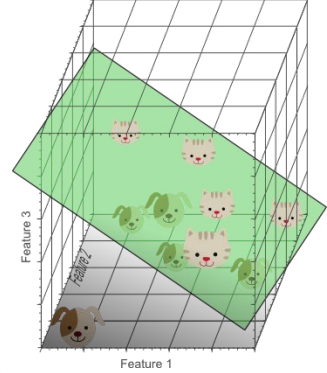
Overview

- Machine learning & Neuromorphic computing
- Towards photonic neuromorphic computing
- **Reservoir computing with signal-mixing cavities**
- Photontorch: optimizing photonic circuits
- Neuromorphic computing with photorefractive crystals



Reservoir Computing

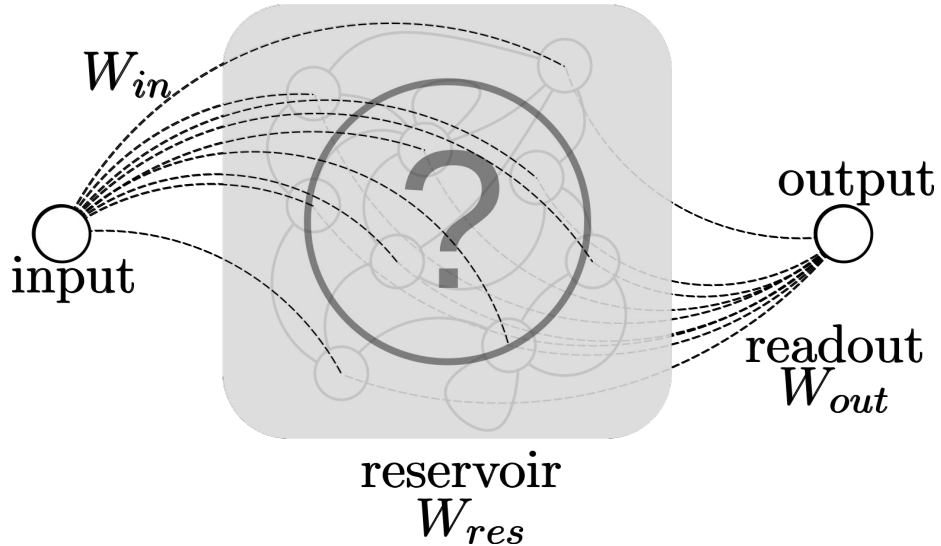
- **preprocesses** the input to a **higher dimensional** space
- has **sufficient memory**



Anything can be used as a reservoir!

As long as the system...

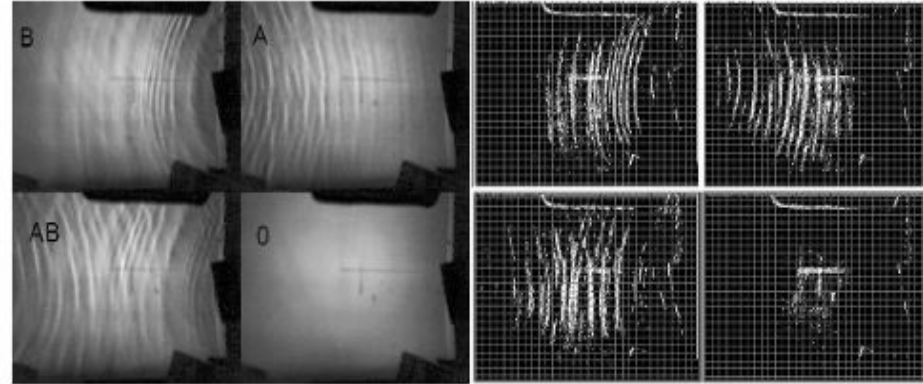
- **preprocesses** the input to a **higher dimensional** space
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Anything can be used as a reservoir!

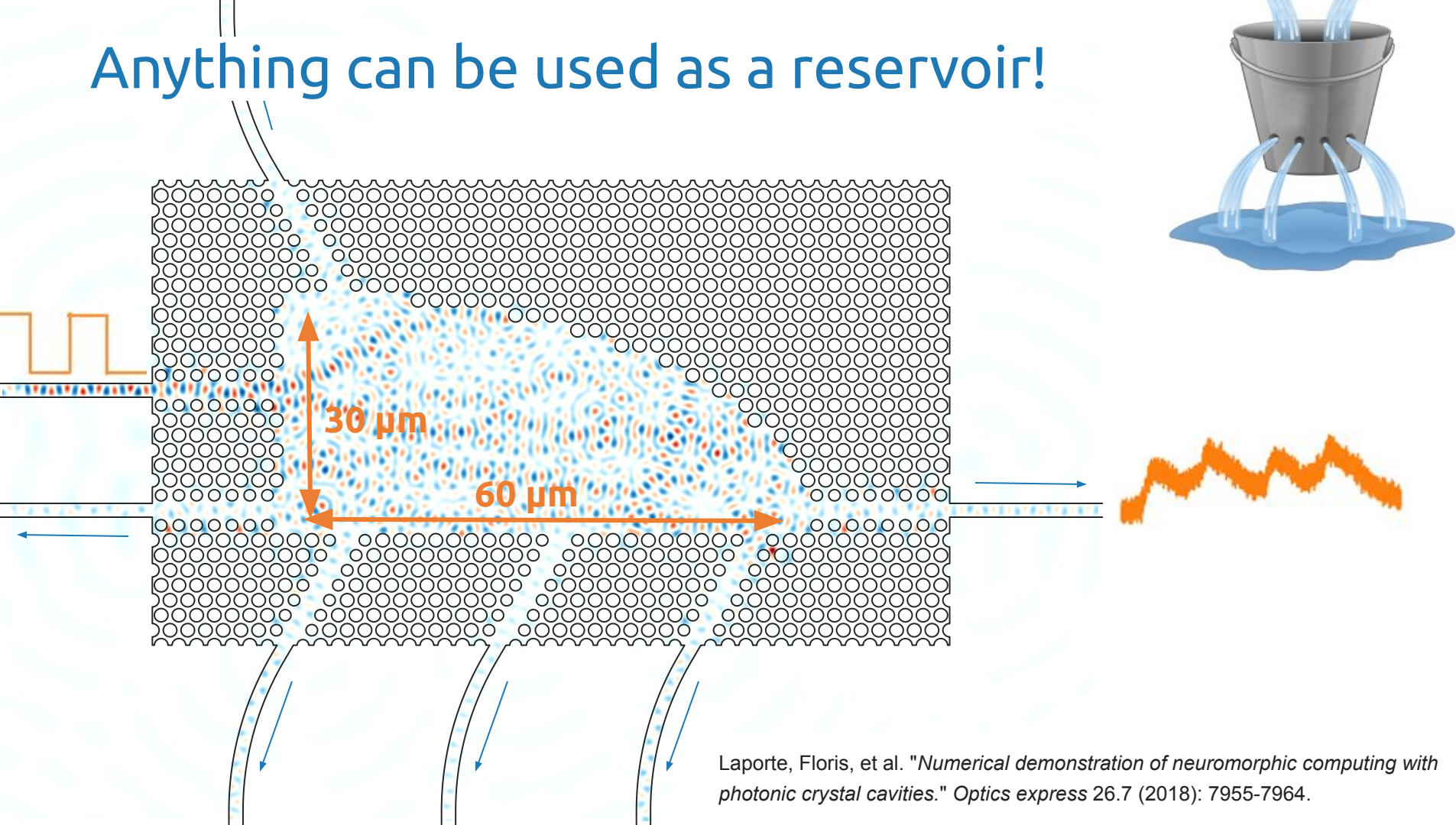
As long as the system...

- **preprocesses** the input to a **higher dimensional** space
- has **sufficient memory**



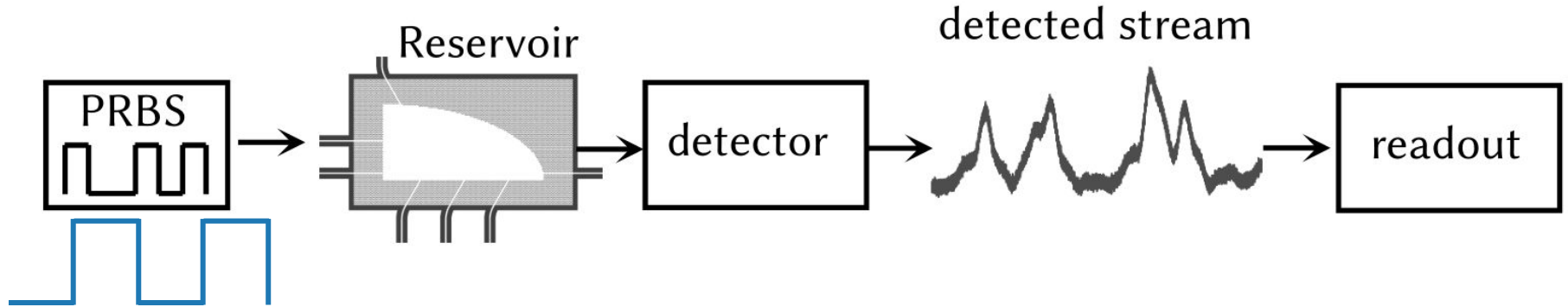
Fernando, C., & Sojakka, S. (2003, September). Pattern recognition in a bucket. In *European conference on artificial life* (pp. 588-597). Springer, Berlin, Heidelberg.

Anything can be used as a reservoir!



Simulating Signal Mixing Cavity

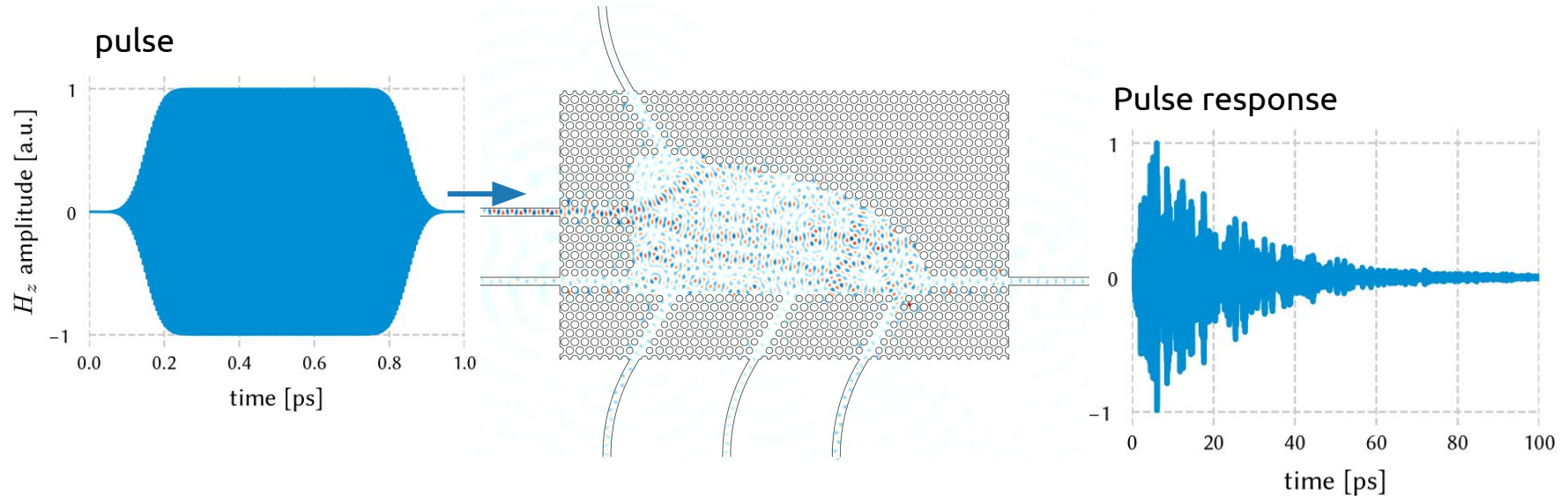
Ideally:



Problem: simulating a single bit takes about 24 hours.

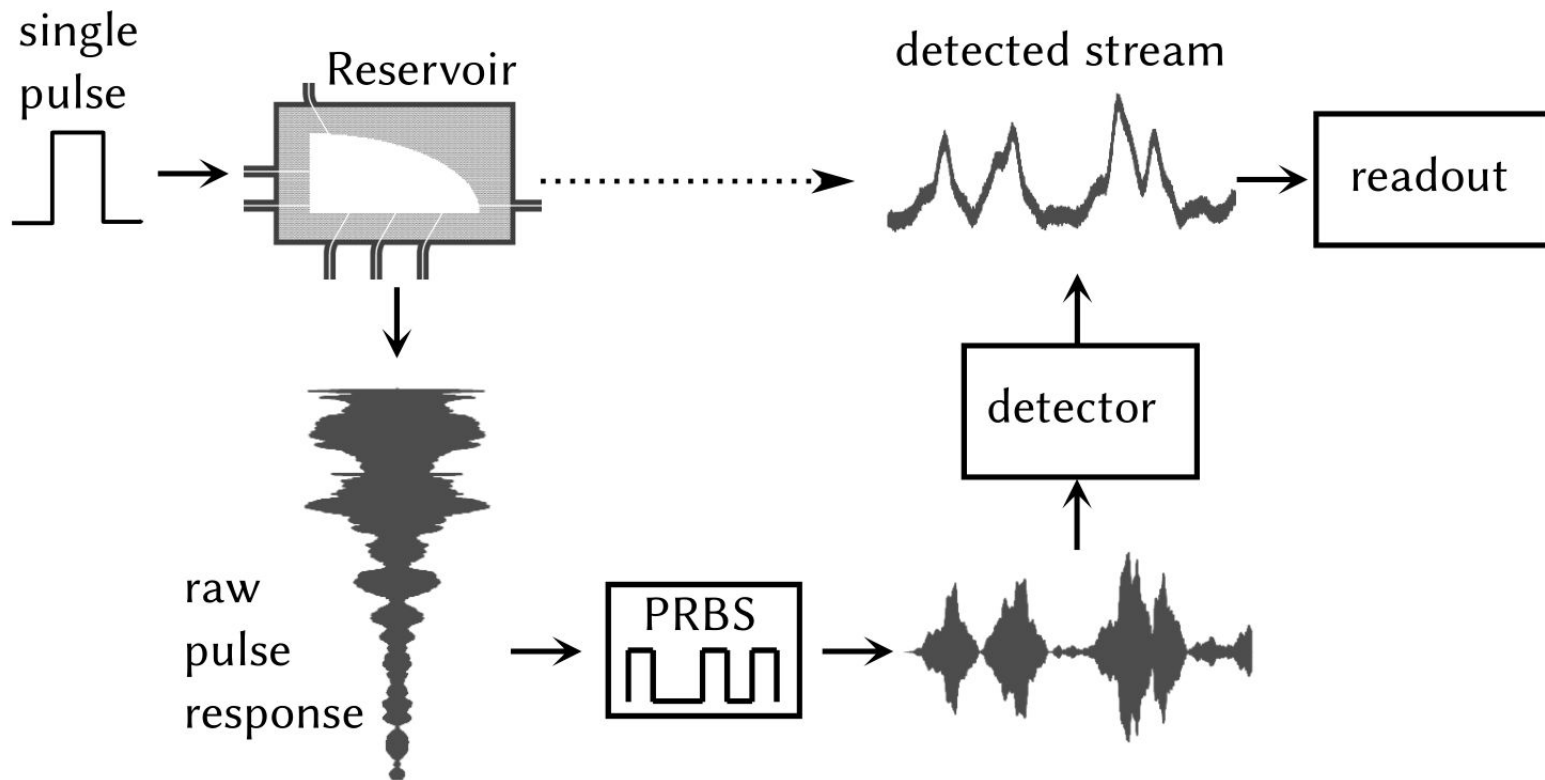
Simulating Signal Mixing Cavity

Problem: simulating a single bit takes about 24 hours.



Simulating Signal Mixing Cavity

In stead:



Simulating Signal Mixing Cavity

Pulse:

$$\mathbf{u}(t) = \begin{pmatrix} \mathbf{E}_{\text{in}}(t) \\ \mathbf{H}_{\text{in}}(t) \end{pmatrix}$$

Response:

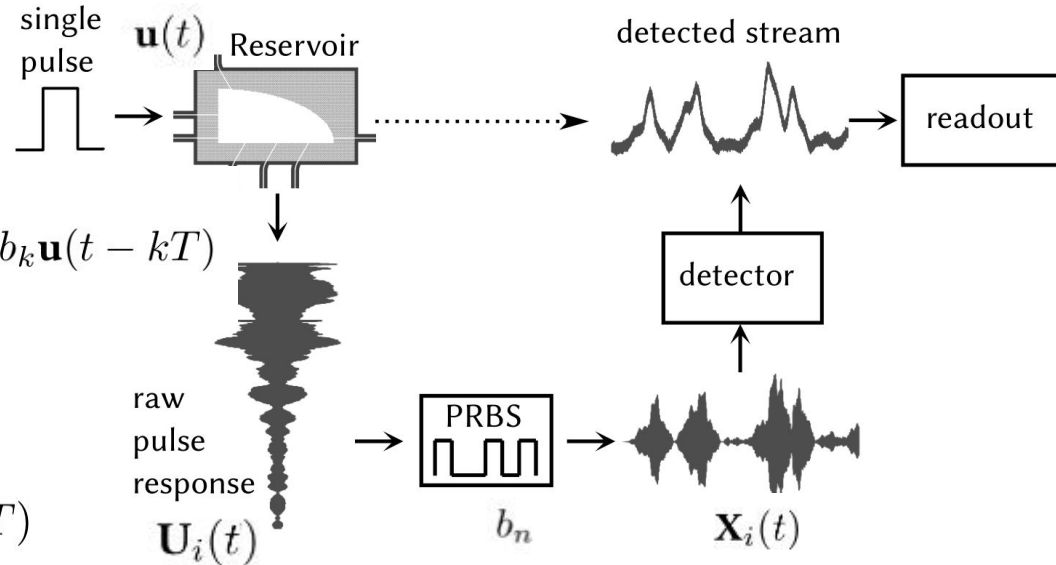
$$\mathbf{U}_i(t)$$

Input stream:

$$\mathbf{x}(t) = \begin{pmatrix} \mathbf{E}_{\text{in}}(t) \\ \mathbf{H}_{\text{in}}(t) \end{pmatrix} = \sum_{n=1}^N b_n \mathbf{u}(t - nT) = b_k \mathbf{u}(t - kT)$$

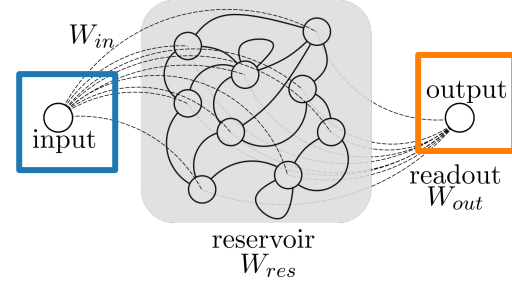
Output stream:

$$\mathbf{X}_i(t) = \begin{pmatrix} \mathbf{E}_{\text{out}}^i(t) \\ \mathbf{H}_{\text{out}}^i(t) \end{pmatrix} = \sum_{n=1}^N b_n \mathbf{U}_i(t - nT)$$

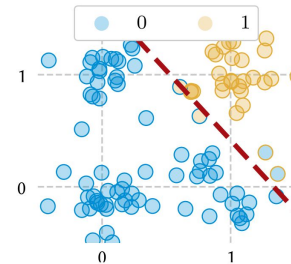
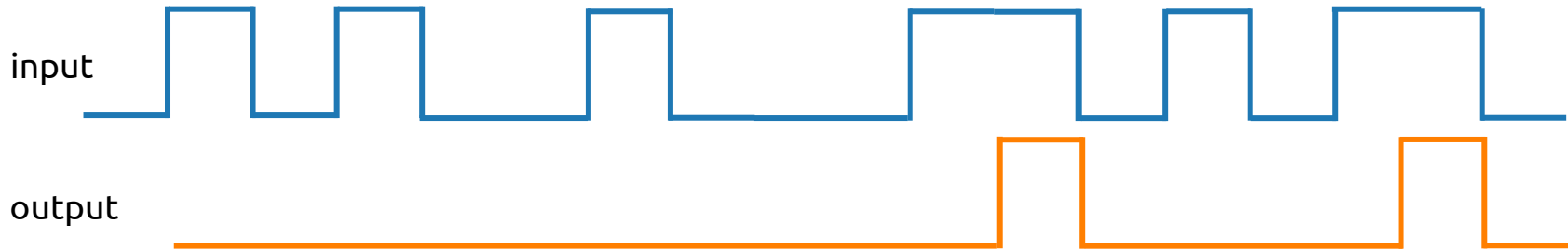


Telecom tasks: **AND**

In telecom, we're working with bits:

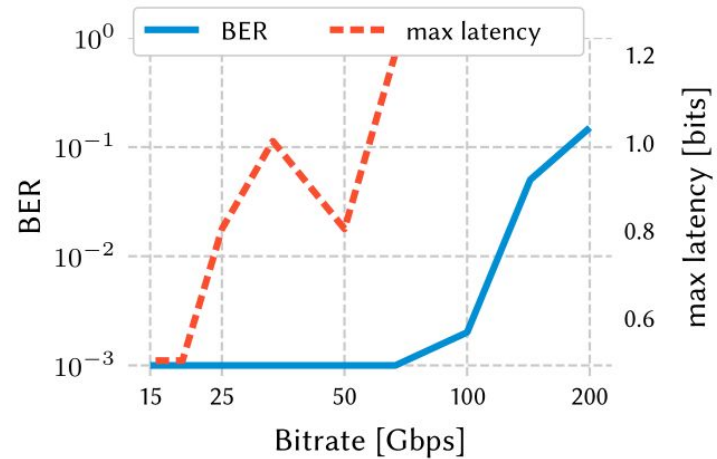
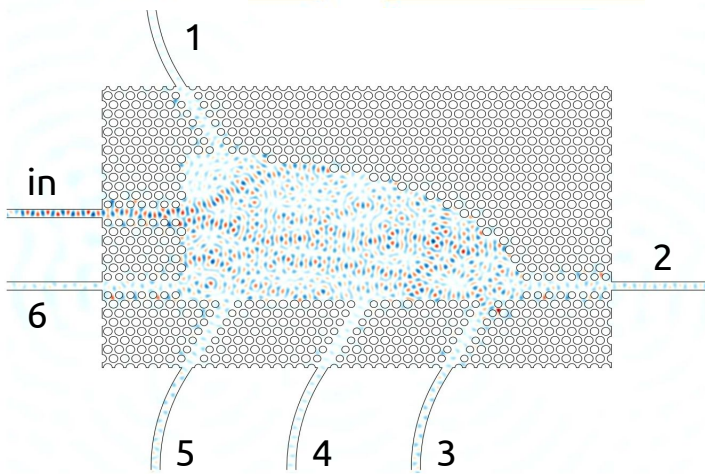
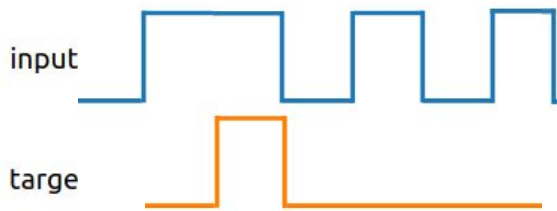


0	1	0	1	0	0	1	0	0	0	1	1	0	1	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0



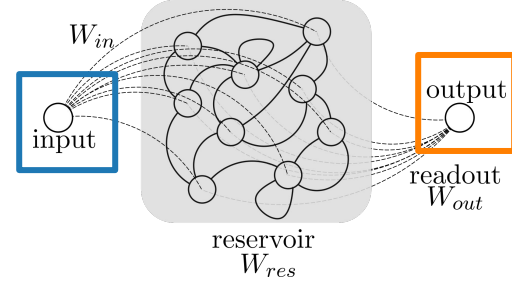
AND Task (simulation)

0 1 1 0 1 0 1
0 0 1 0 0 0 0

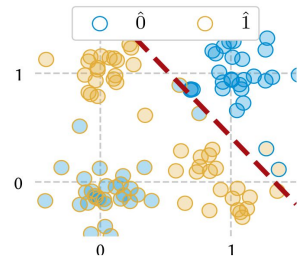
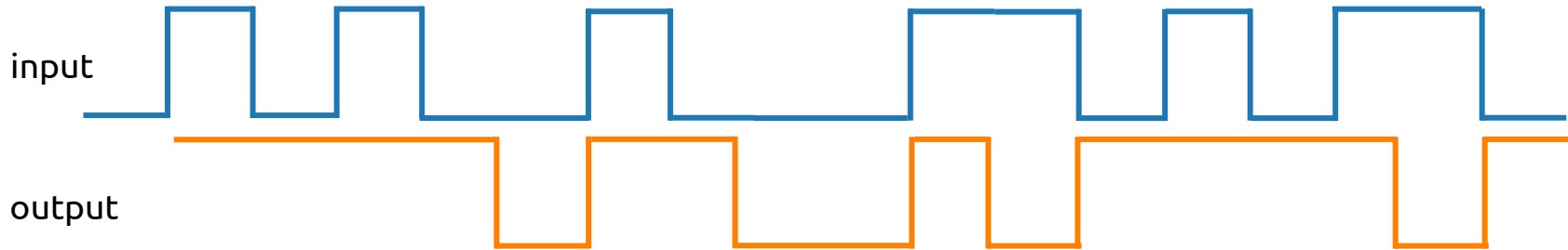


Telecom tasks: XOR

In telecom, we're working with bits:



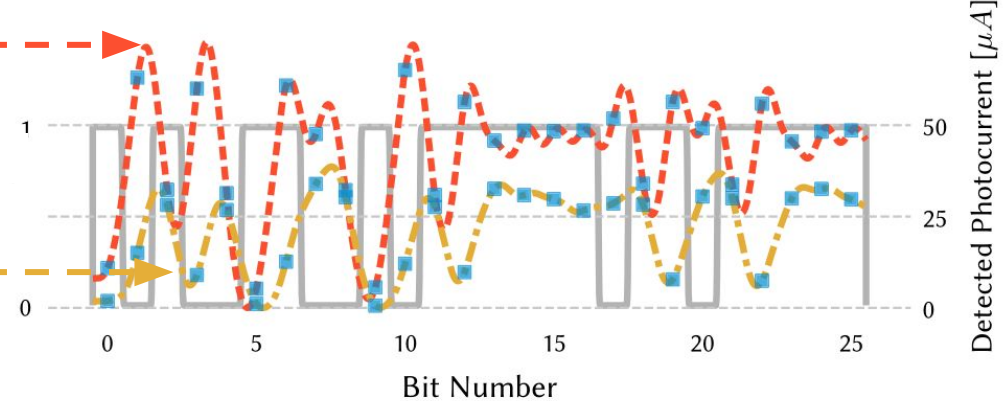
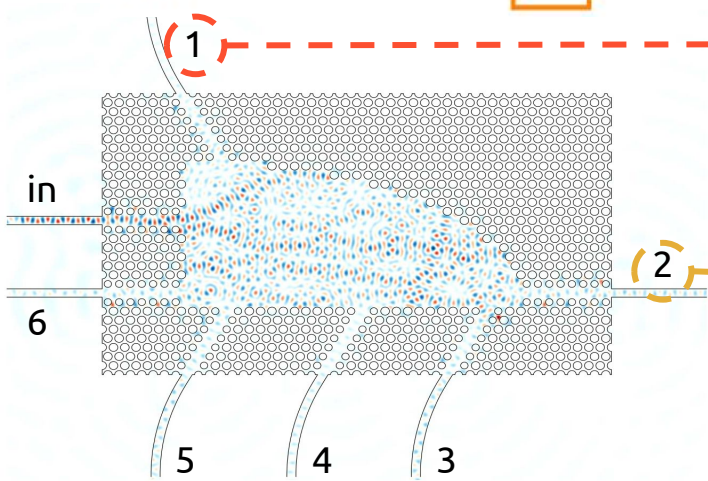
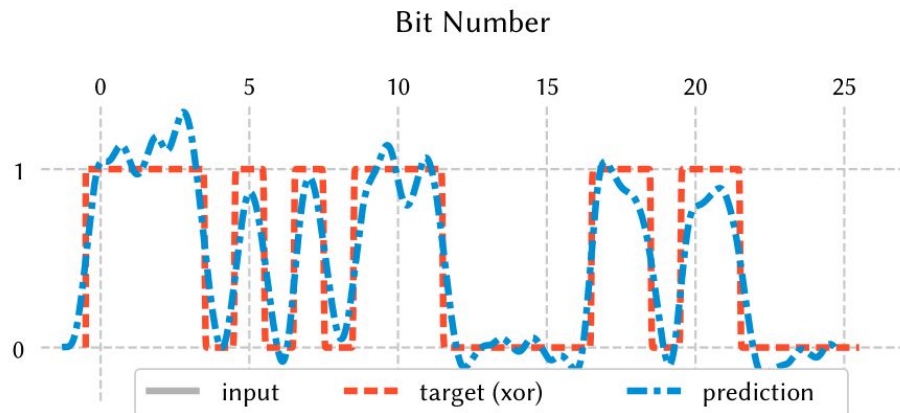
0	1	0	1	0	0	1	0	0	0	1	1	0	1	0	1	1	0
1	1	1	1	0	1	1	0	0	1	0	1	1	1	1	1	0	1



XOR Task (simulation)

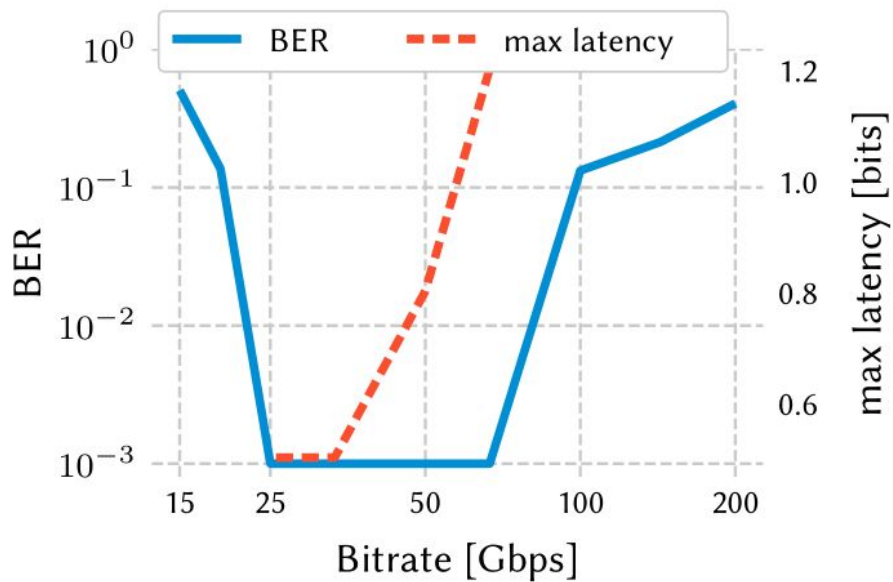
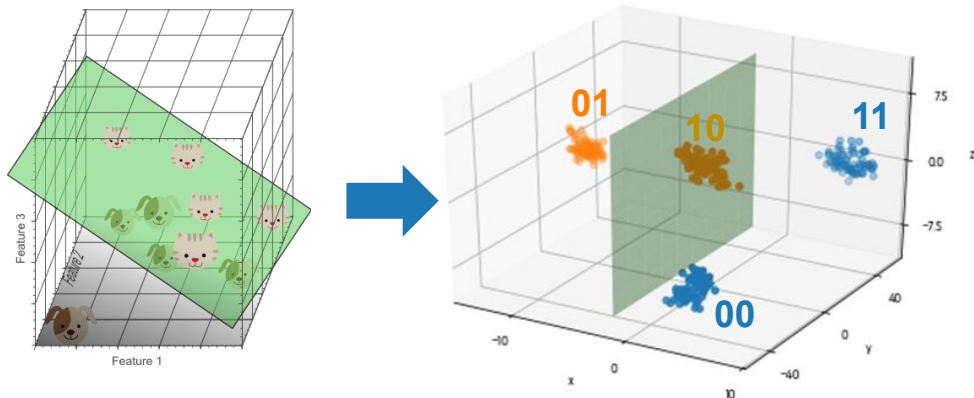
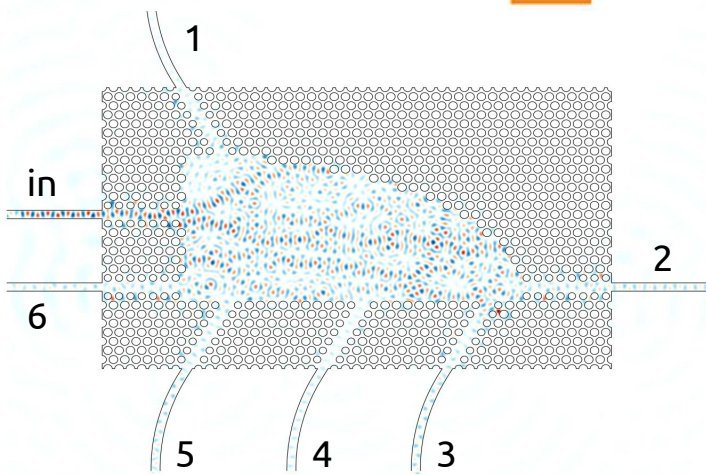
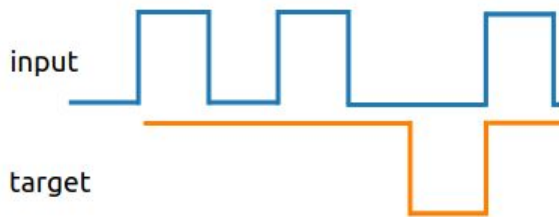
XOR

0 1 0 1 0 0 1
1 1 1 1 0 1

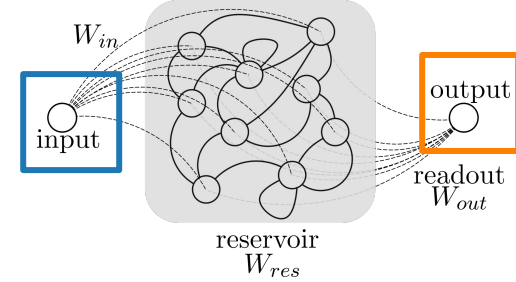


XOR Task (simulation)

0 1 0 1 0 0 1
1 1 1 1 0 1

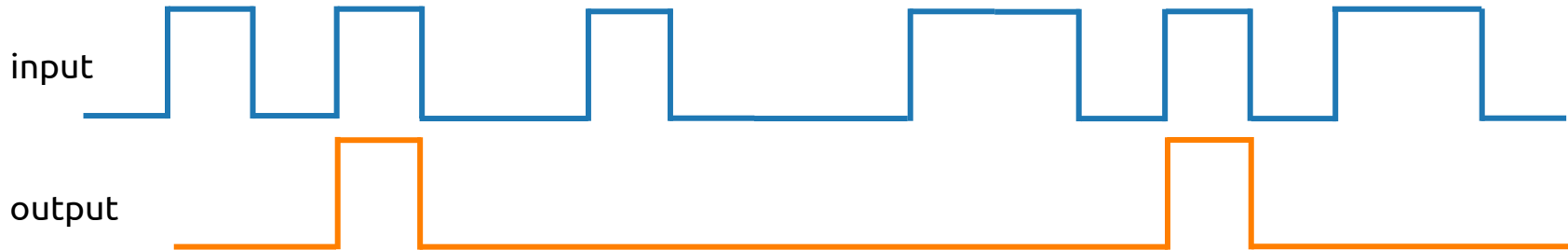


Telecom tasks: Header Recognition



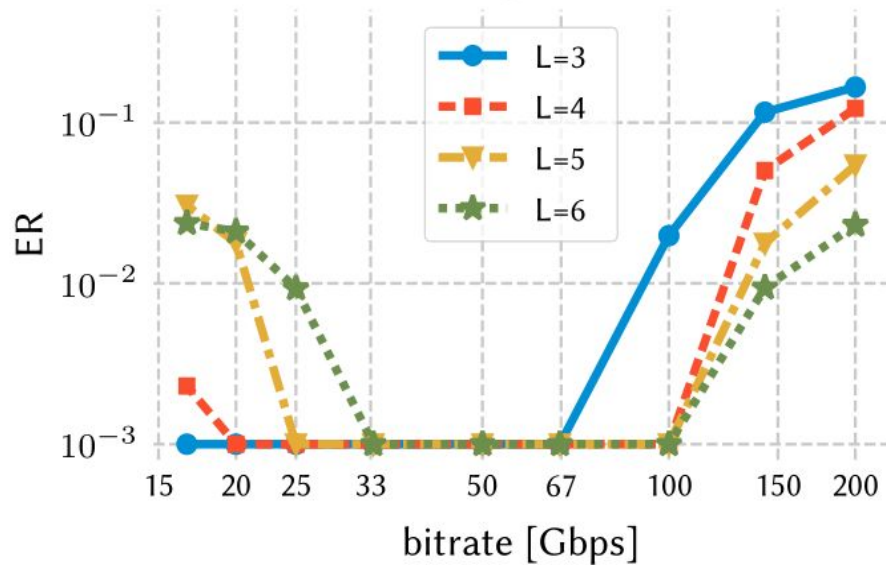
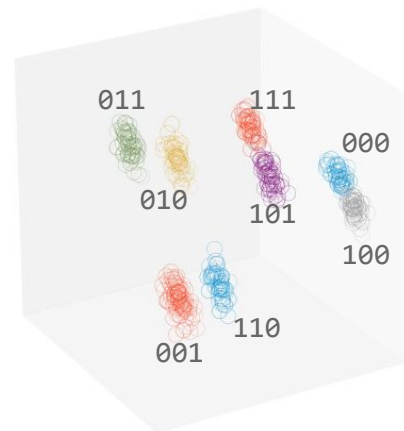
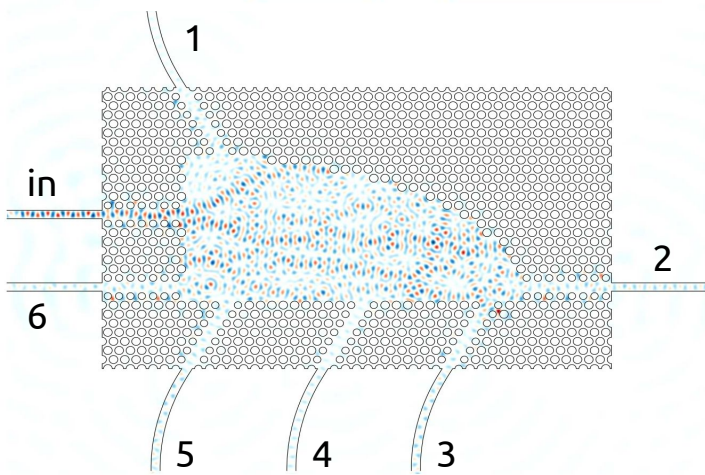
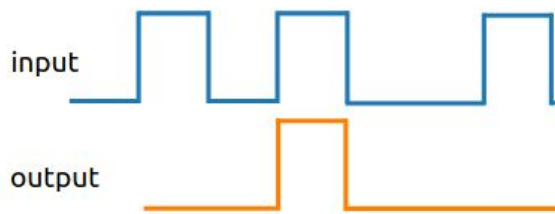
In telecom, we're working with bits:

0	1	0	1	0	0	1	0	0	0	1	1	0	1	1	0		
	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0

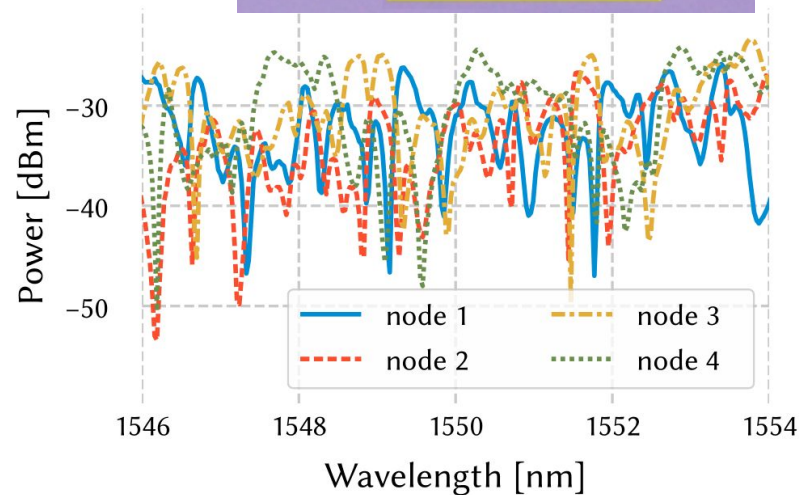
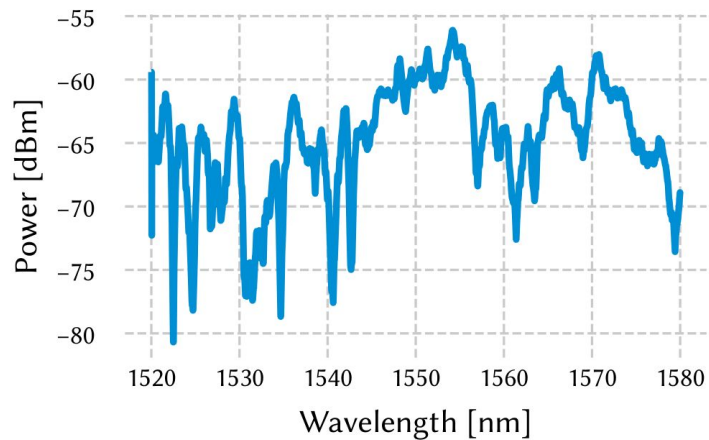
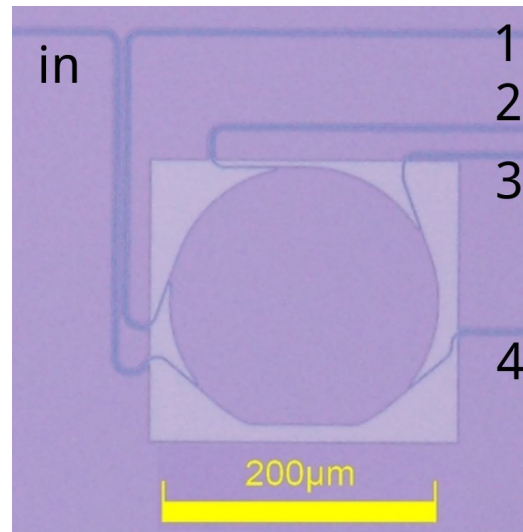
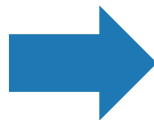
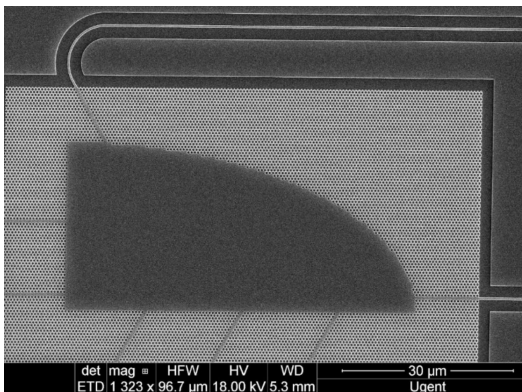


Header recognition (simulation)

0 1 0 1 0 0 1
0 0 1 0 0 0



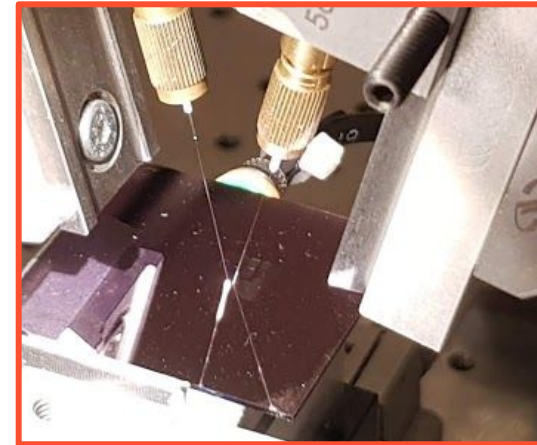
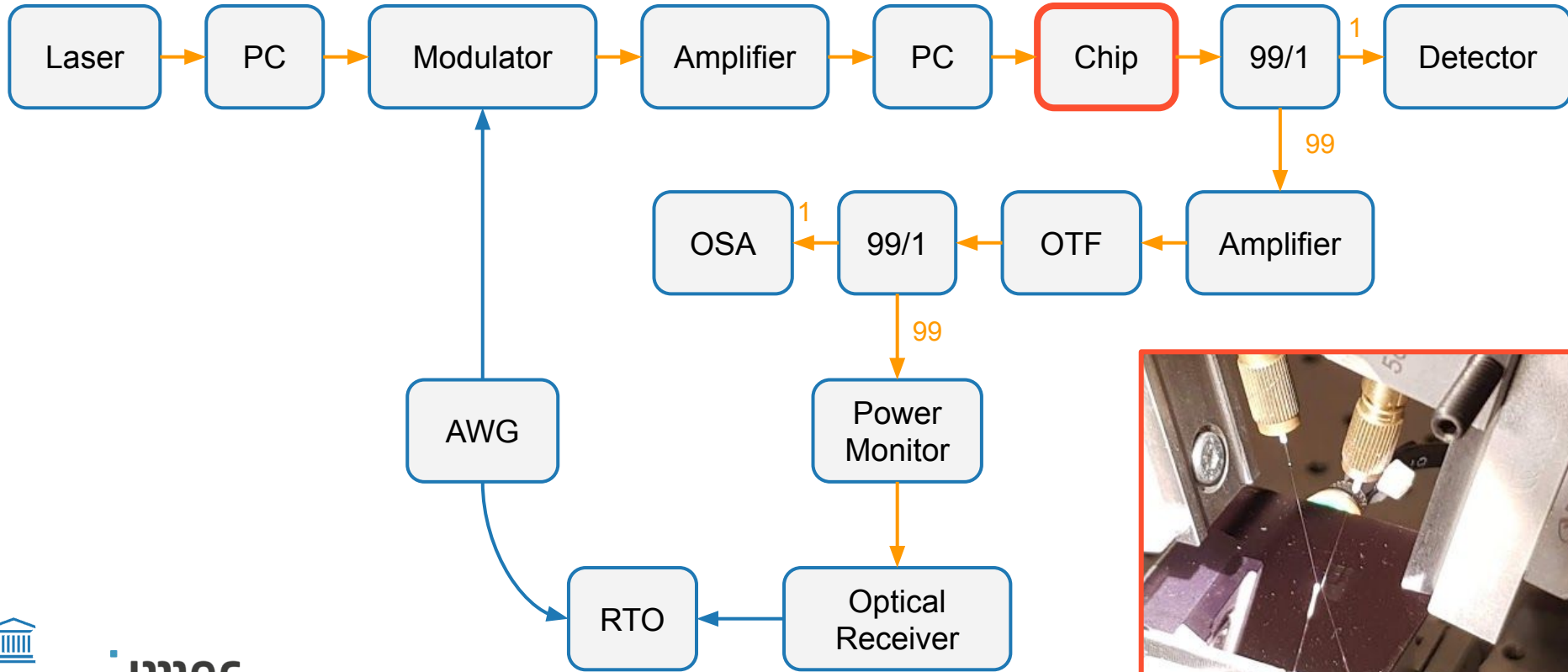
Fabricating Signal Mixing Cavity



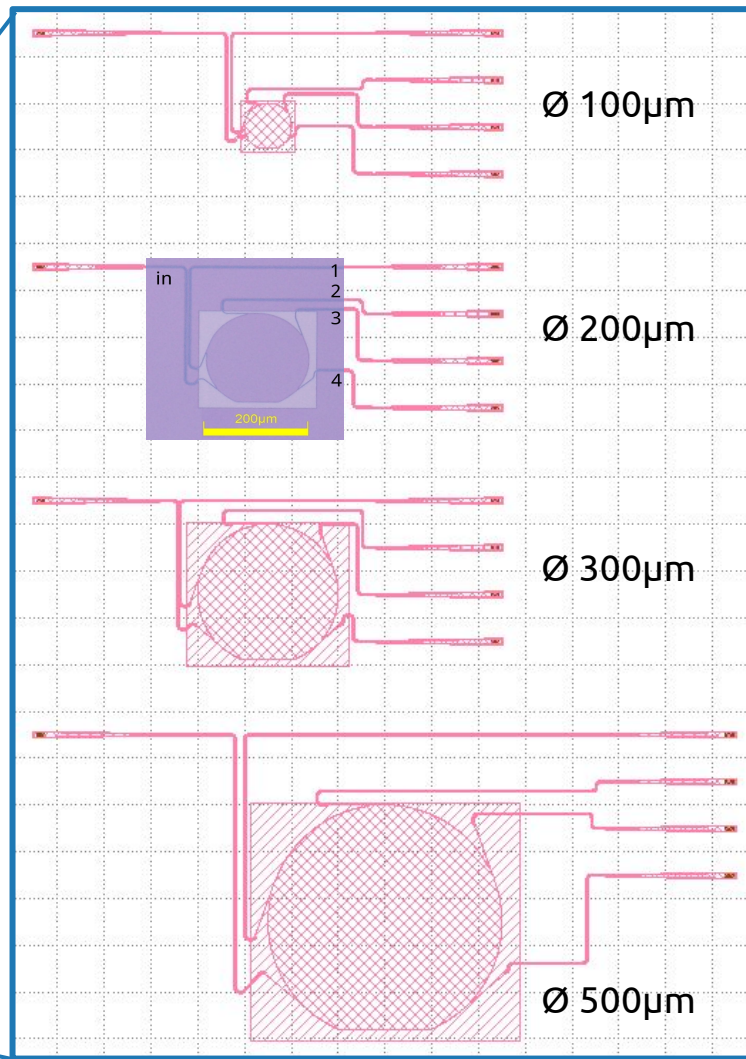
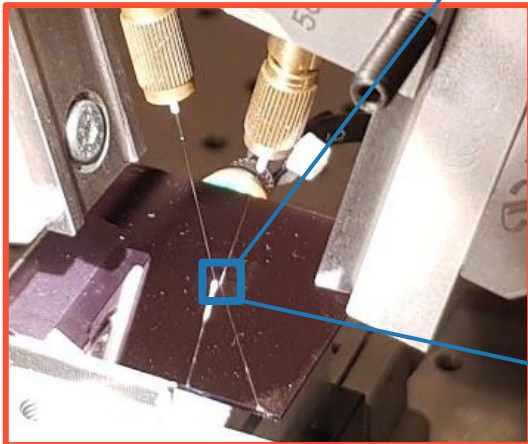
Measurement setup



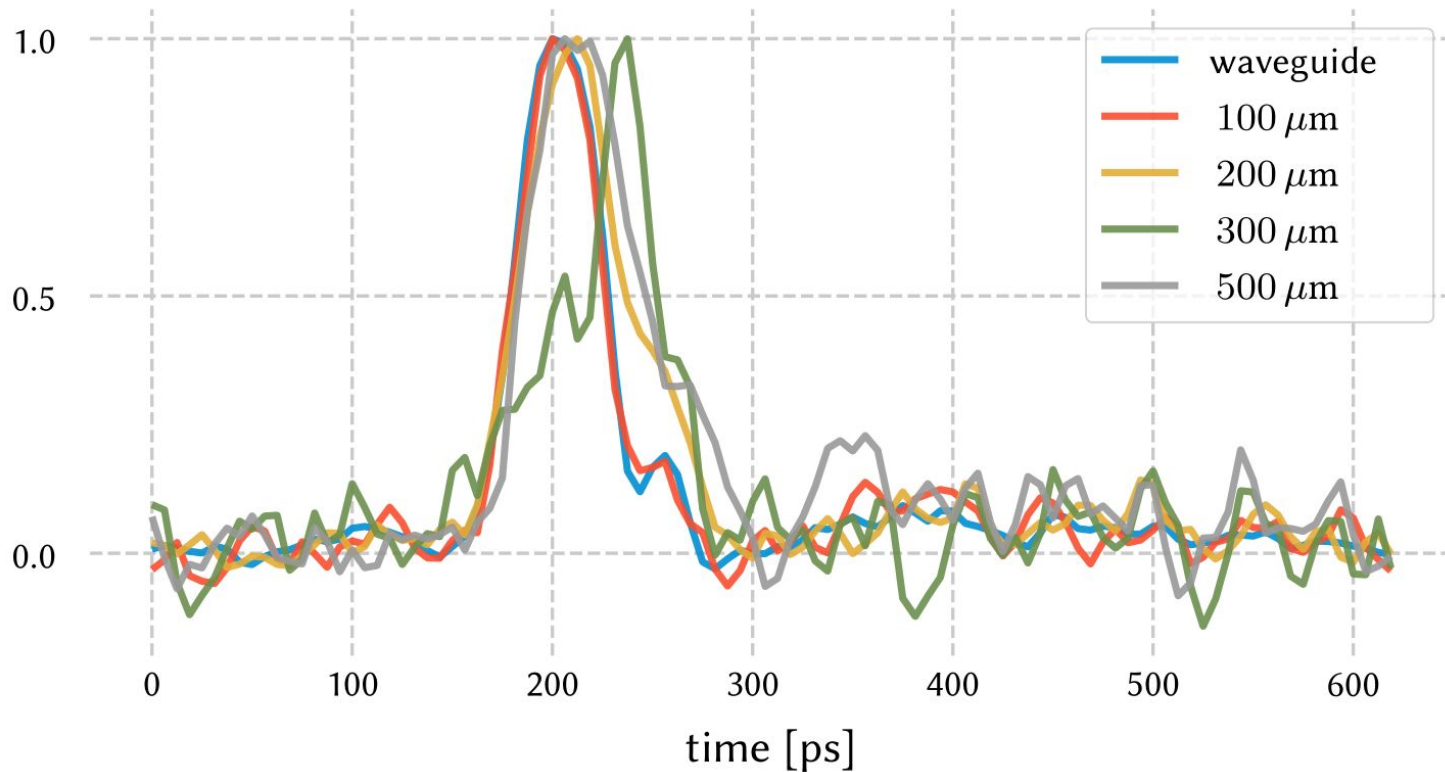
Measurement setup



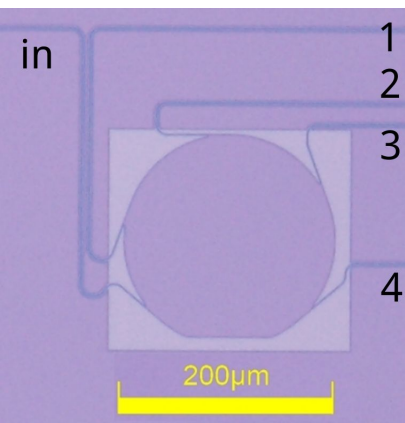
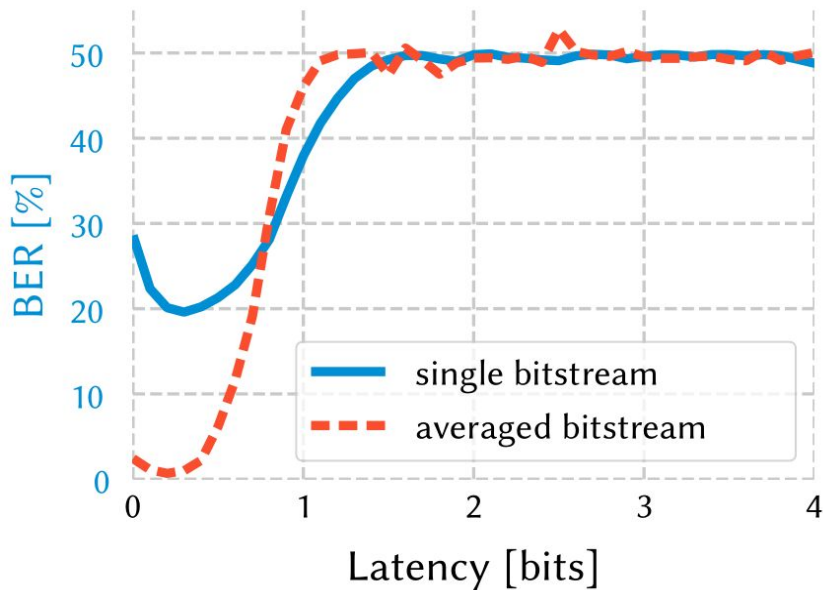
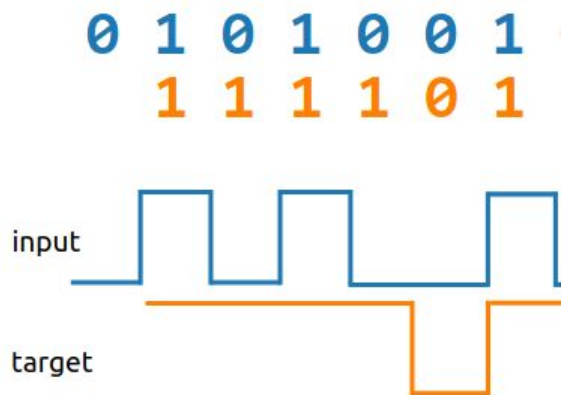
Measurement setup



Fabricated cavities: pulse response



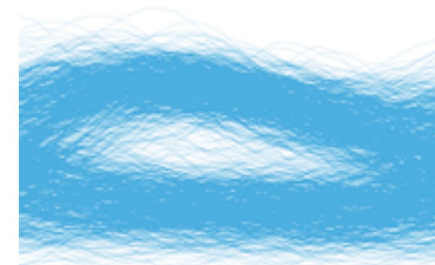
XOR Task (measurement)



Before XOR:

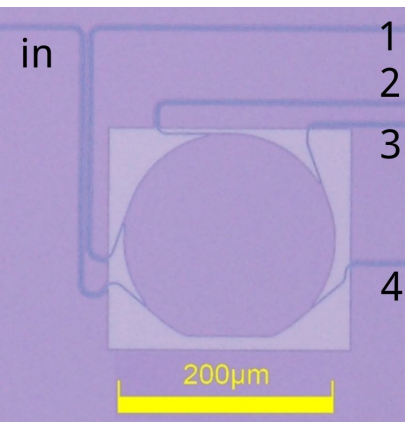
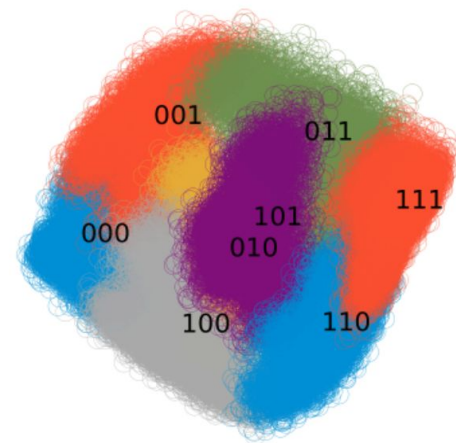
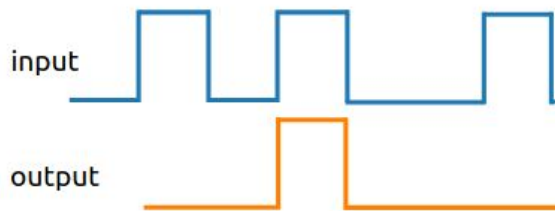


After XOR:

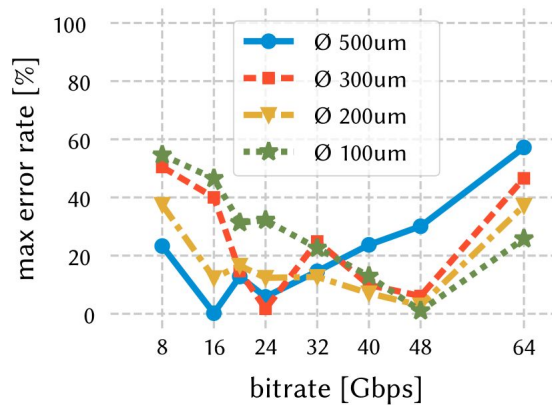


Header recognition (measurement)

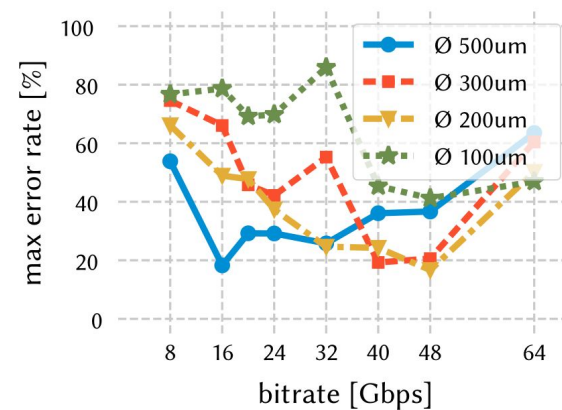
0 1 0 1 0 0 1
 0 0 1 0 0 0



3 bit headers

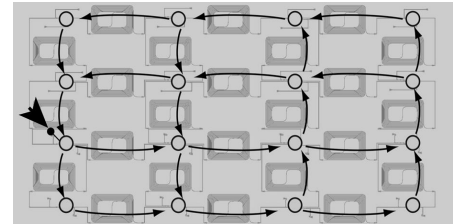
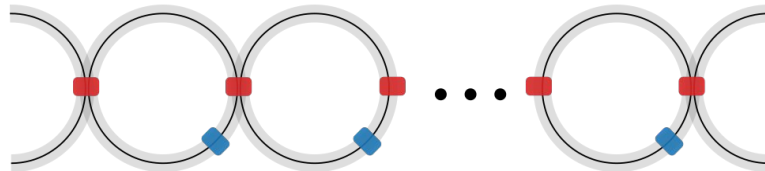


4 bit headers

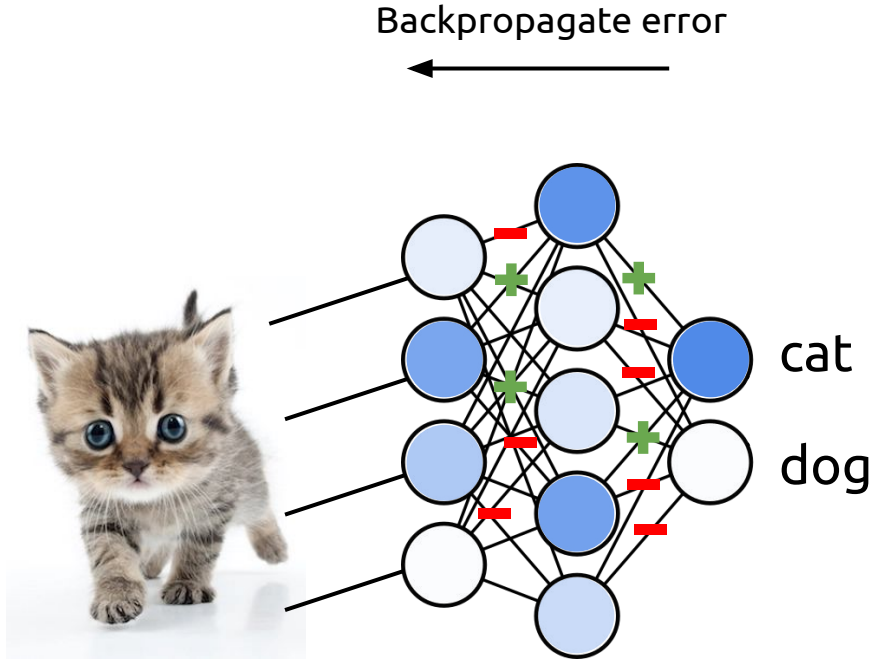


Overview

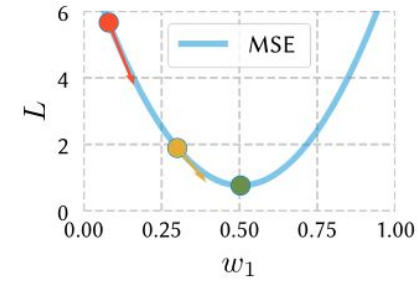
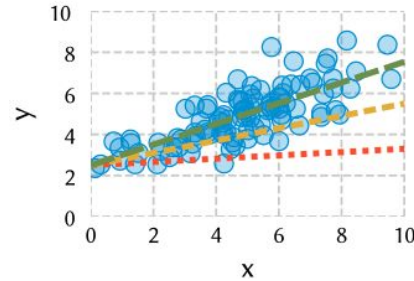
- Machine learning & Neuromorphic computing
- Towards photonic neuromorphic computing
- Reservoir computing with signal-mixing cavities
- **Photontorch: optimizing photonic circuits**
- Neuromorphic computing with photorefractive crystals



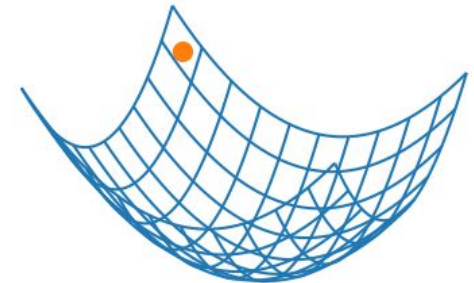
Training neural networks: **backpropagation**



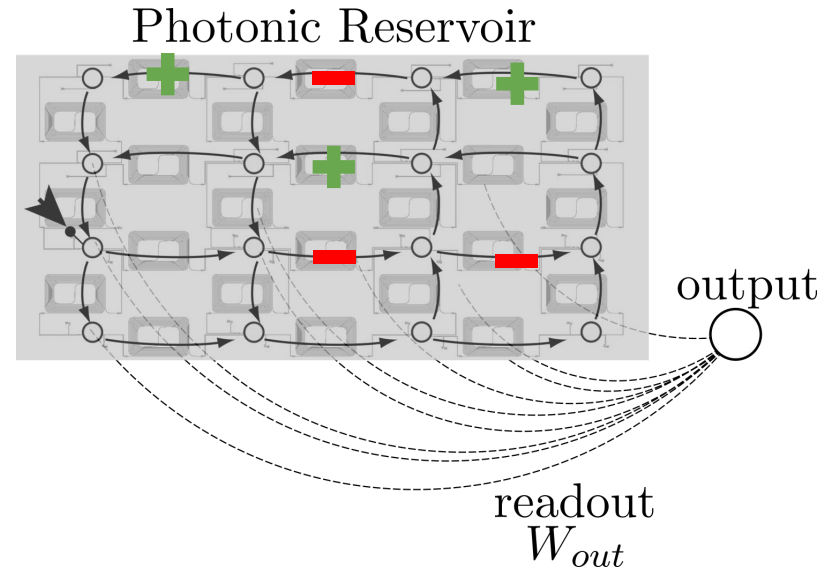
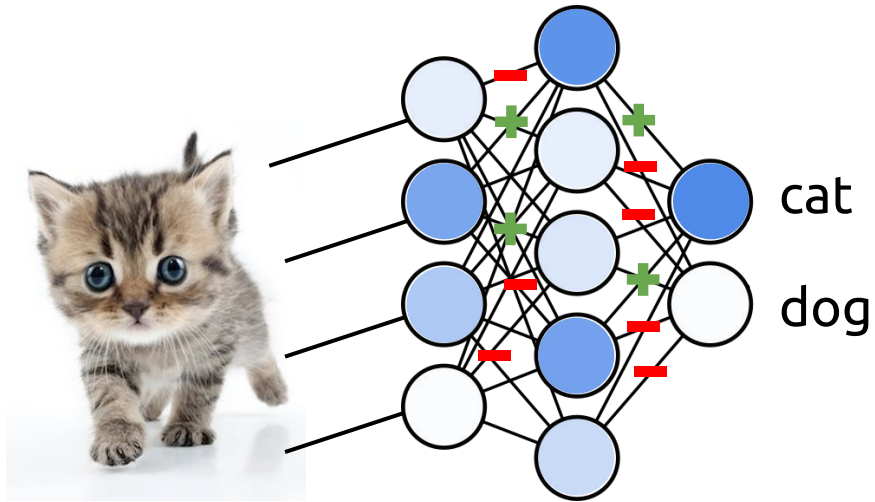
To minimize loss function



$$L = \frac{1}{2m} |y - \hat{y}|^2$$



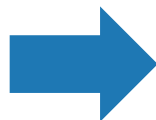
Training **photonic circuits** with backpropagation?



Photontorch: backpropagation through photonic circuits



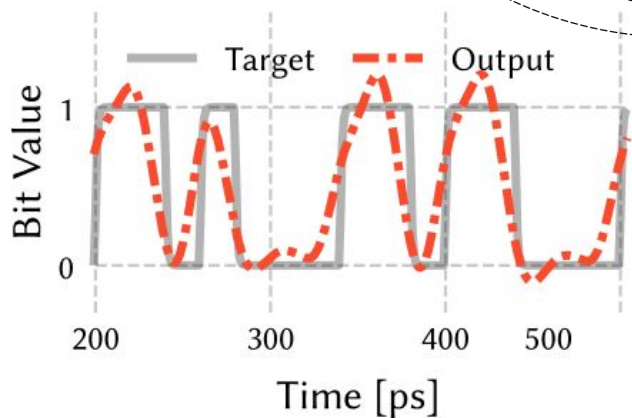
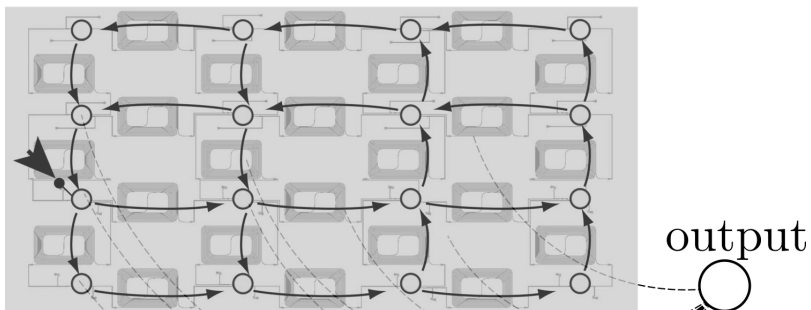
- The simulator needs to **keep track** of the order of operations, i.e. the **computation graph** for the backward pass



This requires a whole **new photonic simulator**

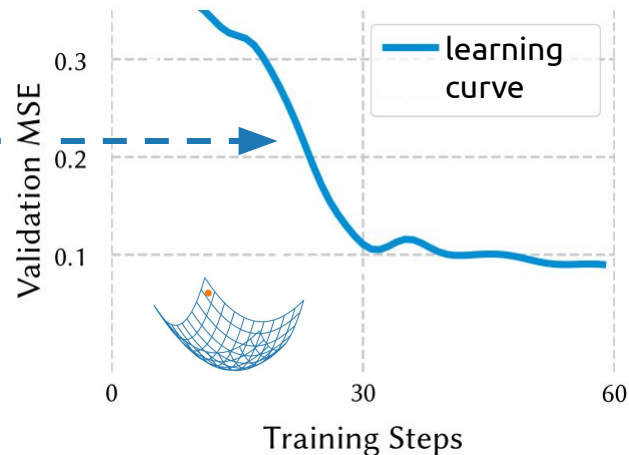
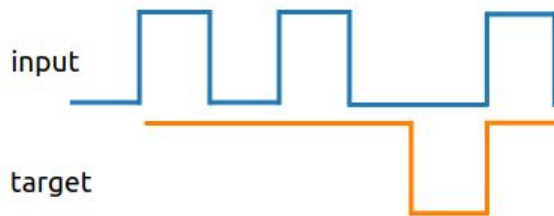
Optimization: Reservoir

Starting point:



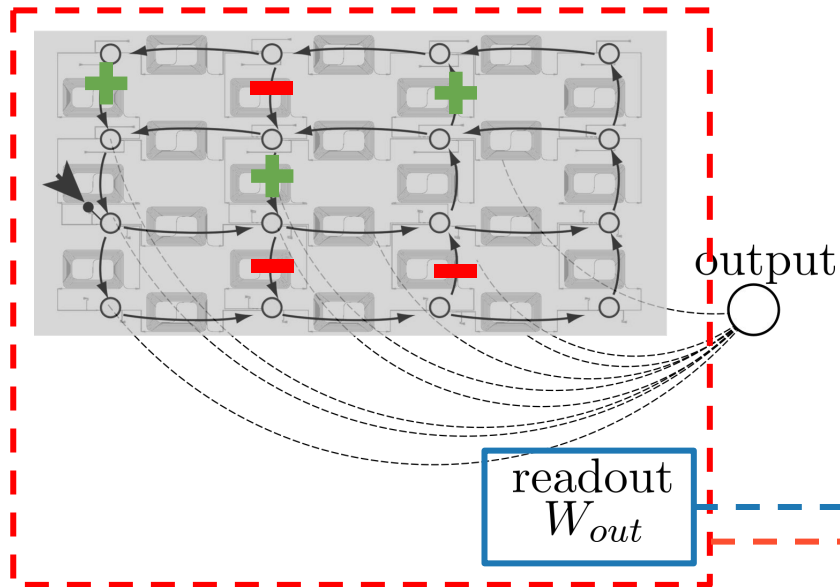
XOR

0	1	0	1	0	0	1
1	1	1	1	0	1	1



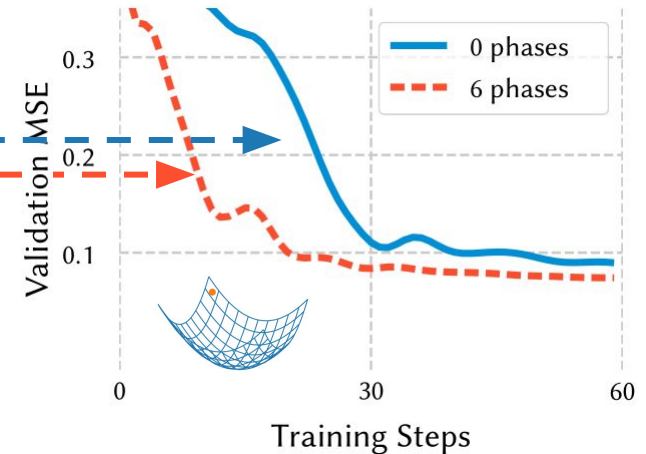
Optimization: Reservoir

Allow to **optimize some phases:**

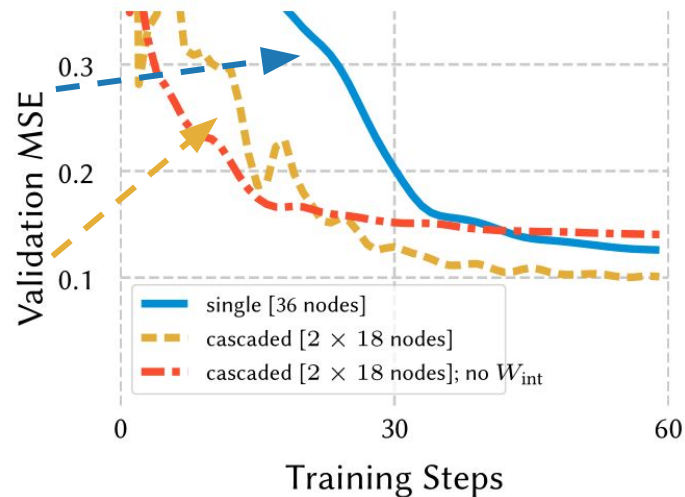
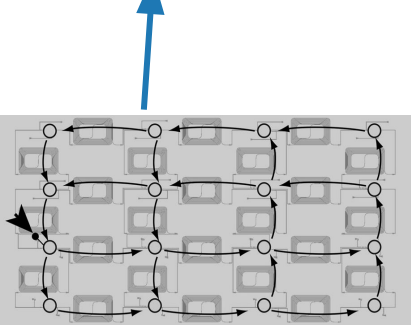
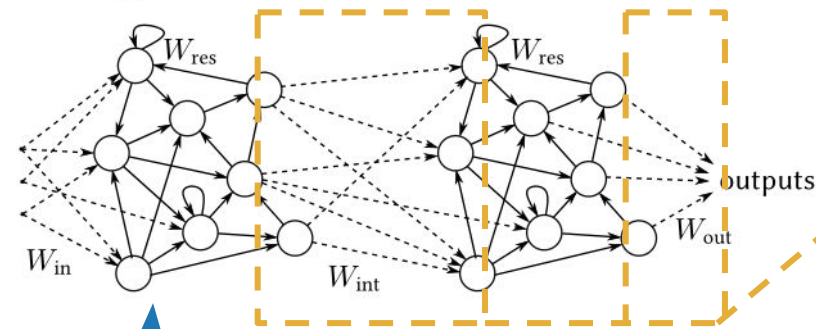
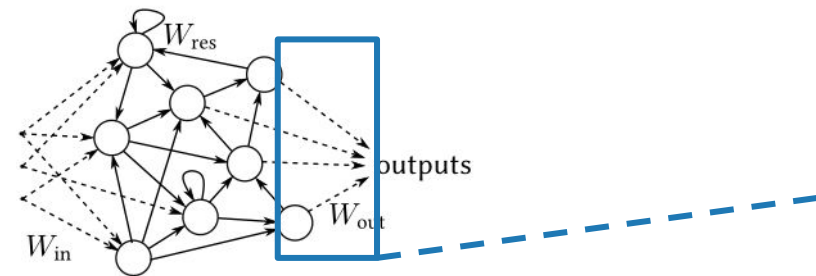


XOR

0	1	0	1	0	0	1
1	1	1	1	0	1	1

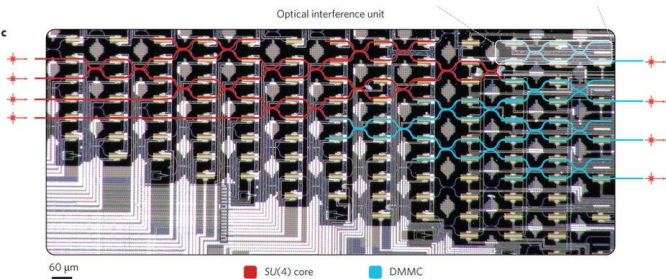
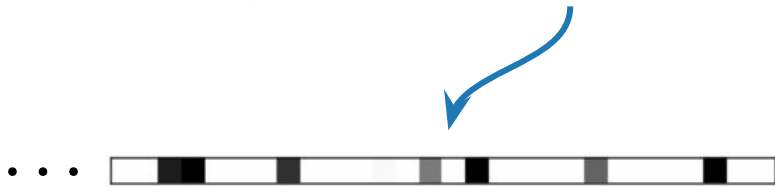
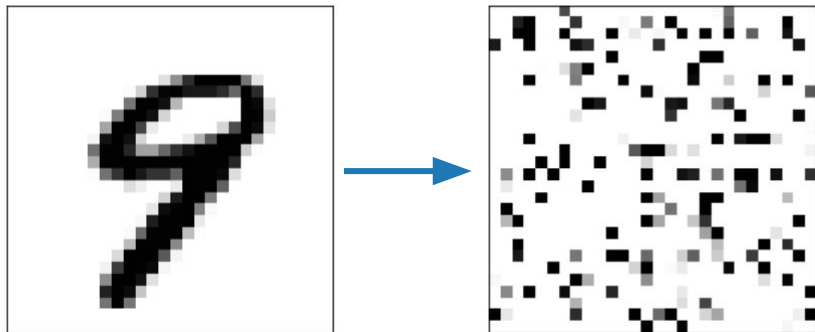


Optimization: Cascaded Reservoir

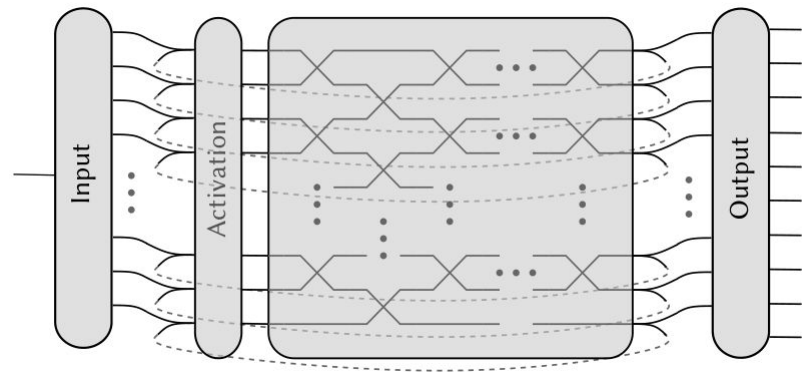
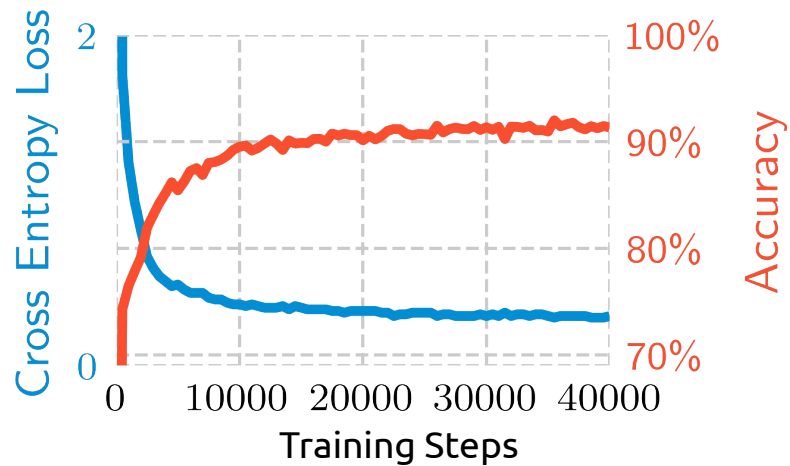


XOR of two bits with one intermediate bit

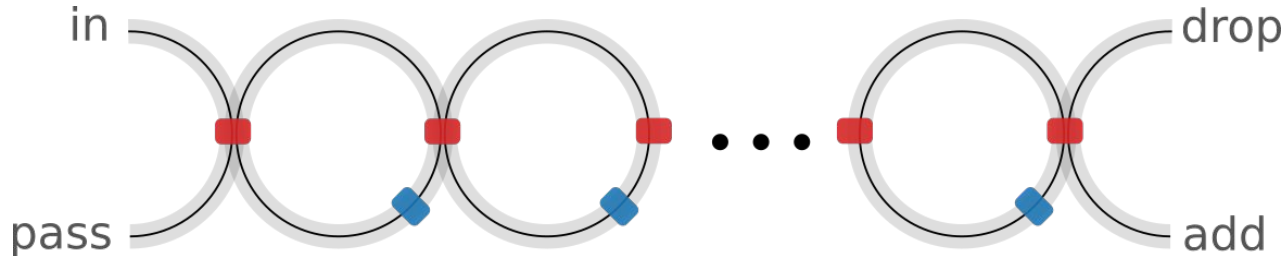
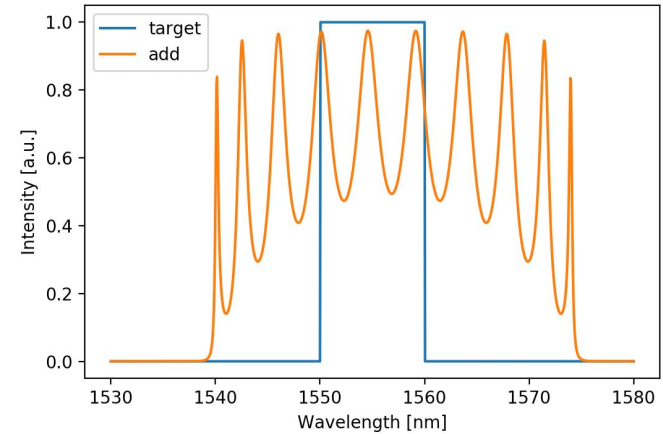
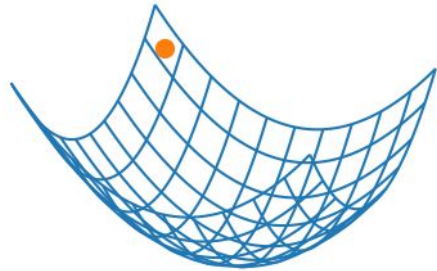
Optimization: MNIST



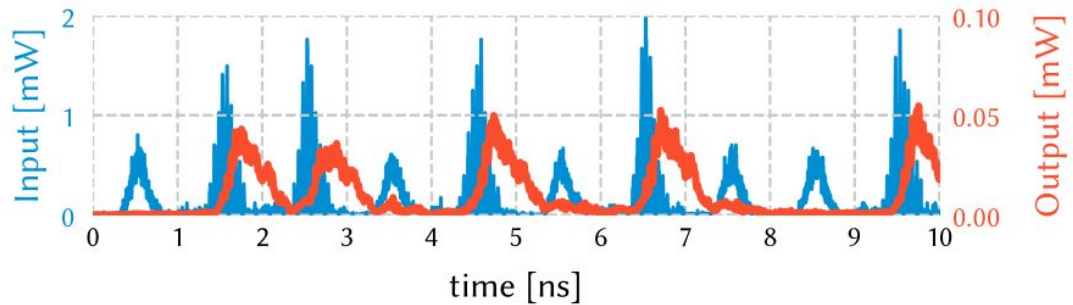
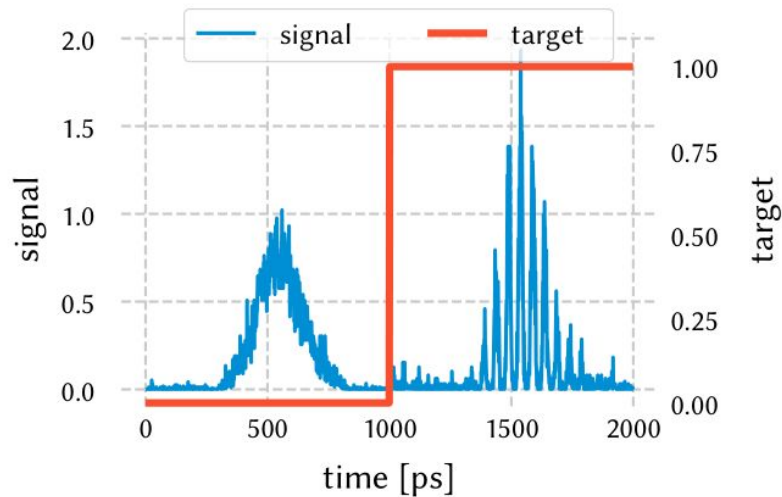
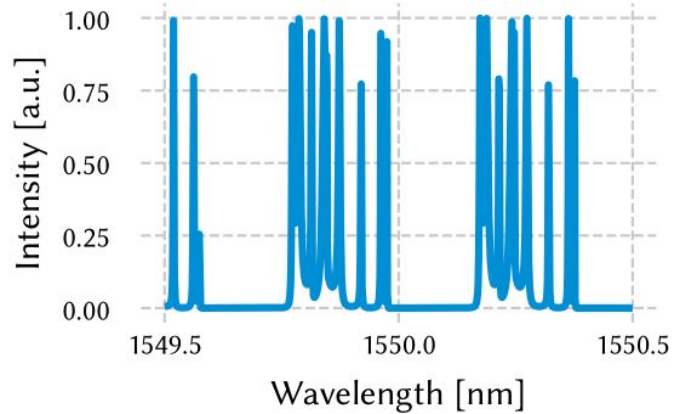
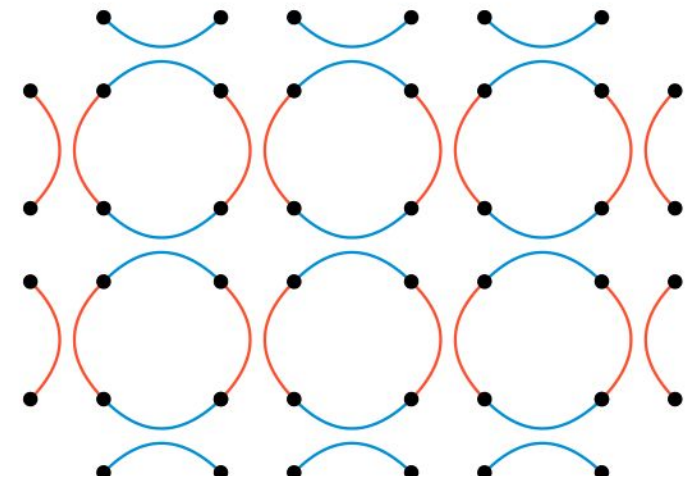
Shen, Nature, 2017



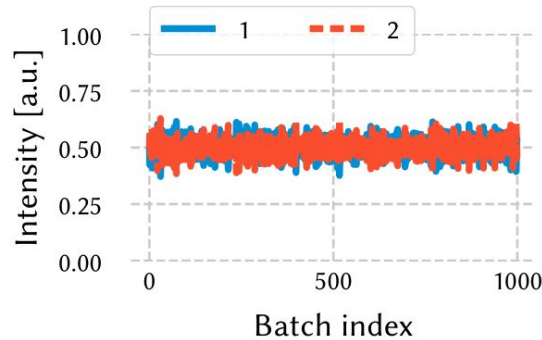
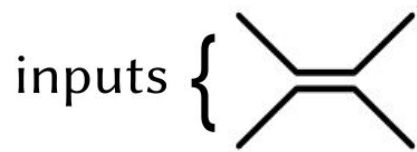
Optimization: CROW



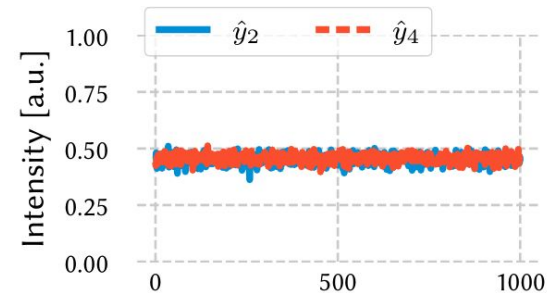
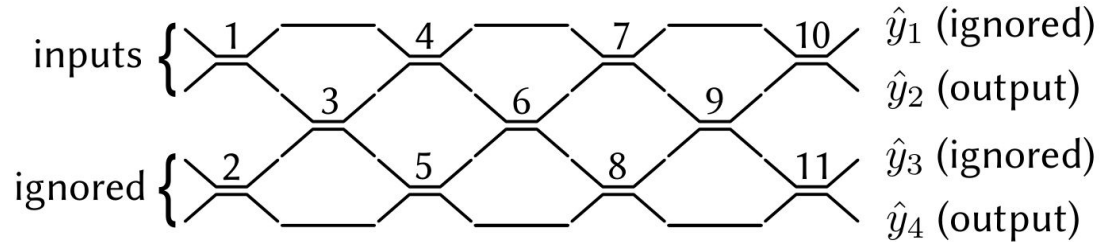
Optimization: ring network



Optimization: built-in tolerance



$\sigma=0.05$

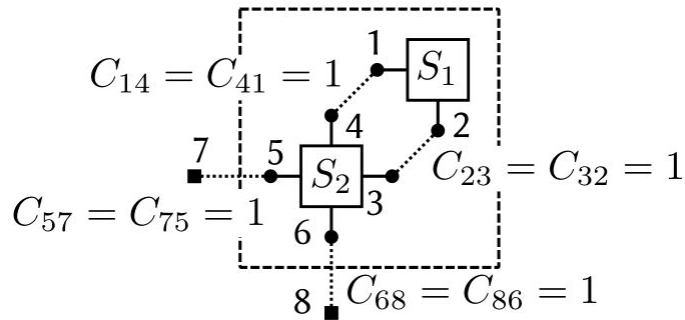
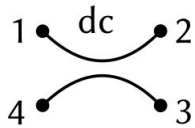
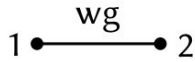


Batch index

$\sigma=0.016$

$$L = \alpha \left(\frac{1}{B} \sum_{b=1}^B \sum_{i=1}^4 (\hat{y}_{bi} - y_i)^2 \right) + \beta \left(\frac{1}{B} \sum_{b=1}^B (\hat{y}_{b2} - \frac{1}{B} \sum_{n=1}^B \hat{y}_{n2})^2 + (\hat{y}_{b4} - \frac{1}{B} \sum_{n=1}^B \hat{y}_{n4})^2 \right)$$

Photontorch



$$S^{\text{wg}} = \begin{pmatrix} 0 & \exp\left(\frac{2\pi i}{\lambda} n_{\text{eff}} L\right) \\ \exp\left(\frac{2\pi i}{\lambda} n_{\text{eff}} L\right) & 0 \end{pmatrix}$$

$$S^{\text{dc}} = \begin{pmatrix} 0 & \tau & i\kappa & 0 \\ \tau & 0 & 0 & i\kappa \\ i\kappa & 0 & 0 & \tau \\ 0 & i\kappa & \tau & 0 \end{pmatrix}$$

$$S = \begin{pmatrix} S_1 & & & \\ & S_2 & & \\ & & \ddots & \\ & & & S_N \end{pmatrix} C = \begin{pmatrix} \begin{array}{cccccc|cc} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \end{pmatrix}$$

Frequency domain:

$$S_{\text{circuit}} = C_{\text{ext}}^T S (I - C_{\text{int}} S)^{-1} C_{\text{ext}}$$

Photontorch: very parallelizable

Frequency domain:

$$S_{\text{circuit}} = C_{\text{ext}}^T S (I - C_{\text{int}} S)^{-1} C_{\text{ext}}$$

Time domain:

- Ideally: $\text{FT}(S_{\text{circuit}})$ \longrightarrow VF, IIR, FIR, ...
- Approximation:

$$\begin{aligned} \begin{pmatrix} x^{\text{ML}} \\ x^{\text{MC}} \end{pmatrix} &= \begin{pmatrix} C^{\text{MLML}} & C^{\text{MLMC}} \\ C^{\text{MCML}} & C^{\text{MCMC}} \end{pmatrix} \begin{pmatrix} S^{\text{MLML}} & 0 \\ 0 & S^{\text{MCMC}} \end{pmatrix} \star \begin{pmatrix} x^{\text{ML}} \\ x^{\text{MC}} \end{pmatrix} \\ &= \begin{pmatrix} C^{\text{MLML}} & C^{\text{MLMC}} \\ C^{\text{MCML}} & C^{\text{MCMC}} \end{pmatrix} \begin{pmatrix} S^{\text{MLML}} x^{\text{ML}} \\ S^{\text{MCMC}} \star x^{\text{MC}} \end{pmatrix} \end{aligned}$$

$$\frac{\partial u}{\partial t}(t) = f(t, u, x)$$

If GVD is important

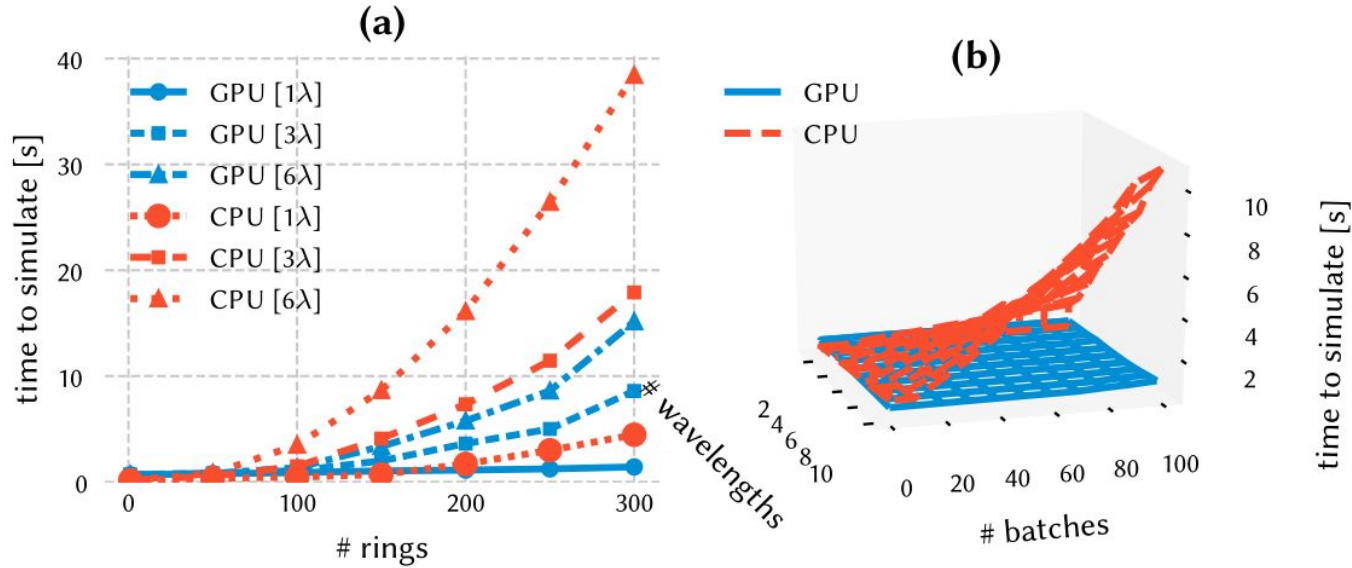
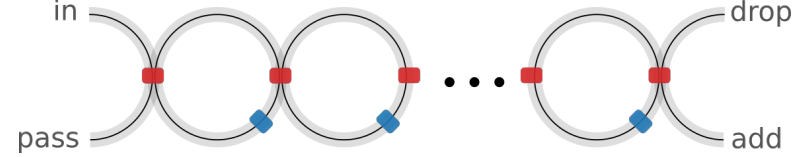
$$\tilde{C} = \left(C^{\text{MCMC}} + C^{\text{MCML}} \cdot S^{\text{MLML}} \cdot (1 - C^{\text{MLML}} S^{\text{MLML}})^{-1} C^{\text{MLMC}} \right)$$

$$x^{\text{MC}} = \tilde{C} S^{\text{MCMC}} \begin{pmatrix} x_1^{\text{MC}}(t - dt_1) \\ x_2^{\text{MC}}(t - dt_2) \\ \vdots \\ x_P^{\text{MC}}(t - dt_P) \end{pmatrix}$$

No dispersion taken into account

$$x_{(q+1)mnb} = \sum_i^N \sum_j^N \tilde{C}_{mni} S_{mij} \star x_{qmjb}$$

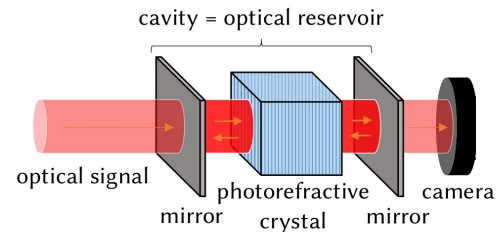
Performance



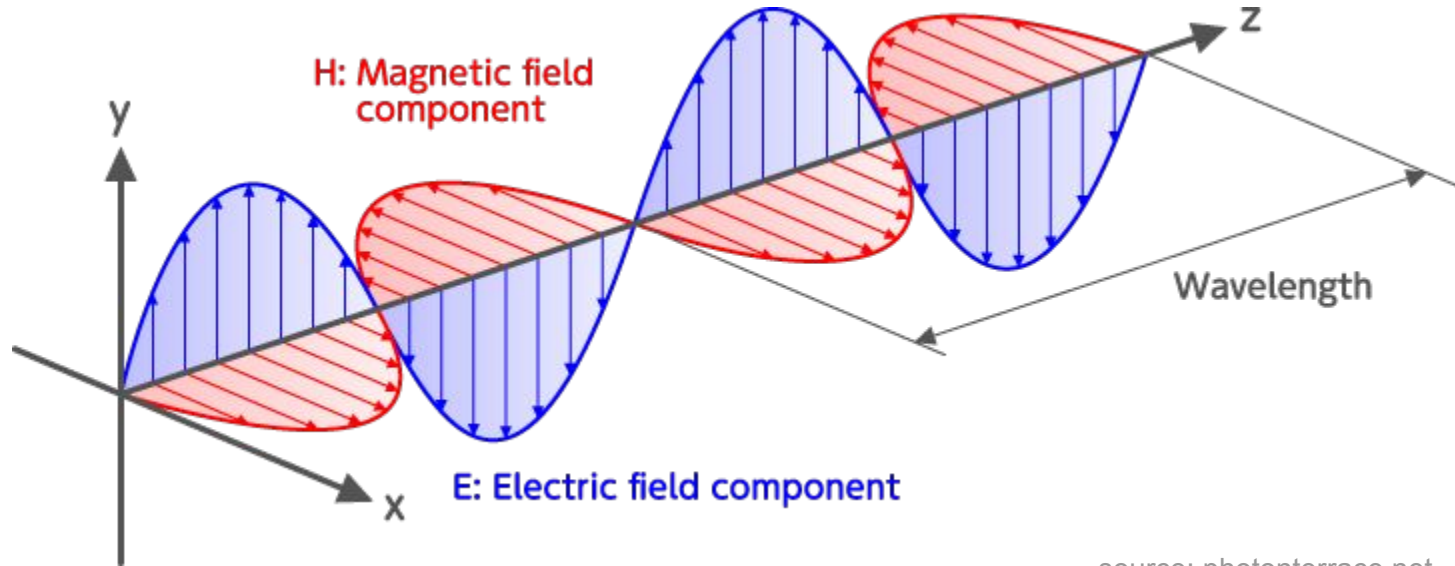
$$x_{(q+1)mnb} = \sum_i^N \sum_j^N \tilde{C}_{mni} S_{mij} \star x_{qmjb}$$

Overview

- Machine learning & Neuromorphic computing
- Towards photonic neuromorphic computing
- Photontorch: optimizing photonic circuits
- Reservoir computing with signal-mixing cavities
- **Neuromorphic computing with photorefractive crystals**

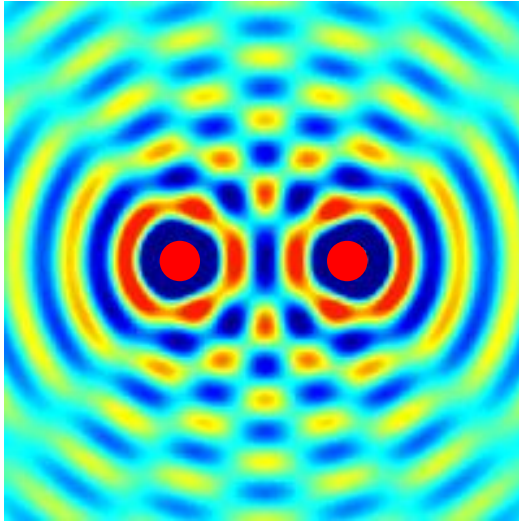
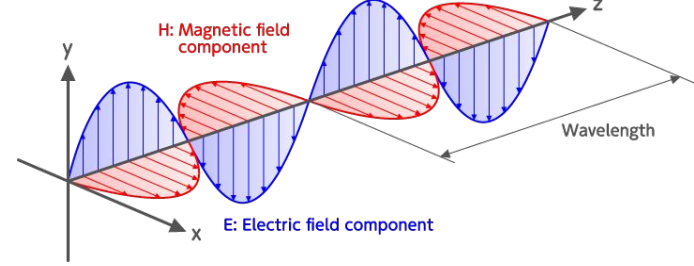


Light is an electromagnetic wave

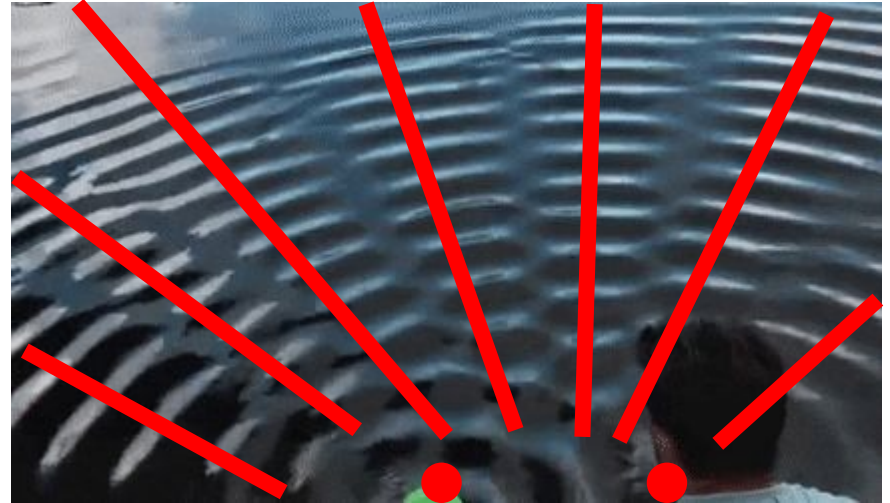
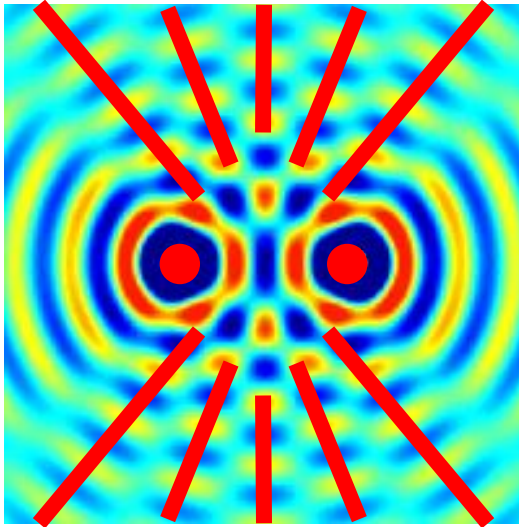
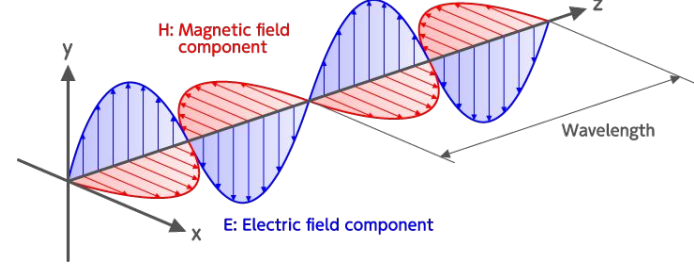


source: photonterrace.net

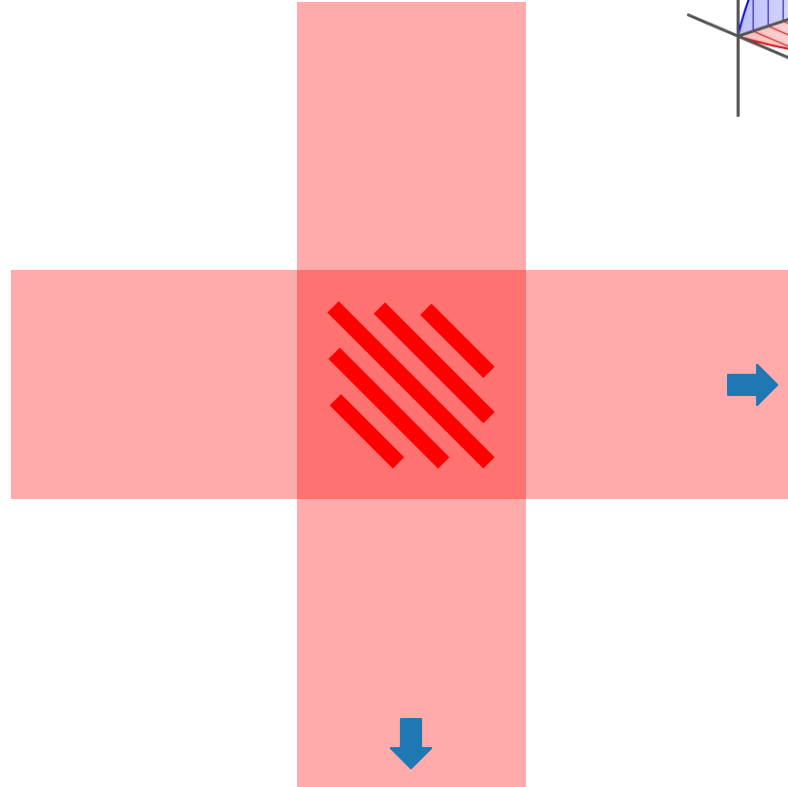
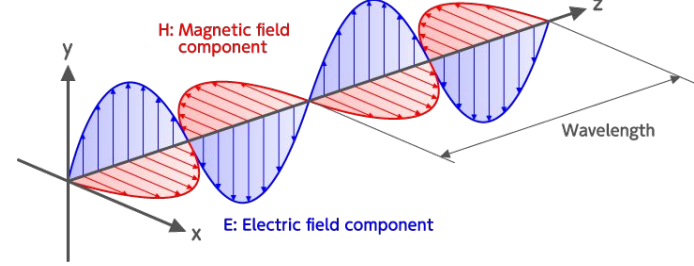
Interference



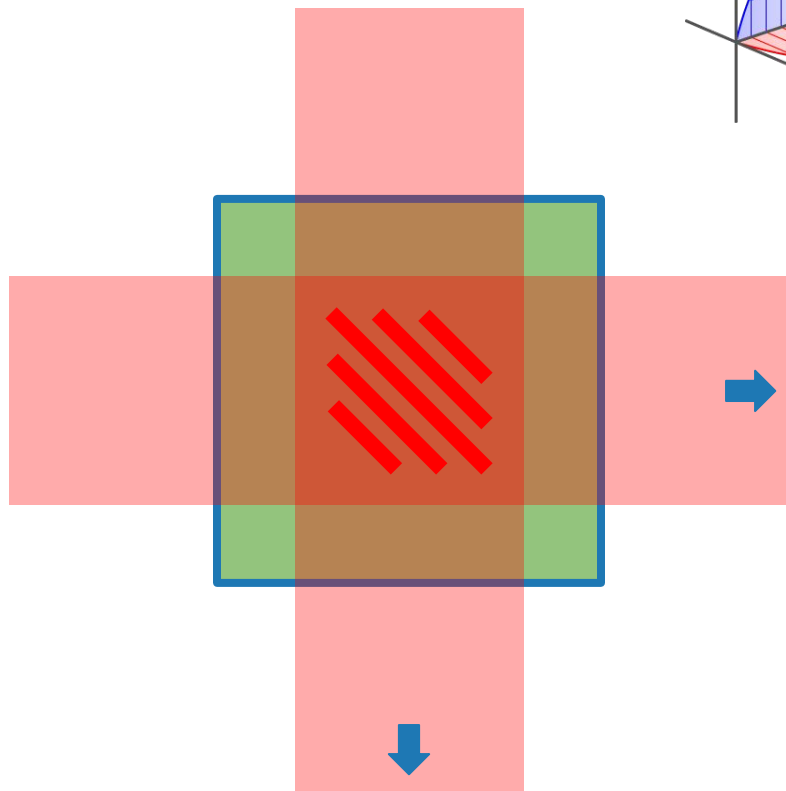
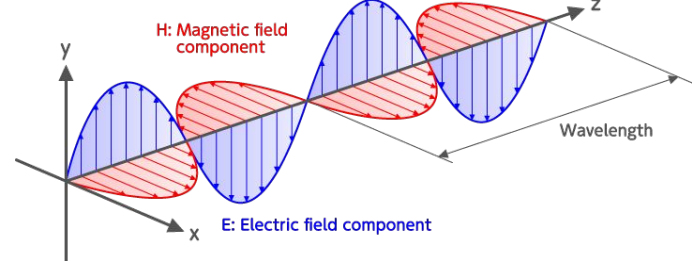
Interference



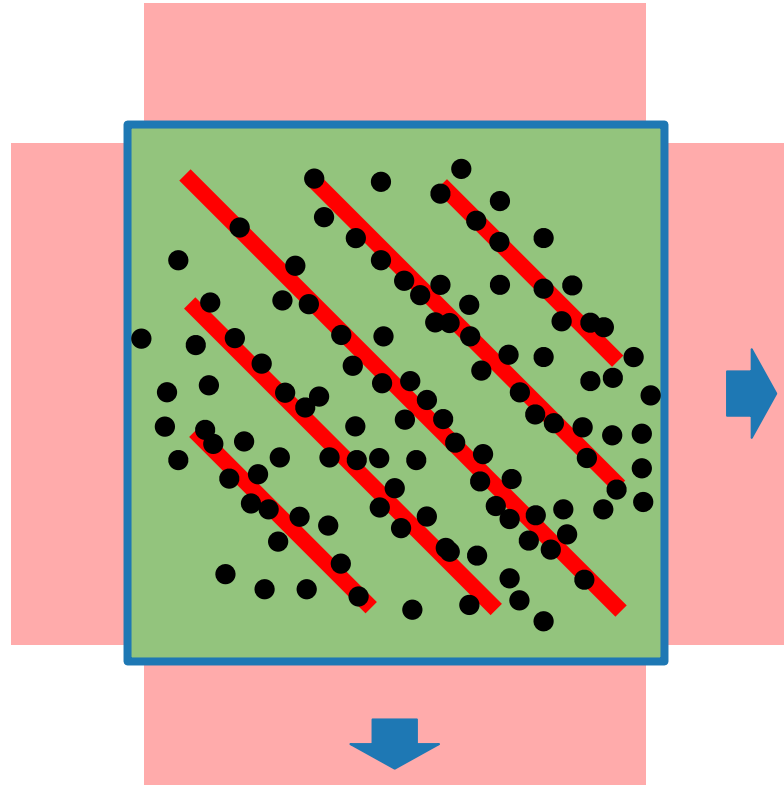
Interference



Photorefractive effect

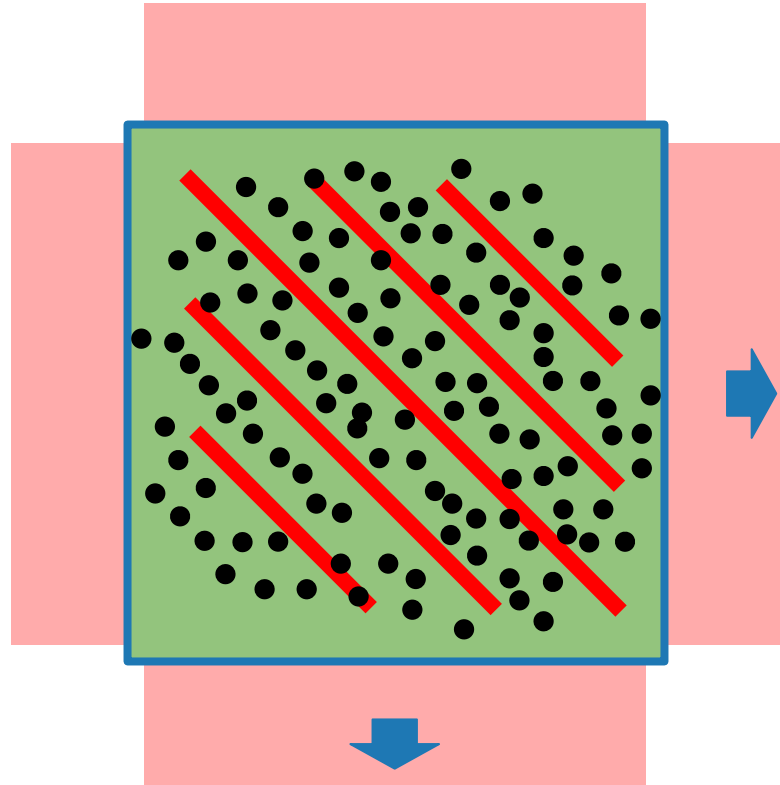


Photorefractive effect



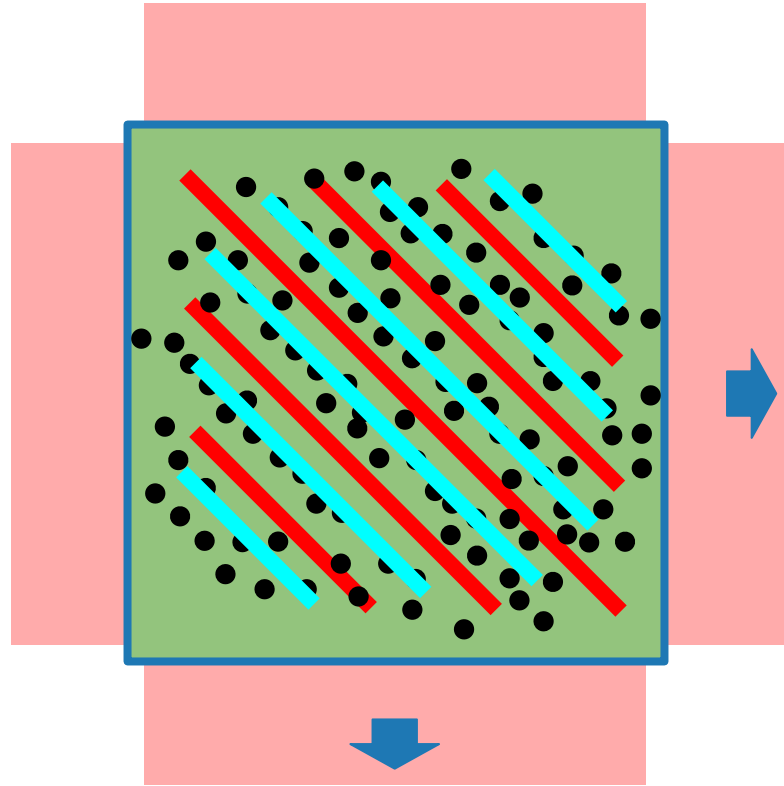
$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu k T}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect



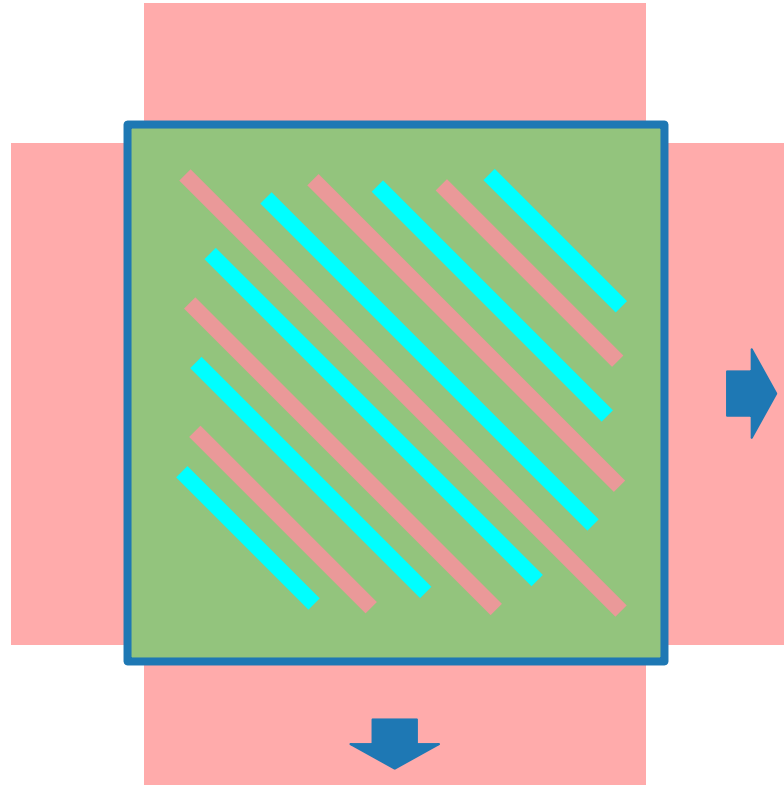
$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu k T}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect



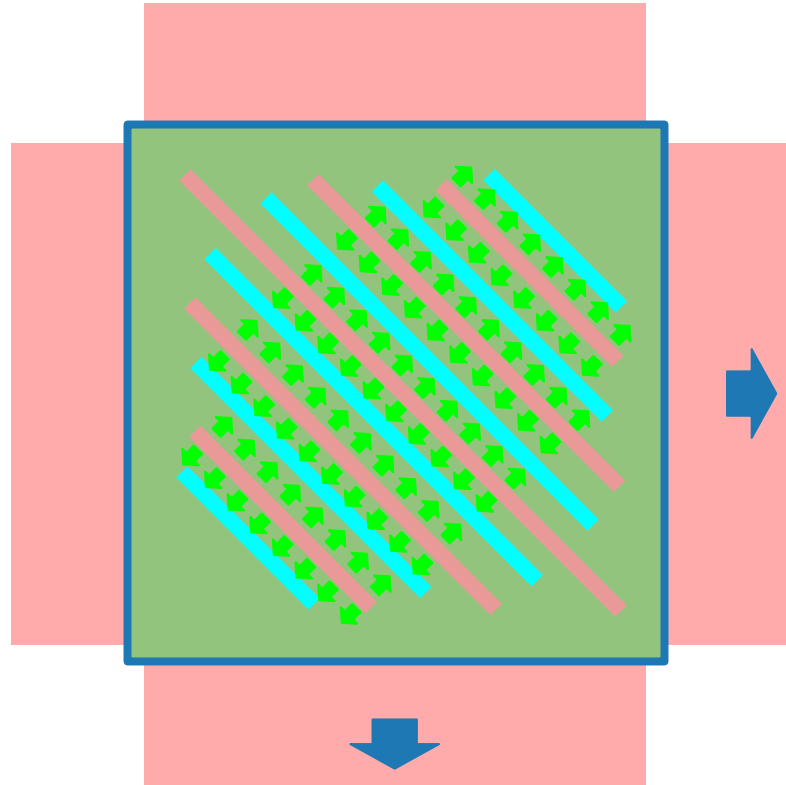
$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu kT}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect



$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu k T}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect

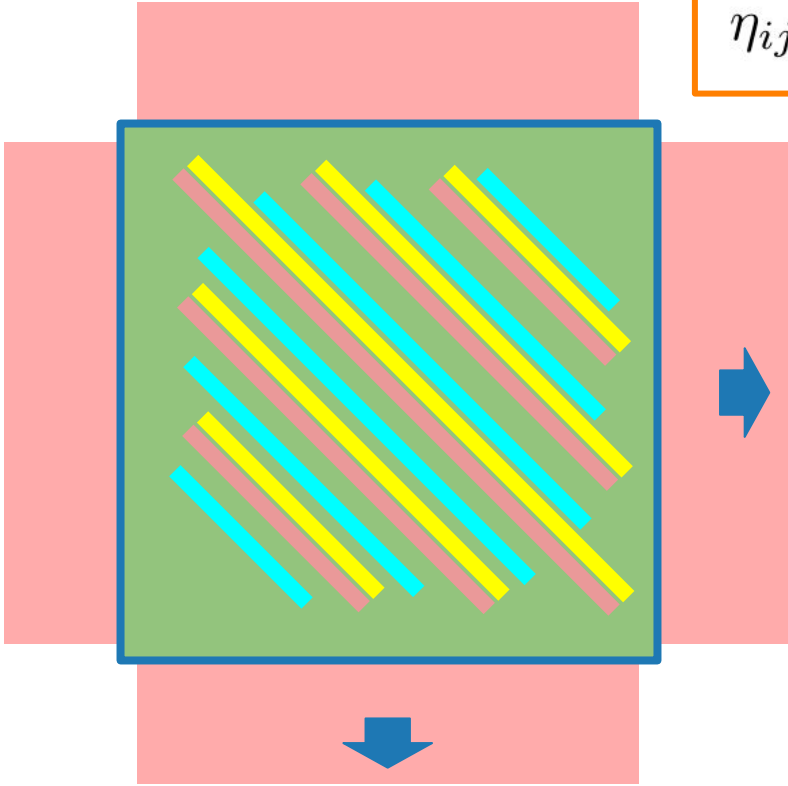


$$\nabla \cdot \mathbf{S} = \frac{\rho}{\epsilon_s}$$

$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu k T}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect

$$\eta_{ij}(\mathbf{S}) = \eta_{ij}(0) + r_{ijk}S_k$$

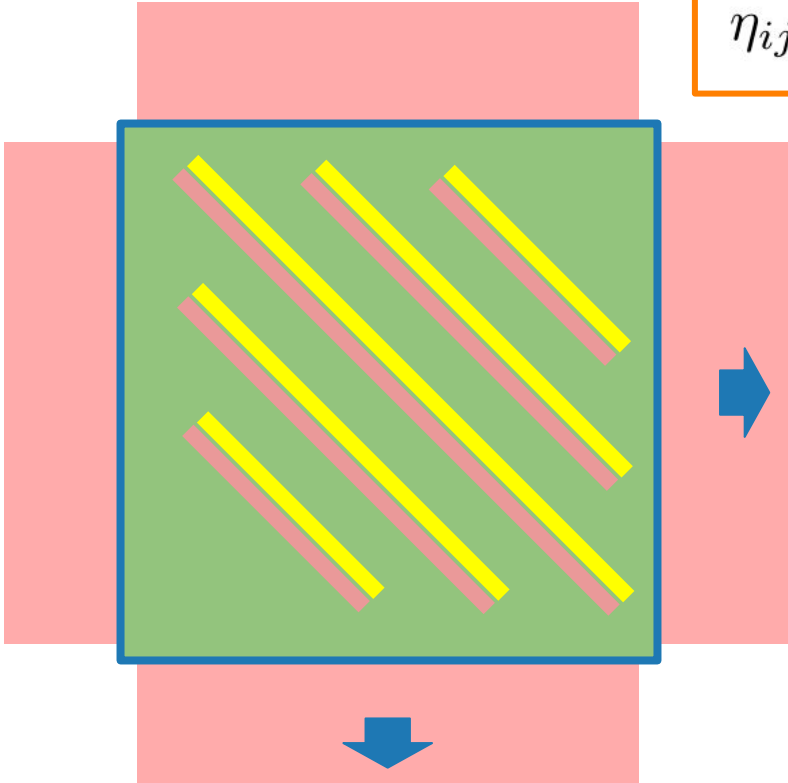


$$\nabla \cdot \mathbf{S} = \frac{\rho}{\epsilon_s}$$

$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu kT}{e} \nabla n - \mu n \mathbf{S}$$

Photorefractive effect

$$\eta_{ij}(\mathbf{S}) = \eta_{ij}(0) + r_{ijk}S_k$$



$$\nabla \cdot \mathbf{S} = \frac{\rho}{\epsilon_s}$$

$$\frac{dn}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+ + \frac{\mu kT}{e} \nabla n - \mu n \mathbf{S}$$

Bringing it all together

Kukhtarev equations:

$$\frac{dn}{dt} = \frac{dN_D^+}{dt} + \nabla \cdot \mathbf{J}$$

$$\frac{dN_D^+}{dt} = (sI + \beta)(N_D - N_D^+) - \gamma n N_D^+$$

$$\mathbf{J} = \frac{\mu k T}{e} \nabla n - \mu n \mathbf{S}$$

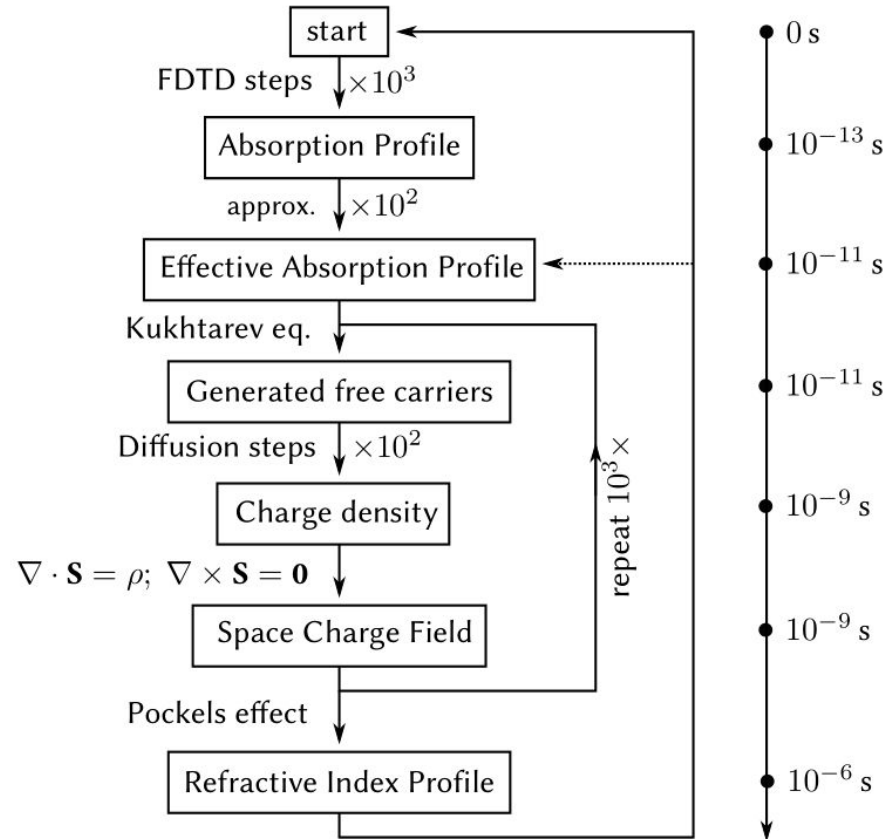
Diffusion Equation:

$$\frac{\partial n}{\partial t} = \frac{\partial n}{\partial t} \Big|_{\text{diff}} + \frac{\partial n}{\partial t} \Big|_{\text{drift}} = D \nabla^2 n - \nabla \cdot \mathbf{F}$$

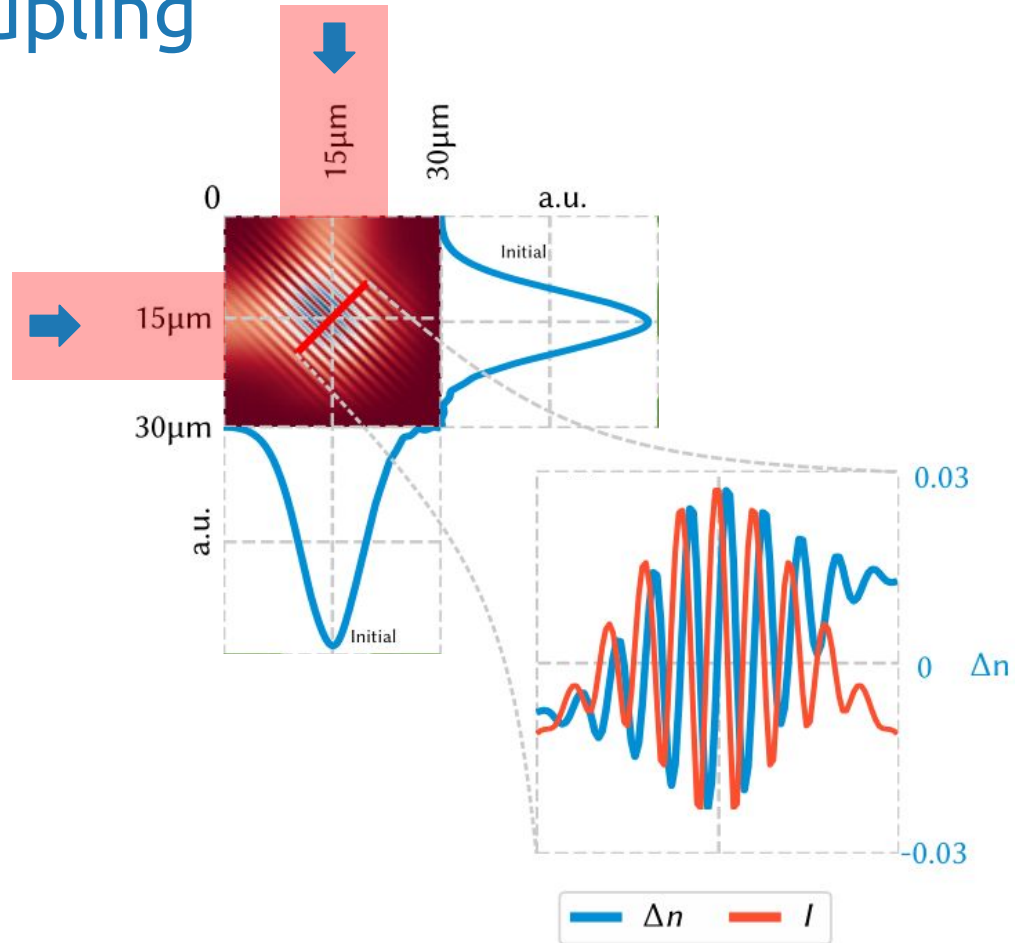
Maxwell equations:

$$\nabla \cdot \mathbf{S} = \frac{\rho}{\epsilon_s}$$

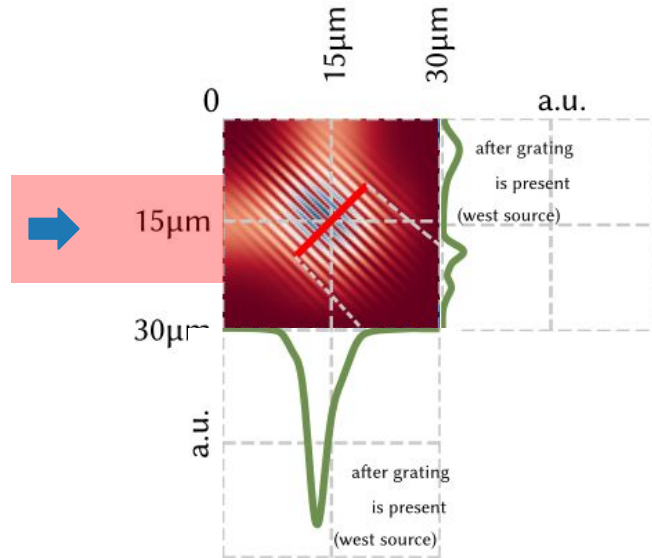
$$\nabla \times \mathbf{S} = \mathbf{0}$$



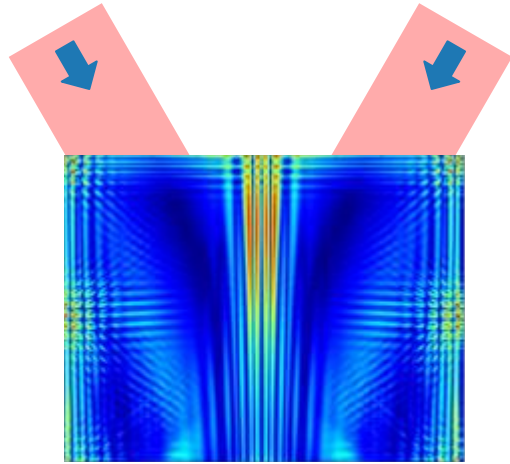
Beam Coupling



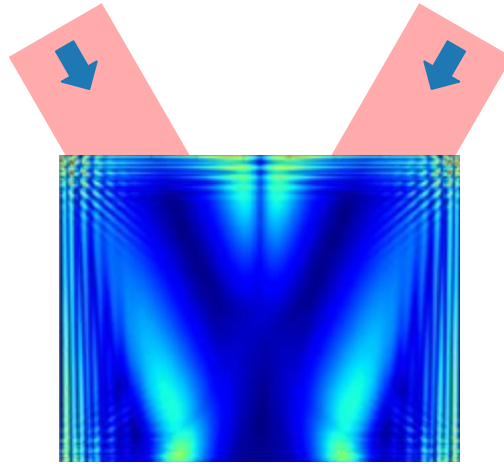
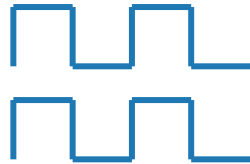
Beam Coupling



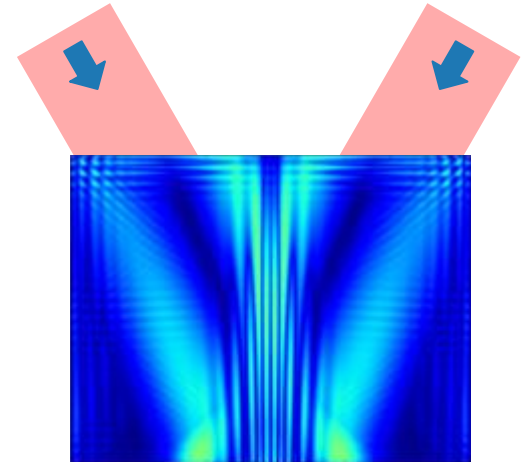
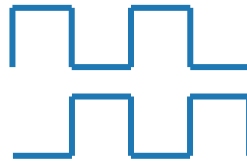
Self learning with photorefractive crystals



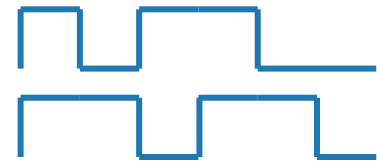
Purely Interfering
(same bits arrive at the same time)



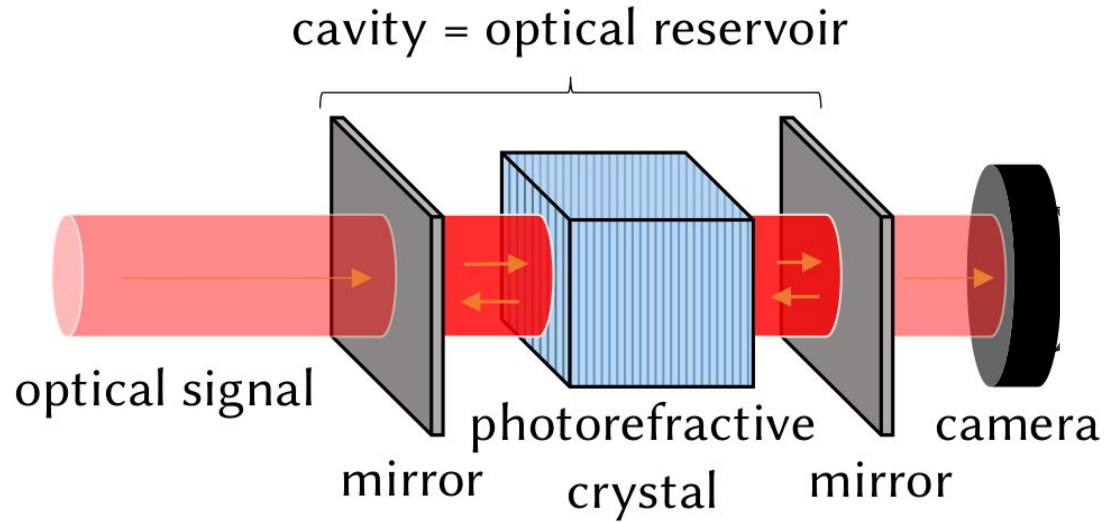
Alternating
(opposite bits arrive at the Alternating times)



Random
(two random bitstream,
Sometimes interfering,
Sometimes alternating)



Self learning with photorefractive crystals

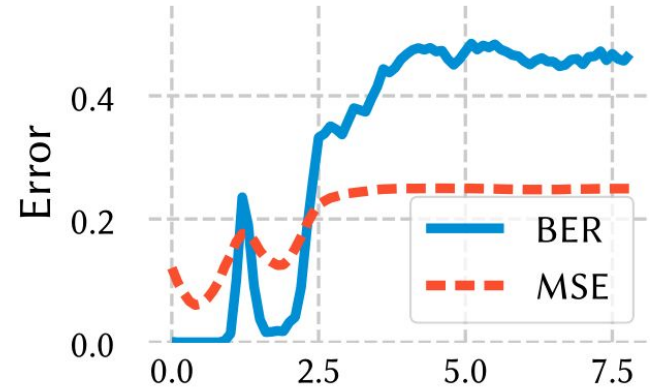


XOR Task

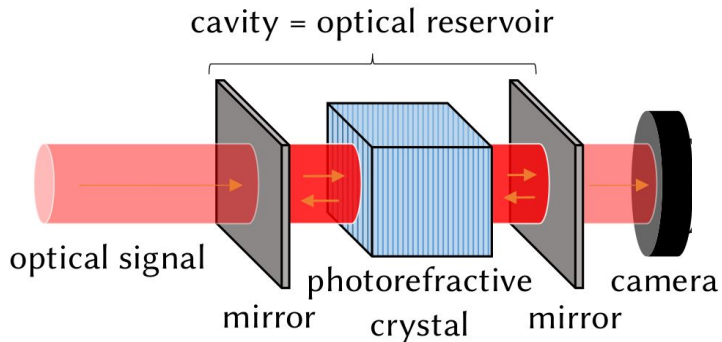
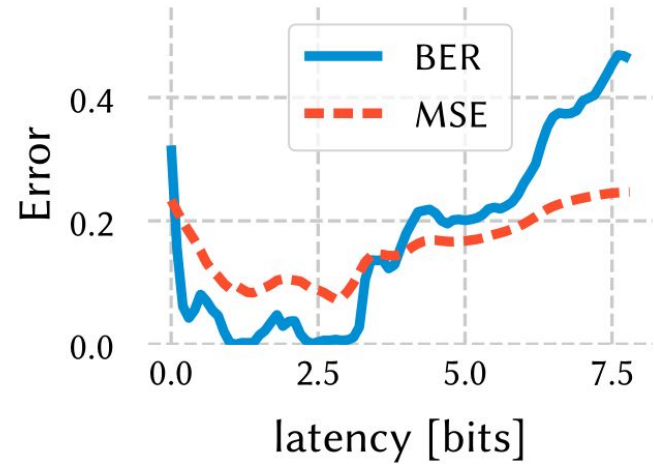
0 1 0 1 0 0 1
1 1 1 1 0 1



Before "priming":



After "priming":



Conclusions

Conclusions

- Reservoir computing with **on-chip cavities** seems to be a promising alternative to traditional node-based designs:
 - Benchmark tasks like **HREC and XOR show promising results**, both in simulation and experiments.
- **Photontorch** shows the viability of optimizing photonic circuits through **backpropagation**
 - Completely **new way of optimizing** photonic circuits
 - Very **parallelizable** (→ Fast)
 - wavelength multiplexing
 - waveform multiplexing (batched execution)
- Self-reorganization in photorefractive crystals, such as **priming** the crystal might help for neuromorphic computing schemes **beyond reservoir computing** such as self-learning