Photonics and the brain: hybrid integrated intelligence

Lorenzo Pavesi

University of Trento

BACKUP neuromorphic photonics and the brain

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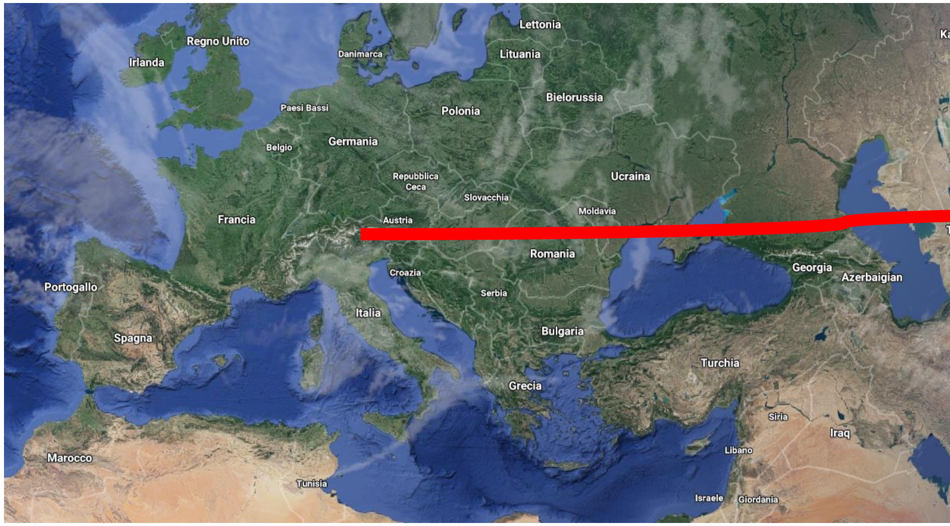
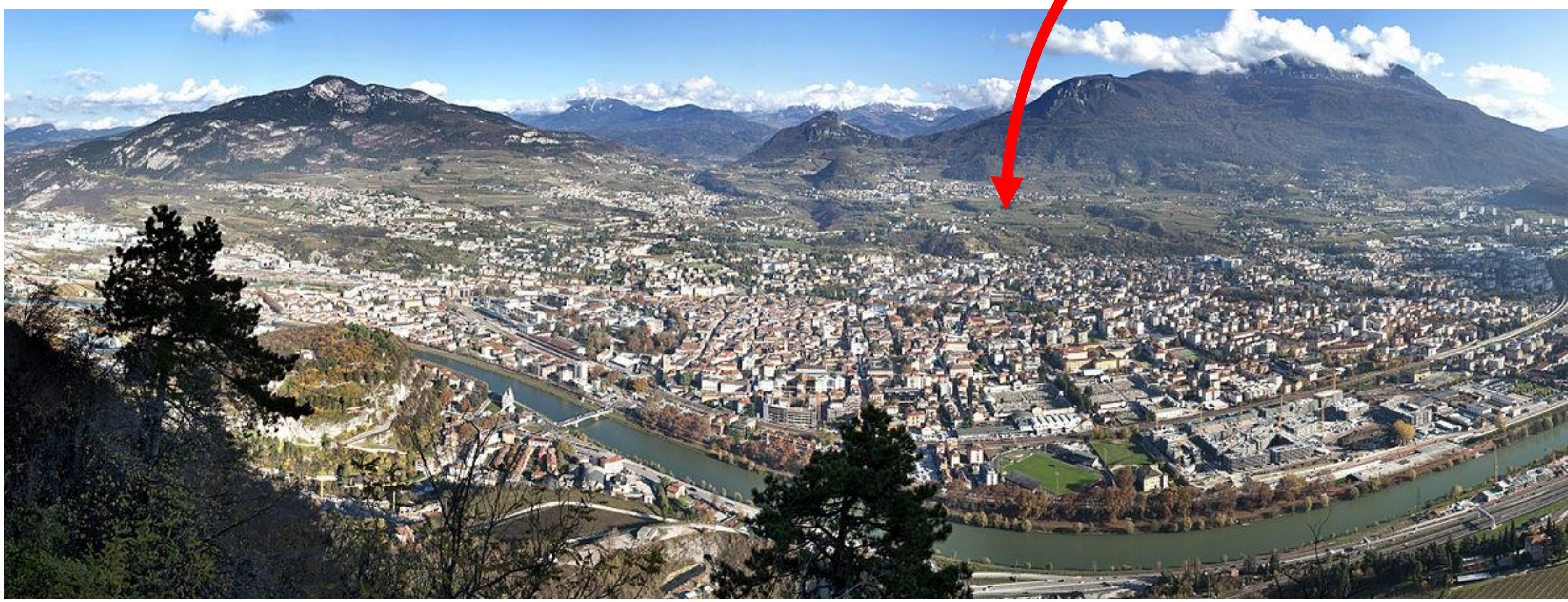
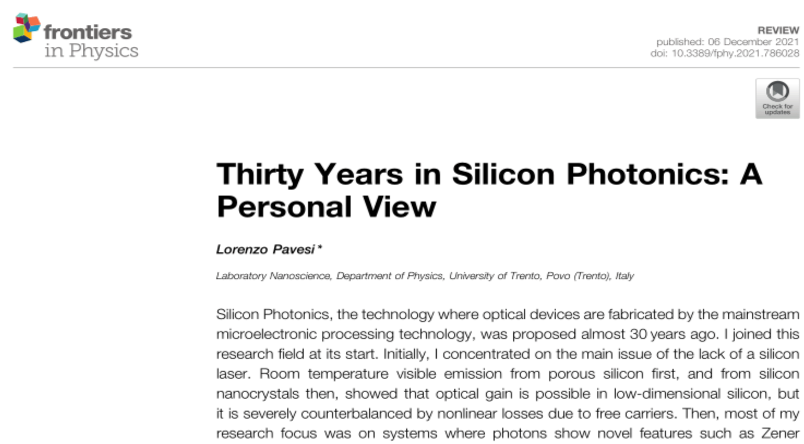




Nanoscience Laboratory

http://nanolab.physics.unitn.it/

Quantum Photonics
Non-Hermitian Photonics
Neuromorphic Photonics


frontiers in Physics

REVIEW
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Thirty Years in Silicon Photonics: A Personal View

*Lorenzo Pavesi**

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Silicon Photonics, the technology where optical devices are fabricated by the mainstream microelectronic processing technology, was proposed almost 30 years ago. I joined this research field at its start. Initially, I concentrated on the main issue of the lack of a silicon laser. Room temperature visible emission from porous silicon first, and from silicon nanocrystals then, showed that optical gain is possible in low-dimensional silicon, but it is severely counterbalanced by nonlinear losses due to free carriers. Then, most of my research focus was on systems where photons show novel features such as Zener tunneling or Anderson localization. Here, the game was to engineer suitable dielectric

Nanoscience Laboratory

prof

researcher

staff

Post-doc

PhD

Master students

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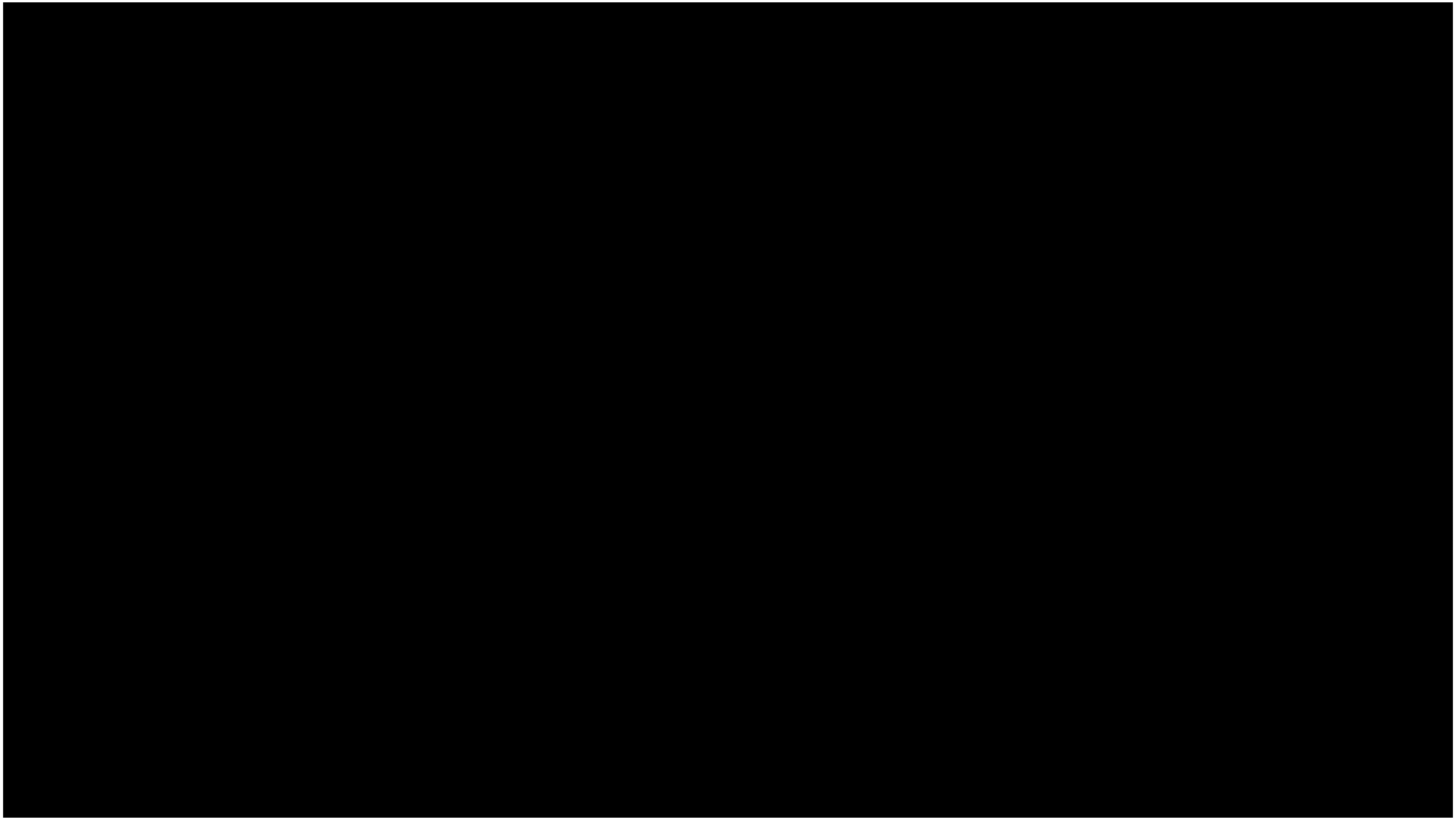
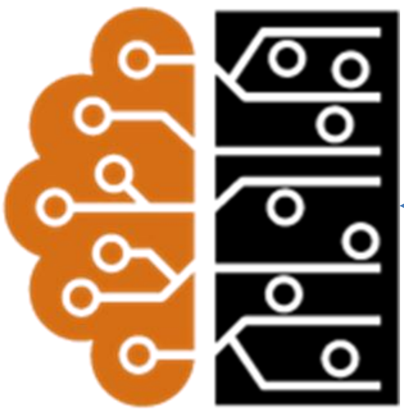


The vision

BIOLOGICAL COLTURE

PHOTONIC INTEGRATED CIRCUIT



HYBRID ARTIFICIAL-BIOLOGICAL NETWORK

Outline

- Photonics for artificial neural networks
  - The optical neuron
  - How to add memory to the neuron
  - Few neuronal networks at work
- Photonics to form biological networks
  - Light to sculpt neuronal circuits
  - Light to induce memories
  - Software emulation of neuronal circuits
- Hybrid artificial networks
  - The first steps

Outline

- Photonics for artificial neural networks
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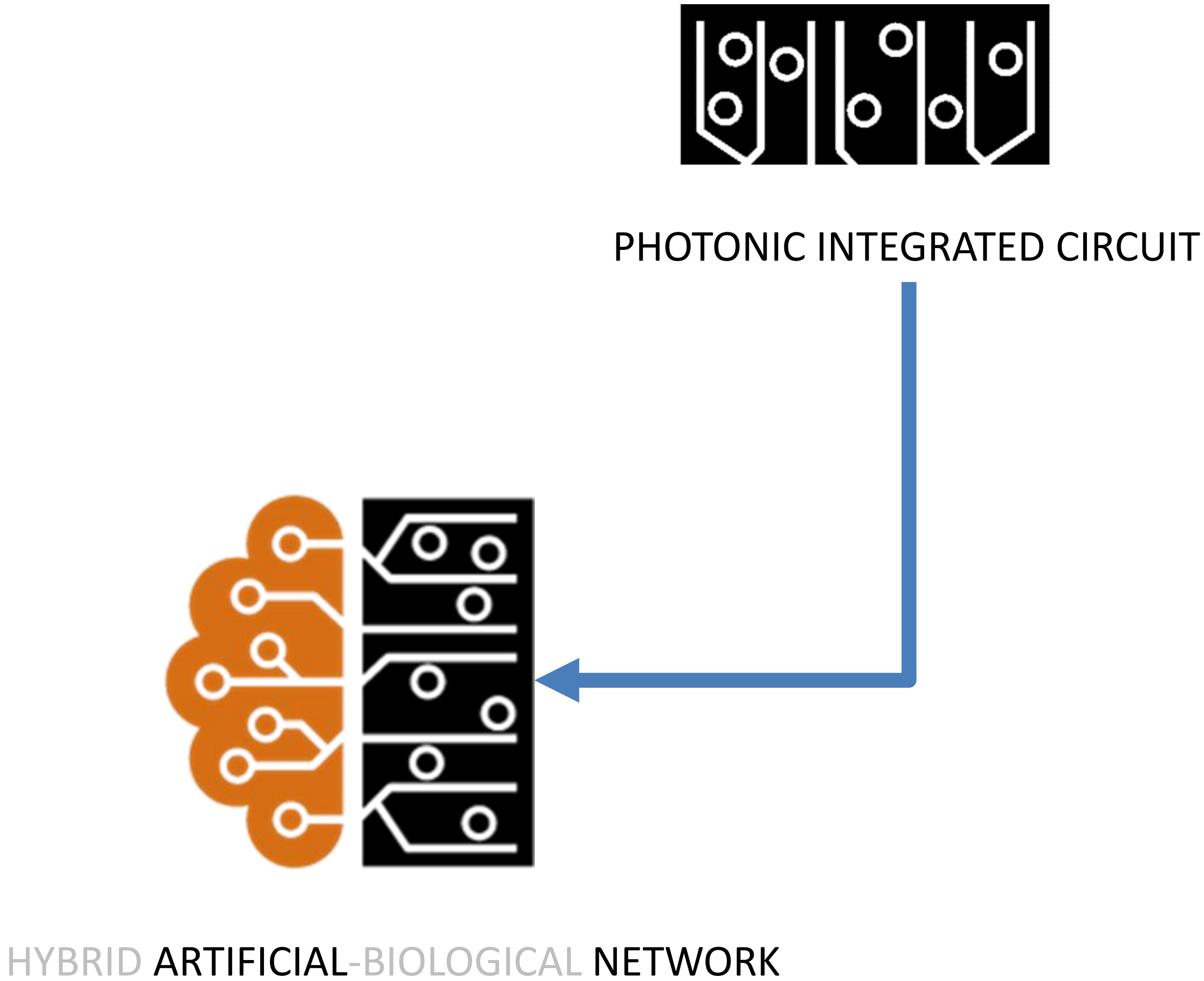

PHOTONIC INTEGRATED CIRCUIT
HYBRID ARTIFICIAL-BIOLOGICAL NETWORK

Photonics neural networks

MATTIA MANCINELLI

STEFANO BIASI

GIANMARCO ZANARDI

GIOVANNI DONATI

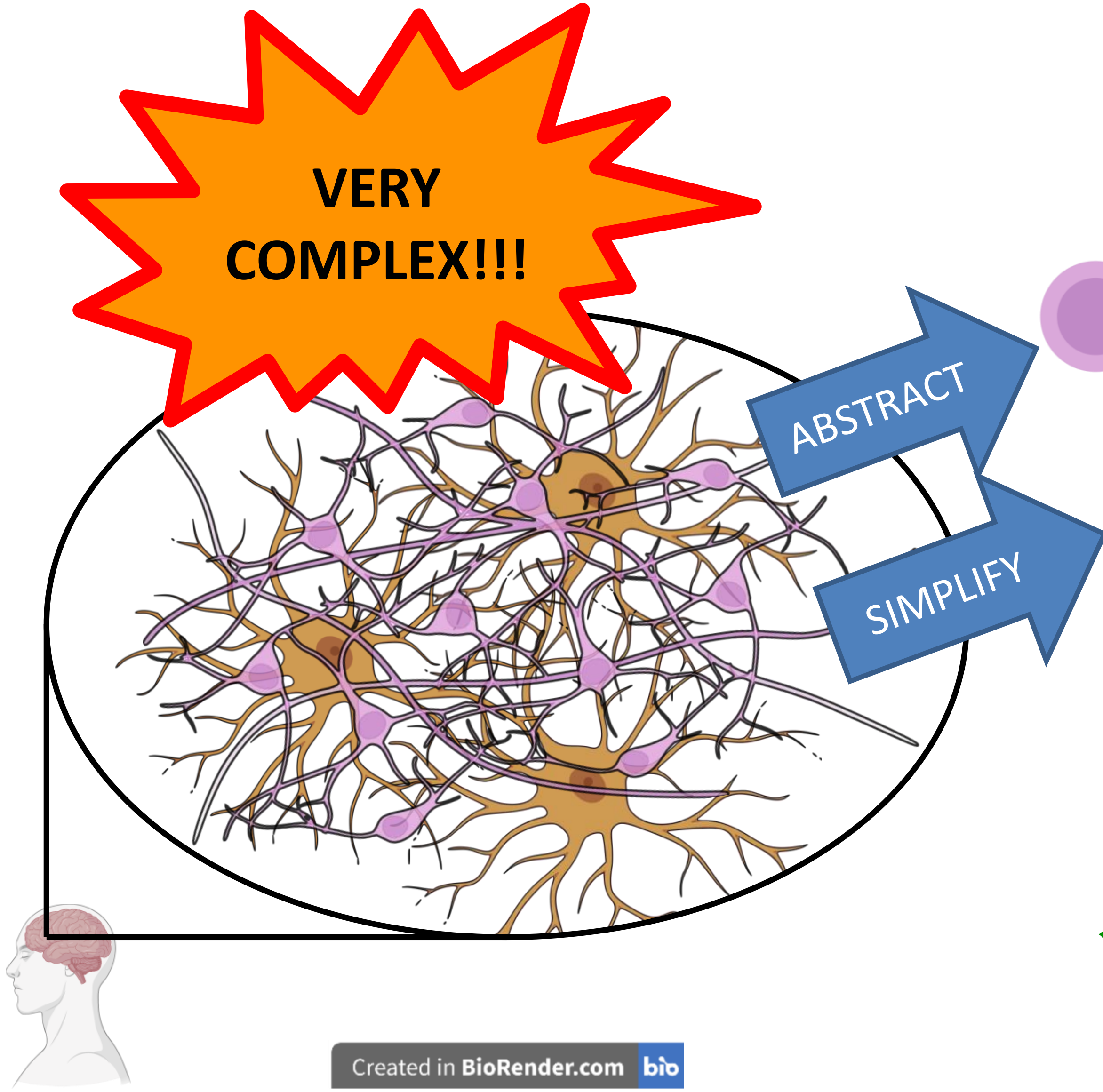
EMILIANO STAFFOLI

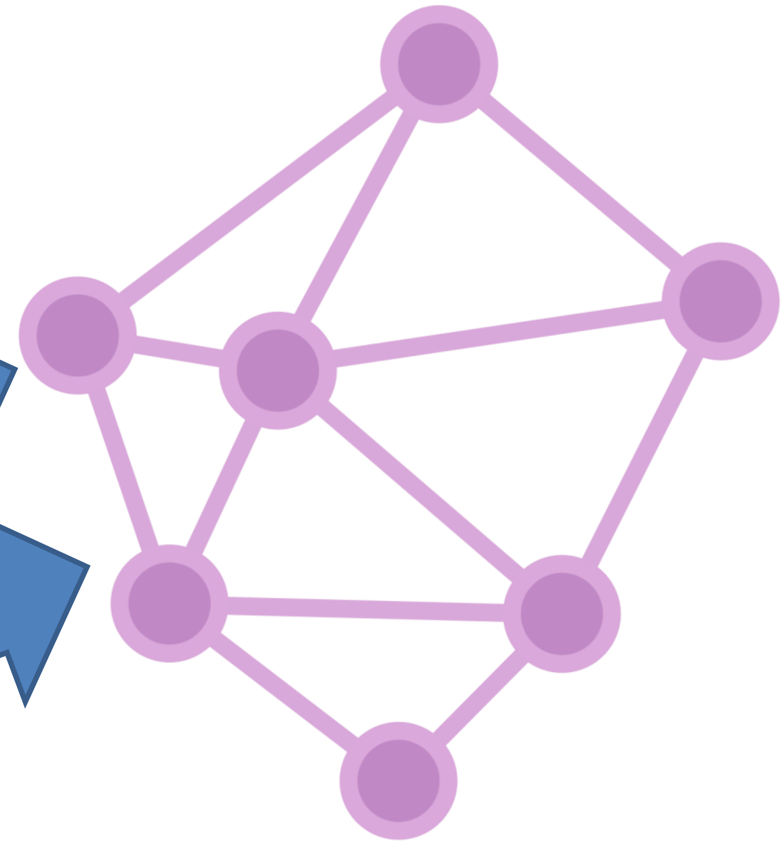
BIO-INSPIRED OPTICAL NEURAL NETWORKS: BRAIN MEETS PHOTONIC CIRCUITS

Artificial Neural Networks

Image from https://syncedreview.com/2017/04/08/the-future-of-computing-neuromorphic/

Artificial Neural Netowrks





- ✓ Gain insight on behaviour
- ✓ Imitate brain through ANN

Photonics-based ANN

Light is fast!

Power efficient (no Joule effect)

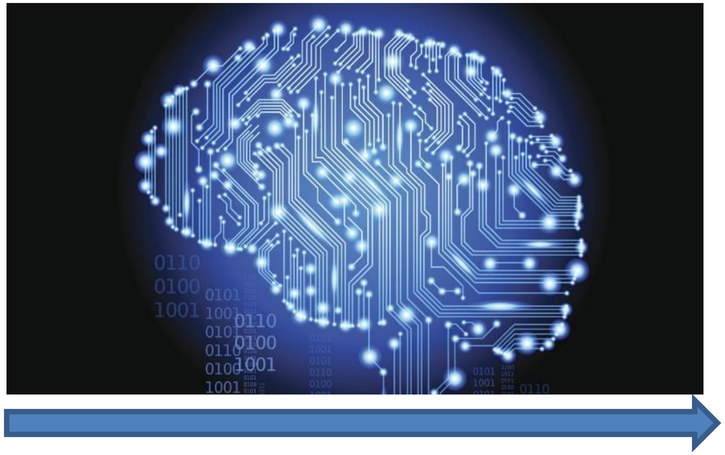
Parallelism (WDM)

Biological neuron timescale ms (10^{-3} s)

Optical neurons timescale ps (10^{-12} s)

Factor of 10^9!!

Brain learning process 15 years

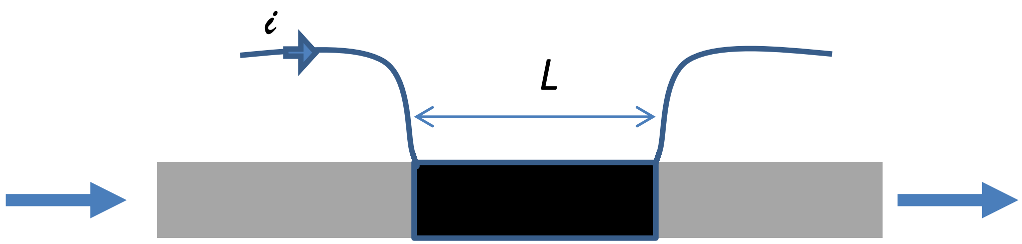


Artificial optical brain 0.5 seconds

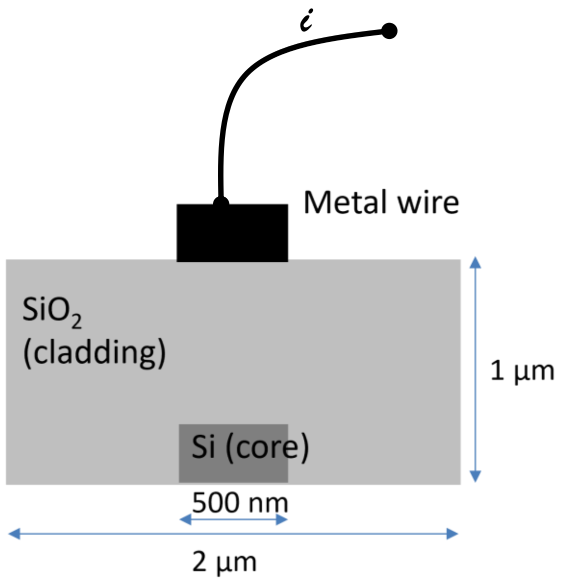
The basic building blocks of photonics

ANN

Thermal phase shifter



$$\left(e^{i\,\Delta\emptyset}\right)$$

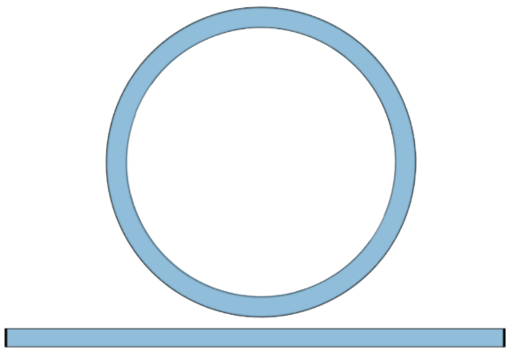


$$\Delta\emptyset = L\frac{2\pi}{\lambda}\frac{dn}{dT}dT$$

$$n = n_0 + \frac{dn}{dT}\Delta T$$

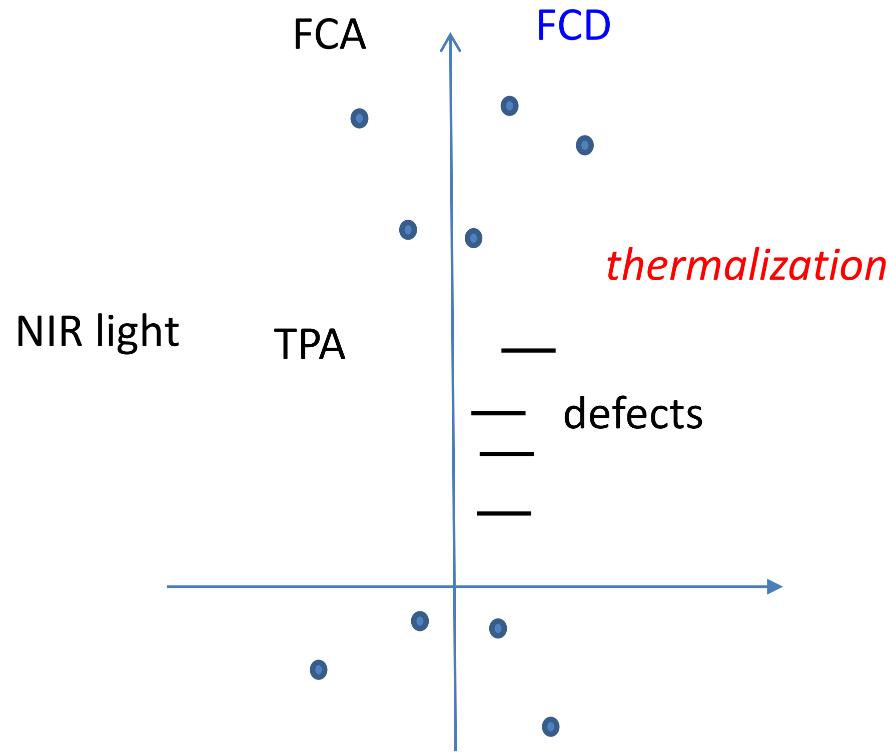
The basic building blocks

Microring resonator



$$m\lambda = 2\pi\, n_{eff}\, R$$

$$n(P) = n_0 + \frac{dn}{dT}\Delta T - \frac{dn}{dN}\Delta N$$

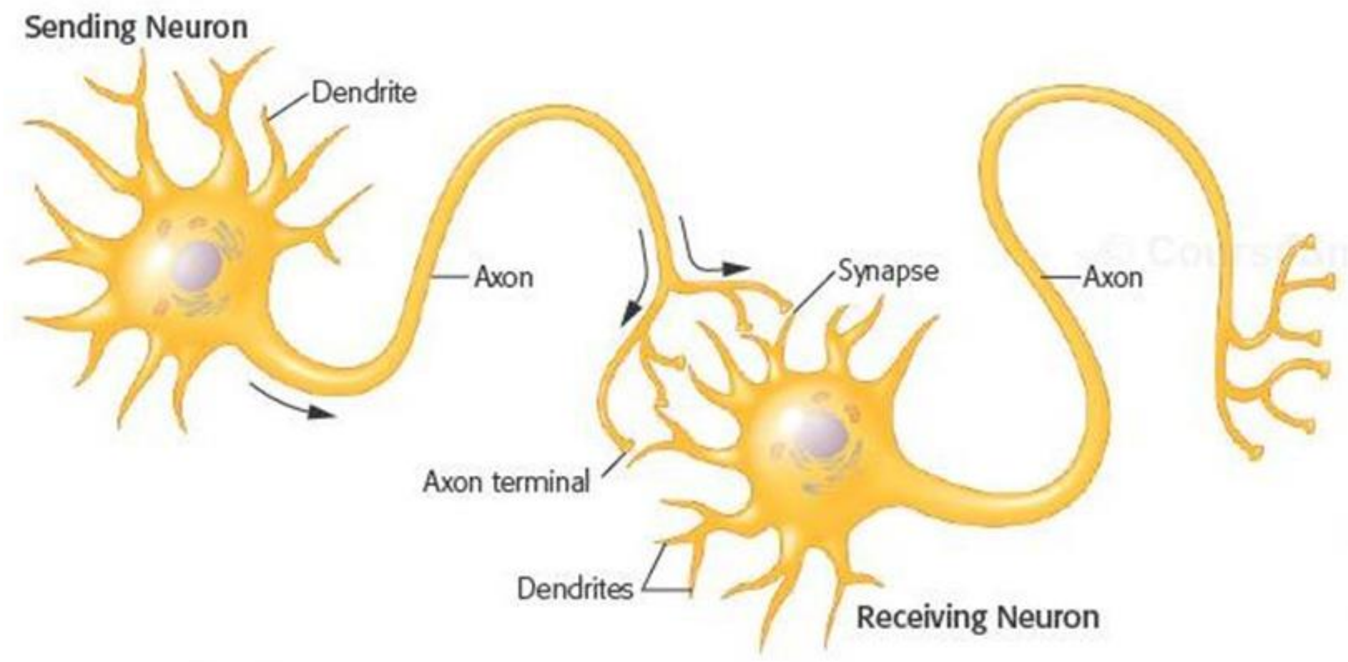


TOE: Thermo-optic effect $\Delta n > 0$ Red shift

FCD: Free carrier dispersion $\Delta n < 0$ Blue shift

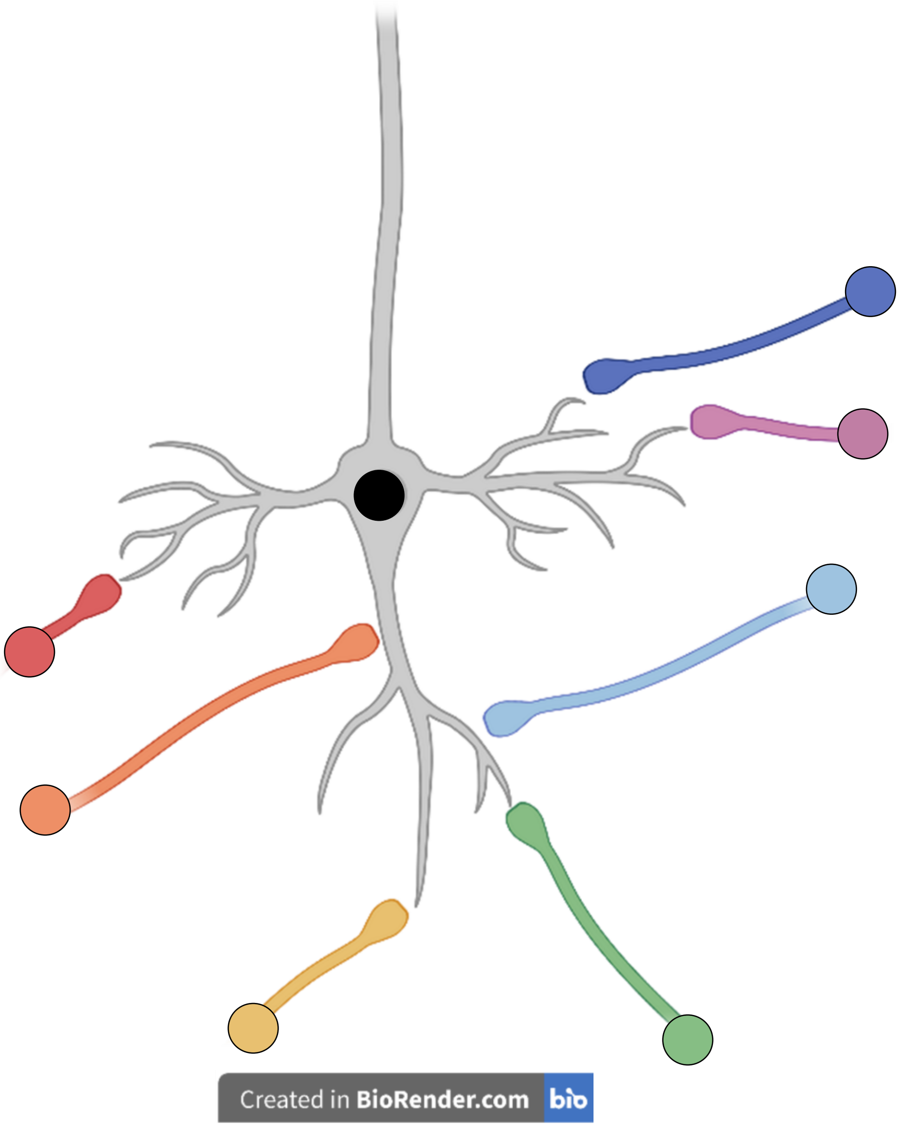
$\tau_{fc} \sim 4\ ns$ $\tau_{TO} \sim 100\ ns$

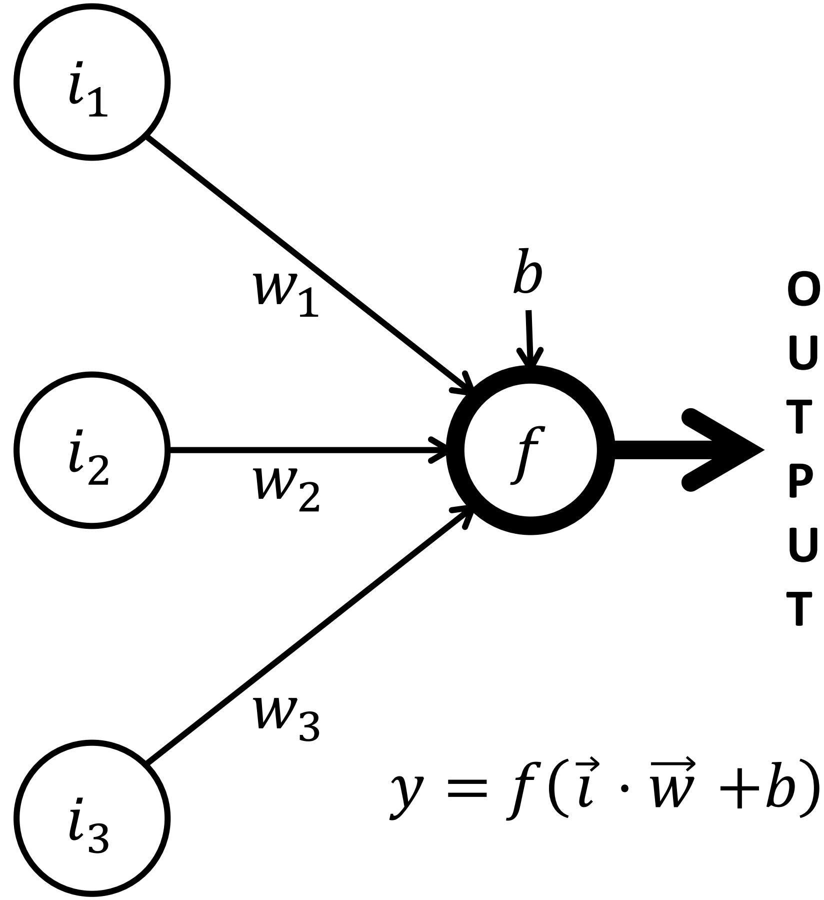
Neurons



Sending Neuron
Dendrite
Axon
Synapse
Axon
Axon terminal
Dendrites
Receiving Neuron

Let’s start with one neuron: the perceptron





$$y = f(\vec{\imath} \cdot \vec{w} + b)$$

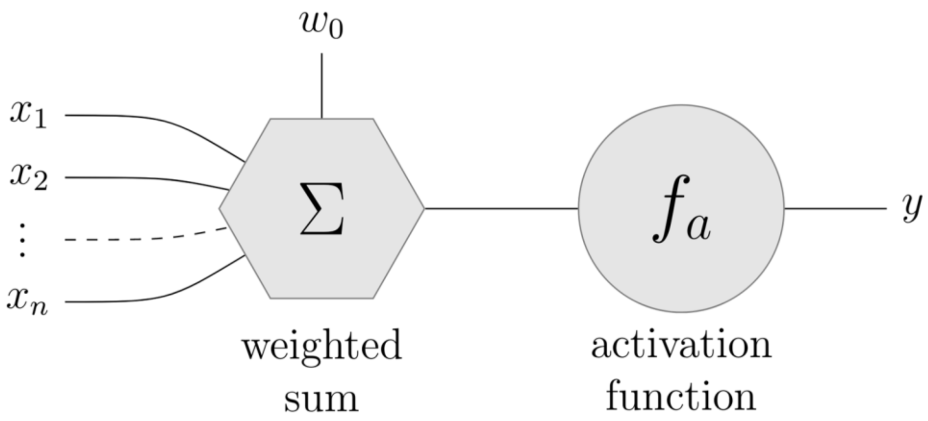
✓ Easily trained (ML)

✓ Can do classification tasks

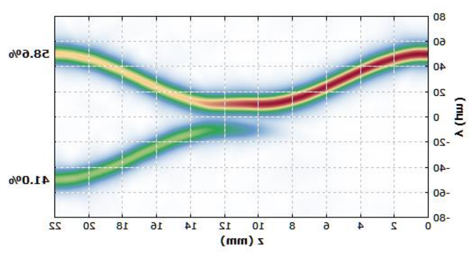
– It has no memory

McCulloch, W., Pitts, W., *Bulletin of Math. Biophys.* **5**:115-133 (1943).

The optical neuron, aka the optical perceptron



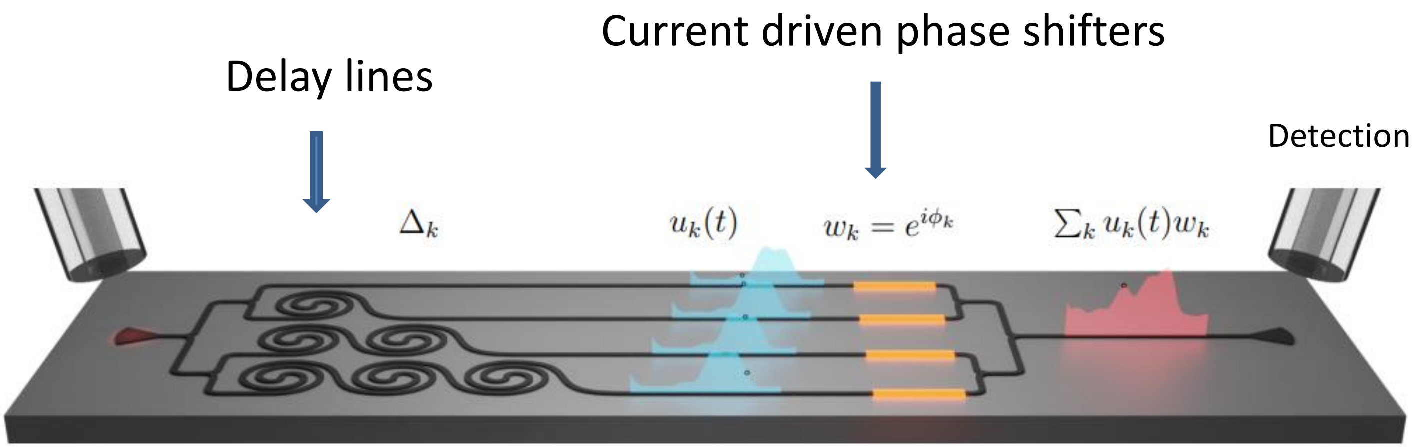
Optical coupler



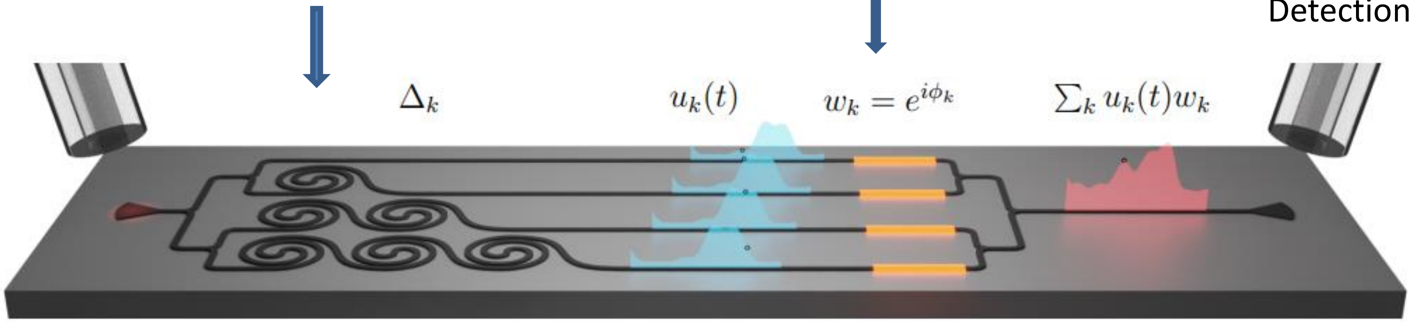
Photodetector

We sum fields, i.e. complex quantities

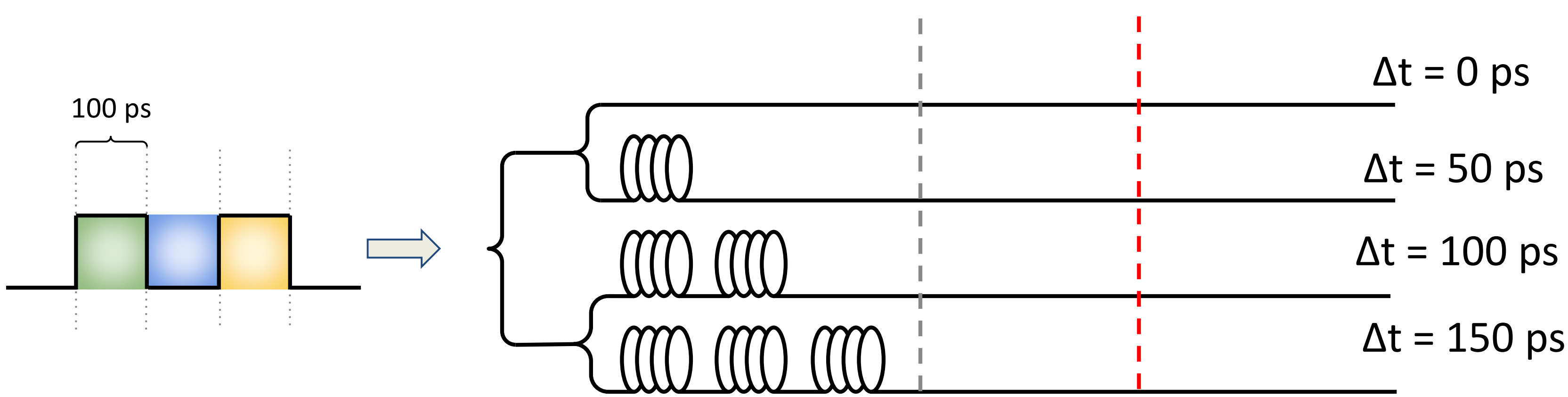
Delayed complex perceptron



Delayed complex perceptron



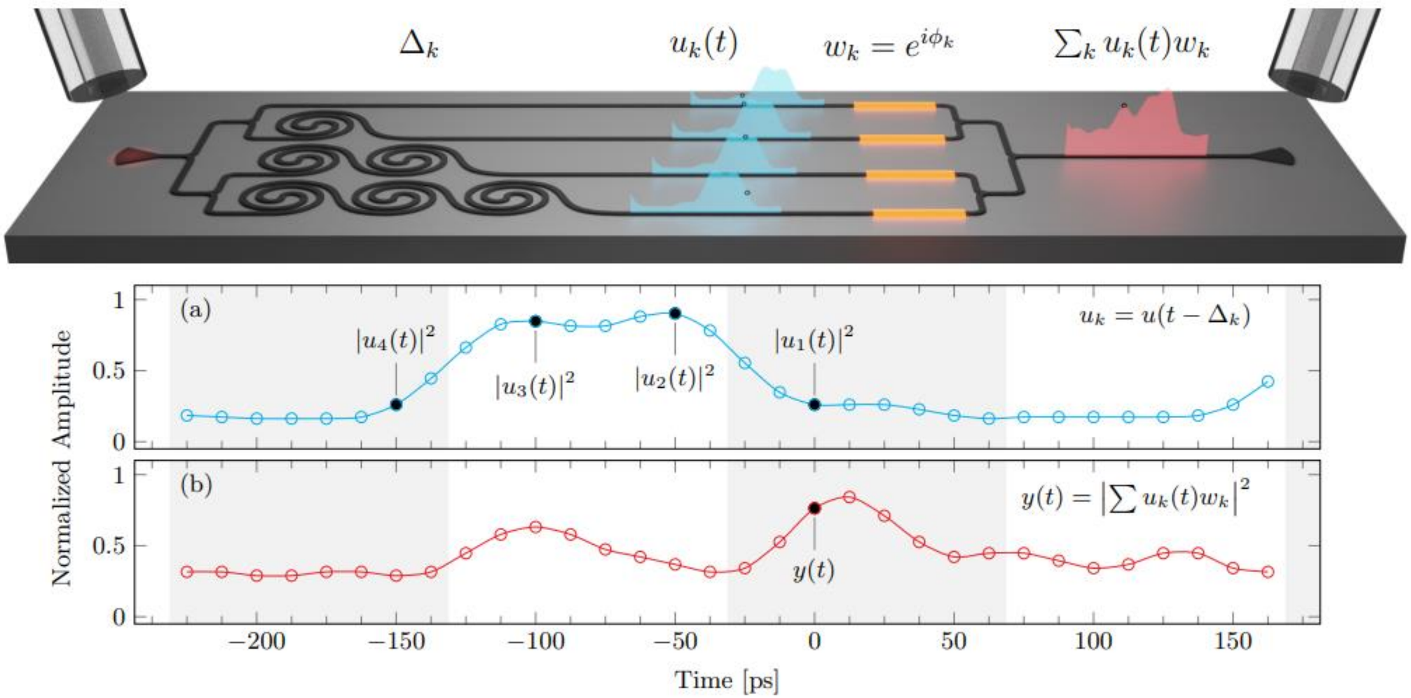
The role of the delay lines



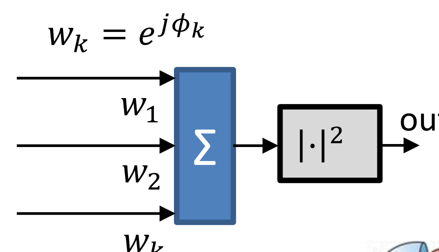
Delayed complex perceptron

Current driven phase shifters

Detection

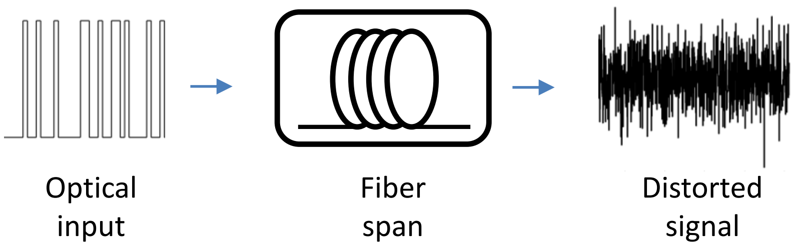


Δ_k=50 ps




2.5 mm
5.2 mm
1.4 mm
0.3 mm

Propagation-related distortions



Chromatic dispersion: frequency dependence of the refractive index $n(\omega)$

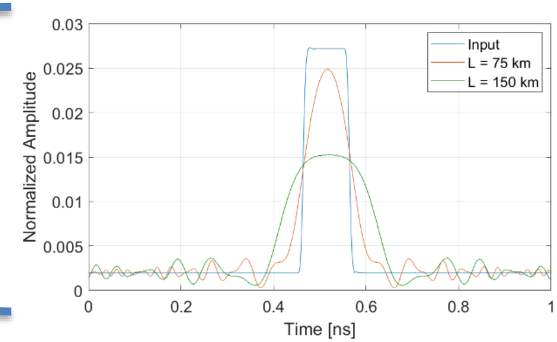
$n(\omega)$ induces $n_g(\omega)$ (group index)

$$n_g(\omega) = \frac{c}{v_g(\omega)}$$

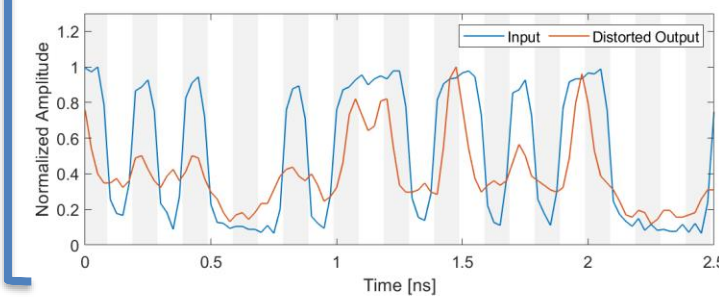
Pulse broadening:

$$\Delta T = \frac{dT}{d\omega}\Delta\omega = \frac{d}{d\omega}\left(\frac{L}{v_g}\right)\Delta\omega = L\beta_2\Delta\omega$$

Effect on single bit



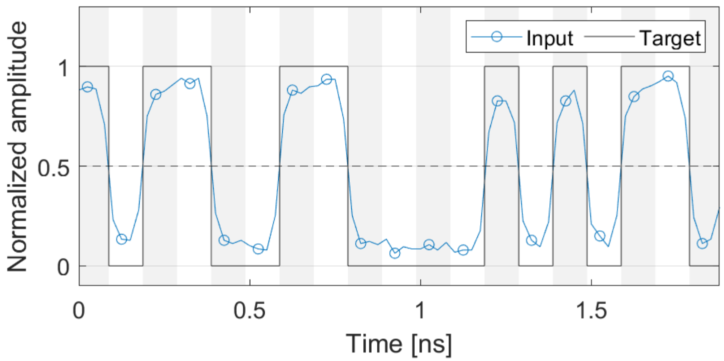
Effect on a sequence of bits



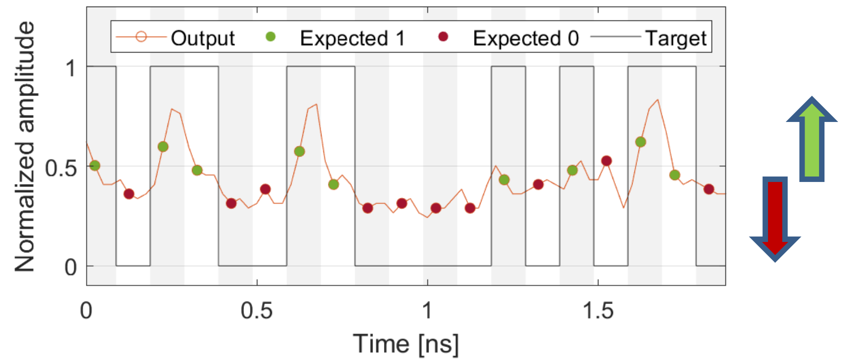
Intersymbol interference

Data processing

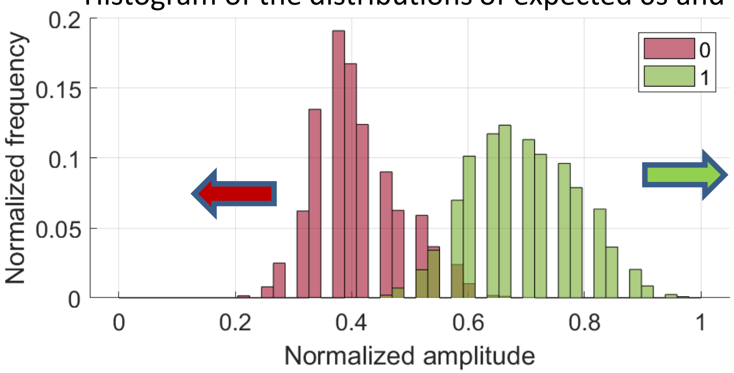
1) Signal acquisition and target construction



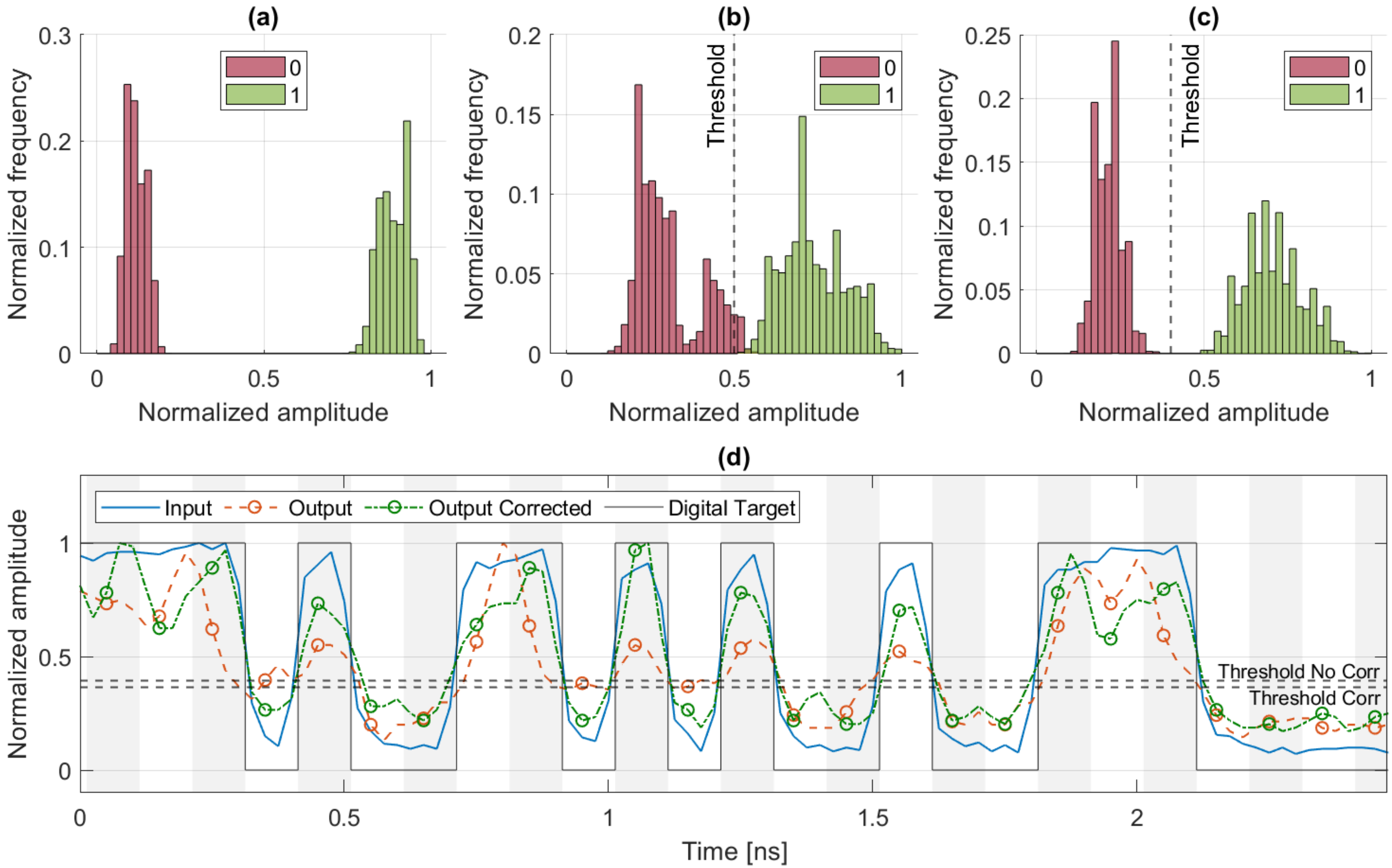
2) Set expected values for each output bit



3) Histogram of the distributions of expected 0s and 1s



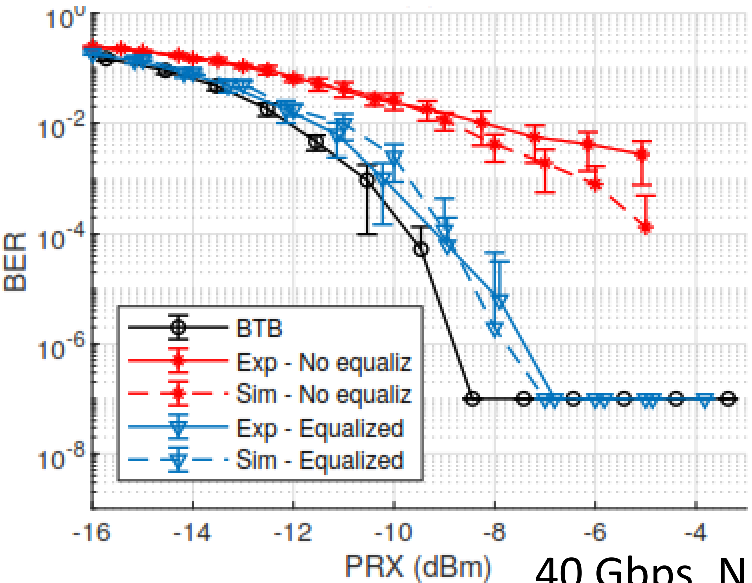
Results



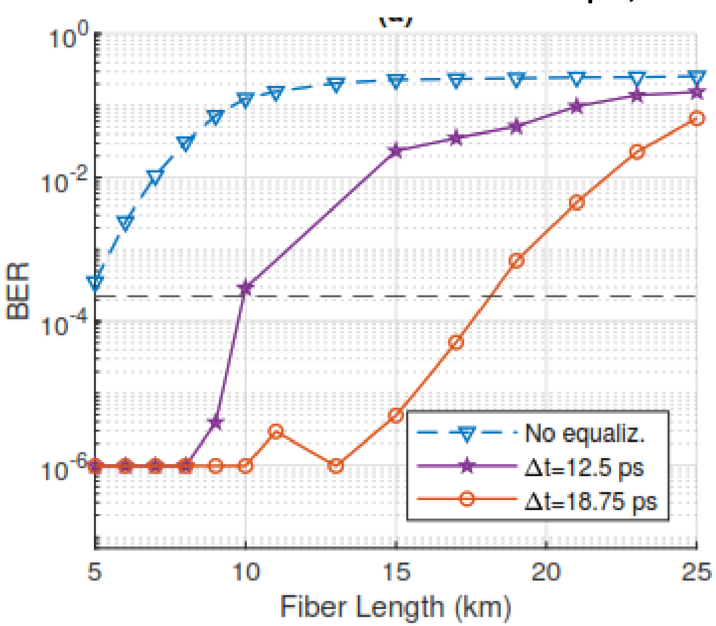
(a)
(b)
(c)
(d)
Normalized frequency
Normalized amplitude
Threshold
0
1
Normalized amplitude
Time [ns]
Input
Output
Output Corrected
Digital Target
Threshold No Corr
Threshold Corr

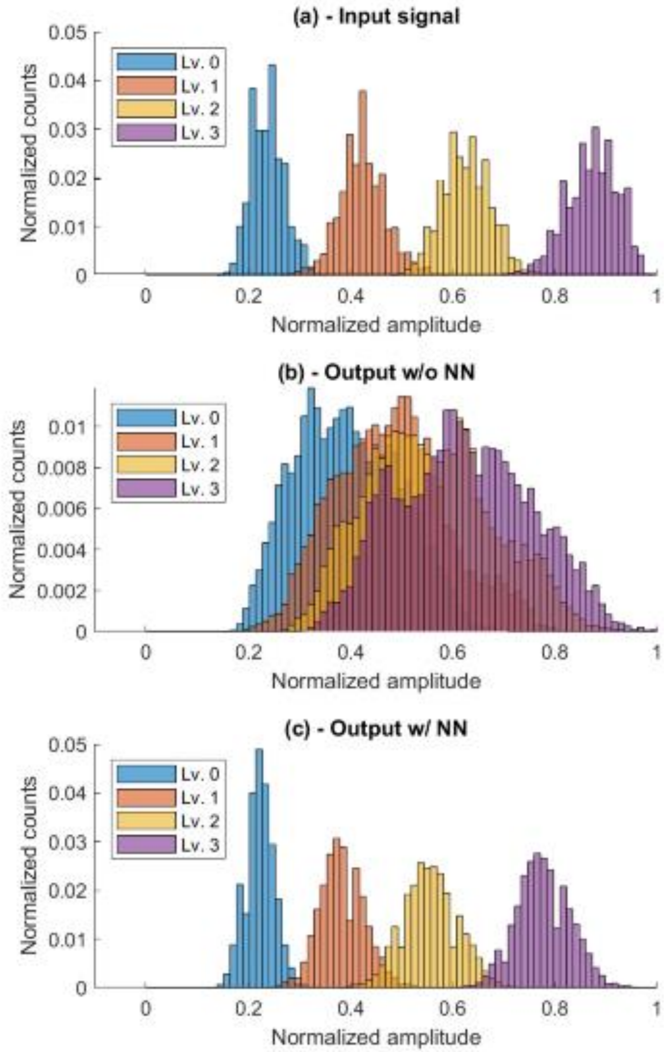
Trained perceptron

10 Gbps, 100 km NRZ



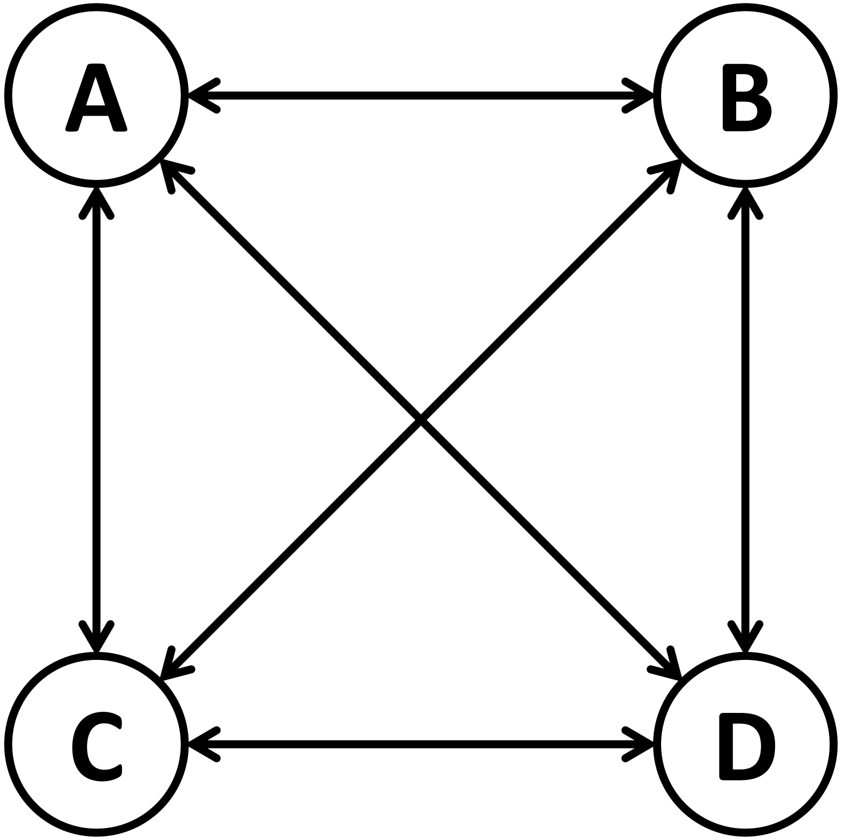
40 Gbps, NRZ





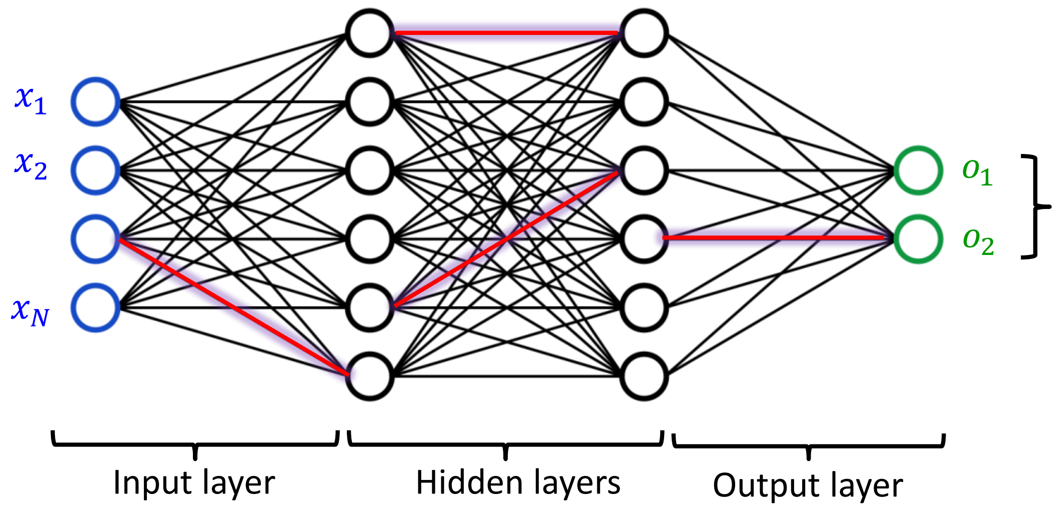
40 Gbps, PAM-4

With perceptrons we can make a network



Feed Forward Network

Input samples
$\boldsymbol{x}$



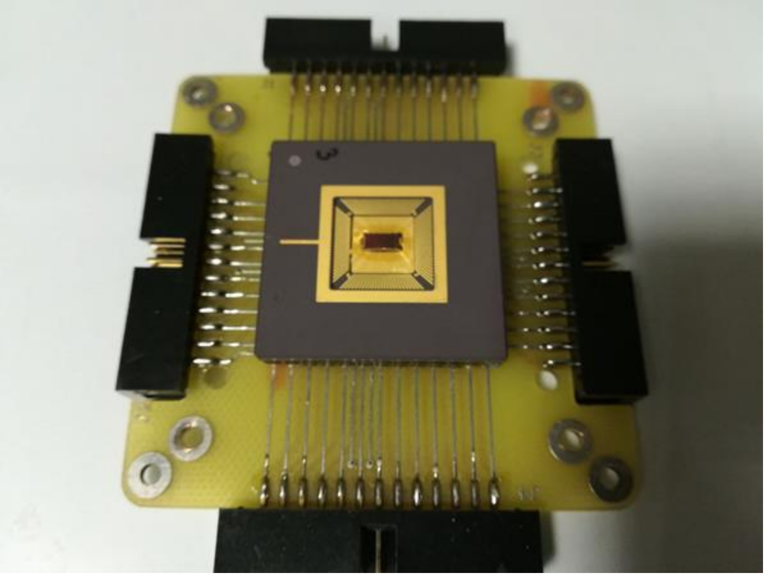
Outputs $\boldsymbol{o} = \boldsymbol{f}_{NL}(\boldsymbol{w}, \boldsymbol{x})$

Target outputs

Trainable synapses $\Longrightarrow$ $C(\boldsymbol{w}) = \sum_k \left\| \boldsymbol{o}\left(\boldsymbol{w}, \boldsymbol{x}^{(k)}\right) - \tilde{\boldsymbol{o}}_k \right\|^2$

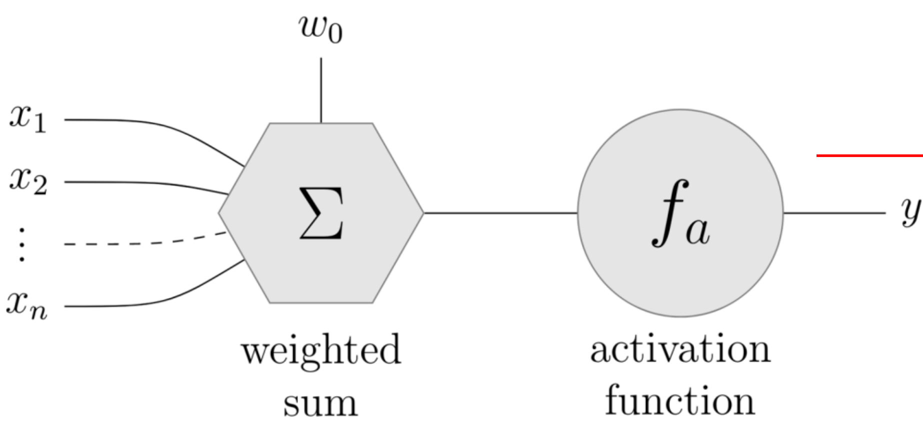
$\text{Min}_{\boldsymbol{w}}\, C(\boldsymbol{w})$

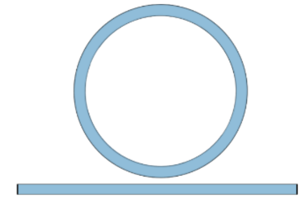
Feed forward network as a universal function approximator



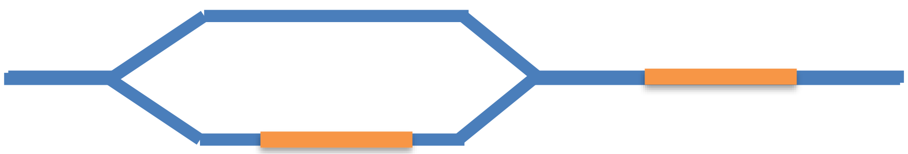
Feed Forward Neural Network

Optical neuron





Nonlinearity by microring resonator

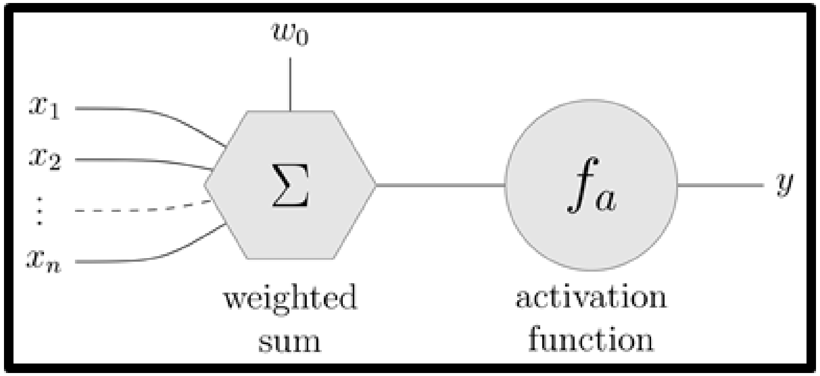


$$\frac{1}{2}A\left(1+e^{i\,\Delta\emptyset}\right)e^{i\Delta\theta}\;e^{-i\omega t}$$

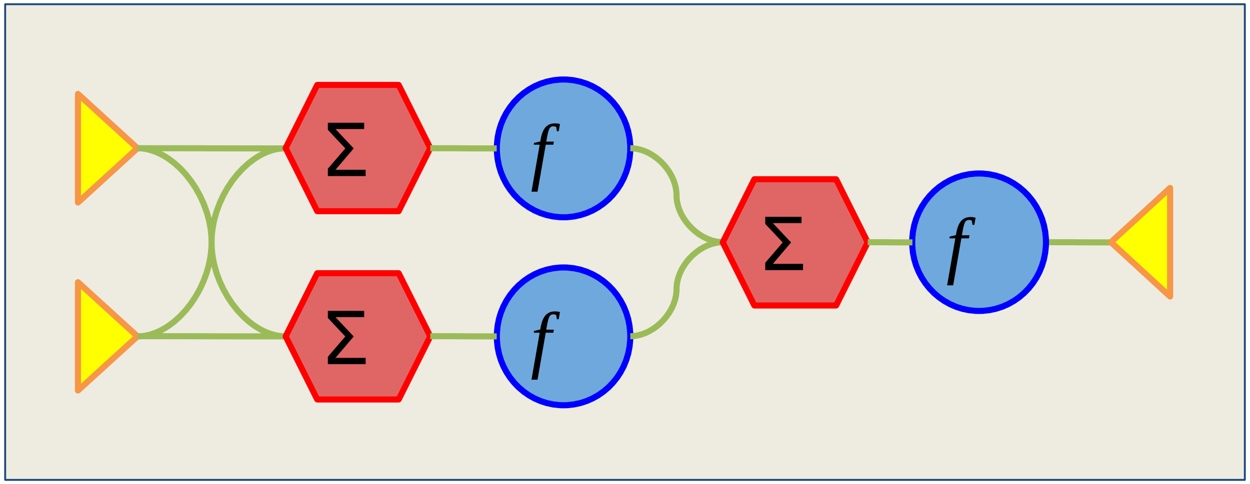
MZI Phase shifter

$$\Delta\emptyset = L\frac{2\pi}{\lambda}\frac{dn}{dT}dT \qquad \Delta\theta = L\frac{2\pi}{\lambda}\frac{dn}{dT}dT$$

Feed Forward Neural Network



Simple deep learning network

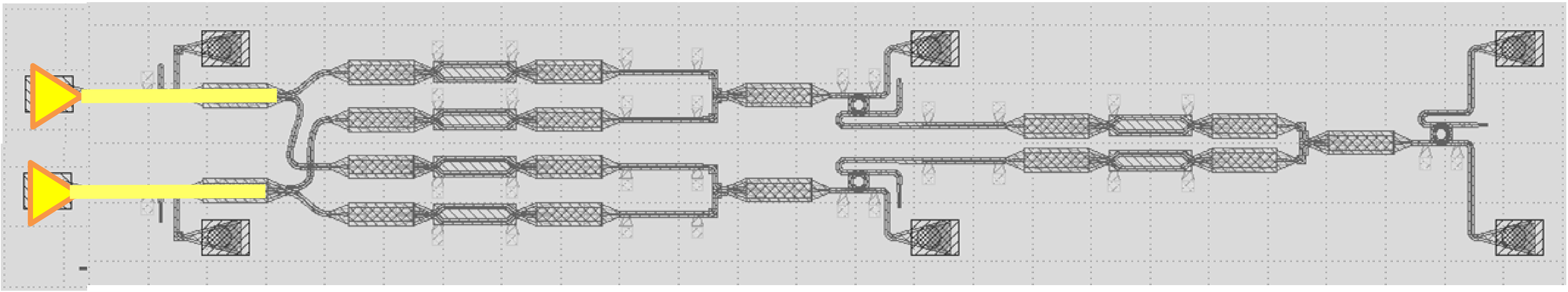


2 input neurons

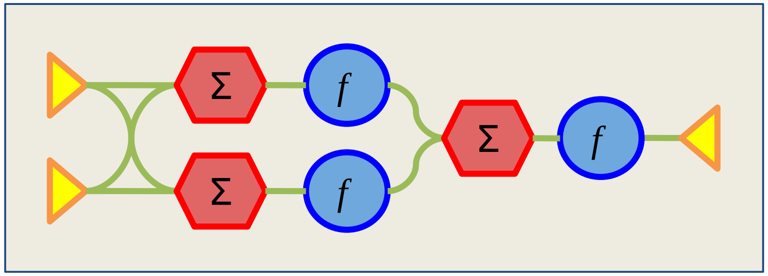
2 neurons in the hidden layer

1 output neuron

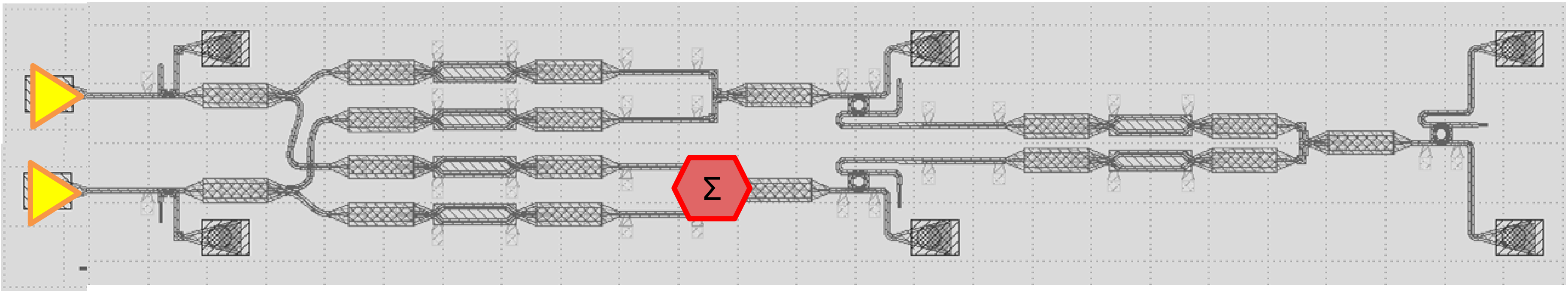
Feed Forward Neural Network



Input layer

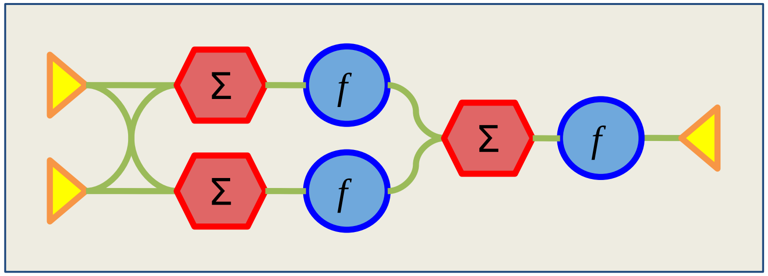


Feed Forward Neural Network

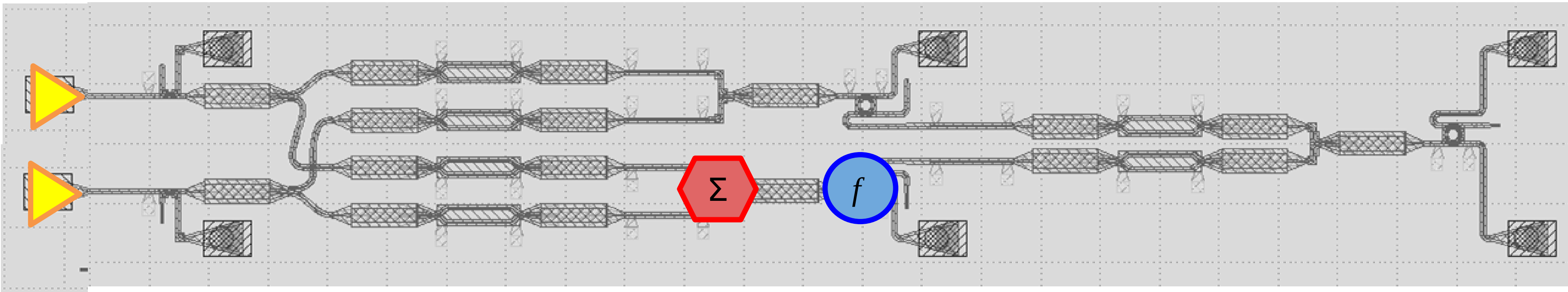


Input layer

Hidden layer

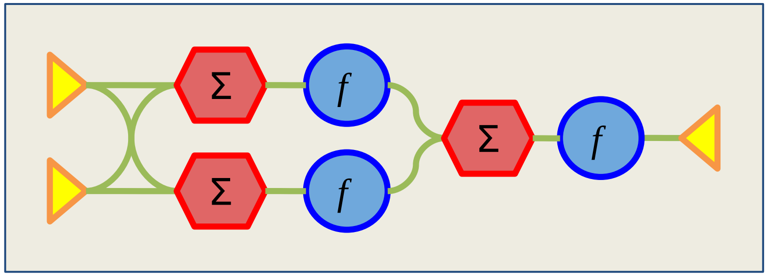


Feed Forward Neural Network

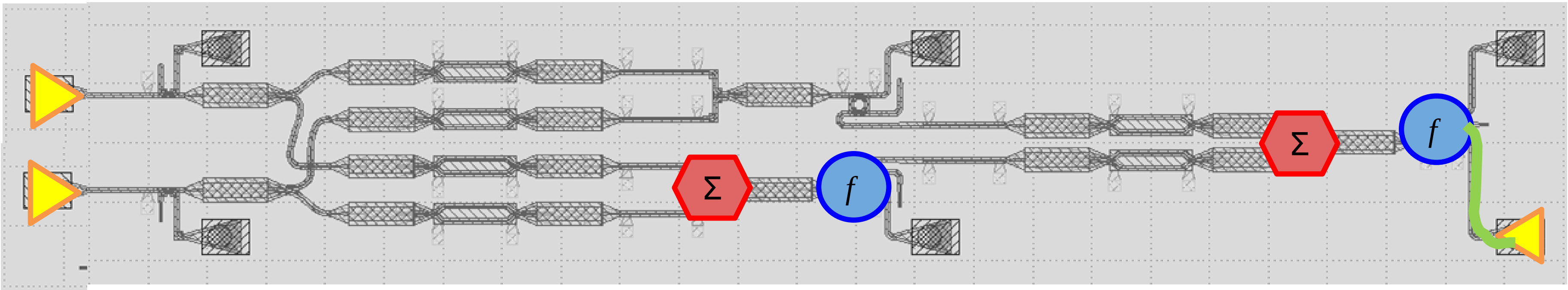


Input layer

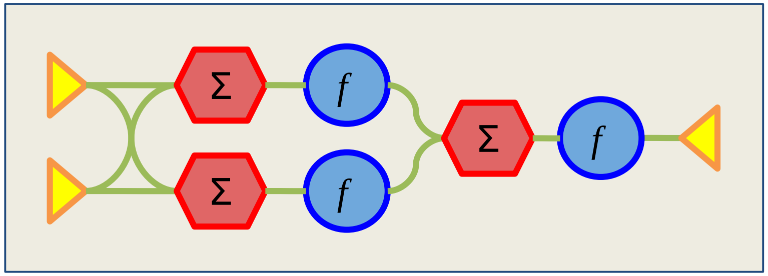
Hidden layer



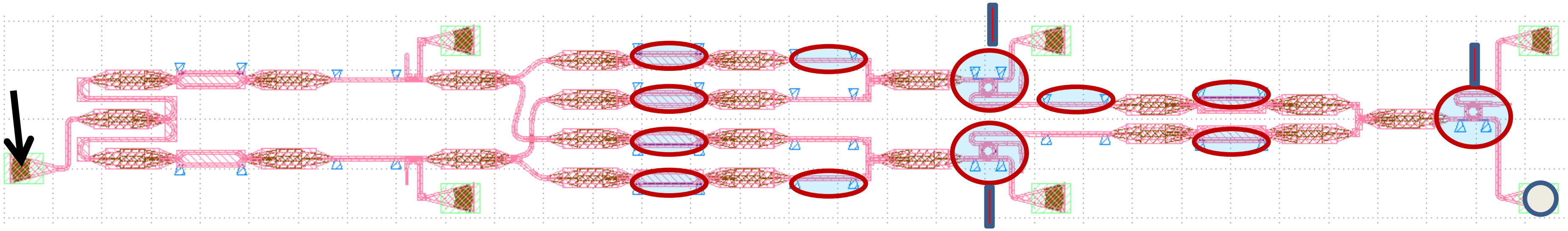
Feed Forward Neural Network

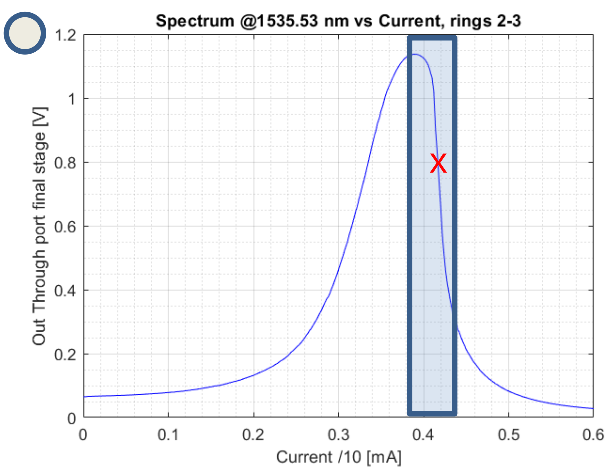


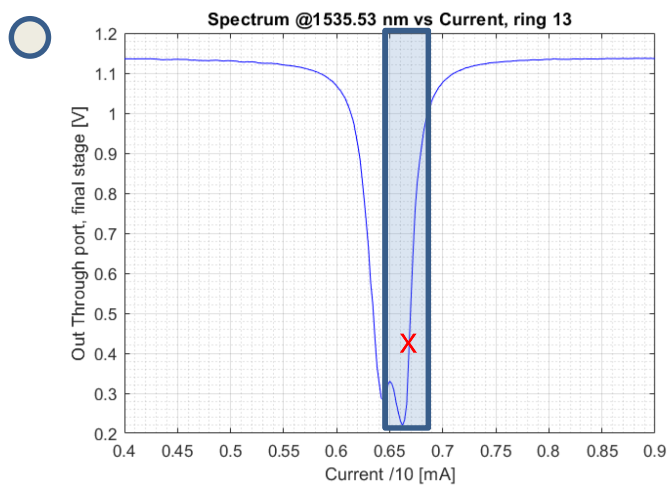
Input layer | Hidden layer | Output layer



A feed-forward neural network







Free parameters for the **training process:**

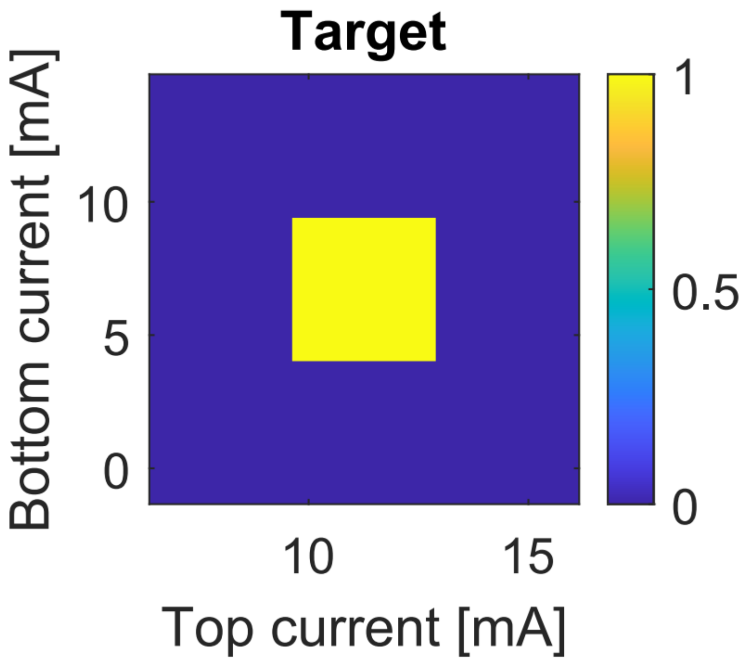
3 rings

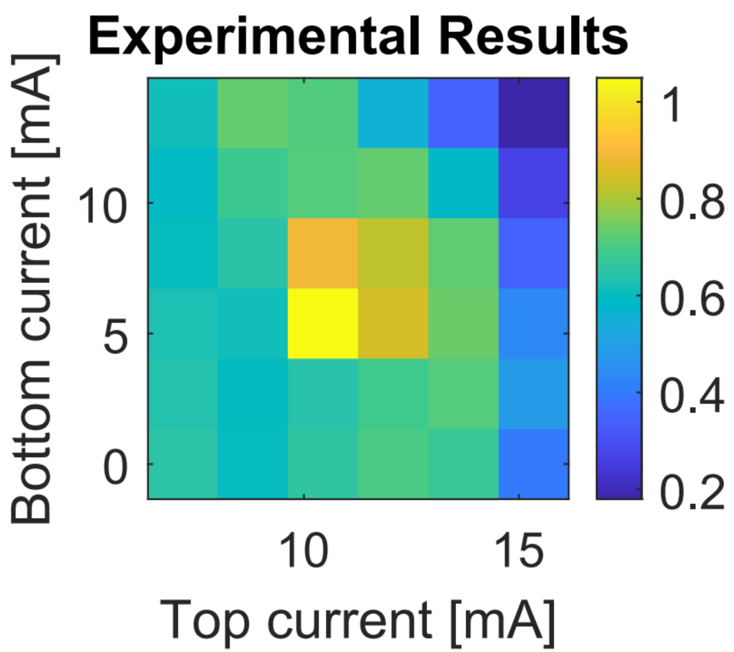
9 heater **for the phases**

→ **12**

A feed-forward neural network

Example a 6x6 pixel square shape



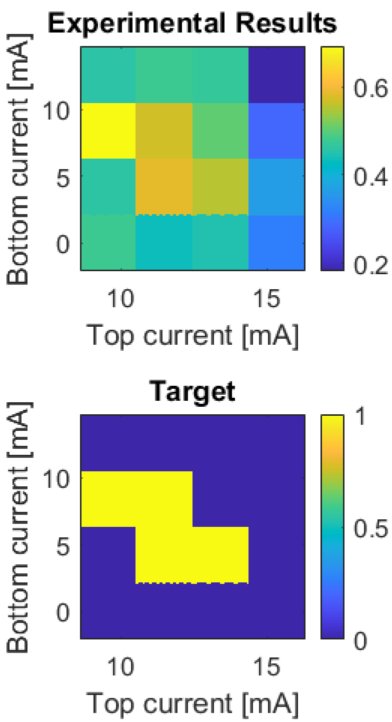


P(5) are our **base** for the **square shape**

Execution time = 25 min

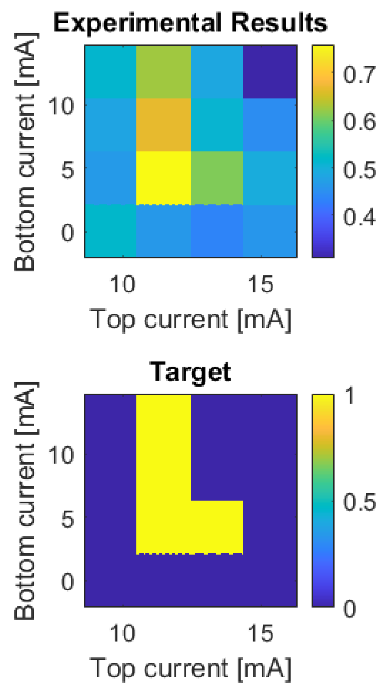
A feed-forward neural network: other tasks

“Z” shape



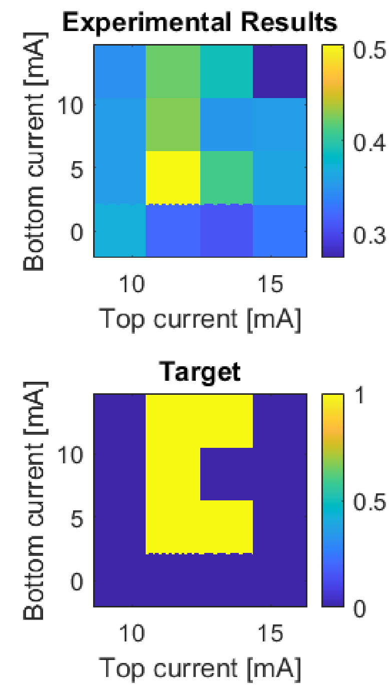
Mean(Δ) = 0.034±0.02

“L” shape



Mean(Δ) = 0.045±0.01

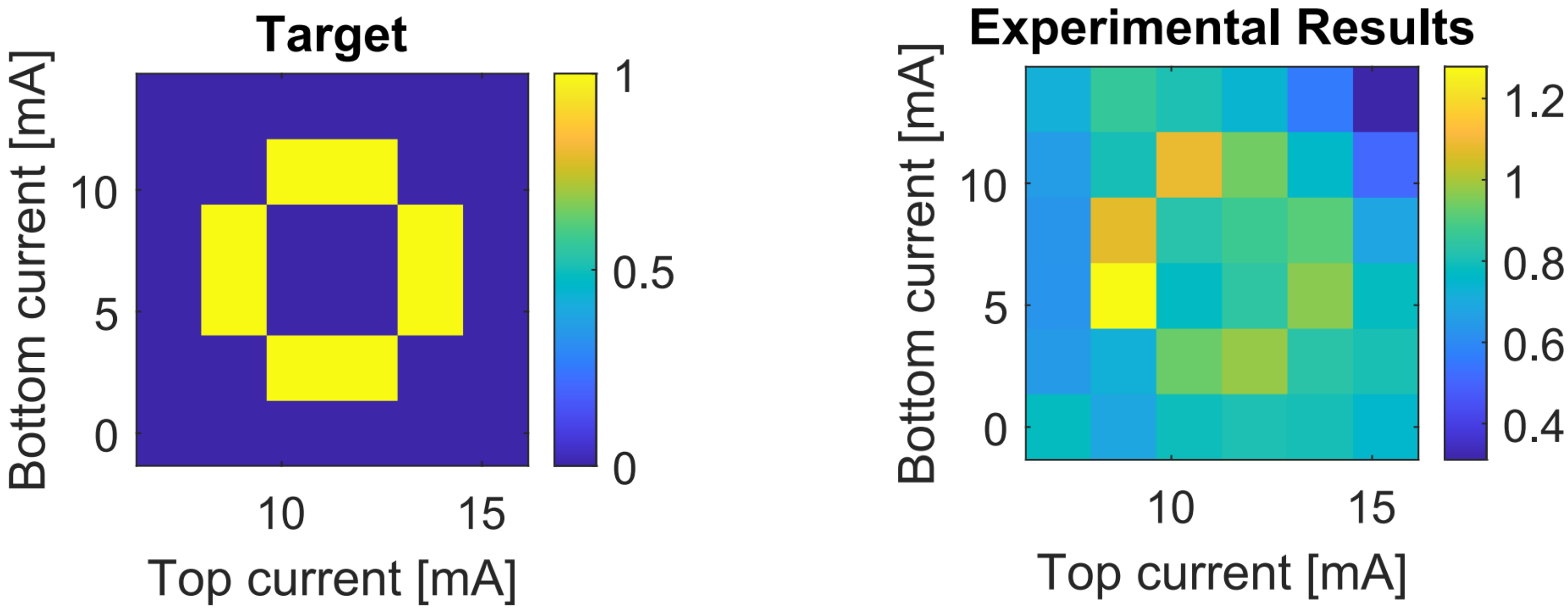
“C” shape



Mean(Δ) = 0.021±0.02

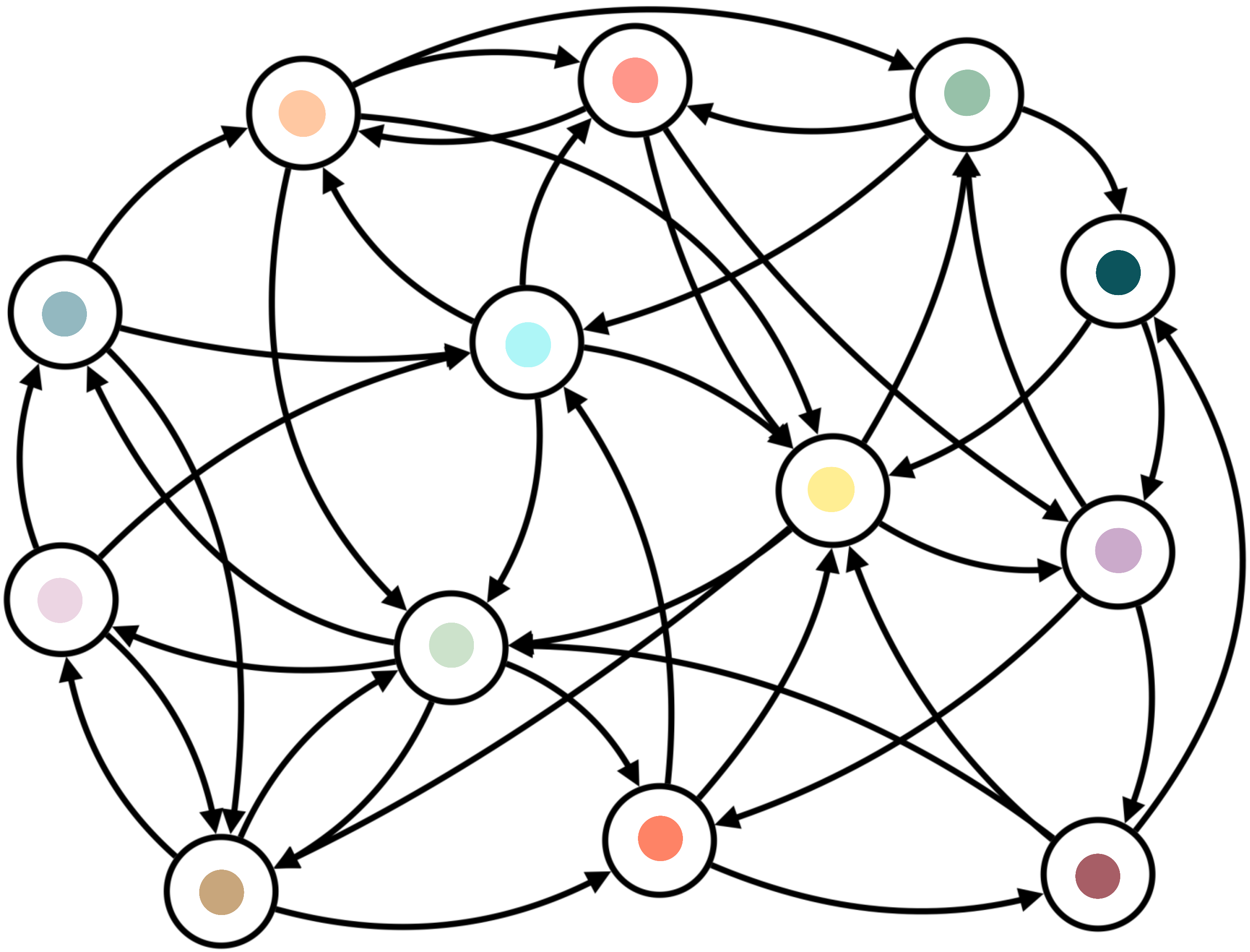
A feed-forward neural network: other tasks

6 x 6 Hole shape



Execution time = 30 min

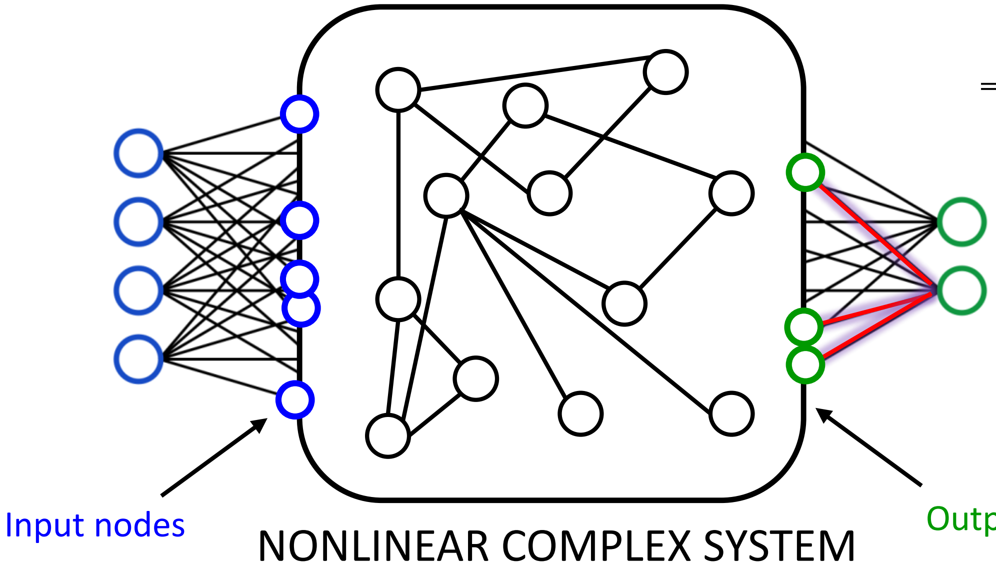
Recurrent Neural Network



– Harder to train

✓ It has memory!!!

Reservoir computing



TRAINING THE OUTPUT LAYER

$$o_k = \sum_{j=1}^{N} w_{kj} y_j + w_{k0}$$

$$C(\boldsymbol{w}) = \sum_k \left\| \boldsymbol{o}\left(\boldsymbol{w}, \boldsymbol{x}^{(k)}\right) - \tilde{\boldsymbol{o}}_k \right\|^2 + \lambda \|\boldsymbol{w}\|^2$$

$\mathrm{Min}_{\boldsymbol{w}} C(\boldsymbol{w})$

Linear combination + Ridge regression

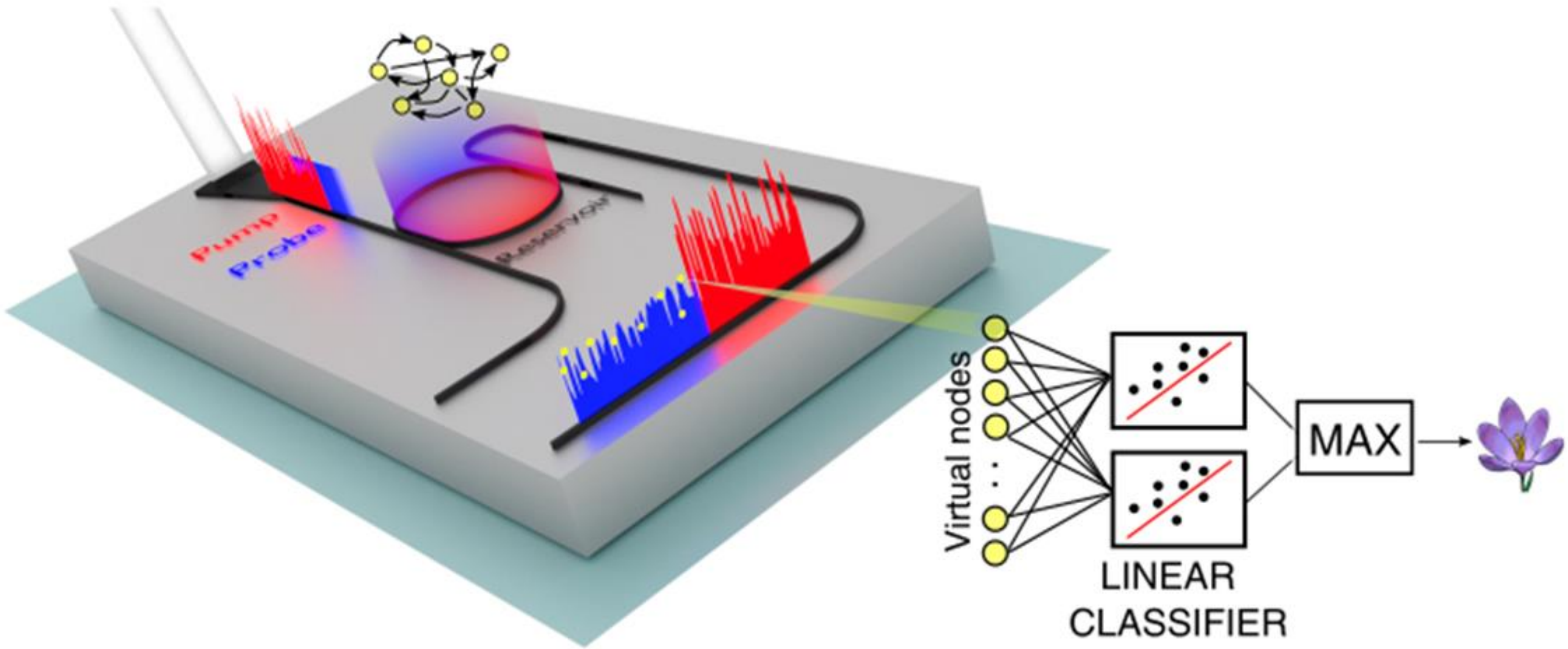
Has sparse connectivity

Has fading memory

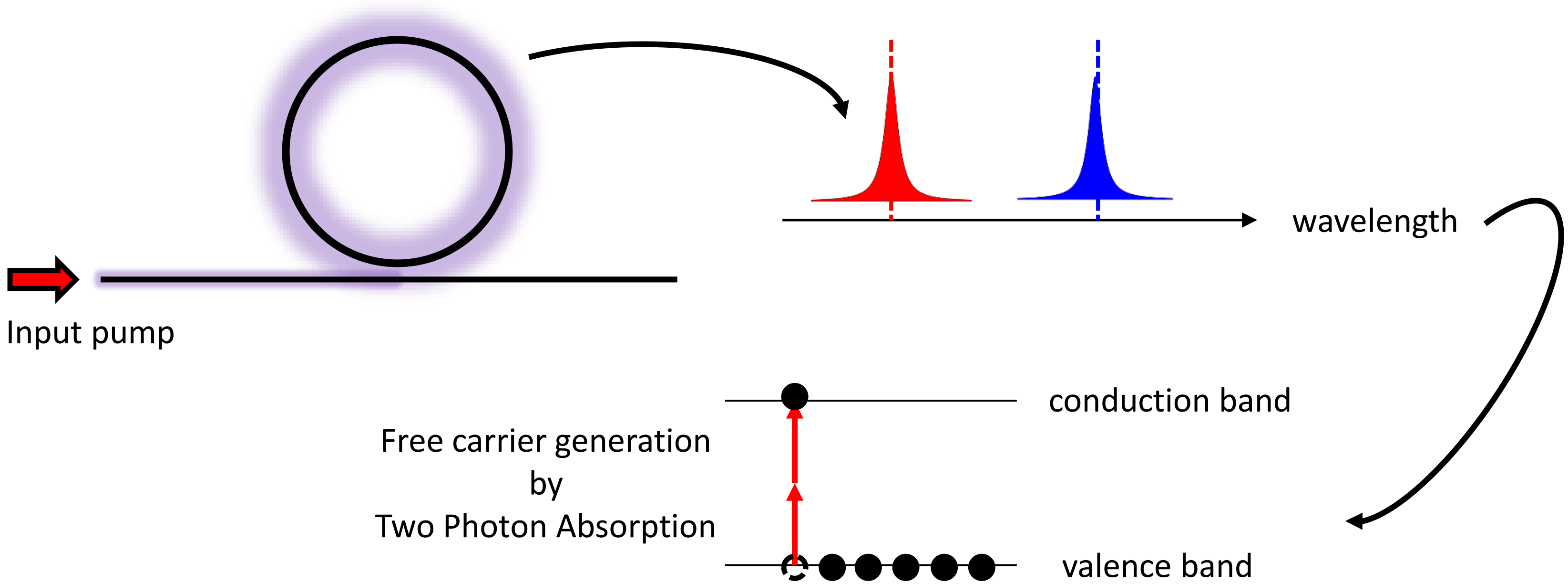
Is highly sensitive to intial conditions

Is Untrained

Reservoir computing based on a silicon microring and time multiplexing for binary and analog operations

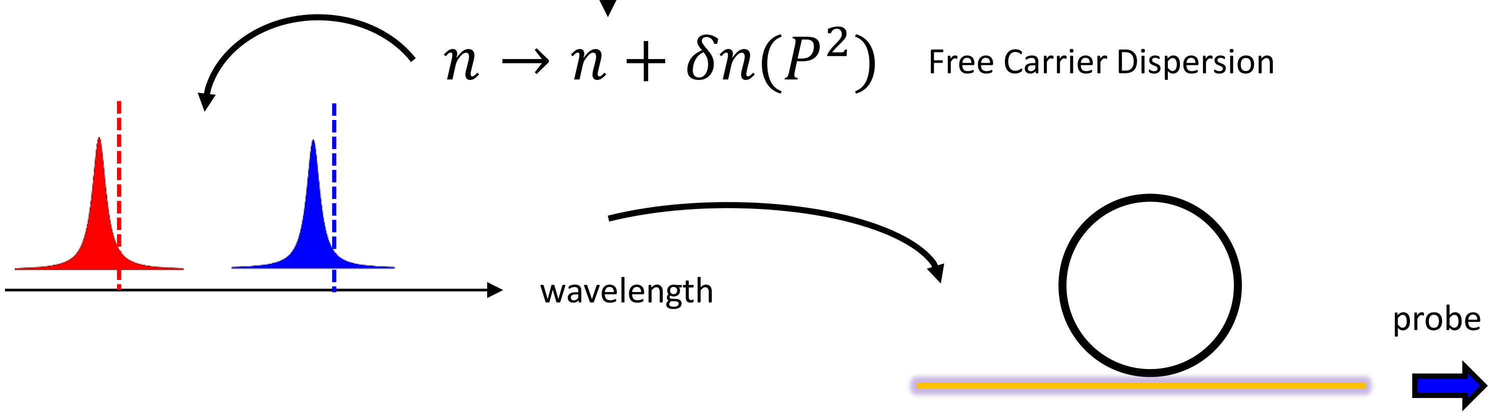


Pump and probe technique



$$n \rightarrow n + \delta n(P^2)$$

Free Carrier Dispersion



Inter-node coupling and fading memory

Fading memory on a time scale of the FC lifetime

Quadratic in the pump power
TPA provides nonlinearity

Probe power at the drop

Output depends on the past

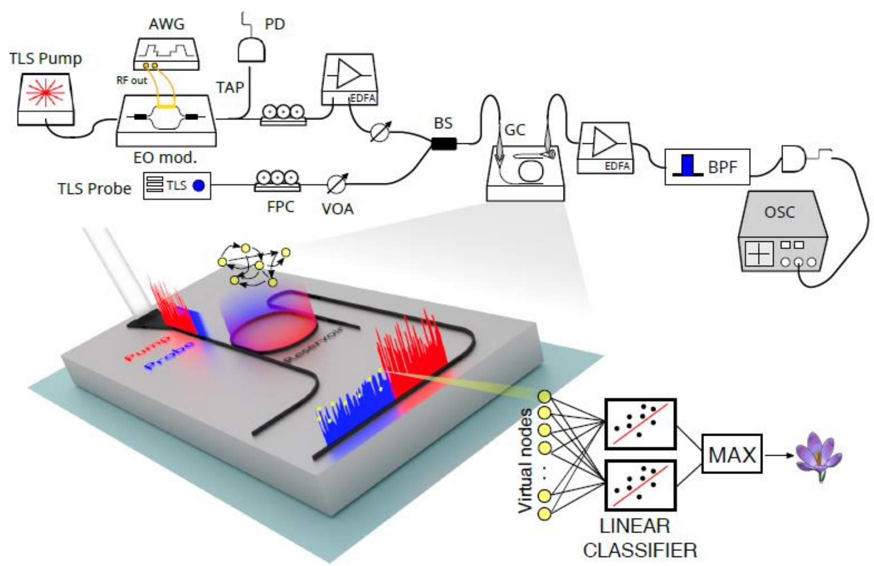
Recursive virtual node relation

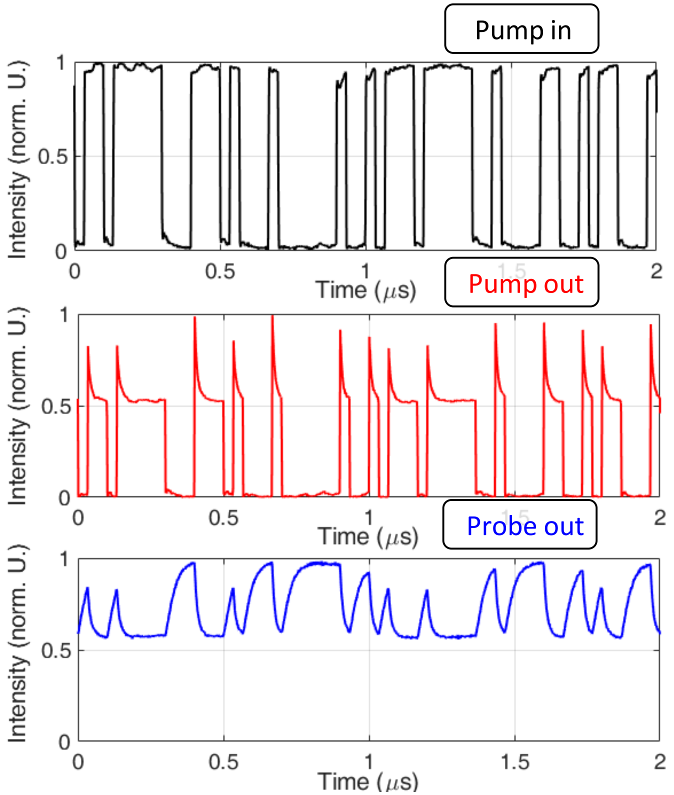
$$u_{pr}(t) = c_0 + c_1 \int_{-\infty}^{t} e^{-\left(\frac{t-\xi}{\tau_{\mathrm{fc}}}\right)} u^2(\xi) d\xi + c_2 \int_{-\infty}^{t} \underbrace{e^{-\left(\frac{t-\xi}{\tau_{\mathrm{fc}}}\right)} u^2(\xi)} u_{pr}(\xi) d\xi,$$

Adjacent nodes couping strength

Non linear coupling between virtual nodes

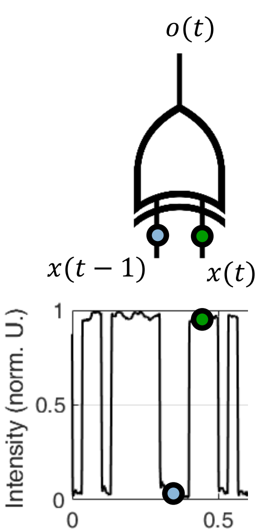
Experiment: digital inputs



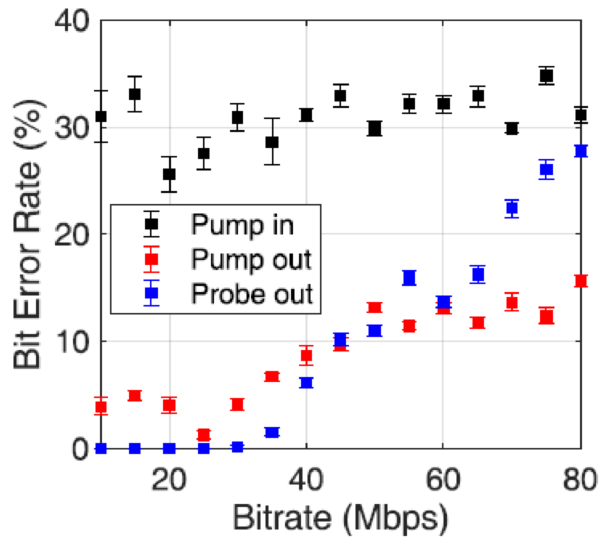


Experiment: 1 bit delayed XOR

TASK

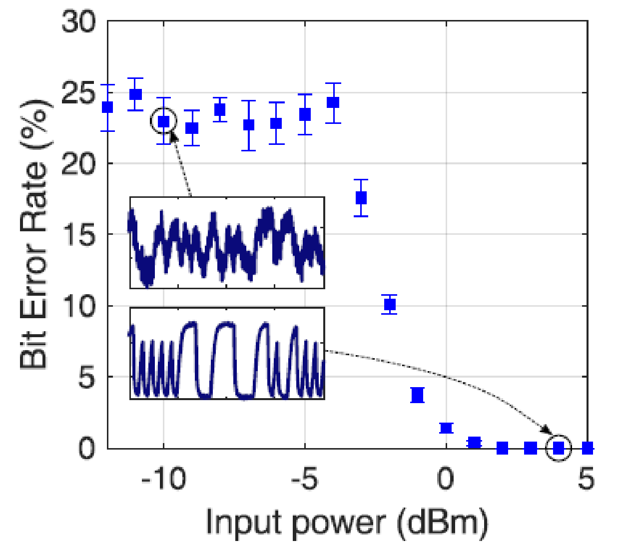


Inputs		Outputs
X	Y	Z
0	0	0
0	1	1
1	0	1
1	1	0



Speed limited by free carrier lifetime

Free carrier lifetime $\sim 45\ ns$
Decay rate: $22\ MHz$



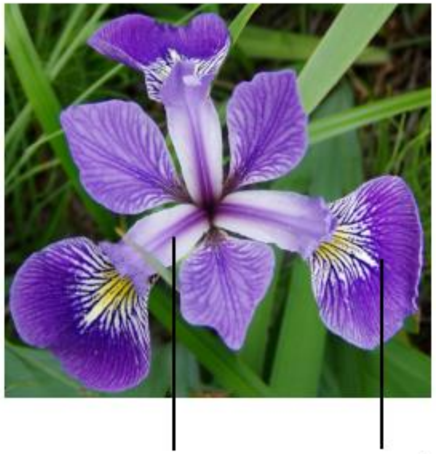
Free carrier dynamics activation @ $\sim 0\ dBm$

Analog input: Iris species recognition

iris setosa

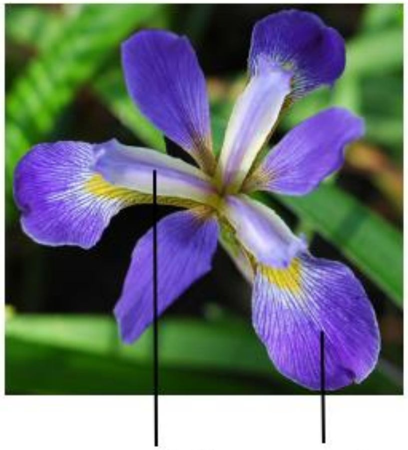
petal sepal

iris versicolor

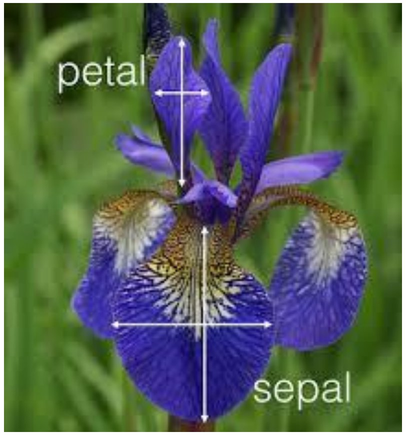


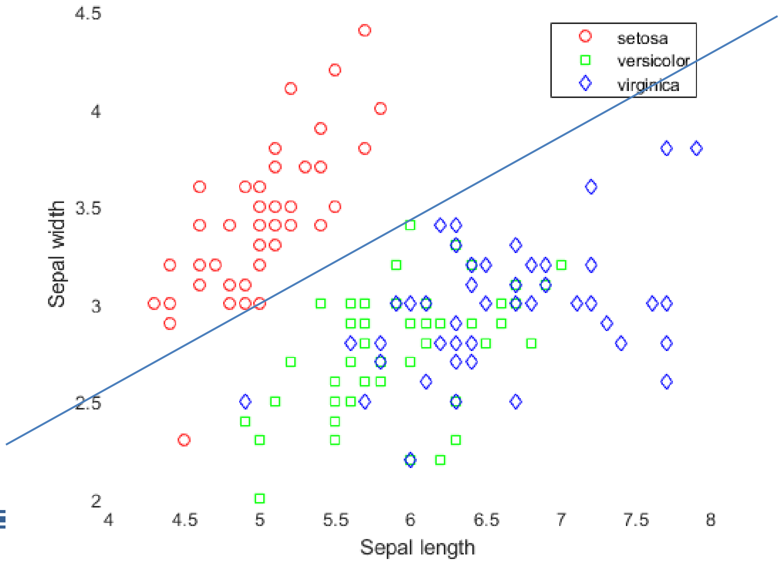
petal sepal

iris virginica



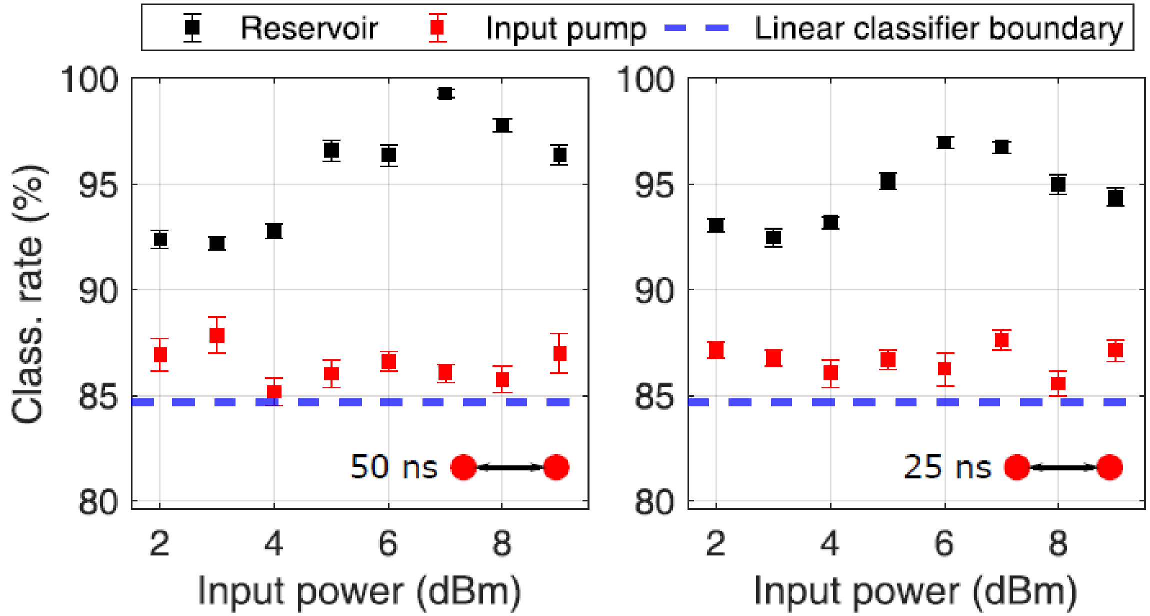
petal sepal

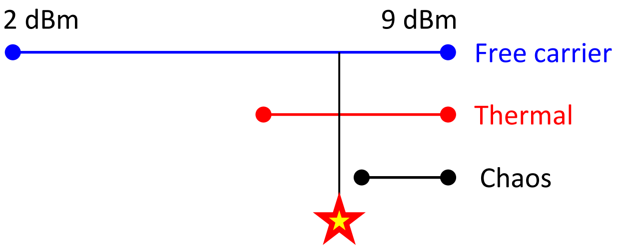




Not linearly separable

Experiment: Iris species recognition



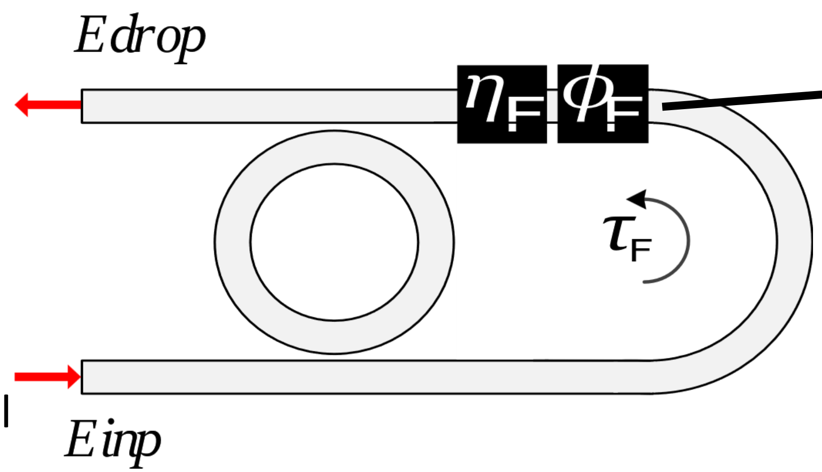


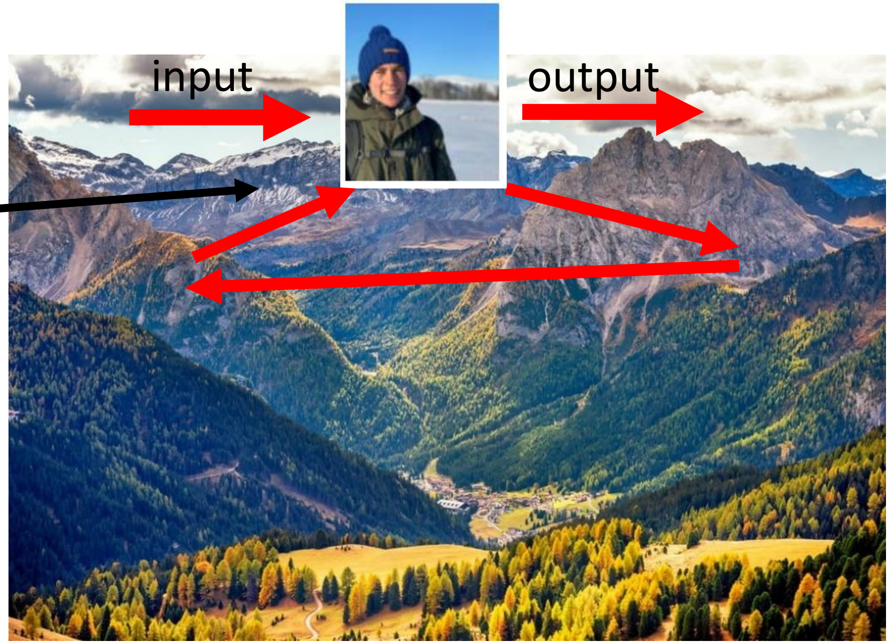
Optimal performance
(maximum input separability)

~ 380000 flower classified per second
99.3 ± 0.2 accuracy

Single node reservoir with longer memory

Silicon microring resonator coupled to an external feedback :

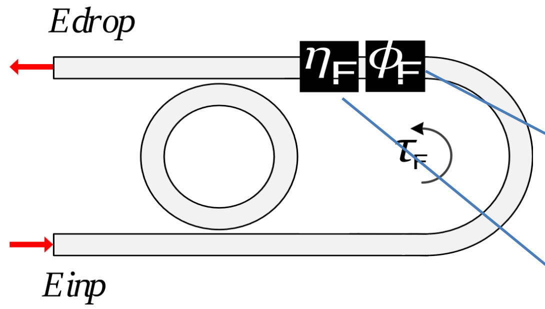




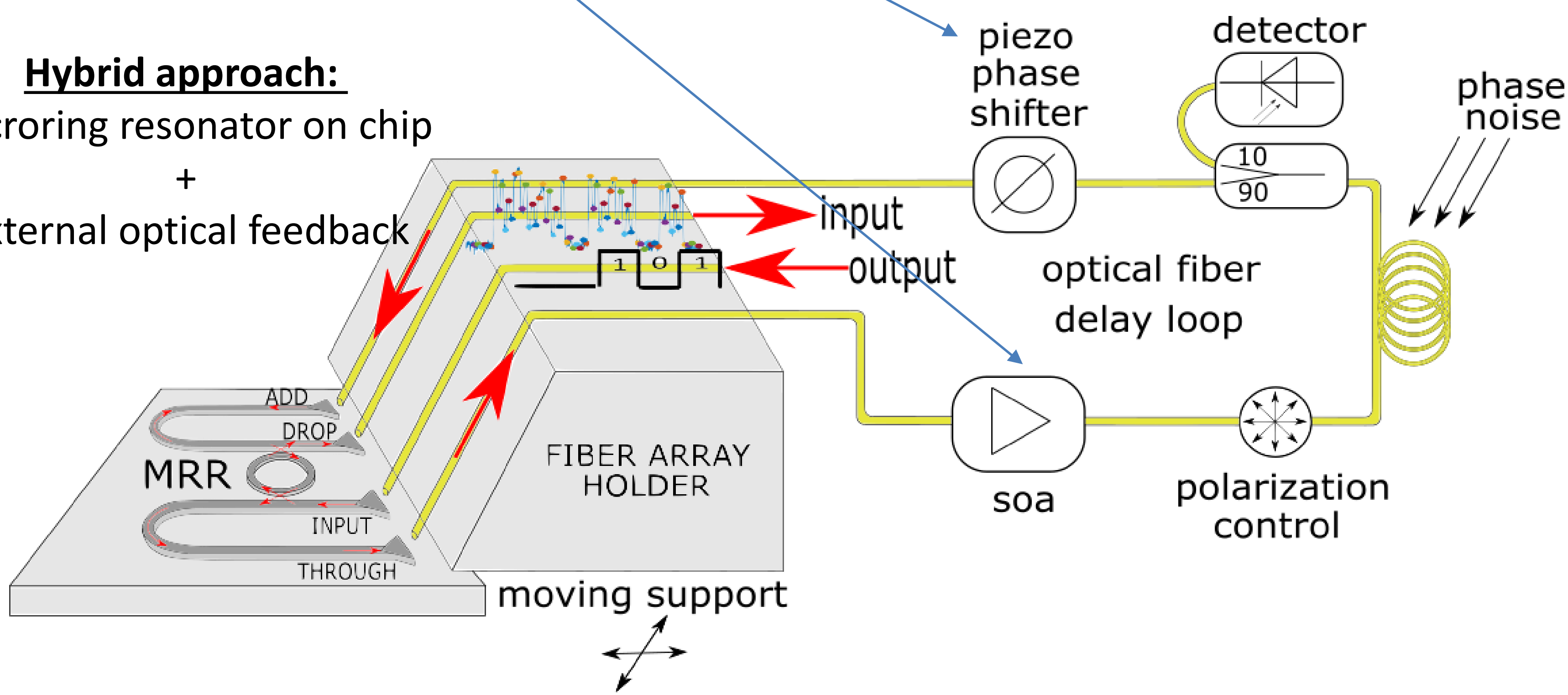
- η_F → echo light strength
- ϕ_F → echo light phase

Echo state network

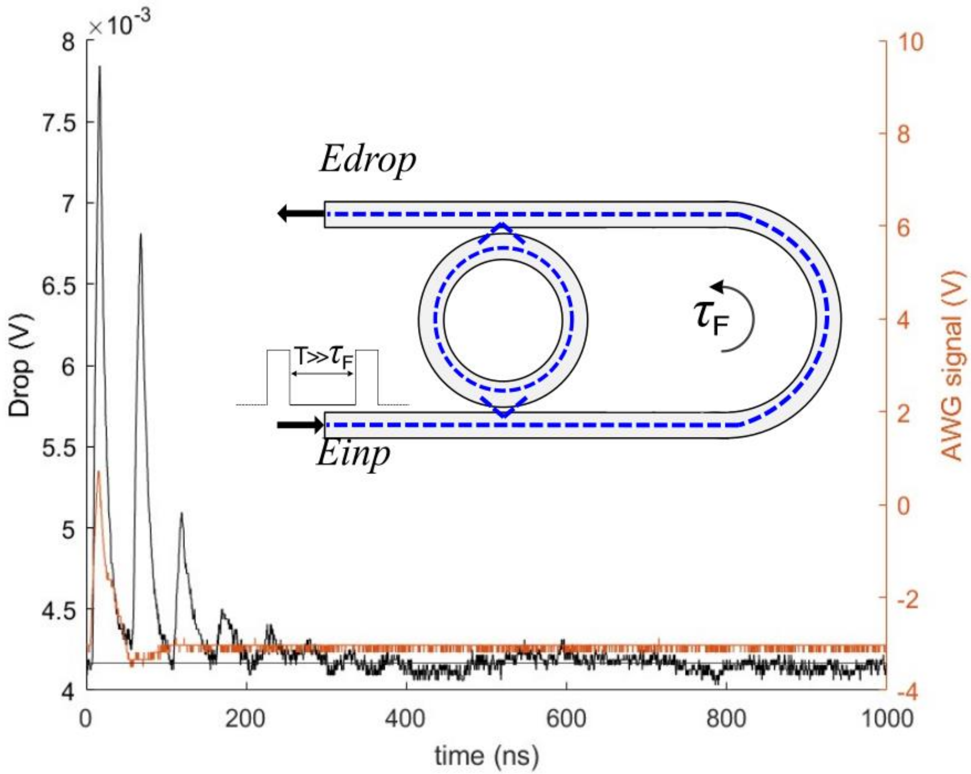
Experimental implementation



Hybrid approach:
microring resonator on chip
+
External optical feedback

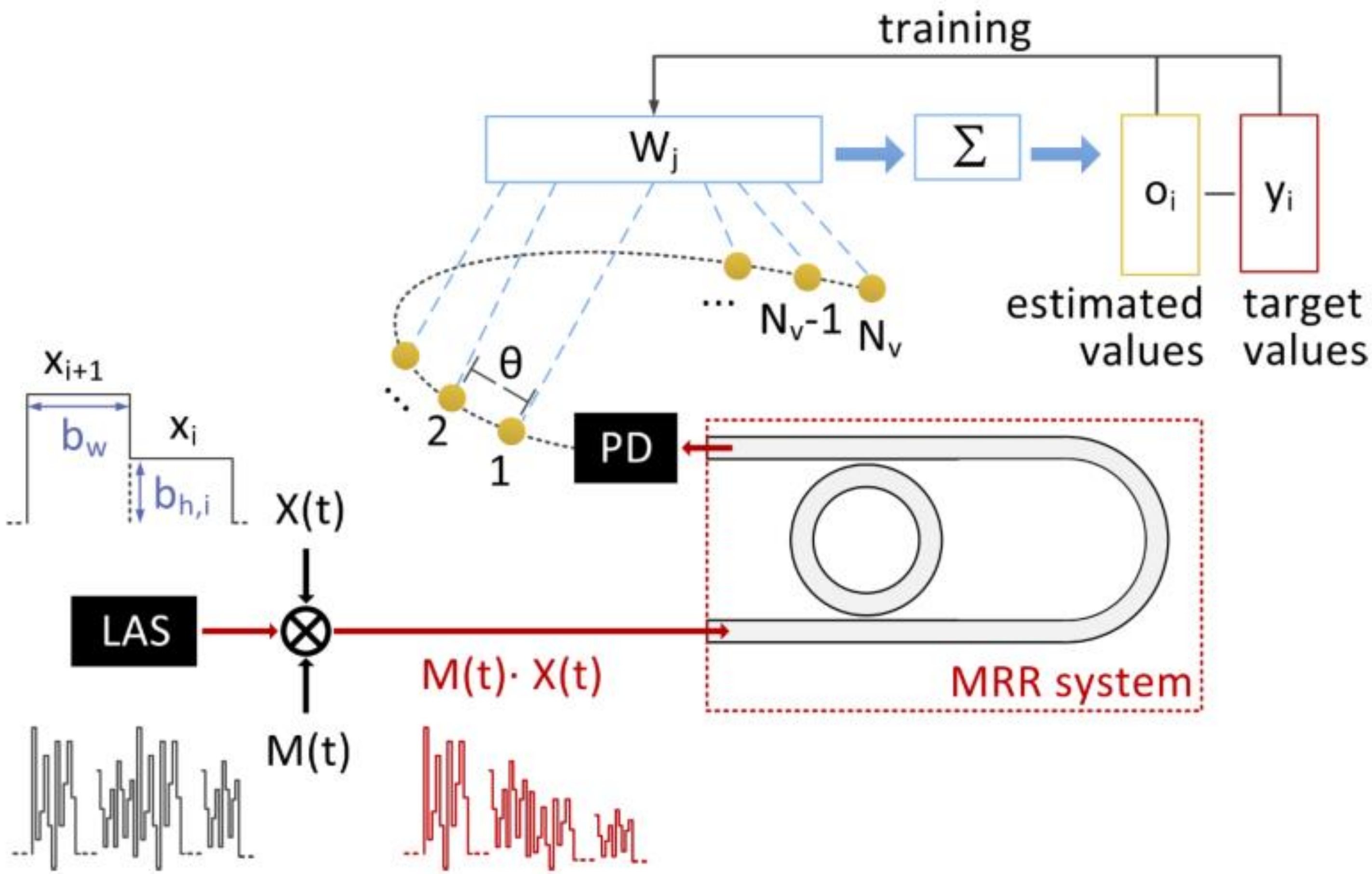


Single node reservoir with longer memory

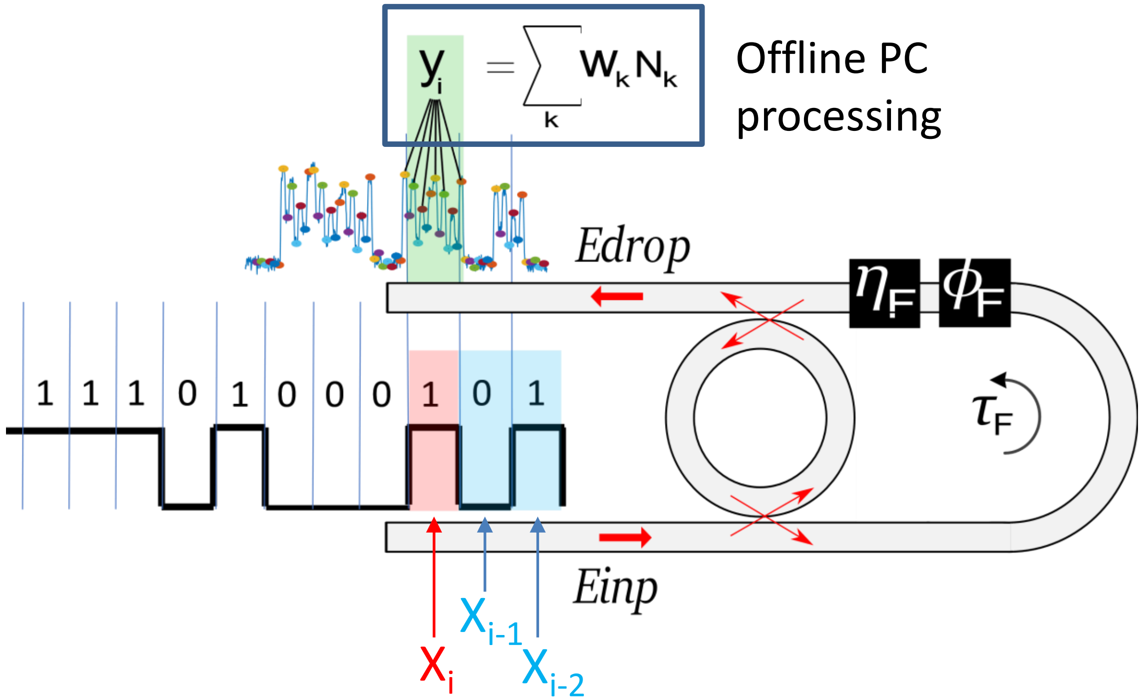


- Consistency
- Separation property
- Approximation property
- Fading memory

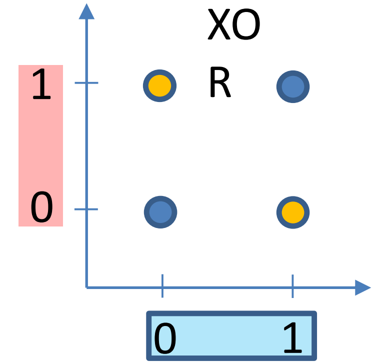
Time delay Reservoir Computing



Digital tasks



Offline PC processing



Not linearly separable !

Input 1	Input 2	TASKS (target)				
ACTUAL BIT (X_i)	DELAYED BIT(X_{i-j})	MC (Y_i)	AND (Y_i)	XOR (Y_i)	OR (Y_i)	NAND (Y_i)
0	0	0	0	0	0	1
0	1	1	0	1	1	1
1	0	0	0	1	1	1
1	1	1	1	0	1	0

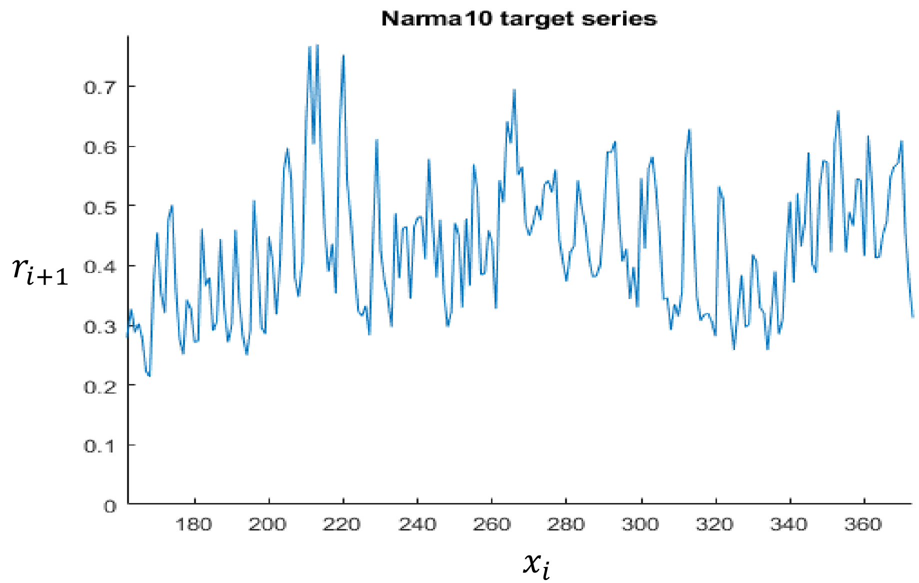
Time series forecasting

Narma 10 benchmark task

x_i: input series, uniformely distributed in [0,0.5]

Target:

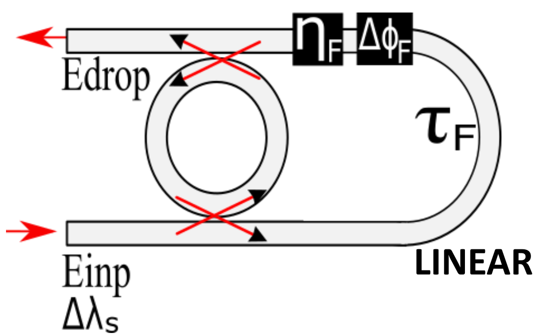
$$r_{i+1} = 0.3r_i + 0.05r_i\left(\sum_{j=0}^{9} y_{i-j}\right) + 1.5x_i x_{i-9} + 0.1$$

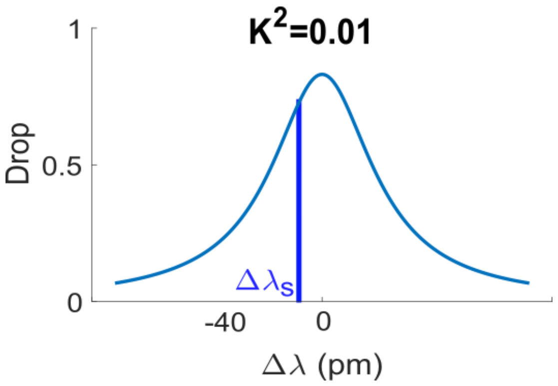


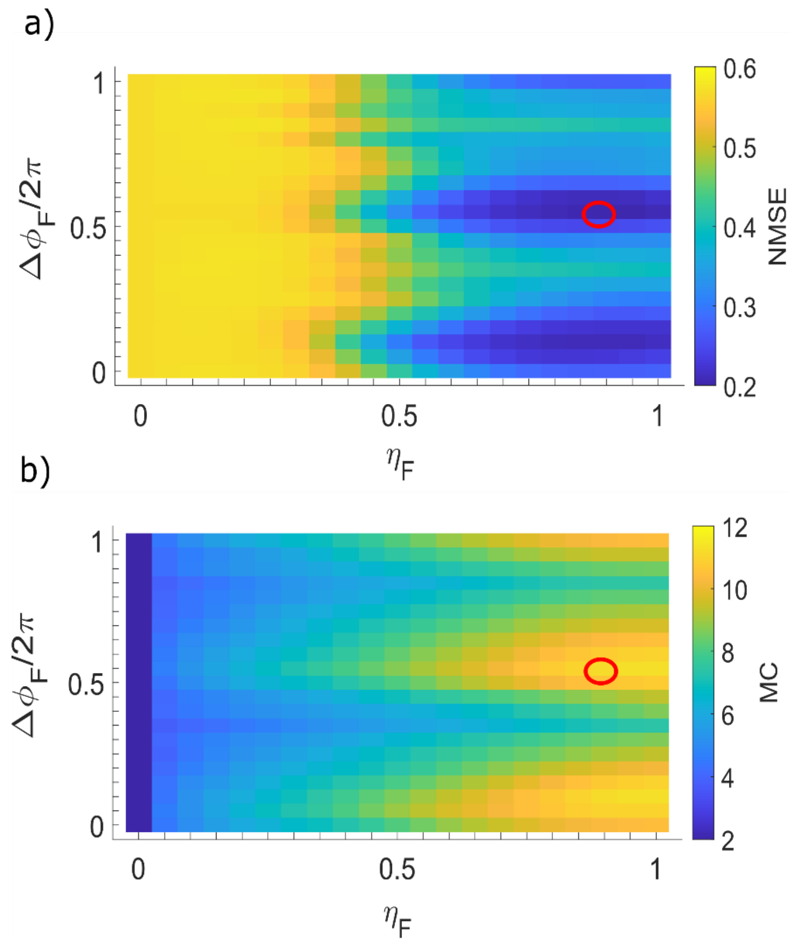
This task needs 10 bit of memory to be solved.

Time series forecasting

Narma 10 benchmark task



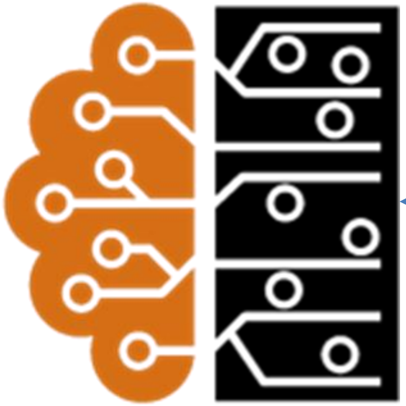




- MRR in linear regime and strong feedback allow the largest linear memory capacity
- Memory exploited: optical (feedback).
- Nonlinearity exploited: photodetection square law.

The vision

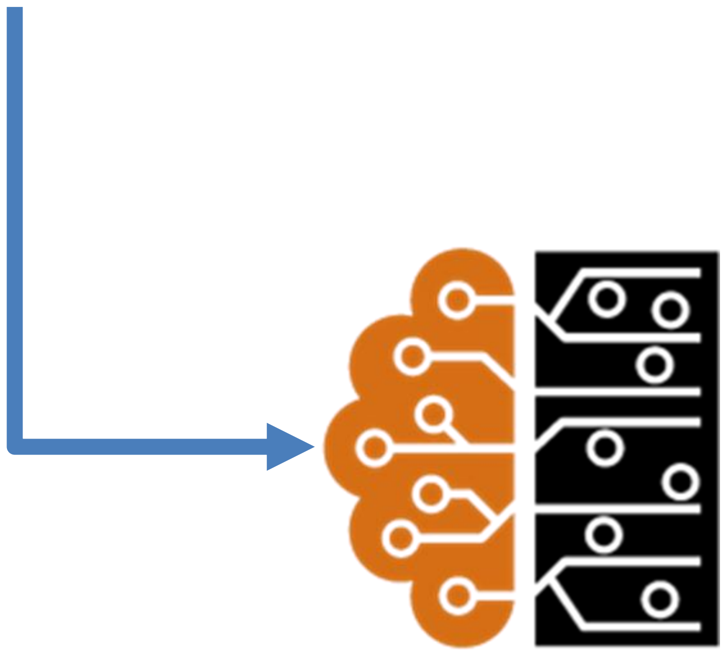
PHOTONIC INTEGRATED CIRCUIT



HYBRID ARTIFICIAL-BIOLOGICAL NETWORK

The vision

BIOLOGICAL COLTURE

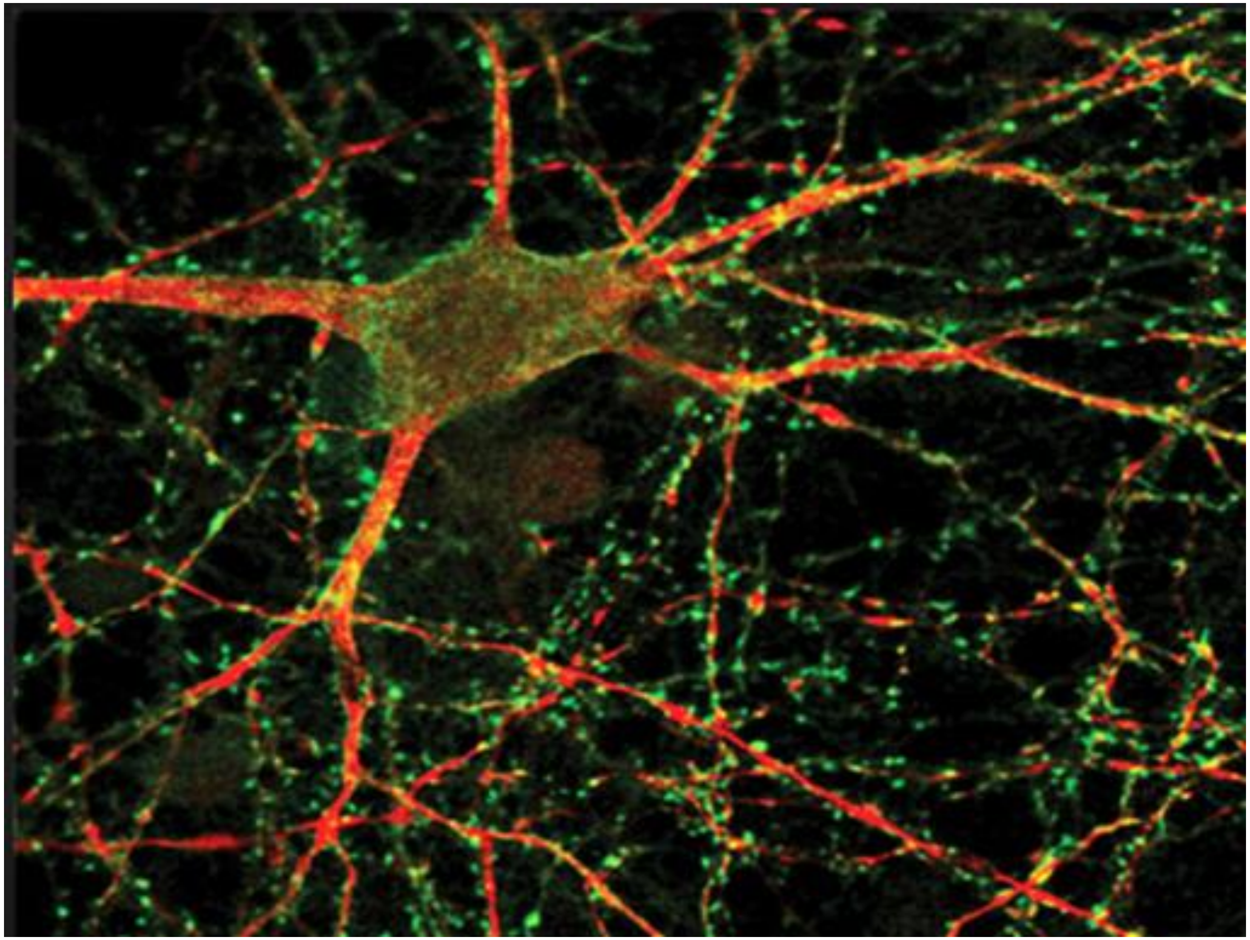


HYBRID ARTIFICIAL-BIOLOGICAL NETWORK

Outline

- Photonics for artificial neural networks
  - The optical neuron
  - How to add memory to the neuron
  - Few neuronal networks at work
- Photonics to form biological networks
  - Light to sculpt neuronal circuits
  - Light to induce memories
  - Software emulation of neuronal circuits
- Hybrid artificial networks
  - The first steps

The experimental platform



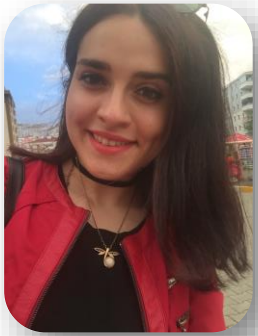
The experimental platform

Beatrice Vignoli

Clara Zaccaria

Francesca Pischedda

Ilya Auslender



Asiye Malkoc

Yasaman Heydari

Paolo Brunelli

Exploring Neuronal Circuits

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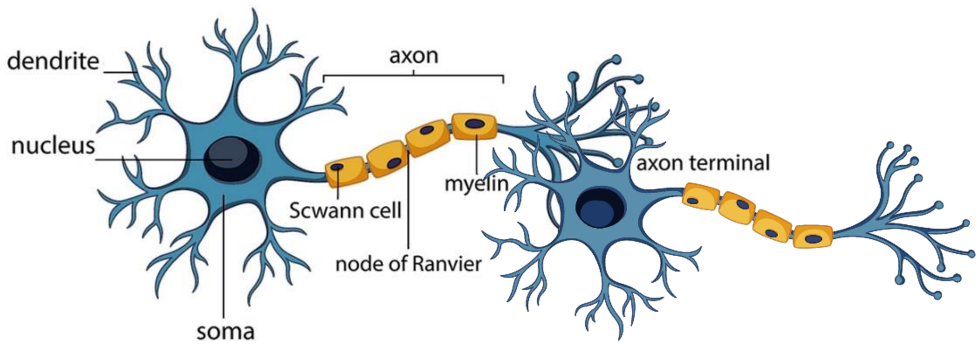
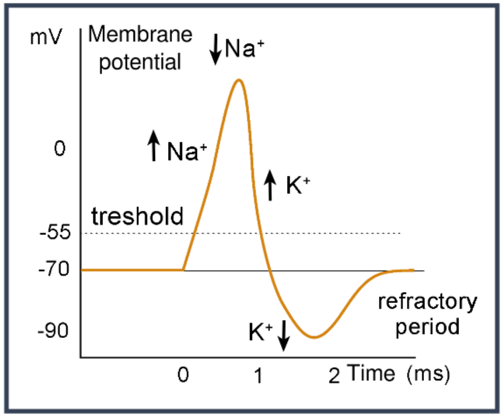
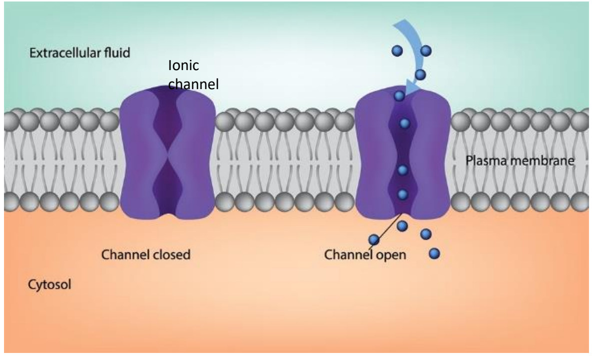
Neuronal communication

Action potential

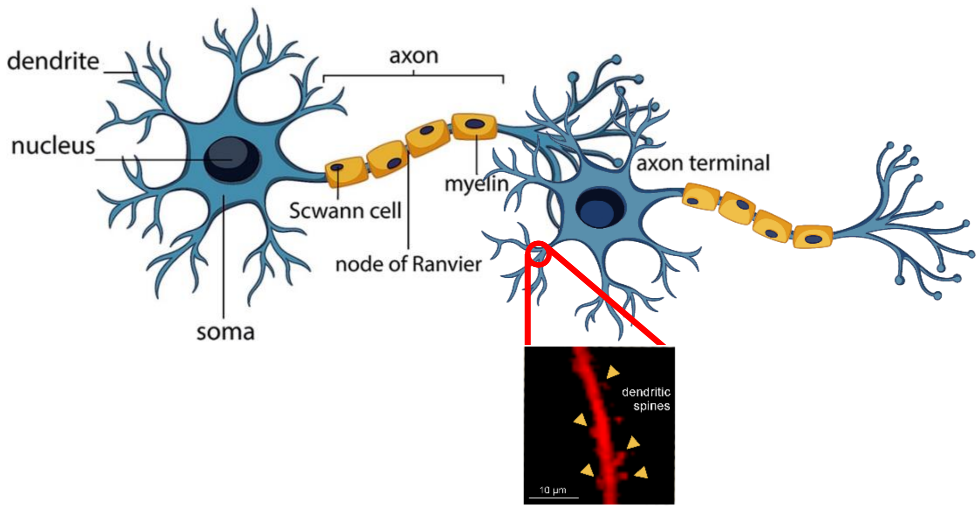


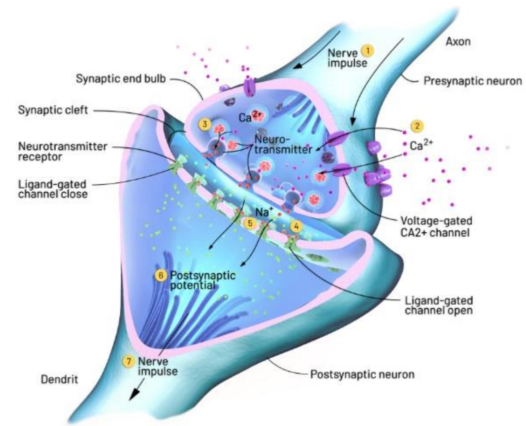


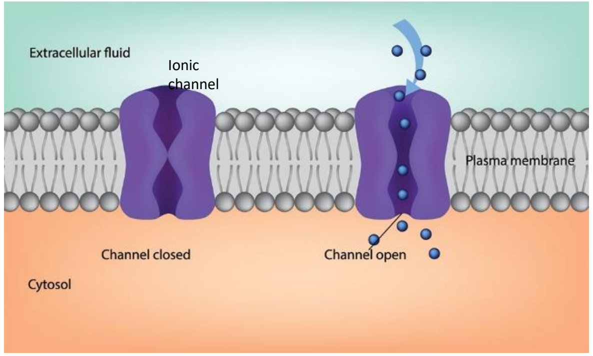


Neuronal communication

Action potential





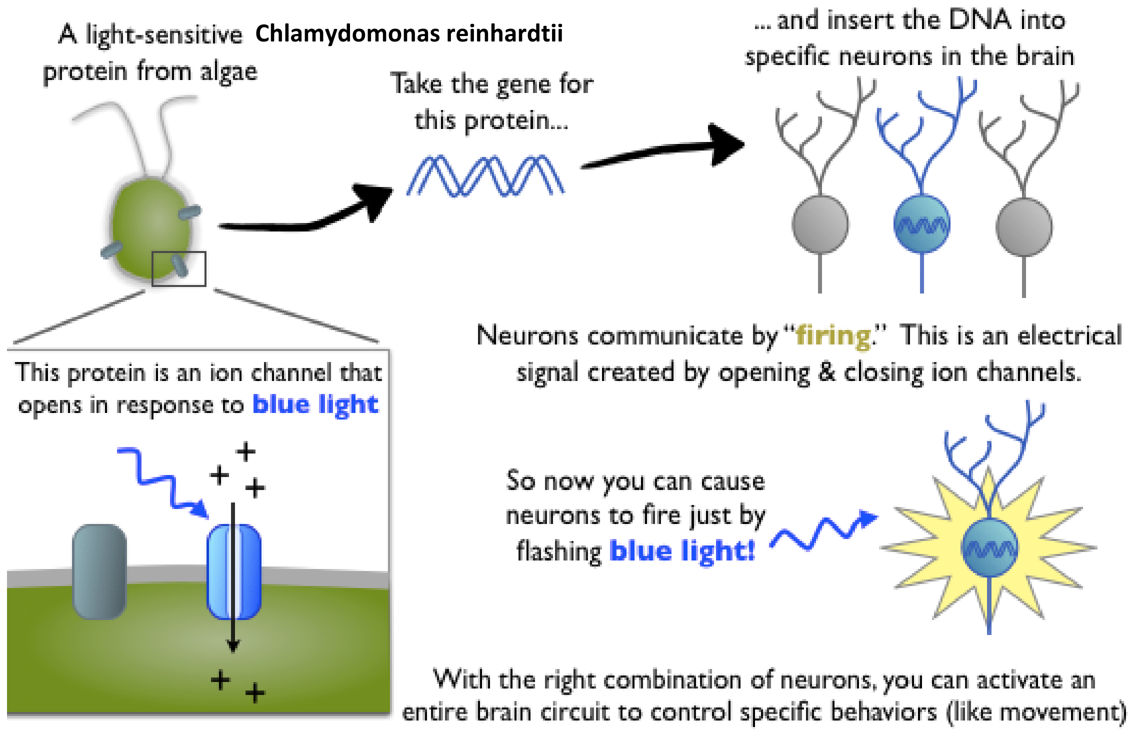


How do we influence neuron activity

Optogenetics

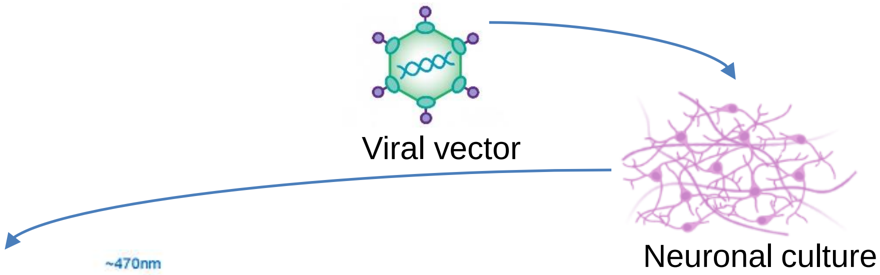
Karl Desseiroth, Stanford University, 2005

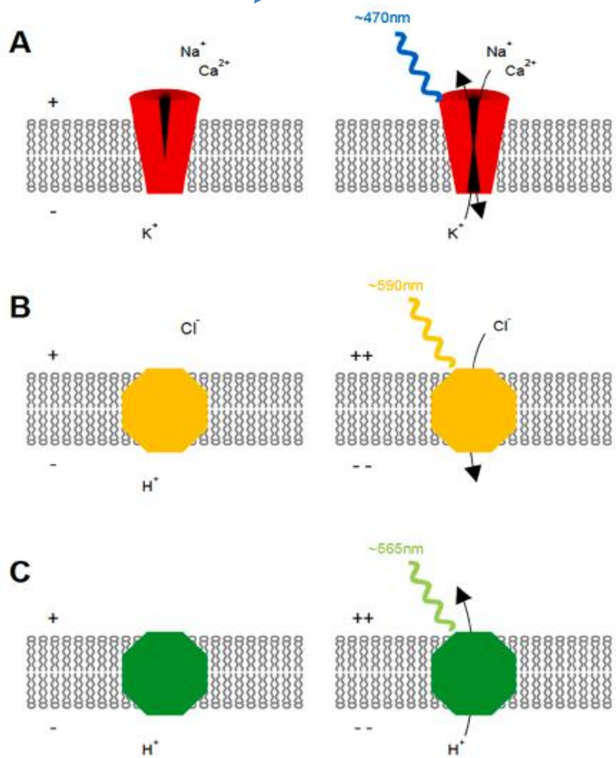
https://www.hhmi.org/scientists/karl-deisseroth



LIGHT CAN ACTIVATE NEURONS

Optogenetics



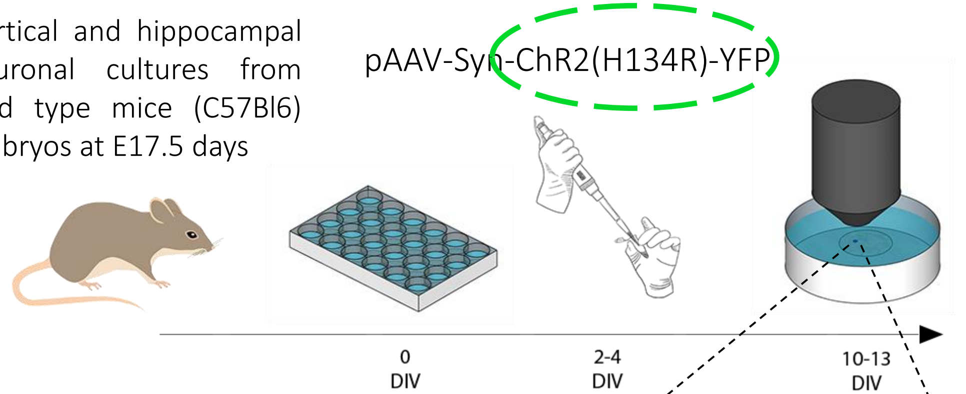


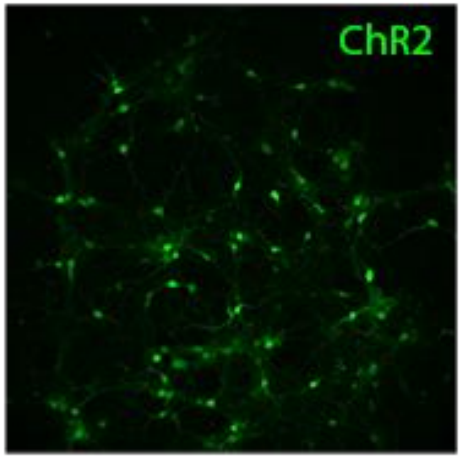
- Excitatory Channelrhodopsin2 (ChR2) depolarizes neurons through activation of the inward Na^+ and Ca^{2+} ion currents and K^+ outward current.
- Inhibitory Halorhodopsin channel (NpHR) when exposed to the 590nm light, facilitates Cl^- inward flow in neurons,
- Inhibitory Archaerhodopsin (Arch) in presence of 565nm light pumps out H^+ from neurons.

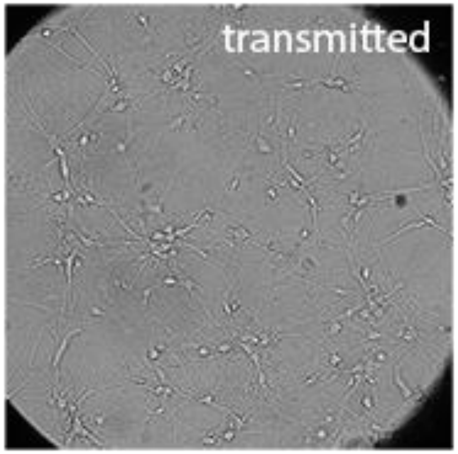
Matthew C. Walker et.al., Neuropharmacology (2020)

Optogenetic excitation of neurons

Cortical and hippocampal neuronal cultures from wild type mice (C57Bl6) embryos at E17.5 days







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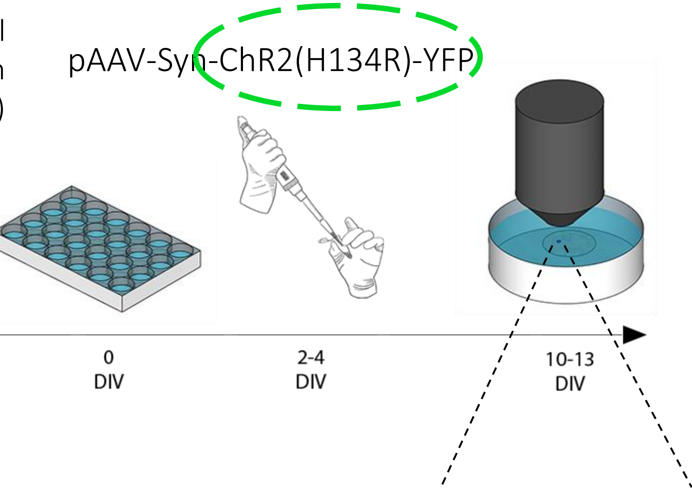
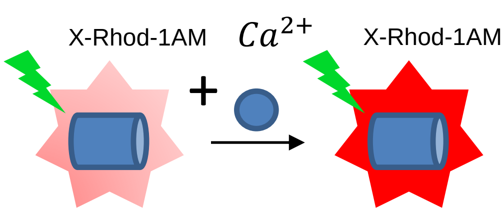
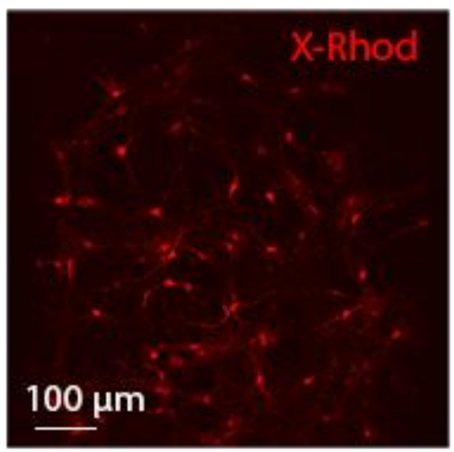
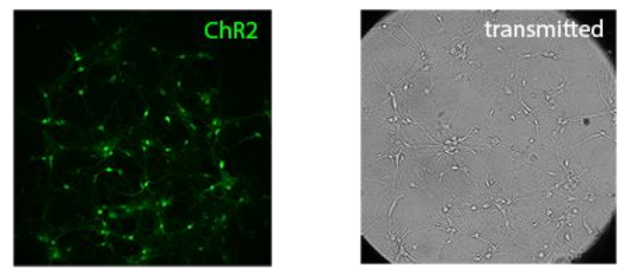


X-Rhod-1AM calcium indicator

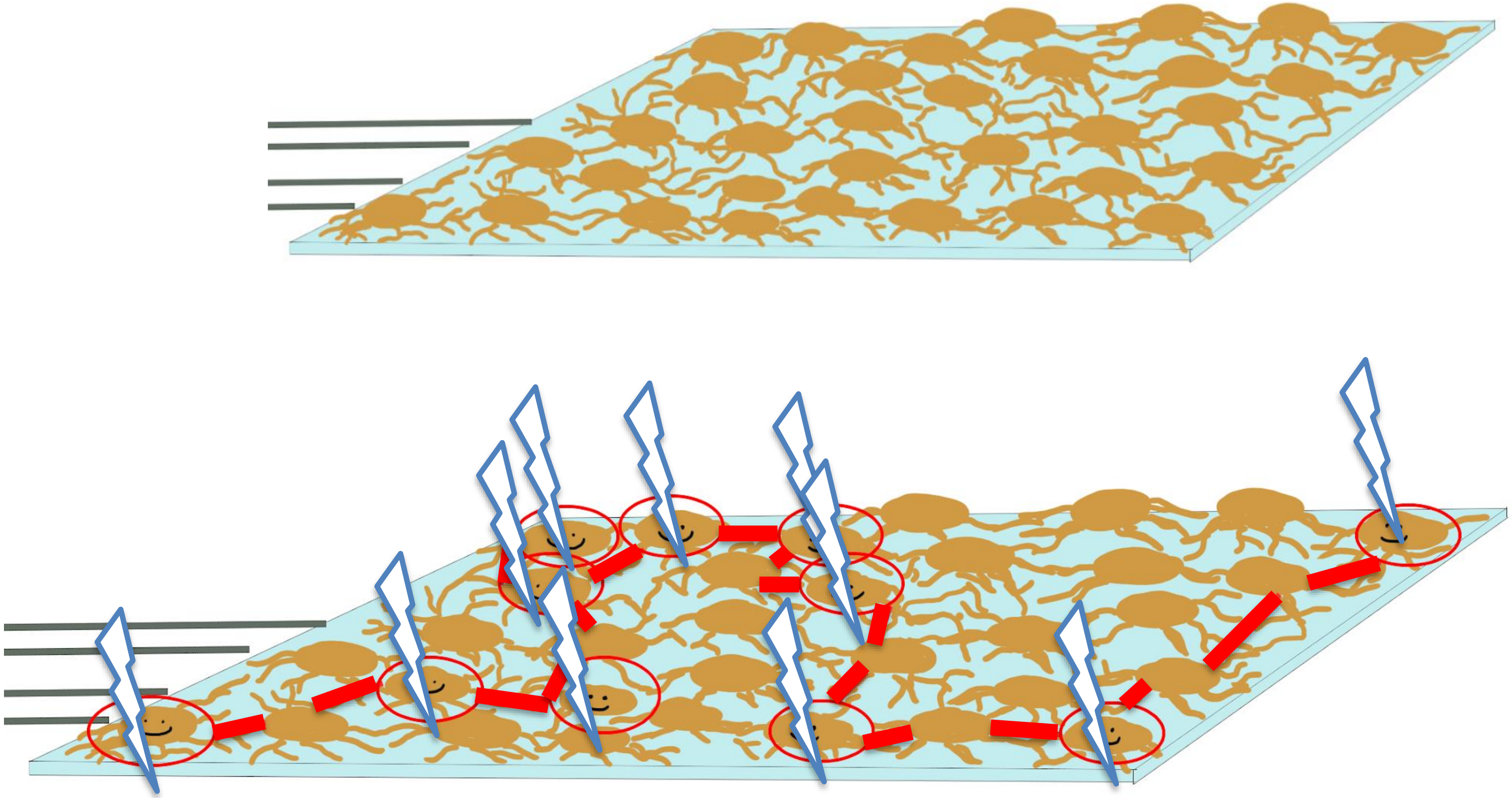




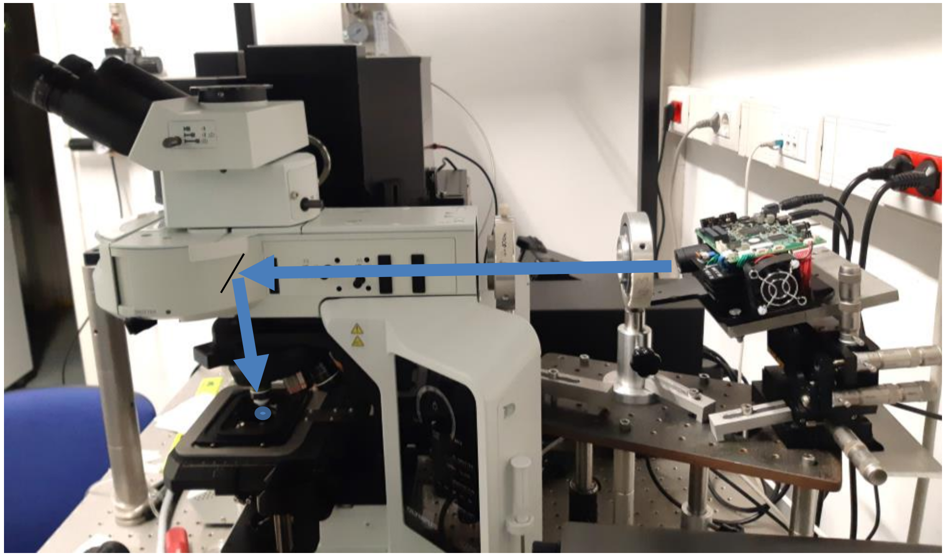


Writing a neuronal circuit

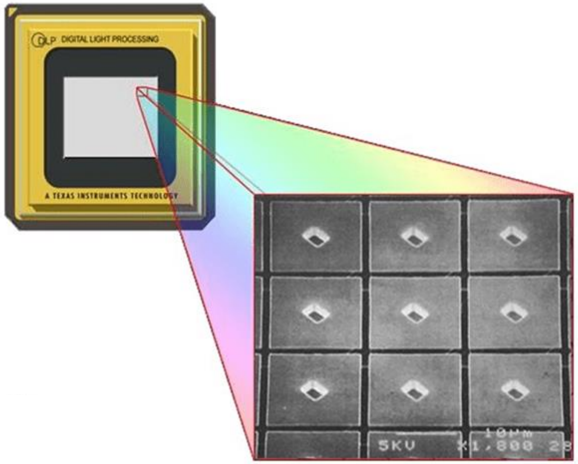
Patterned illumination activates a group of interconnected neurons



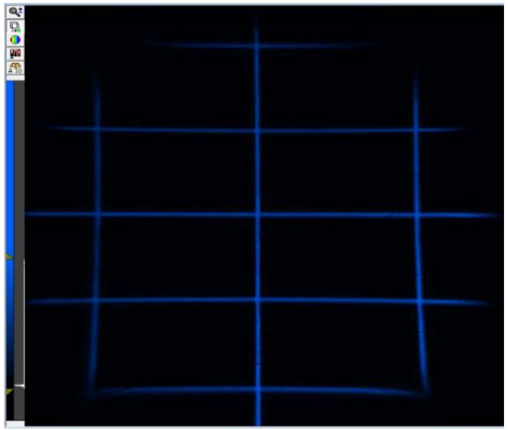
Writing a neuronal circuit : patterned illumination

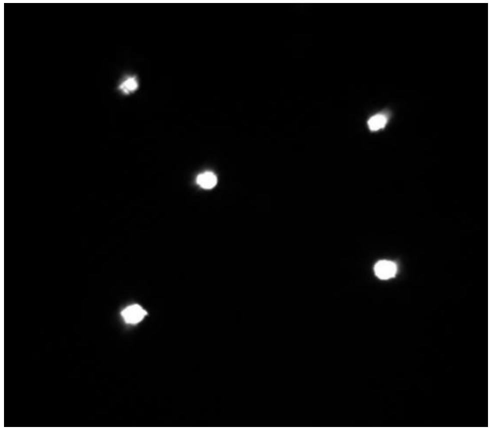


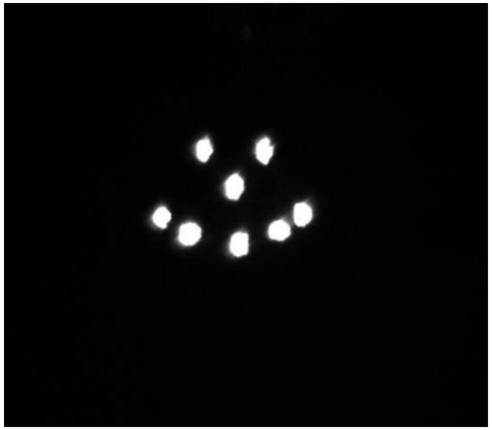
16 mW/mm2



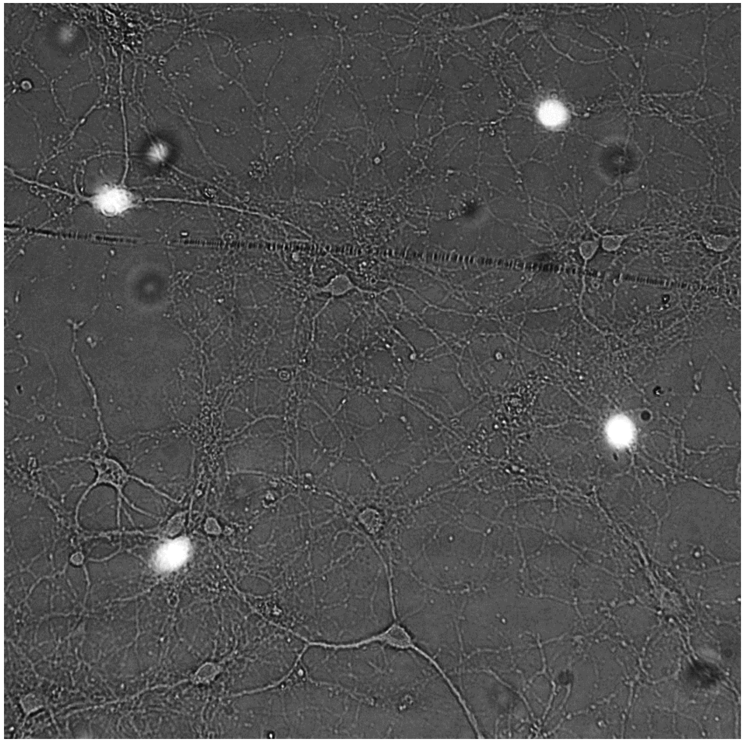
Digital Light Processing (DLP)

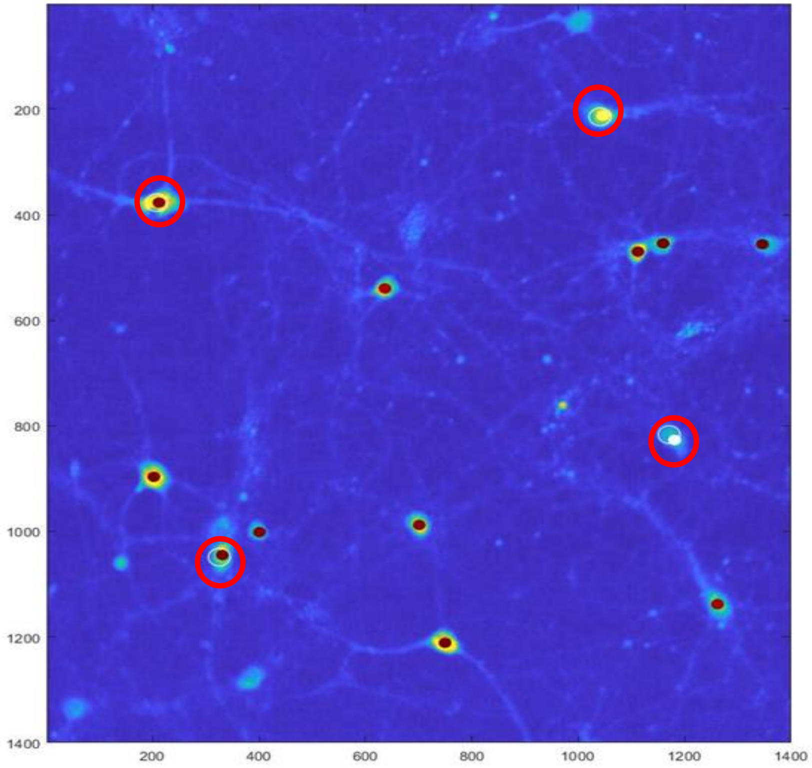






Writing a neuronal circuit : patterned illumination





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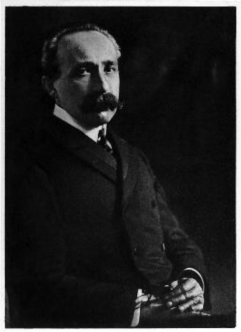
What is memory?



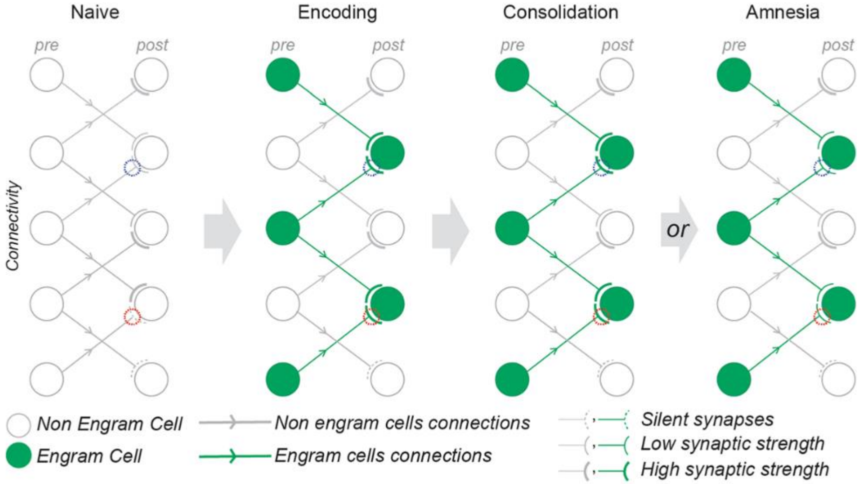
Richard Semon 1904

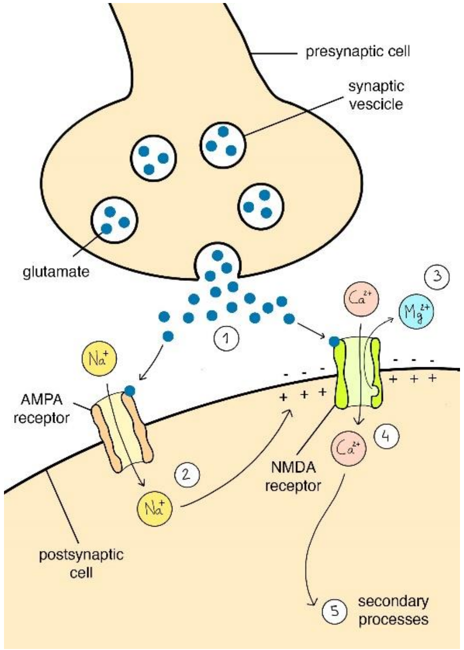
Donald O. Hebb 1949

Simultaneous complex of excitations *that induce changes in the brain.*

Strenghtening of synapses *between neurons that were simultaneously excited.*

Engram*: ensemble of cells activated,* ***molecularly or structurally modified*** *by an experience.*



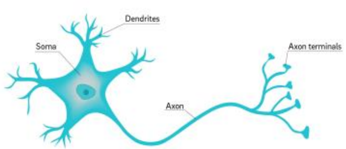


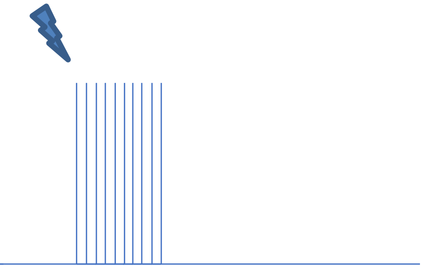
Poo et al. BMC Biology 4(2016)1:40 DOI 10.1186/s12915-016-0261-6

potentiation

Hebb Theory "Neurons that fire together wire together"

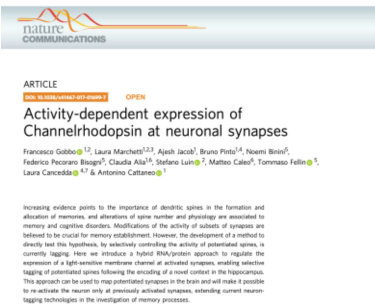
Digital Light Projector (DLP): are we able to potentiate neurons?





LTP temporal pattern: 10 trains of 13 pulses at 100 Hz, repeated at 0.5 Hz
+ Doxycycline

Digital Light Projector (DLP): are we able to detect potentiation in neurons?



nature COMMUNICATIONS

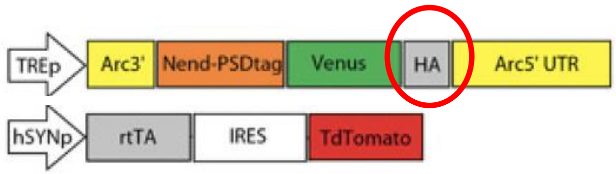
ARTICLE

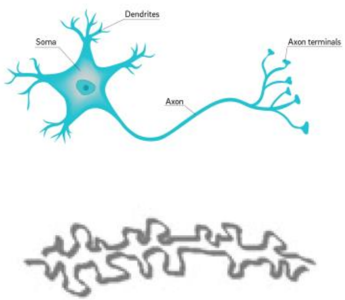
DOI: 10.1038/s41467-017-01699-7 OPEN

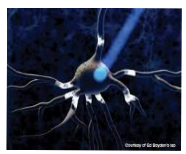
Activity-dependent expression of Channelrhodopsin at neuronal synapses

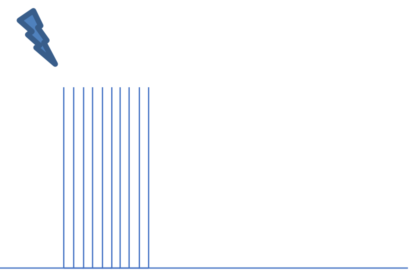
Francesco Gobbo[1,2], Laura Marchetti[1,2,3], Ajesh Jacob[1], Bruno Pinto[1,4], Noemi Binini[5], Federico Pecoraro Bisogni[5], Claudia Alia[1,6], Stefano Luin[2], Matteo Caleo[6], Tommaso Fellin[5], Laura Cancedda[4,7] & Antonino Cattaneo[1]

Increasing evidence points to the importance of dendritic spines in the formation and allocation of memories, and alterations of spine number and physiology are associated to memory and cognitive disorders. Modifications of the activity of subsets of synapses are believed to be crucial for memory establishment. However, the development of a method to directly test this hypothesis, by selectively controlling the activity of potentiated spines, is currently lagging. Here we introduce a hybrid RNA/protein approach to regulate the expression of a light-sensitive membrane channel at activated synapses, enabling selective tagging of potentiated spines following the encoding of a novel context in the hippocampus. This approach can be used to map potentiated synapses in the brain and will make it possible to re-activate the neuron only at previously activated synapses, extending current neuron-tagging technologies in the investigation of memory processes.

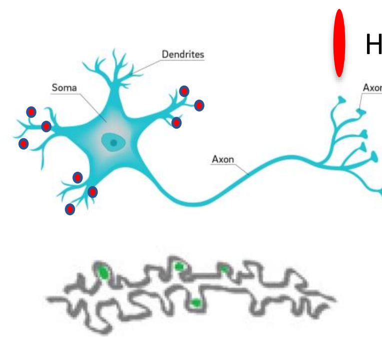






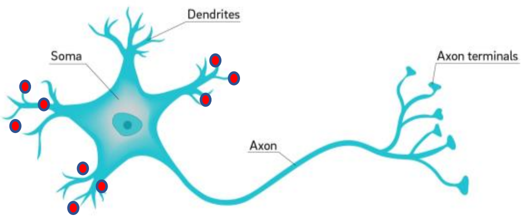


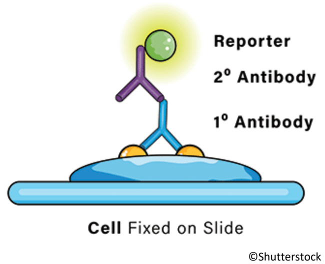
LTP temporal pattern: 10 trains of 13 pulses at 100 Hz, repeated at 0.5 Hz
+ Doxycycline



Potentiated spine = strengthened connection

Analysis and results



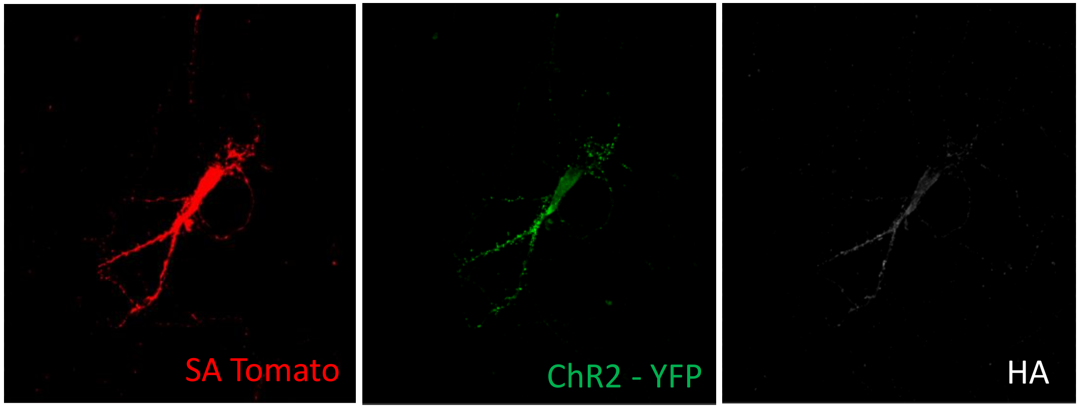


Immuno
Cytochemistry

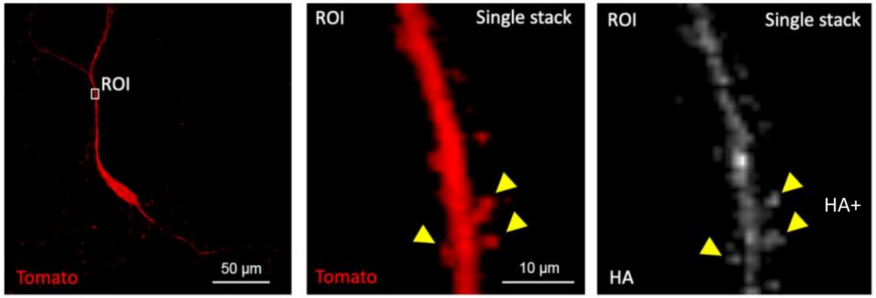
TOMATO → transfection Synactive

green (not amplified) → ChR2-YFP

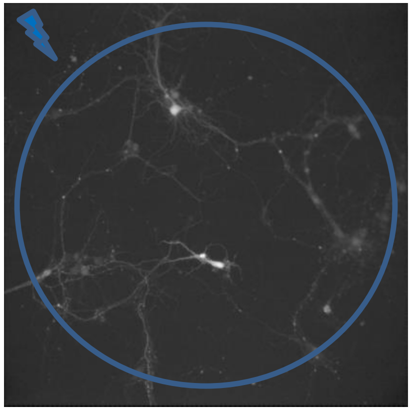
Anti-HA → HA protein



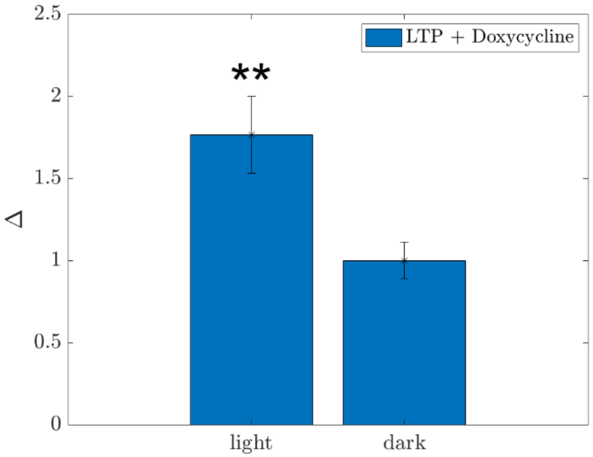
Analysis and results



$$\Delta = \overline{\left(\frac{N_{HA+}/N_{tot}}{(N_{HA+}/N_{tot})_{control}}\right)}$$

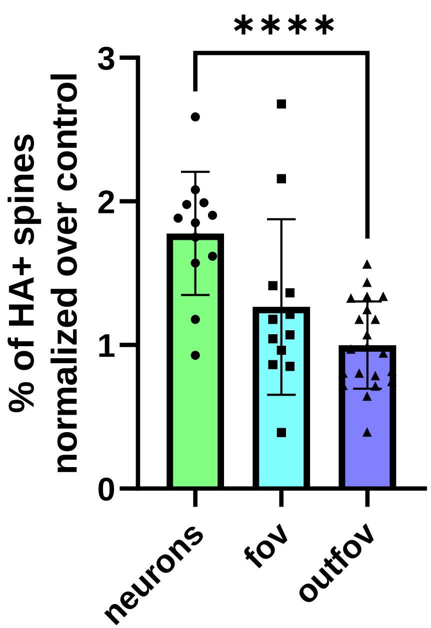


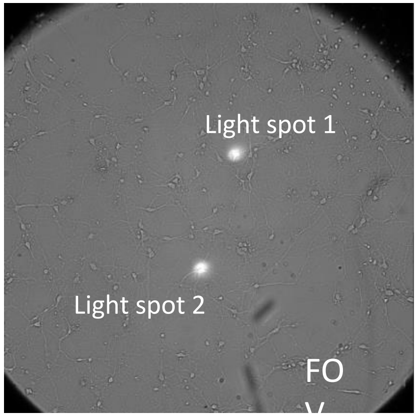
WHOLE FIELD ILLUMINATION

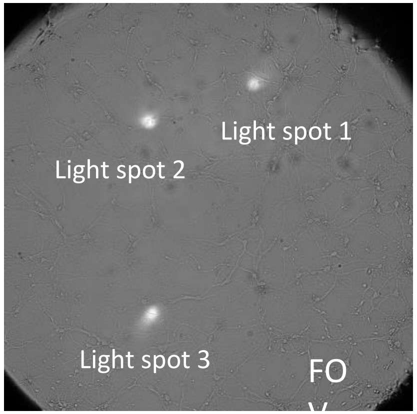


Analysis and results

2 neurons stimulation



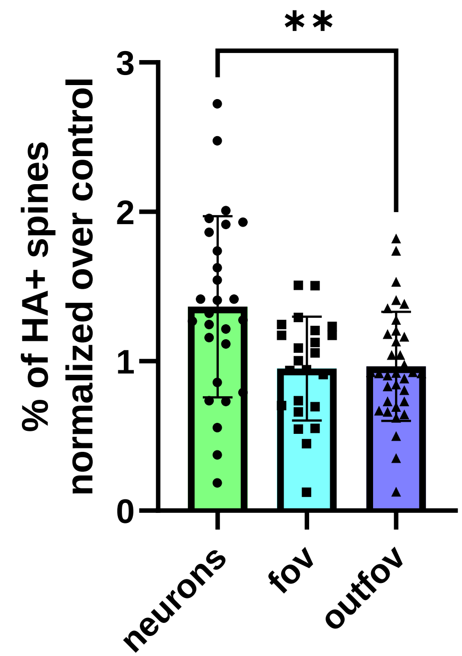




LTP-like pattern

10 trains of 13 pulses at 100 Hz, repeated at 0,5 Hz

3 neurons stimulation

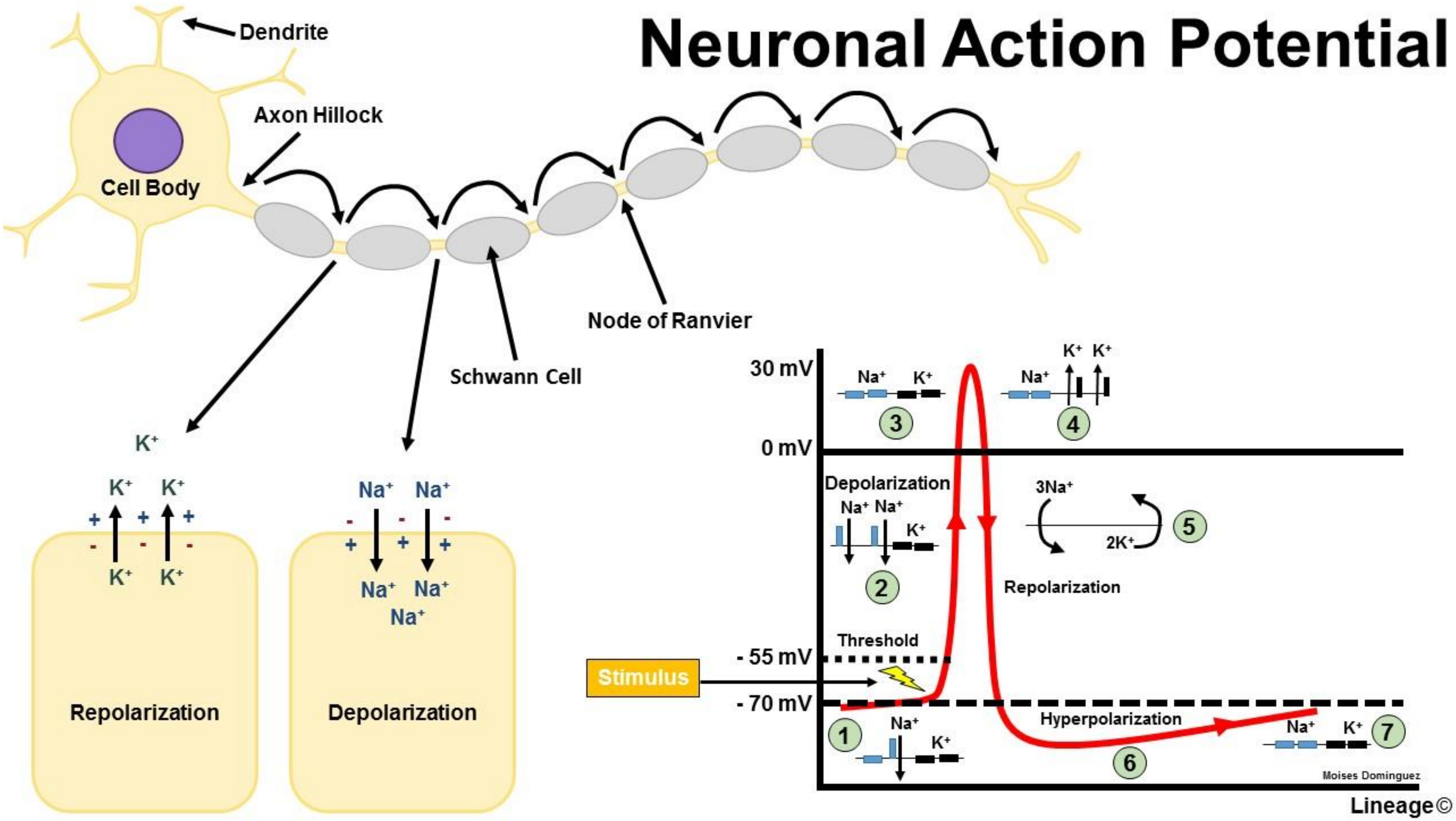


Potentiation of spines of simultaneously excited neurons → we created the engram.

Outline

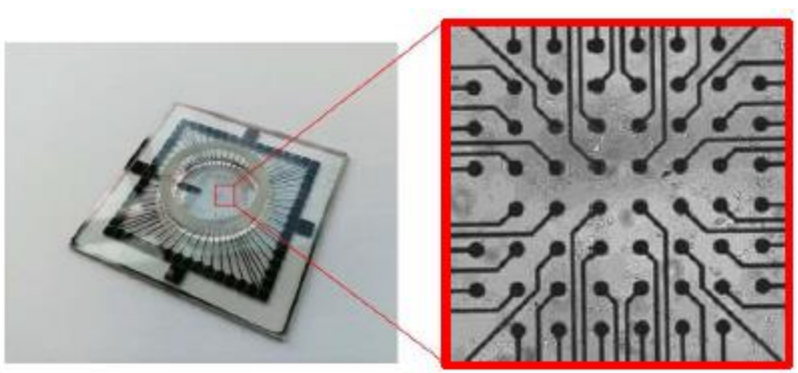
- Photonics for artificial neural networks
  - The optical neuron
  - How to add memory to the neuron
  - Few neuronal networks at work
- Photonics to form biological networks
  - Light to sculpt neuronal circuits
  - Light to induce memories
  - Software emulation of neuronal circuits
- Hybrid artificial networks
  - The first steps

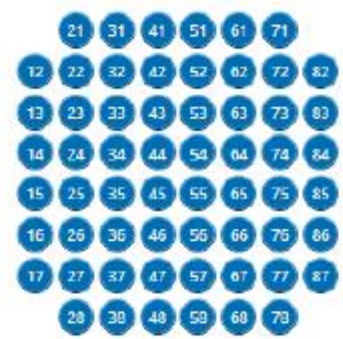
What is the action potential?

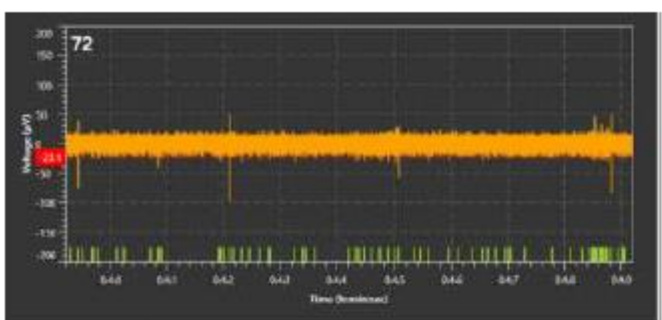


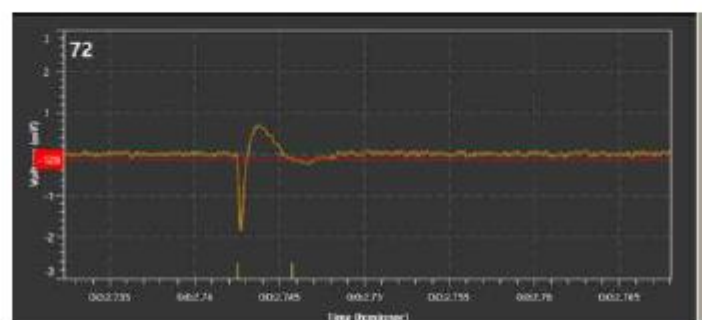
Multi-Electrode Arrays (MEA)

- An extracellular electrophysiological assessment.
- A conventional MEA has a square recording area ranging in length from 700 µm to 5 mm.
- 60 electrodes are arranged in an 8 x 8 grid with interelectrode intervals of 100, 200, or 500 m in this area.
- Planar TiN (titanium nitride) electrodes are available in sizes of 10, 20, and 30 µm

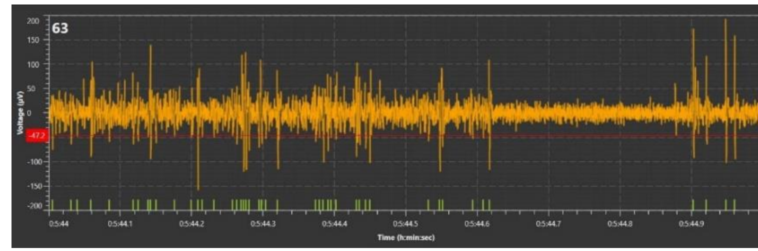








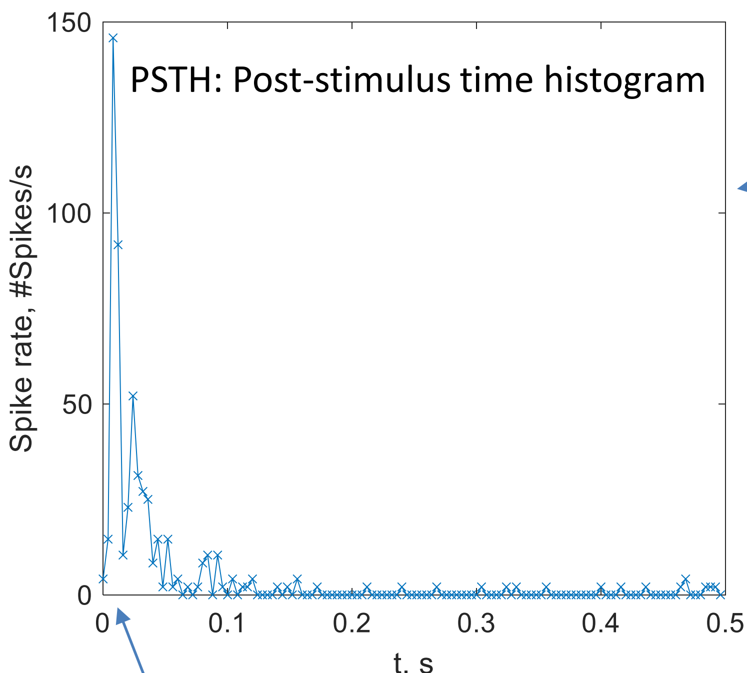
Measurements of response to a stimulus



$$PSTH[t,ch] = \frac{1}{\Delta t N_{stim}} \sum_{i=1}^{N_{stim}} N_i[t,ch]$$

Number of stimulation periods

Spike count in [t, t+Δτ] time bin



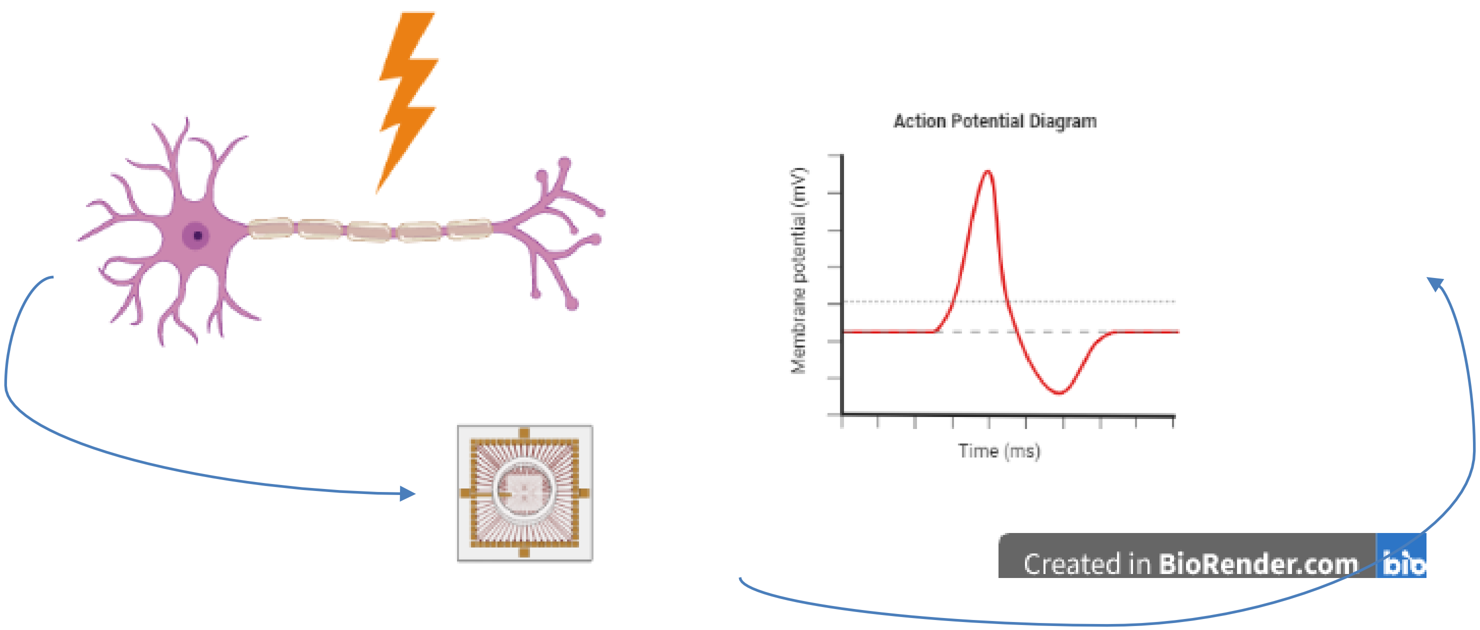
t= 0 : start of stimulus

$$A[ch] = \int_{T_{PS}} PSTH[t,ch]dt$$

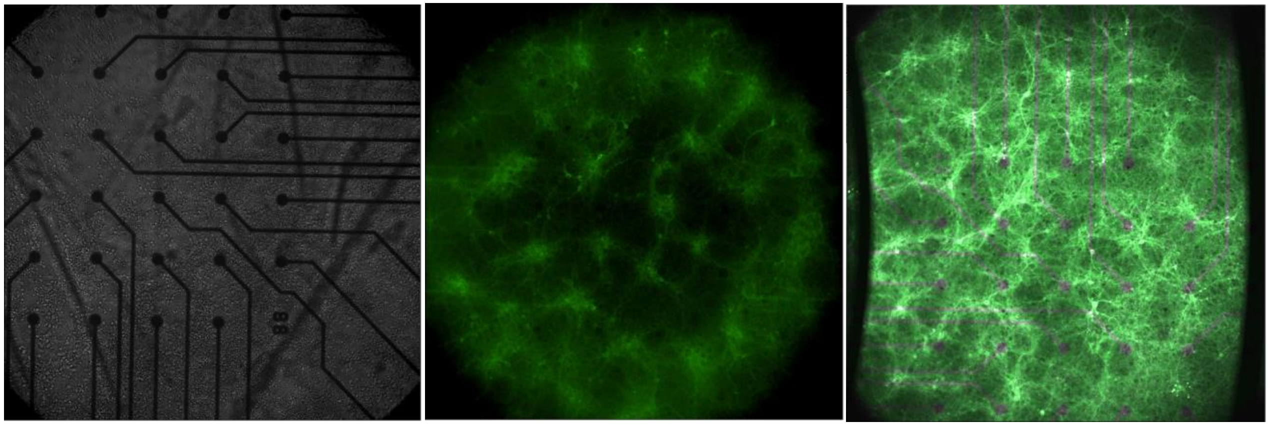
Area under the PSTH curve: quantifies the overall response of each channel to the stimulation.

So, what we want to do?

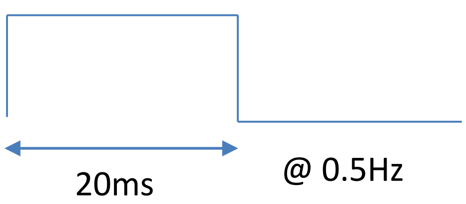
We want to use light to influence neuronal activity and then record the neuronal activity via MEA



Light stimulation patterns

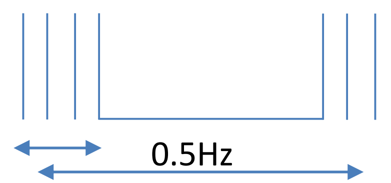


Test stimulus: low frequency. Used to measure the response of the cultures

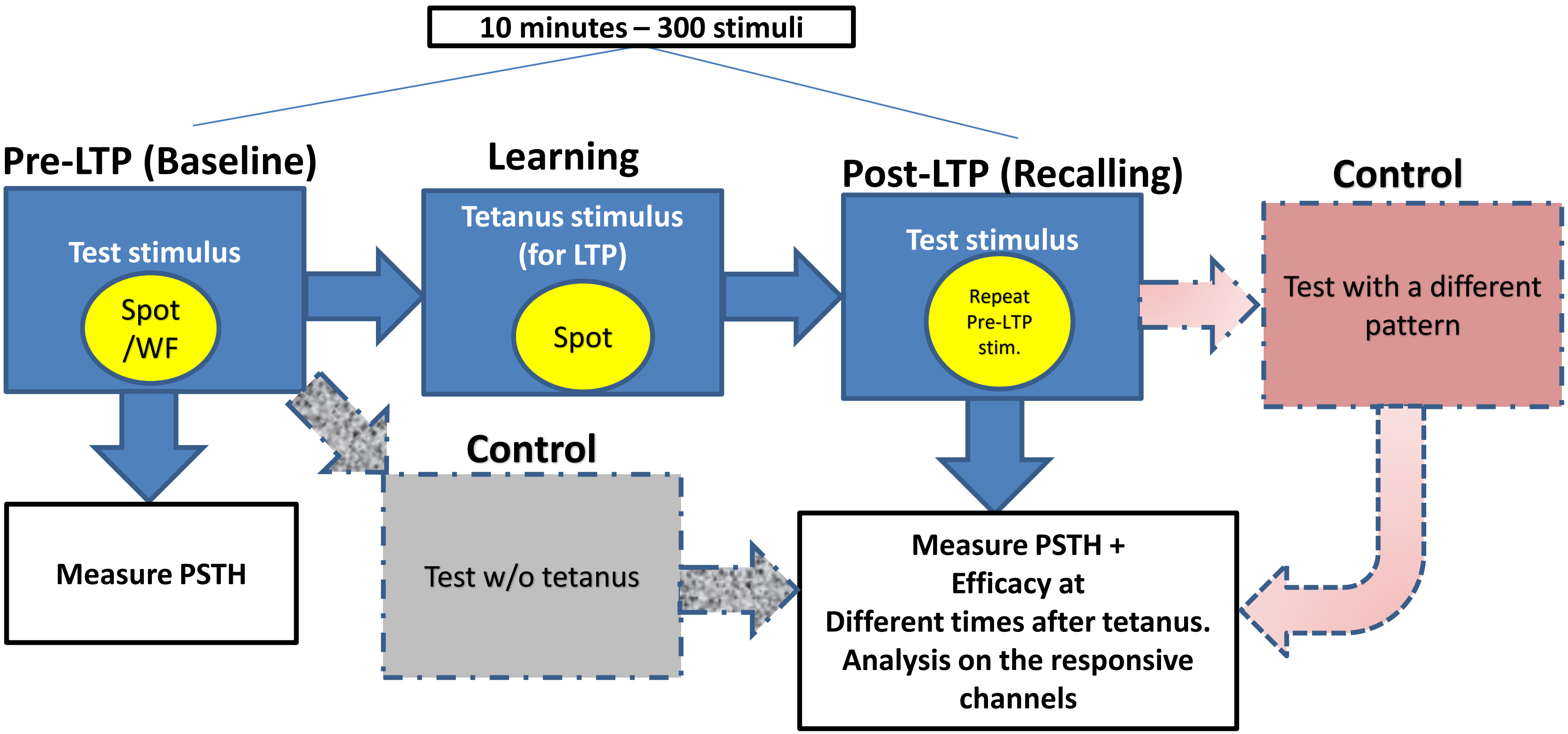


Tetanic stimulus: High frequency. Used to induce a change in the synaptic connections (e.g., LTP)

Train of N pulses of 5ms on @50Hz



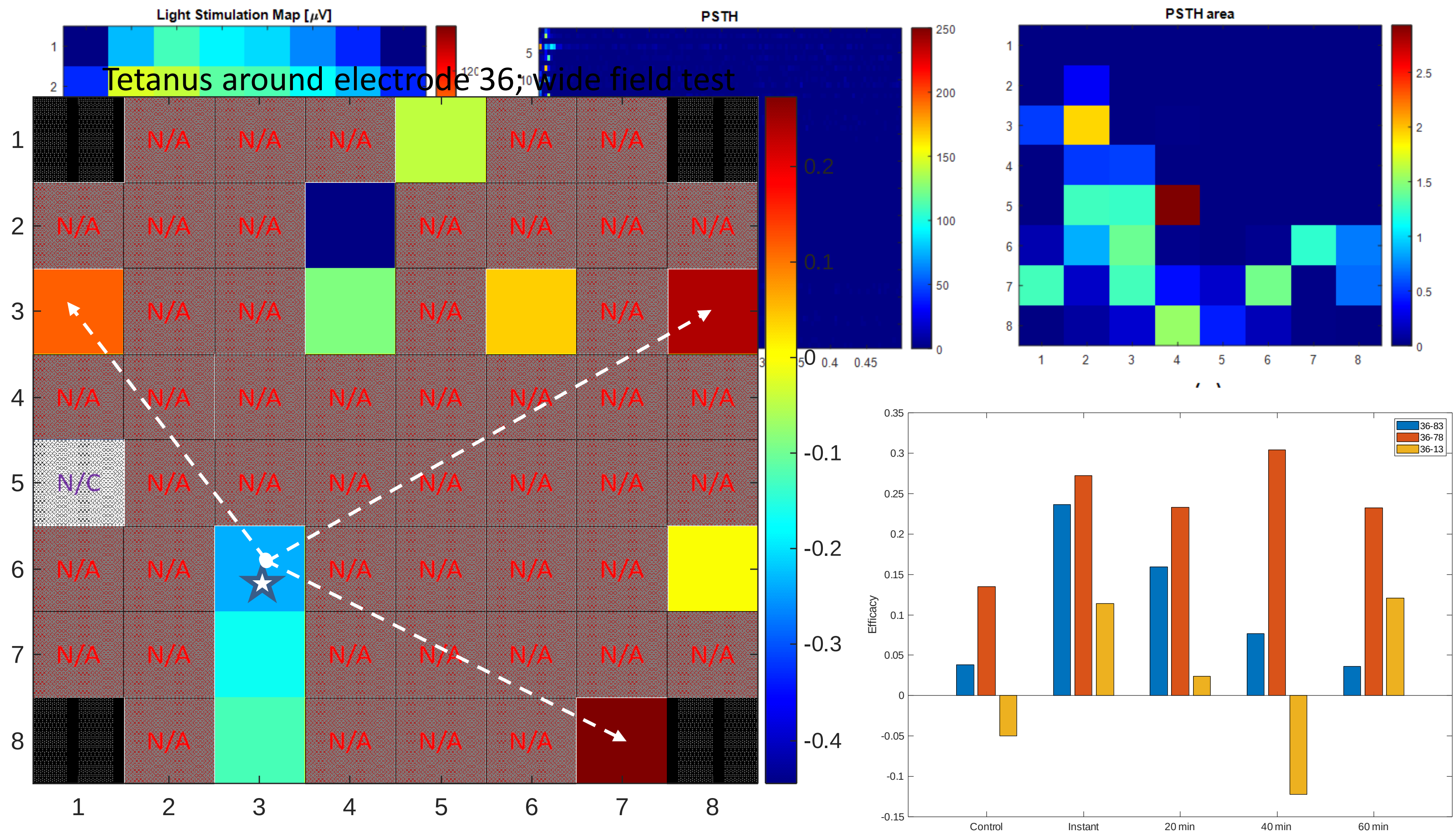
Long-term potentiation: Experimental protocol



Marie Skłodowska-Curie Actions

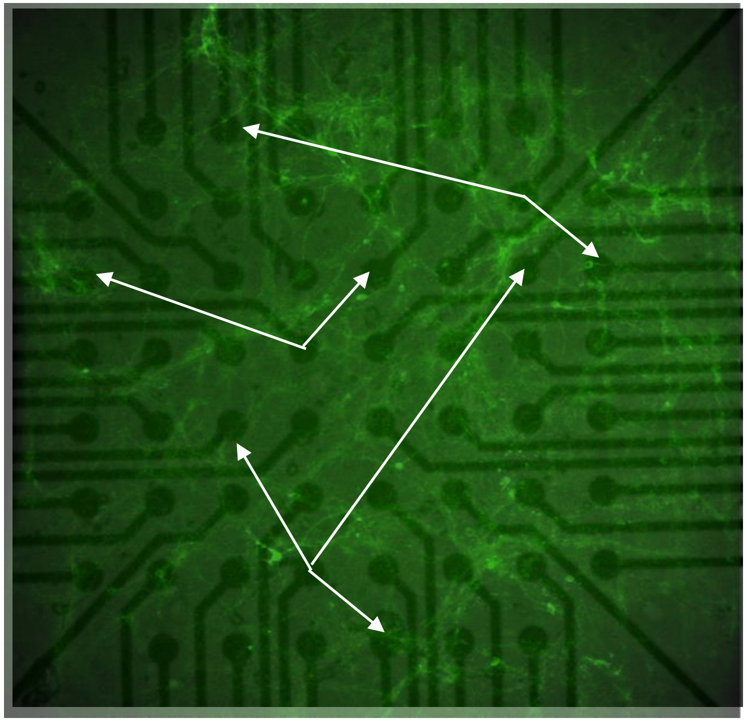
Memory writing and reading

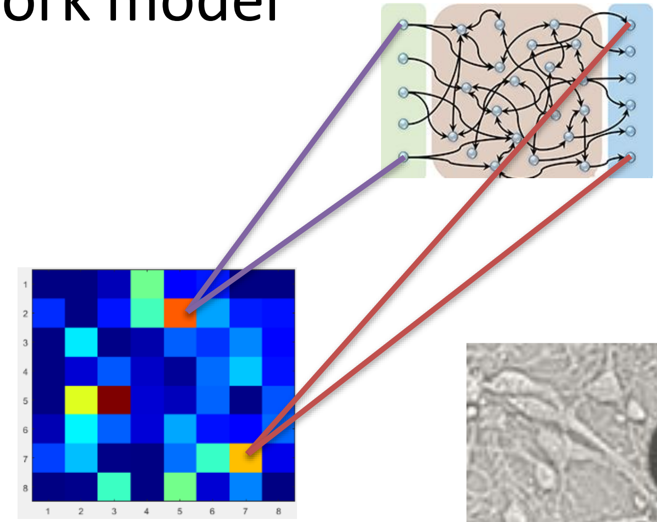
ISLAND read and write neurons

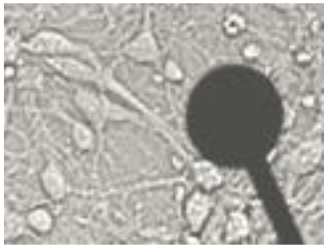


Network modeling

From MEA signals to a macro-network model

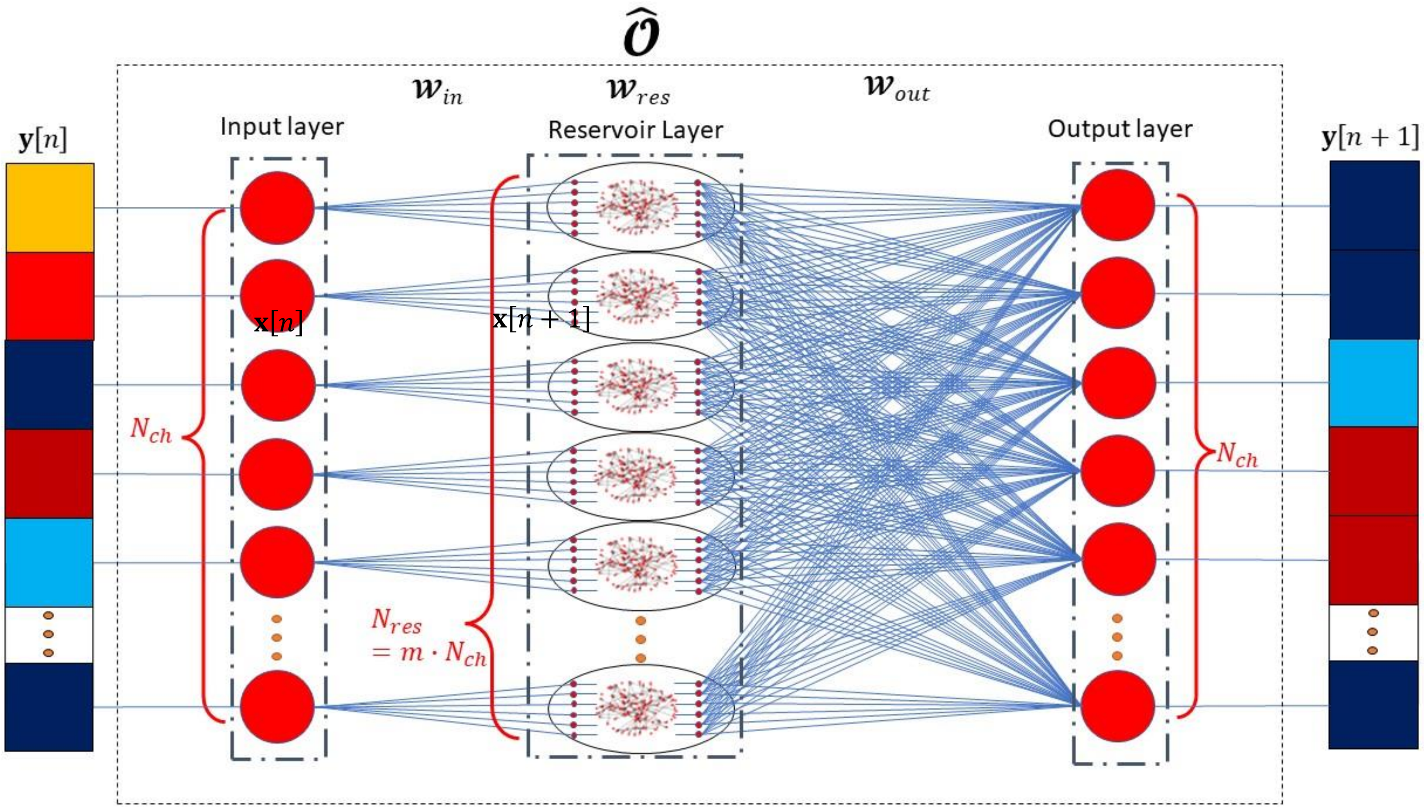






Objective:
Simplify the complicated neuronal network into a macro-scale network consisting of nodes corresponding to the measurement domain (electrodes).

ANN architecture



$$\mathbf{x}[n] = \boldsymbol{f}_{NL}(\mathbf{W}_{\text{in}}\mathbf{y}[n] + \mathbf{W}_{\text{res}}\mathbf{x}[n-1])$$

$$\mathbf{y}[n+1] = \mathbf{W}_{\text{out}}\mathbf{x}[n]$$

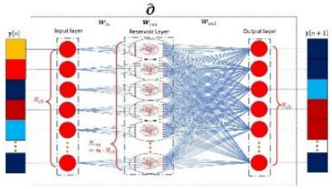
Network modeling

MEA recording (Raw Data)

Spike trains

Bursts

Network bursts



ANN model

Model training

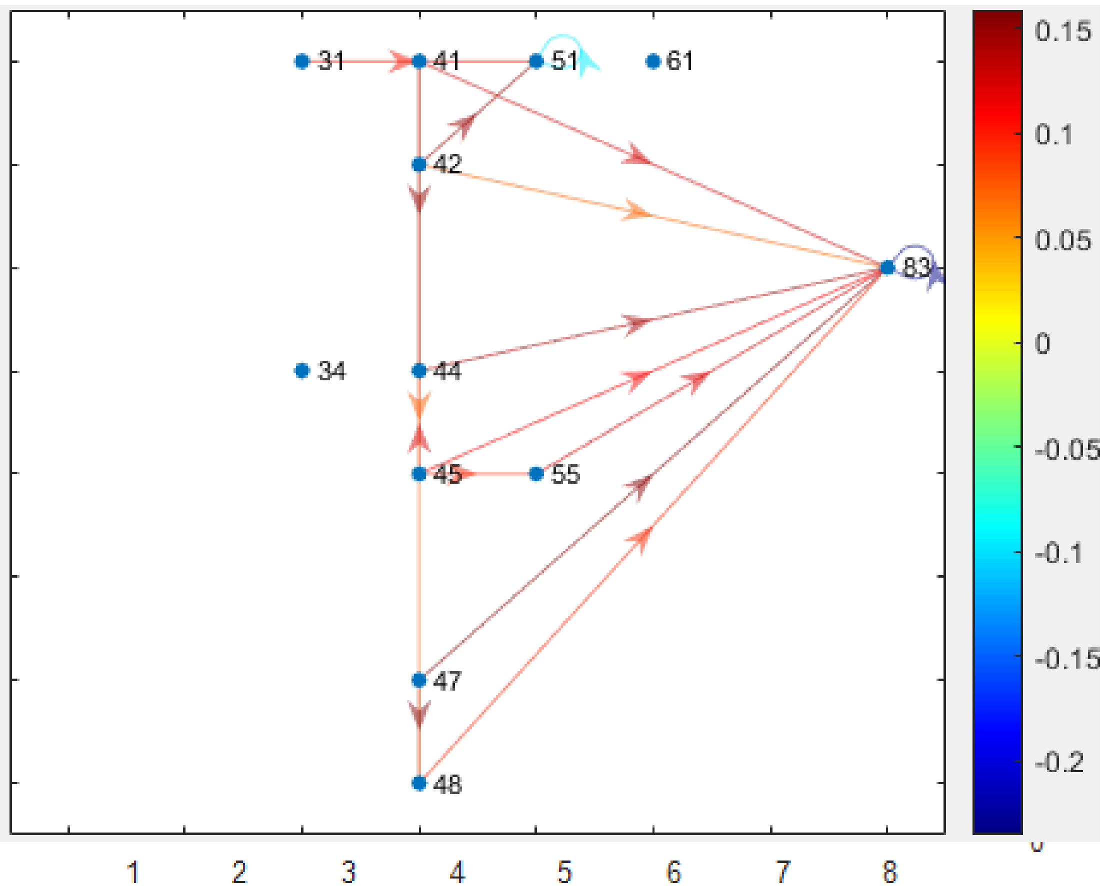
Validation with the initial recorded dataset

Validation with experimental patterned stimulus

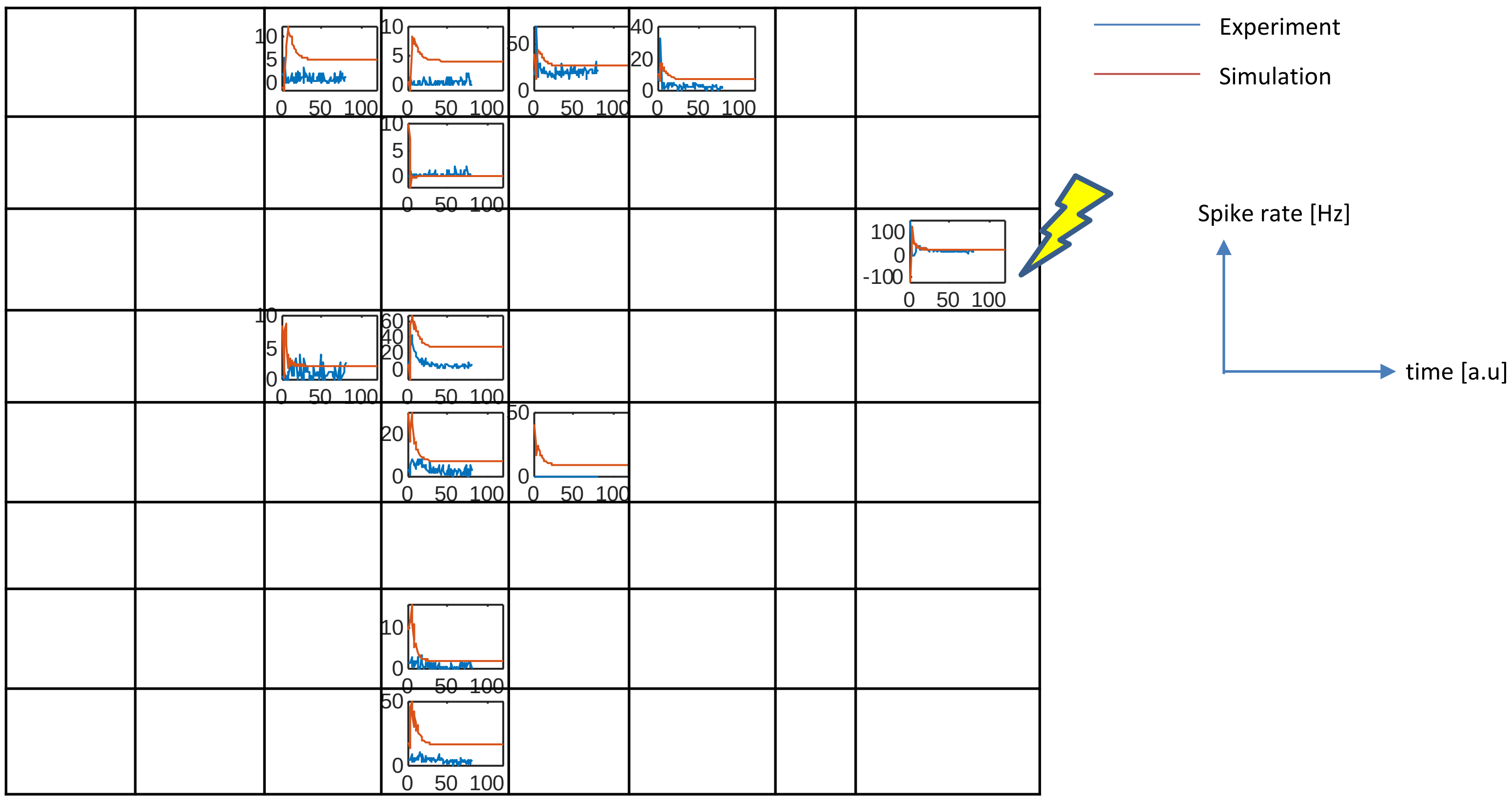
Connectivity Map

Network simulation

Network modeling



Network modeling



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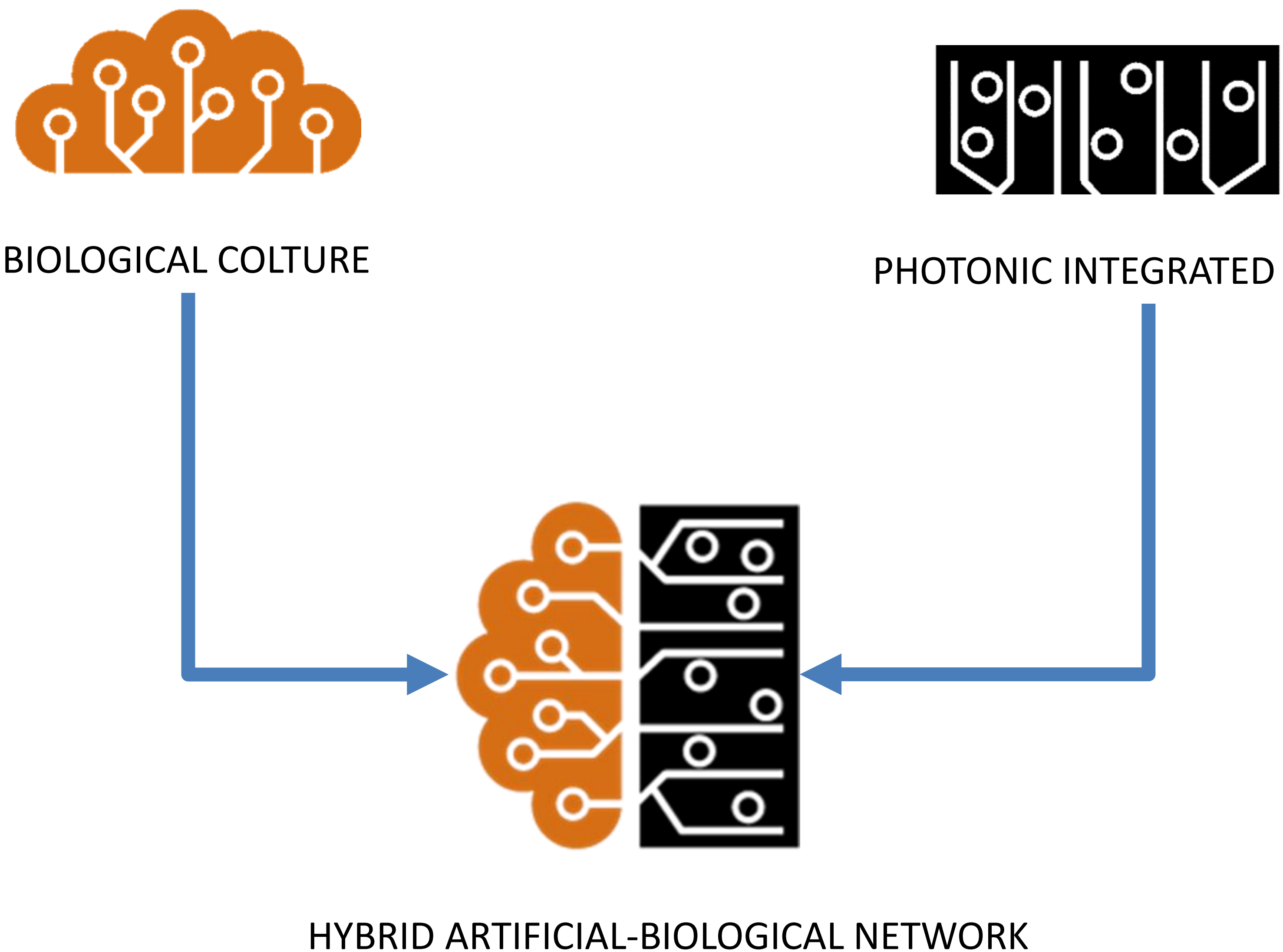
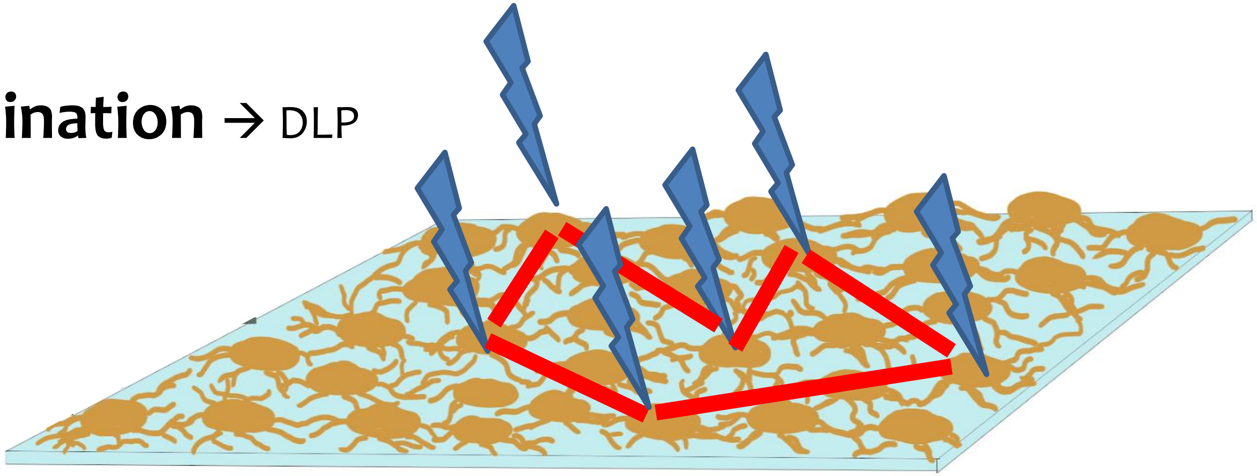
The vision


BIOLOGICAL COLTURE
PHOTONIC INTEGRATED CIRCUIT
HYBRID ARTIFICIAL-BIOLOGICAL NETWORK

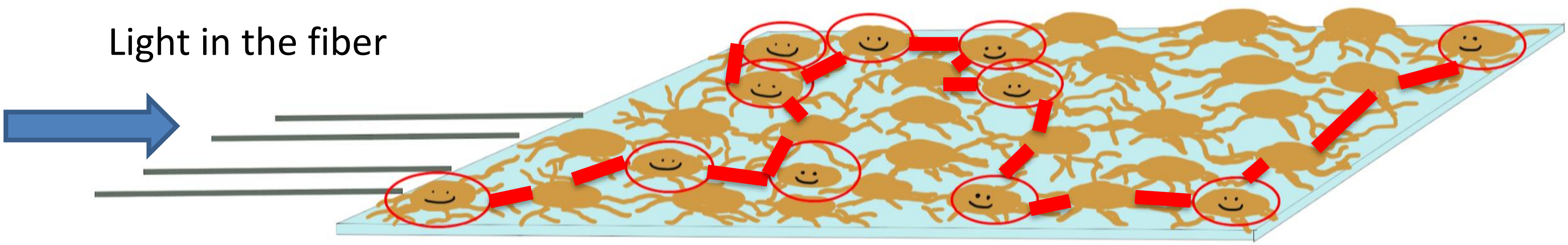
Writing a neuronal circuit

Top illumination → DLP



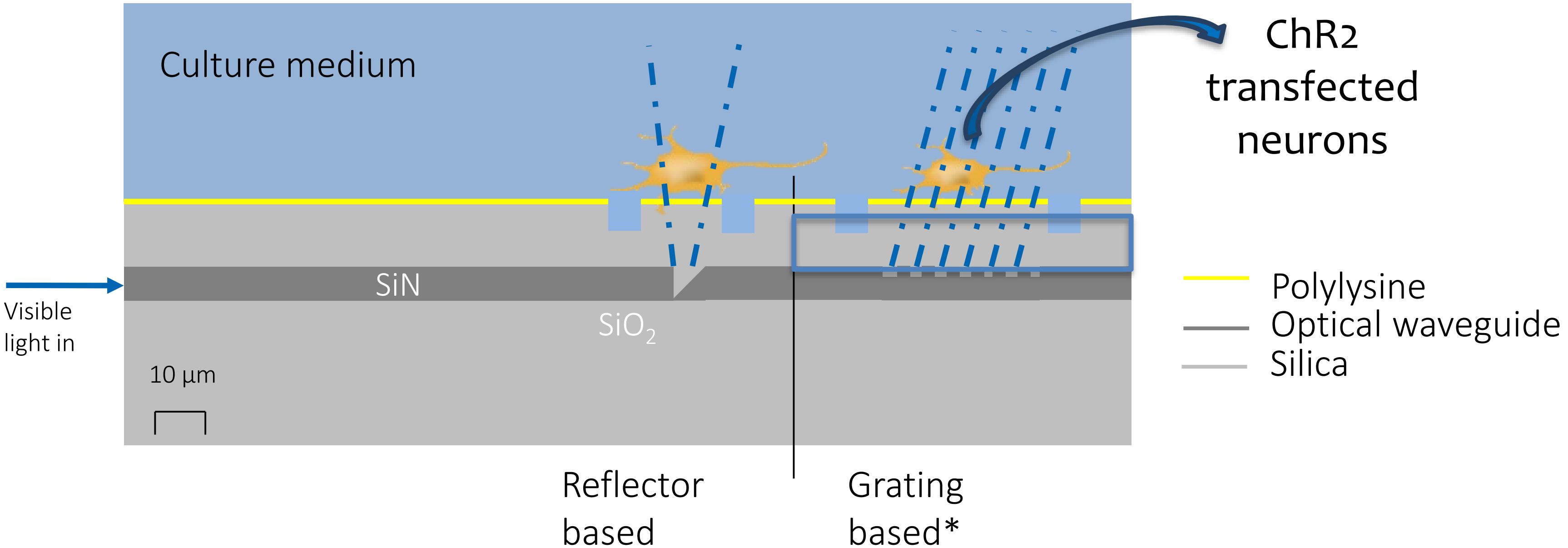
Bottom illumination → photonic chip

Light in the fiber



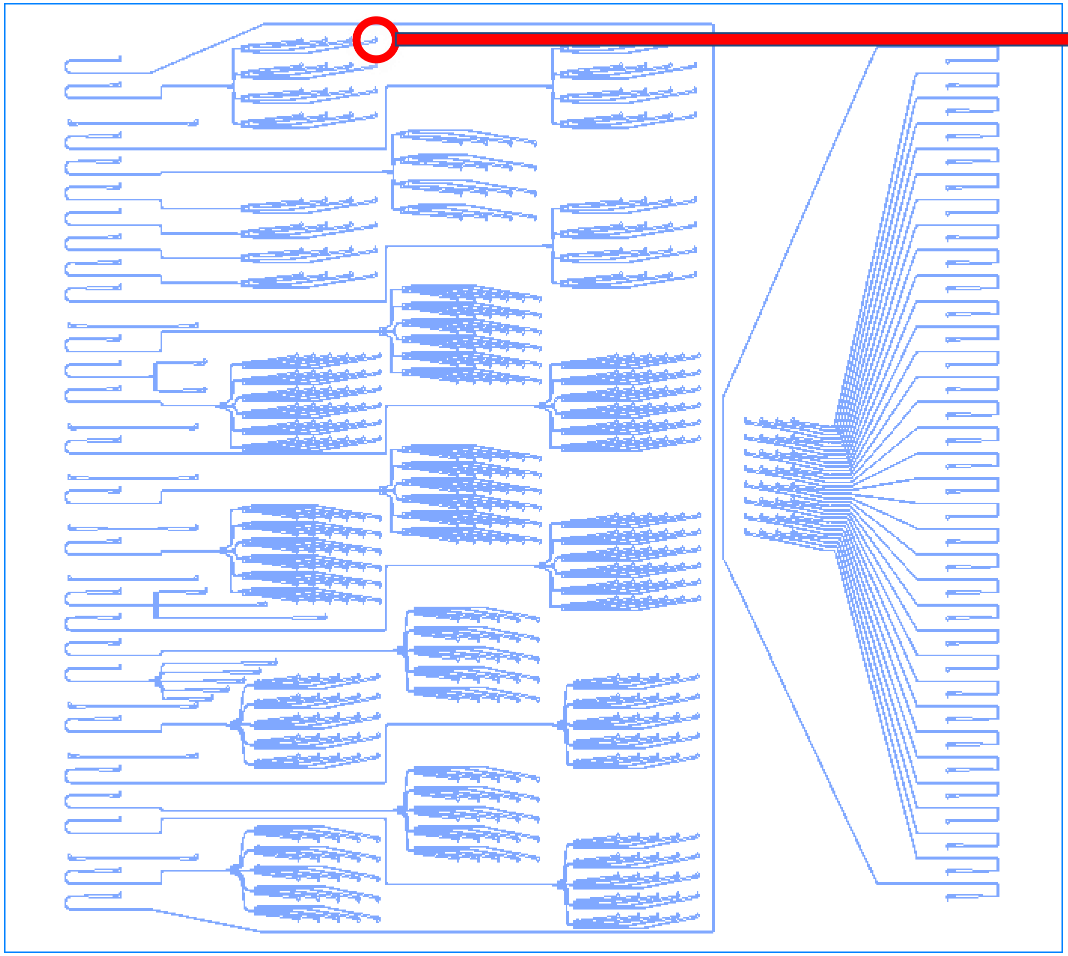
Photonic chip

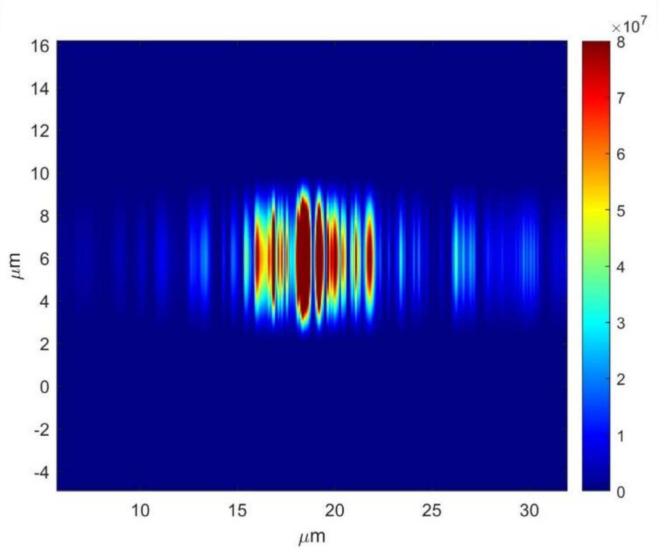
- Design of the structures in the visible range of the spectrum
- Design of scattering structures
- Respect biological constrains: 10 $\frac{\text{mW}}{mm^2}$ on 10 um diameter body

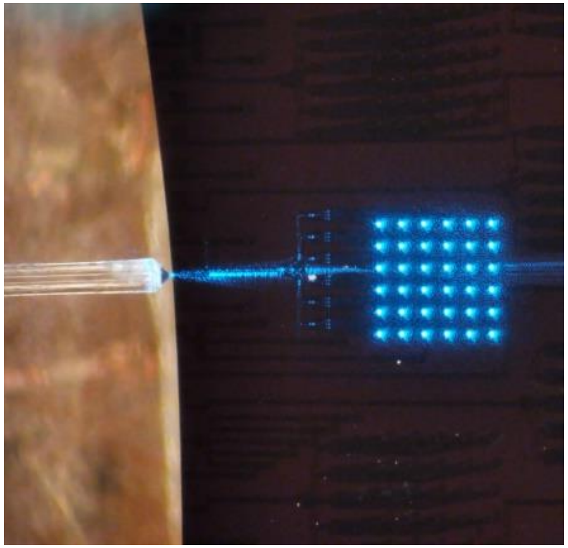


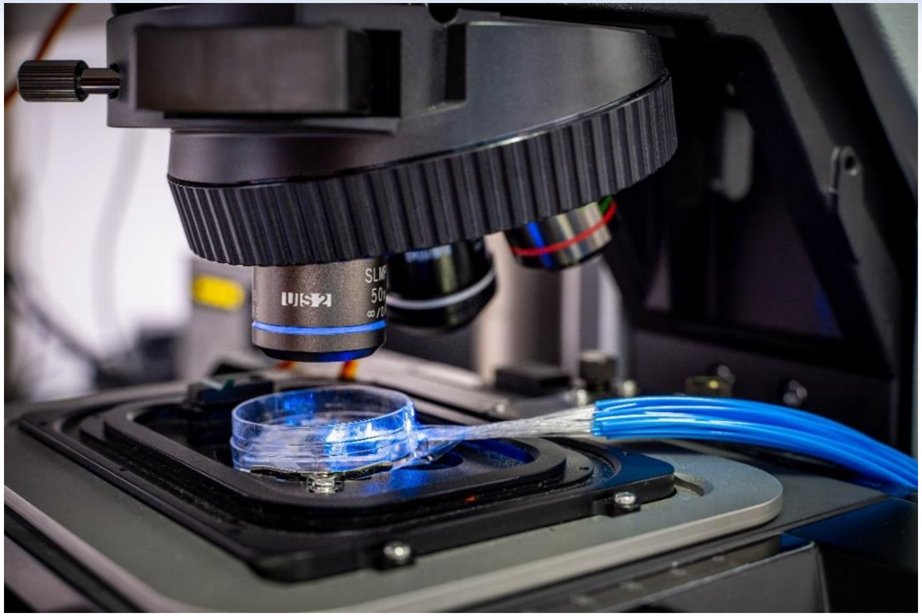
* Clara Zaccaria et. al., «Transfer matrix for grating design»

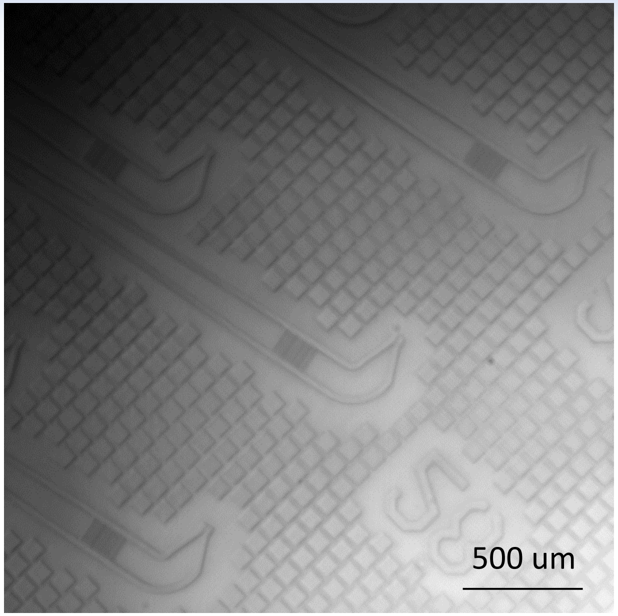
Scattering grating

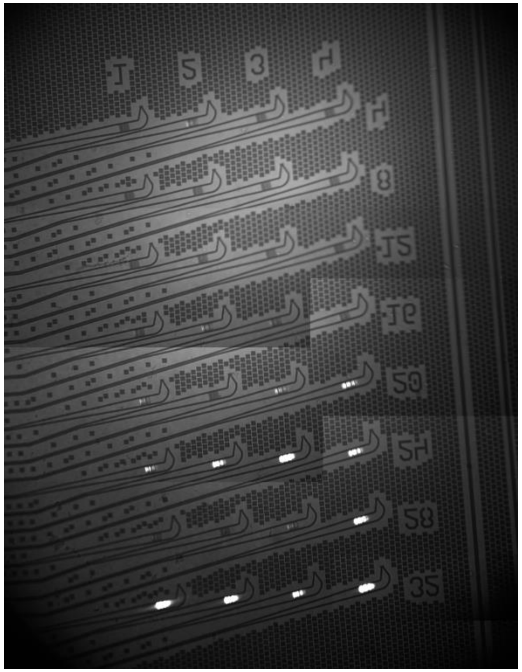


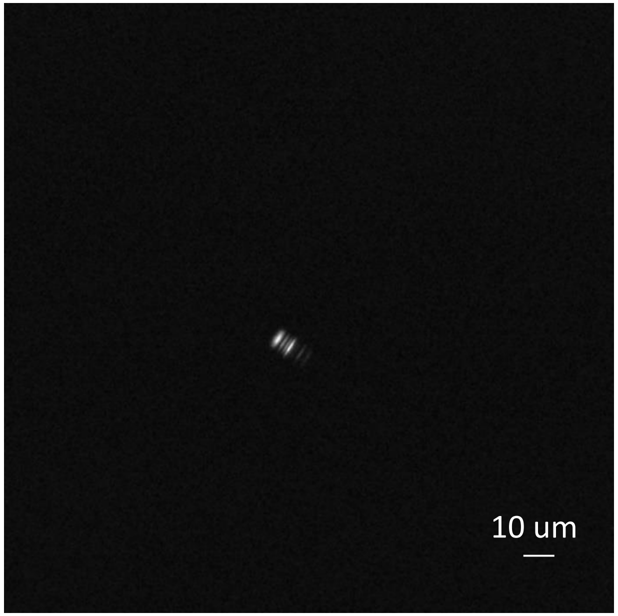




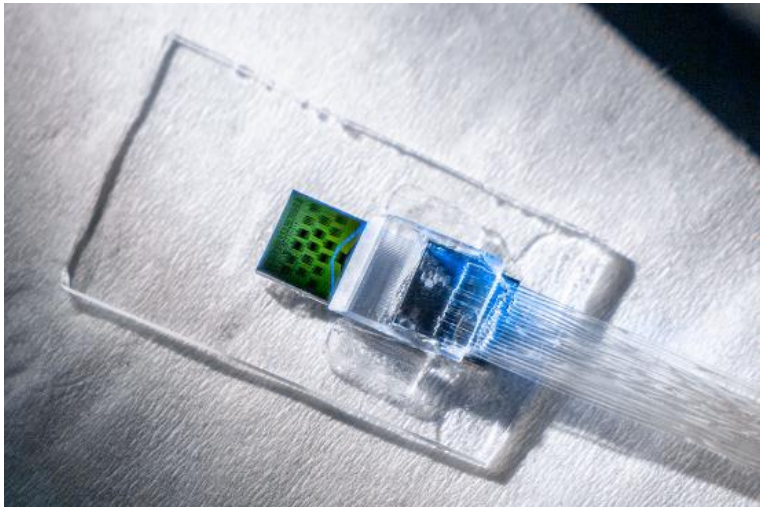

UIS 2

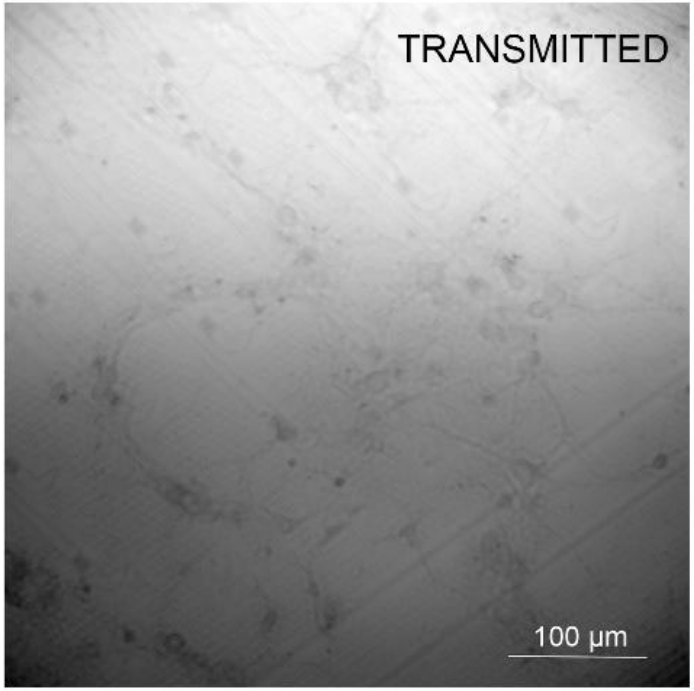

500 um

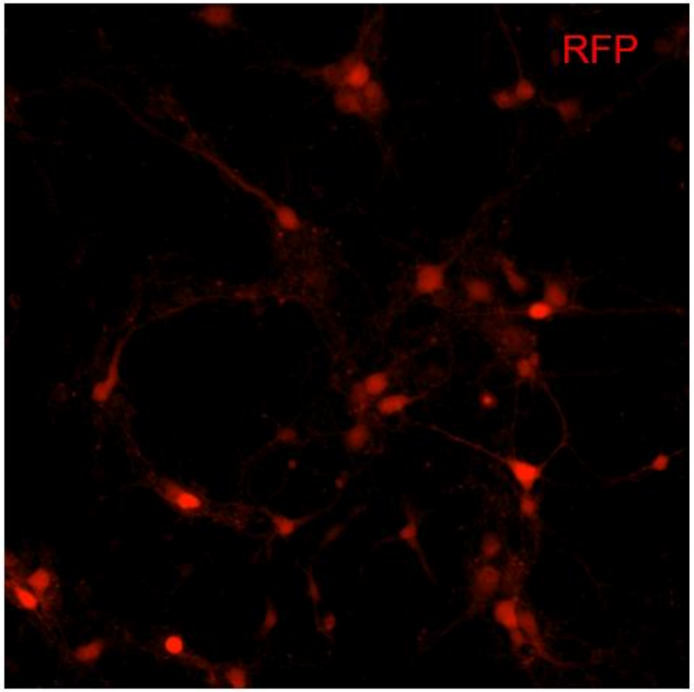



10 um

Neurons on the photonic chip

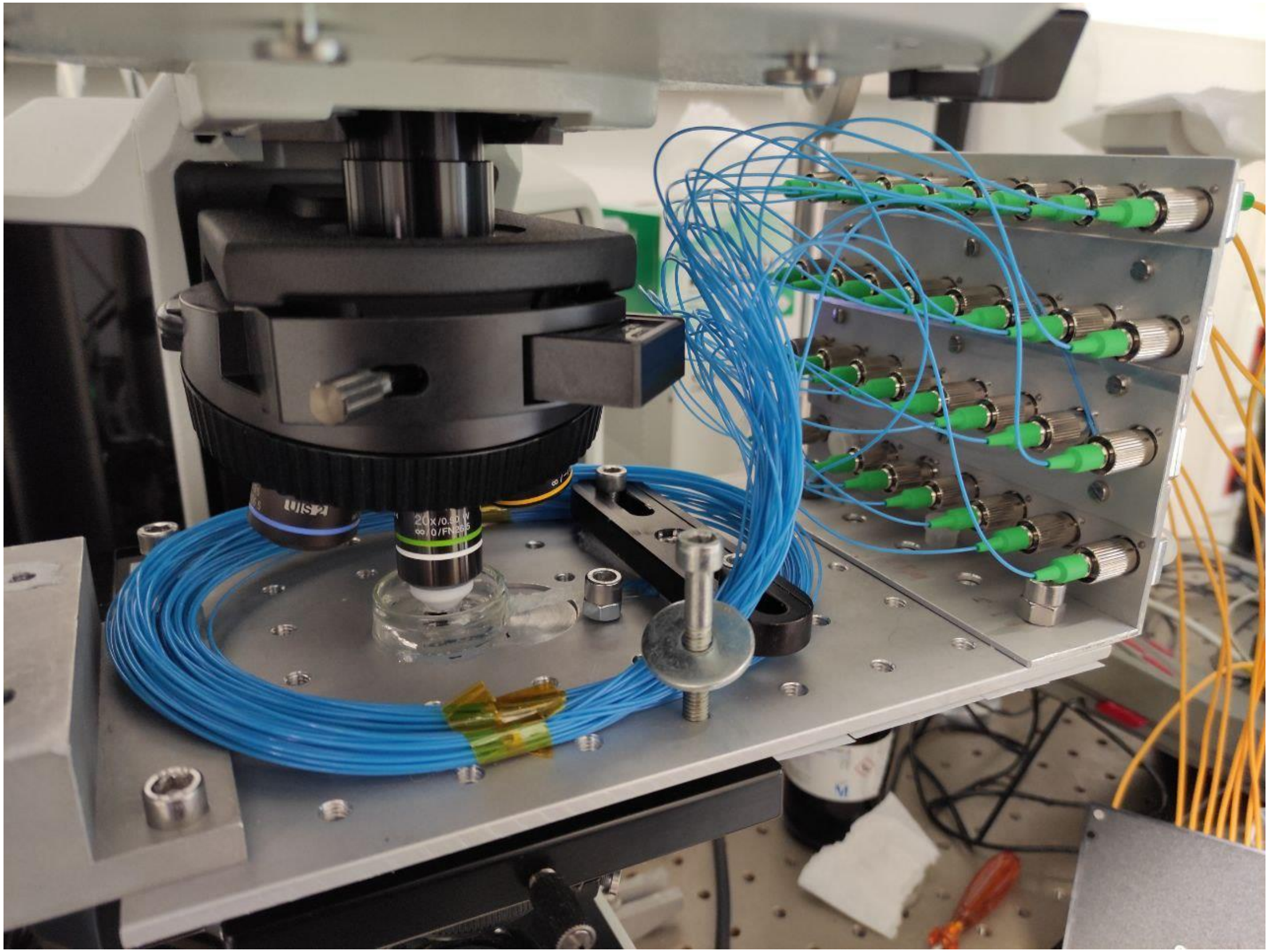






Neurons can grow on the surface of the chip

The final system



Conclusions

- Photonics neural networks are effective in computing
- Biological neural networks can record memories
- Optical signals can be used to connect photonics and biological networks

- We are on the way to achieve the vision

Acknowledgements

BACKUP
neuromorphic
photonics
and the brain

European Research Council
Established by the European Commission

https://r1.unitn.it/back-up/