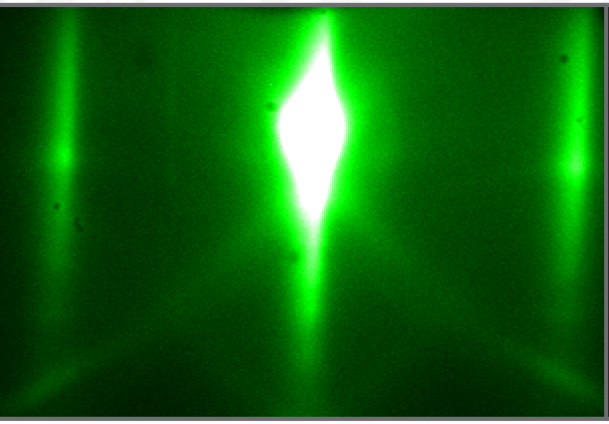
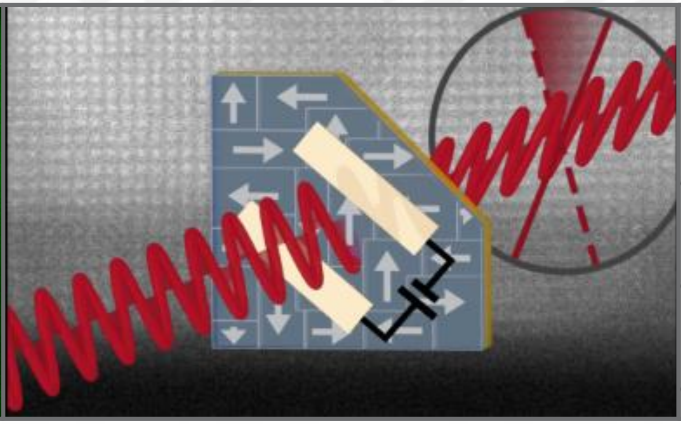
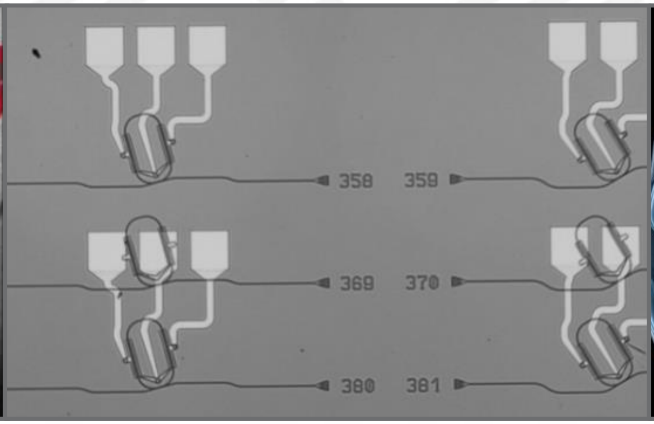
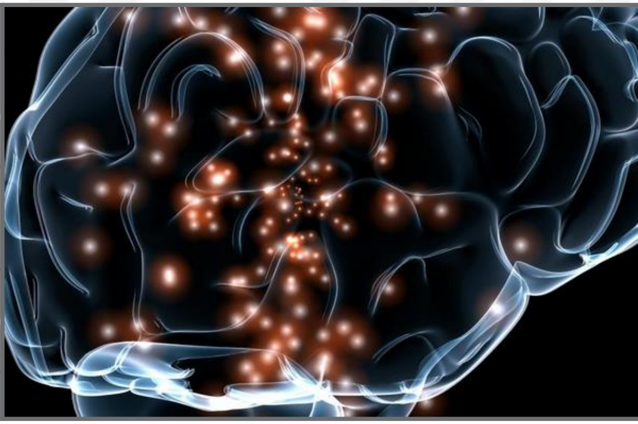
Advancing silicon photonics for traditional and novel computing paradigms

Bert Jan Offrein





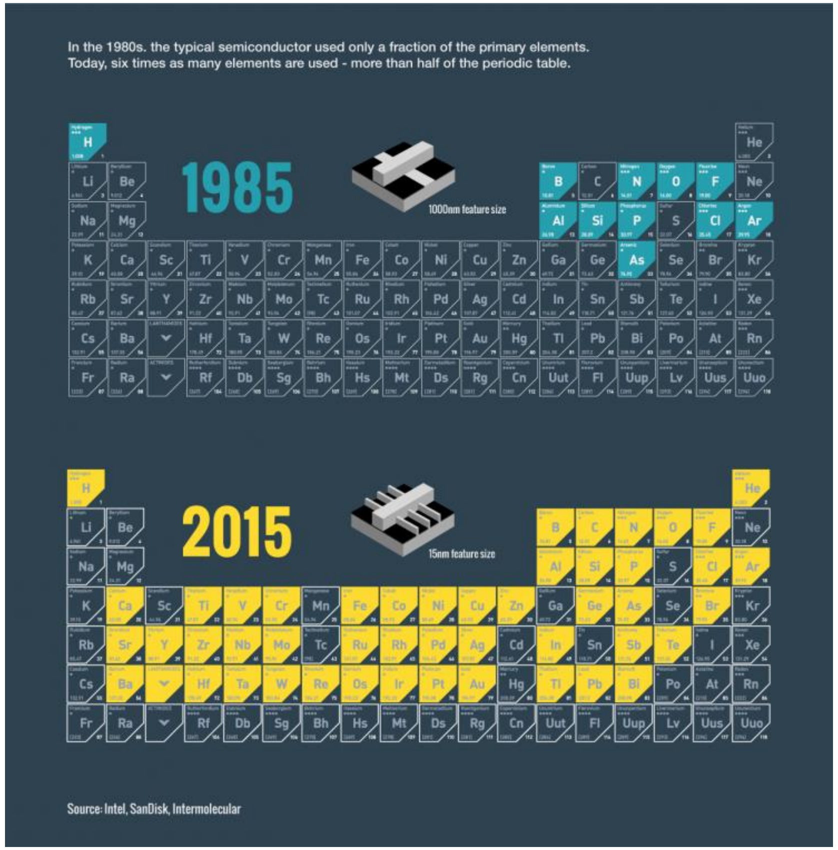




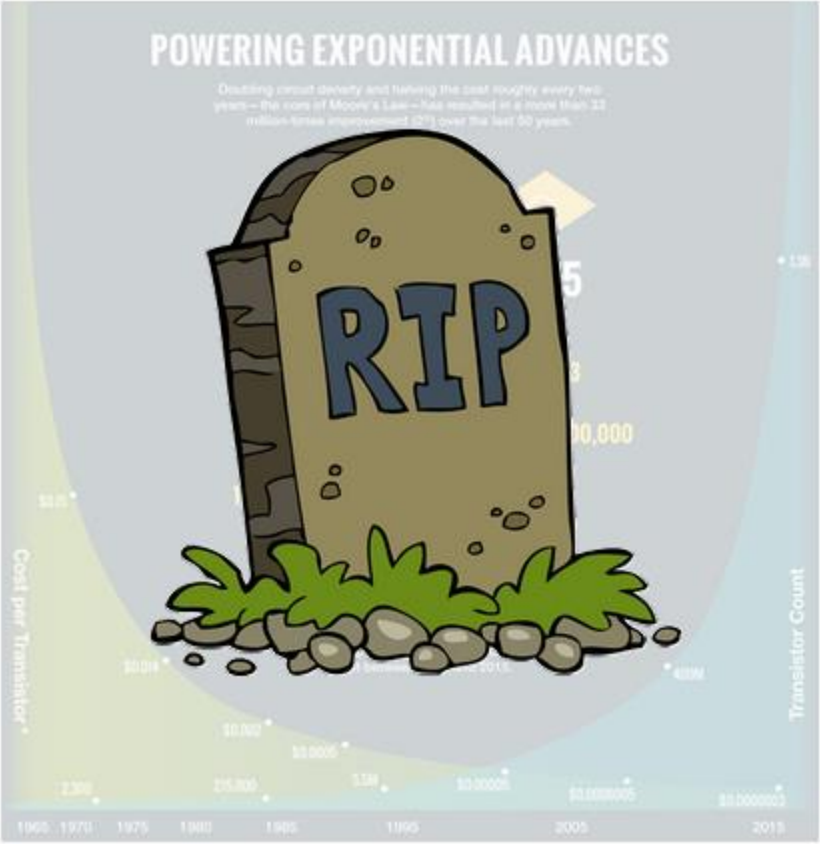
Neuromorphic Devices and Systems Group

Three pillars for Si technology

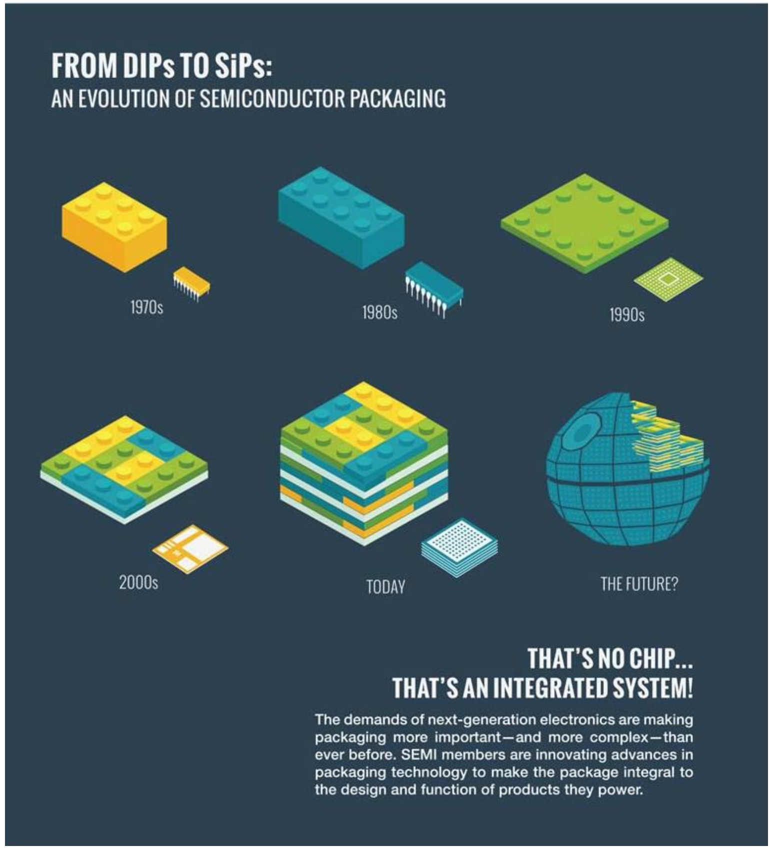
Materials



Scaling



Packaging



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Experiment: “Human Brain vs. Computer”

Task 1: Mathematics

$$\sqrt{2} = ?$$

Task 2: Image recognition

Traditional silicon scaling ended
New types of problems gain interest

Explore new functionalities, More than Moore
Explore new computing paradigms

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Outline

- Facilitate traditional scaling - Optical interconnects
  – CMOS Silicon Photonics
    - Pockels modulators, integrating $BaTiO_3$

- New computing paradigms – Neuromorphic computing
  – Dedicated hardware for neural networks
    - Photonic Synaptic Processor

- Conclusions

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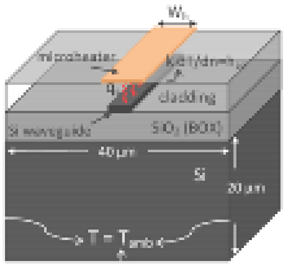
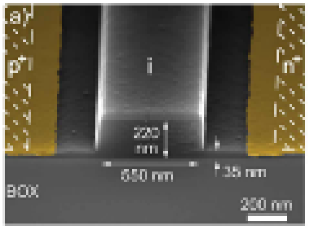
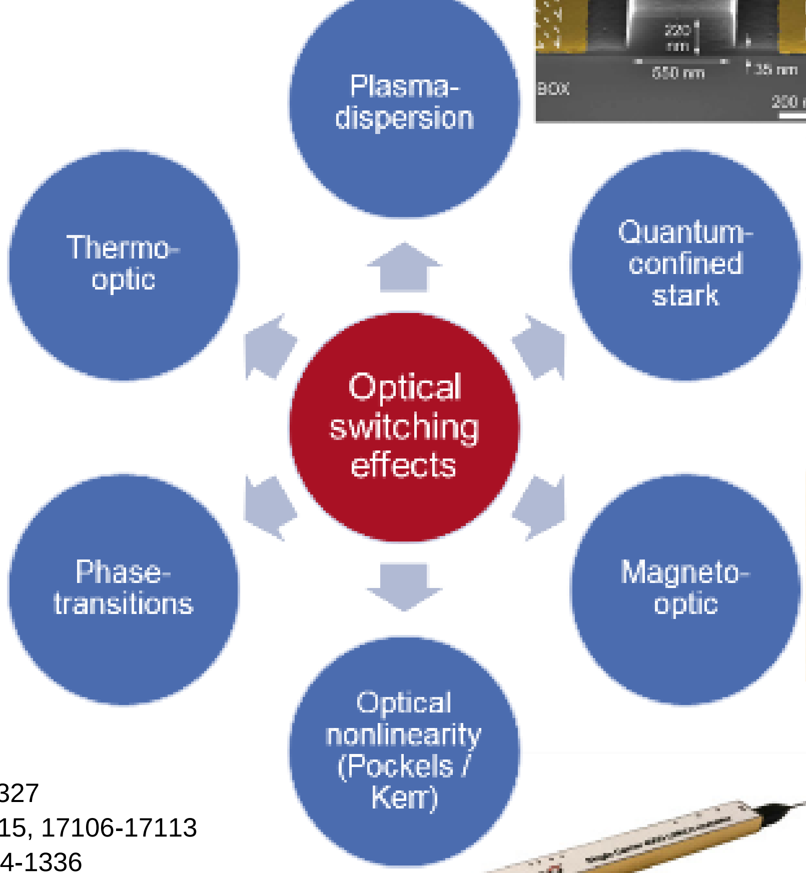
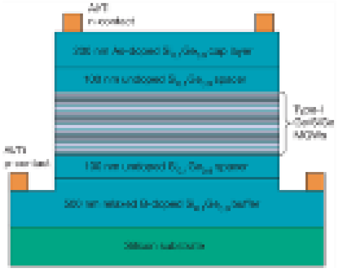
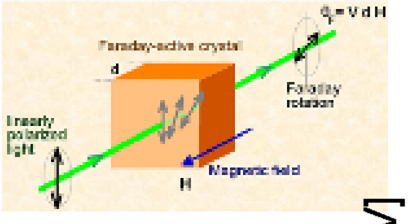
Integrated silicon photonics: modulators

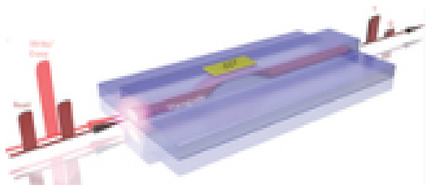












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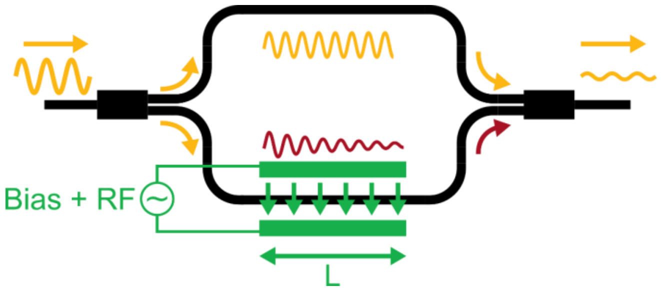

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- Warusawithana, Science, 324 (2009)
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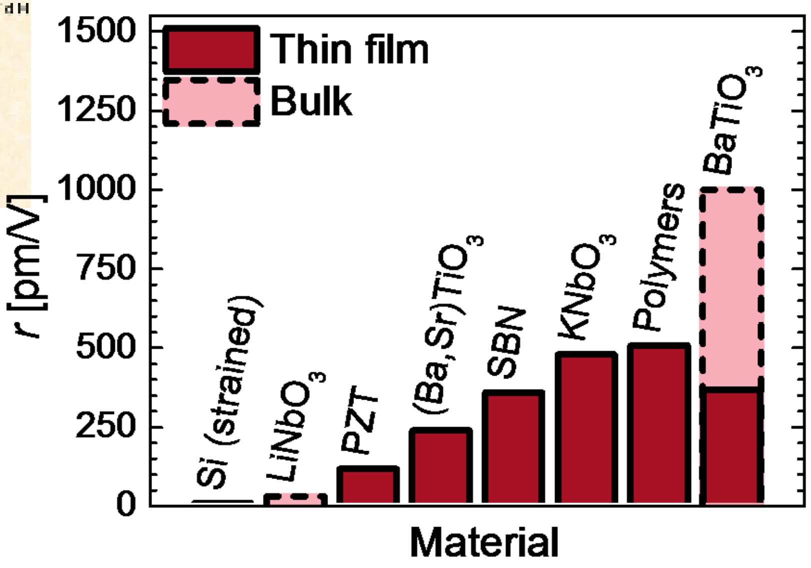

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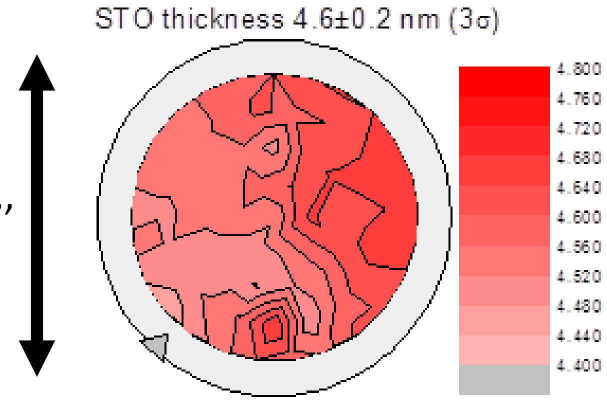
Barium titanate on silicon

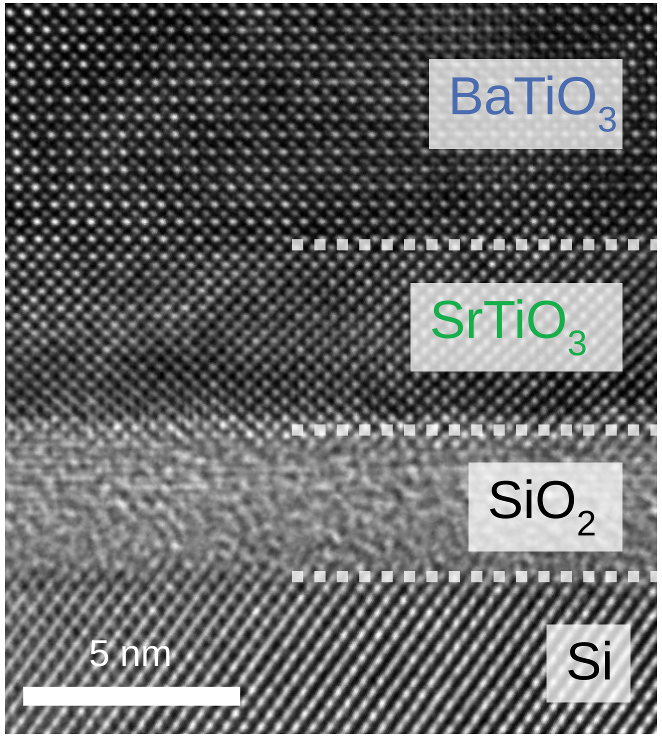
- Molecular beam epitaxy (MBE) or other (PVD, PLD, CVD)
- $BaTiO_3$ deposition on $SrTiO_3$ / Si templates
  - Tetragonal crystal structure
  - Thickness dependant polarization
- Availability on 200mm



Thickness variations of the 4 nm thick film across the wafer

$SrTiO_3$

Si



Abel et al., Nanotechnology 2013, 24, 285701

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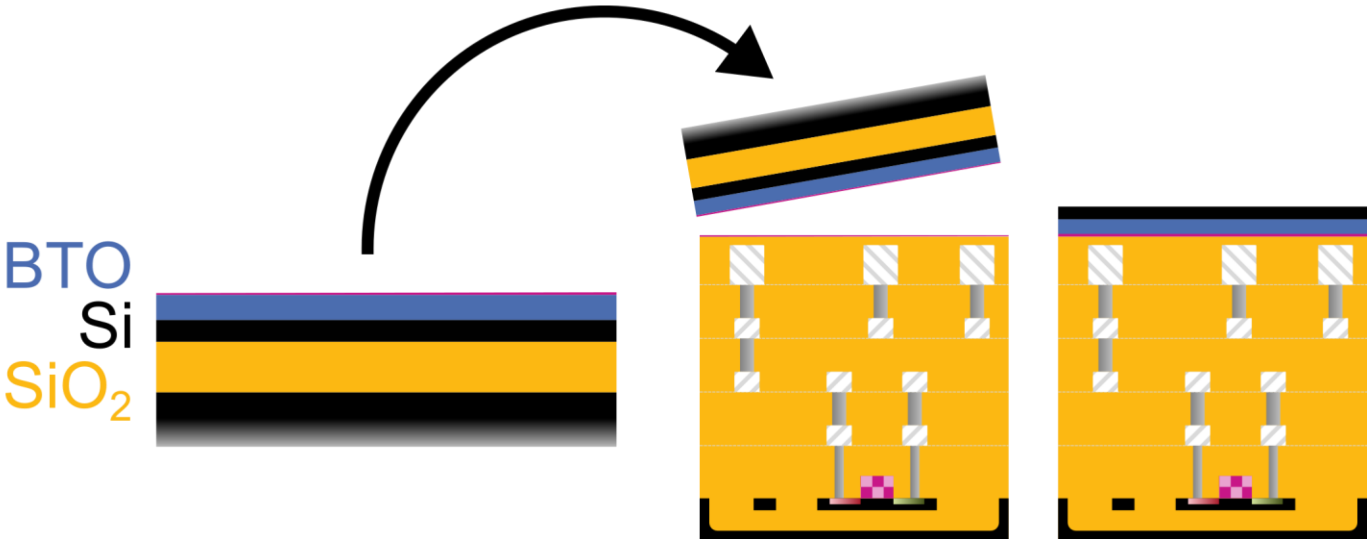
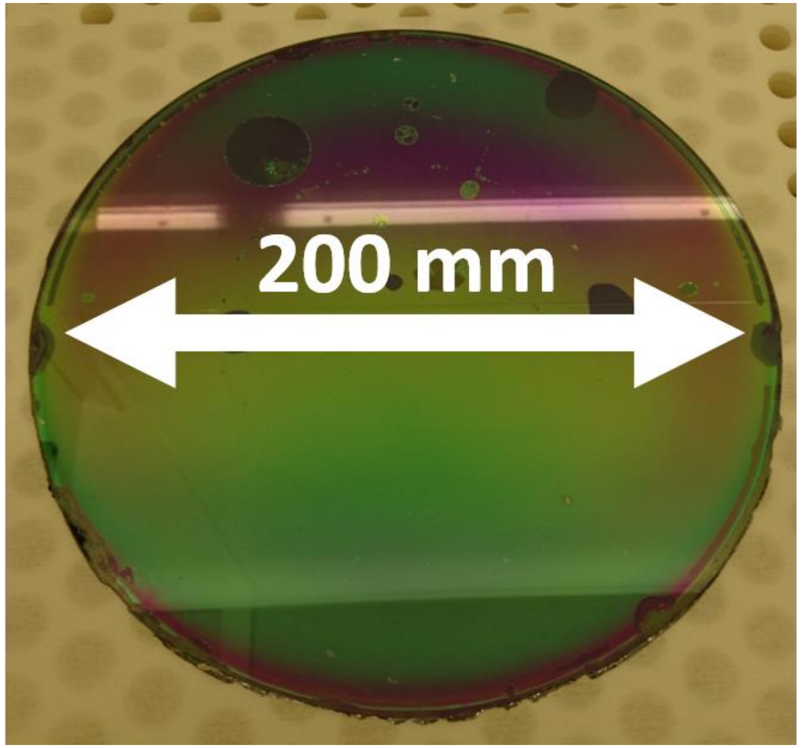
BaTiO3 integration

- Back-end-of-line integration
  - Direct epitaxy not possible on interlayer dielectric
- Transfer by wafer bonding
  - Back-end-of-line compatible
  - Thermal budget <400°C



Eltes et al., IEDM, 2017



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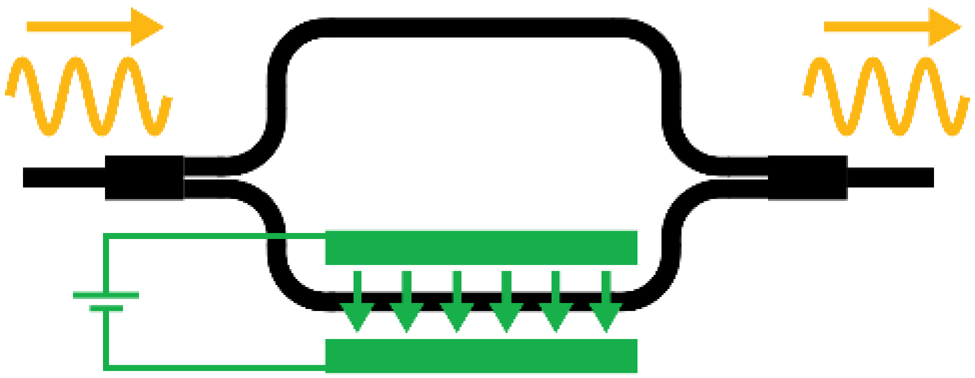
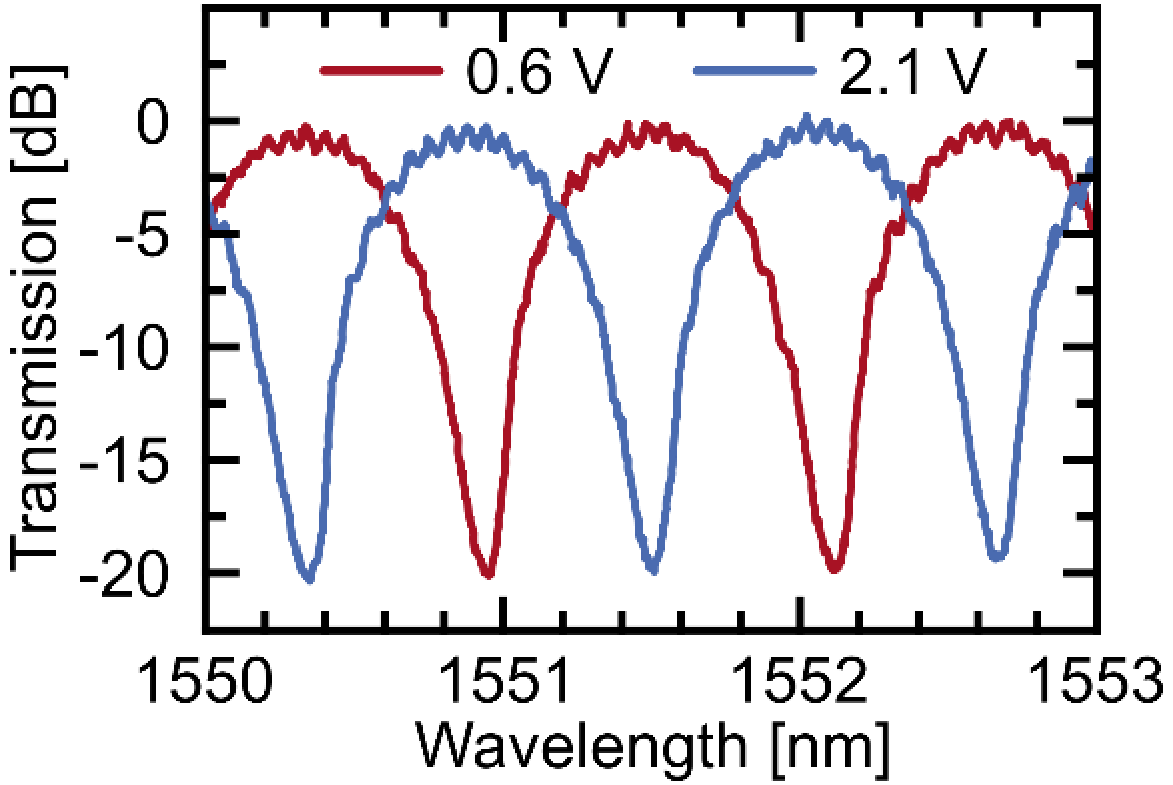
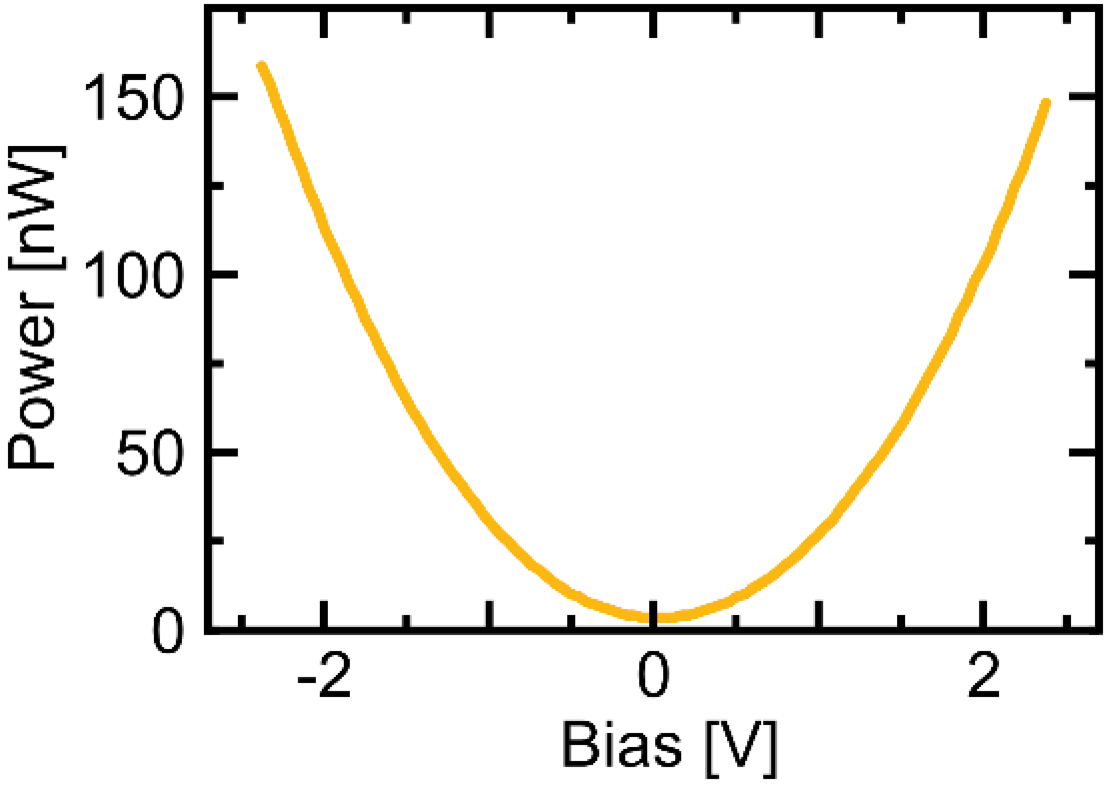
Active devices : DC characterization

- Voltage induced phase shift
- Very low DC power







F. Eltes et al., IEDM Tech. Dogest 2017

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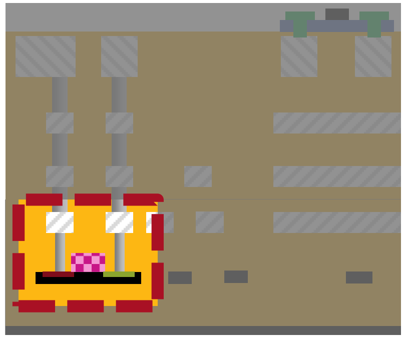
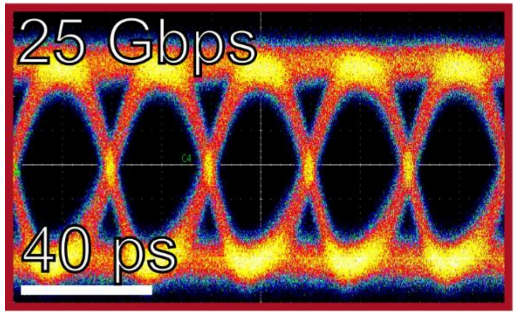
Impact on FEOL components

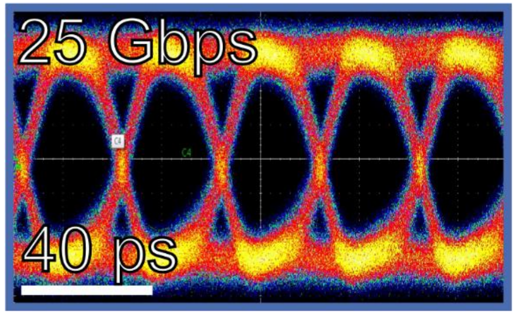
- No degradation of Ge photo diodes

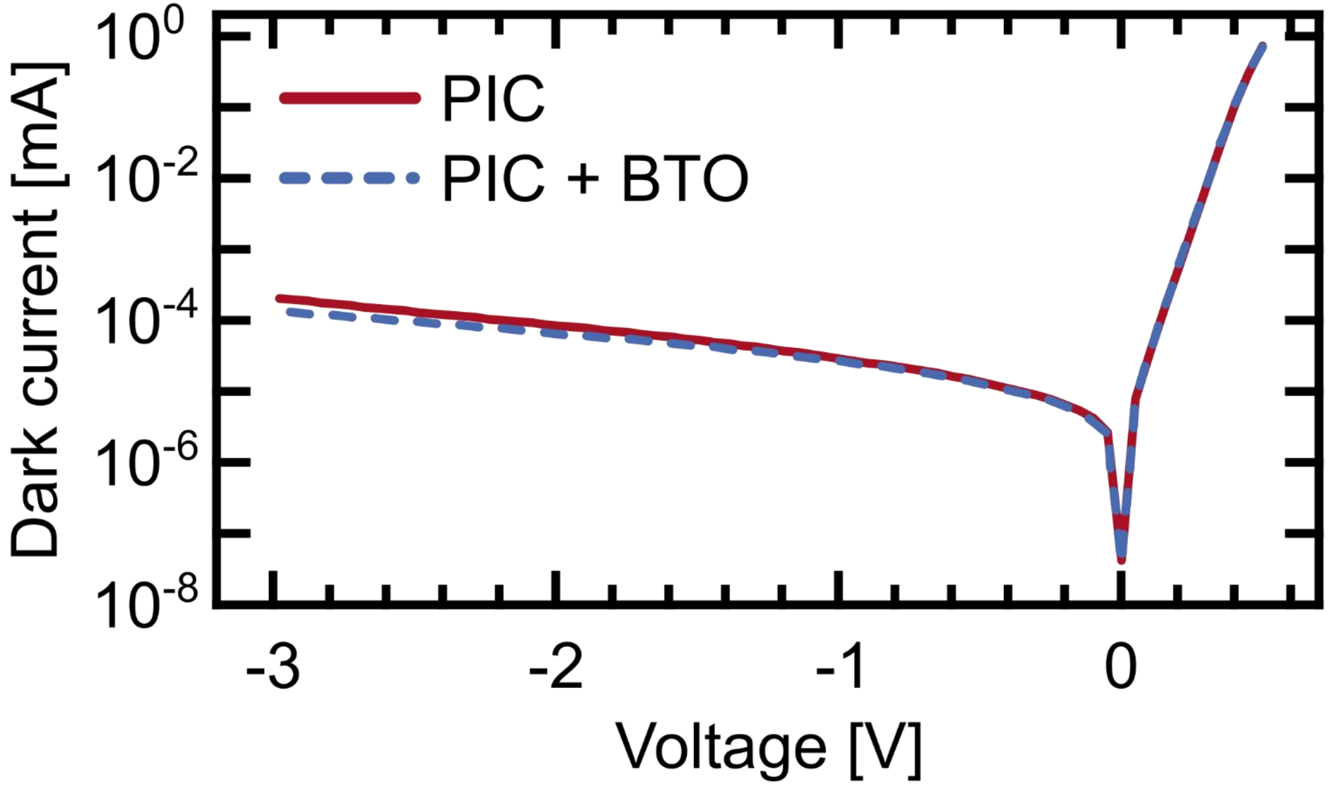


PIC



PIC + BTO





Eltes et al., IEDM, 2017

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Benchmark

Principle	Carrier modulation			Pockels
Structure	p-n	MOS	EAM	
Material	Si[1]	Si[2]	Ge[3]	BTO[6]
$V_{\pi}L$ [V·cm]	2.8	0.2	-	0.3
$V_{\pi}L\alpha$ [V·dB]	27	13	-	1.7
BW [GHz]	40	-	>50	2/20
Integration	+	+	+	+
Phase modulation only	-	-	-	+

Pursuing applications in

- High-speed modulators
- Ultra-low optical device tuning (pW)
- Cryogenic eo modulators for optical interfacing to quantum computers
- Non-volatile optical weights in photonic neuromorphic systems

[1]Patel, Opt. Exp. 2015 [2]Webster, OFC, 2015 [3]Srinivasan, JLT, 2016 [6]Eltes, IEDM, 2017

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Outline

- Facilitate traditional scaling- Optical interconnects
  - CMOS Silicon Photonics
    - Pockels modulators, integrating $BaTiO_3$
    - Embedded lasers and detectors, integrating III-V stacks
- New computing paradigms – Neuromorphic computing
  - Dedicated hardware for neural networks
    - Resistive Synaptic Processor
    - Photonic Synaptic Processor
- Conclusions

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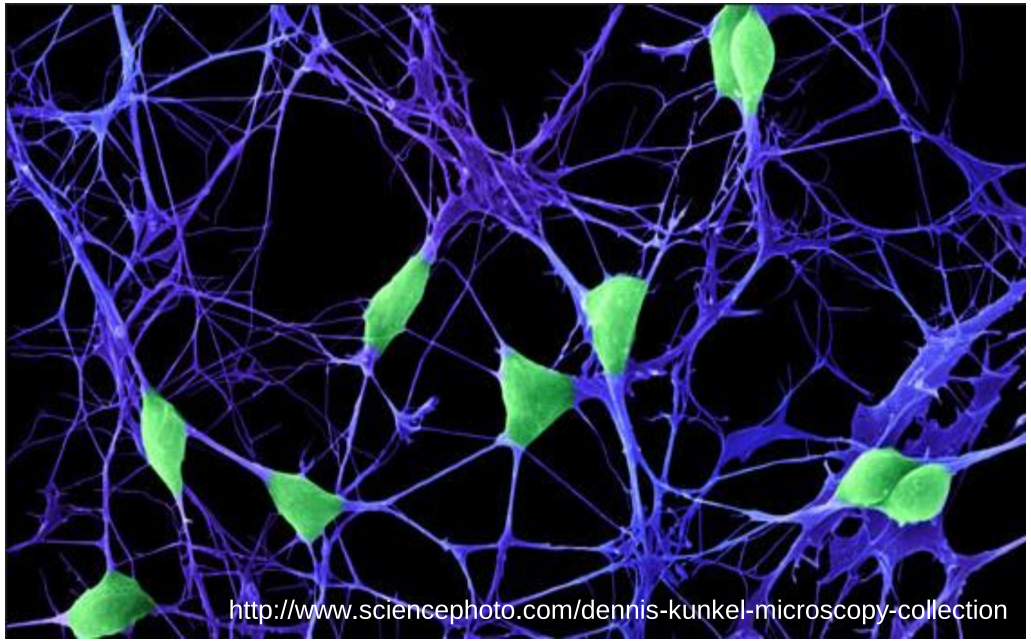
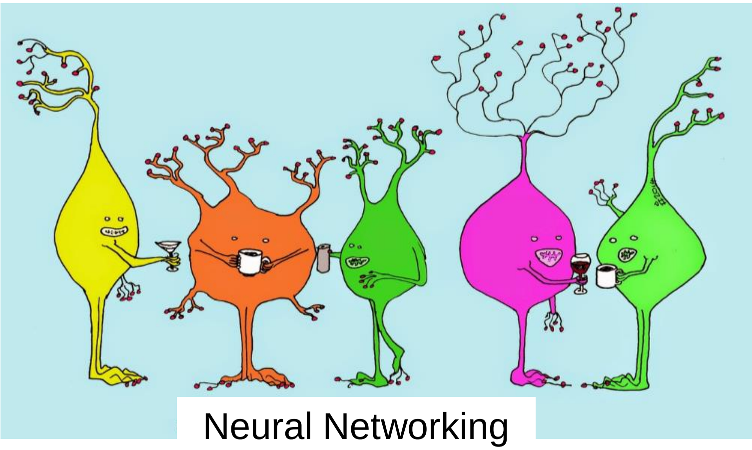
Neuromorphic Computing

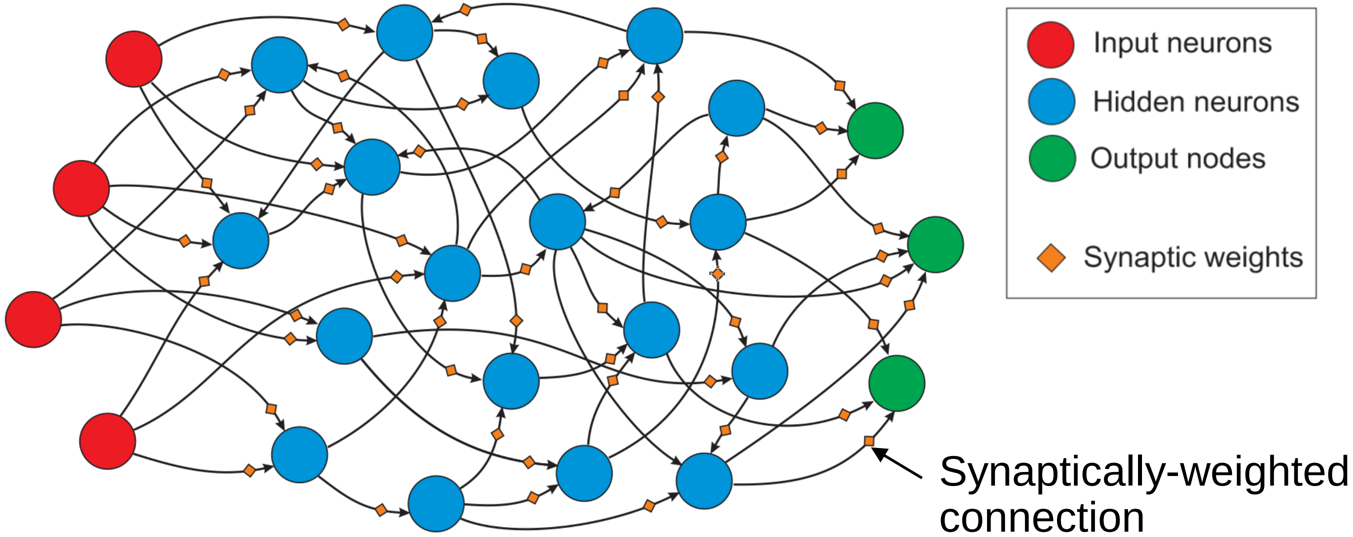
Brain at neural network level





Neural Networking

Complex model of brain-like neural network



This brain model is too complex to be fully and precisely modelled

⇩

Breakthrough in implementation and applicability of neuromorphic computing came with the concept of using simplified Artificial Neural Networks (ANNs)

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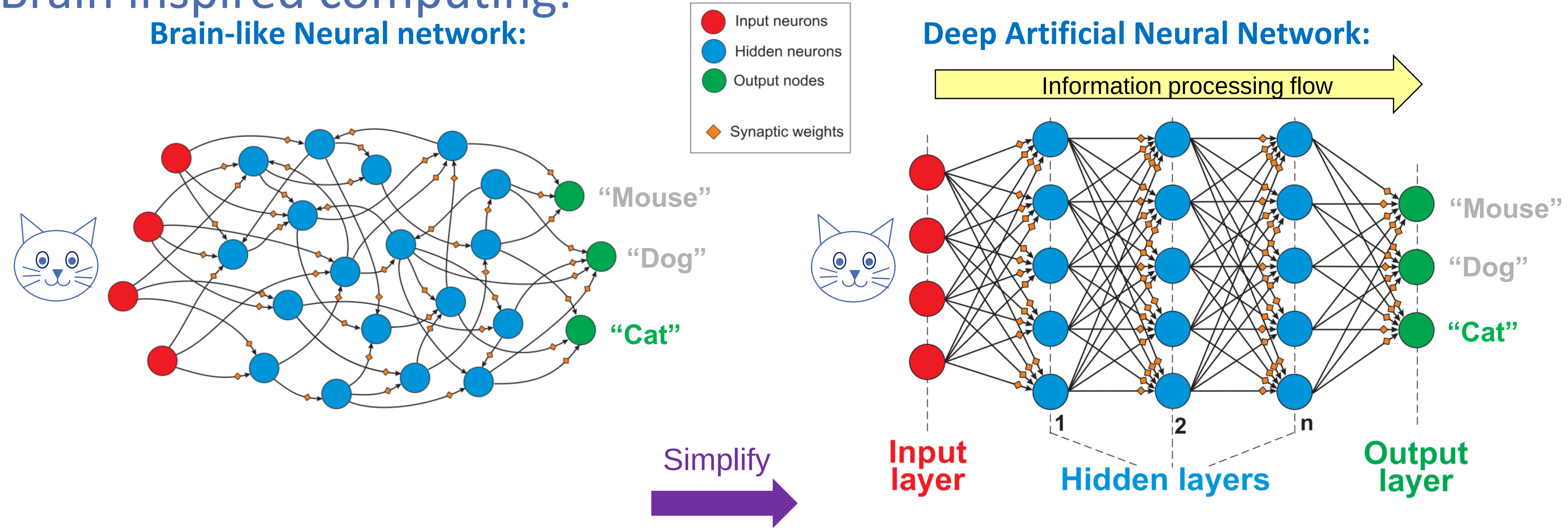
Brain inspired computing:

Brain-like Neural network:

Deep Artificial Neural Network:



- Omni-directional signal flow
- A-synchronous pulse signals
- Information encoded in signal timing

➔ Difficult to implement efficiently on standard computer hardware

- Feed-forward sequential processing
- Information encoded in signal amplitude
- Neuron activation: Accumulate + Threshold
- **Training: Backpropagation Algorithm**

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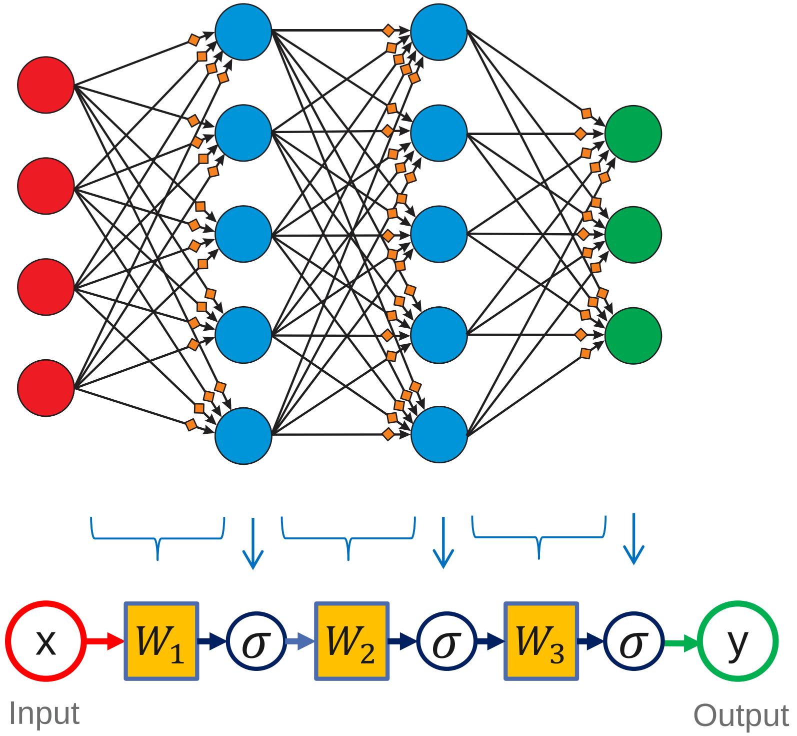
Training: Backpropagation algorithm

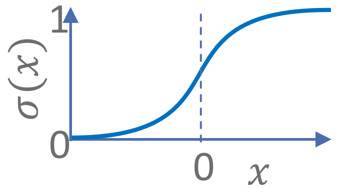
Neural net as chain of vector operations:



→ : Signal vector

W_n : Synaptic weight matrix

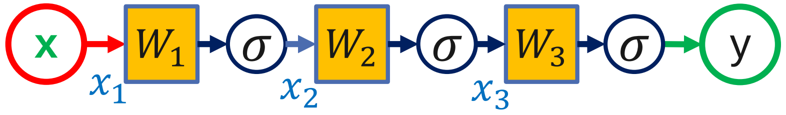
σ : Per-element neural activation function (sigmoid)



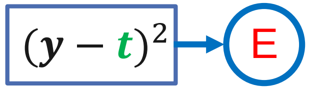
Backpropagation algorithm:

For many training cases **x** with target response **t**:

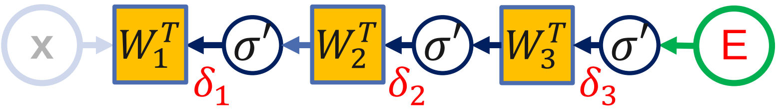
1. Forward Propagate:



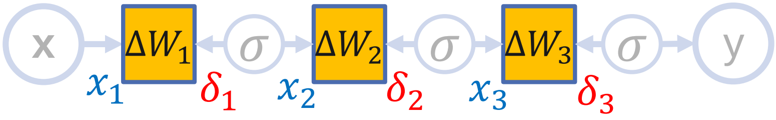
2. Determine output error:



3. Backward Propagate: Determine neuron input influence δ on error **E**:



4. Adjust the active weights, proportional to their influence on the error: $\Delta W = -\eta\, \boldsymbol{x} \otimes \boldsymbol{\delta}$



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Efficient training of Deep Artificial Neural Networks:

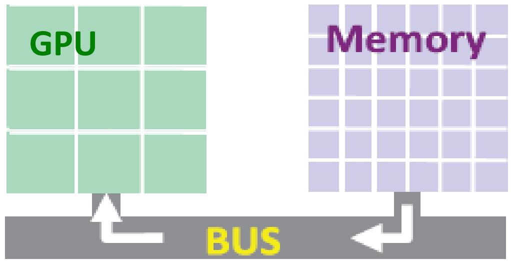
Training by Backpropagation Method:

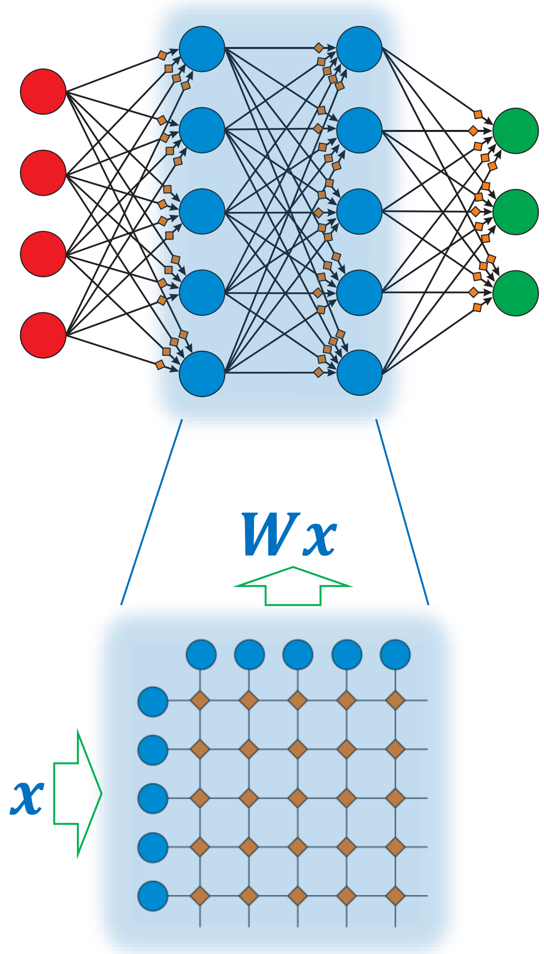
- **Processing dominated by many large matrix operations**
  - Forward Propagation: $W_{1,2..}$
  - Backward Propagation: $W^T_{1,2..}$
  - Weight Update: $\Delta W_{1,2..}$

Scale $\propto N^2$

Neurons/layer

- **Inefficient on standard Von Neumann systems**:
  - (Mostly) Serial processing
  - Low computation to IO ratio → Memory bottleneck





For fast and efficient neural network data processing:

- Fully parallel processing
- Tight integration of processing and memory
- Analog signal processing

Crossbar arrays

- Electrical
- Optical

📖 G. W. Burr et al., "Tech. Dig. - Int. Electron Devices Meet. IEDM, vol. 2016–Febru, no. 408, p. 4.4.1-4.4.4, 2016.
📖 T. Gokmen and Y. Vlasov, Front. Neurosci., vol. 10, no. JUL, pp. 1–13, 2016.

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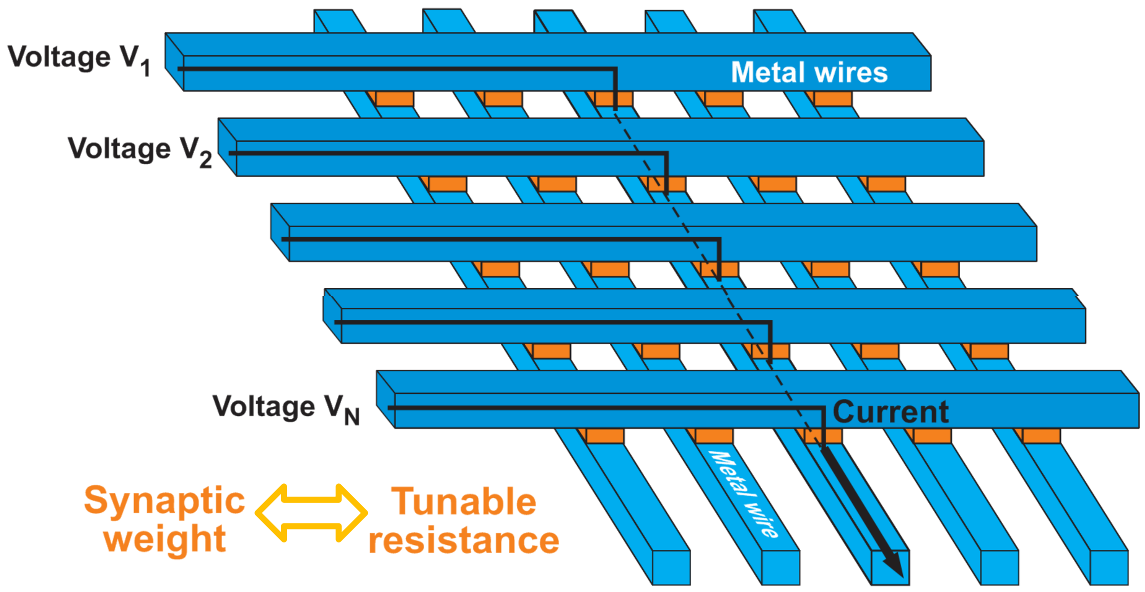
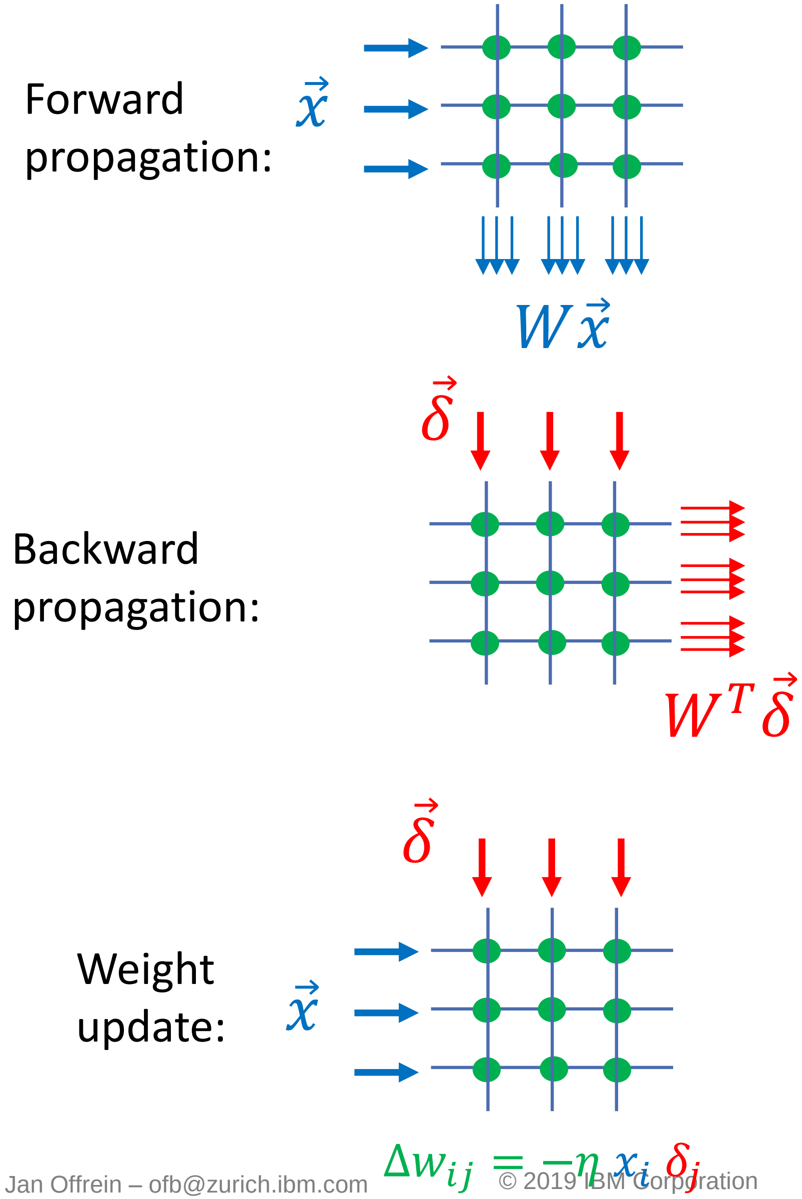
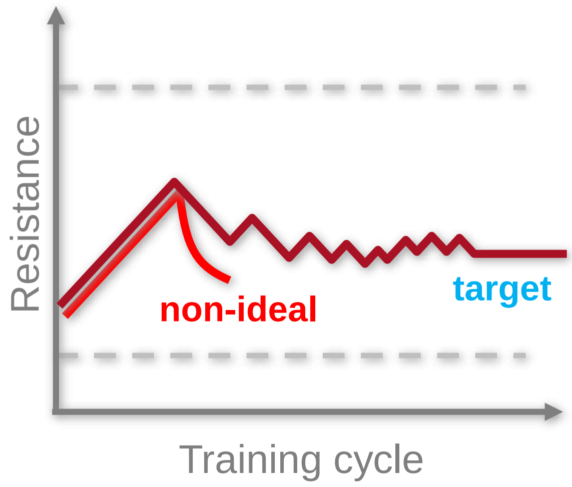
Analog crossbar arrays:

Electrical crossbar array:





- **Weight update:** proportional to signals on row and column
  - Symmetric increase and decrease of weight
  - ~1000 analog levels required
- **Physical challenge**: Identify material systems that meet these requirements



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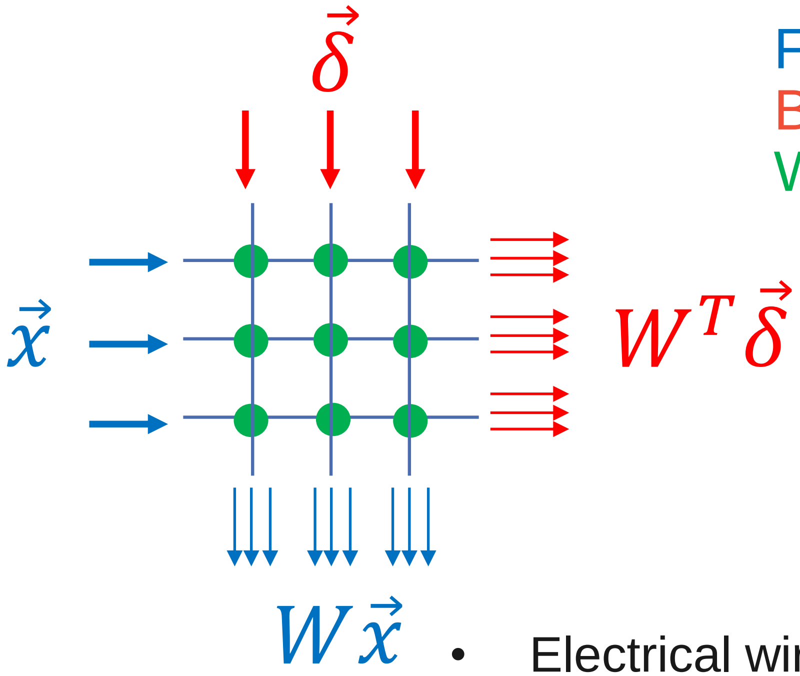
Photonic crossbar unit - operating principle

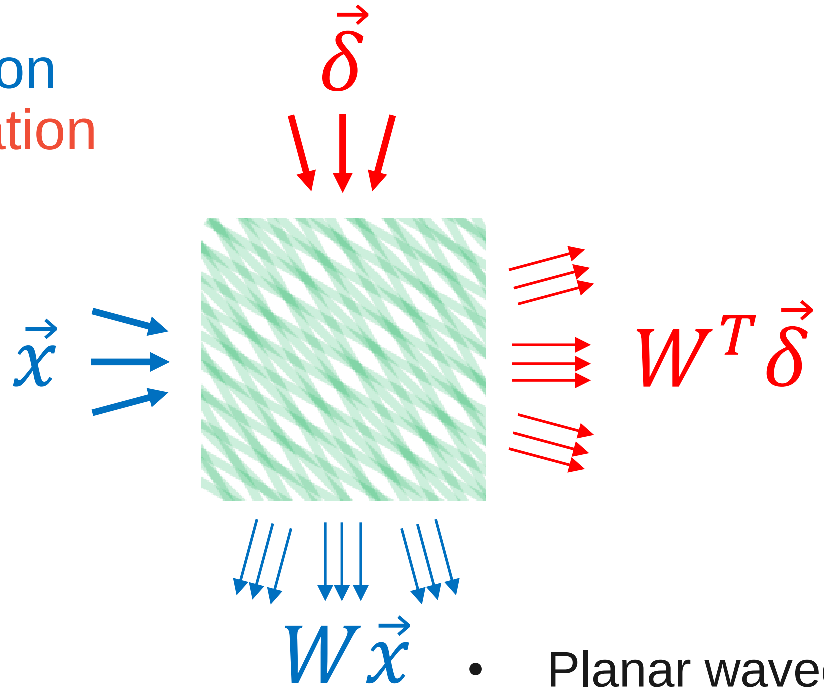
Electrical crossbar



Forward propagation
Backward propagation
Weights

- Electrical wires
- Local weights
- Resistance tuning

Photonic crossbar



- Planar waveguiding
- Distributed weights
- Refractive index tuning

Writable photorefractive gratings provide the same functionality as the tunable resistive elements in a crossbar unit

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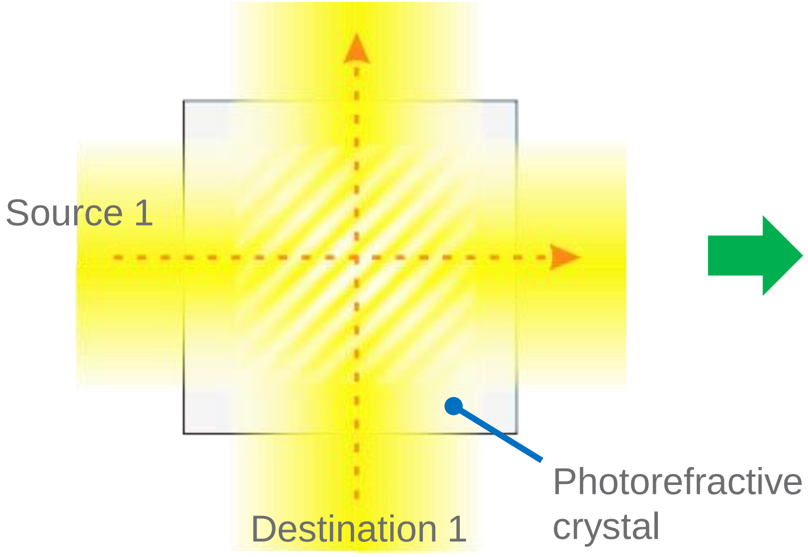
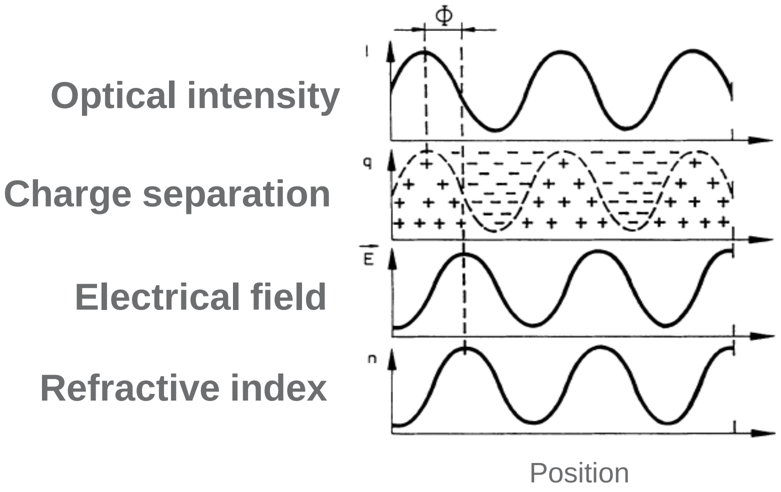
Optical crossbar arrays: Holographic storage and signal processing

Weight Storage:

Interference pattern:

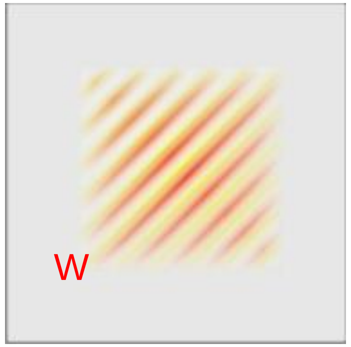


Photorefractive effect:



Cornelia Denz, Optical Neural Networks, 1998.

Stored diffraction grating:



Synaptic weights are stored as refractive index gratings in a photorefractive material:

- Grating are written by two interfering optical beams
- Photorefractive effect: Optically active electron traps + Pockels effect → refractive index grating
- Linear and symmetric process

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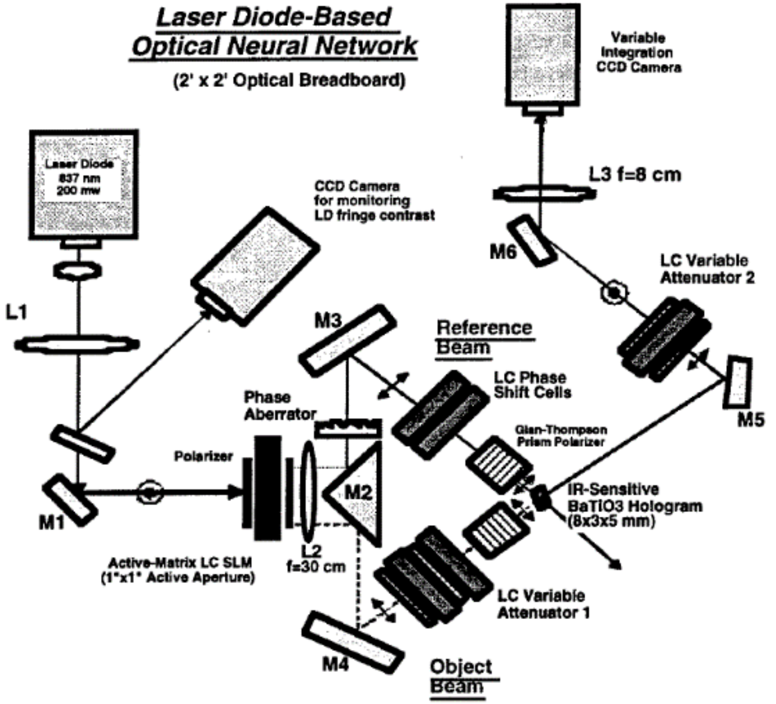
IBM

Optical crossbar arrays: Integrated Solution

Concept demonstrated in bulk optics

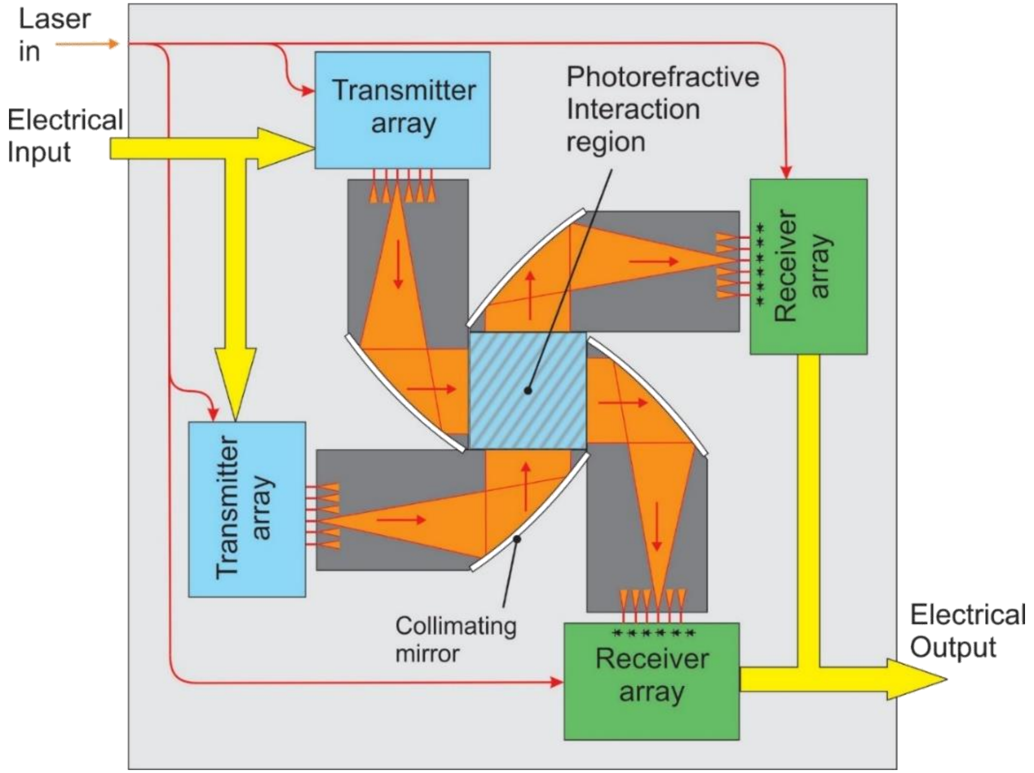
- Backpropagation training of neural networks with hidden layers
- Large setup, slow electro-optics, stability issues



📖 Yuri Owechko and Bernard H. Soffer, "Holographic neurocomputer utilizing laser diode light source“, 1995

Our approach: Miniaturize using Integrated Optics

- Electro-optic conversion and beam shaping optics on a silicon photonics chip
- Memory: Photorefractive thin film on silicon



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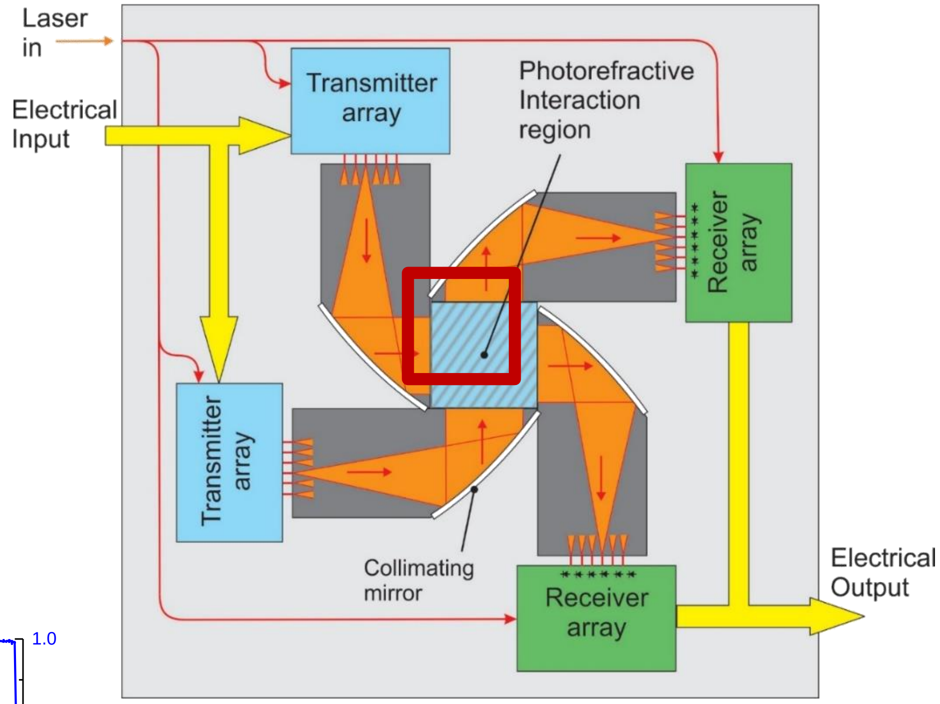
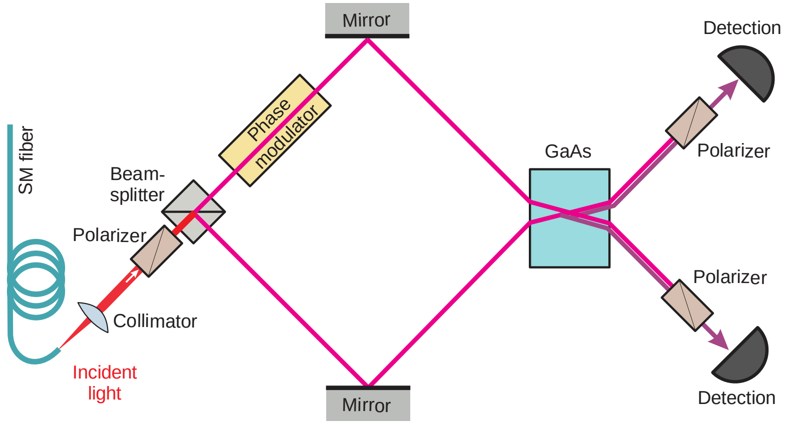
Photonic weight processing unit: Building blocks

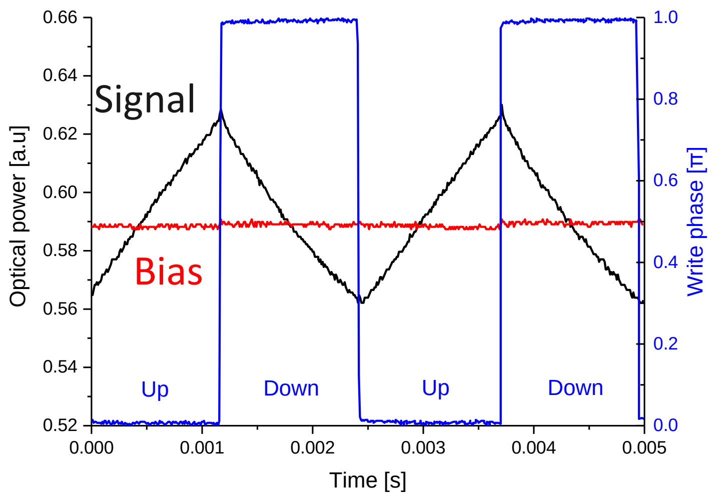


Photorefractive interaction region:

- Stores synaptic weights as refractive index gratings
- Photorefractive material: Semi-Insulating GaAs
  - Matches Si-Photonics wavelength range
  - Compatible with III-V on Silicon processes

Two-wave mixing in bulk GaAs crystal ≈ single synapse:





- Low asymmetry
- High dynamic range
- Bipolar weight storage
- To be confirmed in thin film

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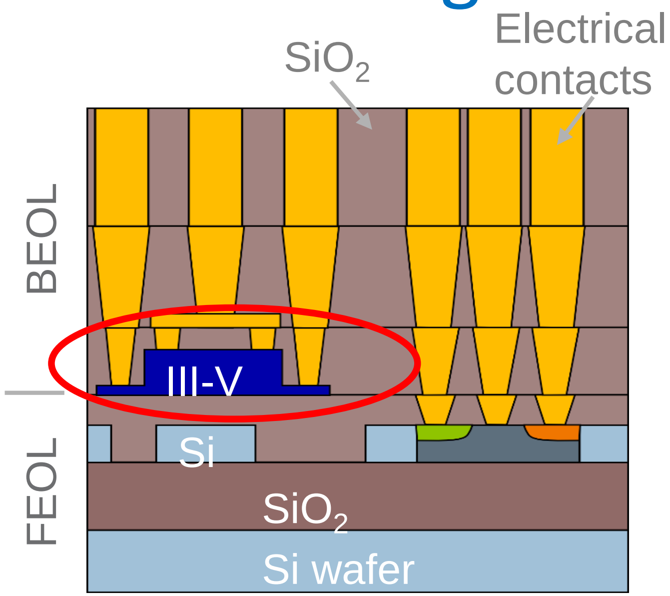
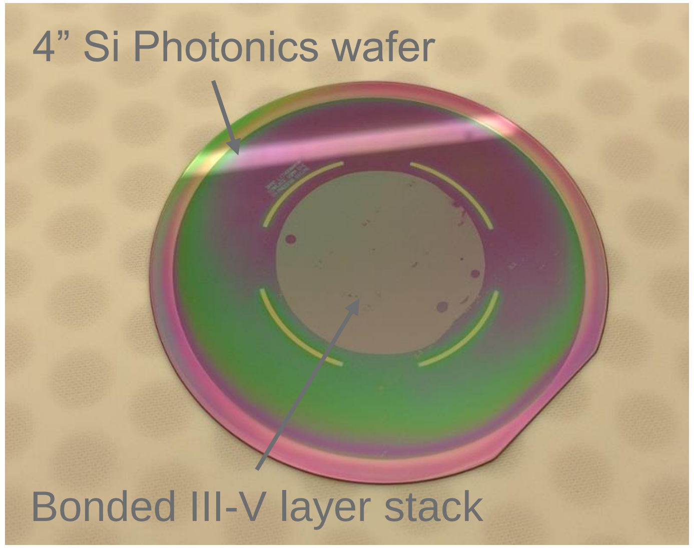
Photonic weight processing unit: Building blocks

Integration of the photorefractive layer:

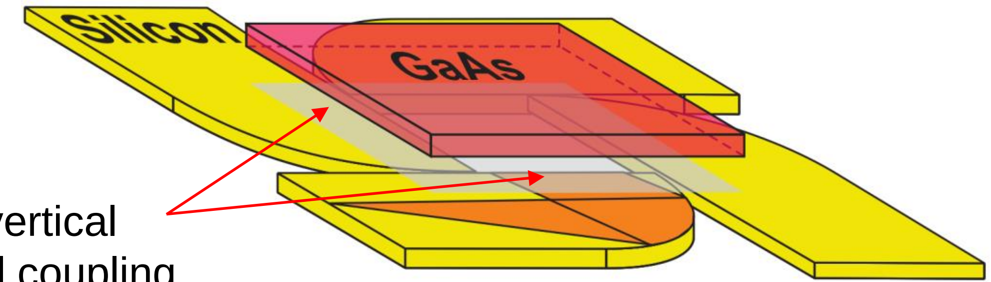
- Bonding technology as demonstrated for other III-V on Si projects:
  - Gain layers for integrated light sources
- Oxide bonding to Silicon-photonics stack



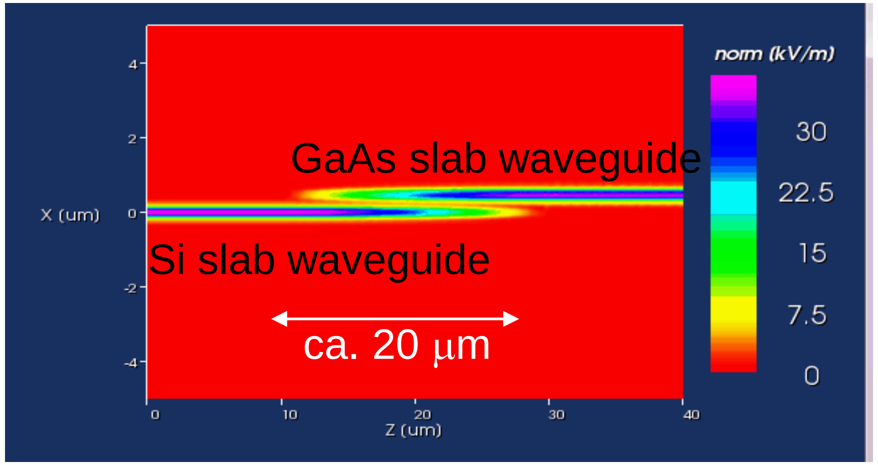


M. Seifried *et al.*, "Monolithically Integrated CMOS-Compatible III–V on Silicon Lasers“ doi: 10.1109/JSTQE.2018.2832654.

- Vertical directional coupling for efficient coupling of light between Si-photonic and GaAs layers



Vertical directional coupling



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Summary

- Silicon technology remains the basis for computing devices
  - Leverage existing processes, infrastructure and know-how
  - Continuous extending of materials and function

- Silicon Photonics is currently becoming a major driver for employing optical interconnects
  - Intra- and inter-datacenter communication
  - Integration is functions is a must for cost and assembly reasons

- New computing paradigms – Neuromorphic computing - provides a path to handle unstructured data
  - Analog signal processing in crossbar arrays
  - Parallel processing of key algorithms in neural networks
  - Electrical and optical implementations

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Thank you
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