Silicon Photonics for Neuromorphic Computing

Acceleration of Deep Neural Network training

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Overview

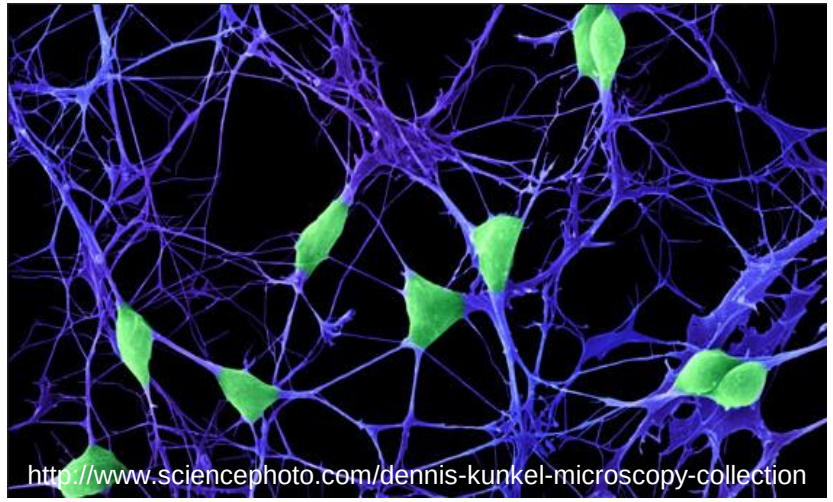
- Neuromorphic computing ➔ Artificial Deep Neural Networks
  - Training of deep neural networks
  - Processing of synaptic weights
  - Need for non Von-Neumann computing architectures
- Analog synaptic weight storage and processing in crossbar arrays
  - Electric crossbar arrays
  - Optical crossbar array using holographic storage and signal processing
- Integrated optical crossbar array in Silicon Photonics
  - Optical components
  - Holographic storage medium
- Summary & Outlook

Neuromorphic computing = Brain inspired computing

Motivation: The outstanding features of the (human) brain:

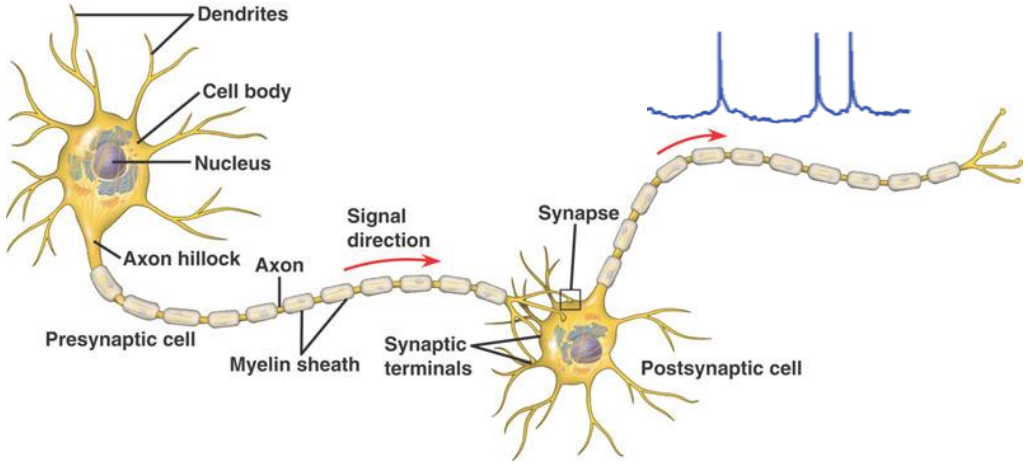
- **Power efficiency** (human brain consumes ~ 20 W)
- **Remarkable pattern recognition performance:** Recognition of (subtle) patterns buried in noise

Brain at neural network level:



- Human brain: ~ 100 billions neurons
- Each neuron is connected to 1'000 – 10'000 other neurons by synapses
- Signal transmitted by a synapse is adjustable: "synaptic weight"

Neuron level:

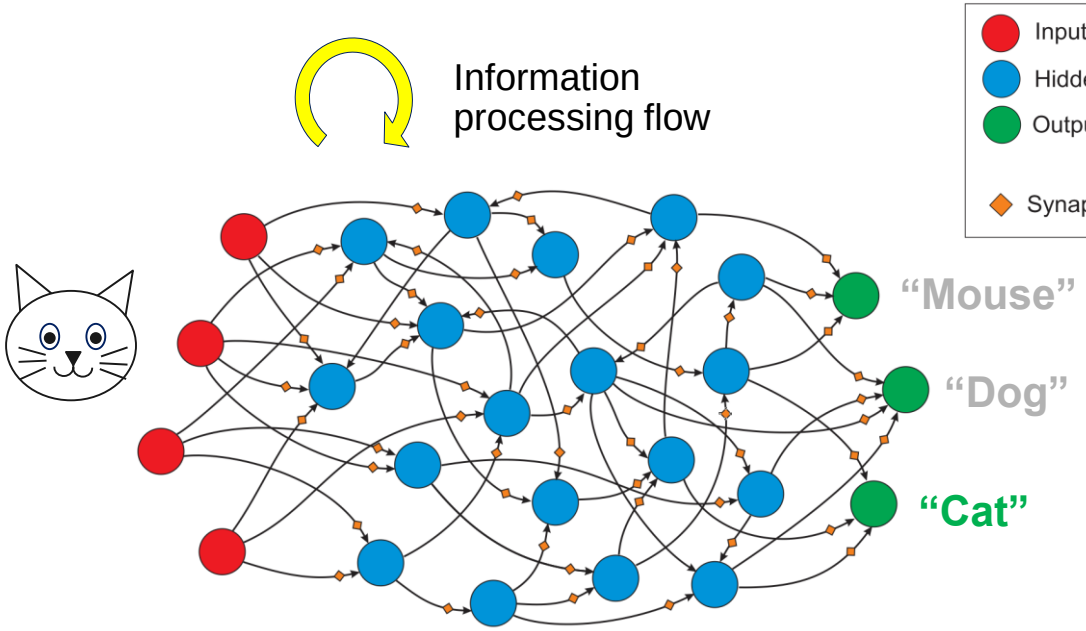


http://biomedicalengineering.yolasite.com/neurons.php

- Signaling between neurons: Spikes, spike trains
- Neuron activation: "Leaky Integrate and Fire"
- Learning: Adjustment of the synaptic weights
  - Spike Timing Dependent Plasticity: "Neurons that fire together wire together"

Brain inspired computing:

Brain-like Neural network:

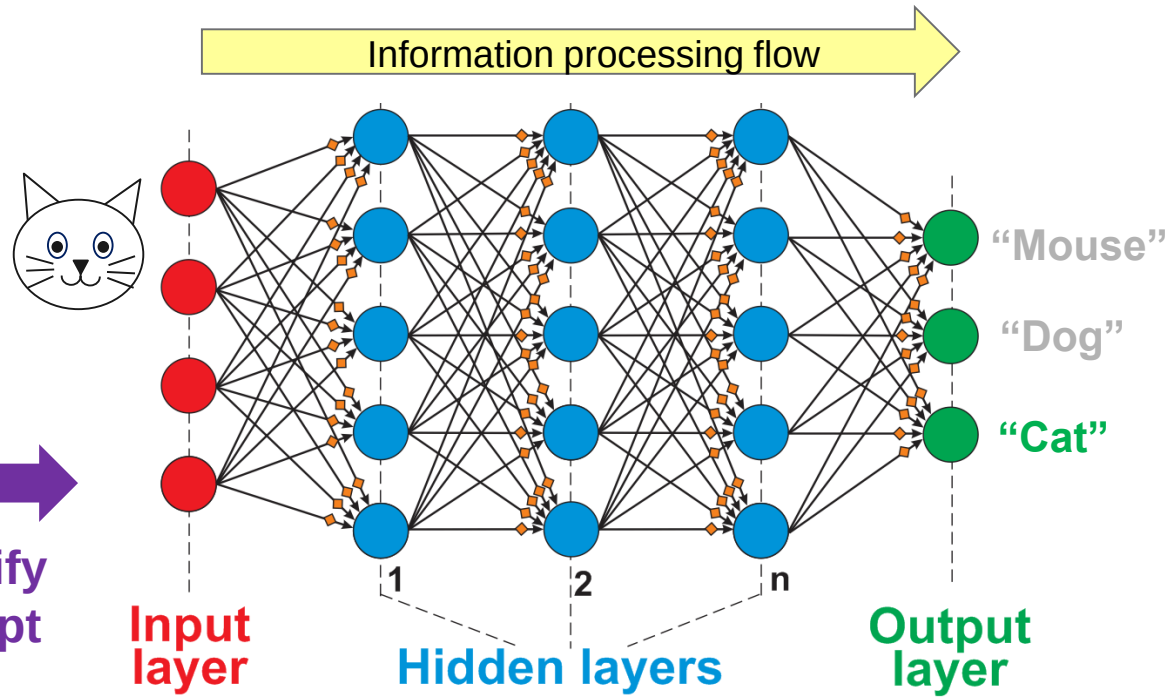


- Omni-directional signal flow
- A-synchronous pulse signals
- Information encoded in signal timing

➔ **Difficult to implement efficiently** on standard computer hardware

Simplify & Adapt

Deep Artificial Neural Network:

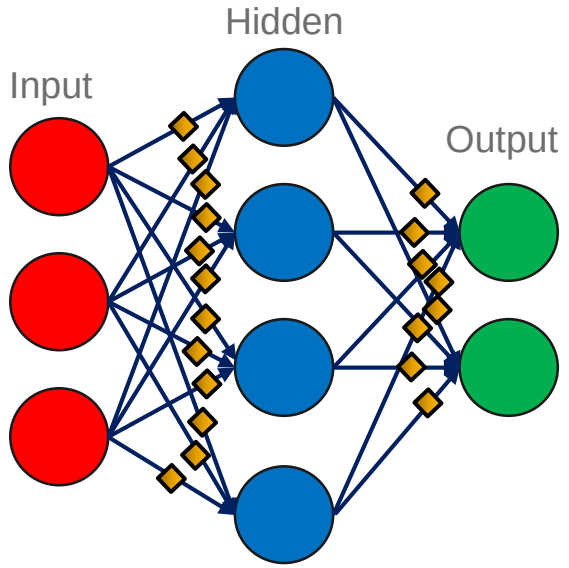


- **Better fit to standard hardware**:
  - Feed-forward sequential processing
  - Information encoded in signal amplitude
  - Multiply and Accumulate for weighted connections
  - Neuron activation: (soft) threshold function
- **Training: Backpropagation Algorithm**

Artificial Neural Network: Computations

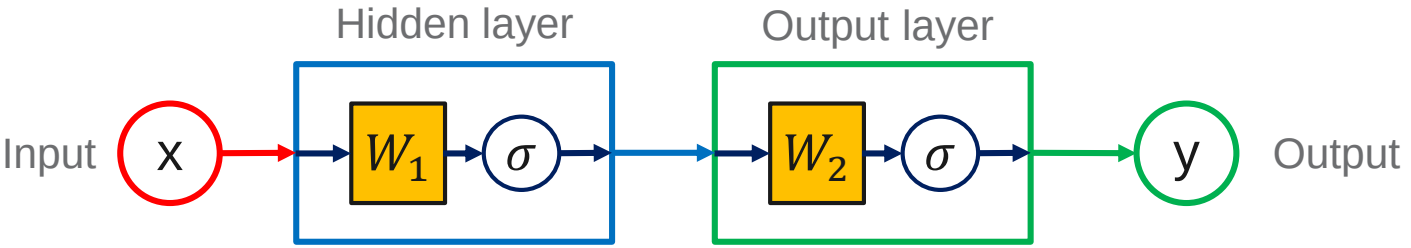
Components:

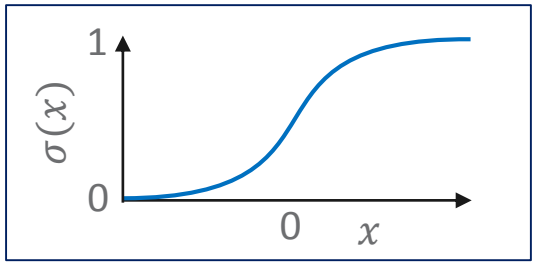
- Layers of neurons
- Synaptic interconnections



Mathematical operations:

- Thick lines: signal vectors
- W: Synaptic weight matrix
- σ: per-element neural activation function (sigmoid)

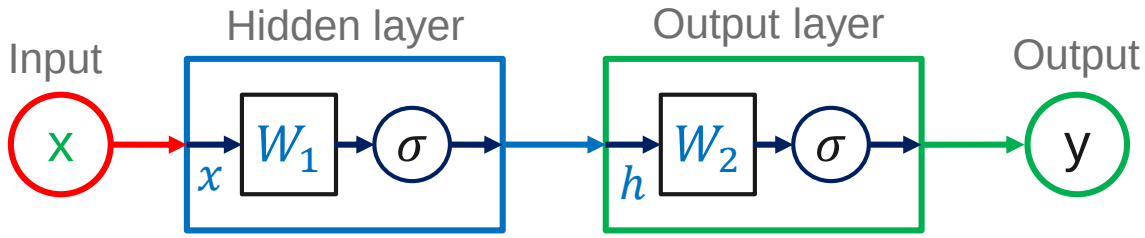




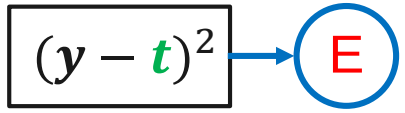
ANN Training: Backpropagation algorithm

Training case x with target response t:

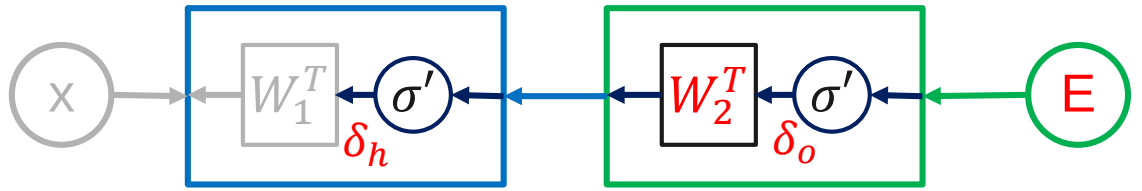
1. Forward Propagate ➔ Response **y**



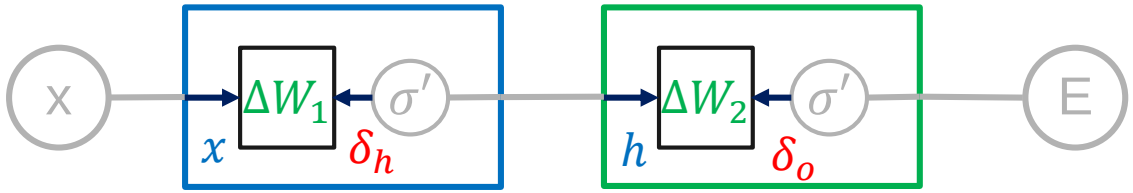
2. Determine output error:



3. Backward Propagate: Find neuron input signals that contributed most to the error



4. Find weights that were active, and that contributed to the error. Adjust weights to reduce error: $\Delta w_{ij} = -\eta \ \delta_i \ x_j$



5. Repeat for many, many different testcases

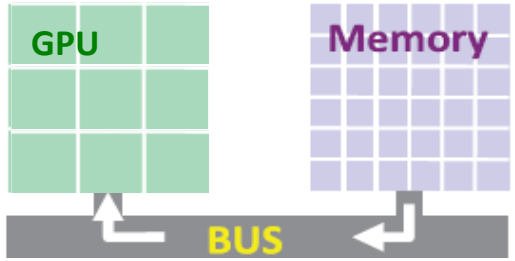
Efficient training of Deep Artificial Neural Networks:

- Training by Backpropagation Method:
  - Forward Propagation: $W_{1,2..}$
  - Backward Propagation: $W^T_{2,3..}$
  - Weight Update: $\Delta W_{1,2..}$

- **Many large matrix operations**
  - Scale $\propto N^2$ (Neurons/layer)

- **Large training datasets**: Thousands of training cases

Weight matrix processing has limited efficiency on standard Von Neumann systems:
- (Mostly) Serial processing
- Low computation to IO ratio → Memory bottleneck



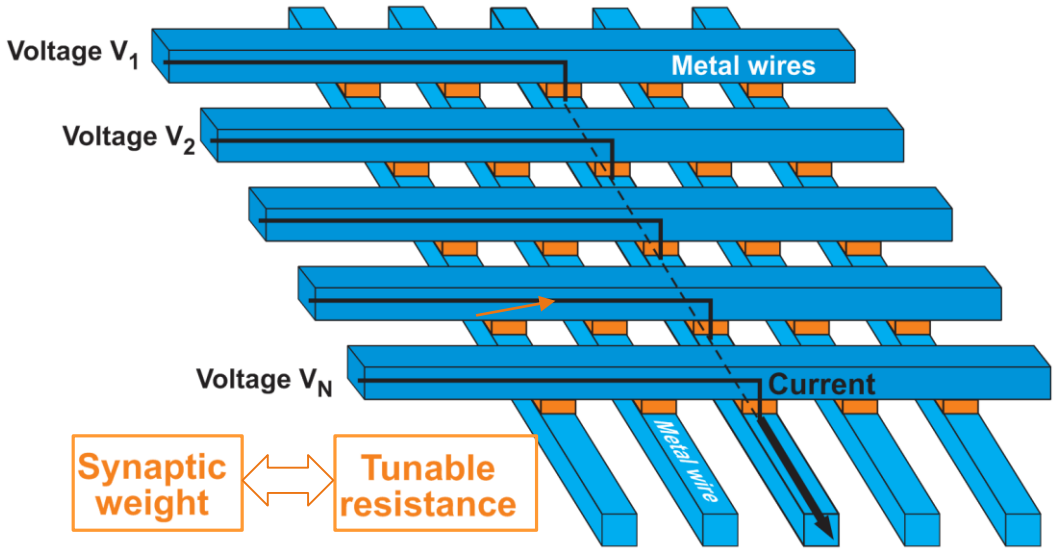
- **To accelerate weight matrix processing: Borrow some concepts from the brain:**
  - Analog signal processing
  - Fully parallel processing
  - Tight integration of processing and memory

Crossbar arrays

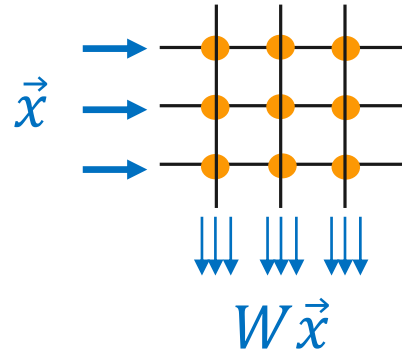
📖 G. W. Burr et al., "Tech. Dig. - Int. Electron Devices Meet. IEDM, vol. 2016–Febru, no. 408, p. 4.4.1-4.4.4, 2016.
📖 T. Gokmen and Y. Vlasov, Front. Neurosci., vol. 10, no. JUL, pp. 1–13, 2016.

Analog crossbar arrays:

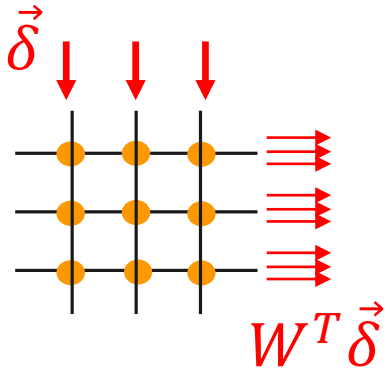
Electrical crossbar array:



Forward propagation:



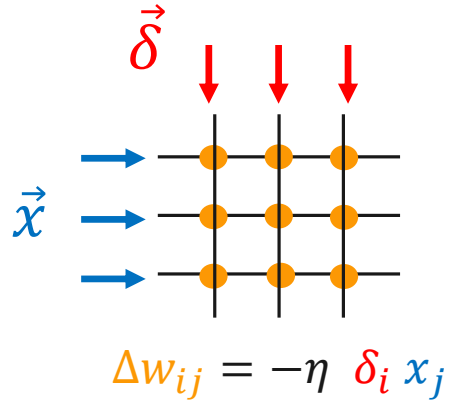
Backward propagation:



Challenge: Tunable weights

- Update must be proportional to signals on row and column
  - Symmetric increase and decrease of weight
  - ~1000 analog levels required
- **Difficult to find material systems** that meet these requirements

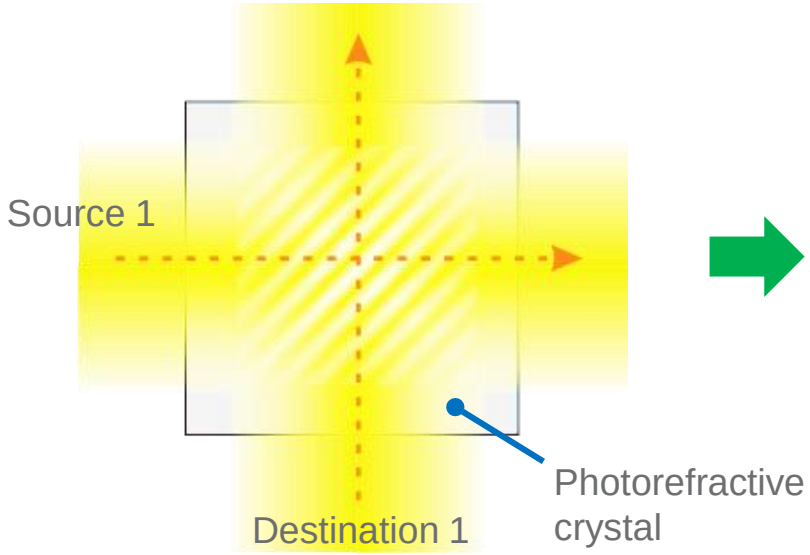
Weight update:



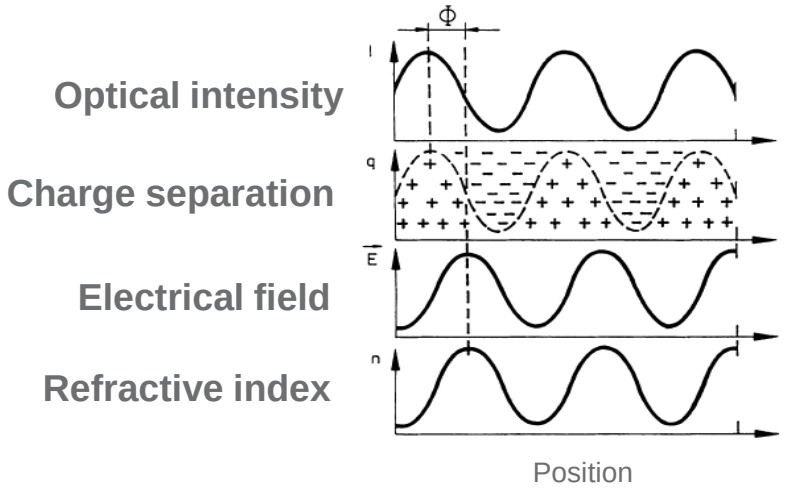
Optical crossbar arrays: Holographic storage and signal processing

Weight Storage:

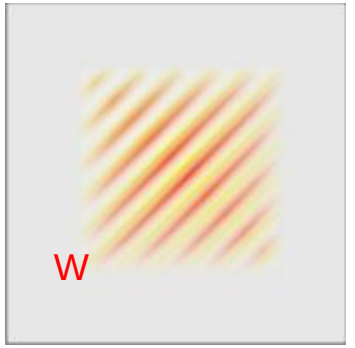
Interference pattern:



Photorefractive effect:



Stored diffraction grating:



📖 Cornelia Denz, Optical Neural Networks, 1998.

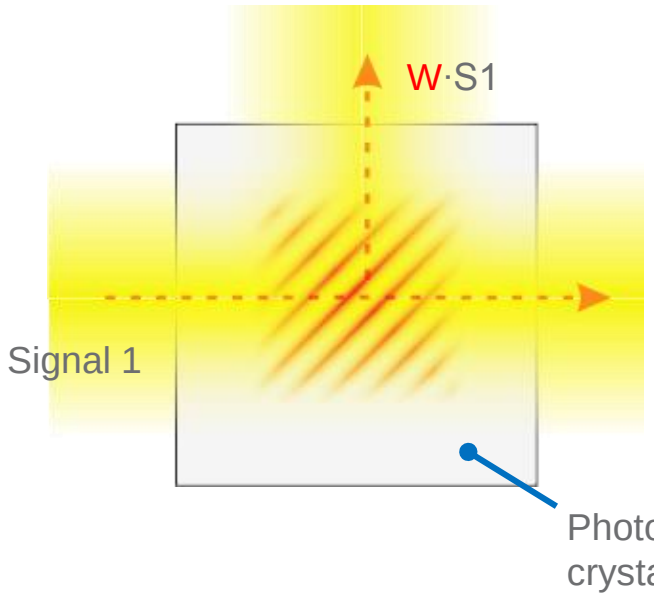
Synaptic weights are stored as refractive index gratings in a photorefractive material:

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

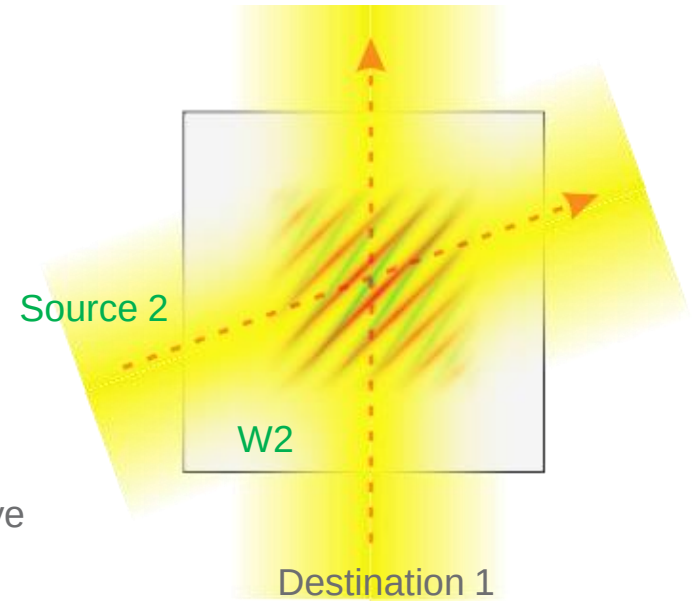
Optical crossbar arrays: Holographic storage and signal processing

Synaptic weight processing:

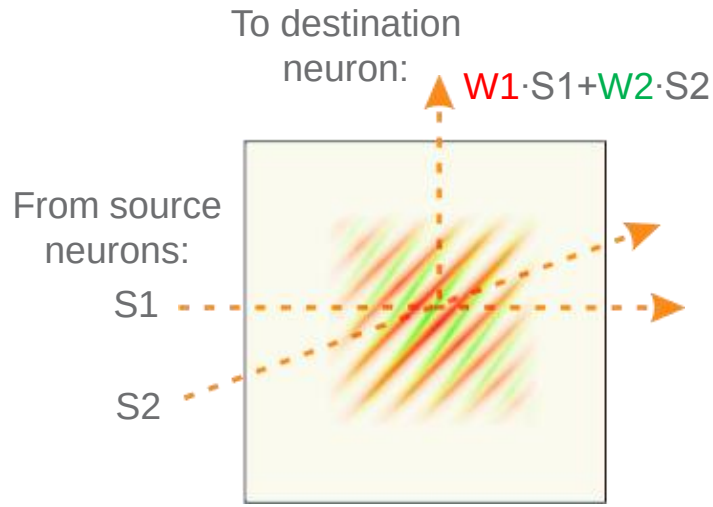
Diffraction grating readout:



Write a second grating:



Multiply & accumulate on two gratings:



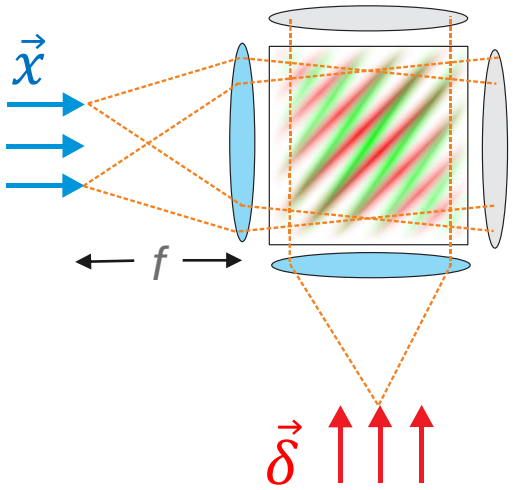
Synaptic weight gratings diffract light from optical input beams to optical output beams

- Different input/output signals are encoded by different beam angles in the crystal
- There is a unique grating for every input-output beam combination
- Optical signaling: amplitude & phase ➔ Bipolar signals and weights

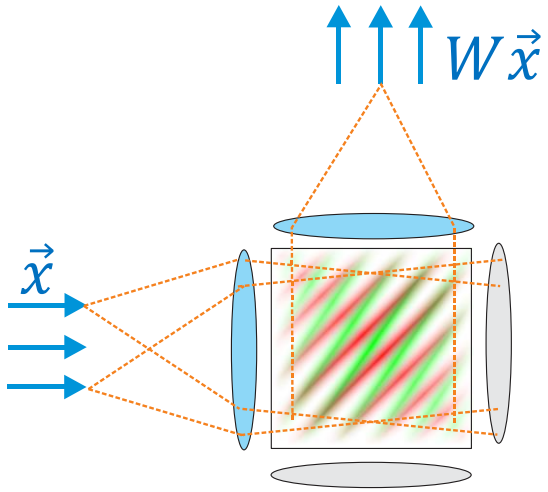
Optical crossbar arrays: Weight processing operations

- Add lenses to shape the optical beams:
  - Arrays of point sources → collimated beams under different angles → arrays of point images

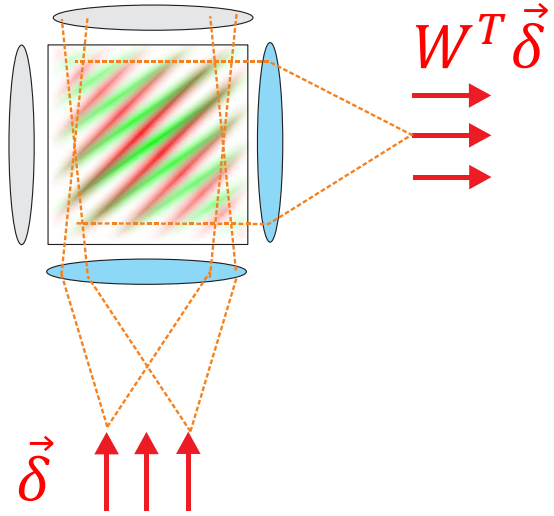
Weight update:



Forward propagation:



Backward propagation:

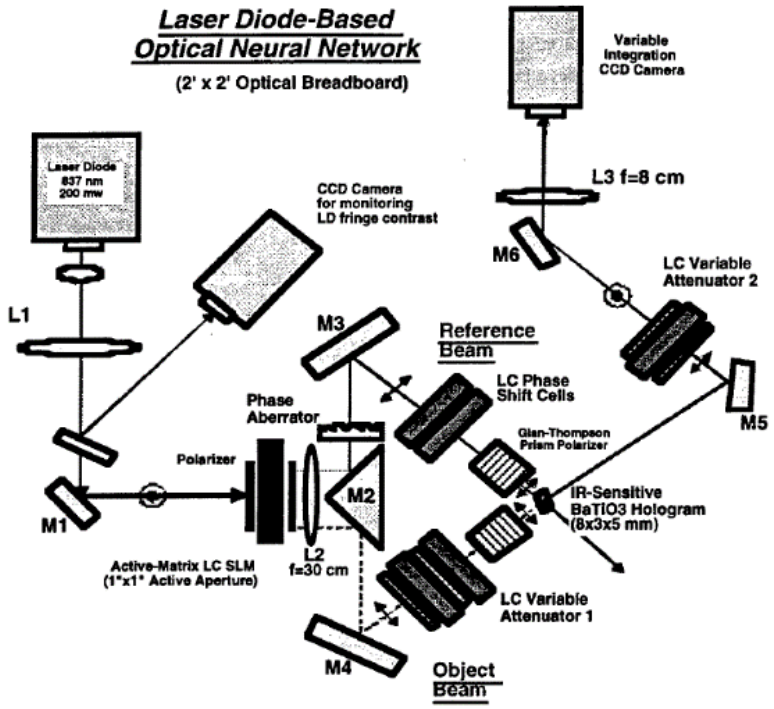


- All weight processing operations for backpropagation supported

Optical crossbar arrays: Integrated Solution

Concept demonstrated in 3D free-space optics

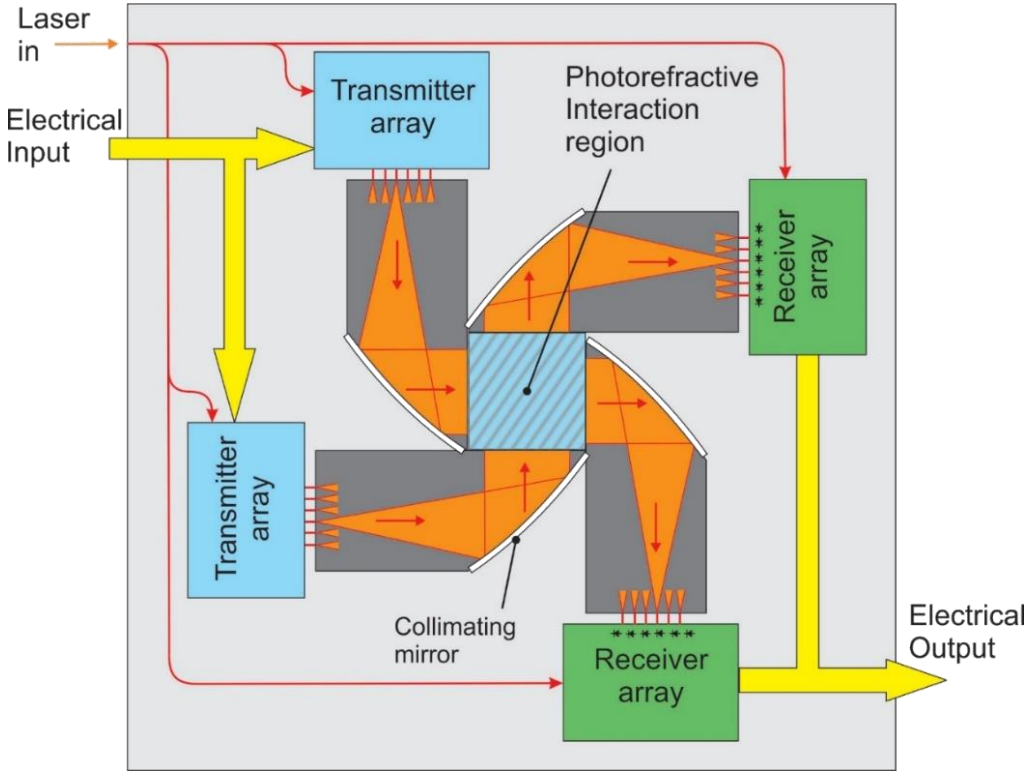
- In the 90s (Hughes Research Laboratories)
- Backpropagation training of ANNs shown
- Large setup, slow electro-optics, stability issues



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

Our approach: Miniaturize using Integrated Optics

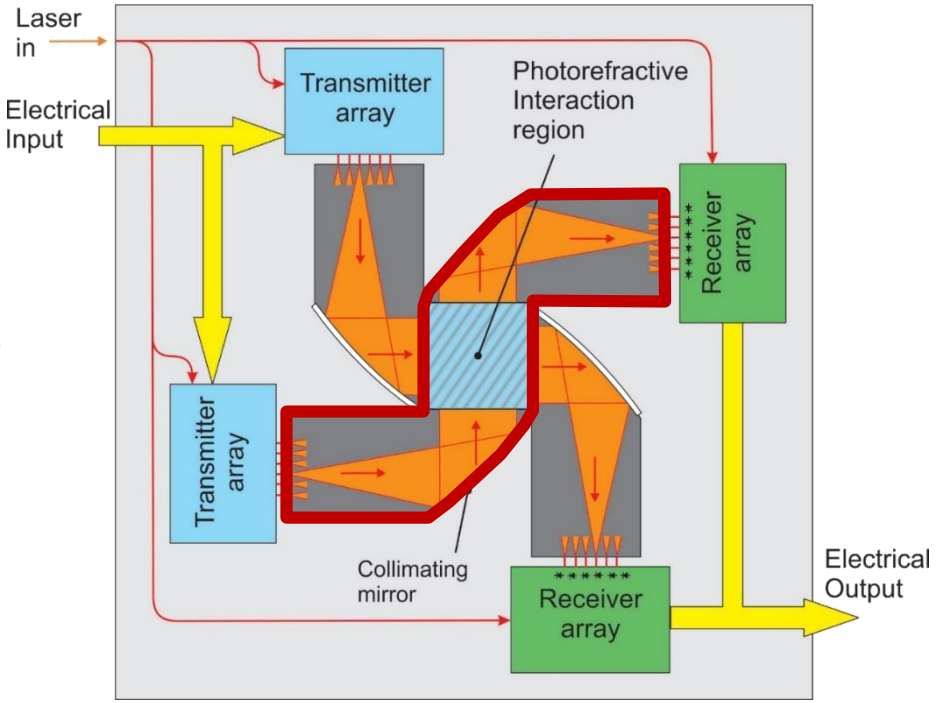
- Electro-optic conversion and beam shaping optics on a Silicon-Photonics chip
- Memory: Photorefractive thin film on silicon



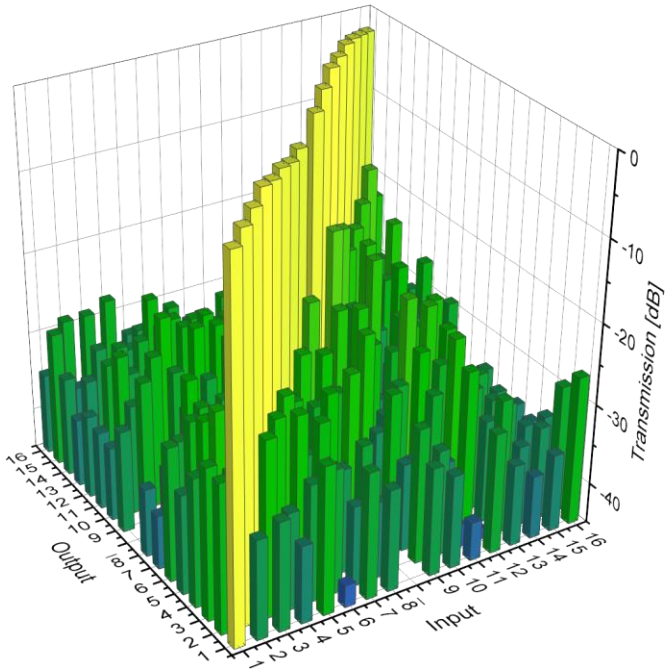
Photonic weight processing unit: Building blocks

Beam shaping optics:

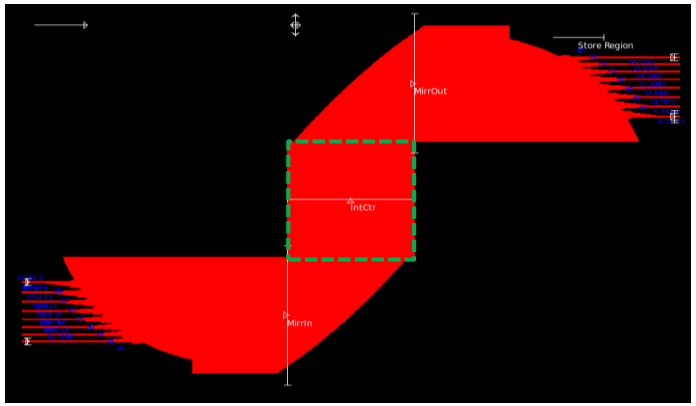
- Converts between point sources and plane waves
  - Parabolic collimating mirrors
  - Curved/tilted focal planes for aberration correction.



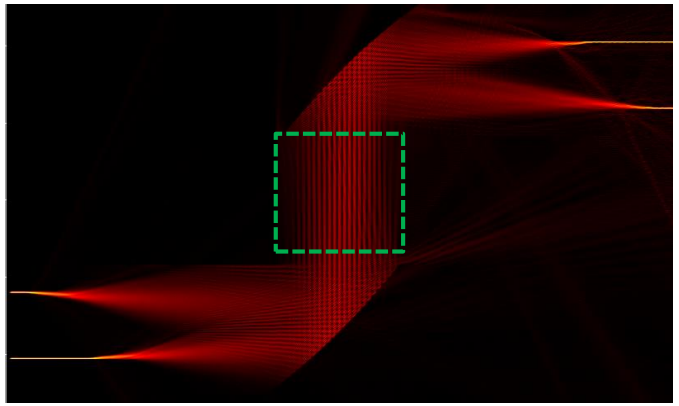
Measured transmission:



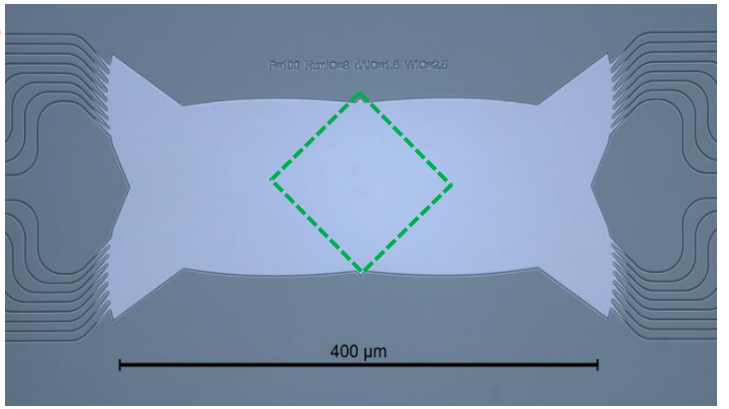
layout



Simulated transmission



Si-Photonics hardware:

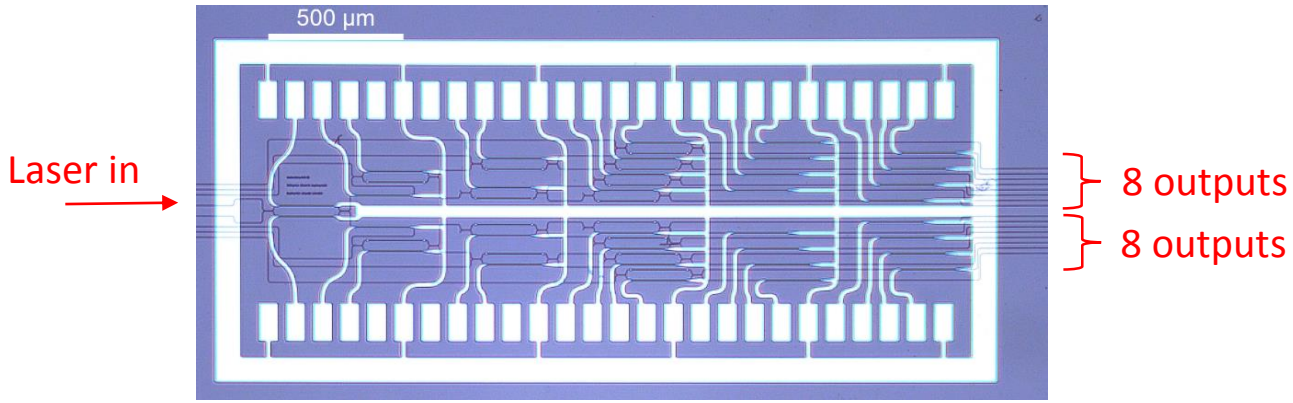


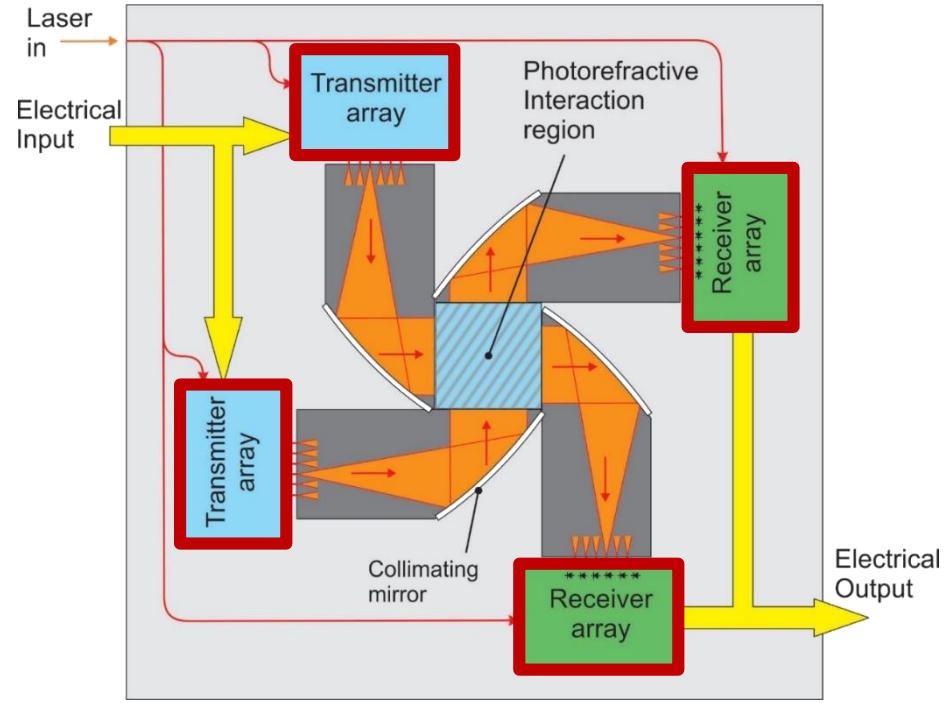
Photonic weight processing unit: Building blocks

Transmitter array:

- Encodes input vectors onto arrays of coherent optical sources.
- Control of amplitude and phase
- Based on standard Si-Photonics components

Si-Photonics hardware:





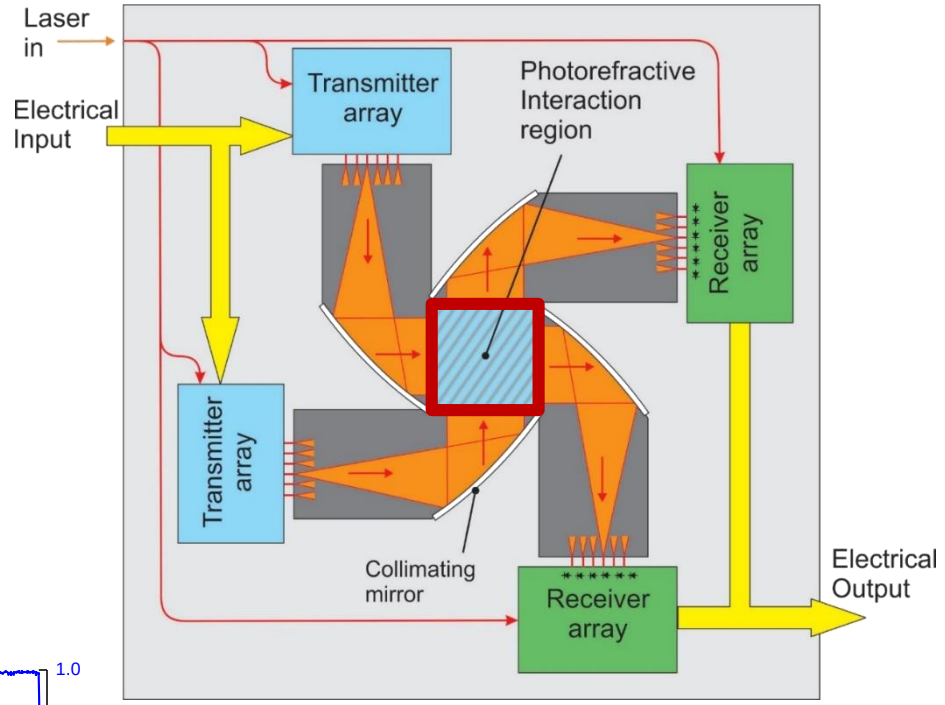
Receiver array:

- Detects amplitude and phase of output signals
- Standard Si-Photonics detector array

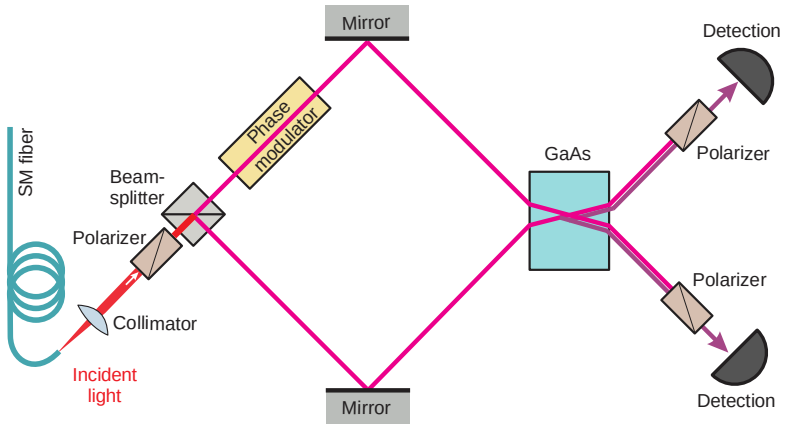
Photonic weight processing unit: Building blocks

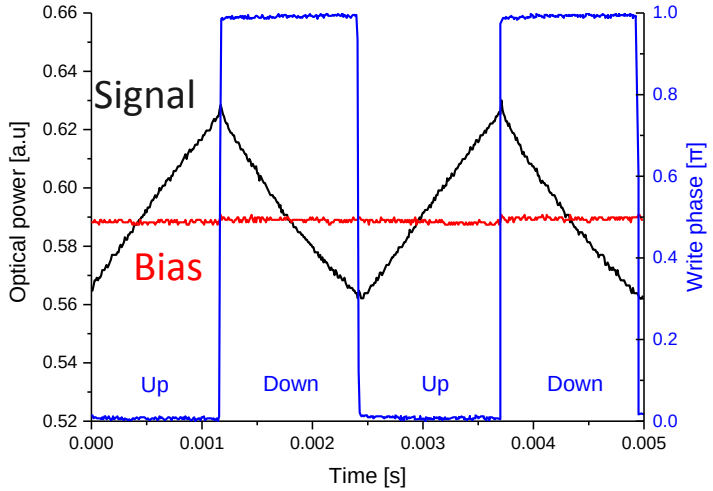
Photorefractive interaction region:

- 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:



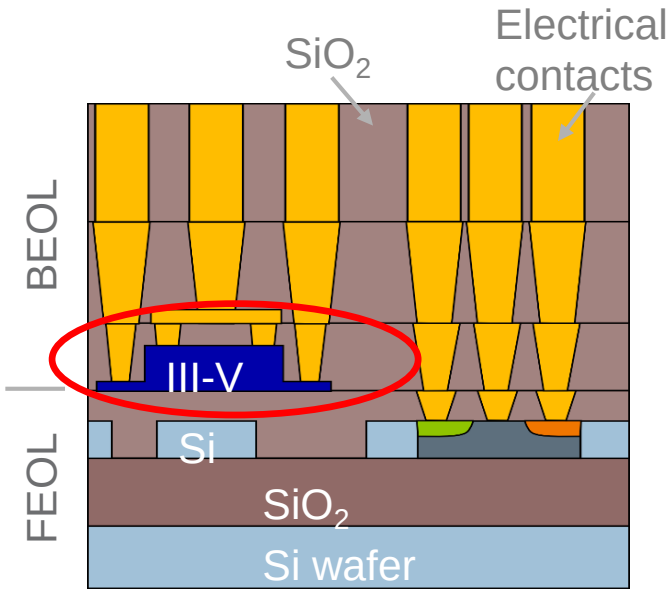


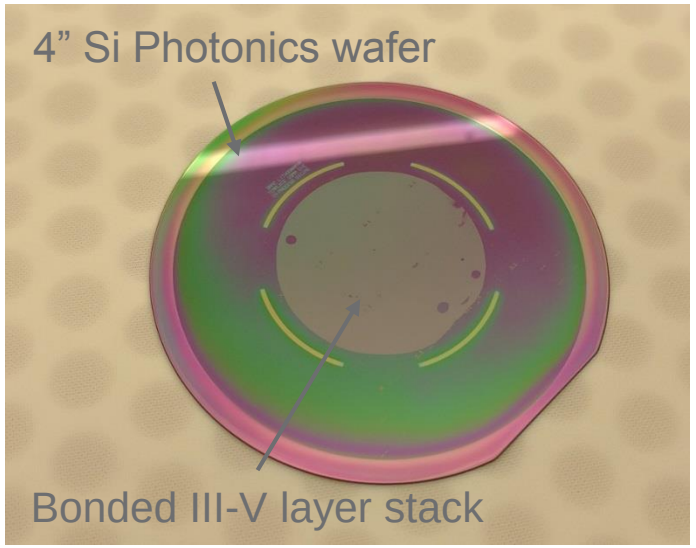
- Low asymmetry
- High dynamic range
- Bipolar weight storage
- To be confirmed in thin film

Photonic weight processing unit: Building blocks

Integration of the photorefractive layer:

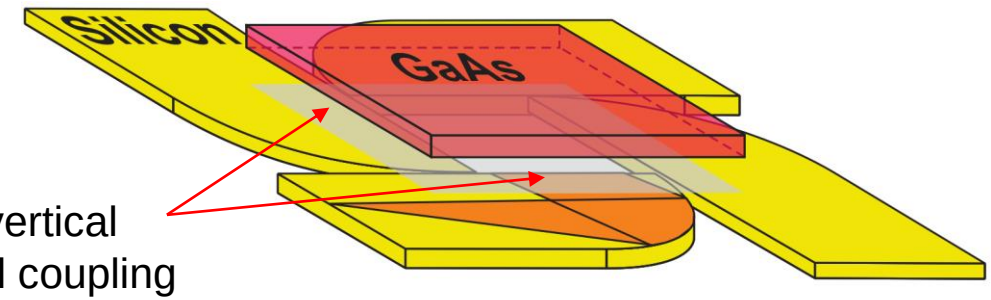
- Bonding technology as demonstrated for other III-V on Si projects:
  - Gain layers for integrated light sources
- Oxide bonding to Silicon-photonics stack



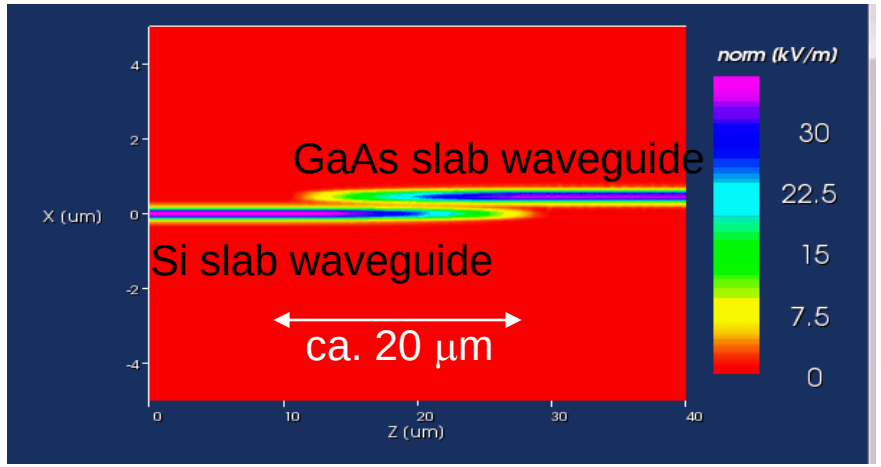


M. Seifried *et al*., "Monolithically Integrated CMOS-Compatible III–V on Silicon Lasers“ doi: 10.1109/JSTQE.2018.2832654.

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

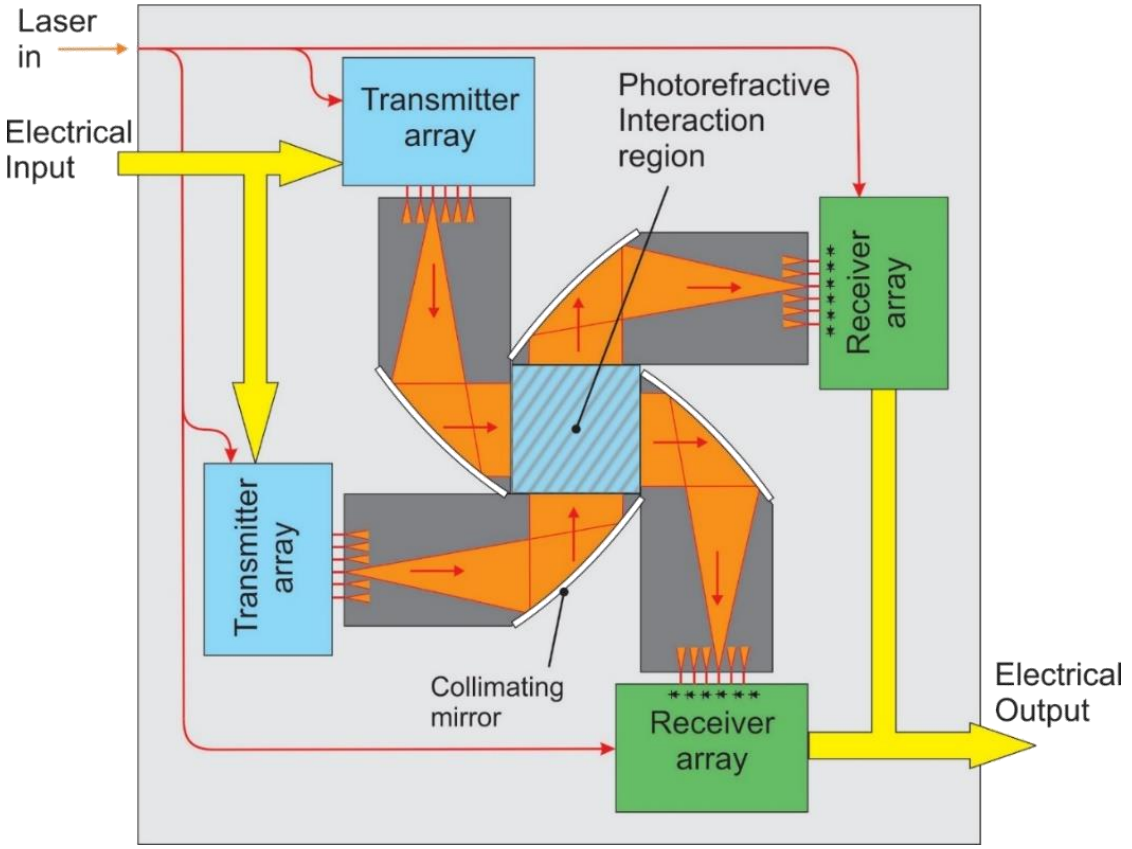


Vertical directional coupling



Summary and Outlook

- **Optical holographic storage and signal processing:**
  - Provides all necessary operations for accelerating training and evaluation of Deep Artificial Neural Networks
- **Integrated photonic synaptic weight processor:**
  - Silicon Photonics for electro-optical conversion and beam shaping
  - GaAs photorefractive layer for holographic weight storage and processing
- **First step: Demonstration of principle**
  - 8 x 8 matrix using in-house facilities
  - BRNC cleanroom @ IBM - Zurich
- **Next: Large scale demonstrator**
  - Si-Photonics foundry
  - III-V integration support required



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