



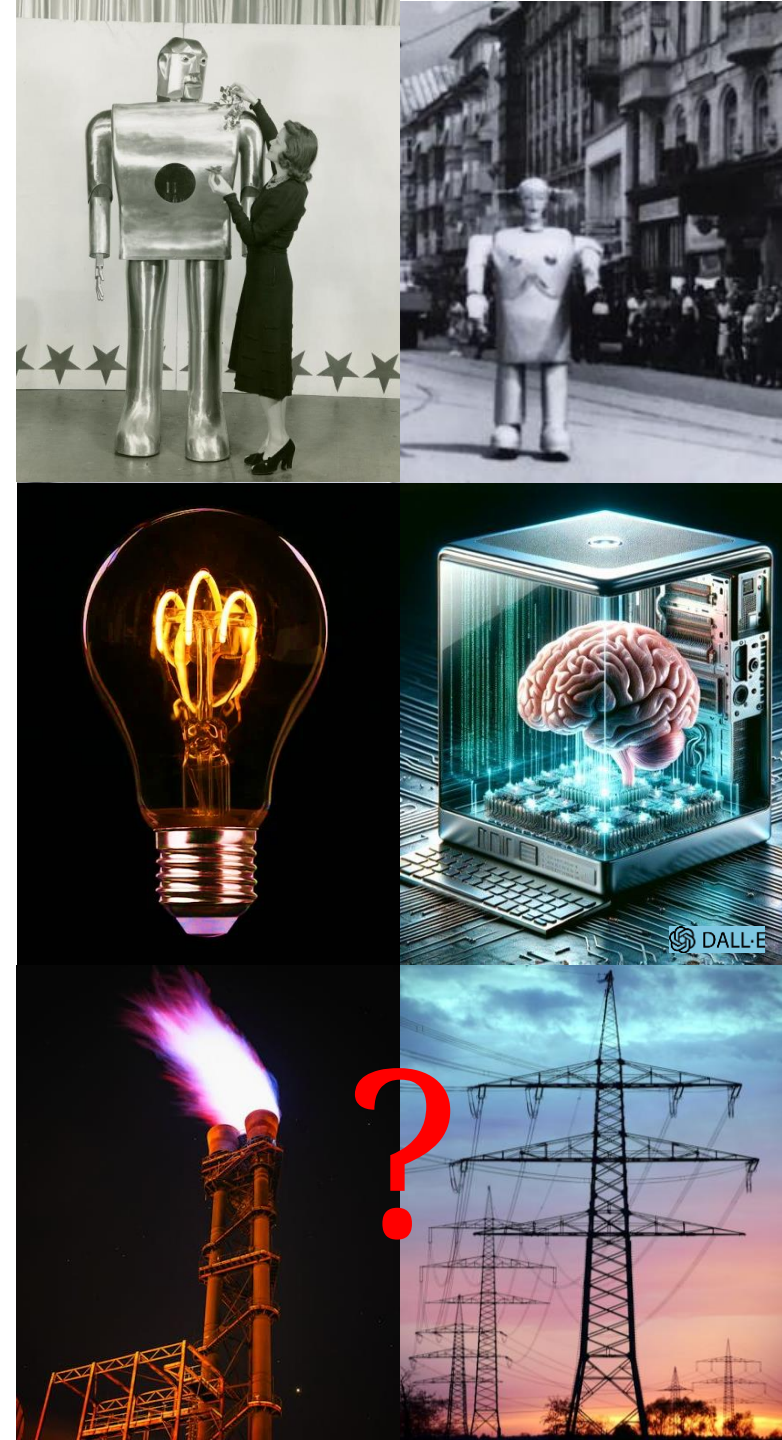
super computing systems

Light + AI 3.0 = NextGen DC

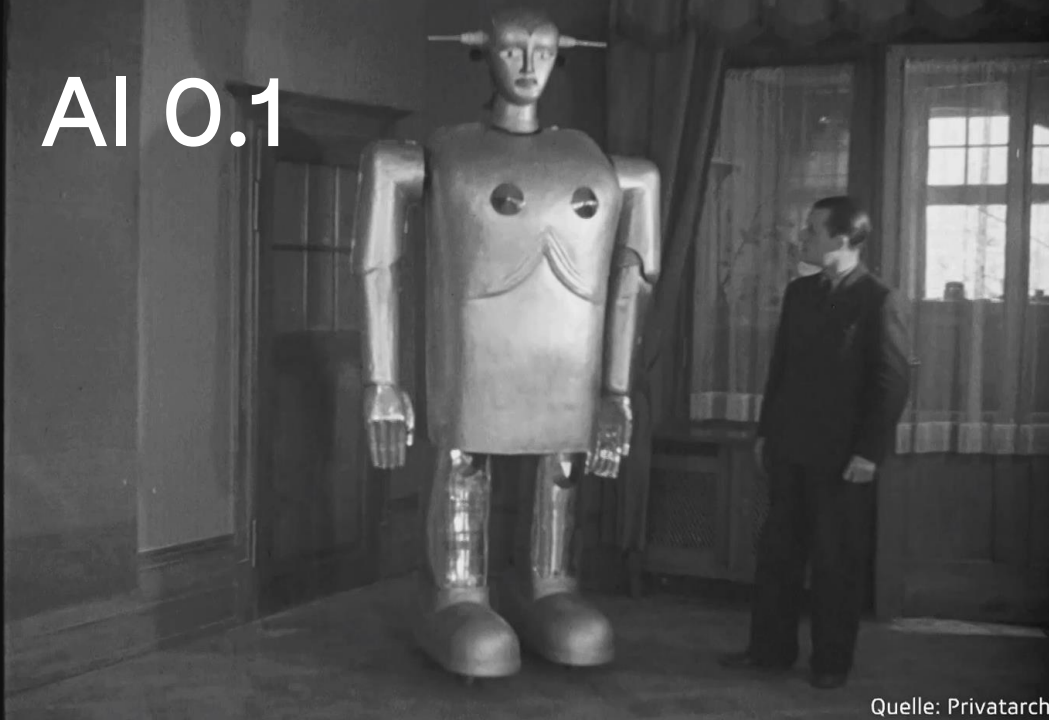
More Light and AI 3.0 Shape the Future of Data Centers

TEC Forum 2025

Christof Bühler, Supercomputing Systems AG



AI 0.1



Quelle: Privatarhiv Remo Huber

AI 2.0



https://www.youtube.com/watch?v=JzlsvFN_5HI

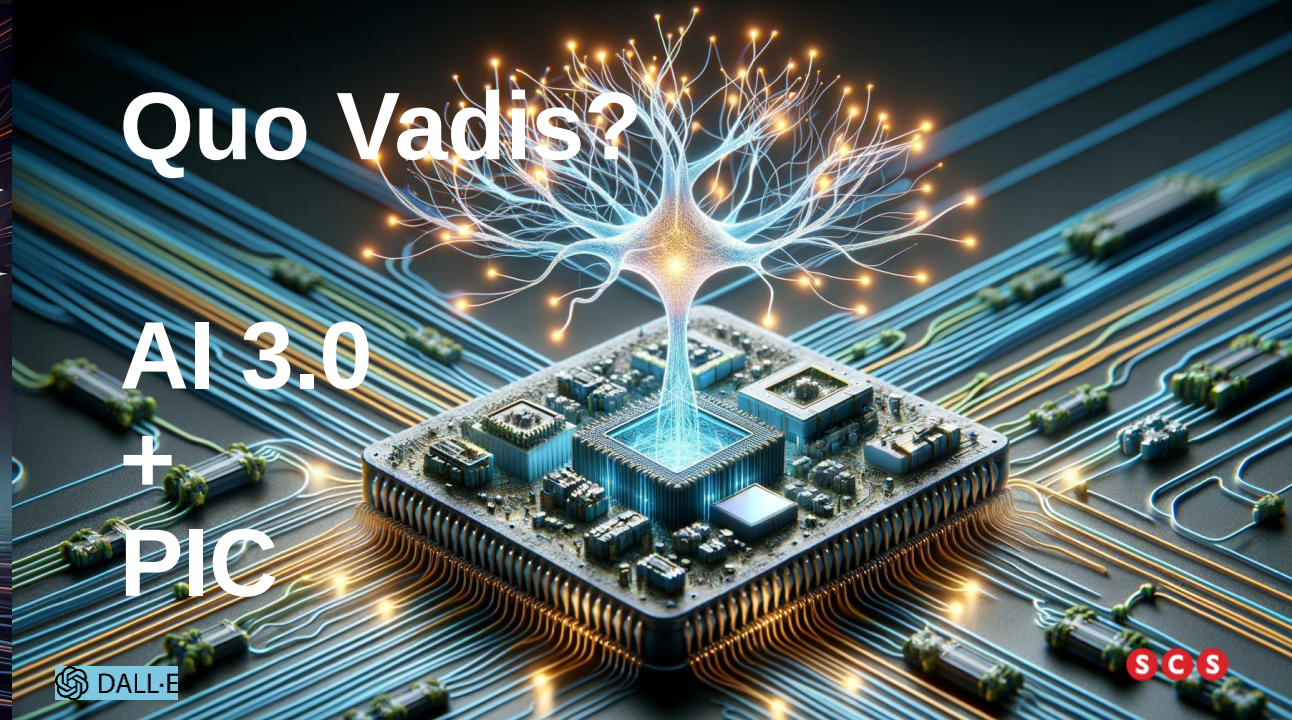
Dark Side of AI



DALL·E

Quo Vadis?

AI 3.0 + PIC



DALL·E

SCS

AI $\neq$ Human Brain

Machine Learning



> 7 million test kilometers



Millions of labeled photos



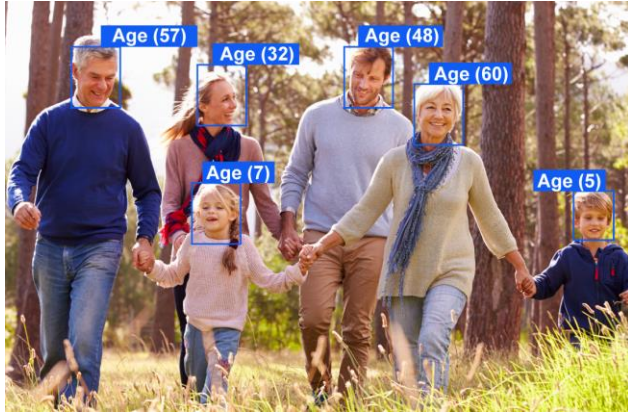
Many engineers

Human learning

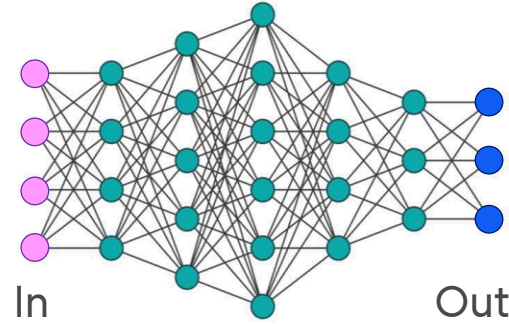


20 - 30h driving lessons

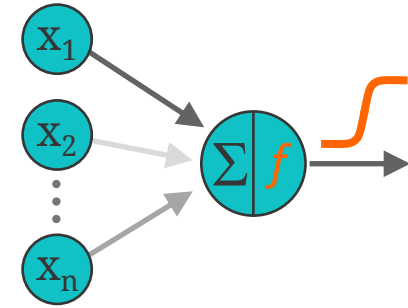
AI : Programming Becomes Training



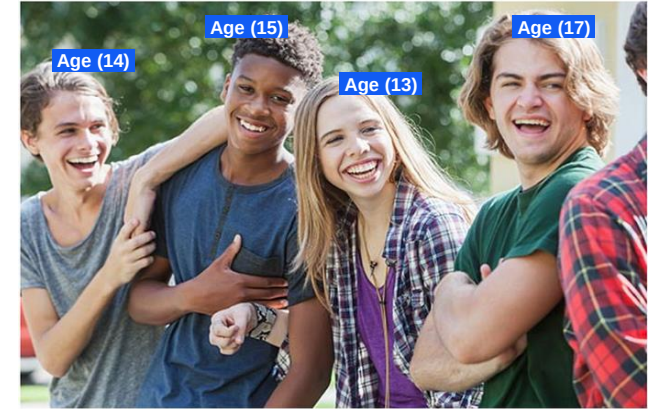
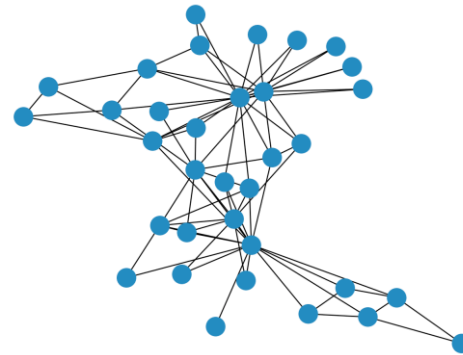
Learning Algorithm



Artificial Neuron

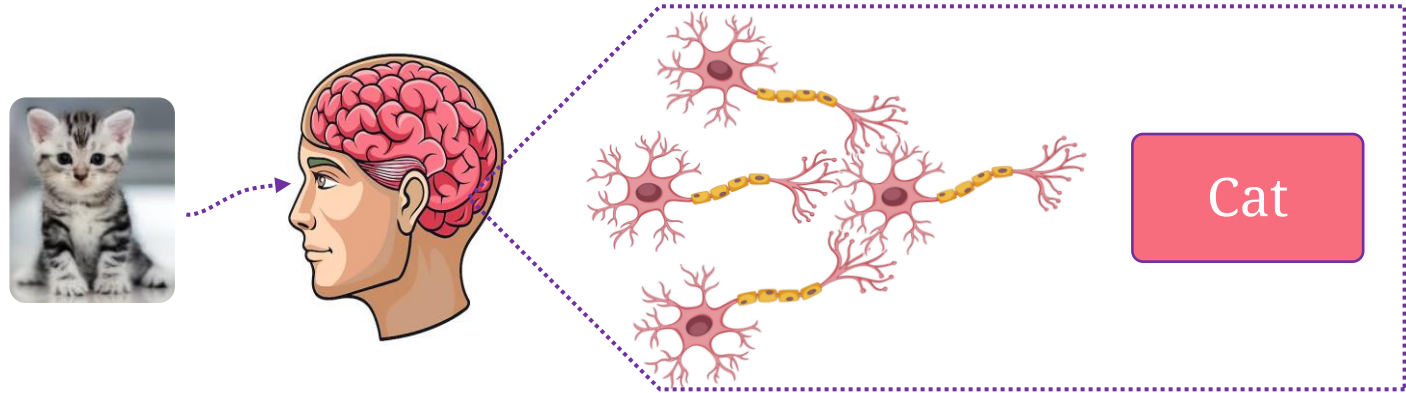


AI Model

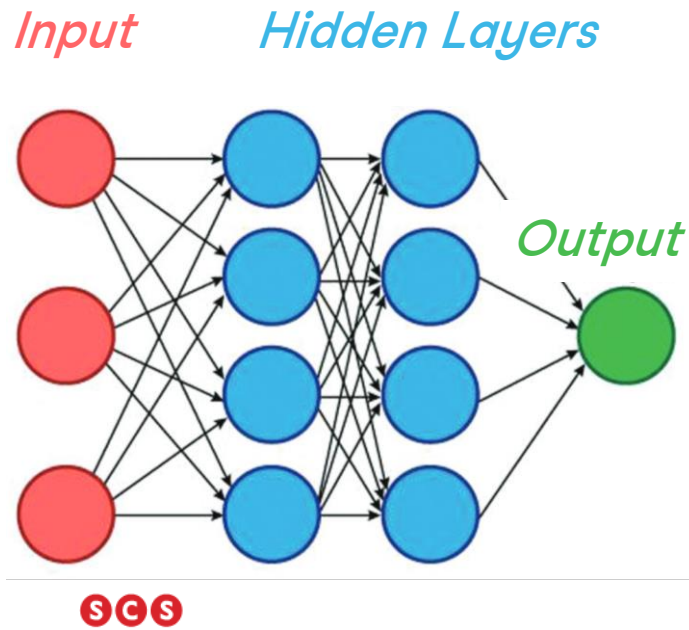


AI : Refresher in 60+ Seconds

Biology

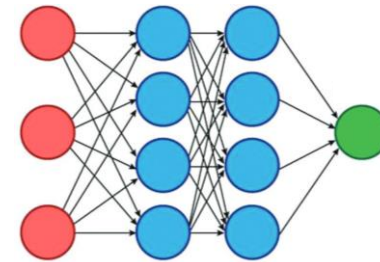


Technical



Training

Z_t



$G_w(Z_t)$

Iteration t

D_t

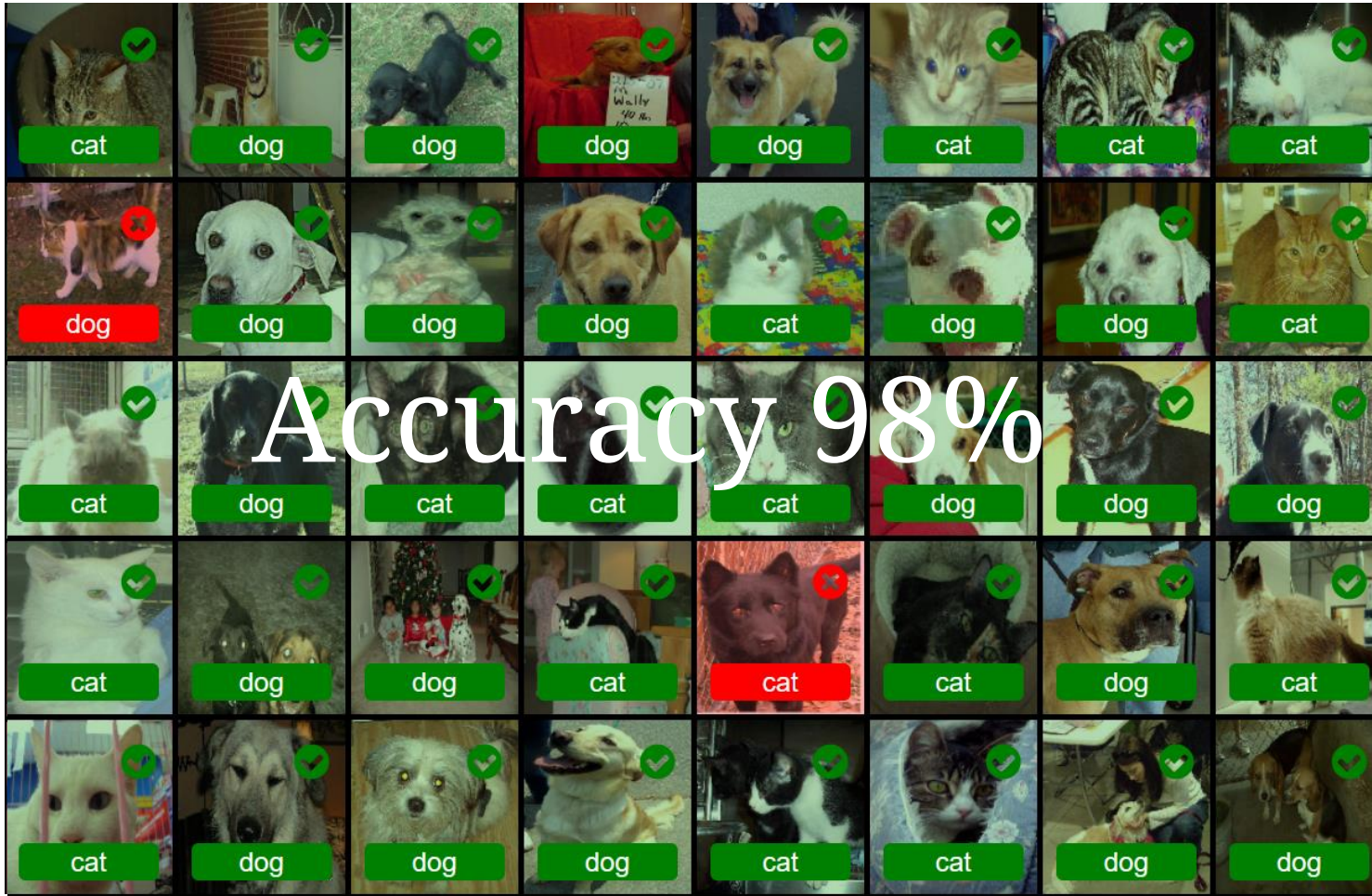
Backprop: How much missing? $E = \|D_t - G_w(Z_t)\|^2$

Learning: adjust weights

$$W^{t+1} = W^t - \alpha \frac{\partial E}{\partial W} (W^t)$$



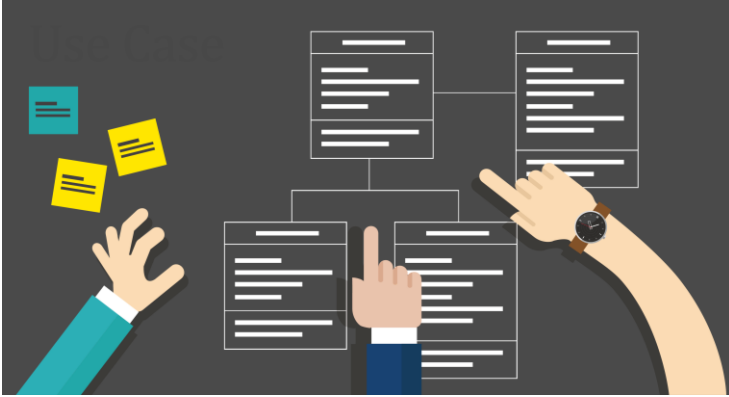
Have Fun with AI tools



<http://ai-demo.scs.ch>

<http://ai-demo.scs.ch/#/dashboard>

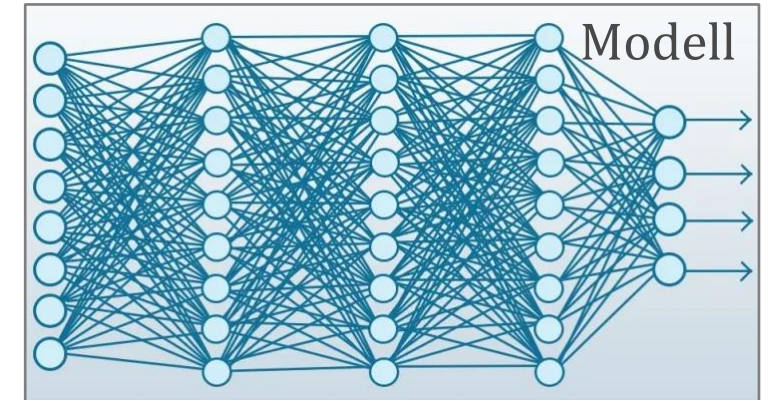
AI / ML : Challenges



Must offer real added value



Enough & unbiased



Finding the right complexity



Costs: often >> than expected

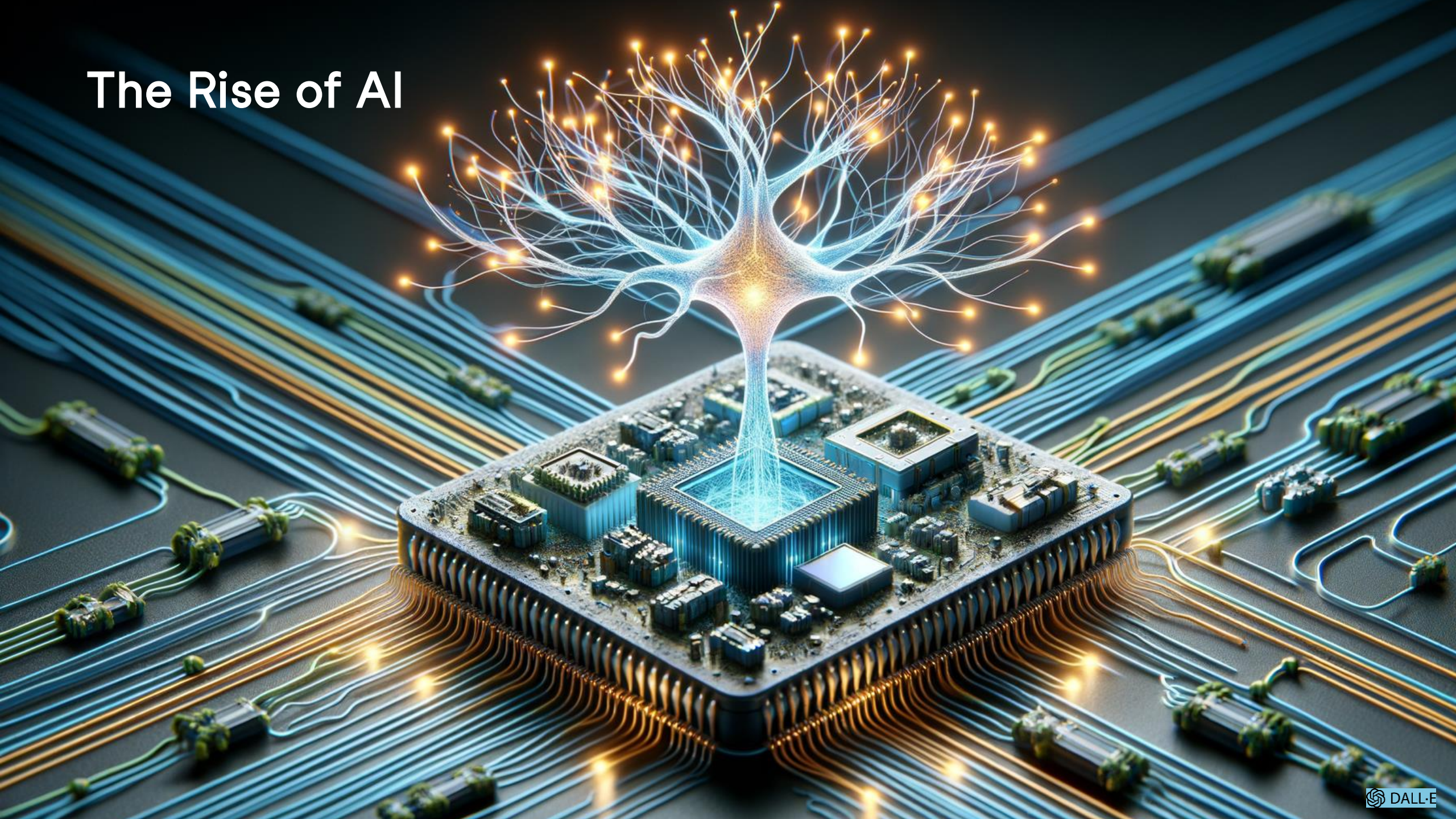


Planning ahead



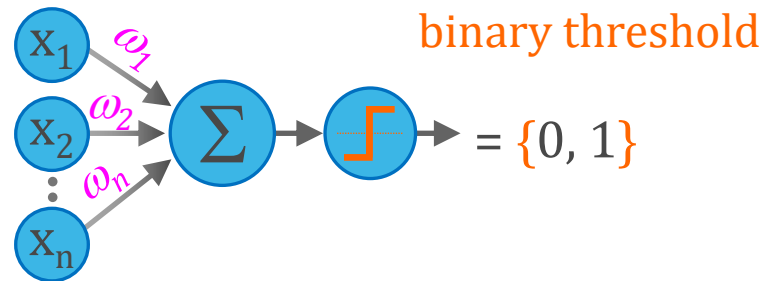
Expectations: often too high

The Rise of AI

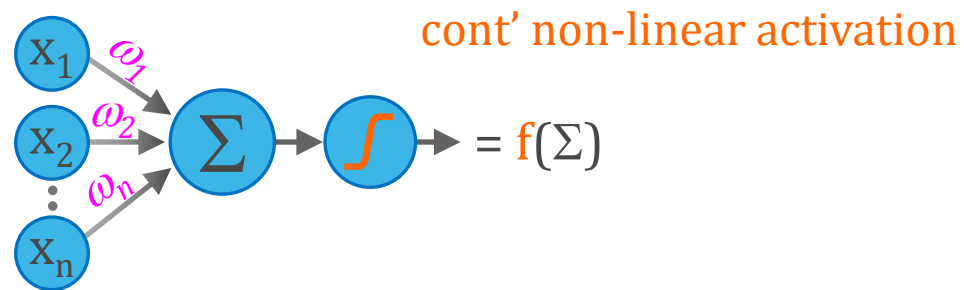


The Rise of AI

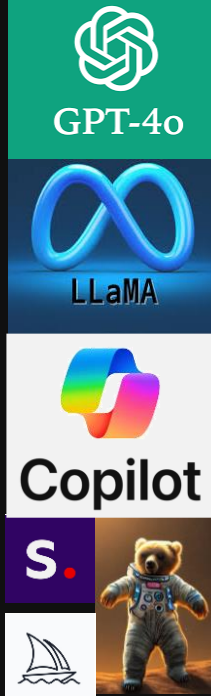
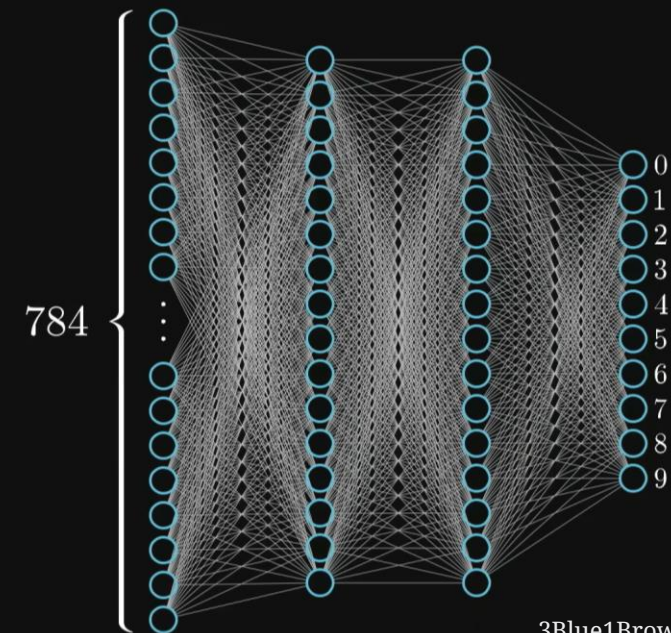
AI 1.0



AI 2.0



∴ KI 2.0: x_n -in x_m -out $\Rightarrow$ not intelligent yet useful



Issues and Light Awaits

Smartness

AI 1.0 << AI 2.0 << AI 3.0 << ... << AGI* < Brain

AI «sucks» $\Rightarrow$ energy, speed, smartness

Scaling

👉 Technical, economical and intellectual



AI 3.0: Neuromorphic Computing (NC)

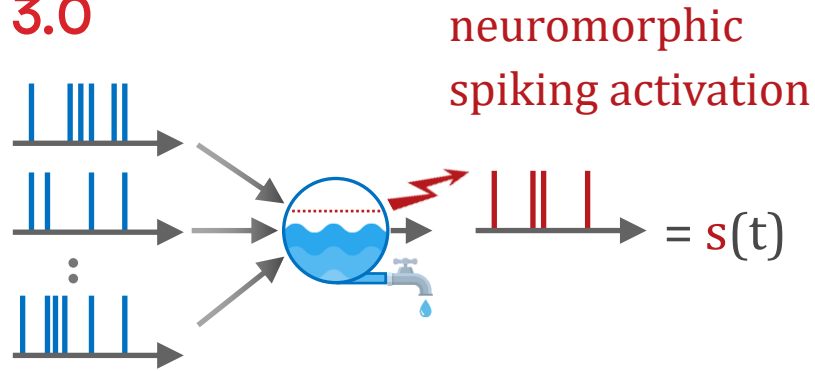
- λ -based, sparse, async. communication
- highly parallel: 10^5 - 10^6 cores
- low-power, real time, adaptive learning

🔴 KI 3.0: λ -in λ -out» ... a leap towards AGI?!



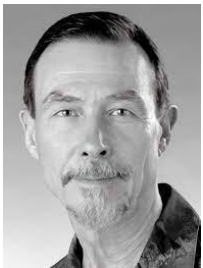
The Rise of AI: Light Awaits?

AI 3.0



Simplified LIF model

LIF: Leaky Integrate & Fire



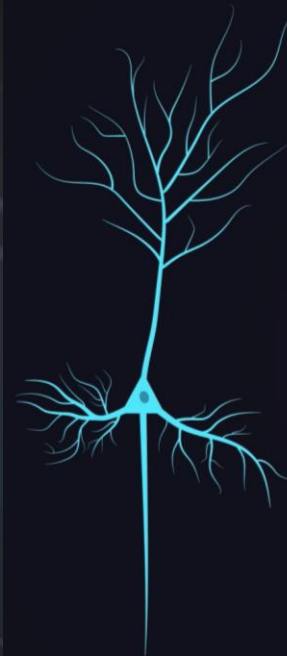
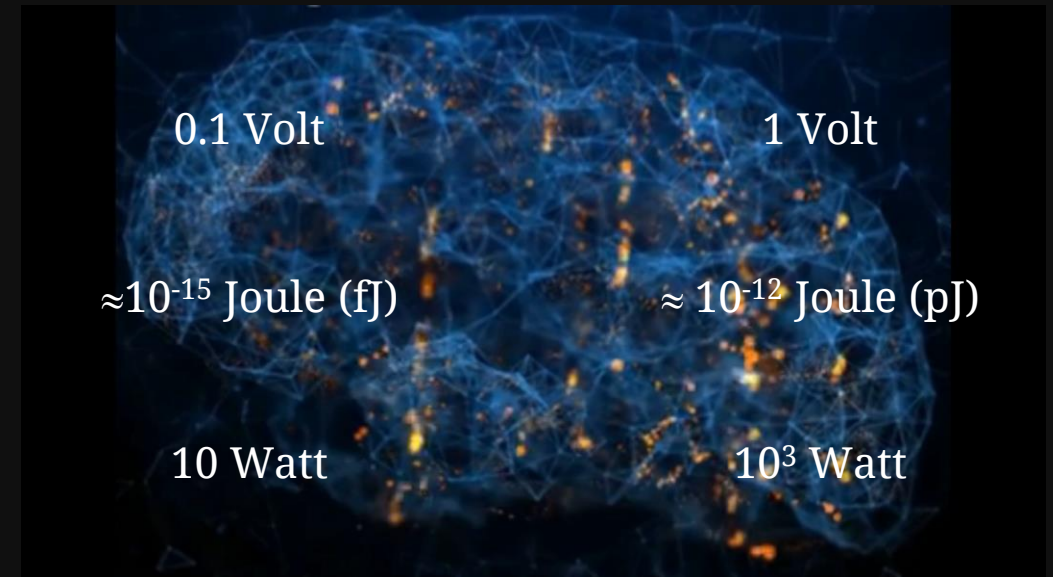
Carver Mead (*1934 U.S.): The Father of Neuromorphic Computing (NC)

1988: NC has higher likelihood of neuronal dynamics ...

- Neuromorphic computing mimics nature: spike-based communication & sparsity

Biological Neurons

Artificial Neurons



Detailed Biophys. Model

$$\begin{aligned}
 C_m \frac{dV}{dt} &= \bar{g}_{Na} m^3 h (E_{Na} - V) \\
 &\quad + \bar{g}_K n^4 (E_K - V) + g_L (E_L - V) \\
 \frac{dm}{dt} &= \alpha_m(V) (1 - m) - \beta_m(V) m \\
 \frac{dh}{dt} &= \alpha_h(V) (1 - h) - \beta_h(V) h \\
 \frac{dn}{dt} &= \alpha_n(V) (1 - n) - \beta_n(V) n
 \end{aligned}$$

Hodgkin-Huxley 1952



The Rise of Hardware

From CPU to NPU

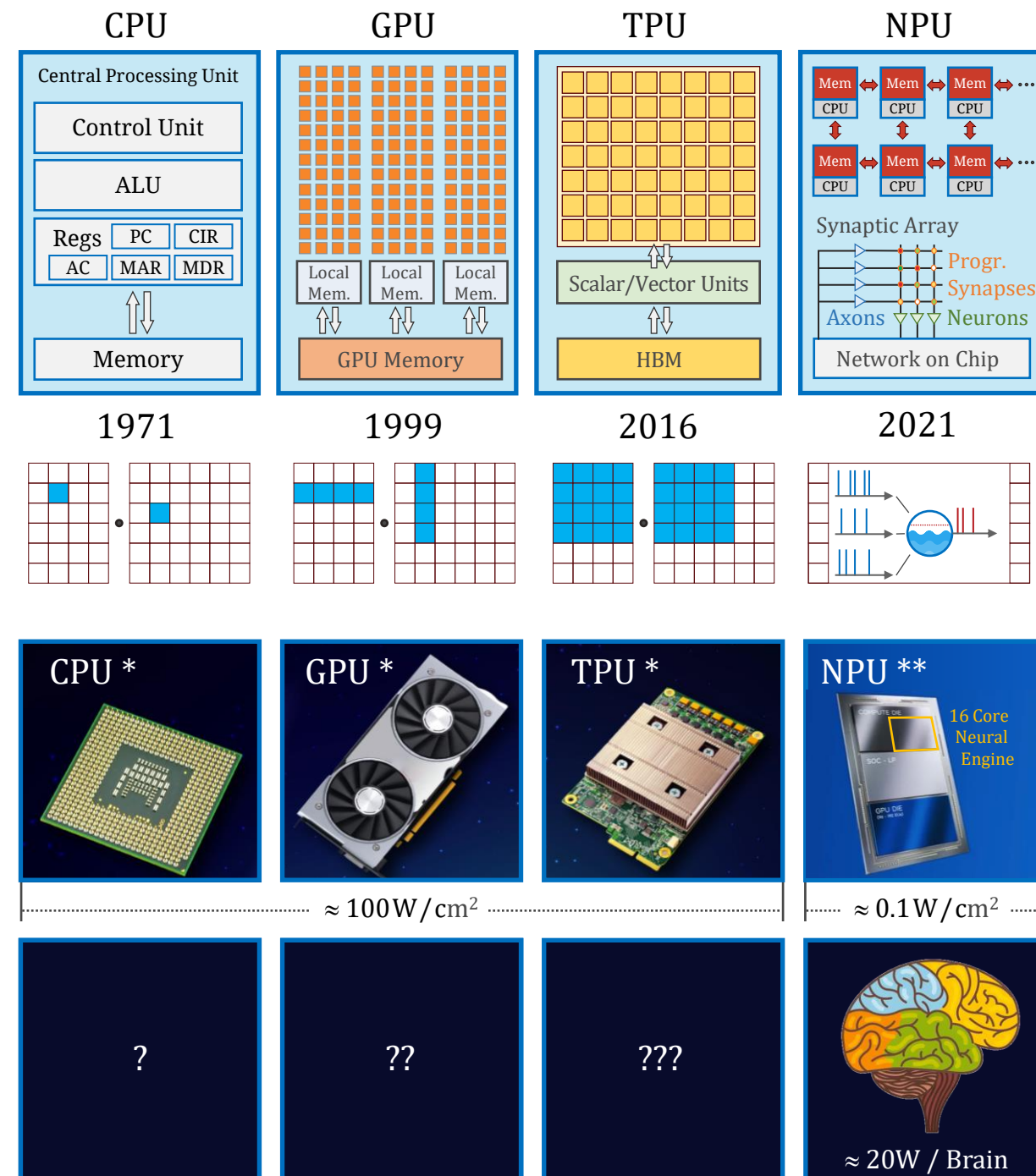
Or from numbers x_1 to spikes 

From NPU to Brain

Neuromorphic hardware

- relays, in part, on asynchronous communication
- uses spikes for power efficiency
- runs highly parallel: $10^5 - 10^6$ cores
- targets low-power, real time, dynamic apps.

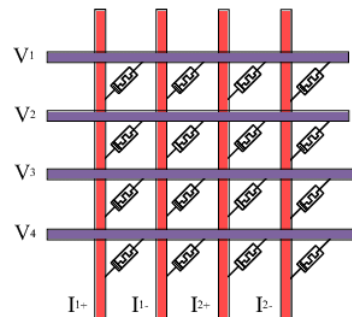
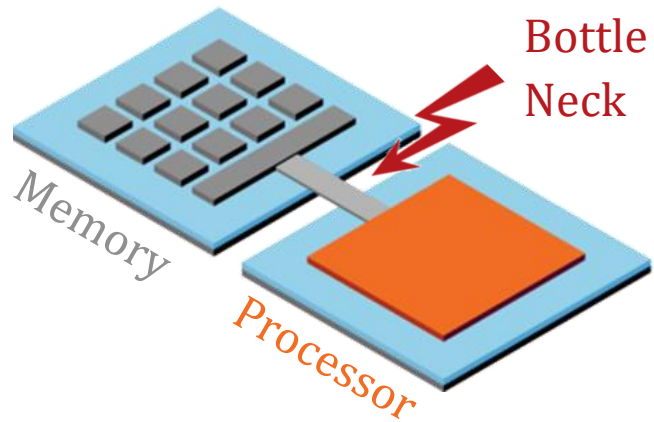
• The next step towards AGI is probably neuromorphic computing.



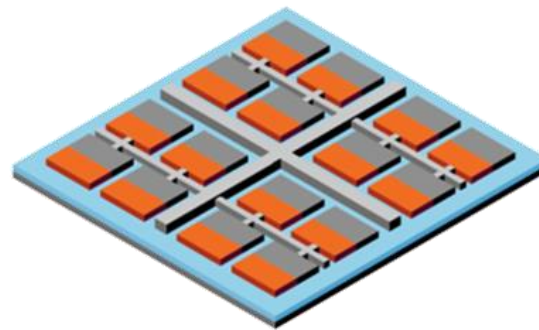
The Issue of Energy

Process Near / In Memory & Sparsity

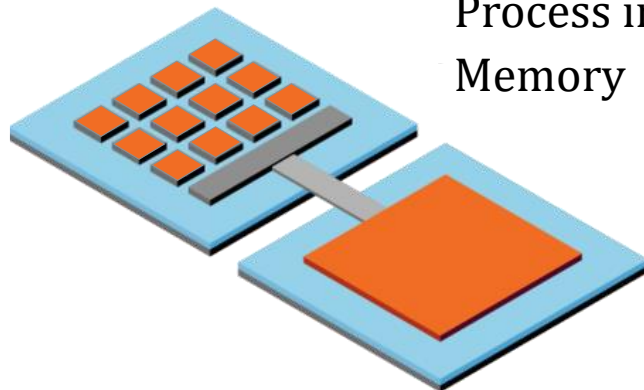
Von Neumann
Architecture



Near Memory
Computing



Process in
Memory



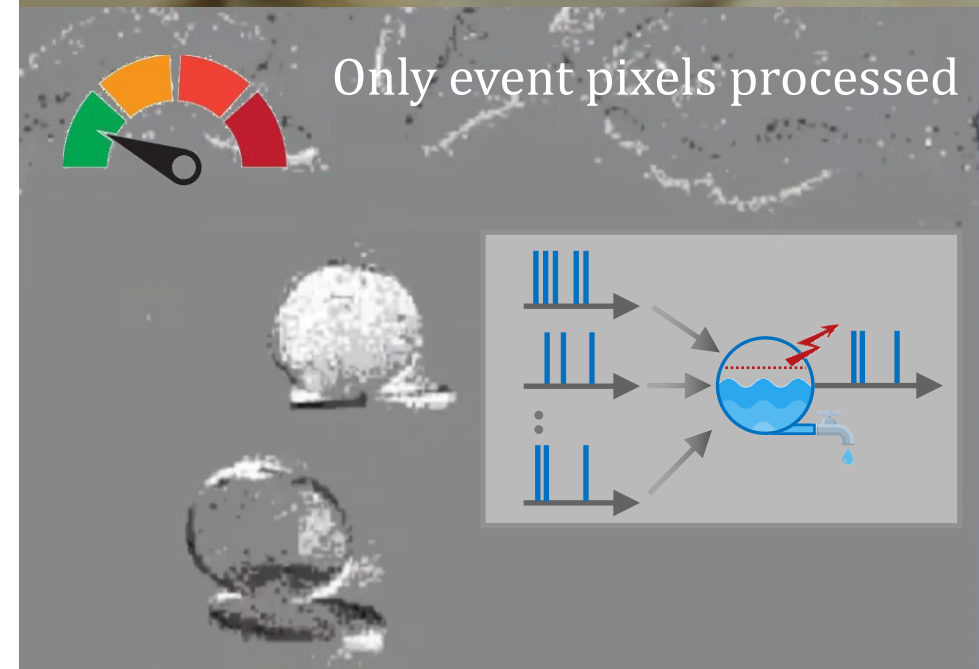
Every pixel processed



Source: www.freepik.com/free-video



Only event pixels processed



Source: Prof. Tobi Delbruck - INI ETH

Neuromorphic Hardware

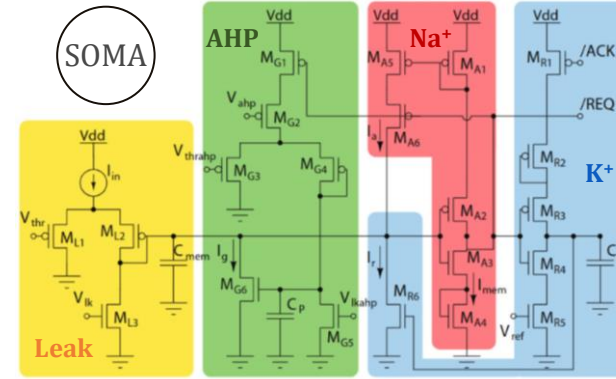
Many Approaches: Analog ... Digital

Analog / Mixed

- + High bio-realism
- + Long time scales
- + Ultra-low power
- ✗ Sensitive to noise
- ✗ Expensive (area, design)
- ✗ Few manufactures

Digital

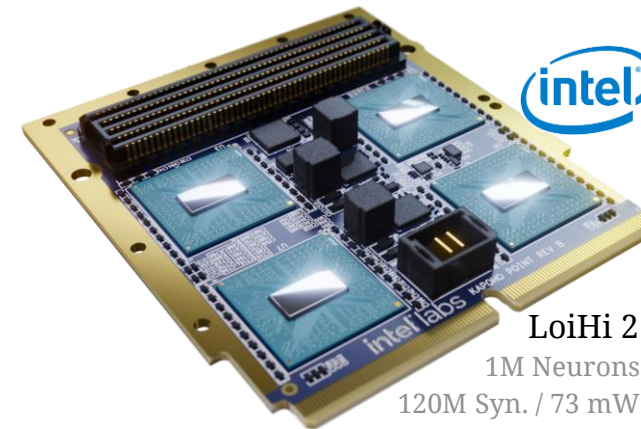
- + High signal fidelity
 - + High chip density
 - + Faster design
 - ✗ Von Neuman Architecture
 - ✗ Large on-chip memory
- SNN: Power ↘ up to 1000× / Speed ↗ up to 10×



LIF Neuron: Fully Analog Circuit



ICNS, Western Sydney University

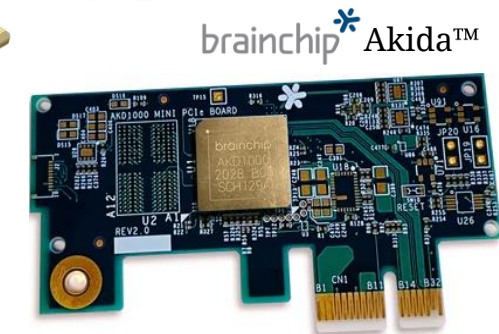


Loihi 2
1M Neurons
120M Syn. / 73 mW

AIWIRE Kapoho Point Eval-Board



SynSense Speck™
Vision NSoC: DVD 128×128pix
320k Neurons / ≈5mW



brainchip Akida™
1.2M Nrnns.
10b Syn.
2 mW



IBM NorthPole

1M Neurons
256M Synapses
73 mW / Chip

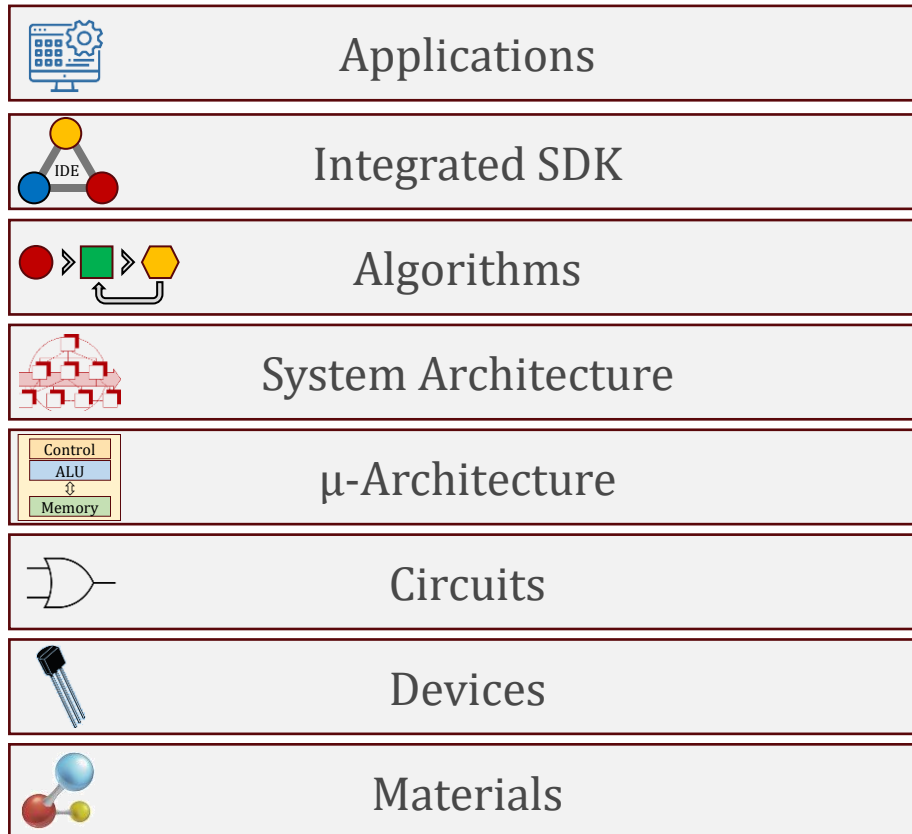


SEMICONDUCTOR ENGINEERING
DEEP INSIGHTS FOR THE TECH INDUSTRY

NorthPole scale-out assembly (Prototype)

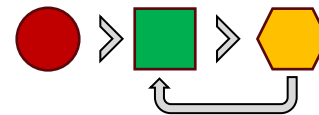
Eco System

Neuromorphic Computing Stack



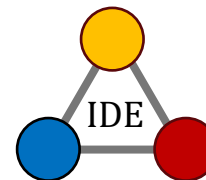
 Growing pallet of open-source SDKs

SNN Algorithms



Supervized		Unsupervized	
Boltzmann	Evolutionary	Self-organizing	Hebbian
Other			Spike Time Dependent Plasticity (STDP) Schuman C. et al. A survey of neuromorphic computing and neural networks in hardware, arXiv 1705.06963, 2017 (box size: # of papers)
Back-Propagation			

SNN Integrated Development Tools (non-exhaustive list)



 www.snntorch.readthedocs.io/en/latest

 www.spinnaker.io

 www.nest-simulator.org

 www.briansimulator.org

 www.binds.cs.umass.edu/bindsnet.html

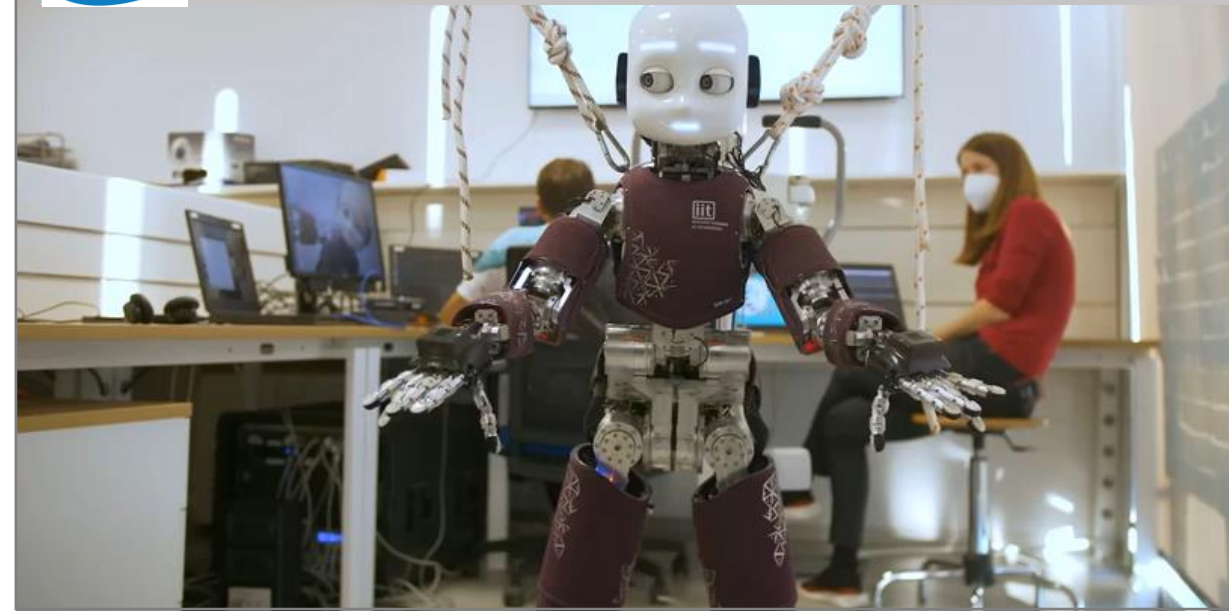
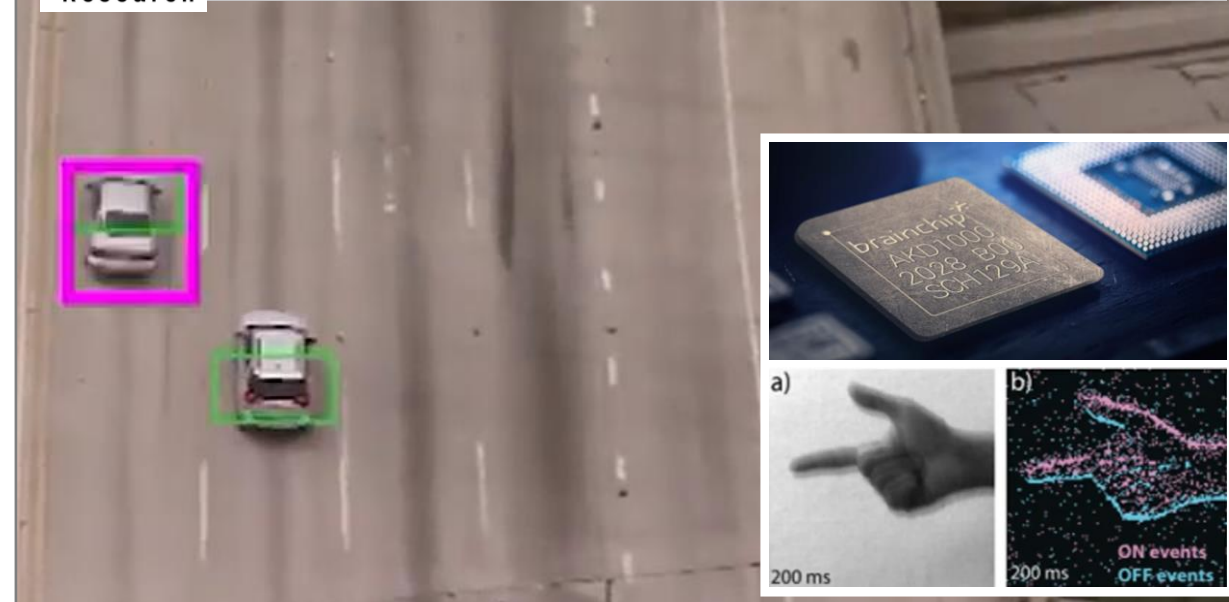


Applications of SNNs

Broad range of suitable fields

- + **AI:** brain-like processing, adaptive learning over time
- + **Robotics:** real-time decisions in dynamic settings
- + **IoT:** local, low-power data processing w/o cloud
- + **Security / Surveillance:** real-time recognition of complex patterns and anomalies, e.g. in videos
- + **Automotive:** Real-time processing of vast and dynamic sensor data for advanced driver-assistance
- + **Healthcare:** efficient & adaptive processing of complex data, e.g. for personalized medicine
- +
- SNNs: Potential game-changer across many academic & industrial applications

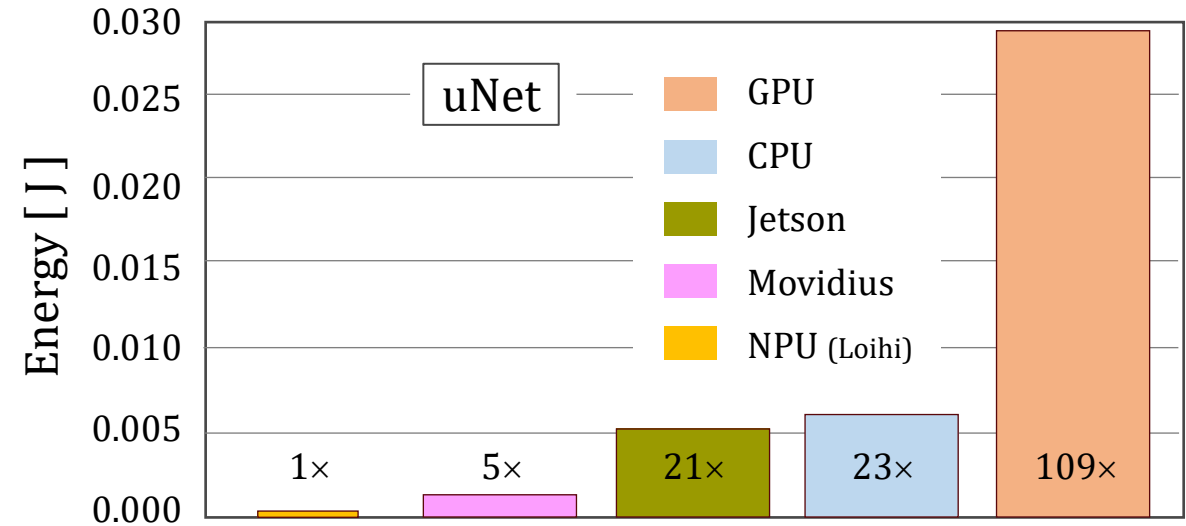


NC: Quo Vadis?

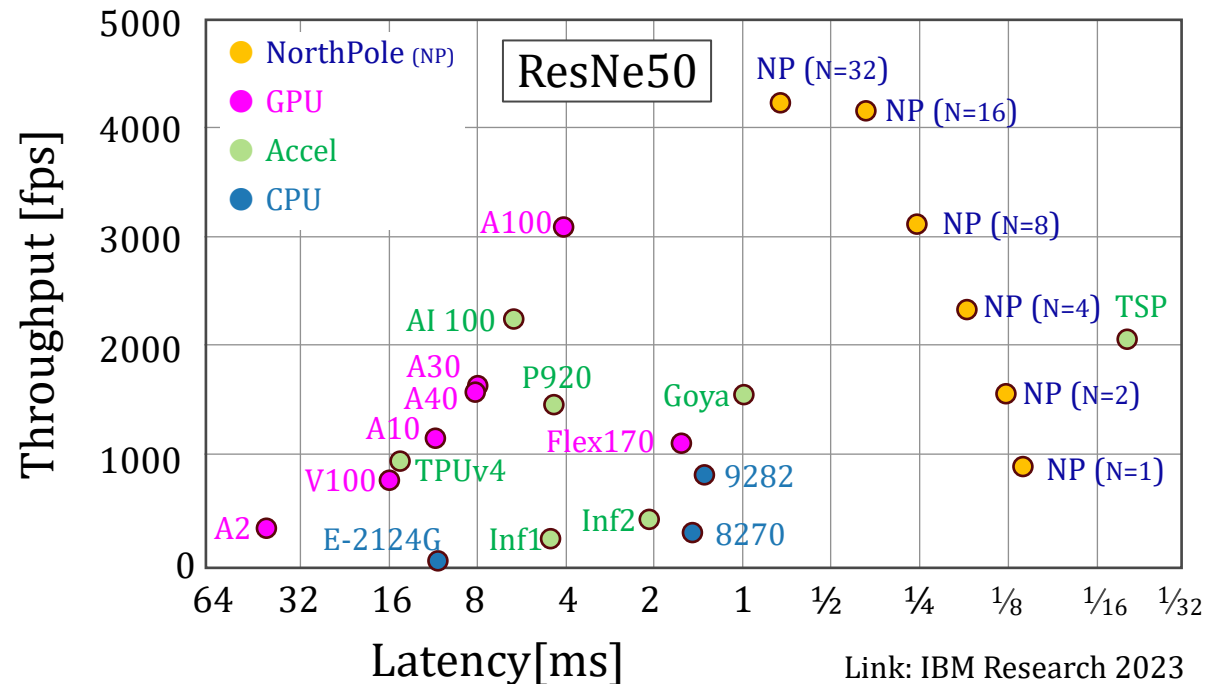
Pros and Cons

- + Energy ↘, Speed ↗, Scalability ✓
 - + Parallel sparse / event-driven computing
 - + Adaptive learning via neuron firing rules
 - + Fault tolerance
 - + Holds vast promise ... ✗ yet faces many challenges
 - ✗ Maturity of Technology of HW, SW & tools
 - ✗ Compatibility issues with existing ecosystems
 - ✗ Complex data processing w.r.t. std. ANNs
 - ✗ Limited Vendor Options / Security concerns
- SNNs: Intense research with emerging applications ... ready to leave the lab!

Dynamic Energy per Inference

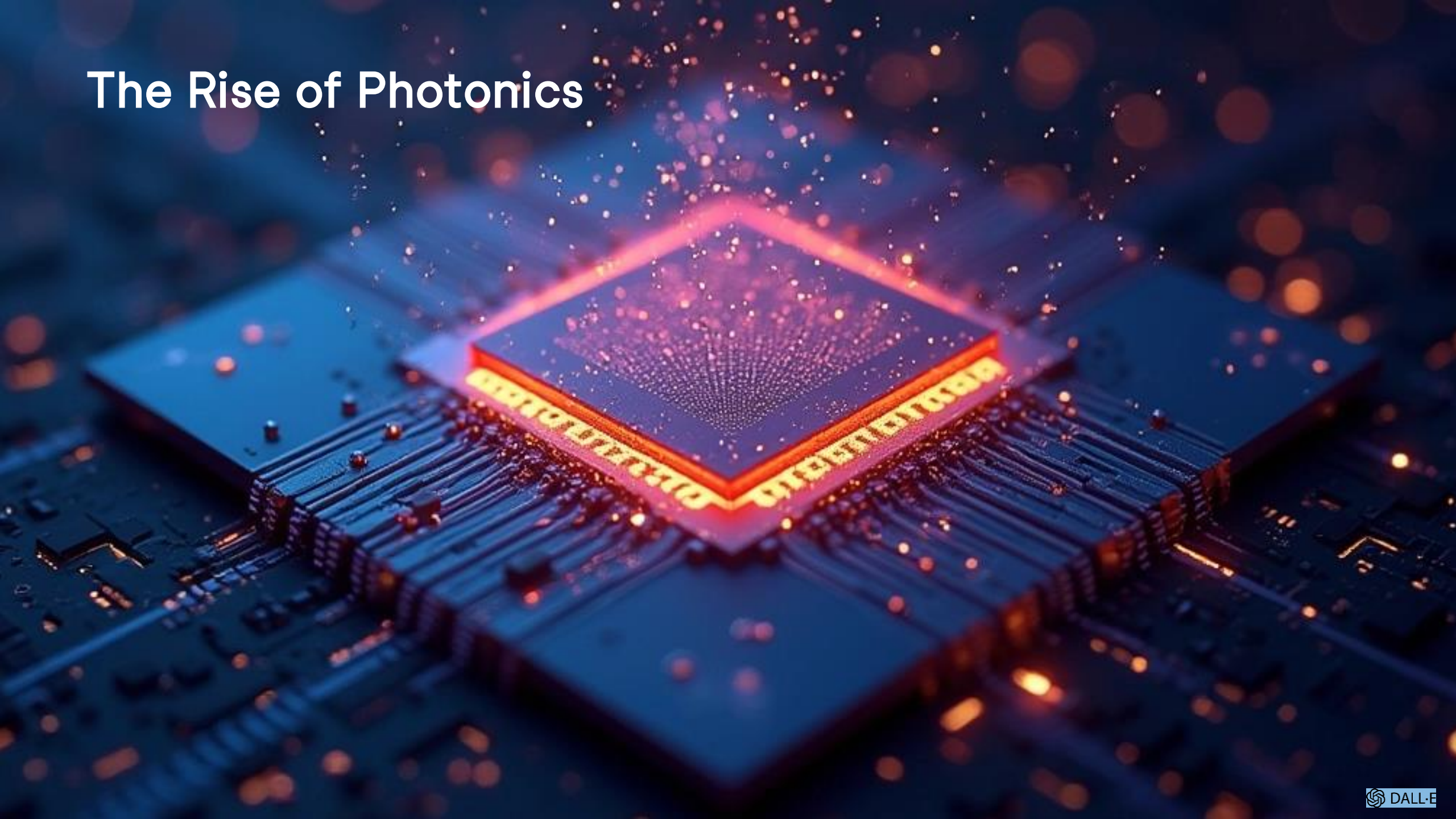


Link: K. Patel et al. 2021



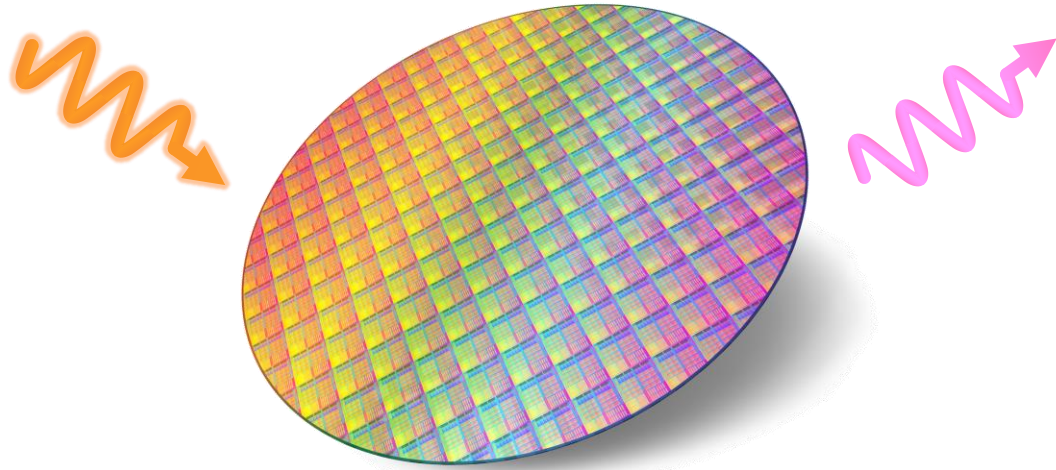
Link: IBM Research 2023

The Rise of Photonics



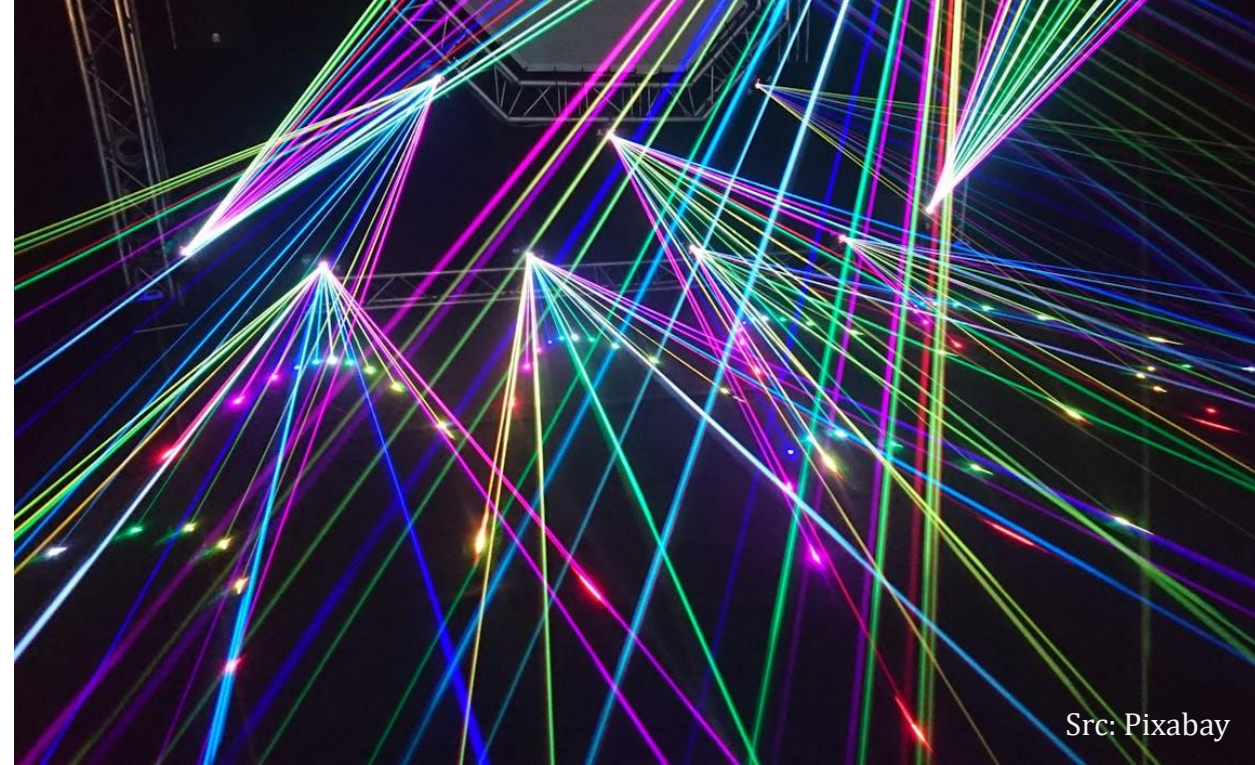
The Rise of Photonic ICs

Manipulating Light on Silicon Chips

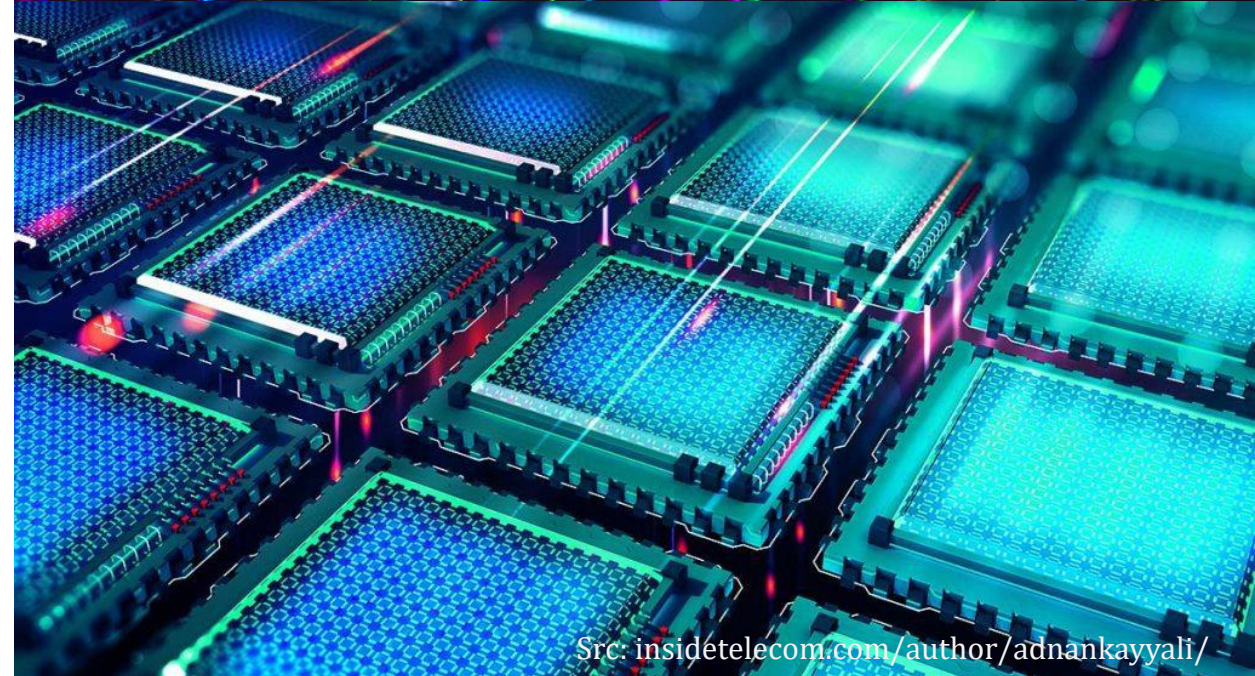


- | | |
|---------------------|-------------------------------|
| + Energy efficiency | × Complexity |
| + High bandwidth | × Process requirements |
| + Compactness | × Tech. stack $\neq$ standard |

⦿ Nano-scale CMOS Process: Si-Photonics $\triangleq$ MEMS



Src: Pixabay



Src: insidetelecom.com/author/adnankayyali/

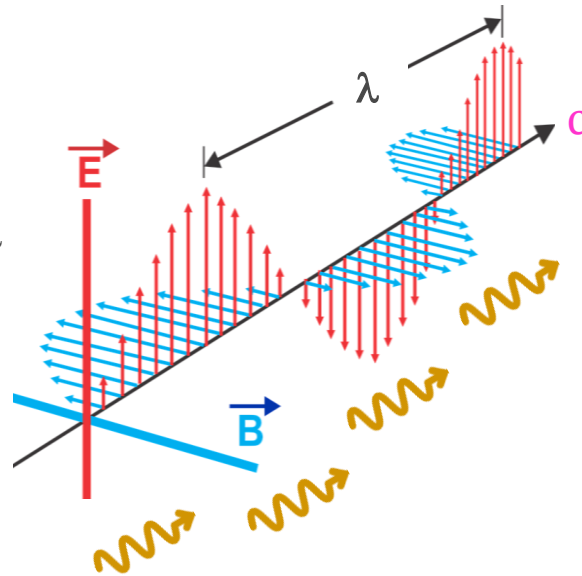
The Rise of Photonic ICs

What is Light?

1) Electromagnetic wave

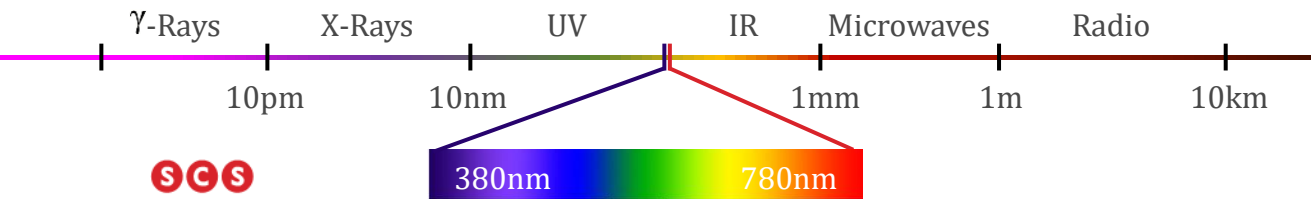
- Speed $c = 300'000 \text{ km/h}$
- Wavelength: λ
- Frequency: ν
- Electrical Field: E
- Magnetic Field: B

$$c = \nu \times \lambda$$



2) Flux of Photons

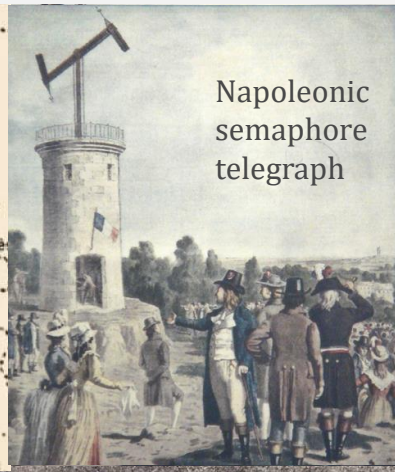
- Energy: $h \times \nu$



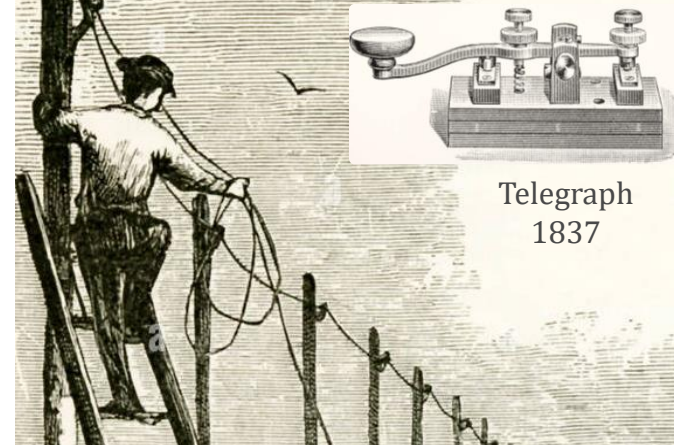
Optical Communication is Not New



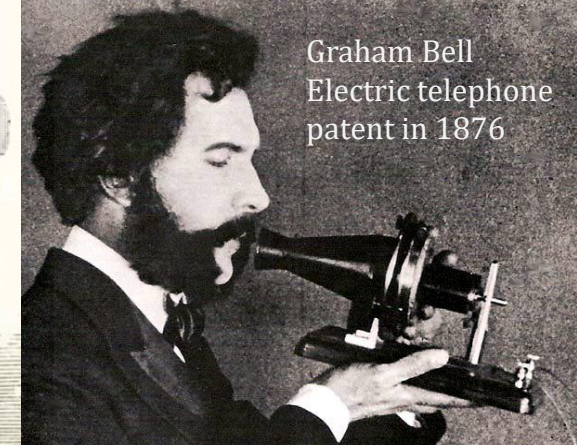
Src: Sean D'Souza



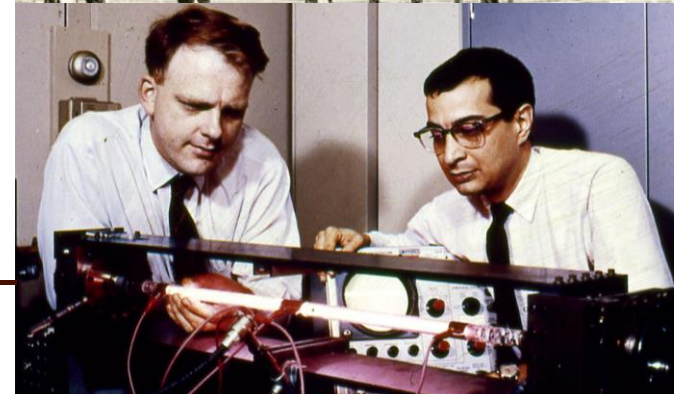
Napoleonic
semaphore
telegraph



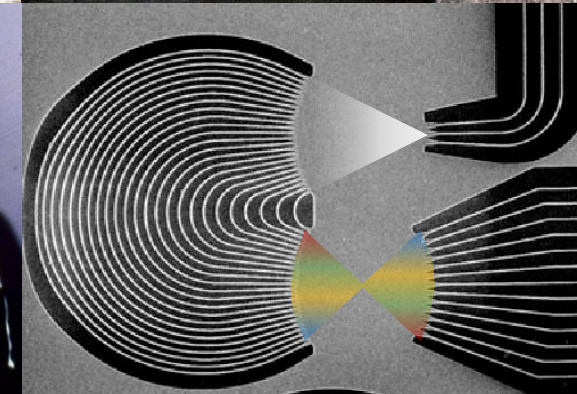
Telegraph
1837



Graham Bell
Electric telephone
patent in 1876



Rubin Impulse laser, $\lambda = 694\text{nm}$, 1960



1st PIC, AWG, Meint Smit, 1980

More .. Less

Key Advantages

More channel capacity (Shannon-Hartley)

$$C = B \cdot \log_2 (1 + S/N)$$

C : CH-capacity [bps]
 B : used bandwidth [Hz]
 S/N : Signal-to-Noise Ratio

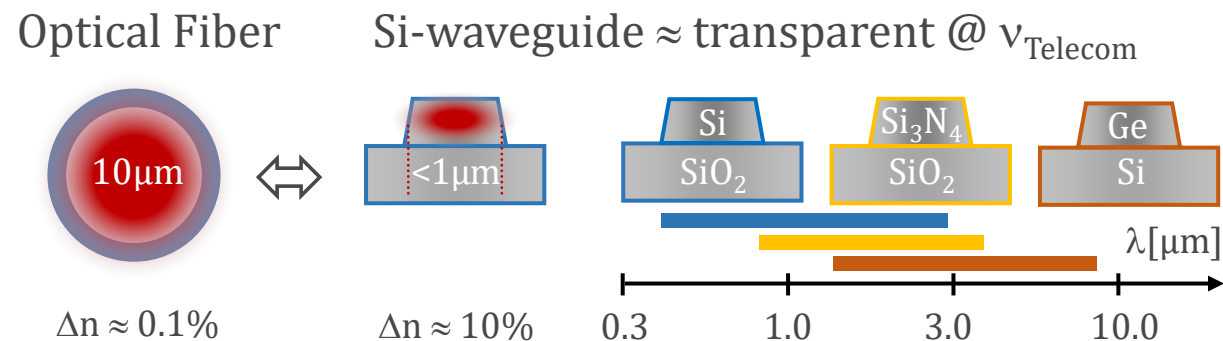
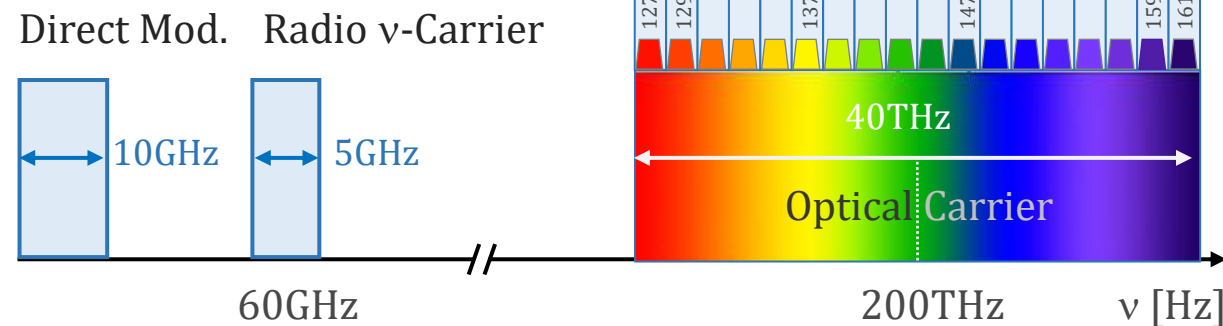
e.g. 125GHz $\approx$ Δ 1nm @ 1.5 μ m

Better scaling & miniaturization

- Sub- μ m waveguides: high n-contrast
- CMOS process compatible

Less energy

- Electrical  : $\approx$ Nanojoule per bit flip
- Optical  : $\approx$ Picojoule per bit flip

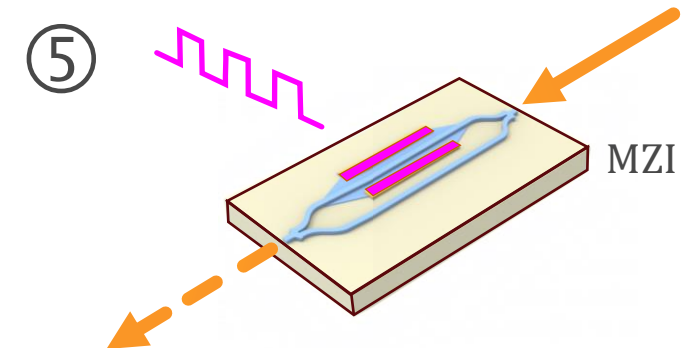
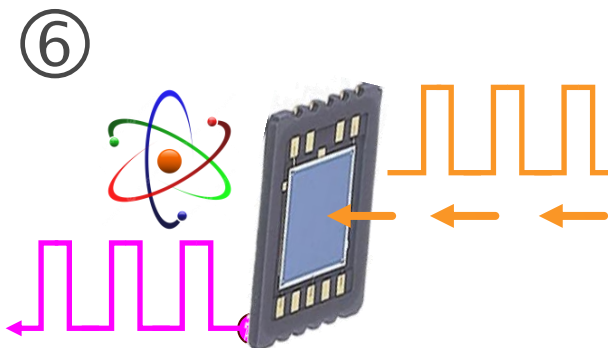
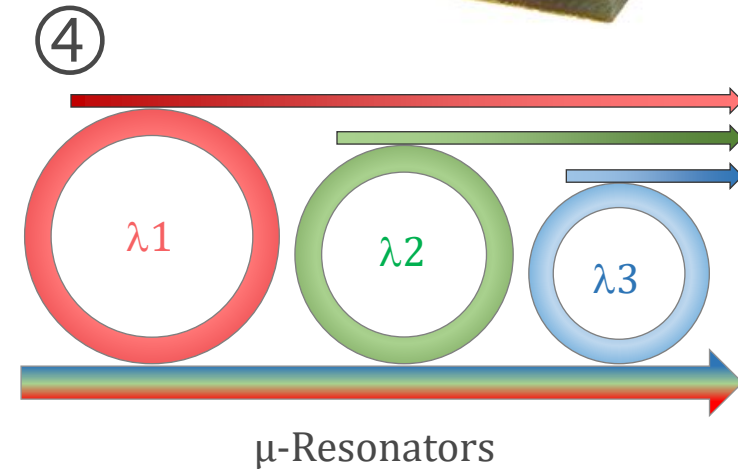
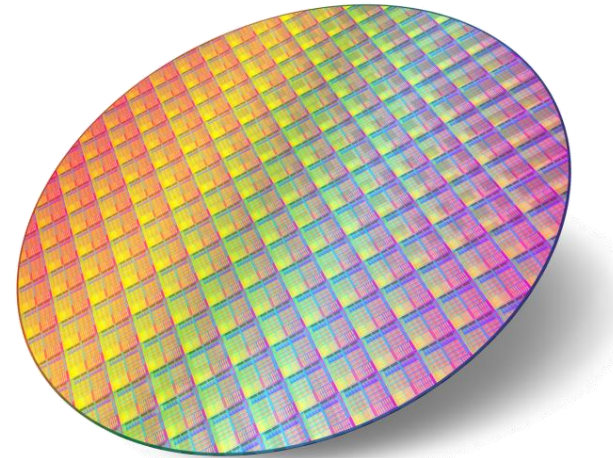
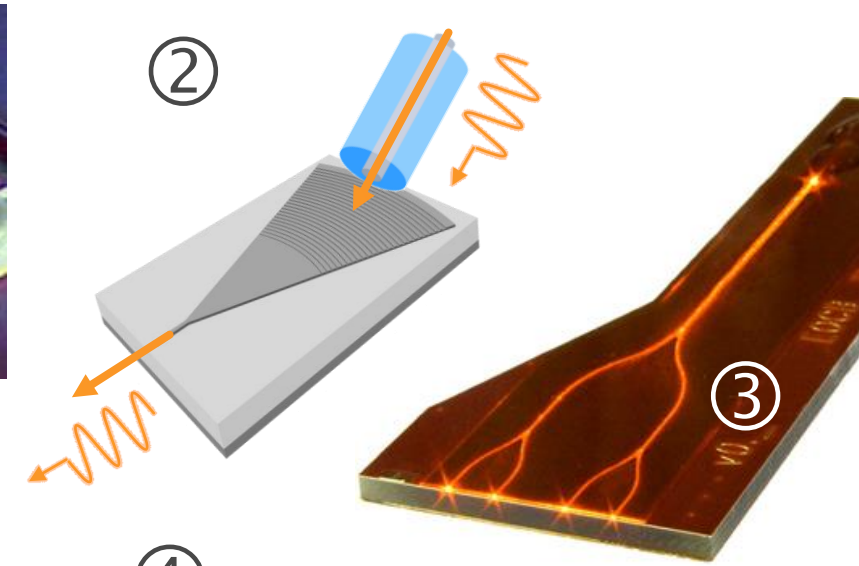
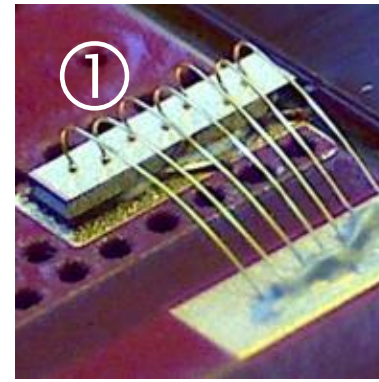


Photonic Integration

Key Ingredients

- ① Light source
- ② Light coupling
- ③ Light transport
- ④ λ -Filtering / λ -multiplexing
- ⑤ Signal modulation
- ⑥ Signal detection
- ⑦ Supporting electronics

⋯ Challenges: Laser integration: Si $\neq$ III-V
CMOS precision: $\approx 1\text{nm}$



Applications

Performance Scaling with Si-Photonics

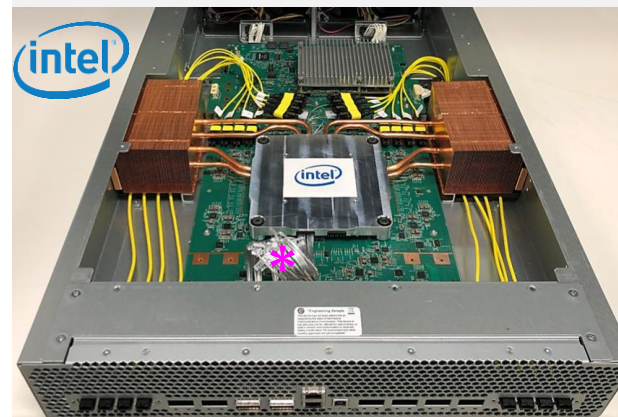
Today	Tomorrow	Future
100-800 Gbps	1.6-6.4 Tbps	4-64 Tbps
25 pJ/bit	<15 pJ/bit	< 3 pJ/bit
SFPs	PIC / 3D MCP	PIC & EIC

Increasing optical interconnects

- Rack-to-Rack $\Rightarrow$ Chip-2-Chip $\Rightarrow$ On-Chip

- Trends: Classic SFP $\Rightarrow$ co-packaged PICs
Chip-2-chip tracks $\Rightarrow$ PICs

Industry 1st Ethernet switch with CPO: Barefoot Tofino 2



4 co-packaged optic ports

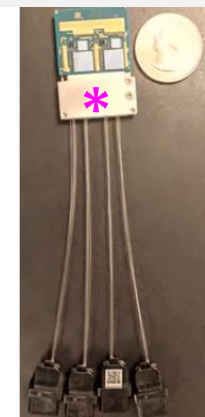
- 64x 100G ports

Tofino 2 vs. std. SFP

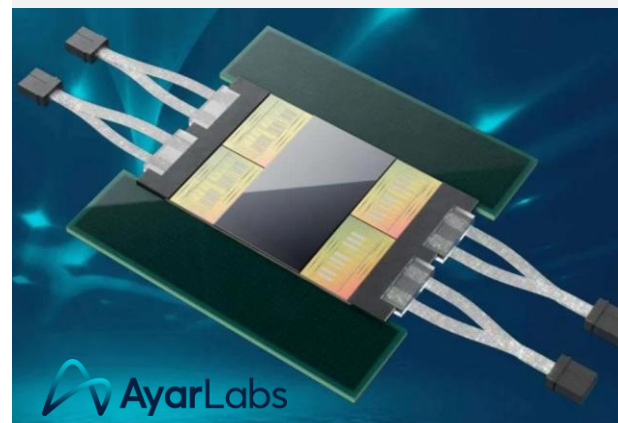
- BW density $\nearrow$: 40x
- PWR $\searrow$: 30%

Apps $\Rightarrow$ I/O

- Rack-2-Rack



1st UCIe compatible optical interconnect: TeraPHY



16 co-packaged optic ports

- 8 Tbps BW

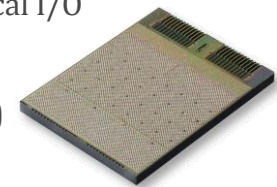


TeraPHY vs. electrical I/O

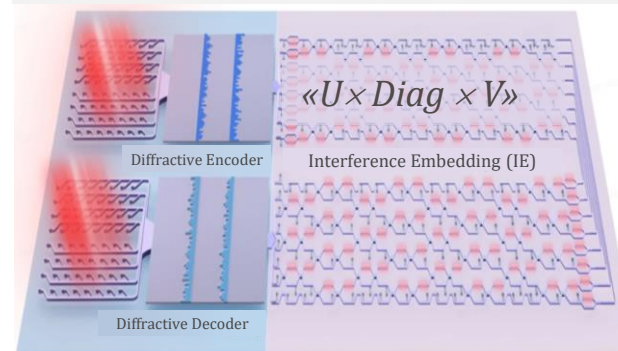
- Data rate $\nearrow$: 5x

Apps $\Rightarrow$ I/O (mm - km)

- Chip-to-Chip
- Rack-to-Rack



Large-scale high-throughput photonic AI chiplet: TaiChi



Optical neural net (ONN)

- 14mio neurons / chip



GPU H100 vs. TaiChi

- Energy $\searrow$: 1000x

Apps $\Rightarrow$ AI @ Chip

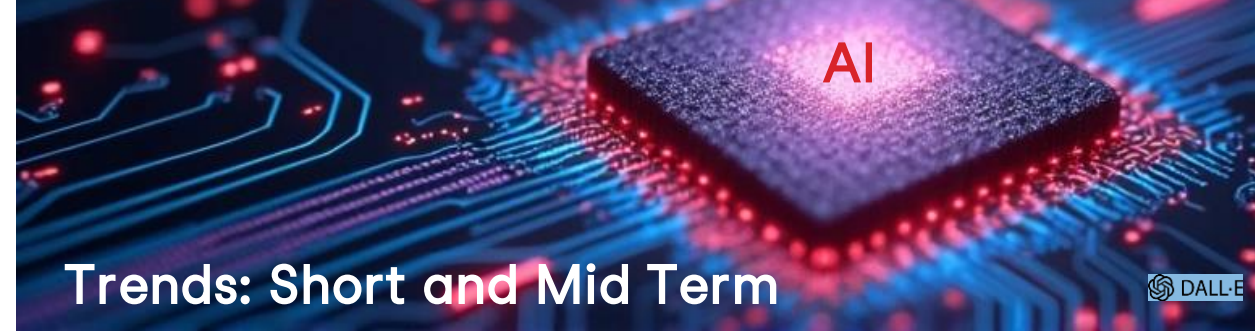
- Scene recognition $\leq$ 1k classes
- Content generation AGI



Si-Photonics: Quo Vadis?

Pros and Cons

- + High integration @ waver scale
- + High bandwidth: I/O bottleneck ↗
- + Cost-effective manufacturing
- + Energy efficiency
- ✗ Material limitations
- ✗ Complex packaging
- ✗ Optical losses & thermal sensitivity
- ✗ Extreme CMOS process accuracy: $\approx 1\text{nm}$



Trends: Short and Mid Term

- PICs can enhance DC-performance with high-speed, energy-efficient interconnects:
 - Optical transceivers: BW ↗, distance ↗, space ↗
 - Server interconnects: copper cables $\Rightarrow$ SiPh links
 - On-board CPO for optical chip-2-chip links
- PIC with optical artificial neural nets may
 - Fuel scalable AI advancements
 - Extend Moore's Law trajectory



Take away

Neuromorphic Computing is

- λ -based, sparse, async. communication
- low-power, real time, adaptive learning
- ready to leave the lab!

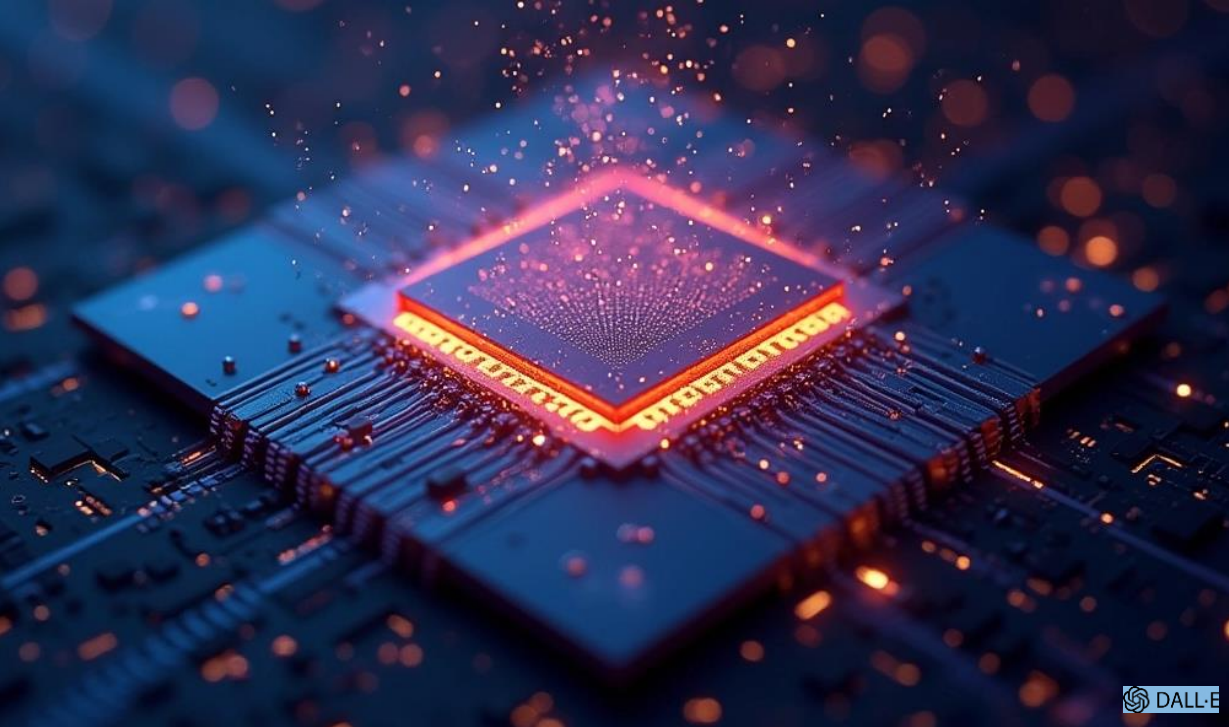
Silicon Photonics is

- ready to enhance DC-performance with high-speed, energy-efficient interconnects

... and may

- boost scalable AI applications
- extend Moore's Law trajectory!

Where do you see the greatest potential for you?





super computing systems

Supercomputing Systems

*Thank
you*



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SCS besteht aus 140 hochqualifizierten Ingenieuren, Informatikern & Physikern, die sich für die Lösung technologischer Herausforderungen begeistern.

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