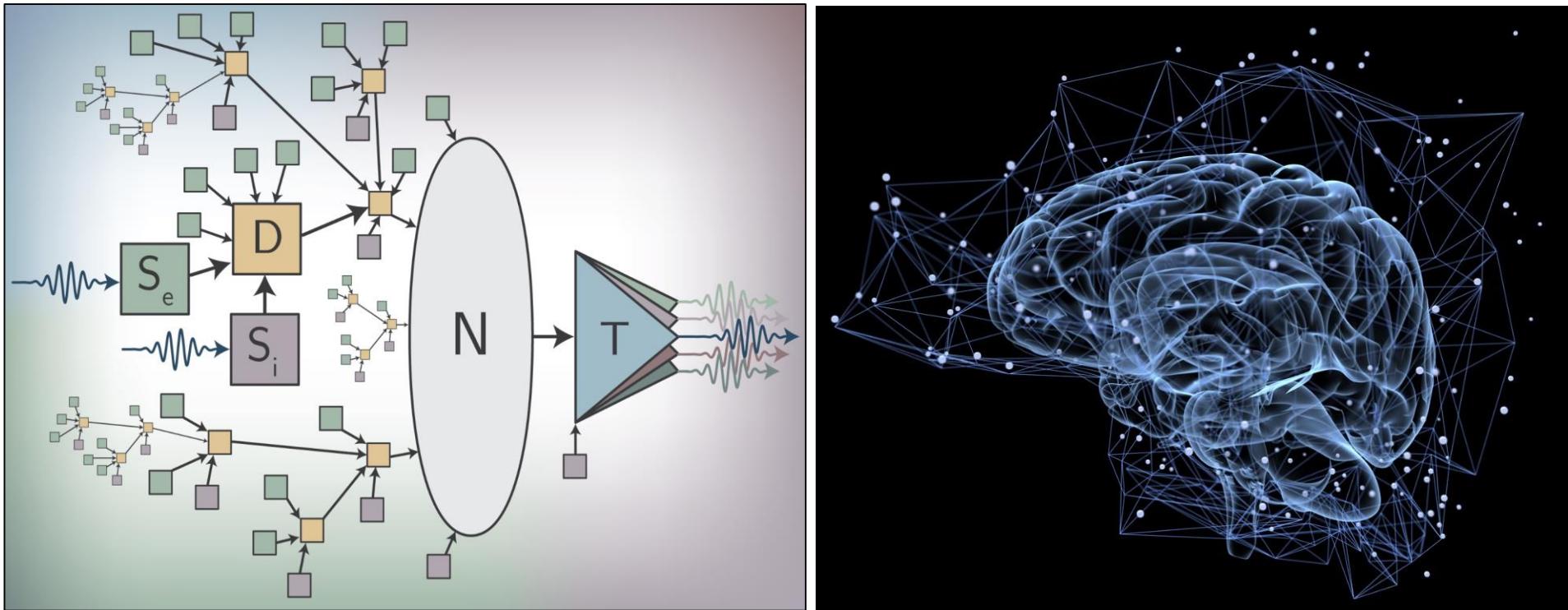


“Super” Neuromorphic Computing with Photonic and Superconducting Devices

Superconductors, light, and the “age of cognition”



Jeff Chiles, Sonia Buckley, Adam McCaughan, Saeed Khan, Bryce Primavera,
Rich Mirin, Sae Woo Nam, Jeff Shainline
NIST, Physical Measurement Laboratory

High Performance Single Photon Detectors

- Superconducting nanowire single photon detector
- Superconducting Transition-Edge Sensors
- Microwave Kinetic Inductance Detectors
- Conventional Applications
 - Advanced sensors for astronomy and astrophysics
 - High Energy Physics – rare particle event searches
 - Quantum Information / Quantum Computation

Photonic Quantum Information Requirements

	Quantum Communication	Quantum Computing (Photonic)	Quantum Computing (atoms)	Entanglement-based random numbers
Wavelength	1550 nm	Visible, Near-IR	UV	Near-IR
Detection Efficiency	As high as possible	As high as possible	>80%	>67%
Dark / Background counts		As low as possible		
Timing jitter		As low as possible		
Maximum count rate		As high as possible		

Conventional Single-Photon Detectors

	Wavelength Range	QE (%), max	DCR (cps)	Jitter	Max Count Rate (cps)
PMT (visible)	400-900 nm	40	100	300 ps	10×10^6
PMT (IR)	1000-1600 nm	2	200K	300 ps	10×10^6
Silicon (thick)	400-1050 nm	65	25	400 ps	10×10^6
Silicon (thin)	400-1000 nm	49	25	35 ps	10×10^6
InGaAs APD	950-1600 nm	20	75K	350 ps	10×10^3

- Commercially available
- Relatively inexpensive

M. D. Eisaman, J. Fan, A. Migdall, and S. V. Polyakov, Rev. Sci. Instrum. 82, 071101 (2011)

Low Temperature Physics = High Performance

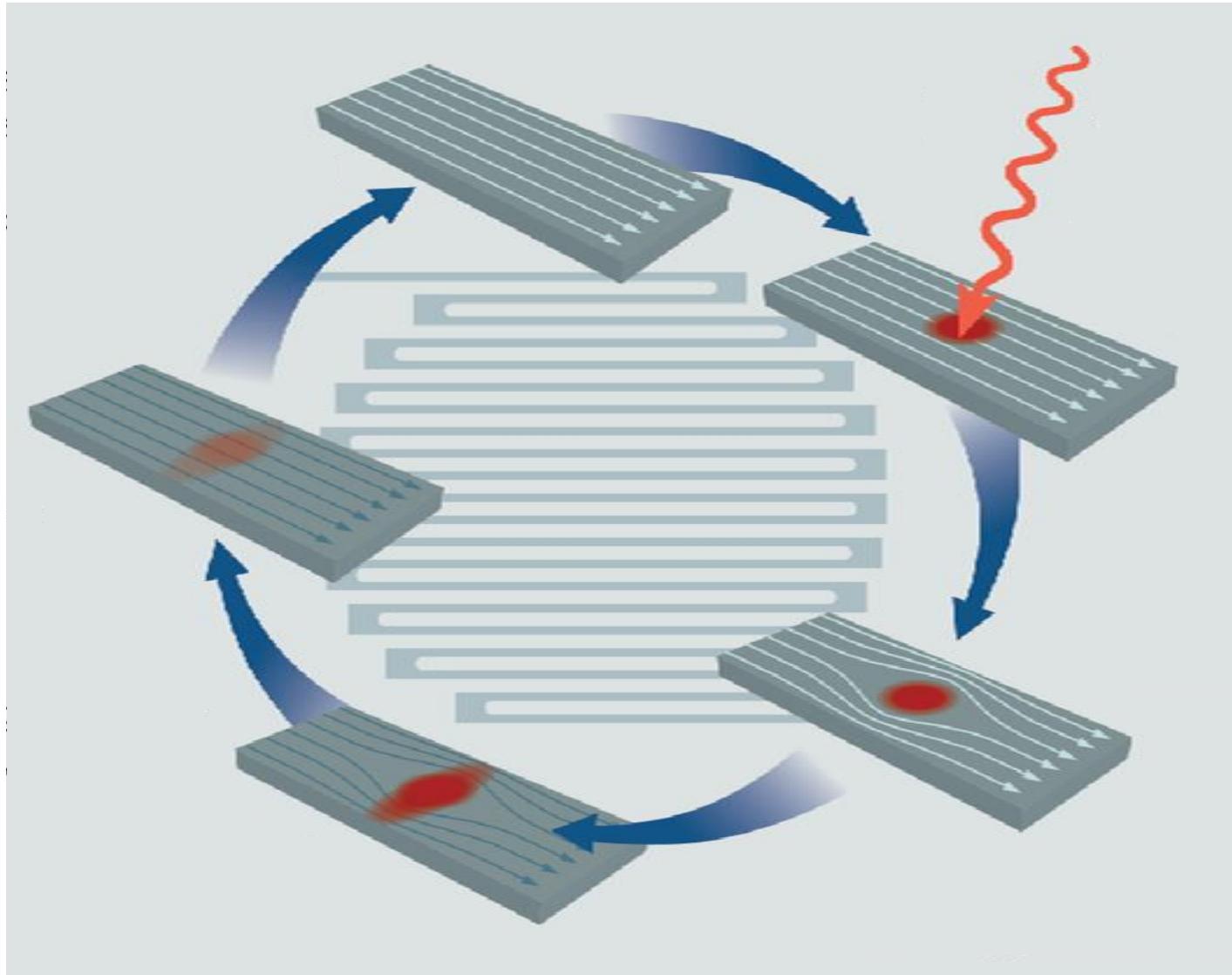
	Wavelength Range	QE (%), max	DCR (cps)	Jitter	Max Count Rate (cps)
W-TES (NIST)	UV-1850 nm+	>98%	<<1	10-100 ns	100×10^3
SNSPD: NbN	UV-5 um	>90%	100-1000	~3 ps	100×10^6
SNSPD: WSi	UV-5 um	~98%	<<10 ⁻⁵	~5 ps	10×10^6

TES: Transition Edge Sensor

SNSPD: Superconducting Nanowire Single Photon Detector

- No afterpulsing problems
- Excellent prospects for longer wavelengths

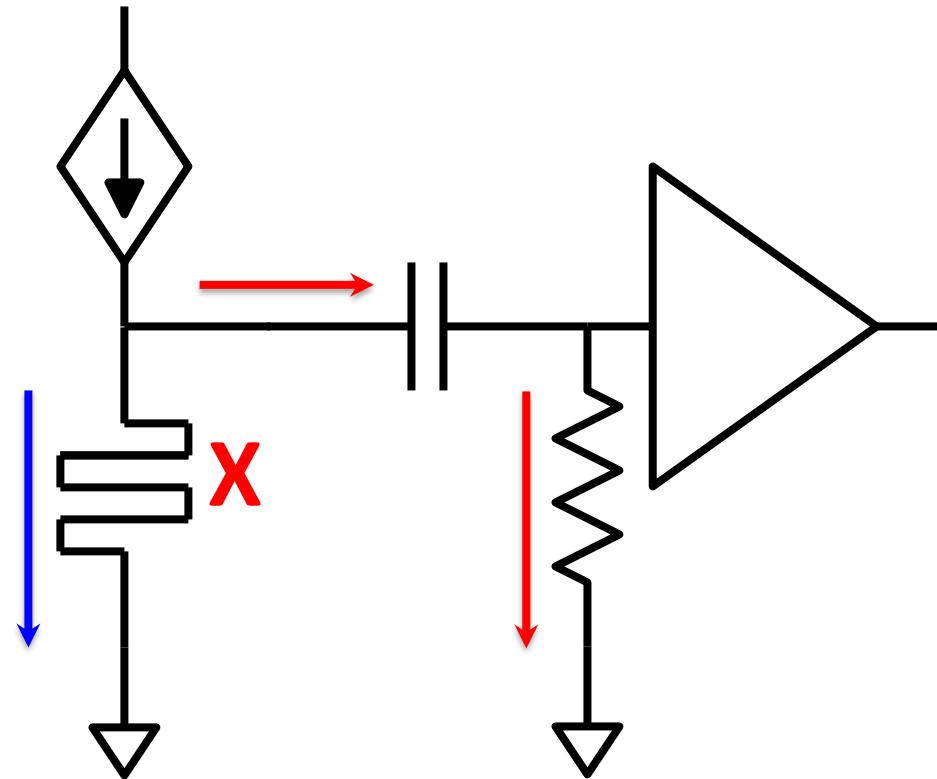
Superconducting Nanowire Single Photon Detectors:



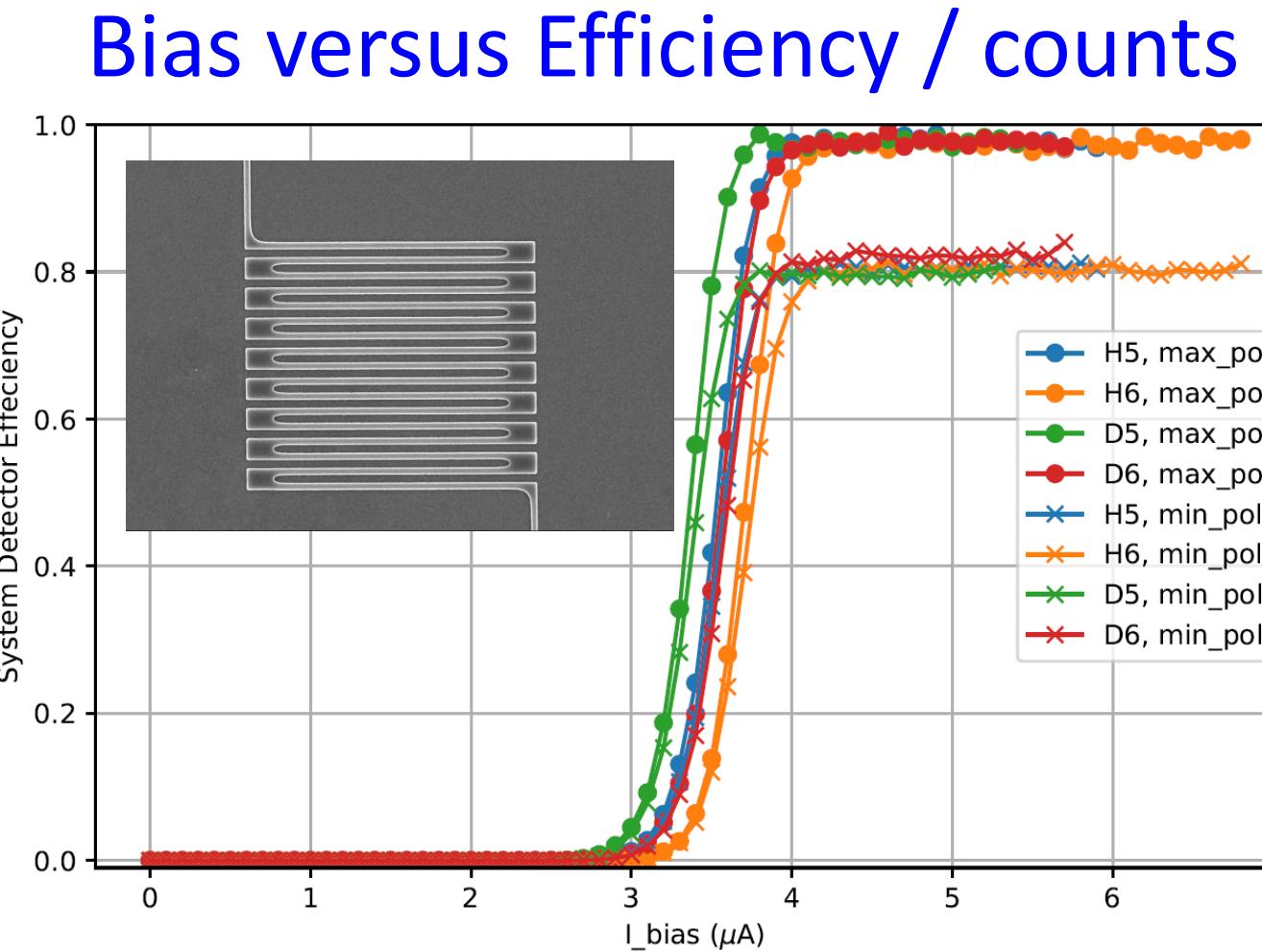
- ultra-thin (2nm to 8nm)
- Anomalous kinetic inductance
- NbN, NbTiN
 - 2K operating temperature
 - ~80nm wide
- **New materials:**
- W-Si, Mo-Si, Mo-Ge
 - 1K operating temperature
 - ~150nm

5 microns wide

Simplicity of Superconducting Nanowire Single Photoncs Detectors



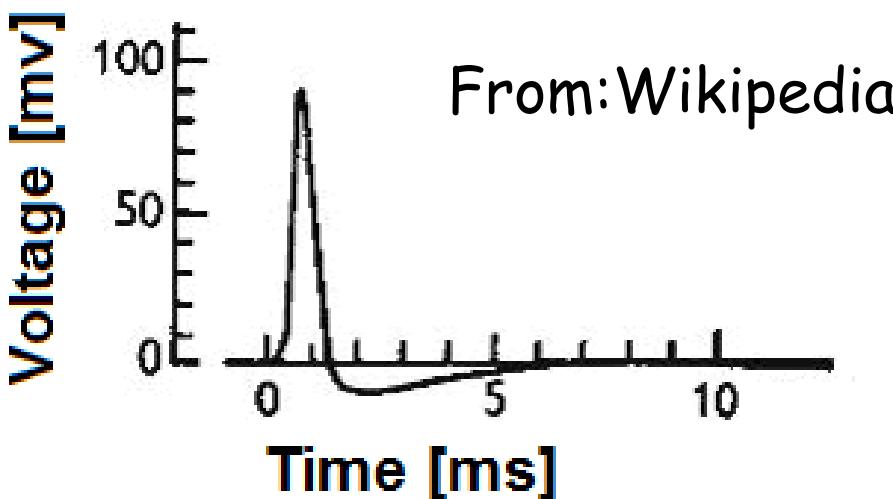
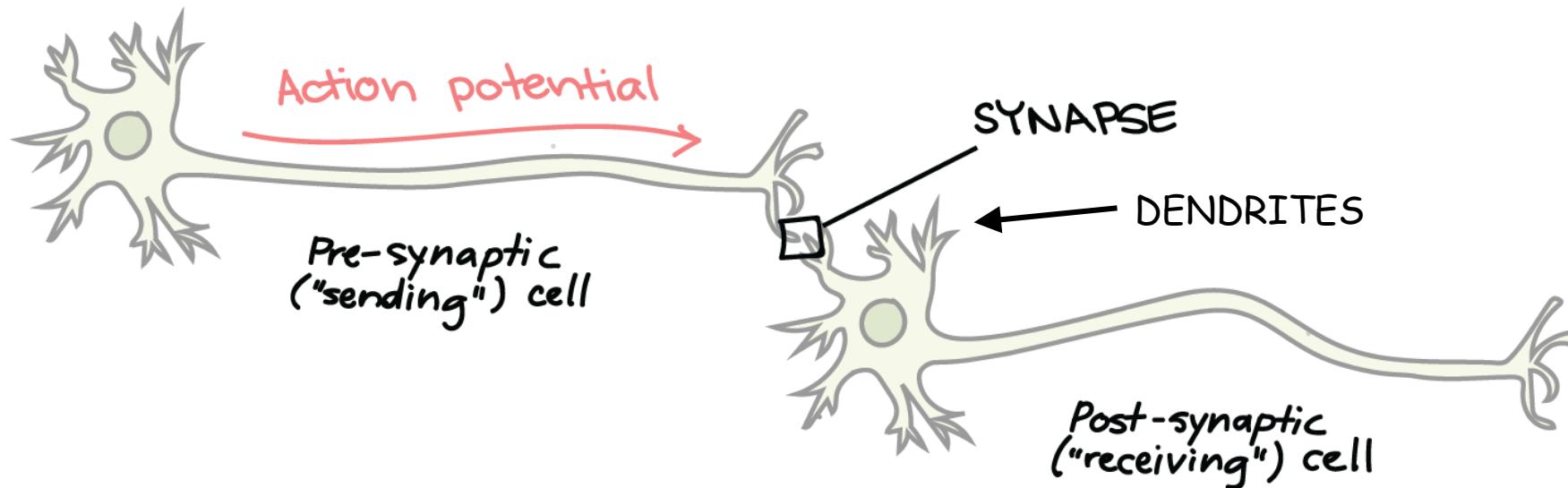
Simple Readout



Future of Computing

- High Performance Computing. (HPC)
 - Traditional model of computation
- Quantum Computing and Networking (QC)
 - Can outperform HPC in some tasks
- Neuromorphic Computing (NC)
 - “Neuroscience” inspired architecture
 - Dedicated Hardware

Structure of a Biological Neuron

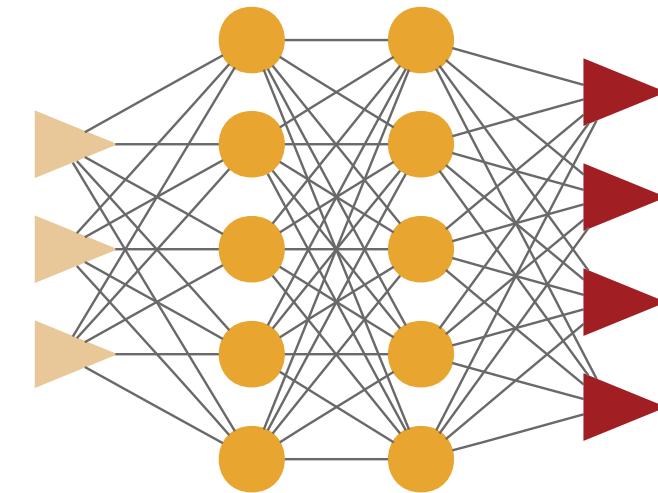
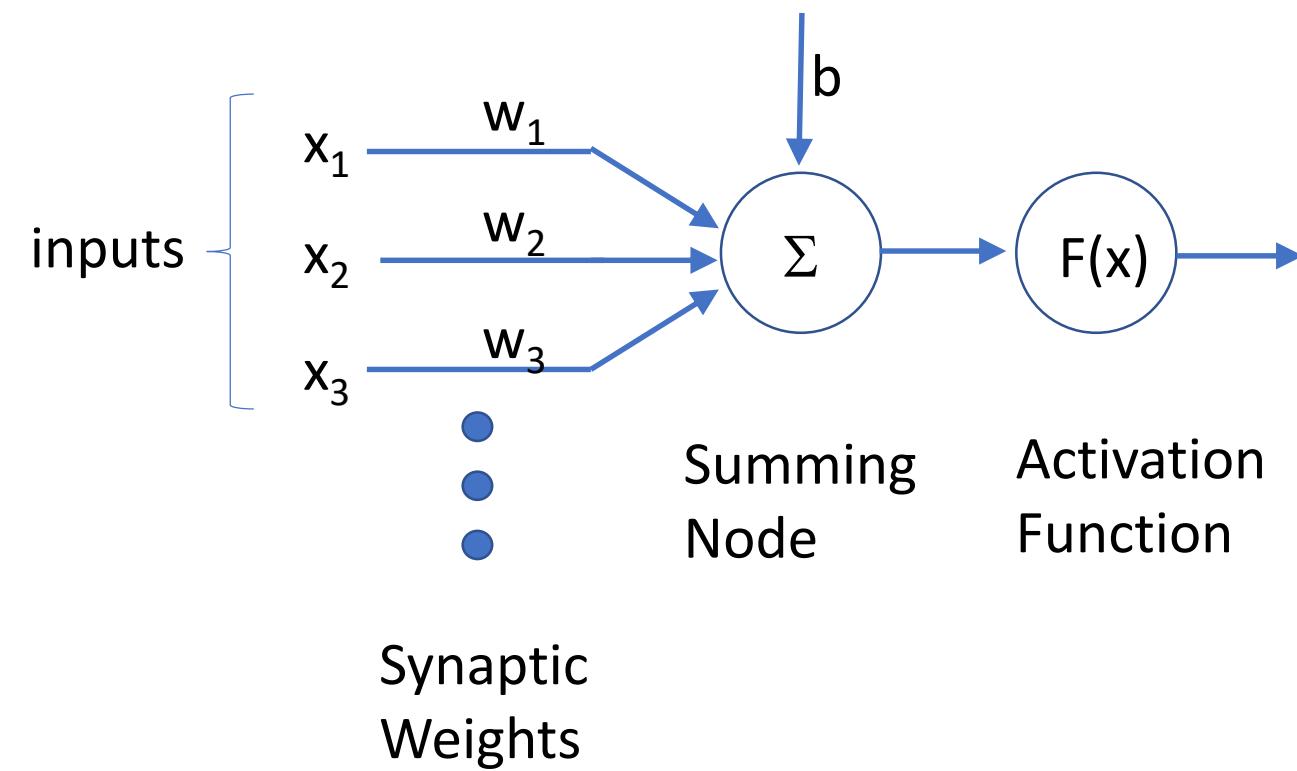


<https://www.khanacademy.org/science/biology/human-biology/neuron-nervous-system/a/the-synapse>

Fast Introduction to Neural Networks

Artificial Neuron

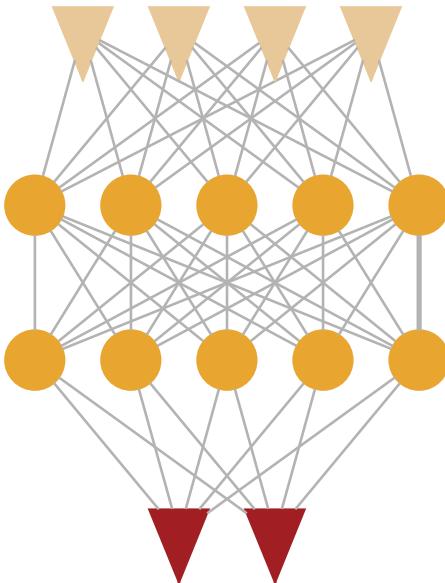
Network of Neurons



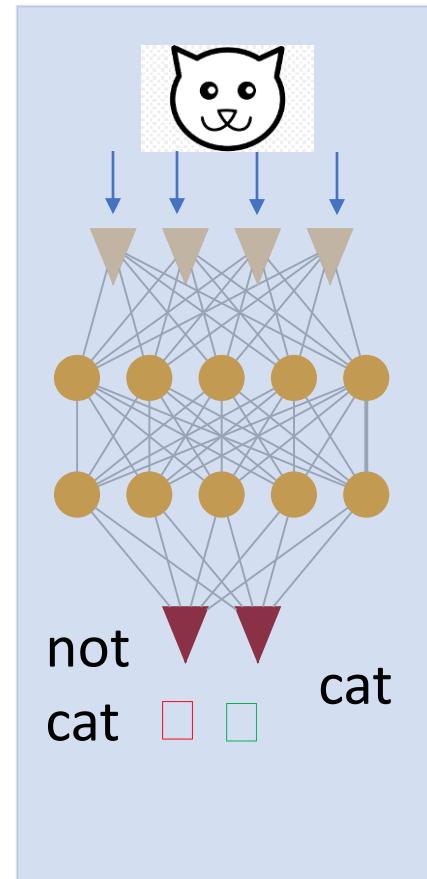
- Input Cell / Layer
- Hidden Cell / Layer
- Output Cell / Layer

Supervised Learning

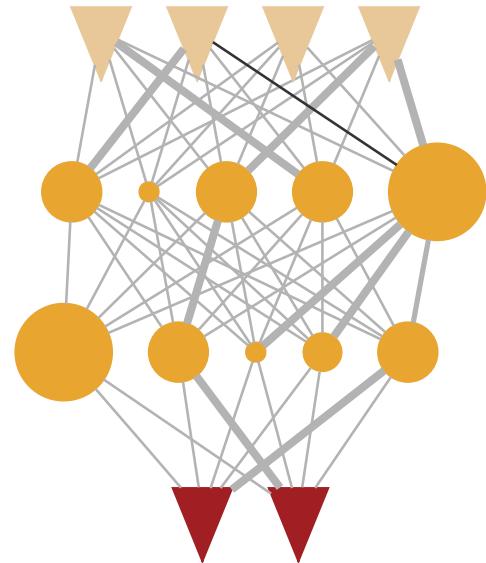
Untrained
Neural Network



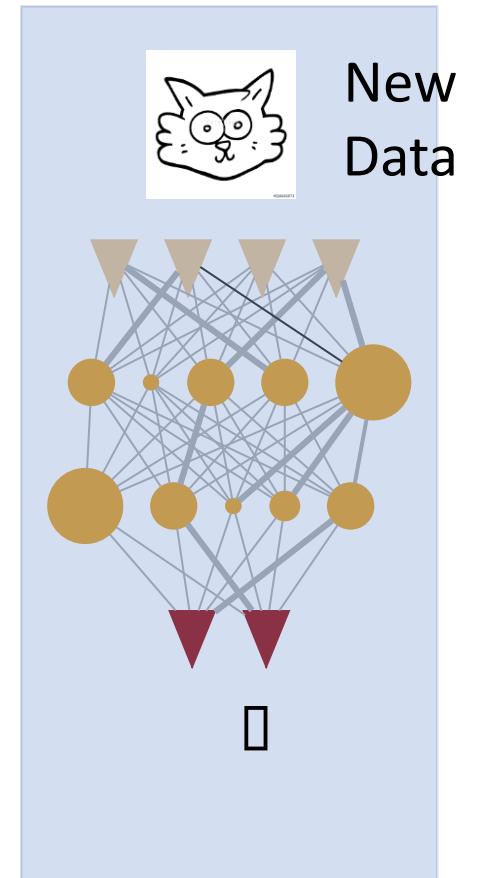
Training



Trained
Neural Network



Inference



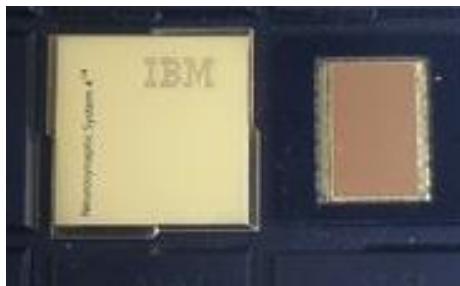
Machine learning hardware

- Today, there is large demand to perform “neural network” operations

- Image Classification
- Speech Recognition
- Natural Language Processing: “translation”



- Dedicated Neuromorphic Hardware



TrueNorth, IBM

see Merolla et al.,
Science, 2011.



Human Brain Project

- Other Technology platforms Neuromorphic have attracted venture interest



2nd and 3rd Generation Neural Networks

2nd Generation: “Proven”

- Limited Biological “inspiration”
- Matrix-vector multiplication
- Seeking weight matrix
- Trained by supervisory system
- Limited History
- Task specific

3rd Generation: “Less Proven”

- More Biologically inspired
- Information in dynamical state
- Spiking neurons communicate in rate and timing
- Potential for learning without supervision
- Information integrated across space and time
- General cognitive systems

Question: Why do we need Generation 3?

Answer: Energy Efficiency and Size

Consumption	CO ₂ e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL) w/ tuning & experimentation	39 78,468
Transformer (big) w/ neural architecture search	192 626,155

- “How do you make the largest scale artificial neural network?”
 - Human Brain:
 - 10 billion neurons
 - 1 neuron fans out to 10,000 neurons
- What are the fundamental limits?
- How do you evaluate the performance?
- How do physical characteristics of the devices relate to the performance of the neuromorphic computer?

<https://arxiv.org/abs/1906.02243v1>

Spiking Neural Networks / Dedicated Hardware

- Biologically Inspired
 - Spiking Signals, Energy Efficient
 - Rate and Time encoding
- Differentiated local processing
- Information integration across:
 - Space (network structure)
 - Time (dynamics)
 - Experience (plasticity)



Can we get to a size scale for “Cognitive” Systems?

Energy and Training Targets

Human

Power

2500
kCal/day =
100Watts

Clock speed

1 Hz to
1kHz

Training time

18
years

Artificial

Power

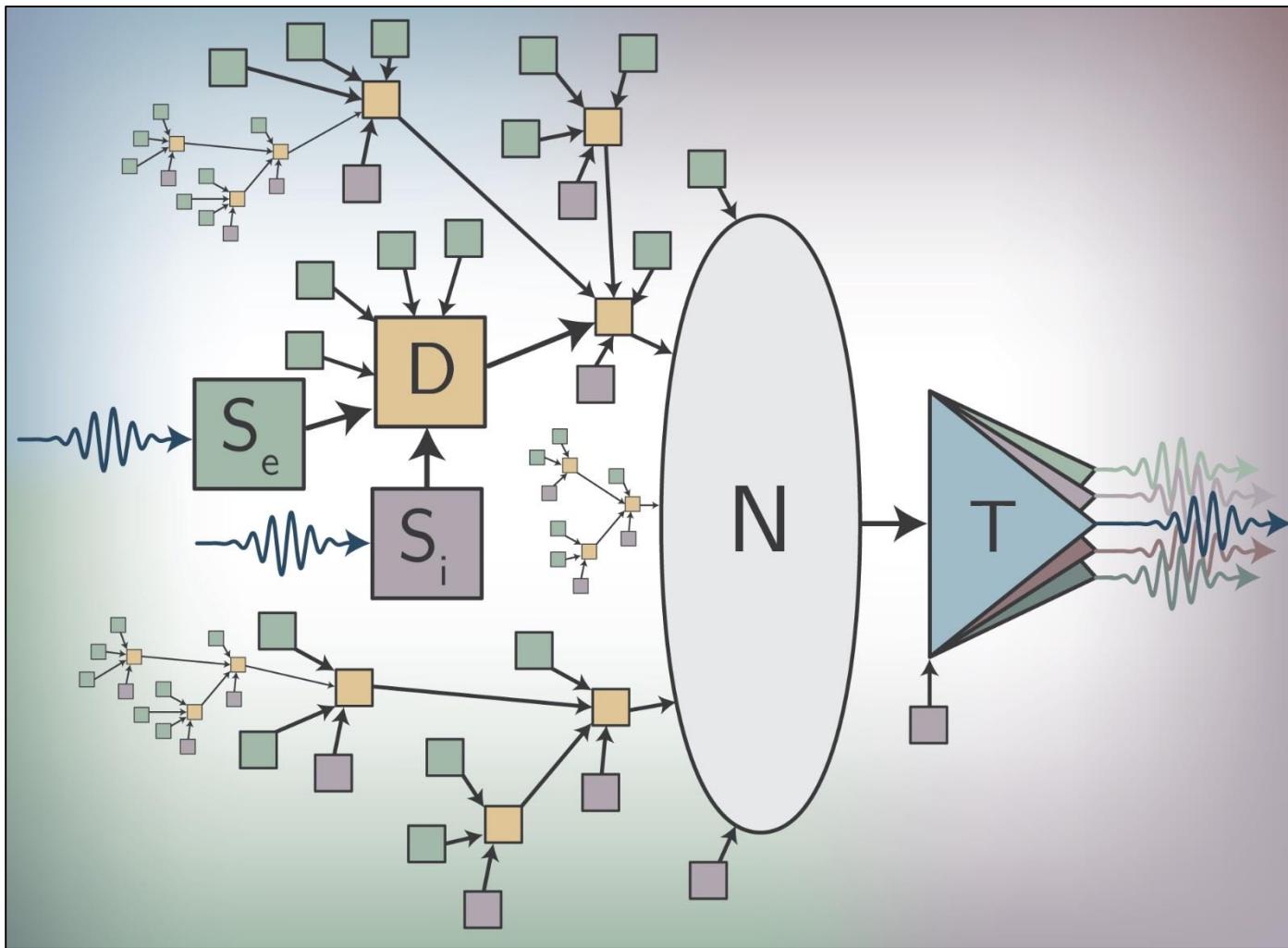
100 kW to 1
MW

Clock speed

1 Mhz
to
10MHz

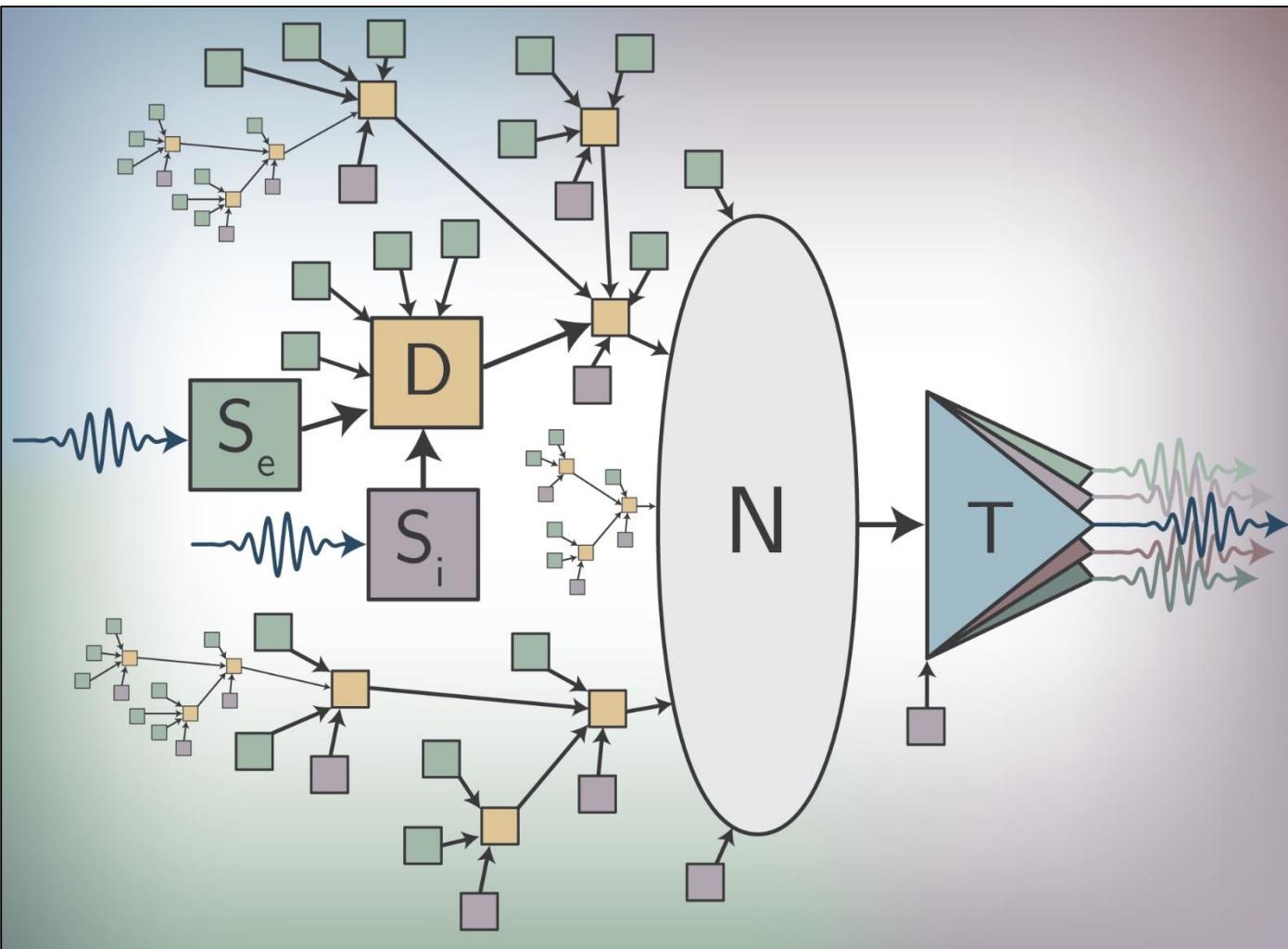
Training time

1 week



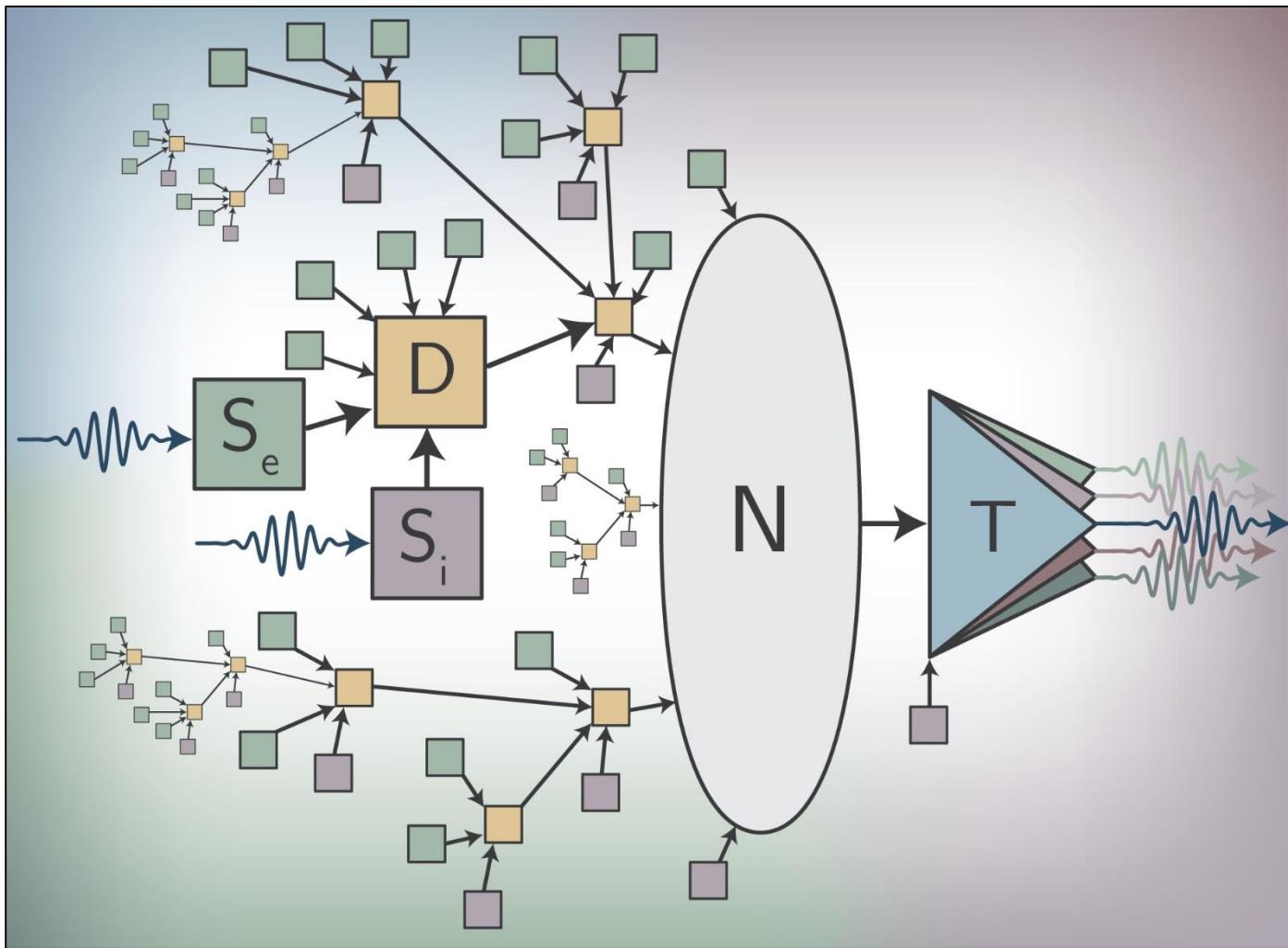
Fluxonic processing of
photonic synapse events

Spiking neural networks
jeffrey.shainline@nist.gov



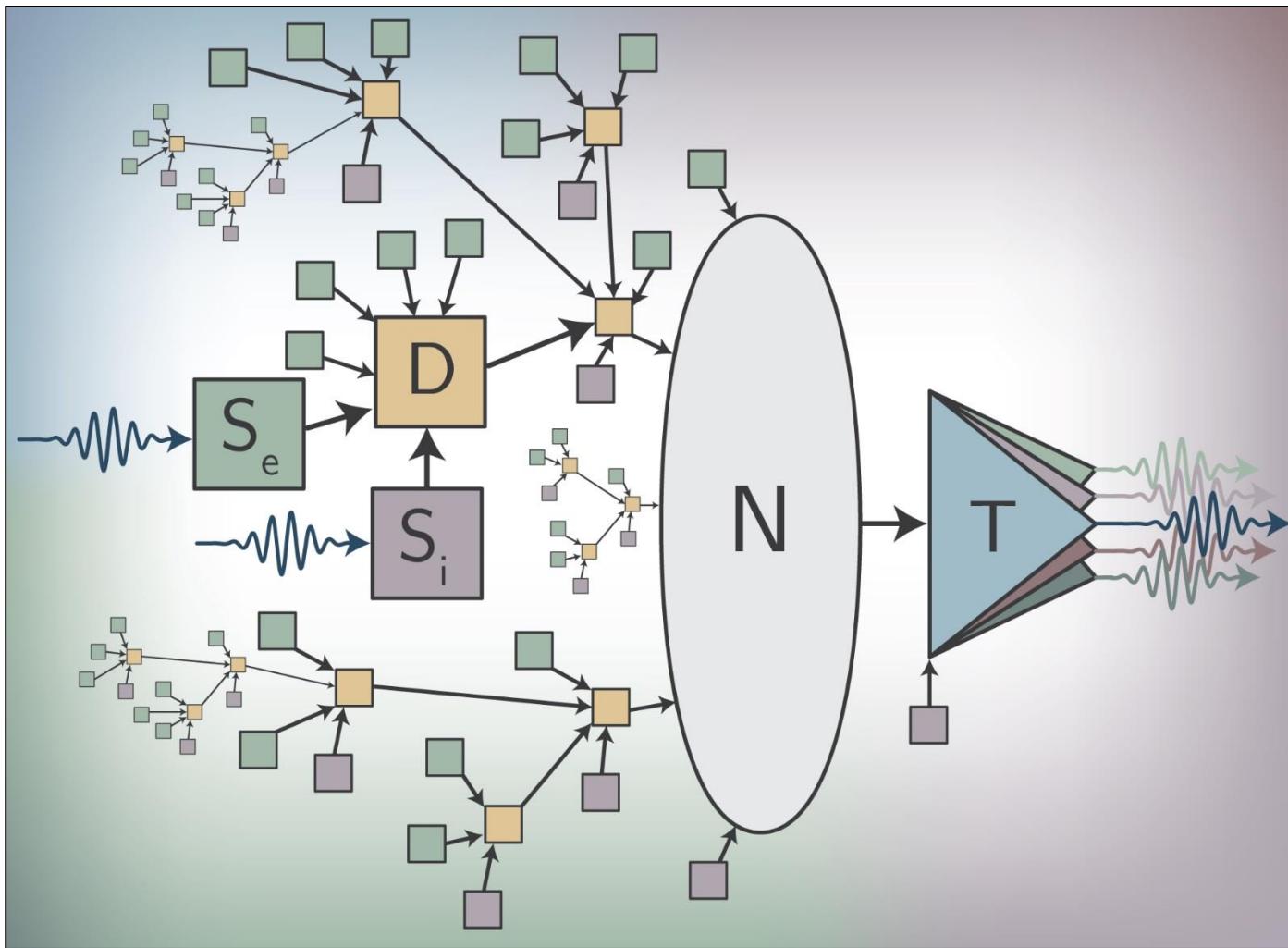
Fluxonic processing of
photonic synapse events

Light for communication



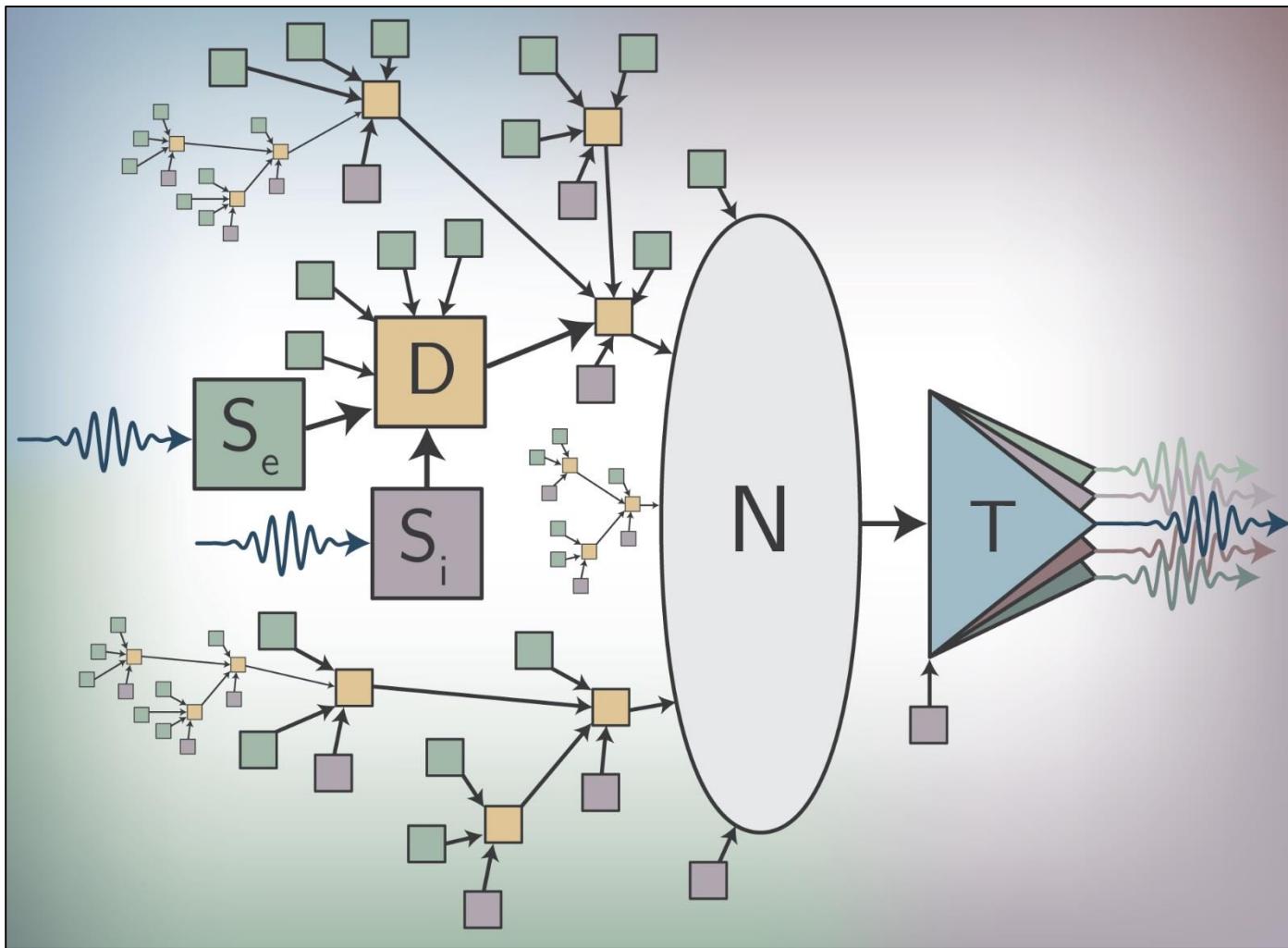
Fluxonic processing of
photonic synapse events

Superconducting electronics
for single-photon detection



Fluxonic processing of
photonic synapse events

Superconducting electronics
for neural computation



Fluxonic processing of
photonic synapse events

Neuromorphic supercomputing

Device requirements for massive connectivity

Dense local fanout

Long-range connectivity

We seek very large systems

Energy efficiency is paramount

Principal conjecture:

Use light for communication

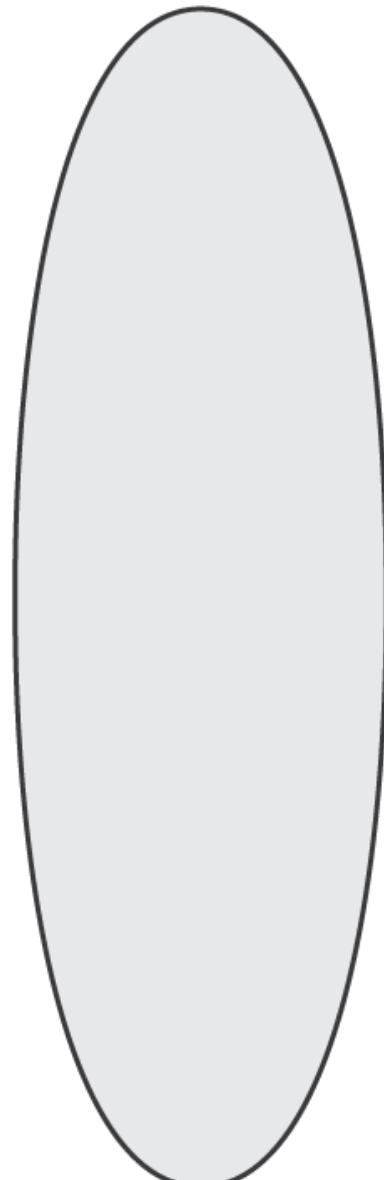
Photons don't have charge or mass

Use single-photons for communication

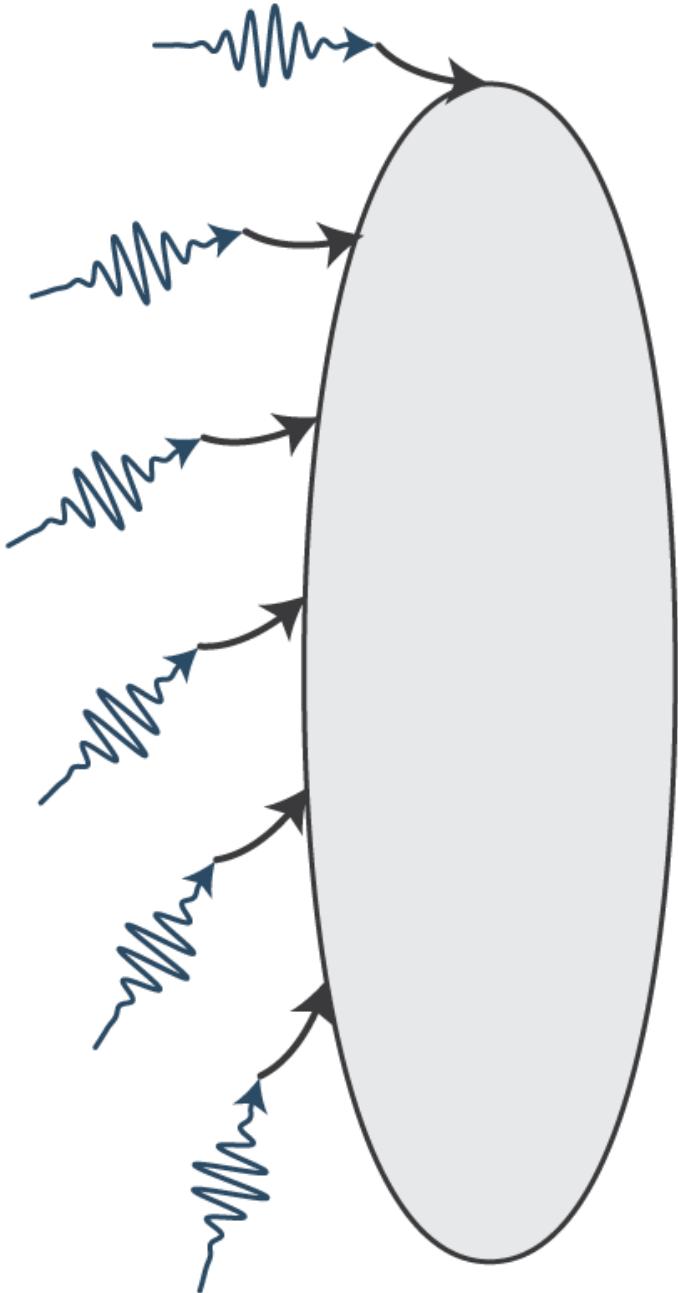
Neurons that signal with single photons

Neurons that signal with single photons

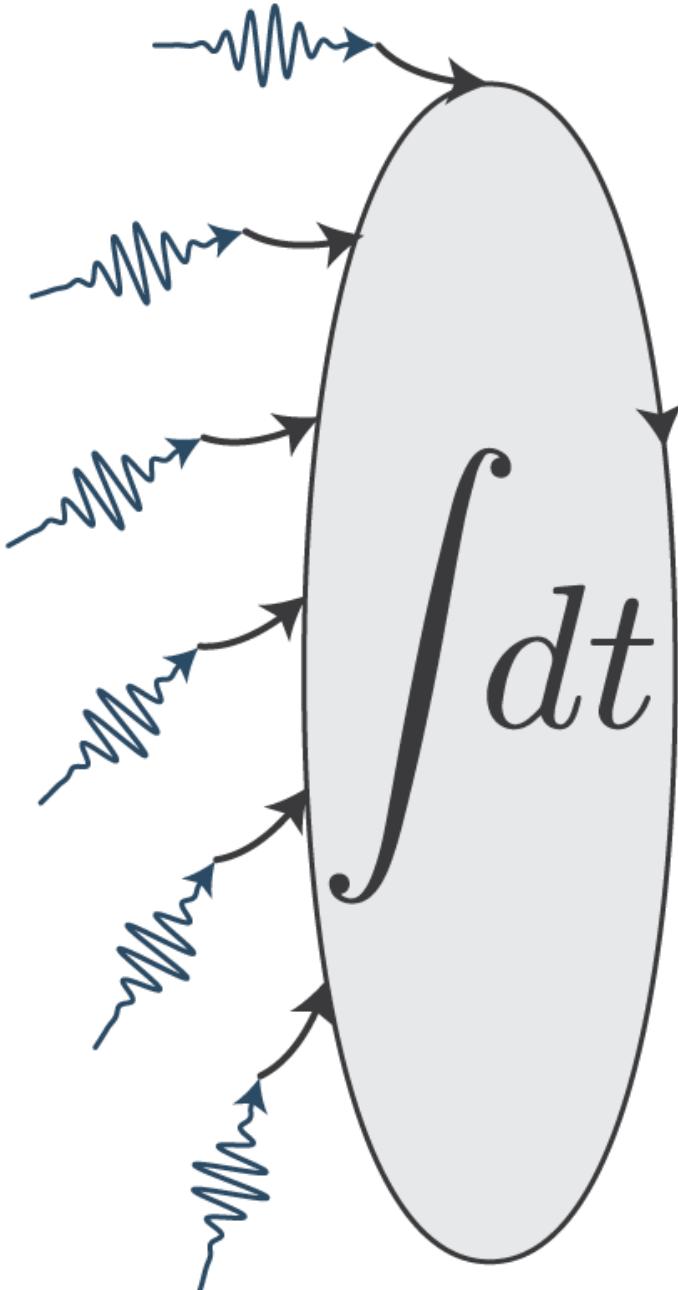
How do they work?



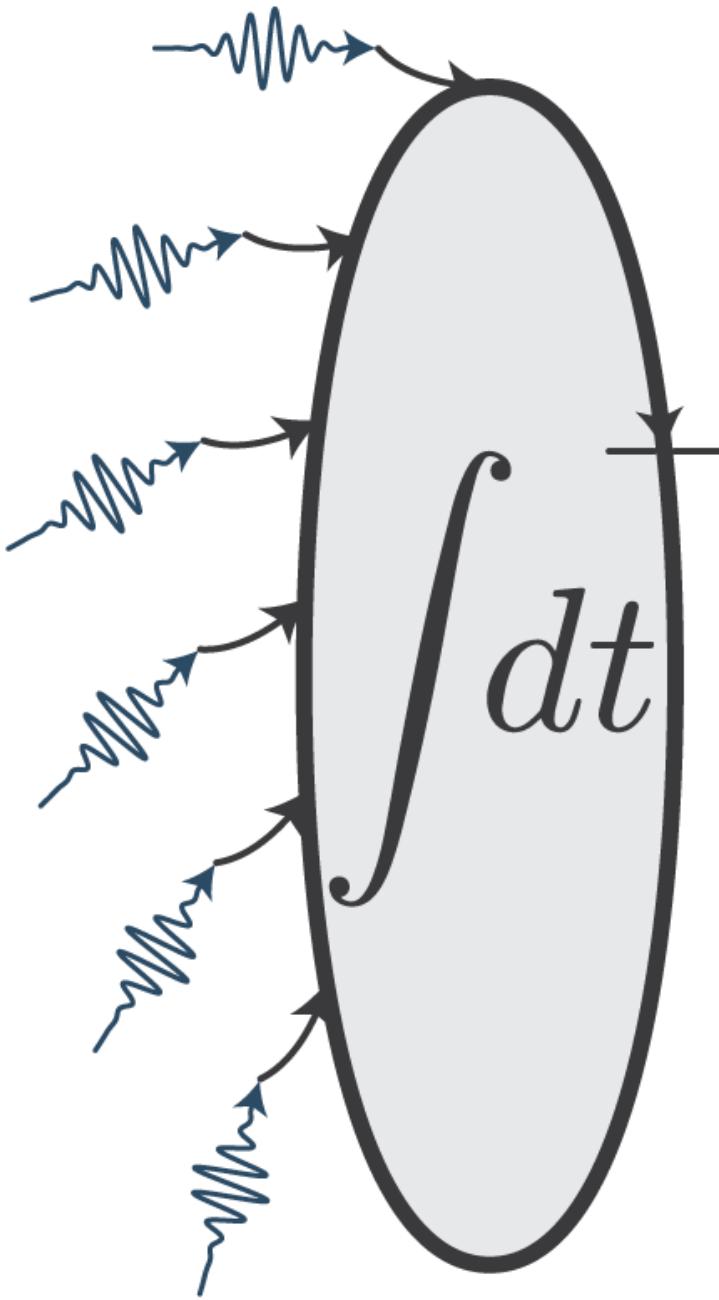
Superconducting loop



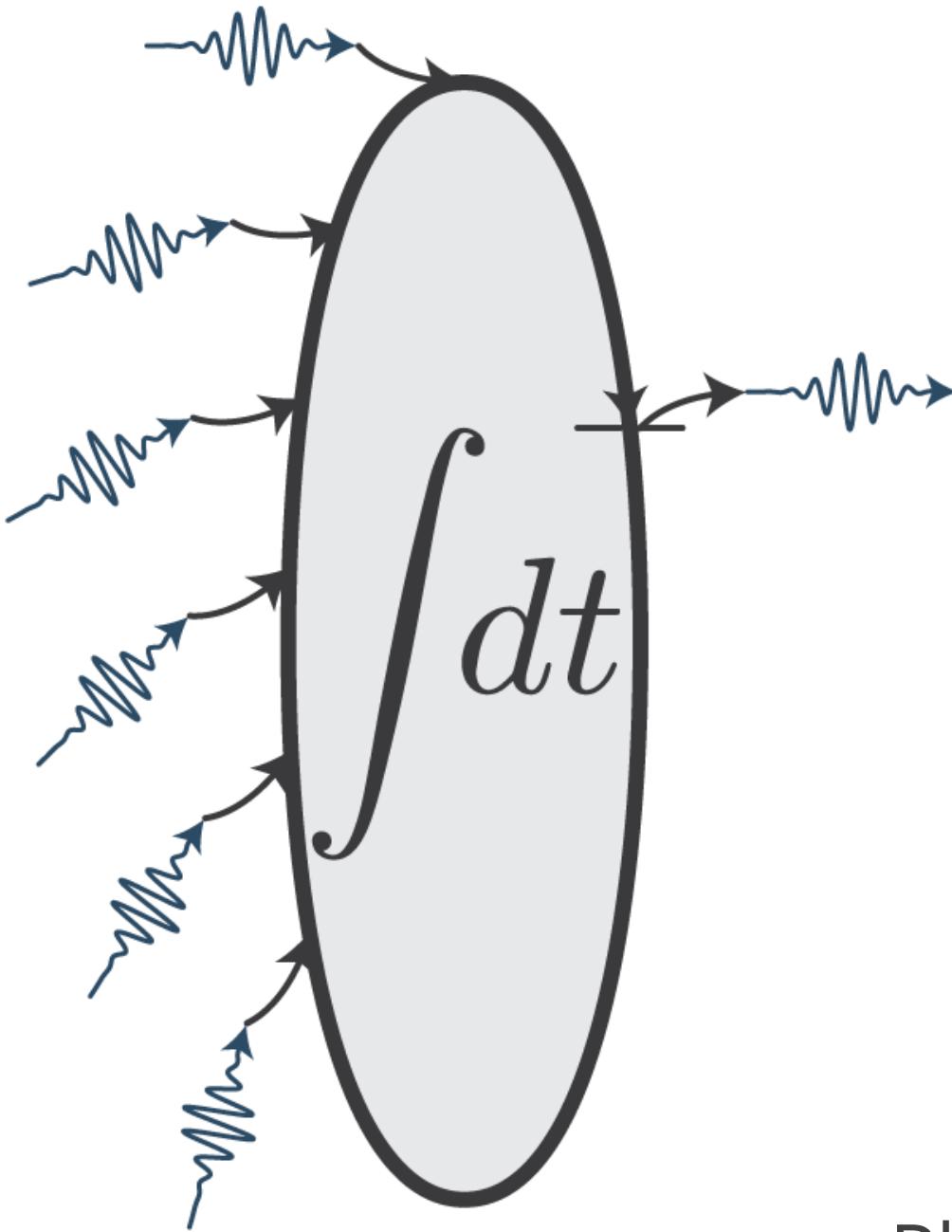
Photons add current



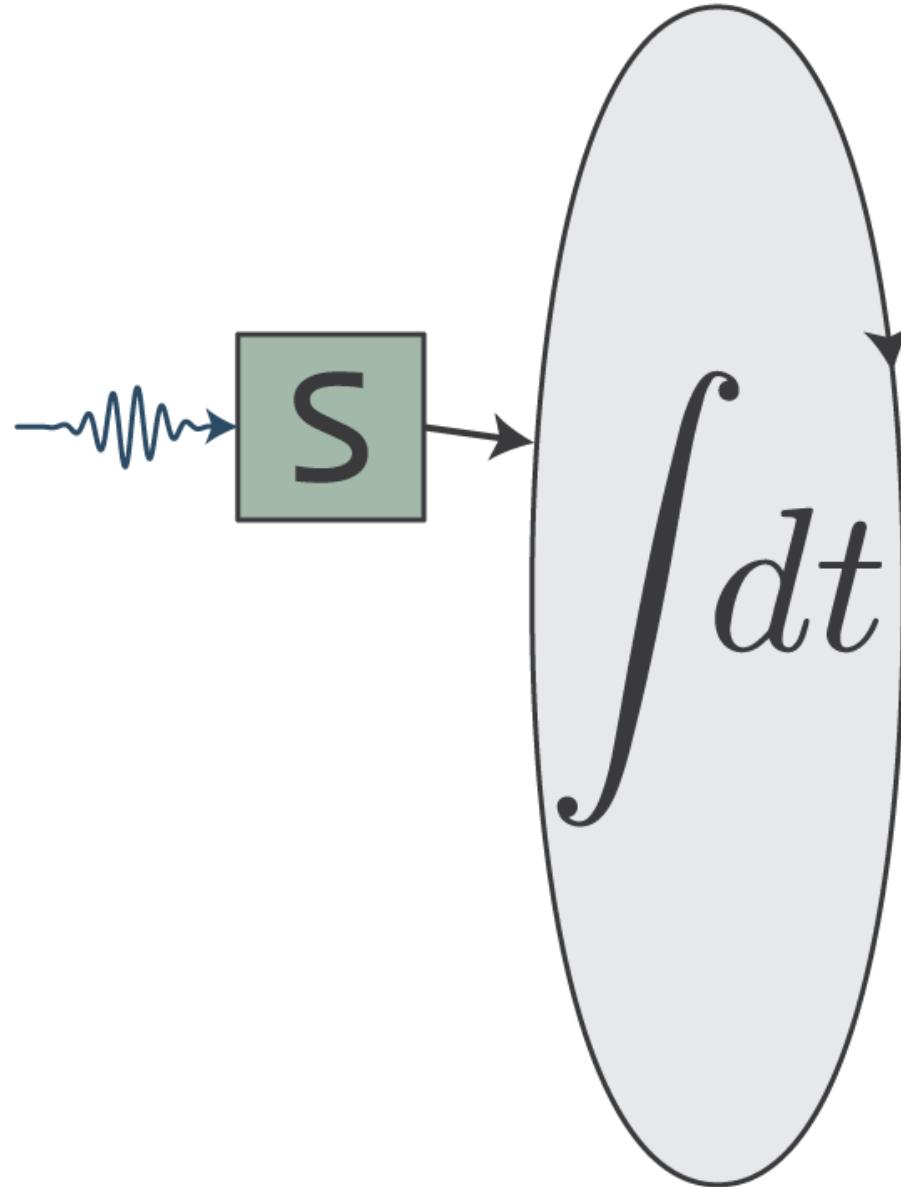
Current gets integrated



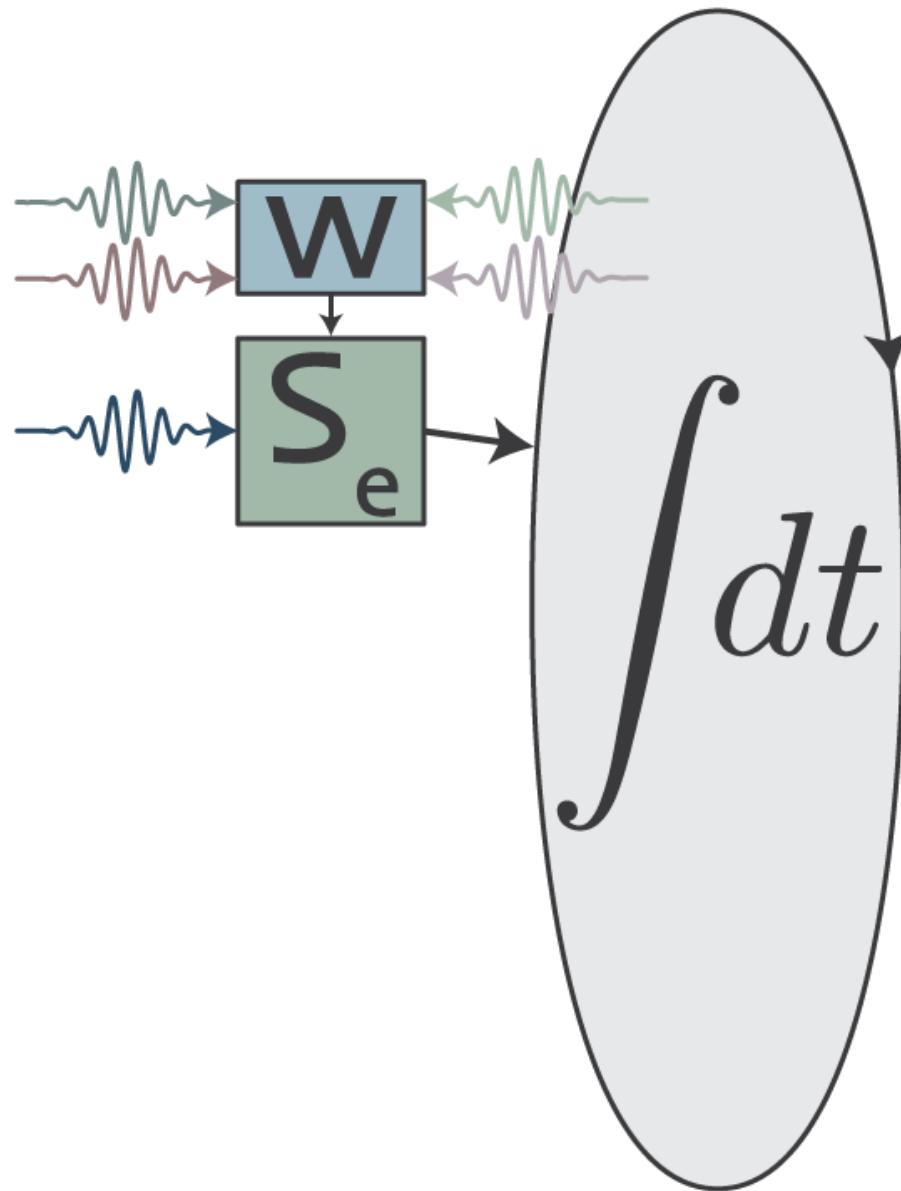
Current threshold



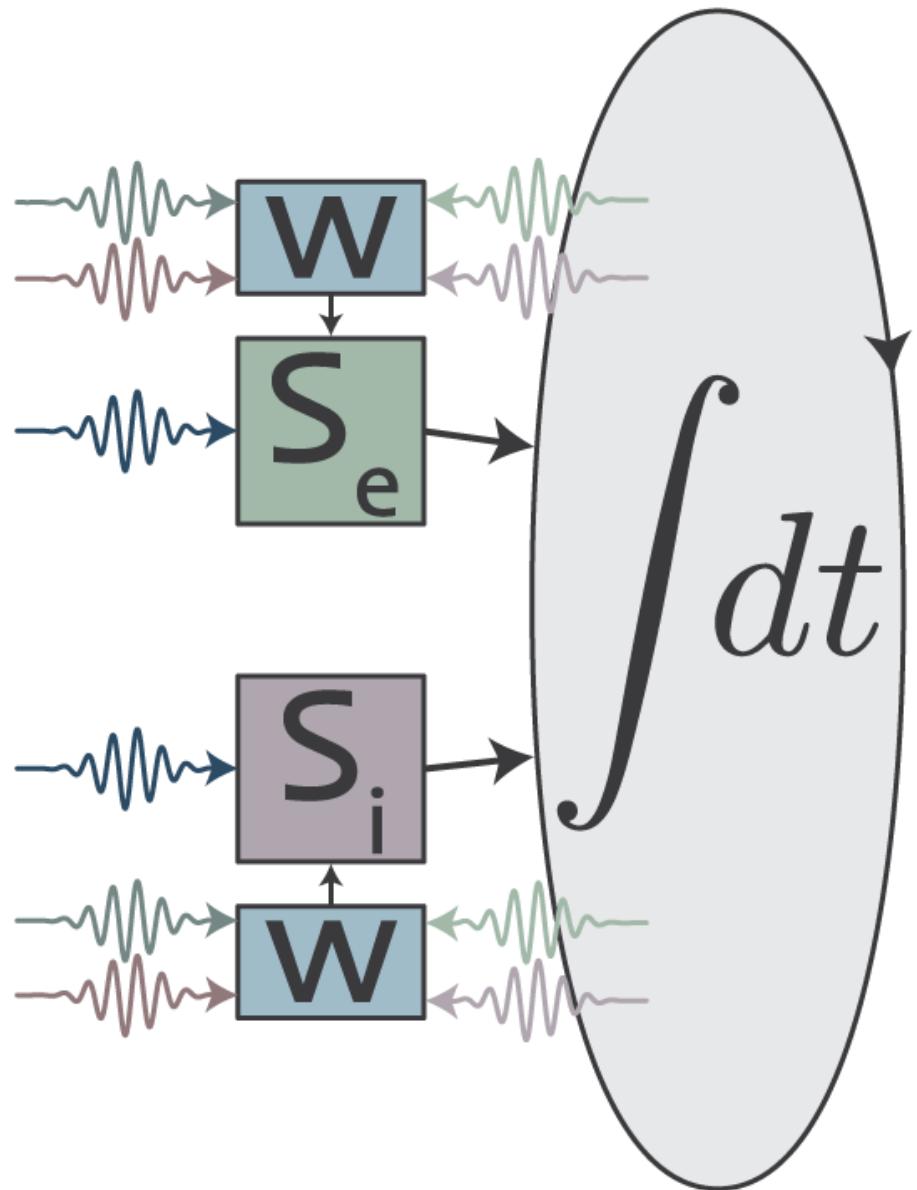
Photons produced



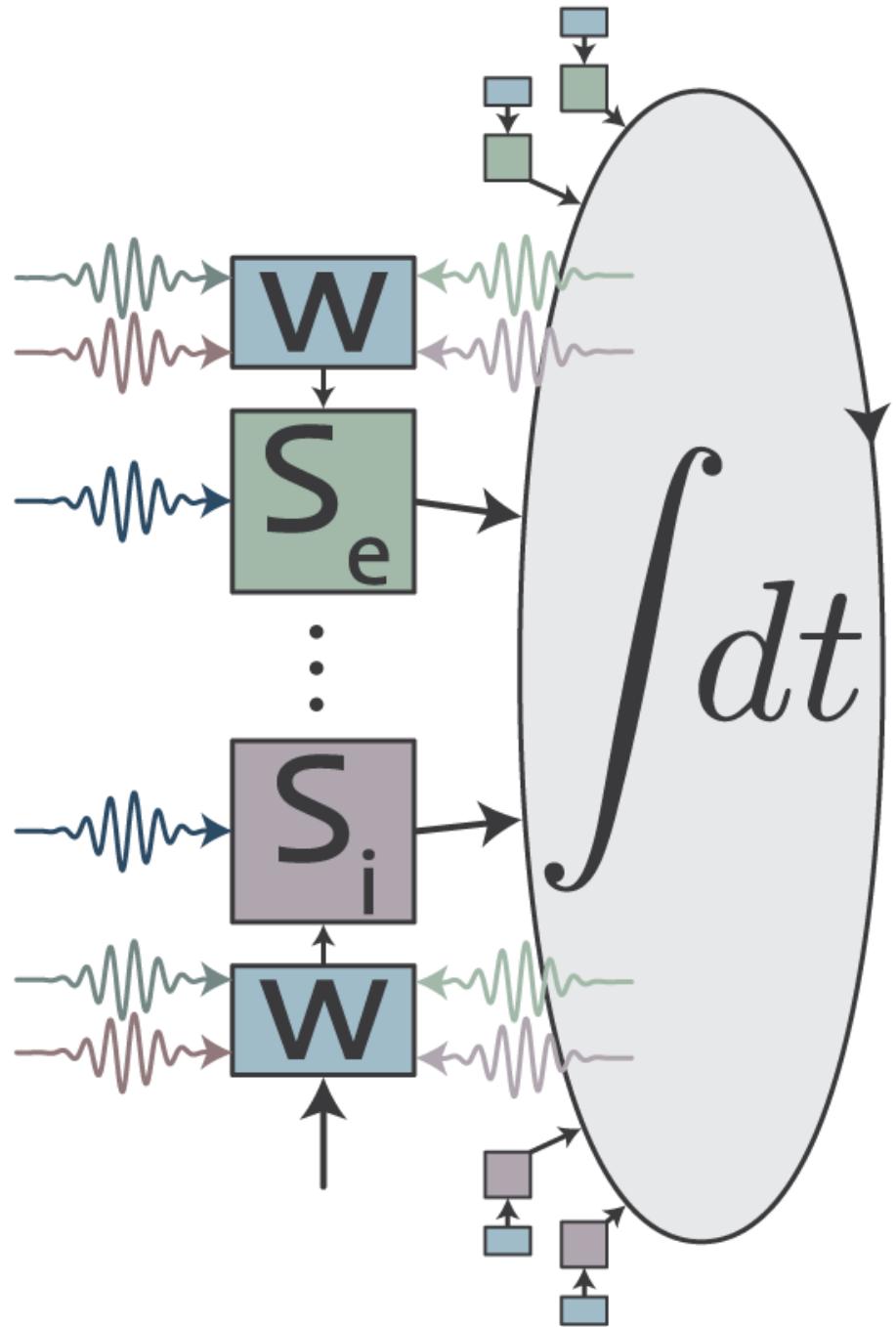
Synapse transduces



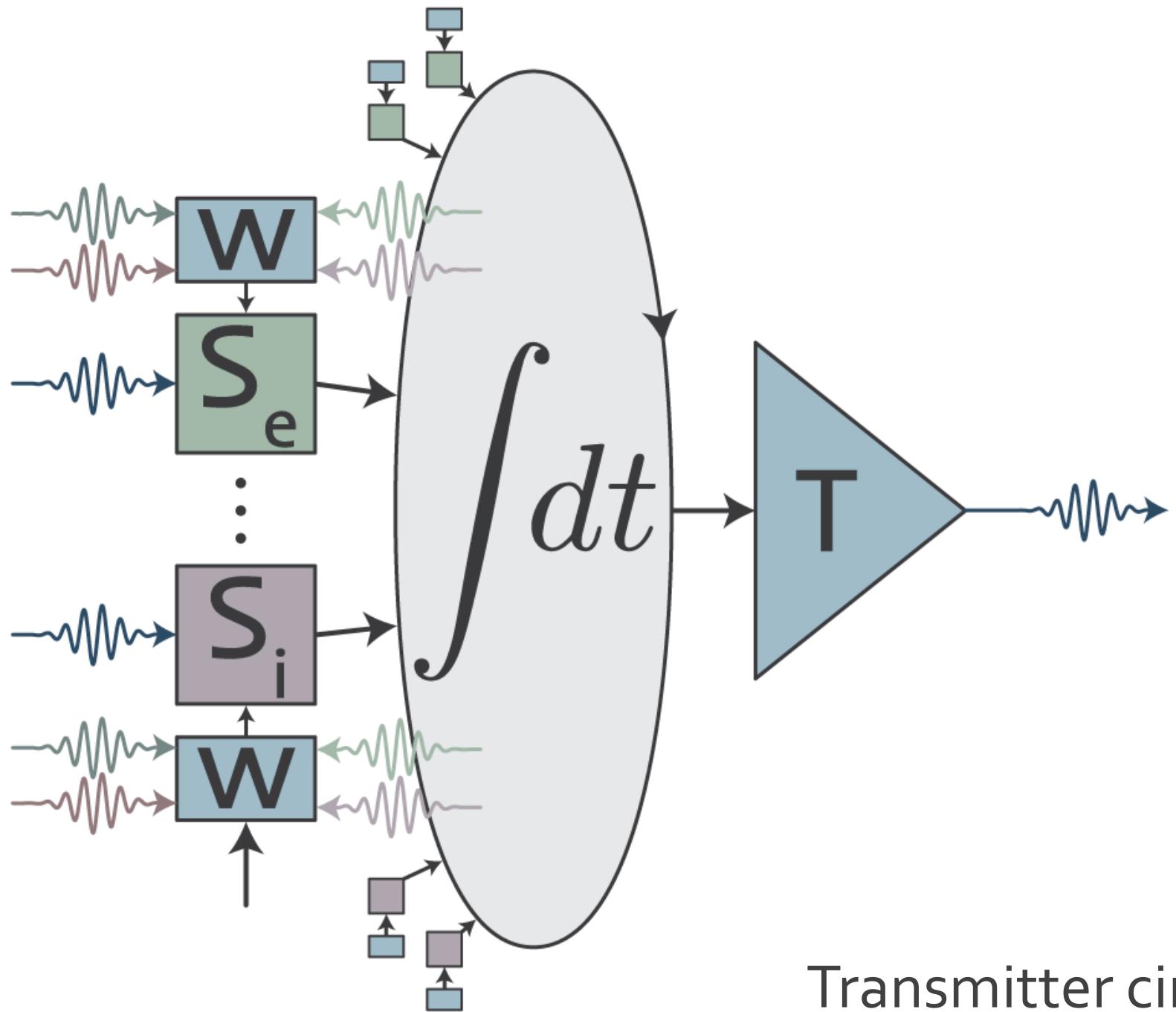
Photons update weight



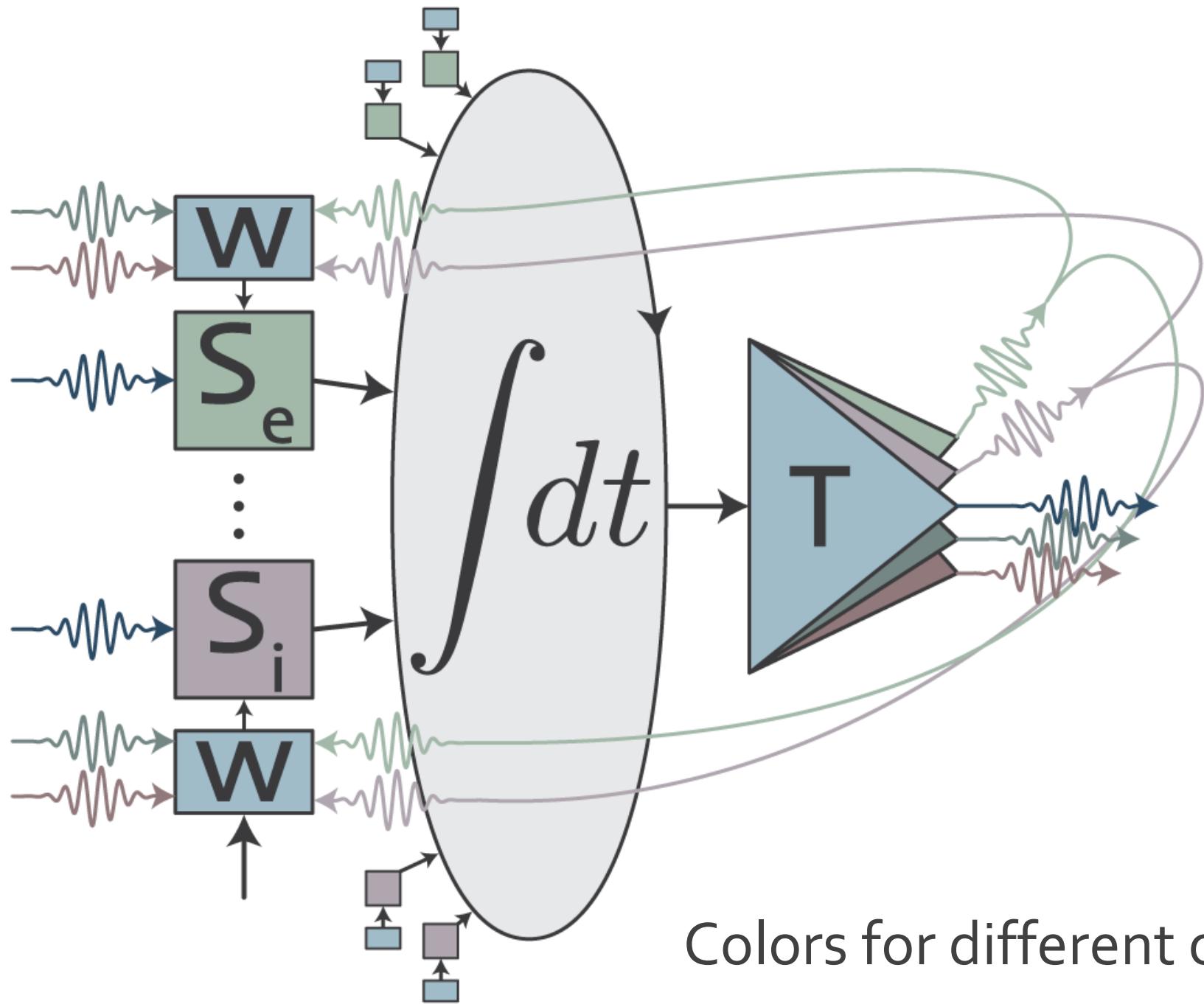
Inhibitory synapses



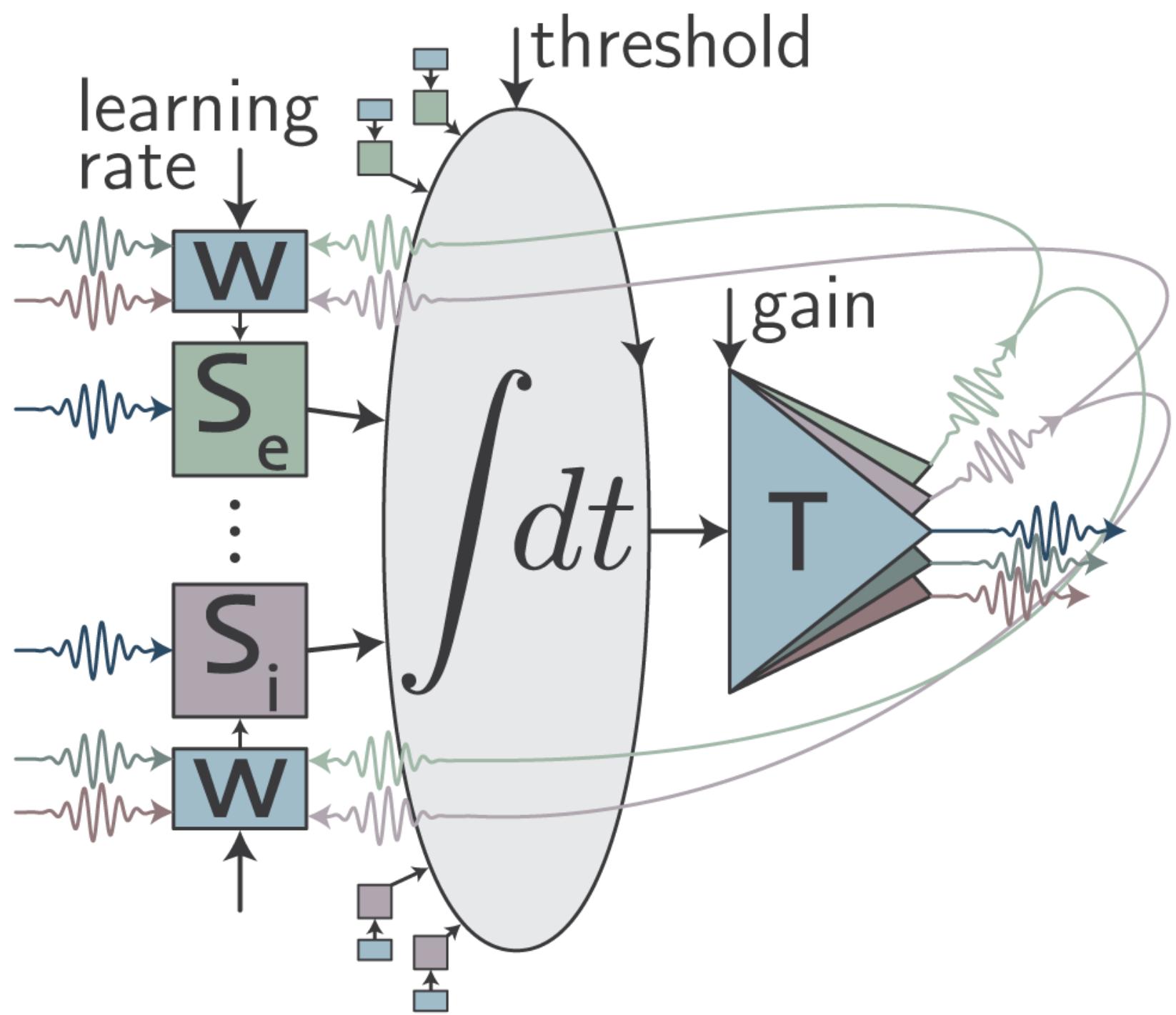
Many synapses



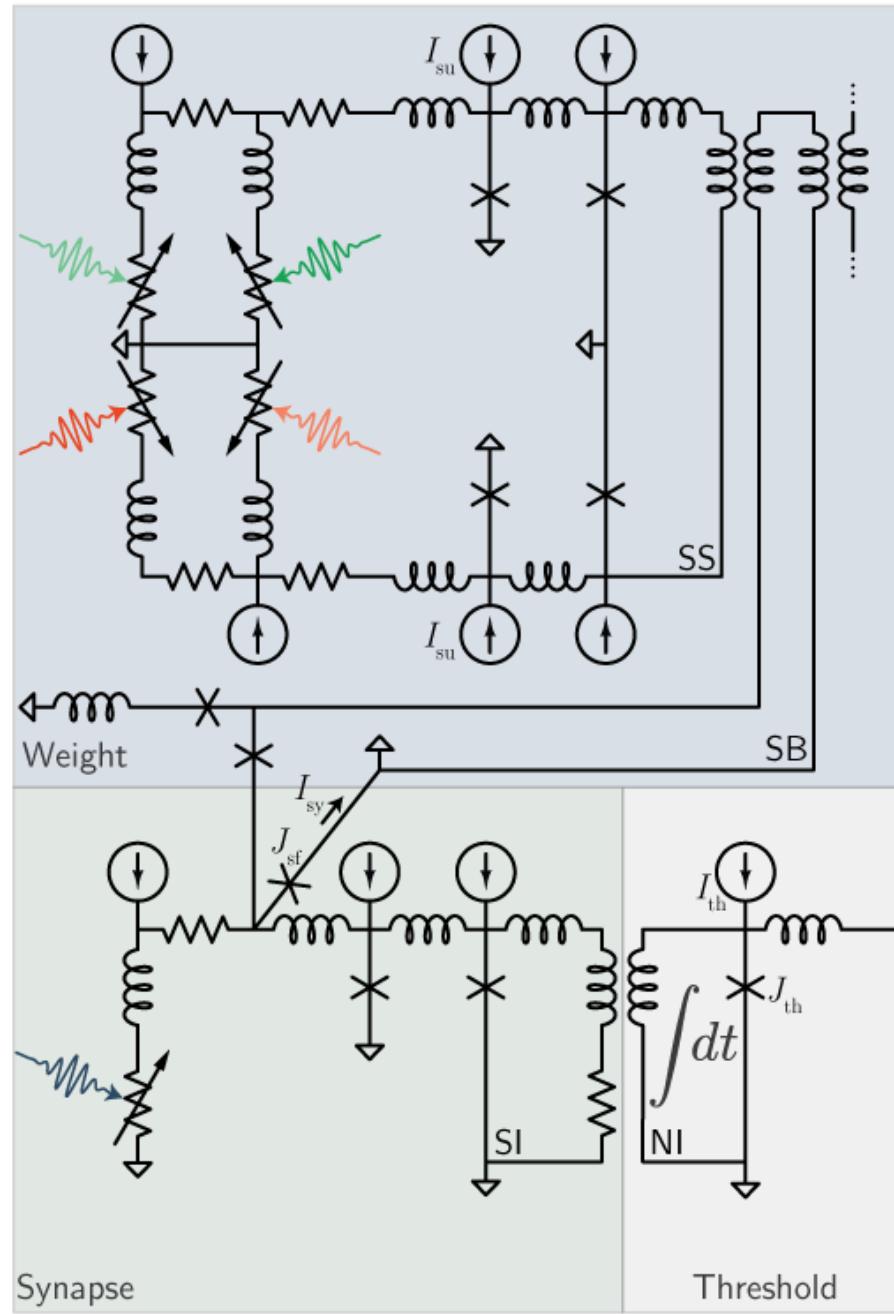
Transmitter circuits



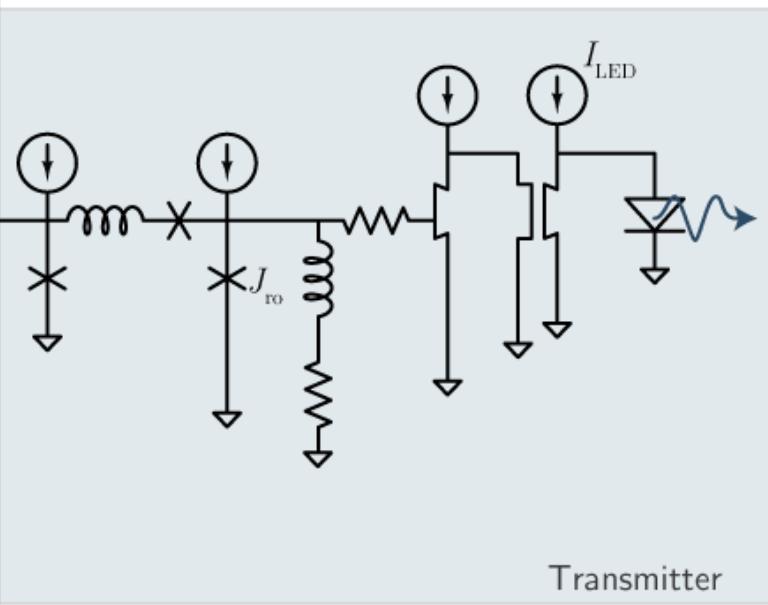
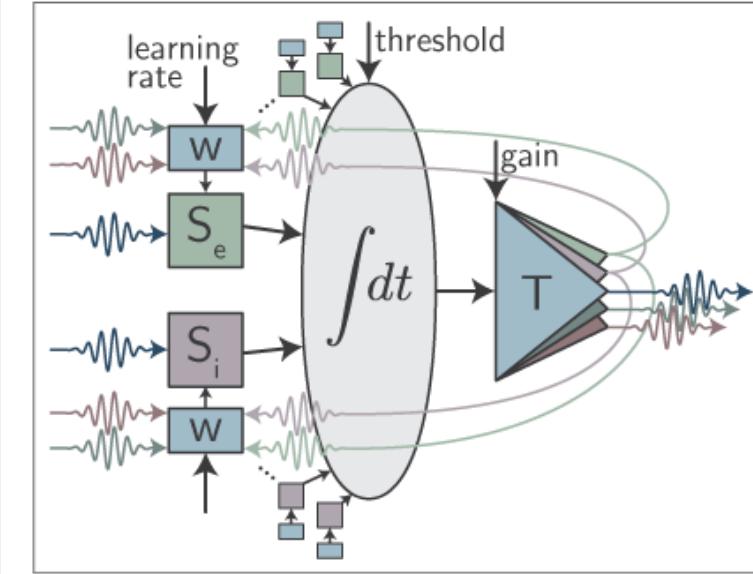
Colors for different operations



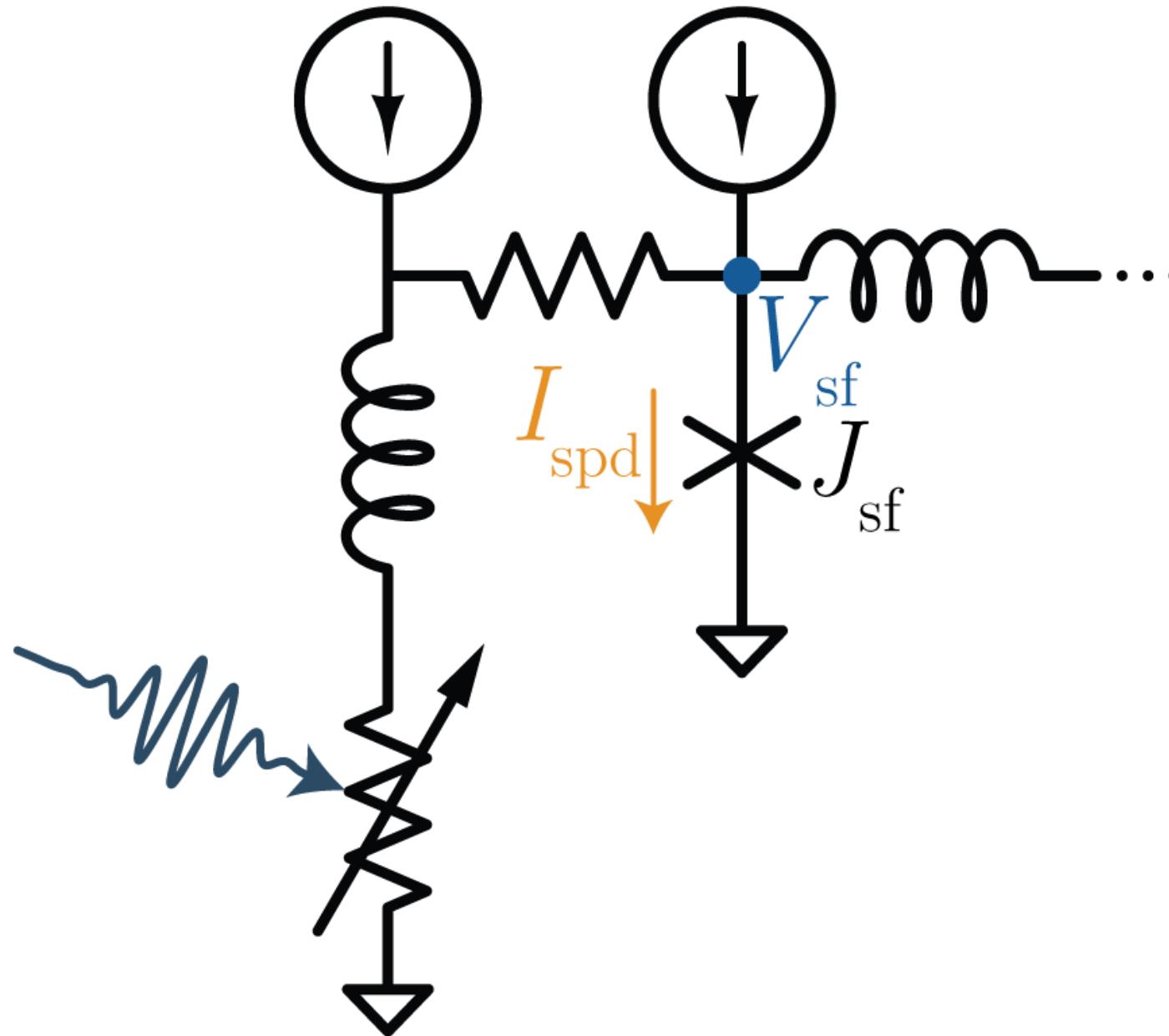
Loop neuron



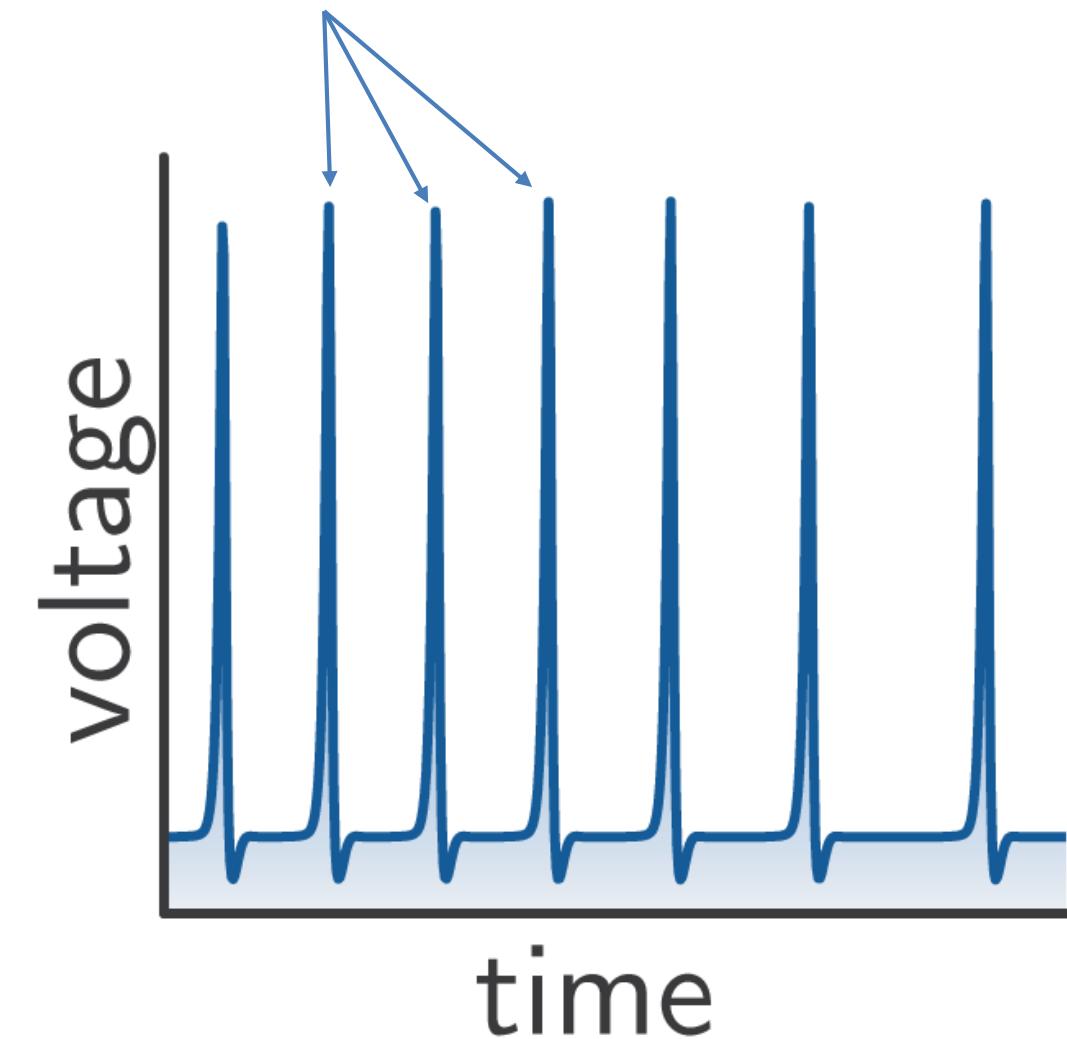
Shainline et al., arXiv:1805.01929 (2018).
Shainline, arXiv:1904.02807 (2019)

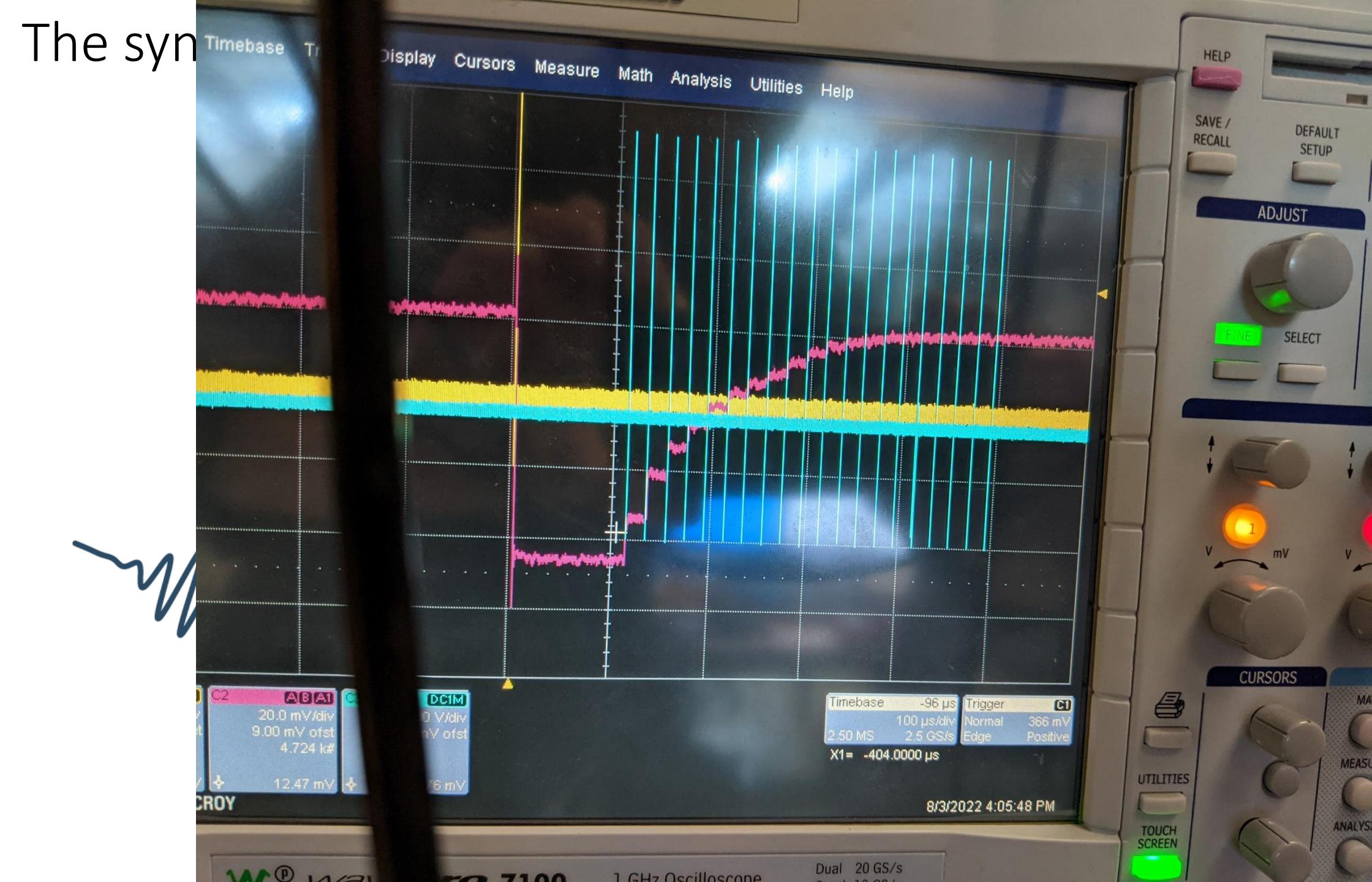


Photon-to-fluxon transducer



these are fluxons





Long-range = photons
Short-range = electronics / SFQ

Pulsed neural networks consisting of single-flux-quantum spiking neurons

T. Hirose, T. Asai, and Y. Amemiya
Physica C, 463:1072, 2007.

SCIENCE ADVANCES | RESEARCH ARTICLE

APPLIED SCIENCES AND ENGINEERING

Ultralow power artificial synapses using nanotextured magnetic Josephson junctions

Michael L. Schneider,* Christine A. Donnelly, Stephen E. Russek, Burm Baek, Matthew R. Pufall, Peter F. Hopkins, Paul D. Dresselhaus, Samuel P. Benz, William H. Rippard

PHYSICAL REVIEW E 82, 011914 (2010)

Josephson junction simulation of neurons

Patrick Crotty,¹ Dan Schult,² and Ken Segall¹

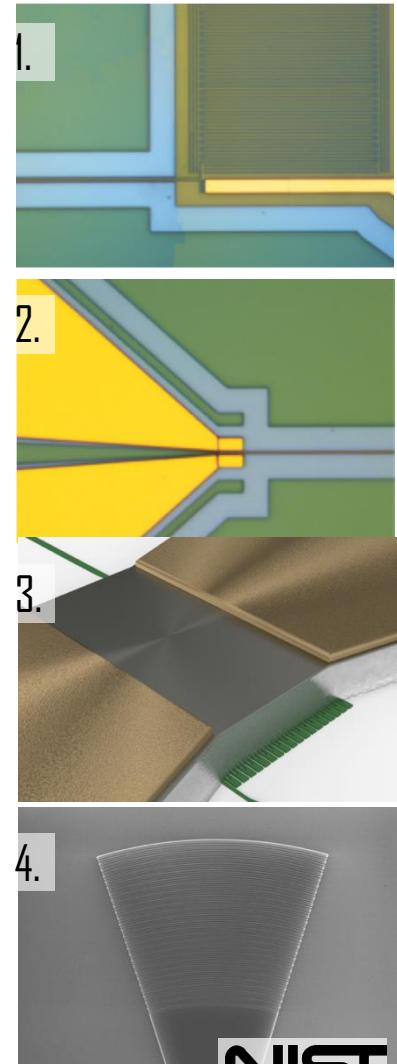
<https://arxiv.org/abs/1907.00263>

A Power Efficient Artificial Neuron Using Superconducting Nanowires

Emily Toomey, Ken Segall, Karl Berggren

SOEN technical approach superconducting optoelectronic networks

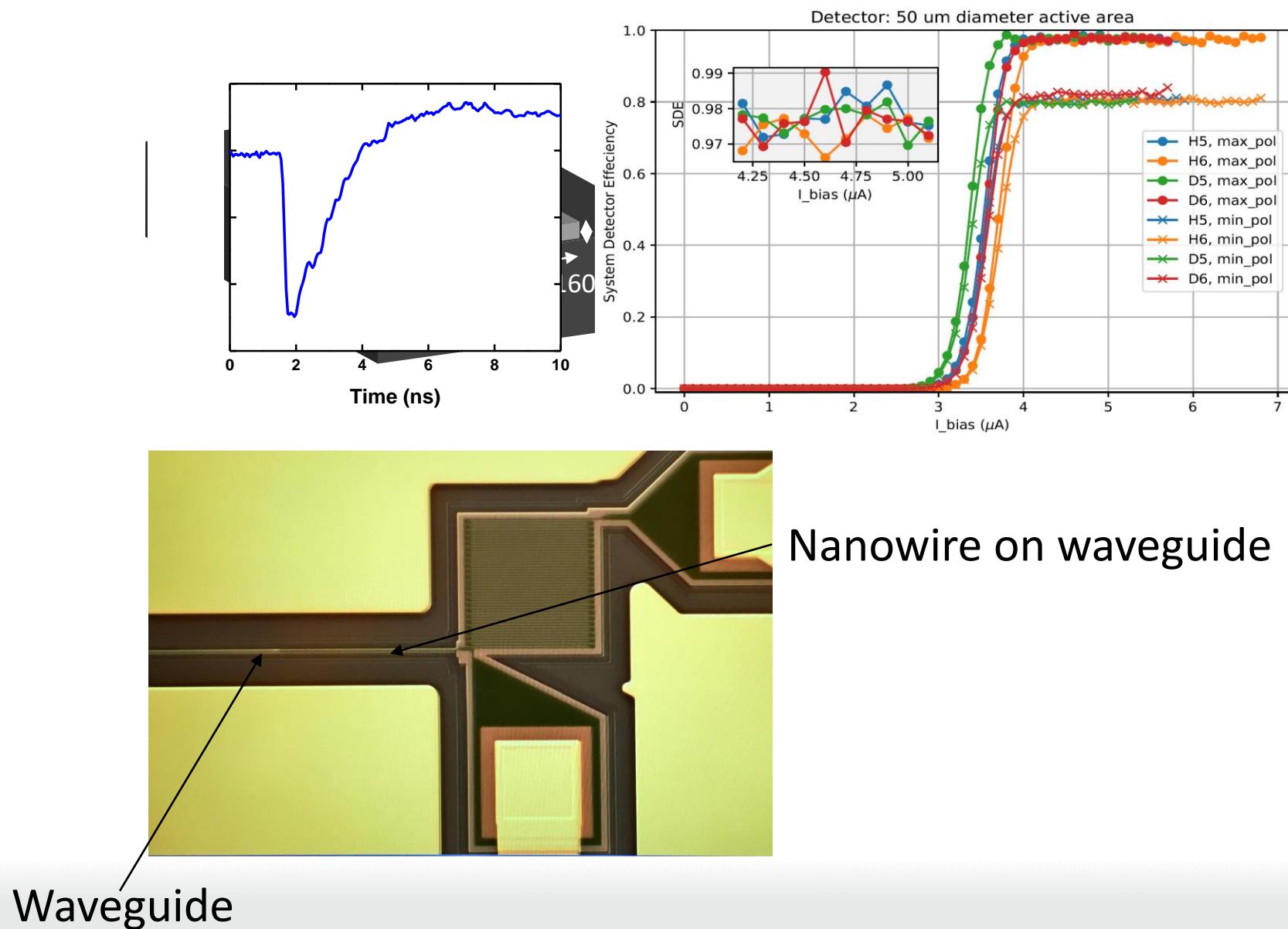
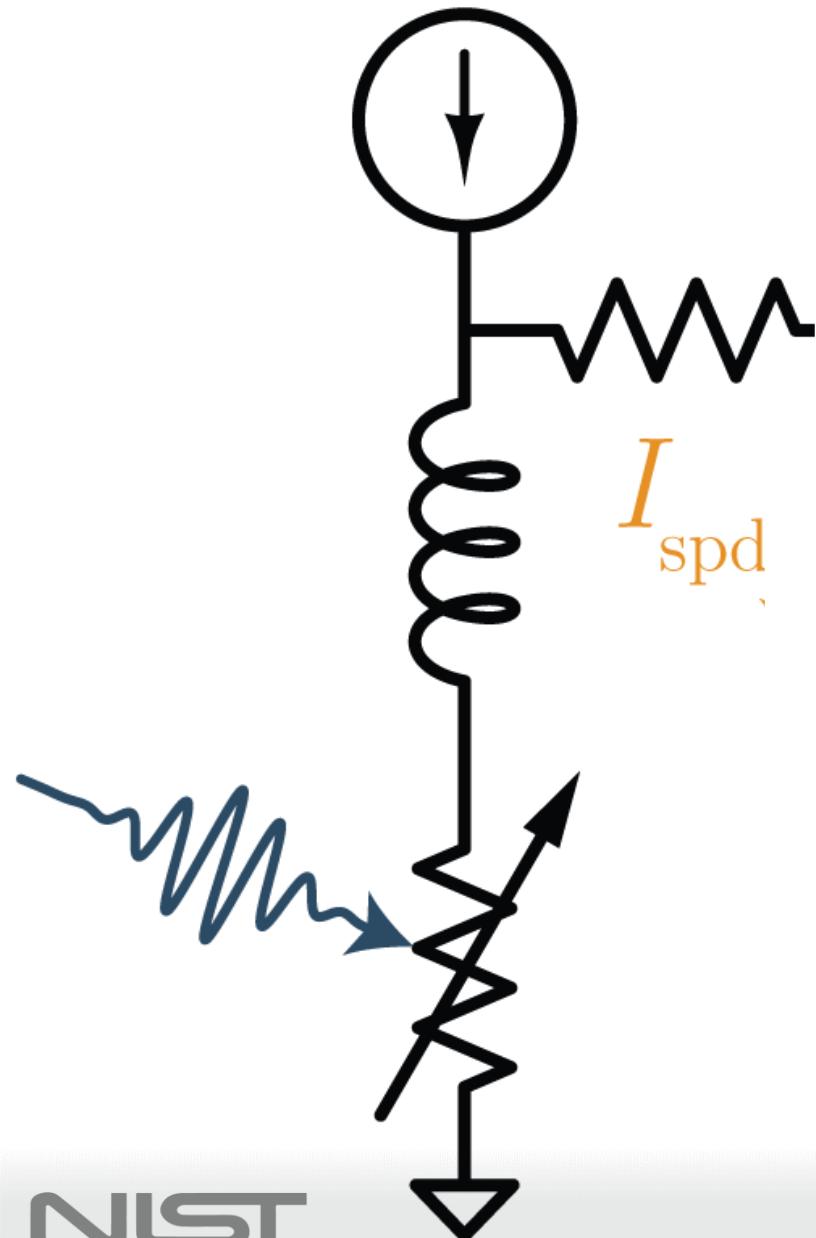
1. Single photons for minimum spike energy
(superconducting single-photon detectors)
2. Cold optoelectronics for monolithic integration
(all-silicon light-emitting diodes)
3. Cold electronics (SFQ) for nonlinear processing
(Josephson junctions, cryotron switches)
4. Light for interconnects
(silicon photonics)



J. M. Shainline, S. M. Buckley, R. P. Mirin, and S. W. Nam, "Superconducting optoelectronic circuits for neuromorphic computing," Phys. Rev. Applied, Mar 2017.

cryogenic silicon photonics platform: recent results

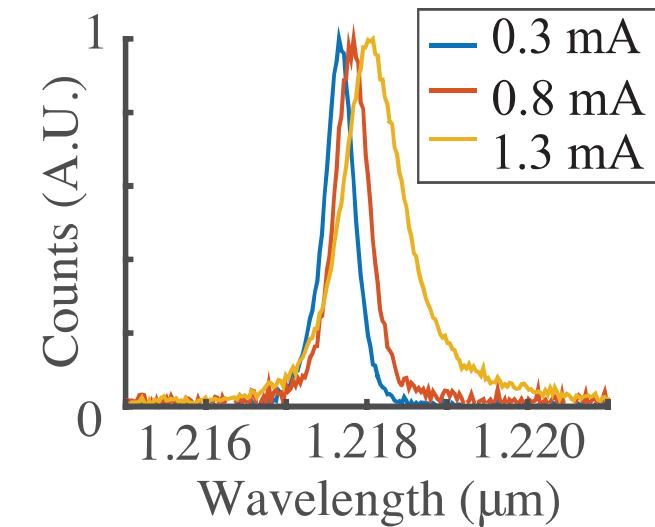
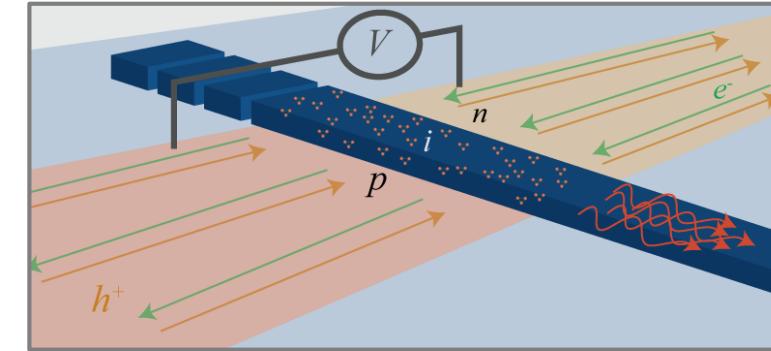
Superconducting Nanowire Detector



All-silicon light emitting diodes

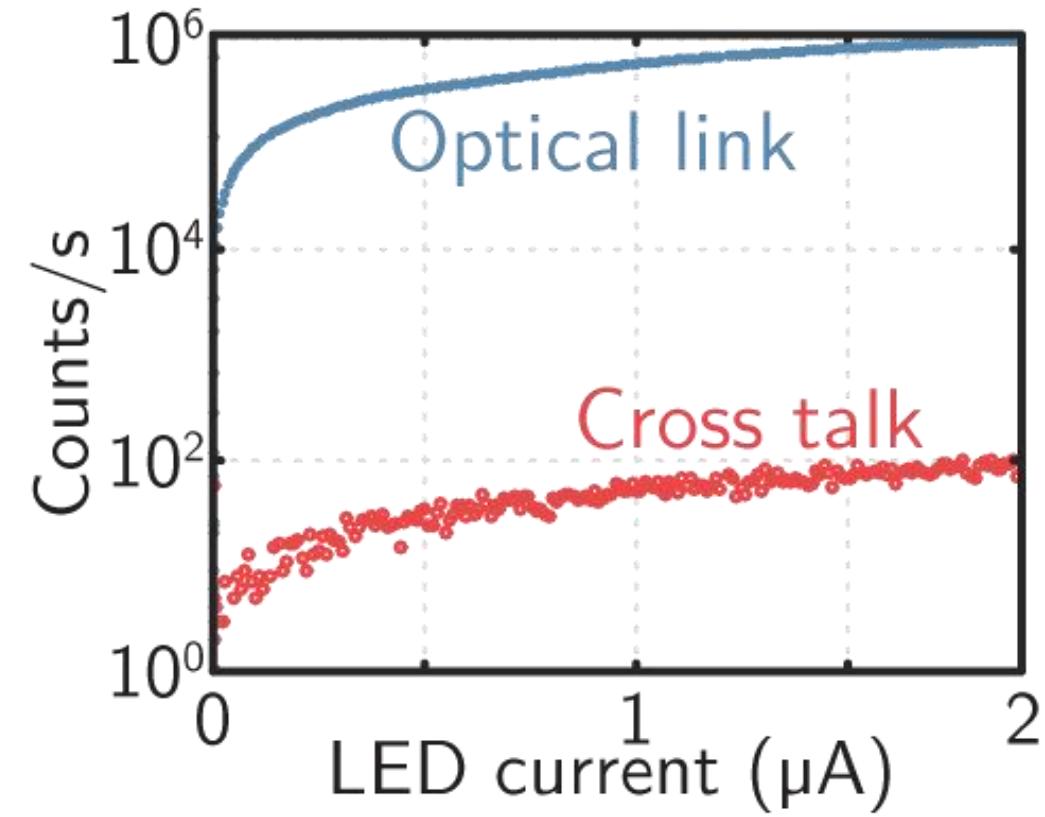
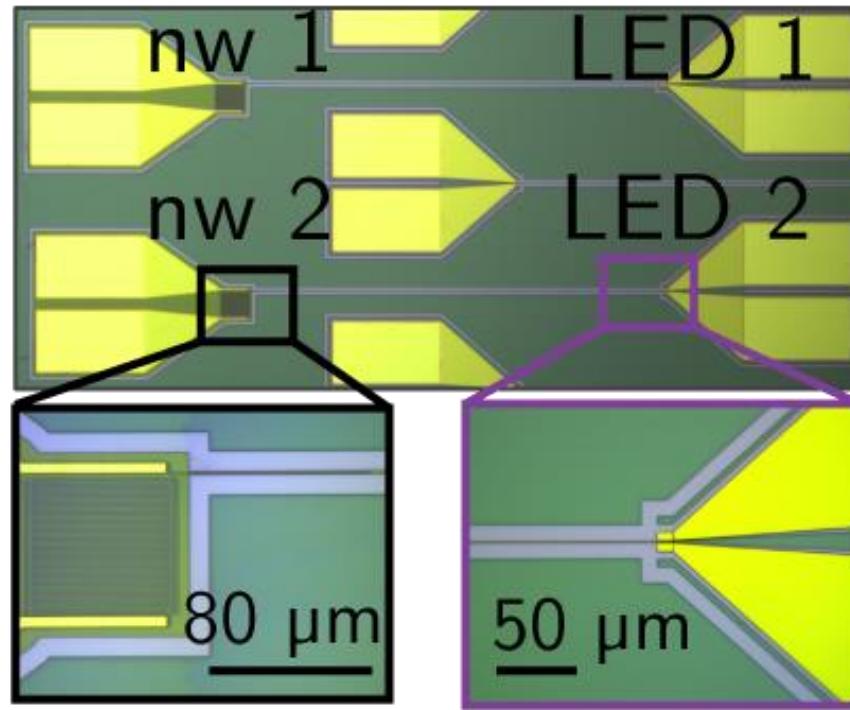
NIST

- Si defect centers have optical transitions
- Low temp. inhibits non-radiative pathways
- Electrical pumping with PN junction
- W-centers: 1220nm emission



Co-integration: Silicon LEDs + SNSPDs

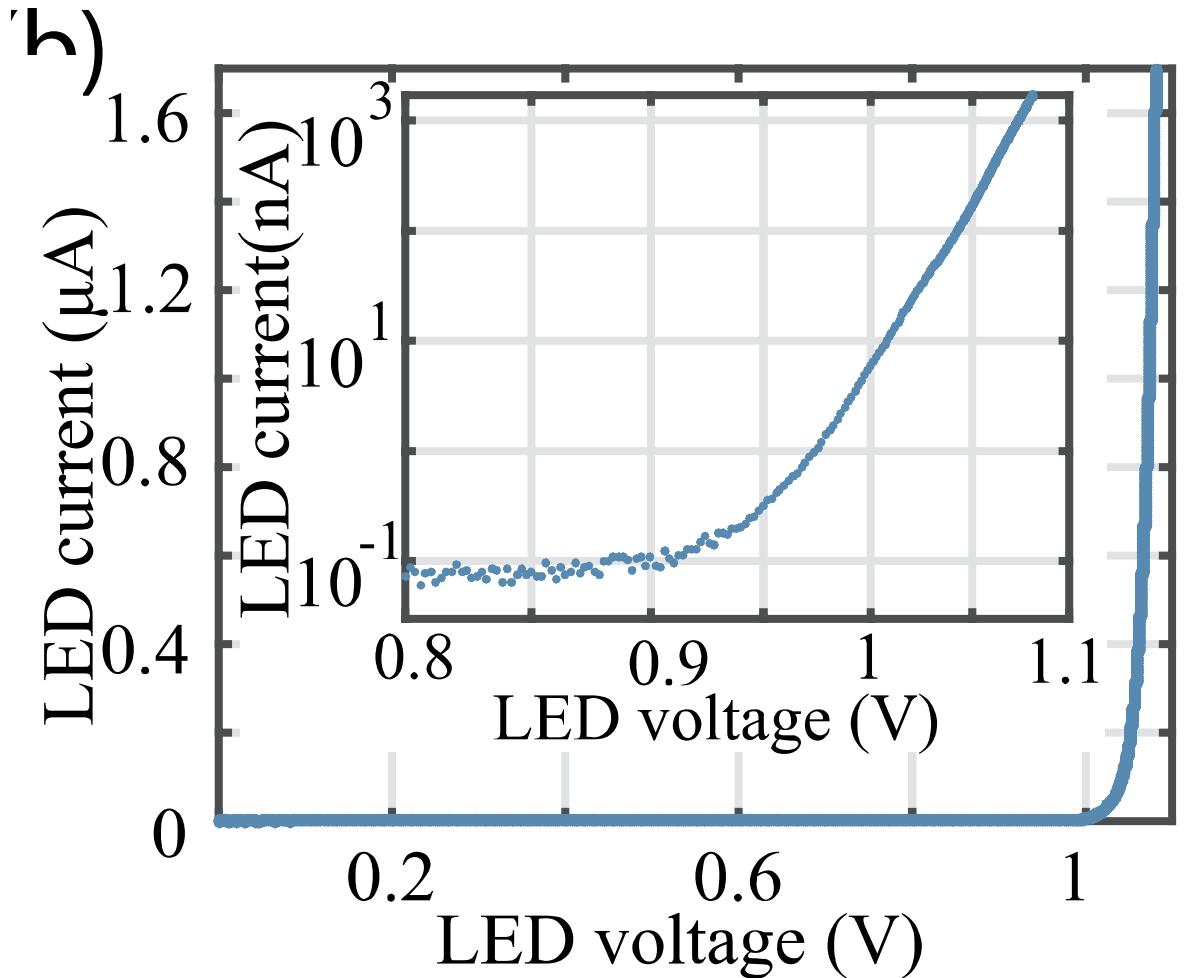
NIST



All-silicon light emitting diodes

NIST

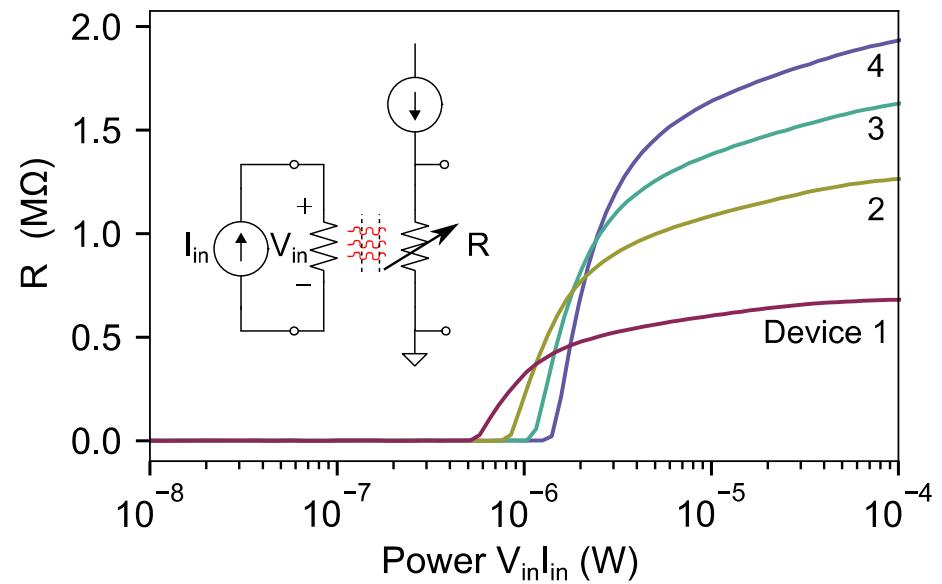
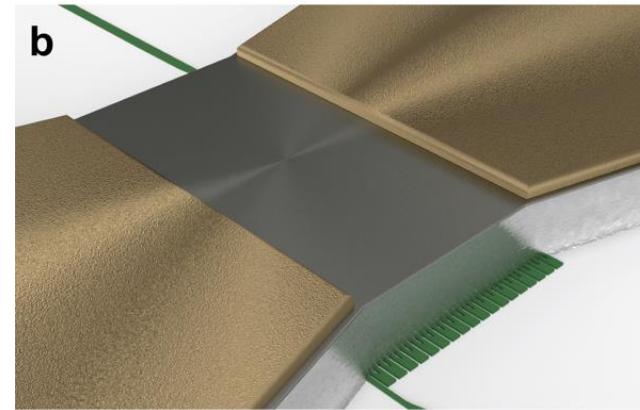
- LED turn-on voltage is ~ 1 V
- SNSPD can output ~ 1 mV



Nano-cryotron thermal switch

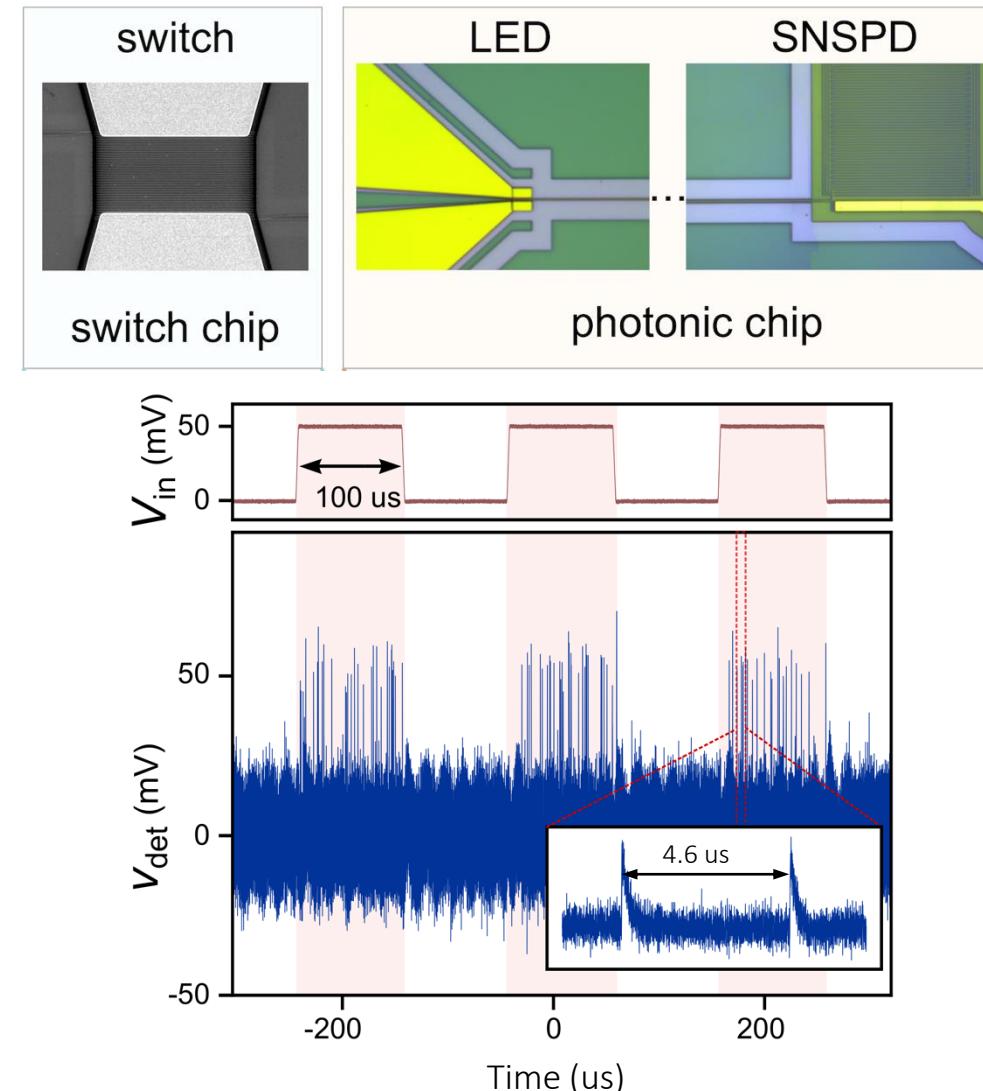
NIST

- millivolt input -> Volt output
- No Josephson Junctions needed
- Reset about 10ns



A. McCaughan et al. "A compact, ultrahigh impedance superconducting thermal switch for interfacing superconductors with semiconductors and optoelectronics," arXiv:1903.10461, 2019.

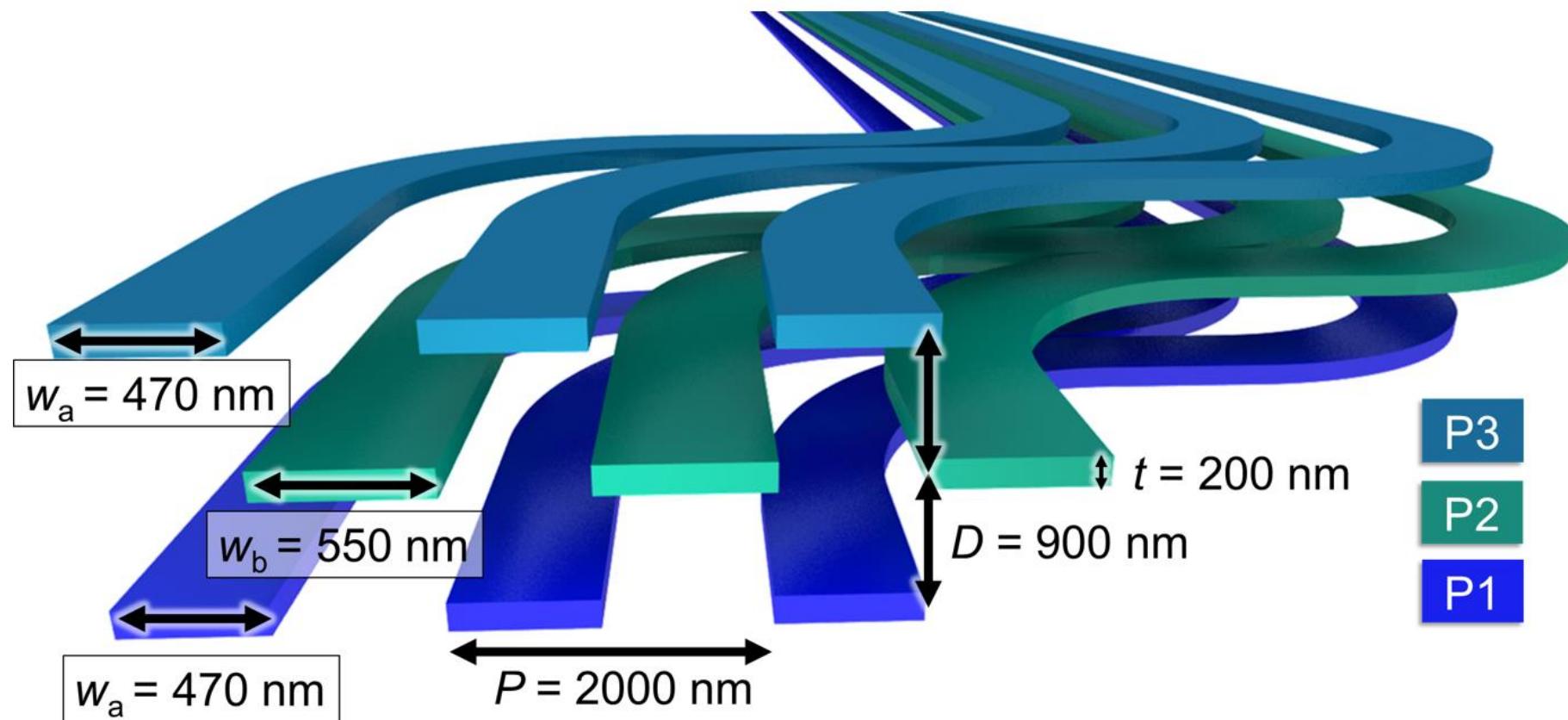
Superconductor-to-semiconductor interface



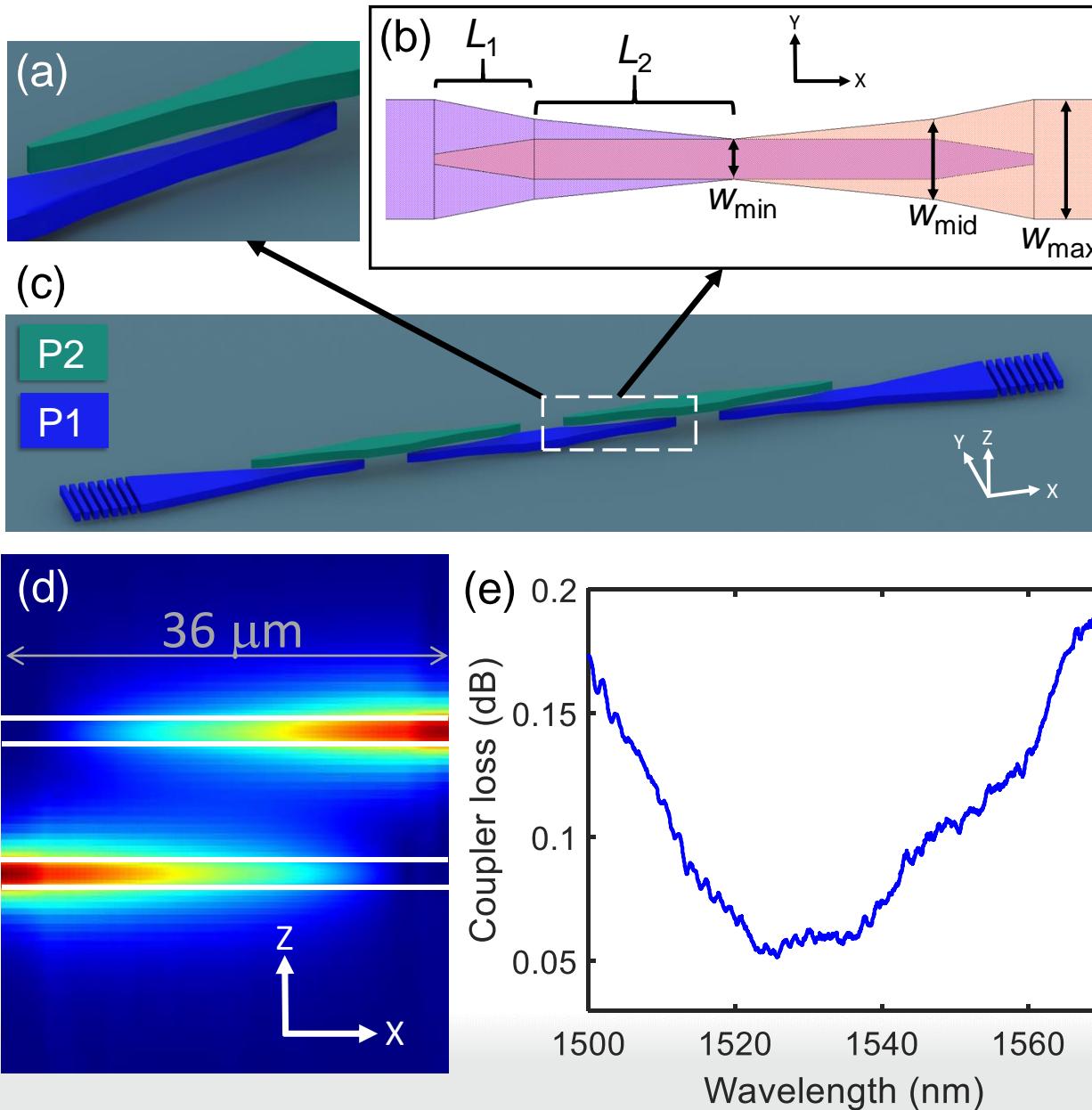
A. McCaughan et al. "A compact, ultrahigh impedance superconducting thermal switch for interfacing superconductors with semiconductors and optoelectronics," arXiv:1903.10461, 2019.

First steps toward photonic networks

Three planes of amorphous silicon
waveguides

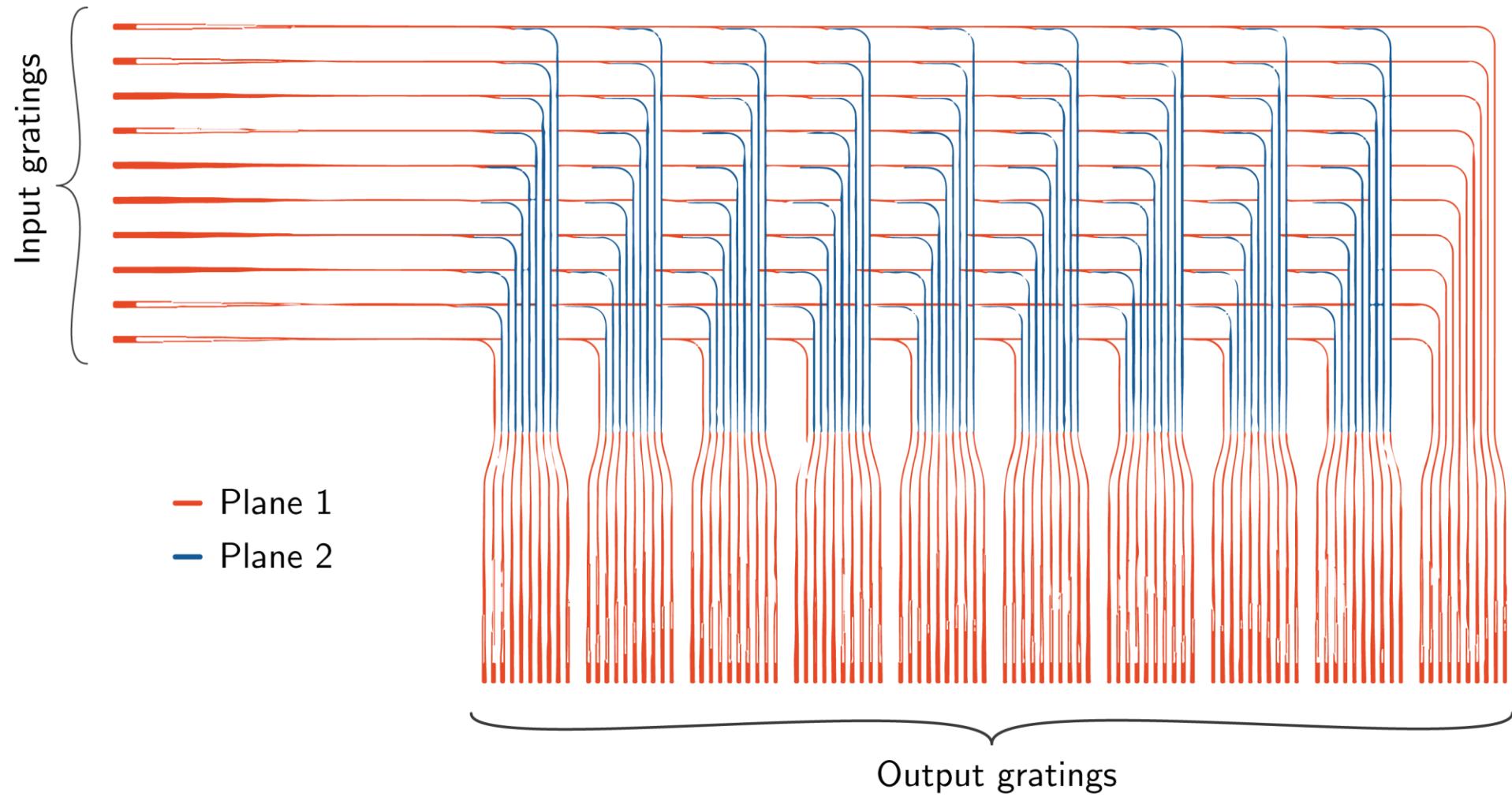


Inter-planar couplers

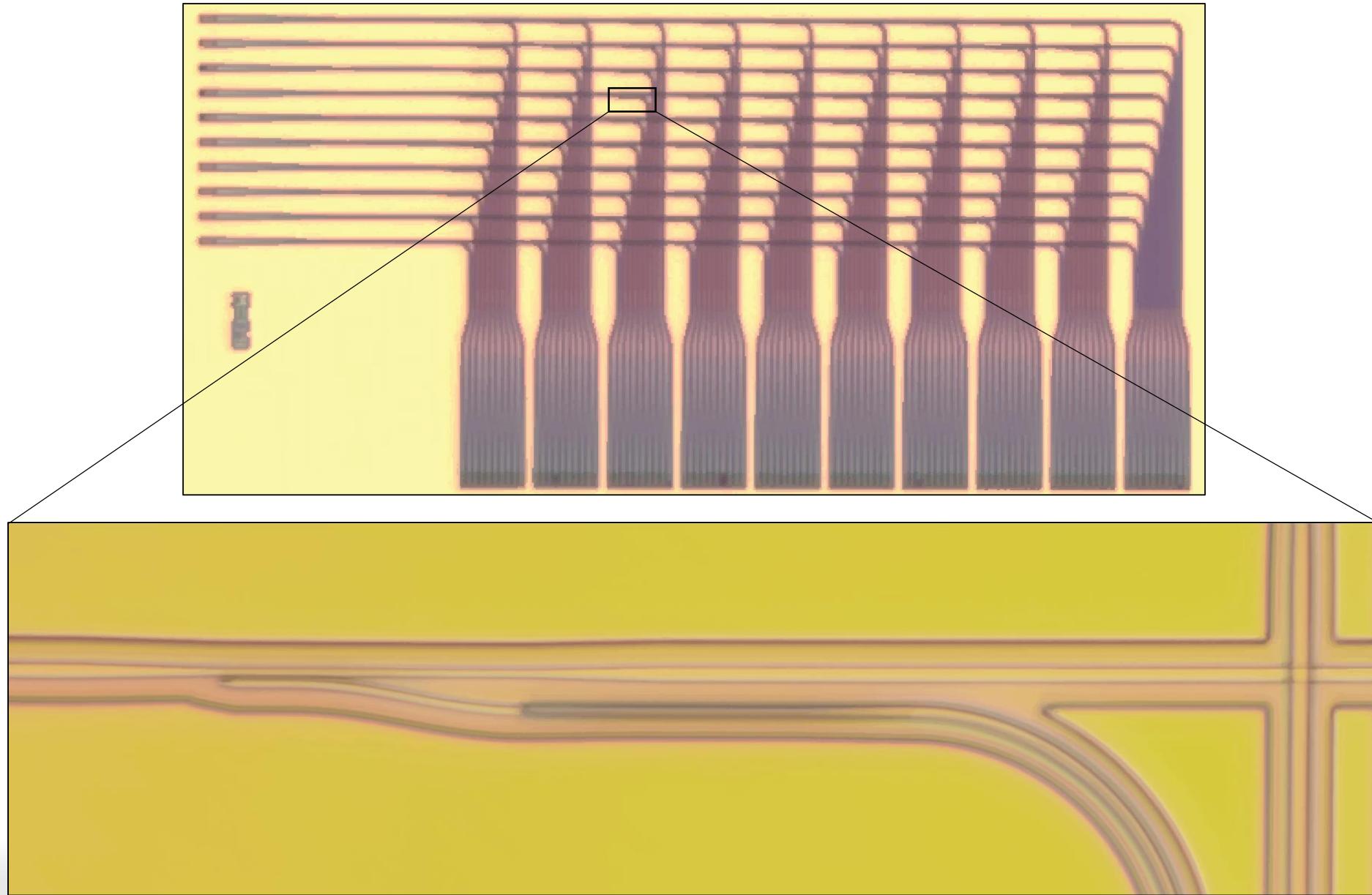


- 0.05 dB loss
- 36 μm length

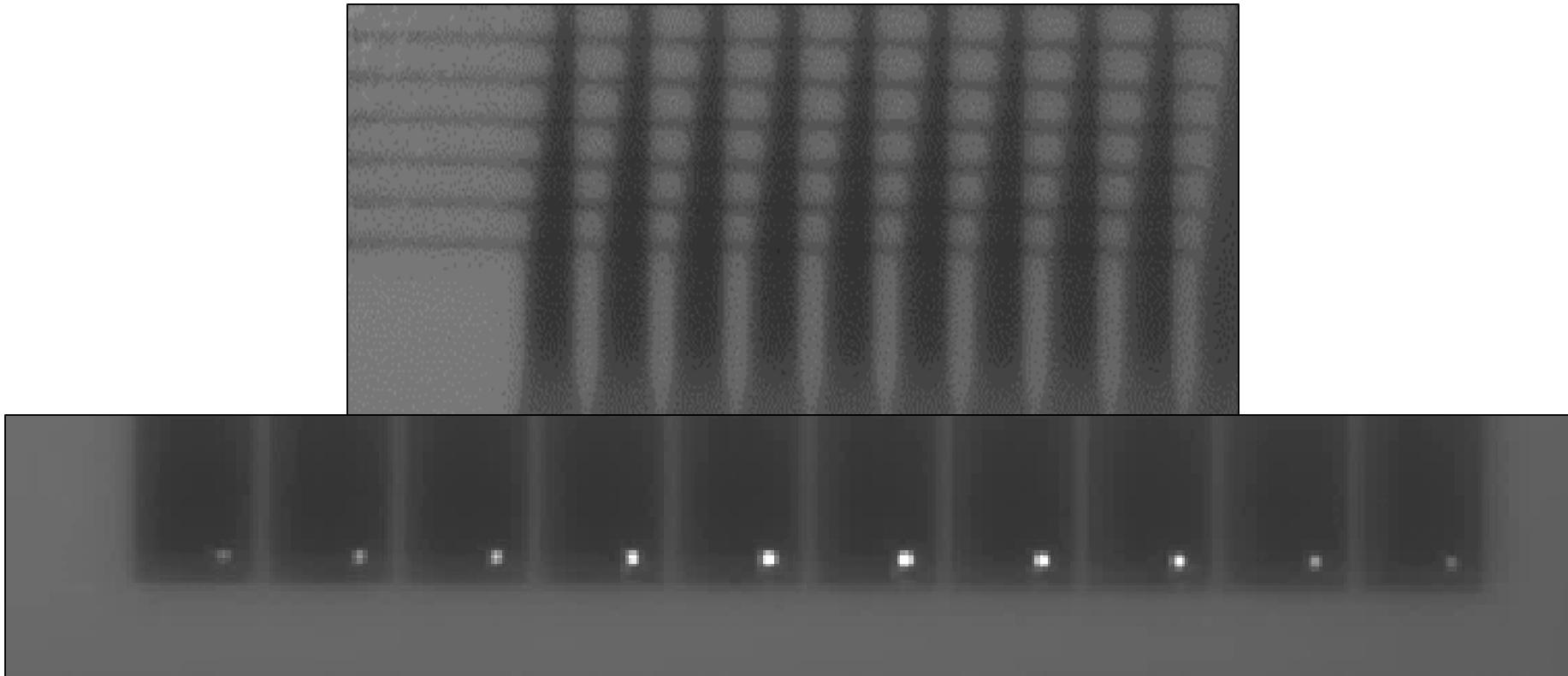
Chiles et al, APL Photonics 2
116101 (2017).



Chiles et al, APL Photonics 3 106101 (2018).

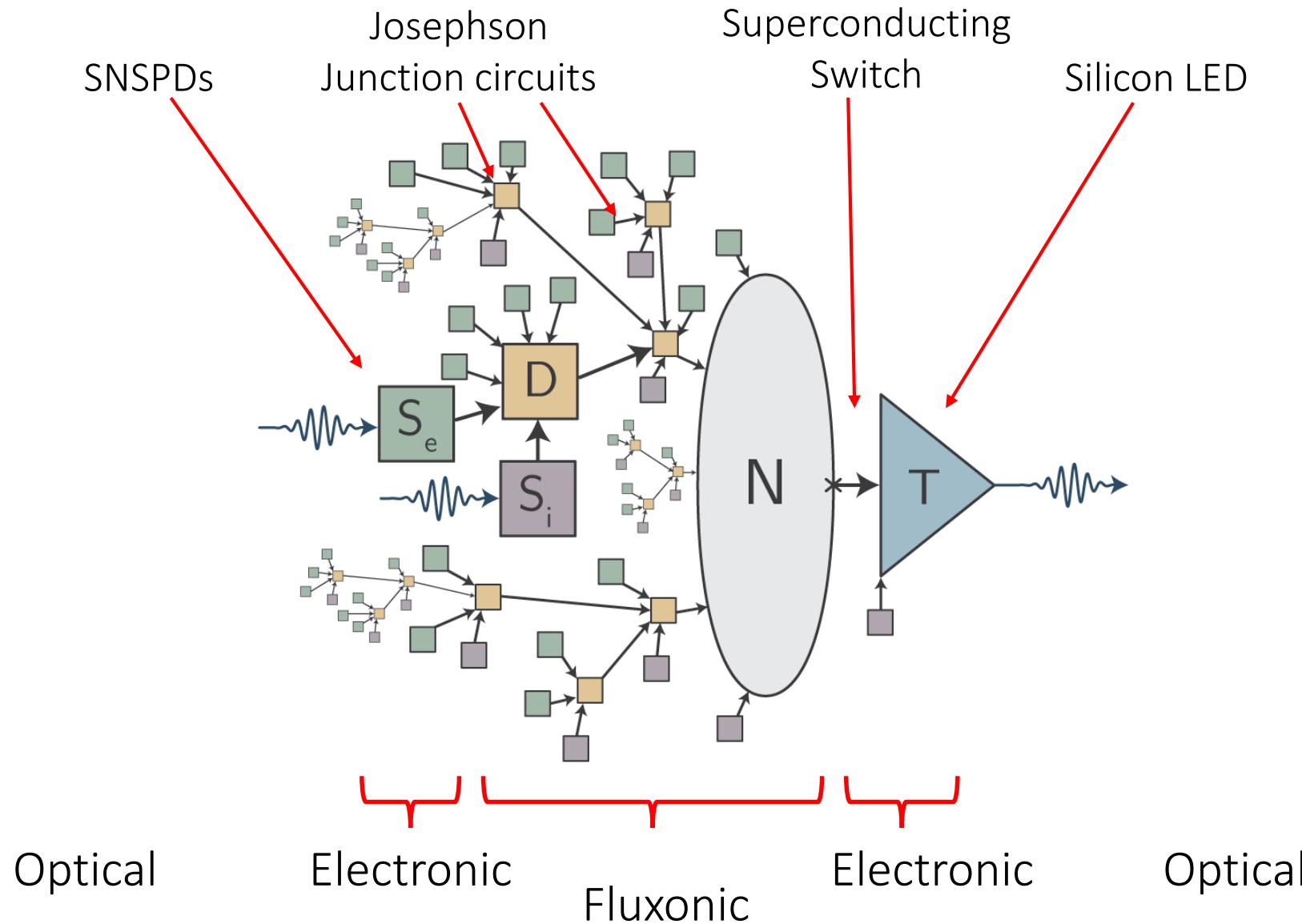


10×100 routing couplers

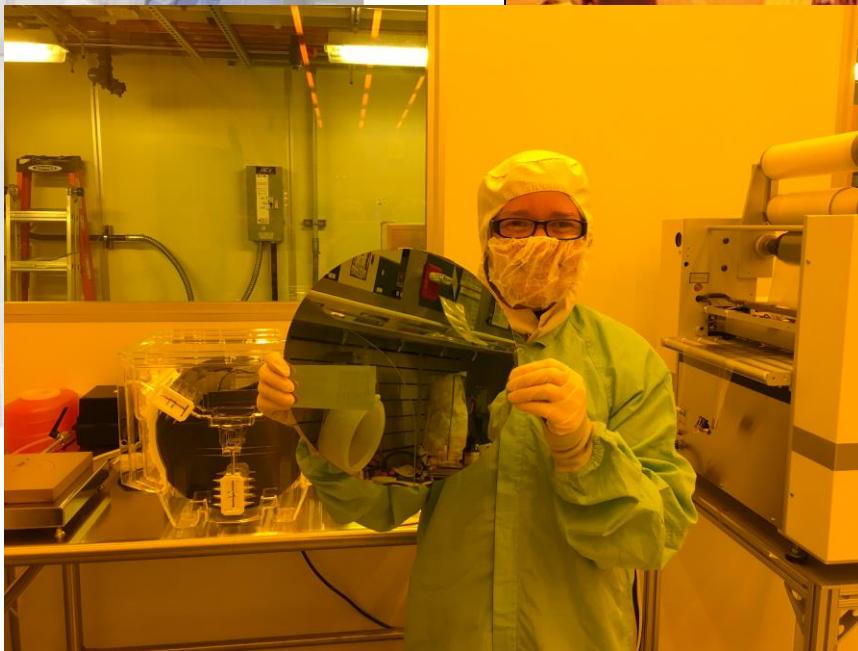
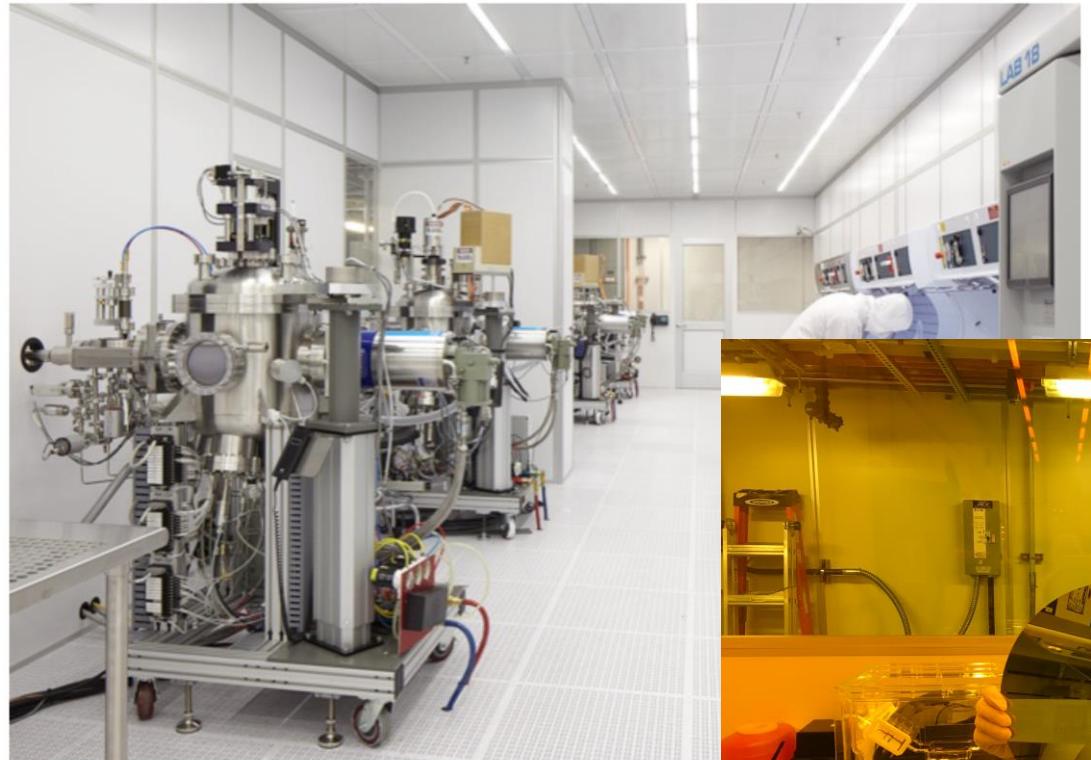


Full Superconducting Optoelectronic Neuron

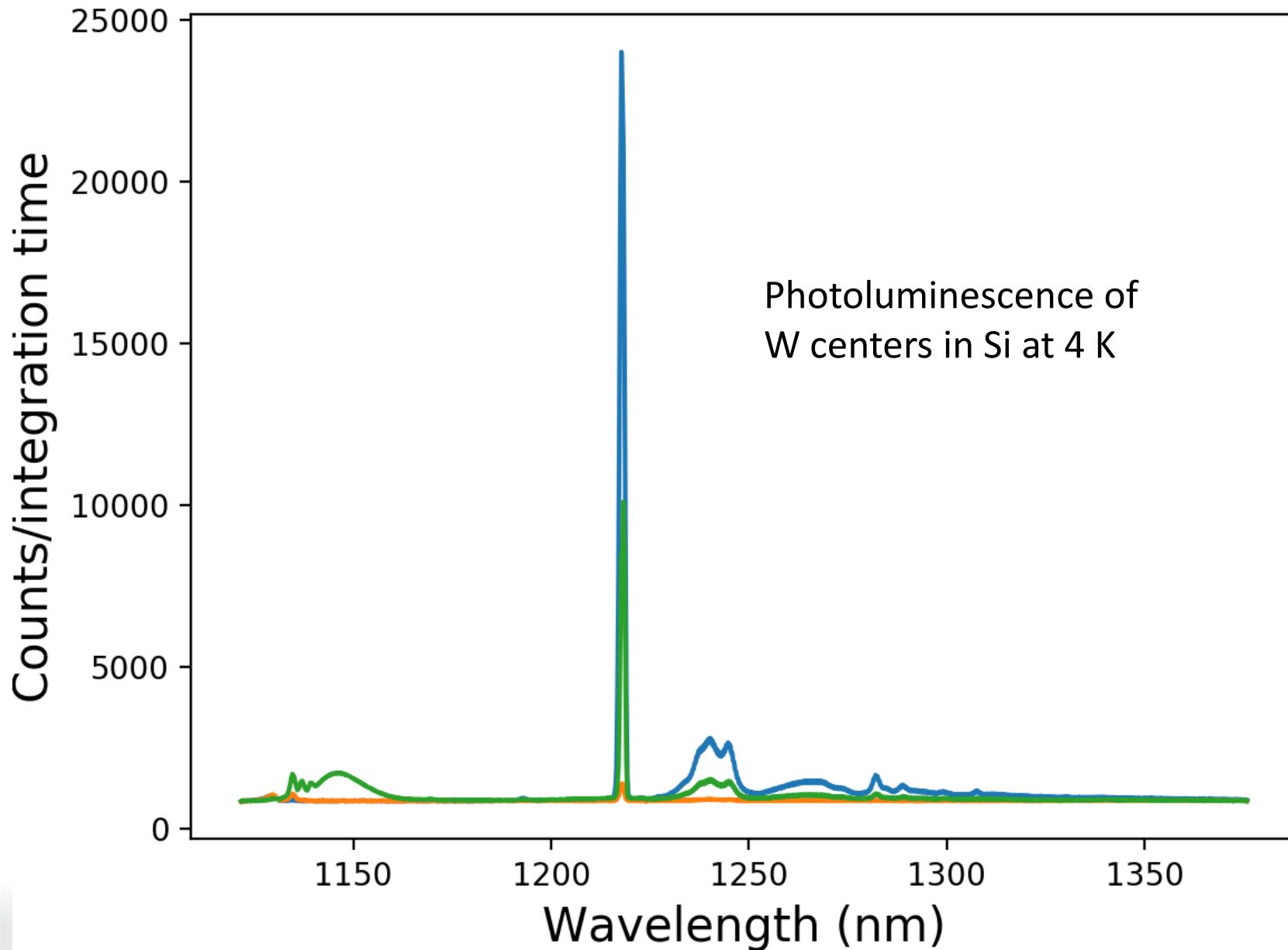
NIST



Eventual transfer to 300 mm foundry

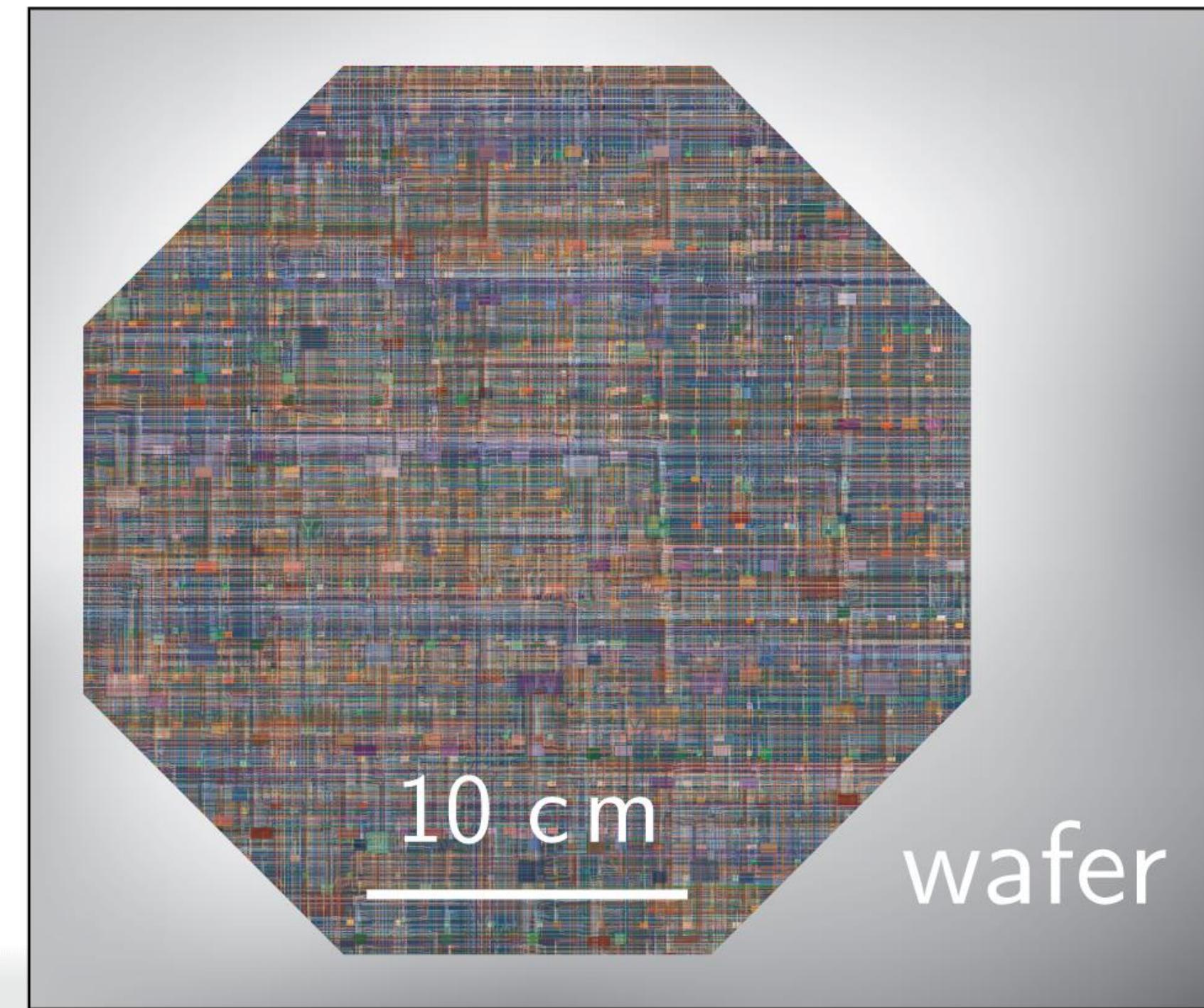


Light sources on 300-mm wafers

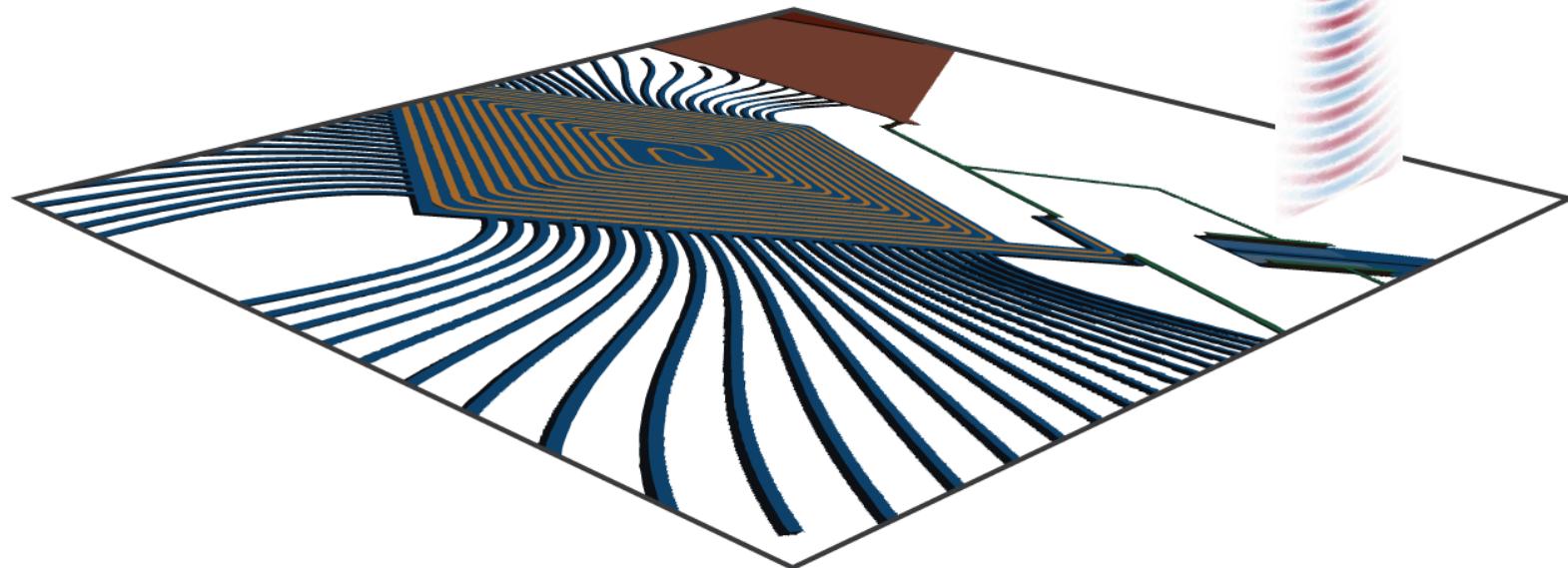
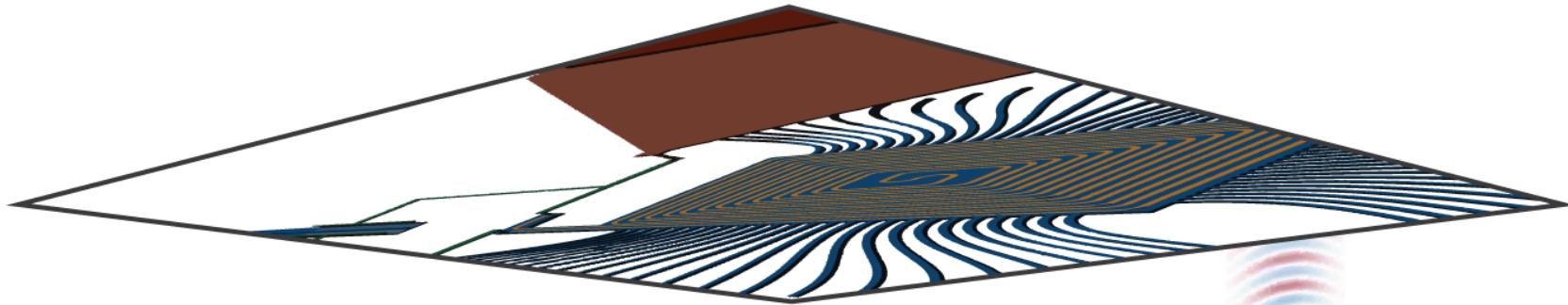


- Fabricated at SUNY Poly by Pops Papa Rao and team
- Measured at NIST by our team

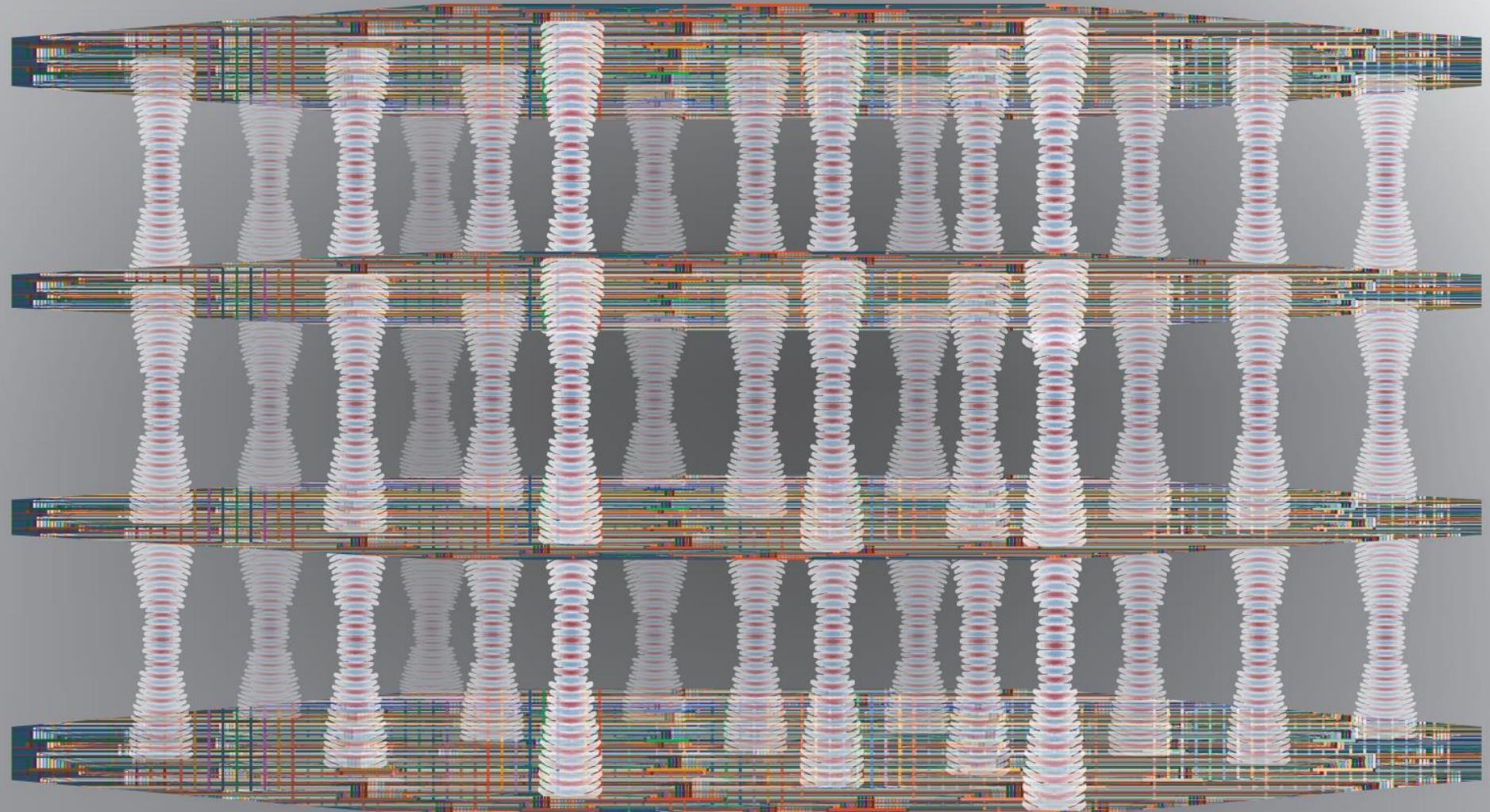
Wafer-scale
modules



Free-space interconnects for 3D

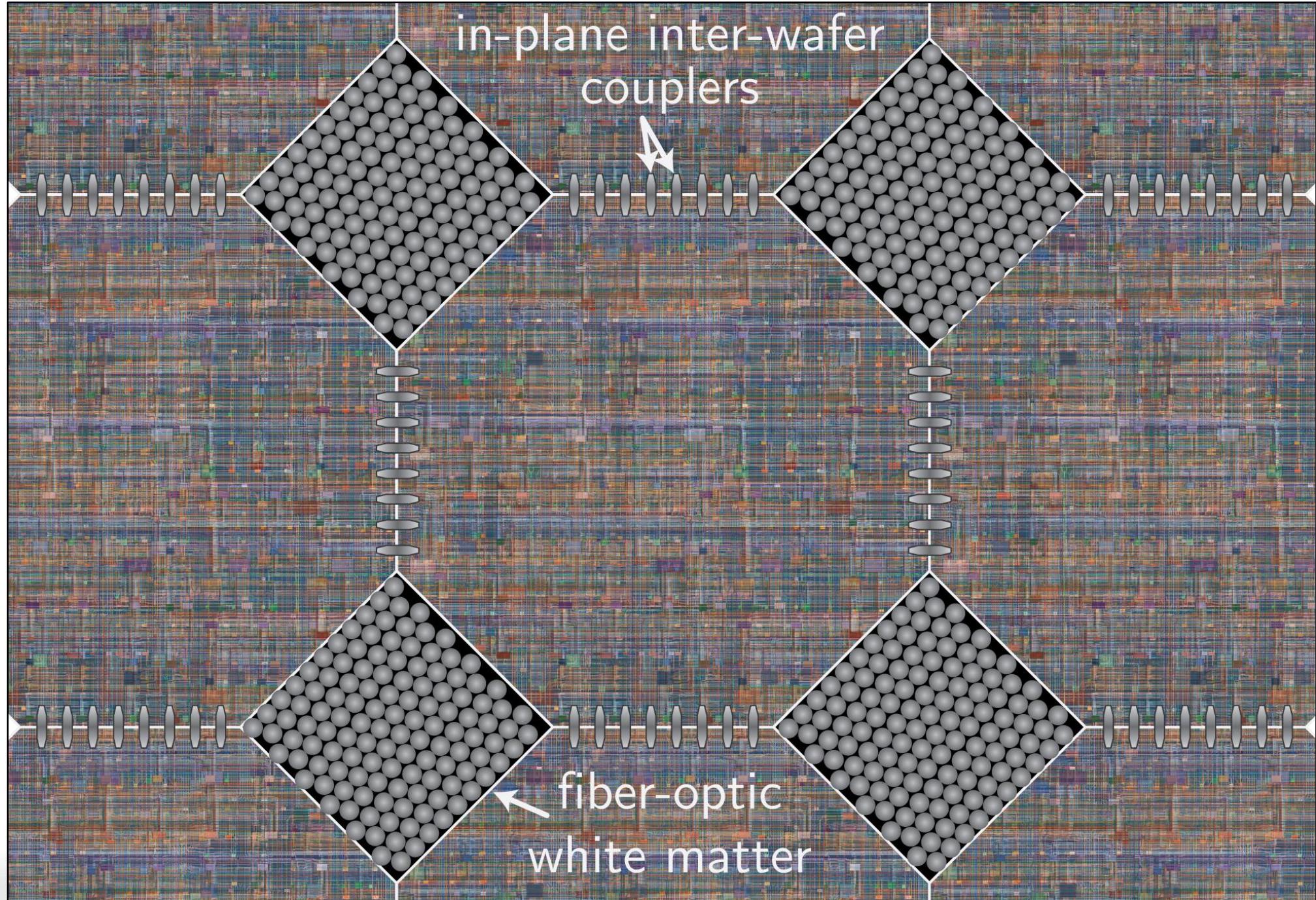


Free-space
inter-wafer
interconnects



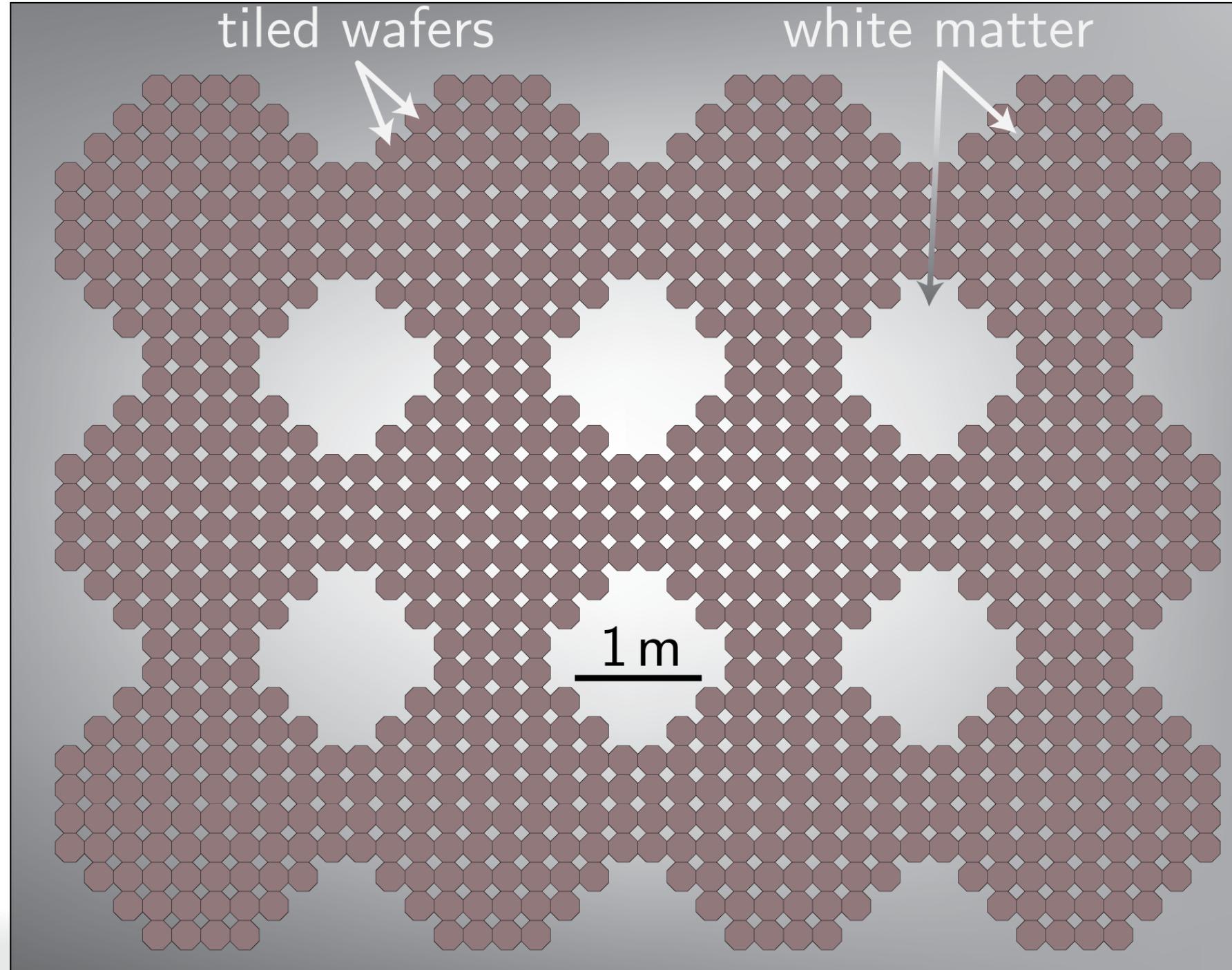
column

Multi-wafer
modules

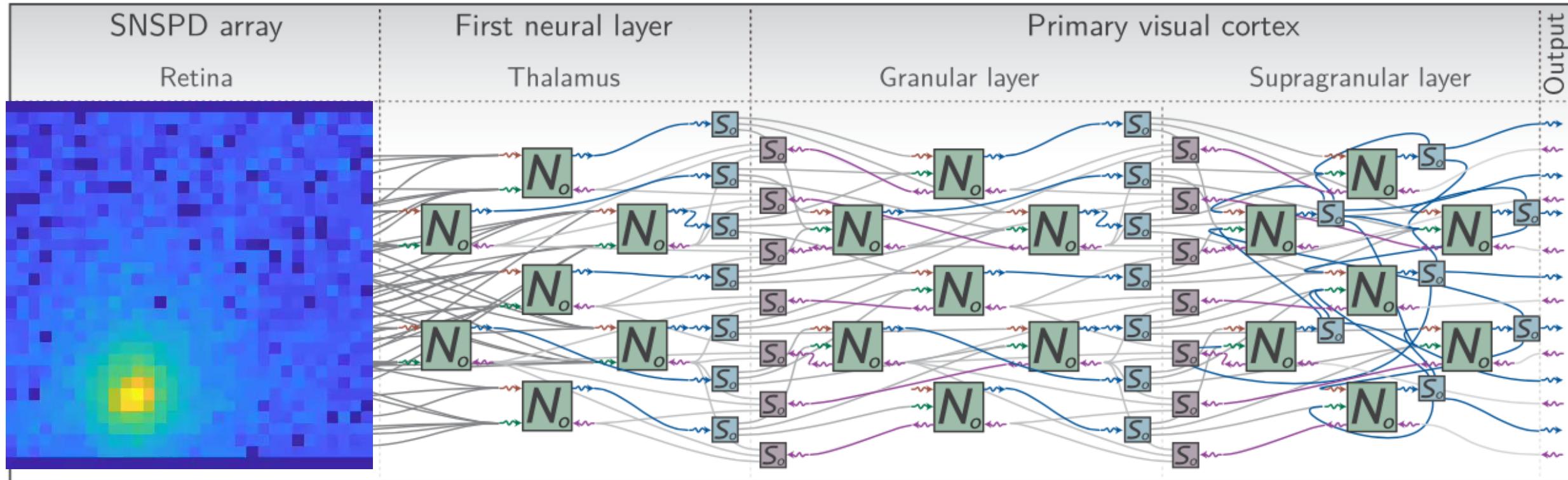


Brain-scale
systems?

> 100 Billion
neurons



What can we do in five years?



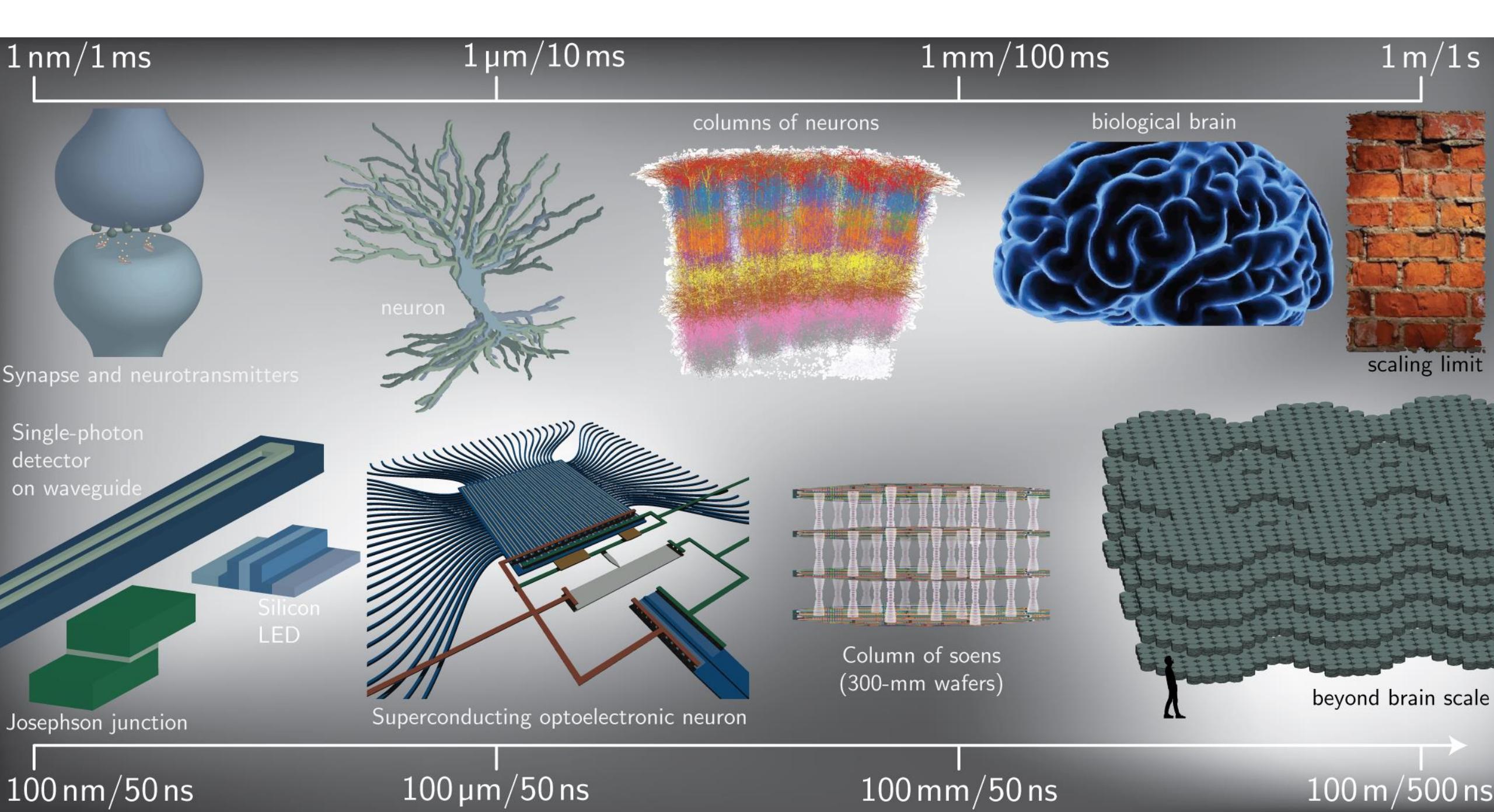
Artificial visual cortex

Superconducting optoelectronic networks



- Dense local fan-out with photonics
- Long-range communication at light speed
- Computing and memory with superconducting electronics

Would this reach the limits of cognition?



Summary

- Low Temperature Devices have the potential to be important in **super-neuromorphic computing**
 - Light for communication
 - Superconductors for computation
 - Complex neuro circuits



Can we get to a size scale for “Cognitive” Systems?

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- Rich Mirin
 - Jeff Shainline
 - Sonia Buckley
 - Adam McCaughan
 - Alex Tait
 - Jeff Chiles
 - Saeed Khan
 - Krister Shalm
 - Marty Stevens
 - Adriana Lita
 - Varun Verma
 - Nima Nader
 - Mike Mazurek
 - Dileep Reddy
 - Eric Stanton
 - Galen Moody
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