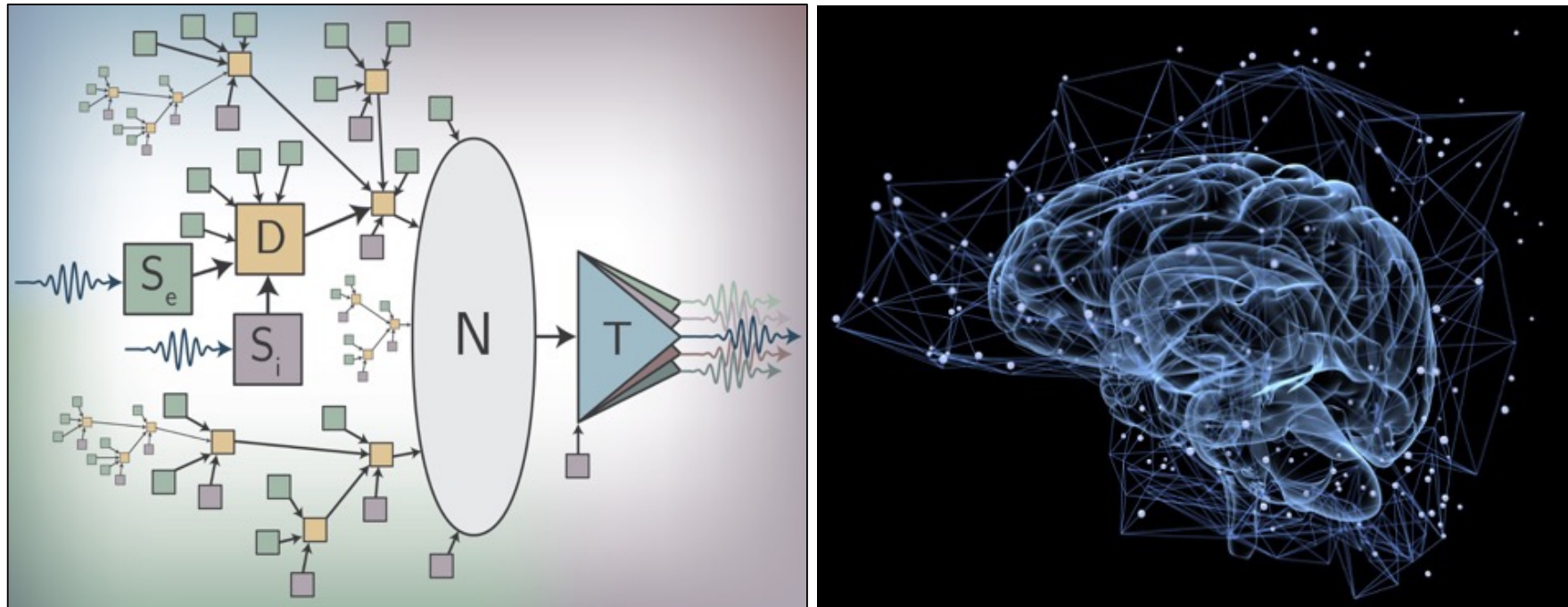


“Super” Neuromorphic Computing with Photonic and Superconducting Devices

Superconductors, light, and the “age of of cognition”

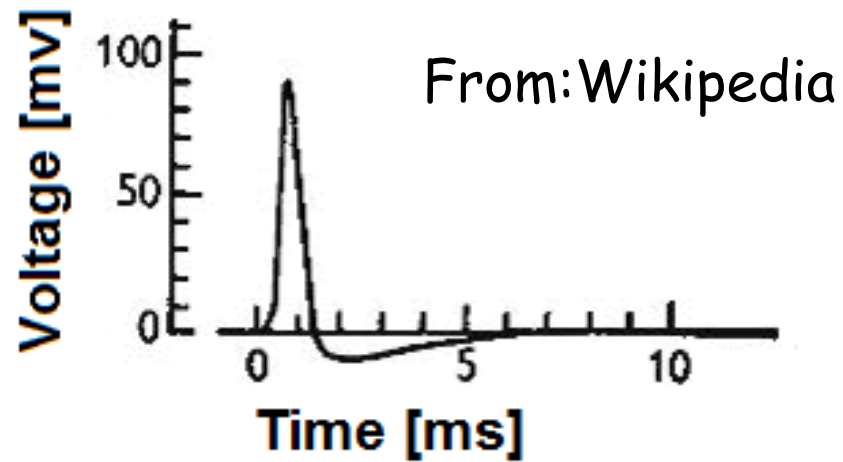
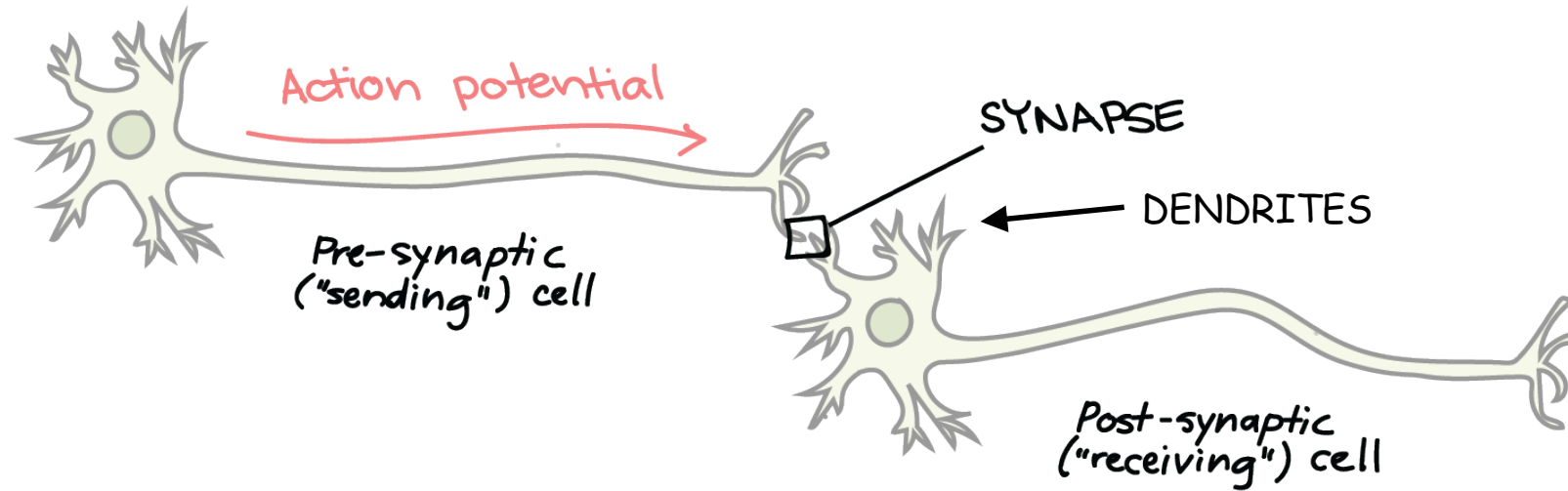


Jeff Chiles, Sonia Buckley, Adam McCaughan, Alex Tait, Saeed Khan, Bryce Primavera,
Rich Mirin, Sae Woo Nam, Jeff Shainline
NIST, Physical Measurement Laboratory

Future of Computing

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

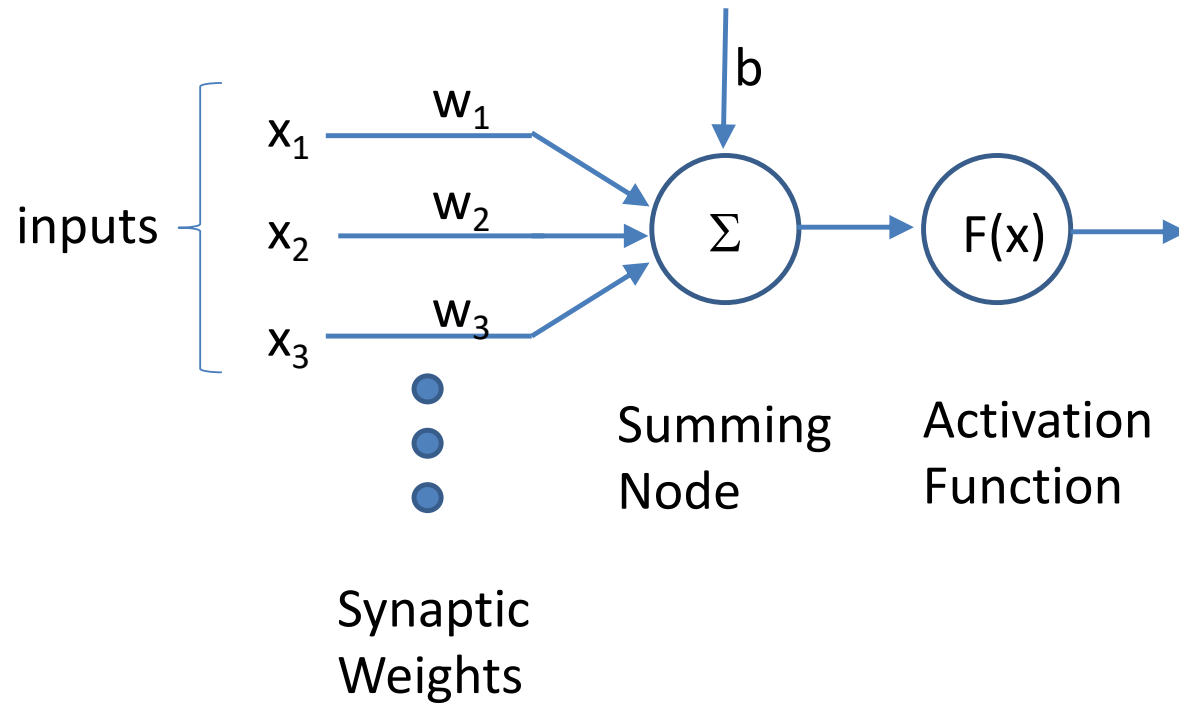
Structure of a Biological Neuron



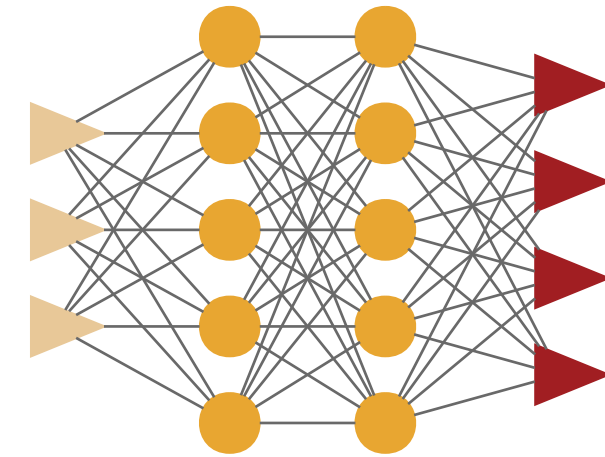
<https://www.khanacademy.org/science/biology/human-biology/neuron-nervous-system/a/the-synapse>




Fast Introduction to Neural Networks

Artificial Neuron



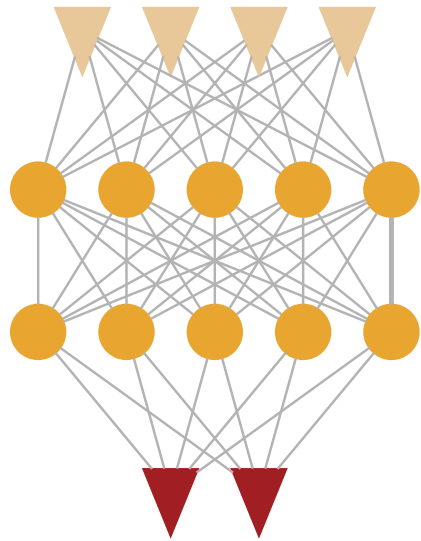
Network of Neurons



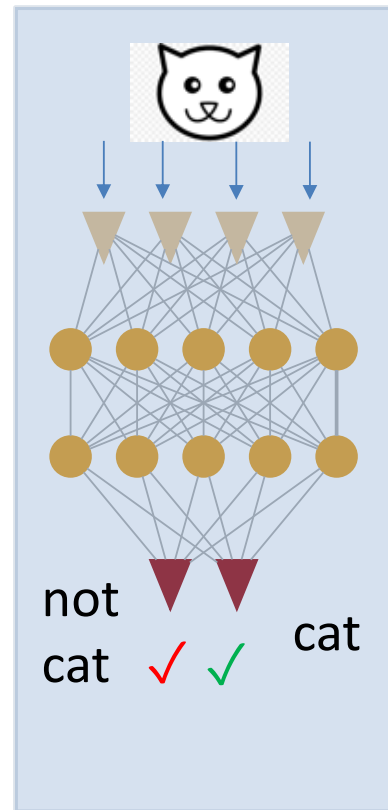
-  Input Cell / Layer
-  Hidden Cell / Layer
-  Output Cell / Layer

Supervised Learning

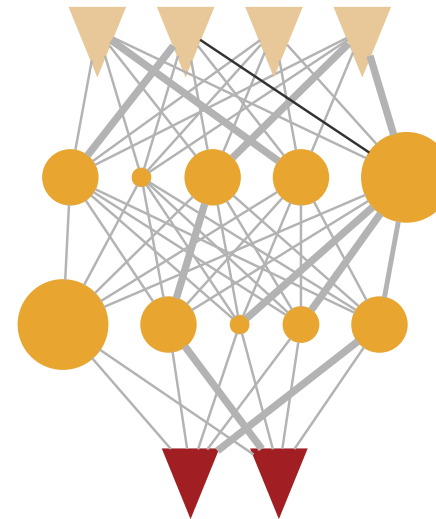
Untrained
Neural Network



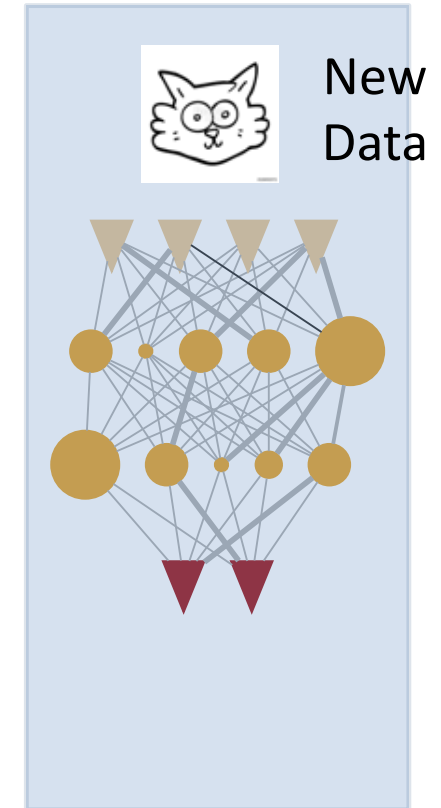
Training



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.



- 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 | CO₂e (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) | 39 |
| w/ tuning & experimentation | 78,468 |
| Transformer (big) | 192 |
| w/ neural architecture search | 626,155 |

- “How do you make the largest scale artificial neural network?”
 - Human Brain:
 - 100 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?

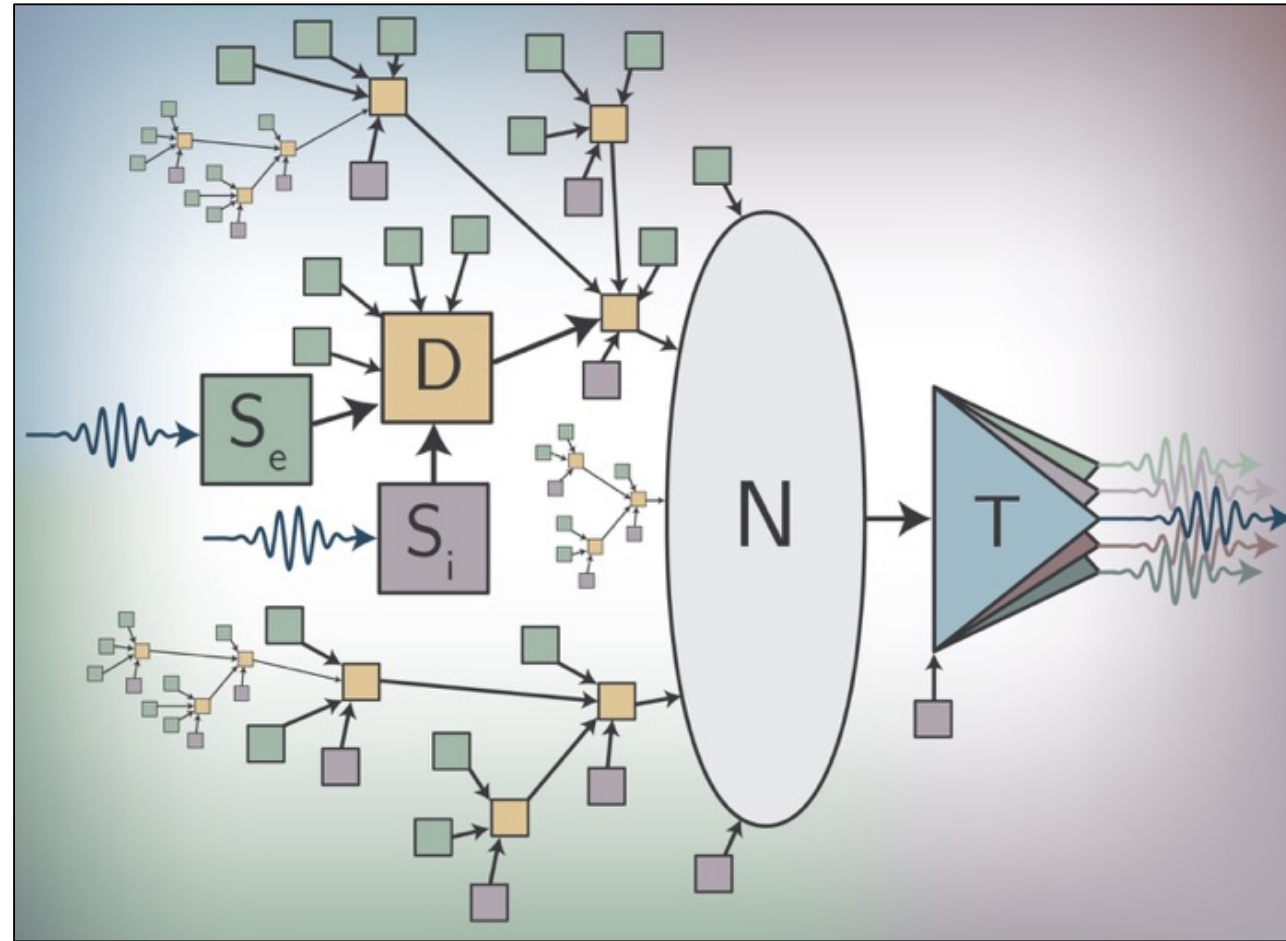
<https://arxiv.org/abs/1906.02243v1>

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)



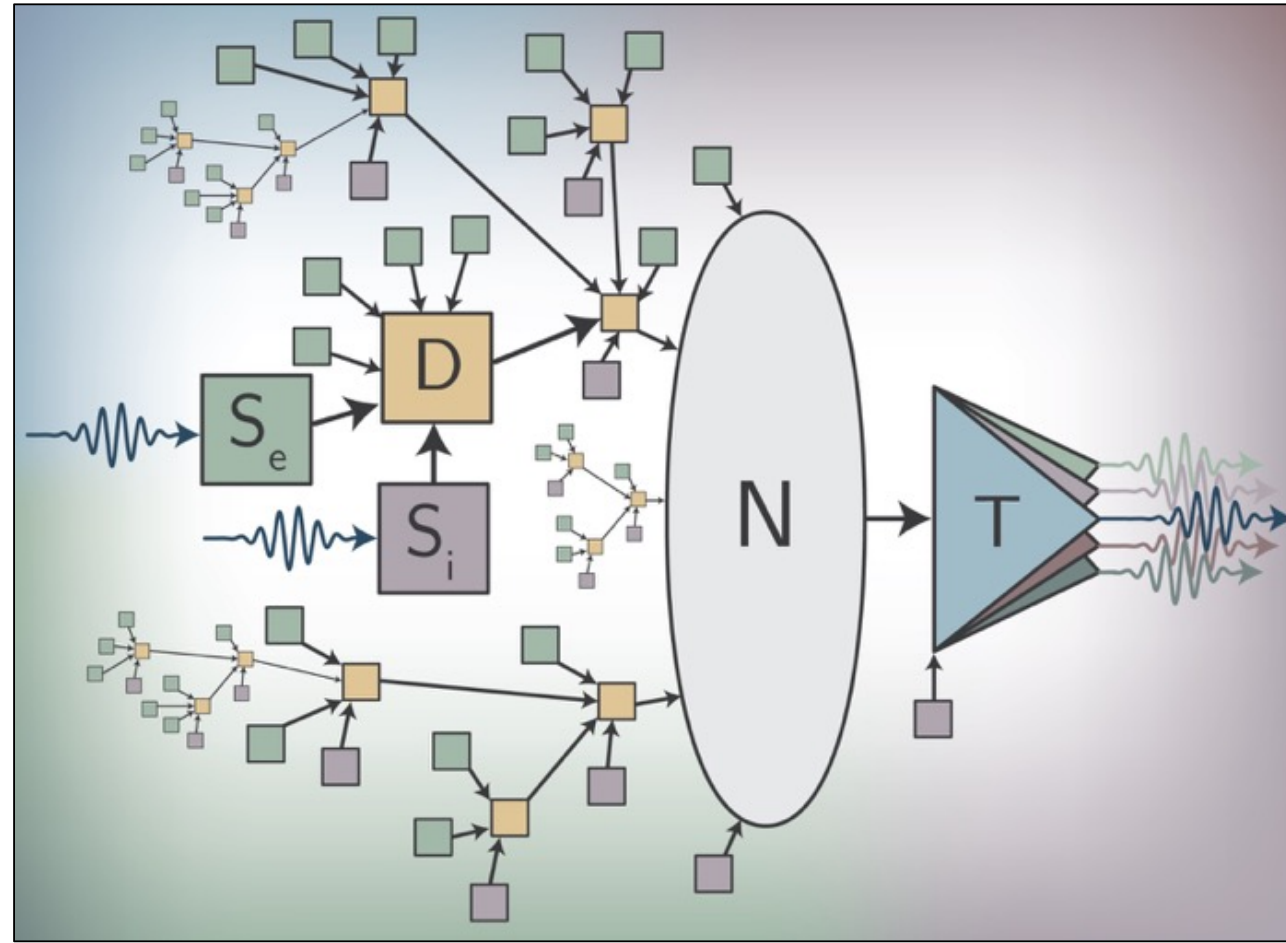
Can we get to a size scale for "Cognitive" Systems?



Fluxonic processing of
photonic synapse events

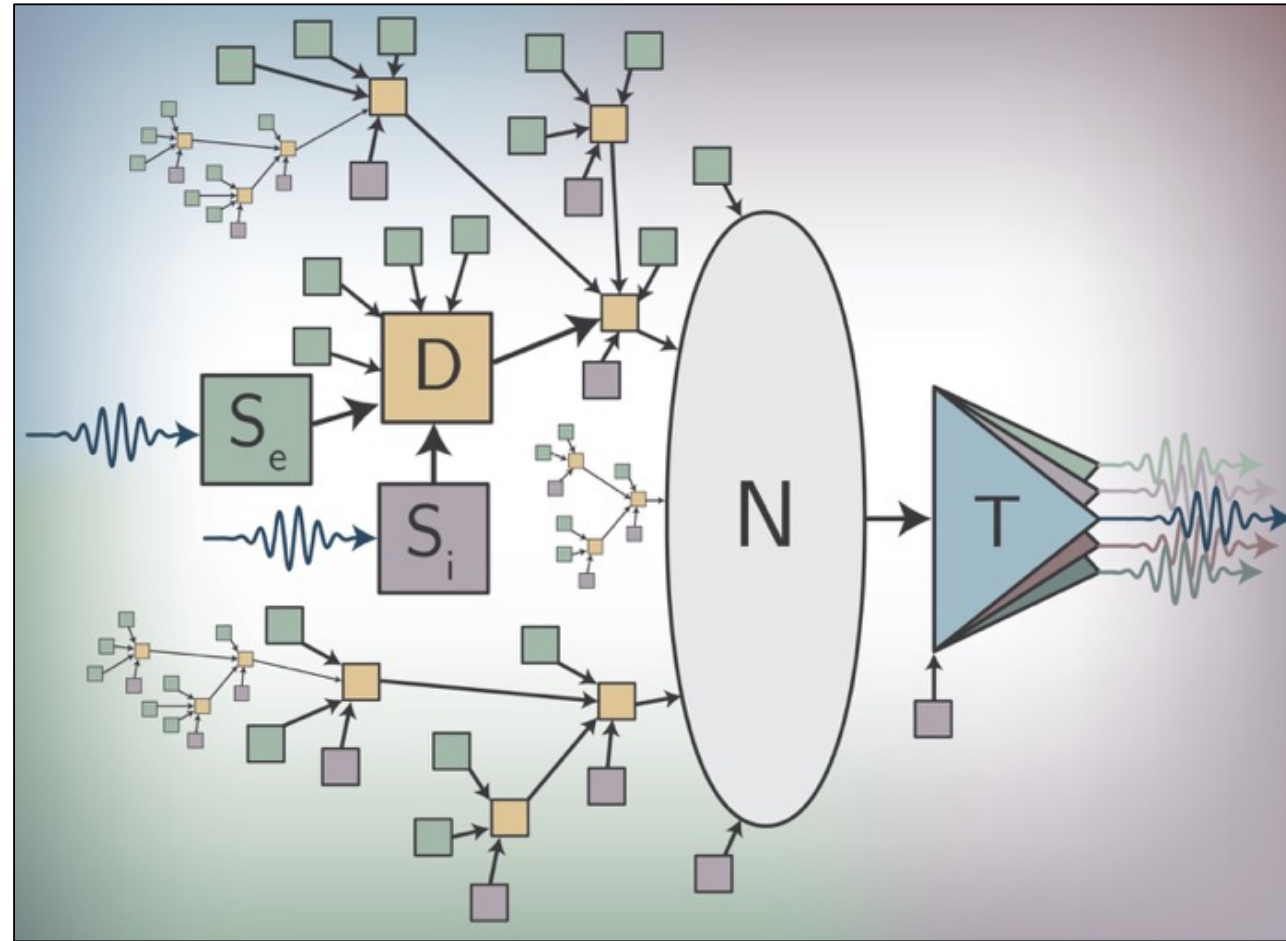
Spiking neural networks

jeffrey.shainline@nist.gov



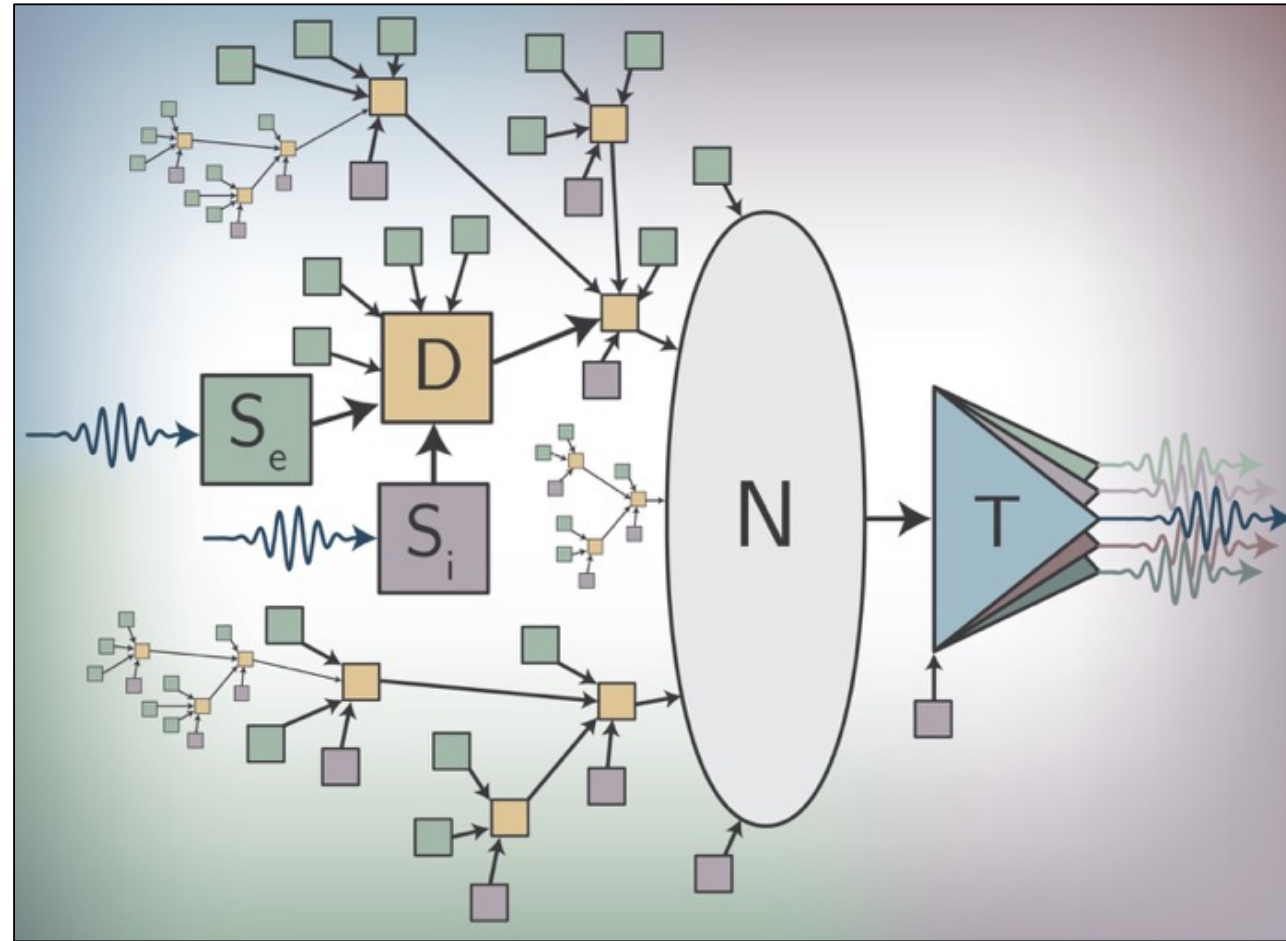
Fluxonic processing of
photonic synapse events

Light for communication



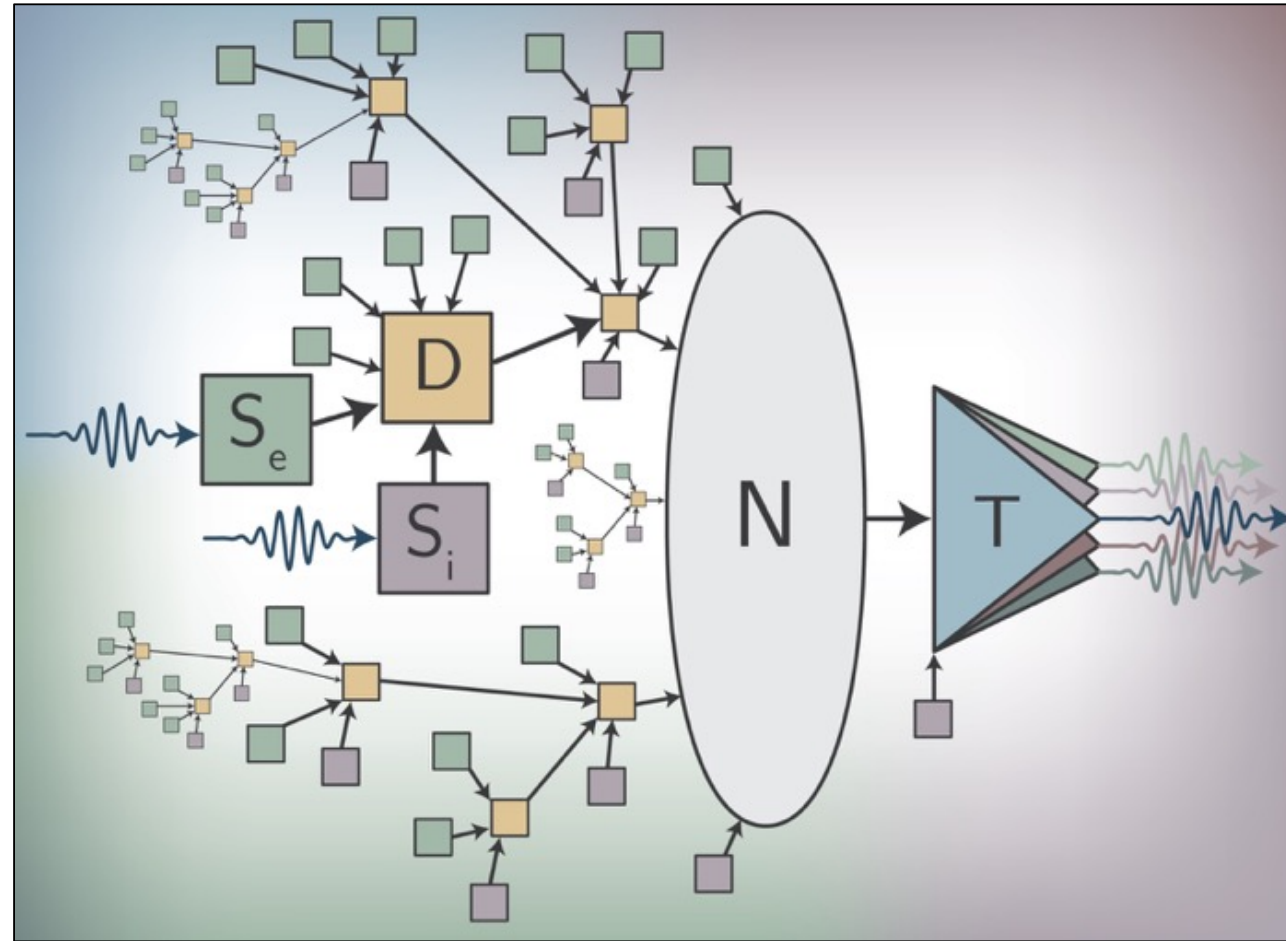
Fluxonic processing of
photonic synapse events

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

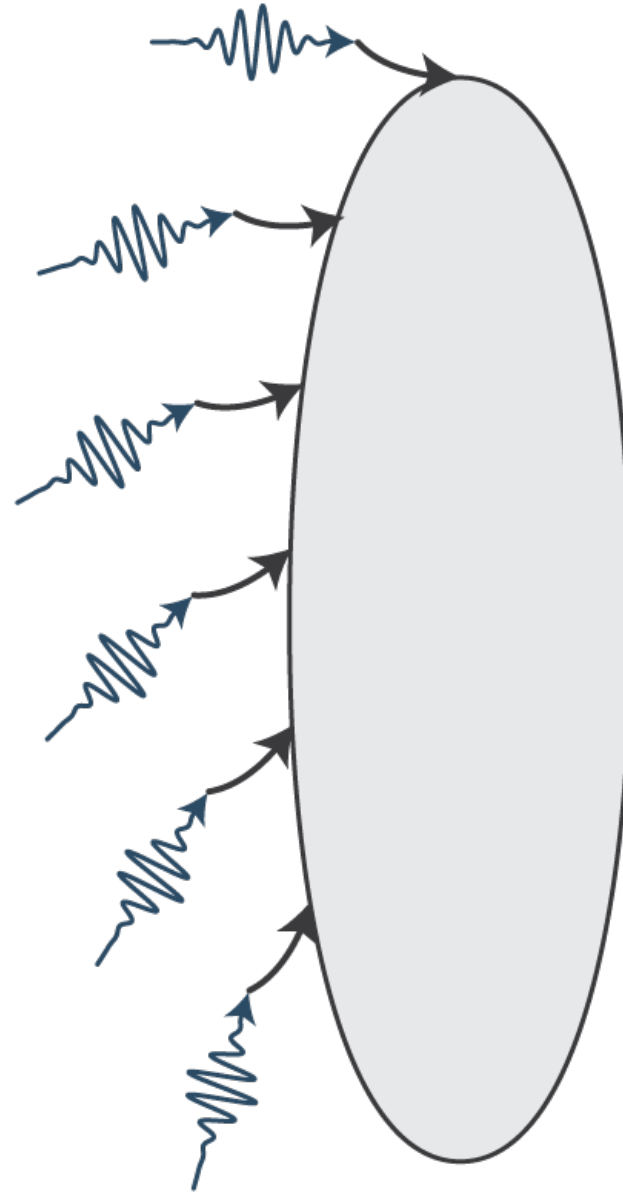
Neurons that signal with single photons

Neurons that signal with single photons

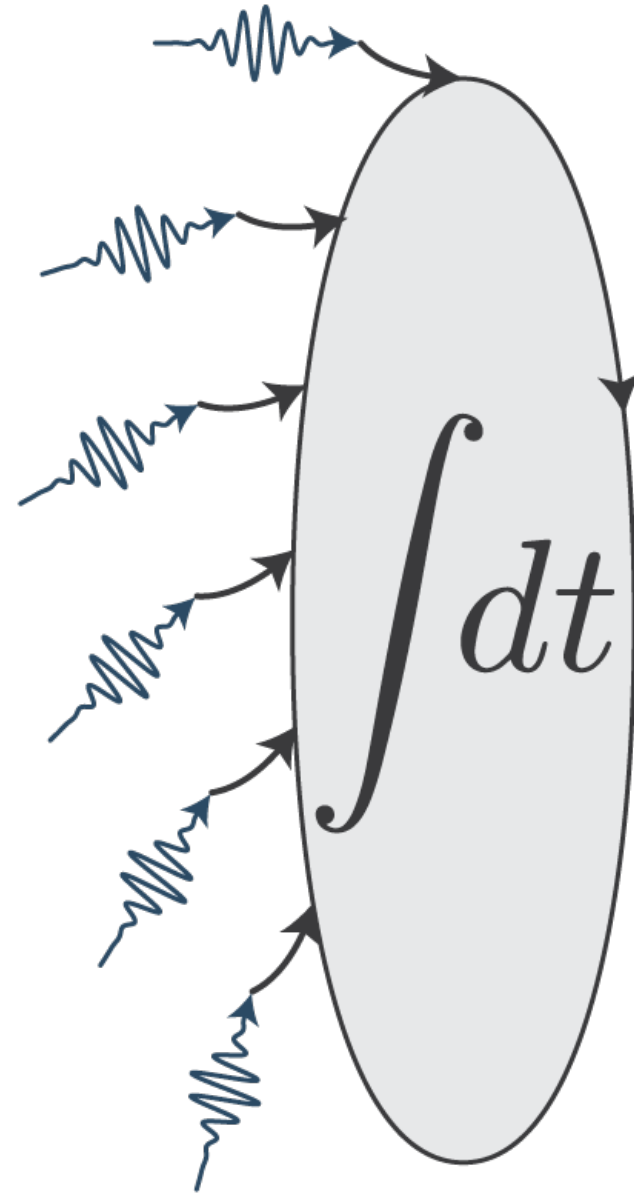
How do they work?



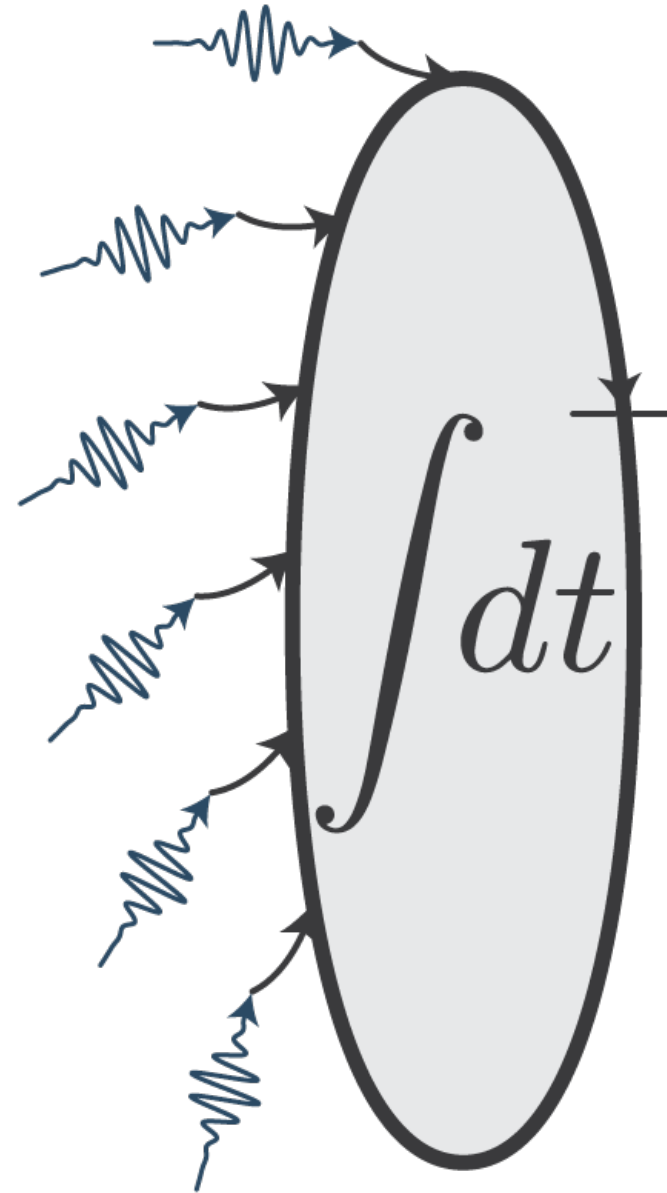
Superconducting loop



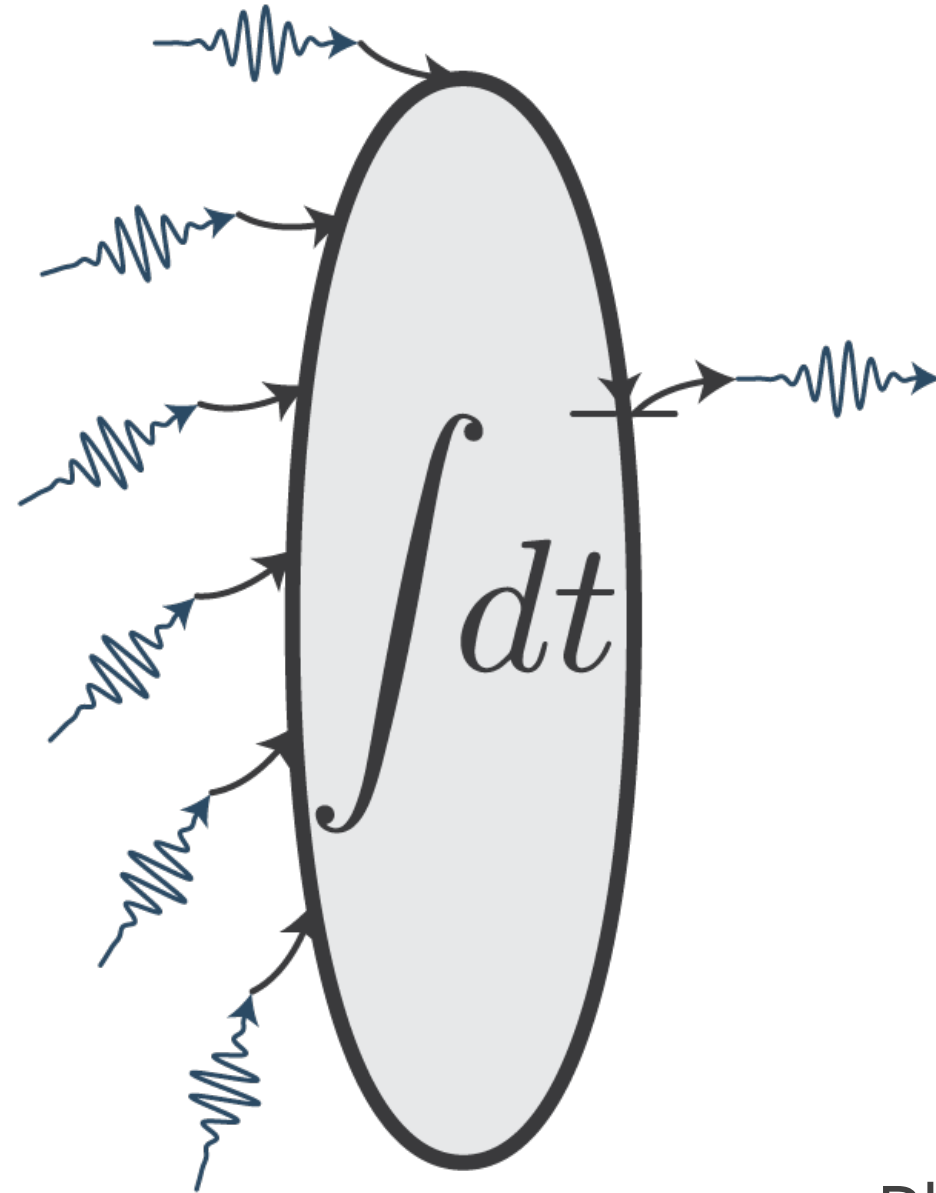
Photons add current



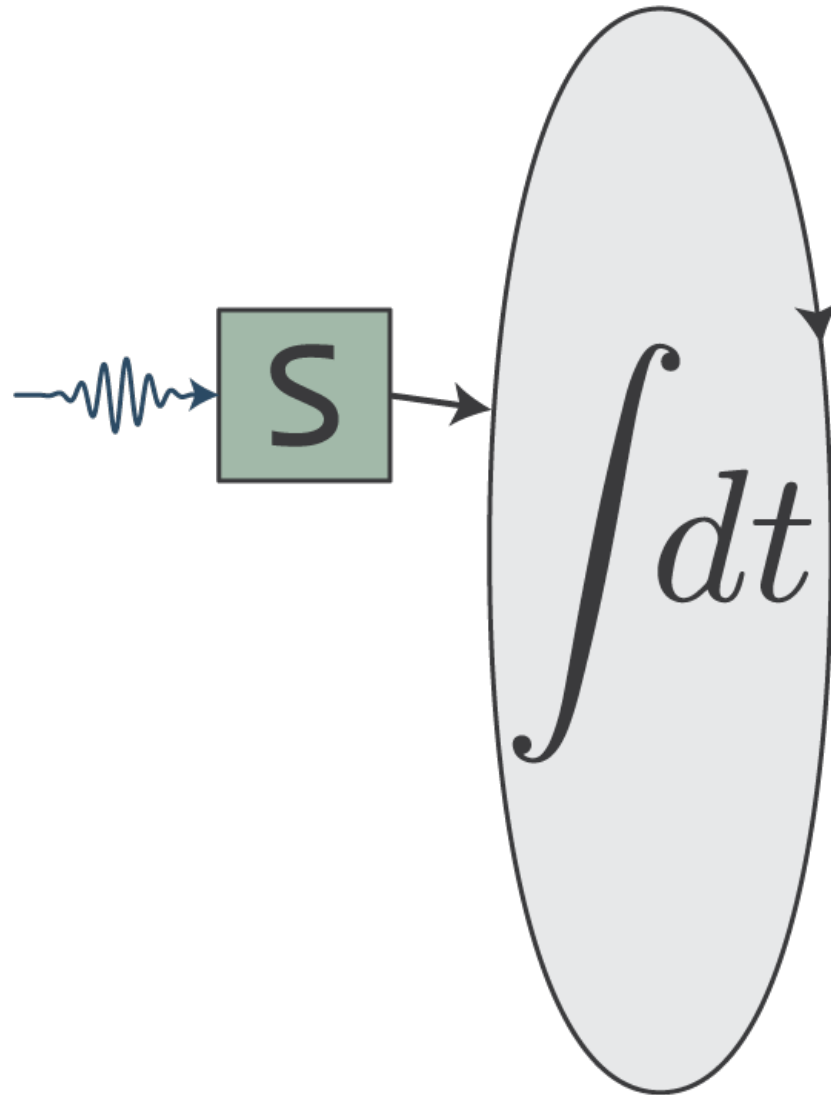
Current gets integrated



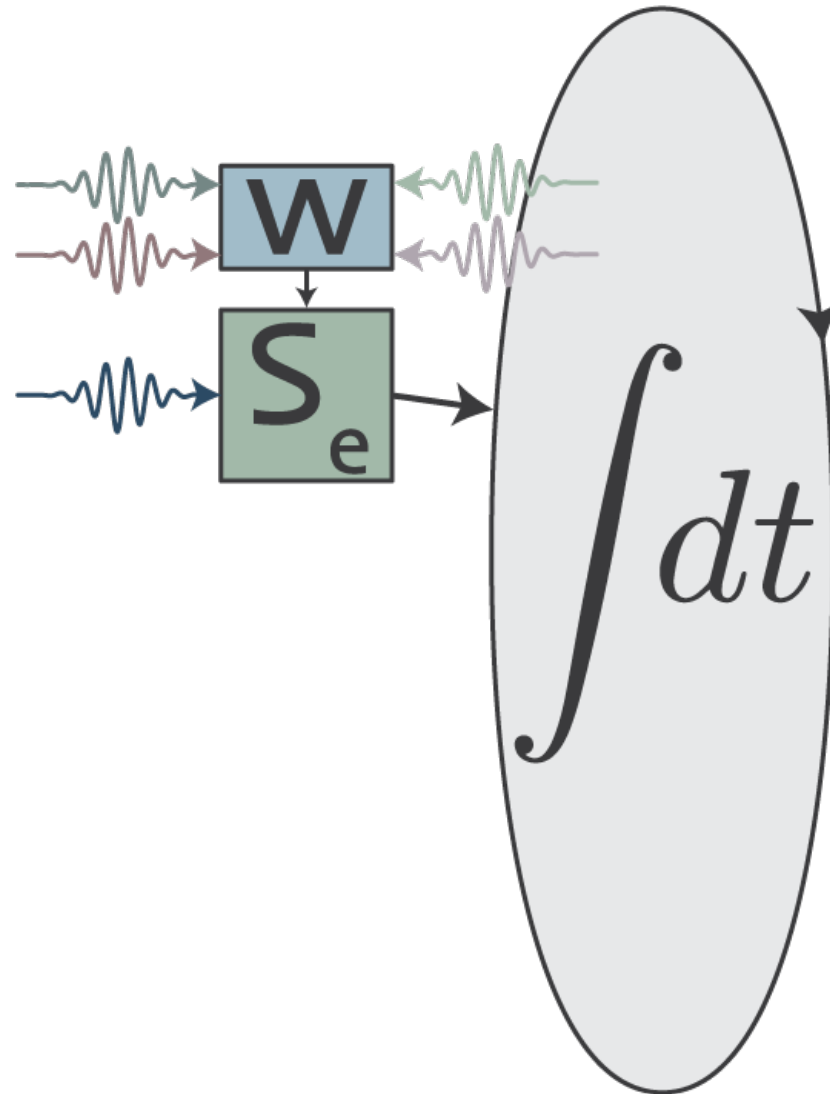
Current threshold



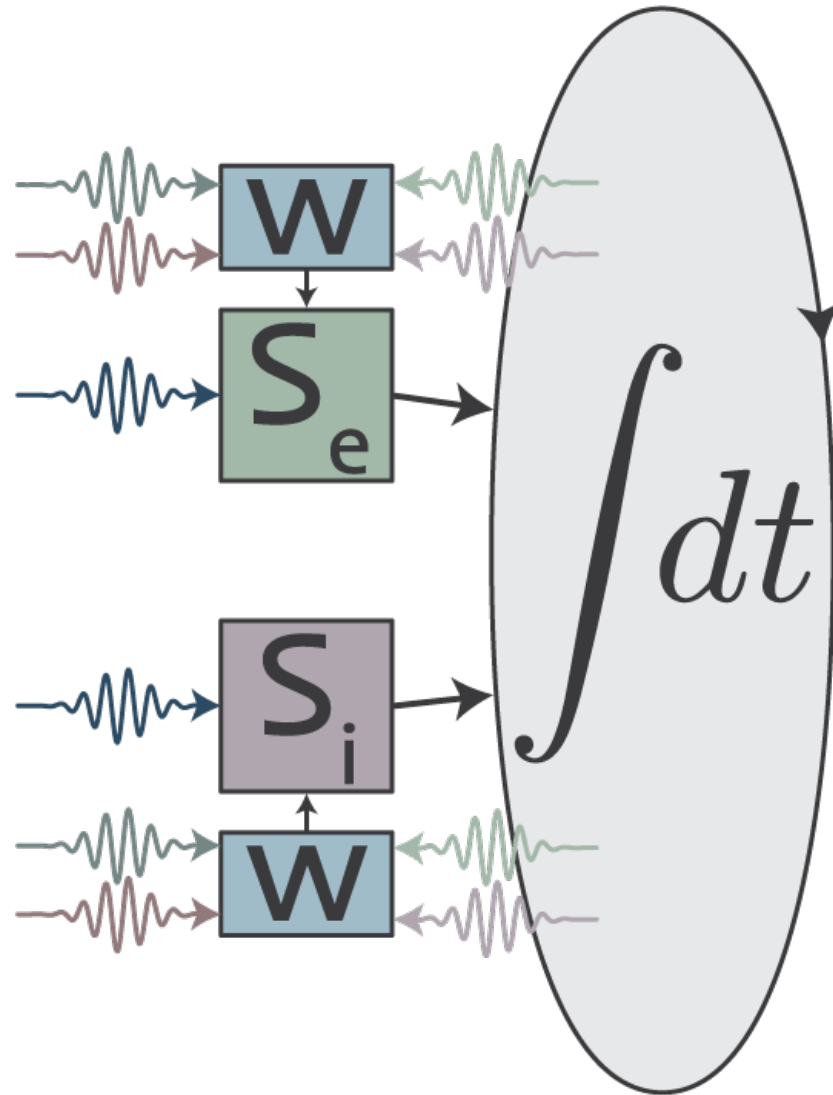
Photons produced



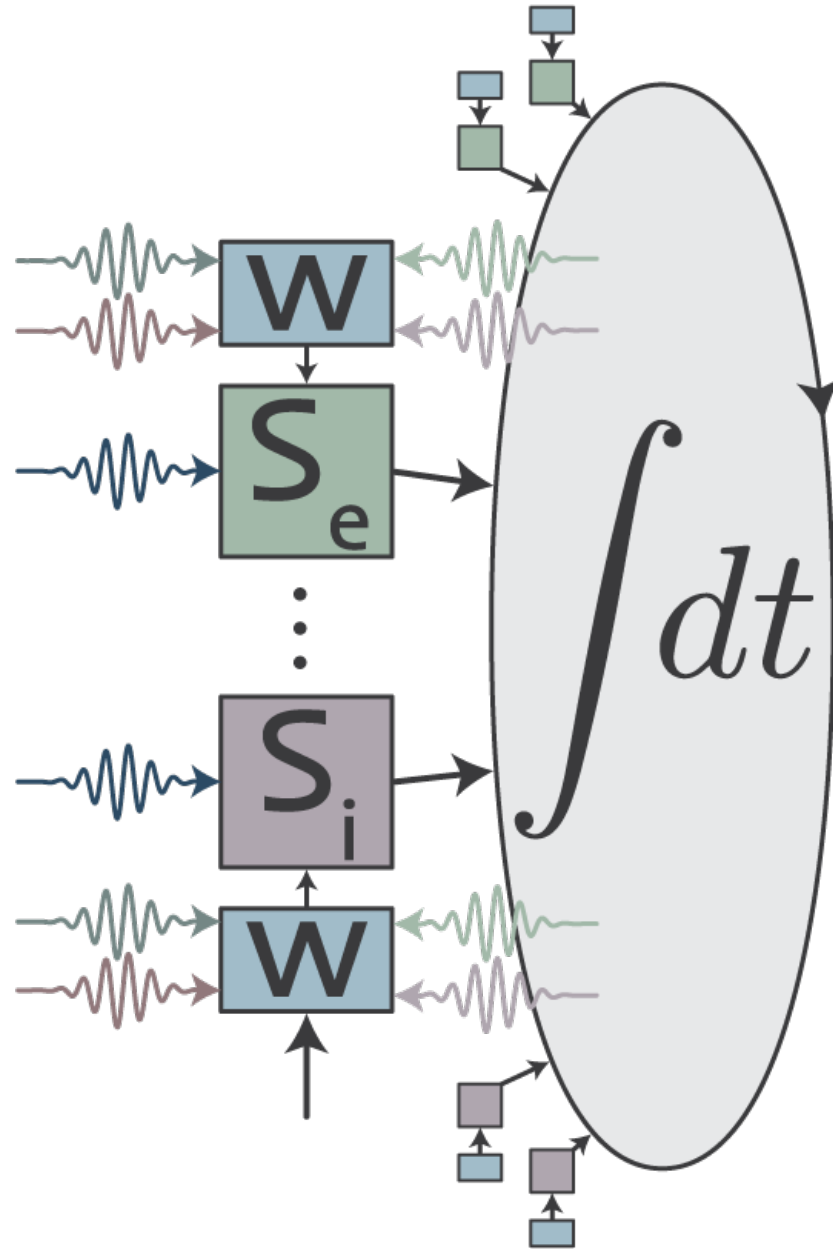
Synapse transduces



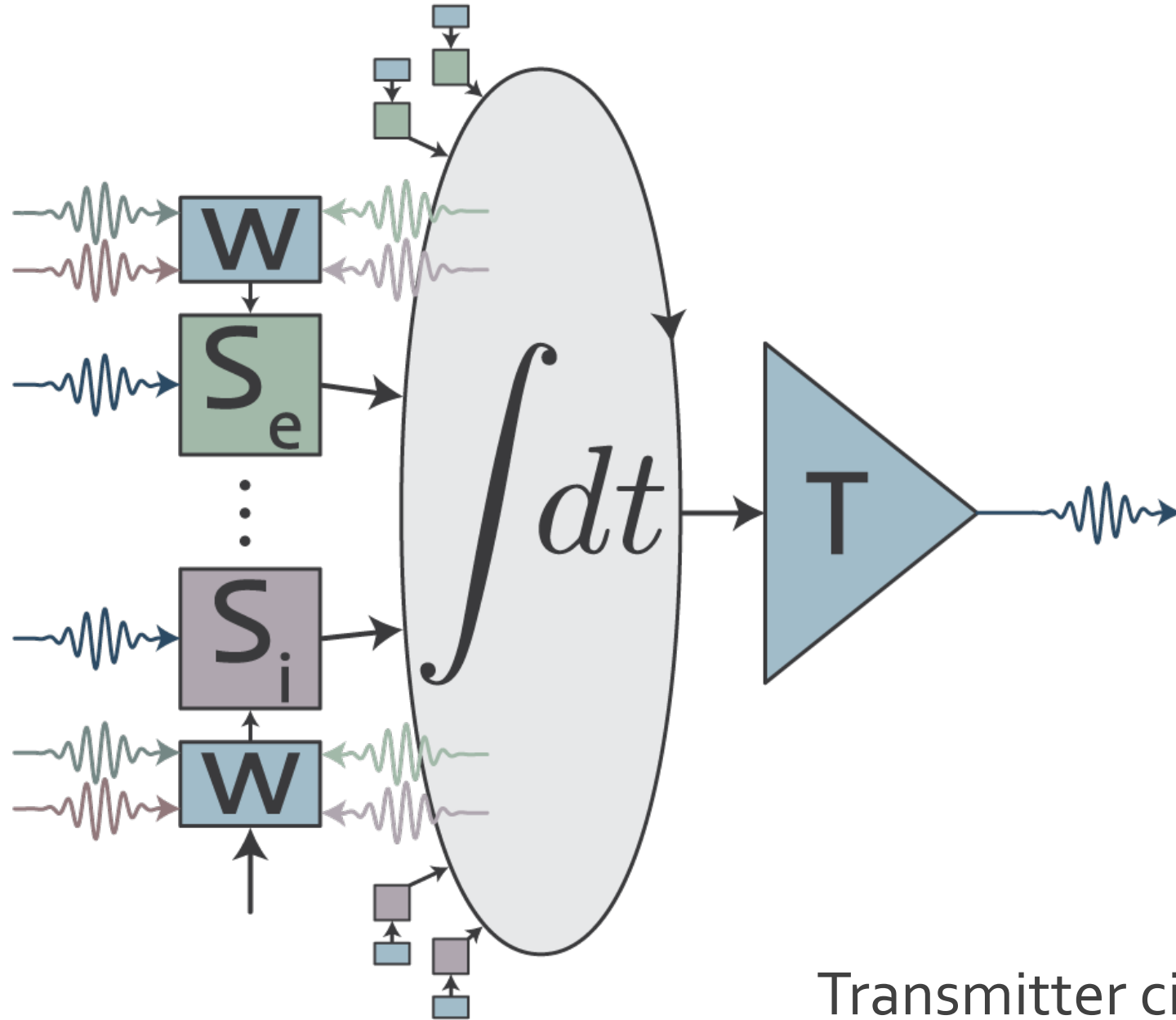
Photons update weight



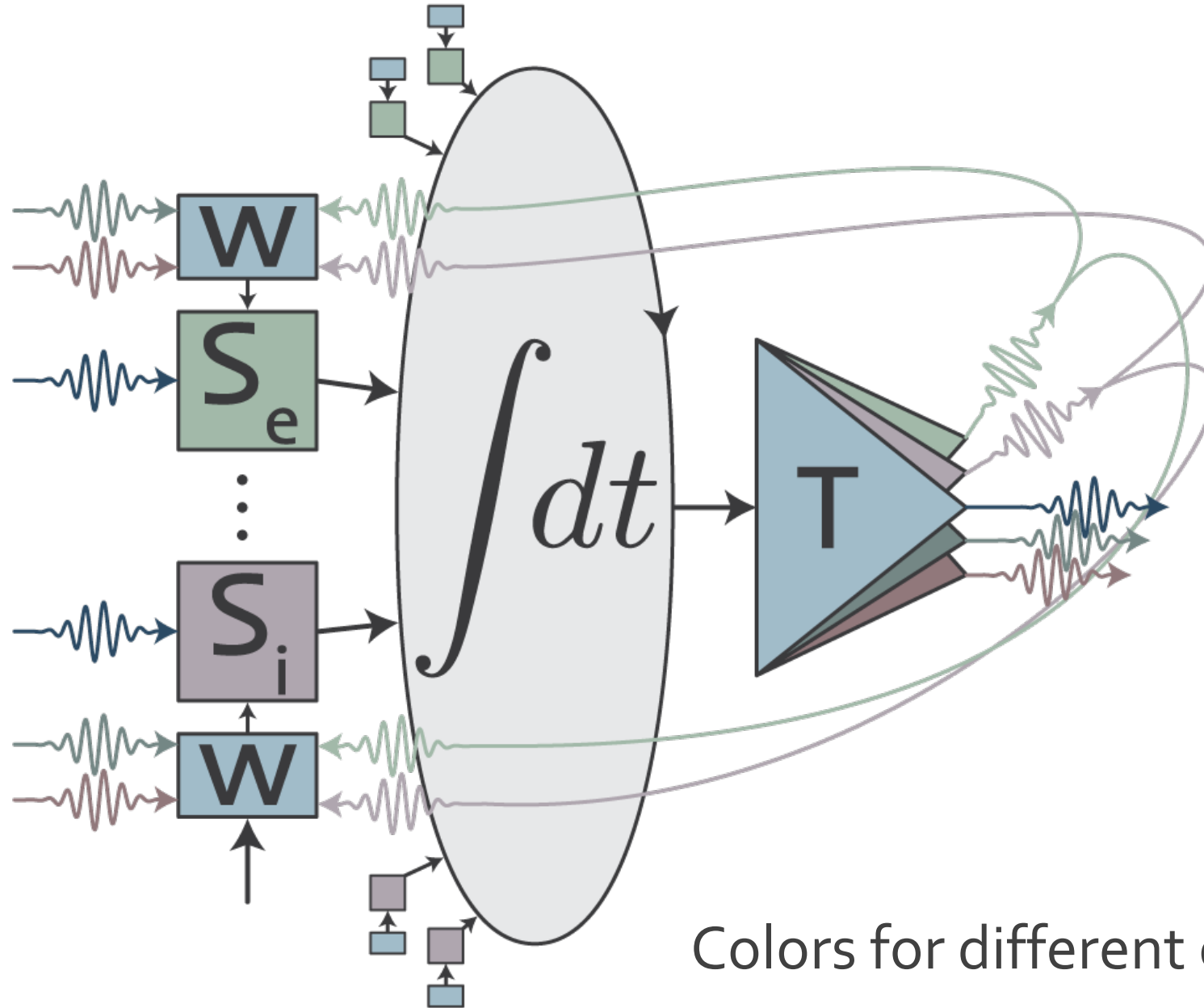
Inhibitory synapses



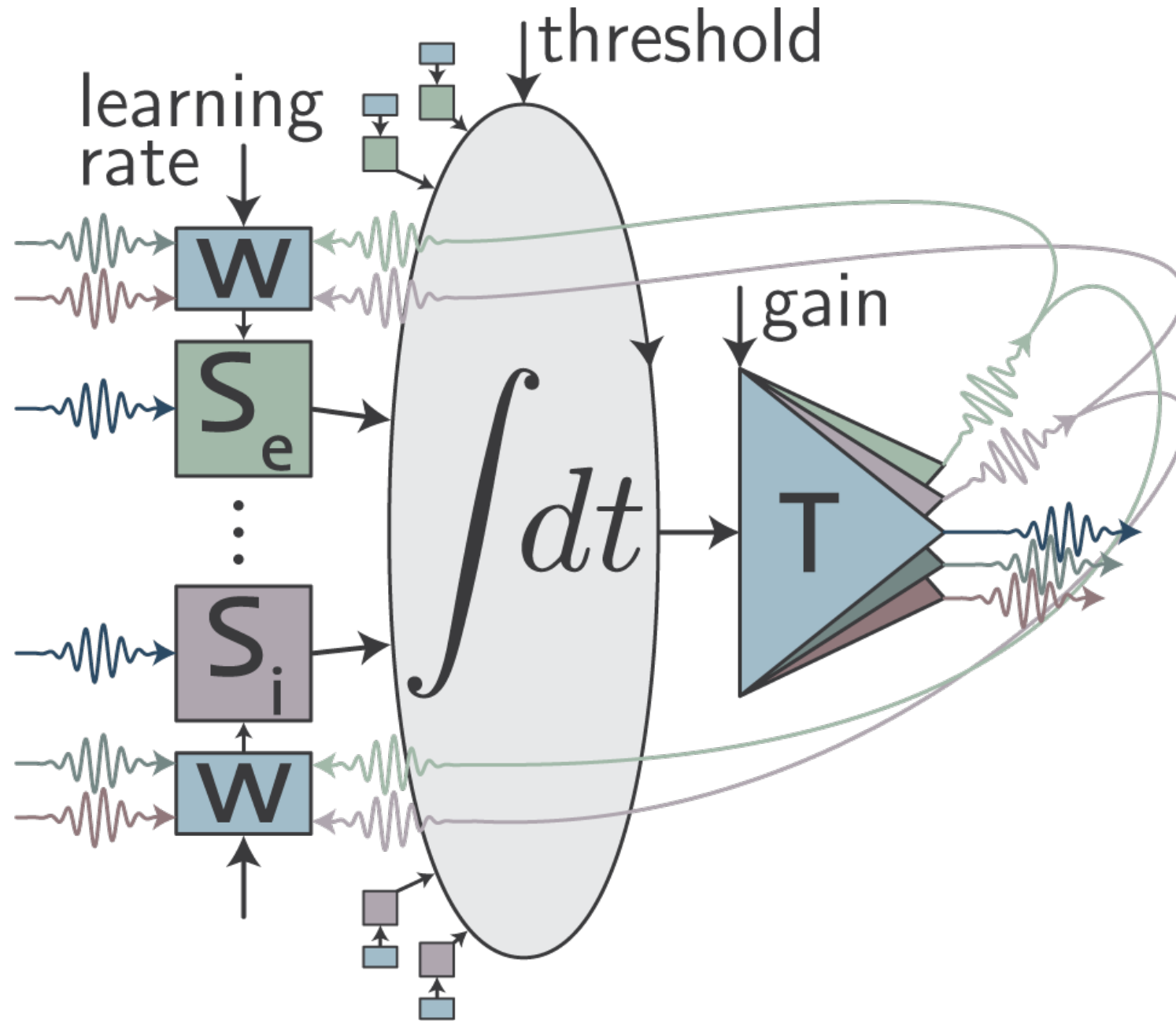
Many synapses



Transmitter circuits

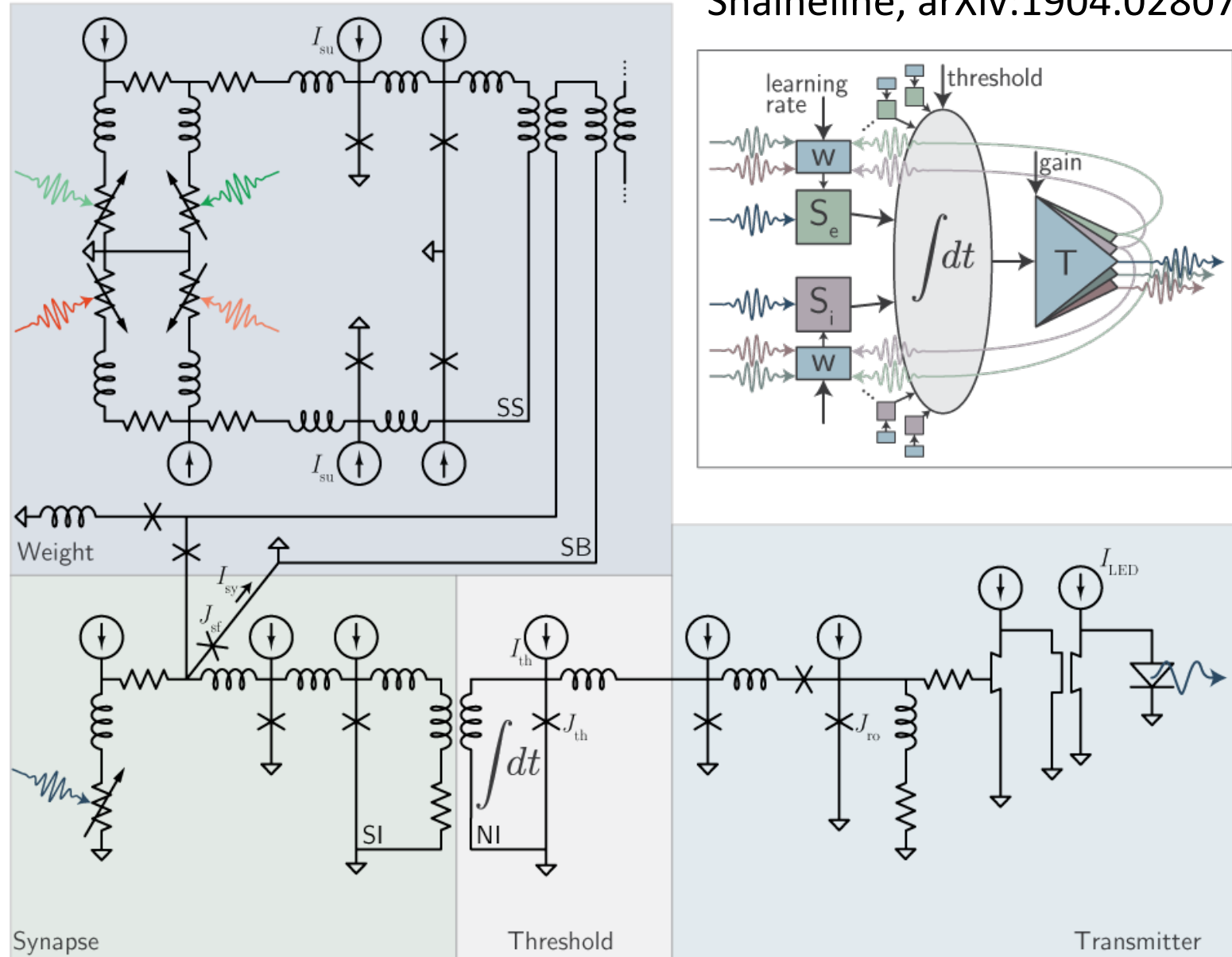


Colors for different operations

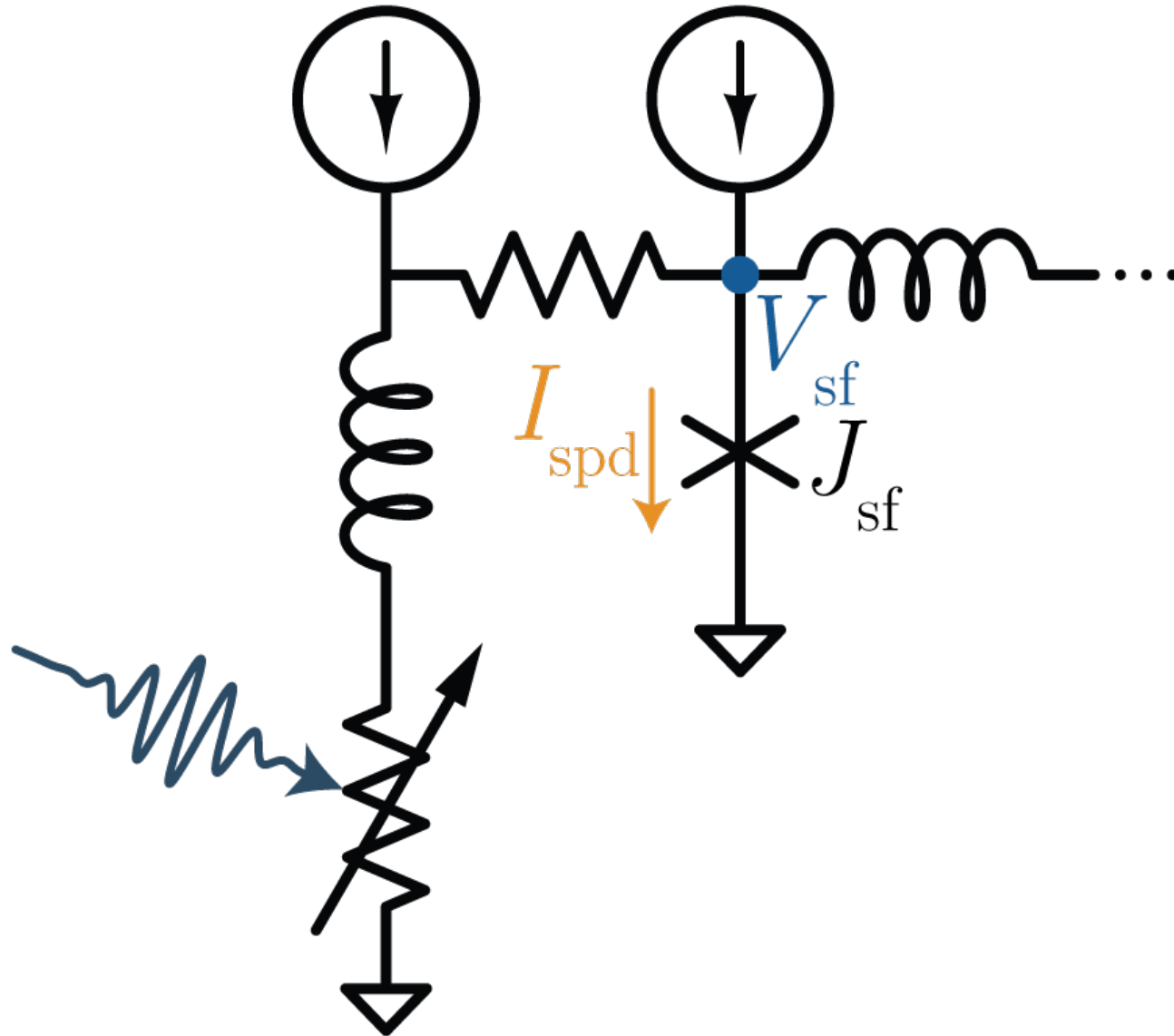


Loop neuron

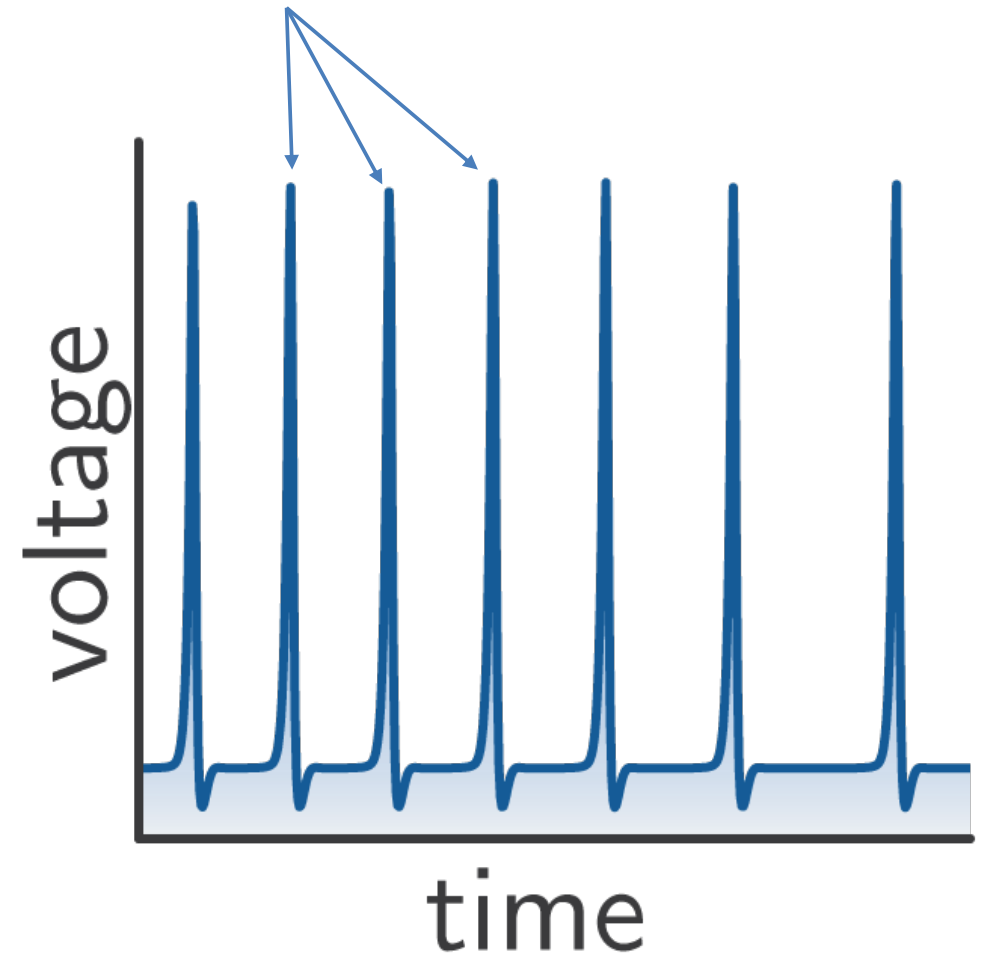
Shainline et al., arXiv:1805.01929 (2018).
 Shainline, arXiv:1904.02807 (2019)



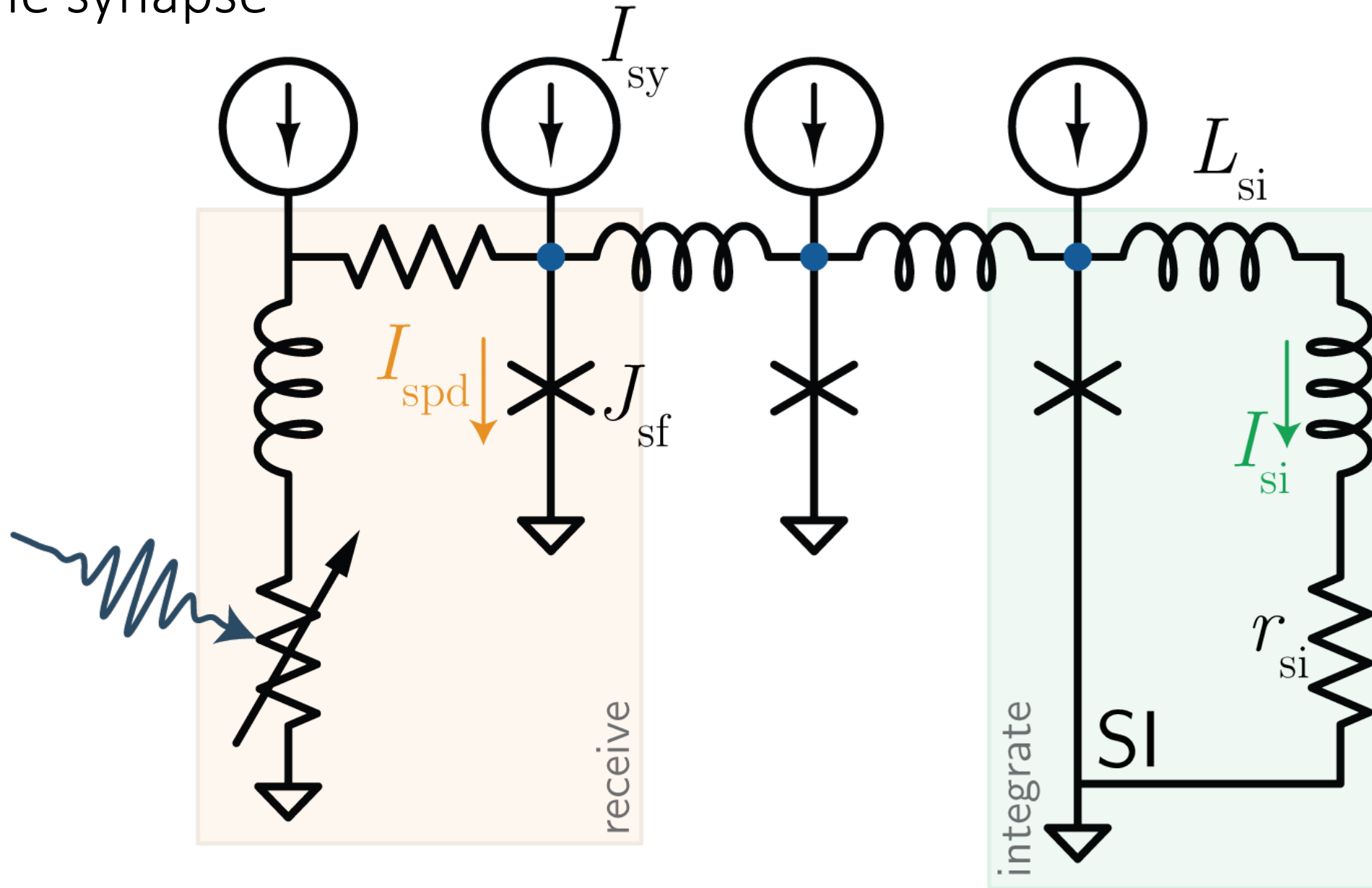
Photon-to-fluxon transducer



these are fluxons



The synapse



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

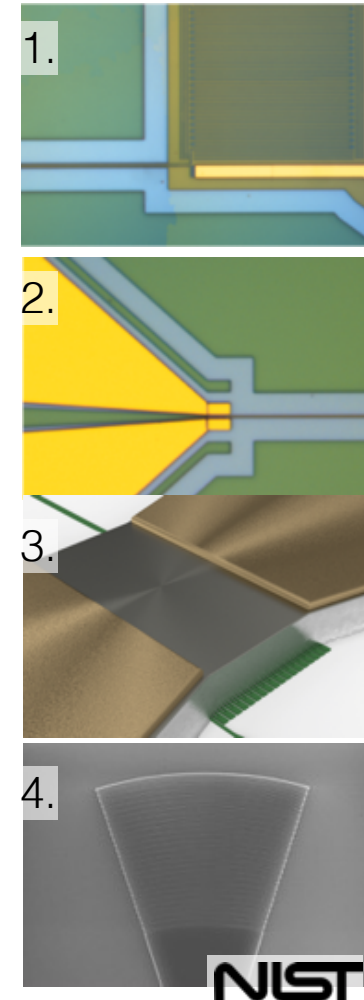
<https://arxiv.org/abs/1907.00263>

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)

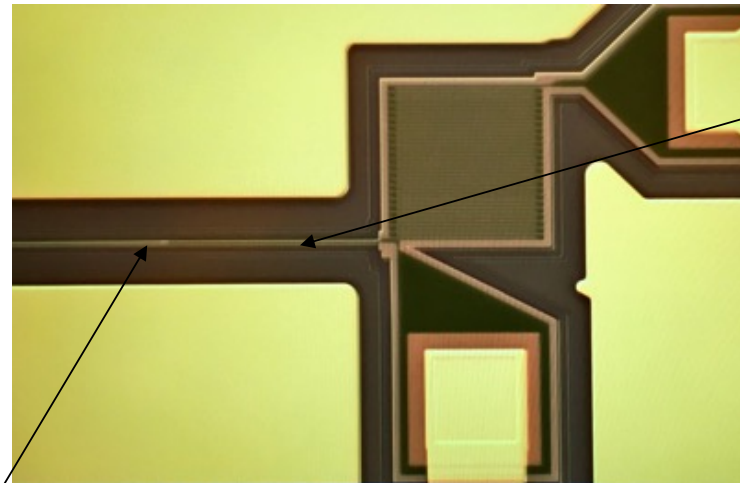
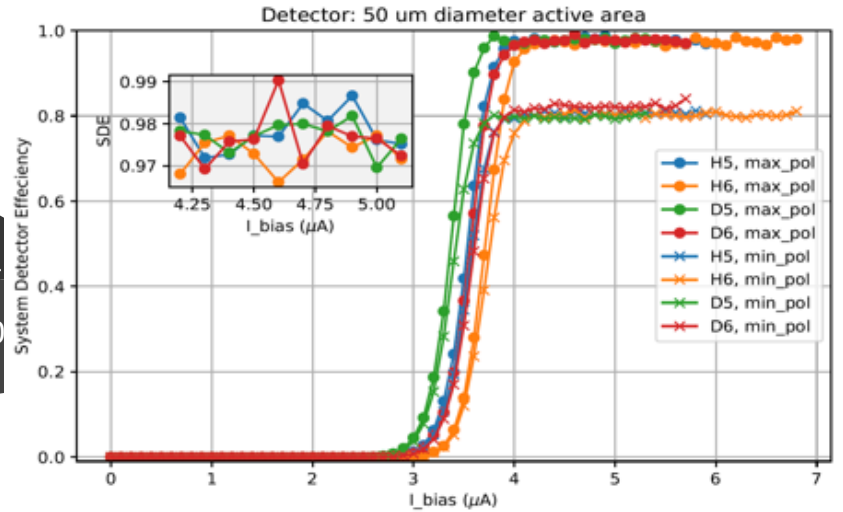
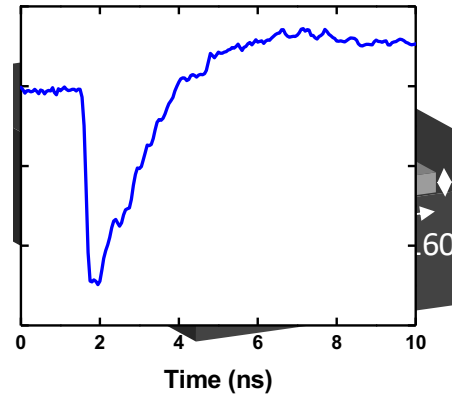
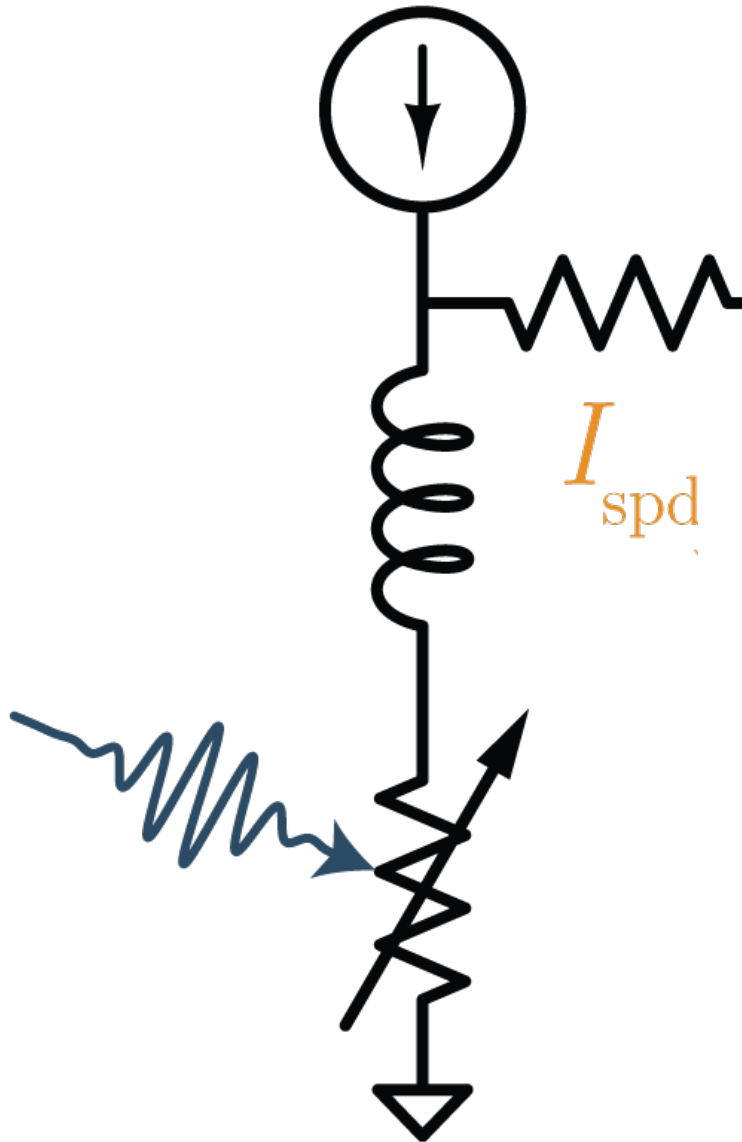


J. M. Shainline, S. M. Buckley, R. P. Mirin, and S. W. Nam, "Superconducting optoelectronic circuits for neuromorphic computing," Phys. Rev. Applied, Mar 2017.



cryogenic silicon photonics platform: recent results

Superconducting Nanowire Detector

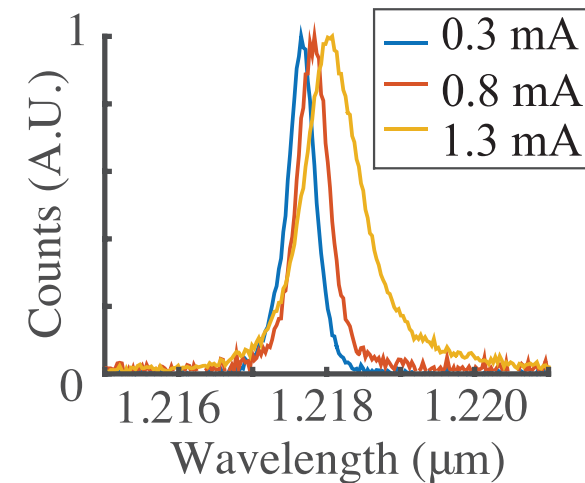
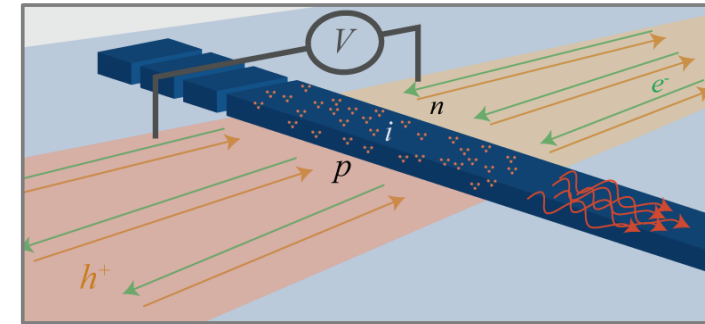


Nanowire on waveguide

Waveguide

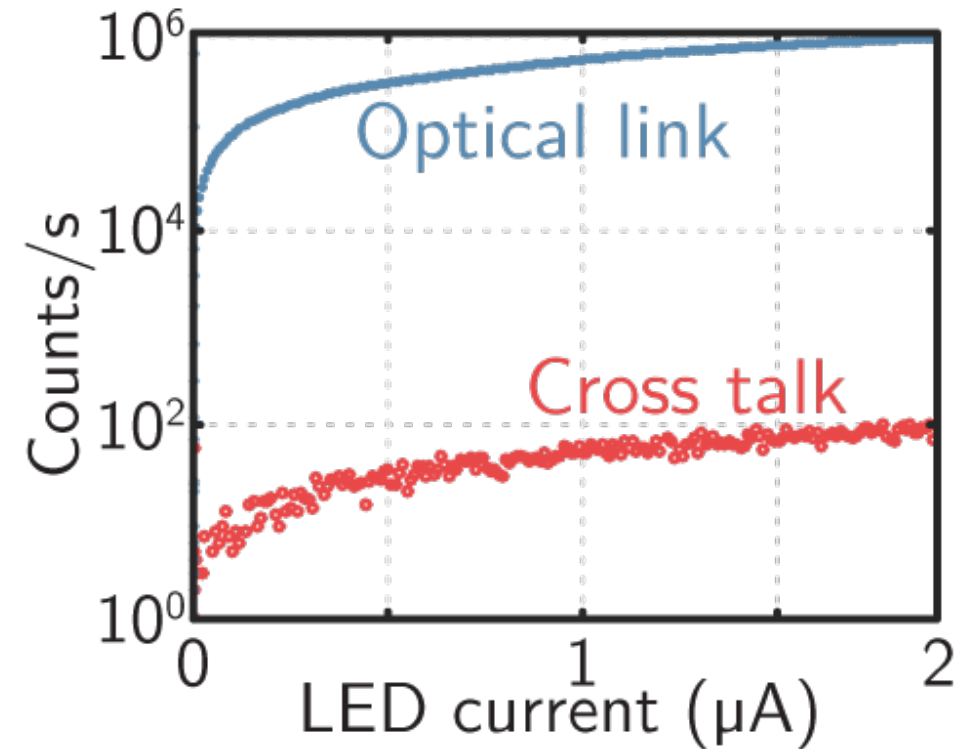
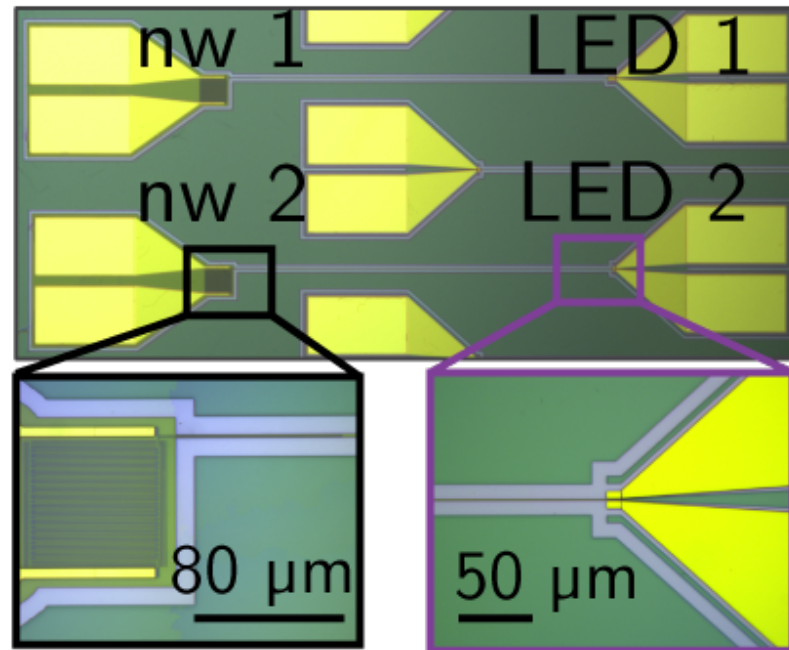
All-silicon light emitting diodes

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



S. M. Buckley et al. "All-silicon light-emitting diodes waveguide-integrated..." APL, 2017.

Co-integration: Silicon LEDs + SNSPDs

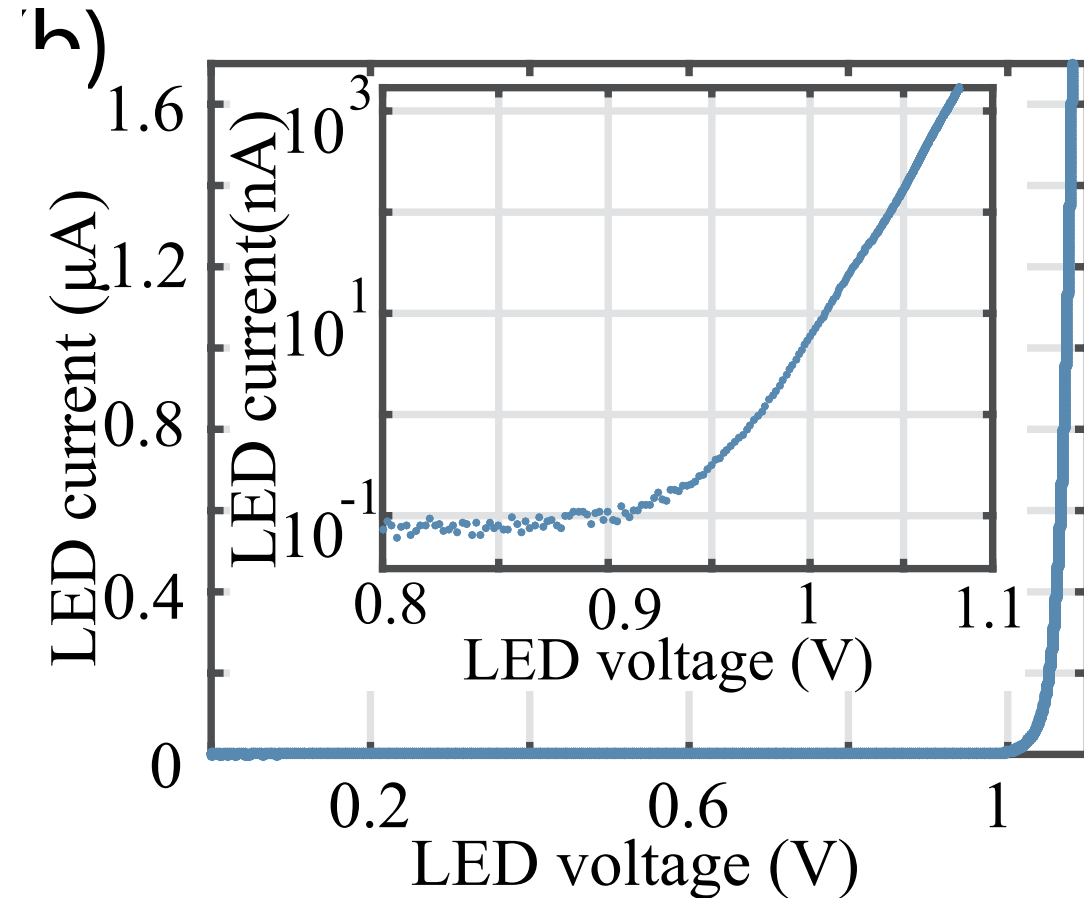


S. M. Buckley et al. "All-silicon light-emitting diodes waveguide-integrated..." APL, 2017.

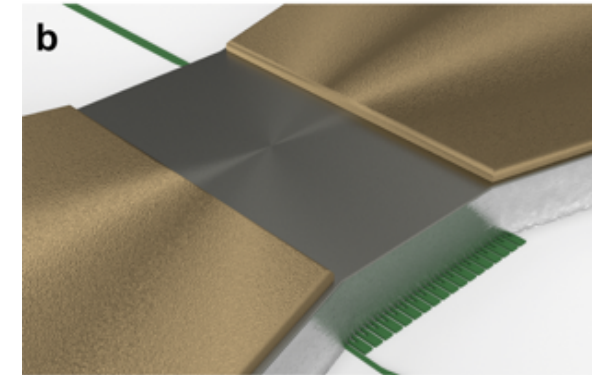
All-silicon light emitting diodes



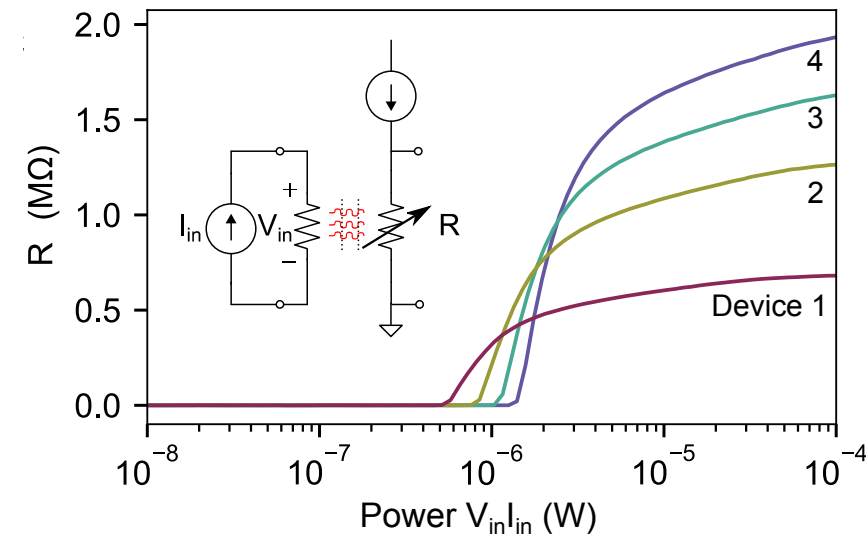
- LED turn-on voltage is ~ 1 V
- SNSPD can output ~ 1 mV



Nano-cryotron thermal switch

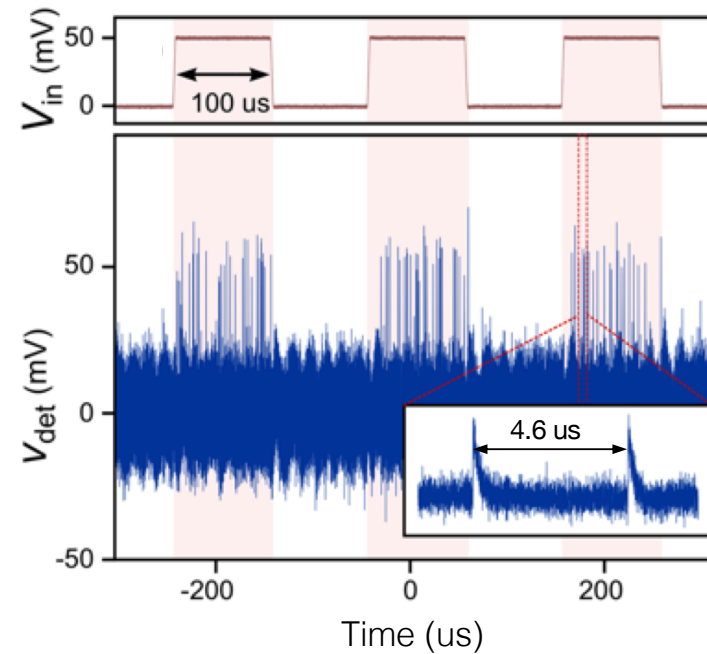
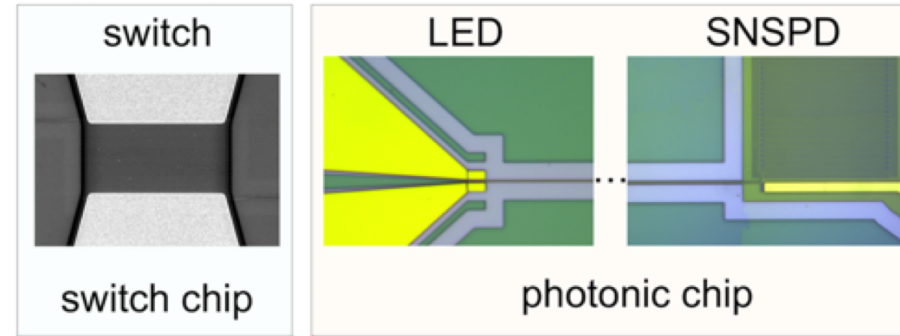


- millivolt input -> Volt output
- No Josephson Junctions needed
- Reset about 10ns



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

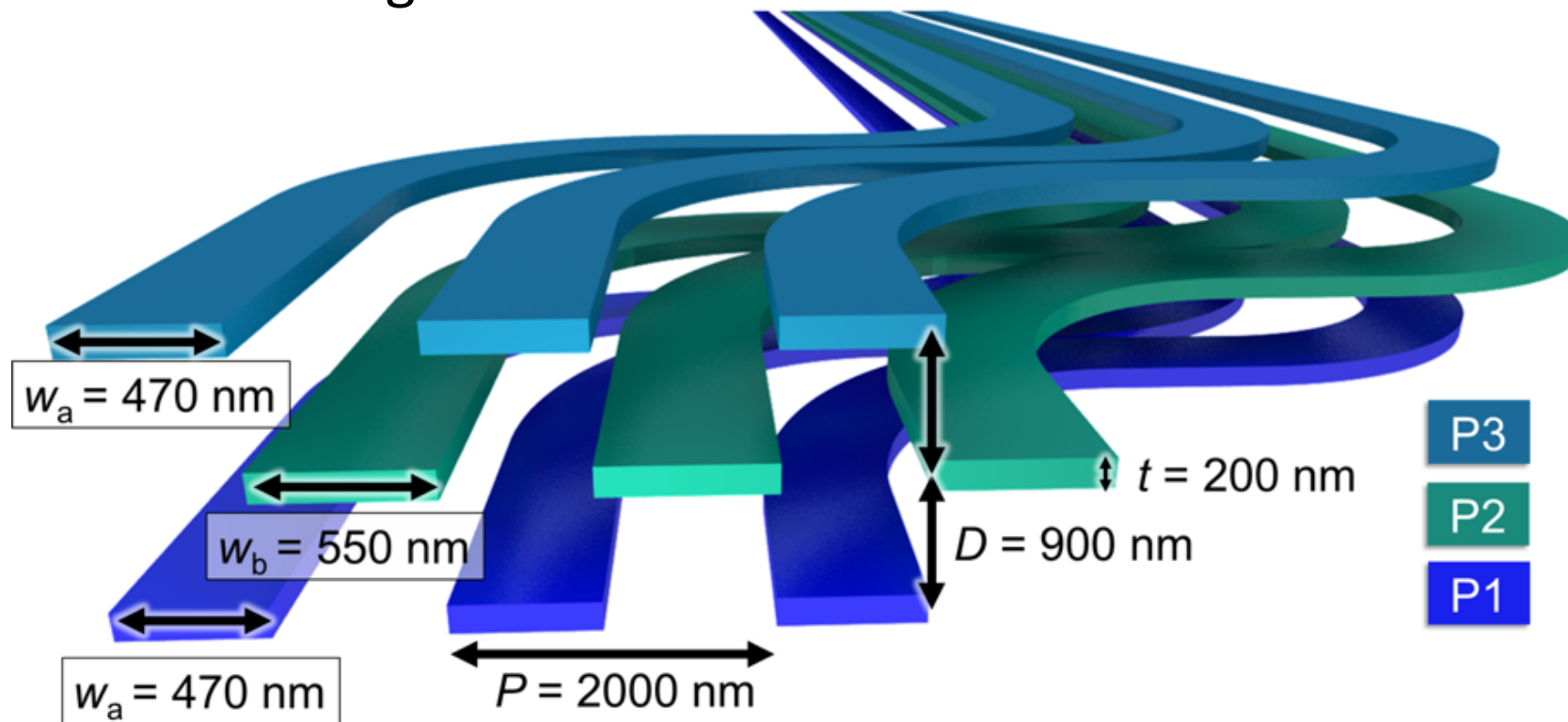
Superconductor-to-semiconductor interface



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

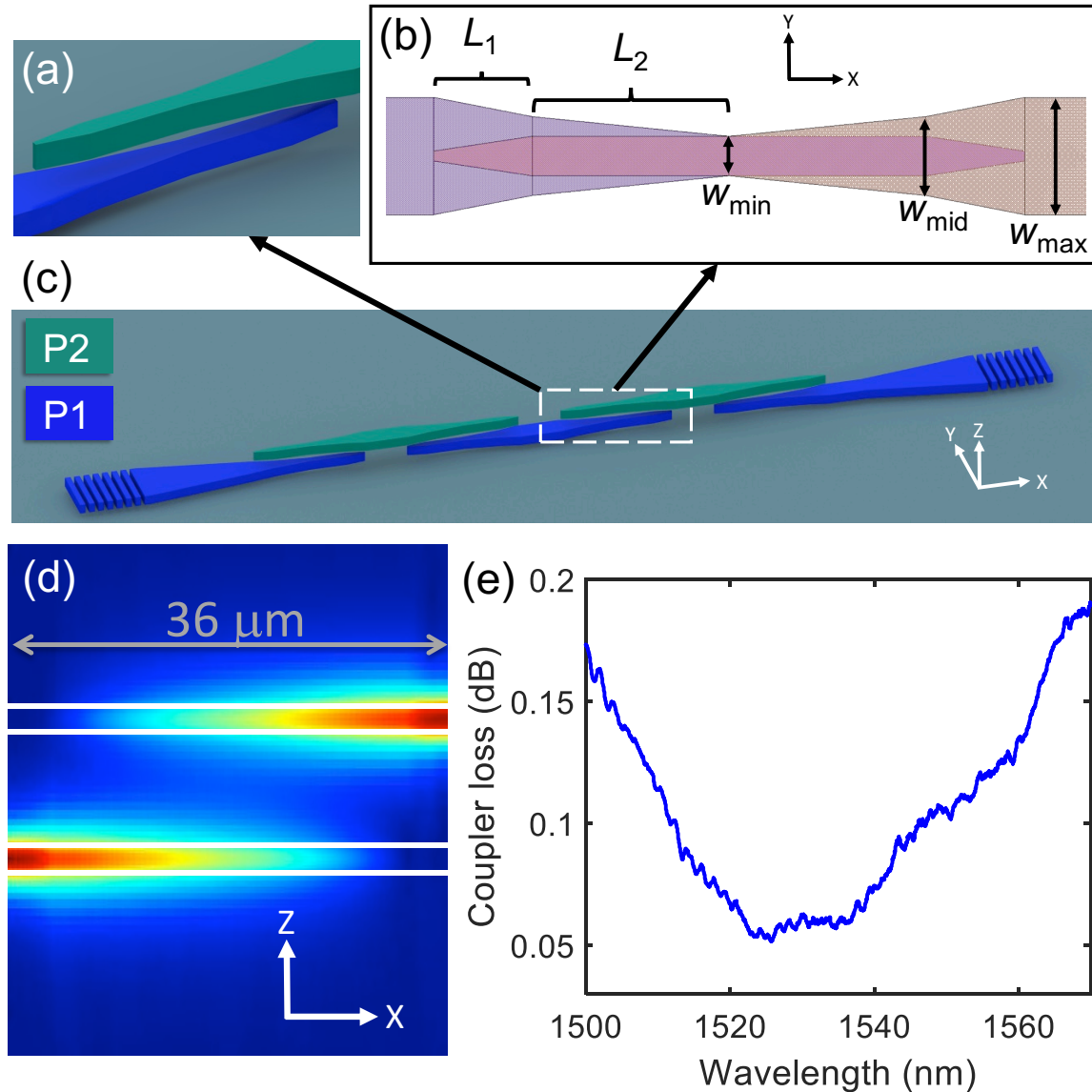
First steps toward photonic networks

Three planes of amorphous silicon waveguides



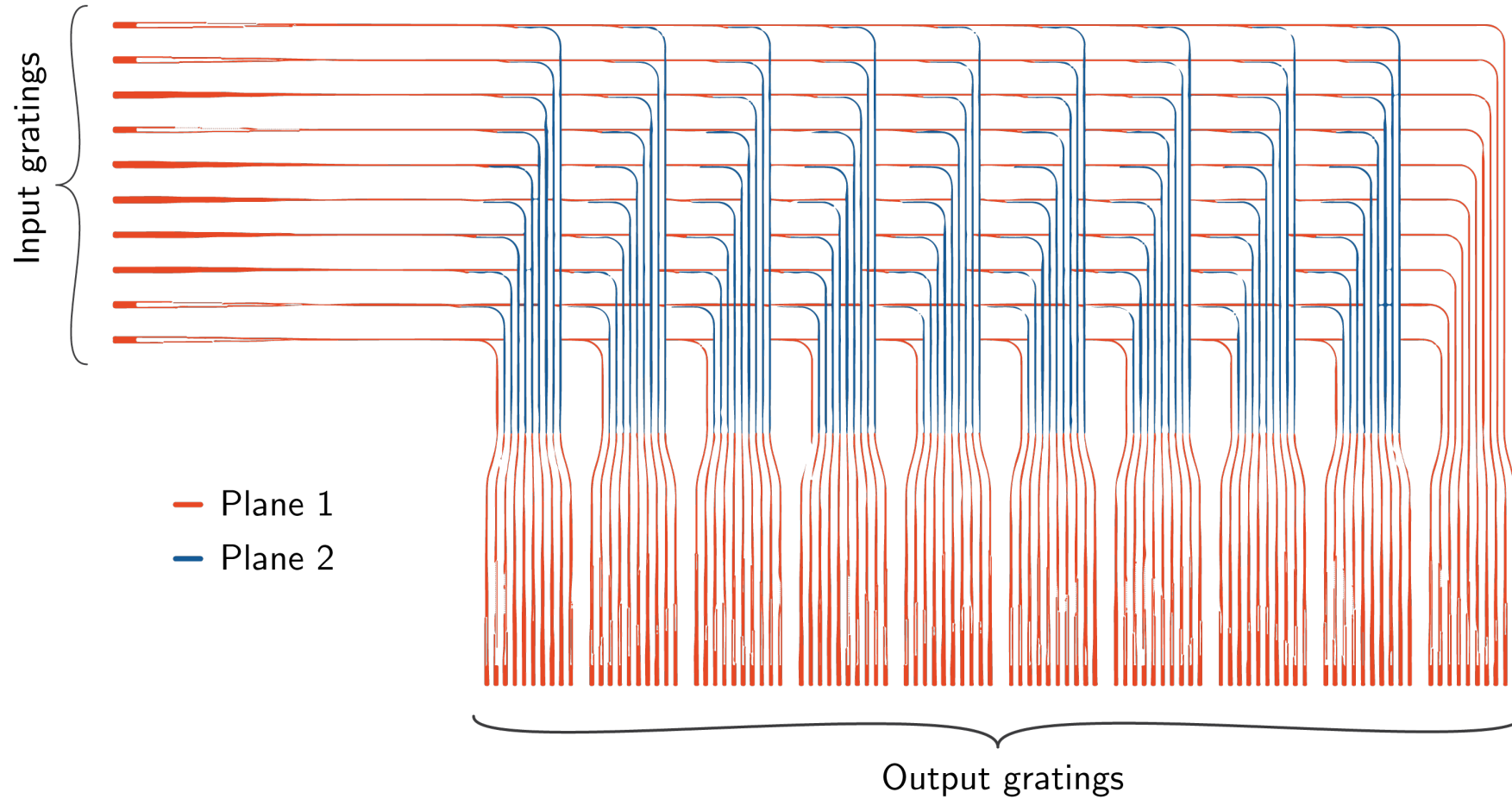
Chiles et al., APL Photonics 2, 116101 (2017)

Inter-planar couplers

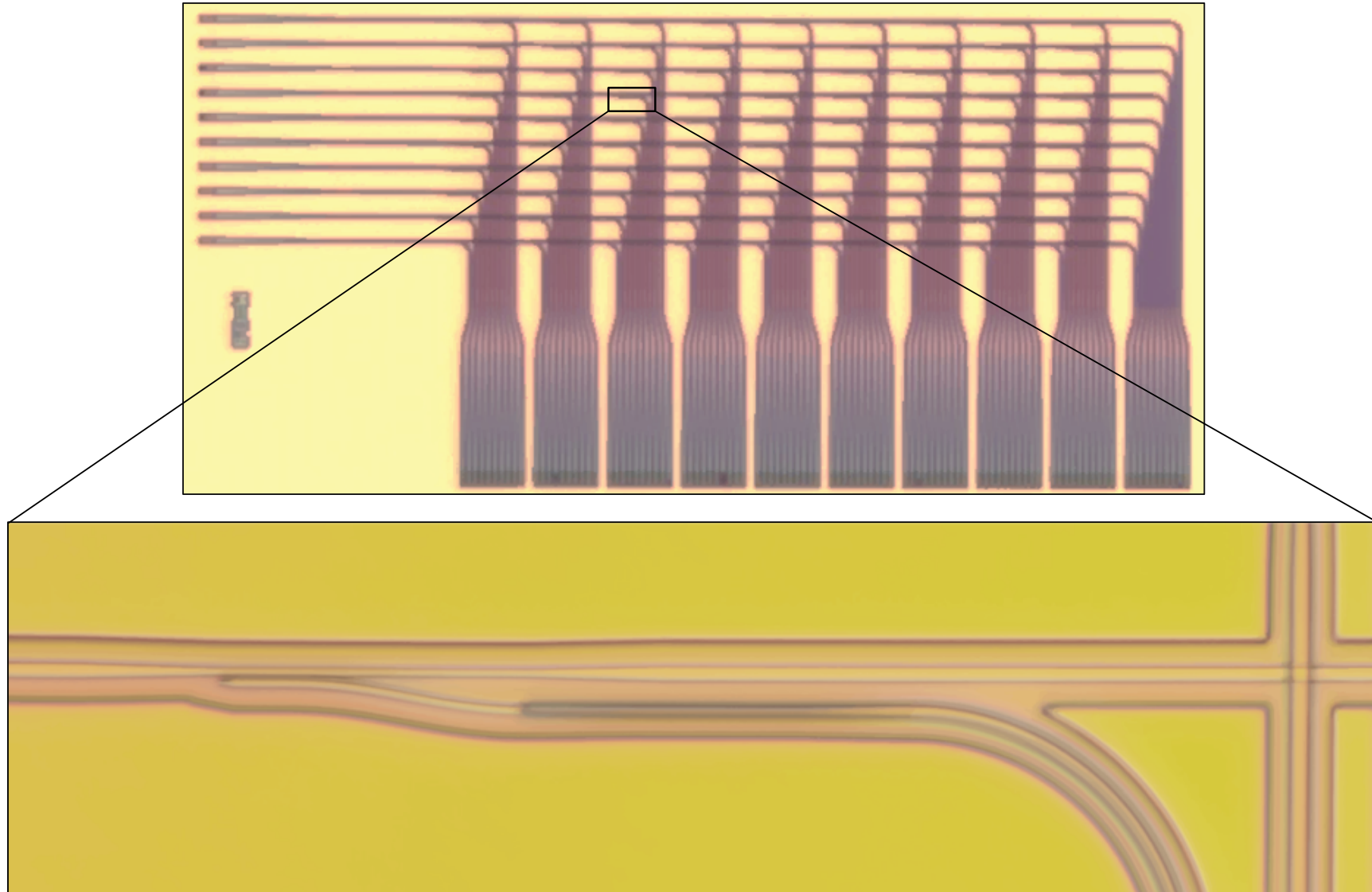


- 0.05 dB loss
- 36 μm length

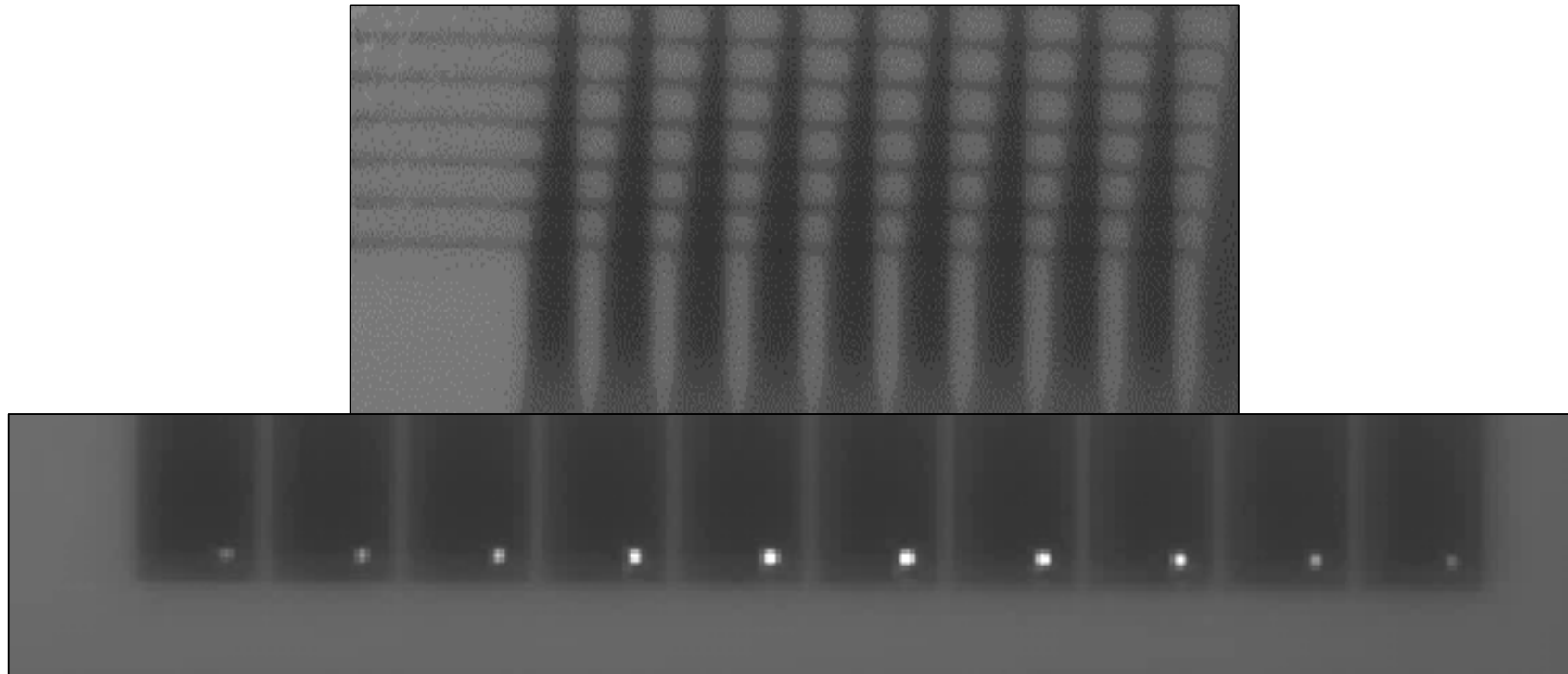
Chiles et al, APL
Photonics **2** 116101
(2017).



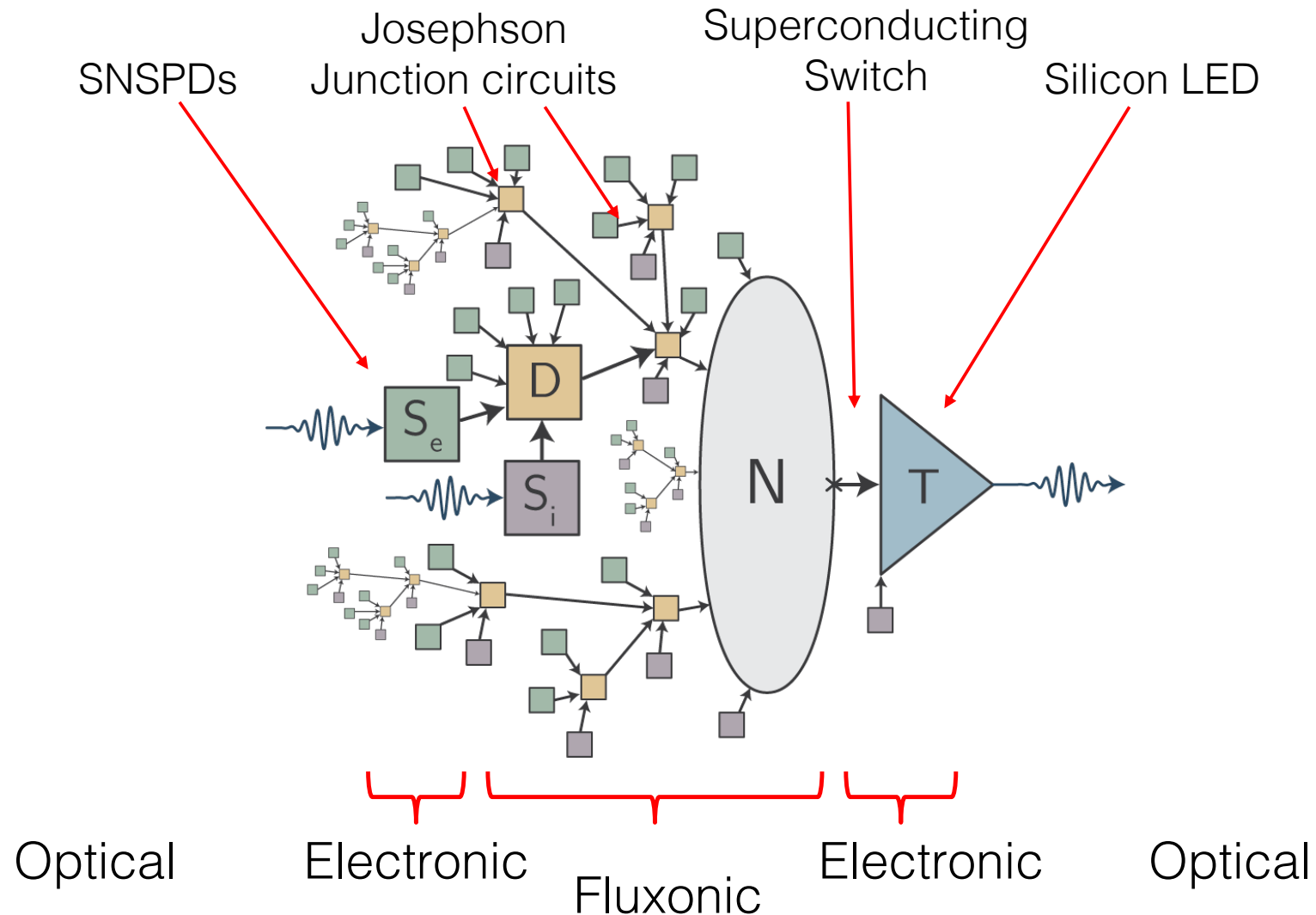
Chiles et al, APL Photonics 3 106101 (2018).



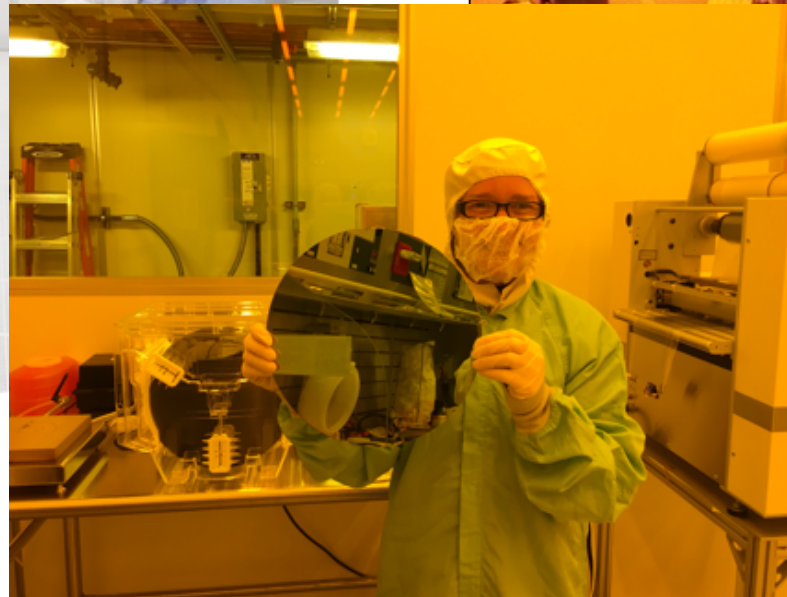
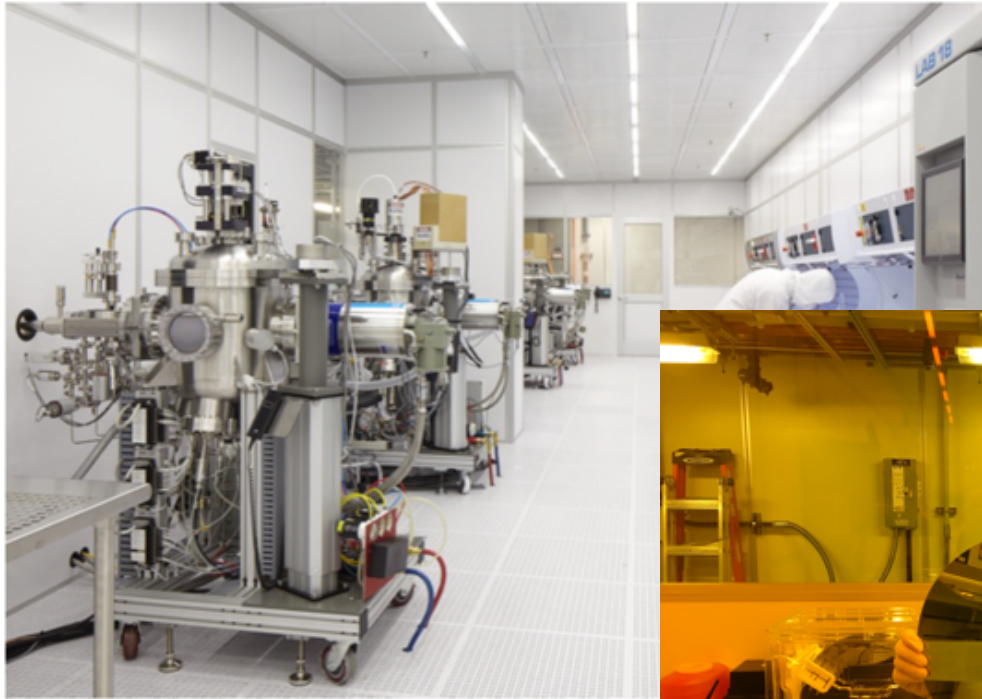
10 x 100 routing couplers



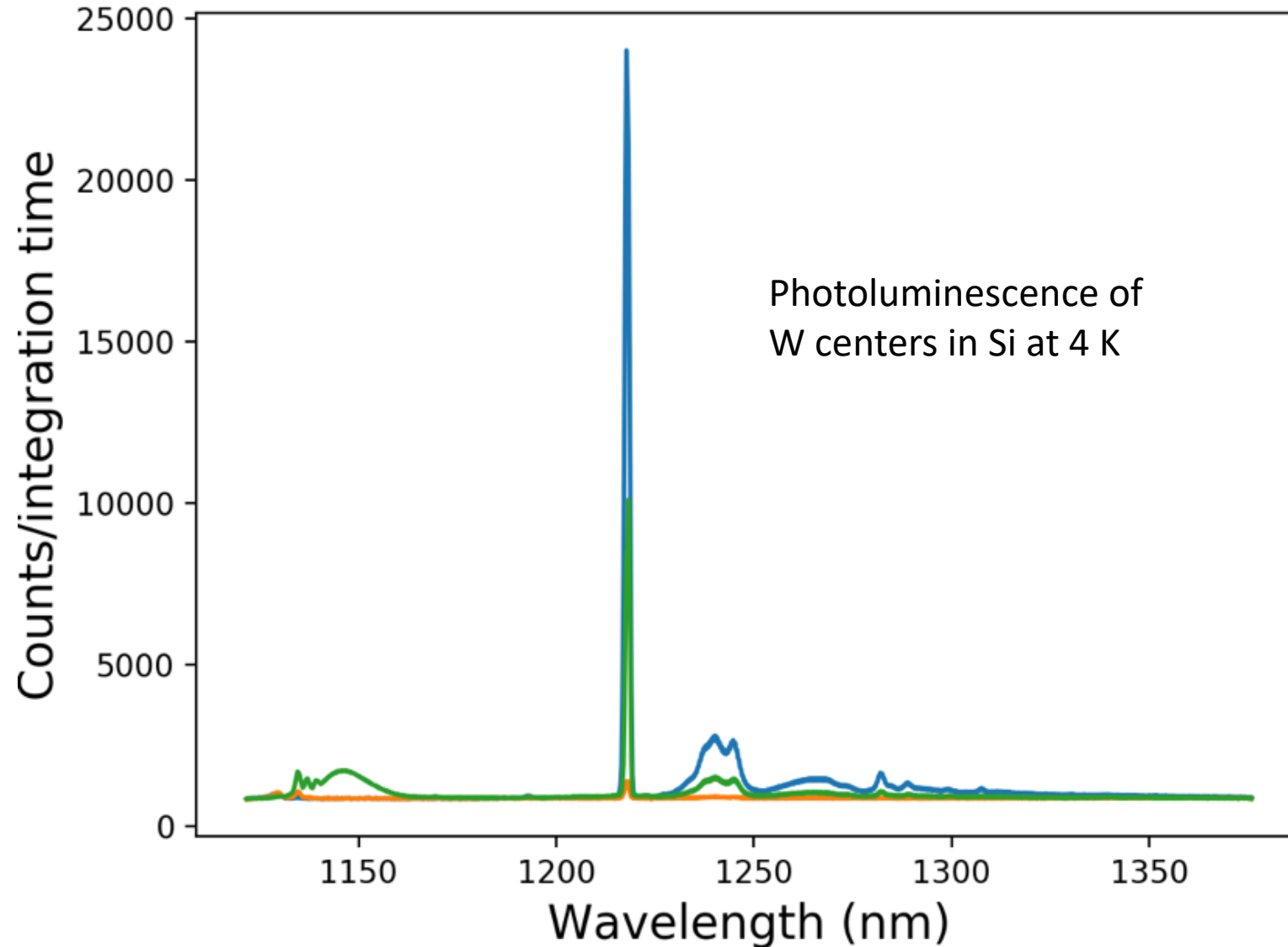
Full Superconducting Optoelectronic Neuron



Eventual transfer to 300 mm foundry

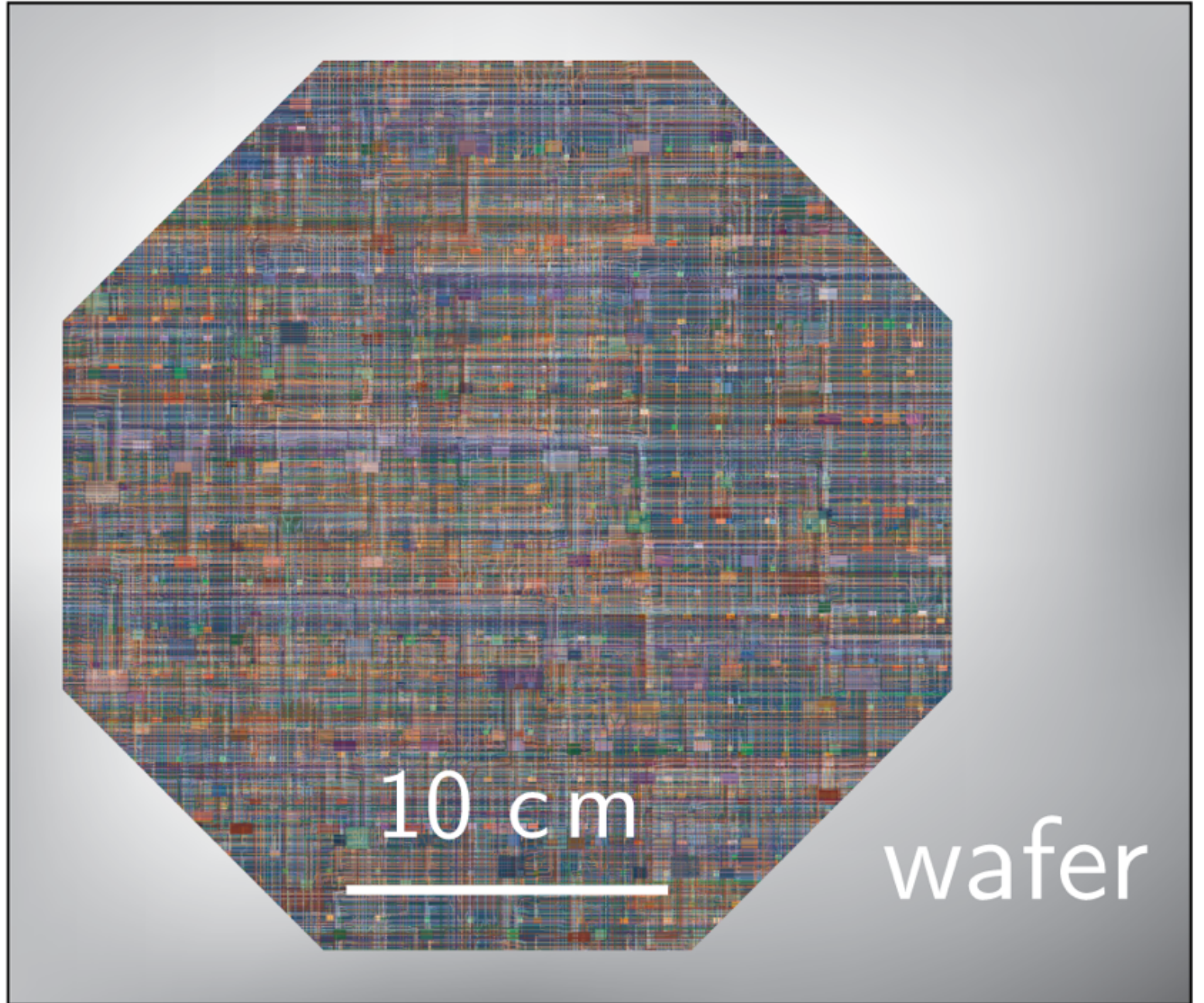


Light sources on 300-mm wafers

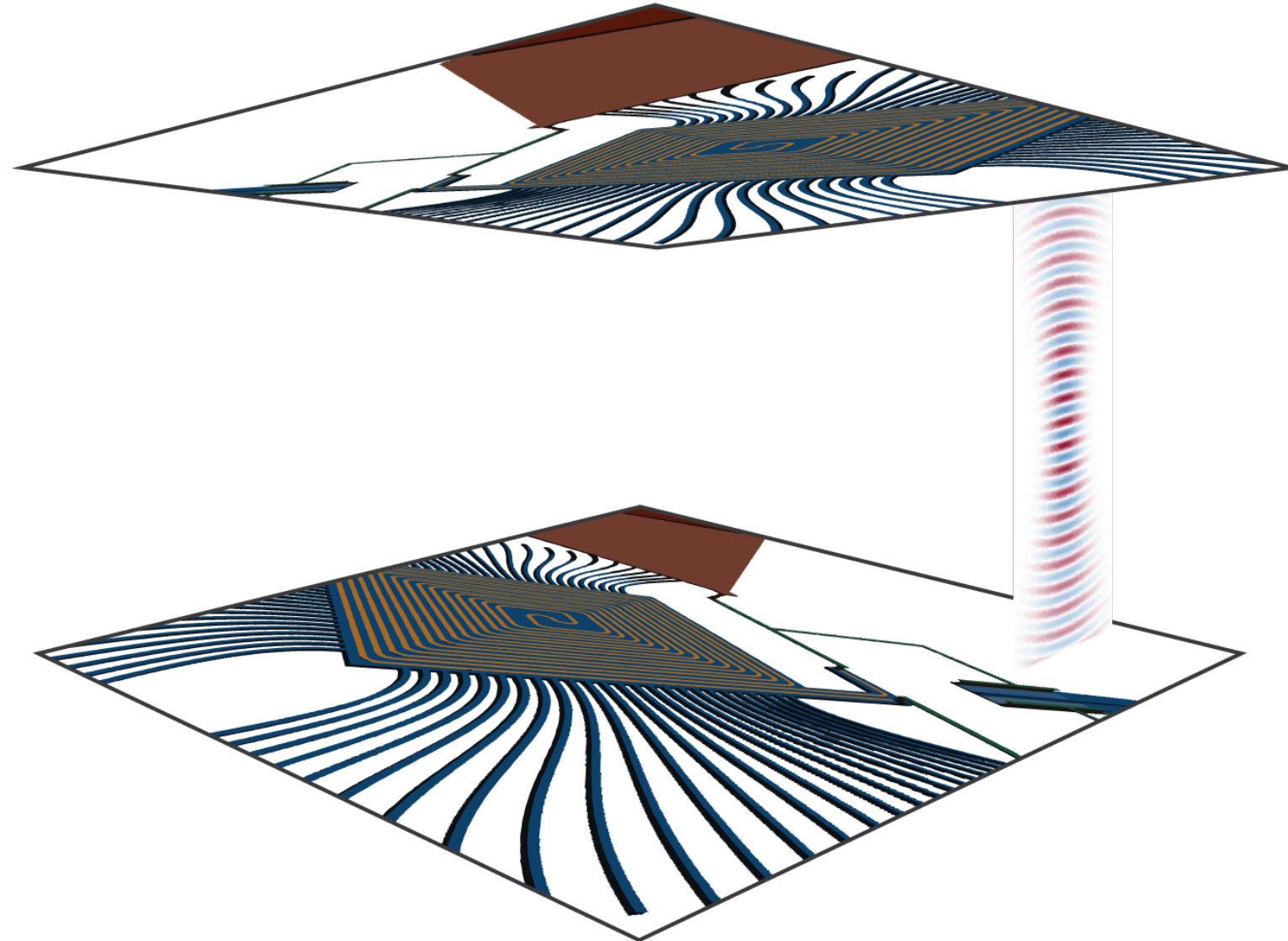


- Fabricated at SUNY Poly by Pops Papa Rao and team
- Measured at NIST by our team

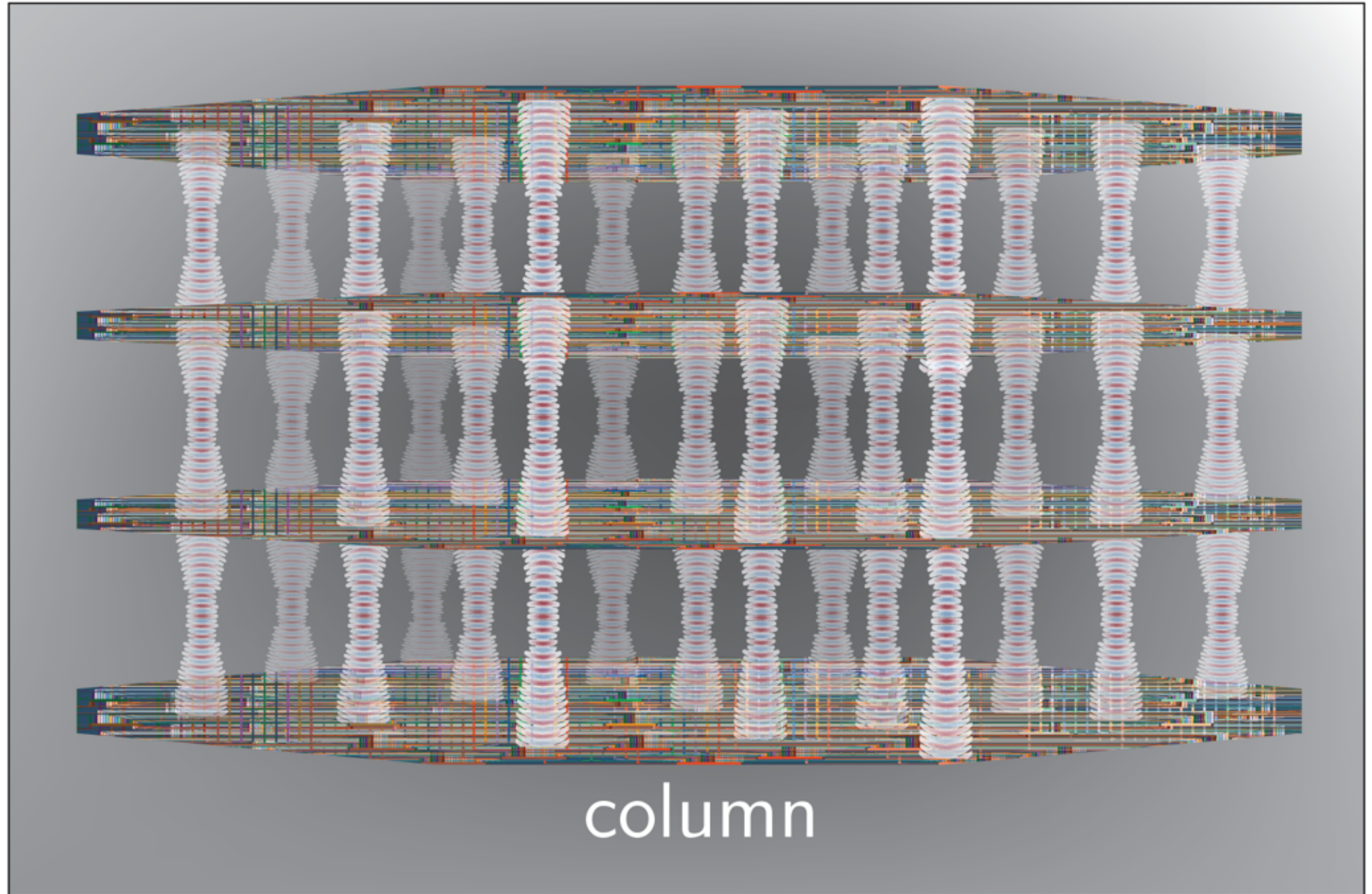
Wafer-scale
modules



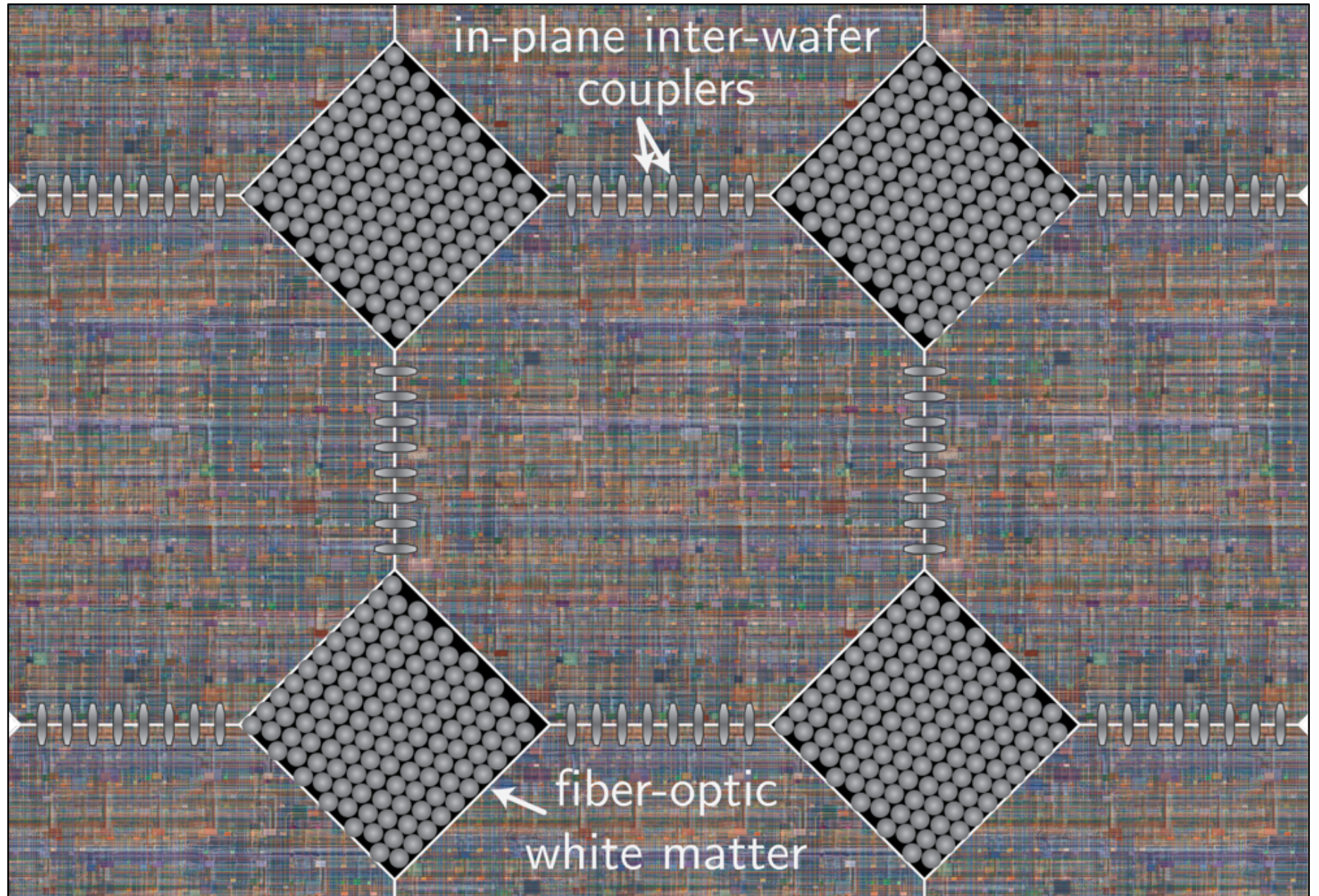
Free-space interconnects for 3D



Free-space
inter-wafer
interconnects

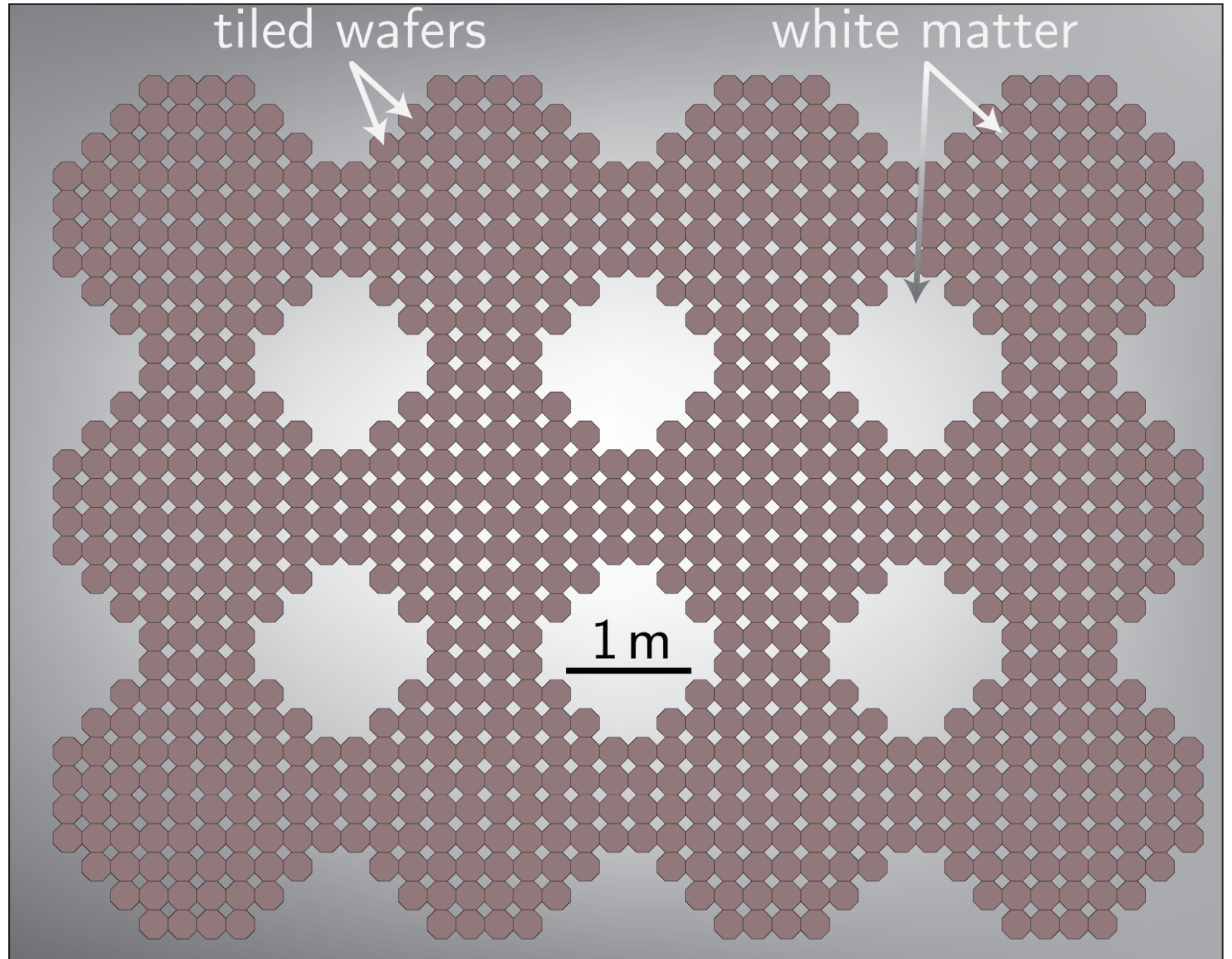


Multi-wafer
modules

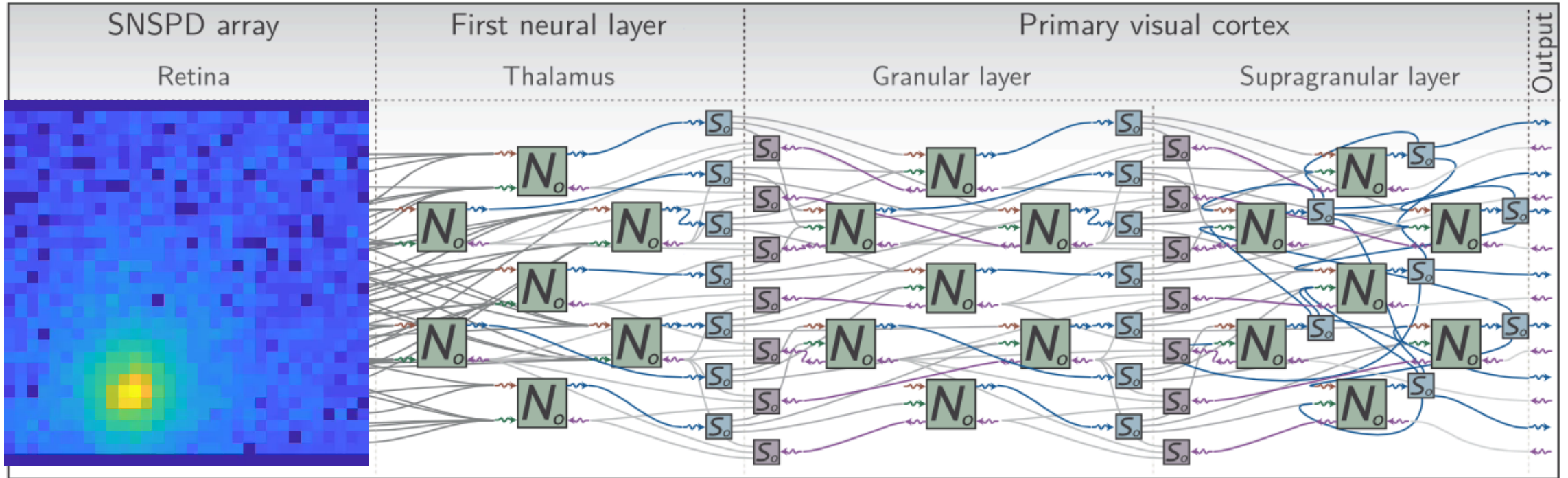


Brain-scale
systems?

> 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?

- 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
- Kevin Silverman
- Thomas Gerrits

saewoo.nam@nist.gov

MIT, JPL, Suny-Poly

Boulder Labs