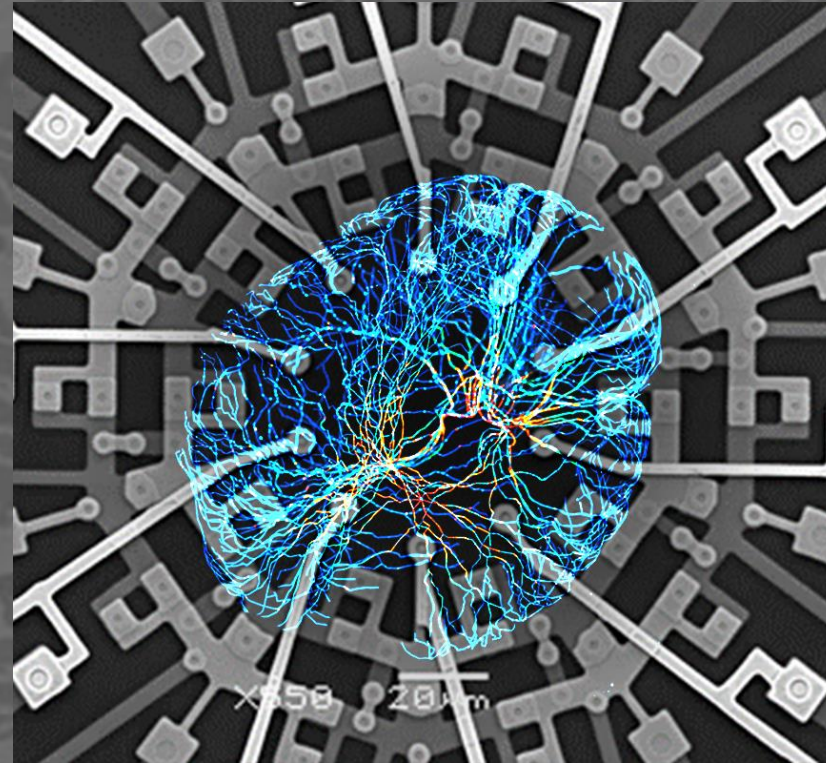


# Neuromorphic Computing Using Superconducting Electronics



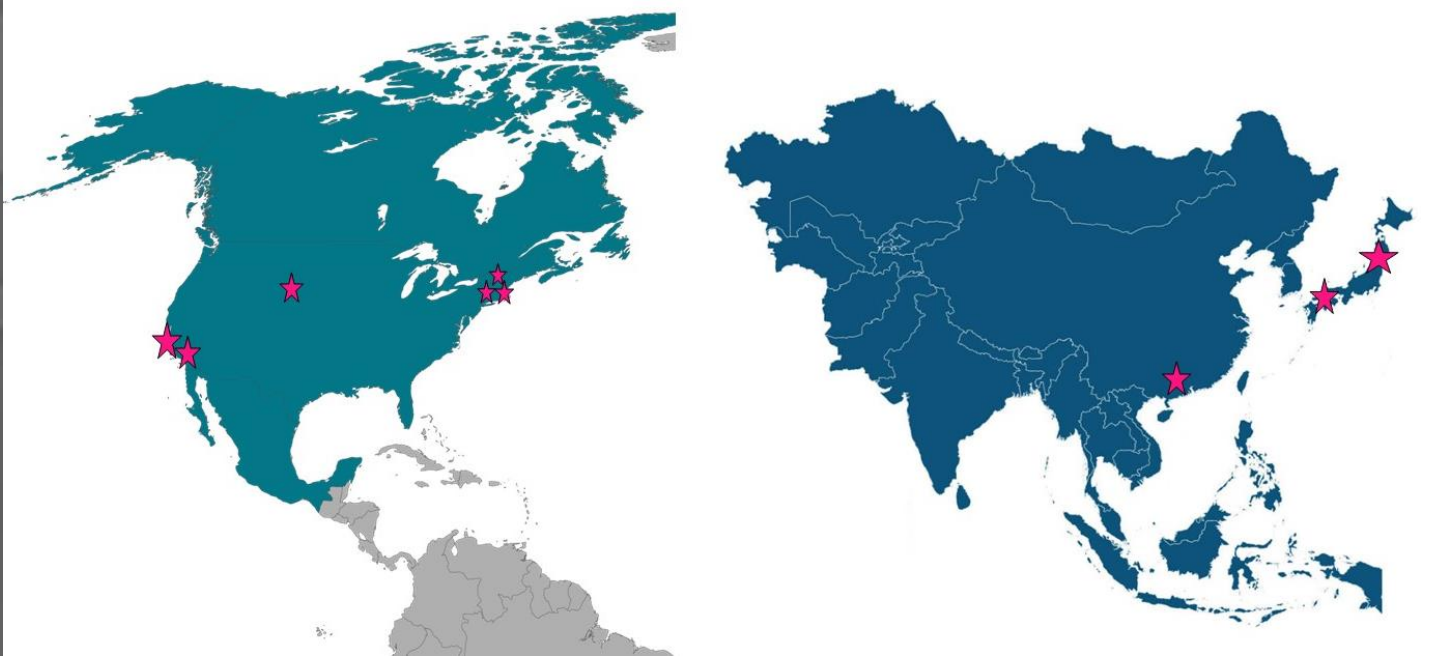
Ken Segall, Colgate University

# Outline

- I. Introduction: What is neuromorphic computing? Why are computers starting to look like the brain? What can superconductors offer?
- II. What does the brain do? Can superconductors do the same thing?
  1. Synaptic weighting → **Today's A.I.**
  2. Spiking
  3. Learning
  4. Optimization
  5. Connecting and networking
- III. Projections, applications, outlook - can we make a superconducting brain?

**Takeaway: Time to get in the game, and go big!**

# Superconducting Neuromorphic Community



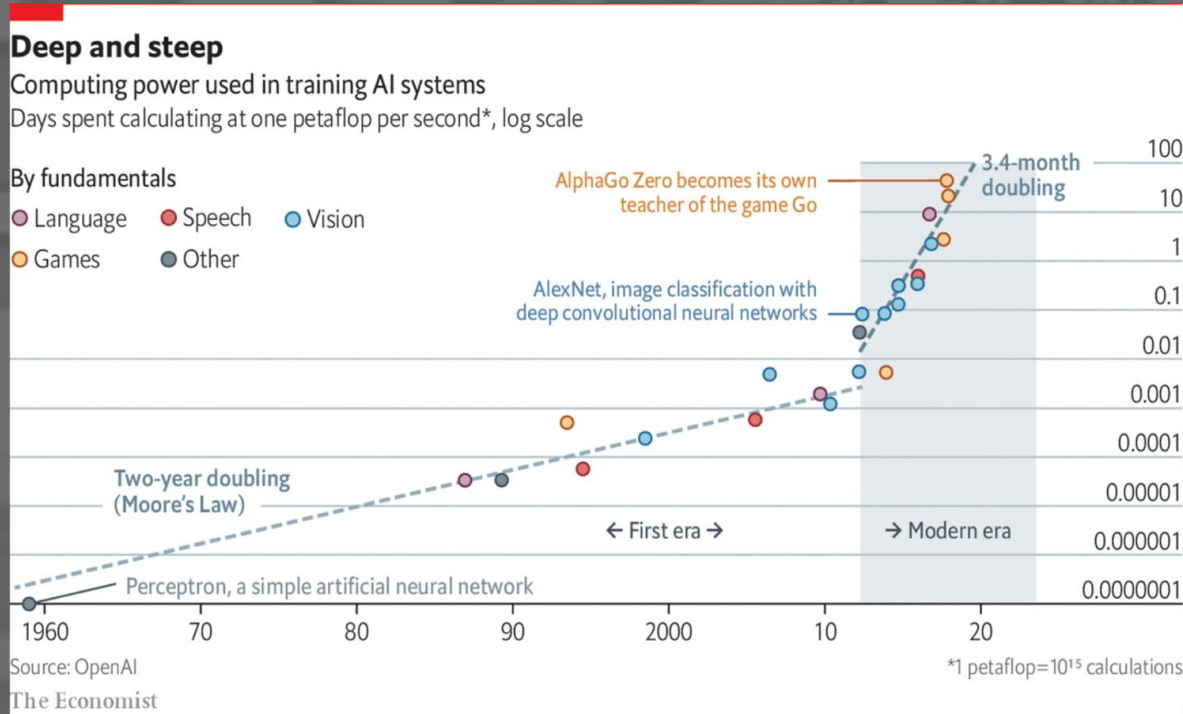
- Colgate University, Hamilton, NY
- MIT and MIT LL, Boston, MA
- NIST, Boulder, CO
- UCSD, San Diego, CA
- USC, Los Angeles, CA
- SUNY Stony Brook, Stony Brook NY
- Yokohama University, Yokohama, Japan
- Tohoku University, Sendai, Japan
- University of Chinese Academy of Sciences, Beijing, China

Others: Moscow State University, Auburn University, Raytheon/BBN, Ankara University, Lawrence Berkley Lab, IFN-CNR Rome

- I. Introduction ←
- II. Brain activities:
  - 1. Synaptic Weighting
  - 2. Spiking
  - 3. Learning
  - 4. Optimization
  - 5. Networking
- III. Looking forward

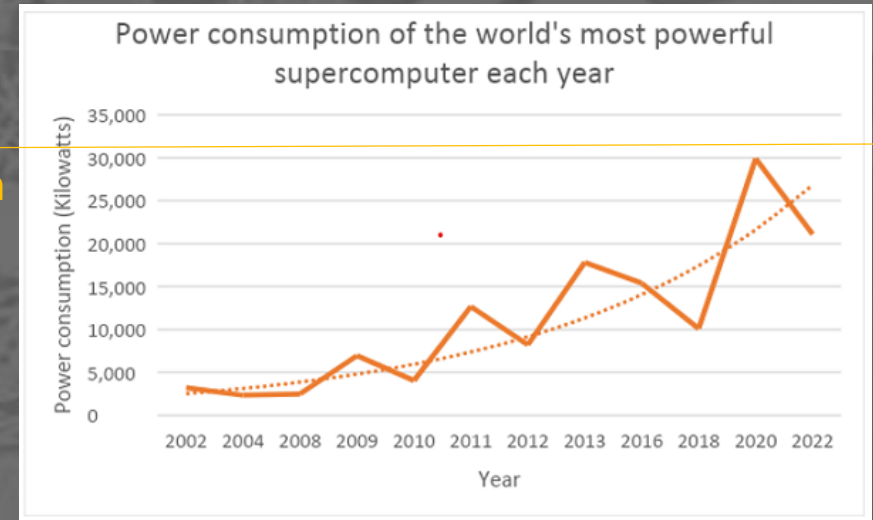
# INTRODUCTION

# Training A.I. : A lot of time and energy!



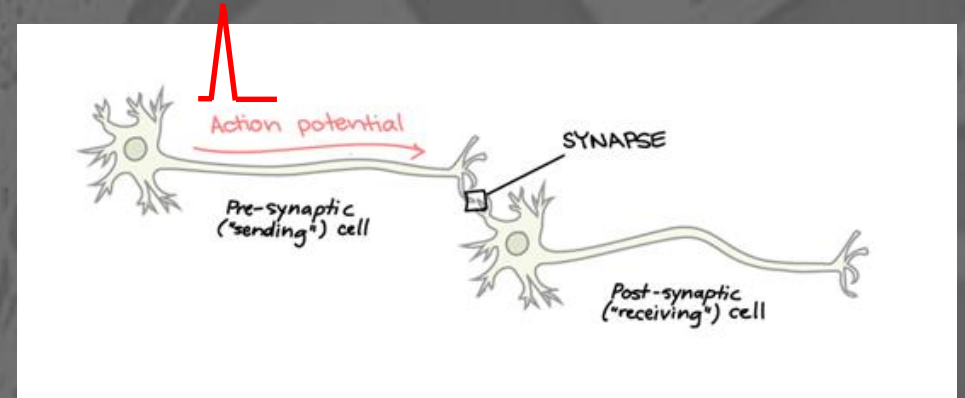
Days of training (at 10<sup>15</sup> FLOPs)

Electrical consumption of Utica, NY



Source: [insidehpc.com](https://insidehpc.com)

# Enter: The brain!



- 86 billion neurons
  - 100 trillion synapses
  - 20 W of power
- The low power consumption of the brain makes it a good candidate for a computer
  - Terminology: Neurons (somas), synapses, axons and dendrites

# Neuromorphic Computing

- Focuses on building hardware whose operating principles are based on the human brain
- Mostly utilizing semiconductor components (for now..)
- A key goal is energy efficiency, but it also aims to enable new computational capabilities
- Working platforms exist
- Applications: Replacing deep learning, Event-driven image processing, robotics, optimization, brain simulation, and others to be determined!

	True North	Loihi	SpiNNaker
# Neurons	$1.0 \times 10^6$	$4 \times 10^5$	$1.8 \times 10^4$
Energy/Syn. Op.	26 pJ	78 pJ	11.3 nJ
SOPS/watt	$3.8 \times 10^{10}$	$1.3 \times 10^{10}$	$9 \times 10^7$

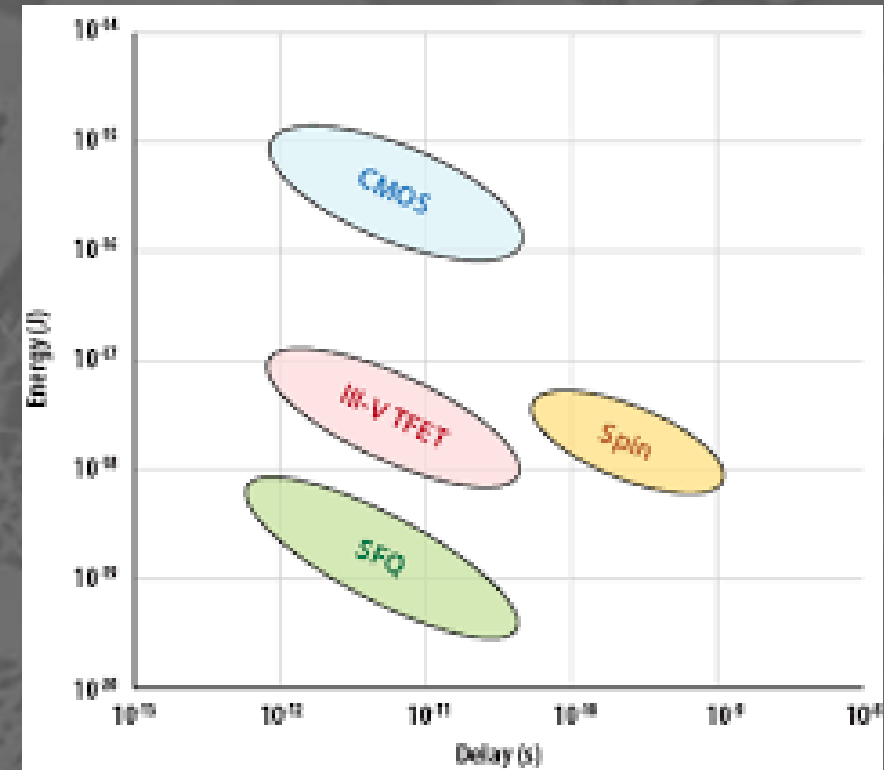
Frenkel et al. arxiv 2106.01288 (2023)

Related work: Accelerating AI training with SCE (see work by IMEC), Processing In Memory approach (see Zhu et al. Super. Sci. & Tech. 37, 095022, 2024)

# Why Superconductors?

- Energy efficiency (even with the cooling...)
- Speed (more spikes in a shorter time)
- Biological realism
- Better scaling properties (if we go big!)

Lower  
Power

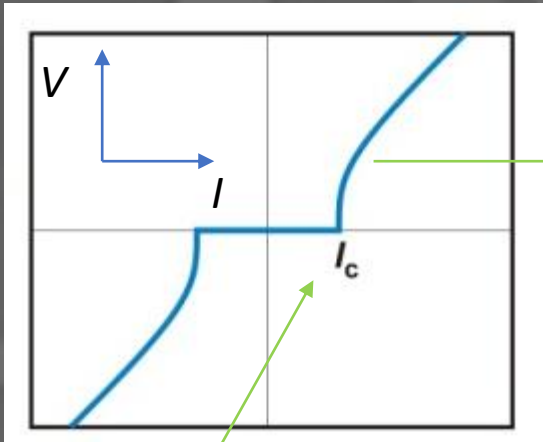
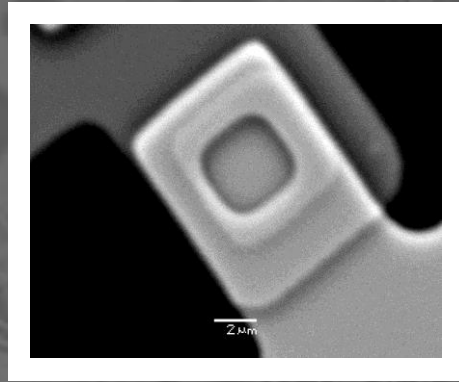
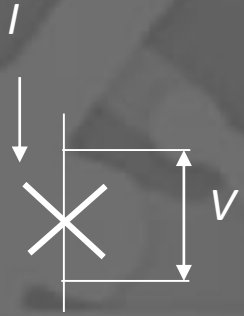


Underappreciated!

\*MIT Lincoln Laboratory, "Forecasting superconductive electronics technology," The Next Wave, vol.20, no.3, 2014

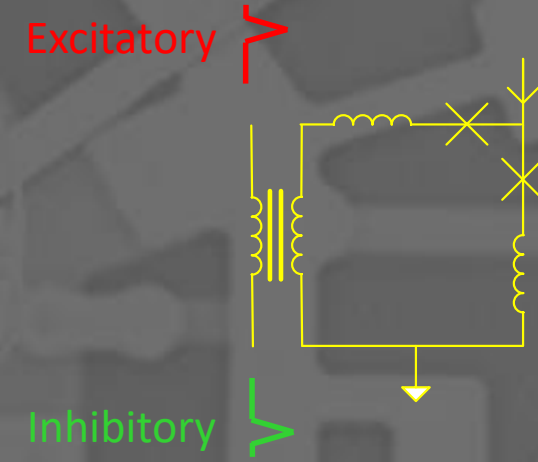
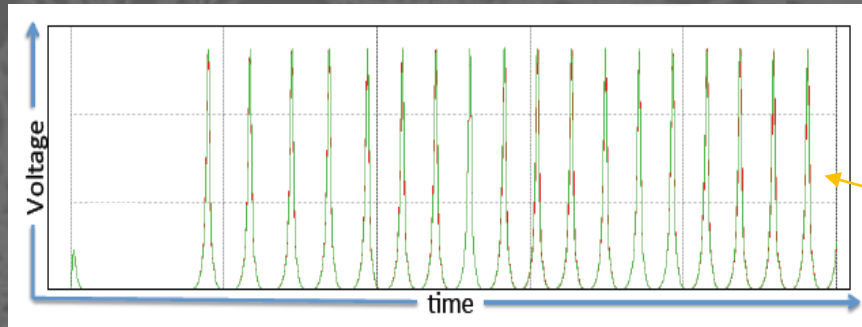


# Superconducting Electronics for Neuroscientists



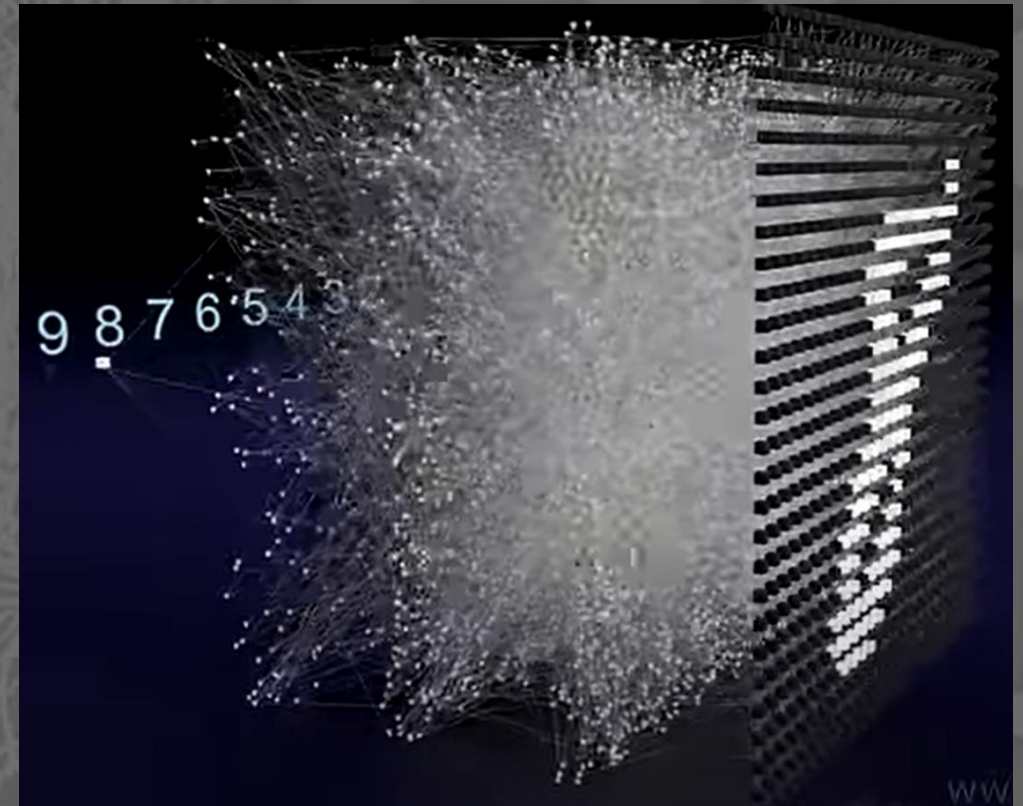
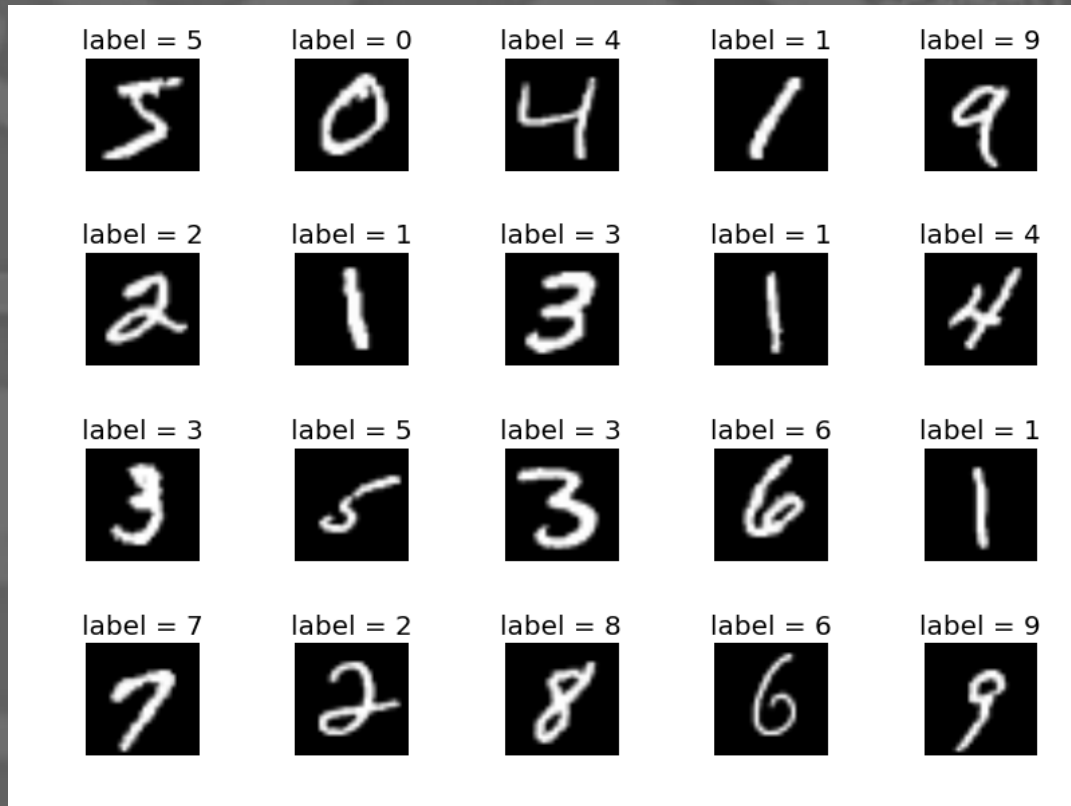
(with inductive shunt)

Single-flux quantum (SFQ) pulses



- Spiking and thresholding – similar to neurons, except very fast!
- Coupling through mutual inductance
- Circuit simulations (WR-SPICE) are very accurate

# Benchmarking Neuromorphic Systems

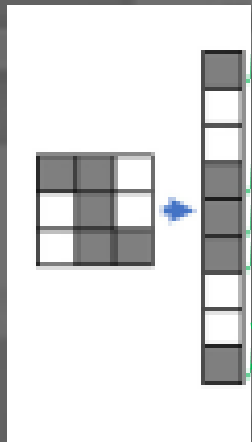


- MNIST data set
- Deep learning systems (software!) regularly attain  $\sim 95\%$  with  $\sim 10^{-2}$  J/inference

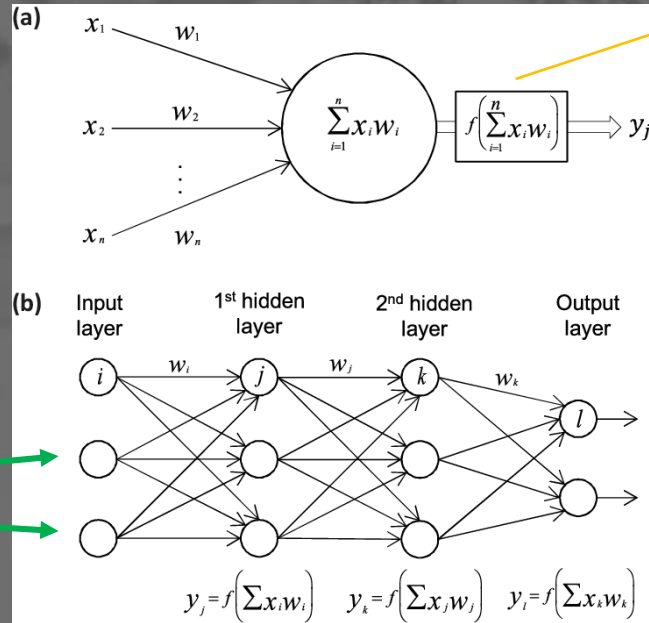
- I. Introduction
- II. Brain activities:
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## THE BRAIN DOES...SYNAPTIC WEIGHTING

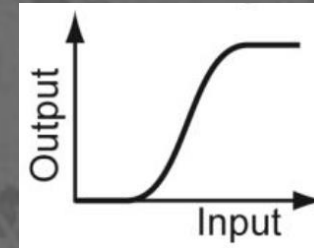
# Neural networks and training



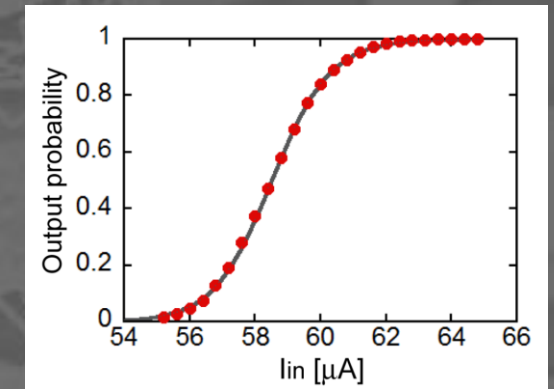
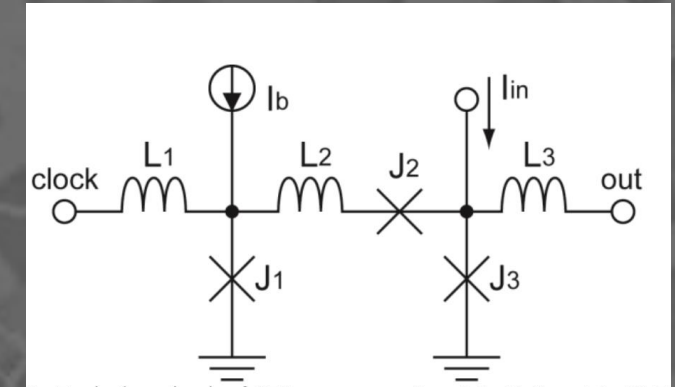
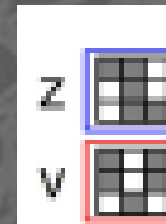
0  
1



Researchgate.net



Sigmoid function

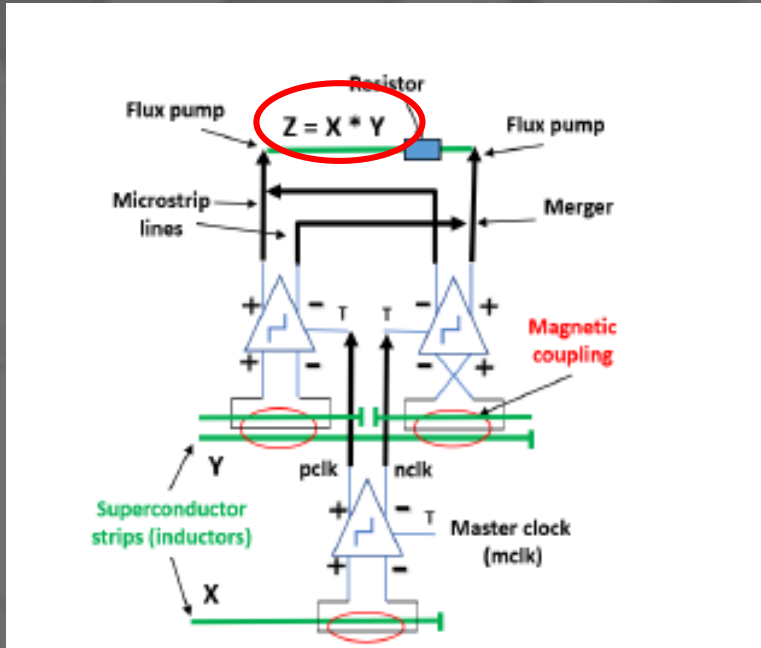


Yamanashi and Yoshikawa *IEEE TAS* **23**  
1701004 (2013)

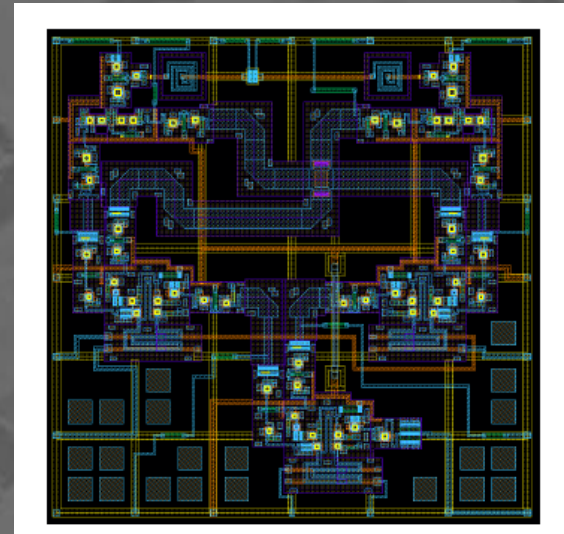
- Large neural networks (“Deep Learning”) can learn to recognize complex patterns
- Training utilizes a backpropagation algorithm with requires a differentiable function

Experiment

# Just Multiply and Add!



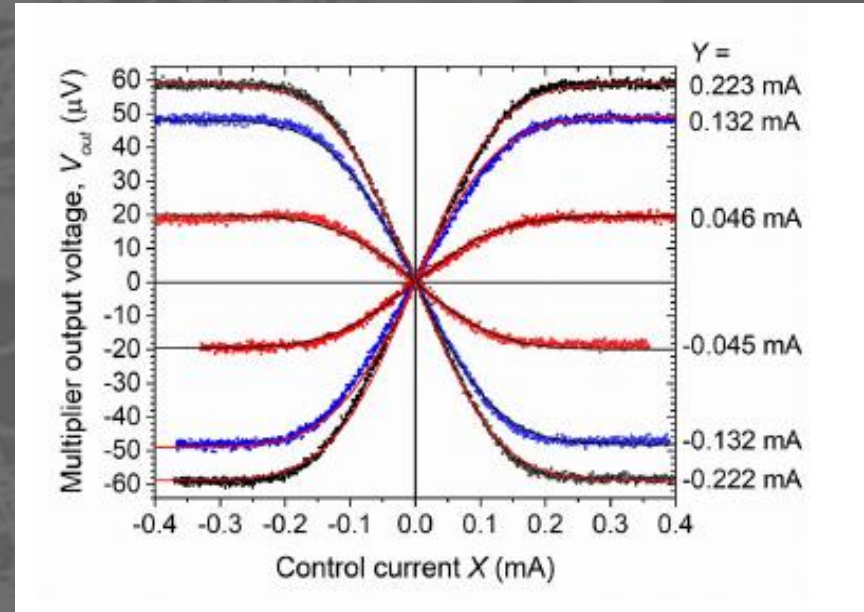
110 um



2EPo1B-01

Semenov et al. IEEE TAS 33, 5 p.1-8 (2023)

- “BioSFQ” logic family includes multiplication, division, addition and other operations with both signs
- Converts back and forth between frequency and current

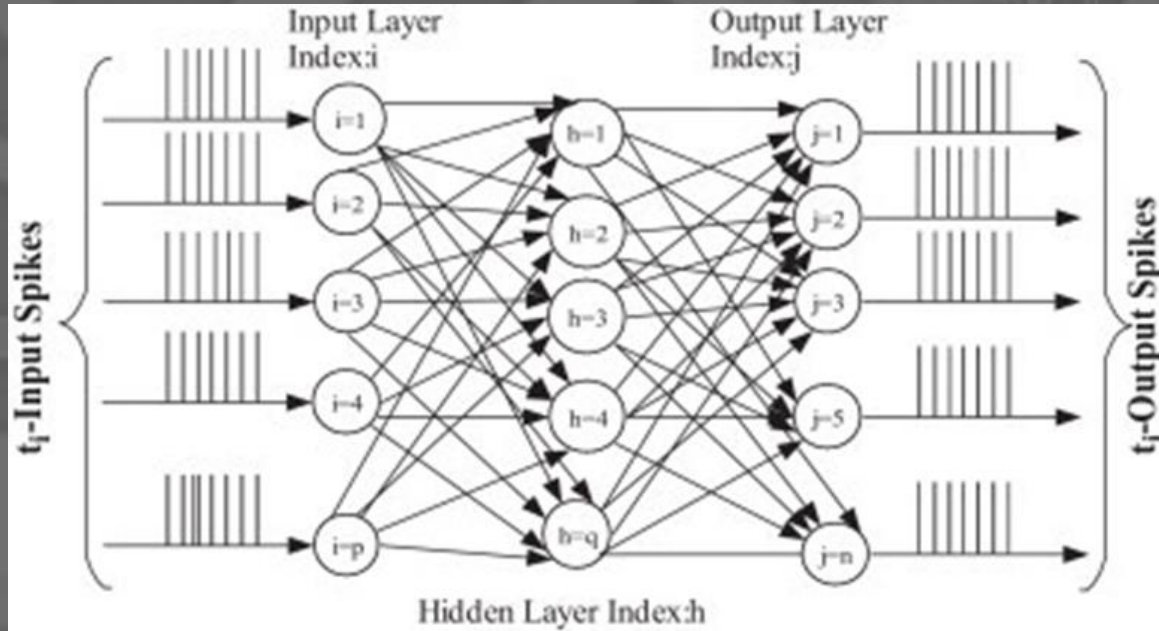


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# THE BRAIN DOES...SPIKING

# Spiking Neural Networks (SNNs)

(Deep Learning  $\sim 10^7$  nJ)

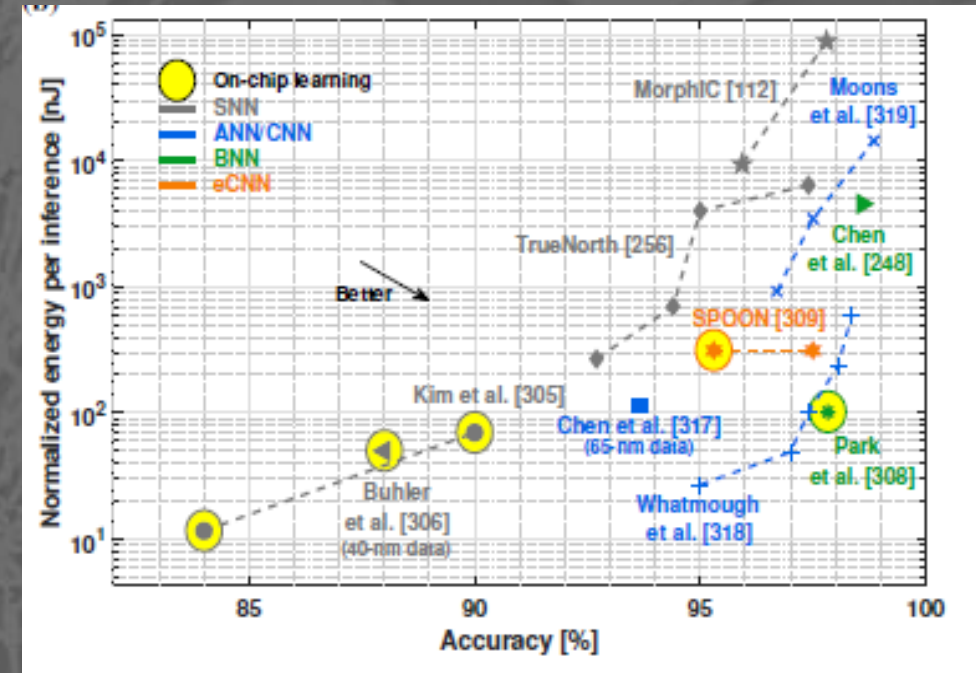


Towardsdatascience.com

- Event driven – more energy efficient!
- Better for spatial-temporal data

Energy

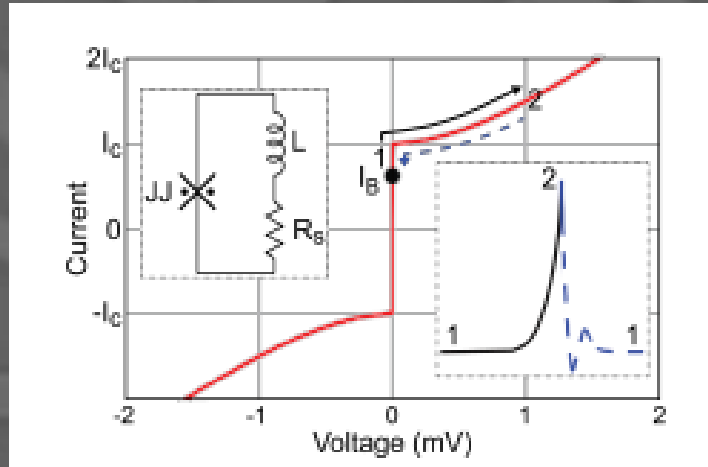
Accuracy



Frenkel et al. arxiv 2106.01288 (2023)

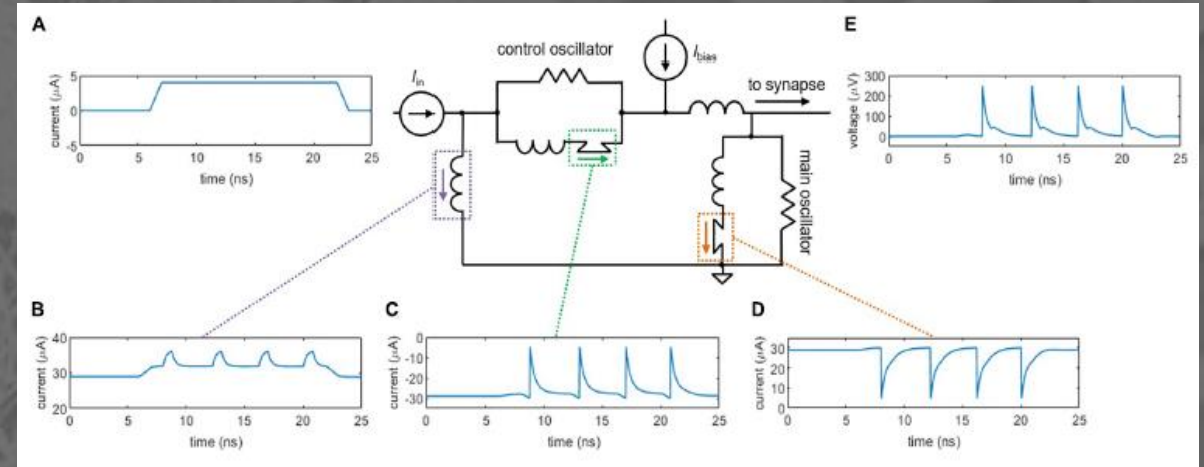
MNIST Classification

# Superconducting spiking neurons



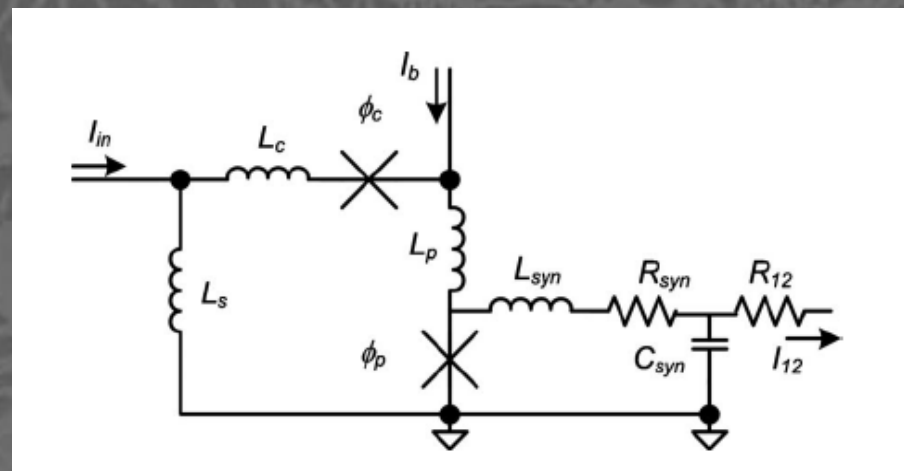
Single junction neurons

Karamuftuoglu et al. arxiv 2402.16384 (2024)



Nanowire neurons

Toomey et al. *Frontiers of Neuro.* **13**, 933 (2019)



Josephson Junction neurons

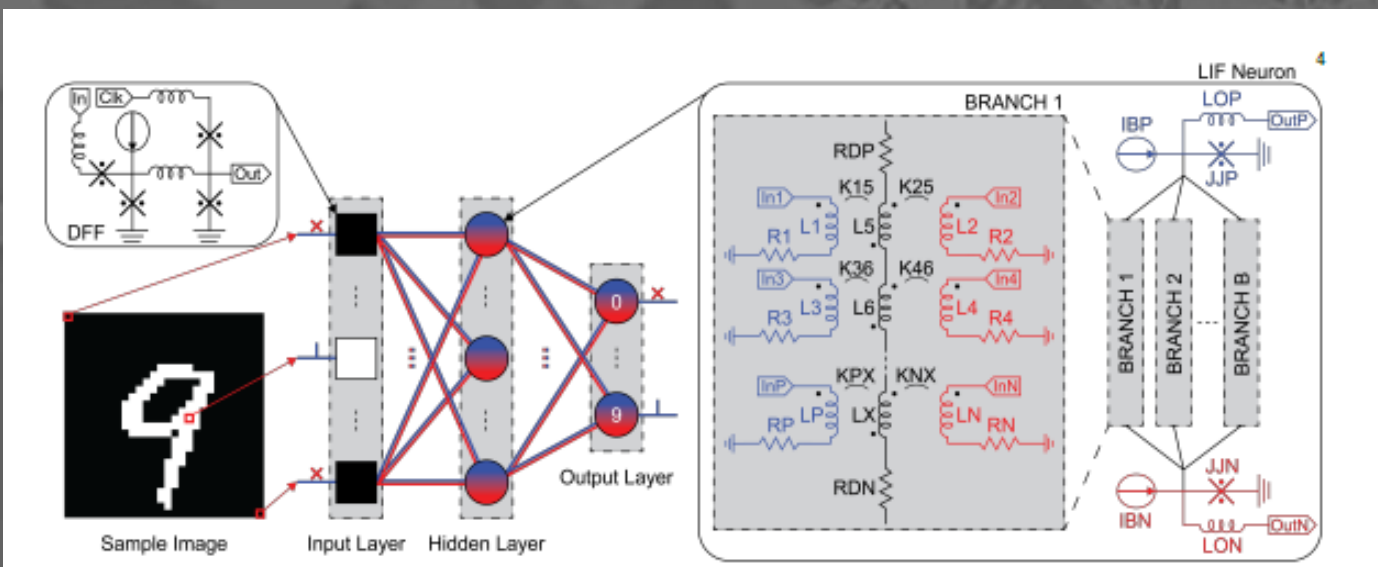
Crotty, Schult and Segall *Phys. Rev.* **E82**, 011914 (2010)



# SNN Inference

Simulation

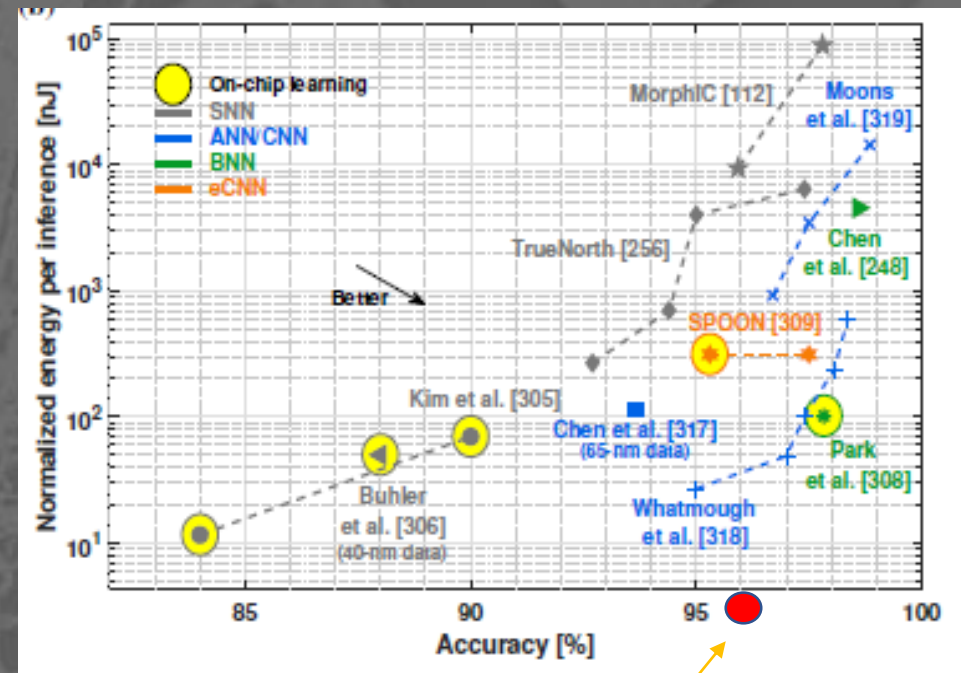
MNIST classification



Karamuftuoglu et al. arxiv 2402.16384 (2024)

4EPo1C-06

- 32-synapse fan-in
- 5-layer network (3 hidden layers) with over 1000 total neurons



96.1 % accuracy  
1.5 nJ per inference

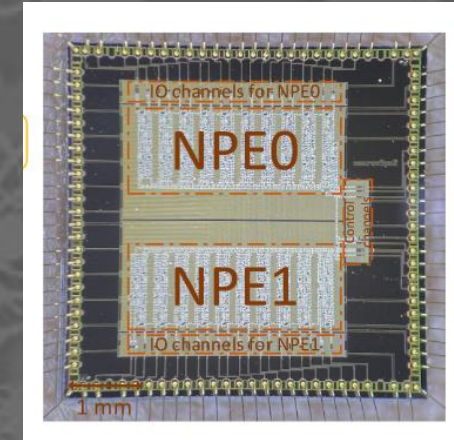
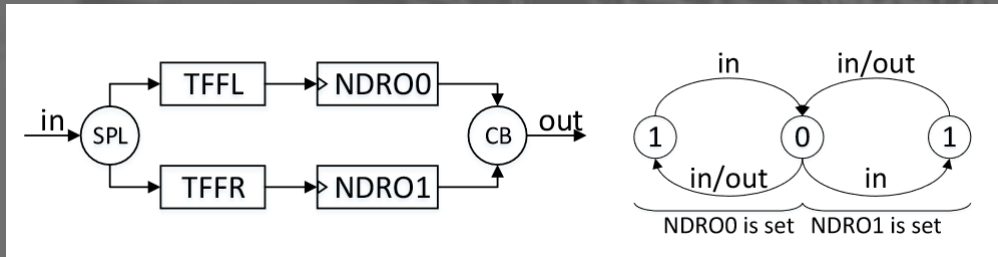
Experiment

# Experimental SNN

First fully superconducting SNN!

**SUSHI: Ultra-High-Speed and Ultra-Low-Power Neuromorphic Chip Using Superconducting Single-Flux-Quantum Circuits**

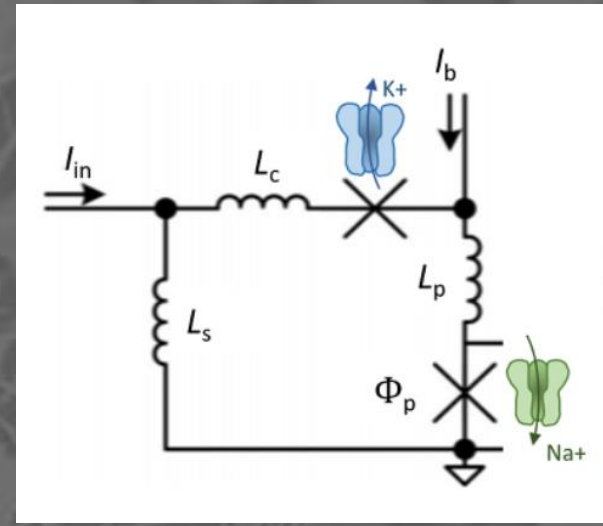
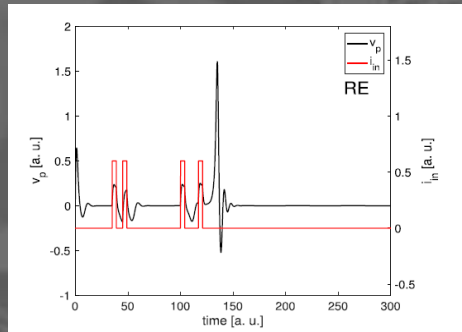
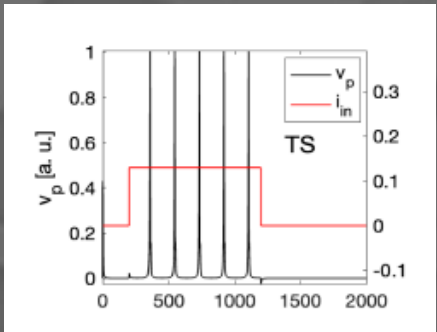
Liu et al. *MICRO '23 proceedings (2023)*



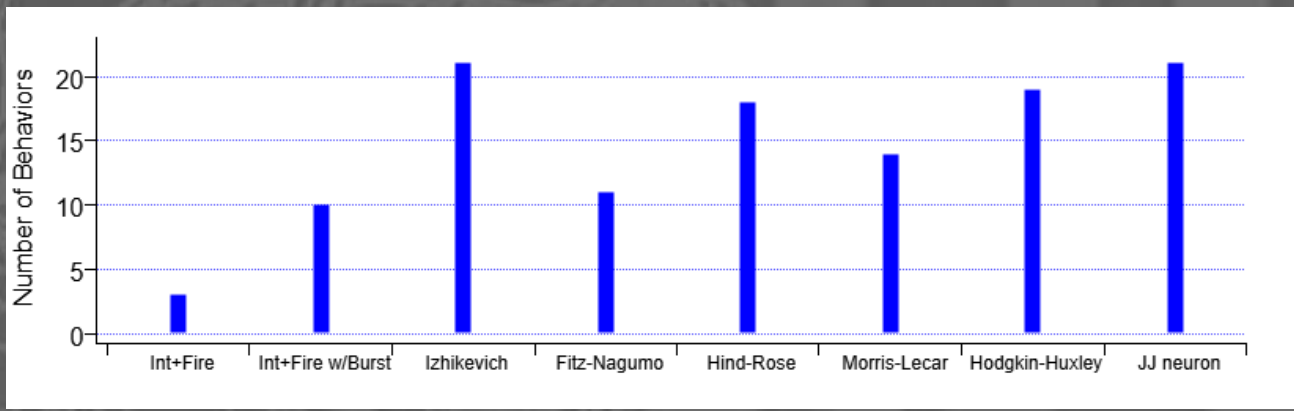
- 4x4 Fully-connected network
- Spiking neuron achieved with SFQ gates, Weighting achieved with nested NDROs
- $8 \times 10^{10}$  SOPS/watt (with cooling), better than True North

Simulation

# Biological Realism



behavior	$\eta$	$\Gamma$	$\lambda$	$\Lambda_s$	$\Lambda_p$	$i_b$
TS	1.2	1.53	0.16	0.35	0.55	2.19
TB	0.95	1.81	0.11	0.44	0.46	(sin)
IIS	1.2	1.53	0.16	0.35	0.55	2.19
IIB	0.95	1.81	0.11	0.44	0.46	(sin)
PS	1.71	1.55	0.13	0.49	0.48	2.085
PB	1.58	1.64	0.09	0.61	0.1	0.95
RS	1.708	1.55	0.13	0.51	0.48	2.14
RB	0.95	0.758	0.11	0.44	0.46	(sin)
C1	0.96	1.55	0.26	0.49	0.48	1.93
C2	0.96	1.04	0.26	0.46	0.46	1.93
MM	0.941	1.683	0.03	0.49	0.48	1.928
SFA	1.79	2.67	0.001	0.52	0.48	1.9
DAP	1.26	1.593	0.183	0.54	0.46	2.017
STO	1.71	0.649	0.13	0.49	0.48	1.9
SL	1.71	1.55	0.13	0.49	0.48	2.143
IN	1.115	2.114	0.1	0.5	0.5	2.053
BI	1.0	0.93	0.064	0.5	0.46	1.906
RE	1.71	0.649	0.13	0.49	0.48	(sin)
TV	1.1	1.5	0.1	0.5	0.5	1.96

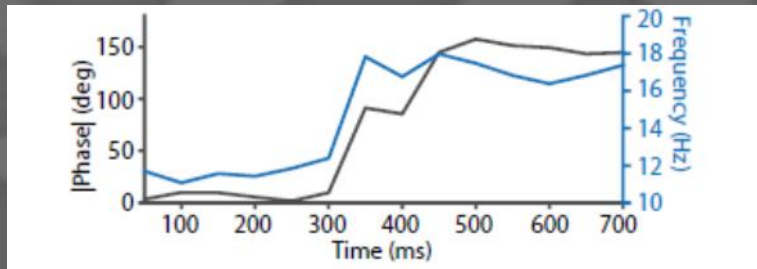


Crotty, Schult and Segall, *IEEE TAS 33*, 1800806 (2023)

## Izhikevich Behaviors

Experiment

# Flipping the phase

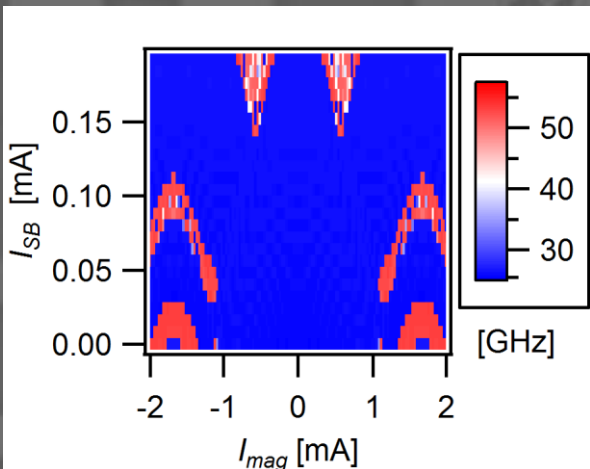


Dotson et al.

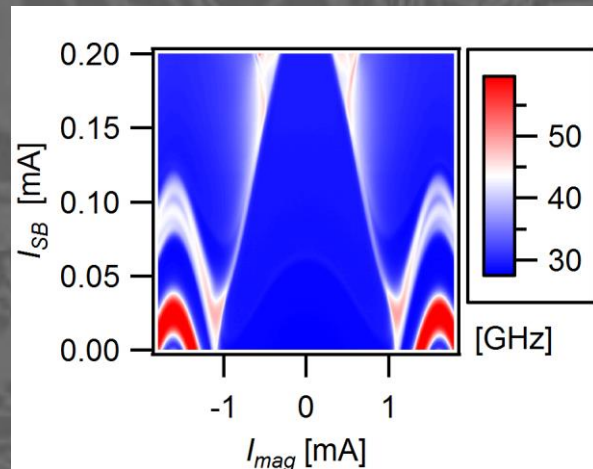
Phase-flip bifurcation in primates



Mutually-coupled JJ neurons



Simulation  
10<sup>3</sup> pts in 60 h



Experiment  
10<sup>6</sup> pts in 51 m

Blue = in-phase  
Red = antiphase

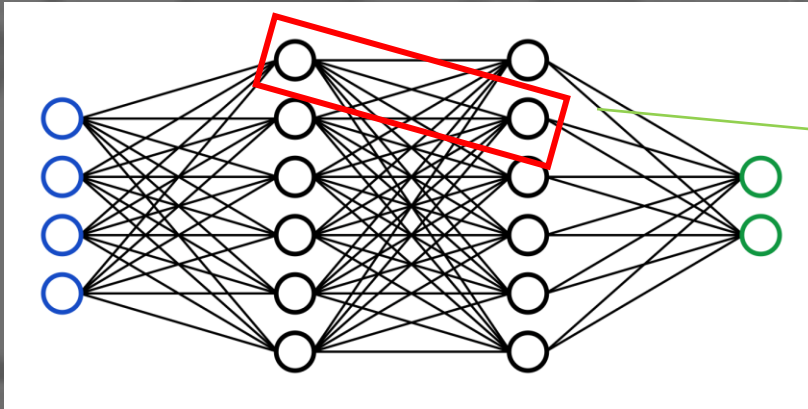


Segall et al. *Physical Review E* 95, 032220 (2017)

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# THE BRAIN DOES...LEARNING

# Types of Learning

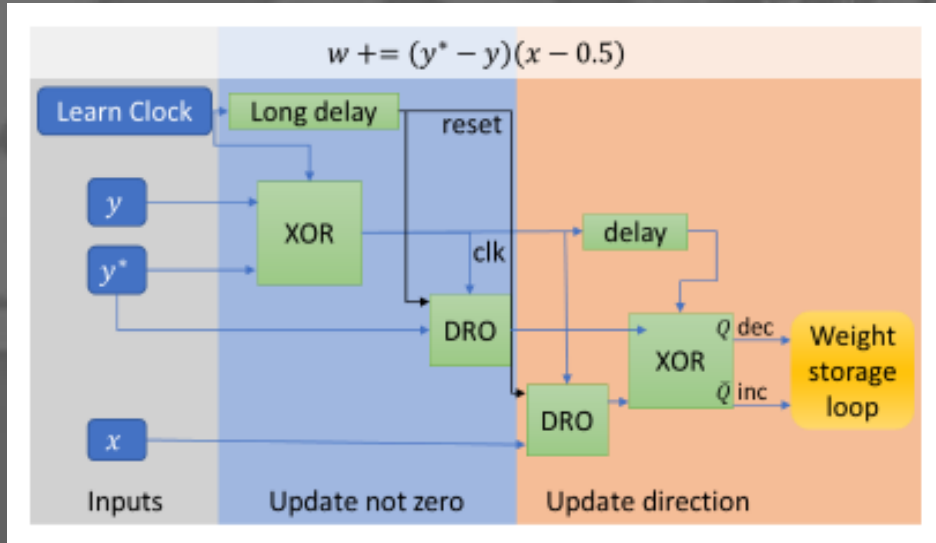


- Supervised learning: Updated weights calculated with a numerical formula
- Reinforcement learning: Weights are nudged up and down with local rules based only on the global output
- Reservoir computing: Only a small fraction of the weights are adjustable, the rest are fixed in a “reservoir”
- Unsupervised learning: The weights *adjust themselves* according to the coincident firing of the two neurons

More biological

# Reinforcement Learning

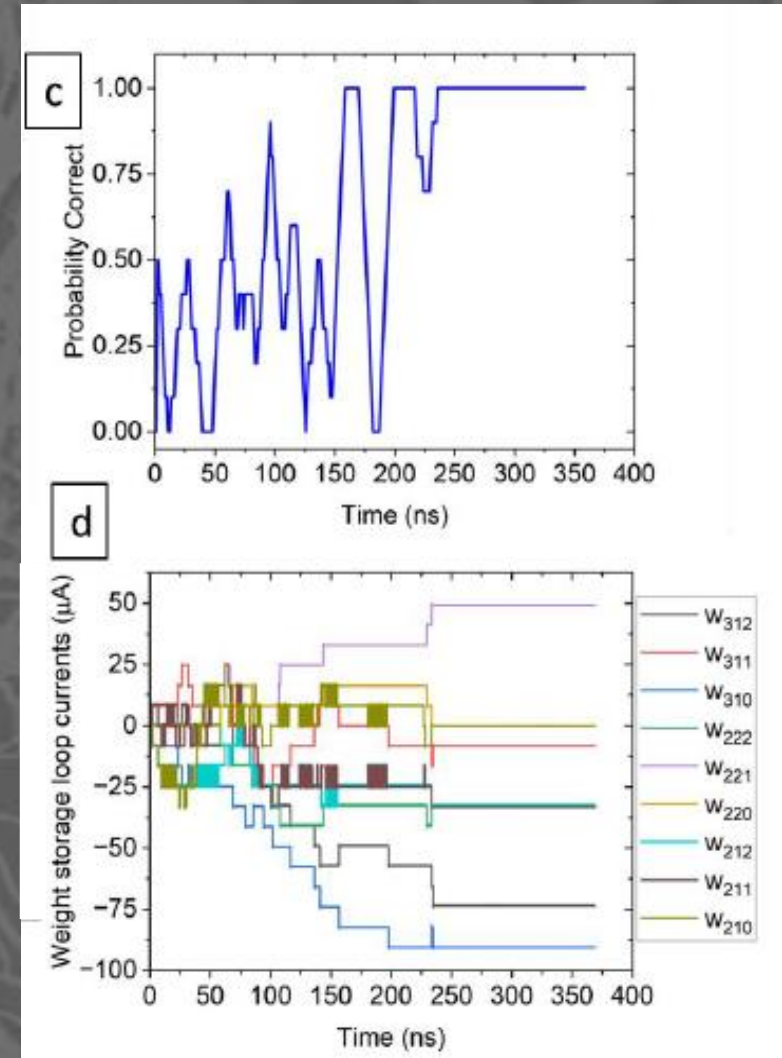
Simulation



Schneider et al. arxiv 2404.18774 (2024)

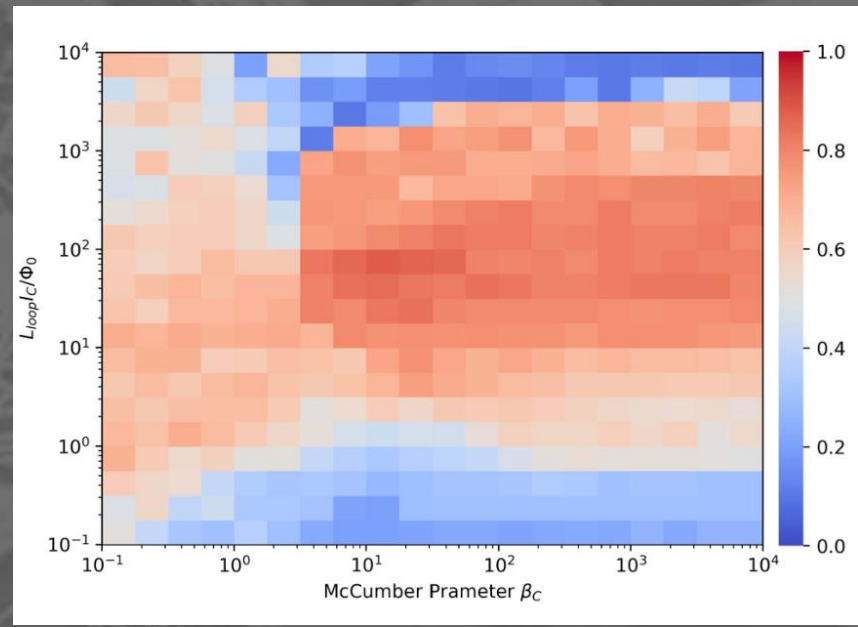
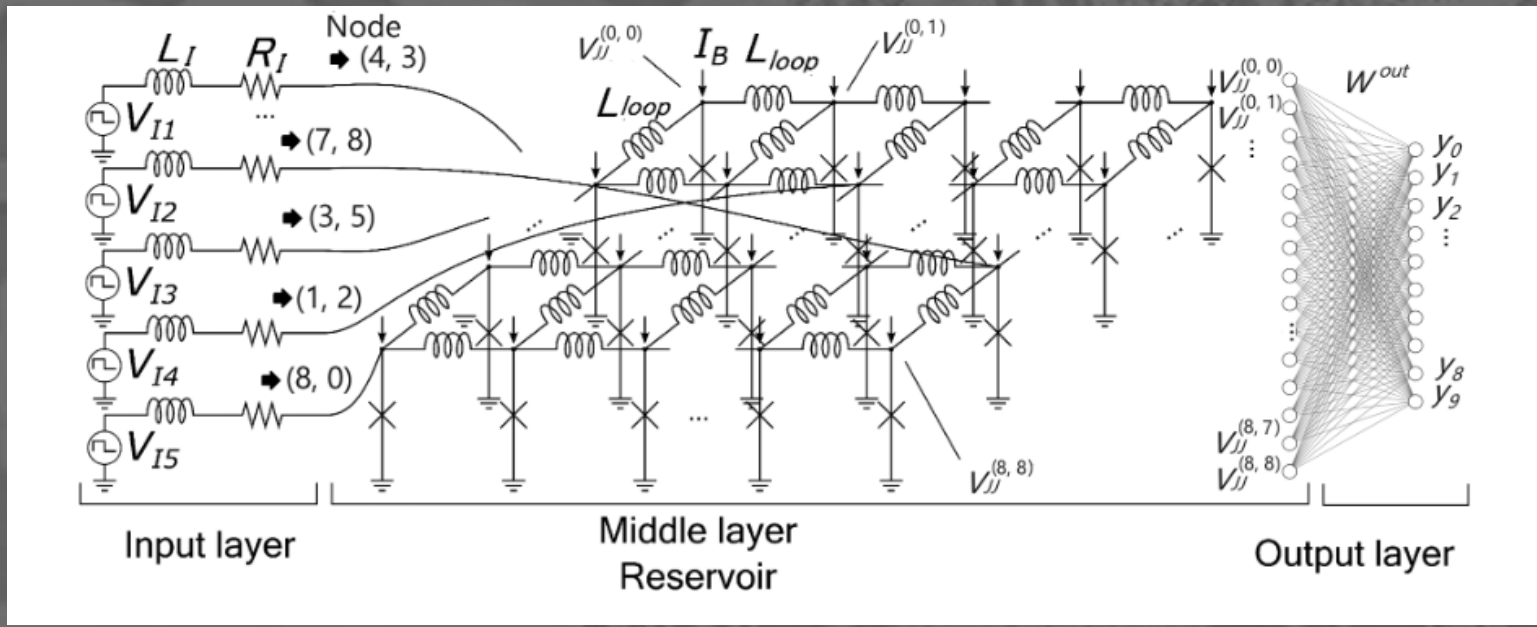
Could lead to really fast training!!

5EOr1B



Simulation

# Reservoir Computing

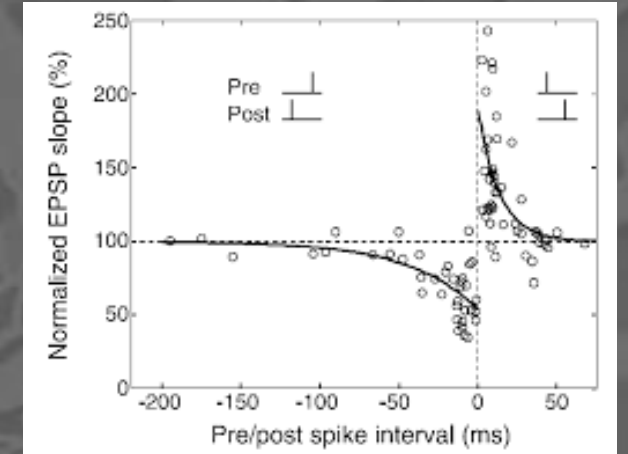
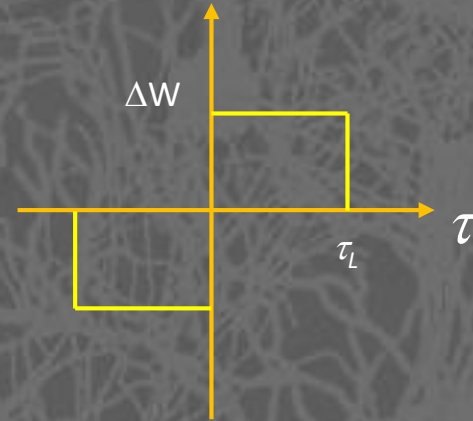
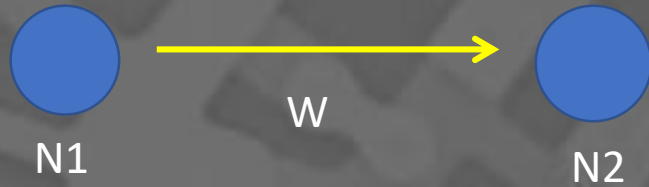


Watanabe et al. *IEEE TAS* 34, 1700204 (2024)

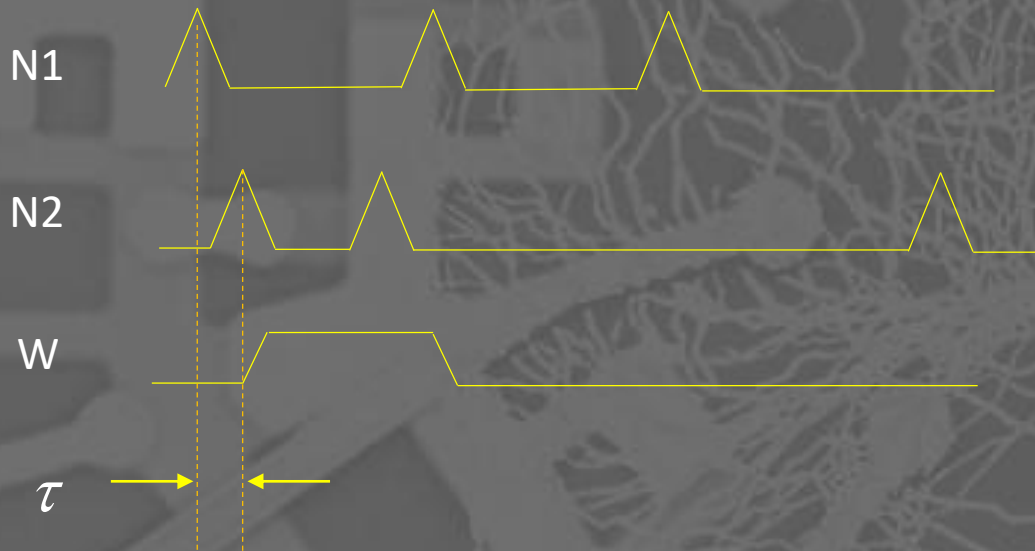
MNIST Data set  
Peak accuracy = 88%



# Unsupervised Learning



Froemke et al, 2006



- “Things that fire together wire together”
- Called “Spike Timing Dependent Plasticity” (STDP)

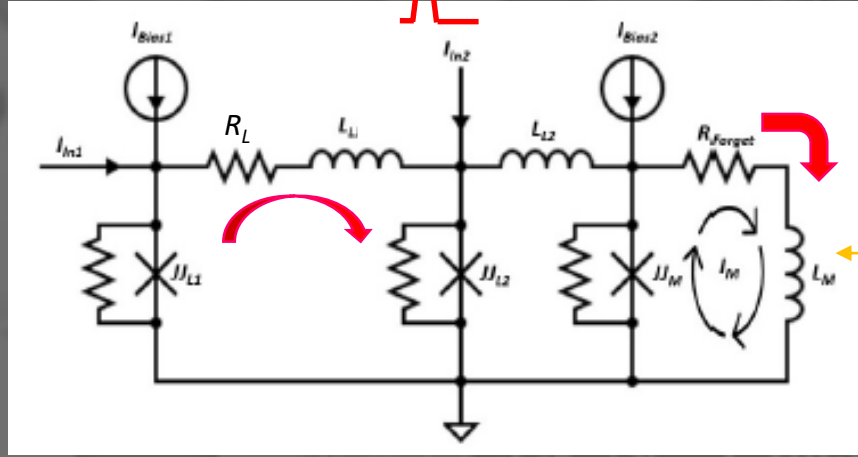
Simulation

# Superconducting STDP

N1



N2

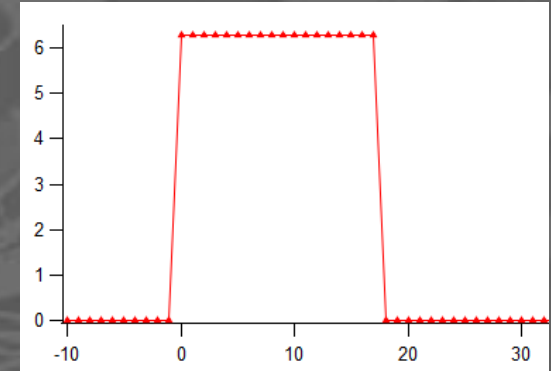


Flux = Weight

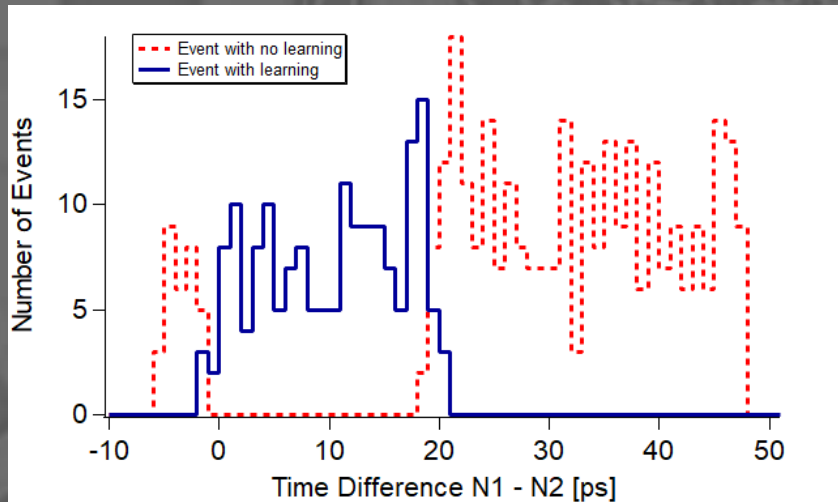
$$\tau_L \approx L_L / R_L$$



JJ<sub>L2</sub> phase



Time [ps]



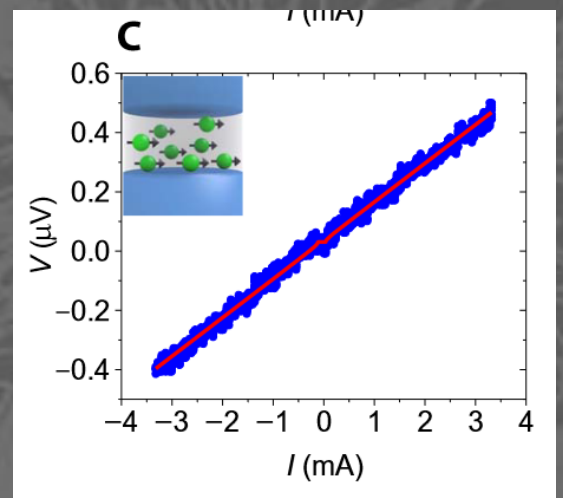
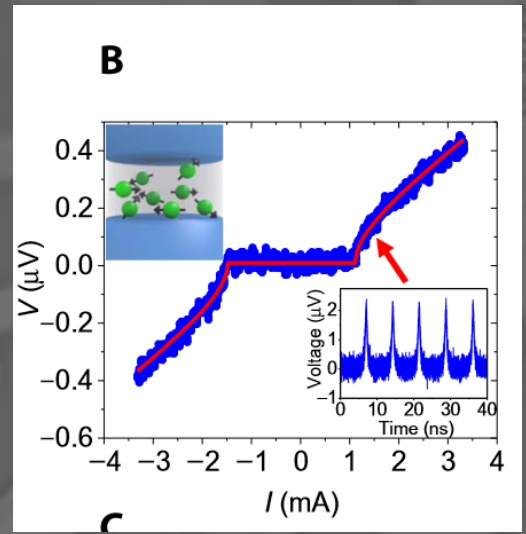
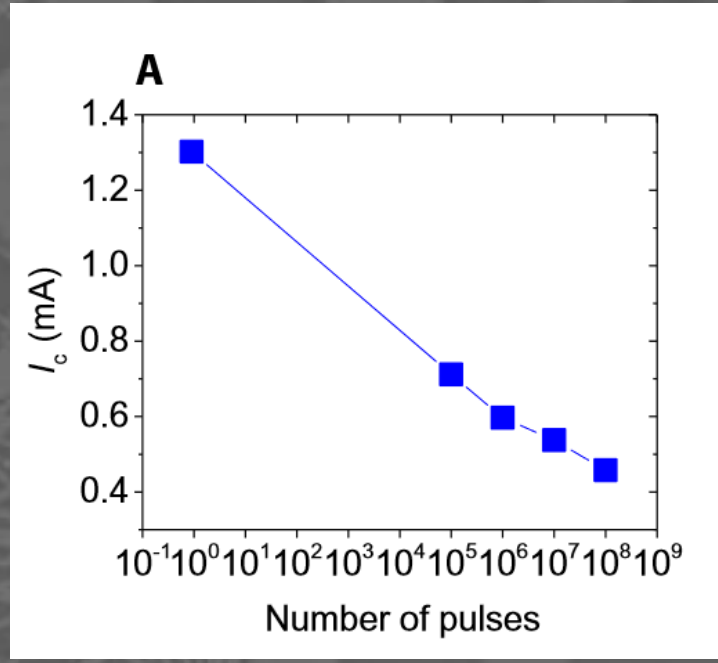
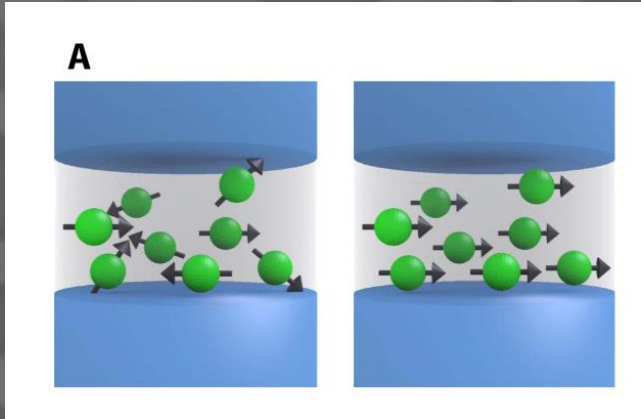
Segall et al. *Appl. Phys. Lett.* 122, 242601 (2023).

(Measurement in preparation)

Experiment

# Learning to align..

## Magnetic Josephson Junction (MJJ)



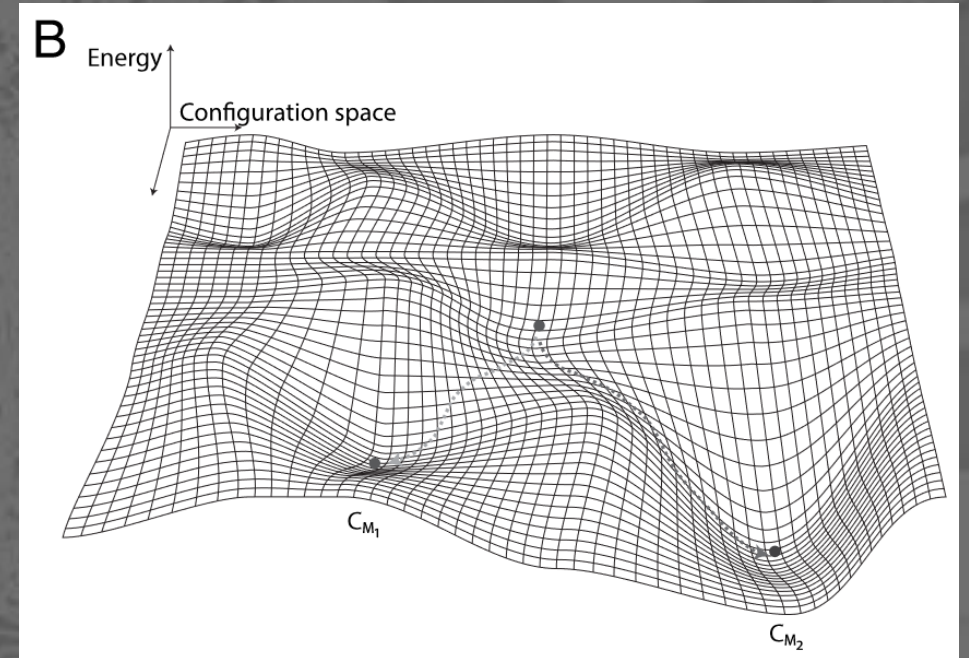
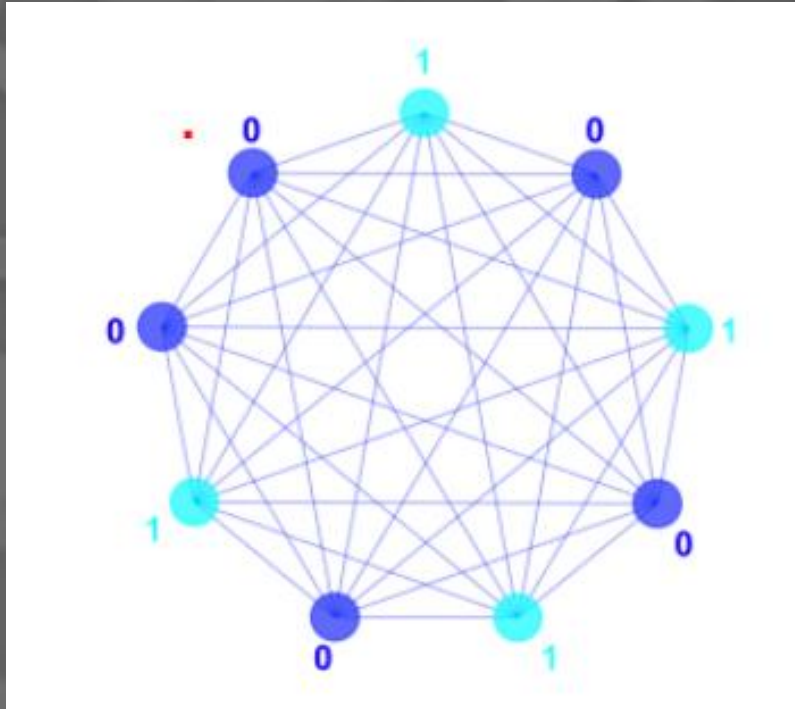
Schneider et al. *Sci. Adv.* 4, 1701329 (2018)

- Device "trains" itself as current pulses are applied!

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## THE BRAIN DOES...OPTIMIZATION

# Hopfield Networks



$$U = -(1/2)x^t W x - b^t x$$

Lyapunov Function:  $\frac{dU}{dt} \leq 0$

Can be used to:

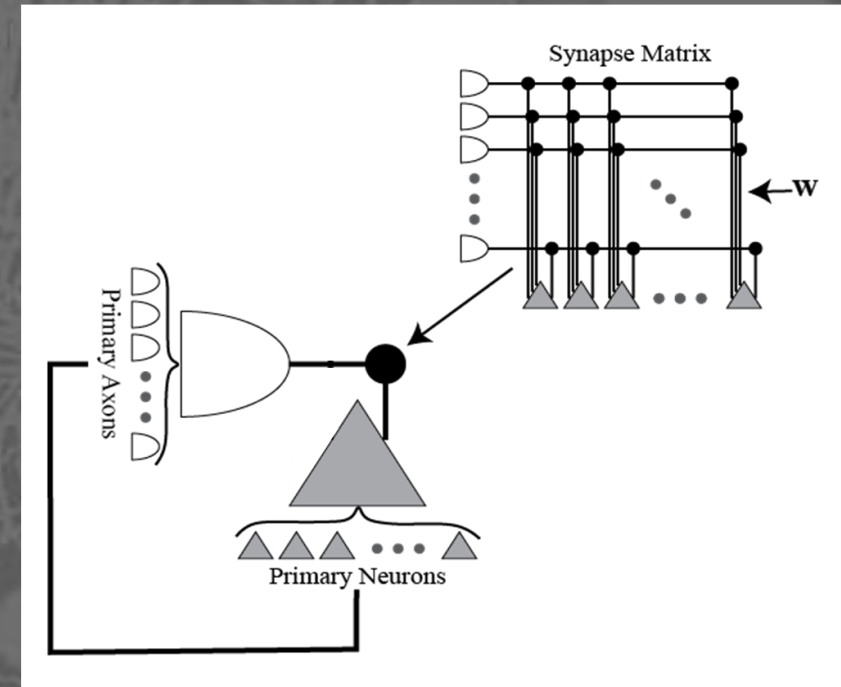
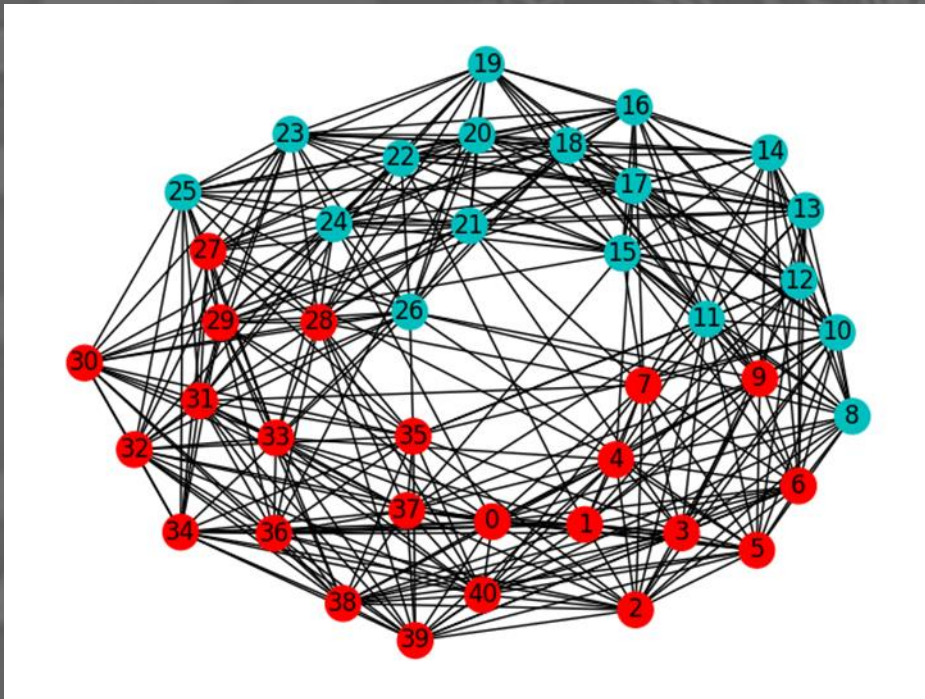
1. Solve optimization problems
2. Model associative memory

Simulation

# QUBO and Graph partitioning

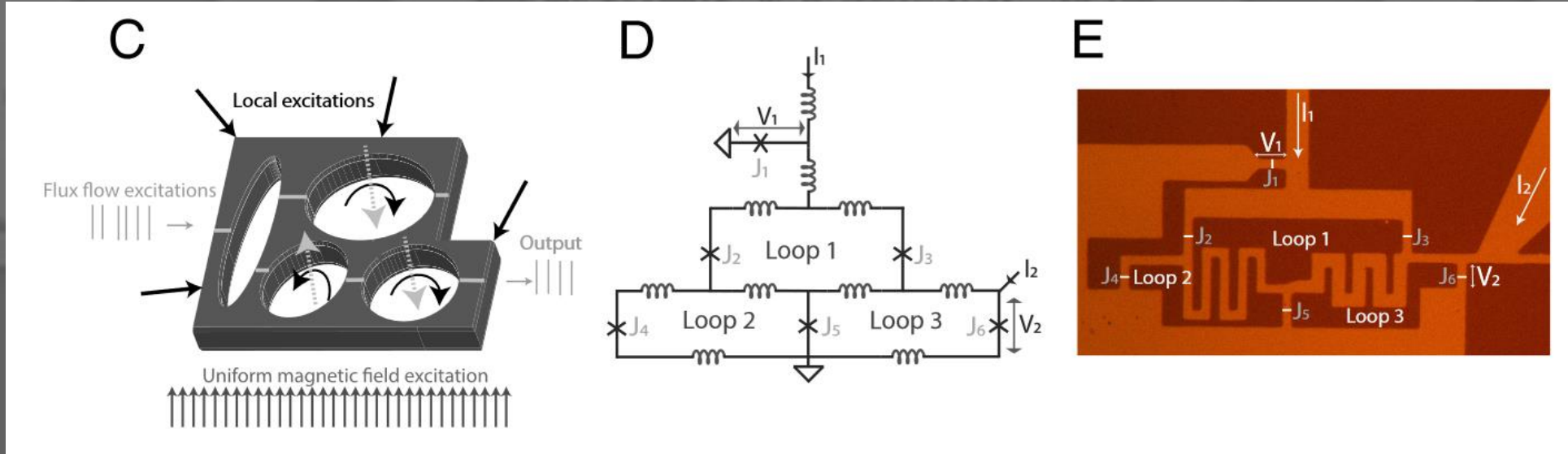
$$U = -x^t W x - b^t x \longrightarrow$$

Maps onto NP-complete problems like Traveling Salesman and Graph Partitioning (GP)!



JJ network to solve GP: 5EOr1B-05 (Adler)

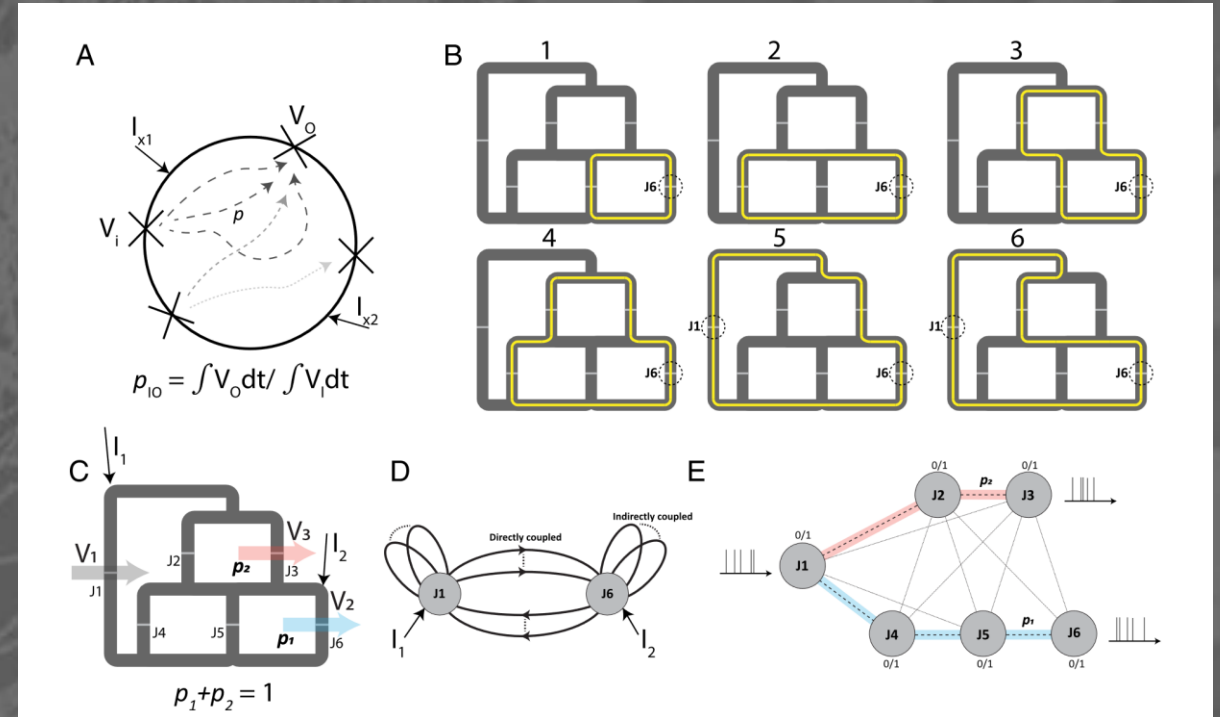
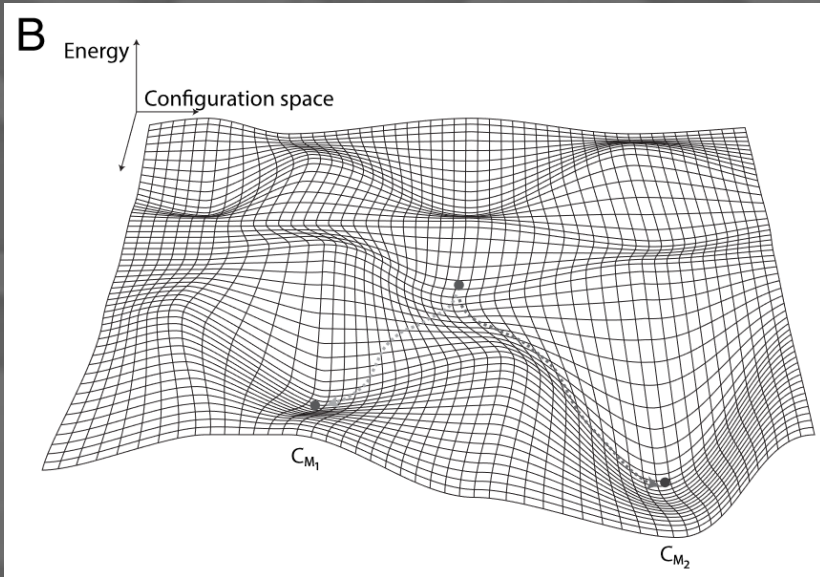
# Associative Memories and Categorization



Goeti et al. PNAS 212 2314995121 (2024)

- Four loops with JJs in a high-Tc material
- Fluxons can be added by pulsing the junctions

# Coupling neurons into networks



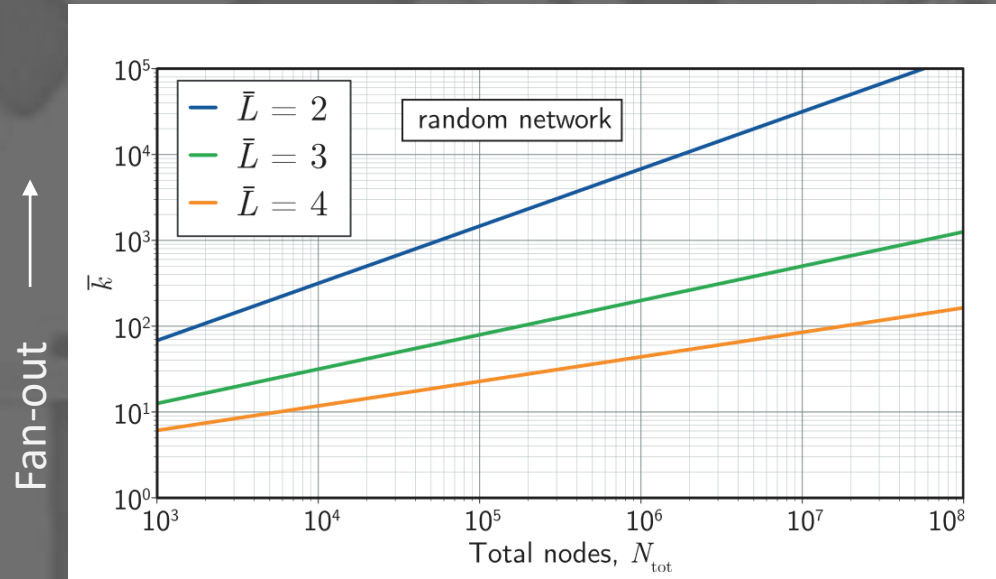
- With a large number of fluxons you get a large configuration space
- JJs act like neurons, closed loops act like connections
- Neural behavior observed!



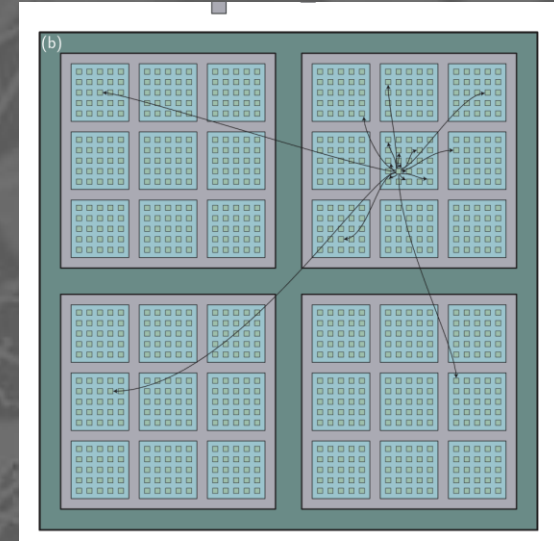
- I. Introduction
- II. Brain activities:
  - 1. Synaptic Weighting
  - 2. Spiking
  - 3. Learning
  - 4. Optimization
  - 5. Networking ←
- III. Looking forward

# THE BRAIN DOES...COMMUNICATION AND NETWORKING

# Communication across different brain regions



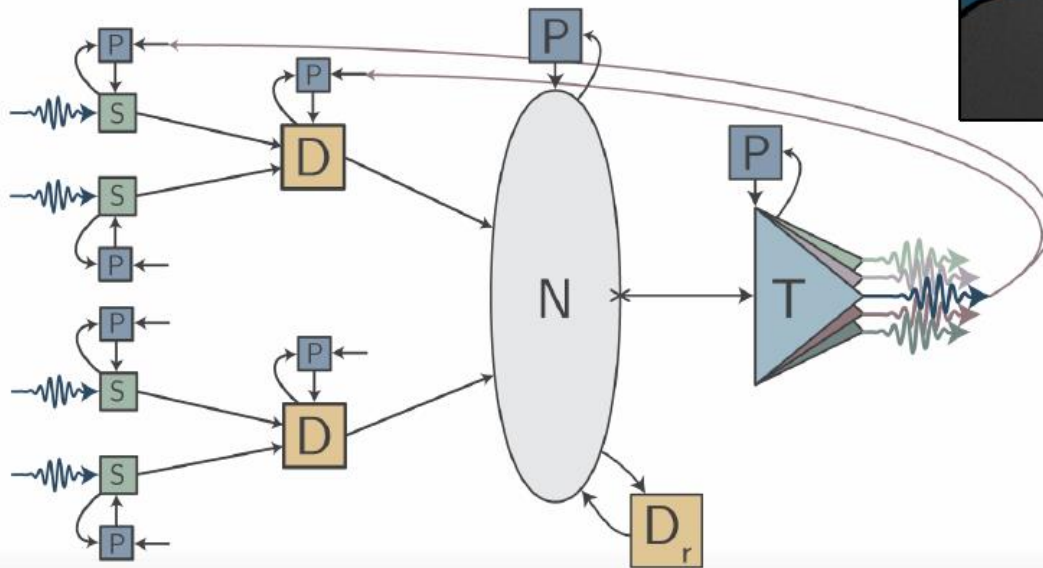
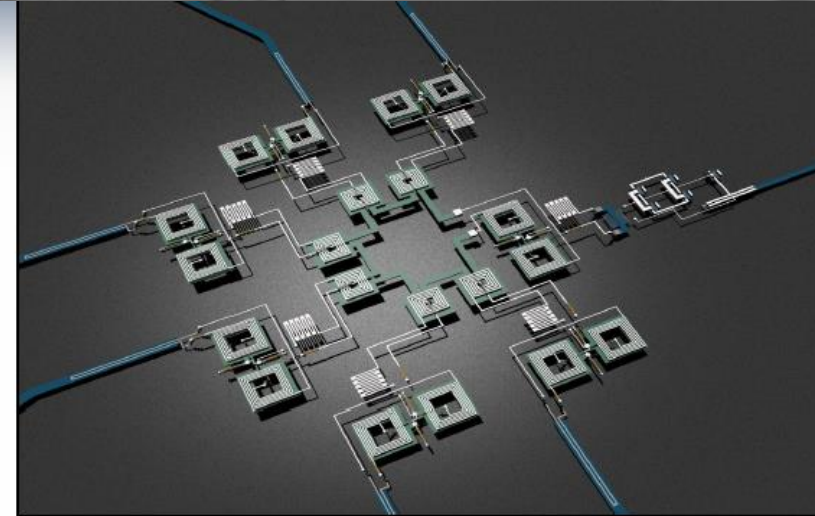
J. Shainline *Appl. Phys. Lett.* 118, 160501 (2021)



- Each neuron in the brain connects to  $\sim 5000$  other neurons
- Will be challenging to realize this level of fan-in/fan-out with only superconducting electronics
- Can we do better? Is human-level AI possible?

# Superconductors for computation, light for communication

Superconducting  
optoelectronic  
neuron (SOEN)

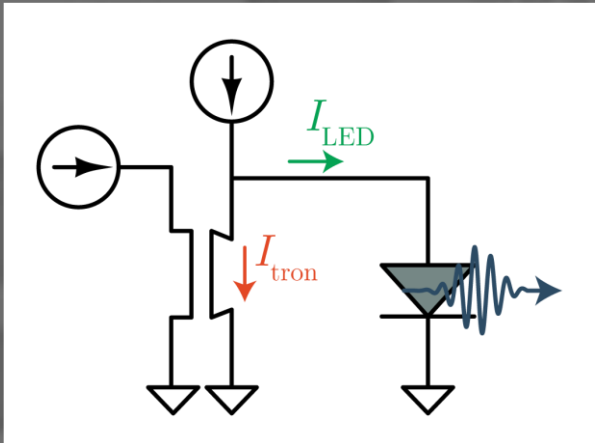
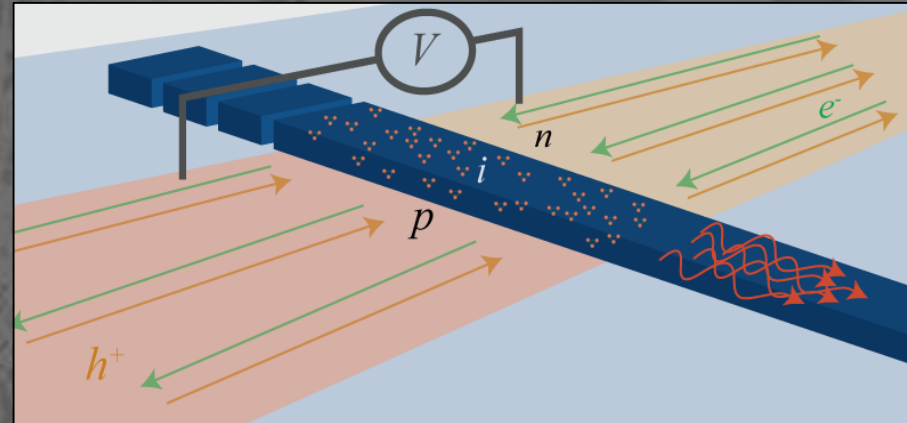
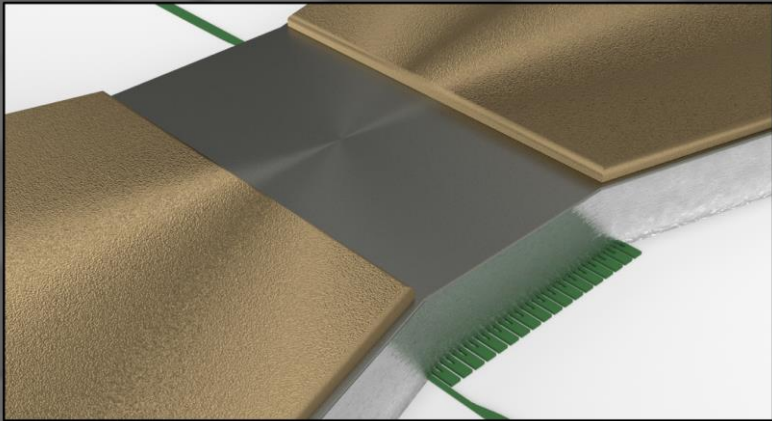


S = synapse  
D = dendrite  
P = plasticity block  
N = neuron cell body  
T = transmitter

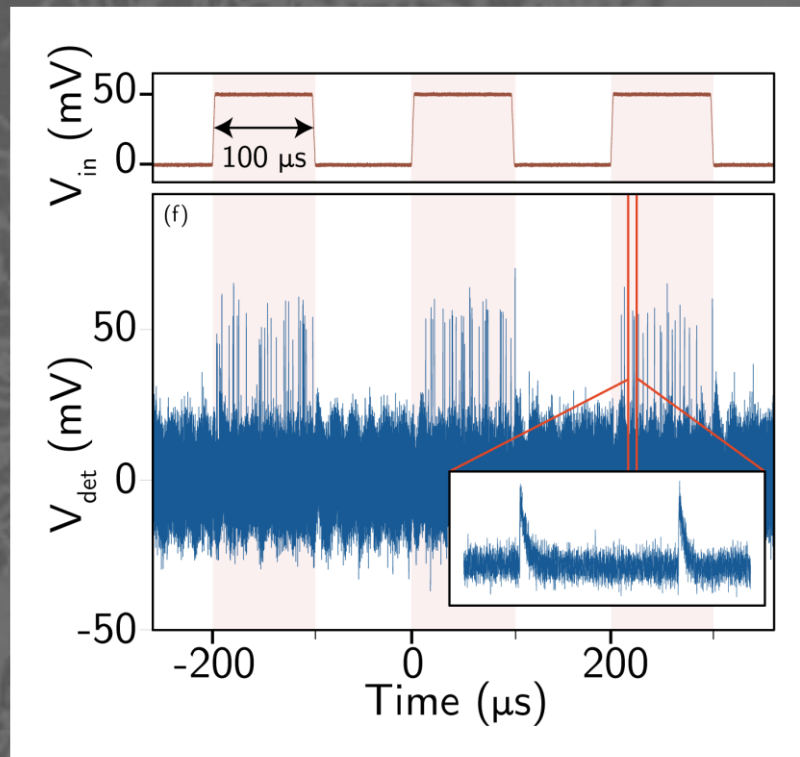
5EOr1B

J. Shainline *Appl. Phys. Lett.* 118, 160501 (2021)

# From SFQ to light...

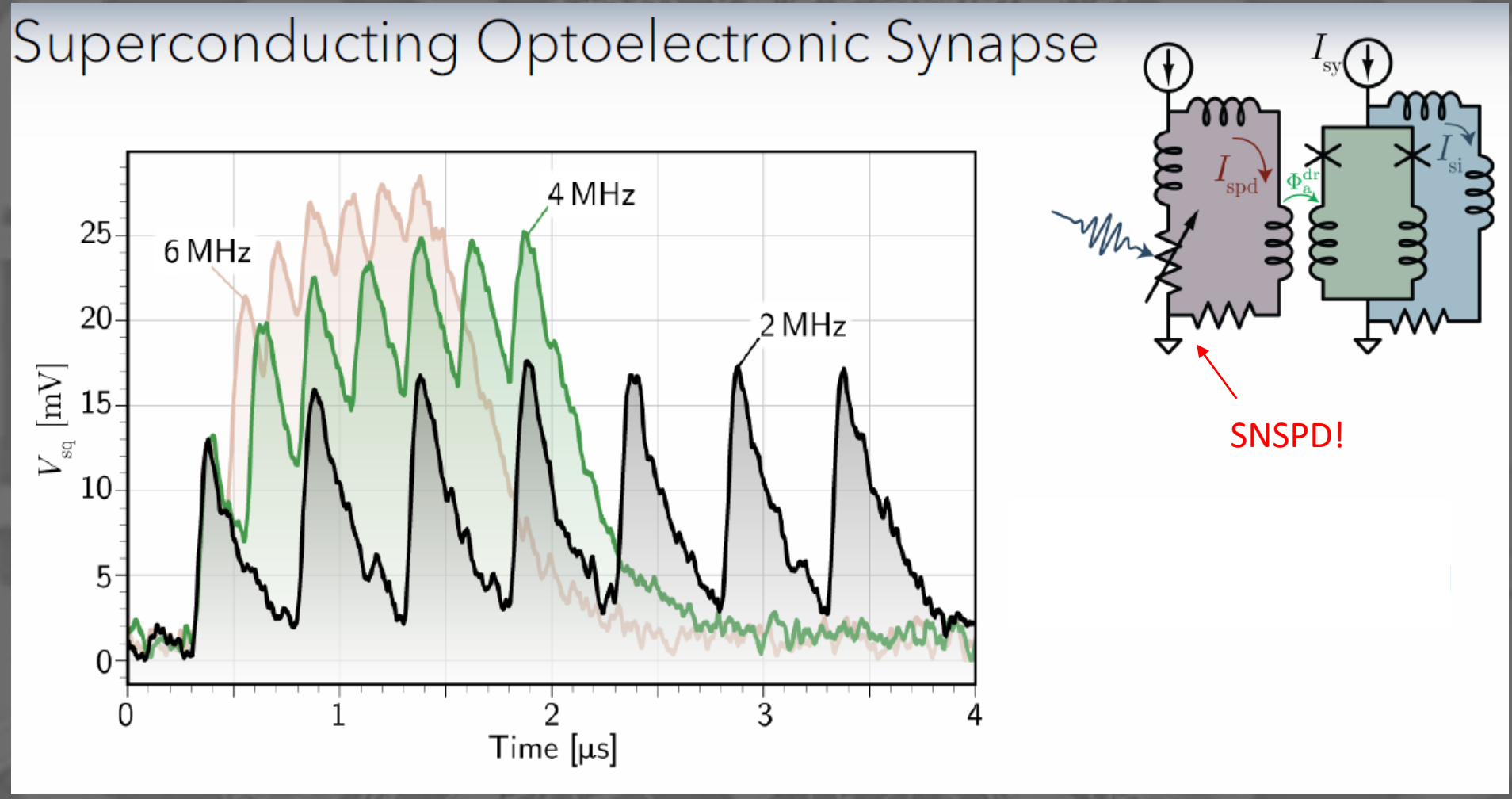


McCaughan et al., Nat. Electron., 2, 451 (2019)



Experiment

# And from light back to SFQ!

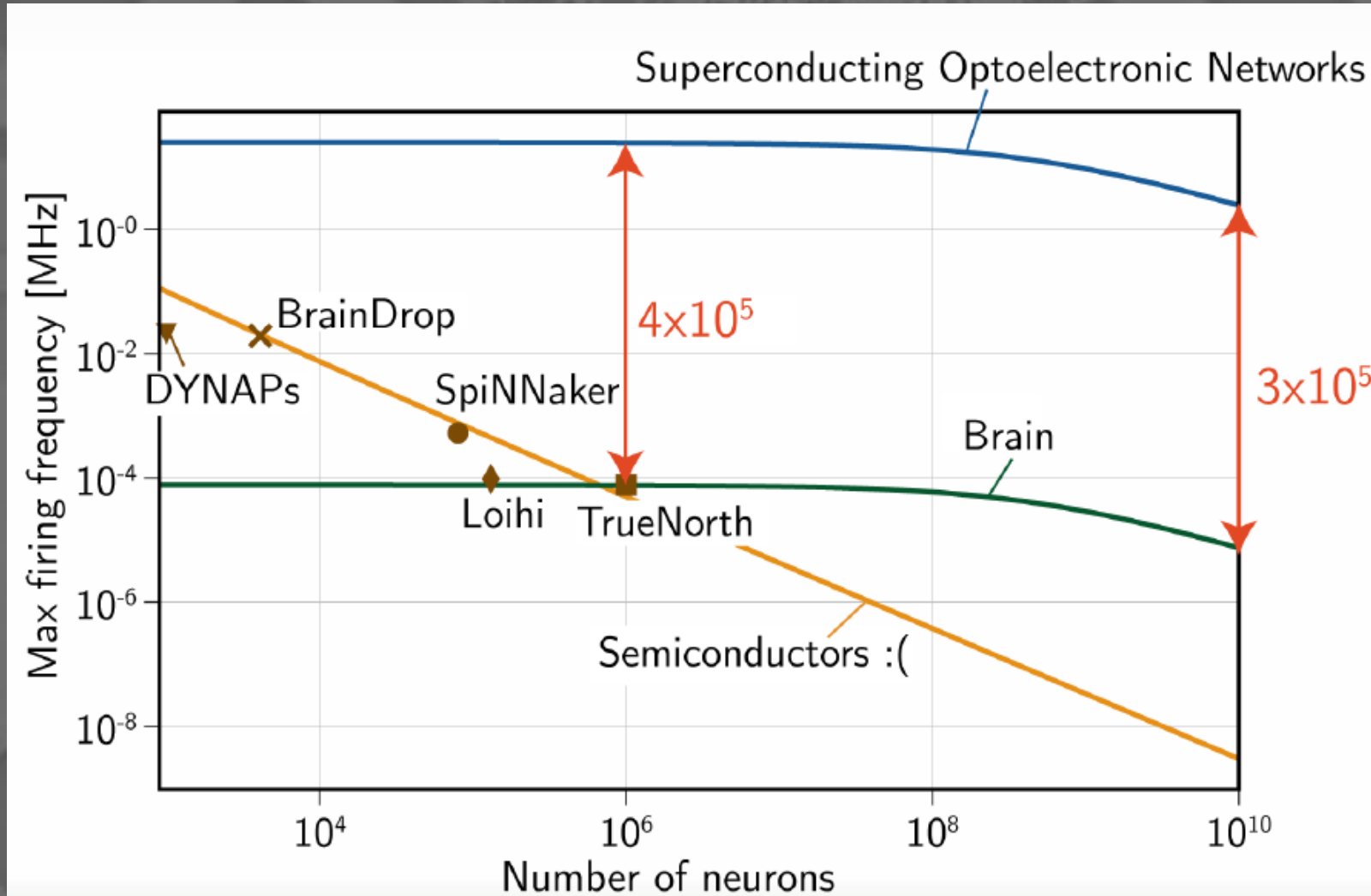


Khan, Primavera et al. Nature Electronics (2022)

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# LOOKING FORWARD...

# More bandwidth....



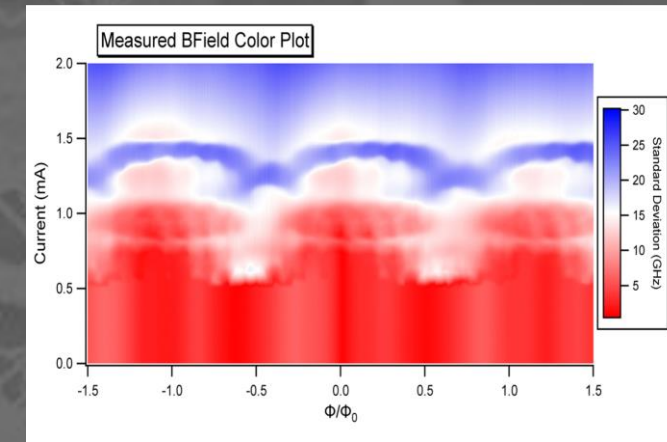
# With more spikes...

**$N$  Neurons: AP/Neuron/sec (w/ sparse connections)**

Assume  $10^9$  FLOPS  $\longrightarrow$

Model	$N=100$	$N=10,000$	$N=1 \times 10^6$
Hodgkin-Huxley Model	$8.3 \times 10^3$	83	0.83
Mammalian CNS	$1 \times 10^3$	$1 \times 10^3$	$1 \times 10^3$
JJ Neuron	$1 \times 10^{10}$	$1 \times 10^{10}$	$1 \times 10^{10}$

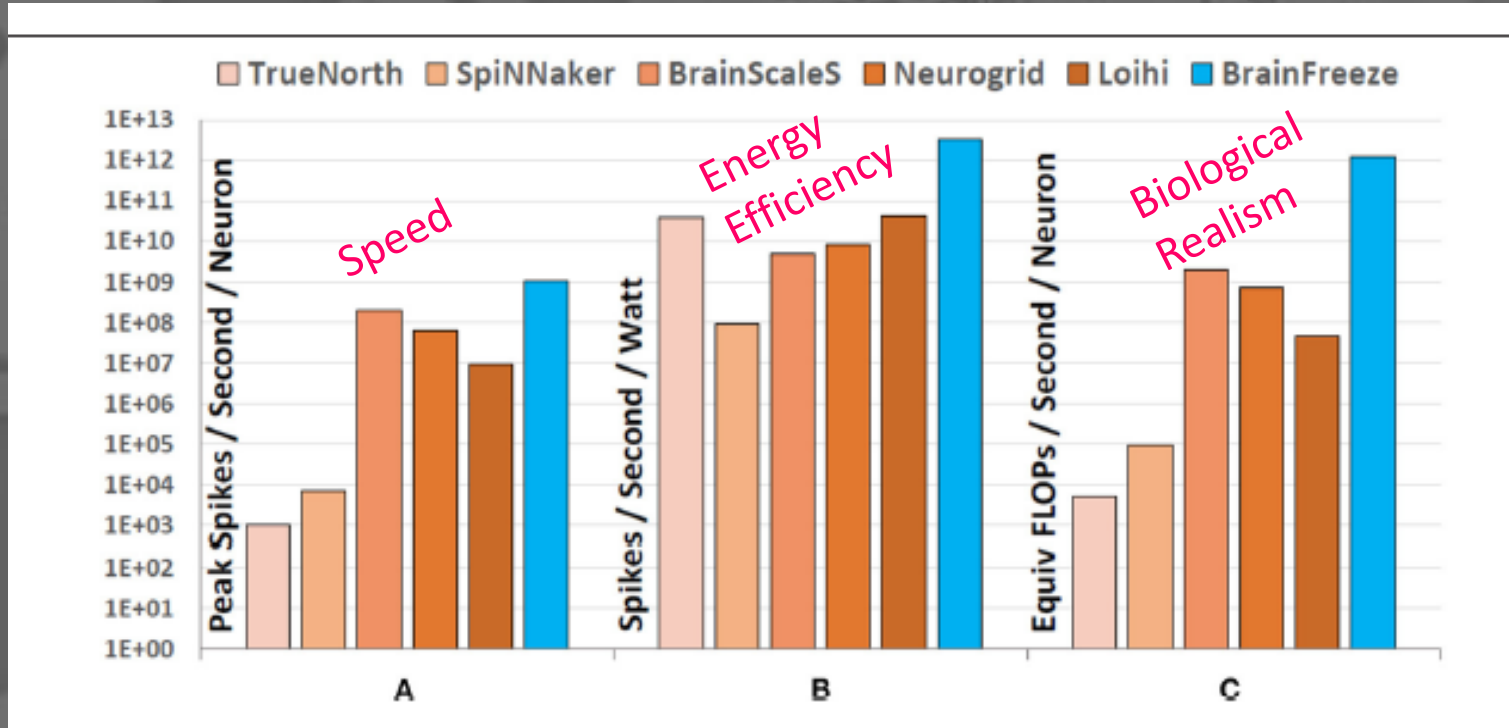
Best for long term dynamics:  
A lifetime (90 years) of learning in  
5 minutes of lab time!!



Voltage measurements to predict epileptic seizures  
(5EOr-1B tomorrow)



# And more efficiency and biological realism...



Tshirhart and Segall, *Frontiers of Neuroscience* (2021)

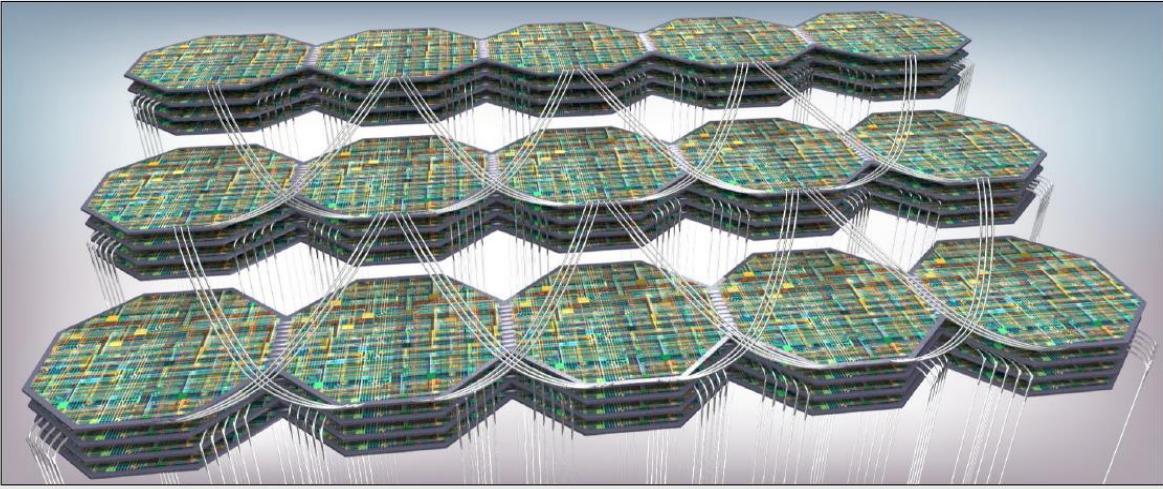
- Mixed-signal architecture (analog neurons, digital connections)
- Assumes only available published superconducting technology
- Utilizes Multi-Chip Modules (MCMs)

# So let's go big!

## Superconducting optoelectronic networks (SOENs)

10 billion neurons  
10 trillion synapses  
2-meter cube

10kW - 1MW  
 $\eta_{LED} = 10\% - 0.1\%$



## Superconducting Brain Conception (courtesy J. Shainline)

- Energy efficiency advantage comes mostly from interconnects – win more with a bigger system!

- Fast inference (real-time malware detection?)
- Whole brain simulation (Artificial General Intelligence?)
- Fast computation (mediate plasma instabilities in fusion?)
- Large-scale optimization (planet-scale sustainability trade-offs?)

# Conclusions

- Neuromorphic computing aims to make computer hardware that works according to principles of the human brain
- The brain's activities of synaptic weighting, spiking, learning, optimization and networking can all be made with superconducting electronics
- The field is expanding, and now is the time to go big!

## Acknowledgements:

- Talk preparation: Mike Schneider, Jeff Shainline, Elie Track, Timur Filippov
- Colgate Faculty/Postdocs: Dan Schult, Patrick Crotty, Oleksiy Svitelskiy
- Colgate Students: Matt LeGro, Sam Adler, Sarah Miller, Shreeya Khadka (and many others!)