Nonlinear Classification Without a Processor

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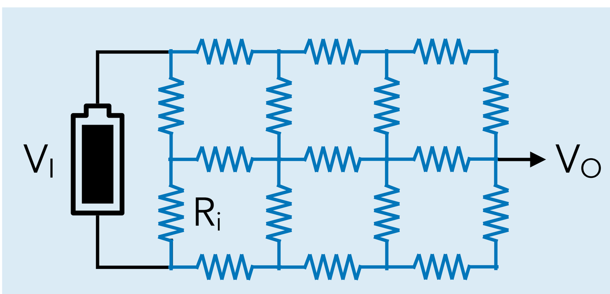
We build 'learning metamaterials.'

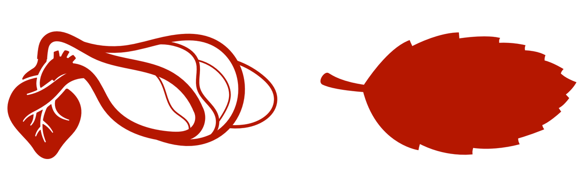


$f(V_I, \vec{R}) = V_O$

Our system is an ensemble of variable resistors that self-adjust based on local rules to produce a desired output from a given input.

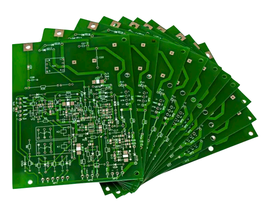
That is, it learns by example.

Active, out-of-equilibrium system with complex dynamics where **learning is an emergent property.**



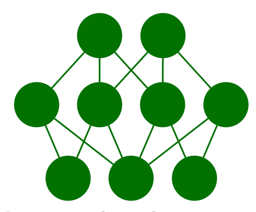
Biological systems

This is in contrast to the typical ways we construct desired functions:



by design: circuitboard

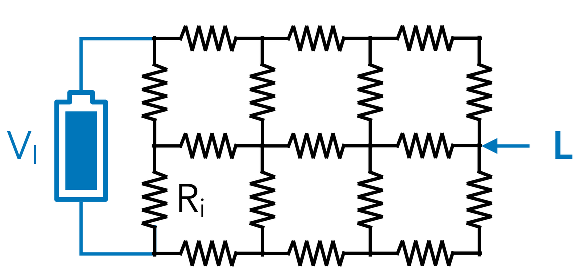
inflexible, prone to damage



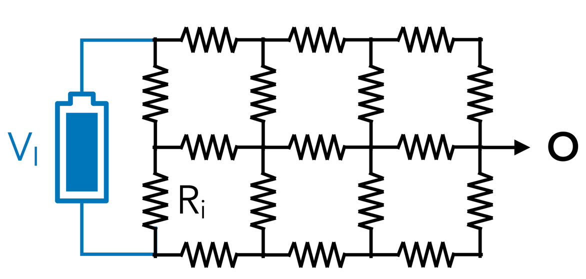
by calculation: digital ML

power hungry, inefficient

Our system uses physics + contrastive learning.



Clamp inputs & outputs



Free: apply inputs.

We build twin networks so we can access two electrical states.

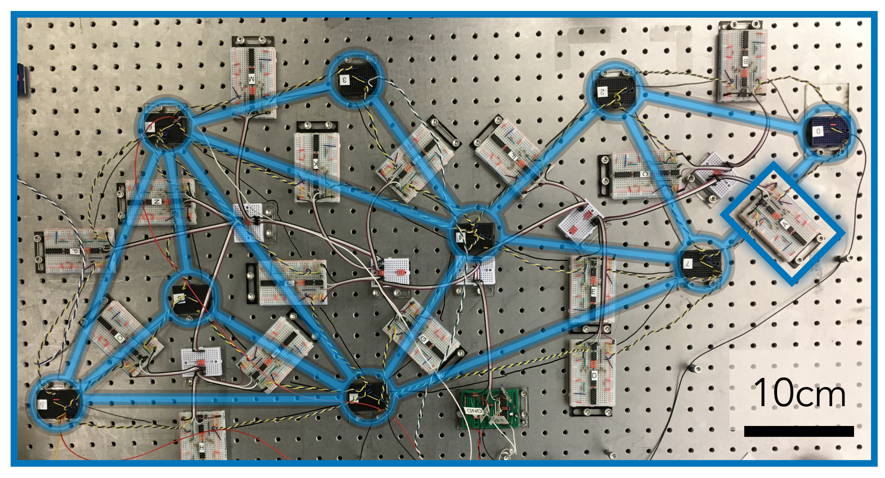
In the free state, **physics generates the output** O. In the clamped state, we enforce (or nudge towards) the label L. [1]

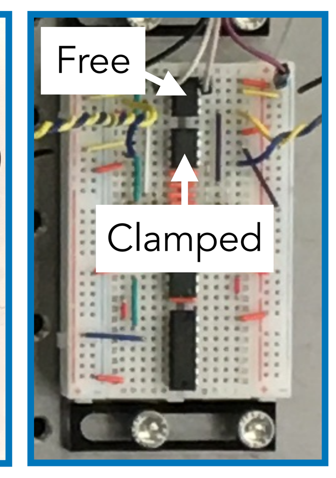
$$\Delta R_i = -\frac{\partial}{\partial R_i}[P_C - P_F] = \left[(V_i^C)^2 - (V_i^F)^2\right] R_i^{-2}$$

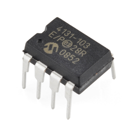
The **edges self-adjust to minimize the power difference** between the two states.

Using this local rule (and no outside calculation), the ensemble creates the desired functionality. That is, **learning is decentralized and physics-driven.**

Linear Network [2]

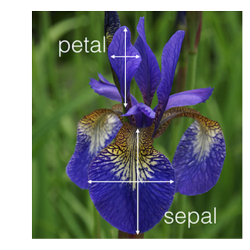


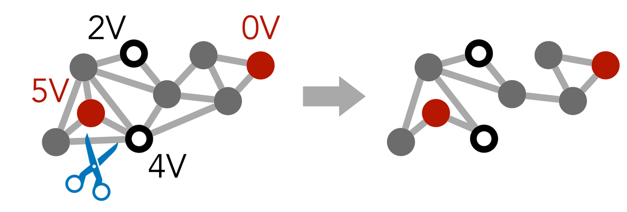




Digital variable resistors: linear, discrete resistances only.

Network able to **classify flowers from measurements** (iris dataset >95%)

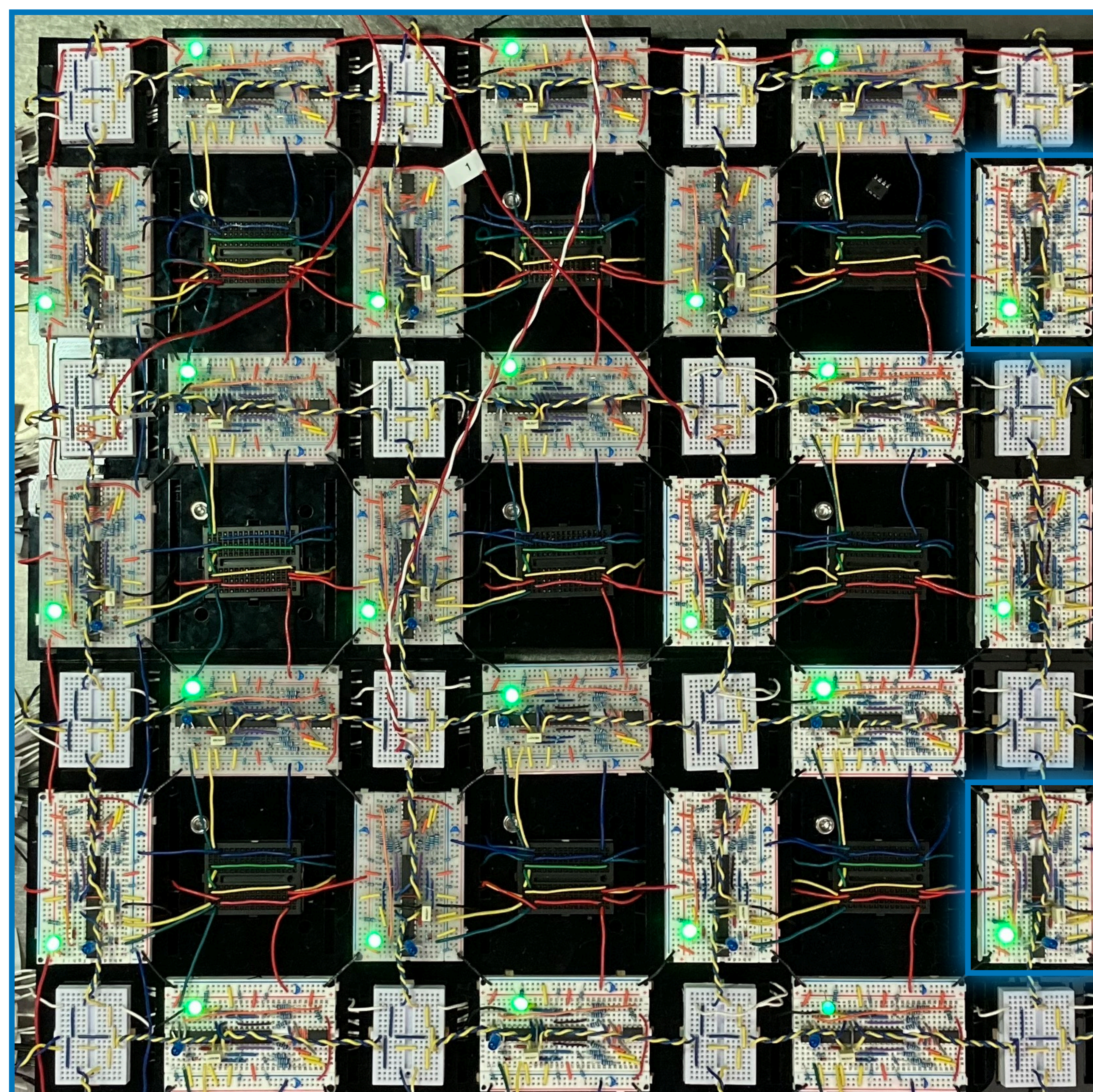


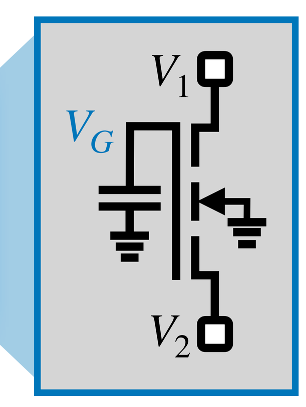


The ensemble is **robust to damage.**

This linear system is already useful for investigating physical learning: better solutions with **desynchronous updates**, and learns faster **out of equilibrium**. [3,4]

Nonlinear Network [5]

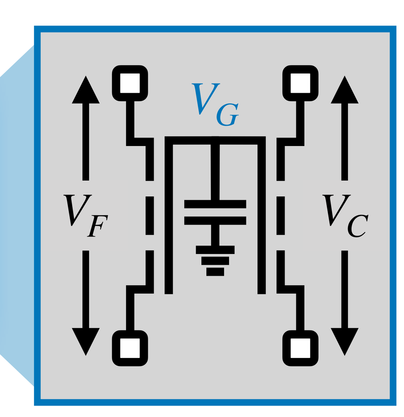




We use **transistors** as **nonlinear** resistors.

$$R^{-1} \propto V_G - V_{th} - \frac{V_1 + V_2}{2}$$

Twin edges (free & clamped) are the base unit of our system.



Updates are **continuous** and **local**

$$\dot{V}_G \propto V_F^2 - V_C^2$$

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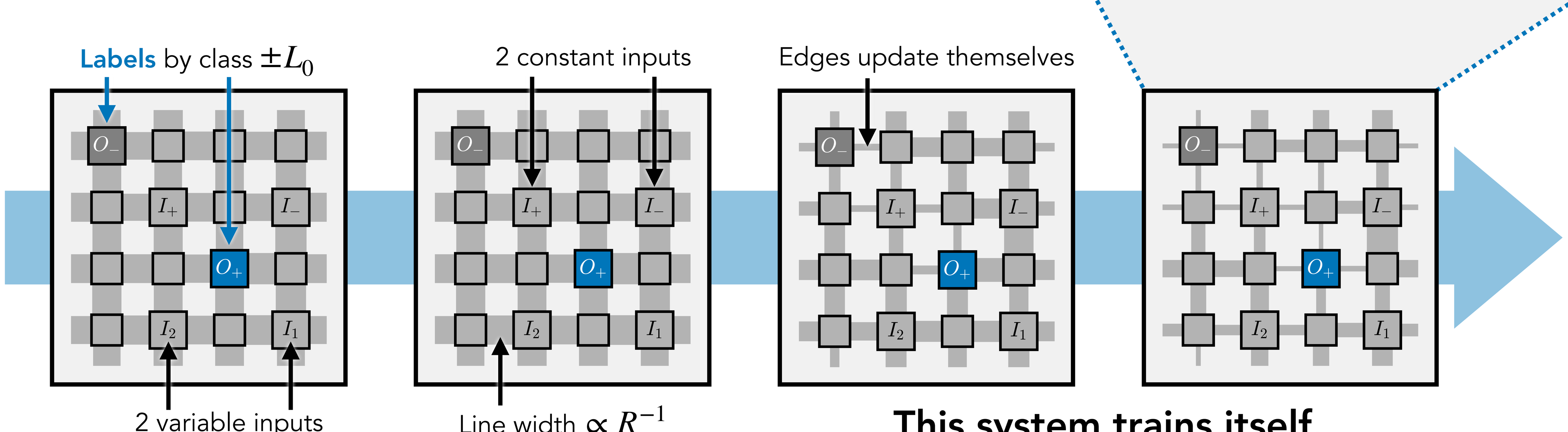
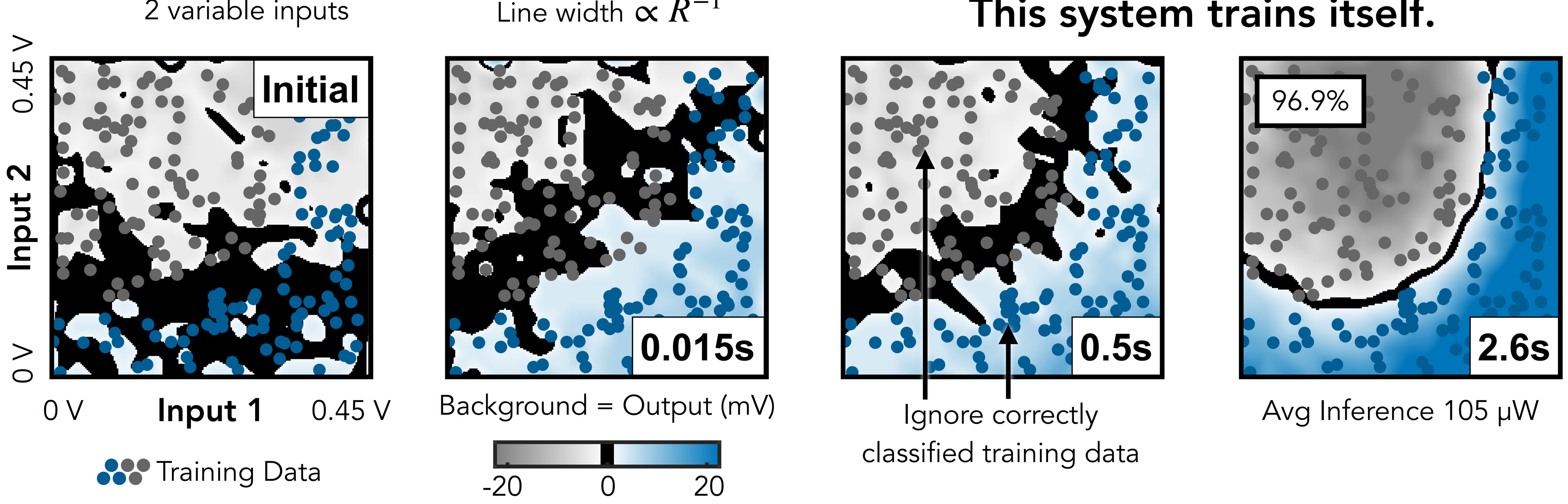


This system trains itself.



Training Data

Background = Output (mV)

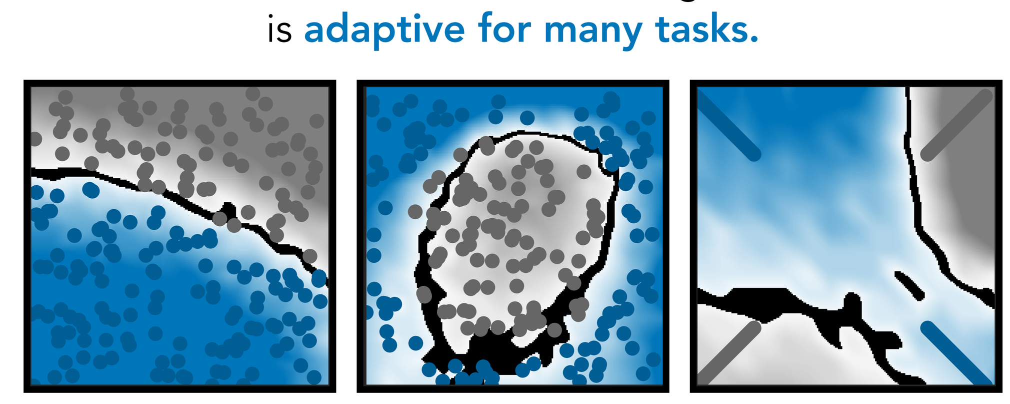
Ignore correctly classified training data

Avg Inference 105 μW

Applying inputs and labels triggers evolution. We allow the system to update only on incorrectly classified datapoints. The result is an **approximation of gradient descent on cross-entropy, but using entirely local rules.**

Because the resulting solution is a passive analog system, inference is **low power ~100 μW and rapid (μS)** [6]

One I/O and network configuration is **adaptive for many tasks.**



100% 99 μW | 94.3% 91 μW | 100% 84 μW

Even lower power may be achieved via modified learning rules [7].

[1] M Stern, et. al. *PRX* 2021
[2] S Dillavou, M Stern et. al. *PRApplied* 2022
[3] JF Wycoff, S Dillavou et. al. *J Chem Phys* 2022
[4] M Stern, S Dillavou, et. al. *PRR* 2022
[5] S Dillavou et. al. arXiv 2311.00537
[6] Power calculated as sum of dissipation over edges
[7] M Stern, S Dillavou, et. al. arXiv 2310.10437

Our method is built on many works studying learning, e.g.
Contrastive learning: JR Movellan 1991
Equilibrium propagation: Scellier & Bengio 2017
Tuning in silico networks: Goodrich et. al. *PRL* 2015
Directed aging: Pashine et. al. *Sci Adv* 2019

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Looking forward, we aim to scale up our networks to create **fast, efficient neuromorphic hardware** for machine learning and studying emergent learning.