Challenges in Neuromorphic Computing

Tackling Reliability and Scalability via Noise-aware Learning

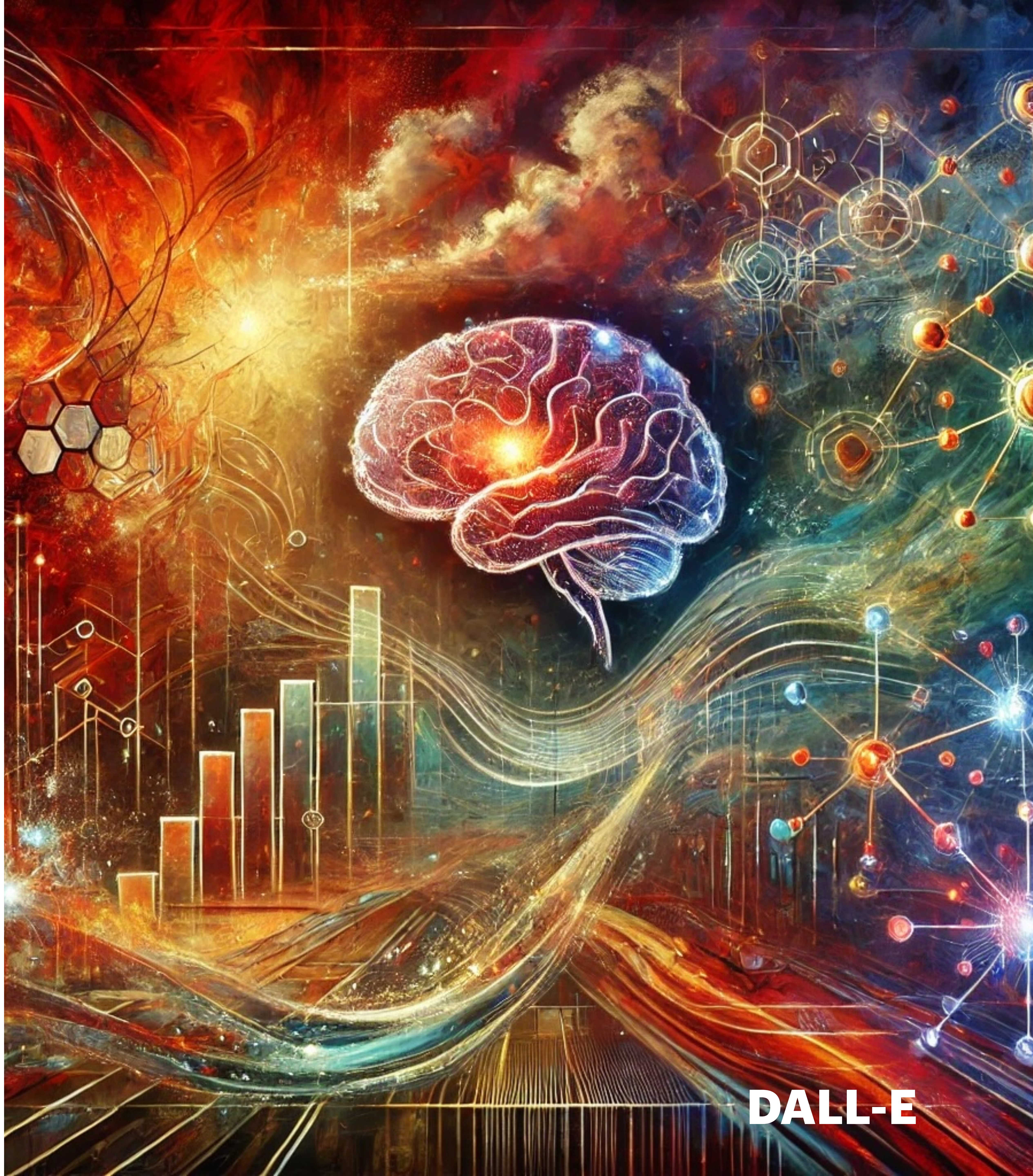
Professor Eleni Vasilaki, Computer Science, University of Sheffield

Challenges

Neuromorphic Computing

- Variability
- Scalability
- ...

AI



Challenges

Variability

Neuromorphic Computing and Engineering

LETTER • OPEN ACCESS

Machine learning using magnetic stochastic synapses

Matthew O A Ellis[4,5,1], Alexander Welbourne[4,2], Stephan J Kyle[2], Paul W Fry[3], Dan A Allwood[2], Thomas J Hayward[2] and Eleni Vasilaki[1]

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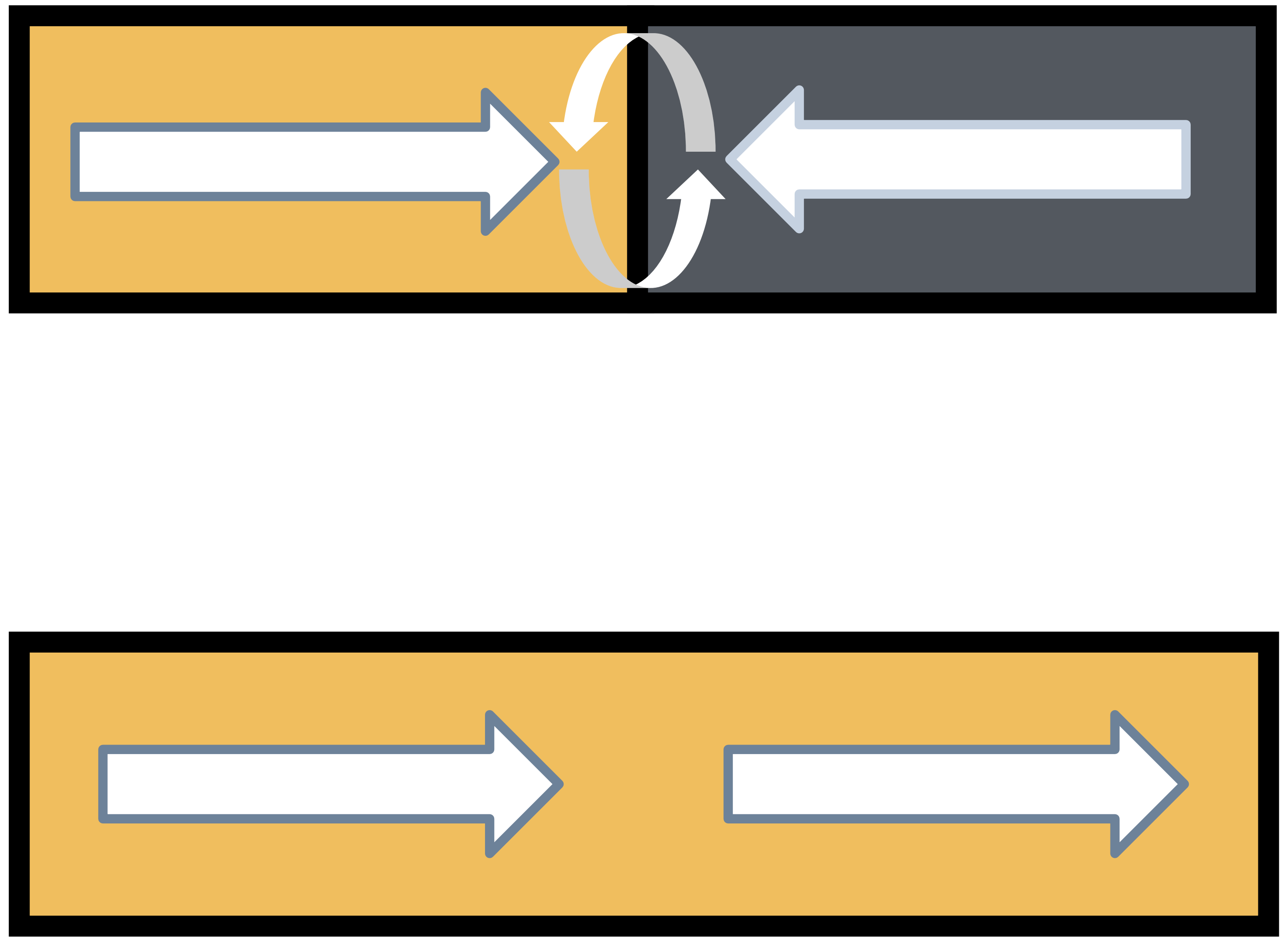
Focus on Neuromorphic Circuits and Systems using Emerging Devices

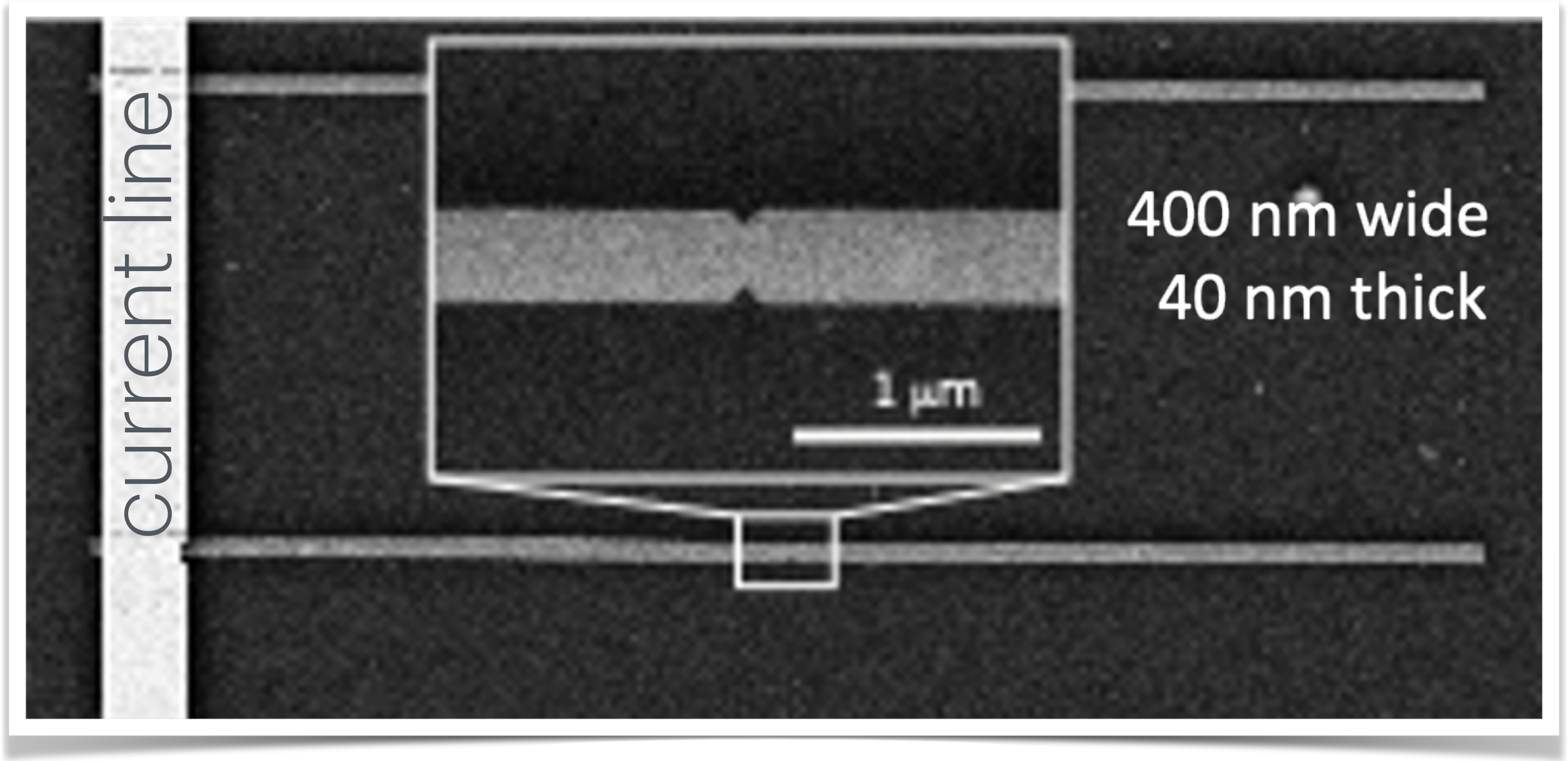
Citation Matthew O A Ellis *et al* 2023 *Neuromorph. Comput. Eng.* **3** 021001

DOI 10.1088/2634-4386/acdb96

Domain wall (DW)



Magnetic field h

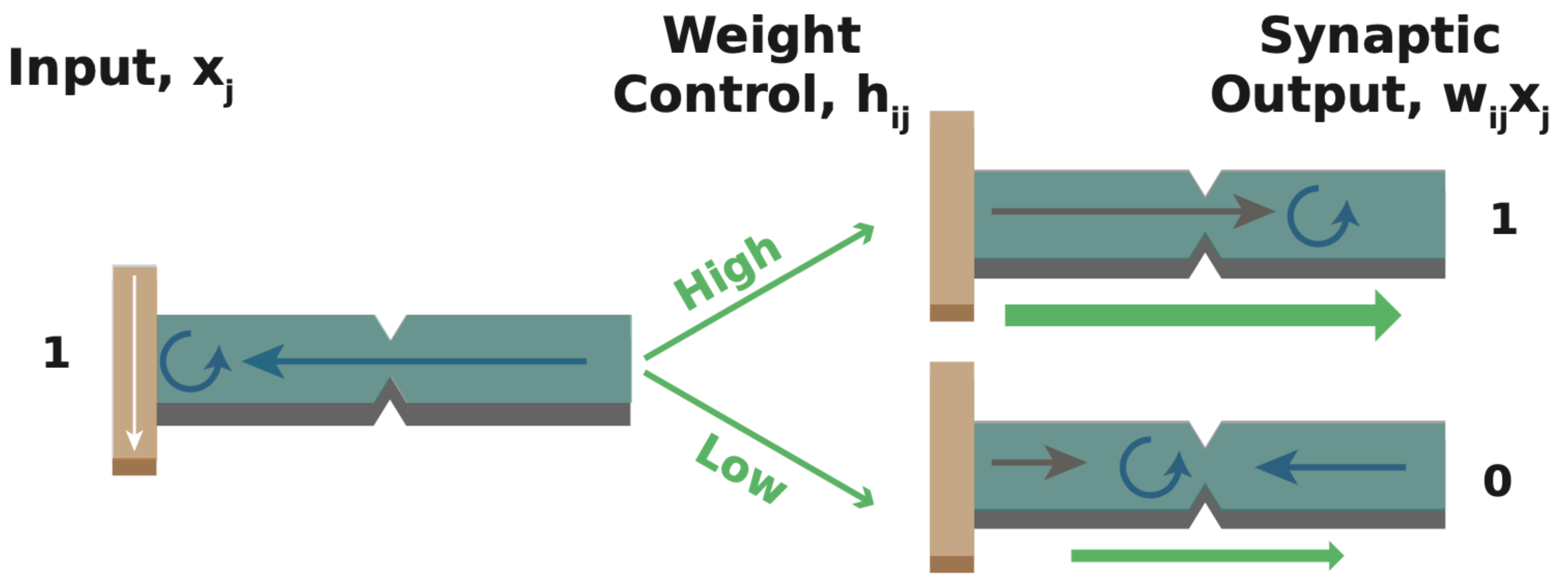


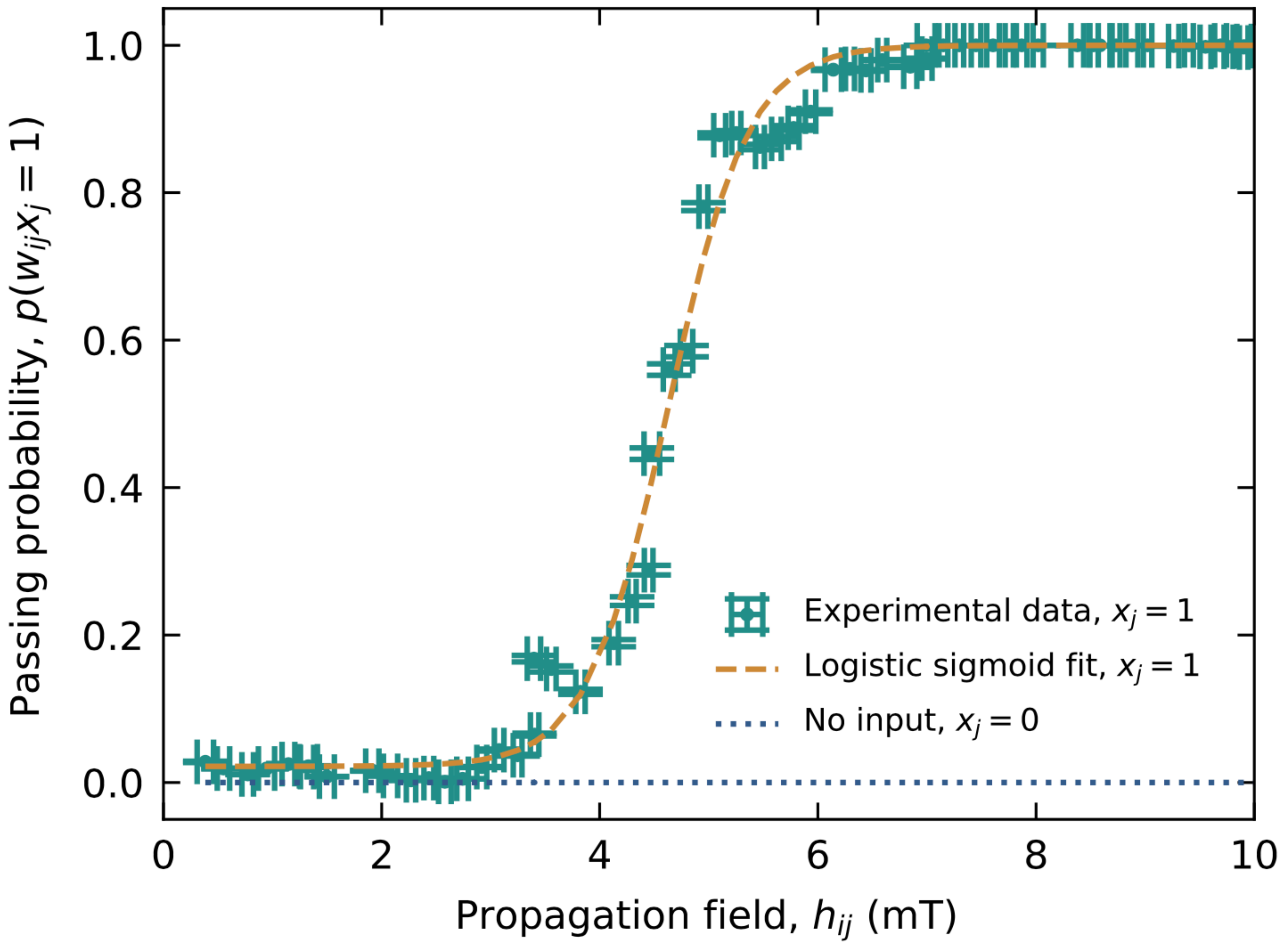
Ni80Fe20 nanowires

Vortex DW holds binary information

Domain wall logic

Magnetic field h

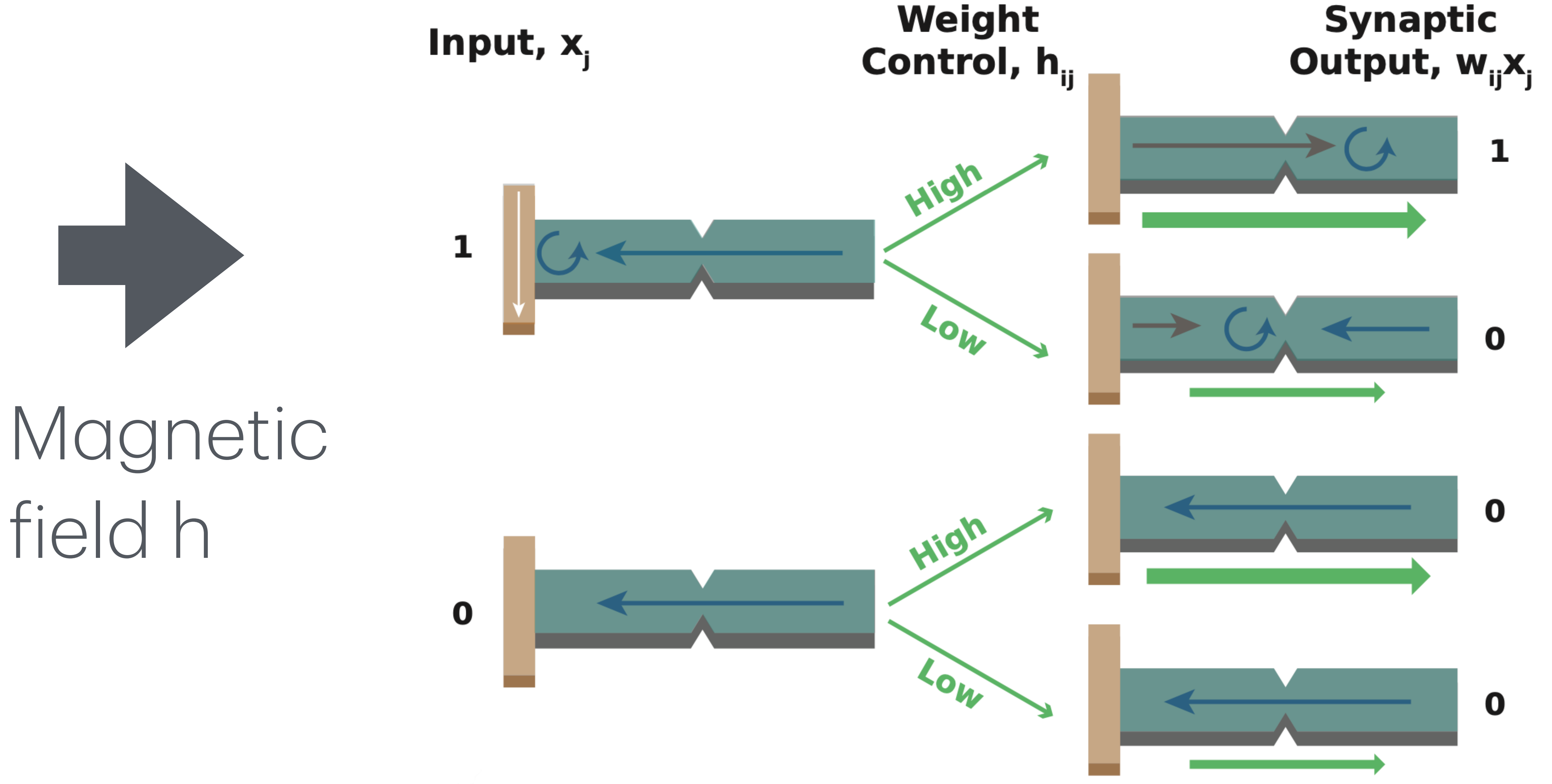


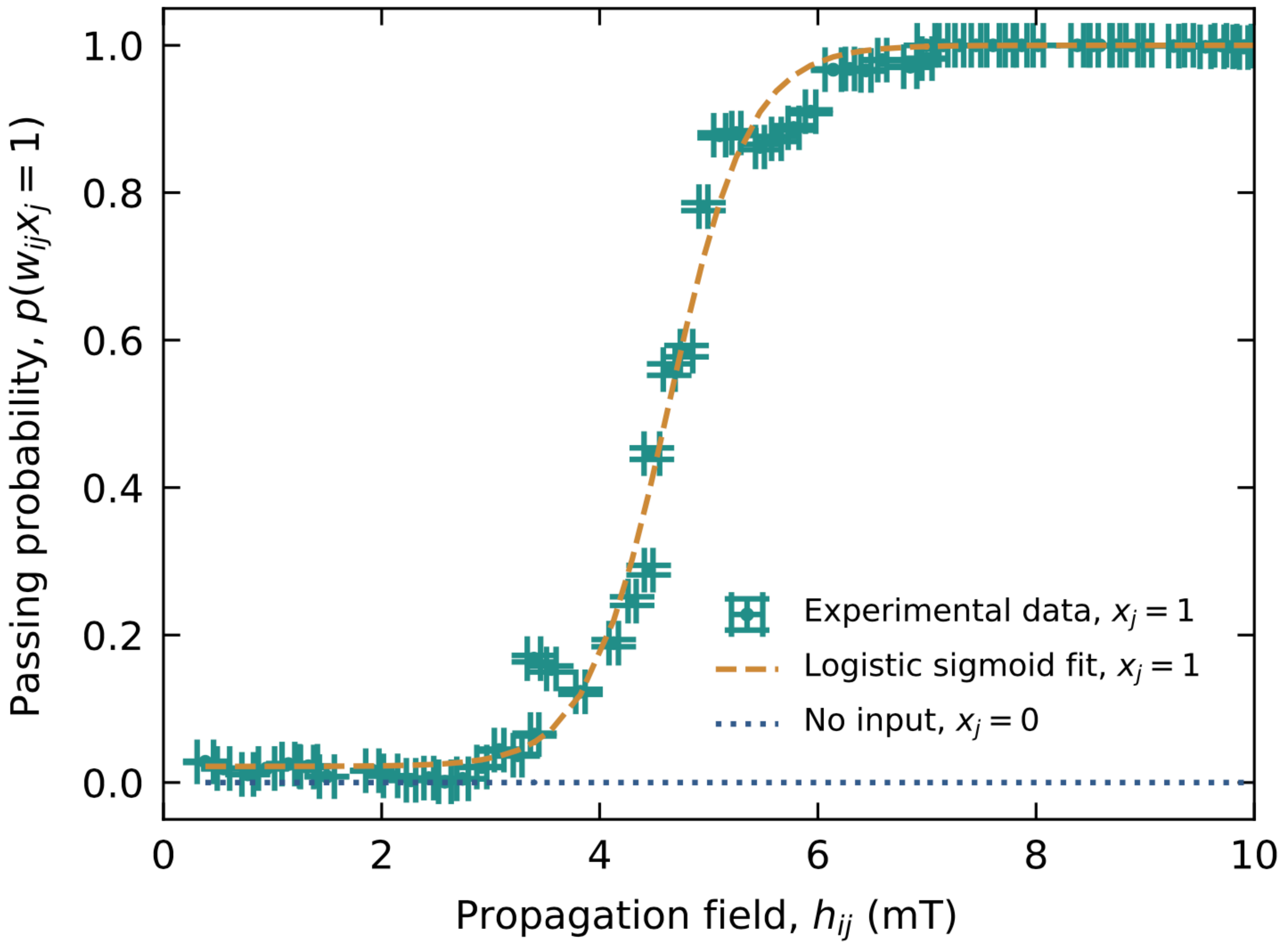


By changing h we can manipulate the passing probability


DALL-E

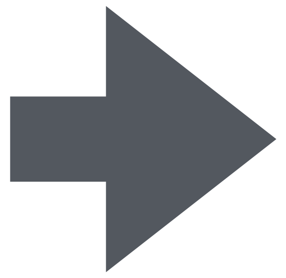
Domain wall logic



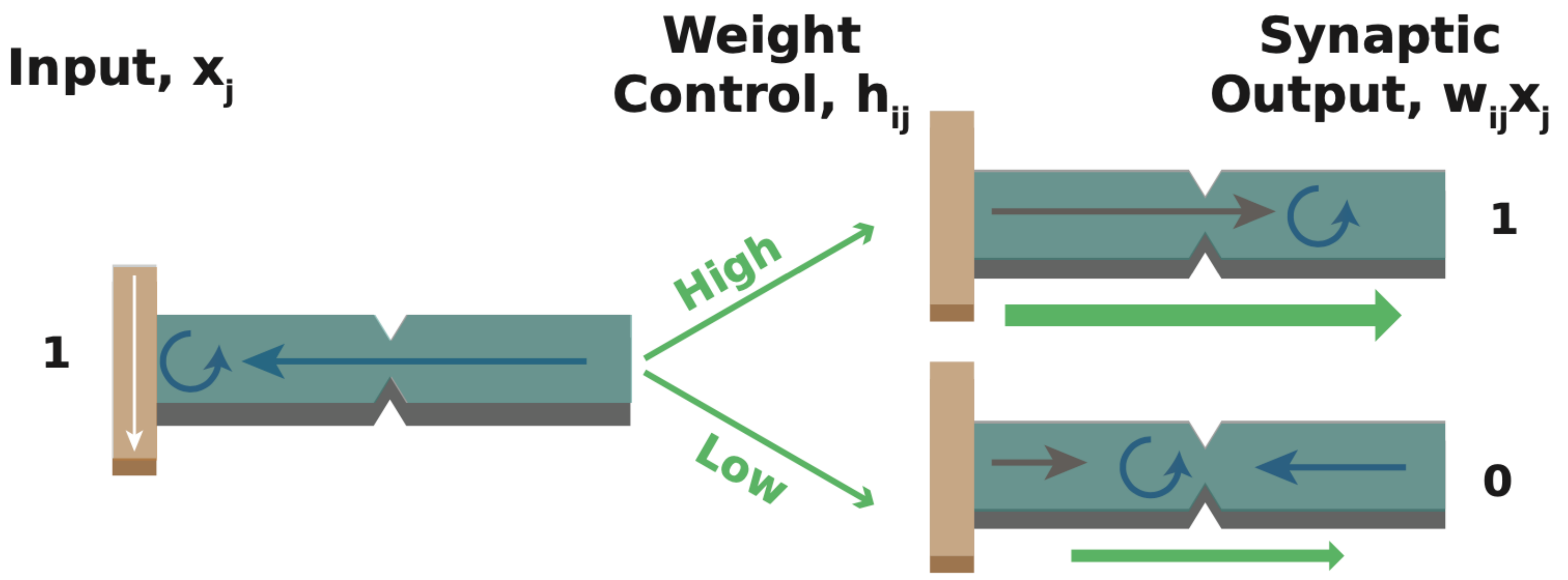


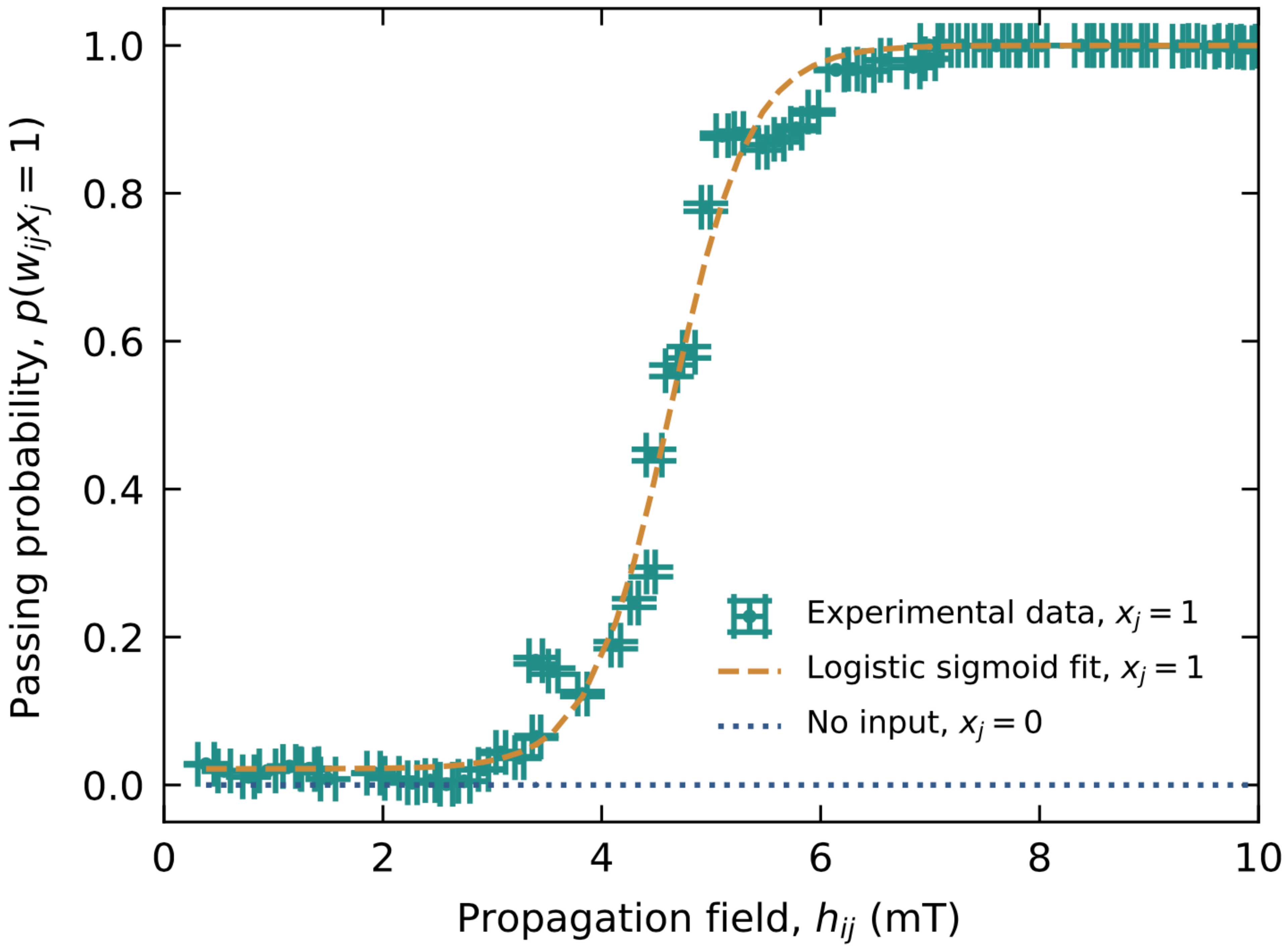
$$w_{ij} = \begin{cases} 1 & \text{with probability } f\left(h_{ij}\right) \\ 0 & \text{otherwise} \end{cases}$$

Domain wall logic



Magnetic field h

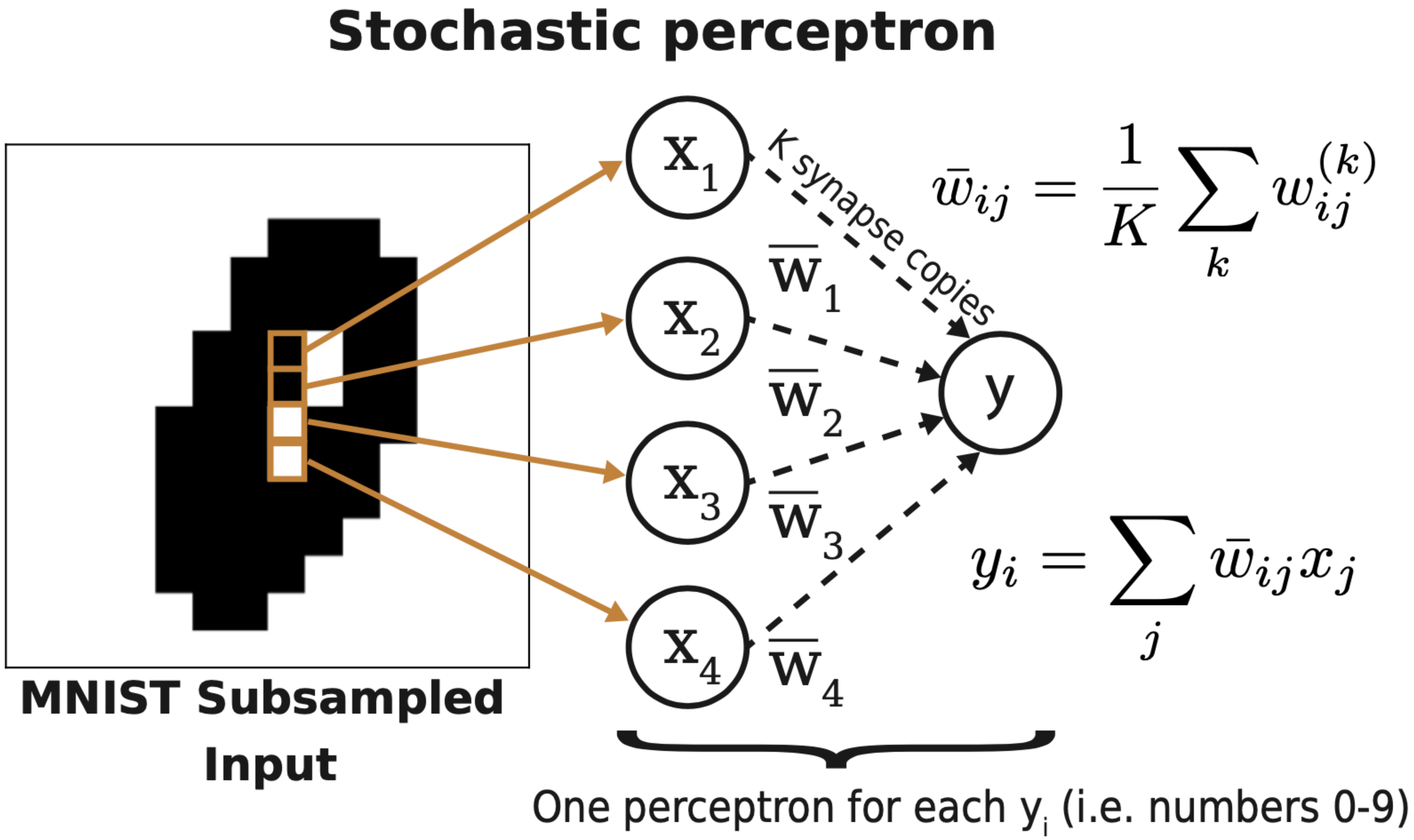




By sampling many times (or have many parallel devices) we go from binary to analogue

Magnetic synapse

Lab: resemble the same device K times



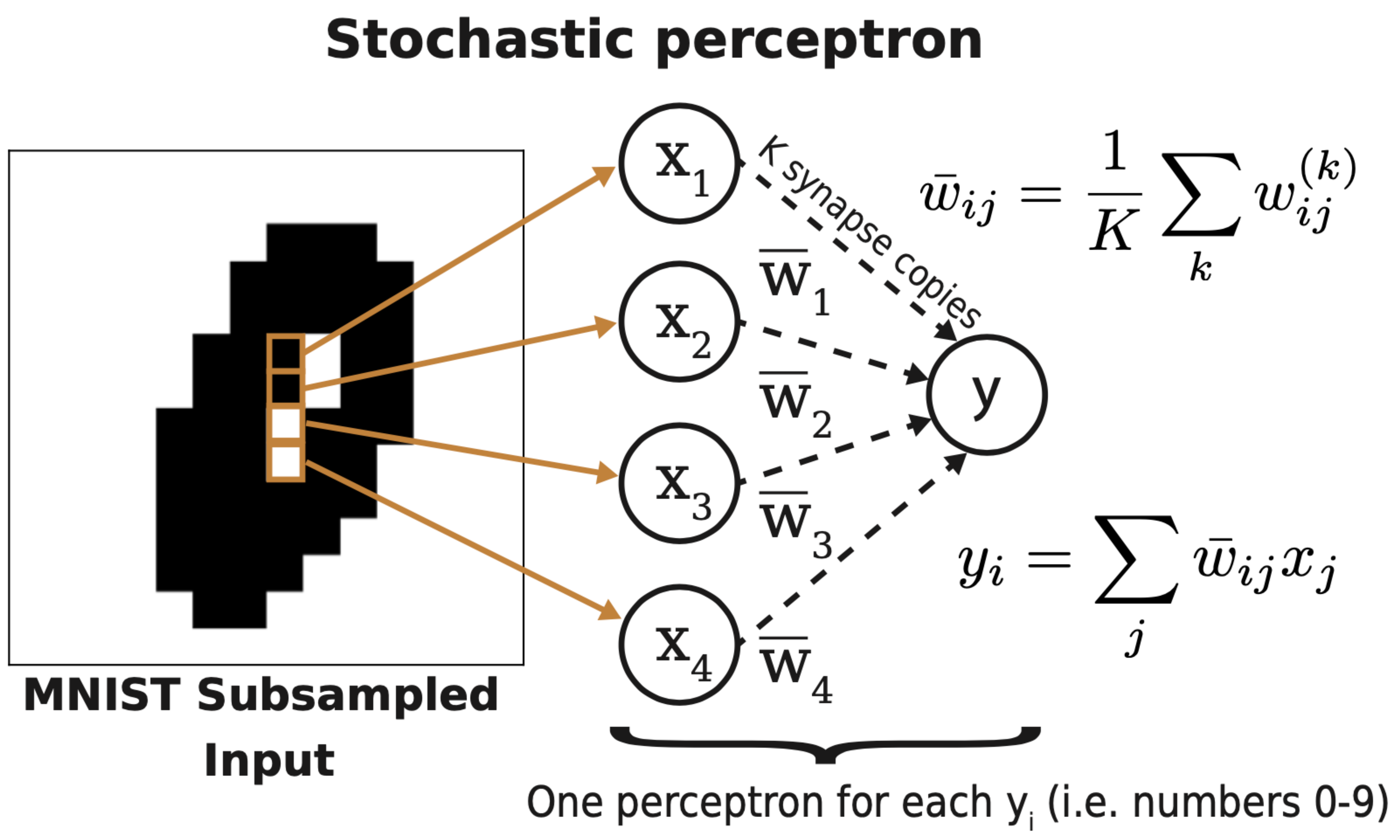
Magnetic synapse

$$y_i = f(h_{ij}, x_j)$$

Adjust the field for each synapse to get the "desirable" output

$$\mathscr{L} = g(y_i, y_i^d)$$

$$\Delta h_{ij} \propto -\frac{\partial \mathscr{L}}{\partial h_{i,j}}$$



Magnetic synapse

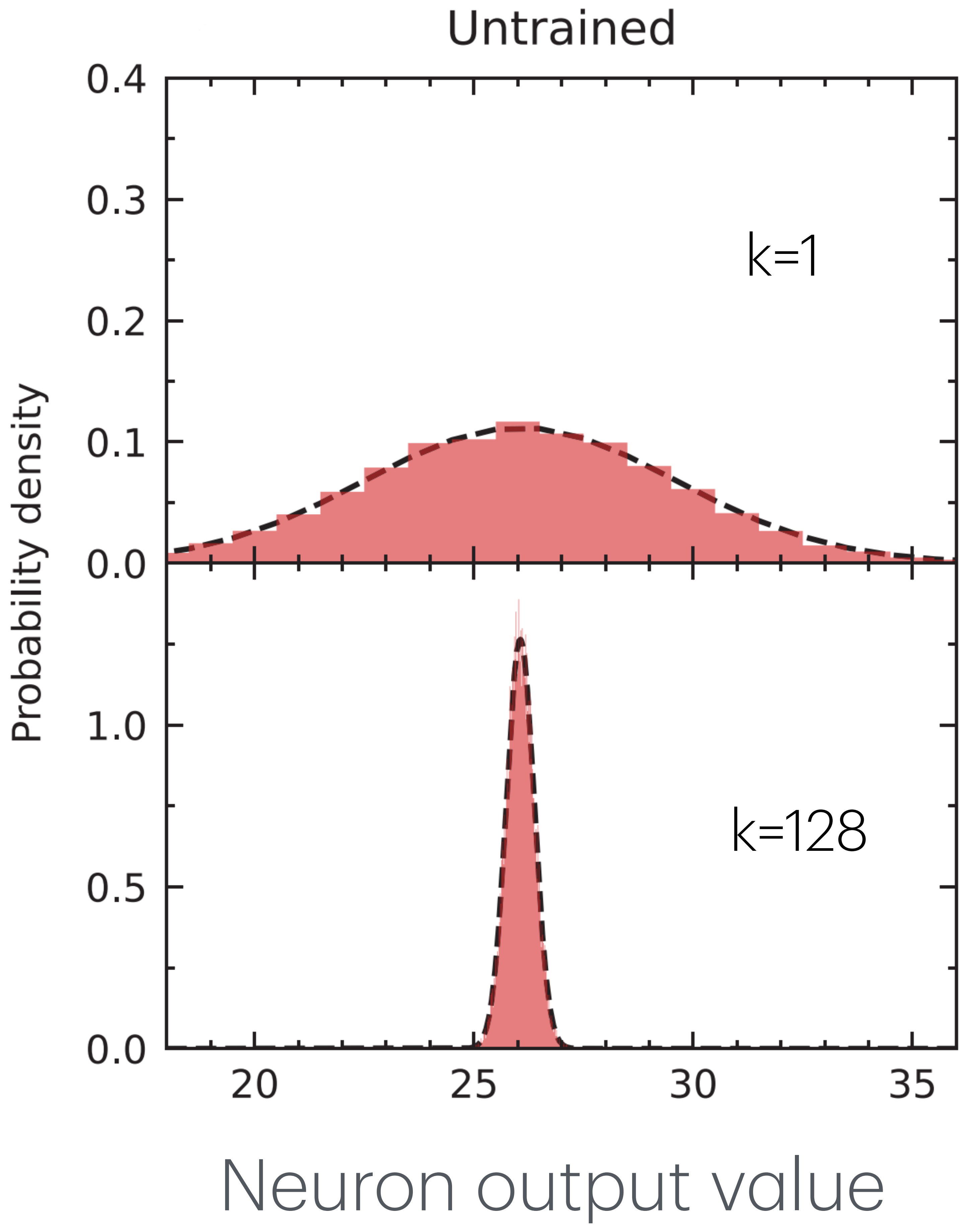
$$y_i = \frac{1}{K} \sum_j \sum_k w_{ij}^{(k)} x_j$$

$$\tilde{y}_i = \mu_i + \sigma_i \xi_i, \quad \xi_i \text{ sample from N(0,1)}$$

$$\mu_i = \sum_j f(h_{ij}) x_j$$

$$\sigma_i^2 = \frac{1}{K} \sum_j f(h_{ij}) x_j \left[1 - f(h_{ij}) x_j \right]$$

fields initialised to give the largest possible variance



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$$\sigma_i^2 = \frac{1}{K} \sum_j f(h_{ij}) x_j \left[1 - f(h_{ij}) x_j \right]$$

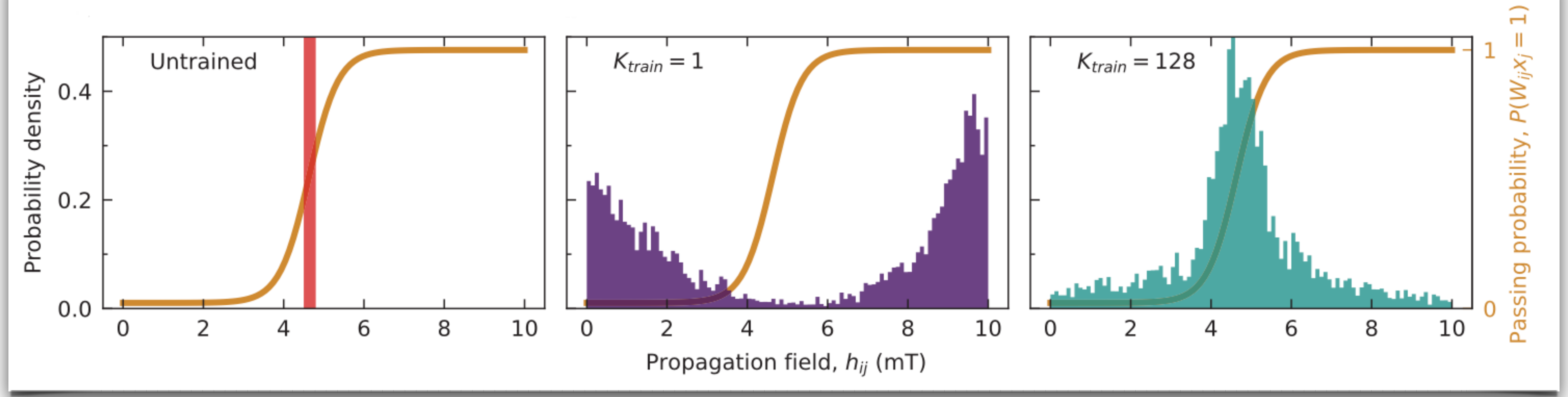
$$\Delta h_{ij} = -\eta \frac{\partial \mathscr{L}(\tilde{y})}{\partial \tilde{y}_i} \frac{\partial \tilde{y}_i}{\partial h_{ij}} \qquad \eta\text{: learning rate}$$

$$= -\eta \frac{\partial \mathscr{L}(\tilde{y})}{\partial \tilde{y}_i} \left(\frac{\partial \mu_i}{\partial h_{ij}} + \frac{\partial \sigma_i}{\partial h_{ij}} \xi_i \right)$$

mean

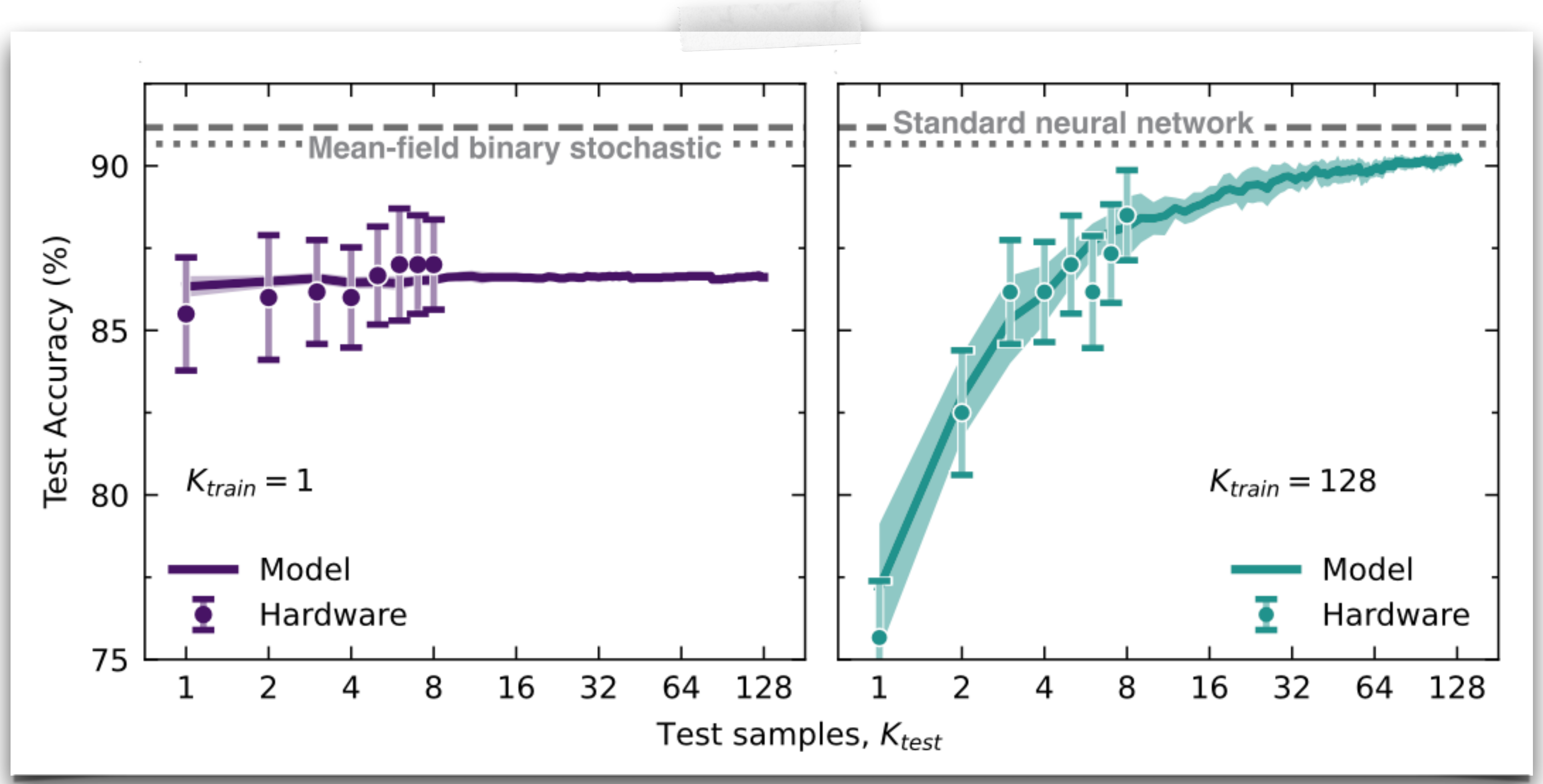
variance

An algorithm that learns from the variance



$$\sigma_i^2 = \frac{1}{K} \sum_j f(h_{ij}) x_j \left[1 - f(h_{ij}) x_j \right]$$

Transferability to Hardware



Effective due to noise modelling

Challenges

Scalability

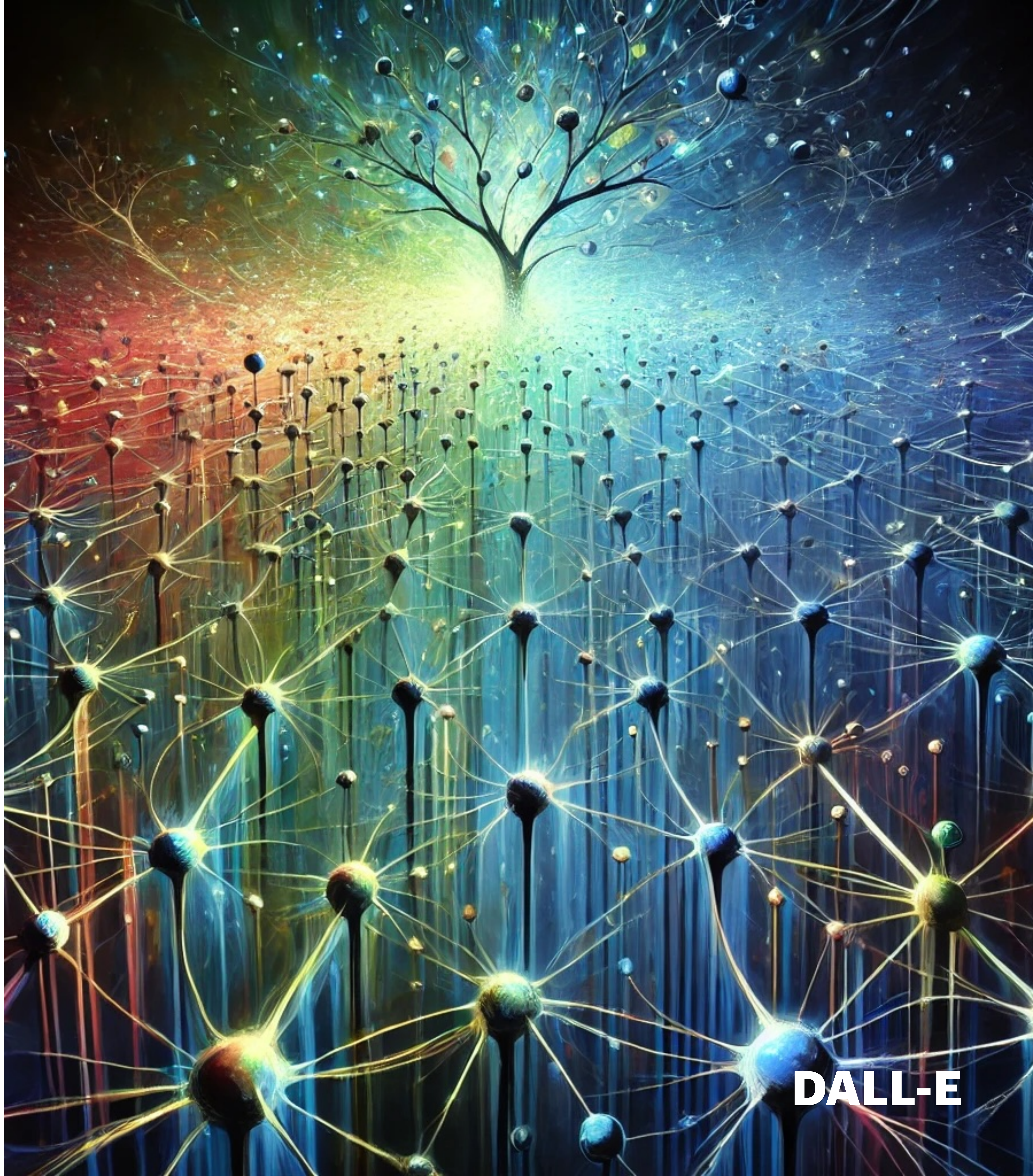
nature > nature communications > articles > article

Article | Open access | Published: 27 August 2024

Neuromorphic overparameterisation and few-shot learning in multilayer physical neural networks

Kilian D. Stenning, Jack C. Gartside, Luca Manneschi, Christopher T. S. Cheung, Tony Chen, Alex Vanstone, Jake Love, Holly Holder, Francesco Caravelli, Hidekazu Kurebayashi, Karin Everschor-Sitte, Eleni Vasilaki & Will R. Branford

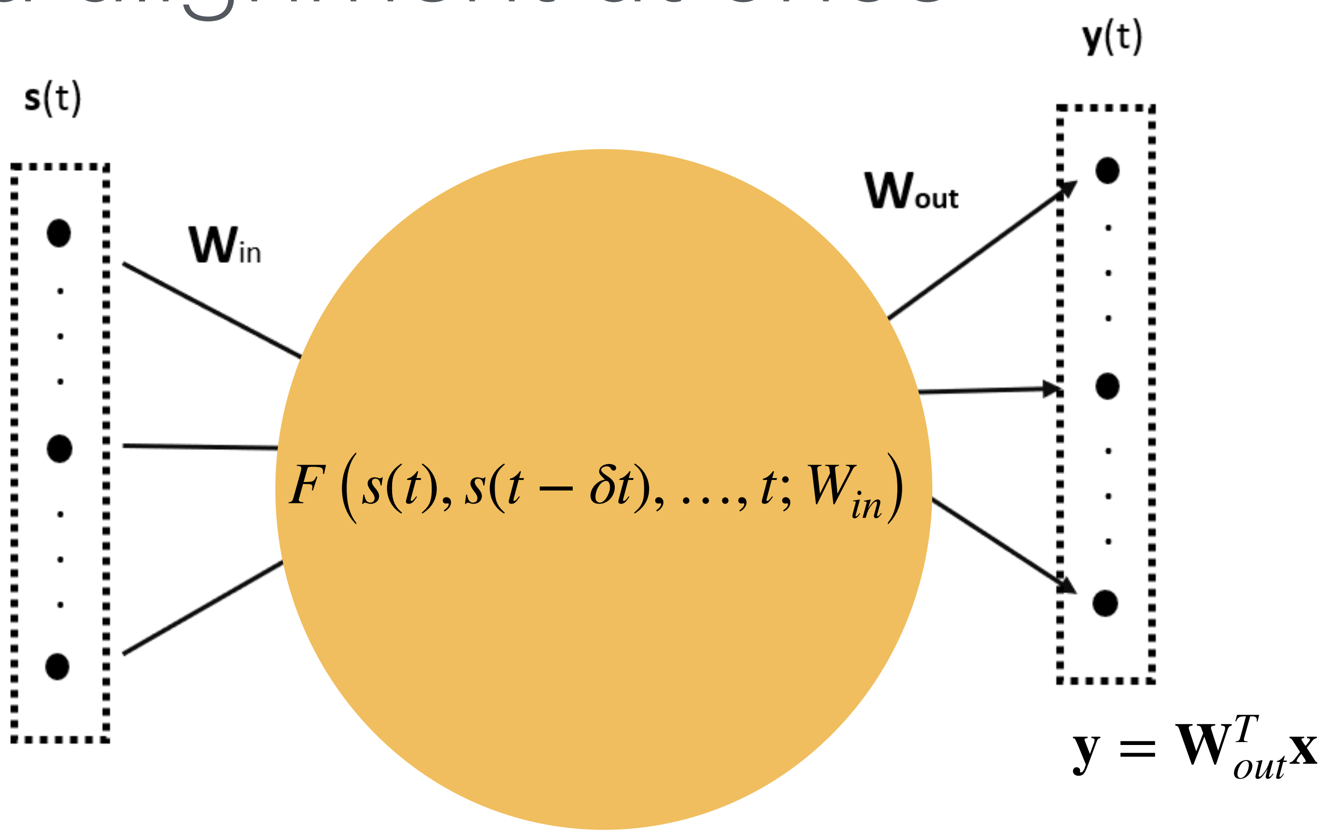
Nature Communications **15**, Article number: 7377 (2024) | Cite this article



Physical reservoir computing

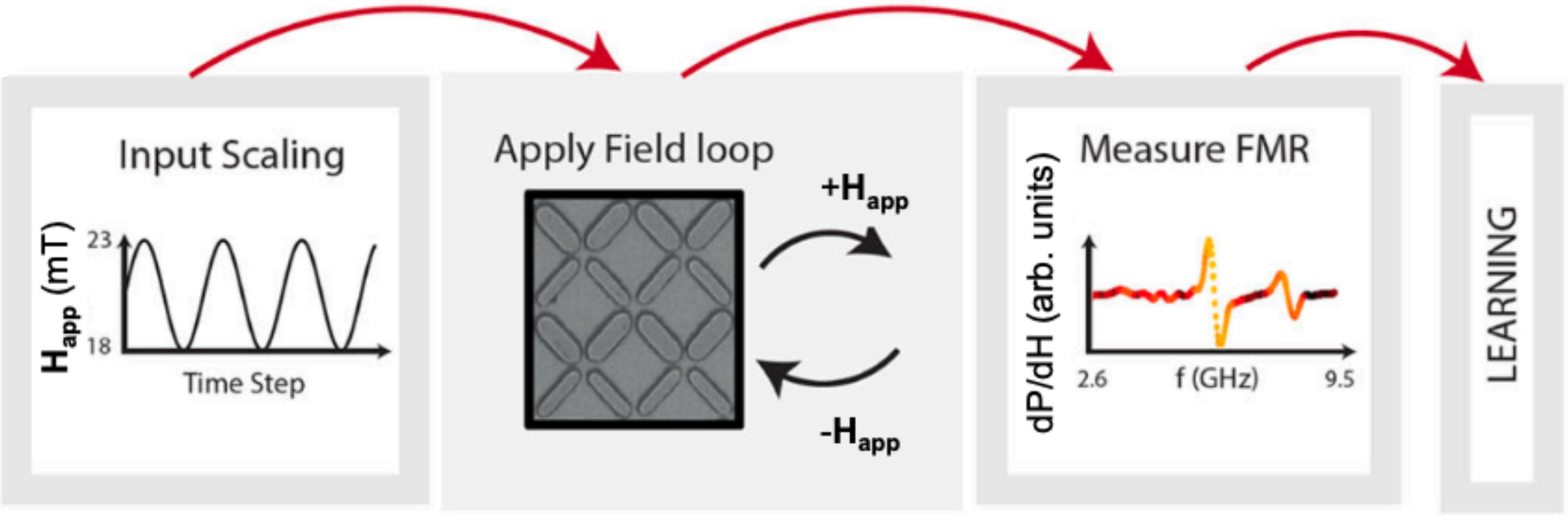
Cannot satisfy their preferred alignment at once

Spin Ice



Exploit high dimensionality and non-linearity to achieve a "rich" representation

Learning only output connections



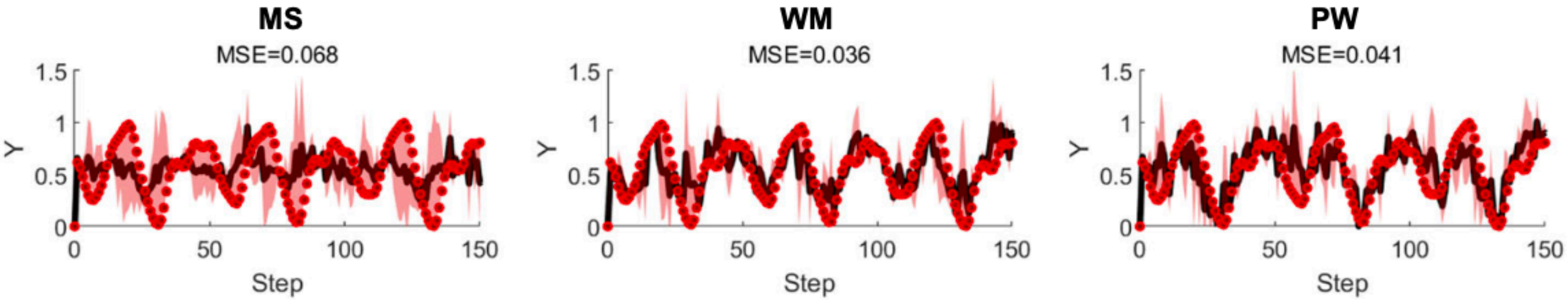
$$H_{app} = H_0 + H_{scale} * S(t)$$

Ferromagnetic resonance (FMR) spectroscopy

Nanomagnetic (spin ice) reservoirs

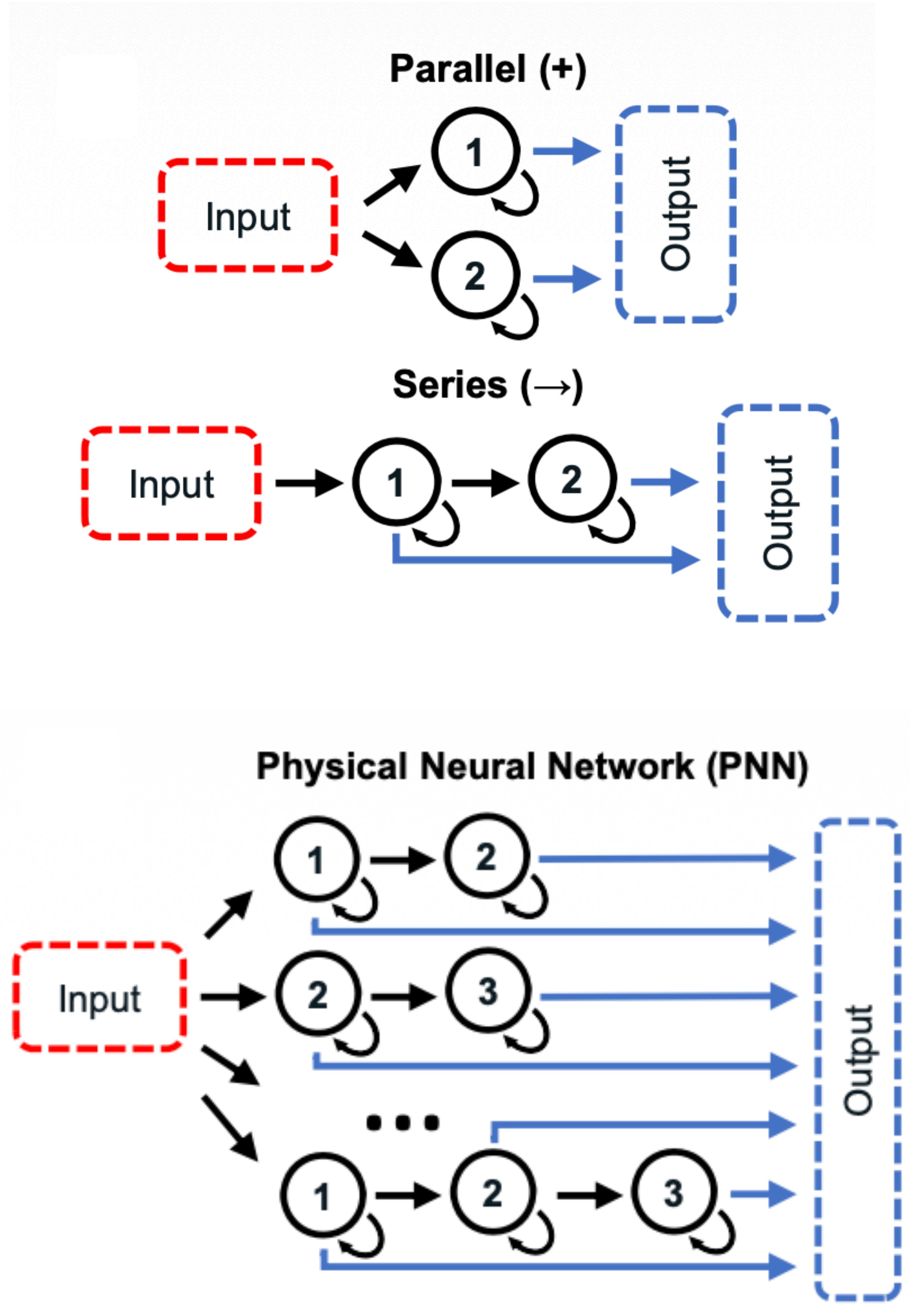
Mackey Glass
Future Prediction *t*+7

$$\frac{dx(t)}{dt} = \beta \frac{x(t-\tau)}{1 + x(t-\tau)^n} - \gamma x(t)$$



Square macrospin-only (MS); Width-modified (WM); Disorderded Pinwheel (PW).

Physical neural network



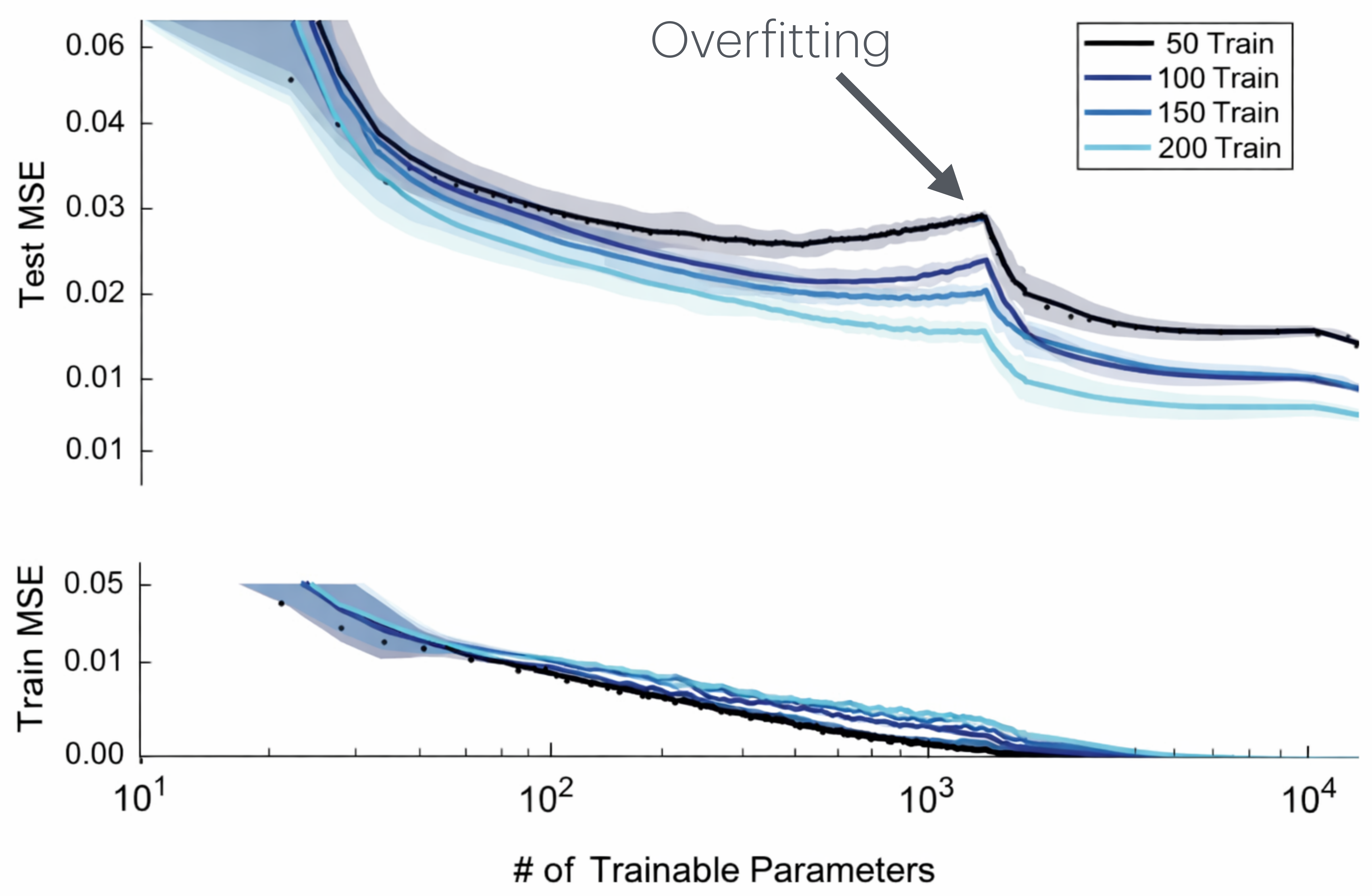
Simple connecting criteria

- Low memory to high memory reservoir
- Pick one output frequency channel (per node)
- Choose channel by
  - Corr with past inputs or
  - $NL=1-R^2$ of channel
- Rescale channel to next node's input range

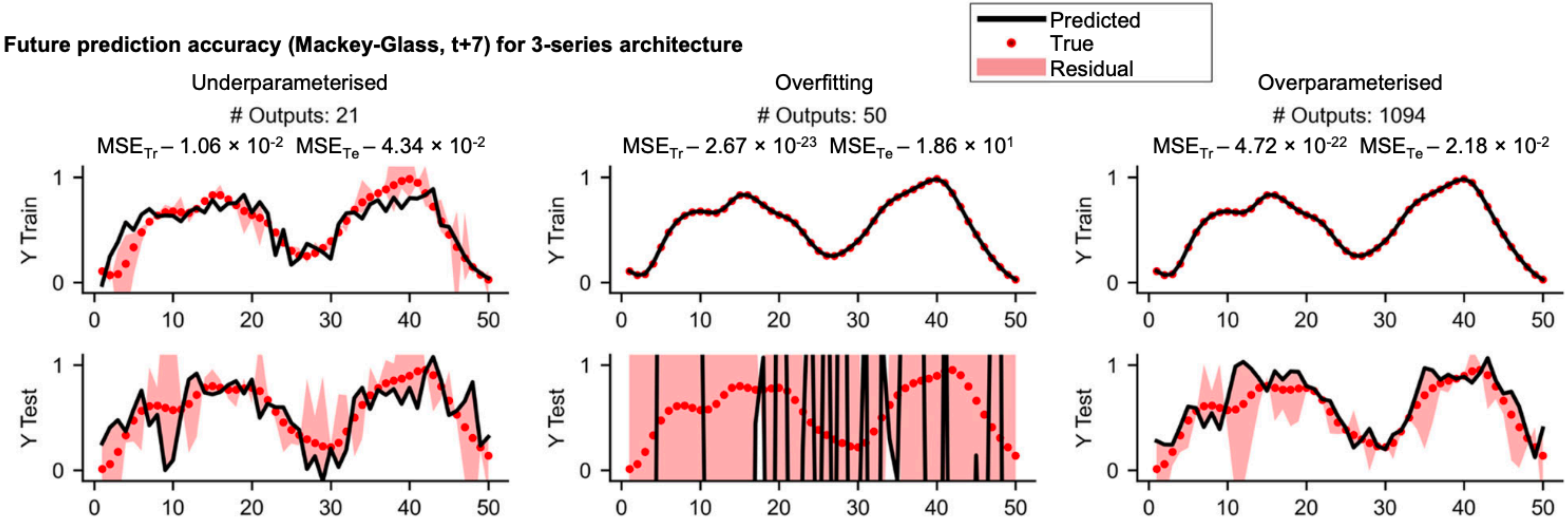
Selection of output channels: uncorrelated

Shallow learning

Overparametrisation in physical systems



Overparametrisation in physical systems



~40% lower test MSE to the best single reservoir.

Challenges

Variability + Scalability

nature communications

Article

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Noise-aware training of neuromorphic dynamic device networks

Received: 3 December 2024

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Luca Manneschi[1,5], Ian T. Vidamour[1,5], Kilian D. Stenning[2], Charles Swindells[1], Guru Venkat[1], David Griffin[3], Lai Gui[2], Daanish Sonawala[2], Denis Donskikh[2], Dana Hariga[1], Elisa Donati[4], Susan Stepney[3], Will R. Branford[2], Jack C. Gartside[2], Thomas J. Hayward[1], Matthew O. A. Ellis[1] & Eleni Vasilaki[1]

ADVANCED FUNCTIONAL MATERIALS

Full Paper | Open Access

2021

Dynamically Driven Emergence in a Nanomagnetic System

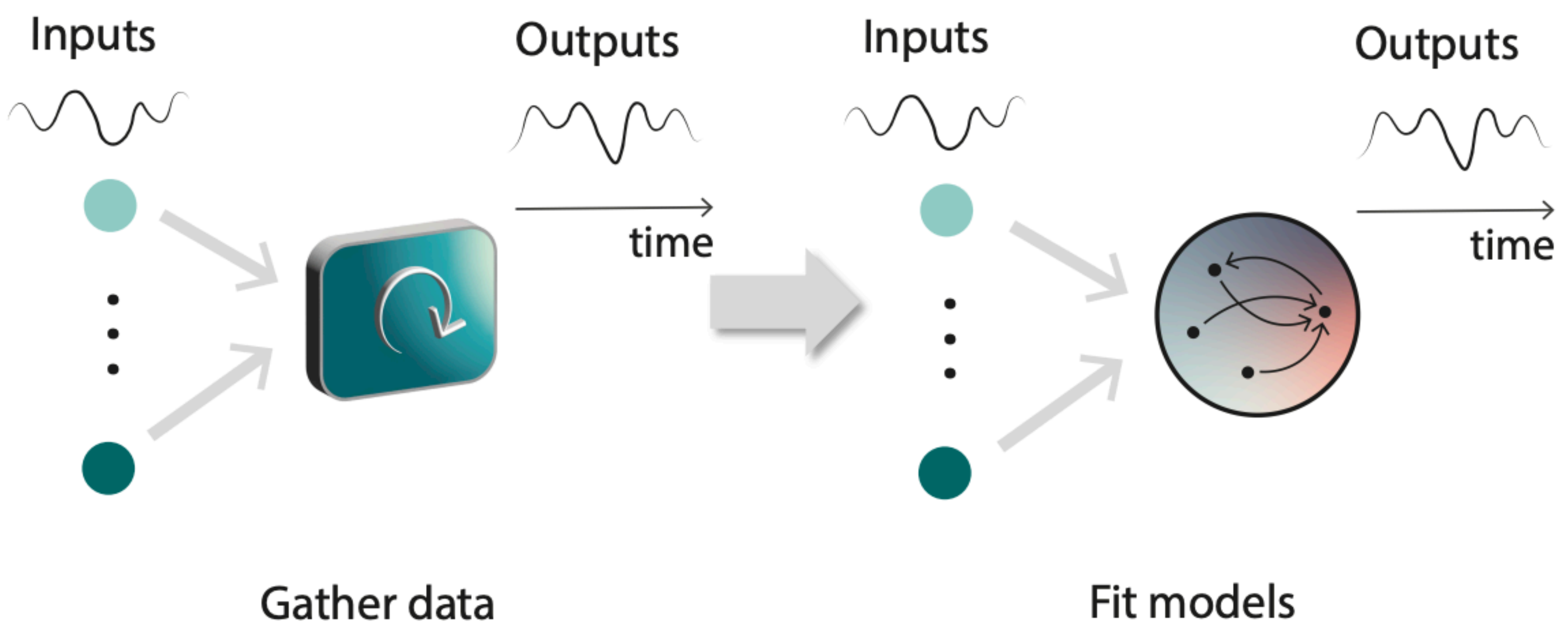
Richard W. Dawidek, Thomas J. Hayward, Ian T. Vidamour, Thomas J. Broomhall, Guru Venkat, Mohanad Al Mamoori, Aidan Mullen, Stephan J. Kyle, Paul W. Fry, Nina-Juliane Steinke, Joshaniel F. K. Cooper, Francesco Maccherozzi, Sarnjeet S. Dhesi, Lucia Aballe, Michael Foerster, Jordi Prat, Eleni Vasilaki, Matthew O. A. Ellis, Dan A. Allwood

Obstacle for interconnecting devices

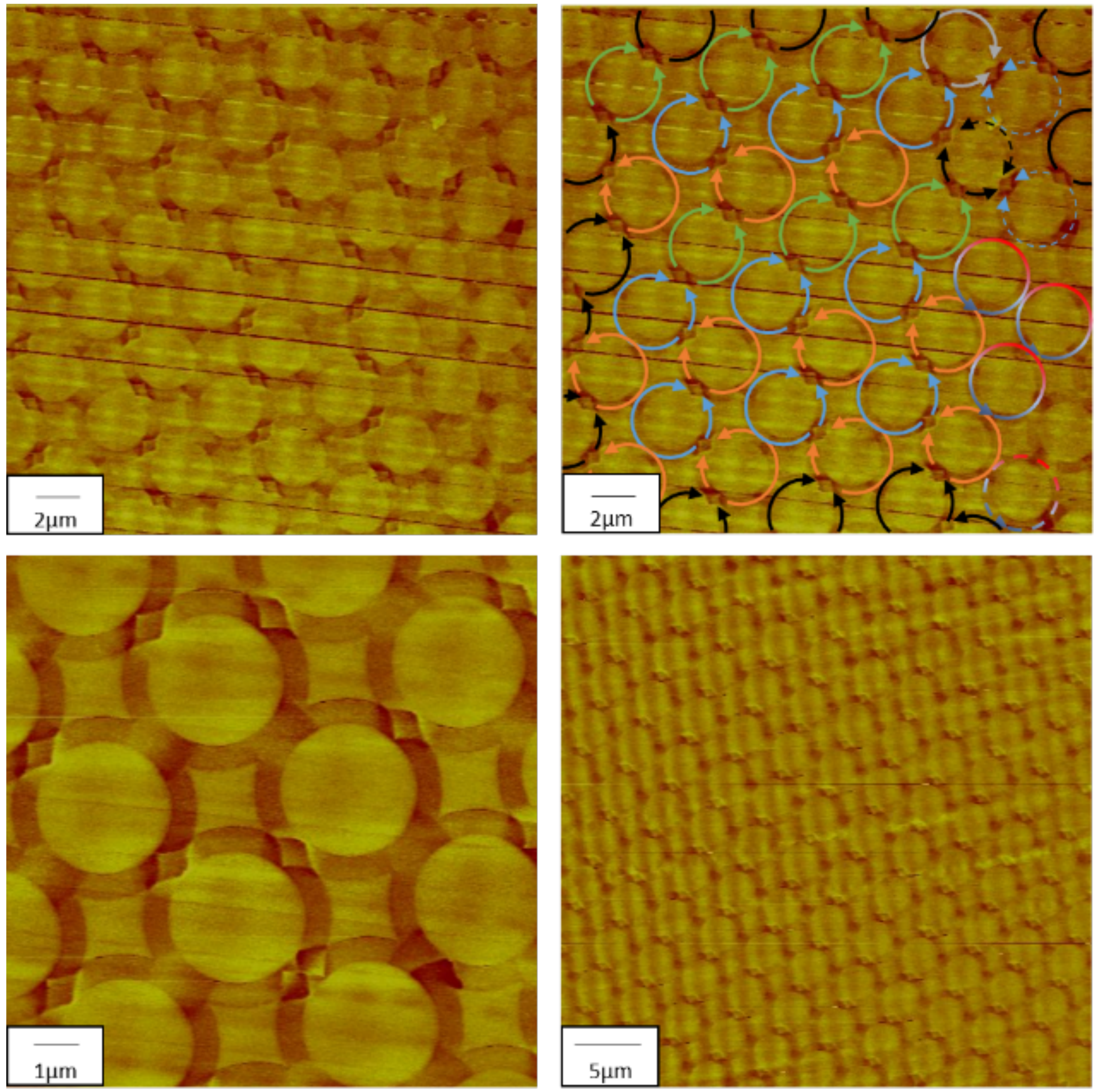
Many devices lack mathematical models

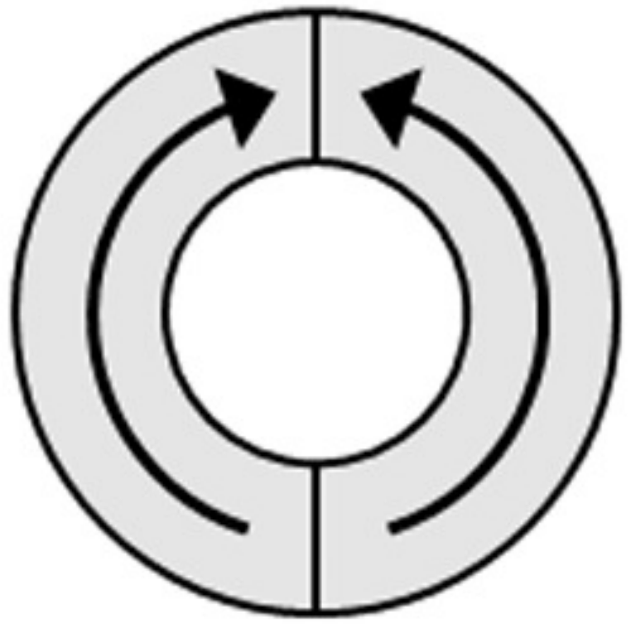
Devices without dependancies through time: Wright et al Nature 2022

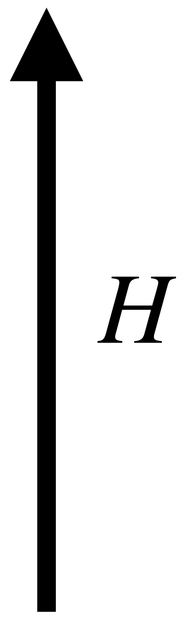
Digital twins via AI techniques



NanoRing arrays

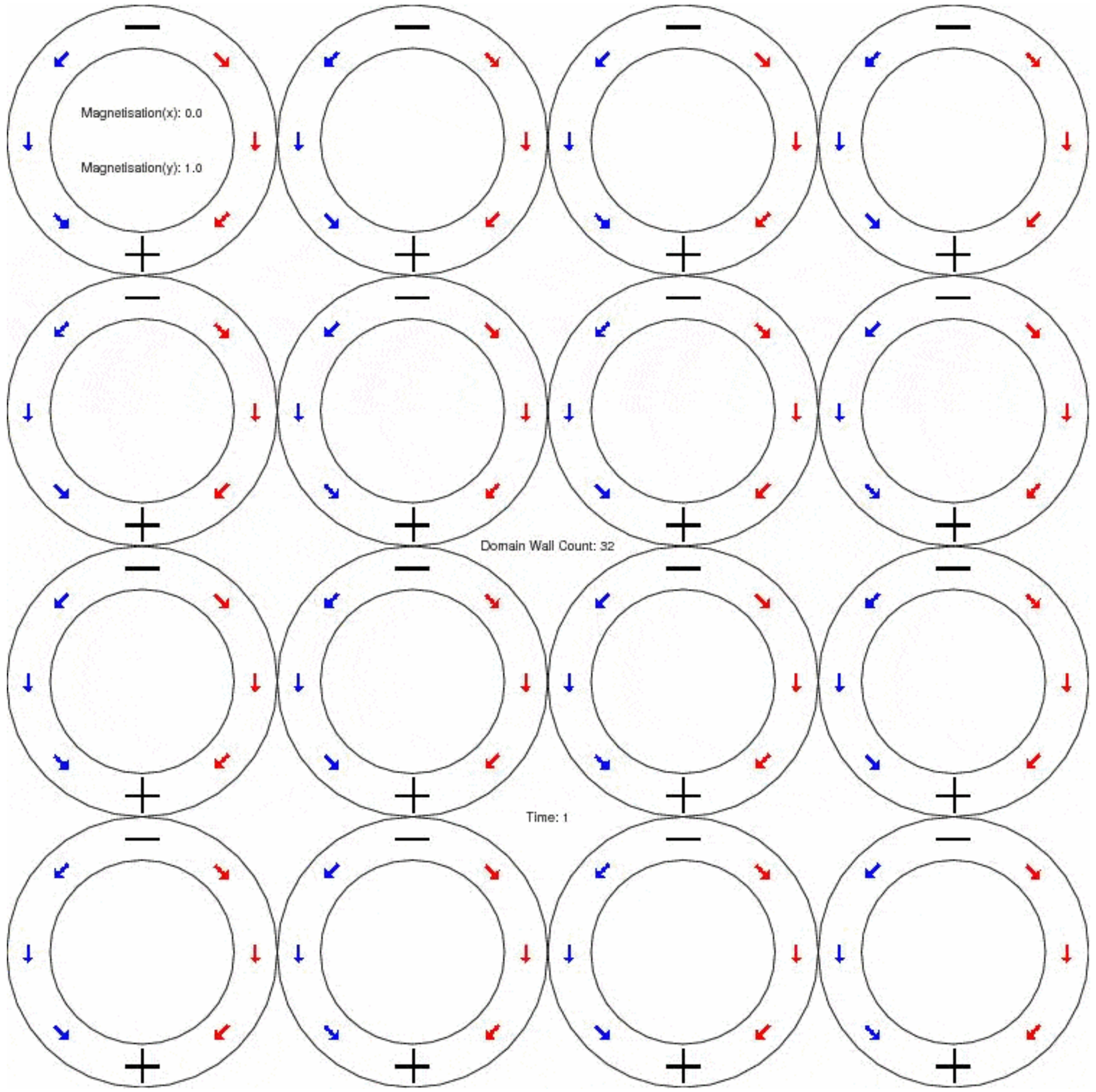






Negoita, Hayward, Allwood, APL (2012)

NanoRing array device



Rotating field:

$$H_{app} = H_0 + H_{scale} * S(t)$$

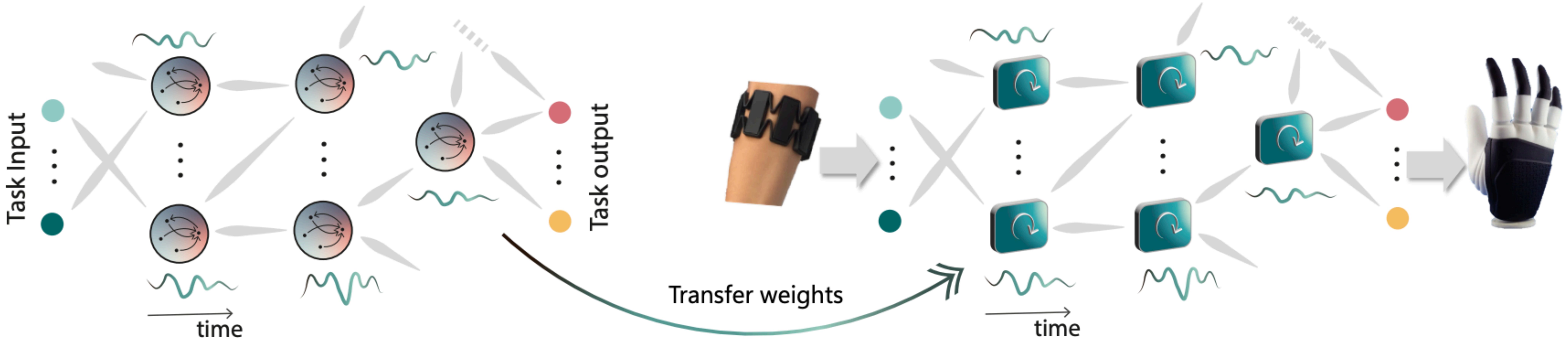
Output:

Magnetisation across device

(Non-linear)

Dawidek, Hayward et al. (2021), Advanced Functional Materials.

Digital twins via AI techniques



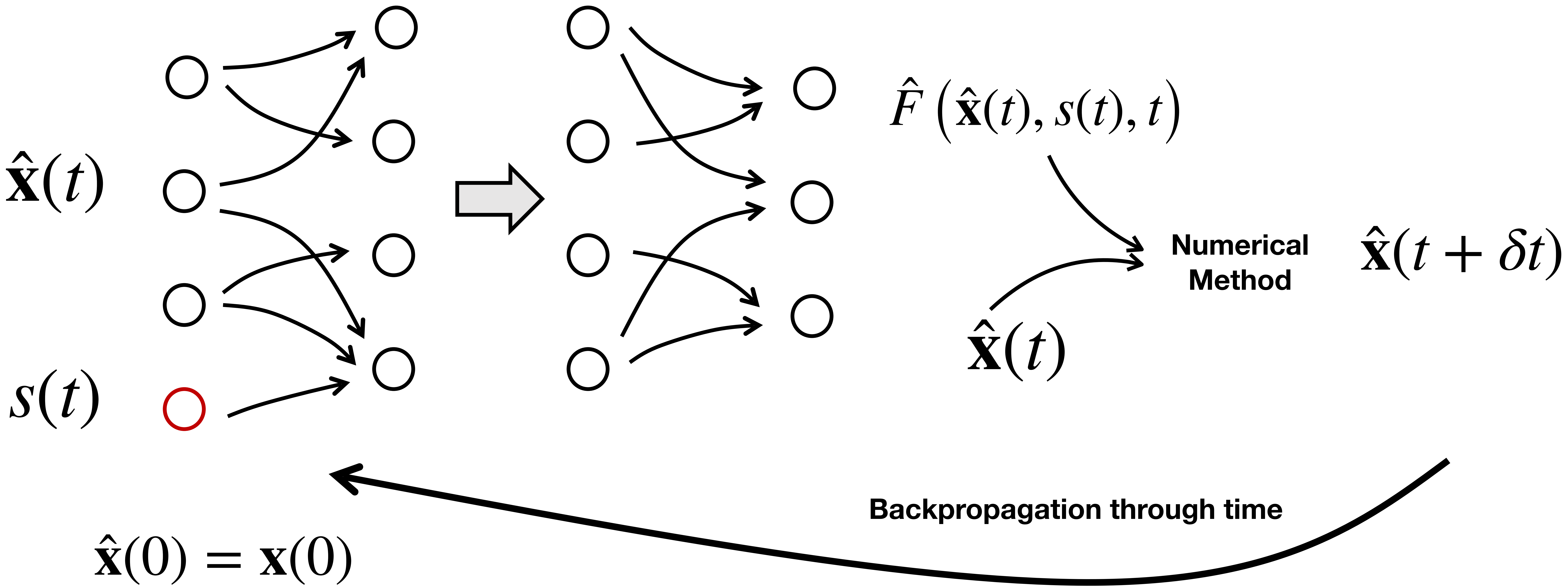
Optimising device interconnectivity via digital twins

Neural ODEs

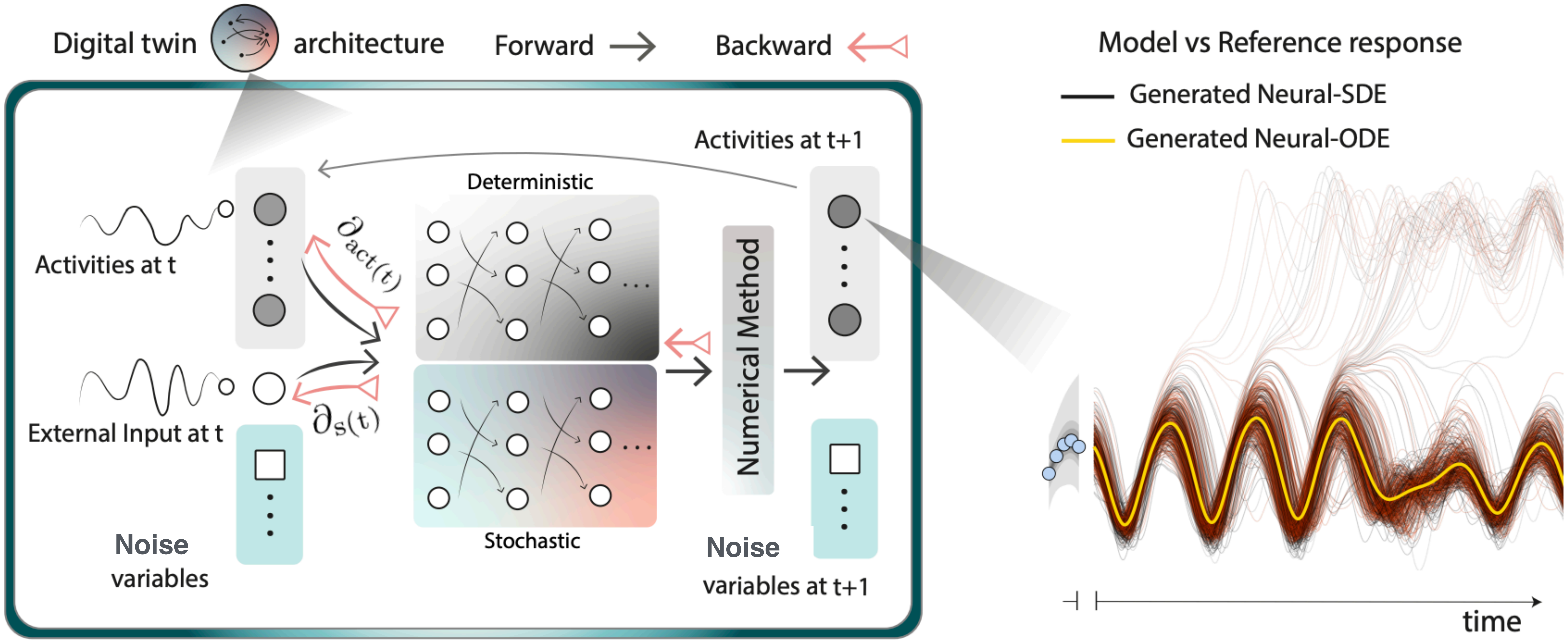
Chen X. et al, Nat Comms 2022
Chen RTQ. et al, NeurIPS 2018

$$\frac{d\mathbf{x}}{dt} = F\left(\mathbf{x}(t), s(t), t\right)$$

$$\mathscr{L} = \sum_{\mu} \sum_{t} \sum_{i} \left(x_i^{(\mu)}(t + \delta t) - \hat{x}_i^{(\mu)}(t + \delta t; \mathbf{W}) \right)^2$$



Learning the device noise

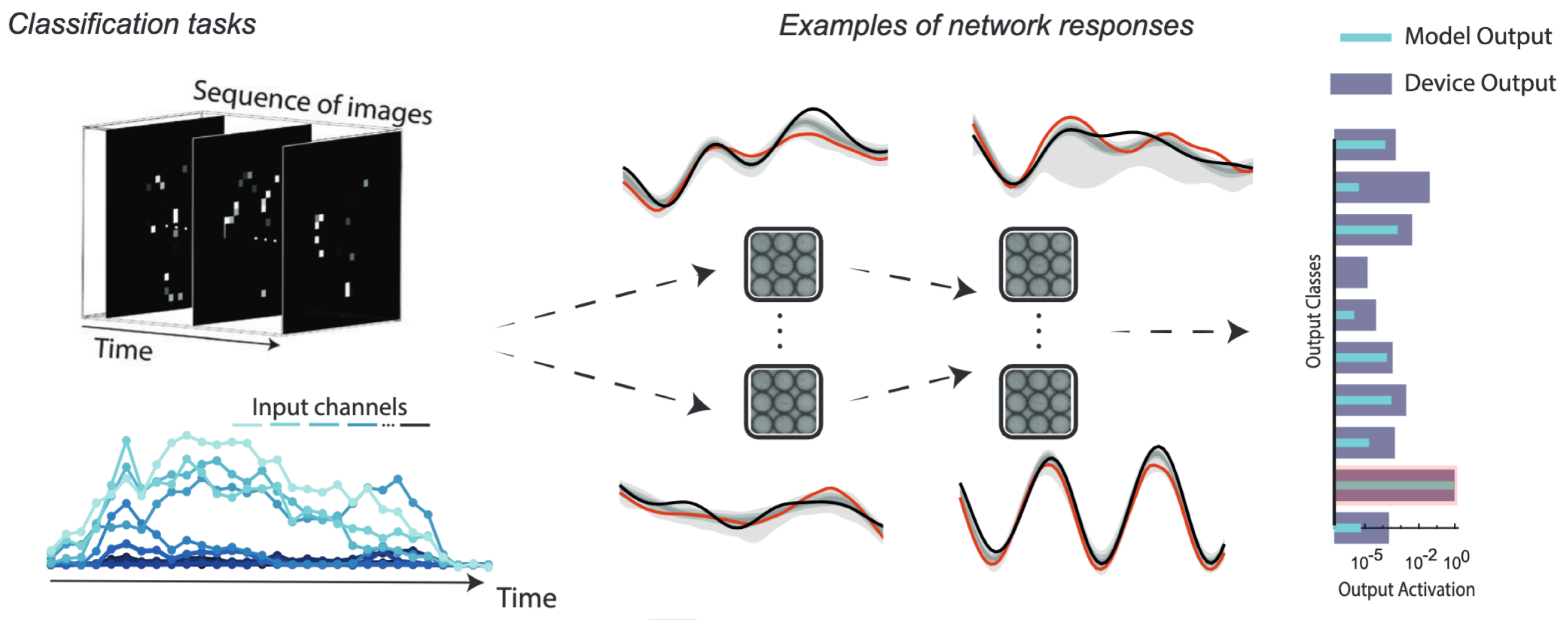


Generative Adversarial Network (GAN)

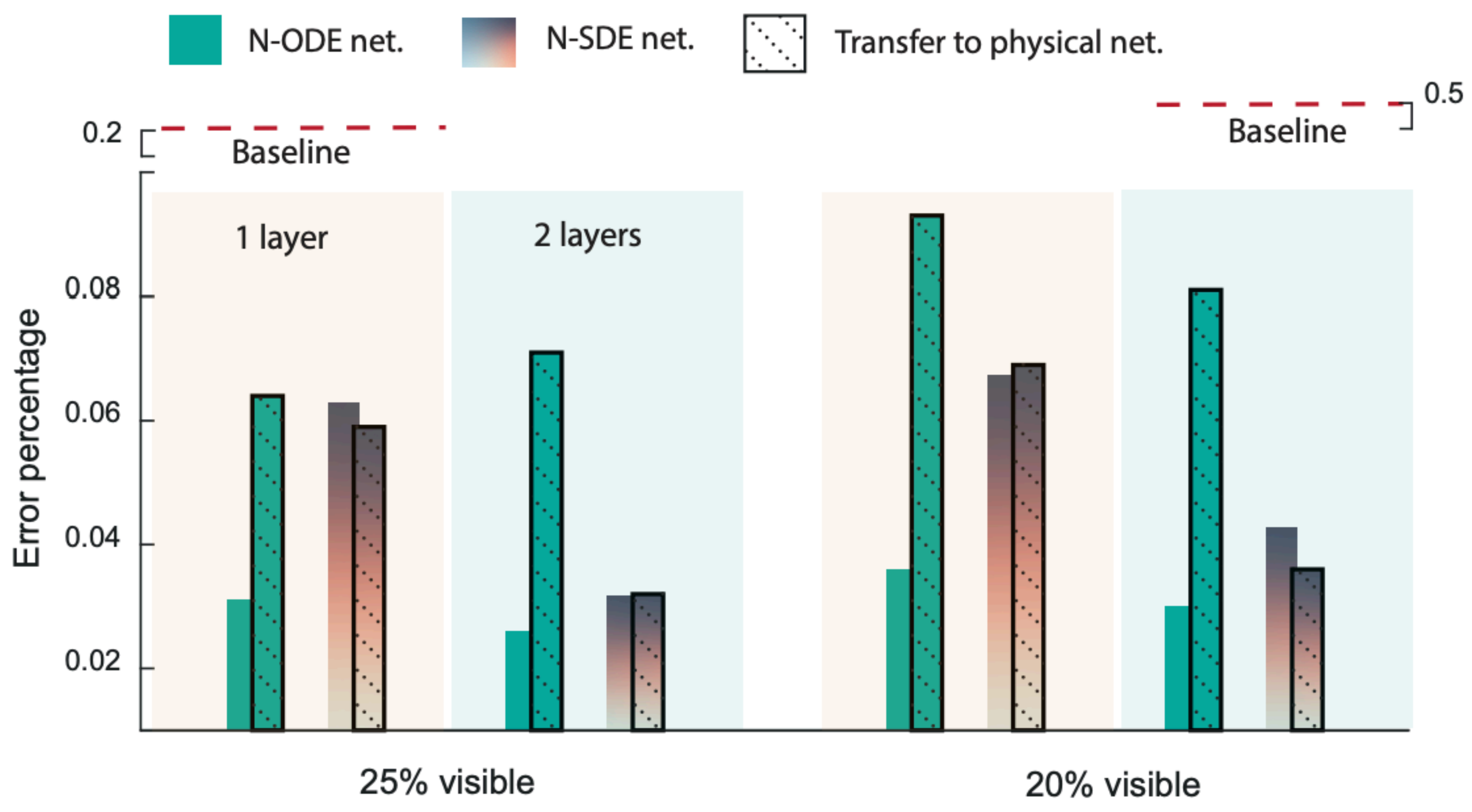
Chen X. et al, Nat Comms 2022
Chen RTQ. et al, NeurIPS 2018

Kidger, P. PhD 2022
Kidger, P. ICML 2021

Classification Tasks



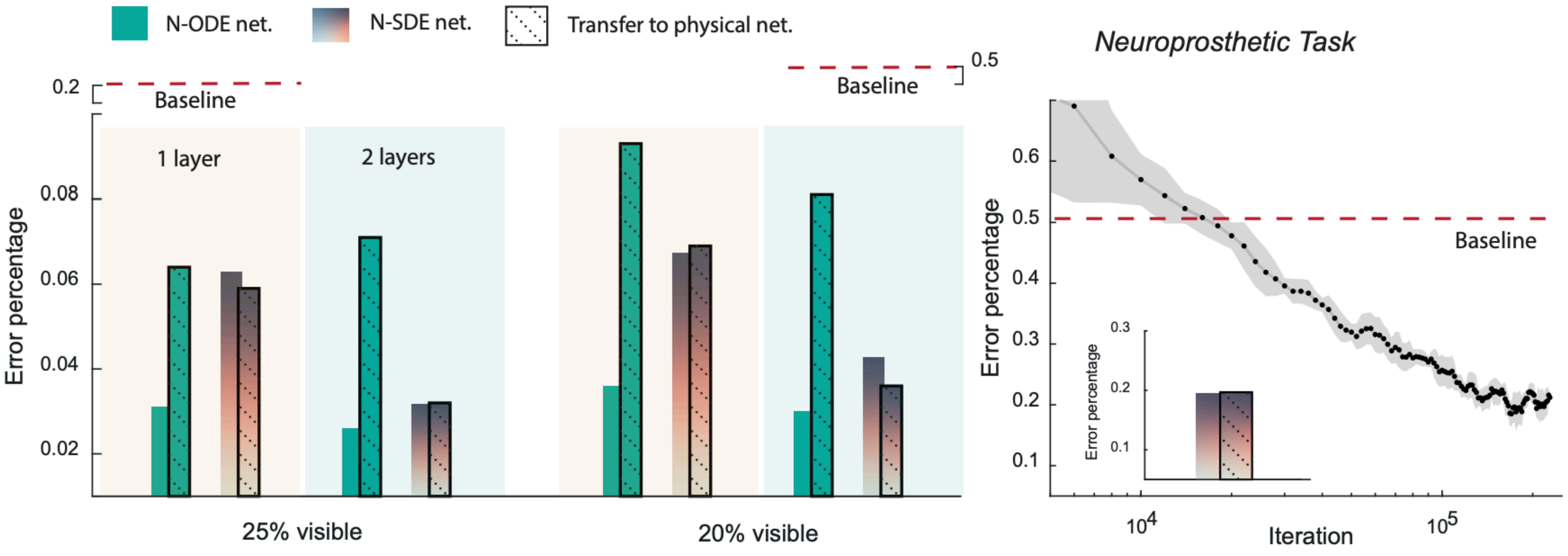
The importance of noise in transferability



Easier task

Harder task

The importance of noise in transferability



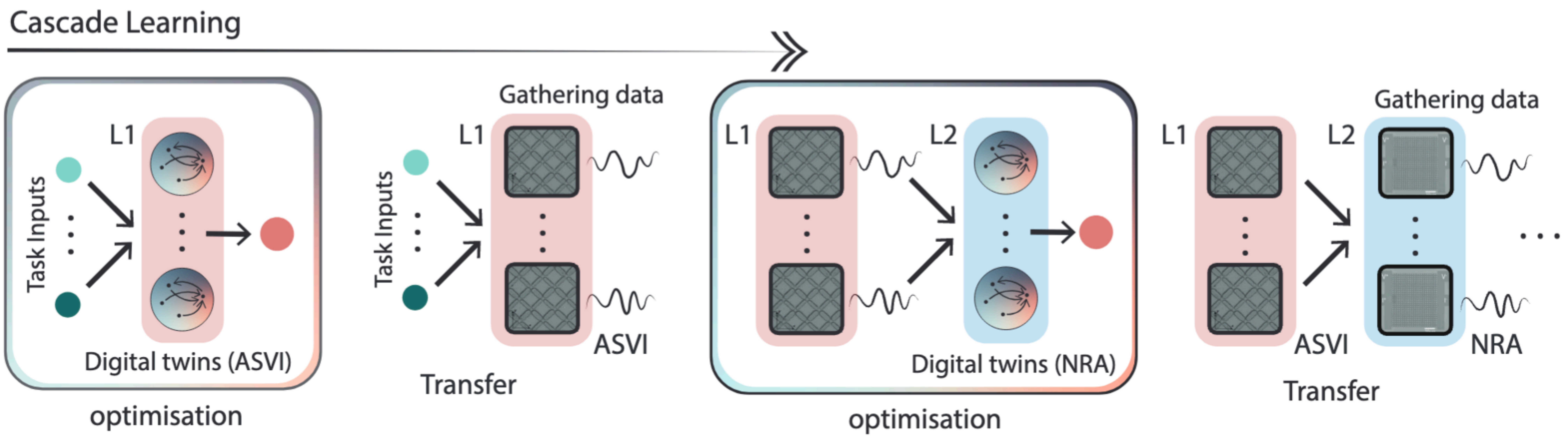
Easier task

Harder task

Regression is unforgiving

Mackey-Glass

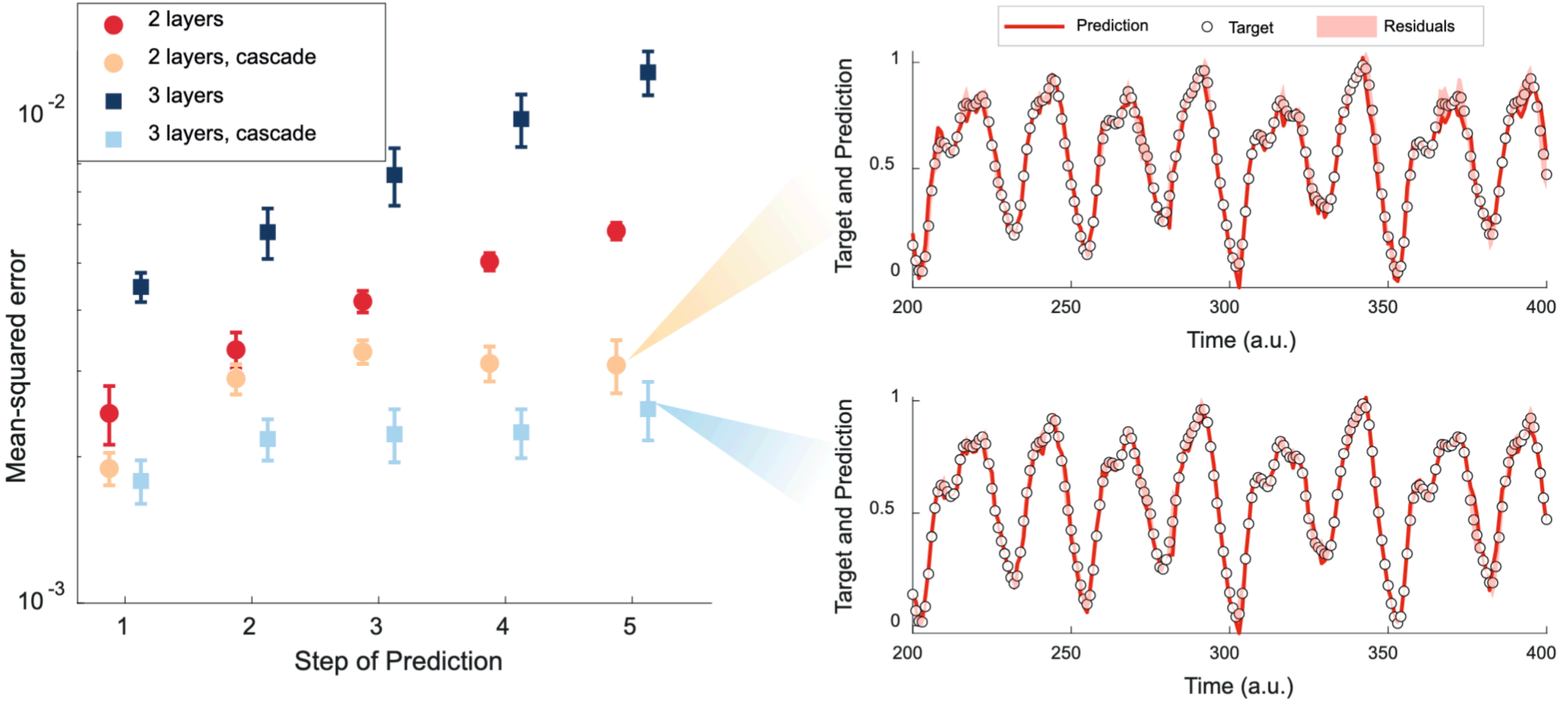
$$\frac{dx(t)}{dt} = \beta \frac{x(t-\tau)}{1 + x(t-\tau)^n} - \gamma x(t)$$



Artificial Spin Vortex Ice Devices + NanoRing Arrays

Marquez et al, IEEE TNNLS 2018
Fahlman & Lebiere, NeurIPS 1989

Regression Task



Summary

- Variability and scalability are key challengers for neuromorphic computing.
- Noise-aware models and optimisation methods can help with these challenges.
- Results demonstrate the double descent phenomenon as a property of over-parameterised models that can be exhibited by physical systems.

Team:

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Charles Swindells


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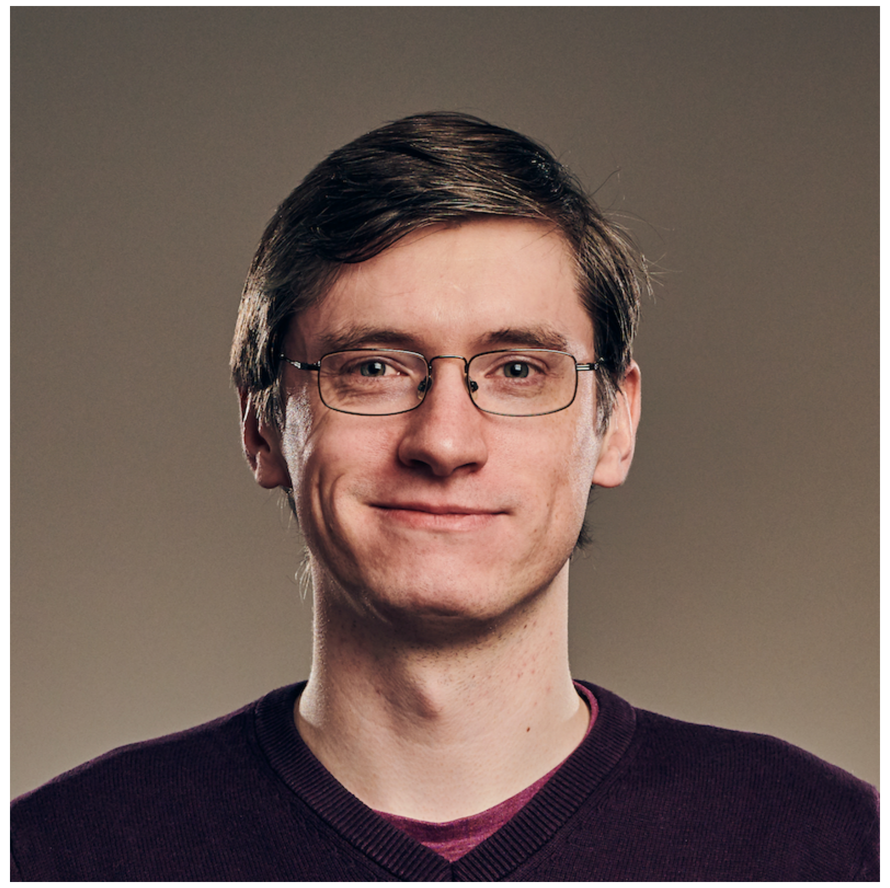
Tom Hayward

Material Science


Ian Vidamour


Luca Manneschi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Engineering and Physical Sciences Research Council

Imperial


Kilian D. Stenning


Jack C. Gartside


Will R. Branford

nature > nature communications > articles > article

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Neuromorphic Computing and Engineering

LETTER • OPEN ACCESS

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Thank you!