



FUNCTIONAL  
MAGNETIC  
MATERIALS



The  
University  
Of  
Sheffield.

# Magnetism for Neuromorphic Computing

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Engineering and  
Physical Sciences  
Research Council



European  
Commission

Horizon 2020  
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for Research & Innovation

# Outline

1. Introduction to Neuromorphic Hardware.
2. Feed Forward Neural Networks.
3. Spintronic Neural Networks.
4. Reservoir Computing.
5. Spintronic Reservoir Computing.

# AI is Amazing...

Write me a short poem about why AI is cool



## The Wonder of AI

Born of code, a spark in the mind,  
Infinite answers, endlessly kind.  
From puzzles unsolved to dreams unfurled,  
AI breathes life into a boundless world.  
It learns, it grows, it shares, it speaks,  
Reaching the heights that curiosity seeks.  
A partner in thought, in art, in play,  
It shapes tomorrow from seeds of today.  
With logic and wonder, it breaks every rule,  
That's why we say: AI is cool.

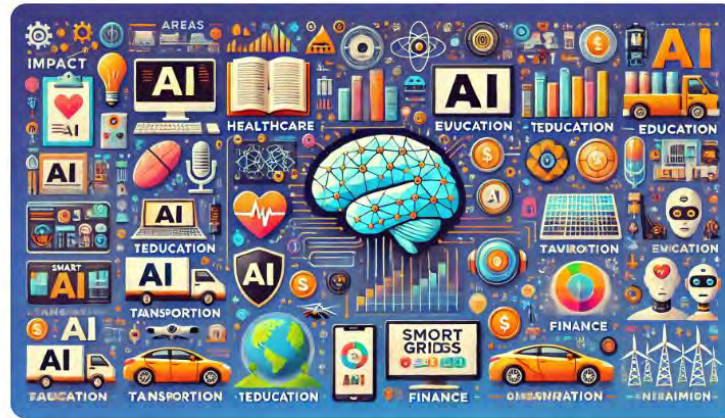
## Healthcare

## Transport

## Customer Service

## Finance

Make me an info-graphic showing the areas AI may have impact



Here is an infographic showcasing the areas where AI has significant impact. It visually represents sectors like healthcare, education, transportation, environment, finance, and entertainment with clear icons and vibrant design elements. Let me know if you'd like any edits or additional sections!



Can you write me code to generate a pytorch neural network with 2 inputs, 2 hidden layers with ten nodes and 1 output node?



Here's the code to define a PyTorch neural network with the specified architecture:

Pytorch Nn 2inputs

```
1 import torch
2 import torch.nn as nn
3
4 class SimpleNeuralNetwork(nn.Module):
5     def __init__(self):
6         super(SimpleNeuralNetwork, self).__init__()
7         # Define the network layers
8         self.fc1 = nn.Linear(2, 10) # Input layer to first hidden layer
9         self.fc2 = nn.Linear(10, 10) # First hidden layer to second hidden layer
10        self.fc3 = nn.Linear(10, 1) # Second hidden layer to output layer
11        self.activation = nn.ReLU() # Activation function
12
13    def forward(self, x):
14        # Define the forward pass
```

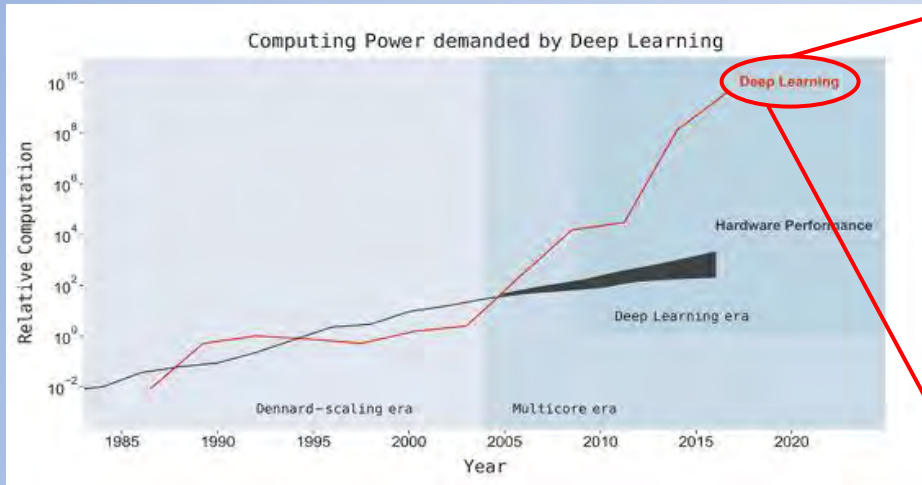
## Entertainment

## Energy

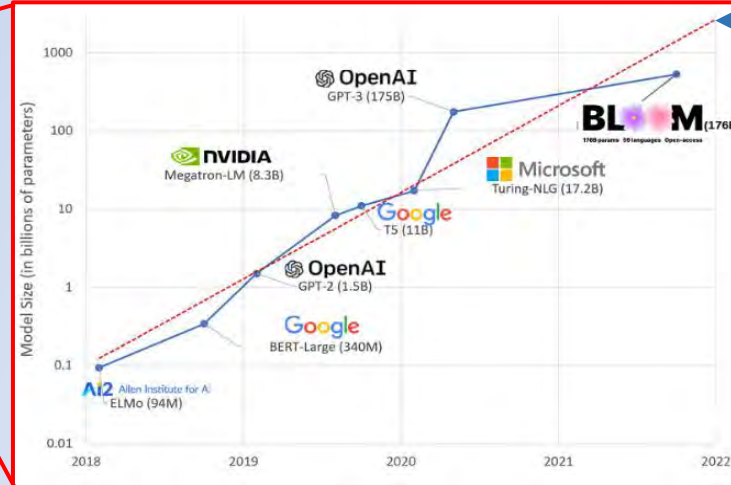
## Manufacturing

## Security

# ...but has problematic impacts...



'The Computational Costs of Deep Learning', N.C. Thompson *et al.* (2022)



"The mounting human and environmental costs of generative AI" Ars Technica (2023)

Scale of AI models is increasing faster than performance of hardware...

With terrifying consequences for power usage and carbon emissions...

## Common carbon footprint benchmarks

in lbs of CO2 equivalent

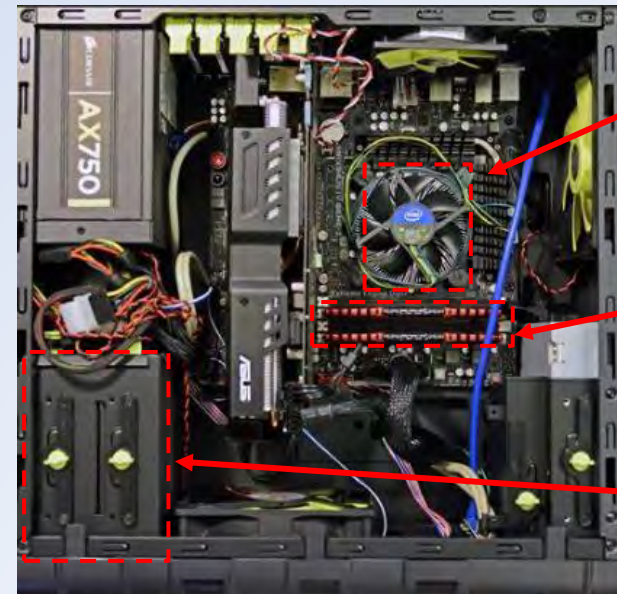
Roundtrip flight b/w NY and SF (1 passenger)	1,984
Human life (avg. 1 year)	11,023
American life (avg. 1 year)	36,156
US car including fuel (avg. 1 lifetime)	126,000
Transformer (213M parameters) w/ neural architecture search	626,155

Chart: MIT Technology Review - Source: Strubell *et al.* - Created with Datawrapper

# ...because computers aren't like brains!

- While **modern CPUs/GPUs** can train and run large ANN this is only because CMOS technology is so good at maths!
  - Brute force **simulate** of neural architectures by doing vector maths.
- **Power inefficient!**
  - Training one deep neural network has carbon footprint of entire lifecycle of a car.
  - Human brain consumes ~20 W, equivalent HPC would consume ~10 MW.

**Neuromorphic technologies** use the properties of functional materials to attempt to more directly **emulate neural architecture**.



**CPU**  
8 – 16 parallel threads  
Minimal local memory  
Strictly Digital  
Precise but noise intolerant

**Short Term Memory**  
~4 GB – 32 GB

**Long Term Memory**  
~256 GB to 2 TB



**Massively Parallel!**

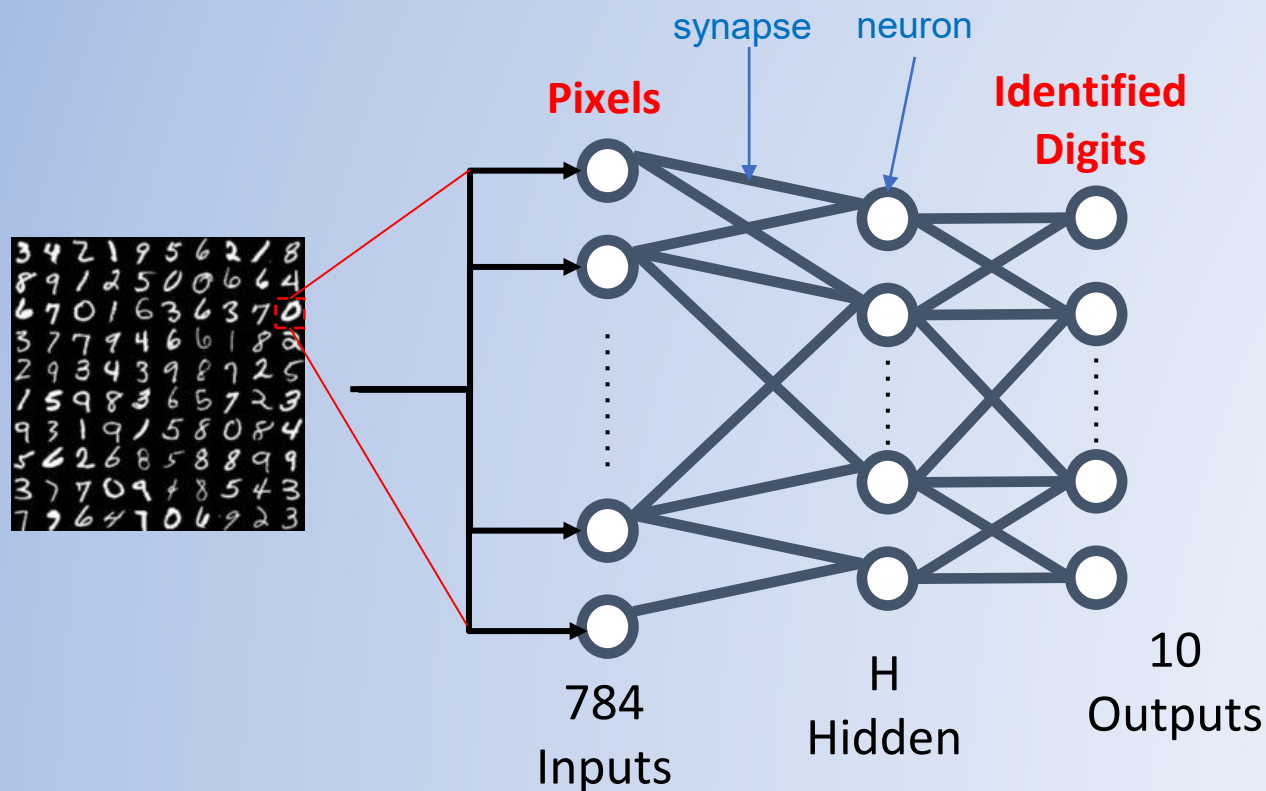
**Memory embedded with compute!**

**Analogue not Digital**

**Imprecise, but noise tolerant.**

# Feed-forward Neural Networks

- Typical approach represented by **feed-forward neural network**.
  - Consists of layers of **neurons** connected by **unidirectional synapses** with analogue tuneable **weights  $w_i$** .
  - Weights are "**trained**" to allow network to perform task (e.g. identification of hand-written digits).

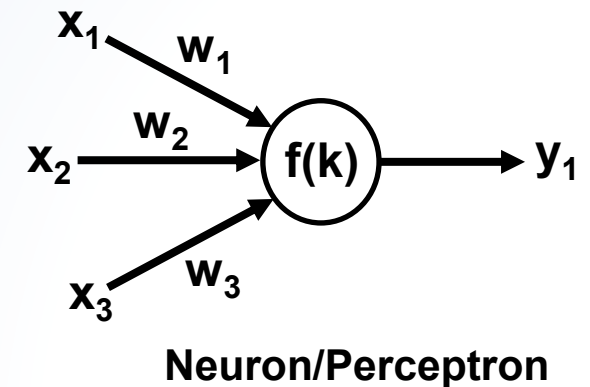
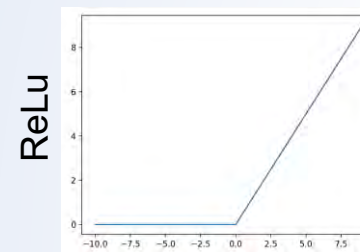
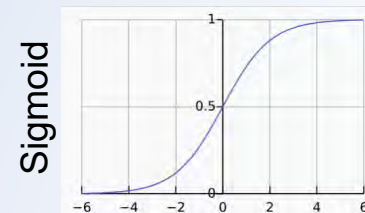


$$y_i = f(k_i)$$

Neuron output

$$k_i = \sum_j w_{ij} x_j + b_i$$

Weight      Synapse input      Bias



# Training FFNN

- Most commonly train FFNN/Multilayer Perception **weights** by **supervised learning**.
- Minimise error of network against a **training set** ( $\mathbf{x}_{\text{target}}, \mathbf{y}_{\text{target}}$ ):

$$C = (\mathbf{y}_{\text{target}} - \mathbf{y}_{\text{output}})^2$$

**loss function**

- Train weights by iterative **gradient descent**:

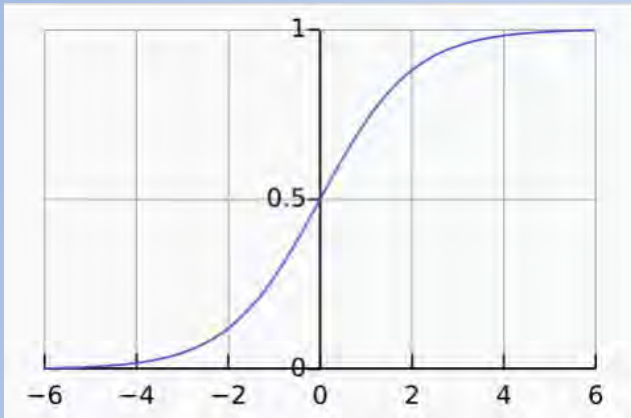
$$\mathbf{w}_{n+1} = \mathbf{w}_n - \gamma \nabla C(\mathbf{w}_n)$$
$$\nabla C(\mathbf{w}_n) = \frac{\partial C}{\partial \mathbf{w}_n}$$

**learning rate**

- Gradient function calculated using **backpropagation algorithm** (applies chain rule through network to understand how loss depends on weights).
- Iterate until error converges and test network on **unseen data (test set)**.

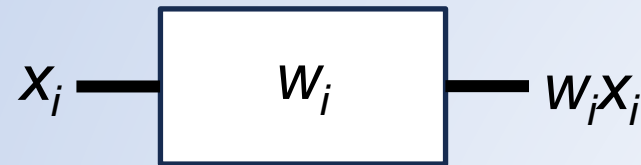
# What do we need to make a magnetic neural network?

## Neuron



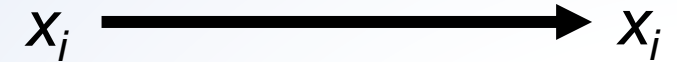
- Addition of **synaptic inputs**.
- Apply **non-linear activation**.

## Synapse



- **Multiplies** input by **weight**.
- Weight ideally local and non-volatile

## Interconnect



- **Transports** data through the network.



# Lots of magnetism groups working on this!

## Neuromorphic computing with nanoscale spintronic oscillators

Jacob Torrejon<sup>1</sup>, Mathieu Krawinkel<sup>1</sup>, Flavio Abreu Araujo<sup>1</sup>, Sumitro Triatnetjo<sup>1</sup>, Gauri Khaitan<sup>1</sup>, Damien Querliouf<sup>1</sup>, Paolo Bortolotti<sup>1</sup>, Vincent Cros<sup>1</sup>, Kay Yakushiji<sup>1</sup>, Akito Fukushima<sup>1</sup>, Hiroshi Kubota<sup>1</sup>, Shunji Yuasa<sup>1</sup>, Mark D. Stiles<sup>1</sup> & Julie Grollier<sup>1</sup>

Neurons in the brain behave as nonlinear oscillators, which develop rhythmic activity and interact to process information<sup>1</sup>. Taking inspiration from this behaviour to realize high-density, low-power neuromorphic computing will require very large numbers of nanoscale oscillator oscillators. A simple experimental indicator that a spintronic oscillator is suitable for this role is its ability to fit 10<sup>4</sup> oscillators organized in a two-dimensional chip the size of a thumb, the lateral dimensions of which must be smaller than one micrometre. This leads to a number of challenges to the stability of the data in a reliable way. For this reason, they propose<sup>2,3</sup> and several candidates, including superconducting oscillators, a proof of concept computing using nanoscale oscillators has been shown experimentally that a nanoscale spintronic oscillator<sup>4,5</sup> can be used

## Nanoscale Room-Temperature Multilayer Skyrmionic Synapse Neural Networks

Runze Chen<sup>1,2</sup>, Chen Li<sup>1,2\*</sup>, Yu Li<sup>1</sup>, James J. Miles<sup>1</sup>, Giacomo Indiveri<sup>3</sup>, Vasilis F. Pavlidis<sup>2</sup> and Christoforos Moutafis<sup>1,2\*</sup>

<sup>1</sup> Nano Engineering and Spintronic Technologies (NEST) Group, Department of Computer Engineering, University of Manchester, Manchester M13 9PL, United Kingdom  
<sup>2</sup> Advanced Processor Technologies (APT) Group, Department of Computer Science, University of Manchester, Manchester M13 9PL, United Kingdom  
<sup>3</sup> Institute of Neuroinformatics, University of Zurich and ETH Zurich, 8057 Zurich

(Received 28 February 2020; revised 1 May 2020; accepted 15 June 2020; published 30 July 2020)

## Reservoir Computing in Artificial Spin Ice

Johannes H. Jensen and Gunnar Tufte

Department of Computer Science,  
Norwegian University of Science and Technology, Trondheim, Norway  
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## Perspective: Spintronic synapse for artificial neural network

Cite as: J. Appl. Phys. 124, 151904 (2018); <https://doi.org/10.1063/1.5042317>  
Submitted: 31 May 2018 • Accepted: 20 August 2018 • Published Online: 08 October 2018

Shunsuke Fukami and Hideo Ohno

COLLECTIONS

## Reservoir Computing with Planar Nanomagnet Arrays

Deng Zhen<sup>1</sup>, Nathan R. McDonald<sup>1</sup>, Alexander I. Gubanov<sup>1</sup>, Lisa Lovett<sup>1</sup>, Chand D. Thacker<sup>1</sup>, Joseph S. Prendergast<sup>1</sup>, Department of Electrical and Computer Engineering, The University of Texas at Dallas, Richardson, TX 75080-3021, USA  
[zhen.deng@utdallas.edu, alexander.gubanov@utdallas.edu, jprendergast@utdallas.edu]  
[Apt Nano Research Laboratory - Information Electronics, Rome, Italy (shunsuke.fukami@uniroma3.it, hideo.ohno@uniroma3.it)]

**Abstract**—Reservoir computing is an emerging methodology for neuromorphic computing that is especially well-suited for hardware implementation in low-power and energy-efficient spintronic devices. This work proposes a novel hardware implementation of a general reservoir computing using planar nanomagnet arrays. A small nanomagnet reservoir is demonstrated experimentally to be able to classify single-bit binary data with 100% accuracy. These nanomagnet reservoirs are promising candidates for the general case of dedicated neural hardware.

1. INTRODUCTION

## Reservoir Computing with Random Skymion Textures

D. Pinna<sup>1,\*</sup>, G. Bourianoff<sup>2,4</sup> and K. Everschor-Sitte<sup>1</sup>

<sup>1</sup> Institute of Physics, Johannes Gutenberg-Universität, Mainz 55128, Germany  
<sup>2</sup> Intel Corporation, Austin, Texas 78746, USA

(Received 22 May 2020; accepted 13 October 2020; published 10 November 2020)

## Voltage-controlled superparamagnetic ensembles for low-power reservoir computing

Cite as: Appl. Phys. Lett. 118, 202402 (2021); [doi:10.1063/5.0048911](https://doi.org/10.1063/5.0048911)  
Submitted: 27 February 2021 • Accepted: 28 April 2021 • Published Online: 17 May 2021

A. Welbourne<sup>1,2</sup>, A. L. R. Levy<sup>1,2</sup>, M. O. A. Ellis<sup>1,2</sup>, H. Chen<sup>1</sup>, M. J. Thompson<sup>1</sup>, E. Vasilaki<sup>1,2</sup>, D. A. Allwood<sup>1,2</sup> and T. J. Hayward<sup>1,2</sup>

AFFILIATIONS

## Neuromorphic computation with a single magnetic domain wall

Razvan V. Ababei<sup>1,2</sup>, Matthew O. A. Ellis<sup>2</sup>, Ian T. Vidamour<sup>1</sup>, Dhilan S. Devadasan<sup>1</sup>, Dan A. Allwood<sup>1</sup>, Eleni Vasilaki<sup>2</sup> & Thomas J. Hayward<sup>1</sup>

Machine learning techniques are commonly used to model complex relationships but implement on digital hardware are relatively inefficient due to poor matching between conventional computer architectures and the structures of the algorithms they are required to simulate. Neuromorphic devices, and in particular reservoir computing architectures, utilize the inherent properties of physical systems to implement machine learning algorithms and so have the potential to be much more efficient. In this work, we demonstrate that the dynamics of individual domain walls in magnetic nanowires are suitable for implementing the reservoir computing paradigm in hardware. We model the dynamics of a domain wall placed between two anti-notches in a nickel nanowire using both collective coordinates model and micromagnetic simulations. When driven by an oscillating magnetic field, the domain exhibits non-linear dynamics within the potential well created by the anti-notches that are analogous to those of the Duffing oscillator. We exploit the domain wall dynamics for reservoir computing by modulating the amplitude of the applied magnetic field to inject time-multiplexed signals into the reservoir, and show how this allows us to perform machine learning tasks including the classification of (1) sine and square waves; (2) spoken digits; and (3) non-temporal 2D toy handwritten digits. Our work lays the foundation for the creation of nanoscale neuromorphic devices in which individual magnetic domain walls are used to perform complex data analysis tasks.

## Pure voltage-driven spintronic neuron based on stochastic magnetization switching behaviour

Jia-Hui Yuan<sup>1</sup>, Ya-Bo Chen<sup>2</sup>, Shu-Qing Dou<sup>1</sup>, Bo Wei<sup>1</sup>, Huan-Qing Cui<sup>1</sup>, Ming-Xu Song<sup>1</sup> and Xiao-Kuo Yang<sup>1,2\*</sup>

<sup>1</sup> Fundamentals Department, Air Force Engineering University, Xi'an 710051, People's Republic of China  
<sup>2</sup> College of Computer, National University of Defense Technology, Changsha 410005, People's Republic of China

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Accepted for publication 23 December 2021  
Published 18 January 2022

### Abstract

Voltage-driven stochastic magnetization switching in a nanomagnet has attracted more attention

## LETTER

## Vowel recognition with four coupled spin-torque nano-oscillators

Miguel Romero<sup>1</sup>, Philippe Lalanne<sup>2</sup>, Sumitro Triatnetjo<sup>1</sup>, Flavio Abreu Araujo<sup>1</sup>, Vincent Cros<sup>1</sup>, Paolo Bortolotti<sup>1</sup>, Juan Torrejon<sup>1</sup>, Kay Yakushiji<sup>1</sup>, Akito Fukushima<sup>1</sup>, Hiroshi Kubota<sup>1</sup>, Shunji Yuasa<sup>1</sup>, Maymon Ermekei<sup>1</sup>, Damien Querliouf<sup>1</sup>, Berni Hertzfeldt<sup>1</sup>, Nicolas Locajale<sup>1</sup>, Damien Querliouf<sup>1</sup> & Julie Grollier<sup>1\*</sup>

In recent years, artificial neural networks have become the flagship algorithm of artificial intelligence<sup>1</sup>. In these systems, neuron activation functions are static, and computing is achieved through standard arithmetic operations. By contrast, a prominent branch of neuromorphic computing embraces the dynamical nature of the brain and proposes to model each component of a neural network with dynamical functionality, such as oscillations, and to rely on emergent physical phenomena, such as synchronization<sup>2,3</sup>, for solving complex problems with small networks<sup>4,5</sup>. This approach is especially interesting for hardware implementations, because emerging nanoscale devices can provide compact and energy-efficient nonlinear auto-oscillators that mimic the periodic spiking activity of biological neurons<sup>6,7</sup>. The dynamical coupling between oscillation selection and control of the frequency of each oscillator through the microwave spin torque it creates<sup>8</sup>. The sum of all microwave emissions is detected by a spectrum analyzer. Importantly, we can control the frequency of each oscillator by adjusting the direct current flowing through each layer (Mushinski and Everschor-Sitte Fig. 1). Here, for computing, we choose direct currents leading to close but not identical frequencies. The light blue curve in Fig. 1, shows a four-peak spectrum typical of this regime of incoherent coupling where the dynamics of the oscillators are correlated but do not lead to mutual synchronization. The inputs to the neural network are encoded in the frequencies  $f_1$  and  $f_2$  of two fixed amplitude microwave signals. Injected in a ring (see fabrication above the active magnetic layer), they modify the dynamics of the oscillators through the radiofrequency magnetic fields they generate. Figure 1a shows that when the frequency of one of the microwave sources is swept, each oscillator synchronizes to the source in turn. Indeed, when the frequency of the source gets close to the frequency of one of the oscillators, the strong signal of the source pulls the other

• I'm just going to **mostly talk** about **our efforts** in the area...

# Lots of magnetism groups working on this!

**Neuromorphic computing with nanoscale spintronic oscillators**  
Jacob Torrejon<sup>1</sup>, Mathieu Kiselev<sup>1</sup>, Flavio Abreu Araujo<sup>1</sup>, Sumitro Tamargo<sup>1</sup>, Gauri Khaitan<sup>1</sup>, Damien Querliouf<sup>1</sup>, Paolo Bortolotti<sup>1</sup>, Vincent Cros<sup>1</sup>, Kay Yakushev<sup>1</sup>, Akito Fukushima<sup>1</sup>, Hiroshi Kubota<sup>2</sup>, Shunji Yuasa<sup>3</sup>, Mark D. Stiles<sup>1</sup> & Julie Grollier<sup>1</sup>

Neurons in the brain behave as nonlinear oscillators, which develop rhythmic activity and interact to process information<sup>1</sup>. Taking inspiration from this behavior to realize high-density, low-power neuromorphic computing will require very large numbers of nanoscale nonlinear oscillators. A simple and scalable architecture to fit 10<sup>9</sup> oscillators organized in a two-dimensional array on a chip the size of a thumb, the lateral dimensions must be smaller than one micrometer, that is, smaller than the size of a bacterium. For this reason, design proposals<sup>2,3</sup> and several candidates, including superconducting<sup>4</sup> oscillators, a proof of concept using nanoscale oscillators has been proposed. Here we show experimentally that a nanoscale (a magnetic tunnel junction)<sup>5,6</sup> can be used as a neuron in a neuromorphic network. We also determine the regime of magnetization dynamics that leads to the greatest performance. These results, combined with the ability of the spintronic oscillators to interact with each other, show that nanoscale spintronic oscillators are a promising candidate for neuromorphic computing.

**Nanoscale Room-Temperature Multilayer Neural Network**  
Runze Chen<sup>1,2</sup>, Chen Li<sup>1,2,3</sup>, Yu Li<sup>1</sup>, James Vasiliadis<sup>1</sup>, Vasilis F. Pavlidis<sup>1,2</sup> and  
<sup>1</sup>Nano Engineering and Spintronic Technologies (NET), University of Manchester  
<sup>2</sup>Advanced Processor Technologies (APT) Group, Department of Computer Science, University of Manchester, Manchester, M13 9PL, UK  
<sup>3</sup>Institute of Neuroinformatics, University of Zurich, Winterthurerstrasse 190, CH-8057 Zurich, Switzerland  
(Received 28 February 2020; revised 1 May 2021)

**Reservoir Computing in a Nanoscale Spintronic Network**  
Johannes H. Jensen and G. E. W. Bristow  
Department of Computer Science and Technology, Norwegian University of Science and Technology, Trondheim, Norway  
johannes.jensen@ntnu.no

## Perspective: Spintronic synapse for artificial

### Why?

- Non-volatile memory!
- Inherent non-linearity!
- CMOS compatibility!
- High speed (up to THz)!
- Low power!
- Physics based interconnects (exchange, magnetostatic coupling)!

Check for updates

**Voltage-controlled stochastic magnetization switching for low-power neuromorphic computing**

Cite as: Appl. Phys. Lett. **118**, 202402 (2021); doi:10.1063/5.0048911  
Submitted: 27 February 2021 · Accepted: 28 April 2021 · Published Online: 17 May 2021

A. Welbourne,<sup>1,2</sup> A. L. R. Levy,<sup>1,2</sup> M. O. A. Ellis,<sup>3</sup> H. Chen,<sup>1</sup> M. J. Thompson,<sup>1</sup> E. Vasiliadis,<sup>3</sup> D. A. Allwood,<sup>1,2</sup> and T. J. Hayward<sup>1,2</sup>

**AFFILIATIONS**

Received 7 October 2021; revised 16 December 2021  
Accepted for publication 23 December 2021  
Published 18 January 2022

**Abstract**  
Voltage-driven stochastic magnetization switching in a nanomagnet has attracted more attention

CrossMark

**with four coupled spin-torque**

Flavio Abreu Araujo<sup>1</sup>, Vincent Cros<sup>1</sup>, Paolo Bortolotti<sup>1</sup>, Juan Tamargo<sup>1</sup>, Shunji Yuasa<sup>2</sup>, Maxime Ernault<sup>1</sup>, Damien Vanden-Aryve<sup>1</sup>, Ilirien Hertzlinke<sup>1</sup>, and Julie Grollier<sup>1</sup>

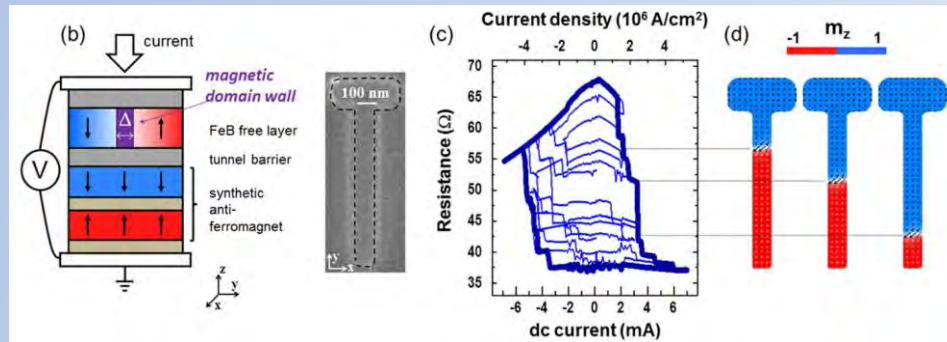
We propose to hardware the neural network illustrated in Fig. 1a<sup>1</sup> with the set-up illustrated in Fig. 1b. The four neurons in Fig. 1a are experimentally implemented with four spin-torque nano-oscillators (STNOs) (see Methods<sup>18</sup>). The double arrow connections between neurons (blue in Fig. 1a) indicate that the output of neurons influences the behavior of neurons and vice versa. We implement these symmetric neural interconnections by connecting electrically the four oscillators using millimeter-long wires as schematized in Fig. 1b in this configuration, the microwave current generated by each oscillator propagates in the electrical microwave loop and its time influence the dynamics, and in particular the frequency, of the other oscillators through the microwave spin-torque it creates<sup>19</sup>. The sum of all microwave emissions is detected by a spectrum analyzer. Importantly, we can control the frequency of each oscillator by adjusting the direct current flowing through each two-MTJs and External Data Fig. 11. Here, for computing, we choose direct currents leading to close but not identical frequencies. The light blue curve in Fig. 11 shows a four-peak spectrum typical of this regime of incoherent coupling where the dynamics of the oscillators are correlated but do not lead to mutual synchronization.

The inputs to the neural network are encoded in the frequencies  $f_1$  and  $f_2$  of two fixed amplitude microwave signals. Injected in a strip line fabricated above the active magnetic layers, they modify the dynamics of the oscillators through the radiofrequency magnetic fields they generate. Figure 1d shows that when the frequency of one of the microwave sources is swept, each oscillator contributes to the source in turn. Indeed, when the frequency of the source gets close to the frequency of one of the oscillators, the strong signal of the source pulls the other

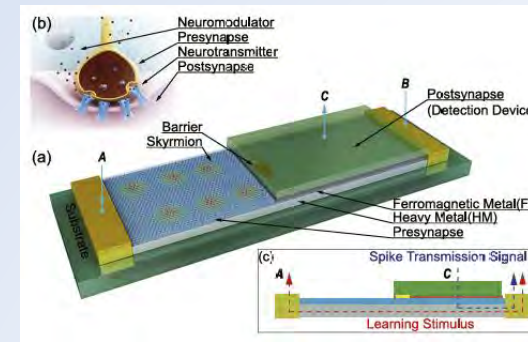
• I'm just going to **mostly talk** about **our efforts** in the area...

# Spintronic Synapses

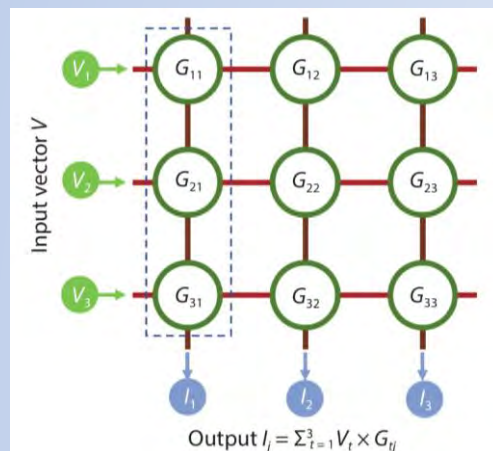
- Most proposals for **magnetic synapses** are based magnetoresistive memristors.
- Stores an analogue weight using e.g. **position of DWs/Skyrmions** in a multilayer nanotrack...



S. Lequeux *et. al.* Sci. Rep. **6**, 31510 (2016)



Y. Huang *et. al.* Nanotechnology **28**, 08LT02 (2017)

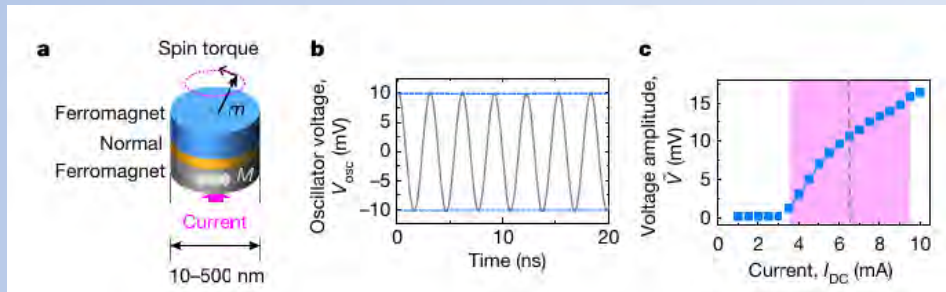


Integrating into **cross-bar arrays** allows **multiply and accumulate** via Kirchoff's law...

# Spintronic Neurons

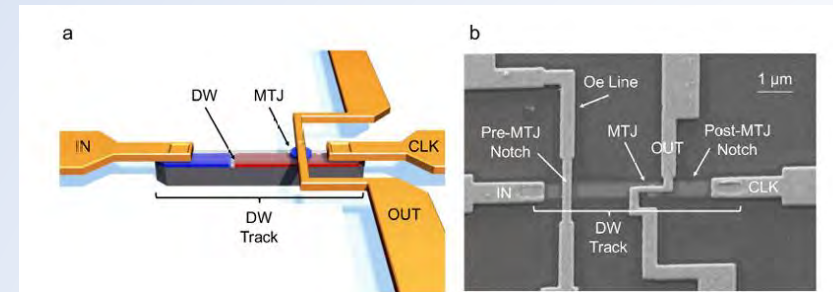
- **Spintronic neurons** produce a non-linear or step-like response to current input.

## STO-based leaky integrator neuron



Torrejon et. al. Nature **547**, 428 (2017)

## DW-based Spiking Neuron

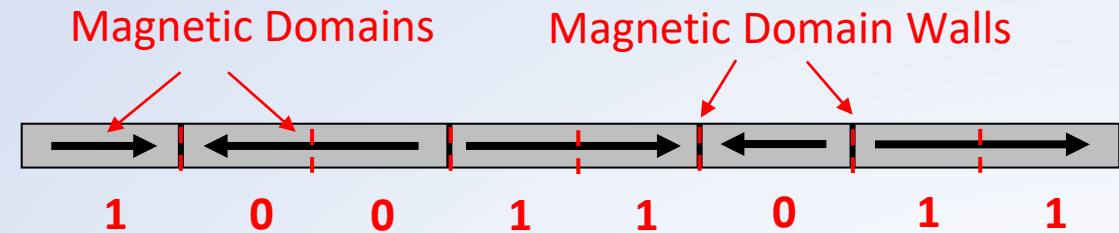


Leonard et. al. Appl. Phys. Lett. **122**, 262406 (2023)

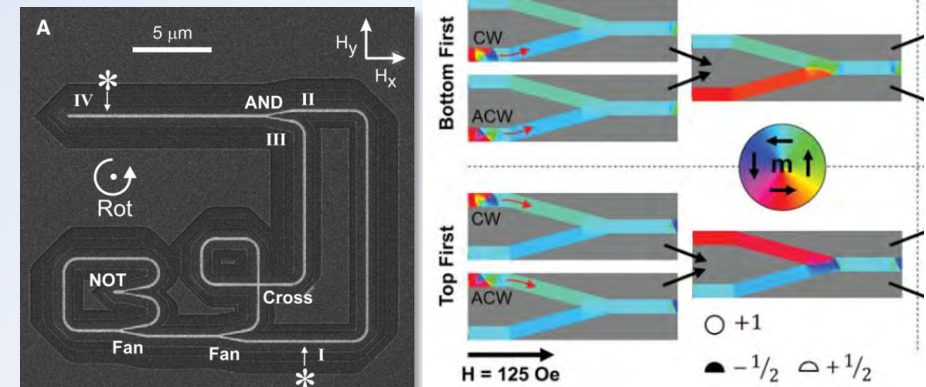
- Spintronic synapses and neurons would typically be integrated into a **CMOS architecture** to create neural circuits (i.e. **interconnects are electrical**)

# Domain Wall Devices

- The devices we've looked at so far could **integrate** with **conventional microelectronics**.
- But could we create **neural networks** that are **all magnetic**?

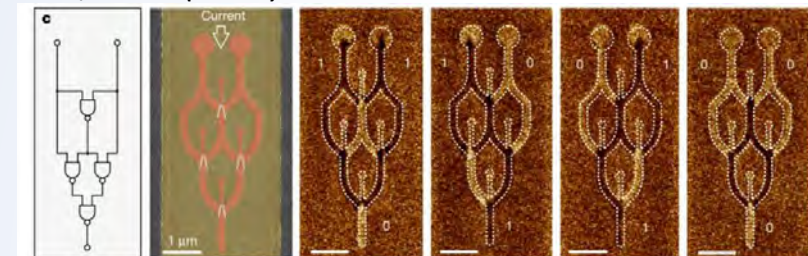


## Domain Wall Logic



Allwood et al. *Science*  
309, 1688 (2005)

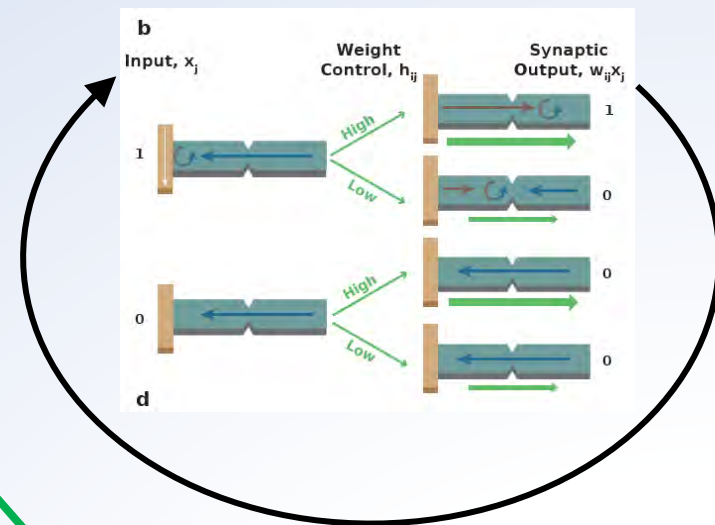
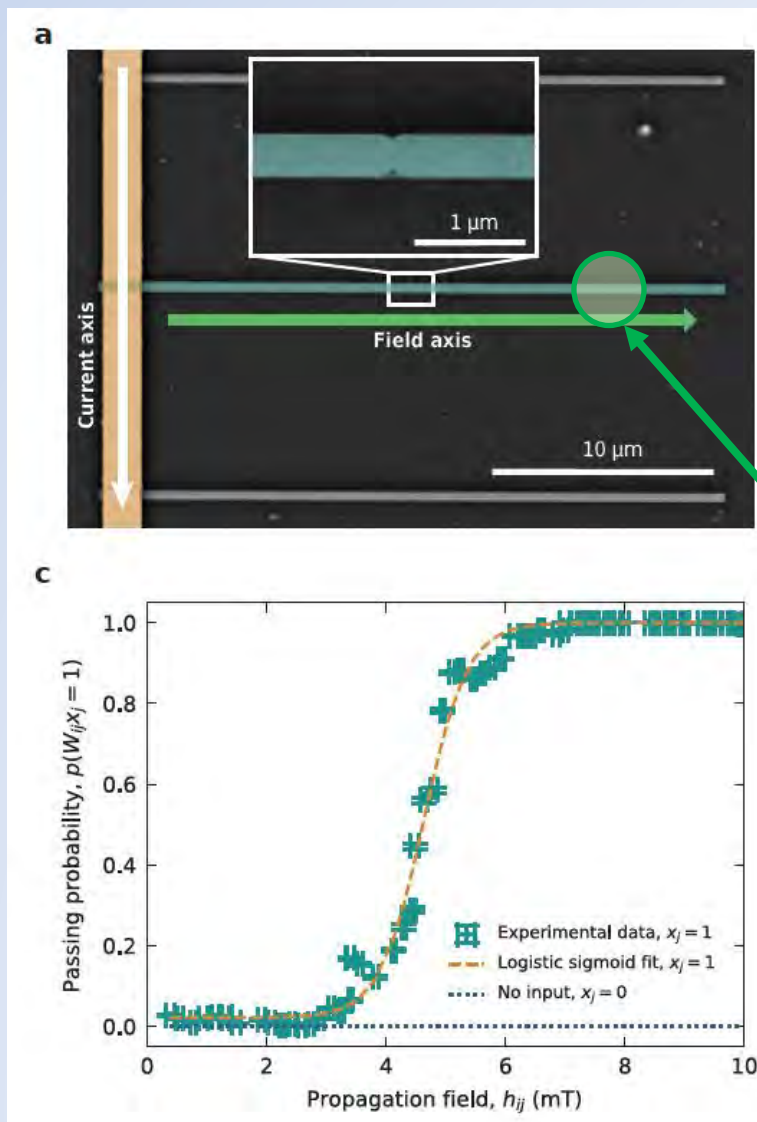
Omari et al. *Adv. Func. Mat.*  
29, 1807282 (2019)



Luo et al. *Nature* 579, 214 (2020)

# Stochastic Magnetic Synapses

- **How can we create an analogue weight from a digital system?**
  - Domain walls either present or absent!
- DW pinning at defects is stochastic!
  - Probability of DW passing defect  $P_{\text{pass}}$ .
  - **Problem for digital devices!!**
- Experimental measurements show that  $P_{\text{pass}}$  can be **tuned sigmoidally** between 0 and 1 using externally applied bias field  $H_{\text{bias}}$ .
- Over repeat measurements create an **analogue response** from the synapse to represent its weight!

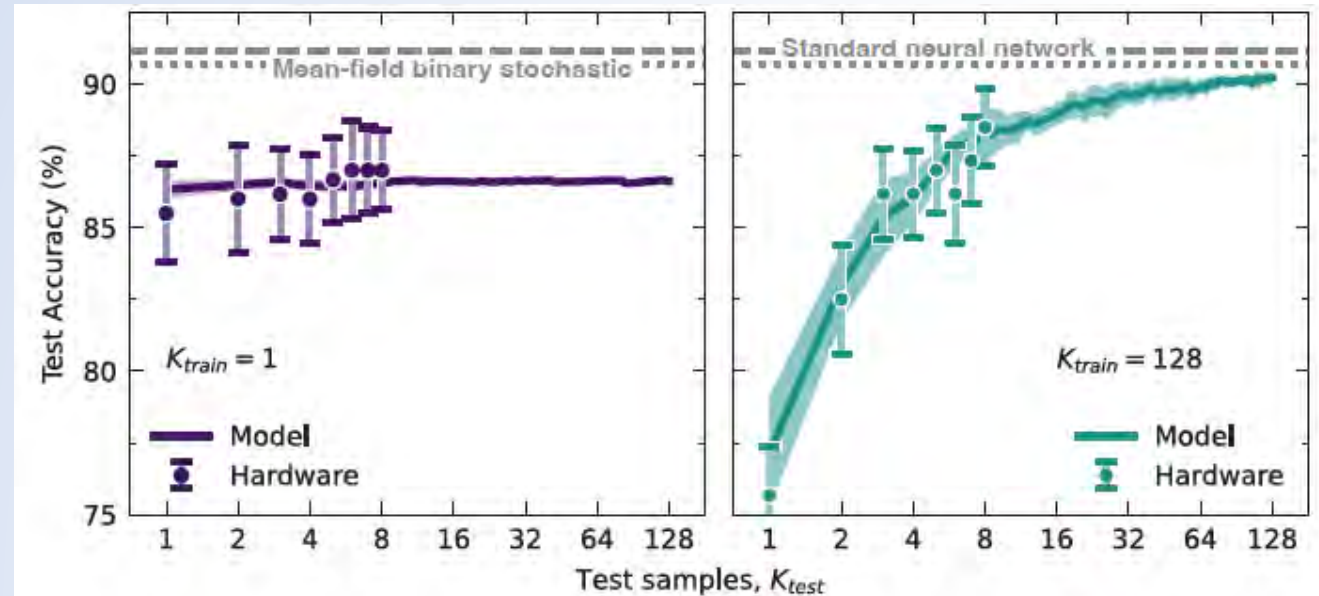
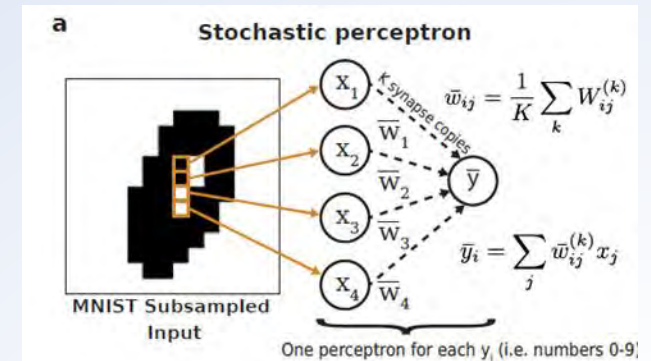
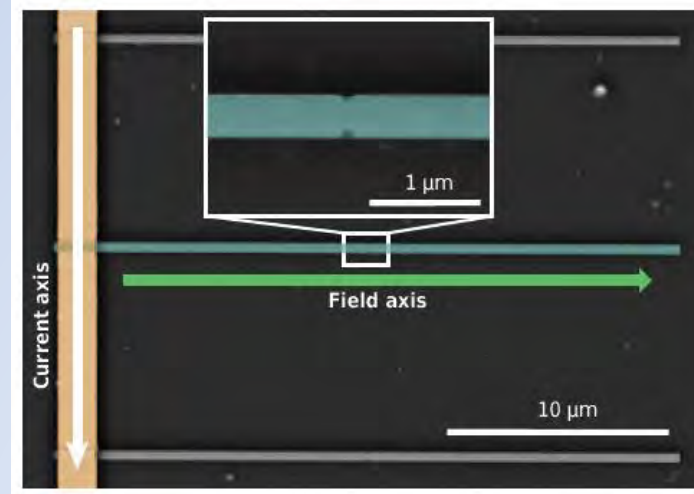


Average N times

Laser spot measures if DW passes defect site

# Experimental Demonstration

- Experimentally demonstrate **feasibility** using serial measurements of a **single DW synapse** to mimic network.
  - Identify **written digits** from the MNIST database
- Successful** experimental implementation of stochastic synapses.
  - 87 % accuracy in MNIST task.**
- Can adapt training to **accuracy/latency** required.
  - Tuneable power/precision!



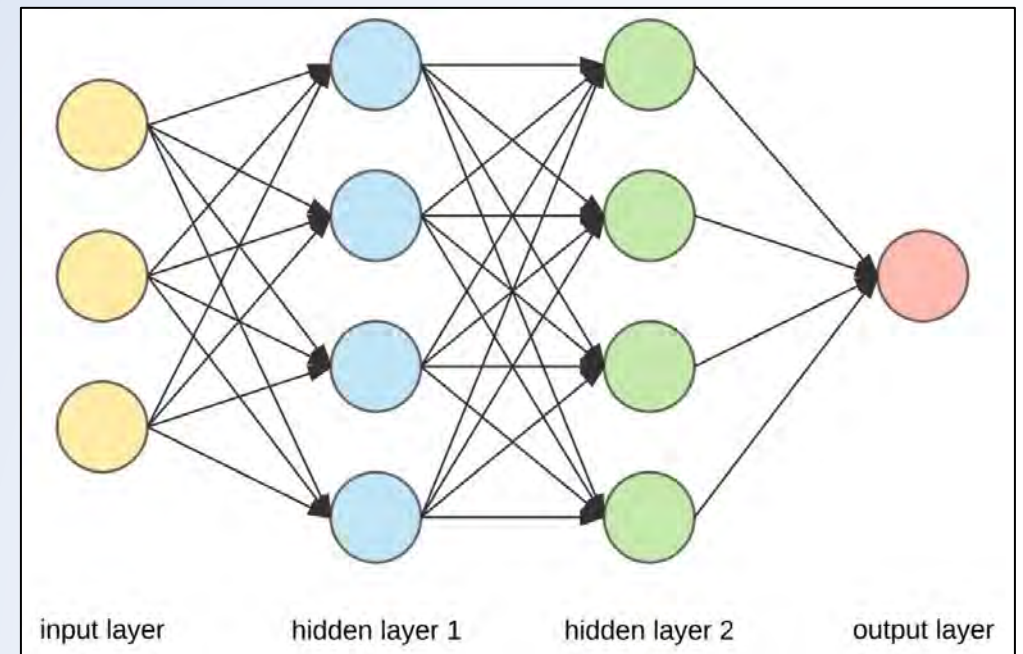
# All Magnetic FFNN?

- We've made a **synapse**, but how do we create a whole neural network using **magnetic materials alone**?
  - Remove interconnects/Von Neuman bottleneck!

**We've made this....**



**...but we want to make this.**

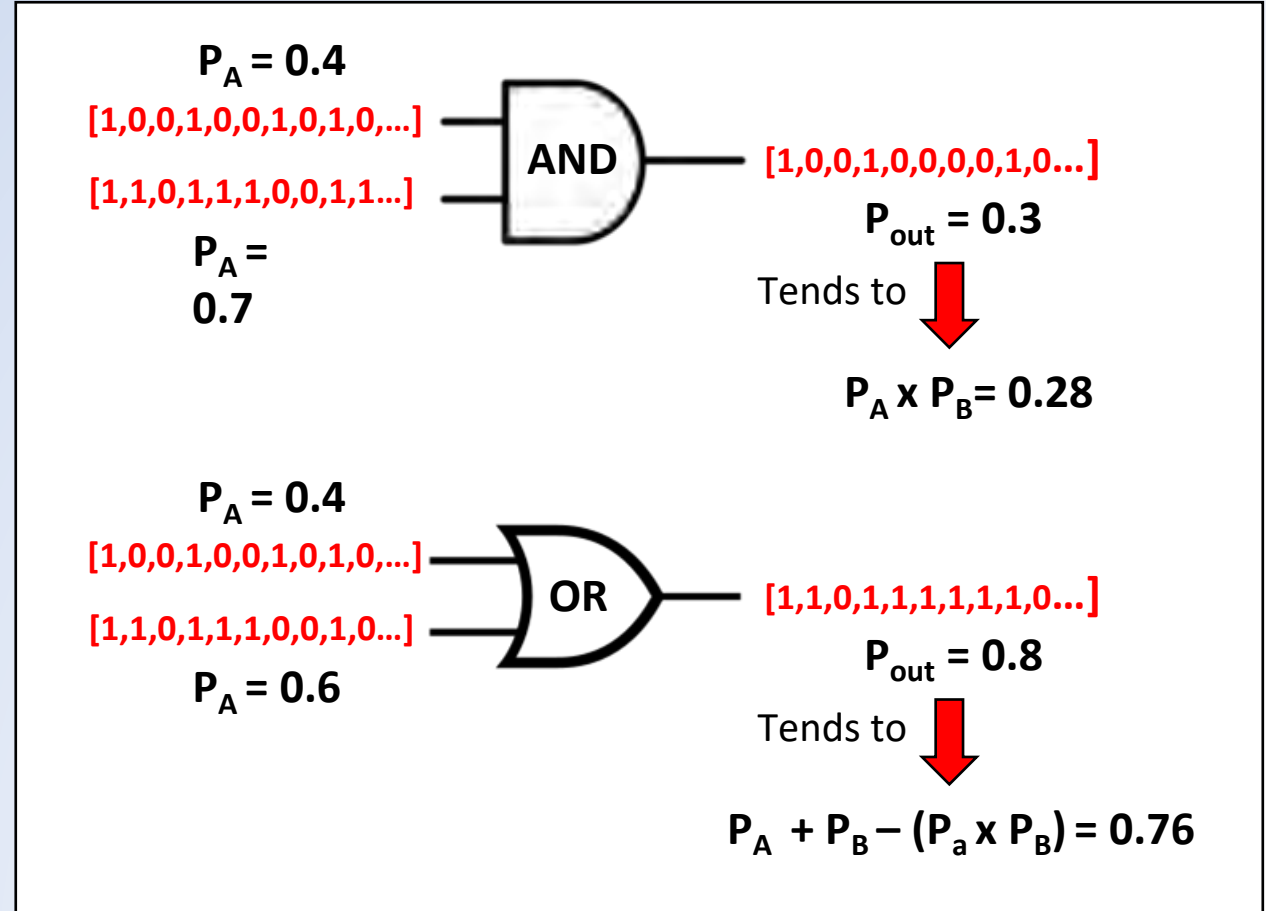




# Stochastic Computing

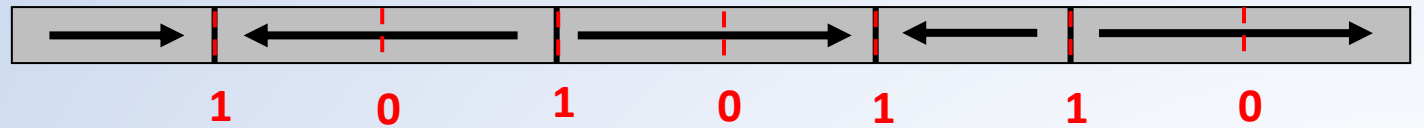
- In **stochastic computing** floating point numbers are represented by streams of binary bits.
  - Fraction of “1”s in a bitstream defines the number.
- Passing these through conventional **logic gates** naturally performs **numerical calculations**:
  - $AND = P_A \times P_B$
  - $OR = P_A + P_B - (P_A \times P_B)$
  - $NOT = 1 - P_A$

Provides **rapid estimates** that become more accurate over time.



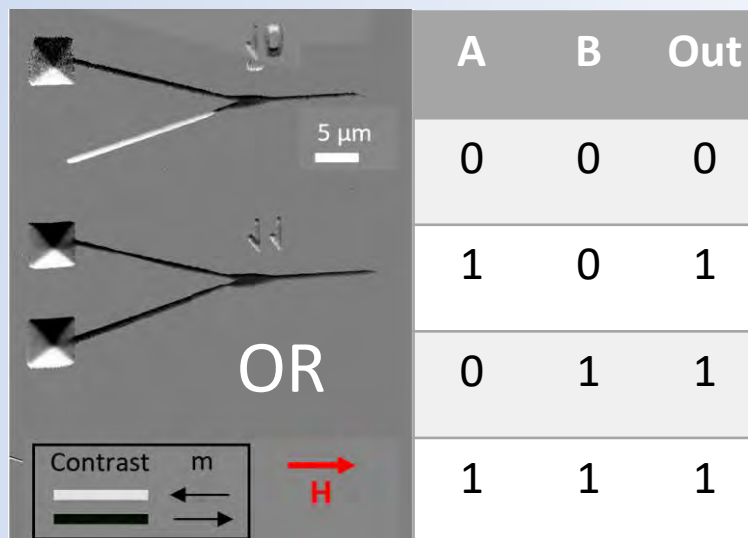
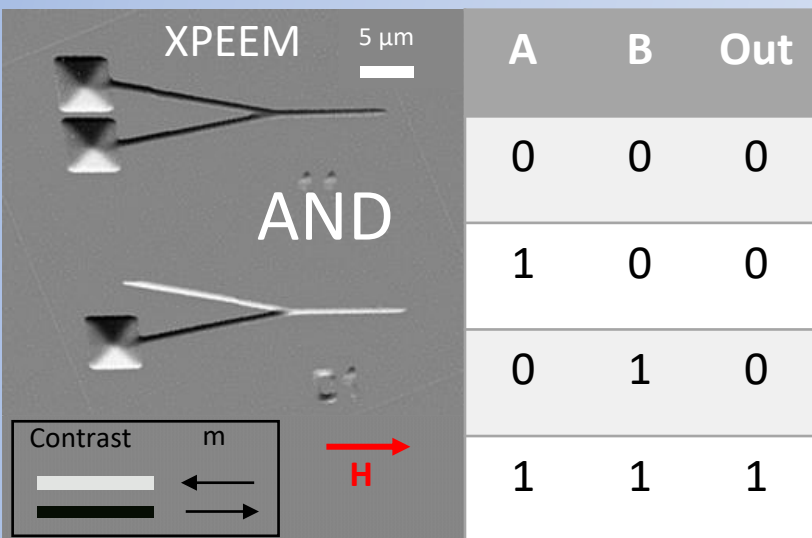
# Stochastic Computing with DWs

- Represent data by **presence (1) or absence (0) of a DW**.

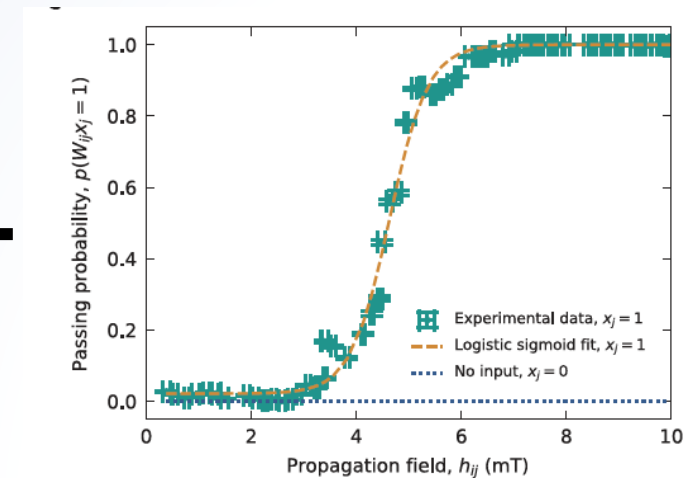


Deterministic DW Logic Gates

Stochastic DW injection

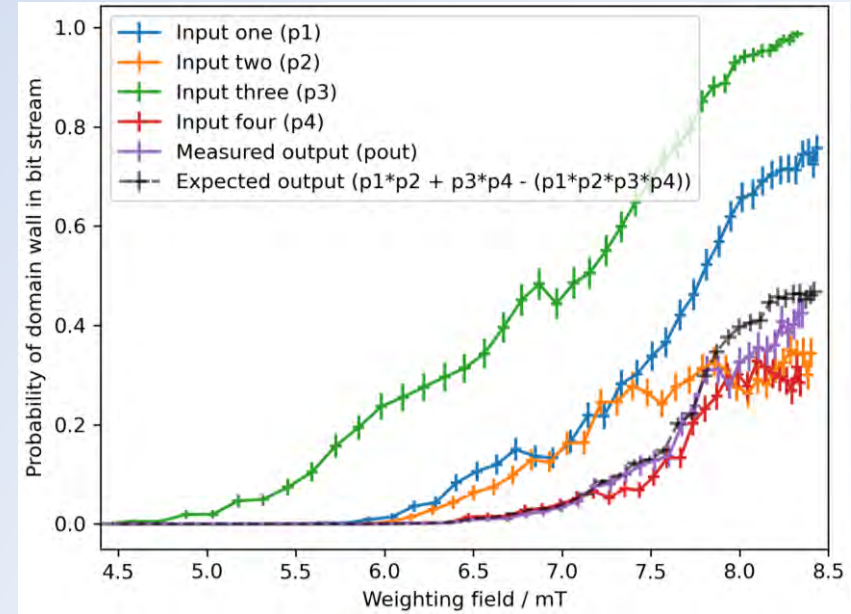
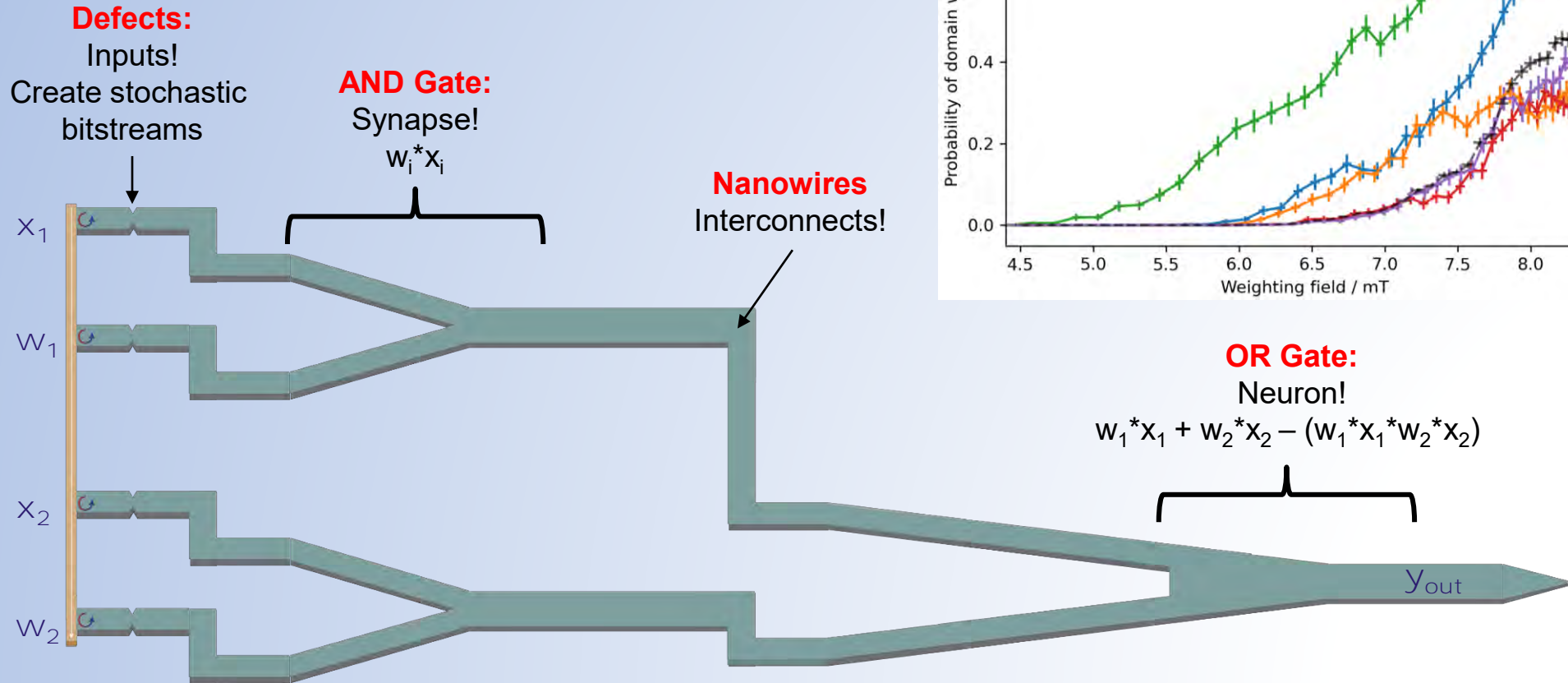


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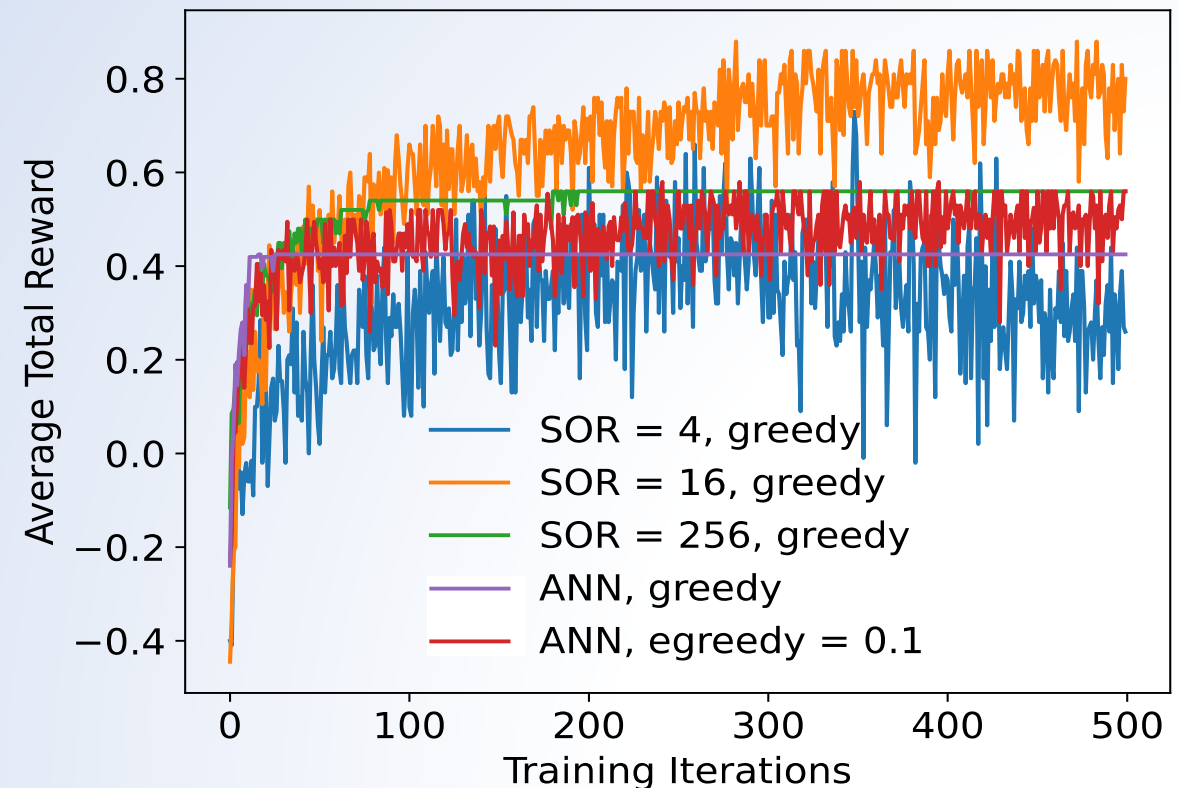
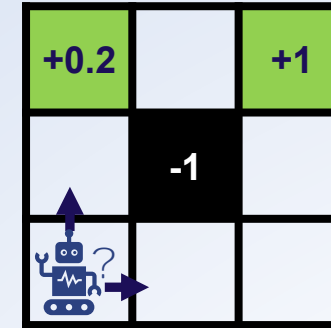
# All Magnetic FFNN

Use magnetic nanowires to create a simple **2 synapse, 1 neuron, neural network**.



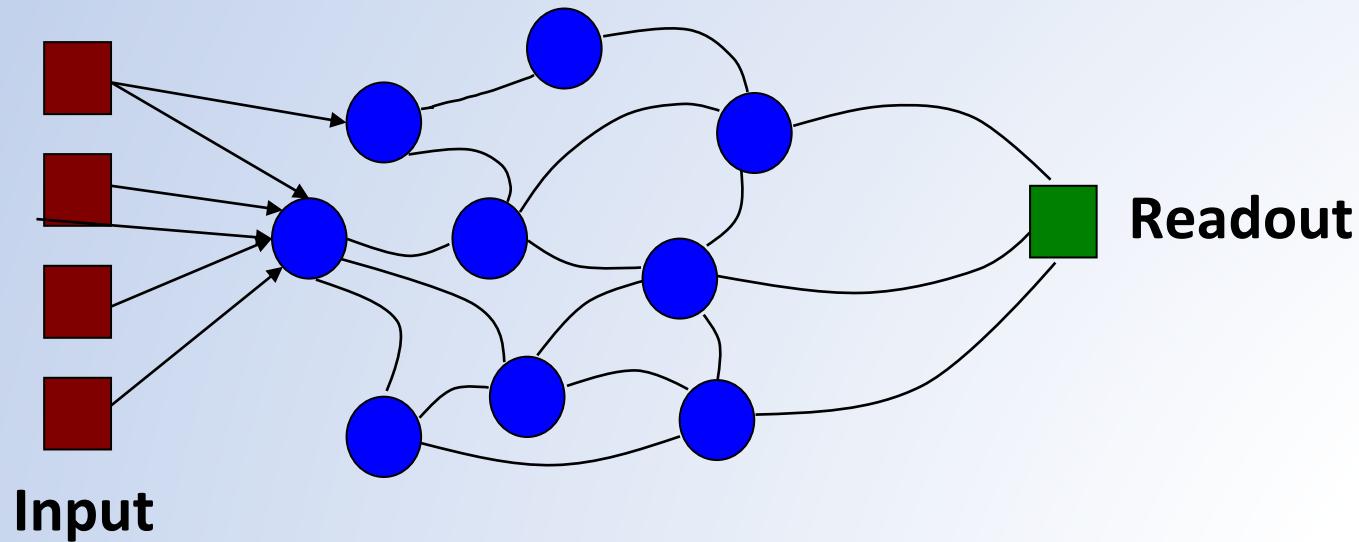
# Exploiting Stochasticity: Reinforcement Learning

- Can the **randomness** of our devices be **useful**?
  - Yes – in reinforcement learning!
- Model for a simple maze **navigation** task.
- Our device can **explore** without any additional random number generation!



# Recurrent Neural Networks

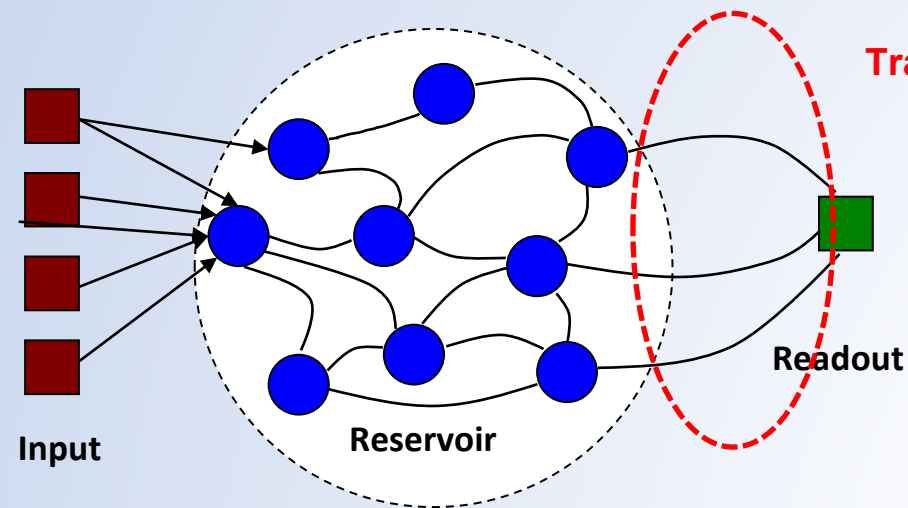
- Feed forward networks create a **static transform** of input data, but many interesting problems are time dependent.
- Recurrent networks create **time-dependent transforms** of data...



- Very computationally powerful, and well-suited to time series analysis.
- Much harder to train as need to “unravel” network in time to train (**backpropagation through time**).

# Reservoir Computing

- **Reservoir computing** developed is a development of recurrent neural networks.
- Recurrent network with fixed synaptic weights (**the reservoir**) connected to a trainable **readout layer**.

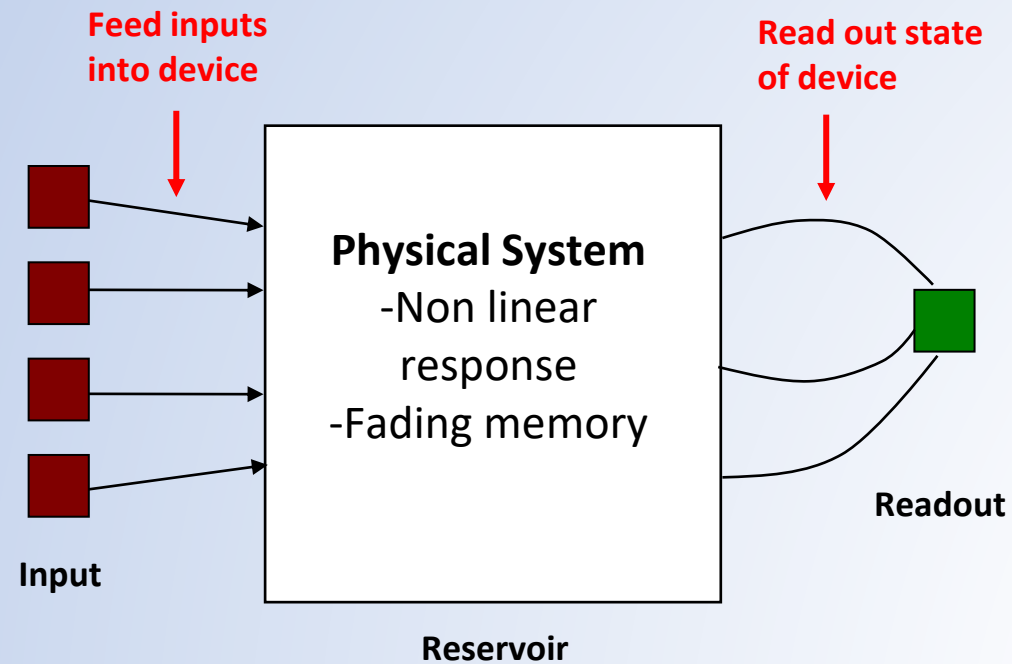


$$y(t) = \sum_N w_i u_i(t) + b$$

- Role of the reservoir is to **transform** input data into a form that is **more easily classifiable**.

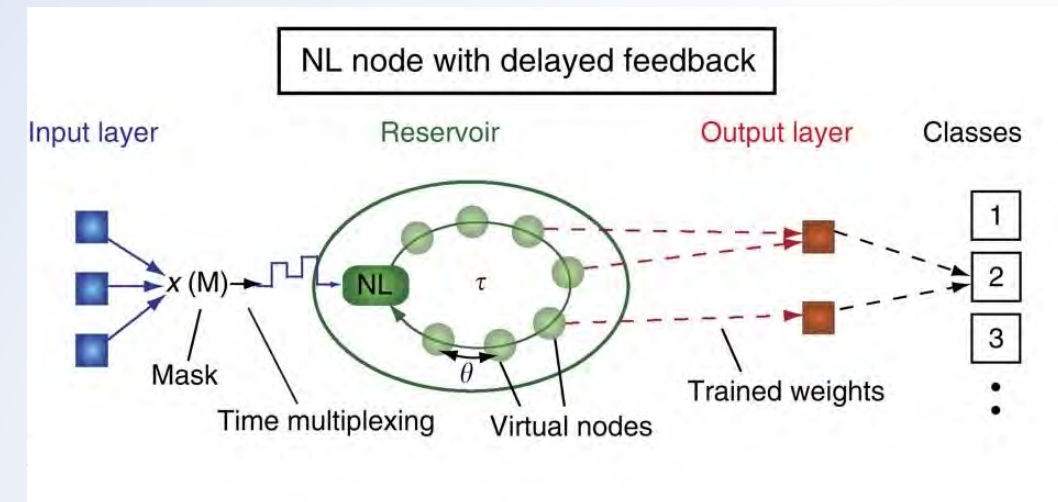
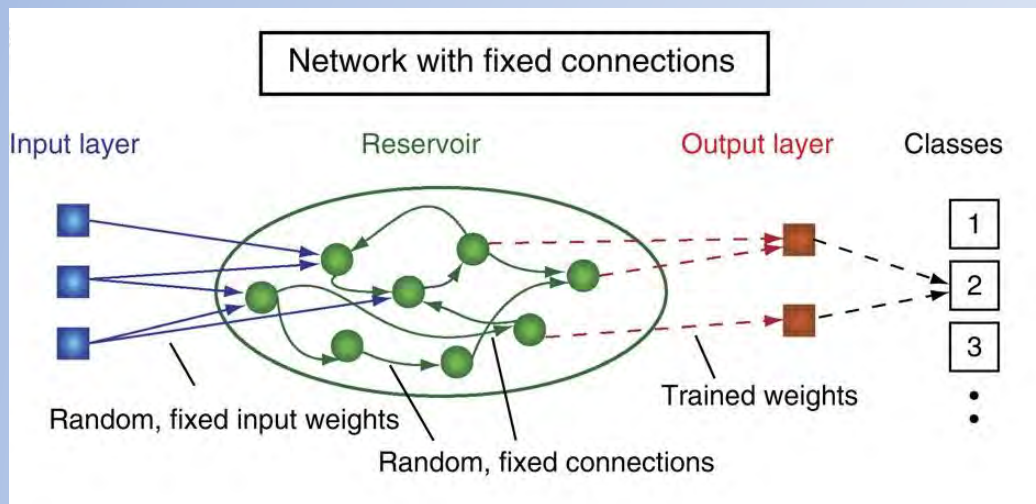
# Physical Reservoir Computing

- For **hardware realisations** as the reservoir can be replaced any **physical system** that has the following properties:
  - **Non-linear response** to input.
  - **Fading memory** of past inputs.



# Time multiplexed RC

- Some devices only have **one input** and **one output**.
- How can we create a **multi-input** and **multi-output** device?
  - **Time multiplexing!**



Nodes of network **spatially** distributed

Nodes of network **temporally** distributed



# Nanomagnetic RC Platforms

- There's lots of ideas out there! We published this last year, but it's probably already missing a lot!

## A perspective on physical reservoir computing with nanomagnetic devices

Cite as: *Appl. Phys. Lett.* **122**, 040501 (2023); doi: [10.1063/5.0119040](https://doi.org/10.1063/5.0119040)  
 Submitted: 7 August 2022 · Accepted: 31 December 2022 ·  
 Published Online: 23 January 2023



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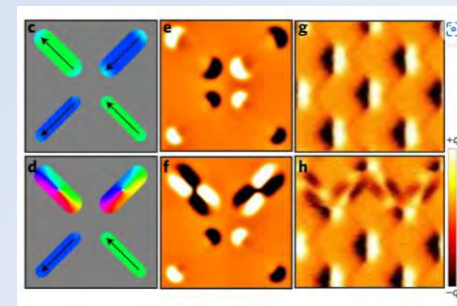
<sup>a)</sup>Authors to whom correspondence should be addressed: [t.hayward@sheffield.ac.uk](mailto:t.hayward@sheffield.ac.uk) and [e.vasilaki@sheffield.ac.uk](mailto:e.vasilaki@sheffield.ac.uk)

### ABSTRACT

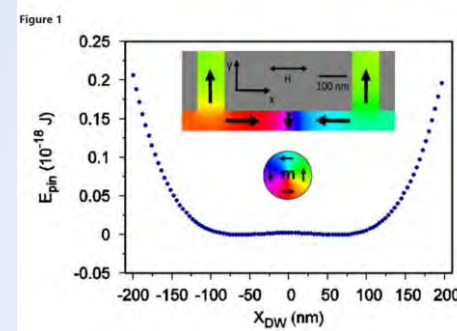
Neural networks have revolutionized the area of artificial intelligence and introduced transformative applications to almost every scientific field and industry. However, this success comes at a great price; the energy requirements for training advanced models are unsustainable. One promising way to address this pressing issue is by developing low-energy neuromorphic hardware that directly supports the algorithm's requirements. The intrinsic non-volatility, non-linearity, and memory of spintronic devices make them appealing candidates for neuromorphic devices. Here, we focus on the reservoir computing paradigm, a recurrent network with a simple training algorithm suitable for computation with spintronic devices since they can provide the properties of non-linearity and memory. We review technologies and methods for developing neuromorphic spintronic devices and conclude with critical open issues to address before such devices become widely used.

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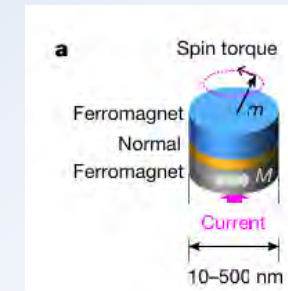
D.A. Allwood, T.J. Hayward *et al.*  
*Appl. Phys. Lett.* **122**, 040501 (2023)



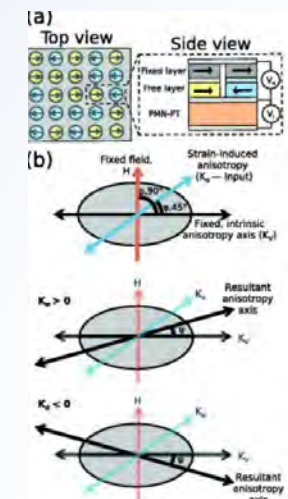
Spin Ices



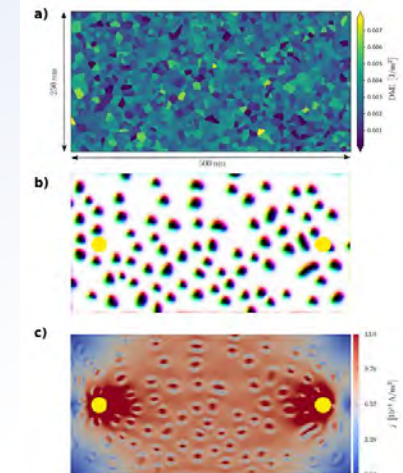
Domain Walls



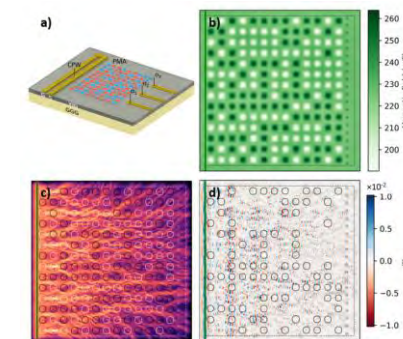
STOs



Super Paramagnets



Skyrmions

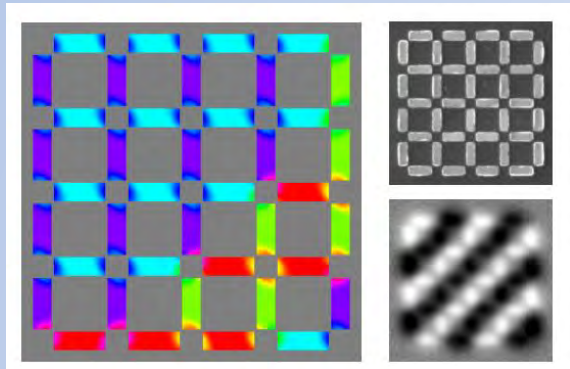


Magnons

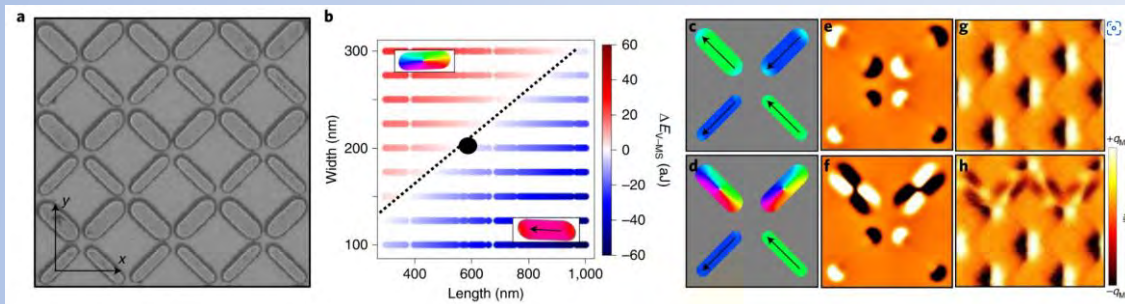
# RC with Magnetic Metamaterials

- Magnetic Meta Materials like **Artificial Spin Ices** and **Nanoring Ensembles** consist of large numbers of interconnected elements.
- Huge **state space**, **emergent behaviour** → potential ideal for reservoir computing!

## ASI

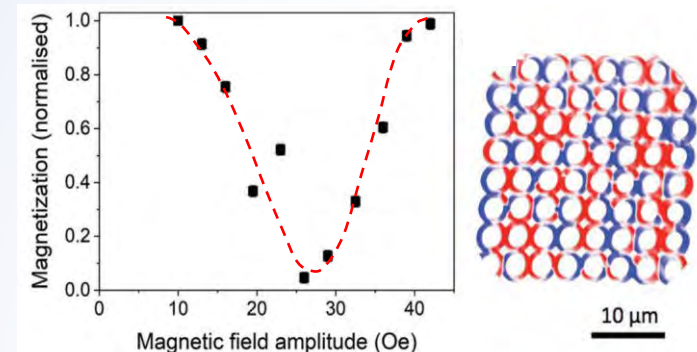
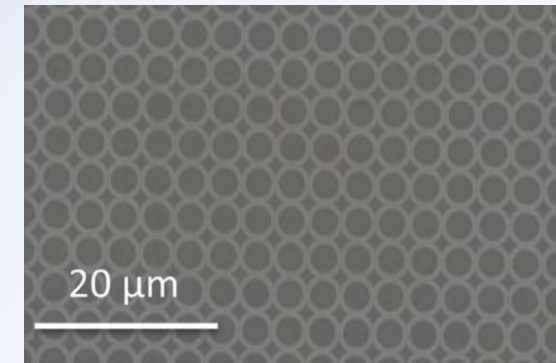


J.H. Jensen *et. al.* Artificial Life Conference Proceedings, 15-22 (2018)



J.C. Gartside *et. al.* Nature Nanotechnology 17 (5), 460-469 (2022)

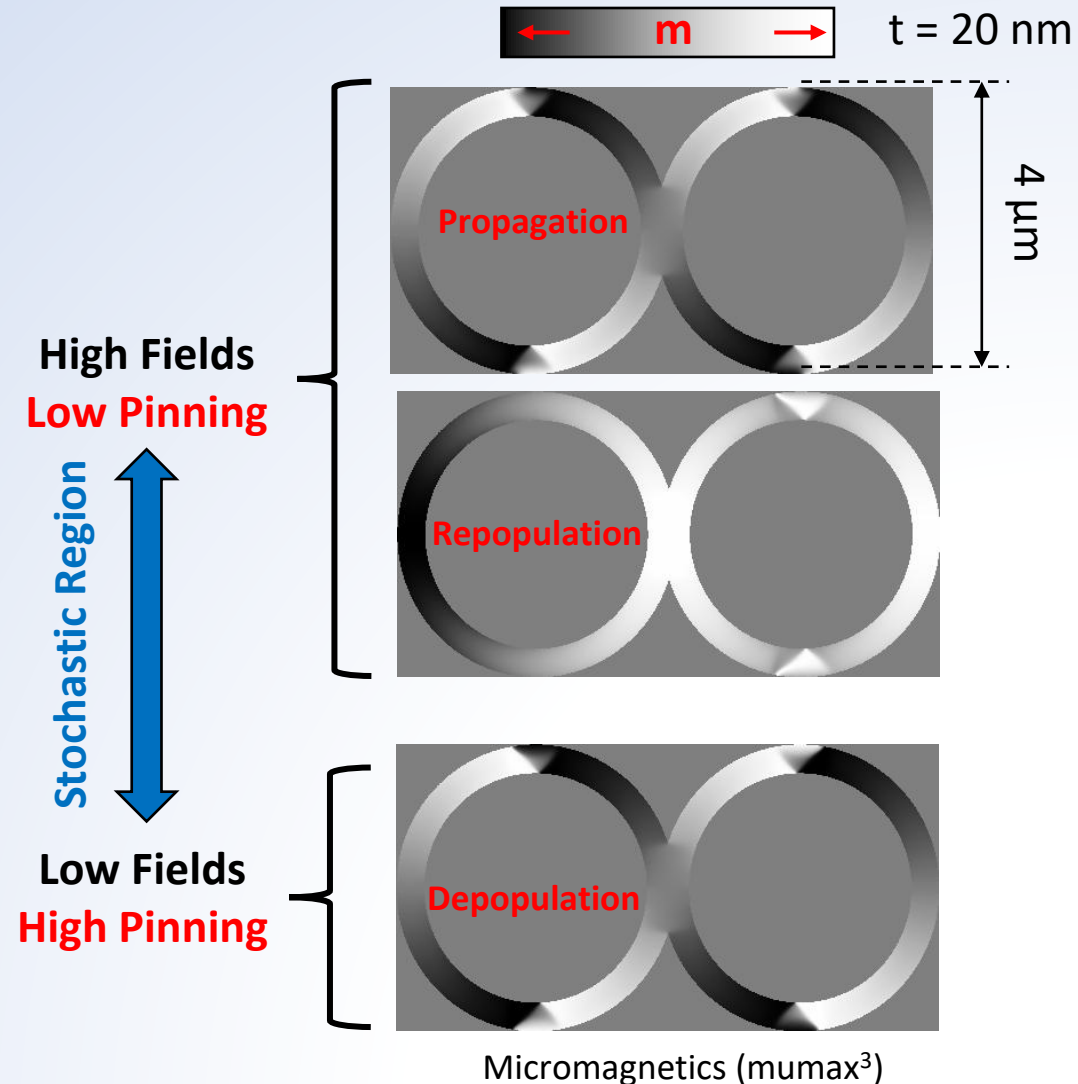
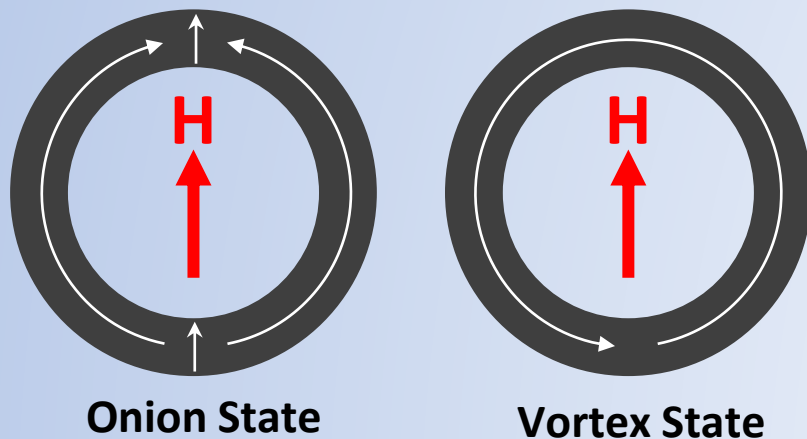
## NRE



R.W. Dawidek, T.J. Hayward *et. al.* Adv. Func. Mater. 31, 2008389 (2021)

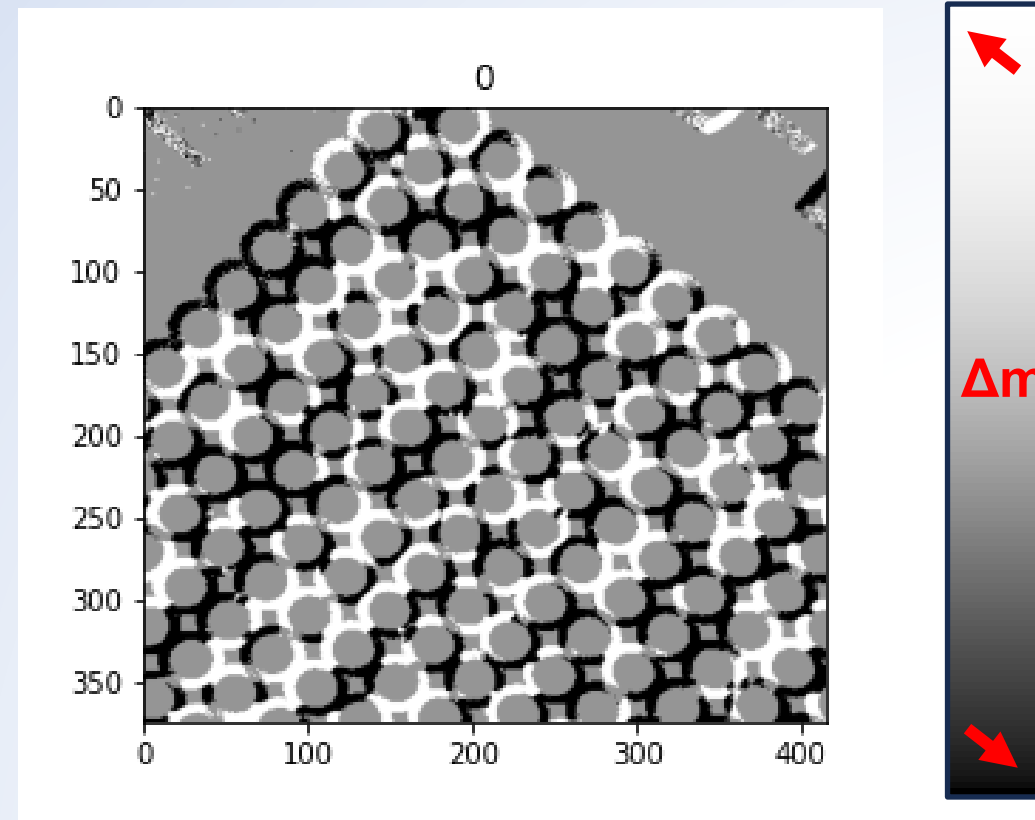
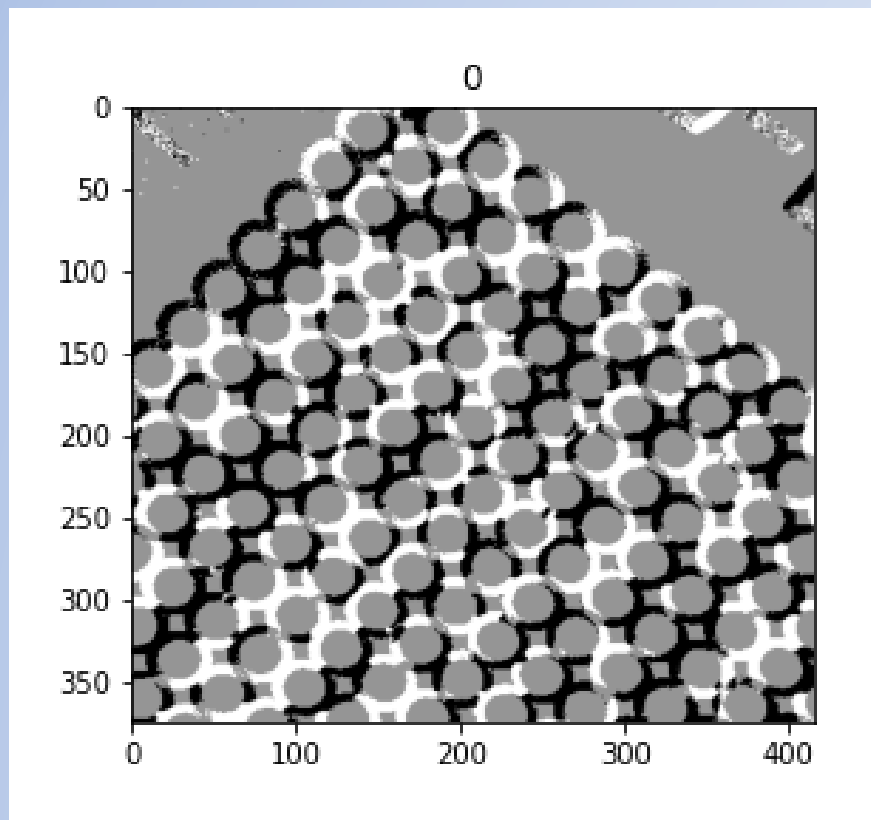
# Domain Walls in Ring-shaped Nanowires

- **Ring-shaped nanowires** form two magnetic states.
  - **Onion state** – DWs rotate with rotating applied field.
  - **Vortex state** – circulating magnetisation.
- When multiple rings are connected the **junctions act as pinning sites**.
  - Produce **domain wall interactions** that may cause **population** or **depopulation** of DWs in the rings.
- At intermediate applied fields these processes will be **stochastic!**



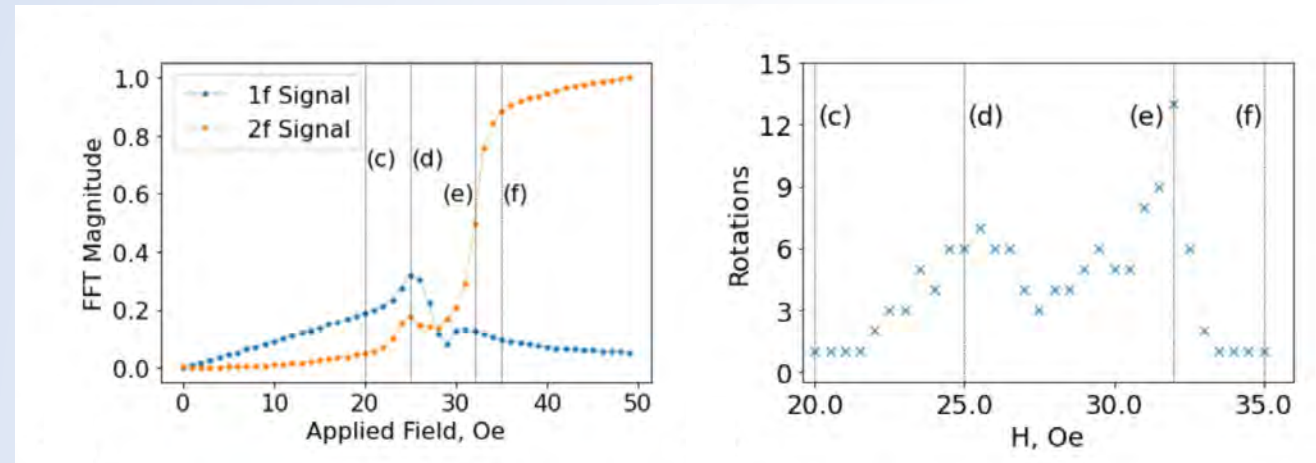
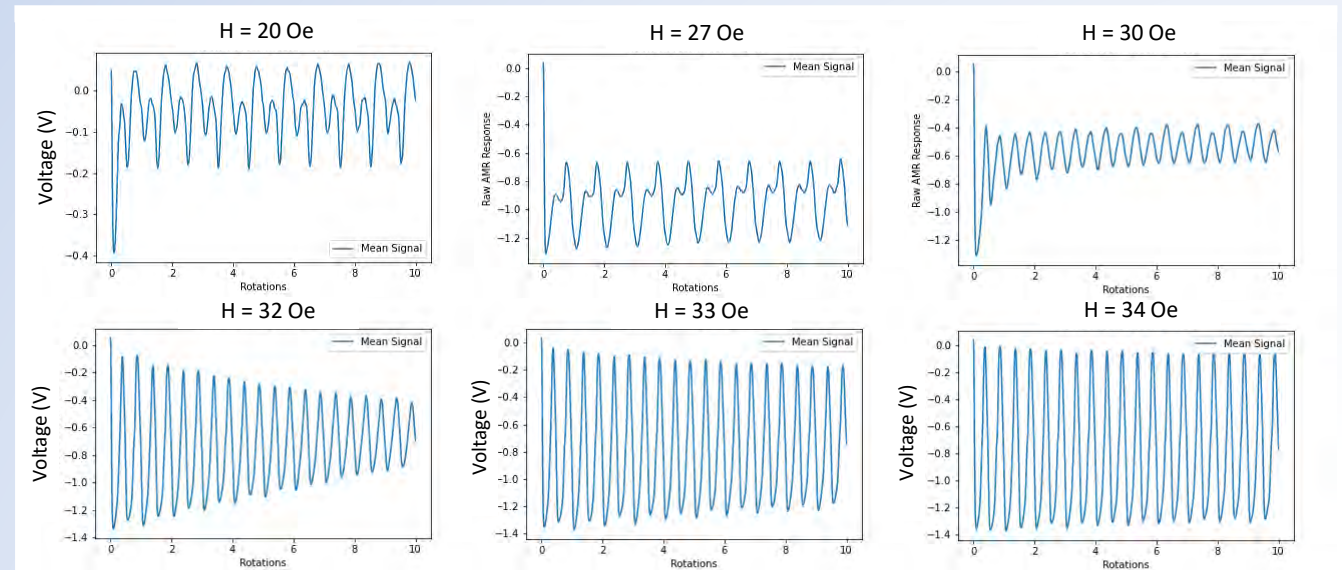
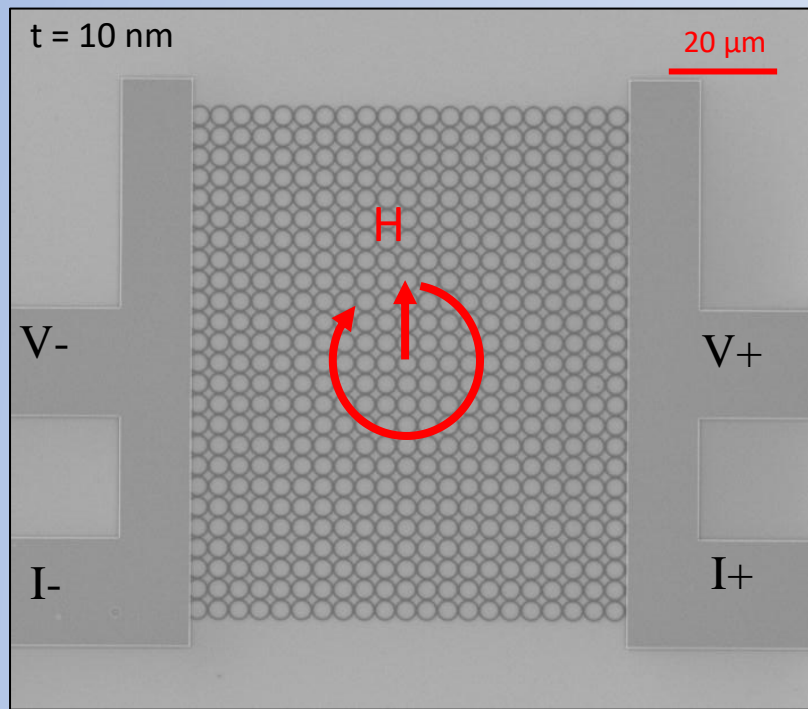
# Emergent Behaviour in Ring Ensembles

- Complex, emergent interactions in large, **interconnected arrays!**
- PEEM measurements allow us to **directly visualise** the behaviours!



# Creating Electrical Devices

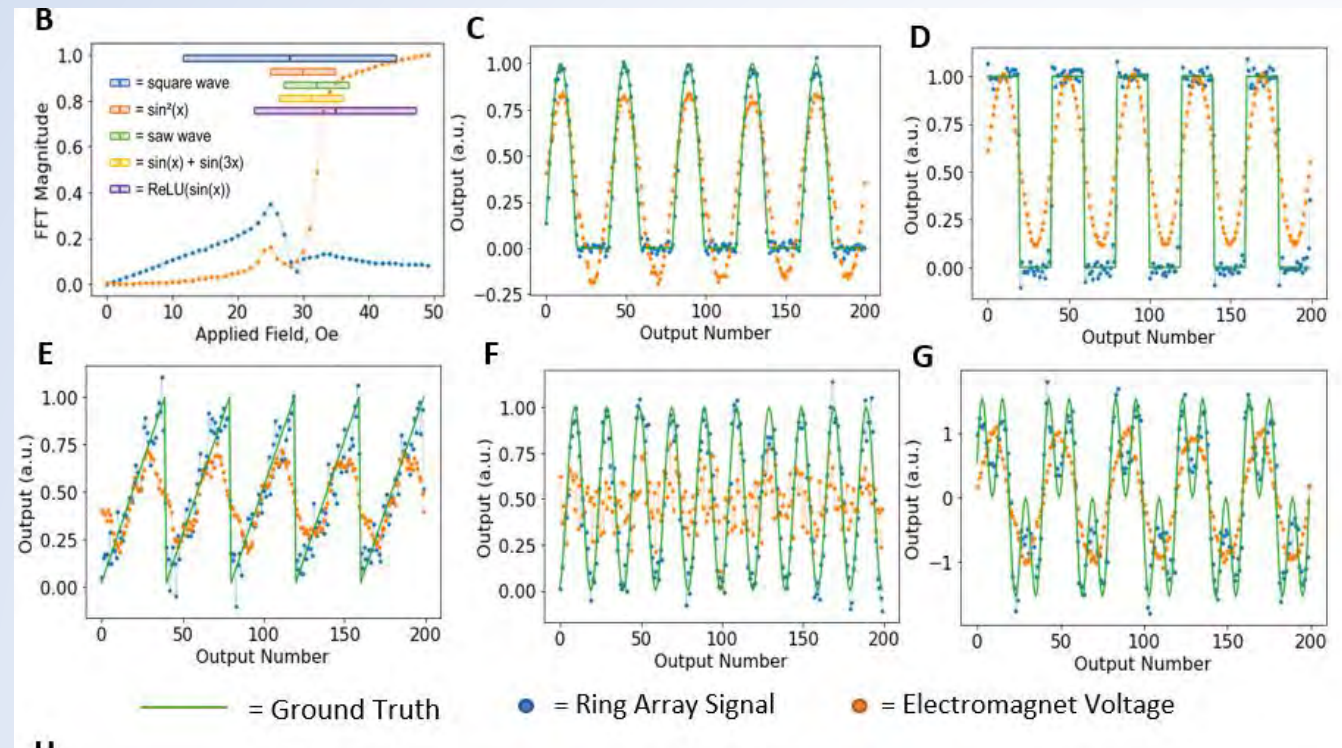
- Create **electrically contacted** arrays.
- Measure **anisotropic magnetoresistance** (AMR).
  - Essentially measures number, size and position of DWs in the system.
- Rich signals produced when rotating magnetic fields applied.
  - Frequency components at **1x** and **2x** field frequency.
  - Non-linear variation, fading memory! ✓✓✓



# RC: Signal Reconstruction

- **Transform** sine wave into other periodic waveforms.
- Simple approach:
  - Encode data in **amplitude of rotating field**.
- Low mean square error (**MSE**) for all waveforms tested.
  - Referenced to equivalent operation on electromagnet voltage.

$$H = H_0 + \Delta H * x(t)$$



# RC: More Complex Tasks

## Spoken Digit Recognition

Input



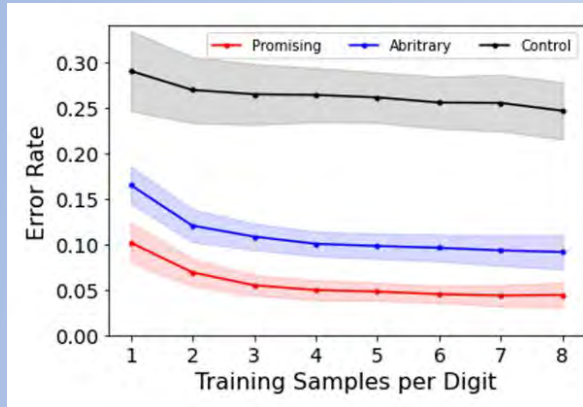
3

Output

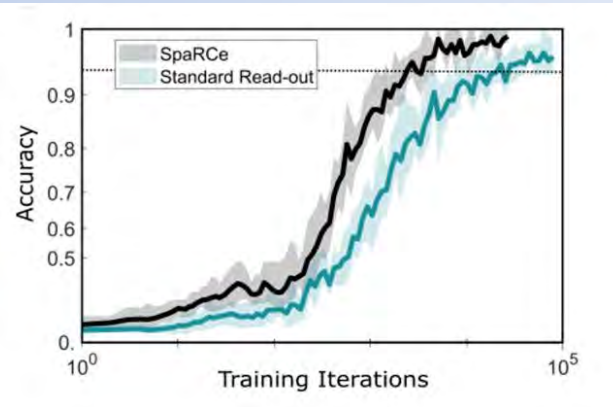
3!

- Classify digits 0-9 for 5x female speakers from TI-46 database
- Data preprocessed via a Mel-Frequency Cepstral filter.

### Offline Training



### Online Training



I.T. Vidamour et. al Comms. Phys. 6, 230 (2023)

## NARMA-N Time Series

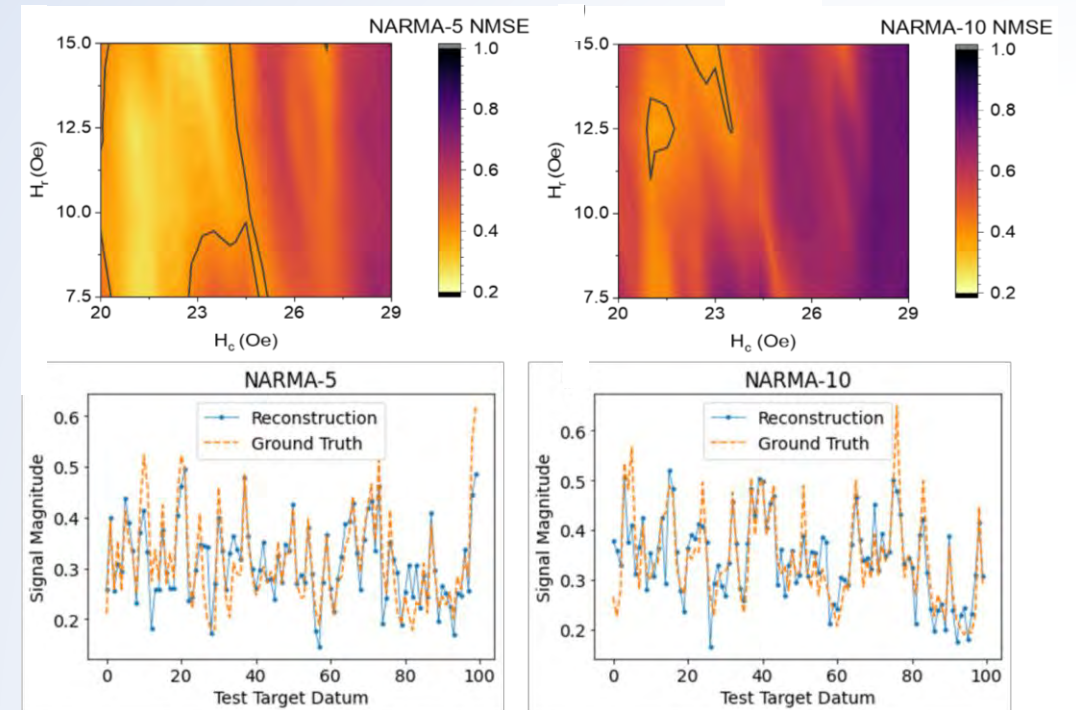
Input

$$x_t \rightarrow y_{t+1} = F(y_t, y_{t-1}, \dots, y_{t-N}, x_t, x_{t-1}, \dots, x_{t-N})$$

(White noise)

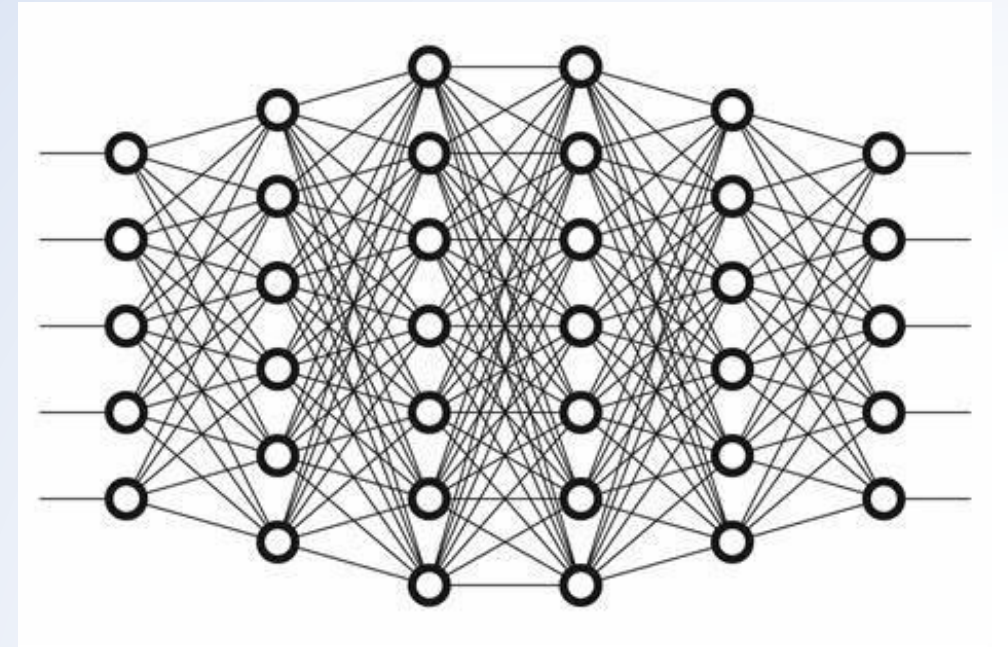
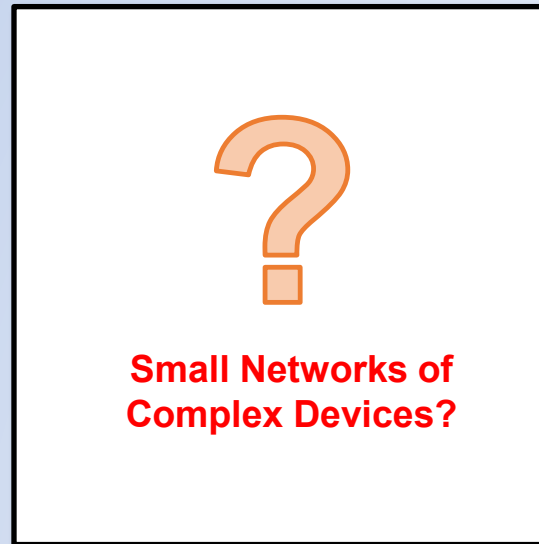
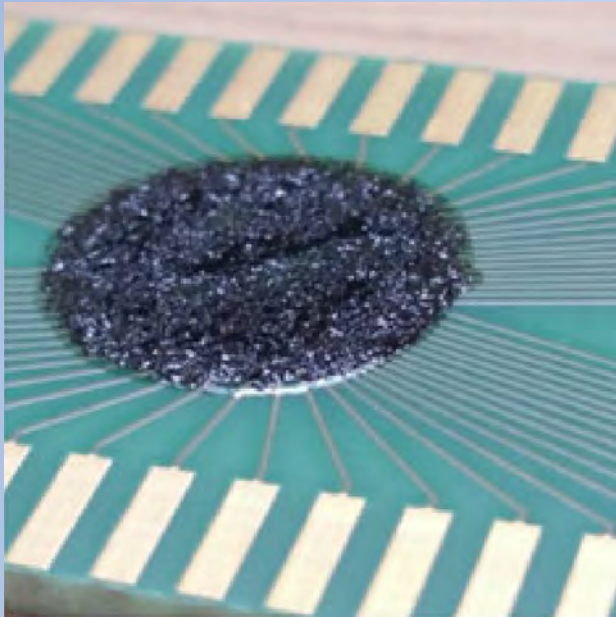
(Non-linear transform of last N inputs and outputs)

Output



# Dynamic System Networks

- Tendency towards a **false dichotomy** in how we think about physical neuromorphic computing...
- But what if we didn't think **so digitally....**



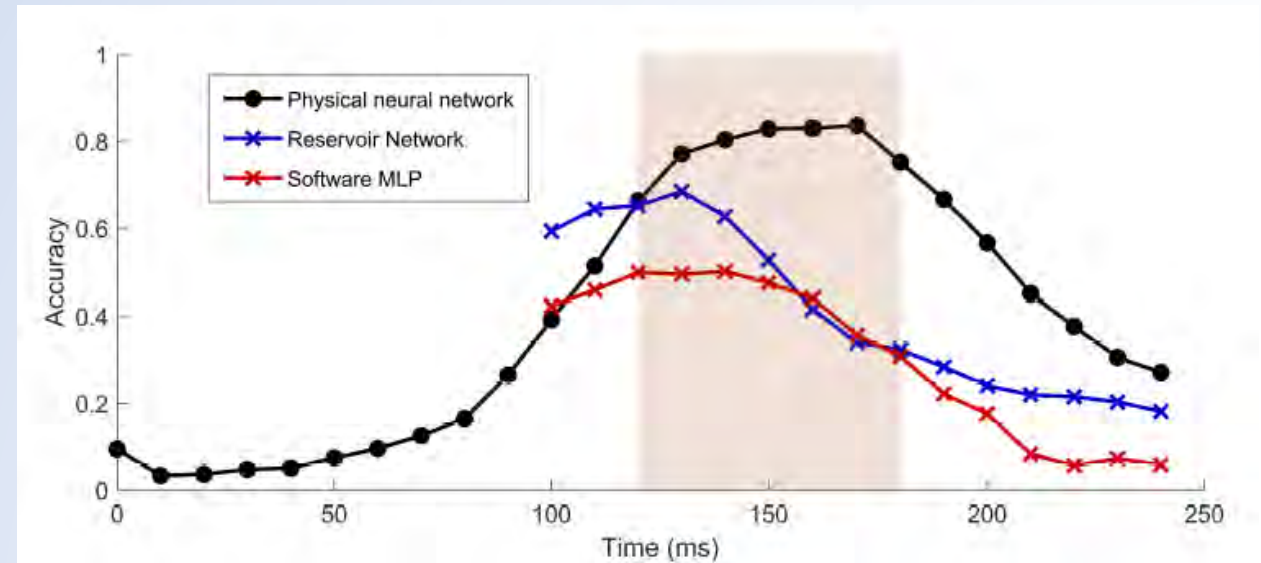
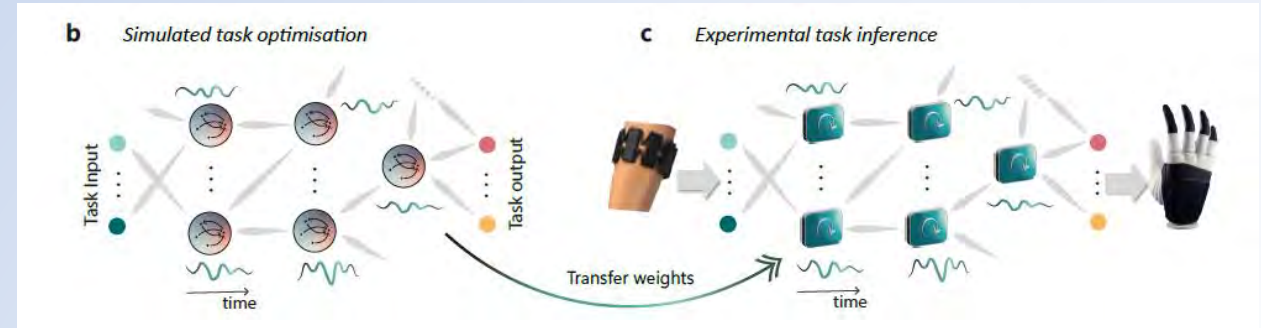
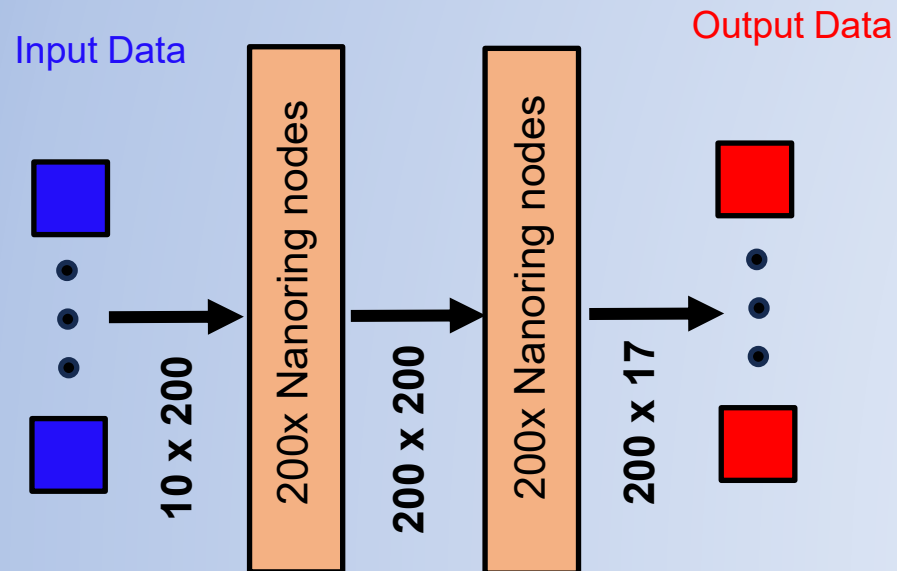
**Complex Device, Monolithic**

**Simple Devices, Networked**



# Real World Task: Neuroprosthetics

- Train nanoring array **network** to recognise **hand gestures**:
  - Ninapro database.
  - Recognise 17 hand gestures.
  - 27 subjects.
  - 10 channels of electrode input data.



I.T. Vidamour et. al. *under review*

# Conclusions

- Magnetic materials offer exciting possibilities for create new types of **neuromorphic hardware!**
- **Do the materials/devices/phenomena you are studying have any exciting functionality that could be explored for these applications?**