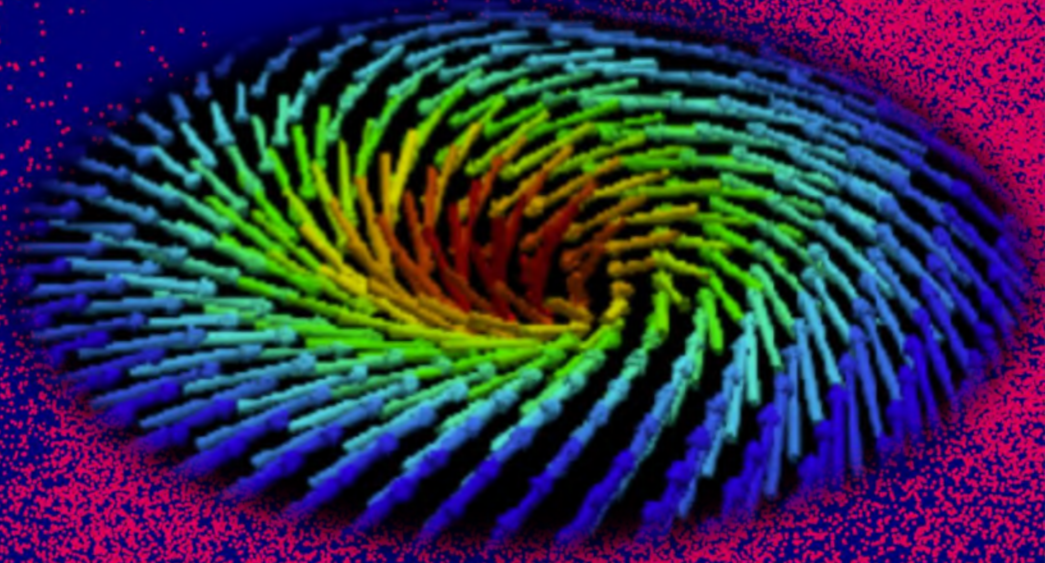
IMPERIAL

Topological Magnetic Textures for Functional Systems

ESM2025



Jack C. Gartside

Associate Professor, Physics & Neuromorphic Computing

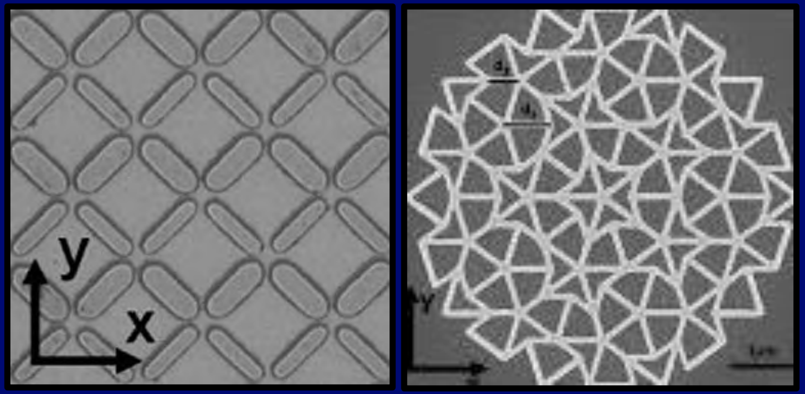
PI Neuromorphic Metamaterials Group

Department of Physics, **Imperial College London**

Quick Introduction: Me & my group

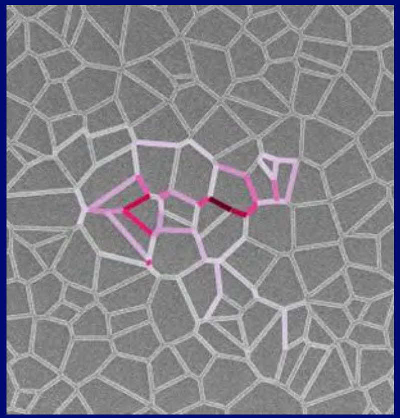
Neuromorphic Metamaterials Grou
Imperial College London

Magnetic Metamaterials
State writing, Magnonics, Neuromorphic Computing



Jack Gartside

Photonic Metamaterials
Strongly coupled lasing networks, Neuromorphic computing



Jakub Dranczewski
Nanophotonics,
Neuromorphic Computing

Alex Wright
Magnonics,
Nanomagnetism

Wai Kit Ng
Nanophotonics,
Neuromorphic
Computing

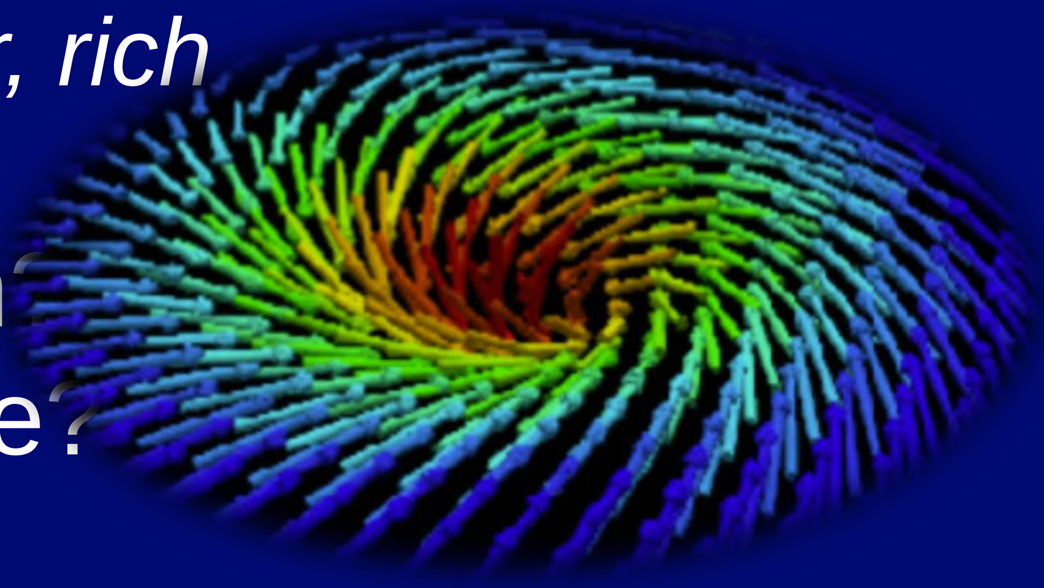
Shugo Yoshii
Magnonics,
Photon-Magnon
Coupling

Tingjun Zheng
Magnonics,
Magneto-Optics

Tobias Farchy
Neuromorphic
Computing,
Nanophotonics,
Nanomagnetism

Talk Outline

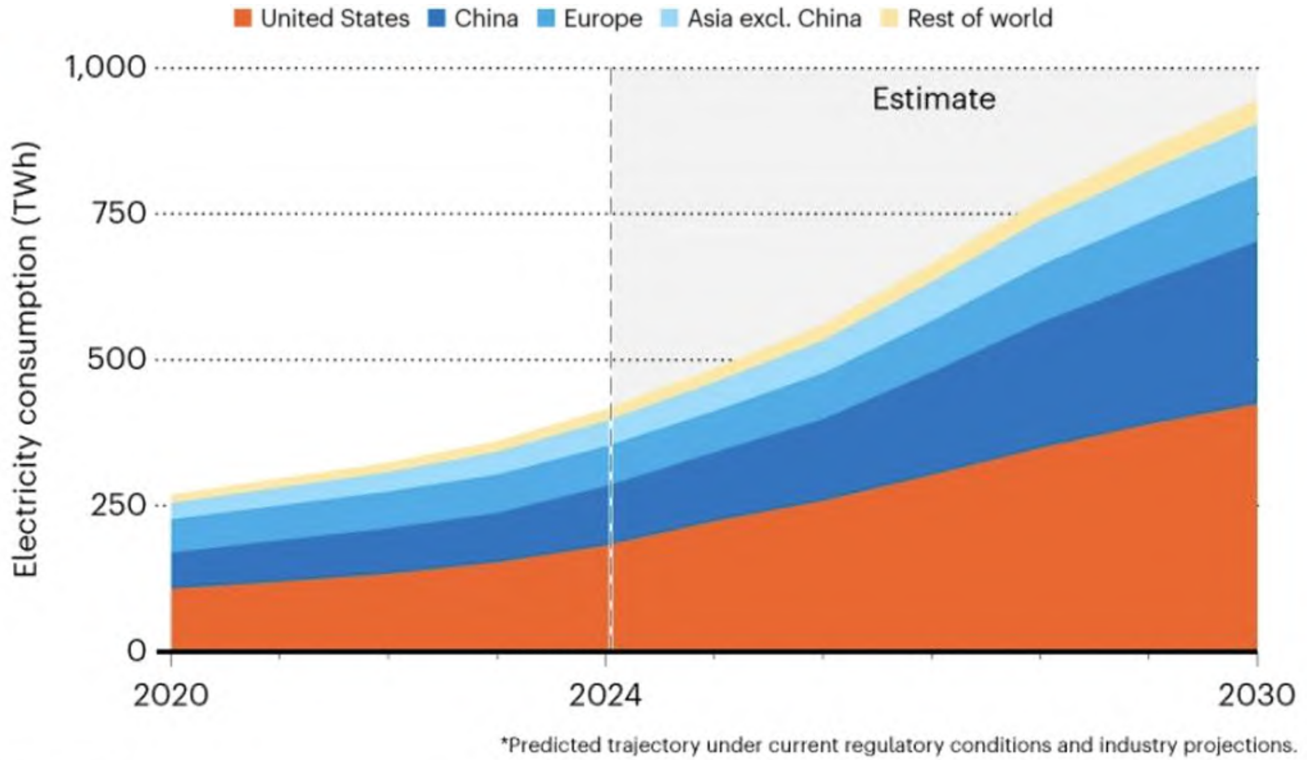
- Why do we want new devices?
- What do we mean by topological textures?
  - *Topological defects, winding numbers*
- Why are they interesting for applications?
  - *Stability, control, low power, rich dynamics/magnonics*
- What can we do with them?
- What still needs to be done?



The Challenge:
AI has a **huge** Energy and Data problem

AI Energy Use

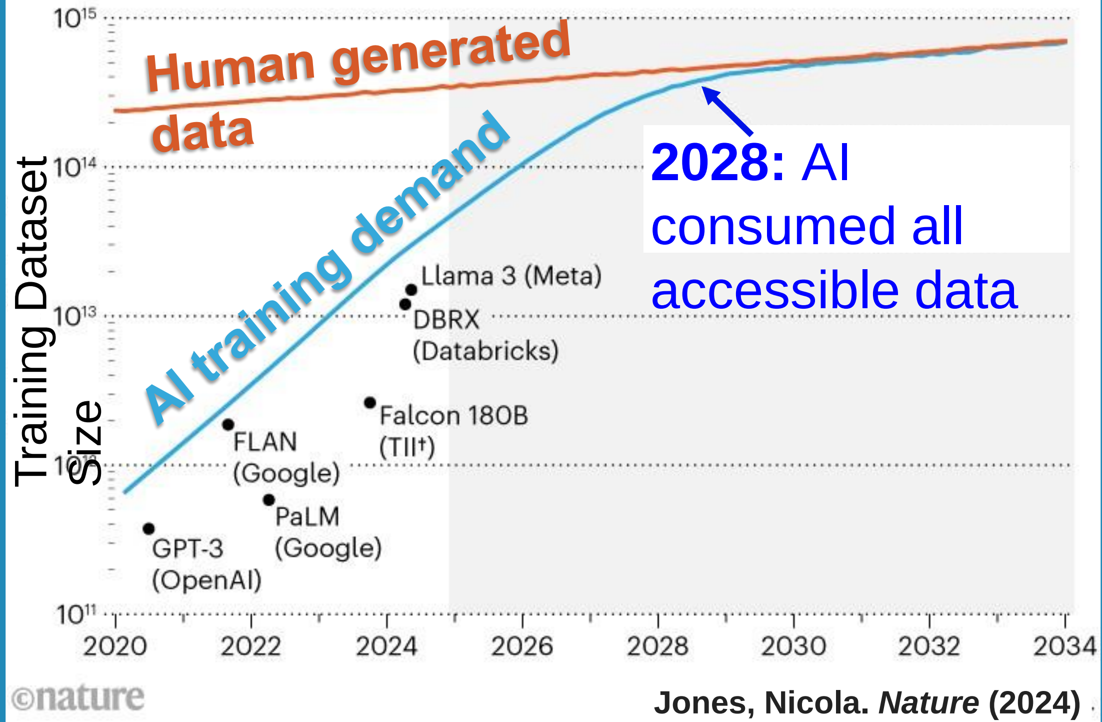
- Global AI energy use **doubles every 3.4 months**
- **500 TWh** increase by **2030**



Chen, Sophia. *Nature* (2025)

AI Training Data Demand

- We will **run out of AI training data** by **2028**



Jones, Nicola. *Nature* (2024)

The Challenge:

AI has a **huge Energy** and **Data** problem

- Root cause: **Hardware**

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- **Biological Brains** consume just ~**20 W** & learn from **extremely few examples**

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- Specialised sub-regions: **Cortices**

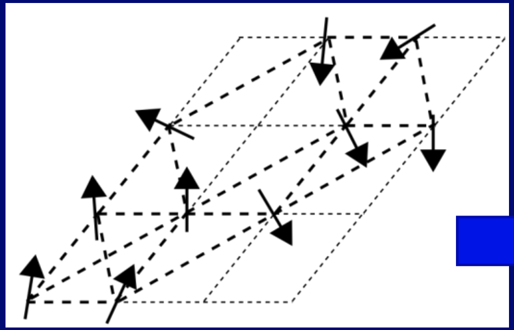
The Challenge:
AI has a **huge Energy** and **Data** problem

- Root cause: **Hardware**
- **Biological Brains** consume just ~**20 W** & learn from **extremely few examples**
- Specialised sub-regions: **Cortices**

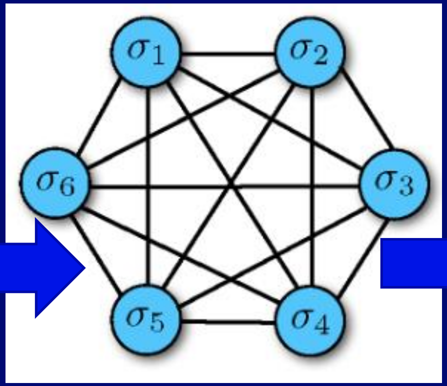
Can we develop a **Brain-Like** Processor?

Magnetism: A Promising Physics-based Solution

Artificial Neural Networks: Magnetically Inspired

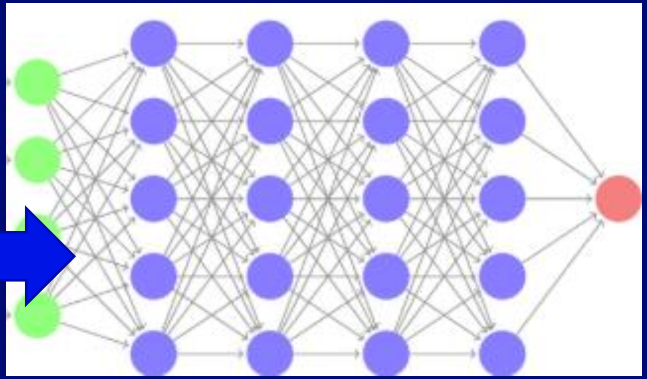


Complex Magnetic System:
Spin Glass
Sherrington-Kirkpatrick



Hopfield Networks

Nobel Prize for Physics: 2024



Deep Neural Networks

Benefits of magnetism:

- **Memory, Non Volatility**, & **Reconfigurability**
- **GHz speed**, **Strong Coupling**

Magnetism: Promising physics-based solution

Hamiltonian

spin at site i

Spin glasses

Sherrington-Kirkpatrick model

$$H = \sum_{ij} J_{ij} s_i s_j + \sum_i h_i s_i$$

couplings between sites

external magnetic field at i'th site

energy function

state of neuron i

Neural networks

Hopfield model

$$E = \sum_{ij} w_{ij} v_i v_j + \sum_i \theta_i v_i$$

weights of the learning rule

activation threshold for i'th neuron

Magnetism: Promising physics-based solution

Spin glasses

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state of neuron i

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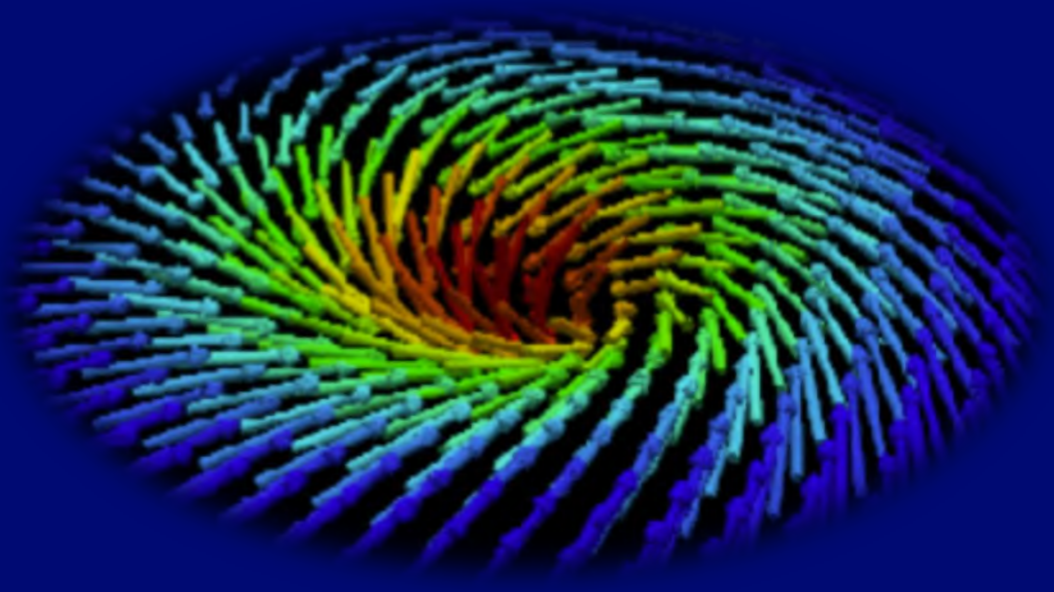
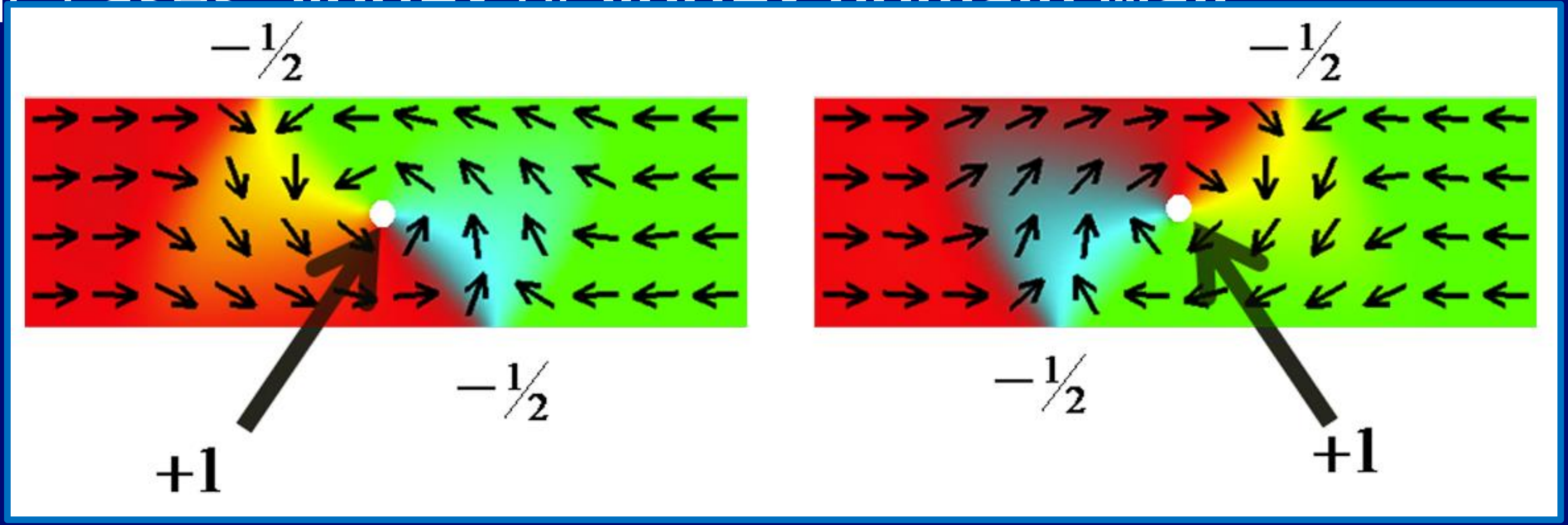
So we have synergy – but why ‘topology’?



What even are Topological Textures? – A brief detour…

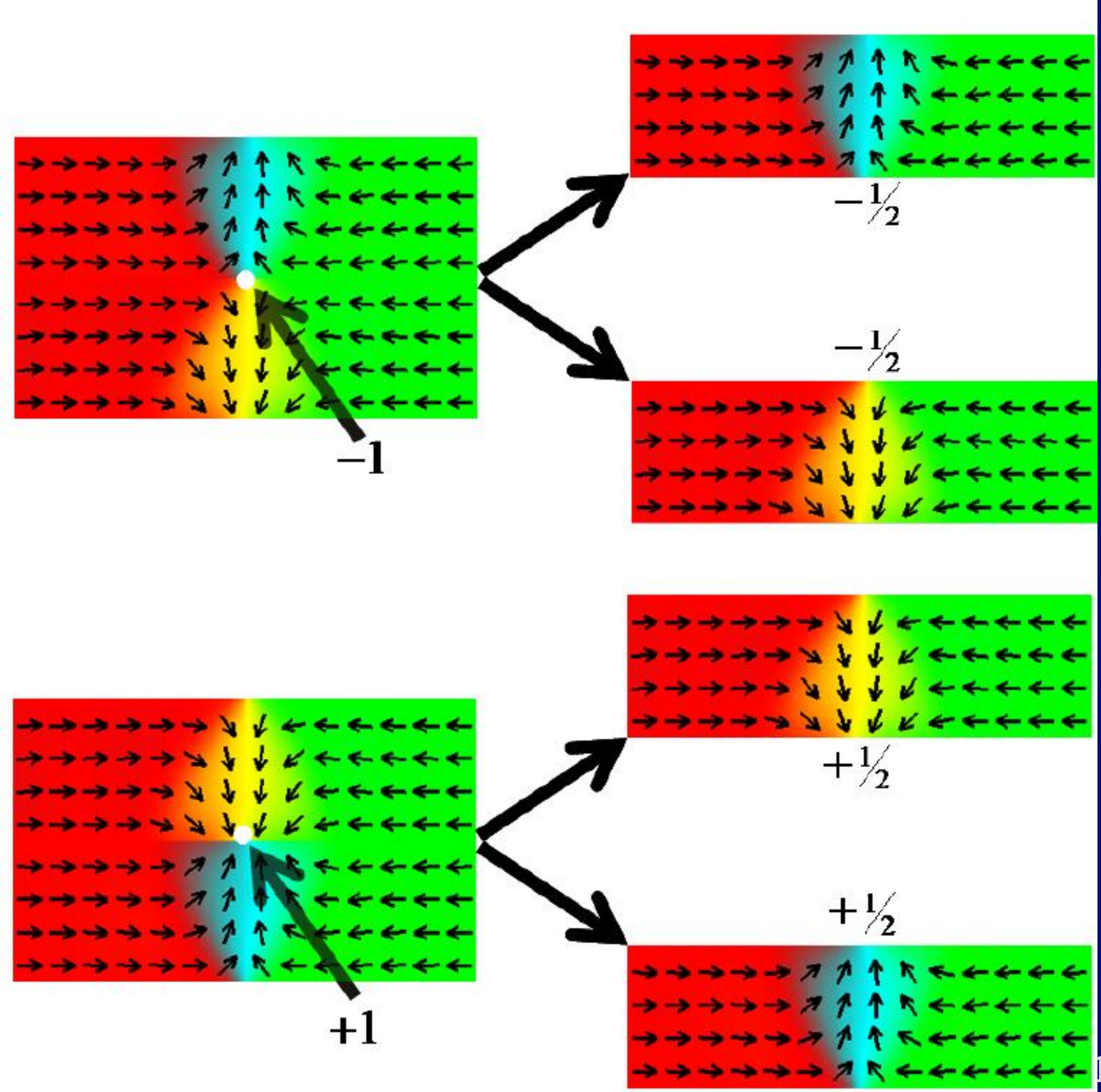
- Topology is perhaps best defined by ‘winding numbers’
- How many times does your magnetisation wrap around the unit circle as you go around some defect?
- Classic cases: **Vortex** or **vortex domain wall**



Pushp, Aakash, et al. "Domain wall trajectory determined by its fractional topological edge defects." *Nature Physics* 9.8 (2013): 505-511.

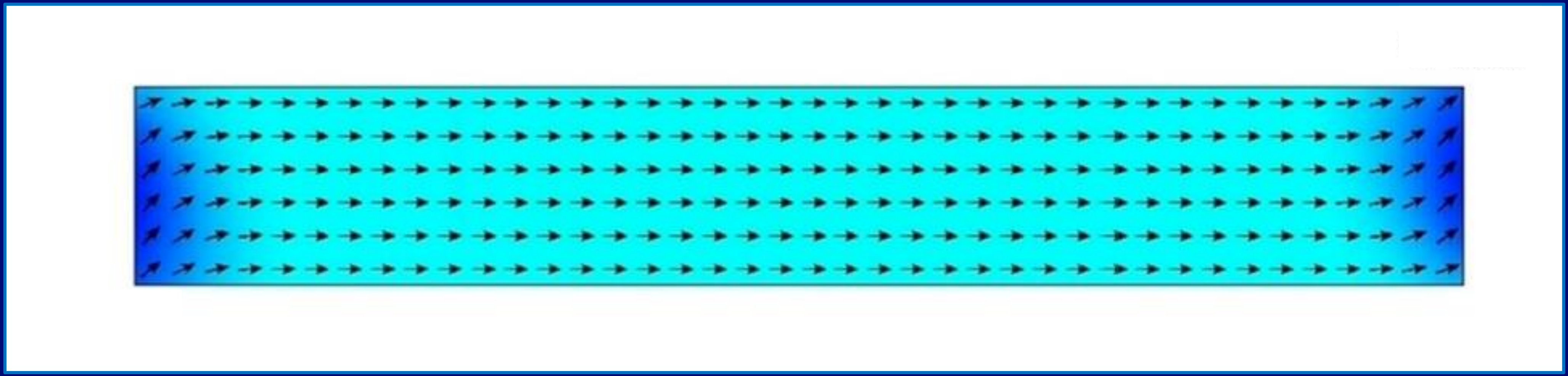
Topological Textures

- Integer winding numbers must live in the ‘bulk’
- Half-integer/fractional live on the edges



Topological Textures

- Everything is ‘topological’ really...
- Flat, finite magnetic systems must have a net ‘winding number’ = 1 – number of holes *(Poincare-Hopf theorem)*
- E.g. a macrospin nanoisland needs +1:



- But where is the winding?!

Topological Textures

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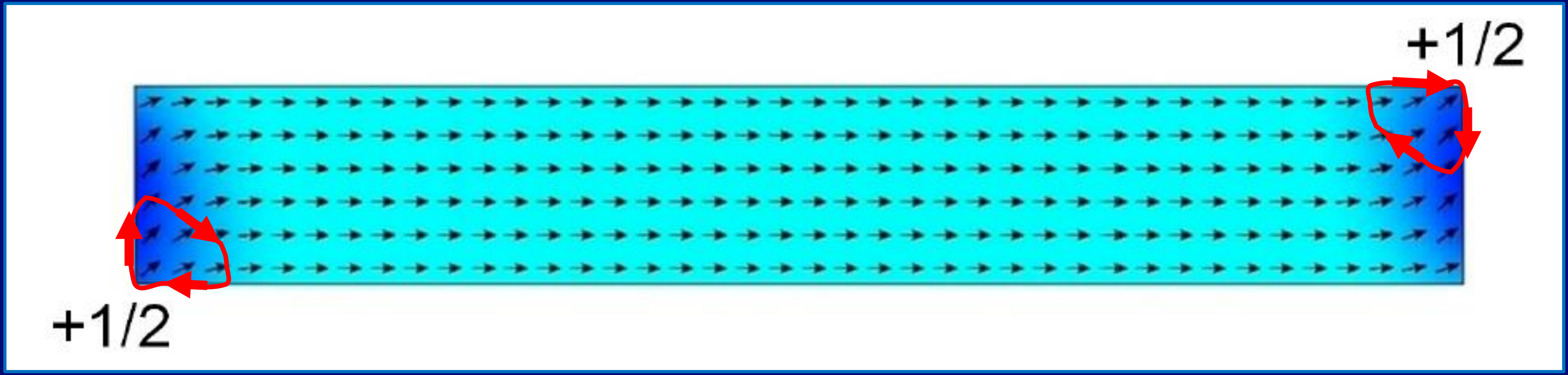

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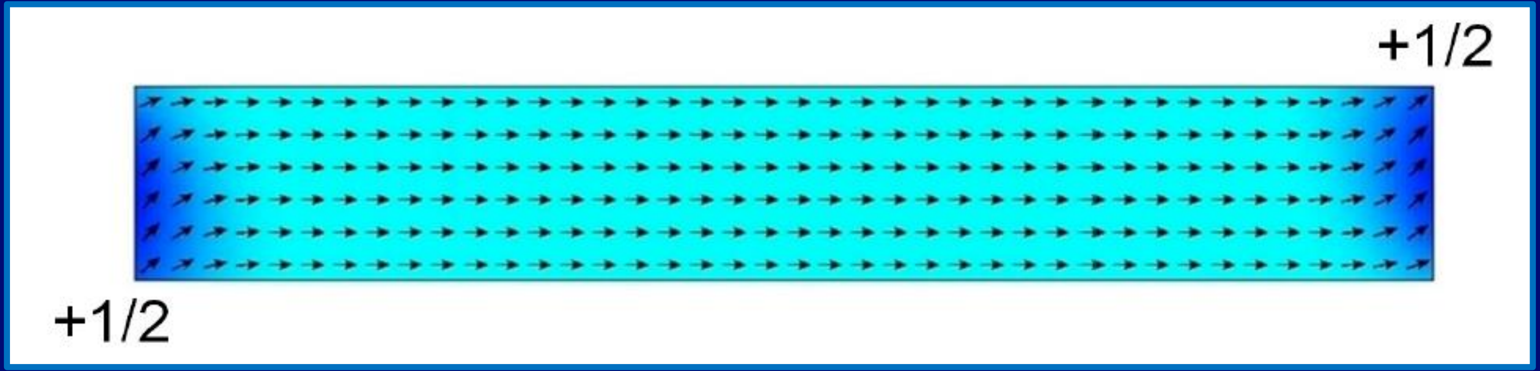
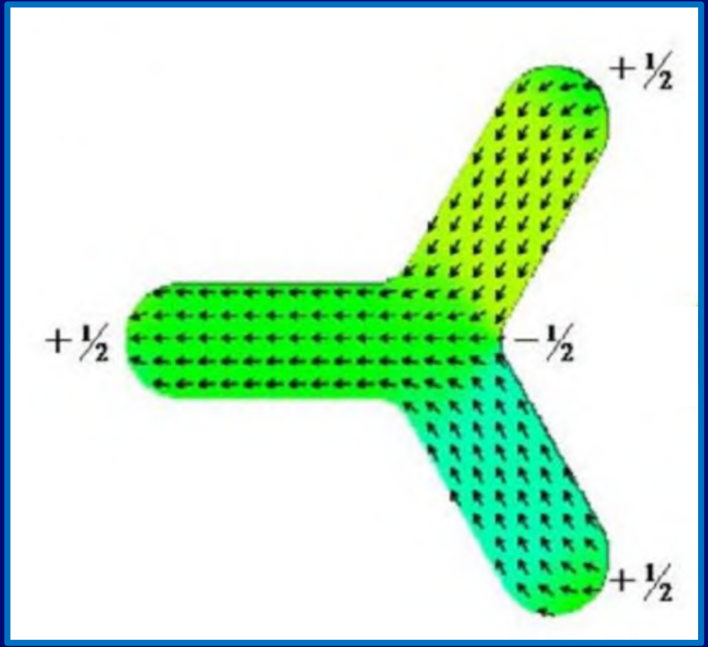
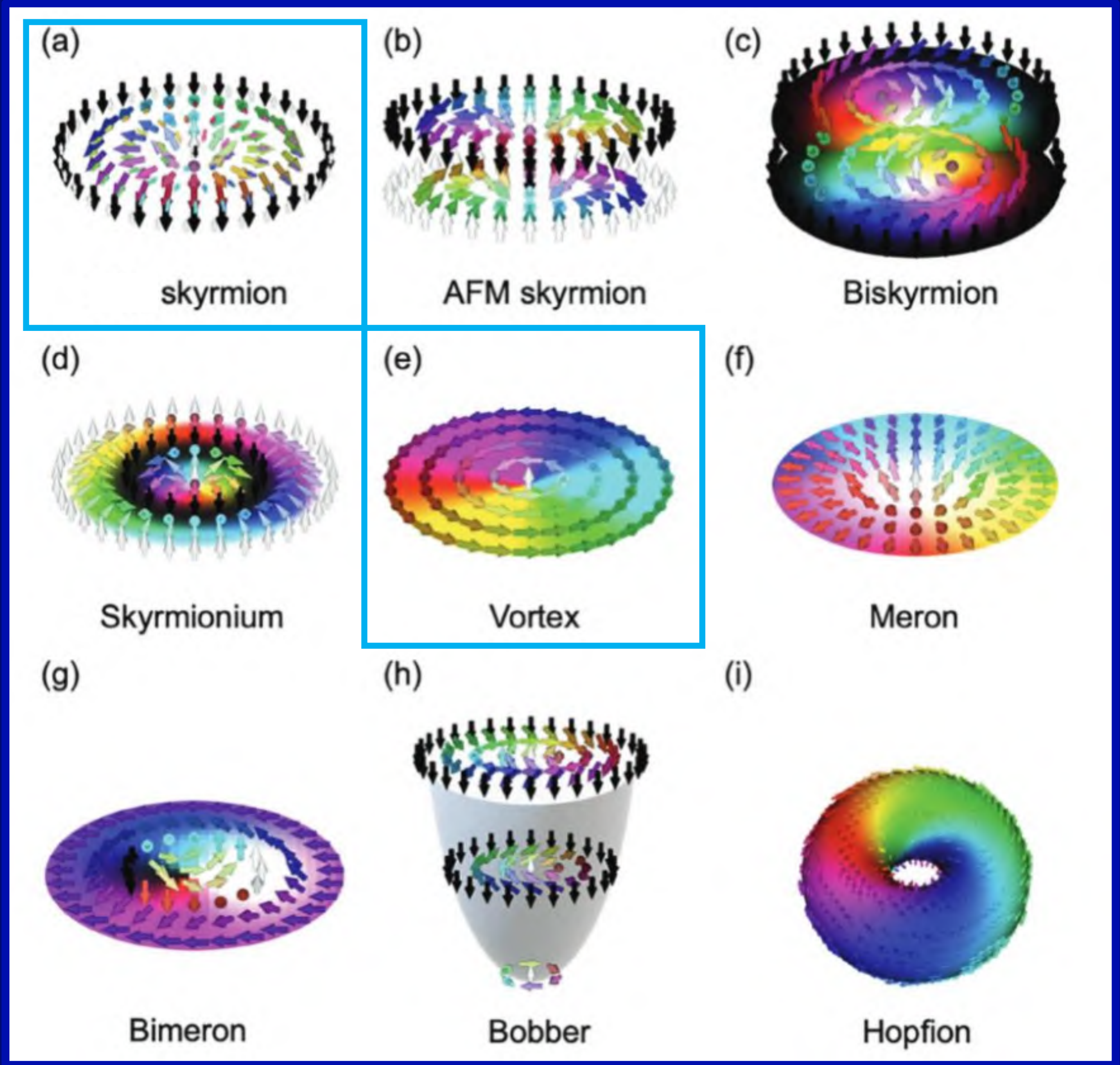




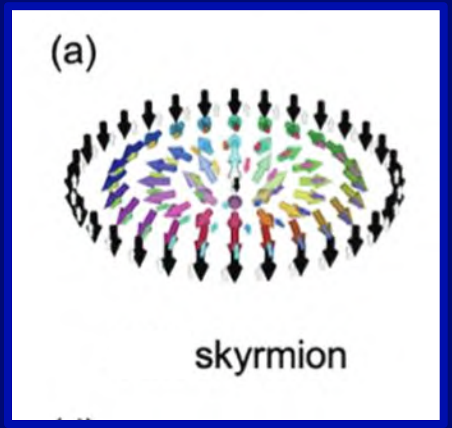
Topological Textures

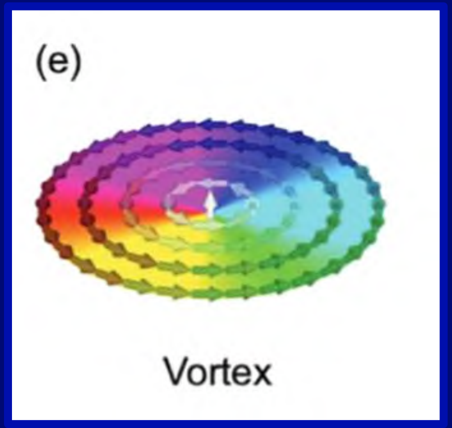
- Today, we'll focus on textures with bulk integer winding numbers



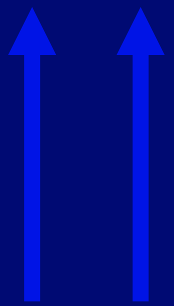
Topological Textures

- Energy terms/Stabilisation

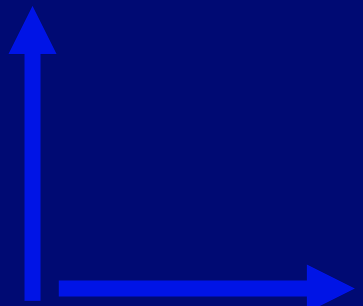




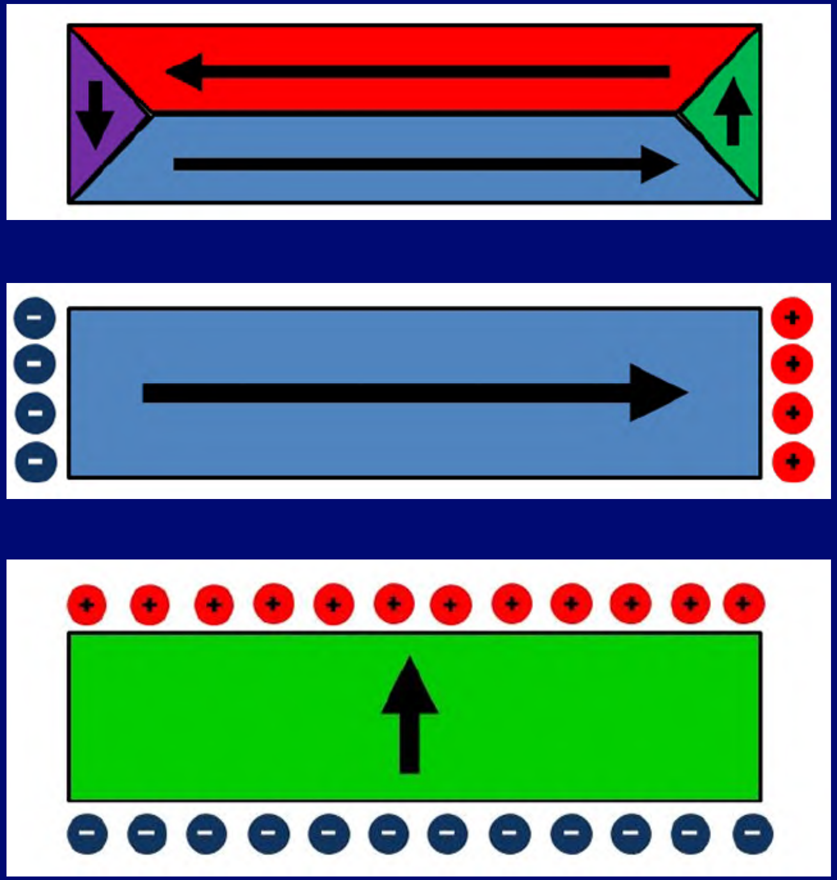
Exchange



DMI



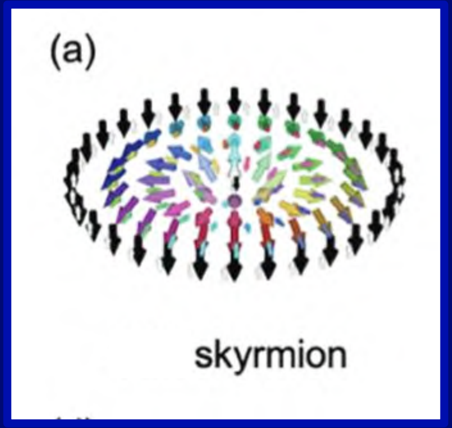
Dipolar happy



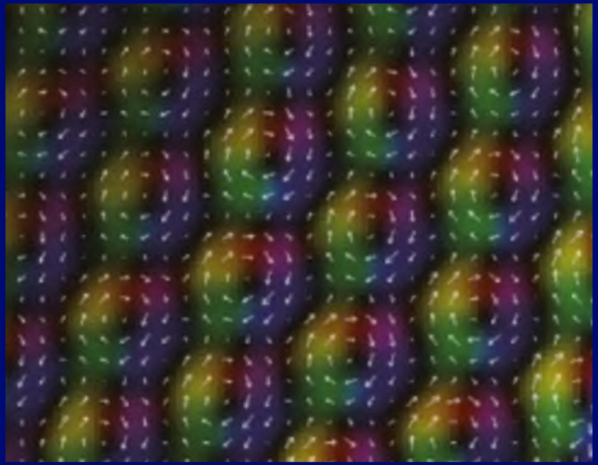
Dipolar sad

Topological Textures

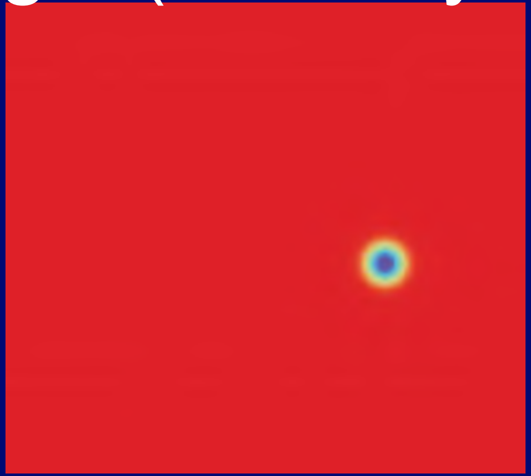
- Energy terms/Stabilisation

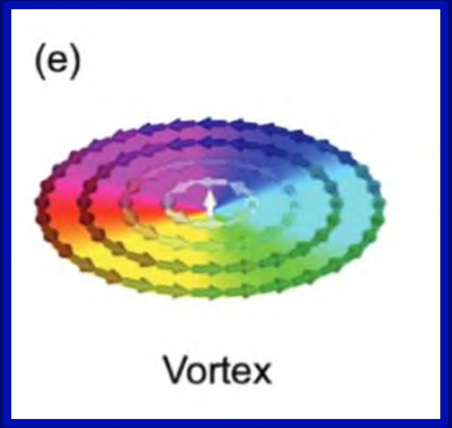


Crystal



Single (often ‘synthetic’)



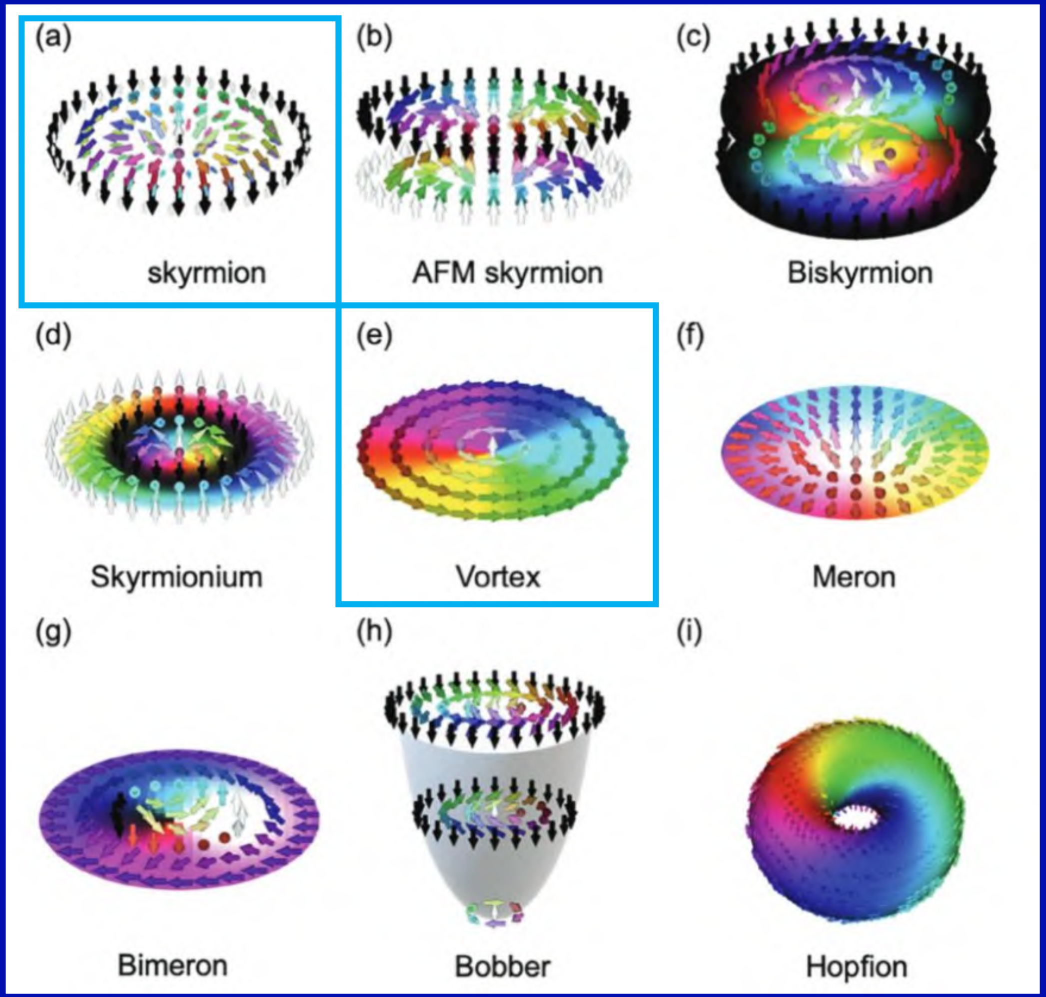


Vortices typically nanostructure-bound

Topological Textures

Pros:

- **Stability** Topology 'protects' these states
  - Big exchange cost to unwind
- **Writeable/Deletable**
  - Grants memory
- **Easy to move**
  - Lower tendency to get stuck/pin
  - J = **10^6-10^8 A/m^2** vs 10^{12} A/m^2 for DWs!
- **Rich textures**
  - Complex GHz dynamics
  - Multiple magnon modes



Topological Textures

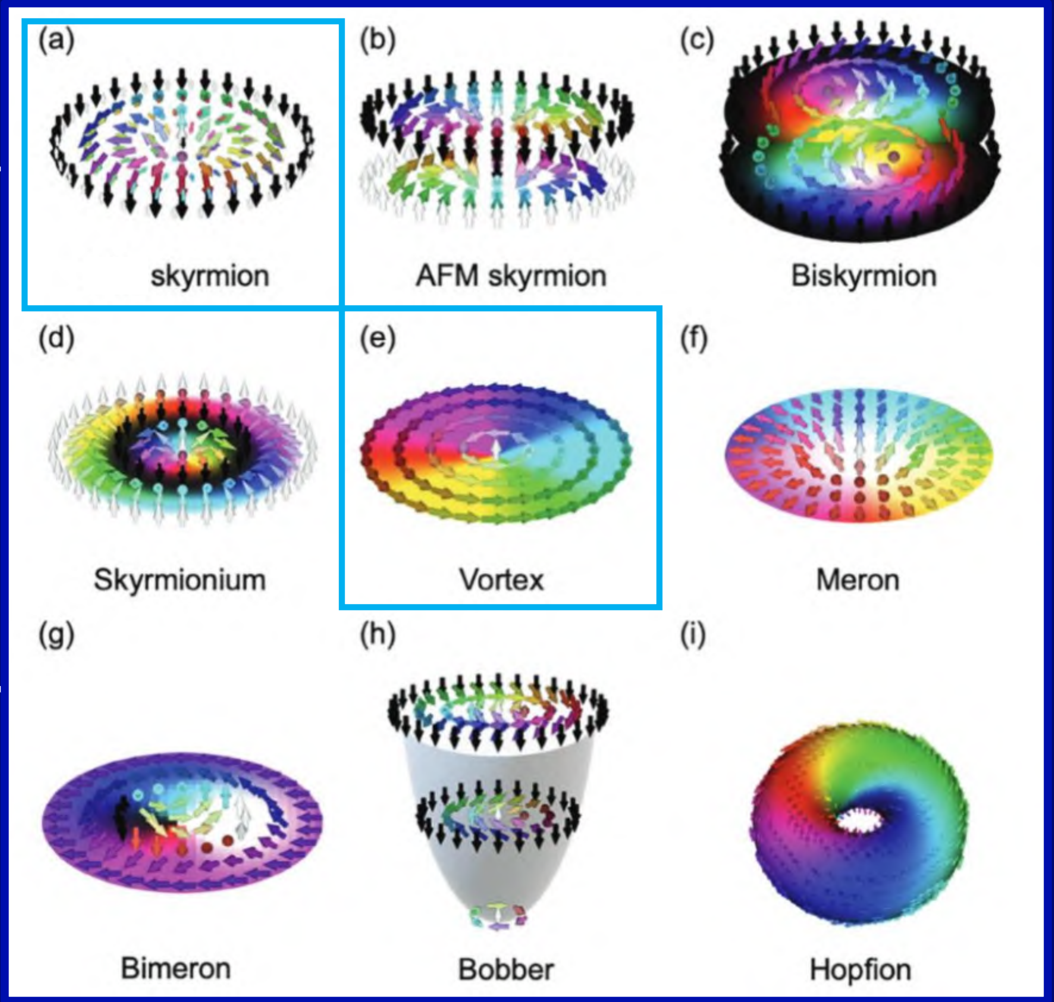
- Potentially offer a lot of what's **best** about magnetism

Pros:

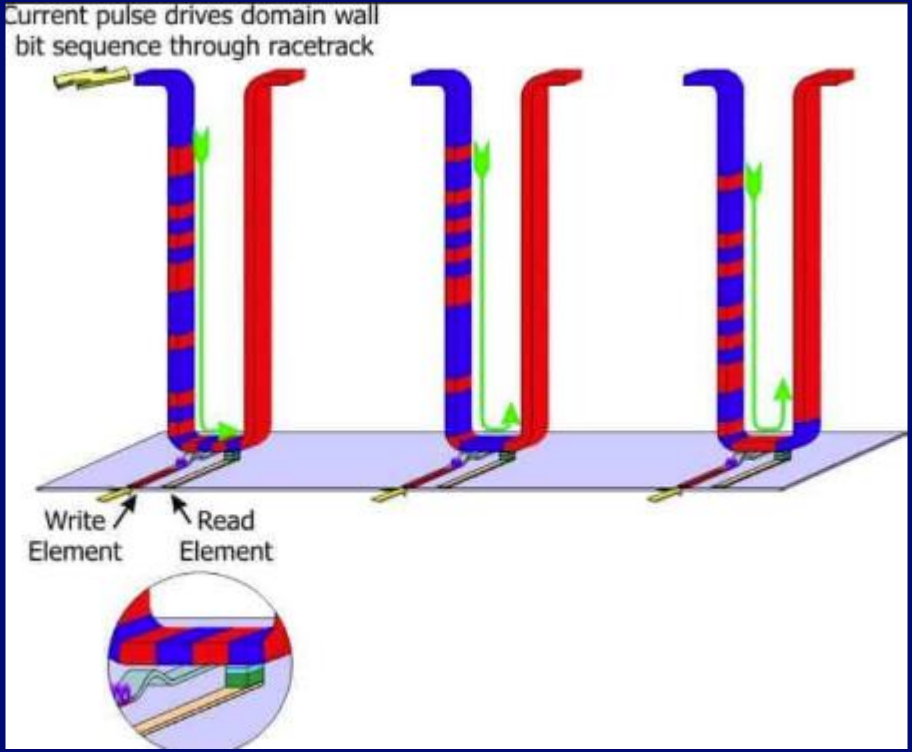
- **Stability** Topology 'protects' these states
- **Writeable/Deletable** Grants memory
- **Easy to move** Lower tendency to get stu
  - J = $\mathbf{10^6\text{-}10^8\ A/m^2}$ vs 10^{12} A/m^2 for DWs!
- **Rich textures** Complex GHz dynamics

Challenges:

- **Materials** Can require high quality material/interface
- **New Physics** Still learning to control ther
- **Hard to scale up**



An example: Moving information on a track



Magnetic Domain-Wall Racetrack Memory

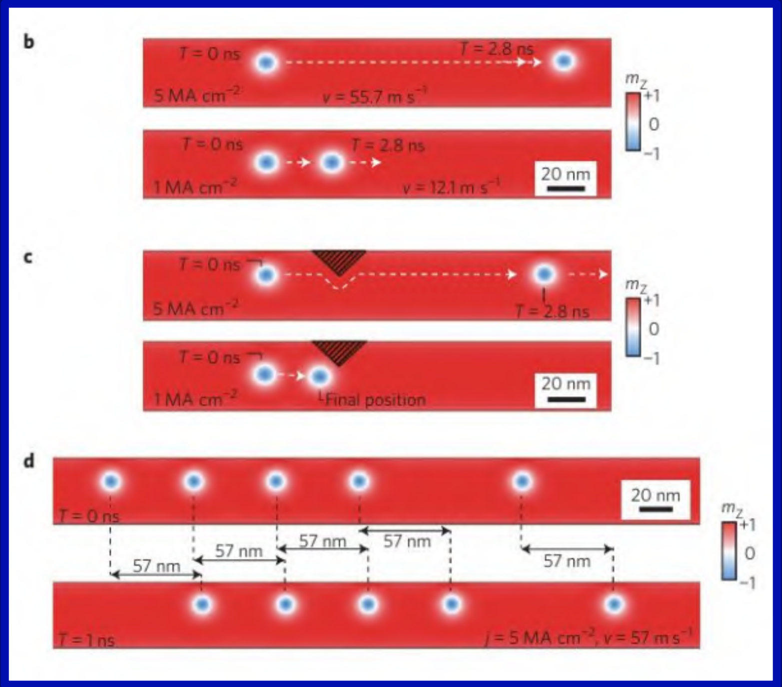
Stuart S. P. Parkin,* Masamitsu Hayashi, Luc Thomas

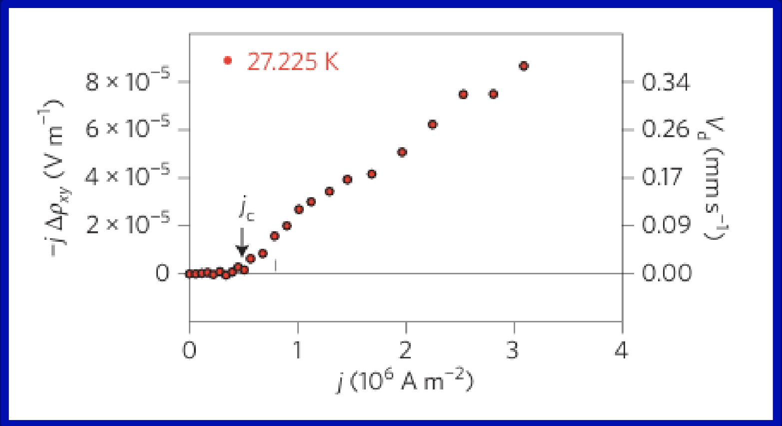
Recent developments in the controlled movement of domain walls in magnetic nanowires by short pulses of spin-polarized current give promise of a nonvolatile memory device with the high performance and reliability of conventional solid-state memory but at the low cost of conventional magnetic disk drive storage. The racetrack memory described in this review comprises an array of magnetic nanowires arranged horizontally or vertically on a silicon chip. Individual spintronic reading and writing nanodevices are used to modify or read a train of ~10 to 100 domain walls, which store a series of data bits in each nanowire. This racetrack memory is an example of the move toward innately three-dimensional microelectronic devices.

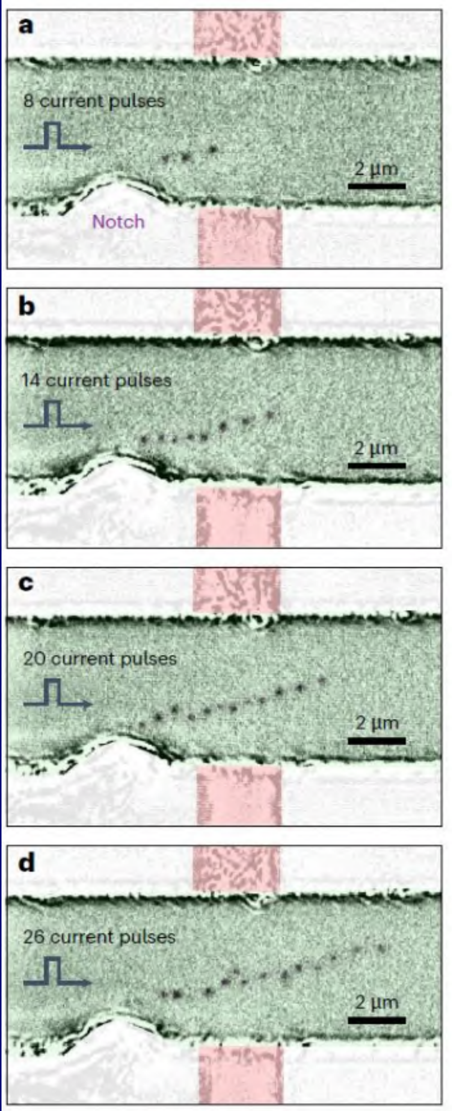
Parkin et al scheme – Elegant yet faced challenges due to intrinsic issues with domain wall physics:

- **High pinning**
- **High current density needed (10^{12} A/m^2)**
- **Significant heating**

An example: Moving information on a track







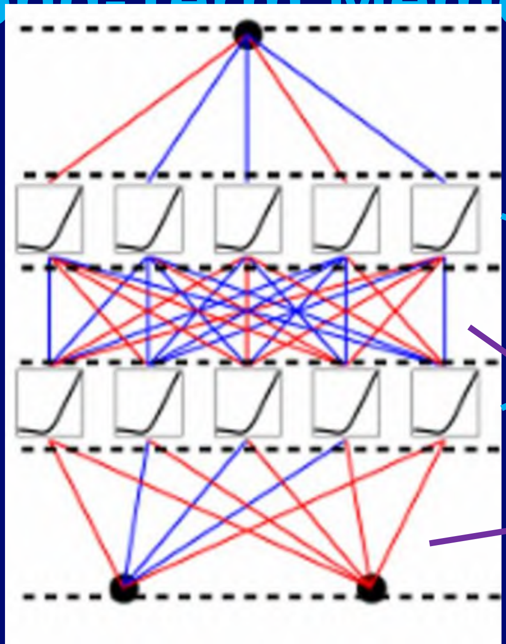
- Use **Skyrmions** instead of **Domain Wall**
- **Much** lower currents J = 10^6 A/m^2
- Able to **distort** shape and avoid pinning
- **Localised** defects
  - Don’t need to span track width like DW
- **However** still have their own challenges t solve!

Fert, Albert, Vincent Cros, and Joao Sampaio. "Skyrmions on the track." *Nature Nanotechnology* 8.3 (2013): 152-156.

da Câmara Santa Clara Gomes, Tristan, Dédalo Sanz-Hernández, et al & Vincent Cros, Julie Grollier, and Nicolas Reyren. "Neuromorphic weighted sums with magnetic skyrmions." *Nature Electronics* (2025)

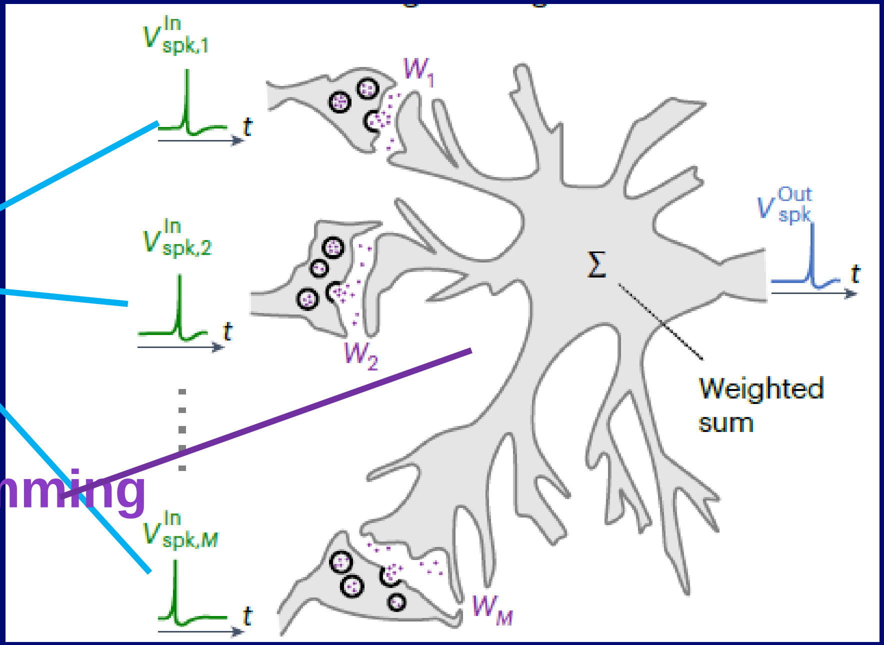
Processing Functionality we want:

- **Moving information** around a device
- **Nonlinear Processing** – without this, can't do complex tasks ('neurons')
- **Programmable 'weights'** – A means to adapt device function to tasks
- **Integrate & sum signals** – 'Synapses'
- **Long-Term Memory**



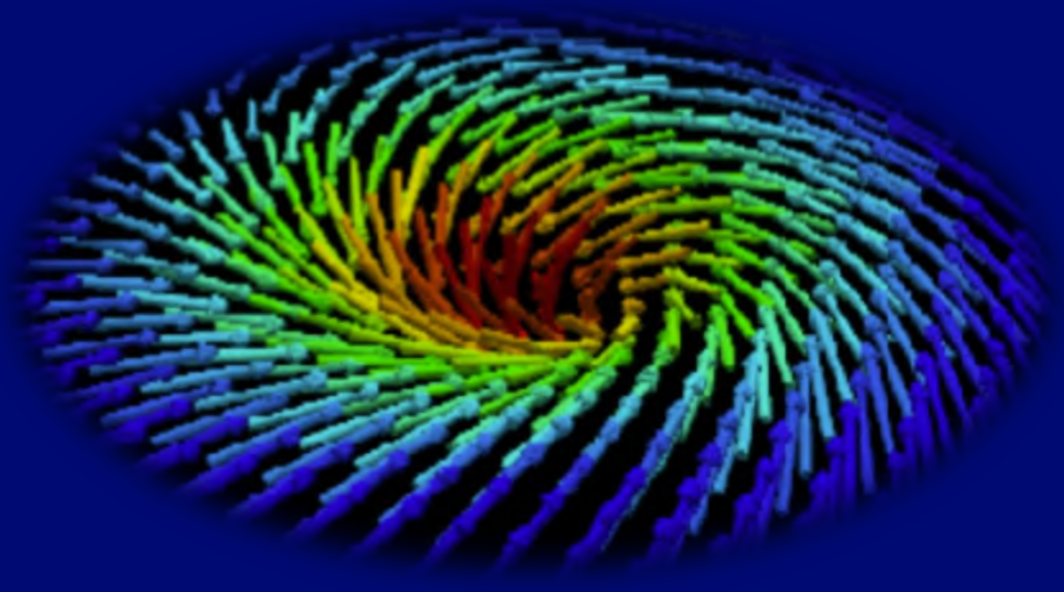
Nonlinearity/neurons

Weights & synaptic summing



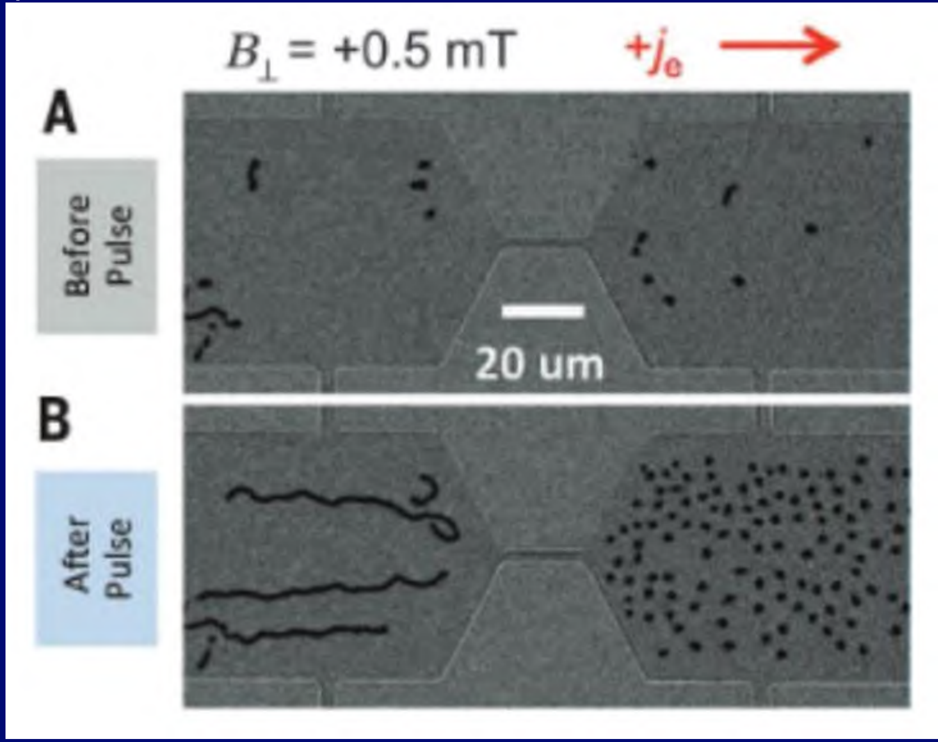
Skyrmions

- Local schemes
- Mean-Field/Global schemes



Skyrmion nucleation – Older studies

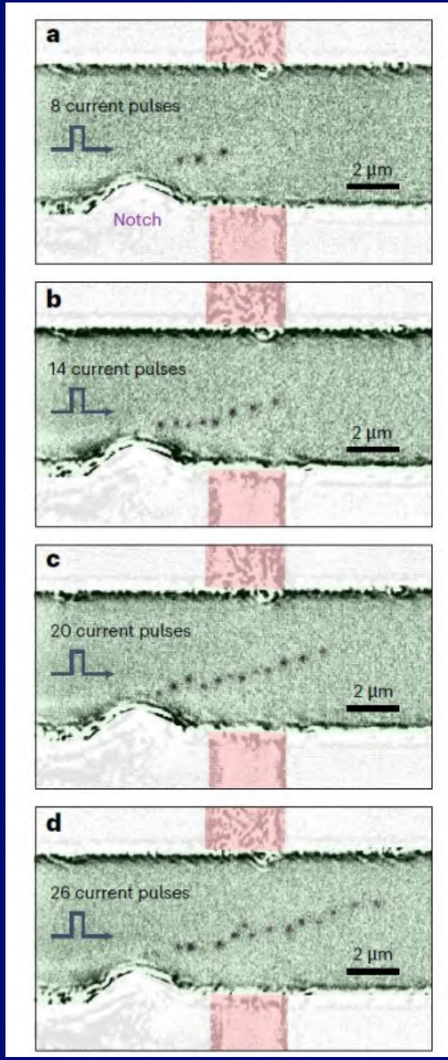
Skyrmion Material Stack: Ta(5 nm)/$Co_{20}Fe_{60}B_{20}$(CoFeB)(1.1 nm)/TaO_x(3 nm)



- Constrictions allow current density **J** to be enhanced to only *locally* nucleate skyrmions
- However, often suffer from some stochasticity
- This is 2015 – things have improved!

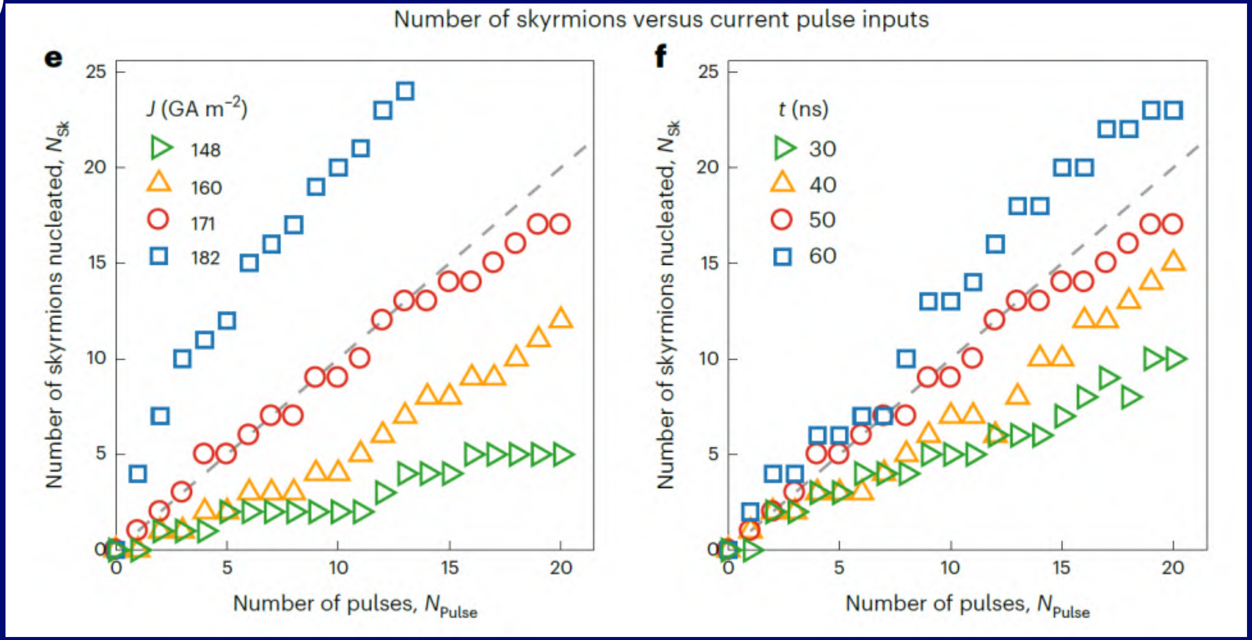
Jiang, Wanjun, et al. "Blowing magnetic skyrmion bubbles." *Science* 349.6245 (2015): 283-286.

Skyrmion nucleation – Recent work



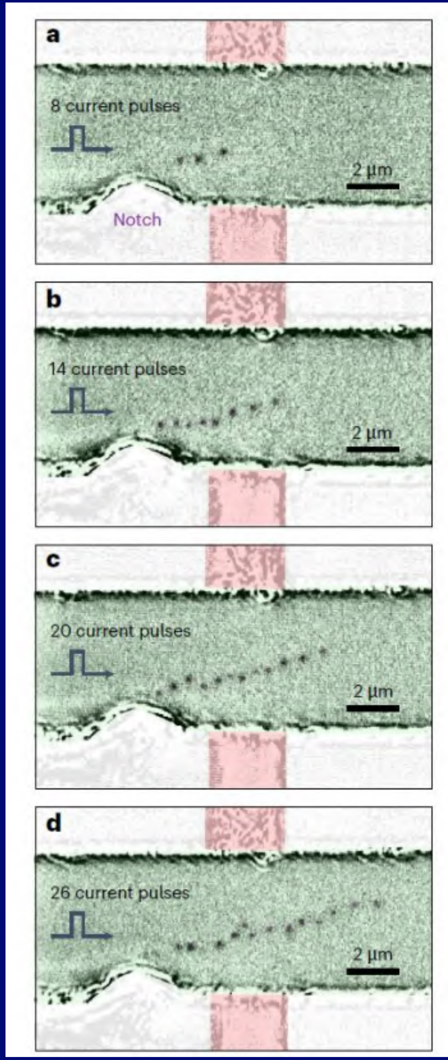
Skyrmion Material Stack: Ta(5 nm)/Pt(8 nm)/[Co(1.2 nm)/Al(3 nm)/Pt(3 nm)]$_{10}$

- Very nice progress: Fine tuned nucleation, controlling pulse current & length.
- Reliably inject & electrically read-out Skyrmions (Ta)



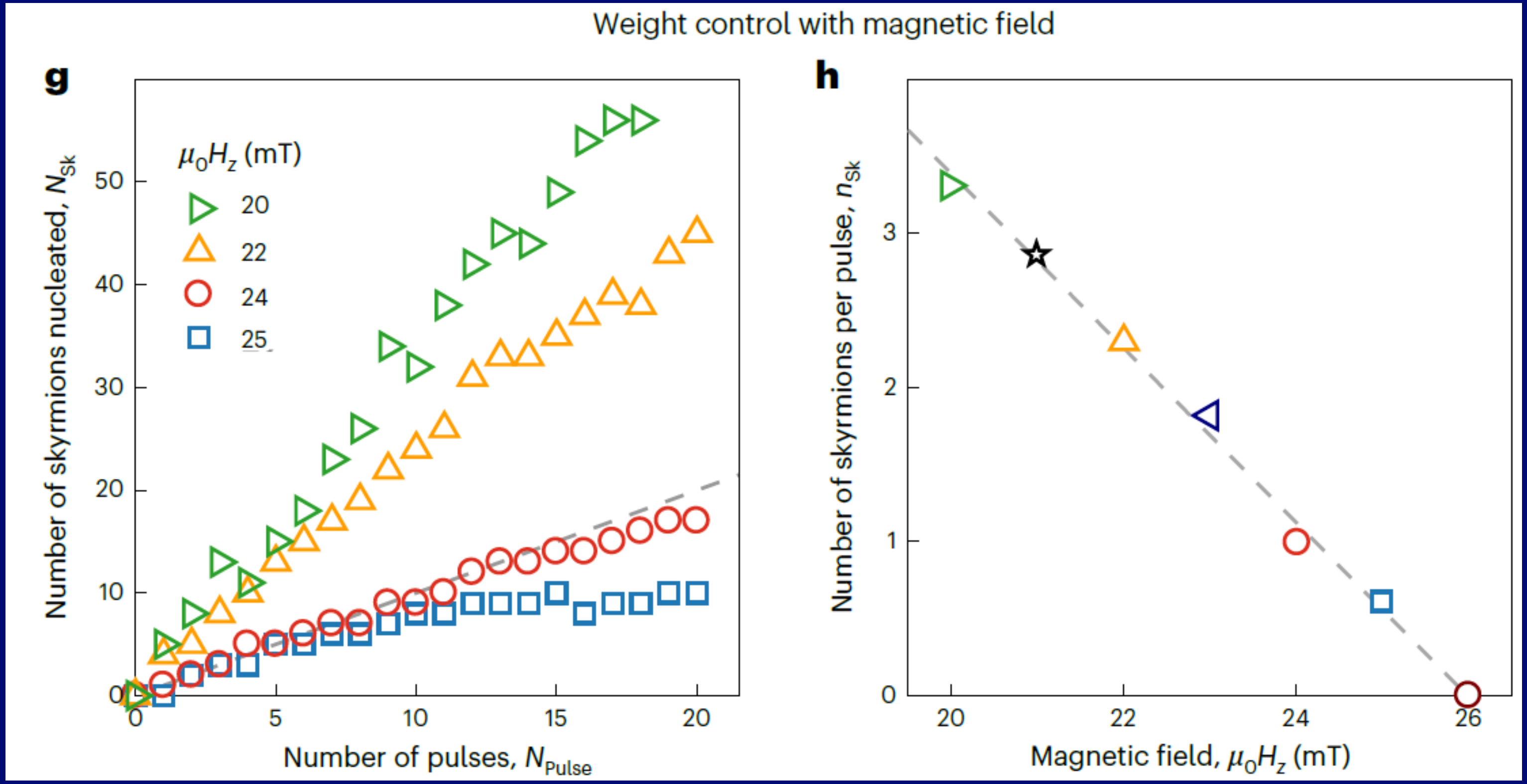
da Câmara Santa Clara Gomes, Tristan, Dédalo Sanz-Hernández, et al & Vincent Cros, Julie Grollier, and Nicolas Reyren. "Neuromorphic weighted sums with magnetic skyrmions." *Nature Electronics* (2025)

Skyrmion weighting



Skyrmion Material Stack: Ta(5 nm)/Pt(8 nm)/[Co(1.2 nm)/Al(3 nm)/Pt(3 nm)]$_{10}$

- Tuning applied field enables synaptic weights:
  - *Applied field increases skyrmion formation cost*



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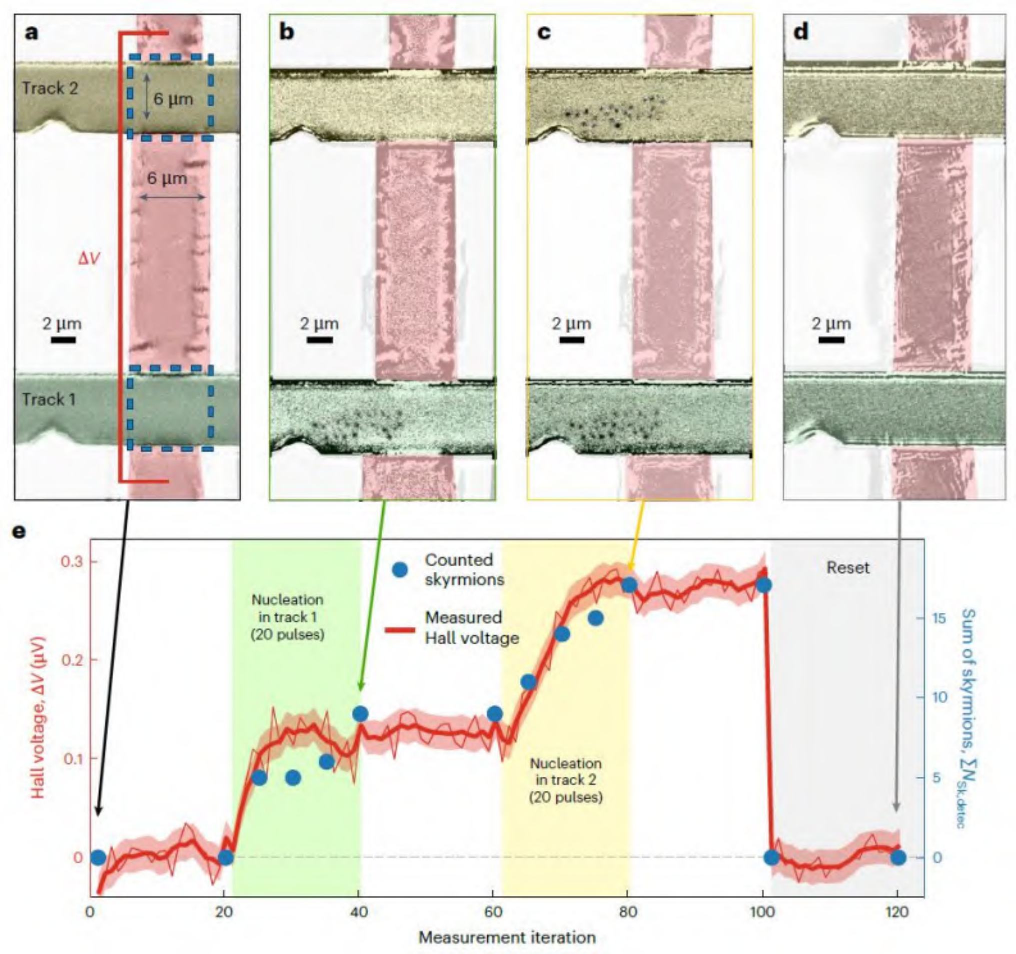
Skyrmion synaptic sums

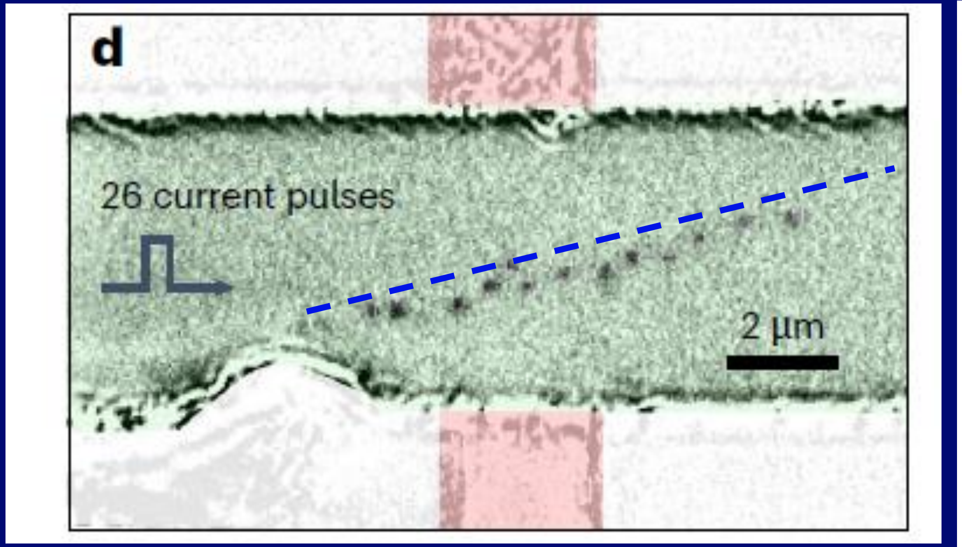
Skyrmion Material Stack: Ta(5 nm)/Pt(8 nm)/[Co(1.2 nm)/Al(3 nm)/Pt(3 nm)]$_{10}$

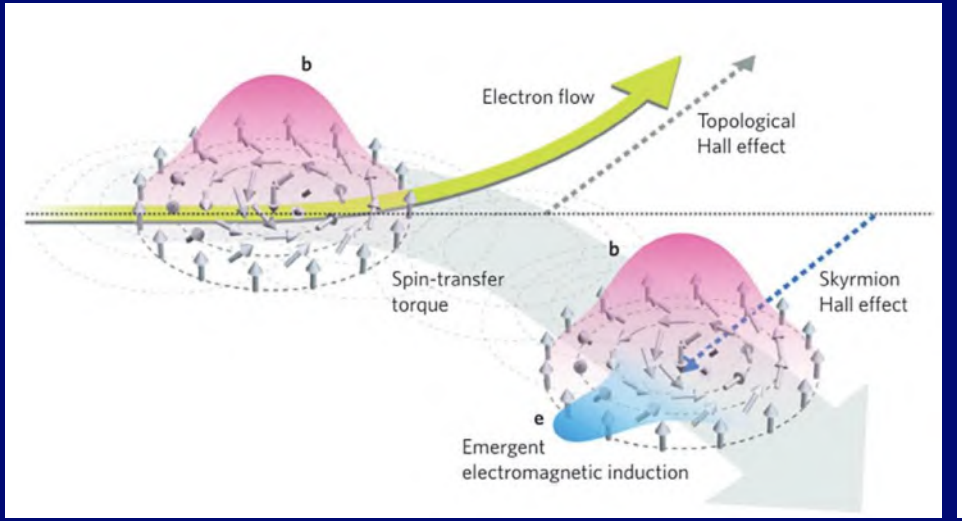


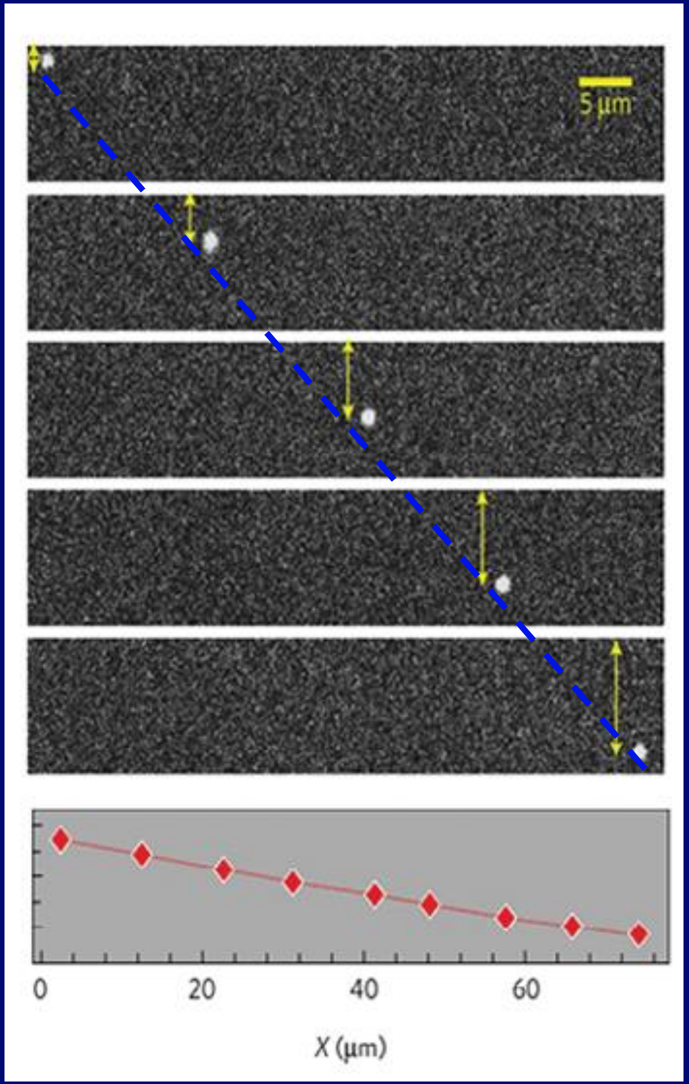
- The Ta stripline non-perturbatively sums over all Skyrmion tracks
- This is a great step – previously could be challenging to read out states without disturbing them
- <u>**20 pJ**</u> to nucleate a Skyrmion
- Beautiful manipulation, still a way far from a device
- Limits:
  - Missing nonlinearity
  - **Skyrmion Hall effect** limits numbers

da Câmara Santa Clara Gomes, Tristan, Dédalo Sanz-Hernández, et al & Vincent Cros, Julie Grollier, and Nicolas Reyren. "Neuromorphic weighted sums with magnetic skyrmions." *Nature Electronics* (2025)

Skyrmion Hall Effect



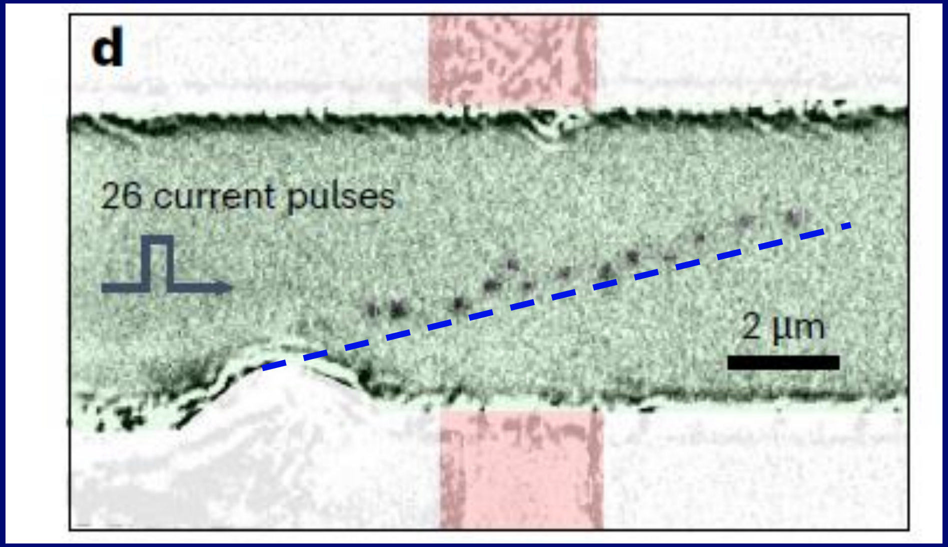


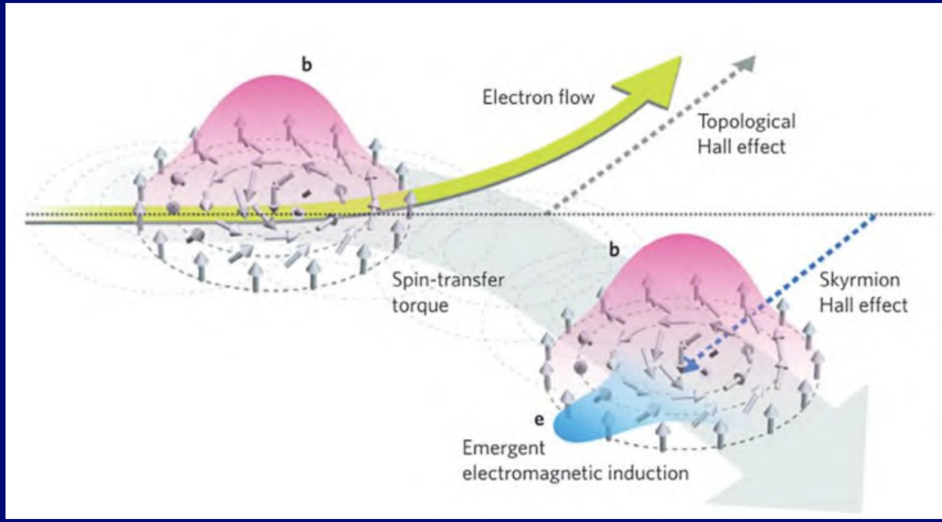


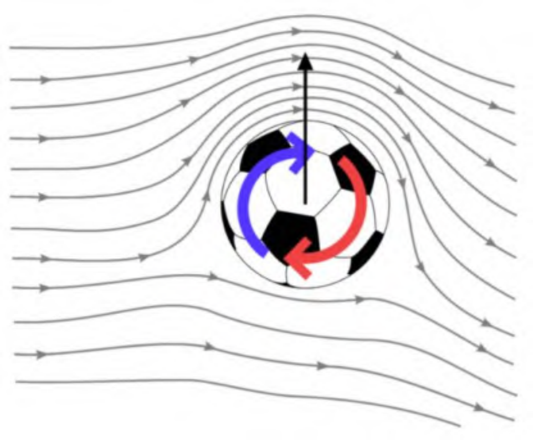
N. Nagaosa, Y. Tokura, *Nat. Nanotechnol.* 2013, *8*, 899.

Jiang, Wanjun, et al. "Direct observation of the skyrmion Hall effect." *Nature Physics* 13.2 (2017): 162-169.

Skyrmion Hall Effect







N. Nagaosa, Y. Tokura, *Nat. Nanotechnol.* 2013, *8*, 899.

Jiang, Wanjun, et al. "Direct observation of the skyrmion Hall effect." *Nature Physics* 13.2 (2017): 162-169.

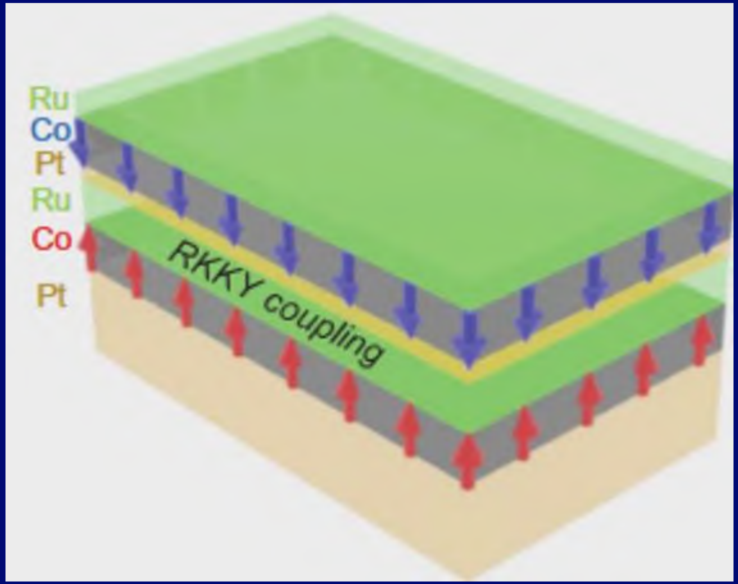
Recent solution:

MAGNETISM

Fast current-induced skyrmion motion in synthetic antiferromagnets

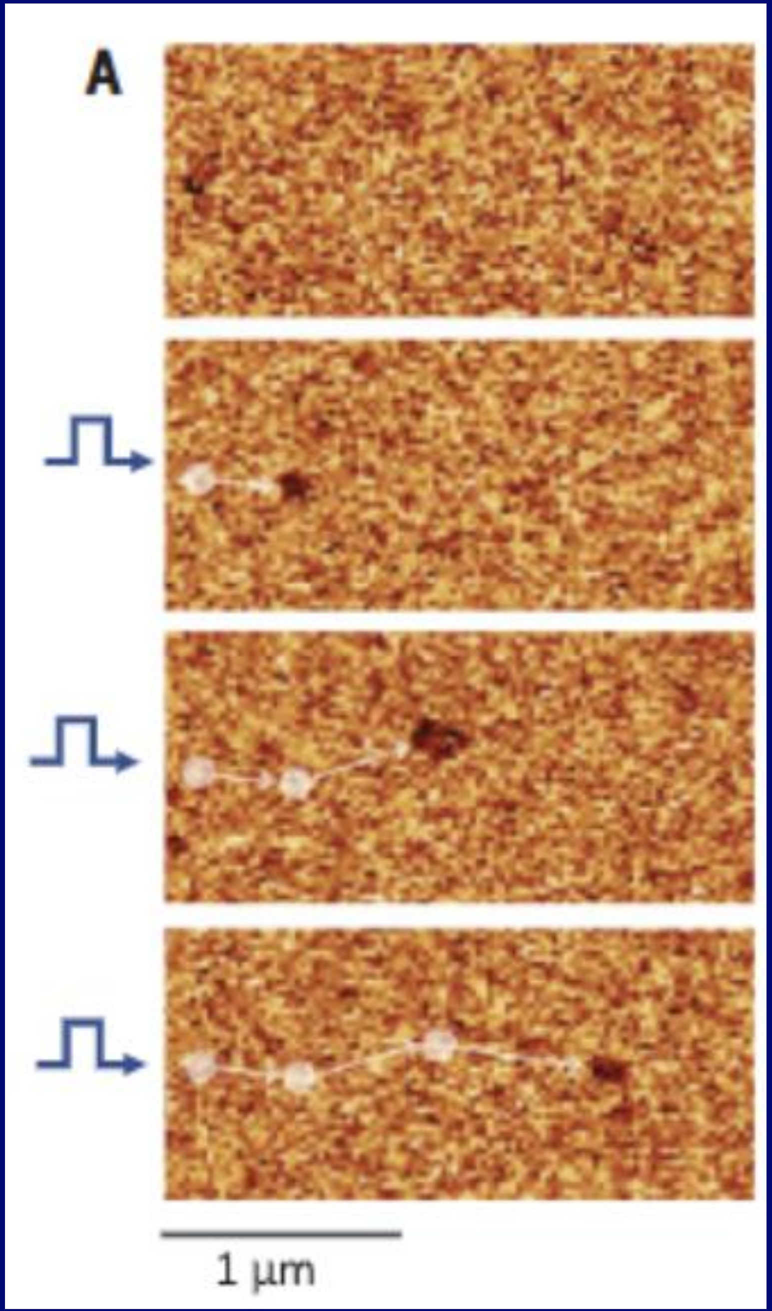
Van Tuong Pham[1,2]†, Naveen Sisodia[1,3]‡, Ilaria Di Manici[1]‡, Joseba Urrestarazu-Larrañaga[1]‡, Kaushik Bairagi[1], Johan Pelloux-Prayer[1], Rodrigo Guedas[1,4], Liliana D. Buda-Prejbeanu[1], Stéphane Auffret[1], Andrea Locatelli[5], Tevfik Onur Menteş[5], Stefania Pizzini[2], Pawan Kumar[6], Aurore Finco[6], Vincent Jacques[6], Gilles Gaudin[1], Olivier Boulle[1]*

Pham, Van Tuong, et al. "Fast current-induced skyrmion motion in synthetic antiferromagnets." *Science* 384.6693 (2024): 307-312.



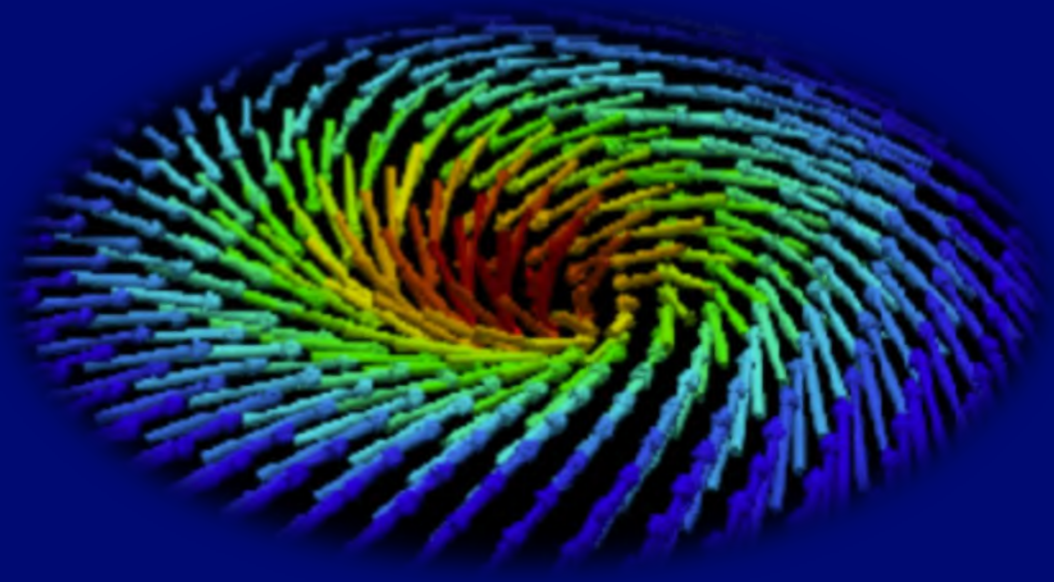
- **Opposing Anti-Ferromagnetic ordered layers:**
- **Cancels Skyrmion Hall Effect**
- <u>But!</u> Higher J…
  - **10^{11} A/m^2**
- Requires optimisation

Straight Line Motion!



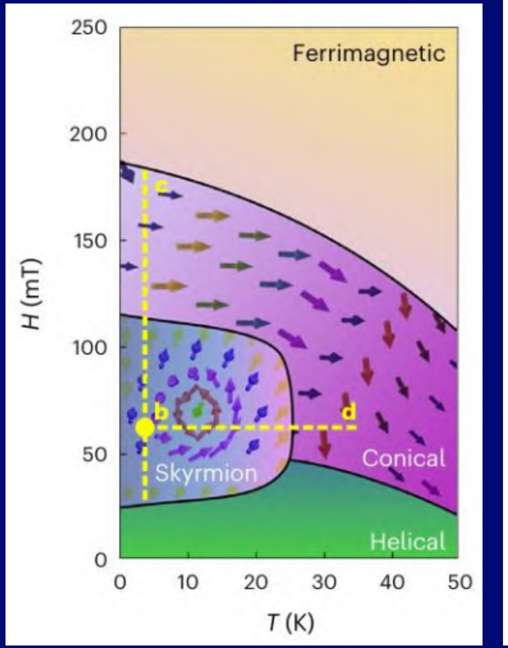
We’ve seen:

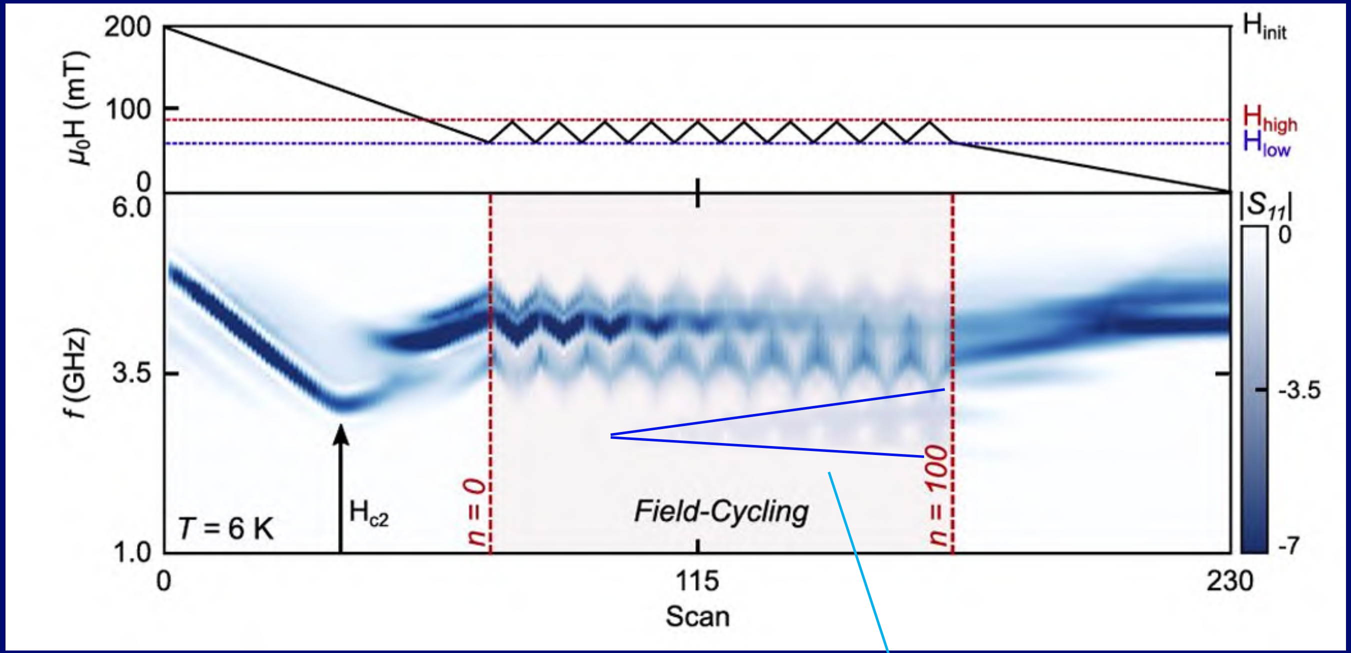
- Precise control - still some distance from full device
- What about approaches using global, not local, control and focusing on implementing computation?

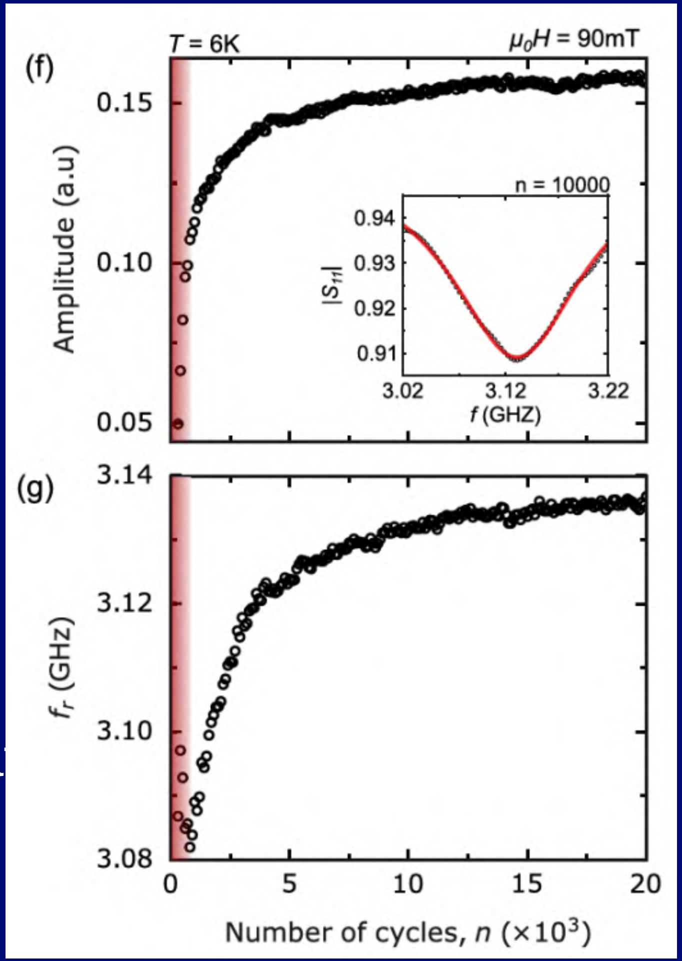


Mean-Field Skyrmion computing schemes

Very gradual evolution of state over 10,000s loops – **Long term memory**







Slowly Growing Skyrmion sta


nature materials

Article

https://doi.org/10.1038/s41563-023-01698-8

Task-adaptive physical reservoir computing

Received: 4 October 2022

Accepted: 19 September 2023

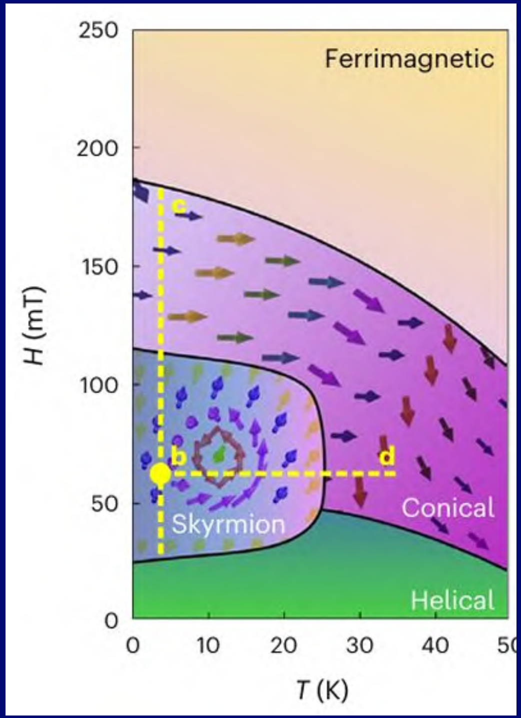
Published online: 13 November 2023

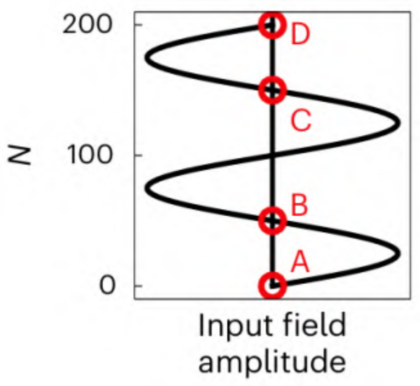
Oscar Lee[1], Tianyi Wei[1], Kilian D. Stenning[2], Jack C. Gartside[2], Dan Prestwood[1], Shinichiro Seki[3], Aisha Aqeel[4,5], Kosuke Karube[6], Naoya Kanazawa[3], Yasujiro Taguchi[6], Christian Back[4], Yoshinori Tokura[3,6,7], Will R. Branford[2,8] & Hidekazu Kurebayashi[1,9,10]

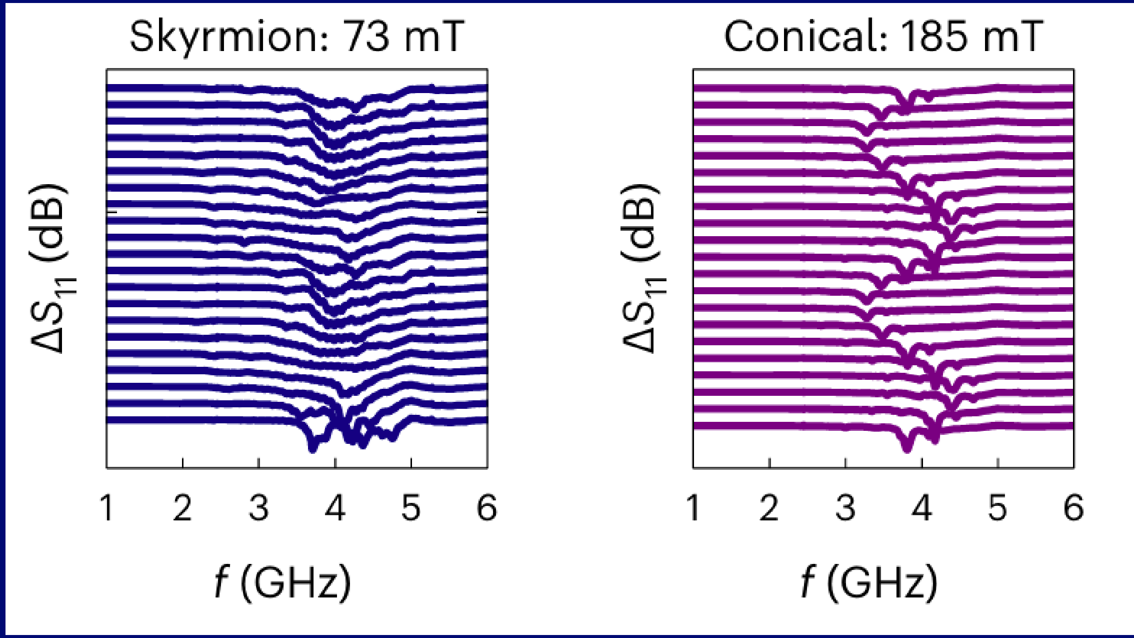
Aqeel, Aisha, et al. "Microwave spectroscopy of the low-temperature skyrmion state in Cu 2 OSeO 3." *Physical Review Letters* 126.1 (2021):

Mean-Field Skyrmion computing schemes

- Is it possible to exploit rich topological texture phase diagram for process







Strong Memory

Nonlinear

nature materials

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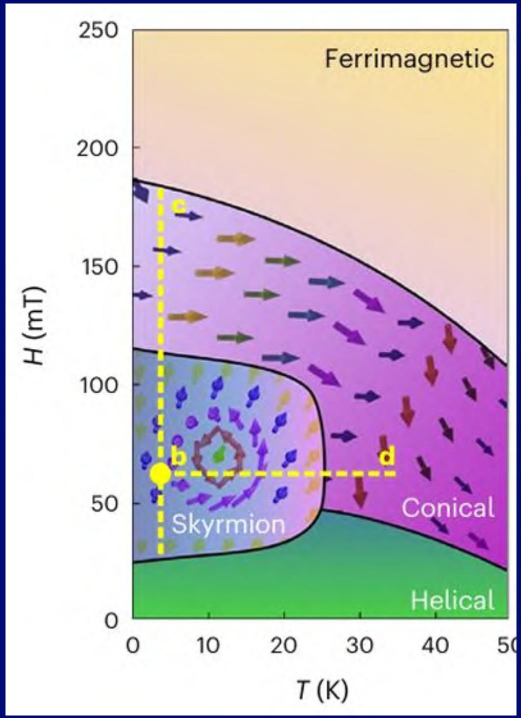
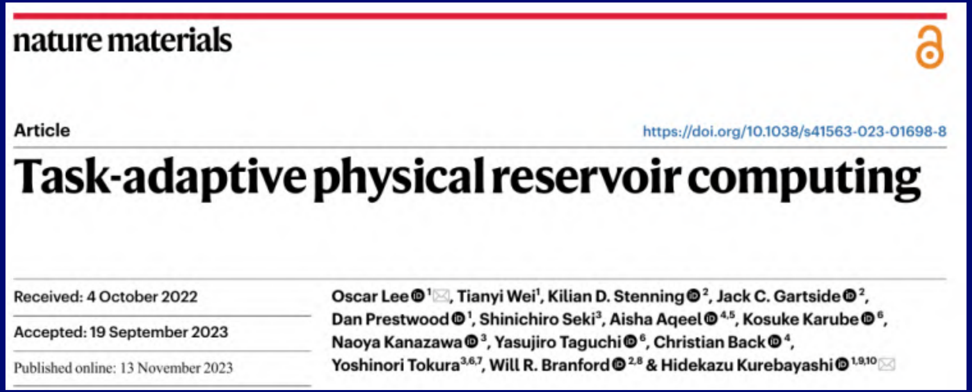
Lee, Oscar, et al. "Task-adaptive physical reservoir computing." *Nature Materials* 23.1 (2024): 79-87.

Mean-Field Skyrmion computing schemes

- But how to compute?
- No control over individual textures





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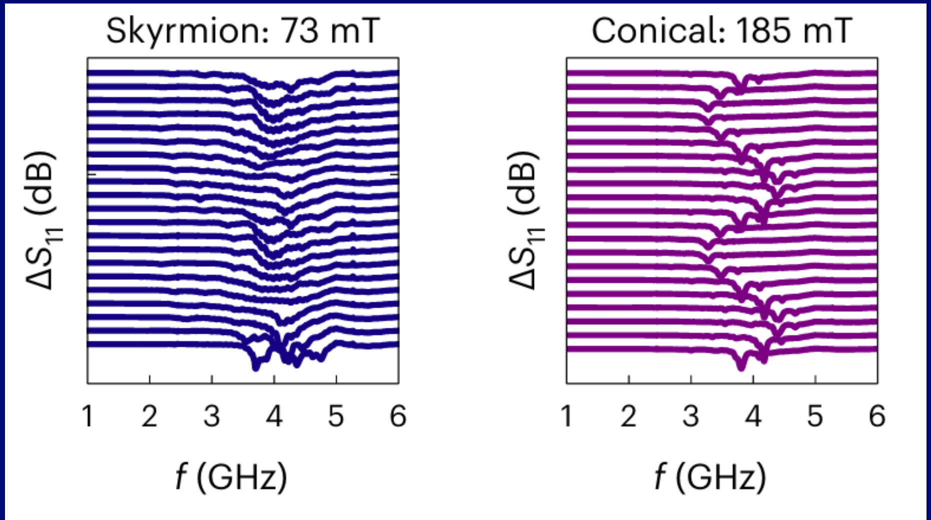


Strong Memory

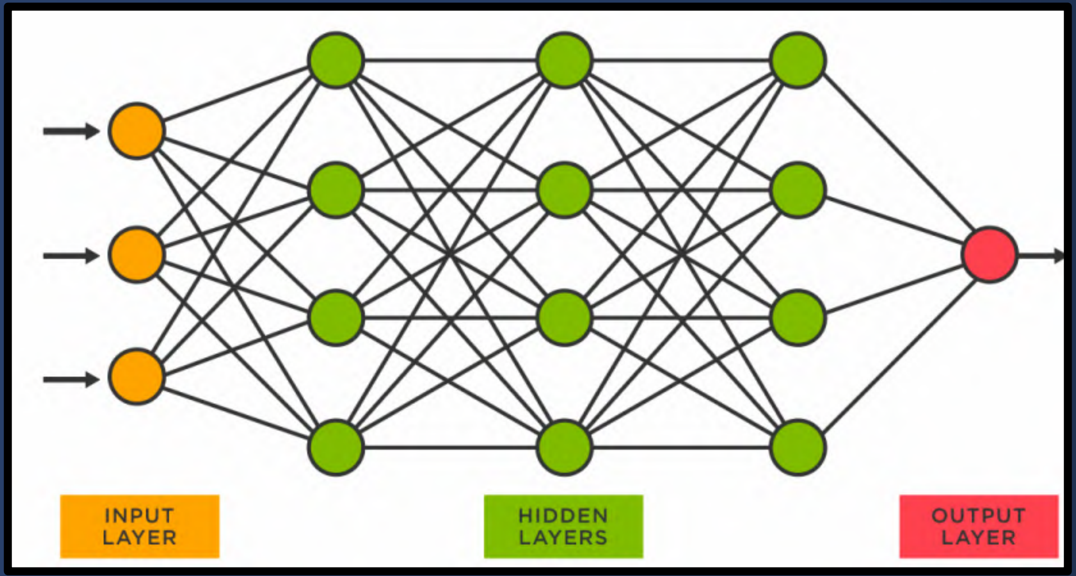
Nonlinear

Lee, Oscar, et al. "Task-adaptive physical reservoir computing." *Nature Materials* 23.1 (2024): 79-87.

Reservoir Computing

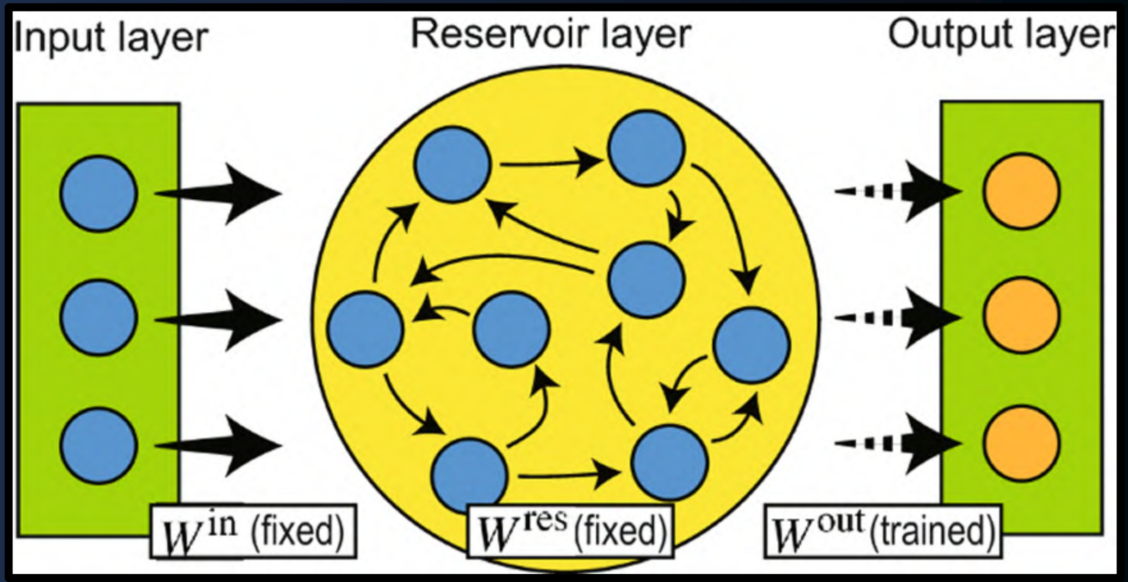
- **Aim:** Map **complex problems** onto **simple linearly solveable ones**
- **Random weight connections** vs. **Fully trainable weights**
- **Low energy** vs. Deep Neural Networks as only train **small output layer**

Deep Neural Network



VS.

Reservoir Computing



1: *energy-uk.org, towardsdatascience.com, OpenAI white paper (2019)*

Field **Topological Magnetic Texture** **Magnon Spectra**

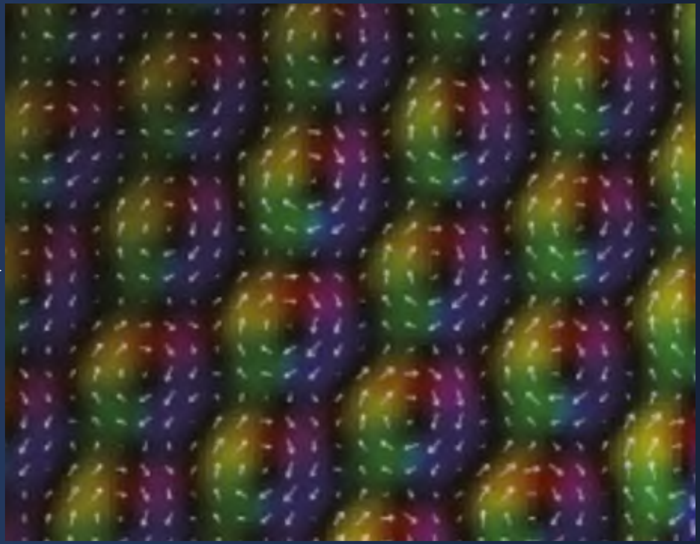
Jack C. Gartside, Imperial College London

Reservoir Computing

- **Aim:** Map **complex problems** onto **simple linearly solveable ones**
- **Random weight connections** vs. **Fully trainable weights**
- **Low energy** vs. Deep Neural Networks as only train **small output layer**

Input Problem:
Hard, nonlinear

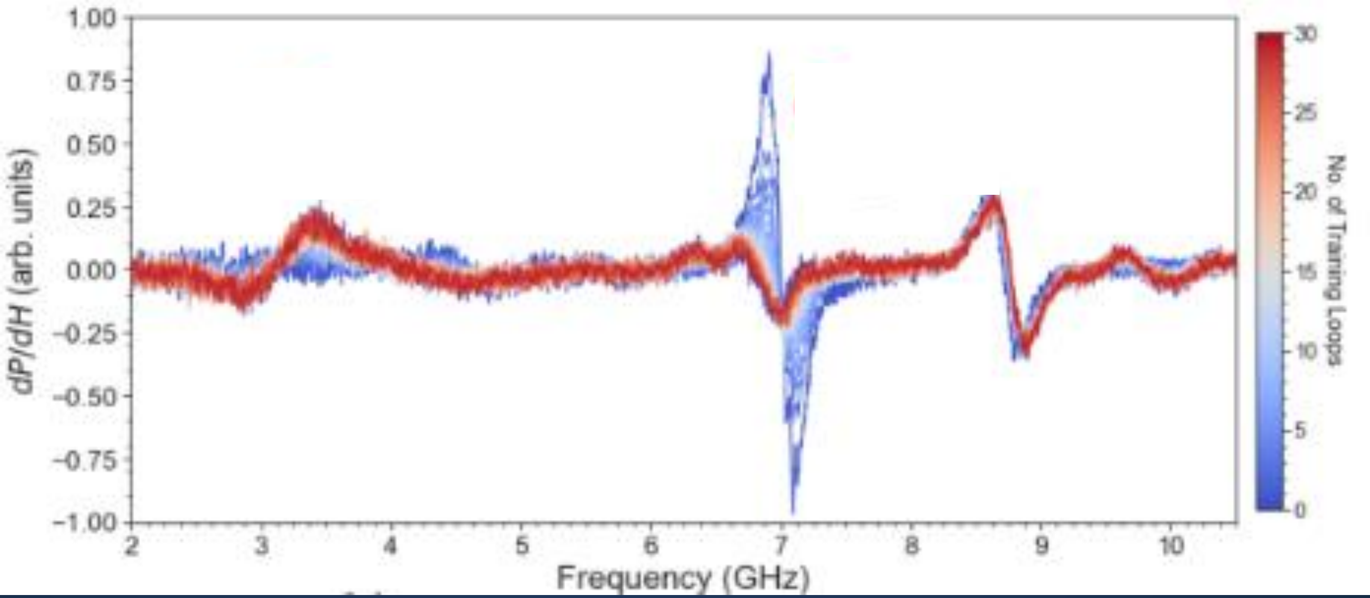
Physical Reservoir
Configured to desired texture



Output Problem
Simple, linear

Readout solution: Frequency-domain spectra

- Each 0.02 GHz frequency channel sensitive to slightly different texture/mode
- 300 FMR bins = 300 output weights/channels for reservoir
- Measure full spectra in ~0.5-1 second



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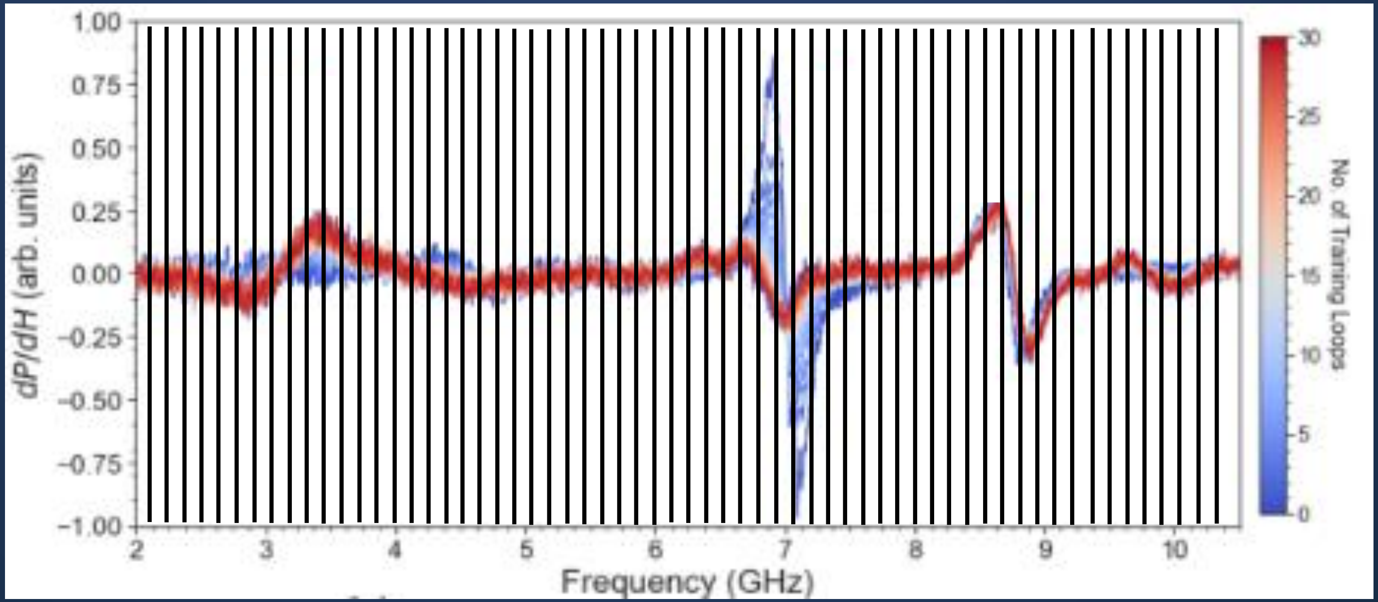
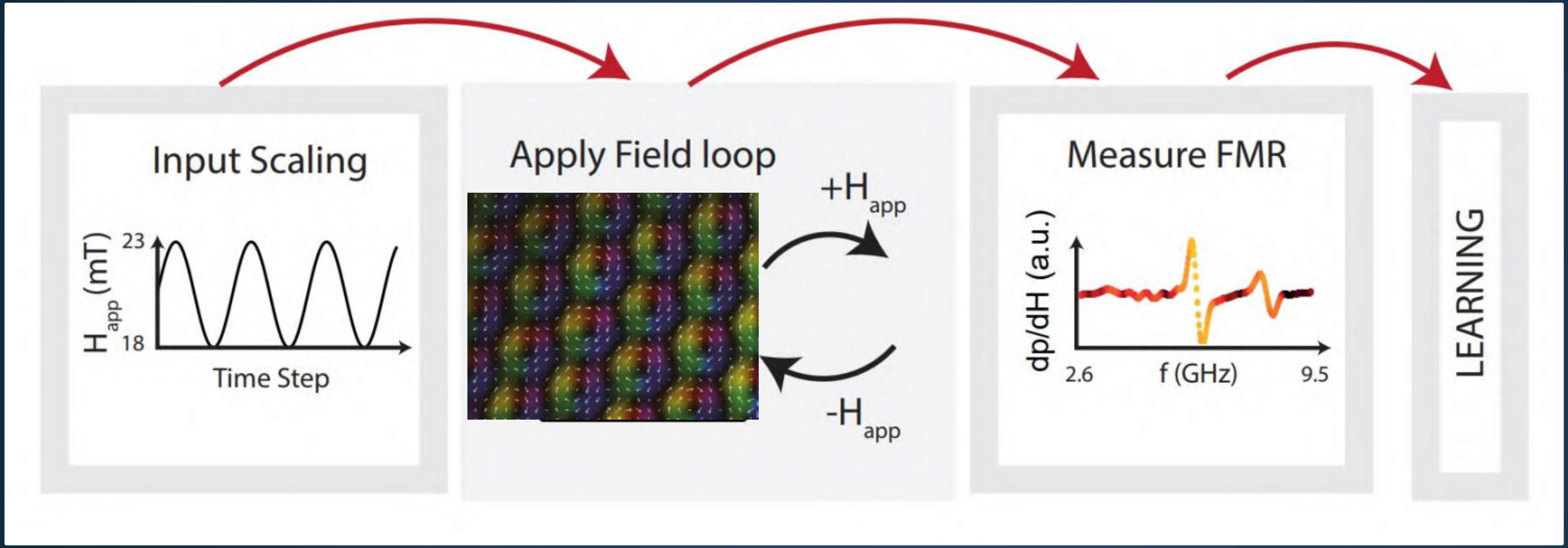


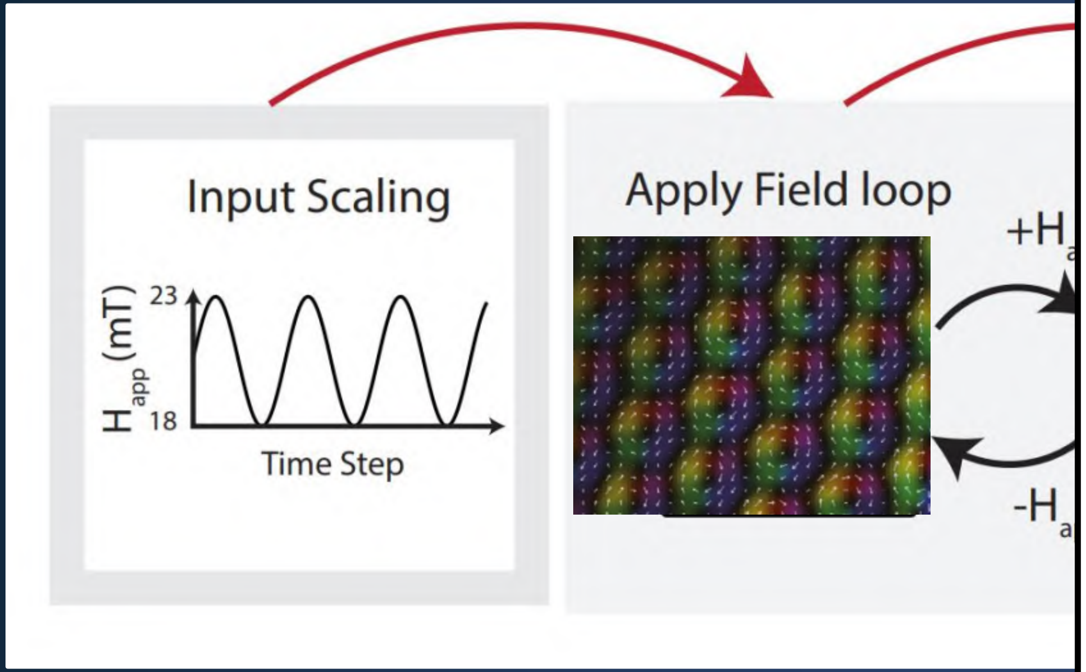
Computing Scheme

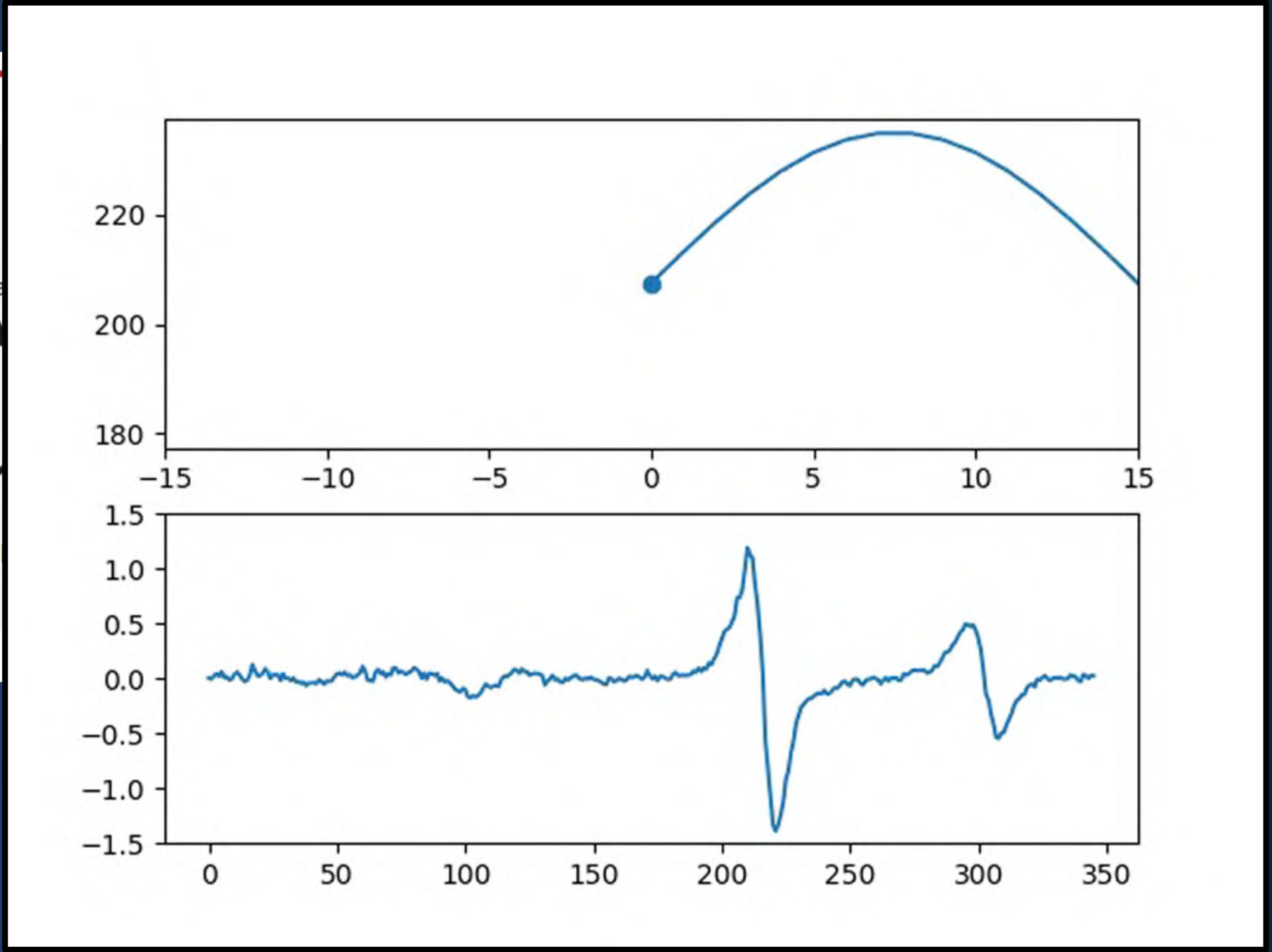


- Input converted to magnetic field loops
- Apply field loops to system
- Measure FMR response
- Each frequency bin is 1 output for training ~300 outputs per sample
- Learning offline – Cheap linear regression

- Vanstone, A. et. al. *New J Phys*, *24*(4), 043017 (2022).
- Gartside, Jack C., Stenning, Kilian D, Vanstone, Alex, et al. *Nature Nanotechnology* (2022): 460-469.
- Stenning, Kilian D., Gartside, Jack C. et al. *arXiv* (2022).

Computing Scheme





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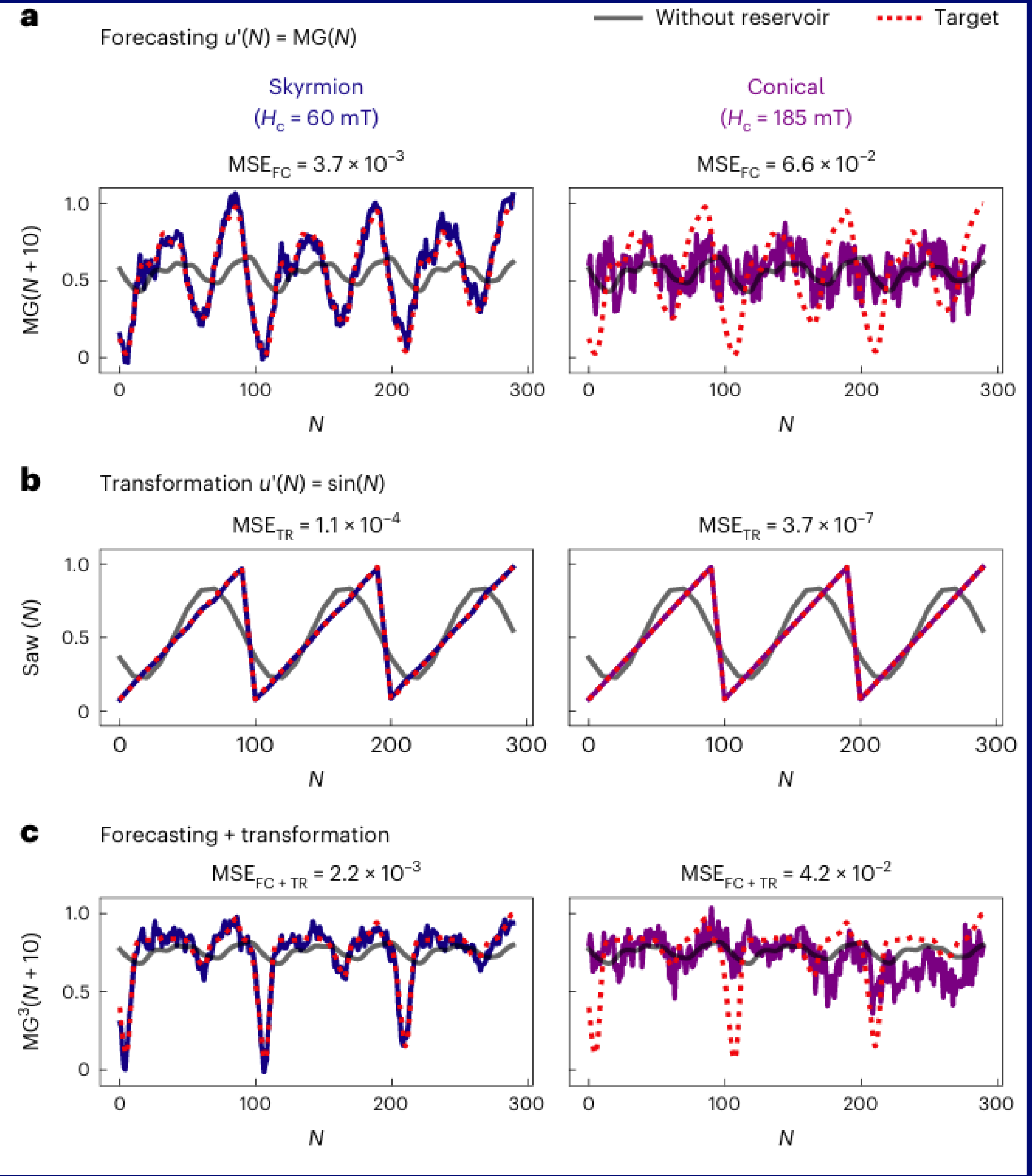
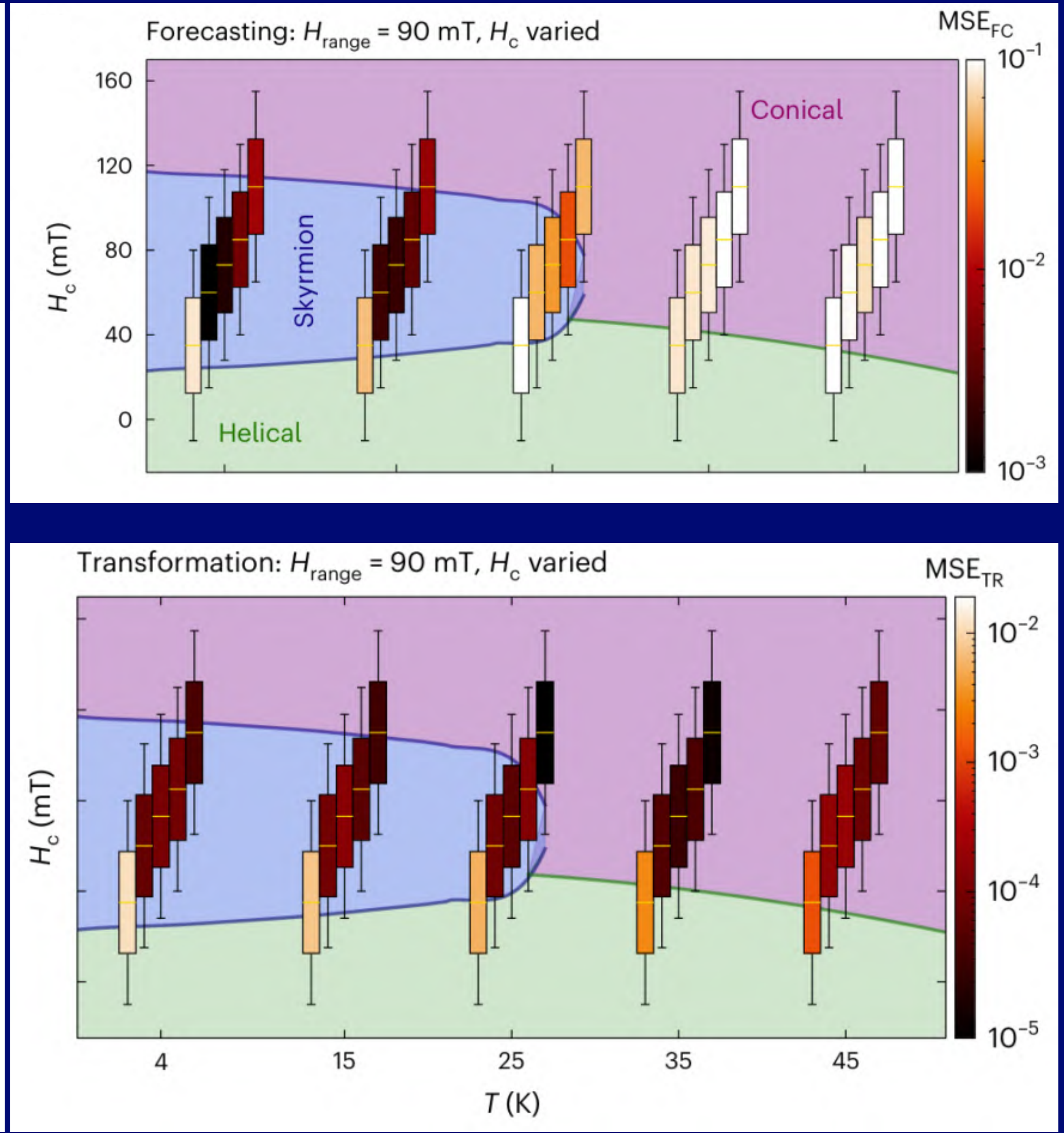
Mean-Field Skyrmion computing – Some tasks

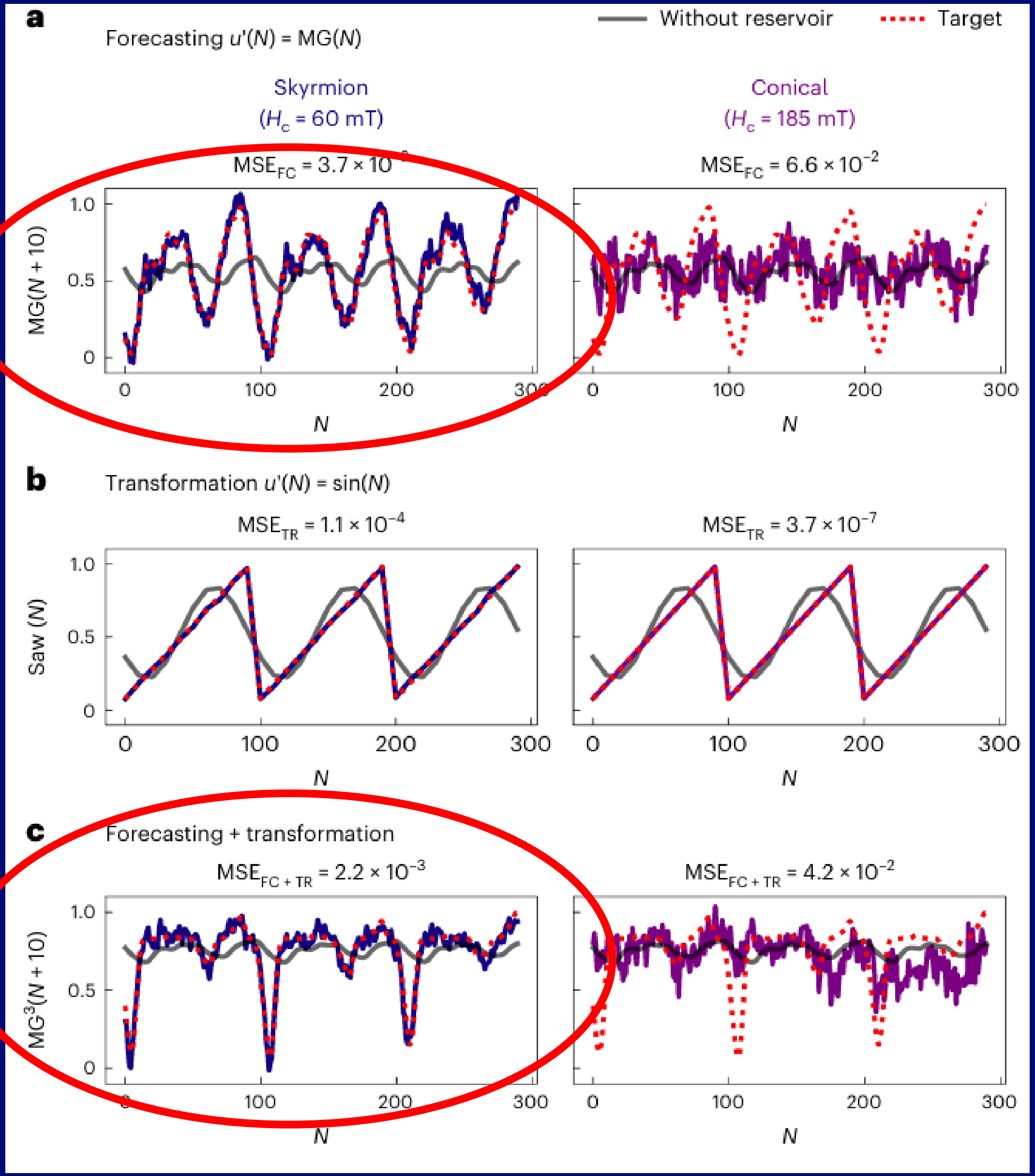


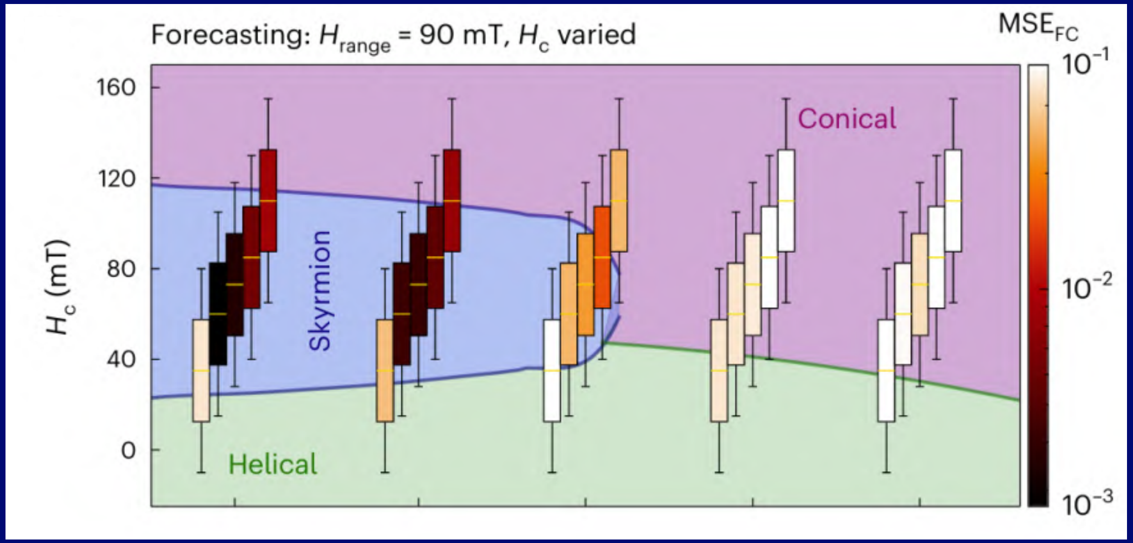


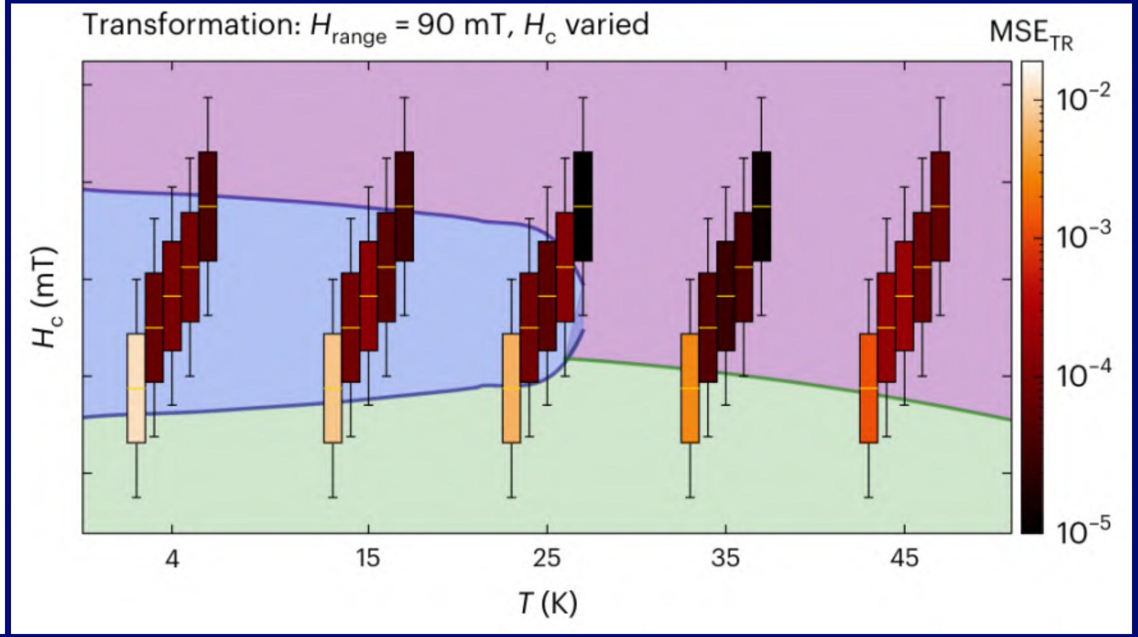
Lee, Oscar, et al. "Task-adaptive physical reservoir computing." *Nature Materials* 23.1 (2024): 79-87.

Mean-Field Skyrmion computing – Some tasks

Need Skyrmions for memory!







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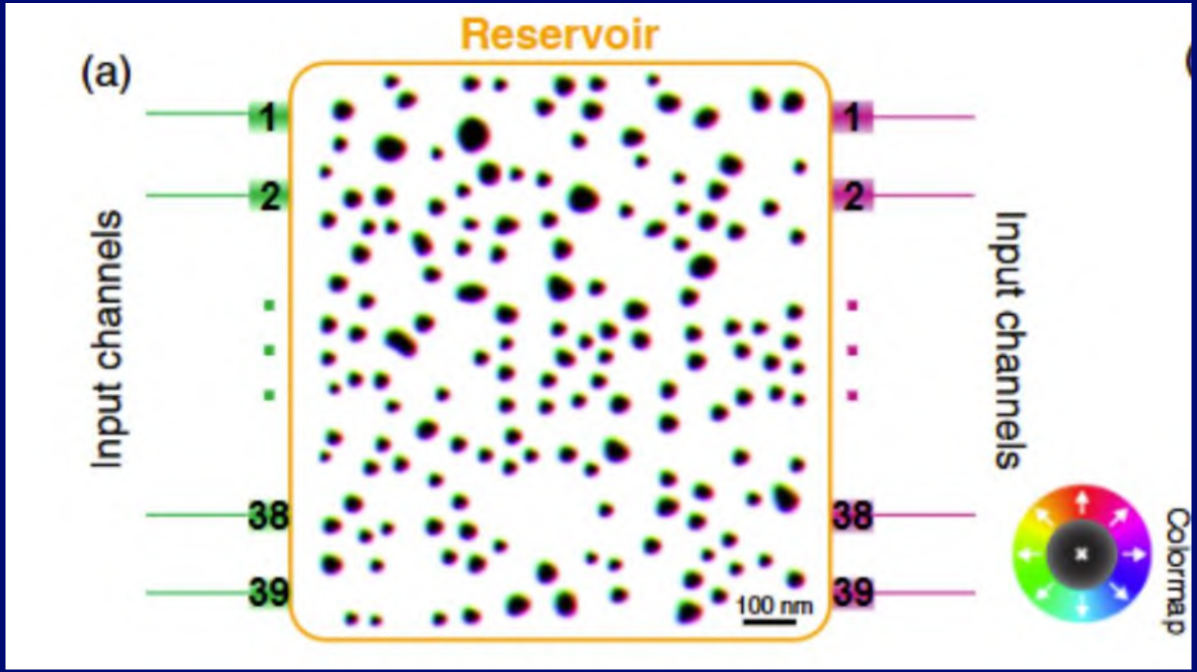
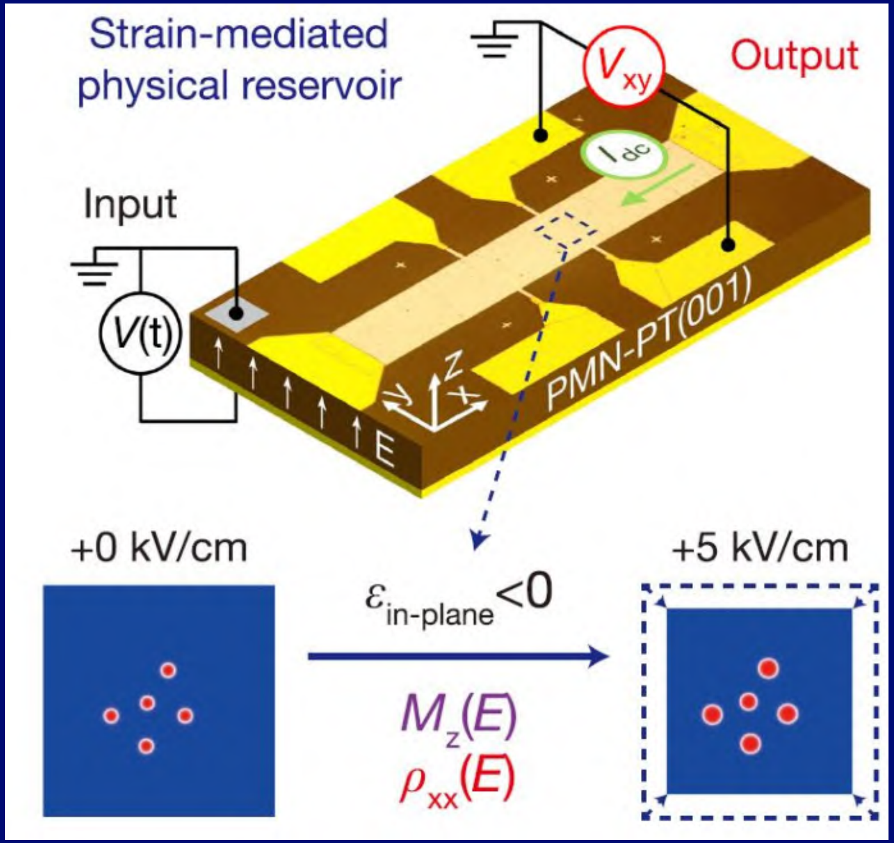
Many Reservoir schemes – Simulation & experiment



Simulation – shows benefit of large number of input channels

Msiska, Robin, et al. "Audio classification with skyrmion reservoirs." *Advanced Intelligent Systems* 5.6 (2023): 2200388.



50 fJ per operation

Sun, Yiming, et al. "Experimental demonstration of a skyrmion-enhanced strain-mediated physical reservoir computing system." *Nature Communications* 14.1 (2023): 3434.

Nice range of recent reviews

REVIEW

ADVANCED MATERIALS
www.advmat.de

Topological Spin Textures: Basic Physics and Devices

*Yuqing Zhou, Shuang Li, Xue Liang, and Yan Zhou**

nature reviews physics https://doi.org/10.1038/s42254-024-00729-w

Perspective

Check for updates

Topological magnetic and ferroelectric systems for reservoir computing

Karin Everschor-Sitte[1], Atreya Majumdar[1], Katharina Wolk[2] & Dennis Meier[2,3]

PERSPECTIVE | JUNE 27 2023

Perspective on unconventional computing using magnetic skyrmions

Oscar Lee; Robin Msiska; Maarten A. Brems; Mathias Kläui; Hidekazu Kurebayashi; Karin Everschor-Sitte

Check for updates

Appl. Phys. Lett. 122, 260501 (2023)
https://doi.org/10.1063/5.0148469

Physics for neuromorphic computing

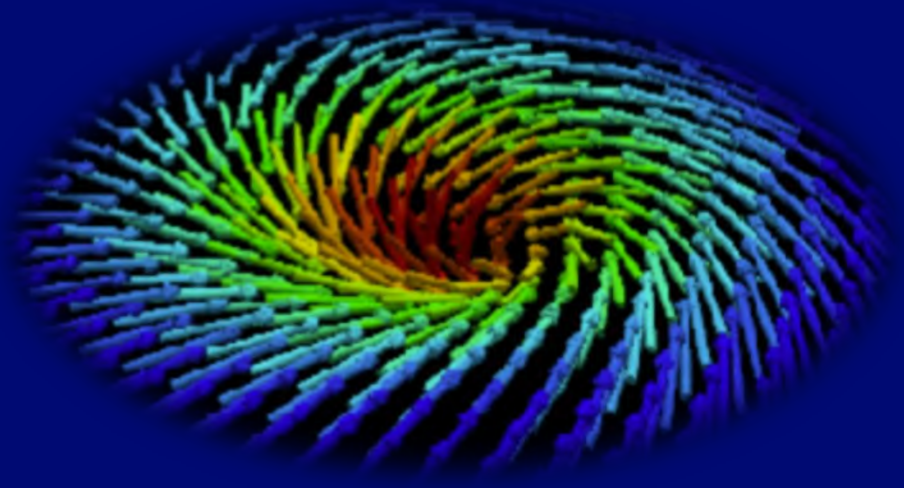
Danijela Marković, Alice Mizrahi, Damien Querlioz and Julie Grollier

Training of Physical Neural Networks

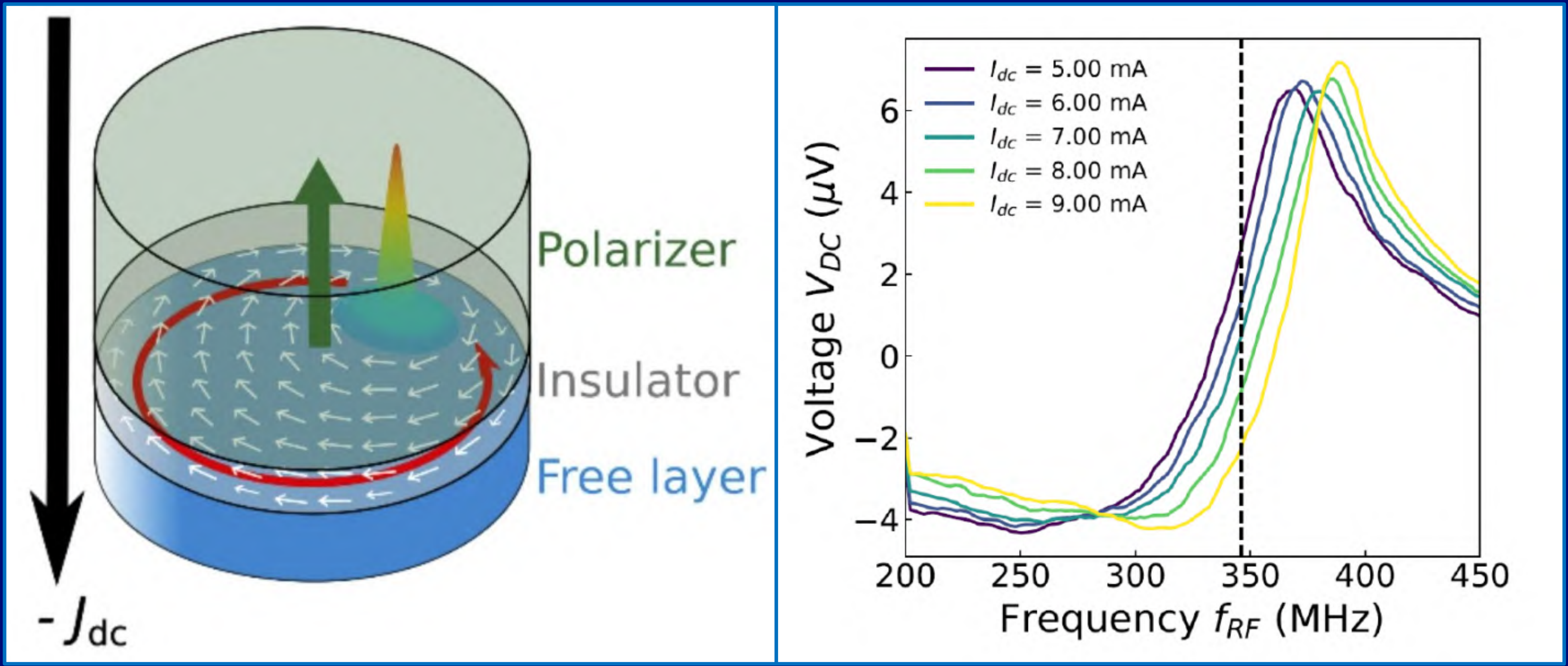
Ali Momeni, Babak Rahmani, Benjamin Scellier, Logan G. Wright, F
Oguz, Francesco Morichetti, Philipp del Hougne, Manuel Le Gallo,
Sylvain Gigan, Florian Marquardt, Aydogan Ozcan, Julie Grollier, A

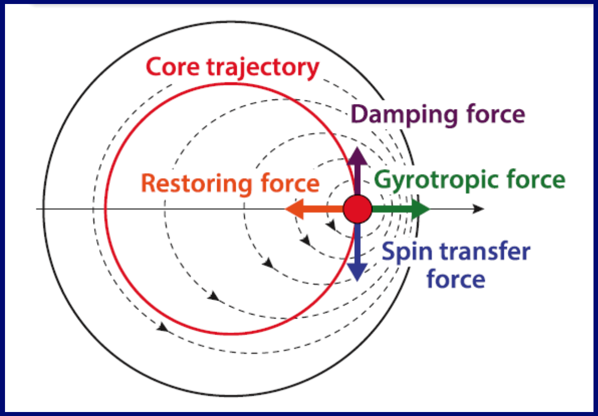
We’ve seen:

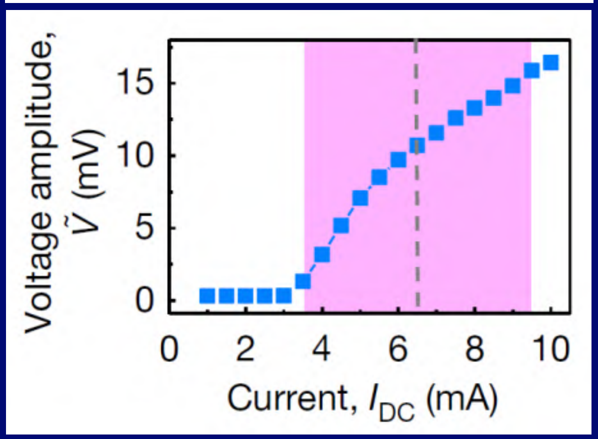
- Precise control - still some distance from full device
- Reservoir computing which solves tasks, but lacks fine
  control. Some reconfigurability but limited
- What about a middle ground?
  - Can we have fine control, and actual computation?
  - Let’s look at **vortex oscillators**



Spin-Torque Vortex Oscillators





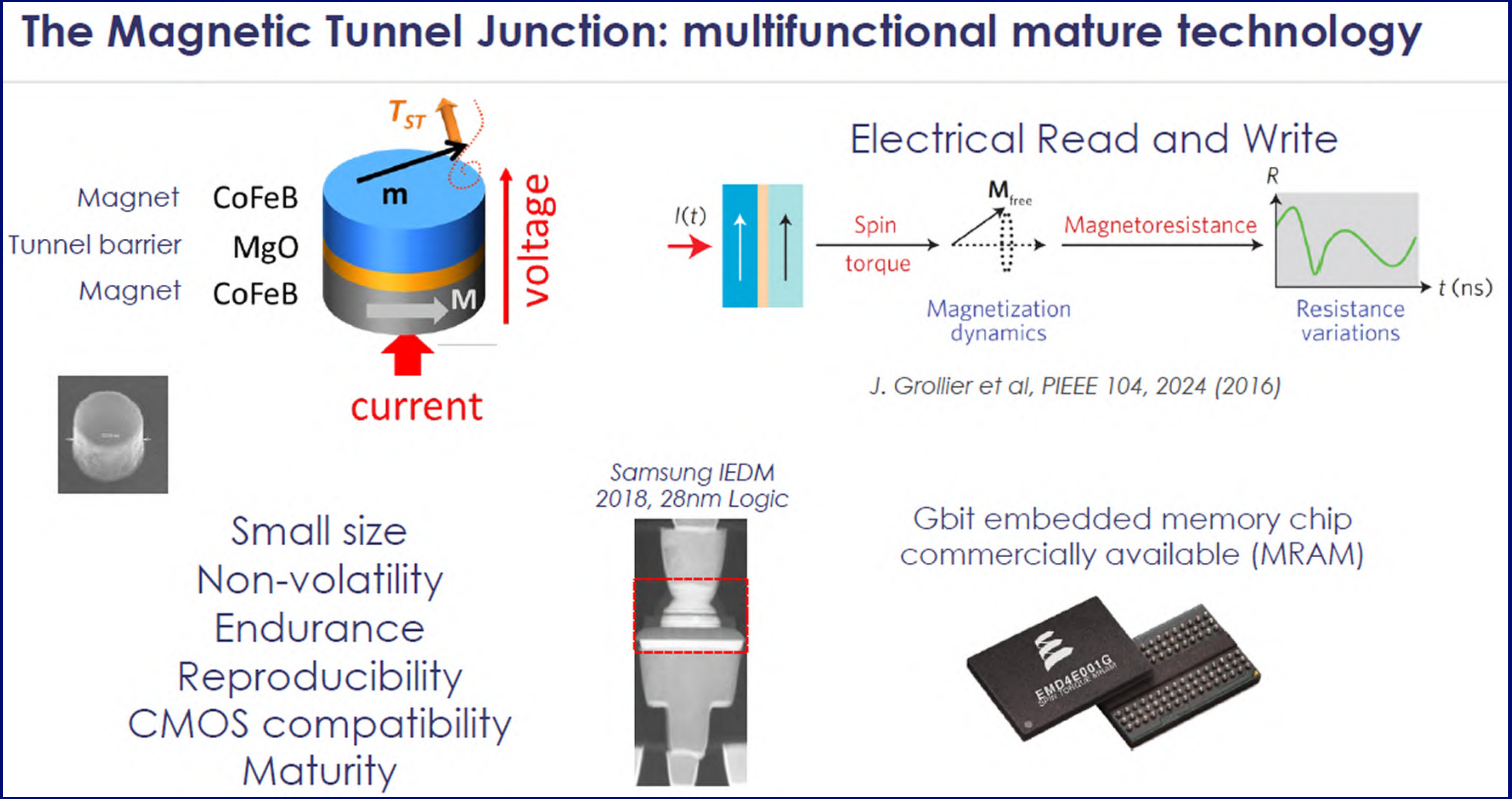


- **Good:** Low linewidth, low input current (mA), relatively high RF power (uW)
  - Nonlinear/threshold input response
- **Less good** Poor upper frequency output (typically 100s MHz to low GHz)

Ross, A., Leroux, N., De Riz, A., Marković, D., Sanz-Hernández, D., Trastoy, J., ... & Grollier, J. (2023). Multilayer spintronic neural networks with radiofrequency connections. *Nature Nanotechnology*, *18*(11), 1273-1280.

Chopin, C., de Wergifosse, S., Moureaux, A., & Abreu Araujo, F. (2024). Current-controlled periodic double-polarity reversals in a spin-torque vortex oscillator. *Scientific Reports*, *14*(1), 24177.

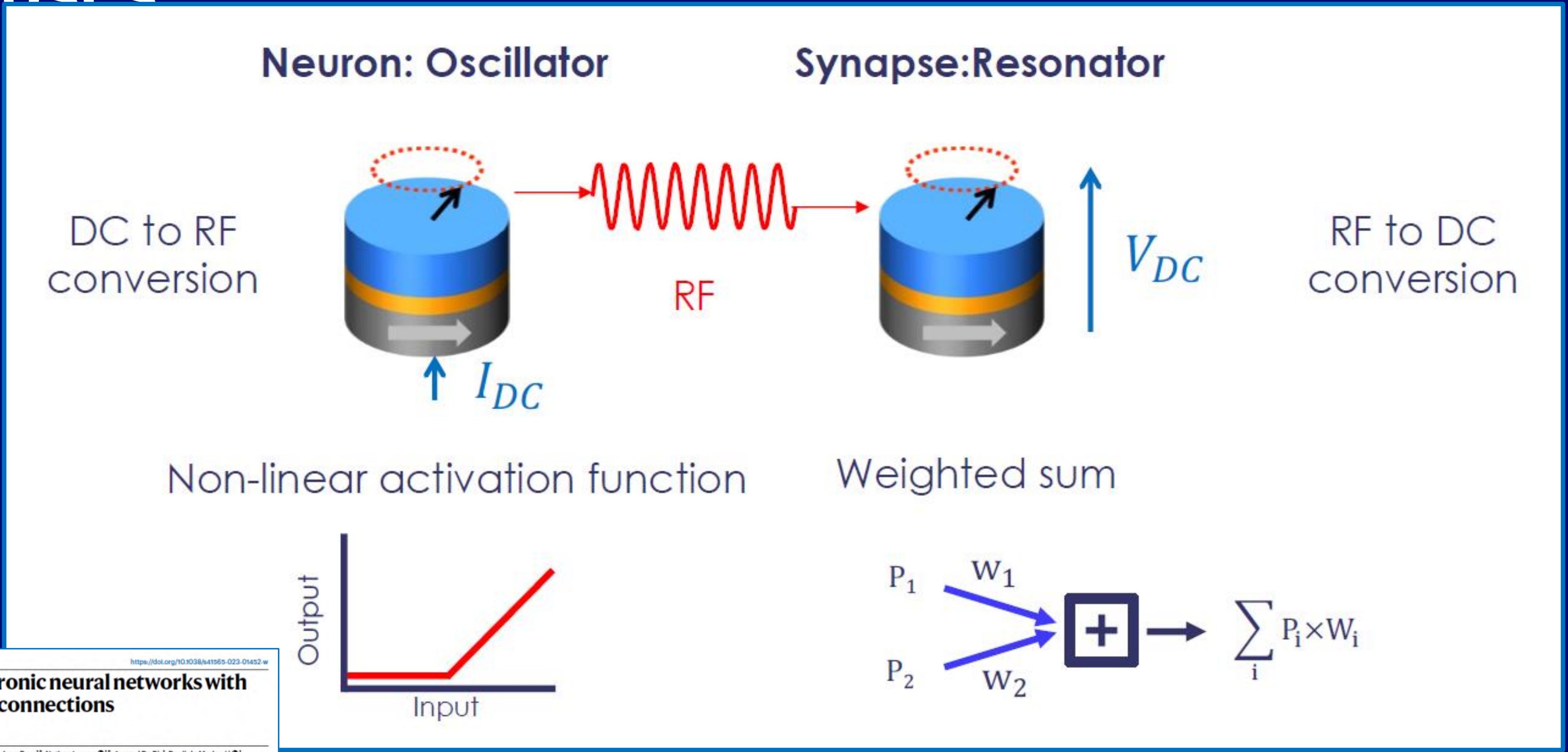
Spin-Torque Vortex Oscillators

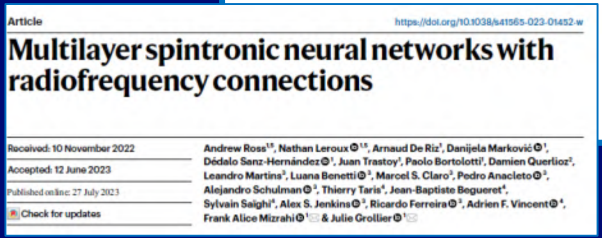


Ross, A., Leroux, N., De Riz, A., Marković, D., Sanz-Hernández, D., Trastoy, J., Bortolotti, P., Querlioz, D., Martins, L., Benetti, L. and Claro, M.S., 2023. Multilayer spintronic neural networks with radiofrequency connections. *Nature Nanotechnology*, *18*(11), pp.1273-1280.

Spin-Torque Vortex Oscillators – Neurons and **Synapses**

DC to RF (spin torque) and RF to DC (spin diode effect) allows bidirectional conversion





Article https://doi.org/10.1038/s41565-023-01452-w

Multilayer spintronic neural networks with radiofrequency connections

Received: 10 November 2022
Accepted: 12 June 2023
Published online: 27 July 2023
Check for updates

Andrew Ross[1,5], Nathan Leroux[1,5], Arnaud De Riz[1], Danijela Marković[1], Dédalo Sanz-Hernández[1], Juan Trastoy[1], Paolo Bortolotti[1], Damien Querlioz[2], Leandro Martins[3], Luana Benetti[3], Marcel S. Claro[3], Pedro Anacleto[3], Alejandro Schulman[3], Thierry Taris[4], Jean-Baptiste Begueret[4], Sylvain Saïghi[4], Alex S. Jenkins[3], Ricardo Ferreira[3], Adrien F. Vincent[4], Frank Alice Mizrahi[1] & Julie Grollier[1]

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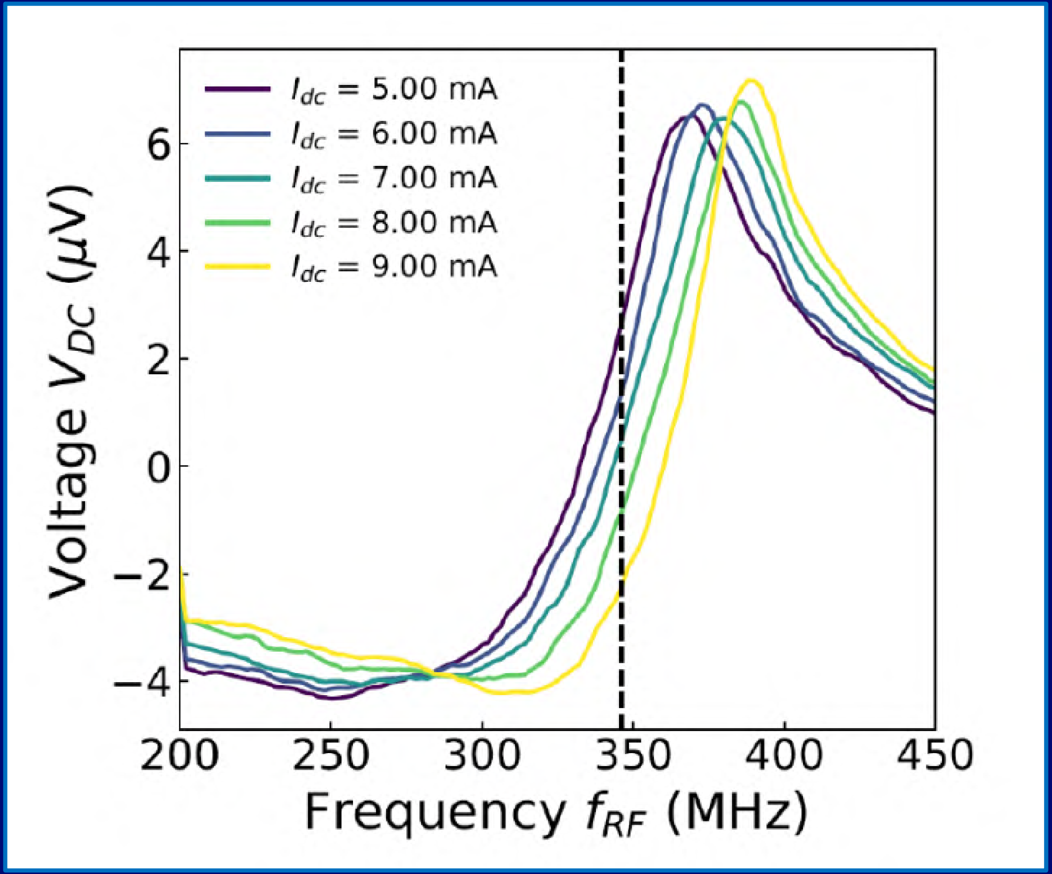
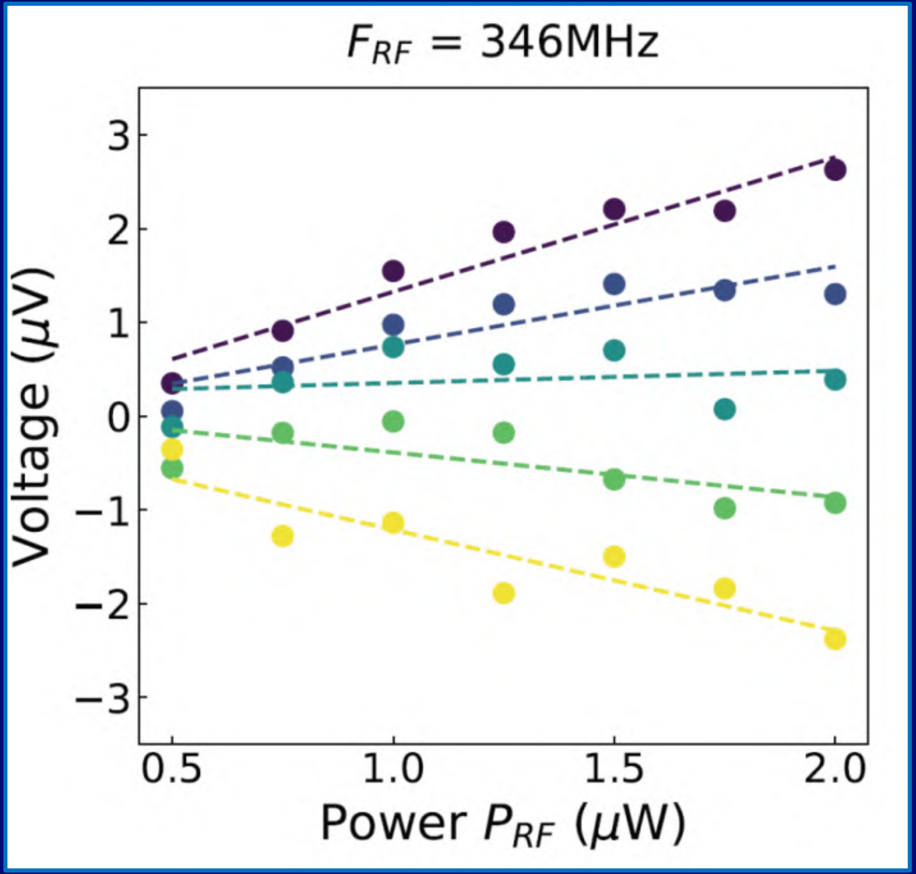
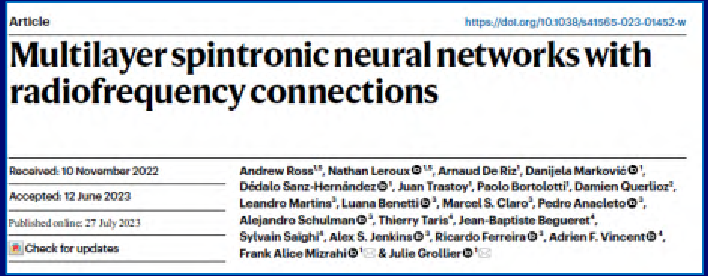
Spin-Torque Vortex Oscillators – Synapses







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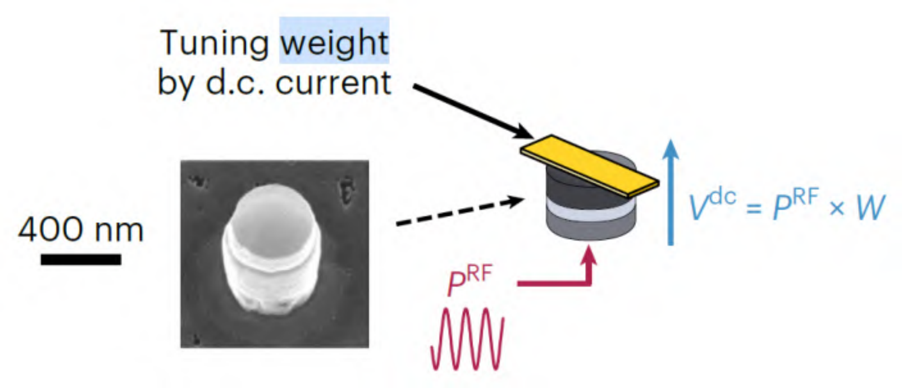

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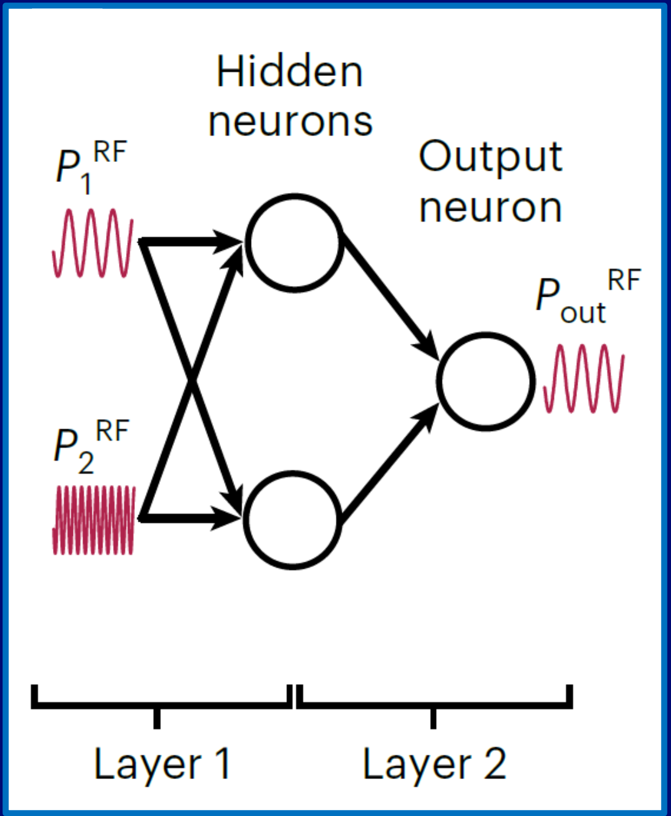
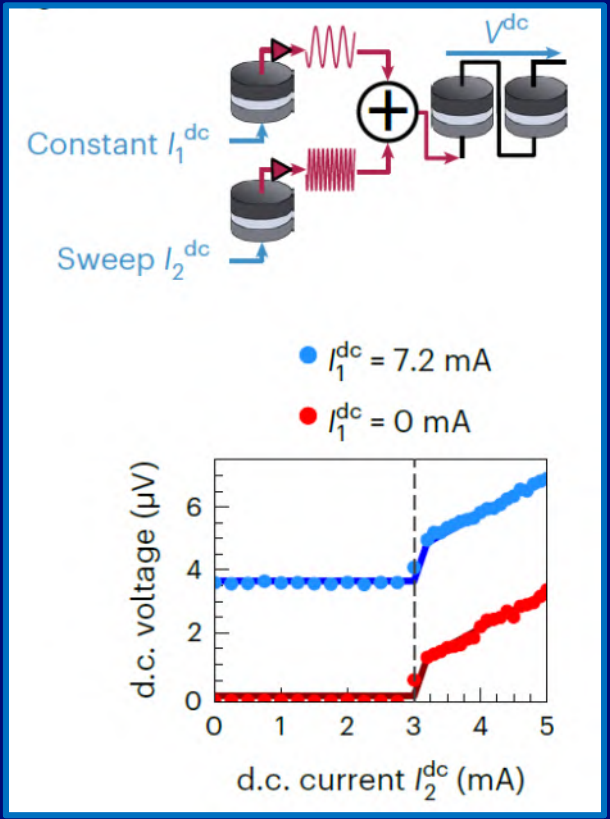
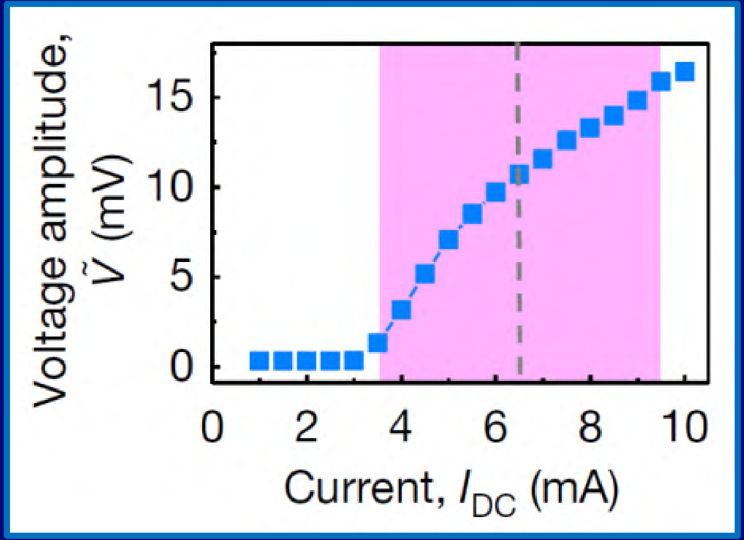
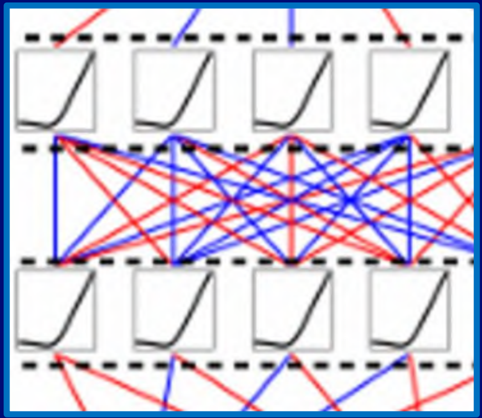
Spin-Torque Vortex Oscillators – Neurons





Nice threshold/ReLU style nonlinearity:





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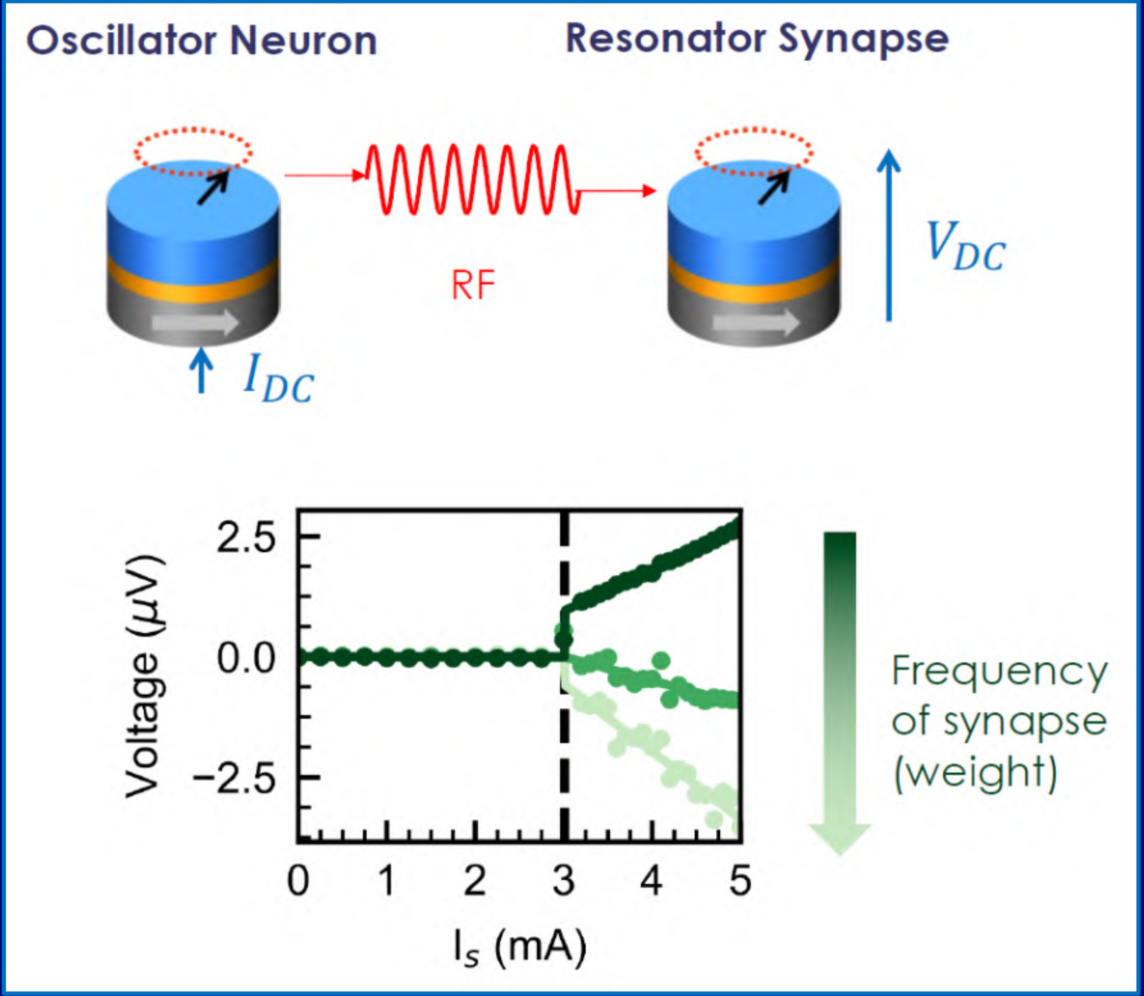
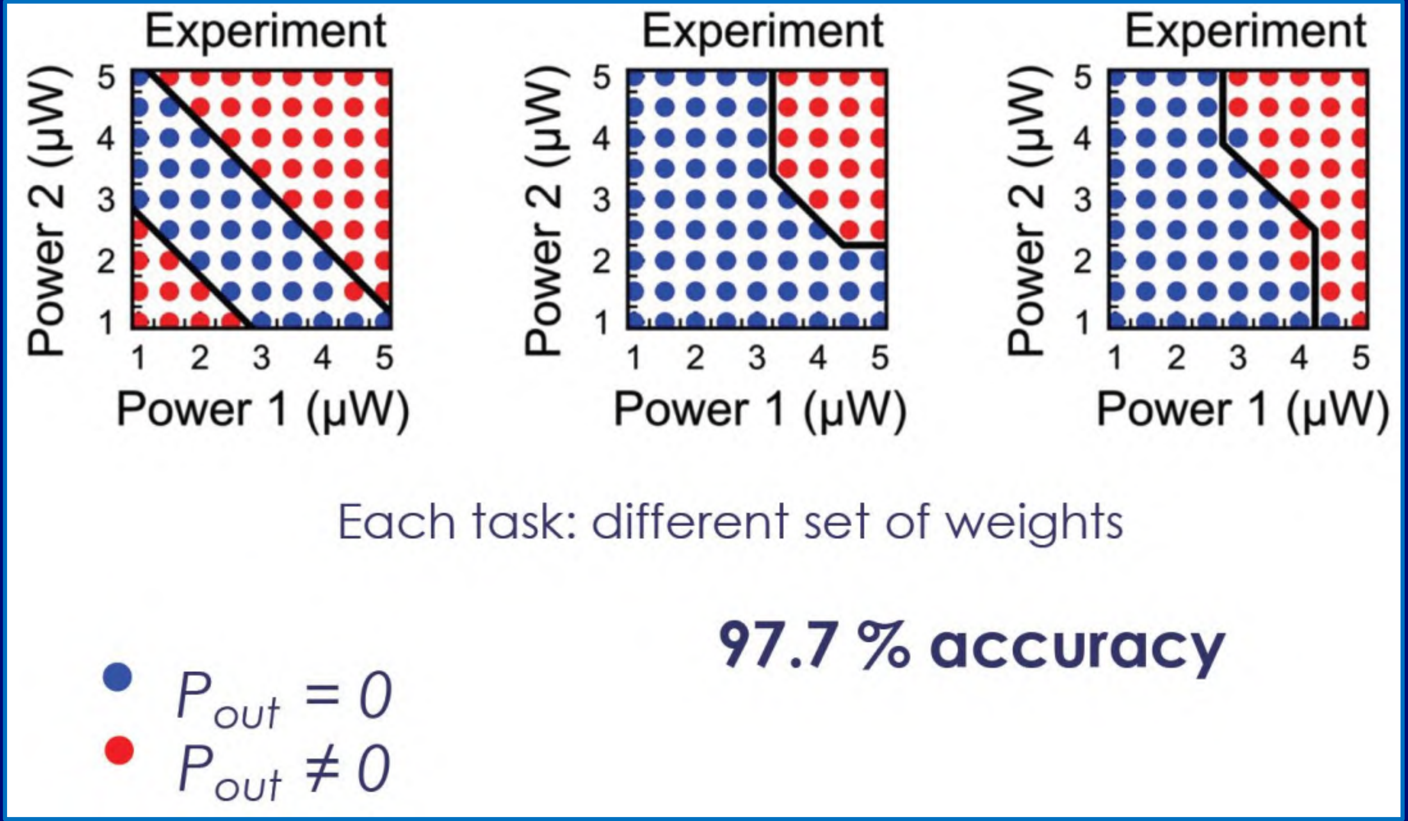
Spin-Torque Vortex Oscillators – Neurons & Synapse together





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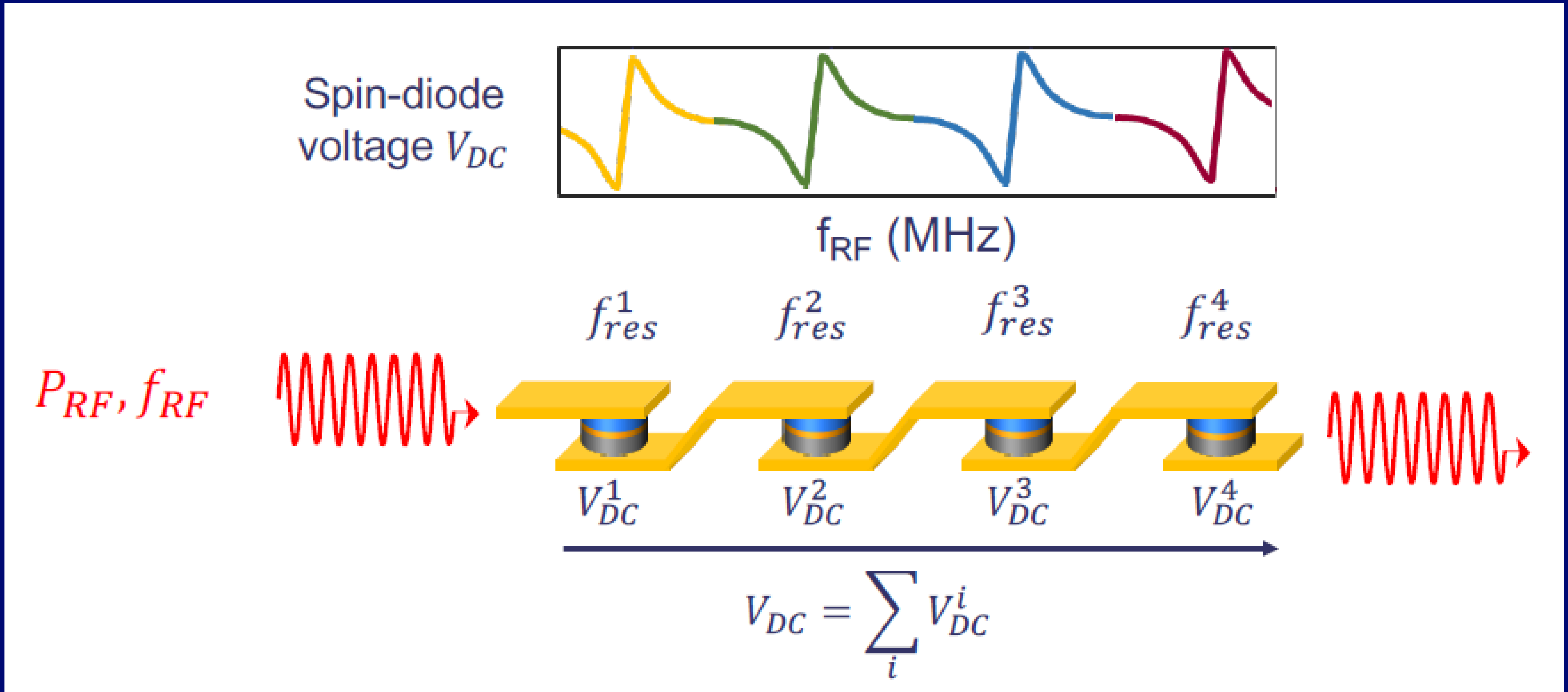
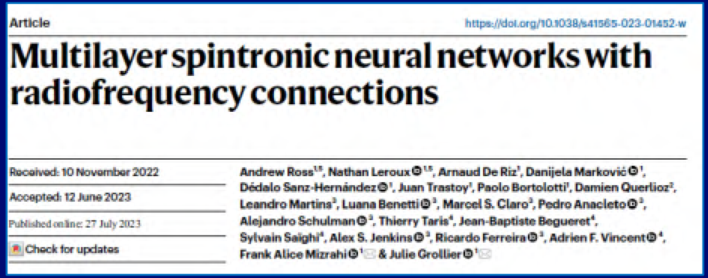
Spin-Torque Vortex Oscillators – Challenges





Article https://doi.org/10.1038/s41565-023-01452-w

Multilayer spintronic neural networks with radiofrequency connections

Received: 10 November 2022

Accepted: 12 June 2023

Published online: 27 July 2023

Check for updates

Andrew Ross[1,5], Nathan Leroux[1,5], Arnaud De Riz[1], Danijela Marković[1], Dédalo Sanz-Hernández[1], Juan Trastoy[1], Paolo Bortolotti[1], Damien Querlioz[2], Leandro Martins[3], Luana Benetti[3], Marcel S. Claro[3], Pedro Anacleto[3], Alejandro Schulman[3], Thierry Taris[4], Jean-Baptiste Begueret[4], Sylvain Saïghi[4], Alex S. Jenkins[3], Ricardo Ferreira[3], Adrien F. Vincent[4], Frank Alice Mizrahi[1] & Julie Grollier[1]

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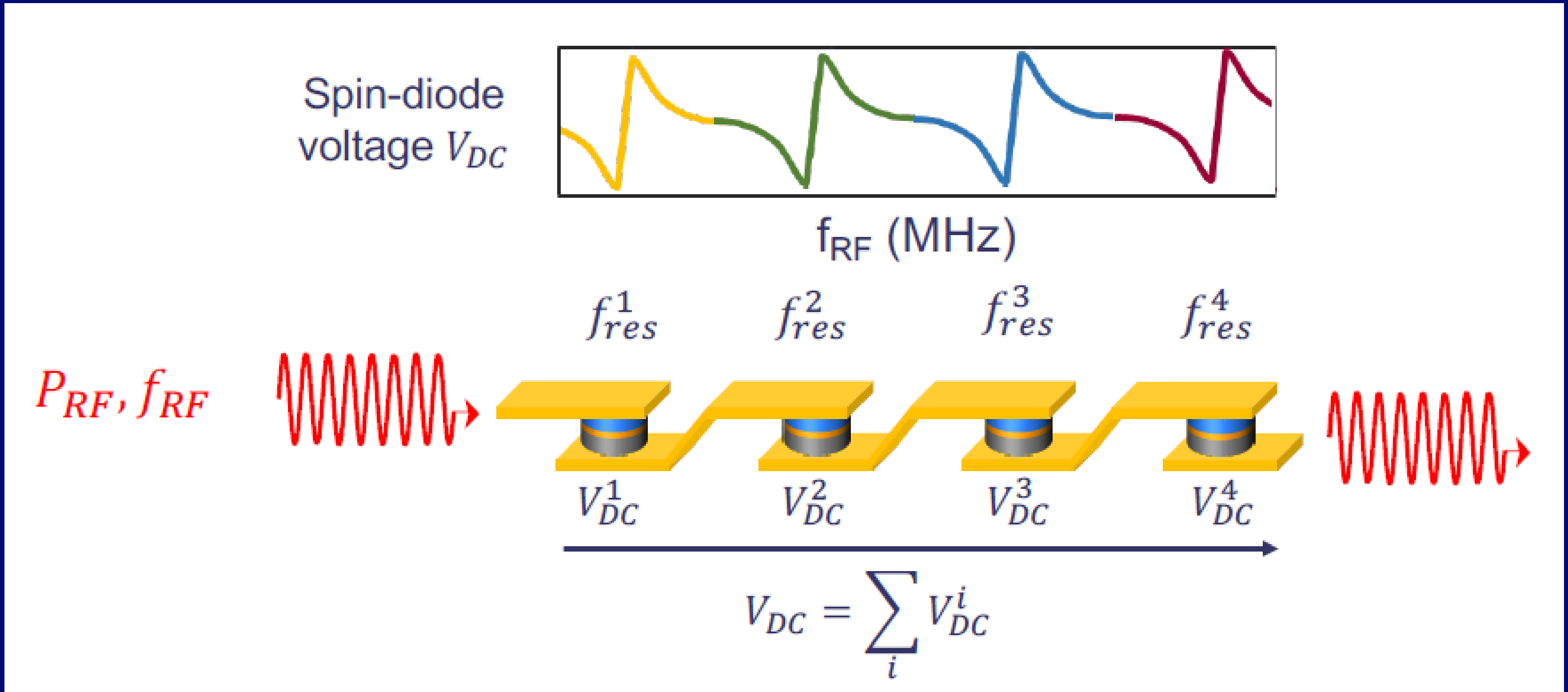
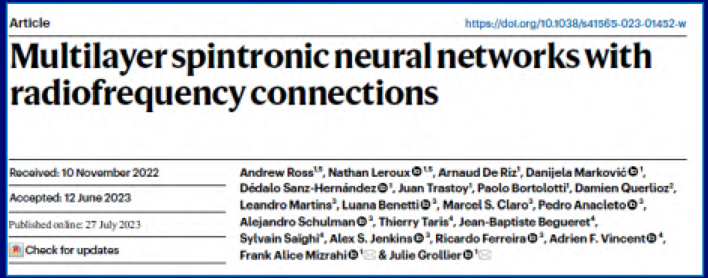
Spin-Torque Vortex Oscillators – Challenges

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Only 3 neurons... **Far** from device scale

Ross, A., Leroux, N., De Riz, A., Marković, D., Sanz-Hernández, D., Trastoy, J., Bortolotti, P., Querlioz, D., Martins, L., Benetti, L. and Claro, M.S., 2023. Multilayer spintronic neural networks with radiofrequency connections. *Nature Nanotechnology*, *18*(11)

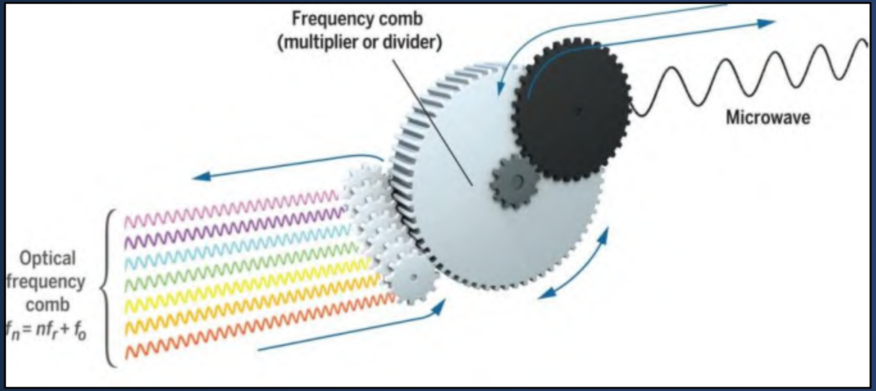
We’ve seen:

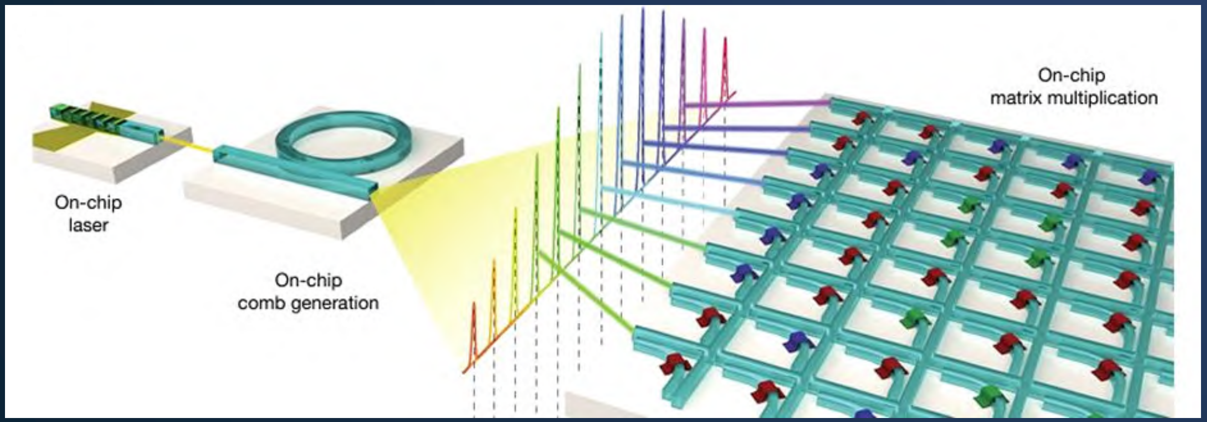
- **Great** scheme!
  - Excellent control
  - Nonlinearity, Synaptic weights
  - Challenge around number of available frequency channels
- Can magnetic textures & magnonics offer solutions?

Magnon Frequency Comb

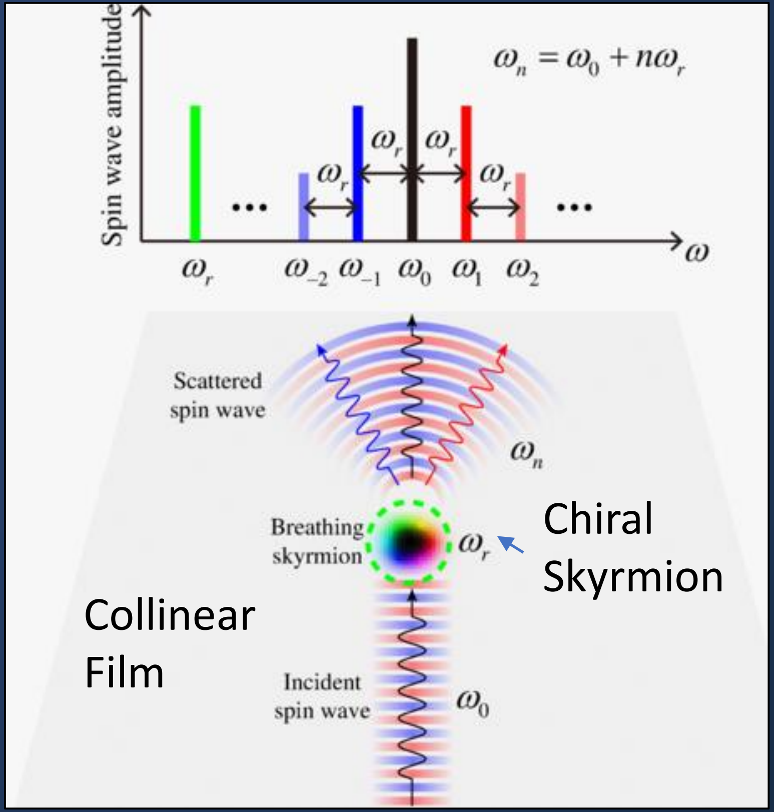
- Optical frequency combs create new modes by coupling microwaves to lasing modes
- Many magnetic device schemes demand more frequency channels/parallelization - **magnetic 'magnon' frequency combs?**
- One theoretical proposal: Couple chiral magnetism to collinear magnetism

Optical Combs: Metrology, Computing





Magnon Comb?



Wang, Zhenyu, et al. "Magnonic frequency comb through nonlinear magnon-skyrmion scattering." *Physical Review Letters* 127.3 (2021): 037202.

Feldmann, Johannes, et al. "Parallel convolutional processing using an integrated photonic tensor core." Nature 589.7840 (2021): 52-58.

Magnon Frequency Comb

PHYSICAL REVIEW LETTERS 127, 037202 (2021)

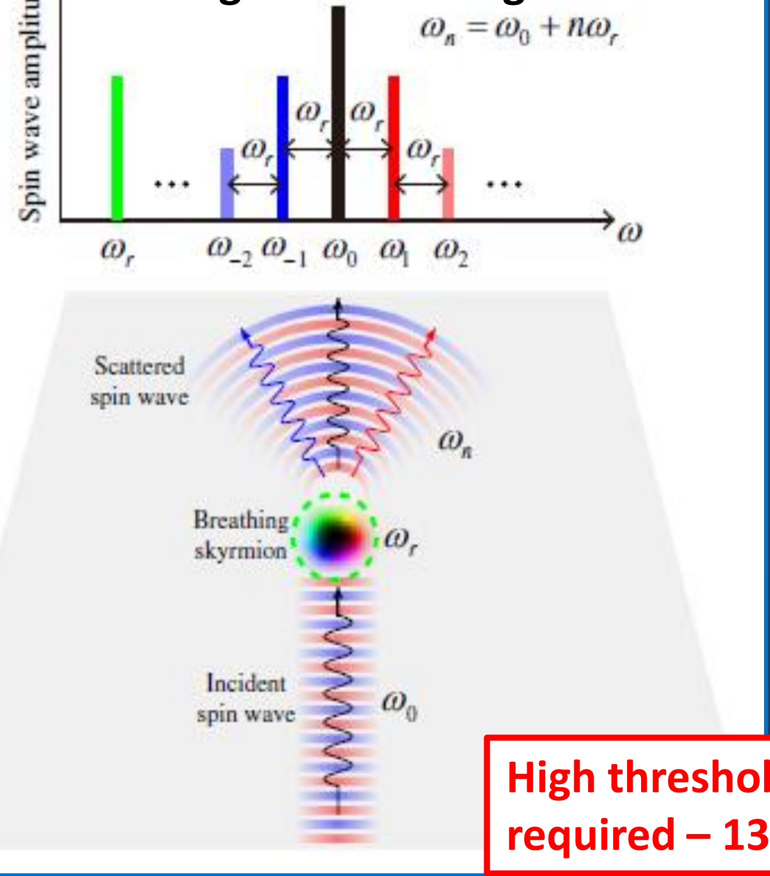
Magnonic Frequency Comb through Nonlinear Magnon-Skyrmion Scattering

Zhenyu Wang,[1] H. Y. Yuan,[2,*] Yunshan Cao,[1] Z.-X. Li,[1] Rembert A. Duine,[2] and Peng Yan[1,†]
[1]*School of Electronic Science and Engineering and State Key Laboratory of Electronic Thin Films and Integrated Devices, University of Electronic Science and Technology of China, Chengdu 610054, China*
[2]*Institute for Theoretical Physics, Utrecht University, 3584 CC Utrecht, Netherlands*

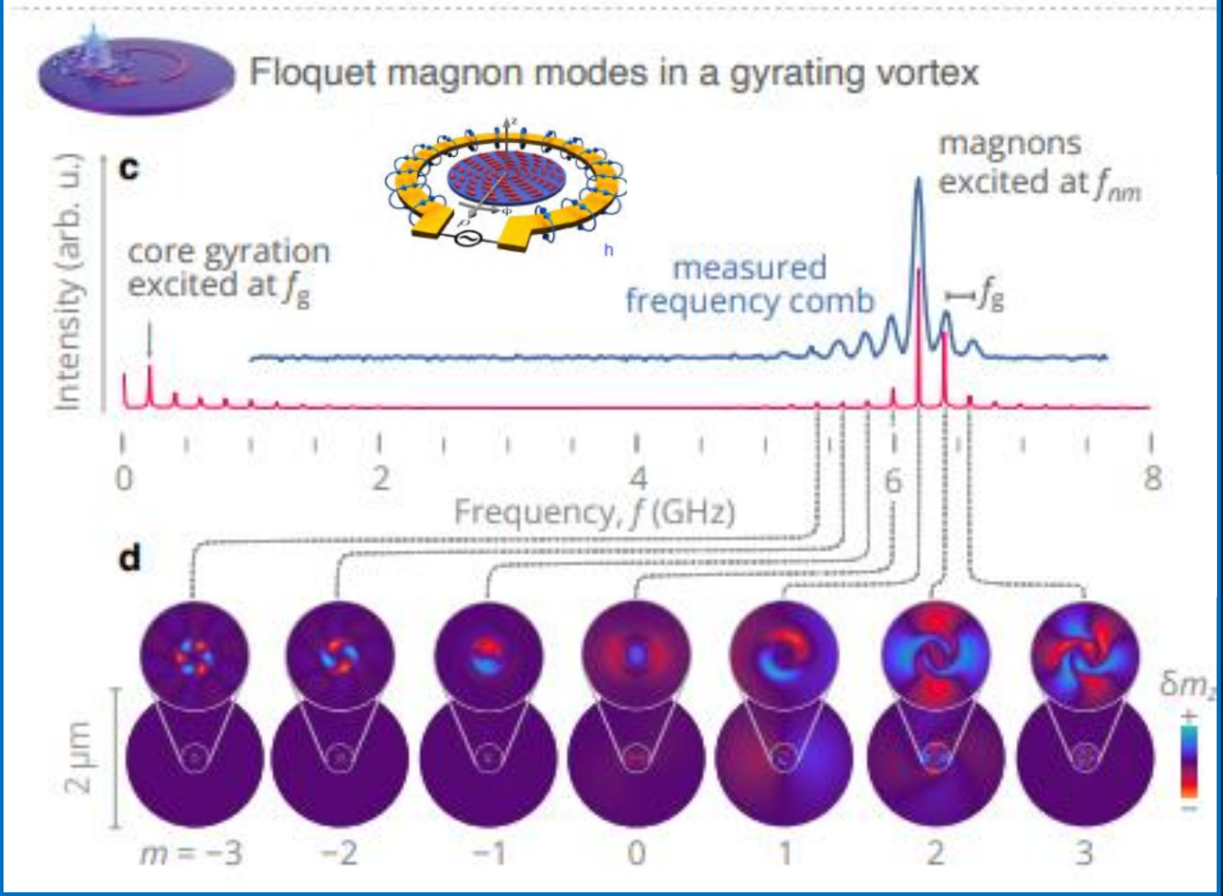
Self-induced Floquet magnons in magnetic vortices

C. Heins,[1,2] L. Körber,[1,2,3] J.-V. Kim,[4] T. Devolder,[4] J. H. Mentink,[3] A. Kákay,[1] J. Fassbender,[1,2] K. Schultheiss,[1,a)] and H. Schultheiss[1,b)]
[1)]*Helmholtz-Zentrum Dresden–Rossendorf, Institut für Ionenstrahlphysik und Materialforschung, D-01328 Dresden, Germany*
[2)]*Fakultät Physik, Technische Universität Dresden, D-01062 Dresden, Germany*
[3)]*Radboud University, Institute of Molecules and Materials, Heyendaalseweg 135, 6525 AJ Nijmegen, The Netherlands*
[4)]*Centre de Nanosciences et de Nanotechnologies, CNRS, Université Paris-Saclay, 91120 Palaiseau, France*

3 magnon scattering

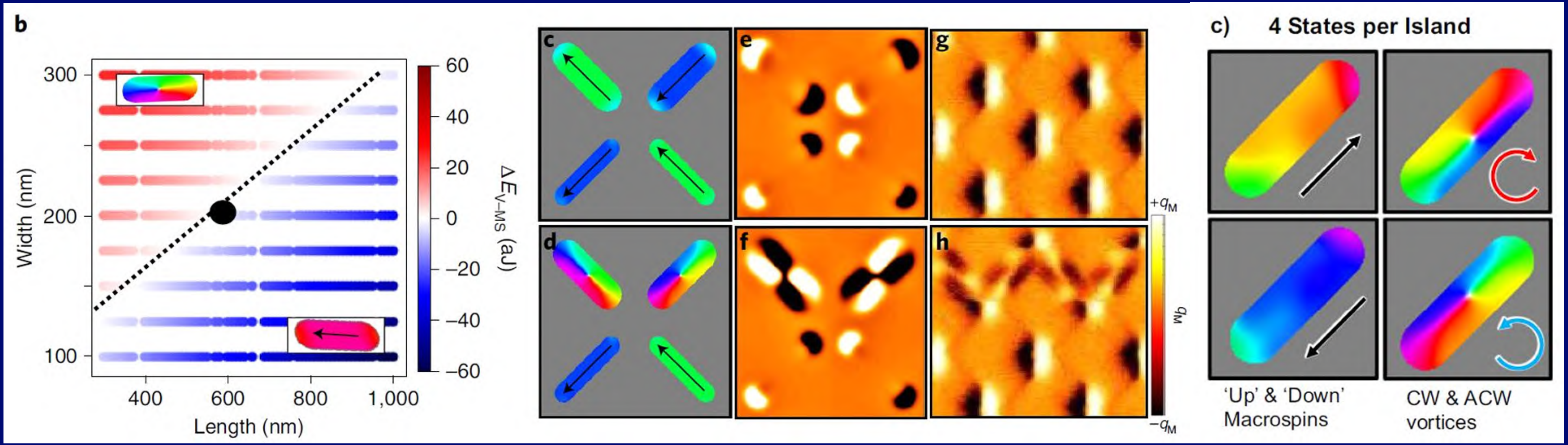


High threshold RF field required – 130 mT



Magnetic Metamaterials with Reconfigurable Textures:

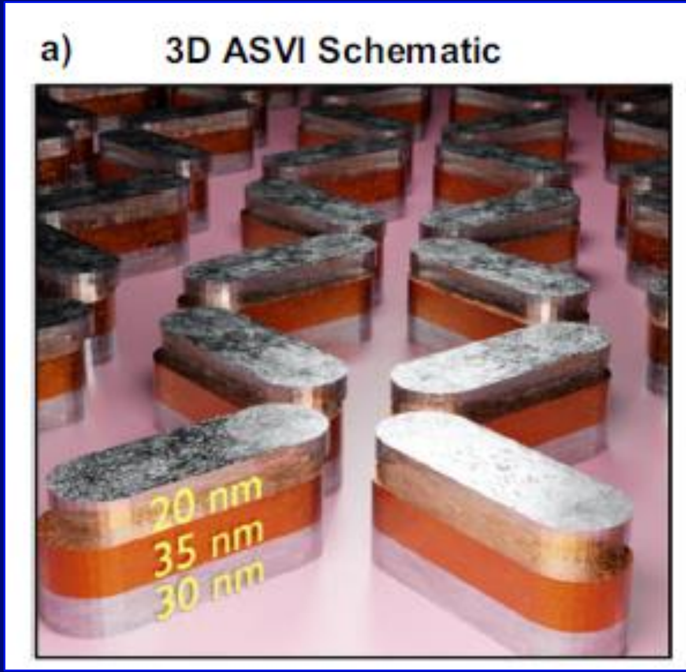
'Multistable' Nanostructures – Vortex or Macrospin, tunable:

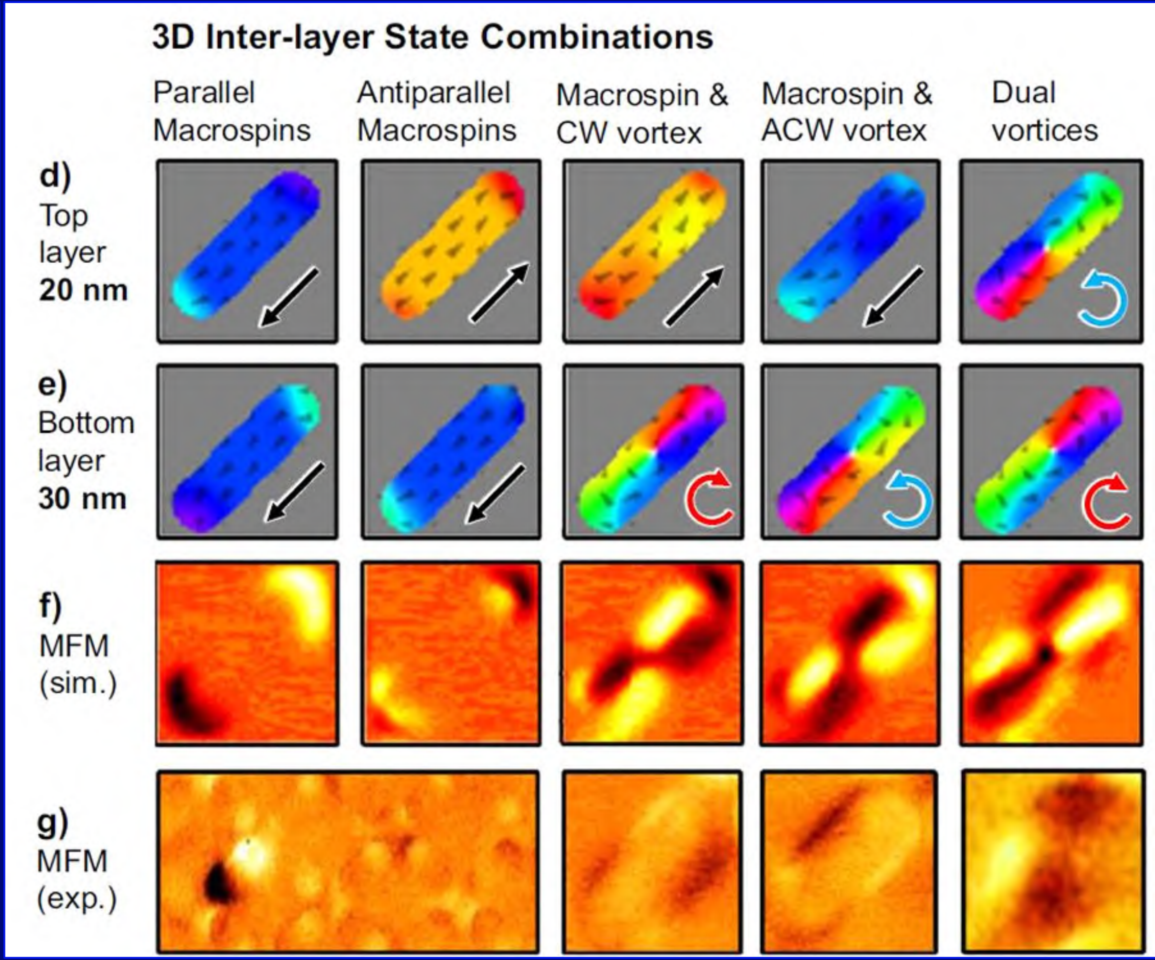


Gartside, Jack C., et al. "Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting." *Nature Nanotechnology* (2022)

Magnetic Metamaterials with Reconfigurable Textures:

‘Multistable’ Nanostructures – 2.5D/3D





Stack dipolar coupled layers:

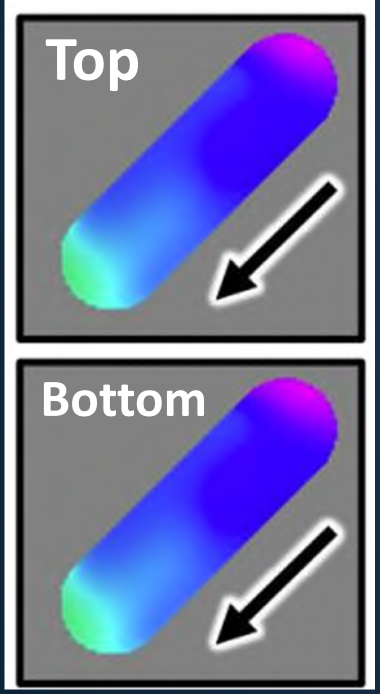
16 states per island

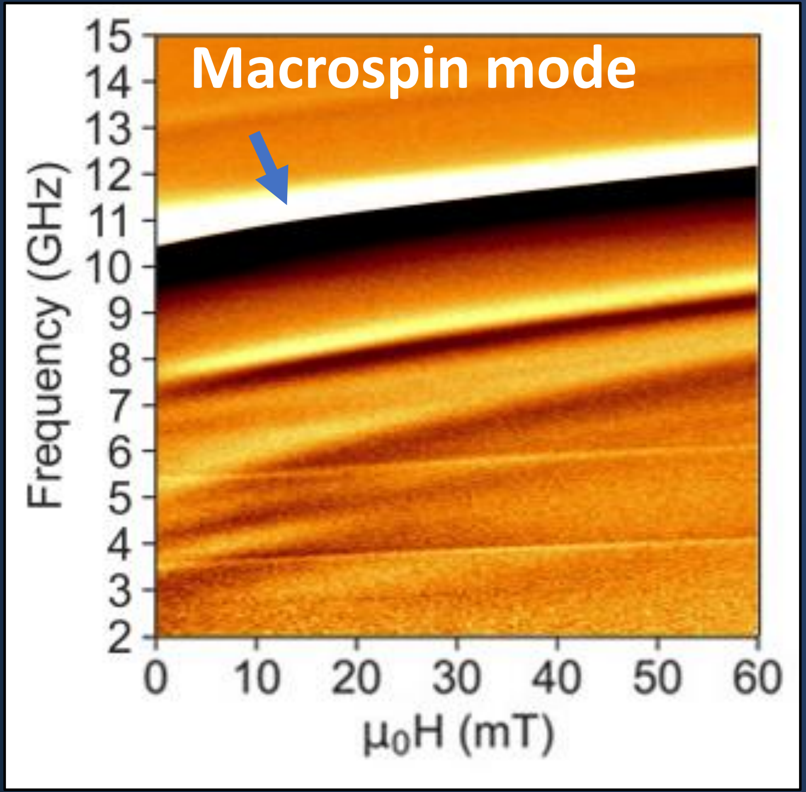
Dion, T., ... & Gartside, J. C. “Ultrastrong magnon-magnon coupling and chiral spin-texture control in a dipolar 3D multilayered artificial spin-vortex ice.” *Nature communications*, 2024

Magnon Frequency Comb

Jack C. Gartside, Imperial College London

- We can do it!
- Couple chiral vortex to collinear macrospin
- Observe **many new modes**
- Evenly spaced (550 MHz)
- Following main macrospin mode in frequency





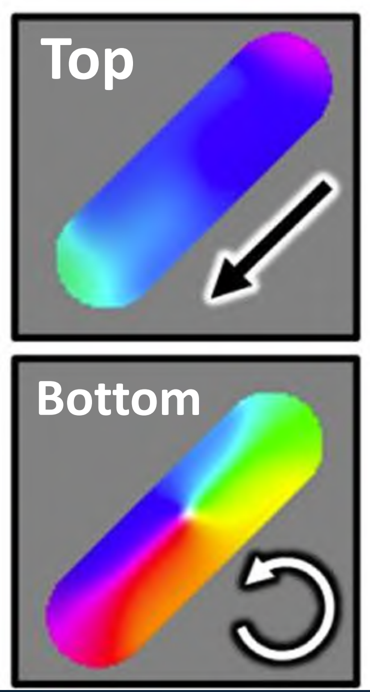
Here no chiral textures

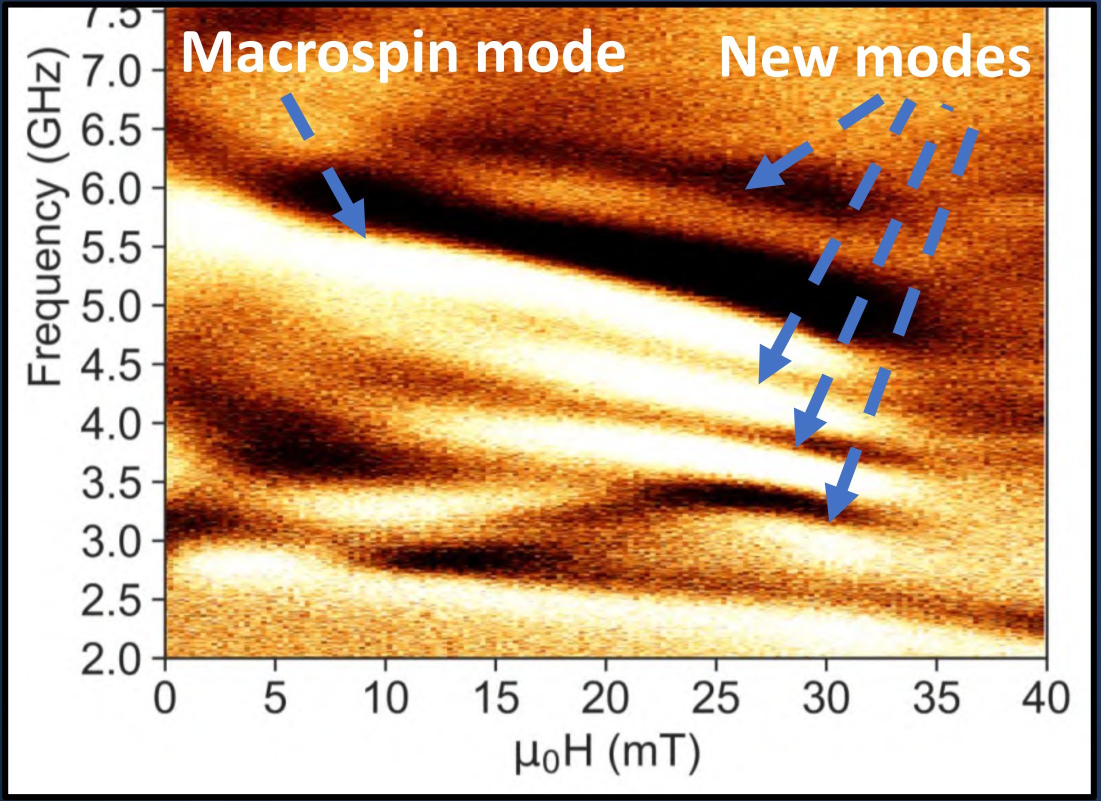
Magnon Frequency Comb

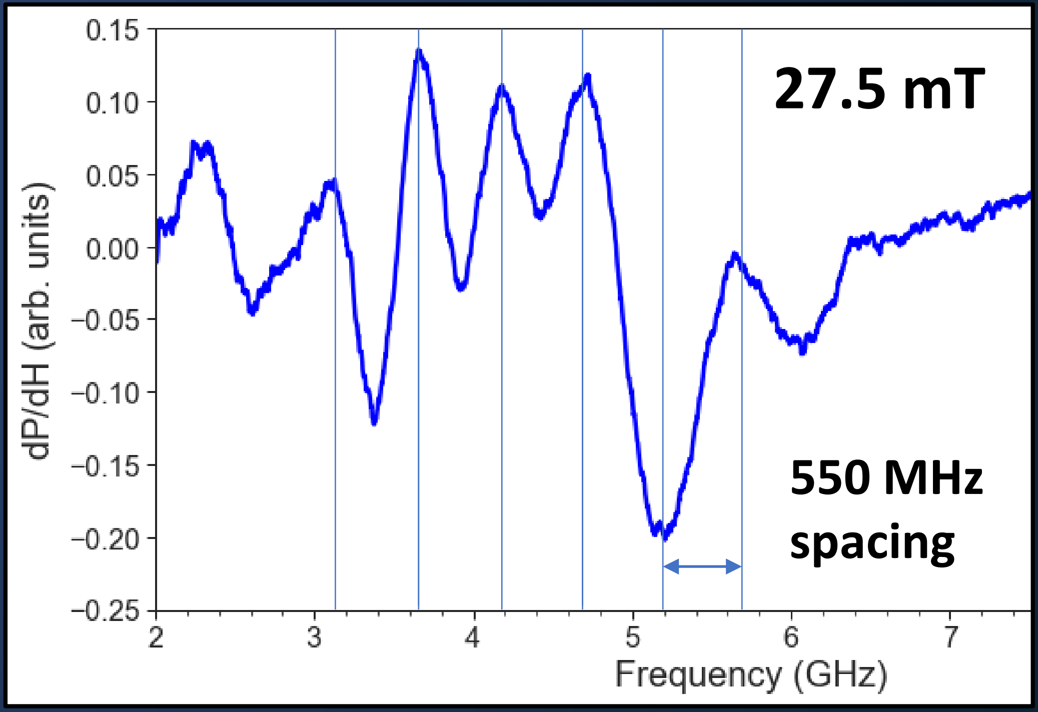
Jack C. Gartside, Imperial College London

- We can do it!
- Couple chiral vortex to collinear macrospin
- Observe **many new modes**
- Evenly spaced (550 MHz)
- Following main macrospin mode in frequency

Here chiral & collinear



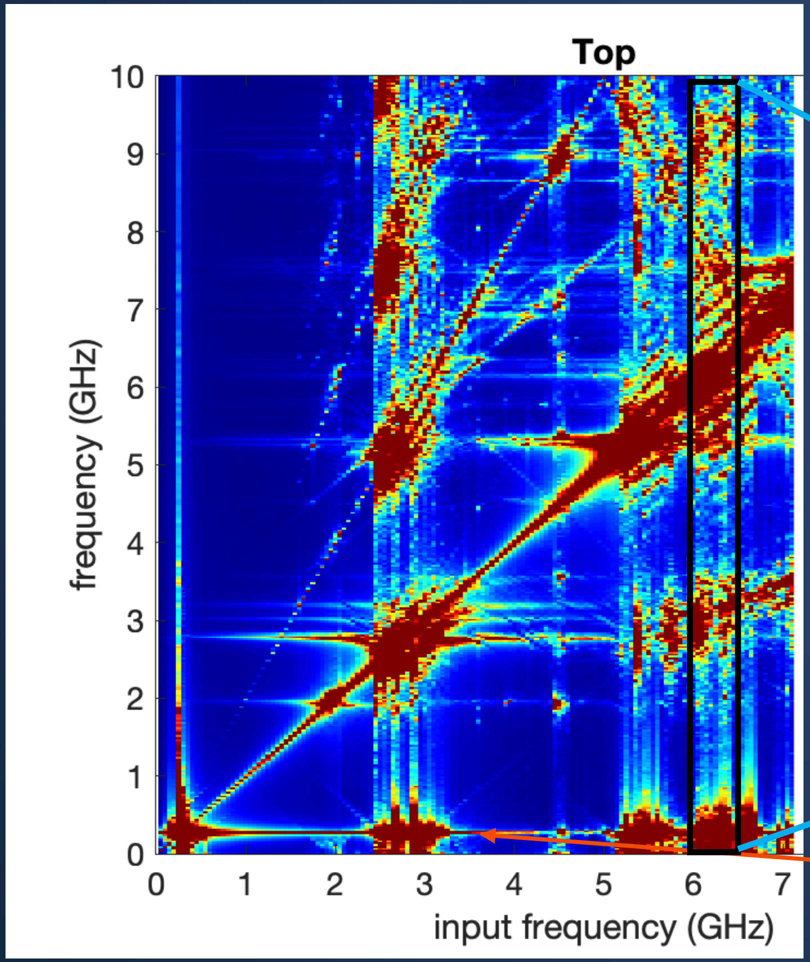


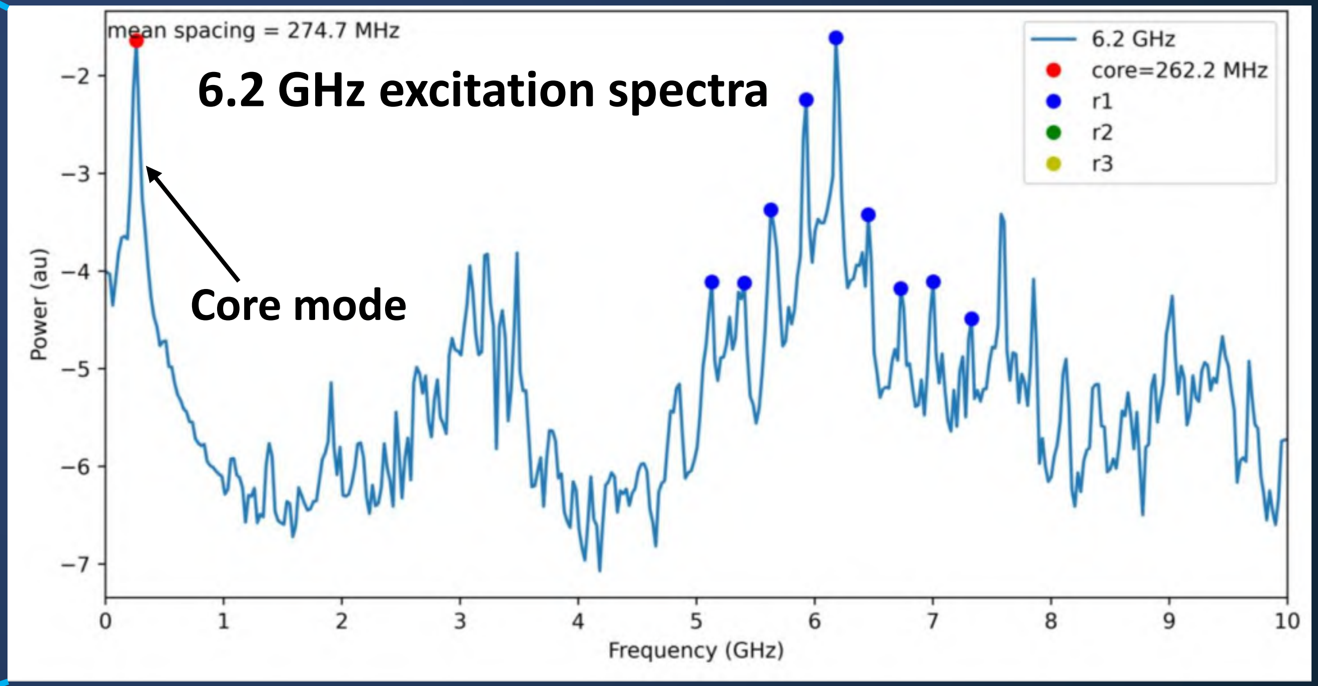


Jack C. Gartside, Imperial College London

Magnon Frequency Comb

- What's happening?
- Vortex **gyrotropic core mode** is 550 MHz… Core stray-field is coupling to macrospin texture
- Dipolar-coupled magnon frequency comb between vortex core & macrospin

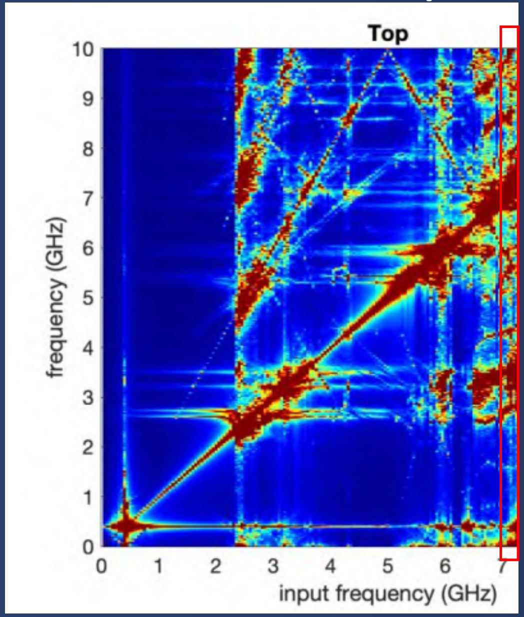


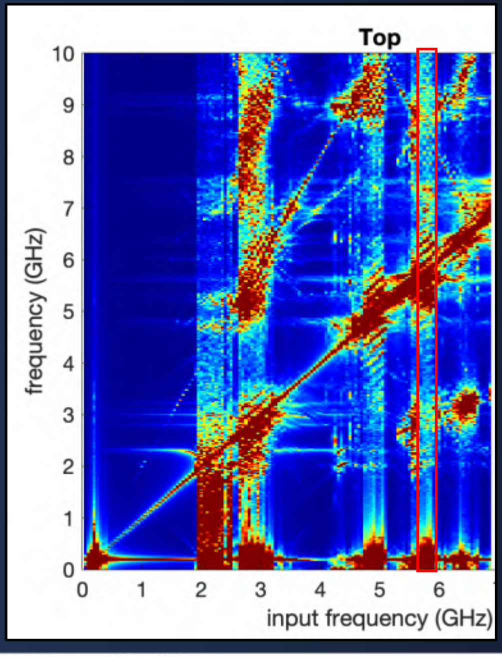


Jack C. Gartside, Imperial College London

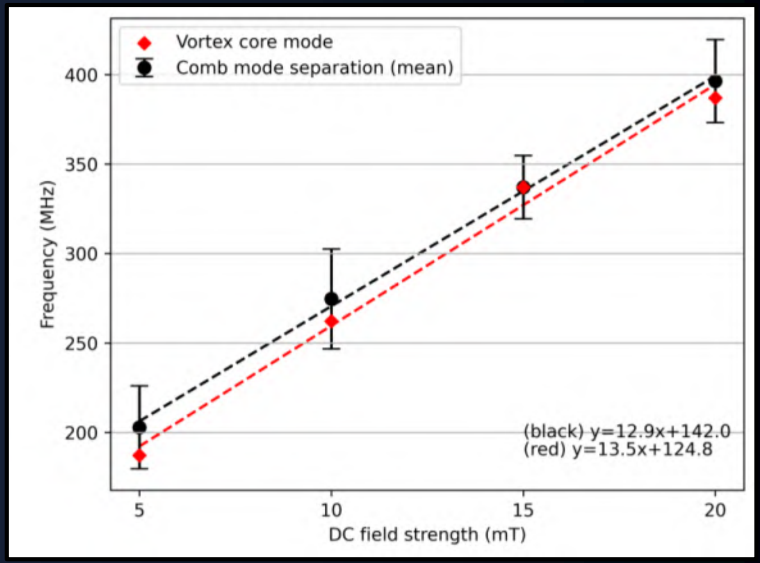
Magnon Frequency Comb

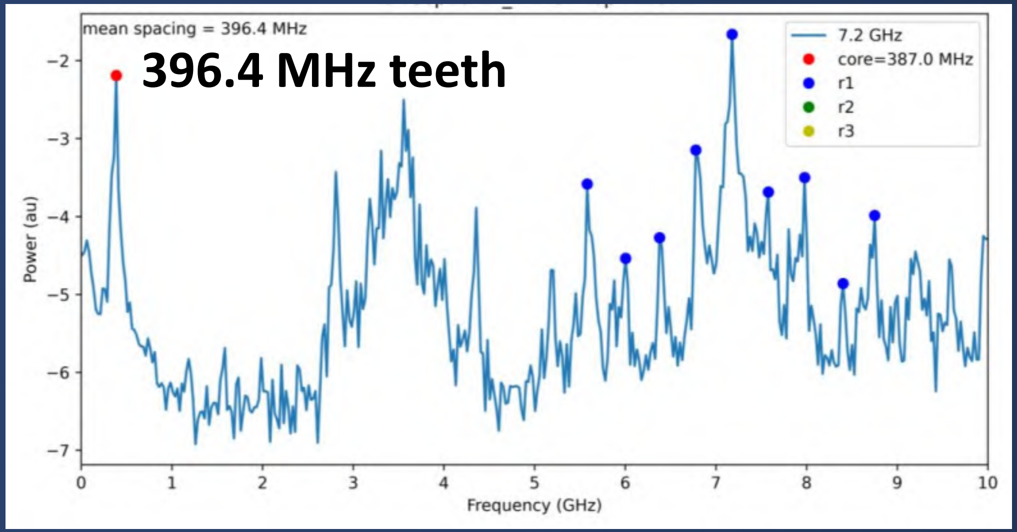
- Control comb teeth spacing via field/core frequency

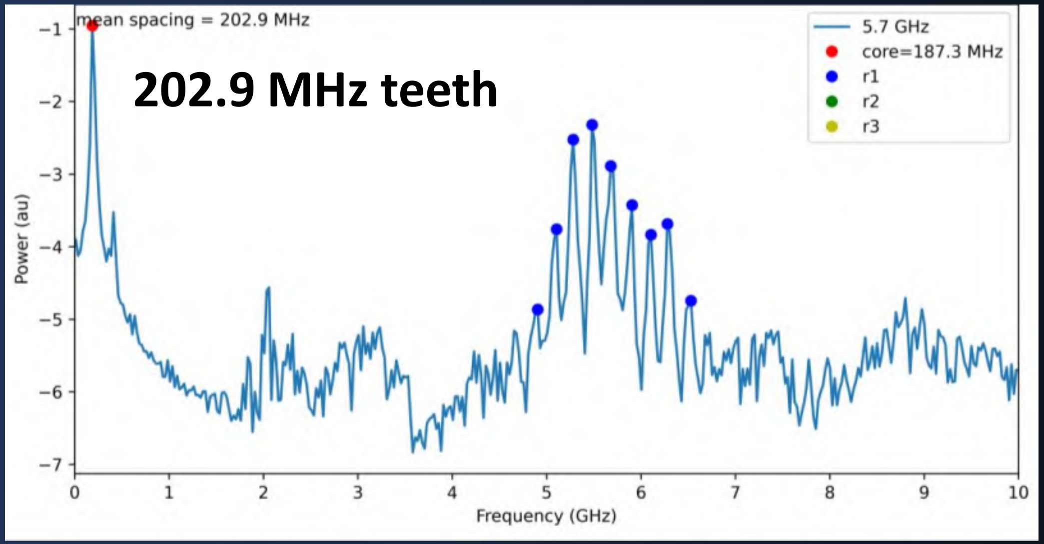




Teeth spacing vs. Vortex core freq.



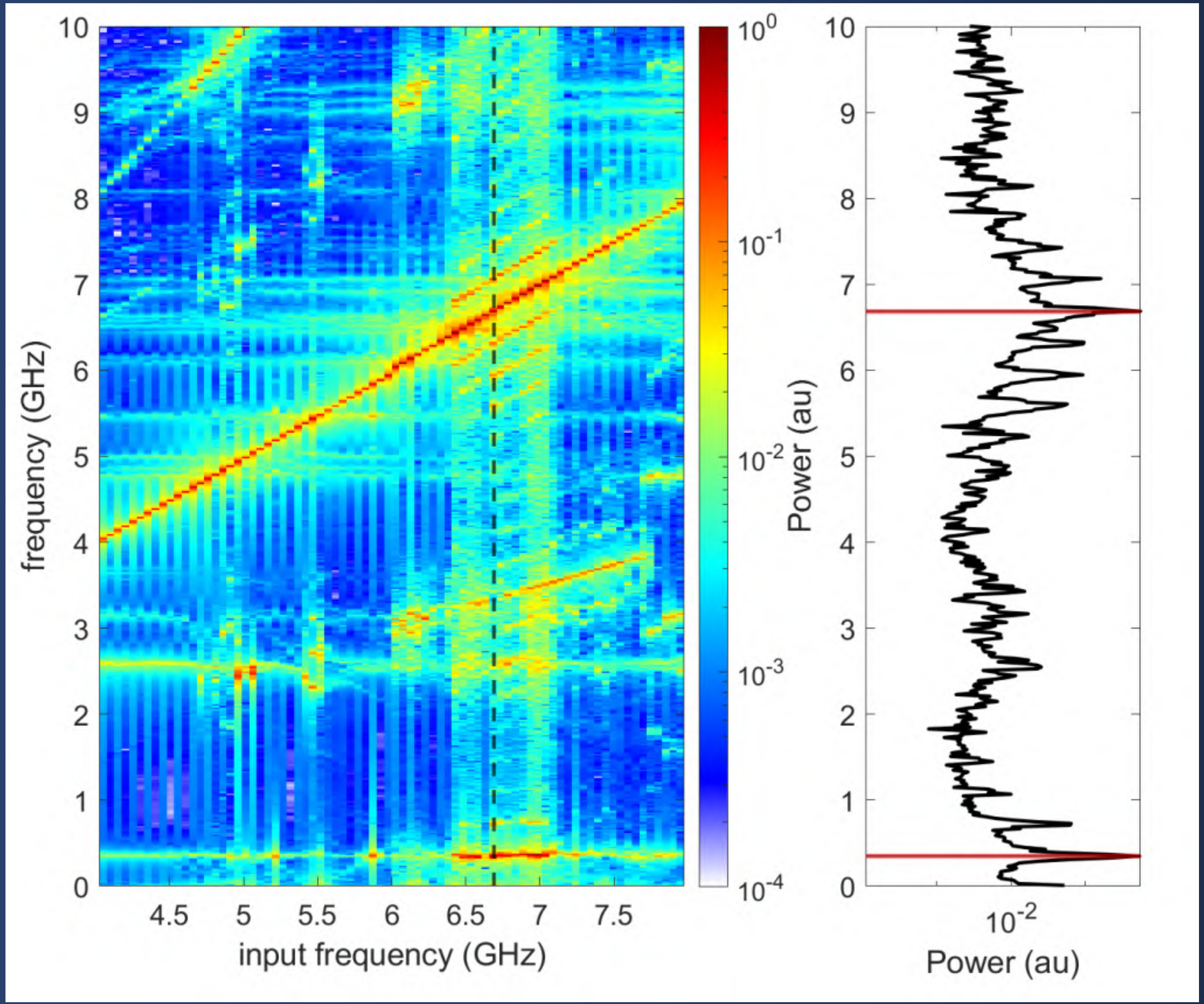


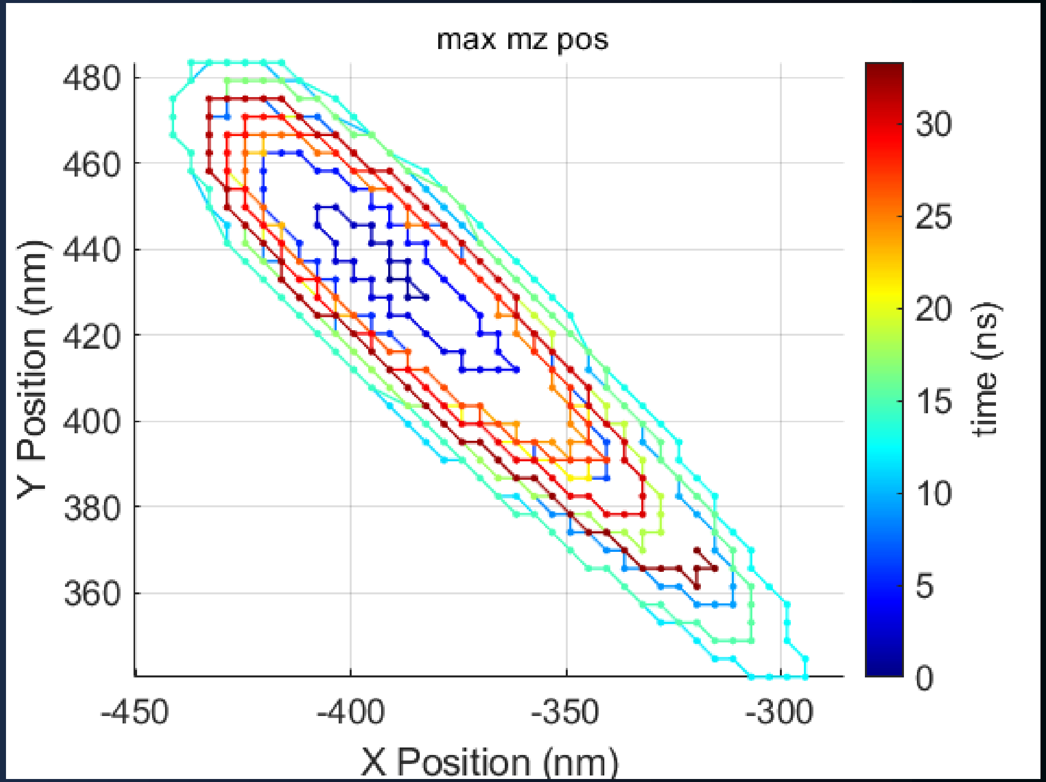


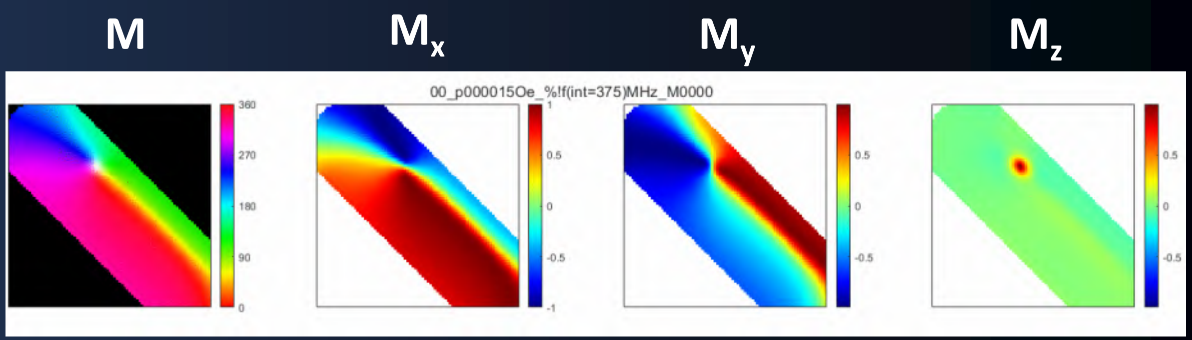
Jack C. Gartside, Imperial College London

Magnon Frequency Comb Vortex Core Dynamics

16 mT

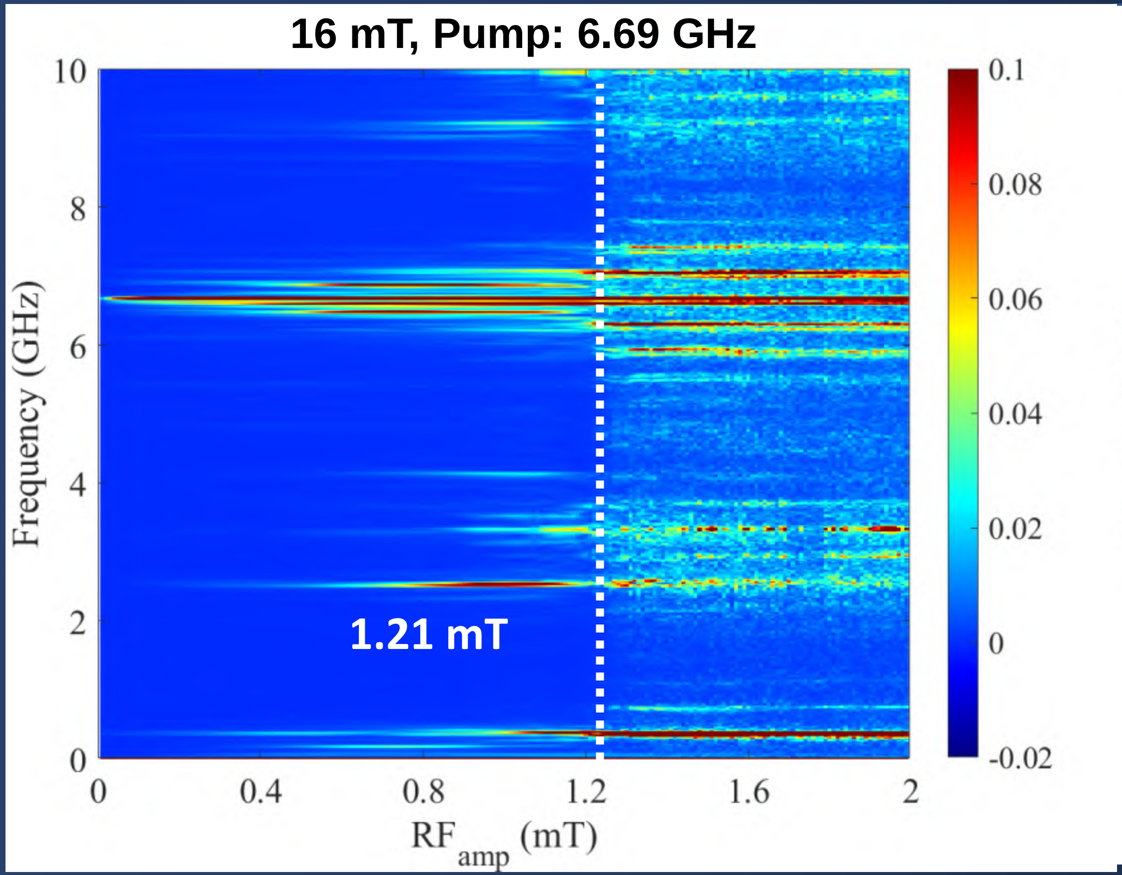


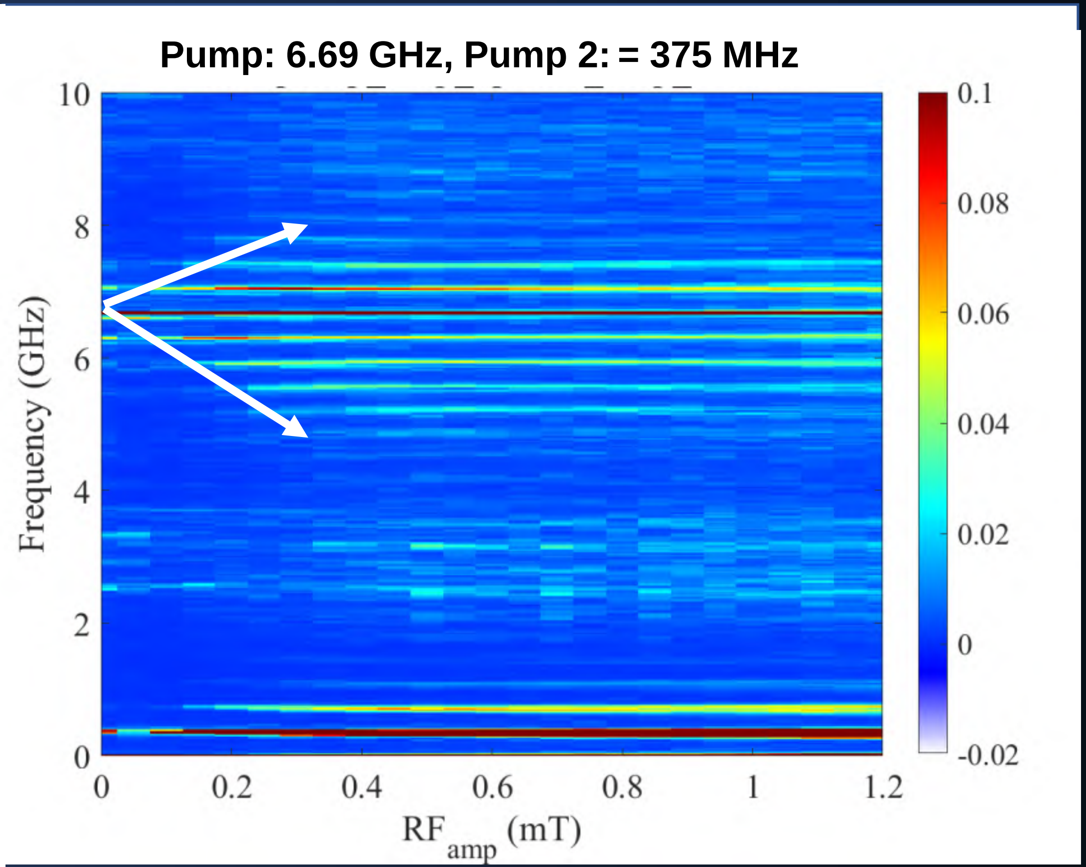




Magnon Frequency Comb

- Low threshold RF powers
- Dipolar free-space inter-texture coupling: potentially powerful & efficient





Conclusions – Topological Textures for Processing

- Topological magnetic textures are rapidly developing with technological benefits
- They provide a lot of what is needed for next-gen hardware
- The gap between fine, small-scale control schemes which cannot compute, and larger, coarser mean-field schemes must be closed
- We should carefully evaluate the correct computing schemes for the physics
- MLPs were invented for CPU/GPUs! Not because they're the best
- New algorithms/architectures which better suit the physics are key
- Take inspiration from other physics! E.g. photonics

Some papers from our group – Feel free to ask me about anything we didn't discuss!

nature communications
Article
https://doi.org/10.1038/s41467-024-48080-z

Ultrastrong magnon-magnon coupling and chiral spin-texture control in a dipolar 3D multilayered artificial spin-vortex ice

ARTICLE
https://doi.org/10.1038/s41467-021-22723-x OPEN

Reconfigurable magnonic mode-hybridisation and spectral control in a bicomponent artificial spin ice

Jack C. Gartside[1,5], Alex Vanstone[1,5], Troy Dion[1,2], Kilian D. Stenning[1], Daan M. Arroo[2,3], Hidekazu Kurebayashi[2] & Will R. Branford[1,4]

Few-Shot Retinomorphic Vision in a Nonlinear Photonic Network Laser

Wai Kit Ng, Jakub Dranczewski, Anna Fischer, T. V. Raziman, Dhruv Saxena, Tobias Farchy, Kilian Stenning, Jonathan Peters, Heinz Schmid, Will R. Branford, Mauricio Barahona, Kirsten Moselund, Riccardo Sapienza, and Jack C. Gartside

ARTICLES
https://doi.org/10.1038/s41565-022-01091-7
nature nanotechnology

Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting

Jack C. Gartside, Kilian D. Stenning, Alex Vanstone, Holly H. Holder, Daan M. Arroo, Troy Dion, Francesco Caravelli, Hidekazu Kurebayashi and Will R. Branford

nature materials
Article
https://doi.org/10.1038/s41563-023-01698-8

Task-adaptive physical reservoir computing

Received: 4 October 2022
Accepted: 19 September 2023
Published online: 13 November 2023

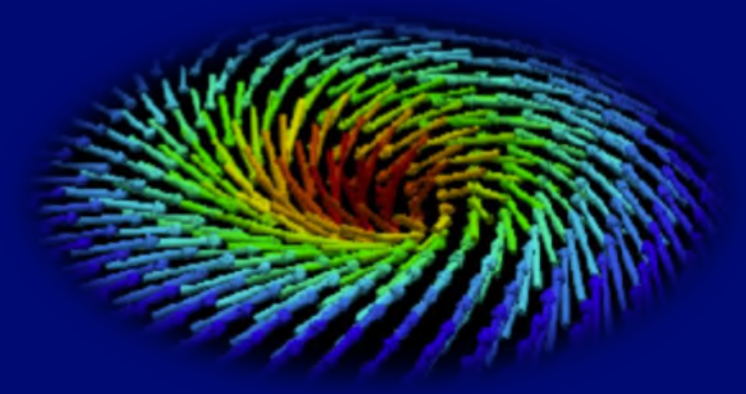
Oscar Lee, Tianyi Wei, Kilian D. Stenning, Jack C. Gartside, Dan Prestwood, Shinichiro Seki, Aisha Aqeel, Kosuke Karube, Naoya Kanazawa, Yasujiro Taguchi, Christian Back, Yoshinori Tokura, Will R. Branford & Hidekazu Kurebayashi

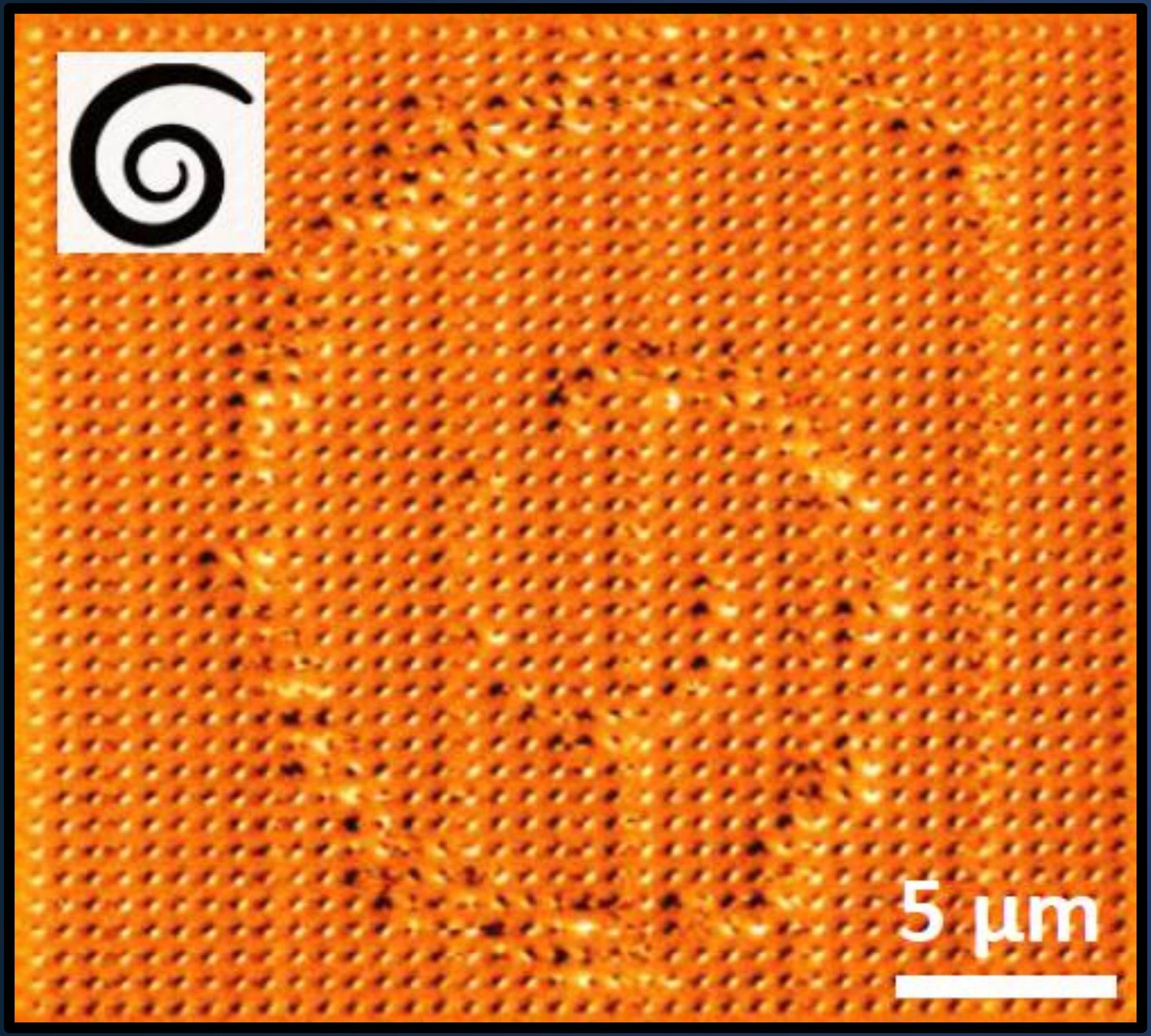
nature communications
Article

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

Received: 29 August 2023
Accepted: 17 July 2024
Published online: 27 August 2024

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





New Routes to Nanomagnetic Writing: Magneto-Plasmonic Inverse Faraday Effect via linearly polarized light

Jack C. Gartside[1,2]

Daniel Bromley[1] , Tingjun Zheng[1], Xiaofei Xiao[1,3] , Holly Holder[1], Tobias Farchy[1], Dimitrie Cielecki[1], Alex Vanstone[1], Kilian D. Stenning[1], Wai Kit Ng[1], Chantal Hareau[4], Xingyu Yang[4], Troy Dion, Olly J Barker[5], Liam O Brien[5], Hidekazu Kurebayashi[6], Mathieu Mivelle[4], Riccardo Sapienza[1,2], **Rupert Oulton[1,2], Will Branford[1,2]**

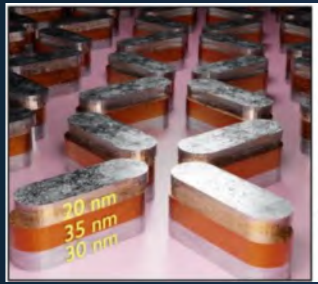
Imperial College London[1]
London Centre for Nanotechnology, University College London[2]
Technology Innovation Institute, United Arab Emirates[3]
Sorbonne University, CNRS[4]
University of Liverpool[5]
University College London[6]

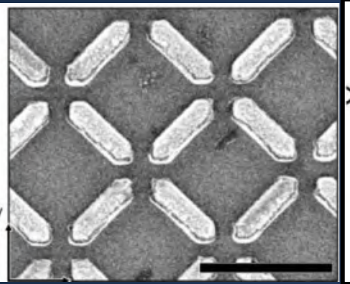
Our team: Neuromorphic Metamaterials Group

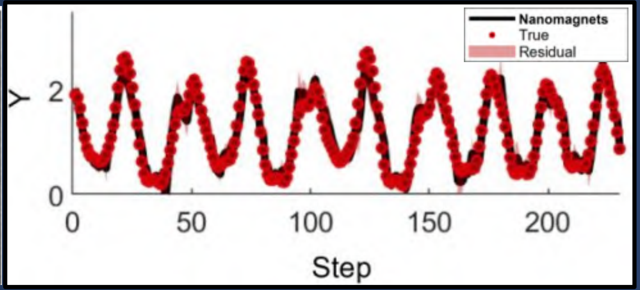
Imperial College London

Spintronic metamaterials

- Magnetic RF/GHz metamaterials (magnons)
- **Future prediction** & classification tasks with **Will Branford & Kilian Stenning**
- Key papers:







ARTICLES | nature nanotechnology

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nature communications

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Received: 27 July 2023
Accepted: 19 April 2024
Published online: 14 May 2024
Check for updates

Troy Dion, Kilian D. Stenning, Alex Vanstone, Holly H. Holder, Rawnak Sultana, Ghanem Alatteili, Victoria Martinez, Mojtaba Taghipour Kaffash, Takashi Kimura, Rupert F. Oulton, Will R. Branford, Hidekazu Kurebayashi, Ezio Iacocca, M. Benjamin Jungfleisch & Jack C. Gartside

nature communications

Article
https://doi.org/10.1038/s41467-024-50633-1

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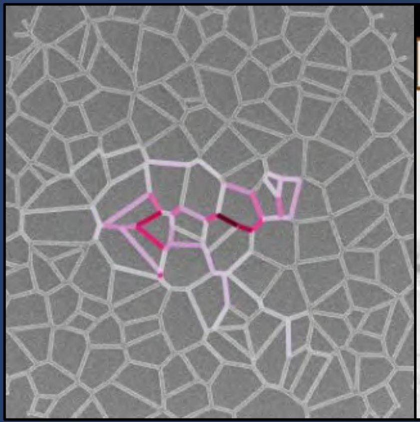
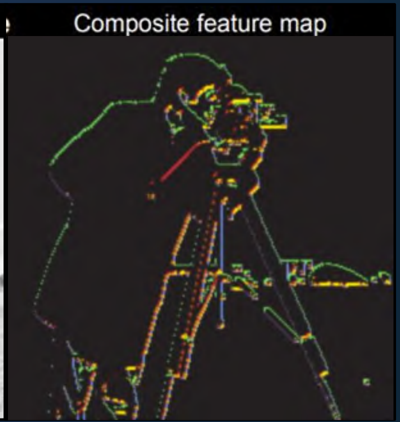
Physical neuromorphic computing, exploiting the complex dynamics of phy-

Photonic metamaterials

- Semiconductor network lasers
- **Machine Vision** & Image processing tasks with **Riccardo Sapienza**
- Key papers:



Retinomorphic Machine Vision in a Network Laser

Wai Kit Ng[1,†], Jakub Dranczewski[1,2,†], Anna Fischer[1,2,†], T. V. Raziman[1,3], Dhruv Saxena[1], Tobias Farchy[1], Kilian Stenning[1,4], Jonathan Peters[1,5], Heinz Schmid[2], Will R. Branford[1,4], Mauricio Barahona[3], Kirsten Moselund[6,7], Riccardo Sapienza[1,*], and Jack C. Gartside[1,5,*]

ARTICLE

https://doi.org/10.1038/s41467-018-08132-7 OPEN

A nanophotonic laser on a graph

Michele Gaio[1], Dhruv Saxena[1], Jacopo Bertolotti[2], Dario Pisignano[3,4,5], Andrea Camposeo[3] & Riccardo Sapienza[1]

Article
https://doi.org/10.1038/s41467-022-34073-3

Sensitivity and spectral control of network lasers

Received: 6 April 2022
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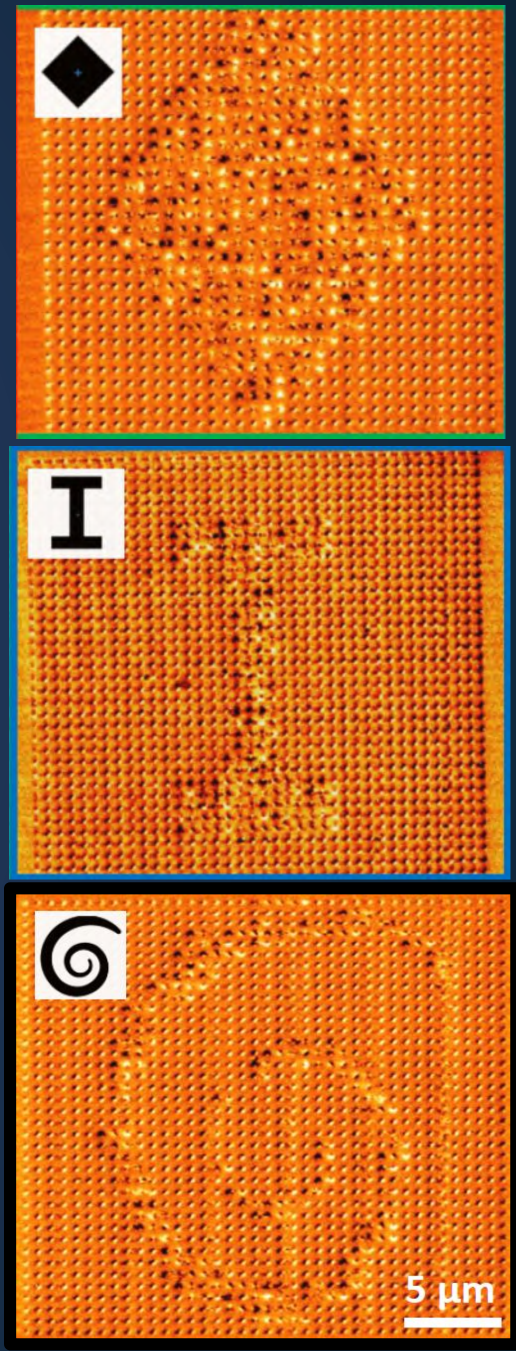
Dhruv Saxena, Alexis Arnaudon, Oscar Cipolato, Michele Gaio, Alain Quentel, Sophia Yaliraki, Dario Pisignano, Andrea Camposeo, Mauricio Barahona & Riccardo Sapienza

Optical magnetic writing via plasmon-enhanced linear Inverse Faraday Effect

Motivation

- **Explore** the need for new nanomagnetic writing techniques
- **Unexpected result: all-optical** switching of NiFe nanomagnets
- **Examine** potential explanation: Magneto-plasmonic Inverse Faraday Effect from linearly polarised light
- **Probe theory** via simulation, prediction, & optical writing experiments

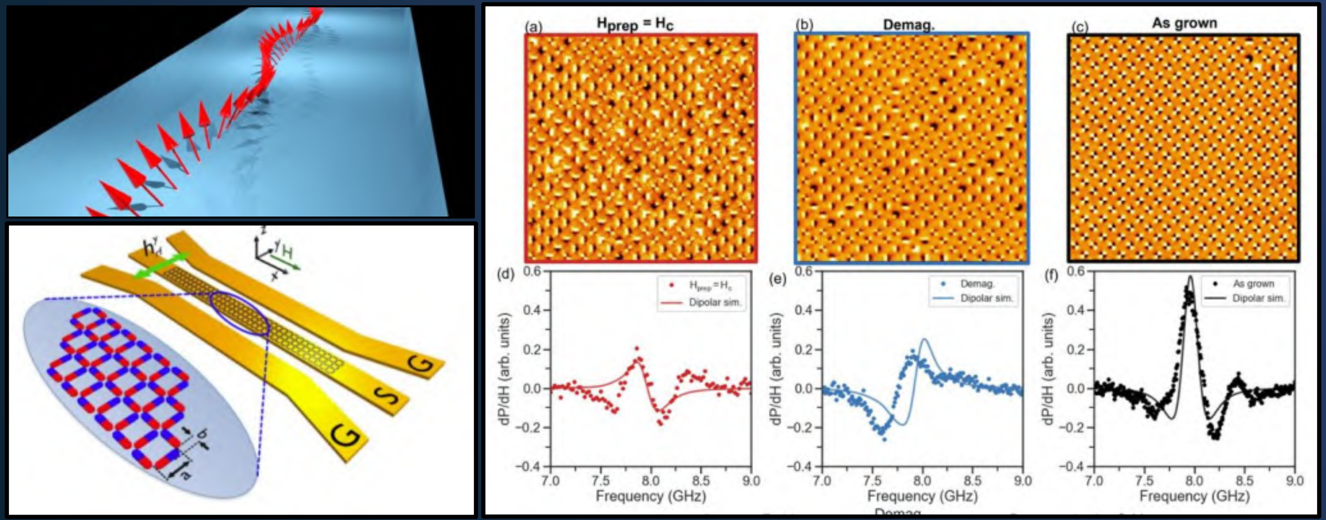


Magnetic nanoarray state control: Magnonics & neuromorphic computation

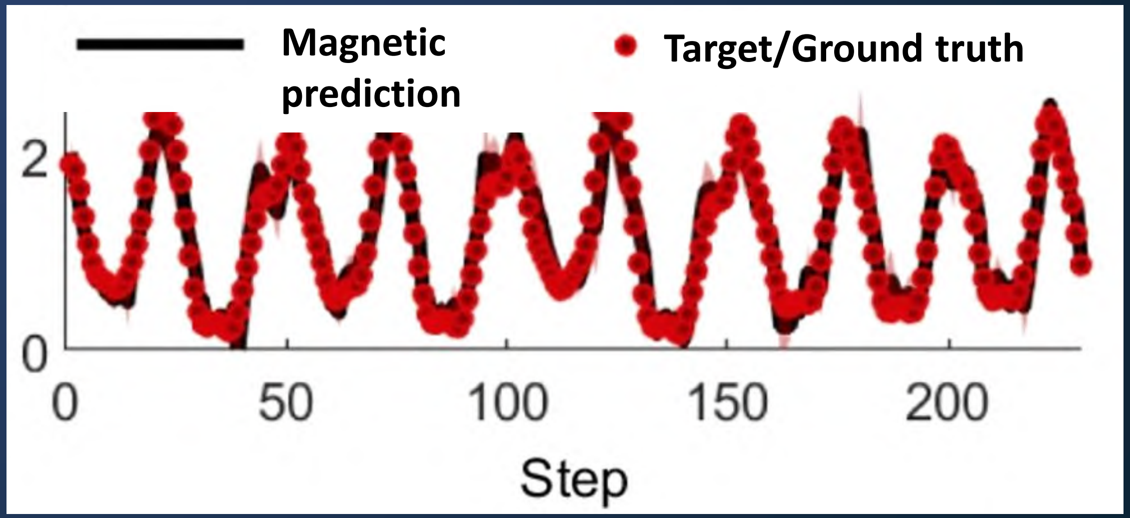
- Magnetic states of artificial spin ice & related arrays give programmable **magnon dynamics**
- These dynamics can be harnessed for **neuromorphic computing**
- Currently, our **'input'** is restricted – just **global field**.
  - Unsuitable for more complex states/processing
- **Motivation:** Develop rapid & local **input/magnetic switching**.
- Magnonics & Neuromorphic work: **Kilian Stenning** & **Alex Vanstone**

Relevant papers: Nat Nano/Mat/Comms:

Different ASI states = Different magnon spectra:



Magnon spectra can predict future chaotic time-series:



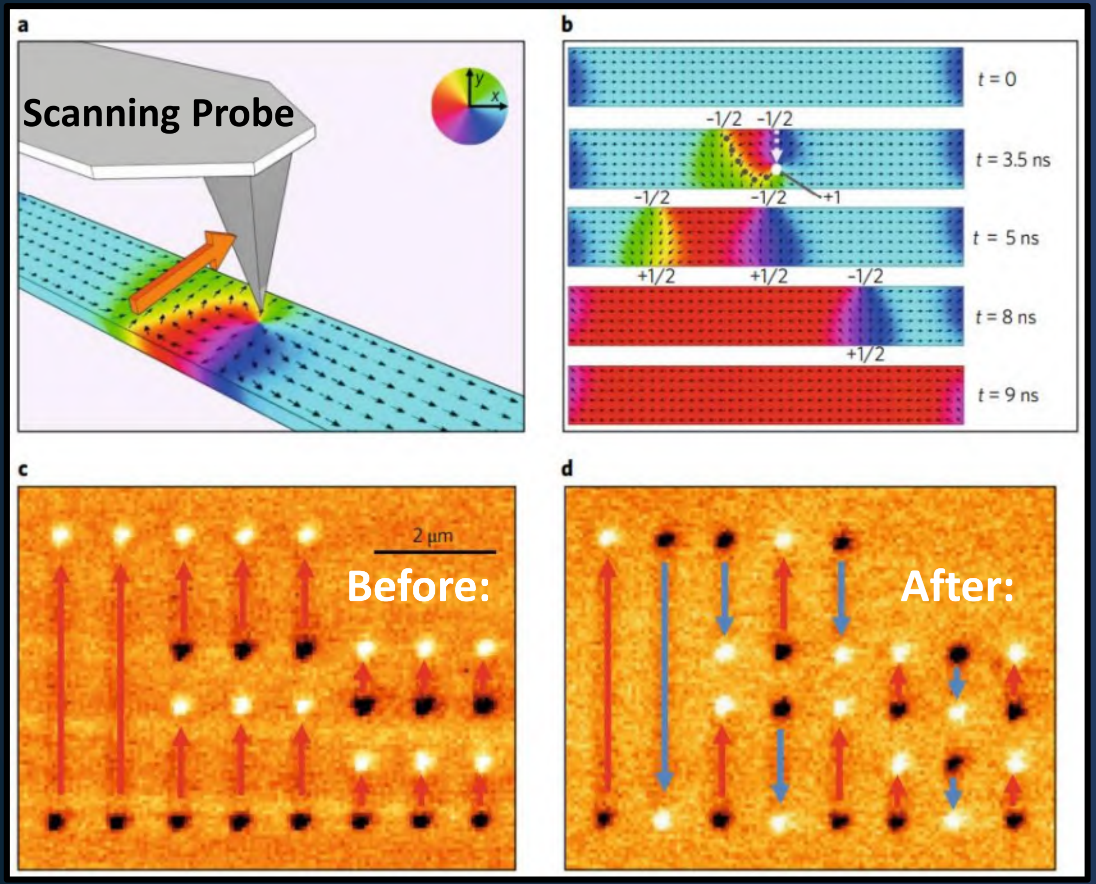
Nanomagnetic writing

- We have worked on developing single-magnet input
    - **Surface probe** technique: Cool, but **slow**
    - **Consider optical approaches?**


nature nanotechnology ARTICLES
https://doi.org/10.1038/s41565-017-0002-1

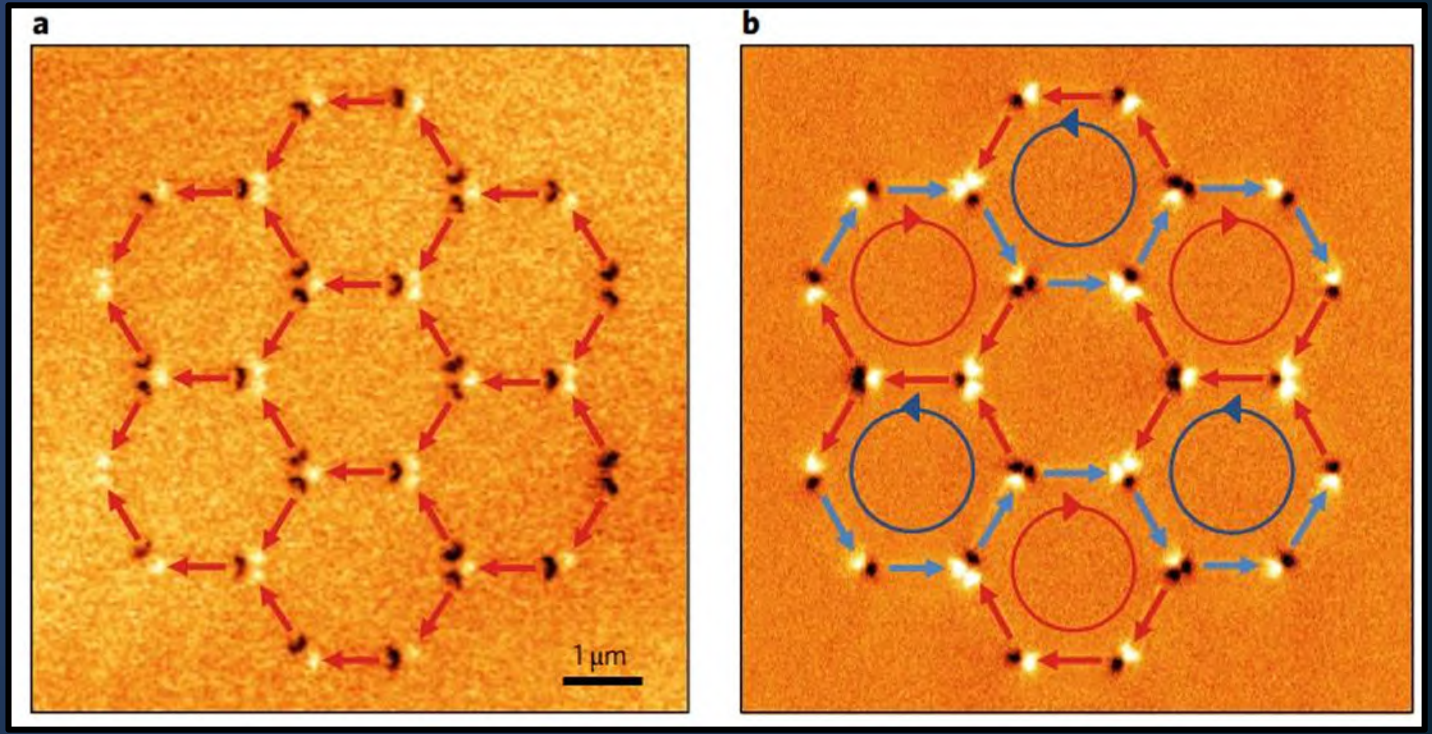
Realization of ground state in artificial kagome spin ice via topological defect-driven magnetic writing

Jack C. Gartside[1*], Daan M. Arroo[1], David M. Burn[2], Victoria L. Bemmer[1], Andy Moskalenko[1], Lesley F. Cohen[1] and Will R. Branford[1]



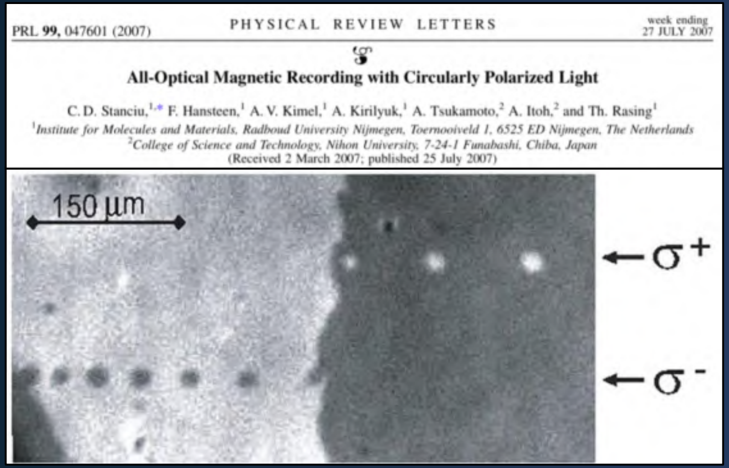
Before: **After:**

Gartside, Jack C. et al, **Nature Nanotechnology** (2018)

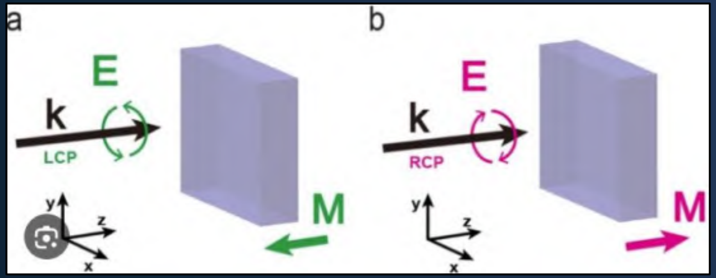


All-Optical Magnetic Switching: Methods/Approaches

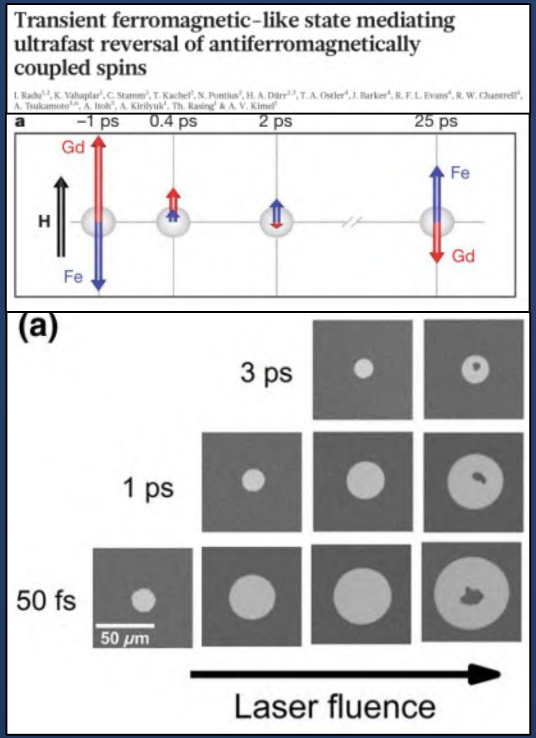
Helicity-dependent switching:
Inverse Faraday effect in GdFeCo + heating. fs-ps laser pulse



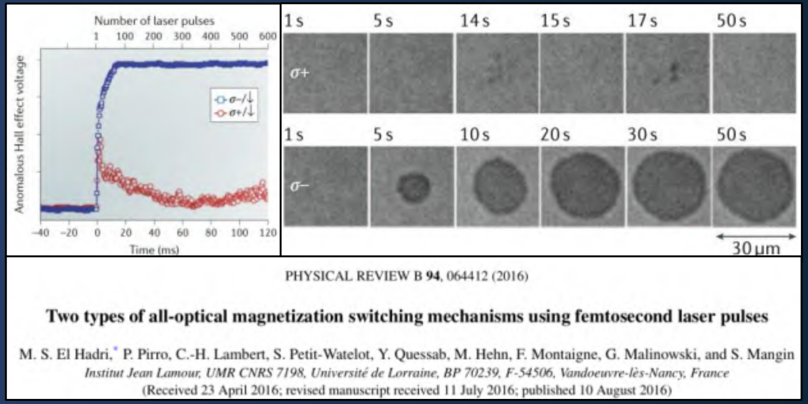
Inverse Faraday Effect:
B field along circularly polarised light direction



Helicity-independent switching:
Exploit different ordering timescales between Gd and Fe sublattices in GdFeCo, Gd/Fe magnetisation inverts. fs-ps laser pulse



Multi-pulse switching in Co/Pt:
Ultrafast demagnetisation combined with symmetry breaking (inverse faraday, magnetic dichroism) givess gradual switching over many pulses (100s-1000s). fs pulses.



Single-pulse switching in Co/Pt:
Multi-layered stack with Cu spacer used to inject spin-polarised currents between layers. 50 fs pulse

Optical writing?

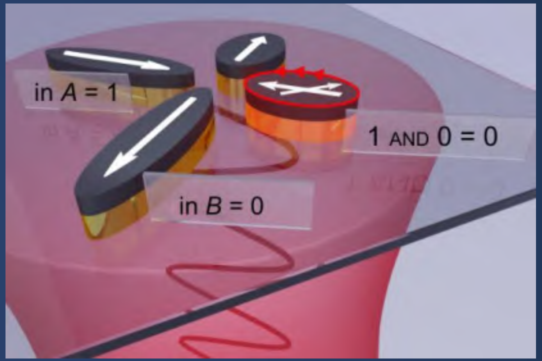
- We were inspired by excellent work of **Naemi Leo** & **Paolo Vavassori**
- Make plasmonic ‘sandwich’ islands of Au/NiFe/Au
- Laser locally heats islands, reducing Hc. Apply global B field to switch

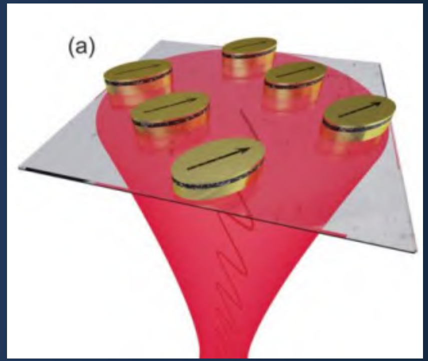
Selective and fast plasmon-assisted photo-heating of nanomagnets†

Matteo Pancaldi, ‡[a] Naëmi Leo [a] and Paolo Vavassori *[a,b]

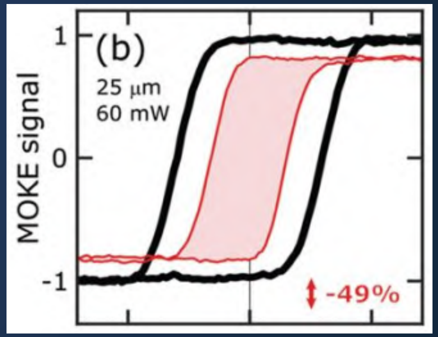
Thermoplasmonic Nanomagnetic Logic Gates

Pieter Gypens,[1] Naëmi Leo,[2] Matteo Menniti,[2] Paolo Vavassori,[2,3] and Jonathan Leliaert[1,*]
[1] *Dept. of Solid State Sciences, Ghent University, 9000 Ghent, Belgium*
[2] *CIC nanoGUNE BRTA, Donostia-San Sebastian E-20018, Spain*
[3] *IKERBASQUE, Basque Foundation for Science, Bilbao E-48009, Spain*





Coercivity reduction of heated islands in red:

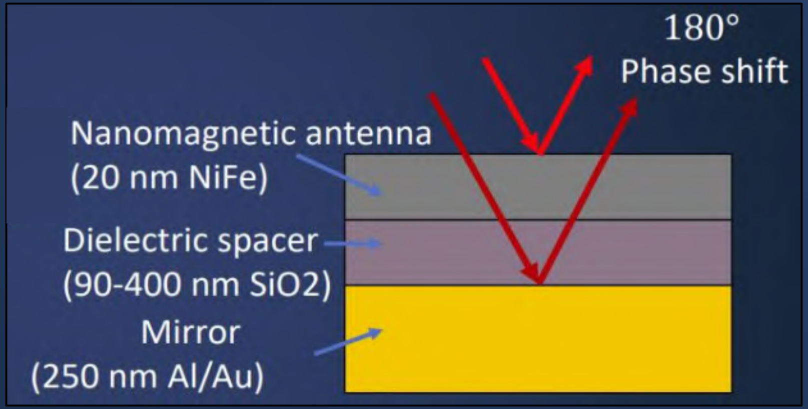


- Could we use a similar approach to tackle our data input/magnonic reconfigurability?

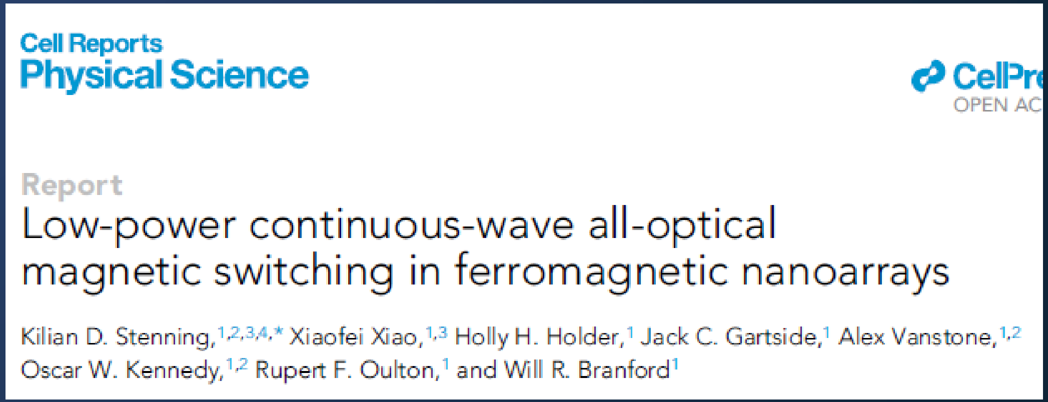
Optical writing – Our initial attempt

- Set up a system with Fabry-Perot like cavity in substrate to increase optical absorption
  - Similar to anti-reflection coating
- Original concept: **Will Branford**
- Experimental execution: **Kilian Stenning & Holly Holder**
- Plasmonics optimisation: **Rupert Oulton & Xiaofei Xiao**
- **Initially try laser illumination in zero B field – CW laser, 2-5 mW, 633 nm**
- **Linearly-polarised** laser

Substrate layers:



Relevant paper:



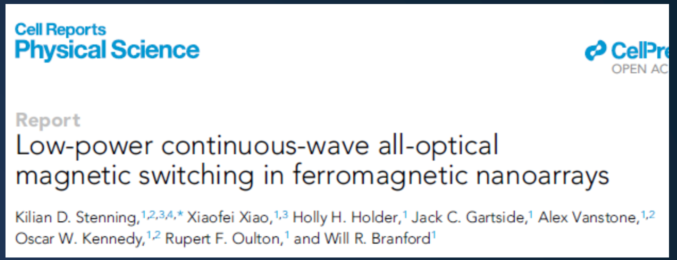
Cell Reports
Physical Science

Report

Low-power continuous-wave all-optical magnetic switching in ferromagnetic nanoarrays

Kilian D. Stenning,[1,2,3,4,*] Xiaofei Xiao,[1,3] Holly H. Holder,[1] Jack C. Gartside,[1] Alex Vanstone,[1,2] Oscar W. Kennedy,[1,2] Rupert F. Oulton,[1] and Will R. Branford[1]

Optical writing – Our initial attempt


Cell Reports Physical Science

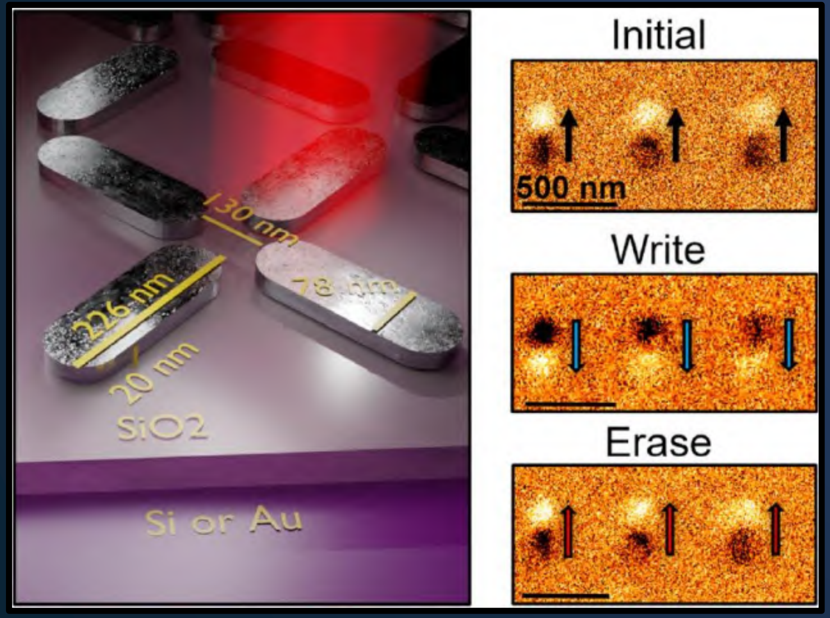
CellPress OPEN ACCESS

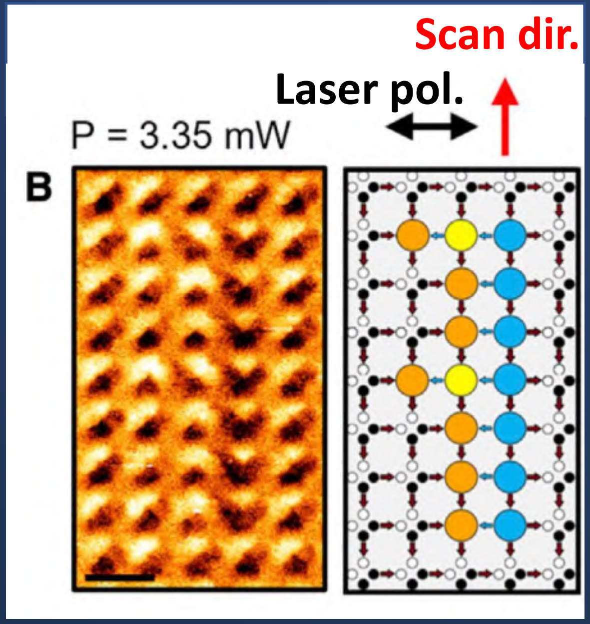
Report

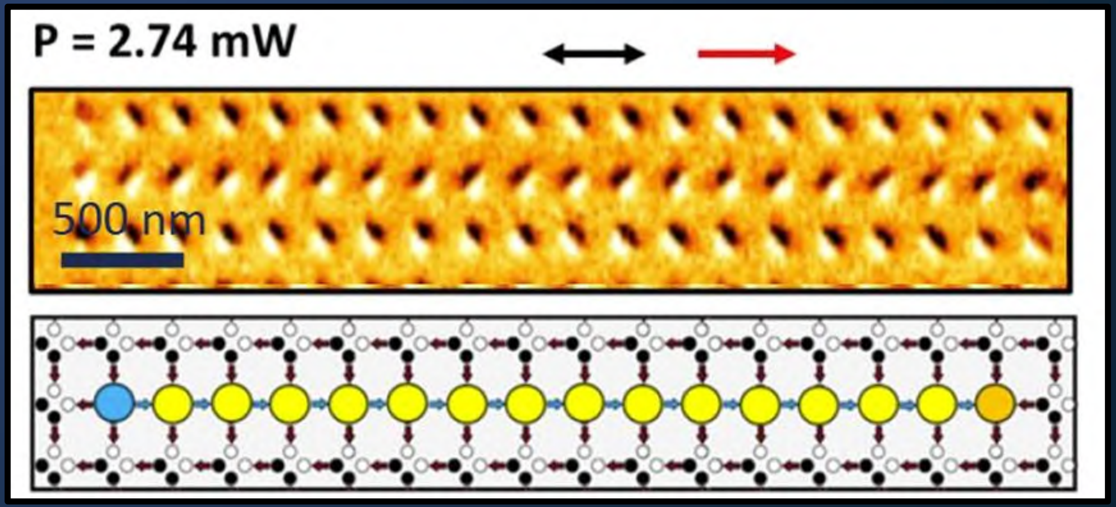
Low-power continuous-wave all-optical magnetic switching in ferromagnetic nanoarrays

Kilian D. Stenning,[1,2,3,4,*] Xiaofei Xiao,[1,3] Holly H. Holder,[1] Jack C. Gartside,[1] Alex Vanstone,[1,2] Oscar W. Kennedy,[1,2] Rupert F. Oulton,[1] and Will R. Branford[1]

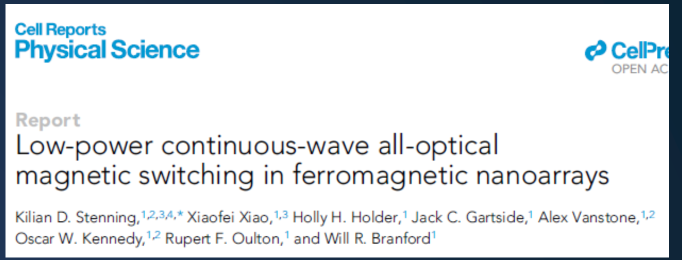
- An **interesting result**
  - **Unexpected:** all-optical magnetic switching typically needs complex materials, intense pulse lasers, often circular polarisation.
    - GdFeCo, fs pulse lasers, kW - MW laser power
    - Typically not shown in nanostructures
  - We experimentally observed **mW** switching in **NiFe nanostructures**



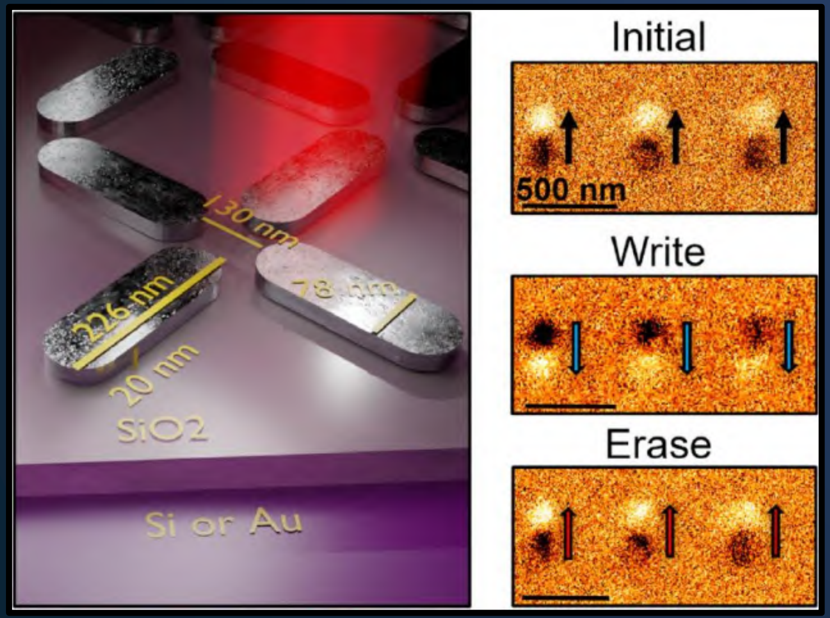


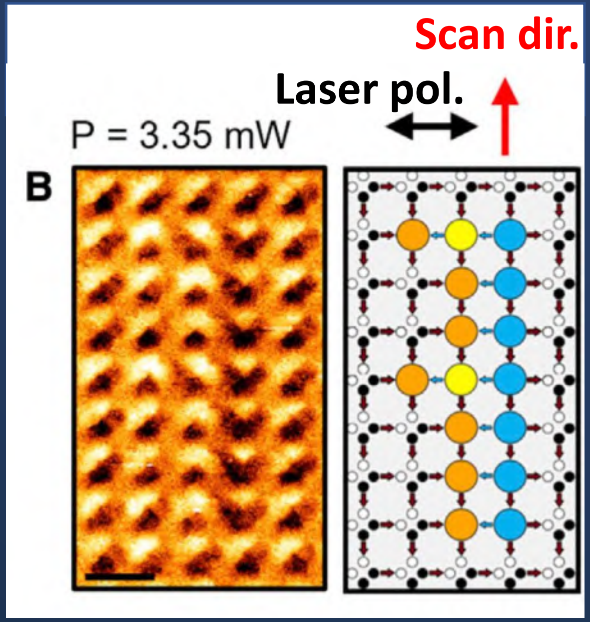


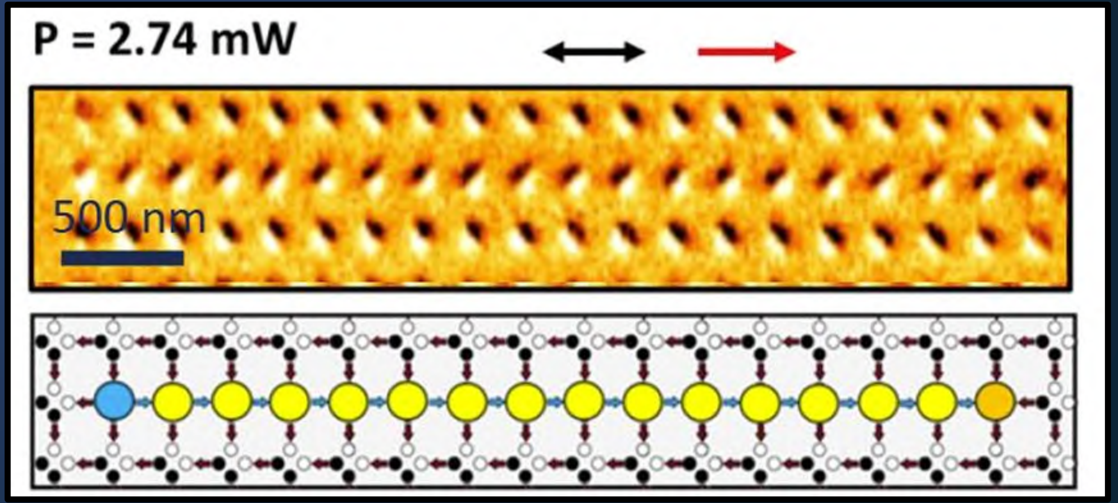
Data Input: Nanomagnetic writing



- **Problems:**
  - Slow – uses CW lasers
  - Focused laser spot – only write 1 bar at a time
  - We **didn't understand** the **underlying physical mechanism**…
    - This point **crucial**. Unable to optimise & refine without proper understanding

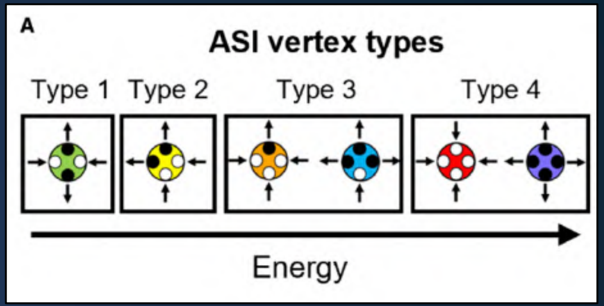


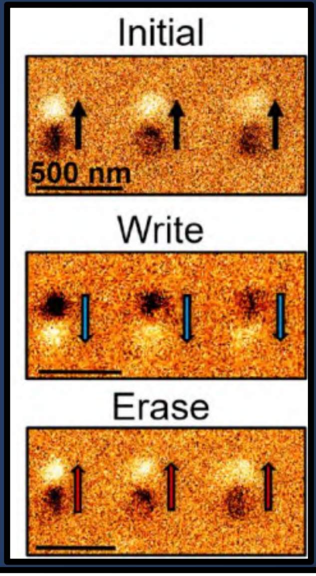


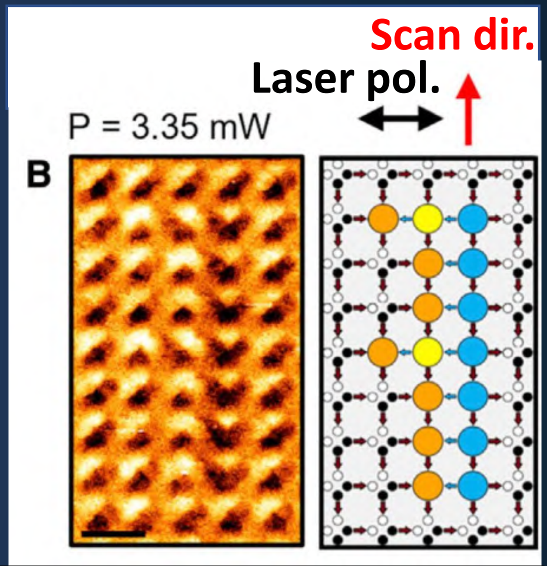


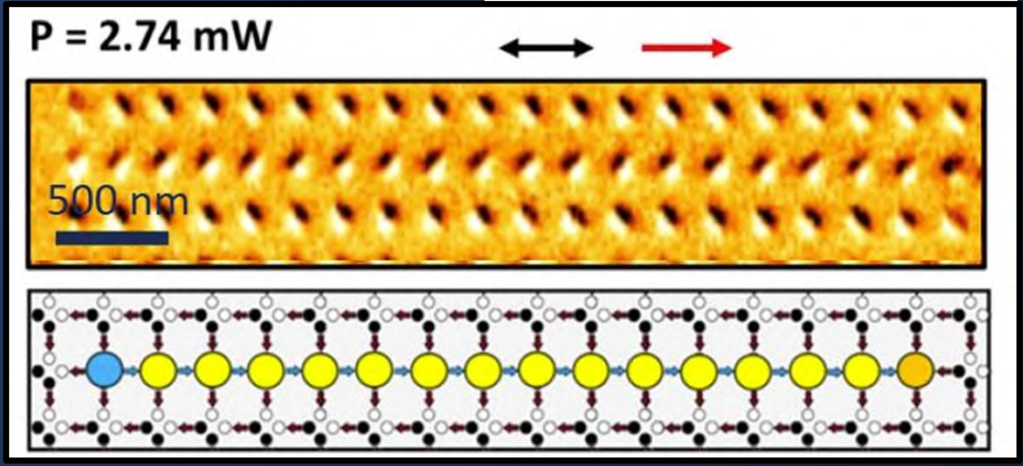
Data Input: Nanomagnetic writing

- **What do we know?**
  - Not purely thermal
    - Written states **not random**
    - Write chains of **high-energy states**
    - **ASI ‘monopole’** states
  - Ultrafast demagnetisation unlikely
    - Laser very weak for this
  - Linearly-polarised light
    - Not helicity-dependent/spin-orbit
    - Not **Inverse Faraday Effect**
      - (conventional one)
  - What options are left?





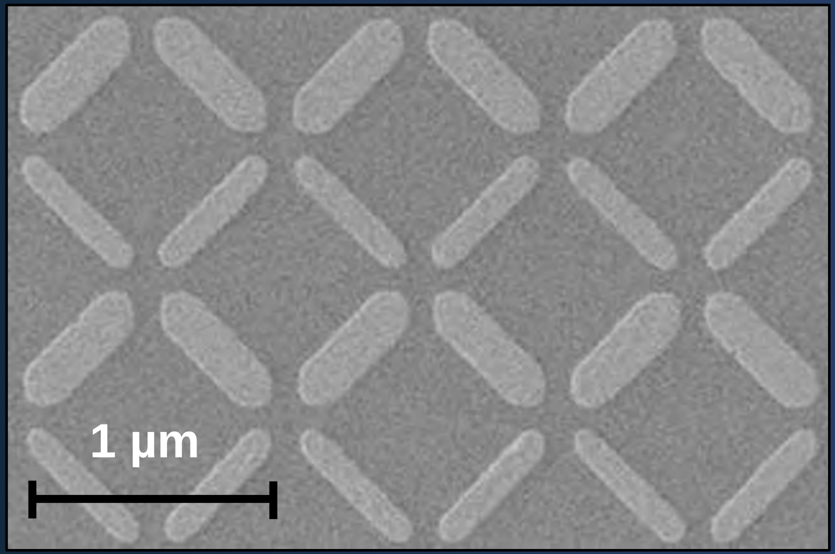




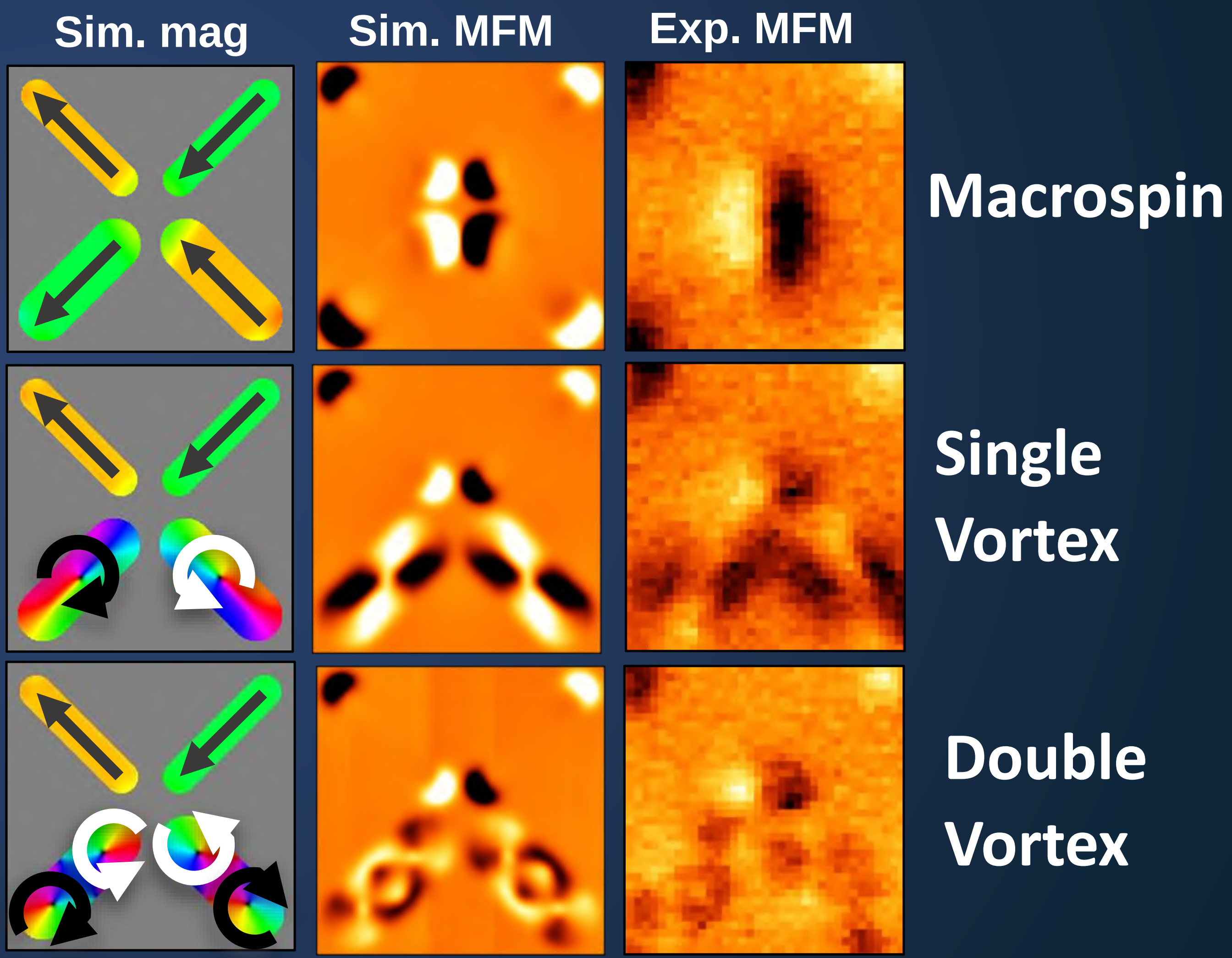
Jack C. Gartside, Imperial College London

Next observation: Optical Vortex Writing

- **Looking for clues…** Try writing **wider nanoislands**
- **This work lead by <u>Holly Holder</u>** – paper upcoming

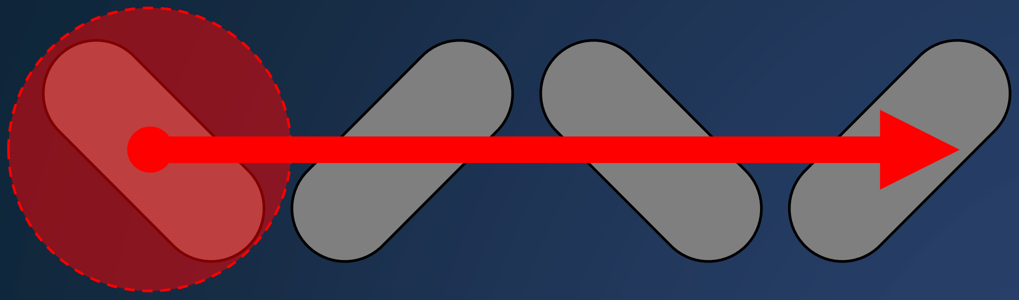


- **Bar lengths ≈ 545 to 600 nm**
- **Wide bar widths ≈ 180 to 205 nm**
- **Thin bar widths ≈ 120 to 135 nm**
- **Bar thicknesses ≈ 20 nm**

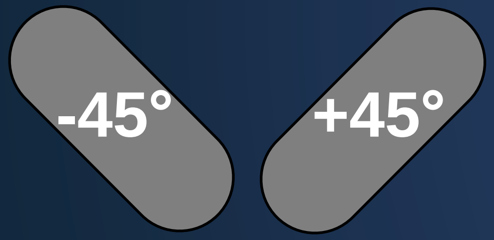


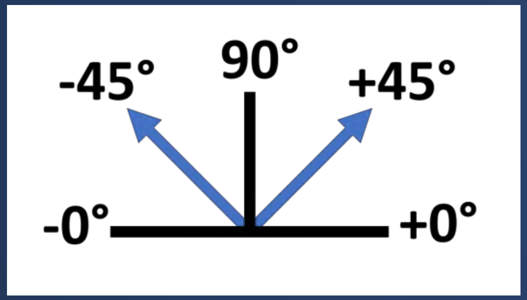
All-optical control of vortex textures

$\lambda = 633$ nm, $P_{CW} = 5.0$ mW

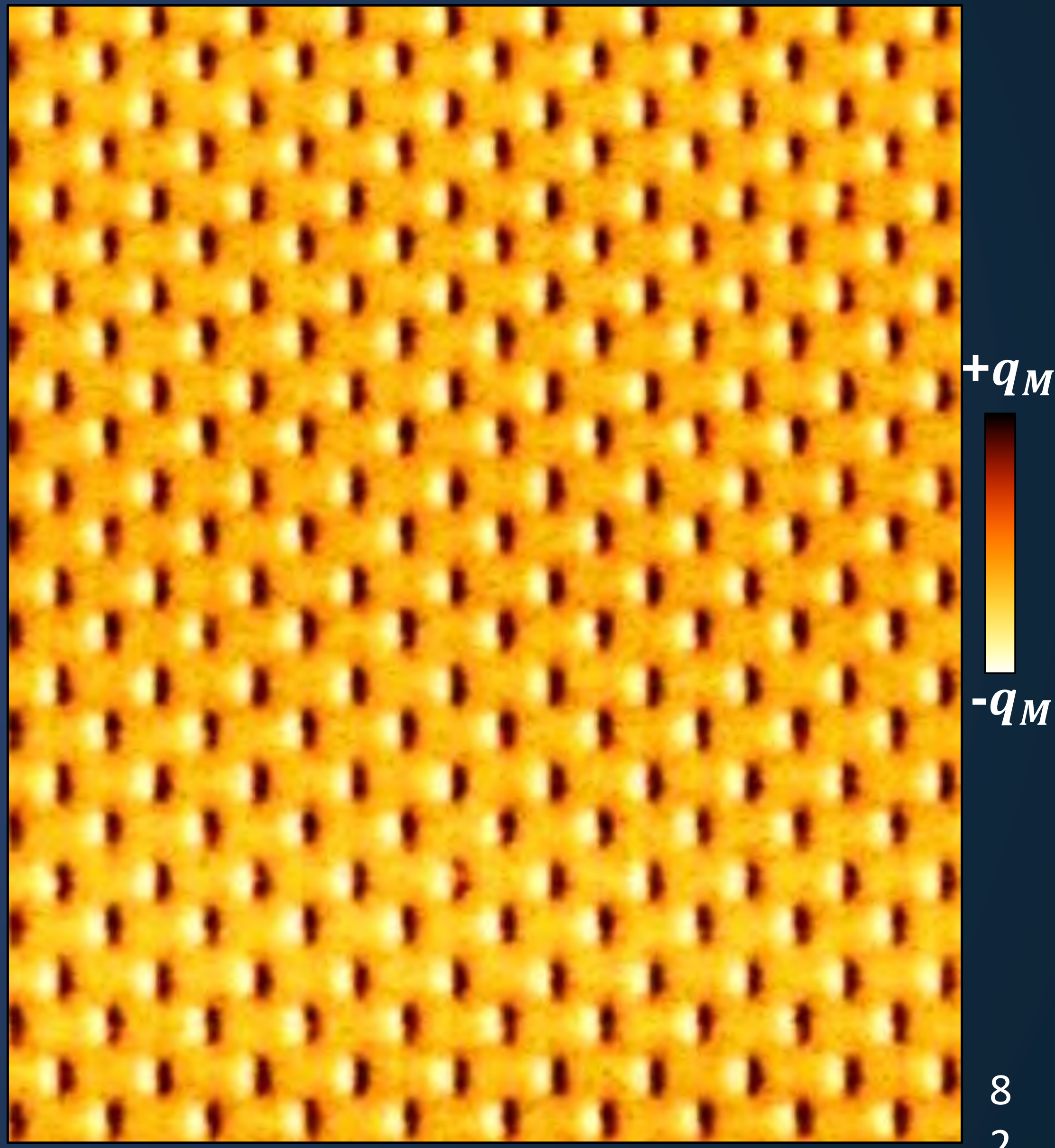


+ Low power (2-5 mW), CW, visible wavelength





Initial field-saturated state



All-optical control of vortex textures

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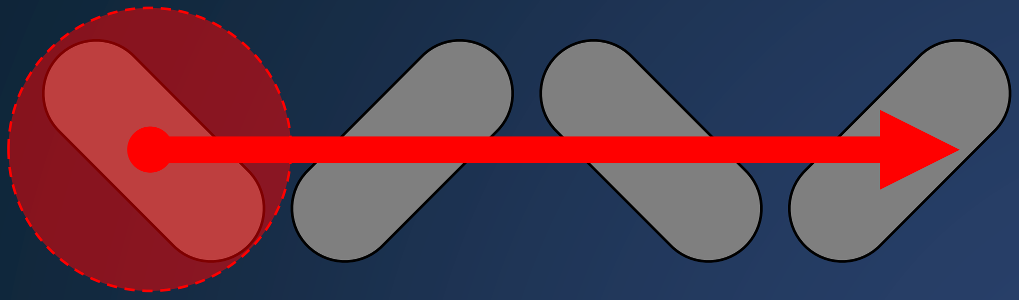
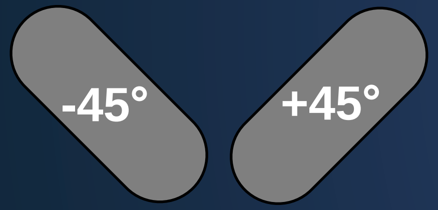
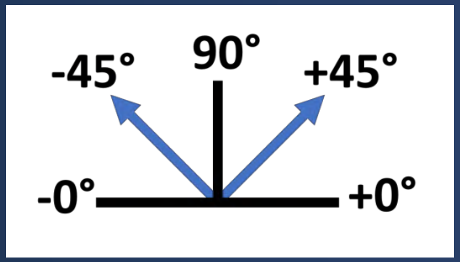


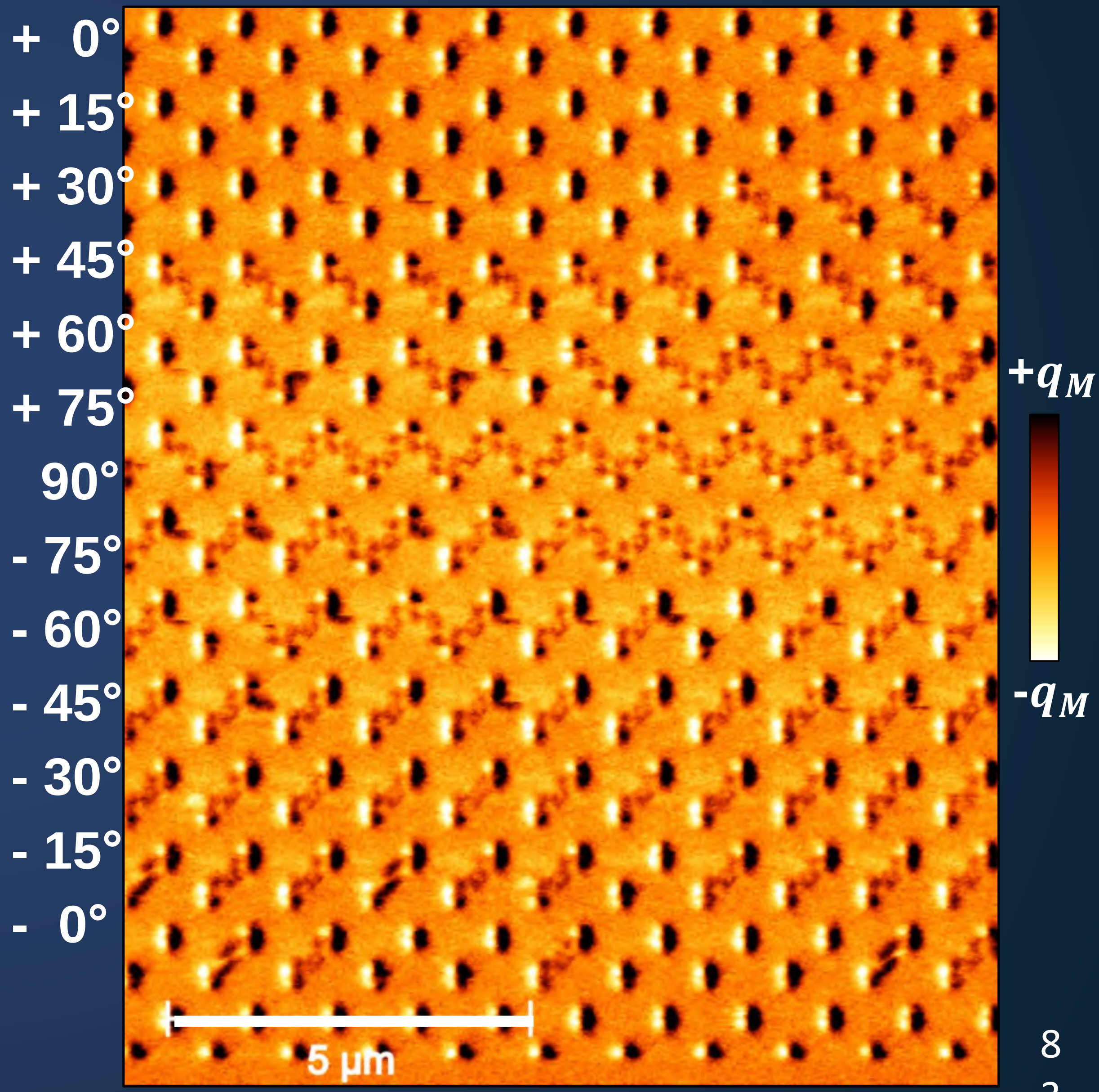
+ Low power (2-5 mW), CW, visible wavelength





- **Optical writing** of **double vortex** states
- **Writing occurs with polarisation on short-axis**
- **Break symmetry** between 0 and 90 degrees.
- **Chirality control:** Only write a single chirality
- What's going on?

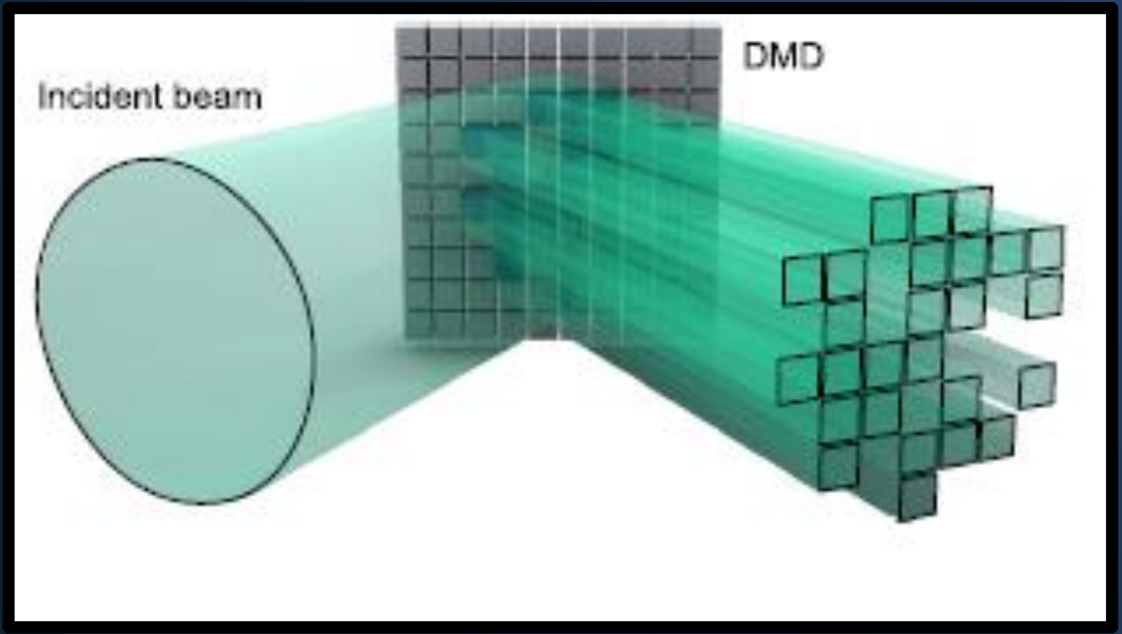
Laser-written double vortices



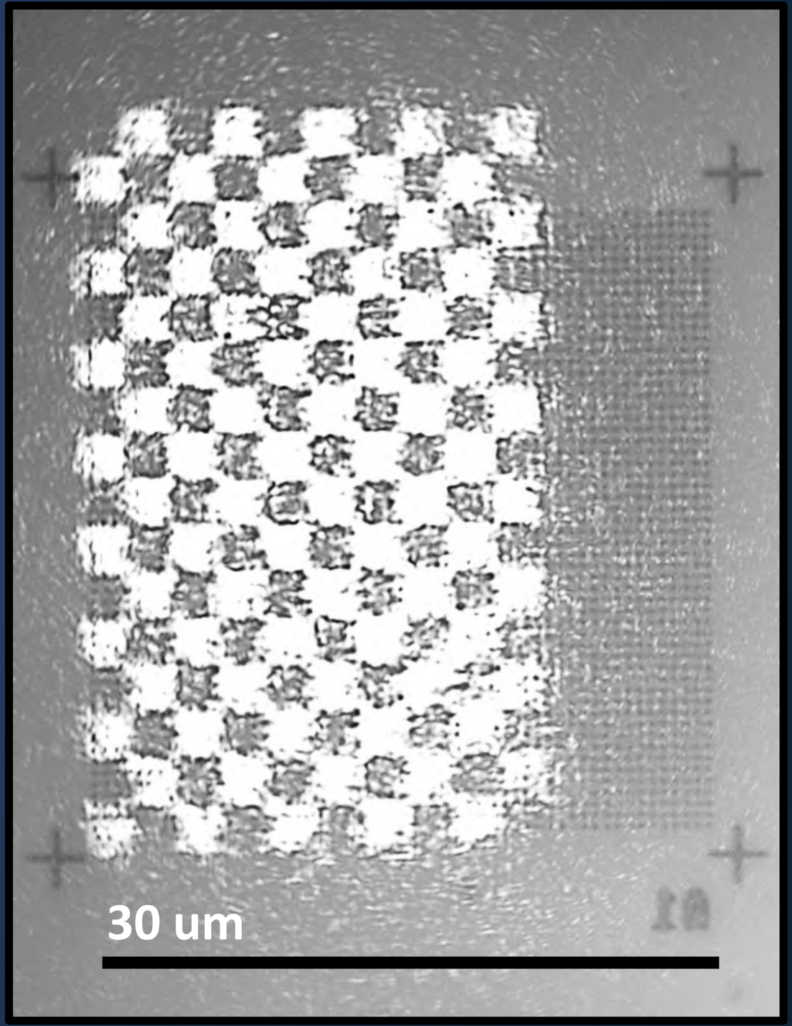
Explore using ps-scale pulsed lasers & DMD

- Continue to explore parameter space – what about **faster laser pulses?**
- Try 100-400 ps laser to examine switching timescale
- Combine with Digital Micromirror Device (DMD)
    - See if our writing works over large areas, spatially-structured light
- Support of collaborator Riccardo Sapienza crucial here
- **Does writing still work?**

Laser parameters:
$\lambda = 532$ nm
t_{pulse} = 100-400 ps
E per nanoisland = 3.6 pJ

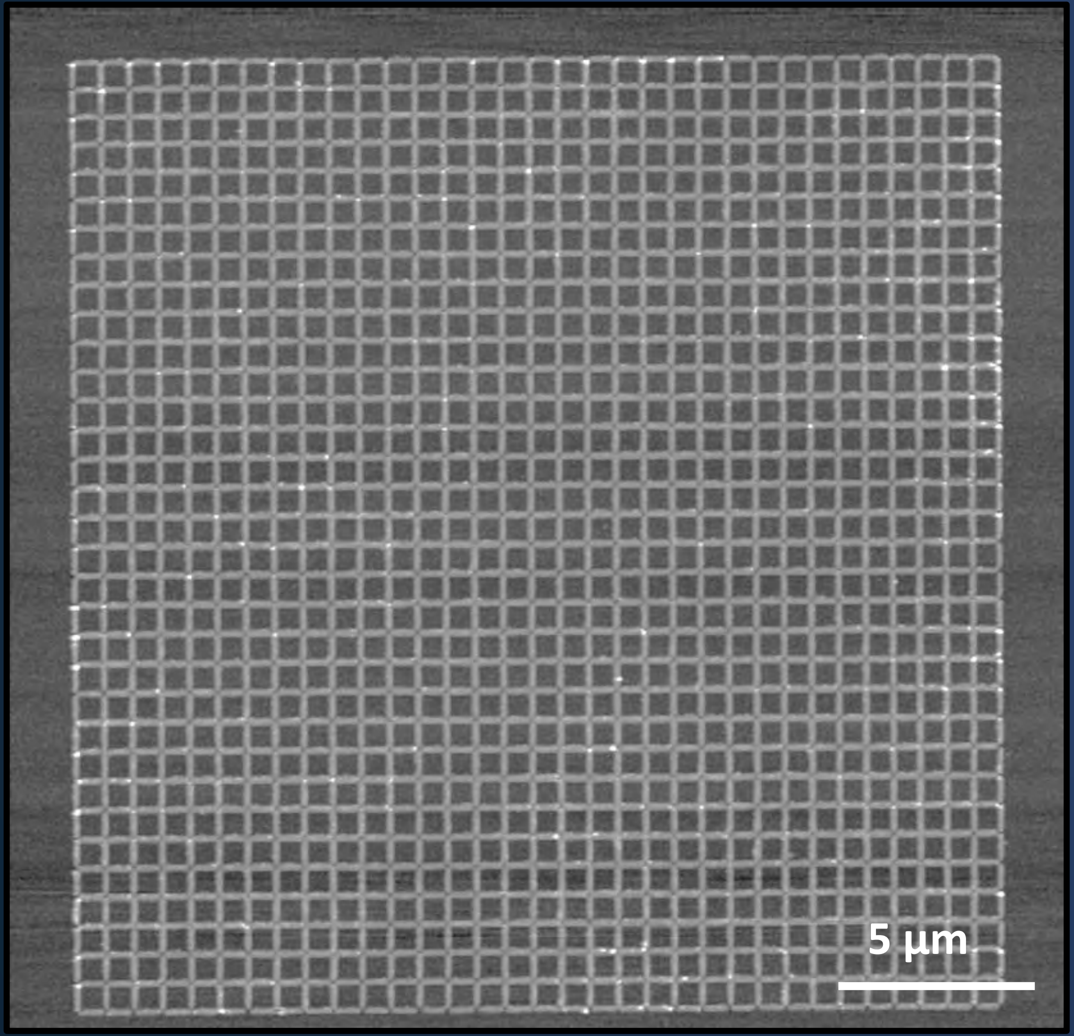


Each DMD 'pixel' ~ 100x100 nm

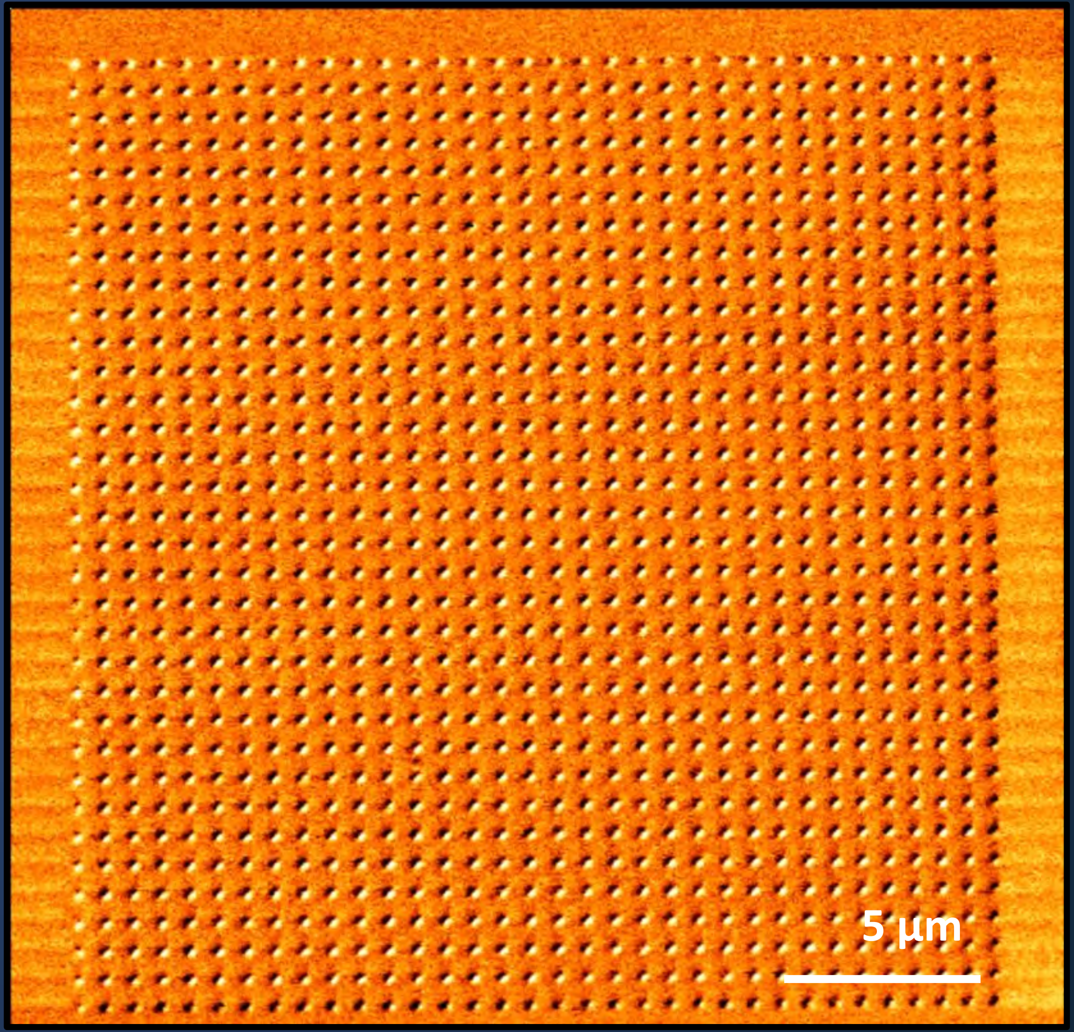


Explore using ps-scale pulsed lasers & DMD

AFM

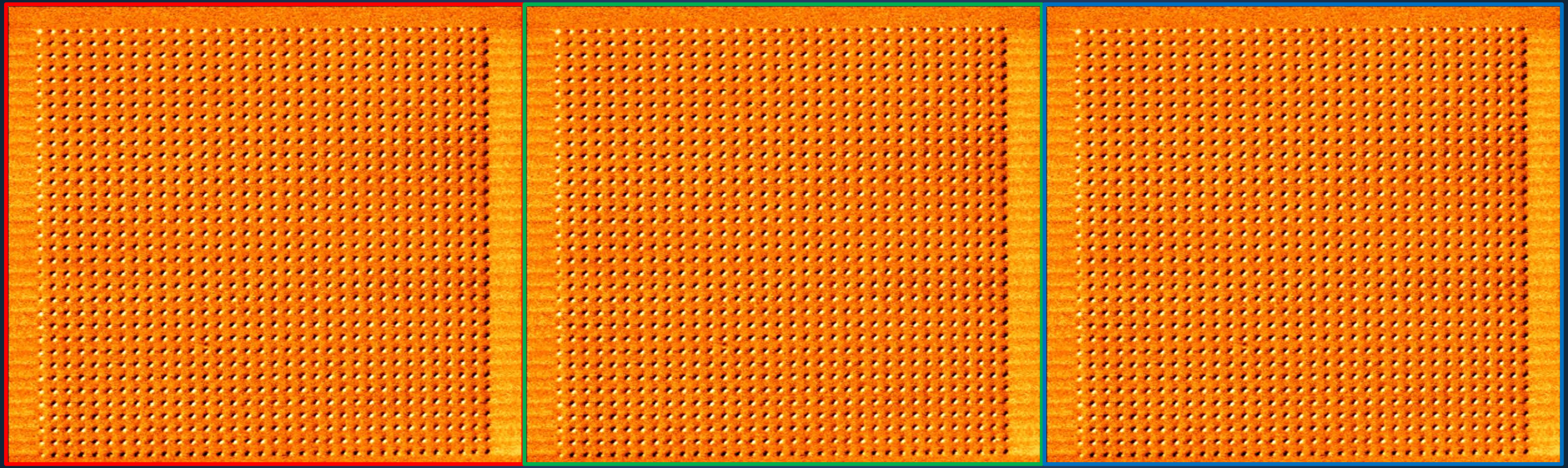


MFM



Explore using ps-scale pulsed lasers & DMD

- Before single-shot 400 ps writing pulse:



Explore using ps-scale pulsed lasers & DMD

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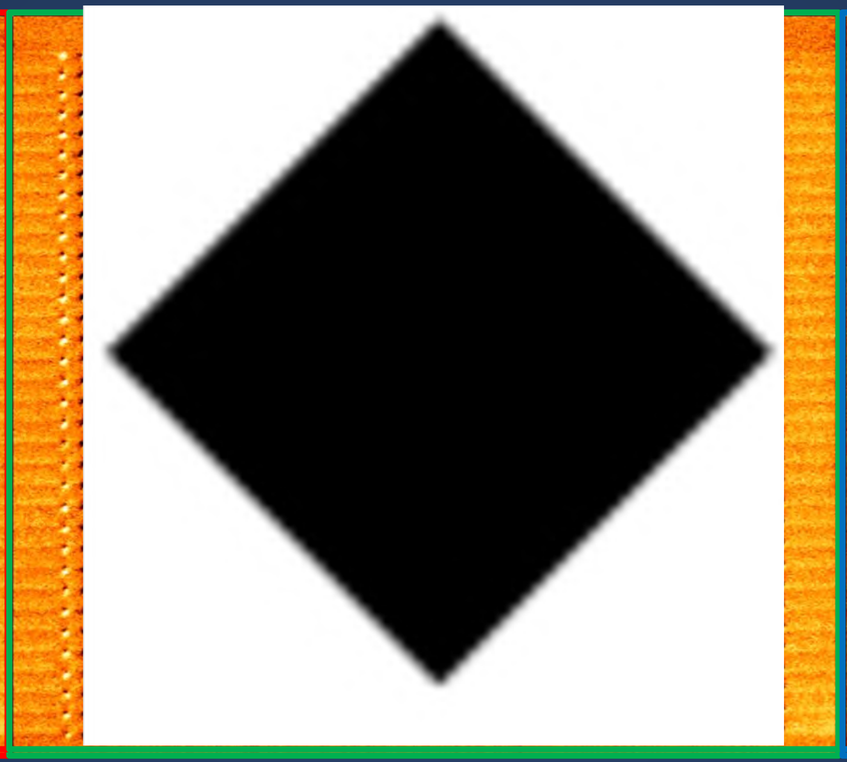
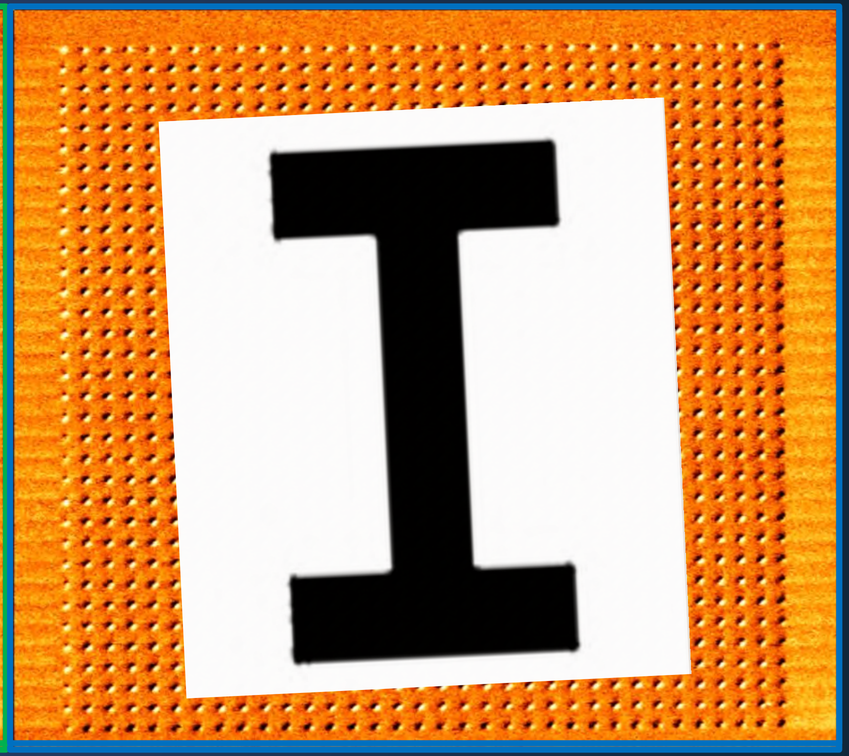
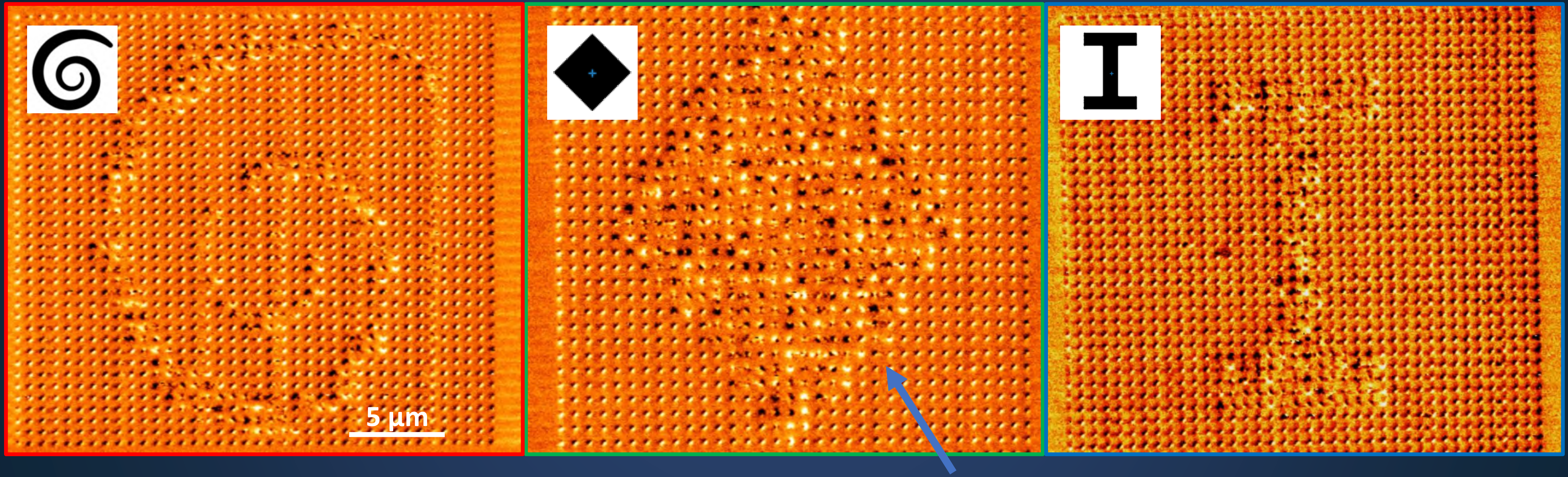




Explore using ps-scale pulsed lasers & DMD

- **After** single-shot 400 ps writing pulse:



805 bits addressed with single pulse

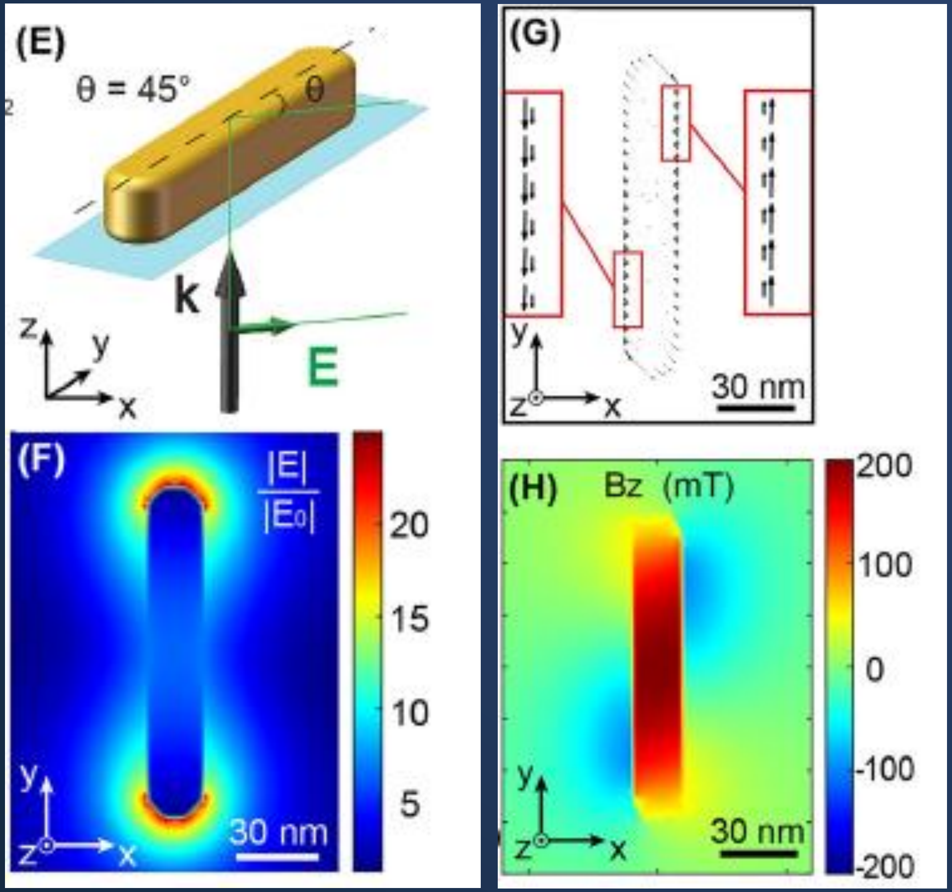
Writing works - Fidelity far from 100%, around 65% bars switched

Interesting results…
But still don’t understand the mechanism

Find an interesting theory paper: Mivelle group, Sorbonne Paris:

Xingyu Yang, Ye Mou, Romeo Zapata, Benoît Reynier, Bruno Gallas and Mathieu Mivelle*

An inverse Faraday effect generated by linearly polarized light through a plasmonic nano-antenna



Key findings:

- **Plasmonic resonances** give rise to **Strong Bz magnetic field** from **linearly-polarised light – 200 mT**
- Requires **long, thin metallic nanoislands**
- **Interesting,** but **confusing** for us: **B field** in **z direction,** our switching in **x,y plane**

Yang, Xingyu, et al. "An inverse Faraday effect generated by linearly polarized light through a plasmonic nano-antenna." *Nanophotonics* 12.4 (2023): 687-694.

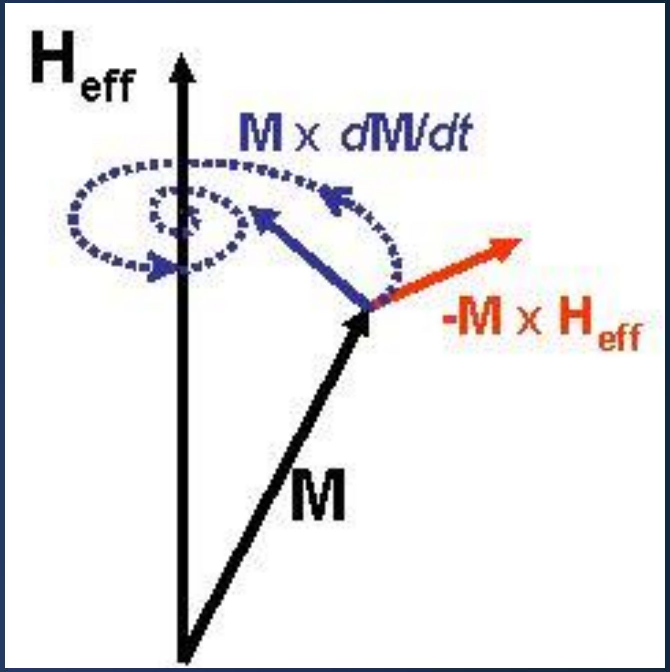
Learn about 'Precessional' Magnetic Switching:

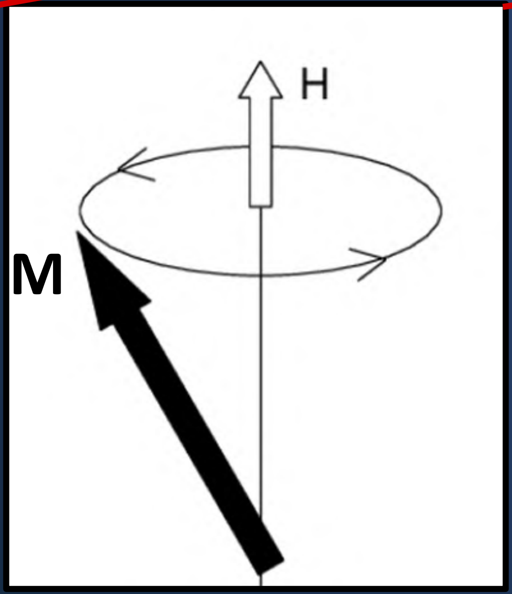
Main equation governing magnetic dynamics:

Landau-Lifshitz Gilbert equation

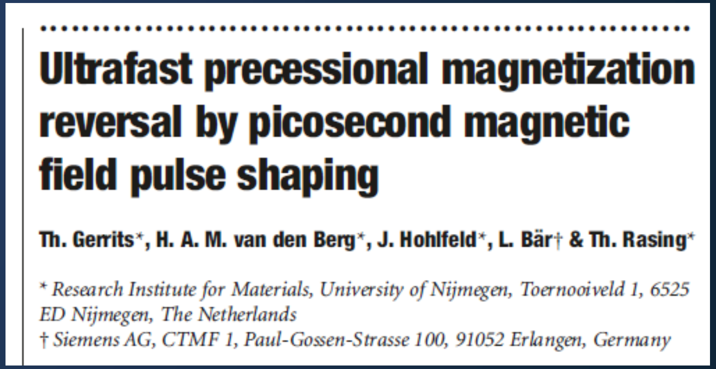
Term in red means **M** will **precess** around B field

$$\frac{d\mathbf{M}}{dt} = -\gamma \mathbf{M} \times \mathbf{H}_{\mathrm{eff}} - \boxed{\lambda \mathbf{M} \times (\mathbf{M} \times \mathbf{H}_{\mathrm{eff}})}$$





- Prior works showed 100-400 ps timescale:
- **They used electrically-generated B field**
- 200-250 mT
- Not optical, Oersted fields



Ultrafast precessional magnetization reversal by picosecond magnetic field pulse shaping

Th. Gerrits*, H. A. M. van den Berg*, J. Hohlfeld*, L. Bär† & Th. Rasing*

** Research Institute for Materials, University of Nijmegen, Toernooiveld 1, 6525 ED Nijmegen, The Netherlands*
† Siemens AG, CTMF 1, Paul-Gossen-Strasse 100, 91052 Erlangen, Germany

Minimum Field Strength in Precessional Magnetization Reversal

C. H. BACK, R. ALLENSPACH, W. WEBER, S. S. P. PARKIN, D. WELLER, E. L. GARWIN, AND H. C. SIEGMANN Authors Info & Affiliations

SCIENCE · 6 Aug 1999 · Vol 285, Issue 5429 · pp. 864-867 · DOI: 10.1126/science.285.5429.864

Simulate a ‘Mivelle group’ Bz field on our Nanomagnets – MuMax3:

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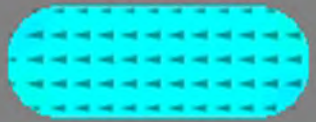
video_length_400_width_140_Msat_400000_Bmax_300.mp4



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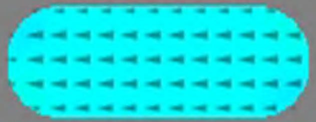

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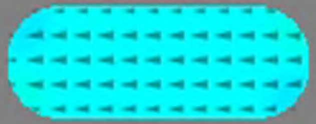

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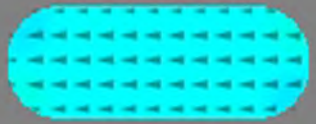

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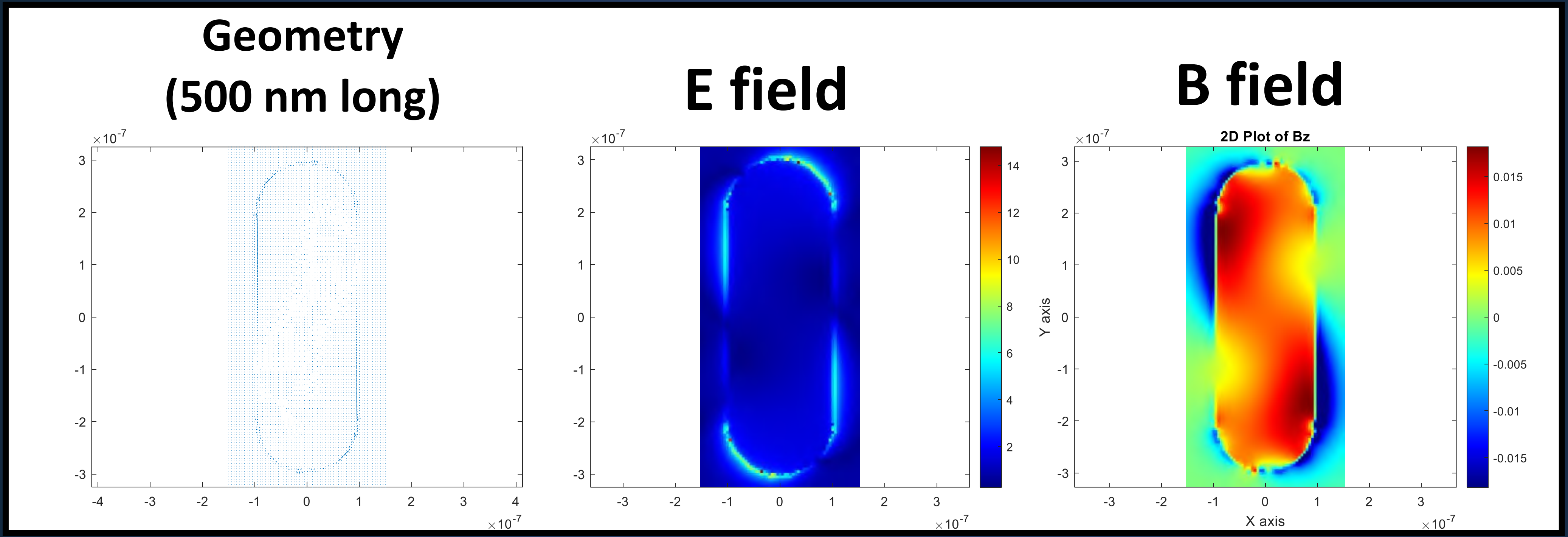
video_length_400_width_160_Msat_400000_Bmax_400.mp4

Simulate magneto-plasmonic effects in our nanoislands

Lumerical simulations of plasmonic IFE field – **Xiaofei Xiao:**



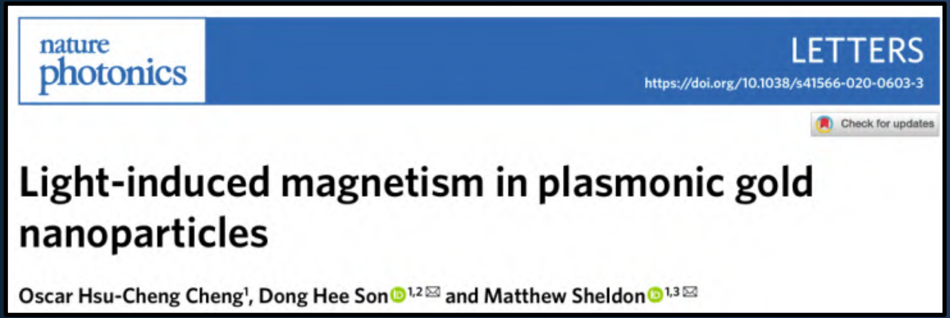
- Mivelle-group plasmonic IFE model shows optically induced Bz field for our nanoislands
- MuMax3 sims predict both double vortex and macrospin writing

Simulate magneto-plasmonic effects in our nanoislands

N.B: Magnetic field amplitudes

- In MuMax, we need ~50 mT to switch. Our IFE sims predict up to **1.1 mT**
- Prior experimental studies (Sheldon group) in Au nanoparticles measured Plasmon-enhanced IFE fields to be 500-1000x higher in experiment vs. simulation.
- Investigation is ongoing by Sheldon/Mivelle groups & others to understand experiment/sim mismatch.

Experimental paper


nature photonics

LETTERS

https://doi.org/10.1038/s41566-020-0603-3

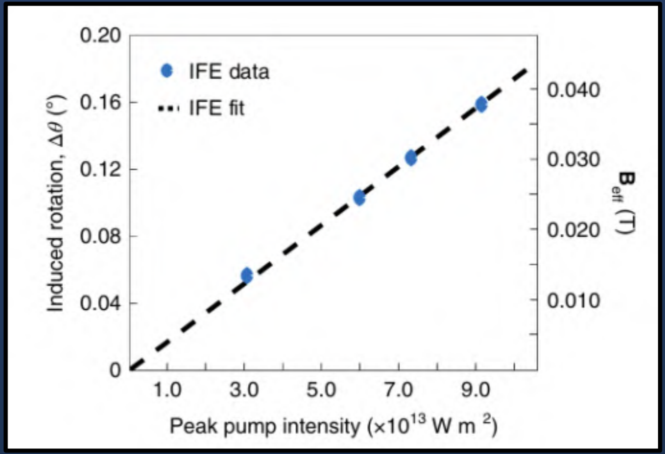
Check for updates

Light-induced magnetism in plasmonic gold nanoparticles

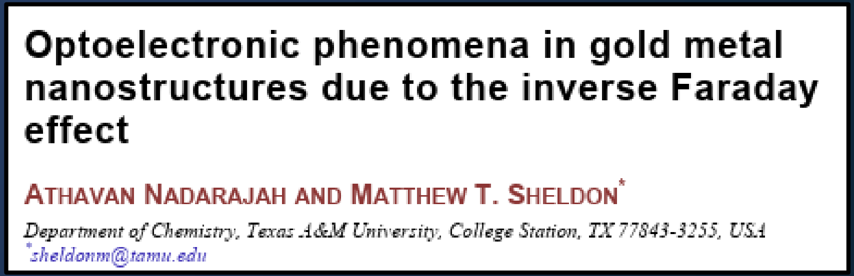
Oscar Hsu-Cheng Cheng[1], Dong Hee Son[1,2] and Matthew Sheldon[1,3]

Cheng, Oscar Hsu-Cheng, Dong Hee Son, and Matthew Sheldon. "Light-induced magnetism in plasmonic gold nanoparticles." *Nature Photonics* 14.6 (2020): 365-368.

40 mT experimentally measured, while **model predicts 0.08 mT**



Simulation paper


Optoelectronic phenomena in gold metal nanostructures due to the inverse Faraday effect

ATHAVAN NADARAJAH AND MATTHEW T. SHELDON*

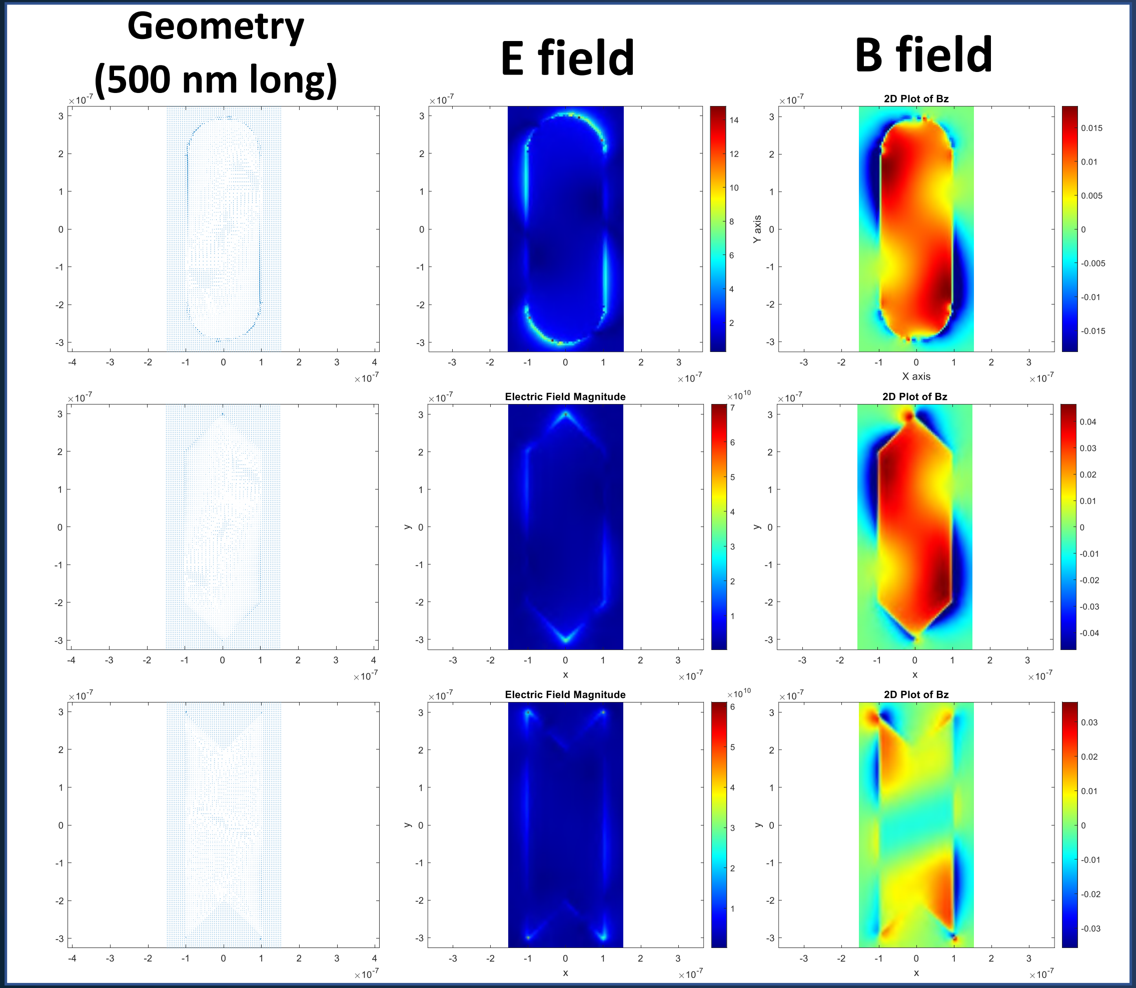
Department of Chemistry, Texas A&M University, College Station, TX 77843-3255, USA

*sheldonm@tamu.edu

Nadarajah, Athavan, and Matthew T. Sheldon. "Optoelectronic phenomena in gold metal nanostructures due to the inverse Faraday effect." *Optics Express* 25.11 (2017): 12753-12764.

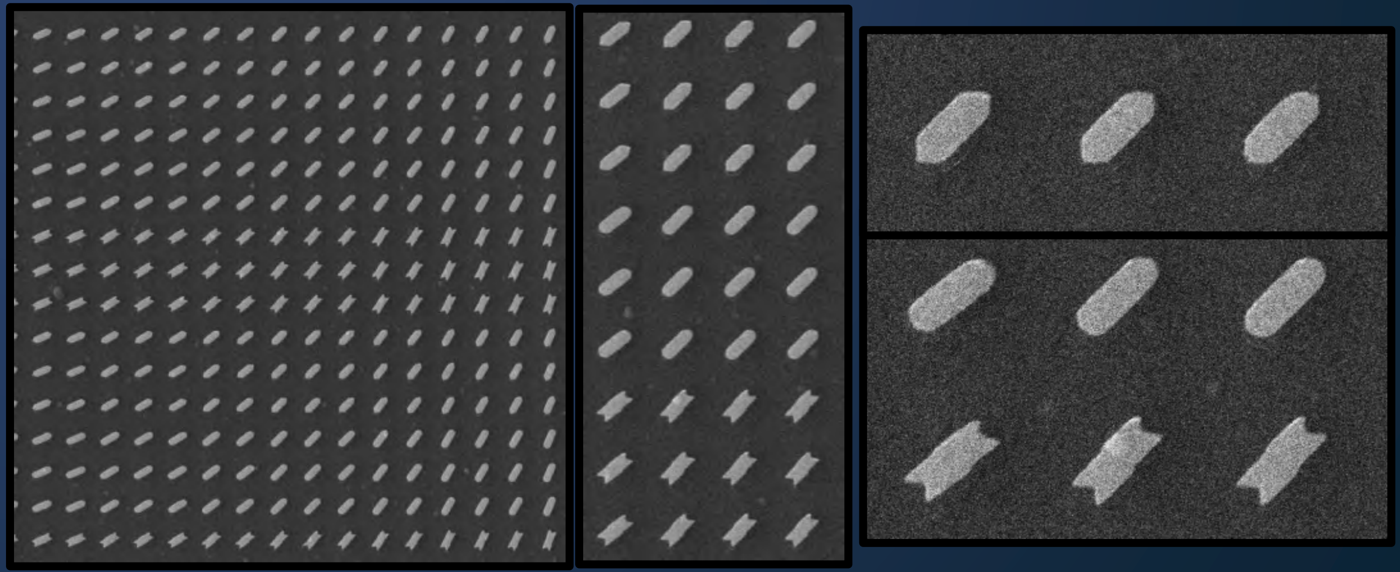
Experiment with plasmon resonances via nanoisland end-shape

Lumerical simulations – **Xiaofei Xiao:**



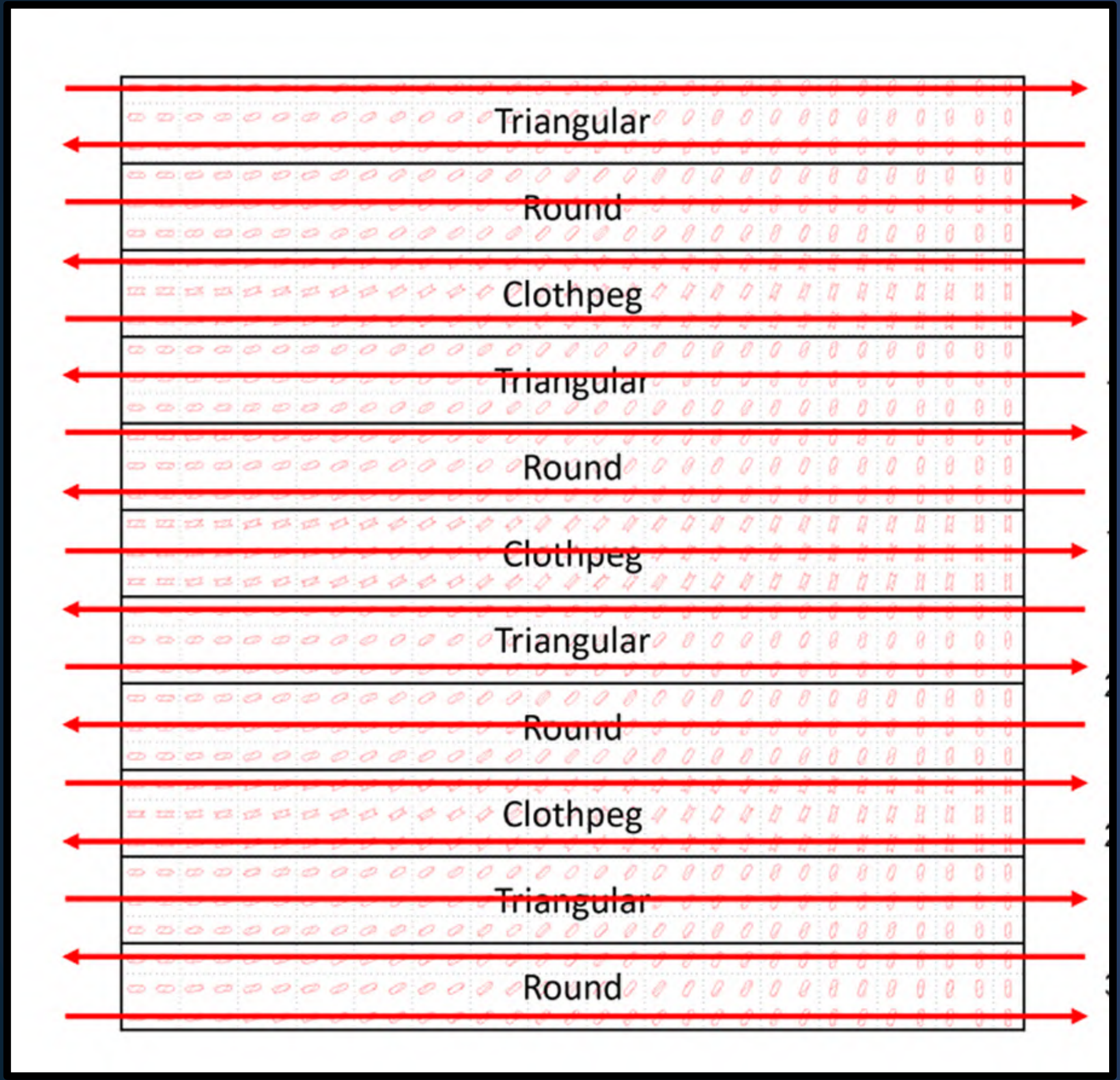
- Want to make experimentally verifiable predictions
- **Vary** nanoisland end geometry & hence **plasmon resonance** to deactivate/minimise B field
- 'M' shaped ends substantially reduce Bz
- Fabricate & test experimentally…

EBL & SEM of different end-shapes: **Tingjun Zheng:**

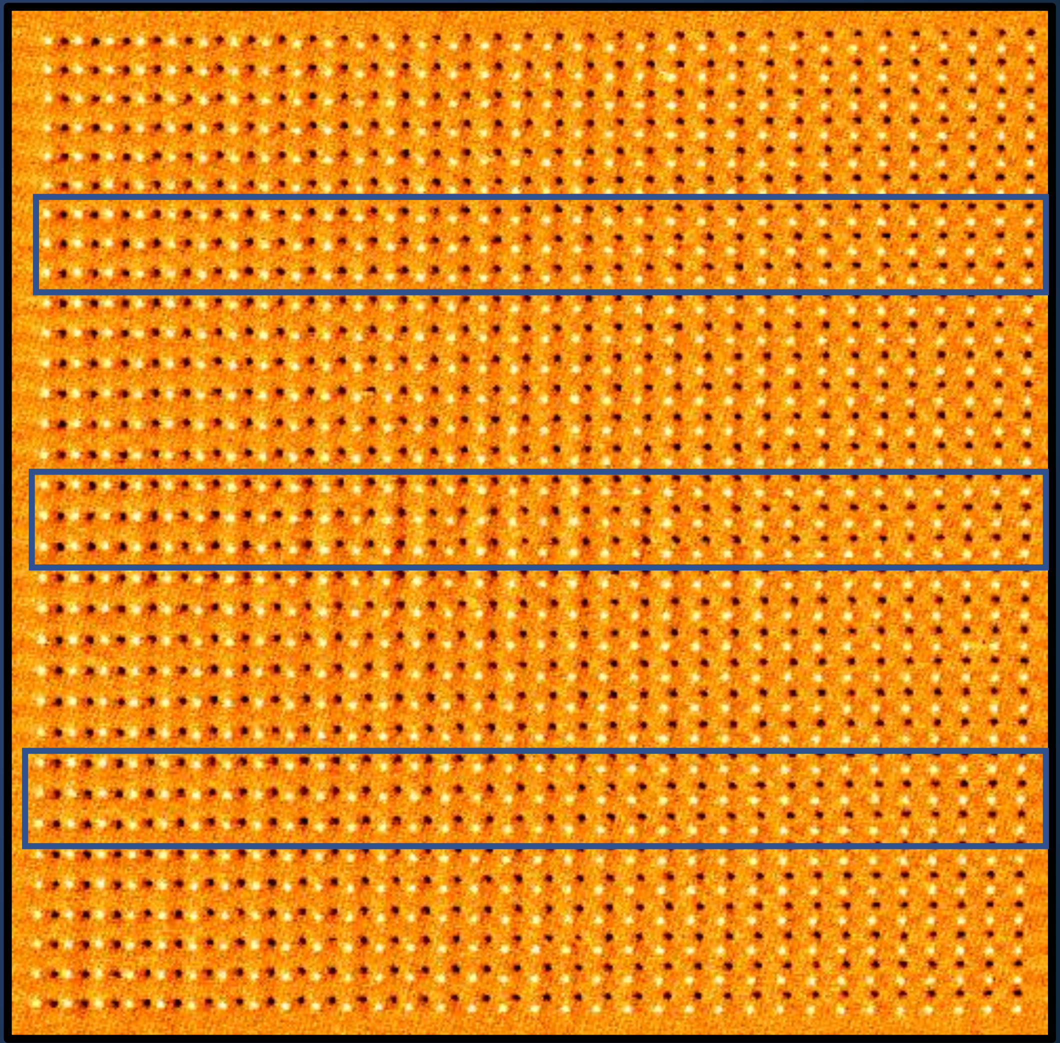


Simulate magneto-optical effects of our nanoislands

- Prepare array with alternating end geometries: **‘Clothes peg’ is M-shaped**

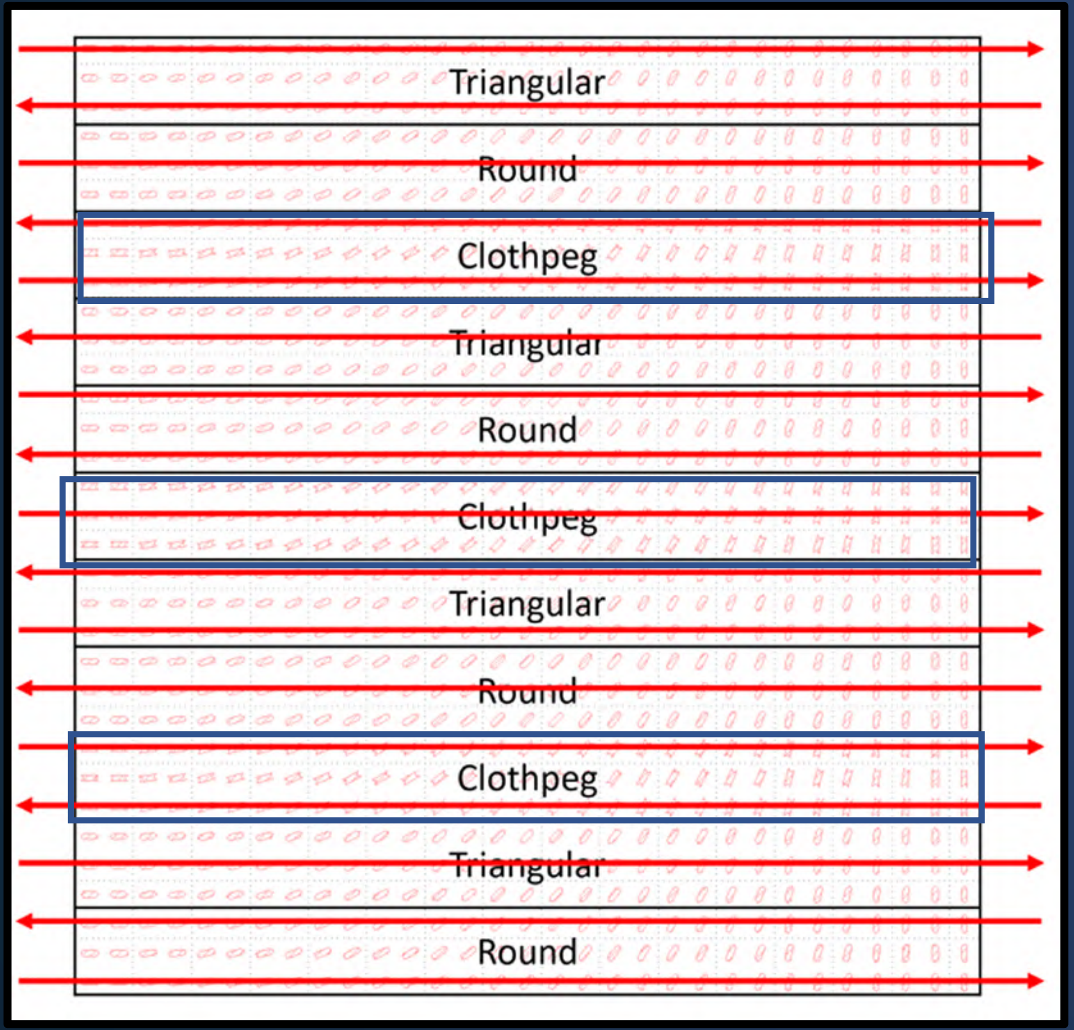


Before writing – saturated state:

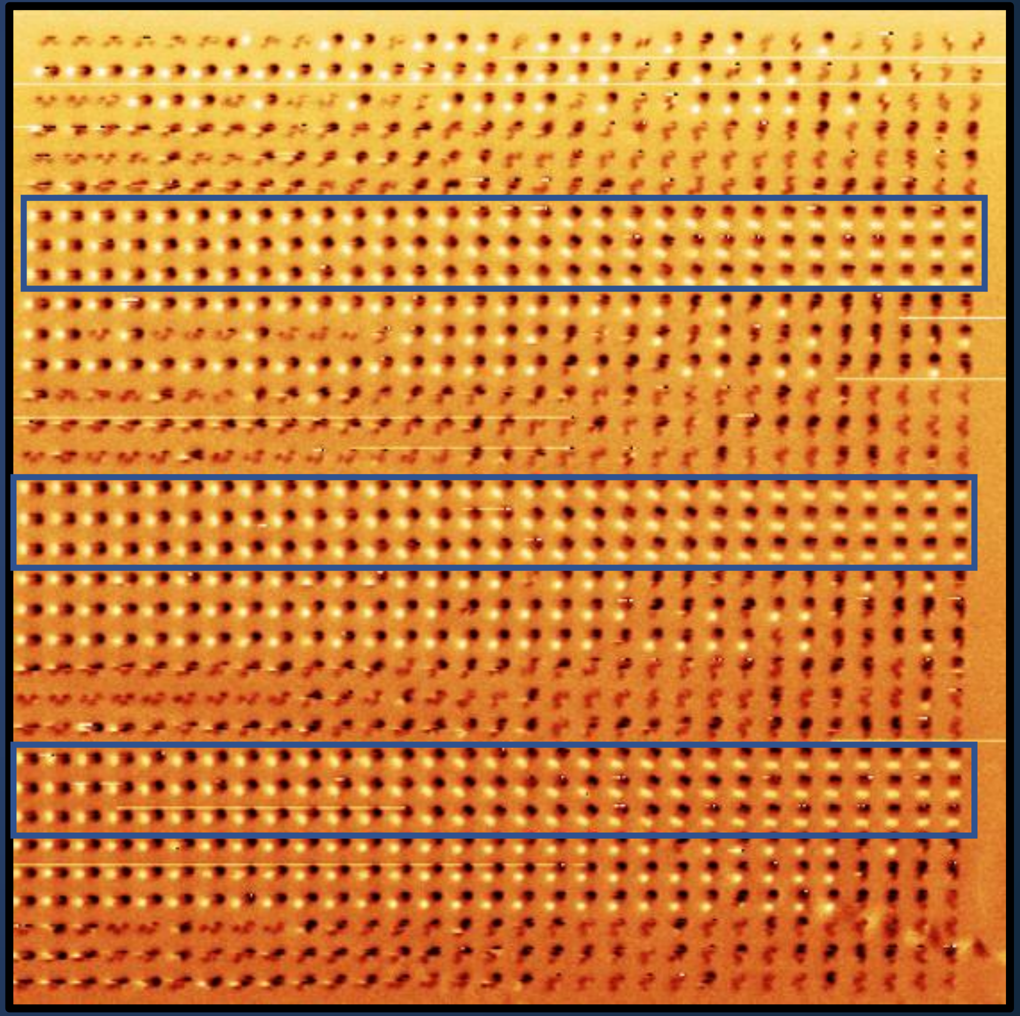


Simulate magneto-optical effects of our nanoislands

- **No optical magnetic switching** observed in M-shaped nanoislands (**540** islands)

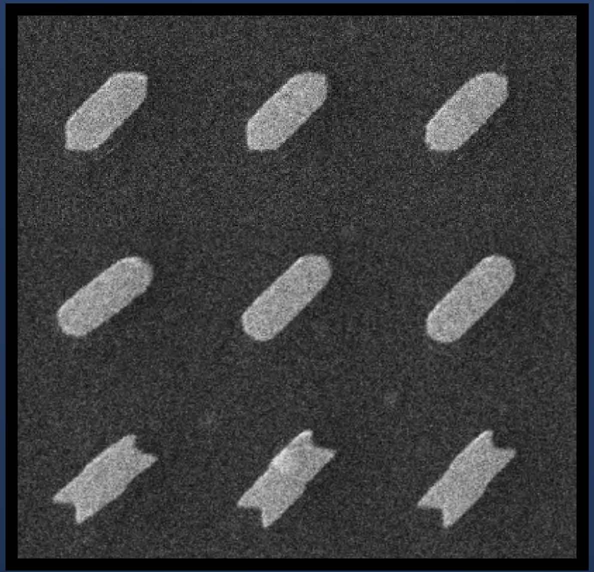


After writing – optical switching:

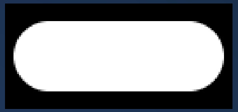


- **Very promising!** M-shaped ends where weak optical Bz field is predicted **don’t switch**
- Experimental evidence of behaviour predicted by optical plasmonic Bz field

- Could there be non-optical reasons?
  E.g. different magnetic properties for M-shaped ends?

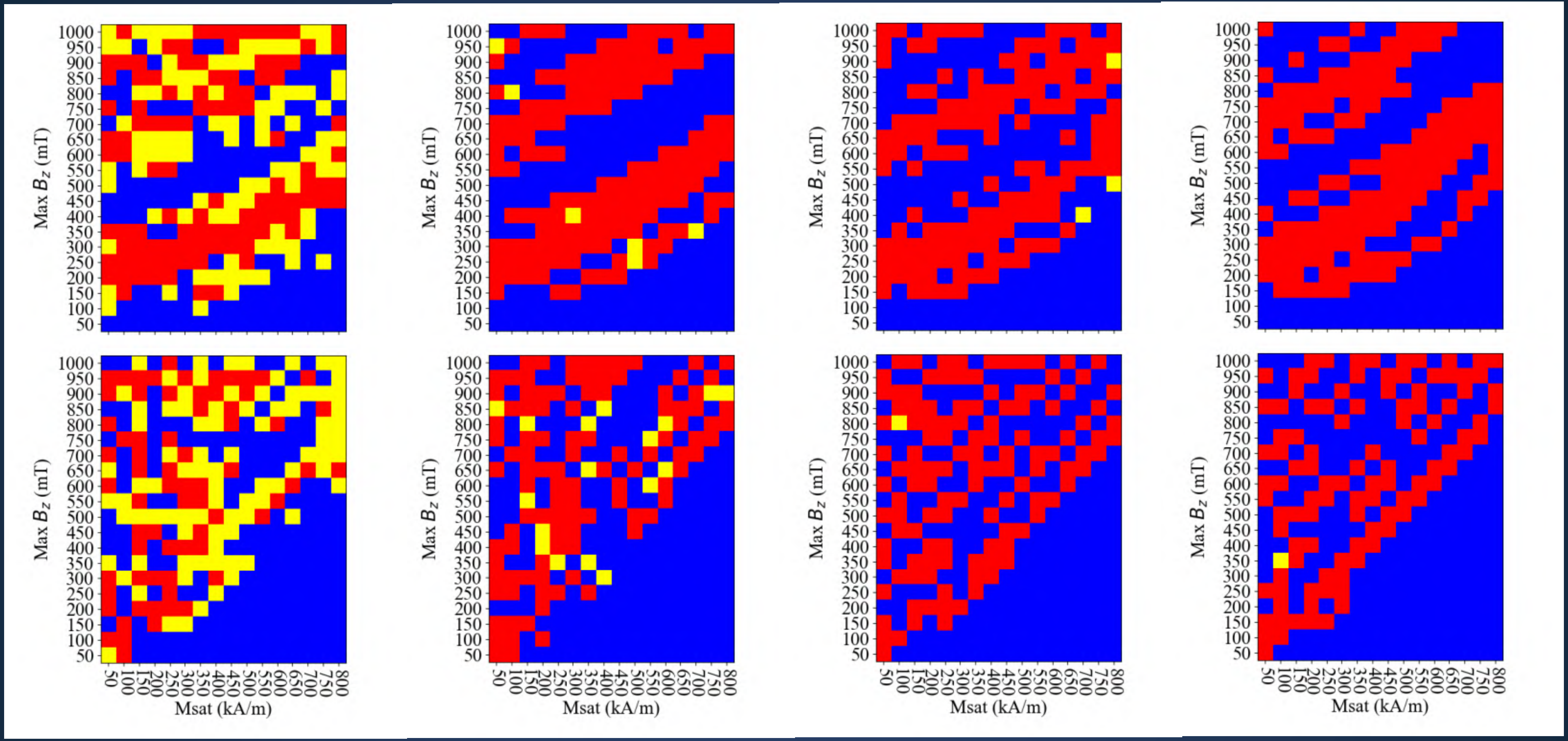


Rounded End – Magnetic sims



100 ps

400 ps

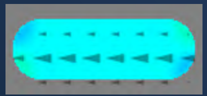


L500 W165 T20

L500 W125 T20

L500 W100 T20

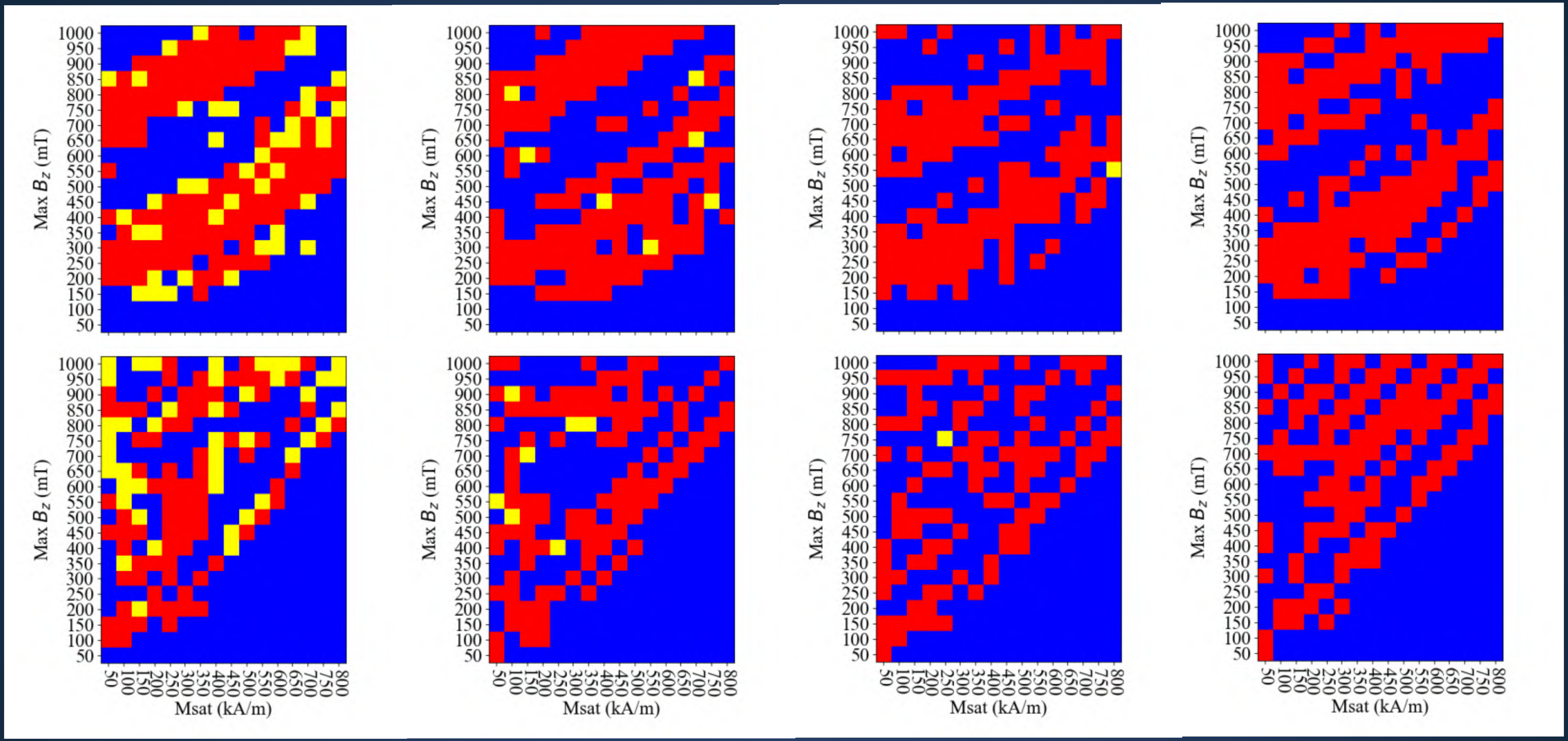
L500 W085 T20

Unflipped	Flipped	Single Vortex	Double Vortex
			

M-shaped End – Magnetic sims

100 ps

400 ps

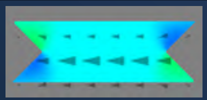
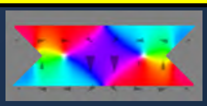


L500 W165 T20

L500 W125 T20

L500 W100 T20

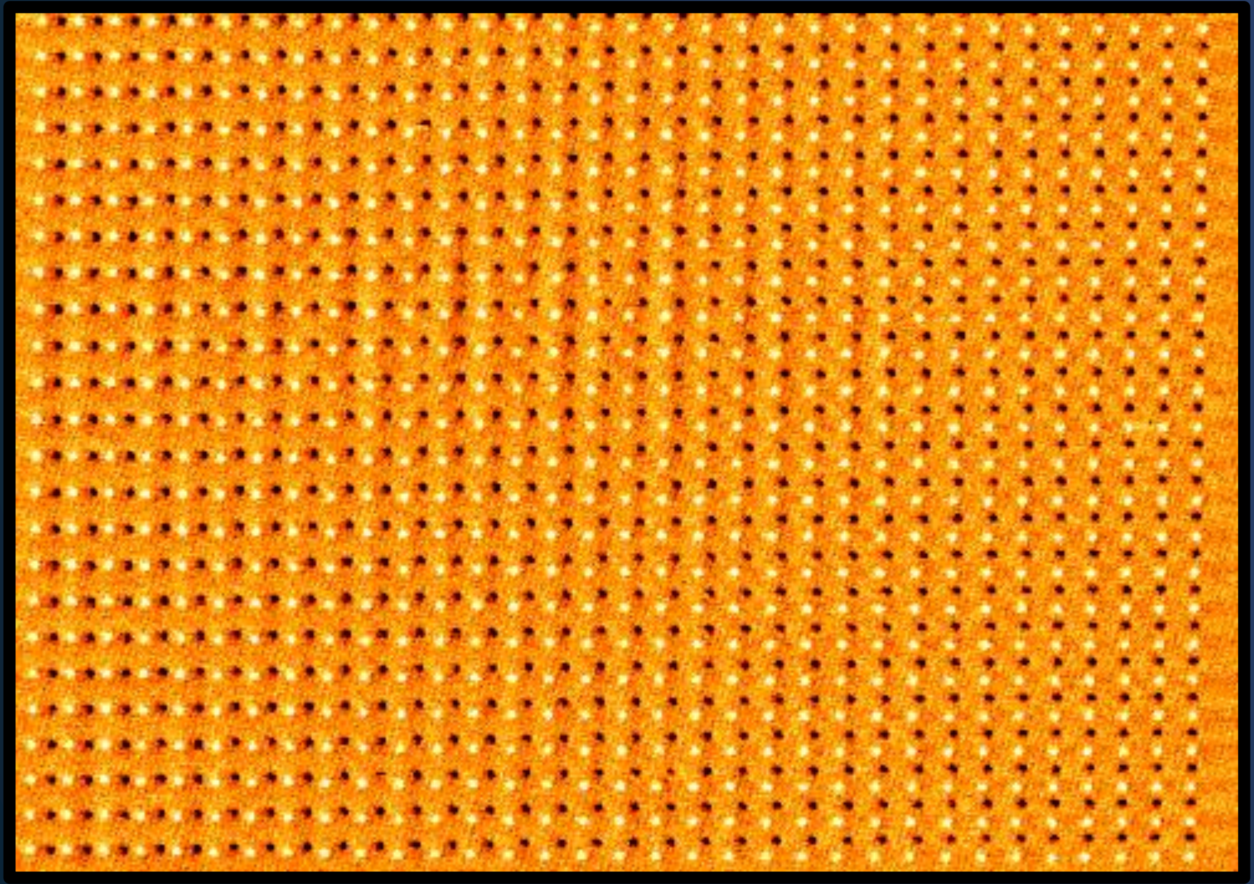
L500 W085 T20

Unflipped	Flipped	Single Vortex	Double Vortex
			

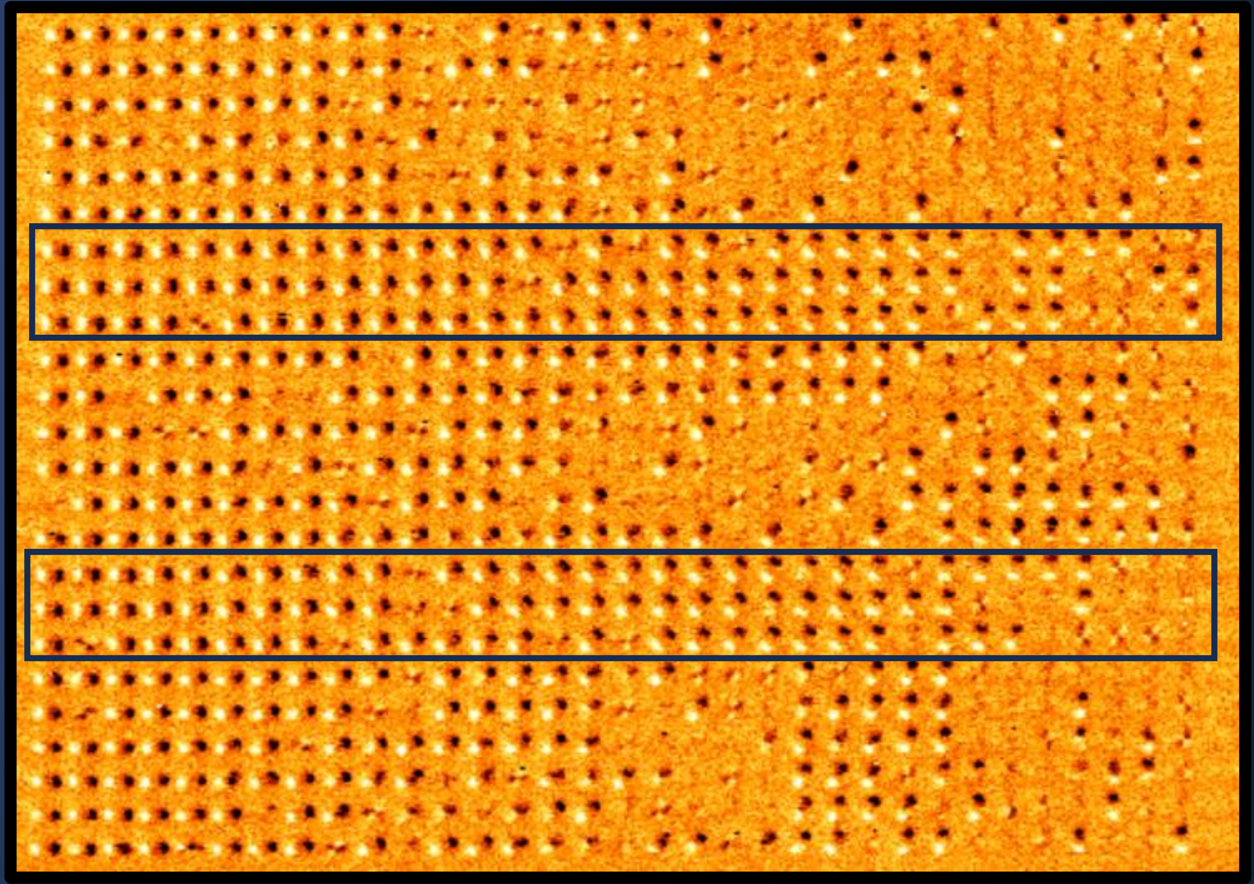
M-shaped Ends

- Experiments at different wavelength. Previously 633 nm, here 532 nm
- Plasmonic effects often sensitive to wavelength
- Some evidence of switching in M-shaped ends:

Before



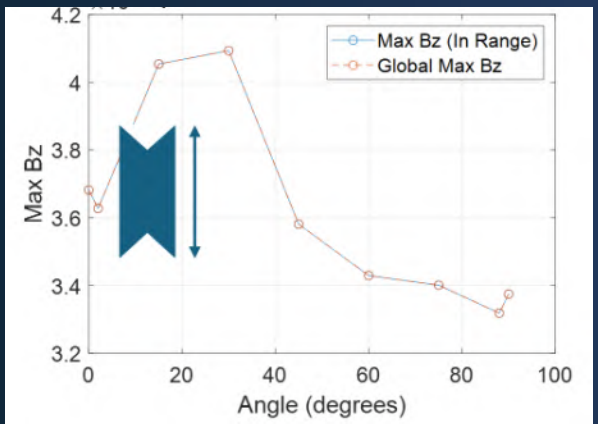
After



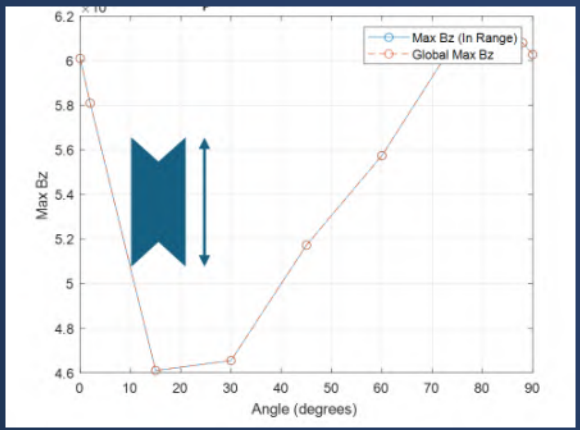
M-shaped Ends

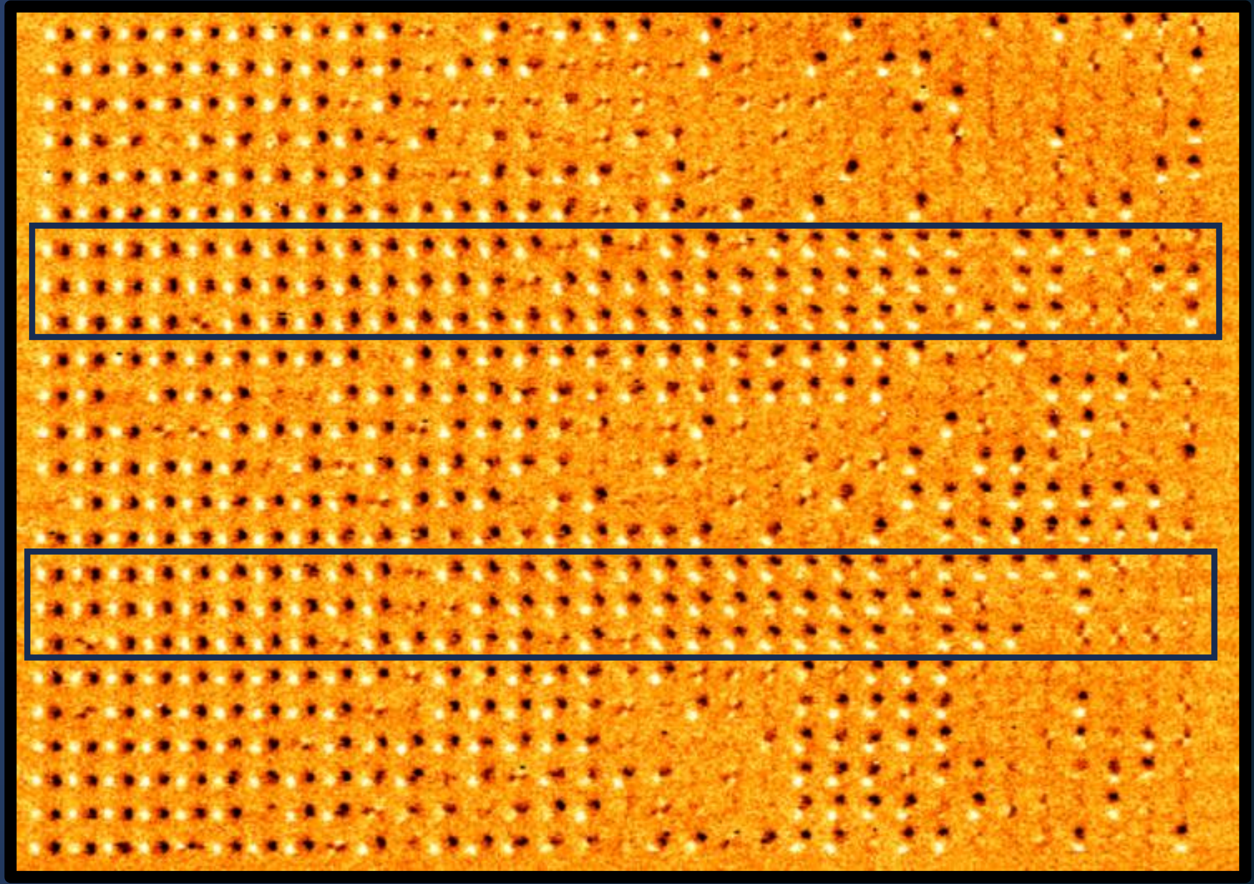
- Simulate plasmonic Bz field at 532 nm vs. 633 nm
- Bz-field suppression for M-shaped islands only occurs at 633 nm
- We need to design geometry for 532 nm Bz field supression

532 nm:



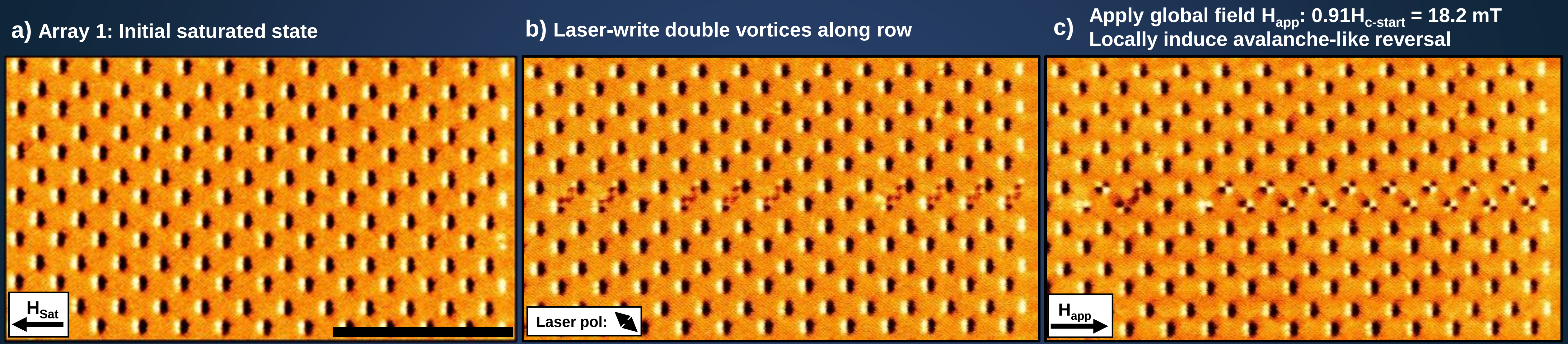
633 nm:





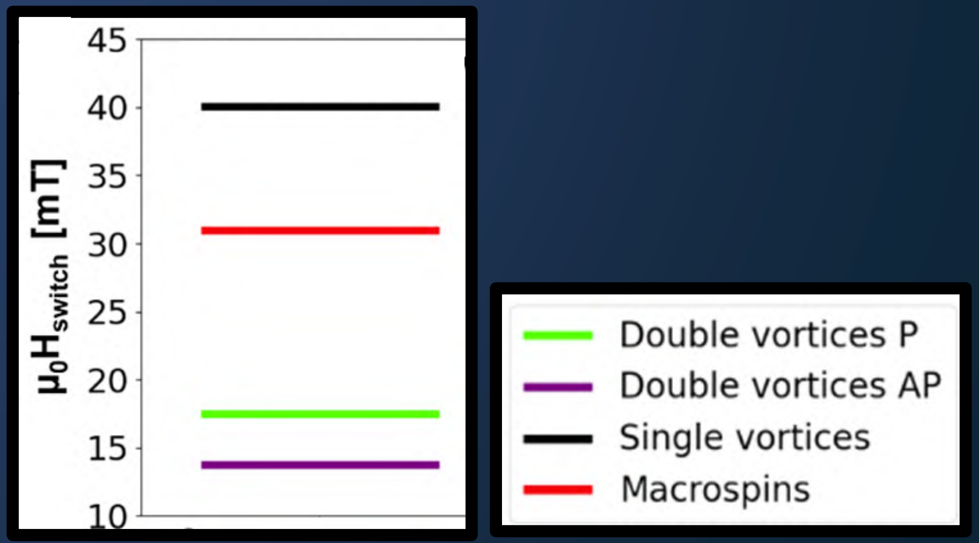
First tests: Optically-written states for array control

Results lead here by **Holly Holder**



Applied field H_{app}: $0.91H_{c\text{-}start}$ = 18.2 mT

- Optically-write **double vortex** states
- Double-vortex **coercive field** low vs. macrospin
  - (14-16 mT vs 32 mT in MuMax)
- Apply field of **18.2 mT** = above double-vortex coercivity, below macrospin coercivity
- Trigger avalanche-like reversal chains seeded by optically-wriiten vortices

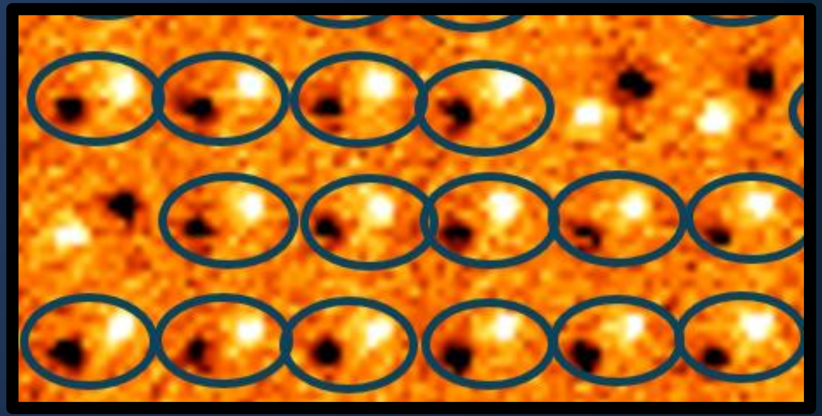


Fidelity – Why isn't it higher?

- Sims show final state of switching is highly sensitive to nanoisland dimensions & field strength
- DMD struggles to provide **perfectly uniform illumination**
  - Replace with simple objective lens to test
- Challenging to fabricate perfectly identical islands via EBL
- 400 ps is a bit long for precessional switching (M may rotate twice)
  - Try shorter 50-150 ps pulses
- Potential for combination of IFE/magneto-optic effect and thermal effects
  - Try optimising ratio of heating to magneto-optic effects via plasmonic/fabrication optimisation

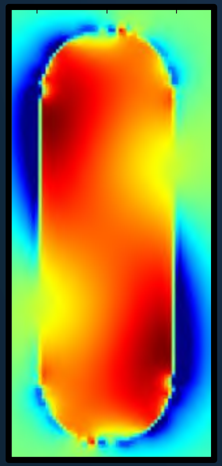
- We observe regions of laser power/polarisation parameter sweeps with higher fidelity (still not perfect):
- Much optimisation is required before we can state what maximum fidelities are experimentally viable.

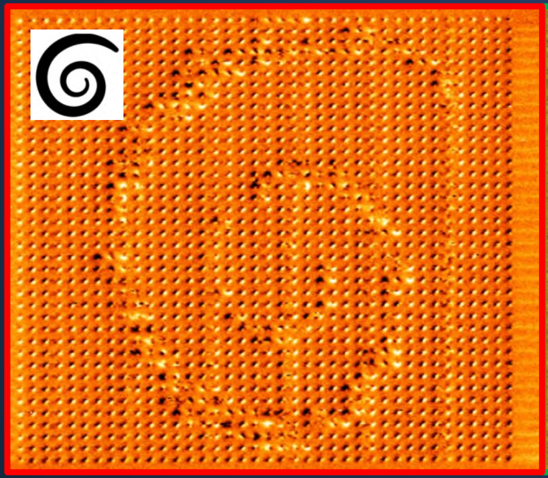
Circles show optically-switched bars:

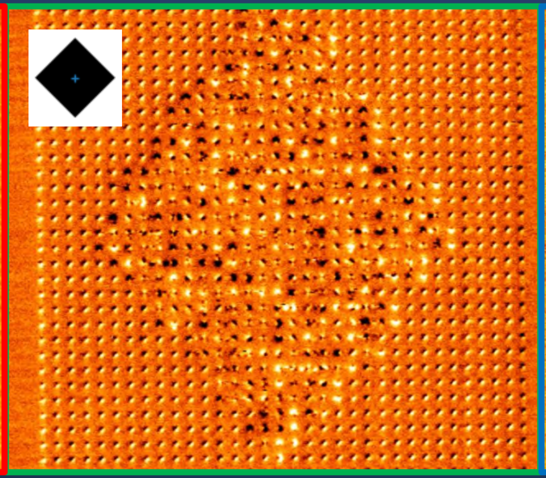


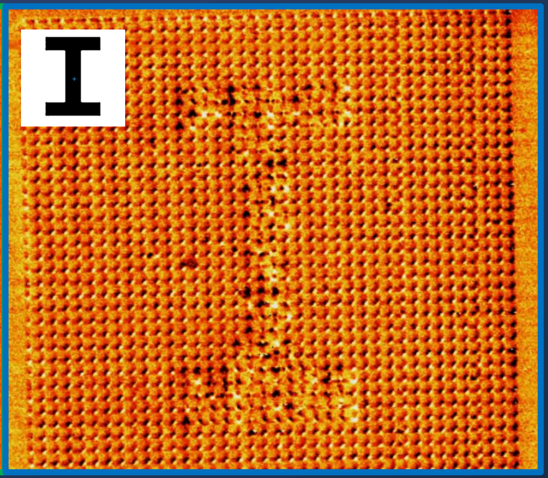
Conclusions

- Explore plasmonically-enhanced Inverse Faraday Effect & precessional reversal as mechanism for observed magnetic switching
- Continue to optimise nanoisland geometry & illumination to improve fidelity
- Deepen understanding of mechanism & sophistication of modelling
- Experiment with using optically-written states for programming ASI dynamics
- Thanks & any questions!



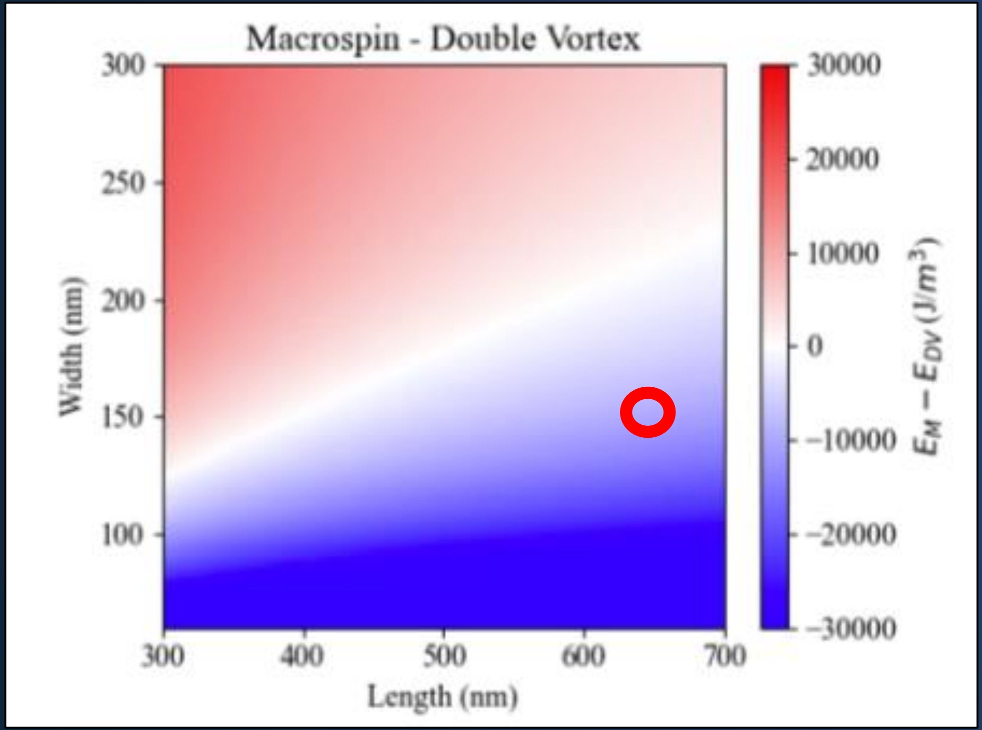


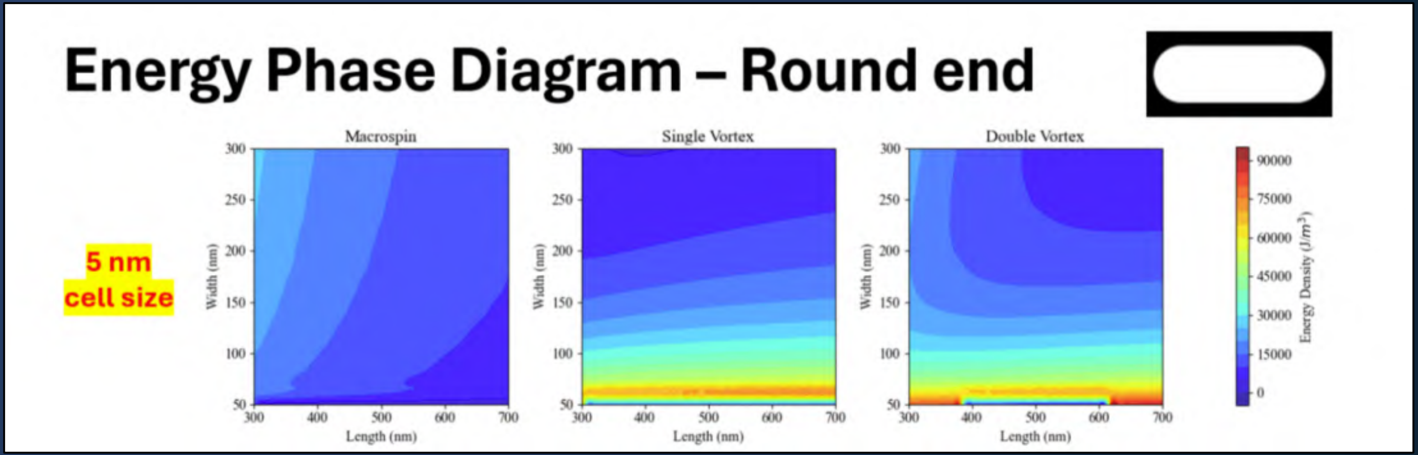




Writing of high-energy double-vortex states:

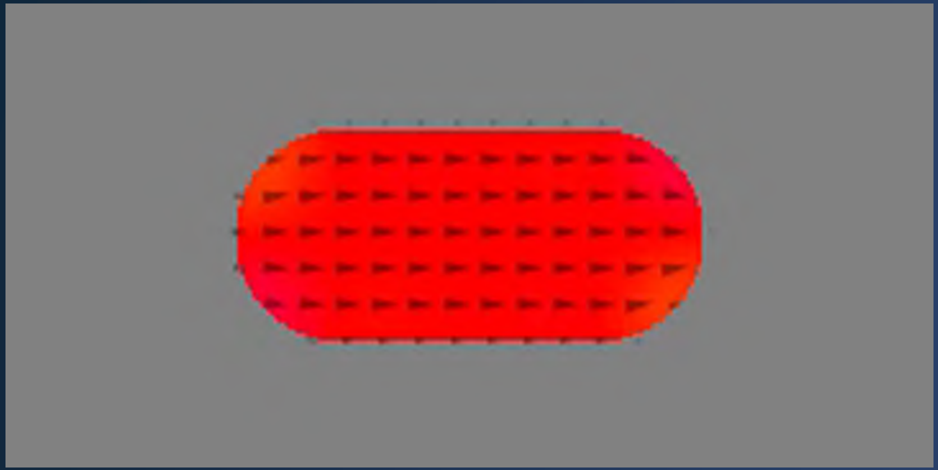
- At 650 x 150 nm islands, double vortex is 2x energy of macrospin state
- **We observe frequent macrospin-double vortex writing in 650 x 150 nm islands**
- Unlikely via purely thermal/demagnetisation effects



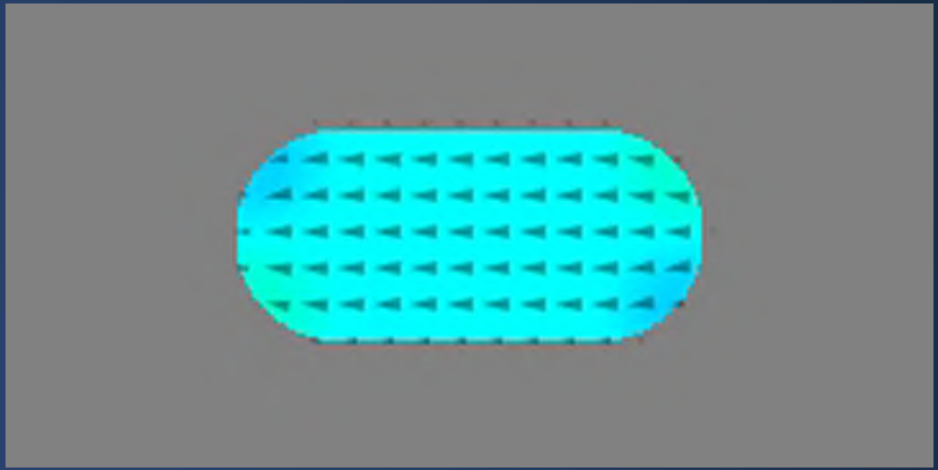


Investigate asymmetry between 0 & 90 deg vortex writing

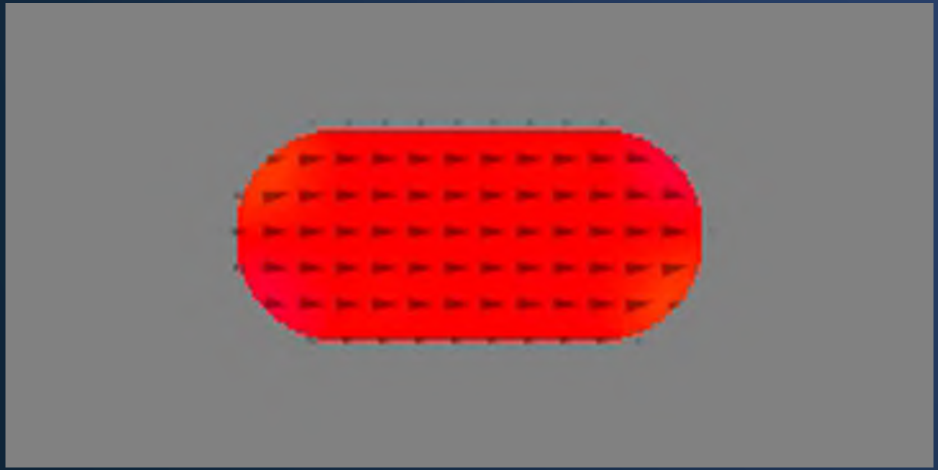
Pos Bz, Pos Mx



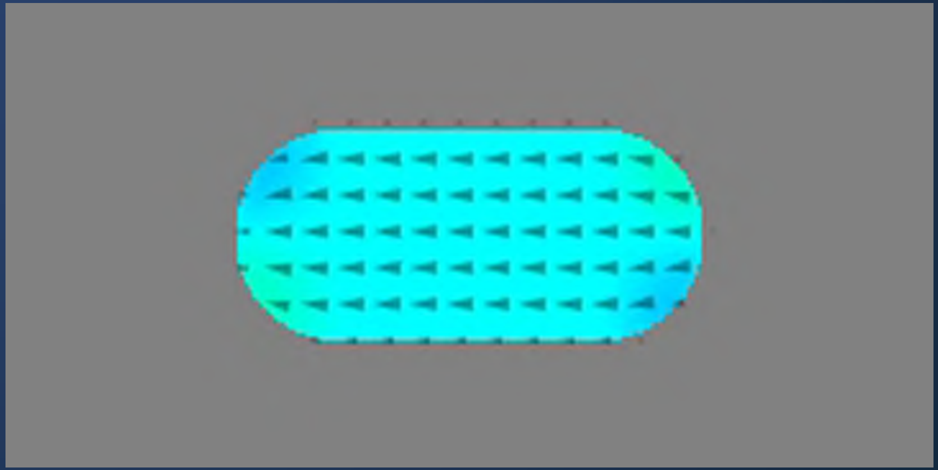
Pos Bz, Neg Mx



Neg Bz, Pos Mx

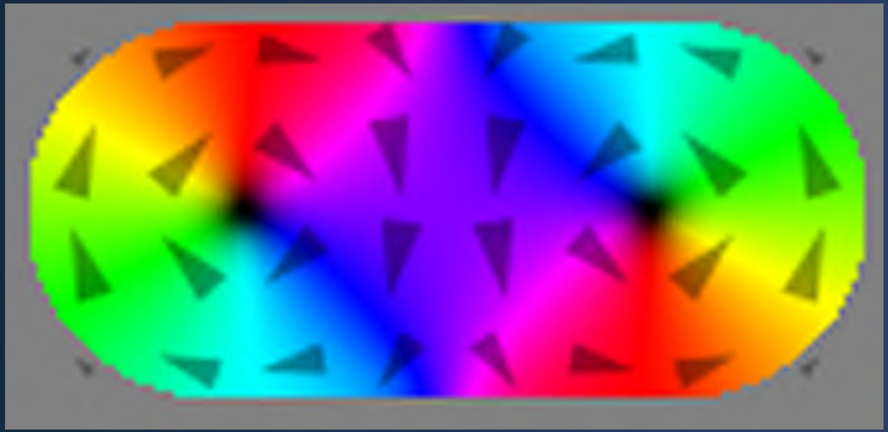


Neg Bz, Neg Mx



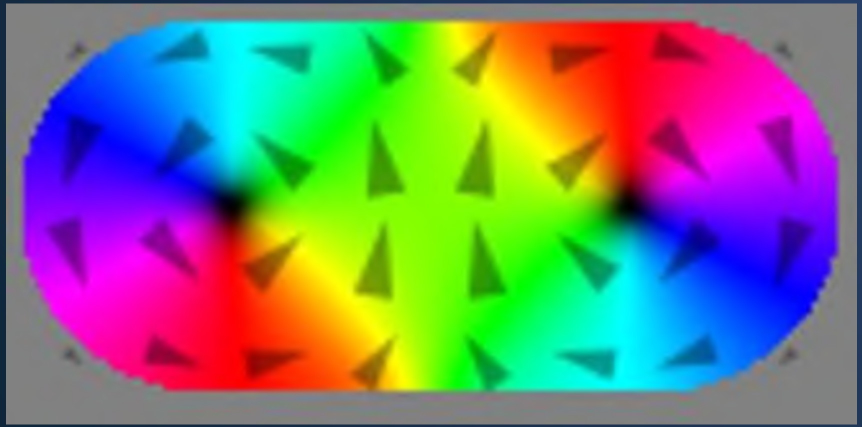
Investigate asymmetry between 0 & 90 deg vortex writing

Neg Bz, Initial Mx = -1

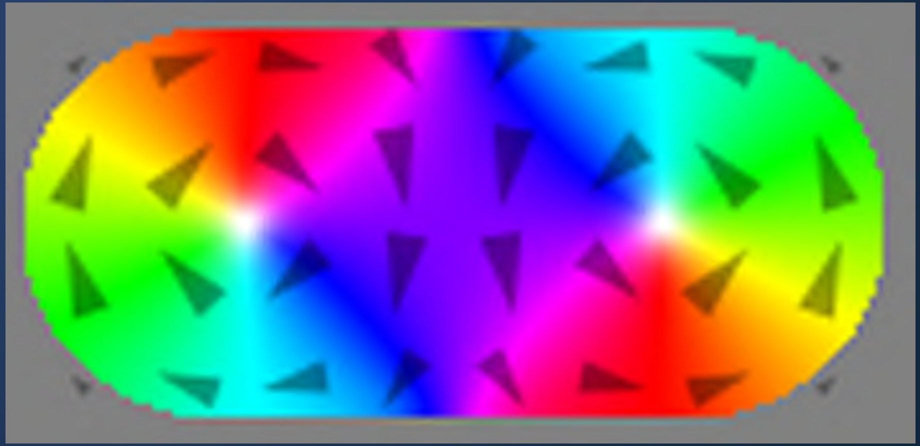


Pos Bz, Initial Mx = -1

Neg Bz, initial Mx = +1

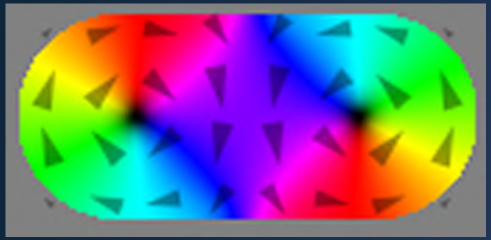


Pos Bz, Initial Mx = +1

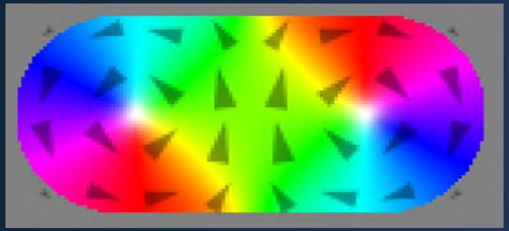


Investigate asymmetry between 0 & 90 deg vortex writing

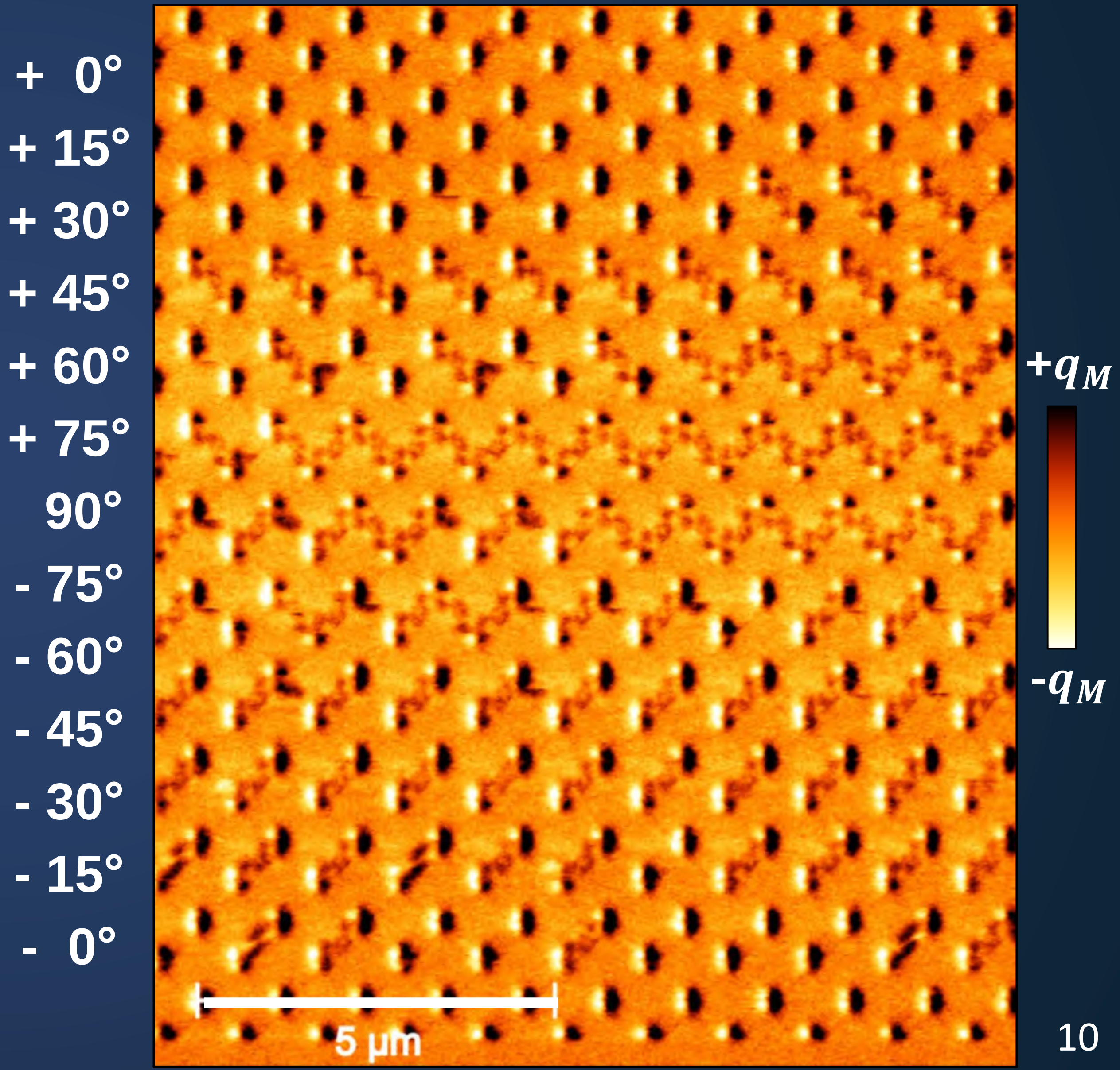
Neg Bz, Initial Mx = -1



Pos Bz, Initial Mx = -1



Laser-written double vortices



Conclusions

- Appears increasingly that we observe **first evidence** of new **all-optical magnetic switching** mechanism
- **“Magneto-Plasmonic Inverse Faraday Effect”** driving Precessional

nature photonics

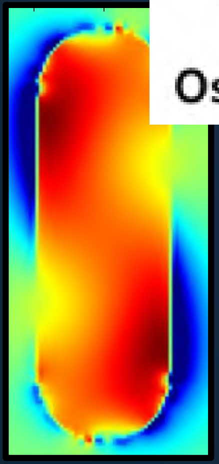
LETTERS

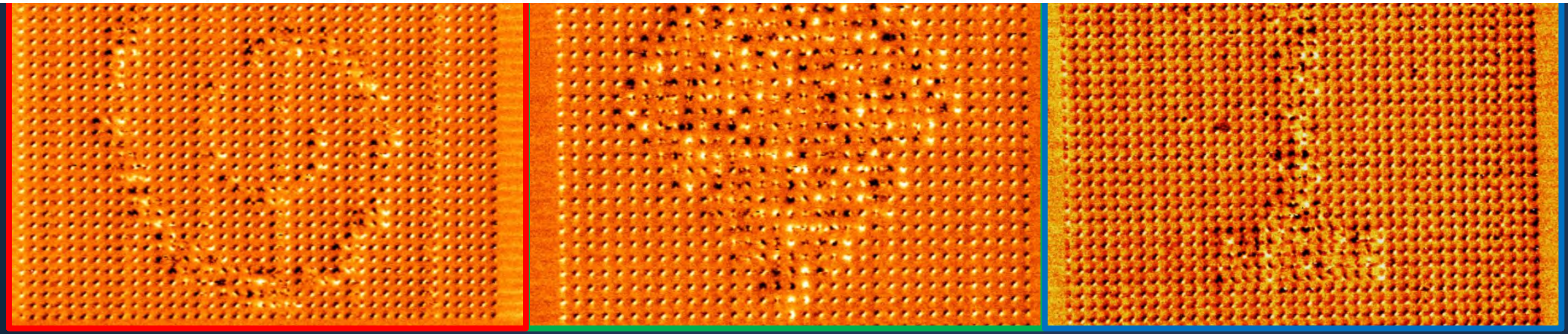
https://doi.org/10.1038/s41566-020-0603-3

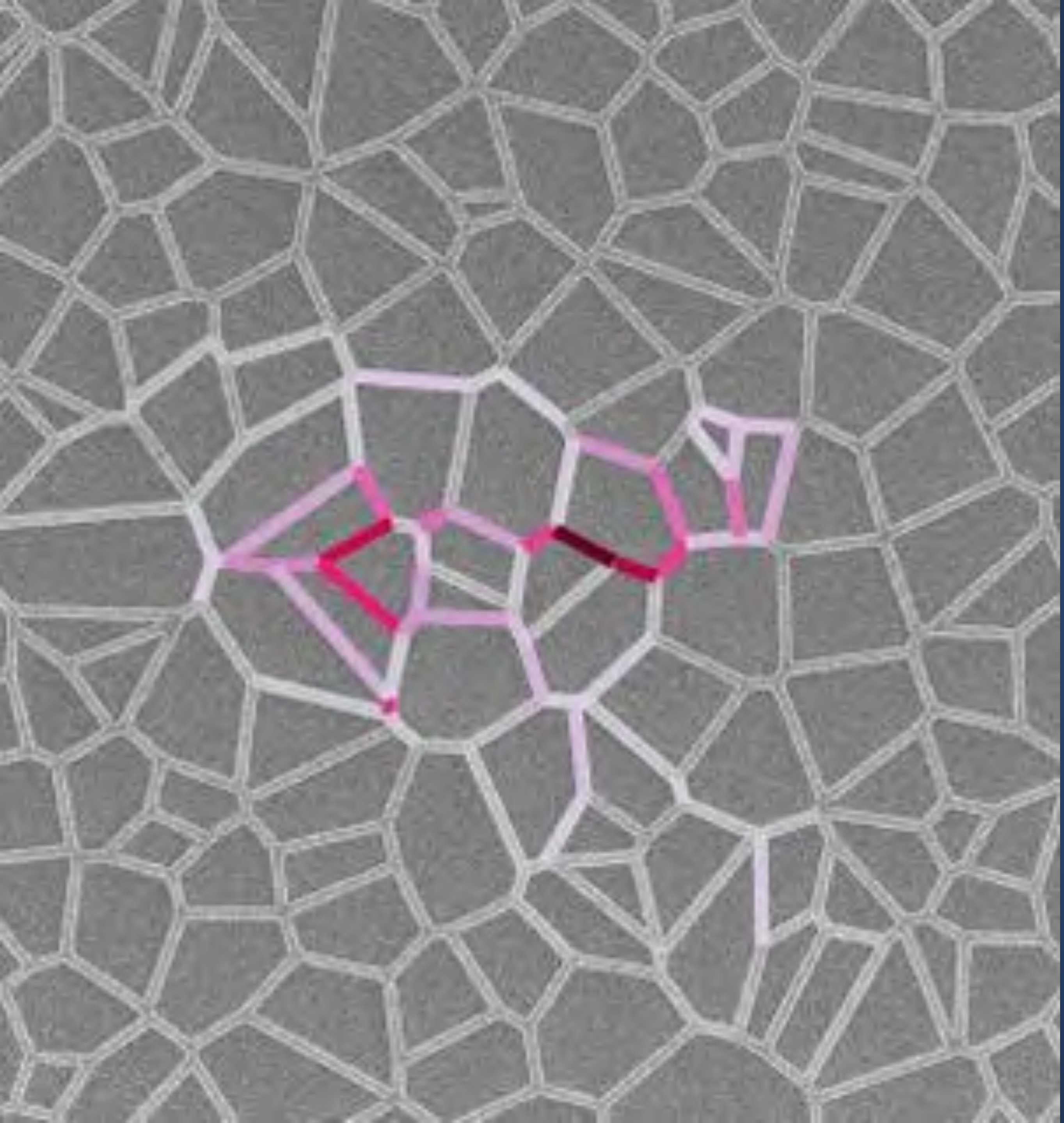
Check for updates

Light-induced magnetism in plasmonic gold nanoparticles

Oscar Hsu-Cheng Cheng[1], Dong Hee Son[1,2] and Matthew Sheldon[1,3]







Retinomorphic Vision in a Nonlinear Photonic Network

Jack C. Gartside[1,2]

Wai-Kit Ng[1] , **Jakub Dranczewski**[1], **Anna Fischer**[1,3] , Dhruv Saxena[1], Tobias Farchy[1], T. V. Raziman[1], Kilian D. Stenning[1], Eunju Moon[1], Heinz Schmid[3], Will Branford[1,2], Mauricio Barahona[1], **Kirsten Moselund**[3,4], **Riccardo Sapienza**[1]

Imperial College London[1]
London Centre for Nanotechnology, University College London[2]
IBM Zurich[3]
Paul Scherrer Institut/EPFL[4]

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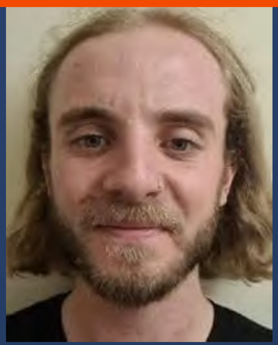
PDRAs:

Dhruv Saxena



Kilian Stenning

TV Raziman

Wai Kit Ng

Paper under review:

Retinomorphic Machine Vision in a Network Laser

Wai Kit Ng[1,†], **Jakub Dranczewski**[1,2,†], **Anna Fischer**[1,2,†], **T. V. Raziman**[1,3], **Dhruv Saxena**[1], **Tobias Farchy**[1], **Kilian Stenning**[1,4], **Jonathan Peters**[1,5], **Heinz Schmid**[2], **Will R. Branford**[1,4], **Mauricio Barahona**[3], **Kirsten Moselund**[6,7], **Riccardo Sapienza**[1,*], and **Jack C. Gartside**[1,5,*]

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[4]London Centre for Nanotechnology, Imperial College London, London, United Kingdom
[5]Univ. Grenoble Alpes, CEA, CNRS, Grenoble INP, SPINTEC, France
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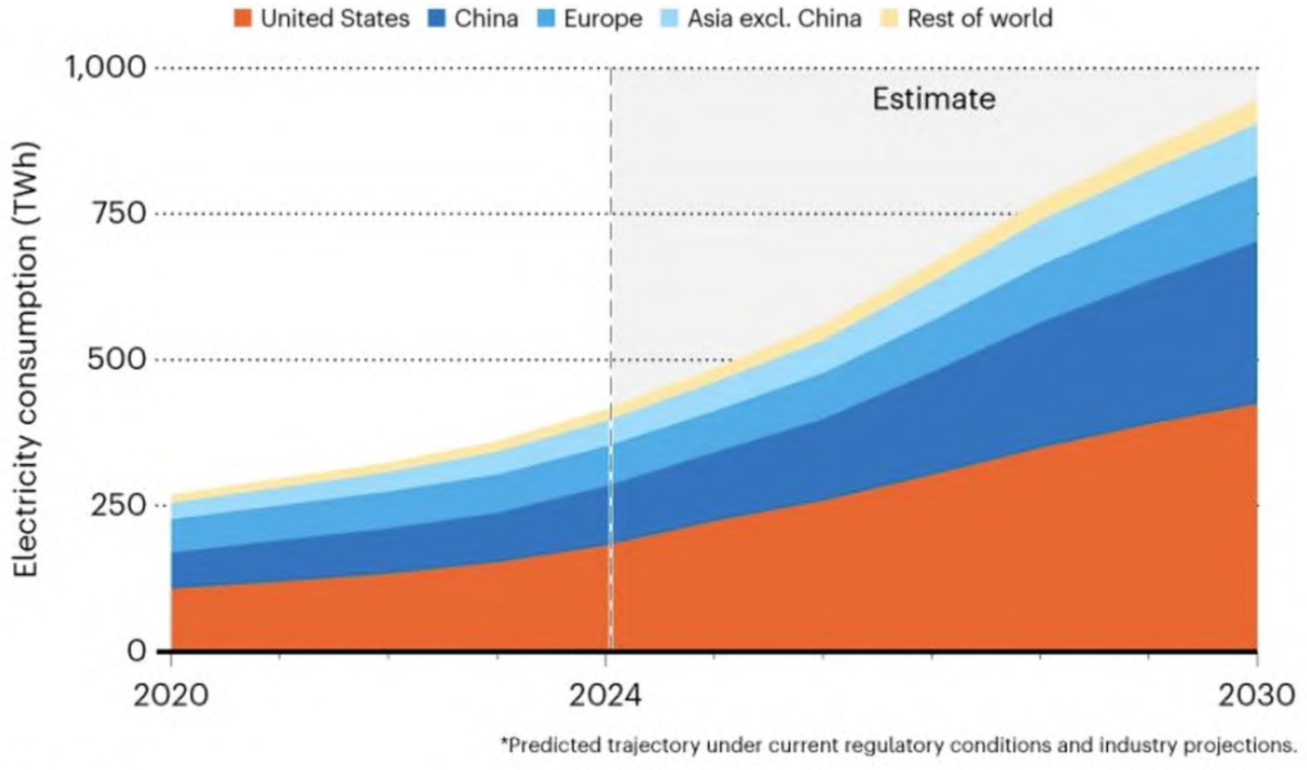
[*]Corresponding author e-mails: j.carter-gartside13@imperial.ac.uk, r.sapienza@imperial.ac.uk

The Challenge:
AI has a **huge** Energy and Data problem

AI Energy Use

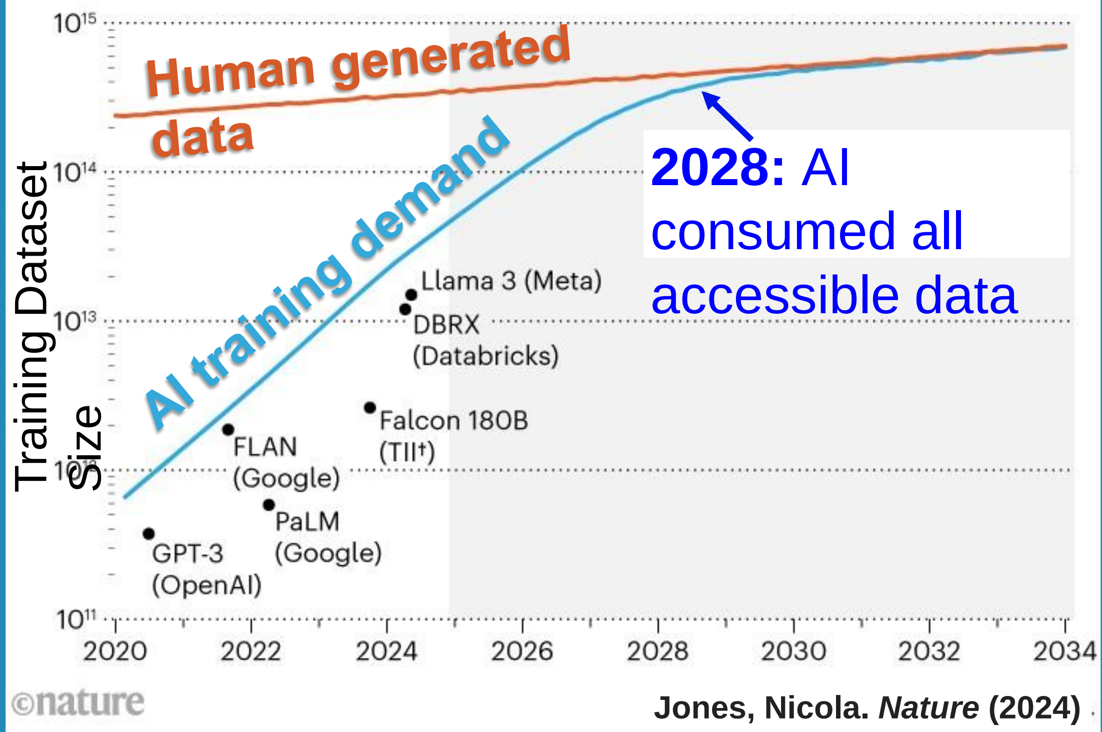
- Global AI energy use **doubles every 3.4 months**
- **500 TWh** increase by **2030**



Chen, Sophia. *Nature* (2025)

AI Training Data Demand

- We will **run out of AI training data** by **2028**



Jones, Nicola. *Nature* (2024)

The Challenge:
AI has a **huge Energy** and **Data** problem

- Root cause: **Hardware**

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- Root cause: **Hardware**
- **Biological Brains** consume just ~**20 W** & learn from **extremely few examples**

The Challenge:

AI has a **huge** **Energy** and **Data** problem

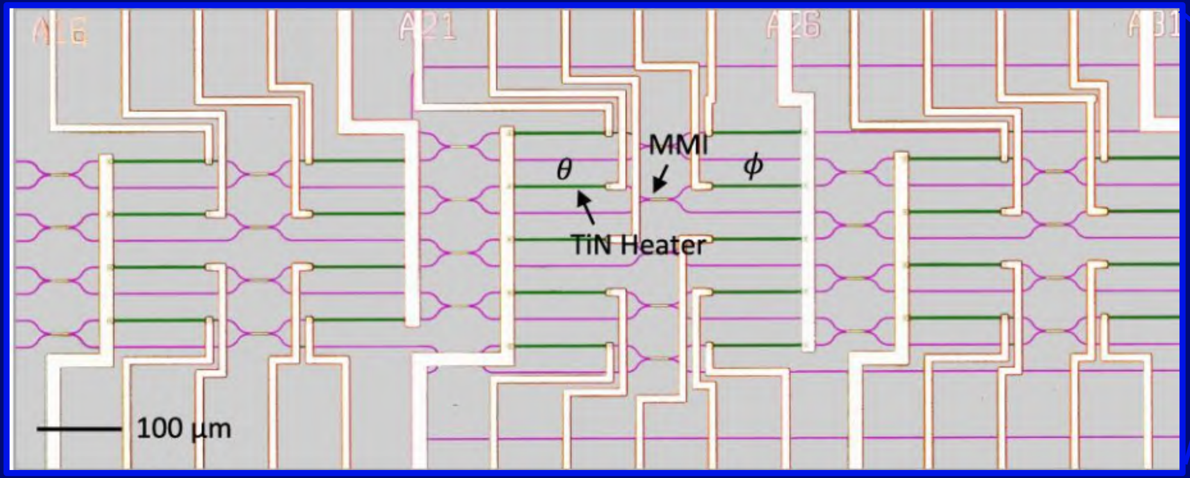
- Root cause: **Hardware**
- **Biological Brains** consume just ~**20 W** & learn from **extremely few examples**

Can we develop a **Brain-Like** Processor?

Neuromorphic Computing: Physics-based AI

- **Neuromorphic Computing:** Implement AI via **Physical Dynamics**
- Many physical systems have been explored
  - all with benefits & **challenges**
- Photonics: Highly promising, but **unsolved challenges**

Photonic Computing:
Excellent Speed & Bandwidth



But!

Large

Footprint: 4.8 mm^2 – only **8 neurons**

Zhang et al, Nature Comms (2022)

Linear

- Majority of schemes lack nonlinearity
- Usually artificially added in post-processing software

My Neuromorphic Refs:

Gartside, Jack C., et al. ***Nature Nanotechnology*** (2022)
Lee, Oscar, **Gartside, Jack C.,** et al. ***Nature Materials*** (2024)
Stenning, Kilian D., **Gartside, Jack C.,** et al. ***Nature Communications*** (2024)
Gartside, Jack C., et al. *Nature Nanotechnology* (2018)

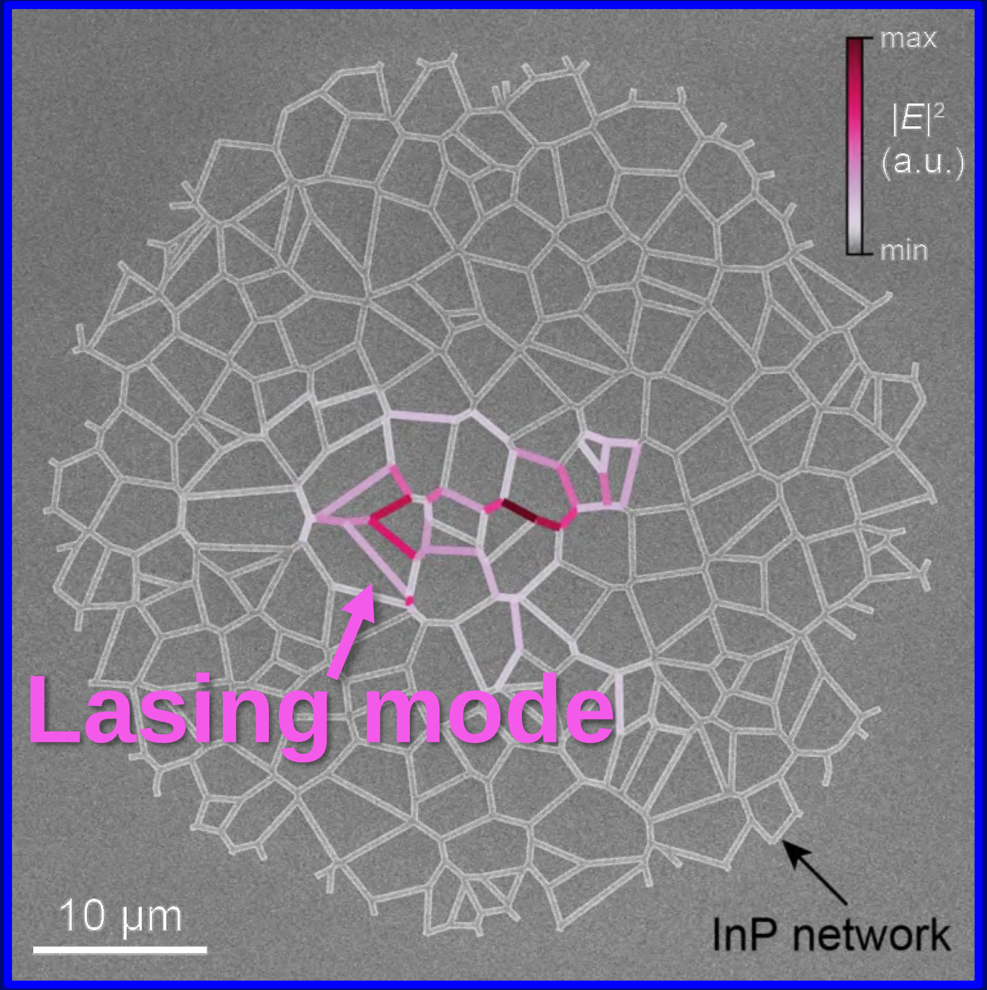
A Potential solution:

Explore **Random Network Lasers**

- **Disordered, nonlinear** photonic dynamics
- Previously **unexplored** for computing

Random Network Laser

Host huge number of nonlinear lasing modes as random walks



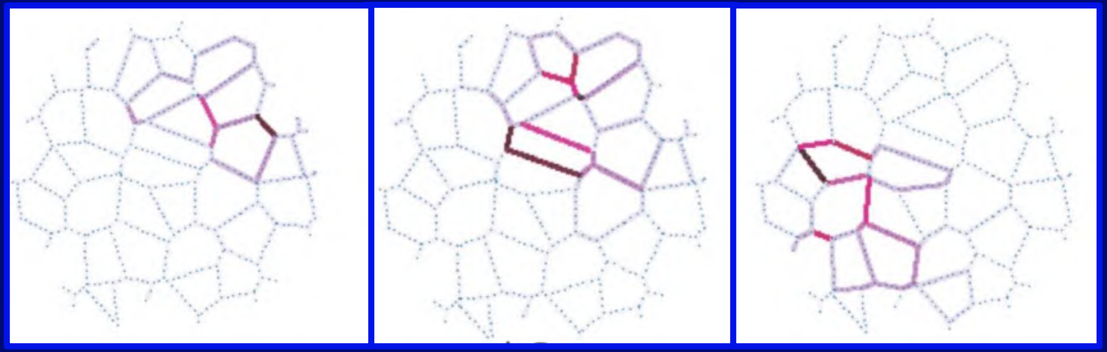
Fast & Efficient

ps timescale
10^{-10} s

nJ operation
10^{-8} J

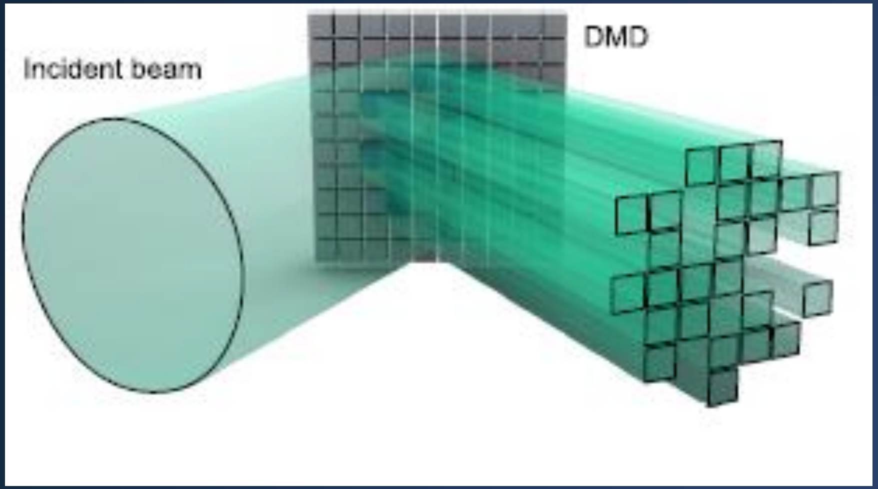
- **Small footprint ~50 µm**
- InP material
- **10^4 'Photonic neurons'**
  - $\times 10^6$ higher neuron density

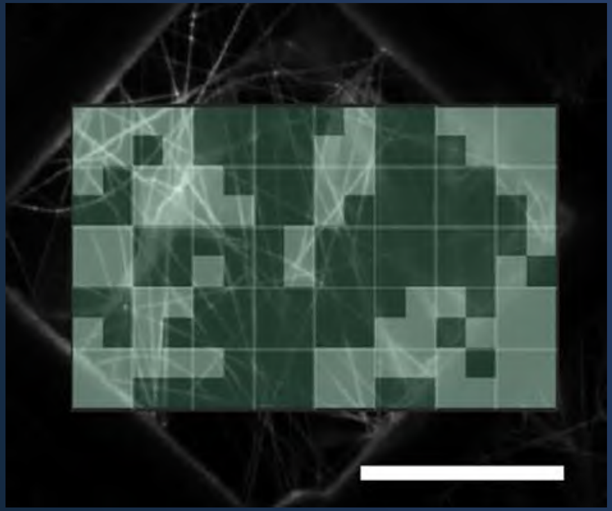
Mode shapes:

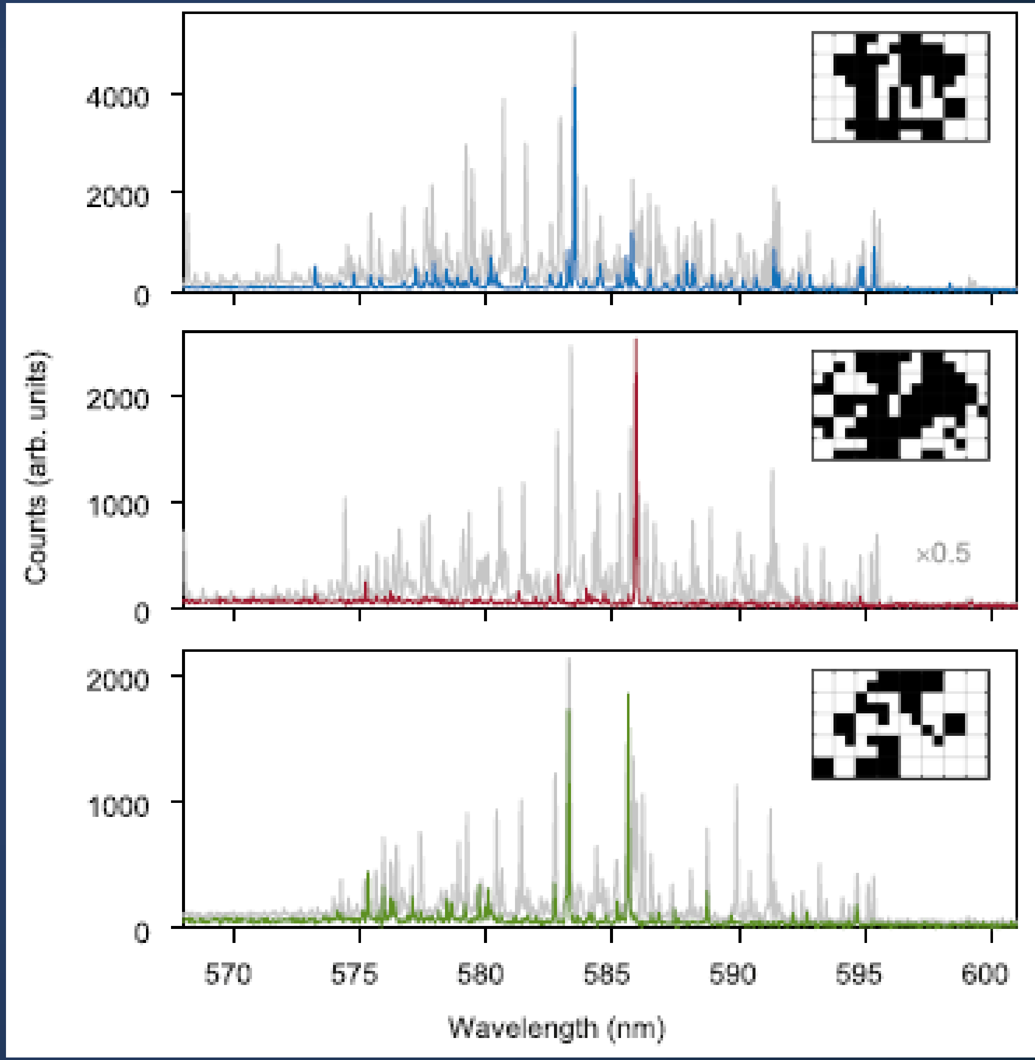


Random Network Lasers: Spatially-controlled input

Different lasing spectra in response to different input light patterns





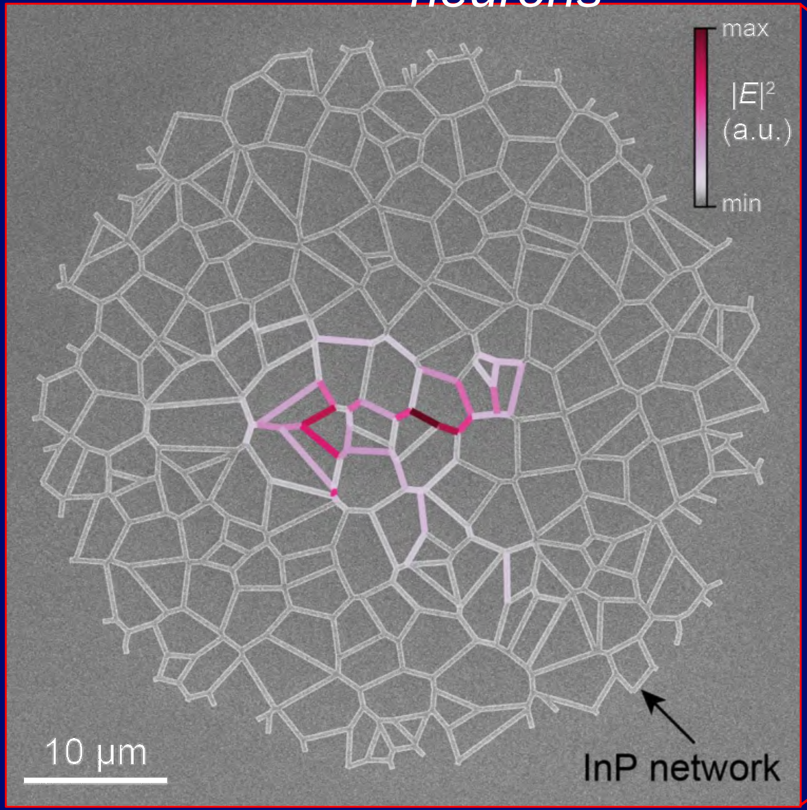


Saxena, D., Arnaudon, A., Cipolato, O., Gaio, M., Quentel, A., Yaliraki, S., ... & Sapienza, R. (2022). Sensitivity and spectral control of network lasers. **Nature Communications**, 13(1), 6493.

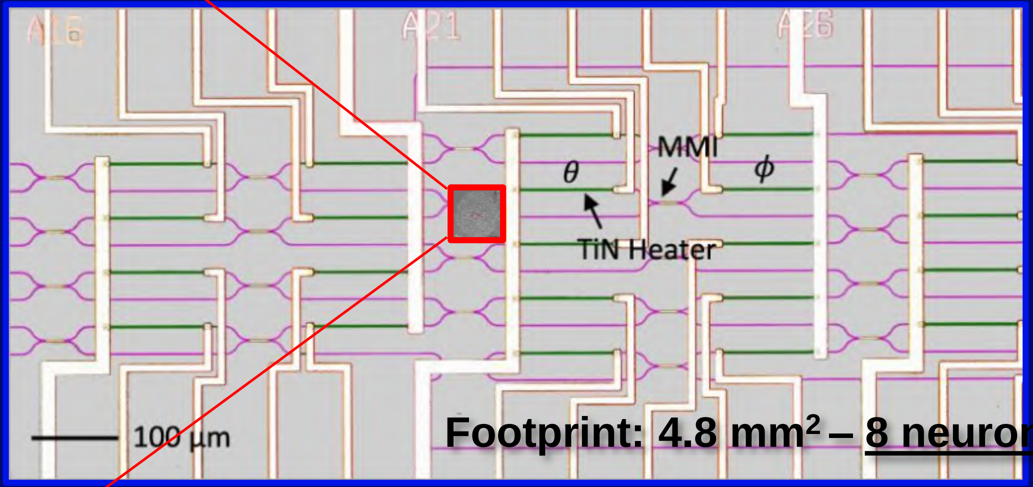
Random Network Laser

Small footprint ~50 μm

10^4 Lasing Modes = nolinear photonic neurons



Far smaller than existing photonic schemes



x2.4 million higher neuron density

Fast & Efficient

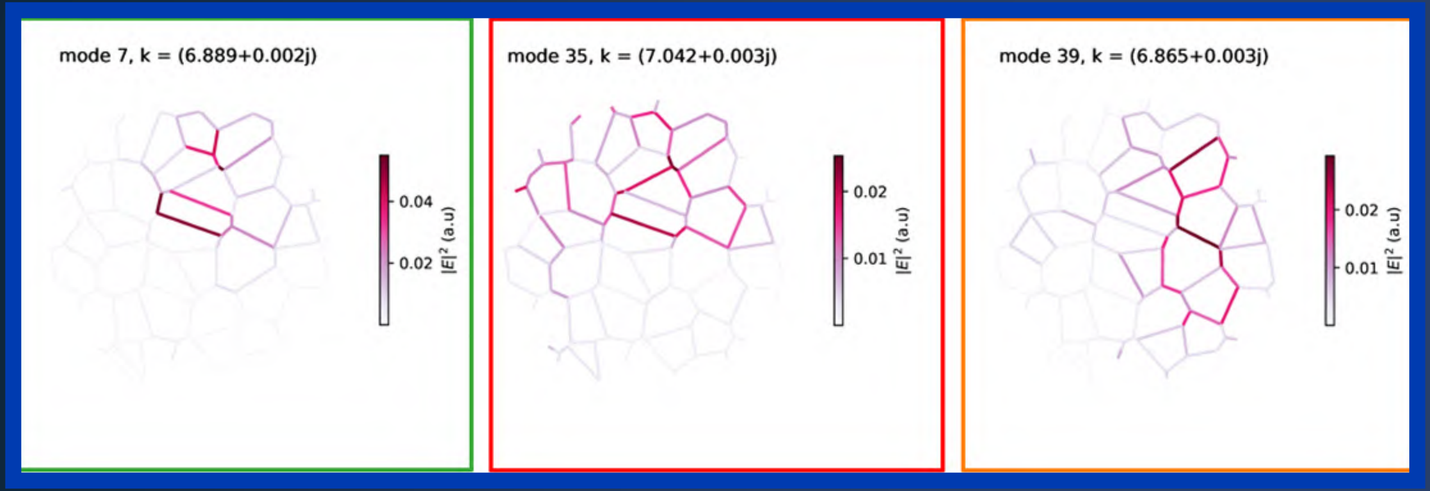
ps timescale
10^{-10} s

nJ operation
10^{-8} J

Random Network Lasers: Machine vision?

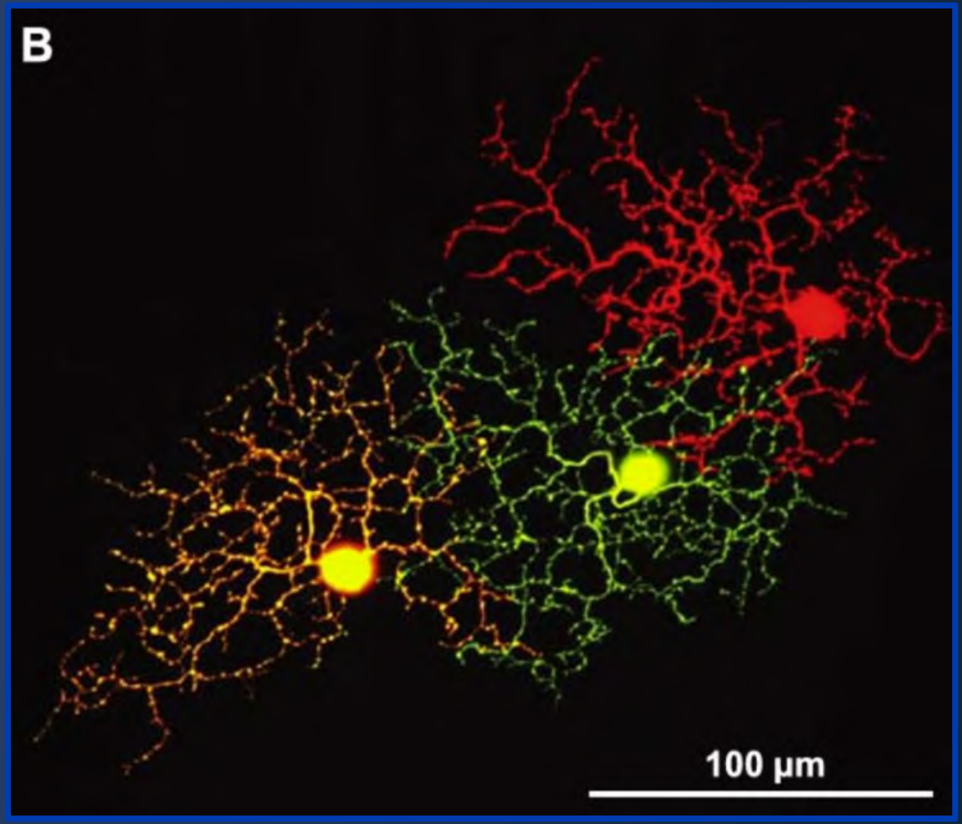
Can we use these systems for neuromorphic processing? Try simulations

Spatially-distributed overlapping modes: Mode competition



Mode A **Mode B** **Mode C**

Retinal Ganglion Cells: Lateral neuron inhibition



Is **lasing mode competition** similar enough to **retinal lateral inhibition** to achieve **neuromorphic image feature detection & machine vision**?

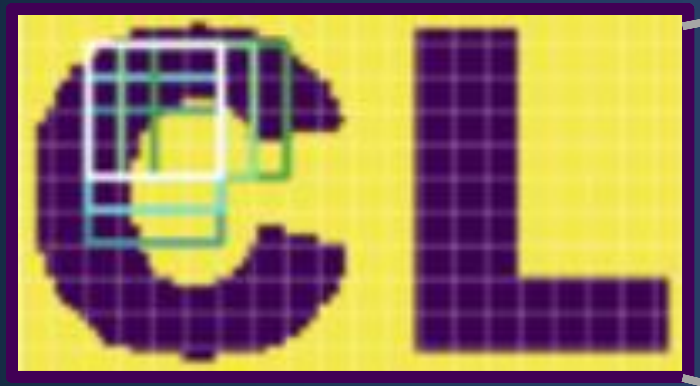
Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Van Wyk, Michiel, W. Rowland Taylor, and David I. Vaney. "Local edge detectors: a substrate for fine spatial vision at low temporal frequencies in rabbit retina." *Journal of Neuroscience* 26.51 (2006): 13250-13263.

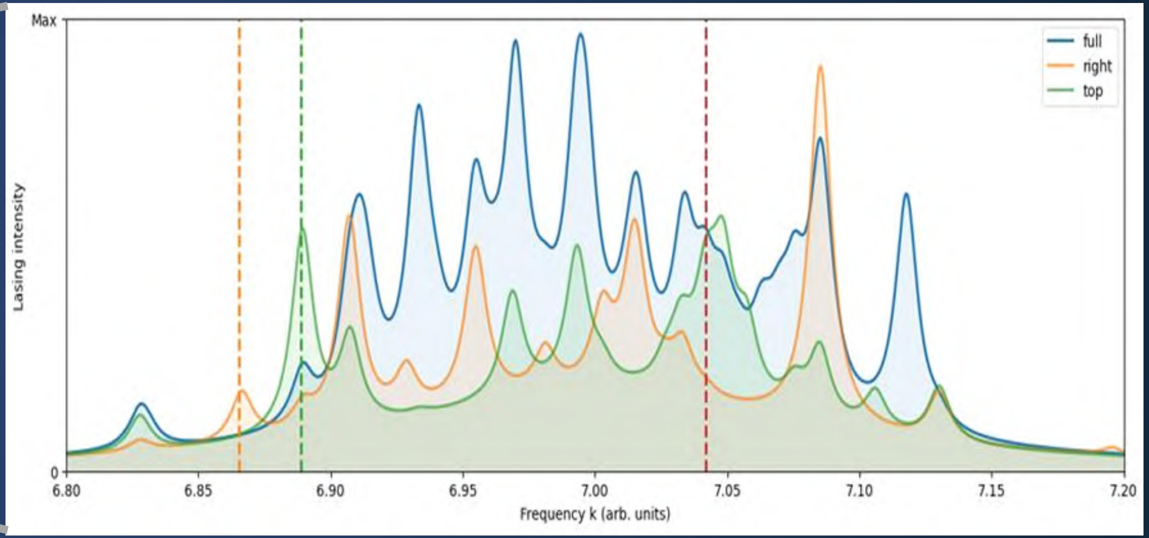
Random Network Lasers: Machine vision

Simulation: Image feature detection test

Raster scan image window across input image



Measure spectra for each position in scan



We can build **‘feature maps’** for each mode,
by plotting lasing amplitude at each pixel position in convolutional scan

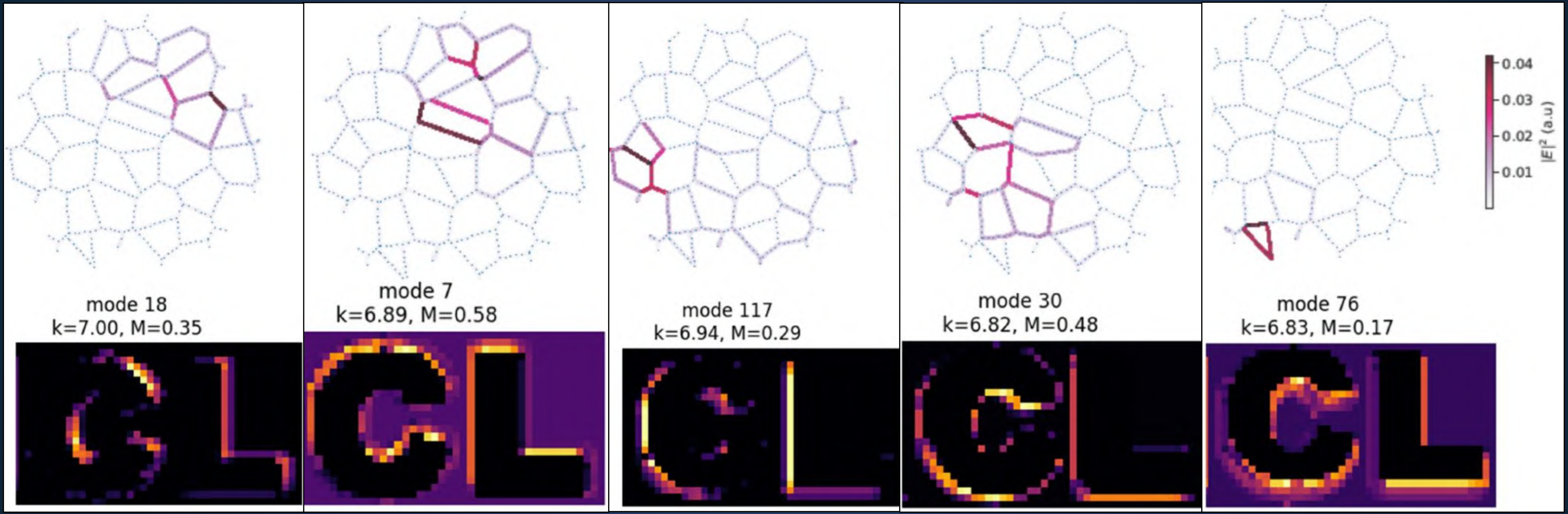
Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Jack C. Gartside, Imperial College London

Random Network Lasers: Machine vision

Modes act as convolutional kernels:

Spectrally-multiplexed parallel feature detection



Different mode wavelengths & spatial profiles detect different features

Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

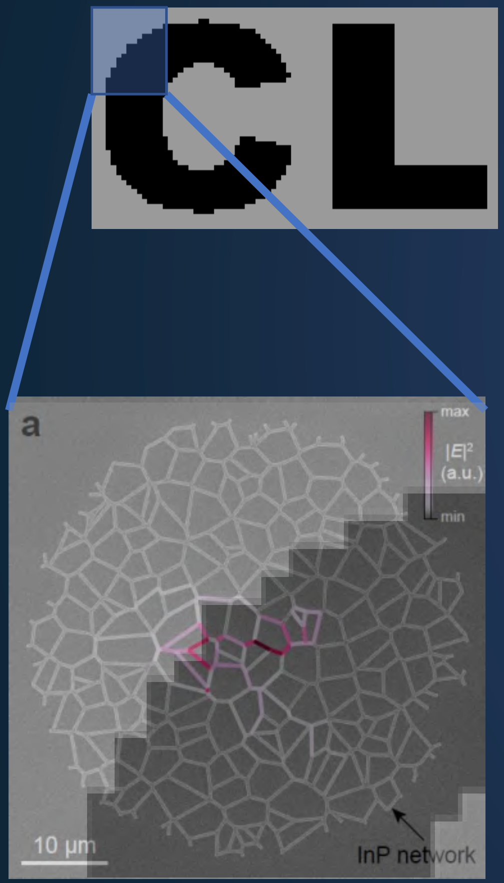
Random Network Lasers: Machine vision

Jack C. Gartside, Imperial College London

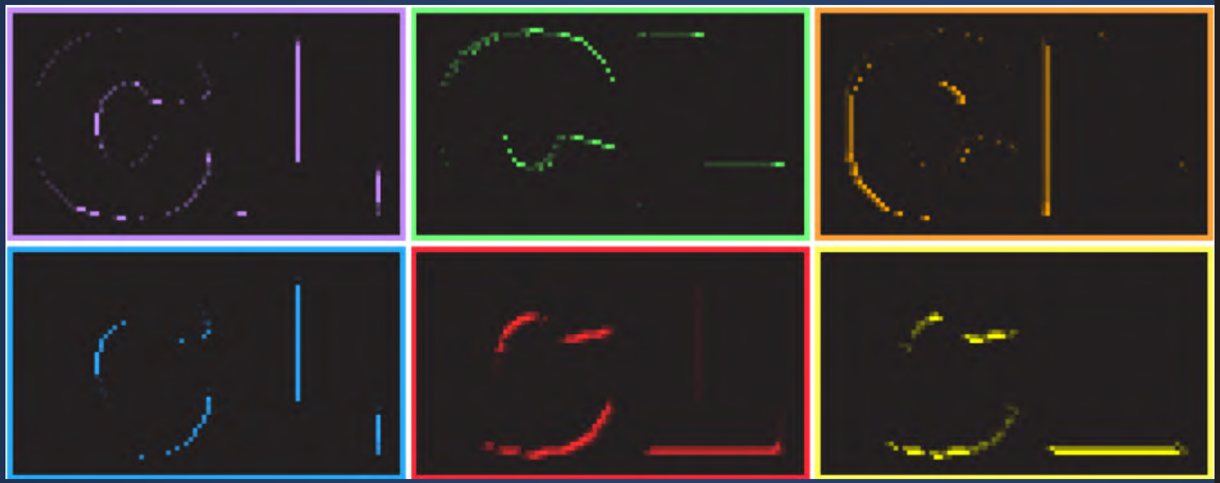
Does it work **Experimentally?**

Yes!

Raster scan image windows onto network/ via DMD



Single mode feature maps



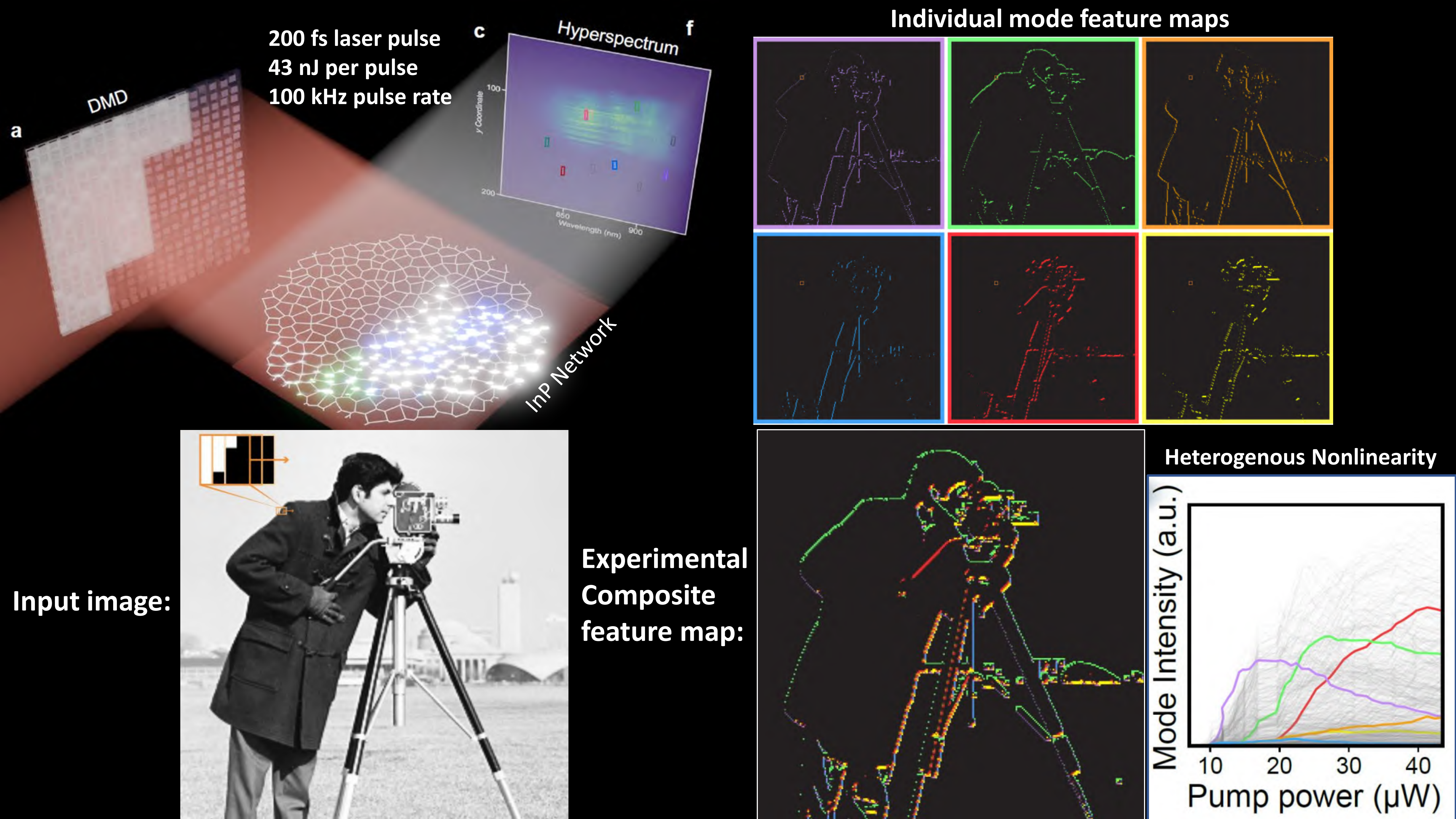
Composite feature map

Experimental **spectrally-multiplexed image convolution** works:

Each feature-map shown is the direct physical output of a spectral channel

PhD student **Jakub Dranczewski** key to feature detection

Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)



a
DMD
200 fs laser pulse
43 nJ per pulse
100 kHz pulse rate
c
Hyperspectrum
f
y Coordinate
100
200
850
900
Wavelength (nm)
InP Network
Individual mode feature maps
Input image:
Experimental
Composite
feature map:
Heterogenous Nonlinearity
Mode Intensity (a.u.)
10
20
30
40
Pump power (μW)

Random Network Lasers: Machine vision

Input image

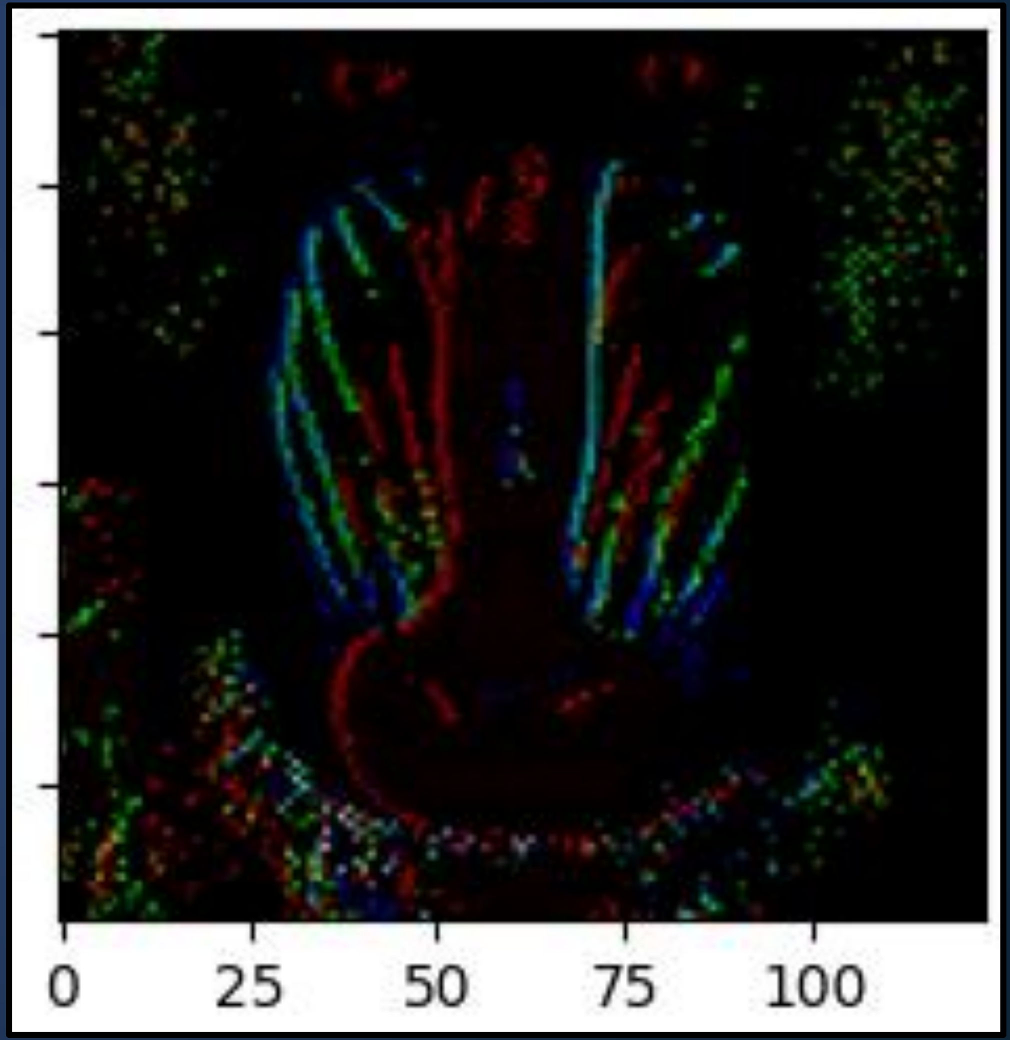
Composite mode feature map

Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Random Network Lasers: Machine vision

Input colour image

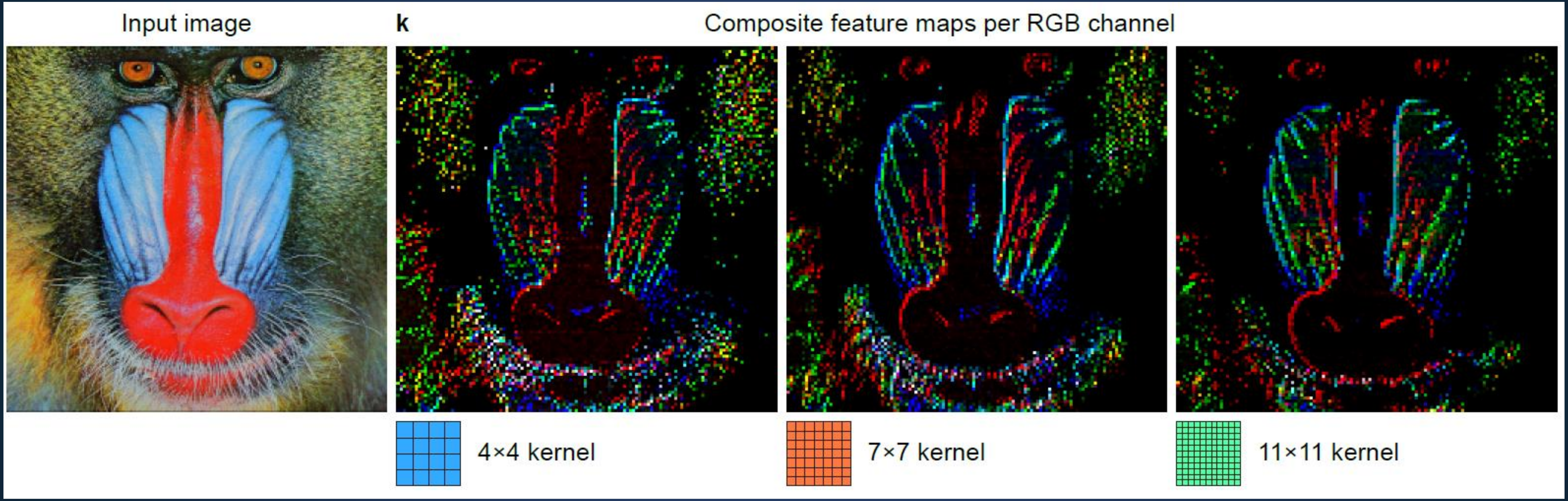
Photonic Network Feature Detection:



Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Random Network Lasers: Machine vision

Freedom of arbitrary kernel sizes:



Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

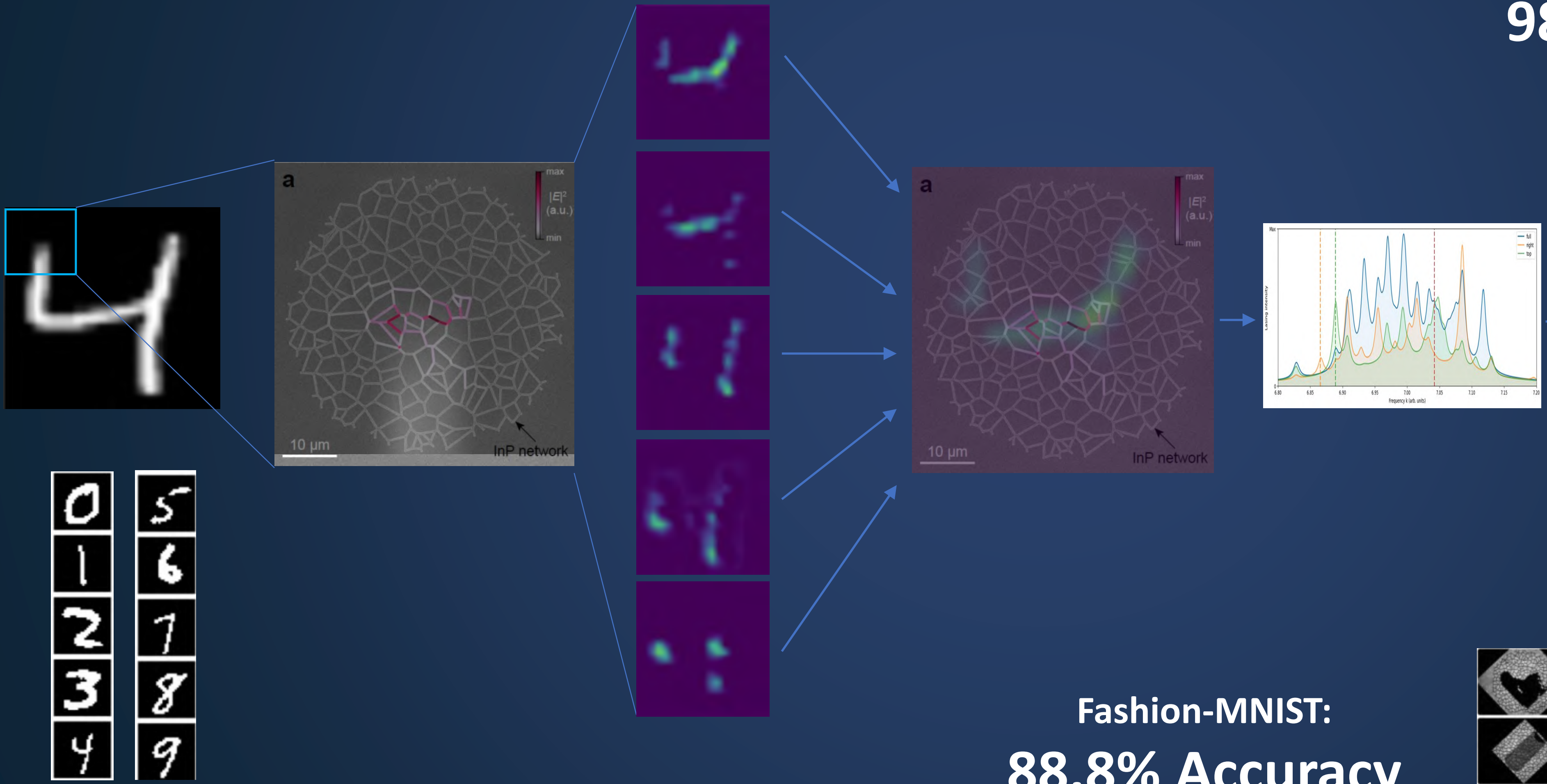
Neuromorphic image classification: 2 layer architecture

1: Raster scan to detect edges

2: Project full edge maps onto network

3: Single logistic regression step on output spectra provides classification

98.4% Accuracy

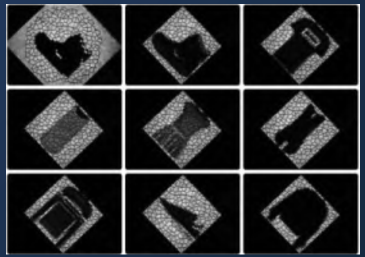


Test Accuracy Score: 0.984

Actual label \ Predicted label	0	1	2	3	4	5	6	7	8	9
0	0.990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000
1	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.010	0.990	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
5	0.000	0.000	0.024	0.012	0.000	0.953	0.000	0.000	0.012	0.000
6	0.000	0.000	0.000	0.000	0.010	0.010	0.979	0.000	0.000	0.000
7	0.000	0.000	0.000	0.009	0.000	0.009	0.000	0.962	0.000	0.019
8	0.000	0.000	0.000	0.000	0.000	0.012	0.012	0.000	0.976	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.012	0.976

Fashion-MNIST:

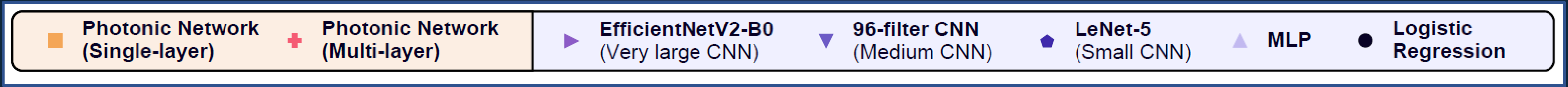
88.8% Accuracy



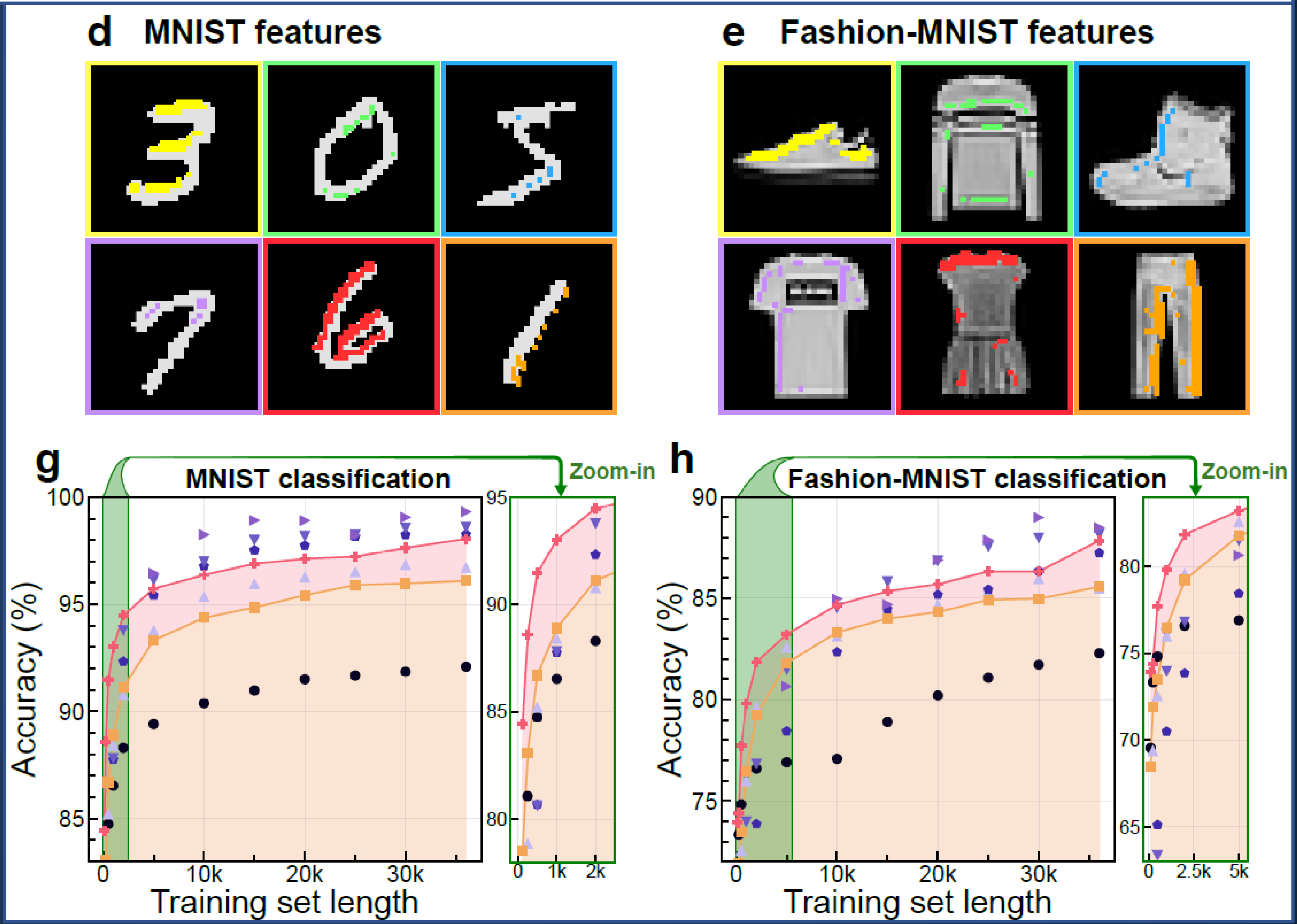
Retinomorphic Machine Vision in a Network Laser, *under review*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Random Network Lasers: Image classification

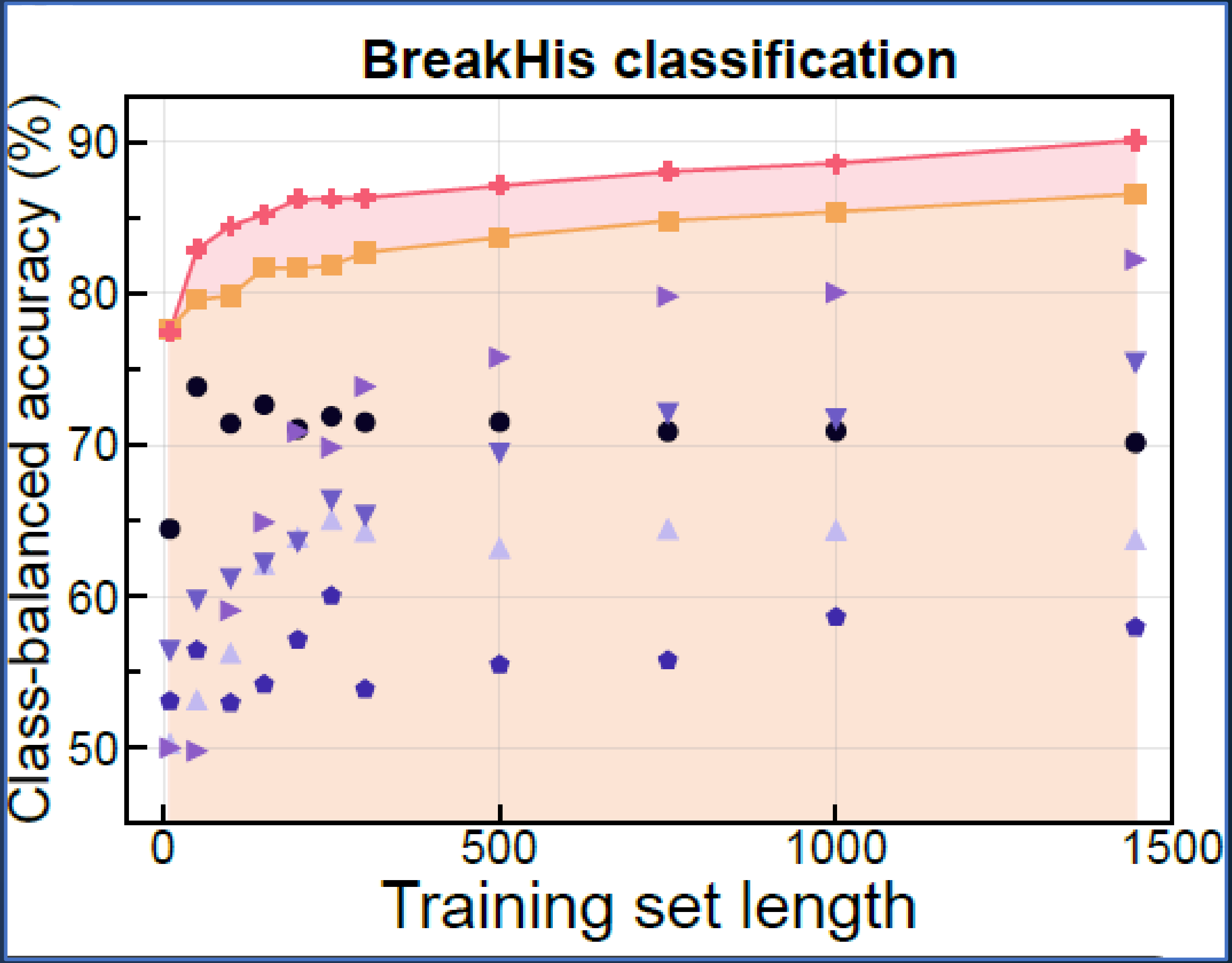
Jack C. Gartside, Imperial College London



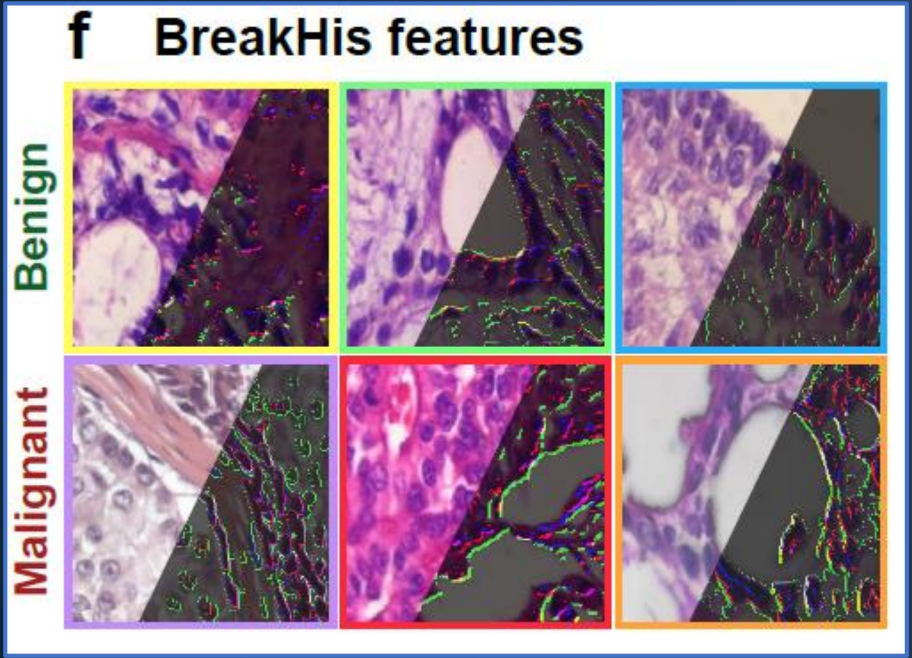
- **Excellent** Few-Shot/ Limited Data performance
- **Beat large modern CNNs** below 5k training examples
- Including 'EfficientNetV2' **(7.9 million parameters)**



Random Network Lasers: Image classification



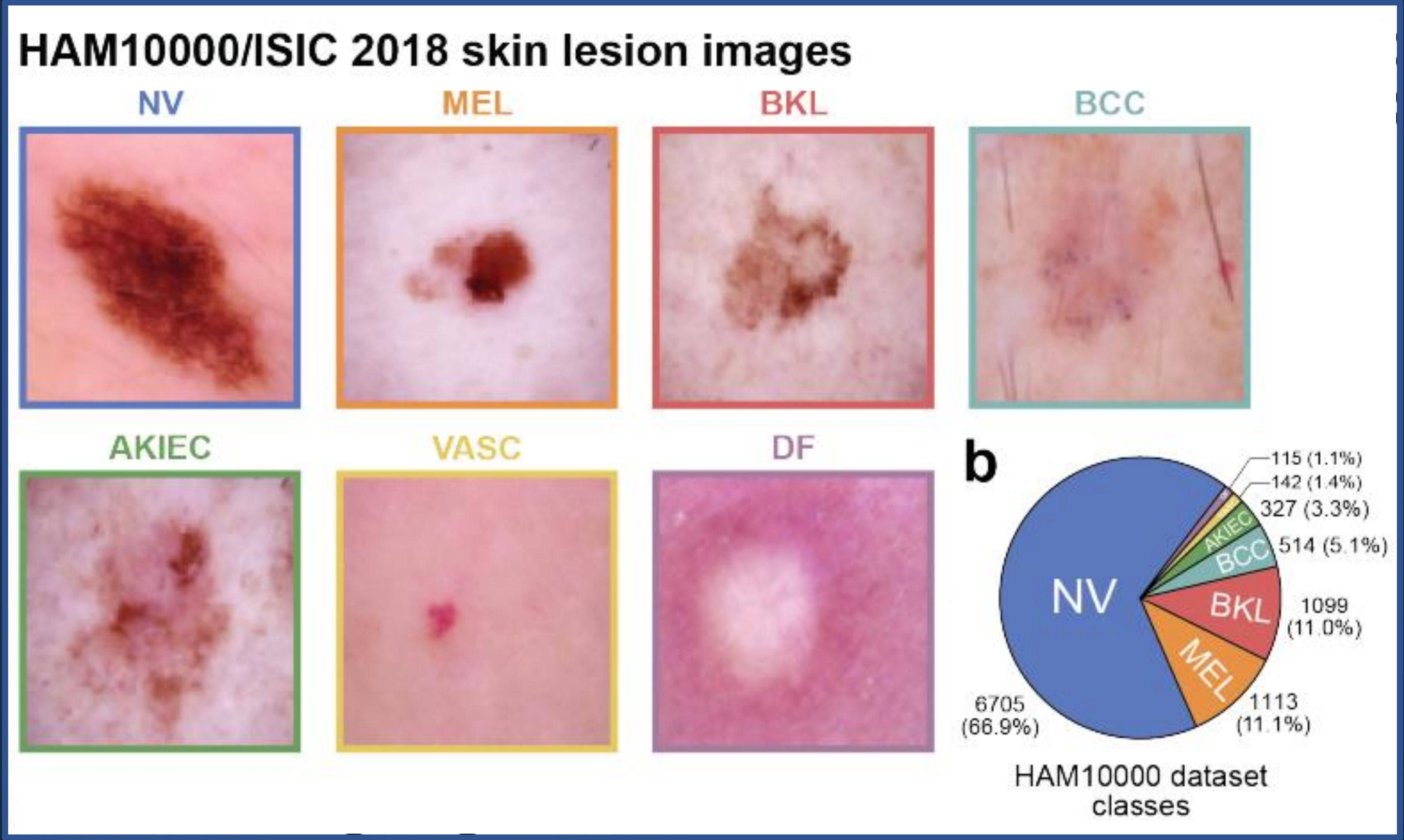
- Try **hard, data scarce** task:
- BreaKHis breast cancer diagnosis
- Our network outperforms all software benchmarks



Random Network Lasers: Image classification

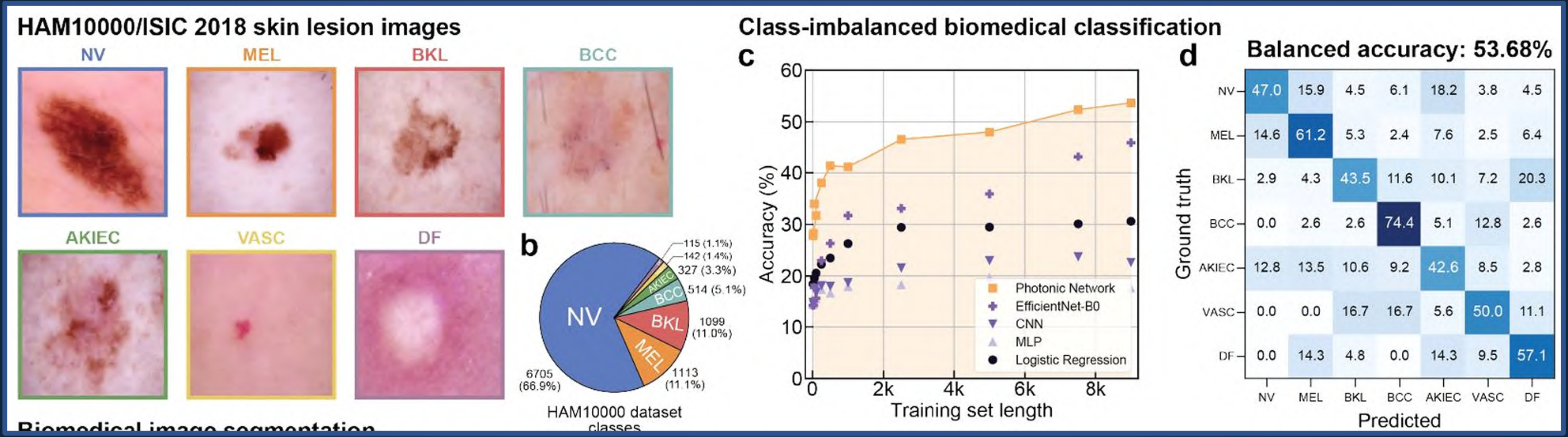
Jack C. Gartside, Imperial College London

- Is it a one-off? Glitch?
- Try even harder task: 7 class skin cancer diagnosis. Heavily **imbalanced**



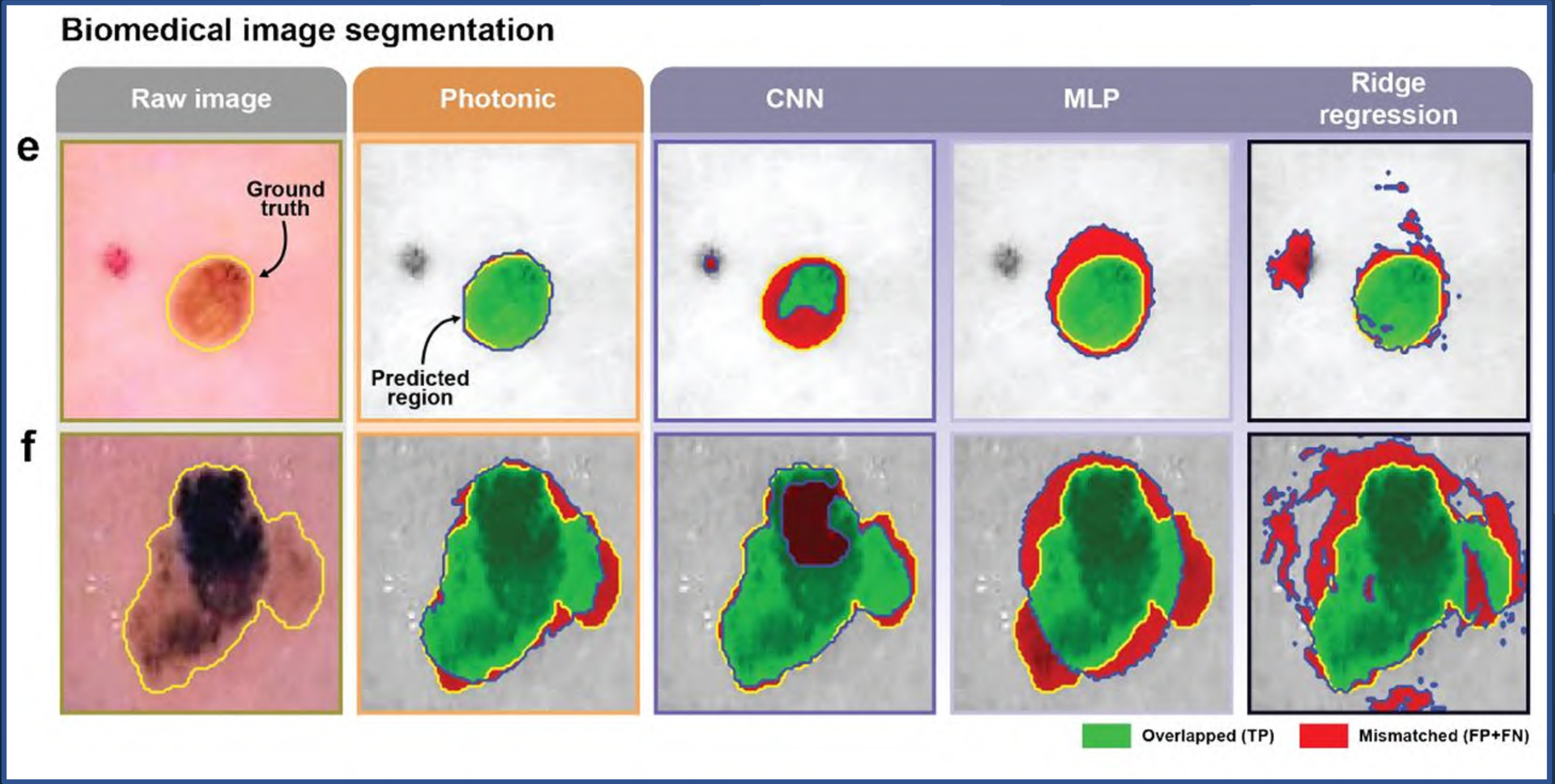
Random Network Lasers: Image classification

- Photonic network outperforms all considered software benchmarks
- 4-6 mins to train, including experiments – vs 16 hrs for EfficientNetV2



Random Network Lasers: Image classification

- How about spatial processing?
- Perform **Segmentation** (spatial location) of tumours
- Again, outperform software benchmarks considered



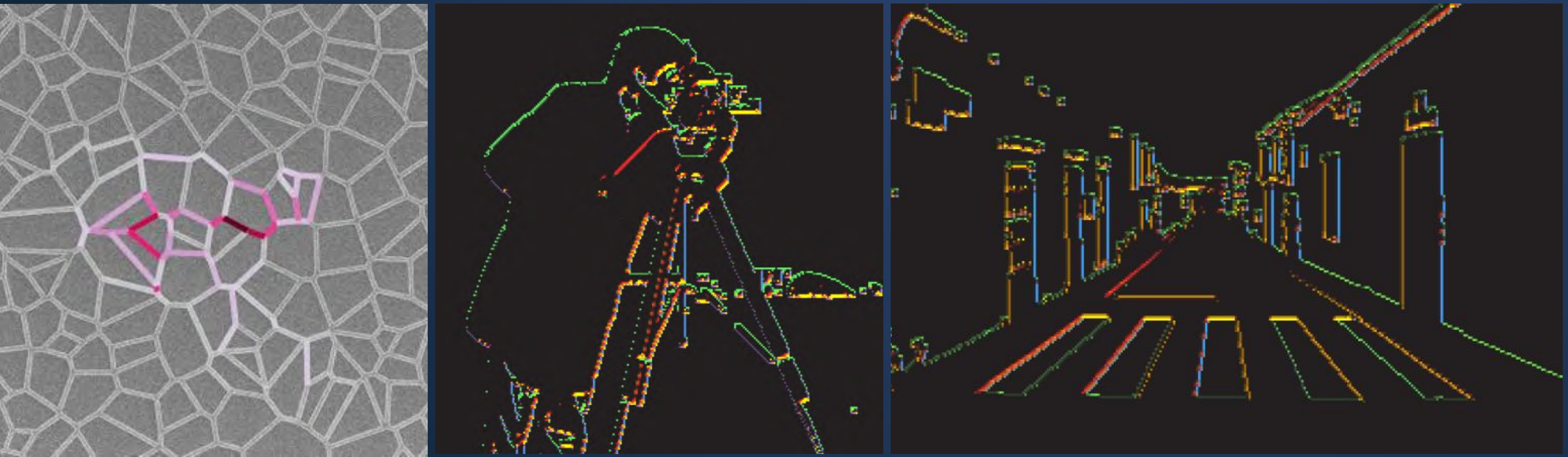
g

	Models \ Metrics	Dice	Jaccard	Pixel accuracy
Software	Ridge regression	79.4%	68.3%	85.9%
Software	MLP	79.9%	68.3%	86.8%
Software	CNN	62.1%	50.6%	80.8%
Hardware	Photonic network	84.5%	74.8%	88.4%

Jack C. Gartside, Imperial College London

Conclusions

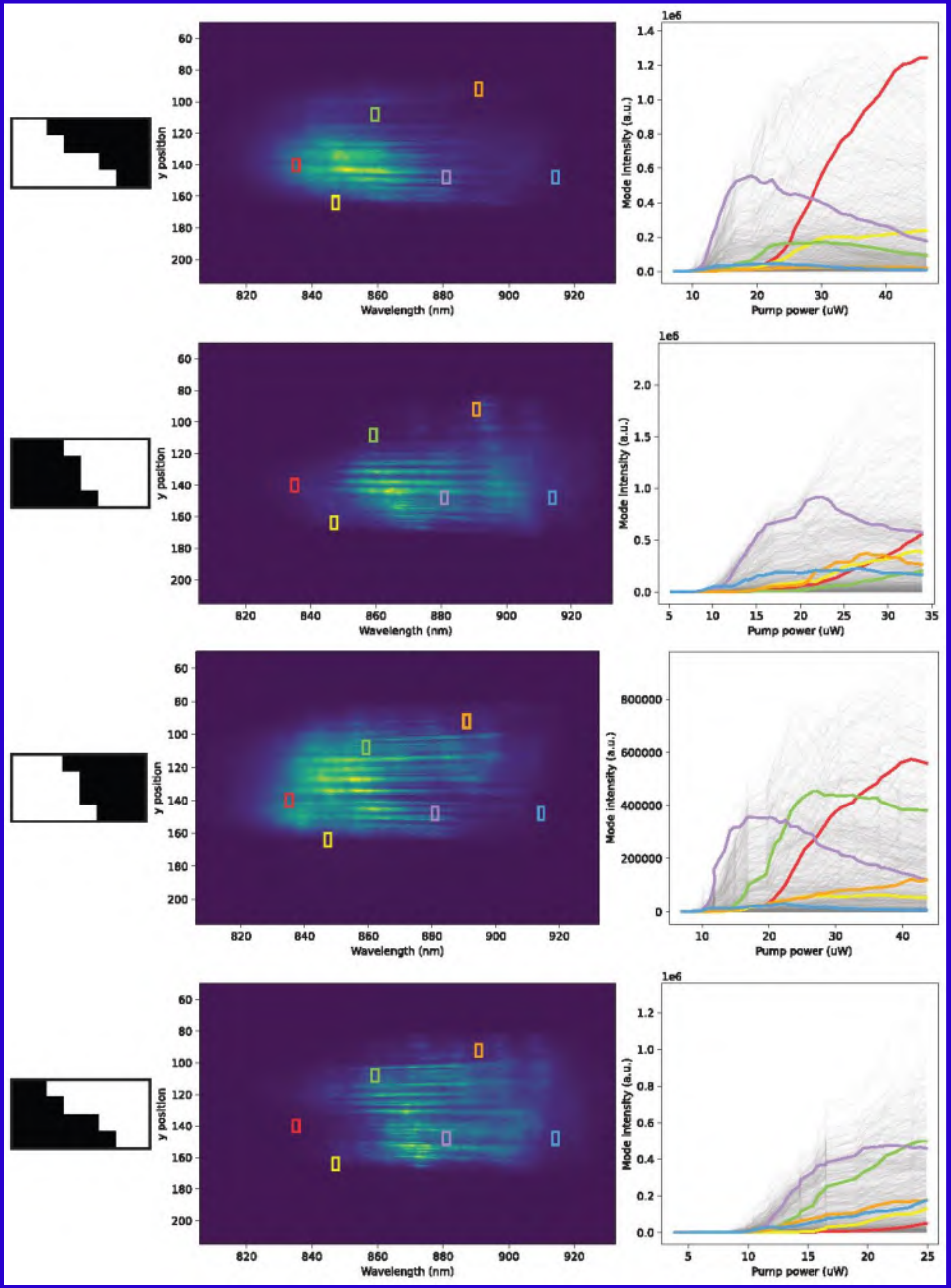
- Evaluated **random network lasers** as a neuromorphic platform
- Highly nonlinear & compact (100 um)
- Photonic analogue of **retinal neuron 'lateral inhibition'** functionali**ty**
- Very strong **few-shot learning**
- We are now **reconfigurably training & programming** network weights
- **Challenges:**
  - Operational speed – currently 100 Hz, 1 kHz relatively easy, DMD limited to 10 kHz
  - Pulsed laser unattractive – exploring on-chip light sources, VCSELs
  - Which algorithms are best suited to the nonlinear dynamics?
- **Thanks & any questions!**



Spintronic metamaterial/computing:

- **Gartside, Jack C.,** et al. "Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting." **Nature Nanotechnology (2022)**
- Lee, Oscar, **Gartside Jack C.** et al. "Task-adaptive physical reservoir computing." **Nature Materials** (2024)
- Dion, Troy, **Gartside Jack C.** et al. "Ultrastrong magnon-magnon coupling and chiral spin-texture control in a dipolar 3D multilayered artificial spin-vortex ice." **Nature Communications** (2024)
- Stenning, Kilian D., **Gartside Jack C.** et al. "Neuromorphic few-shot learning: generalization in multilayer physical neural networks." **Nature Communications**(2024).

Few-Shot Learning Performance? Neuromorphic Neuronal



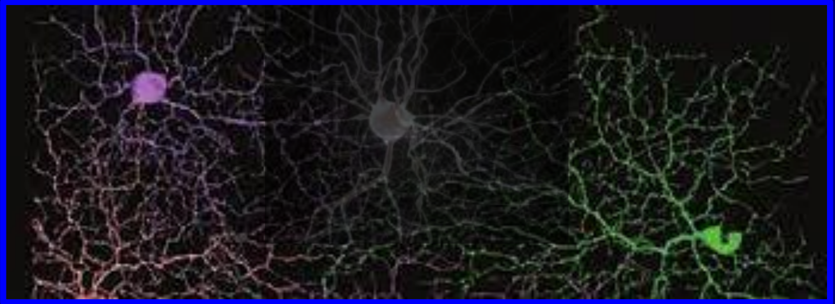
ARTICLE

https://doi.org/10.1038/s41467-021-26022-3 OPEN

nature COMMUNICATIONS

Neural heterogeneity promotes robust learning

Nicolas Perez-Nieves [1], Vincent C. H. Leung [1], Pier Luigi Dragotti [1] & Dan F. M. Goodman [1]



Demystification of Few-shot and One-shot Learning

1st Ivan Y. Tyukin, School of Mathematics and Actuarial Science, University of Leicester

2nd Alexander N. Gorban, School of Mathematics and Actuarial Science, University of Leicester

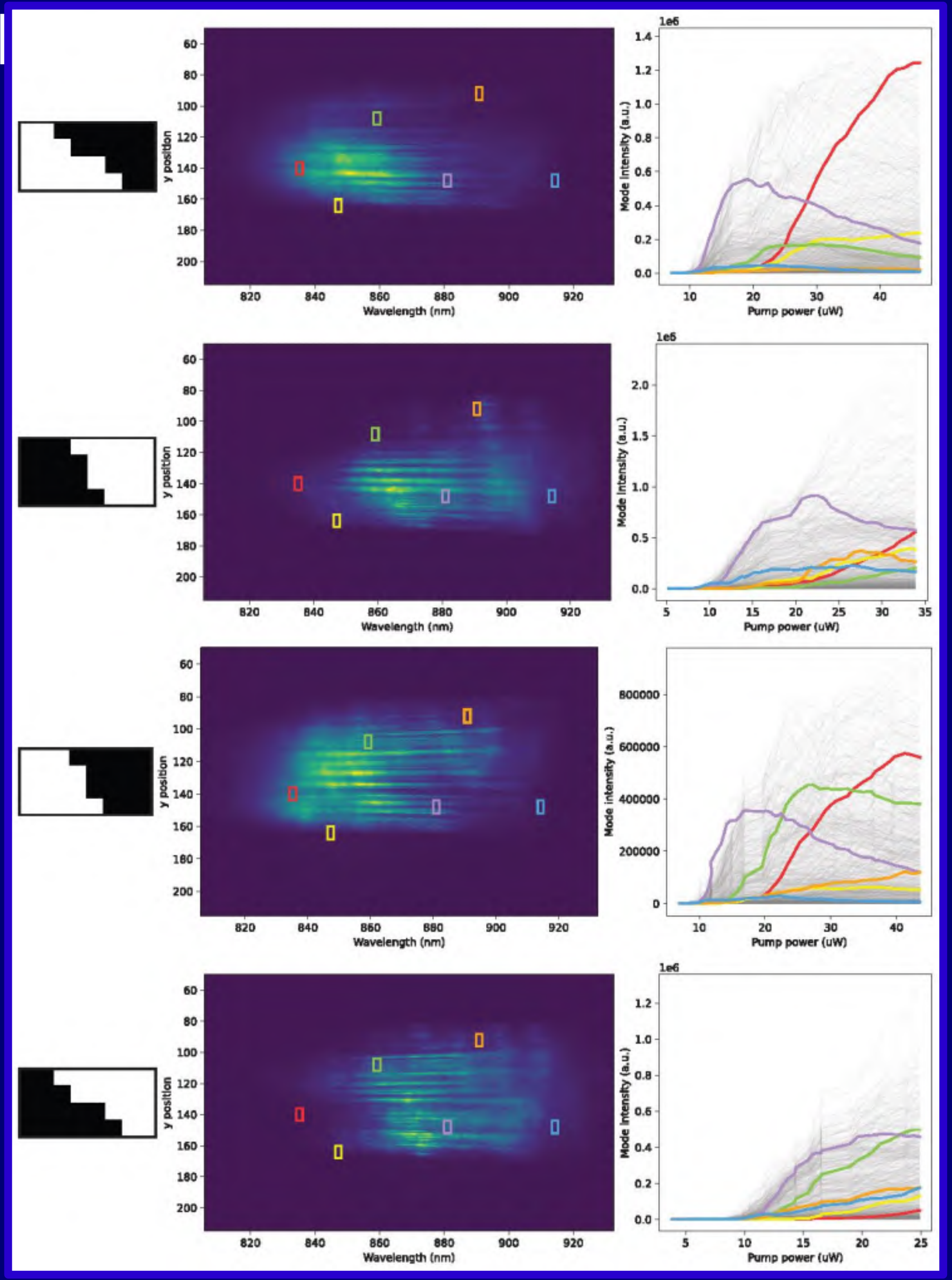
3rd Muhammad H. Alkhudaydi, School of Mathematics and Actuarial Science, University of Leicester

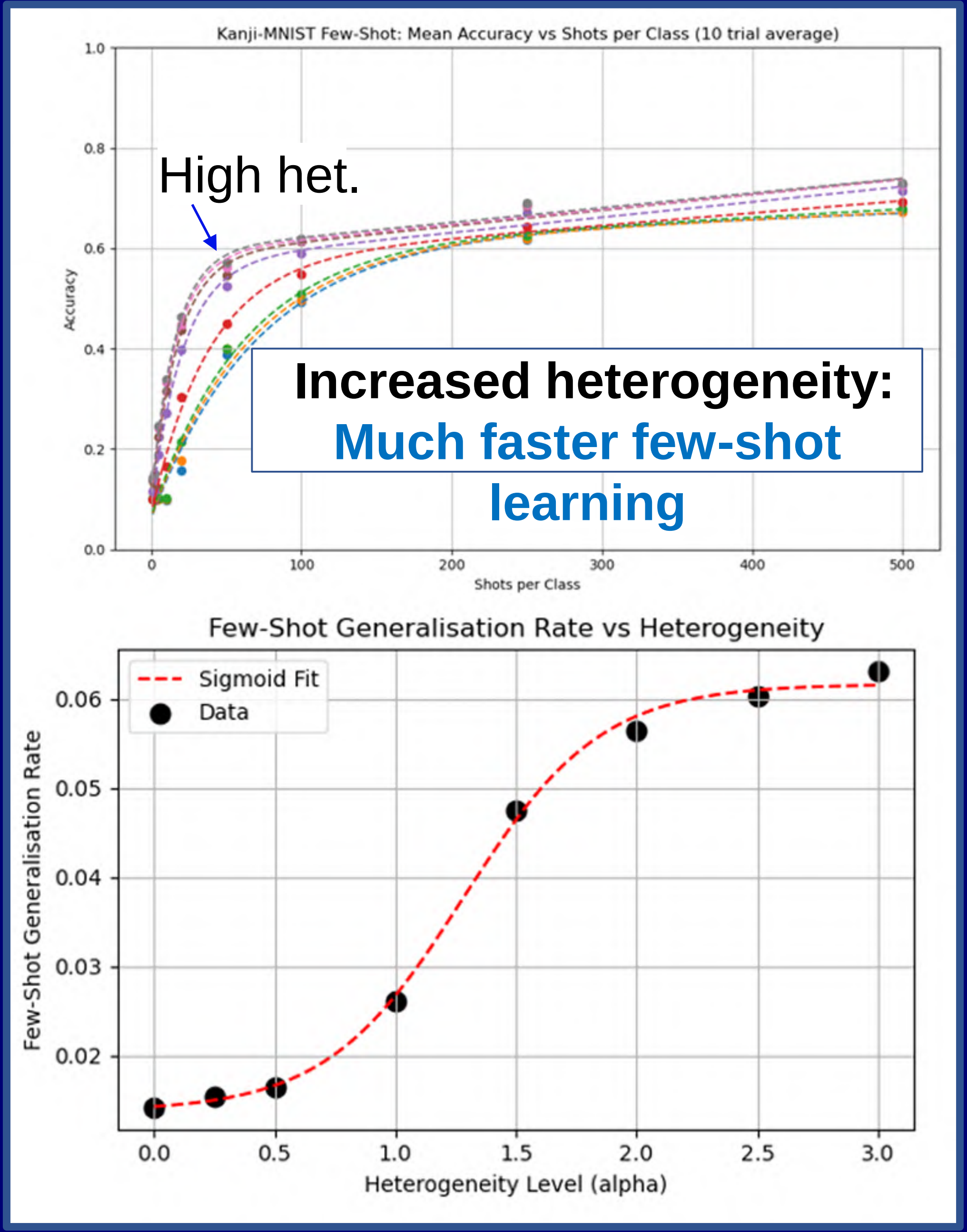
4th Qinghua Zhou, School of Informatics, University of Leicester

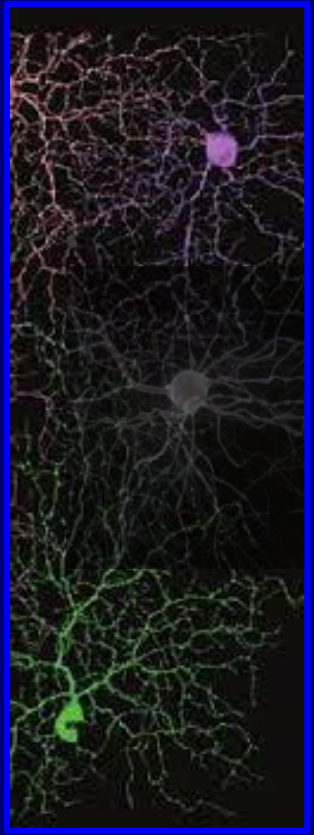
*“if a learning machine is **sufficiently high-dimensional**, then a large class of objects can indeed be **easily learned from few examples**”*

Tyukin, Ivan Y., et al *2021 Demystication of Few Shot & One Shot Learning* IEEE

Few-Shot Learning Performance? Neuromorphic Neuronal







Energy consumption & Software comparison

BreakHis 400x Breast Cancer diagnosis

Training Time:
Photonic network = 4-6 mins (inc. experiment)
ResNet50 = 16 hours

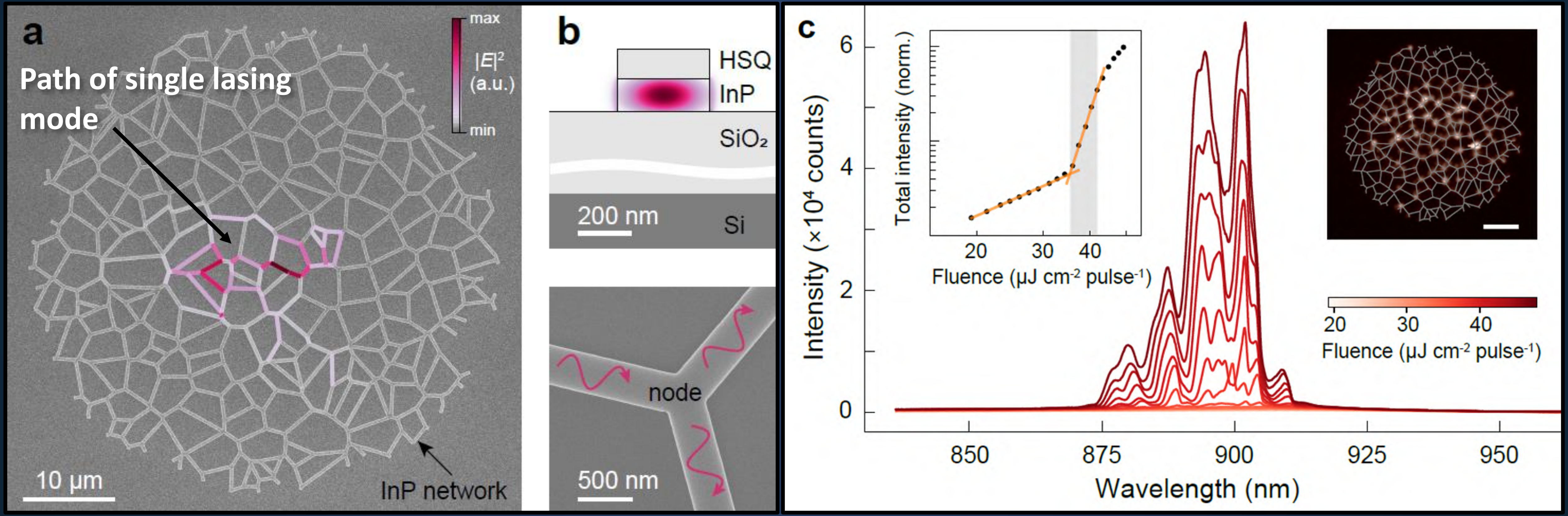
Model	Pretraining	Epochs	Total Training Energy
Photonic network (idealized physics)	–	1	0.324 J
Photonic network (44.35 W wall plug**)**	–	1	12,100 J
EfficientNetB0 (from scratch)	No	40	170.3 J
EfficientNetB0 (pretrained + FT)	Yes	40	**1,970,170.3 J**
ResNet-50 (from scratch)	No	40	1,793.3 J
ResNet-50 (pretrained + FT)	Yes	40	**4,501,793.3 J**
EfficientNet w/20x augmentation	No	40	**3406 J**
ResNet-50 (from scratch)	No	40	**35,866 J**

Inference Energy

Model	Inference Energy per Image
Photonic network (idealized physics)	**12.12 μJ**
Photonic network (44.35 W wall plug**)**	**1.34 J**
EfficientNetB0	158 mJ
ResNet-50	1.66 J

Random Network Lasers: Patterned semiconductor graph (**InP**)

- **Optically pump** to generate photons in InP waveguides
- **Random walks** of light through the network **host lasing mode**
- Leads to **100s – 10,000s** of **strongly-coupled lasing modes** in **um-scale device**

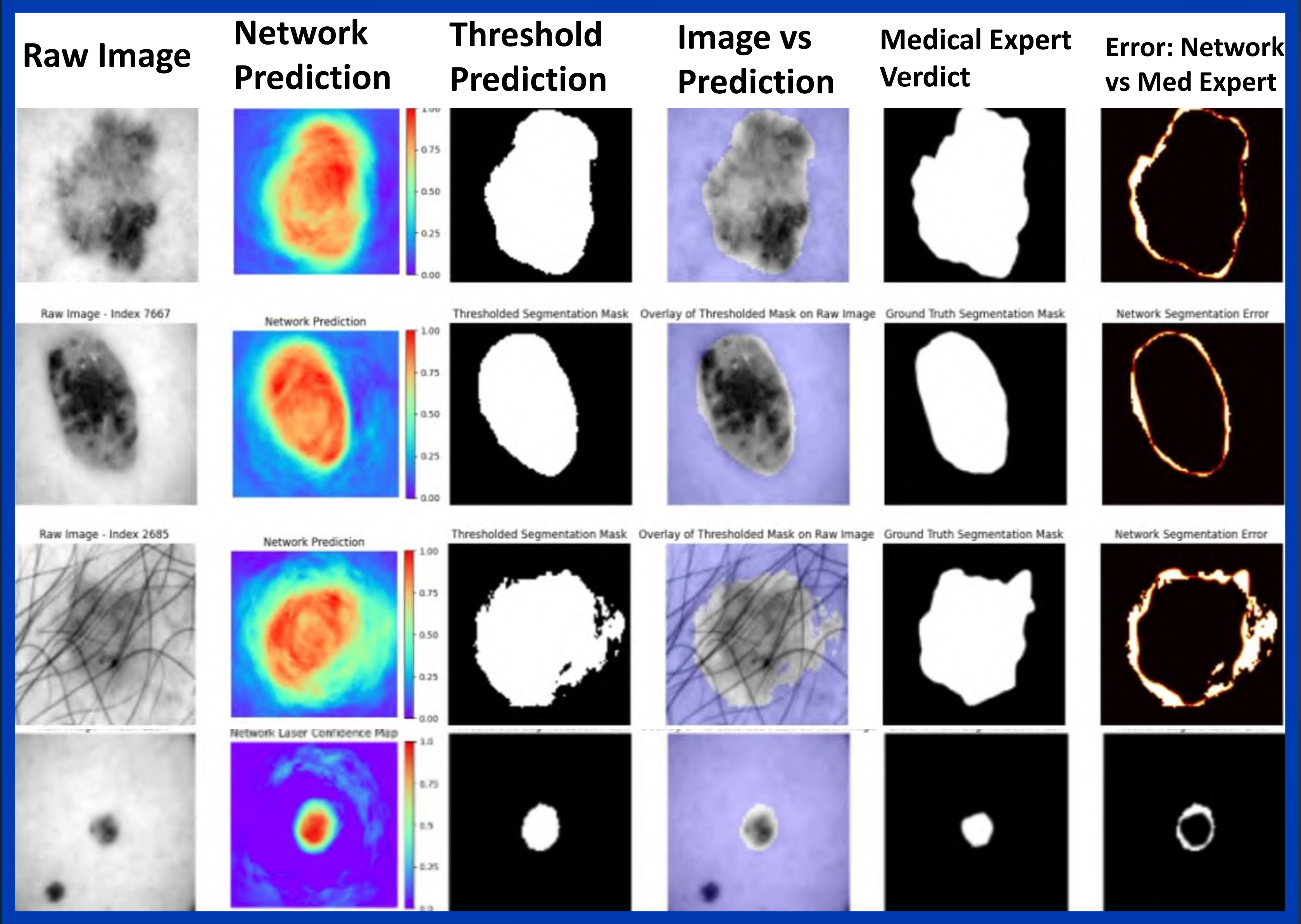


Fine control over graph topology, compatible with **industrial chip fab**

Jack C. Gartside, Imperial College London

Neuromorphic vision for **health & medicine:**

Diagnose, Classify & Spatially Locate Cancer Tumours

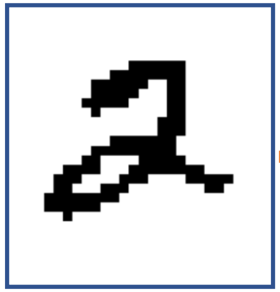


Jack C. Gartside, Imperial College London

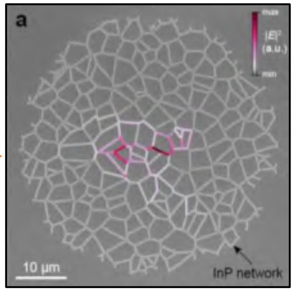
Training photonic dynamics for direct image recognition

Top row: No dynamic training.

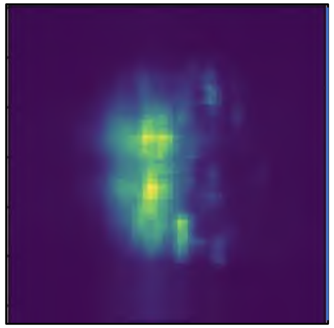
Image input



InP Network



Hyperspectral output



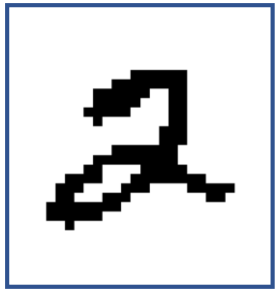
Spatial

Wavelength

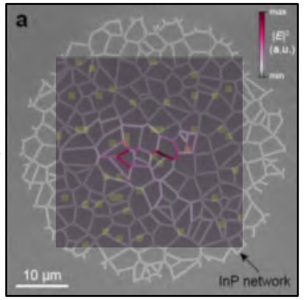
Bottom row:

Trained dynamics via local pumping

Image input

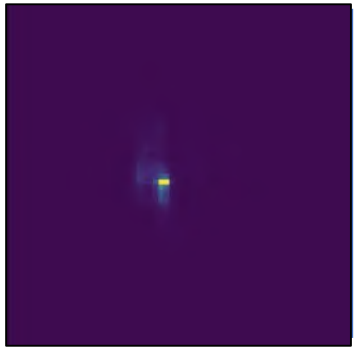


InP Network with
local index variations



Optical index increased
in yellow regions

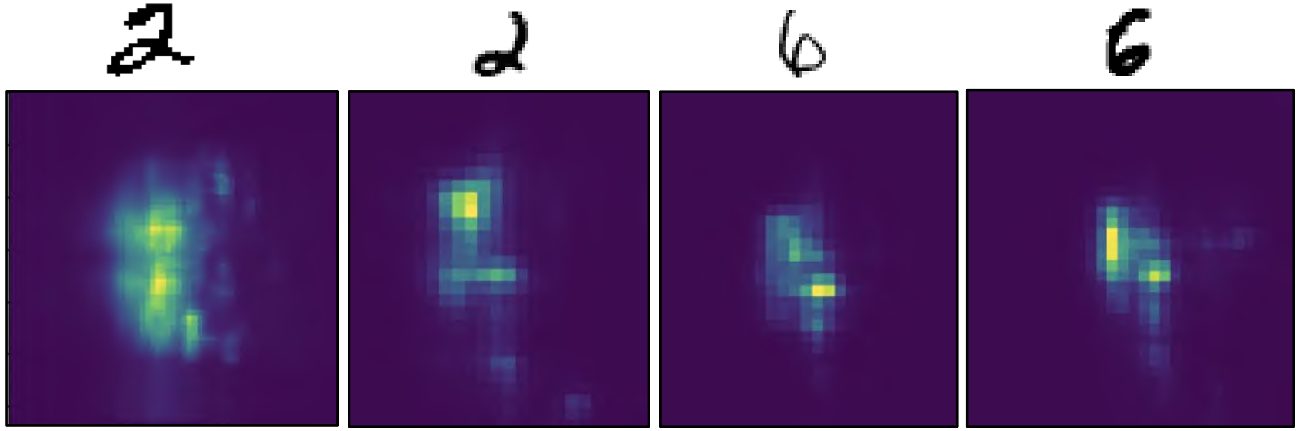
Hyperspectral output



Spatial

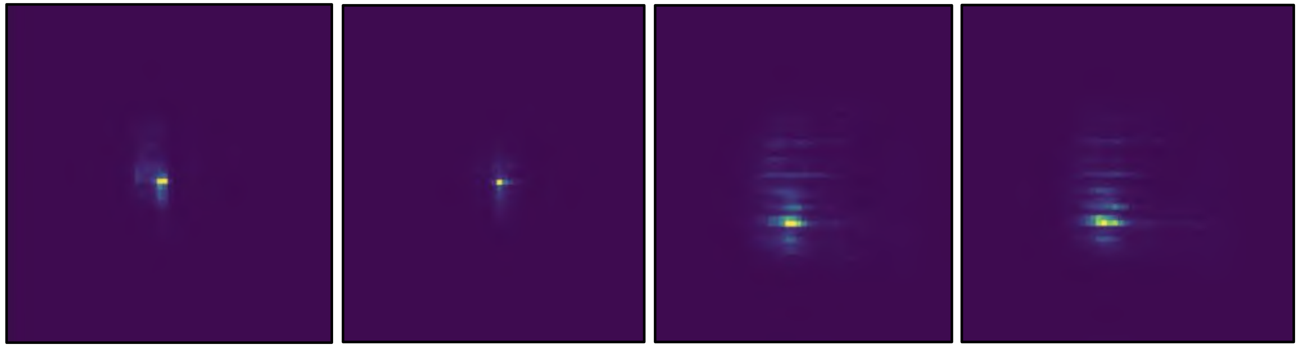
Wavelength

No dynamic training – large spectral variation



Trained photonic dynamics – Clear difference between images

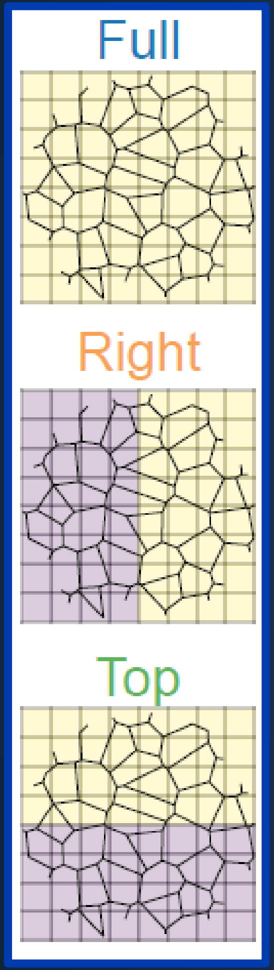
<u>Greatly enhances neuromorphic classification accuracy</u>



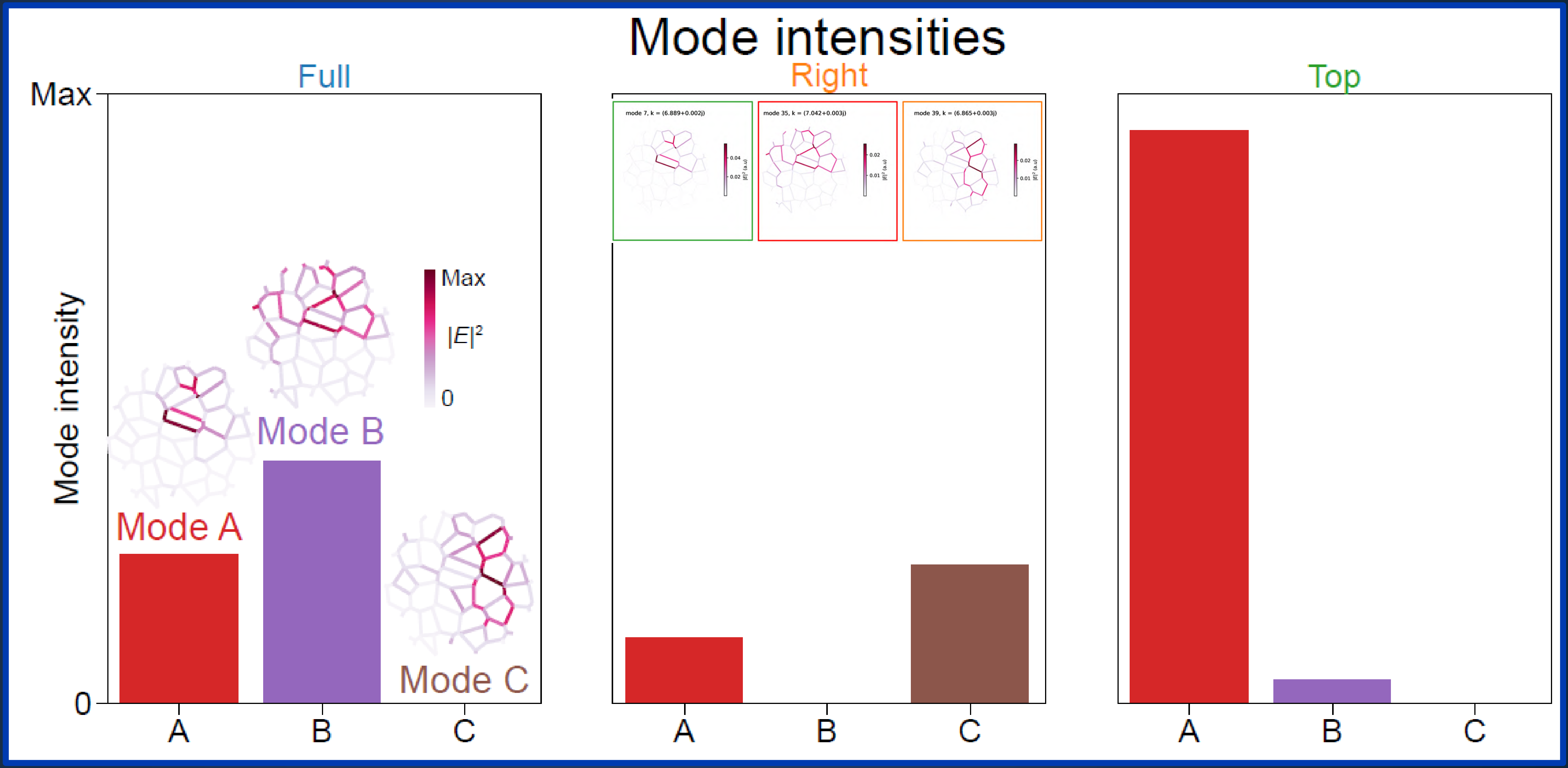
Jack C. Gartside, Imperial College London

Random Network Lasers: Machine vision?

Test simple edge images: **lasing thresholds & intensities** are **feature-sensitive**



Input images



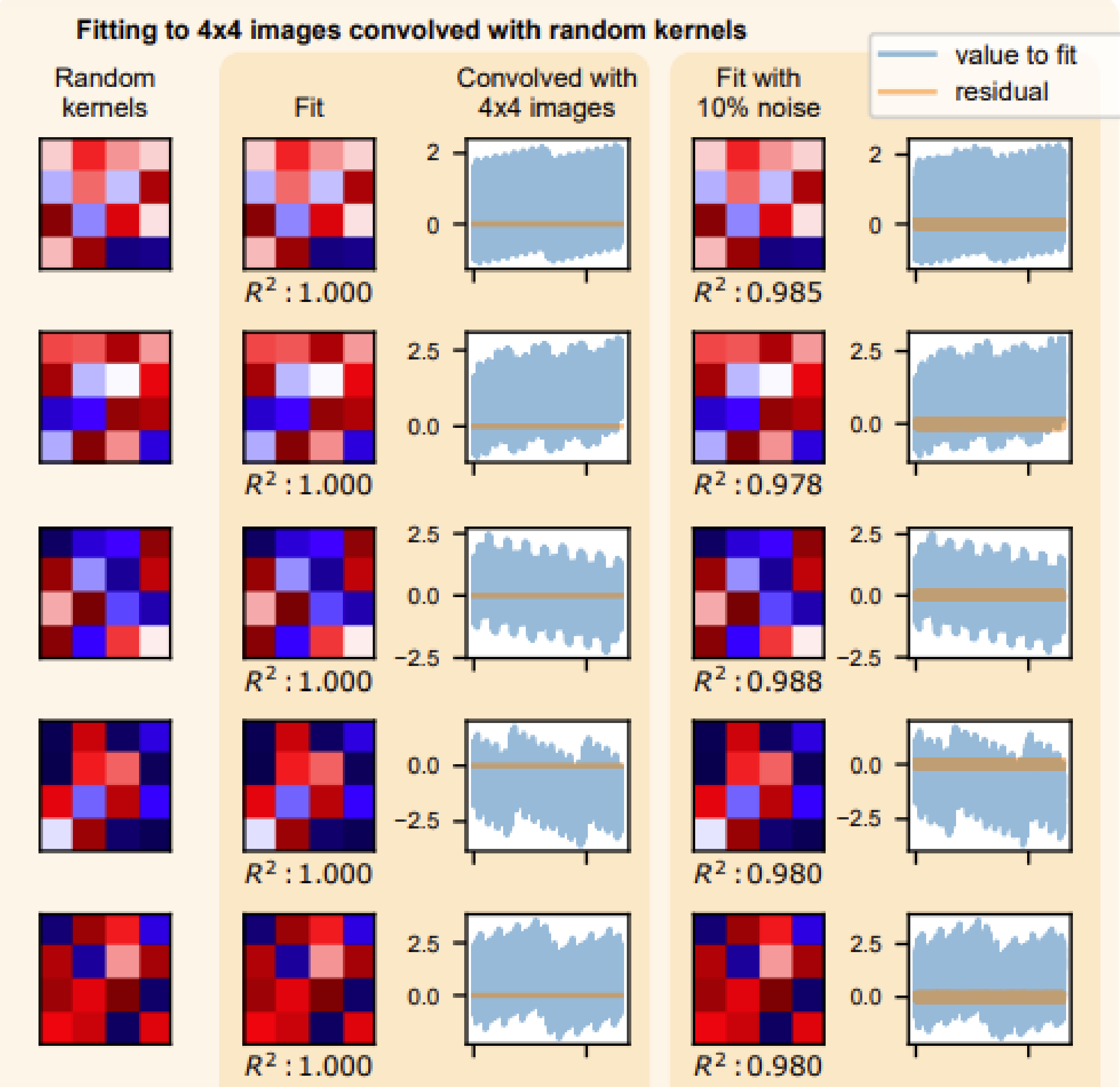
Mode label **Mode label** **Mode label**

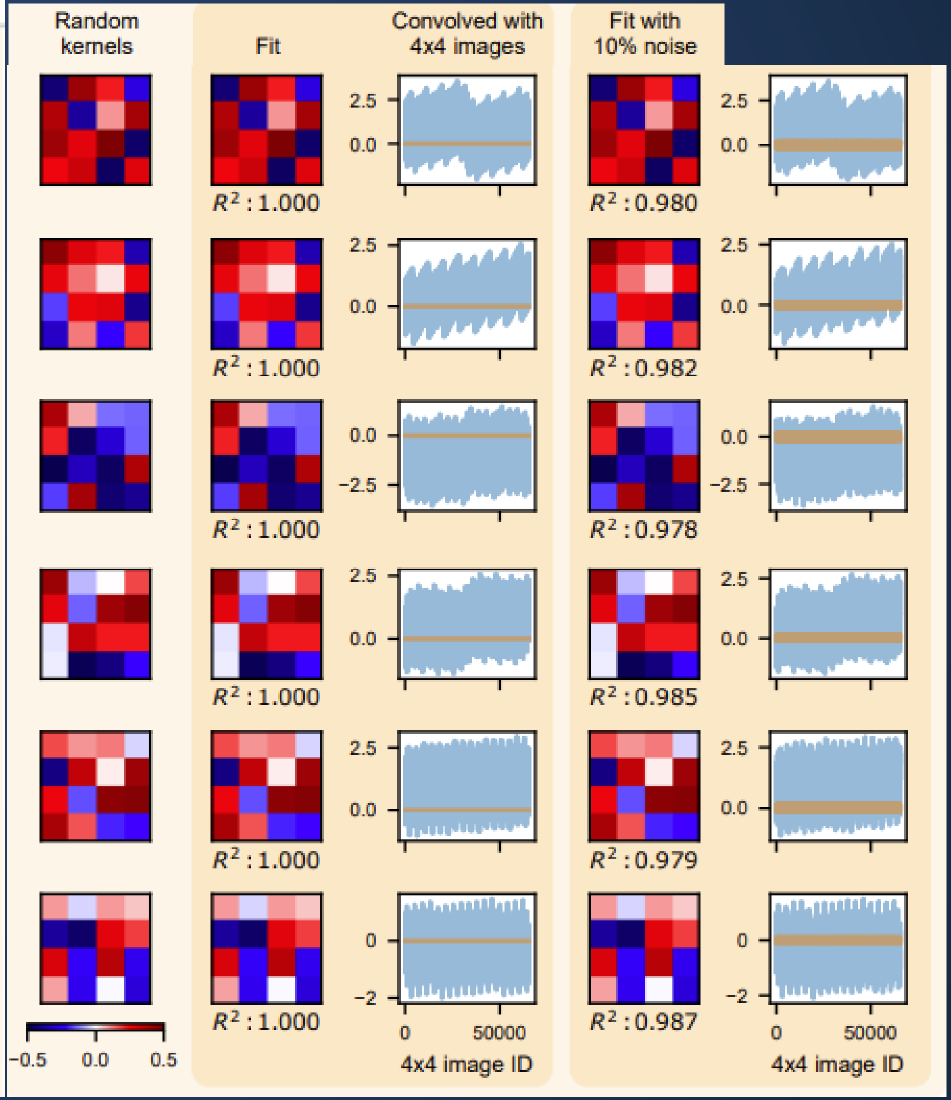
Retinomorphic Machine Vision in a Network Laser, *under review, Science*
Ng, Dranczewski, Fischer, ... & **Gartside** (2024)

Jack C. Gartside, Imperial College London

Linear vs Nonlinear Kernels?

Learning kernels via least squares fit – Control test using randomly generated software kernels. R^2 near perfect:

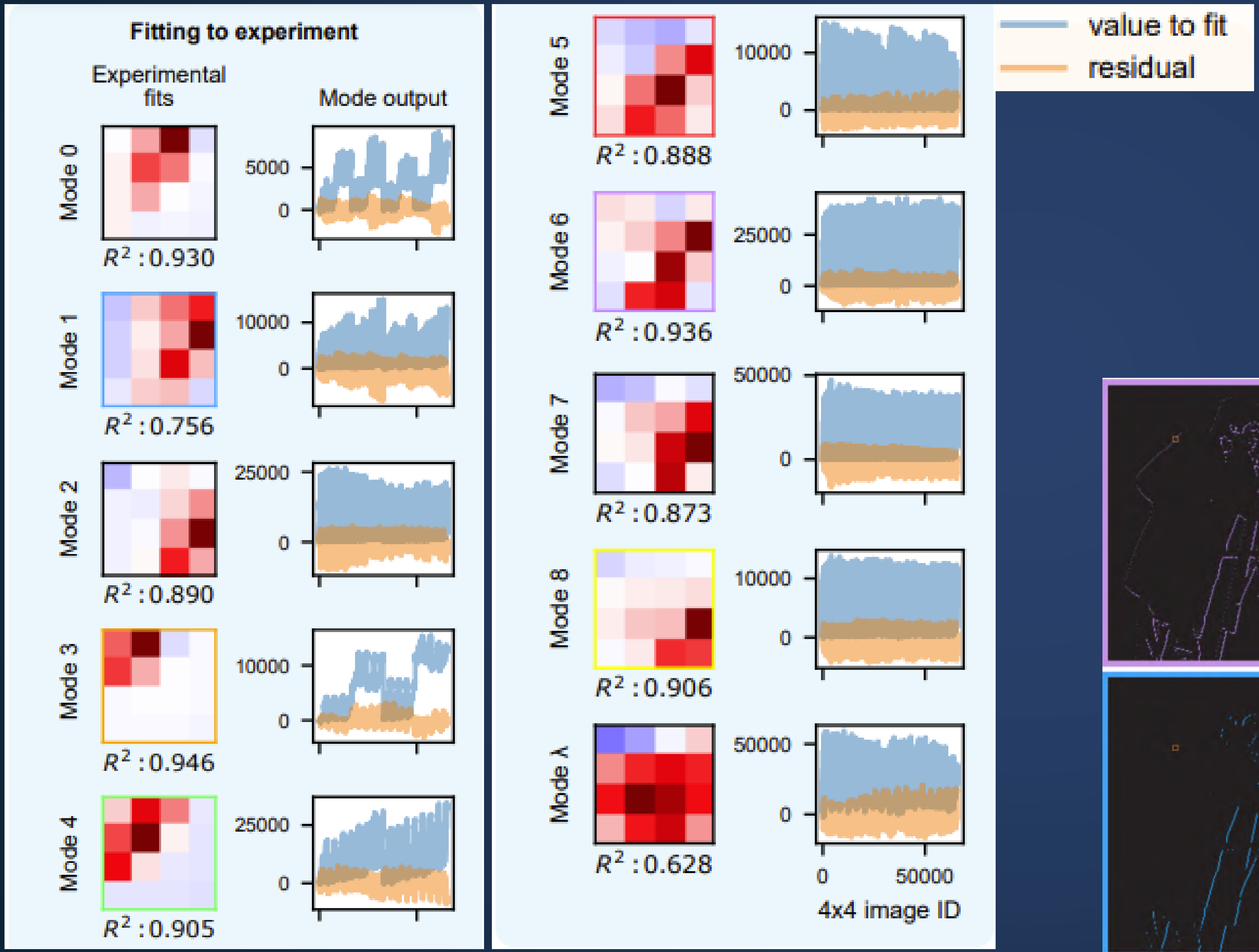


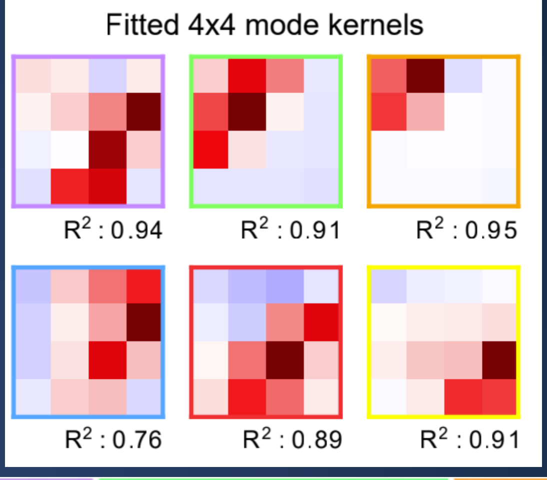


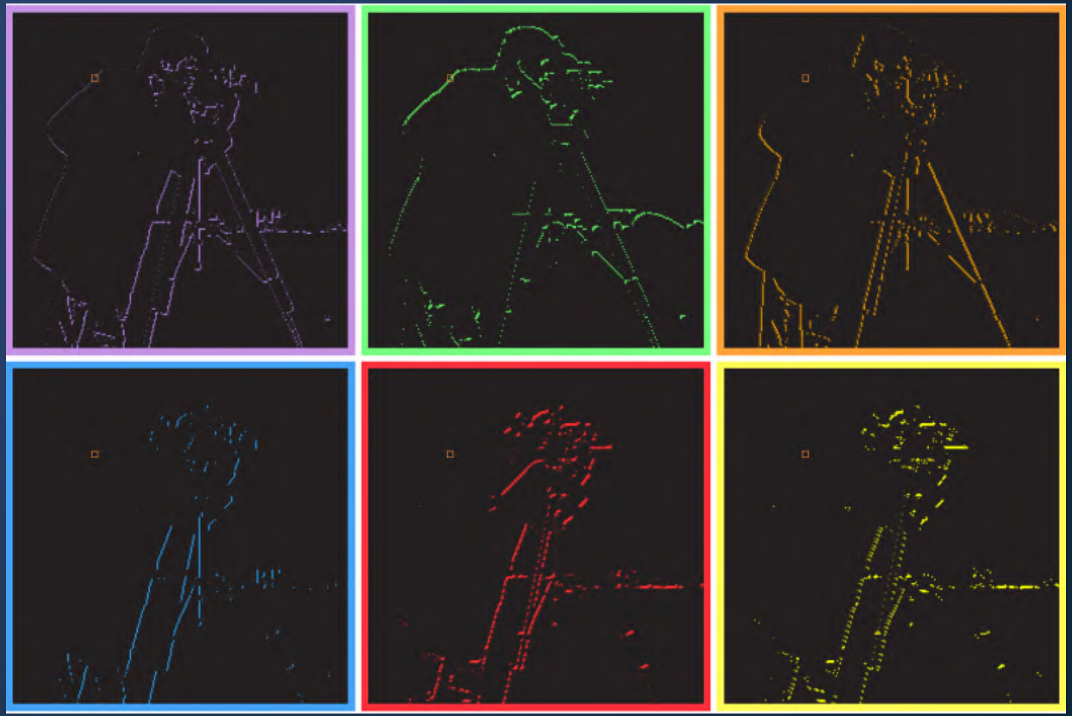
Jack C. Gartside, Imperial College London

Linear vs Nonlinear Kernels?

What about our experimental 'kernels'? Much lower R^2, can't captured some nonlinear physical behaviours?

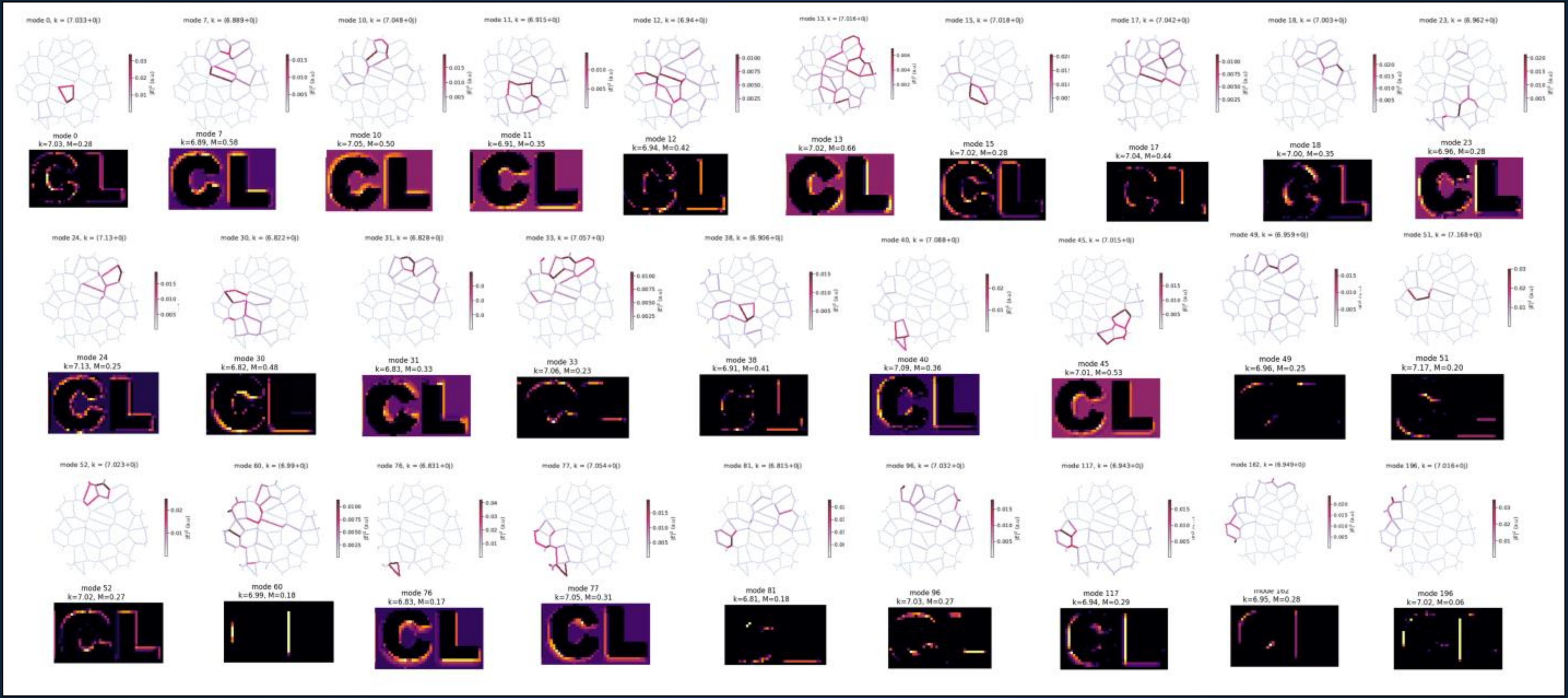






Random Network Lasers: Machine vision

Detect **large amount** of image features: 40 so far in single simulated network

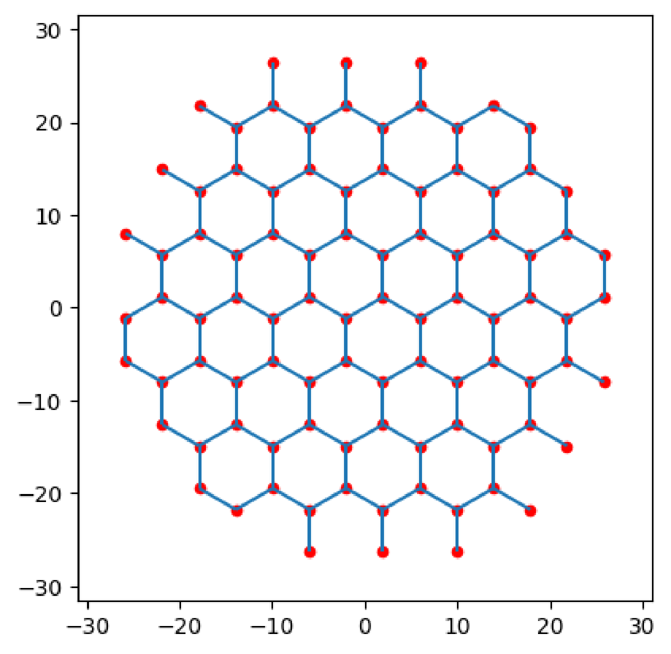


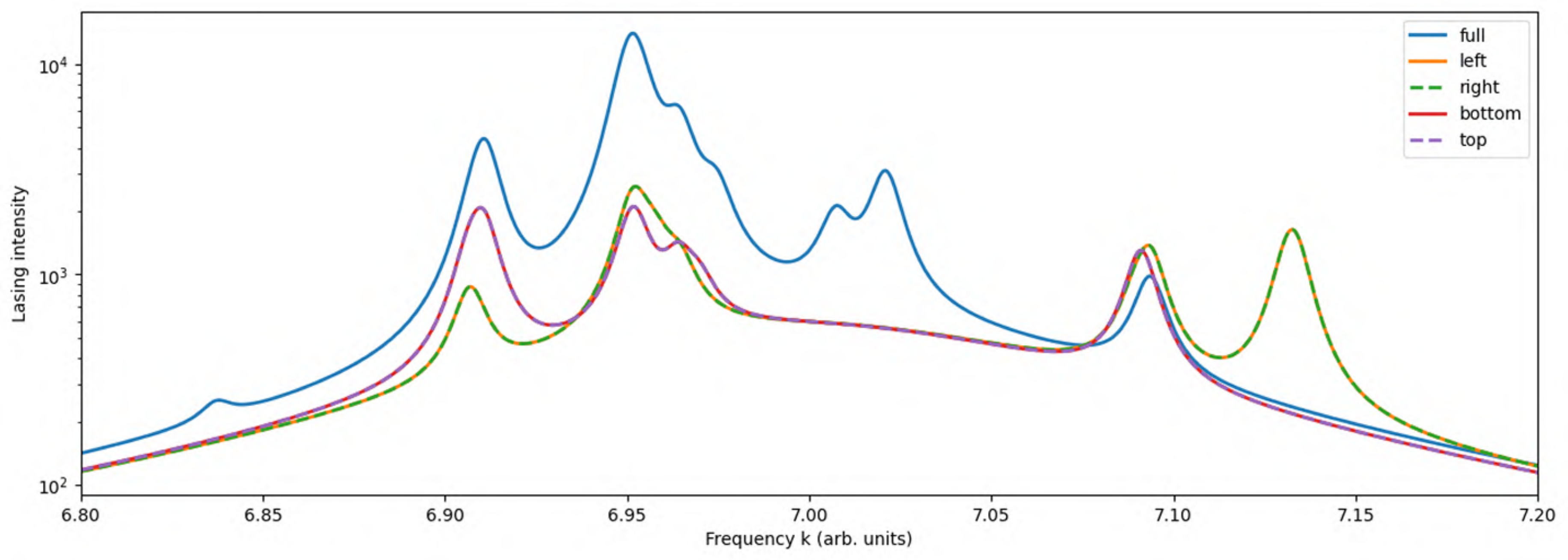
Neuromorphic Image Convolution and Machine Vision in a Network Laser, *in preparation*

Network design

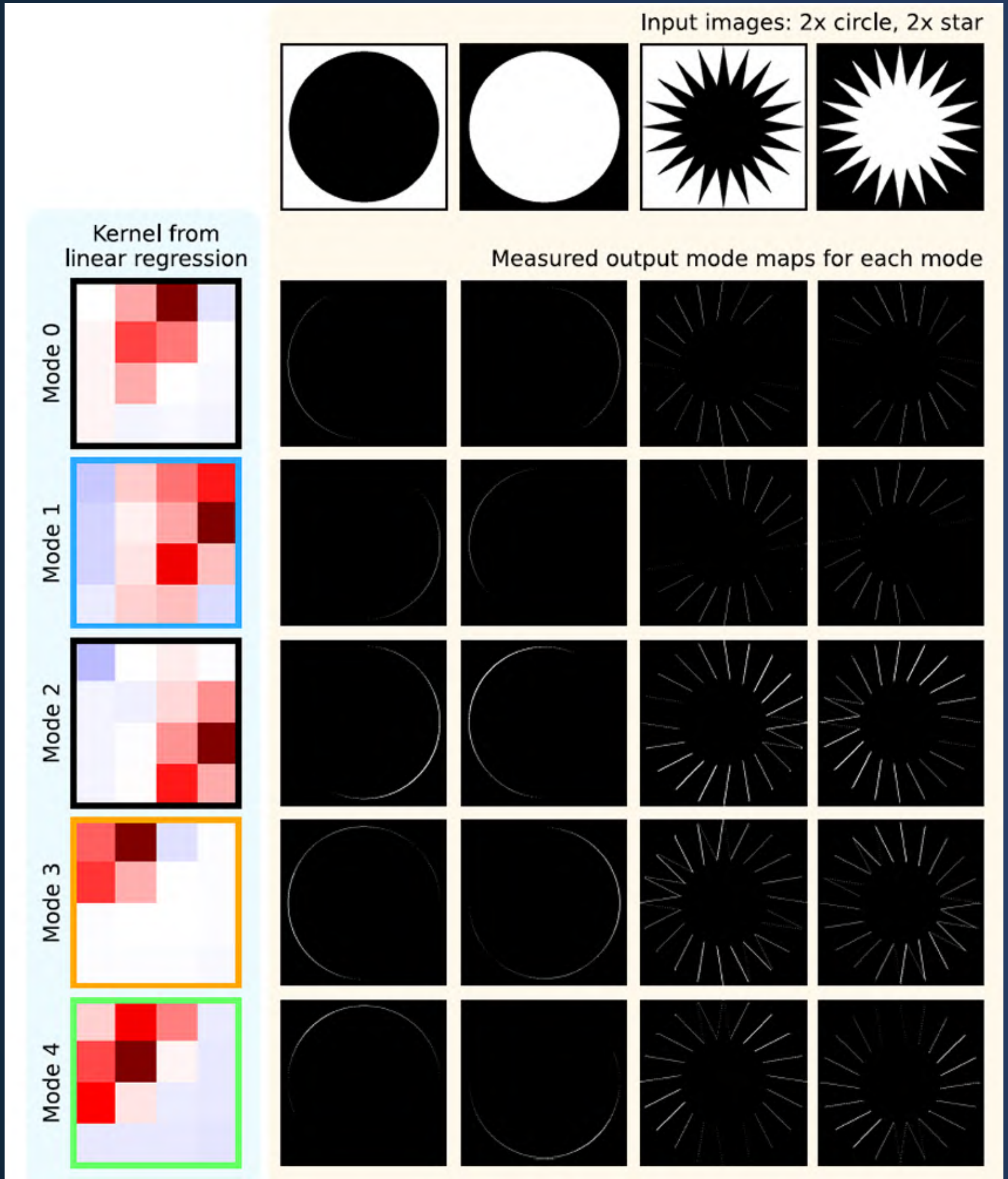
Jack C. Gartside, Imperial College London

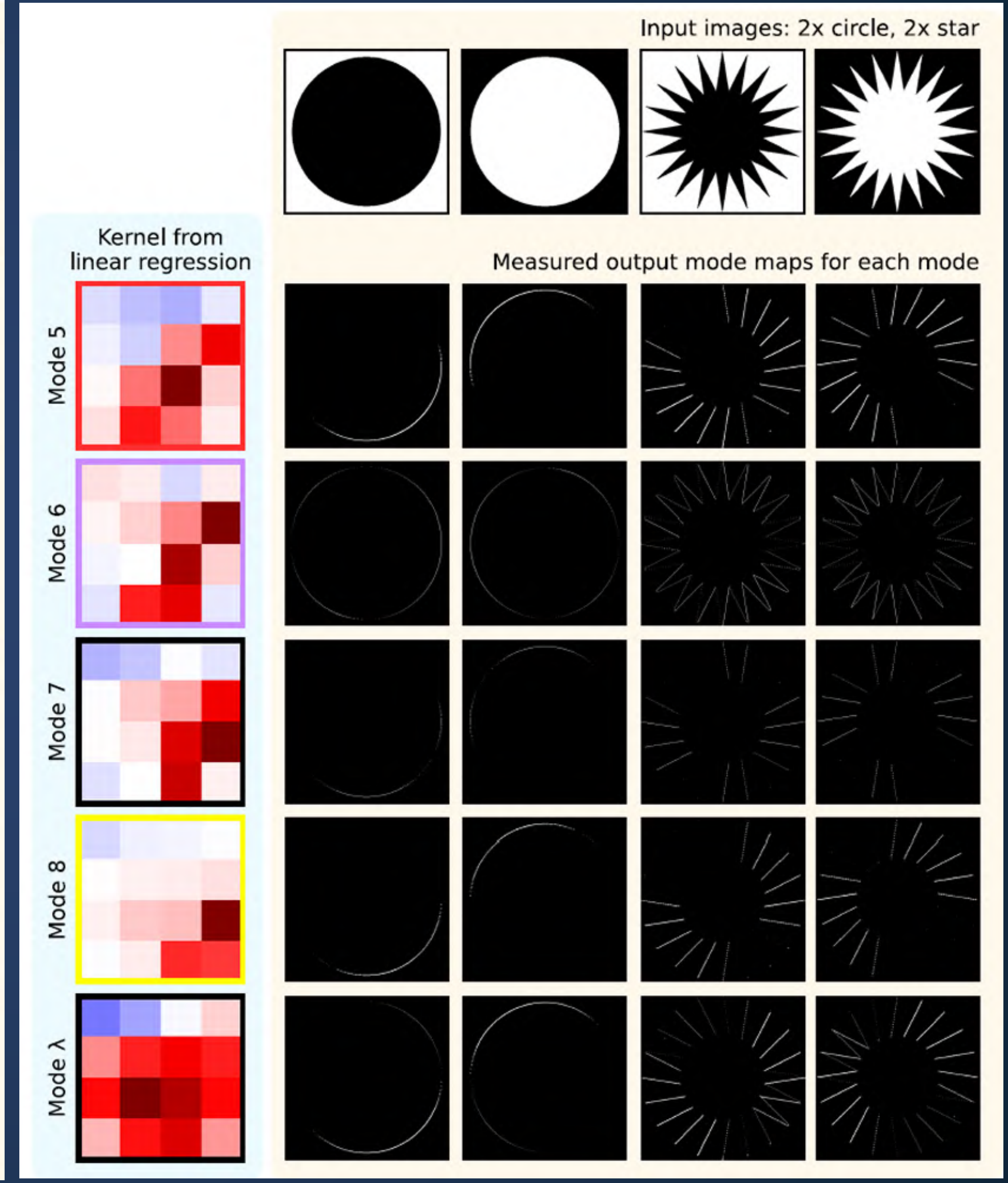
- Ordered networks can't distinguish different vertical or horizontal edges



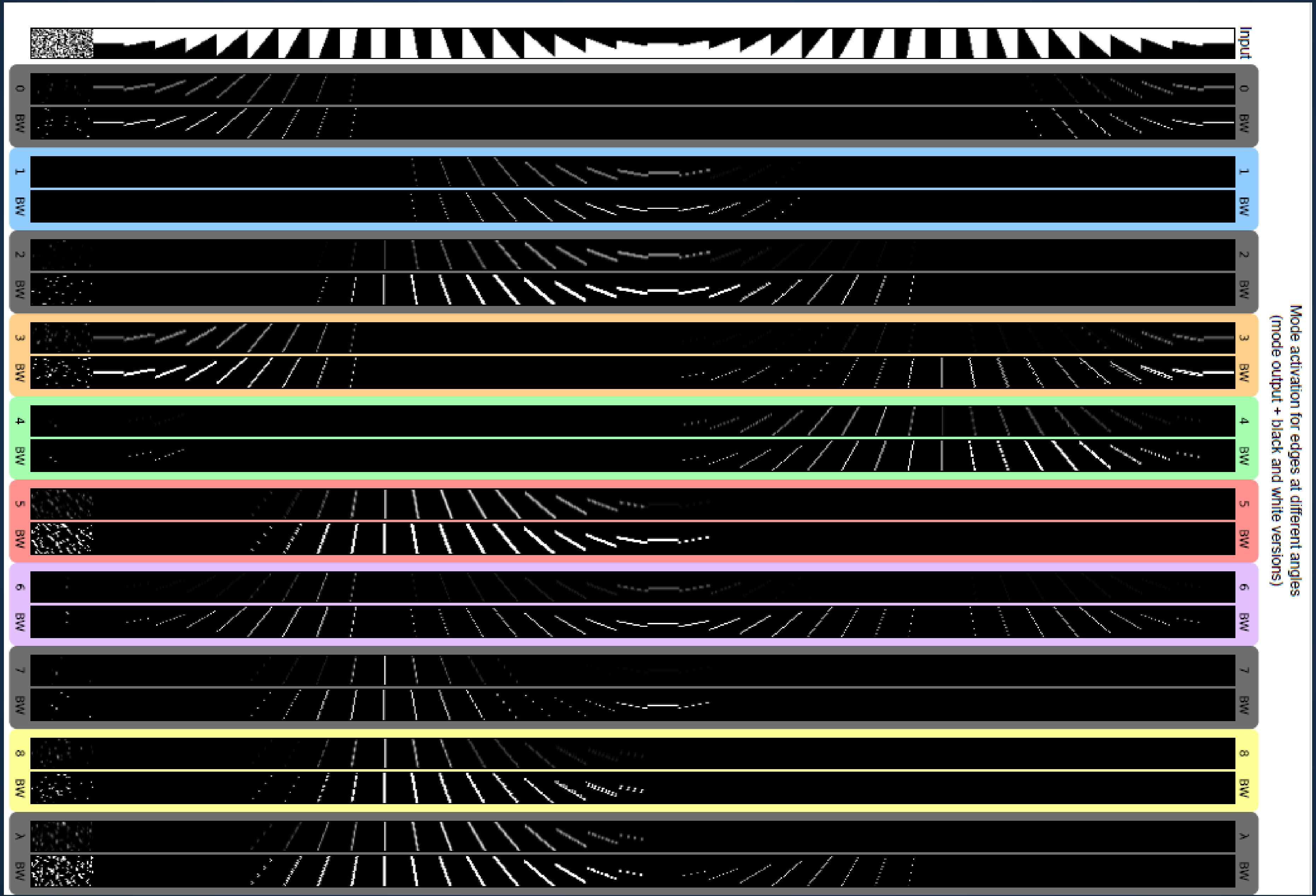


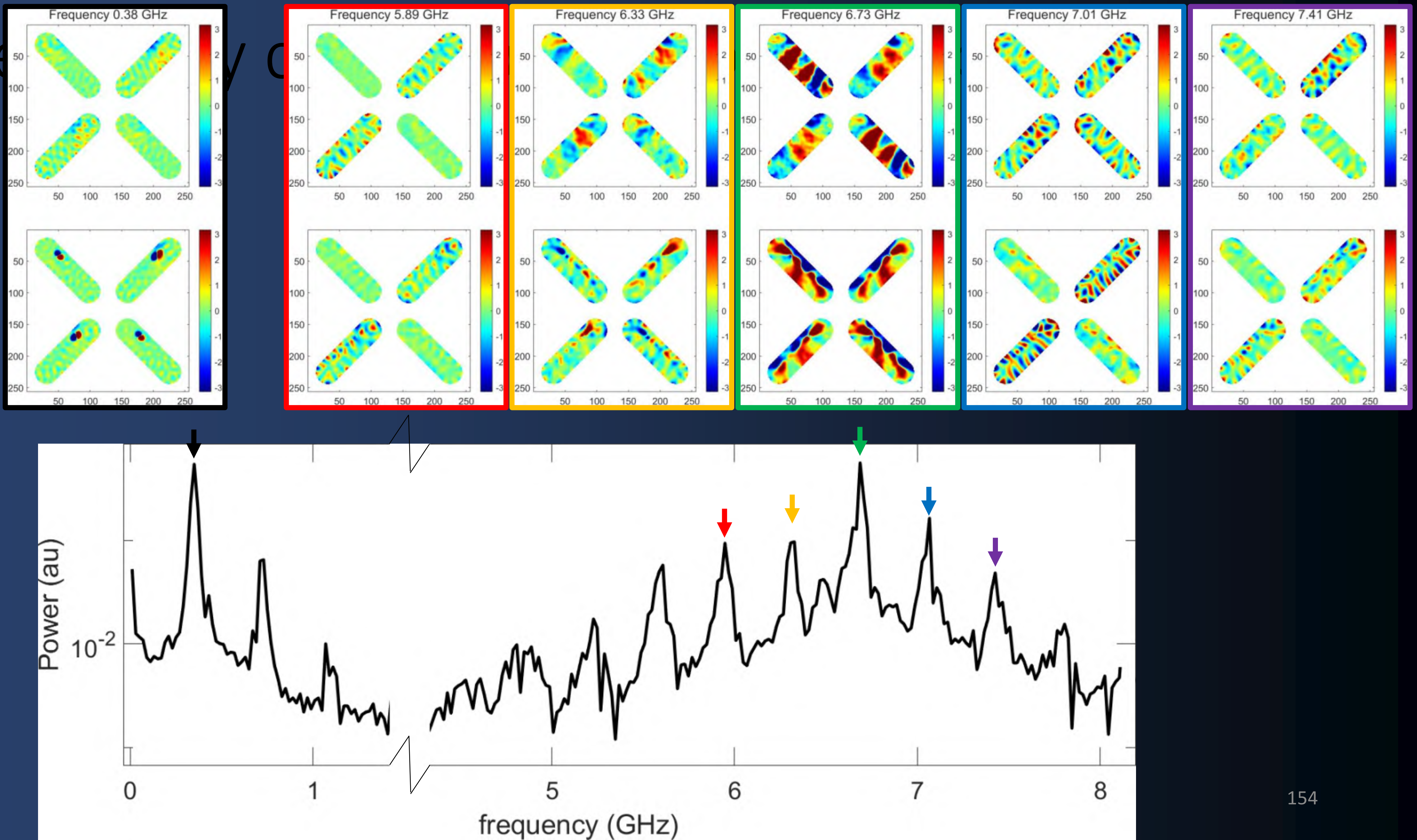
Feature detection cont.

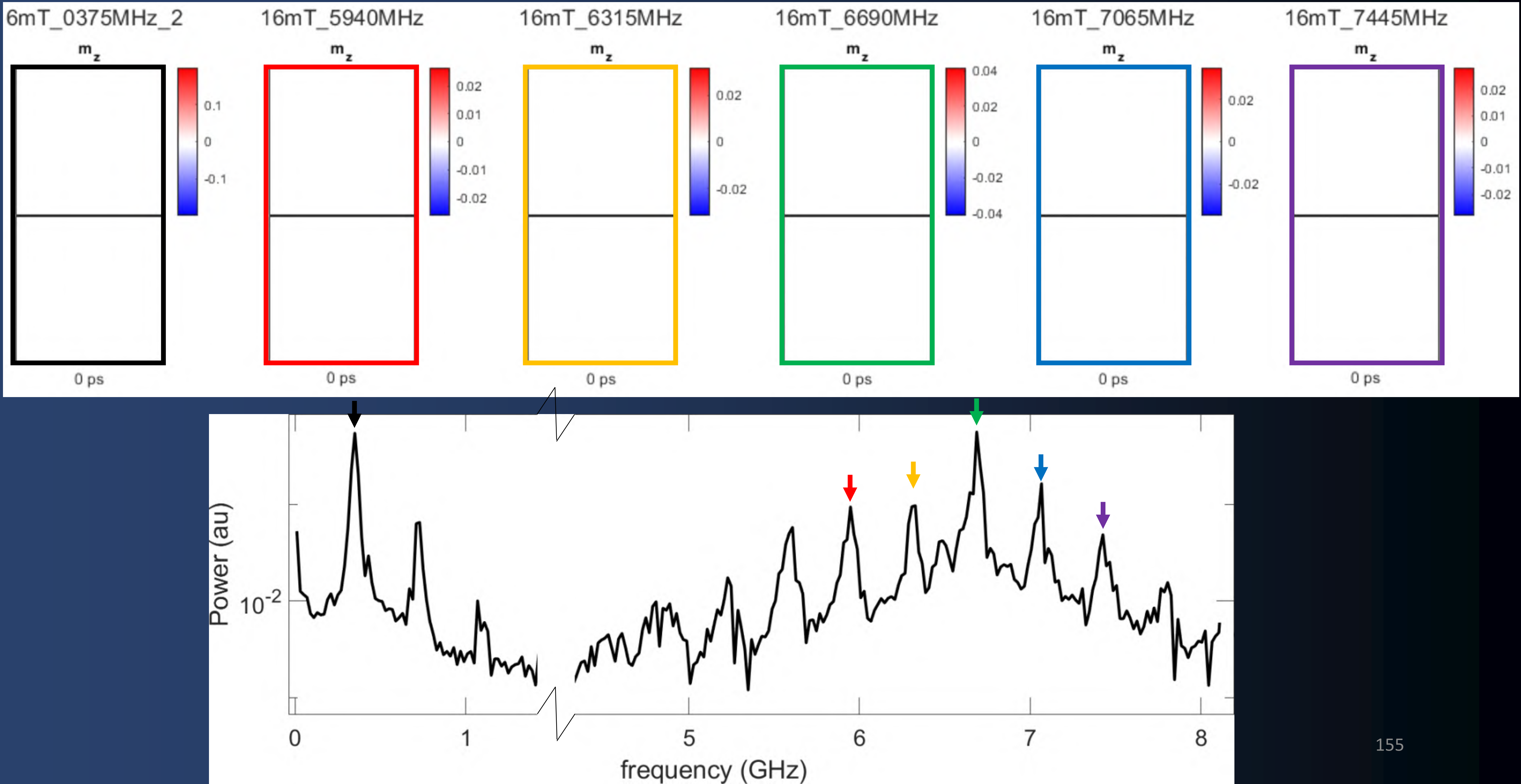




Feature detection cont.




Frequency 0.38 GHz
Frequency 5.89 GHz
Frequency 6.33 GHz
Frequency 6.73 GHz
Frequency 7.01 GHz
Frequency 7.41 GHz
Power (au)
10-2
0
1
5
6
7
8
frequency (GHz)



6mT_0375MHz_2
16mT_5940MHz
16mT_6315MHz
16mT_6690MHz
16mT_7065MHz
16mT_7445MHz
m_z
0 ps
Power (au)
10^-2
frequency (GHz)
0
1
5
6
7
8

- **Title: Using topological magnetic textures in devices**
- Topological magnetism for application based physics
- **What are topological states?**
  - Tbh everything is, but when its spoken about what people typically mean is some state with bulk-localised topological defects with whole integer winding number/topological charge
  - Often, but not always, have some degree of chirality – vortices, skyrmions

- **Why are they interesting?**
  - The biggest special thing about magnetism to me, is the ability to naturally switch between multiple states
  - Most other systems do not have this baked-in to their physics in anywhere near as elegant and easy to control and manipulate as magnetism
  - These topological states can be quite well protected, due to high exchange energy costs to 'unwind' them. This can lead to higher coercive field than collinear textures, and as we can see later, to physical memory
  - They are composed of multiple discrete parts, which gives rise to complex dynamics and resonances – often with more distinct modes than a collinear texture
  - These distinct modes are cool in their own right, but even cooler they can be coaxed into interacting with each other to enable some very nice new nonlinear physics

- **What are we going to look at specifically?**
  - We will look at a few things:
    - Magnetic vortices in nanoislands
    - Skyrmions in thin films
  - We will look at these properties
    - How they can give rise to physical memory
    - How they can give rise to nonlinear magnonics
    - How this can be used for neuromorphic computing (performing AI using complex physical dynamics
    - How to write and control them

• What do I have ready made?

- Some bits about ASI
- Some bits about magnon combing
  - Need Troy’s slides
- Some bits about vortex bistability
  - Need older talks which look into vortex formation in the nature nano paper
- Good stuff about vortex writing
- Some stuff about computing, could do with a better set of stuff showing how it doesn’t work without vortices
- Some better stuff needed for the Nature Materials paper

Nice reviews

REVIEW

ADVANCED MATERIALS
www.advmat.de

Topological Spin Textures: Basic Physics and Devices

*Yuqing Zhou, Shuang Li, Xue Liang, and Yan Zhou**

PERSPECTIVE | JUNE 27 2023

Perspective on unconventional computing using magnetic skyrmions

Oscar Lee ; Robin Msiska ; Maarten A. Brems ; Mathias Kläui ; Hidekazu Kurebayashi ; Karin Everschor-Sitte

Check for updates

Appl. Phys. Lett. 122, 260501 (2023)
https://doi.org/10.1063/5.0148469

nature reviews physics
https://doi.org/10.1038/s42254-024-00729-w

Perspective

Check for updates

Topological magnetic and ferroelectric systems for reservoir computing

Karin Everschor-Sitte[1], Atreya Majumdar[1], Katharina Wolk[2] & Dennis Meier[2,3]

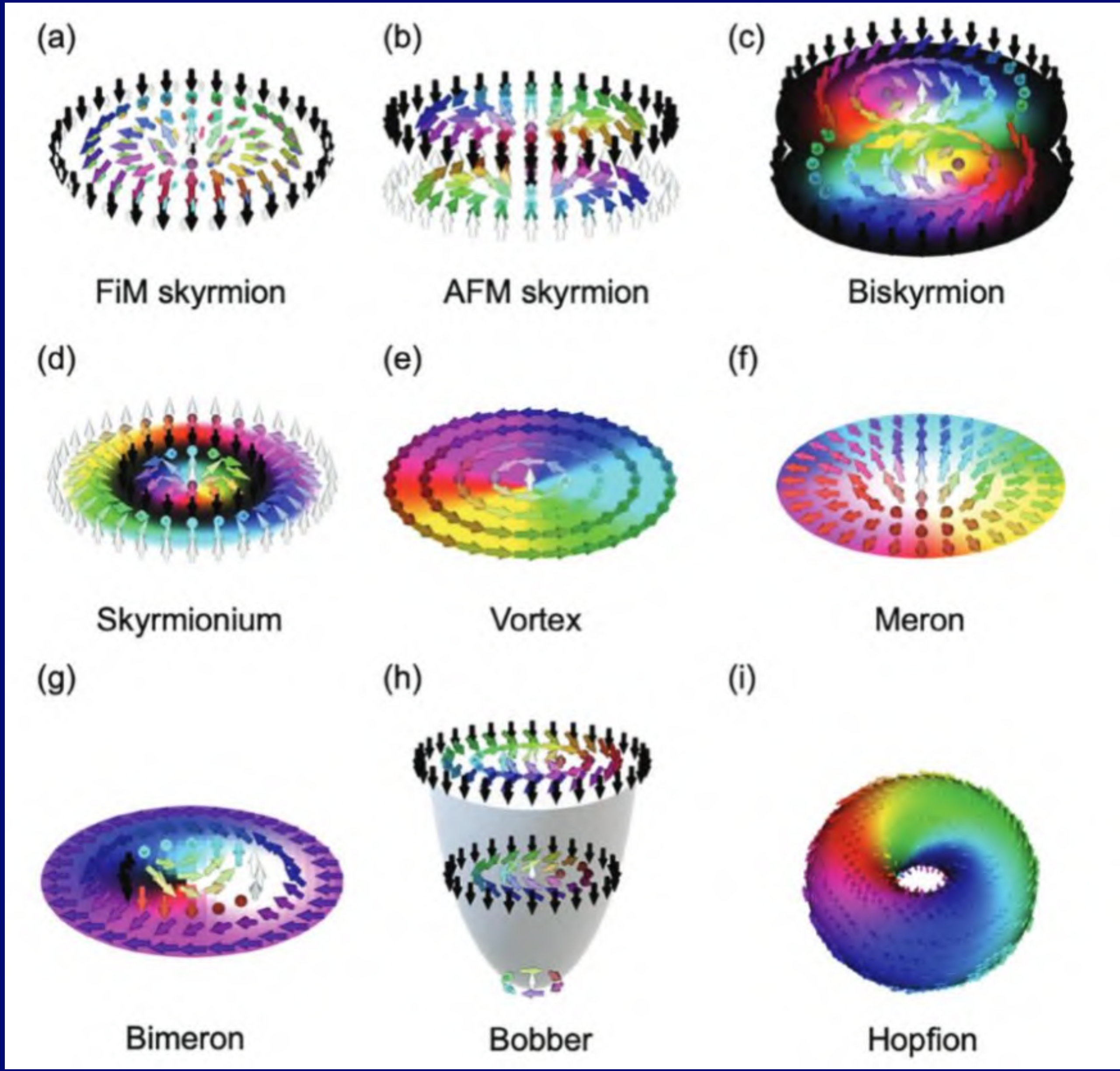
Physics for neuromorphic computing

Danijela Marković, Alice Mizrahi, Damien Querlioz and Julie Grollier

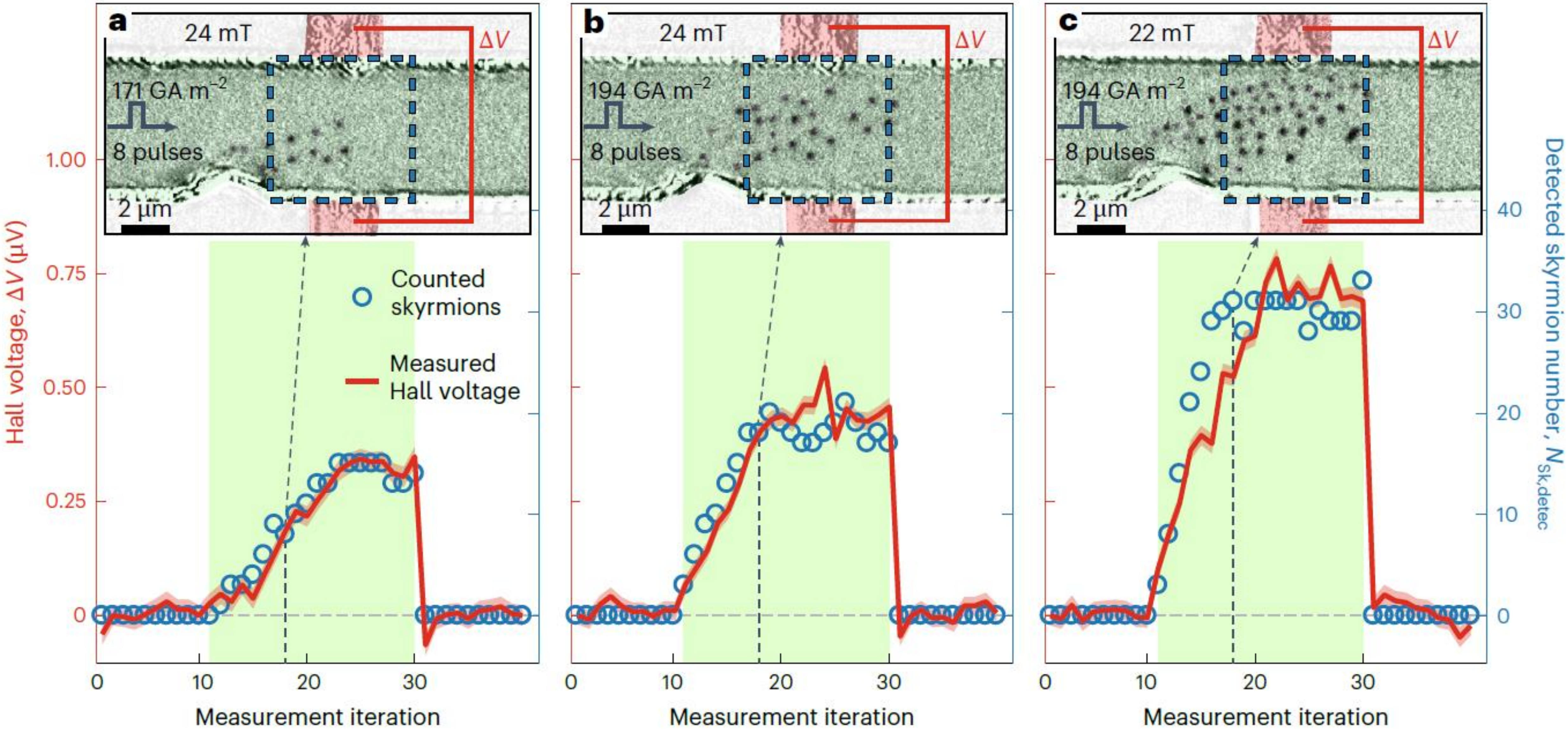
Training of Physical Neural Networks

Ali Momeni, Babak Rahmani, Benjamin Scellier, Logan G. Wright,
Oguz, Francesco Morichetti, Philipp del Hougne, Manuel Le Gallo,
Sylvain Gigan, Florian Marquardt, Aydogan Ozcan, Julie Grollier,

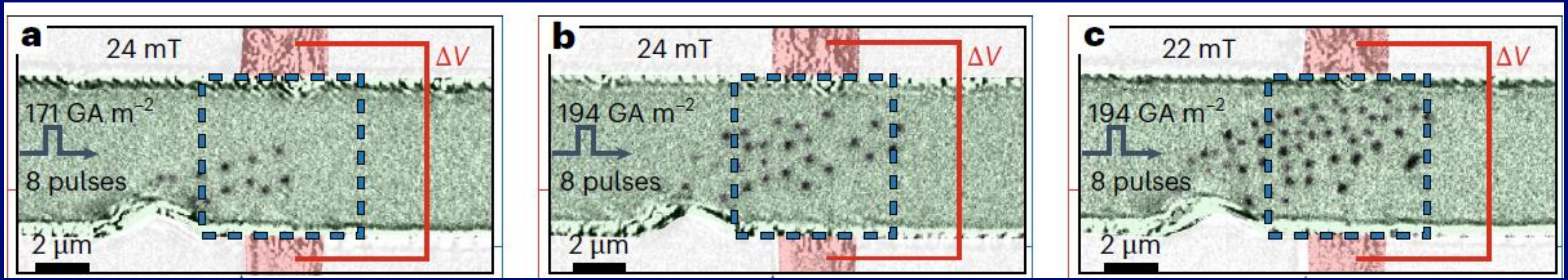
Talk Outline

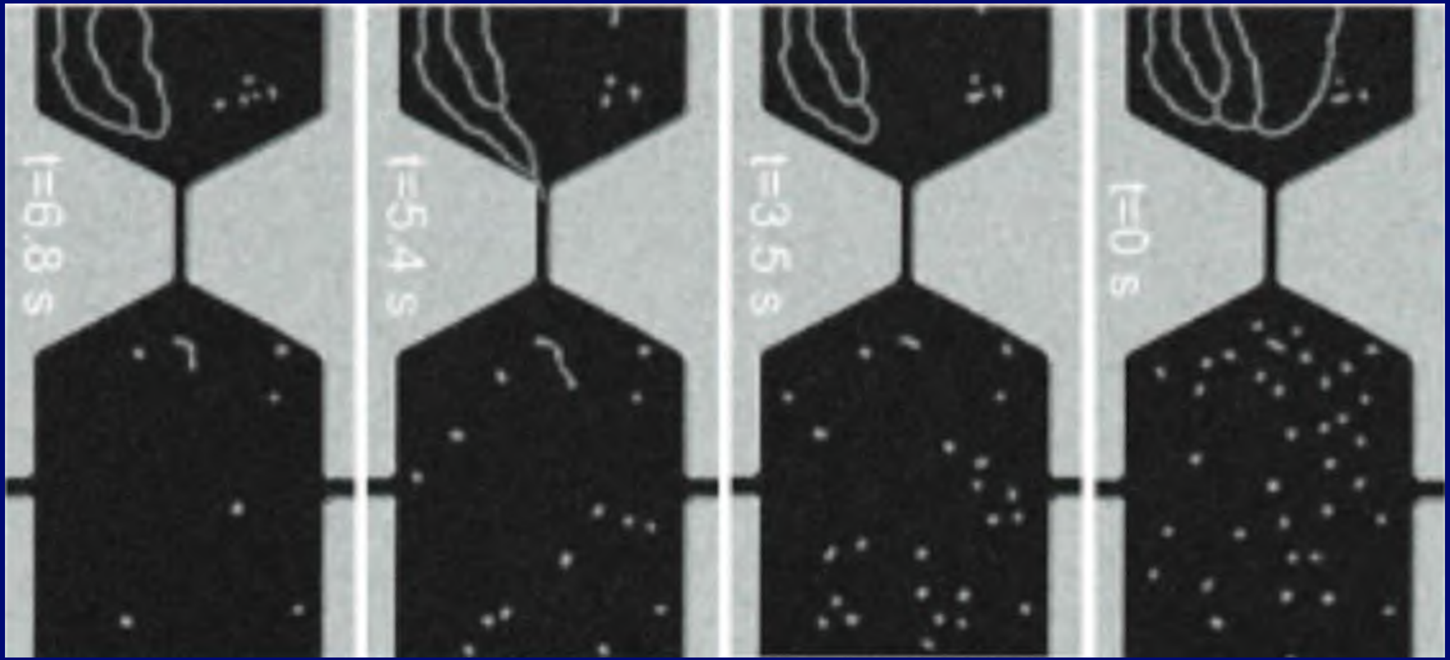


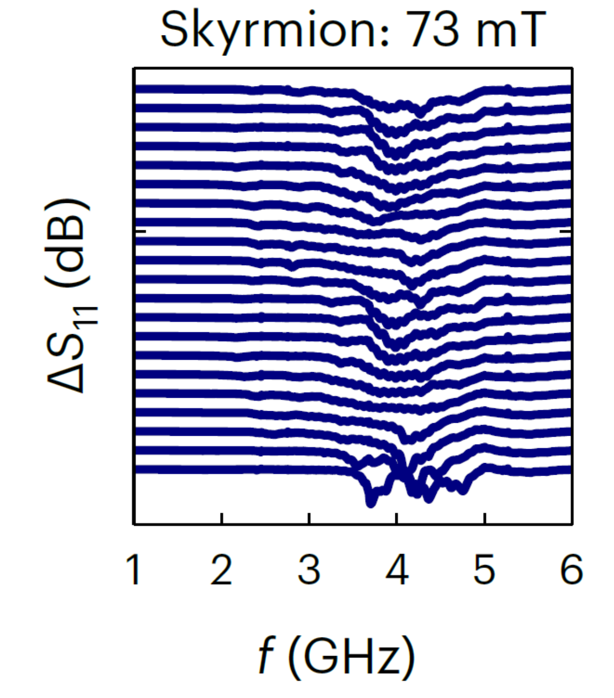
Talk Outline



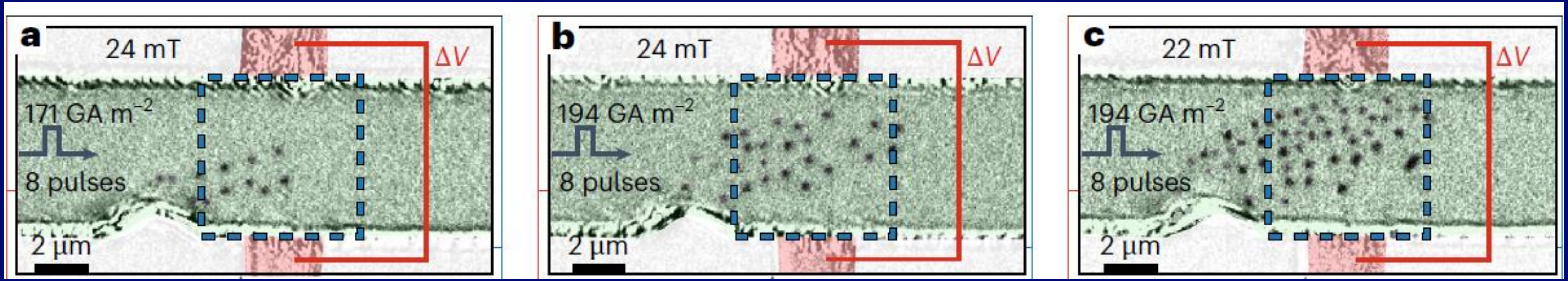
Talk Outline

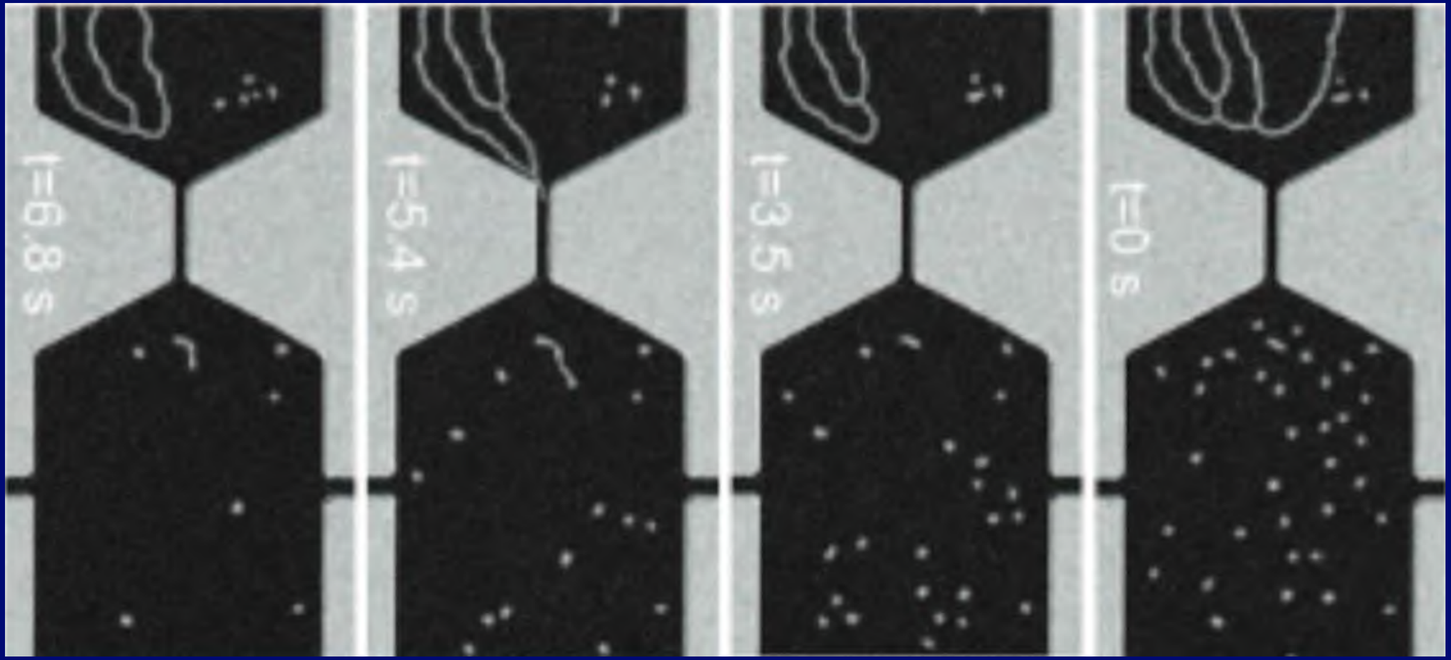


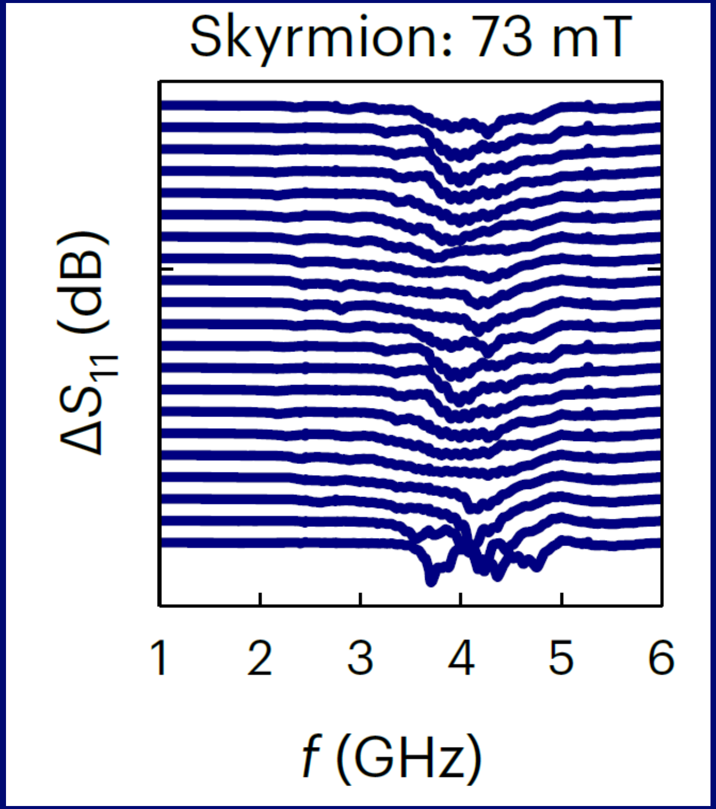




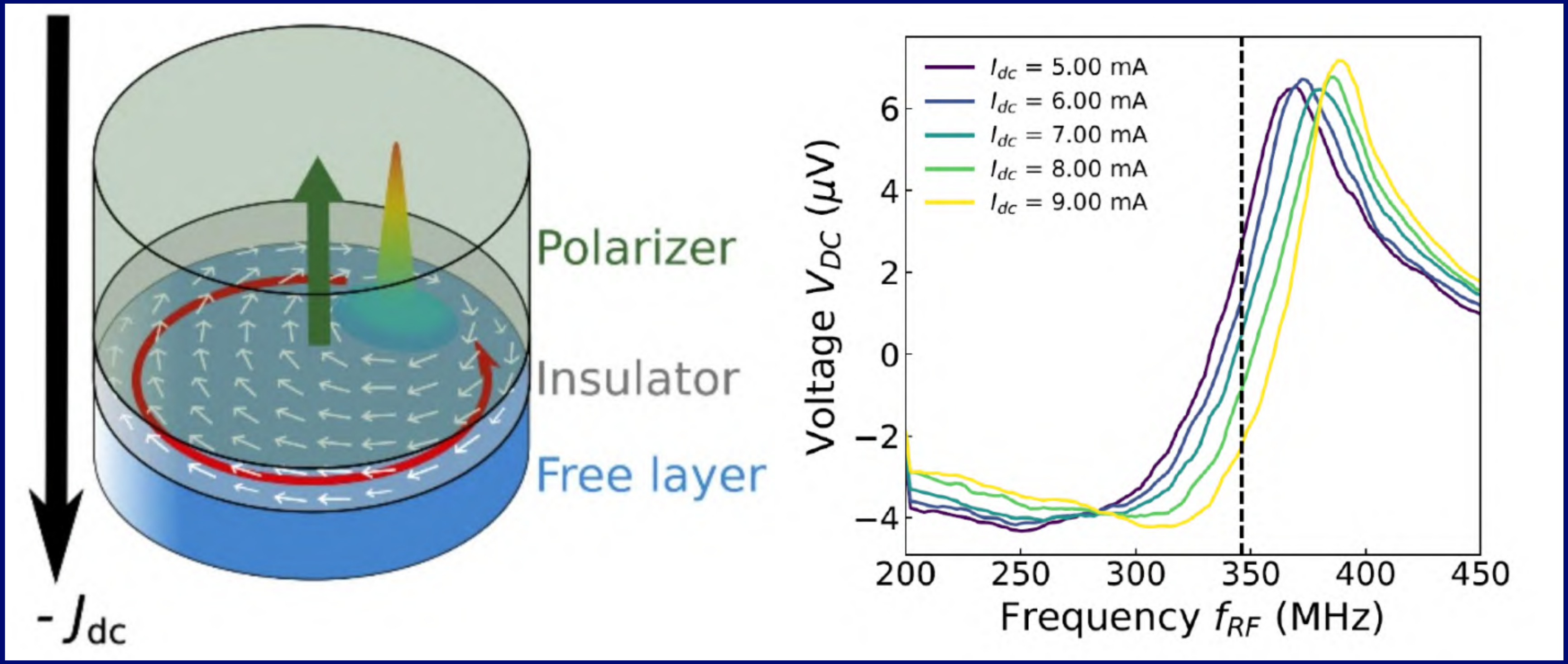
Talk Outline

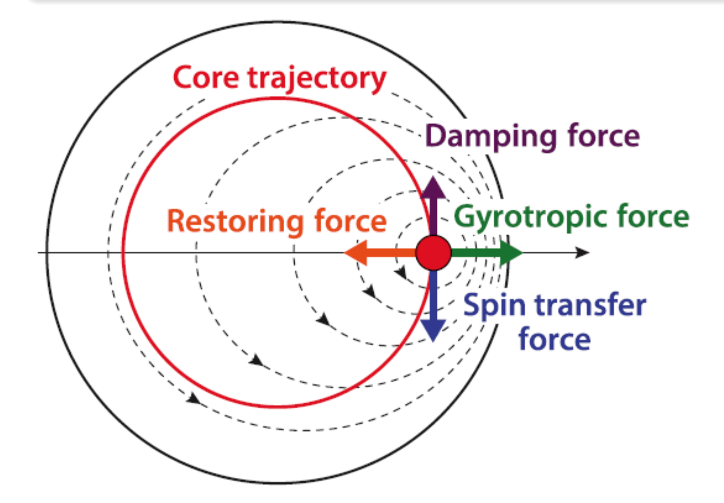


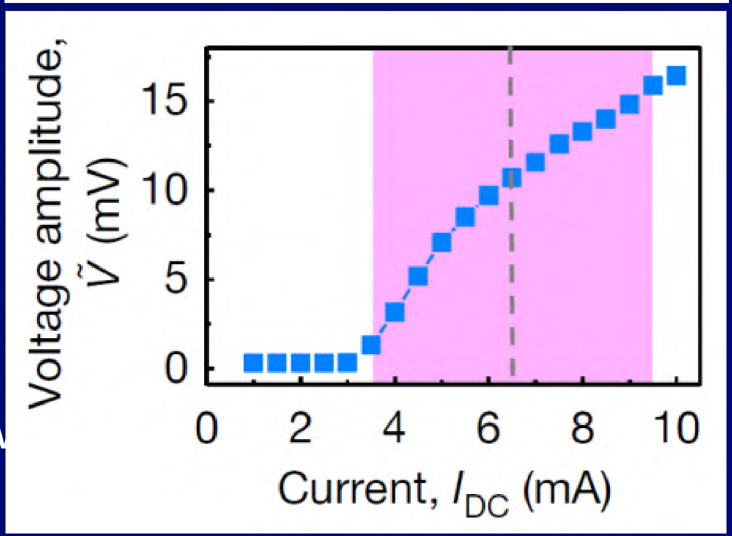




Talk Outline







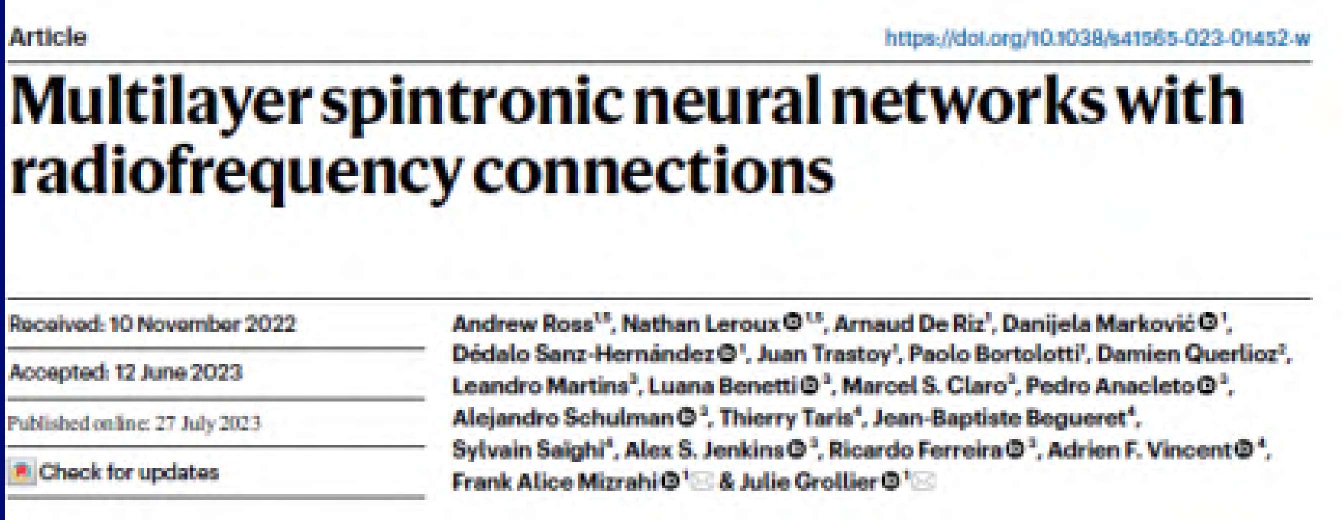
Good: Low linewidth, low input current (mA), relatively high RF power (uW
Less good Poor upper frequency output (typically 100s MHz to low GHz)

Ross, A., Leroux, N., De Riz, A., Marković, D., Sanz-Hernández, D., Trastoy, J., ... & Grollier, J. (2023). Multilayer spintronic neural networks with radiofrequency connections. *Nature Nanotechnology*, *18*(11), 1273-1280.

Chopin, C., de Wergifosse, S., Moureaux, A., & Abreu Araujo, F. (2024). Current-controlled periodic double-polarity reversals in a spin-torque vortex oscillator. *Scientific Reports*, *14*(1), 24177.

Talk Outline

Here, really start to harness the intricacies of the magnetic texture for device-like processing


Article https://doi.org/10.1038/s41565-023-01452-w

Multilayer spintronic neural networks with radiofrequency connections

Received: 10 November 2022

Accepted: 12 June 2023

Published online: 27 July 2023

Check for updates

Andrew Ross[1,5], Nathan Leroux[1,5], Arnaud De Riz[1], Danijela Marković[1], Dédalo Sanz-Hernández[1], Juan Trastoy[1], Paolo Bortolotti[1], Damien Querlioz[2], Leandro Martins[3], Luana Benetti[3], Marcel S. Claro[3], Pedro Anacleto[3], Alejandro Schulman[3], Thierry Taris[4], Jean-Baptiste Begueret[4], Sylvain Saighi[4], Alex S. Jenkins[3], Ricardo Ferreira[3], Adrien F. Vincent[4], Frank Alice Mizrahi[1] & Julie Grollier[1]

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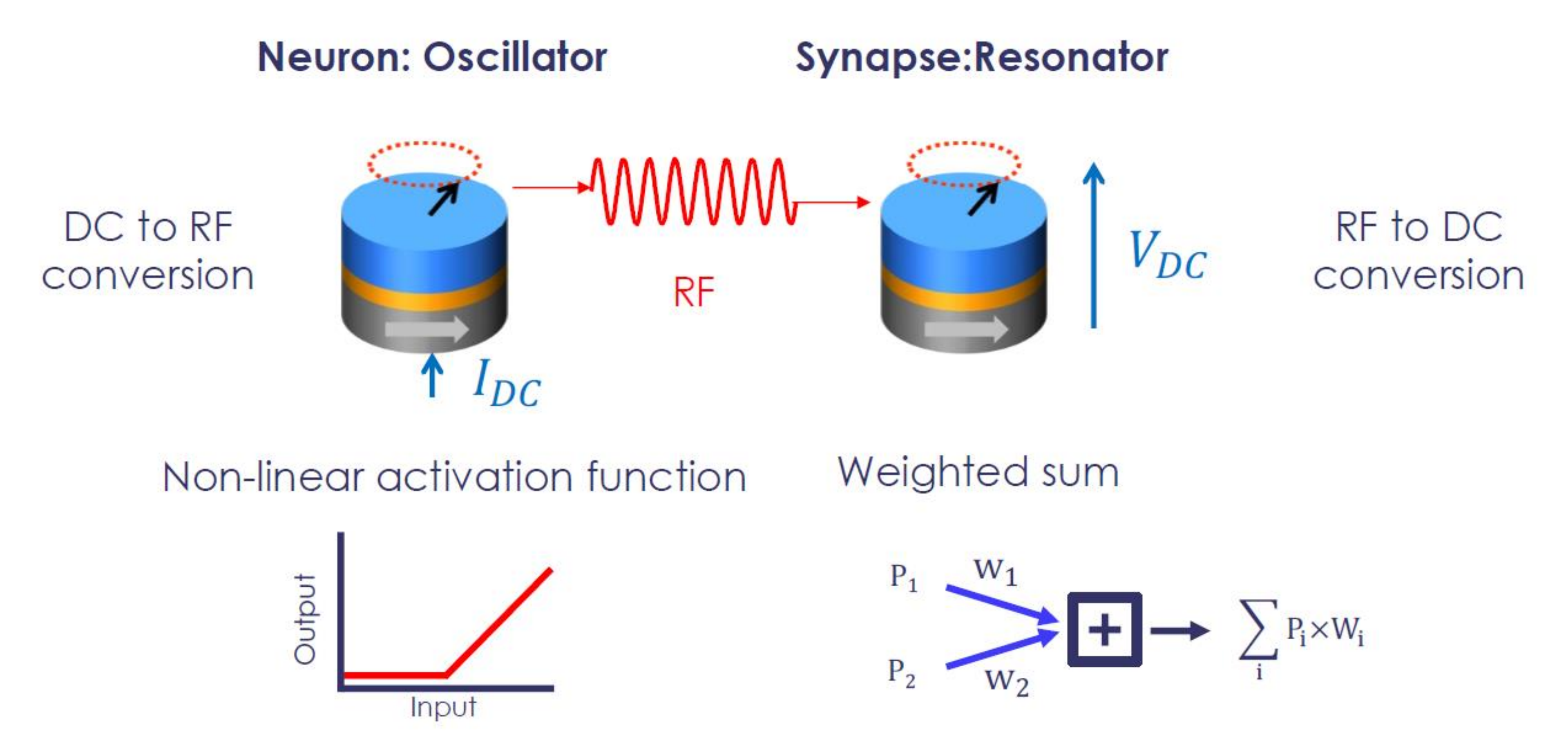
Talk Outline

DC to RF (spin torque) and RF to DC (spin diode effect) allows bidirectional conversion



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Talk Outline

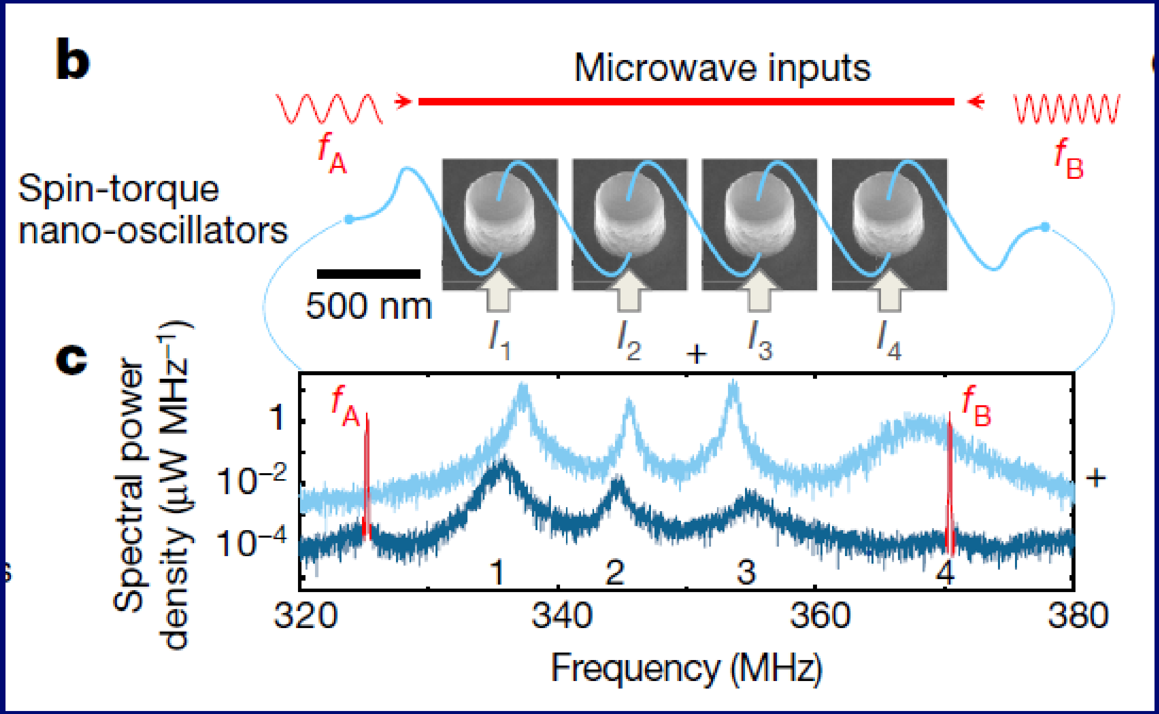
Classic works:

Neuromorphic computing with nanoscale spintronic oscillators

Jacob Torrejon[1], Mathieu Riou[1], Flavio Abreu Araujo[1], Sumito Tsunegi[2], Guru Khalsa[3]†, Damien Querlioz[4], Paolo Bortolotti[1], Vincent Cros[1], Kay Yakushiji[2], Akio Fukushima[2], Hitoshi Kubota[2], Shinji Yuasa[2], Mark D. Stiles[3] & Julie Grollier[1]

Vowel recognition with four coupled spin-torque nano-oscillators

Miguel Romera[1,5], Philippe Talatchian[1,5], Sumito Tsunegi[2], Flavio Abreu Araujo[1,4], Vincent Cros[1], Paolo Bortolotti[1], Juan Trastoy[1], Kay Yakushiji[2], Akio Fukushima[2], Hitoshi Kubota[2], Shinji Yuasa[2], Maxence Ernoult[1,3], Damir Vodenicarevic[3], Tifenn Hirtzlin[3], Nicolas Locatelli[3], Damien Querlioz[3]* & Julie Grollier[1]*



Torrejon, J., Riou, M., Araujo, F. A., Tsunegi, S., Khalsa, G., Querlioz, D., ... & Grollier, J. (2017). Neuromorphic computing with nanoscale spintronic oscillators. *Nature*, *547*(7664), 428-431.

Romera, M., Talatchian, P., Tsunegi, S., Abreu Araujo, F., Cros, V., Bortolotti, P., ... & Grollier, J. (2018). Vowel recognition with four coupled spin-torque nano-oscillators. *Nature*, *563*(7730), 230-234.

Talk Outline

Classic works:

Task becomes linearly separable due to nonlinear physical dynamics

Neuromorphic computing with nanoscale spintronic oscillators

Jacob Torrejon[1], Mathieu Riou[1], Flavio Abreu Araujo[1], Sumito Tsunegi[2], Guru Khalsa[3]†, Damien Querlioz[4], Paolo Bortolotti[1], Vincent Cros[1], Kay Yakushiji[2], Akio Fukushima[2], Hitoshi Kubota[2], Shinji Yuasa[2], Mark D. Stiles[3] & Julie Grollier[1]

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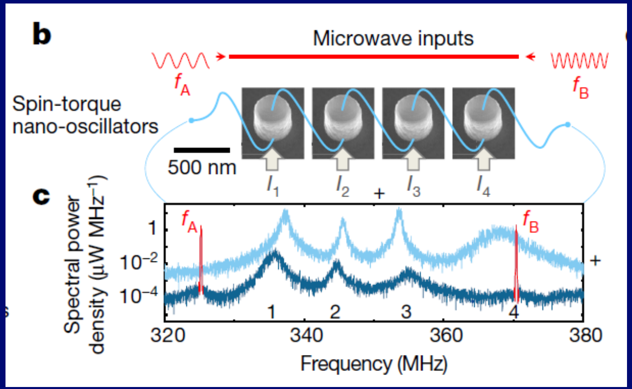

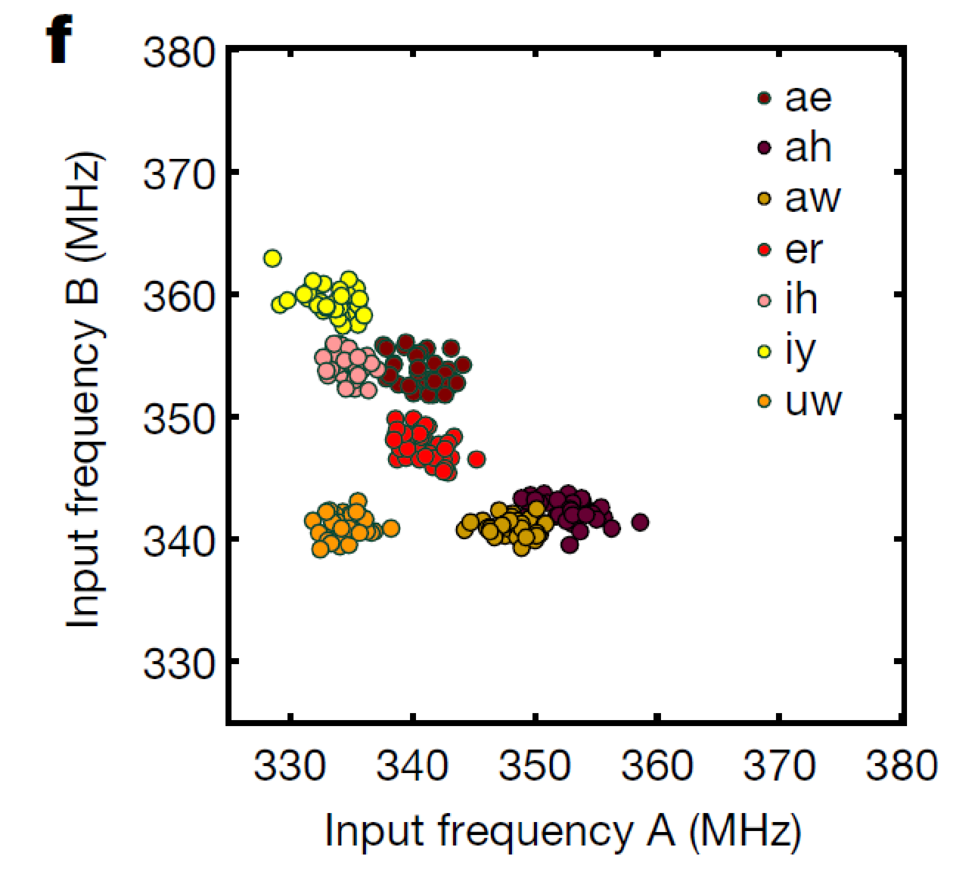

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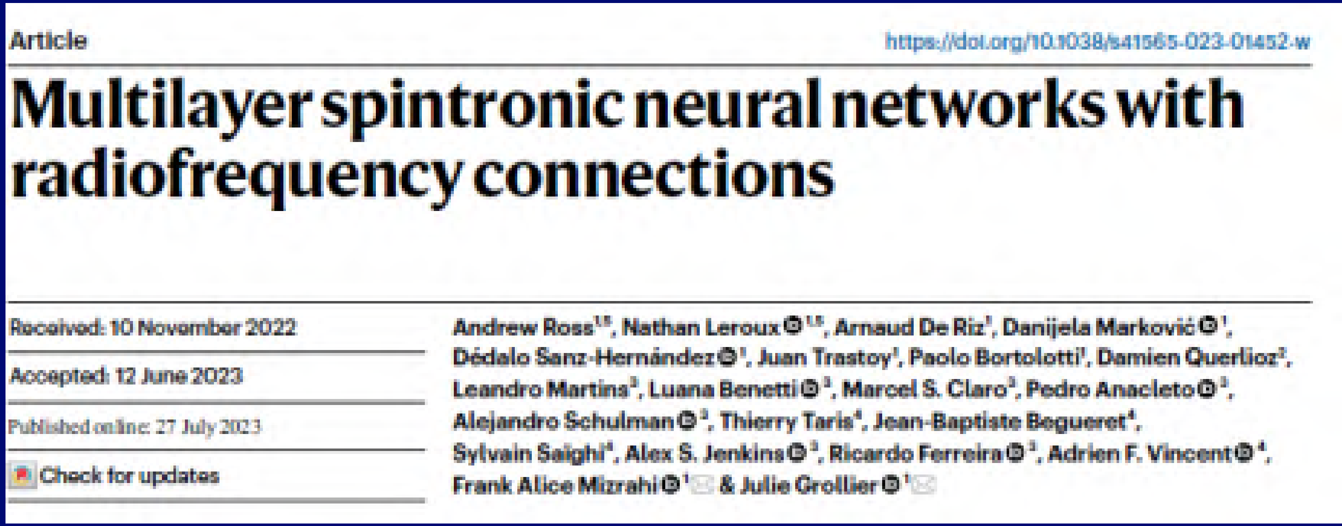
Talk Outline



Article
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Something near the end – what's hard? Interconnects/Scaling
Maybe we should redesign?!

Ross, A., Leroux, N., De Riz, A., Marković, D., Sanz-Hernández, D., Trastoy, J., Bortolotti, P., Querlioz, D., Martins, L., Benetti, L. and Claro, M.S., 2023. Multilayer spintronic neural networks with radiofrequency connections. *Nature Nanotechnology*, *18*(11), pp.1273-1280.

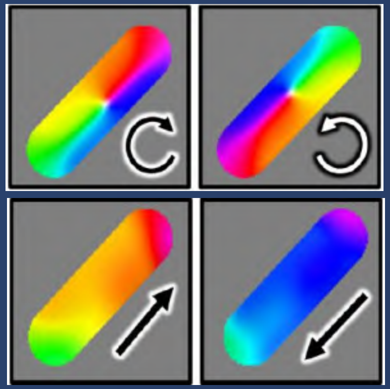
Jack C. Gartside, Imperial College London

Data Input:

- Engineer material complexity to allow simple global-field input
- Bistable **Magnetic textures**
- **Future vision:** All-optical/electrical input
  - 2 patents (2022,2024)

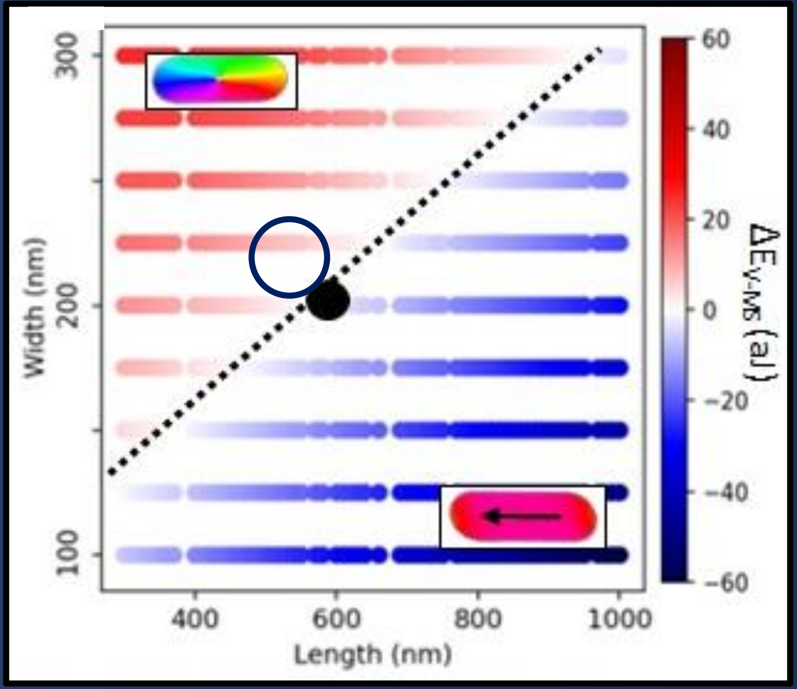
Gartside, Jack C. et al, **Nature Nanotechnology** (2022)

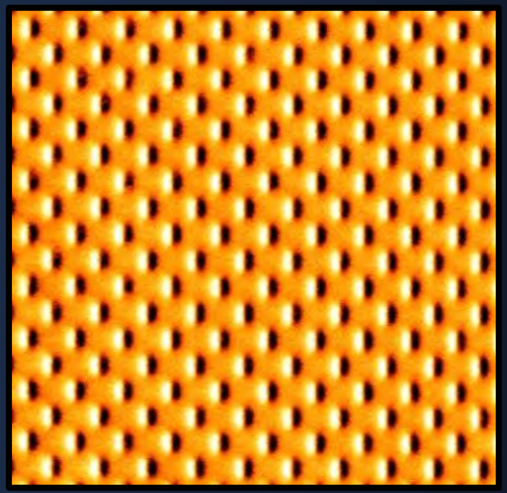
Vortices



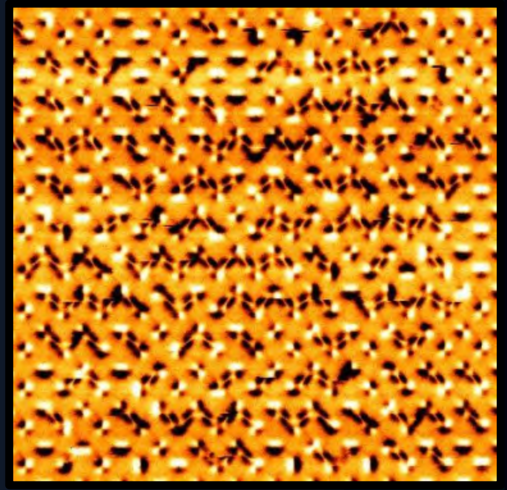
Macrospins

Vortex vs. Macrospin energy:
Find **bistable point**

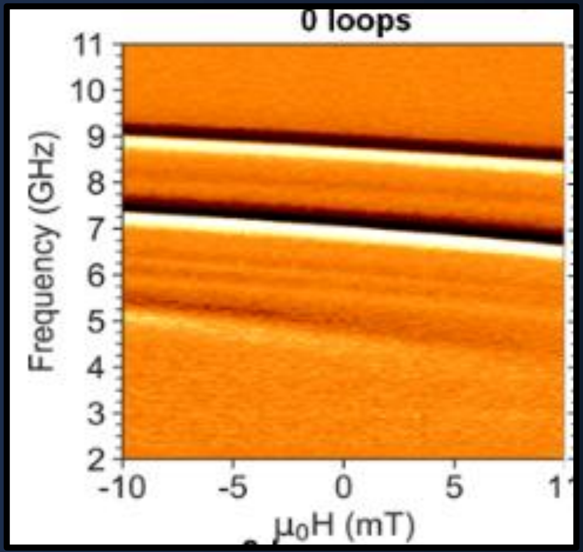




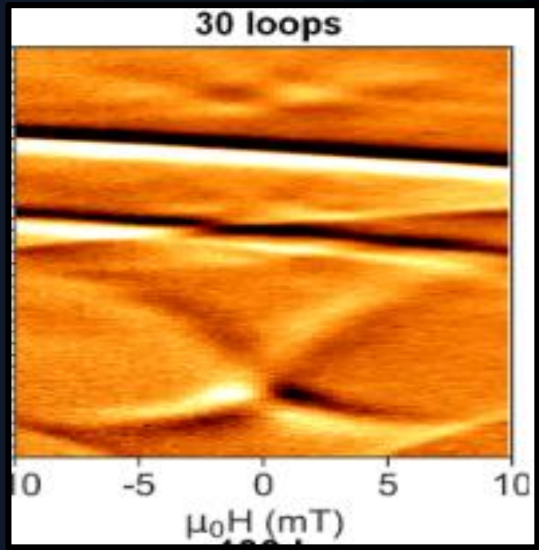
MFM: Macrospin state



MFM: Vortex state



FMR: Macrospin state



FMR: Vortex state

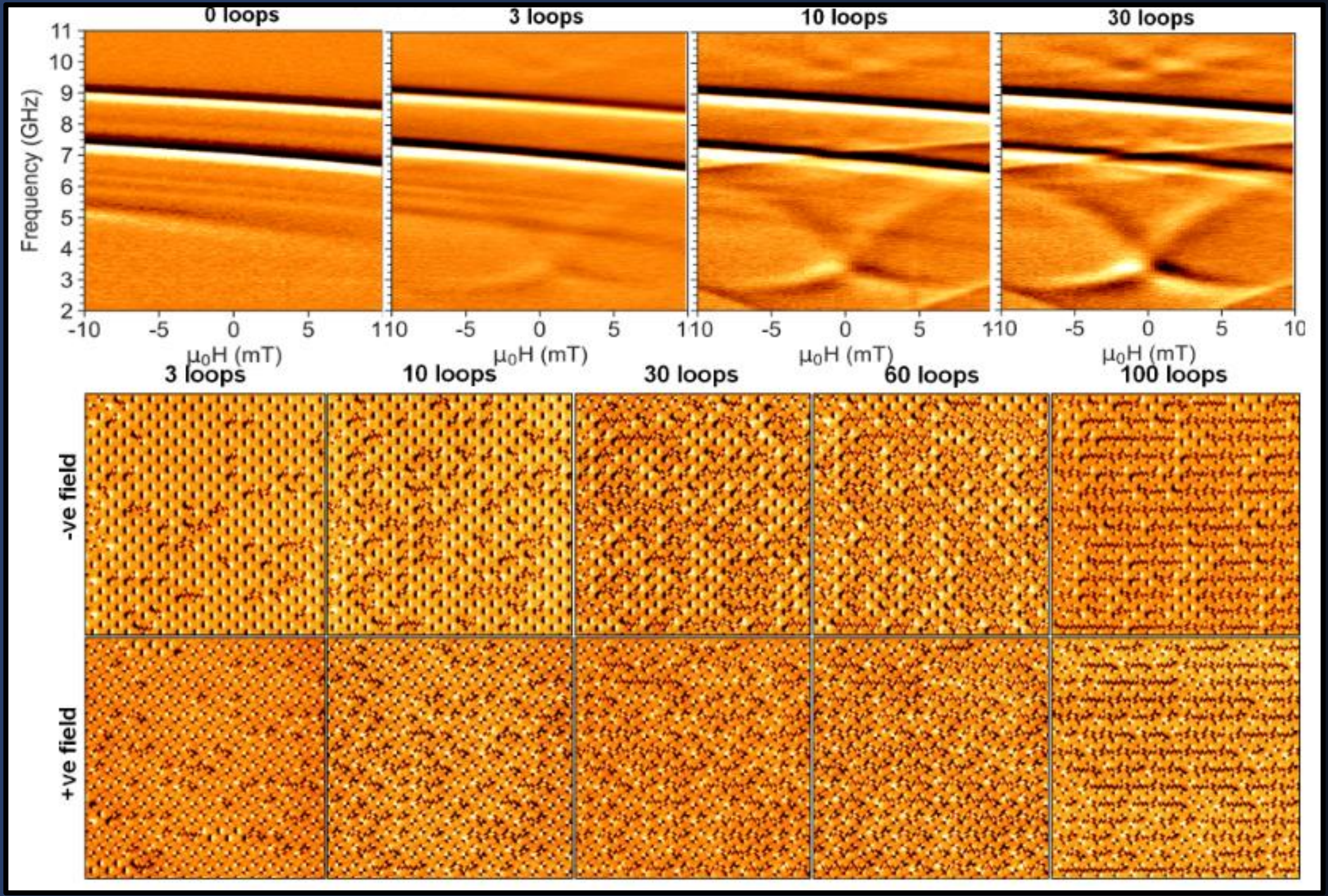
Simulation collaborators: **Troy Dion,** Kyushu **(Japan)**

Data input & readout solved

- **Data Input:** Solved, Engineer physical complexity to allow simple global-field input
- **Data Readout:** Solved, use GHz magnon spectra

Magnon Spectra

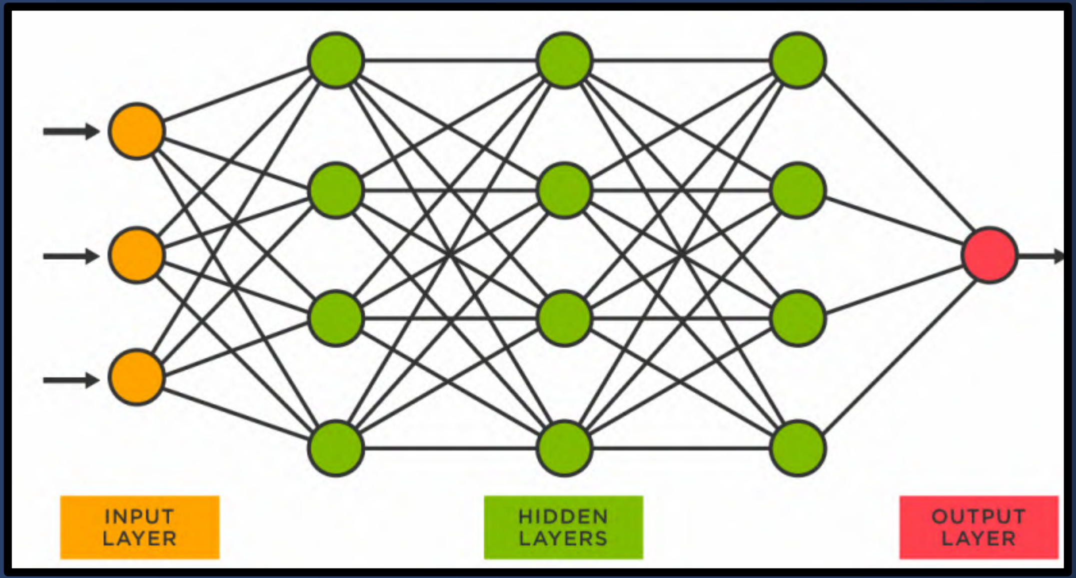
Real-space



Reservoir Computing

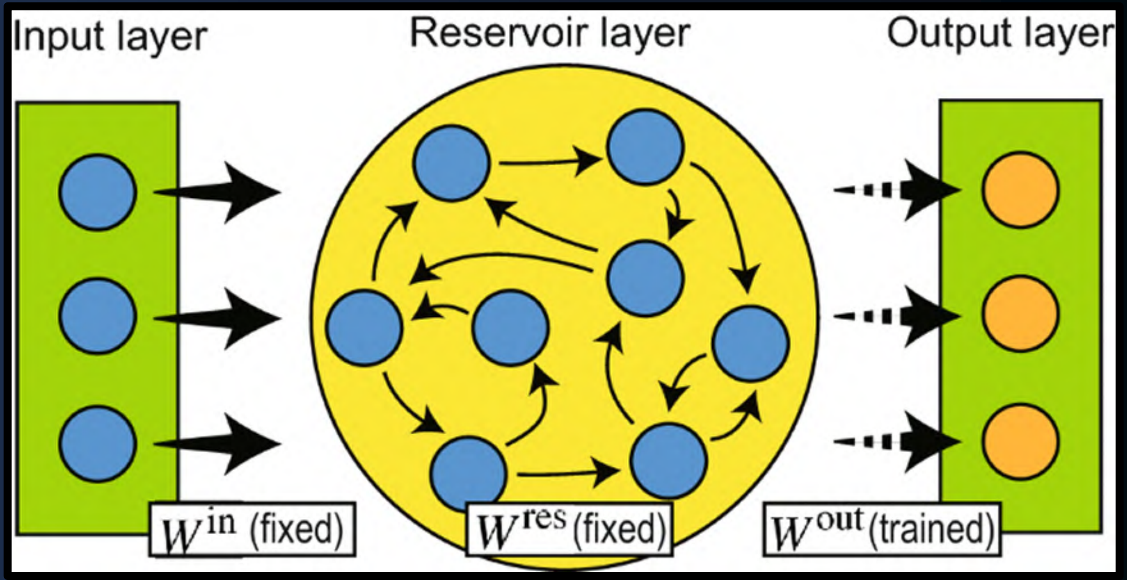
- **Aim:** Map **complex problems** onto **simple linearly solveable ones**
- **Random weight connections** vs. **Fully trainable weights**
- **Low energy** vs. Deep Neural Networks as only train **small output layer**

Deep Neural Network



VS.

Reservoir Computing



1: *energy-uk.org, towardsdatascience.com, OpenAI white paper (2019)*

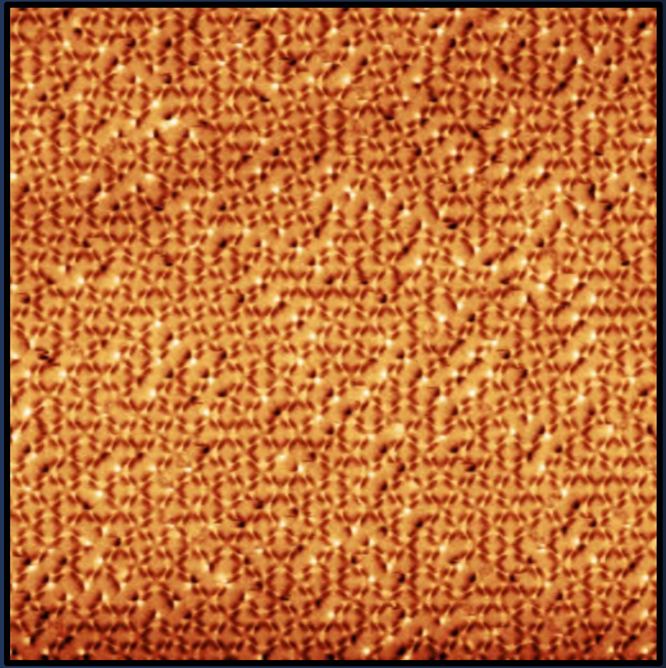
Field **Magnetic Array** **Magnon Spectra**

Reservoir Computing

- **Aim:** Map **complex problems** onto **simple linearly solveable ones**
- **Random weight connections** vs. **Fully trainable weights**
- **Low energy** vs. Deep Neural Networks as only train **small output layer**

Input Problem:
Hard, nonlinear

Physical Reservoir



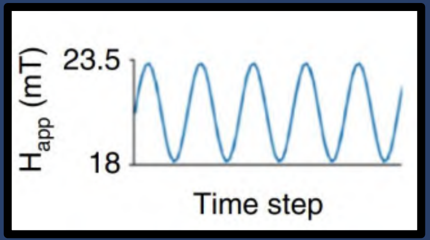
Output Problem
Simple, linear

Reservoir Computing

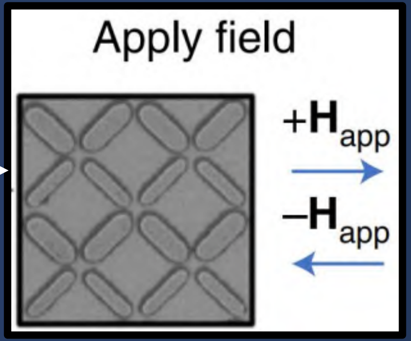
Experimental methodology:

2 Patents filed (2022, 2024)

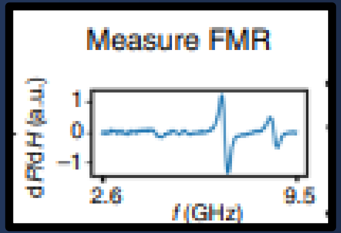
Input dataset



Convert to field



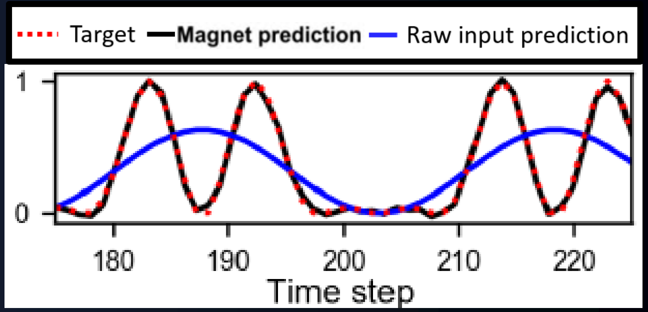
Measure FMR



Linear Regression

$$\begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix}$$

Computation Output



Scheme developed in collaboration with neuromorphic theorists:
F. Caravelli group – Los Alamos National Lab (USA)

- **Gartside, Jack C.** et al, **Nature Nanotechnology** (2022)
- **Lee, O. Gartside, Jack C., Kurebayashi, H.** et al, **Nature Materials** (2023)


ARTICLES
https://doi.org/10.1038/s41565-022-01091-7
nature nanotechnology
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Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting

Jack C. Gartside[1,7], Kilian D. Stenning[1,7], Alex Vanstone[1,7], Holly H. Holder[1], Daan M. Arroo[2,3], Troy Dion[4,5], Francesco Caravelli[6], Hidekazu Kurebayashi[4] and Will R. Branford[1,3]


nature materials
Article
https://doi.org/10.1038/s41563-023-01698-

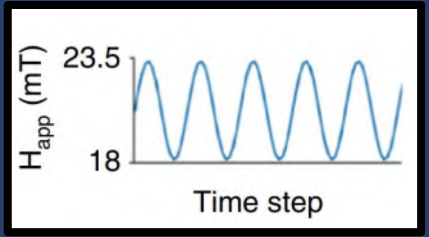
Task-adaptive physical reservoir computing

Reservoir Computing

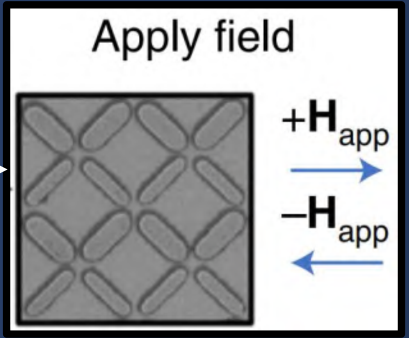
Experimental methodology:

2 Patents filed (2022, 2024)

Input dataset



Convert to field



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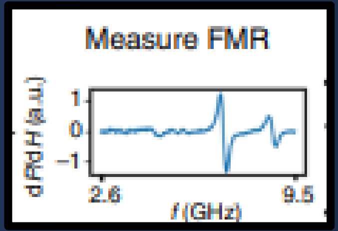

Linear Regression

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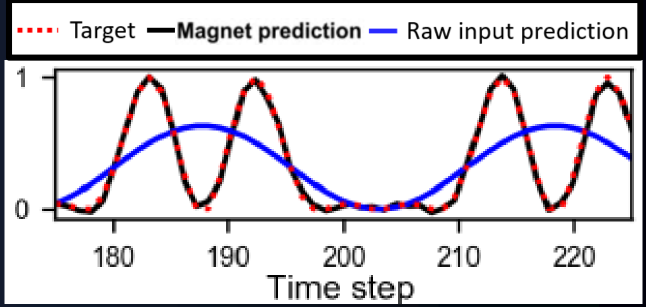
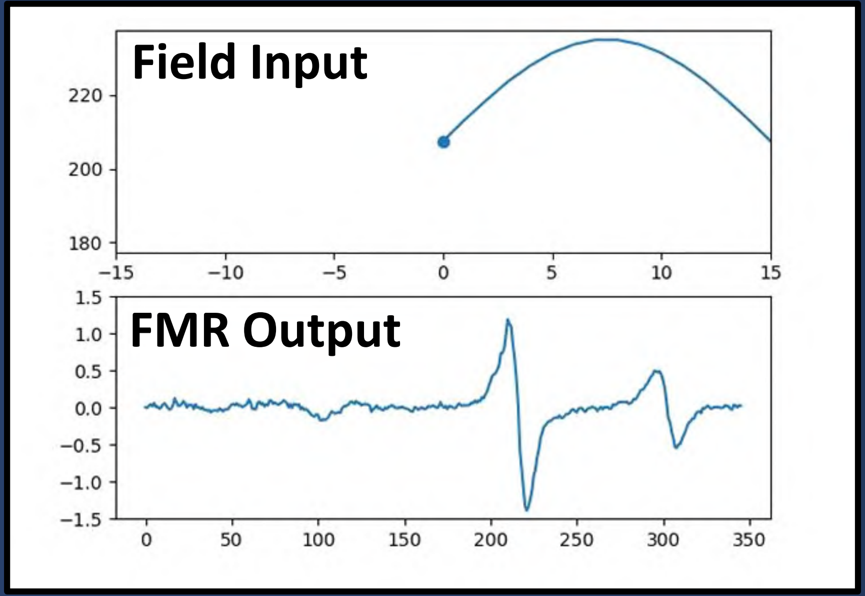
Computation Output





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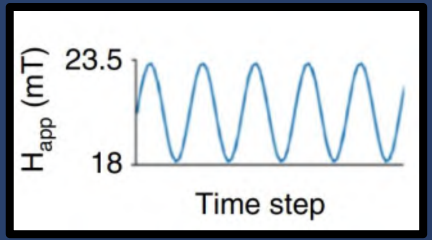
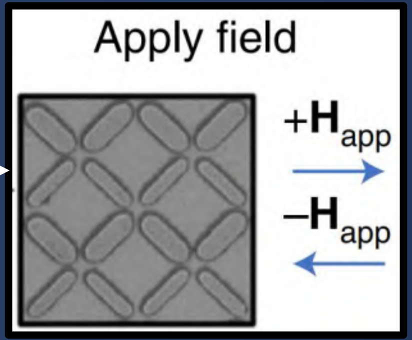


Convert to field



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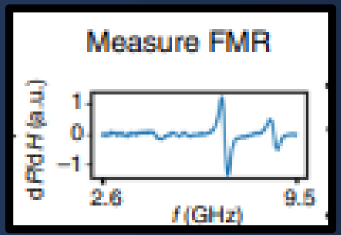

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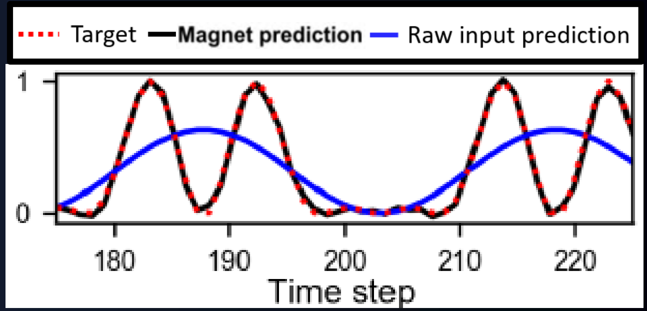
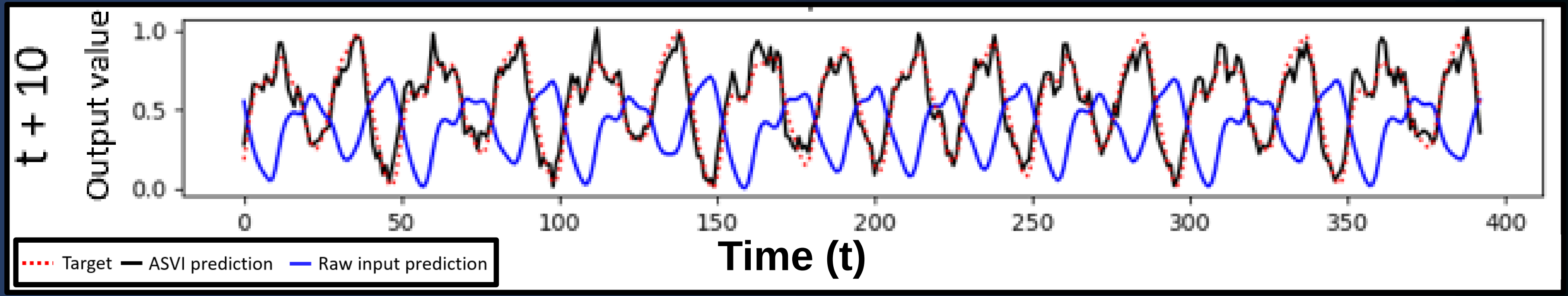
Computation Output





Health-sensing tasks

Solve challenging task: Future prediction (t+10) of **chaotic time-series**

Blood hormone level prediction

- **Gartside, Jack C.** et al, **Nature Nanotechnology** (2022)
- **Lee, O. Gartside, Jack C., Kurebayashi, H.** et al, **Nature Materials** (2023)

ARTICLES

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nature materials

Article

https://doi.org/10.1038/s41563-023-01698-

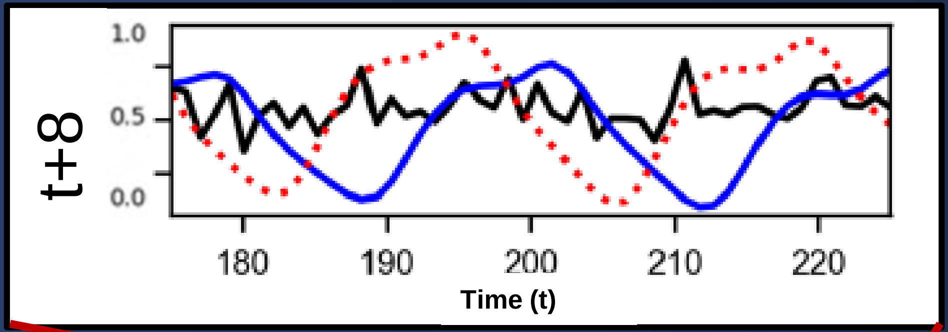
Task-adaptive physical reservoir computing

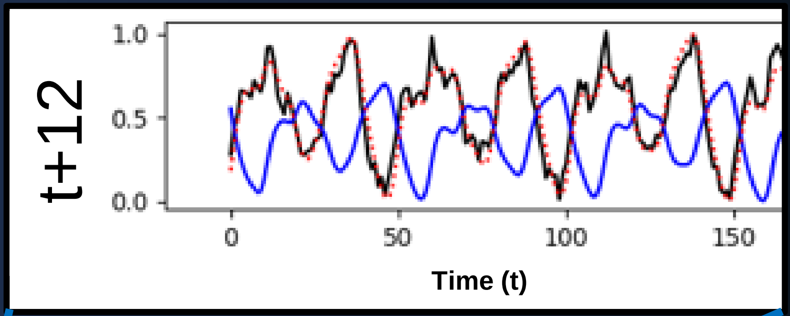
Interconnecting Physical Systems

Jack C. Gartside, Imperial College London

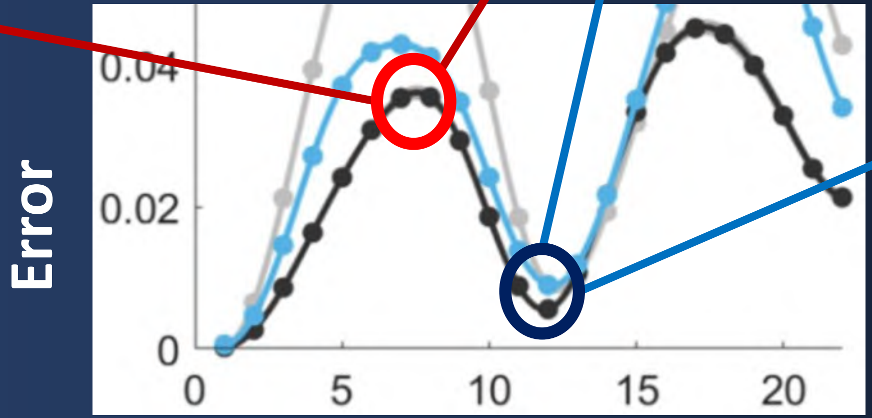
Reservoir Computing

- **Periodic performance:**
  - Single system can't handle multiple timescales
  - t+8 particularly poor
- **Problem:** Single physical systems restricted by fixed dynamics





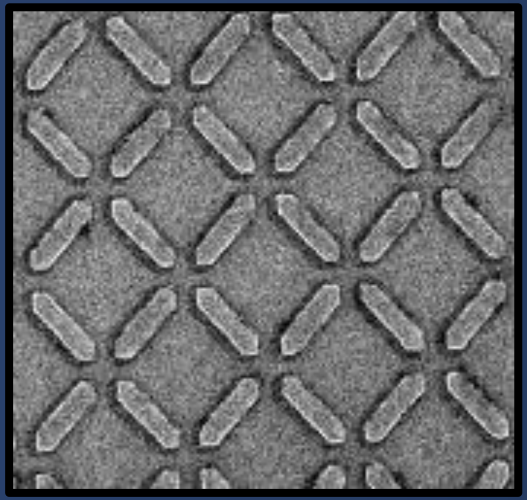
Low error = good computation



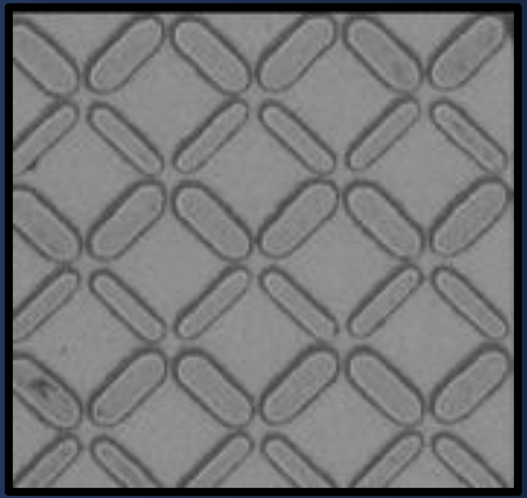
Future prediction step (t+n)

Physical Neural Network Architecture

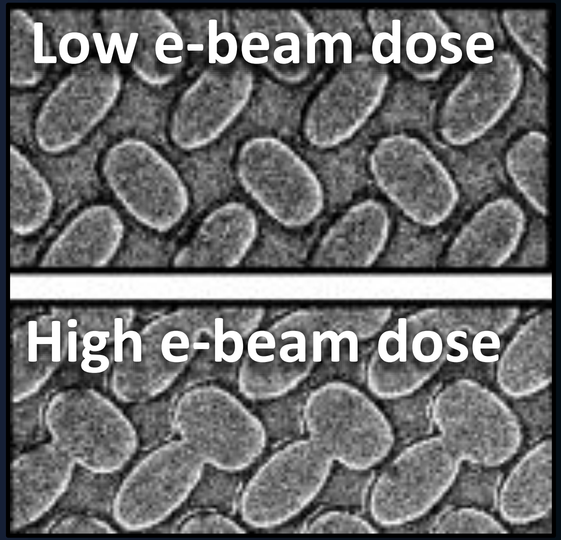
- **Solution:**
  - Interconnect **Multiple arrays** with **distinct dynamics**



Conventional ASI:
No vortices, only macrospins
Short-term memory



Vortex ASVI:
Vortices & macrospins
Long-term memory



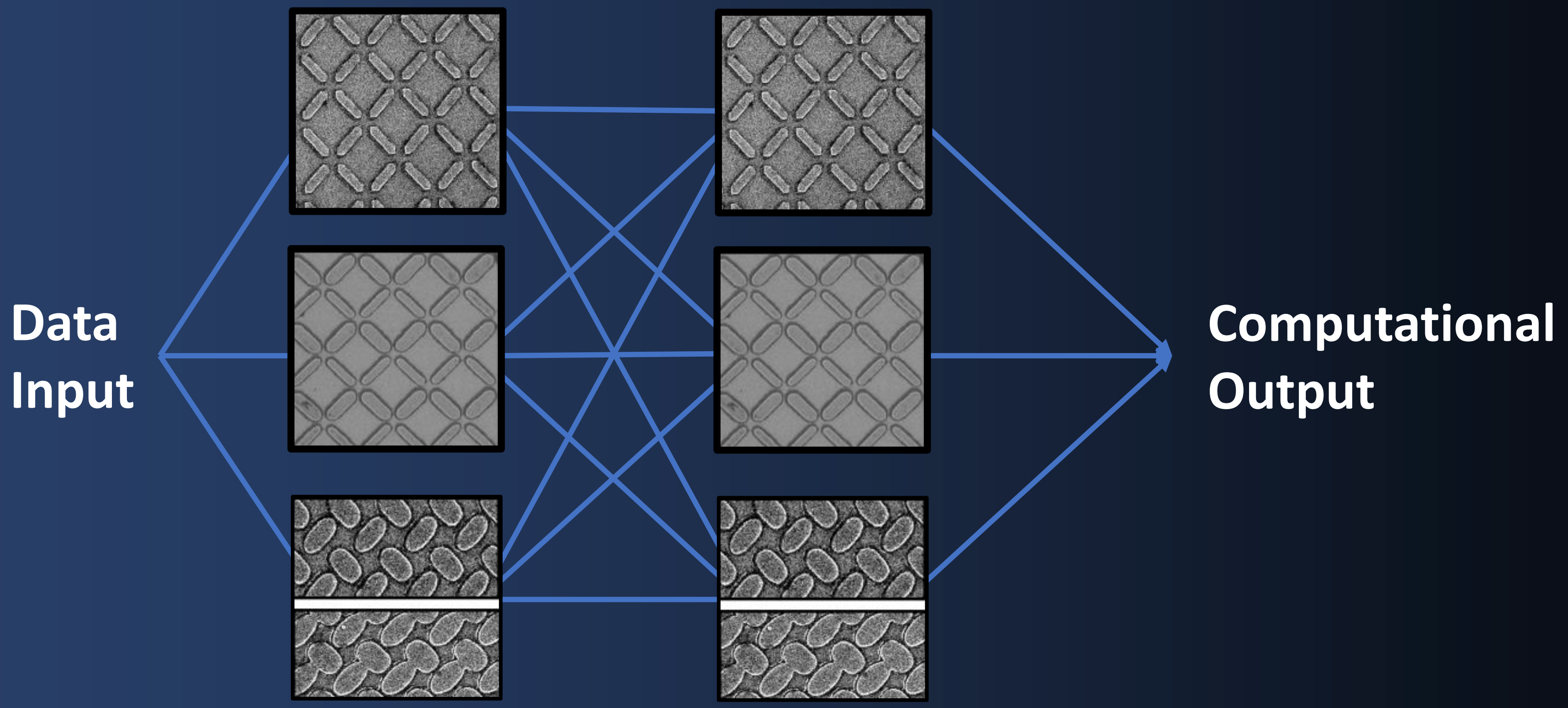
Pinwheel ASVI:
Engineered structural disorder
Strong nonlinearity

Stenning, Kilian D., Gartside, Jack C., et al. "Neuromorphic Few-Shot Learning: Generalization in Multilayer Physical Neural Networks." *arxiv* (2023)

Physical Neural Network Architecture

- Build a small 2x3 layer **physical neural network** - Each ‘**neuron**’ is a **different nanoarray**
- Interconnect **1st-layer output** (GHz amplitude) to **2nd-layer input** (magnetic field)
- Collaborators at University of Sheffield **Dr Luca Manneschi** & **Prof Eleni Vasilaki** co-designed interconnected network architecture

Interconnected arrays



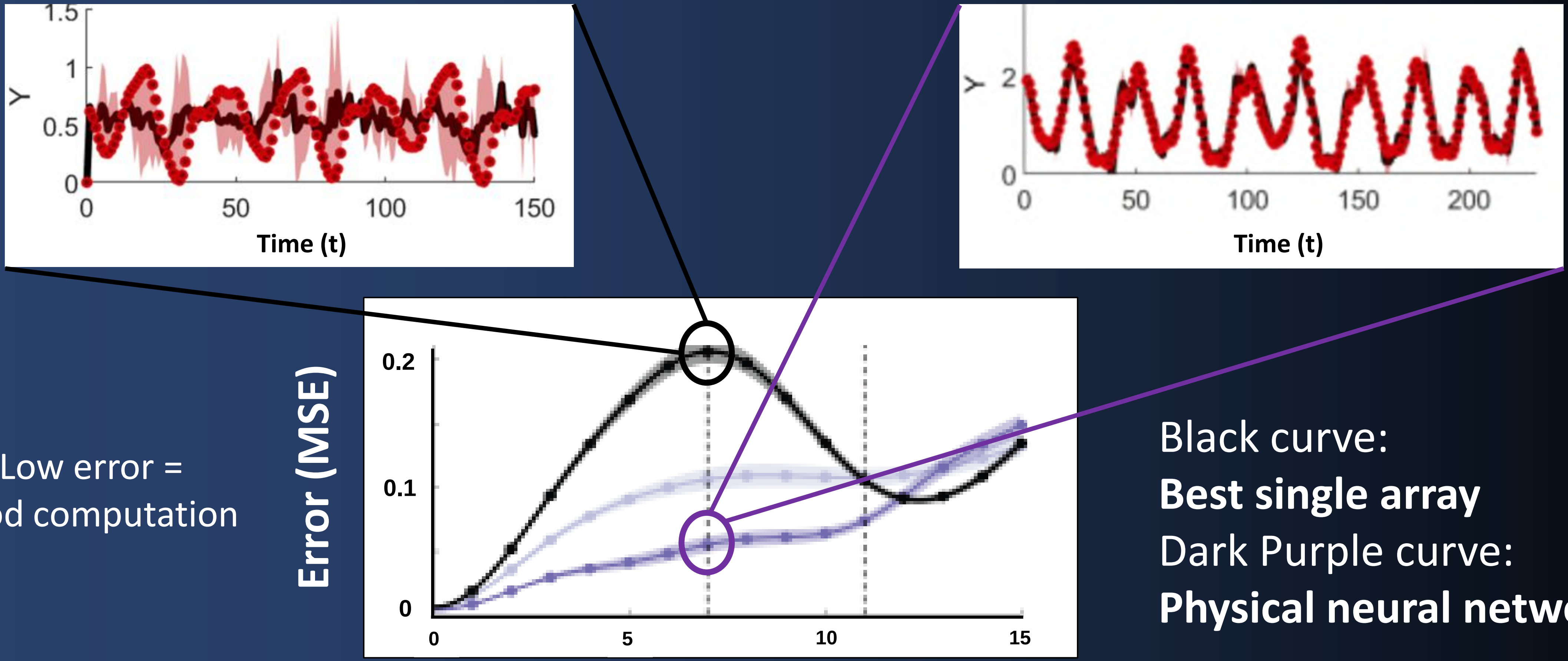
Stenning, Kilian D., Gartside, Jack C., et al. "Neuromorphic Few-Shot Learning: Generalization in Multilayer Physical Neural Networks.“ *arxiv* (2023)

Physical Neural Network Architecture

- Physical Neural Net architecture solves problems – fix periodic performance

Best single nanoarray - poor

Interconnected
Physical neural network - good



Error (MSE)

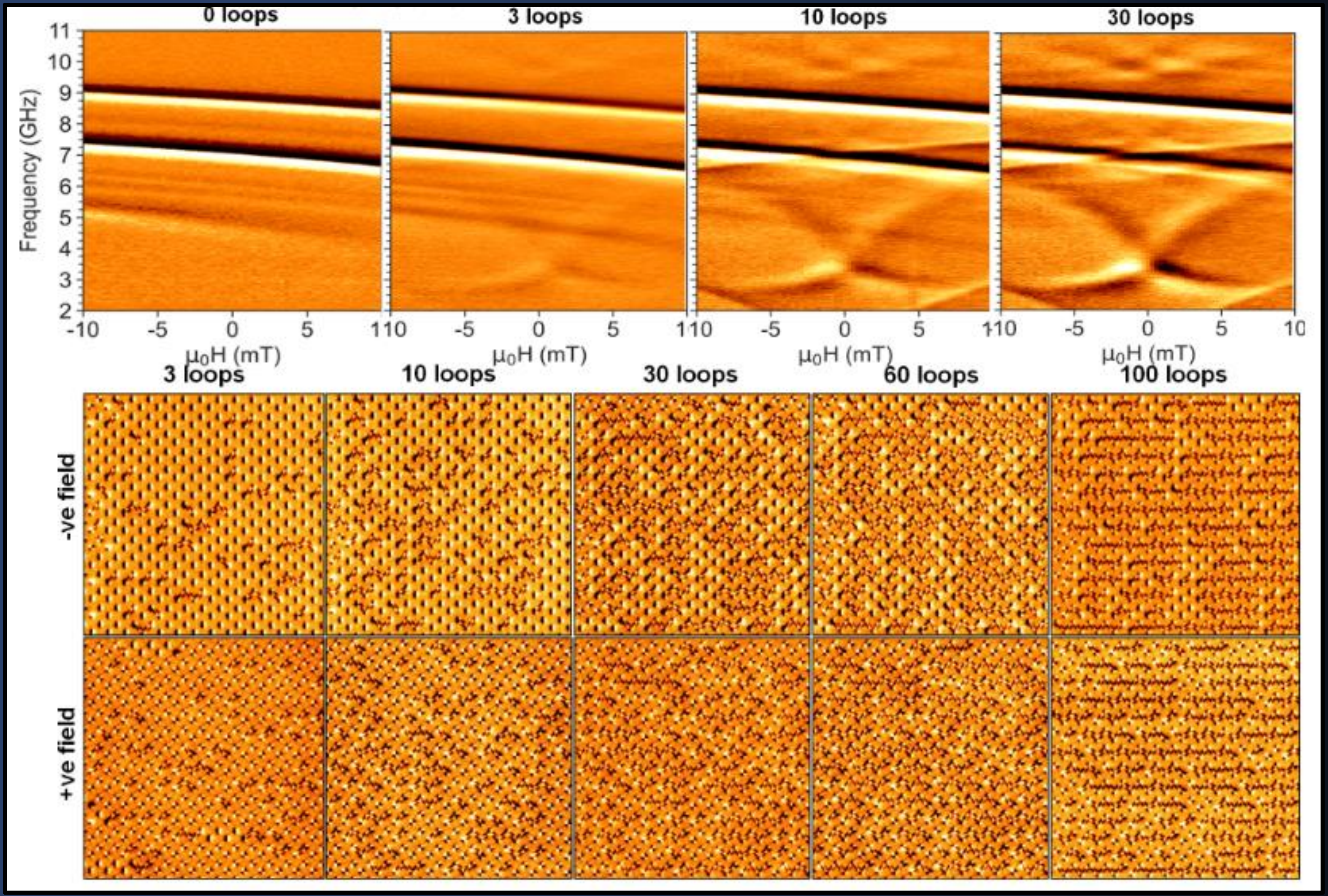
Future prediction step (t+n)

Low error =
good computation

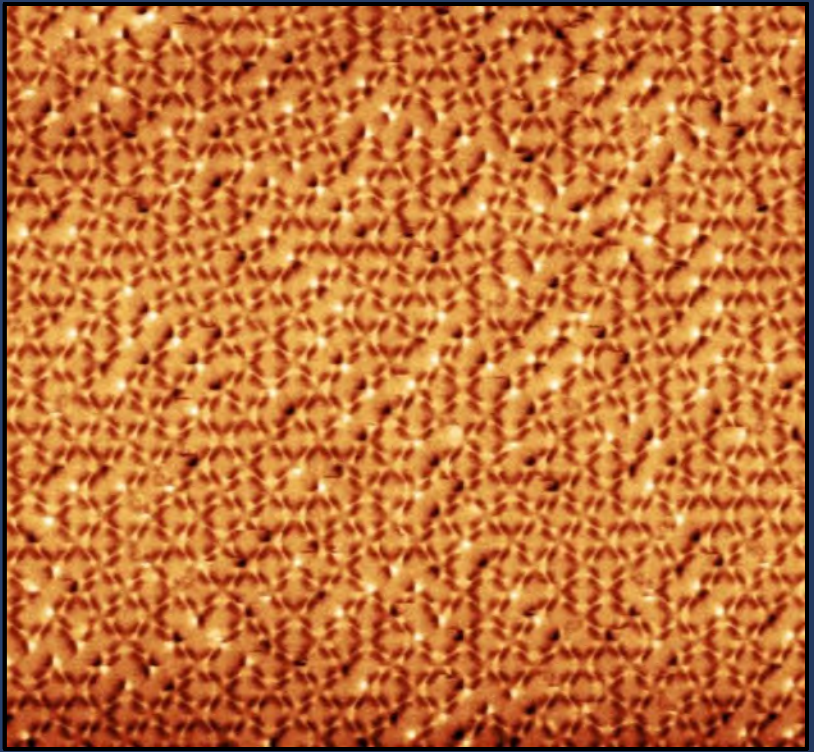
Black curve:
Best single array
Dark Purple curve:
Physical neural network

Stenning, Kilian D., Gartside, Jack C., et al. "Neuromorphic Few-Shot Learning: Generalization in Multilayer Physical Neural Networks." *arxiv* 2023

Analogue tunability of magnon modes & microstate



Artificial Spin-Vortex Ice: Beyond a single magnetic texture

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https://doi.org/10.1038/s41565-022-01091-7

nature nanotechnology

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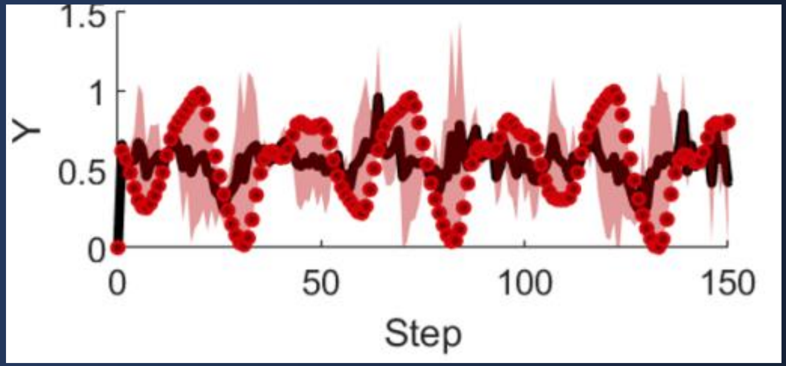
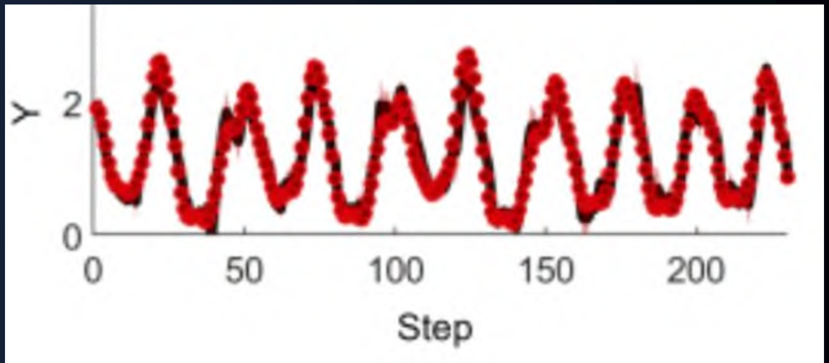
Gartside, Stenning, Vanstone et al,
Nature Nanotechnology (2022)

- **Adding chiral states increases**
  - **Complexity**
  - **Memory**
  - **Neuromorphic Computing performance**
- **How far can we take this Microstate Engineering?**

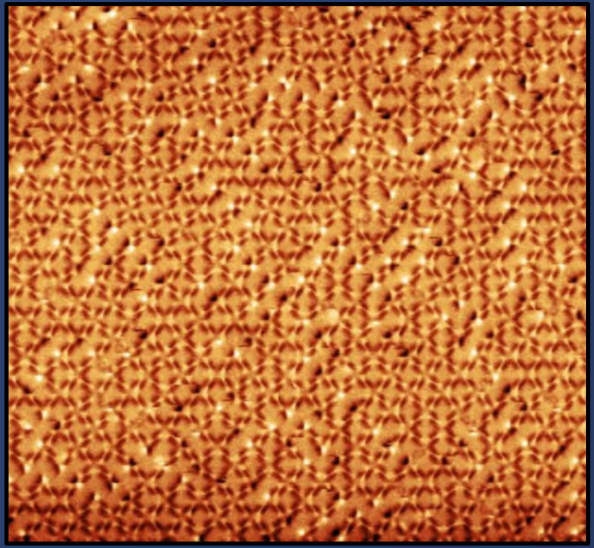
No vortices: (normal ASI)
Bad future prediction



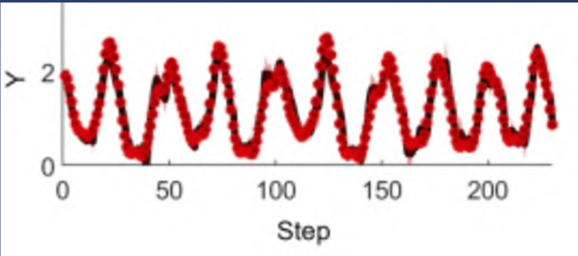
Vortices & macrospins:
Excellent prediction



Microstate Control: Neuromorphic Performance



Vortices & macrospins: Excellent prediction



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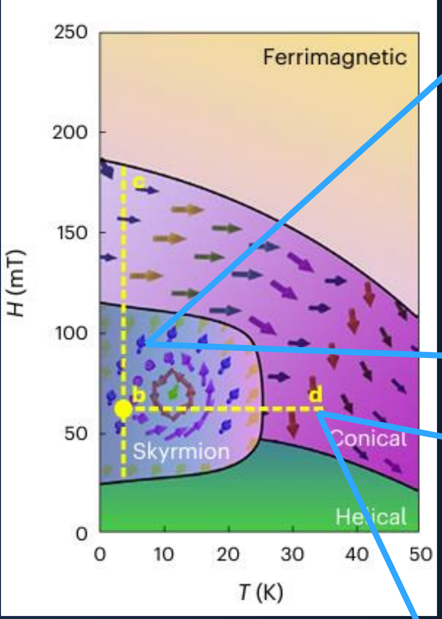
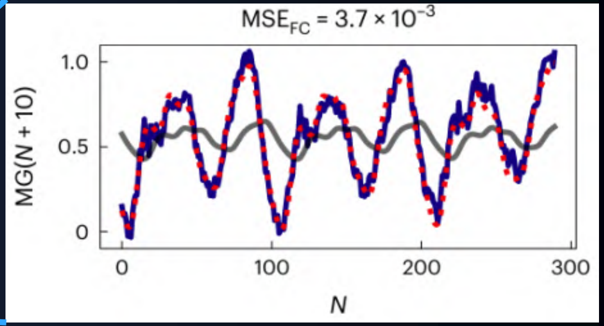
Gartside, Stenning, Vanstone et al,
Nature Nanotechnology (2022)

Show the functional benefits of expanded microstate range via two recent experimental demonstrations,
Nature Nanotechnology (2022)
& Nature Materials (2023)

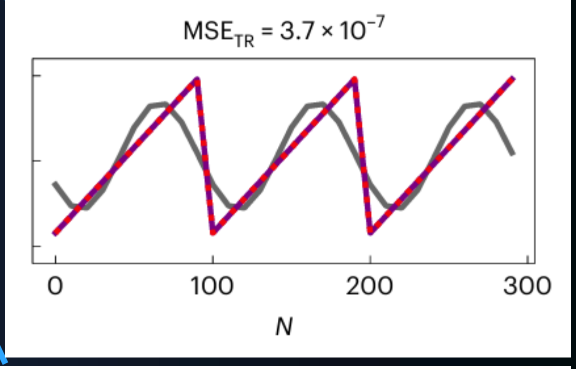


Oscar Lee, Tianyi Wei, Kilian D. Stenning, Jack C. Gartside, et al
Nature Materials (2023)

Skyrmion phase: Prediction



Conical phase: Transformation



nature materials

Article

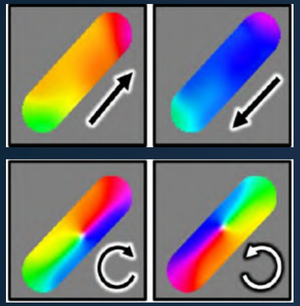
https://doi.org/10.1038/s41563-023-01698-8

Task-adaptive physical reservoir computing

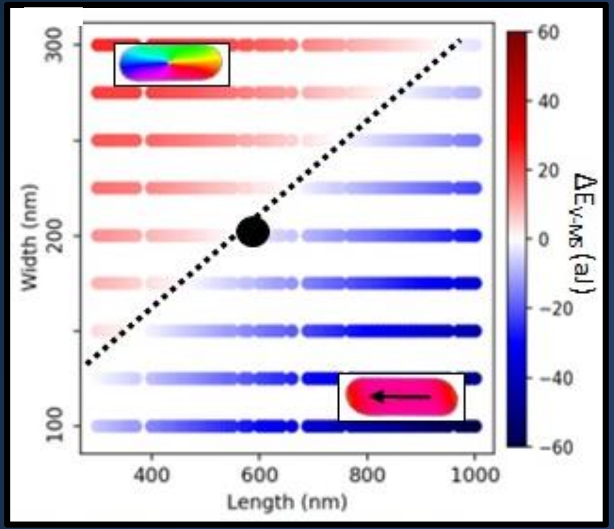
Jack C. Gartside, Imperial College London

Another Solution: Fabricate islands on a **textural tipping point**

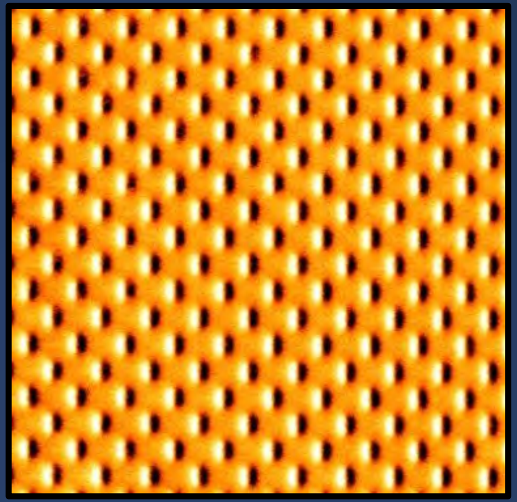
Macrospins



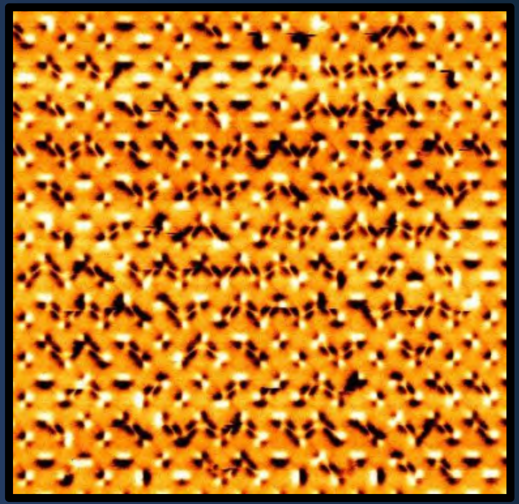
Vortices



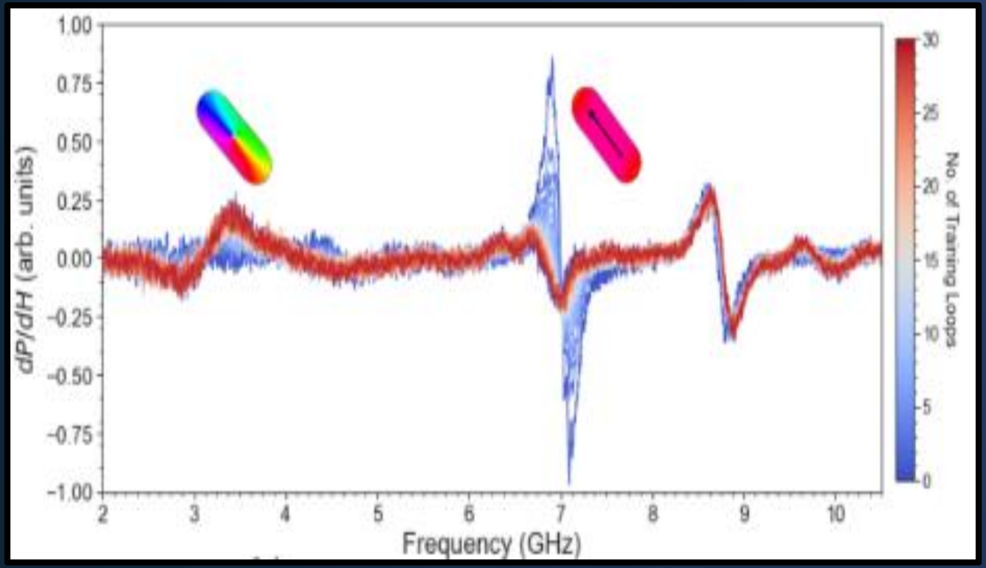
Vortex vs. Macrospin energy: Pick **bistable point**

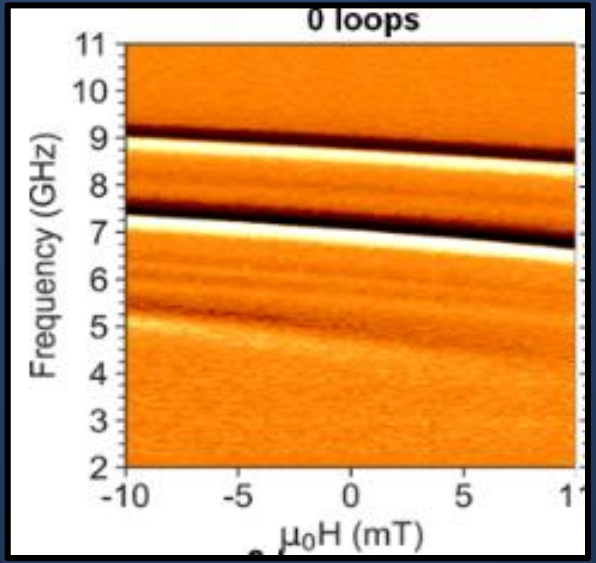


MFM: Saturated -200 mT initial state, Blue Spectra

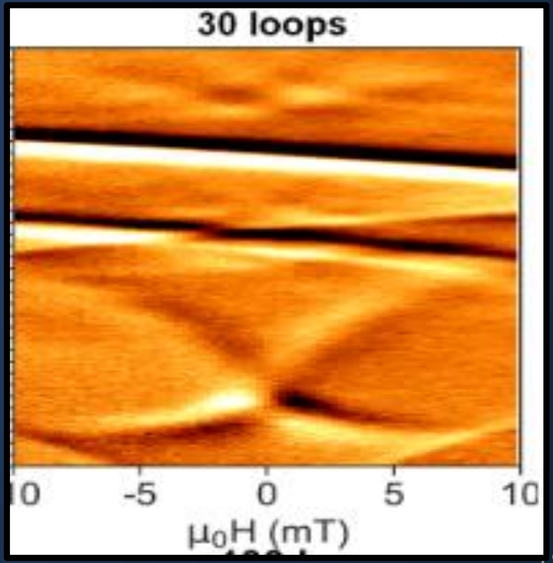


MFM: 30x Field-loops state, Red spectra





FMR: Macrospin state



FMR: Vortex state

Jack C. Gartside, Imperial College London

Conclusions

- **Developed** new **bistable artificial spin system** 'ASVI'
- **Engineering** extra microstate & dynamic richness enhances functionality
- Trilayer ASVI is **extremely rich** & **reconfigurable**
- New phenomena: Ultrastrong Magnon-Magnon Coupling & Magnon Frequency Combing
- **2 year Post-Doc position available! Email me :)**
- **Thanks & any questions!**

Upcoming Work:

Trilayer ASVI for Neuromorphic Computing


nature materials

Article

Task-adaptive physical reservoir computing

Received: 4 October 2022

Accepted: 19 September 2023

Oscar Lee, Tianyi Wei, Kilian D. Stenning, Jack C. Gartside, Dan Prestwood, Shinichiro Seki, Aisha Aqeel, Kosuke Karube, Naoya Kanazawa, Yasujiro Taguchi, Christian Back, Yoshinori Tokura, Will R. Branford & Hidekazu Kurebayashi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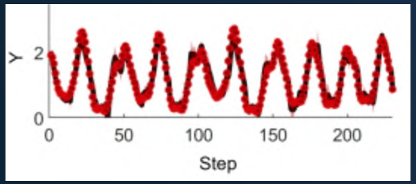
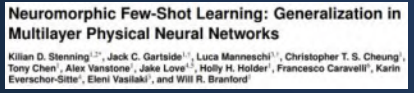
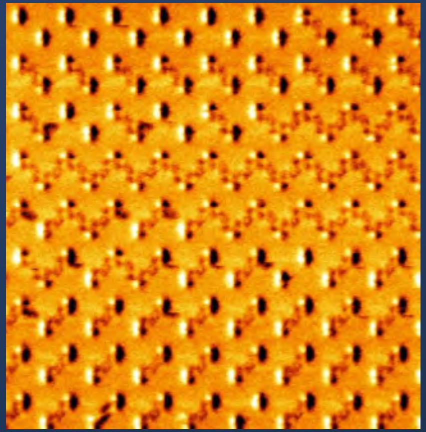


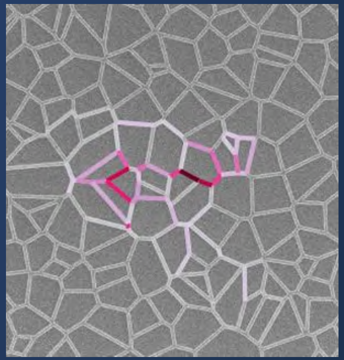

Neuromorphic Few-Shot Learning: Generalization in Multilayer Physical Neural Networks

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

All-Optical Writing of Vortices



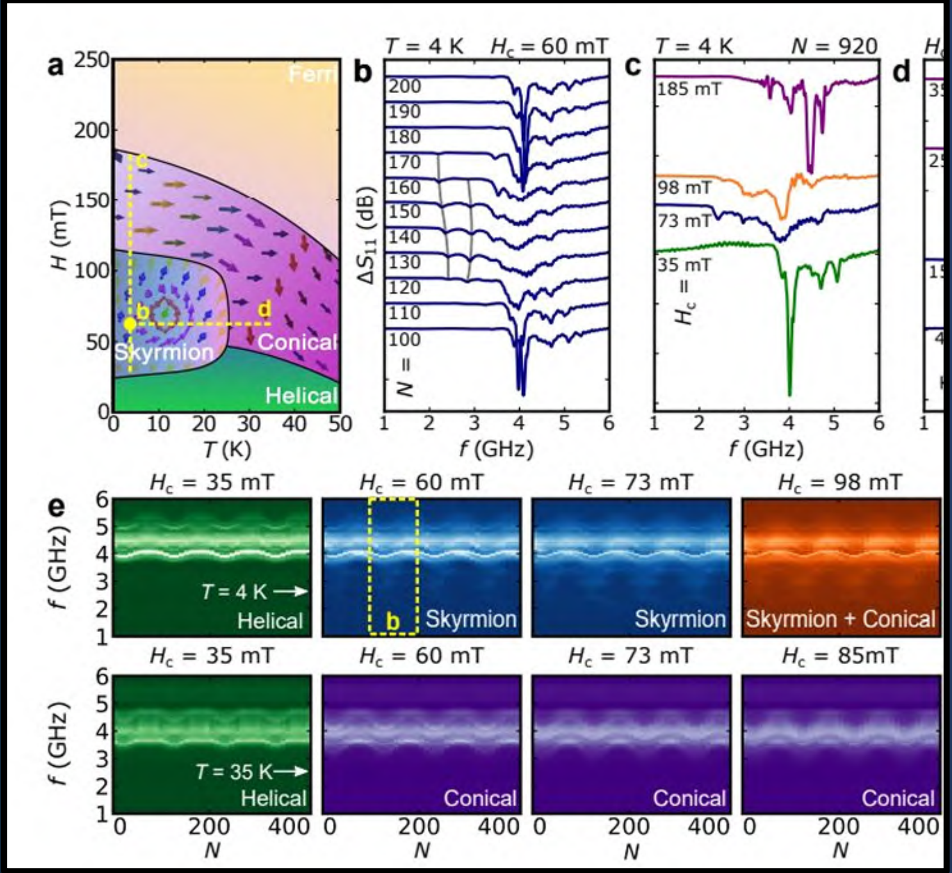
Photonic Neuromorphic Computing

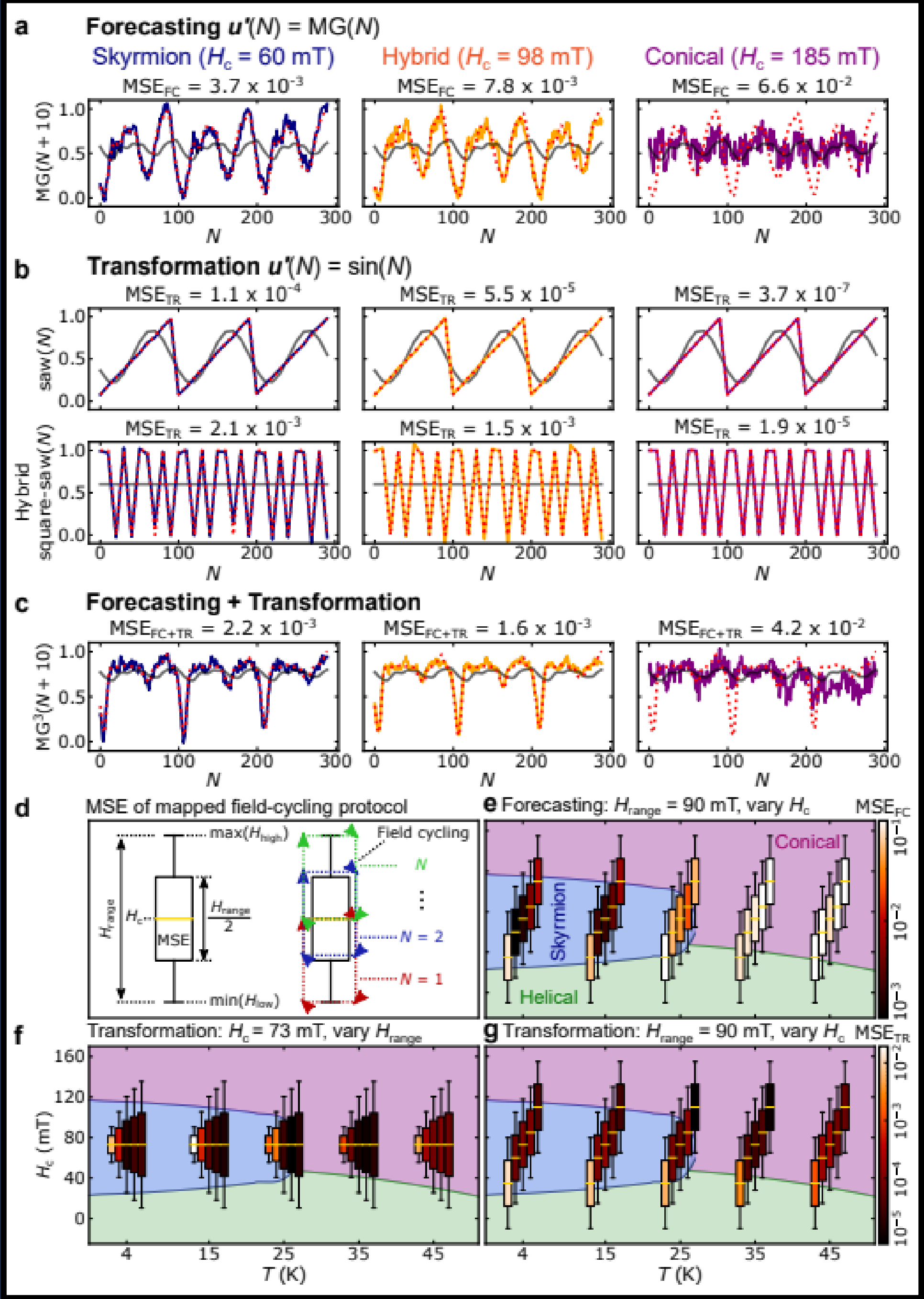


Conclusions

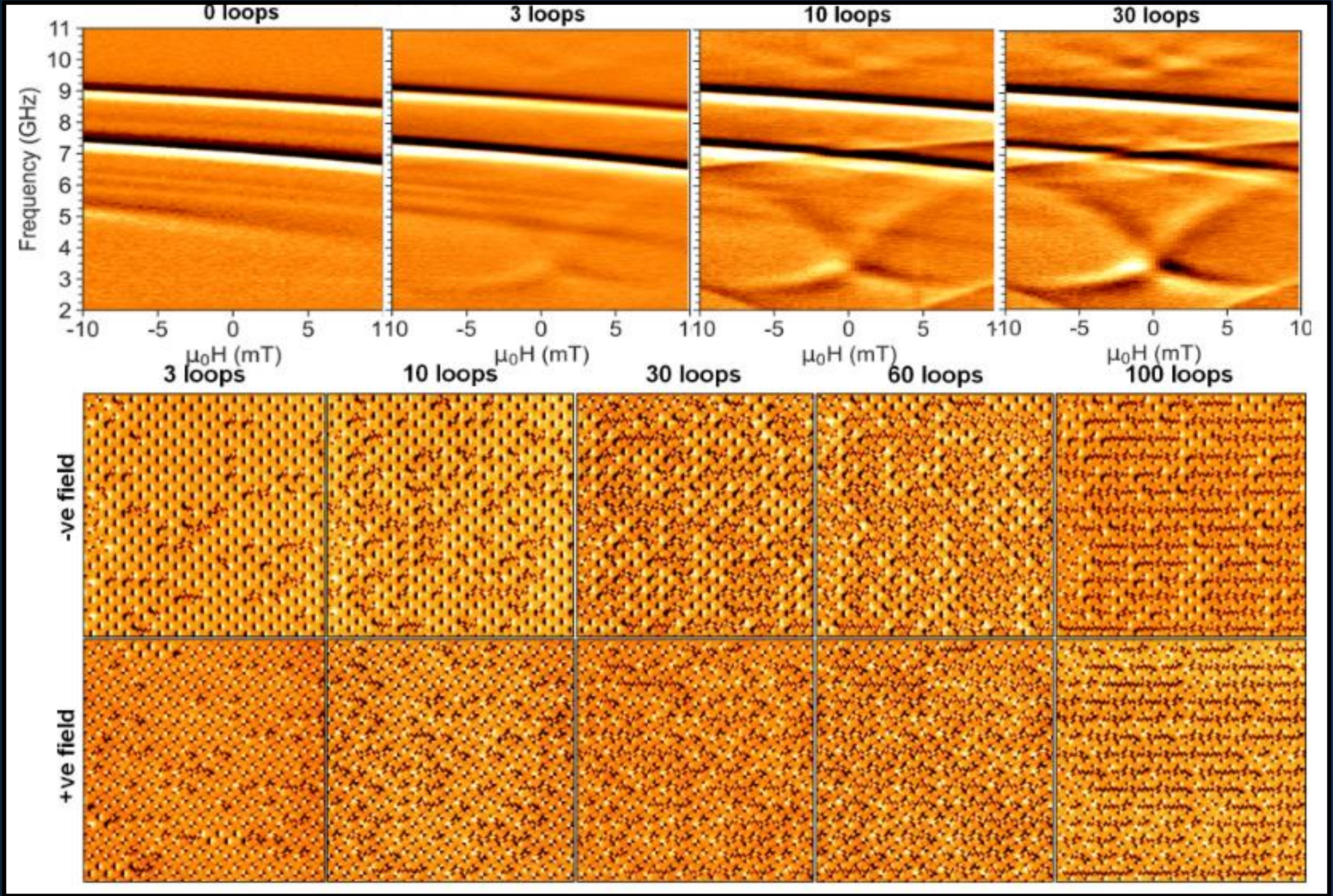
Task-adaptive physical reservoir computing

Oscar Lee[1,*], Tianyi Wei[1], Kilian D. Stenning[2], Jack C. Gartside[2], Shinichiro Seki[3], Aisha Aqeel[4,5], Christian Back[4], Yoshinori Tokura[3,6,7], Will R. Branford[2,8], and Hidekazu Kurebayashi[1,9,**]

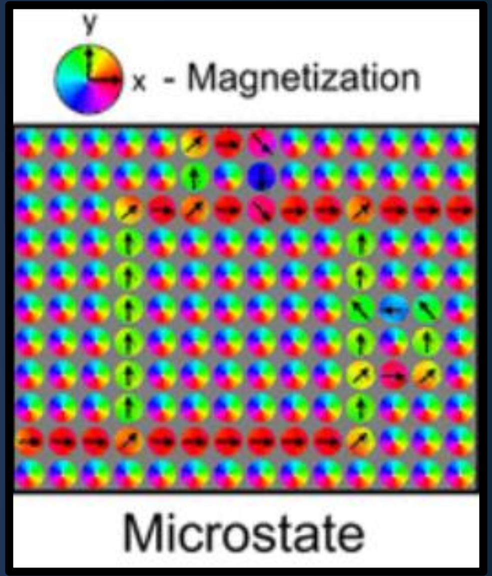


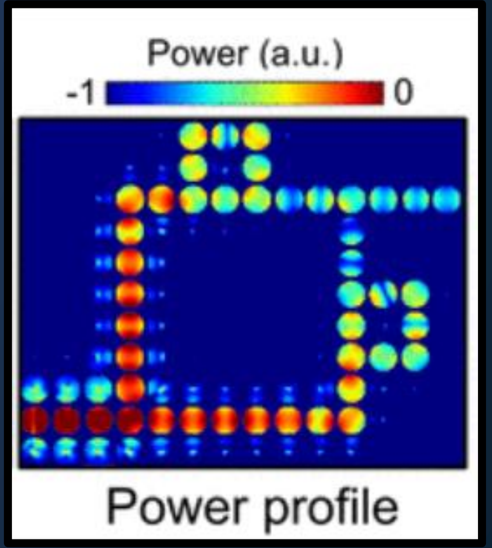


Analogue tunability of magnon modes & microstate

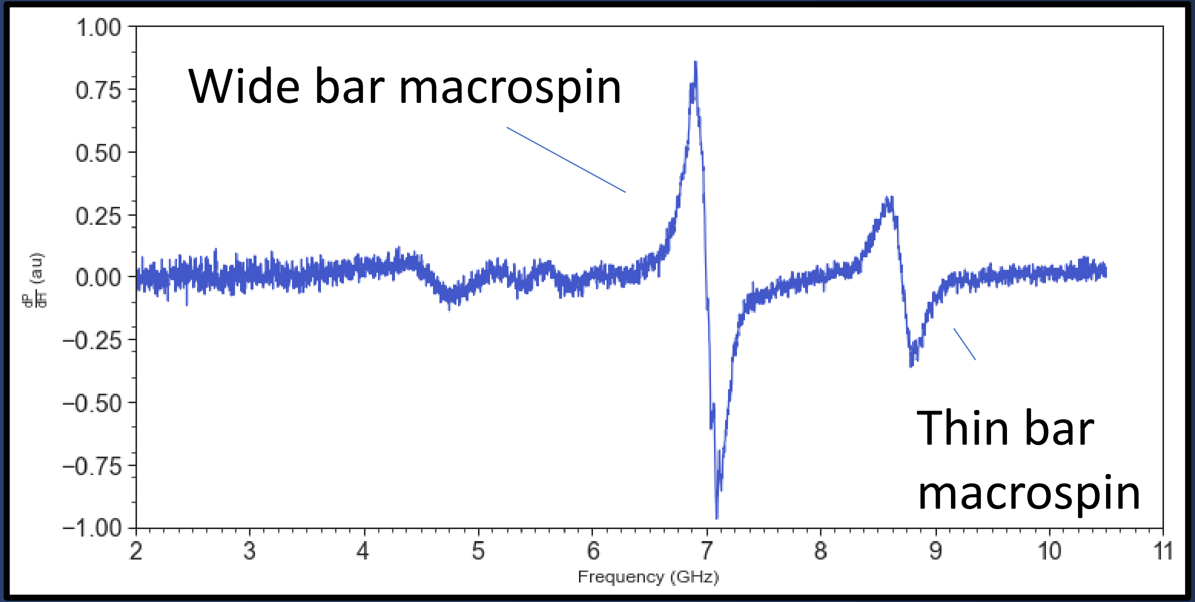


Local waveguiding capabilities

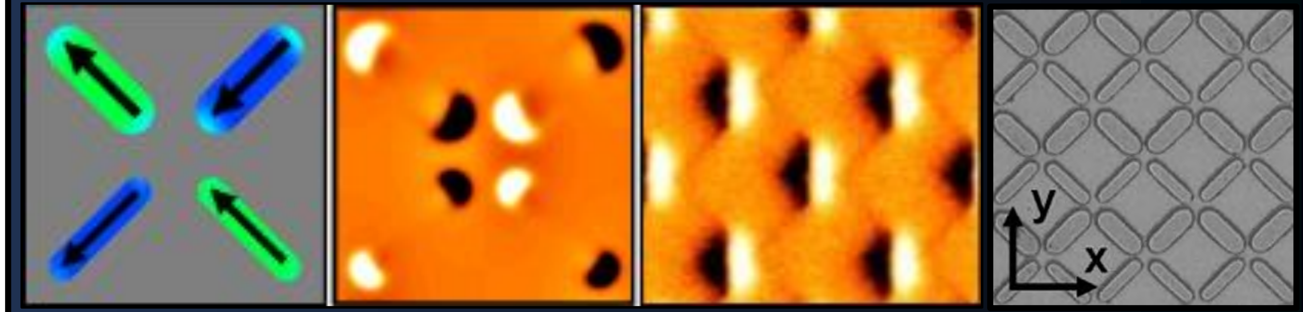




Artificial Spin-Vortex Ice: Beyond a single magnetic texture



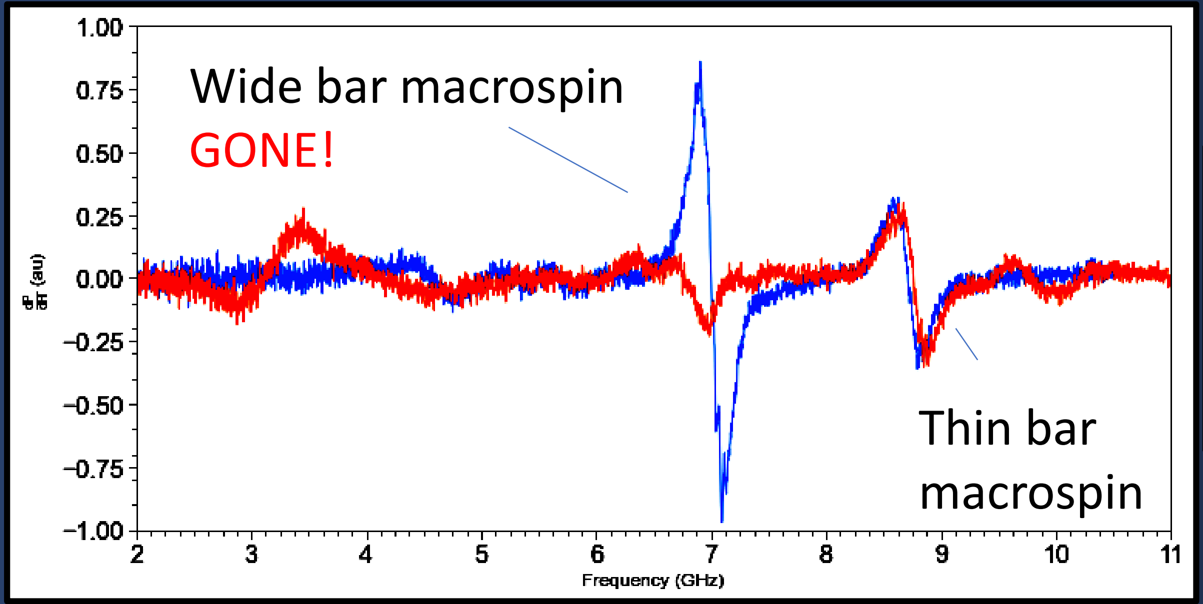
Normal saturated ASI spectra:



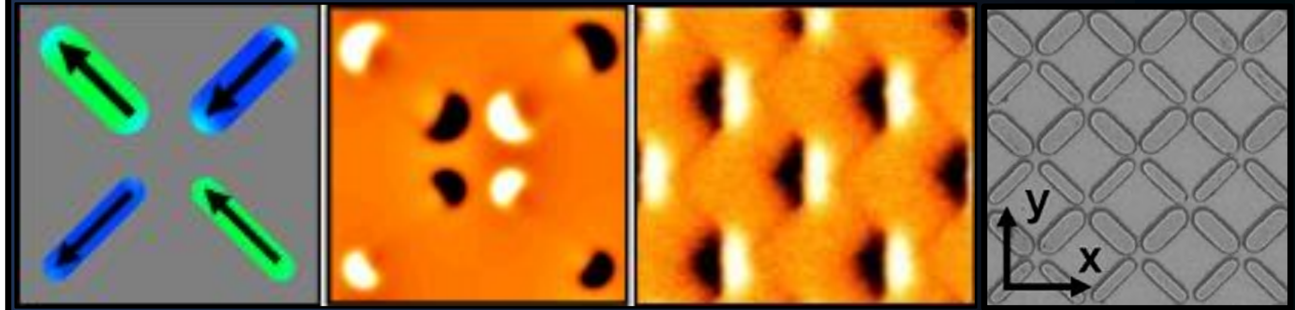
Magnetisation | Simulated MFM | Experimental MFM | SEM

Gartside, Jack C., et al. "Reconfigurable magnonic mode-hybridisation and spectral control in a bicomponent artificial spin ice." **Nature Communications** (2021)

Artificial Spin-Vortex Ice: Beyond a single magnetic texture

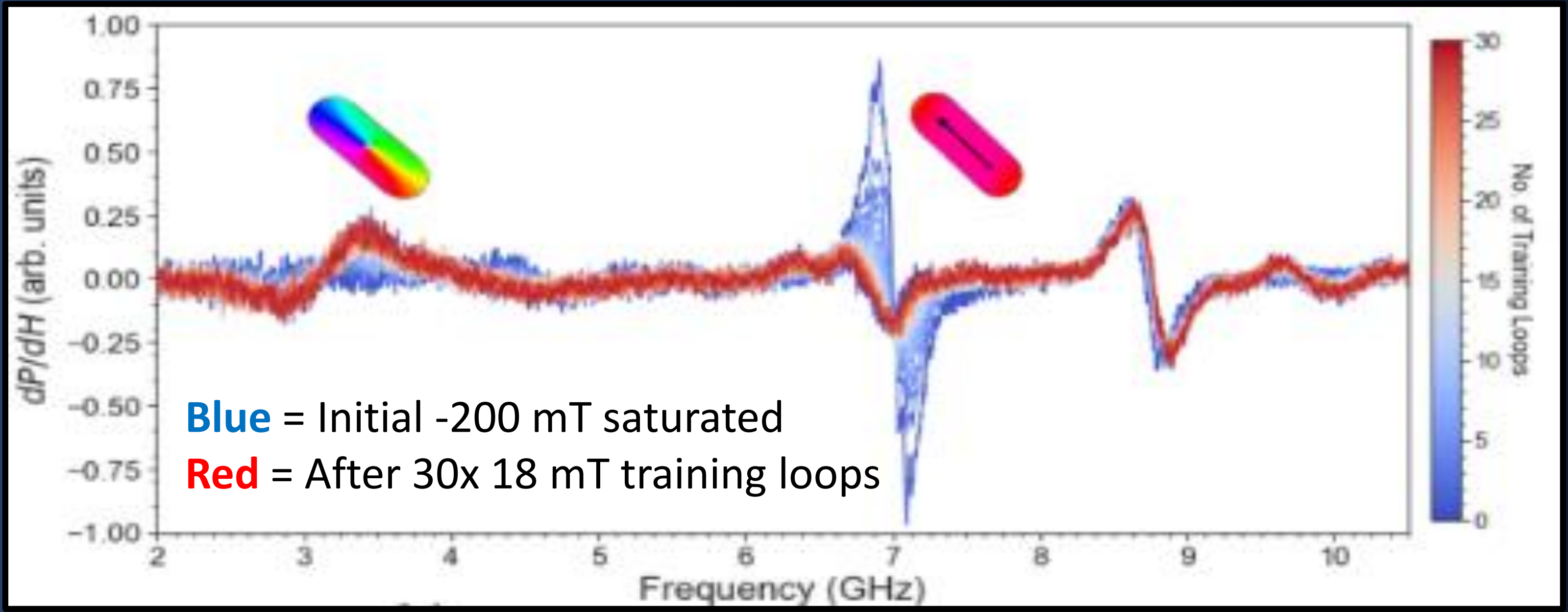


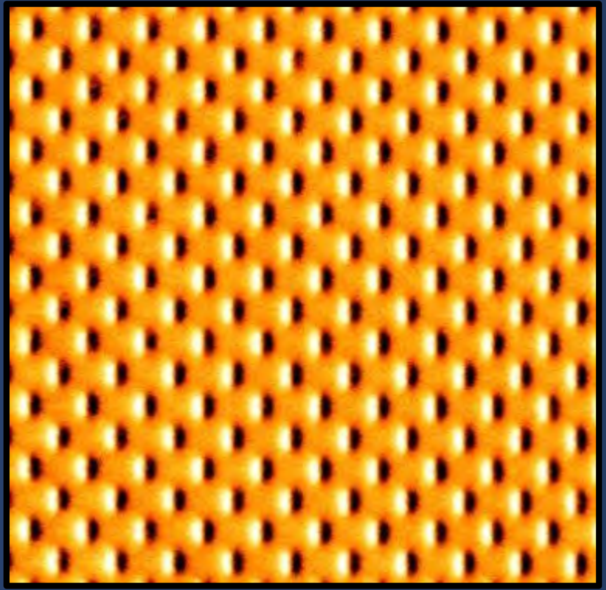
Normal saturated ASI spectra:



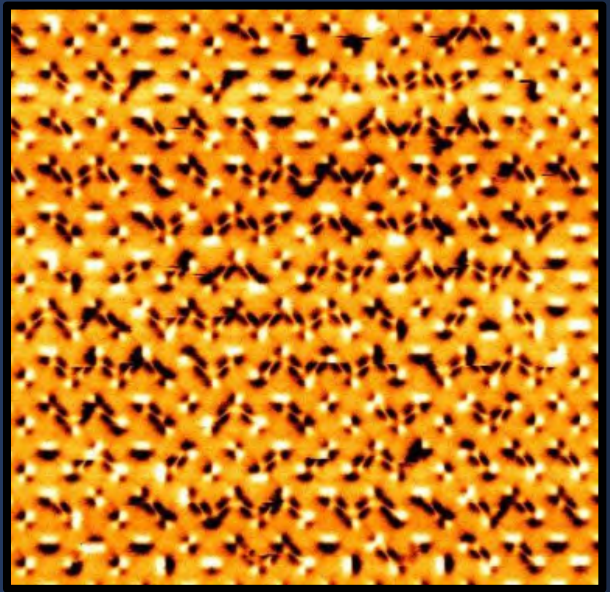
Magnetisation Simulated MFM Experimental MFM SEM

Gartside, Jack C., et al. "Reconfigurable magnonic mode-hybridisation and spectral control in a bicomponent artificial spin ice." **Nature Communications** (2021)

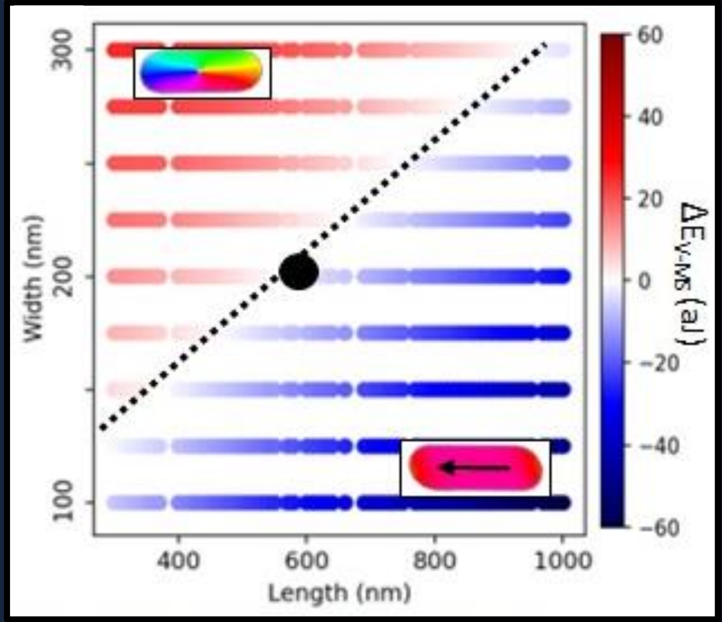




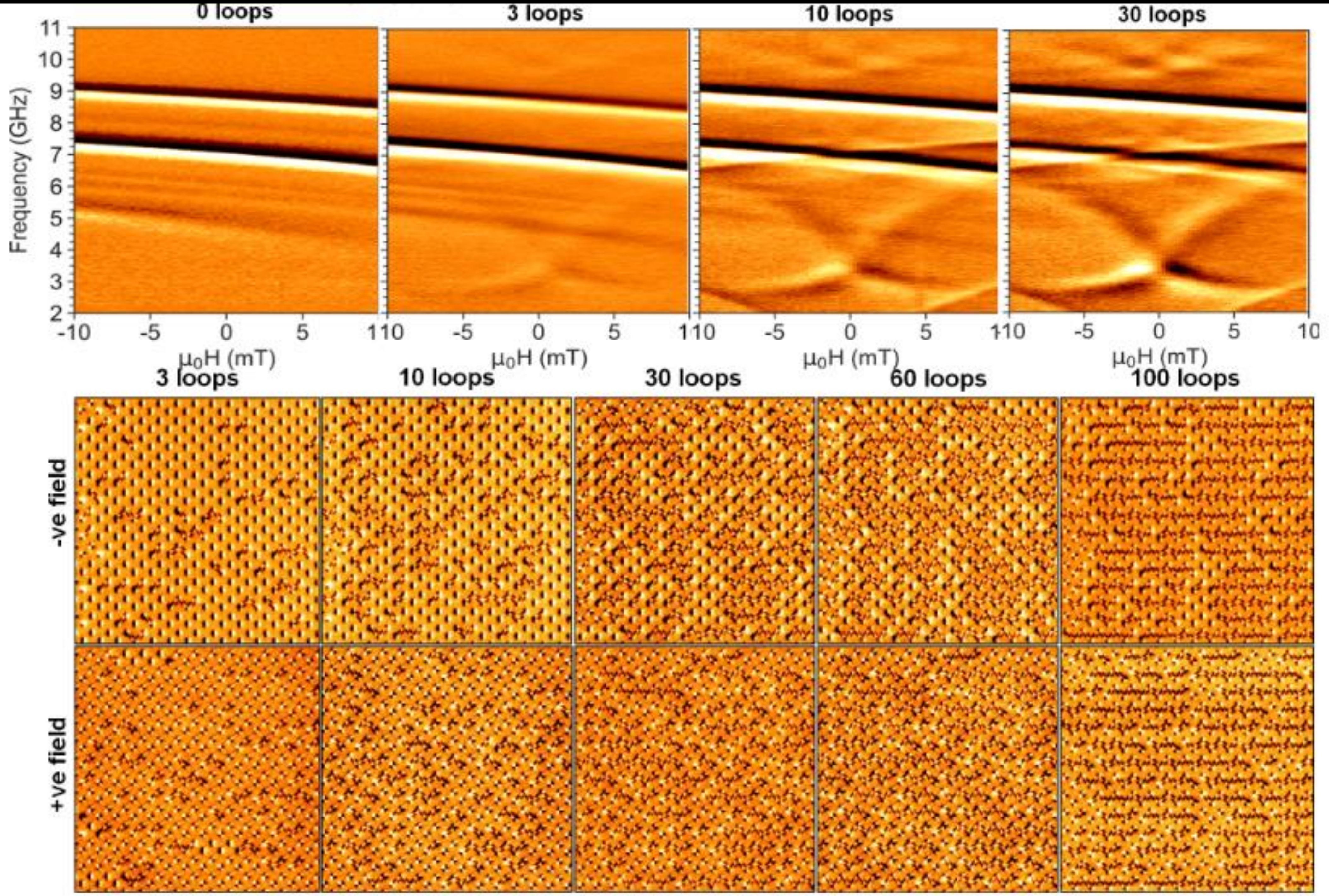
MFM: Saturated -200 mT initial state, Blue Spectra



MFM: 30x Field-loops state, Red spectra

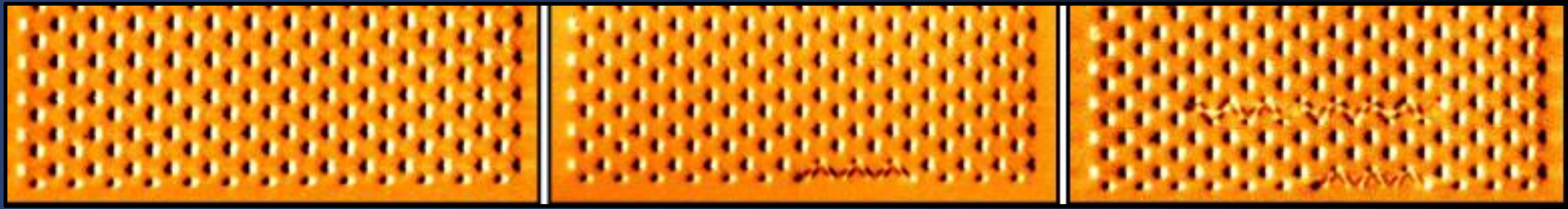


Vortex/Macrospin Demag & Exchange Energy

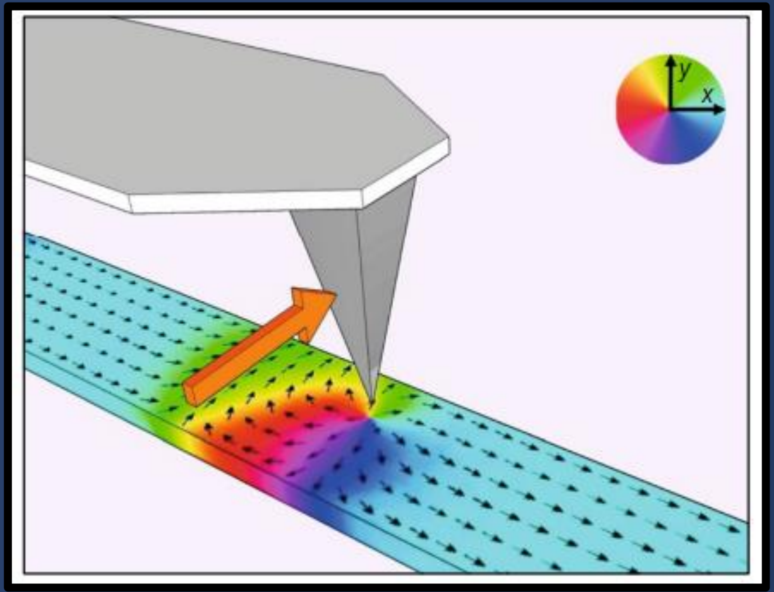

0 loops
3 loops
10 loops
30 loops
Frequency (GHz)
μ0H (mT)
3 loops
10 loops
30 loops
60 loops
100 loops
-ve field
+ve field

Vortex Writing via MFM Tip

Top Frames (1-3): Tip-writing vortices

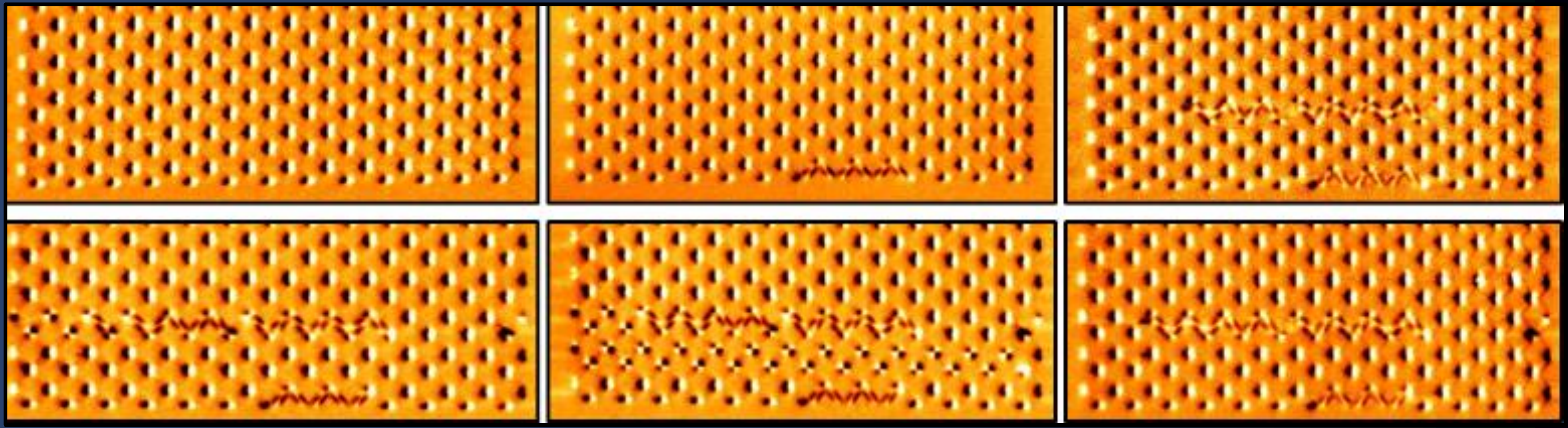


Before **After first tip-write** **Second tip-write**



Vortex Writing via MFM Tip

Top Frames (1-3): Tip-writing vortices

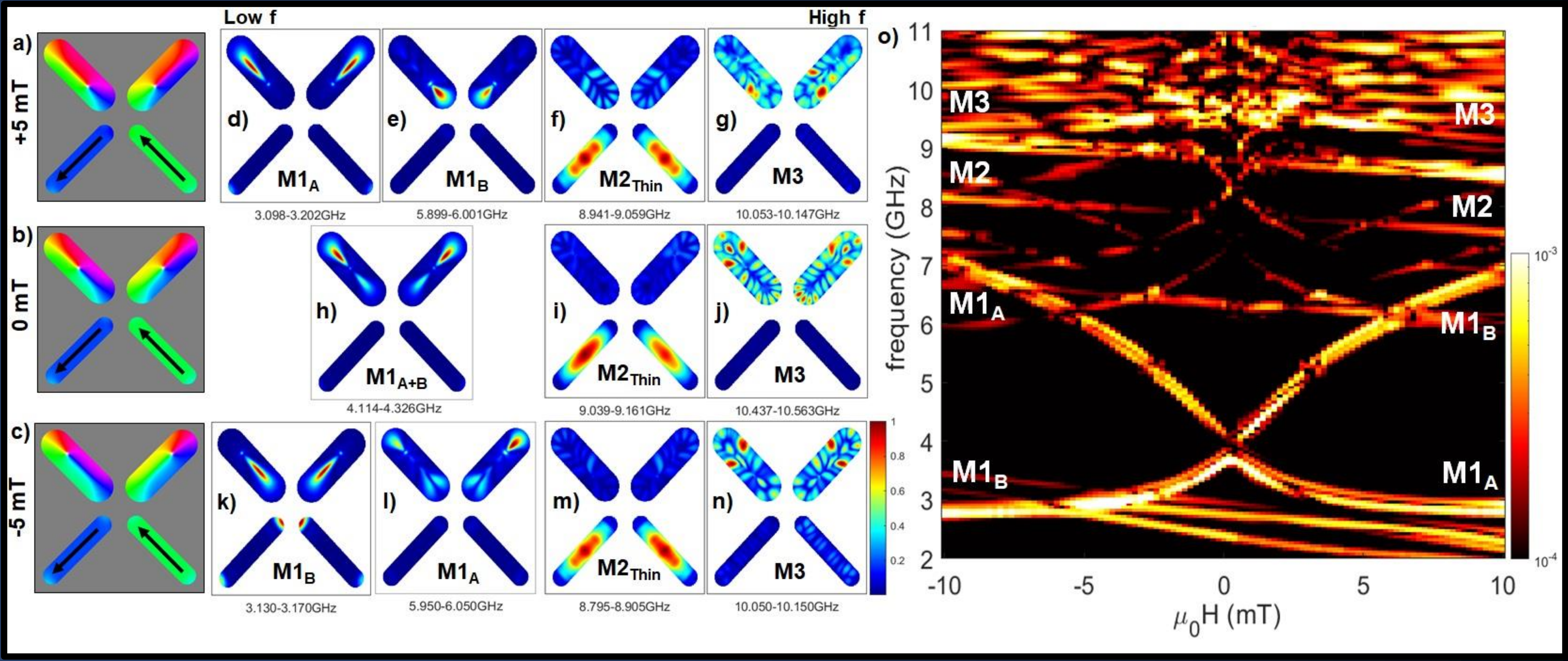


Bottom Frames (4-6):

Field looping of vortex line states at 13 mT (Hc = 16-17 mT)

Extremely Reconfigurable! 😈

Micromagnetic simulation of spatial/frequency FMR response: **T. Dion**



Quick Introduction

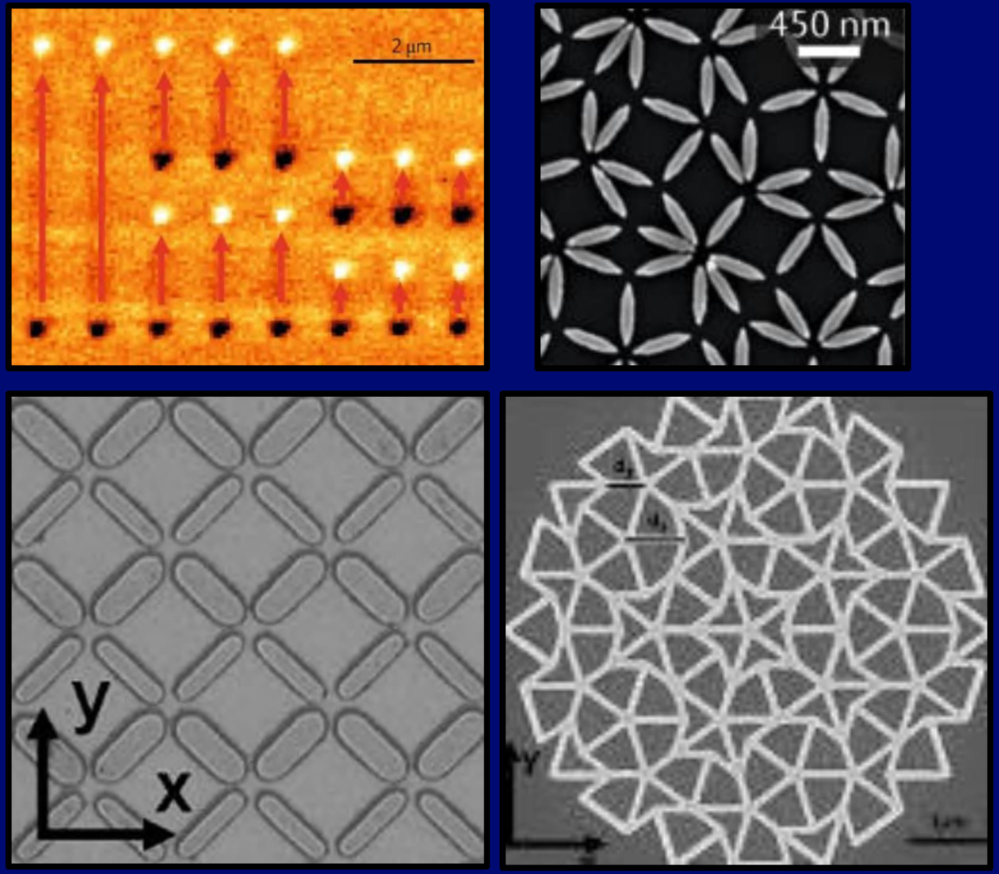
Neuromorphic Metamaterials Gro
Imperial College London

Interests:

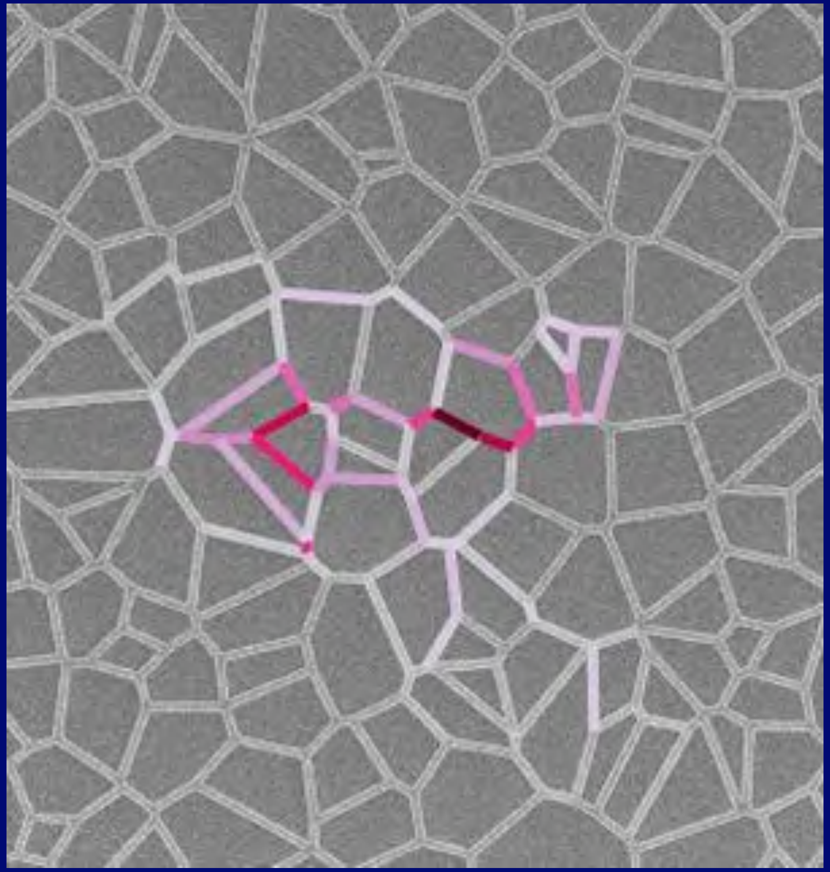
Metamaterials

Simple materials,
doing interesting things via patterning

Magnetic



Photonic

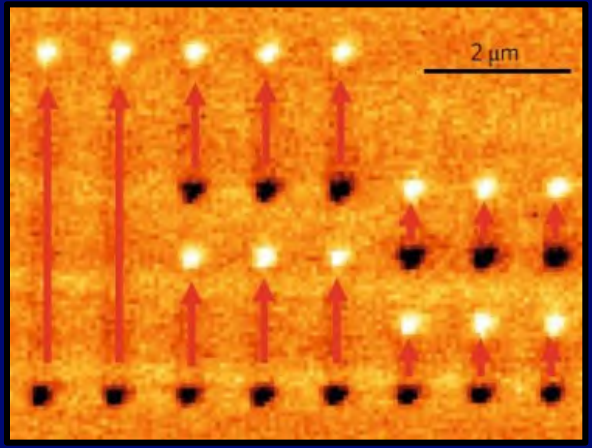


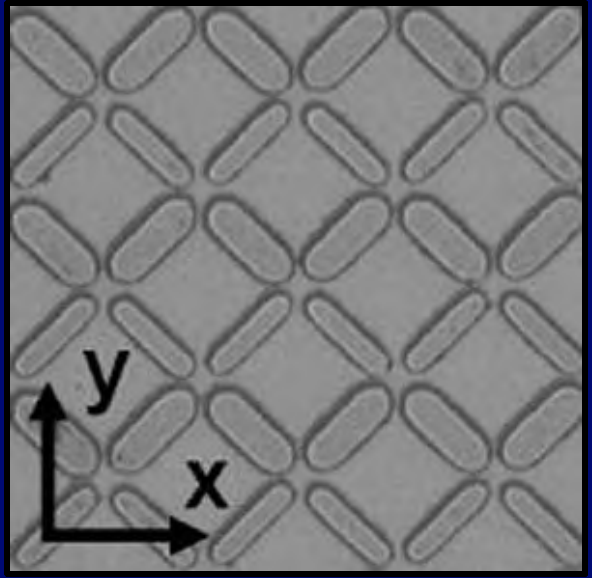
Quick Introduction

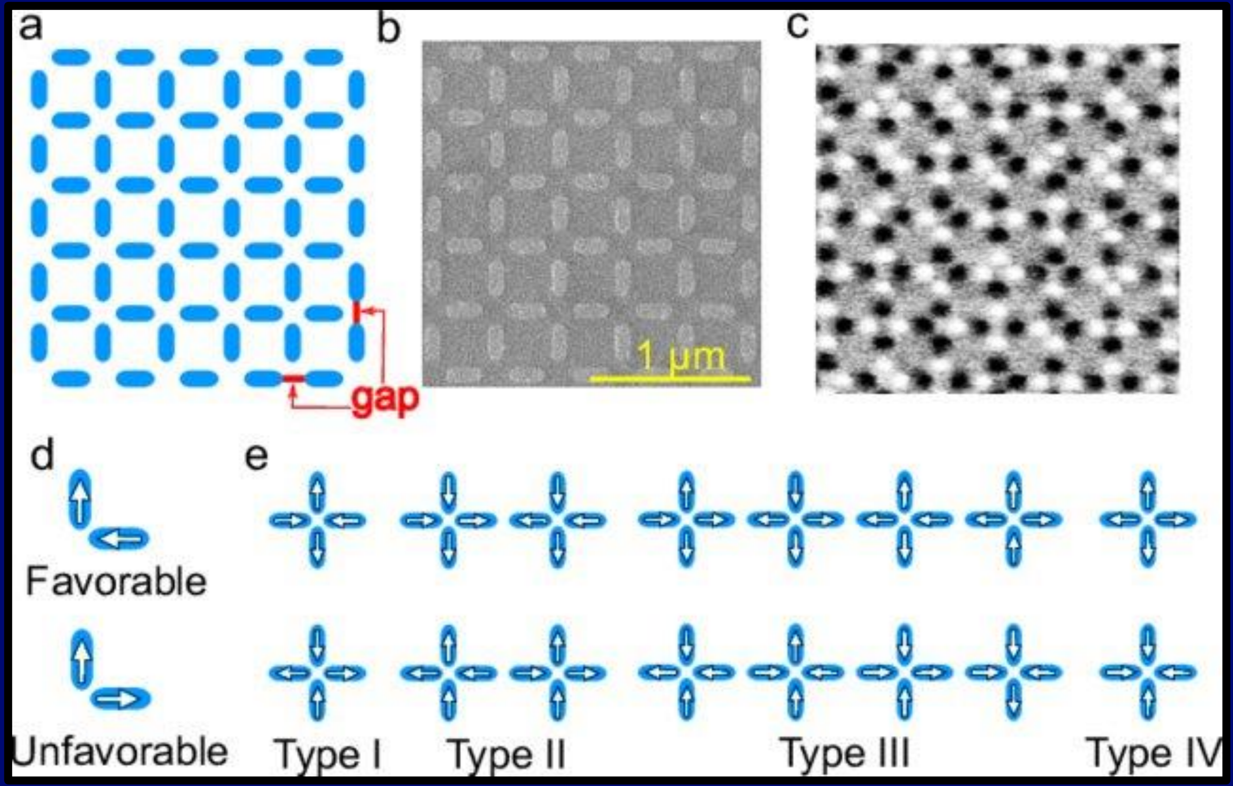
Neuromorphic Metamaterials Group
Imperial College London

Interests:

Magnetic Metamaterials – Huge number of states







Increasing Energy

Huge number of states!
2^N
N = 10^{3-8}

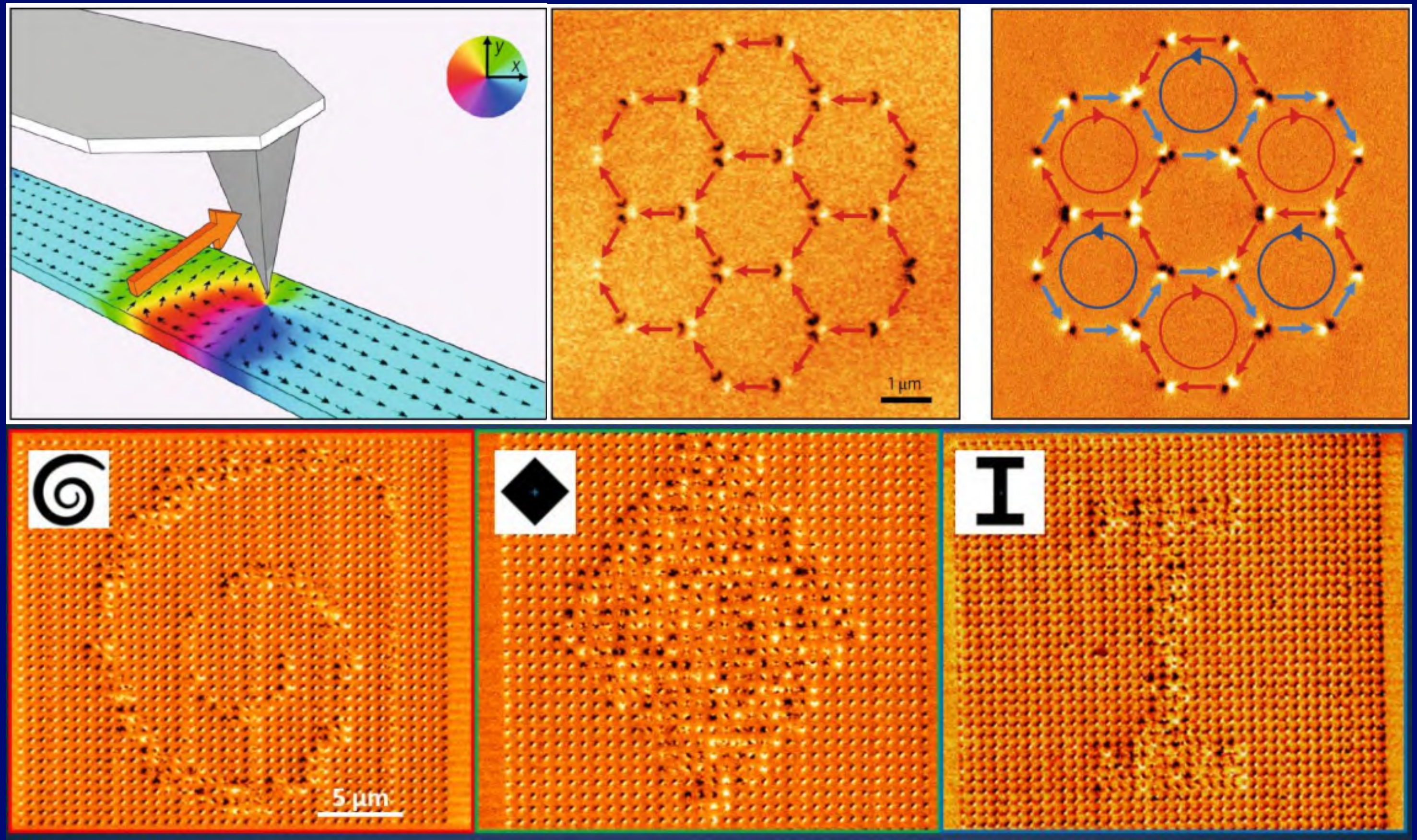
Quick Introduction

Neuromorphic Metamaterials Group
Imperial College London

Interests:

Magnetic Metamaterials – Huge number of states

My work: How to access these states? Nanomagnetic writing



MFM tip

Gartside, Jack C., et al. *Nature nanotechnology* (2018)

Picosecond laser

In preparation

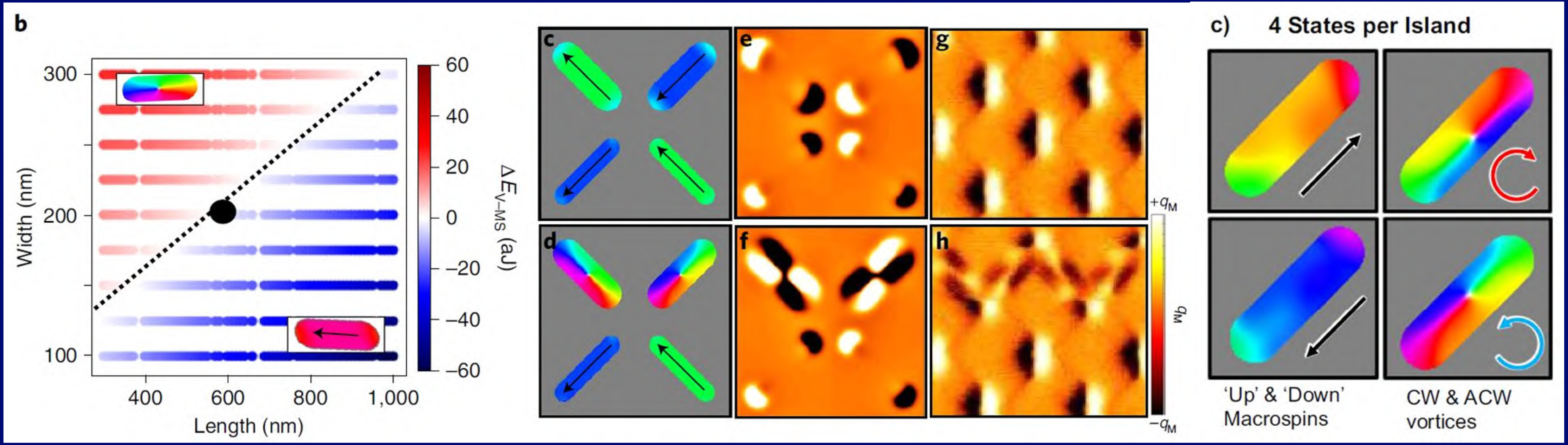
Quick Introduction

Neuromorphic Metamaterials Group
Imperial College London

Interests:

Magnetic Metamaterials – Huge number of states

‘Multistable’ Nanostructures



Gartside, Jack C., et al. "Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting." *Nature Nanotechnology* (2022)

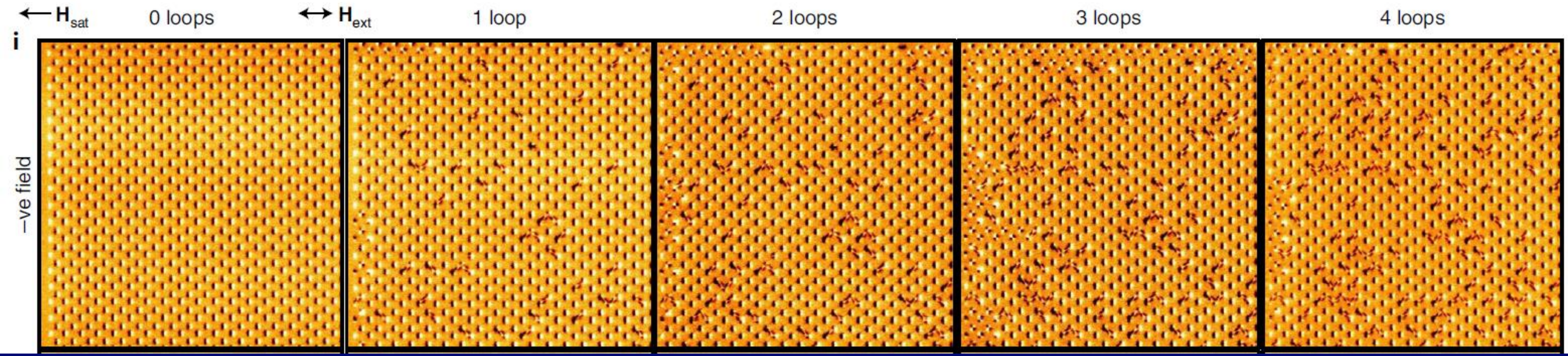
Quick Introduction

Neuromorphic Metamaterials Group
Imperial College London

Interests:

Magnetic Metamaterials – Huge number of states

‘Multistable’ Nanostructures – emergent textural domain growth

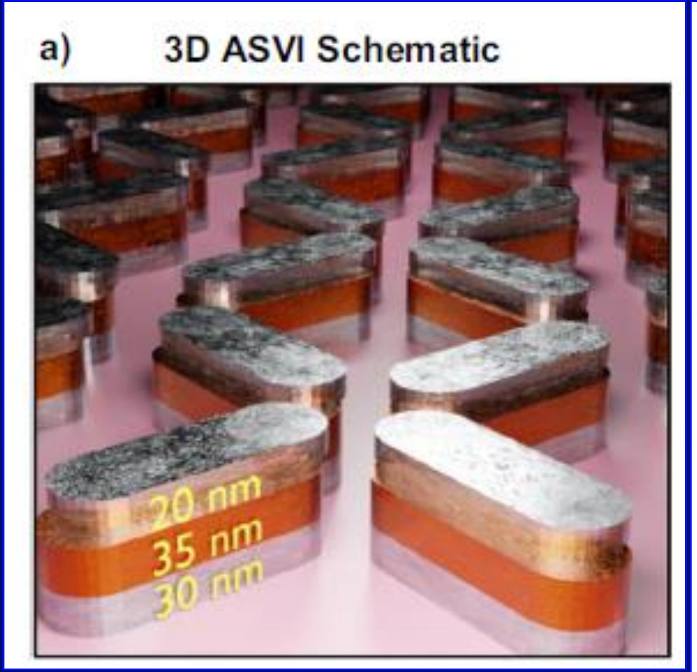


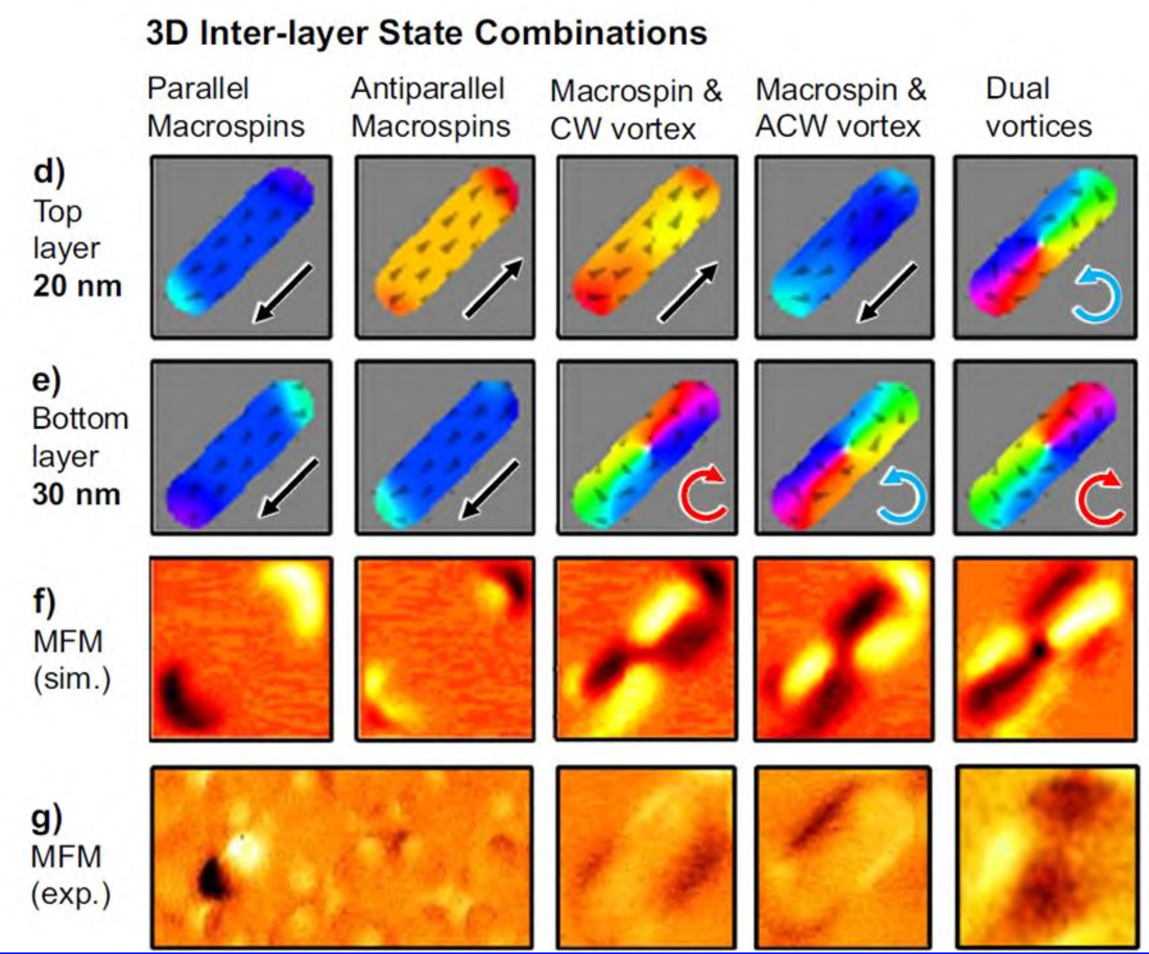
Quick Introduction

Neuromorphic Metamaterials Group
Imperial College London

Interests:
Magnetic Metamaterials – Huge number of states

‘Multistable’ Nanostructures – 2.5D/3D





16 states per island

Dion, T., ... & Gartside, J. C. “Ultrastrong magnon-magnon coupling and chiral spin-texture control in a dipolar 3D multilayered artificial spin-vortex ice.” *Nature communications*, 2024

Quick Introduction

Interests:

Magnetic Metamaterials

The states can program magnon responses, which can be

ARTICLES
https://doi.org/10.1038/s41565-022-01091-7
nature nanotechnology
Check for updates

Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting

nature communications
Article
https://doi.org/10.1038/s41467-024-50633-1

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

Received: 29 August 2023
Accepted: 17 July 2024
Published online: 27 August 2024

Kilian D. Stenning[1,2], Jack C. Gartside[1,2,9], Luca Manneschi[3,9], Christopher T. S. Cheung[1], Tony Chen[1], Alex Vanstone[1], Jake Love[4], Holly Holder[1], Francesco Caravelli[5], Hidekazu Kurebayashi[6,7,8], Karin Everschor-Sitte[4], Eleni Vasilaki[3] & Will R. Branford[1,2]

nature materials
Article
https://doi.org/10.1038/s41563-023-01698-8

Task-adaptive physical reservoir computing

Received: 4 October 2022
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Published online: 13 November 2023

Oscar Lee[1], Tianyi Wei[1], Kilian D. Stenning[2], Jack C. Gartside[2], Dan Prestwood[1], Shinichiro Seki[3], Aisha Aqeel[4,5], Kosuke Karube[6], Naoya Kanazawa[3], Yasujiro Taguchi[6], Christian Back[4], Yoshinori Tokura[3,6,7], Will R. Branford[2,8] & Hidekazu Kurebayashi[1,9,10]

Noise-Aware Training of Neuromorphic Dynamic Device Networks

Luca Manneschi[1,*,†], Ian T. Vidamour[1,*,†], 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], Susan Stepney[3], Will R. Branford[2], Jack C. Gartside[2], Thomas Hayward[1], Matthew O. A. Ellis[1], and Eleni Vasilaki[1]

[1]University of Sheffield, Sheffield S10 2TN, United Kingdom
[2]Blackett Laboratory, Imperial College London, London SW7 2AZ, United Kingdom
[3]University of York, Heslington, York YO10 5DD, United Kingdom
[*]These authors contributed equally
[†]Corresponding author: l.manneschi@sheffield.ac.uk, i.vidamour@sheffield.ac.uk

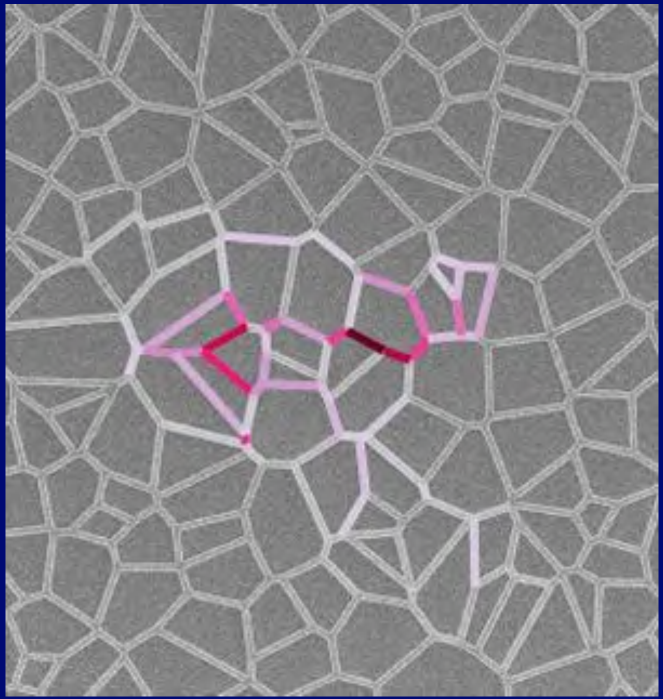
Quick Introduction

Neuromorphic Metamaterials Grou
Imperial College London

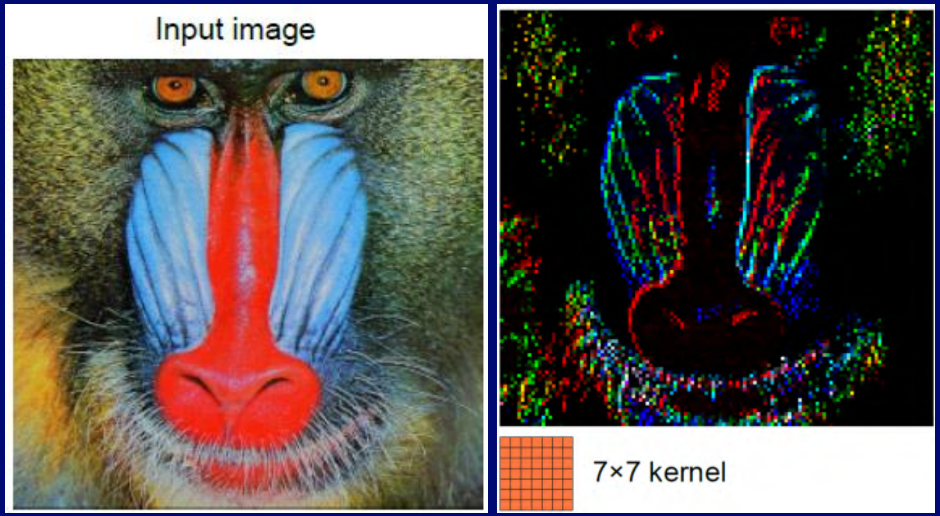
Interests:

Photonic Metamaterials: Mimick retinal neuron dynamics

Iridium Phosphide network



Detect image features



Biomedical diagnosis – 93.4% accur