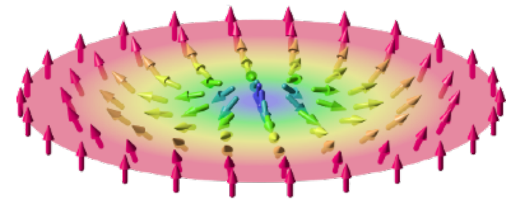
Skyrmions for Unconventional Computing

Karin Everschor-Sitte
Johannes Gutenberg-Universität Mainz



14.11.2019
Spintronics Meets Topology in Quantum Materials
KITP Santa Barbara

Prychynenko, et al., KES, Phys. Rev. Appl. (2018)

Bourianoff, et al., KES, AIP Advances, (2018)

Pinna, et al., KES, arXiv1811.12623

Zázvorka, ..., KES, et al., Kläui, Nature Nanotechnology 2019

Horenko, et al., KES, arXiv1907.04601

Finochio, ..., KES, et al., arXiv1910.07176

Grollier, ..., KES, et al., accepted in Nat. Electron.

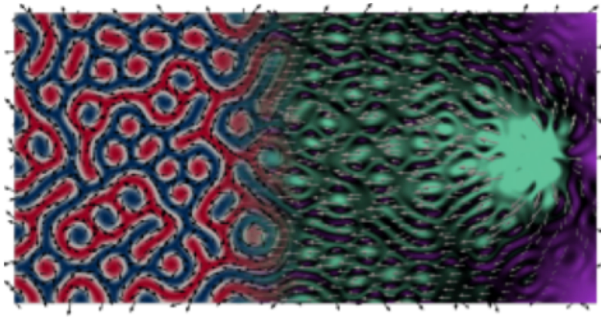
Acknowledgements:

Emmy Noether-Programm DFG
SPP2137 Skyrmionics
SPIN+X SFB/TRR 173 Kaiserslautern • Mainz
Materials Science in Mainz
Emergent Algorithmic Intelligence
The Research Council of Norway

Structure of the talk

Structure of the talk

- Skyrmions for reservoir computing



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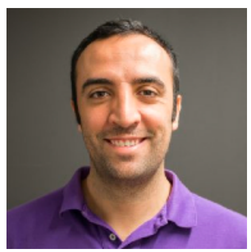
Thanks to


George Bourianoff


Daniele Pinna

work on single skyrmion device


Matthias Sitte


D. Prychynenko


Jairo Sinova

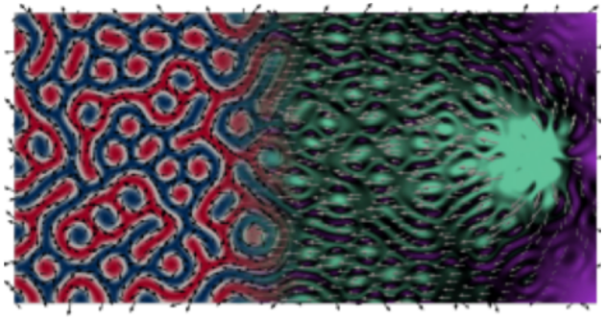

Kai Litzius


Benjamin Krüger


Mathias Kläui

Structure of the talk

- Skyrmions for reservoir computing



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- Skyrmion reshuffler for stochastic computing

Pinna, et al., Phys. Rev. Appl. (2018)

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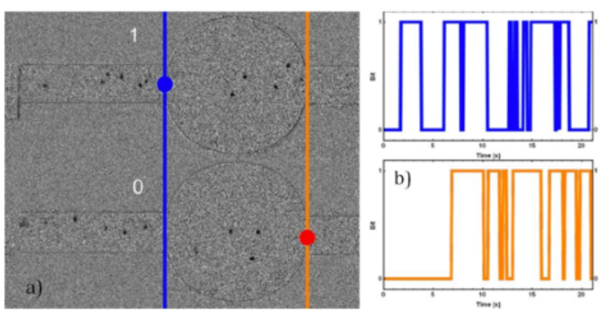

Thanks to

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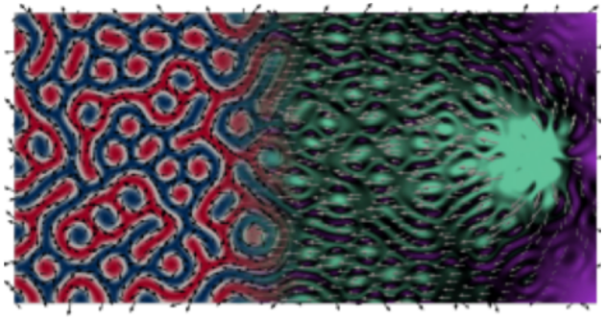

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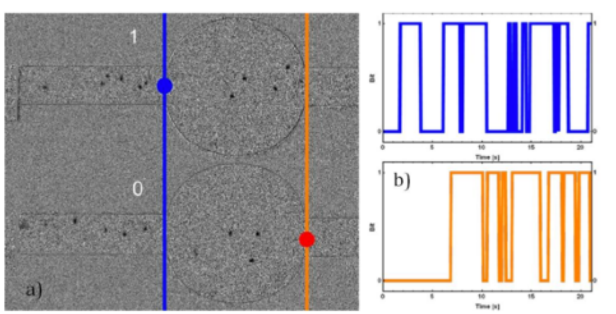

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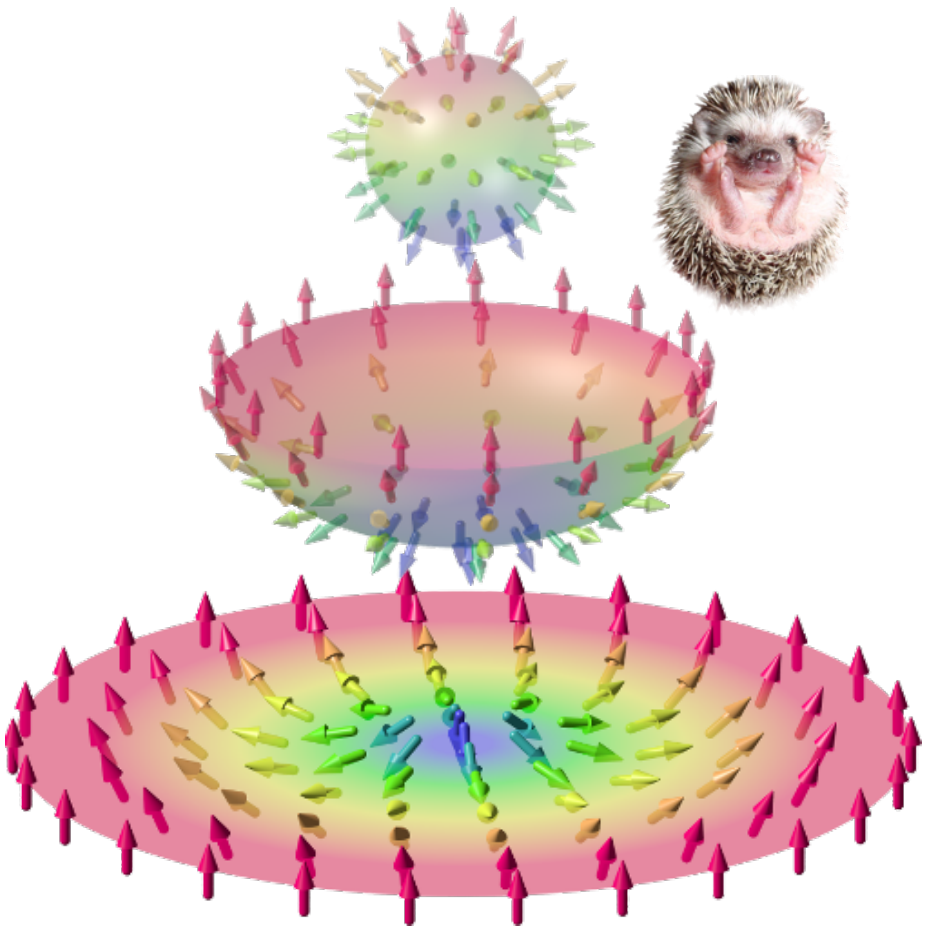
- Data analysis, new tools for "microscopy"?

Horenko, et al., KES, arXiv1907.04601

Illia Horenko

Davi Rodrigues

Terence O'Kane

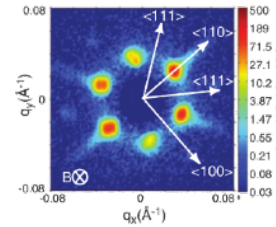


Characterized by winding number

$$\mathcal{W} = \frac{1}{4\pi}\int \hat{\boldsymbol{M}} \cdot (\partial_x \hat{\boldsymbol{M}} \times \partial_y \hat{\boldsymbol{M}})\, dx\, dy$$

Magnetic Skyrmions = Topological magnetic Whirls

- Theoretical predictions **Bogdanov and Yablonskii, Sov. Phys. JETP 1989**
- first experimental observation in 2009 in form of a skyrmion lattice in MnSi



Mühlbauer et al., Science (2009)

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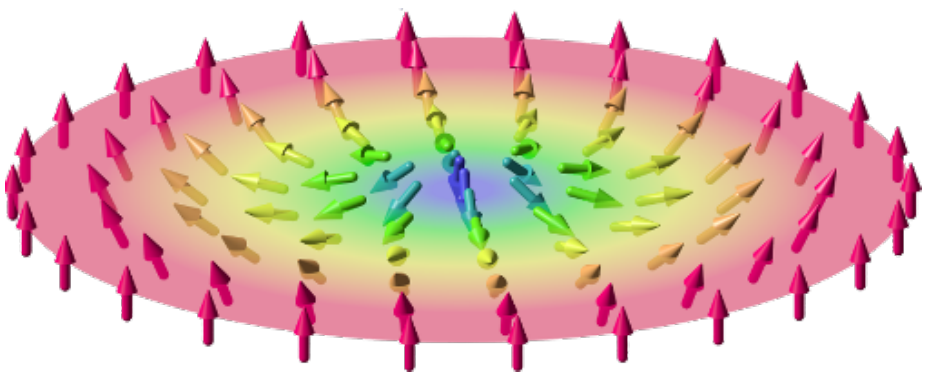

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Topological Whirls In SpinTronics

- Theoretical predictions **Bogdanov and Yablonskii, Sov. Phys. JETP 1989**
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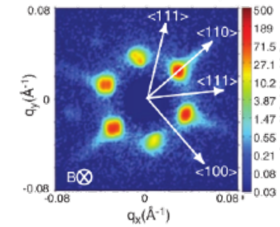
- occur in magnetic systems with competing (twisting) interactions
- particle like character



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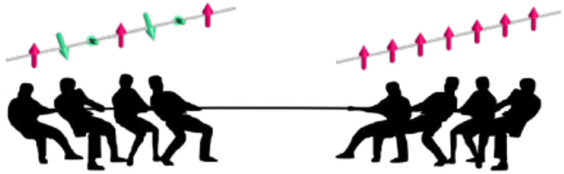

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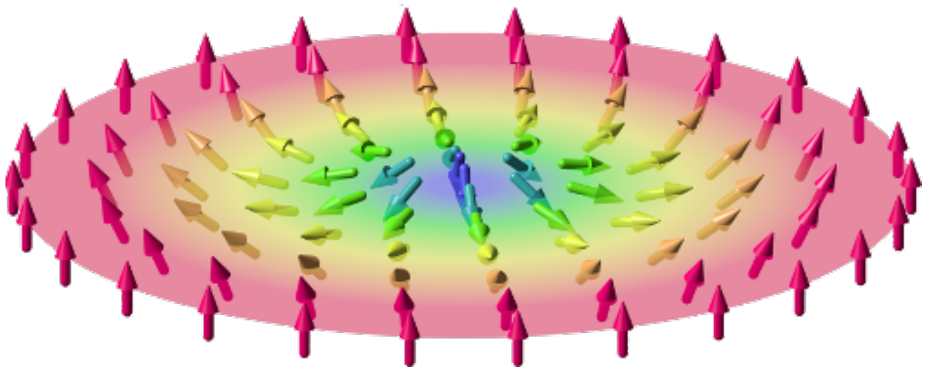

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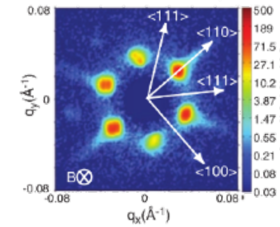
- first experimental observation in 2009 in form of a skyrmion lattice in MnSi
- occur in magnetic systems with competing (twisting) interactions
- particle like character
- can be created, manipulated and destroyed by various means
- for recent review see

KES, et al., JAP 124, (2018), featured article



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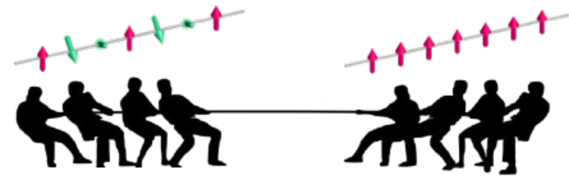

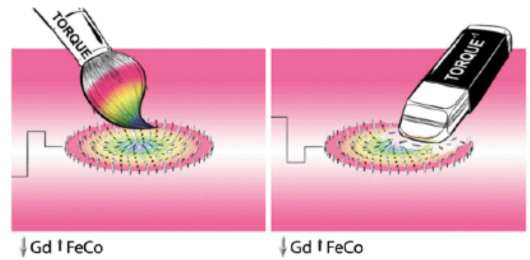

Thanks to Marco Armbruster

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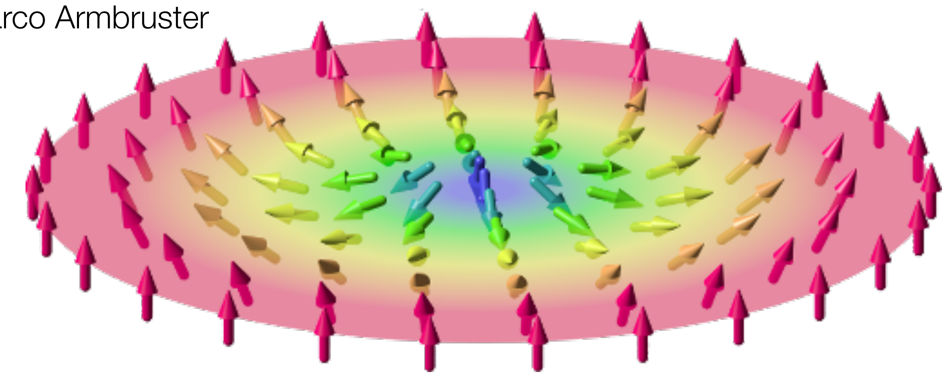
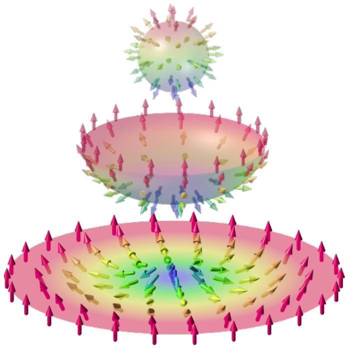


Magnetic skyrmions - why interesting?

1) small and above room temperature

2) topology → stability

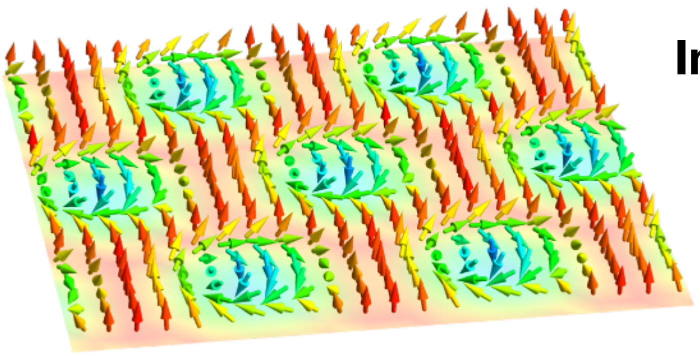


Magnetic skyrmions - why interesting?

1) small and above room temperature

2) topology → stability

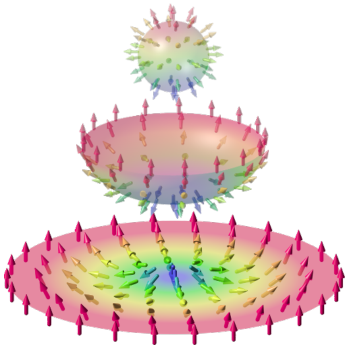
3) react to ultra-low electric currents



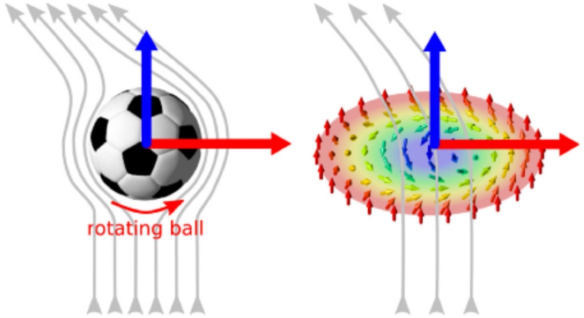
In skyrmion lattice:

$$j \sim 10^6\, A/m^2$$

Jonietz, KES, et. al., Science, (2010)



skyrmion Hall effect



KES, M. Sitte, JAP (2014)

4) Interesting dynamics because of **Magnus force!**

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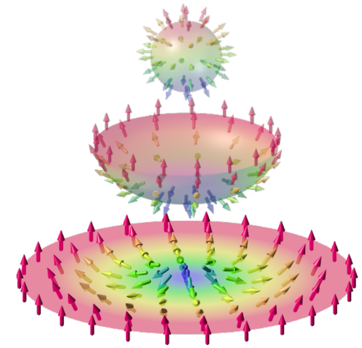

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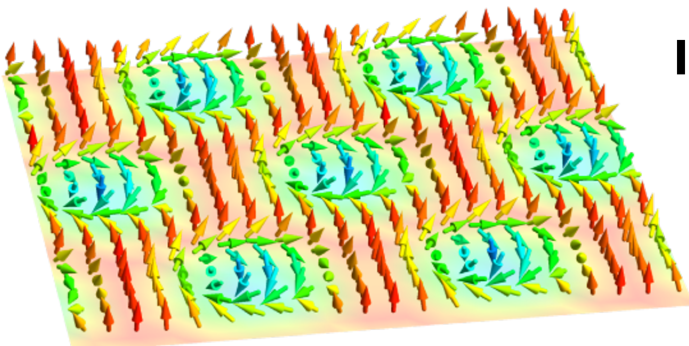

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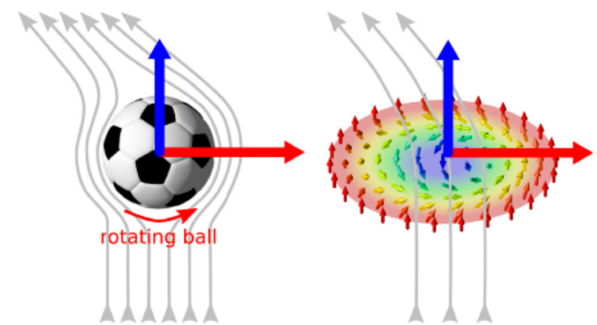


KES, M. Sitte, JAP (2014)

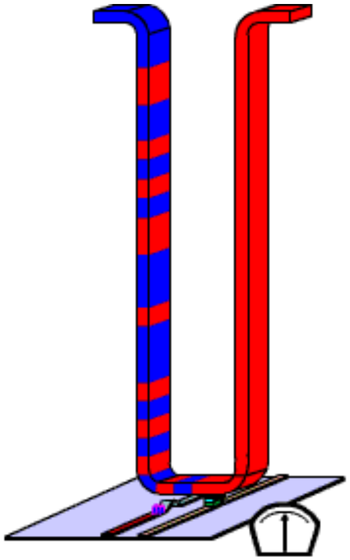
4) Interesting dynamics because of **Magnus force!**

5) potential for spintronics applications

Device relevant systems

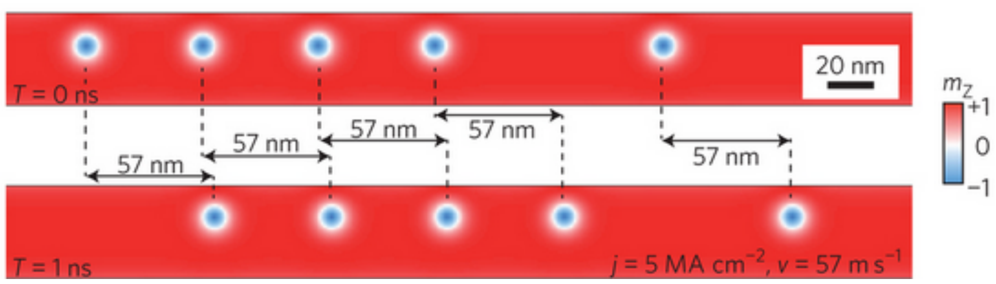
Skyrmion based devices ???

So far often: skyrmion instead of other magnetic texture like DW



Parkin, IBM

Fert, Nature Nano., 2013



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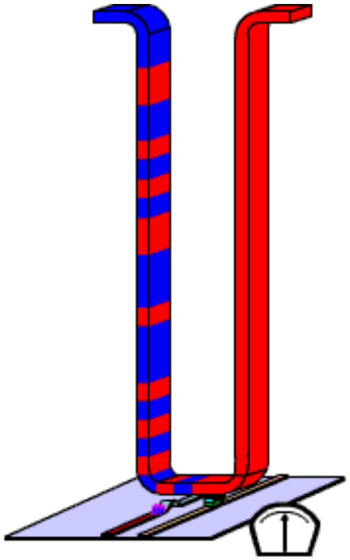

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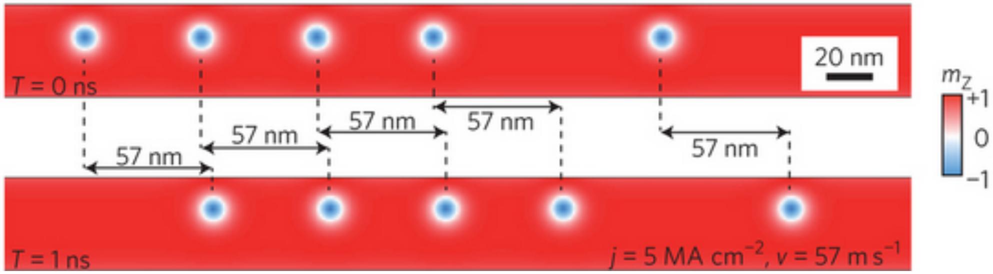
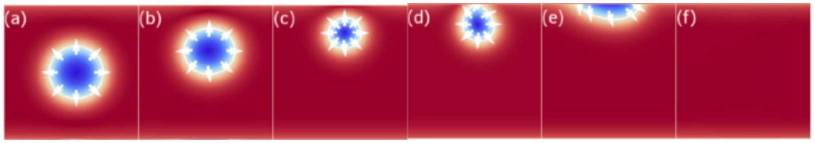


Advantages: skyrmions do not touch the edges

Detrimental: skyrmion Hall effect

KES, et al., JAP 124, (2018), featured article



Skyrmion based devices ???

What is a device that optimally uses the properties of a skyrmion?

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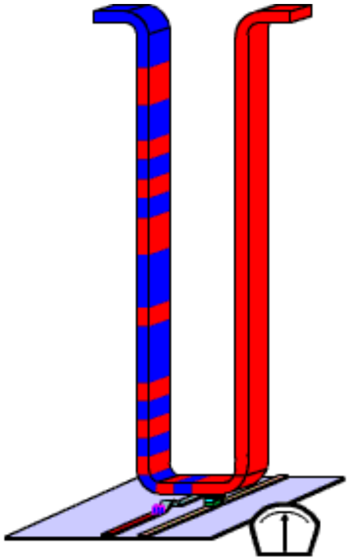

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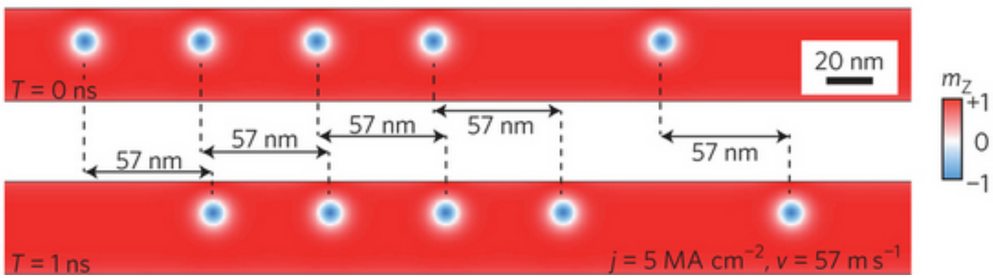

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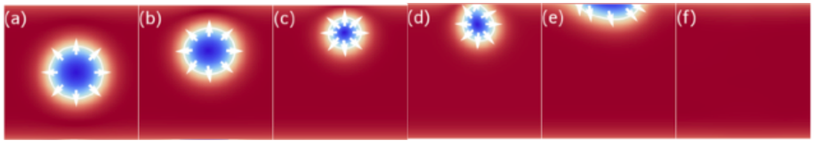

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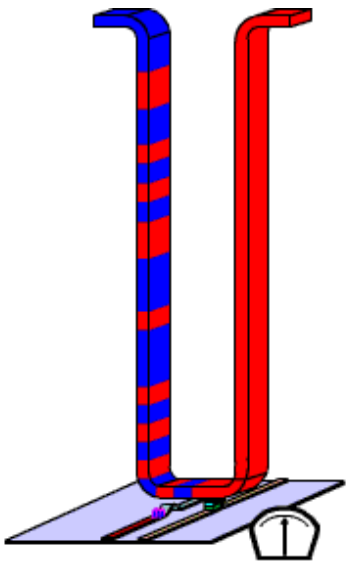

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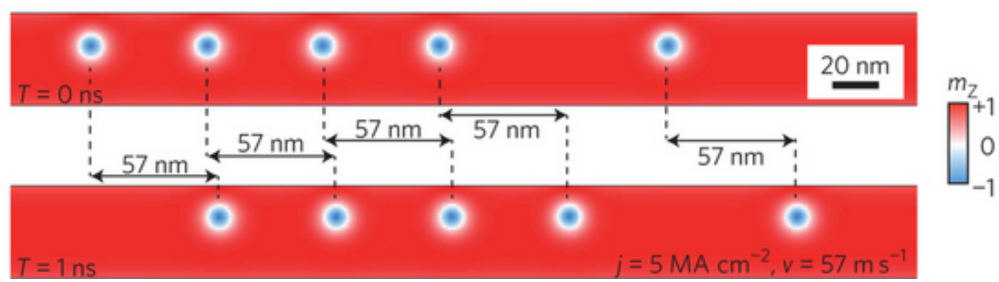

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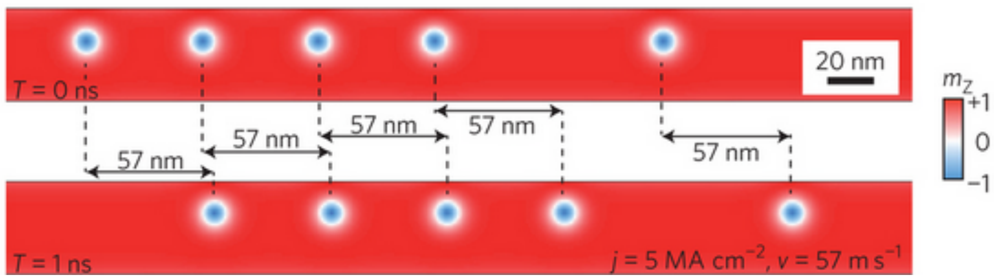

DW → 1d

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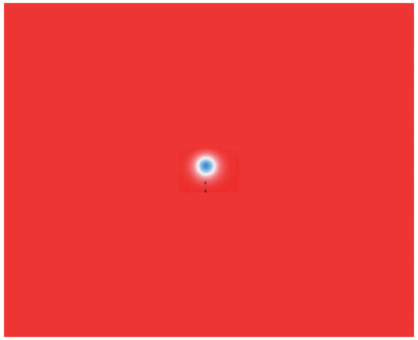

DW ➔ 1d

skyrmion ➔ 2d

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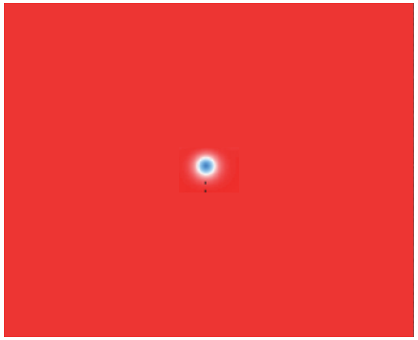

Skyrmions for
Unconventional Computing?

Reservoir Computing

Stochastic Computing

DW → 1d

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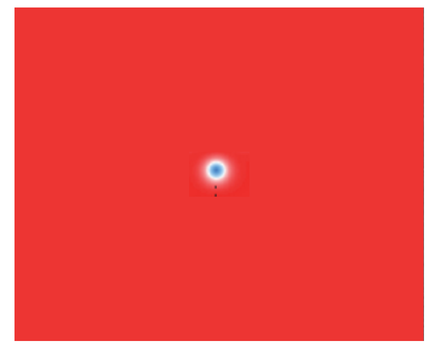

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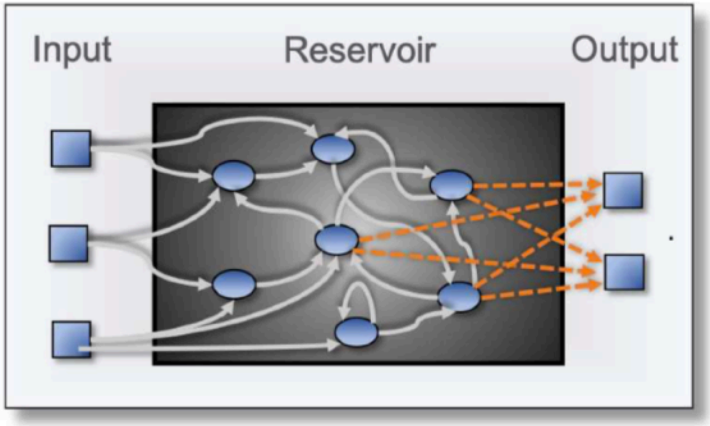
Skyrmions for Unconventional Computing?

Reservoir Computing

Stochastic Computing

TWIST
Topological Whirls In SpinTronics

originally: artificial neural network with



recursive
neural network

feed forward
only

Reservoir computing

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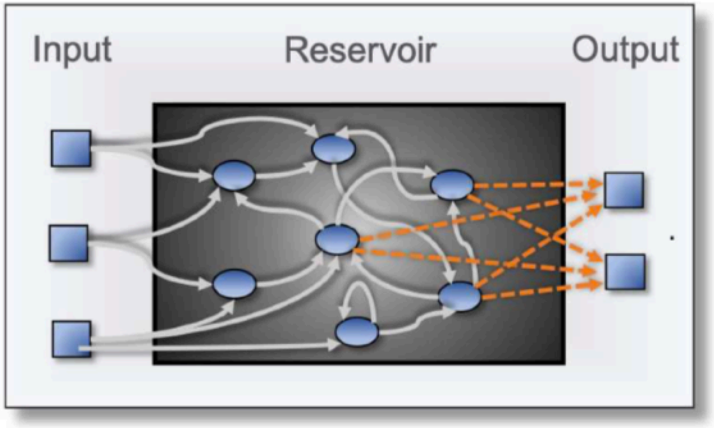

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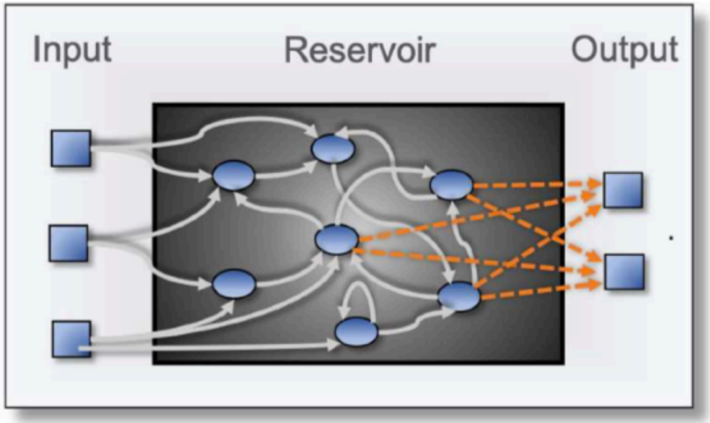
Goal: map a complex problem to a linearly solvable one

- **Network does not need tuning**: internal connections are fixed
- Only output connections are trained

Reservoir computing

originally: artificial neural network with



Goal: map a complex problem to a linearly solvable one

Functionality:

Reservoir projects different spatial-temporal events into a sparsely populated high dimensional space where they become easier to recognise and categorise

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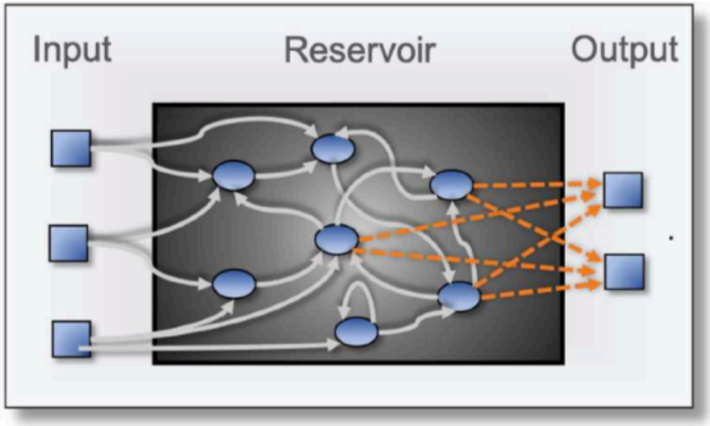

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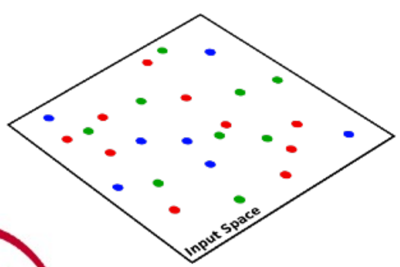

Pinna, et al., KES, arXiv1811.12623

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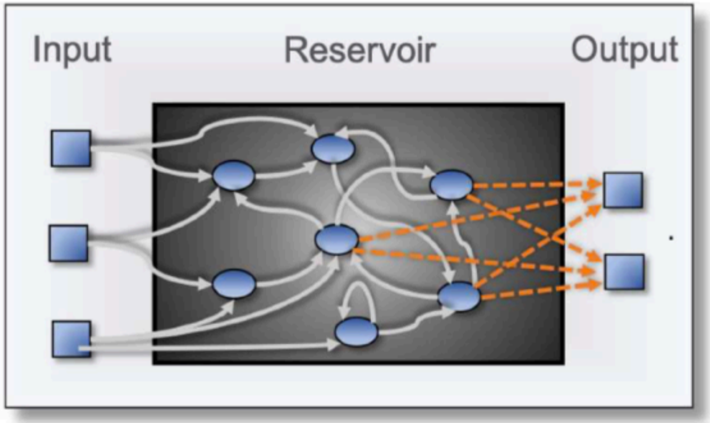

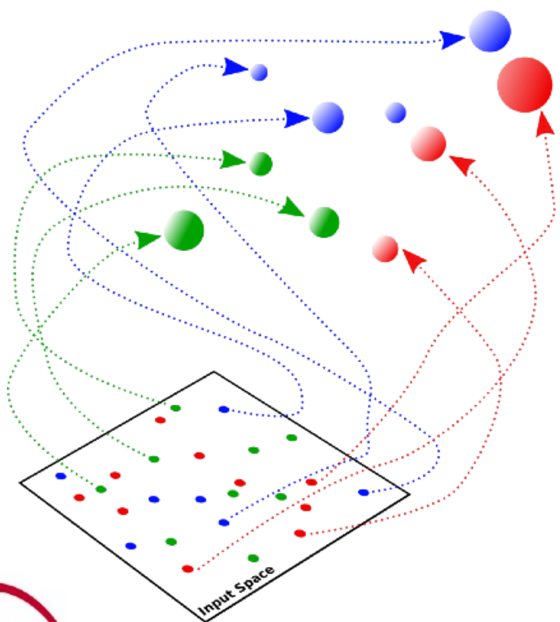

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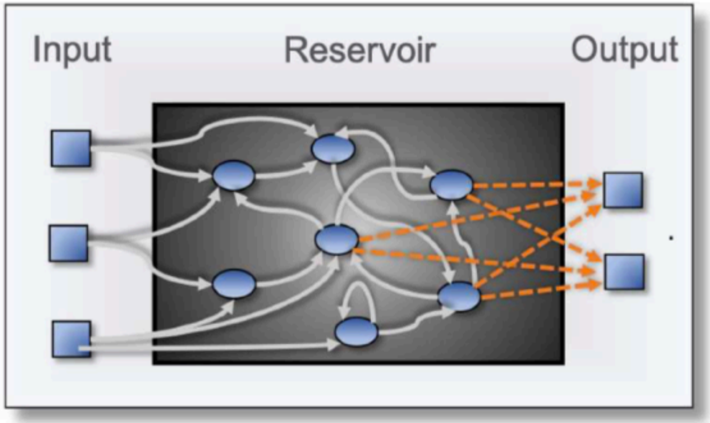

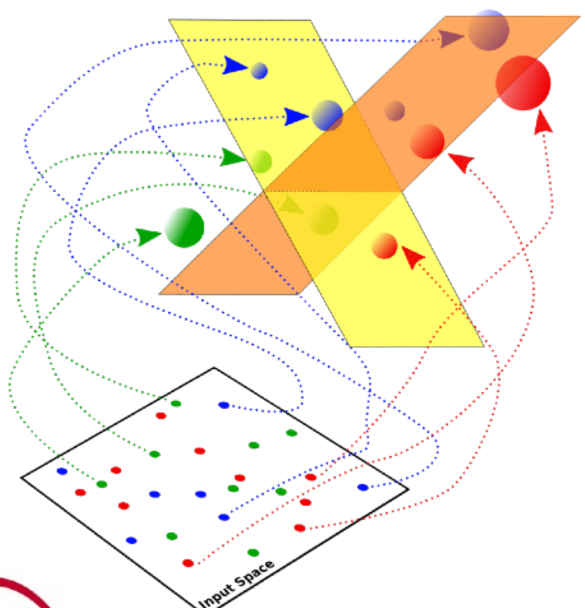

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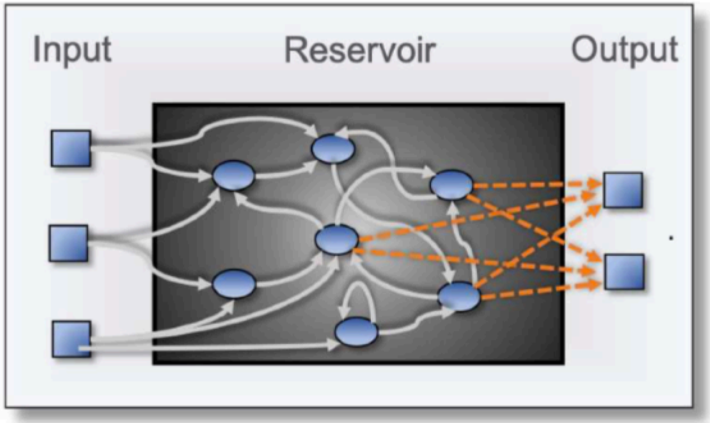

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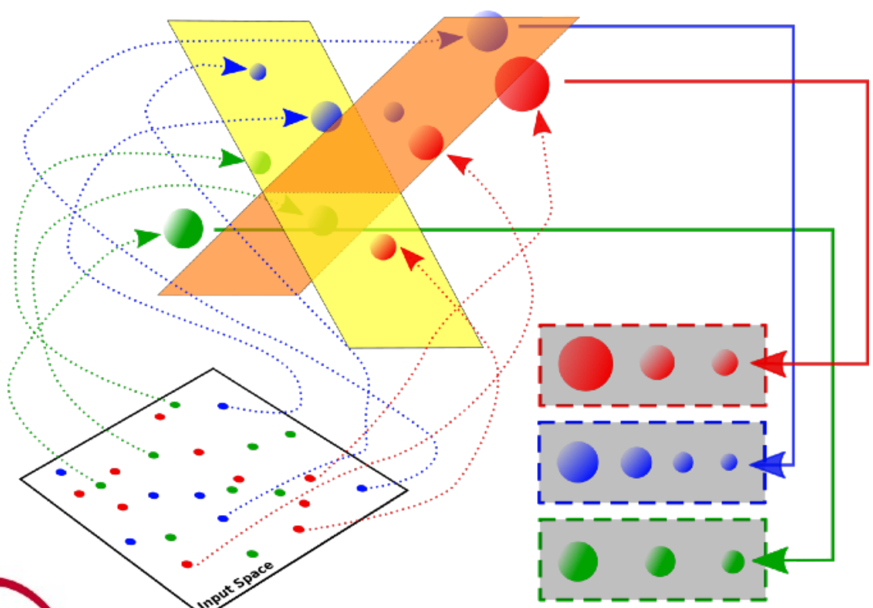

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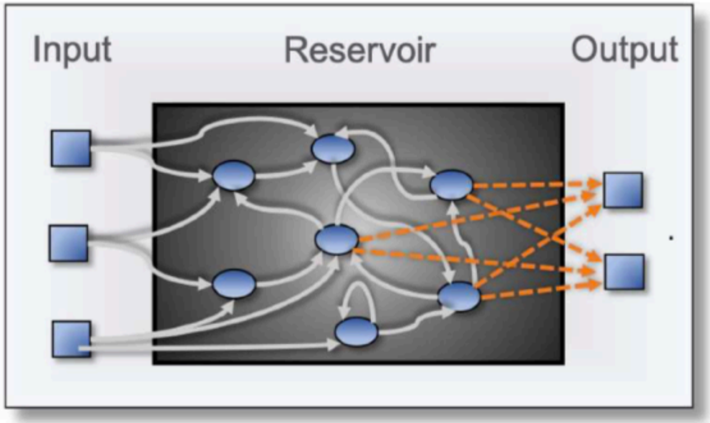
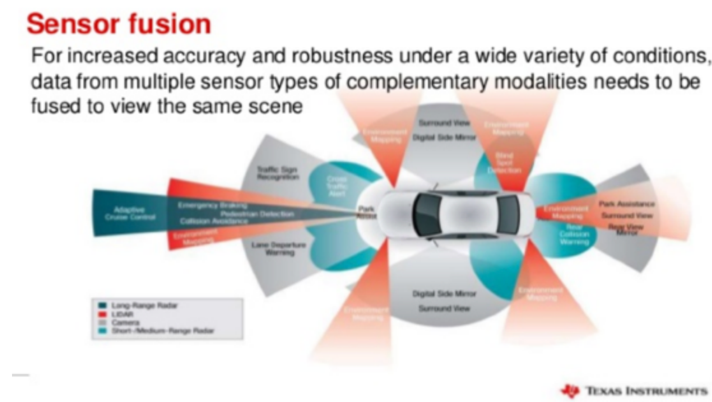
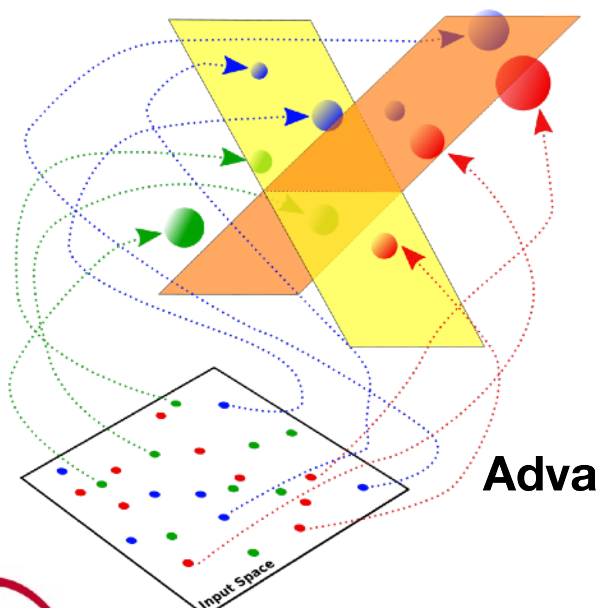


Goal: map a complex problem to a linearly solvable one

Useful for: Recognition and classification of spatial-temporal events like
- speech recognition
- sensor fusion type applications



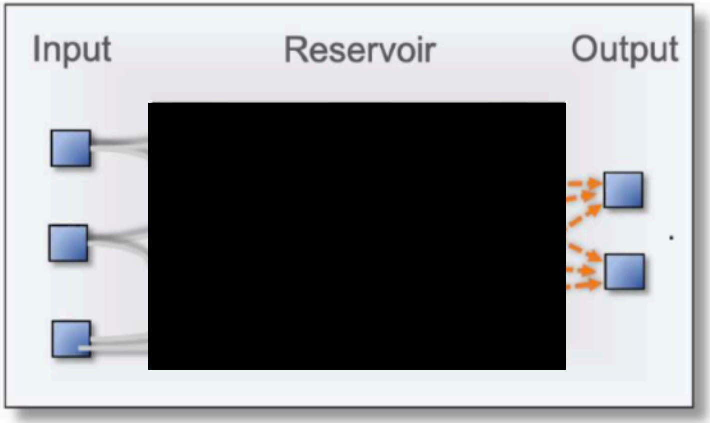


Advantages:
- Multiple output arrays possible to search for different features simultaneously
- No detailed knowledge about reservoir required

Pinna, et al., KES, arXiv1811.12623

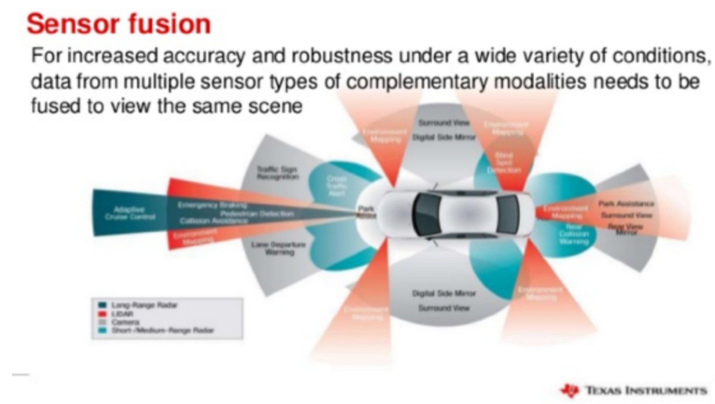
Reservoir computing

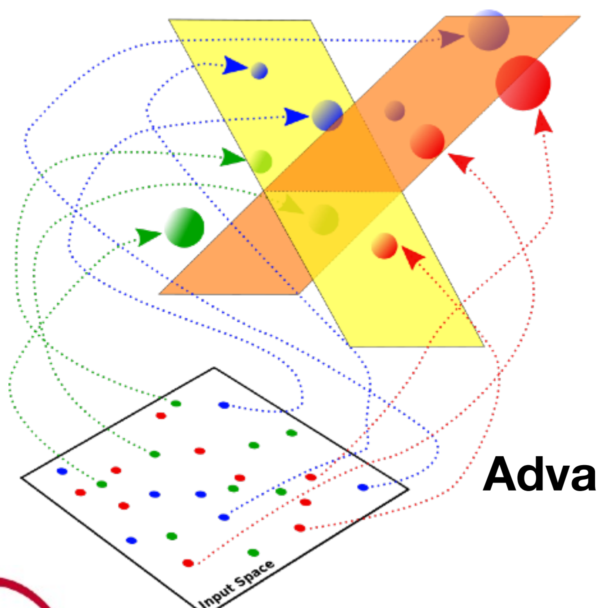
originally: artificial neural network with



Goal: map a complex problem to a linearly solvable one

Useful for: Recognition and classification of spatial-temporal events like
- speech recognition
- sensor fusion type applications



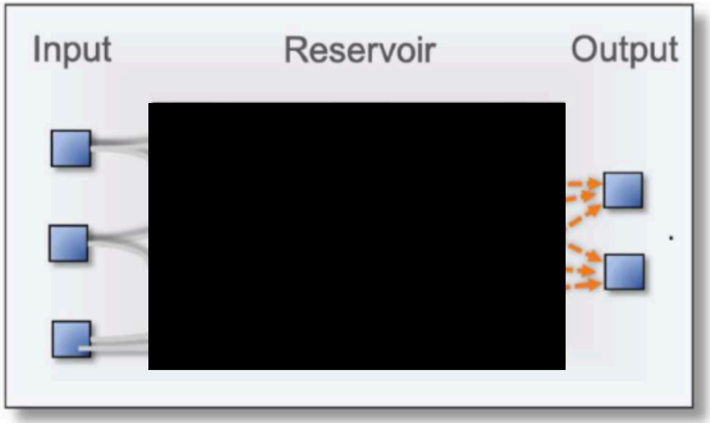


Advantages:
- Multiple output arrays possible to search for different features simultaneously
- No detailed knowledge about reservoir required

Pinna, et al., KES, arXiv1811.12623

Reservoir computing

originally: artificial neural network with



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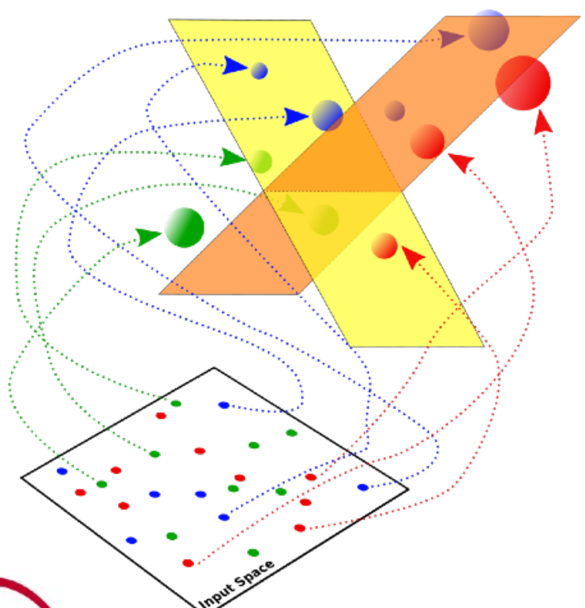

Requirements for reservoir:

- Dimensionality of reservoir's state >> input array
- Response of reservoir nonlinear to input and previous state
- Short term memory (Echo state time > temporal input correlations)

Pinna, et al., KES, arXiv1811.12623

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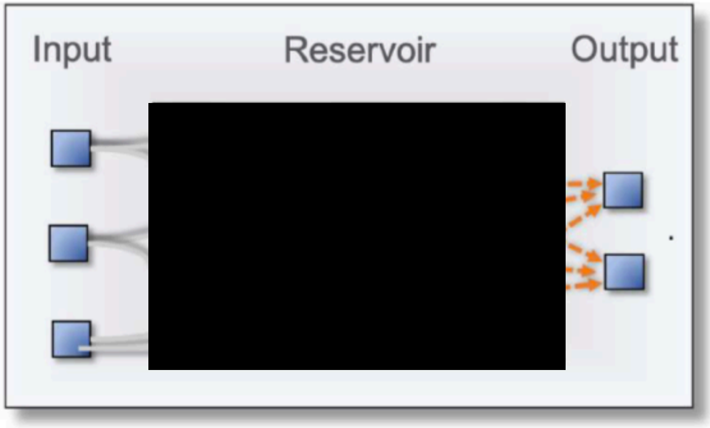

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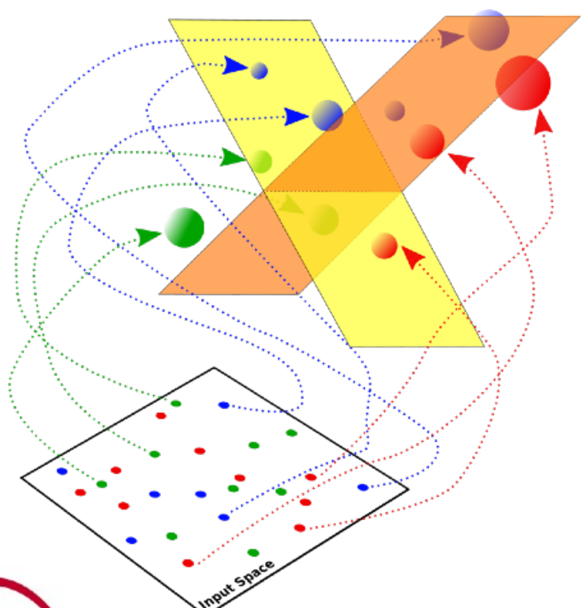
Non-linear, complex system with short term memory

Mass, et al., Neural Comput. (2002)



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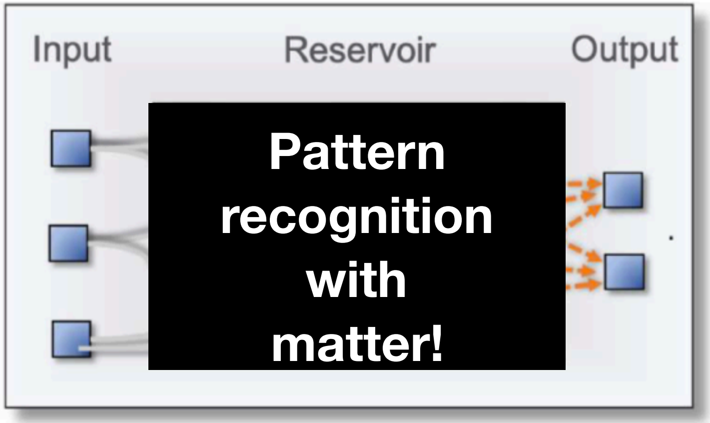

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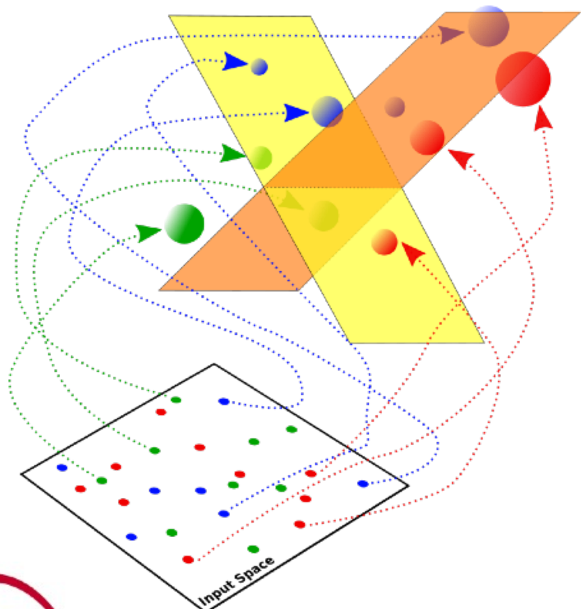

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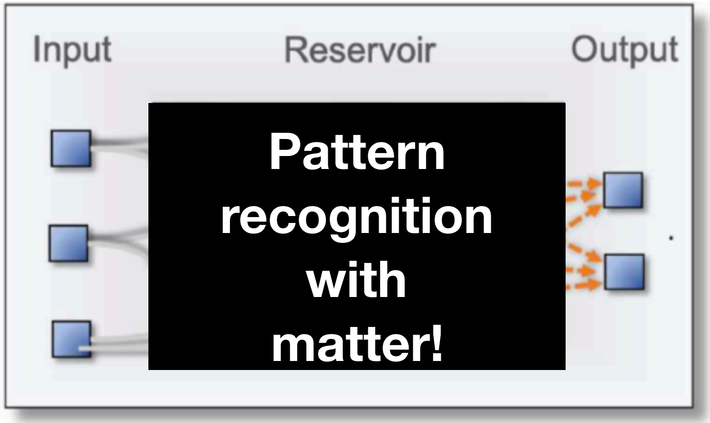

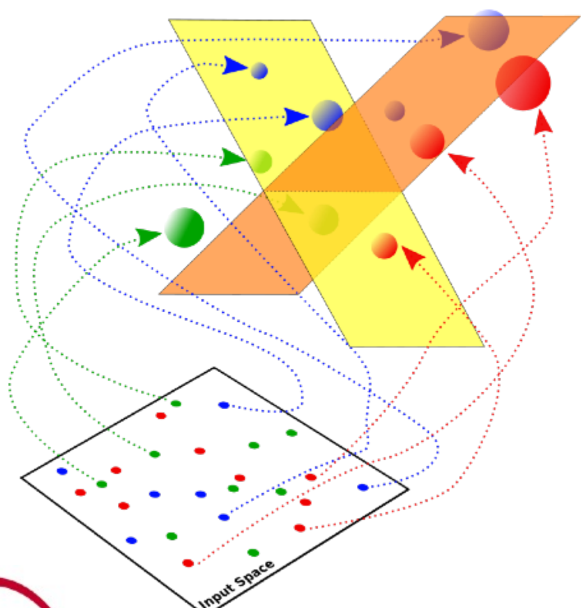

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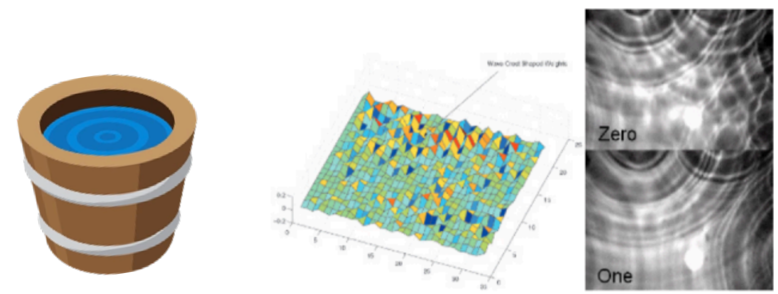

Fernando, et al., Adv. Artificial Life (2005)

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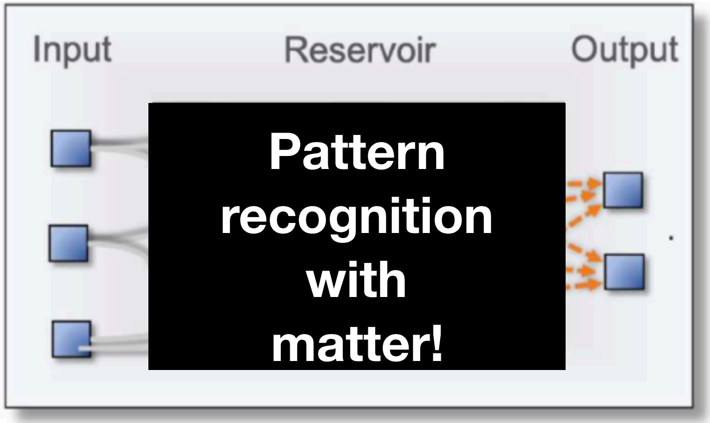

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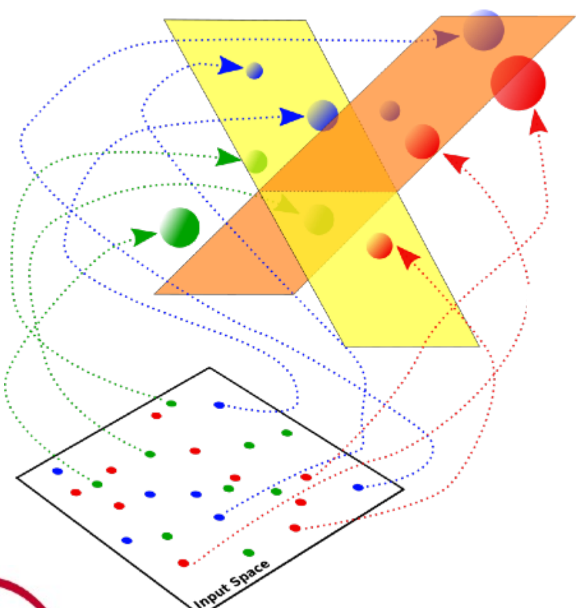

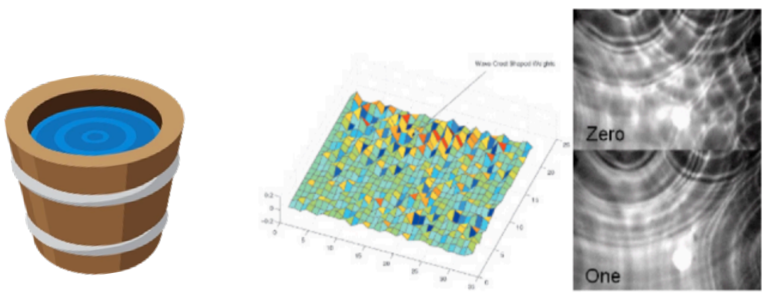

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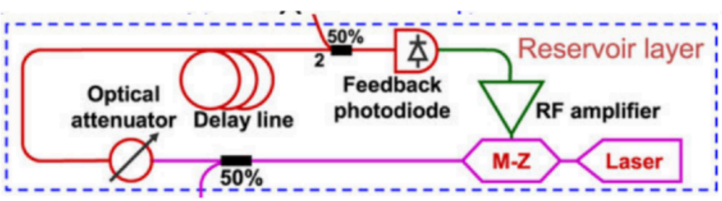

Duport, et al., Sci. Rep. (2016)

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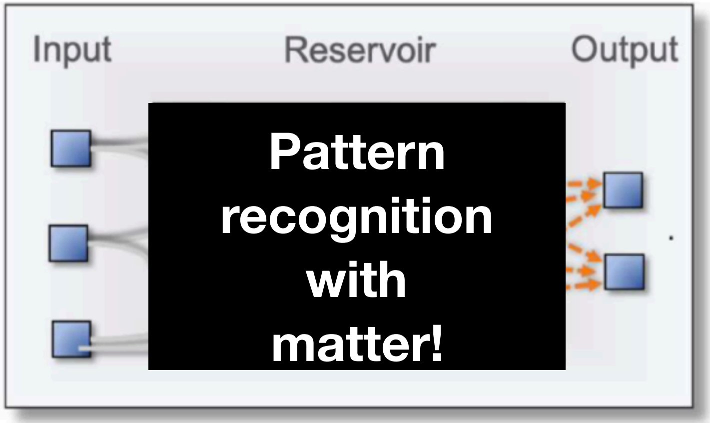

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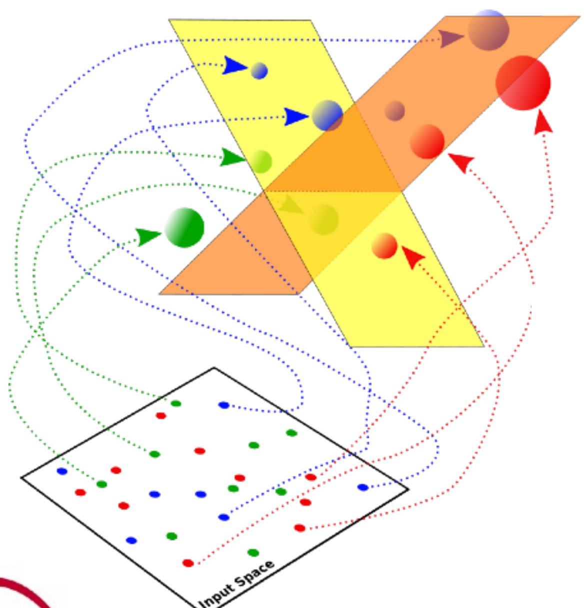

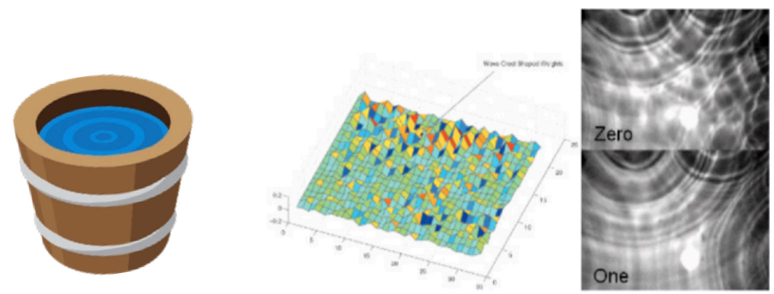

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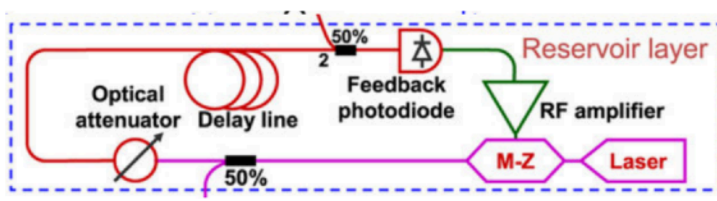

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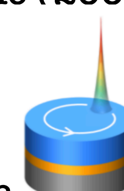
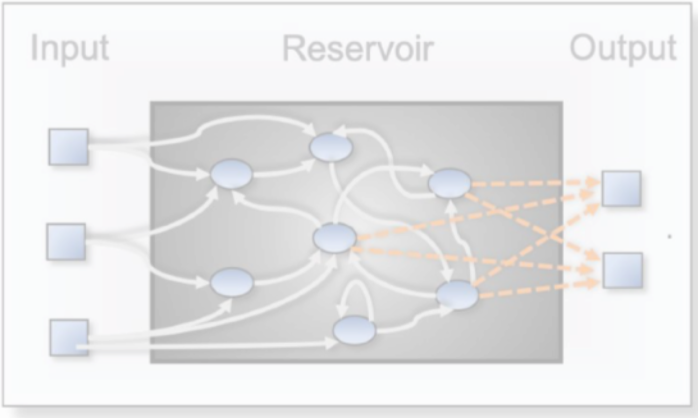


Torrejon, et al., Nature (2017)

Pinna, et al., KES, arXiv1811.12623

Reservoir computing with matter



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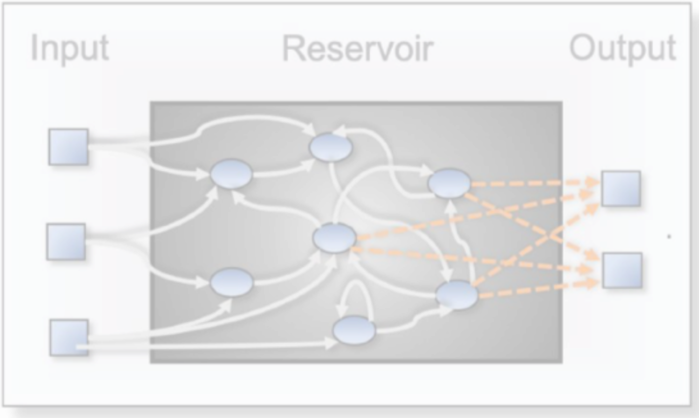

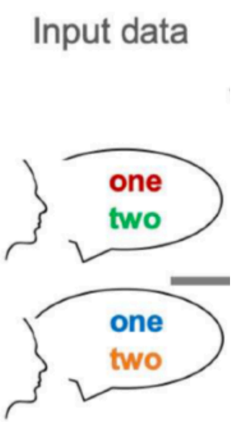

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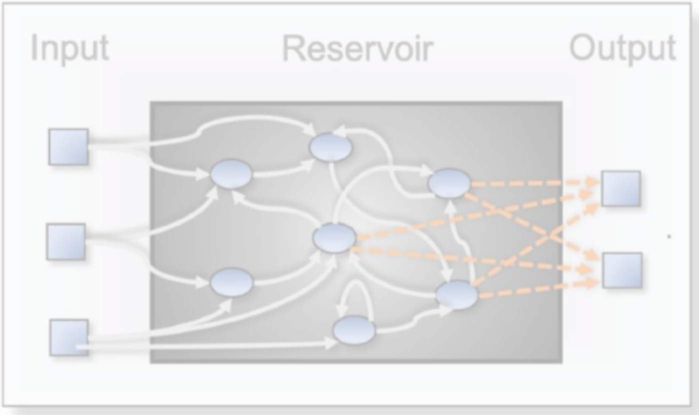

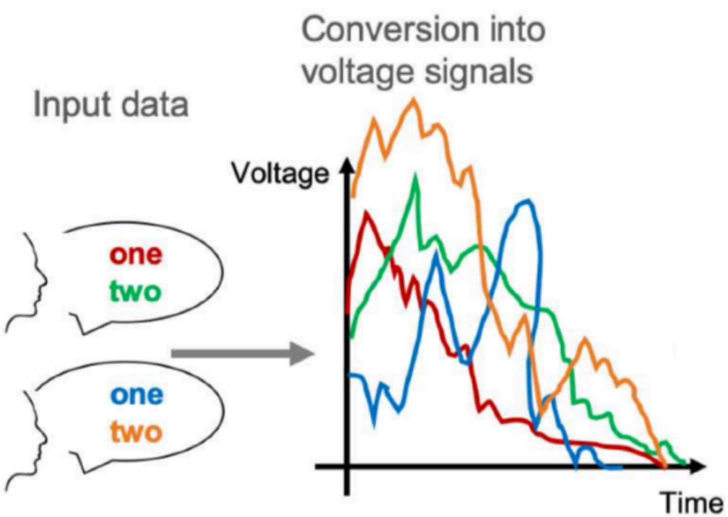

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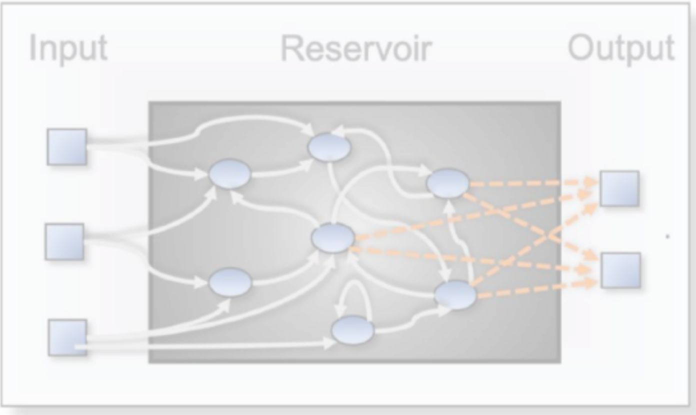

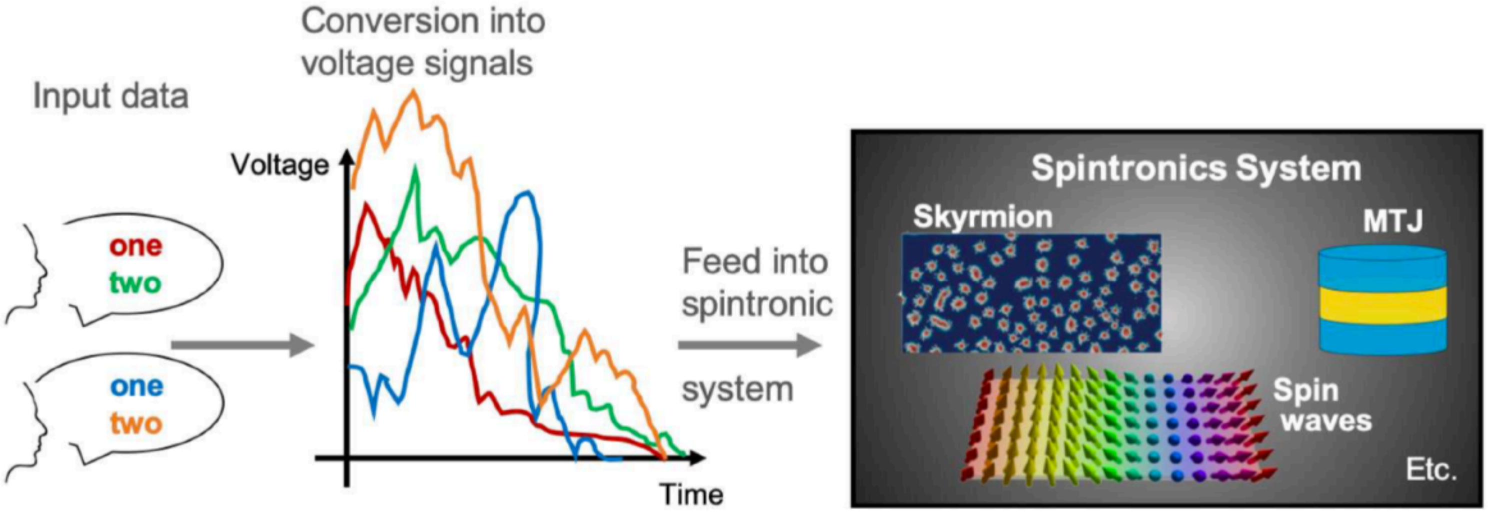

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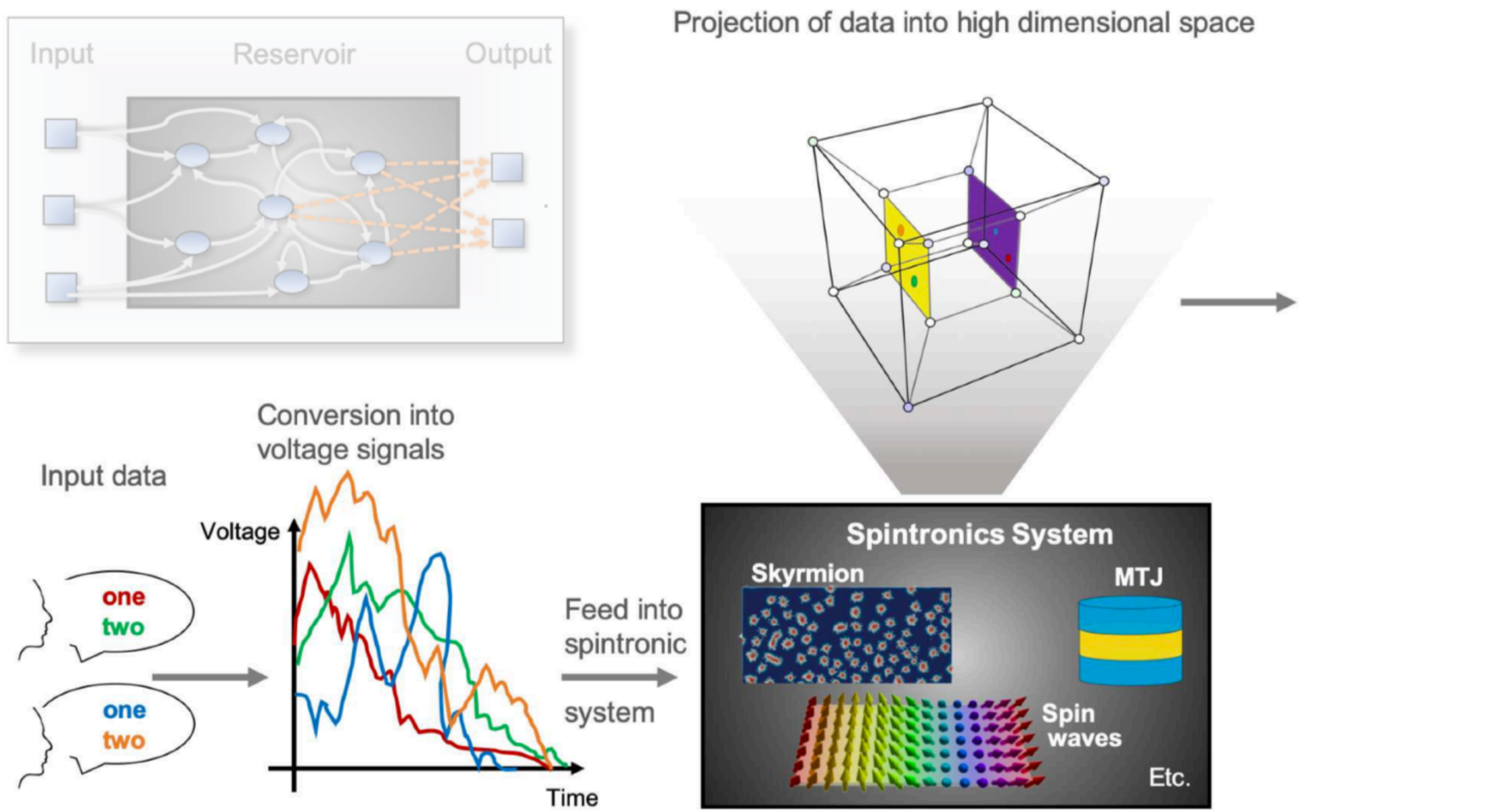
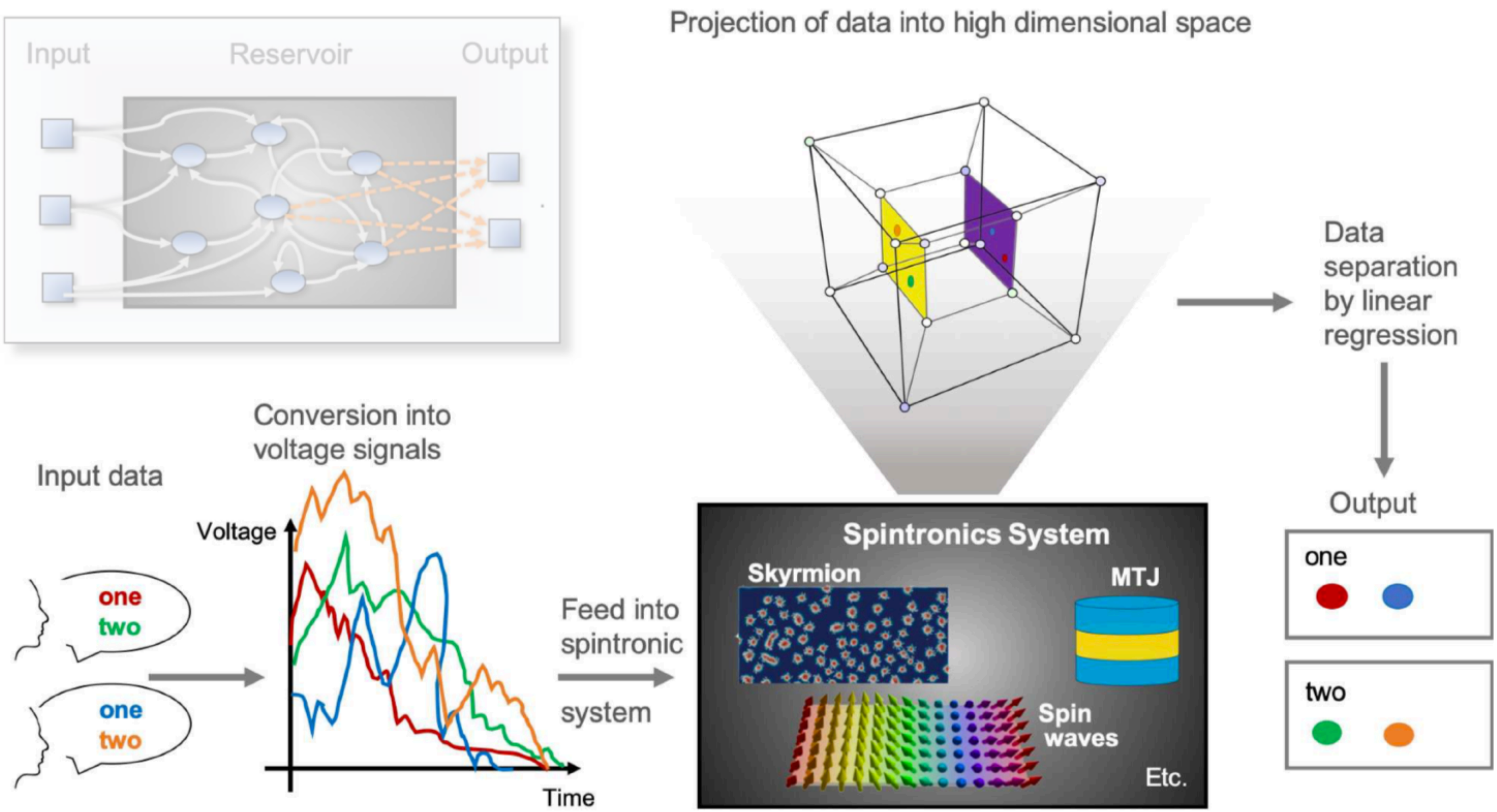
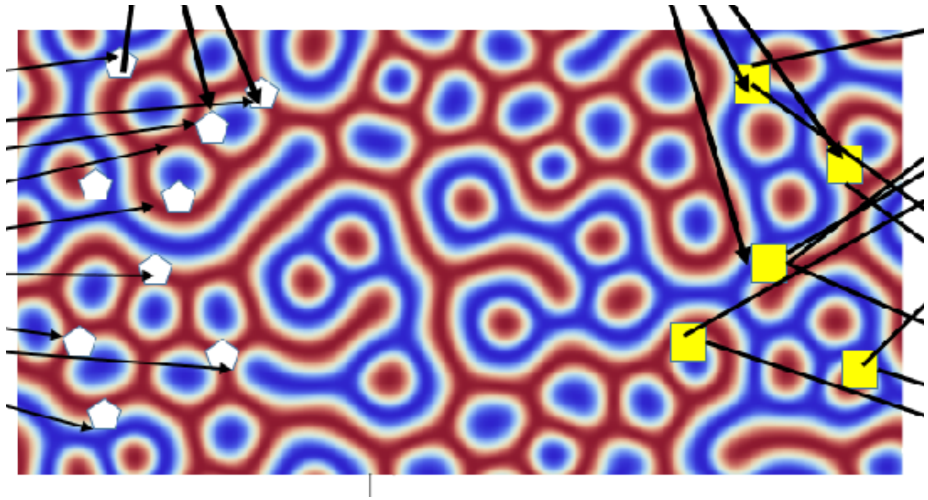


Reservoir computing with matter



Using skyrmions for reservoir computing

TWIST
Topological Whirls In SpinTronics

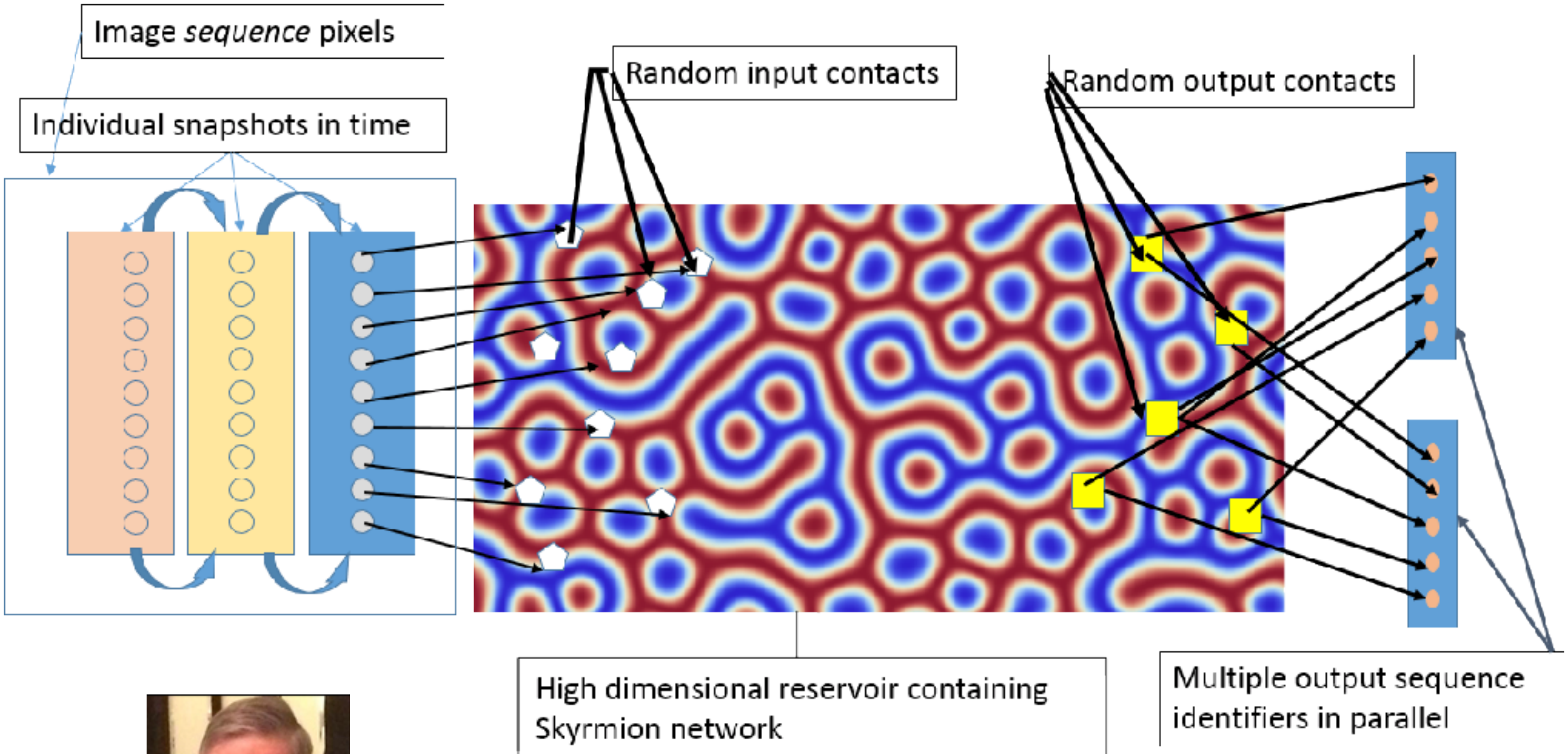


“skyrmion fabrics” as reservoir

George Bourianoff

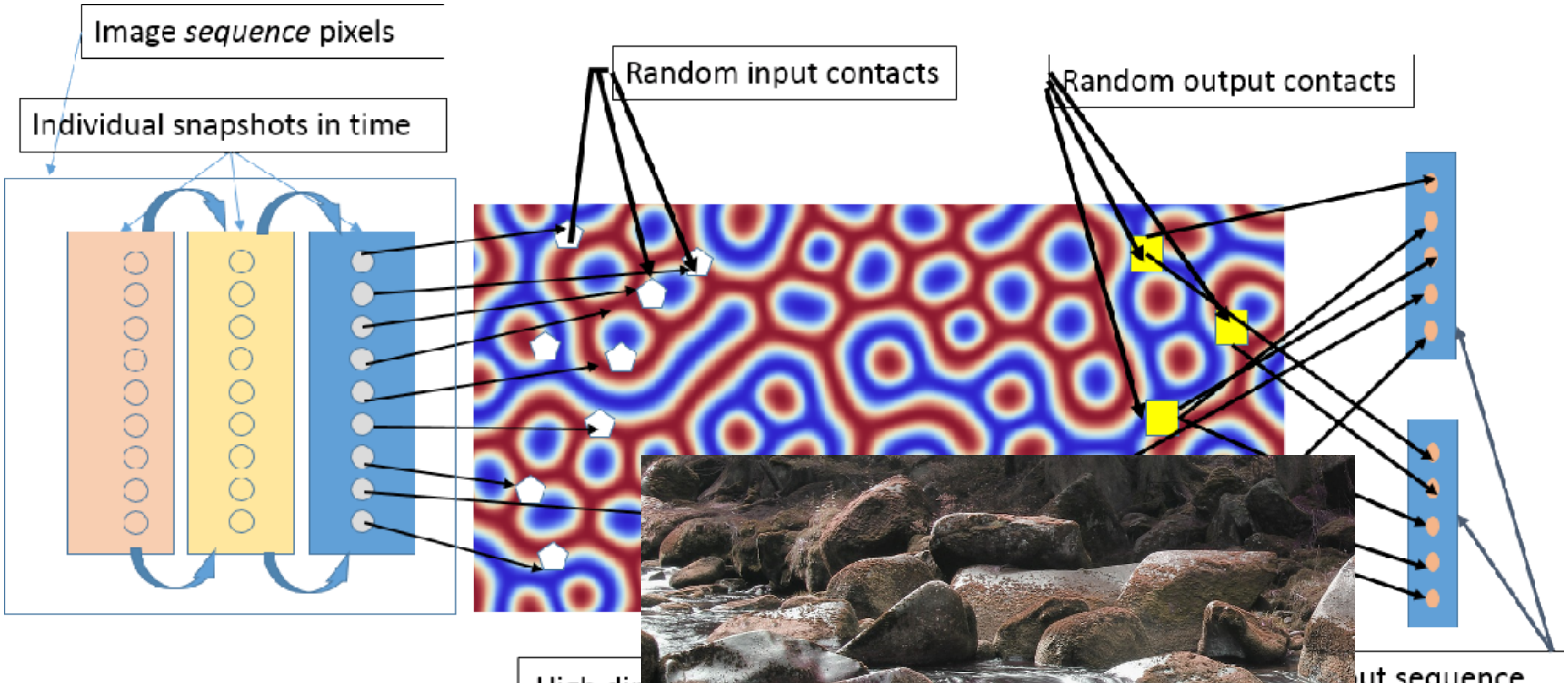
intel

Using skyrmions for reservoir computing




George Bourianoff

Using skyrmions for reservoir computing



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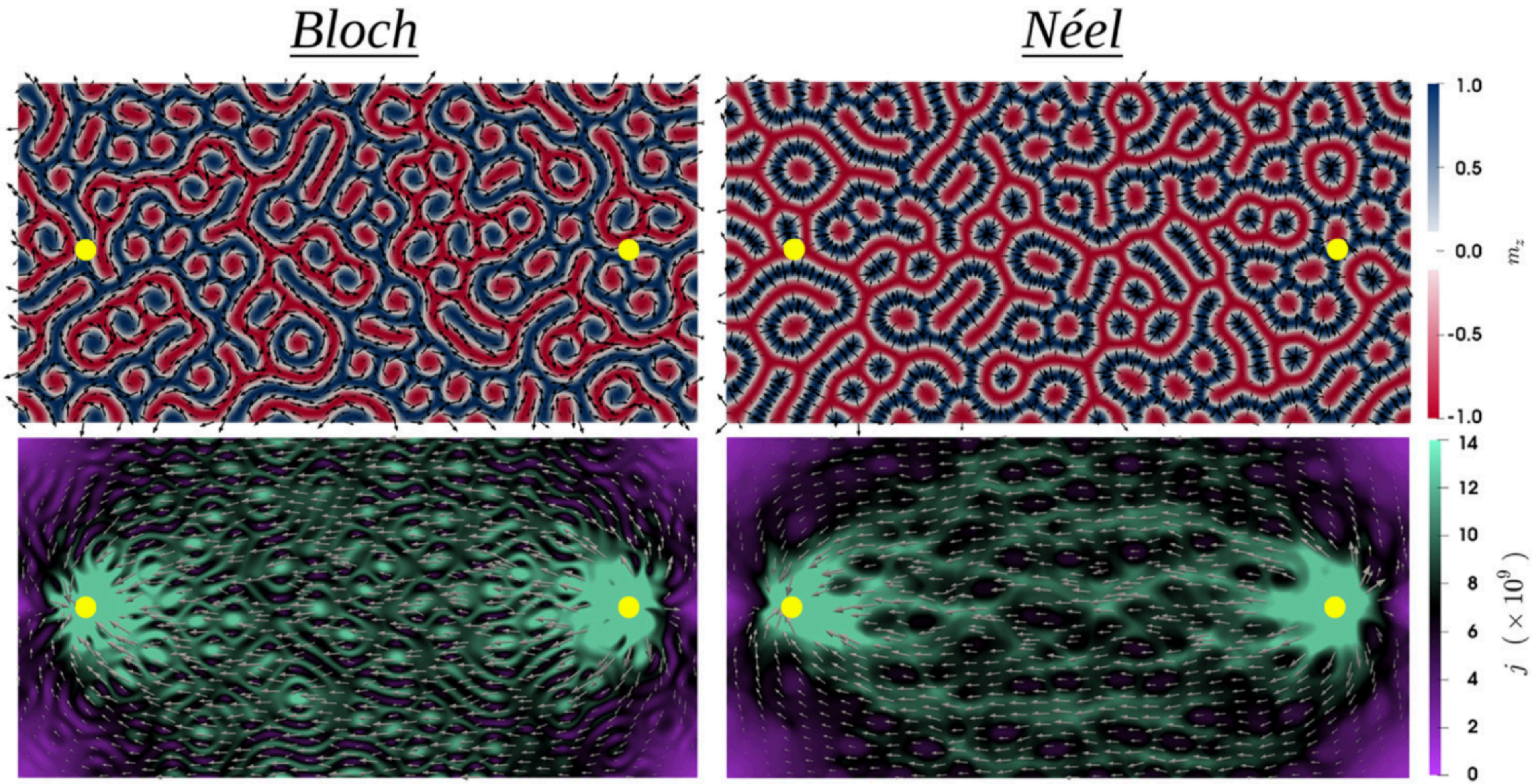
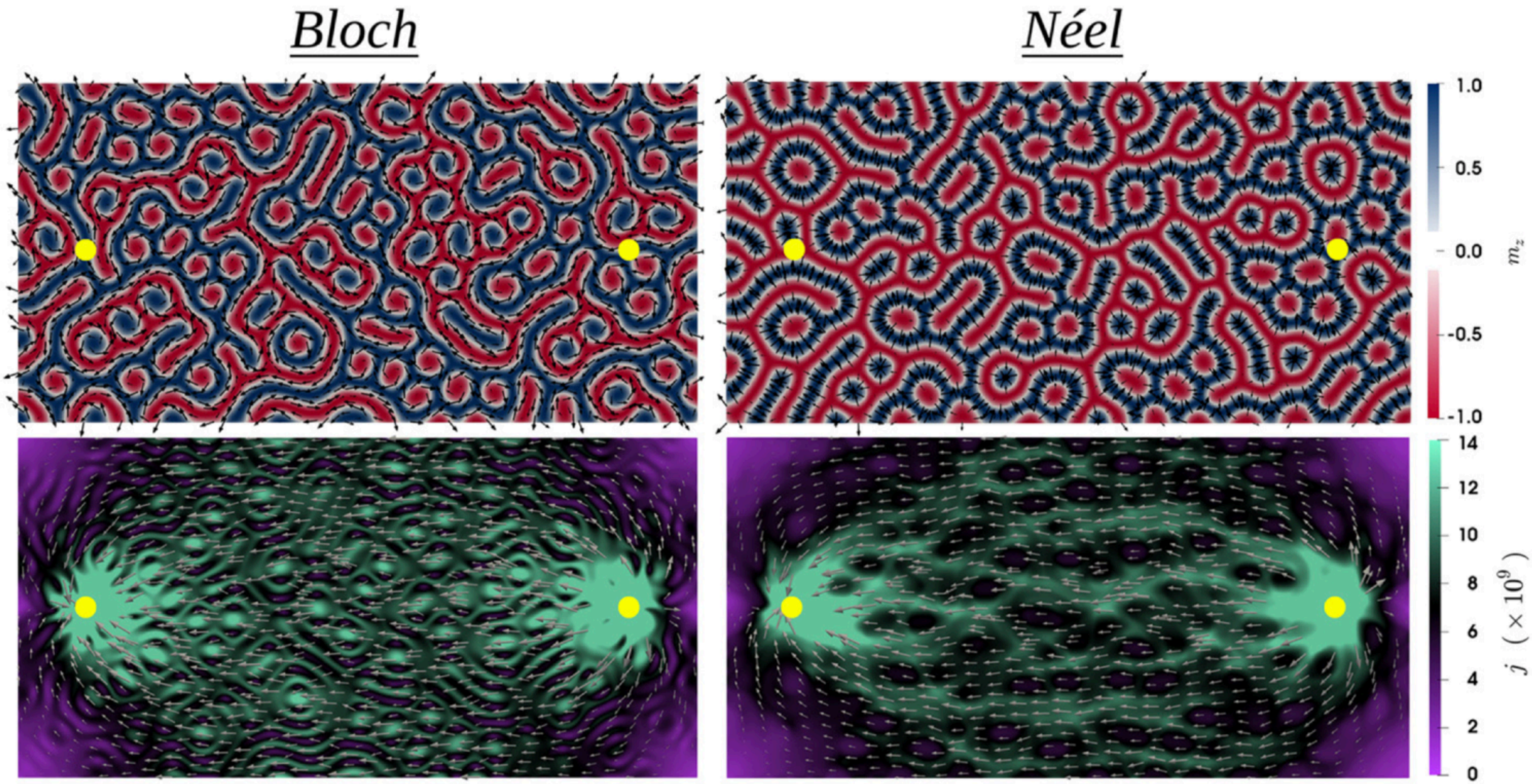


Bourianoff, Pinna, Sitte, KES, AIP Advances, (2018)

First steps towards: skyrmions for reservoir computing

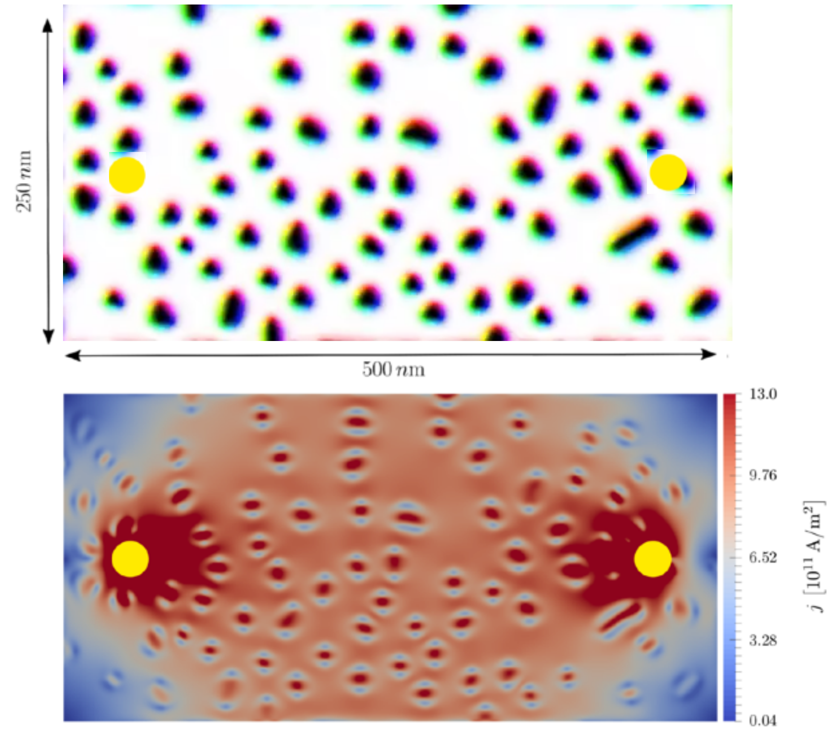
TWIST
Topological Whirls In SpinTronics



current flow based on AMR

Bourianoff, Pinna, Sitte, KES, AIP Advances, (2018) Skyrmions must not displace significantly for the reservoir to work properly

Daniele Pinna

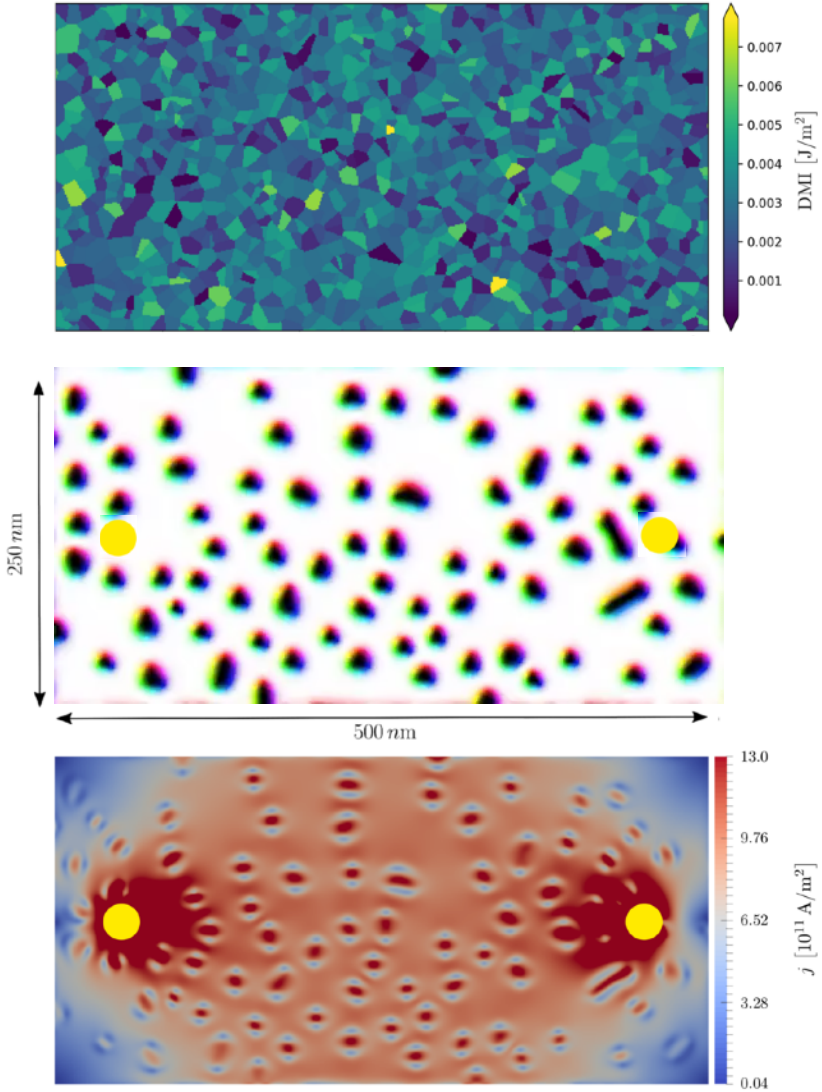


Pinna, et al., KES, arXiv1811.12623

Simulations: model pinning through grains

Skyrmions must not displace significantly for the reservoir to work properly

Daniele Pinna



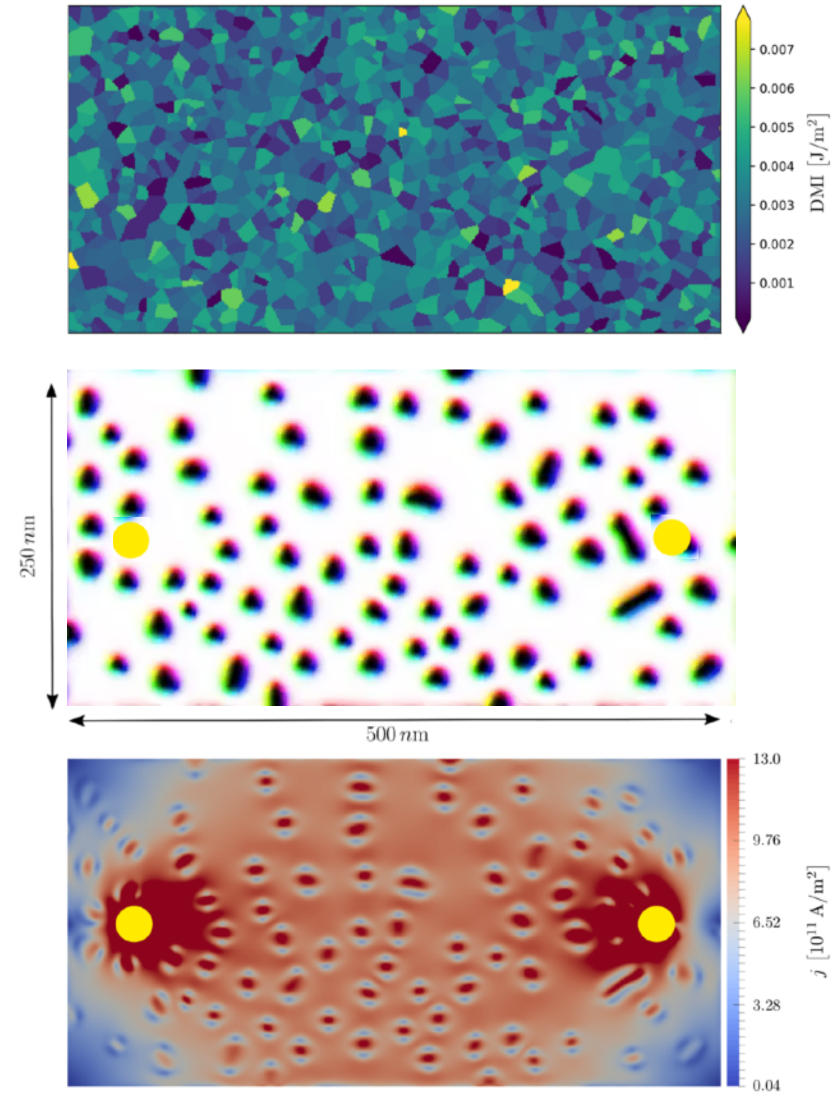
Pinna, et al., KES, arXiv1811.12623

Skyrmion Reservoir

Simulations: model pinning through grains

Skyrmions must not displace significantly for the reservoir to work properly

Texture topology has been shown to **not** change significantly due to thermal and current-driven excitations



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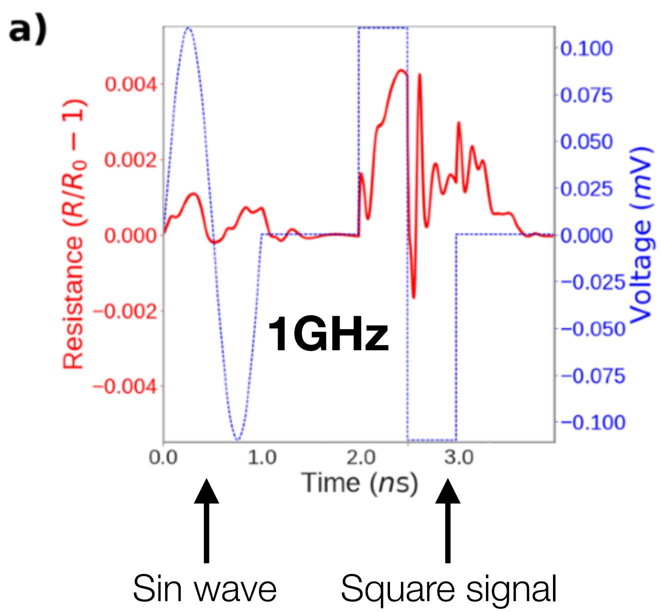
Pinna, et al., KES, arXiv1811.12623

Skyrmion Reservoir



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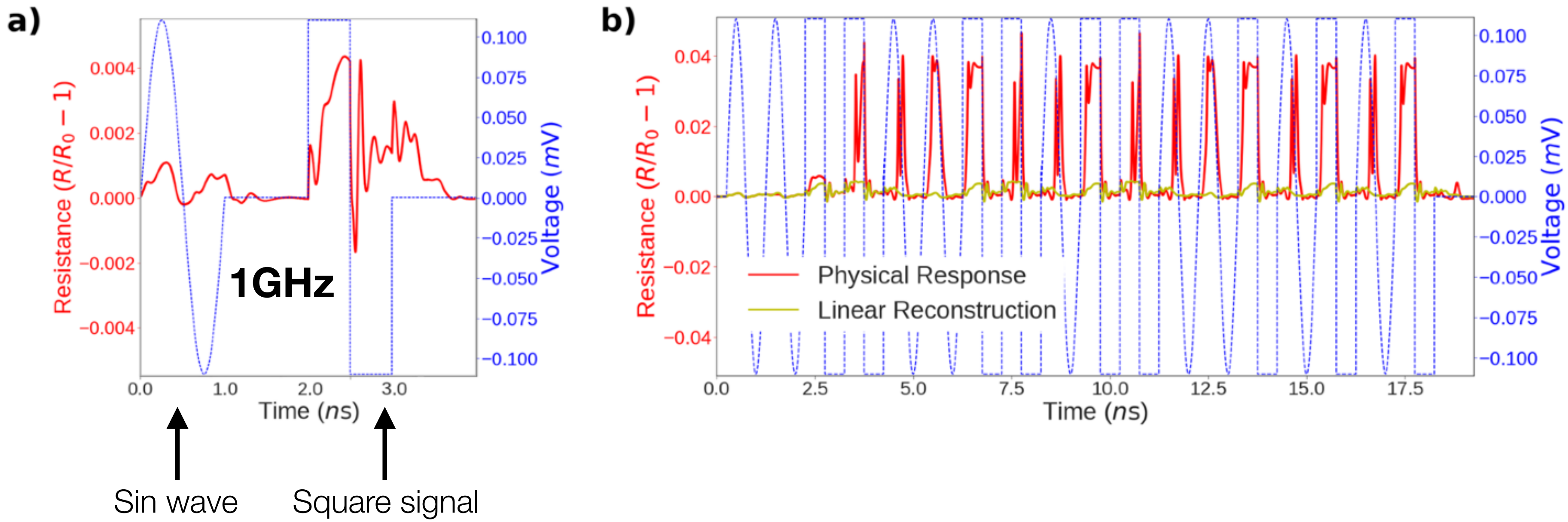

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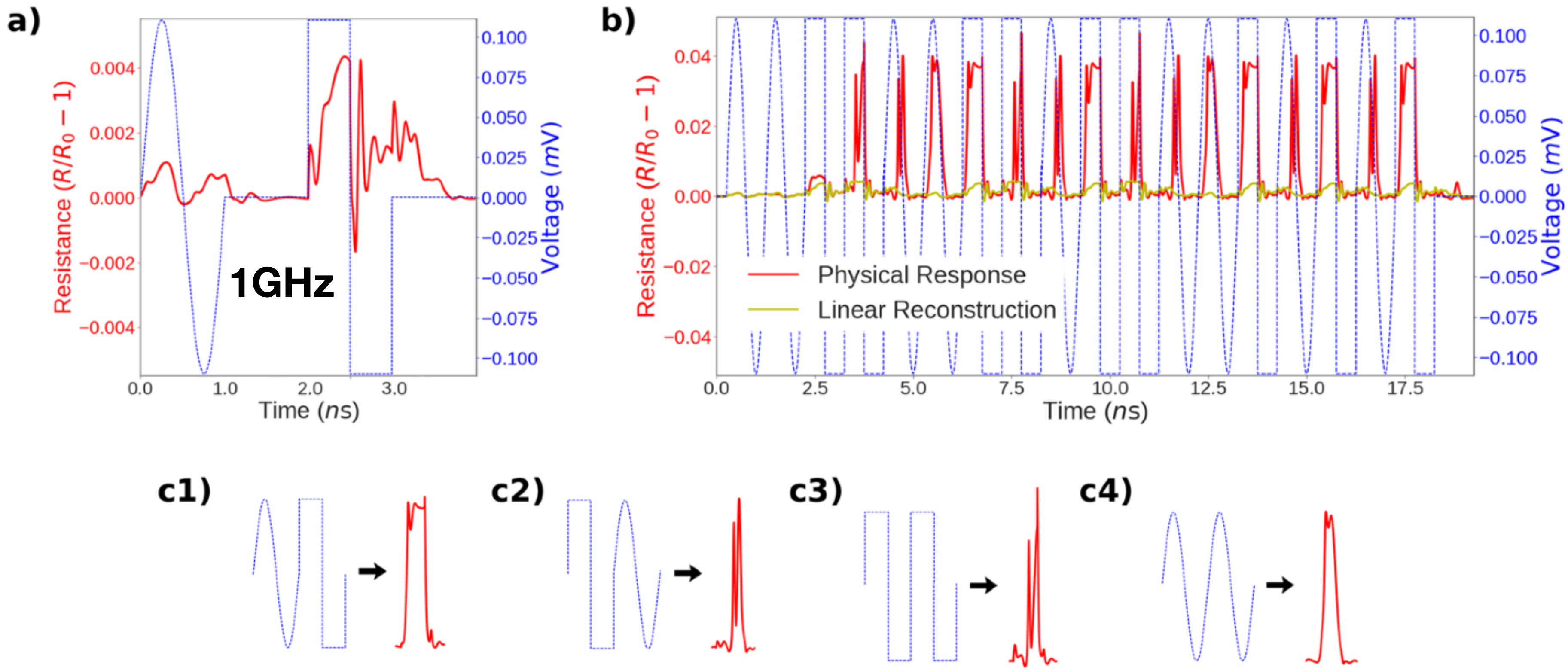
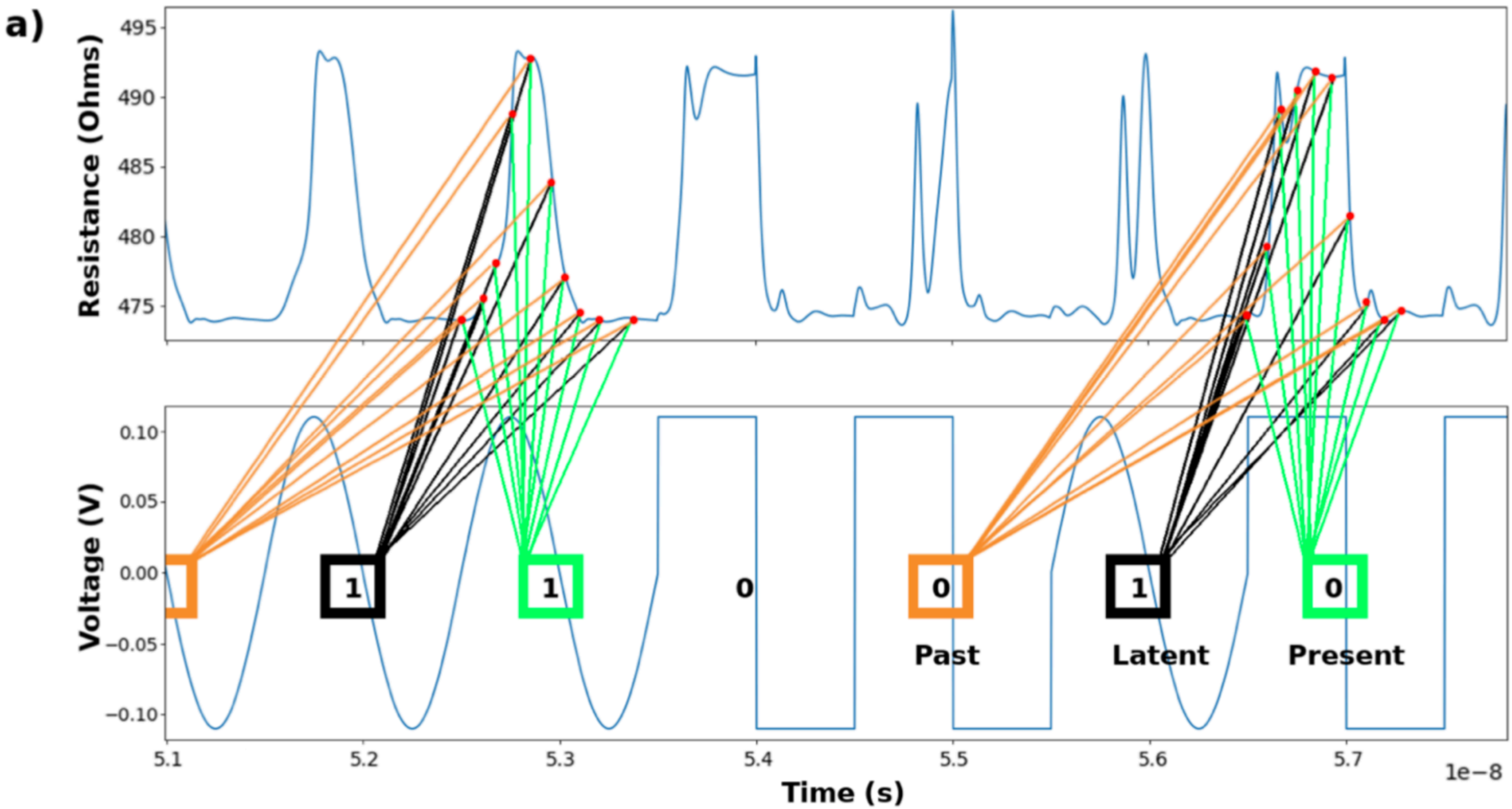


-> simple pattern recognition

Pinna, et al., KES, arXiv1811.12623

Patter recognition - time tracing

TWIST
Topological Whirls In SpinTronics



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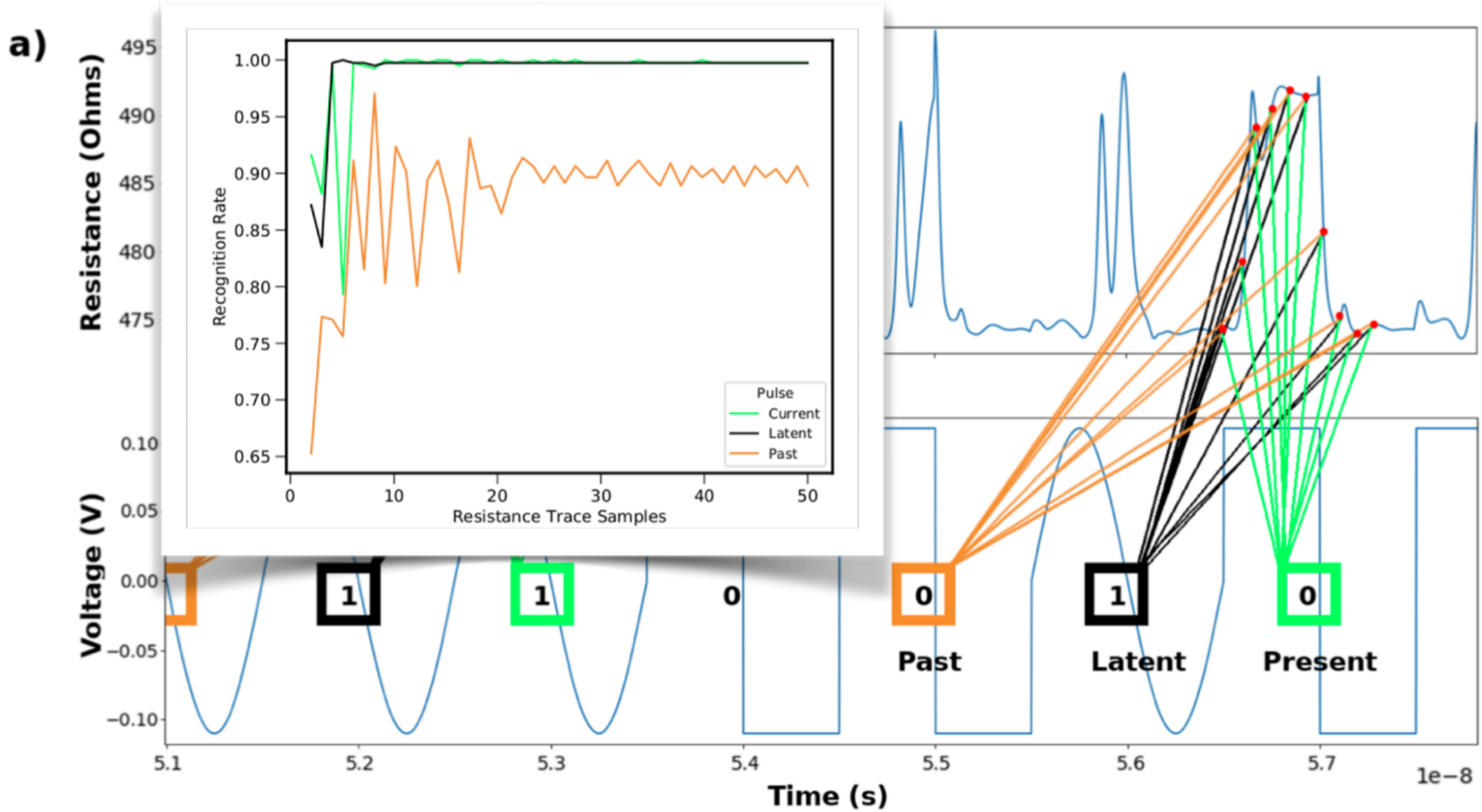
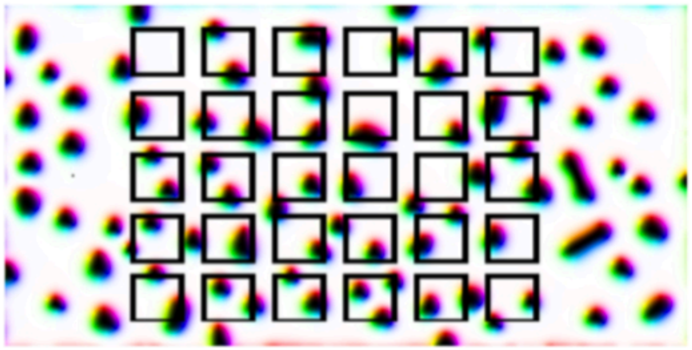


Pinna, et al., KES, arXiv1811.12623

Patter recognition - in space

Exploiting the complex magnetic structure, no time tracing needed!

a)



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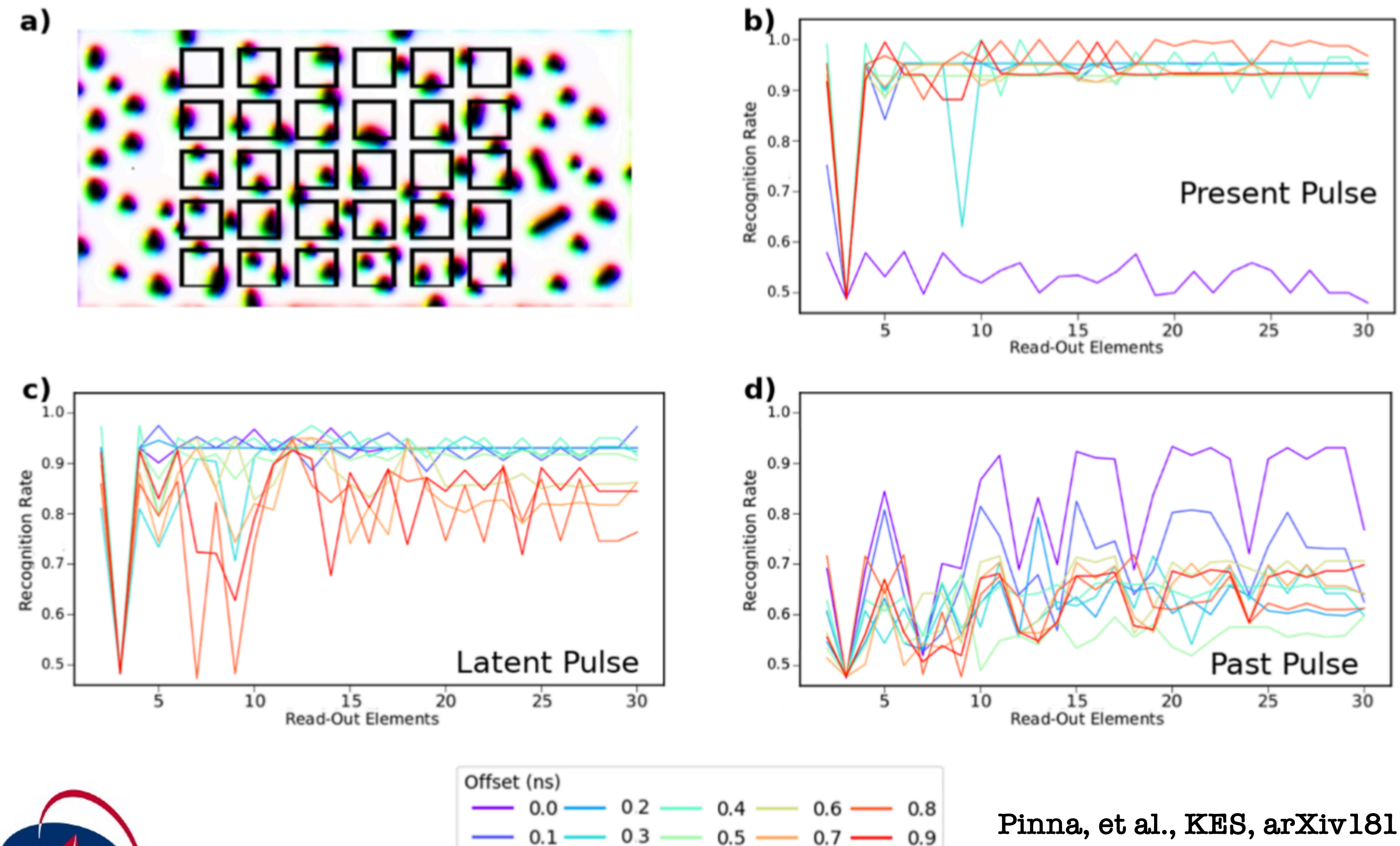
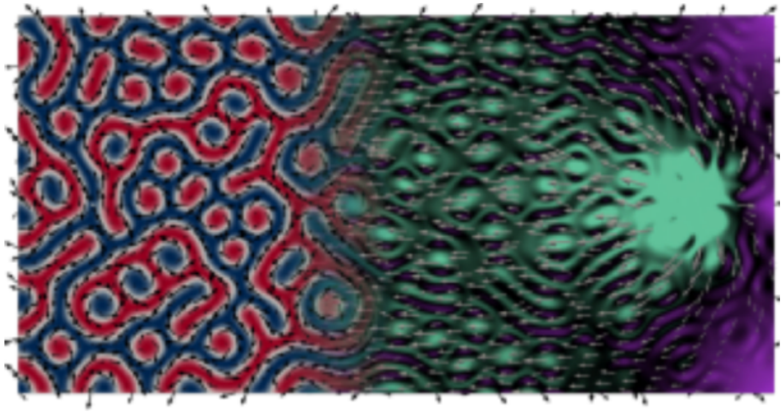


Pinna, et al., KES, arXiv1811.12623

Summary: RC with Skyrmion Fabrics



Non-linear, complex system with short term memory

Simple pattern recognition by a single measurement

Potential advantages of Skyrmion Reservoir:

- small (~nm)
- low energy consumption (~ μW)
- complexity / many degrees of freedom

Prychynenko, et al., KES, Phys. Rev. Appl. (2018)
Bourianoff, et al., KES, AIP Advances, (2018)
Pinna, et al., KES, arXiv1811.12623

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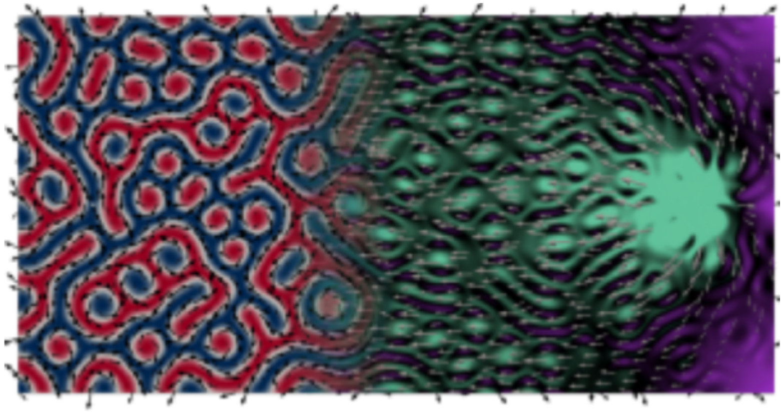

✓ **Non-linear, complex system with short term memory**

✓ Simple pattern recognition by a single measurement

Potential advantages of Skyrmion Reservoir:

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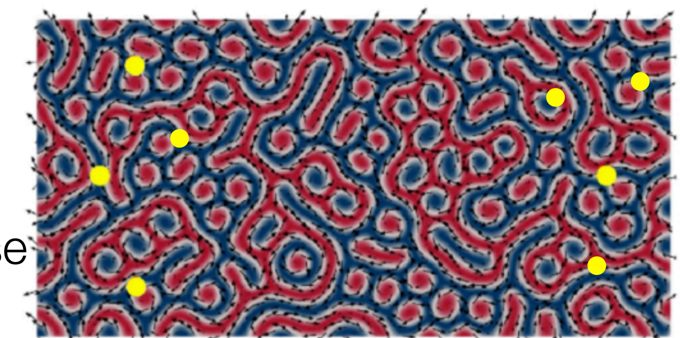
Outlook:

"Finding optimal settings for magnetic texture"

Resistances across multiple input and output contacts

→ capture more information about the fabric's response



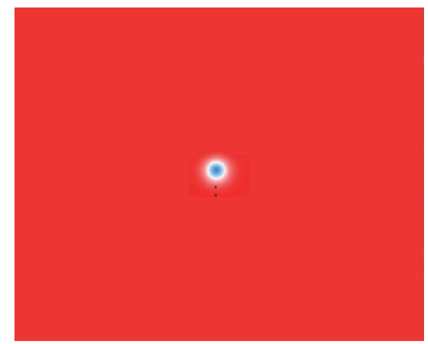
Prychynenko, et al., KES, Phys. Rev. Appl. (2018)

Bourianoff, et al., KES, AIP Advances, (2018)

Pinna, et al., KES, arXiv1811.12623

Skyrmion based devices ???

What is a device that optimally uses the properties of a skyrmion?



Skyrmions for
Unconventional Computing?

Reservoir Computing | Stochastic Computing

DW → 1d

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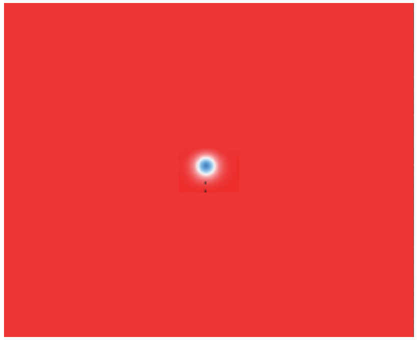


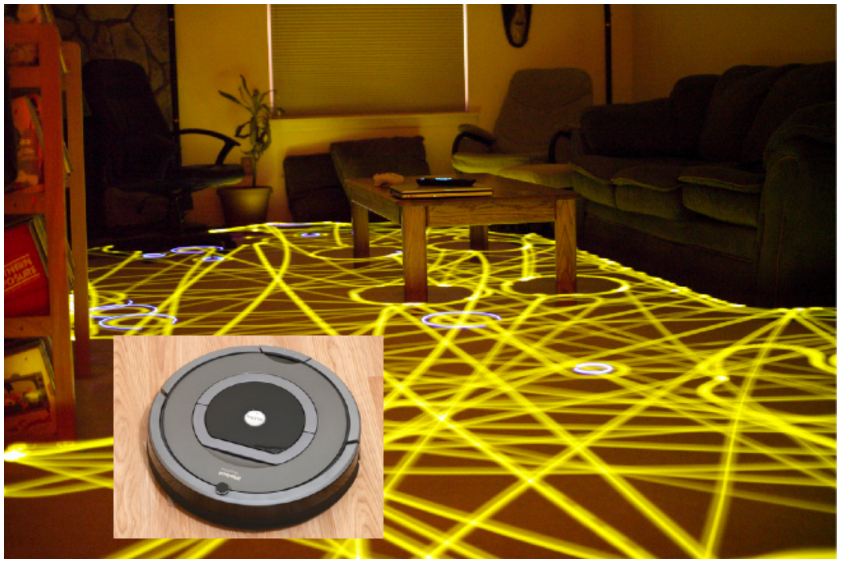
DW → 1d

Skyrmions for
Unconventional Computing?

Reservoir Computing

Stochastic Computing

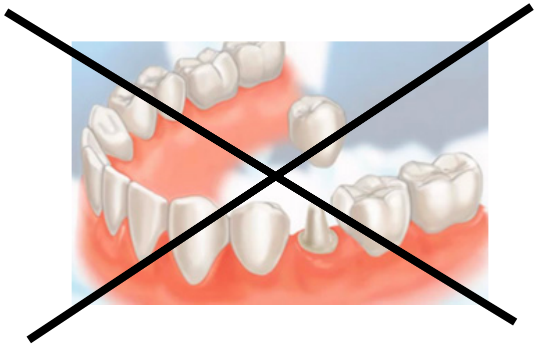
Depending on the application not always a high precision is needed



Speed / efficiency ⟷ Presicison

Depending on the application not always a high precision is needed

Speed / efficiency ⟷ Presicison



Stochastic Computing - Motivation

You win, if red dice is a 6 **and** blue one shows an even number.

Theory

p=1/6

p=1/2

probability of winning: p = 1/6 * 1/2 = 1/12

Stochastic Computing - Motivation

TWIST
Topological Whirls In SpinTronics

You win, if red dice is a 6 **and** blue one shows an even number.

	Theory	Experiment
	p=1/6	
	p=1/2	

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Stochastic Computing - Motivation

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Theory | Experiment

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Theory | Experiment

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law of large numbers:

- results converges to theory with **increasing number** of experiments
- only works if the two cubes are **independent** from each other.

p=1/2

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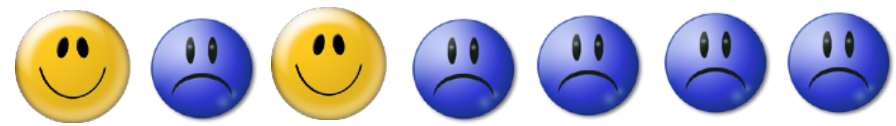

….

1 0

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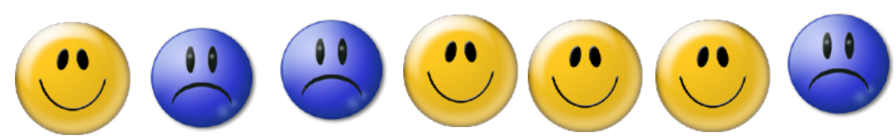

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Stochastic Computing - Motivation

Topological Whirls In SpinTronics

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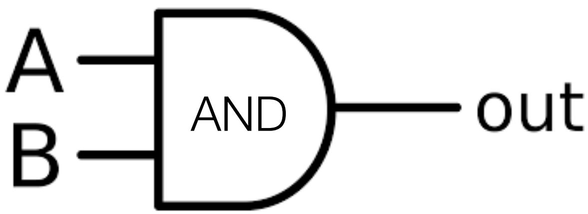
	Theory		Experiment							
	p=1/6	**A**	1	0	1	0	0	0	0	….
	p=1/2	**B**	1	0	0	1	1	1	0	….
probability of winning: p = 1/6 * 1/2		**out**	1	0	0	0	0	0	0	…

You win, if red dice is a 6 **and** blue one shows an even number.

Theory

Experiment

p=1/6



p=1/2

Multiplication by means of an AND gate!

A	1	0	1	0	0	0	0	….
B	1	0	0	1	1	1	0	….
out	1	0	0	0	0	0	0	…

probability of winning: p = 1/6 * 1/2

You win, if red dice is a 6 **and** blue one shows an even number.

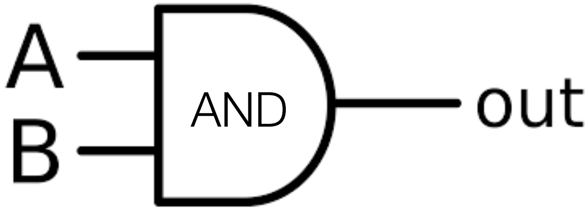
Theory

Experiment

p=1/6

A 1 0 1 0 0 0 0 ….

Multiplication by means of an AND gate!



law of large numbers:
- the longer the signals, the better the accuracy (on average)
- signals must be decorrelated

p=1/2

B 1 0 0 1 1 1 0 ….

probability of winning: p = 1/6 * 1/2

out 1 0 0 0 0 0 0 …

What to do if signals are correlated?

$$A \quad \overbrace{1,1,0,1,0,1,1,1}^{p_A = 6/8}$$

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Pinna, et al., Phys. Rev. Appl. (2018)

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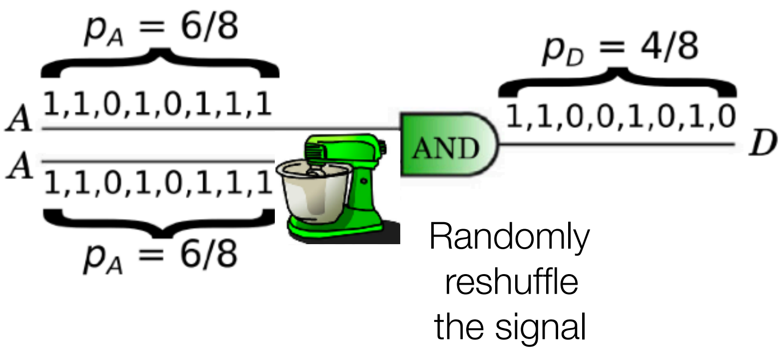

$$p_A \cdot p_A \simeq p_D$$

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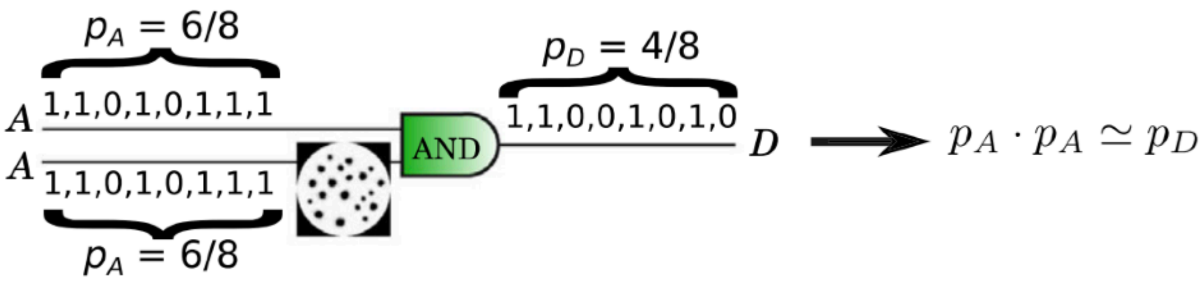

Daniele Pinna

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Skyrmion reshuffler based on thermal noise

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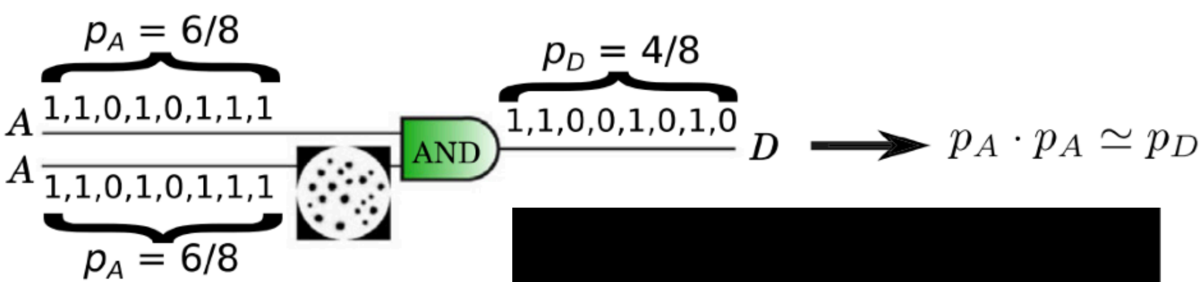

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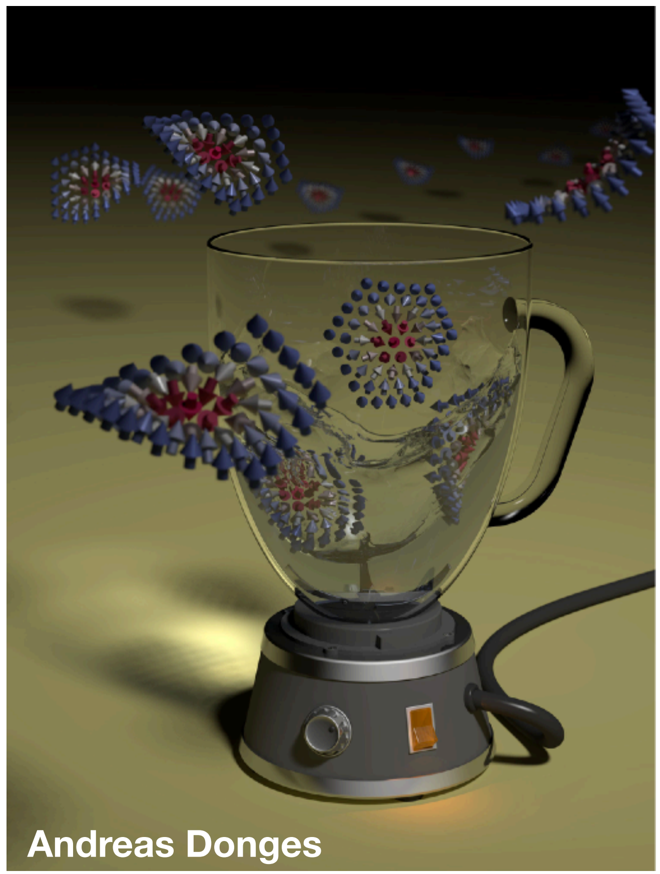

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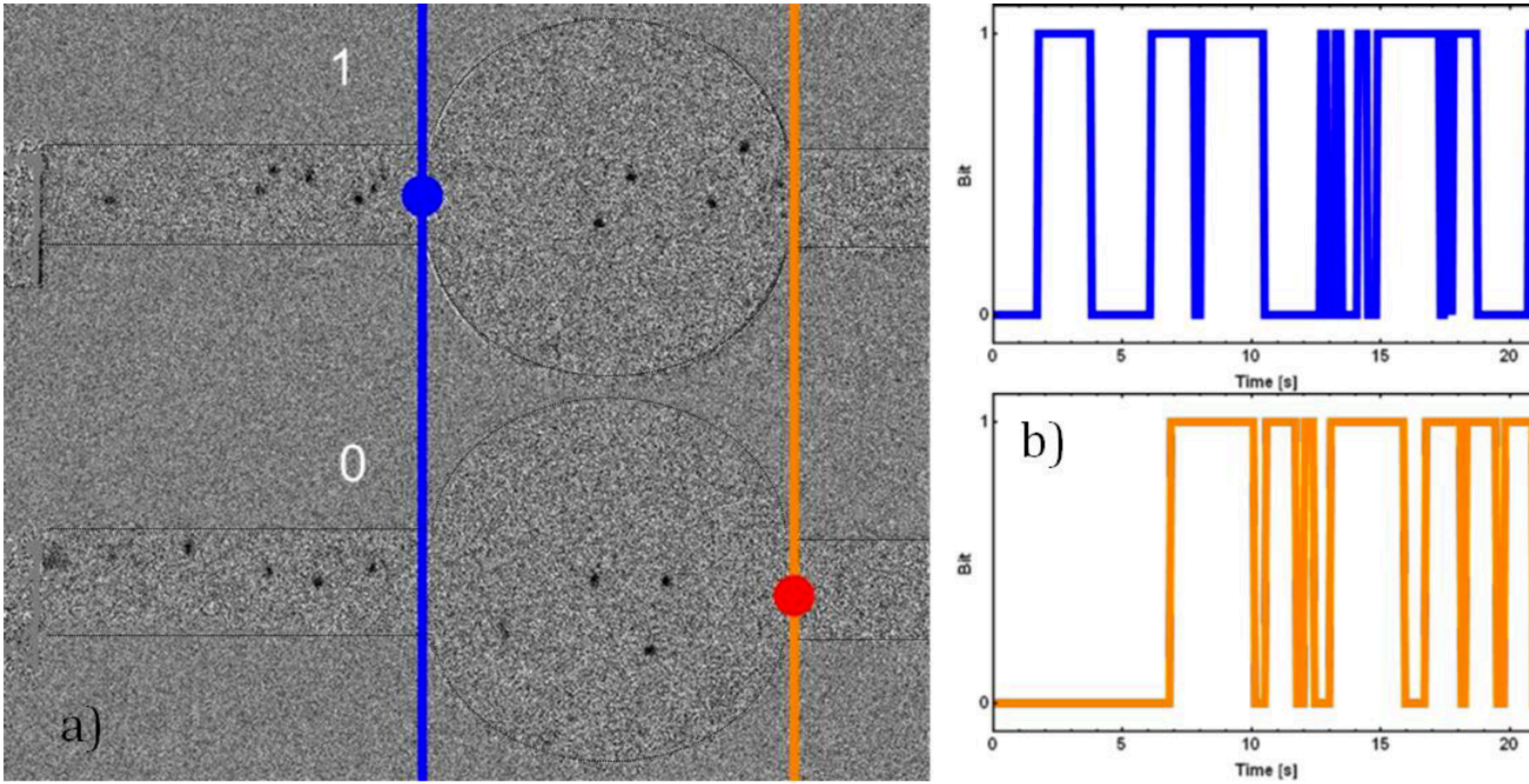

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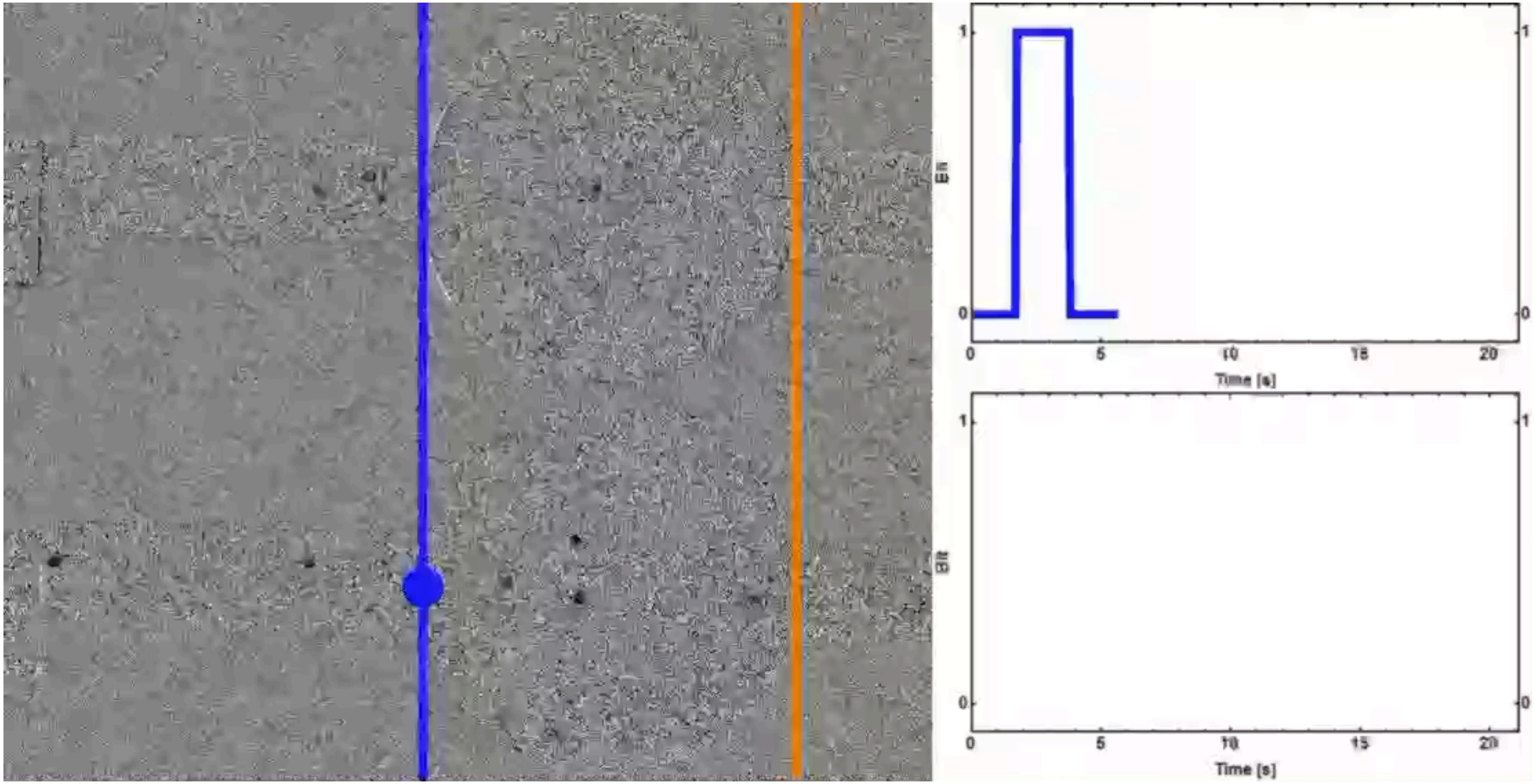

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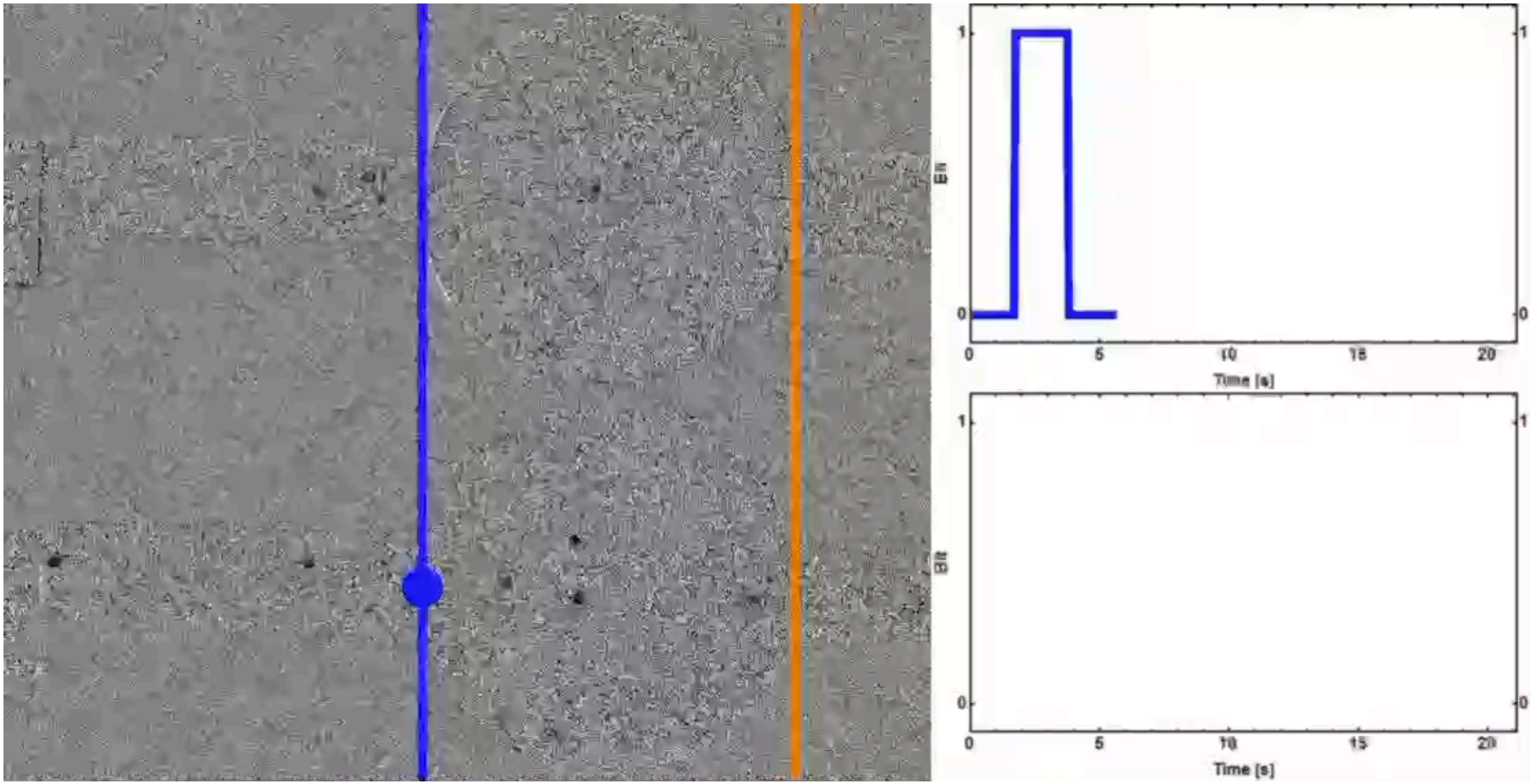

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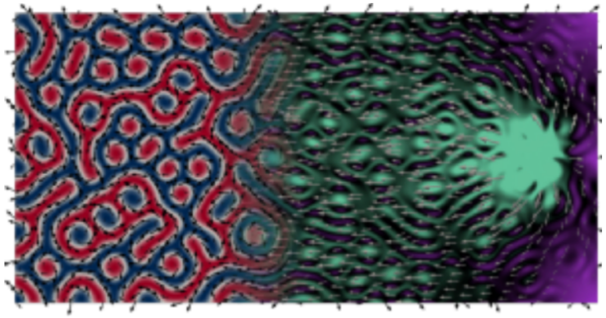
- Skyrmions for reservoir computing



Prychynenko, et al., KES, Phys. Rev. Appl. (2018)

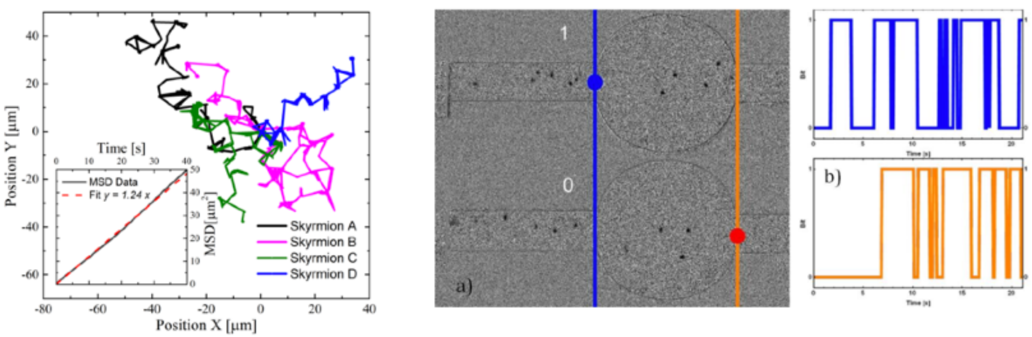
Bourianoff, et al., KES, AIP Advances, (2018)

Pinna, et al., KES, arXiv1811.12623

Pinna, et al., Phys. Rev. Appl. (2018)

- Thermal skyrmion diffusion and skyrmion reshuffler for stochastic computing

Zázvorka, ..., KES, et al., Kläui, Nature Nanotechnology 2019



Thanks to

J. Zázvorka, F. Jakobs, D. Heinze, N. Keil, S. Kromina, S. Jaiswal, K. Litzius, G. Jakob, P. Virnau, D. Pinna, A. Donges, U. Nowak, M. Kläui

- Data analysis, new tools for "microscopy"?

Horenko, et al., KES, arXiv1907.04601

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TWIST
Topological Whirls In SpinTronics

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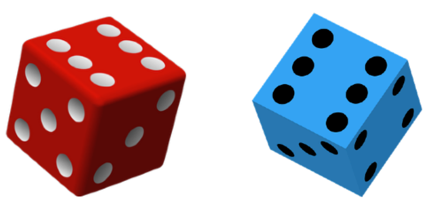

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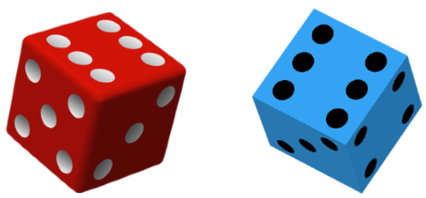

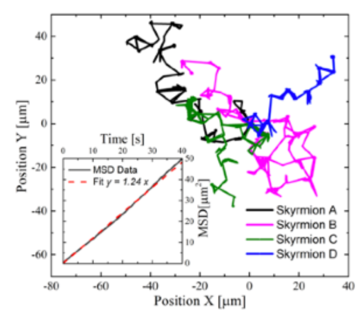

SP/CE

Outlook & personal view

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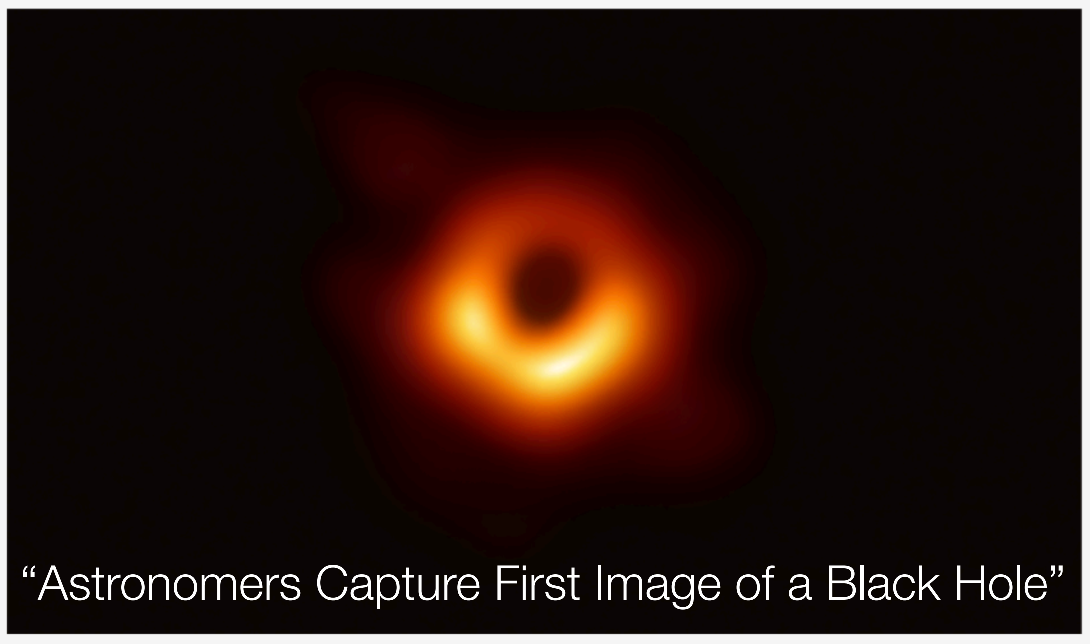

https://www.almaobservatory.org/en/press-release/astronomers-capture-first-image-of-a-black-hole/

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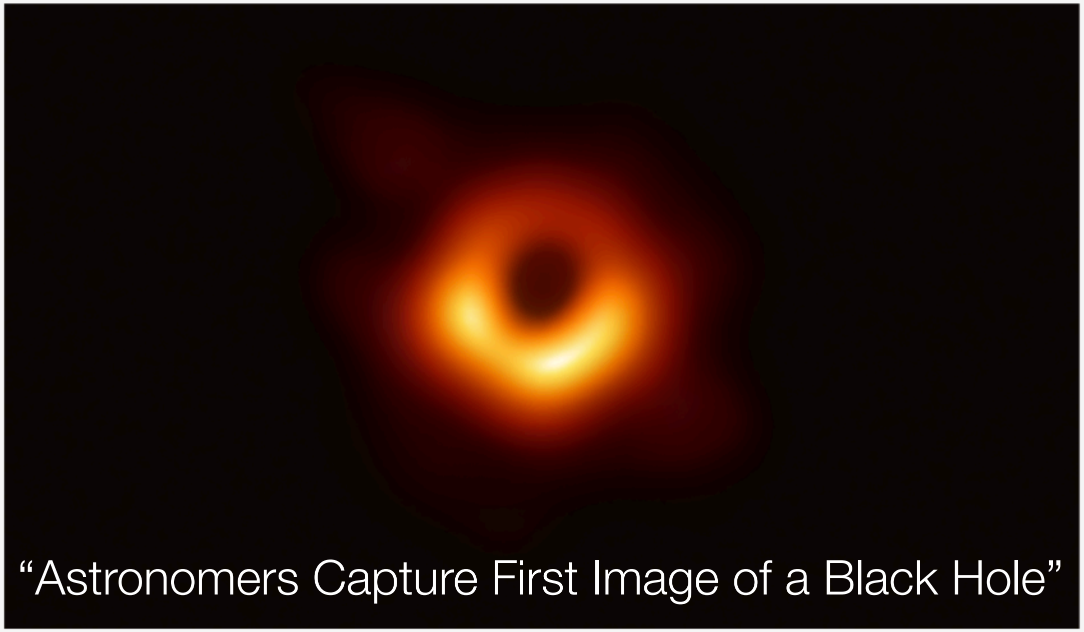

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progress in
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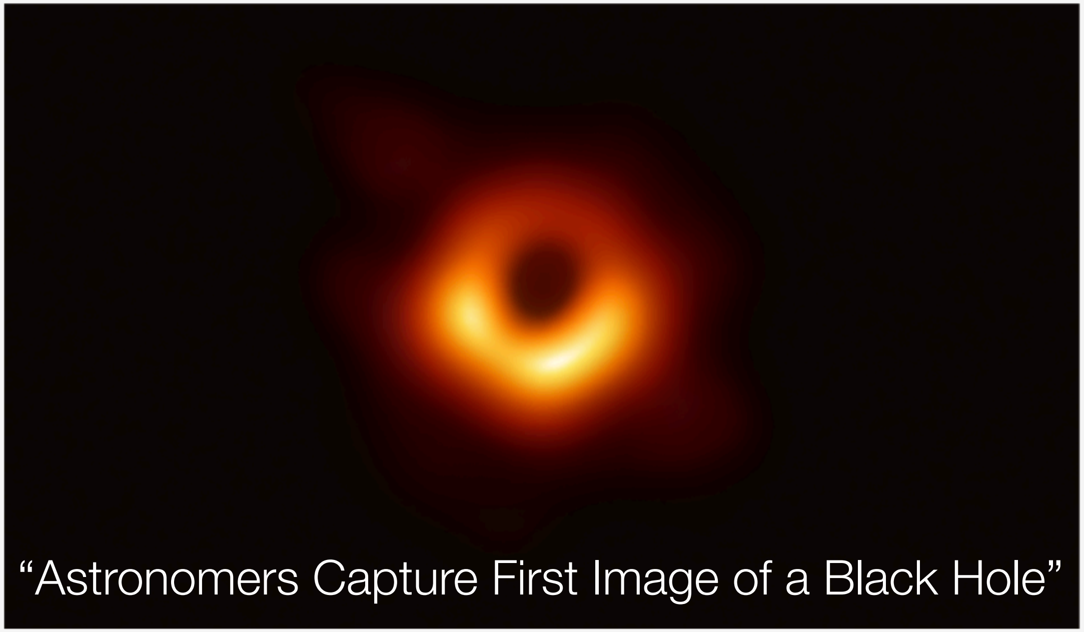
Outlook & personal view



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Horenko, et al., KES, arXiv1907.04601

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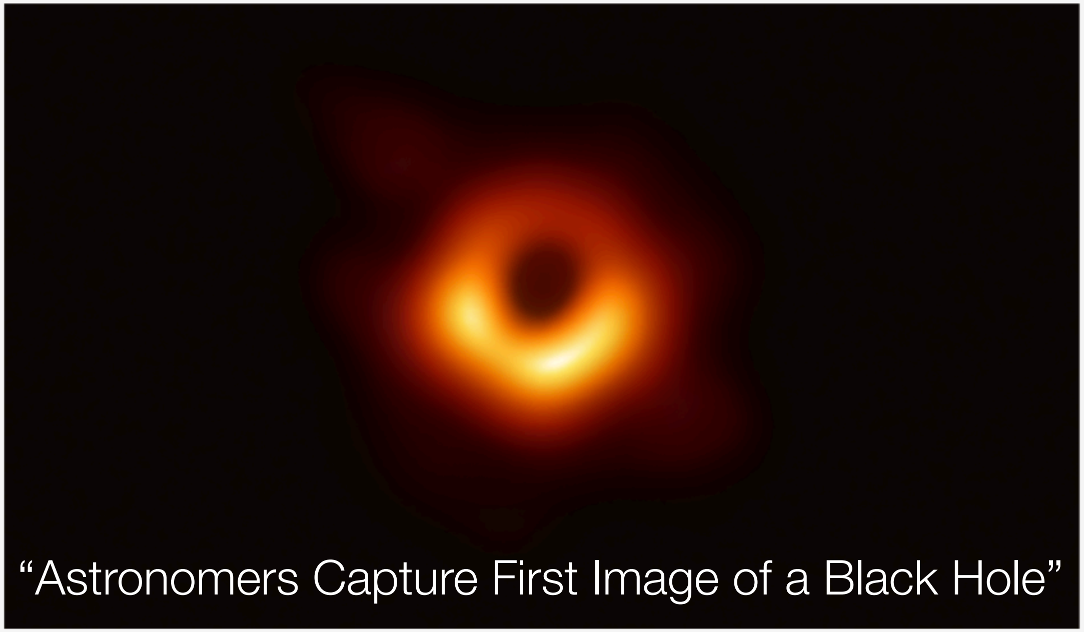

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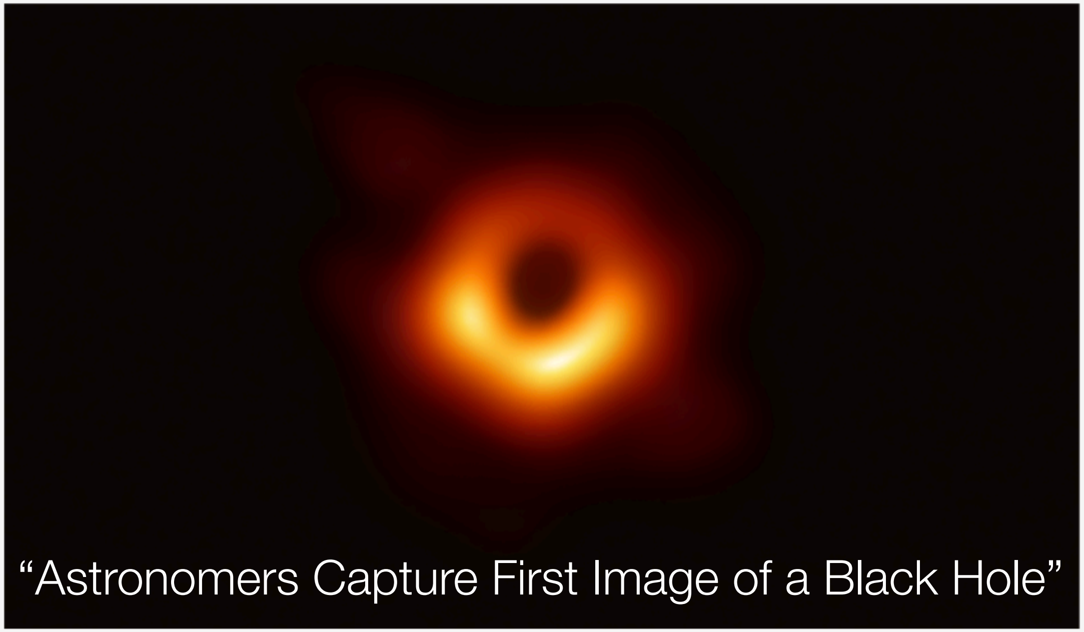

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belong to the most popular latent inference methods

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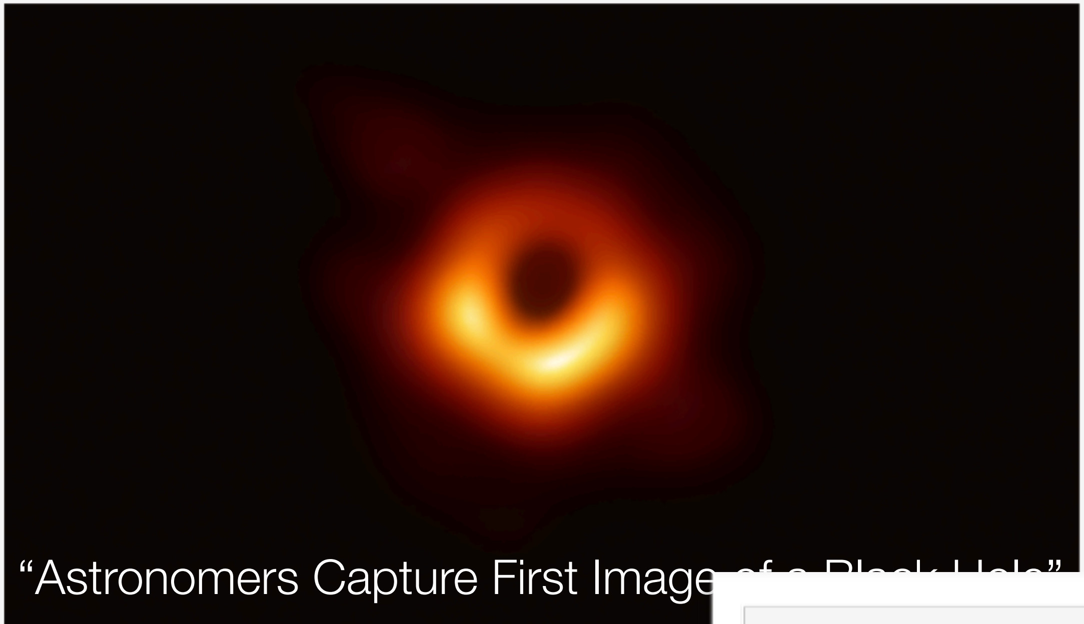
Topological Whirls In SpinTronics



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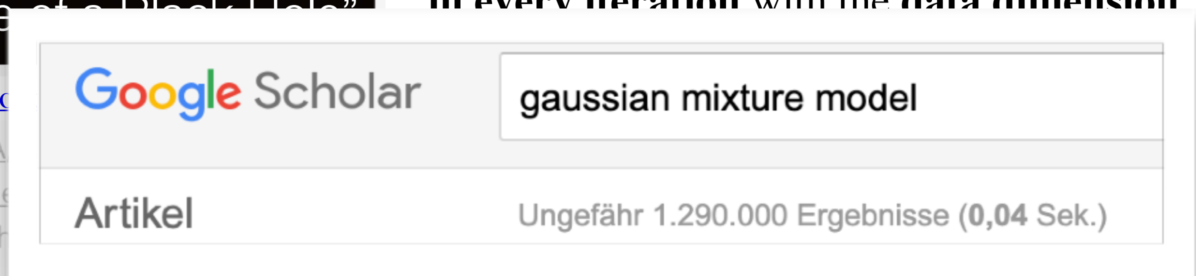

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Google Scholar magnetic skyrmion
Artikel Ungefähr 13.800 Ergebnisse (**0,03** Sek.)

Google Scholar gaussian mixture model
Artikel Ungefähr 1.290.000 Ergebnisse (**0,04** Sek.)

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SP/CE

Data analysis: New tools for “microscopy”?

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Davi Rodrigues
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two low cost tools for extraction of latent patterns

low cost = computational iteration costs and memory requirements are **independent** of the data statistics size & the observed data dimension **Horenko, et al., KES, arXiv1907.04601**

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latent entropy:
encodes **stochasticity** (predictability) of the system

the higher the latent entropy
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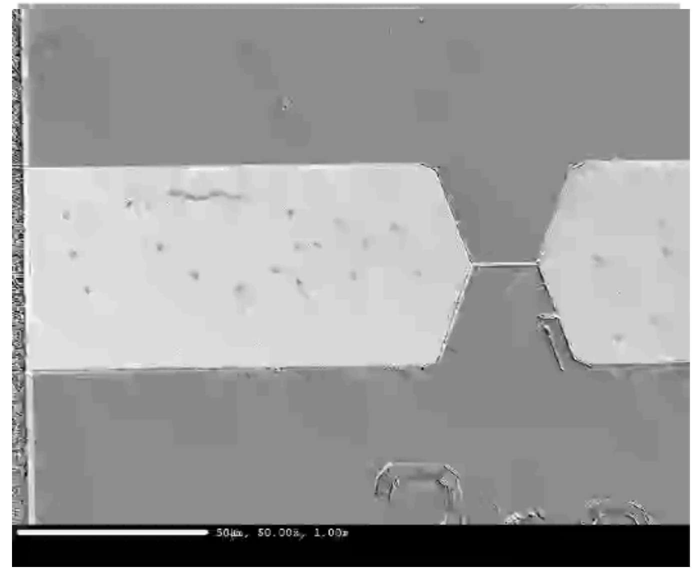
(a) Magnetization measurements (MOKE)



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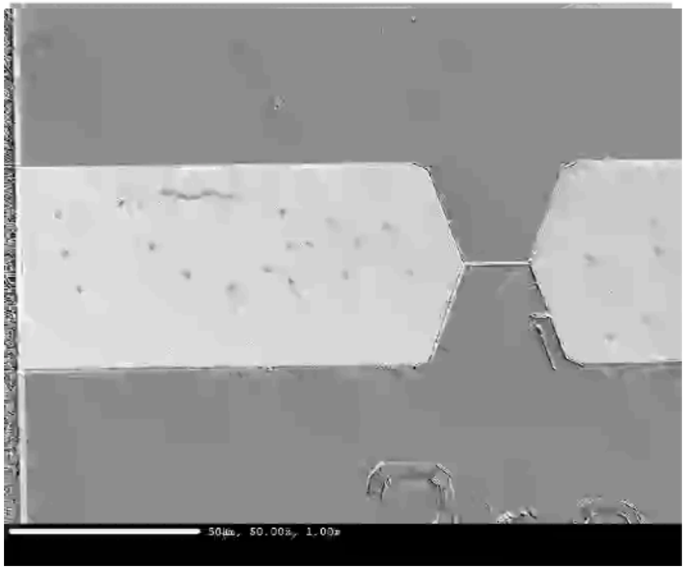

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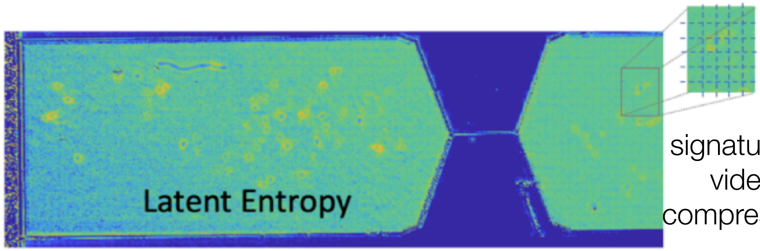
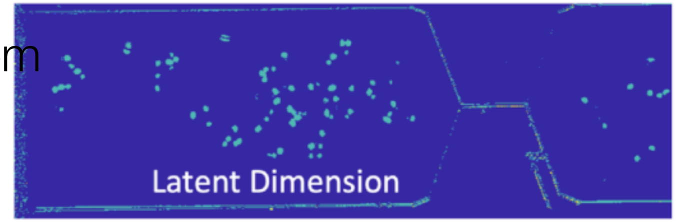


signature of video compression



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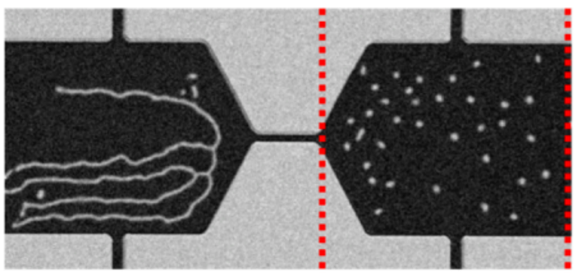
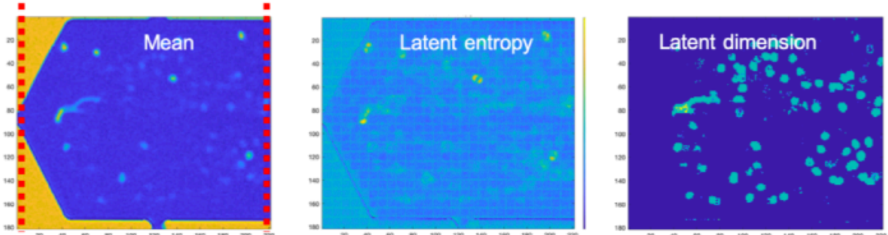


Raw data from

Jiang, et al., Science 2015



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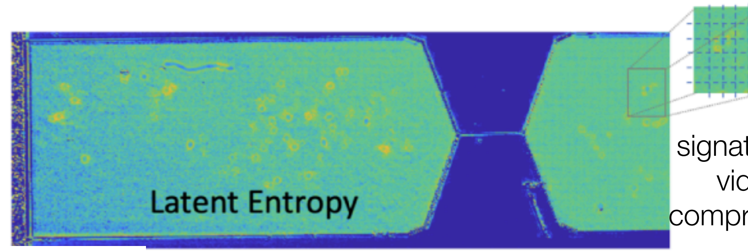

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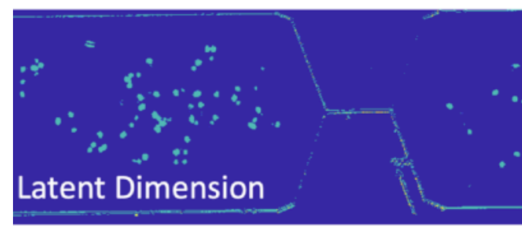

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Data analysis: New tools for “microscopy”?

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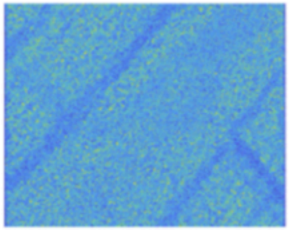
(b) Microscopy of mouse brain

raw video frame



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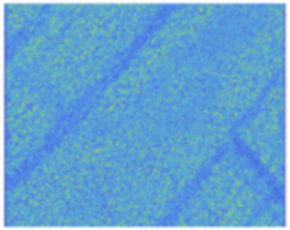

flow of transparent fluid
through the capillars
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recently discovered anatomic organ,
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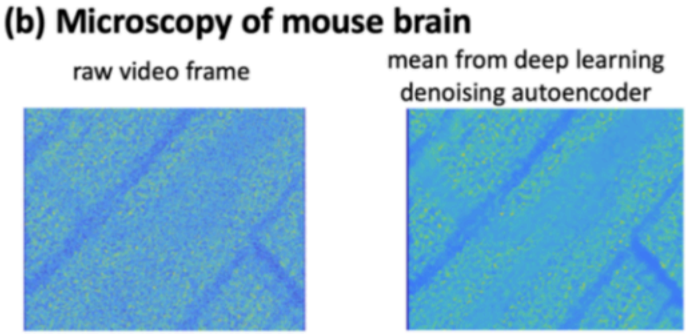

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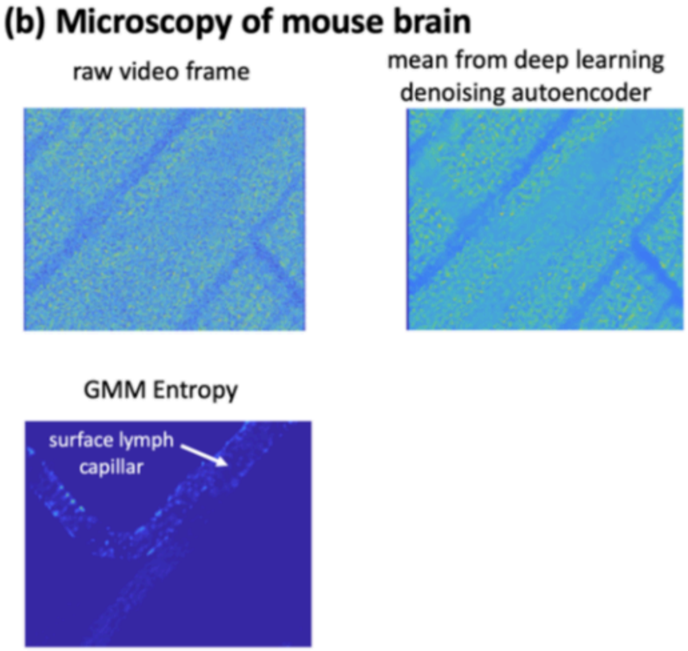

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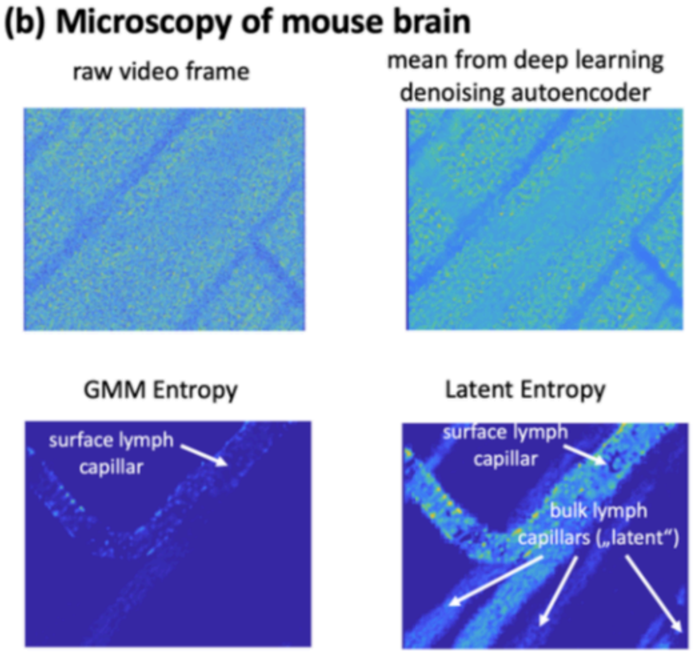
Horenko, et al., KES, arXiv1907.04601

Data analysis: New tools for "microscopy"?



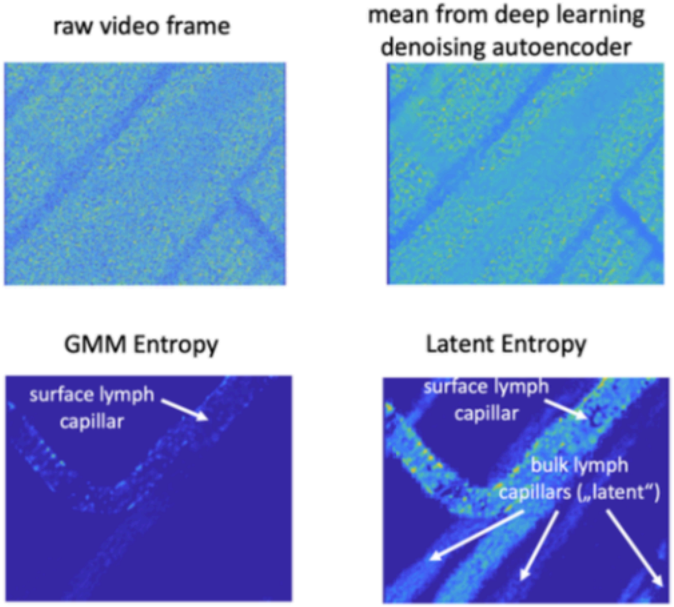
flow of transparent fluid
through the capillars
of the glymphatic system

recently discovered anatomic organ,
responsible for waste clearance

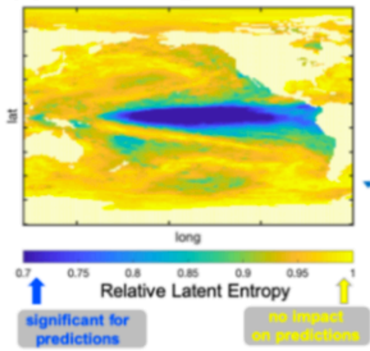
Horenko, et al., KES, arXiv1907.04601

Data analysis: New tools for “microscopy”?

(b) Microscopy of mouse brain



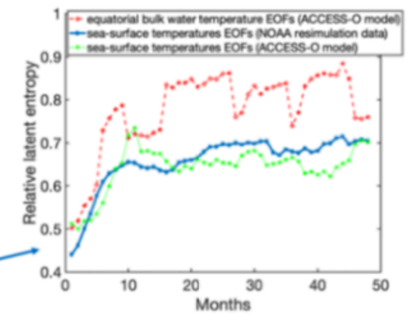
(c) Predicting El Niño Soutern Oscillation (ENSO)



major climate phenomenon with global impact

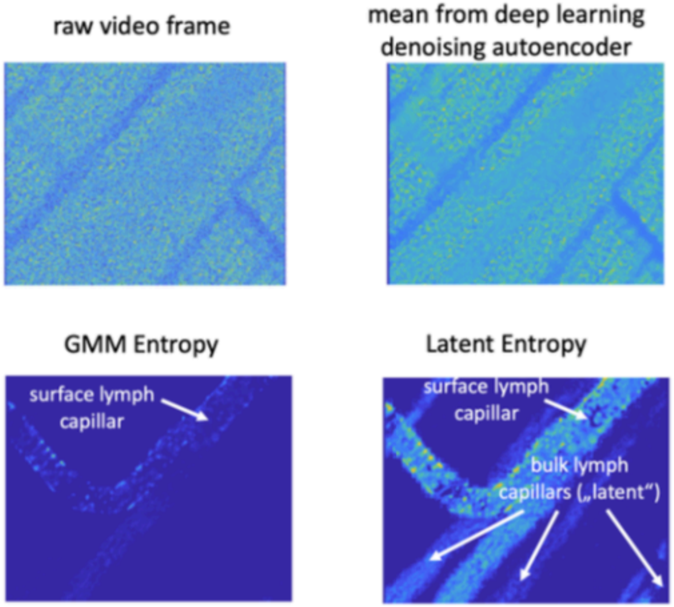
1 month **ENSO** predictions from local surface water temperatures

ENSO predictions from projections on global **E**ssential **O**rthogonal **F**unctions (**EOFs**)

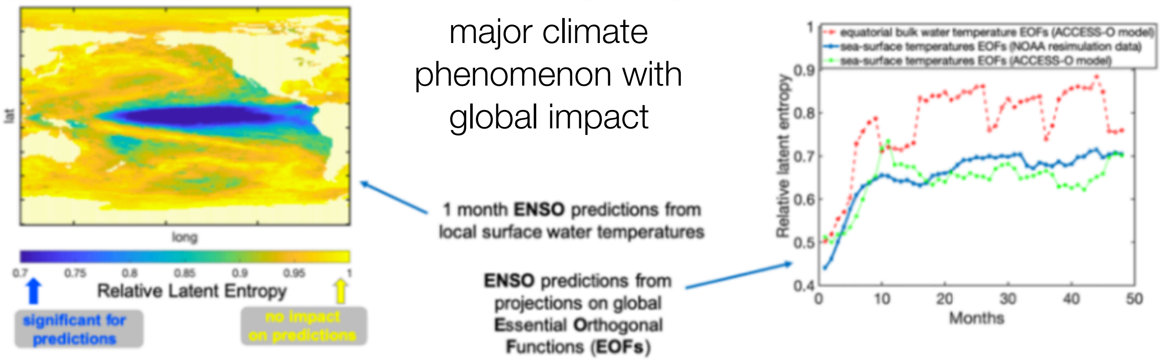


Horenko, et al., KES, arXiv1907.04601

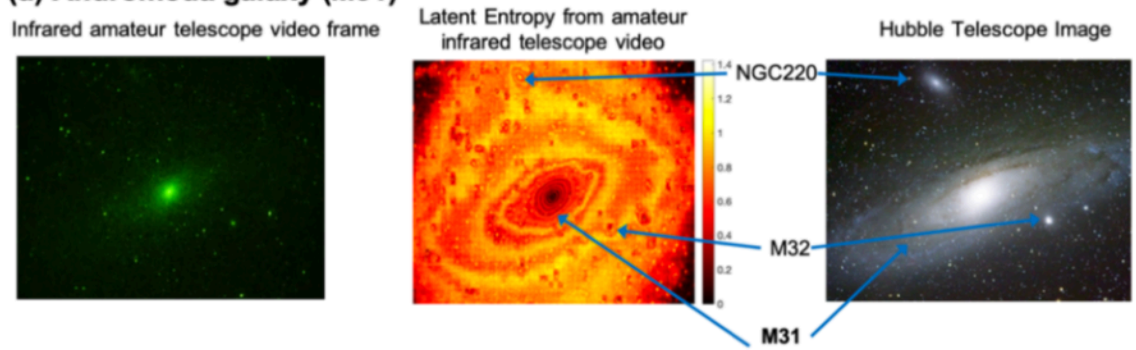
(b) Microscopy of mouse brain



(c) Predicting El Niño Soutern Oscillation (ENSO)



(d) Andromeda galaxy (M31)



Horenko, et al., KES, arXiv1907.04601

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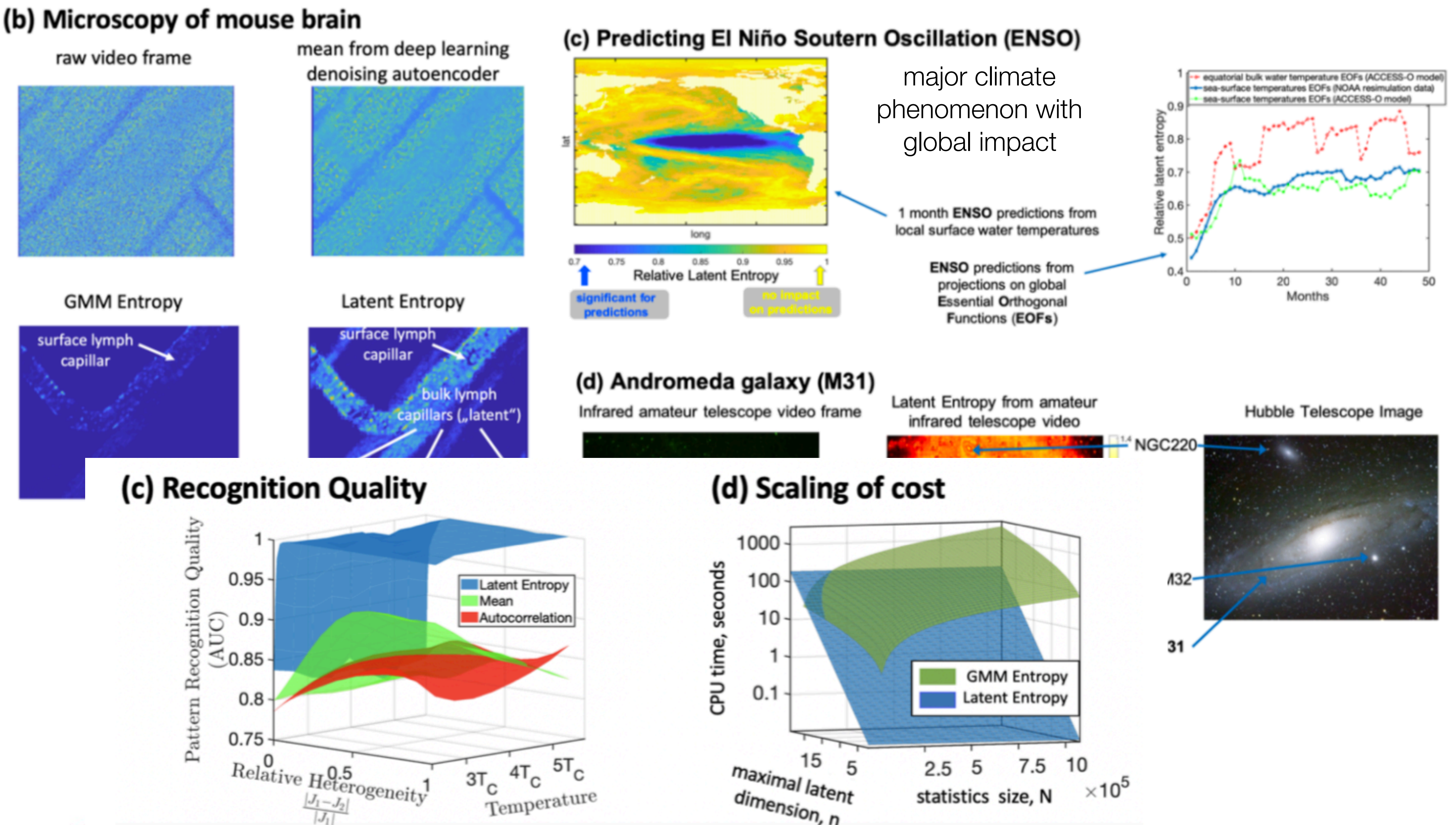
TWIST
Topological Whirls In SpinTronics

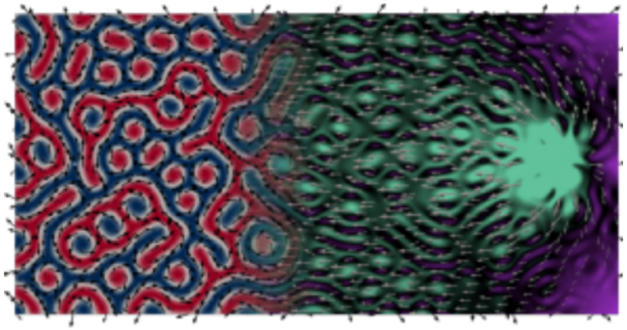


Horenko, et al., KES, arXiv1907.04601

SPICE

THANK YOU FOR YOUR ATTENTION

Skyrmions for reservoir computing



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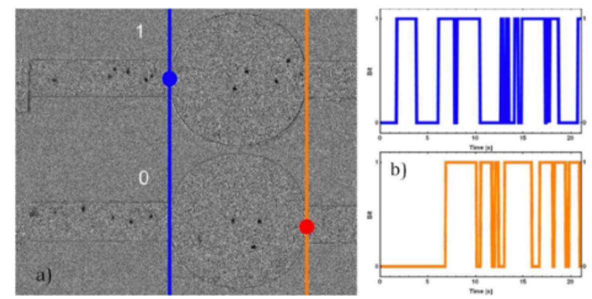
Bourianoff, et al., KES, AIP Advances, (2018)
Pinna, et al., KES, arXiv1811.12623

Skyrmion reshuffler for stochastic computing

Grollier, ..., KES, et al., accepted in Nat. Electron.

Finochio, ..., KES, et al., arXiv1910.07176



Zázvorka, ..., KES, et al., Kläui, Nat. Nano. (2019)

Data analysis: New tools for “microscopy”?

Horenko, et al., KES, arXiv 1907.04601

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