Emergent intelligence from neuromorphic complexity and synthetic synapses in nanowire networks

AIA2019, ESO, Garching
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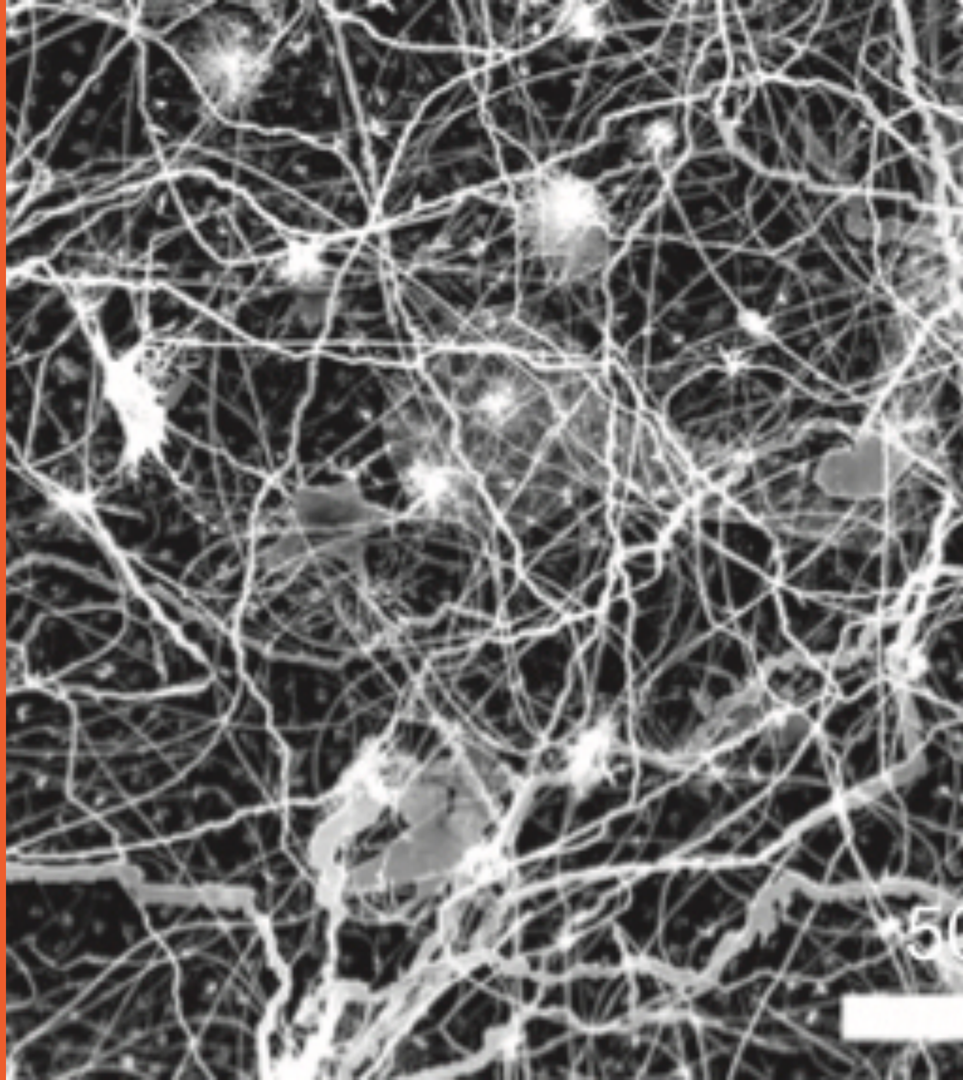
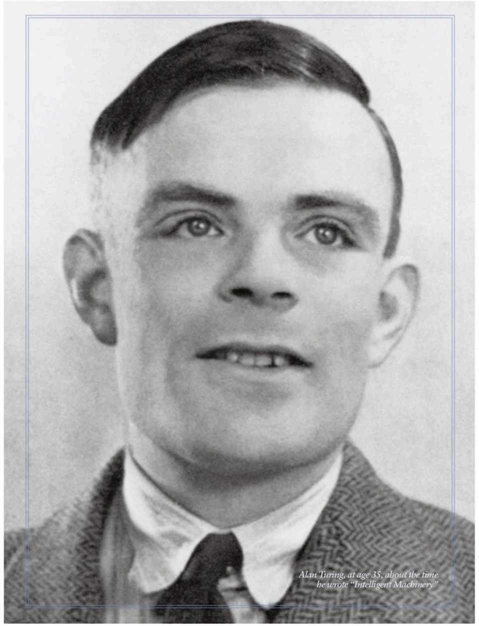


Outline

1) **Background:** AI in historical context
2) **Introduction:** Neuromorphic computing
3) **Synthetic neural networks** with complex topology and *emergent dynamics*
4) **Training & learning** in hardware

AI in historical context

- **1940s:** Alan Turing first proposes “brain-inspired” machine intelligence
- **1950s:** Frank Rosenblatt (Cornell) proposes “perceptron” neuron model
- **1960s:** Marvin Minsky (MIT) argues for multi-layer (feedforward) network
- **1970s:** AI winter
- **1980s:** resurgence
- **1990s:** Carver Mead (Caltech) pioneers “neuromorphic engineering”


Alan Turing, at age 35, about the time he wrote “Intelligent Machinery”

AI in historical context

Neuromorphic Electronic Systems

CARVER MEAD

Invited Paper

Biological information-processing systems operate on completely different principles from those with which most engineers are familiar. For many problems, particularly those in which the input data are ill-conditioned and the computation can be specified in a relative manner, biological solutions are many orders of magnitude more effective than those we have been able to implement using digital methods. This advantage can be attributed principally to the use of elementary physical phenomena as computational primitives, and to the representation of information by the relative values of analog signals, rather than by the absolute values of digital signals. This approach requires adaptive techniques to mitigate the effects of component differences. This kind of adaptation leads naturally to systems that learn about their environment.

Proc. IEEE 1990

Deep learning in 1997

IBM DeepBlue

Gary Kasparov

Image Credit: Bernard H. Humm in Applied Artificial Intelligence

AI in the 21st C

How Artificial Intelligence Will Transform Business

New York Times

Wall St Journal

lest

ks: Assembling Ikea Furniture

Will AI help us navigate Brexit?

KPMG

ging Fintech

Huffington Post

Toyota aims to offer Uber-like services for Tokyo taxis using AI

Business Times

How U.S. Retail Giant Kroger Is Using AI And Robots To Prepare For The 4th Industrial Revolution

Forbes News

n by the end

TechForge Media

A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet.

New York Times, USA

ays AI will help NHS prevent thousands of cancer-related deaths

The Independent, UK

Food store AI sees what you put in basket

BBC News

AI “holy grail”: *general* intelligence

- How to realise more brain-like information processing?

Machine computation	Human thinking
Deterministic	Non-deterministic
Accurate	Creative
Repetitive	Adaptive
Static	Dynamic

Neuron
Review

Neuroscience-Inspired Artificial Intelligence

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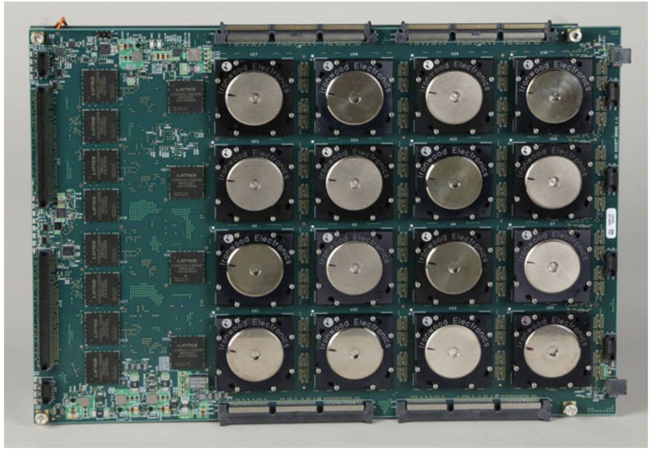
http://dx.doi.org/10.1016/j.neuron.2017.06.011

The fields of neuroscience and artificial intelligence (AI) have a long and intertwined history. In more recent times, however, communication and collaboration between the two fields has become less commonplace. In this article, we argue that better understanding biological brains could play a vital role in building intelligent machines. We survey historical interactions between the AI and neuroscience fields and emphasize current advances in AI that have been inspired by the study of neural computation in humans and other animals. We conclude by highlighting shared themes that may be key for advancing future research in both fields.

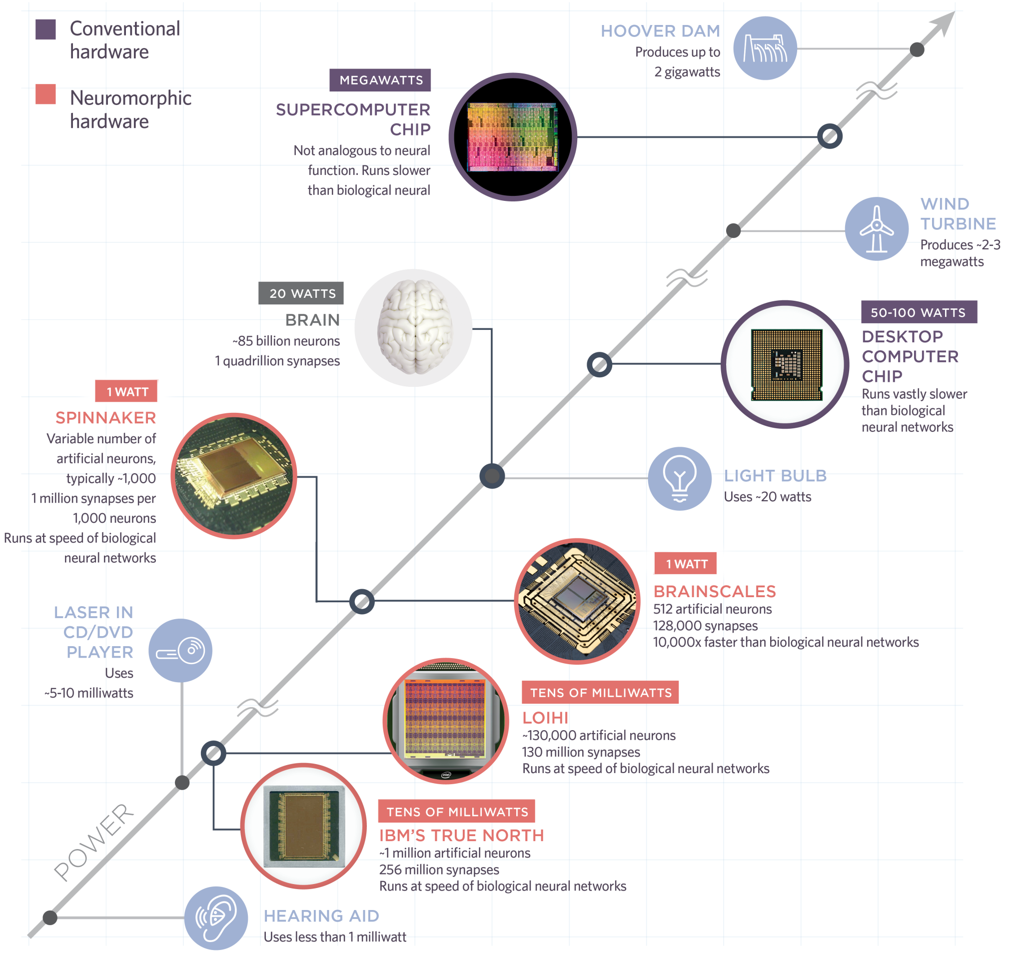
Neuromorphic computing

- Beyond Von Neumann neuromorphic chip architecture



IBM TrueNorth chips

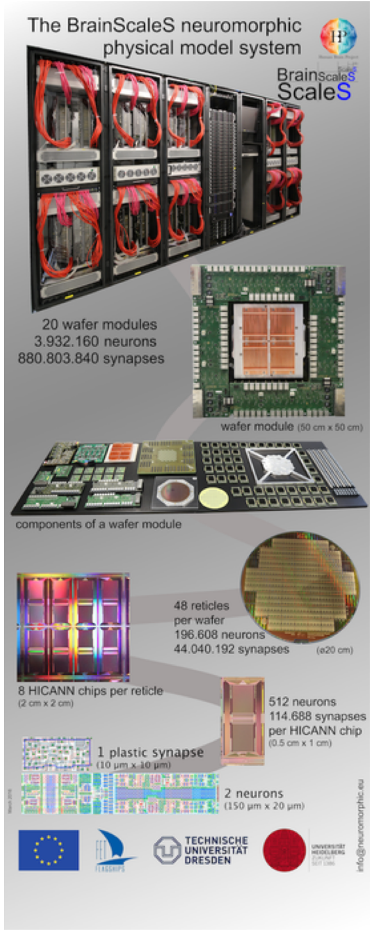
Intel Loihi chip

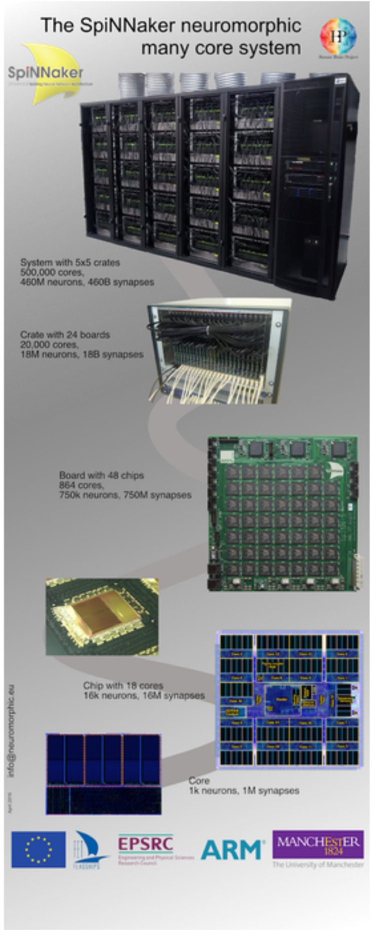

Conventional hardware
Neuromorphic hardware
HOOVER DAM
Produces up to 2 gigawatts
MEGAWATTS
SUPERCOMPUTER CHIP
Not analogous to neural function. Runs slower than biological neural
WIND TURBINE
Produces ~2-3 megawatts
20 WATTS
BRAIN
~85 billion neurons
1 quadrillion synapses
50-100 WATTS
DESKTOP COMPUTER CHIP
Runs vastly slower than biological neural networks
1 WATT
SPINNAKER
Variable number of artificial neurons, typically ~1,000
1 million synapses per 1,000 neurons
Runs at speed of biological neural networks
LIGHT BULB
Uses ~20 watts
1 WATT
BRAINSCALES
512 artificial neurons
128,000 synapses
10,000x faster than biological neural networks
LASER IN CD/DVD PLAYER
Uses ~5-10 milliwatts
TENS OF MILLIWATTS
LOIHI
~130,000 artificial neurons
130 million synapses
Runs at speed of biological neural networks
TENS OF MILLIWATTS
IBM'S TRUE NORTH
~1 million artificial neurons
256 million synapses
Runs at speed of biological neural networks
POWER
HEARING AID
Uses less than 1 milliwatt

Neuromorphic computing

- **Human Brain Project:** neuromorphic chips and electronic circuitry for AI applications

https://www.humanbrainproject.eu/en/silicon-brains/





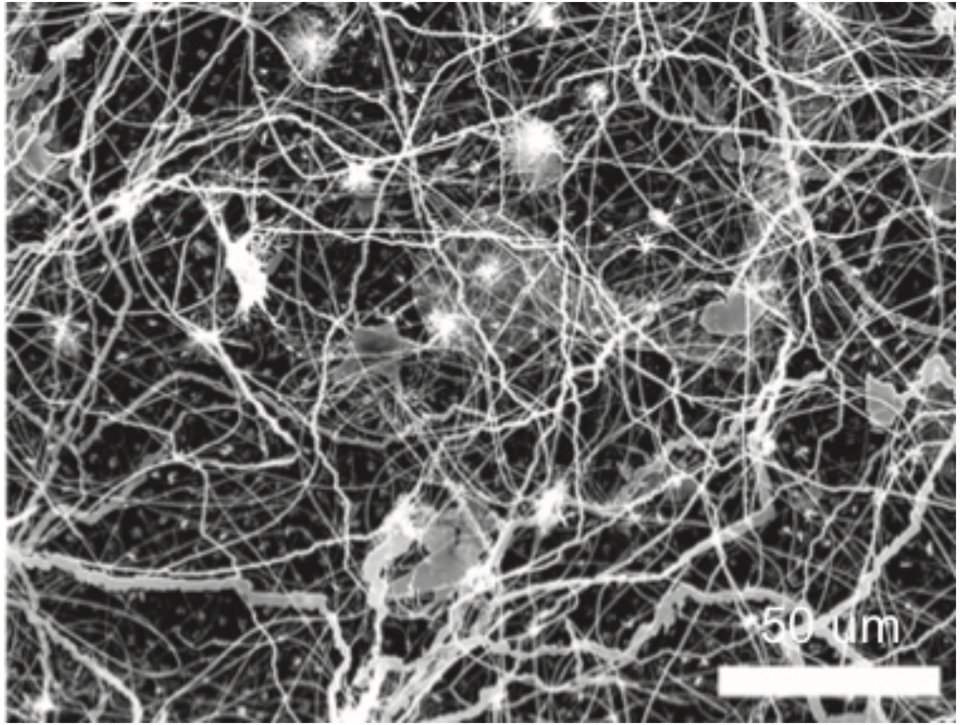
An alternate approach towards brain-like intelligence, beyond silicon?

Neurodynamics + nanotechnology

- The brain is a **complex physical system** whose structure + function are intricately linked → **emergent phenomena**

- **Bottom-up self-assembly** of nano-materials creates bio-mimetic structures → **neural network-like electronic circuitry**

Neuromorphic nanowire networks

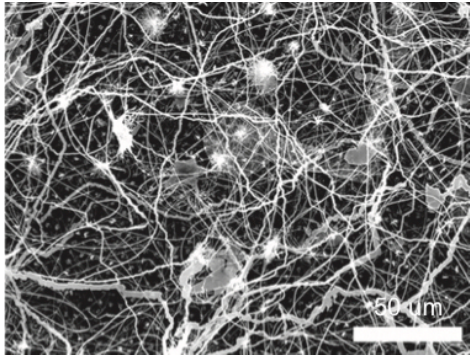


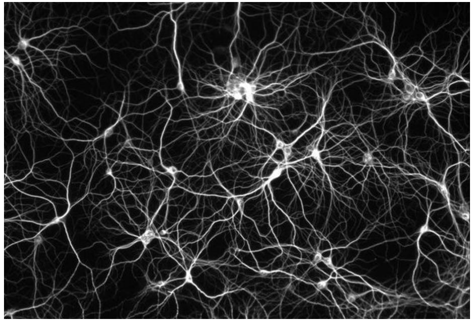
Demis et al. Nanotech. 2015

Neuromorphic nanowire networks

- Nanowires *self-assemble* into a complex, densely interconnected network, with a **topology** similar to a biological neural network

nanowire network

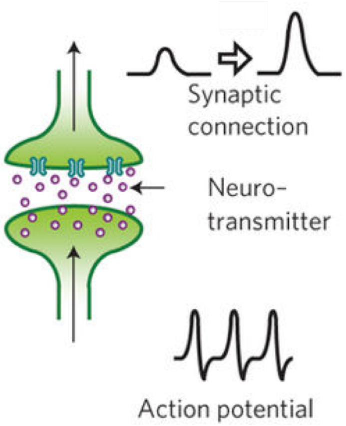


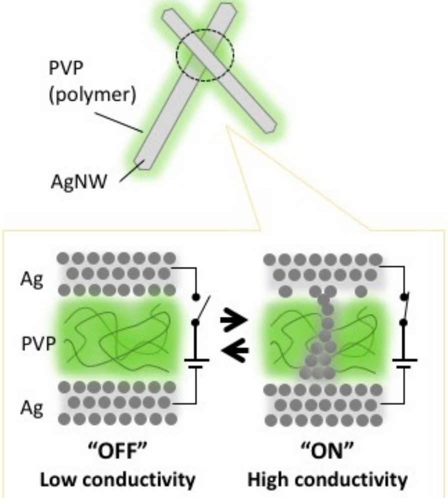


biological neural network

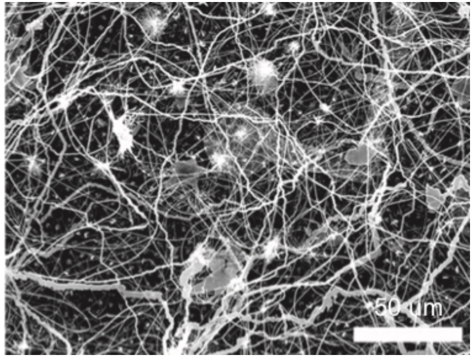
Neuromorphic nanowire networks

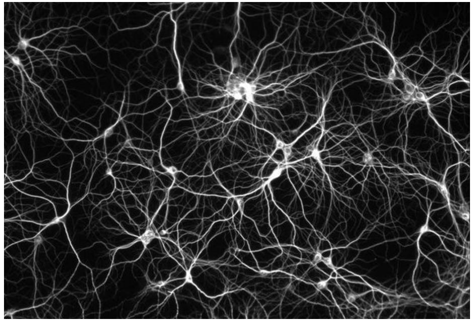
- Nanowires *self-assemble* into a complex, densely interconnected network, like neurons
- When electrically stimulated, junctions respond like "**synthetic synapses**"



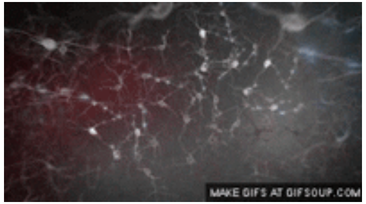


nanowire network



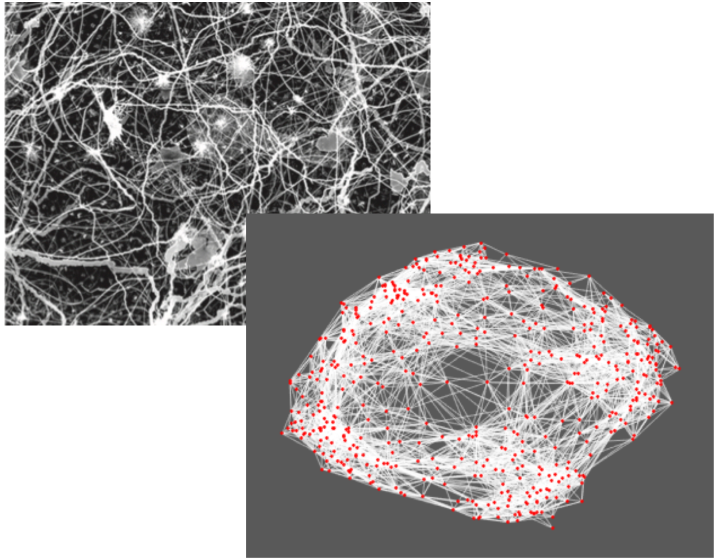


biological neural network



Neuromorphic nanowire networks

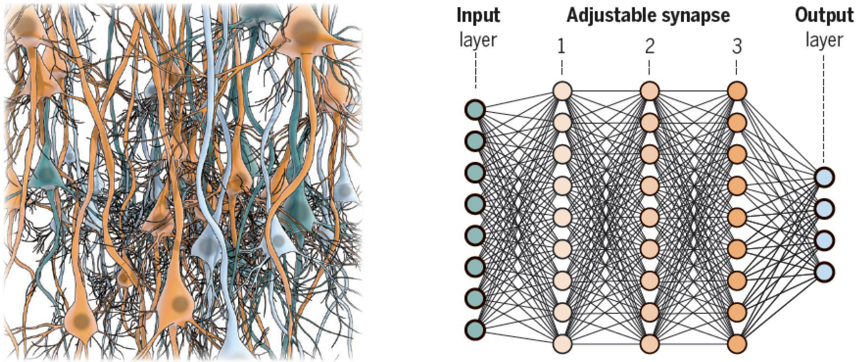
- Key features: topology of network structure, adaptive synthetic synapses



nanowire network
(simulated graph representation)

Brain circuitry and learning

A major open question is whether the highly simplified structures of current network models compared with cortical circuits are sufficient to capture the full range of human-like learning and cognition.

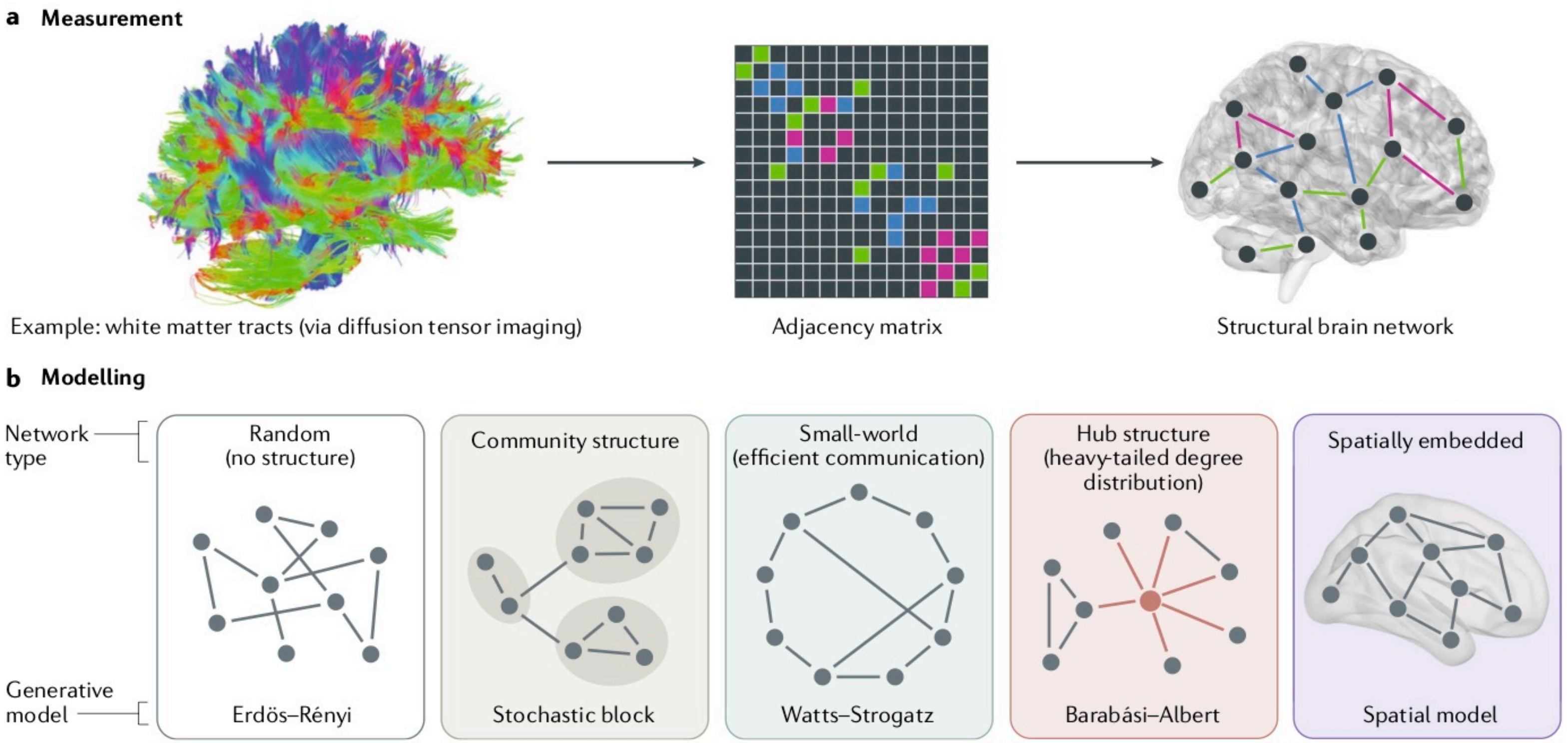


Complex neural network
Connectivity in cortical networks includes rich sets of connections, including local and long-range lateral connectivity, and top-down connections from high to low levels of the hierarchy.

Informed AI network
Biological innate connectivity patterns provide mechanisms that guide human cognitive learning. Discovering similar mechanisms, by machine learning or by mimicking the human brain, may prove crucial for future artificial systems with human-like cognitive abilities.

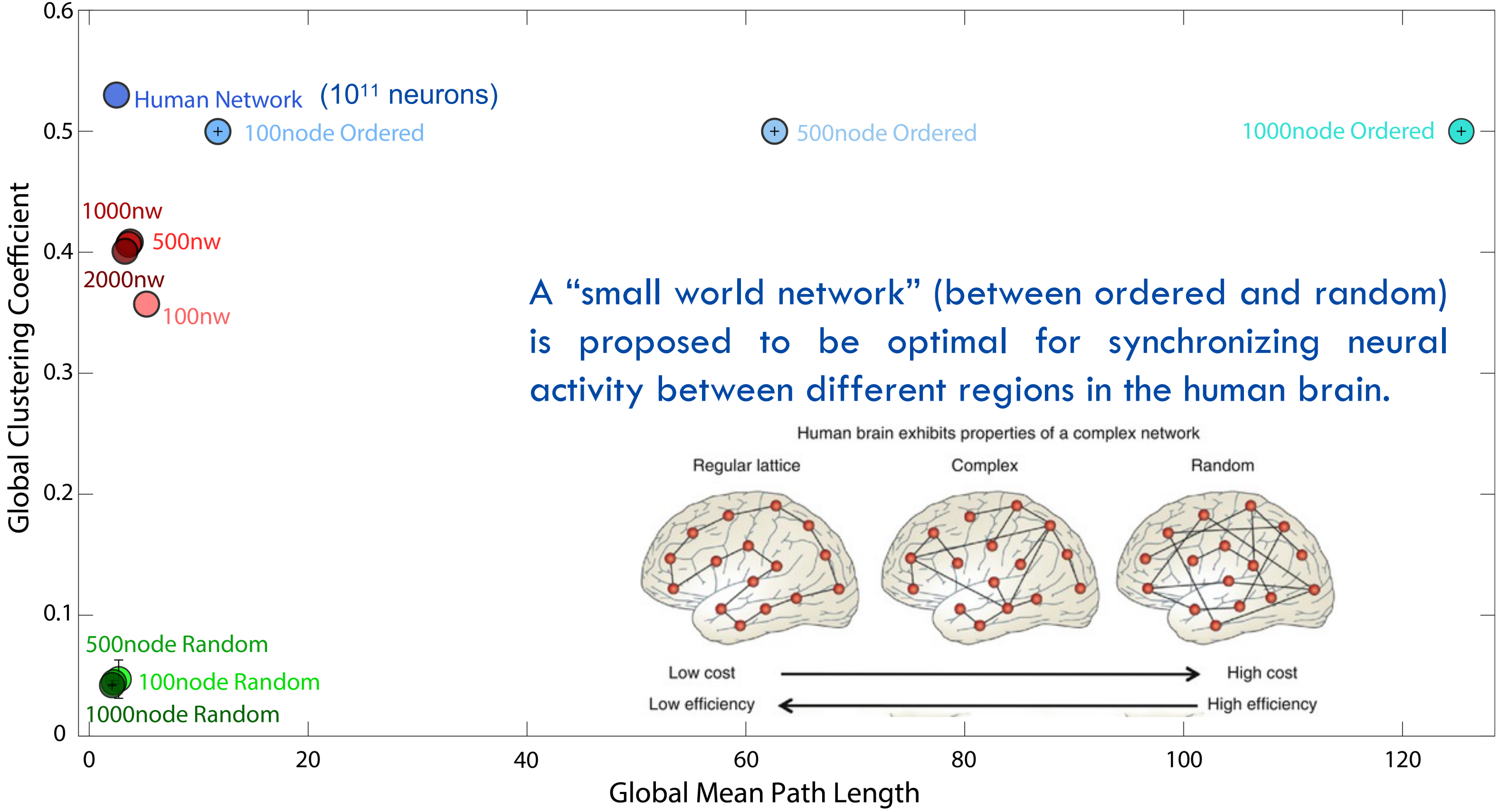
Ullman, Science 2019

Biological neural network models



Lynn & Bassett, Nat. Rev. Phys. 2019

Network topology and connectivity

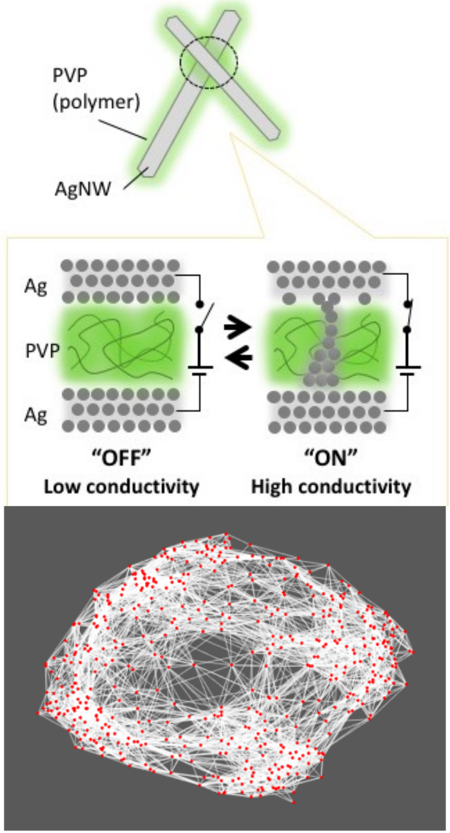


A "small world network" (between ordered and random) is proposed to be optimal for synchronizing neural activity between different regions in the human brain.

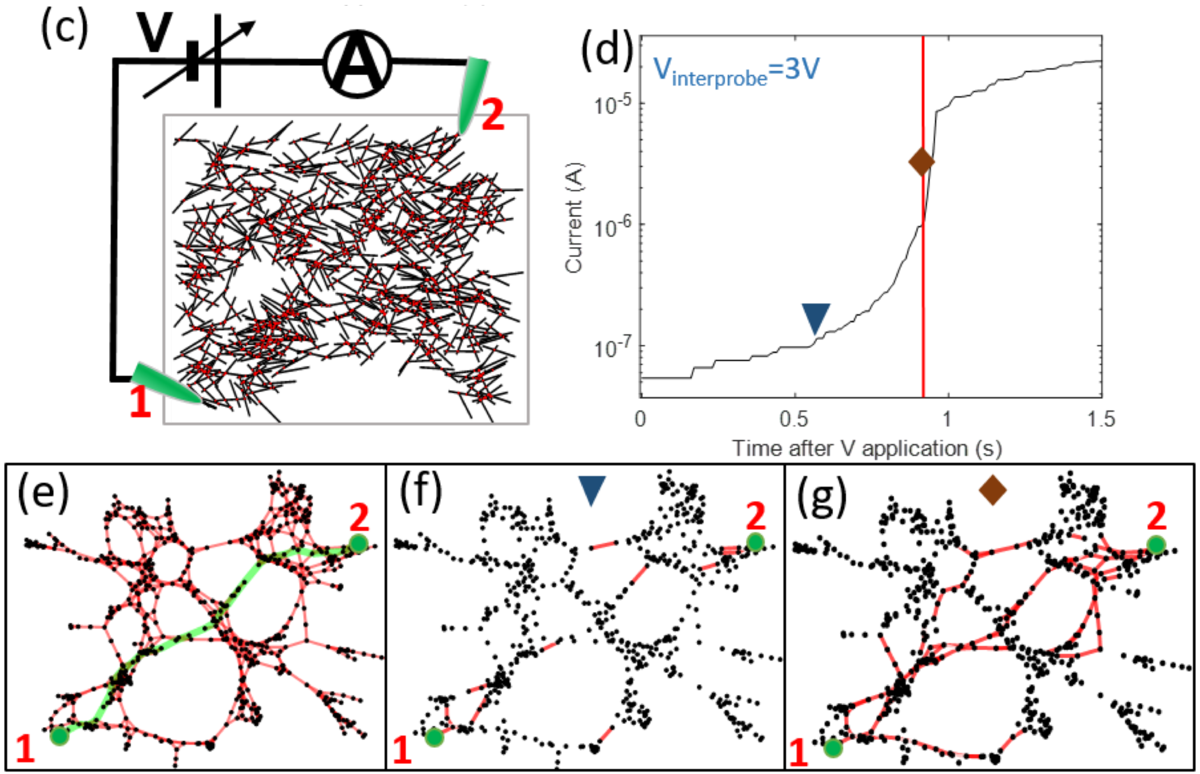
Image credit: A. Loeffler (PhD student)

Neuromorphic nanowire networks - modelling

- **Synthetic synapses:** $V(\lambda) = IR(\lambda)$, $d\lambda/dt = V$ → state variable $\lambda(t)$ depends on history → memory of past states
- **Kirchoff's circuit laws:** $\sum_j I_j = 0 \, , \sum_l V_l = 0$
- Use **adjacency matrix** (structural connectivity) to solve network dynamics as a function of t
- **Network conductivity** (capacity to transmit electrical signals) time series: C(t)

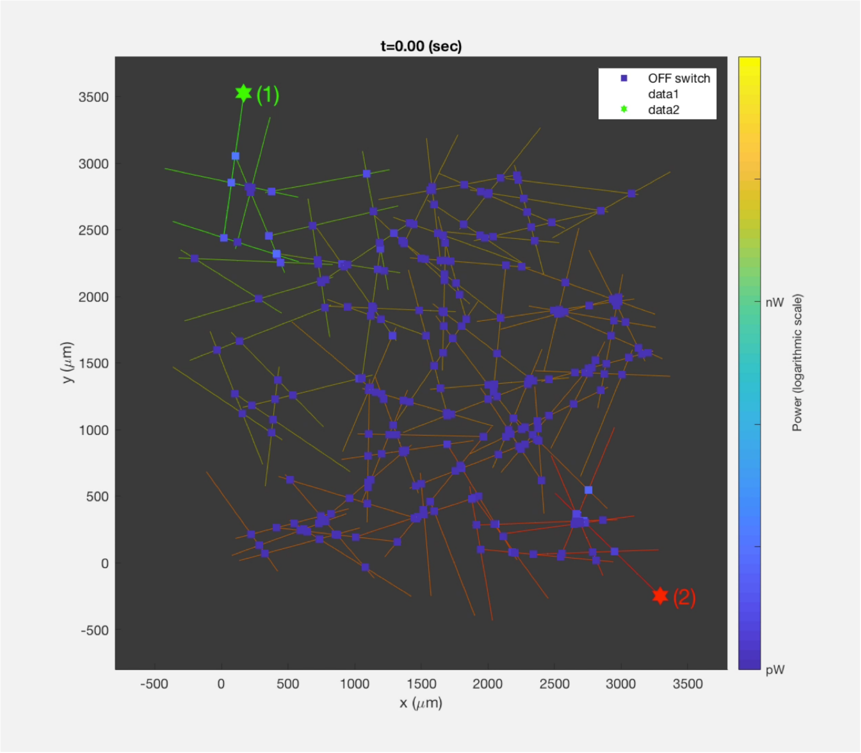


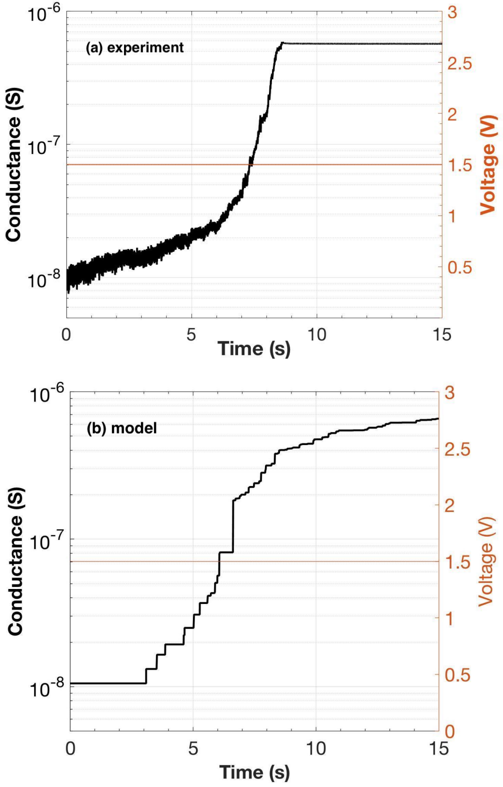
Neuromorphic nanowire networks – modelling



Diaz-Alvarez et al. Sci. Rep. 2019 (in press)

Neuromorphic nanowire networks – signal transduction

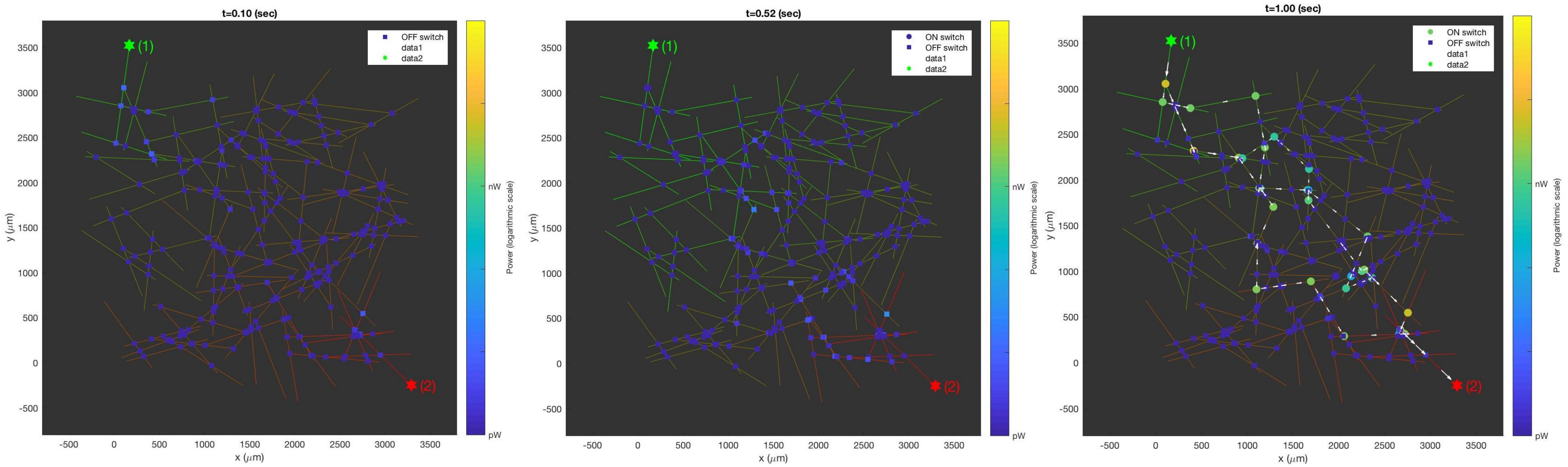




Kuncic et al. IEEE Nano 2018

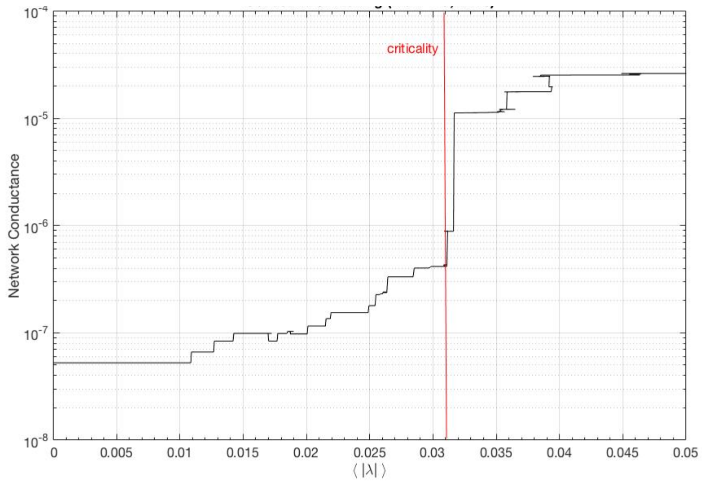
Nonlinear collective dynamics

- Junctions produce nonlinear switching dynamics
- Connected "ON" junctions transmit electrical signal across network, adapting to dynamics

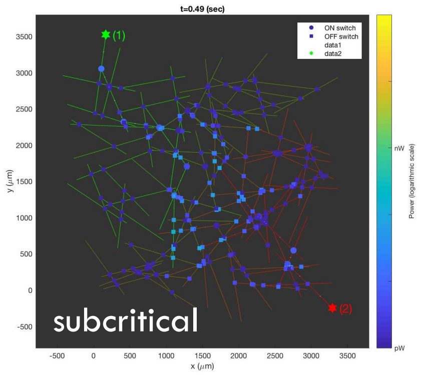


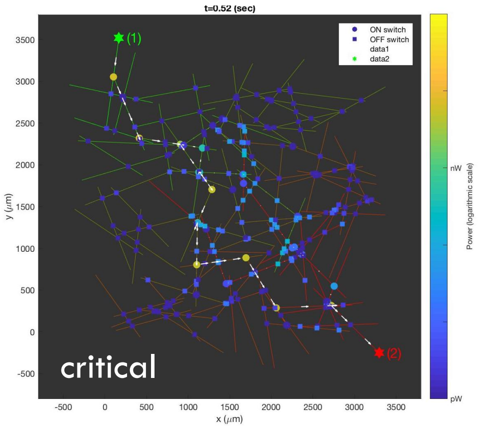
Collective switching and criticality

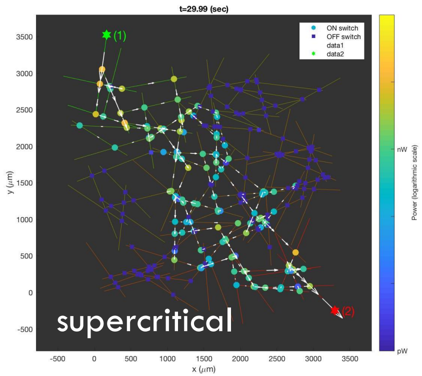
Many macroscopic phenomena airse from collective dynamics of underlying microscopic components - e.g. gravity, superconductivity, cognition.



Critical dynamics occurs in a complex system when its interacting components collectively and spontaneously self-organise to achieve new global states – e.g. spin orientations in Ising model.







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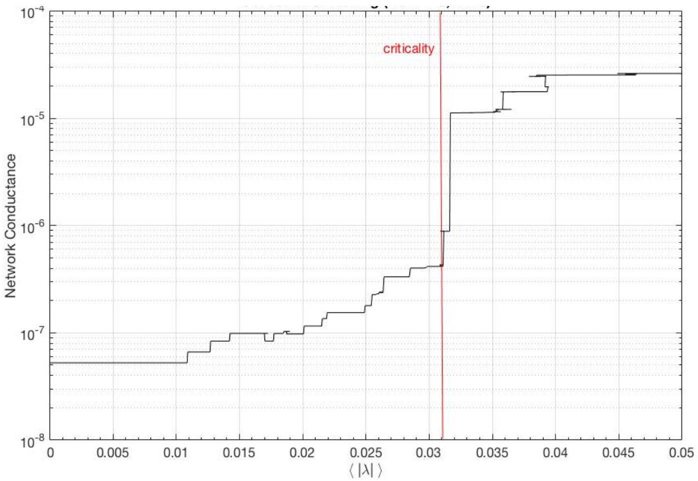
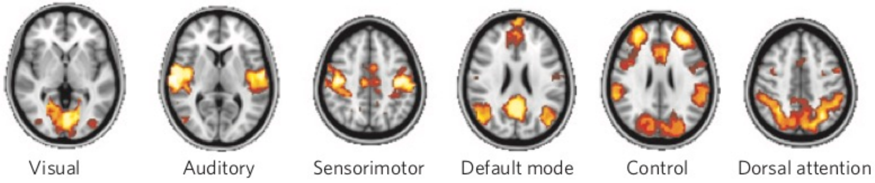


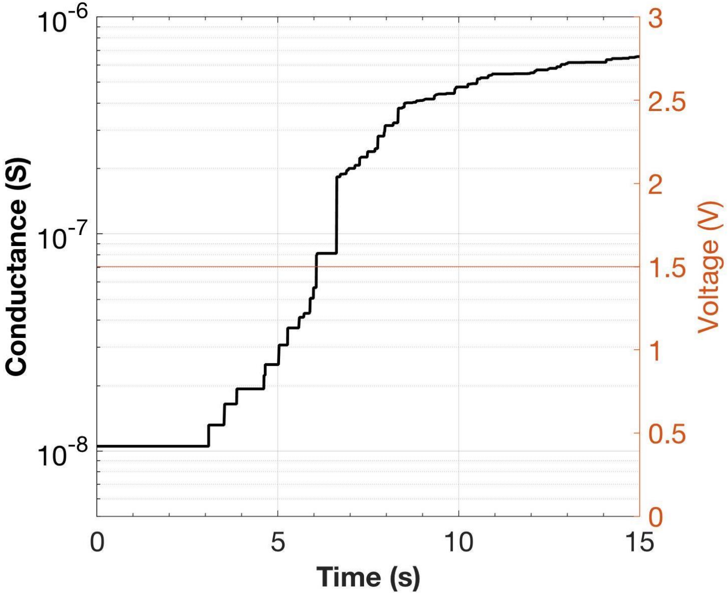
Critical dynamics occurs in a complex system when its interacting components collectively and spontaneously self-organize to achieve new global states – e.g. spin orientations in Ising model.

- The brain is thought to be poised near criticality, where it can access the largest repertoire of behaviours in a flexible way (Chialvo, Nat. Physics 2010)

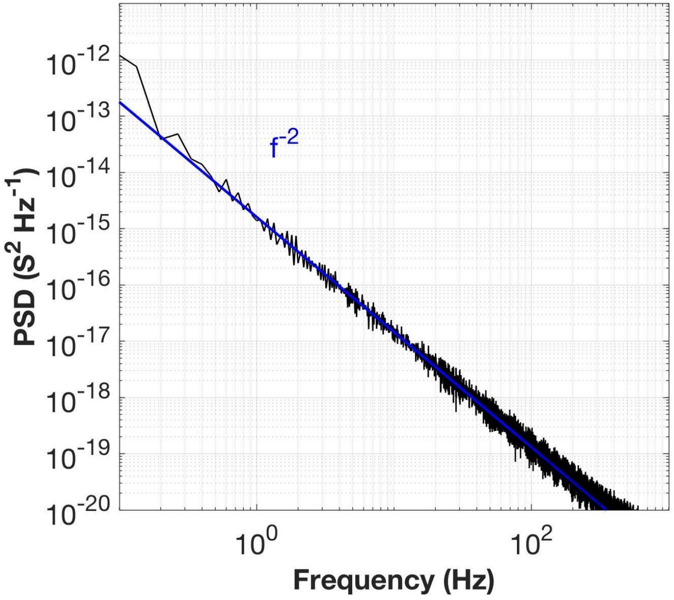


Power spectral density

- Power law spectra with log-log slope -2 → scale-free dynamics, consistent with criticality and fMRI brain data



FFT



Kuncic et al. IEEE Nano 2018

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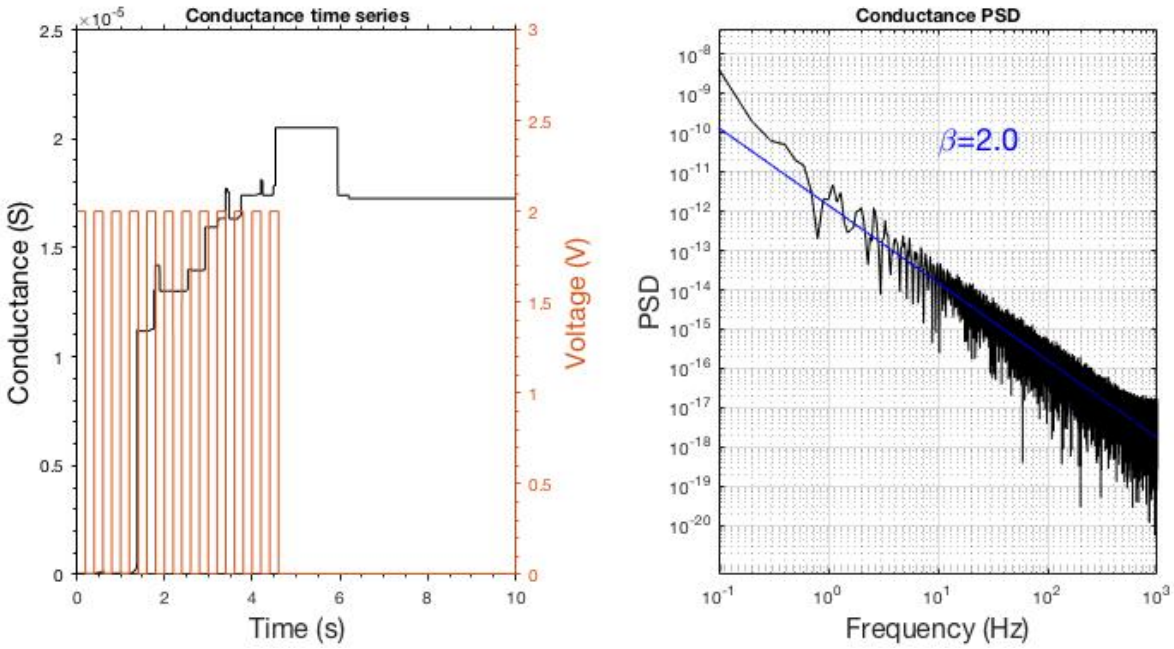
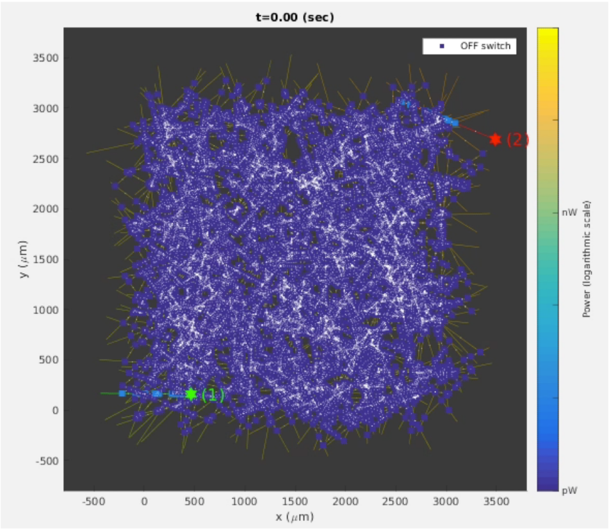
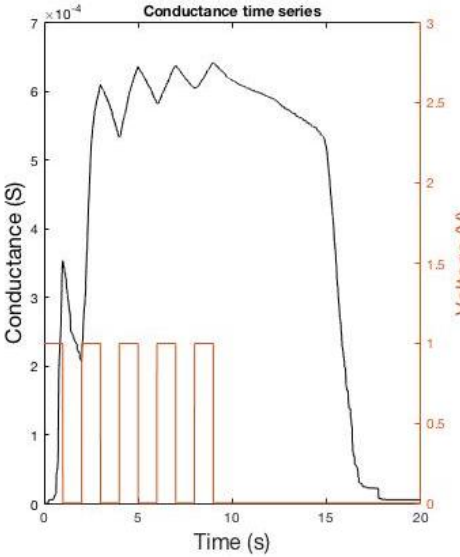
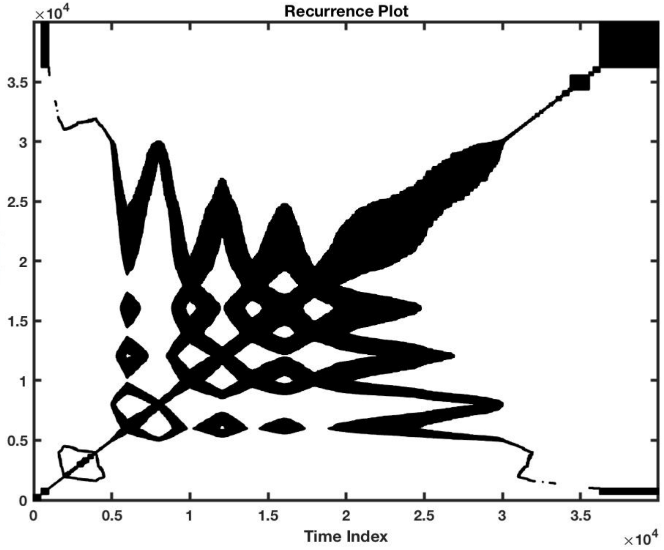


Recurrent dynamics

- Nonlinear feedback loops enable **adaptive dynamics** and **sustained internal activity** without additional inputs
- **Recurrence plot** shows when network revisits previous states



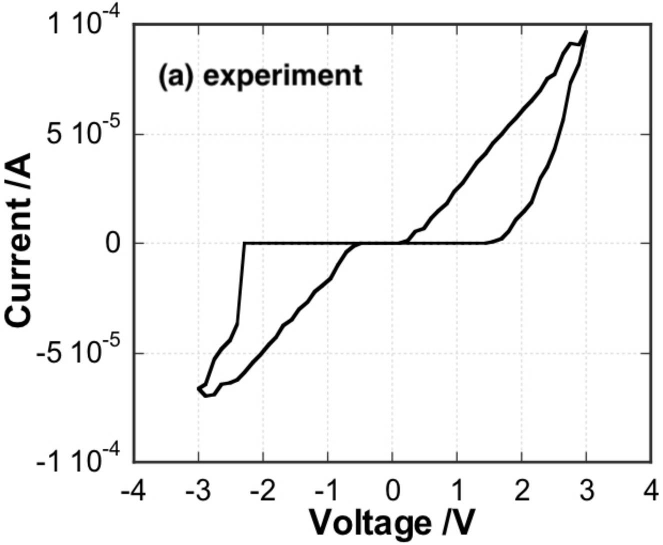


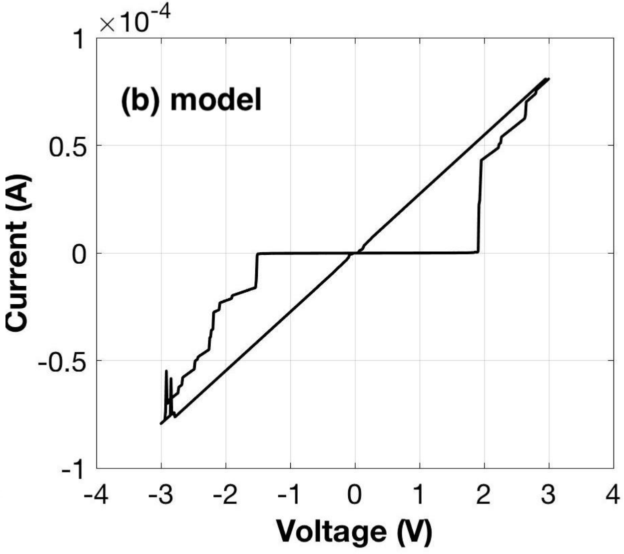


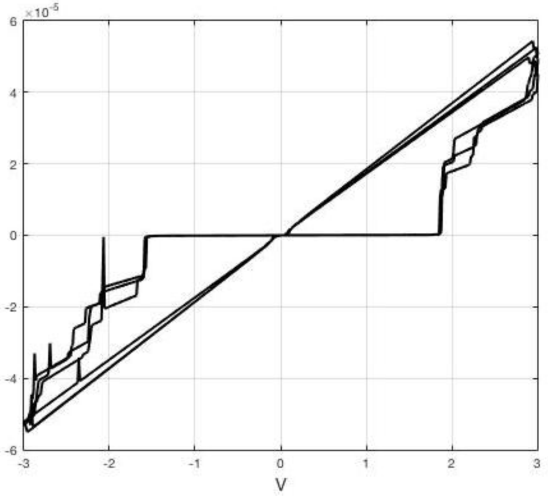
Hysteresis conductance loops

- Network state depends on history of past states → **memory**

I-V phase diagram



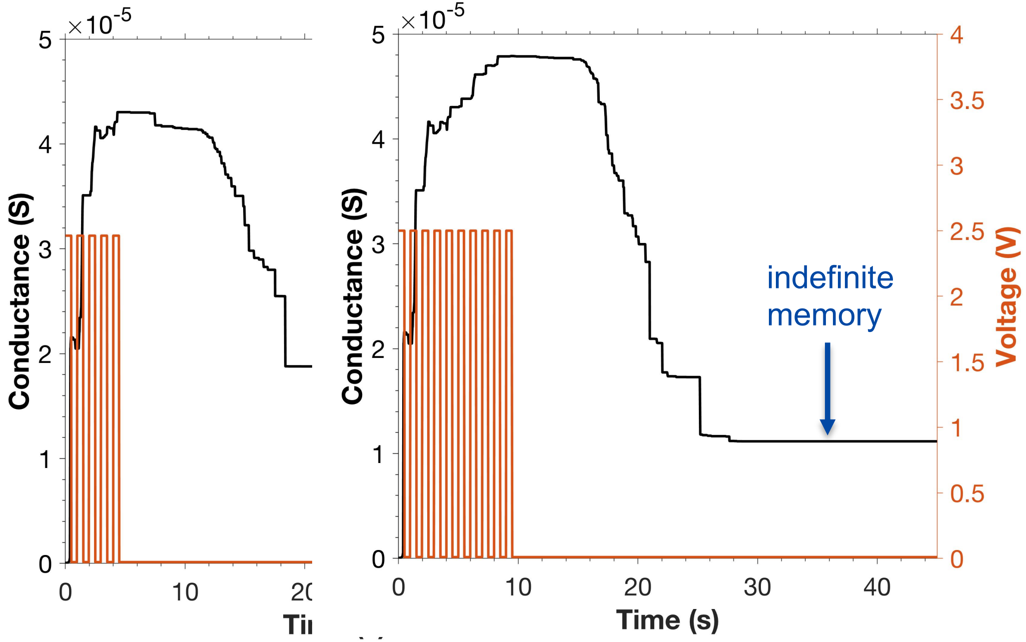




Kuncic et al. IEEE Nano 2018

Collective memory

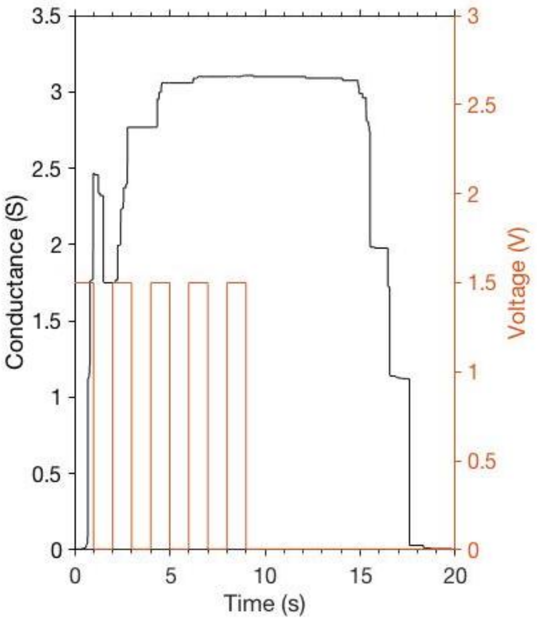
- short-term (fading) vs. long-term (indefinite) → learning capacity

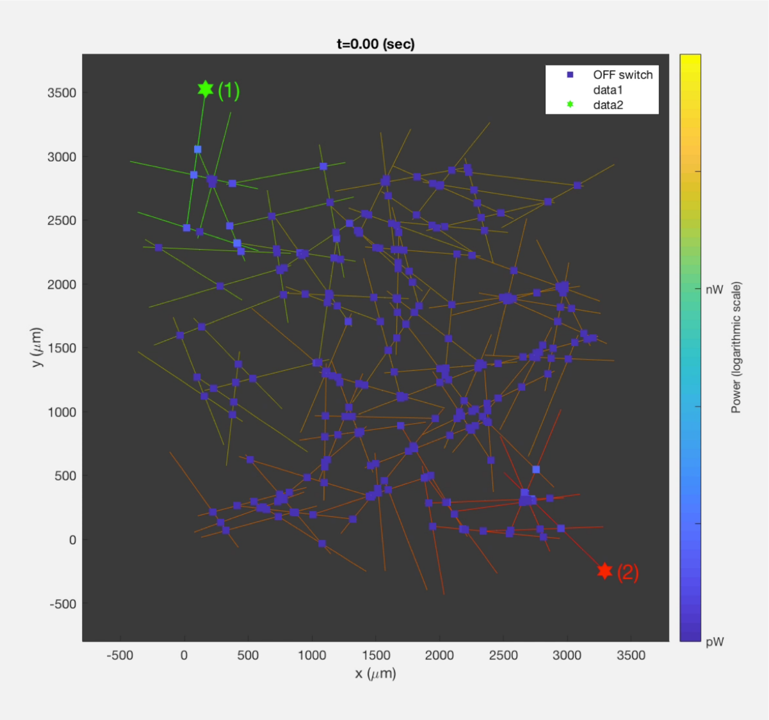


Kuncic et al. IEEE Nano 2018

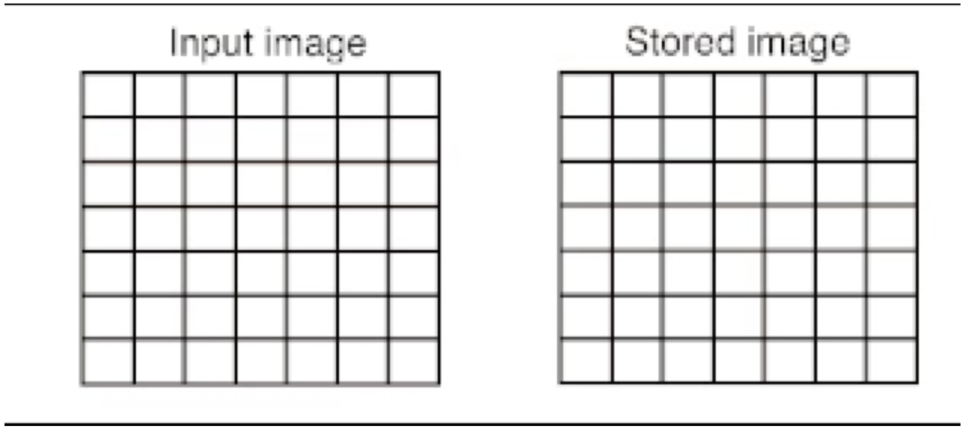
Collective memory

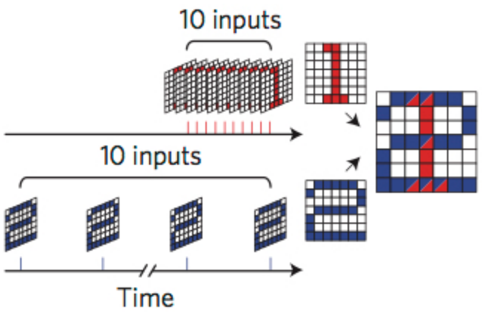
- Repeated stimulus activates same groups of junctions





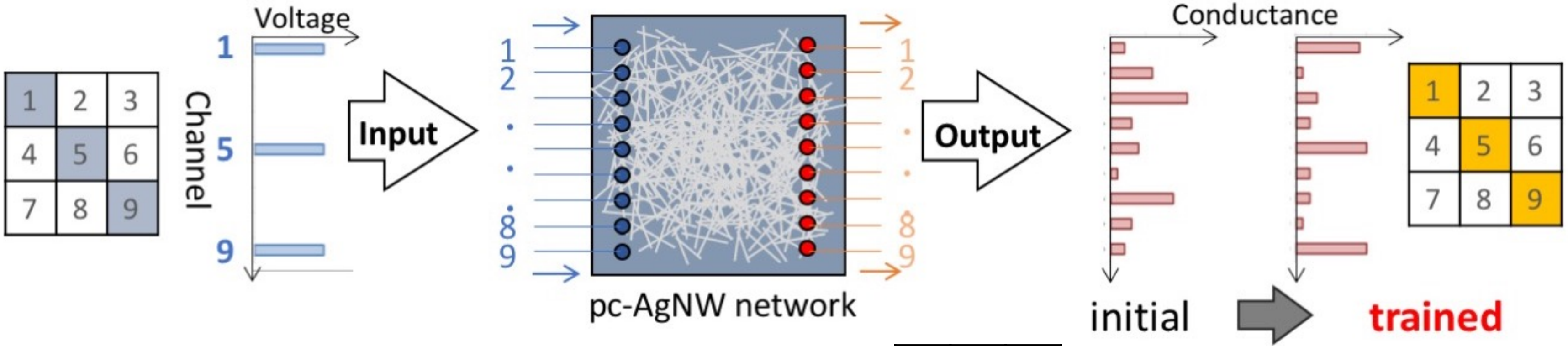
In progress: training and learning



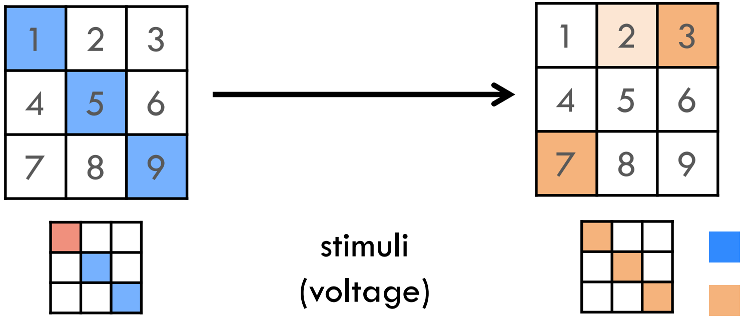


Ohno et al. Nat. Mater. 2011

In progress: associative learning



1) Initial state



Initial output is random

2) Training

stimuli (voltage)

Bias voltage (input)
Highly conductive channel (read)

3) Repeat using several patterns

Credit: R. Higuchi, NIMS-MANA, Japan

Summary and Outlook

1) Artificial Neural Networks (ANNs) approximate real (biological) NNs in *software*
2) Synthetic Neural Networks are a *physical* realisation of real NNs in *hardware*
3) Nanowire networks can naturally produce the **complex topology** and emergent, **collective dynamics** of biological NNs
4) **Criticality, recurrence and memory** are hallmarks of brain-like cognitive function and "*natural*" intelligence
5) Potential beyond-AI applications: **neural network "on-chip"** for robotics, autonomous systems, reservoir computing, cognitive devices, neural interfaces…..

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