



# Neuromorphic information processing with nanowire networks

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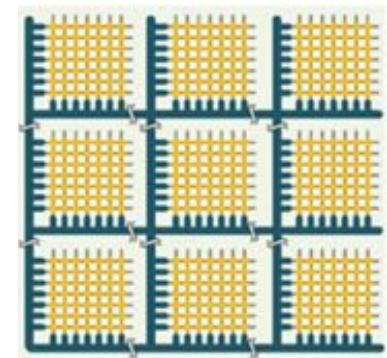
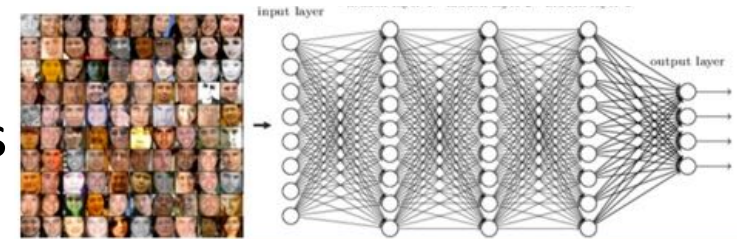


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# Introduction

- **Artificial neural networks** excel at finding patterns in BIG data
  - **Biological neural networks** excel at *adaptively* processing information from data that is noisy, unstructured, unlabeled, sparse, dynamic.....
  - **Neuromorphic memristive hardware** can replicate in-memory processing and synapse-like functionality, *but not neural network circuitry*
- *Neural network-like circuitry in neuromorphic hardware is key to realizing full neuromorphic information processing functionality*



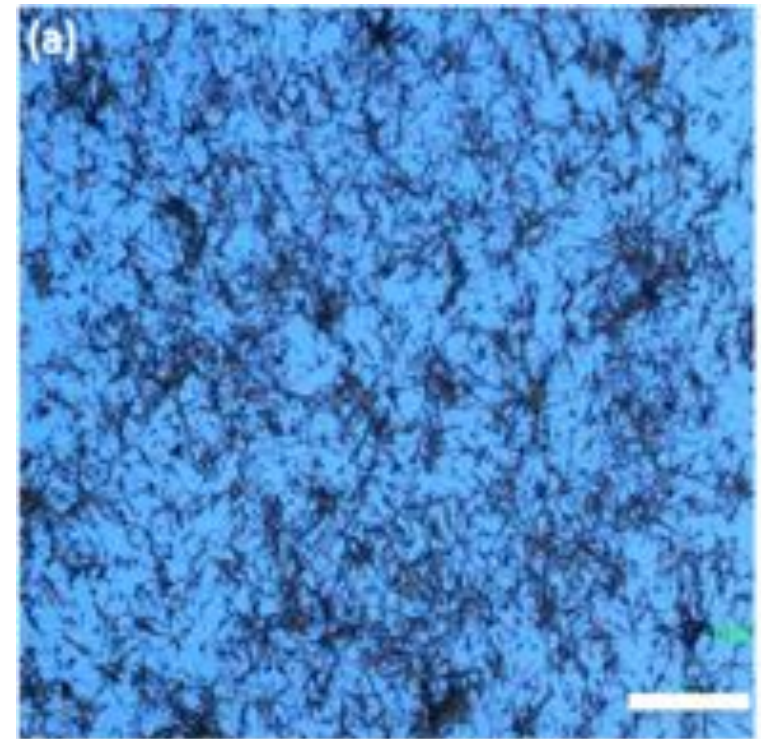
# Motivation and rationale

- Increasing amounts of dynamic data are being generated at IoT edge
- Incompatible with edge-AI → need *on-the-fly* local processing
- Ideally suited to low-power, low-latency neuromorphic processing



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- Our approach integrates neuromorphic *structure* and *function* using scalable, post-CMOS technology: **Nanowire Networks**

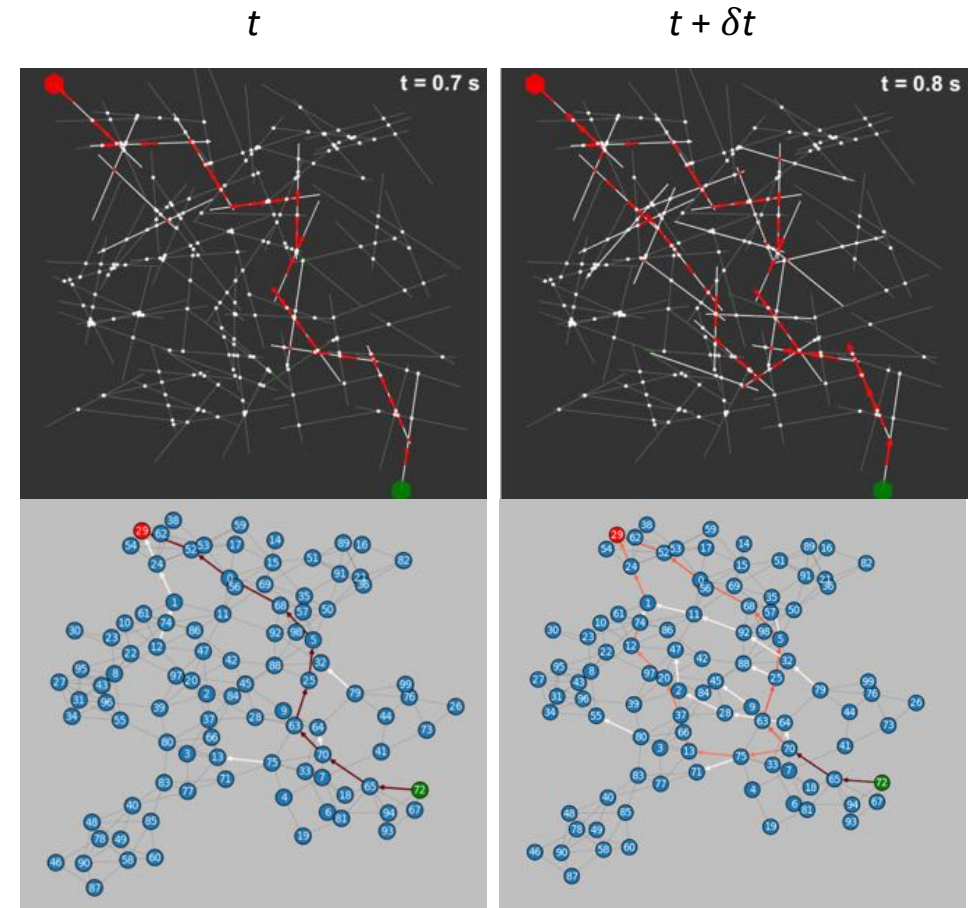


Diaz-Alvarez *et al.* Sci. Rep. (2019)



# Adaptive dynamics

- Ag-PVP nanowire networks exhibit adaptive dynamics in response to electrical stimulation:
  - Memristive switch junctions due to Ag filament formation/dissolution
  - Neural network circuitry optimizes signal transduction
- **Synaptic plasticity**: dynamic redistribution of voltage across memristive junctions as network self-adjusts to dynamic current load

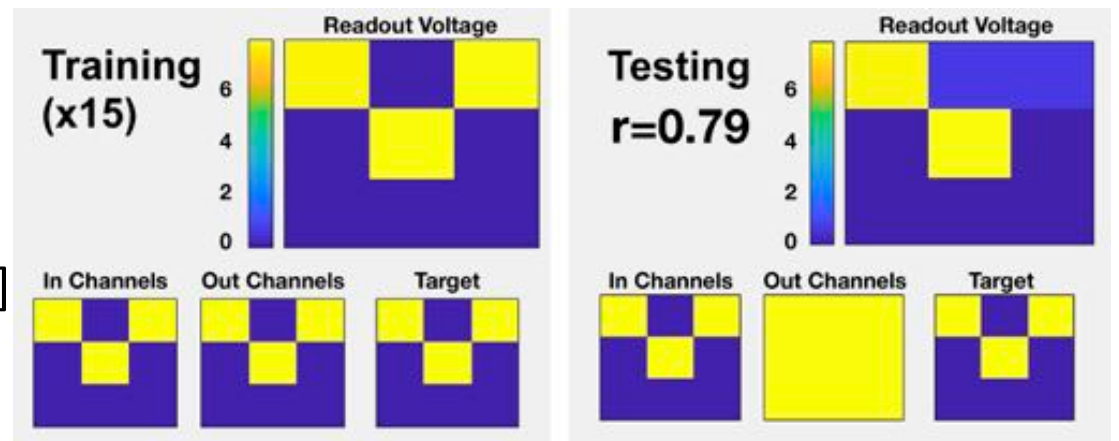
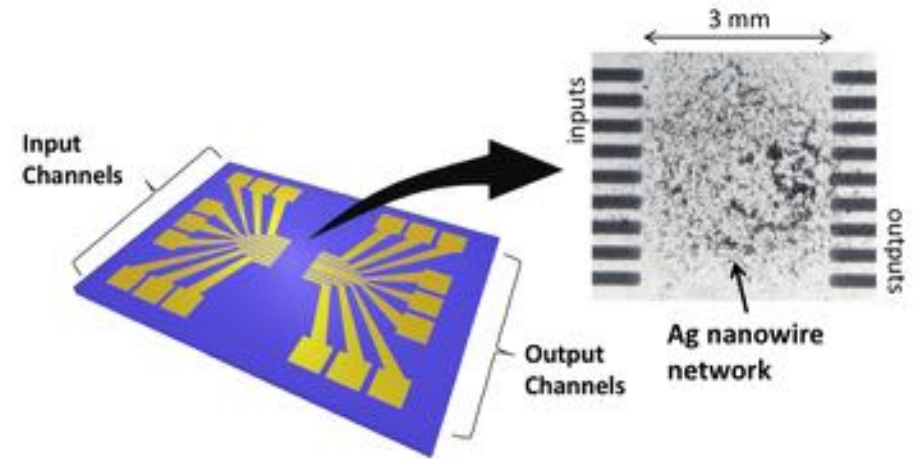


*Adaptive dynamics essential for processing information from natural data.*

# Associative learning

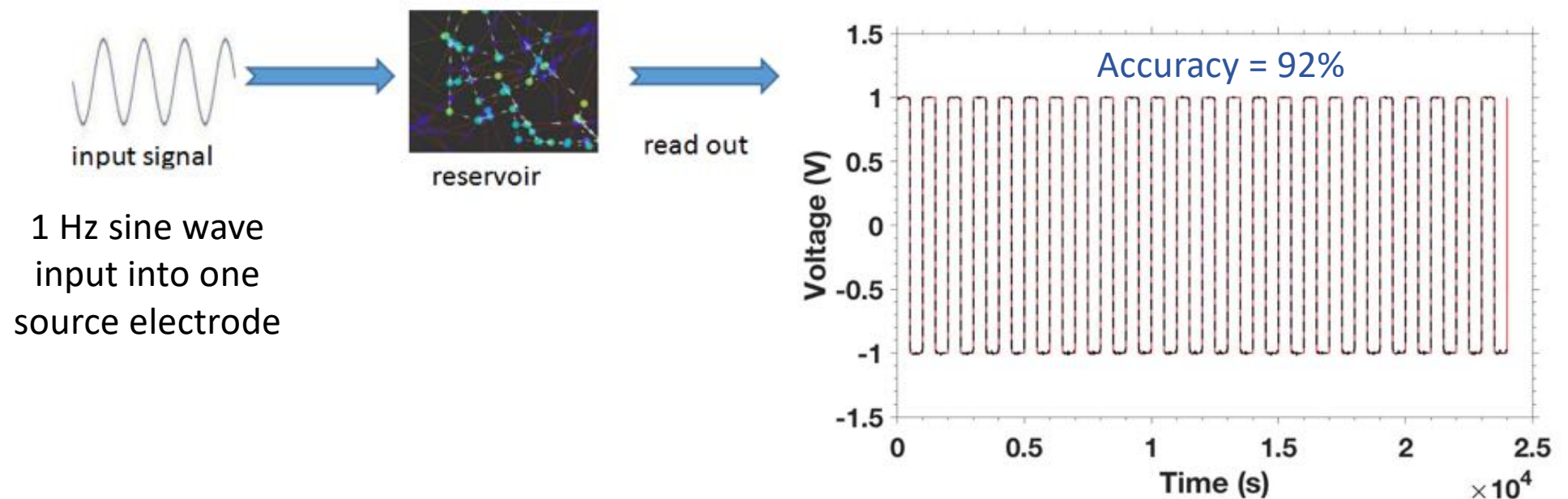
- “training in hardware” demonstrated with an associative memory task: network learns associations between electrical stimuli and spatial patterns
- Network pathways established during training are recalled during testing

[see also Diaz-Alvarez *et al.* AIP Adv. 2020]



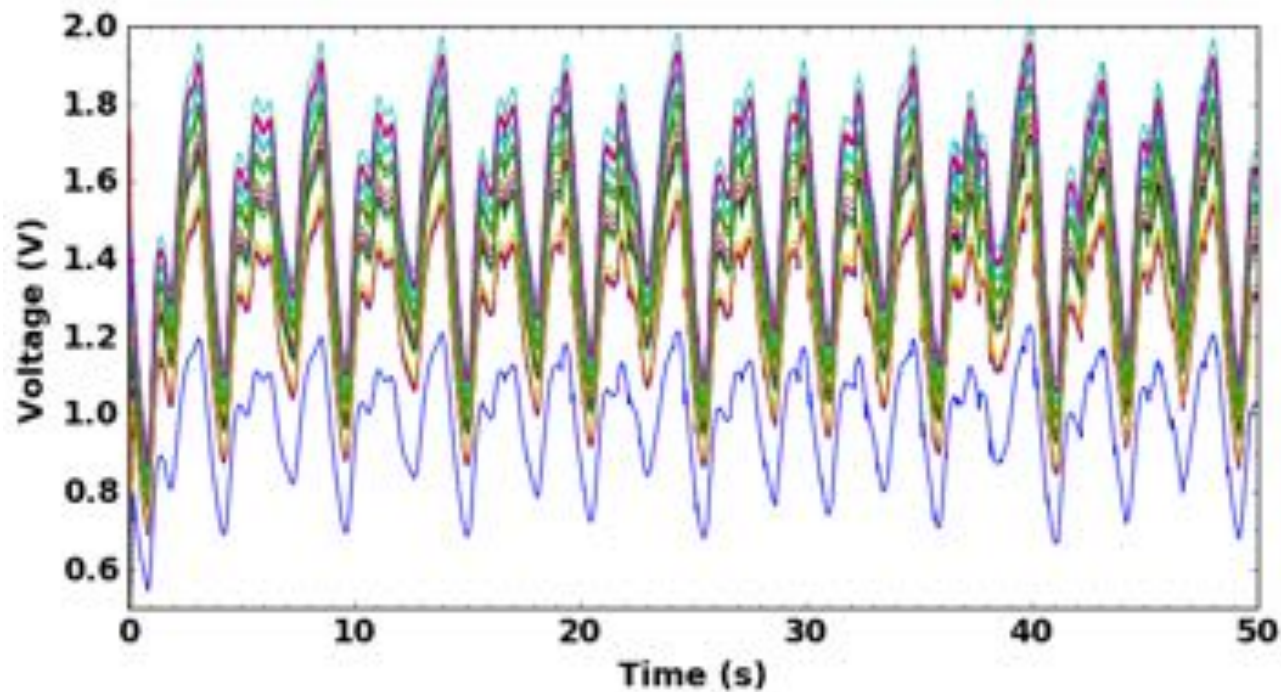
# Nonlinear waveform transformation

- Reservoir computing approach for signal processing tasks
- Training only requires linear regression of nanowire readout



# Time series prediction

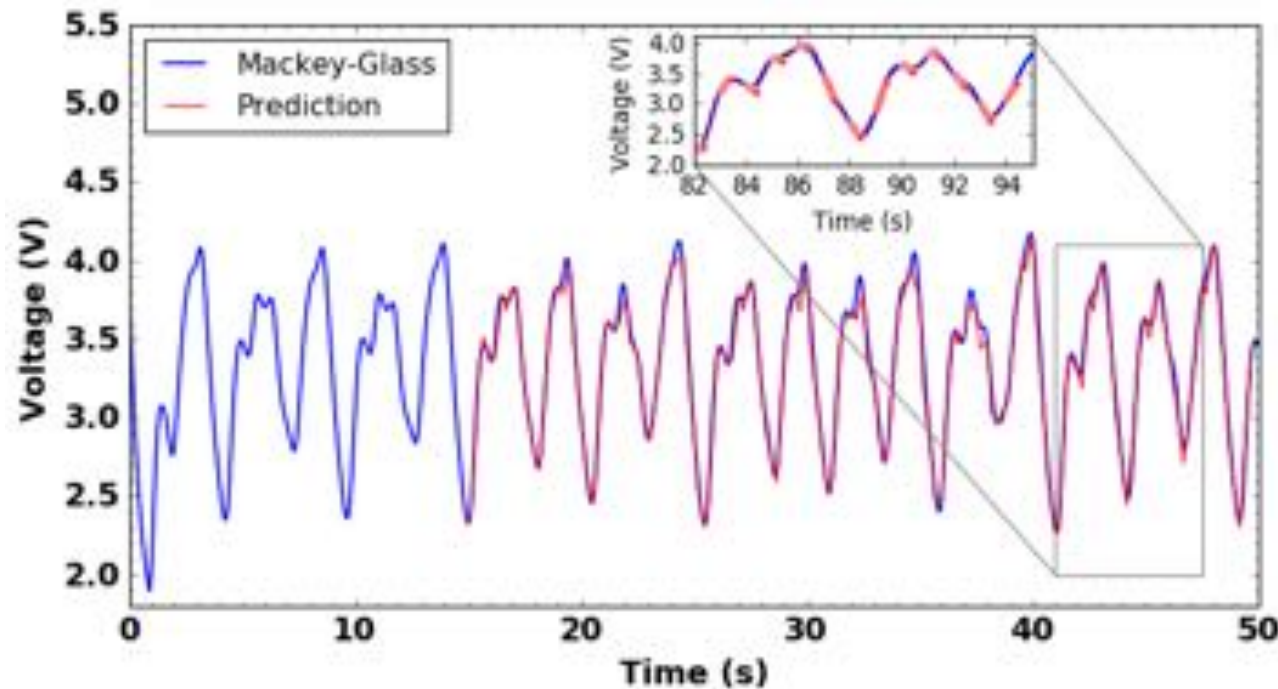
- Mackey-Glass nonlinear times series, delay parameter  $\tau = 17$  (onset of chaos)





# Time series prediction

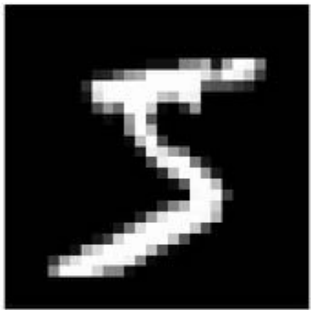
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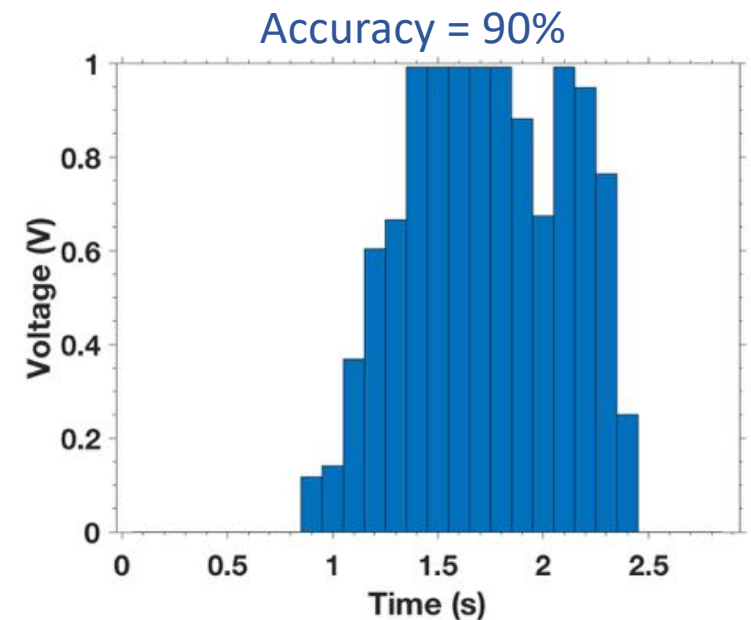
Accuracy = 98%

# Handwritten digit recognition

- MNIST digit image pixels (28x28) converted into stream of  $\Delta t = 0.1$  s voltage pulses with height corresponding to normalized intensity
- Each row is input into a source electrode and linear classification applied to current readout



0	0	0	0	0	0	0	0	0.01	0.07	0.07	0.07	0.49	0.53	0.69	0.10	0.65	1.00	0.97	0.50
0	0	0	0	0.12	0.14	0.37	0.60	0.67	0.99	0.99	0.99	0.99	0.99	0.88	0.67	0.99	0.95	0.76	0.25
0	0	0	0.19	0.93	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.36	0.32	0.32	0.22	0.15	0
0	0	0	0.07	0.86	0.99	0.99	0.99	0.99	0.99	0.99	0.78	0.71	0.97	0.95	0	0	0	0	0
0	0	0	0	0.31	0.61	0.42	0.99	0.99	0.99	0.80	0.04	0	0.17	0.60	0	0	0	0	0
0	0	0	0	0	0.05	0.00	0.60	0.99	0.99	0.35	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0.55	0.99	0.75	0.01	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0.04	0.75	0.99	0.27	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0.14	0.95	0.88	0.63	0.42	0.00	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0.32	0.94	0.99	0.99	0.47	0.10	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0.18	0.73	0.99	0.99	0.59	0.11	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0.06	0.36	0.99	0.99	0.73	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.98	0.99	0.98	0.25	0	0
0	0	0	0	0	0	0	0	0	0	0.18	0.51	0.72	0.99	0.99	0.80	0.01	0	0	0
0	0	0	0	0	0	0	0	0.15	0.58	0.90	0.99	0.99	0.99	0.98	0.71	0	0	0	0
0	0	0	0	0	0	0.09	0.45	0.87	0.99	0.99	0.99	0.99	0.99	0.79	0.31	0	0	0	0
0	0	0	0	0.09	0.26	0.84	0.99	0.99	0.99	0.99	0.99	0.78	0.32	0.01	0	0	0	0	0
0	0	0.07	0.67	0.86	0.99	0.99	0.99	0.99	0.99	0.76	0.31	0.04	0	0	0	0	0	0	0
0.22	0.67	0.89	0.99	0.99	0.99	0.99	0.96	0.52	0.04	0	0	0	0	0	0	0	0	0	0
0.53	0.99	0.99	0.99	0.83	0.53	0.52	0.06	0	0	0	0	0	0	0	0	0	0	0	0



# Conclusion and outlook

- Nanowire networks are capable of **learning associations and complex spatio-temporal patterns**
- Their **neural-like electrical circuitry** confers *adaptive dynamics* advantageous for **on-the-fly information processing at IoT edge**
- Future prospects for processing information from non-ideal, “real world” data, e.g. satellites, sensors



Image credit: SmartSat CRC, Australia