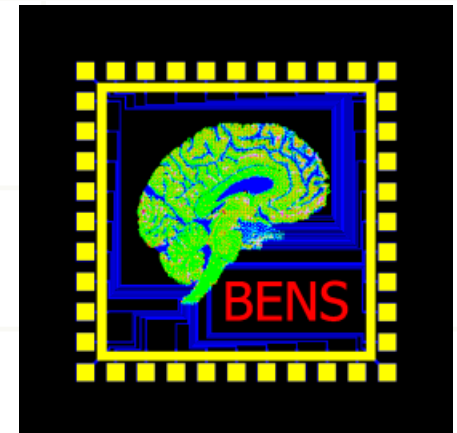
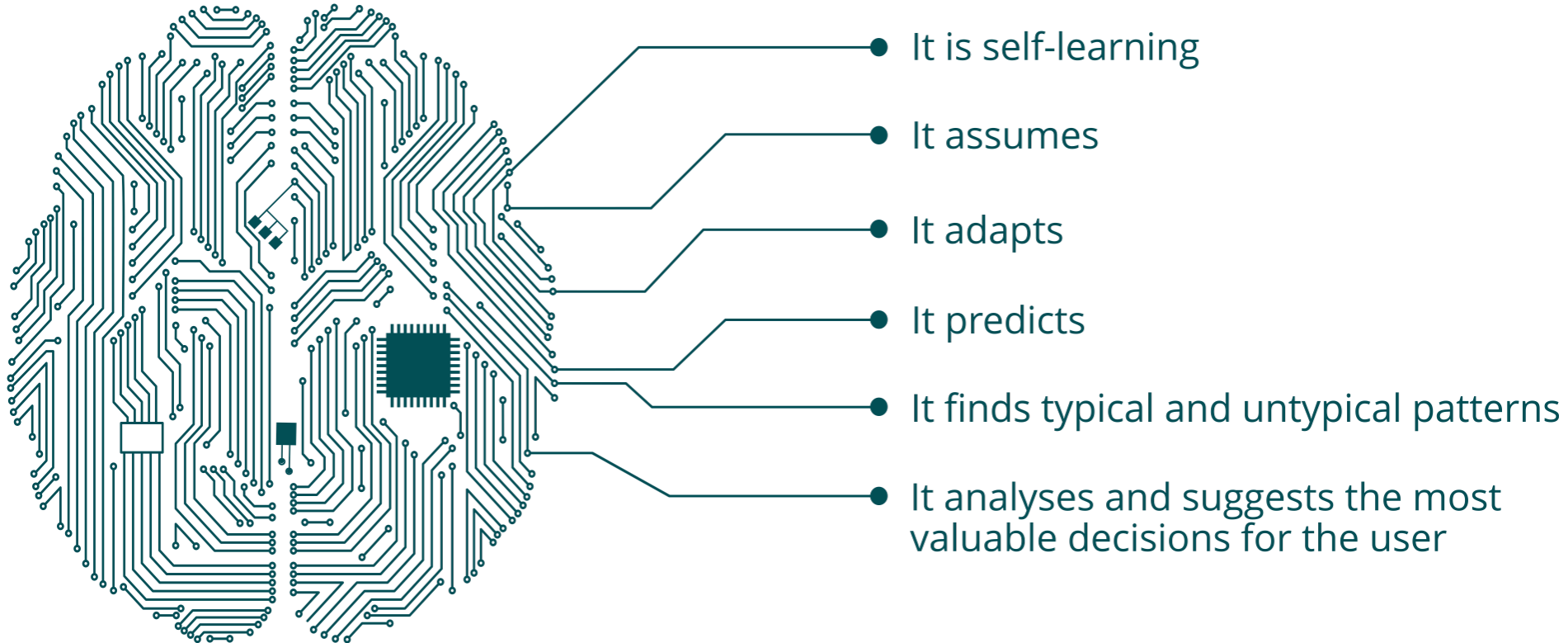


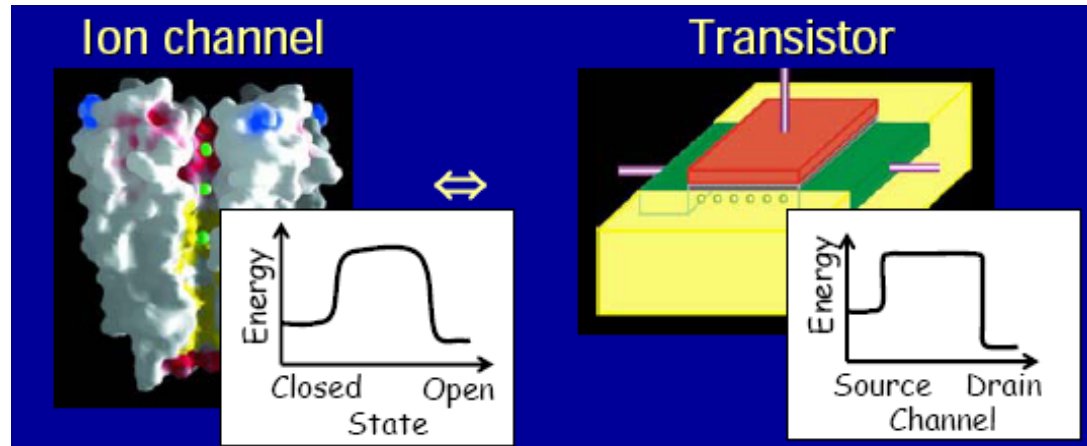
Neuromorphic Engineering: Computational Paradigms Inspired by the Brain

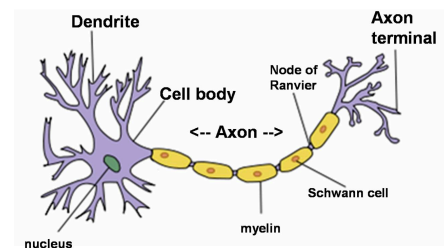
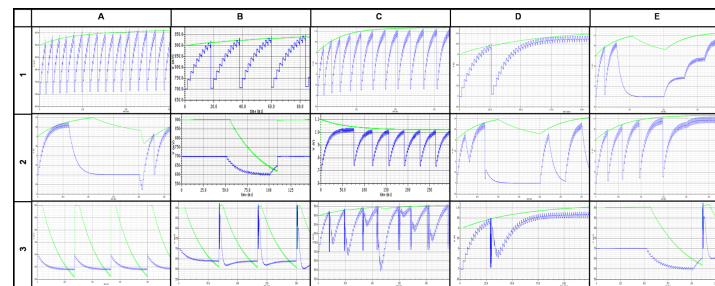
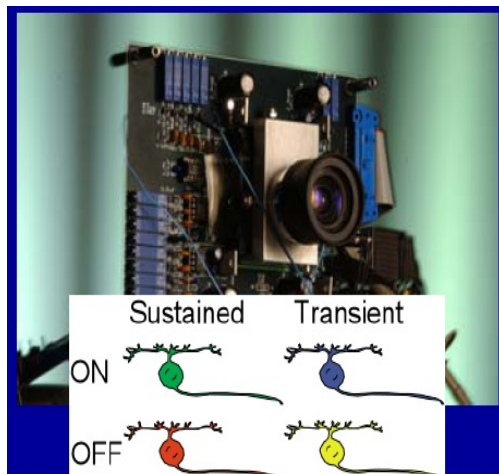
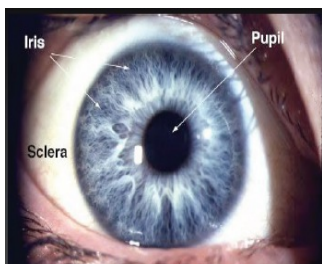
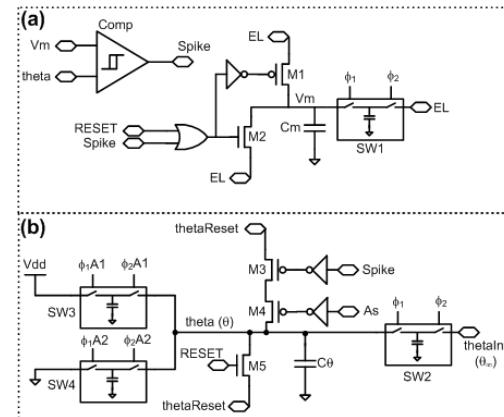
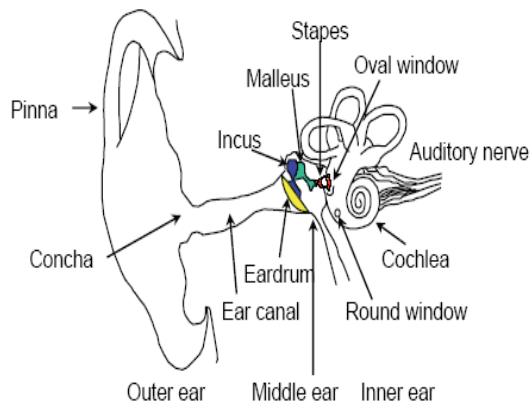
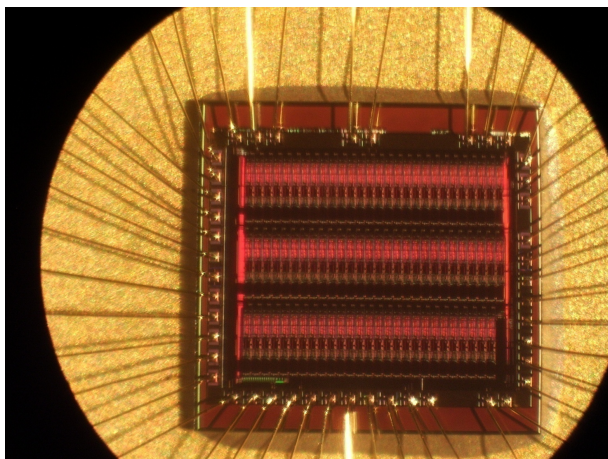
Tara Julia Hamilton
Biomedical Engineering and Neuroscience Group
The MARCS Institute,
University of Western Sydney

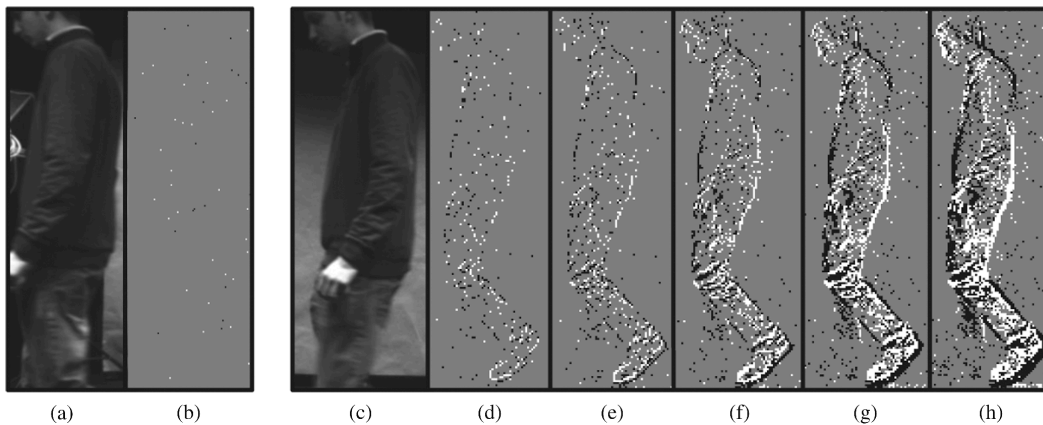
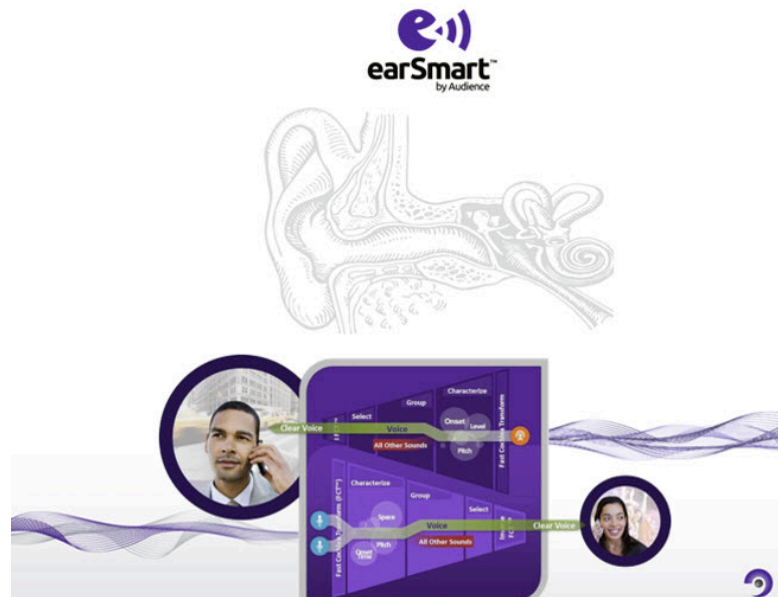


Artificial Intelligence

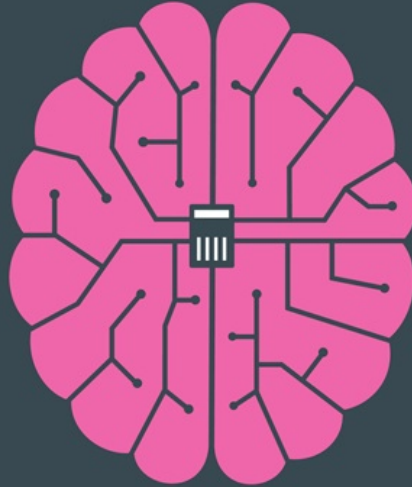








Neuromorphic Chips



10 Breakthrough Technologies 2014

Introduction

Agricultural Drones >

Ultraprivate Smartphones >

Brain Mapping >

Neuromorphic Chips >

Genome Editing >

Microscale 3-D Printing >

Mobile Collaboration >

Oculus Rift >

Agile Robots >

Smart Wind and Solar Power >

Neuromorphic Chips

Microprocessors configured more like brains than traditional chips could soon make computers far more astute about what's going on around them.

Breakthrough

An alternative design for computer chips that will enhance artificial intelligence.

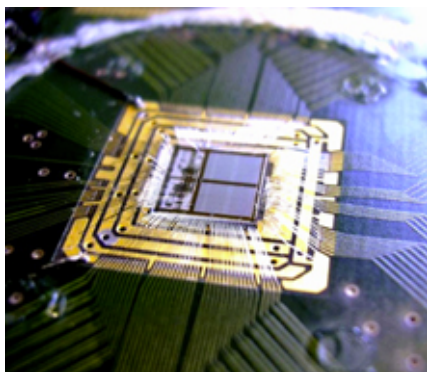
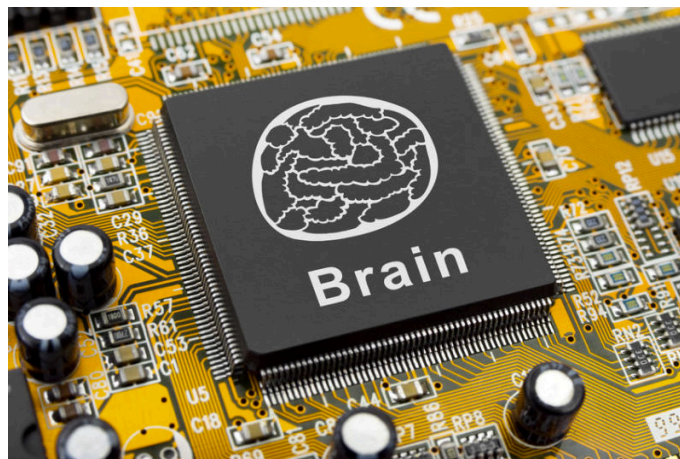
Why It Matters

Traditional chips are reaching fundamental performance limits.

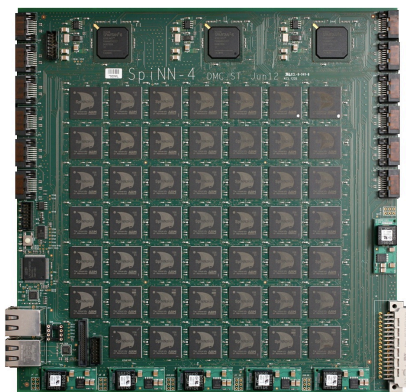
Key Players

+ Qualcomm
+ IBM
+ HRL Laboratories
+ Human Brain Project

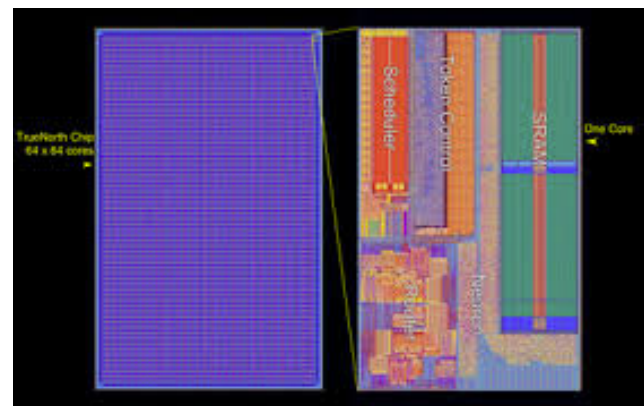
Neuromorphic Processors



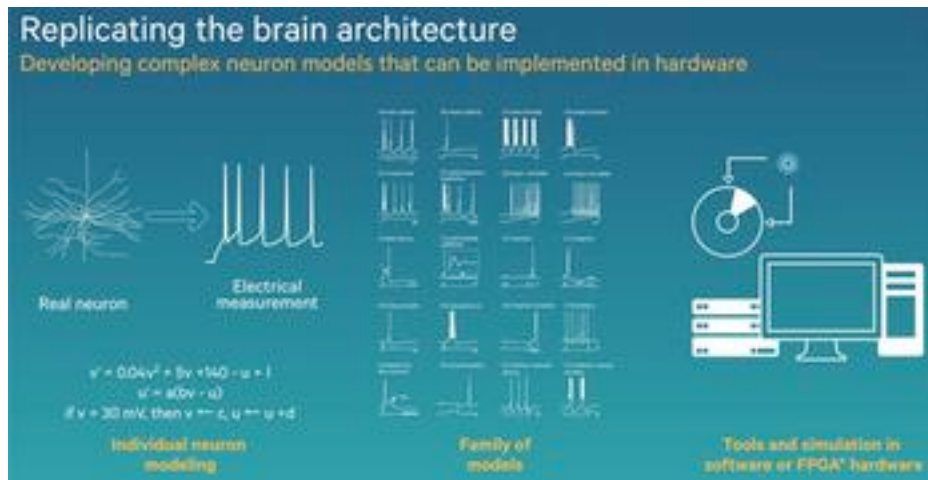
FACETS



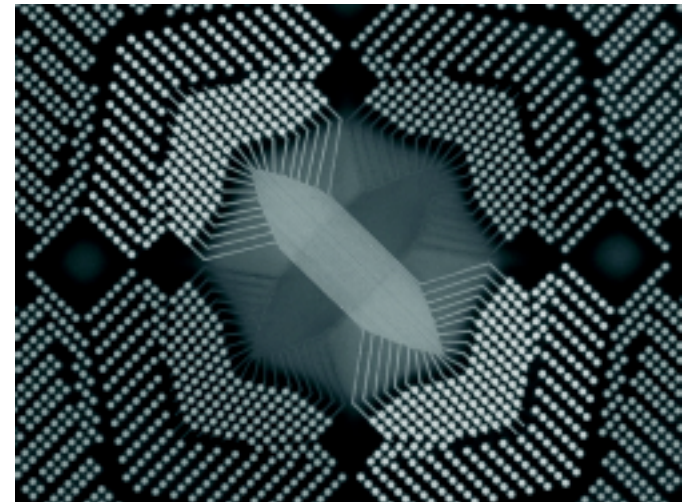
SpiNNaker



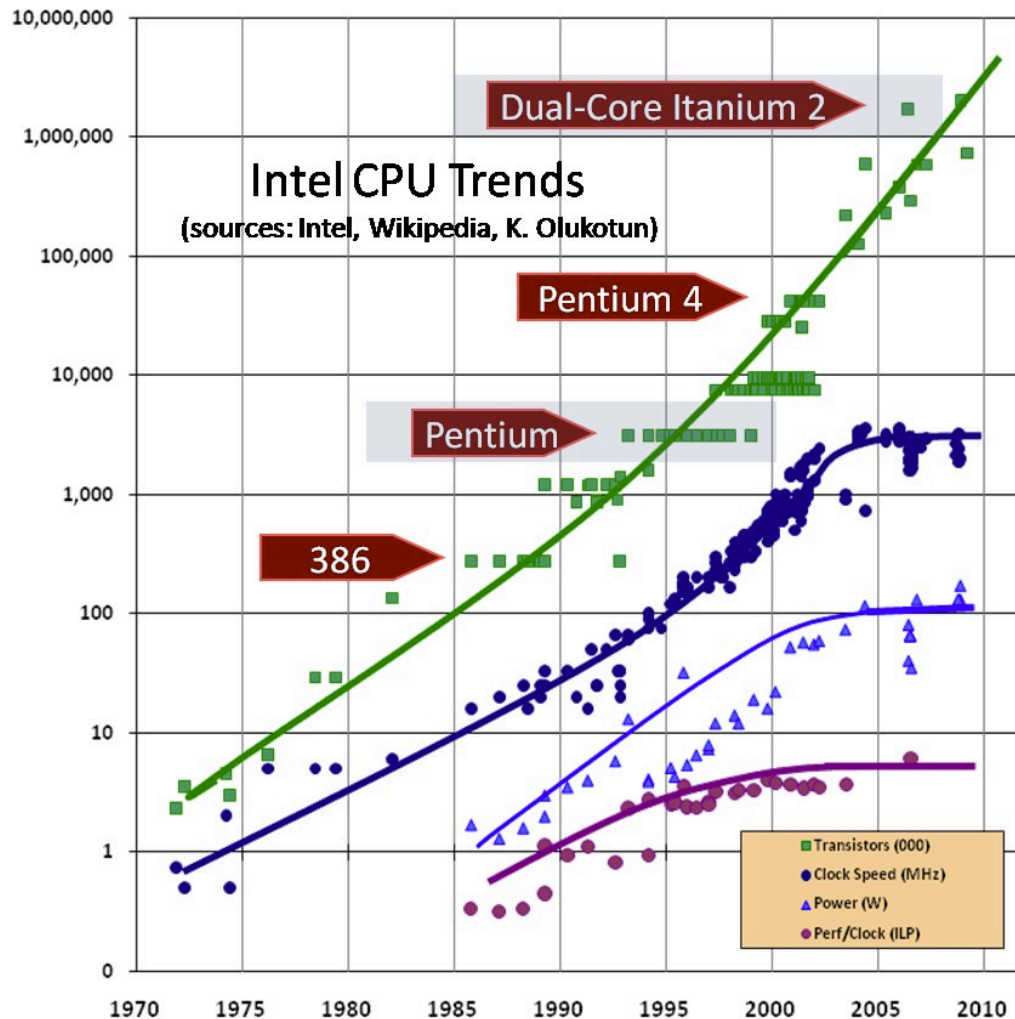
IBM TrueNorth

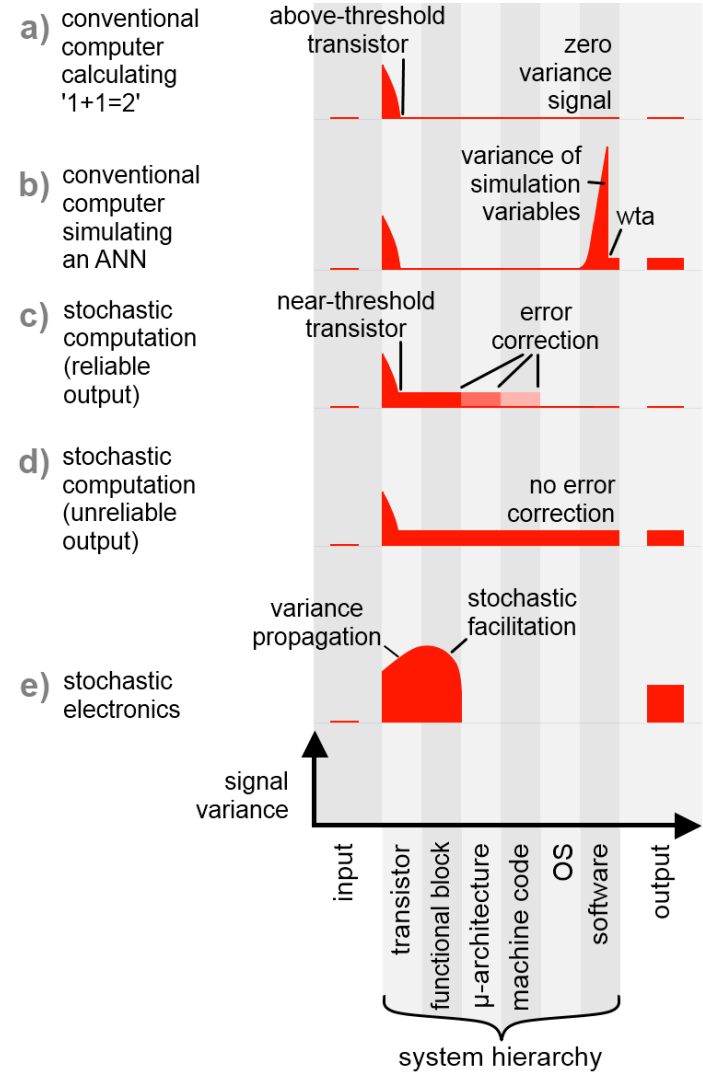
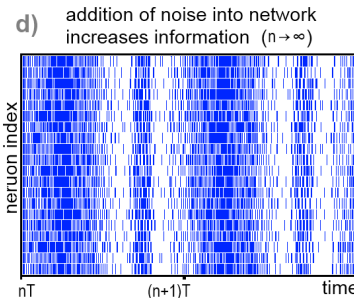
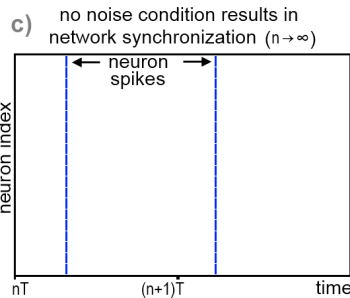
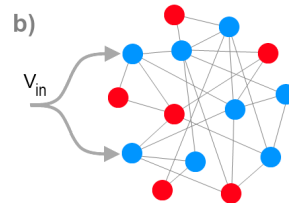
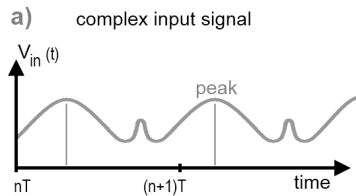


Qualcomm Zeroth Chip

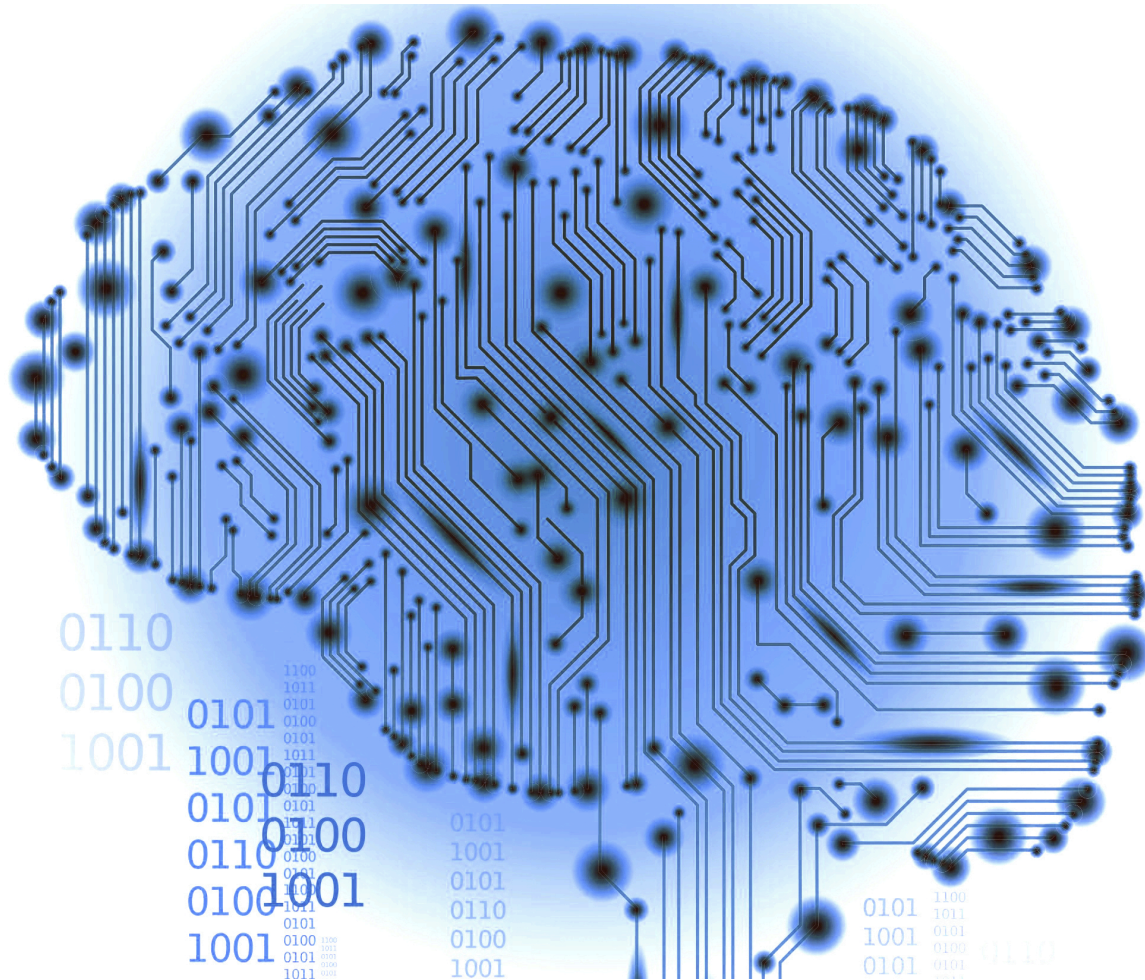


HP SyNAPSE Memristors

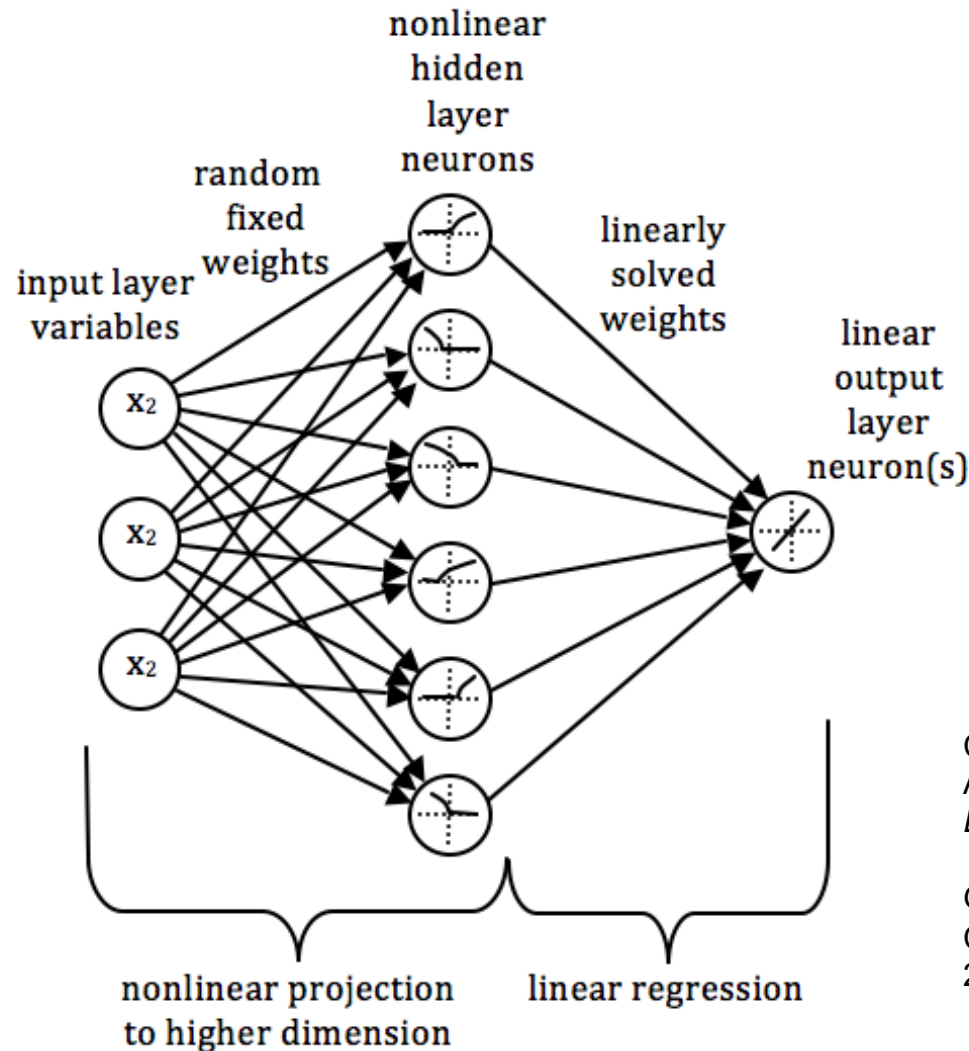




Computation



Linear Solutions of Higher Dimensional Interlayers



C. Eliasmith and C. Anderson, *Neural Engineering*, 2003.

G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew *Neurocomputing*, 2006.

J. Tapson and A. van Schaik, *Neural Networks*, 2013.

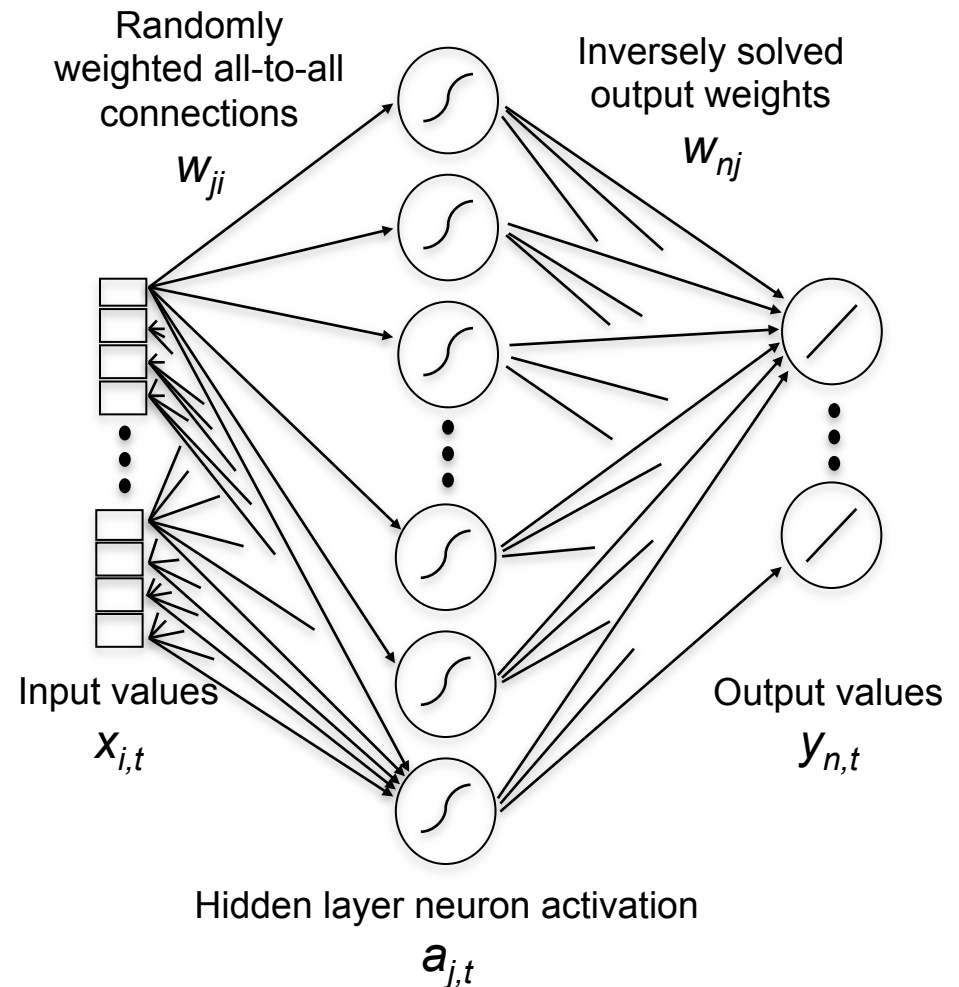
Example: Extreme Learning Machine - definition

$$y_{n,t} = \sum_{j=1}^M w_{nj}^{(2)} f \left(\sum_{i=1}^L w_{ji}^{(1)} x_{i,t} \right)$$

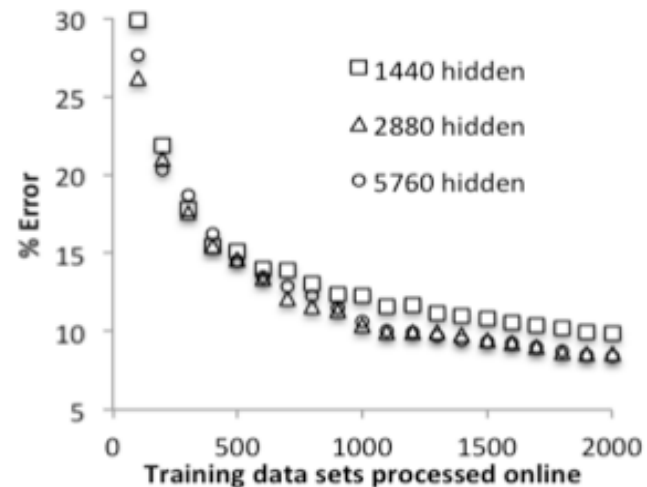
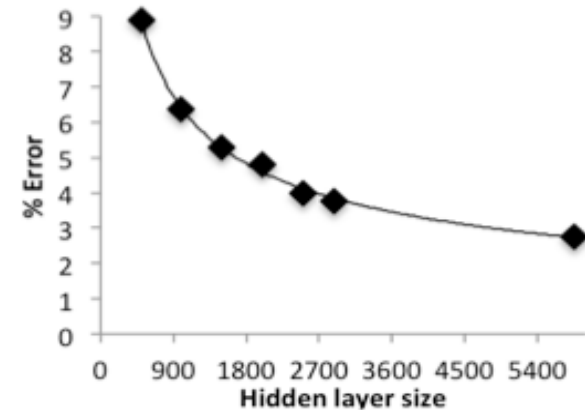
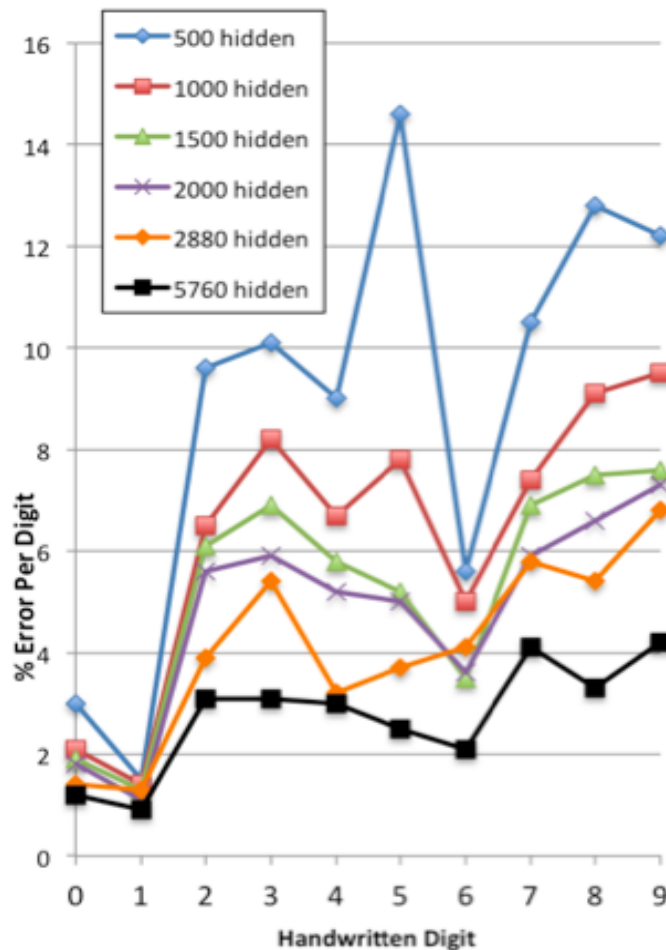
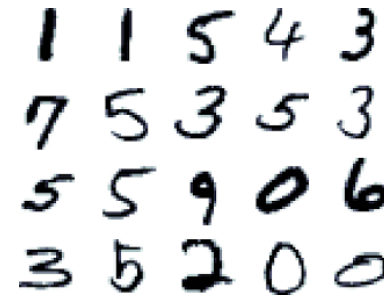
$$a_{j,t} = f \left(\sum_{i=1}^L w_{ji}^{(1)} x_{i,t} \right)$$

$$WA = Y$$

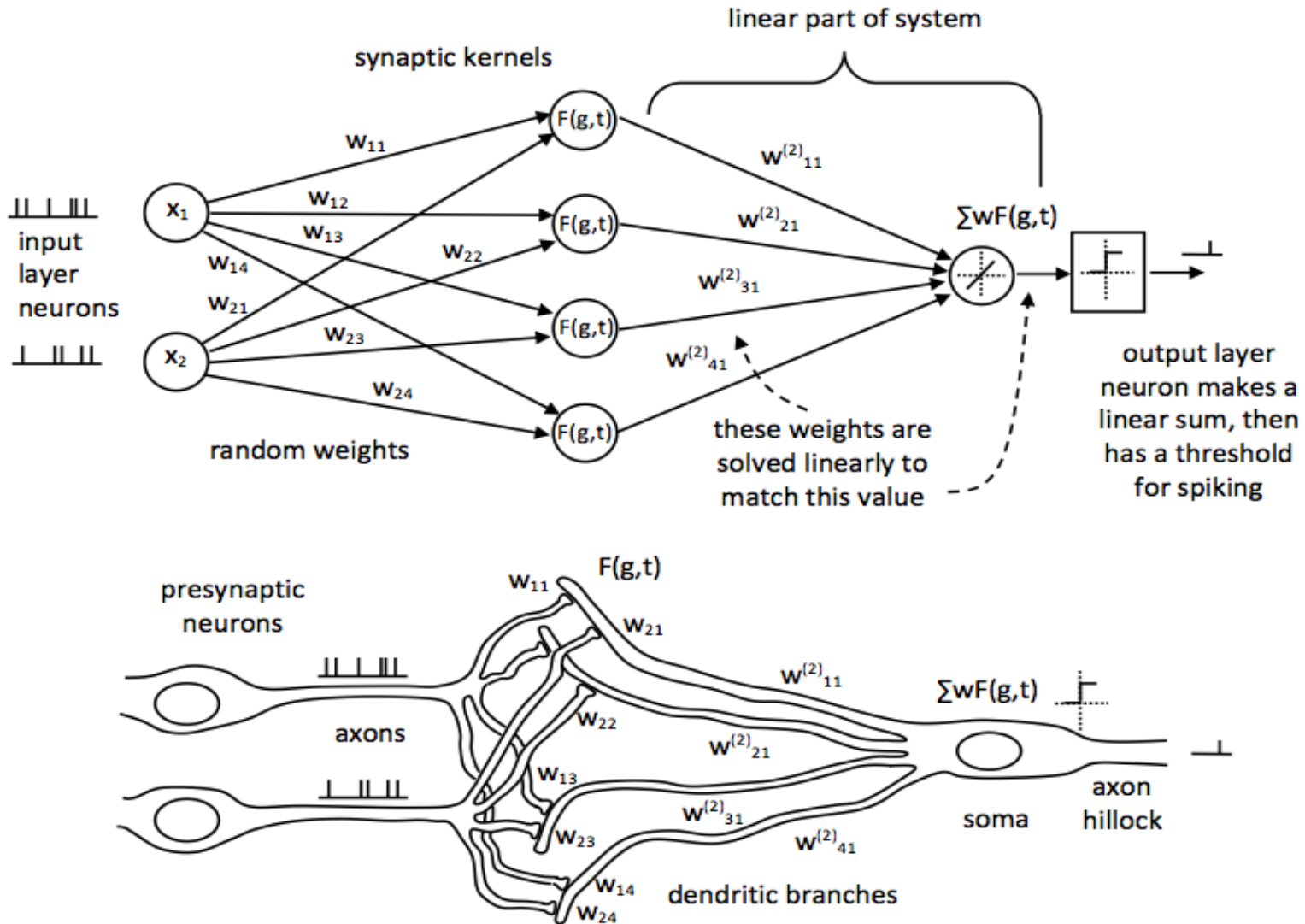
$$W = YA^+$$



Results on MNIST

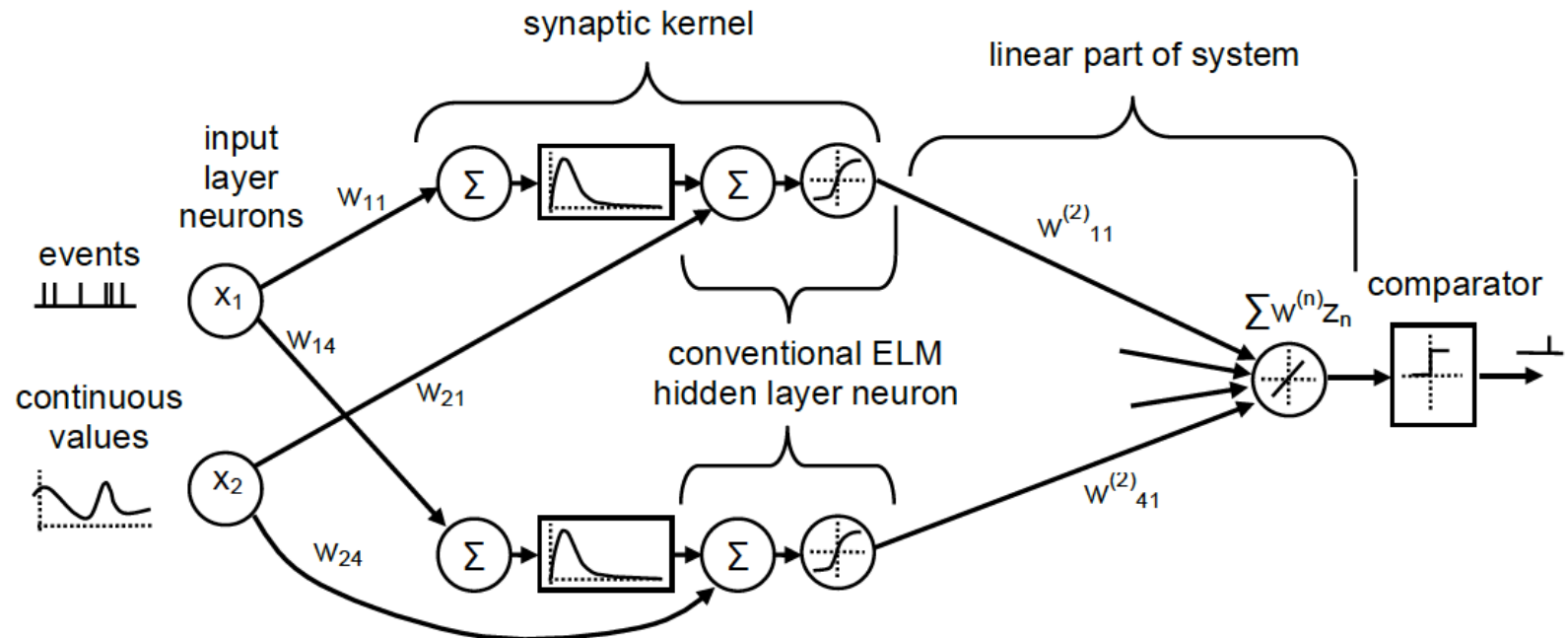


The Synaptic Kernel Inverse Method (SKIM)



The Synaptic Kernel Inverse Method (SKIM)

- We copy the way mammalian neurons work:
 - We convert the spike event into a continuous-time function, at the synapses
 - We weight the inputs from different synapses and sum them at the soma
 - We learn the correct weights with which to combine the synaptic signals



Issues:

Random connections

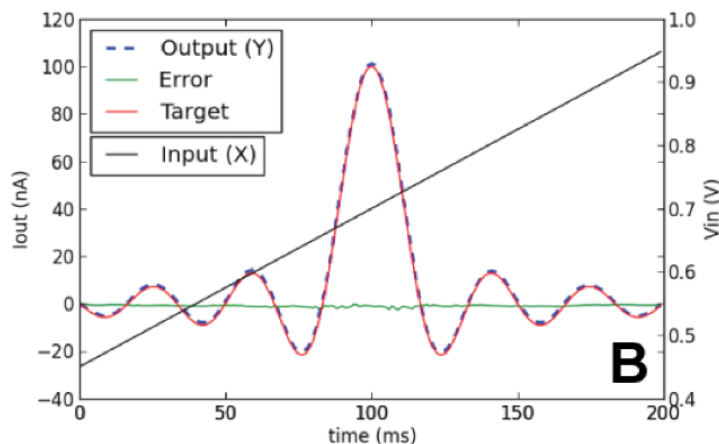
-> process mismatch

Tunable weights

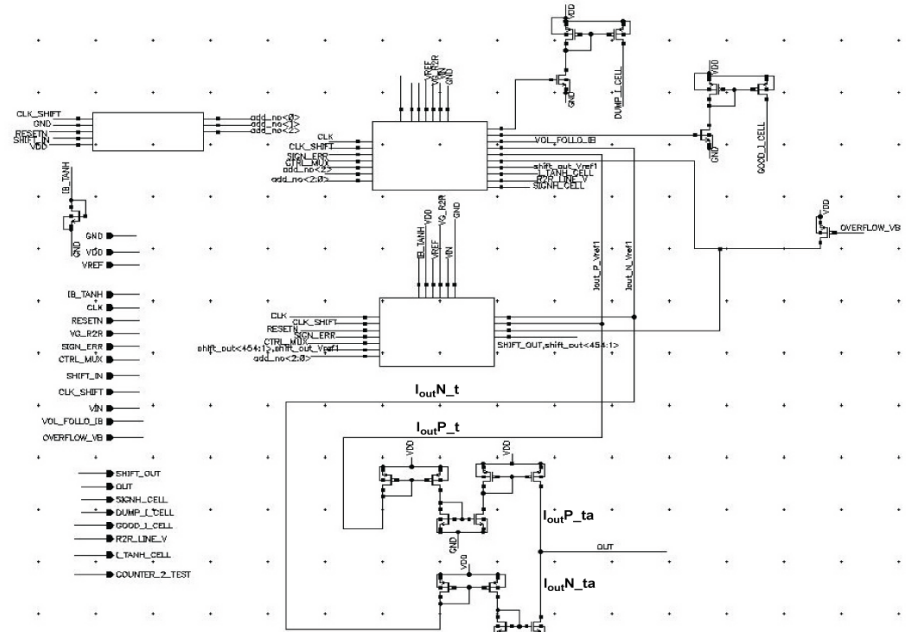
-> multiplying DACS

Pseudoinverse computation

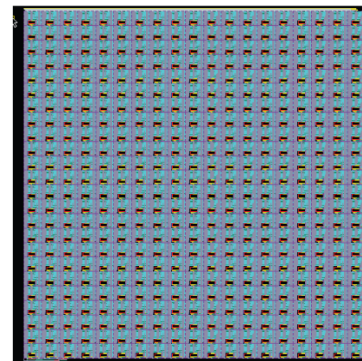
-> gradient descent



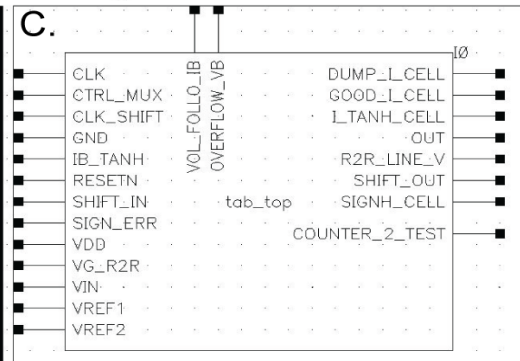
A.



B.

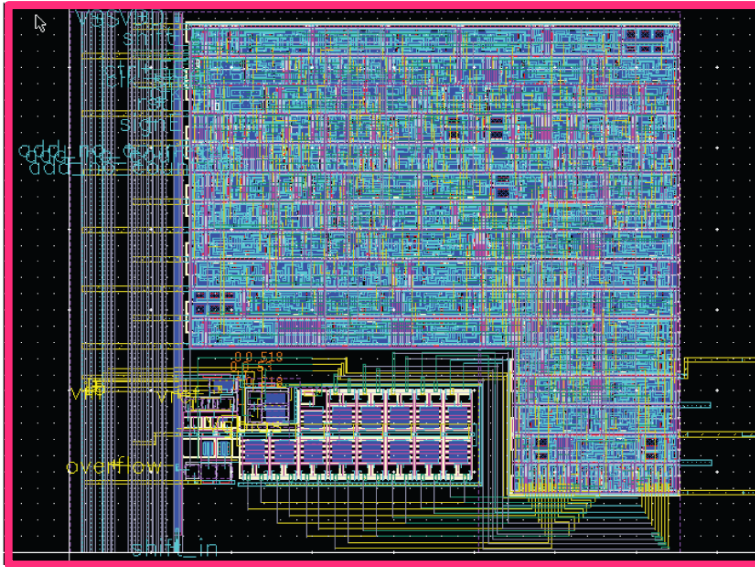


C.

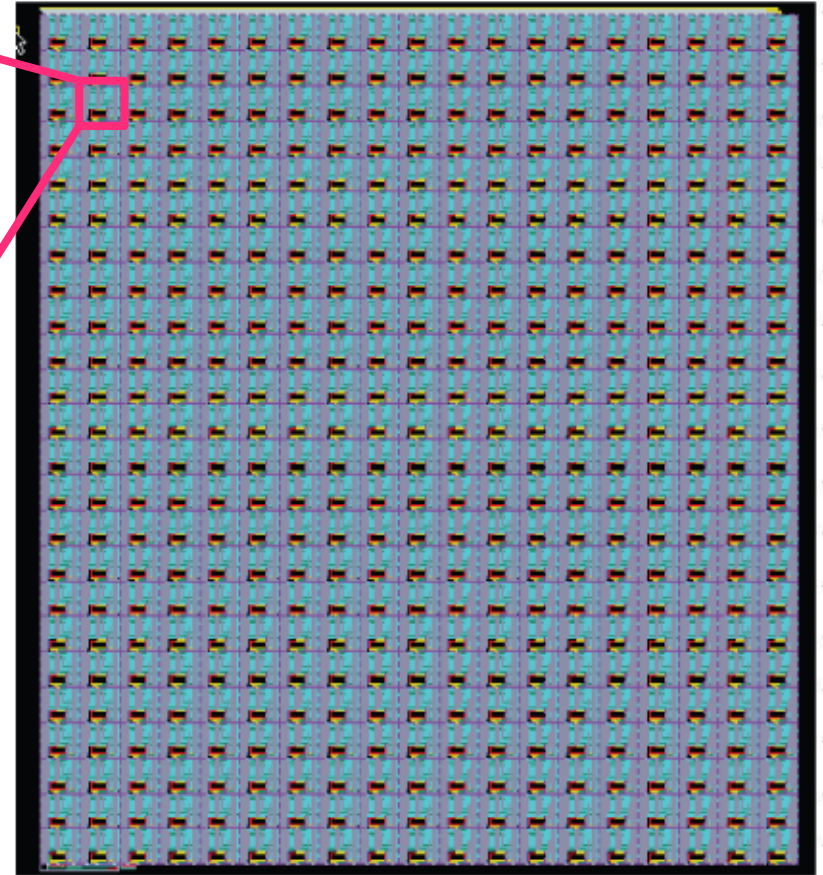


Custom aVLSI circuit

Neuron block



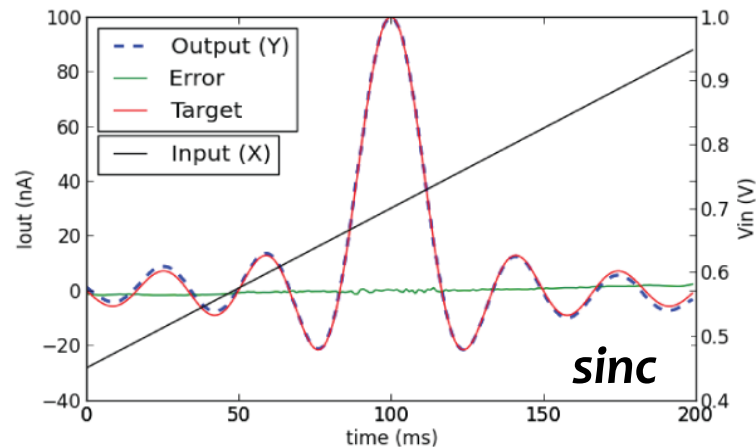
Top Level Tab



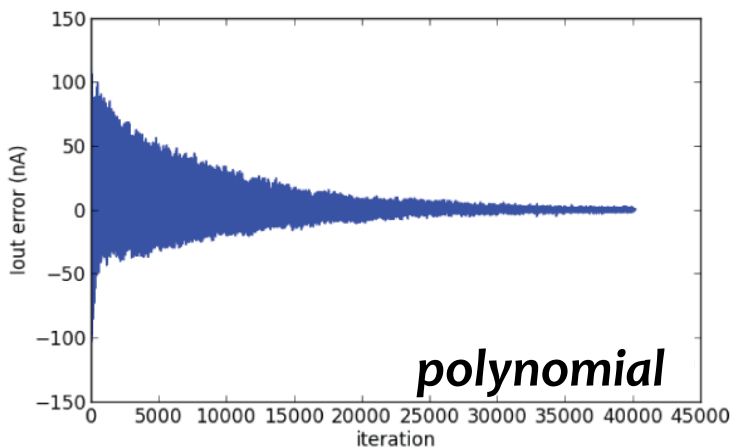
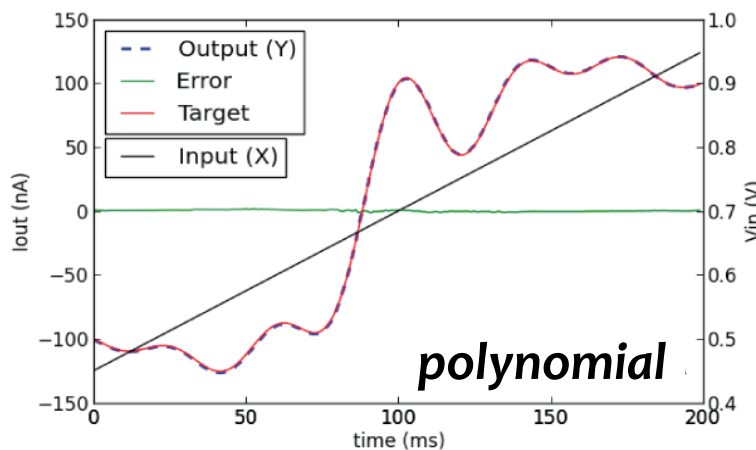
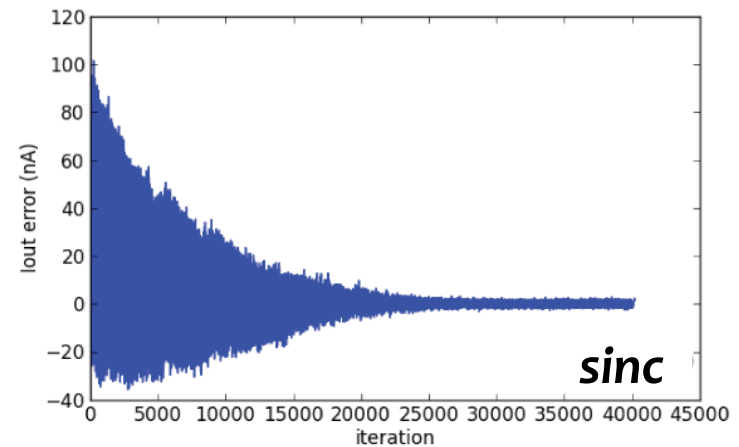
SISO TAB IC fabricated in TSMC65nm technology (1 mm²)

Total 456 neurons.

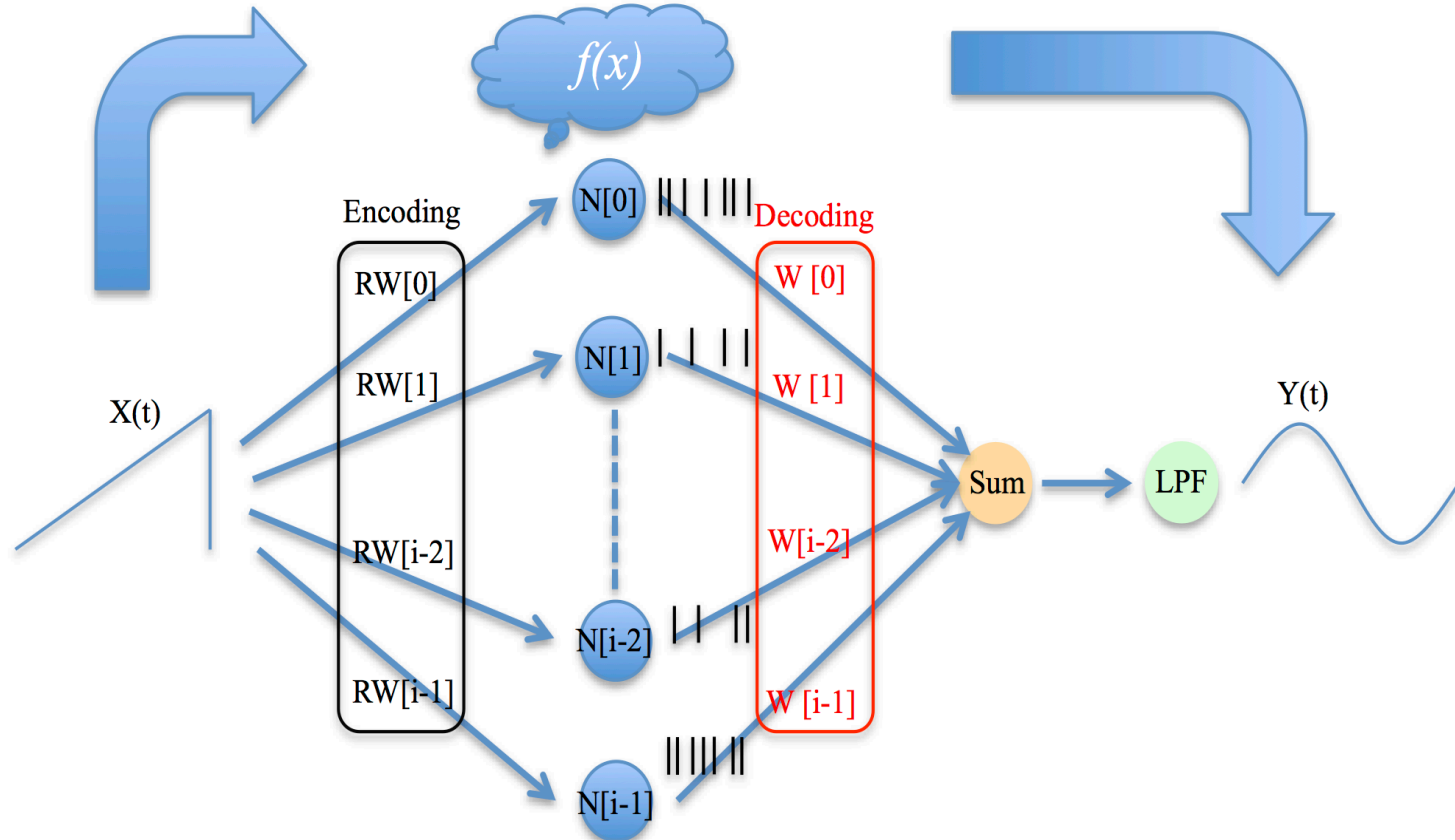
Trained function (*dashed curve*) predicts
the correct output value (*red curve*)



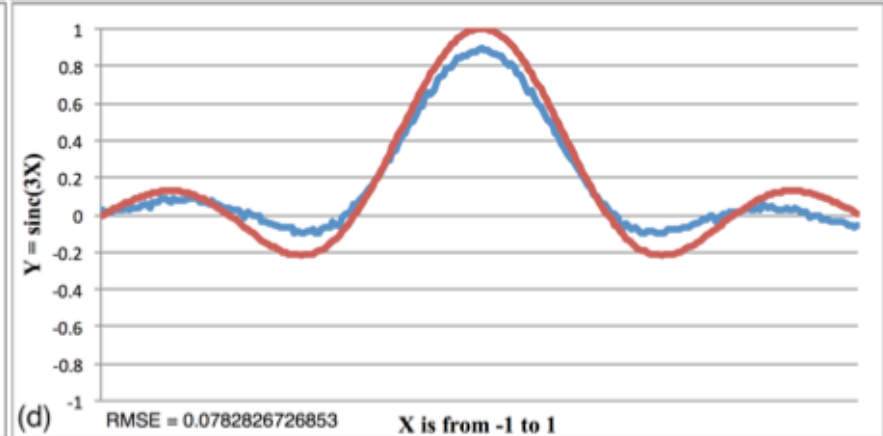
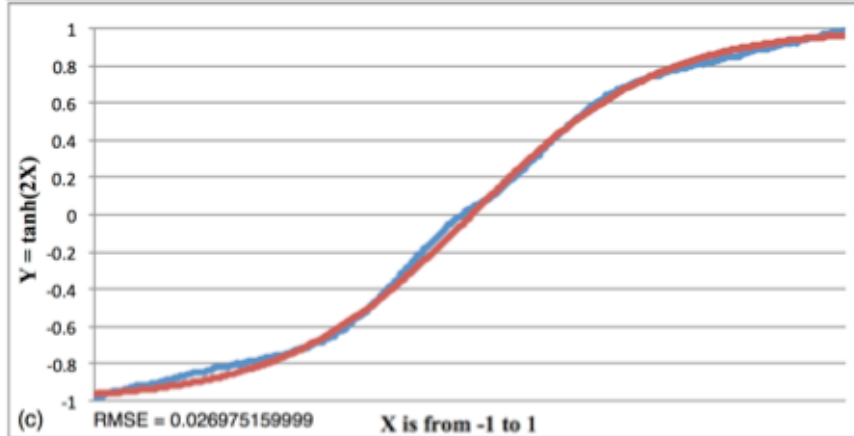
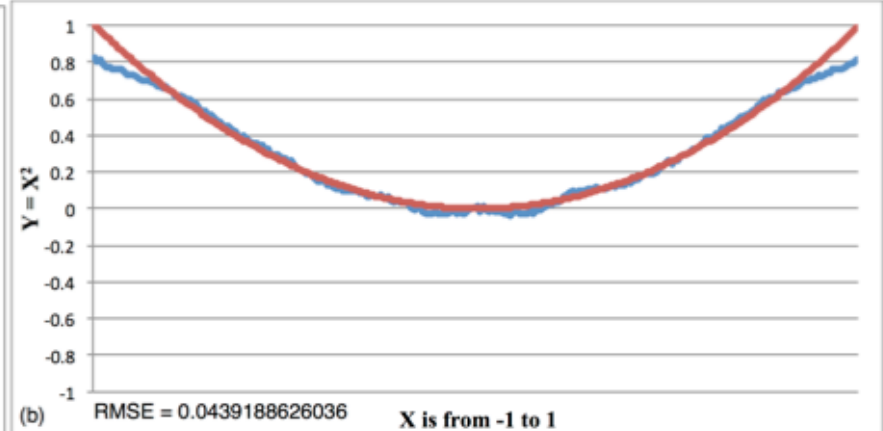
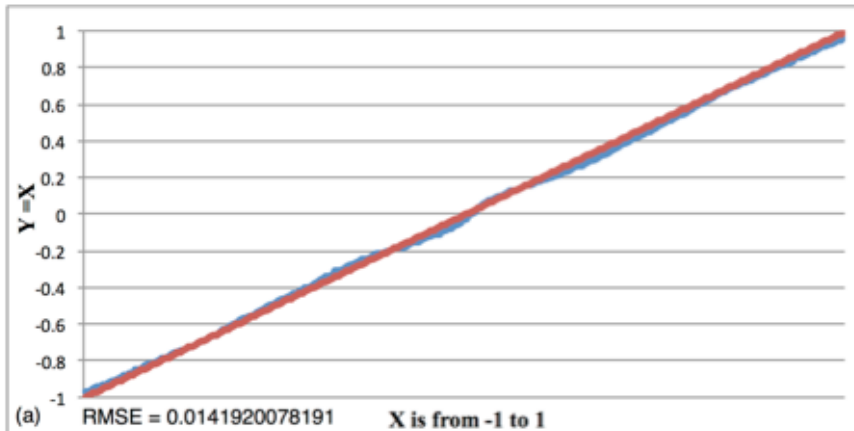
Error converges to minimum
over the learning process



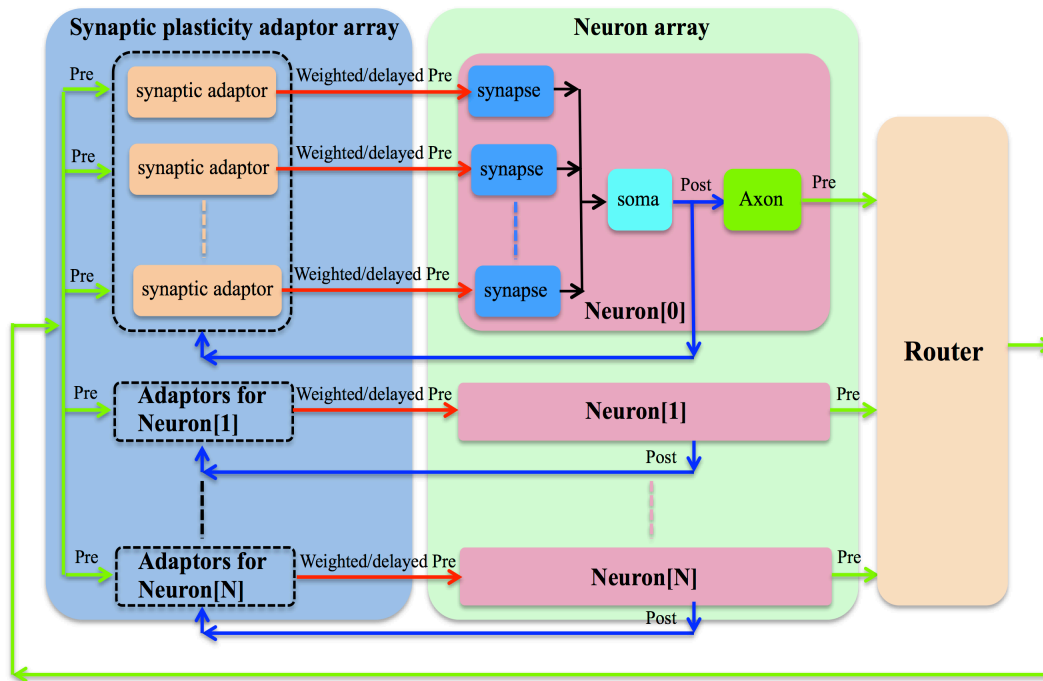
FPGA Approach



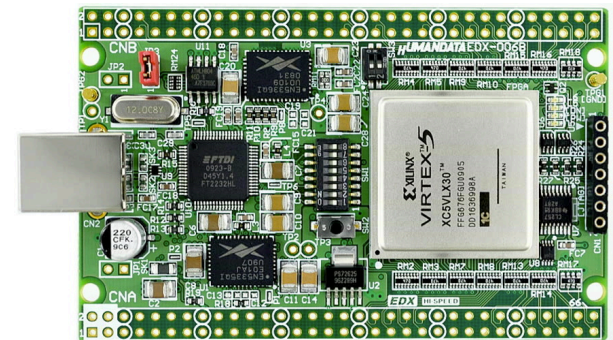
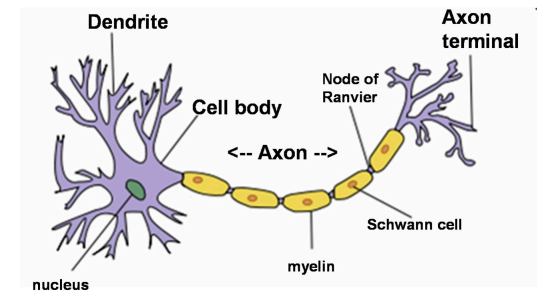
FPGA results



Clockwise from top left: $y = k.x$, $y = x^2$, $y = \tanh(x)$, $y = \text{sinc}(x)$

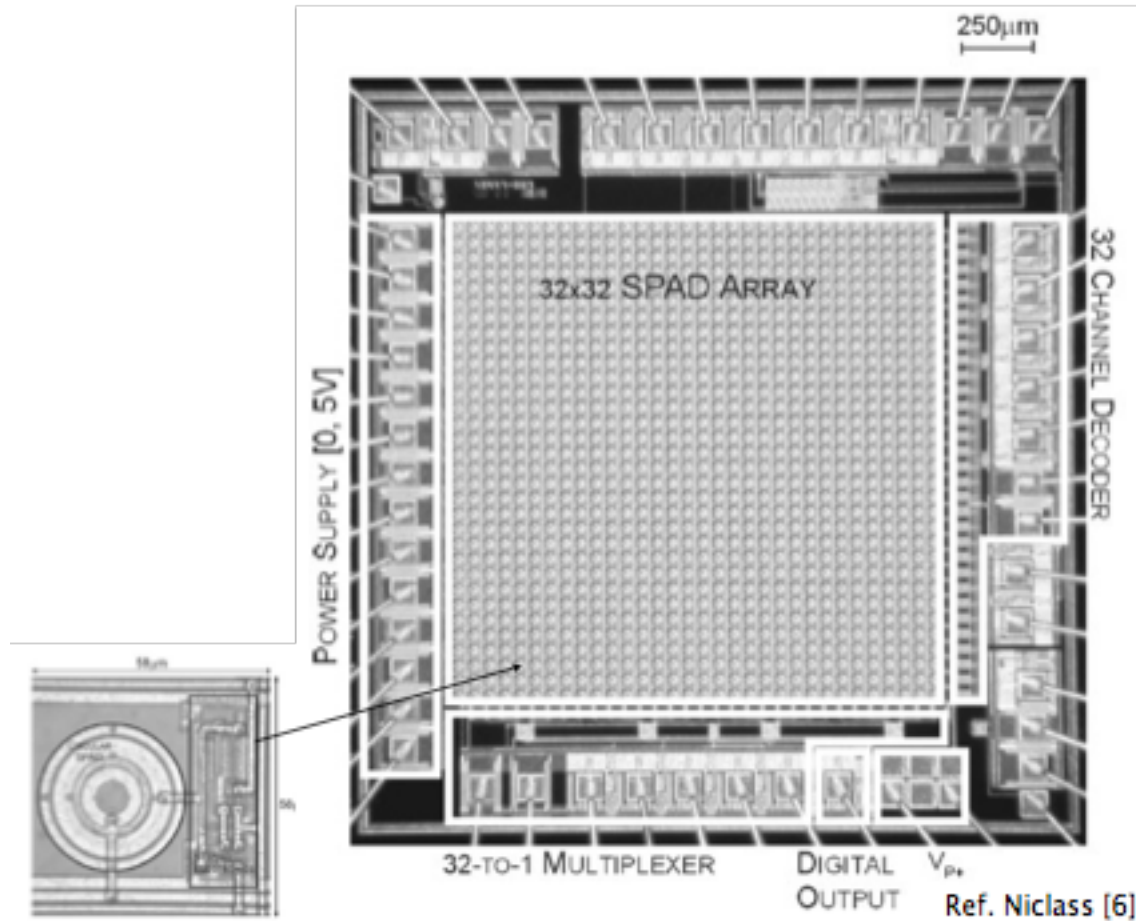


MegaSimulator:
64x10⁹ Synapses



Smart Sensing

Photograph of SPAD Array/Image Sensor

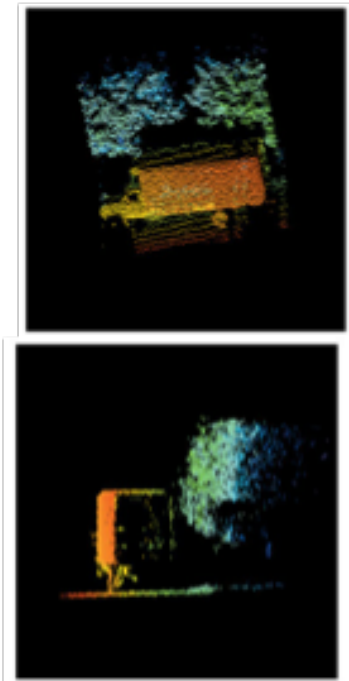
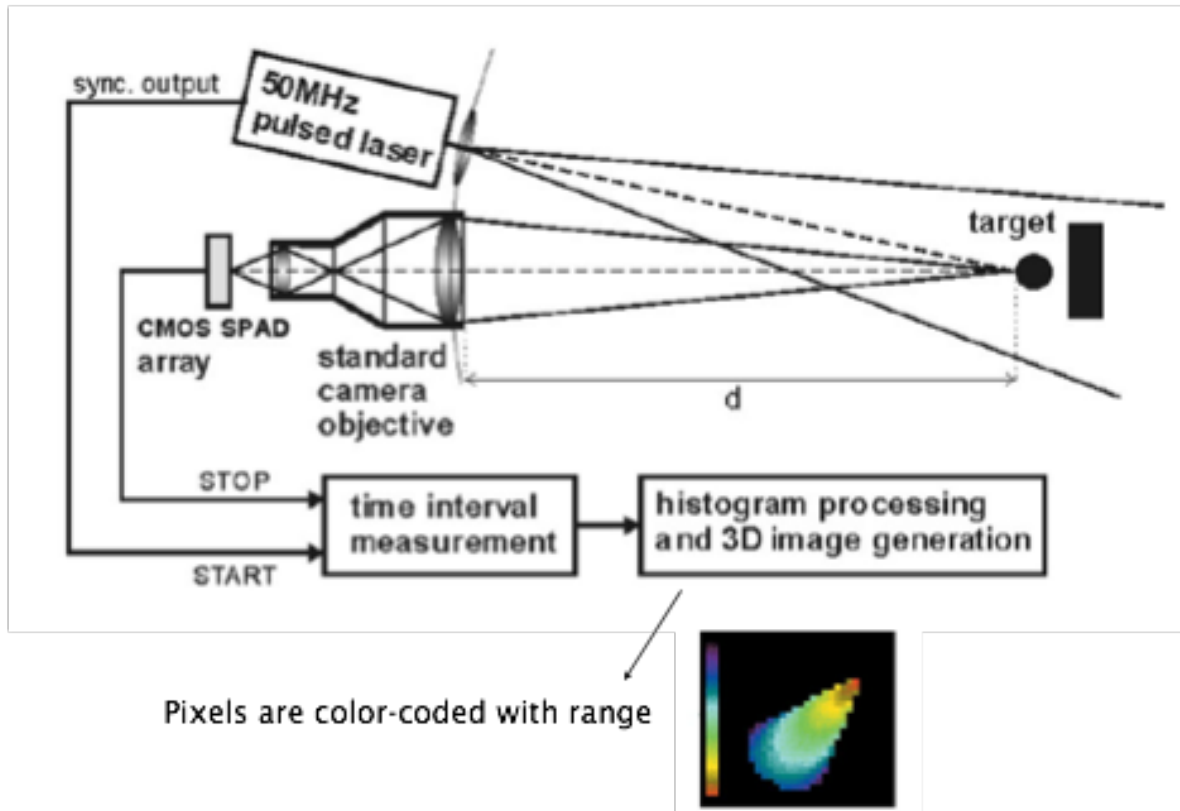


Source: Dr. Dennis Delic, DSTO

Basic Setup: Photon Timing.

Source: Dr. Dennis Delic, DSTO

Using Ranging Mode (TOF) as opposed to Time-Correlated Single Photon Counting (TCSPC).



Example target:
truck next to a
tree.

Traditional Approach

spatio-temporal pattern
generated by SPAD array
is encoded into pixel values



16 bit pixels



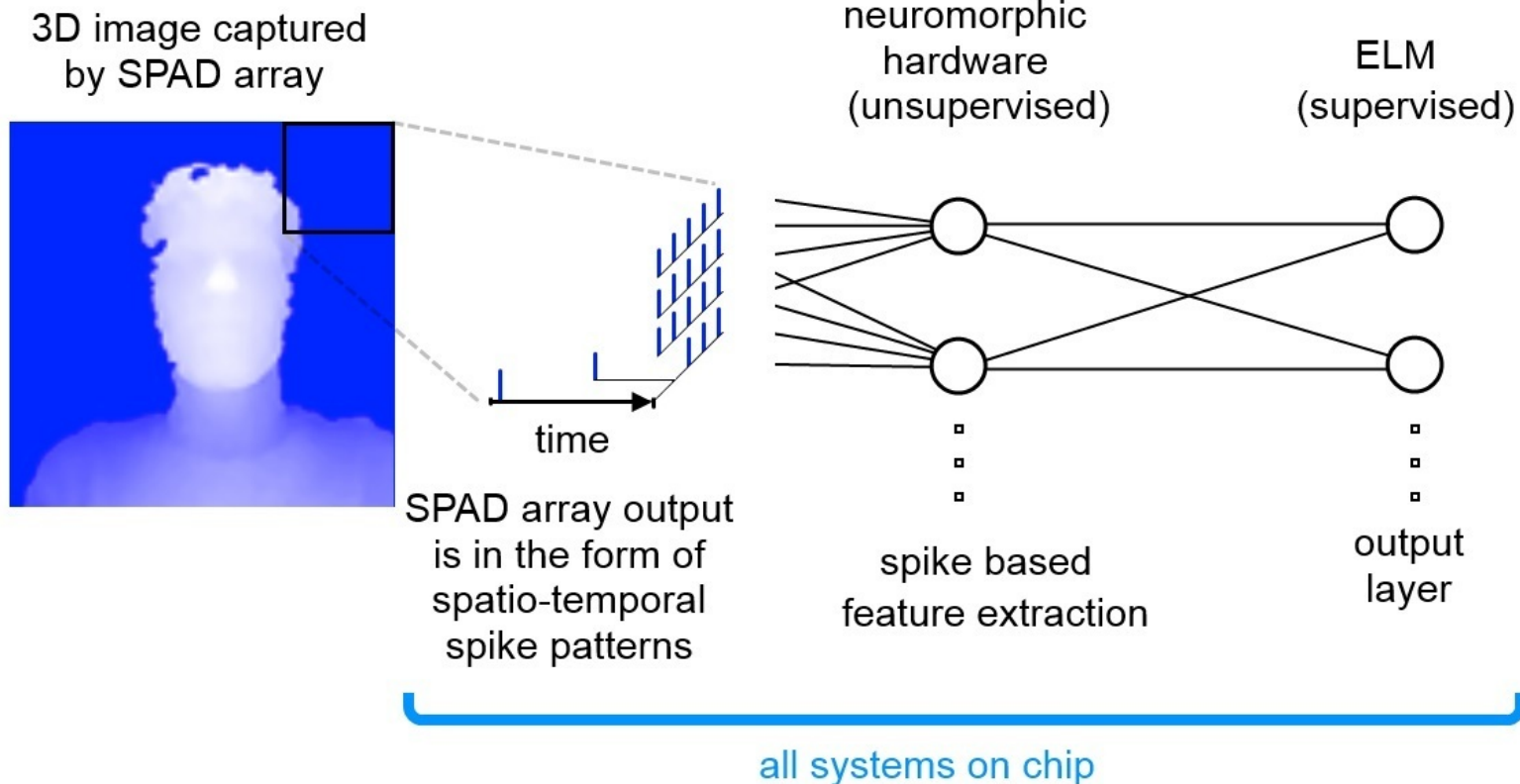
16 bit bus

off-chip processing

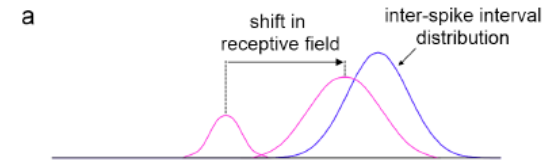
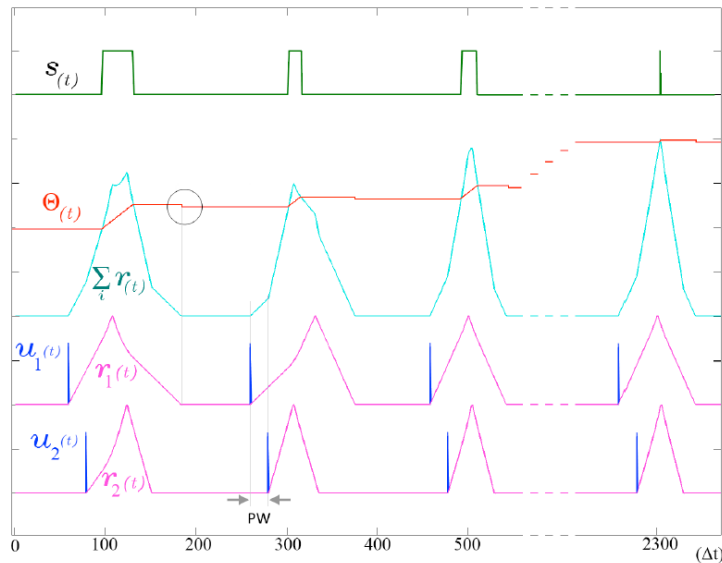
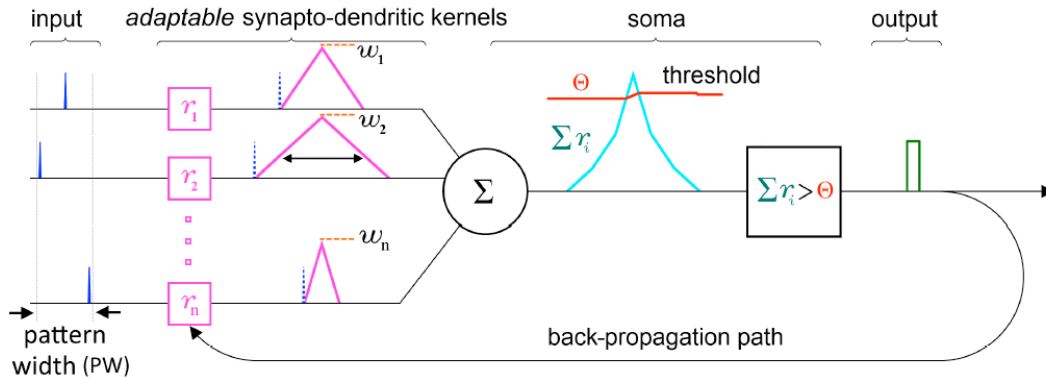


- There are ongoing debates about the information content (coding) in spikes
 - Rate codes
 - Time or interval codes
 - Place codes
 - Population codes
- Spatio-temporal pattern recognition offers a method for processing all of these types of codes

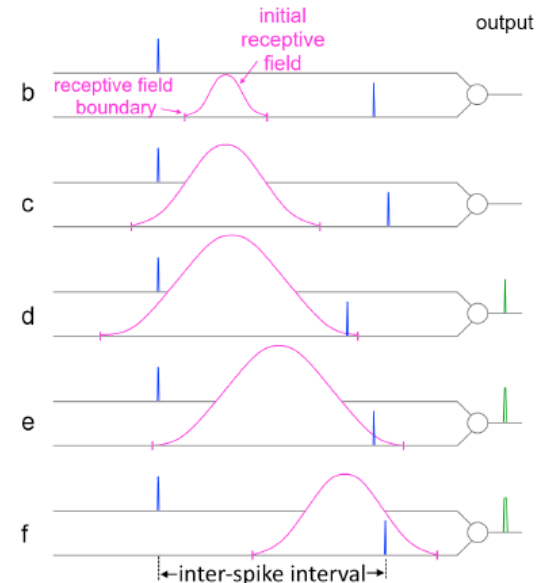
Our Approach



Synaptic Kernel Adaptation Neuron (SKAN)



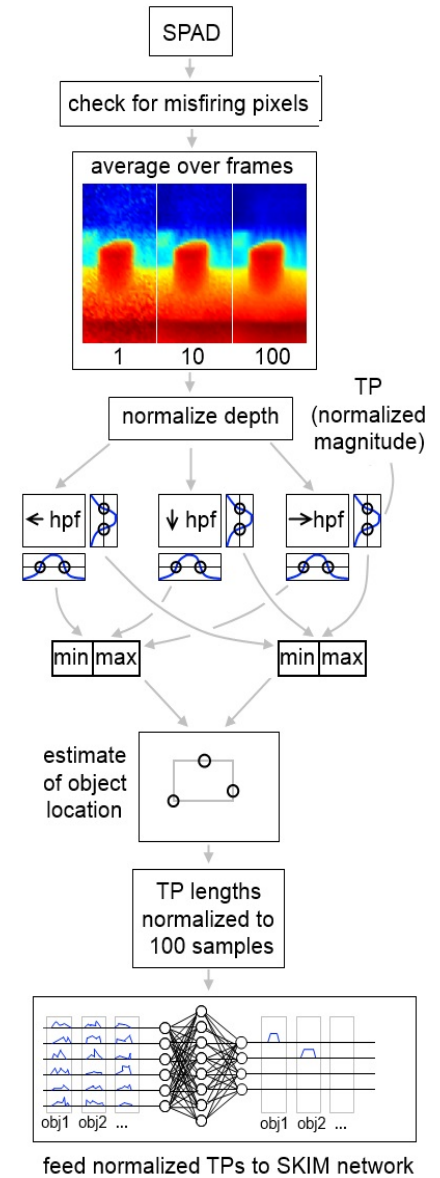
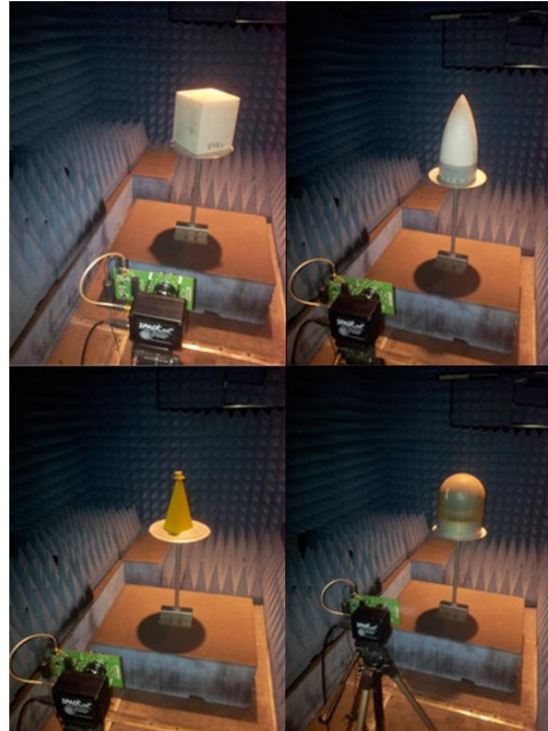
resultant shift in receptive field after multiple inter-spike interval presentations



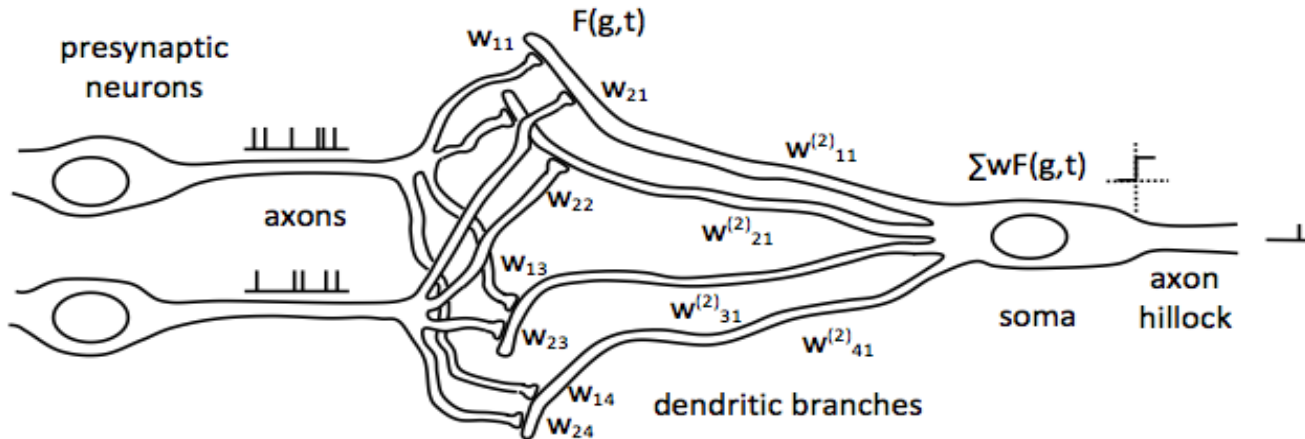
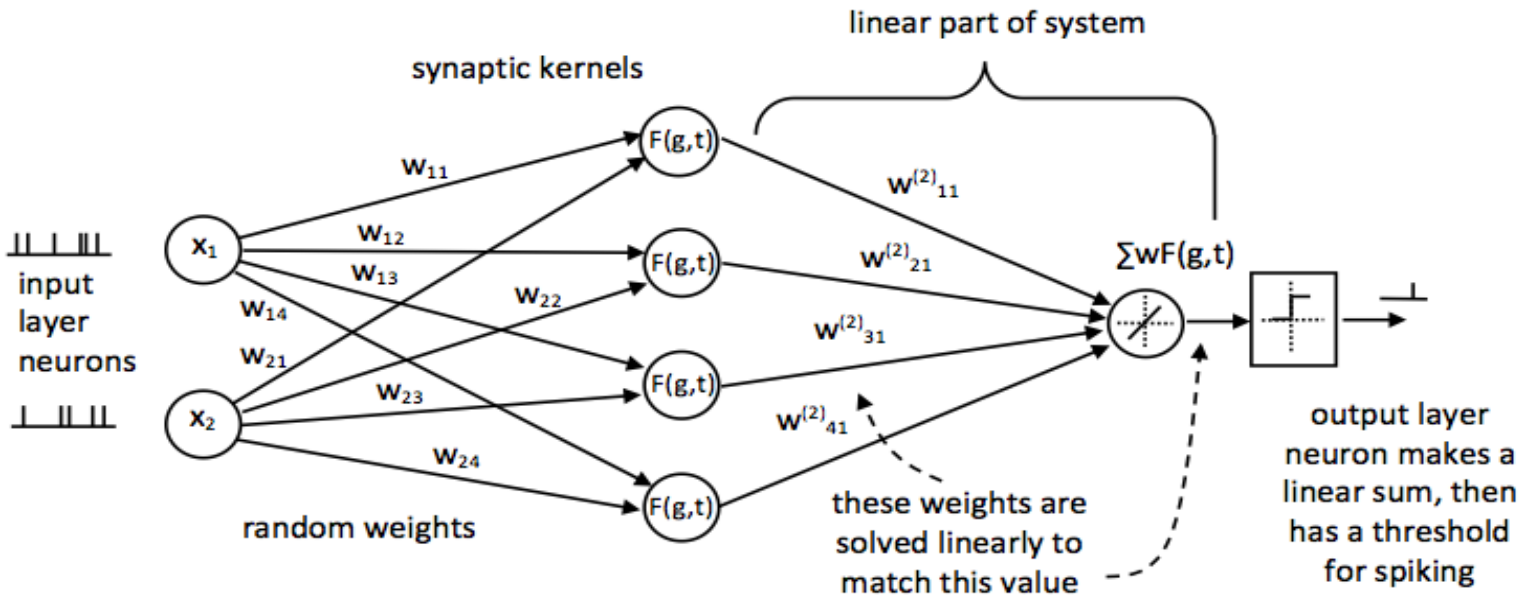
missed input spikes cause the threshold to fall thus expanding the receptive field

...eventually an input spike falls on the receptive field and the neuron spikes, the kernels adapt thus shifting the receptive field

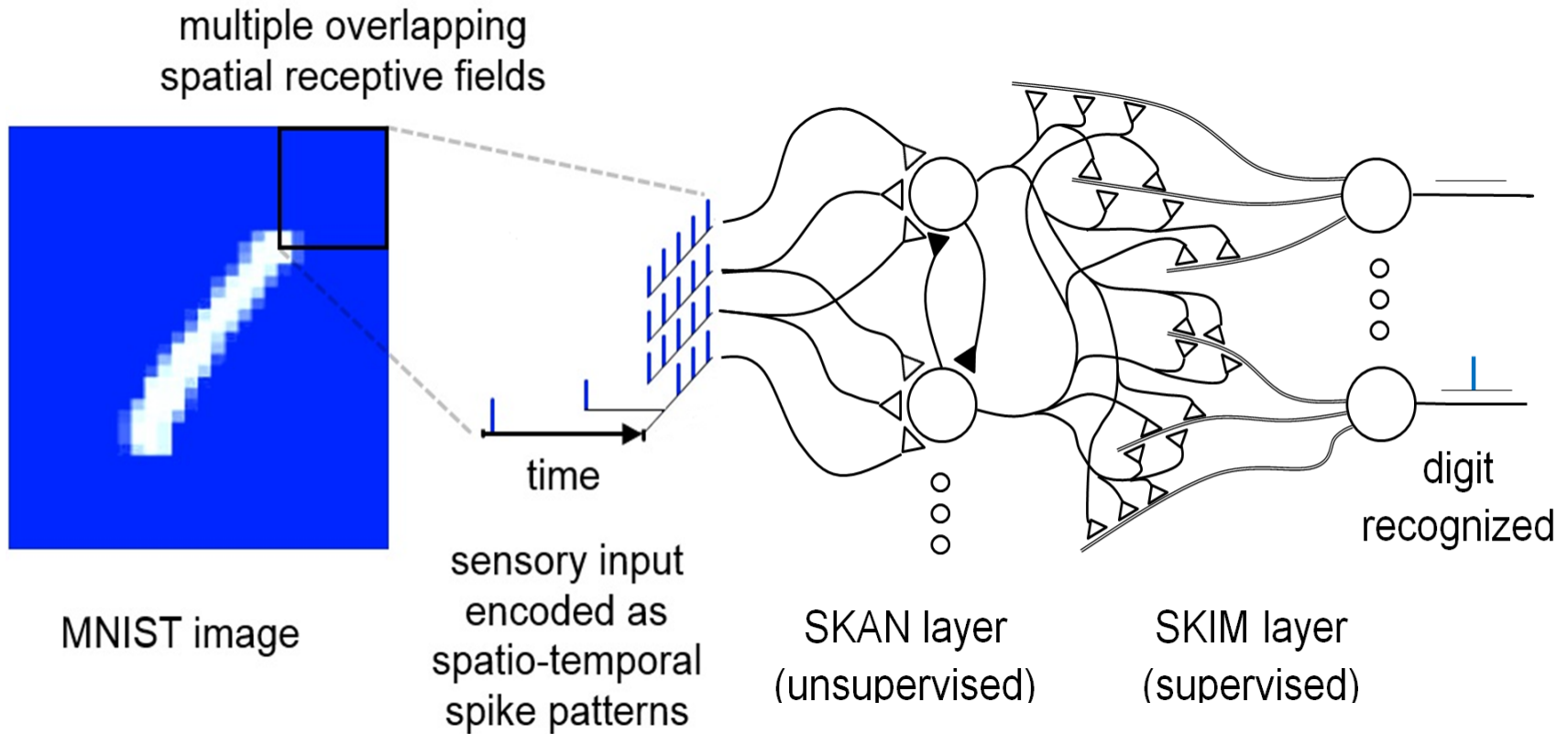
3D recognition with an ELM



3D recognition with an ELM

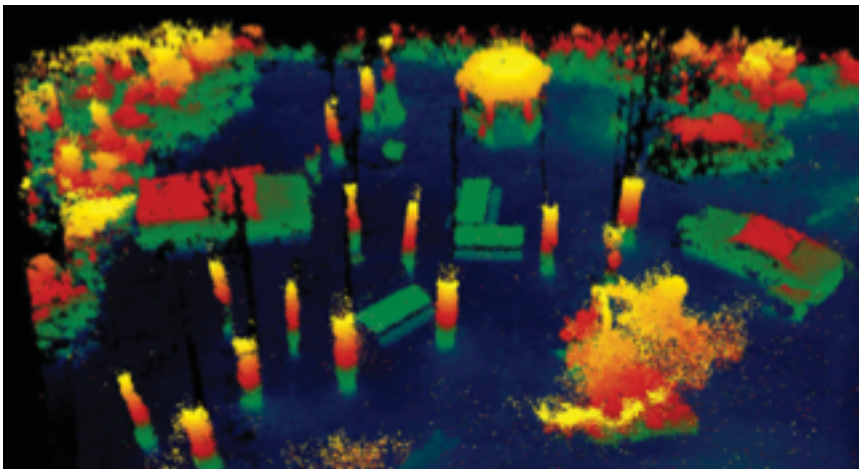
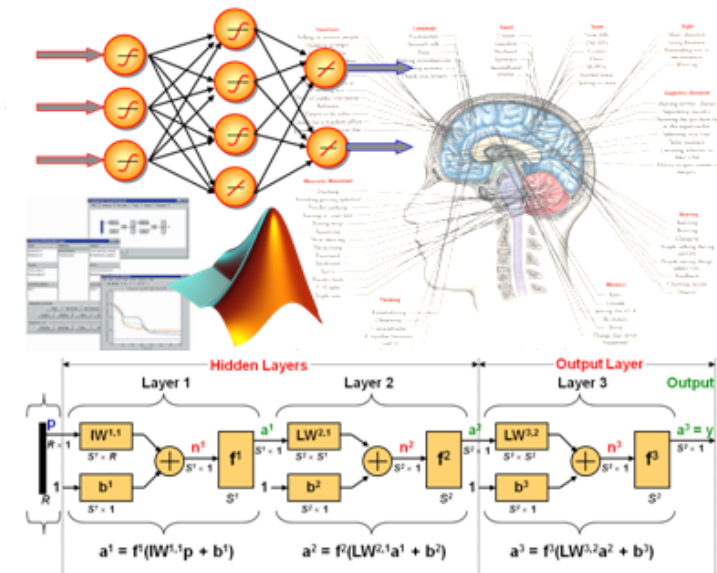
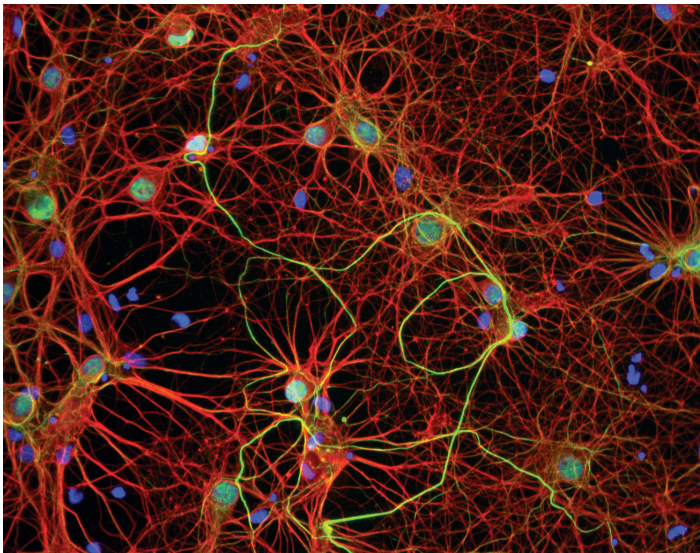


Extension to Deep Networks



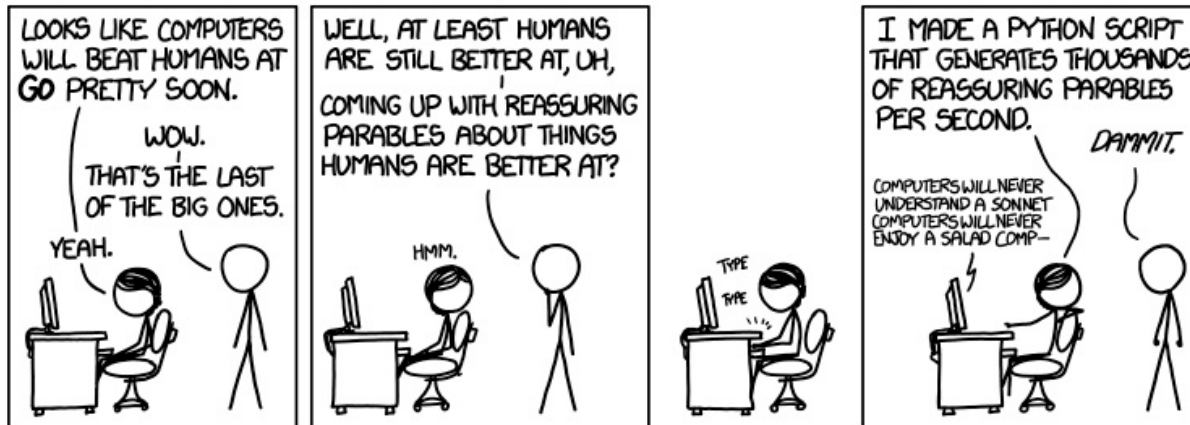
SKAN – see Afshar et al., *Frontiers in Neuroscience*, 2014

Conclusions



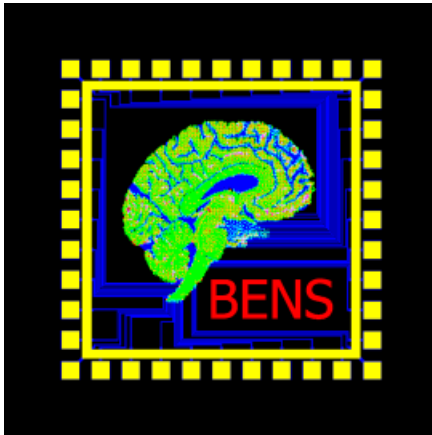
Thank you!

Reassuring

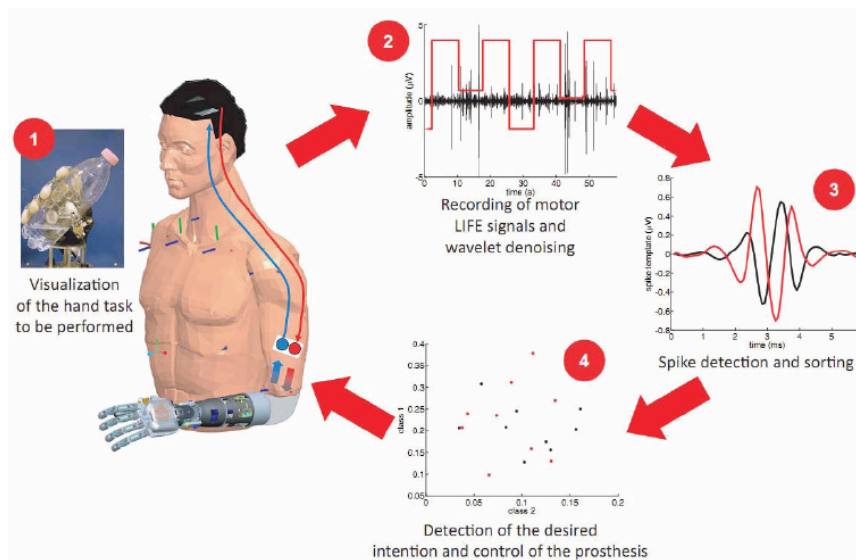
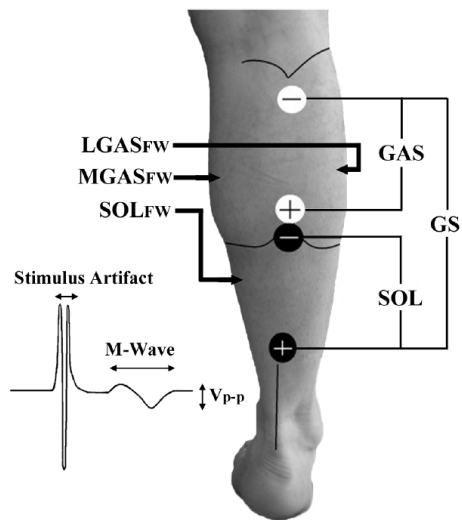
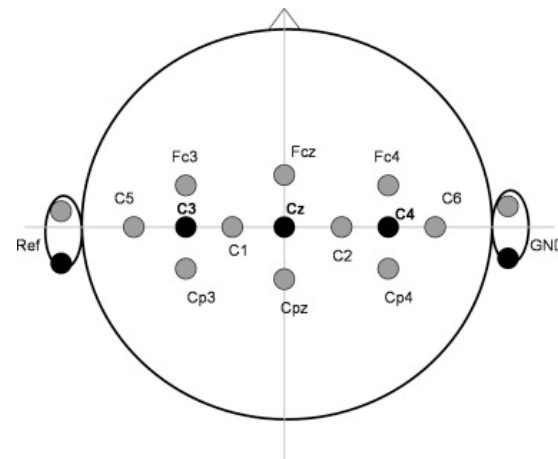
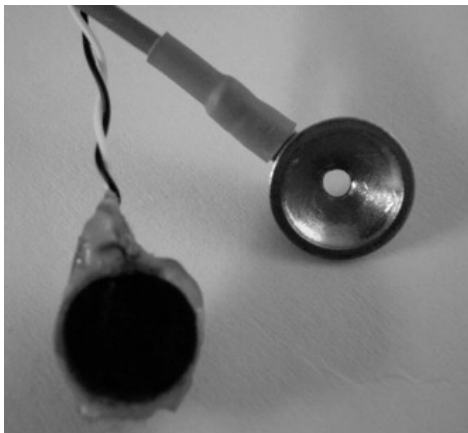
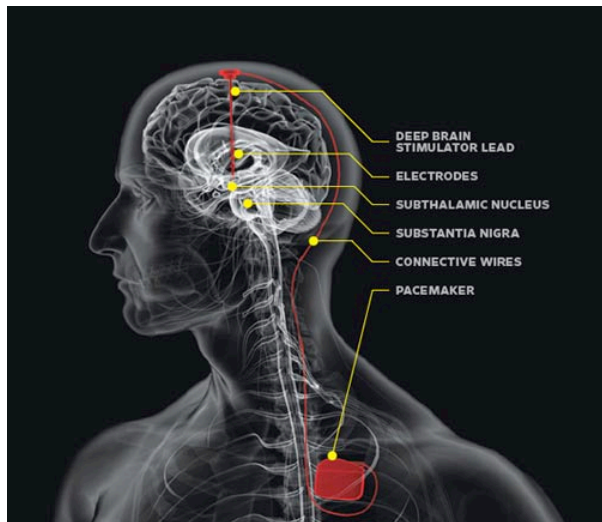


Title text: 'At least humans are better at quietly amusing ourselves, oblivious to our pending obsolescence' thought the human, as a nearby Dell Inspiron contentedly displayed the same bouncing geometric shape screensaver it had been running for years.

Acknowledgements



Saeed Afshar, PhD Student, BENS
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Mark Wang, Postdoc, BENS
André van Schaik, Professor, BENS
Jonathan Tapson, Professor, BENS
Dennis Delic, Fellow, DSTO



Recognition

