Neuromorphic Electronic Agents from sensory processing to autonomous cognitive behavior

Giacomo Indiveri

Institute of Neuroinformatics
University of Zurich and ETH Zurich

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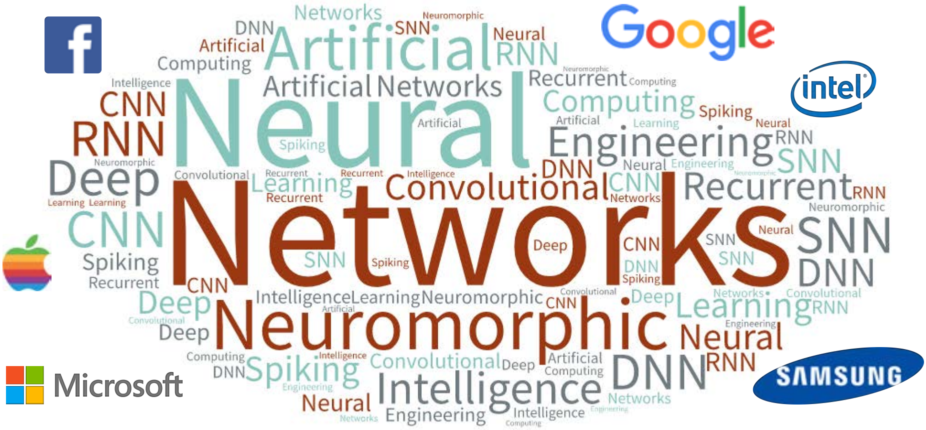
Team Work: Institute of Neuroinformatics

- Melika Payvand (INI)
- Ning Qiao (INI)
- Elisa Donati (INI)
- Yulia Sandamirskaya (INI)
- Lorenz Müller (INI)
- Manu Nair (INI)
- Dongchen Liang (INI)
- Raphaela Kreise (INI)
- Moritz Milde (INI)
- Federico Corradi (imec)
- Marc Osswald (inSightness)

- Richard George (TUD, DE)
- Dora Sumislawska (GeorgiaTech, USA)
- Fabio Stefanini (Columbia Univ., USA)
- Jonathan Binas (Univ. Montreal, CA)
- Emre Neftci (UC Irvine, USA)
- Saber Moradi (Yale, USA)
- Hesham Mostafa (UCSD, USA)
- Chiara Bartolozzi (IIT, Italy)
- Elisabetta Chicca (Univ. Bielefeld, DE)
- Walter Senn (Univ. Bern, CH)
- Stefano Fusi (Columbia Univ., USA)

Neuroinformatics and neuromorphic electronic circuits



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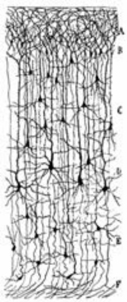

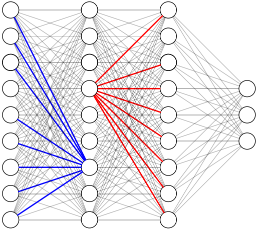

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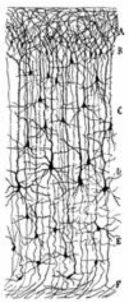

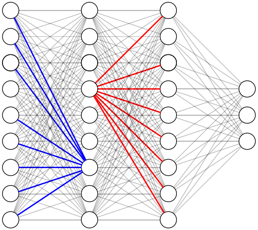

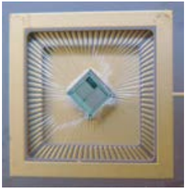

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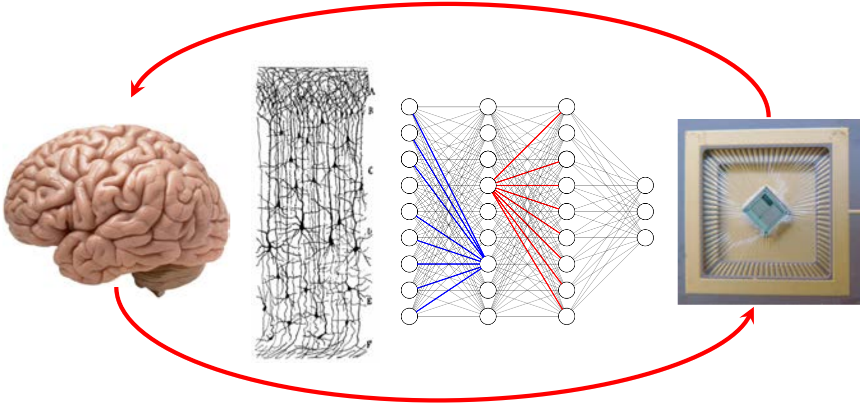
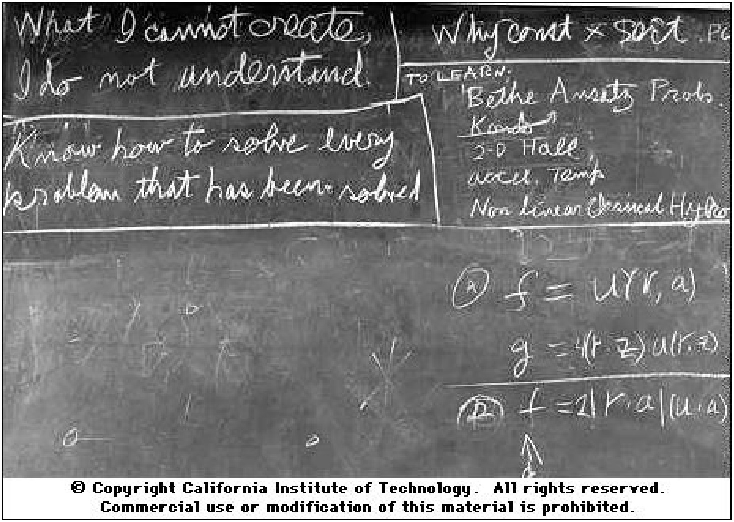


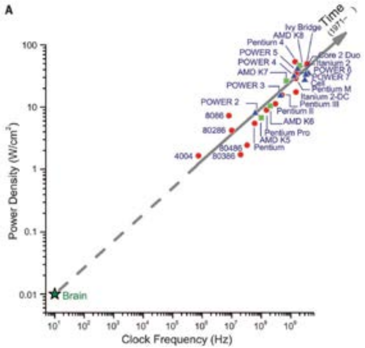
Neuroinformatics and neuromorphic electronic circuits

Understanding by building



- Build neuromorphic circuits to reverse engineer the brain.
- Reverse engineer the brain to build efficient neural processing systems.

Radical paradigm shift in computer hardware technologies



Existence proof: real brains

- Slow, noisy and variable processing elements ("speed" is not a requirement)
- Massively parallel distributed computation, local connectivity (minimize wiring)
- Real-time interaction with the environment
- Complex spatio-temporal pattern recognition

Radical paradigm shift in computer hardware technologies

1 mg weight
1 mm^3 volume
960'000 neurons
10^{-15} J/spike

Existence proof: real brains

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State-of-the-art in neuromorphic electronic circuits

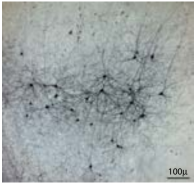
Neuromorphic "computing"

- Dedicated VLSI hardware.
- High performance computing.
- Application driven.
- Conservative approaches.

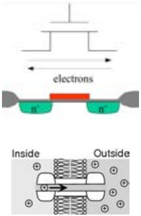
Neuromorphic engineering

- Fundamental research.
- Deeply rooted in biology.
- Emulation of neural function.
- Subthreshold analog and asynchronous digital.

Highly interdisciplinary effort

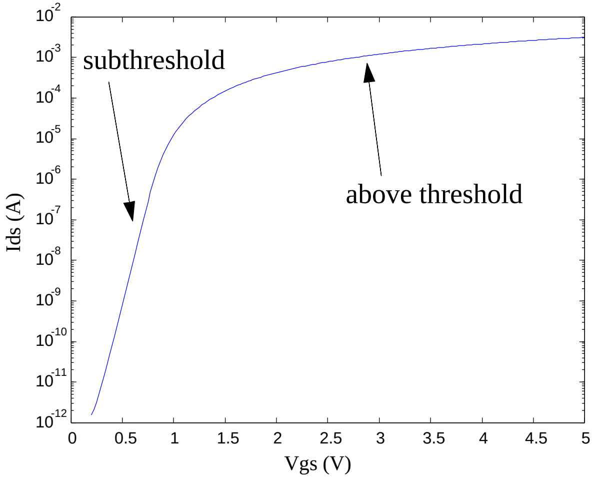


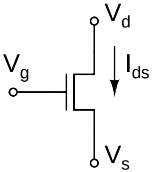
[Nuno da Costa, INI, 2008]



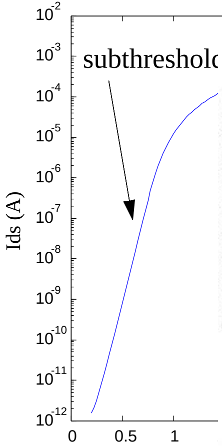
- Study fundamental neuroscience, principles of neuro-physiology, neuro-anatomy, theory of computation, electrical engineering,...
- Exploit the physics of silicon to reproduce the *bio*-physics of neural systems, using subthreshold analog VLSI circuits.
- Develop distributed multi-core spiking architectures using asynchronous digital VLSI circuits.
- Build real–time autonomous cognitive agents able to carry out behavioral tasks in complex environments.

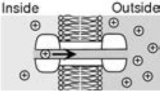
Channel current-voltage relationships





Channel current-voltage relationships





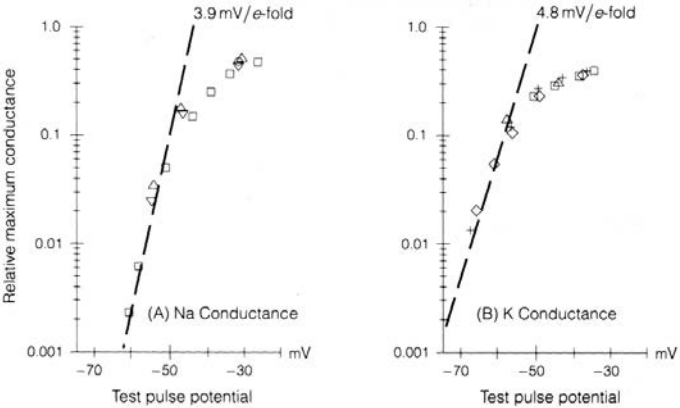
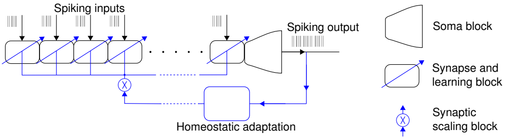
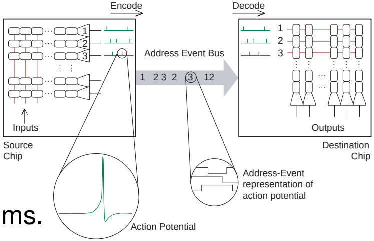


FIGURE 4.6 Exponential current–voltage characteristic of voltage-dependent channels. At high voltages, the fraction of channels that are open approaches unity, causing a saturation of the curves. (*Source:* [Hodgkin et al., 1952b, p. 464].)

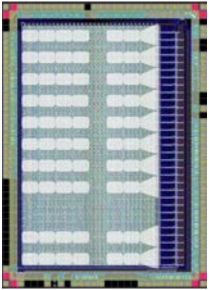
Neuromorphic processors

“Listen to the Silicon”





- Directly emulate the physics of neural systems.
- Massively parallel collections of non-linear circuits.
- Use spikes to communicate and rates to compute.
- Analog, continuous time and digital, asynchronous.
- Ultra-low power circuits (passive and self-clocked)
- Slow, inhomogeneous, imprecise, and noisy.
- Fault tolerant and mismatch insensitive by design.



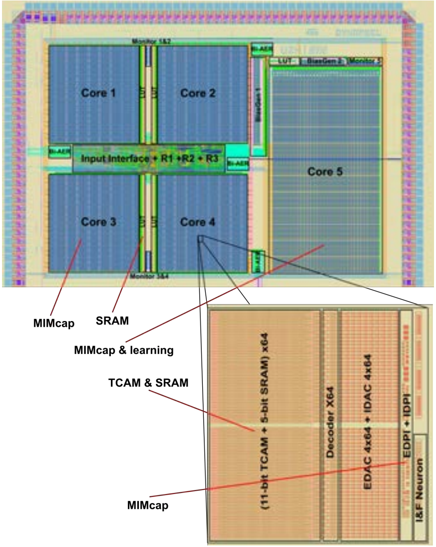
A mixed-signal neuromorphic chip

The DYnamic Neuromorphic Asynchronous Processor (DYNAP)

- Analog and digital co-design
- On-chip inference and learning
- Distributed SRAM and TCAM memory cells
- Capacitors for state dynamics

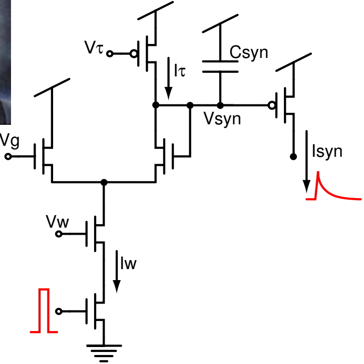
- Ideal for integration with (binary) resistive memories
- Ideal for integration with (learning) memristive devices
- Ideal for integration in 3D VLSI technology

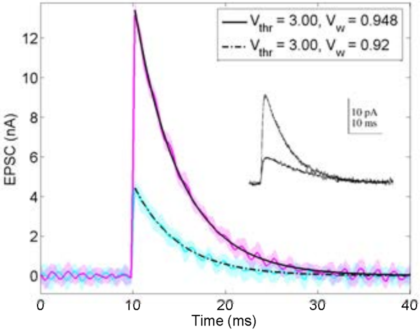
[Qiao and Indiveri, 2016],[EU ICT NeuRAM3 (687299) project]



Analog circuits

Direct emulation of synaptic dynamics



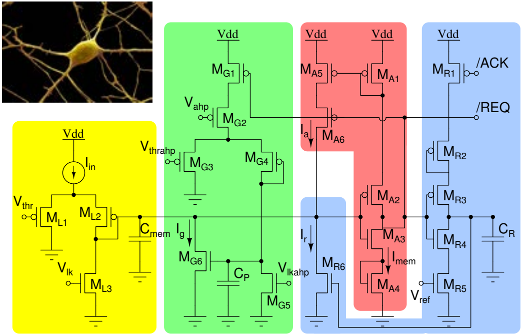


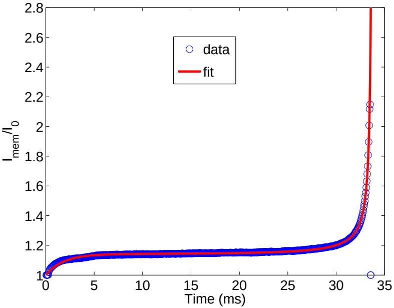
$$\boxed{\tau \frac{d}{dt} I_{syn} + I_{syn} = \frac{I_{thr} I_w}{I_\tau}}$$

[Bartolozzi and Indiveri, 2007]

Analog circuits

A low power silicon neuron





$$\tau \frac{d}{dt} I_{mem} + I_{mem} \approx \frac{I_{th} I_{in}}{I_{\tau}} - I_g + f\left(I_{mem}\right)$$

$$\tau_{ahp} \frac{d}{dt} I_g + I_g = \frac{I_{thr} I_{ahp}}{I_{\tau_{ahp}}}$$

[Indiveri et al., ISCAS 2010]

Analog circuits

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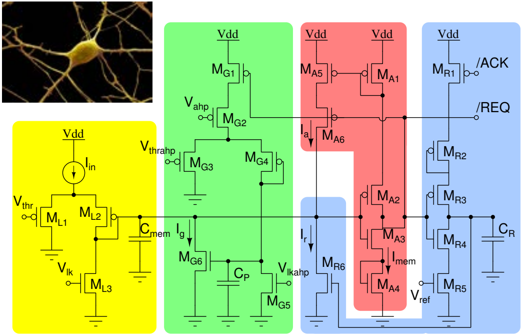

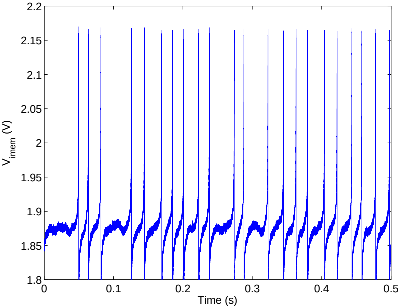

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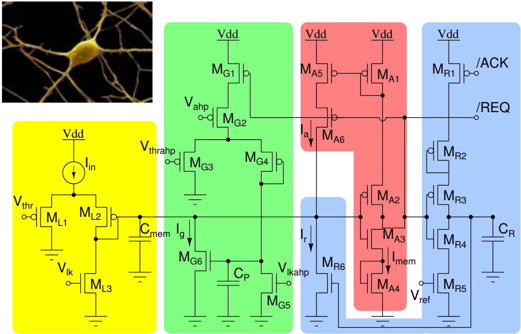

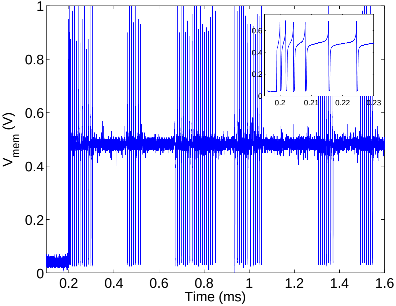

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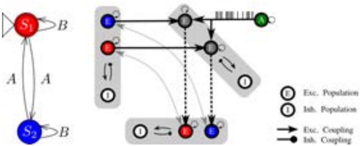
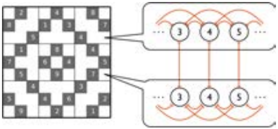
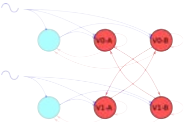
Neuromorphic processor application examples







- Spike-based learning, Spike-Timing Dependent Plasticity [Indiveri, NIPS 2003]
- Short-term and homeostatic plasticity [Chicca et al., P. IEEE 2014], [Qiao et al, TBCAS 2017]
- Supervised and unsupervised learning [Mitra et al., TBCAS 2009], [Kreise et al. BioCAS 2017]
- Inference, cue integration, function approximation [Corneil et al., IJCNN 2012]
- Context- and state-dependent behavior [Neftci et al., PNAS 2013]
- Perceptual bi-stability, decision making [Corradi et al., ISCAS 2015]
- Stochastic computing [Binas et al., ISCAS 2016], [Mostafa et al., Neural Comp., 2014, Nature Comm., 2015]
- Convolutional networks and pattern classification [Qiao et al, Frontiers 2015, IEDM 2015]
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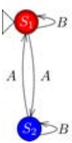
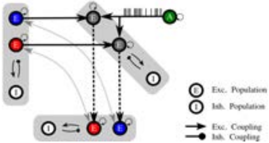
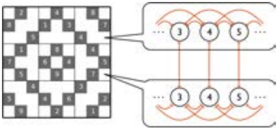
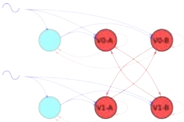
Neuromorphic processor application examples









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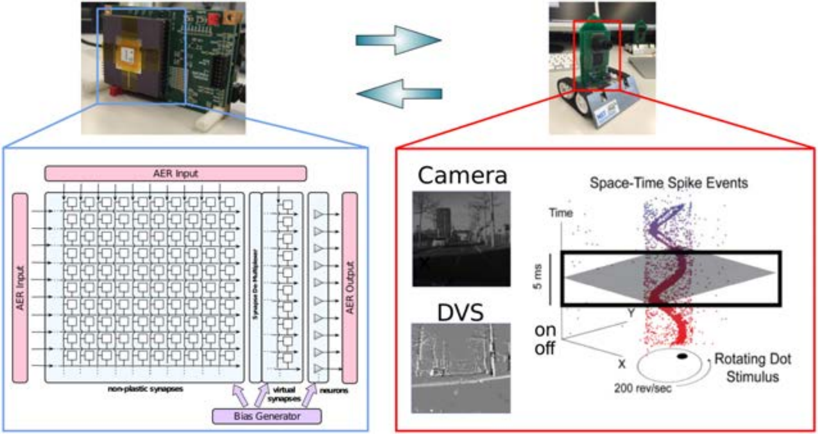
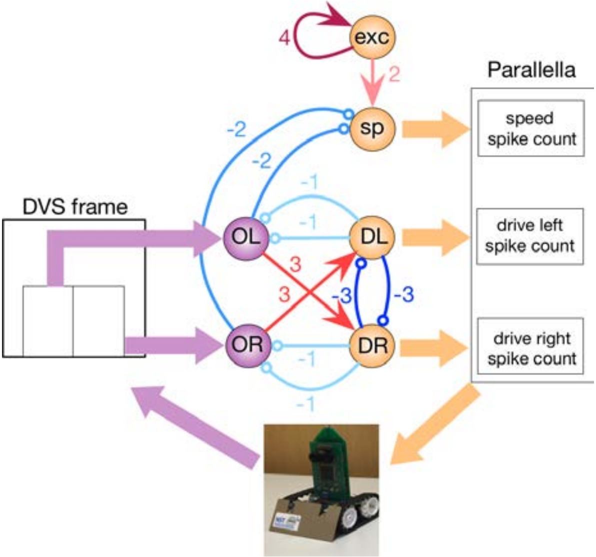
Connecting neuromorphic processors to neuromorphic sensors and robots

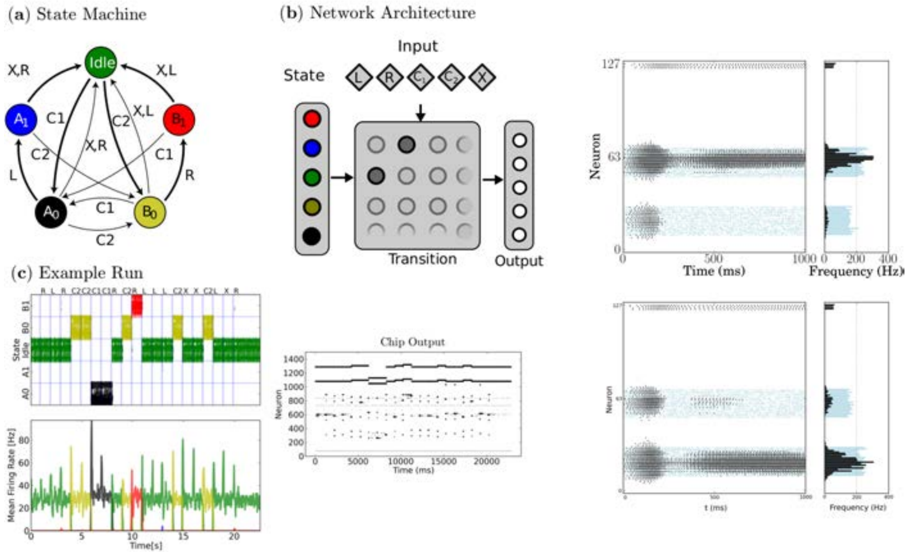


Real-time autonomous behaving agents



[Milde et al. Frontiers, 2017]

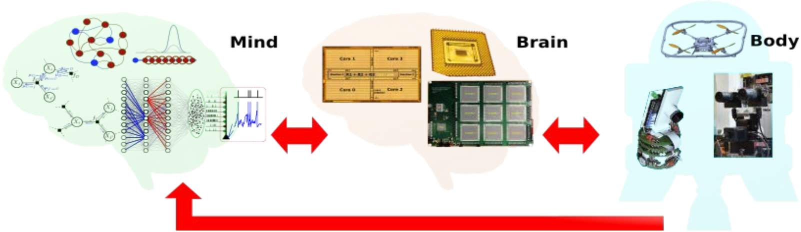
Synthesizing behavior into cognitive agents



[Liang & Indiveri, BioCAS 2017][Neftci et al., PNAS 2013]

Putting it all together

Future outlook



Main research objective

- *Listen to the silicon*: Exploit the physics of semiconductors *and dielectric solid-state materials* to implement “efficient” neural computation (minimum volume and power).
- Understand how to implement neural network and computational neuroscience models in low-power neuromorphic electronic systems for building autonomous agents that can interact intelligently with the environment.

Expected outcome

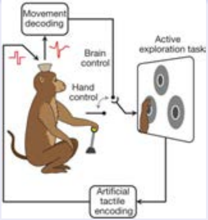
Neuromorphic cognitive systems

- Context dependent learning and processing in real-time hardware
- Working memory and decision making in real-time autonomous systems
- Autonomous cognitive agents that can be "programmed" to carry out procedural tasks

Application areas

Autonomous sensory-motor systems

Embedded systems & emerging memory technologies



Brain machine interfaces and prosthetics

Funding sources

erc

ICT H2020

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SWISS NATIONAL SCIENCE FOUNDATION

aiCTX

institute of neuroinformatics

The end

Thank you for your attention