FROM RESEARCH TO INDUSTRY

cea tech

Neuromophic computing: A new paradigm, Or just an old story?

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Outline

- Short Intro, who are we?
- What is a computing engine?
- The computing paradigm tryptic
- Roadblocks on (Std) computing roadmaps
- What can be done?
- Can we change the computing paradigm?
- Neuromorphic computing with novel devices
- Is it feasible? Can it compute?
- Wrap up, What's up

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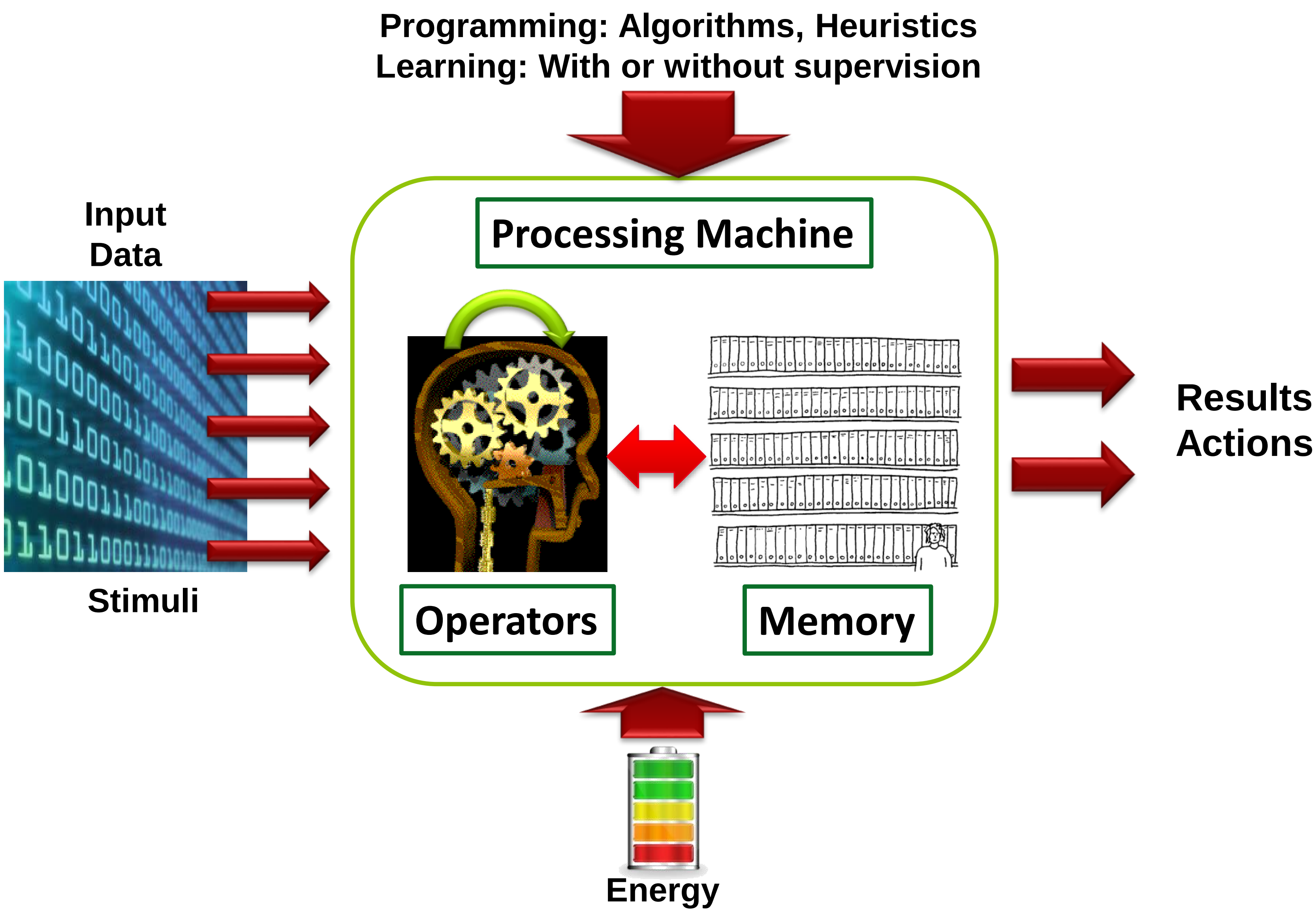
Preamble: Information Processing



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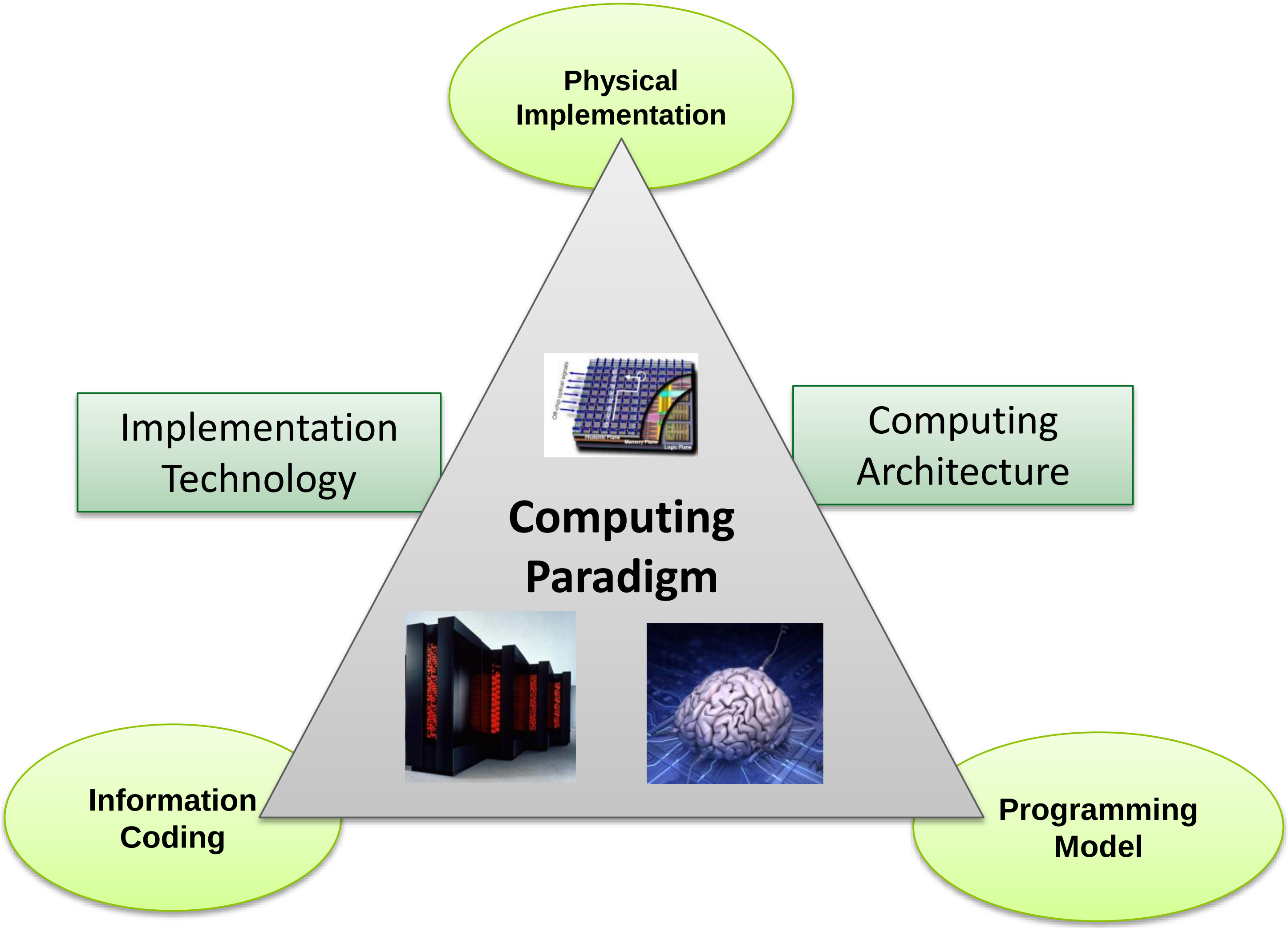
Preamble: The Information Processing Tryptic



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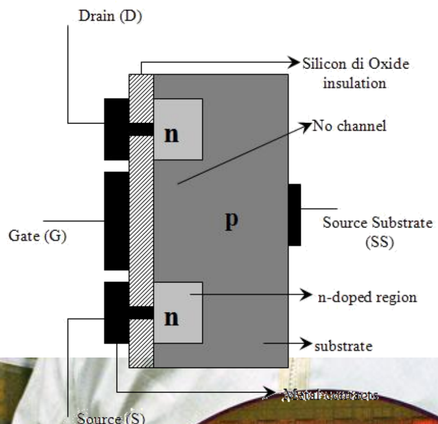
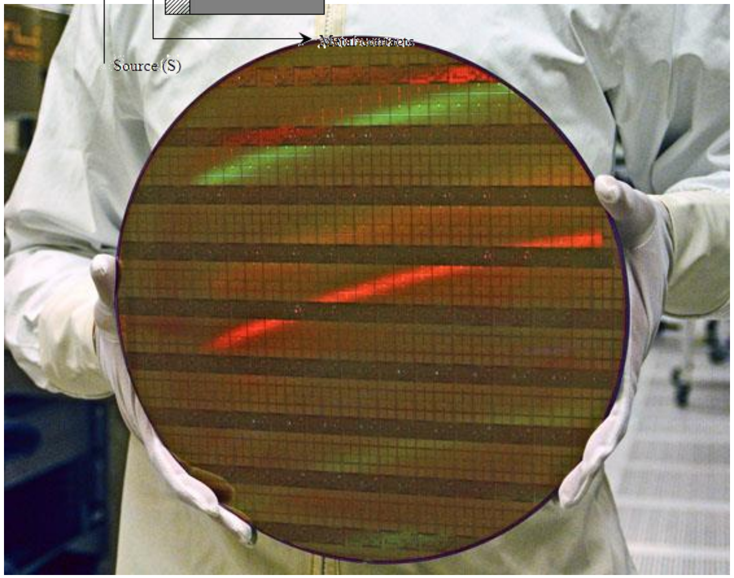
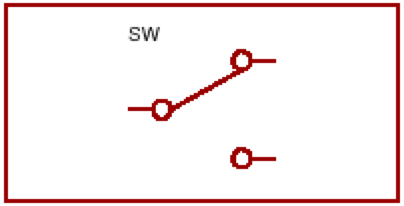
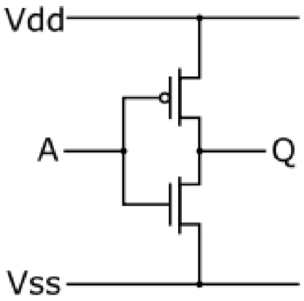
Bit (0,1) and CMOS technology

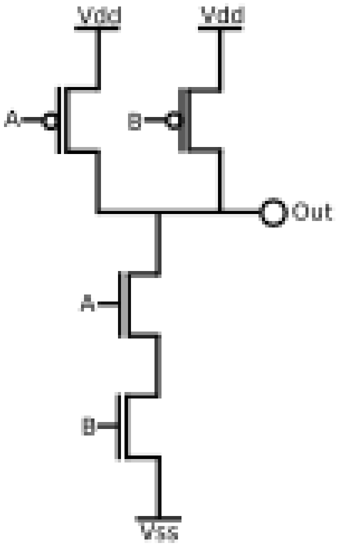
- **Complementary Metal Oxyde Semiconductor**
- **A pretty good switch (bit)**











CMOS inerter (up)
NAND gate (left)
(The function semantics is hardcoded into the circuit layout)

(source wikipedia)

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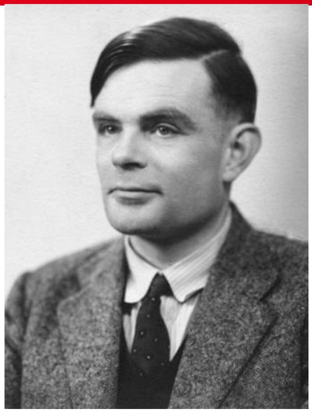
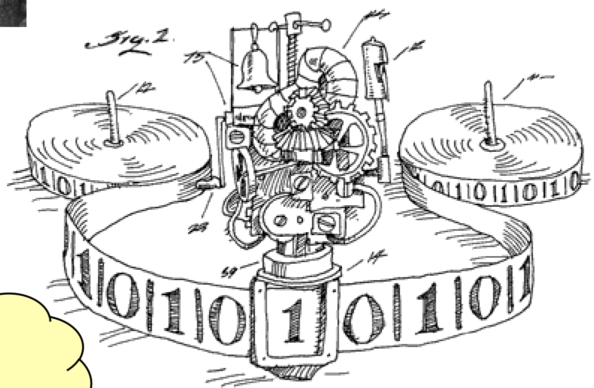
Von Neumann Architecture



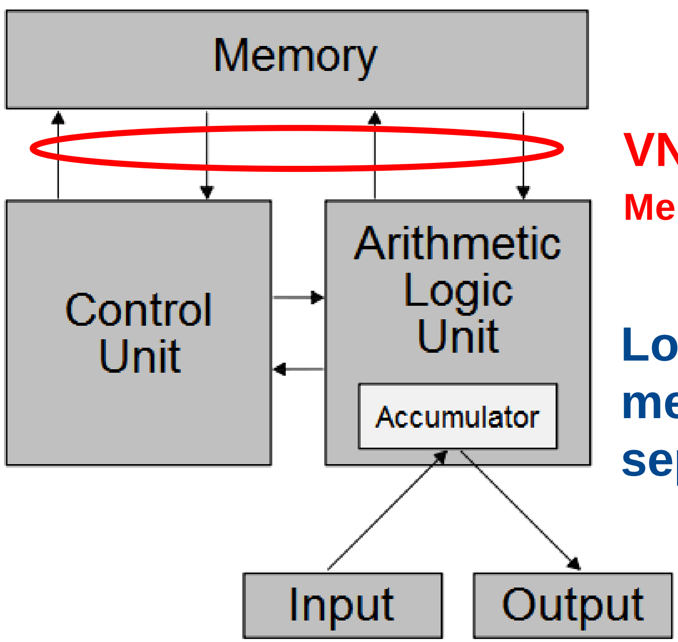
Alan Turing

- **The Von Neumann architecture is an implementation of Turing’s machine**
- **Together with the idea of program stored in memory, the V.N. architecture automates computing tasks**



Why did they name this after me?

John Von Neumann



VN bootleneck

Memory access

Logic and memory are separated

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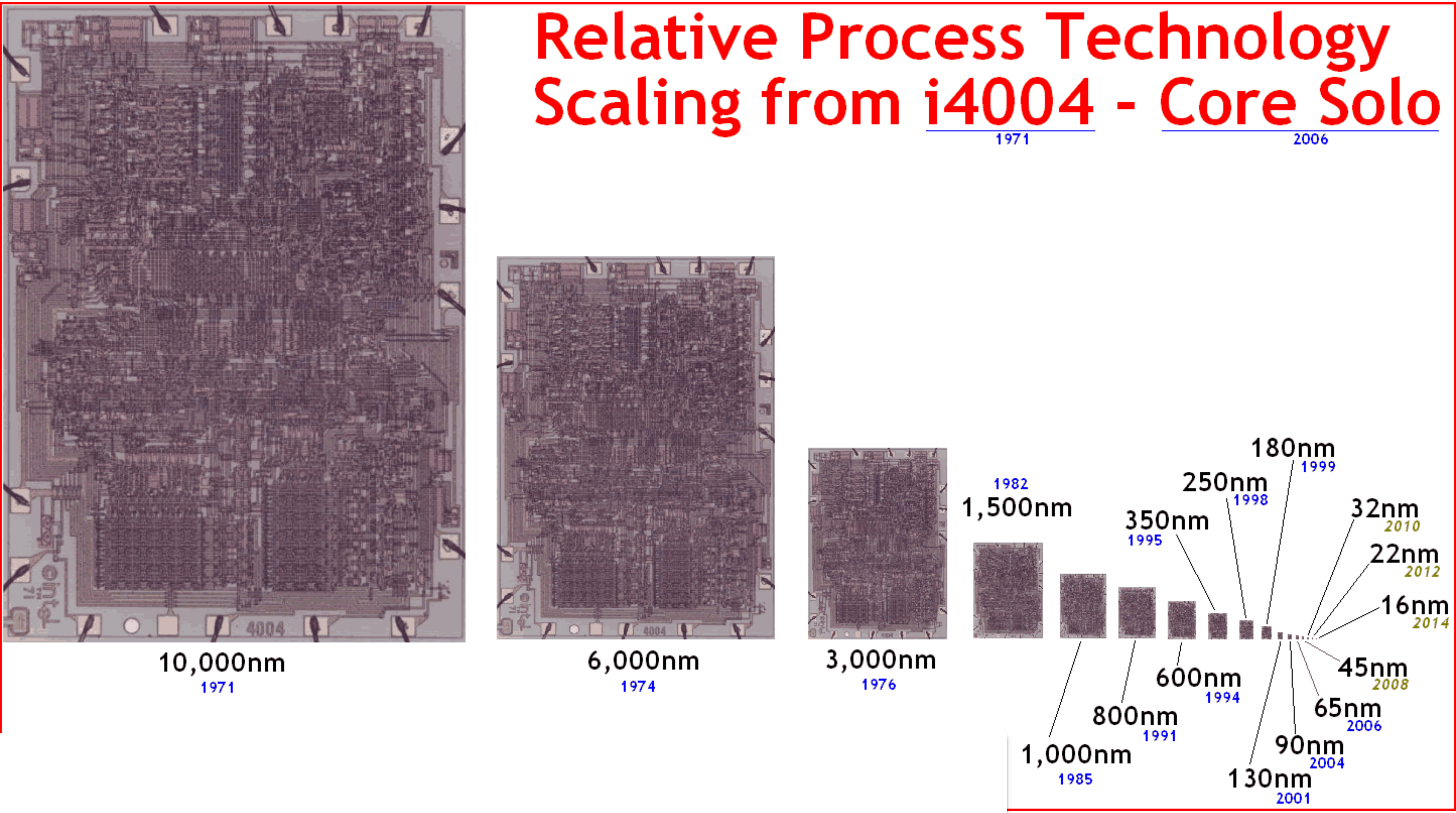
Microprocesors shrinks



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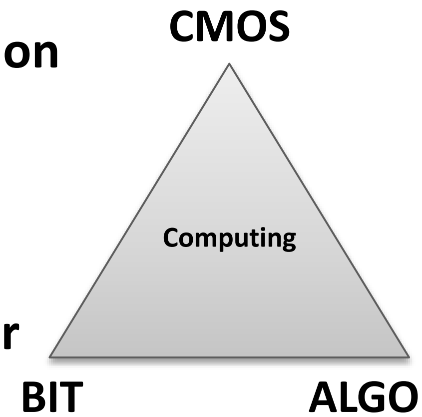
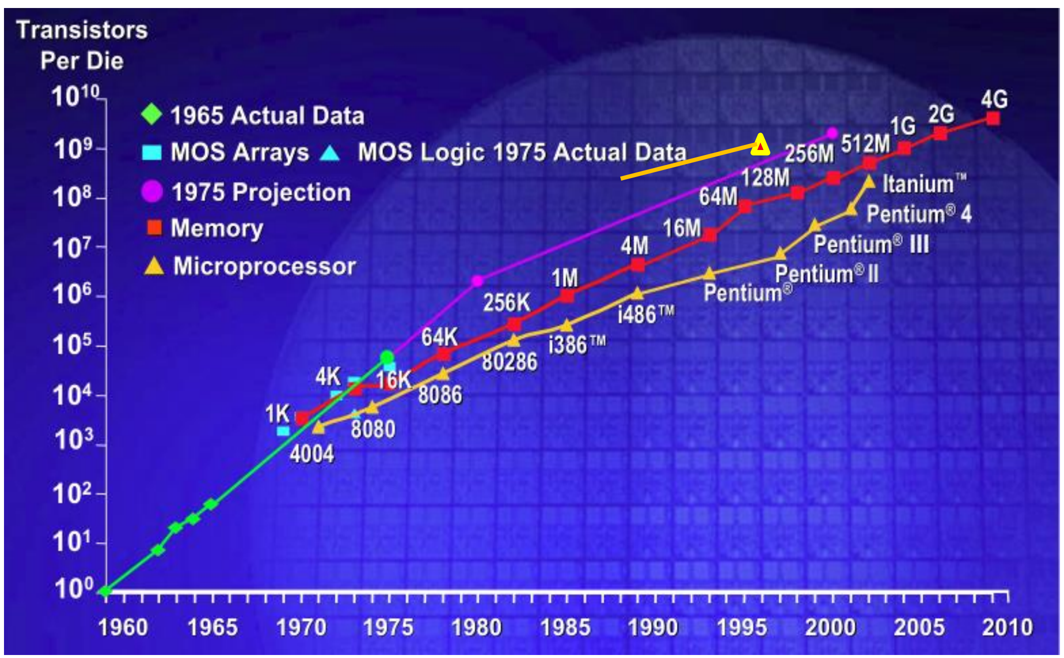
The CMOS VN triangle

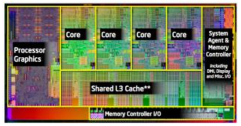
- The « quasi » perfect fit between binary coding, CMOS technology and the VN architecture made for the rapid evolution of computers.
- Every shrinking step allowed for « free » improvements in performances: clock increase, power decrease…
- If this is still true, it's at the price of clever tricks that have their share of problems: reducing Vdd, number of cores

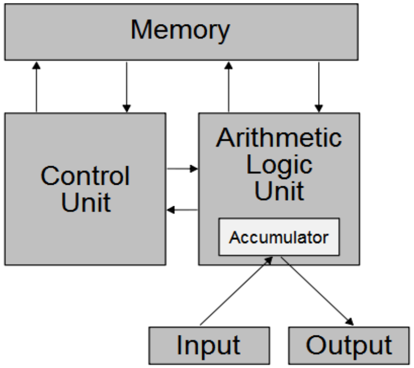


Gordon Moore



Intel Sandy Bridge 32 nm
1 Milliard de Transistors
4 coeurs





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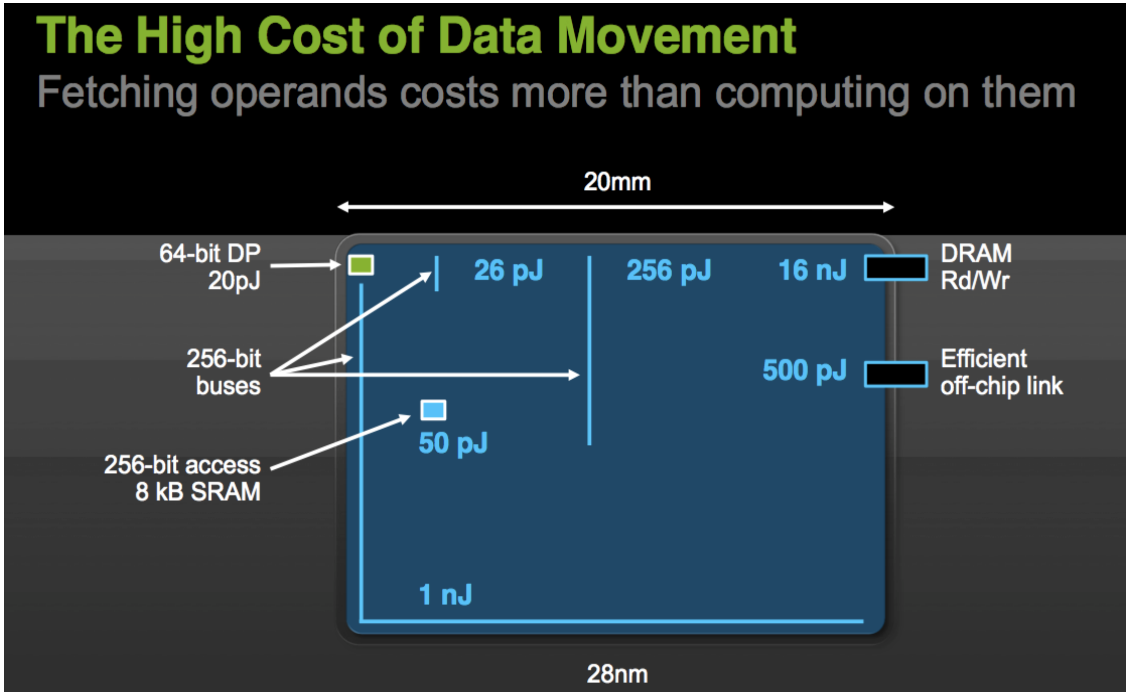
The cost of data movements

- **With 22nm CMOS**
  - The cost of **switching** 1 bit in a transistor is approximately **10^{-18} joule**
  - The cost of **moving** 1 bit on a wire is approximately **10^{-12} joule / mm**
  - Moving a 64 bits word on a 1cm bus @1GHz requires **0.64 W/cm!**
- <u>**Moving data requires much more energy than computing!**</u>



Source: Bill Dally, « To ExaScale and Beyond »
www.nvidia.com/content/PDF/sc_2010/theater/Dally_SC10.pdf

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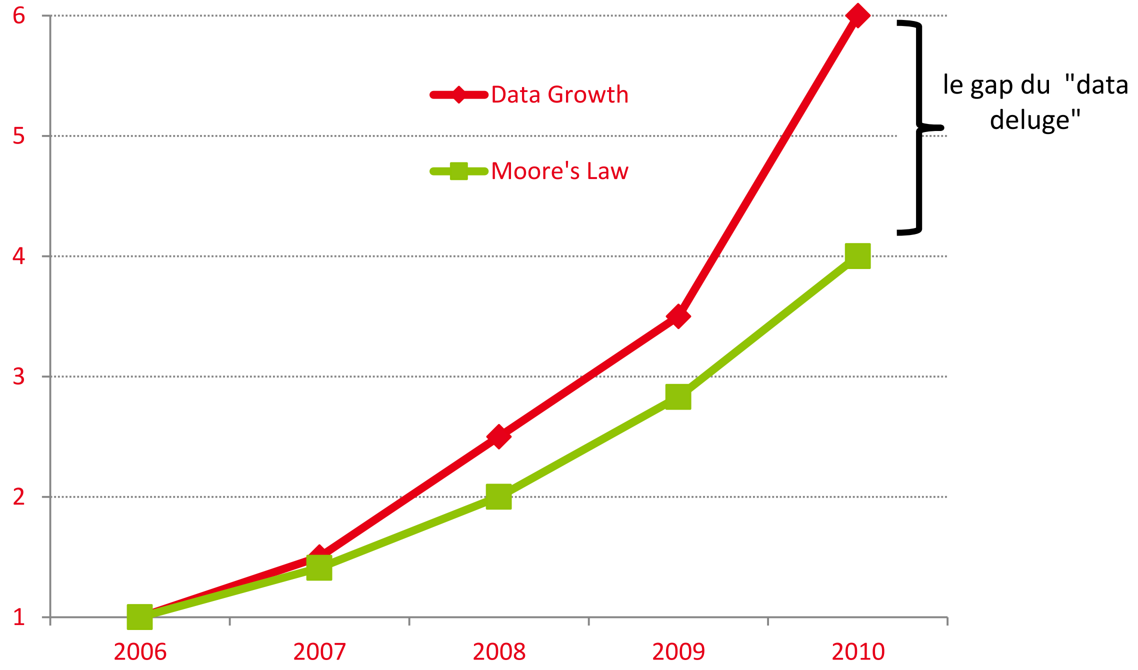
Data deluge

- In 2010 (a long time ago) the world generated more than 1.2 zetta bytes (10^{21}) of new data
- -> 50% more that all data previously generated, and we're in 2015!!!
- The amount of data increases faster that the computing power

1 ZO = 1 DVD stack 300000 km high

1 DVD ~ 5 GB



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OK, What can be done then

Could we imagine something different? another paradigm?

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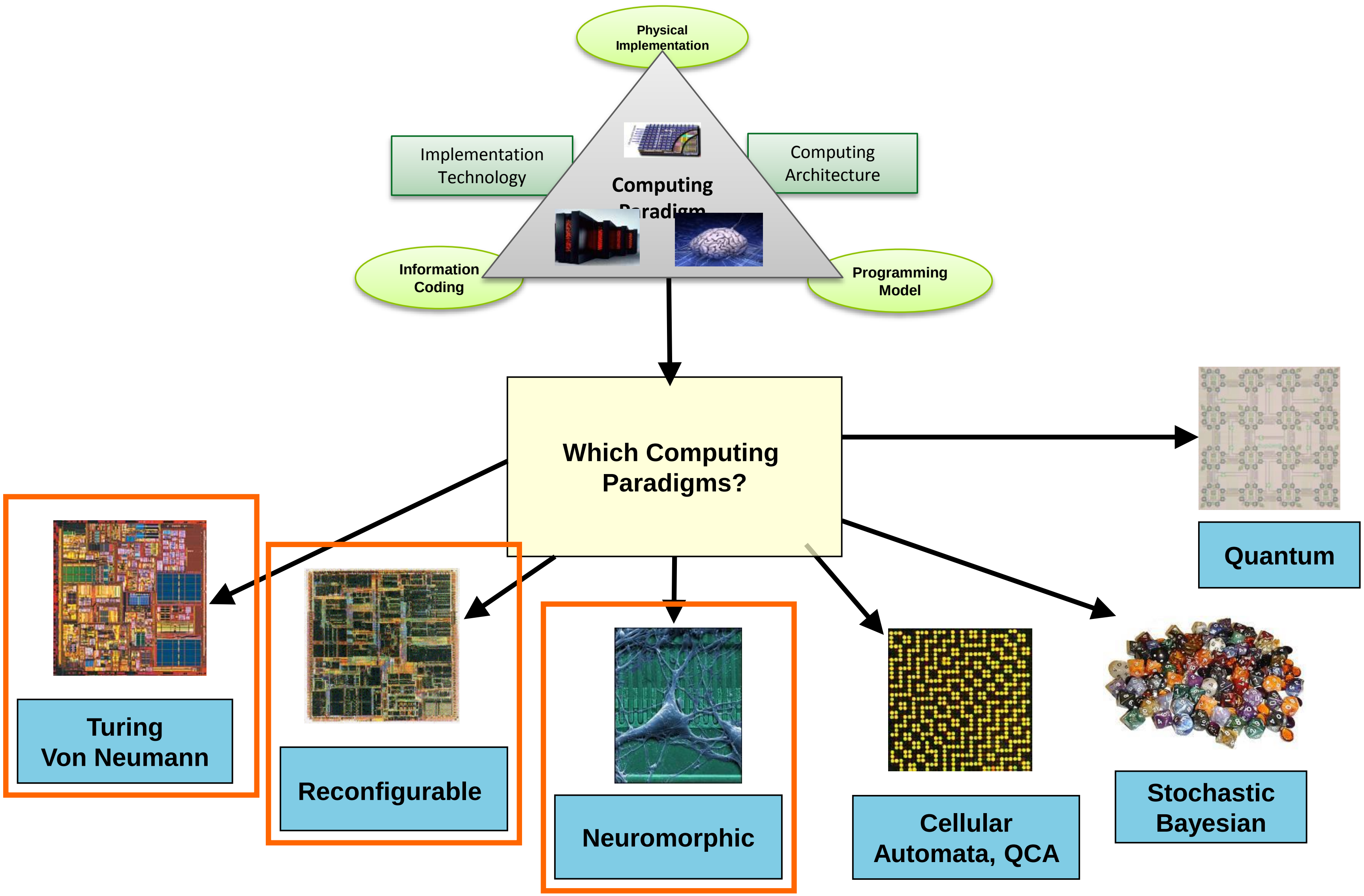
Which Computing Paradigm?



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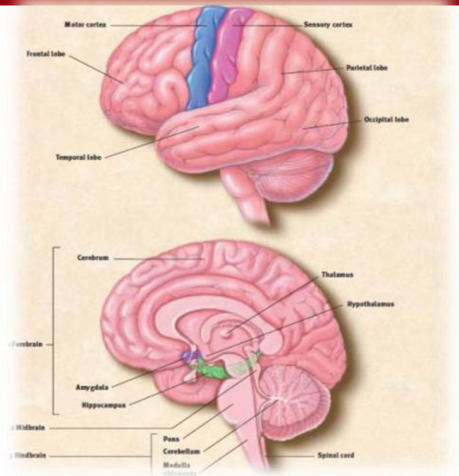
Neuromorphic Computing



- **Parallélisme Massif**
- **Passage à l'échelle (scalability)**
- **Très faible puissance**
- **Tolérance à la variabilité**
- **Idéal pour le traitement des informations naturelles**
- **D'importants programmes de recherche sont en cours: FET-FlagShip Human Brain Project**

1.1×10^4

1.5×10^7

6.2×10^9

1.1×10^{10}

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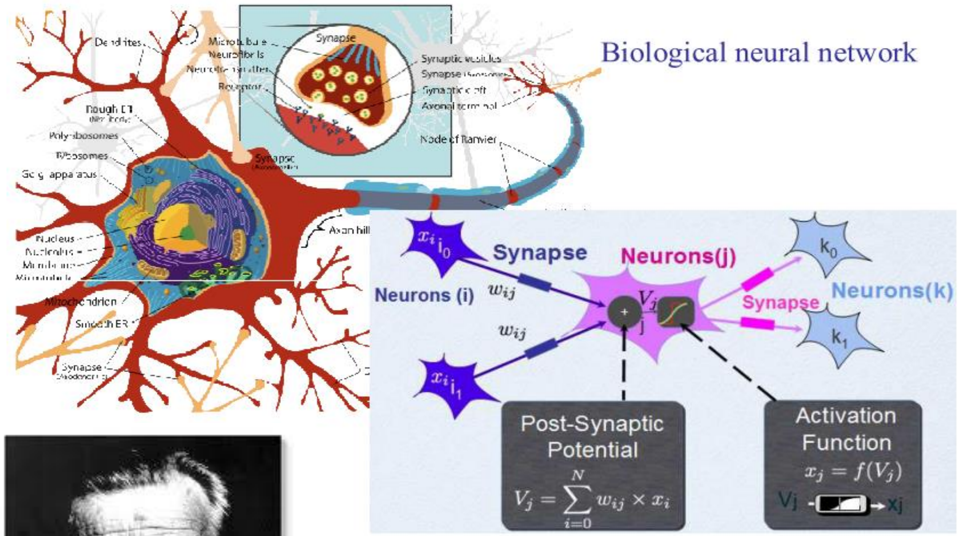
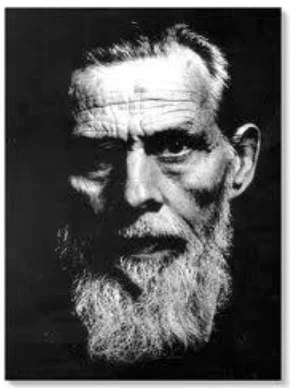
Neuromorphic Computing, an old story!



Artificial neural network

[1] W. S. McCulloch and W. Pitts, “A logical calculus of the ideas immanent in nervous activity,” Bull. Math. Biophysics, no. 5, pp. 115-133, **1943**.



Warren McCulloch

Walter Pitts

deas Immanent in Nervous Activity

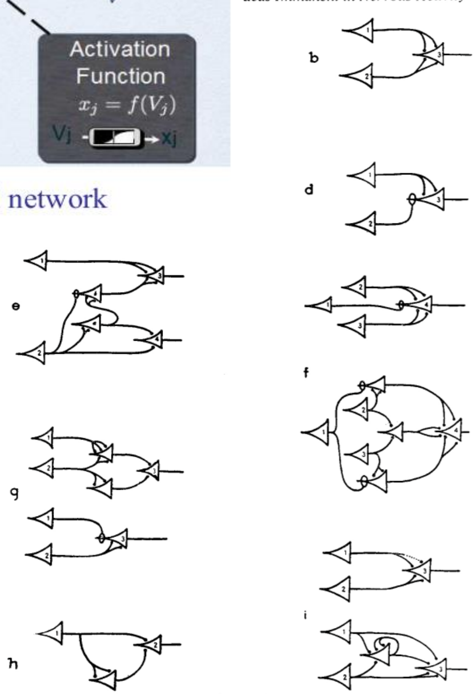


FIGURE 1

A Logical Calculus of Ideas Immanent in Nervous Activity

observations and of these to the facts is all too clear, for it is apparent that every idea and every sensation is realized by activity within that net, and by no such activity are the actual afferents fully determined.

There is no theory we may hold and no observation we can make that will retain so much as its old defective reference to the facts if the net be altered. Tinnitus, paraesthesias, hallucinations, delusions, confusions and disorientations intervene. Thus empiry confirms that if our nets are undefined, our facts are undefined, and to the “real” we can attribute not so much as one quality or “form.” With determination of the net, the unknowable object of knowledge, the “thing in itself,” ceases to be unknowable.

To psychology, however defined, specification of the net would contribute all that could be achieved in that field—even if the analysis were pushed to ultimate psychic units or “psychons,” for a psychon can be no less than the activity of a single neuron. Since that activity is inherently propositional, all psychic events have an intentional, or “semiotic,” character. The “all-or-none” law of these activities, and the conformity of their relations to those of the logic of propositions, insure that the relations of

← **EXPRESSION FOR THE FIGURES**

In the figure the neuron c_i is always marked with the numeral i upon the body of the cell, and the corresponding action is denoted by ‘N’ with i as subscript, as in the text.

Figure 1a $N_2(t) . \equiv . N_1(t-1)$
Figure 1b $N_3(t) . \equiv . N_1(t-1) \vee N_2(t-1)$
Figure 1c $N_3(t) . \equiv . N_1(t-1) . N_2(t-1)$
Figure 1d $N_3(t) . \equiv . N_1(t-1) . \sim N_2(t-1)$
Figure 1e $N_3(t) : \equiv : N_1(t-1) . \vee . N_2(t-3) . \sim N_2(t-2)$
$N_4(t) . \equiv . N_2(t-2) . N_2(t-1)$
Figure 1f $N_4(t) : \equiv : \sim N_1(t-1) . N_2(t-1) \vee N_3(t-1) . \vee . N_1(t-1) . N_2(t-1) . N_3(t-1)$
$N_4(t) : \equiv : \sim N_1(t-2) . N_2(t-2) \vee N_3(t-2) . \vee . N_1(t-2) . N_2(t-2) . N_3(t-2)$
Figure 1g $N_3(t) . \equiv . N_2(t-2) . \sim N_1(t-3)$
Figure 1h $N_2(t) . \equiv . N_1(t-1) . N_1(t-2)$
Figure 1i $N_3(t) : \equiv : N_2(t-1) . \vee . N_1(t-1) . (Ex)t-1 . N_1(x) . N_2(x)$

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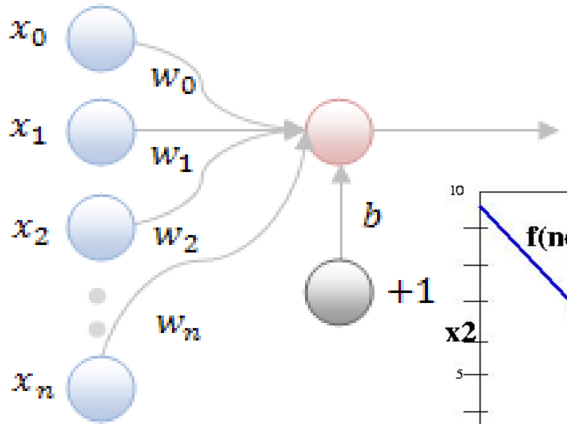
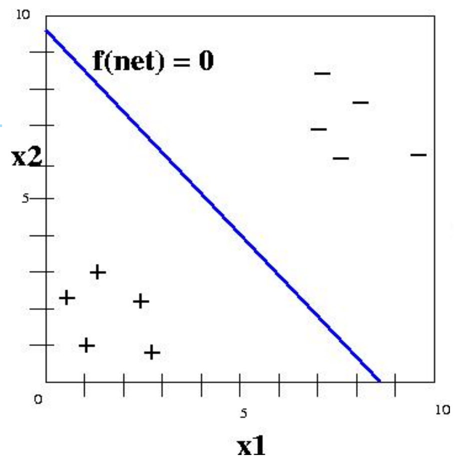
Perceptron: first neuromorphic engine





[1] F. Rosenblatt, “The perceptron: a probabilistic model for information storage and organization in the brain.,” Psychological Review, vol. 65, no. 6, pp. 386-408, **1958**.

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN [1]

F. ROSENBLATT
Cornell Aeronautical Laboratory

If we are eventually to understand the capability of higher organisms for perceptual recognition, generalization, recall, and thinking, we must first have answers to three fundamental questions:

1. How is information about the physical world sensed, or detected, by the biological system?
2. In what form is information stored, or remembered?
3. How does information contained in storage, or in memory, influence recognition and behavior?

and the stored pattern. According to this hypothesis, if one understood the code or "wiring diagram" of the nervous system, one should, in principle, be able to discover exactly what an organism remembers by reconstructing the original sensory patterns from the "memory traces" which they have left, much as we might develop a photographic negative, or translate the pattern of electrical charges in the "memory" of a digital computer. This hypothesis is appealing in its simplicity and ready intelligibility, and a large family of theoretical brain

Frank Rosenblatt

(Robert Hecht-Nilsen: Neurocomputing, Addison-Wesley, 1990)

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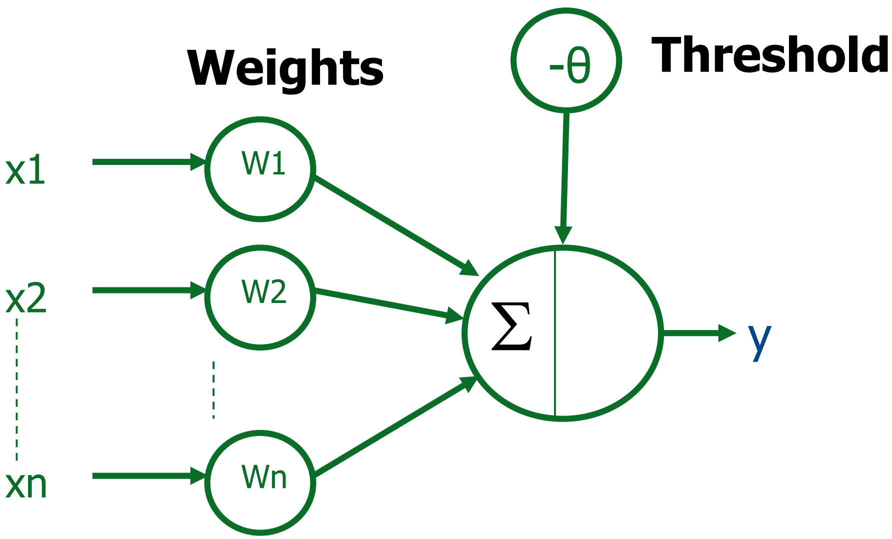
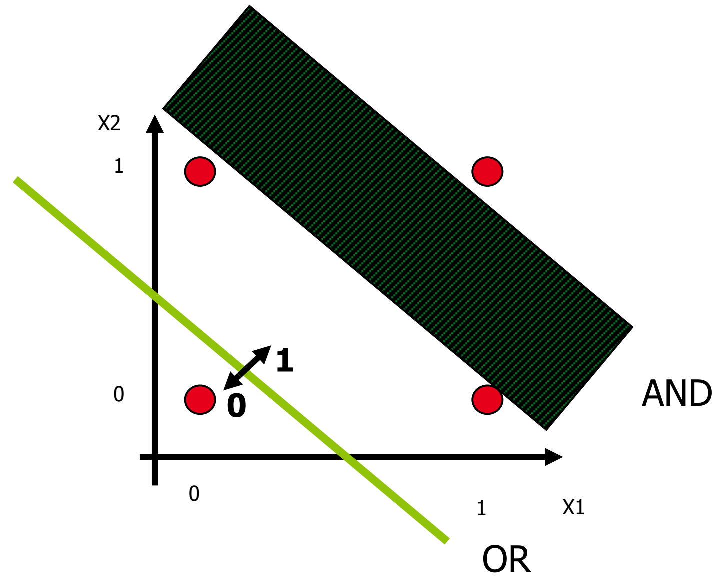
The Good Old Perceptron: principles





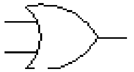
$$y = (X1W1 + X2W2) - \theta$$

$$\chi = \sum_{i=1}^{i=n} w_i x_i$$

$$y = sign(\chi - \theta)$$

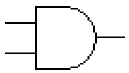
A	B	S
0	0	0
0	1	1
1	0	1
1	1	1

S=A+B (OU)



A	B	S
0	0	0
0	1	0
1	0	0
1	1	1

S=A.B (ET)



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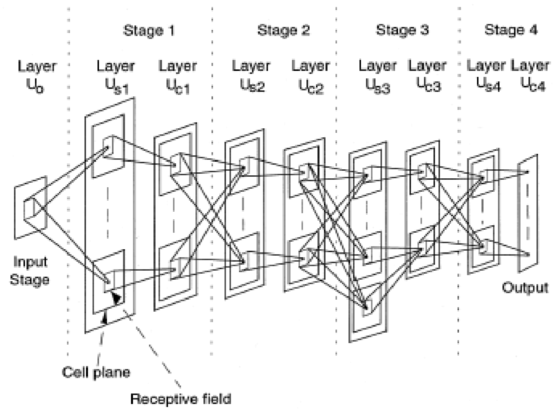
The big depression of the 1970's

- Minsky an Papert's book on Perceptrons is seen by many as the cause of the drop in ANN research (the XOR problem)
  - But that's not fair to their work.

Marvin Minsky & Seymour Papert



Kunihiko Fukushima

[1] M. L. Minsky and S. A. Papert, Perceptrons: An Introduction to Computational Geometry. The MIT Press, 1970

[1] K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position," Biological Cybernetics, vol. 36, no. 4, pp. 193-202, 1980.

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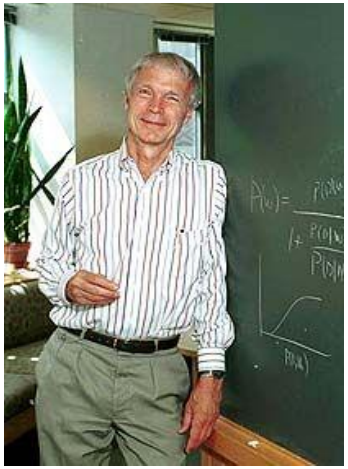
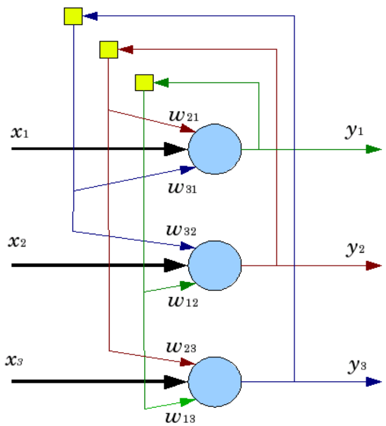
1981, Let's Roll again

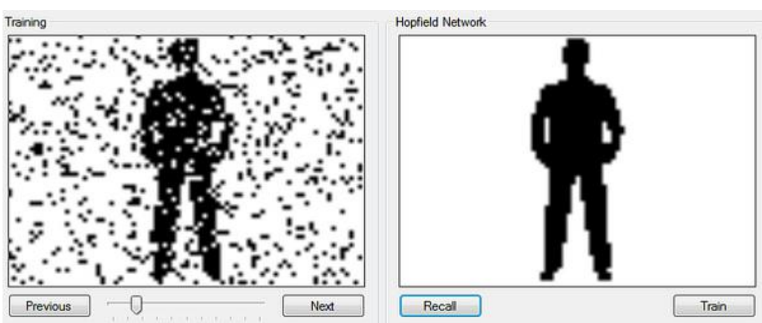


John J. Hopfield



[1] J. J. Hopfield, "Neural Networks and Physical Systems with Emergent Collective Computational Abilities," PNAS, vol. 79, no. 8, pp. 2554-2558, Apr. **1982**.

- The Hopfield net, a recurrent architecture
- Analogy to physics (Ising)
- Potential Applications



Proc. Natl. Acad. Sci. USA
Vol. 79, pp. 2554–2558, April 1982
Biophysics

Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

J. J. Hopfield

Division of Chemistry and Biology, California Institute of Technology, Pasadena, California 91125; and Bell Laboratories, Murray Hill, New Jersey 07974

Contributed by John J. Hopfield, January 15, 1982

ABSTRACT Computational properties of use to biological organisms or to the construction of computers can emerge as collective properties of systems having a large number of simple equivalent components (or neurons). The physical meaning of content-addressable memory is described by an appropriate phase space flow of the state of a system. A model of such a system is given, based on aspects of neurobiology but readily adapted to integrated circuits. The collective properties of this model produce a content-addressable memory which correctly yields an entire memory from any subpart of sufficient size. The algorithm for the time evolution of the state of the system is based on asynchronous parallel processing. Additional emergent collective properties include some capacity for generalization, familiarity recognition, categorization, error correction, and time sequence retention. The collective properties are only weakly sensitive to details of the modeling or the failure of individual devices.

Given the dynamical electrochemical properties of neurons and their interconnections (synapses), we readily understand schemes that use a few neurons to obtain elementary useful biological behavior (1–3). Our understanding of such simple circuits in electronics allows us to plan larger and more complex circuits which are essential to large computers. Because evolution has no such plan, it becomes relevant to ask whether the ability of large collections of neurons to perform "computational" tasks may in part be a spontaneous collective consequence of having a large number of interacting simple neurons.

In physical systems made from a large number of simple elements, interactions among large numbers of elementary components yield collective phenomena such as the stable magnetic orientations and domains in a magnetic system or the vortex

calized content-addressable memory or categorizer using extensive asynchronous parallel processing.

The general content-addressable memory of a physical system

Suppose that an item stored in memory is "H. A. Kramers & G. H. Wannier *Phys. Rev.* **60**, 252 (1941)." A general content-addressable memory would be capable of retrieving this entire memory item on the basis of sufficient partial information. The input "& Wannier, (1941)" might suffice. An ideal memory could deal with errors and retrieve this reference even from the input "Vannier, (1941)". In computers, only relatively simple forms of content-addressable memory have been made in hardware (10, 11). Sophisticated ideas like error correction in accessing information are usually introduced as software (10).

There are classes of physical systems whose spontaneous behavior can be used as a form of general (and error-correcting) content-addressable memory. Consider the time evolution of a physical system that can be described by a set of general coordinates. A point in state space then represents the instantaneous condition of the system. This state space may be either continuous or discrete (as in the case of *N* Ising spins).

The equations of motion of the system describe a flow in state space. Various classes of flow patterns are possible, but the systems of use for memory particularly include those that flow toward locally stable points from anywhere within regions around those points. A particle with frictional damping moving in a potential well with two minima exemplifies such a dynamics.

If the flow is not completely deterministic, the description is more complicated. In the two-well problems above, if the

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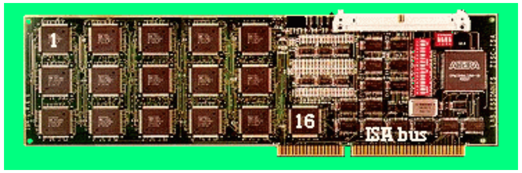
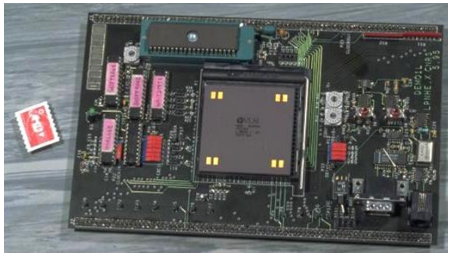
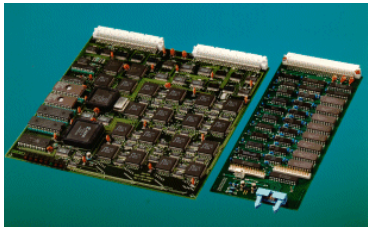
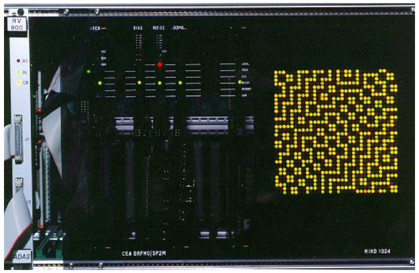
1980's Neurocomputers Galore!...

- Siemens : MA-16 Chips (SYNAPSE-1 Machine)
  - Synapse-1, neurocomputer with 8xM-A16 chips
  - Synapse3-PC, PCI board with 2xMA-16 (1.28 Gpcs)
- Adaptive Solutions : CNAPS
  - SIMD // machine based on a 64 PE chip.
- IBM : ZISC
  - Vector classifier engine
- Philips : L-Neuro
  - 1st Gen 16PEs 26 MCps
  - 2nd Gen 12 PEs 720 MCps
- + Intel (ETANN), AT&T (Anna), Hitachi (WSI), NEC, Thomson (now THALES), etc…
- CEA's MIND machine
  - Hybrid analog/digital: MIND-128
  - Fully digital: MIND-1024









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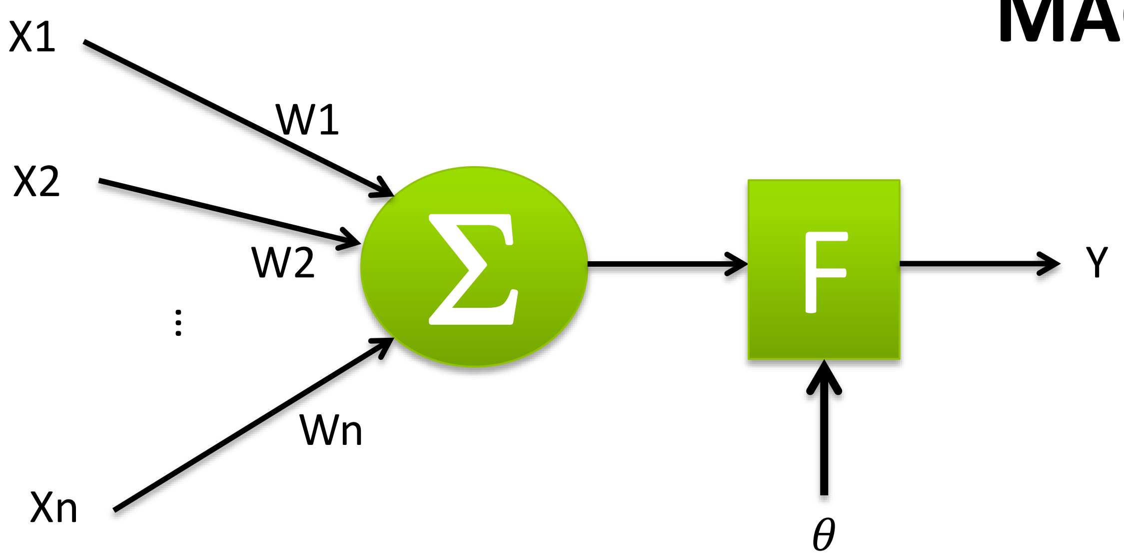
Implementing formal Neurons

MACs



$$Y = F\left(\sum_{i=0}^{n} W_i . X_i - \theta\right)$$

Non linear function

Synaptic Weight

Bias

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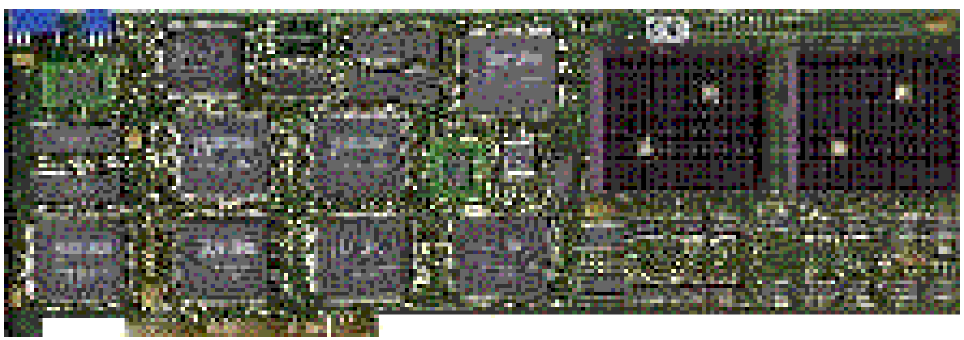
An example : Siemens SYNAPSE

- A matrix multiplying device (MA-16)
  - Peak performance 640 MCps
- Synapse-1, neurocomputer with 8xM-A16
- Synapse3-PC, PCI board with 2xMA-16 (1.28 Gpcs)



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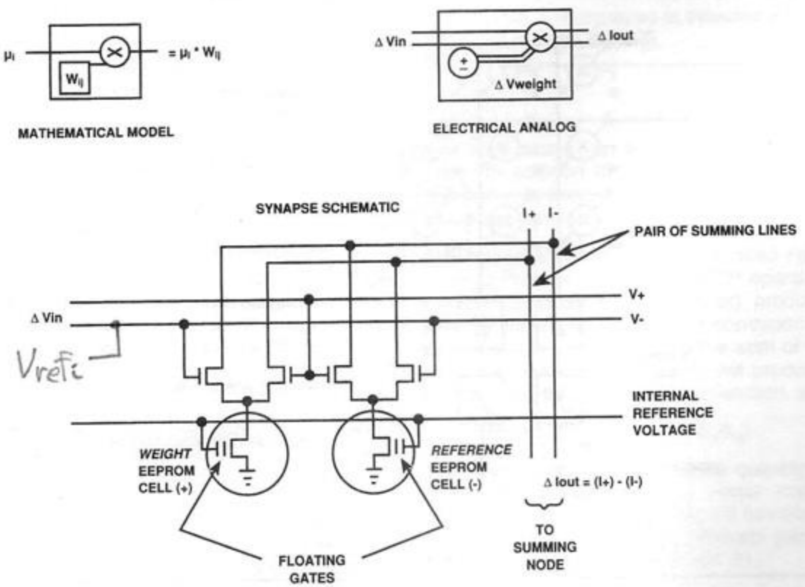
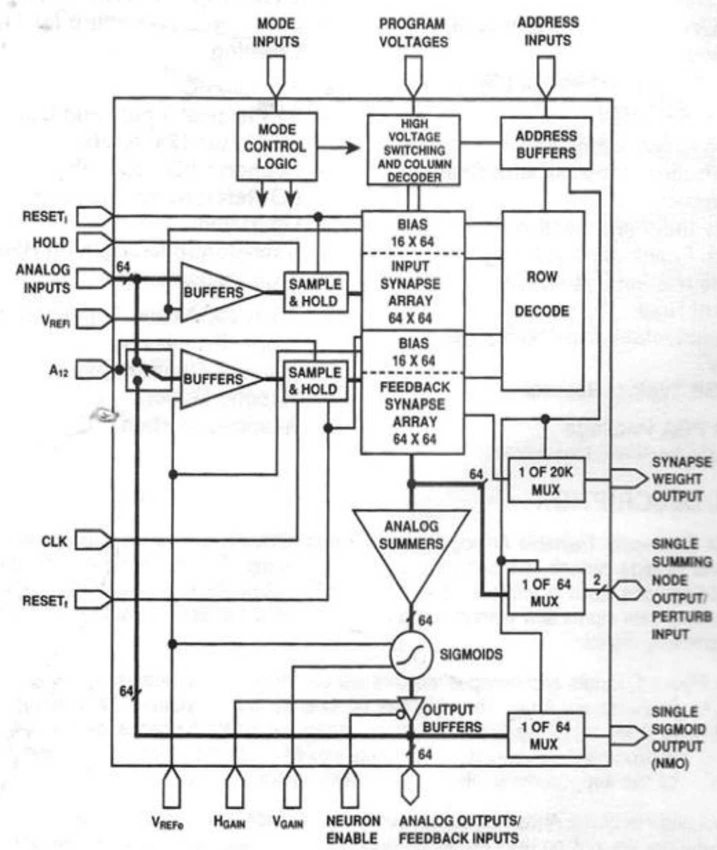
- Intel 80170NX ETANN Chip



Synpase circuit



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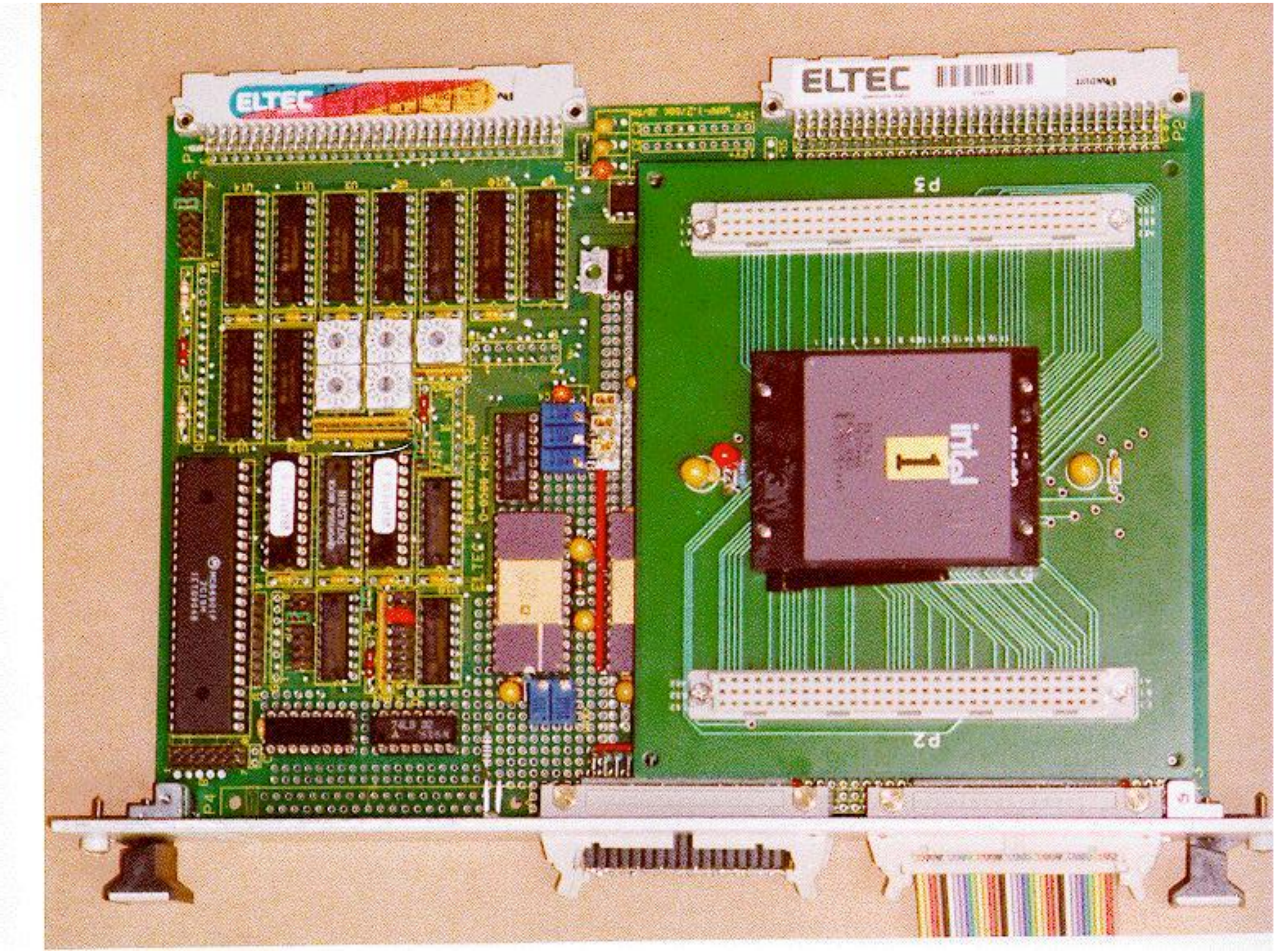
Intel ETANN



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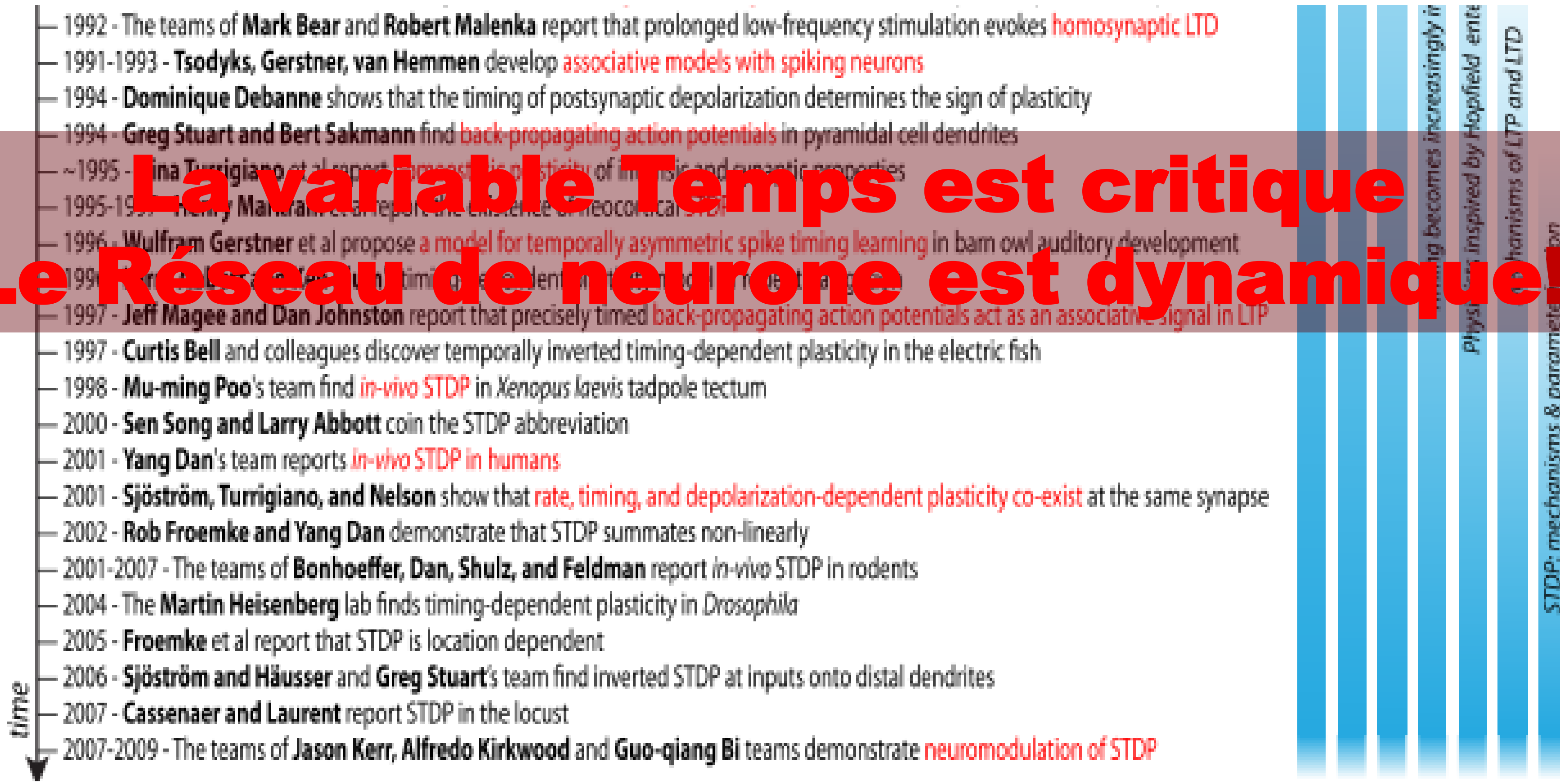
Les Progrès en neurosciences des années 90

- **Montrent les limitations de l'approche du perceptron et introduisent LTP/LTD and STDP**



La variable Temps est critique
Le Réseau de neurone est dynamique!

from Markram et al. "A history of spike-timing-dependent plasticity," in *Frontiers in Synaptic neuroscience*, Vol 3, August 2011

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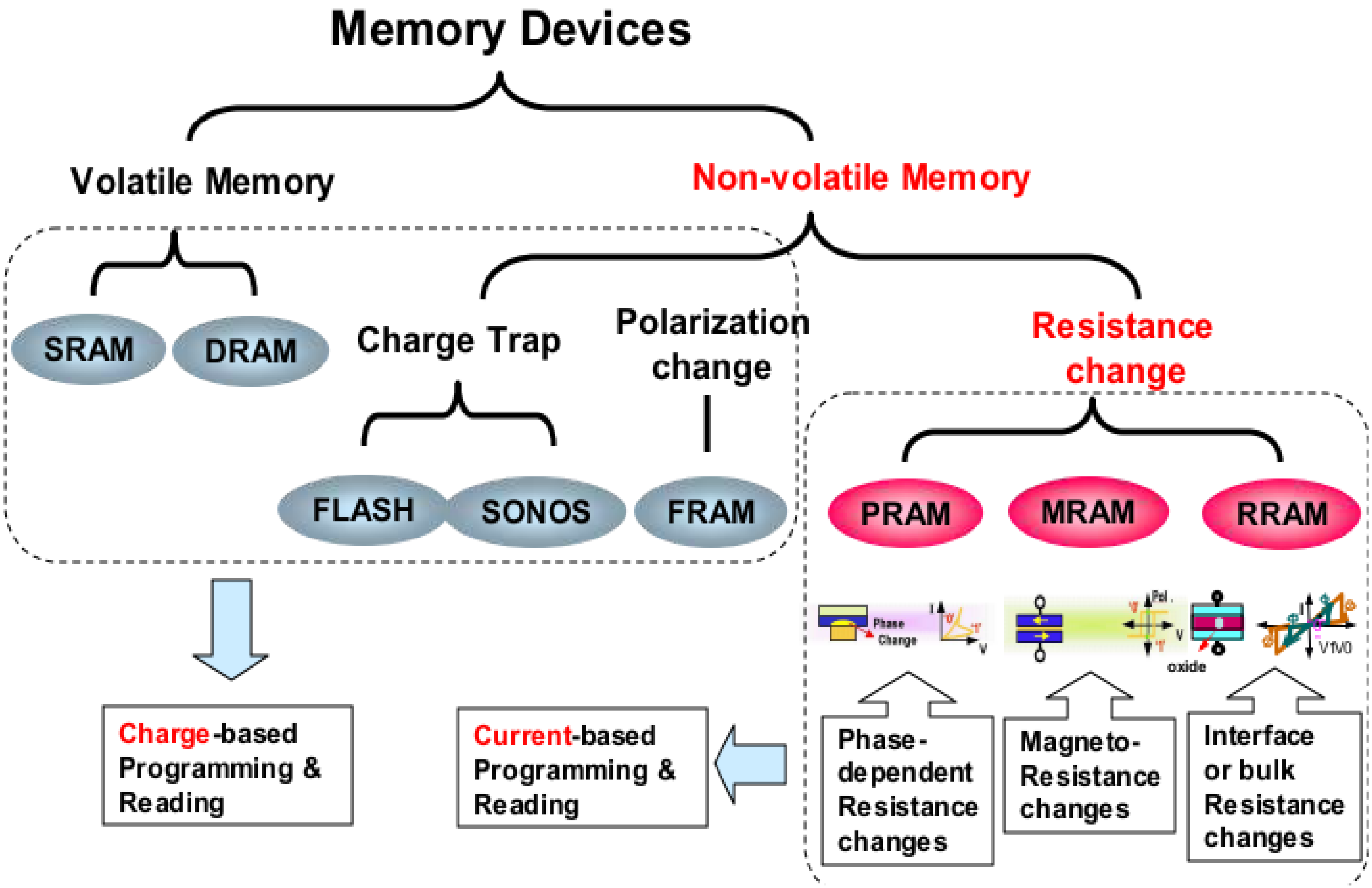
Memory Technology Opportunities



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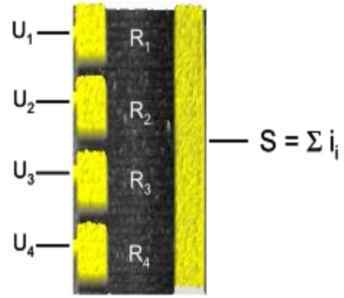
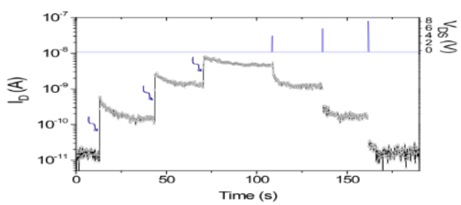
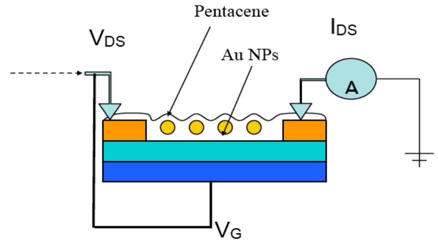
Investigating potential synapstor technologies

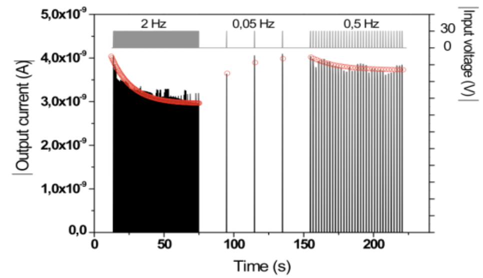
OG-CNTFET





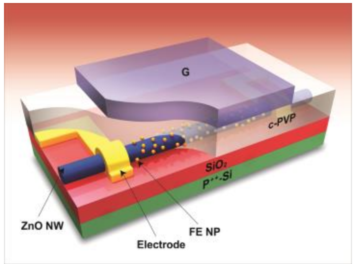
NOMFET



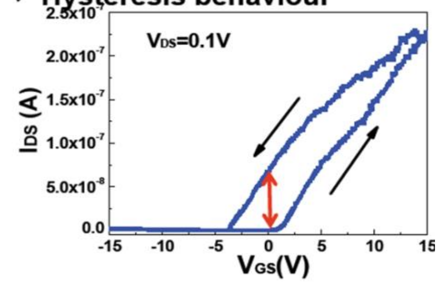


ZnO NW

UNIVERSITY OF CAMBRIDGE



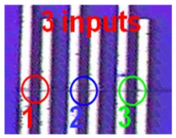
✓ Hysteresis behaviour



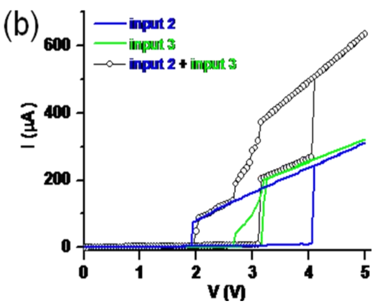
VO2 NW

UNIVERSITY OF CAMBRIDGE

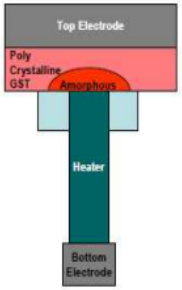
(a)

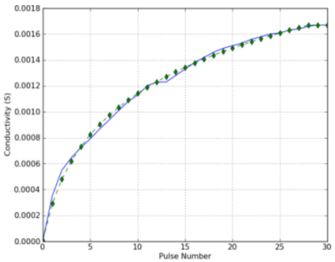


(b)



PCM





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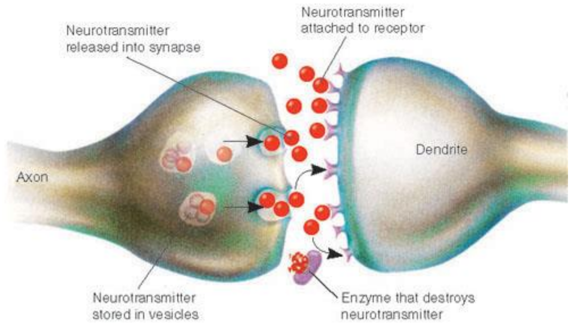
Artificial synapses: the NOMFET example

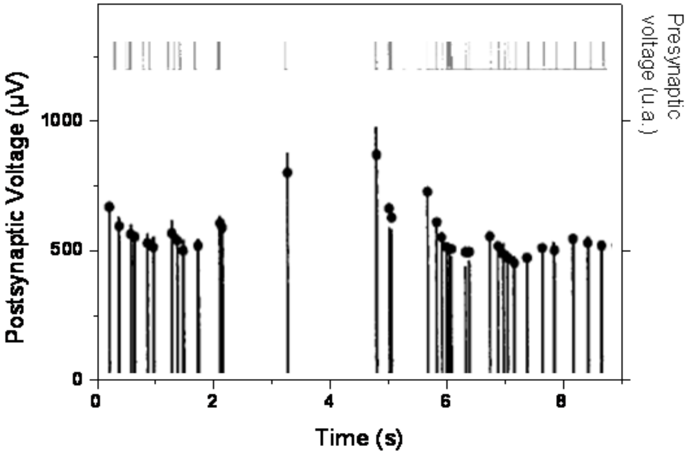
Collaboration. Dominique Vuillaume group, IEMN, CNRS, Lille, France

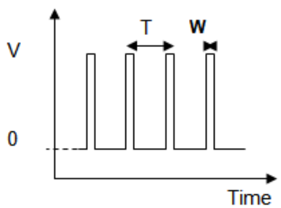
An Organic Nanoparticle Transistor Behaving as a Biological Spiking S

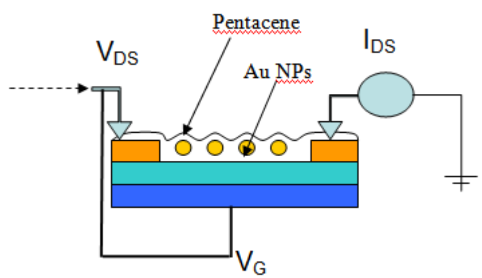
Adv. Funct. Mater. **2010**, *20*, 330–337

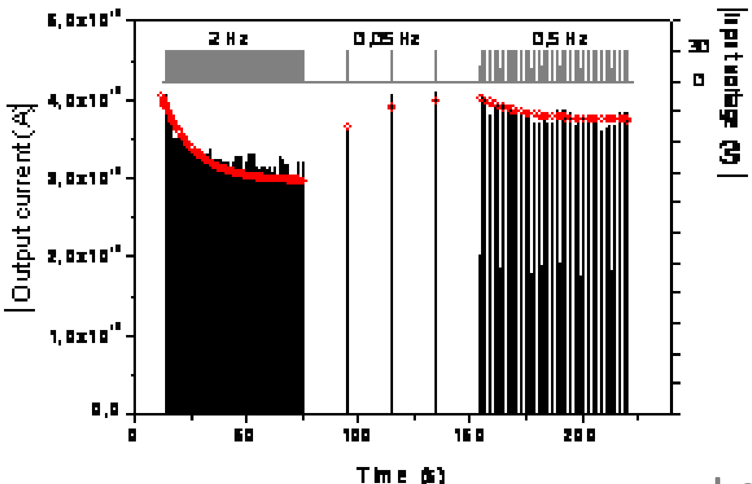
By *Fabien Alibart, Stéphane Pleutin, David Guérin, Christophe Novembre, Stéphane Lenfant, Kamal Lmimouni, Christian Gamrat,* and *Dominique Vuillaume**

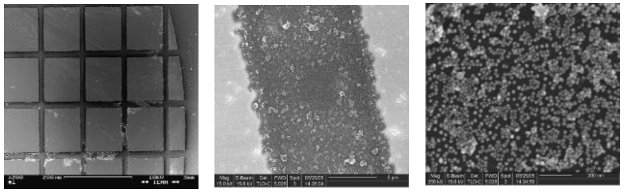












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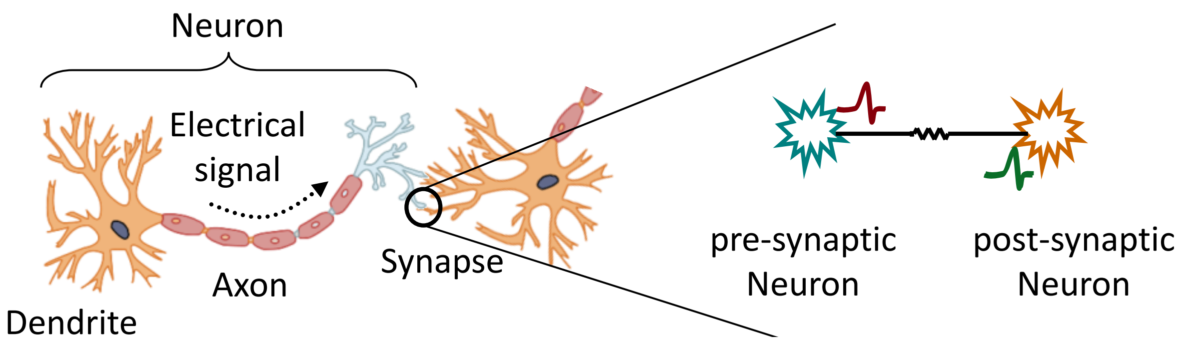
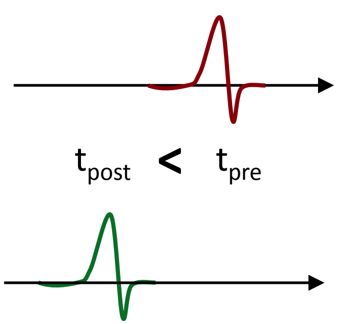
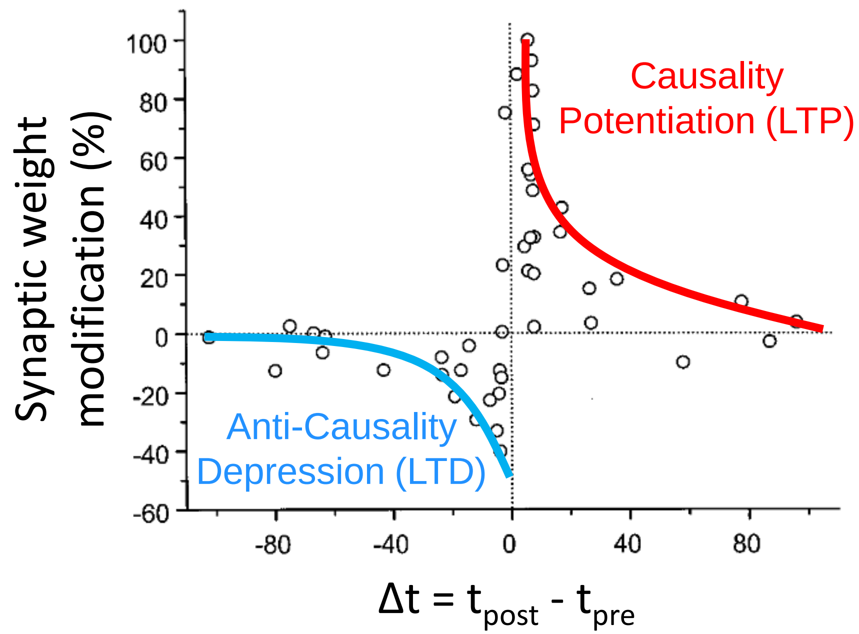
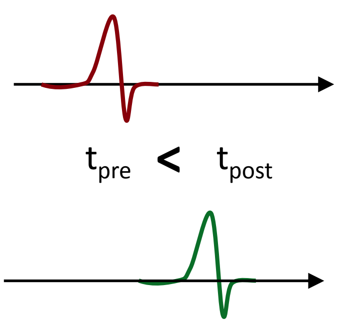
Learning from neuroscience: a STDP Primer



STDP = correlation detector
➔ Possible learning model of the mind







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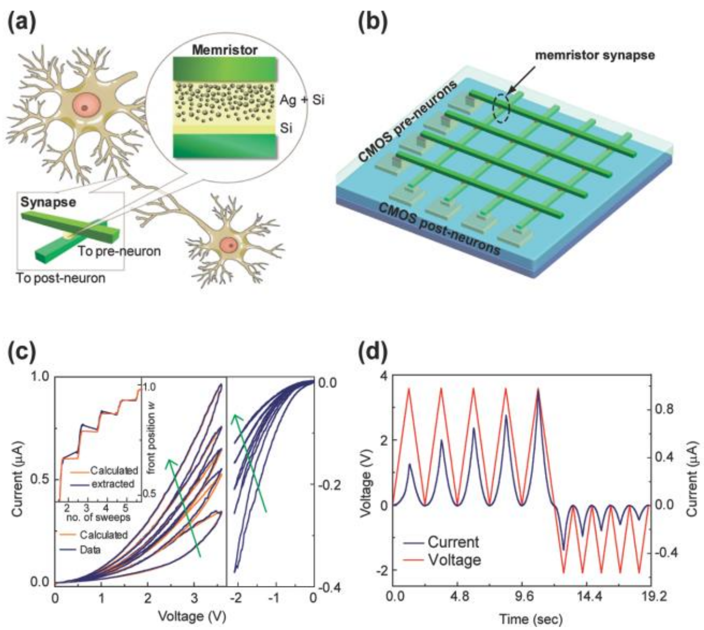
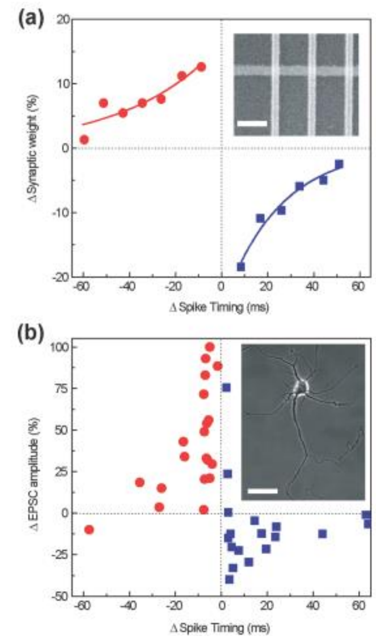
STDP experimental demonstration

U. Michigan, Lu group demonstration

[1] Jo, S.H. et al. Nanoscale Memristor Device as Synapse in Neuromorphic Systems. *Nano Letters* (2010).



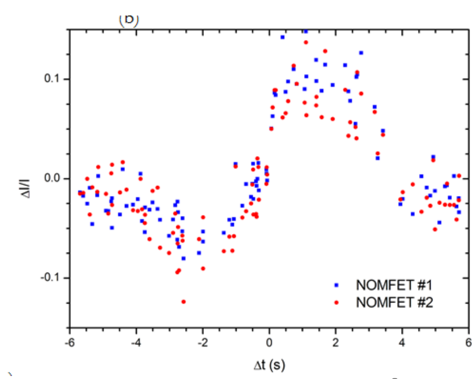


Demonstration on PC memory by Wong group, Stanford

D. Kuzum et al, “Nanoelectronic Programmable Synapses Based on Phase Change Materials for Brain-Inspired Computing,” *Nano Letters*, 2011

Demonstrated on NOMFET devices

F. Alibart et al. “A Memristive Nanoparticle/Organic Hybrid Synapstor for Neuroinspired Computing,”
Advanced Functional Materials, vol. 22, no. 3, pp. 609–616, 2012.



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Then came memristors: a brief memri-story

- Introduced by Leon Chua, 1971

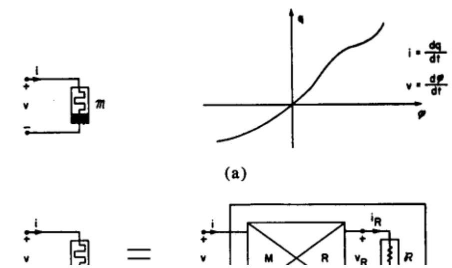
IEEE TRANSACTIONS ON CIRCUIT THEORY, VOL. CT-18, NO. 5, SEPTEMBER 1971 507

Memristor—The Missing Circuit Element

LEON O. CHUA, SENIOR MEMBER, IEEE

Abstract—A new two-terminal circuit element—called the *memristor*—characterized by a relationship between the charge $q(t) \equiv \int_{-\infty}^{t} i(\tau)\, d\tau$ and the *flux-linkage* $\varphi(t) \equiv \int_{-\infty}^{t} v(\tau)\, d\tau$ is introduced as the *fourth basic* circuit element. An electromagnetic field interpretation of this relationship in terms of a quasi-static expansion of Maxwell's equations is presented. Many circuit-theoretic properties of memristors are derived. It is shown that this element exhibits some peculiar behavior different from that exhibited by resistors, inductors, or capacitors. These properties lead to a number of unique applications which cannot be realized with *RLC* networks alone.

Although a physical memristor device without internal power supply has not yet been discovered, operational laboratory models have been built with the help of active circuits. Experimental results are presented to demonstrate the properties and potential applications of memristors.



- Revisited by Strukov et al., 2008

nature Vol 453|1 May 2008|doi:10.1038/nature06932

LETTERS

The missing memristor found

Dmitri B. Strukov[1], Gregory S. Snider[1], Duncan R. Stewart[1] & R. Stanley Williams[1]

Anyone who ever took an electronics laboratory class will be familiar with the fundamental passive circuit elements: the resistor, the capacitor and the inductor. However, in 1971 Leon Chua reasoned from symmetry arguments that there should be a fourth fundamental element, which he called a memristor (short for memory resistor)[1]. Although he showed that such an element has many interesting and valuable circuit properties, until now no one has presented either a useful physical model or an example of a memristor. Here we show, using a simple analytical example, that mem-

propose a physical model that satisfies these simple equations. In 1976 Chua and Kang generalized the memristor concept to a much broader class of nonlinear dynamical systems they called memristive systems[2,3], described by the equations

$$v = \mathcal{R}(w,i)i \qquad (3)$$

$$\frac{dw}{dt} = f(w,i) \qquad (4)$$

- Spotted way back…

JOURNAL OF APPLIED PHYSICS VOLUME 33, NUMBER 9 SEPTEMBER 1962

Low-Frequency Negative Resistance in Thin Anodic Oxide Films

T. W. Hickmott
General Electric Research Laboratory, Schenectady, New York

(Received February 5, 1962)

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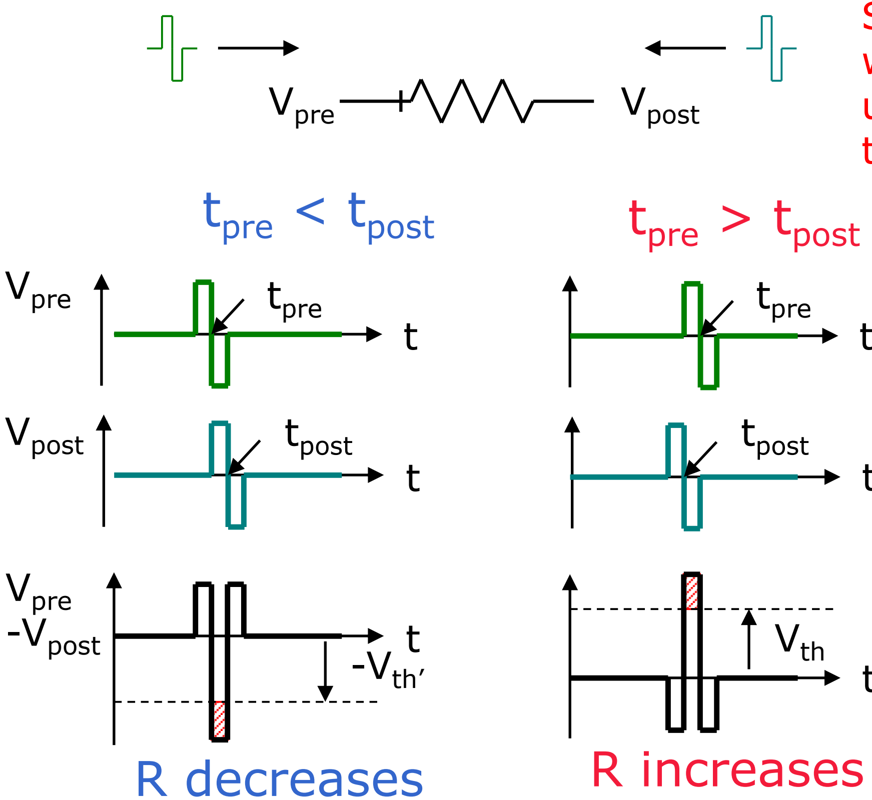
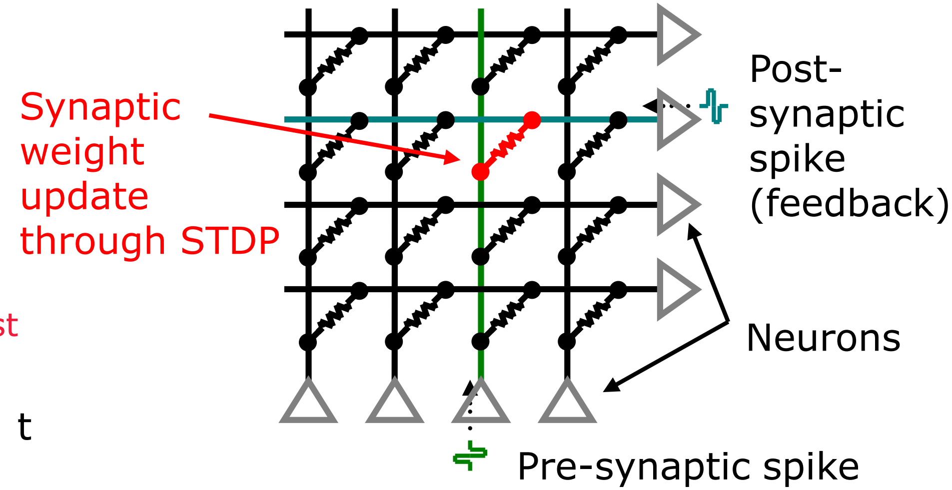
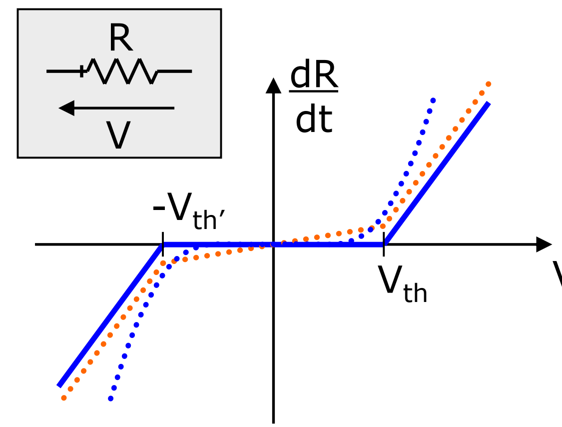
Principle of STDP on Crossbars of Memristors

- First Proposed by Snider(1)







1. G. Snider, *Nanoscale Architectures*, 2008
2. B. Linares-Barranco et al, *Nature Precedings*, 2009

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CAN WE BUILD REAL NEUROMORPHIC SYSTEMS?

CAN THEY LEARN, COMPUTE?

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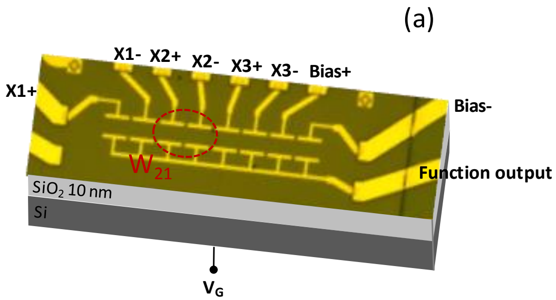
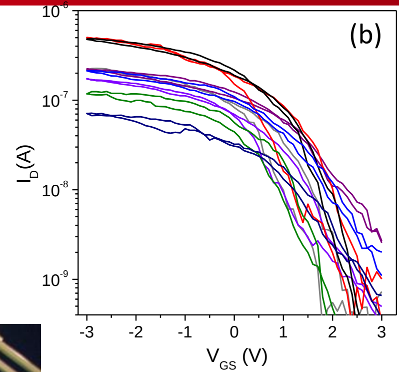
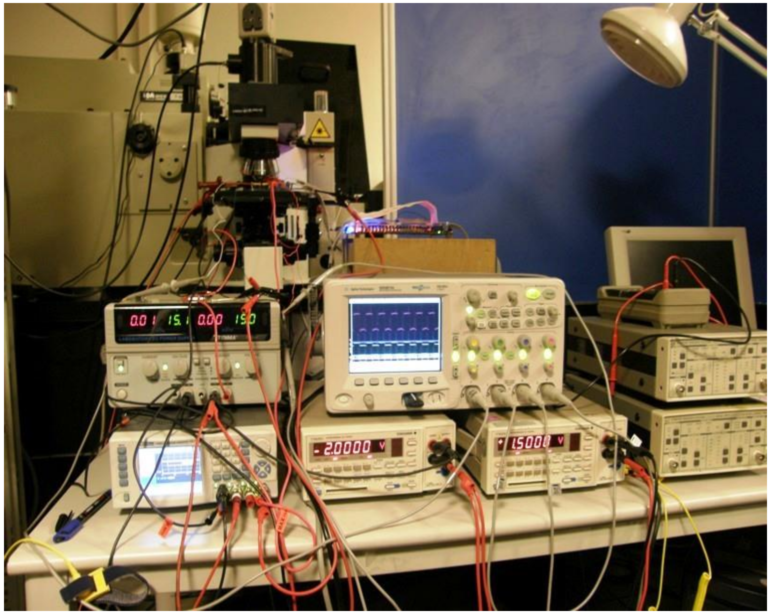
CNT circuit with function learning capabilities



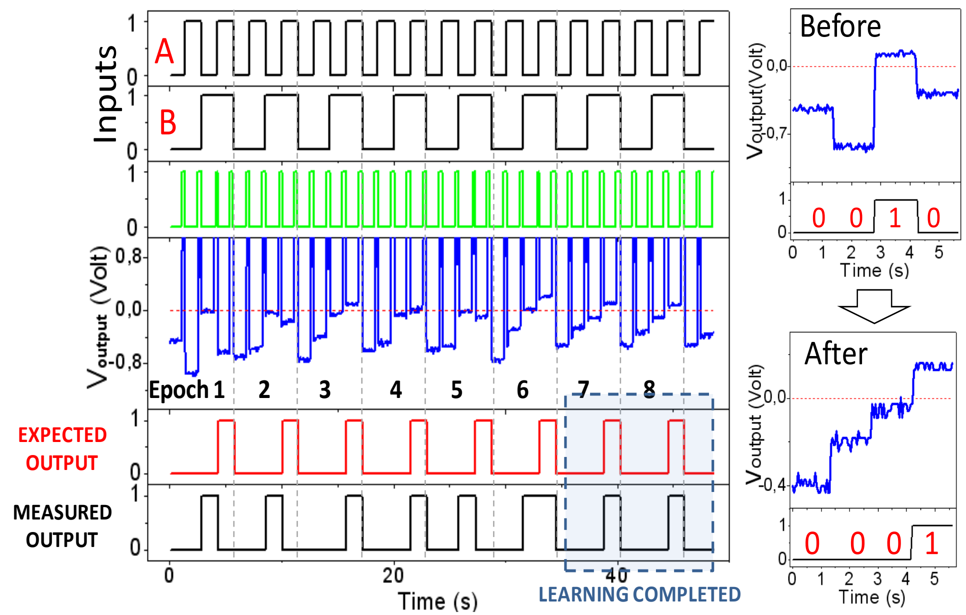


(a) 8 OG-CNTFETs sharing the same gate and output electrodes.
(b) Id(Vgs) transfer characteristics showing large variability in the ON-state but still leading to efficient learning of functions.

Collaboration with Paris-Sud University, J.O. Klein's group



Nanotube devices based crossbar architecture: toward neuromorphic computing, W. Zhao et al. Nanotechnology 21, 175202 (2010).



Exemple of learning of a 2-input boolean function

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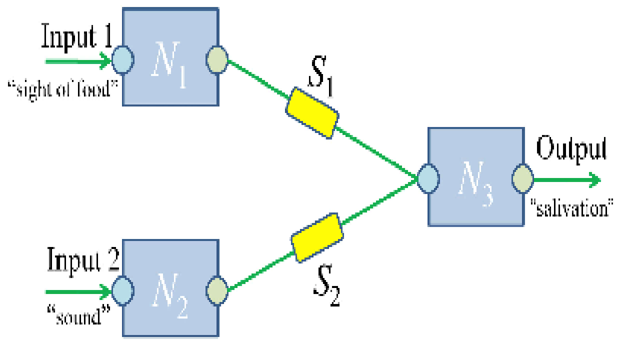
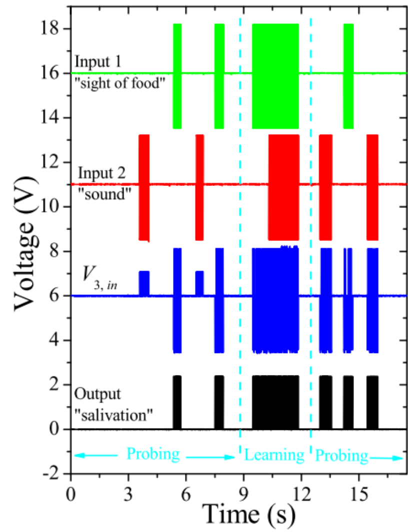
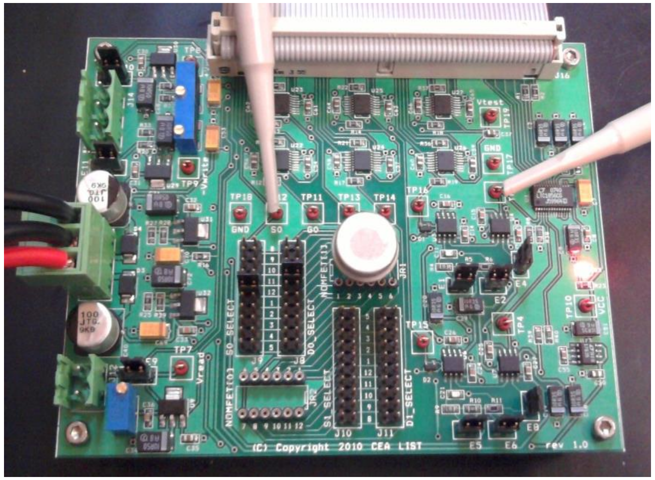
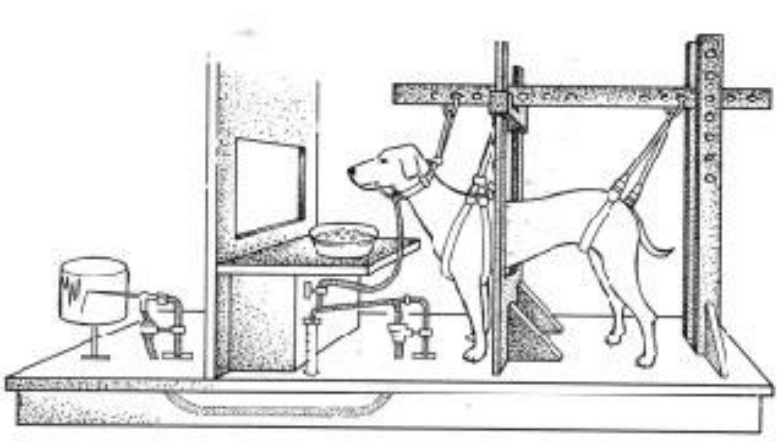
Can it learn? A dog with 2 synapses!

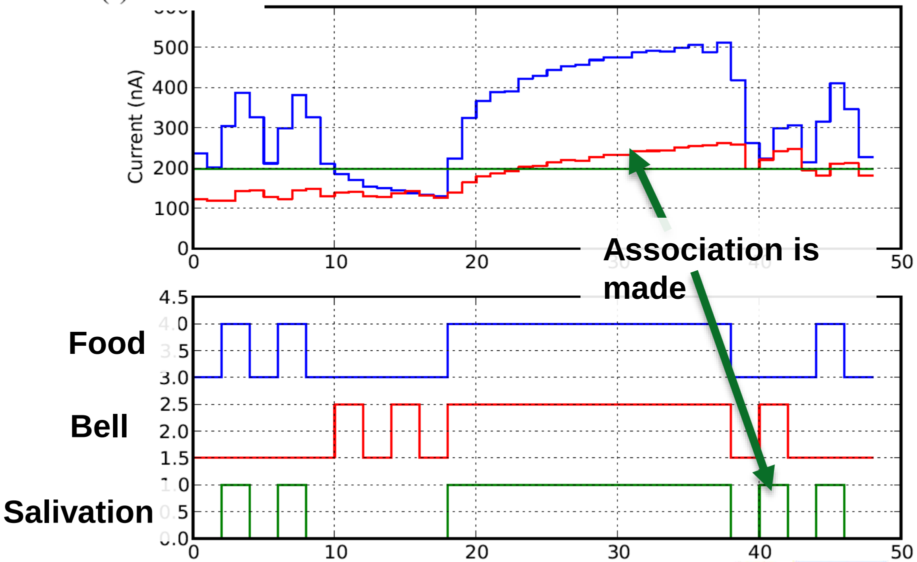


Experimental setup for a Pavlovian associative memory based on memristive devices as proposed by Di Ventra et col.[2]









[1] O. Bichler, W. Zhao, F. Alibart, S. Pleutin, S. Lenfant, D. Vuillaume, C. Gamrat, "Pavlov's Dog Associative Learning Demonstrated on Synaptic-like Organic Transistors", Neural Computation, 2012
[2] Pershin, Y.V. & Di Ventra, M. "Experimental demonstration of associative memory with memristive neural networks." Arxiv *0905.2935* (2009).

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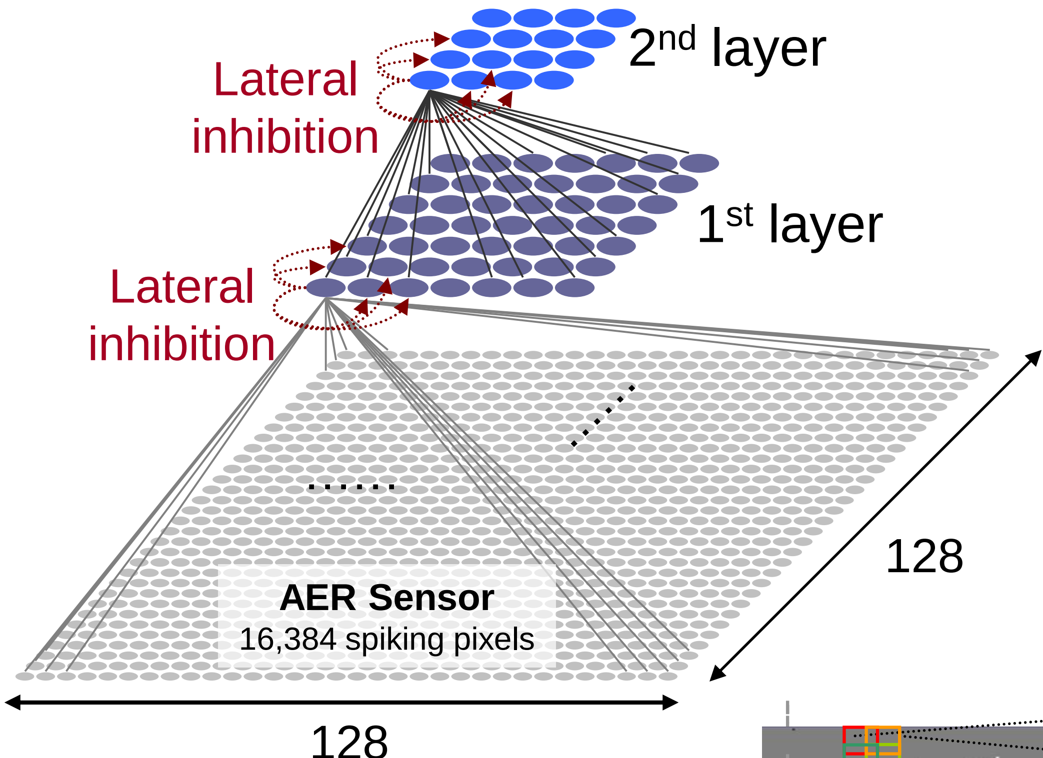
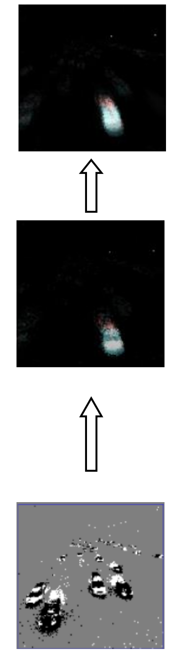
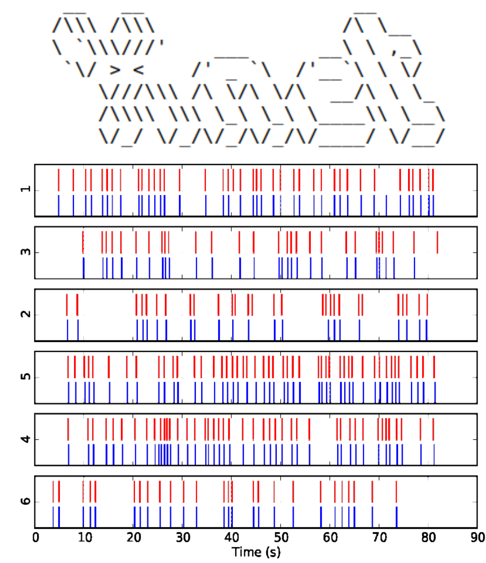
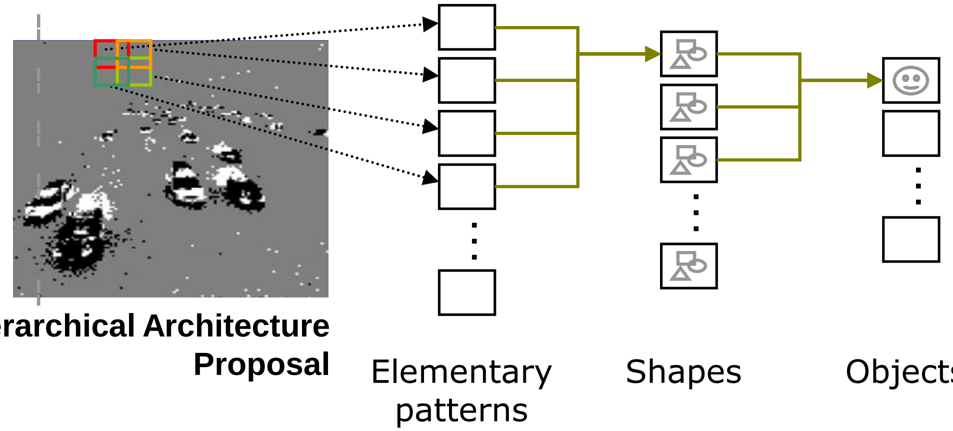
A pretty realistic application example







Two-layers system
~ 2 million devices with STDP



Hierarchical Architecture Proposal

O. Bichler, D. Querlioz, S. J. Thorpe, J.-P. Bourgoin and C. Gamrat, *"Unsupervised Features Extraction from Asynchronous Silicon Retina through Spike-Timing-Dependent Plasticity"*, International Joint Conference on Neural Networks IJCNN August 2011

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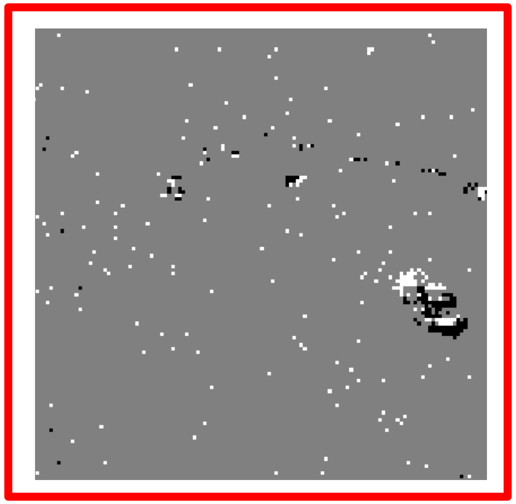
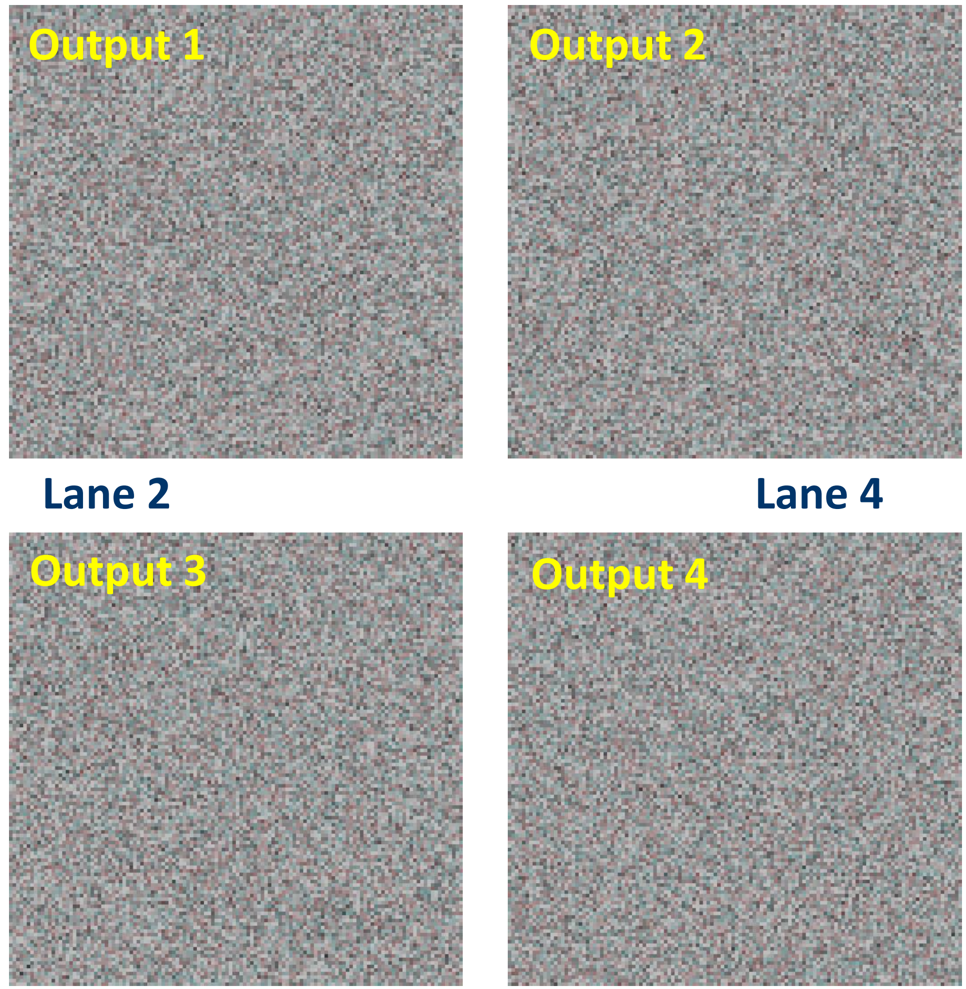
Weights Evolution During Learning

Recorded stimuli



Synaptic maps for 4 neurons on the first layer



Lane 2

Lane 4

Lane 5

Lane 1

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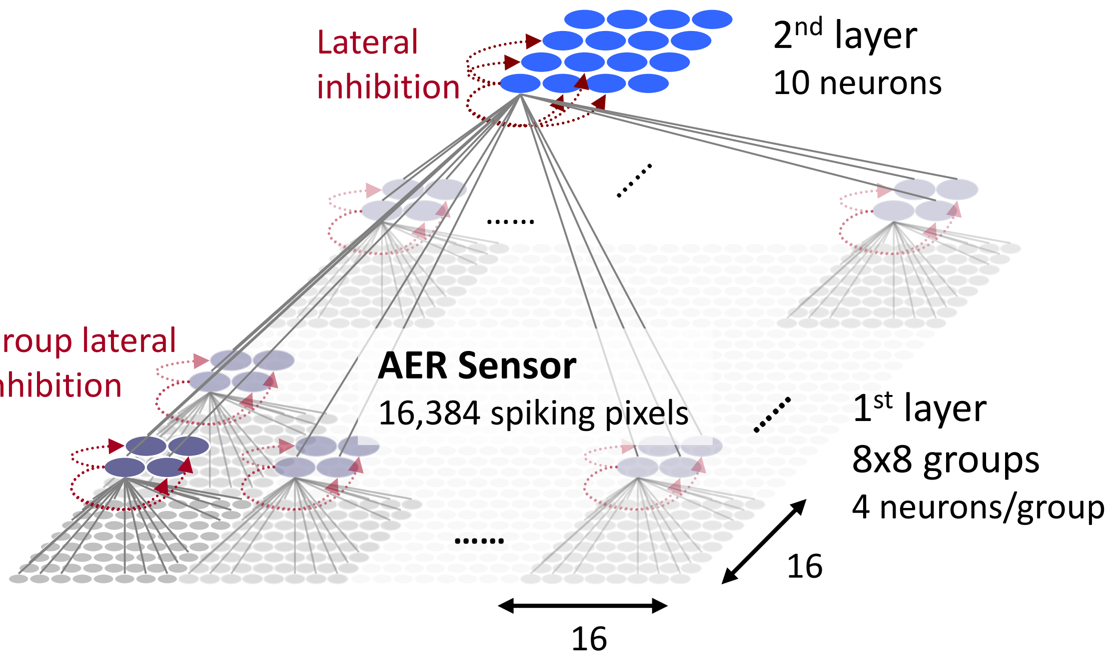
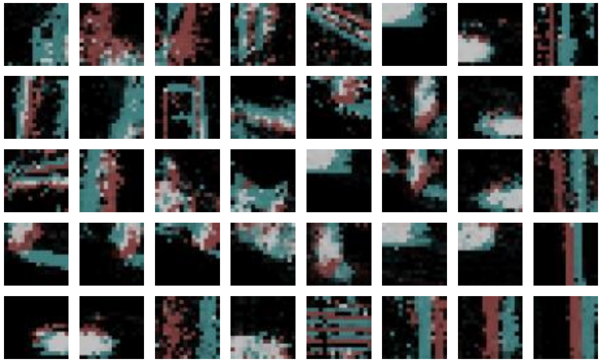
Hierarchical Architecture

- The architecture can be modularized
- Simulation shows that a hierarchy of 16x16 arrays yields the same results





Typical feature maps emerging within devices when exposed to a video scene : walking in the street.

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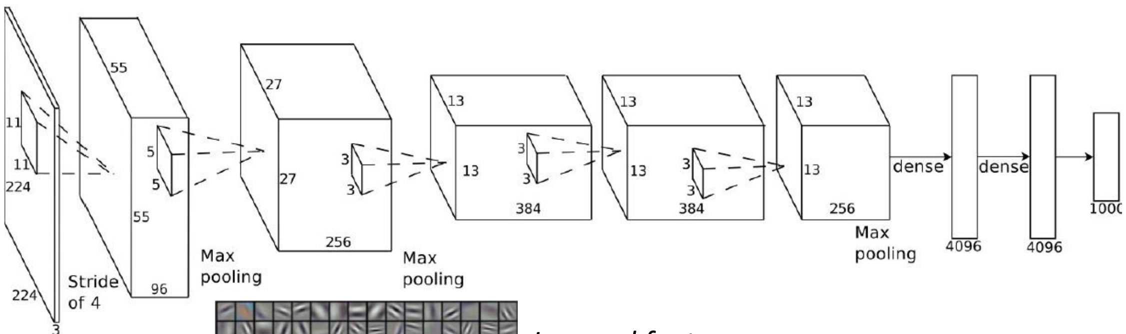
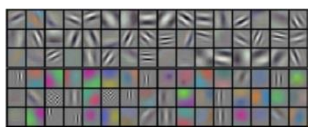
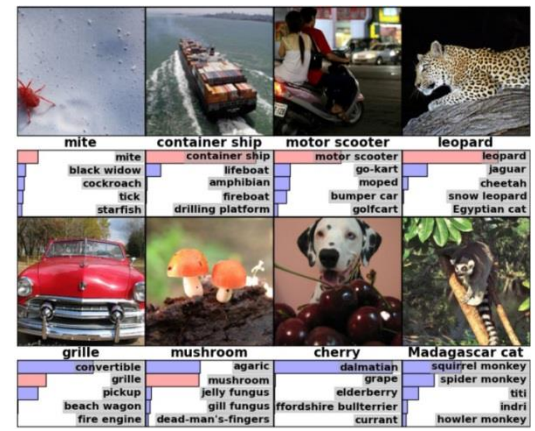
Current trend Deep Neural Networks

- **ImageNet classification** (authors hired by Google) [1]
  - 1.2 million high res images, 1,000 different classes
  - Top-5 17% error rate (huge improvement)

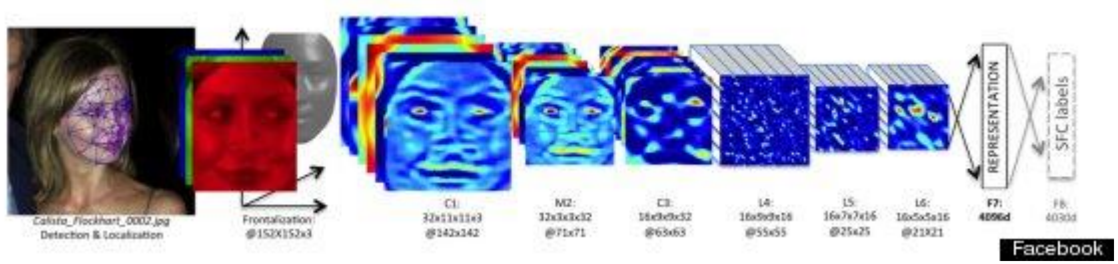




Learned features on first layer



- **Facebook's 'DeepFace' Program** (labs head: Y. LeCun) [2]
  - 4 million images, 4,000 identities
  - 97.25% accuracy, vs. 97.53% human performance



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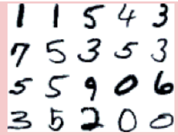
DNN, State of the Art in Recognition

- **Deep Neural Networks** all over the place!

Database	# Images	# Classes	Best score
MNSIT *Handwritten digits* 	60,000 + 10,000	10	99.79% [3]
GTSRB *Traffic sign* 	~ 50,000	43	99.46% [4]
CIFAR-10 *airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck* 	50,000 + 10,000	10	91.2% [5]
Caltech-101 	~ 50,000	101	86.5% [6]
ImageNet IMAGENET	~ 1,000,000	1,000	Top-5 83% [1]
DeepFace 	~ 4,000,000	4,000	97.25% [2]

INCREASING COMPLEXITY

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Wrap up

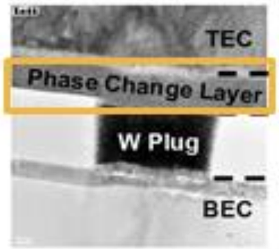
Memristive technologies

≡

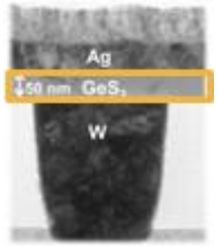
Synaptic-like devices

PCM

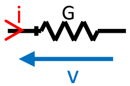
RRAM (CBRAM/OXRAM) (…)



ST/LETI



ALTIS/LETI

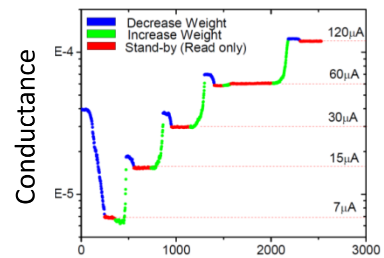


$i = G.v$

$$\frac{dG}{dt} = f(v,G)$$

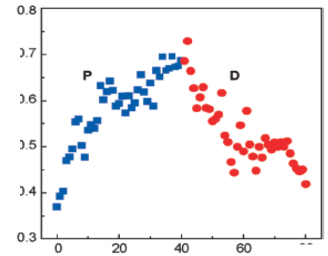
f() non linear

Multi-level



F. Alibart

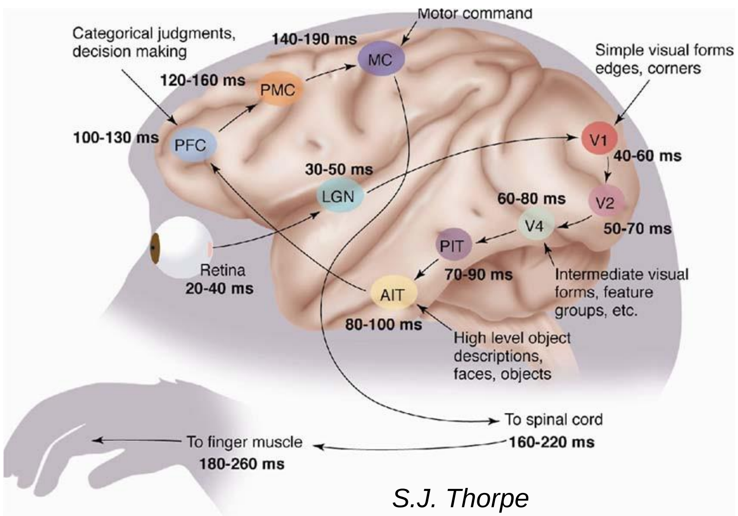
Cumulativity



Wei Lu

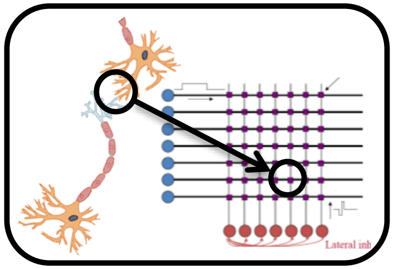
Spike based coding

(Human visual system)



S.J. Thorpe

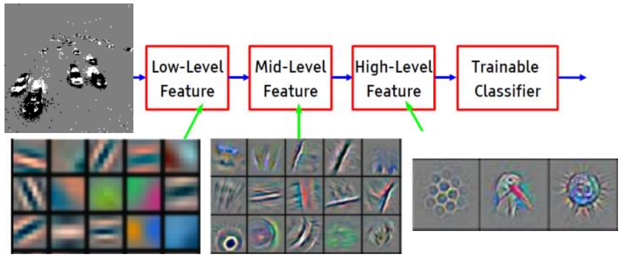
Circuit Design

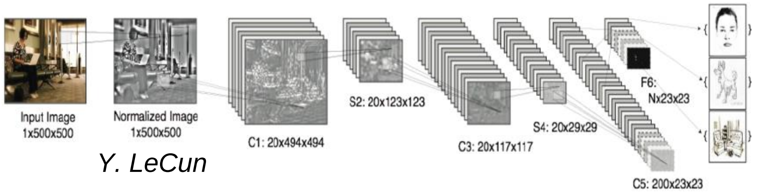


Embedded cognitive functions

Apps : image, audio, natural data sensing

Artificial retina





Y. LeCun

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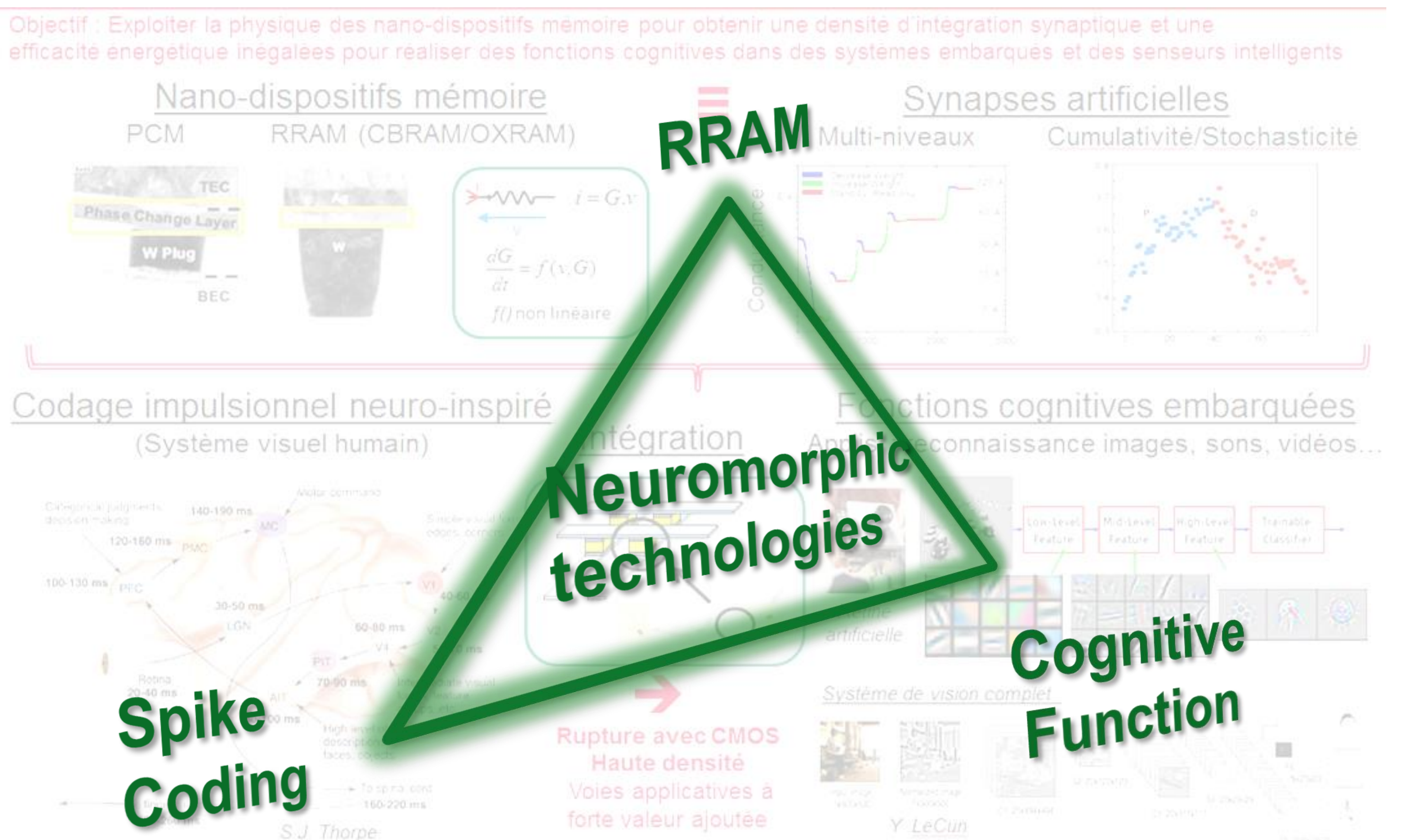
Objectif : Exploiter la physique des nano-dispositifs mémoire pour obtenir une densité d'intégration synaptique et une efficacité énergétique inégalées pour réaliser des fonctions cognitives dans des systèmes embarqués et des senseurs intelligents
Nano-dispositifs mémoire
PCM
RRAM (CBRAM/OXRAM)
TEC
Phase Change Layer
W Plug
BEC
W
$i = G.v$
$\frac{dG}{dt} = f(v, G)$
f() non linéaire
Synapses artificielles
Multi-niveaux
Cumulativité/Stochasticité
Codage impulsionnel neuro-inspiré
(Système visuel humain)
Intégration
Fonctions cognitives embarquées
Apprissage, reconnaissance images, sons, vidéos…
Rétine artificielle
Système de vision complet
Rupture avec CMOS
Haute densité
Voies applicatives à forte valeur ajoutée
S.J. Thorpe
Y. LeCun
RRAM
Neuromorphic technologies
Spike Coding
Cognitive Function

Take away message

- A computing paradigm involes much more than a machine
  - A way to code information
  - A way to manipulate it
  - An architecture (both concrete and abstract) to implement the whole
- There is much more in computing than implementing functions with new materials
  - They shall be interconnectable with (std) electronics
  - Coding is a key element: boolean? Analog? Events?
- Neurmorphic is a good candidate (among others)
  - But lots of « synaptic » devices are required for realistic apps: >>10^6
  - It looks like a promising way for **low power embedded cognitive functions**
- Still a lot of work ahead
  - A more formal approach to event coding -> Works starts with Neurospin
- PhD and Post-Docs position available

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Annoucements

- PhD and Post-Doc positions available @CEA LIST, Saclay
  - **PhD position and grant** on « Spike coding in neuromorphic architectures » in collaboration with Neurospin lab, Saclay.
    - A PhD Subject at the interface of Computer Engineering and Neurosciences
    - Contact and application: olivier.bichler@cea.fr
  - **Post Doc position** available on « Circuit design for dense arrays of synaptic-like memristive devices »
    - Contact: christian.gamrat@cea.fr

- Inaugural Workshop of BioComp GDR
  - October 4-8, 2015, St Paul de Vence
  - http://gdr-biocomp.fr/en/

The goal of the GDR BIOCOMP is to facilitate interdisciplinary exchanges in France around a common goal: the realization of bio-inspired hardware systems.

EVENTS 10 MAY, 2015

First GDR BioComp workshop

Mark your calendars ! The first GDR BioComp workshop will take place from October 4th to 8th (2015) in the Saint Paul de Vence Belambra holiday center. More information to come...

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Last, but certainly not least….

Many thanks to those without whom this would not be

@ CEA LIST
- David Roclin,
- Olivier Bichler
- Van Huy Mai

@ CEA LETI
- Barbara de Salvo,
- Manan Suri
- Elisa Vianello

@ Université Paris-Saclay
- Jacques Olivier Klein
- Damien Querlioz
- Chris Bennett

@ CNRS, IEMN, Lille
- Dominique Vuillaume
- Fabien Allibart
- Stéphane Lenfant

@ CNRS, Toulouse
- Simon Thorpe

@ Chalmers
- Göran Wendin

Our Funding Sources :

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