

Advanced Technologies for Brain-Inspired Computing

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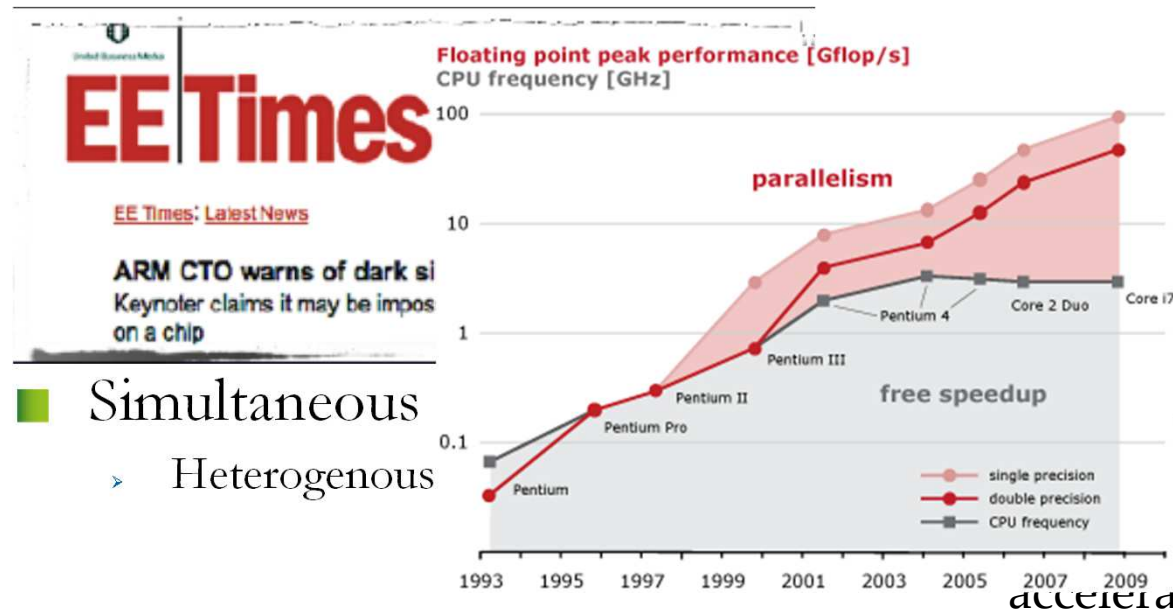
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****CEA-List, Paris, France**

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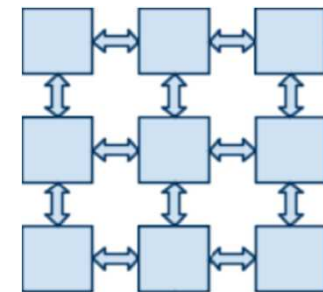
Context: dark silicon...

- Dramatic changes in the area of computing architectures
- Power has become the main limiting factor for the scalability of microprocessors
 - Multi-cores architectures

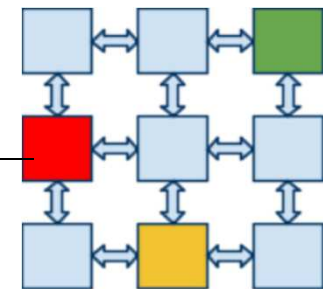


- Simultaneous
 - Heterogenous

- Need for versatile hardware accelerators



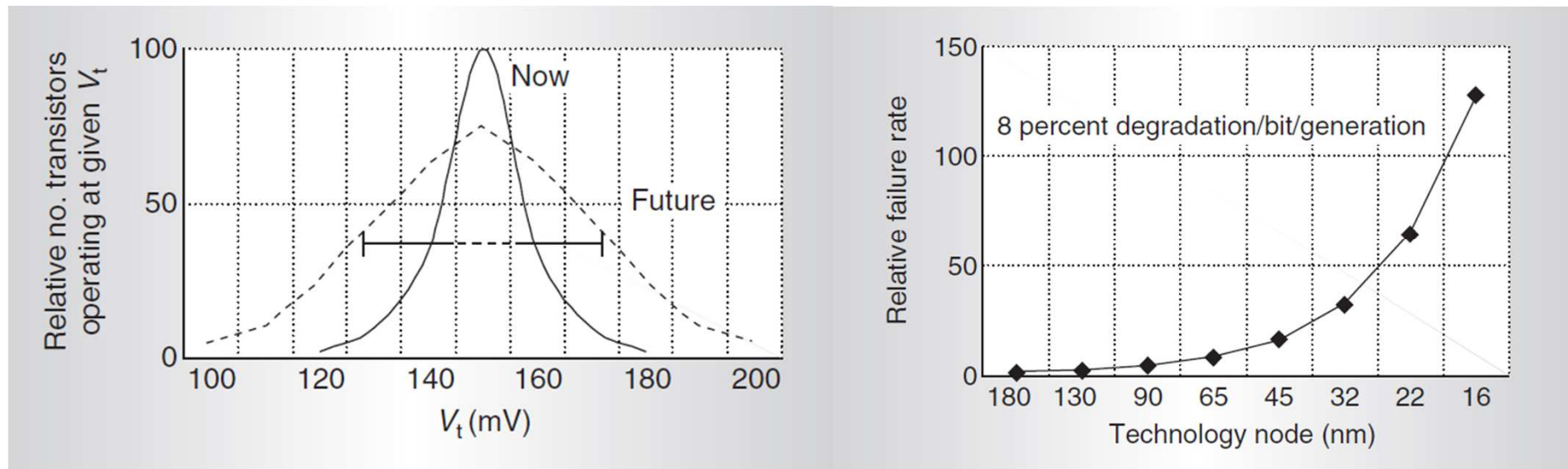
nsistors



accelerator

...and variability

- Dramatic changes in the area of computing architectures
- Robustness issues



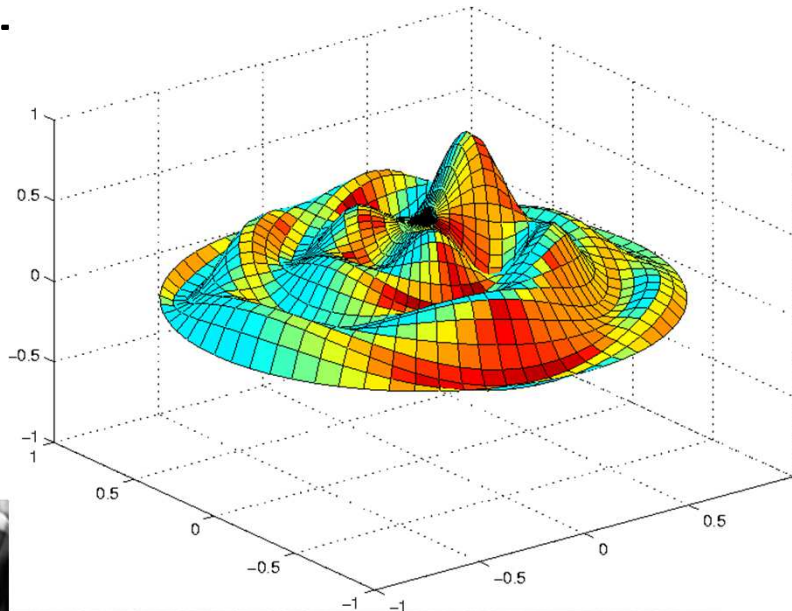
(Borkar 2005)

- Robust accelerators

for new applications

■ Today : scientific computing, cryptography, ...

■ -



ion, Mining, Synthesis



PHOTO: THINKSTOCK/CNNMONEY



A potential answer : Neural networks

- Neural Networks are good candidates

- They provide Robustness

Signal processing

Approximation

- Good application scope

Optimization

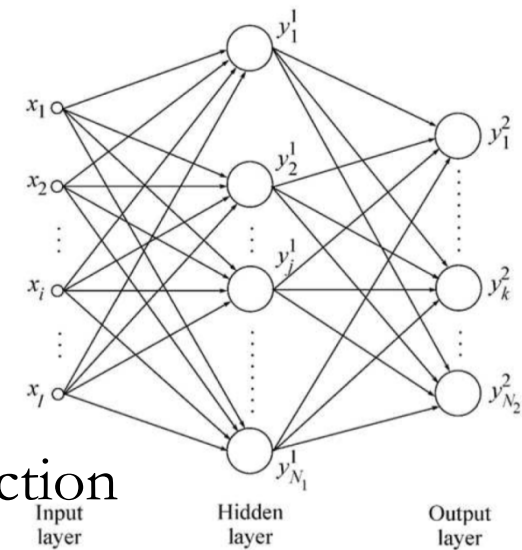
Prediction

Clustering

Classification

- But classically limited by 2D hardware solutions

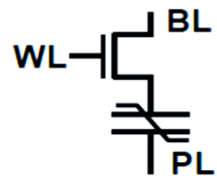
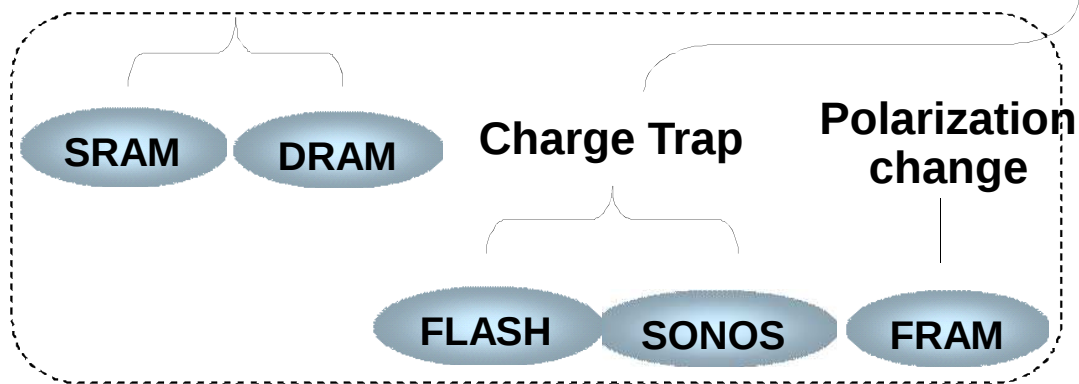
- Limited interconnections, costly long range ones
- But the HW situation has changed !



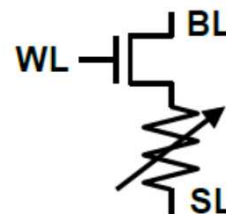
- Context
- **Exploiting resistive memories**
- Analogue neurons and 3D-TSV
- Towards monolithic 3D...
- Conclusion

New memory technologies

Volatile Memory

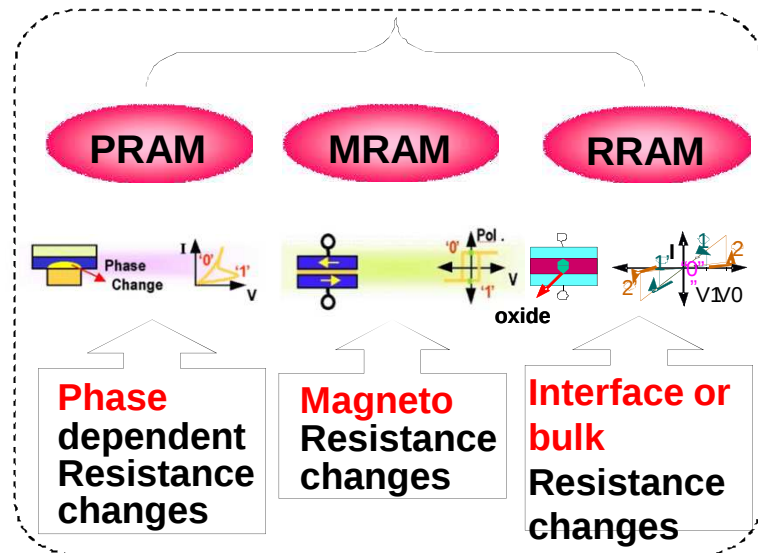


Charge -based Programming & Reading



Non-Volatile Memory

Resistance Change = memristors



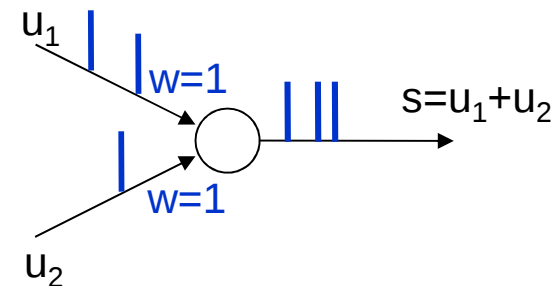
Current -based Programming & Reading

Memristors

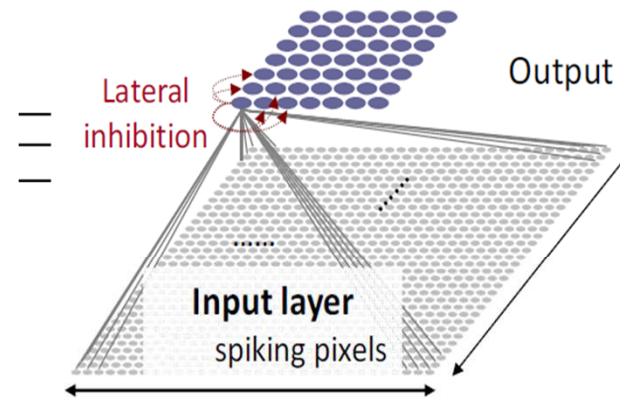
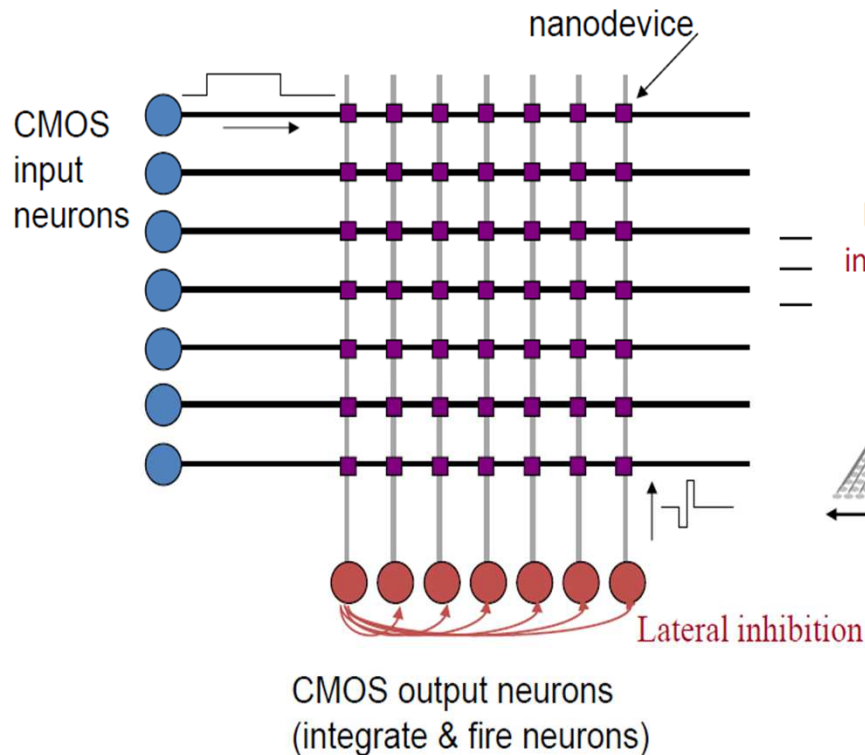
	DRAM	FLASH	MRAM	PRAM	RRAM	
		Nand	STT		OxRAM	CBRAM
Compatibility with CMOS	- -	-	-	+	++	++
Scalability	32nm	15nm	20-30nm	10-20 nm	10 nm	10-20 nm
Density	6-8f ²	4f ²	35-40f ²	4-6f ²	4-6f ²	4-6f ²
Maturity	++	++	-	-	--	--
Byte @	YES	NO	YES	YES	YES	YES
Writing cycle	50ns	0.1 ms	20ns	100 ns	150 ns	1-10 us
Endurance	1,00E+16	1,00E+05	1,00E+15	1,00E+09	→1,00E+06	1,00E+06
Plus	Perf.	NV	Perf. + NV + Endurance	Perf. + NV+ density	Perf. + NV+ density	Vitesse lect+ NV+ densité
Minus	Scalability	Endurance Perf - -	Costly tech. Delay wrt CMOS nodes	consumption	Endurance, Forming	Endurance, Perf.

Memristor as a Synapse

- Concept introduced by Chua
 - “Memristor-The missing circuit element” - 1971
- Strukov & Snider developed it
 - “The missing memristor found” - Nature 2008
 - “Spike-timing-dependent learning in memristive nanodevices” – Nanoarch 2008
- Concept “memristor = synapse weight”
 - So easy ?



Crossbar of Synapses



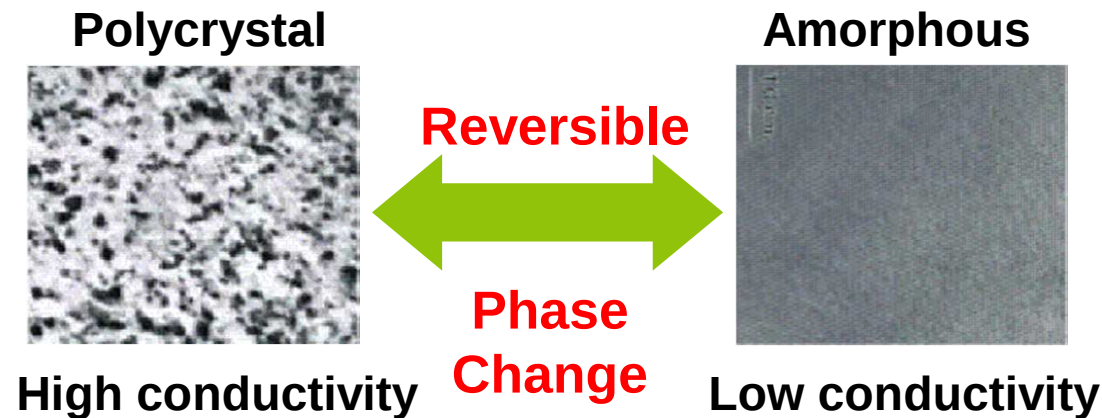
D. Querlioz, et al. "Immunity to Device Variations in a Spiking Neural Network with Memristive Nanodevices," *IEEE TNANO* 2013

- Require "gradually" programming memristors
 - Difficulty is to obtain equivalent potentiation / depression phases

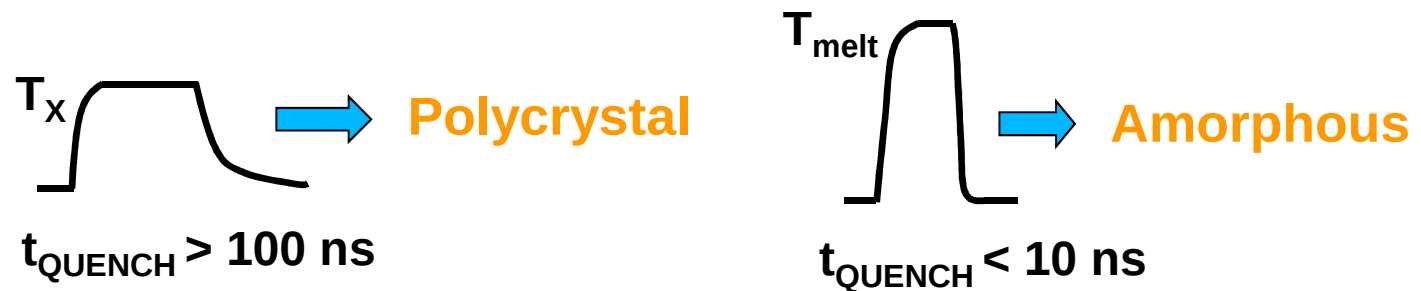
Phase-Change Memories

■ Material with 2 stable phases

- Chalcogenide alloys : GST, GeTe, ...
- Hysteresis cycle between 2 states

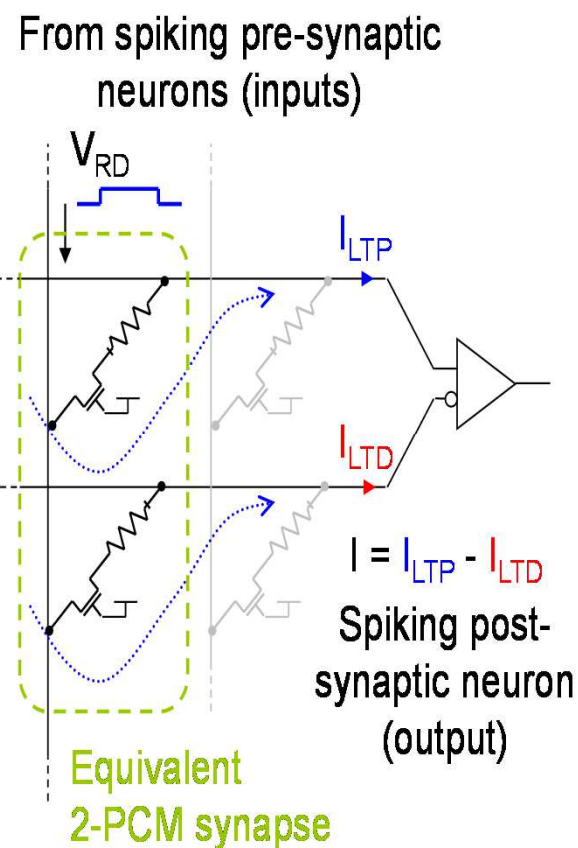
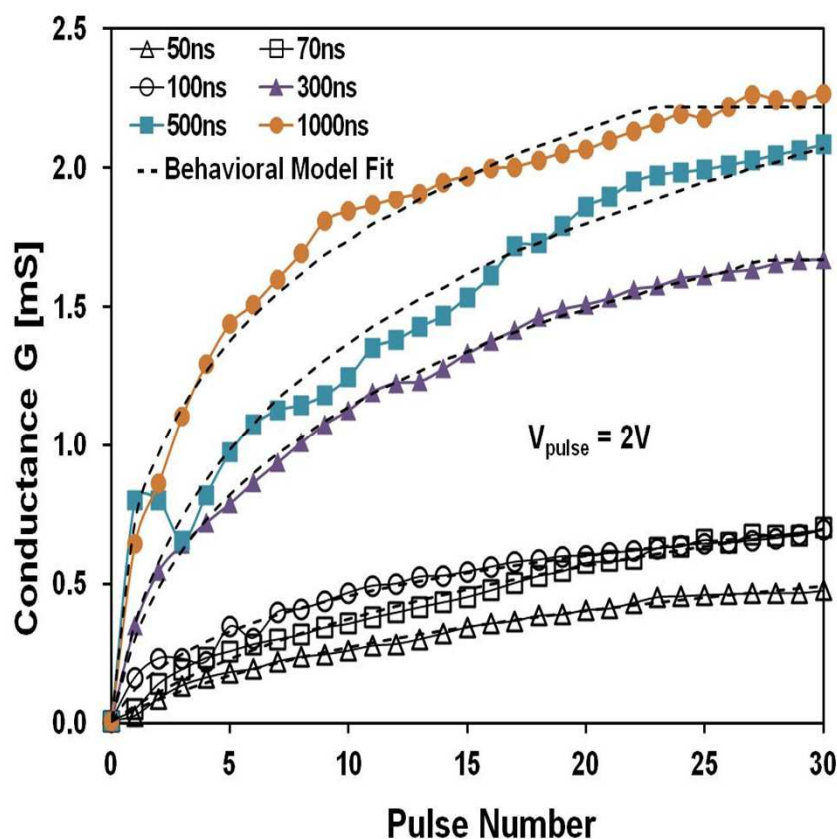


■ Transition by Joule heating



A solution: 2-PCM Synapse

- Symmetric Long-Term-Potentiation and Long-Term depression behavior by using pulsed crystallization.



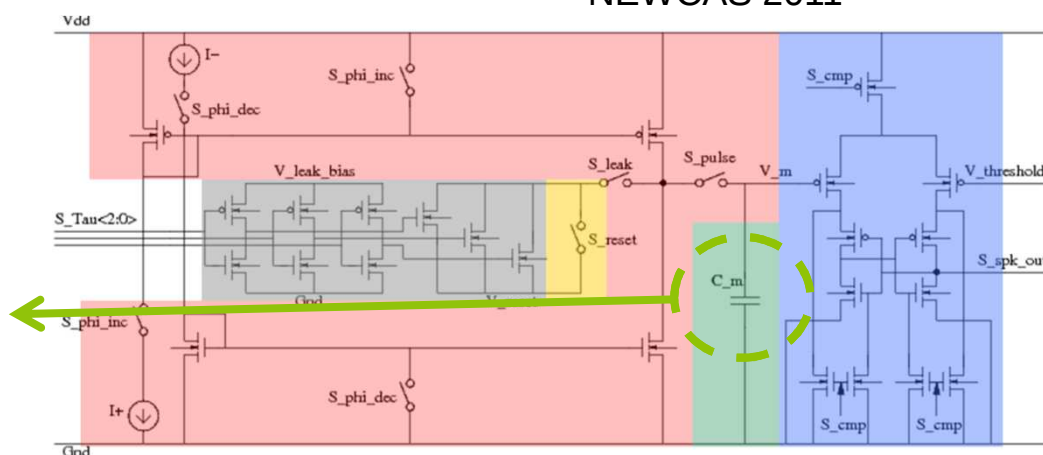
- Context
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- **Analogue neurons and 3D-TSV**
- Towards monolithic 3D...
- Conclusion

Analogue neurons

- Compact design (5x gain vs digital)
- Low power consumption (20x gain vs digital)
- Ability to interface sensors directly with the processing part
- Computational efficiency

A. Joubert et al. "A robust and compact 65 nm LIF analog neuron for computational purposes," IEEE NEWCAS 2011

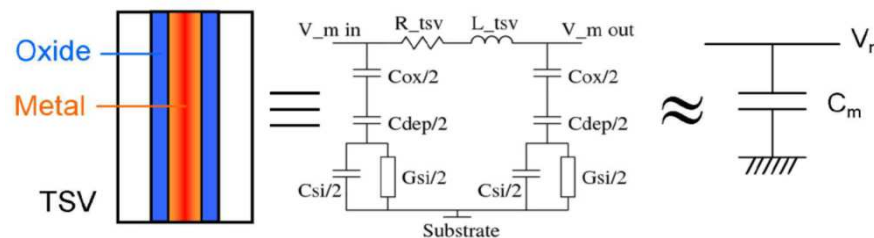
Drawback:
Large capacitance
required (0,5-1pF)
⇒ MIM
⇒ Large area (not
scalable !)



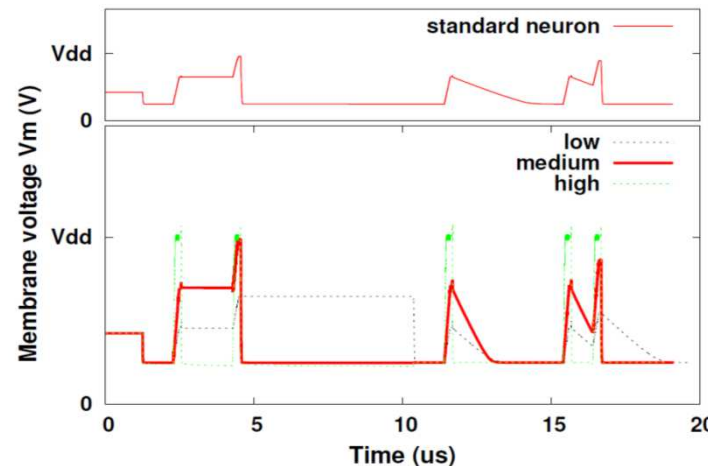
Leaky Integrate and Fire Neuron in CMOS 65nm
accept spikes in 1kHz-1 Mhz range

Through Silicon Vias

- Used for crossing circuits in 3D stacking
- Present large “parasitic” capacitance

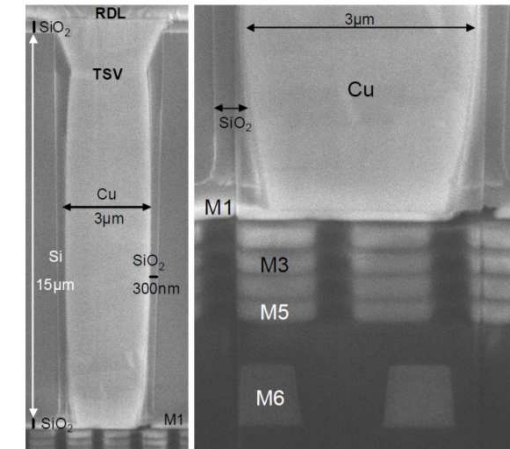
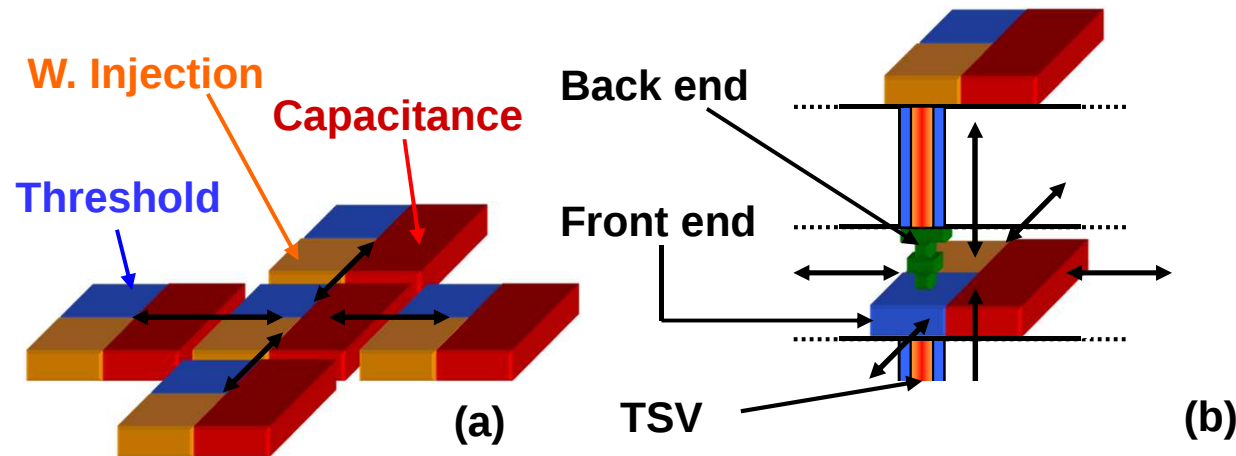


- Demonstrated feasibility

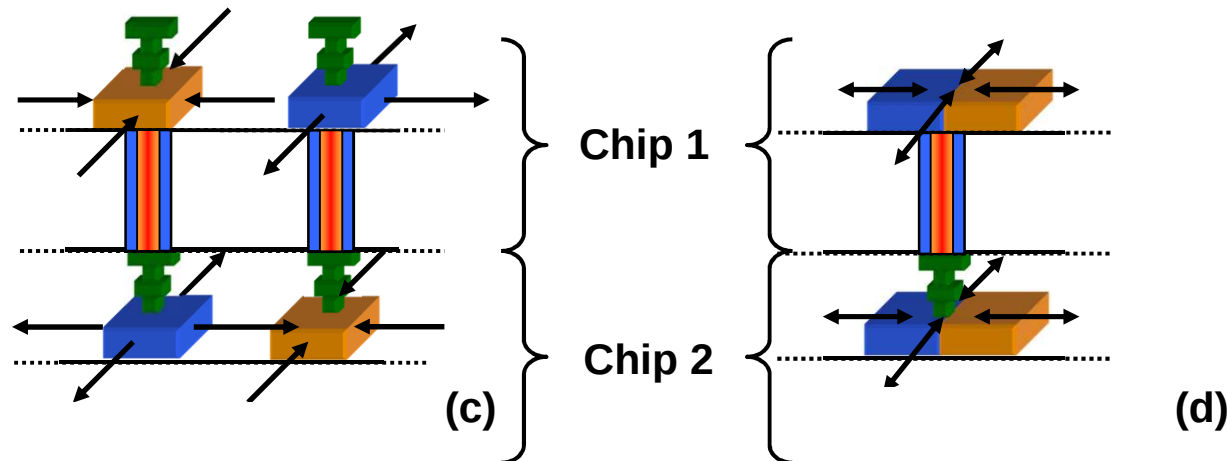


A. Joubert et al., “Capacitance of TSVs in 3-D stacked chips a problem? Not for neuromorphic systems”, DAC’12

3D integration using TSV



Chaabouni et. al. (2010)



(a) Standard 2D neuromorphic architecture

(b) 3D stacking with standard 2D neurons

(c) et (d) 3D stacking with TSV-based neurons

- Context
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- **3D technologies**

- **Parallel Integration**

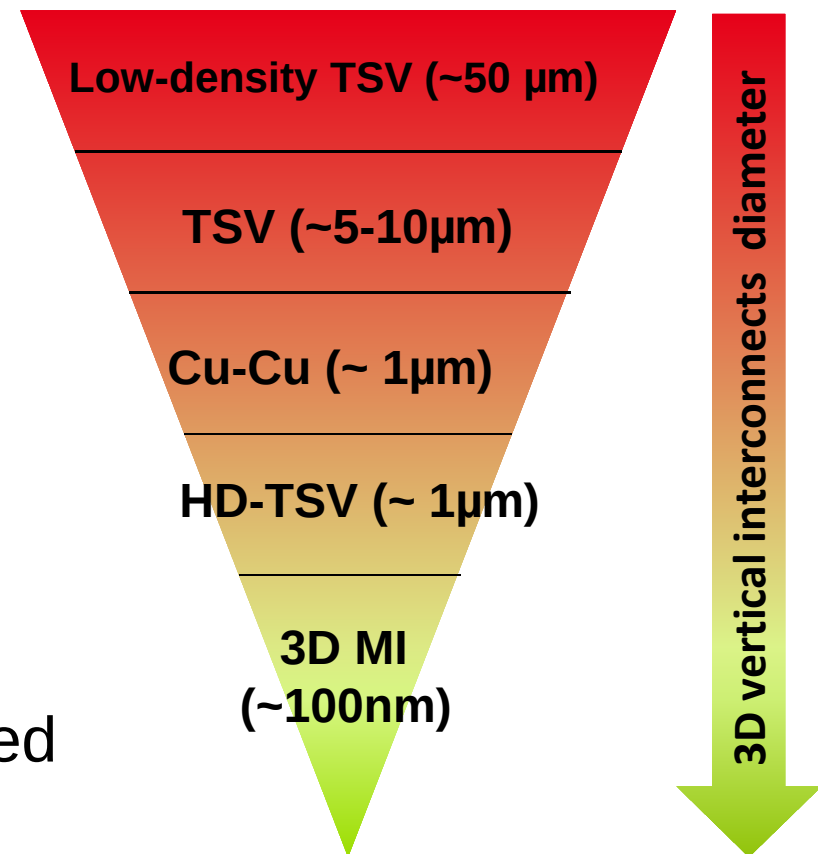
Dies fabricated separately then vertically stacked, such as:

- Through-Silicon-Via (TSV)
- Copper-to-Copper (Cu-Cu) contact
- High-Density TSVs

- **Sequential Integration**

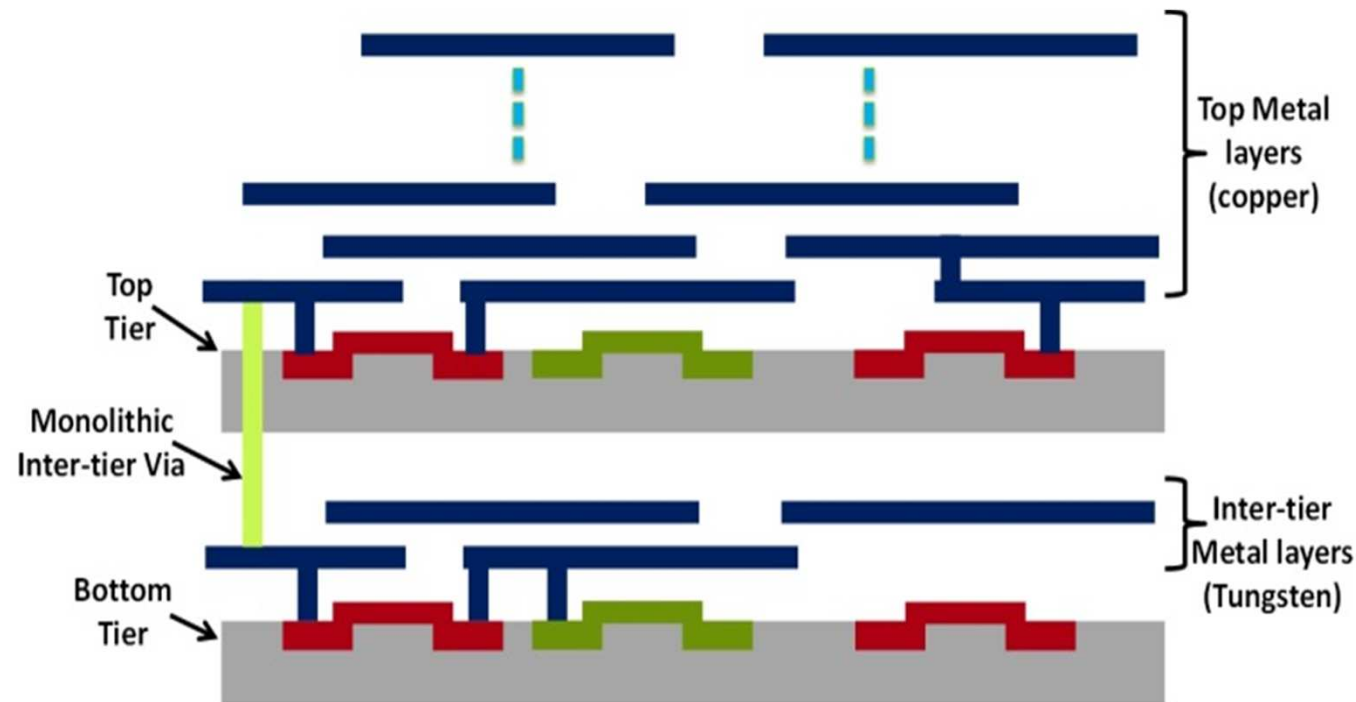
Second transistor layer is fabricated directly on the top of first one.
(Cold process)

- **3D Monolithic Integration (3DMI)**



Monolithic 3D

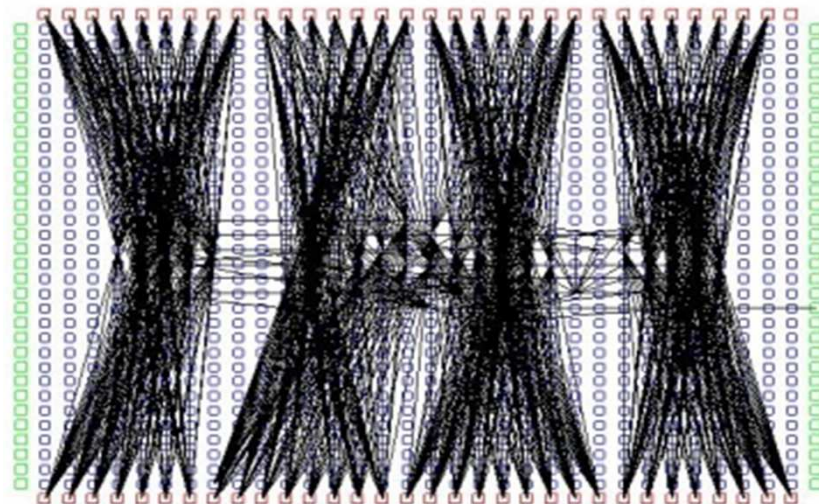
- Integration is monolithic using a “cold” process
 - Allows 100 nm 3D vias pitch
- => Open perspectives for real 3D implementation



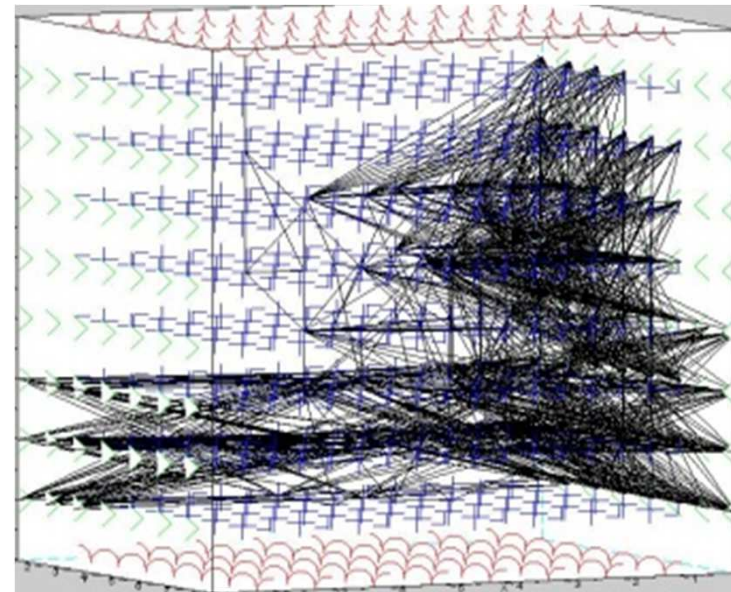
P. Batude et al., "GeOI and SOI 3D Monolithic Cell integrations for High Density Applications" VLSIT 2009

2D versus 3D mapping on NN

- Using 3D TSV allows a “cube” of neurons
- Drastically reduce interconnects
- Example shown here is 3x more efficient in 3D



2-D



3-D

184 neurons with 1181 connections

- Neuromorphic architectures are appealing
 - Solve dark silicon issues
 - Adapted to modern applications
- And can take benefit of advances technologies
 - Synapse => Memristors = RRAM, PCM
 - Neurons => Analogue neurons + high-capacitance TSV
 - Interconnections => high-density 3D
- The path is open for the next neuromorphic revolution!



Questions ?



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