

# Advanced Technologies for Brain-Inspired Computing

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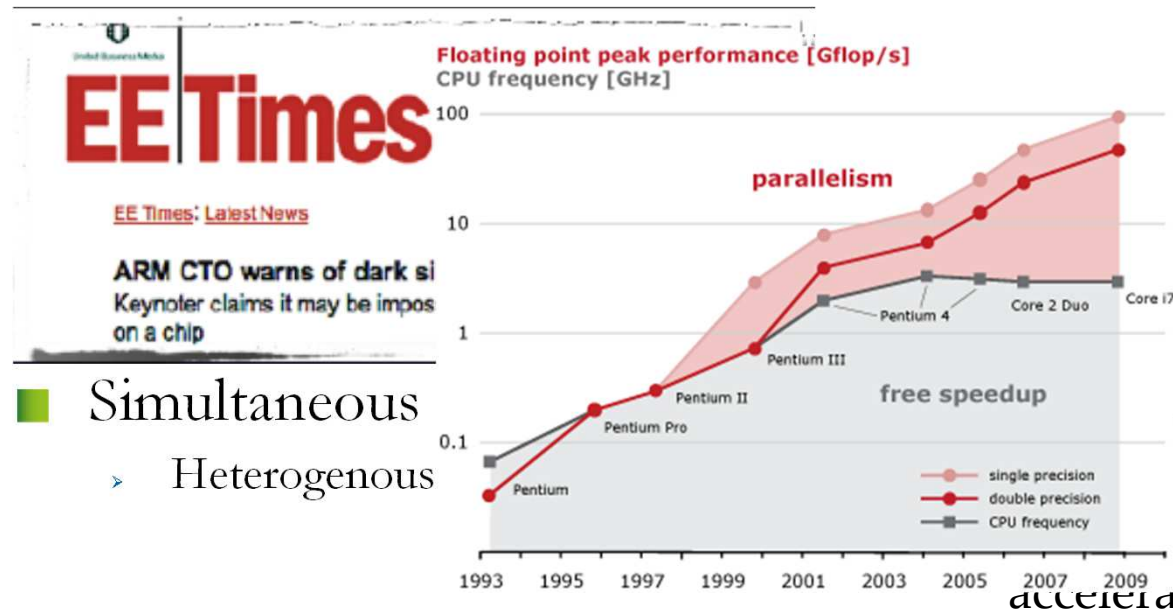
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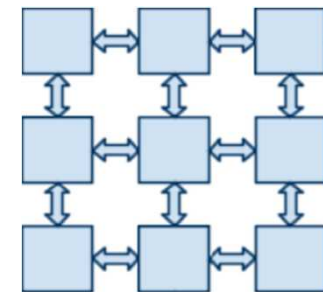
# Context: dark silicon...

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

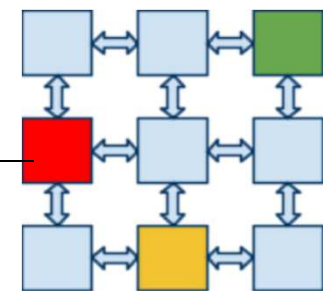


- Simultaneous
  - Heterogenous

- Need for versatile hardware accelerators

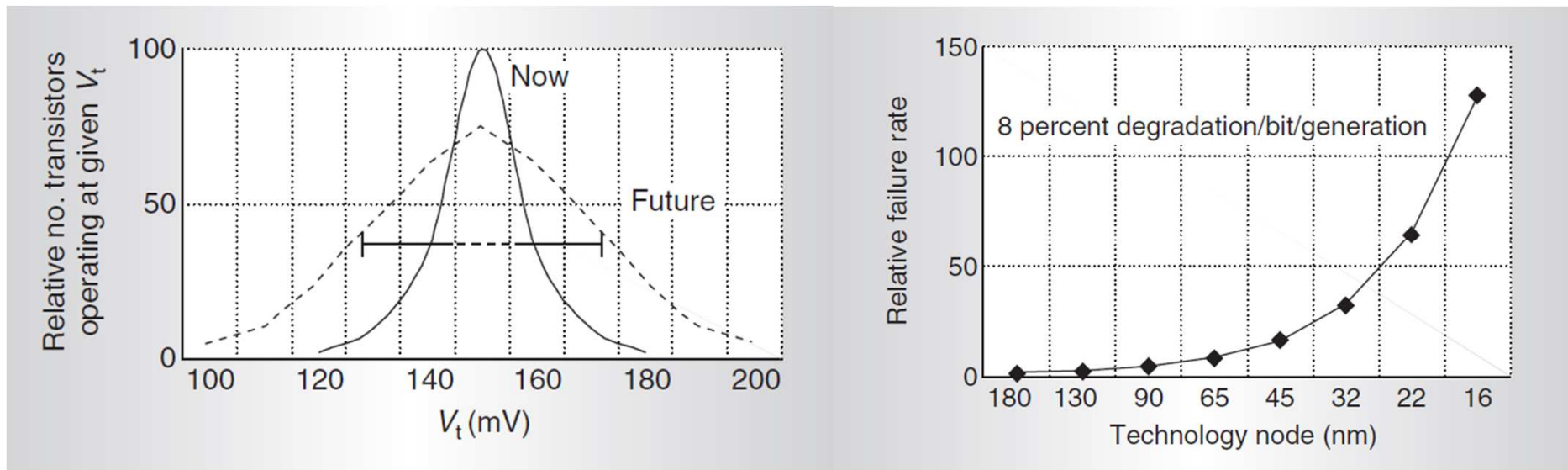


nsistors



# ...and variability

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



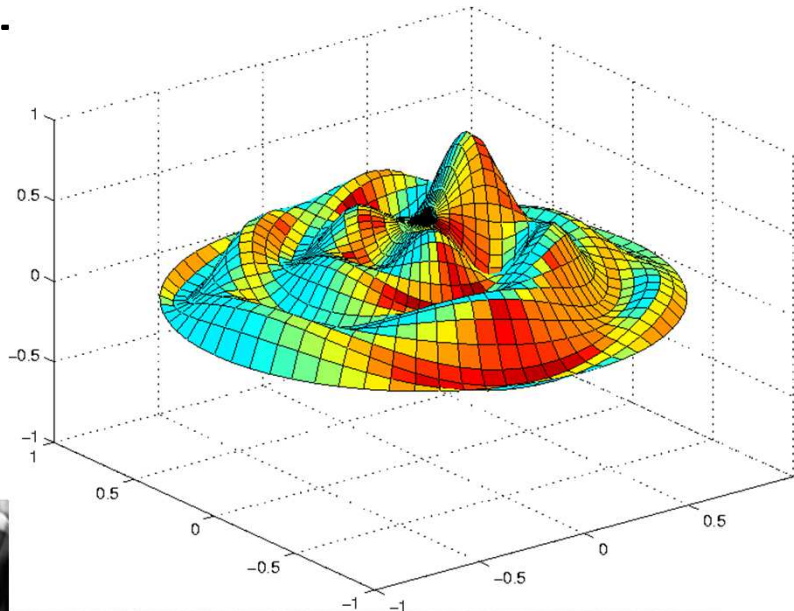
(Borkar 2005)

- Robust accelerators

# for new applications

■ Today : scientific computing, cryptography, ...

■ *ion, Mining, Synthesis*



# A potential answer : Neural networks

- Neural Networks are good candidates

- They provide Robustness

Signal processing

Approximation

- Good application scope

Optimization

Prediction

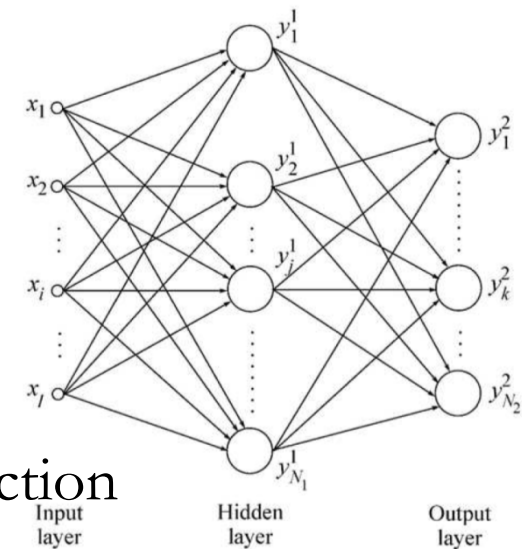
Clustering

Classification

- But classically limited by 2D hardware solutions

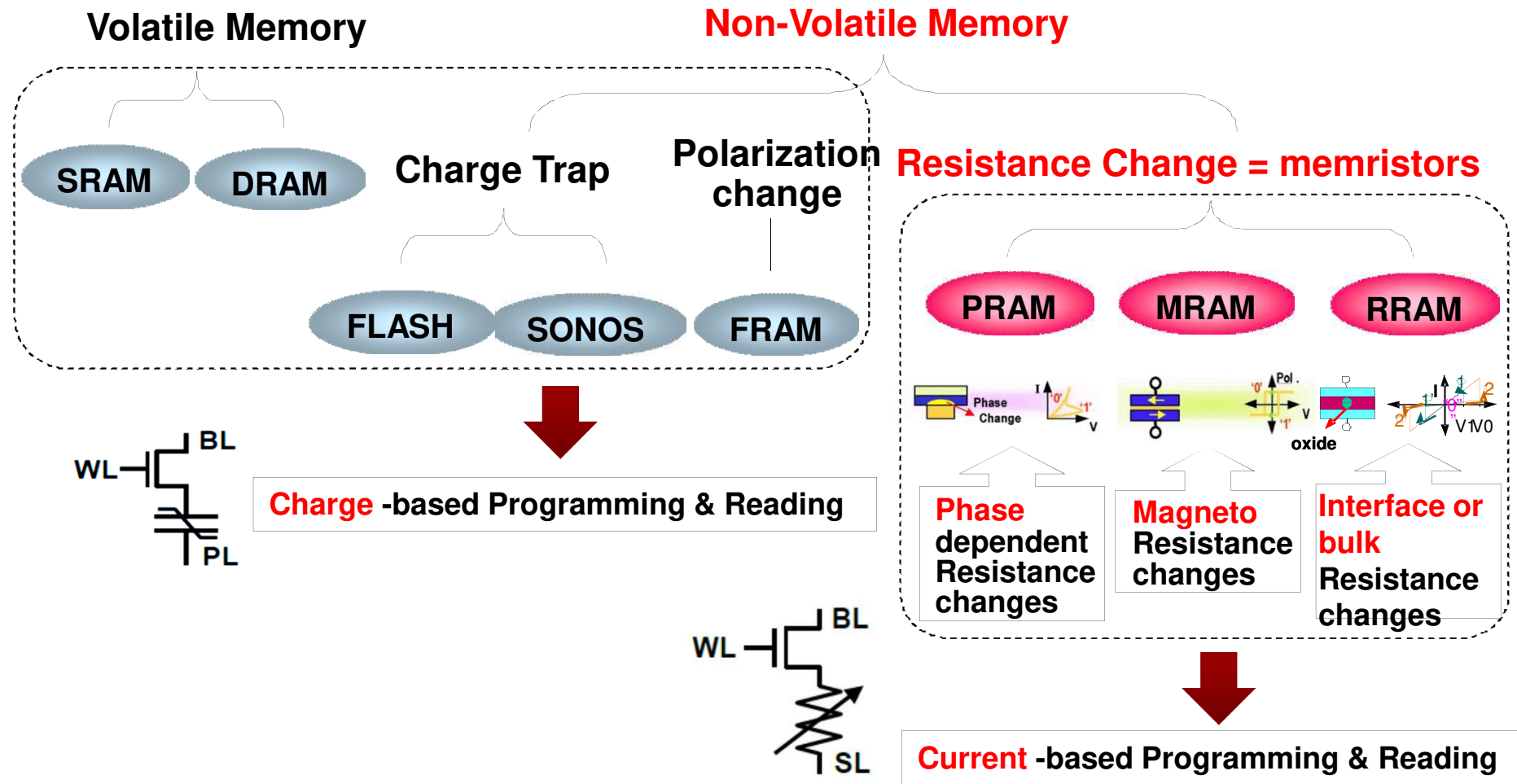
- Limited interconnections, costly long range ones

- But the HW situation has changed !



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

# New memory technologies



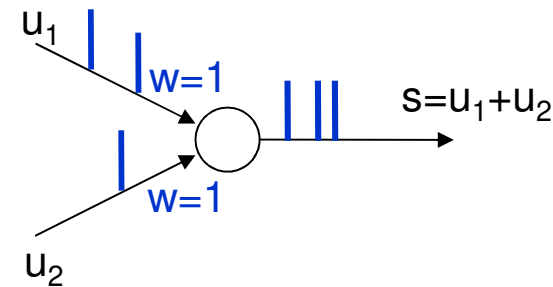
# Memristors

	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 <sup>2</sup>	4f <sup>2</sup>	35-40f <sup>2</sup>	4-6f <sup>2</sup>	4-6f <sup>2</sup>	4-6f <sup>2</sup>
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	consumptio n	Endurance, Forming	Endurance, Perf.

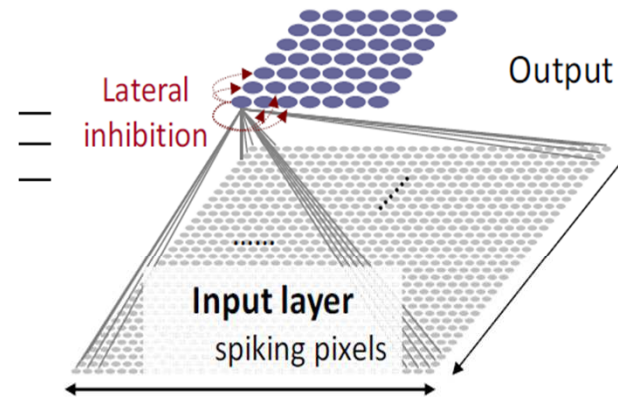
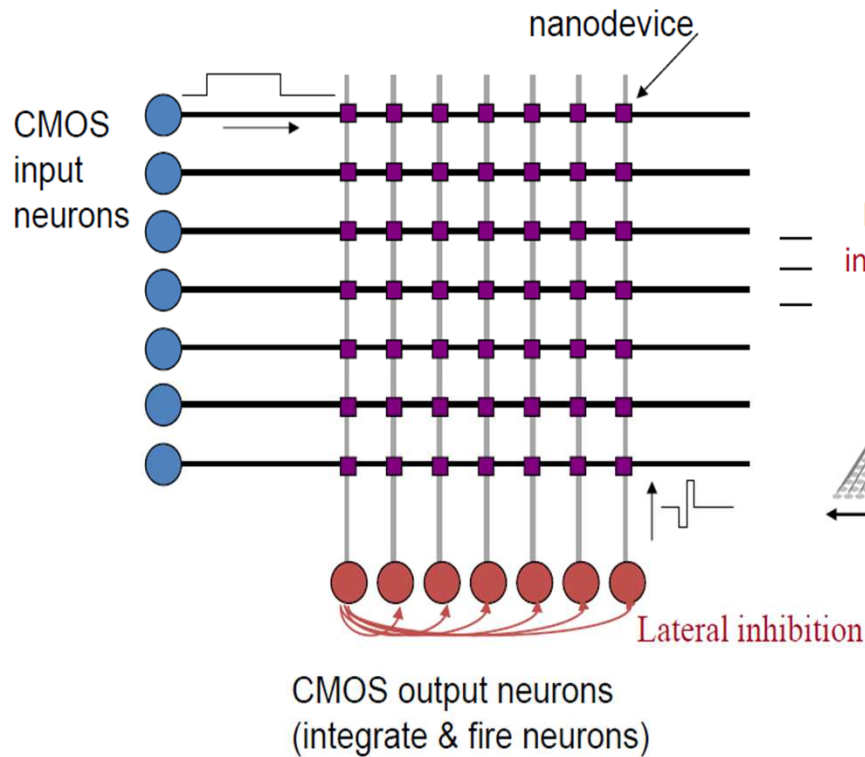


# Memristor as a Synapse

- 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



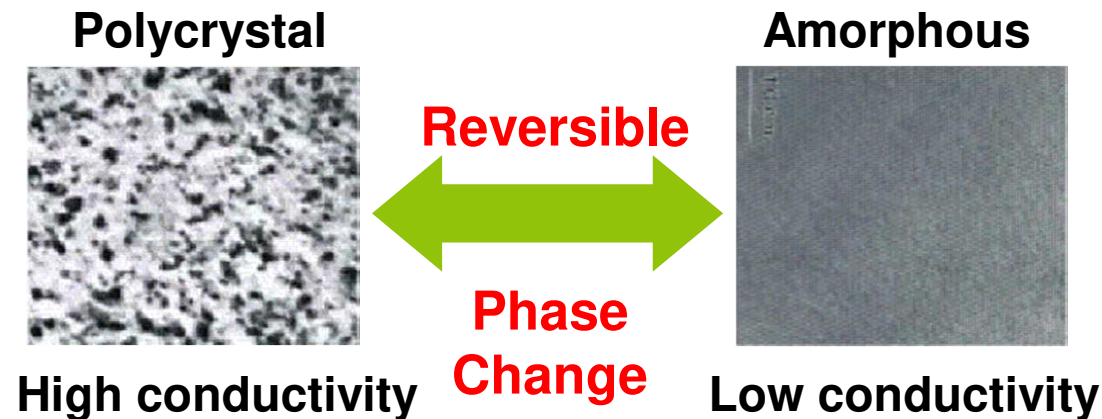
D. Querlioz, et al. "Immunity to Device Variations in a Spiking Neural Network with Memristive Nanodevices," *IEEE TNANO* 2013

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

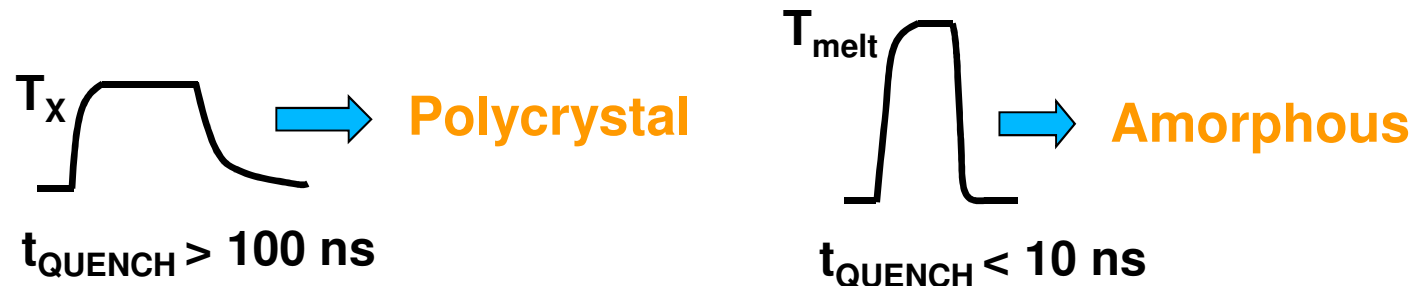
# Phase-Change Memories

## ■ Material with 2 stable phases

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

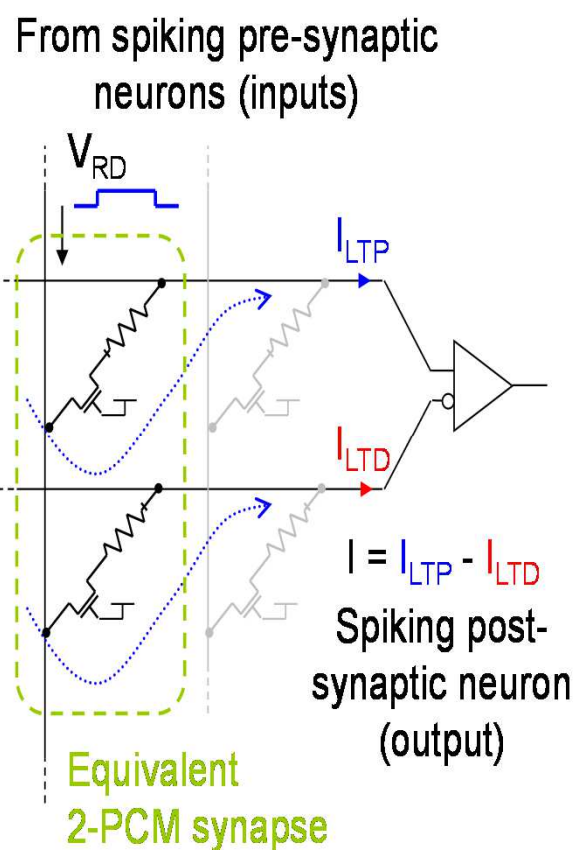
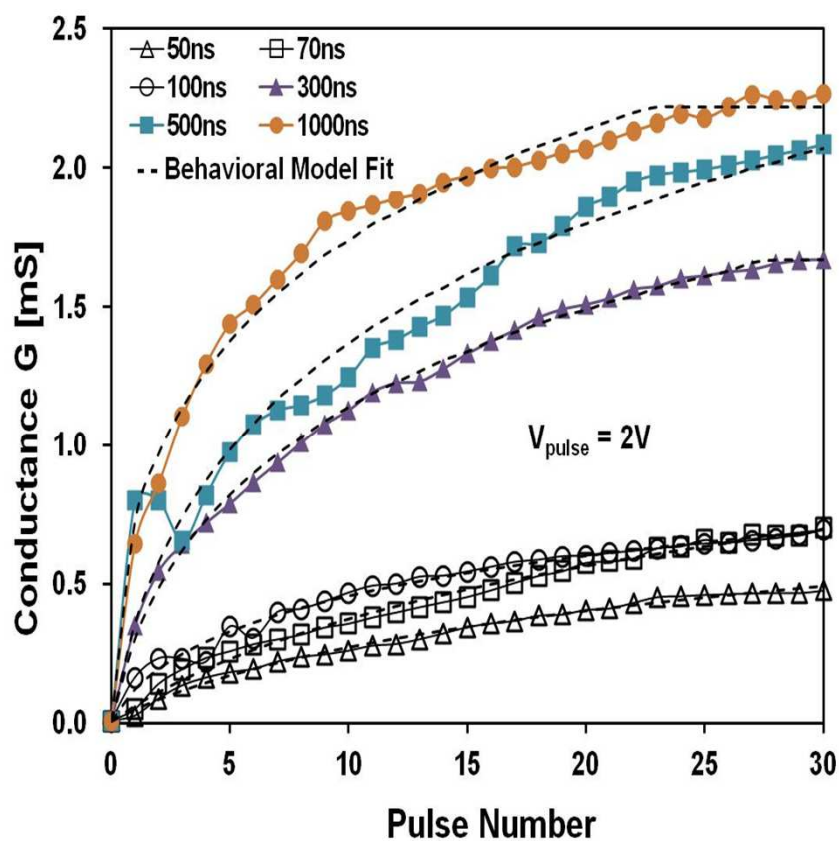


## ■ Transition by Joule heating



# A solution: 2-PCM Synapse

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



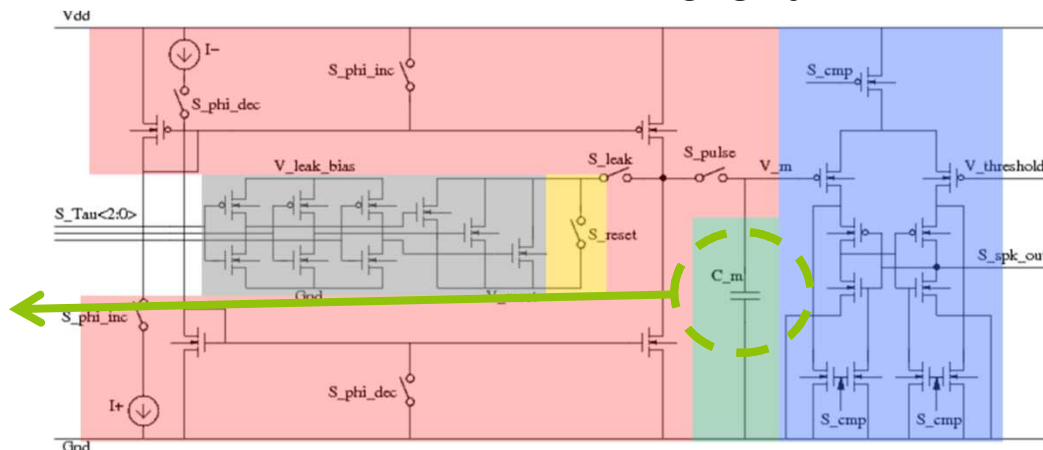
- Context
- Exploiting resistive memories
- **Analogue neurons and 3D-TSV**
- Towards monolithic 3D...
- Conclusion

# 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

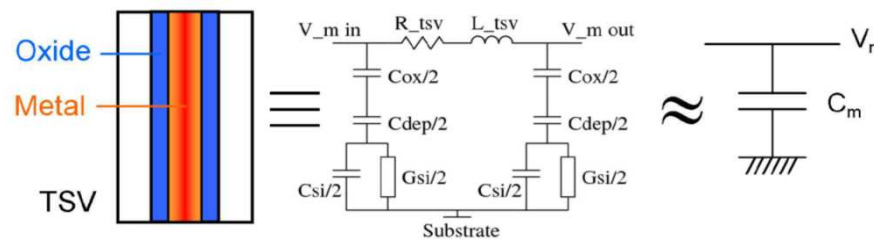
Drawback:  
Large capacitance  
required (0,5-1pF)  
⇒ MIM  
⇒ Large area (not  
scalable !)



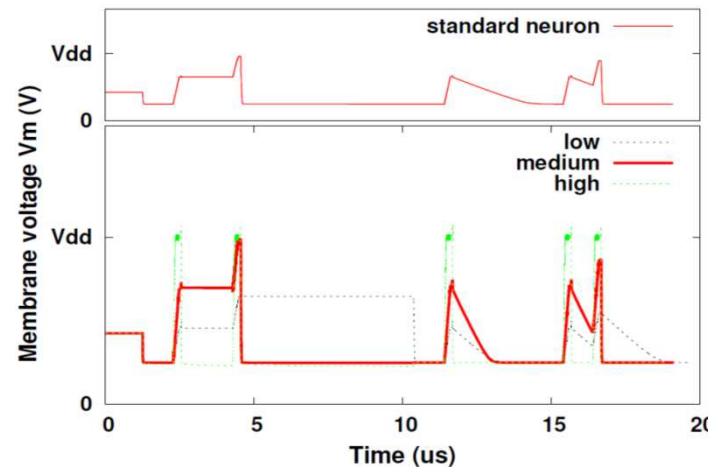
Leaky Integrate and Fire Neuron in CMOS 65nm  
accept spikes in 1kHz-1 Mhz range

# Through Silicon Vias

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

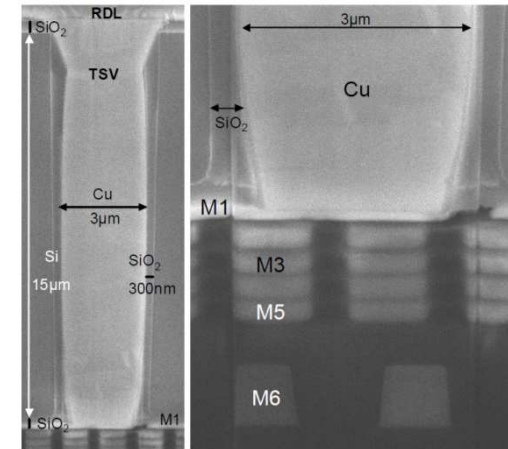
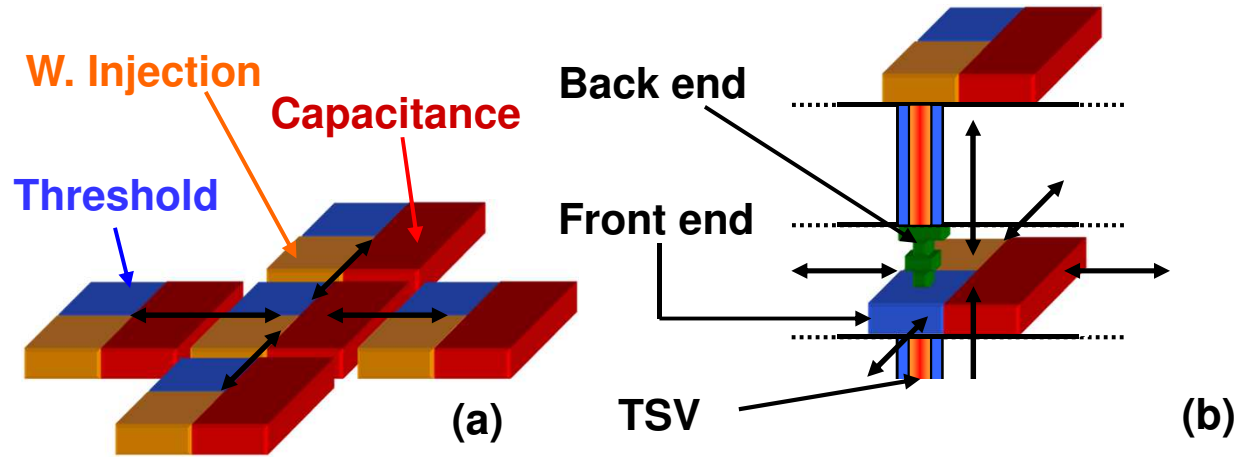


- Demonstrated feasibility

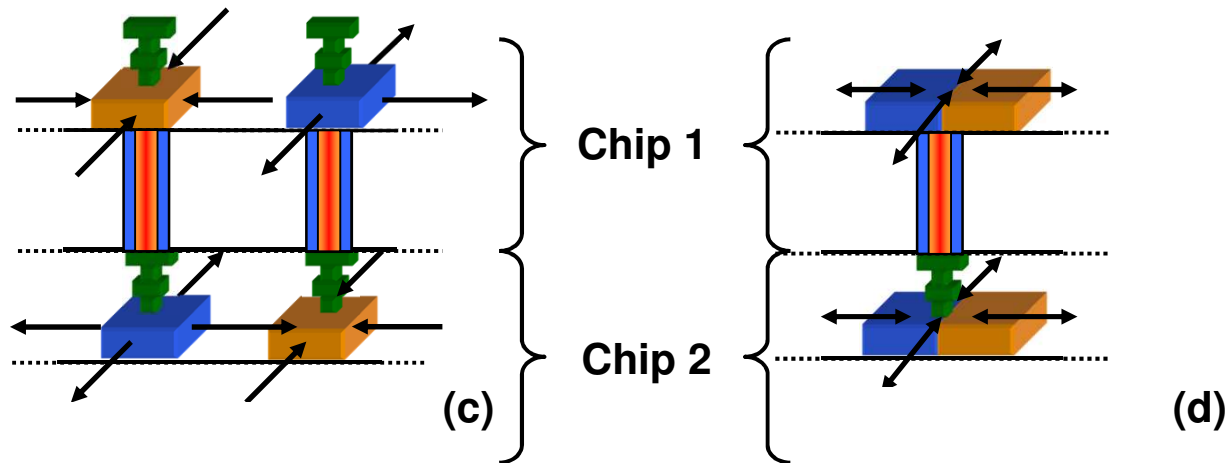


A. Joubert et al., “Capacitance of TSVs in 3-D stacked chips a problem? Not for neuromorphic systems”, DAC’12

# 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**

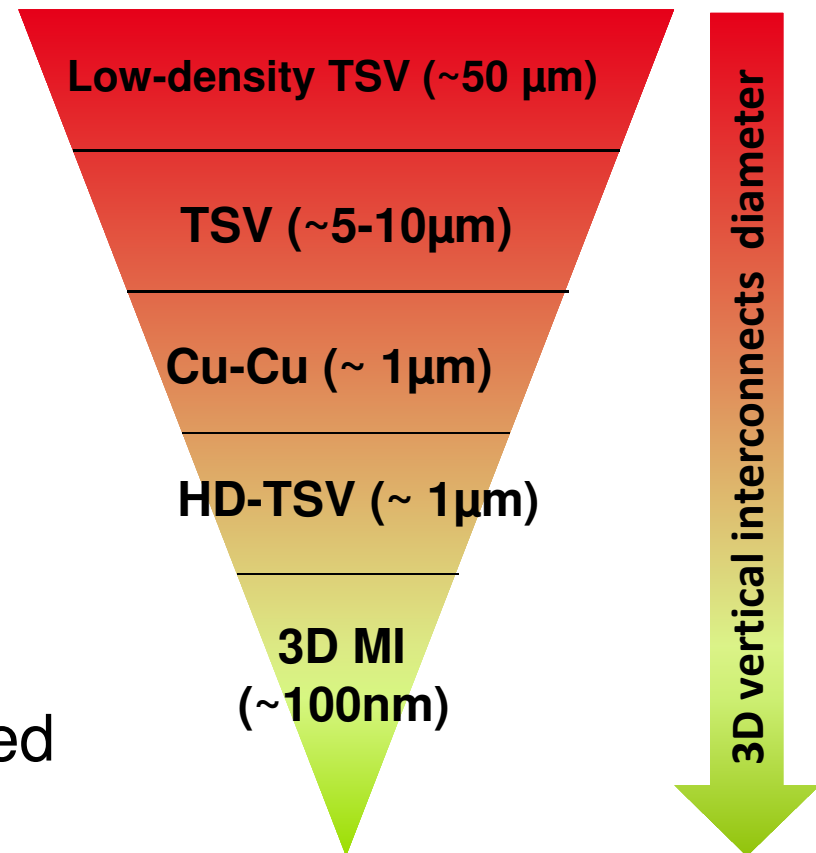
Dies fabricated separately then vertically stacked, such as:

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

- **Sequential Integration**

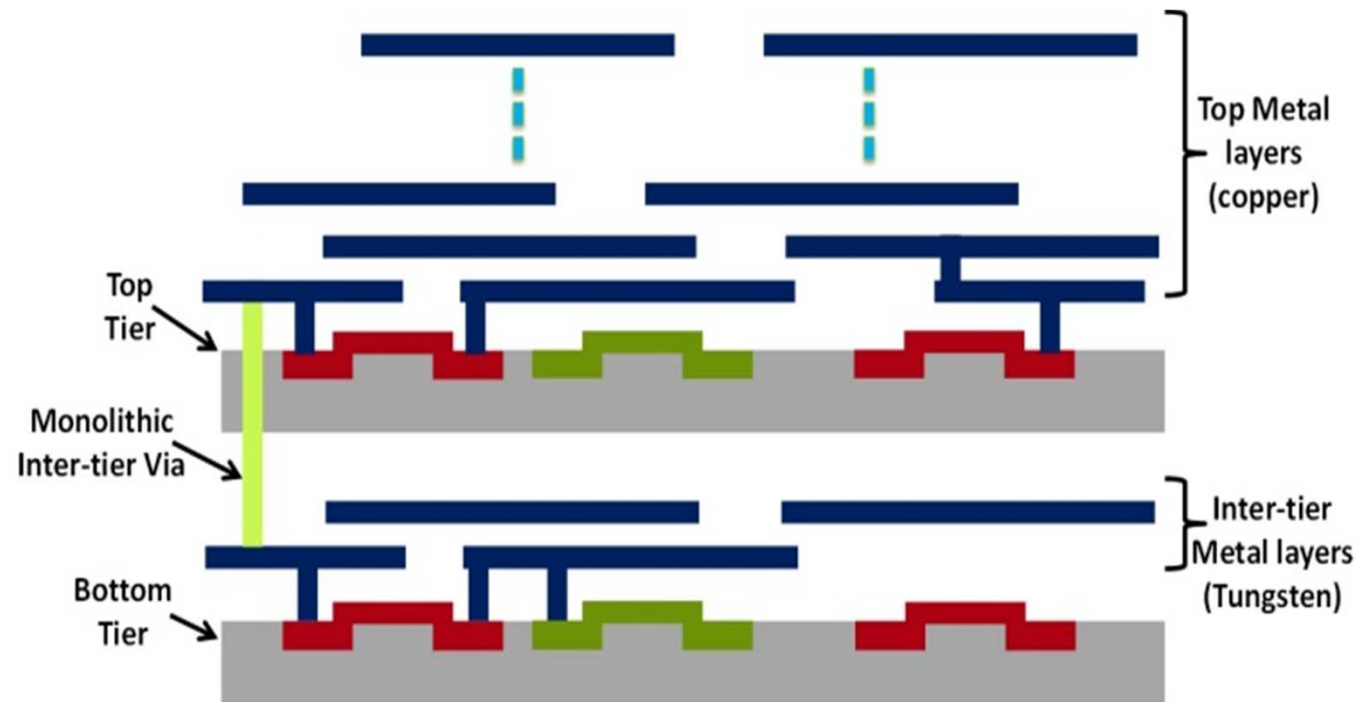
Second transistor layer is fabricated directly on the top of first one.  
(Cold process)

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



# Monolithic 3D

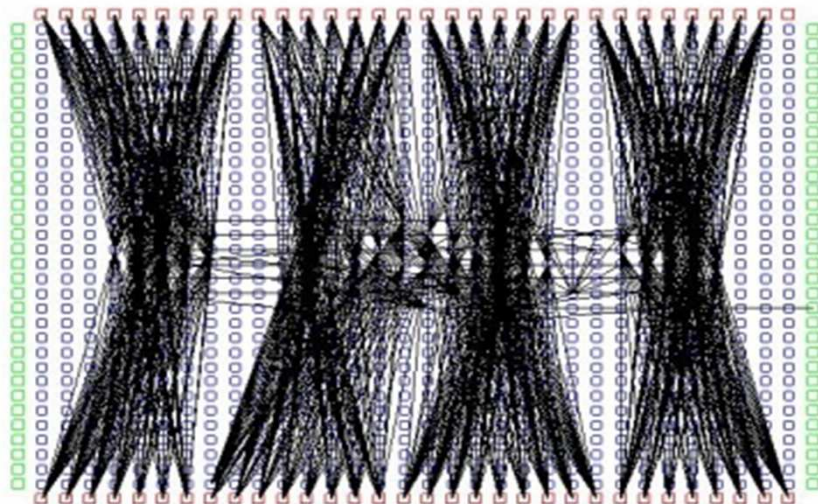
- Integration is monolithic using a “cold” process
  - Allows 100 nm 3D vias pitch
- => Open perspectives for real 3D implementation



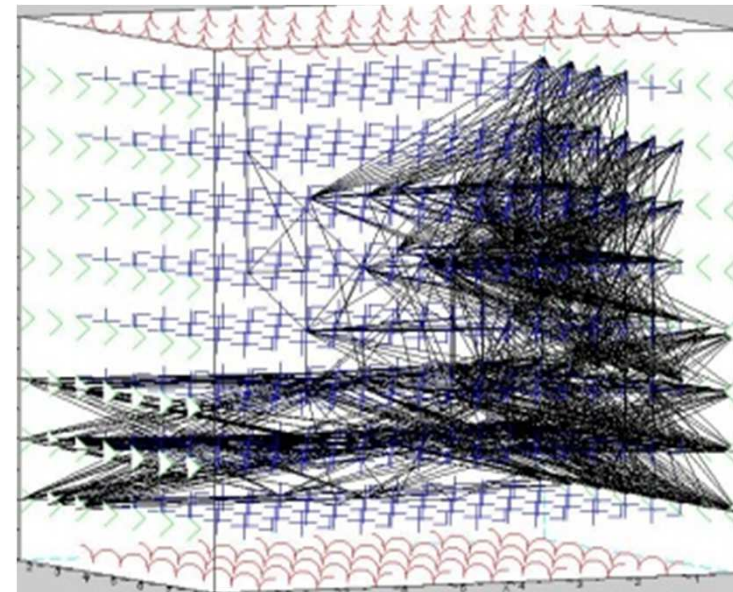
P. Batude et al., "GeOI and SOI 3D Monolithic Cell integrations for High Density Applications" VLSIT 2009

# 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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