Future computer Architectures: Computing in Memory

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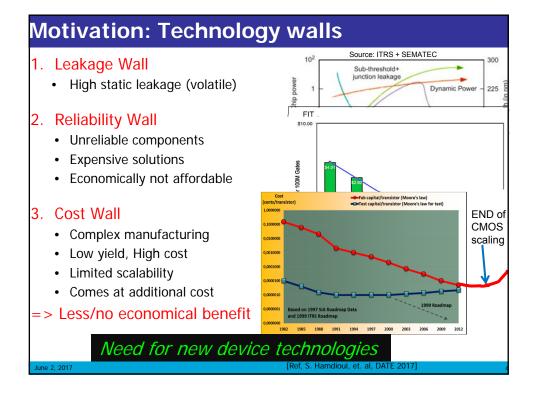


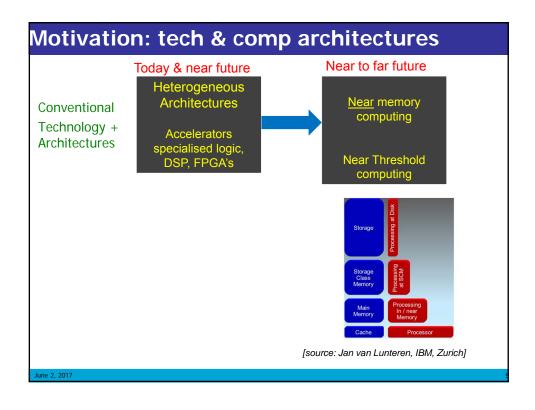
Outline

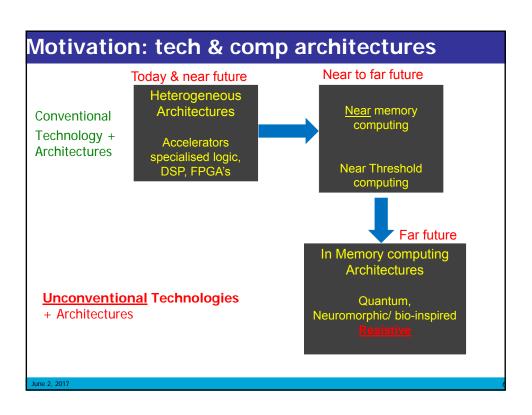
- Motivation
 - The need of new technology and architectures
- Memristor (memristive devices)
 - Promising device, principal of working, potential
- Memrisor for memories
 - Straightforward application
- Memristor for logic
 - Different styles
- Computation-in-memory architecture
 - · Combining all together
- Some results/ potential of CIM
 - · Does it make sense?
- Conclusion

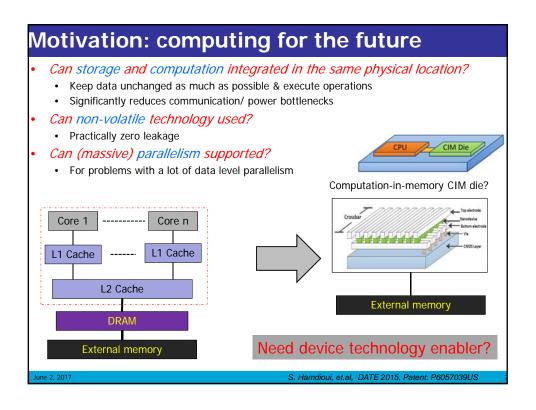
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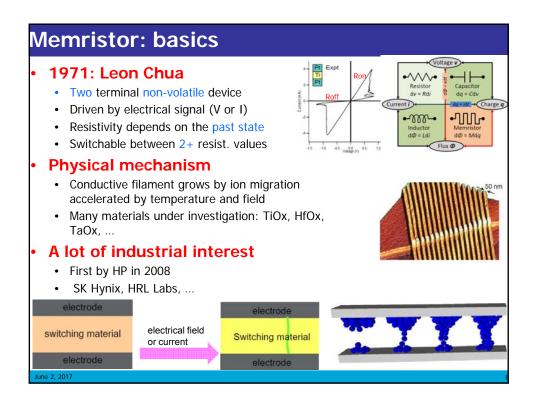
Motivation: Computing walls 1. Power Wall Chip-level energy trends · Dominated by com & memory 70 to 90% for data-ints. Appl 2. Memory Wall · Slow Limited bandwidth Communication bottleneck IS. Borkar, "Exascale Computing: a fact or a fiction?," IPDPS · Stored program principle Energy/Op Operation Cost (8-bit operand) (45 nm) (vs. ALU) ILP Wall 0.05 pJ 1 X **ALU** operation · Insufficient parallelism at instr. level • Programmability Complexity & overhead 10⁴ => Reduced / Saturated performance 10³ Enhancement based on expensive on chip memory (~70% of area) 102 Requires LD & ST: killers of overall perf 10¹ Need of new architectures



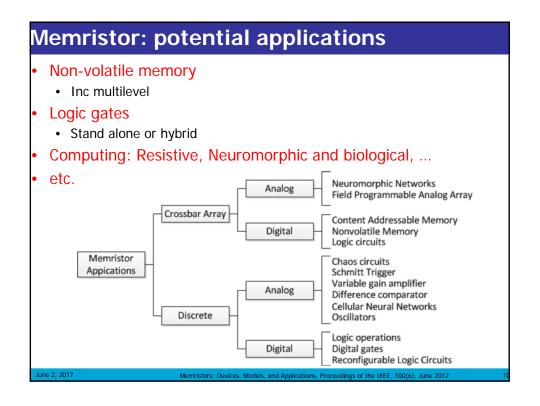


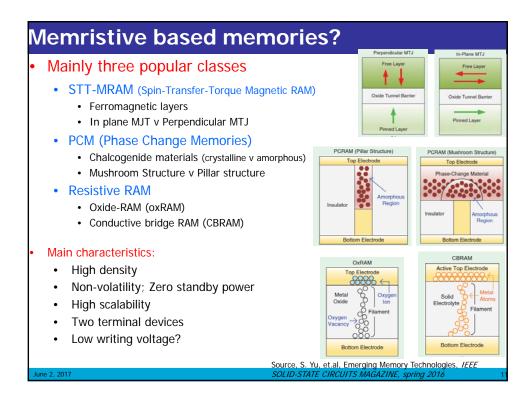






Memristor: Advantages **Dual functionality** Realize both memory and logic functions Enable new computing paradigms Reduce (eliminate) memory wall Low energy consumption · Low/zero leakage: Non-volatility Reduce the overall power consumption Scalability/ Nanometric dimensions · Extreme density at low price and reduce area Sustain the profitability of Moore's law CMOS compatibility Enable the heterogeneous integration Enhance manufacturing at low cost Two terminal passive device structure Realize dense crossbar architectures Stack on CMOS Good endurance & Good Reliability?





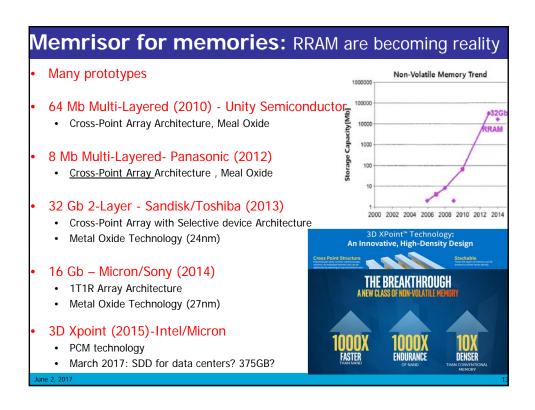
Memristive based memories?

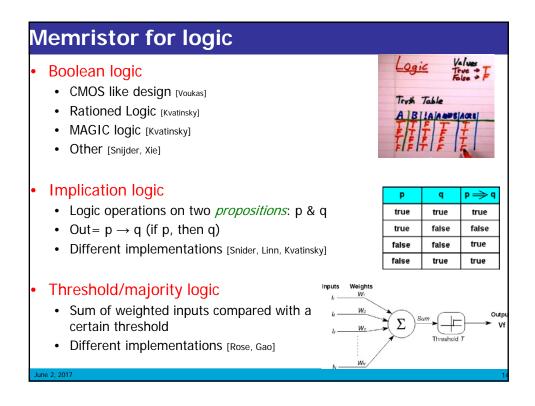
- oxRAM seems to be most promising
 - Very high density (cross-point array structure)
 - Smaller and simpler in respect to MRAM
 - Lower consumption in respect to PCM.
 - Lower programming voltage and faster

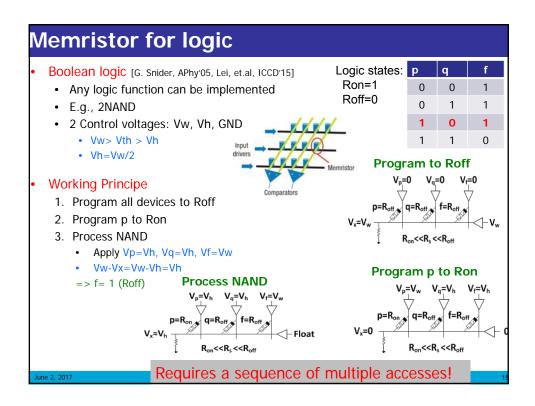
Features	DRAM	FLASH Nand	MRAM STT	PCM	ReRAM	
					OxRAM	CBRAM
Integration	FE	FE	BE	BE	BE	BE
Scalability	32 nm	15 nm	20-30 nm	10-20 nm	10 nm	10-20 nm
Density	4-6f ²	4f ²	35-40f ²	6-8f ²	4-6f ²	4-6f ²
Write voltage	V _{NOM}	>10V	1V	3-5V	1-2.5V	1-2.5V
Write time	50ns	0.1ms	20ns	10ns	10-50ns	100-1000ns
Write energy	90fJ/bit		2.5pJ/bit	20pJ/bit	10-100fJ/bit	10-100fJ/bit
Endurance	1E ⁺¹⁵	1E ⁺⁴⁻⁵	1E ⁺¹²⁻¹⁵	1E ⁺⁹	1E ⁺⁶⁻¹⁰	1E ⁺⁵⁻⁶

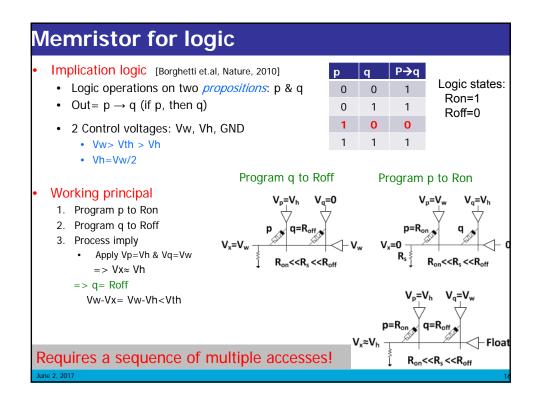
lune 2, 2017 [ref: Clermidy-2014]

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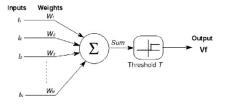






Memristor for logic

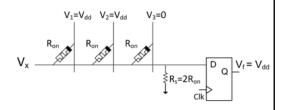
- Threshold logic
 - $f(x_1, x_2, ... x_n) = \begin{cases} 1 & if \sum_{1}^{n} x_i \ge T \\ 0, & otherwise \end{cases}$
 - · Two control voltages: Vdd & GND
 - Two logic states: 0 & 1



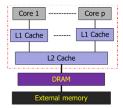
Example

Assume n=3, T=Vth=Vdd/2

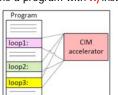
- 1. Program all devices to Ron
- 2. Provide the input voltages
 - Vdd, Vdd, 0
- 3. Vf=1 (Roff)
 - Vx = (4/7) Vdd > Vth



Computation-in-memory: Is there any benefits?



Assume a program with n; instructions



CPU -- CIMA DRAM **External Memory**

- n_p processors
- Latency $\propto (t_L + t_S + t_{ALU})^* (n_i/n_p)$

- n_a parallel crossbar arrays
- Latency $\propto (t_S' + t_{ALU}') * (n_i/n_a)$
- Data already loaded in CIM



Better overall performance

- $t_S'+t_{ALU}' << t_L+t_S+t_{ALU}'$
- $t'_S + t'_{ALU}$ is ~ constant
- t₁ depends on miss rate
- E.g. Large data sizes => higher miss rate

Reduced energy

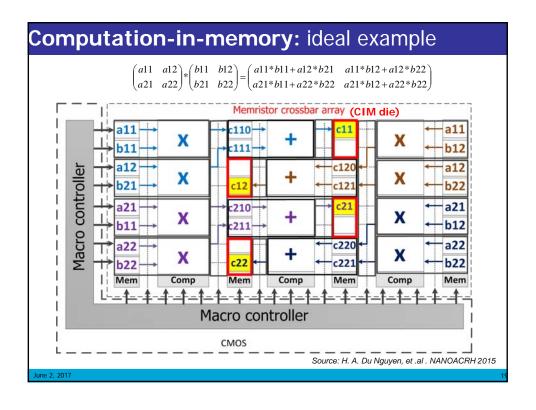
- Significant communication reduction
- Reduce memory & power wall

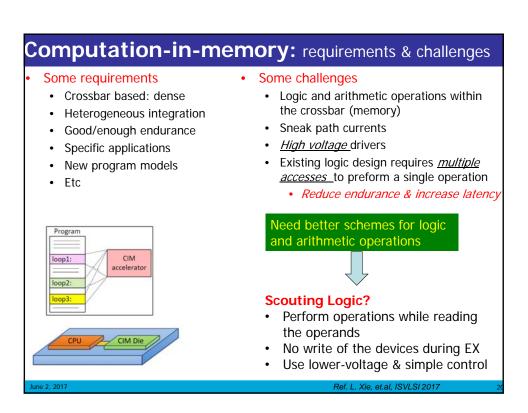
Parallelism is program dependent

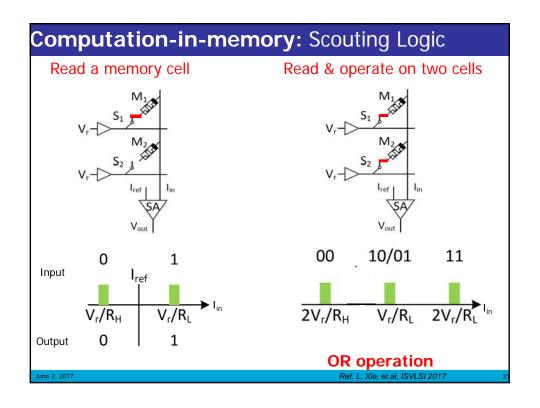
- · CIM consumes much less than cores
- Higher n_p => higher power => dark silicon

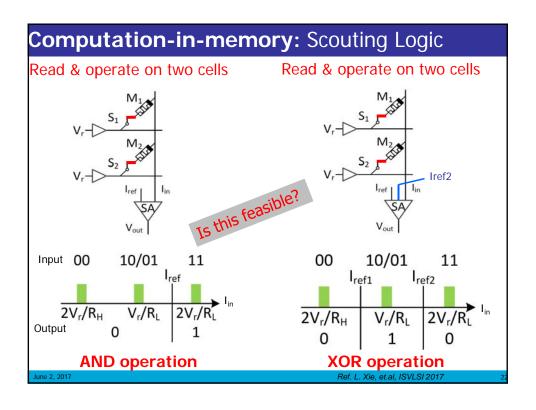
Potential applications

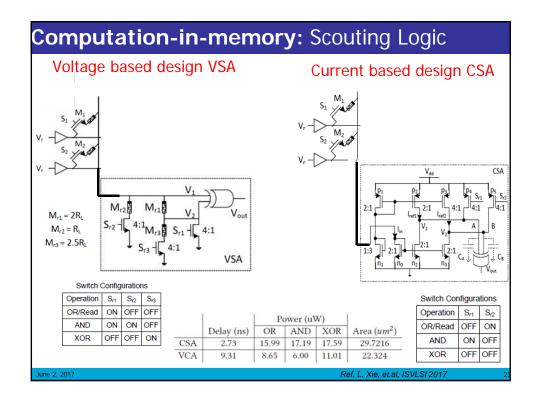
- · Loops on the same data sets
- Bit-wise operation
- · High data volume and reuse
- E.g., bio-sequencing, graph processing.

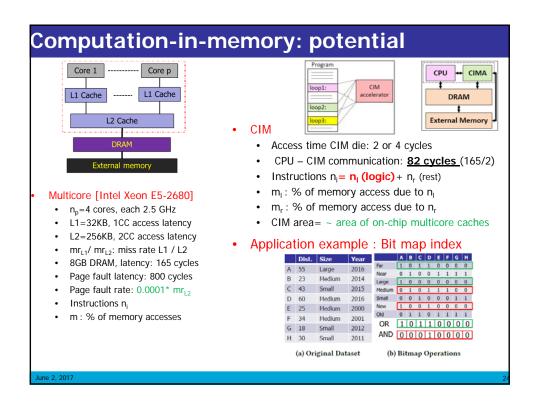


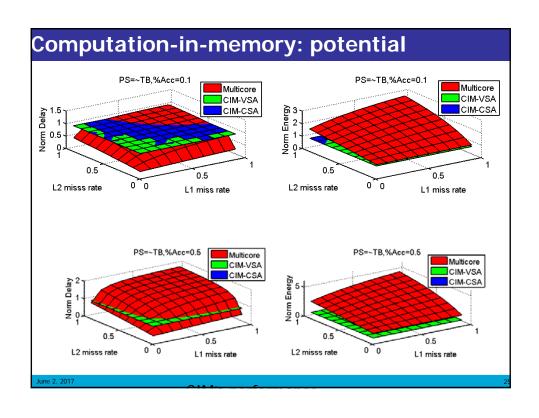


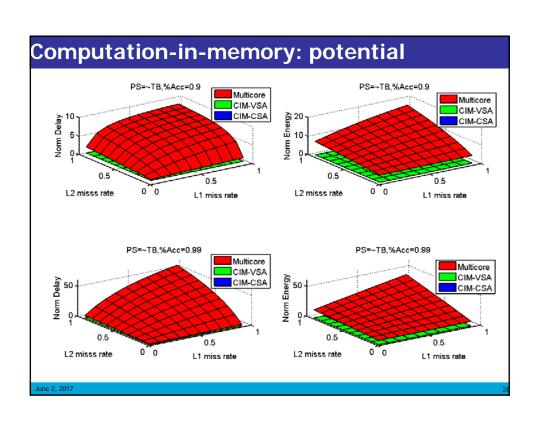












Computation-in-memory: Potential

Examples

- · Healthcare: DNA sequencing
 - we assume we have 200 GB of DNA data to be compared to
 - A healthy reference of 3GB for 50% coverage**

[**E. A. Worthey, Current Protocols in Human Genetics, 2001]

• Mathematic: 10⁶ parallel additions

Assumptions

- Conventional architecture
 - FinFET 22nm multi-core implementation, with scalable number of clusters, each with 32 ALU (e.g comparator)
 - 64 clusters; each cluster share a 8KB L1 cache
- CIM architecture
 - Memristor 10nm crossbar implementation
 - The crossbar size equals to total cache size of CMOS computer

[Source: S. Hamdioui, et.al, DATE 2015]

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Computation-in-memory: Potential

Metrics

- Energy-delay/operation
- Computing efficiency : number of operations per required energy
- Performance area : number of operations per required area

Results

Metric	Archit.	DNA sequencing	10 ⁶ additions		
Energy –Delay/	Conv.	2.02e-03	1.5043e-18	> x100	
operations	CIM	2.34e-06	9.25702-21	/ X100	
Computing Efficiency	Conv.	4.11e01	6.5226e+9	> x100	
	CIM	3.70e04	3.9063e+12	> X100	
Performance Area	Conv.	5.73e06	5.1118e+09	> x100	
	CIM	8.28e09	4.9164e+12		

Key drives: Reduced memory bottleneck, non-volatile technology & parallelism

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Conclusion

- Von-Neumann based computers
 - · Memory & communication bottleneck
 - · Complex progammability of multi-cores
 - · Higher power consumption
 - => Unable to solve (today) and future application at affordable cost
- Short term
 - Specialization: application-specific accelerators (reduced prog)
 - Near memory computing, accelerator around memories (data-centric model)

Long term

- Alternative architecture, beyond Von Neumann & using new device tech
- Resistive computing has a huge potential (CIM architecture)
- · But many open questions: device & materials, HW& SW, algorithms, etc

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