

Memristor based computation-in-memory Architectures for Edge AI

Opportunities and challenges

Said Hamdioui

Head of Quantum and Computer Engineering department
Delft University of Technology & Cognitive-IC
The Netherlands

S.Hamdioui@tudelft.nl



MIM WEBINARS

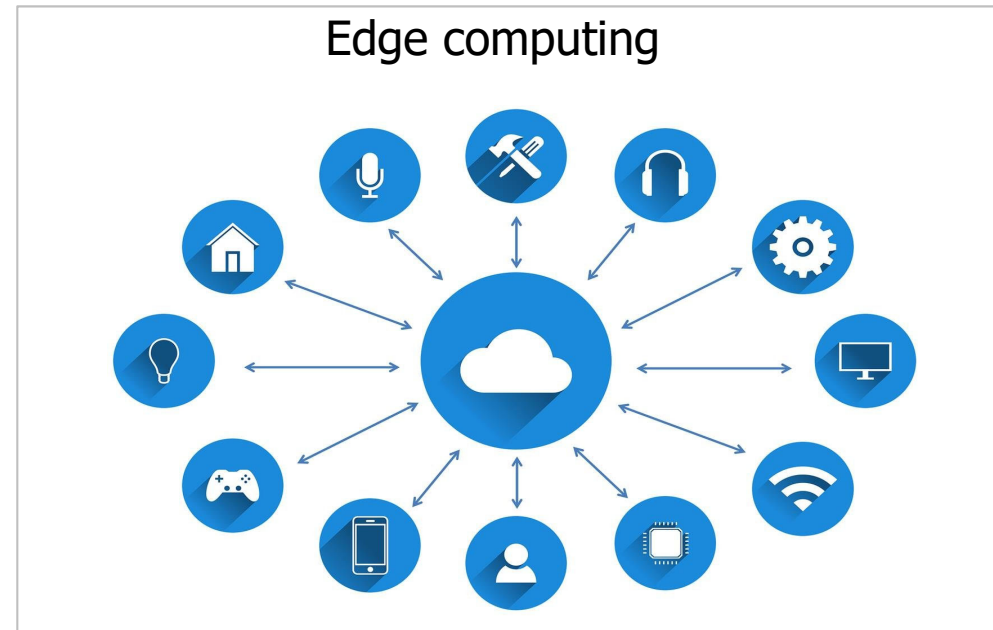
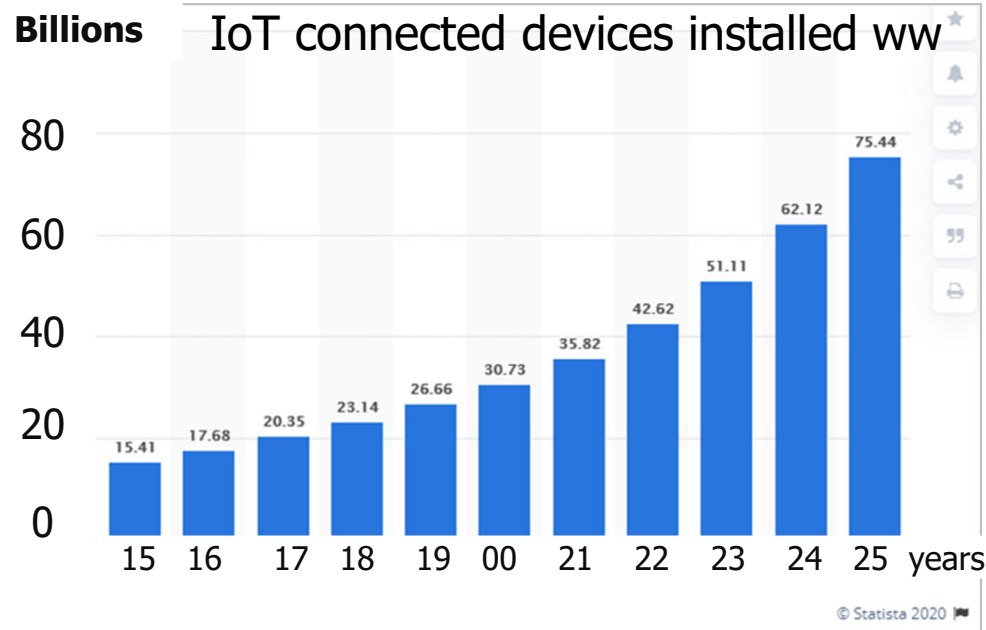
AN IN-MEMORY COMPUTING SERIES

Next Talk: 17/May/2021, 4-5:30pm CET

Outline

- The opportunity and the challenges
 - IoT-edge partnership, HW challenges
- Computer architecture
 - Past and future & classification
- Computation-in-Memory CIM
 - Basics and classification
- CIM circuit design
 - Logic operations, Vector-matric multiplication
- CIM Potential
 - Design flow, application domains, potential improvements
- Challenges
 - The open questions
- Conclusion

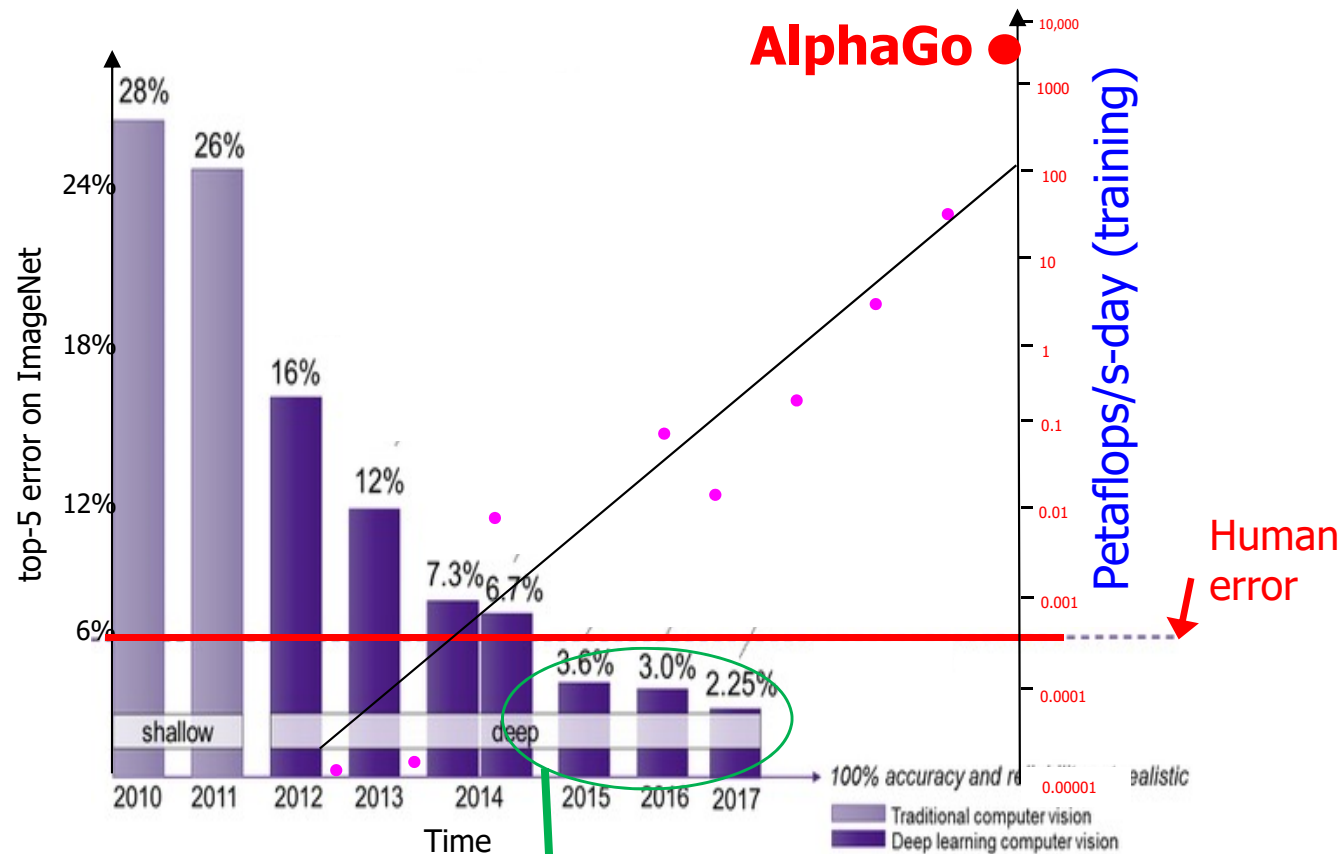
The opportunity: IoT-edge partnership



Many requirements

- **Intelligence**
- **Energy constraints**
- **Local computing**
- Data privacy
- Real-time decisions
- 24/7

The challenges: Intelligence



AI **surpassed** human

Not suitable for Edge Application

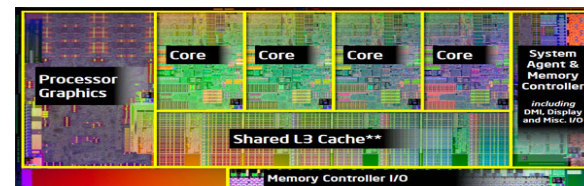
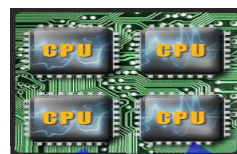
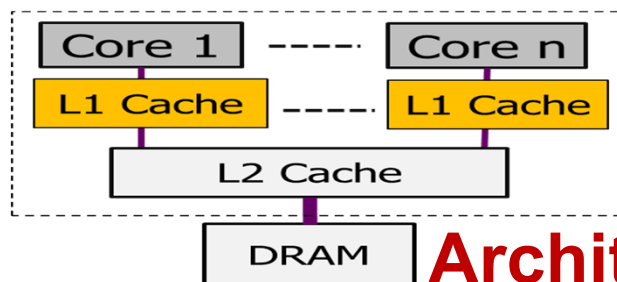
In April 2017, AlphaGo vs. Jie Ke



AlphaGo:
176 GPUs, 1202 CPUs
150,000 Watts

AI requires **huge** resources

The challenges: The HW architecture and technology



Architecture

Operation @32-bit operand	Energy (pJ) @TSMC 45nm	Cost v ALU
ALU: Add	0.1	1x
SRAM: read	5	50x
DRAM: read	640	6,400x

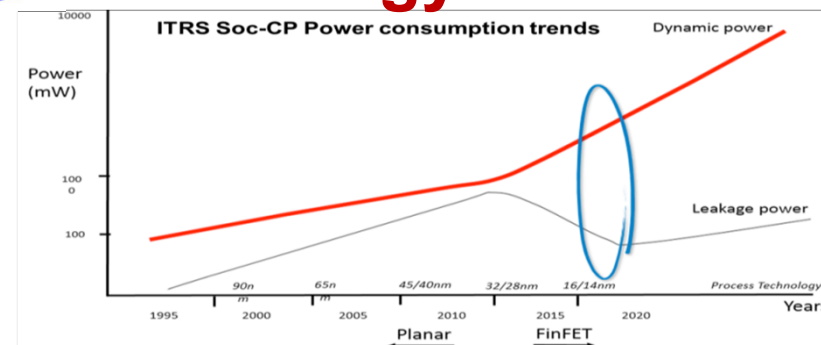
[Source: M. Homowitz et al., ISSCC, 2014]

1. Memory Wall
2. ILP Wall
3. Power Wall

[Source: D. Patterson, future of computer Architecture, 2006]

Need of new Architectures

Technology



[Source: S. Hamdioui, et.al, DATE 2017]

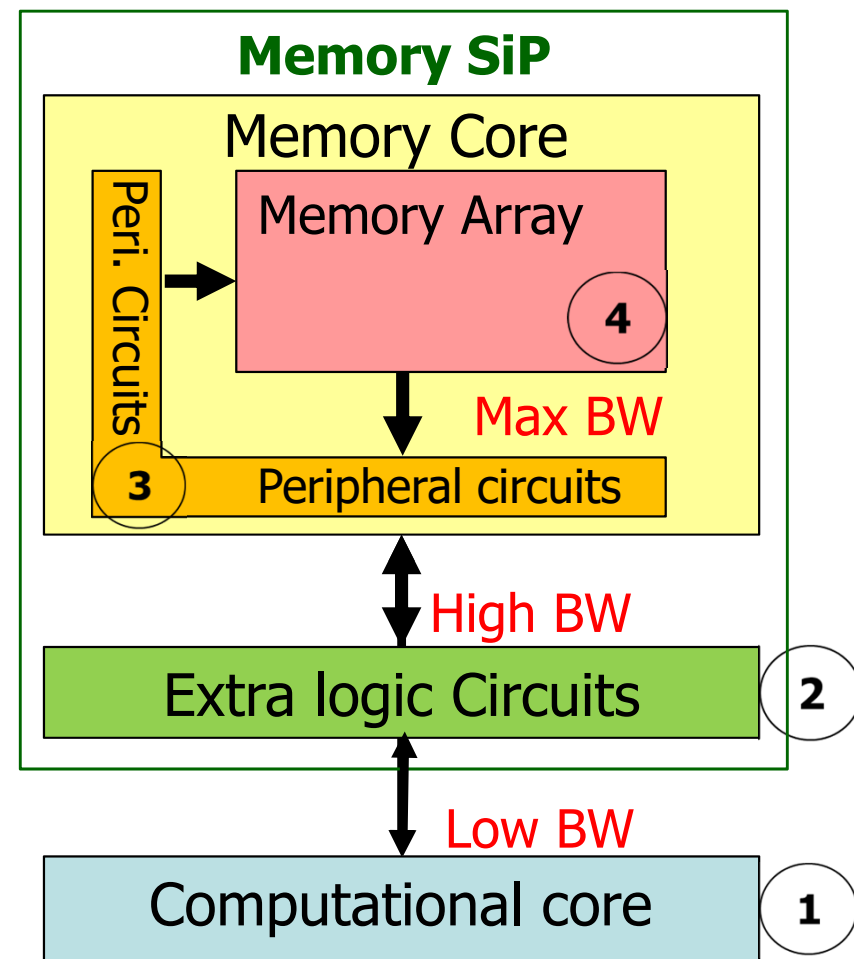
1. Leakage Wall
2. Cost Wall
3. Reliability Wall

Need of new Technologies

Need of Unconventional architectures using unconventional technologies

Computer Architectures: Classification

- **COM: Computation-Out-Memory**
 1. Far (COM-F)
 2. Near (COM-N)
- **CIM: Computation-In-Memory**
 3. Periphery (CIM-P)
 4. Array (CIM-A)
- **Hybrid architectures**
- **Status**
 - COM: commercialized & conv technologies
 - CIM: Research, conv & unconv technologies



Computer Architectures: Comparison

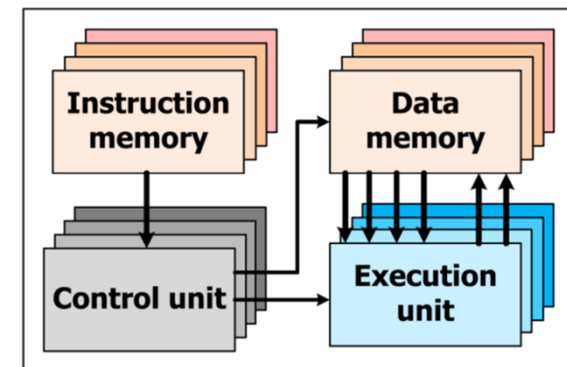
Type	Off-chip Data mov.	Computations reqrs.		Available Band-width	Memory design effort			Scalability
		D. align	Cmplex.Fu		Array	Periphery	controller	
CIM-A	No*	Yes	H. latency	Max	High	Low/ Medium	High	Low
CIM-P	No*	Yes	H. Cost	High-Max	Low-medium	High	Medium	Medium
COM-N	Yes	NR	Low cost	High	Low	Low	Low	Medium
COM-F	Yes	NR	Low cost	Low	Low	Low	Low	High

- Other attributes**

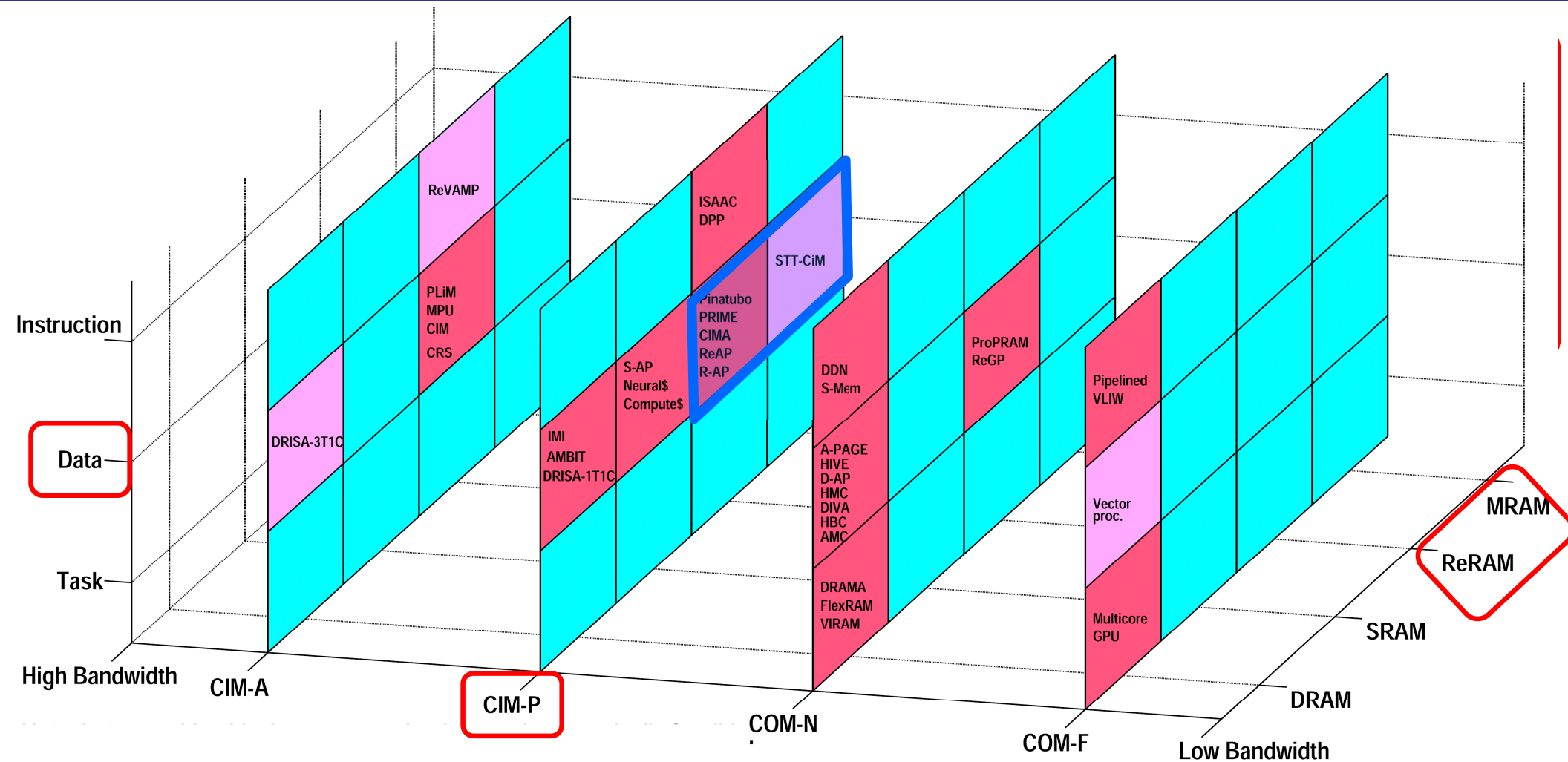
- Endurance requirements

- Other metrics classification**

- **Memory Technology:** SRAM, DRAM, MRAM, ReRAM, ...
- **Computation parallelism:** **Task** (e.g., multi-core), **Data** (e.g., SIMD), **Instruction** (e.g., VLIW)



Computer Architectures: overview



[Source: H.A. Du Nguyen, et. al, "A classification of memory-centric computing" ACM JETC, 16(2), pp.1-26", 2020]

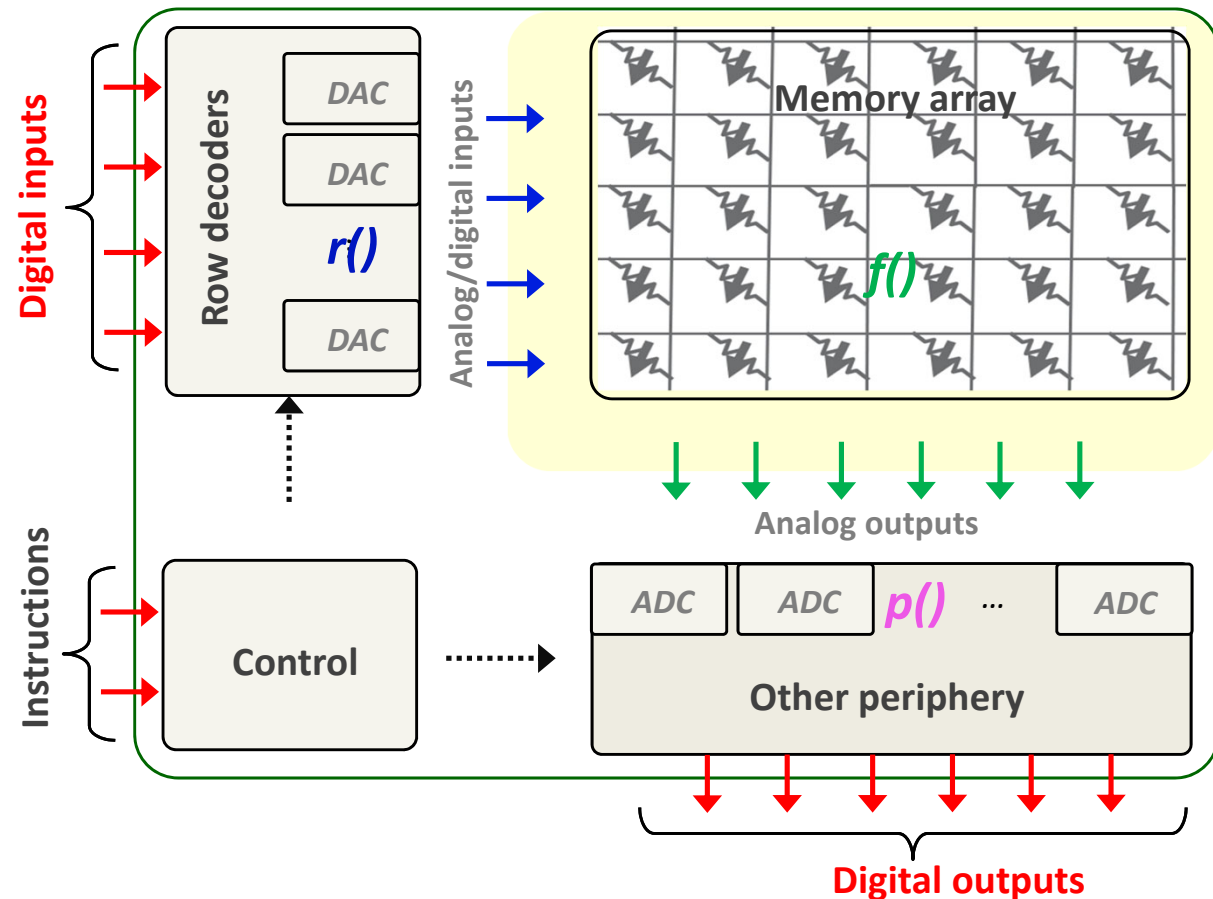
Computation-in-Memory: Basics

- Single or multi functions

- $r()$
- $r()$ & $f()$?
- $p()$ & $f()$?
- $r()$ & $p()$ & $f()$
- Etc.

- CIM-P

- **Major** changes in periphery
 - $p()$ and/or $r()$
- Basic: no changes in array
- Hybrid: some changes in array



Computation-in-Memory: Classification

CIM-A

Output in **Array**

CIM-**Ar**

Input: All **resistive**

CIM-**Ah**

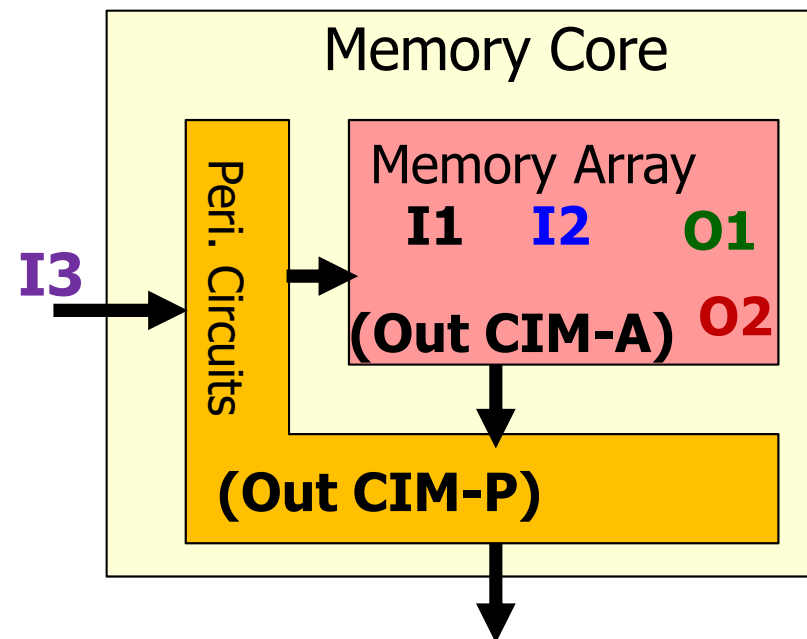
Input: **Hybrid**

CIM-P

Output in **Periphery**

- **Example**

- CIM-Ar: **O1**=**I1** OR **I2**
- CIM-Ah: **O2**=**I2** OR **I3**

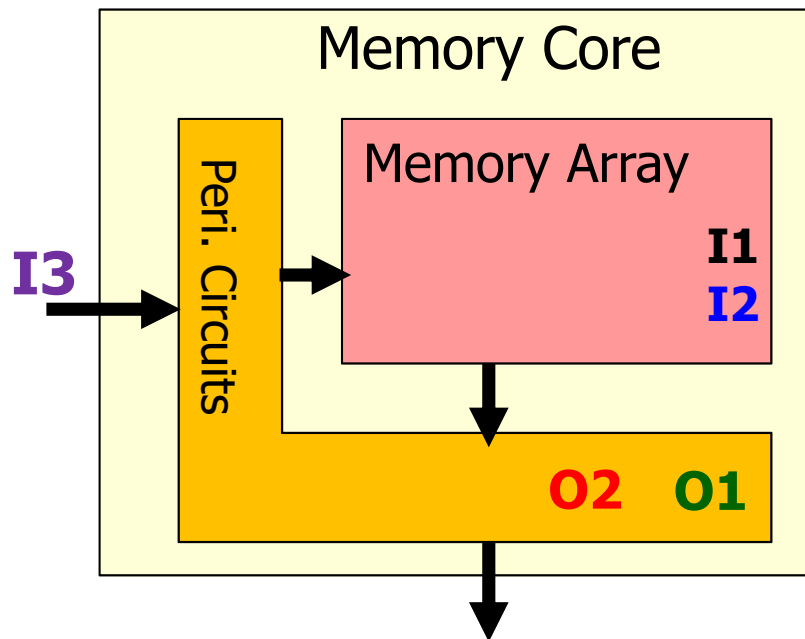


[Source: M. Abu Lebdeh, et. al, "Memristive device based circuits for computation-in-memory architectures", ISCAS 2019]

Computation-in-Memory: Classification

CIM-A Output in array	
CIM-Ar Input: All resistive	CIM-Ah Input: Hybrid

CIM-P Output in Periphery	
CIM-Pr Input: All resistive	CIM-Ph Input: Hybrid



- **Example**
 - CIM-Pr: **O1**=**I1** OR **I2**
 - CIM-Ah: **O2**=**I2** OR **I3**

Computation-in-Memory: Classification

CIM-A Output in array		CIM-P Output in Periphery	
CIM- Ar Input: All resistive	CIM- Ah Input: Hybrid	CIM- Pr Input: All resistive	CIM- Ph Input: Hybrid
SNIDER [2005] e.g., NAND IMPLY [2010] e.g., IMP, NAND MAGIC [2014] e.g., NOT, NOR Fast Boolean [2015]	Resi. Accu. [2003] Majority Logic [2016]	Pinatubo [2016] OR, AND, XOR Scouting [2017] OR, AND, XOR	VMM [2016, 2017] BCMM V [2017] BDP [2018]

Recent work mainly on CIM-P?

CIM circuit design: CIM-Ar

• Snider logic

- Primitive logic operations: NAND, INV
- 2 Control voltages: V_w , V_h
 - $V_w > V_{th} > V_h$
 - $V_w - V_h < V_{th}$

• Working principal (e.g., 2NAND)

1. Store

- Program p to R_{on}
- Program q to R_{off}

2. Compute

- Initialize f to **R_{off}**
- Process NAND
 - $V_x \approx V_h$; $V_w - V_x = V_w - V_h < V_{th}$
 $\Rightarrow f = R_{off}$

Suitable for crossbar
 $\rightarrow$ density

Requires multiple
 accesses

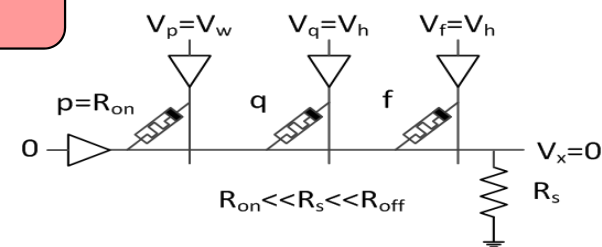
Requires array
 redesign

Logic states:

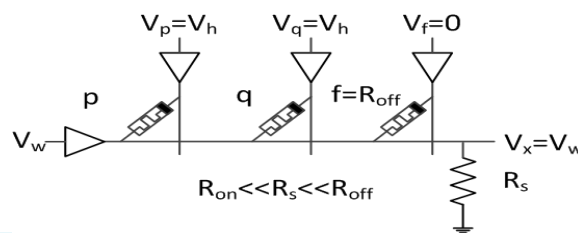
In/blue: $R_{off}=1; R_{on}=0$

p	q	f
0	0	1
0	1	1
1	0	1
1	1	0

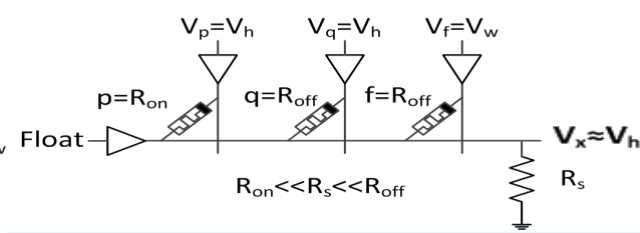
Program p to R_{on}



Initialize f to R_{off}



Process NAND



[Source: Snider et.al, APA, 2005; Xie et al. ICCD, 2015]

CIM circuit design: CIM-Ah

• Majority logic [Gaillardon et.al, DATE, 2016]

- Logic operation: Majority Function
- Inputs: p, q, z
- Out: $z = \text{MAJ}(p, \bar{q}, z)$
- 2 Control voltages: V_w, GND
 - $V_w > V_{th}$

Logic states:

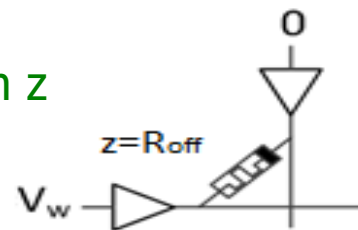
- In p & q : $V_w=1$; $\text{GND}=0$
- In z : $R_{on}=1$; $R_{off}=0$
- Out: $R_{on}=1$; $R_{off}=0$

+ Suitable for crossbar
- Needs data movement (p, q)
- Parallelism?

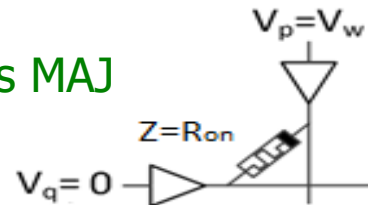
• Working principal

1. Program z to R_{off}
 2. Process MAJ
 - Apply $V_p=V_w$ & $V_q=\text{GND}$
 - $V_w - 0 = V_w > V_{th}$
- $\Rightarrow z = R_{on}$

Program z



Process MAJ

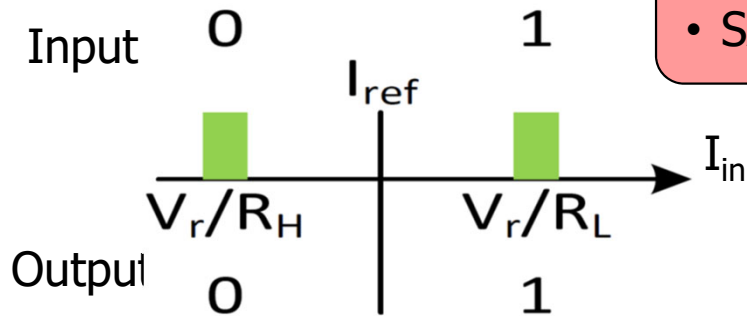
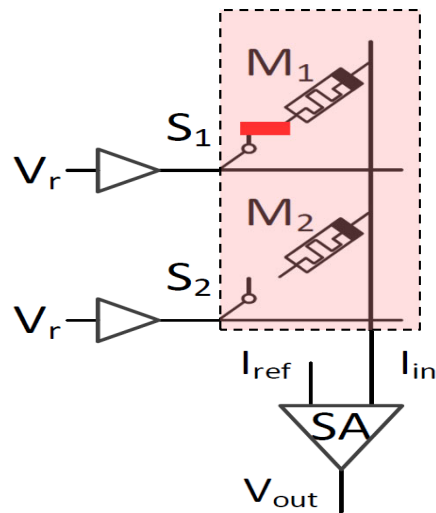


p	q	z	MAJ($p, \bar{q}, z$)
0	0	0	0
0	0	1	1
0	1	0	0
0	1	1	0
1	0	0	1
1	0	1	1
1	1	0	0
1	1	1	1

CIM circuit design: CIM-Pr example

Scouting Logic

Read a memory cell



Parallelism

-> performance

Operations

1 cycle: E efficiency

Reduced com.

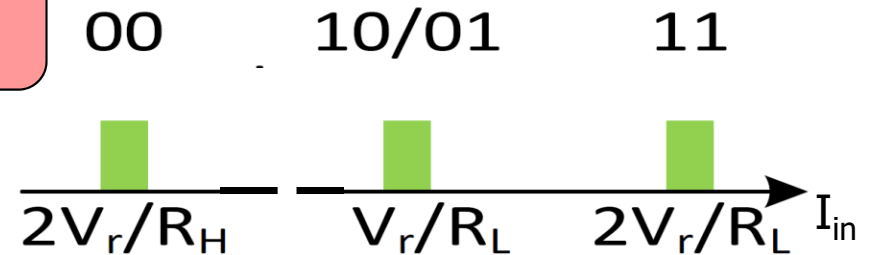
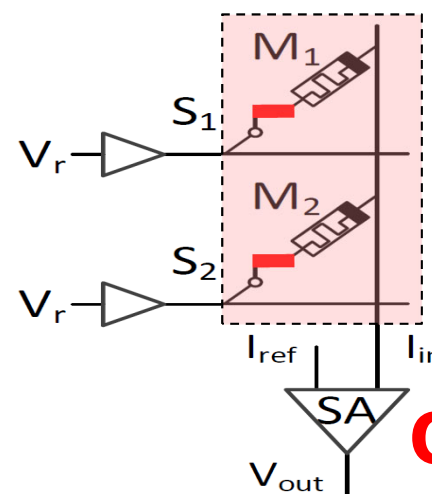
-> E efficiency

Read intensive

Endurance

- Data alignment
- SA & AD medication

Read & operate on two cells

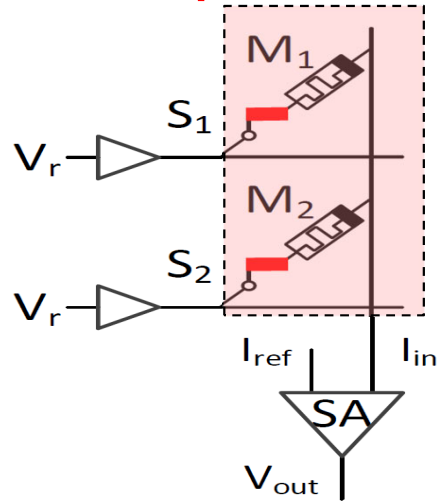


OR operation

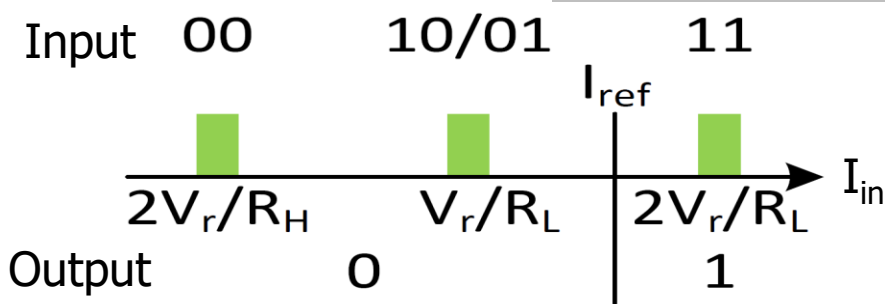
CIM circuit design: CIM-Pr example

Read & operate on two cells

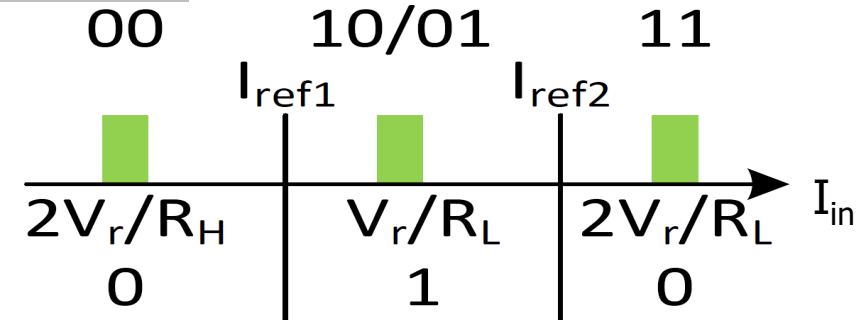
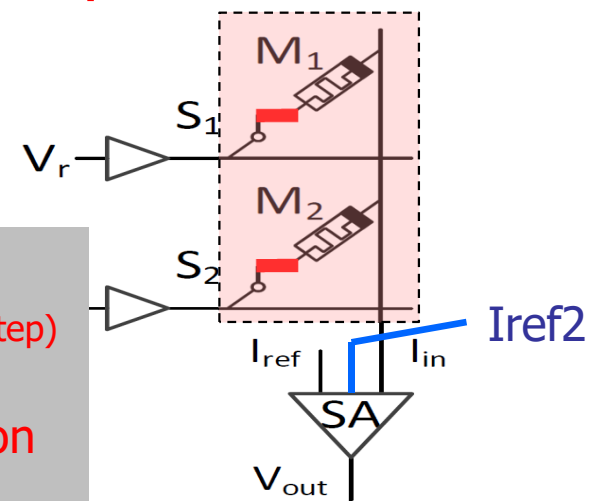
Read & operate on two cells



- + Less requirements on endurance
- + Once access per operation (single step)
- + No major changes in array
- Modification of SA and AD selection
- Data alignment



AND operation

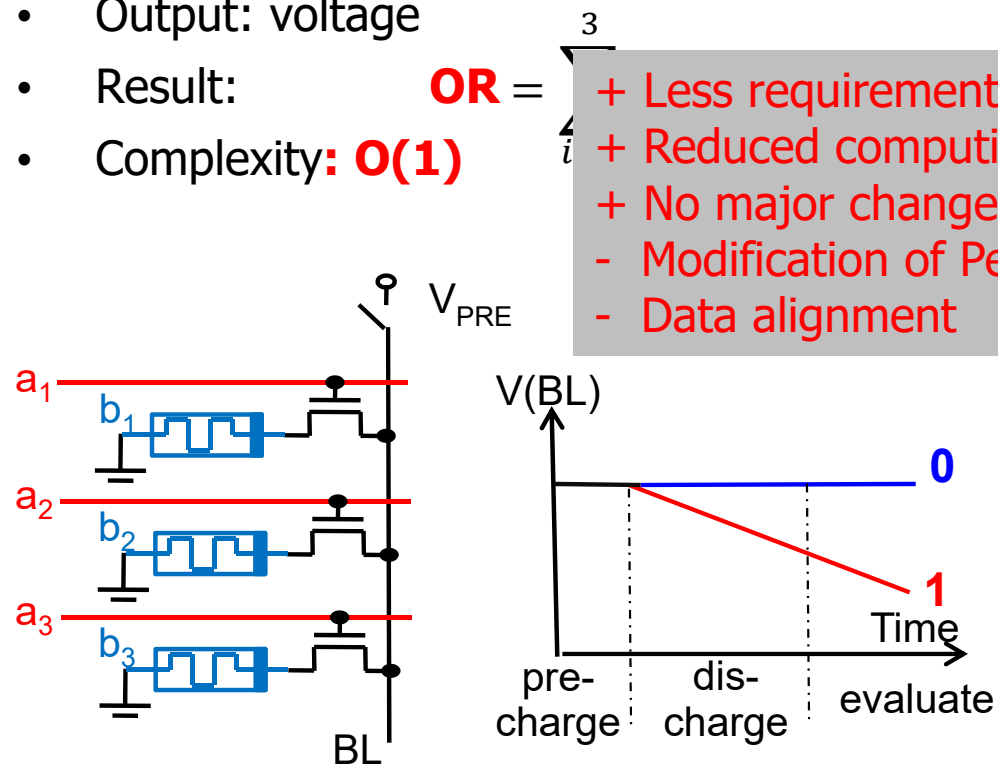


XOR operation

CIM circuit design: CIM-P^h example

Vector dot product: $\mathbf{a} \cdot \mathbf{b}$

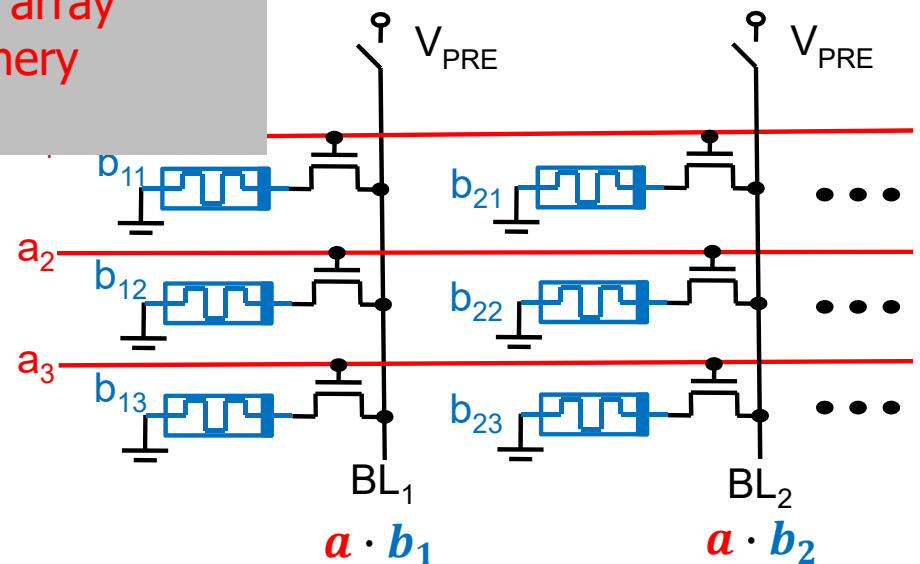
- $\mathbf{a} \cdot \mathbf{b} = a_1 \cdot b_1 + a_2 \cdot b_2 + a_3 \cdot b_3$
- Inputs: voltage and resistance
- Output: voltage
- Result: **OR** =
- Complexity: **$O(1)$**



- + Less requirements on endurance
- + Reduced computing complexity
- + No major changes in array
- Modification of Periphery
- Data alignment

Vector matrix multiplication

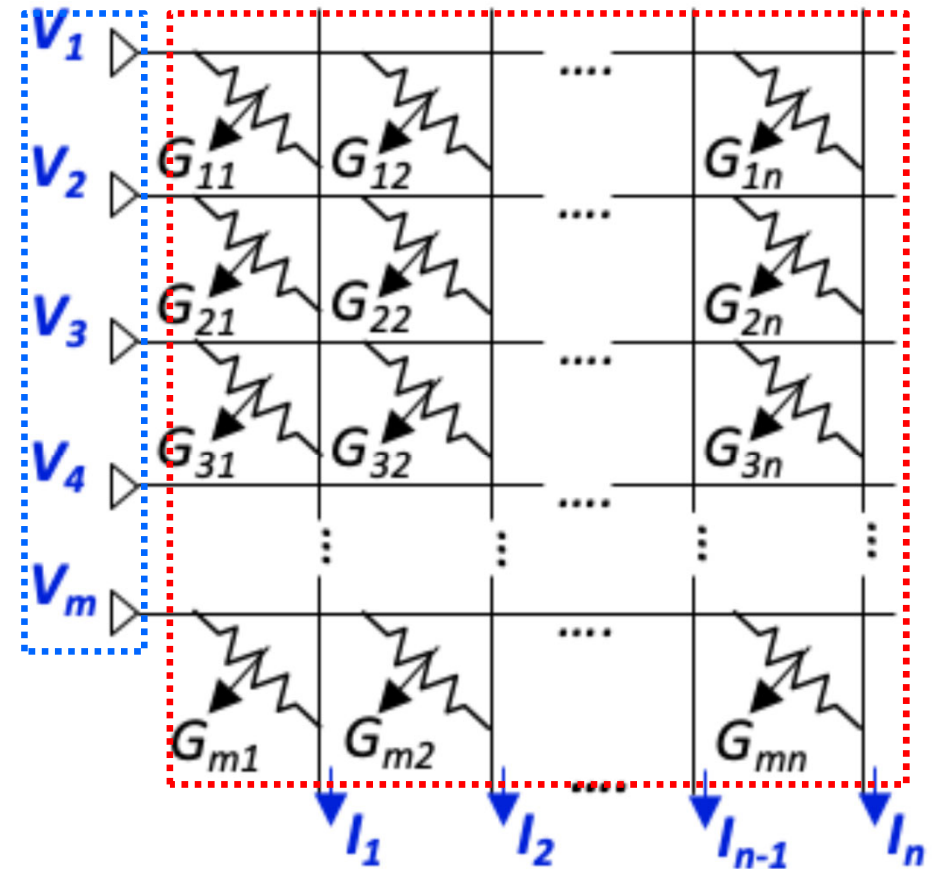
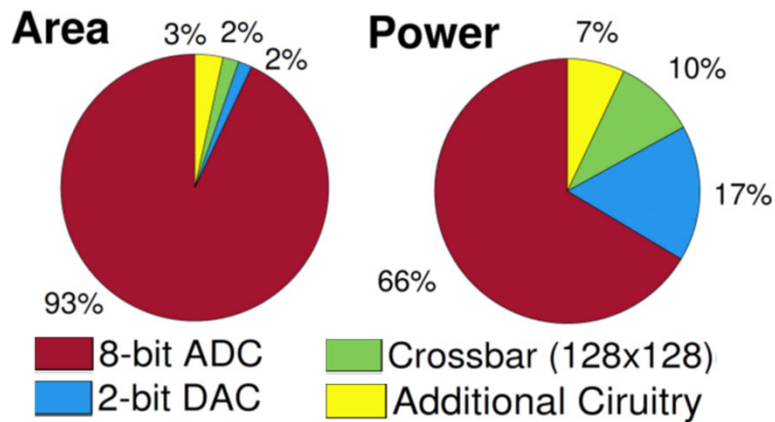
- $\mathbf{v} = \mathbf{a} \cdot \mathbf{B} = [\mathbf{a} \cdot \mathbf{b}_1, \mathbf{a} \cdot \mathbf{b}_2, \dots, \mathbf{a} \cdot \mathbf{b}_N]$
- Extendable to matrix x matrix
- Complexity
 - **$O(1)$** : vector * matrix
 - **$O(n)$** : matrix * matrix



CIM circuit design: CIM-Ph

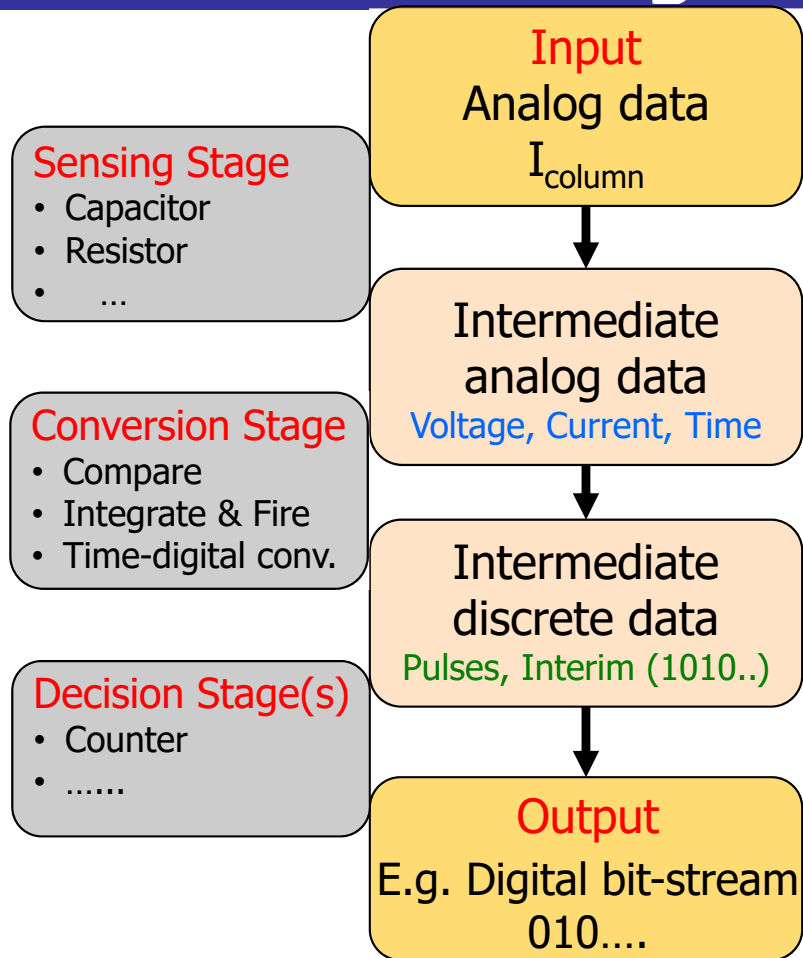
• Multiply-Accumulate

- $I_i = \sum \mathbf{V}_j \cdot \mathbf{G}_{ij}$
- $I_1 = \mathbf{V}_1 \cdot \mathbf{G}_{11} + \mathbf{V}_2 \cdot \mathbf{G}_{21} + \dots \mathbf{V}_m \cdot \mathbf{G}_{m1}$
- Complexity: **$O(1)$**

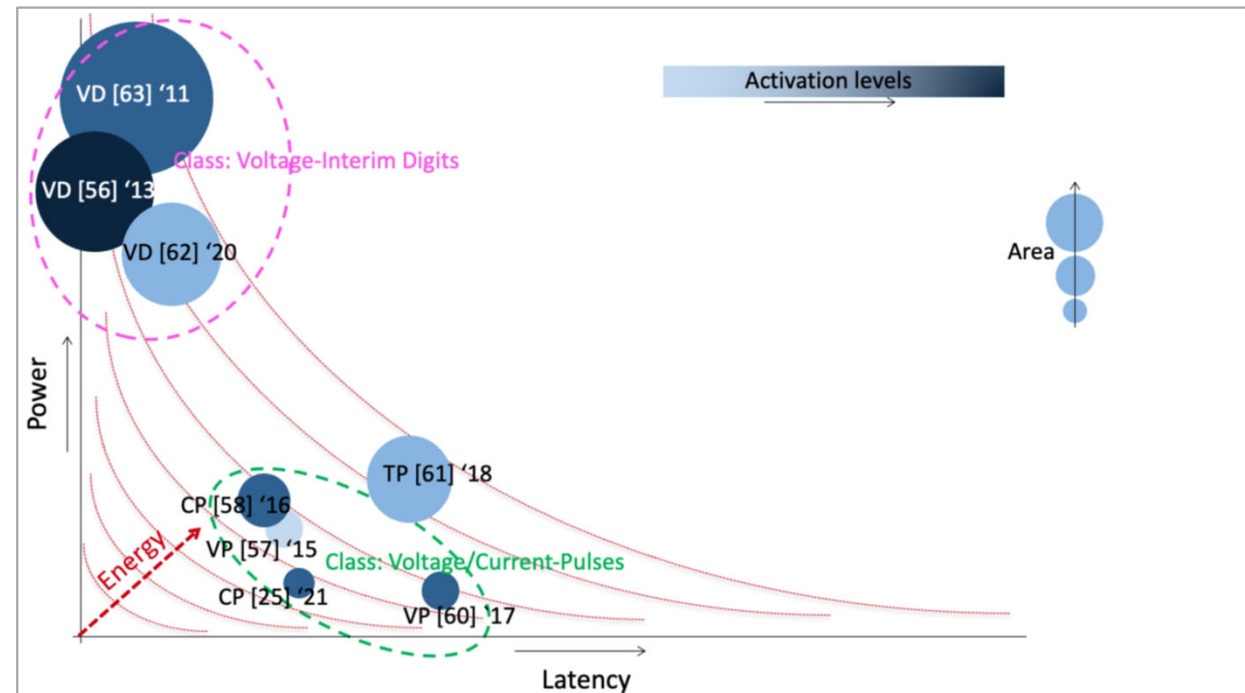


[A. Shafiee et al., "ISAAC: A convolutional neural network accelerator with in-situ analog arithmetic in crossbars," in ISCA, 2016]

CIM circuit design: ADC design / classification



- Six classes: (Voltage, Current, Time) x (Pulse, Interim)



Major challenge: appropriate accuracy at low energy & high speed

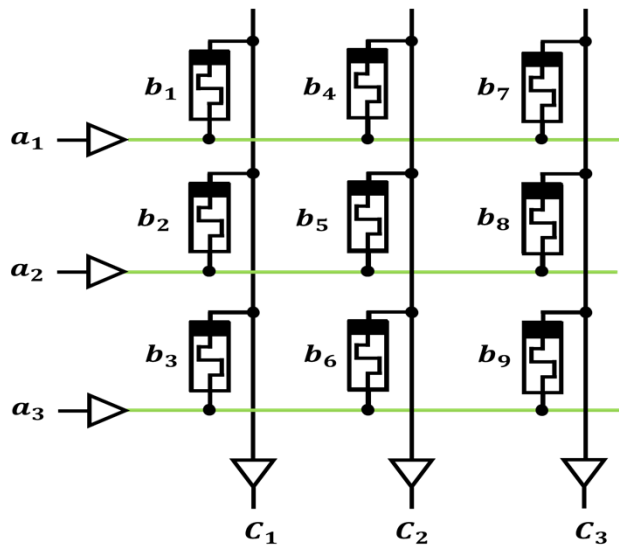
[Source: A. Singh, et. al, "SRIF: Scalable and reliable integrate and fire circuit ADC for memristor-based CIM architectures", TCAS-1, 2021]

[Source: A. Singh, et. al, "Low Power Memristor-based Computing for Edge-AI Applications", ISCAS 2021]

CIM circuit design: CIM-Ph

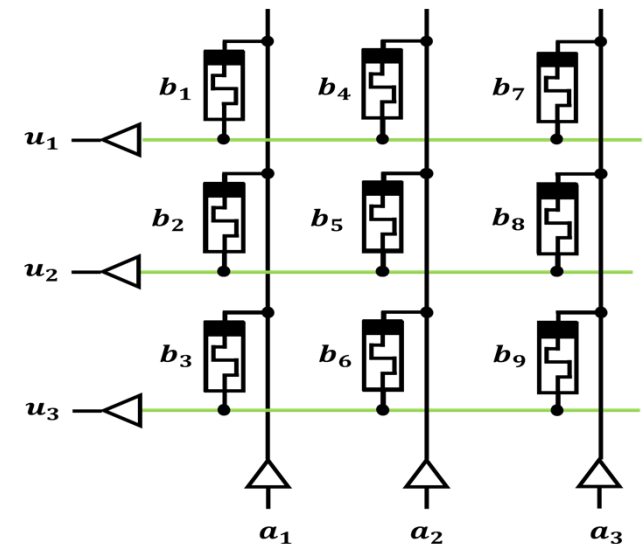
Non-Transposed B Matrix

$$\begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} \begin{bmatrix} b_1 & b_4 & b_7 \\ b_2 & b_5 & b_8 \\ b_3 & b_6 & b_9 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}$$



Transposed B Matrix

$$\begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} \begin{bmatrix} b_1 & b_4 & b_7 \\ b_2 & b_5 & b_8 \\ b_3 & b_6 & b_9 \end{bmatrix}^T = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$



Can configurable periphery enable different functions? At what cost?

Computation-in-Memory: CIM-A v CIMP designs

Shmoo plot for IMPLY (CIM-Ar)

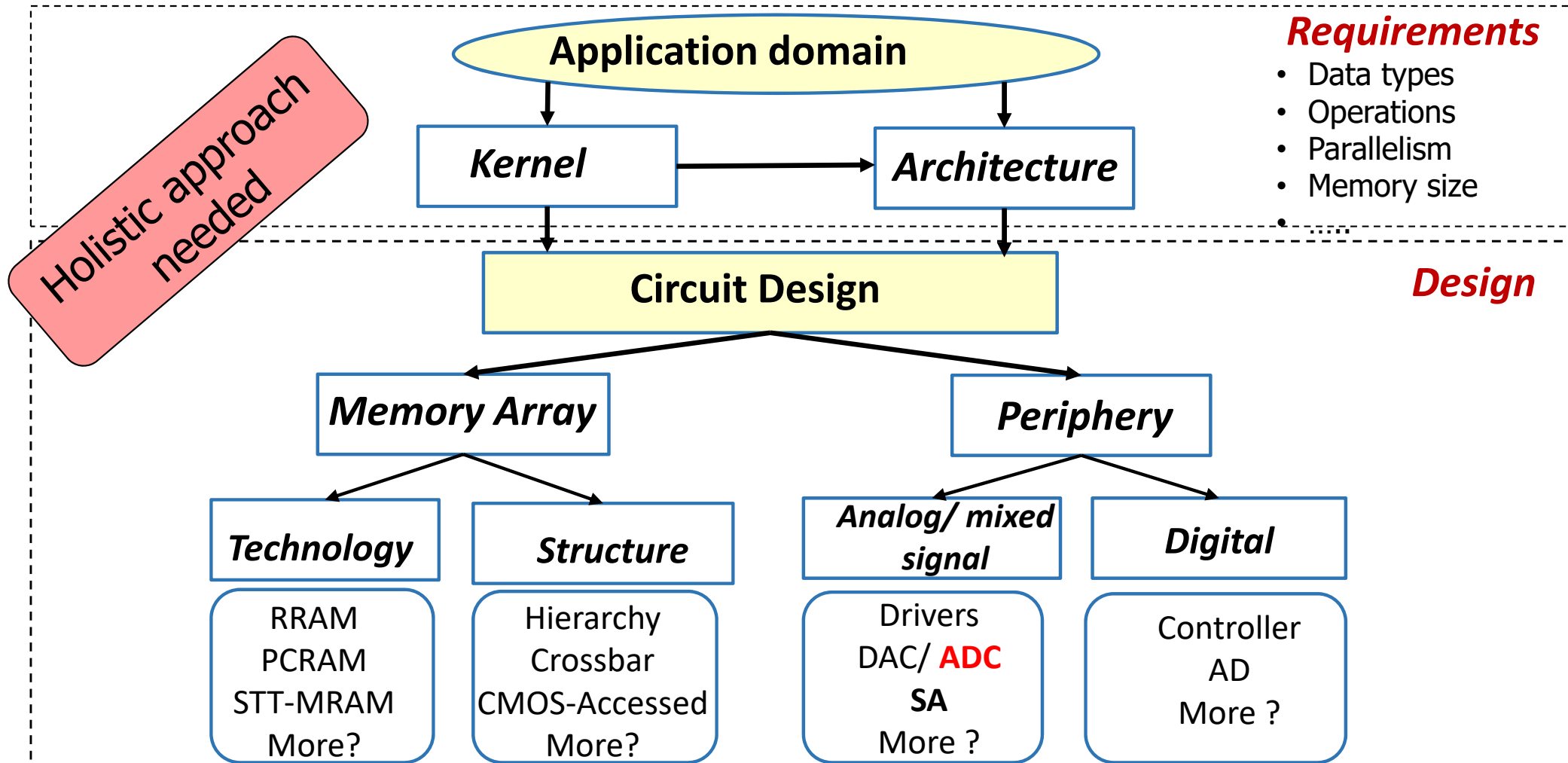
Voltage	10	50	100	200	500	1000	$\frac{R_{off}}{R_{on}}$
1.3	F	F	F	F	F	F	
1.4	F	F	F	F	F	F	
1.5	F	F	F	F	F	F	
1.6	F	F	F	F	F	F	
1.7	P (2%)	P (5%)	P (35%)	P (20%)	P (2%)	F	
1.8	F	F	P (15%)	P (35%)	P (20%)	P (3%)	
1.9	F	F	P (3%)	P (35%)	P (30%)	P (15%)	
2	F	F	F	P (20%)	P (40%)	P (25%)	
2.1	F	F	F	P (3%)	P (40%)	P (35%)	
2.2	F	F	F	F	P (30%)	P (45%)	
2.3	F	F	F	F	P (20%)	P (40%)	
2.4	F	F	F	F	P (3%)	P (40%)	
2.5	F	F	F	F	P (1%)	P (30%)	
2.6	F	F	F	F	F	P (20%)	
2.7	F	F	F	F	F	P (15%)	
2.8	F	F	F	F	F	P (3%)	
2.9	F	F	F	F	F	F	
3	F	F	F	F	F	F	

Shmoo plot for Scouting OR (CIM-Pr)

Voltage	10	50	100	200	500	1000	$\frac{R_{off}}{R_{on}}$
0.2	F	F	F	F	F	F	
0.3	P (2%)	P (161%)	P (256%)	P (375%)	P (587%)	P (813%)	
0.4	P (60%)	P (296%)	P (439%)	P (620%)	P (942%)	P (1285%)	
0.5	P (120%)	P (444%)	P (642%)	P (890%)	P (1333%)	P (1804%)	
0.6	P (120%)	P (444%)	P (642%)	P (890%)	P (1333%)	P (1804%)	
0.7	P (130%)	P (469%)	P (675%)	P (935%)	P (1398%)	P (1890%)	
0.8	P (190%)	P (790%)	P (1113%)	P (1520%)	P (2244%)	P (3015%)	
0.9	P (70%)	P (345%)	P (507%)	P (710%)	P (1072%)	P (1458%)	
1	F	P (98%)	P (170%)	P (260%)	P (421%)	P (592%)	
1.1	F	P (37%)	P (87%)	P (150%)	P (262%)	P (381%)	
1.2	F	F	P (20%)	P (60%)	P (132%)	P (208%)	
1.3	F	F	P (1%)	P (35%)	P (95%)	P (160%)	
1.4	F	F	F	F	P (37%)	P (83%)	
1.5	F	F	F	F	P (16%)	P (54%)	
1.6	F	F	F	F	F	P (30%)	
1.7	F	F	F	F	F	P (19%)	
1.8	F	F	F	F	F	F	
1.9	F	F	F	F	F	F	

CIM-P operates at low R_{off}/R_{on} ratio & low voltages
 CIM-P is less sensitive to device variations

Computation-in-Memory: Design flow



[Source: Jintao Yu, et.al, "The Power of Computation-in-Memory Based on Memristive Devices", ASP-DAC, paper 6A-2, 2020]

CIM potential: Database query example



Data Set

	Dist	Size	Year
A	55	Large	2016
B	23	Medium	2014
C	43	Small	2015
D	60	Medium	2016
E	25	Medium	2000
F	34	Medium	2001
G	18	Small	2012
H	30	Small	2011

QUERY: find DATA
satisfy
{far or large}

Bitmap Indexing

	A	B	C	D	E	F	G	H
Far	1	0	1	1	0	0	0	0
Near	0	1	0	0	1	1	1	1
Large	1	0	0	0	0	0	0	0
Medium	0	1	0	1	1	1	0	0
Small	0	0	1	0	0	0	1	1
New	1	0	0	1	0	0	0	0
Old	0	1	1	0	1	1	1	1

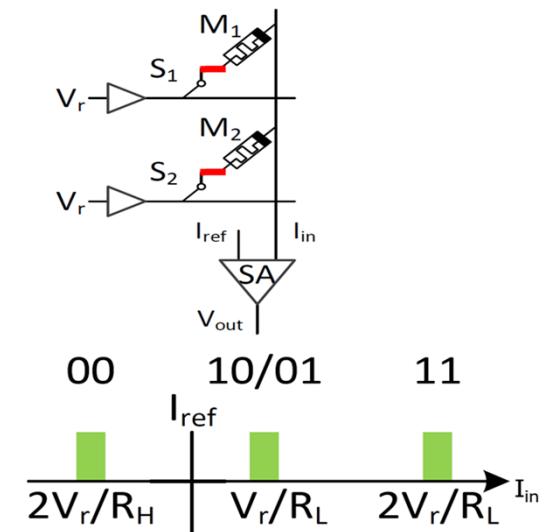
OR

1 0 1 1 0 0 0 0

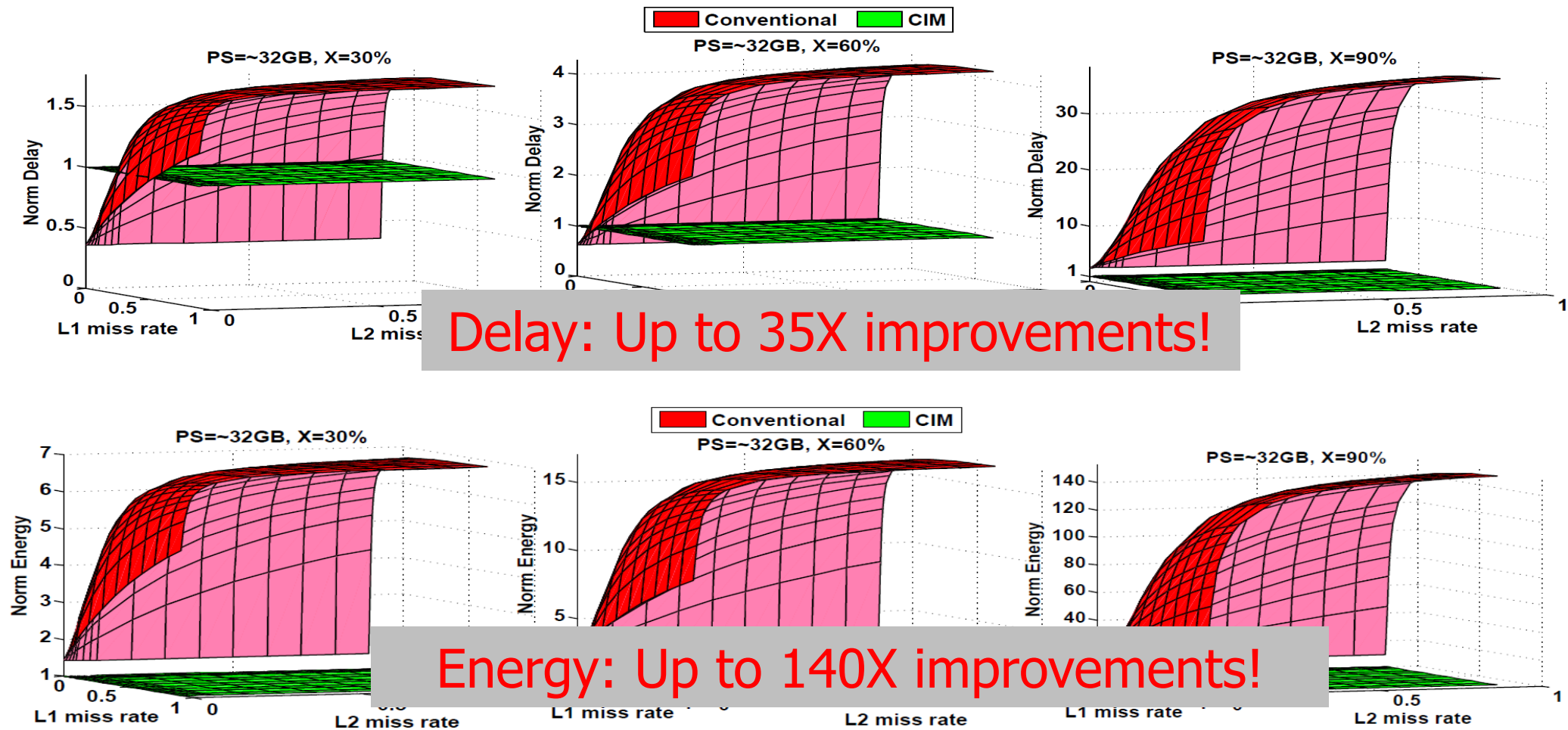
Requirements:

- Kernel:** bitwise OR
- Architecture:** CIM-Pr
 - I1 and I2: stored in a database (in memory)
 - O: read out

Circuit Design: Scouting



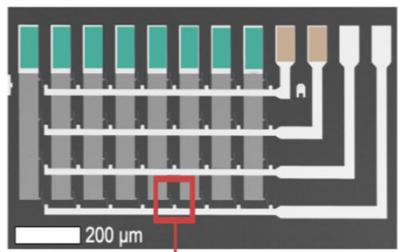
CIM potential: Database query example



CIM potential: Database query demo

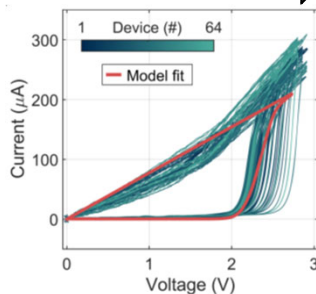
- Manufactured PCM + circuit simulation

4x8 **1R** crossbar

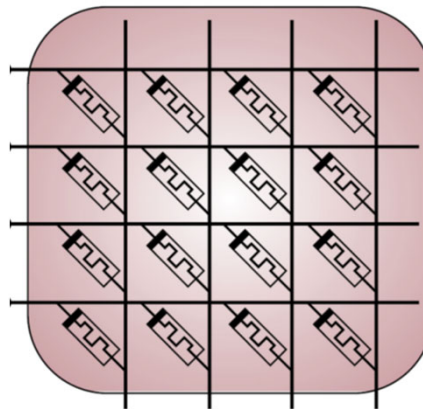


Ron/Roff: 20K/1M
Vread: 0.2V

Calibrated
model

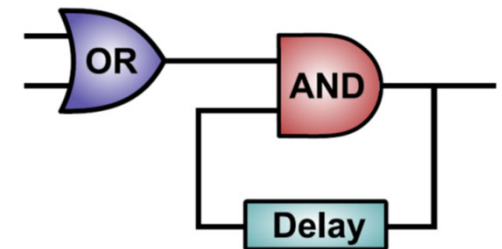


41x303 crossbar circuit



65nm periphery

- Sense amplifier
- Cascade logic**
- etc.



- Results

- 11-step** query in **36 ns**
- Total energy: **20 pJ** (power: 558 μW)

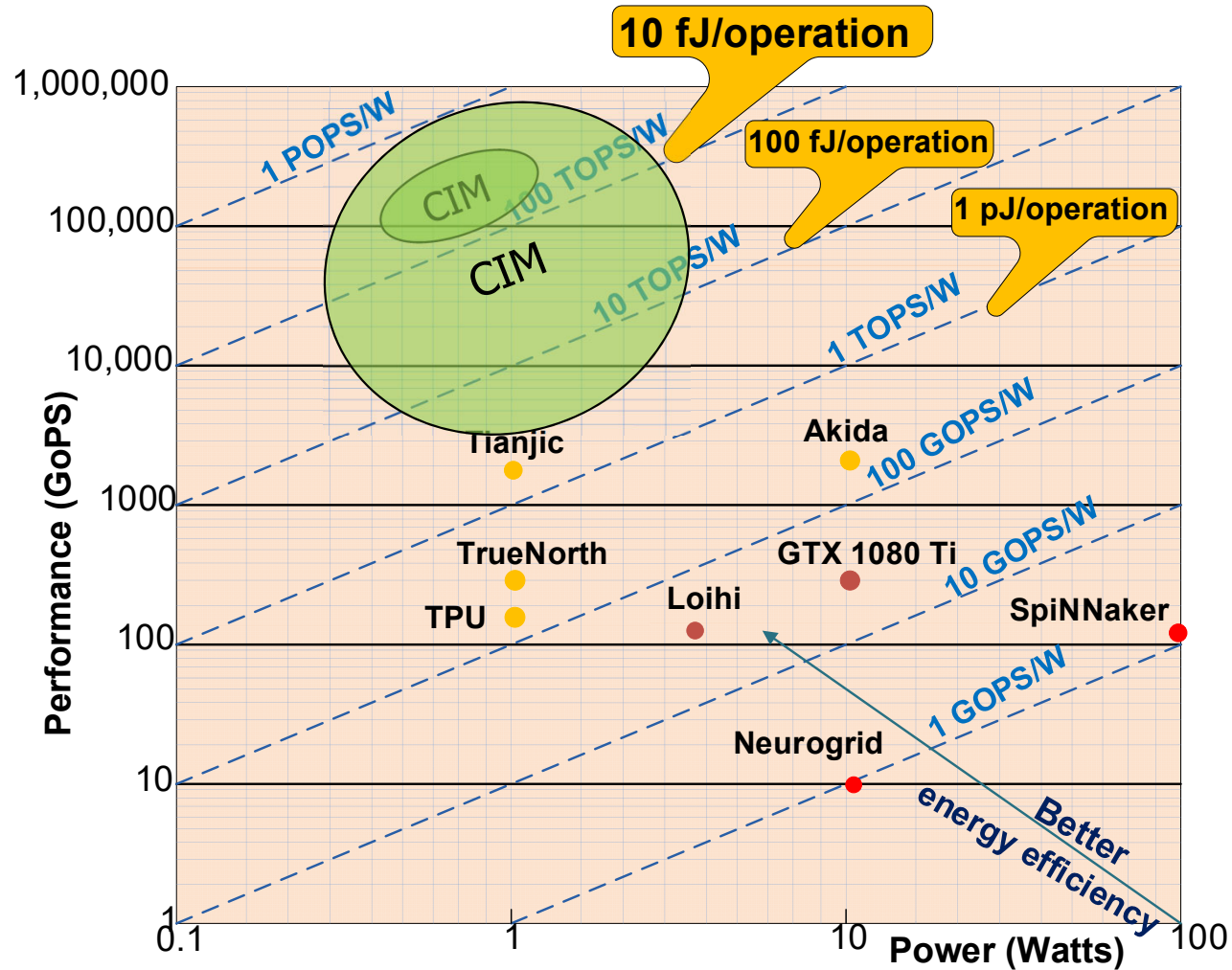
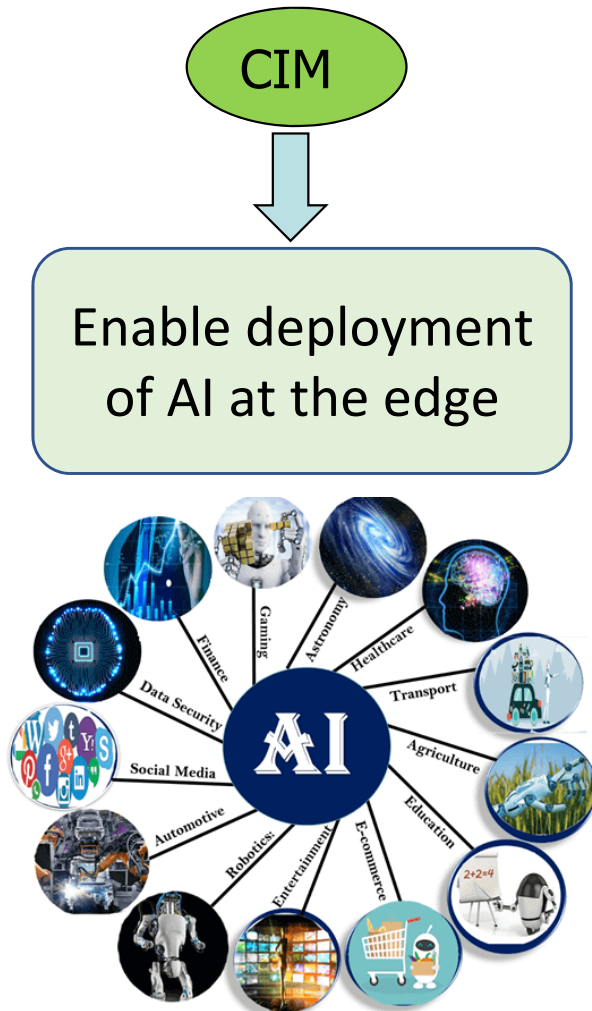
6fj/ operation

Throughput: **92.9 GOPS**

Efficiency: **166 TOPS/W**

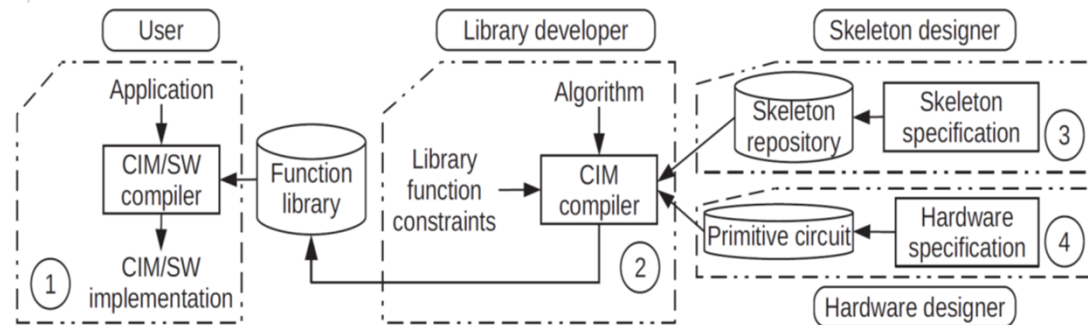
[Source: Iason Giannopoulos et.al, "In-Memory Database Query", Advanced Intelligent Systems, open access, 2020]

Potential of CIM: Enabling edge/IoT applications



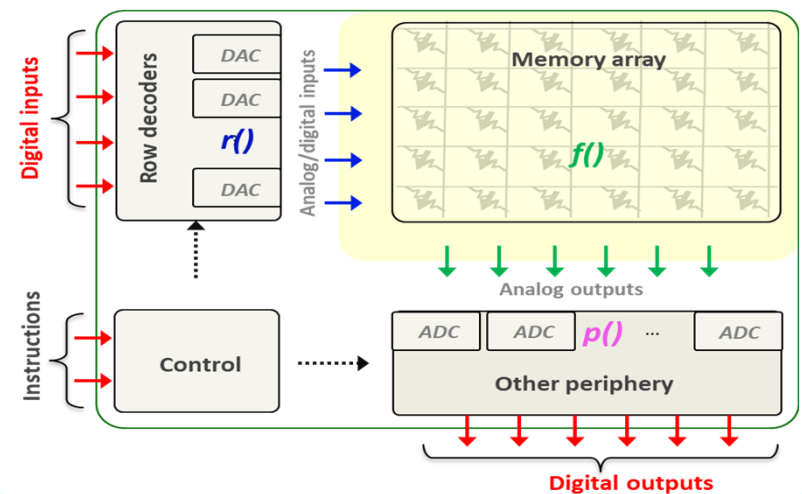
Challenges

- Tools & Application**
- Profilers & compilers
 - Mapping applications on architecture
 - EDA tool chains
 - Bridging algorithms to the architecture and even to the device characteristics
 - Simulators



[Source: J. Yu, et al., "ISAAC: Skeleton-Based Synthesis Flow for Computation-in-Memory Architectures," in IEEE Trans on ETC (TETC), 8(2), 2020]

- Architecture**
- Micro v macro architectures
 - Intra- and inter-communication
 - Virtual memory address translation mechanism
 - Coherence and synchronization of CIM kernels
 - Design exploration



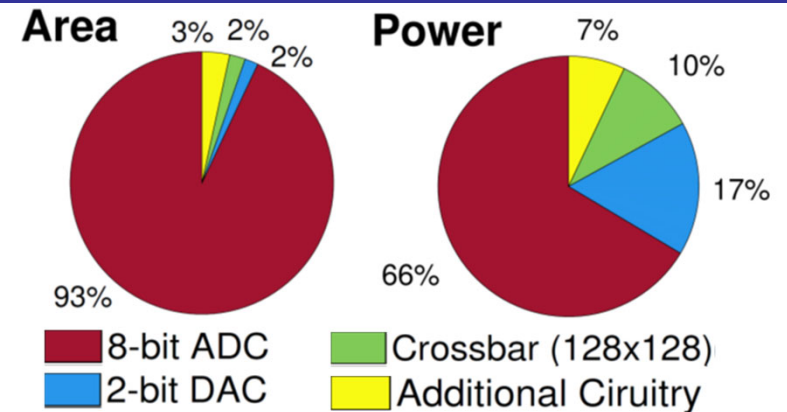
Challenges

Circuit design

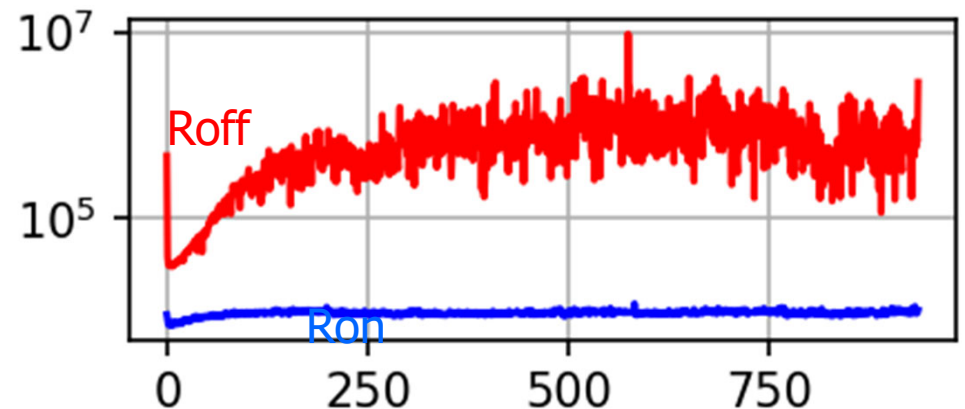
- Fast and energy efficient signal conversion circuits (DAC, ADC)
- High precision programming of NVM
- Precise measurement of current
 - Vector x matrix: output as current
- Design for non-idealities
- Managing sneak paths

Technology

- Device-to-device variability, R ratio
- Multi-state behavior
- Energy switching
- Threshold behaviors
- Endurance
- 3D Integration & stacking, yield



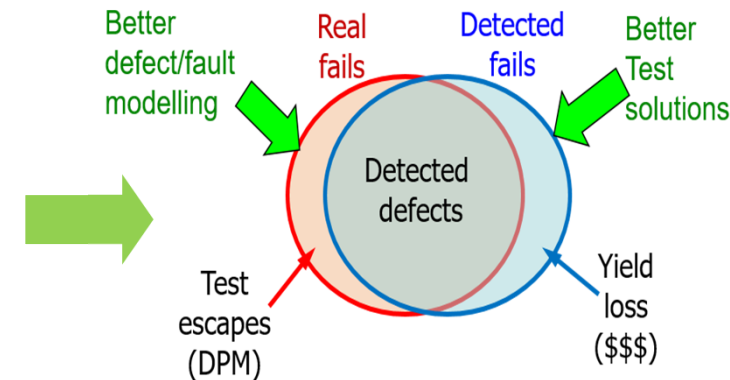
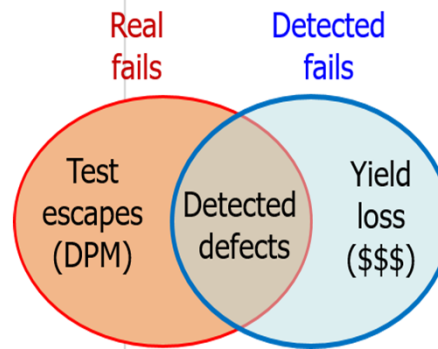
[A. Shafiee et al., "ISAAC: A convolutional neural network accelerator with in-situ analog arithmetic in crossbars," in ISCA, 2016]



Challenges

Test

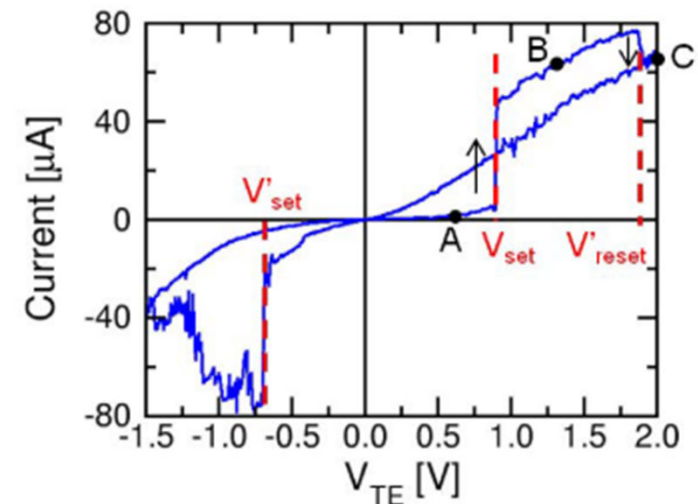
- There are “known unknowns”
- Defects not fully understood
- Fault models & test solutions
- DFX, BIST, BISR
- Memory v Comp configuration



Reliability

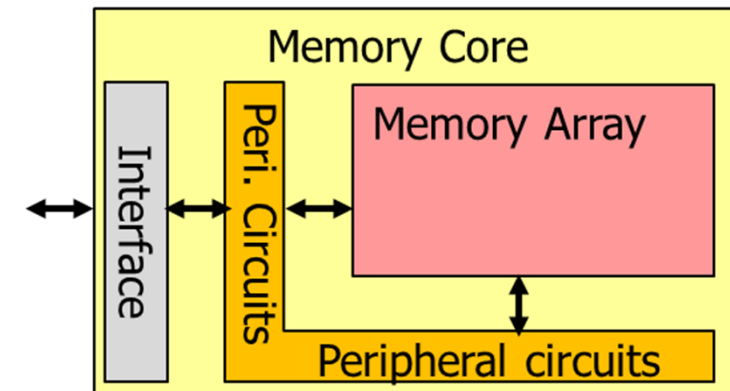
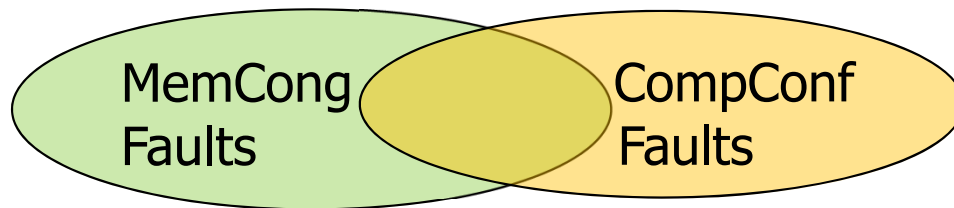
- Endurance
- Fault tolerance
- Cycle-to-cycle variability
- Degradation
- Intermittent unpredicted switching

[Source: M. Fieback, et. al, "Intermittent Undefined State Fault in RRAMs", ETS 2021, Nominated for BPA]

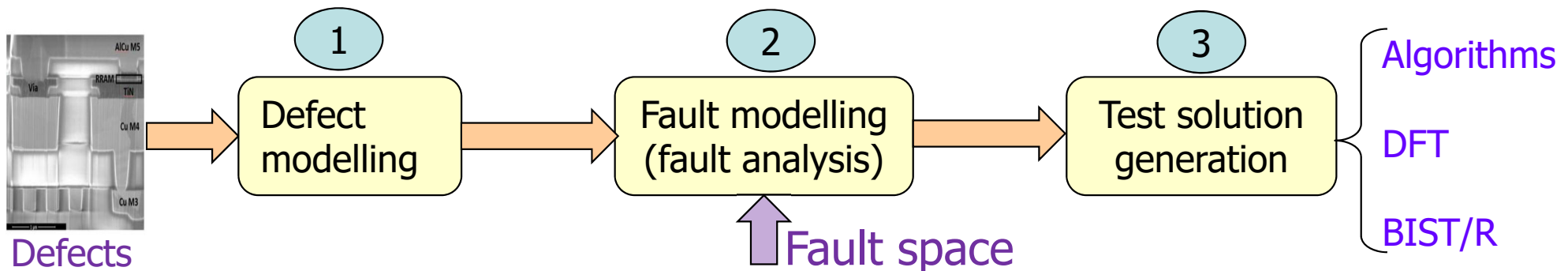


Testing CIM device

- Test for two configurations
 - **Memory config**: Read, Write
 - **Computation config**: Read, Write, Compute



- Use typical structural approach

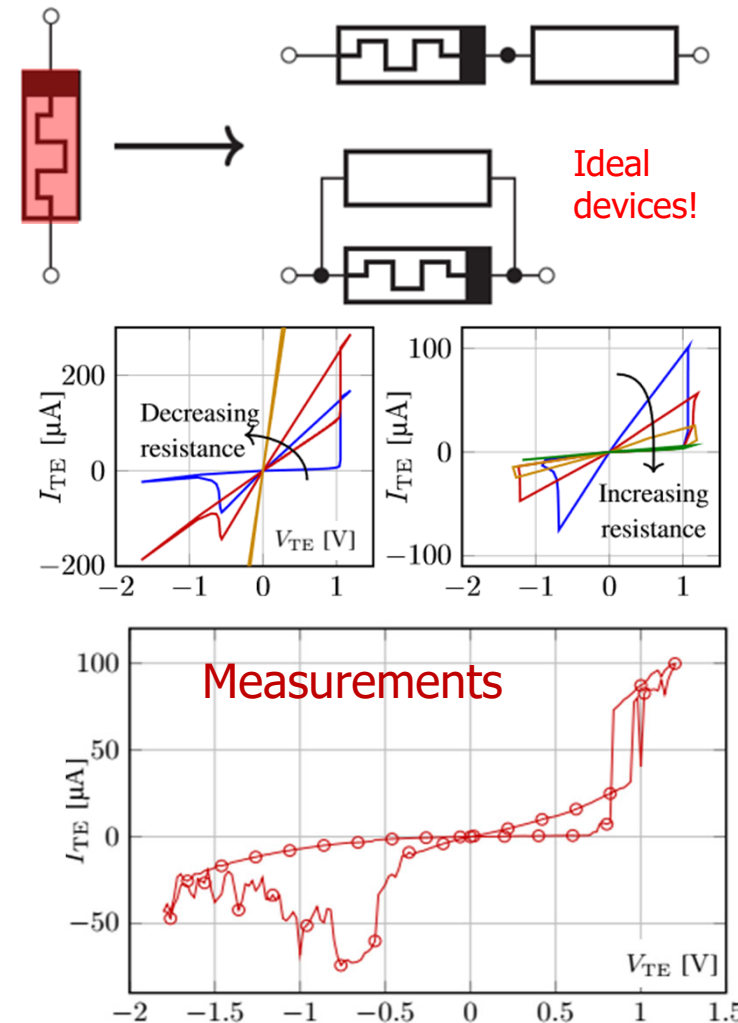


Testing CIM device: Device-Aware-Test

- **State of the art**
 - Defects modeled as **linear resistors**
 - Inappropriate for many defects
 - Cannot guarantee 0DPM
- **CIM uses new device technologies**
 - New failure mechanisms/ modes
- **Need of accurate defect modeling**
 - Incorporate defective behavior in device model
 - Crucial and critical for high quality test solutions

R-model fails to detect all defects

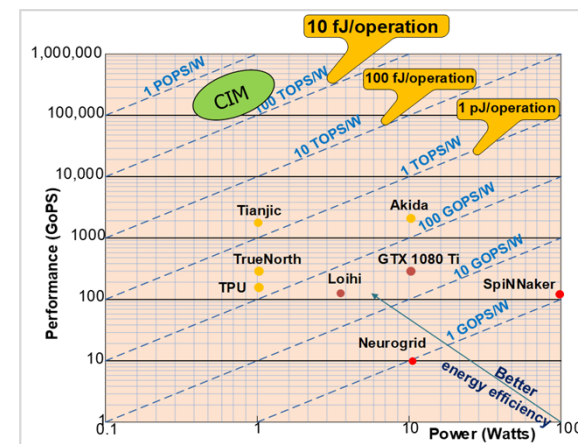
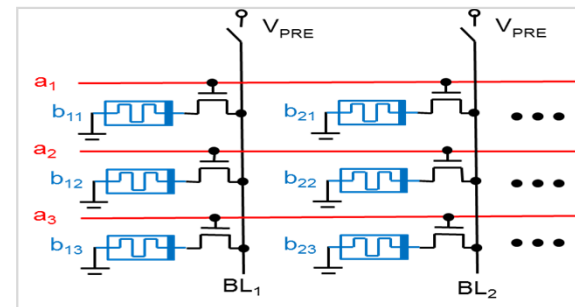
Device-Aware Test



Conclusion

- **Emerging applications requires new chips**
 - IoT-Edge partnership: Data-centric computing & Huge data storage
 - Rethink: micro-architectures, design, Reliability, security, communication,
 - Efficiency: Order of fj/operation
- **Key enablers: new architectures and technologies**
 - Arch: CIM, artificial neural network, bio-inspired NN, AP, ...
 - Tech: NV memories, 3D processing/stacking, photonics, ...
- **Huge potential**
 - Order of magn. improvements in computational efficiency
 - Huge storage, reduced communication
 - Cheap implementation of basic operations
- **BUT still many challenges**
 - Technology, circuit, architecture, prog models, Testing, Reliability
 - Full application evaluation rather than small isolated kernels

Edge computing

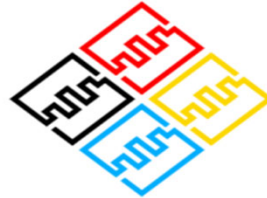


Acknowledgement

<http://www.mnemosene.eu/>



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Thanks