



# A > 64 Multiple States and > 210 TOPS/W High Efficient Computing by Monolithic Si/CAAC-IGZO + Super-Lattice Ferroelectric for Ultra-Low Power Edge AI Application

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**PSMC 力晶積成電子**

**SEL**  
SEMICONDUCTOR ENERGY LABORATORY



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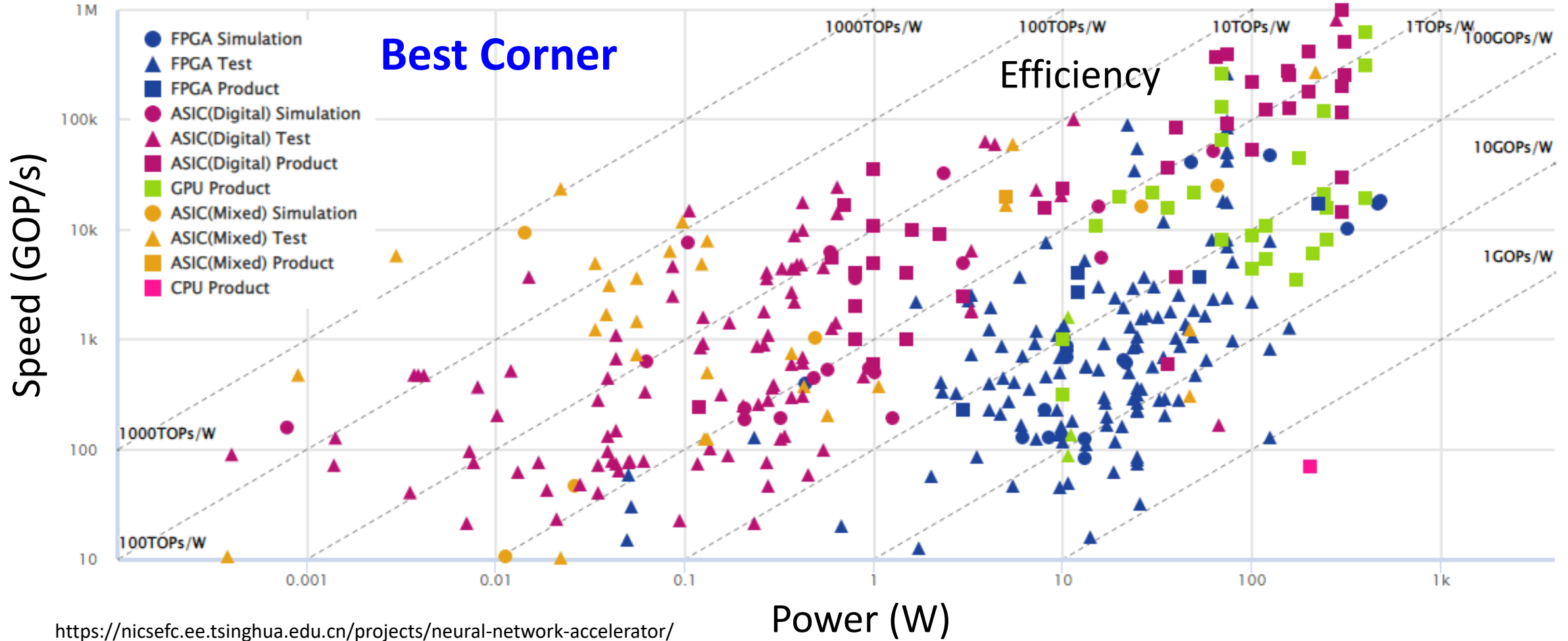
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<sup>3</sup> National Taiwan University, Taipei, Taiwan. E-mail: [mhliao@ntu.edu.tw](mailto:mhliao@ntu.edu.tw)

# Outline

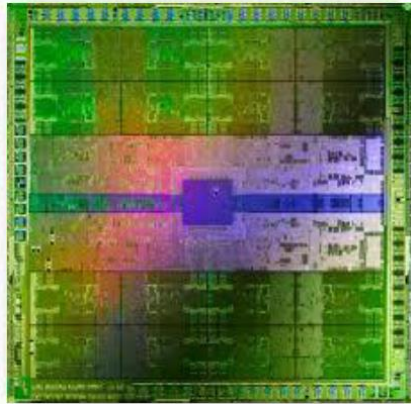
- Introduction
- Experiments and Fabrications
- AiMC Chip Design and Operation
- Performance, Stability, and Reliability
- Benchmark & Conclusion

# Accelerators for AI: Neural Network Accelerator

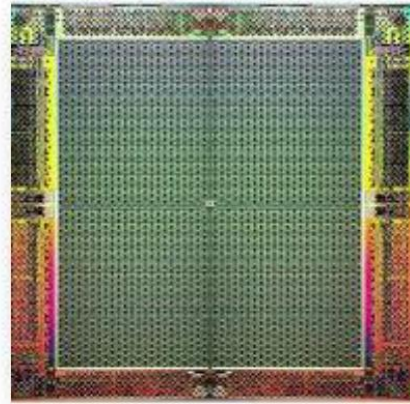


- High efficient AI accelerators (FPGA, ASIC, CPU, and GPU) are developed for different computing applications.

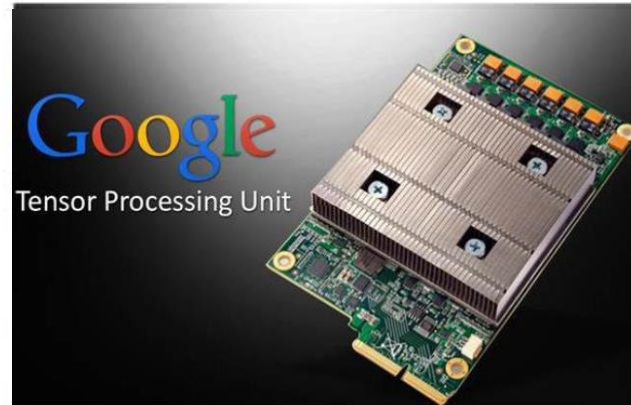
# Accelerators for AI: GPU/FPGA/TPU/Compute-in-memory



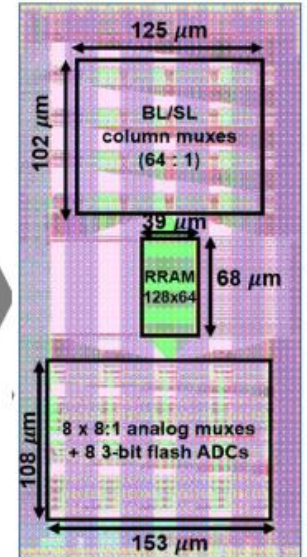
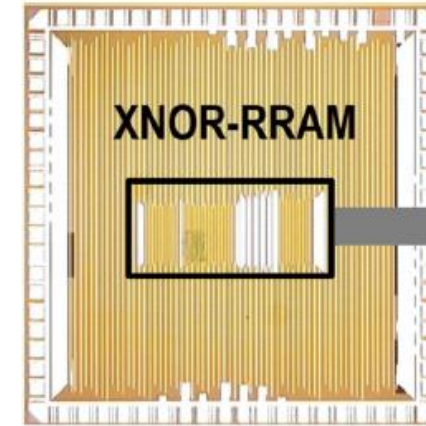
GPU



FPGA



TPU



Compute-in-memory (CIM)

Conventional computing platforms

~ 0.1 TOPS/W

Floating-point

IEDM 2020 Short Course 2: Analog Memory Needs for AI (GIT)

- Compute-in-memory (CIM) chip is promising especially in the edge inference when model has pre-trained.
- It also supports incremental learning with new data input when deployed to the field.

Digital CMOS ASICs

~ 1-10 TOPS/W

Fixed-point

Analog CMOS (or eNVMs)

~ 10-100 TOPS/W

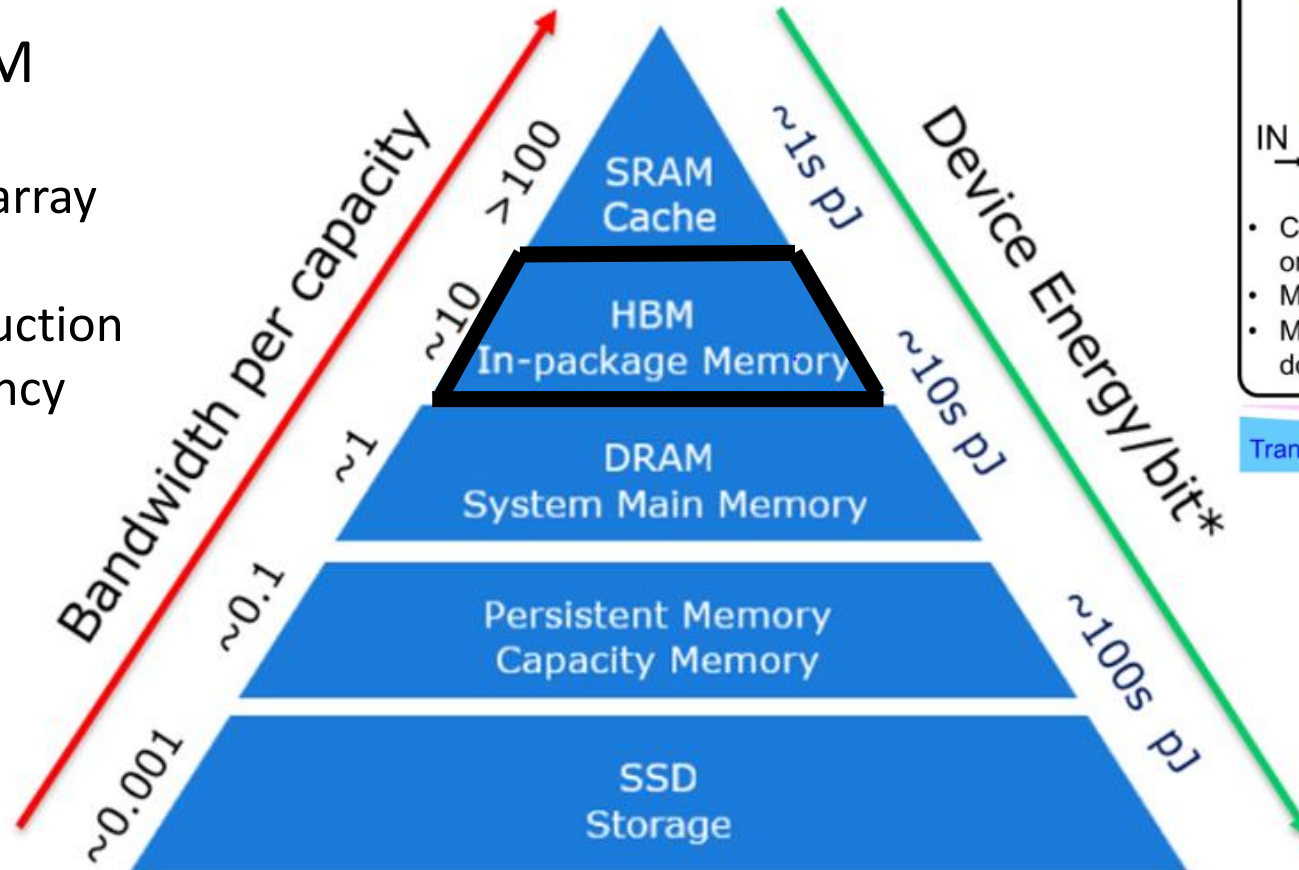
Low-precision → accuracy?



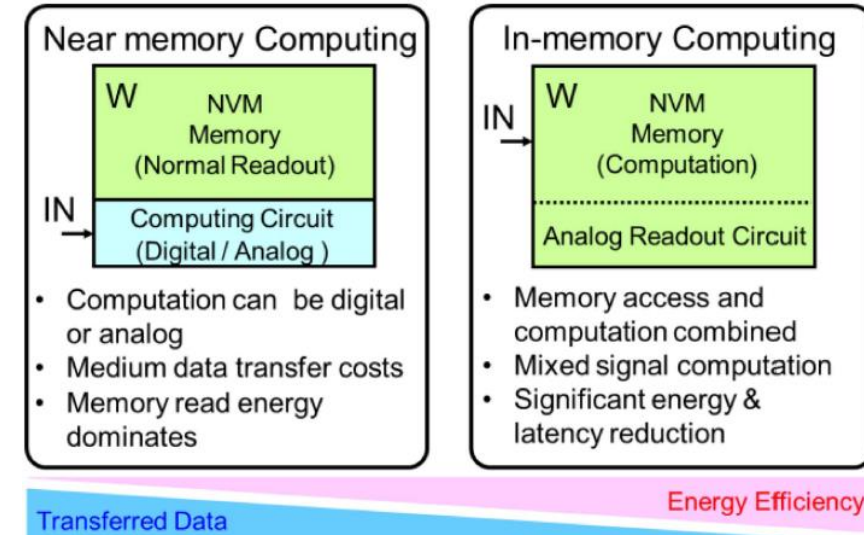
# Memory Classification & High Band-Width Memory

## Features of HBM

- 3D stack
- CMOS under array
- Faster
- Footprint reduction
- Energy efficiency



Intel & Shen Meng et al., Journal of Lightwave, 2019.

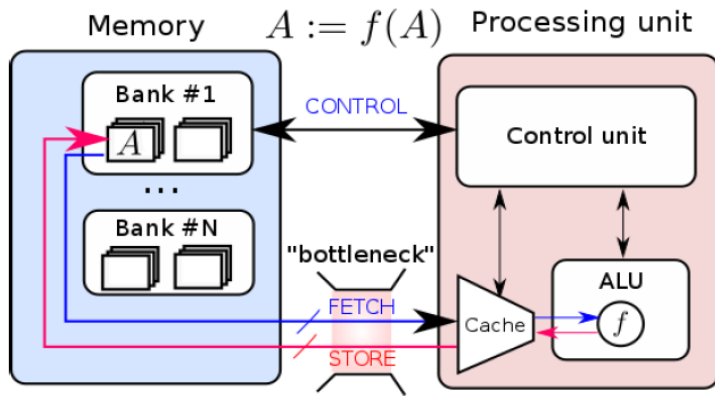


J.M. Hung et al., *Soild-State Circuit Society*, Vol. 1, pp. 171-183, 2021.

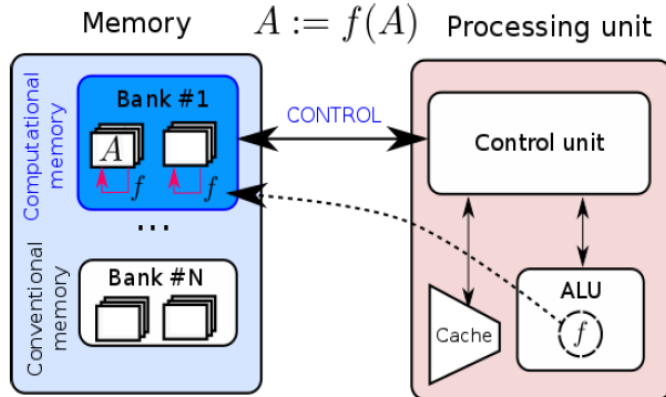
- Compute-in-memory (CIM) chip can also be used as L1-L3 memories, considering bandwidth and energy/bit.

# Near Memory and In-Memory Computing

## Processing unit & Conventional memory

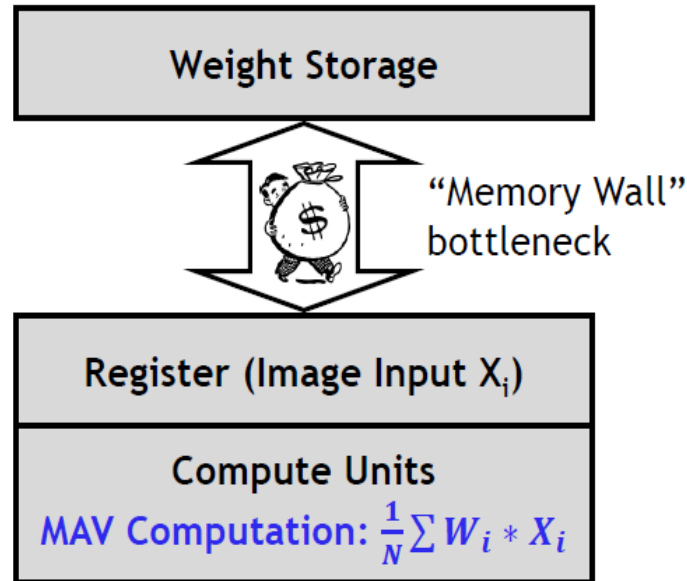


## Processing unit & Computational memory



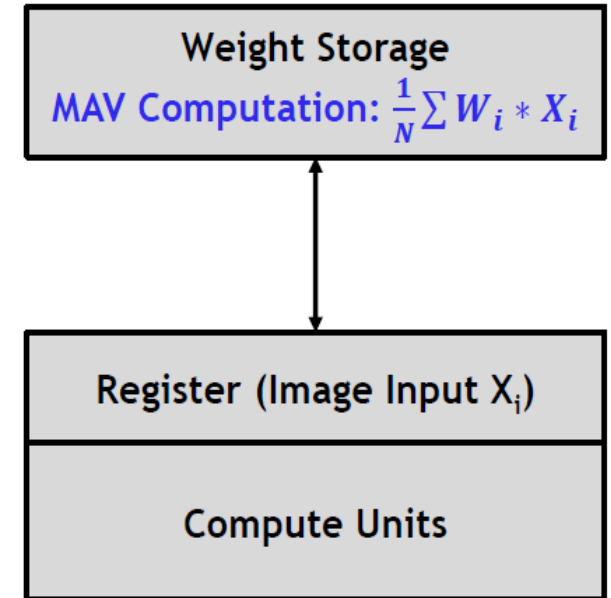
IEDM 2019 Tutorial 2: In Memory Computing for AI (IBM)

## Von Neumann computing



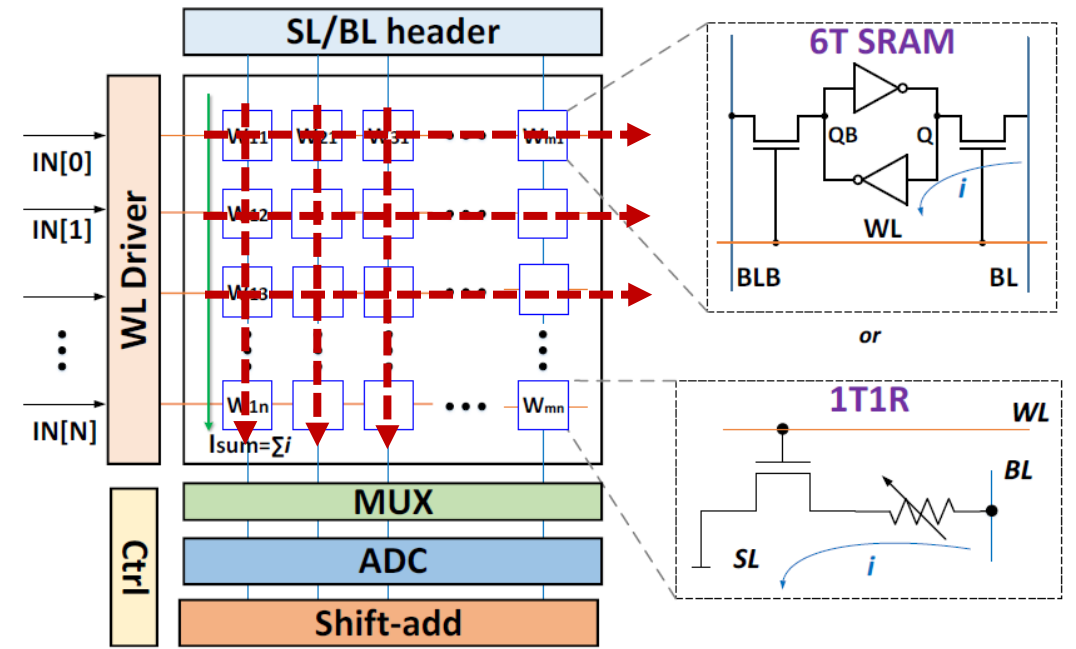
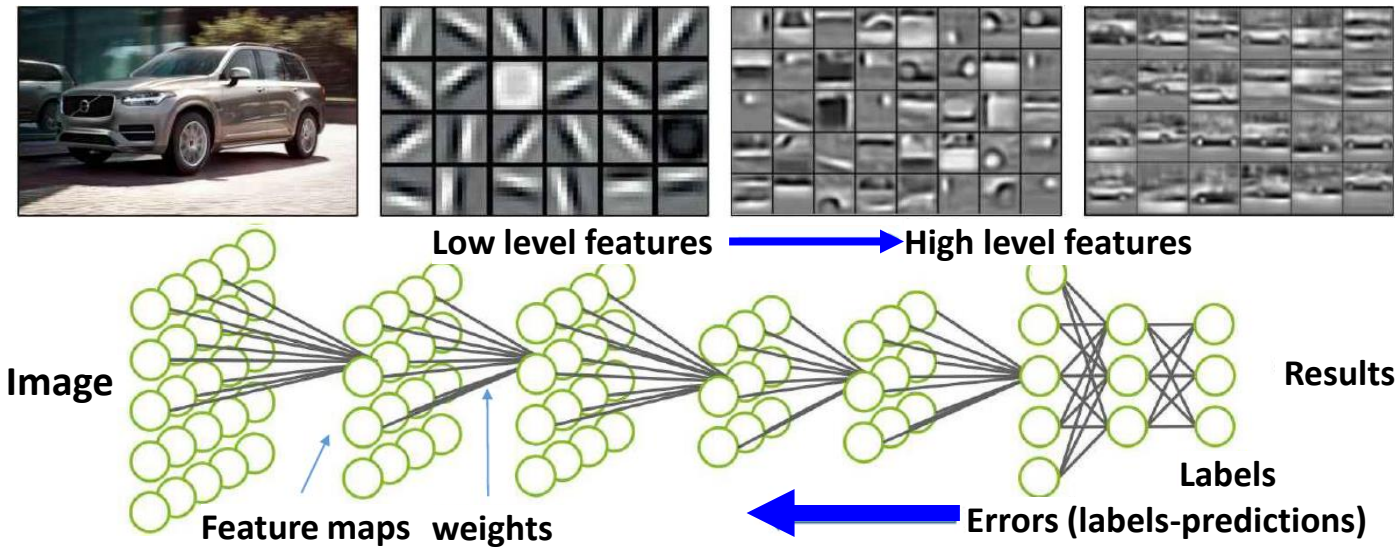
VLSI 2022 C12-4 (University of Texas)

## In-memory computing



- Compute-in-memory (CIM) chip reduces data movement between memory and processing units.
- It performs the computation within a memory array and release the "memory wall".

# AI Computing and Analog Computing Concept



IEDM 2020 Short Course 2: Analog Memory Needs for AI (GIT)

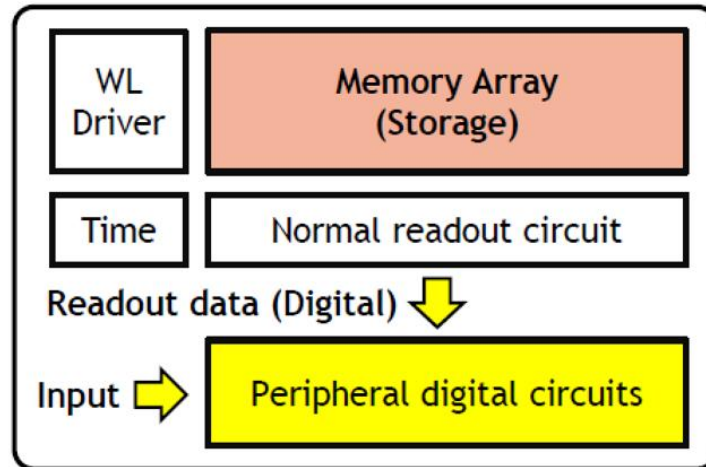
IEDM 2020 Short Course 2: Analog Memory Needs for AI (GIT)

- AI Computing has two basic functions:
  - ✓ Training: write intensive to synaptic weight memories.
  - ✓ Inference: read intensive to synaptic weight.
- Analog Computing: Intensive computation needs 『Vector-matrix-multiplication』 by 『analog/multi-states』 for parallel computing.

# Digital *versus* Analog Computing in Memory

## Digital Near-Memory

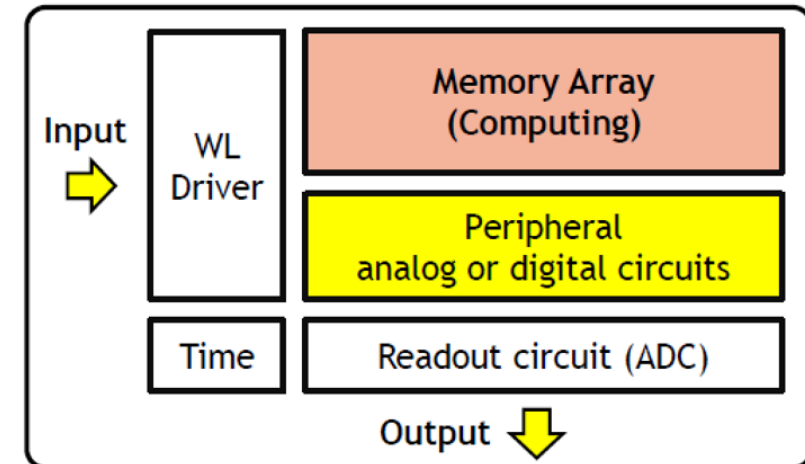
- Digital signal computation
- Multiply and accumulation in peripheral digital circuit
- No accuracy loss



[Y.-C. Chiu (NTHU), et al, ISSCC, 2022]

## Analog In-Memory

- Mixed signal computation
- Multiply in cell array
- Accumulation in peripheral analog or digital circuit
- High energy efficiency



[S. D. Spetalnick (Georgia Tech), et al., ISSCC, 2022]

[W.-S. Khwa (TSMC), et al, ISSCC, 2022]

[J.-M. Hung (NTHU), et al, ISSCC, 2022]

Chang et. al., VLSI (2022)

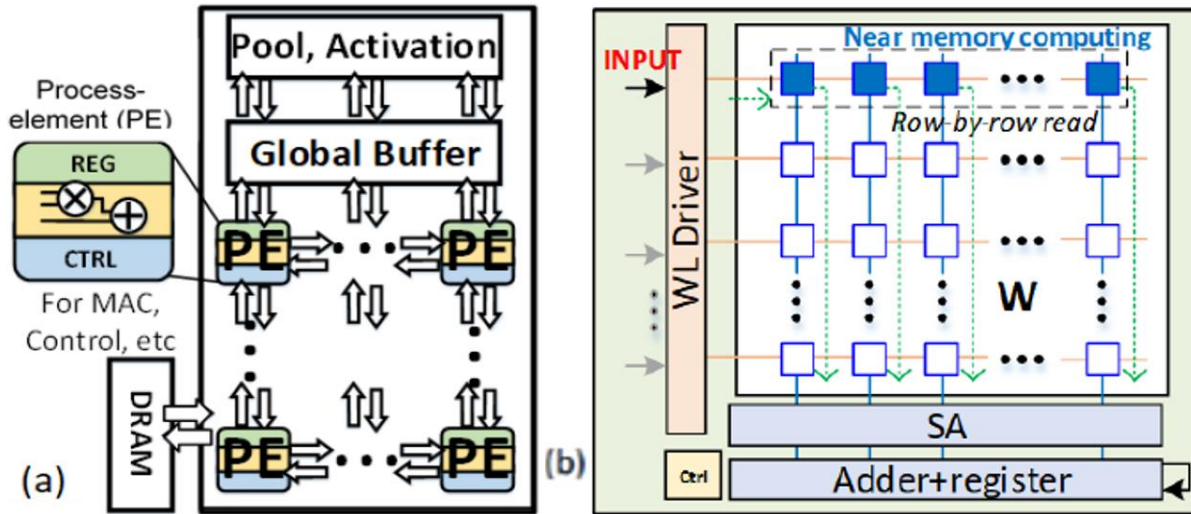
- Digital: Multiply and accumulation in peripheral digital logic → No accuracy loss.
- Analog: Multiply in Cell array, Accumulation in peripheral analog/digital circuit → High energy efficiency/parallel computing.



# Digital *versus* Analog Computing in Memory

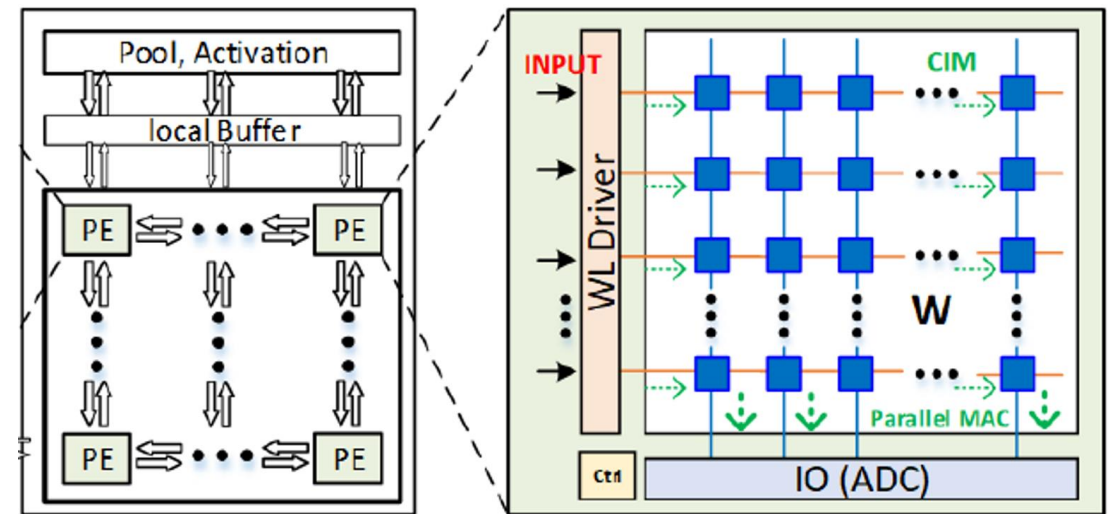
## Digital Near-Memory

Digital accelerator (TPU-like)      Near-memory-compute accelerator (row-by-row)



## Analog In-Memory

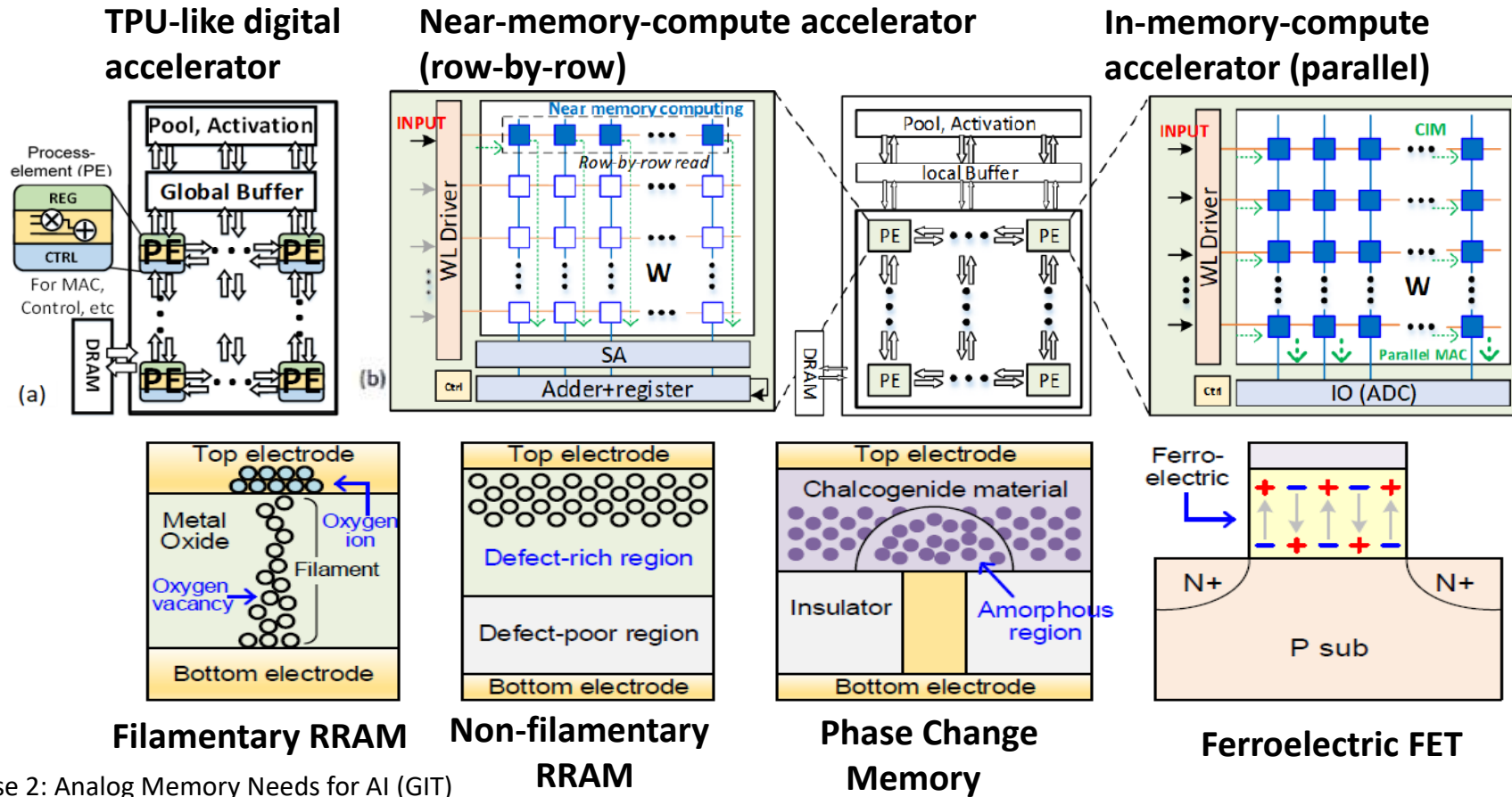
In-memory-compute accelerator (parallel)



IEDM 2020 Short Course 2: Analog Memory Needs for AI (GIT)

- Digital:
  - ✓ Single row access (TPU-like).
  - ✓ Row by Row with digital address at periphery.
- Analog: Parallel access and ADC for total sum quantization.

# Analog Computing in Memory Candidates

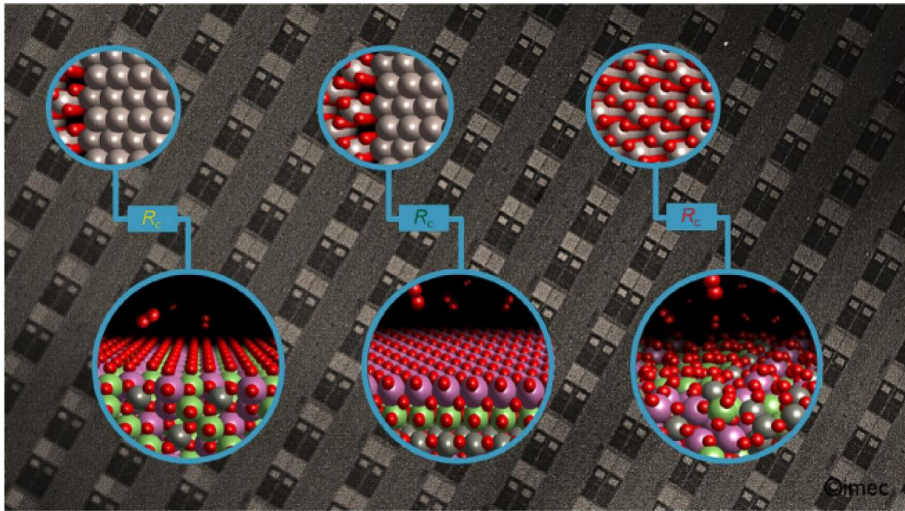


IEDM 2020 Short Course 2: Analog Memory Needs for AI (GIT)

- Analog: Parallel access and ADC for total sum quantization.
- RRAM, PCRAM, FE-RAM can be used for Analog computing.
- In this work, we propose new CAAC-IGZO + MIM w/SL-FE scheme.

# IGZO: Material Properties

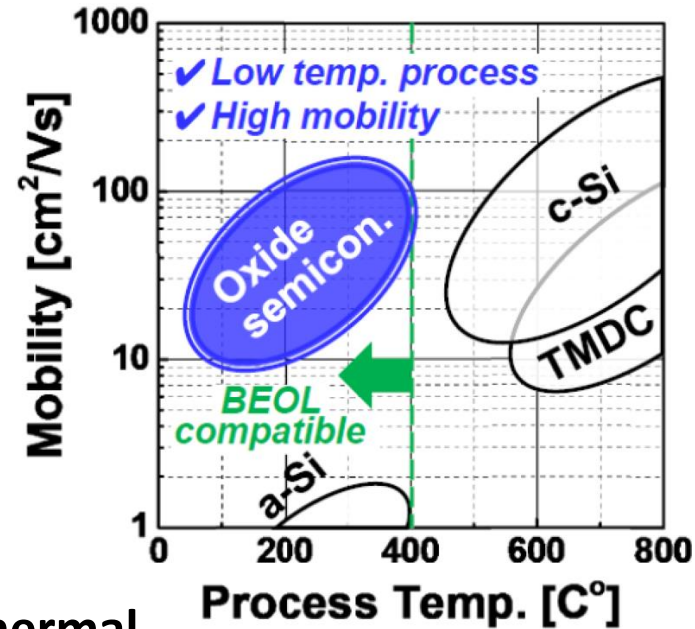
## ④ Good uniformity



- Contact metal
- Oxygen
- Indium
- Gallium
- Zinc

ACS Appl. Electron. Mater. Vol. 3(9), p. 4037, (2021)

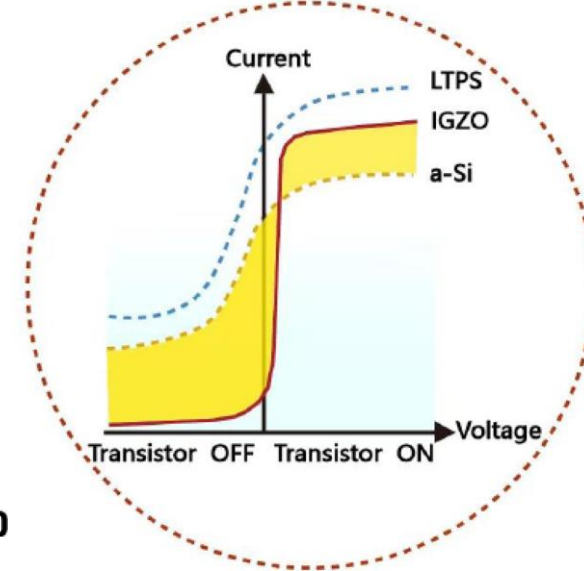
## ② Moderate mobility



## ③ Low thermal budget

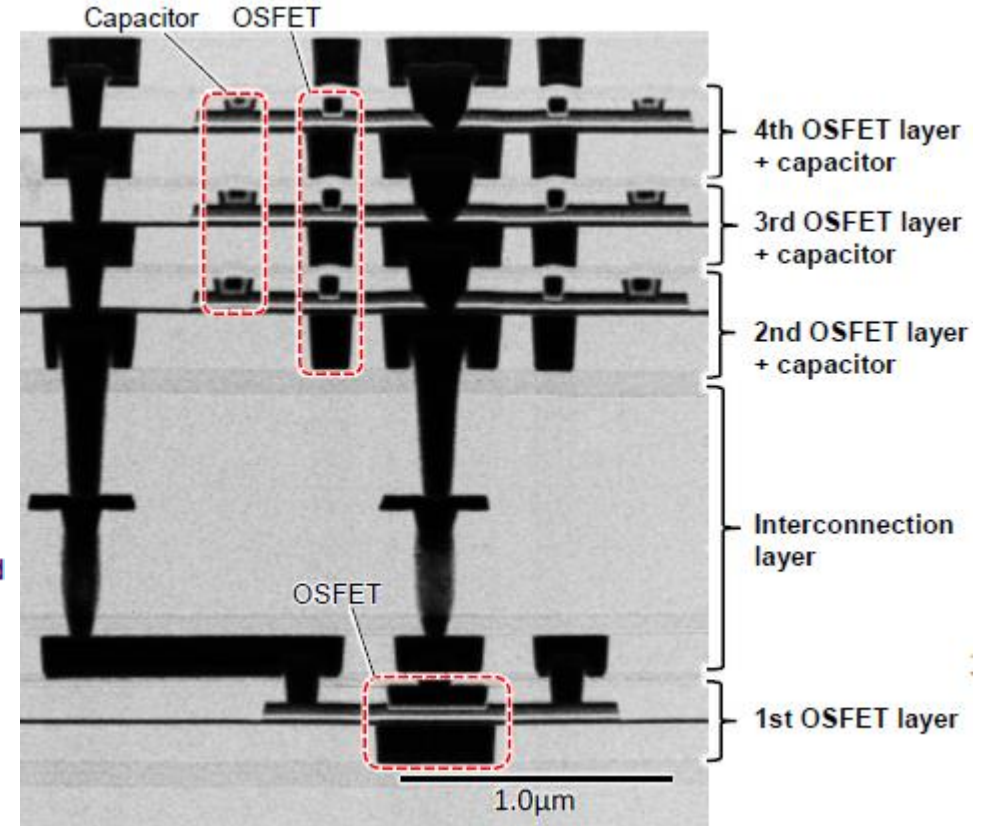
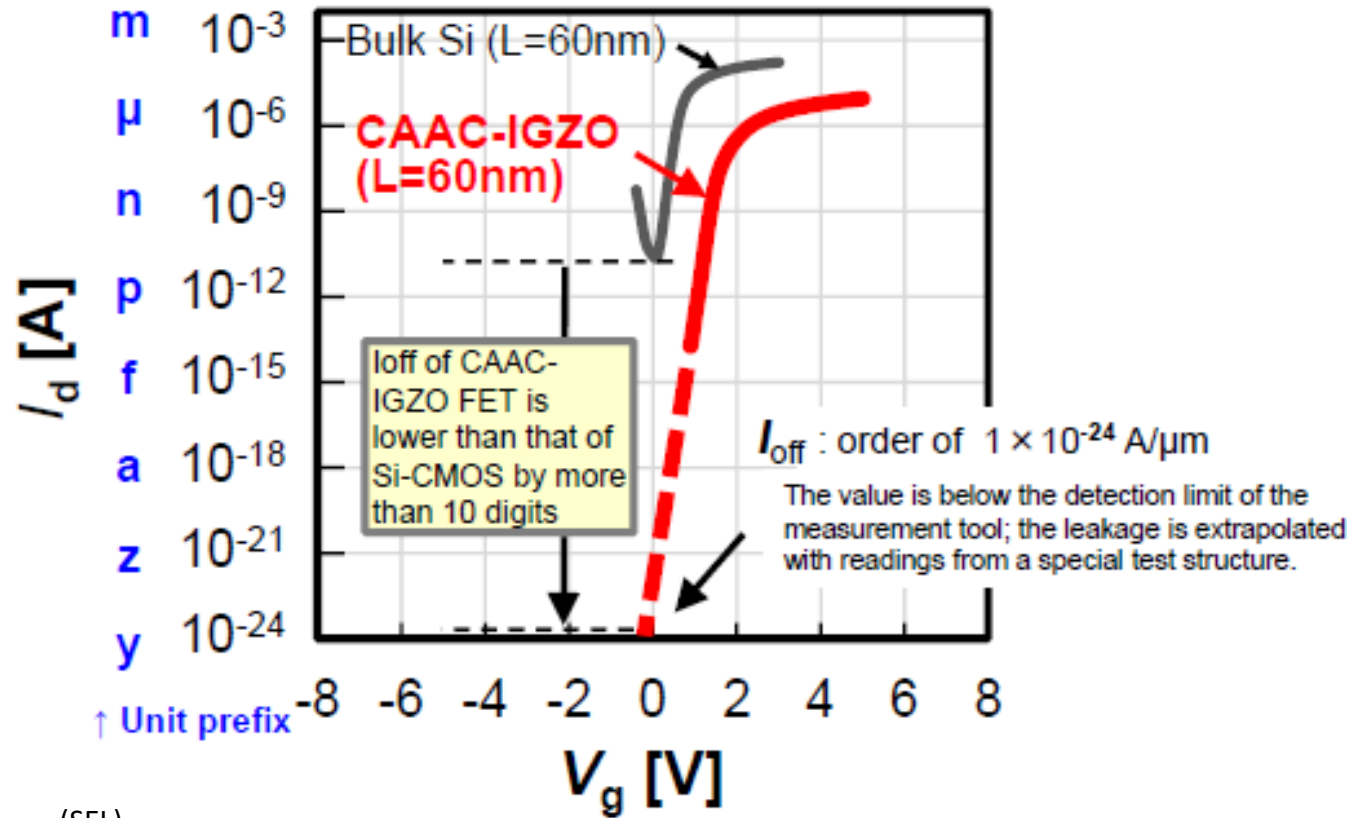
Wu et. al., VLSI (2020) and E. Fortunato et. al., Adv. Mater., (2012)

## ① Ultra-low off-state current



- IGZO is BEoL compatible, with acceptable mobility, low off-state current, low power consumption, high scalability, and excellent uniformity.

# IGZO: Monolithic Properties



CIMTEC Plenary talk 2022 (SEL)

- IGZO  $I_{off} \sim 10^{-24} \text{ A}/\mu\text{m}$ ,  $I_{on}/I_{off} \sim 10^{19}$ .
- Most other CIM chips (RRAM,..) suffer high read current with high IR power consumption.
- IGZO Low Temp. process with monolithic in BEoL is suitable for multi-stackings.



# Highlights in this work

- Monolithic OS (IGZO) as BEoL device
- SL  $\text{ZrO}_x/\text{AlO}_x/\text{ZrO}_x$  (SL-ZAZ) MIM capacitor
- Multi-states and High efficient Analog Memory  
Macro
- Efficiency, Temperature effect, Stability, and Reliability

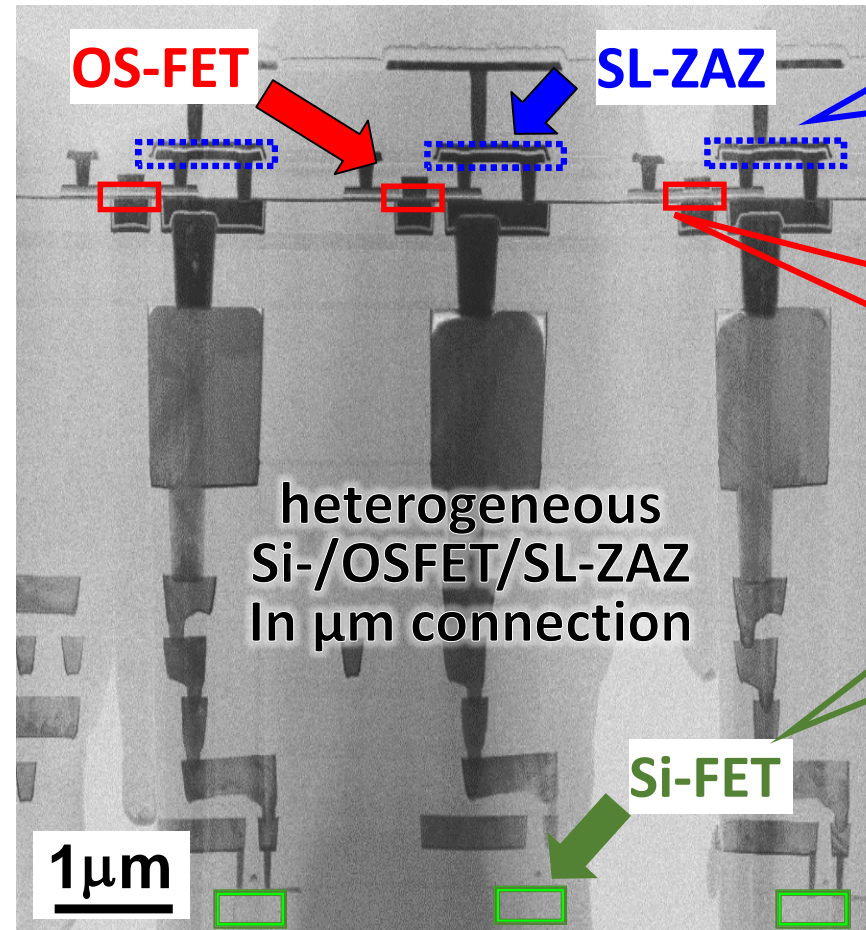
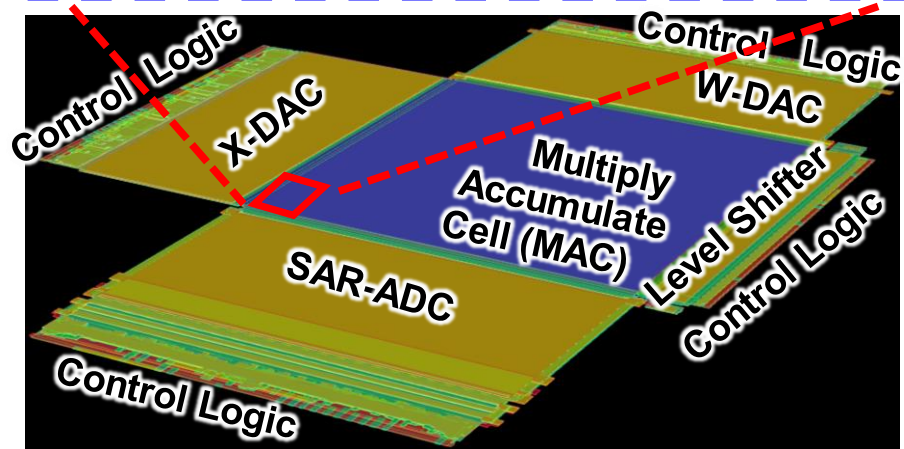
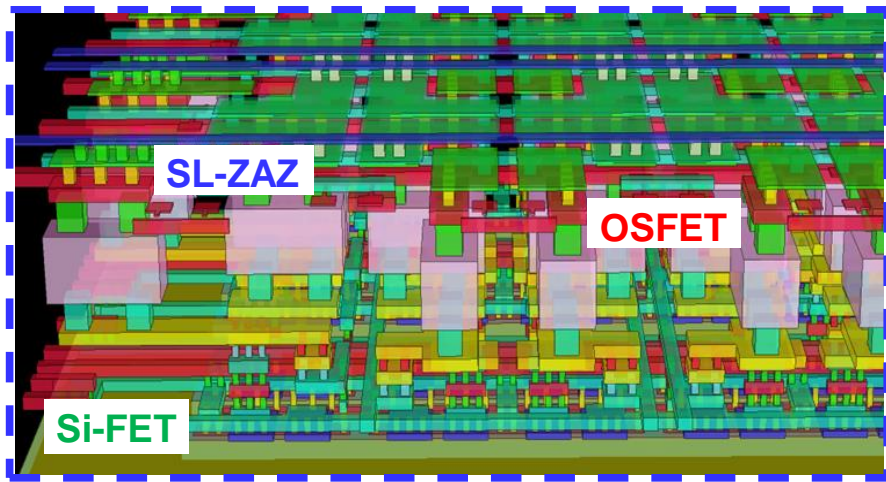


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- Introduction
- **Experiments and Fabrications**
- AiMC Chip Design and Operation
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# Monolithic 3D Integration

- Integrated FEoL Si devices + BEoL OS devices and SL MIM to achieve Analog in-memory computing (AiMC) macro.



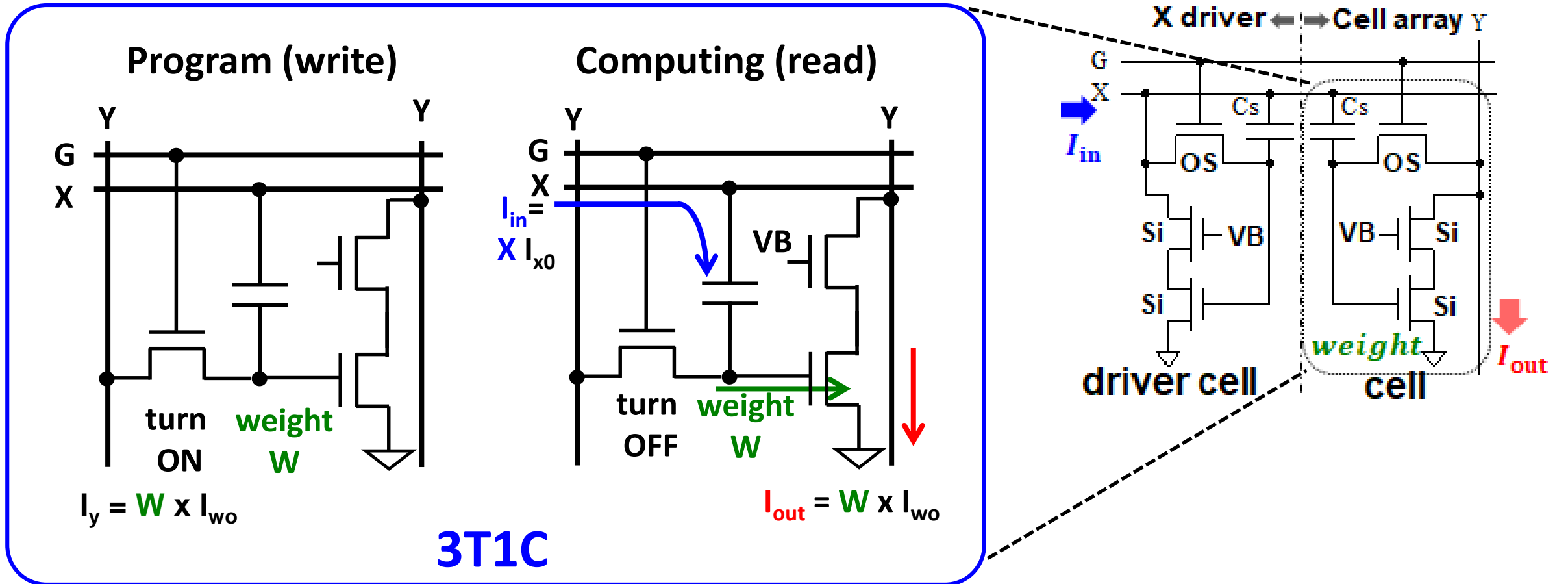
- MIM Capacitor - SL-ZAZ

- OS Devices - Low leakage

- Si Devices - CMOS

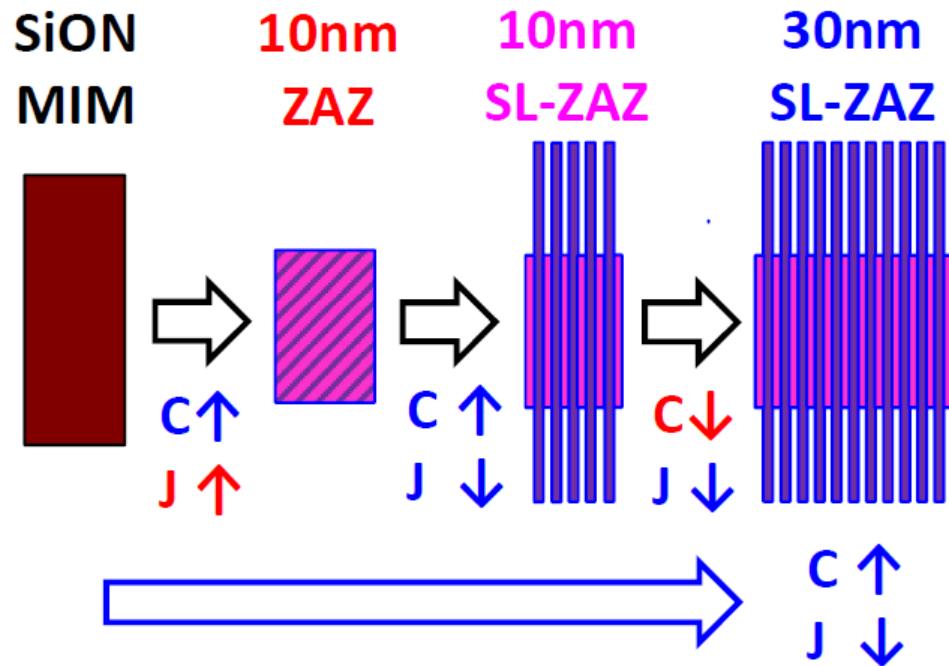
# Cell Array Structure

- Memory cell operates at sub-threshold with nA read current.
- Analog multiplication:  $I_{out} = \text{Weight } (W) \times I_{in} (X)$ .



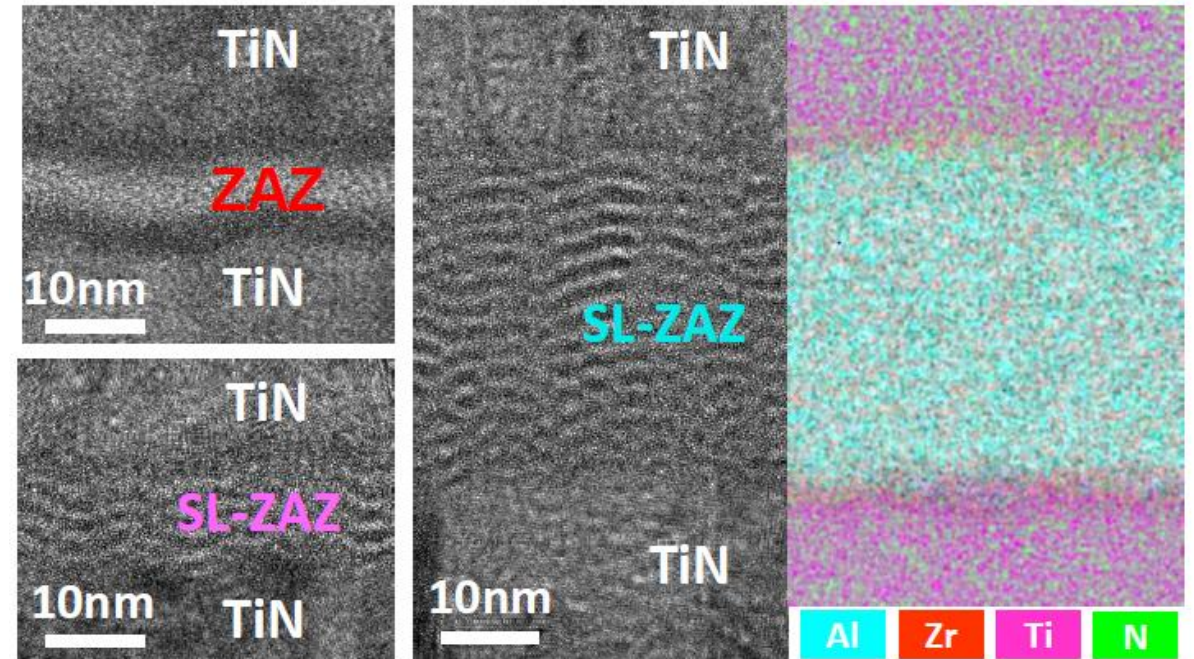
# Super-Lattice $ZrO_x/AlO_x/ZrO_x$ (SL-ZAZ) in MIM

- The laminated-ZAZ structure is processed by ALD.
- Optimize the ZAZ stacked structure for C & J performance.



ZAZ: K=17

SL-ZAZ: K=22

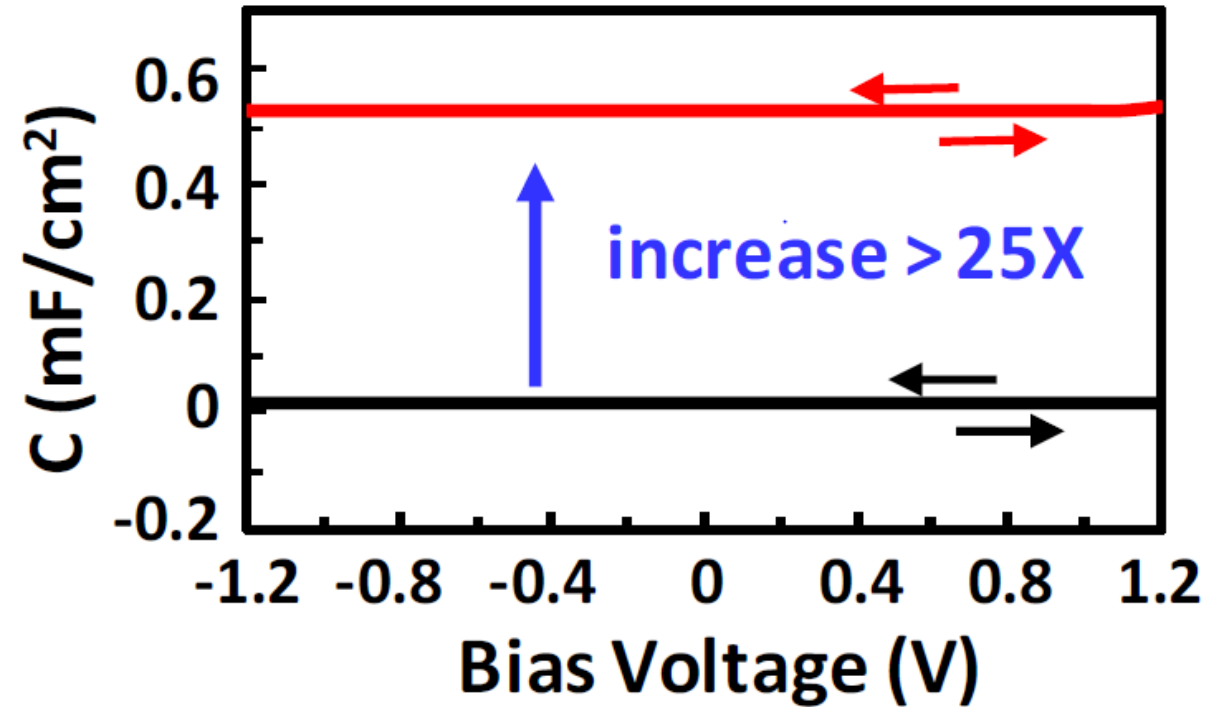
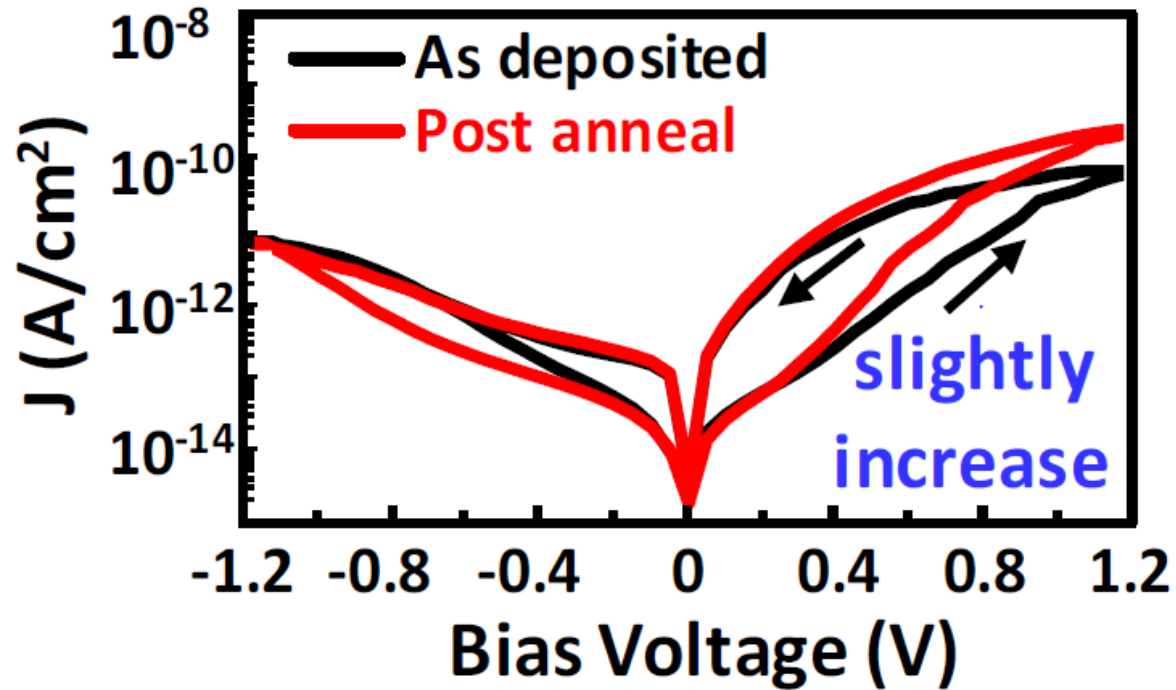


Sample from NTNU Prof. M.-H. Lee's group



# Super-Lattice $\text{ZrO}_x/\text{AlO}_x/\text{ZrO}_x$ (SL-ZAZ): RTA effect

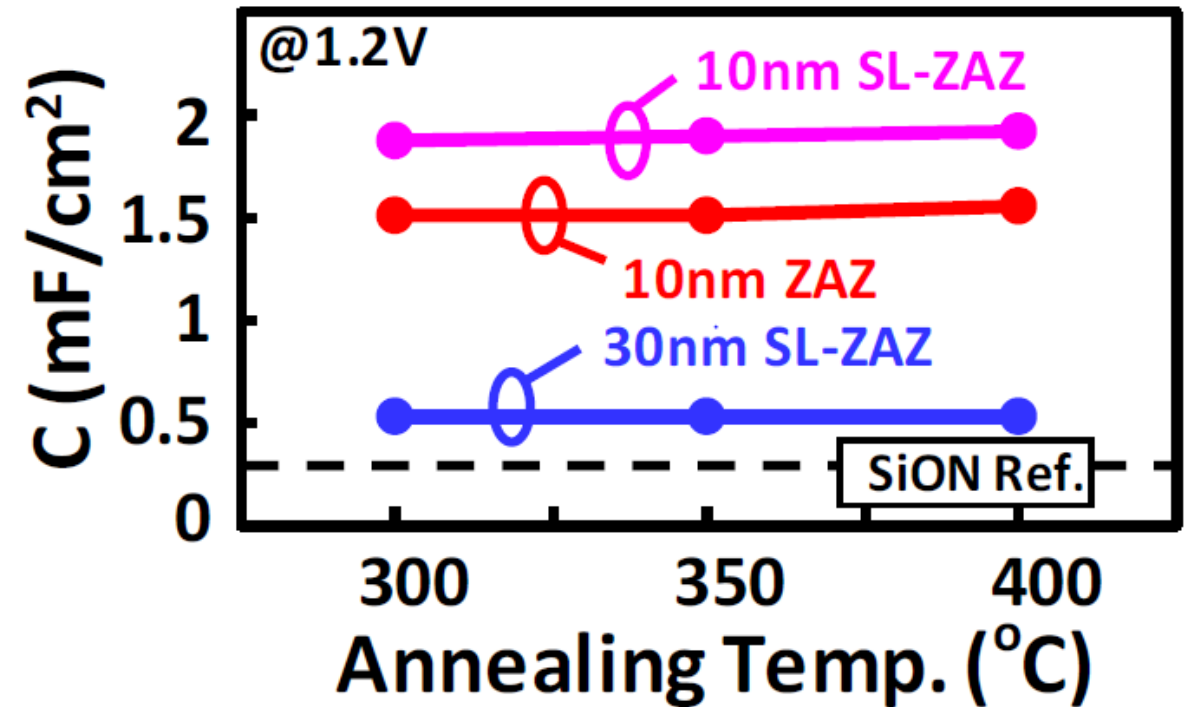
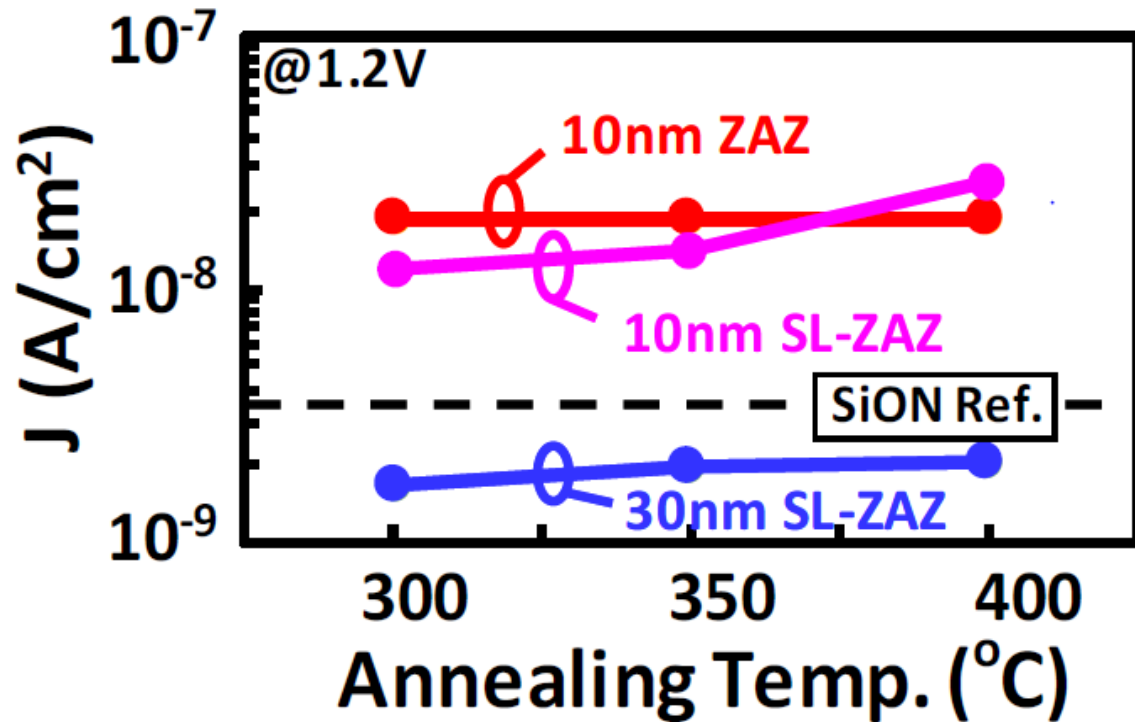
- RTA annealing for SL-ZAZ.
- **25X** Capacitance improvement.





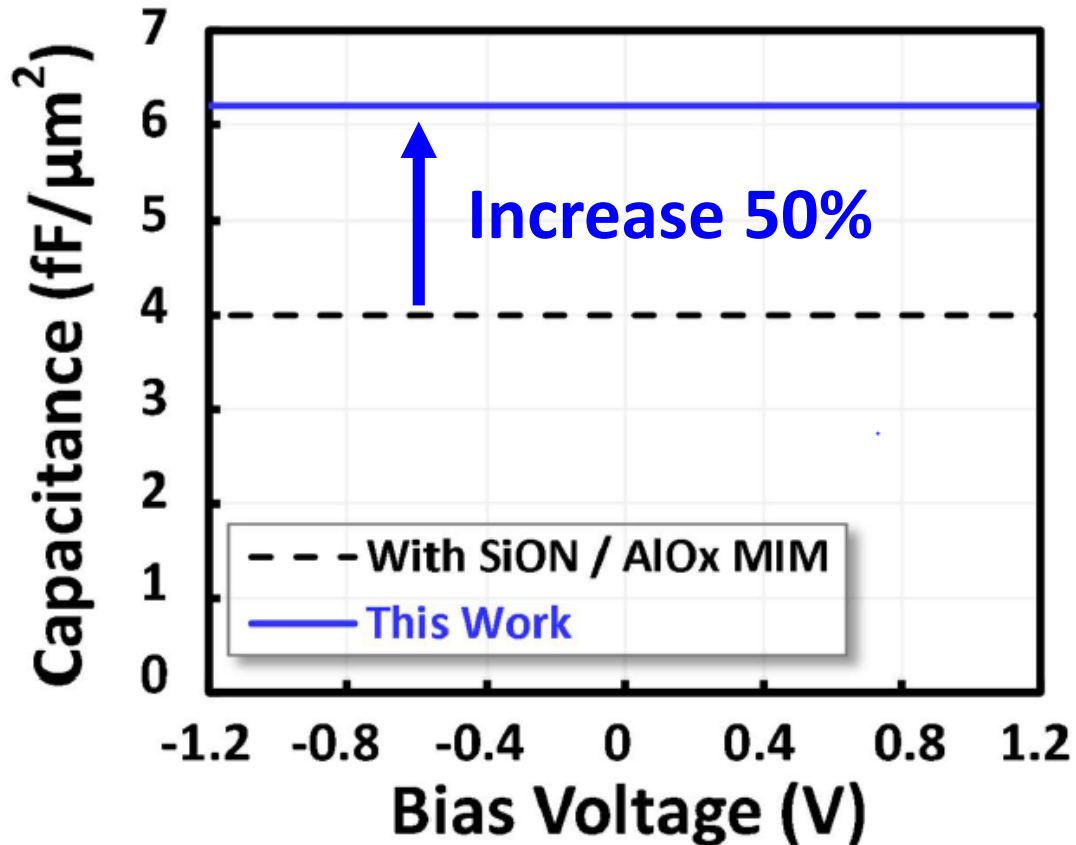
# Super-Lattice $\text{ZrO}_x/\text{AlO}_x/\text{ZrO}_x$ (SL-ZAZ)

- 30 nm ZAZ & 400 °C anneal is used.

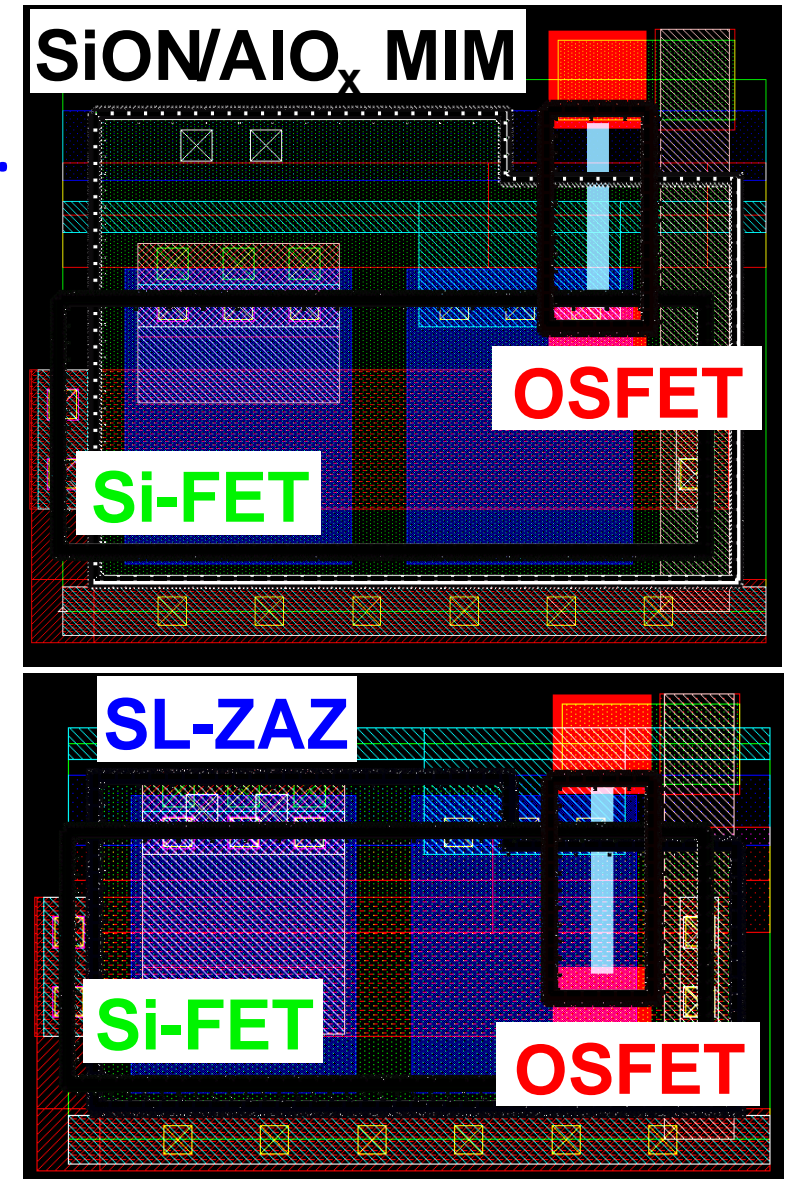


# Super-Lattice $ZrO_x/AIO_x/ZrO_x$ (SL-ZAZ)

- SL-ZAZ has better capacitor performance.
  - **50%** capacitance improvement than SiON.
  - **25%** Cell area reduction. (calculation)

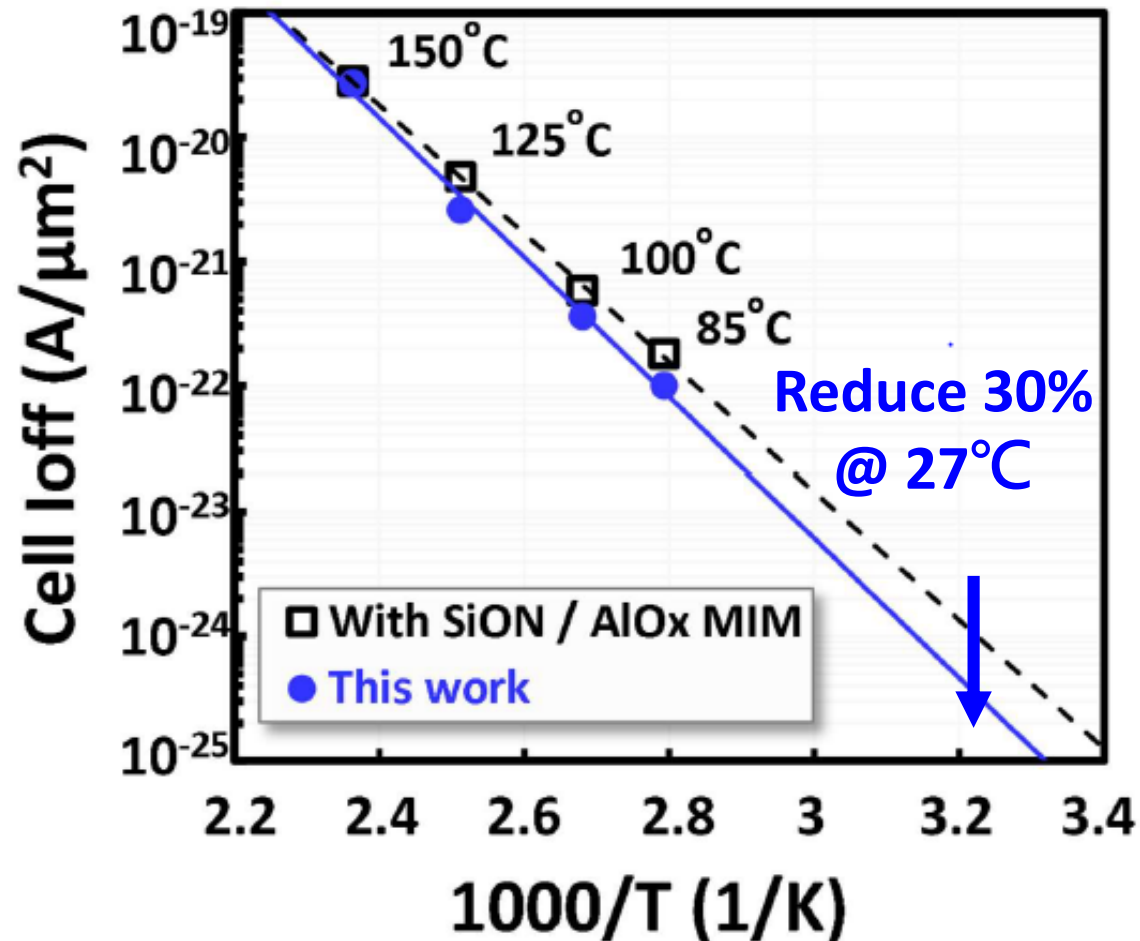


Cell area  
25%  
reduction



# Super-Lattice $\text{ZrO}_x/\text{AlO}_x/\text{ZrO}_x$ (SL-ZAZ)

- SL-ZAZ has better capacitor performance than SiON MIM.
  - **30%** Cell  $I_{\text{off}}$  reduction.



# Outline

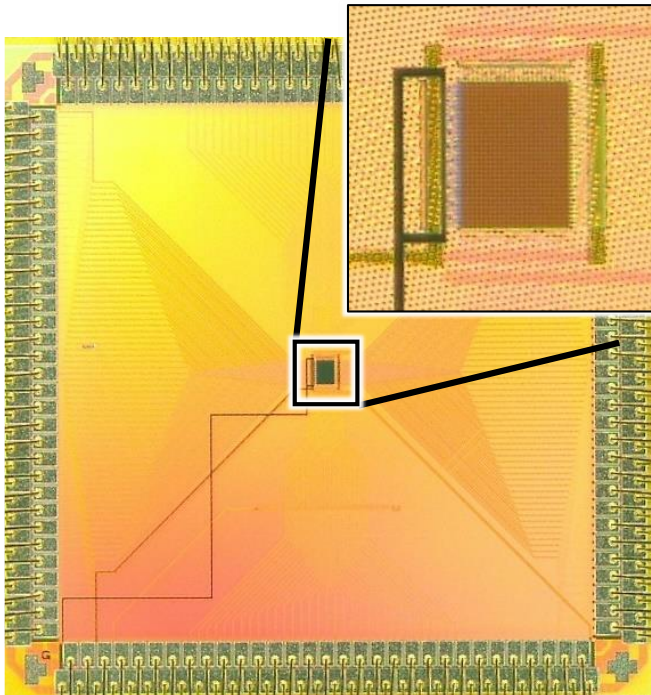
- Introduction
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# Analog in Memory Computing (AiMC) Chip

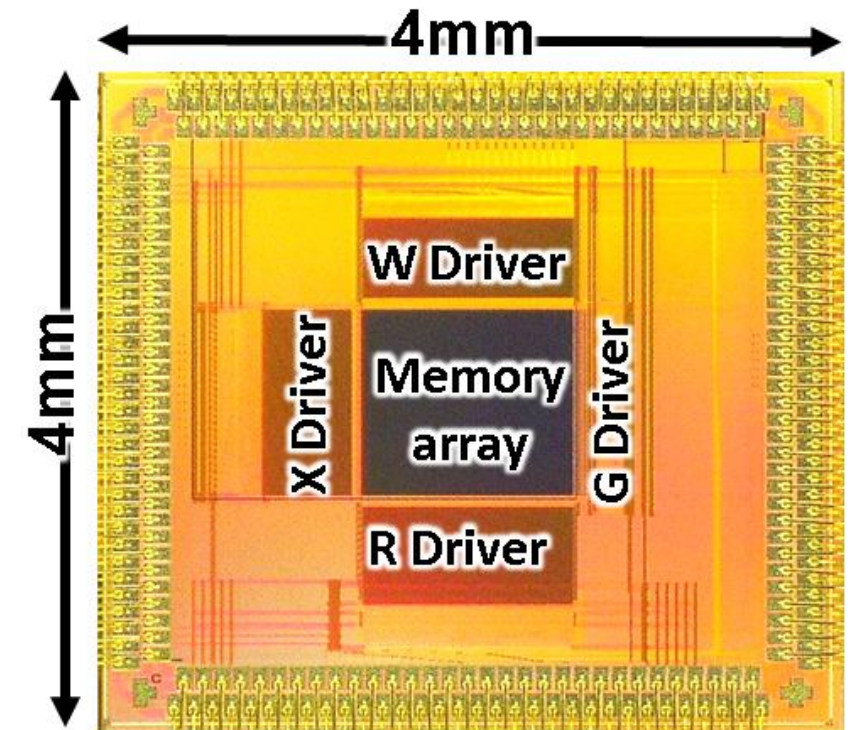
- The key chip performance and information.

IEDM 2021: 8 states  
With SiON/AlO<sub>x</sub> MIM

IEDM 2022: **64** states  
With SL-ZAZ MIM



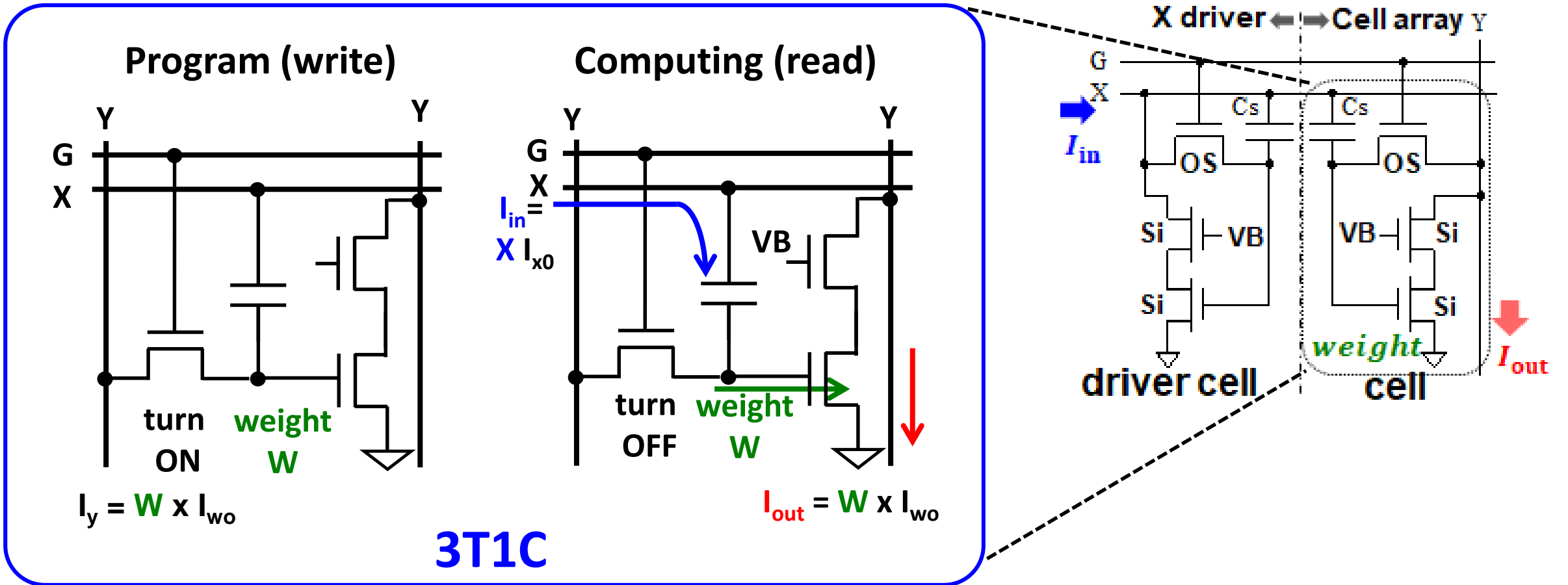
	Specifications
Die Area	4 mm x 4 mm
Precision	92.30%
Memory size	256 kb
Supply voltage	1.5 V
Frequency	Logic: 8MHz MAC: 20kHz
Performance	5.4 GOPS
Power Consumption	<b>25.6 <math>\mu</math>W</b>
Energy Efficiency	<b>210 TOPS/W</b>





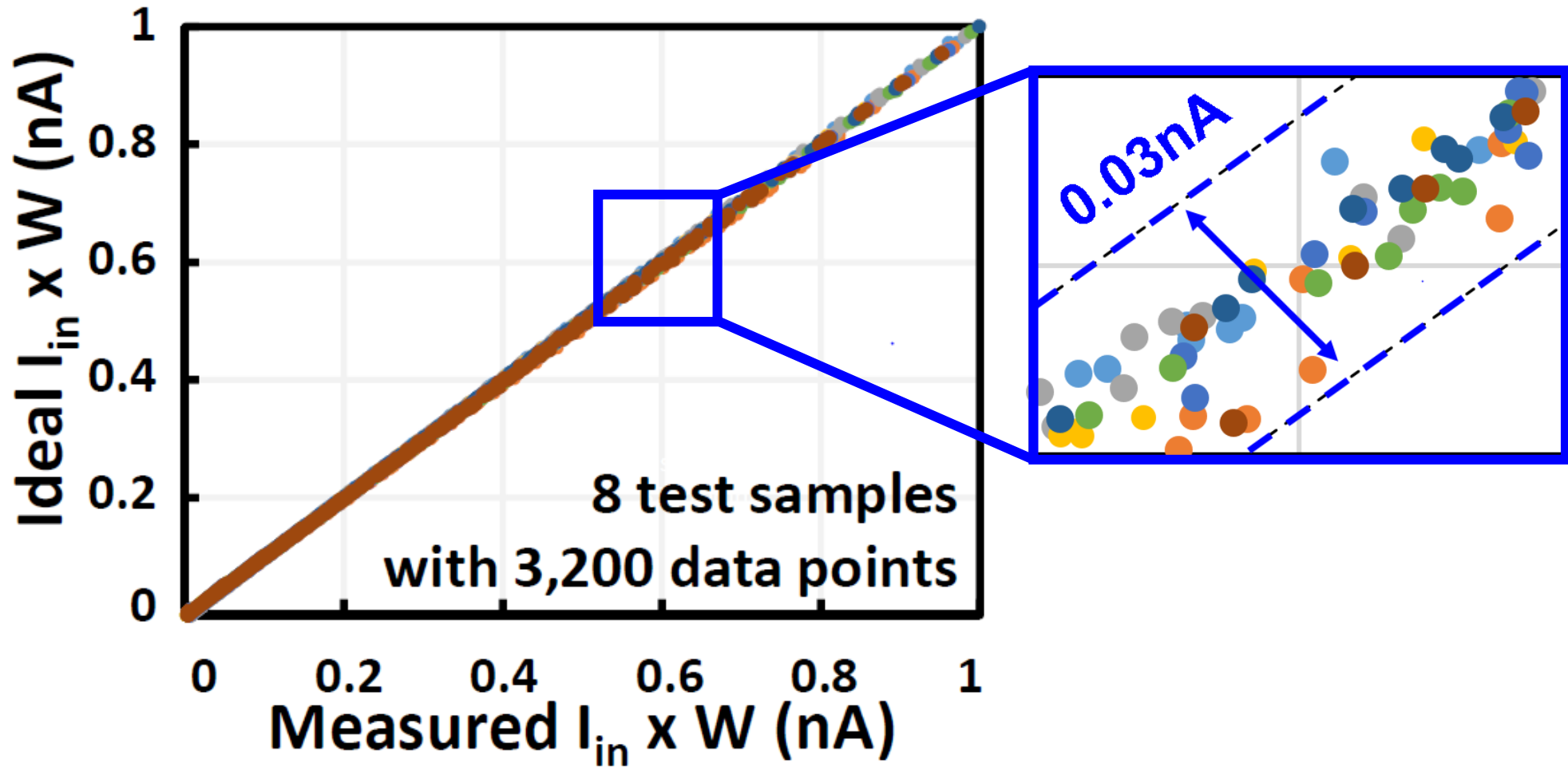
# Cell Operation

- Our memory cell operate at sub-threshold with nA read current.
- Analog multiplication:  $I_{out} = \text{Weight } (W) \times I_{in} (X)$ .



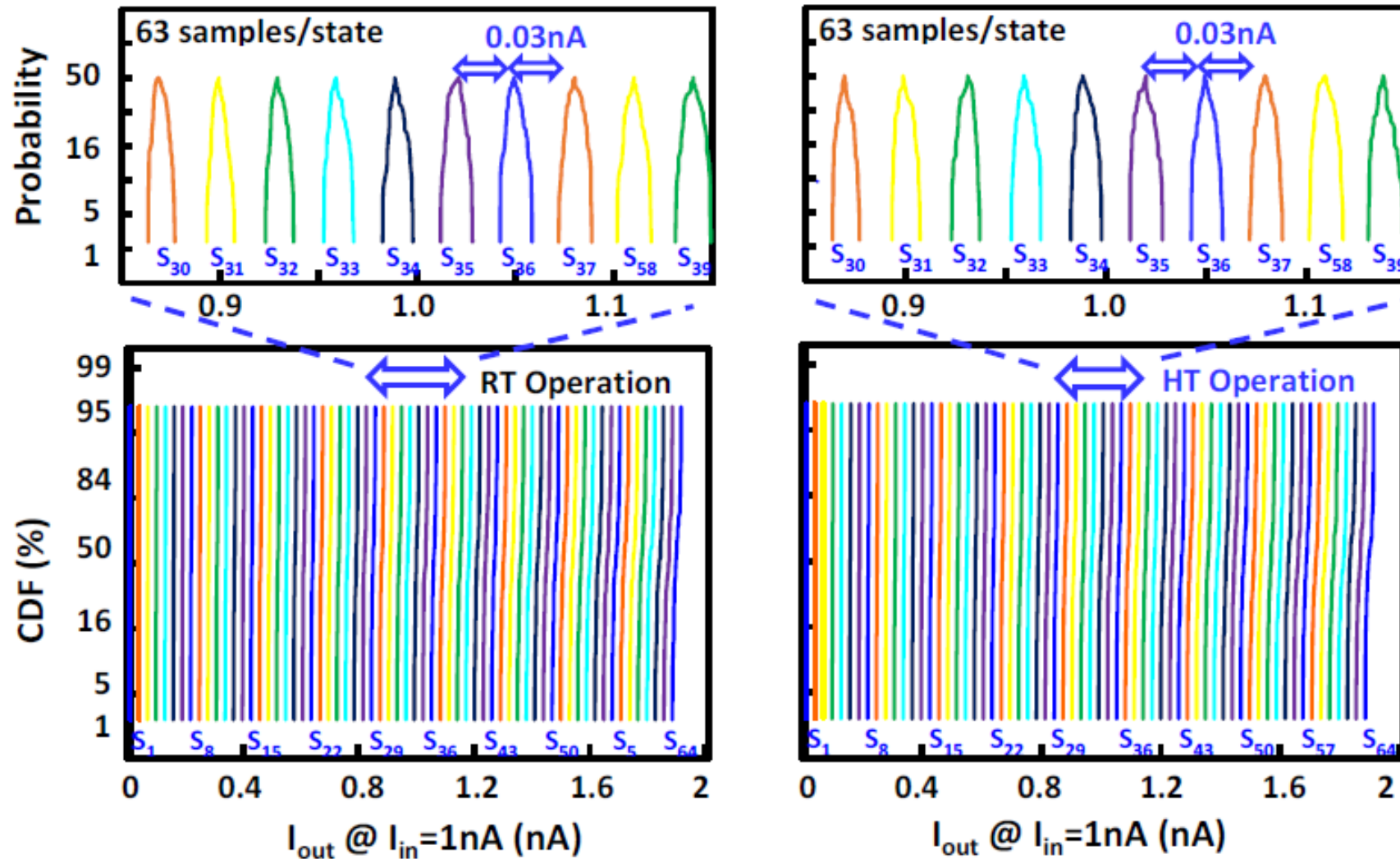
# Analog Multi-states

- **0.03 nA** variation band width (w/ 3,200 data in 8 test samples).



# Analog Multi-states

- **64** distinct weighting states at RT and HT (125°C) with highly cell-to-cell stability.



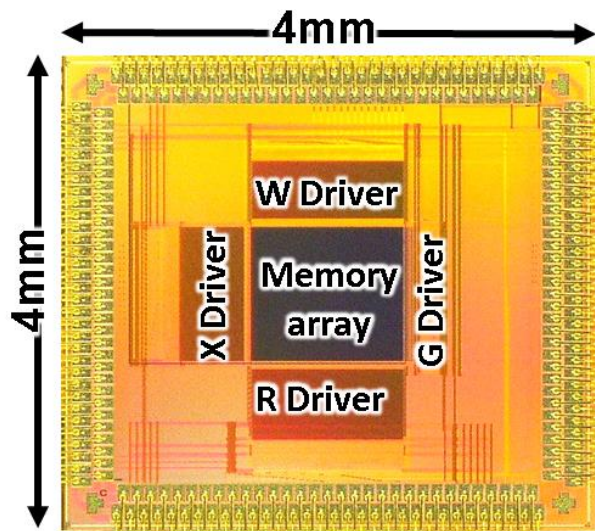
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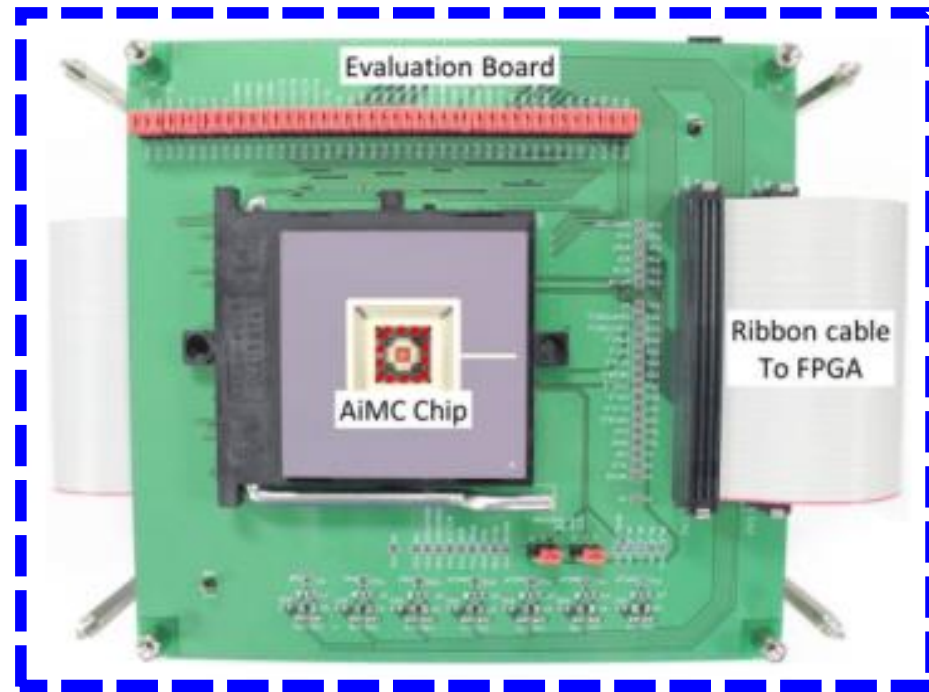


# Test environment

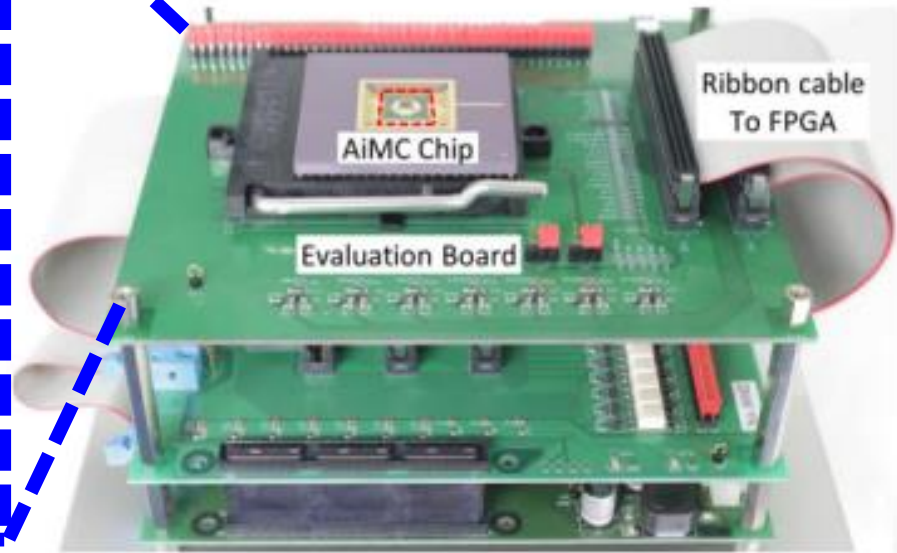
- The measurement environment of AiMC.



top view

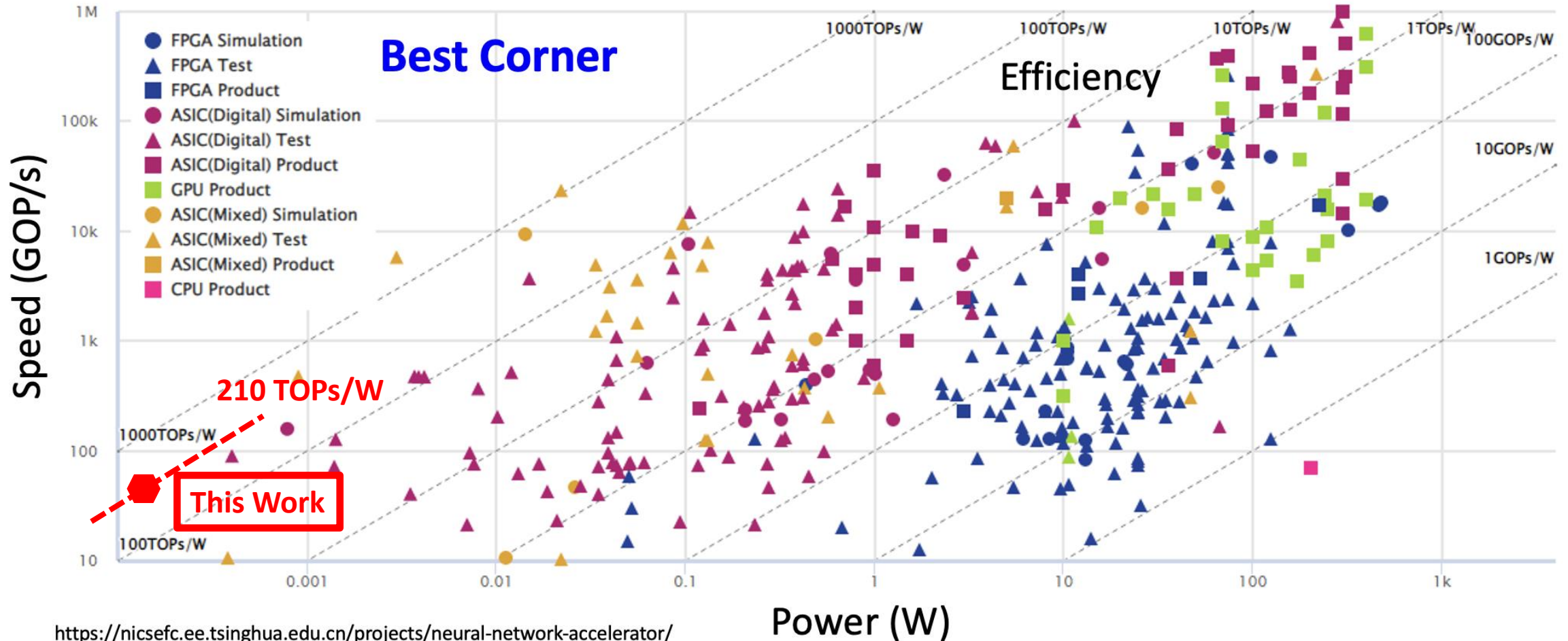


Si/CAAC-IGZO AiMC chip  
on testing board



# Performance

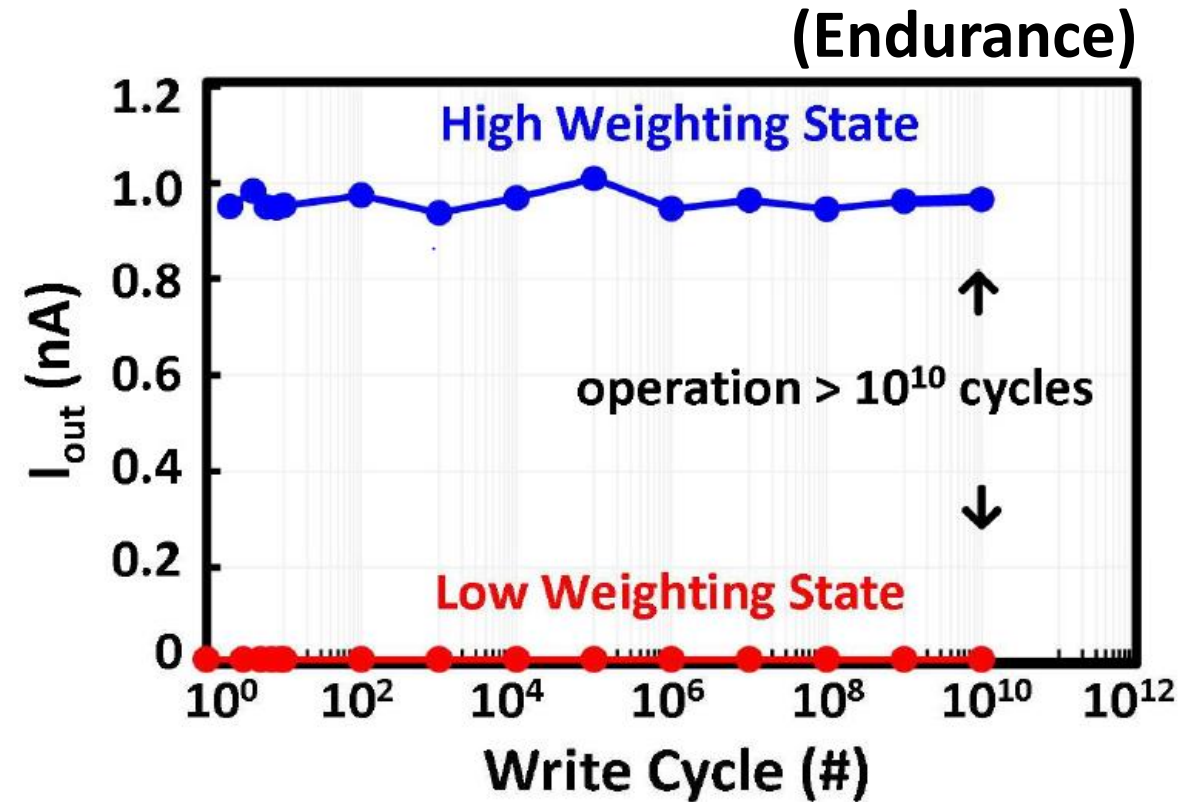
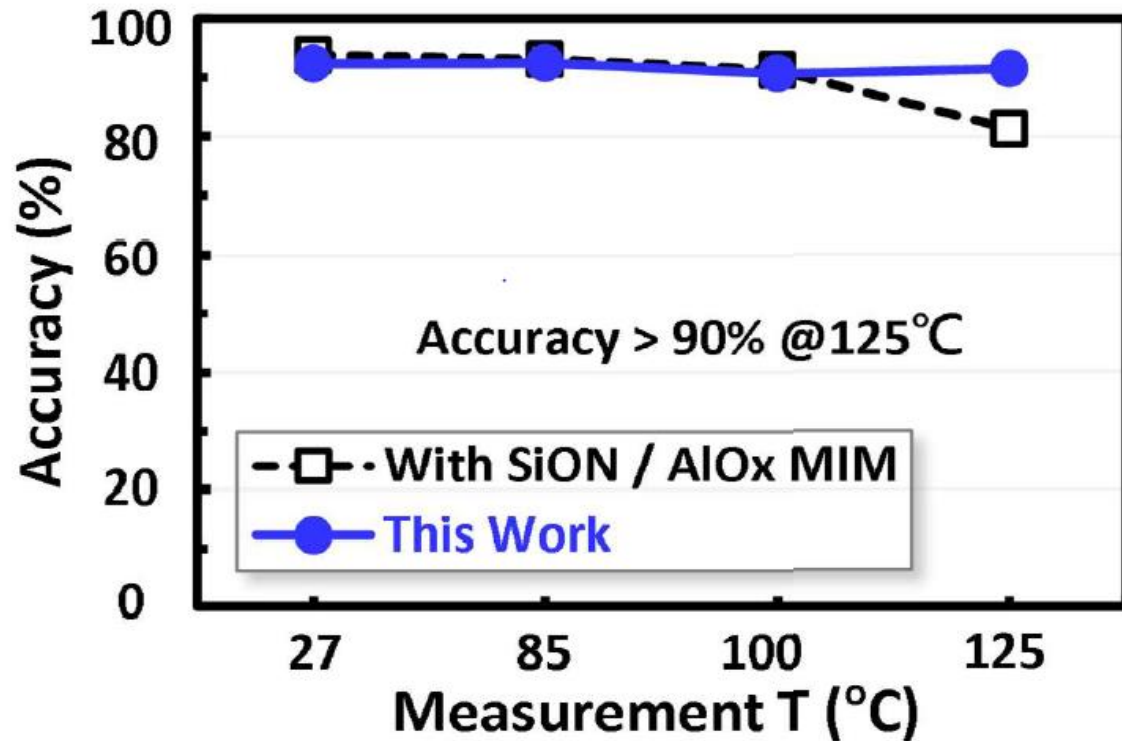
- **210 TOPS/W** and **25.6  $\mu$ W** in our AiMC.



<https://nicsefc.ee.tsinghua.edu.cn/projects/neural-network-accelerator/>

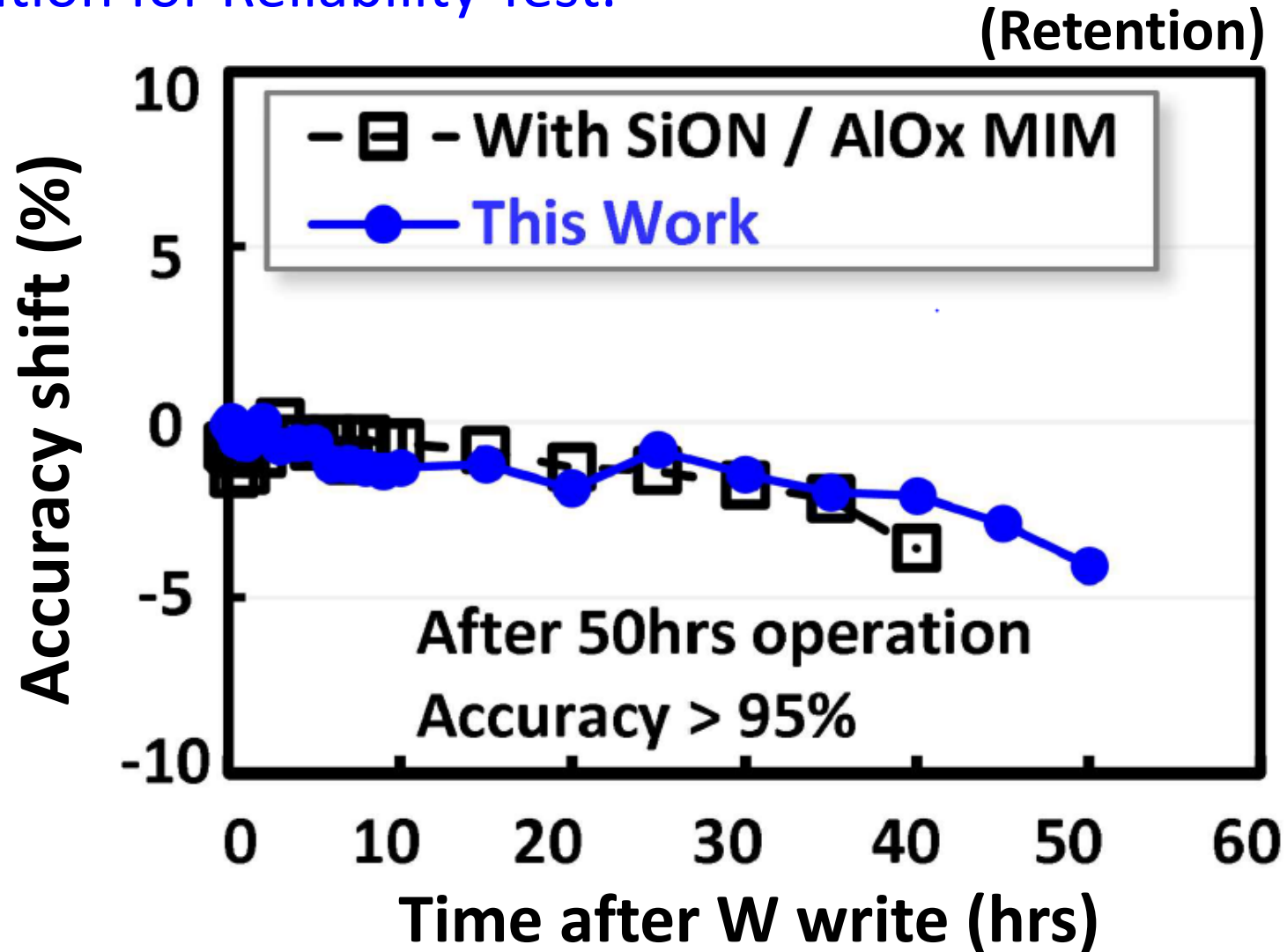
# Stability and Temperature Effect

- **>90%** accuracy (MNIST) at both RT and HT.
- Stability is also promising.



# Reliability Test

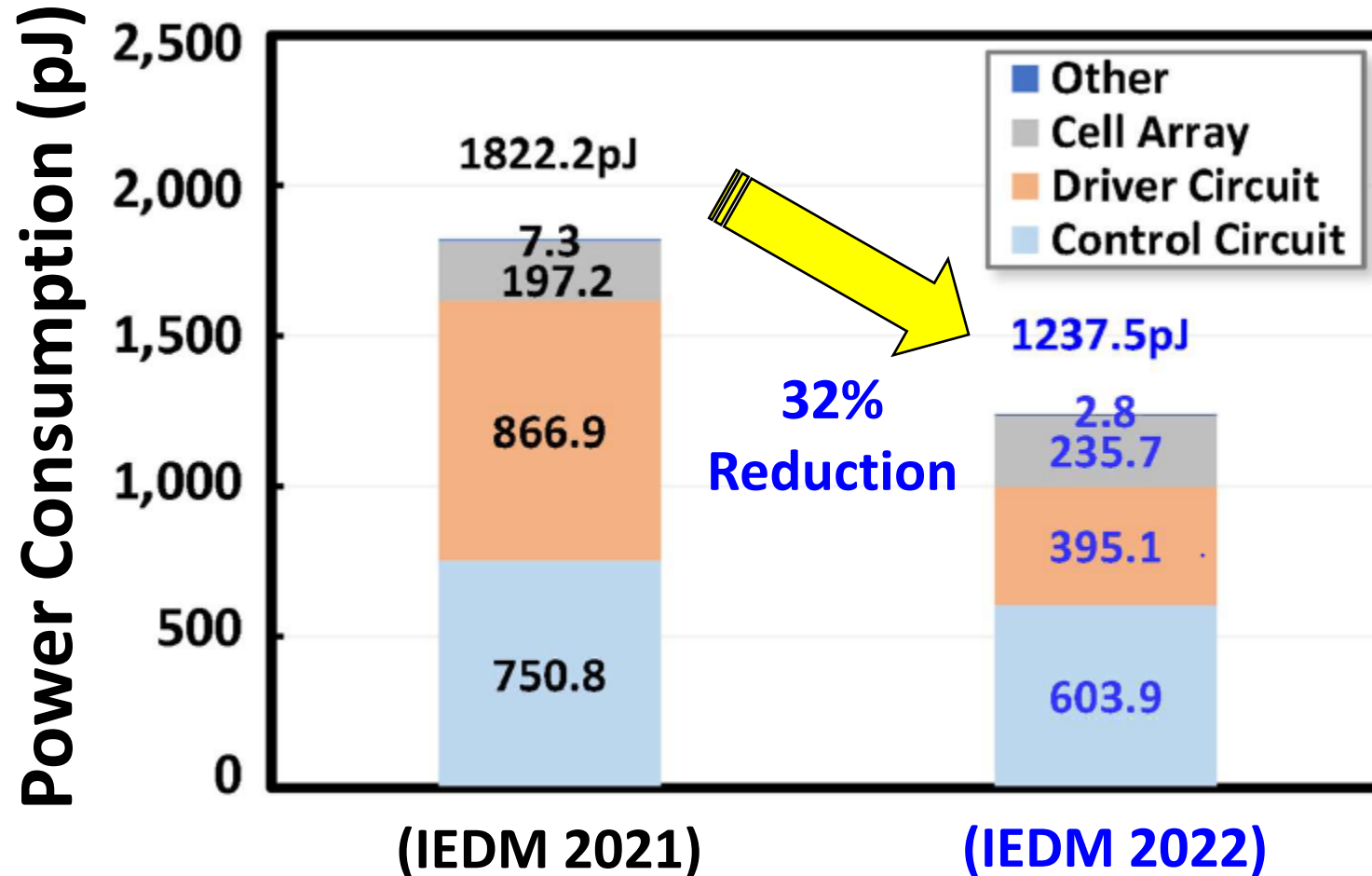
- 50 hrs operation for Reliability Test.





# Power Consumption

- This AiMC is outperformance in terms of energy efficiency/consumption.
- **32%** power consumption reduction/improvement to IEDM 2021.



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# Benchmark

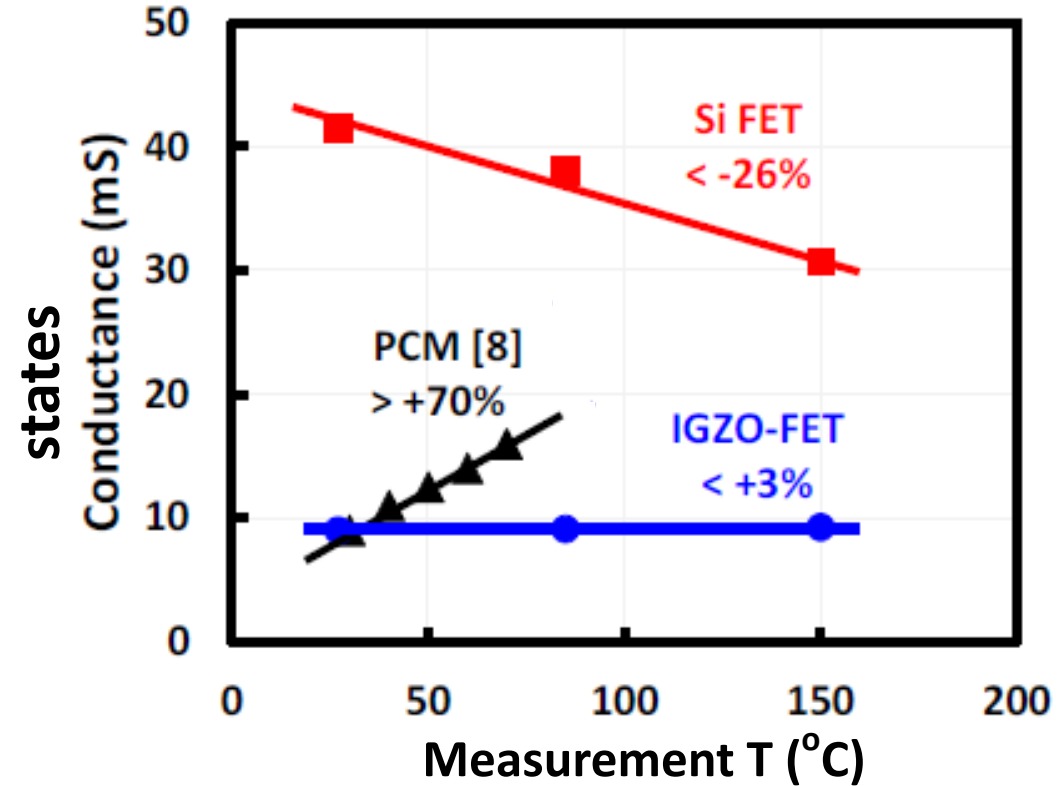
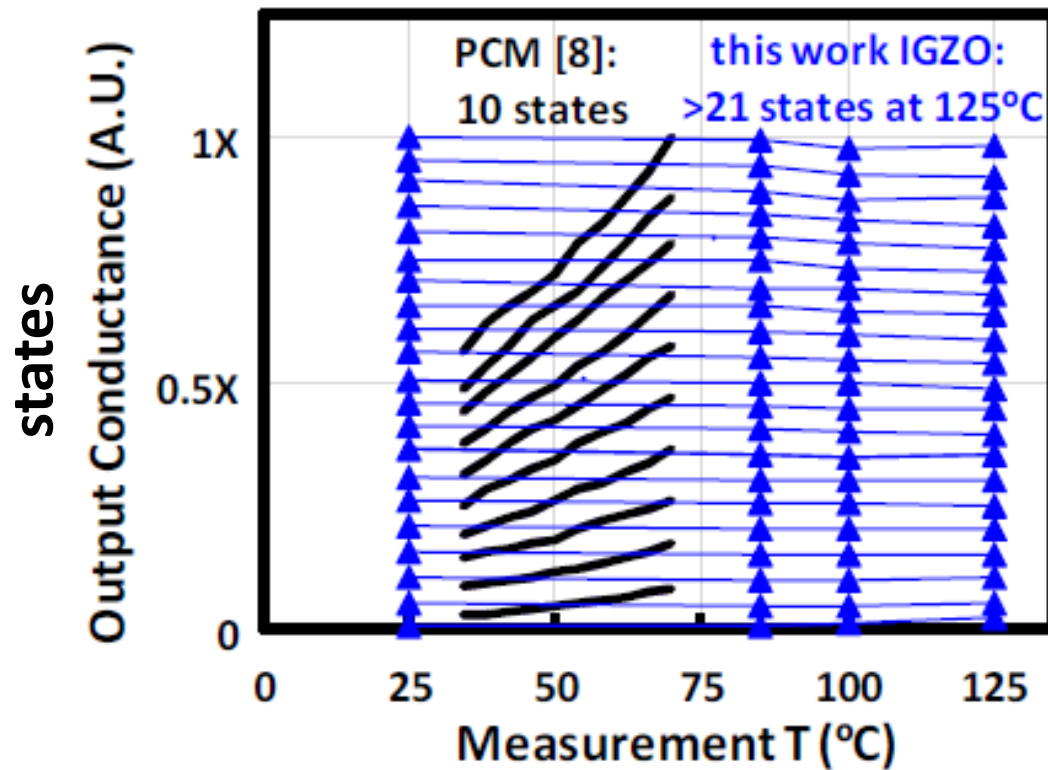
- The CAAC-IGZO/Si hybrid AiMC is outperformance in terms of energy efficiency, multiple states for analog computing.
  - **210** TOPS/W
  - **64** states

Reference	Device cell	Icell	Cell size	Weighting state	Efficiency	Accuracy
This work	CAAC-IGZO + SL-ZAZ	<1nA	256kb	Analog (>64 states)	210 TOPS/W	92.3% <sup>*1</sup>
IEDM 2021 [9]	CAAC-IGZO	<1nA	256kb	Analog (8 states)	143 TOPS/W	93.2% <sup>*1</sup>
VLSI 2021 [4]	PCM	<8mA	65.5kb	Analog	10.5 TOPS/W	85.6% <sup>*2</sup>
ISSCC 2020 [1]	RRAM	<4mA	158.8kb	Analog	78.4 TOPS/W	94.4% <sup>*1</sup>
Nature 2022 [6]	STT-MRAM	N.A.	64 x 64	Digital (1b x 1b)	405 TOPS/W	93.2% <sup>*1</sup>
IEDM 2021 [2]	HZO Capacitive	N.A.	16kb	1 bit	105TOPS/W (sim.)	N.A.
VLSI 2021 [5]	FE-FinFET	N.A.	2 x 2	3 bits	N.A.	97.91%(sim.)

\*1 MNIST; \*2 CIFAR-10

# Benchmark

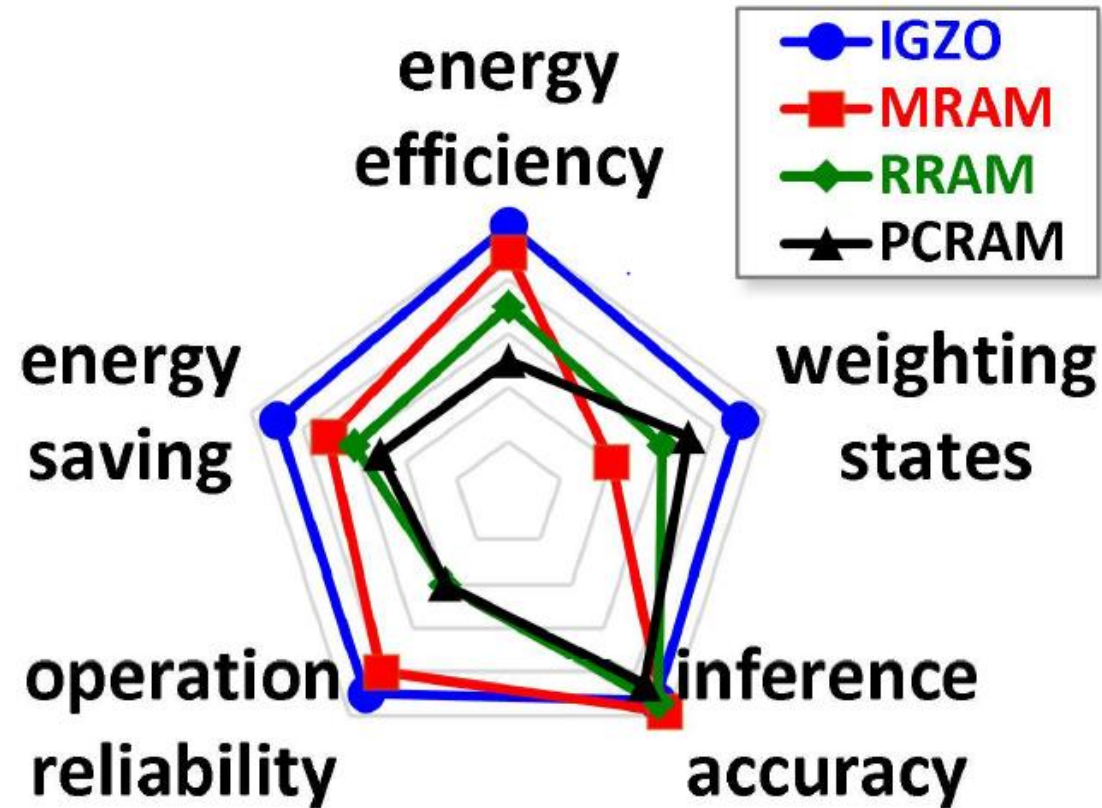
- The CAAC-IGZO/Si hybrid AiMC is outperformance in terms of energy efficiency, multiple states for analog computing.
  - **125 °C** High Temp. operation capability



[8] I. Boybat, IEDM, 2021, pp.609.

# Benchmark

- The CAAC-IGZO/Si hybrid AiMC is outperformance in terms of energy efficiency, multiple states for analog computing.



[Ref]

MRAM: S. Jung, Nature, 2022.

RRAM: H. Jia, JSSC, 2020.

PCRAM: R. Khaddam-Aljameh, VLSI, 2021.



# Conclusions

- The **monolithic CAAC-IGZO/Si technology** is fully integrated with available Si CMOS process + SL MIM.
- The CAAC-IGZO/Si hybrid CMOS ring oscillator is capable of **reducing 25% layout area**.
- The AiMC with **210 TOPS/W** energy efficiency, **> 64** weighting states, **92.3%** inference accuracy, and **125°C** operation have been demonstrated.

**Thanks**

## Contact Information:

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