

Compute-In-Memory Design For Al

Bonan YanPeking University
June 16, 2025





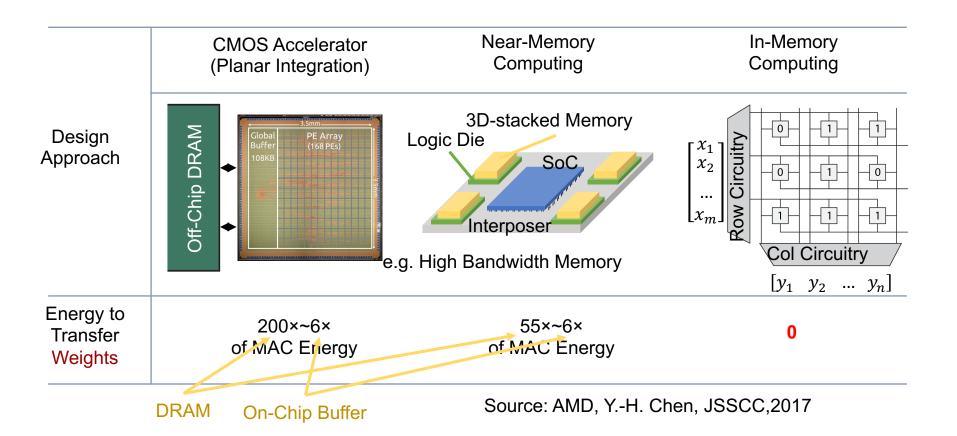




Outline

- Introduction of The Focused Paper
 - A 1.041Mb/mm² 27.38TOPS/W Signed-INT8 Dynamic-Logic-Based ADC-Less SRAM Compute-In-Memory Macro in 28nm with Reconfigurable Bitwise Operation for AI and Embedded Applications [ISSCC'2022]
- Our Subsequent Related Works
 - SRAM CIM [TCAS-I'2024, HPCA'2025]
 - RRAM CIM [Nature Electronics'2024]
 - Near-Memory Accelerator for Reinforcement Learning [DATE'2025]

Motivation

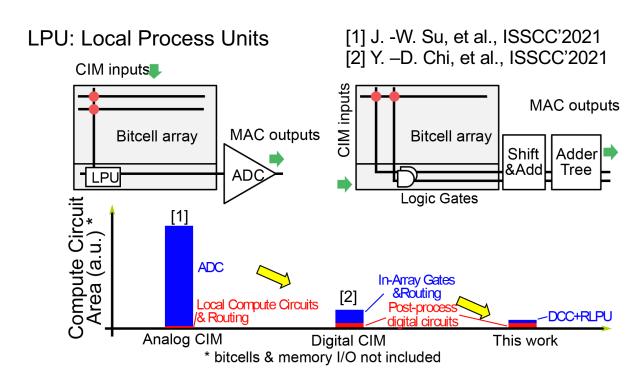


Challenges

Challenge 1: Large Compute Circuit Area

Challenge 2: Limited CIM Function

Challenge 3: CIM to DNN Deploy



Need Smaller Compute Circuits & CIM Architecture

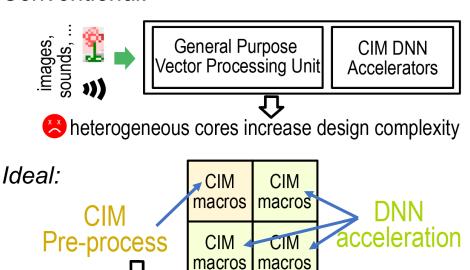
Challenges

Challenge 1: Large Compute Circuit Area

Challenge 2: Limited CIM Function

Challenge 3: CIM to DNN Deploy

Conventional:



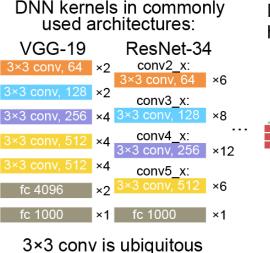
Need reconfigurable algorithmic/logic e.g. XOR, OR, IMPLY, etc.

Challenges

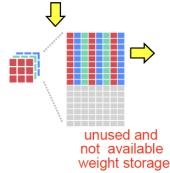
Challenge 1: Large Compute Circuit Area

Challenge 2: Limited CIM Function

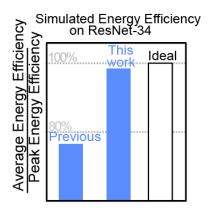
Challenge 3: CIM to DNN Deploy



Direct mapping has low utilization



low weight spatial utilization rate cause low average energy efficiency

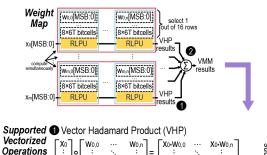


Key Contributions

Challenge 1: Large compute circuit area



ADC-Less Vector-Hadamard-Product (VHP) Architecture



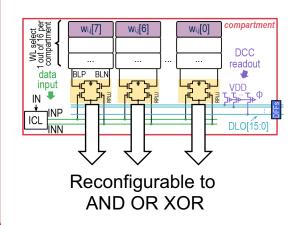
 $\begin{bmatrix} W_{0,0} & \cdots & W_{0,n} \\ \vdots & \ddots & \vdots \\ W_{m,0} & \cdots & W_{m,n} \end{bmatrix} = \begin{bmatrix} \sum_i X_i \cdot W_{i,0} & \cdots & \sum_i X_i \cdot W_{i,m} \end{bmatrix}$

2 Vector-Matrix Multiply (VMM)

Challenge 2: Limited CIM function



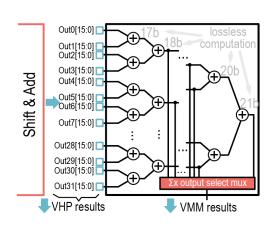
Reconfigurable Local Process Units (RLPU) +Dynamic Logic Compute Circuits (DCC)



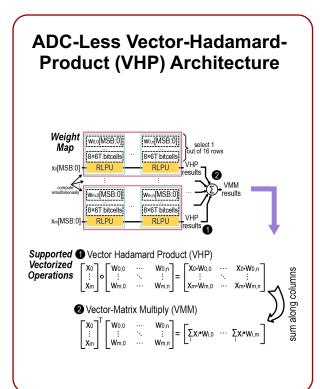
Challenge 3: CIM to DNN deploy

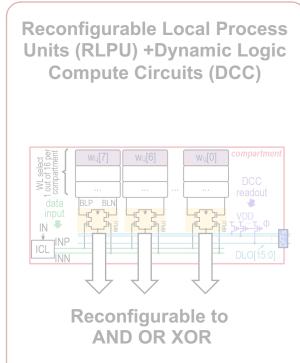


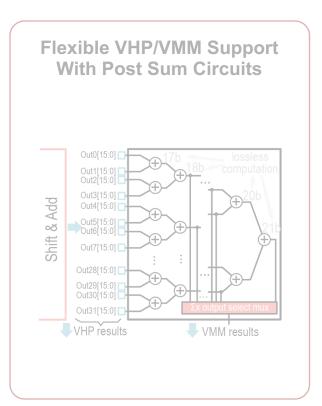
Flexible VHP/VMM Support With Post Sum Circuits



Key Contributions

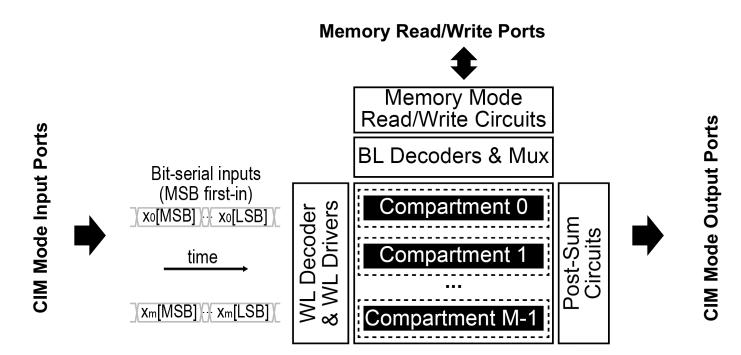






Compartment-Based Macro Organization

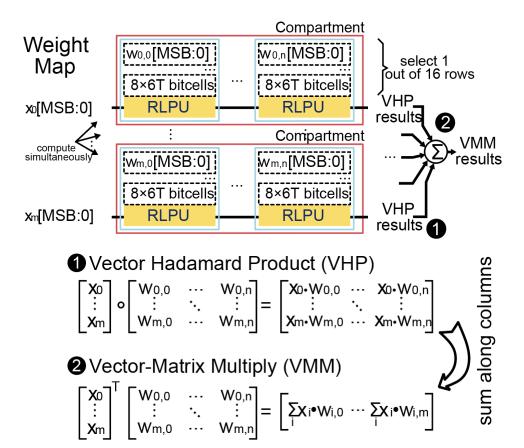
Separate ports to support Vector Hadamard Product (VHP) operations:



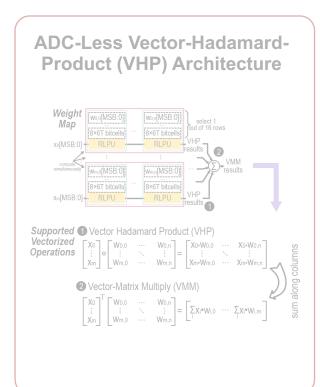
Macro VHP Architecture

Compartmentbased vector element selection

Effective vector-matrix multiplication (VMM)

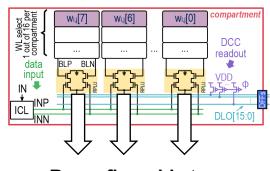


Key Contributions



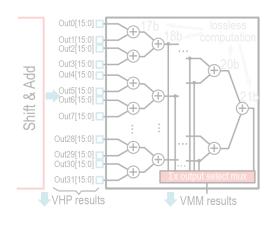


Reconfigurable Local Process Units (RLPU) +Dynamic Logic Compute Circuits (DCC)



Reconfigurable to AND OR XOR

Flexible VHP/VMM Support With Post Sum Circuits



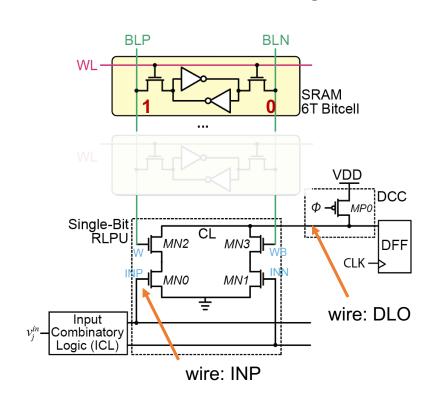
Principle of RLPU+DCC

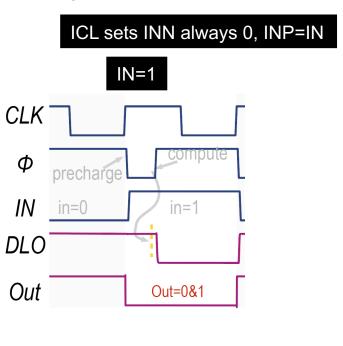
Inside a compartment BLP BLN WL select 1 out of 16 per compartment compartment **W**i,j[0] Wi,j[7] Wi,j[6] Select SRAM one 6T Bitcell DCC column readout **VHP** VDD data Results BLP BLN input Single-Bit RLPU √MN2 DCC INP **ICL** DLO[15:0] Input Combinatory Logic (ICL) NNI data output Reconfigure through ICL RLPU: Reconfigurable Local Process Units Available bitwise logic options: DCC: Dynamic logic Compute Circuits

AND, OR, XOR

Principle of RLPU+DCC

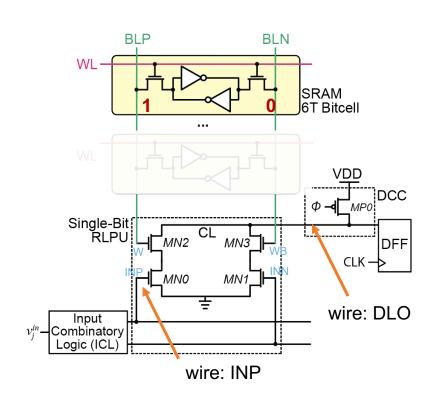
Take RLPU configured to AND as an example

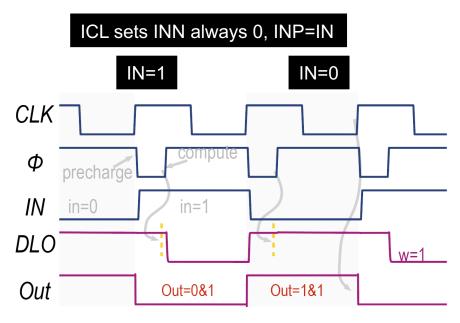




Principle of RLPU+DCC

Take RLPU configured to AND as an example





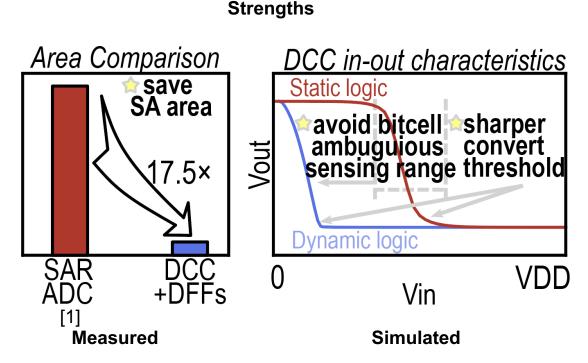
RLPU Reconfigurability

All possible bitwise configurations

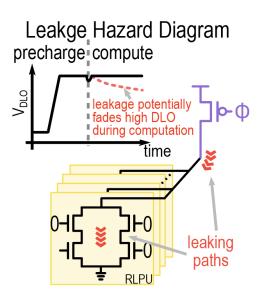
Dynamic Logic Output = $\overline{INP \cdot w + INN \cdot \overline{w}}$

RPLU Logic	Config via ICL	IN	INF	INN	w	w	Dynamic Logic Output DLO[k]	RPLU Logic Result Out[k]	Applications	Element multiplication	
		0	0	0	0	1	1	0	, the module is	-Vector matrix	
AND	INP=IN	1	1	0	0	1	1 inve	ortod 0		multiplications	
(multiply)	INN=0	0	0	0	1	0	1	erted 0		-Hadamard product	
(manupiy)		1	1	0	1	0	0	1			
	INP= <u>0</u> INN=IN	0	0	1	0	1	0	0			
OR		1	0	0	0	1	1 <u>n</u>	oț 1		CIM data mask	
		0	0	1	1	0	1 linve	erted 1		Cilvi data iliask	
		1	0	0	1	0	1	1			
	INP=IN INN=IN	0	0	1	0	1	0	0			
XOR		1	1	0	0	1	1 <u>n</u>	ot 1		Hamming distance	
		0	0	1	1	0	1 inve	erted 1		Computation	
		1	1	0	1	0	0	0		Computation	

DCC Characteristics

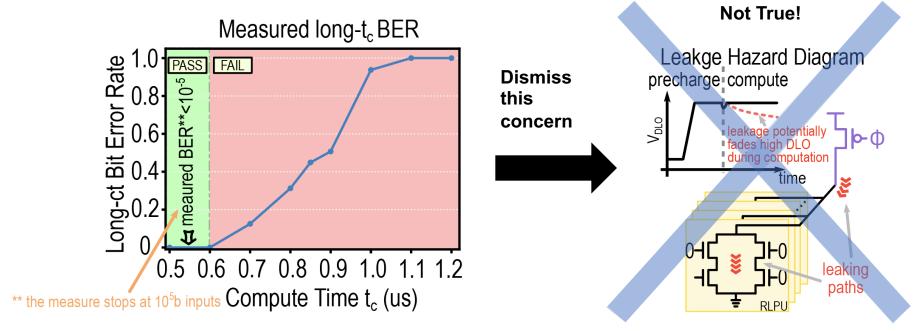


Possible Weakness??



[1] X. S., et al., ISSCC'2020

DCC Measurement

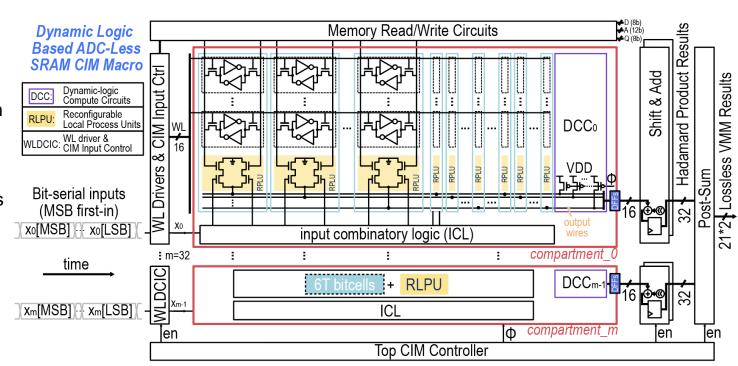


Common compute time is <10ns

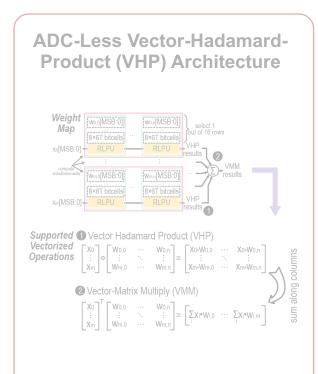
Entire Architecture

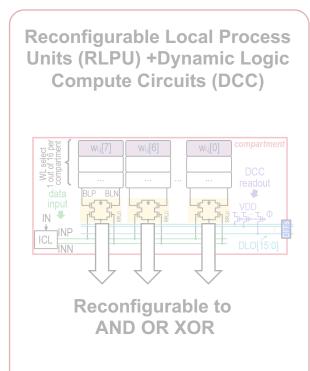
Novelty:

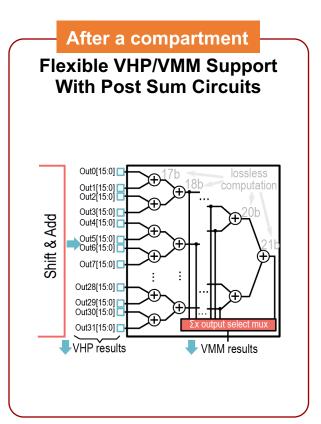
- Compartment -based organization
- · VHP architecture
- DCC+RLPU circuits



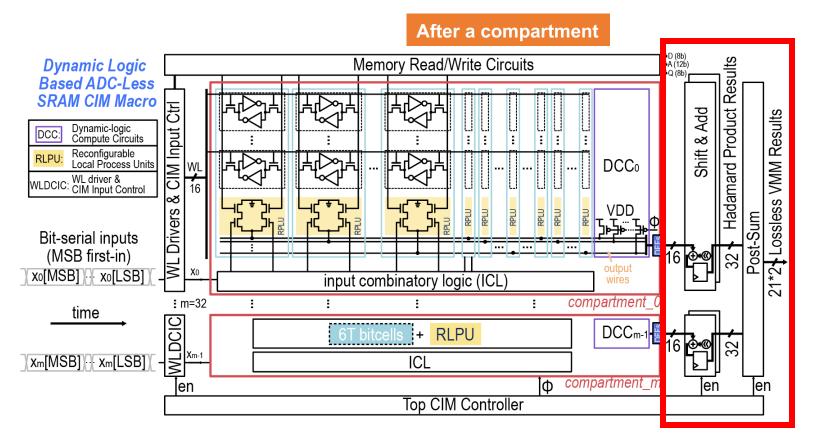
Key Contributions



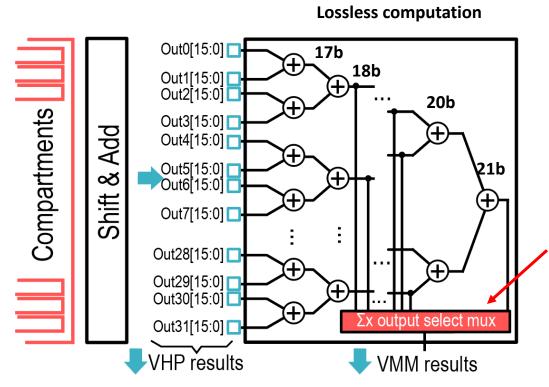




Introduction of Post-Sum Circuits



Post-Sum Circuits

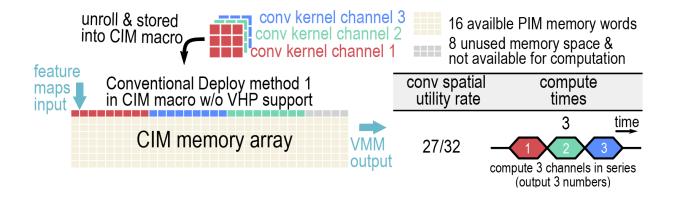


- Shift & Add: Combine Bit-Serial Inputs
- Adder Tree: Convert Hadamard Products Into VMM Results

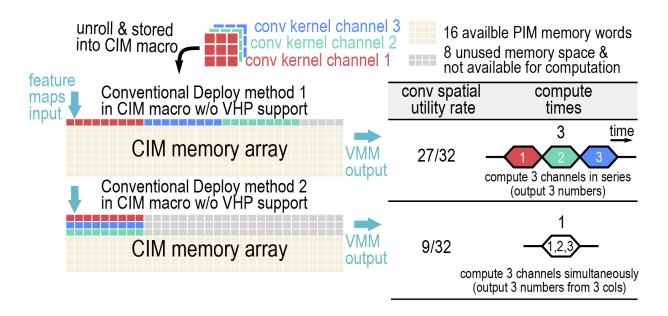
We Have A Little Trick Here: Arrange A ∑9 Here

∑k: sum of the k numbers

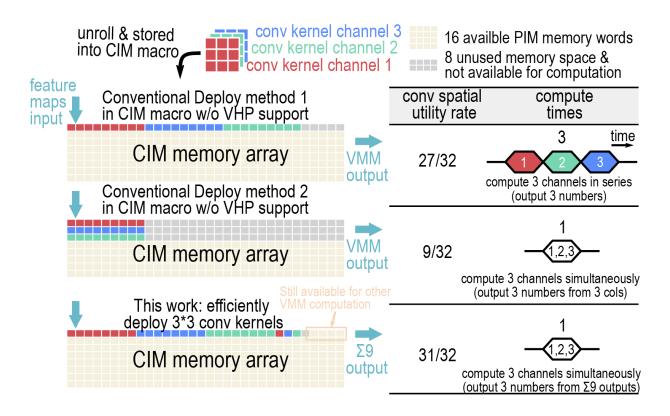
Why ∑k?



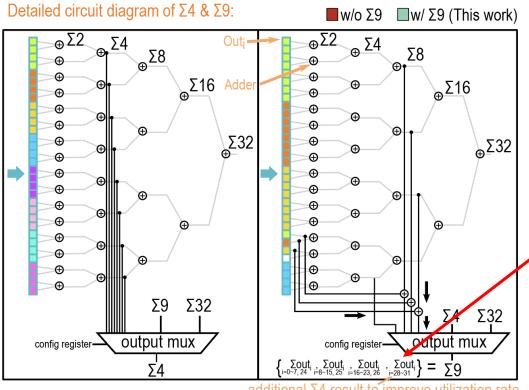
Why ∑k?



Why ∑k?



How ∑k?



■ ∑4: for 2*2 Conv Kernel

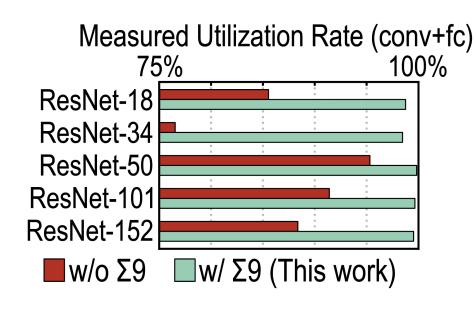
■ ∑9: for 3*3 Conv Kernel

Three groups of ∑9 and One 54 fits in a 32-element output vector

Why "32": our design has 32 compartments

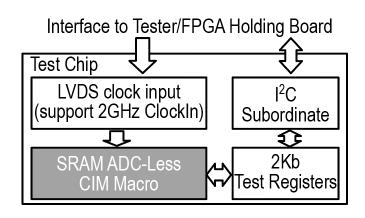
additional Σ4 result to improve utilization rate

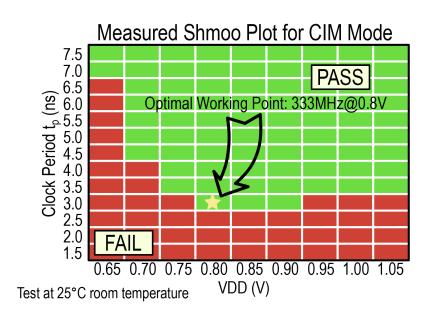
∑k Benefits



- Increase Utilization Rate
 - (Regular Shaped) CIM Macro is Naturally Good At Dense (Fully-Connected) Layer
 - ∑9 is Added Specially for Ubiquitous 3*3 Conv Kernel

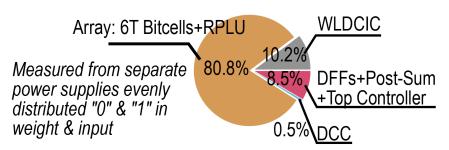
Measurement





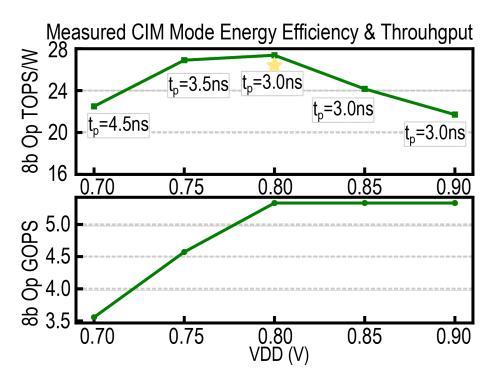
Measurement

Measured Power Breakdown



Testing Configuration:

- Average values w/ precision (input, weight)=(8b,8b)
- Benchmarked by conv & fc layers of quantized ResNet-34 & MobileNet, data reload not included



Comparison

On Form Factor

CIM Macro Type		Analo	g CIM	Digital CIM			
Work	ISSCC'18 [1]	ISSCC'20 [2]	JSSC'21 [3]	ISSCC'21 [4]	ESSCIRC'19 [5]	ISSCC'21[6]	This Work
Technology	65nm	28nm	7nm	28nm	65nm	22nm	28nm
Array Size	4Kb	64Kb	4Kb	384Kb	16Kb	64Kb	32Kb
Cell Type	S6T	6T	8T	6T	6T	6T	6T
Macro Area	N/A	0.362mm ²	0.0032mm ²	1.4mm ^{2†}	0.2272mm ²	0.202mm ²	0.030mm ²
CIM Weight Density	N/A	177Kb/mm ² @28nm	1250Kb/mm ² @7nm	234Kb/mm ² @28nm	71Kb/mm ² @65nm	317Kb/mm ² @22nm	1067Kb/mm² @28nm
CIM Weight Density (normalized to 28nm)	N/A	177Kb/mm ²	78Kb/mm ²	234Kb/mm ²	383Kb/mm ²	196Kb/mm ²	1067Kb/mm²
Power Supply	1V, 0.8V	0.7V-0.9V	1V, 0.8V	0.7-0.9V	0.6V-0.8V	0.72V	0.8V

[†] Estimated from [4]

Comparison

On Function Diversity

CIM Macro Type		Analo	g CIM	Digital CIM			
Work	ISSCC'18 [1]	ISSCC'20 [2]	JSSC'21 [3]	ISSCC'21 [4]	ESSCIRC'19 [5]	ISSCC'21[6]	This Work
Technology	65nm	28nm	7nm	28nm	65nm	22nm	28nm
Compute Circuits	CMI-VSA	LMAR-SAR- ADC	Flash ADC	Ph-ADC	CMOS Static Logic	CMOS Static Logic	Dynamic Logic Compute Circuit
Support Bitwise Operation	AND	AND	AND	AND	AND	AND	AND, XOR, OR
Fundamental Vector Operation	VMM	VMM	VMM	VMM	VMM	VMM	Hadamard Product, VMM

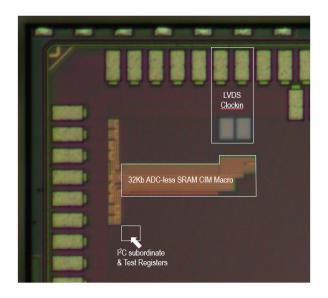
Comparison

On Computation & Efficiency

CIM Macro Type		Analo	g CIM	Digital CIM			
Work	ISSCC'18 [1]	ISSCC'20 [2]	JSSC'21 [3]	ISSCC'21 [4]	ESSCIRC'19 [5]	ISSCC'21[6]	This Work
Input Bits	1	4b/8b	4b	4b/8b	1b-16b	1b-8b	1b-8b
Weight Bits	1	4b/8b	4b	4b/8b	4b/8b/12b/16b	4b/8b/12b/16b	1b/4b/8b
Output Bits	1	12b (4b/4b) 20b (8b/8b)	4b	12b (4b/4b) 20b (8b/8b)	8b-23b	16b (4b/4b) 24b (8b/8b)	VMM: 21b VHP: 8b (8b/8b)
Cycle Time	2.3ns	4.1ns (4b/4b) 8.4ns (8b/8b)	4.5ns (1.0V) 5.5ns (0.8V)	4ns (4b/4b) 7.2ns (8b/8b)	N/A	10ns (4b/4b) 18ns (8b/8b)	3ns/input bit
Energy Efficiency** (TOPS/W)	55.8 (1b/1b)	58.1(4b/4b) 14.1(8b/8b)	351 (1b/1b)	77.3(4b/4b) 18.9(8b/8b)	117.3 (1b/1b)	24.7 (8b/8b)	27.38 (8b/8b)
CIM Weight Density (normalized to 28nm)	N/A	177Kb/mm ²	78Kb/mm²	234Kb/mm ²	383Kb/mm ²	196Kb/mm²	1067Kb/mm²
SWaP (FoM)*** (TOPS/W·Mb/mm²)	N/A	161	26.7	283	8.13	303	1826

^{**} Average energy efficiency, no sparsity employed ***. The figure of merit (FoM) SWaP (space, wattage and performance)=(Weight Density*Performance)/Power=Weight Density*Energy Efficiency

Summary For This Digital SRAM CIM Design



- VHP Organization Architecture
 - Increase Flexibility
- RLPU+DCC Design
 - Simplified ADC-Less CIM Operation
- ∑k Technique for CIM Macro Post-Sum Circuits
 - Increase Conv Kernel Utilization Rate

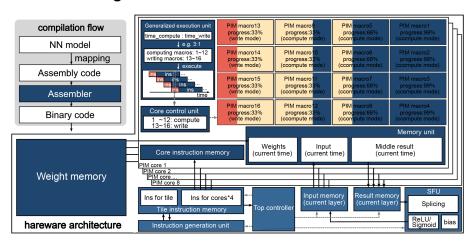
Chip Demo Video:

https://www.bilibili.com/video/BV15b4y1H7gP

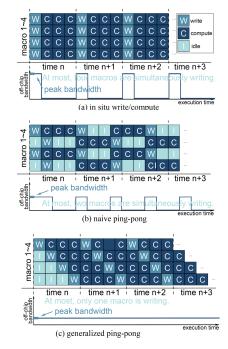
Subsequent Works: PIM SoC Open-Source Project

PIM-SoC Design: (graduate course project @ PKU)

- PIM Macros (Verilog Behaviors)
- Programmable Interface



Available at: https://github.com/rw999creator/gpp-pim https://arxiv.org/abs/2411.13054 Simulate Complex Dataflows w/ instructions



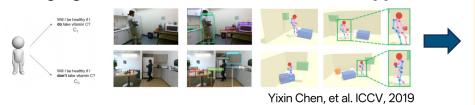
6/24/25

SRAM CIM For Markov Chain Monte Carlo Sampler

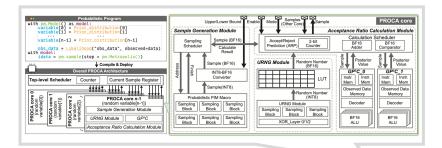
Algorithm

-ramework

Emerging Emboddied Al "Think&Estimate" Applications



Our Solution: PROCA Architecture



- Markov Chain Monte Carlo (MCMC) Acceleration
- Speedup 172~4871× vs. Intel Xeon Gold CPU
- Speedup 42~1058× versus NVIDIA A100 GPU

Deep Learning (DL)

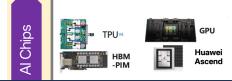
Densenet, Efficientnet, Resnet, LlaMA, LlaMA2, Mixtral, GPT3, GPT4, MobileNet, ShuffleNet, RegNet, SqueezeNet, ViT, Transformer, MNASNet, GoogleNet,...

Probabilistic Al

Bayesian Regression, VAE, Hidden Markov Models, Normalizing Flows, Deep Markov Model, Causal Effect VAE, Gaussian Mixture Model, Gibbs Sampling, Metropolis-Hasting, Probabilistic Circuits, ...







Lack Chip Infrastructure!

Yihan Fu, et al., TCAS-l'2025 Yihan Fu, et al., HPCA'2025

RRAM CIM Based Universal Ising Machine

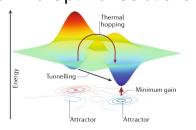
NP-Hard Combinatorial **Optimizations Problems**

Deploy to Ising Graphs

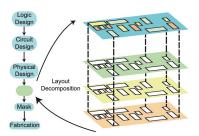


$$H_P = \sum_{i,j=1}^N J_{ij} \sigma_i \sigma_j + \sum_{i=1}^N h_i \sigma_i$$

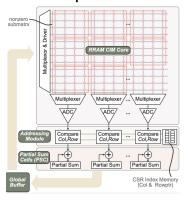
Simulated Annealing Methods to Find Optimal Solutions

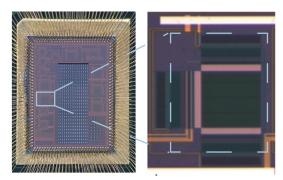


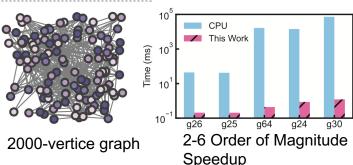
Graph Coloring in EDA (layout decomposition)



Develop RRAM-PIM Chip for Universal Ising Machine

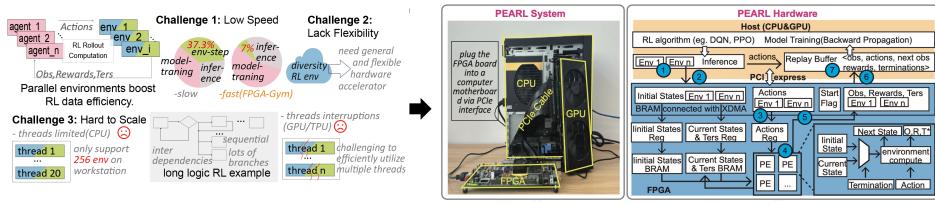






Near-Memory Computing Accelerator for RL

- PEARL: FPGA-based Reinforcement Learning Environment Accelerator
- https://github.com/Selinaee/FPGA Gym



Challenges: GPU can accelerator policy computing, but **NOT** environment update

Introduce near-memory pipelining to accelerate RL rollout,

More Ways to Know Us: bonany.cc

- 1. [HPCA'25] Fu, Yihan, et al. "PROCA: Programmable Probabilistic Processing Unit Architecture with Accept/Reject Prediction & Multicore Pipelining for Causal Inference".
- 2. [DATE'25] Li, Jiayi, et al. "PEARL: FPGA-Based Reinforcement Learning Acceleration with Pipelined Parallel Environments".
- 3. [Nature Communications'25] Yue, Wenshuo, et al., "Physical Unclonable In-Memory Computing for Simultaneous Protecting Private Data and Deep Learning Models".
- 4. [Nature Electronics'24] Yue, Wenshuo, et al., "A Scalable Universal Ising Machine Based on Interaction-Centric Storage and Compute-In-Memory." 7, 904–913 (2024).
- 5. [IEEE TCAS-I'24] Fu, Yihan, etc. "Probabilistic Compute-in-Memory Design for Efficient Markov Chain Monte Carlo Sampling." vol. 71, no. 2, pp. 703-716, 2024.
- 6. [ISSCC'22] Yan, Bonan*, et al., 2022. "A 1.041-Mb/mm² 27.38-TOPS/W Signed-INT8 Dynamic-Logic-Based ADC-Less SRAM Compute-in-Memory Macro in 28nm with Reconfigurable Bitwise Operation for AI and **Embedded Applications.**"

- 1 SRAM-PIM Chip Function Demo
- (2) FPGA-Gym for RL Framework





Acknowledgement

















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