

SparseP

Towards Efficient Sparse Matrix Vector Multiplication
on Real Processing-In-Memory Architectures

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Our Work

Efficient Algorithmic Designs

The first open-source Sparse Matrix Vector Multiplication (SpMV) software package, **SparseP**, for real Processing-In-Memory (PIM) systems

SparseP is Open-Source

SparseP: <https://github.com/CMU-SAFARI/SparseP>

Extensive Characterization

The first comprehensive analysis of SpMV on the first real commercial PIM architecture

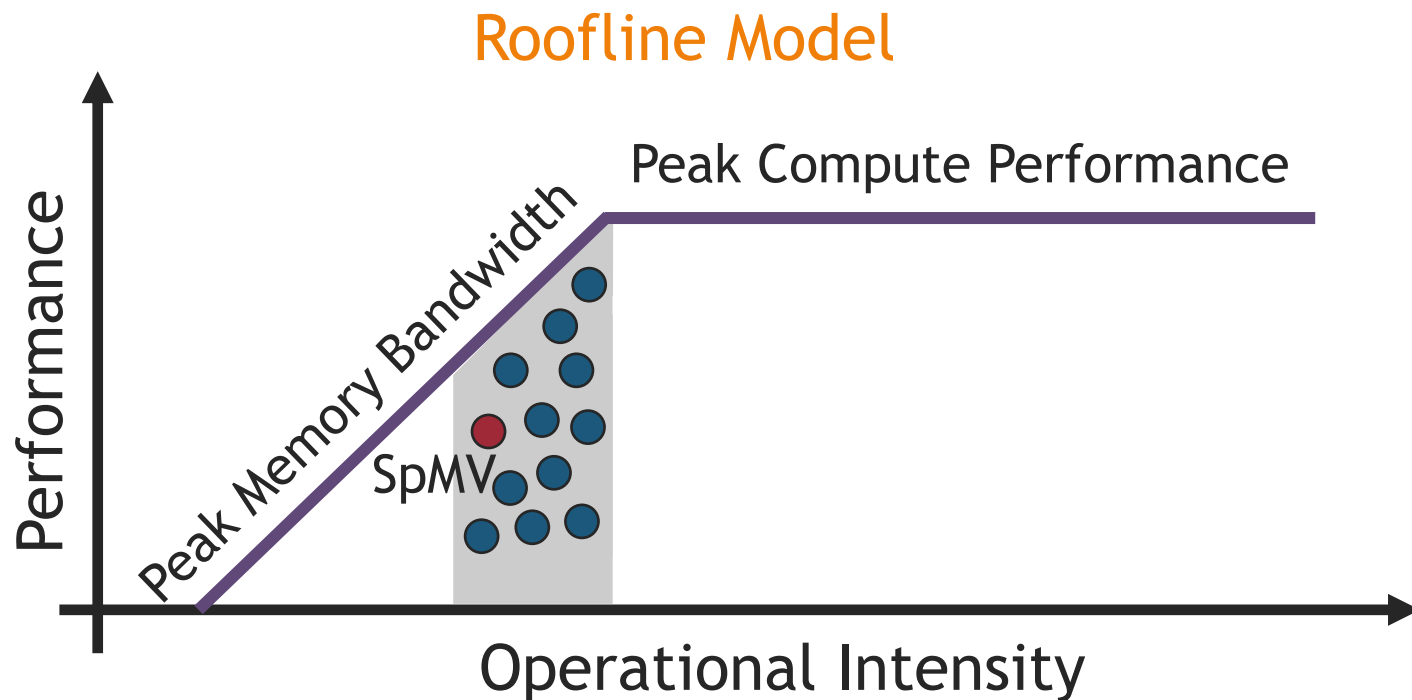
Recommendations for Architects and Programmers

Full Paper: <https://arxiv.org/pdf/2201.05072.pdf>

Sparse Matrix Vector Multiplication

Sparse Matrix Vector Multiplication (SpMV):

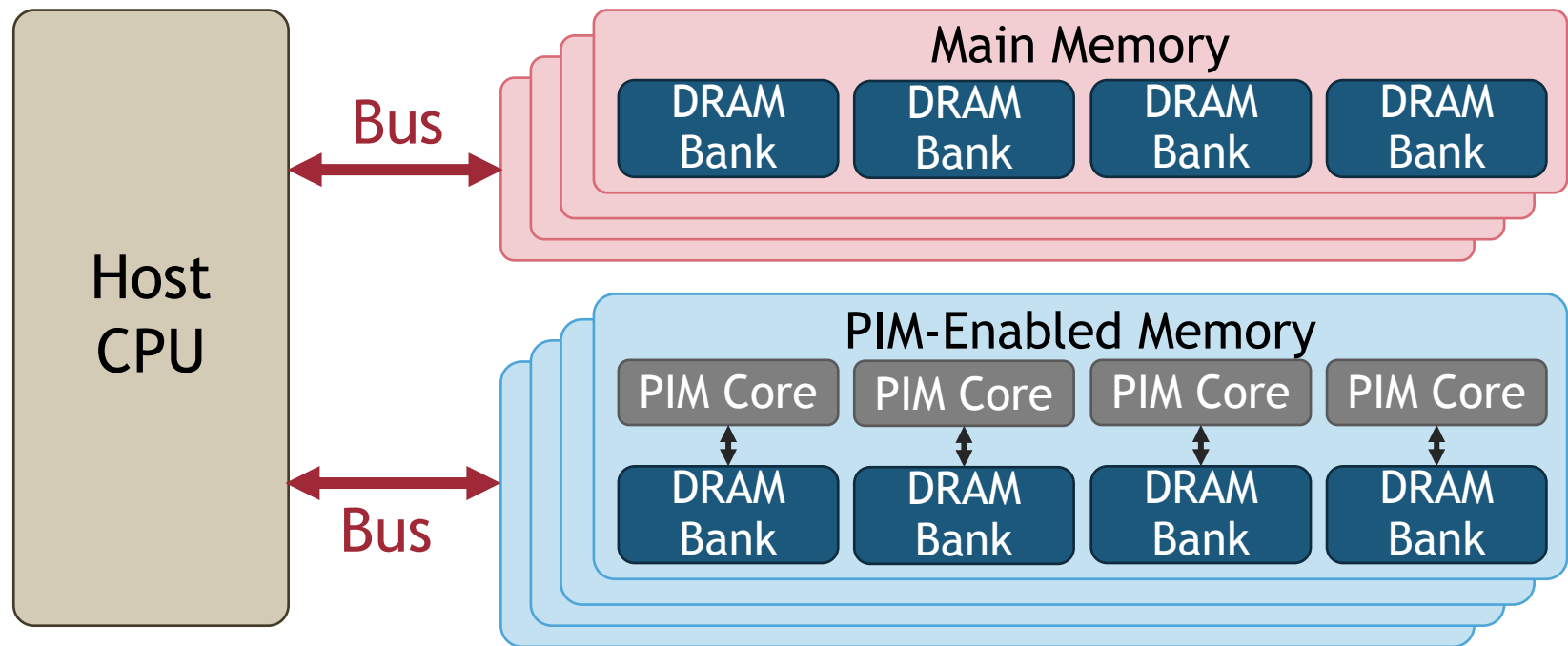
- Widely-used kernel in graph processing, machine learning, scientific computing ...
- A highly memory-bound kernel



Real Processing-In-Memory Systems

Real **Near-Bank** Processing-In-Memory (**PIM**) Systems:

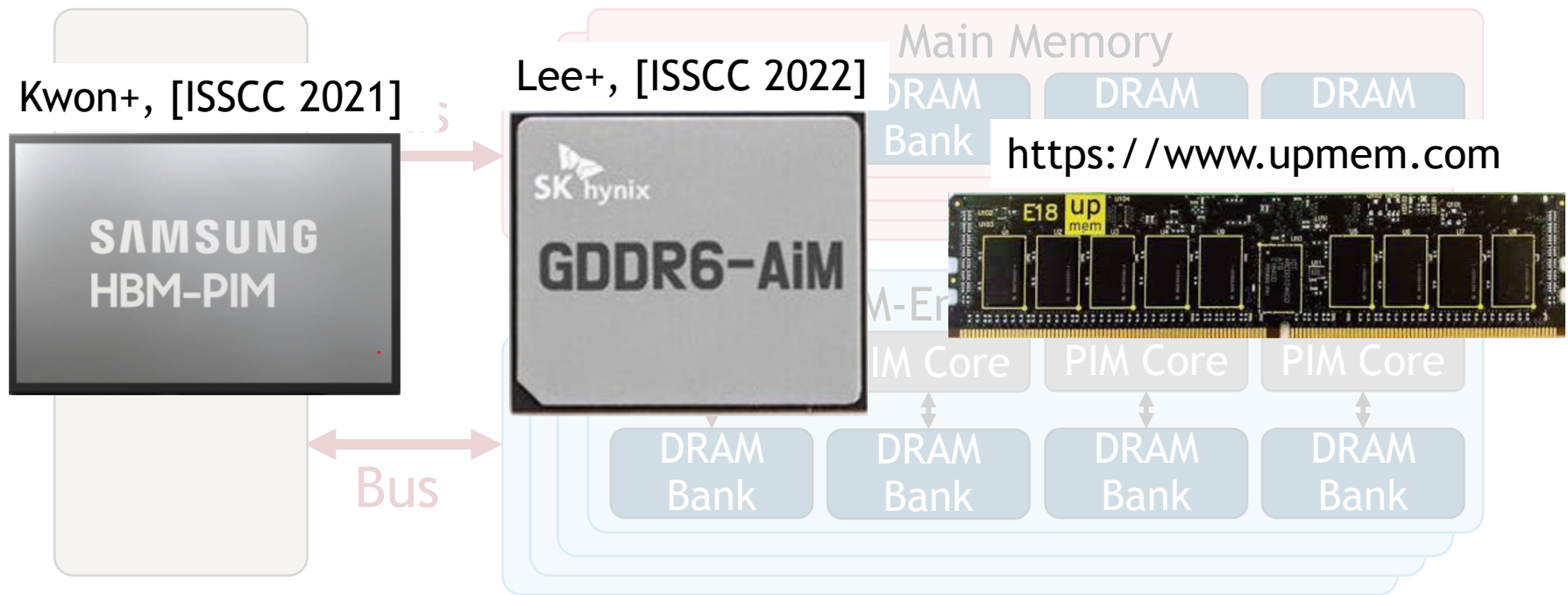
- High levels of **parallelism**
- Low memory access latency
- Large aggregate memory **bandwidth**



Real Processing-In-Memory Systems

Real **Near-Bank** Processing-In-Memory (**PIM**) Systems:

- High levels of **parallelism**
- Low memory access latency
- Large aggregate memory **bandwidth**



SparseP: SpMV Library for Real PIMs

Our Contributions:

1. Design **efficient SpMV kernels** for current and future PIM systems
 - **25 SpMV kernels**
 - 4 compressed matrix formats (CSR, COO, BCSR, BCOO)
 - 6 data types
 - 4 data partitioning techniques
 - Various load balancing schemes among PIM cores/threads
 - 3 synchronization approaches
2. Provide a **comprehensive analysis** of SpMV on the first commercially-available **real PIM system** **up mem**
 - **26** sparse matrices
 - Comparisons to state-of-the-art **CPU** and **GPU** systems
 - **Recommendations** for software, system and hardware designers

Outline

SpMV Kernels for Real PIM Systems

Key Takeaways from Our Study

Conclusion

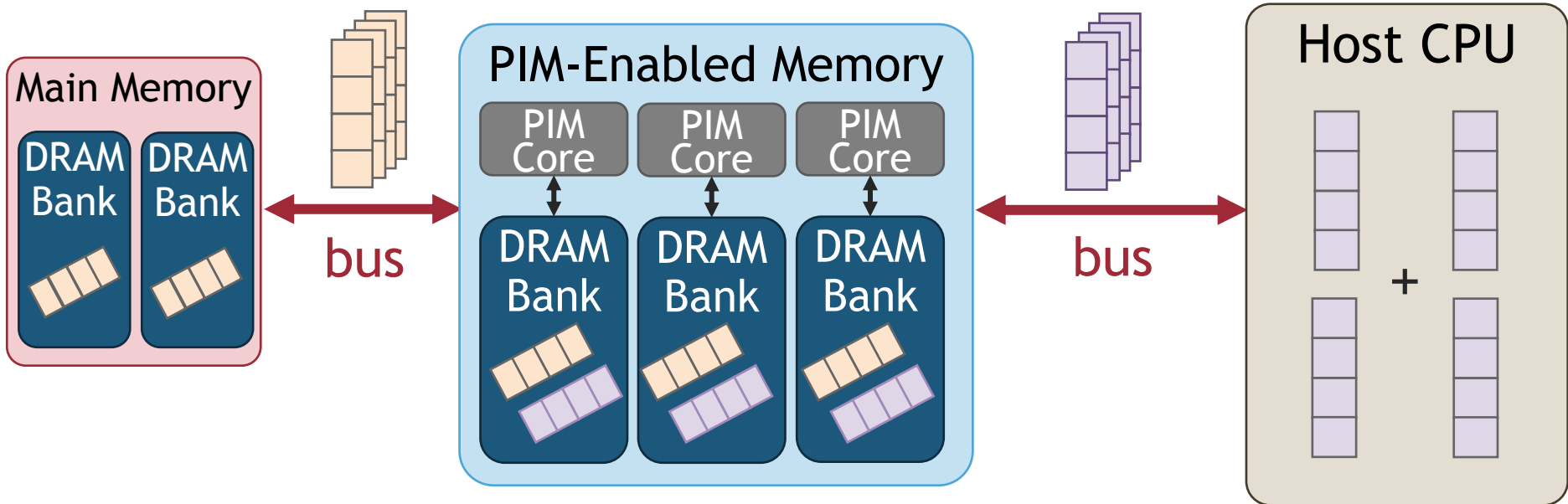
SpMV Execution on a PIM System

①
Load the
input vector

②
Execute the
kernel

③
Retrieve the
partial results

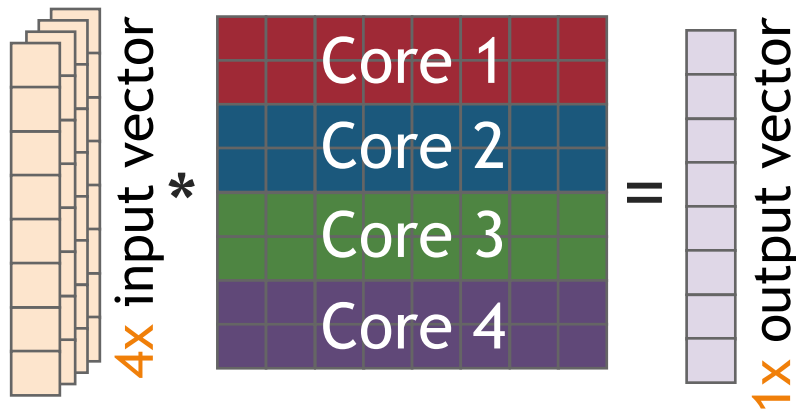
④
Merge the
partial results



Data Partitioning Techniques

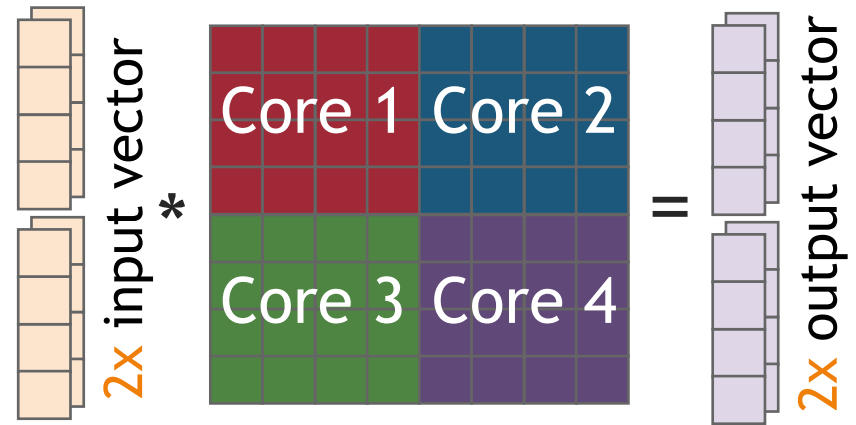
SparseP supports two types of data partitioning techniques:

1D Partitioning



perform the **complete**
SpMV computation
only on PIM cores

2D Partitioning



trade-off
computation vs
data transfer costs

1D Partitioning Technique

Load-Balancing Approaches:

- CSR, COO:
 - Balance Rows
 - Balance NNZs *
- BCSR, BCOO:
 - Balance Blocks ^
 - Balance NNZs ^

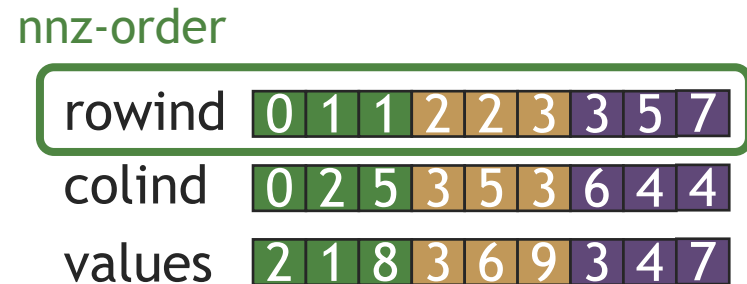
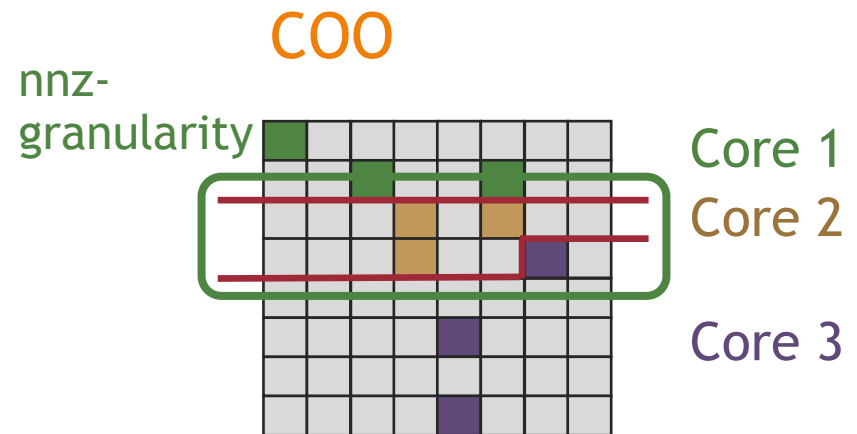
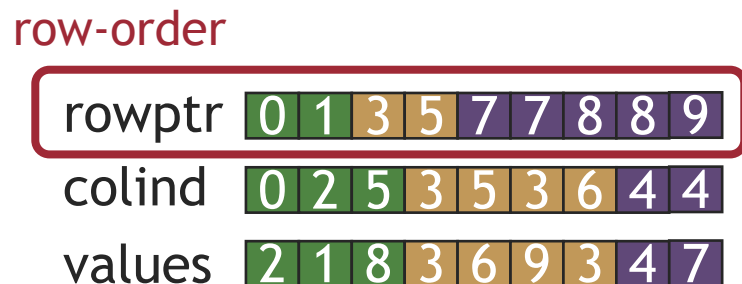
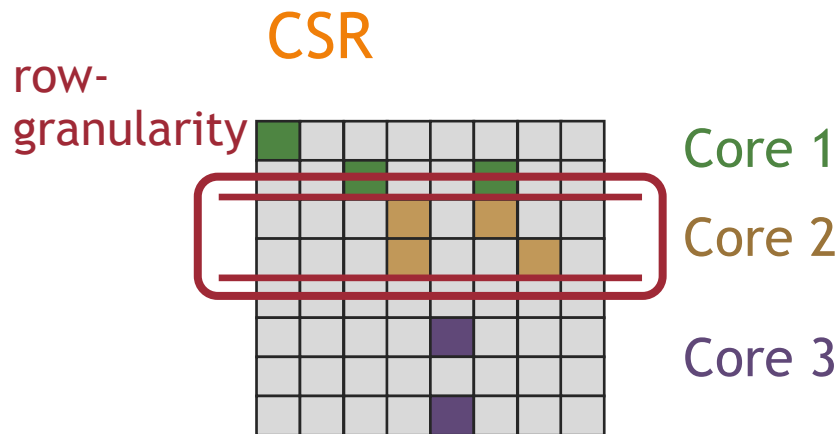
* row-granularity for CSR

^ block-row-granularity for BCSR

1D Partitioning Technique

Load-Balancing of #NNZs:

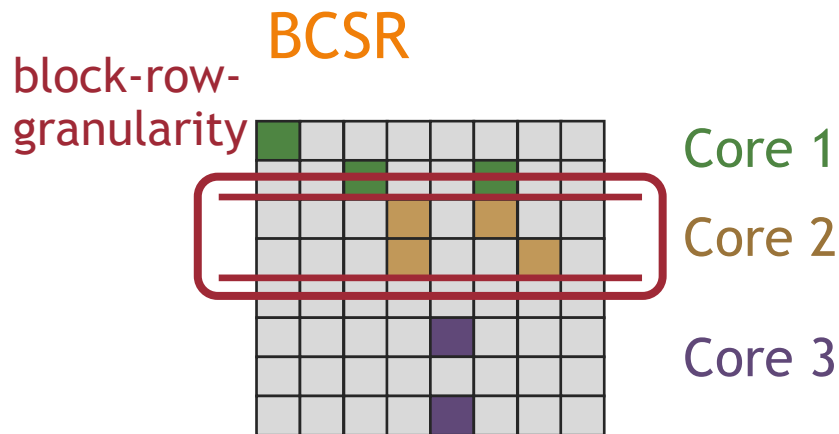
- CSR (row-granularity), COO



1D Partitioning Technique

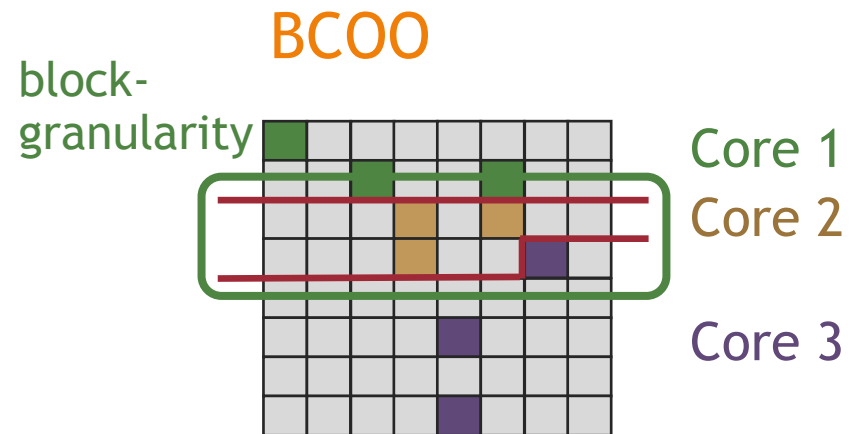
Load-Balancing of #NNZs:

- CSR (row-granularity), COO
- BCSR (block-row-granularity), BCOO



block-row-order

rowptr	0	1	3	5	7	7	8	8	9
colind	0	2	5	3	5	3	6	4	4
values	2	1	8	3	6	9	3	4	7

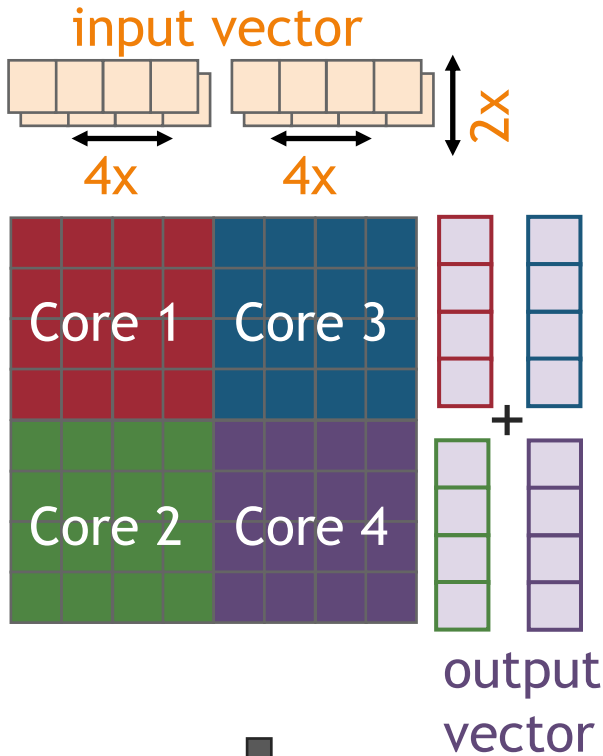


block-order

rowind	0	1	1	2	2	3	3	5	7
colind	0	2	5	3	5	3	6	4	4
values	2	1	8	3	6	9	3	4	7

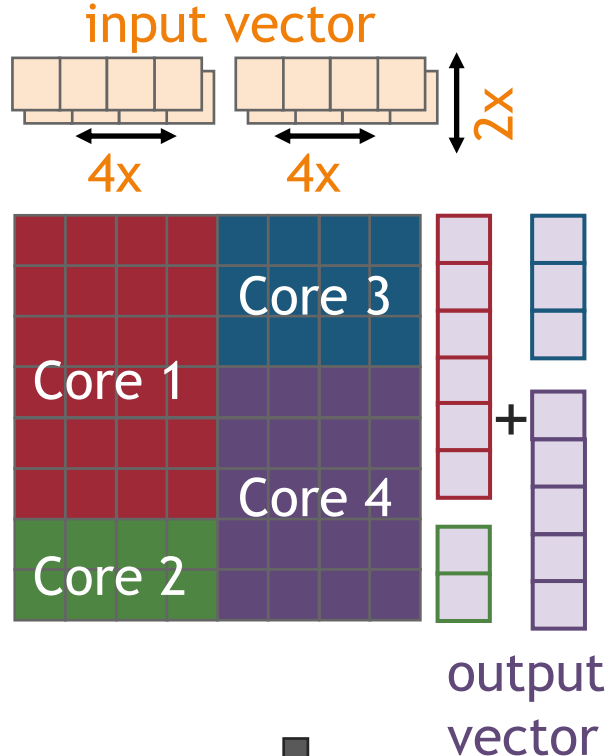
2D Partitioning Technique

Equally-Sized Tiles



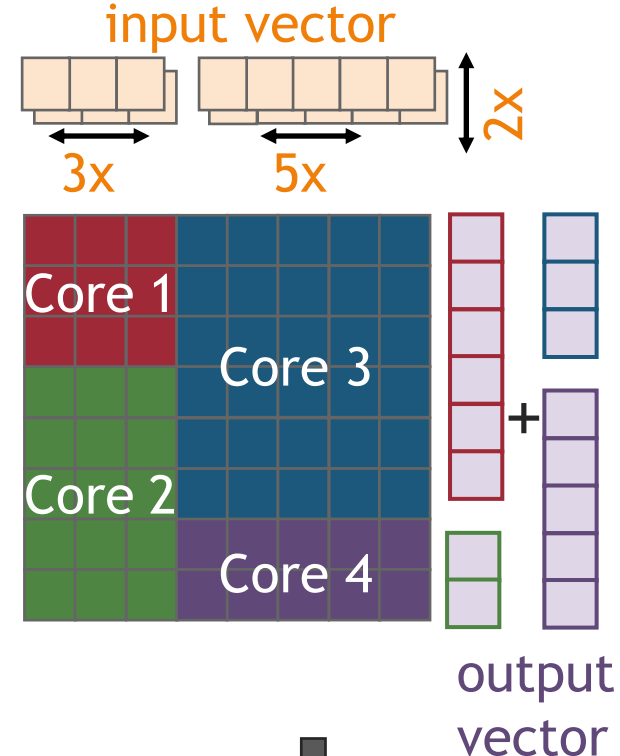
High NNZ **imbalance**
across PIM cores

Equally-Wide Tiles



High NNZ **balance**
across PIM cores of the
same **vertical** partition

Variable-Sized Tiles

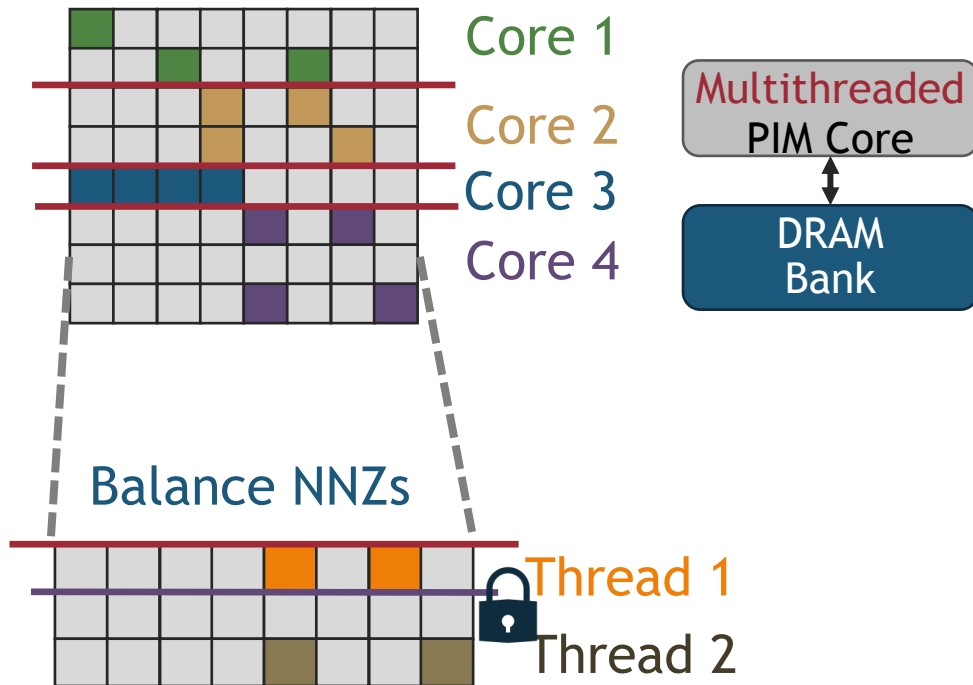


High NNZ **balance**
across **all** PIM cores

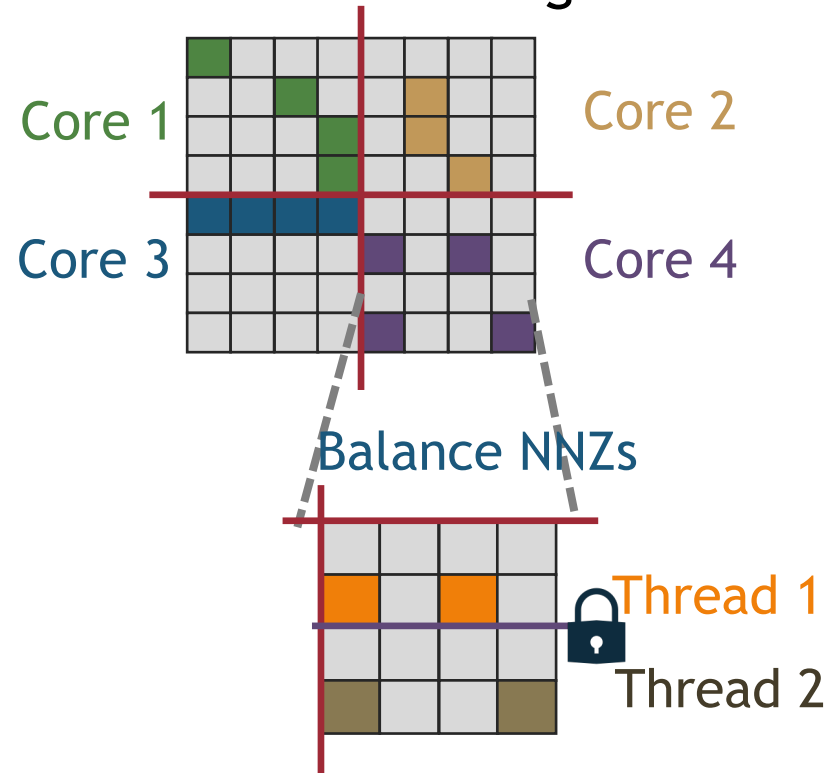
Parallelization across Threads

Multithreaded PIM Cores:

1D Partitioning



2D Partitioning



- Various **load-balance** schemes across threads
- Various **synchronization** approaches among threads

SparseP Software Package

25 SpMV kernels for PIM Systems →

<https://github.com/CMU-SAFARI/SparseP>

Partitioning	Matrix Format	Load-Balancing
9x 1D Kernels	CSR	rows, nnzs *
	COO [△]	rows, nnzs *, nnzs
	BCSR	blocks [^] , nnzs [^]
	BCOO [△]	blocks, nnzs
4x 2D Equally-Sized Tiles	CSR	--
	COO [△]	--
	BCSR	--
	BCOO [△]	--
6x 2D Equally-Wide Tiles	CSR	nnzs *
	COO [△]	nnzs
	BCSR	blocks [^] , nnzs [^]
	BCOO [△]	blocks, nnzs
6x 2D Variable-Sized Tiles	CSR	nnzs *
	COO [△]	nnzs
	BCSR	blocks [^] , nnzs [^]
	BCOO [△]	blocks, nnz

Load-balance

across PIM cores/threads:

* row-granularity (CSR)

[^] block-row-granularity (BCSR)

Synchronization

among threads of a PIM core:

[△] lb-cg, lb-fb, lf (COO, BCOO)

Data Types:

- 8-bit integer
- 16-bit integer
- 32-bit integer
- 64-bit integer
- 32-bit float
- 64-bit float

Outline

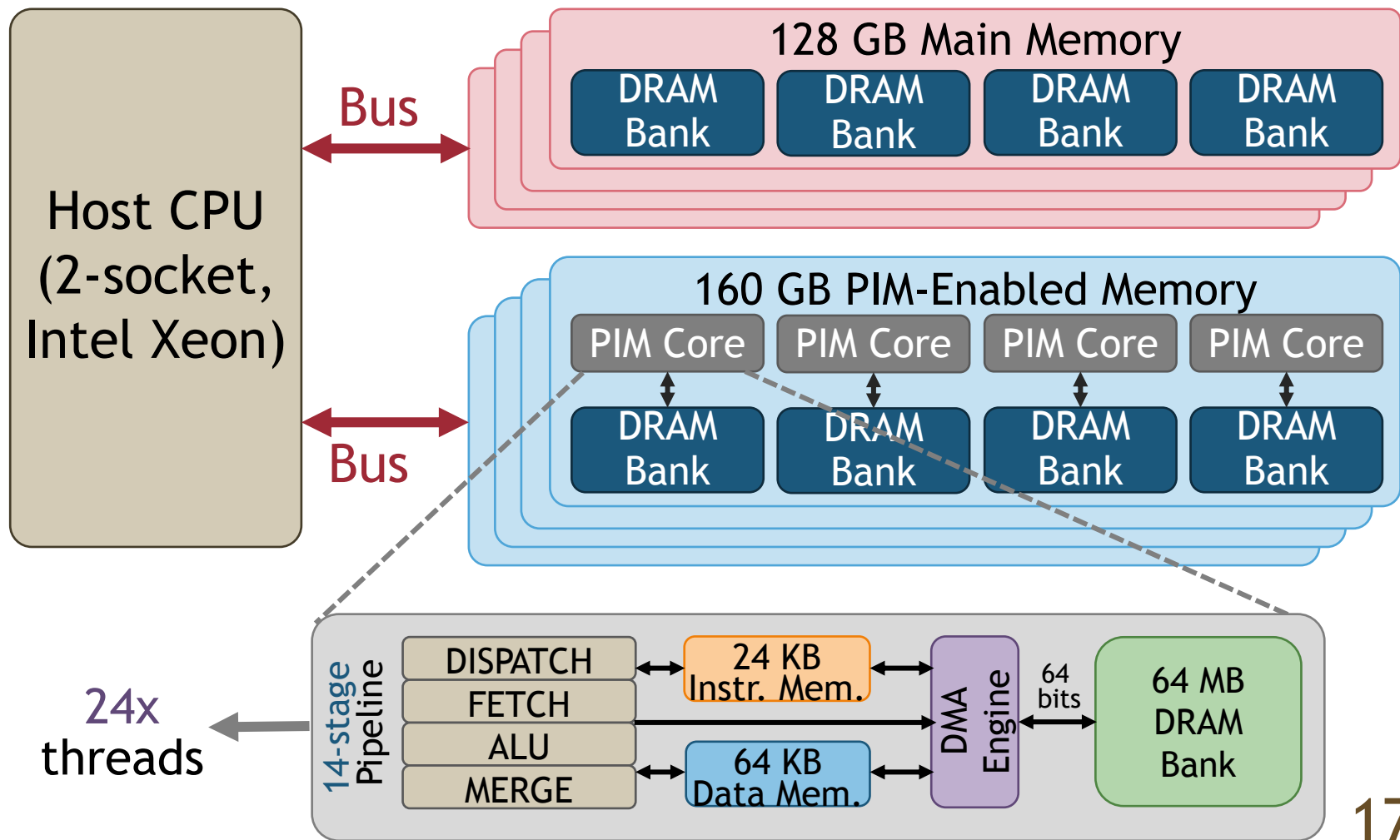
SpMV Kernels for Real PIM Systems

Key Takeaways from Our Study

Conclusion

UPMEM-based PIM System

- 20 UPMEM PIM DIMMs with 2560 PIM cores in total
- Each multithreaded PIM core supports 24 threads

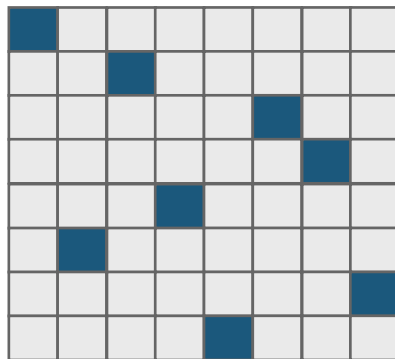


Sparse Matrix Data Set

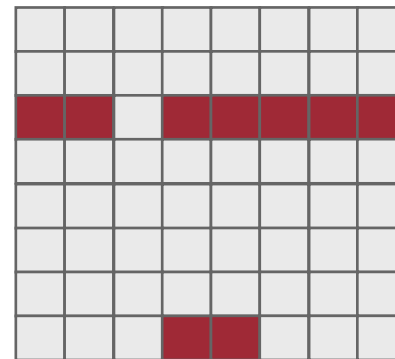
26 sparse matrices*:

- Diverse **sparsity** patterns
- Variability on **irregular** patterns
- Variability on **block** patterns

Regular Matrix



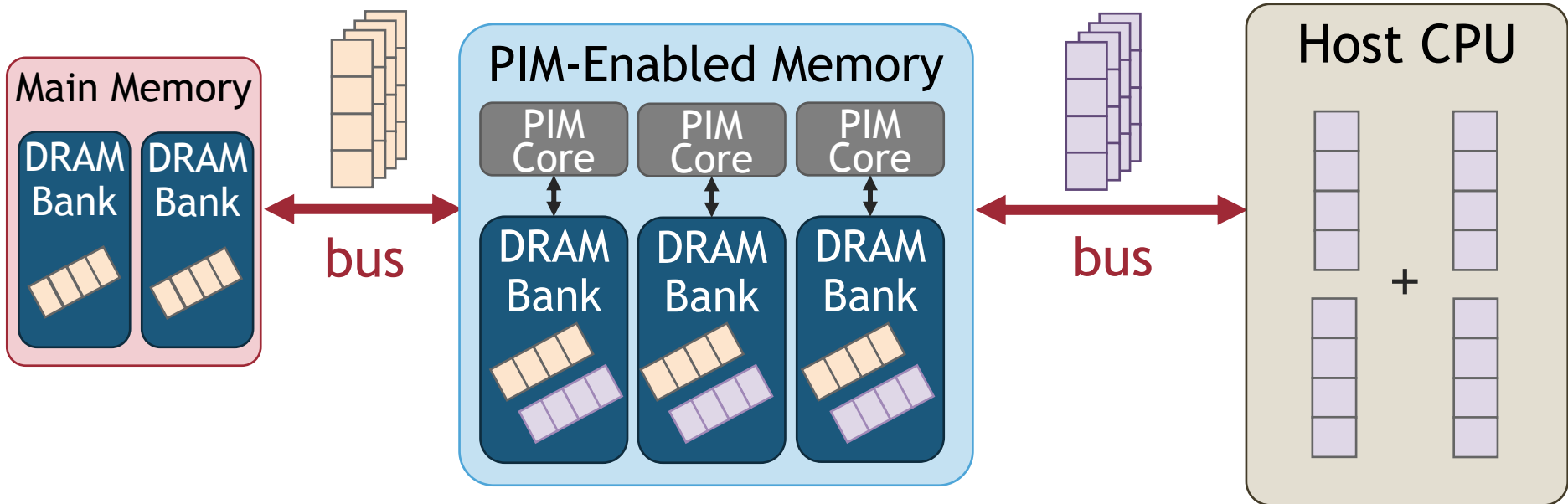
Scale-Free Matrix



* Suite Sparse Matrix Collection: <https://sparse.tamu.edu/>

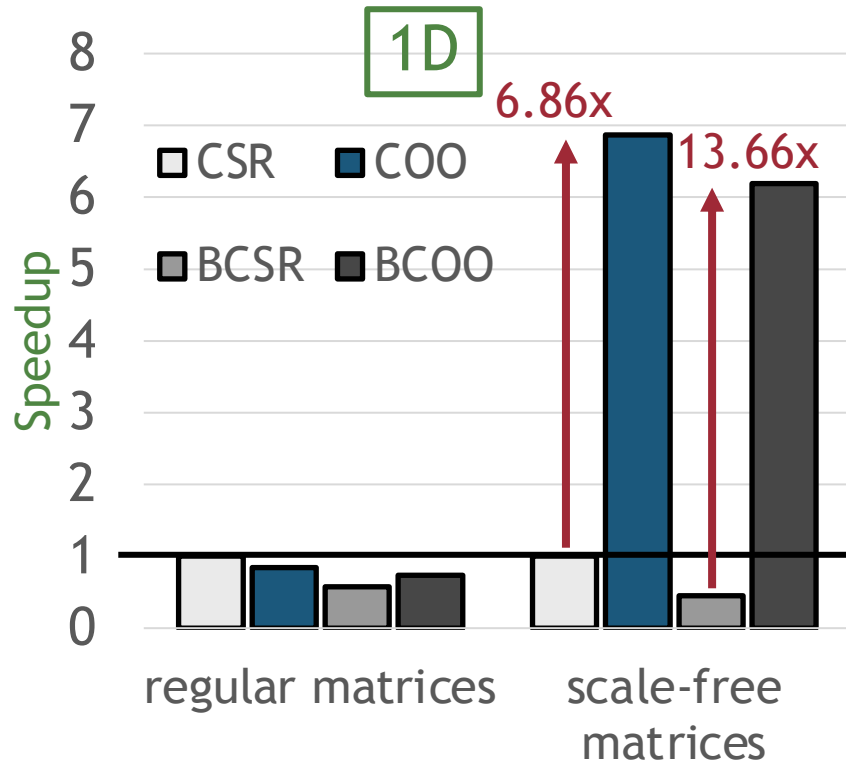
Kernel Execution on PIM Cores

- 1 Load the input vector
- 2 Execute the kernel
- 3 Retrieve the partial results
- 4 Merge the partial results

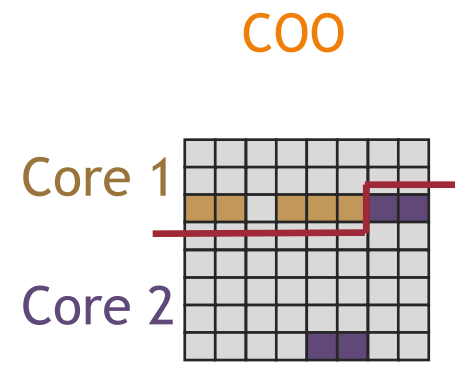
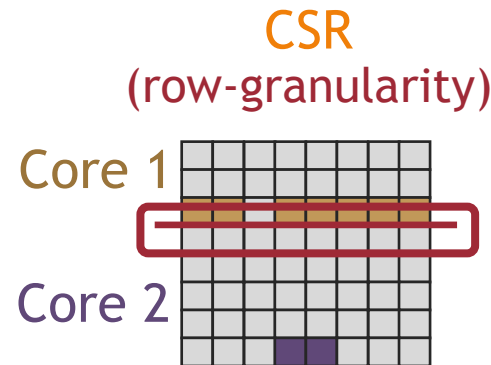


Comparison of Compressed Formats

2048 PIM Cores, 32-bit integer



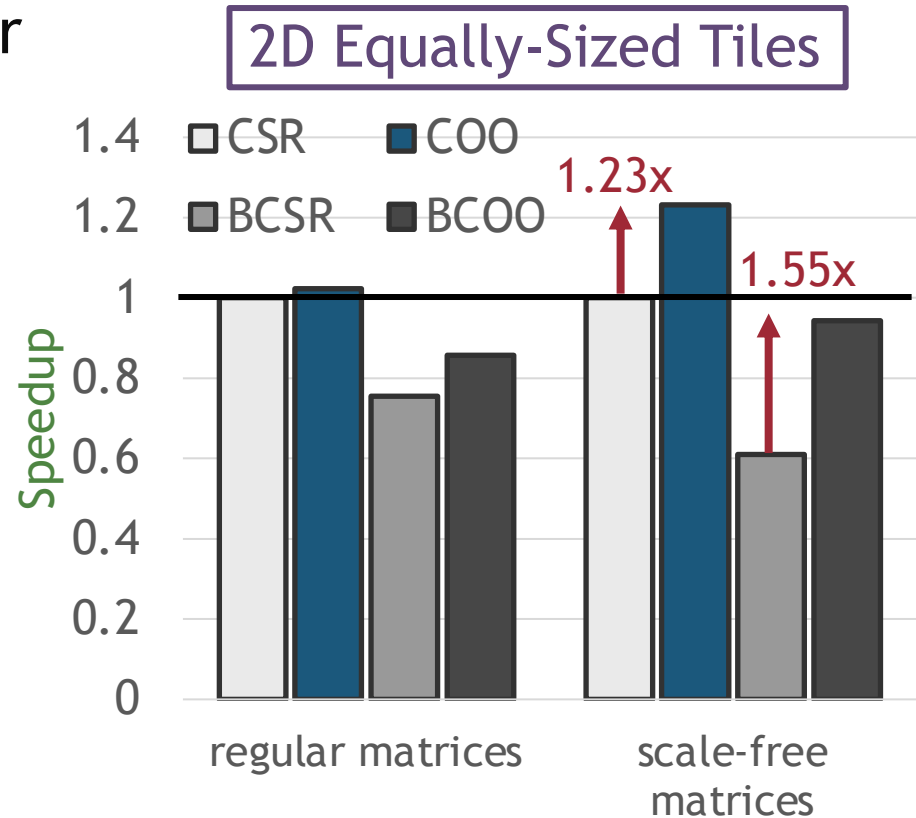
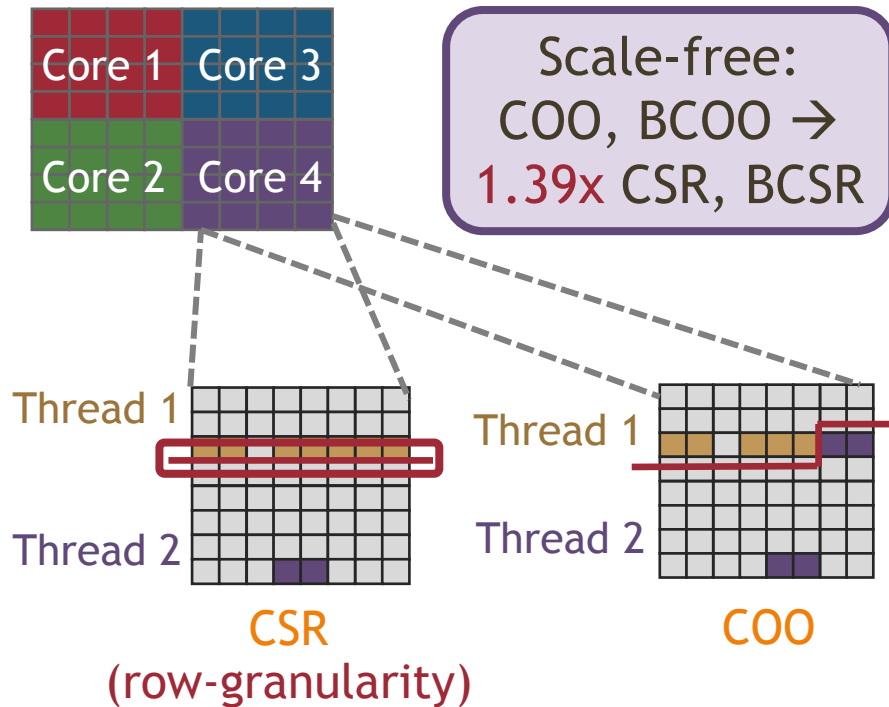
Scale-free: COO, BCOO →
10.26x CSR, BCSR



In **scale-free** matrices, **COO** + **BCOO** provide higher non-zero element balance across PIM **cores** than **CSR** + **BCSR**, respectively.

Comparison of Compressed Formats

2048 PIM Cores, 32-bit integer



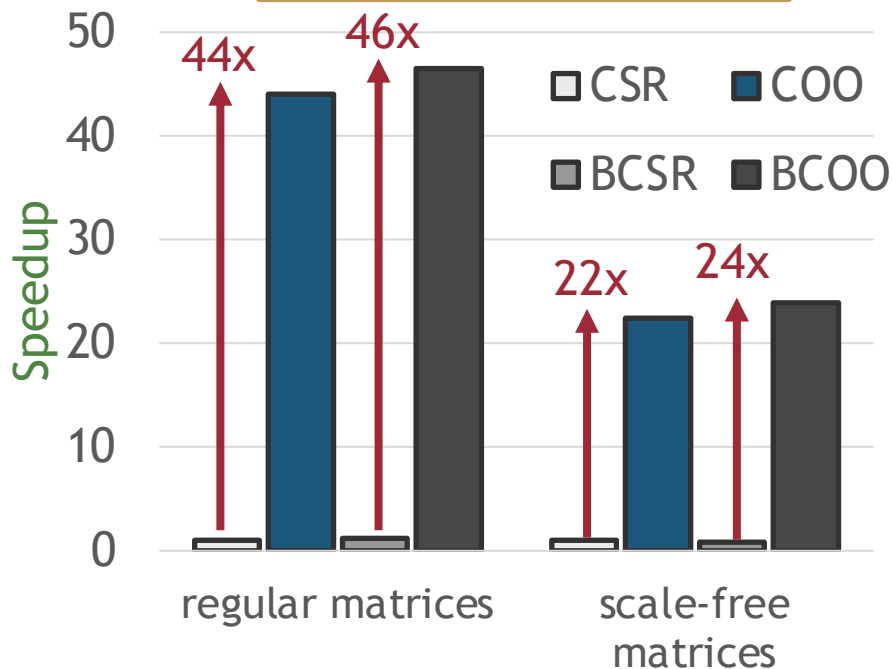
In **scale-free** matrices, **COO** + **BCOO** provide higher non-zero element balance across **threads** than **CSR** + **BCSR**, respectively.

Comparison of Compressed Formats

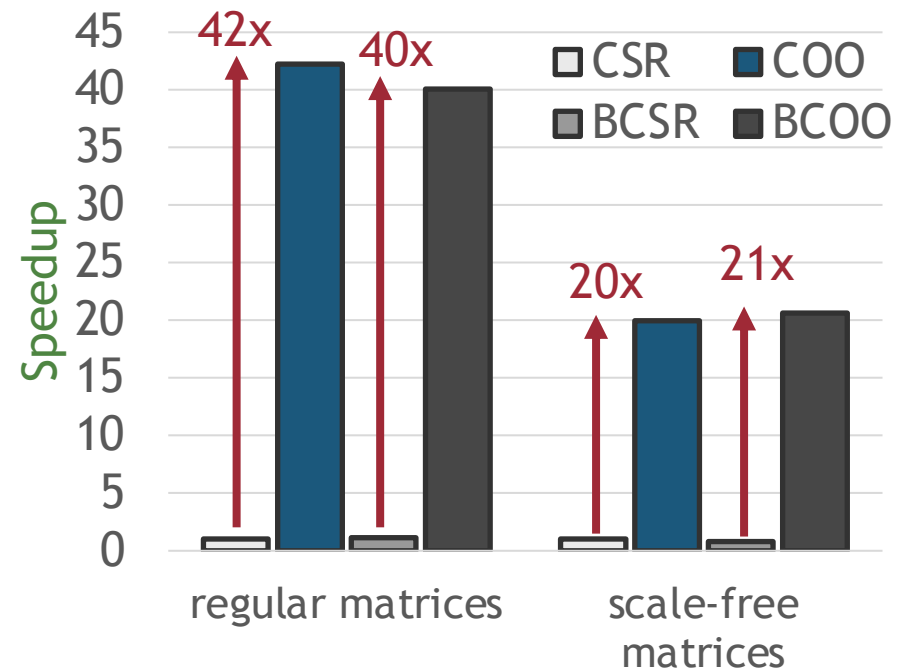
2048 PIM Cores, 32-bit integer

COO, BCOO → 32.38x CSR, BCSR

2D Equally-Wide Tiles



2D Variable-Sized Tiles



COO + BCOO formats provide higher non-zero element balance across PIM cores + threads than CSR + BCSR, respectively.

Comparison of Compressed Formats

2048 PIM Cores, 32-bit integer

1D

2D Equally-Sized

Key Takeaway 1

The **compressed matrix format** used to store the input matrix **determines** the **data partitioning** across DRAM banks of PIM-enabled memory. As a result, it affects the **load-balance** across PIM cores (and threads of a PIM core) with corresponding **performance** implications.

regular matrices

scale-free
matrices

regular matrices

scale-free
matrices

2D Equally-Wide

2D Variable-Sized

Recommendation 1

Design **compressed** data structures that can be **effectively** partitioned across DRAM banks, with the goal of providing **high computation balance** across PIM cores (and threads of a PIM core).

regular matrices

scale-free
matrices

regular matrices

scale-free
matrices

End-to-End Performance

①

Load the
input vector

②

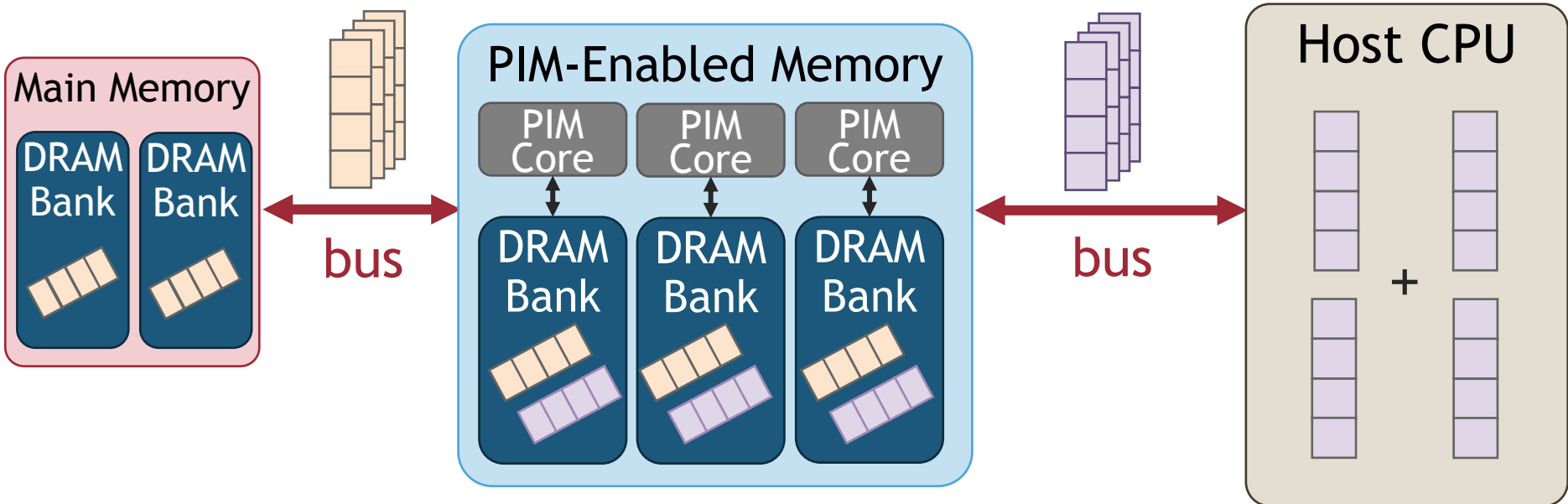
Execute the
kernel

③

Retrieve the
partial results

④

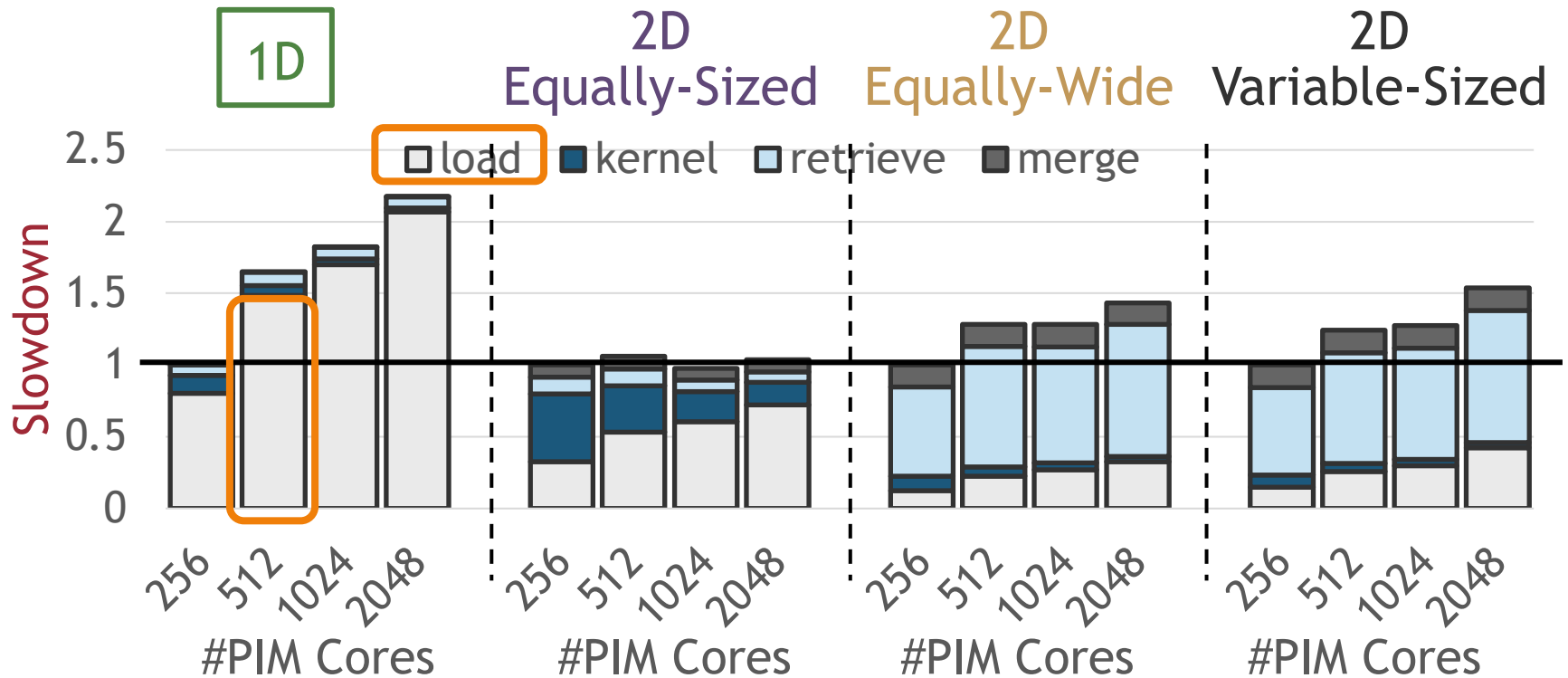
Merge the
partial results



Scalability

COO format, 32-bit integer

The scalability is limited by the **load** time



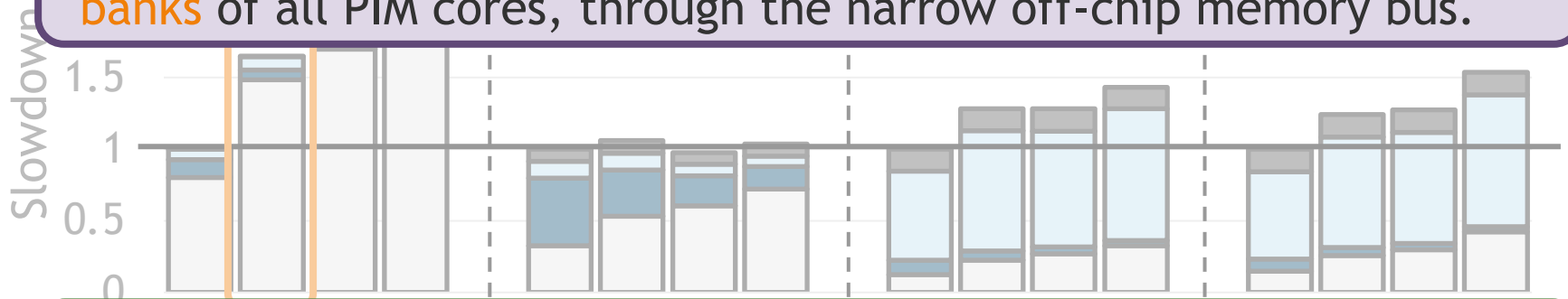
1D: #bytes to **load** the input vector grows **linearly** to #PIM cores

Scalability

COO format, 32-bit integer

Key Takeaway 2

The 1D-partitioned kernels are severely **bottlenecked** by the high data transfer costs to **broadcast** the whole **input** vector **into DRAM banks** of all PIM cores, through the narrow off-chip memory bus.



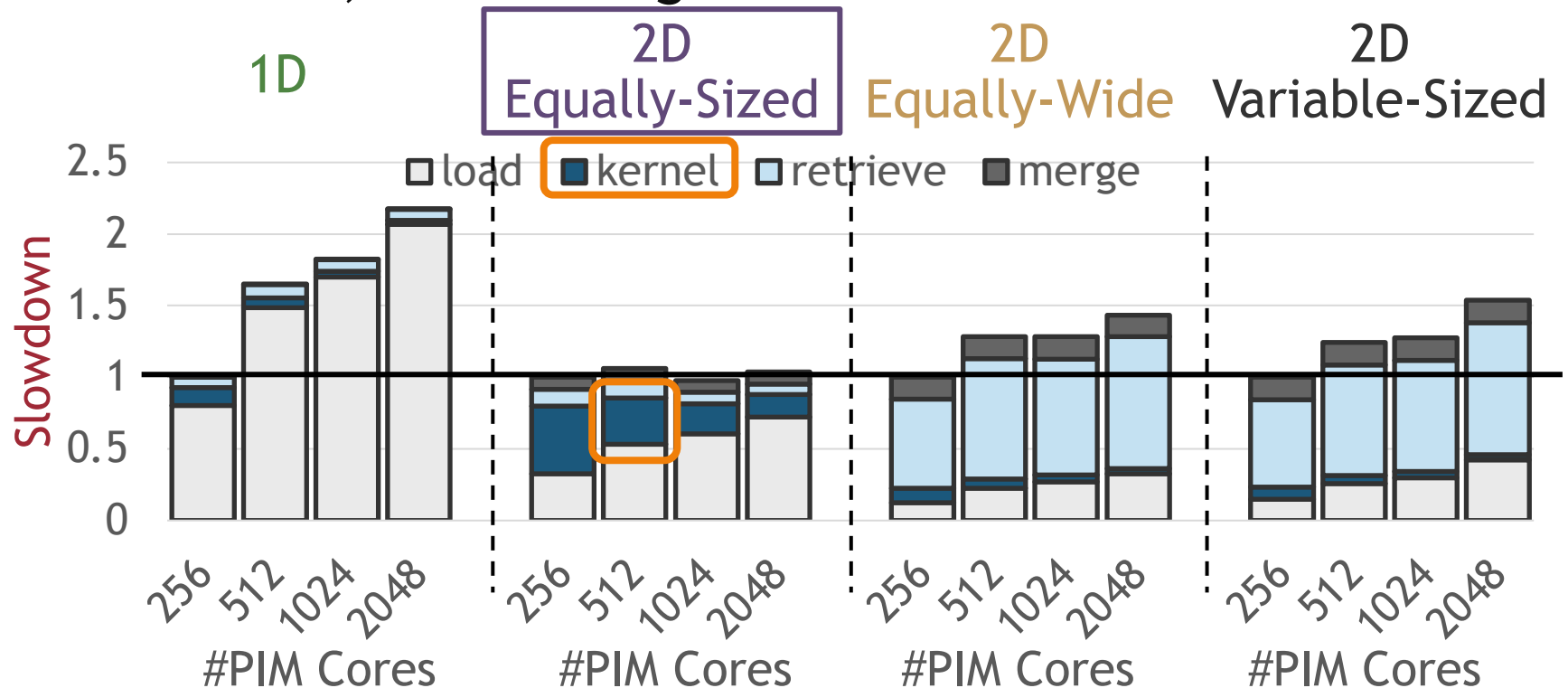
Recommendation 2

Optimize the **broadcast collective** in data transfers to PIM-enabled memory to efficiently copy the **input data** into DRAM banks in the PIM system.

Scalability

COO format, 32-bit integer

The scalability is limited by the **kernel** time

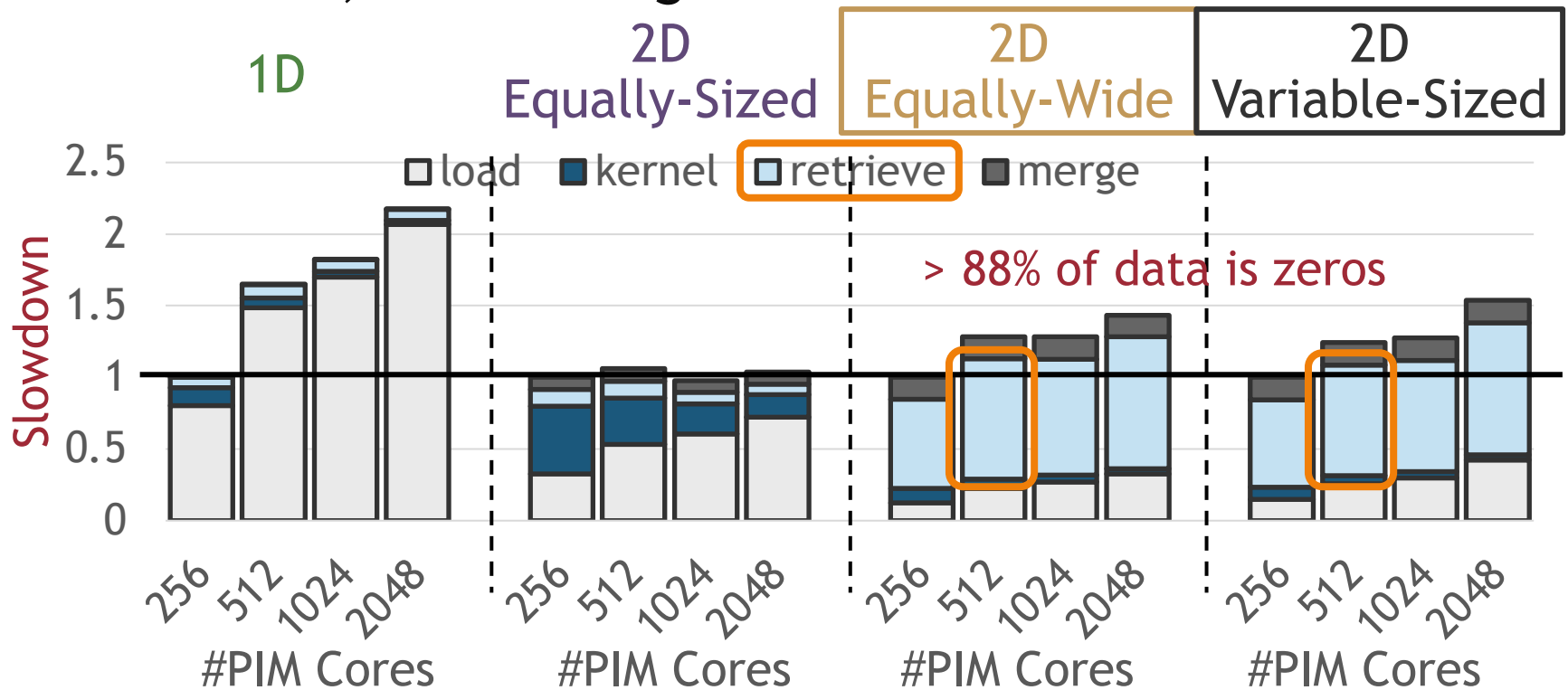


2D Equally-Sized: **kernel** time is limited by only a **few** PIM cores assigned to the 2D tiles with the **largest** #NNZs

Scalability

COO format, 32-bit integer

The scalability is limited by the **retrieve** time



2D Equally-Wide + 2D Variable-Sized:

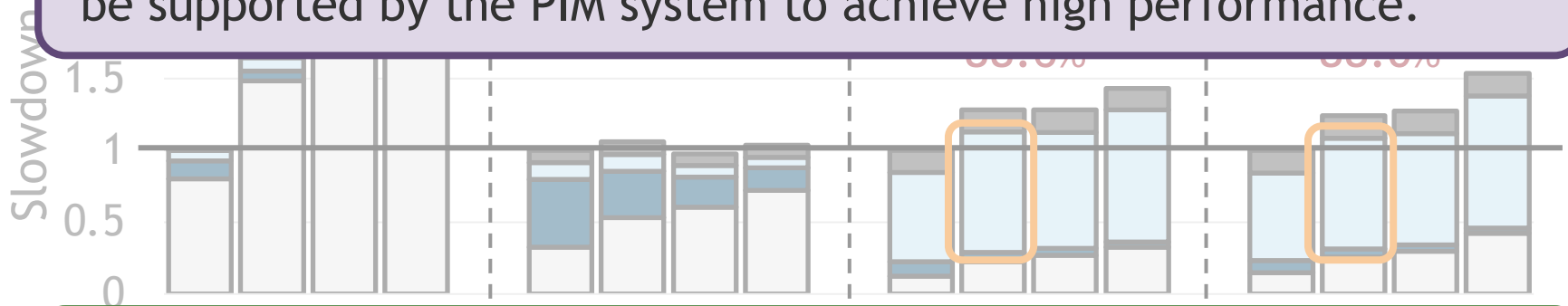
high amount of **zero padding** to **gather** the output vector →
parallel transfers supported at **rank granularity** = 64 PIM cores

Scalability

COO format, 32-bit integer

Key Takeaway 3

The 2D equally-wide and variable-sized kernels need **fine-grained parallel data transfers** at DRAM bank granularity (**zero padding**) to be supported by the PIM system to achieve high performance.

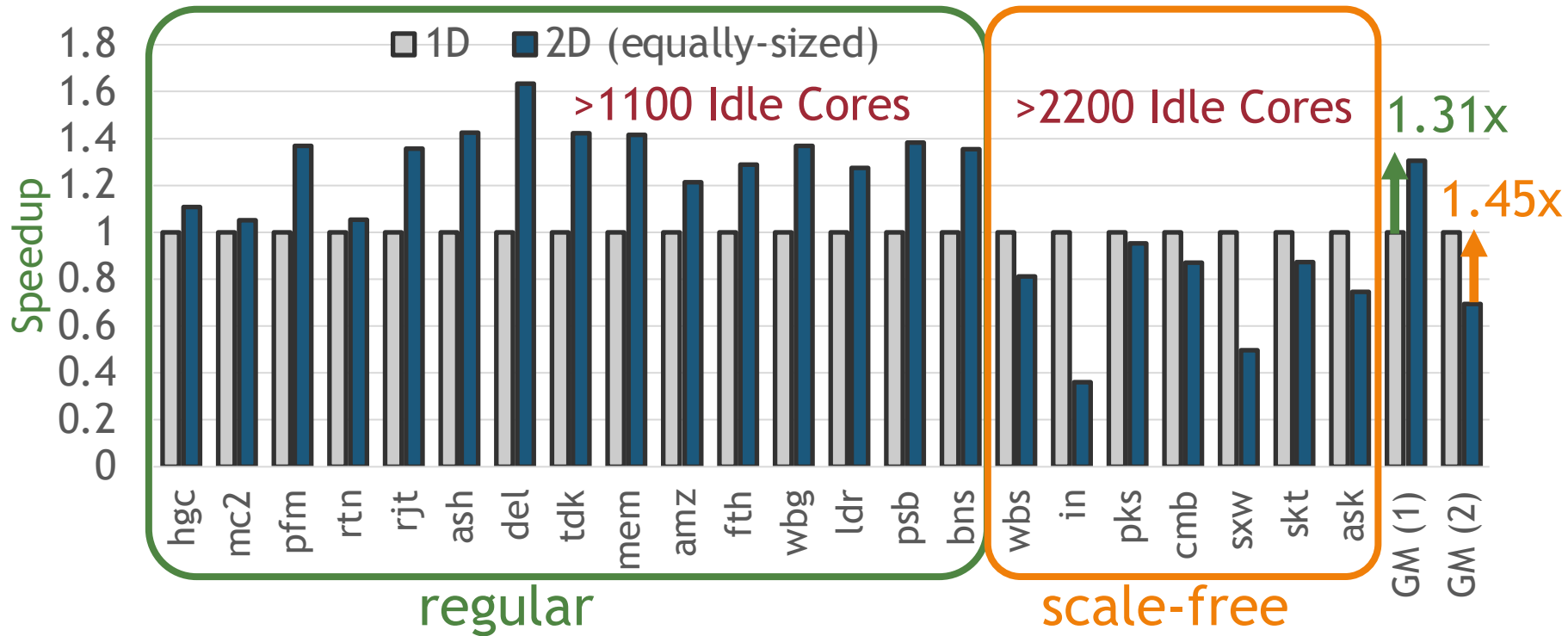


Recommendation 3

Optimize the **gather collective** operation at **DRAM bank granularity** in data transfers from PIM-enabled memory to efficiently retrieve the **output results** to the host CPU.

1D vs 2D

Up to 2528 PIM Cores, 32-bit float

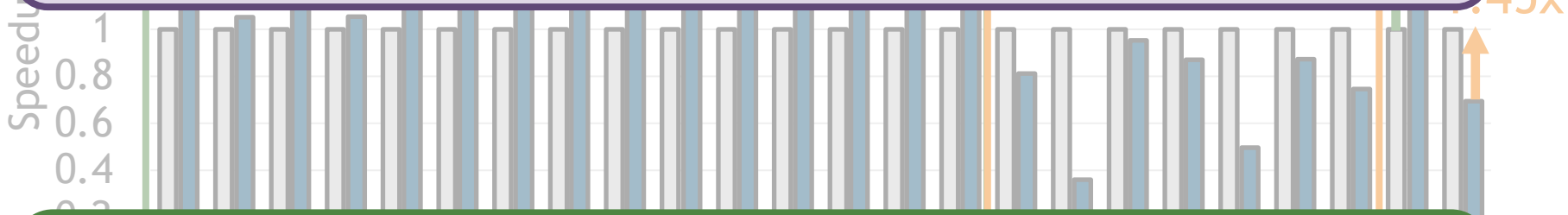


Best-performing SpMV execution:
trades off computation with lower data transfer costs

1D vs 2D

Key Takeaway 4

Expensive **data transfers** to/from PIM-enabled memory performed via the narrow memory bus impose significant performance **overhead** to end-to-end SpMV execution. Thus, it is hard to **fully exploit** all available PIM cores of the system.



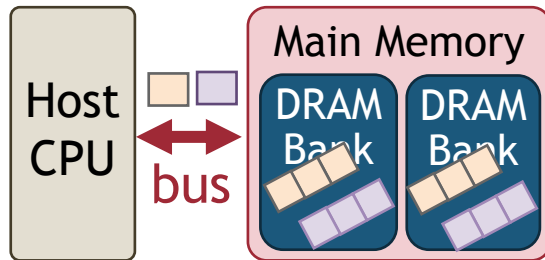
Recommendation 4

Design **high-speed communication channels** and **optimized libraries** in data transfers to/from PIM-enabled memory, provide **hardware support** to effectively **overlap** computation with data transfers in the PIM system, and/or **integrate** PIM-enabled memory as the main **memory** of the system.

SpMV Execution on Various Systems

CPU System

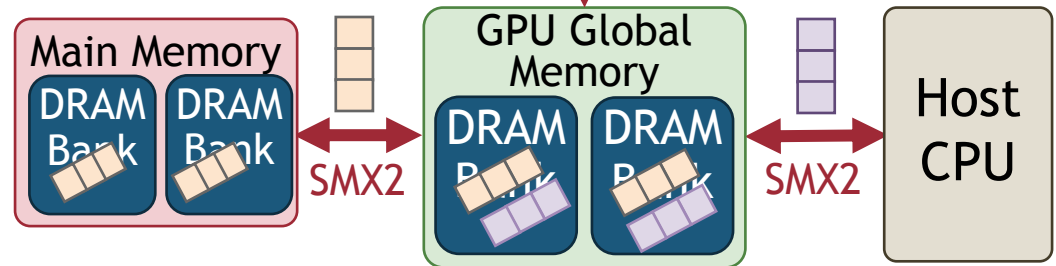
① Execute the kernel



GPU System

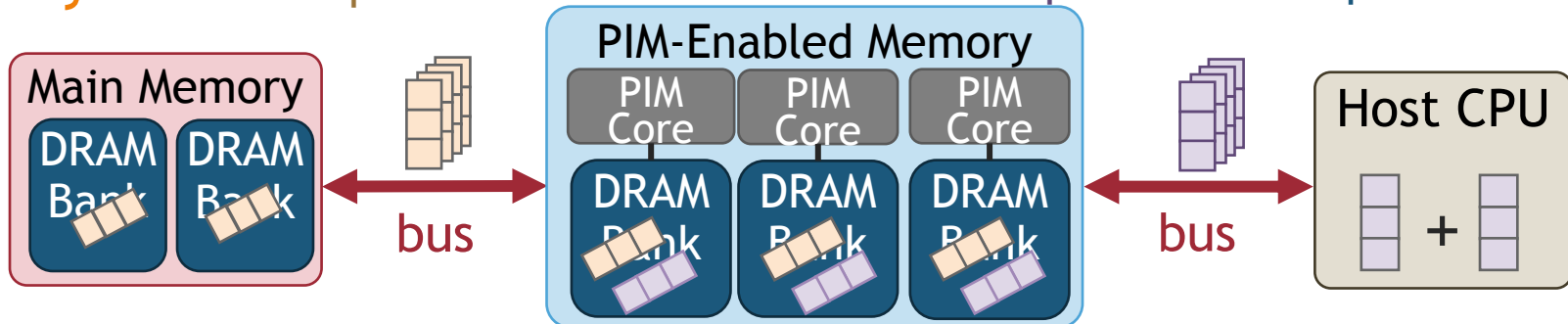
② Execute the kernel

① Load the input vector
③ Retrieve the final vector



Real PIM System

① Load the input vector
② Execute the kernel
③ Retrieve the partial results
④ Merge the partial results



CPU/GPU Comparisons

System		Peak Performance	Bandwidth	TDP	Processor-Centric
CPU	Intel Xeon Silver 4110	660 GFlops	23.1 GB/s	2x85 W	
GPU	NVIDIA Tesla V100	14.13 TFlops	897 GB/s	300 W	Memory-Centric
PIM	UPMEM 1st Gen.	4.66 GFlops	1.77 TB/s	379 W	

33

CPU/GPU Comparisons

- **Kernel-Only (COO, 32-bit float):**
 - CPU = 0.51% of Peak Perf.
 - GPU = 0.21% of Peak Perf.
 - PIM (1D) = **50.7%** of Peak Perf.

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- **End-to-End** (COO, 32-bit float):
 - CPU = **4.08 GFlop/s**
 - GPU = 1.92 GFlop/s
 - PIM (1D) = 0.11 GFlop/s

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Many more results in the full paper:
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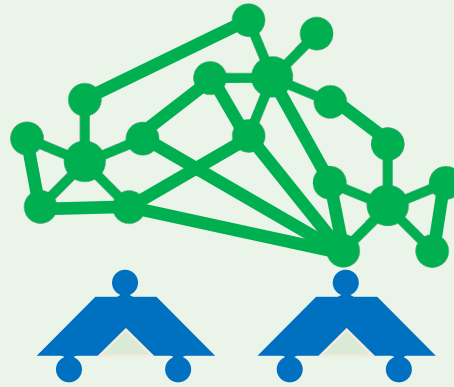
Conclusion

- **SpMV** is a fundamental linear algebra kernel for important applications (HPC, machine learning, graph analytics...)
- SpMV is a **highly memory-bound** kernel in processor-centric systems (e.g., CPU and GPU systems)
- Real near-bank PIM systems can tackle the **data movement bottleneck** (high parallelism, large aggregate memory bandwidth)
- Key Contributions:
 - **SparseP**: first **open-source** SpMV library for real PIM systems
 - Comprehensive **characterization** and **analysis** of SPMV on the first real PIM system
 - **Recommendations** to improve multiple aspects of future PIM hardware and software

Our Work

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Full Paper: <https://arxiv.org/pdf/2201.05072.pdf>



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