SMASH

Co-Designing Software Compression and Hardware-Accelerated Indexing for Efficient Sparse Matrix Operations

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SAFARI

ETH zürich

Carnegie Mellon University

Executive Summary

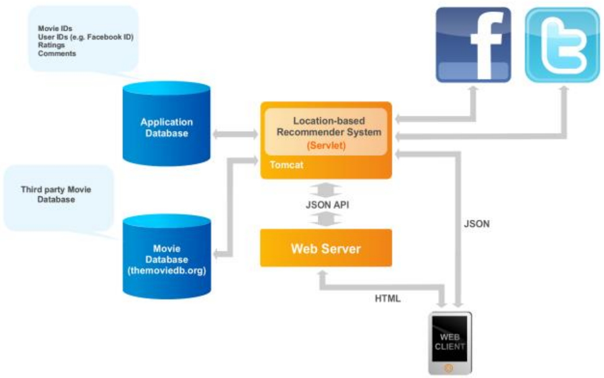
- Many important workloads heavily make use of **sparse matrices**
  - Matrices are **extremely sparse**
  - **Compression** is essential to avoid storage/computational overheads
- Shortcomings of existing compression formats
  - **Expensive discovery of the positions of non-zero elements or**
  - **Narrow applicability**
- **SMASH**: hardware/software cooperative mechanism for efficient sparse matrix storage and computation
  - ***Software***: Efficient compression scheme using **a hierarchy of bitmaps**
  - ***Hardware***: Hardware unit interprets the **bitmap hierarchy** and accelerates indexing
- Performance improvement: **38% and 44%** for **SpMV** and **SpMM** over the widely used CSR format
- SMASH is **highly efficient, low-cost** and **widely applicable**

Presentation Outline

1. Sparse Matrix Basics
2. Compression Formats & Shortcomings
3. SMASH
4. Evaluation
5. Conclusion

Sparse Matrix Operations are Widespread Today

Recommender Systems


Movie IDs
User IDs (e.g. Facebook ID)
Ratings
Comments
Application Database
Third party Movie Database
Movie Database (themoviedb.org)
Location-based Recommender System
(Servlet)
Tomcat
JSON API
Web Server
JSON
HTML
WEB CLIENT

- Collaborative Filtering

Graph Analytics

- PageRank
- Breadth First Search
- Betweenness Centrality

Neural Networks

- Sparse DNNs
- Graph Neural Networks

Real World Matrices Have High Sparsity

f

0.0003%

non-zero elements

YouTube

2.31%

non-zero elements

Sparse matrix compression is essential to enable efficient storage and computation

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Limitations of Existing Compression Formats

❶

General formats optimize for storage → **Expensive discovery of the positions of non-zero elements**

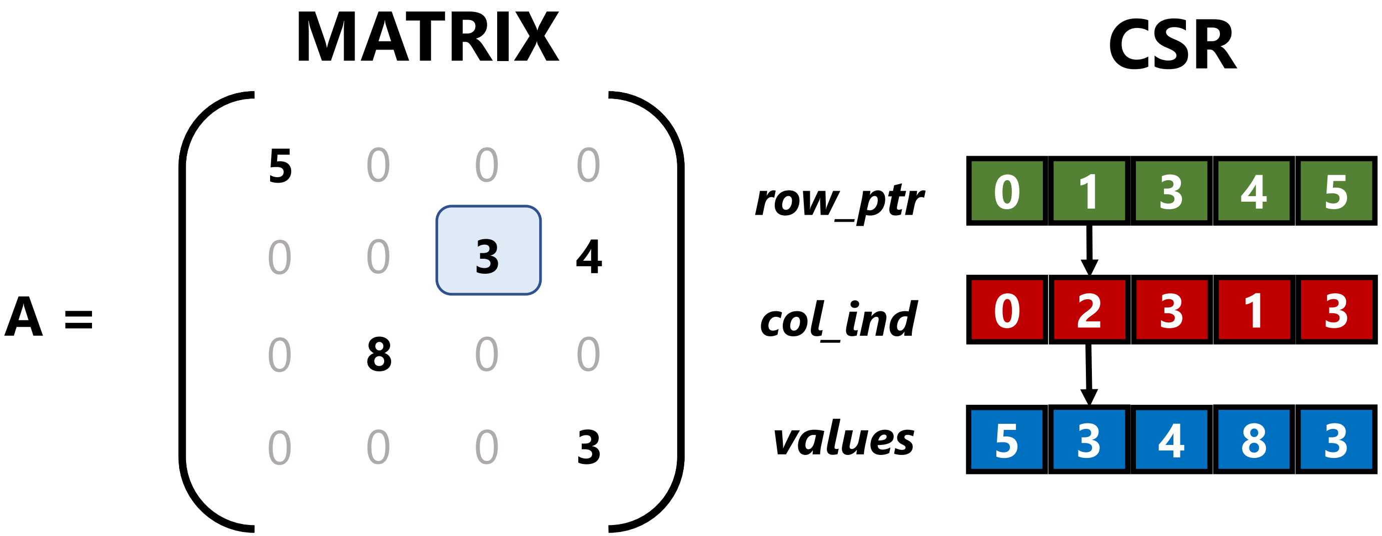
Widely Used Format: Compressed Sparse Row

- Used in multiple **libraries** & **frameworks**:
  Intel MKL, TACO, Ligra, Polymer

- Stores **only the non-zero elements**
  of the sparse matrix

- Provides **high compression ratio**

Basics of CSR: Indexing Overhead



MATRIX

$$A = \begin{pmatrix} 5 & 0 & 0 & 0 \\ 0 & 0 & \boxed{3} & 4 \\ 0 & 8 & 0 & 0 \\ 0 & 0 & 0 & 3 \end{pmatrix}$$

CSR

row_ptr	0	1	3	4	5
col_ind	0	2	3	1	3
values	5	3	4	8	3

Multiple instructions are needed to discover the position of a non-zero element

Requires multiple data-dependent memory accesses

Indexing Overhead in Sparse Kernels

Sparse Matrix Vector Multiplication (SpMV)

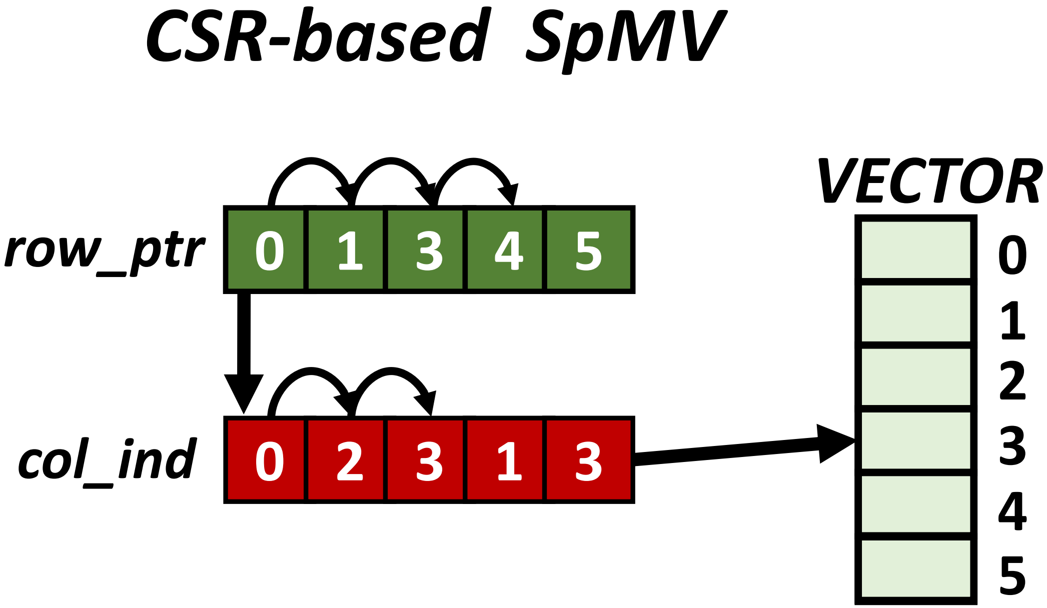
Indexing for every non-zero element of the sparse matrix to multiply with the corresponding element of the vector.

Sparse Matrix Matrix Multiplication (SpMM)

Index matching for every inner product between the 2 sparse matrices.

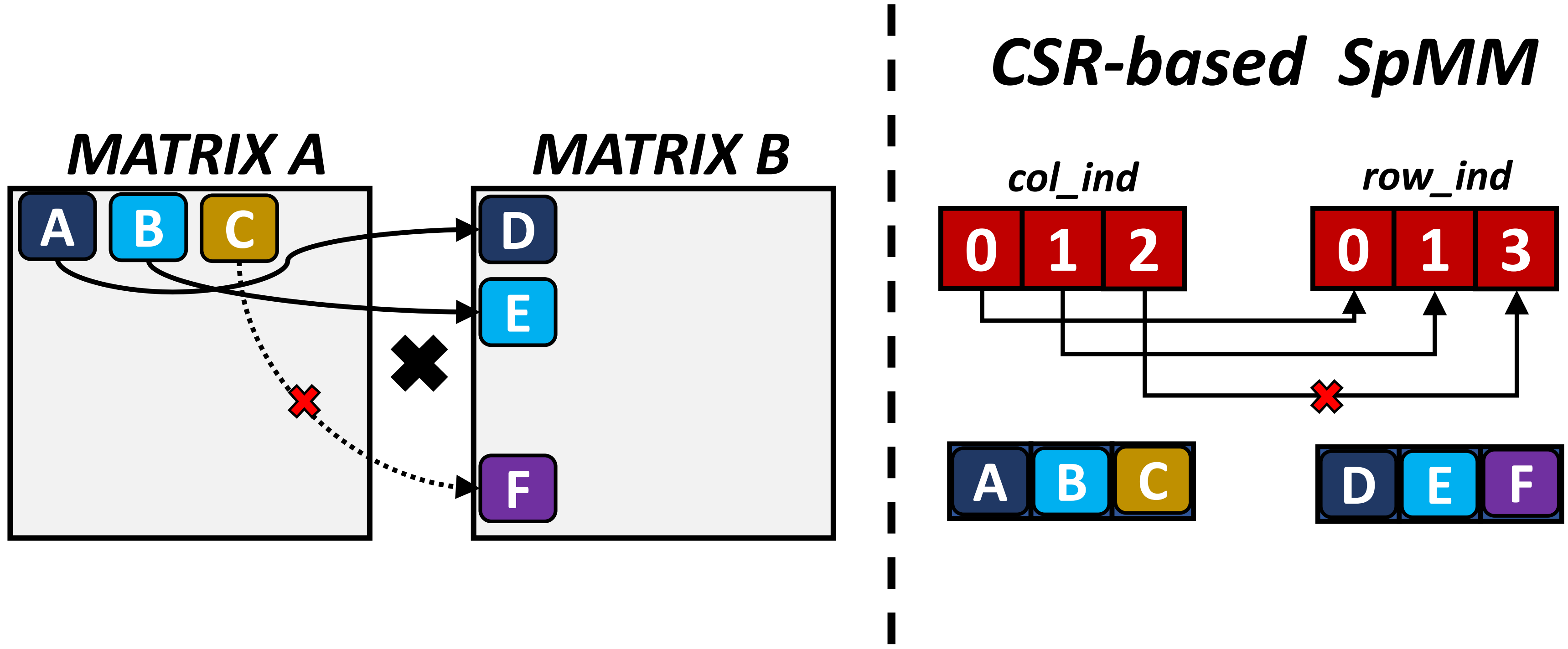
Indexing is expensive for major sparse matrix kernels

Indexing in SpMV



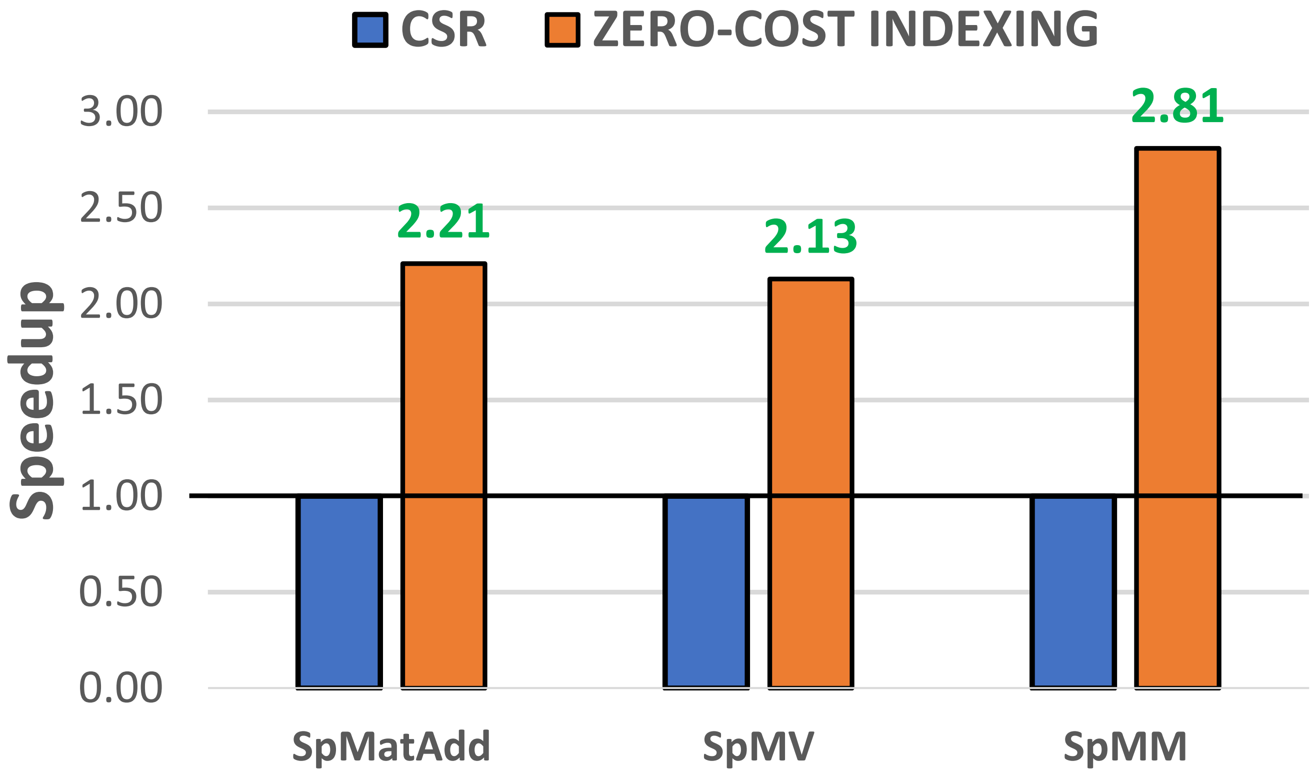
SpMV requires indexing for every non-zero element

Indexing in SpMM



SpMM requires indexing for every inner product

Performing Indexing with Zero Cost



Reducing the cost of indexing can accelerate sparse matrix operations

Limitations of Existing Compression Formats

❶

General formats optimize for storage → Expensive discovery of the positions of non-zero elements

❷

Specialized formats assume specific matrix structures and patterns (e.g., diagonals) → Narrow applicability

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Our Goal

Design a sparse matrix compression mechanism that:

- **Minimizes** the indexing **overheads**
- Can be used across a **wide range** of sparse matrices and sparse matrix operations
- Enables **high compression ratio**

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    - Software Compression Scheme
    - Hardware Acceleration Unit
    - Cross-Layer Interface

4. Evaluation

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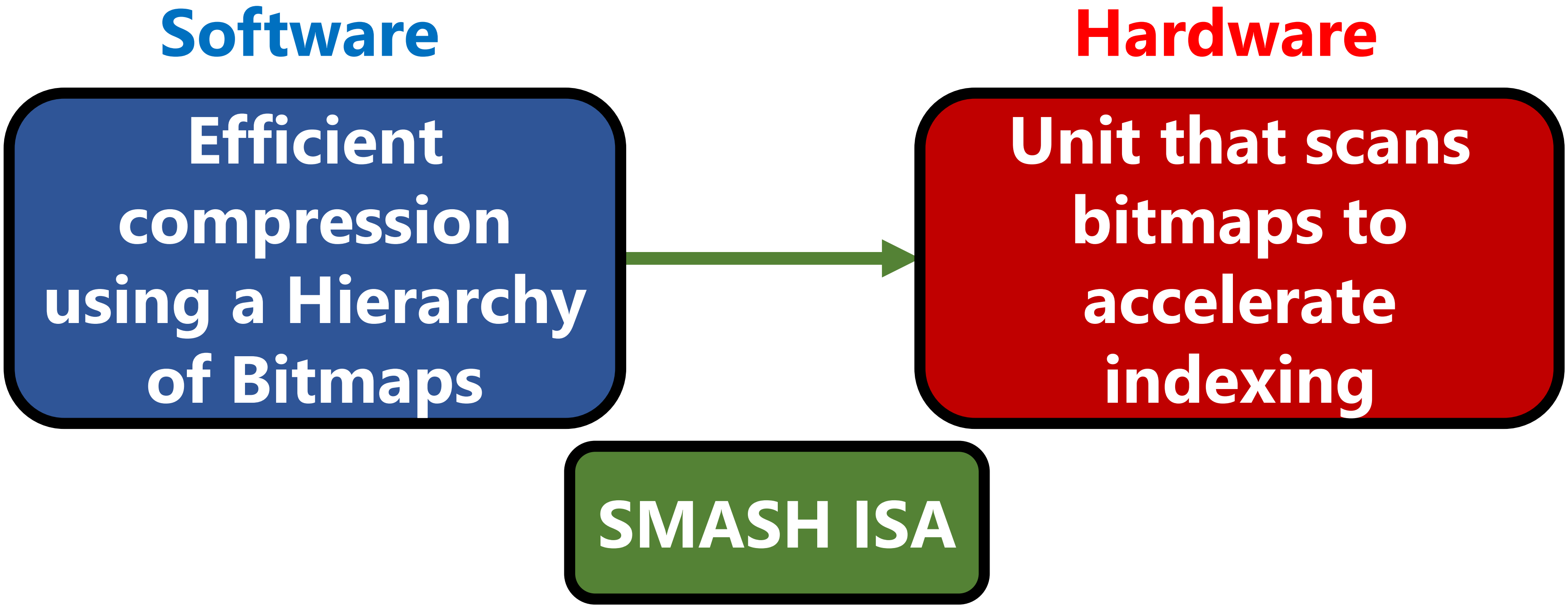
SMASH: Key Idea

Hardware/Software cooperative mechanism:

- Enables **highly-efficient** sparse matrix compression and computation
- **General** across a diverse set of sparse matrices and sparse matrix operations



Software

Efficient compression using a Hierarchy of Bitmaps

Hardware

Unit that scans bitmaps to accelerate indexing

SMASH ISA

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SMASH: Software Compression Scheme

Software

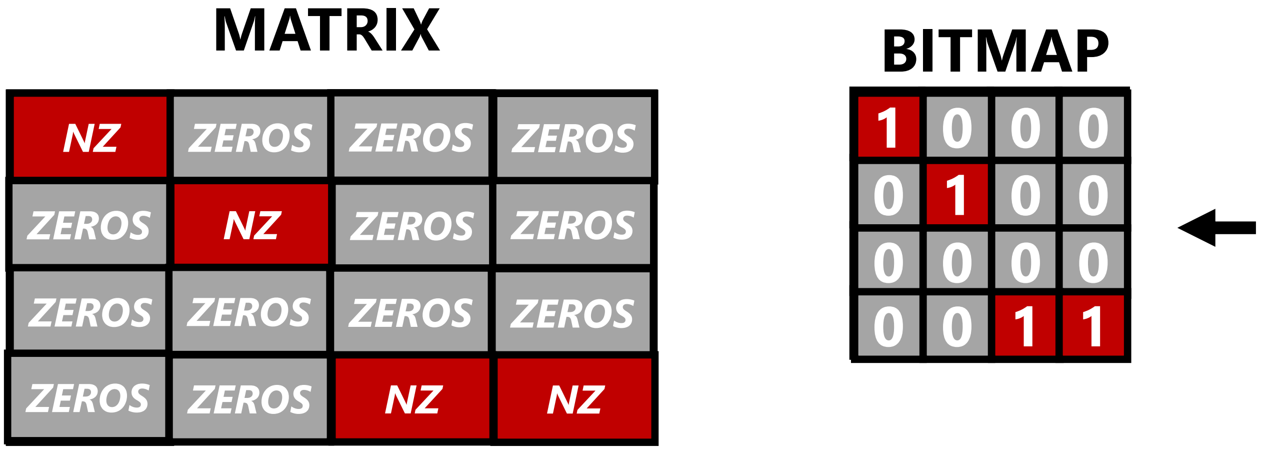
Efficient compression using a Hierarchy of Bitmaps

- Encodes the positions of non-zero elements using bits to maintain **low storage overhead**

SMASH: Software Compression Scheme

BITMAP:

Encodes if a block of the matrix contains any non-zero element



MATRIX

NZ	ZEROS	ZEROS	ZEROS
ZEROS	NZ	ZEROS	ZEROS
ZEROS	ZEROS	ZEROS	ZEROS
ZEROS	ZEROS	NZ	NZ

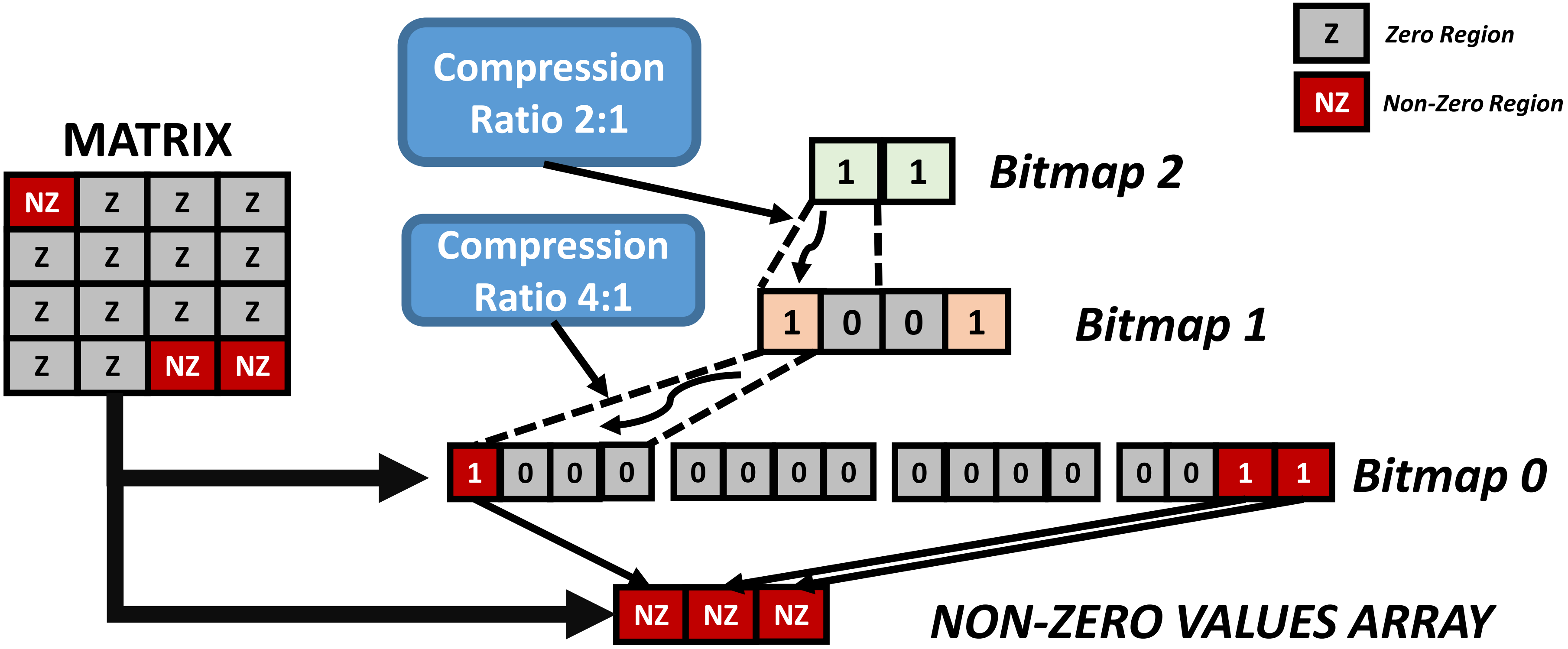
BITMAP

1	0	0	0
0	1	0	0
0	0	0	0
0	0	1	1

Might contain high number of zero bits

Idea: Apply the same encoding recursively to compress more effectively

Hierarchy of Bitmaps



MATRIX

NZ	Z	Z	Z
Z	Z	Z	Z
Z	Z	Z	Z
Z	Z	NZ	NZ

Storage Efficient

Fast Indexing

Hardware Friendly

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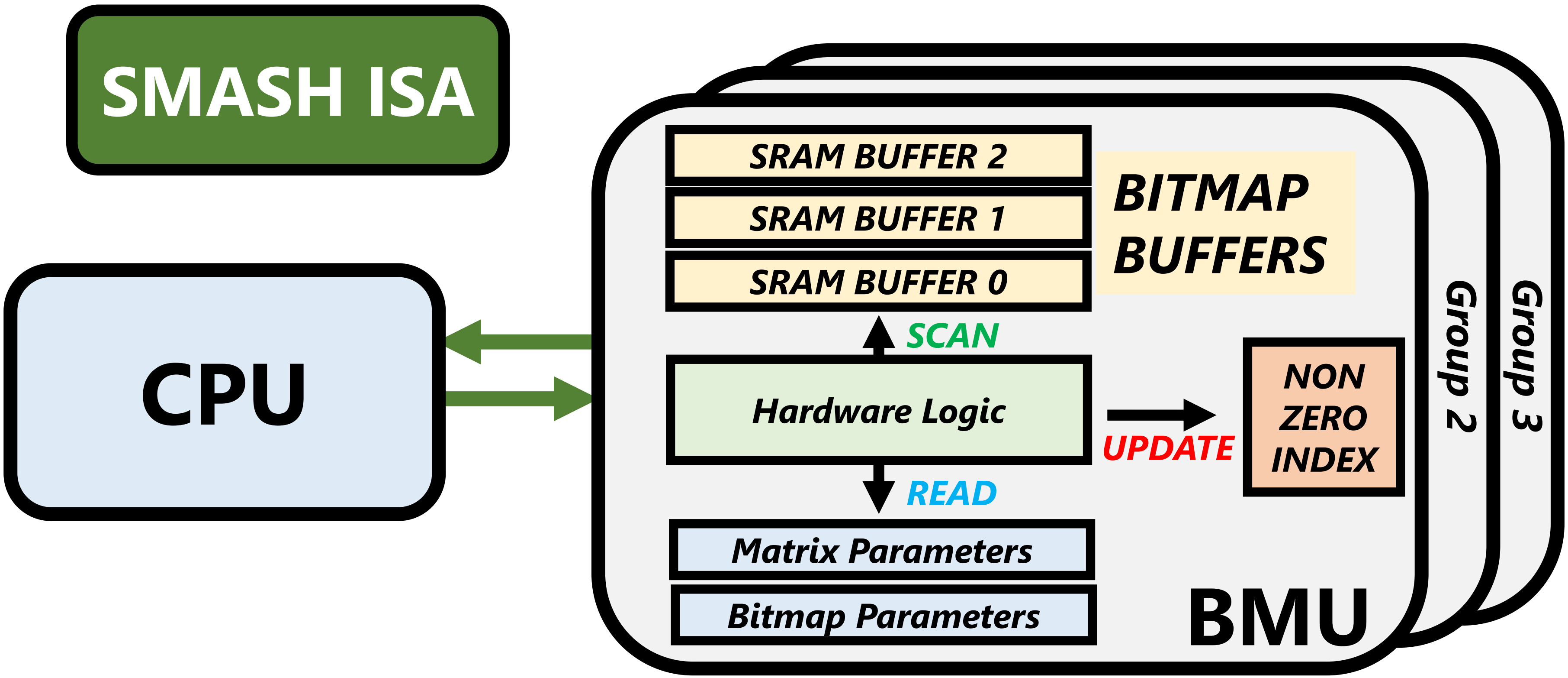
SMASH: Hardware Acceleration Unit

Hardware

Unit that scans bitmaps to accelerate indexing

- **Interprets** the **Bitmap Hierarchy** used in software
- **Buffers** the **Bitmap Hierarchy**
  and **scans** it using bitwise operations

Bitmap Management Unit (BMU)



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SMASH: Cross-Layer Interface

Need for a cross-layer interface that enables software to control the BMU

- **Communicate** the **parameters** needed to calculate the index
- **Query** the BMU to **retrieve the index** of the next non-zero element

SMASH ISA

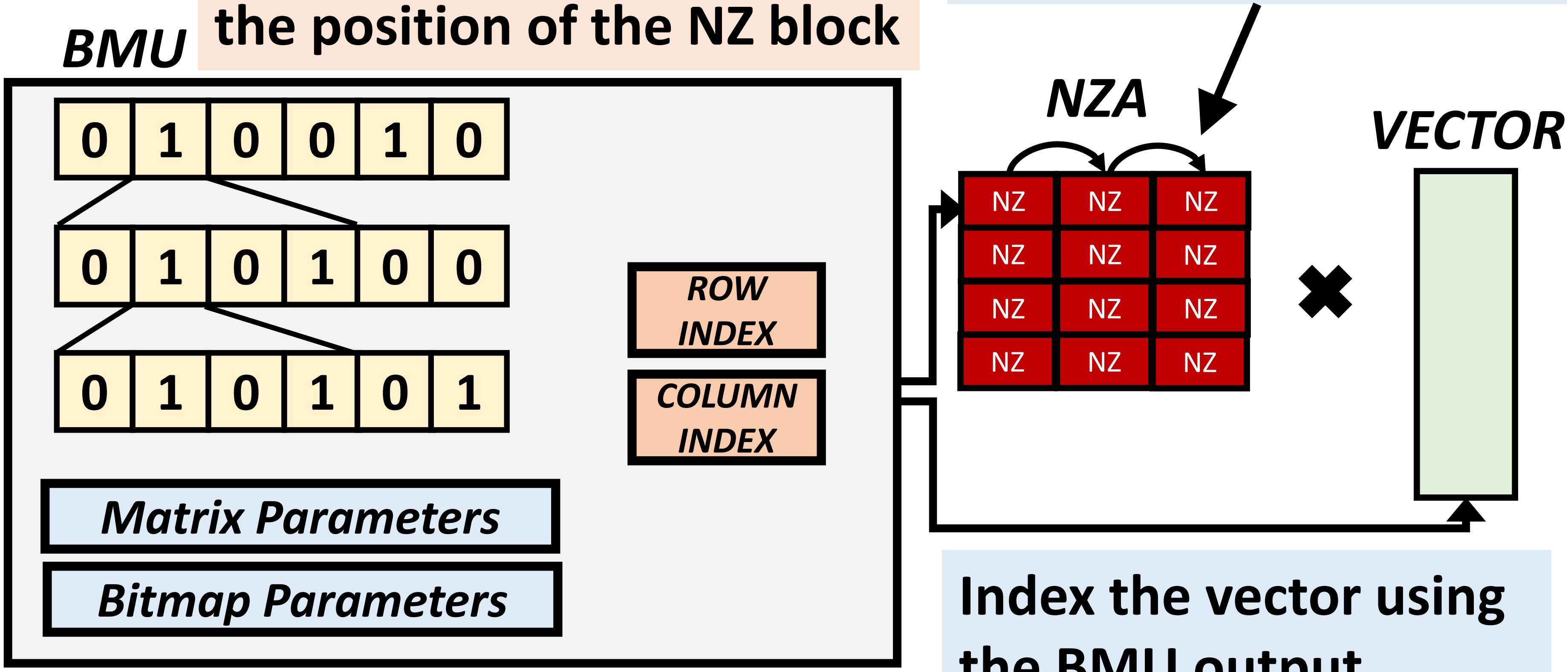
```
MATINFO
BMAPINFO
RDBMAP
PBMAP
RDIND
```

Enables SMASH to flexibly accelerate a diverse range of operations on any sparse matrix

Use Case: SpMV

Query the BMU to discover the position of the NZ block

STREAM THROUGH THE NON-ZERO BLOCKS



Index the vector using the BMU output

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Methodology

https://github.com/CMU-SAFARI/SMASH

Simulator: *ZSim* Simulator [1]

Workloads:

- **Sparse Matrix Kernels**

  SpMV & SpMM from TACO [2]

- **Graph Applications**

  PageRank & Betweenness Centrality from Ligra [3]

Input datasets:

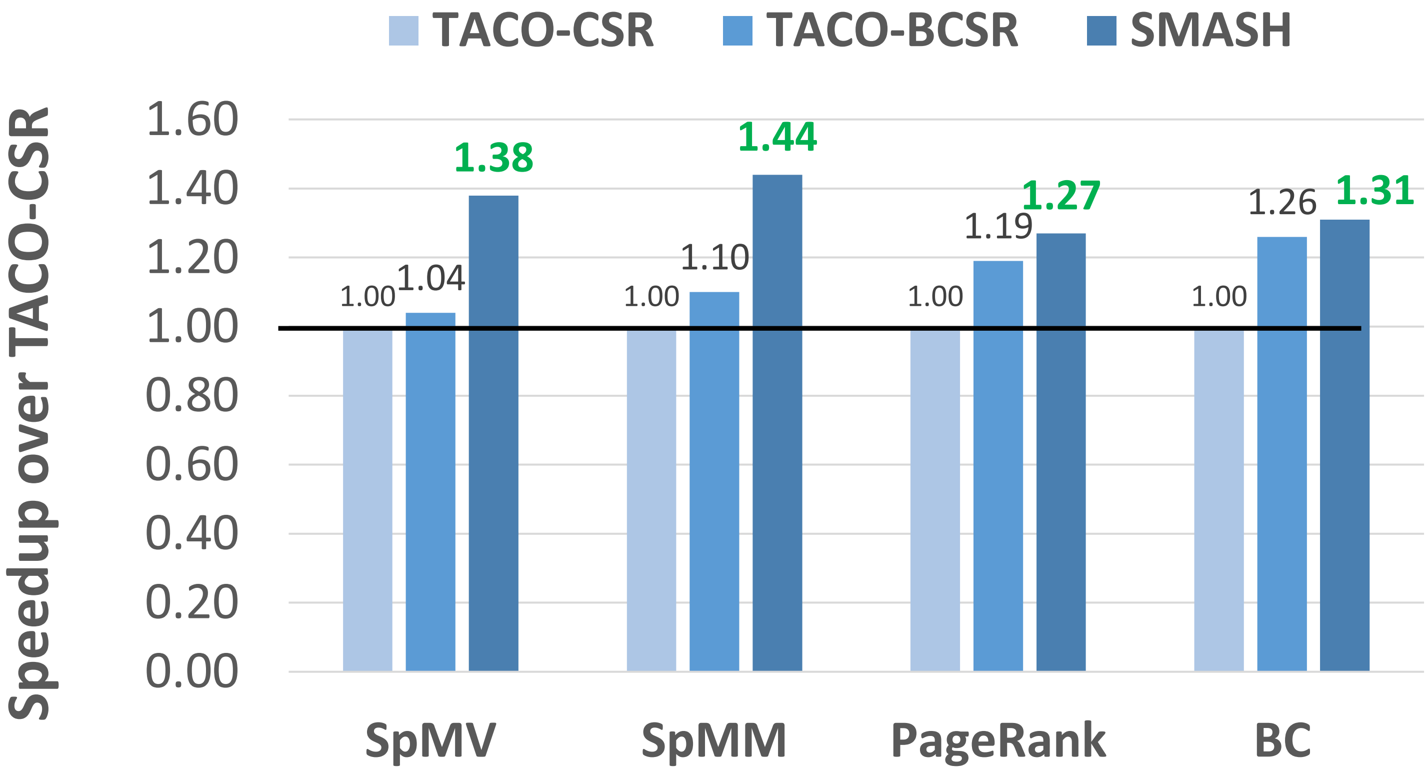
15 diverse sparse matrices & 4 graphs
from the Sparse Suite Collection [4]

[1] *Sanchez et al.* "ZSim: Fast and Accurate Microarchitectural Simulation of Thousand-Core Systems" ISCA'13
[2] *Kjolstad et al.* " taco: A Tool to Generate Tensor Algebra Kernels" ASE'17
[3] *Shun et al. "Ligra: A Lightweight Graph Processing Framework for Shared Memory" PPoPP'13*
[4] *Davis et al. "The University of Florida Sparse Matrix Collection" TOMS'11*

Evaluated Sparse Matrices

	Name	# Rows	Non-Zero Elements	Sparsity (%)
M1:	descriptor_xingo6u	20,738	73,916	0.01
M2:	g7jac060sc	17,730	183,325	0.06
M3:	Trefethen_20000	20,000	554,466	0.14
M4:	IG5-16	18,846	588,326	0.17
M5:	TSOPF_RS_b162_c3	15,374	610,299	0.26
M6:	ns3Da	20,414	1,679,599	0.40
M7:	tsyl201	20,685	2,454,957	0.57
M8:	pkustk07	16,860	2,418,804	0.85
M9:	ramage02	16,830	2,866,352	1.01
M10:	pattern1	19,242	9,323,432	2.52
M11:	gupta3	16,783	9,323,427	3.31
M12:	nd3k	9,000	3,279,690	4.05
M13:	human_gene1	22,283	24,669,643	4.97
M14:	exdata_1	6,001	2,269,500	6.30
M15:	human_gene2	14,340	18,068,388	8.79

Performance Improvement Using SMASH



SMASH provides significant performance improvements over state-of-the-art formats

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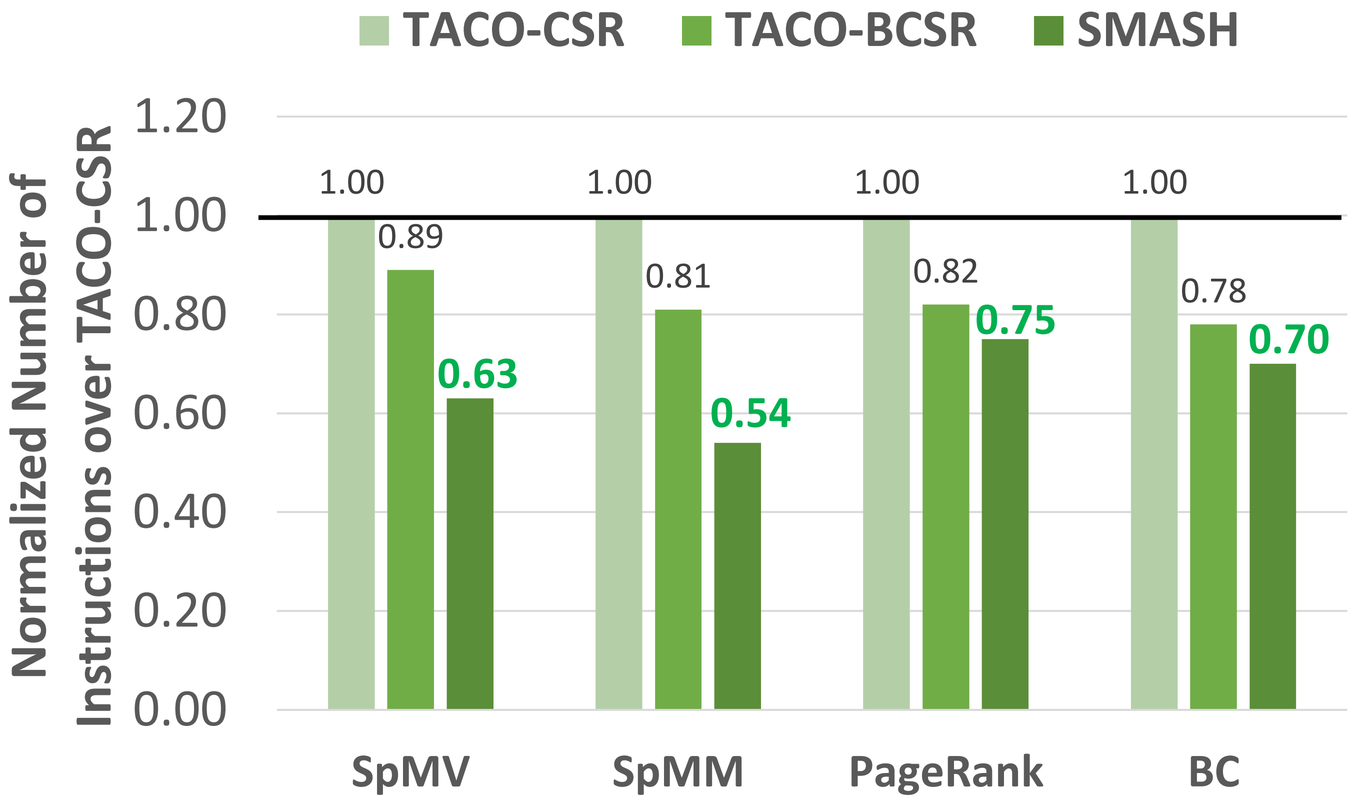
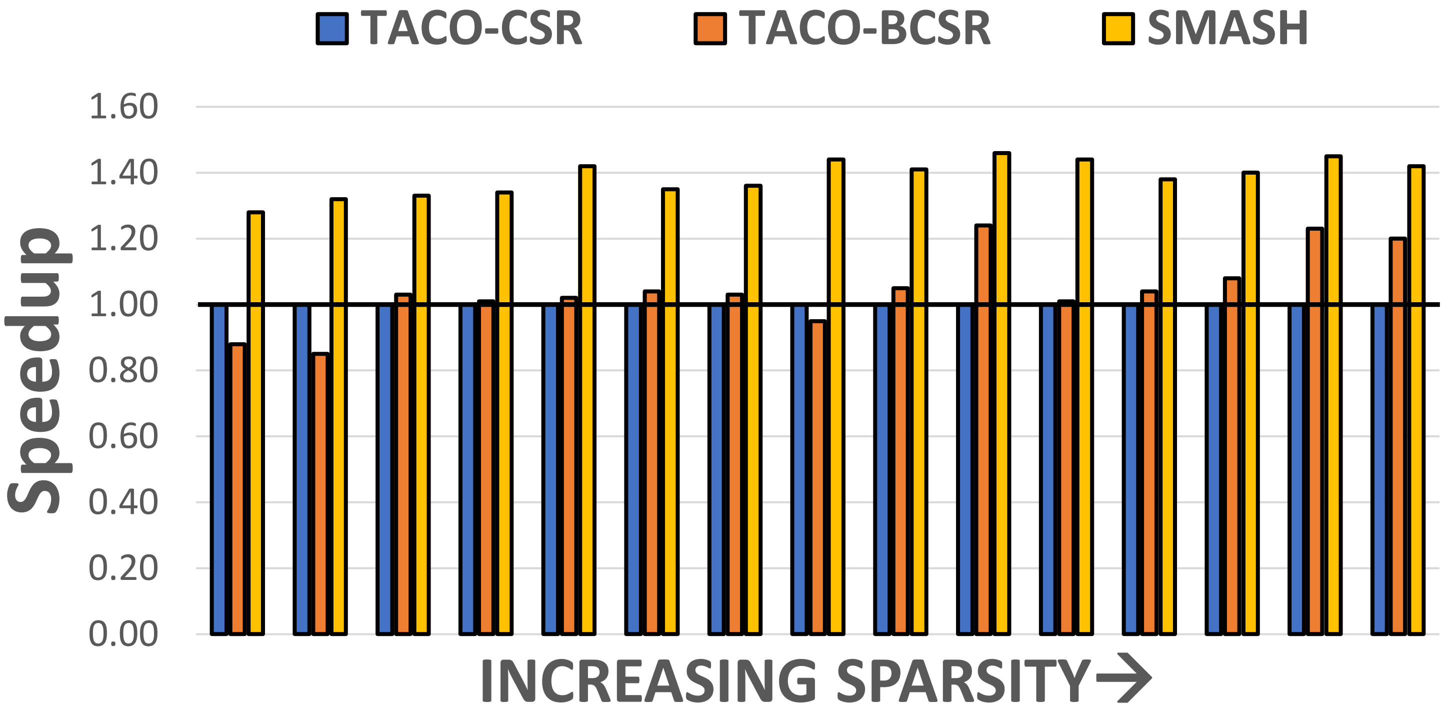
Number of Executed Instructions



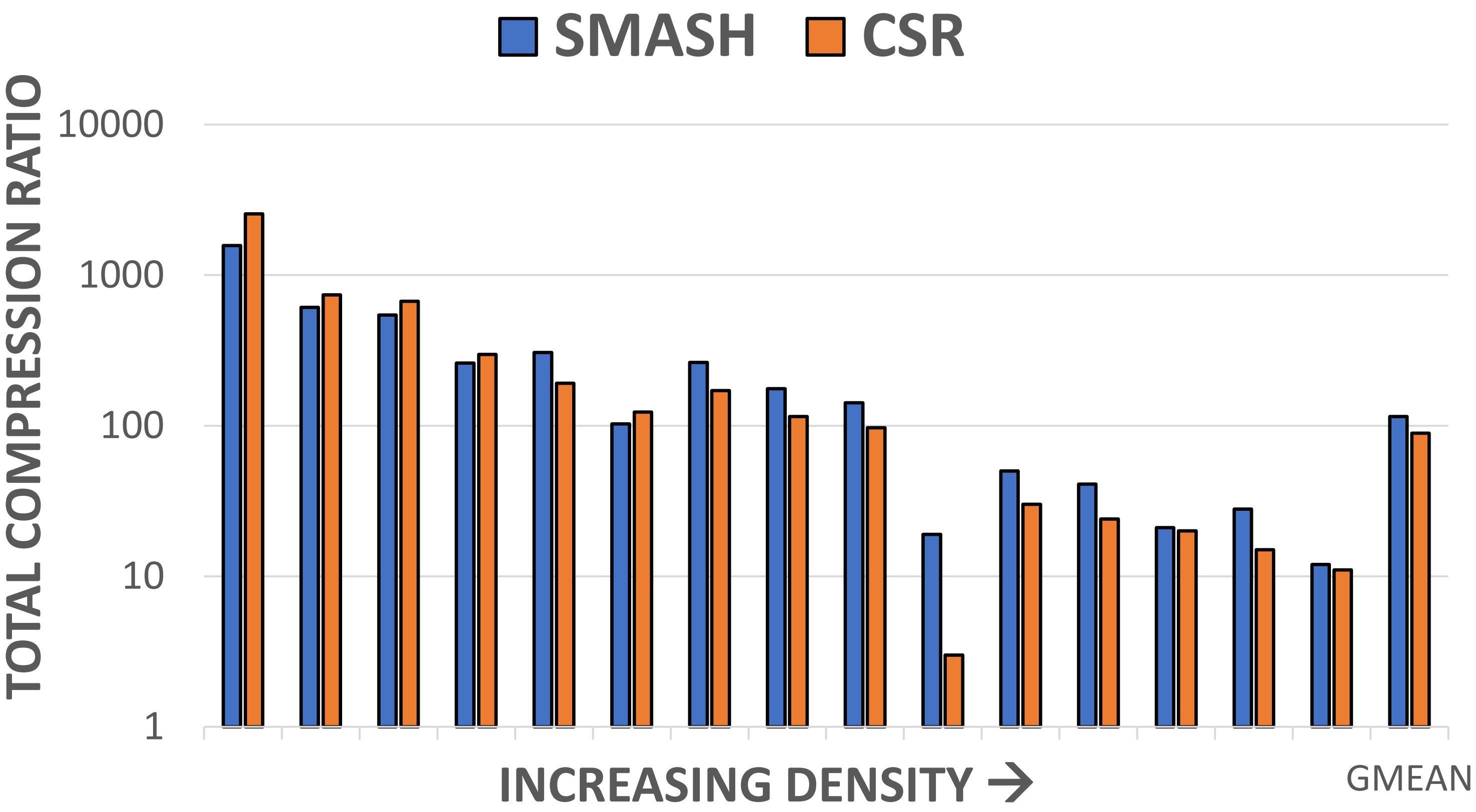
SMASH significantly reduces the number of executed instructions

Sparsity Sweep for SpMV



SMASH provides speedups regardless of the sparsity of the matrix

Storage Efficiency



SMASH efficiently compresses sparse matrices

Hardware Area Overhead

SMASH configuration

- Support for 4 matrices in the BMU
- 256 bytes / SRAM buffer
- 140 bytes for registers & counters

0.076% area overhead over an Intel Xeon CPU

SMASH incurs negligible area overhead

Other Results in the Paper

- Compression ratio sensitivity analysis
- Distribution of non-zero elements
- Detailed results for SpMM
- Conversion from CSR to SMASH overhead
- Software-only approaches executed in a real machine

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Summary & Conclusion

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Discussion

- How does SMASH work when the algorithm traverses the matrix in an irregular way?
- Remove decompression from the critical path?
- Use In-memory bitwise operations to find which operations result in 0s (before execution)?
- Determine the bitmap parameters on the fly?
- Can we use a similar mechanism in GPUs?

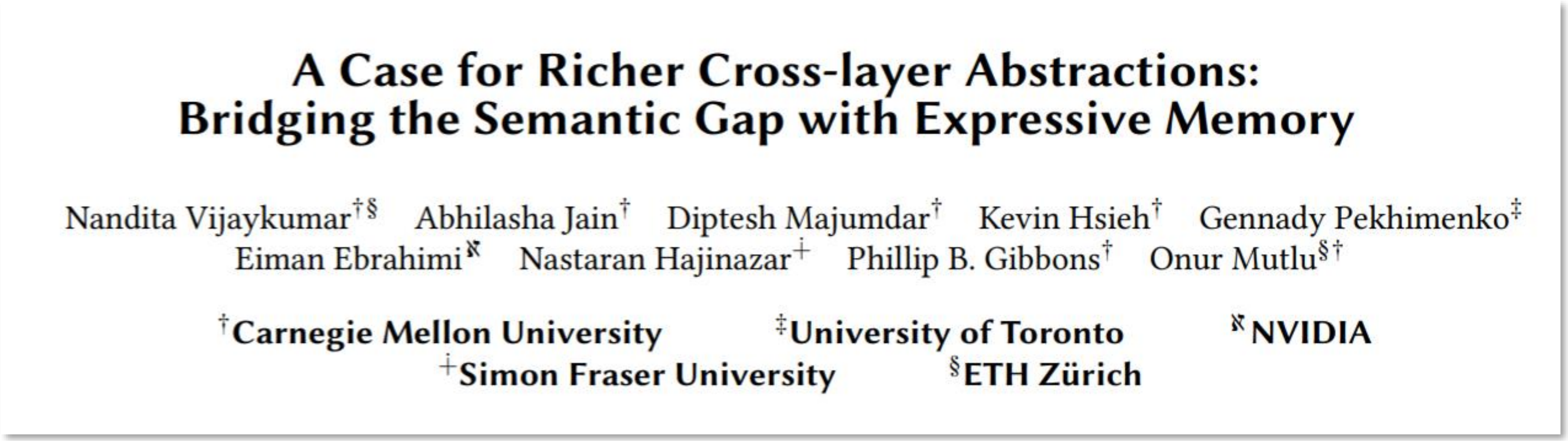
New Directions: Sparse Workloads

Metadata Management

Traversal Scheduling

Metadata Management

A Case for Richer Cross-layer Abstractions: Bridging the Semantic Gap with Expressive Memory
Nandita Vijaykumar, Abhilasha Jain, Diptesh Majumdar, Kevin Hsieh, Gennady Pekhimenko,
Eiman Ebrahimi, Nastaran Hajinazar, Phillip B. Gibbons, Onur Mutlu
ISCA 2018 *Slides (pptx) (pdf) Lightning Talk Slides (pptx) (pdf) Lightning Talk Video*



A Case for Richer Cross-layer Abstractions: Bridging the Semantic Gap with Expressive Memory

Nandita Vijaykumar[†§] Abhilasha Jain[†] Diptesh Majumdar[†] Kevin Hsieh[†] Gennady Pekhimenko[‡]
Eiman Ebrahimi[ℵ] Nastaran Hajinazar[+] Phillip B. Gibbons[†] Onur Mutlu[§†]

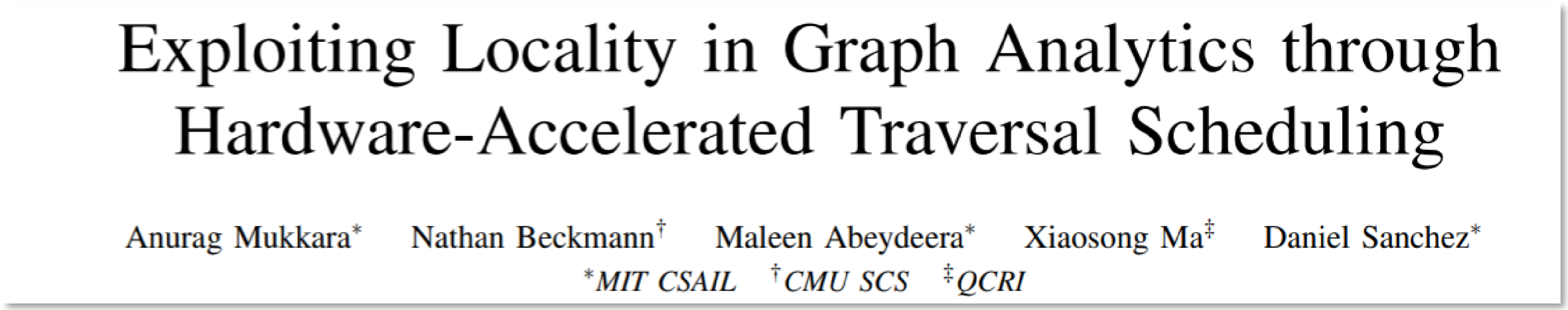
[†]Carnegie Mellon University [‡]University of Toronto [ℵ]NVIDIA
[+]Simon Fraser University [§]ETH Zürich

Metadata Management

- What kind of **high-level semantic information** are needed to enable efficient memory optimizations in sparse workloads?
- What kind of **memory optimizations** can we enable using high-level semantic information?
- How can we perform **low-cost metadata management** without introducing performance overheads?

Traversal Scheduling in Graph Analytics

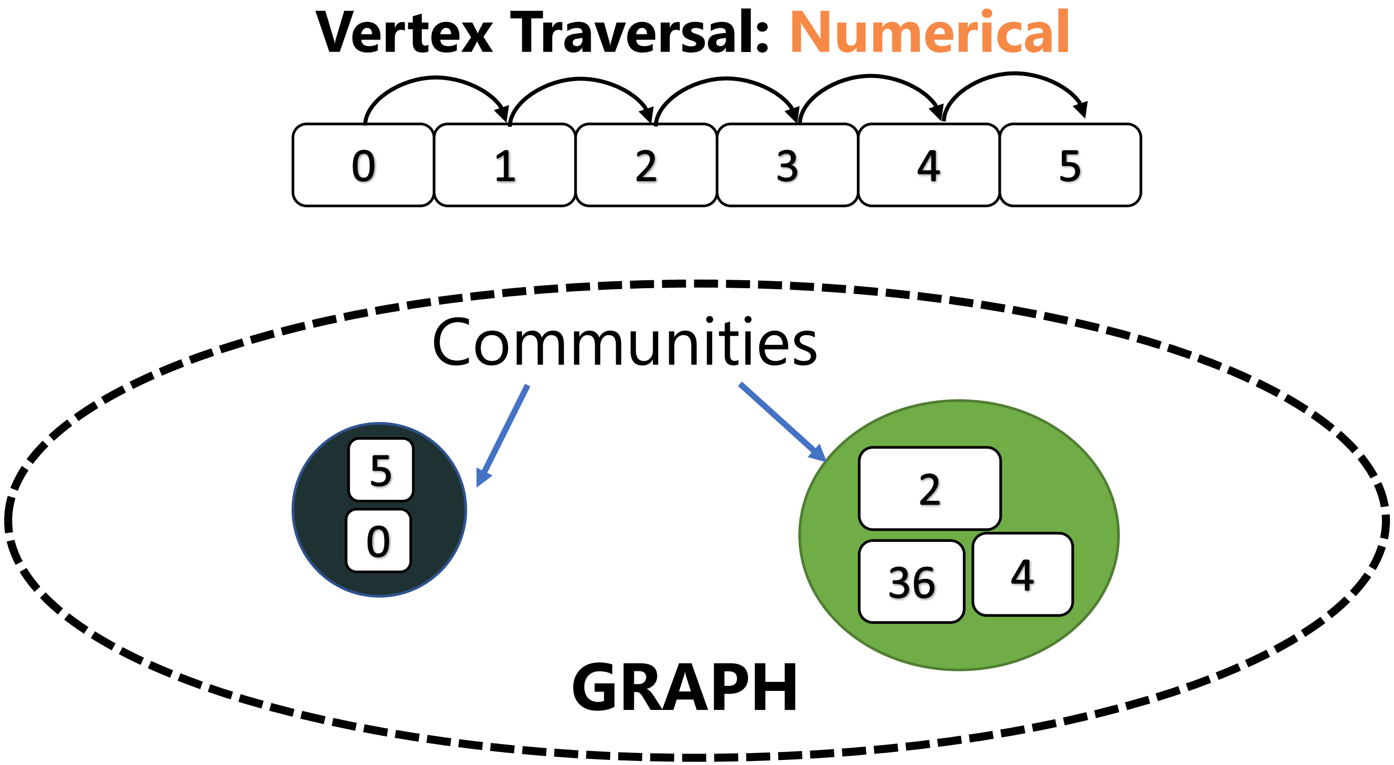
Mukkara et al. MICRO 2018 [PDF]



Exploiting Locality in Graph Analytics through Hardware-Accelerated Traversal Scheduling

Anurag Mukkara[*] Nathan Beckmann[†] Maleen Abeydeera[*] Xiaosong Ma[‡] Daniel Sanchez[*]
[*]*MIT CSAIL* [†]*CMU SCS* [‡]*QCRI*

Traversal: Numerical Vertex Ordering



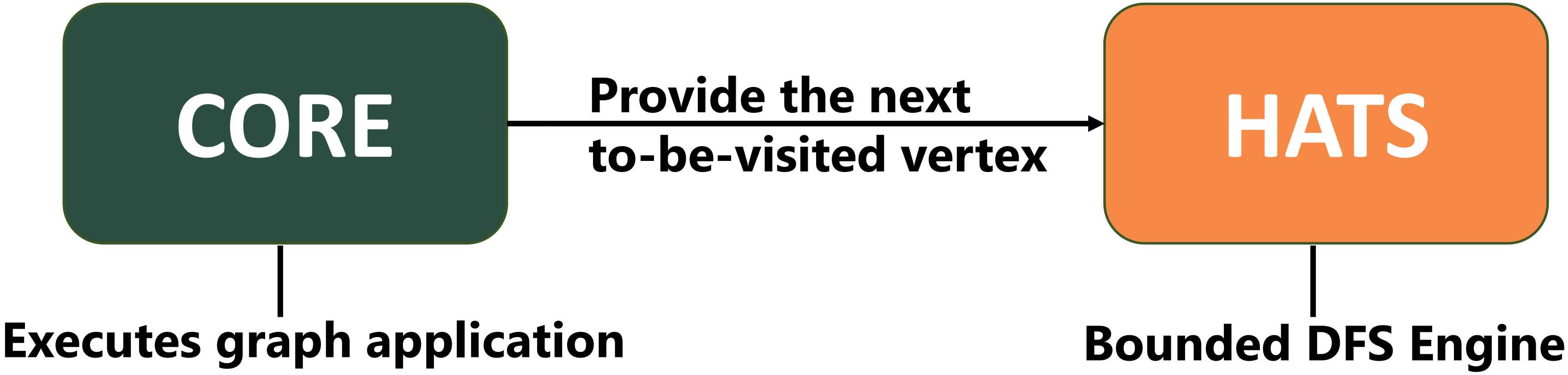
Performing the graph traversal in numerical order does NOT align with the community-driven semantics of the graph input.

WE NEED TO TRAVERSE INTELLIGENTLY

State-of-the-art: Heuristic-based

State-of-the-art Hardware-based Reordering [HATS MICRO 18]:

- Detect communities online/during runtime
- Heuristic-based Depth-First Search approach
- Hardware-accelerator to support the heuristic-based community search



Need for a more fundamental and robust reordering technique

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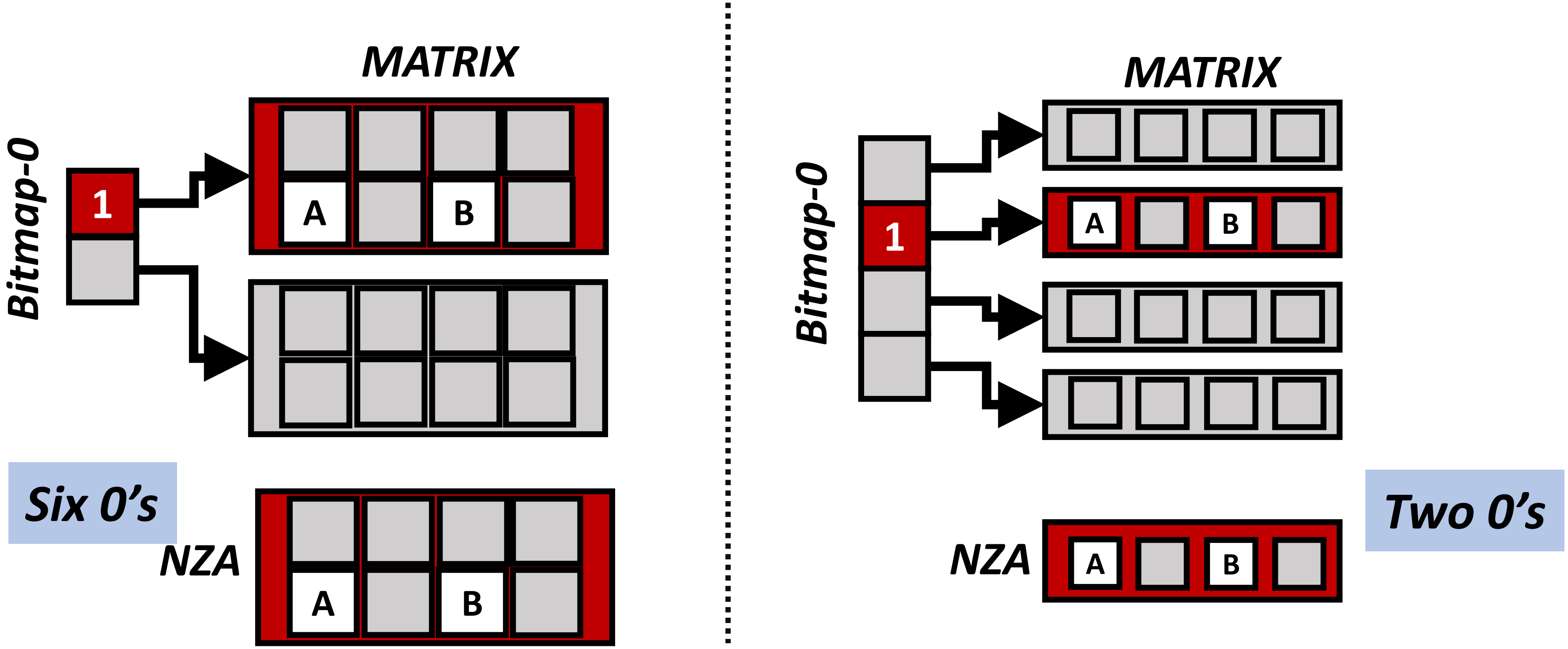
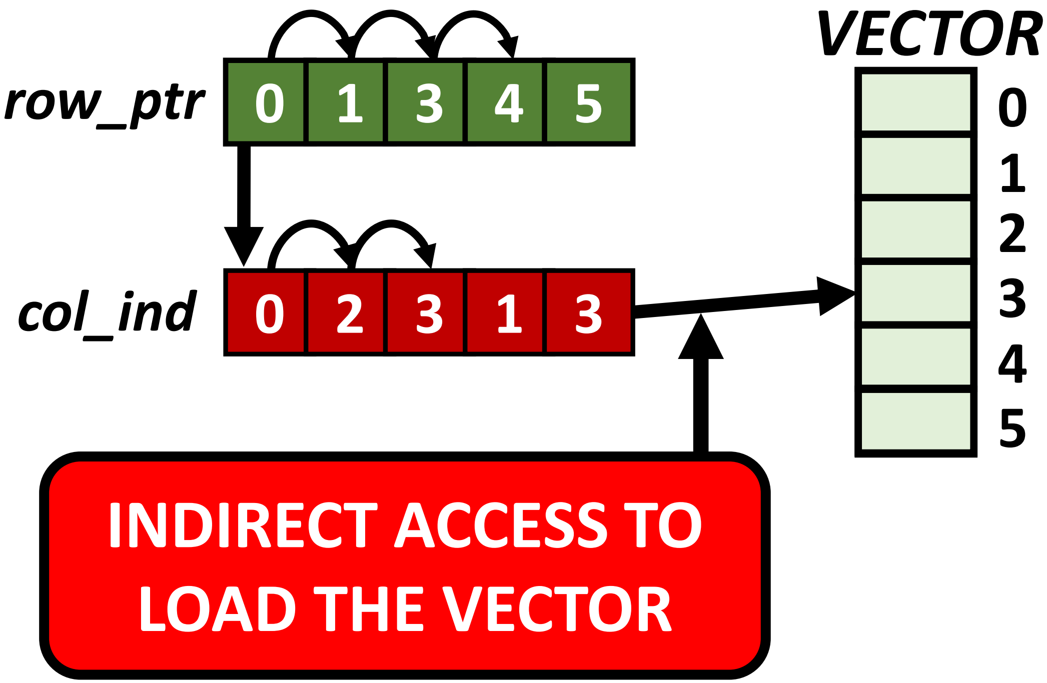
Compression Ratio

SMALL BITMAPS VS **ZERO COMPUTATION**



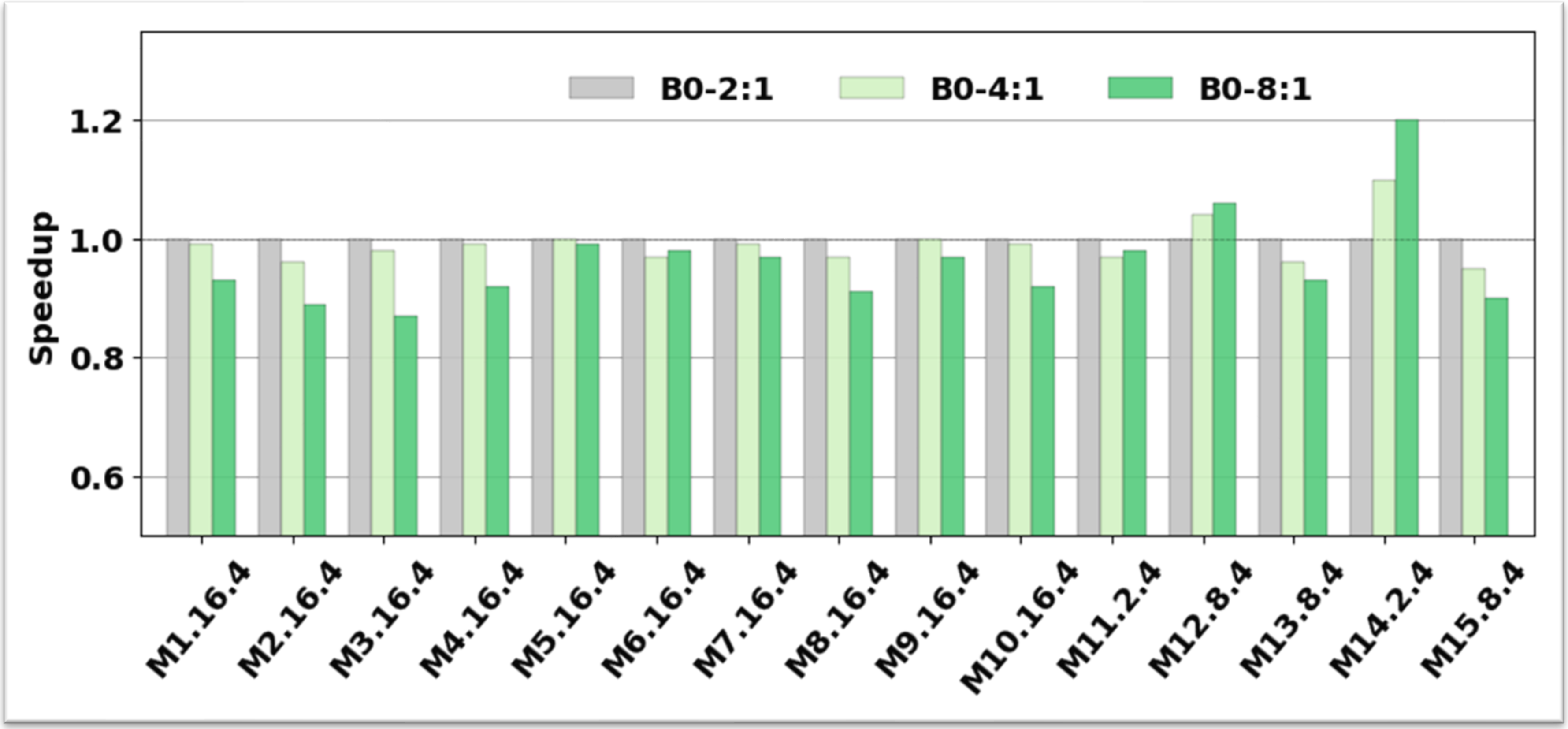
CSR-based SpMV

CSR-based SpMV

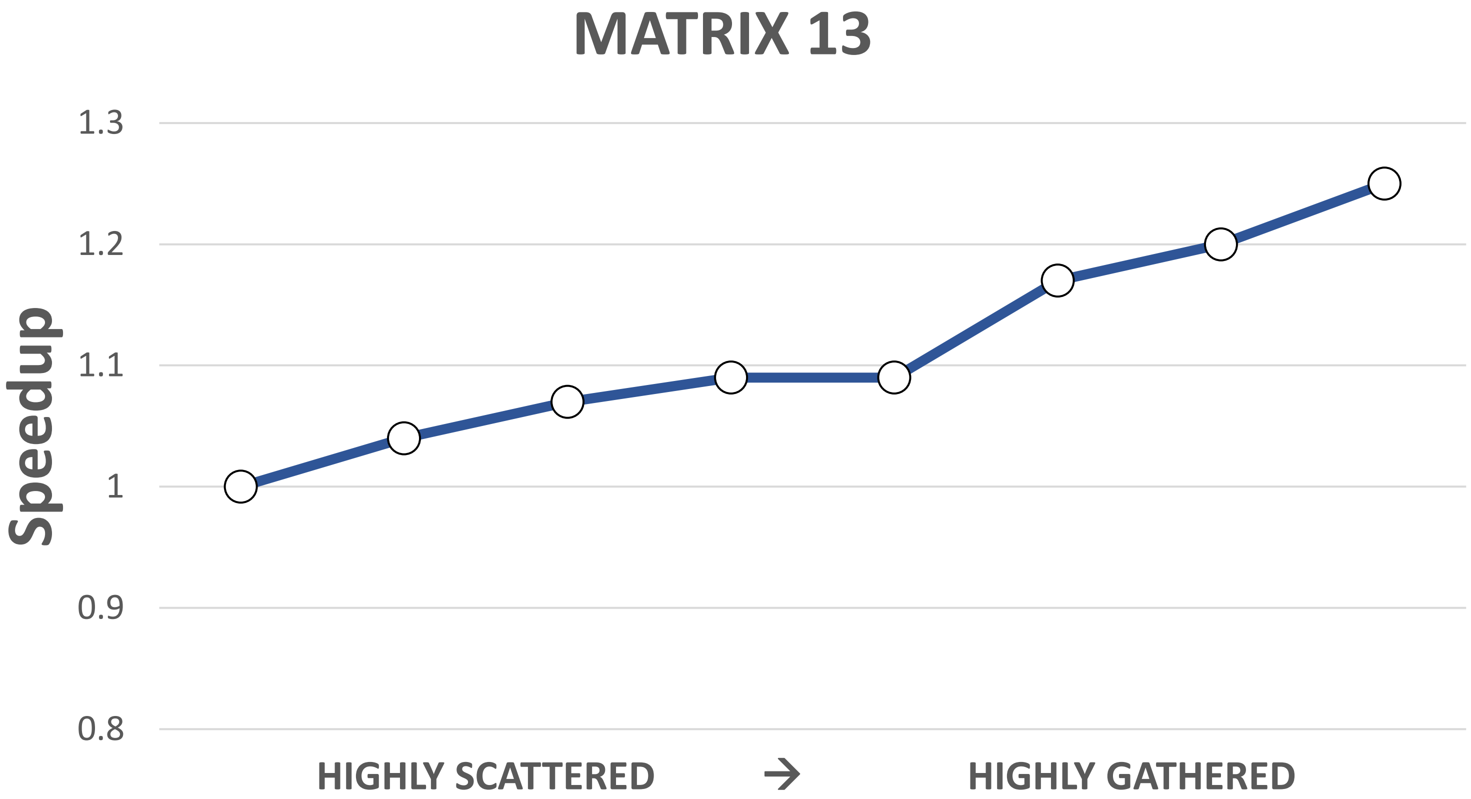


INDIRECT ACCESS TO LOAD THE VECTOR

Effect of Compression Ratio

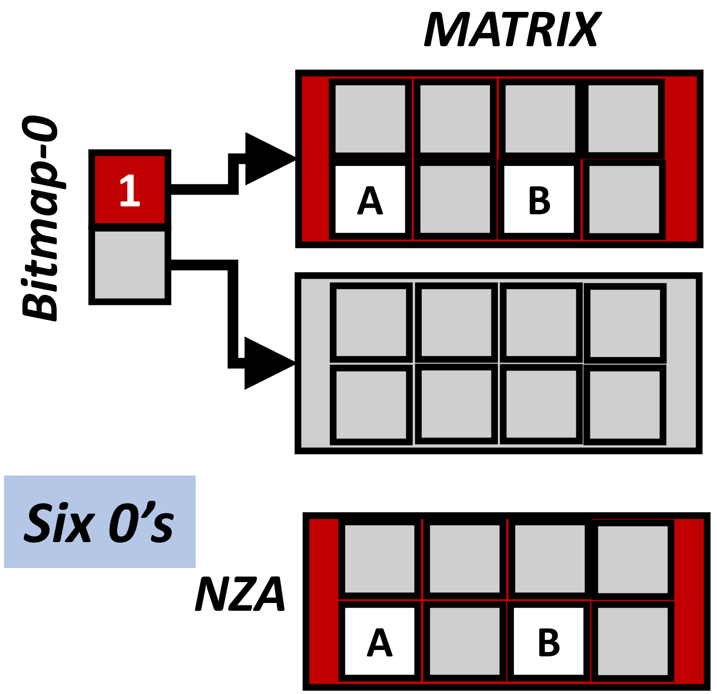


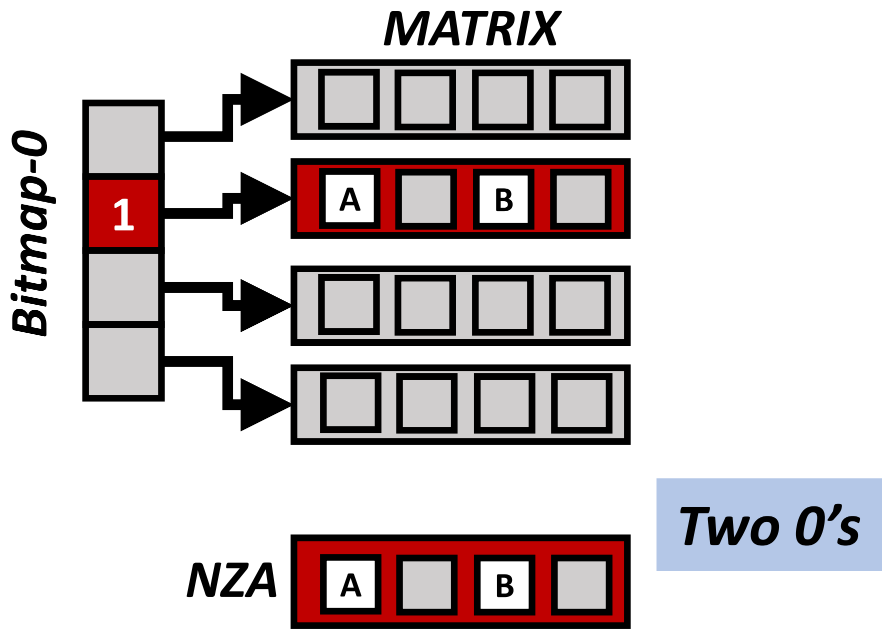
Distribution of non-zero elements



Compression Ratio Selection

SMALL BITMAPS VS ZERO COMPUTATION


MATRIX
Bitmap-0
1
A
B
Six 0’s
NZA
A
B


MATRIX
Bitmap-0
1
A
B
NZA
A
B
Two 0’s