

# ASCELLA: Accelerating Sparse Computation by Enabling Stream Accesses to Memory

Bahar Asgari, Ramyad Hadidi, Hyesoon Kim



**comparch**

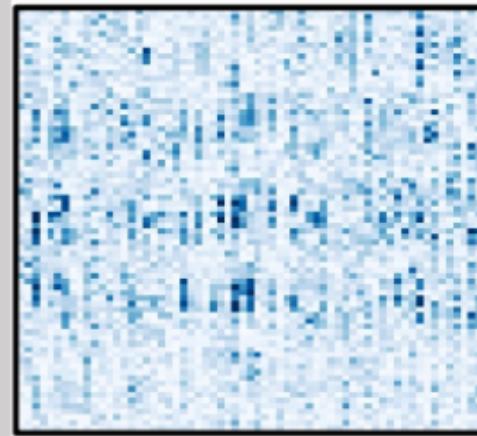


# Sparse matrices are everywhere!

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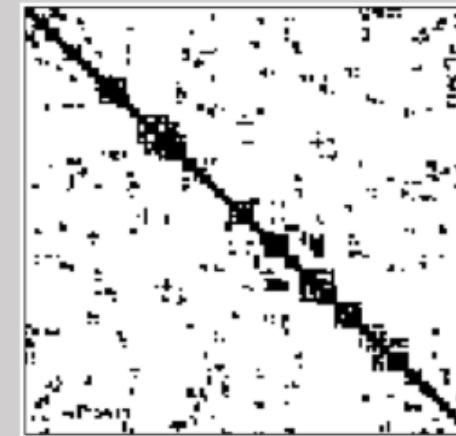
Sparse matrix vector multiplication (SpMV) is a main operation in:

**Neural Networks**



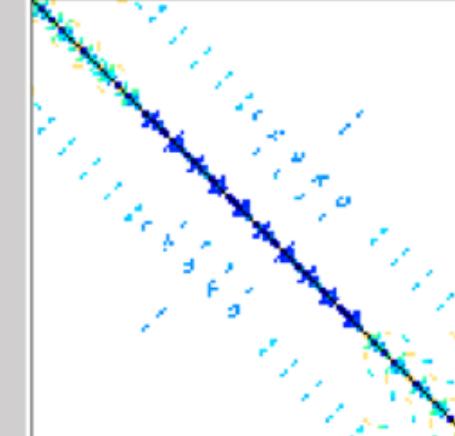
The weight matrix  
is sparse

**Graph Analytics**



The adjacency matrix  
is sparse

**Differential Equations**



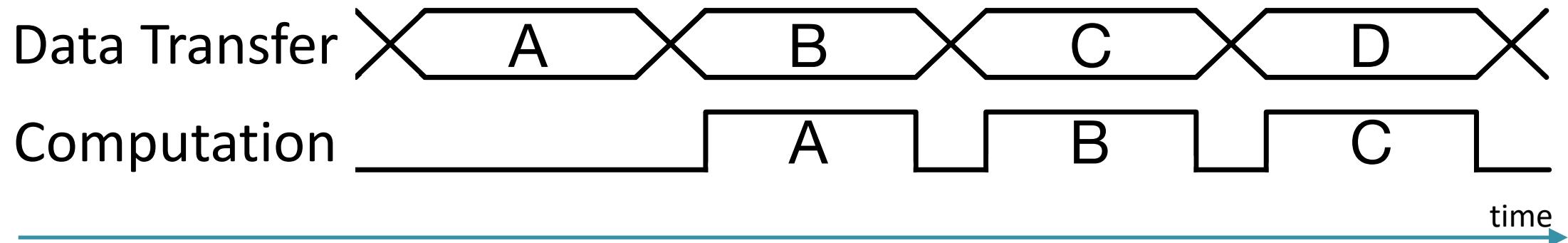
The coefficient matrix  
is sparse



# An ideal hardware accelerator for SpMV

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- ▶ SpMV can be accelerated:
  - ▶ By stream data from memory
  - ▶ By using a parallel dot product engine
- ▶ Ideally, we want compute time and data-transfer time for blocks of data (e.g., A, B, C, and D) to be equal:

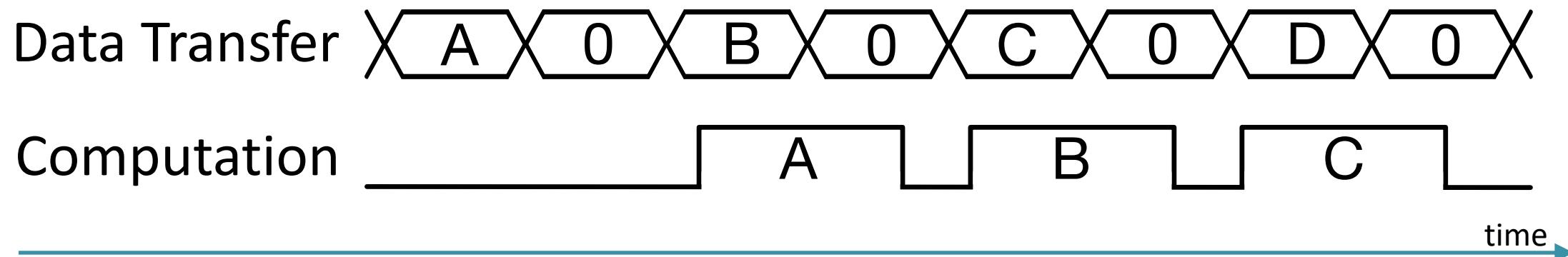


\*a block is the unit of streaming data from memory



# Decompression can cause a bottleneck

- ▶ Sparse matrices are often stored and transferred in compressed forms
  - ▶ Example: compressed sparse row (CSR) and blocked CSR (BCSR)
- ▶ The compressed data must be first decompressed
- ▶ Decompression is slow and causes bottleneck





# Why decompression is slow?

CSR and BCSR use three vectors to represent a sparse matrix

- ▶ Row indices (offsets)
- ▶ Column indices
- ▶ Values

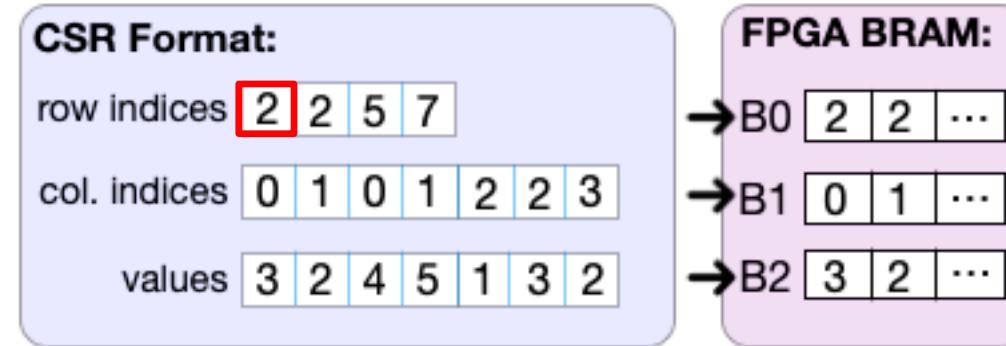
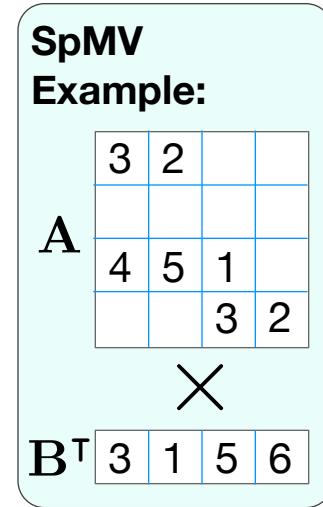
To decompress a non-zero row, we need to

- ▶ First, read one element of row indices
- ▶ Then, read column indices and values as required



# Decompression from CSR format

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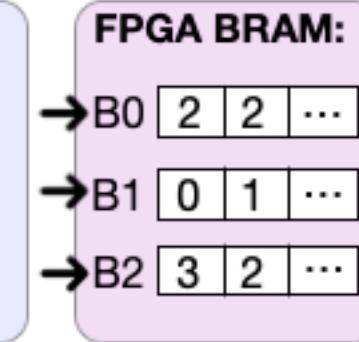
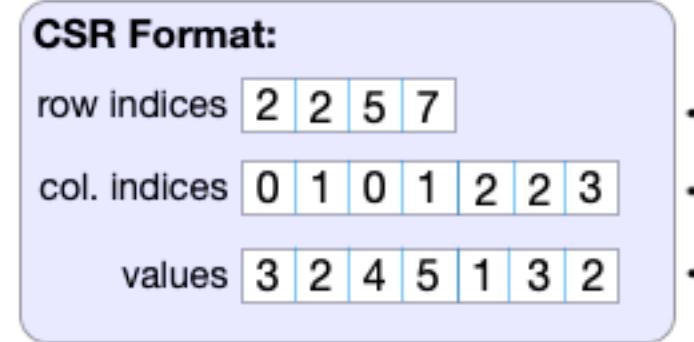
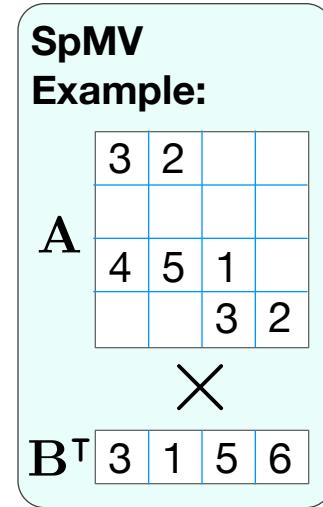


<b>BRAM Accesses Timeline:</b>						
cycle: 0	1	2	3	4	5	6
<b>R</b> B0 → 2						
	8	9	10	11	12	13



# Decompression from CSR format

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**BRAM Accesses Timeline:**

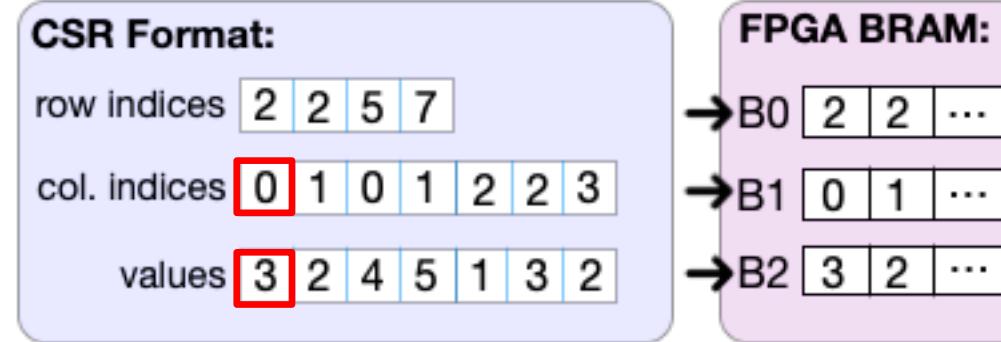
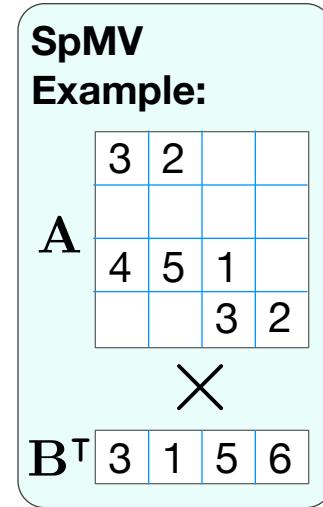
**R** Read Operation    **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0 $\rightarrow$ 2	<b>C</b> 2-0=2					
cycle: 7	8	9	10	11	12	13



# Decompression from CSR format

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**BRAM Accesses Timeline:**

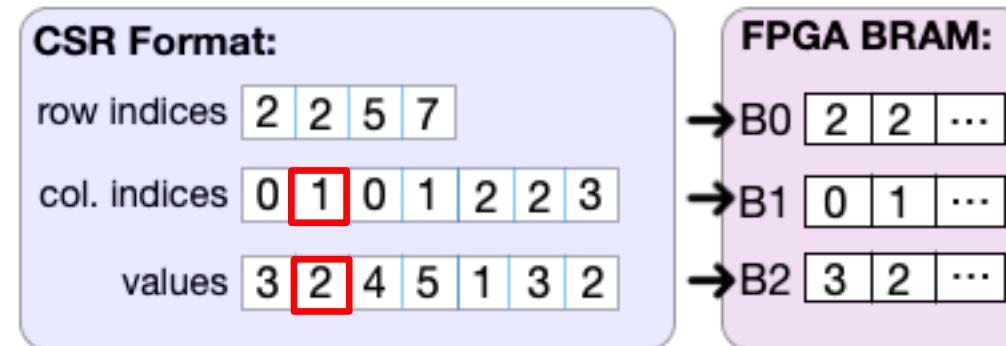
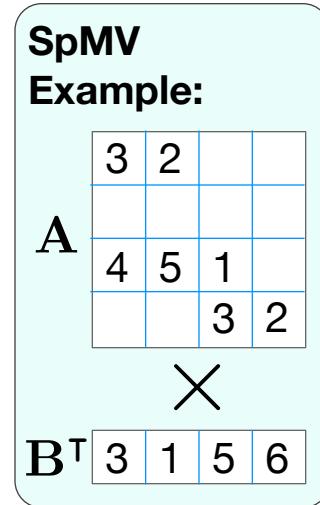
**R** Read Operation    **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0 $\rightarrow$ 2	<b>C</b> 2-0=2	<b>R</b> B1 $\rightarrow$ 0 <b>R</b> B2 $\rightarrow$ 3				
cycle: 7	8	9	10	11	12	13



# Decompression from CSR format

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**BRAM Accesses Timeline:**

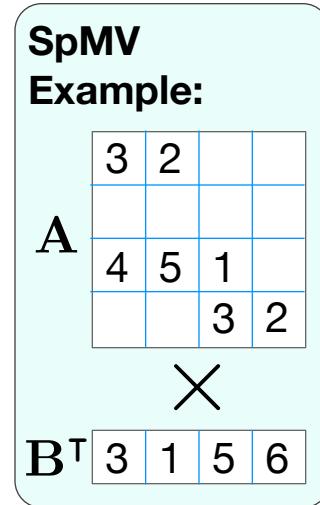
R Read Operation      C Compute Operation

cycle: 0	1	2	3	4	5	6
R B0 → 2	C 2-0=2	R B1 → 0 R B2 → 3	R B1 → 1 R B2 → 2			
cycle: 7	8	9	10	11	12	13



# Decompression from CSR format

10



**BRAM Accesses Timeline:**

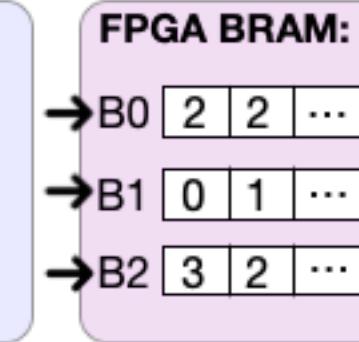
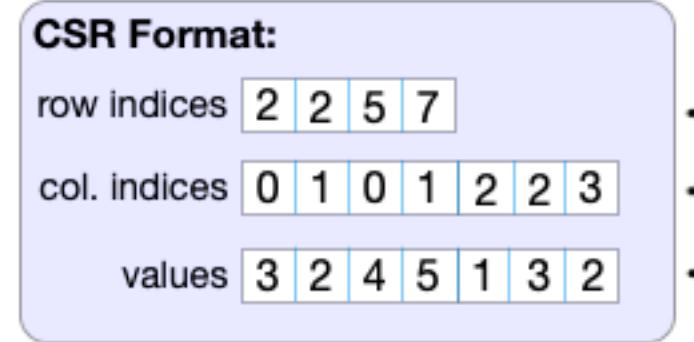
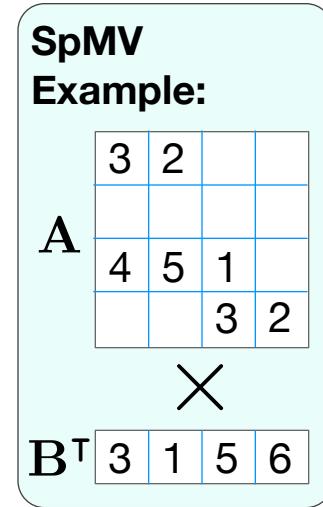
**R** Read Operation      **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→2	<b>C</b> 2-0=2	<b>R</b> B1→0 <b>R</b> B2→3	<b>R</b> B1→1 <b>R</b> B2→2	<b>R</b> B0→2		
cycle: 7	8	9	10	11	12	13



# Decompression from CSR format

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**BRAM Accesses Timeline:**

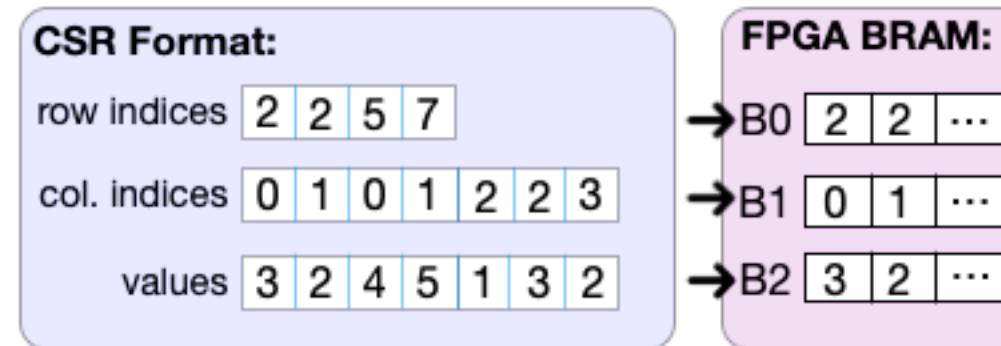
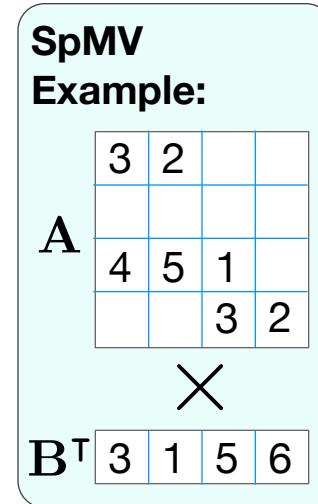
R Read Operation      C Compute Operation

cycle: 0	1	2	3	4	5	6
R B0→2	C 2-0=2	R B1→0 R B2→3	R B1→1 R B2→2	R B0→2	C 2-2=0	
	8	9	10	11	12	13



# Decompression from CSR format

12



**BRAM Accesses Timeline:**

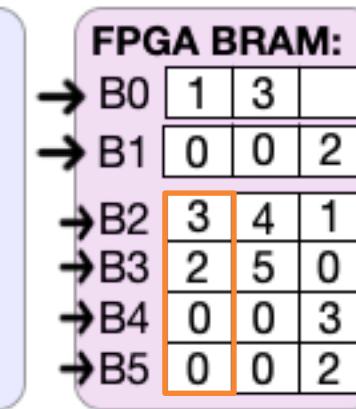
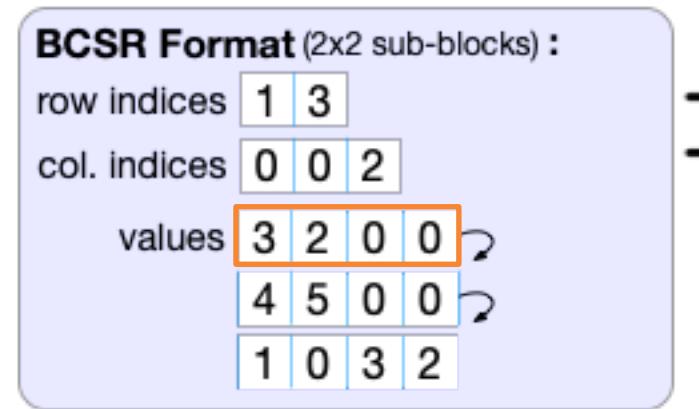
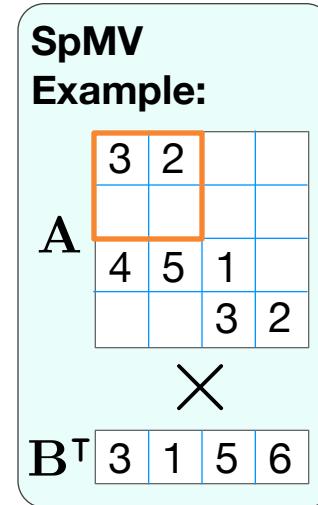
**R** Read Operation      **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→2	<b>C</b> 2-0=2	<b>R</b> B1→0 <b>R</b> B2→3	<b>R</b> B1→1 <b>R</b> B2→2	<b>R</b> B0→2	<b>C</b> 2-2=0	<b>R</b> B0→5
cycle: 7	8	9	10	11	12	13
<b>C</b> 5-2=3	<b>R</b> B1→0 <b>R</b> B2→4	<b>R</b> B1→1 <b>R</b> B2→5	<b>R</b> B1→2 <b>R</b> B2→1	<b>C</b> 7-5=2	<b>R</b> B1→2 <b>R</b> B2→3	<b>R</b> B1→3 <b>R</b> B2→2



# Decompression from BCSR format

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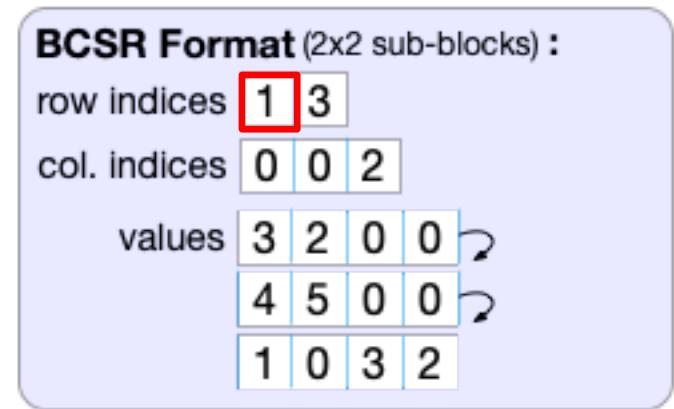
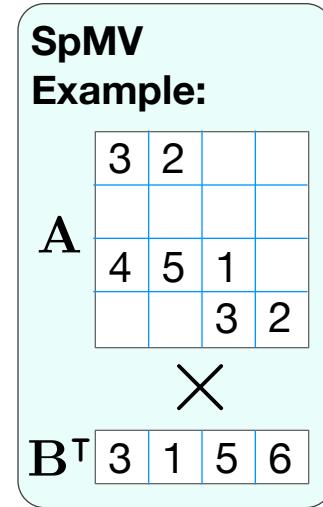


<b>BRAM Accesses Timeline:</b>						
cycle: 0	1	2	3	4	5	6



# Decompression from BCSR format

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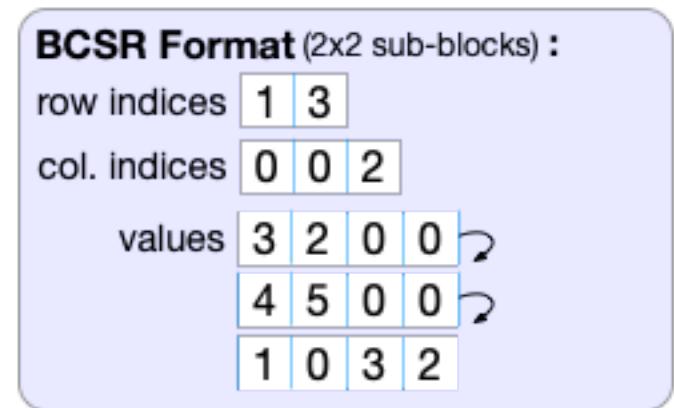
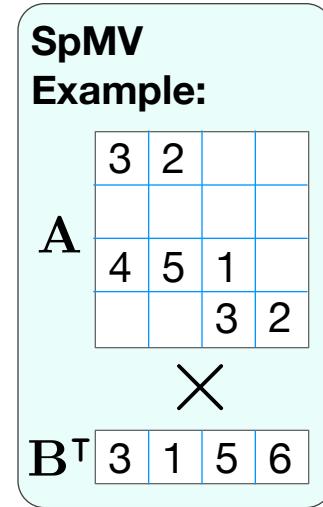


BRAM Accesses Timeline:						
cycle: 0	1	2	3	4	5	6
<b>R</b> B0 → 1						



# Decompression from BCSR format

15

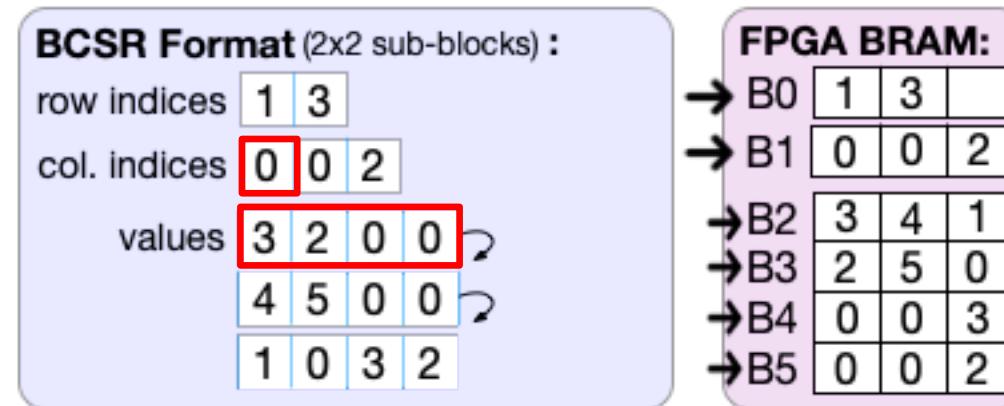
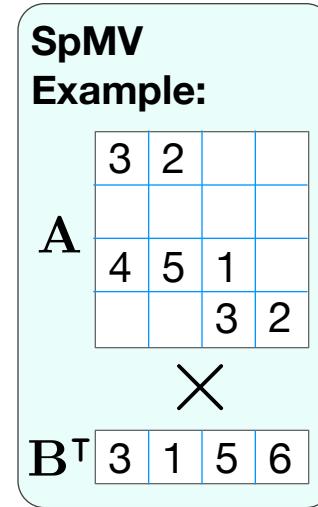


<b>BRAM Accesses Timeline:</b>							
cycle: 0	1	2	3	4	5	6	
<b>R</b> B0 → 1	<b>C</b> 1-0=1						



# Decompression from BCSR format

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**BRAM Accesses Timeline:**

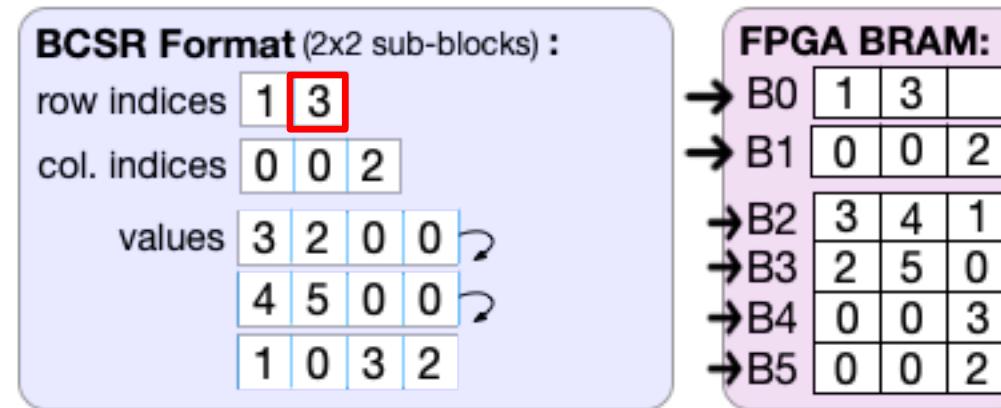
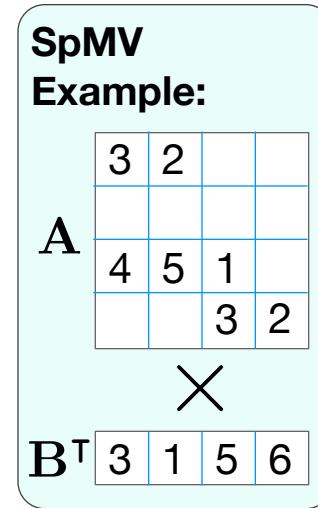
**R** Read Operation      **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→1	<b>C</b> 1-0=1	<b>R</b> B1→0				
		<b>R</b> B2→3				
		<b>R</b> B3→2				
		<b>R</b> B4→0				
		<b>R</b> B5→0				



# Decompression from BCSR format

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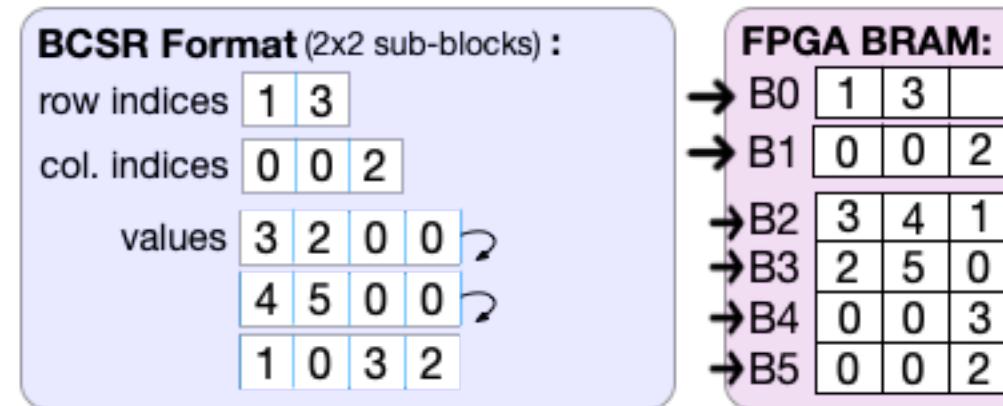
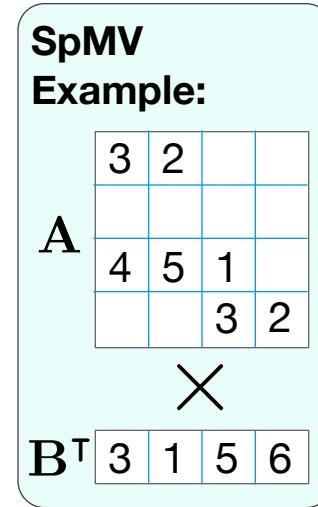
**BRAM Accesses Timeline:**

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→1	<b>C</b> 1-0=1	<b>R</b> B1→0 <b>R</b> B2→3 <b>R</b> B3→2 <b>R</b> B4→0 <b>R</b> B5→0	<b>R</b> B0→3			



# Decompression from BCSR format

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**BRAM Accesses Timeline:**

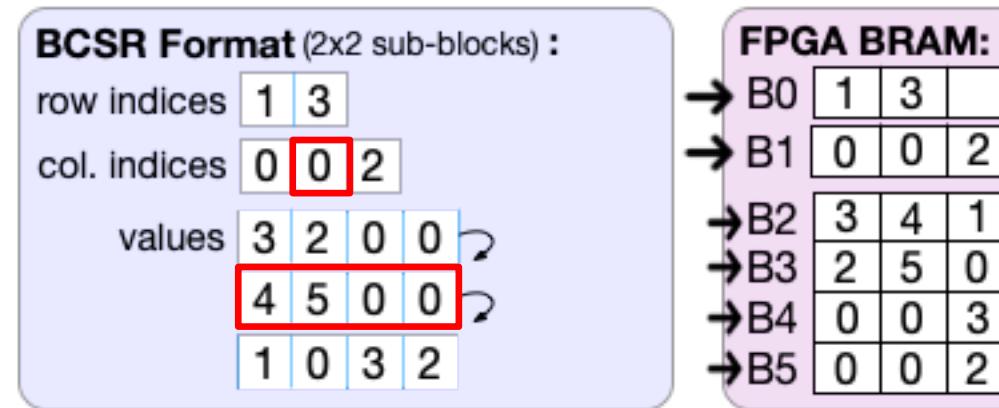
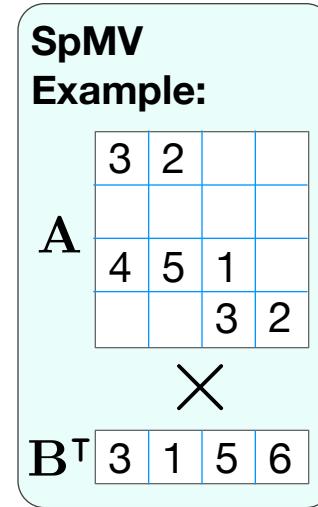
**R** Read Operation      **C** Compute Operation

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→1	<b>C</b> 1-0=1	<b>R</b> B1→0 <b>R</b> B2→3 <b>R</b> B3→2 <b>R</b> B4→0 <b>R</b> B5→0	<b>R</b> B0→3	<b>C</b> 3-1=2		



# Decompression from BCSR format

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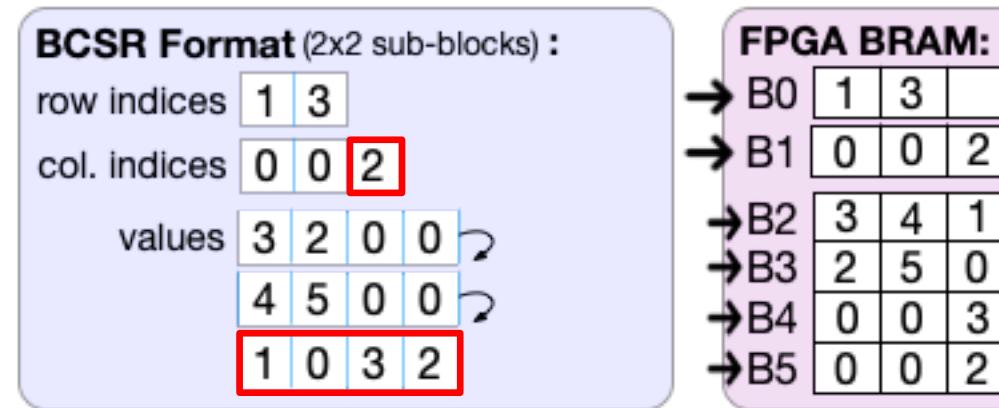
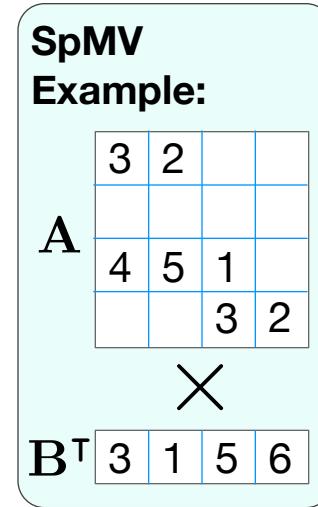
**BRAM Accesses Timeline:**

<i>cycle: 0</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
<b>R</b> B0→1	<b>C</b> 1-0=1	<b>R</b> B1→0 <b>R</b> B2→3 <b>R</b> B3→2 <b>R</b> B4→0 <b>R</b> B5→0	<b>R</b> B0→3	<b>C</b> 3-1=2	<b>R</b> B1→0 <b>R</b> B2→4 <b>R</b> B3→5 <b>R</b> B4→0 <b>R</b> B5→0	



# Decompression from BCSR format

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**BRAM Accesses Timeline:**

cycle: 0	1	2	3	4	5	6
<b>R</b> B0→1	<b>C</b> 1-0=1	<b>R</b> B1→0	<b>R</b> B0→3	<b>C</b> 3-1=2	<b>R</b> B1→0	<b>R</b> B1→2
		<b>R</b> B2→3			<b>R</b> B2→4	<b>R</b> B2→1
		<b>R</b> B3→2			<b>R</b> B3→5	<b>R</b> B3→0
		<b>R</b> B4→0			<b>R</b> B4→0	<b>R</b> B4→3
		<b>R</b> B5→0			<b>R</b> B5→0	<b>R</b> B5→2



# Key Challenge of Decompressing CSR and BCSR

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Creating each row of data has following overheads:

- ▶ One access to the meta data
- ▶ One computation

Reading the column indices and values is sequential because

- ▶ We do not know in advance which elements of column indices and values are going to be accessed.
- ▶ We cannot partition and allocate those two vectors across the blocks of BRAM to guarantee parallel reads.



# Key Insights and Solutions

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To address the challenge we propose Ascella

Ascella achieves the ideal streaming for sparse problems by

- ▶ Avoiding extra accesses to meta data
- ▶ Providing deterministic parallel accesses to data

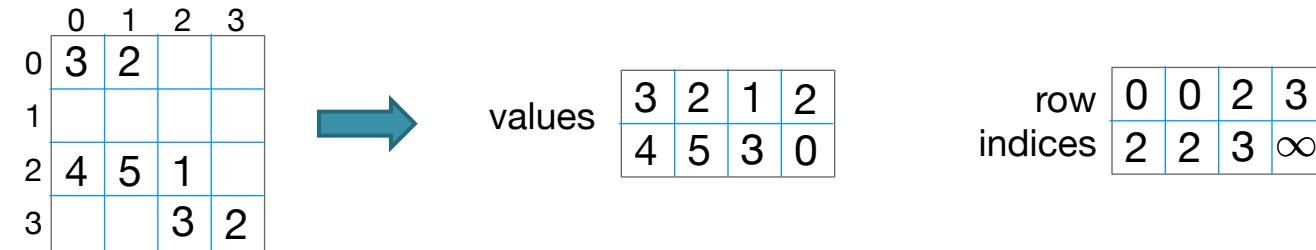
Ascella is an accelerator for SpMV that sustains a balance between computation and data-transfer time



# Contributions of Ascella

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Ascella uses a compressed format similar to list of lists (LIL<sup>1</sup>):



Ascella implements a lightweight microarchitecture that

- ▶ Connects the streamlines of memory to the parallel dot-product engine
- ▶ Enables ideal data streaming

<sup>1</sup>[https://docs.scipy.org/doc/scipy/reference/generated/scipy.sparse.lil\\_matrix.html](https://docs.scipy.org/doc/scipy/reference/generated/scipy.sparse.lil_matrix.html)



# Decompression mechanism of Ascella

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**SpMV Example:**

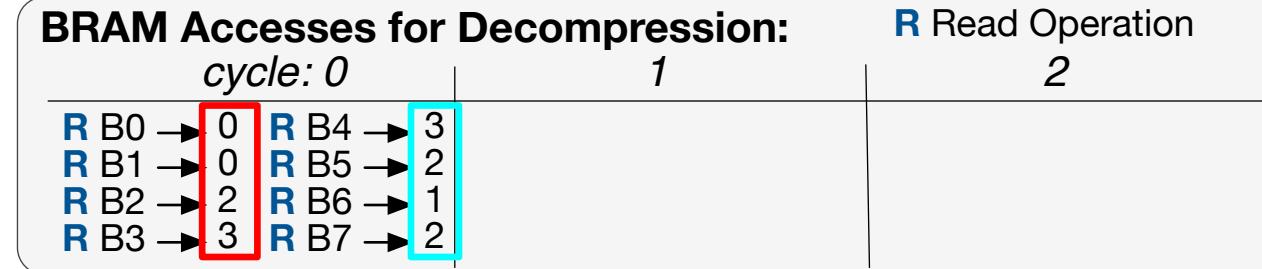
A	$\begin{matrix} 3 & 2 \\ 4 & 5 & 1 \\ & & 3 & 2 \end{matrix}$
	X
$B^T$	$\begin{matrix} 3 & 1 & 5 & 6 \end{matrix}$

**LIL Format**

row indices	0	0	2	3
values	2	2	3	$\infty$
row indices	3	2	1	2
values	4	5	3	0

**Mapping to BRAM Blocks**

B0	B1	B2	B3	B4	B5	B6	B7
0	0	2	3	3	2	1	2
2	2	3	$\infty$	4	5	3	0





# Decompression mechanism of Ascella

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SpMV Example:	
A	$\times$
3 2	
4 5 1	
	3 2
B <sup>T</sup>	3 1 5 6

LIL Format	row indices	values
	0 0 2 3	
	2 2 3 $\infty$	
	3 2 1 2	
	4 5 3 0	

Mapping to BRAM Blocks	B0 B1 B2 B3	B4 B5 B6 B7
	0 0 2 3	3 2 1 2
	2 2 3 $\infty$	4 5 3 0

BRAM Accesses for Decompression:			
cycle: 0		R Read Operation	
R B0 $\rightarrow$ 0	R B4 $\rightarrow$ 3	R B0 $\rightarrow$ 2	R B4 $\rightarrow$ 4
R B1 $\rightarrow$ 0	R B5 $\rightarrow$ 2	R B1 $\rightarrow$ 2	R B5 $\rightarrow$ 5
R B2 $\rightarrow$ 2	R B6 $\rightarrow$ 1	R B2 $\rightarrow$ 2	R B6 $\rightarrow$ 1
R B3 $\rightarrow$ 3	R B7 $\rightarrow$ 2	R B3 $\rightarrow$ 3	R B7 $\rightarrow$ 2



# Decompression mechanism of Ascella

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SpMV Example:	
A	$\times$
3 2	
4 5 1	
	3 2
B <sup>T</sup>	3 1 5 6

LIL Format	row indices	values
	0 0 2 3	
	2 2 3 $\infty$	
	3 2 1 2	
	4 5 3 0	

Mapping to BRAM Blocks	B0 B1 B2 B3	B4 B5 B6 B7
	0 0 2 3	3 2 1 2
	2 2 3 $\infty$	4 5 3 0

BRAM Accesses for Decompression:			
cycle: 0		1	2
R B0 $\rightarrow$ 0	R B4 $\rightarrow$ 3	R B0 $\rightarrow$ 2	R B4 $\rightarrow$ 4
R B1 $\rightarrow$ 0	R B5 $\rightarrow$ 2	R B1 $\rightarrow$ 2	R B5 $\rightarrow$ 5
R B2 $\rightarrow$ 2	R B6 $\rightarrow$ 1	R B2 $\rightarrow$ 2	R B6 $\rightarrow$ 1
R B3 $\rightarrow$ 3	R B7 $\rightarrow$ 2	R B3 $\rightarrow$ 3	R B7 $\rightarrow$ 2
		R B2 $\rightarrow$ 3	R B6 $\rightarrow$ 2
		R B3 $\rightarrow$ 3	R B7 $\rightarrow$ 3

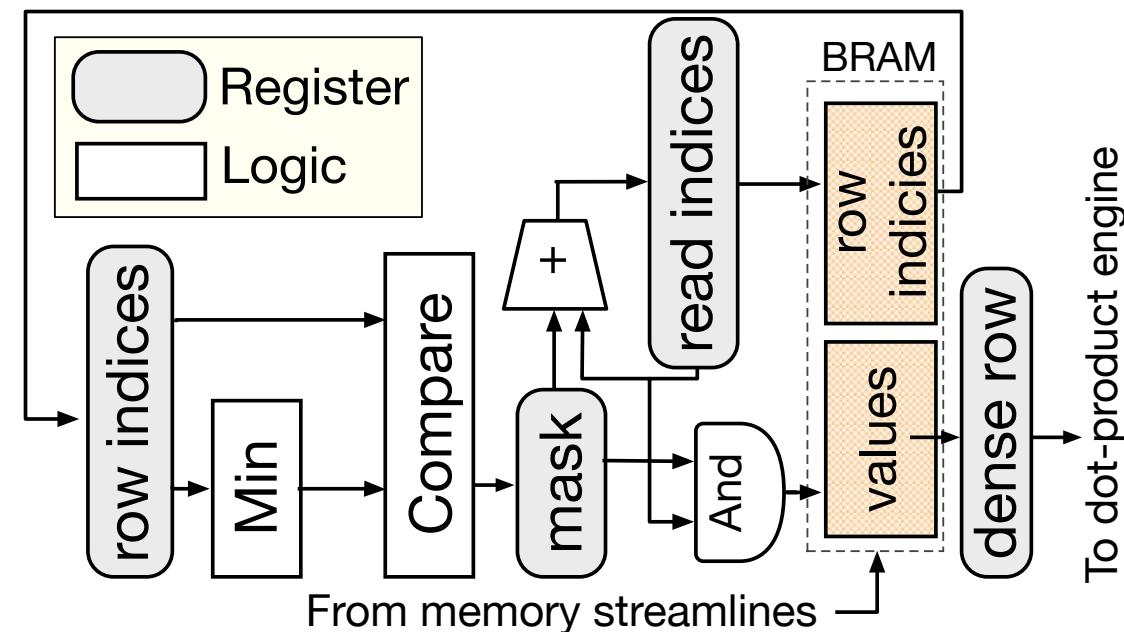


# Microarchitecture of Ascella

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At each step of decompression:

- ▶ *read indices* are used to read the *row indices*
- ▶ the minimum of *row indices* is used to create a *mask*
- ▶ the mask
  - ▶ Selects values of *dense row*
  - ▶ Updates the *read indices*

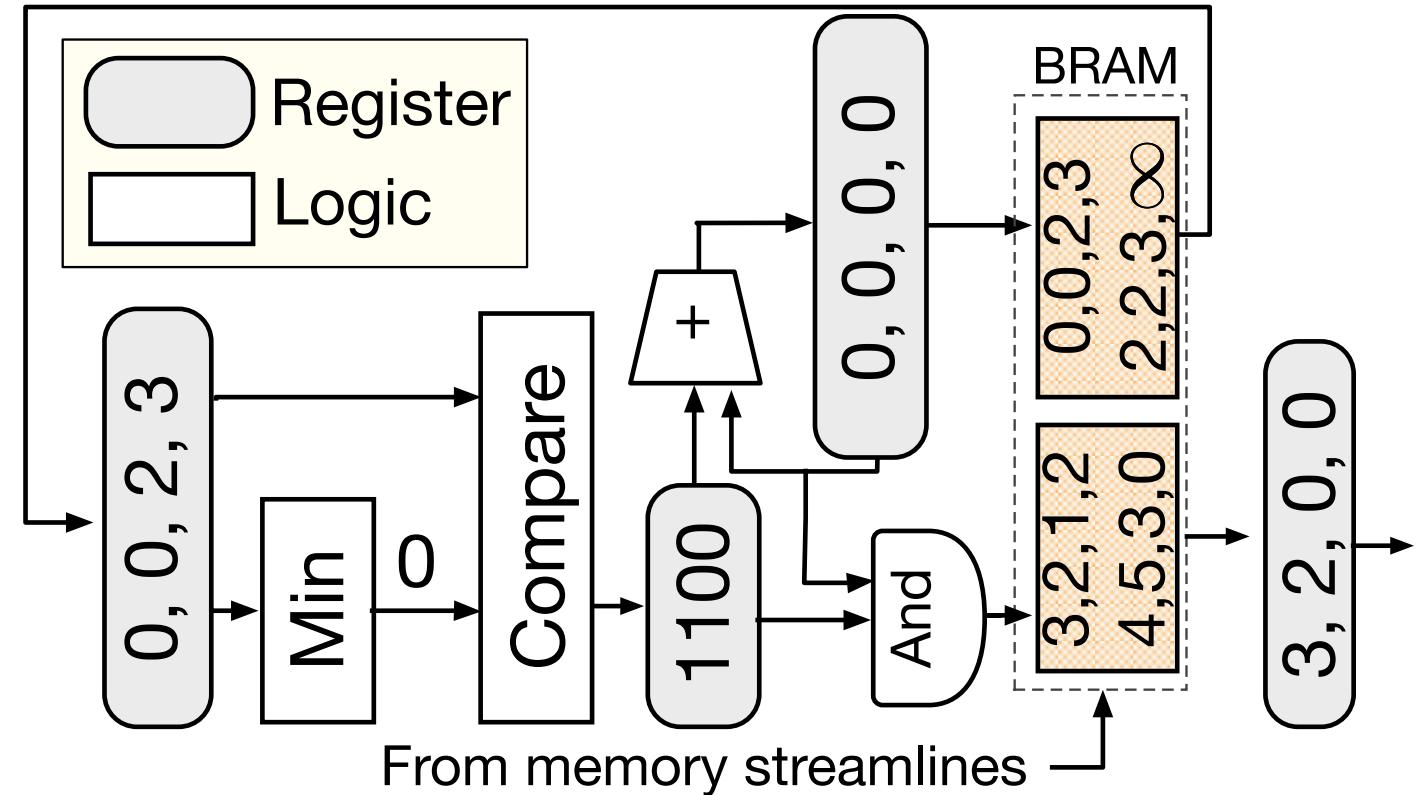
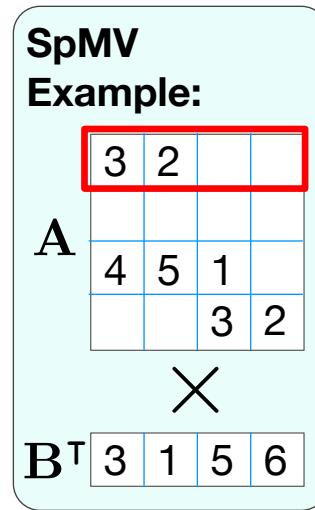




# Microarchitecture of Ascella

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Creating the first row:

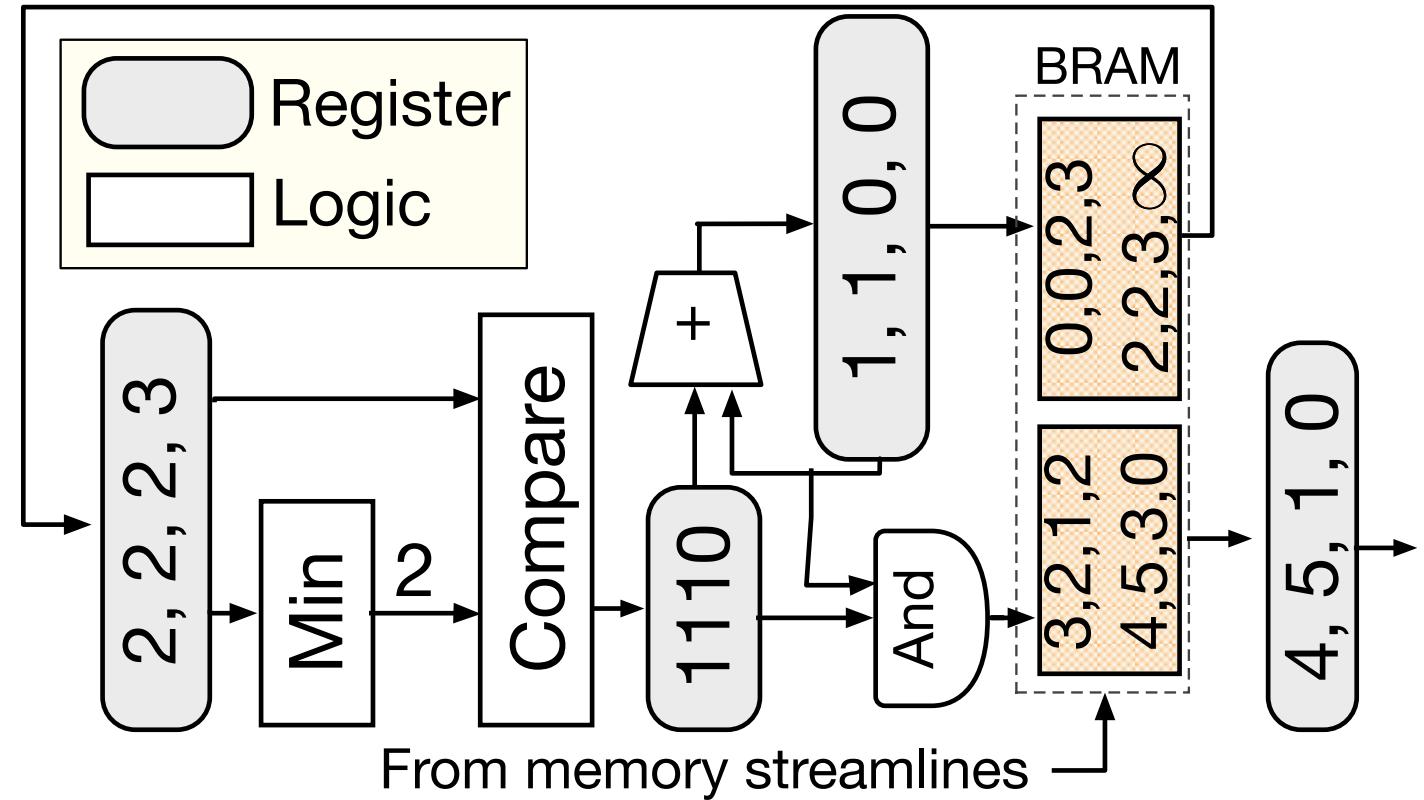
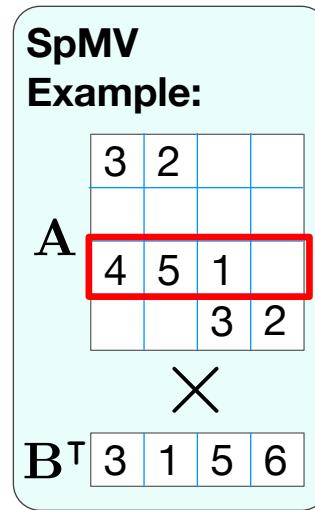




# Microarchitecture of Ascella

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Creating the third row:

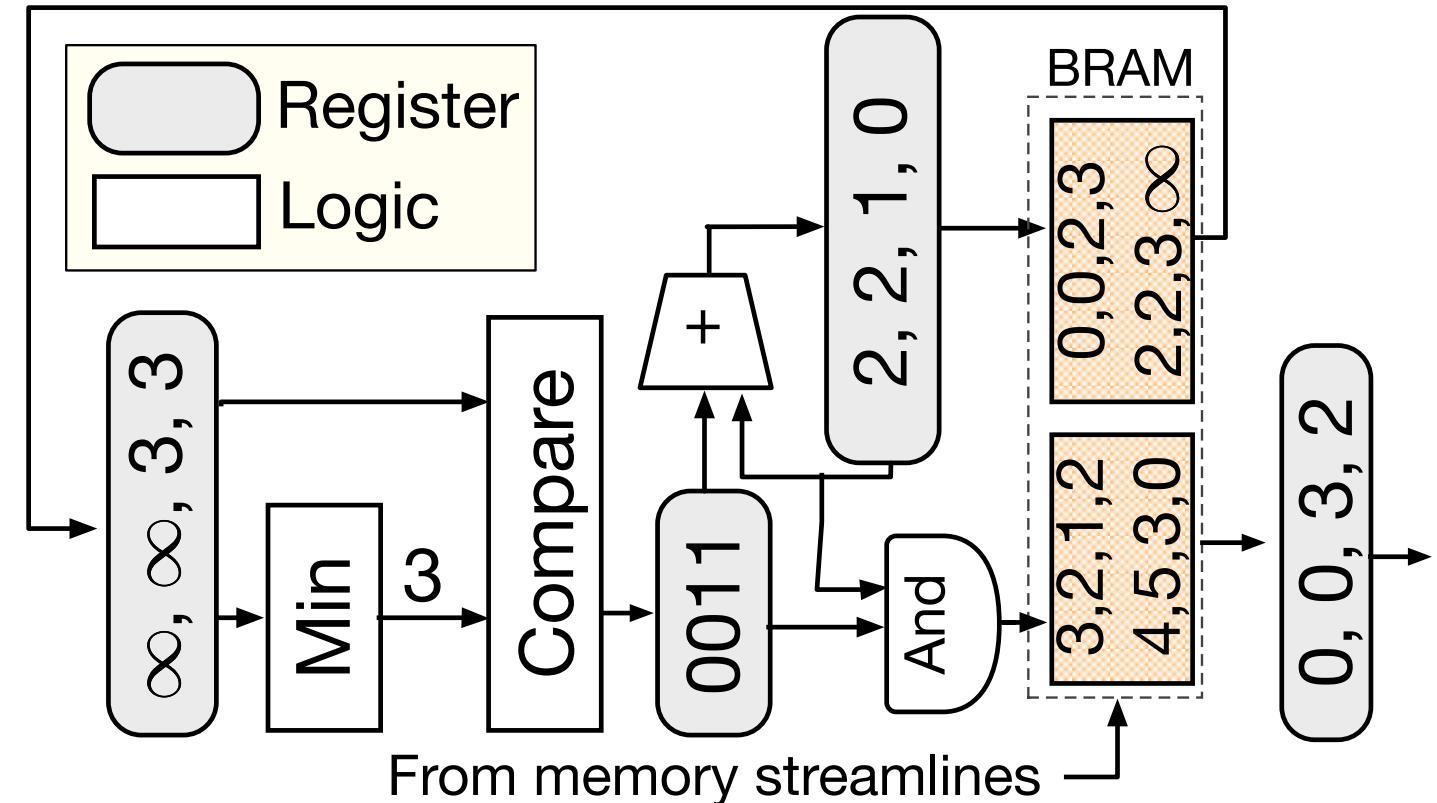
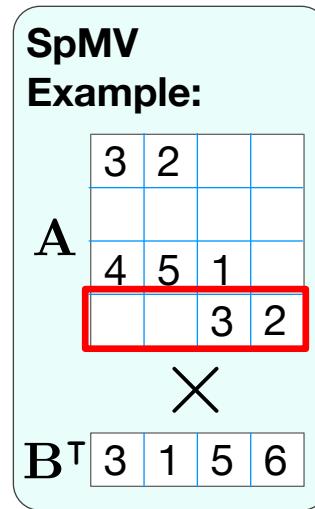




# Microarchitecture of Ascella

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Creating the last row:





# Experimental Setup

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We apply SpMV on a group of matrices from SuiteSparse collection

We implement Ascella and the baselines

- ▶ Using Xilinx Vivado HLS
- ▶ On ZYNQ XC7Z020FPGA.

Our comparison metrics are

- ▶ Latency
- ▶ Recourse utilization

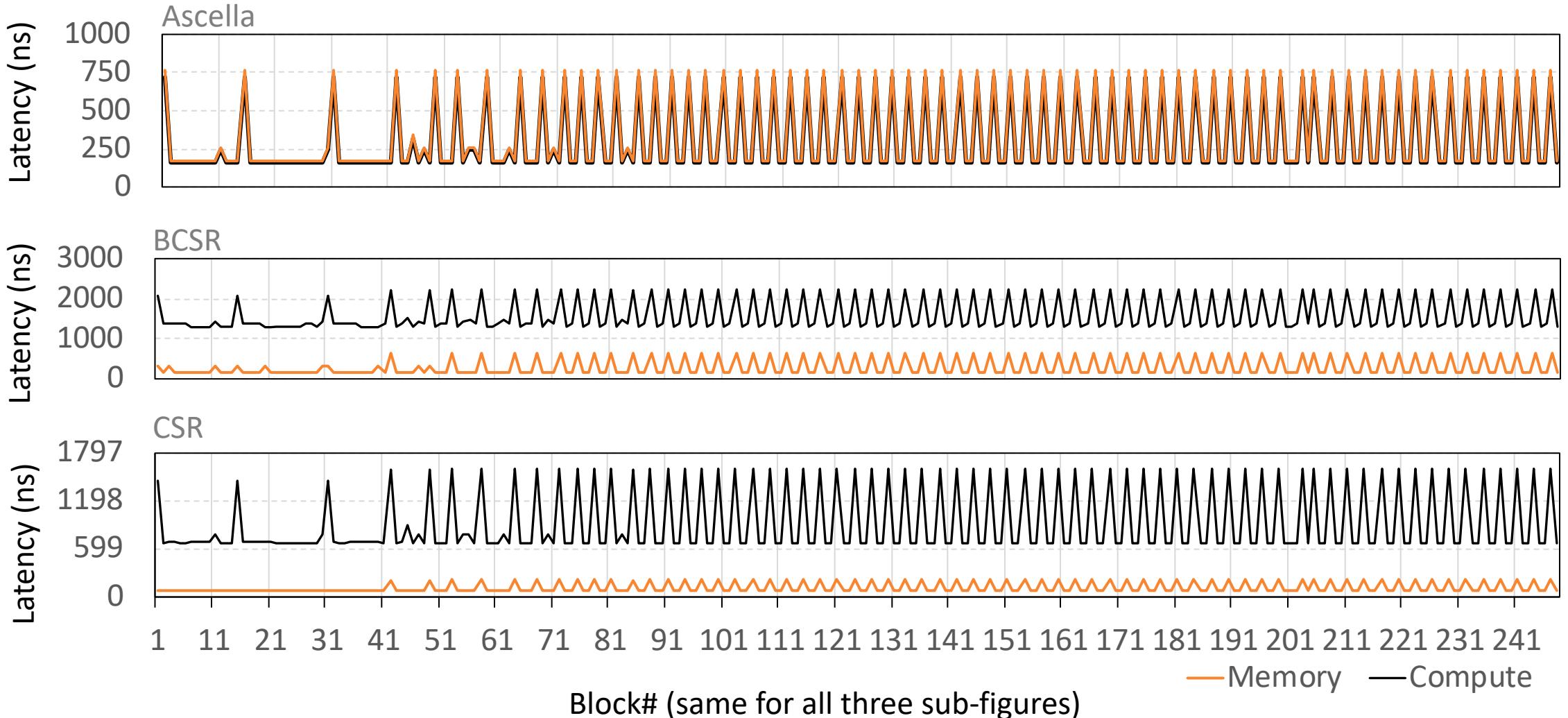
The configurations of Ascella and baselines include

- ▶ AXI stream interfaces
- ▶ DDR3 memory
- ▶ 100 MHz frequency
- ▶ 32-bit integers



# Performance Evaluation

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Dataset: thermomech-TC

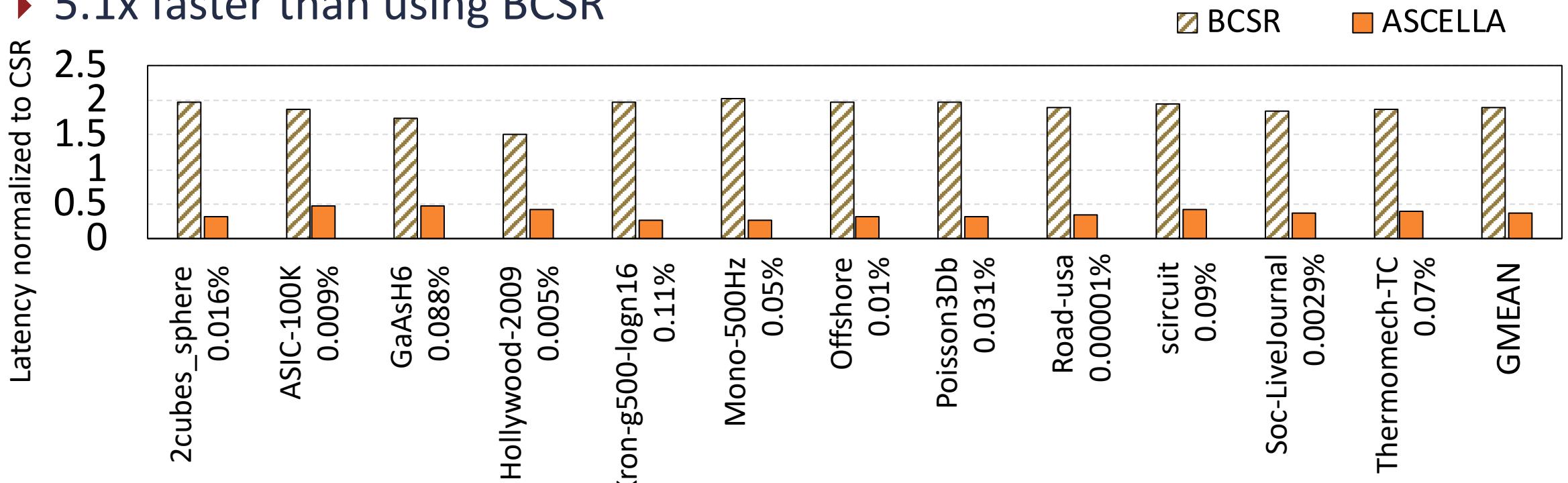


# Performance Evaluation

33

On average, Ascella executes SpMV

- ▶ 2.7x faster than using CSR
- ▶ 5.1x faster than using BCSR

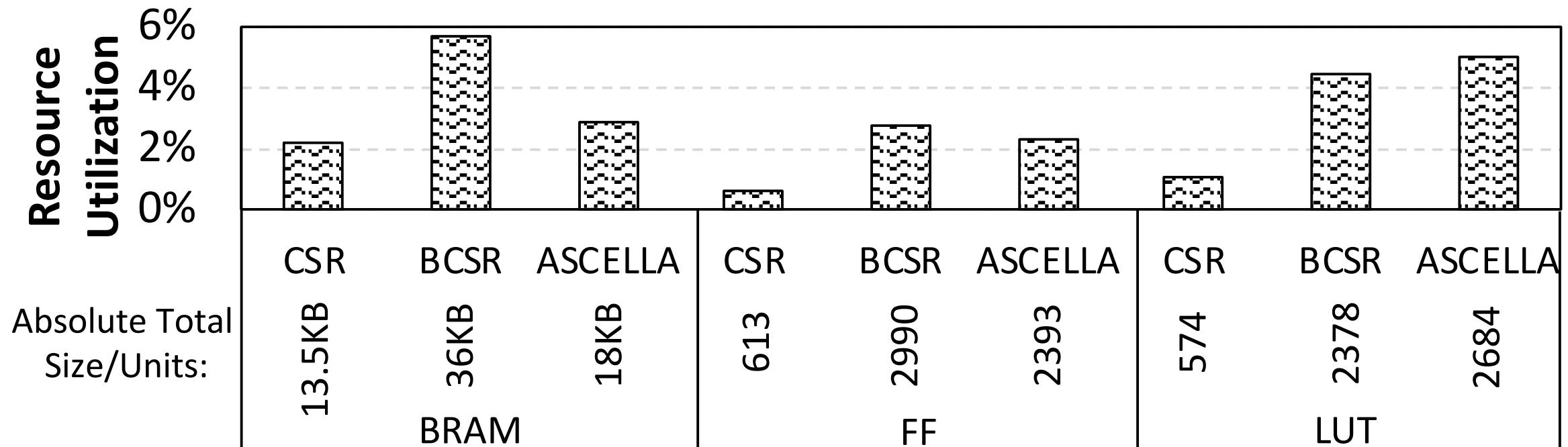




# Resource Utilization

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- ▶ BCSR and Ascella use more BRAM because of partitioning.
- ▶ CSR has the lowest flip-flop and look-up table (LUT) utilization because it does not implement any parallelism.





# Conclusions

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Ascella is a streaming accelerator for sparse problems that

- ▶ Streams the non-zero values of sparse matrices and processes them as they come at the same pace
- ▶ Is a significant step towards accelerating larger sparse problems because its storage format
  - ▶ facilitates partitioning large matrices
  - ▶ is supported in Python libraries, which makes the implementation straightforward