

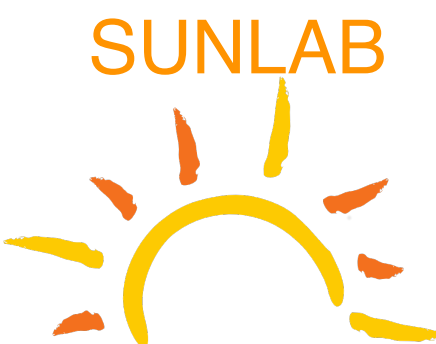
HiCOO: Hierarchical Storage of Sparse Tensors

Jiajia Li^{1,2}, Jimeng Sun¹, Richard Vuduc¹

¹ Georgia Institute of Technology

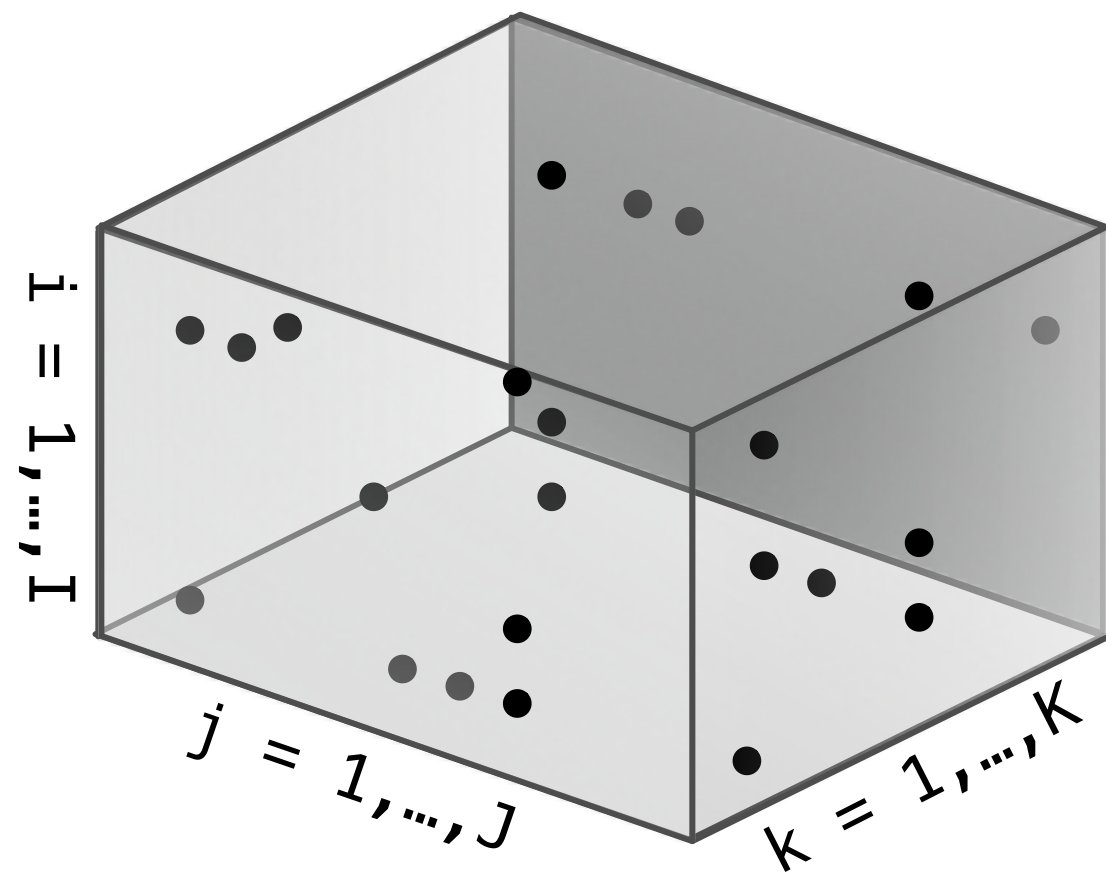
² Pacific Northwest National Laboratory

November 13, 2018 @ SC18



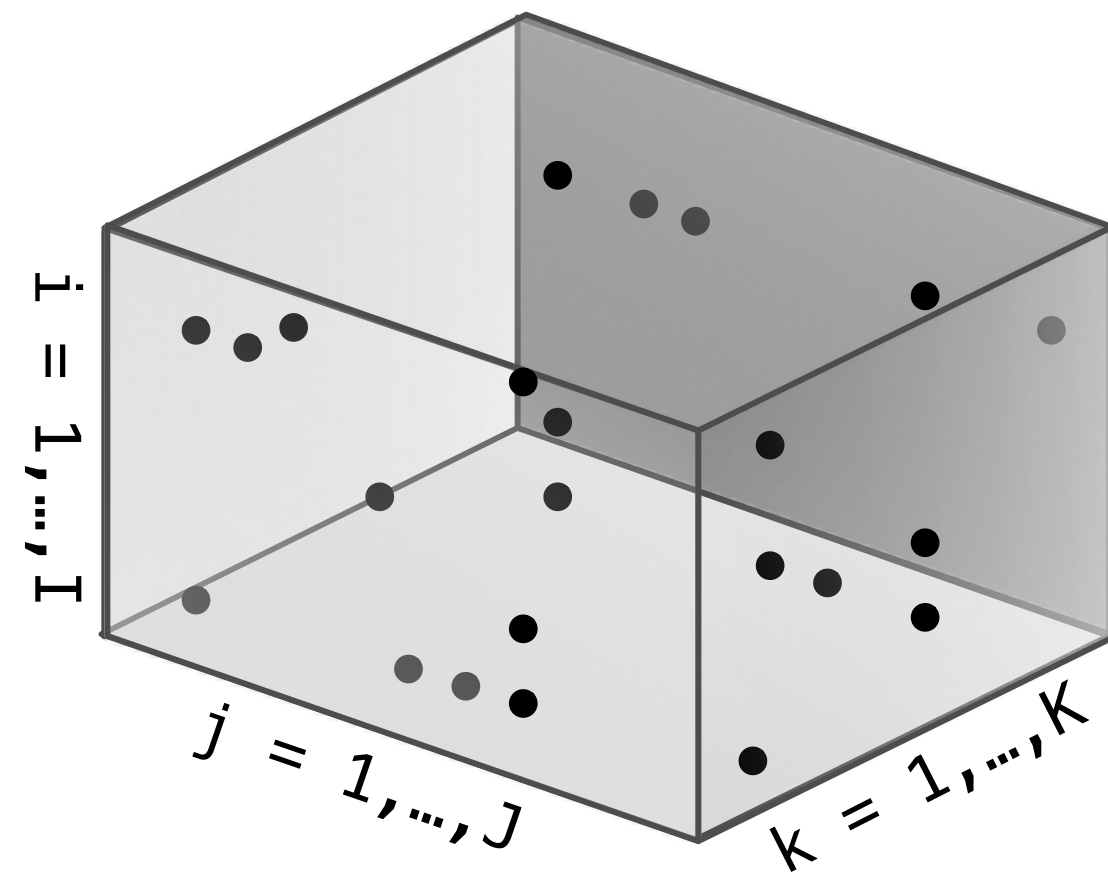
Tensors & Decompositions

- Tensors, multi-way arrays, provide a natural way to represent multi-relational data.
- Special cases: matrices, vectors
- Tensor mode or order: tensor dimension.
- Data tensors in applications are usually SPARSE, meaning consisting mostly of zero entries.



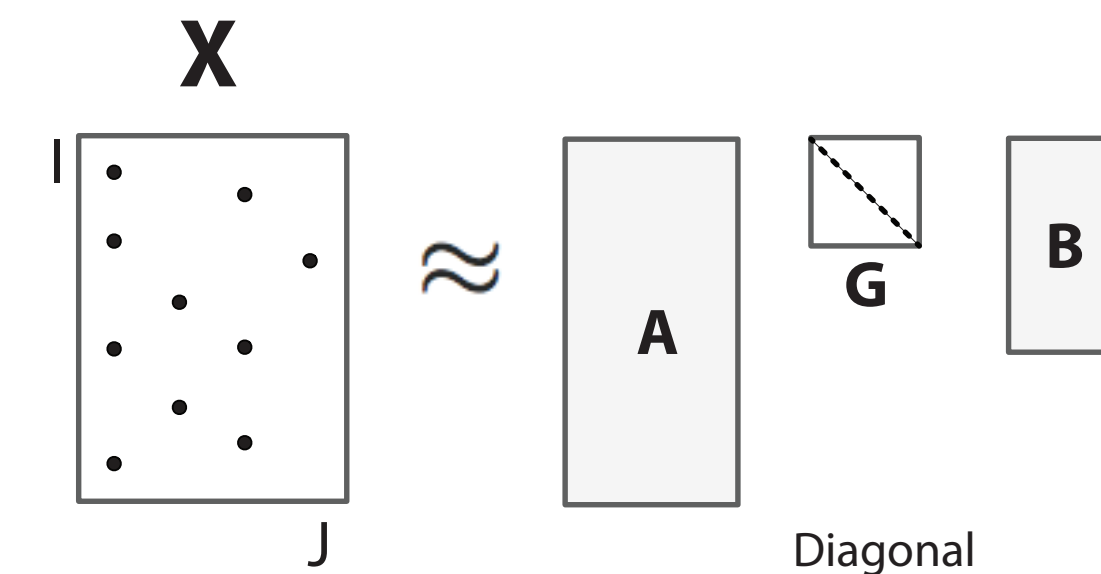
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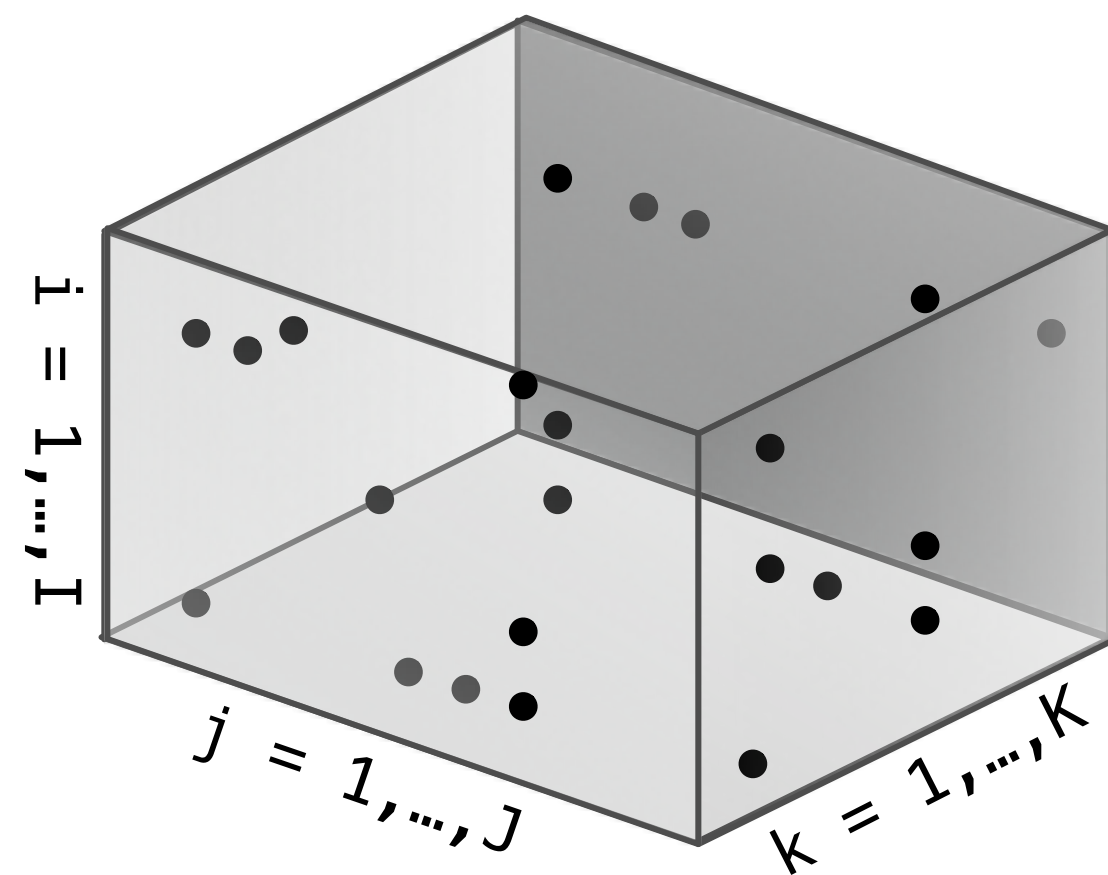
- Tensor decompositions: the natural generalization of matrix decompositions to tensors.

Singular Value Decomposition (SVD)



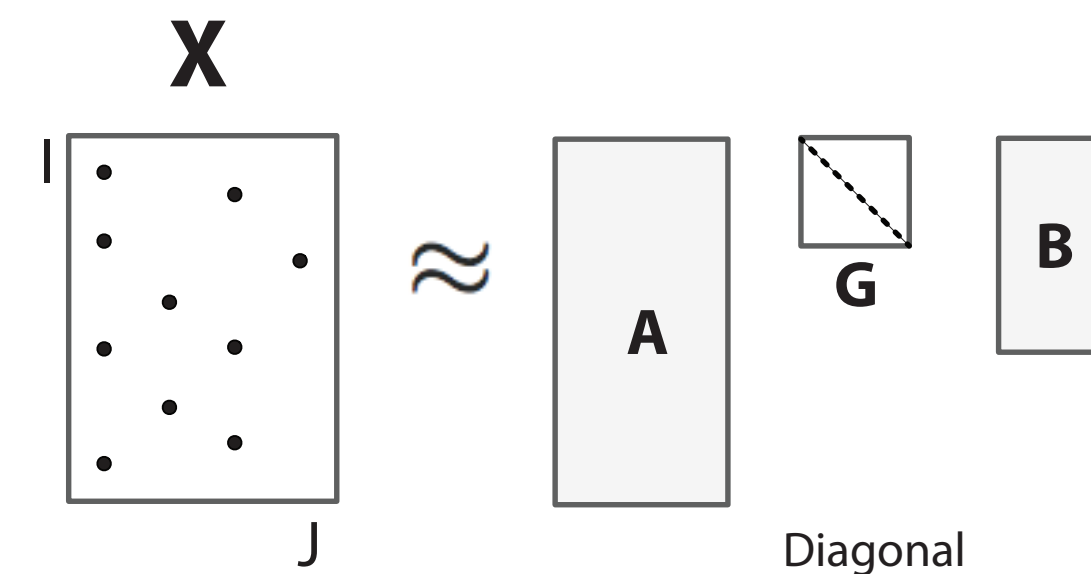
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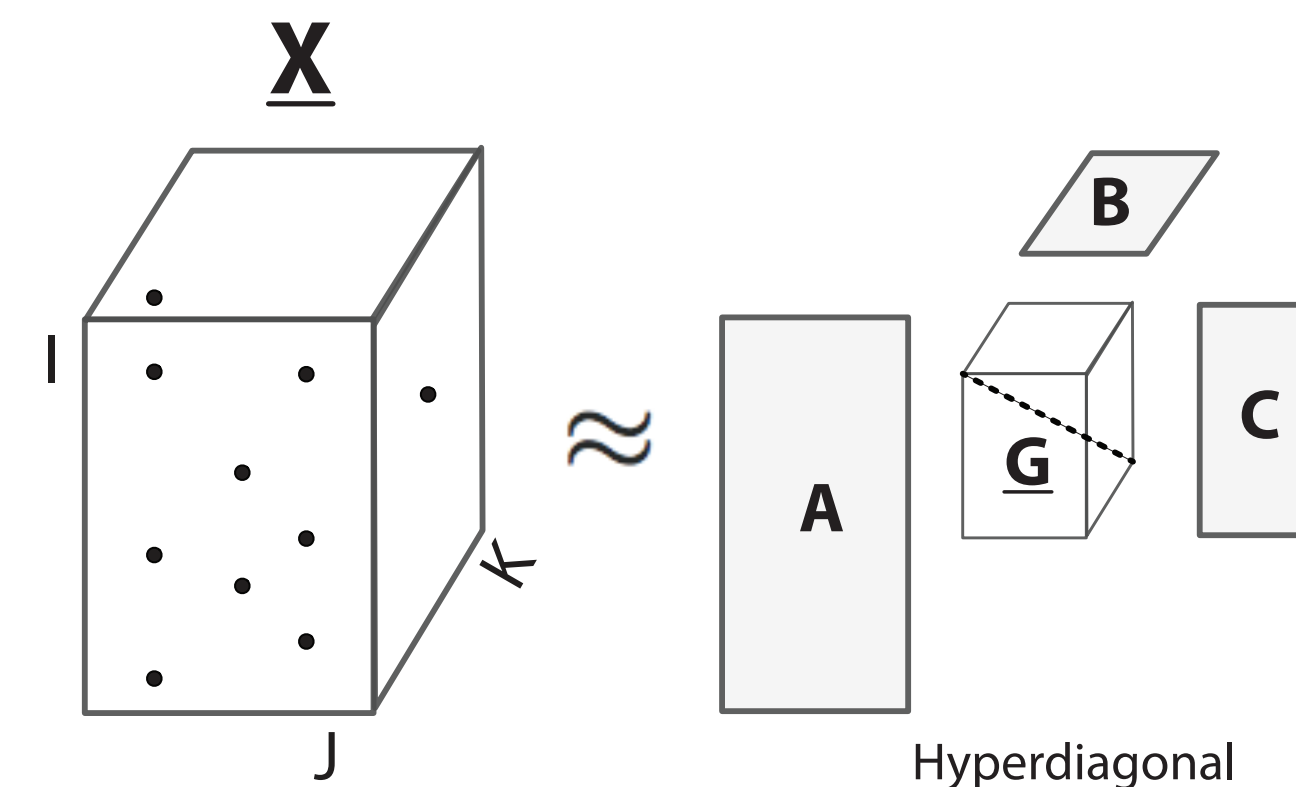


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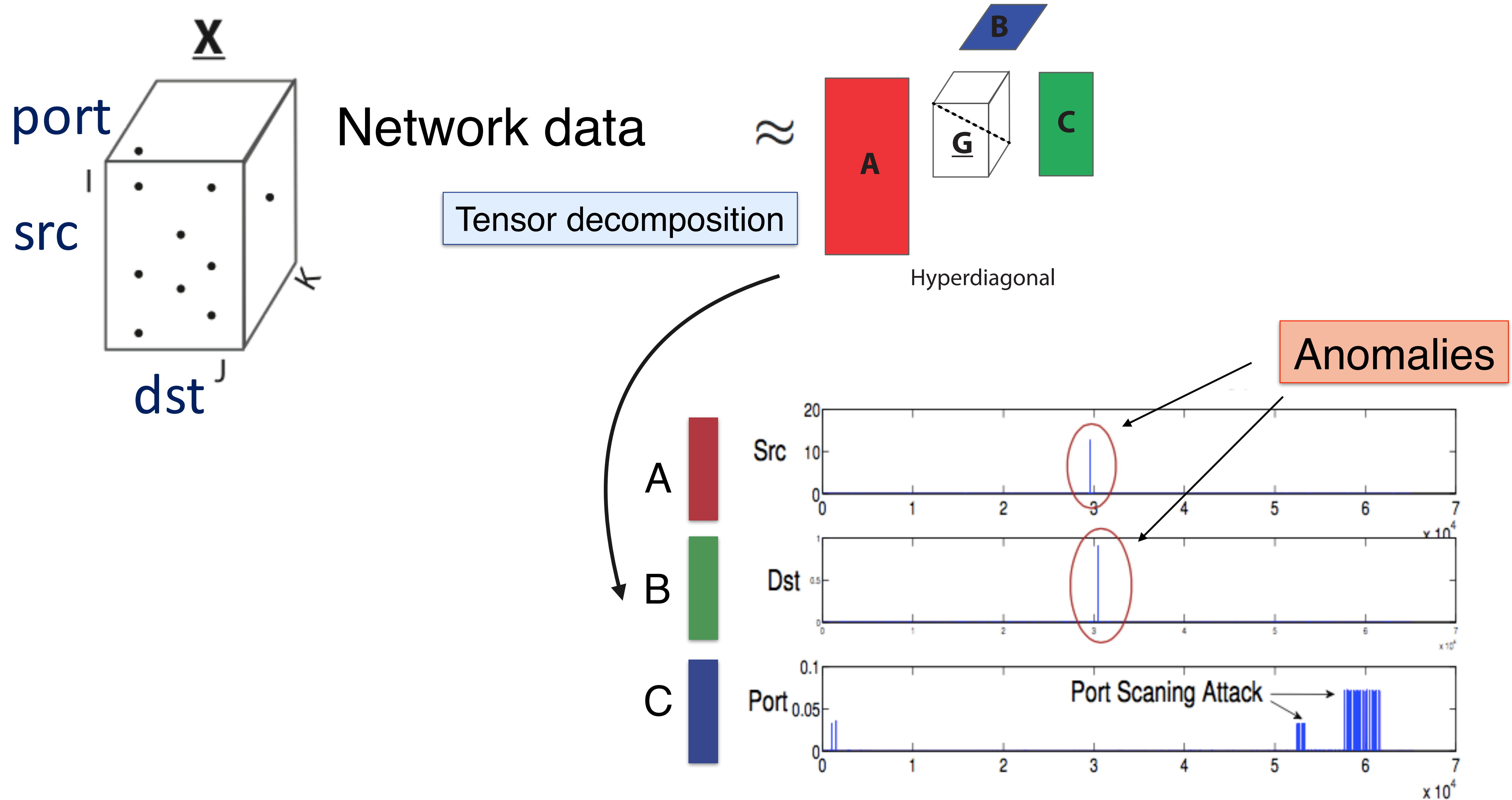
Singular Value Decomposition (SVD)



CANDECOMP/PARAFAC Decomposition (CPD)

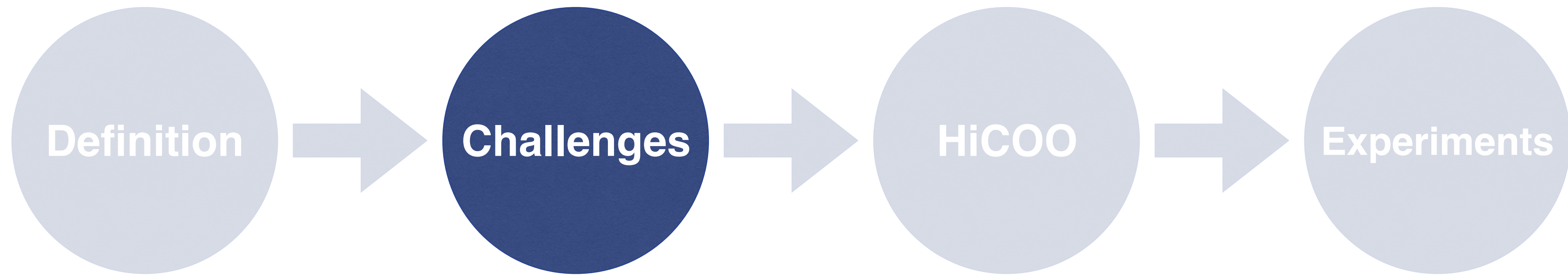


Tensor Decomposition for Anomaly Detection



Source: ParCube, by Papalexakis et al. ECML-PKDD 2012

Outline



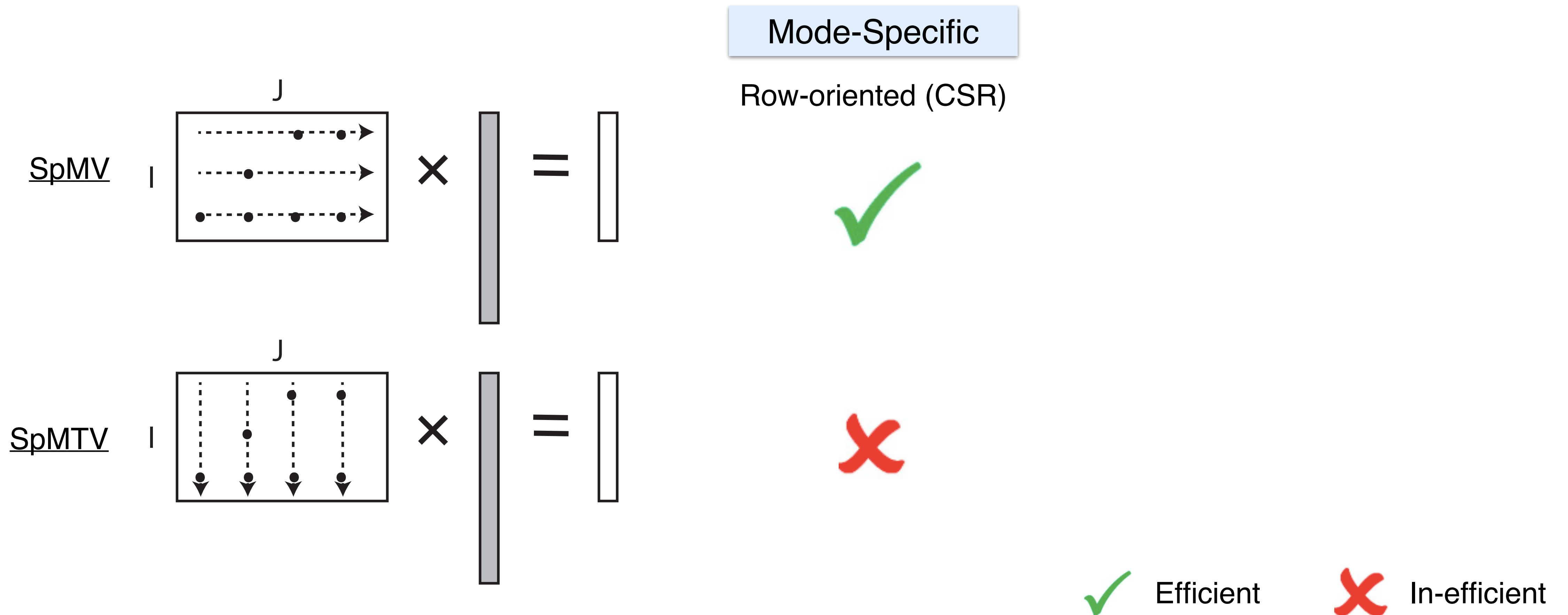
Challenges

- Compactness: A space-efficient data structure
- Mode-Genericity: Efficient traversals of the data structure for computations

Mode Genericity

- Matrix case:

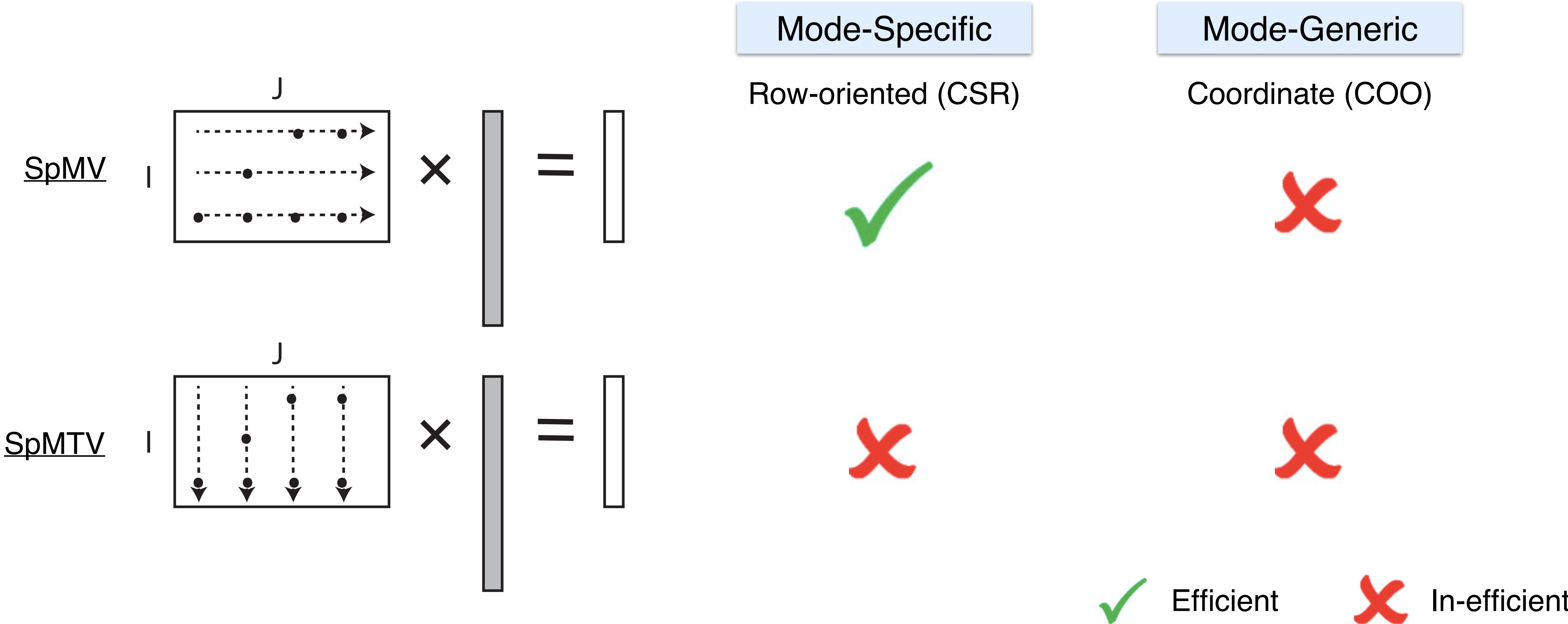
Do both matrix-vector multiplication and matrix-transpose-vector multiplication.



Mode Genericity

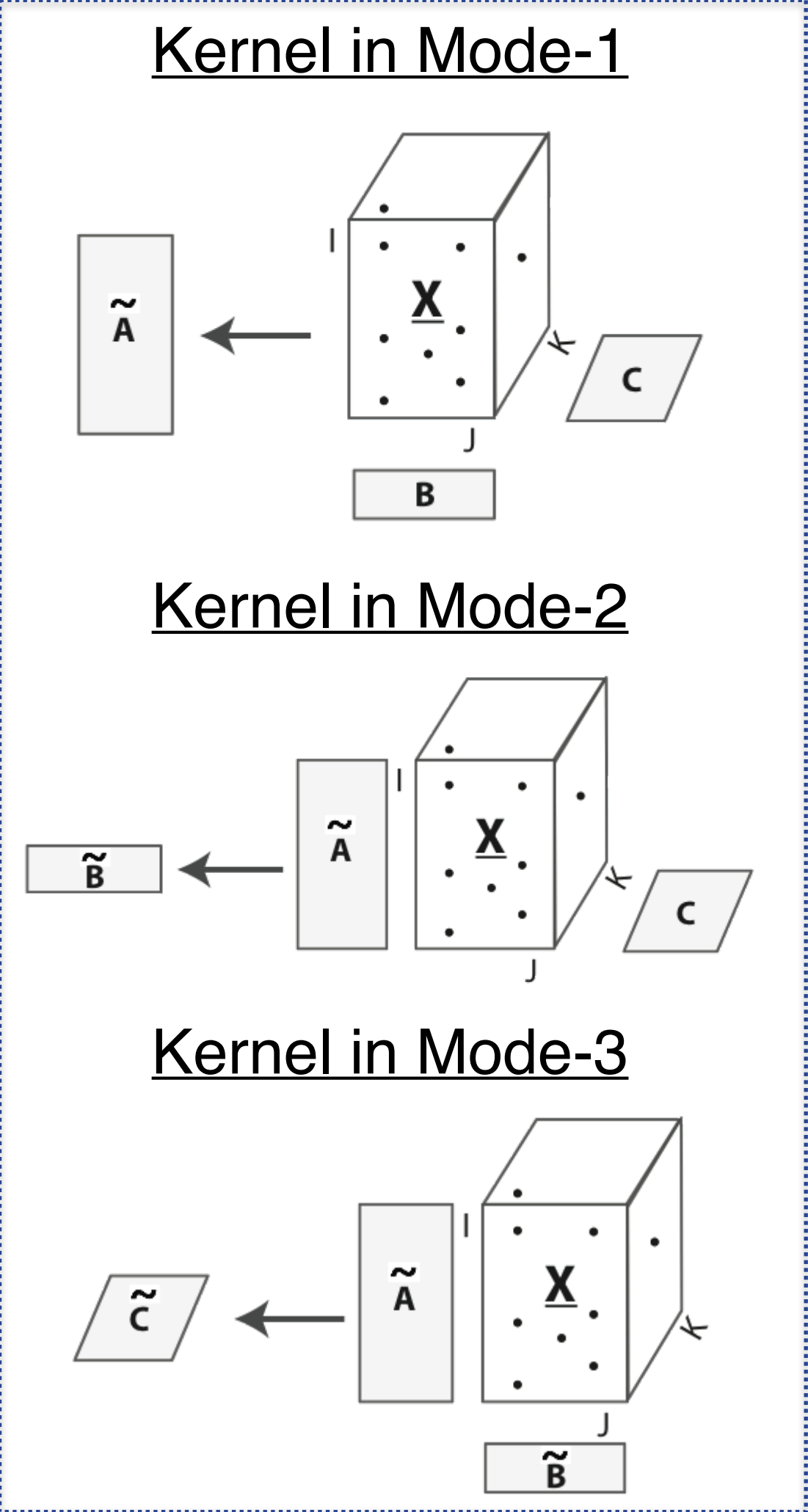
- Matrix case:

Do both matrix-vector multiplication and matrix-transpose-vector multiplication.



Mode Genericity

Tensor decomposition



Mode-Specific

Mode-1 oriented (CSF/FCOO)

Mode-Generic

Coordinate (COO)



Efficient



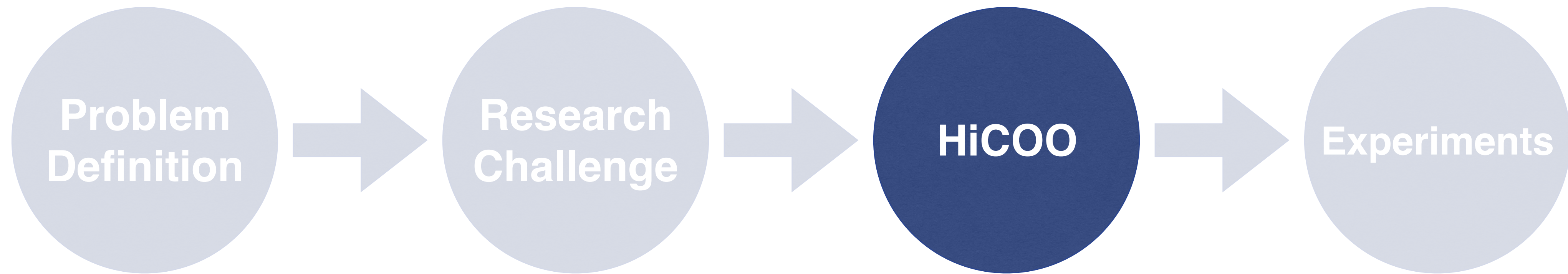
In-efficient

Outline

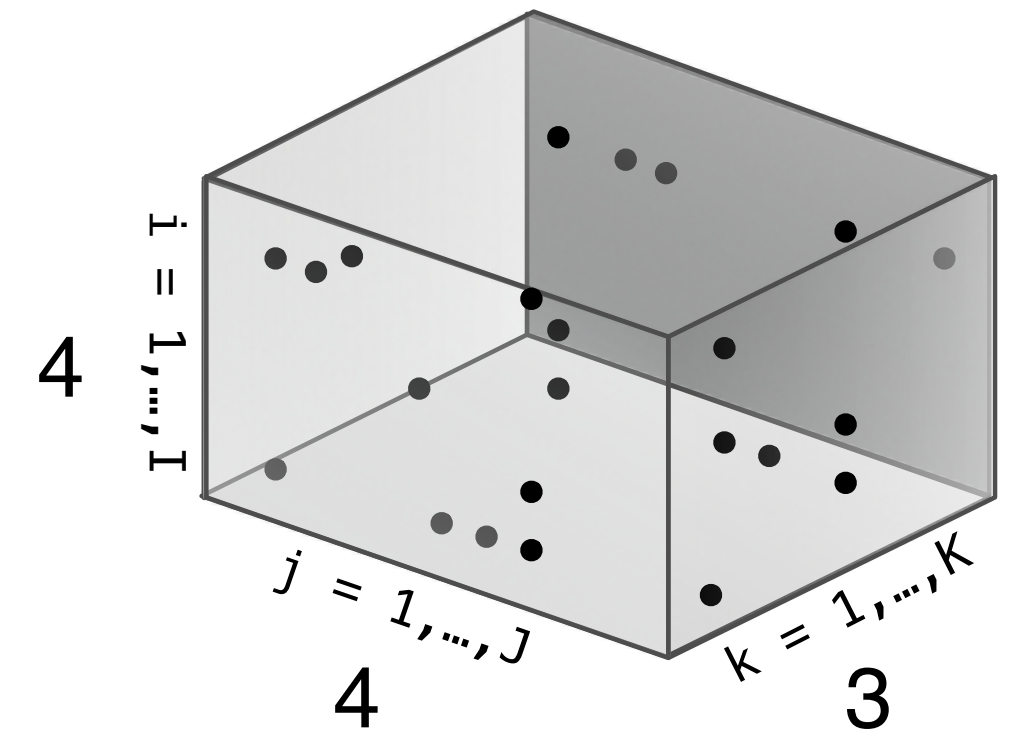
QUESTION: Is there a data structure that is BOTH compact and mode-generic?

Outline

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Baseline Sparse Tensor Formats in This Work



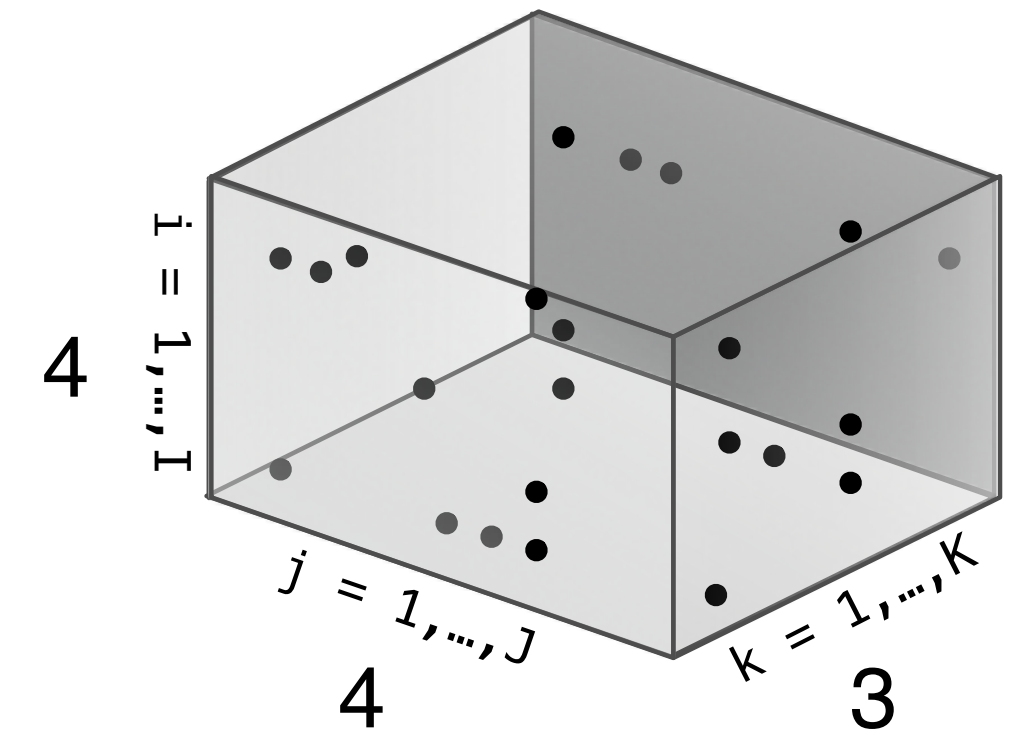
Baseline Sparse Tensor Formats in This Work

- COO: coordinate formats [Bader et al., 2006]

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

(a) COO

Mode-Generic

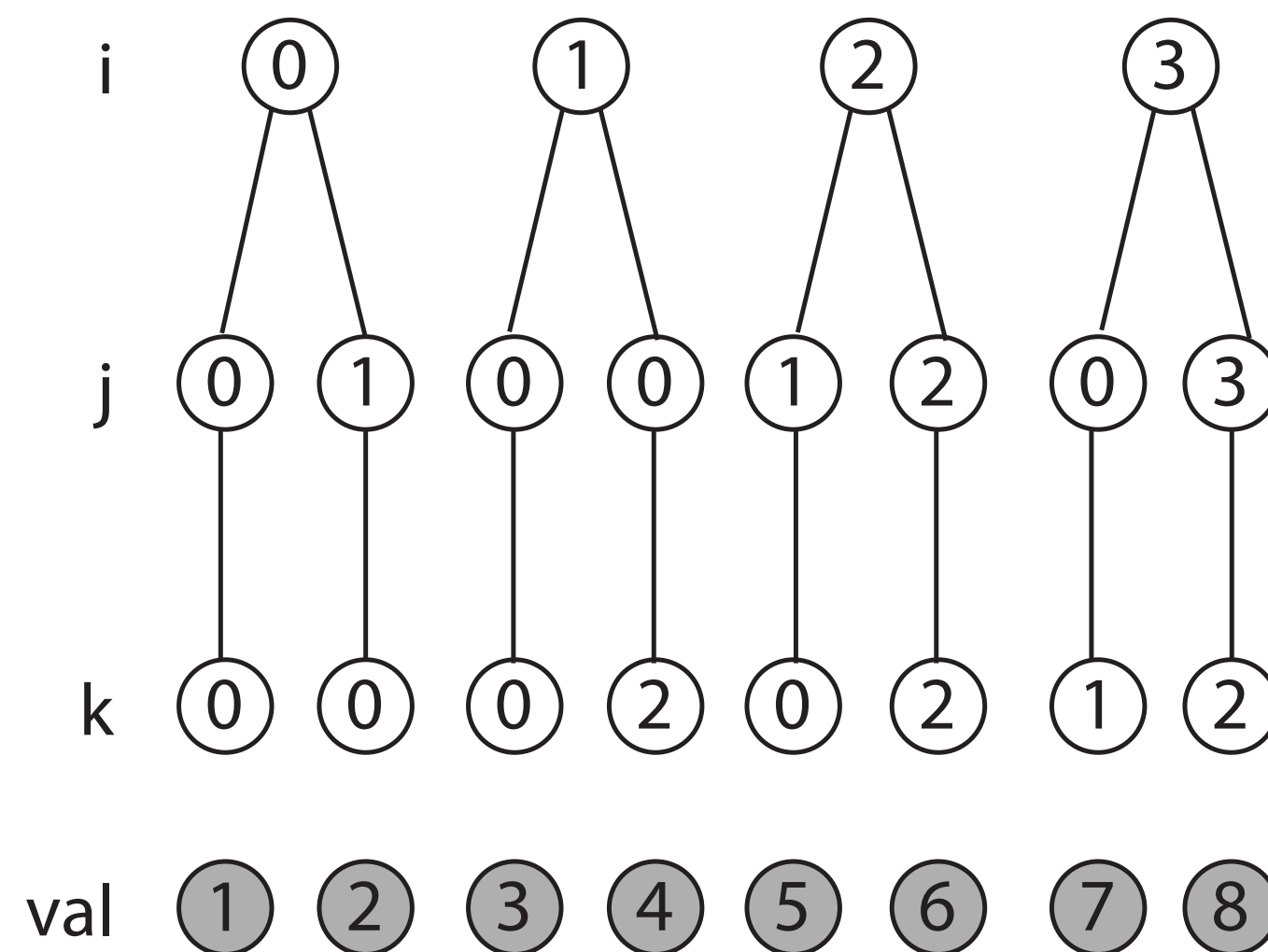


Baseline Sparse Tensor Formats in This Work

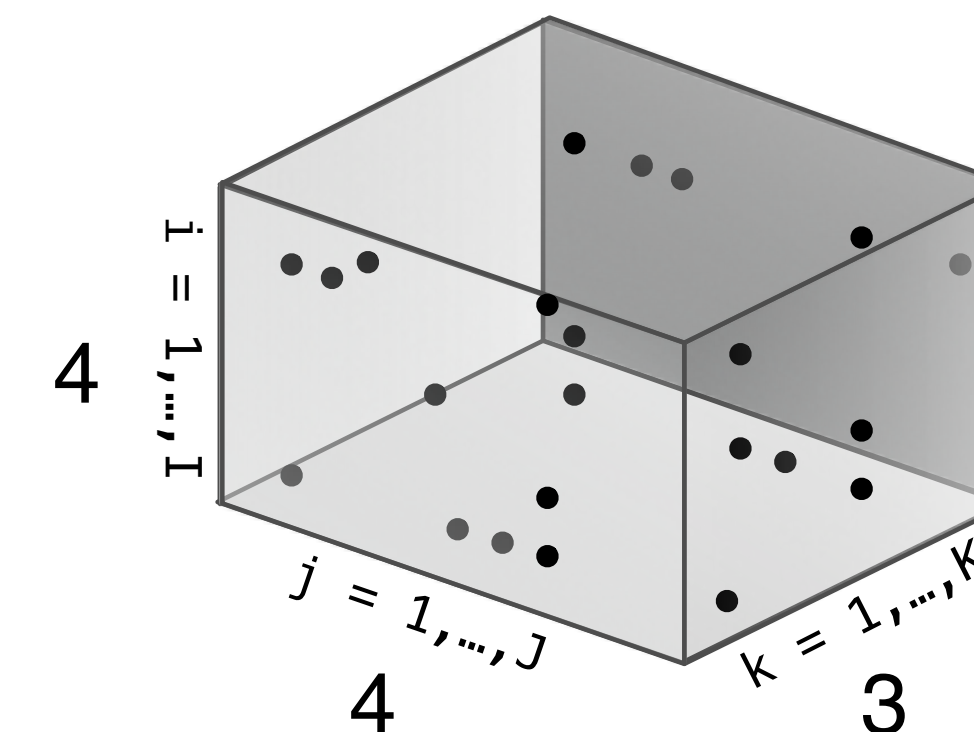
- COO: coordinate formats [Bader et al., 2006]
- CSF: Compressed Sparse Fibers, extension of CSR. [Smith et al. 2015]

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

(a) COO



(b) CSF



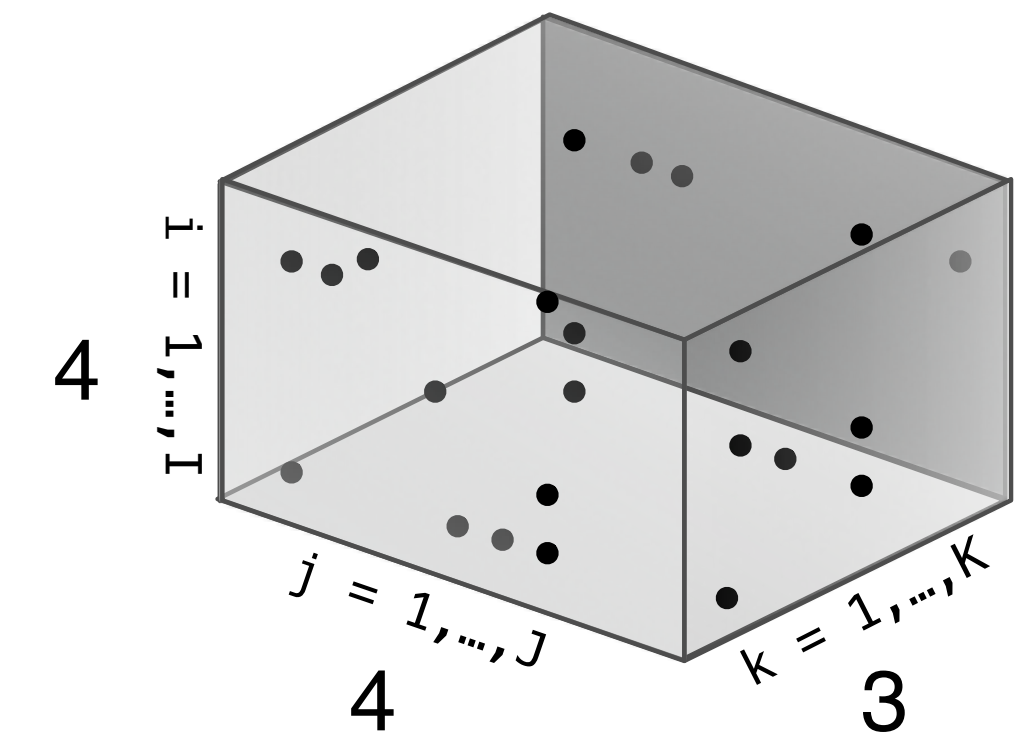
Mode-Generic

Mode-Specific

prefer different representations for different modes.

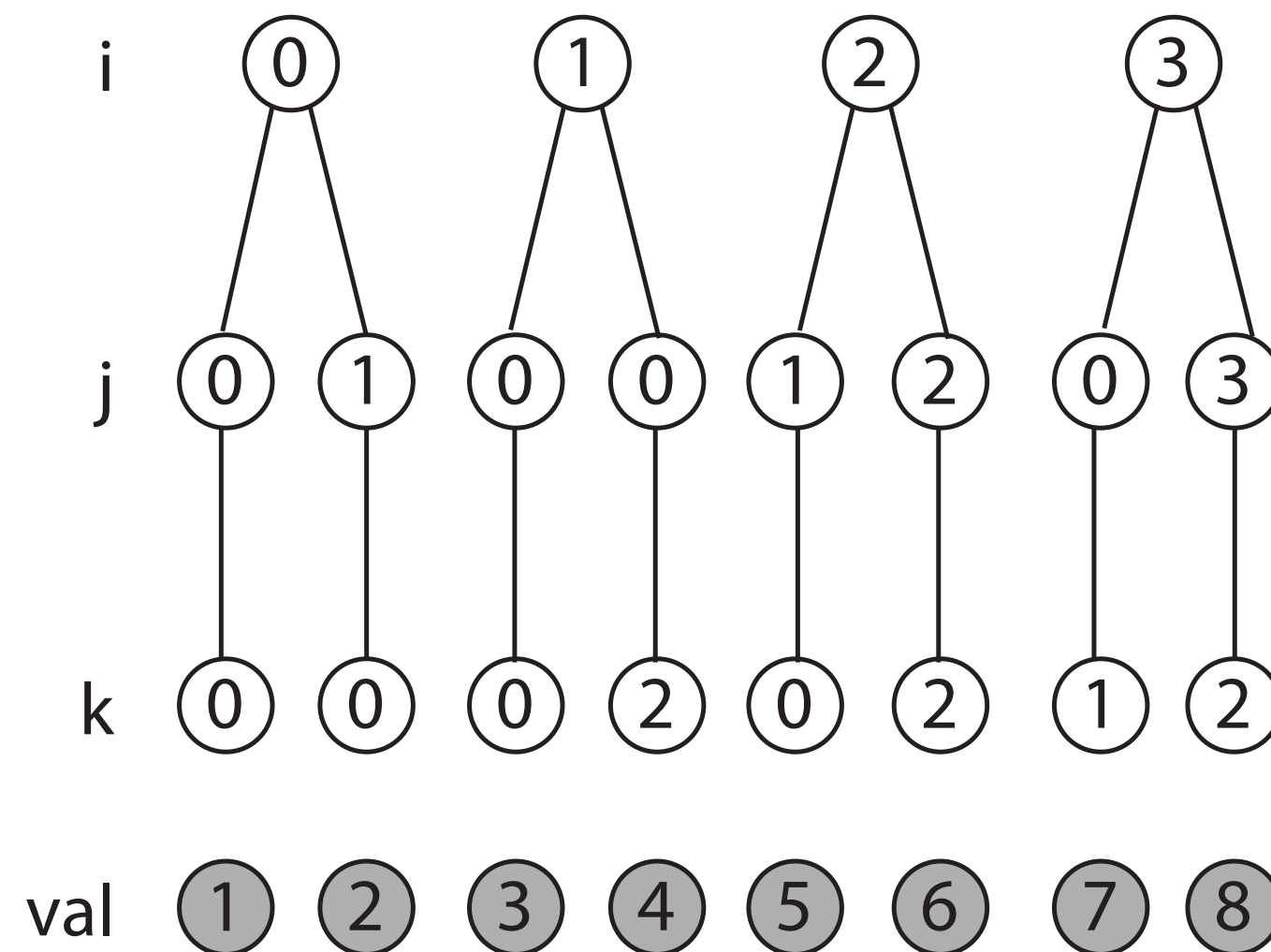
Baseline Sparse Tensor Formats in This Work

- COO: coordinate formats [Bader et al., 2006]
- CSF: Compressed Sparse Fibers, extension of CSR. [Smith et al. 2015]
- F-COO: Flagged COO format [Liu et al., 2017]



i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

(a) COO



(b) CSF

	bf	j	k	val
sf[0]=1	1	0	0	1
	0	1	0	2
	1	0	0	3
	0	0	2	4
sf[1]=1	1	1	0	5
	0	2	2	6
	1	0	1	7
	0	3	2	8

(c) F-COO

Mode-Generic

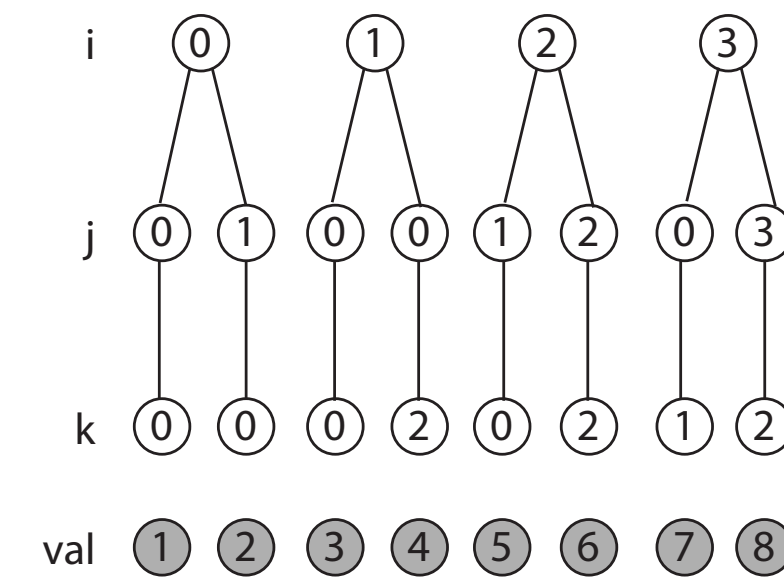
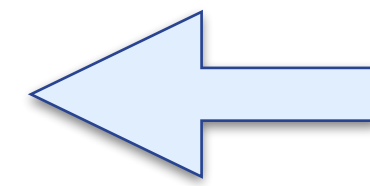
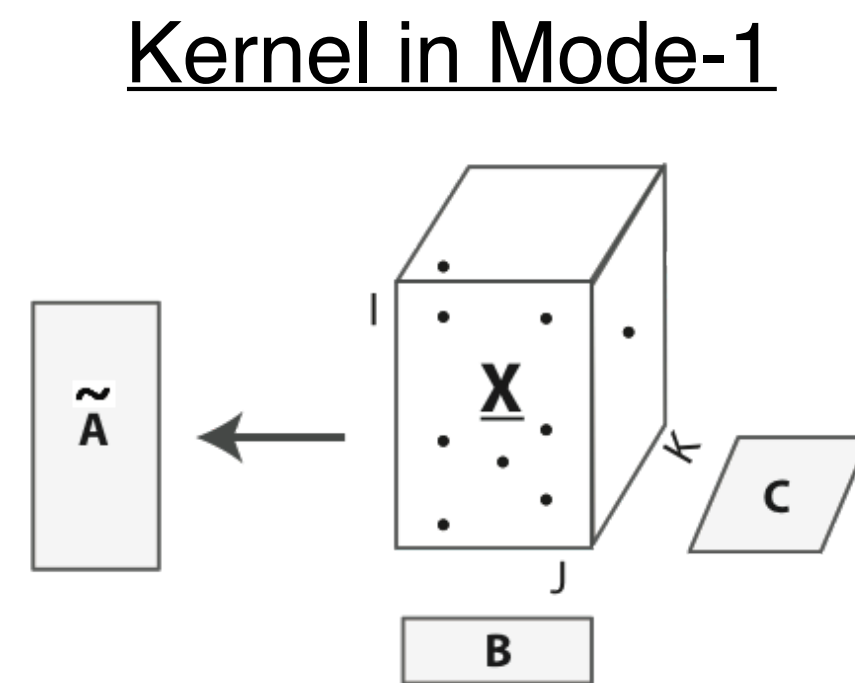
Mode-Specific

prefer different representations for different modes.

Mode-Specific Tensor Formats

- Three CSF/F-COO representations are required/preferred for three kernels.

**Tensor
Decomposition**

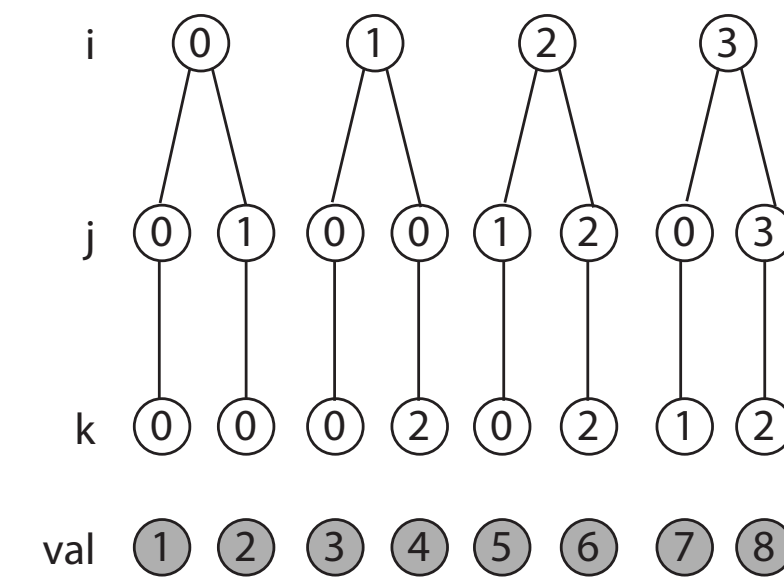
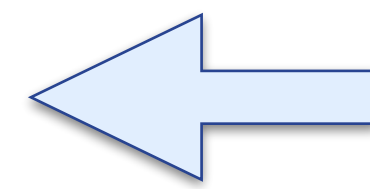
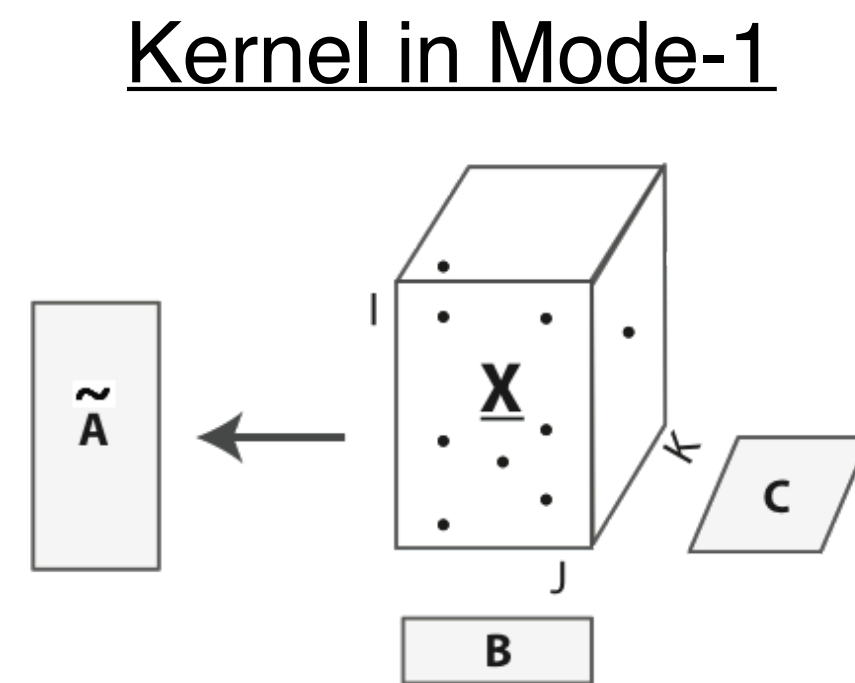


CSF-1

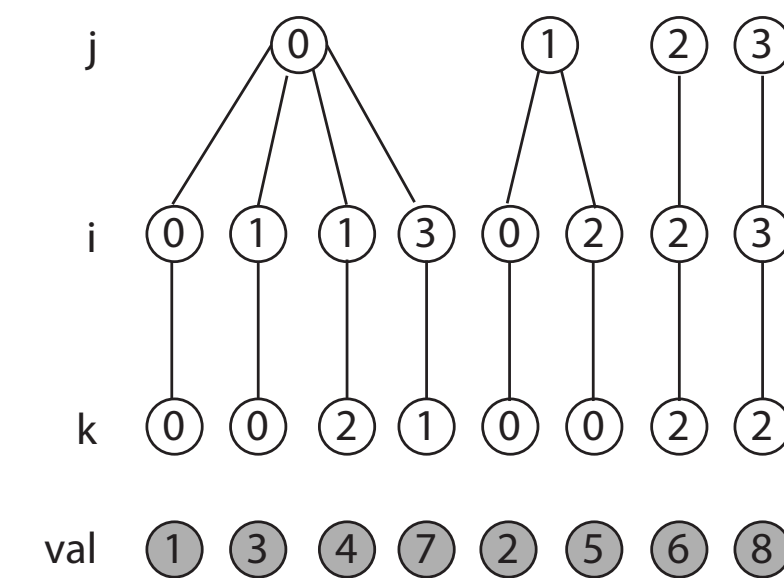
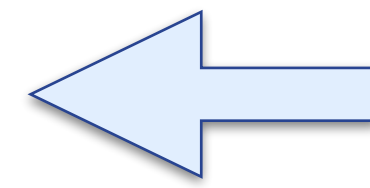
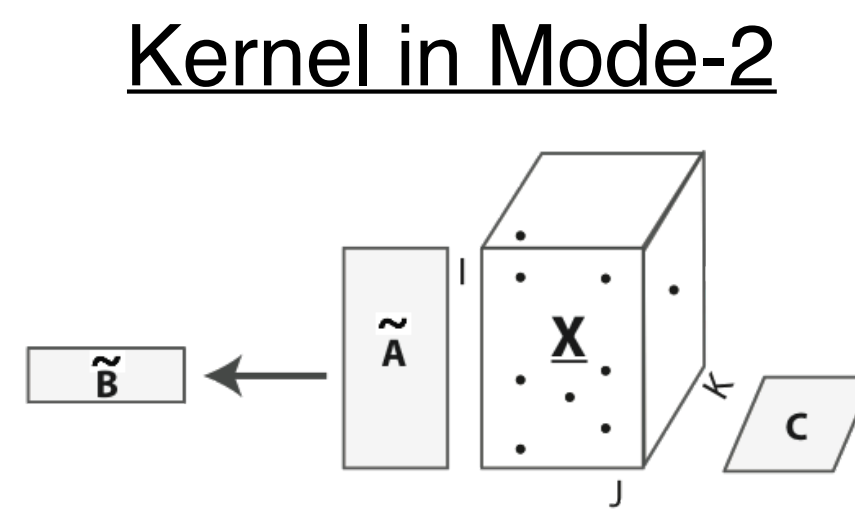
Mode-Specific Tensor Formats

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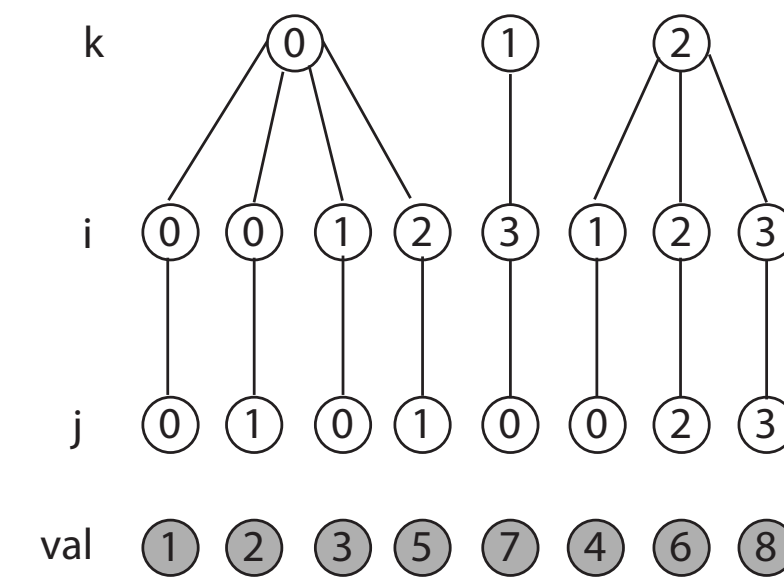
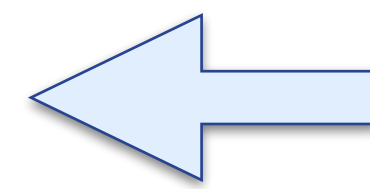
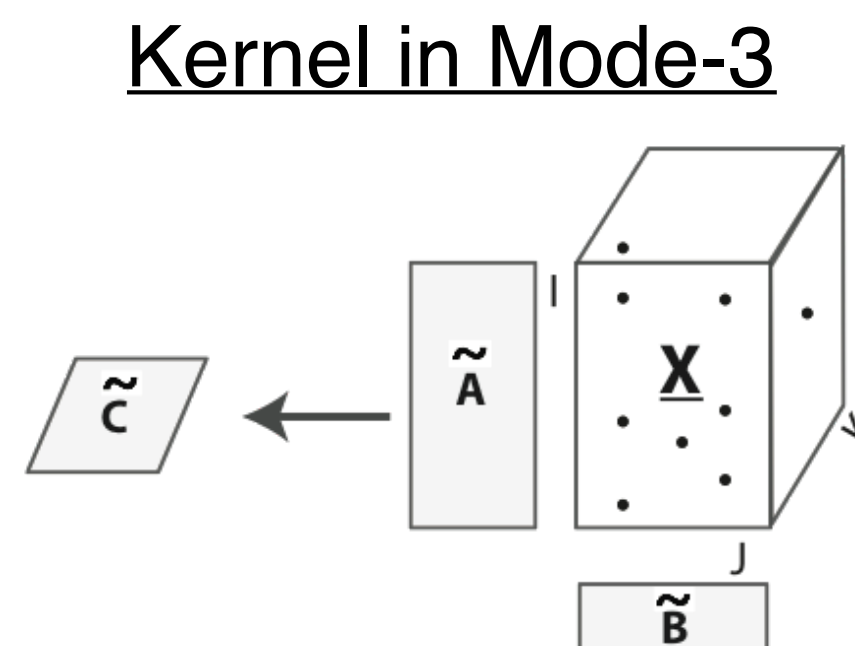
Tensor Decomposition



CSF-1



CSF-2

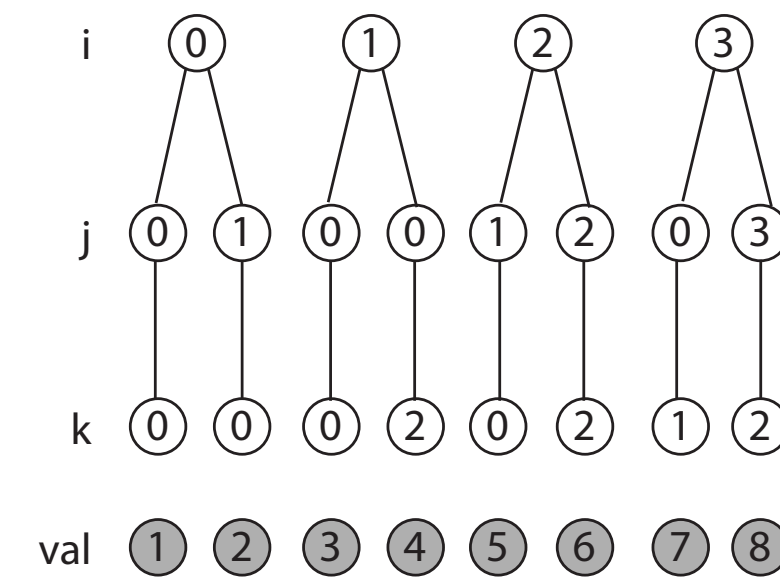
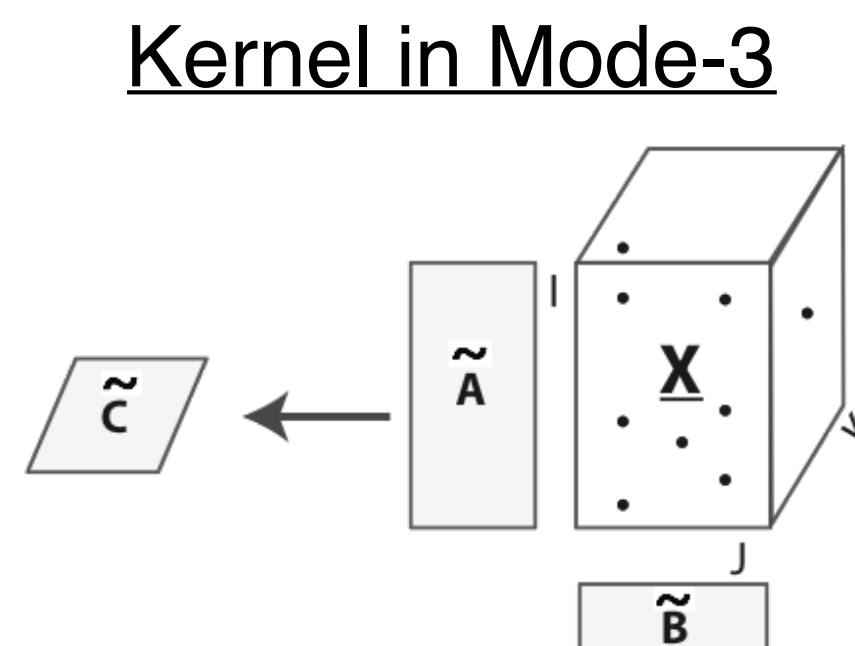
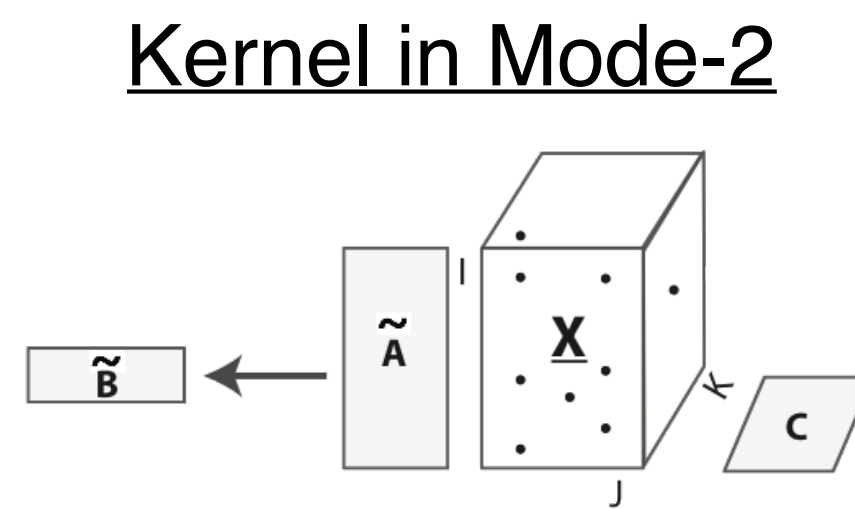
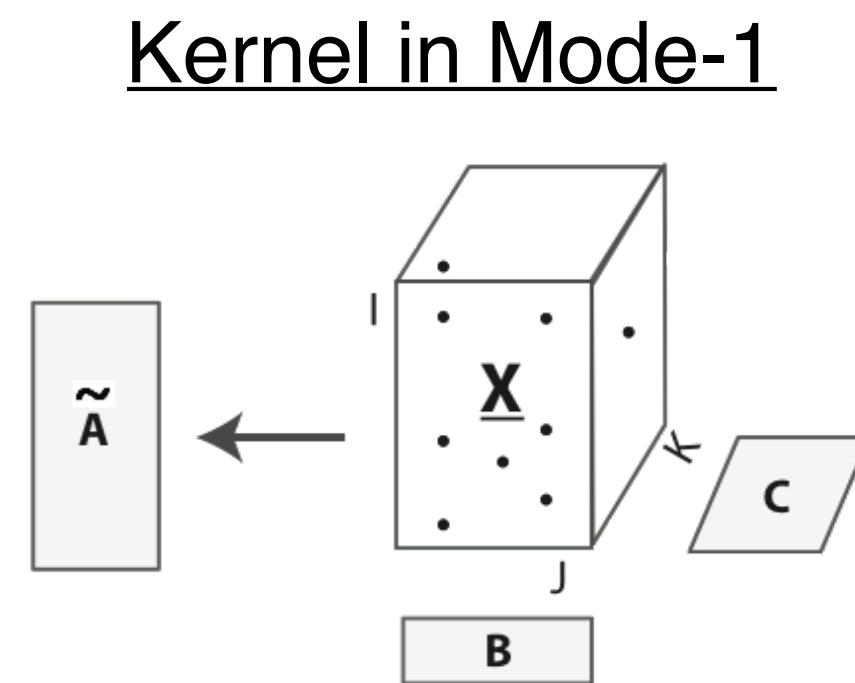


CSF-3

Mode-Specific Tensor Formats

- Three CSF/F-COO representations are required/preferred for three kernels.

Tensor Decomposition



CSF-1

Performance payoff

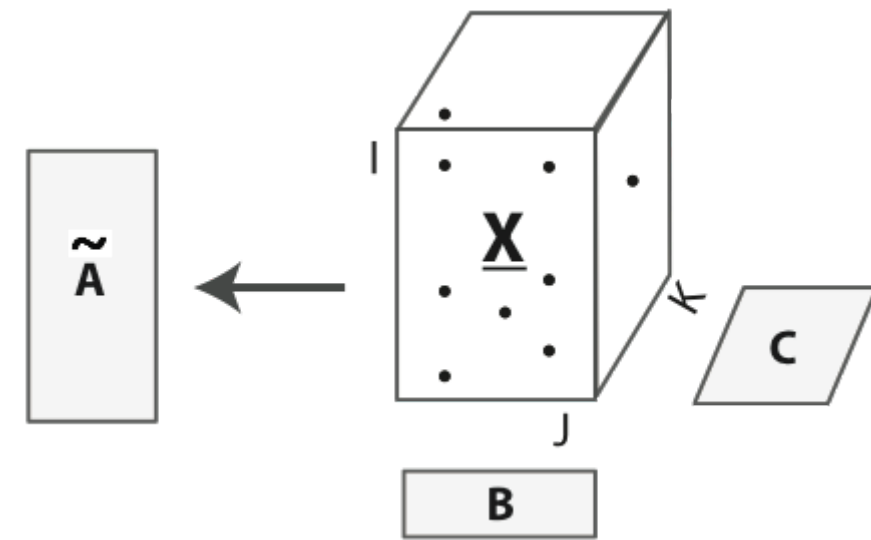
Mode Orientation

Tensor decomposition

Mode-Specific

Mode-Generic

Kernel in Mode-1



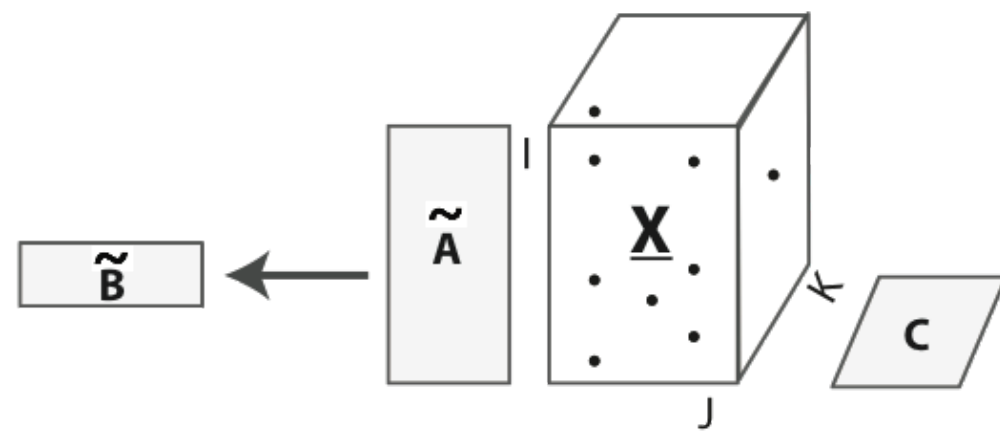
Mode-1 oriented (CSF/FCOO)

Coordinate (COO)

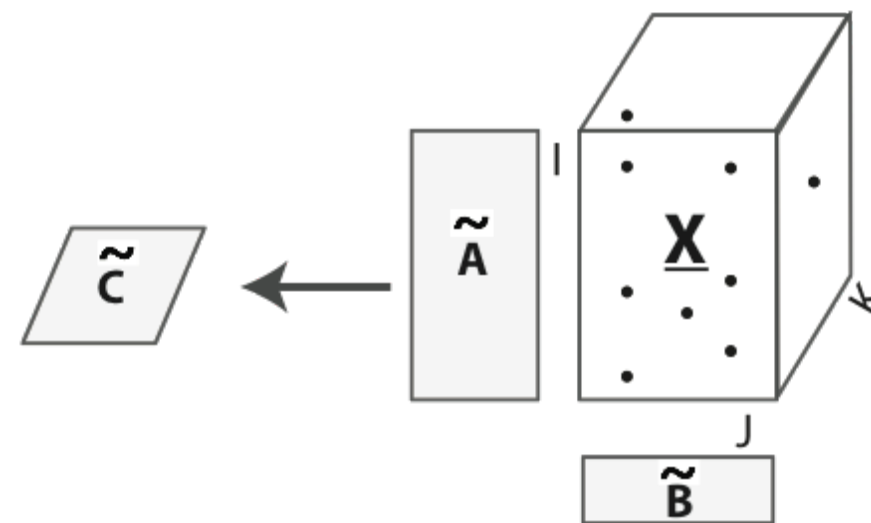
HiCOO



Kernel in Mode-2



Kernel in Mode-3



Efficient



In-efficient

HiCOO Format

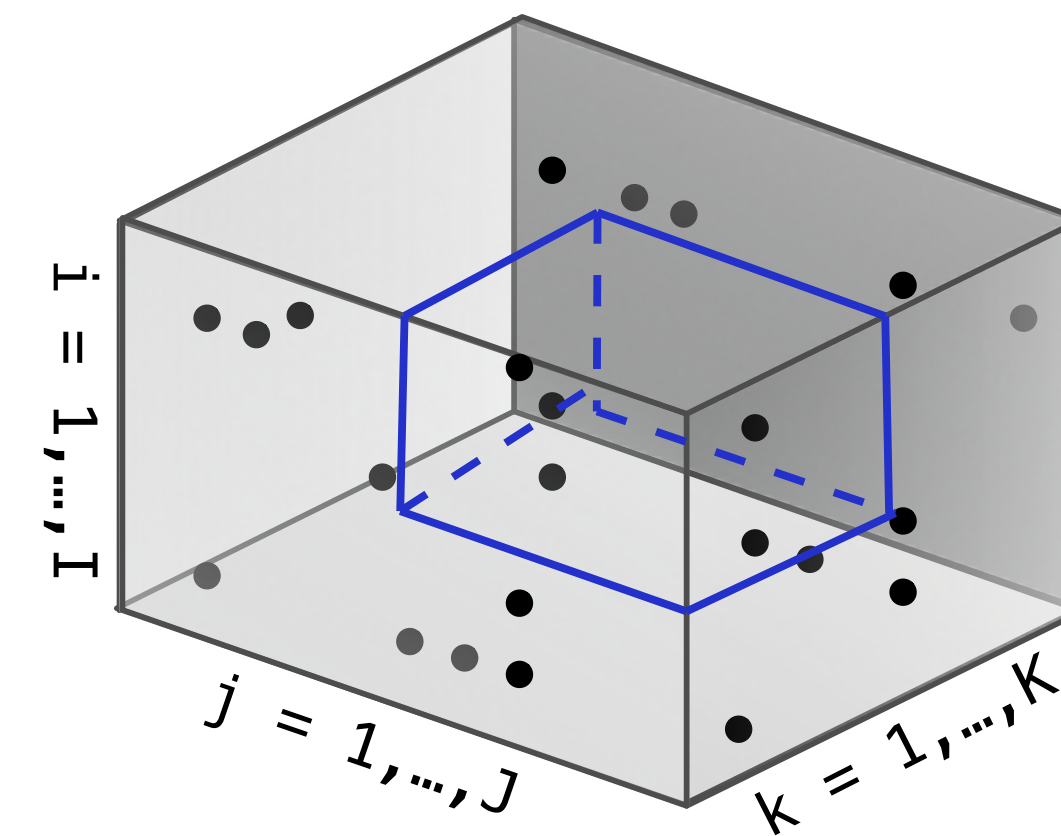
- Store a sparse tensor in units of small sparse blocks

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

	bptr	bi	bj	bk	ei	ej	ek	val
B1	0	0	0	0	0	0	0	1
					0	1	0	2
					1	0	0	3
B2	3	0	0	1	1	0	0	4
B3	4	1	0	0	0	1	0	5
					1	0	1	7
B4	6	1	1	1	0	0	0	6
					1	1	0	8

HiCOO



Block size: 2*2*2

HiCOO Format

- Store a sparse tensor in units of small sparse blocks

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

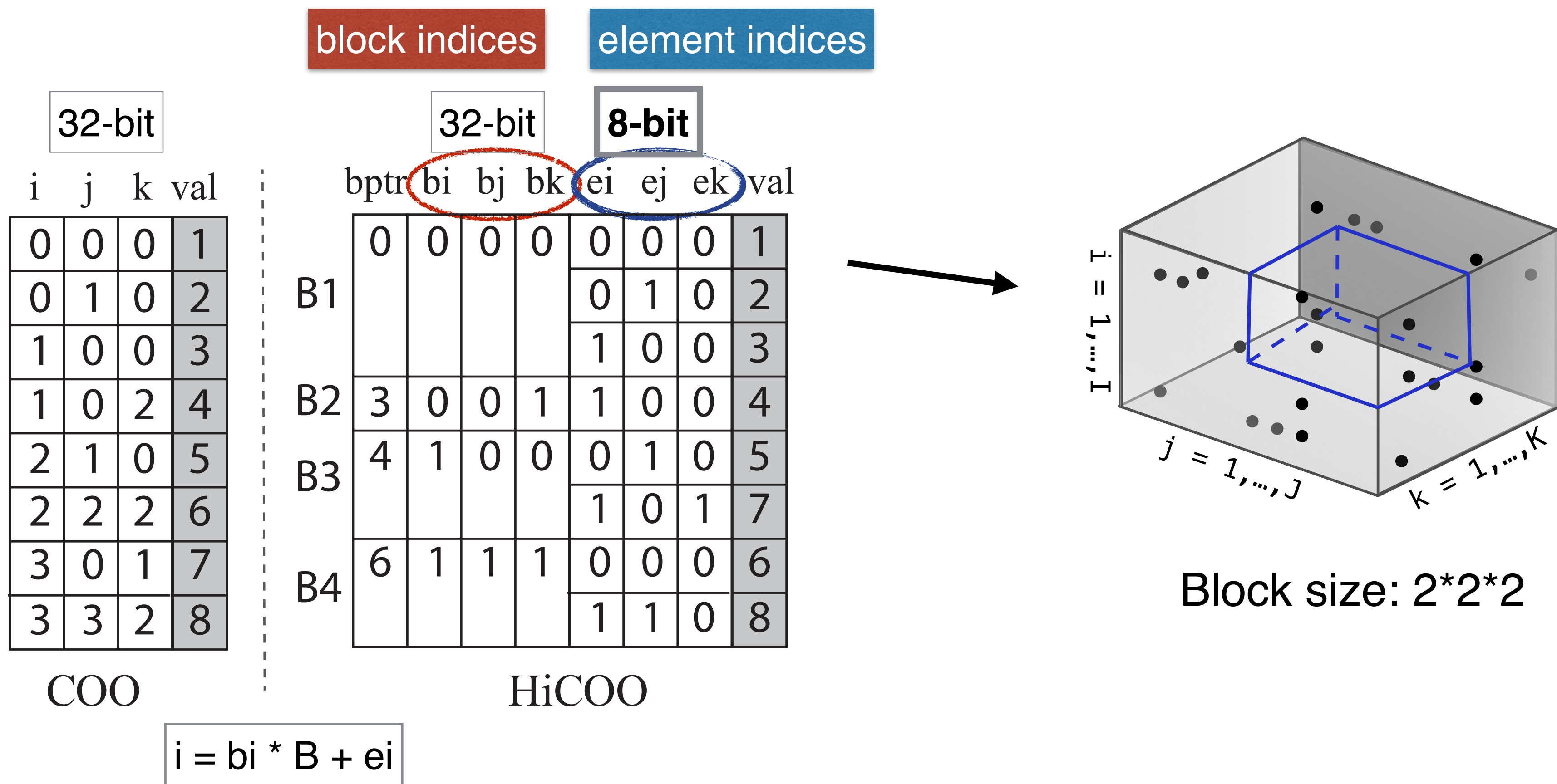
COO

	bptr	bi	bj	bk	ei	ej	ek	val
	0	0	0	0	0	0	0	1
B1					0	1	0	2
					1	0	0	3
B2	3	0	0	1	1	0	0	4
B3	4	1	0	0	0	1	0	5
					1	0	1	7
B4	6	1	1	1	0	0	0	6
					1	1	0	8

HiCOO

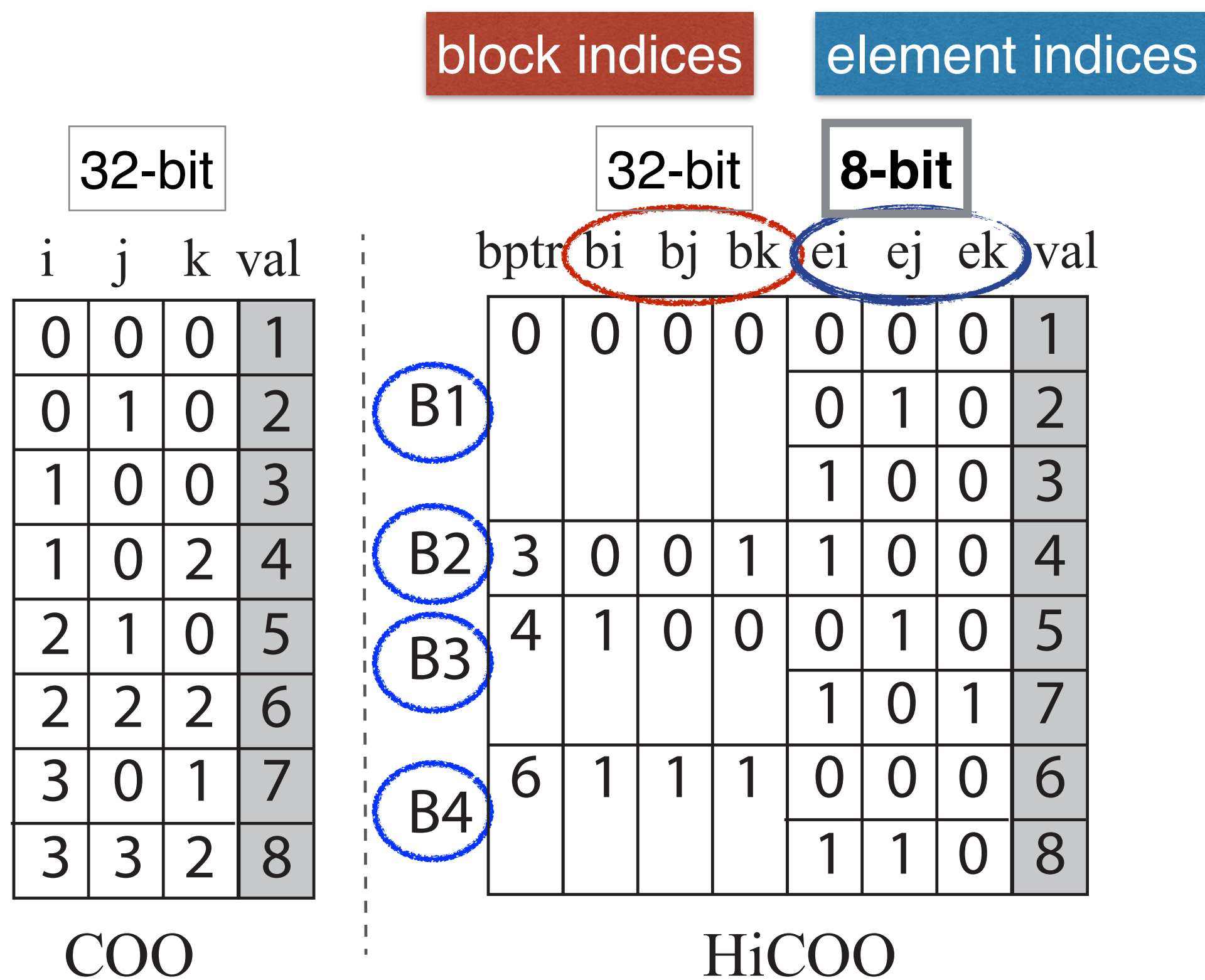
HiCOO Format

- Store a sparse tensor in units of small sparse blocks
- Shorten the bit-length of element indices



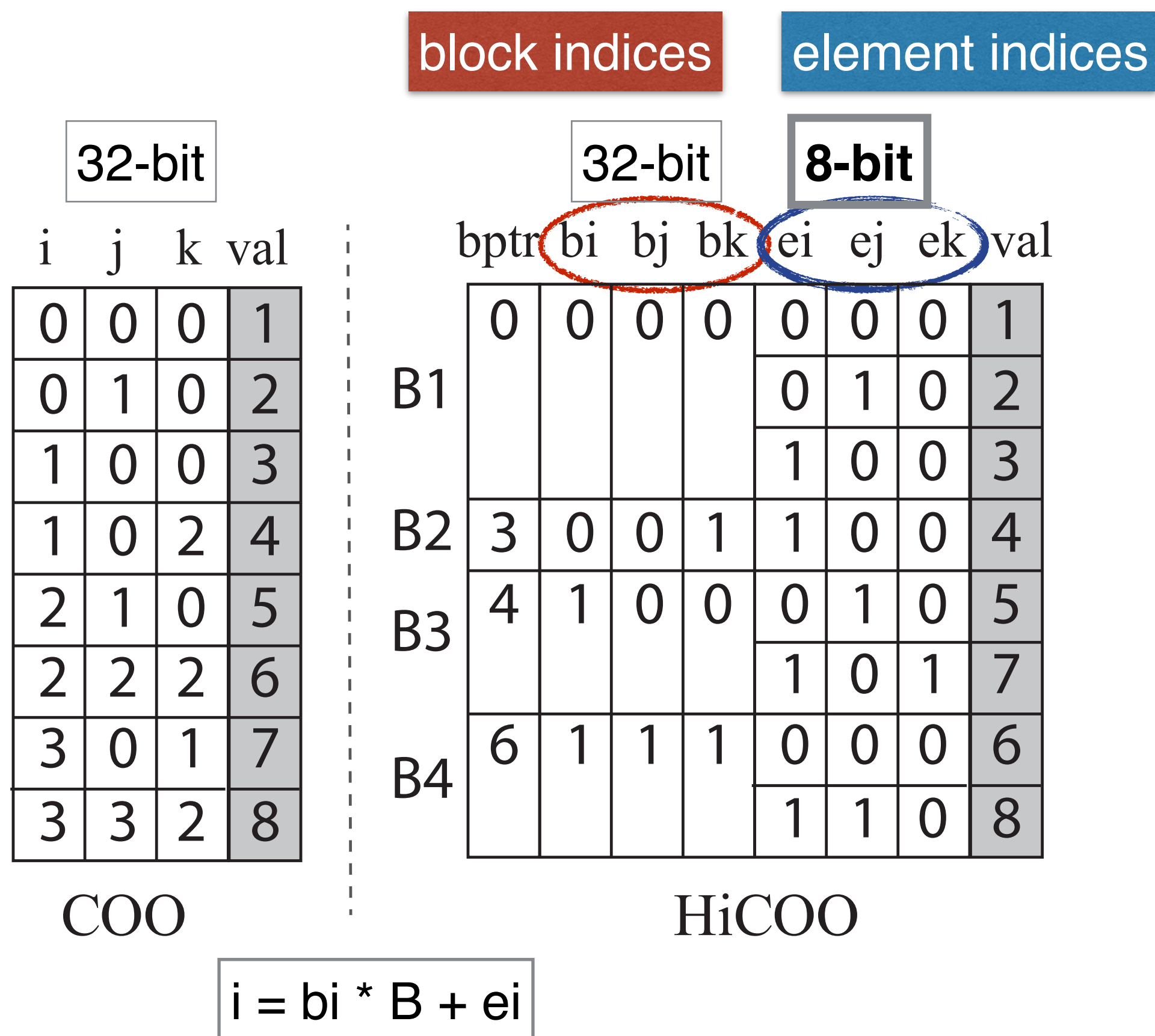
HiCOO Format

- Store a sparse tensor in units of small sparse blocks
- Shorten the bit-length of element indices
- Compress the number of block indices



HiCOO Format

- Store a sparse tensor in units of small sparse blocks
 - Shorten the bit-length of element indices
 - Compress the number of block indices



COO indices:
 $= nnz * 3 * 32$

HiCOO indices:
 $= nnz * 3 * 8 + nnb * (3 * 32 + 32)$

nnz: #Nonzeros; nnb: #Non-zero blocks

HiCOO Format

- Store a sparse tensor in units of small sparse blocks
 - Shorten the bit-length of element indices
 - Compress the number of block indices
 - For arbitrary-order sparse tensors.

32-bit				32-bit				8-bit			
i	j	k	val	bptr	bi	bj	bk	ei	ej	ek	val
0	0	0	1	B1	0	0	0	0	0	0	1
0	1	0	2		0	1	0	2			
1	0	0	3		1	0	0	3			
1	0	2	4	B2	3	0	0	1	1	0	4
2	1	0	5	B3	4	1	0	0	0	1	5
2	2	2	6		1	0	1	7			
3	0	1	7	B4	6	1	1	1	0	0	6
3	3	2	8		1	1	0	8			

For the tensor: Reduce its storage and memory footprints

For matrices: Better data locality

Format Conversion

$|\beta_{\text{int}}| \beta_{\text{float}}$

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

Z-Order
Sorting
→

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
3	0	1	7
2	2	2	6
3	3	2	8



$$i = b_i * B + e_i; \quad j = b_j * B + e_j; \quad k = b_k * B + e_k$$

Format Conversion

$|\beta_{\text{int}}| \beta_{\text{float}}$

i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

Z-Order
Sorting

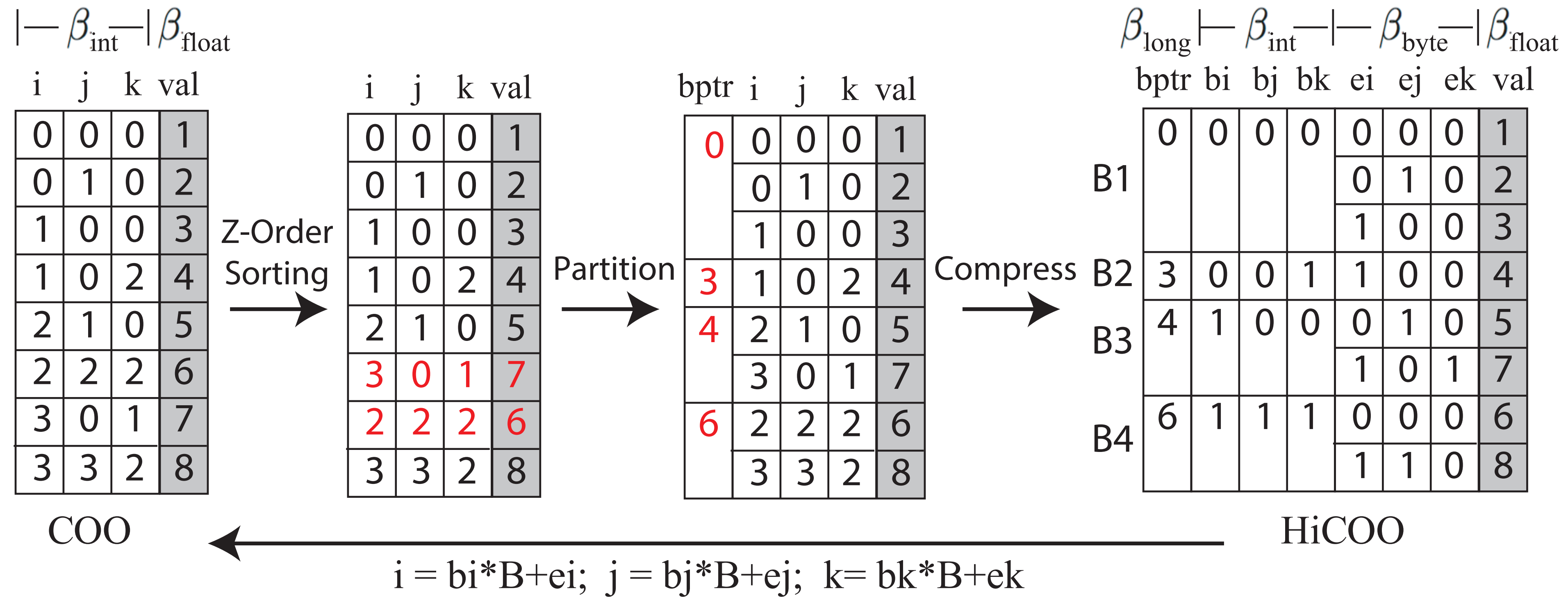
i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
3	0	1	7
2	2	2	6
3	3	2	8

Partition

bptr	i	j	k	val
0	0	0	0	1
	0	1	0	2
	1	0	0	3
3	1	0	2	4
4	2	1	0	5
	3	0	1	7
6	2	2	2	6
	3	3	2	8

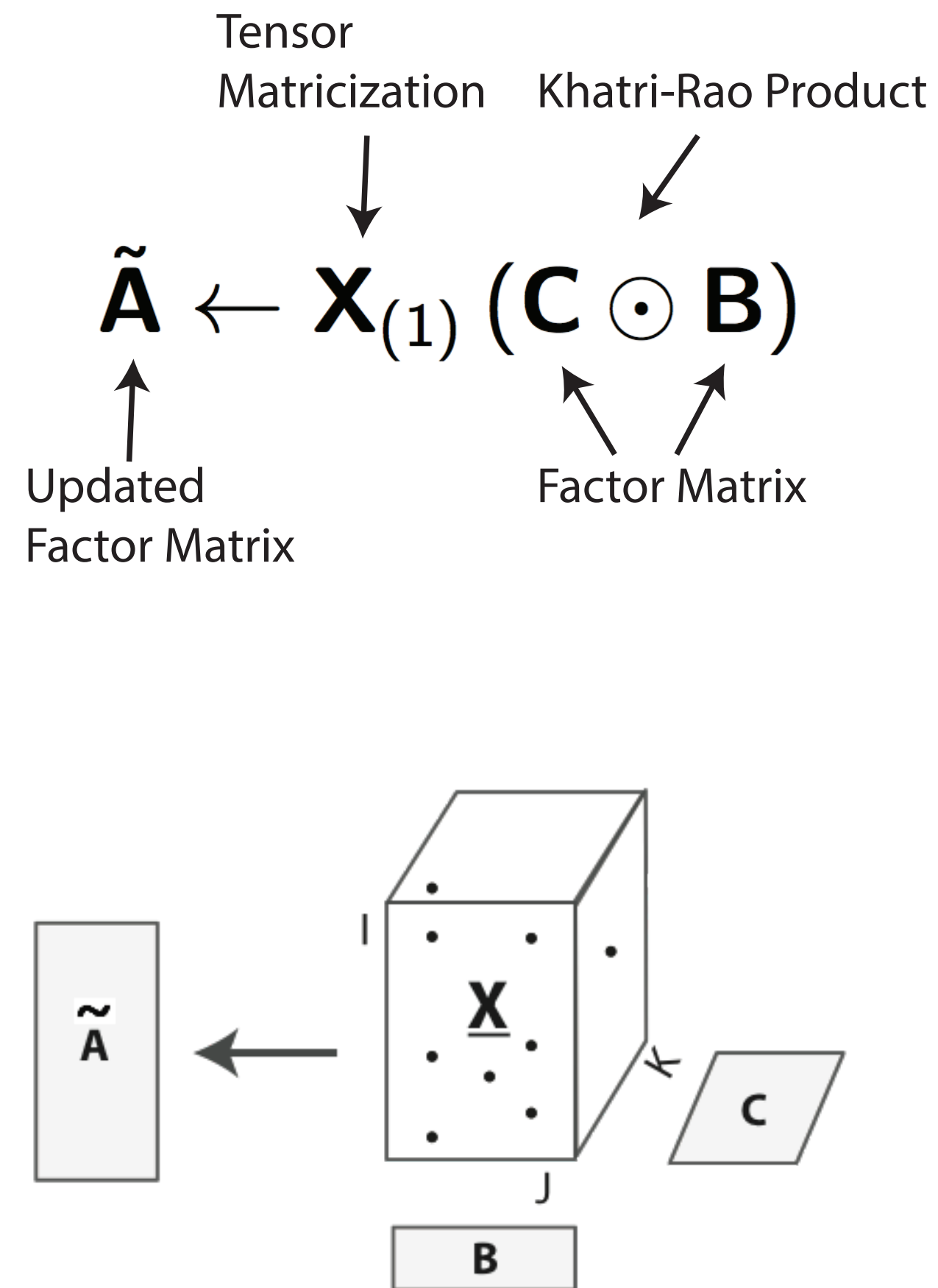
$i = b_i * B + e_i; j = b_j * B + e_j; k = b_k * B + e_k$

Format Conversion

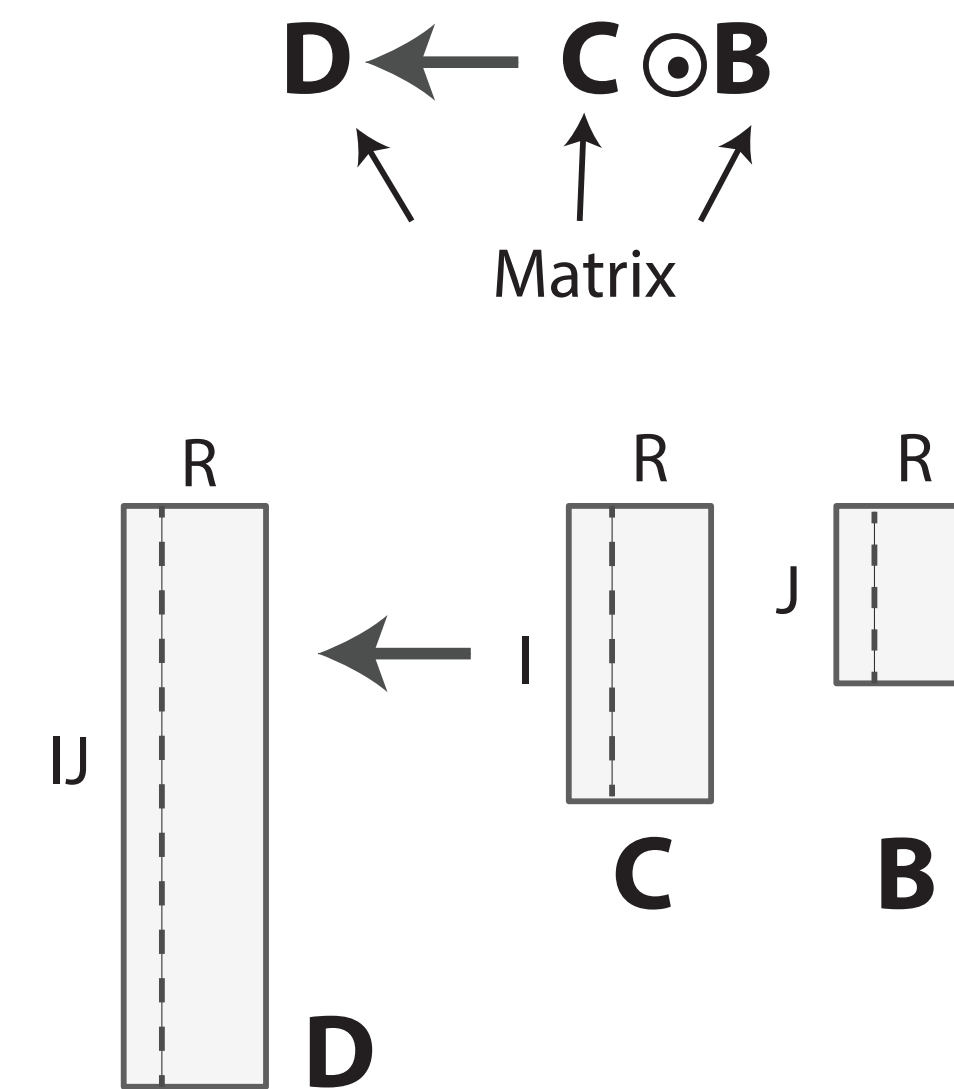


MTTKRP Operation

- Matriced Tensor Times Khatri-Rao Product (MTTKRP)

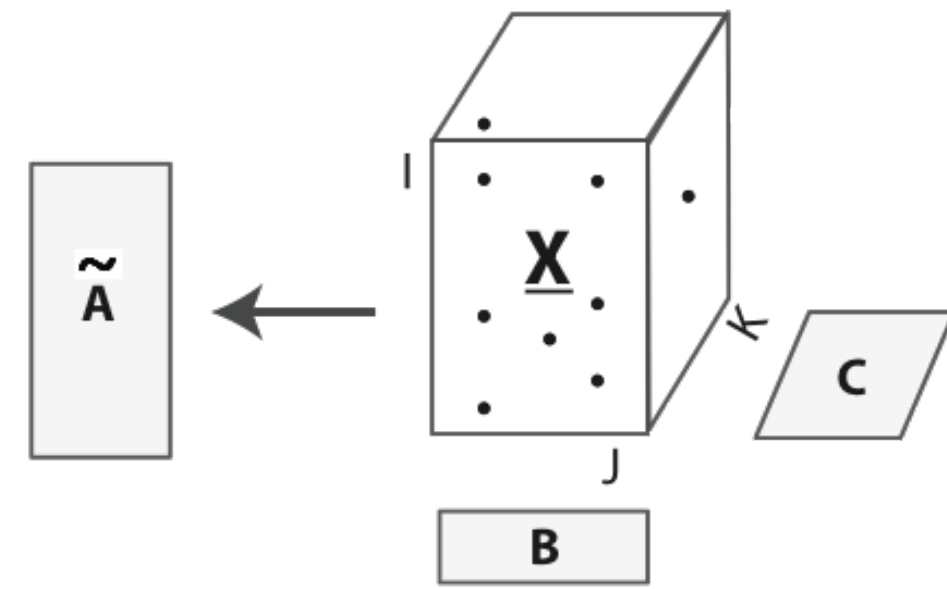
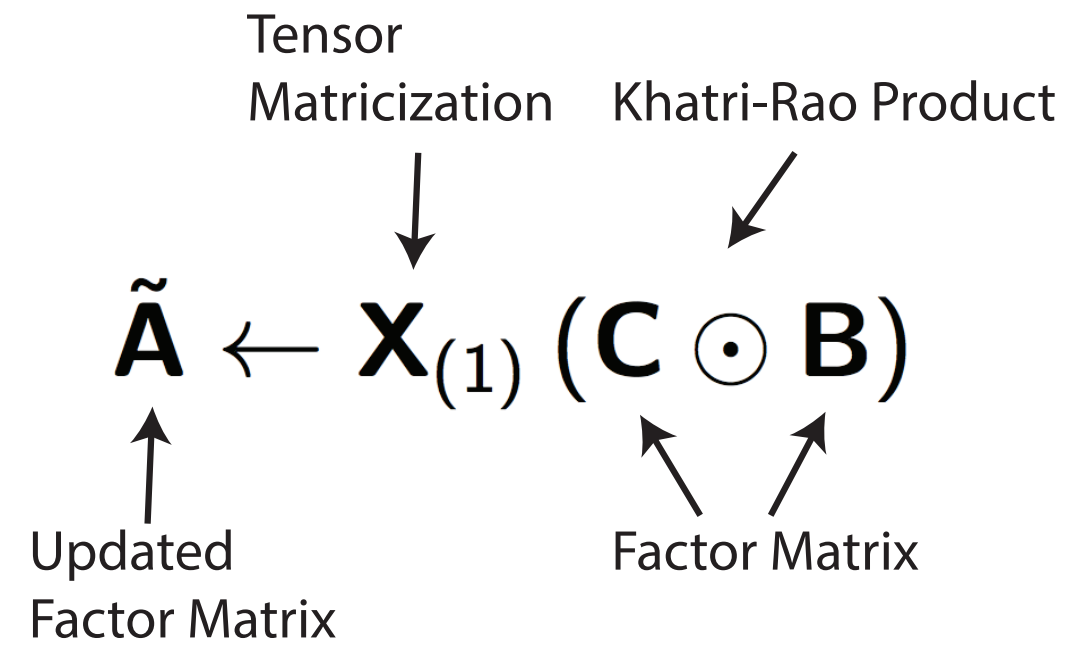


- Khatri-Rao Product

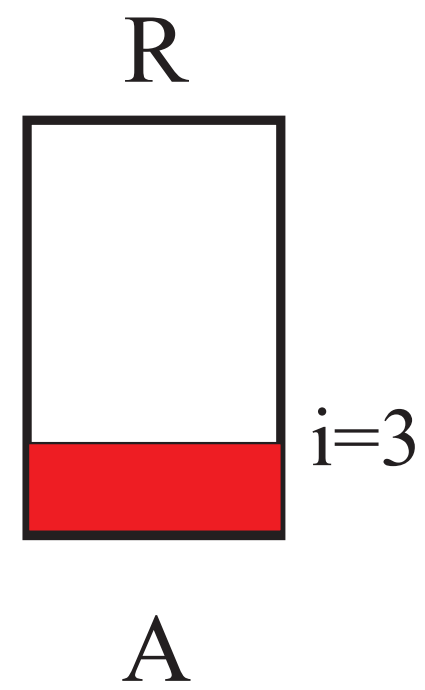


MTTKRP is the performance bottleneck of CP decomposition.

COO-MTTKRP

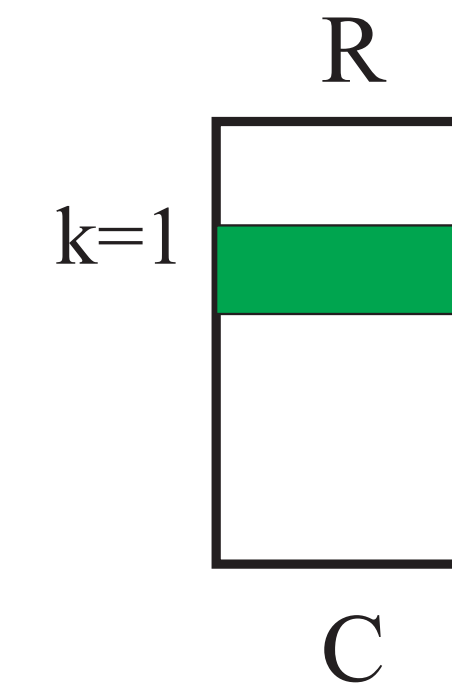
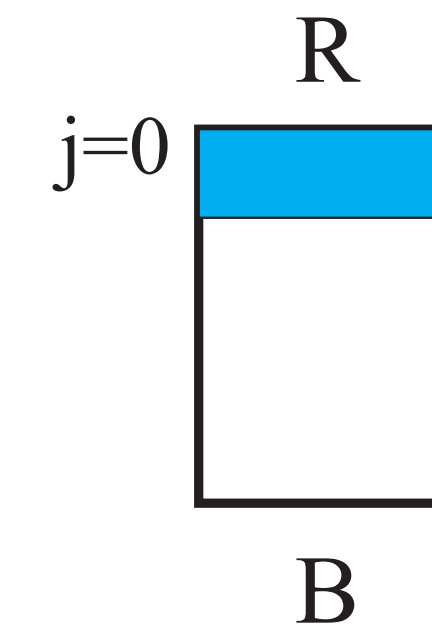


COO-MTTKRP algorithm in mode-1



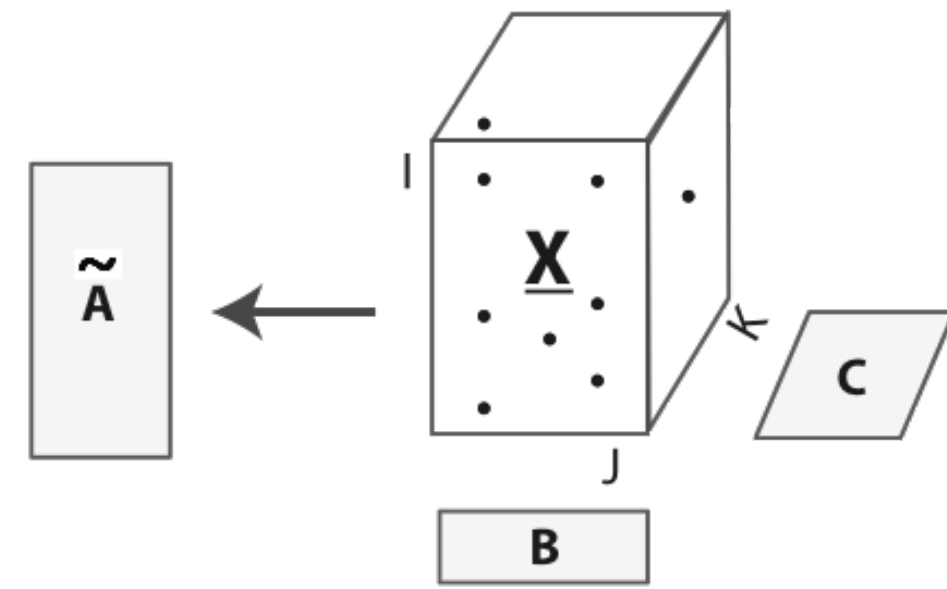
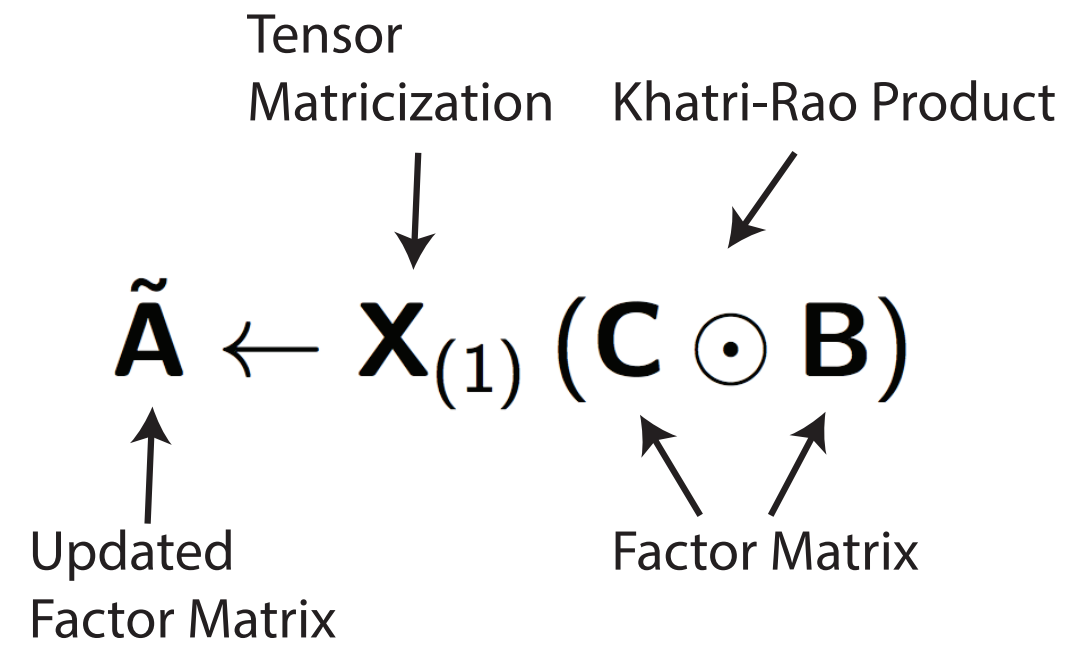
i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

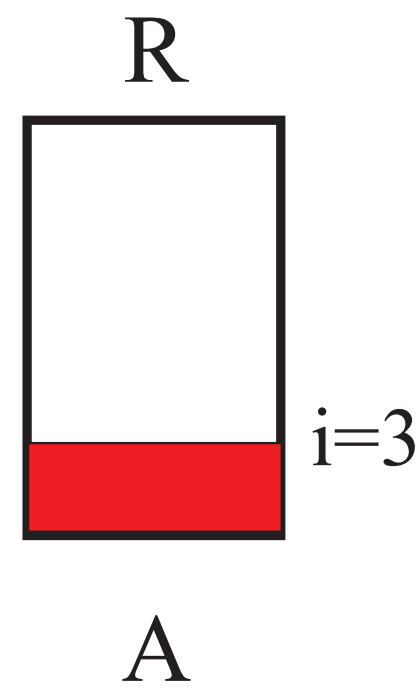


Entry-wise ← • (*)

COO-MTTKRP

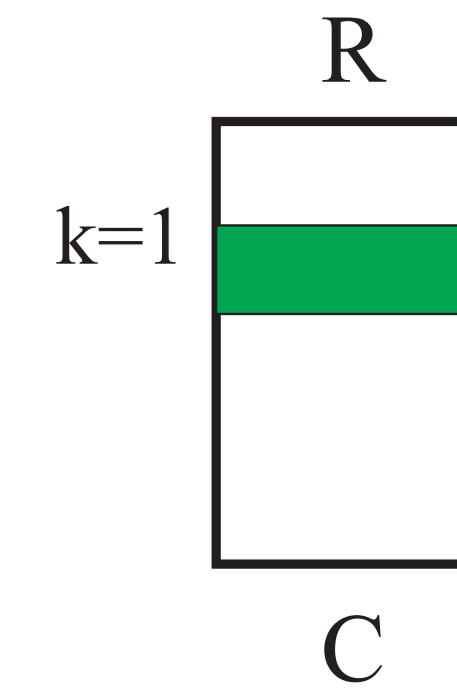
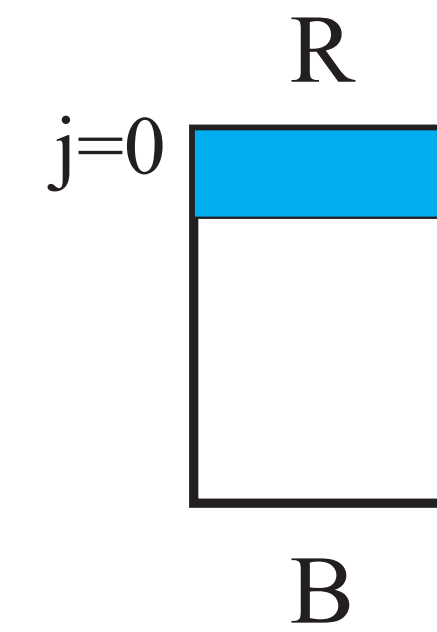


COO-MTTKRP algorithm in mode-1



i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
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3	0	1	7
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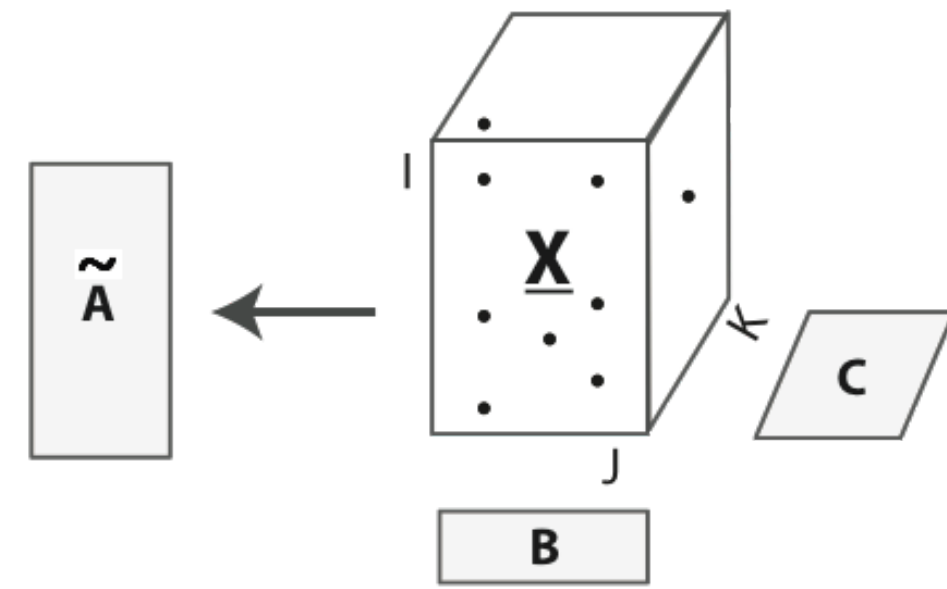
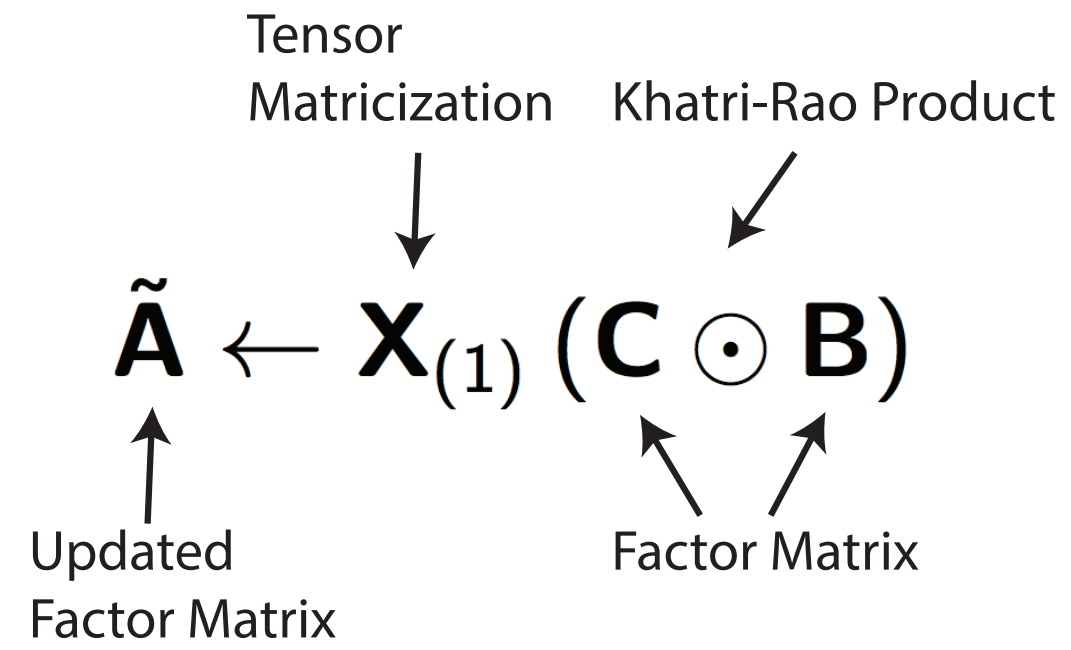
COO



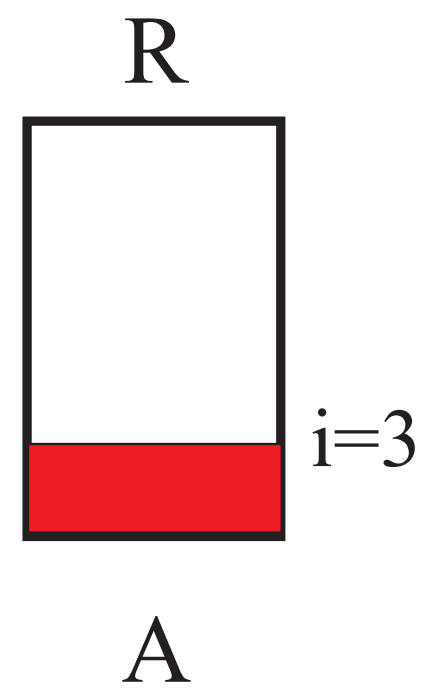
Entry-wise

$$\text{red box} \leftarrow 7 \cdot (\text{blue box} * \text{green box})$$

COO-MTTKRP

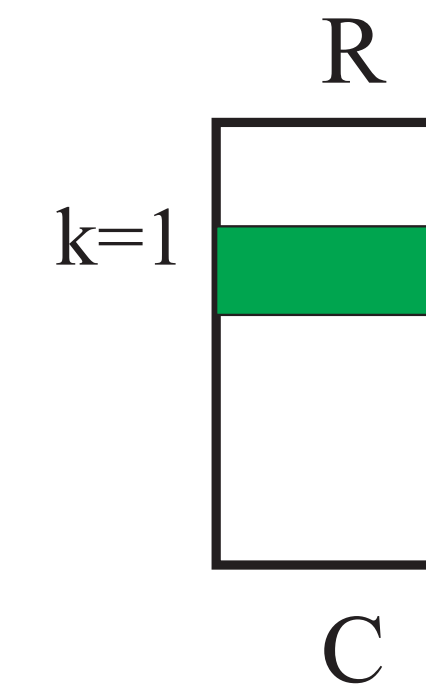
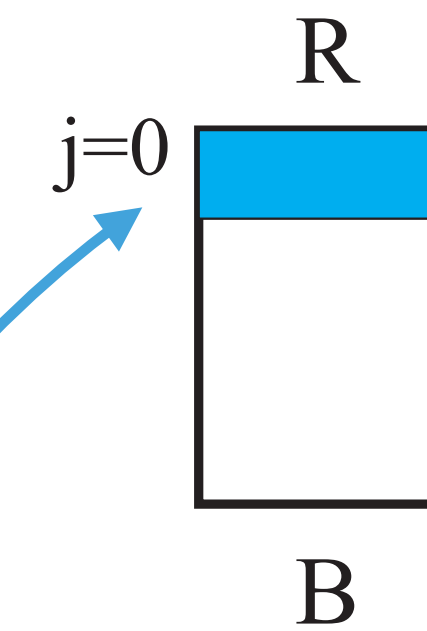


COO-MTTKRP algorithm in mode-1



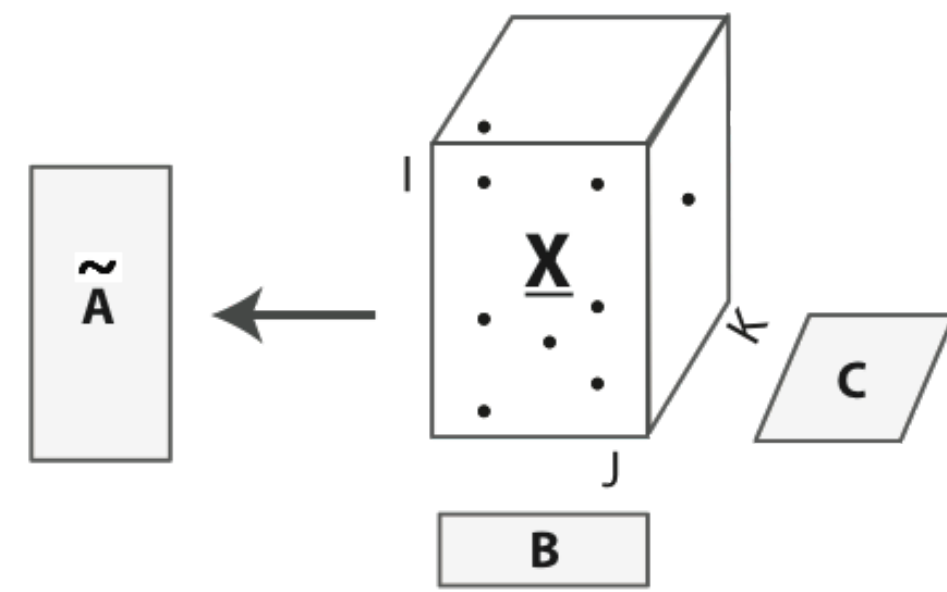
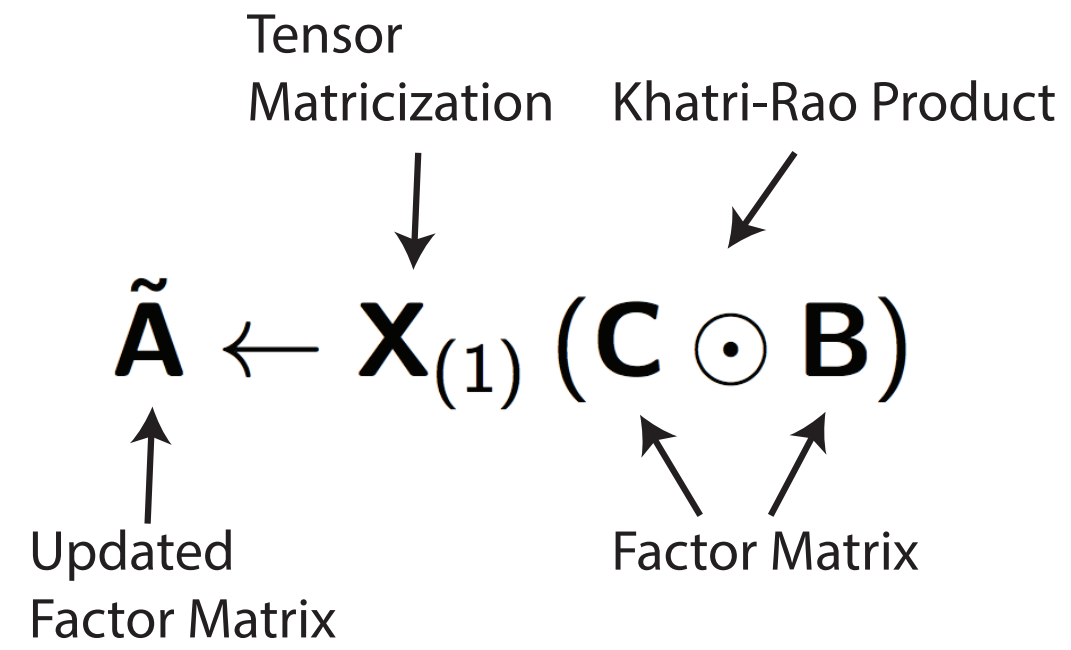
i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

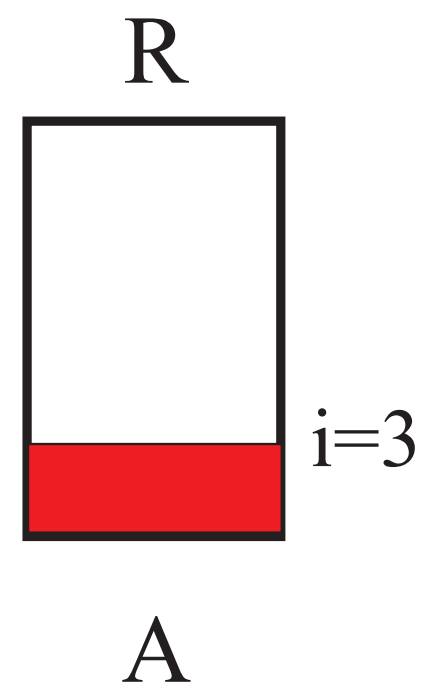


Entry-wise ← • (*)

COO-MTTKRP

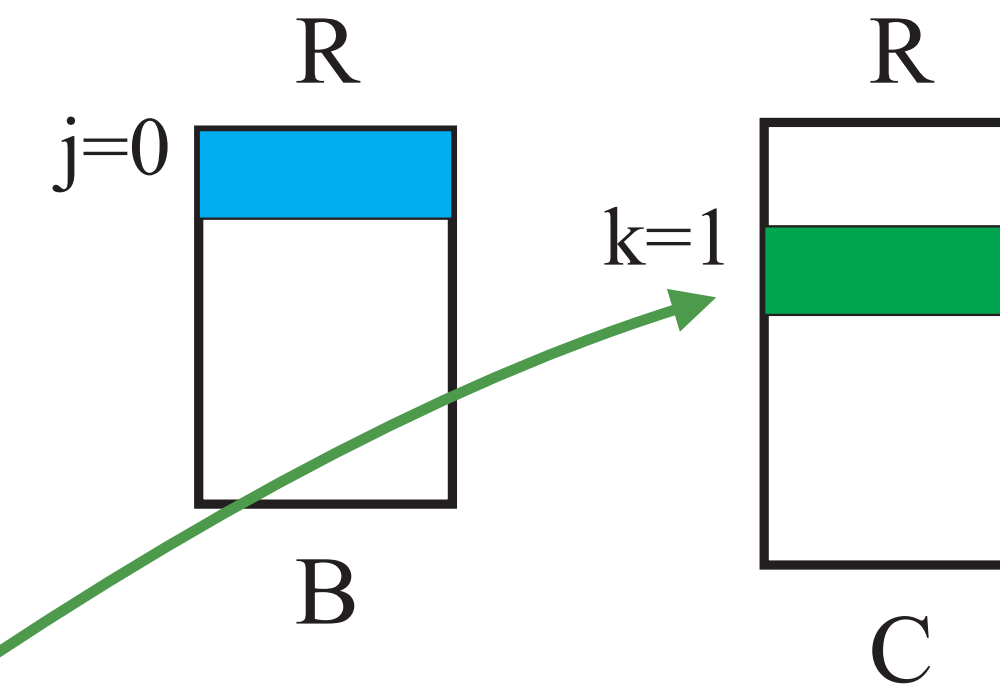


COO-MTTKRP algorithm in mode-1



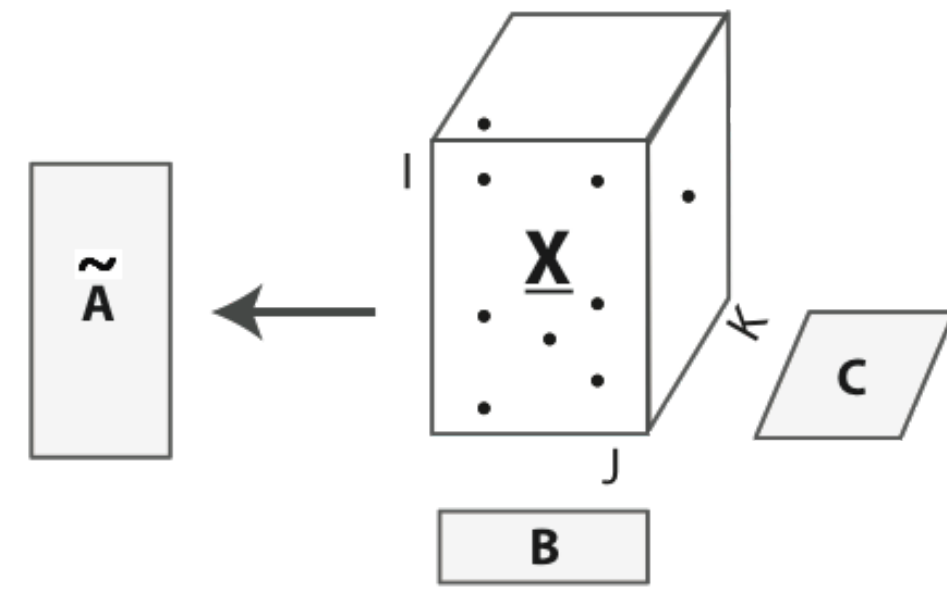
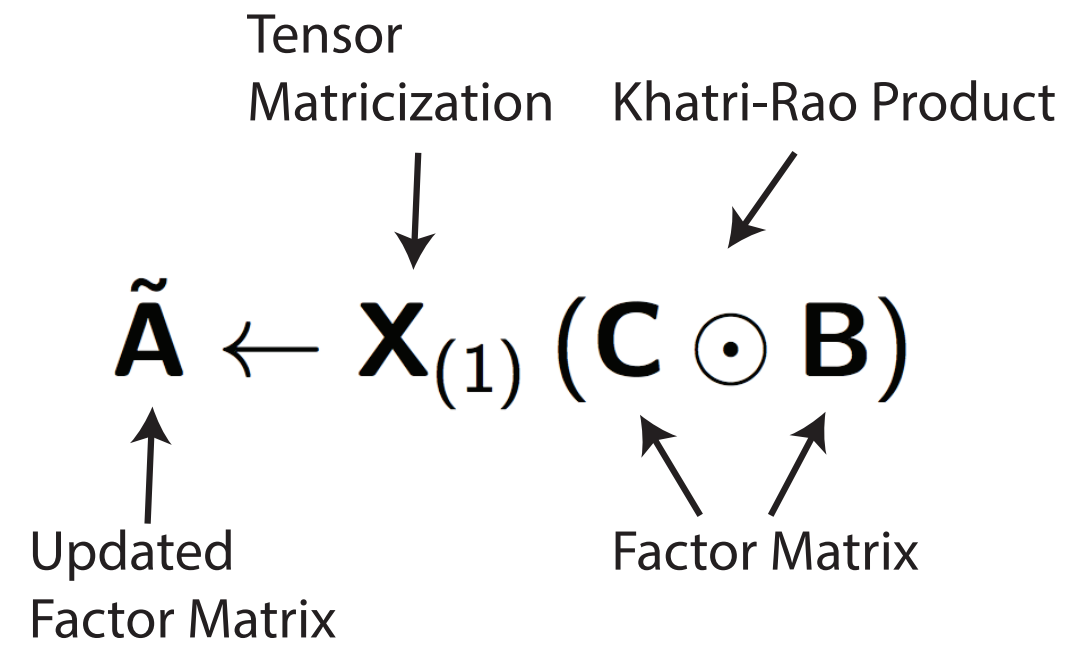
i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

COO

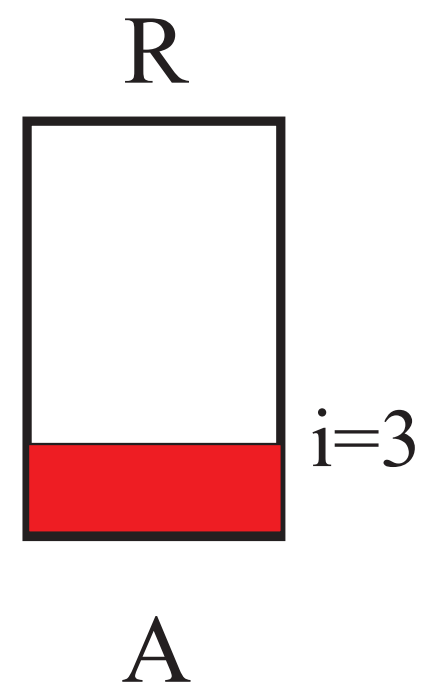


Entry-wise ← • (*)

COO-MTTKRP

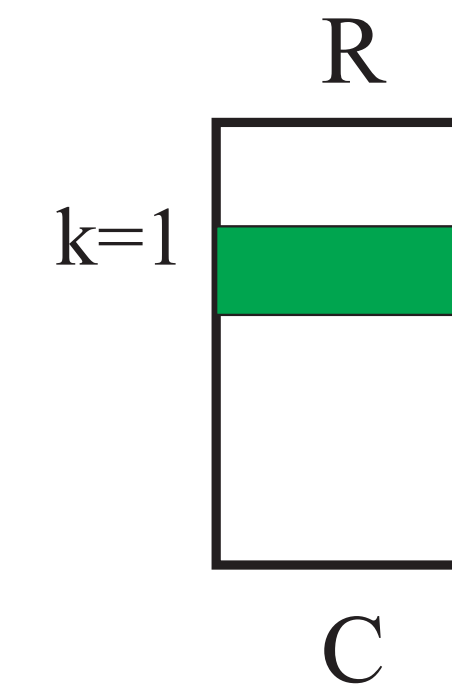
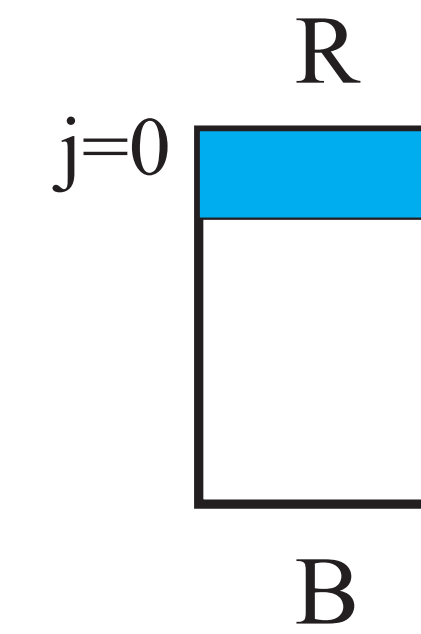


COO-MTTKRP algorithm in mode-1



i	j	k	val
0	0	0	1
0	1	0	2
1	0	0	3
1	0	2	4
2	1	0	5
2	2	2	6
3	0	1	7
3	3	2	8

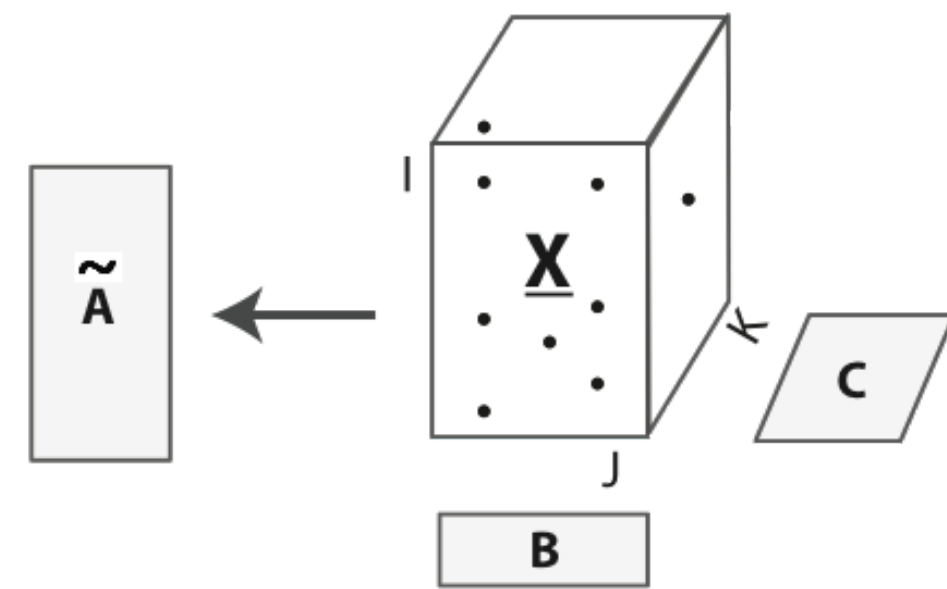
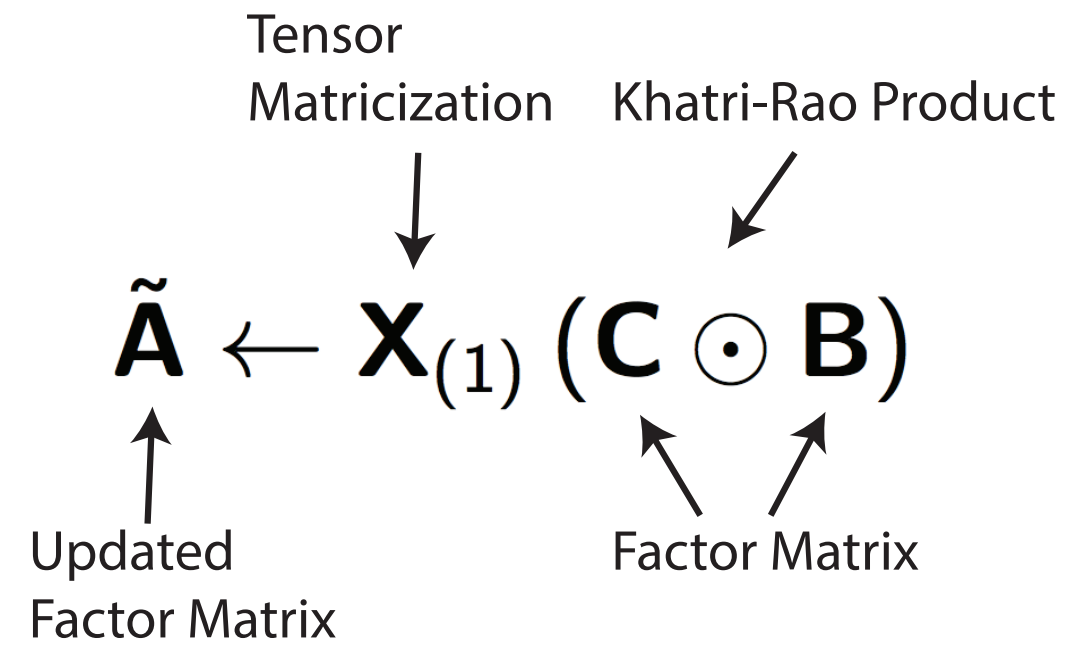
COO



Entry-wise



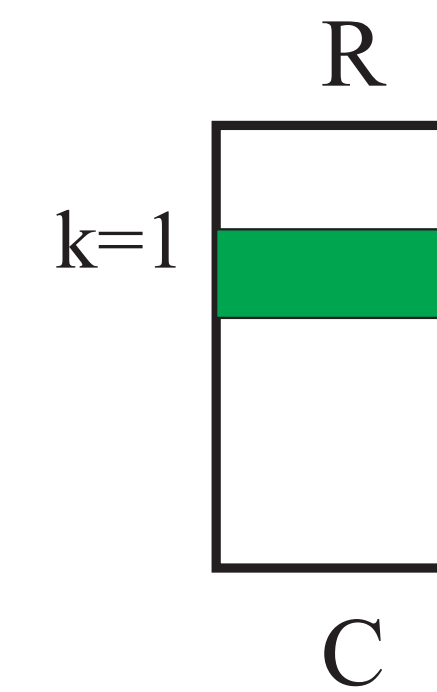
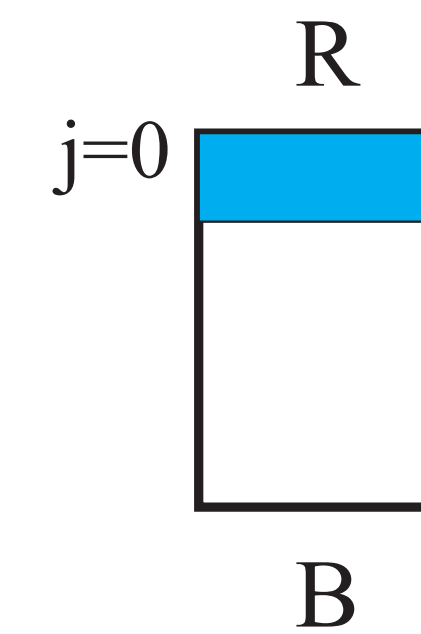
COO-MTTKRP



COO-MTTKRP algorithm in mode-1

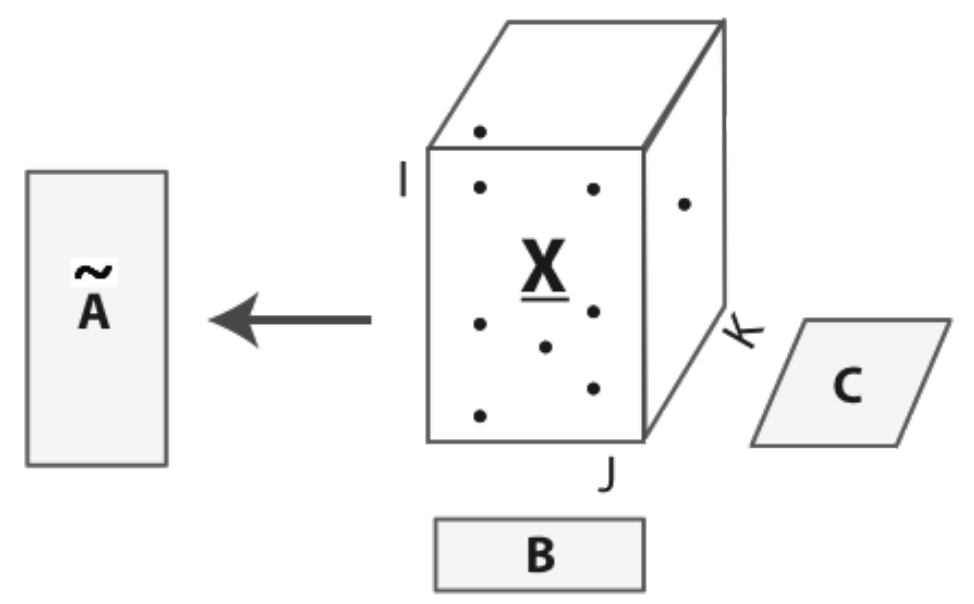
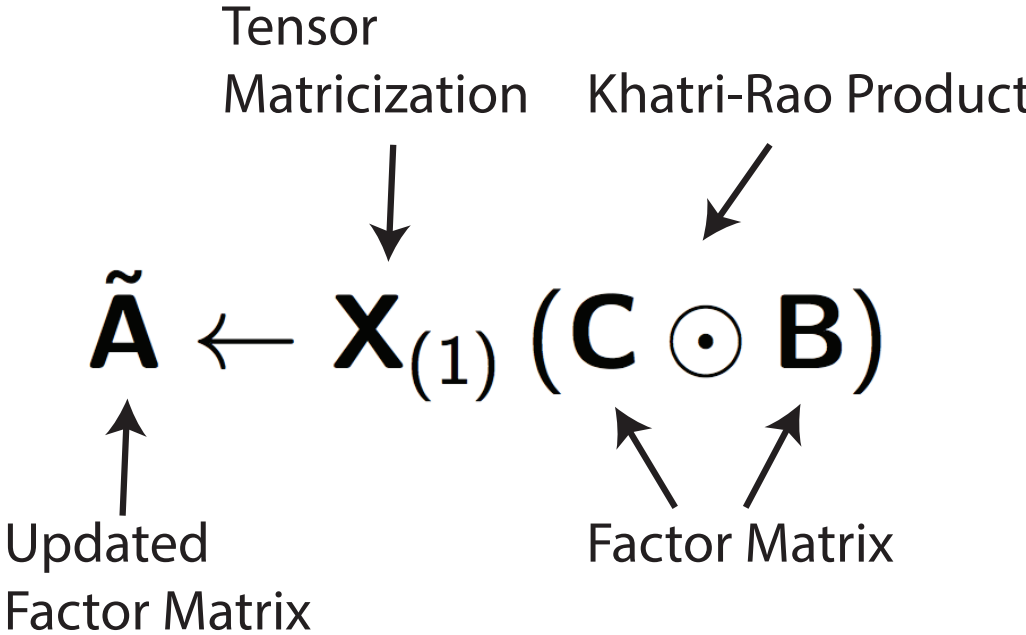
R		i j k val			
		0	0	0	1
		0	1	0	2
		1	0	0	3
		1	0	2	4
		2	1	0	5
		2	2	2	6
		3	0	1	7
		3	3	2	8

COO

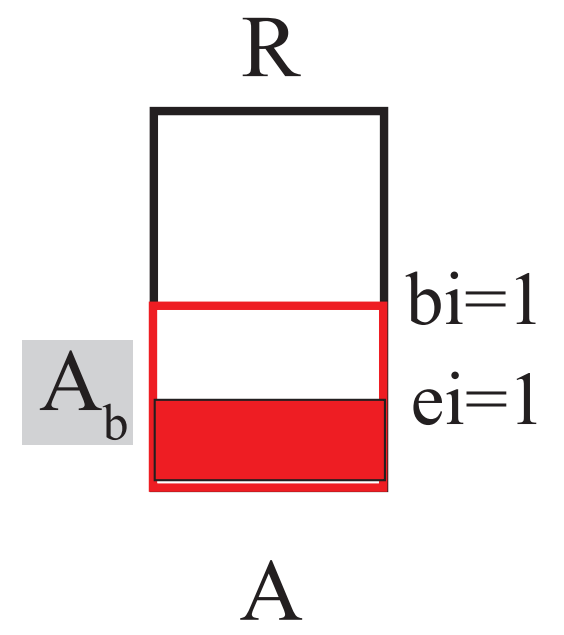


Entry-wise ← • (*)

HiCOO-MTTKRP

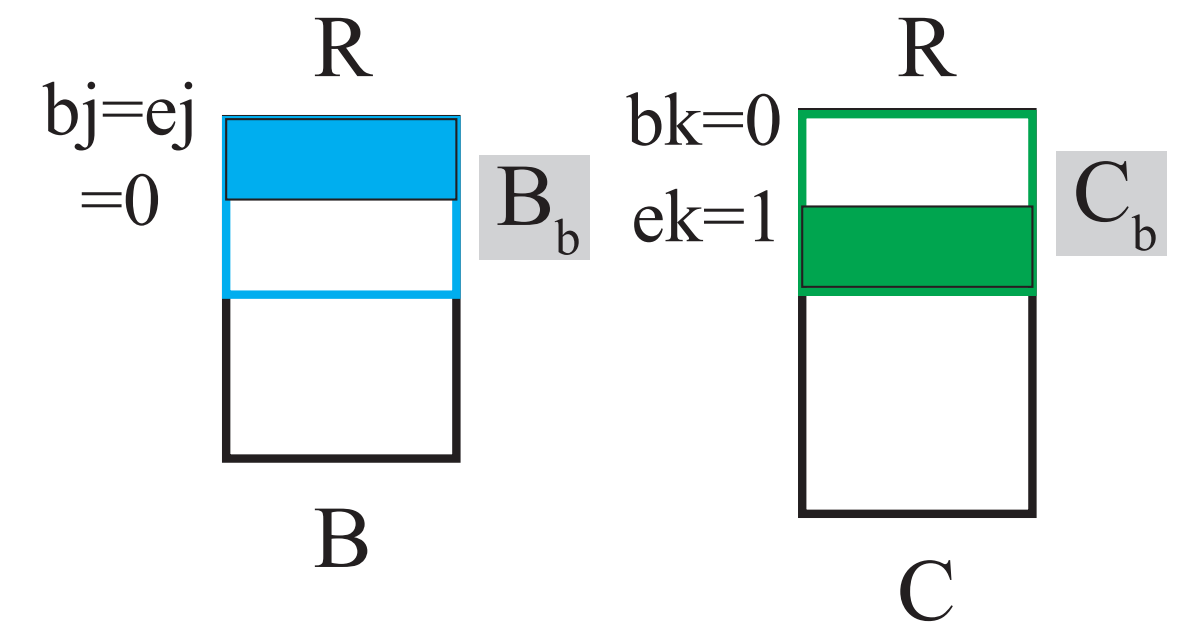


HiCOO-MTTKRP algorithm in mode-1



	bptr	bi	bj	bk	ei	ej	ek	val
B1		0	0	0	0	0	0	1
					0	1	0	2
					1	0	0	3
B2	3	0	0	1	1	0	0	4
B3	4	1	0	0	0	1	0	5
					1	0	1	7
B4	6	1	1	1	0	0	0	6
					1	1	0	8

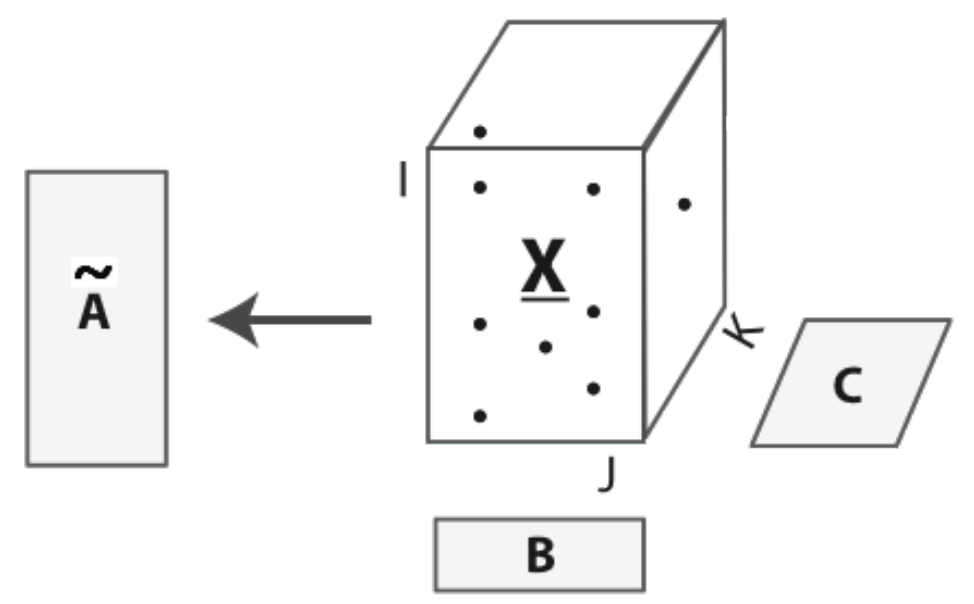
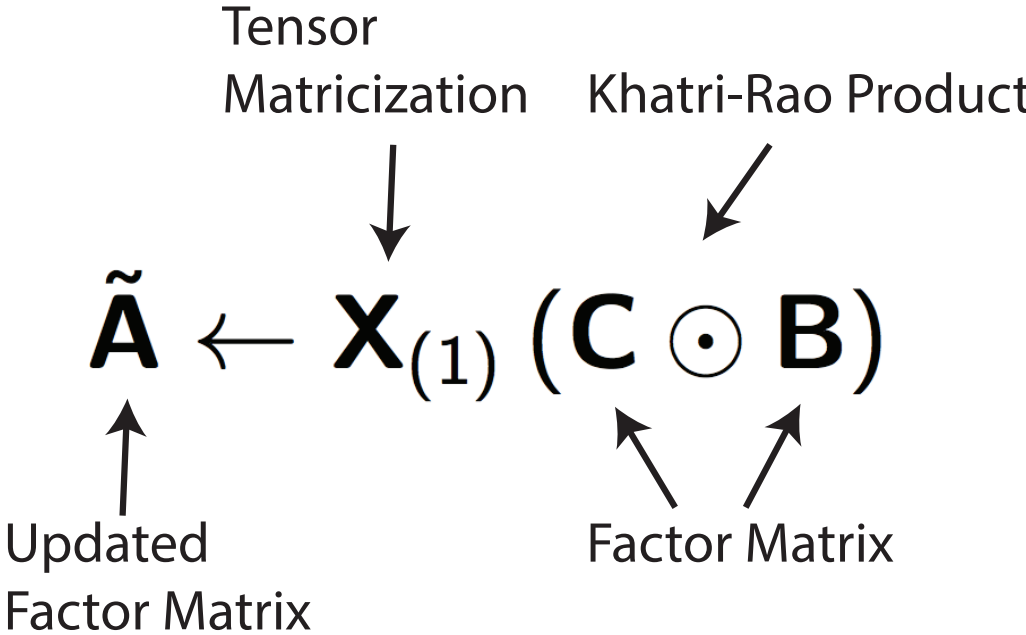
HiCOO



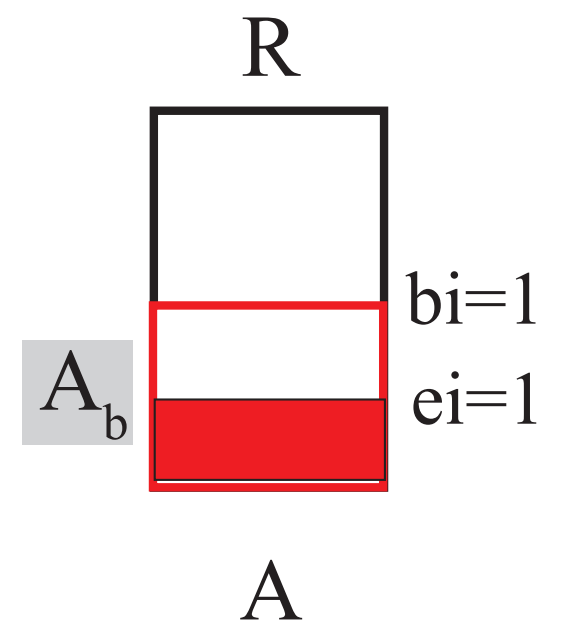
Entry-wise

$\mathbf{A}_b \leftarrow 7 \cdot (\mathbf{B}_b * \mathbf{C}_b)$

HiCOO-MTTKRP

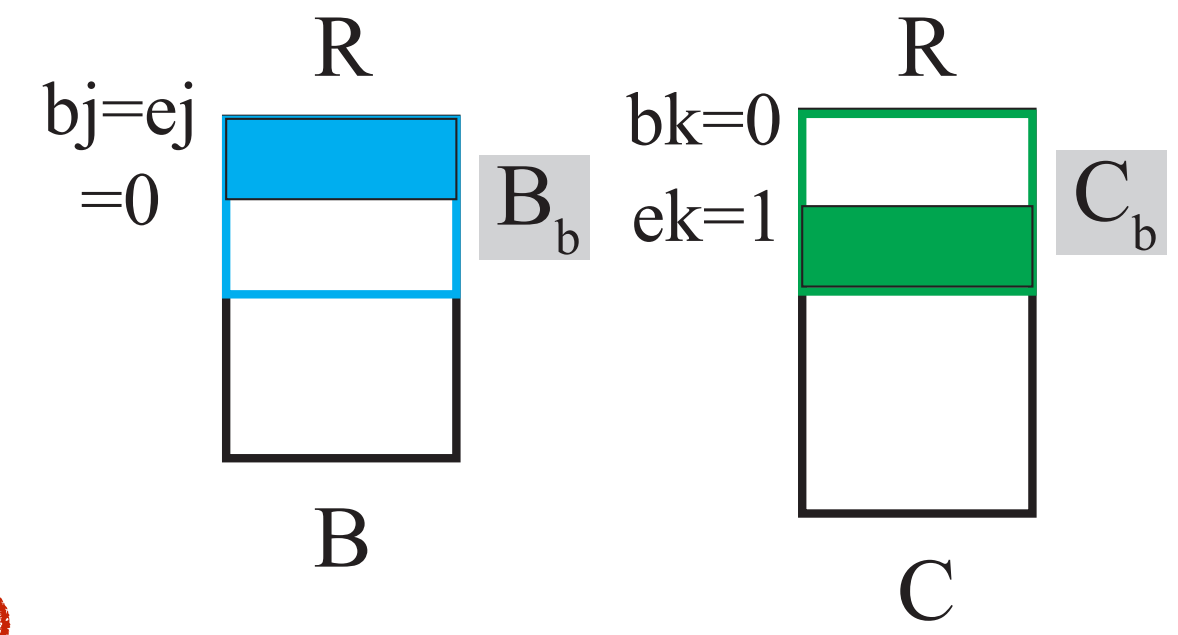


HiCOO-MTTKRP algorithm in mode-1

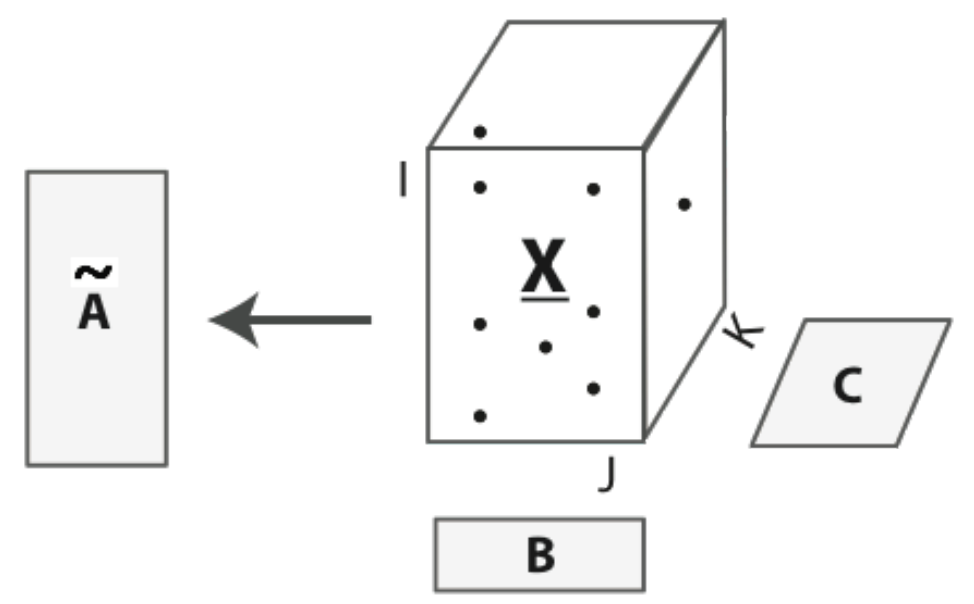
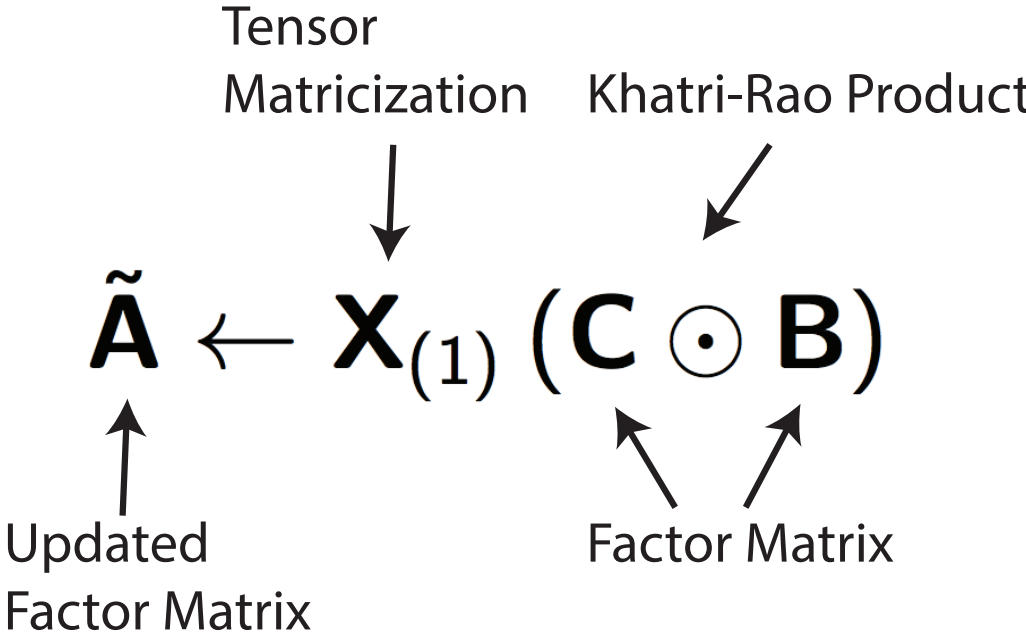


	bptr	bi	bj	bk	ei	ej	ek	val
B1		0	0	0	0	0	0	1
					0	1	0	2
					1	0	0	3
B2	3	0	0	1	1	0	0	4
B3	4	1	0	0	0	1	0	5
					1	0	1	7
B4	6	1	1	1	0	0	0	6
					1	1	0	8

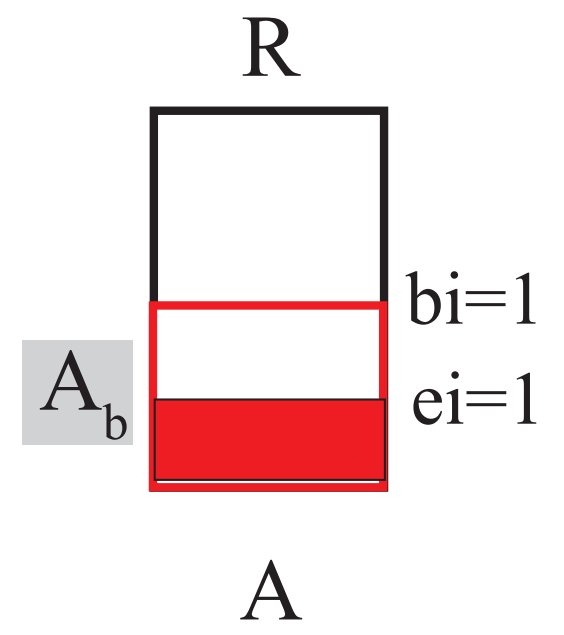
HiCOO



HiCOO-MTTKRP

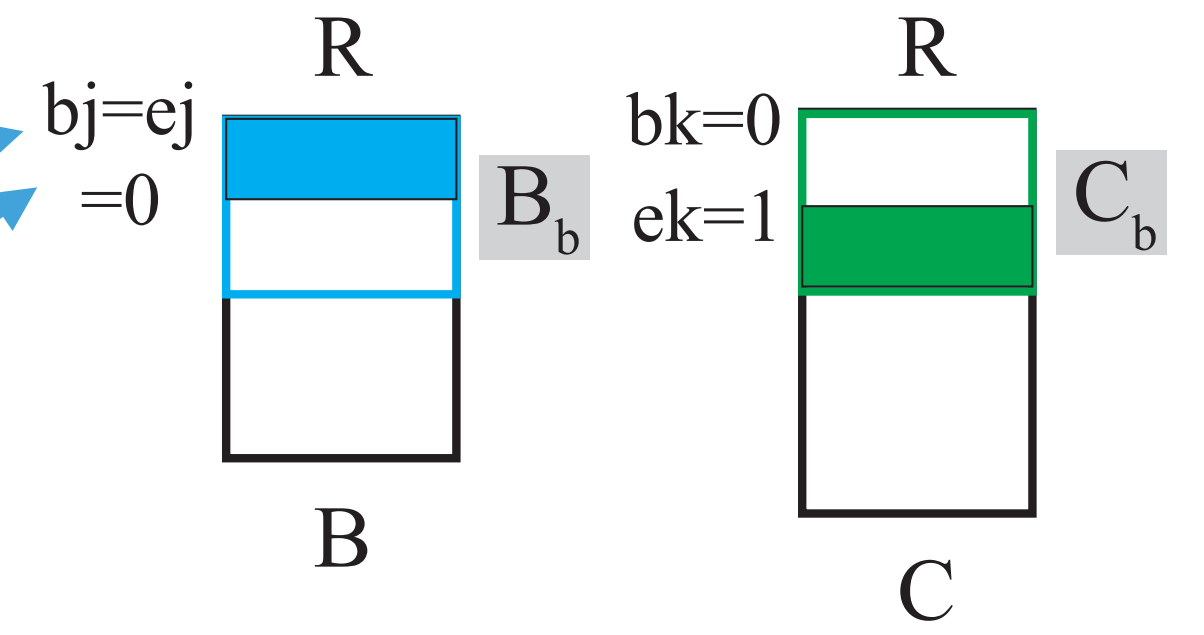


HiCOO-MTTKRP algorithm in mode-1

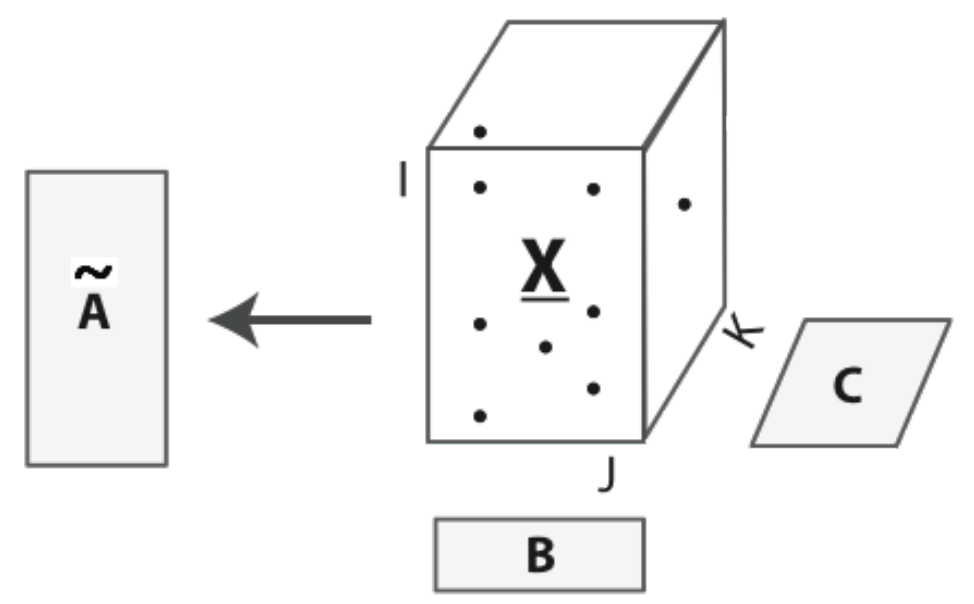
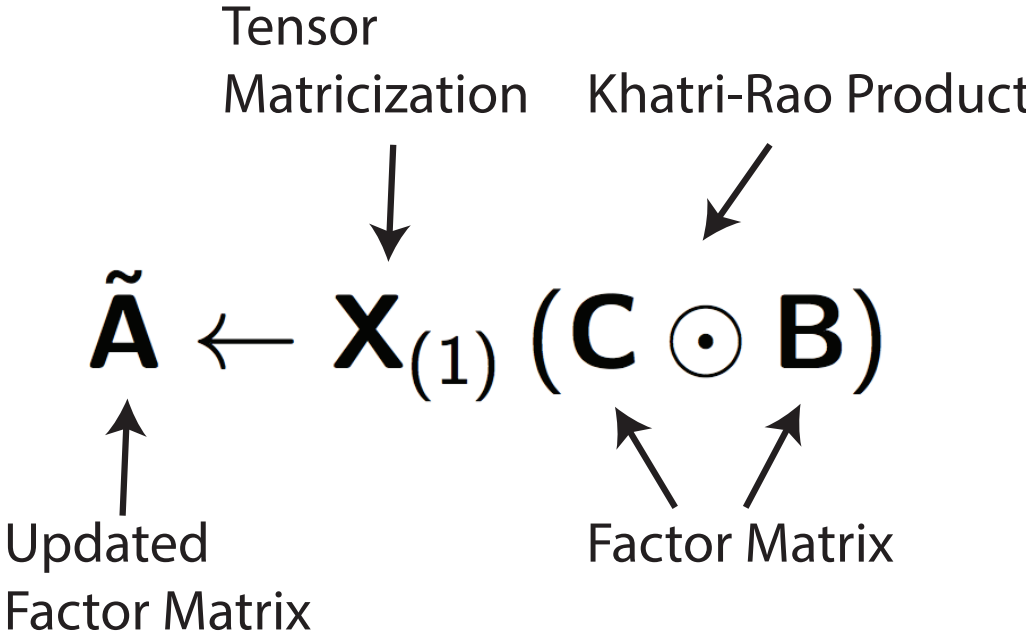


	bptr	b_i	b_j	b_k	e_i	e_j	e_k	val
B1		0	0	0	0	0	0	1
					0	1	0	2
					1	0	0	3
B2	3	0	0	1	1	0	0	4
B3	4	1	0	0	0	1	0	5
					1	0	1	7
B4	6	1	1	1	0	0	0	6
					1	1	0	8

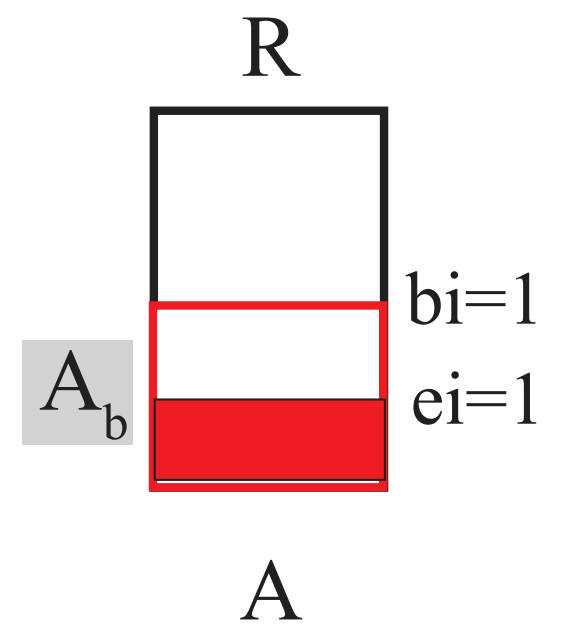
HiCOO



HiCOO-MTTKRP

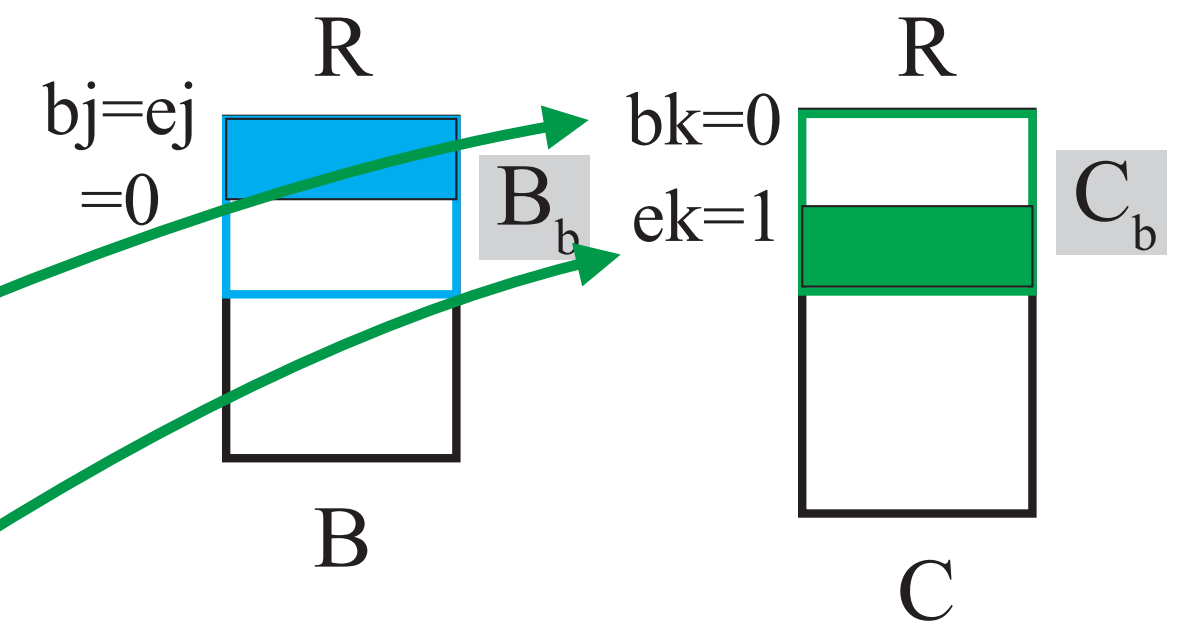


HiCOO-MTTKRP algorithm in mode-1

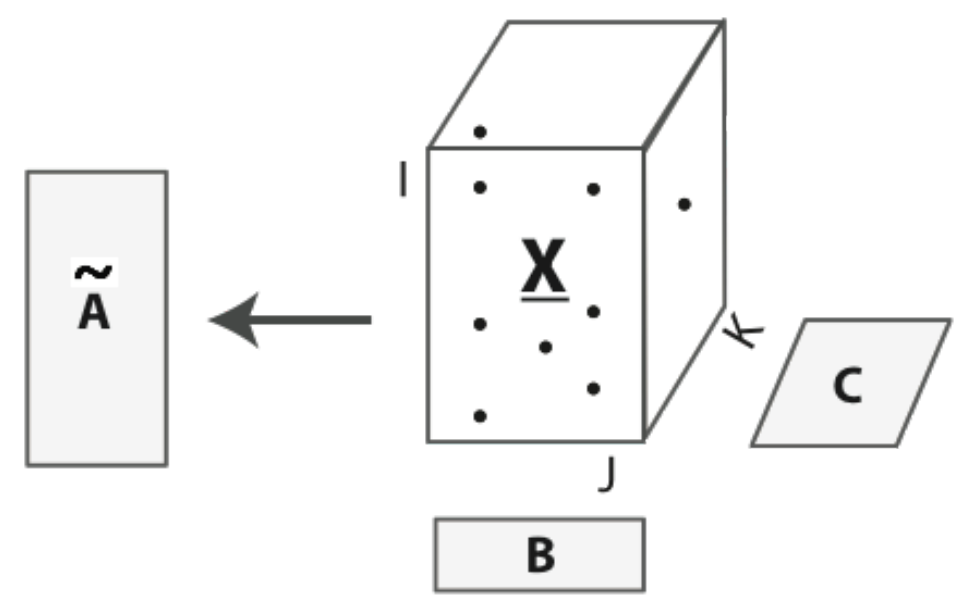
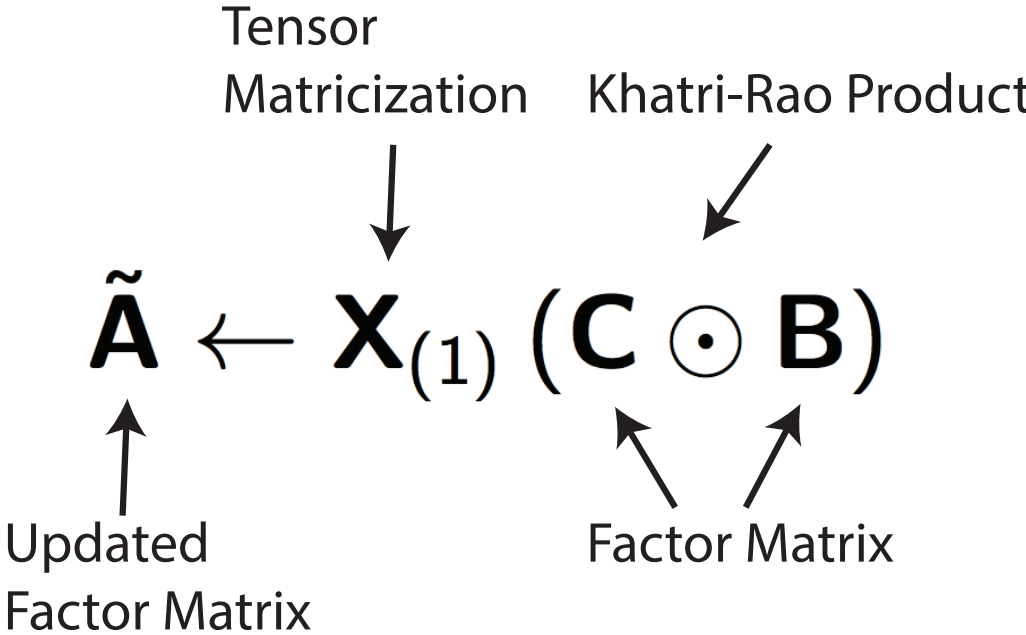


	bptr	b_i	b_j	b_k	e_i	e_j	e_k	val	
B1		0	0	0	0	0	0	1	
					0	1	0	2	
					1	0	0	3	
B2	3	0	0	1	1	0	0	4	
B3		4	1	0	0	1	0	5	
					1	0	1	7	
B4		6	1	1	1	0	0	0	6
					1	1	0	8	

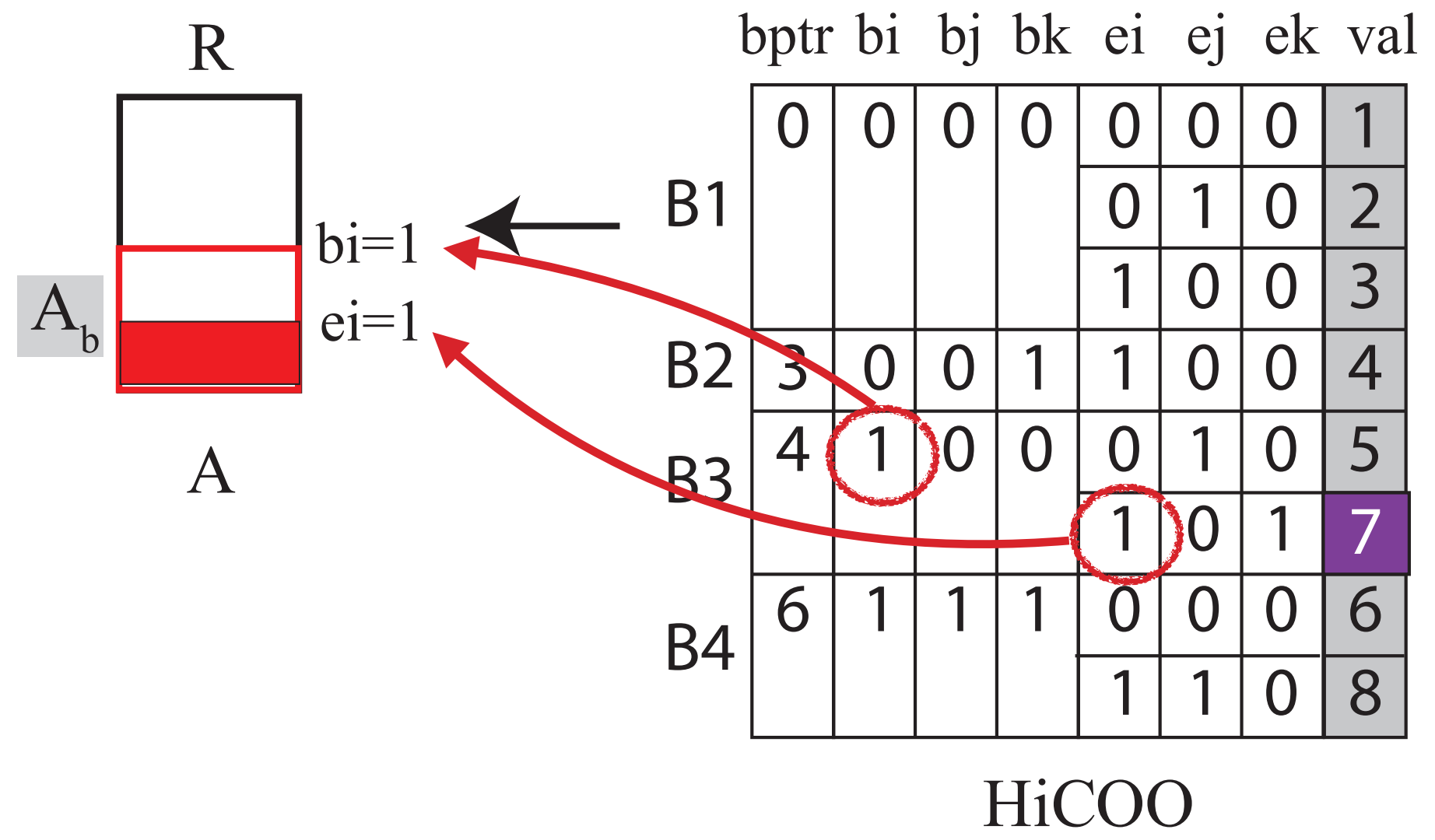
HiCOO



HiCOO-MTTKRP



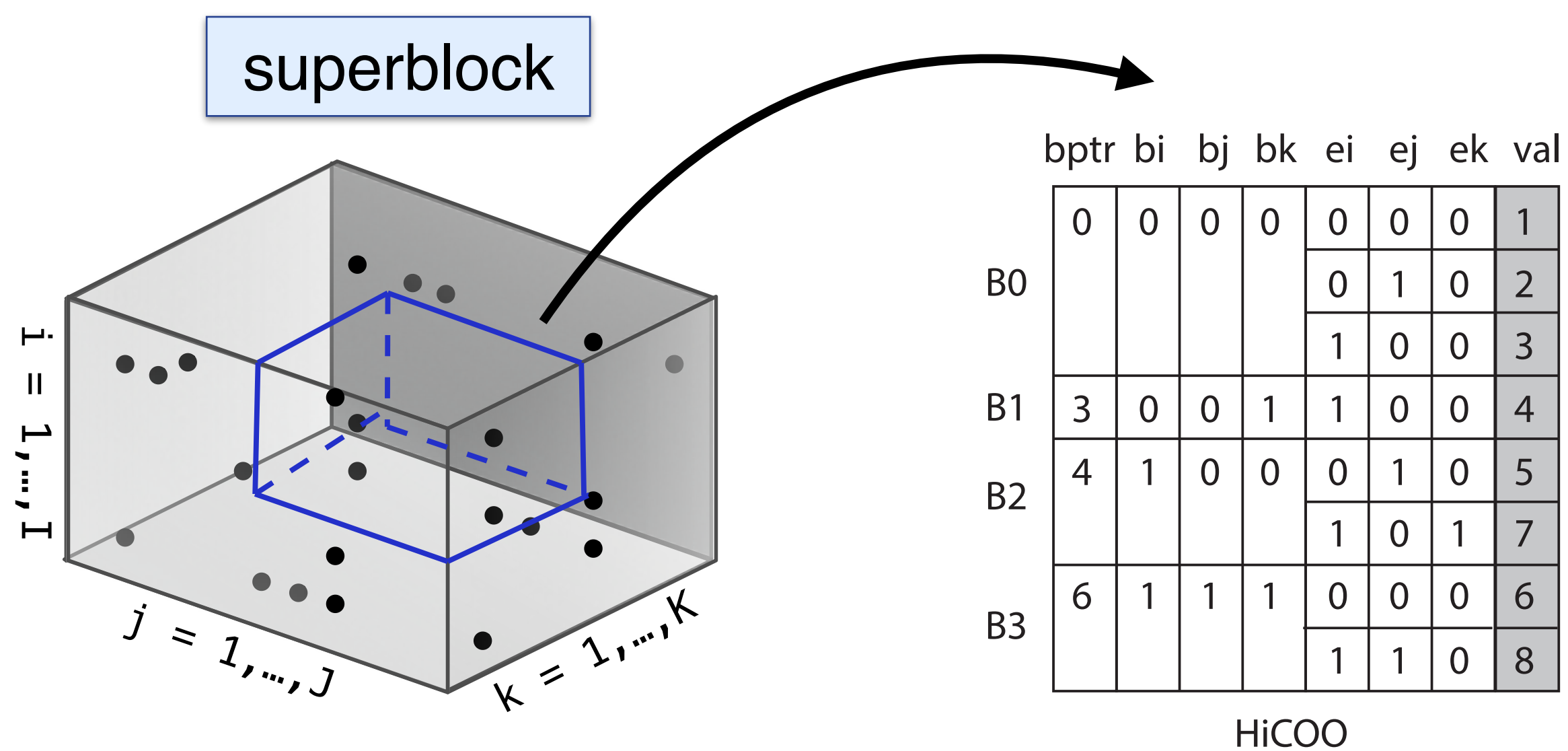
HiCOO-MTTKRP algorithm in mode-1



Entry-wise $\mathbf{A}_b \leftarrow \mathbf{7} \cdot (\mathbf{B}_b * \mathbf{C}_b)$

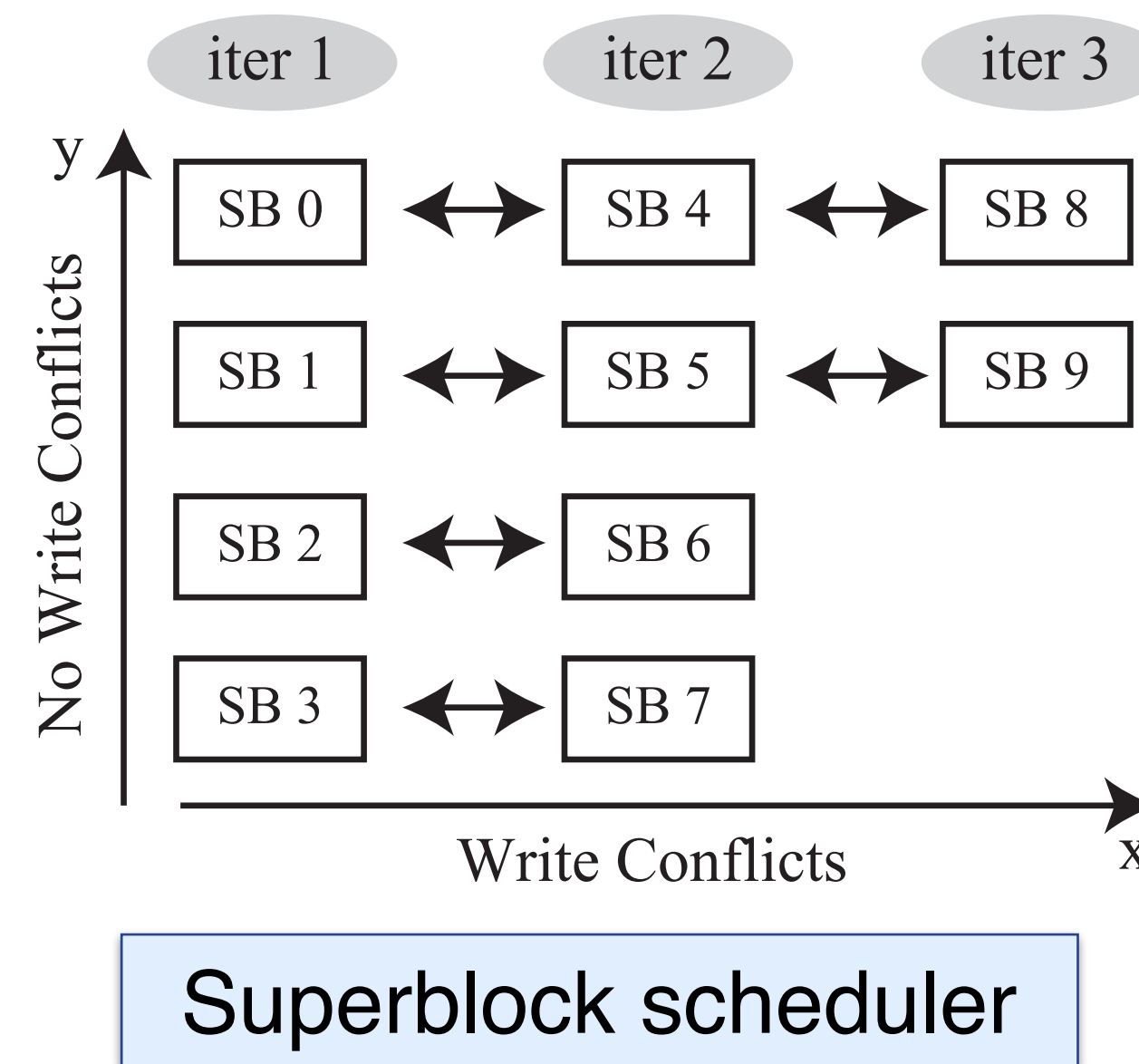
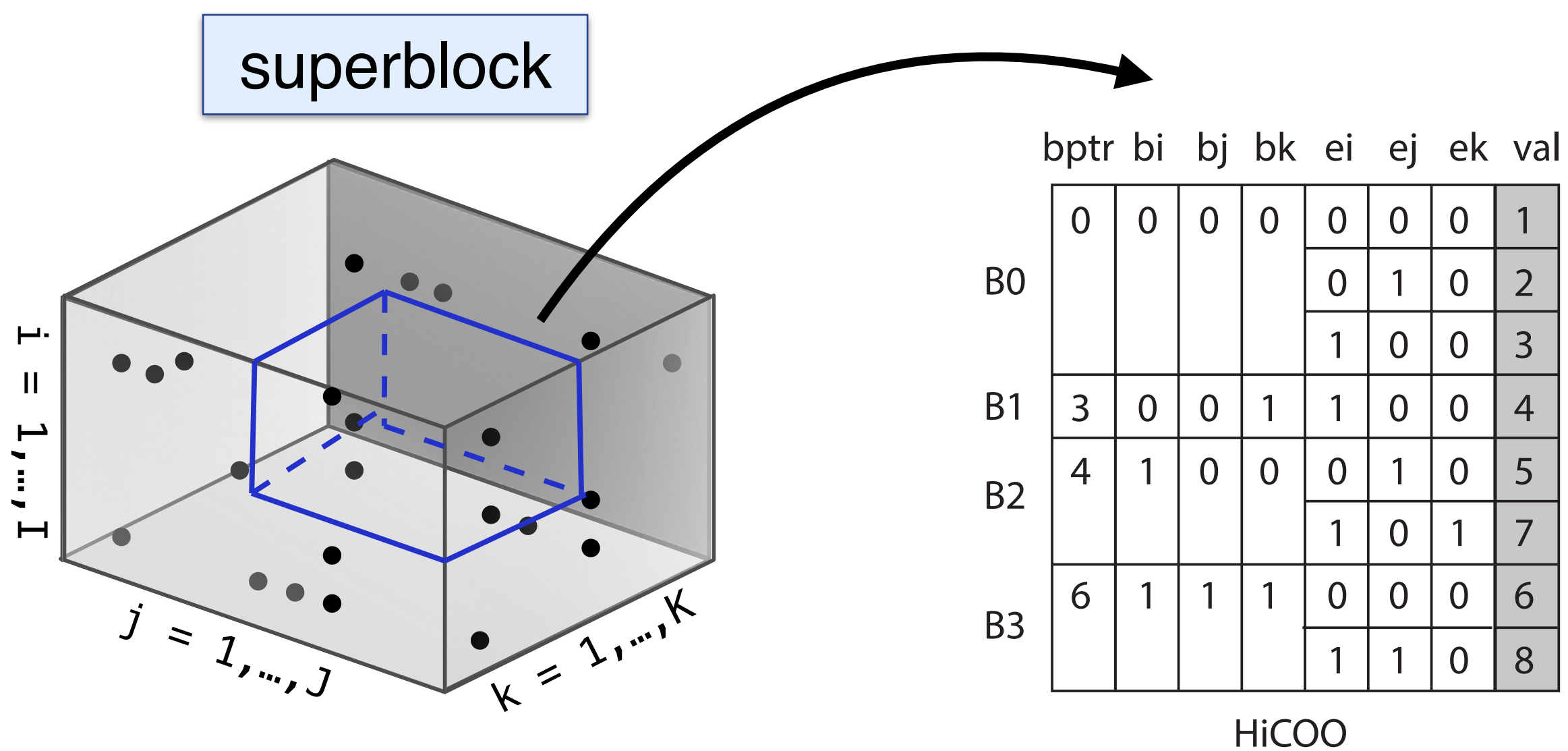
Two-level Blocking for Efficient Thread Parallelism

- Use two-level blocking strategy
 - Large superblocks (logical) + small blocks (physical)

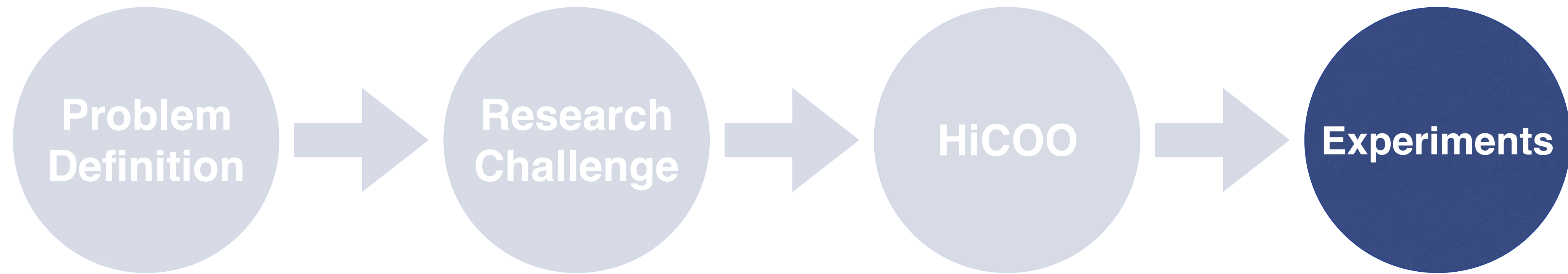


Two-level Blocking for Efficient Thread Parallelism

- Use two-level blocking strategy
 - Large superblocks (logical) + small blocks (physical)
 - To avoid using locks, we schedule superblocks according to scheduler with two parallel strategies (direct + privatization).
 - Increase only a bit extra storage.



Outline



Platform and Dataset

- **Platform:** Intel Xeon CPU E7-4850 v3 platform consisting 56 physical cores with icc 18.0.2 and parallelized by OpenMP.
- **Dataset:** FROSTT [Smith et al. 2017], HaTen2 [Jeon et al. 2015], and healthcare data [Perros et al. 2017].

DESCRIPTION OF SPARSE TENSORS.

Tensors	Order	Dimensions	#Nonzeros	Density
nell2	3	$12K \times 9K \times 29K$	77M	2.4×10^{-5}
choa	3	$712K \times 10K \times 767$	27M	5.0×10^{-6}
darpa	3	$22K \times 22K \times 24M$	28M	2.4×10^{-9}
fb-m	3	$23M \times 23M \times 166$	100M	1.1×10^{-9}
fb-s	3	$39M \times 39M \times 532$	140M	1.7×10^{-10}
deli	3	$533K \times 17M \times 2.5M$	140M	6.1×10^{-12}
nell1	3	$3M \times 2M \times 25M$	144M	9.1×10^{-13}
crime	4	$6K \times 24 \times 77 \times 32$	5M	1.5×10^{-2}
nips	4	$2K \times 3K \times 14K \times 17$	3M	1.8×10^{-6}
enron	4	$6K \times 6K \times 244K \times 1K$	54M	5.5×10^{-9}
flickr	4	$320K \times 28M \times 2M \times 731$	113M	1.1×10^{-14}
deli4d	4	$533K \times 17M \times 2M \times 1K$	140M	4.3×10^{-15}

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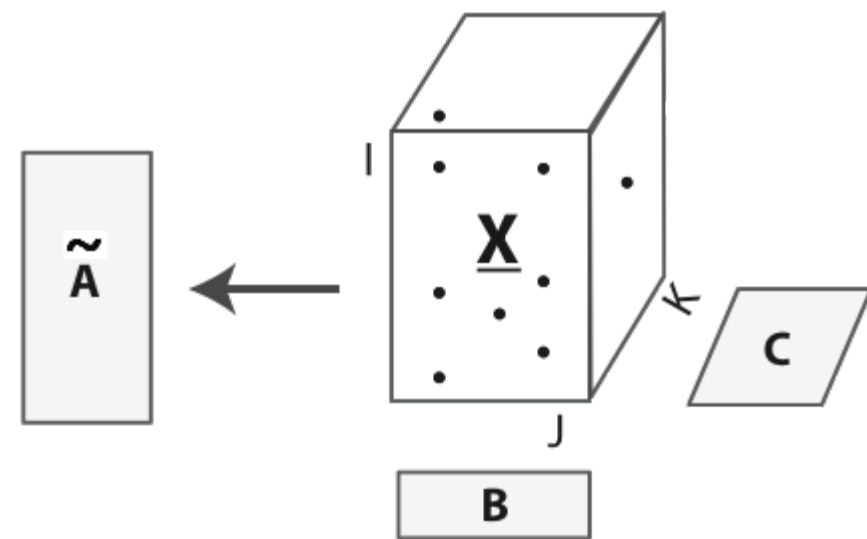
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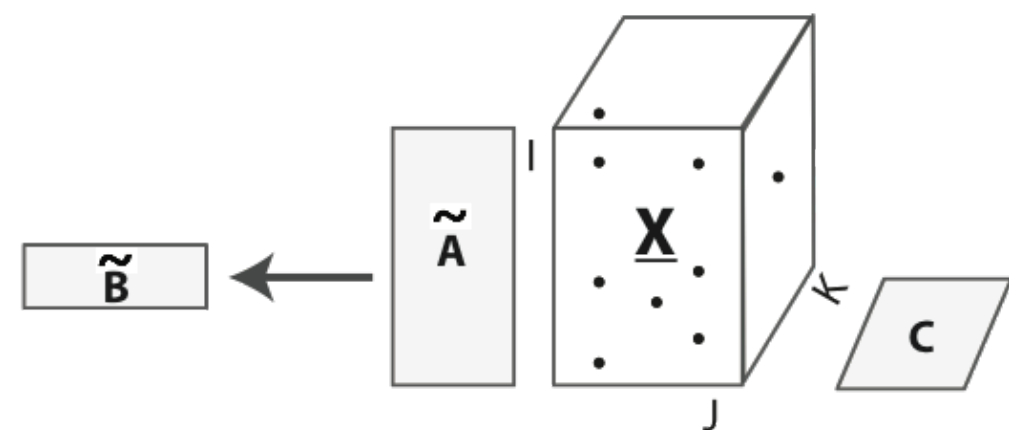
Multicore MTTKRP in all Modes

CP decomposition

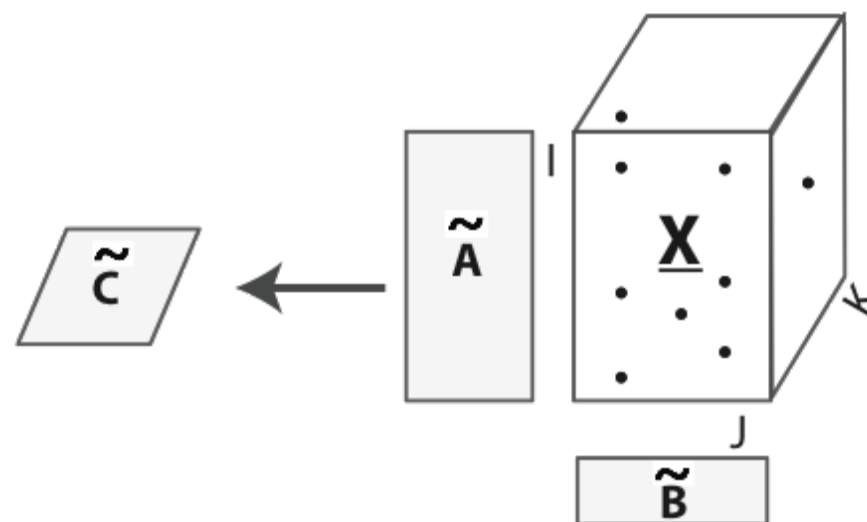
MTTKRP in Mode-1



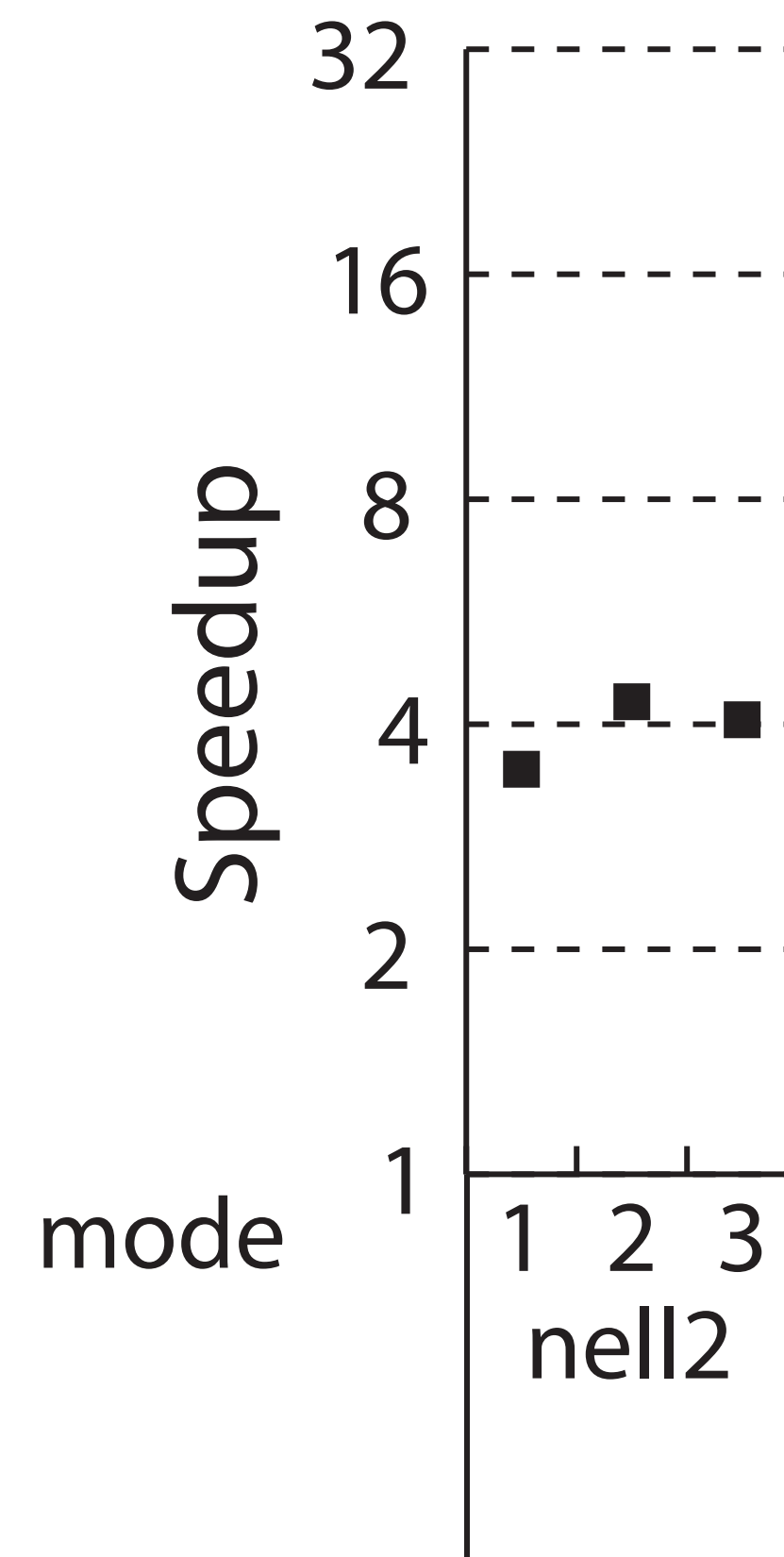
MTTKRP in Mode-2



MTTKRP in Mode-3



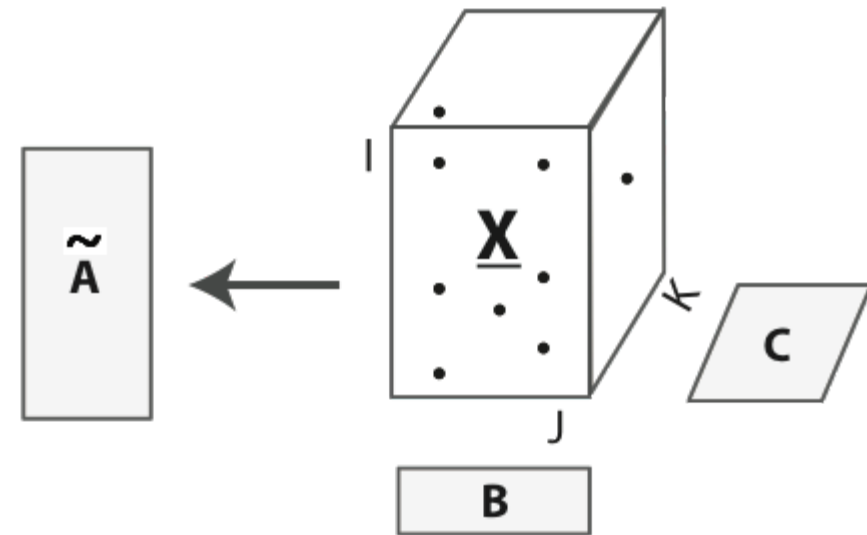
- ParTI! library: Speedups of HiCOO over COO



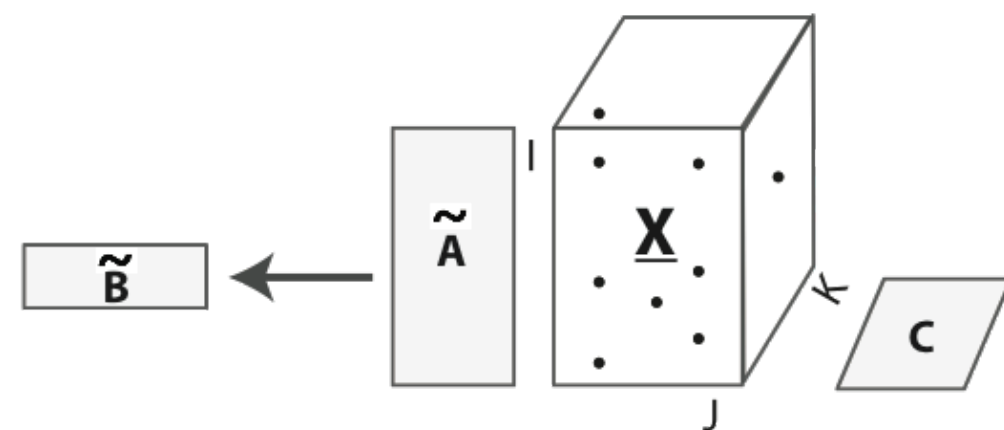
Multicore MTTKRP in all Modes

CP decomposition

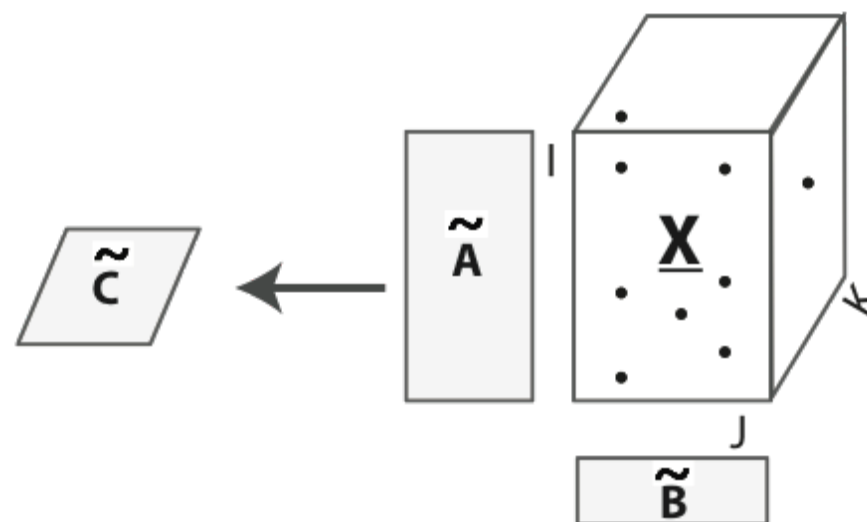
MTTKRP in Mode-1



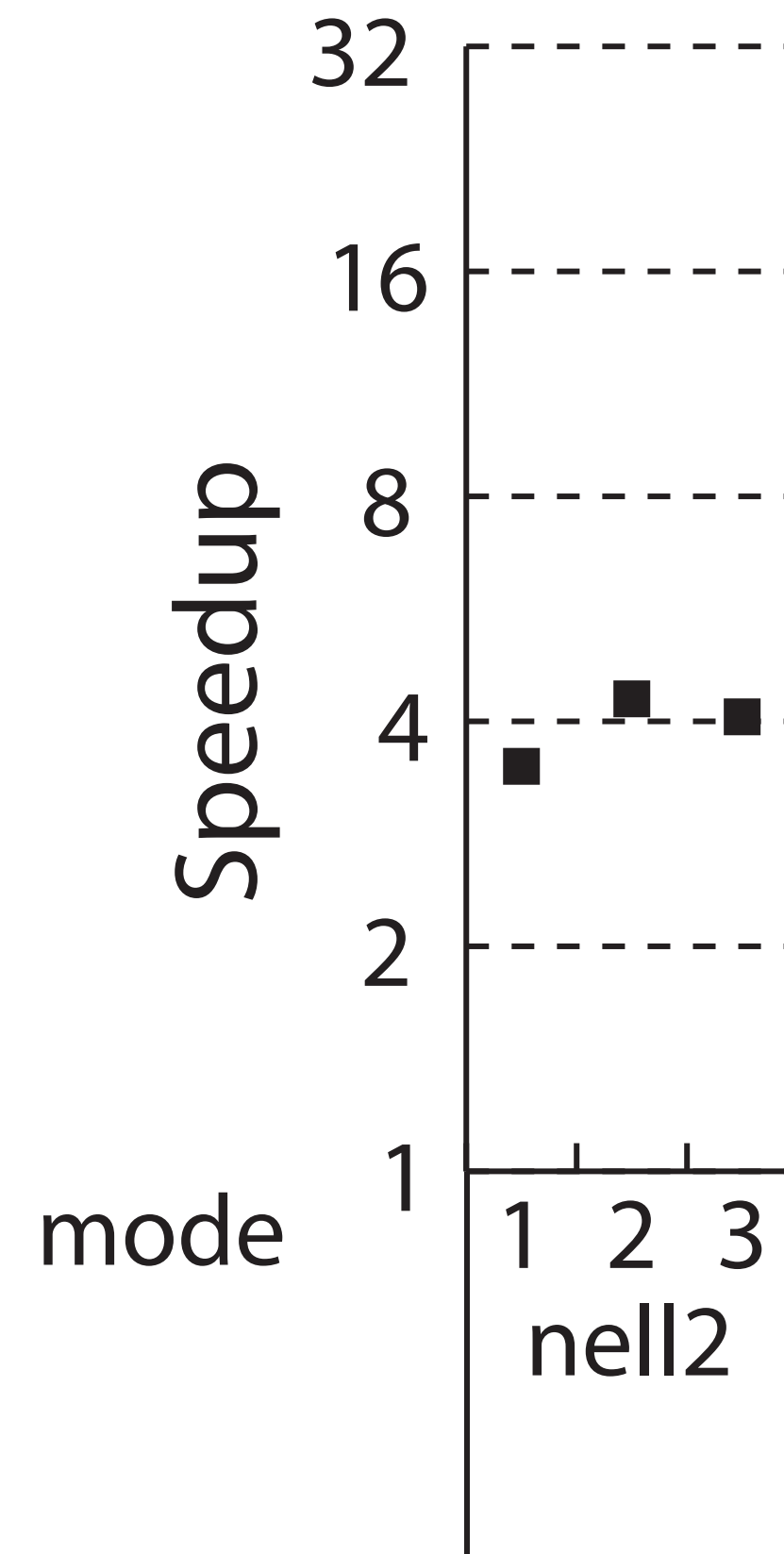
MTTKRP in Mode-2



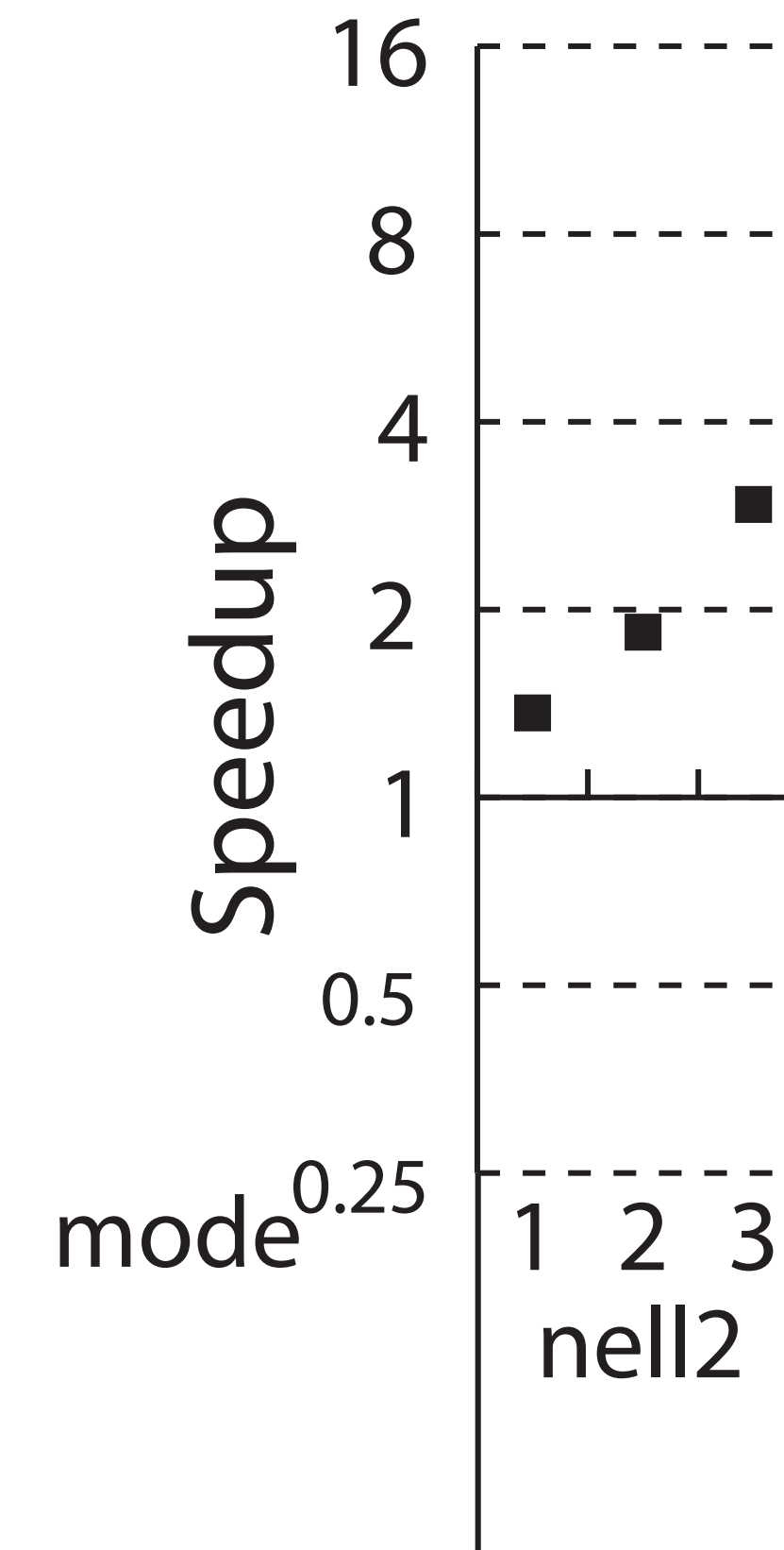
MTTKRP in Mode-3



- ParTI! library: Speedups of HiCOO over COO

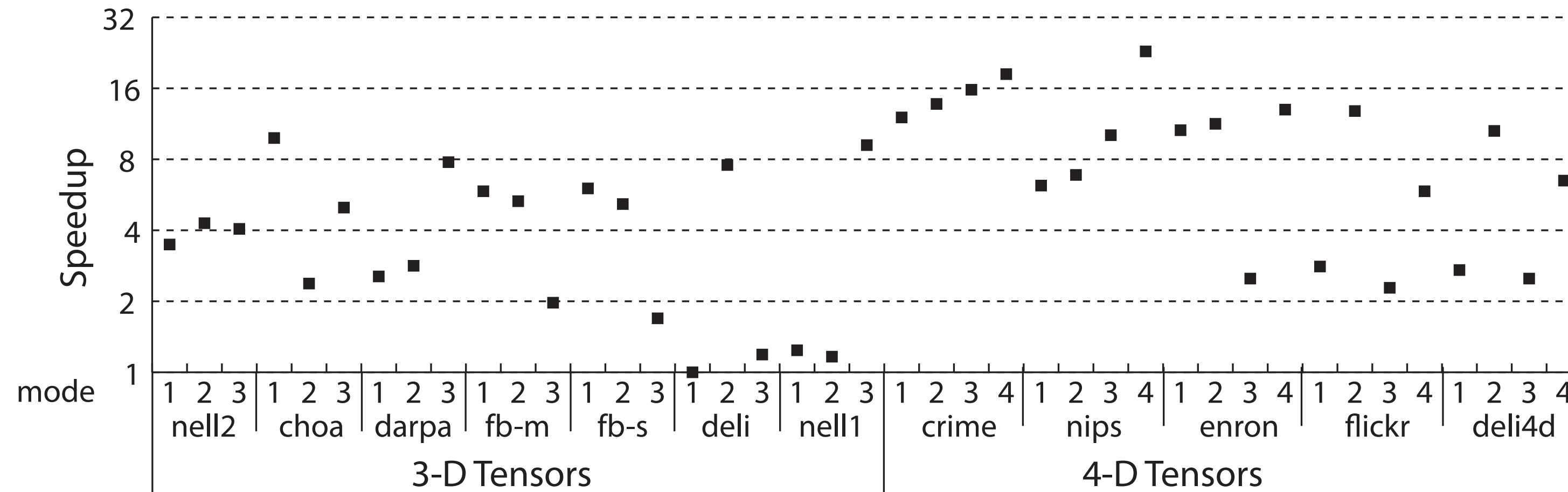


- SPLATT library: Speedups of HiCOO over CSF



Multicore MTTKRP in all Modes

- ParTI! library: Speedups of HiCOO over COO

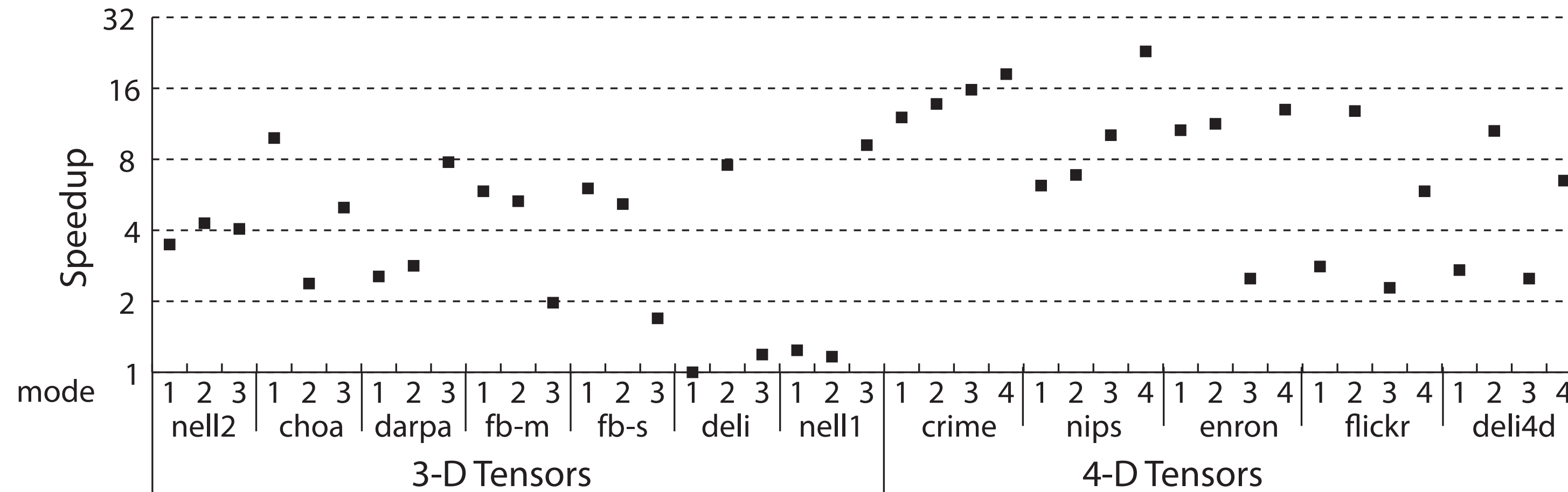


6.8x

Average speedup

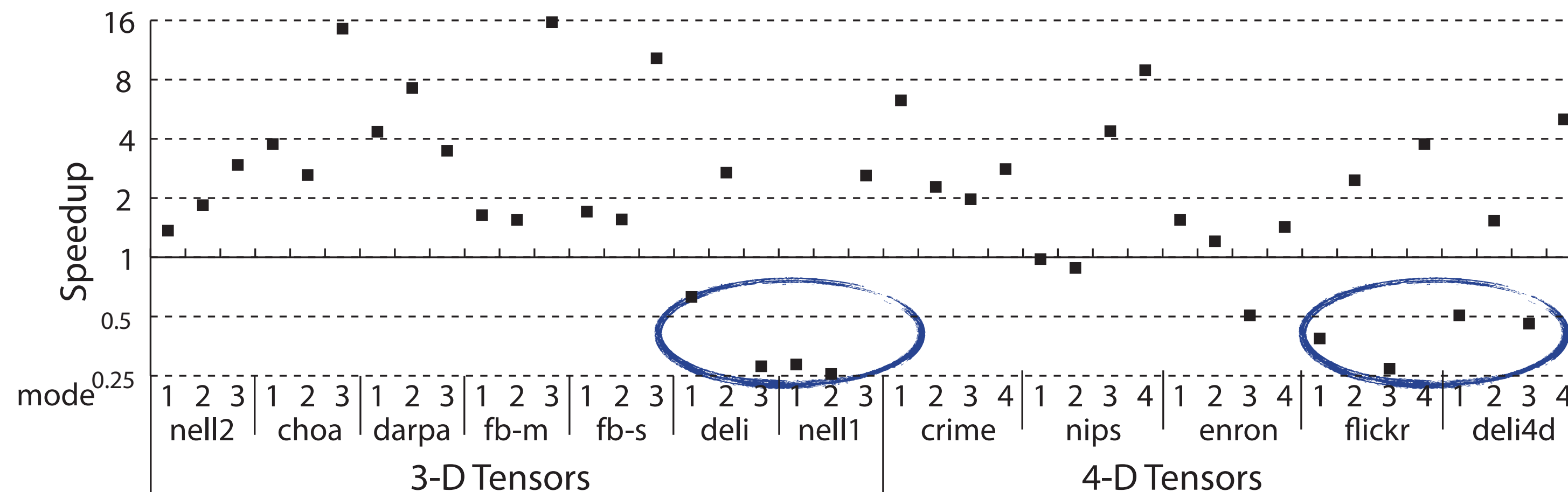
Multicore MTTKRP in all Modes

- ParTI! library: Speedups of HiCOO over COO



6.8x

- SPLATT library: Speedups of HiCOO over CSF

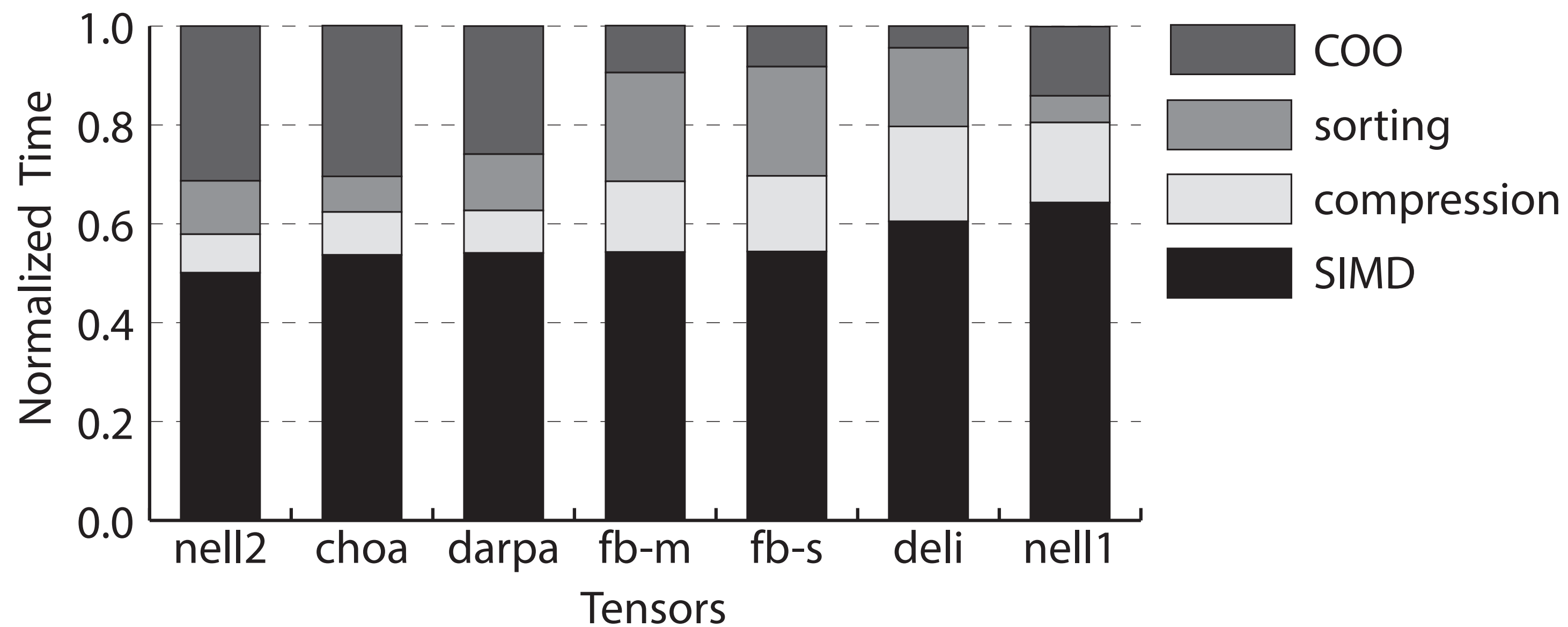
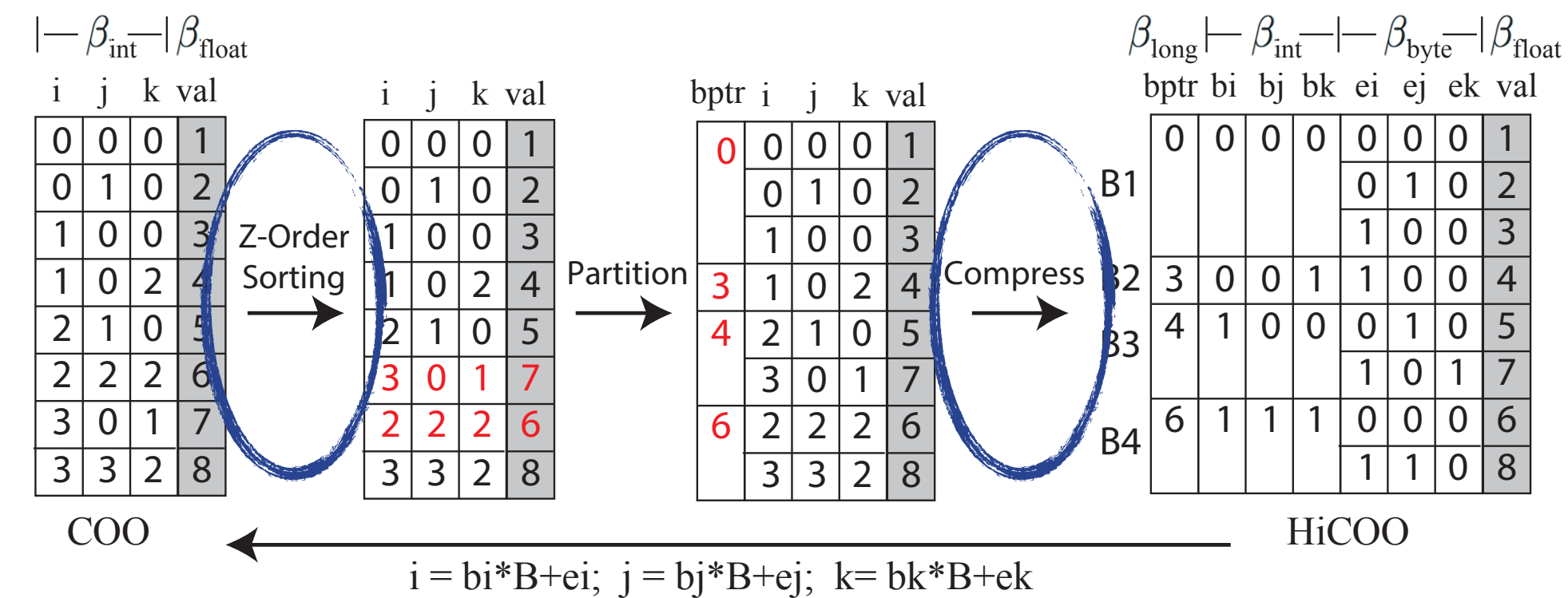


Average speedup

3.1x

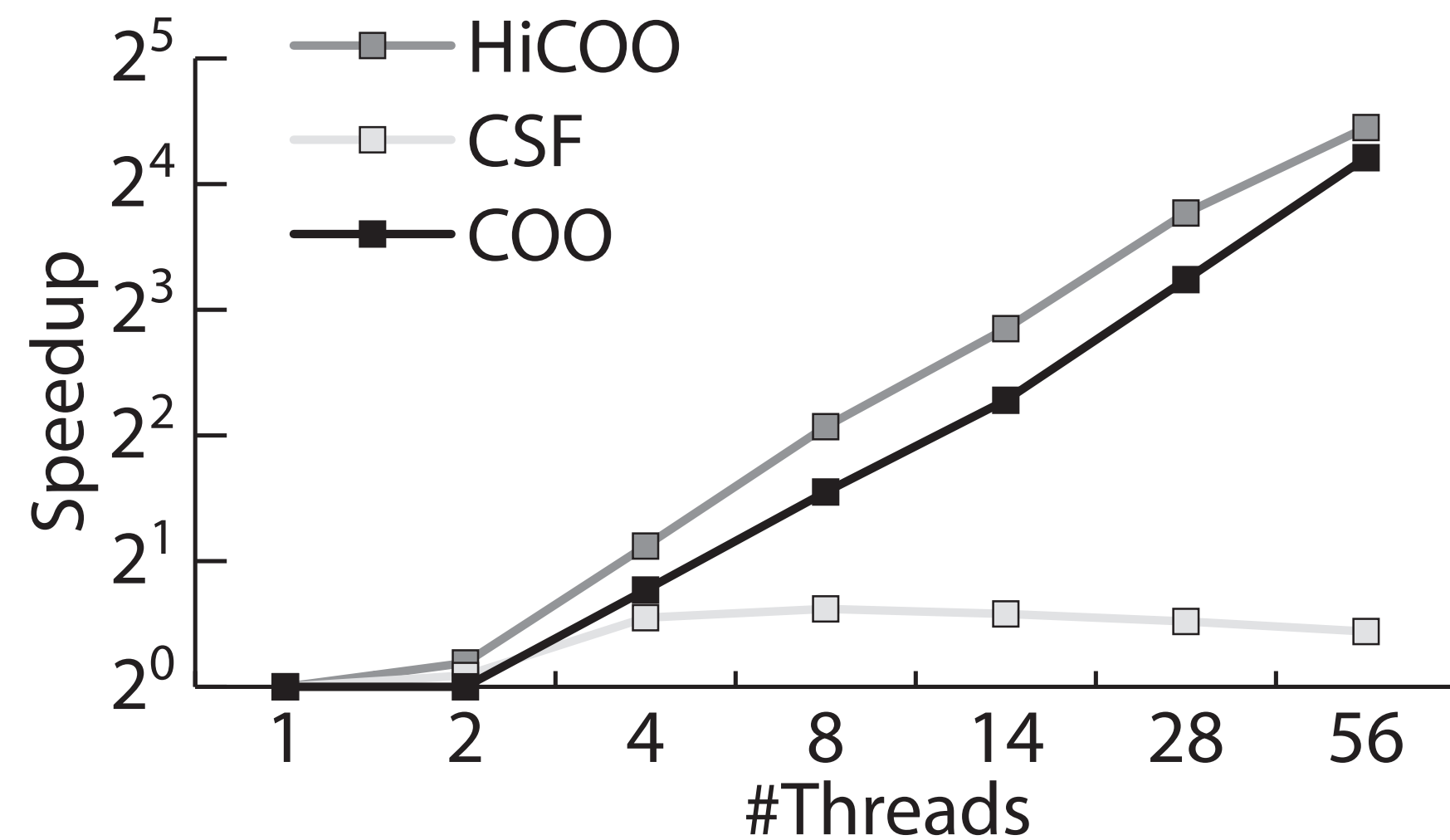
Optimization Impact

- Z-order sorting: +18%
- Index compression: +20%
- SIMD: +22%

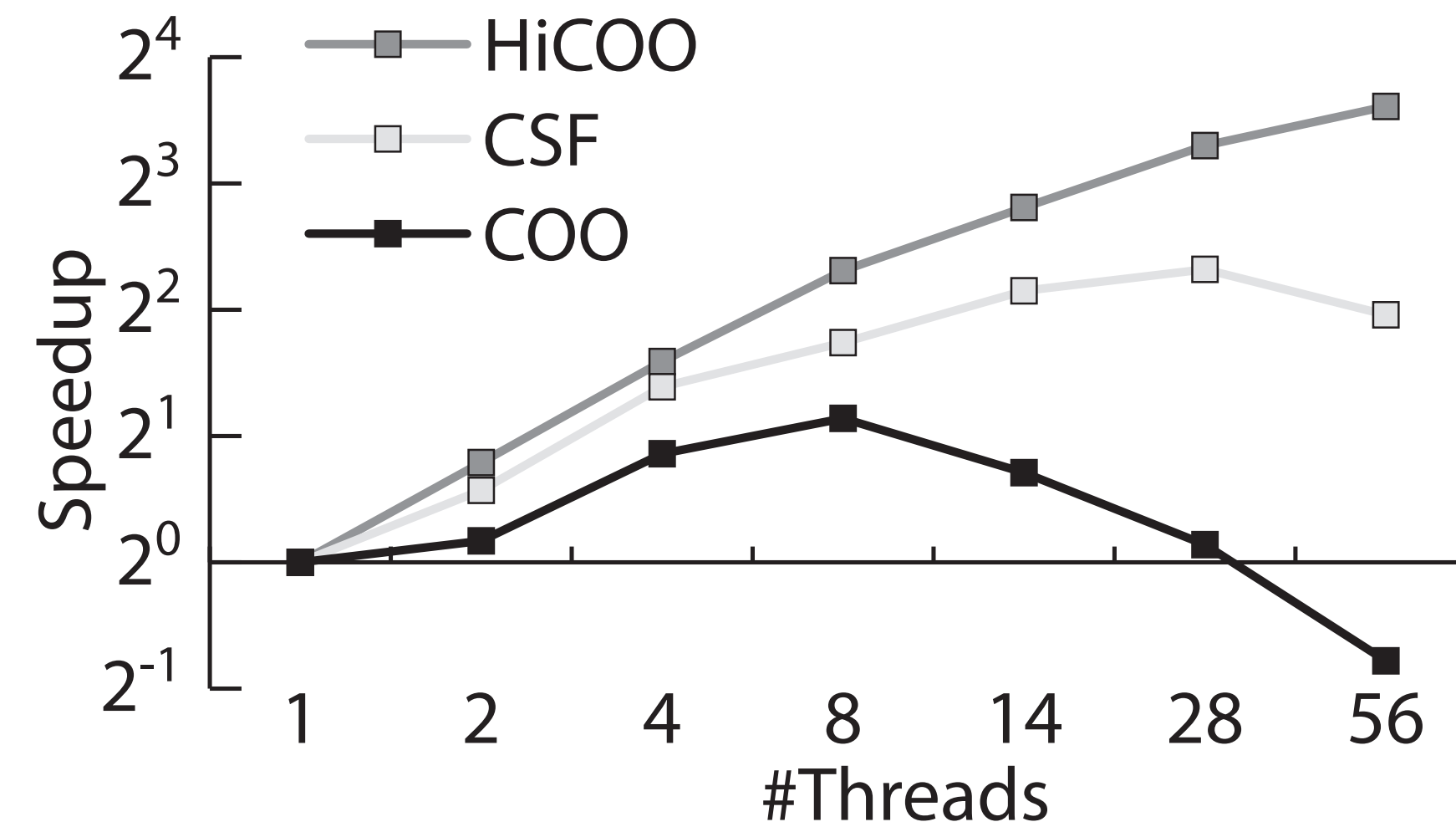


Thread Scalability

- Thread scalability of parallel COO, CSF, and HiCOO MTTKRPs on two representative cases.
- HiCOO achieves the best scalability.



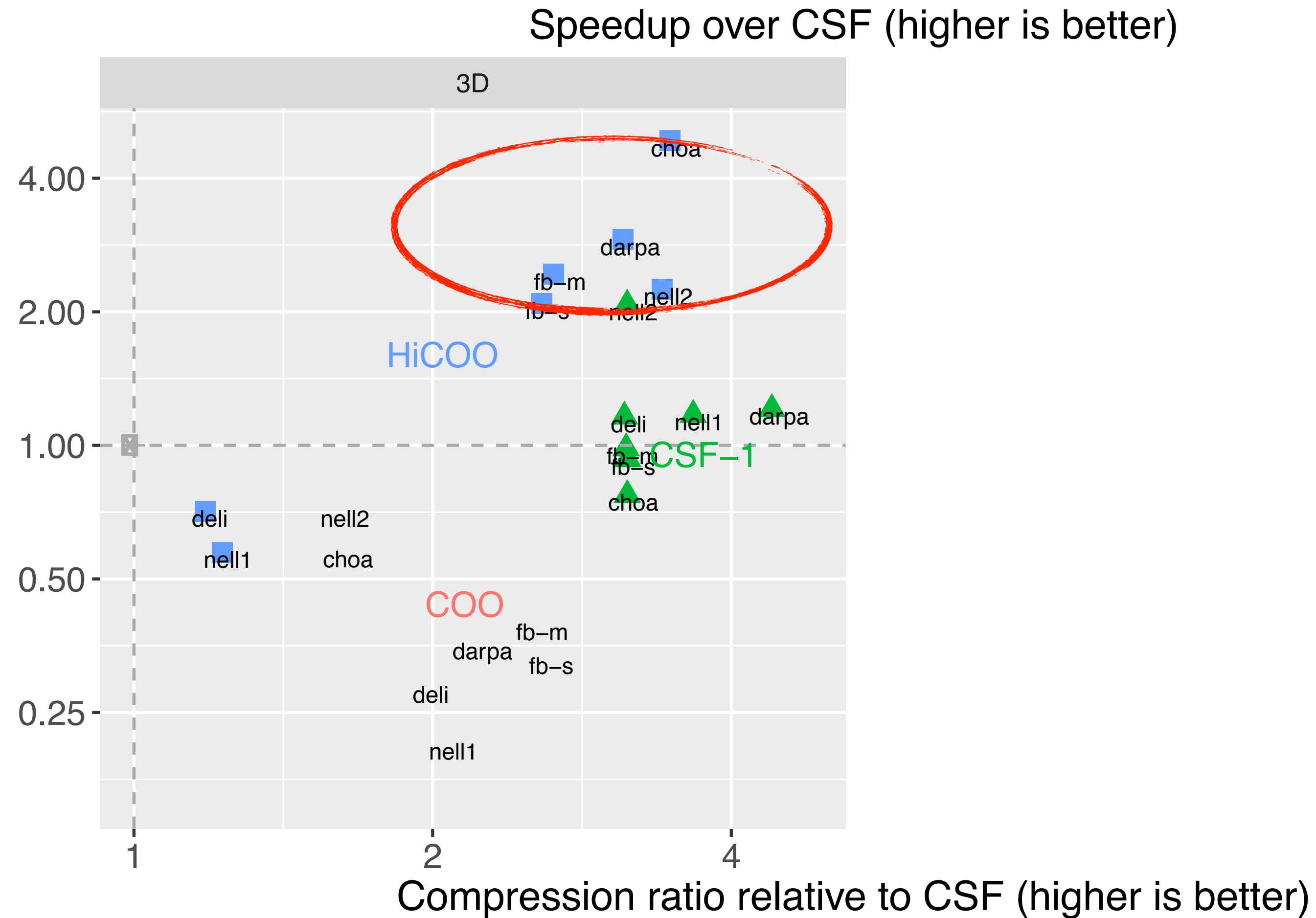
tensor fb-s in mode 3
(shortest mode)



tensor choa in mode 1
(longest mode)

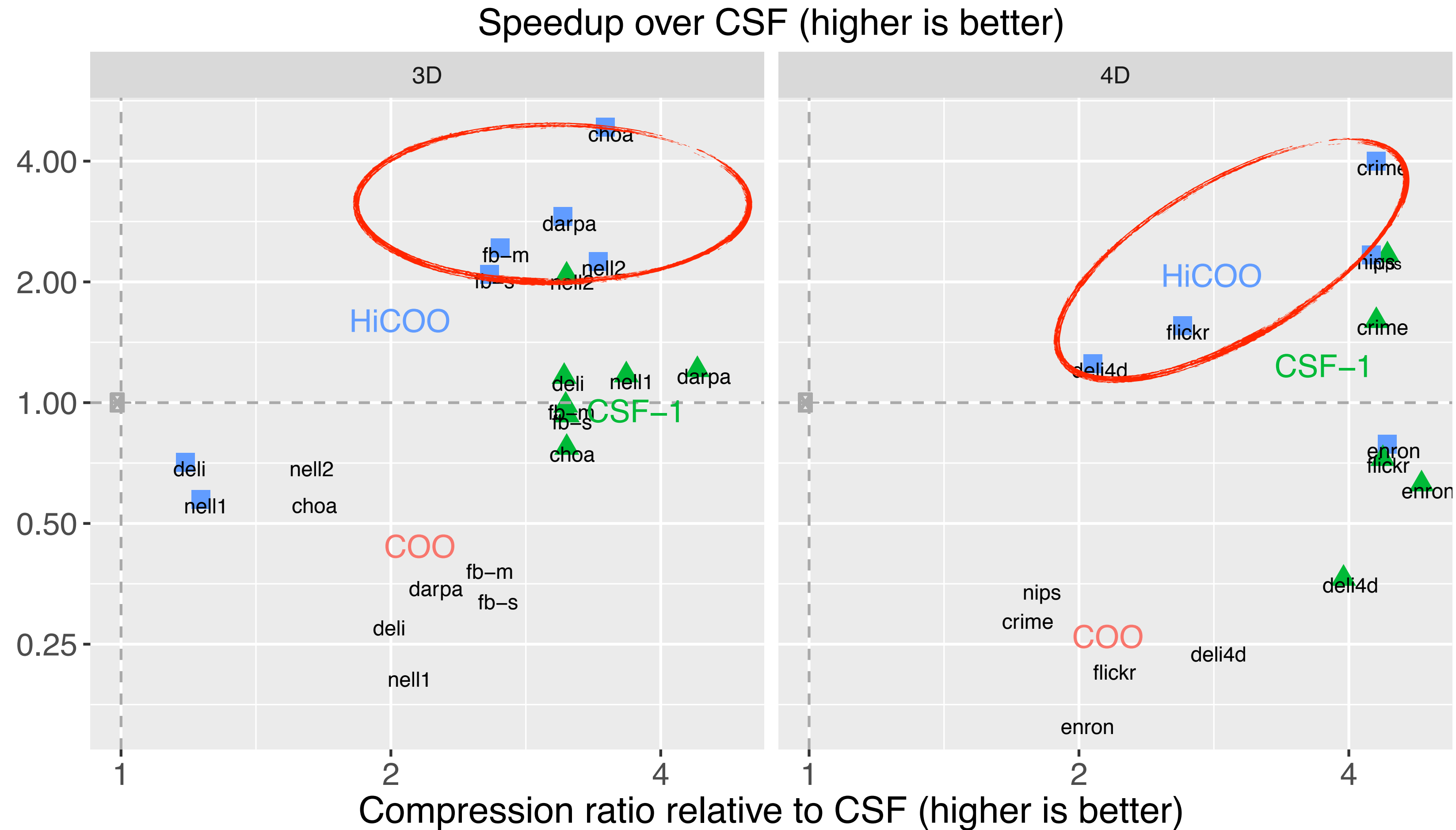
Multicore CP-ALS

- HiCOO outperforms COO by 6.2× and CSF up to 2.1× on average.



Multicore CP-ALS

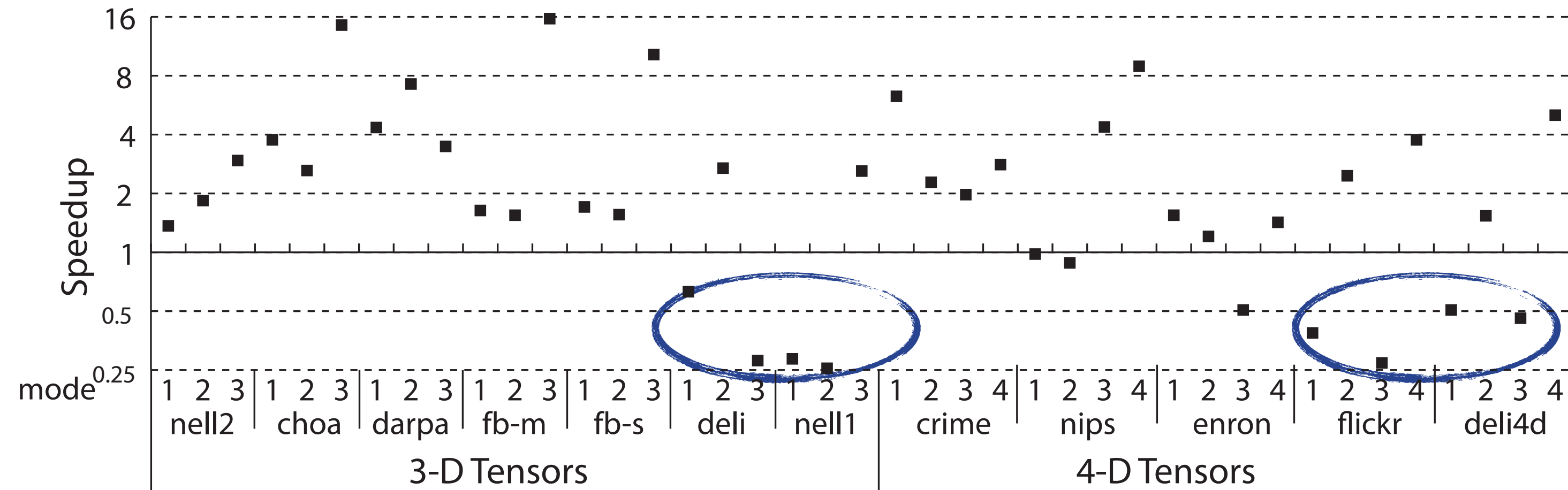
- HiCOO outperforms COO by 6.2× and CSF up to 2.1× on average.



Performance and Storage Analysis

Parameters	Meaning	Effect	Preferable values
B	Block size	Data locality	$B \leq \frac{S_{cache}}{NR\beta_{float}}$
L	Superblock size	Parallel granularity	depends
α_b	Block ratio	Tensor format size	small $\alpha_b < \frac{\beta_{int} - \beta_{byte}}{\beta_{int} + \beta_{long} / N}$
$\overline{C_b}$	Average slice size per tensor block	Amount of Memory traffic	large

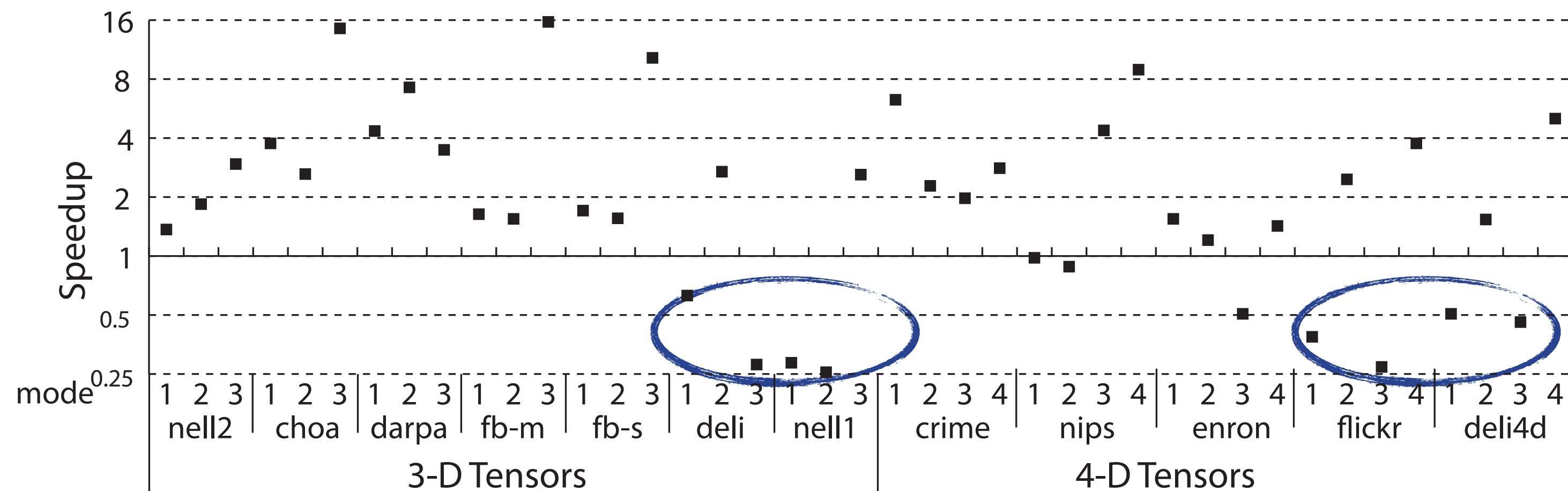
Performance and Storage Analysis cont.



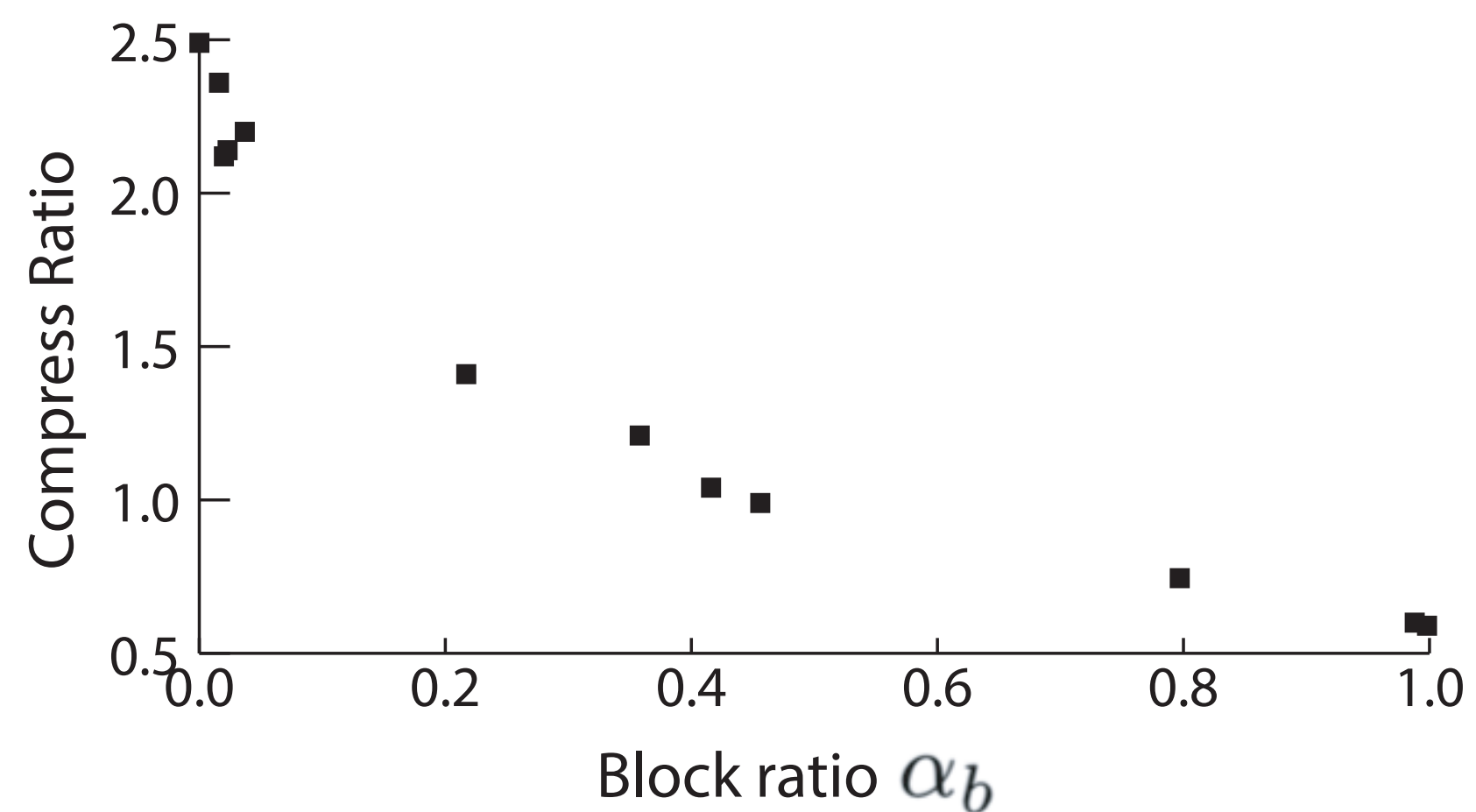
Speedups of HiCOO over CSF

Tensors	α_b	\bar{c}_b	Compress Ratio
nell2	0.020	0.302	2.12
choa	0.023	0.070	2.14
darpa	0.217	0.016	1.41
fb-m	0.416	0.011	1.04
fb-s	0.456	0.010	0.99
deli	0.988	0.008	0.60
nell1	0.998	0.008	0.59
crime	0.000	666.892	2.49
nips	0.016	0.416	2.36
enron	0.037	0.031	2.20
flickr	0.358	0.014	1.21
deli4d	0.797	0.009	0.74

Performance and Storage Analysis cont.



Speedups of HiCOO over CSF



Tensors	α_b	$\overline{c_b}$	Compress Ratio
nell2	0.020	0.302	2.12
choa	0.023	0.070	2.14
darpa	0.217	0.016	1.41
fb-m	0.416	0.011	1.04
fb-s	0.456	0.010	0.99
deli	0.988	0.008	0.60
nell1	0.998	0.008	0.59
crime	0.000	666.892	2.49
nips	0.016	0.416	2.36
enron	0.037	0.031	2.20
flickr	0.358	0.014	1.21
deli4d	0.797	0.009	0.74

HiCOO: Hierarchical Storage of Sparse Tensors

- Mode-generic format for arbitrary-order sparse tensors.
- Code: <https://github.com/hpcgarage/ParTI> (v1.0.0)
- Future steps:
 - Extend to sparse TTM and Tucker decomposition.
 - Optimize HiCOO-MTTKRP on GPUs.
 - Accelerate tensor reordering and format construction process.

32-bit				32-bit				8-bit				
i	j	k	val	bptr	bi	bj	bk	ei	ej	ek	val	
0	0	0	1	B0	0	0	0	0	0	0	1	
0	1	0	2		0	1	0	2				
1	0	0	3		1	0	0	3				
1	0	2	4	B1	3	0	0	1	1	0	0	4
2	1	0	5	B2	4	1	0	0	0	1	0	5
2	2	2	6		1	0	1	7				
3	0	1	7	B3	6	1	1	1	0	0	0	6
3	3	2	8		1	1	0	8				

(a) COO

(b) HiCOO

A haiku for HiCOO
 — By Richard W. Vuduc

Flexible format
 Of hierarchical sparse blocks
 Small, and often fast

Acknowledgement

