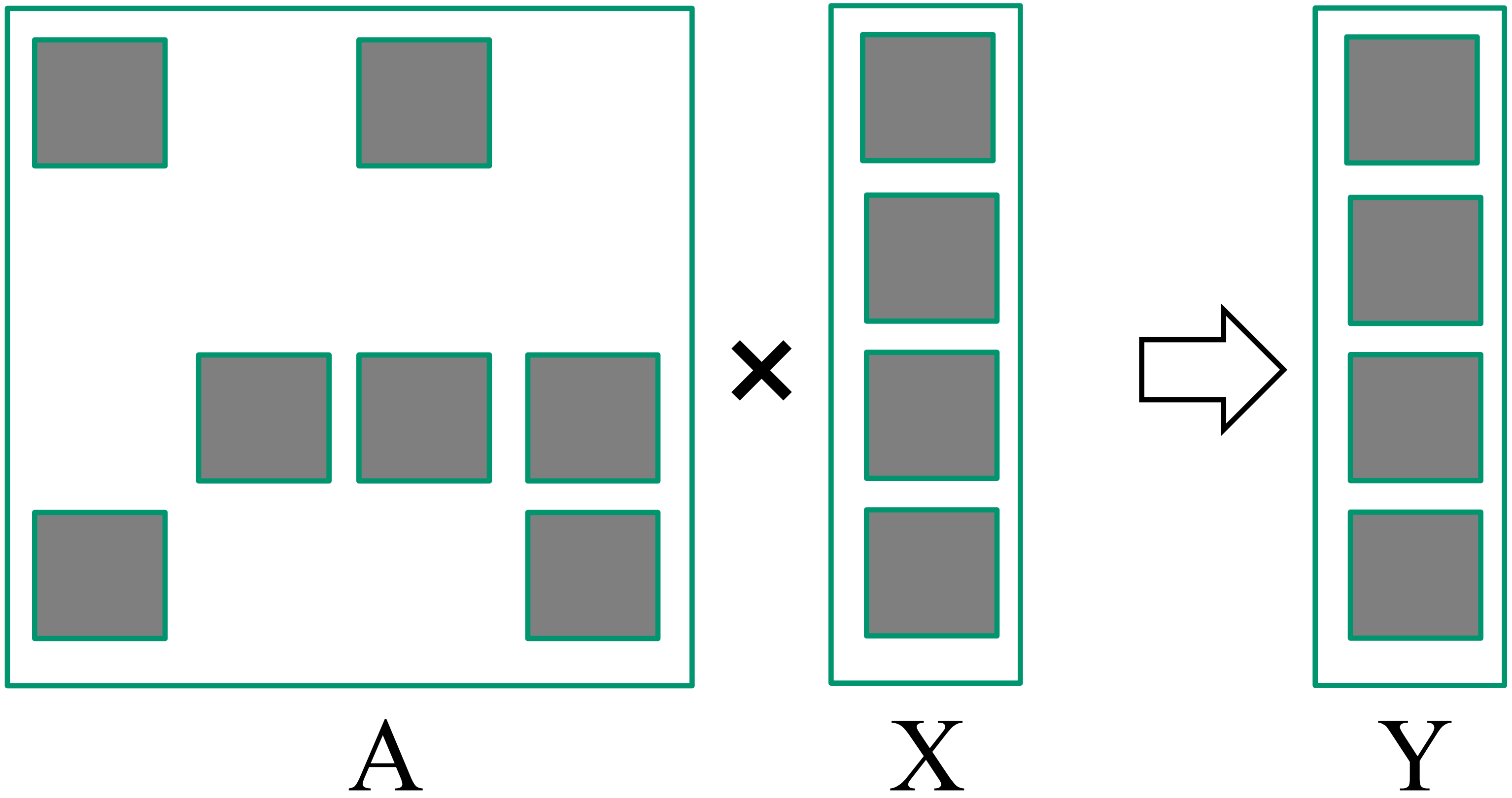
ECE408/CS483/CSE408

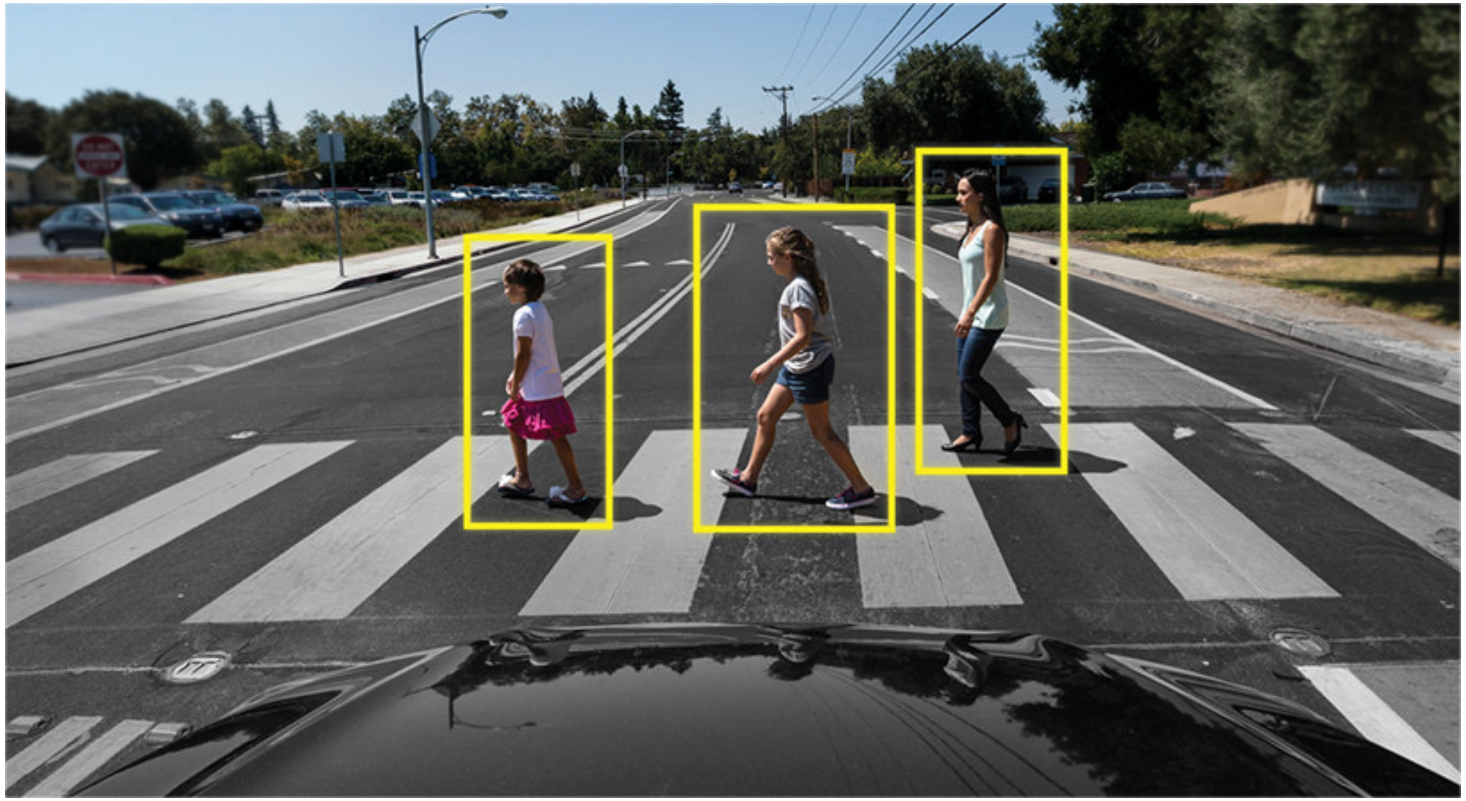
Applied Parallel Programming

Lecture 20
Parallel Sparse Methods II

Sparse Matrix-Vector Multiplication (SpMV)



Why are interesting data often sparse?



- Pedestrians occupy less than 5% of the pixels
- Let's consider the computation of a deep CNN that is detecting pedestrians.
- Zero weights and also lots of zero features

Compressed Sparse Row (CSR) Format

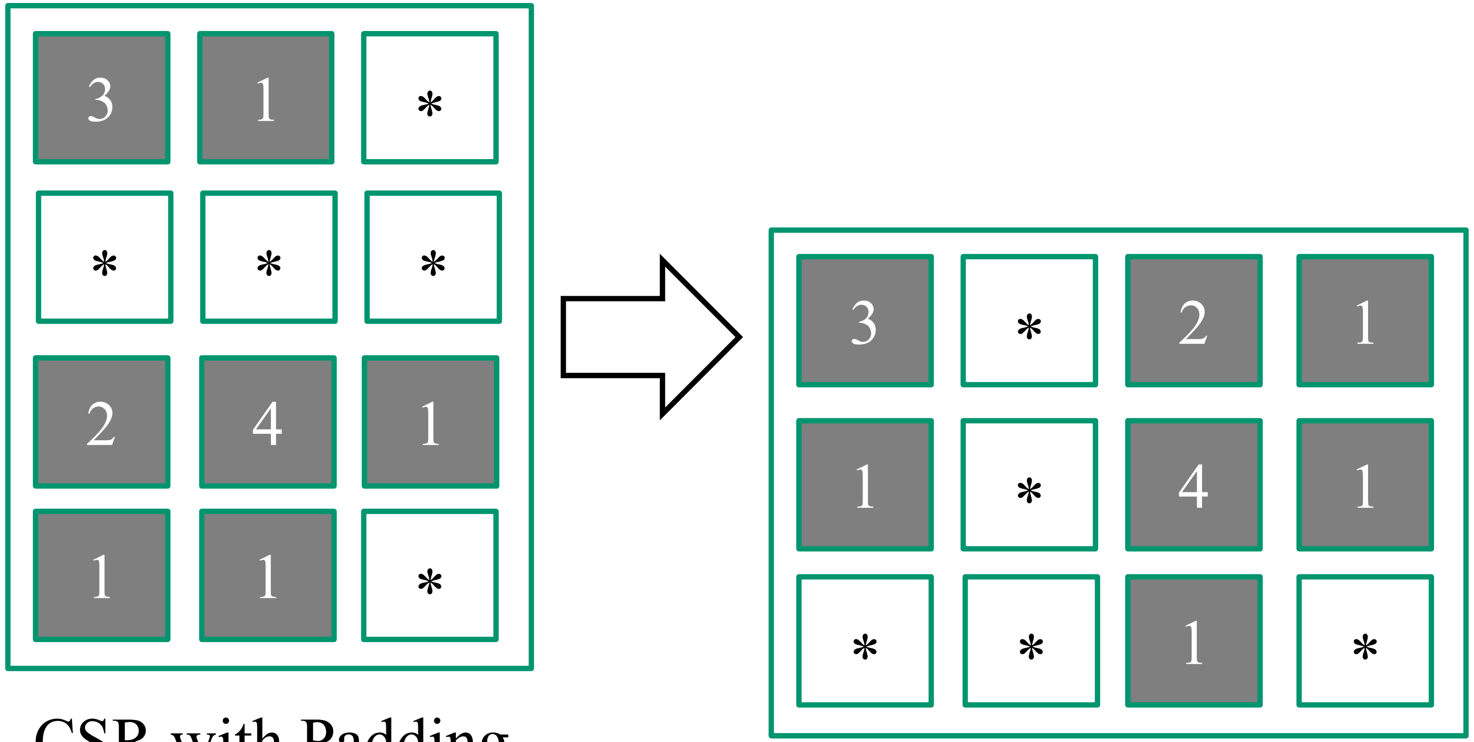
CSR Representation

		Row 0		Row 2			Row 3		
Nonzero values	`data[7]`	{ 3,	1,	2,	4,	1,	1,	1	}
Column indices	`col_index[7]`	{ 0,	2,	1,	2,	3,	0,	3	}
Row Pointers	`row_ptr[5]`	{ 0,	2,	2,	5,	7 }			

Dense representation

Row 0	3	0	1	0	Thread 0
Row 1	0	0	0	0	Thread 1
Row 2	0	2	4	1	Thread 2
Row 3	1	0	0	1	Thread 3

Regularizing SpMV with ELL(PACK) Format



CSR with Padding

Transposed

- Pad all rows to the same length
  - Inefficient if a few rows are much longer than others
- Transpose (Column Major) for DRAM efficiency
- Both data and col_index padded/transposed

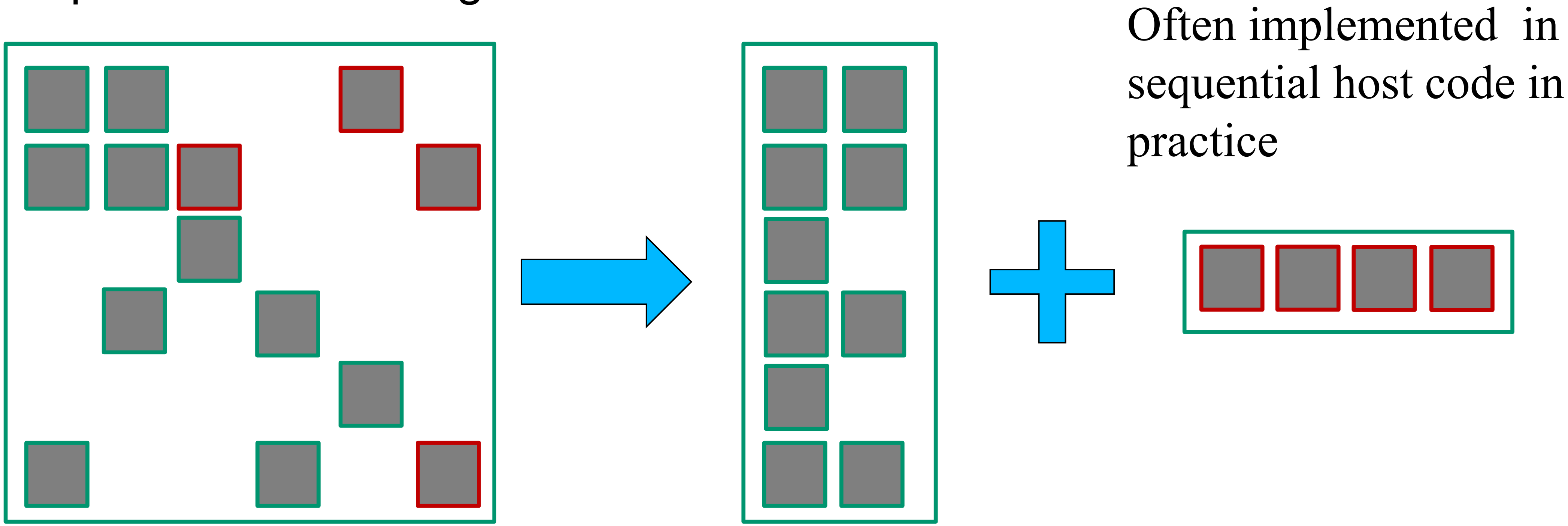
Coordinate (COO) format

- Explicitly list the column & row indices for every non-zero element

			Row 0		Row 2			Row 3		
Nonzero values	`data[7]`	{	3,	1,	2,	4,	1,	1,	1	}
Column indices	`col_index[7]`	{	0,	2,	1,	2,	3,	0,	3	}
Row indices	`row_index[7]`	{	0,	0,	2,	2,	2,	3,	3	}

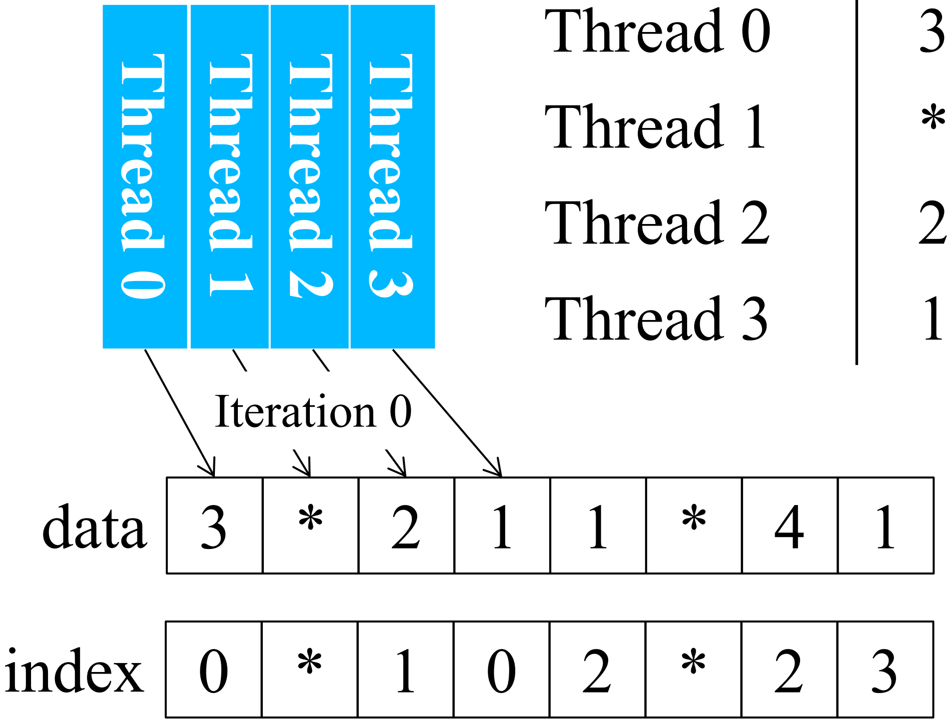
Hybrid Format (ELL + COO)

- ELL handles *typical* entries
- COO handles *exceptional* entries
  - Implemented with segmented reduction



Reduced Padding with Hybrid Format

	data		col_index	
Thread 0	3	1	0	2
Thread 1	*	*	*	*
Thread 2	2	4	1	2
Thread 3	1	1	0	3

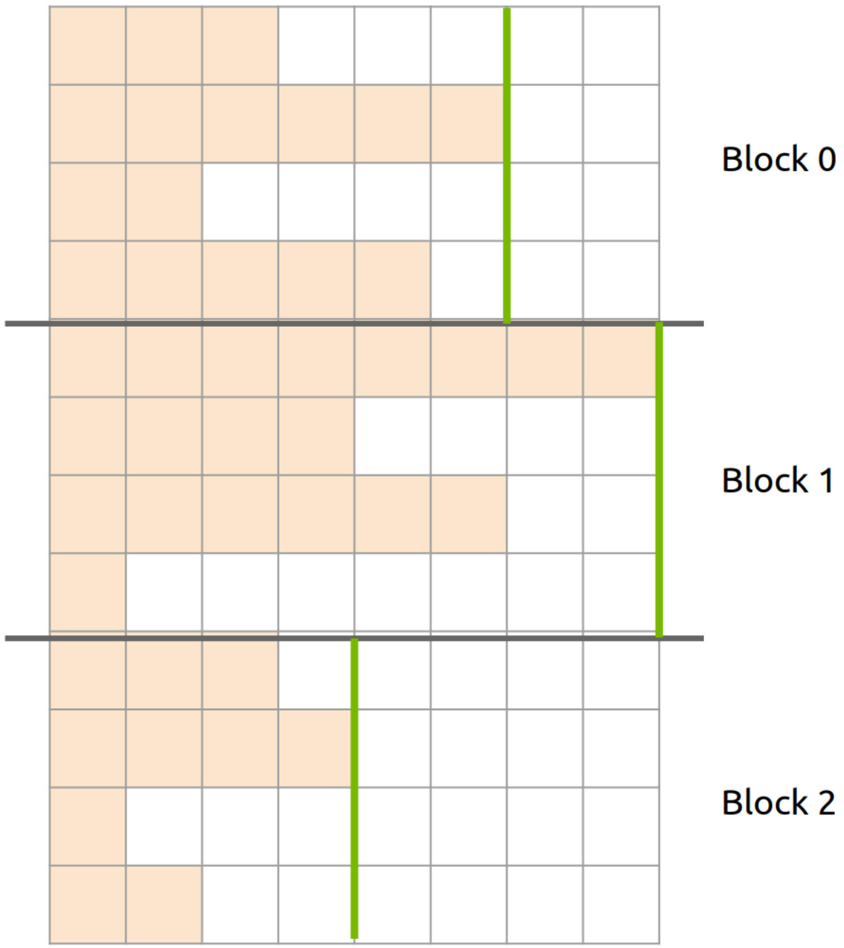


ELL

data	1
col_index	3
row_index	2

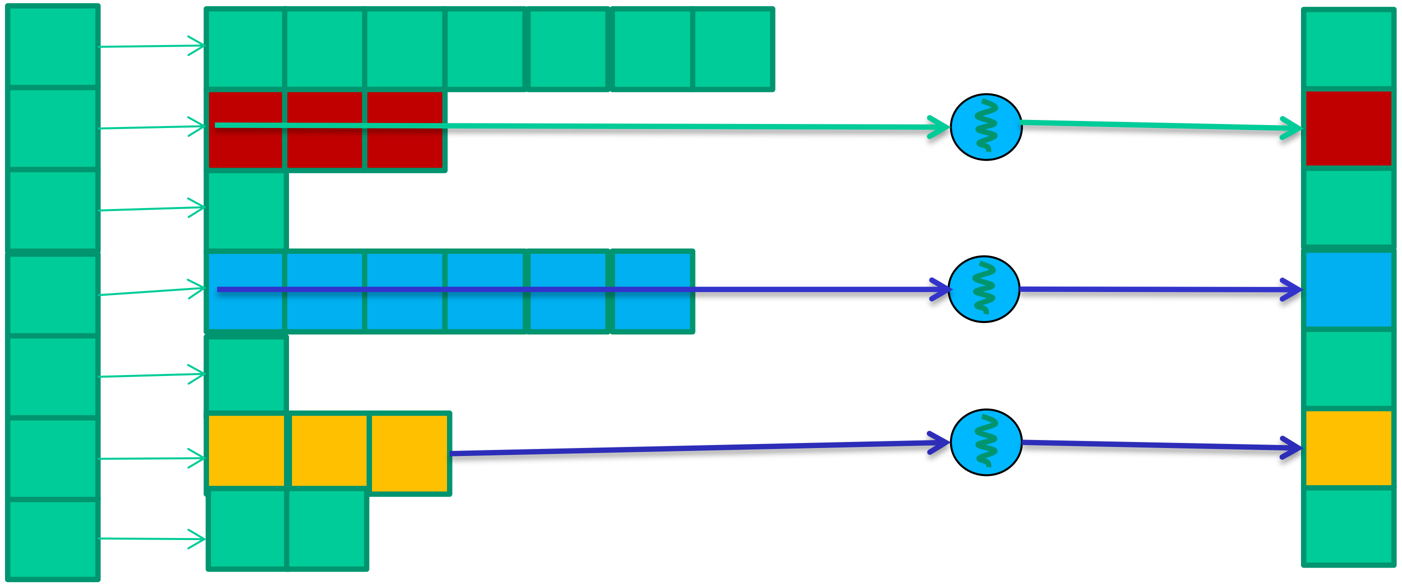
COO

CSR Run-time

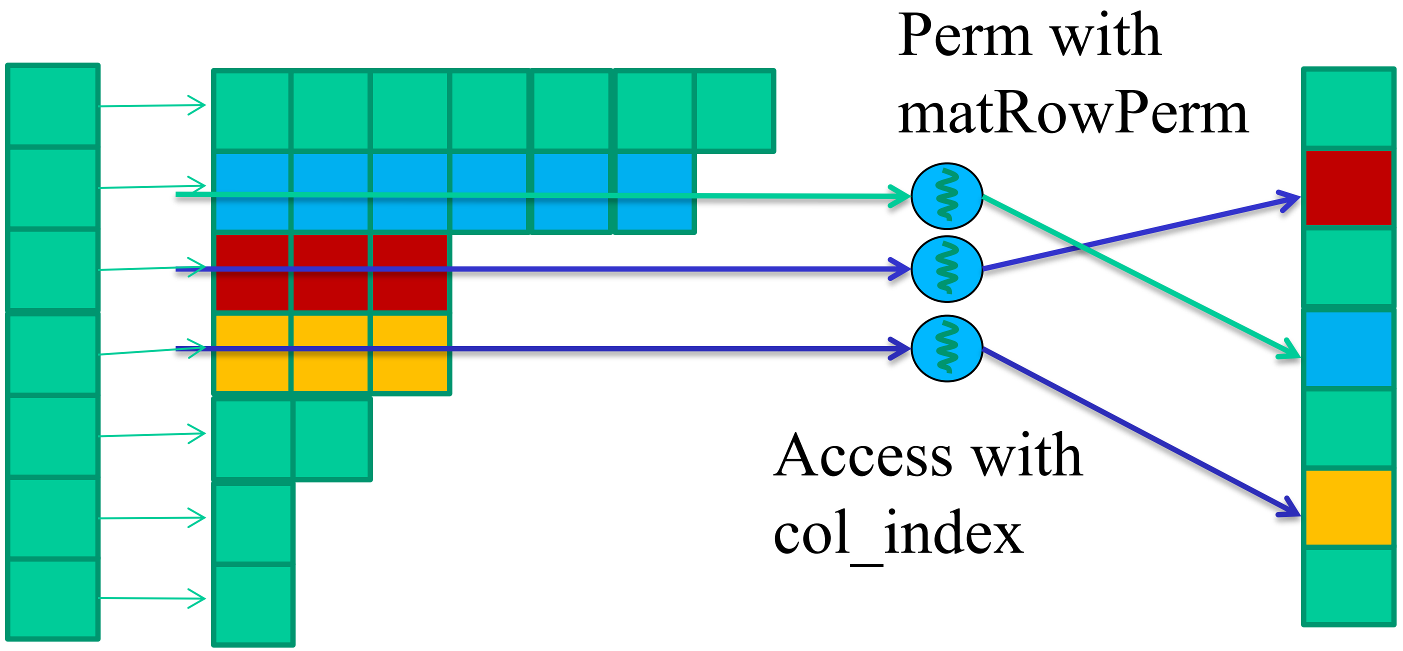


Block performance is determined by longest row

CSR-based SpMV

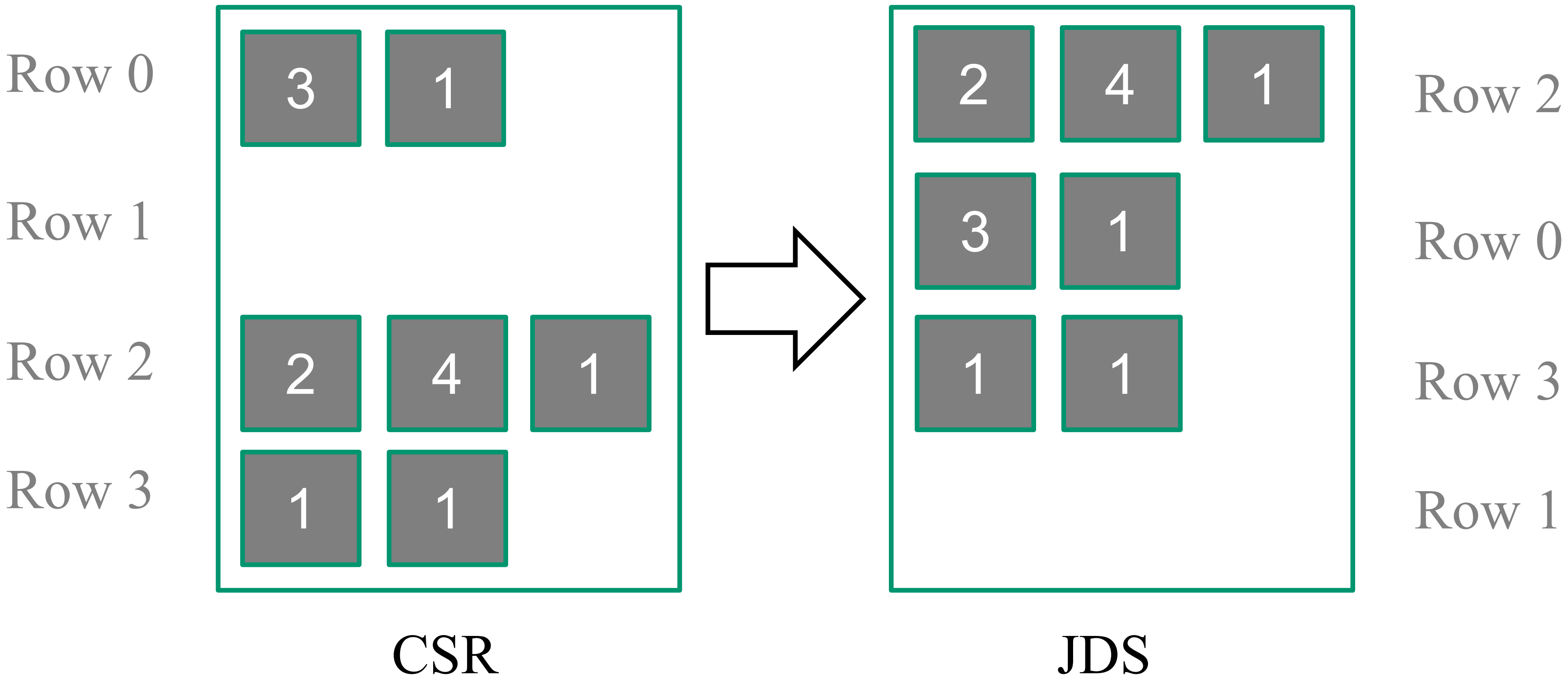


JDS (Jagged Diagonal Sparse) Kernel Design for Load Balancing



Sort rows into descending order according to number of non-zero. Keep track of the original row numbers so that the output vector can be generated correctly.

Sorting Rows According to Length (Regularization)



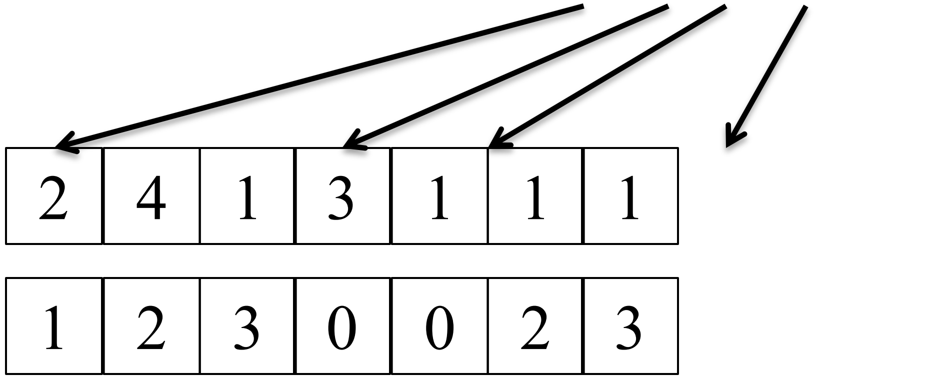
CSR to JDS Conversion

		Row 0	Row 2	Row 3
Nonzero values	data[7]	{ 3, 1,	2, 4, 1,	1, 1 }
Column indices	col_index[7]	{ 0, 2,	1, 2, 3,	0, 3 }
Row Pointers	row_ptr[5]	{ 0,	2, 2,	5, 7 }

		Row 2	Row 0	Row 3
Nonzero values	data[7]	{ 2, 4, 1,	3, 1,	1 1 }
Column indices	col_index[7]	{ 1, 2, 3,	0, 2,	0, 3 }
JDS Row Pointers	jds_row_ptr[5]	{0,	3,	5, 7,7 }
JDS Row Indices	jds_row_perm[4]	{2,	0,	3, 1 }

JDS Summary

Nonzero values	data[7]	{ 2, 4, 1, 3, 1, 1, 1 }
Column indices	jds_col_index[7]	{ 1, 2, 3, 0, 2, 0, 3 }
JDS row indices	jds_row_perm[4]	{ 2, 0, 3, 1 }
JDS Row Ptrs	jds_row_ptr[5]	{ 0, 3, 5, 7, 7 }



A Parallel SpMV/JDS Kernel

```
1. __global__ void SpMV_JDS(int num_rows, float *data, int *col_index,
               int *jds_row_ptr, int *jds_row_perm, float *x, float *y) {
2.    int row = blockIdx.x * blockDim.x + threadIdx.x;
3.    if (row < num_rows) {
4.      float dot = 0;
5.      int row_start = jds_row_ptr[row];
6.      int row_end =   jds_row_ptr[row+1];
7.      for (int elem = row_start; elem < row_end; elem++) {
8.        dot += data[elem] * x[col_index[elem]];
        }
9.      y[jds_row_perm[row]] = dot;
      }
   }
```

		Row 2	Row 0	Row 3	
Nonzero values	data[7]	{ 2, 4, 1,	3, 1,	1 1	}
Column indices	col_index[7]	{ 1, 2, 3,	0, 2,	0, 3	}
JDS Row Pointers	jds_row_ptr[5]	{0,	3,	5,	7,7 }
JDS Row Indices	jds_row_perm[4]	{2,	0,	3,	1 }

JDS vs. CSR - Control Divergence

- Threads still execute different number of iterations in the JDS kernel for-loop
  - However, neighboring threads tend to execute similar number of iterations because of sorting.
  - Better thread utilization, less control divergence

Nonzero values	data[7]	{ 2, 4, 1, 3, 1, 1, 1 }
Column indices	col_index[7]	{ 1, 2, 3, 0, 2, 0, 3 }
JDS row indices	Jds_row_perm[4]	{ 2, 0, 3, 1 }
JDS Row Ptrs	Jds_row_ptr[5]	{ 0, 3, 5, 7, 7 }

data	2	4	1	3	1	1	1
col_index	1	2	3	0	2	0	3

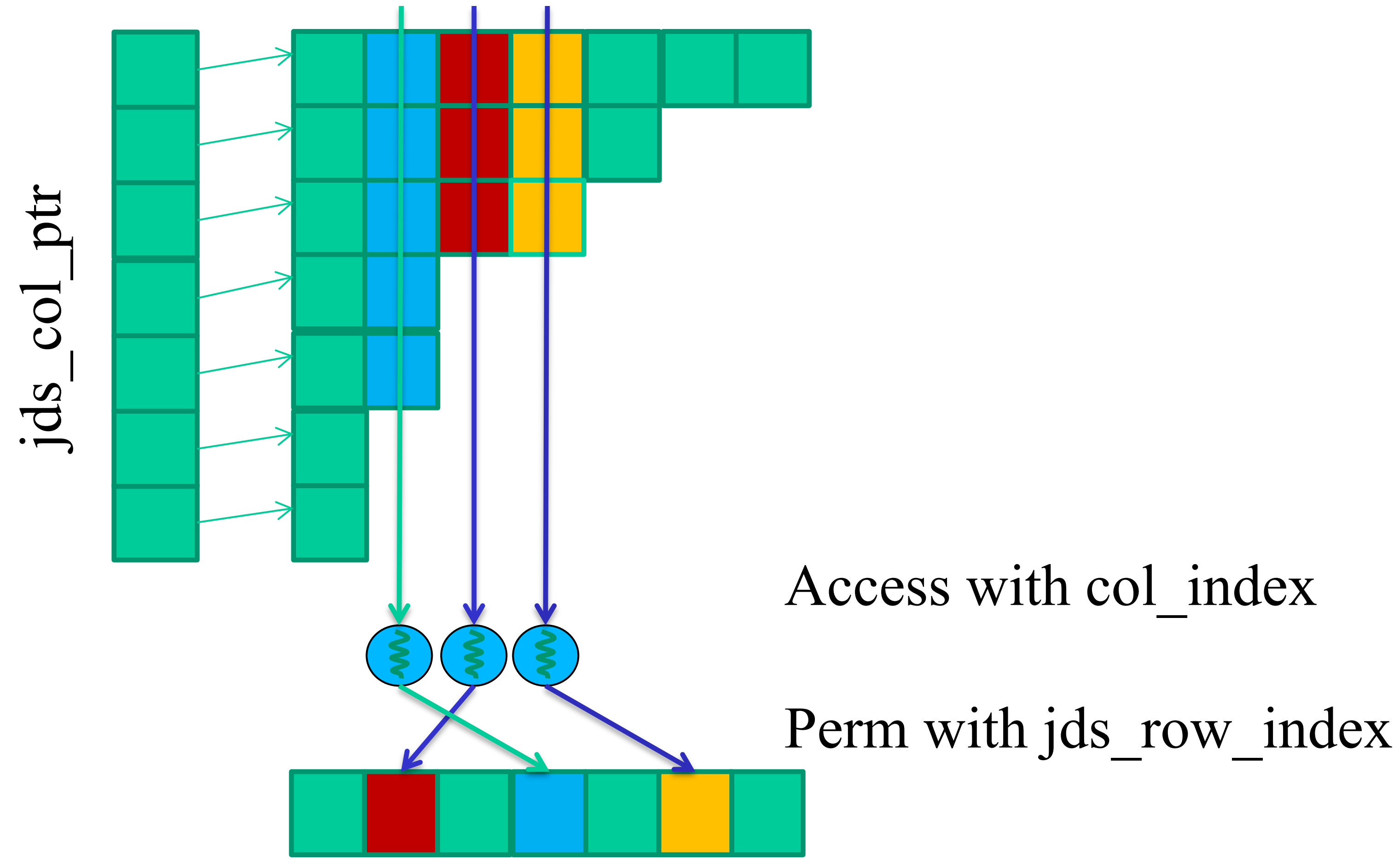
JDS vs. CSR Memory Divergence

- Adjacent threads still access non-adjacent memory locations

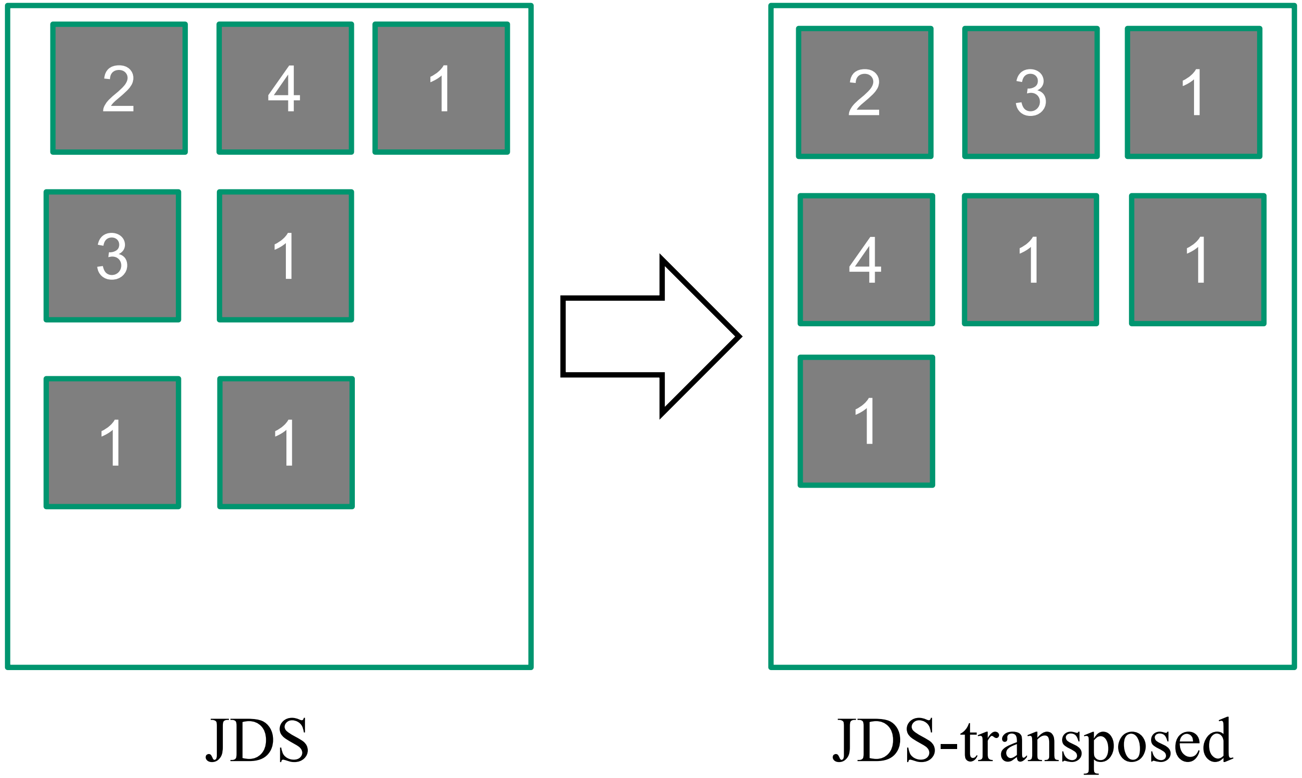
Nonzero values	data[7]	{ 2, 4, 1, 3, 1, 1, 1 }
Column indices	col_index[7]	{ 1, 2, 3, 0, 2, 0, 3 }
JDS row indices	jds_row_perm[4]	{ 2, 0, 3, 1 }
JDS Row Ptrs	jds_row_ptr[5]	{ 0, 3, 5, 7, 7 }

data	2	4	1	3	1	1	1
col_index	1	2	3	0	2	0	3

JDS with Transposition



Transposition for Memory Coalescing



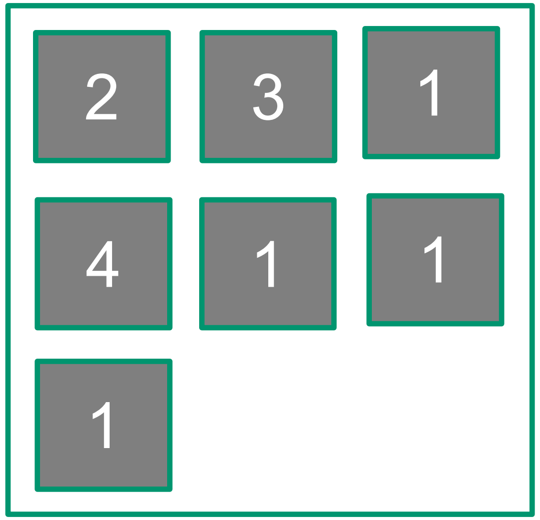
JDS Format with Transposed Layout

Row 0	3	0	1	0	Thread 0
Row 1	0	0	0	0	Thread 1
Row 2	0	2	4	1	Thread 2
Row 3	1	0	0	1	Thread 3

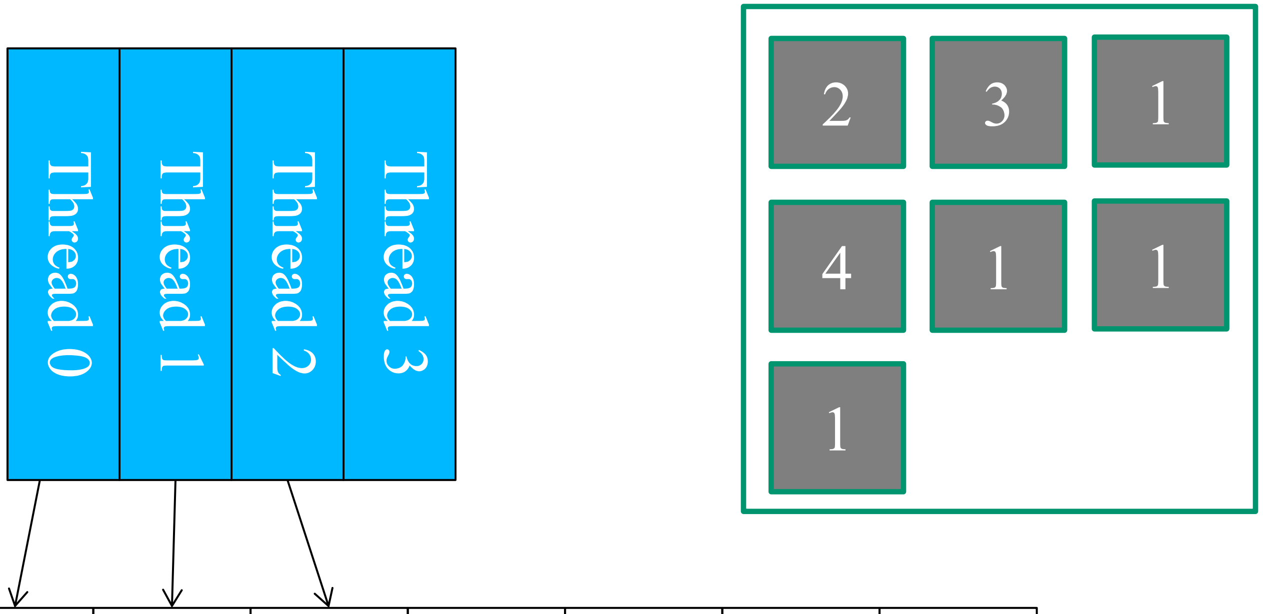
JDS row indices jds_row_perm[4] { 2, 0, 3, 1 }

JDS column pointers jds_t_col_ptr[4] { 0, 3, 6, 7 }

data	2	3	1	4	1	1	1
col_index	1	0	0	2	2	3	3

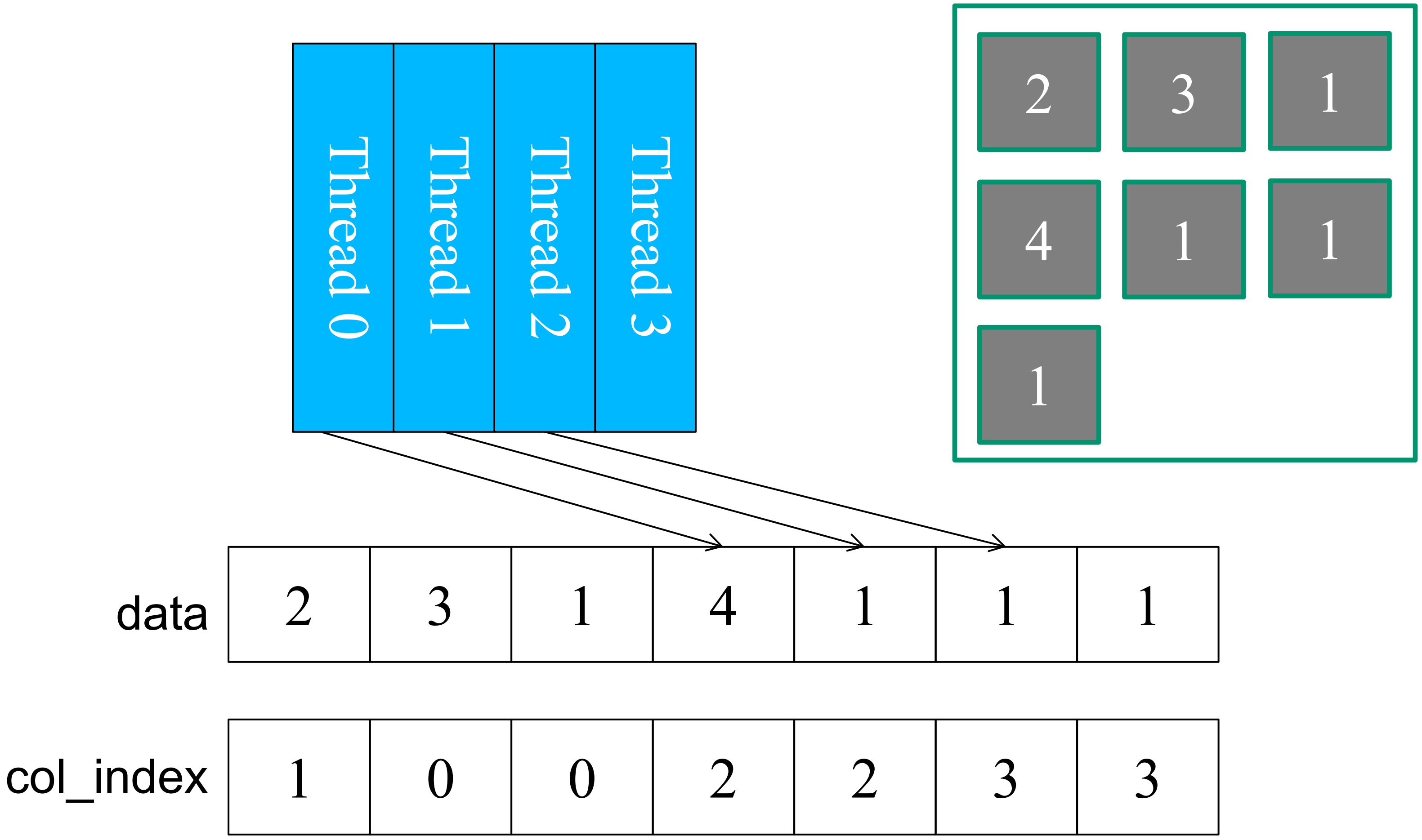


JDS with Transposition: Memory Coalescing

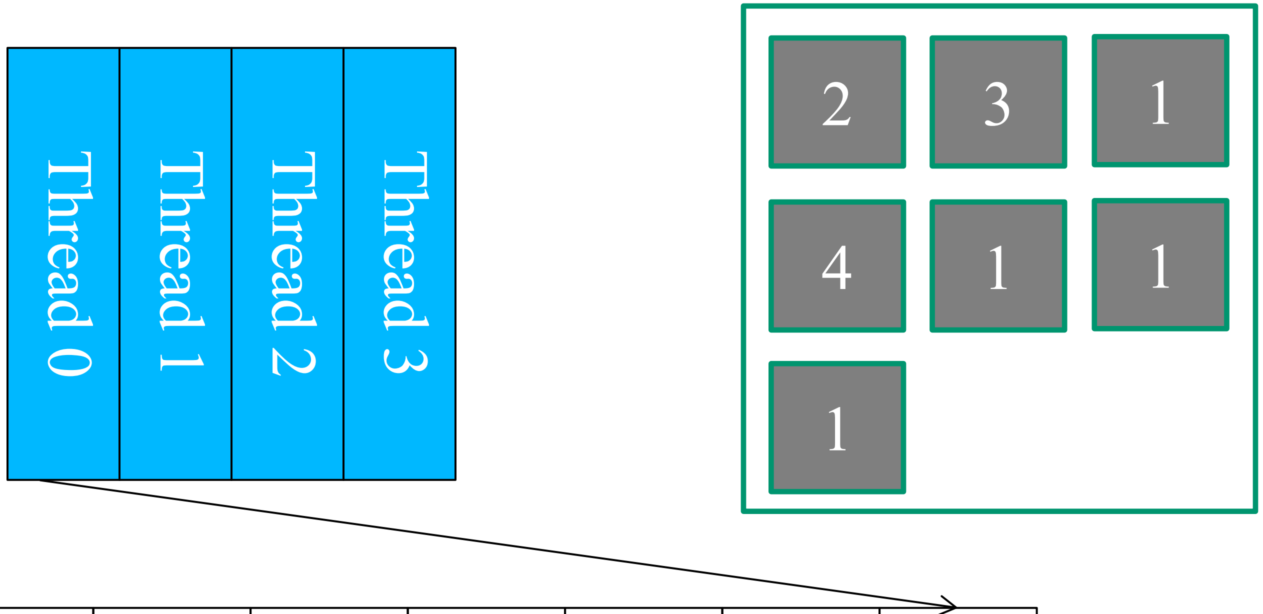


data	2	3	1	4	1	1	1
col_index	1	0	0	2	2	3	3

JDS with Transposition: Memory Coalescing



JDS with Transposition: Memory Coalescing



data	2	3	1	4	1	1	1
col_index	1	0	0	2	2	3	3

A Parallel SpMV/JDS_T Kernel

```
__global__ void SpMV_JDS_T(int num_rows, float *data, int *col_index,
              int *jds_t_col_ptr, int *jds_row_perm, float *x, float *y) {
    int row = blockIdx.x * blockDim.x + threadIdx.x;
    if (row < num_rows) {
      float dot = 0;
      unsigned int sec = 0;
      while (jds_t_col_ptr[sec+1] - jds_t_col_ptr[sec] > row) {
         dot += data[jds_t_col_ptr[sec]+row] *
                x[col_index[jds_t_col_ptr[sec]+row]];
         sec++;
      }
      y[jds_row_perm[row]] = dot;
    }
}
```

		Sec 0	Sec 1	Sec 2	
Nonzero values	data[7]	{2, 3, 1,	4, 1, 1	1	}
Column indices	col_index[7]	{1, 0, 3,	2, 2, 3	3	}
JDS_T Column Pointers	jds_t_col_ptr[5]	{0,	3,	6,	7,7 }
JDS Row Indices	jds_row_perm[4]	{2,	0,	3,	1 }

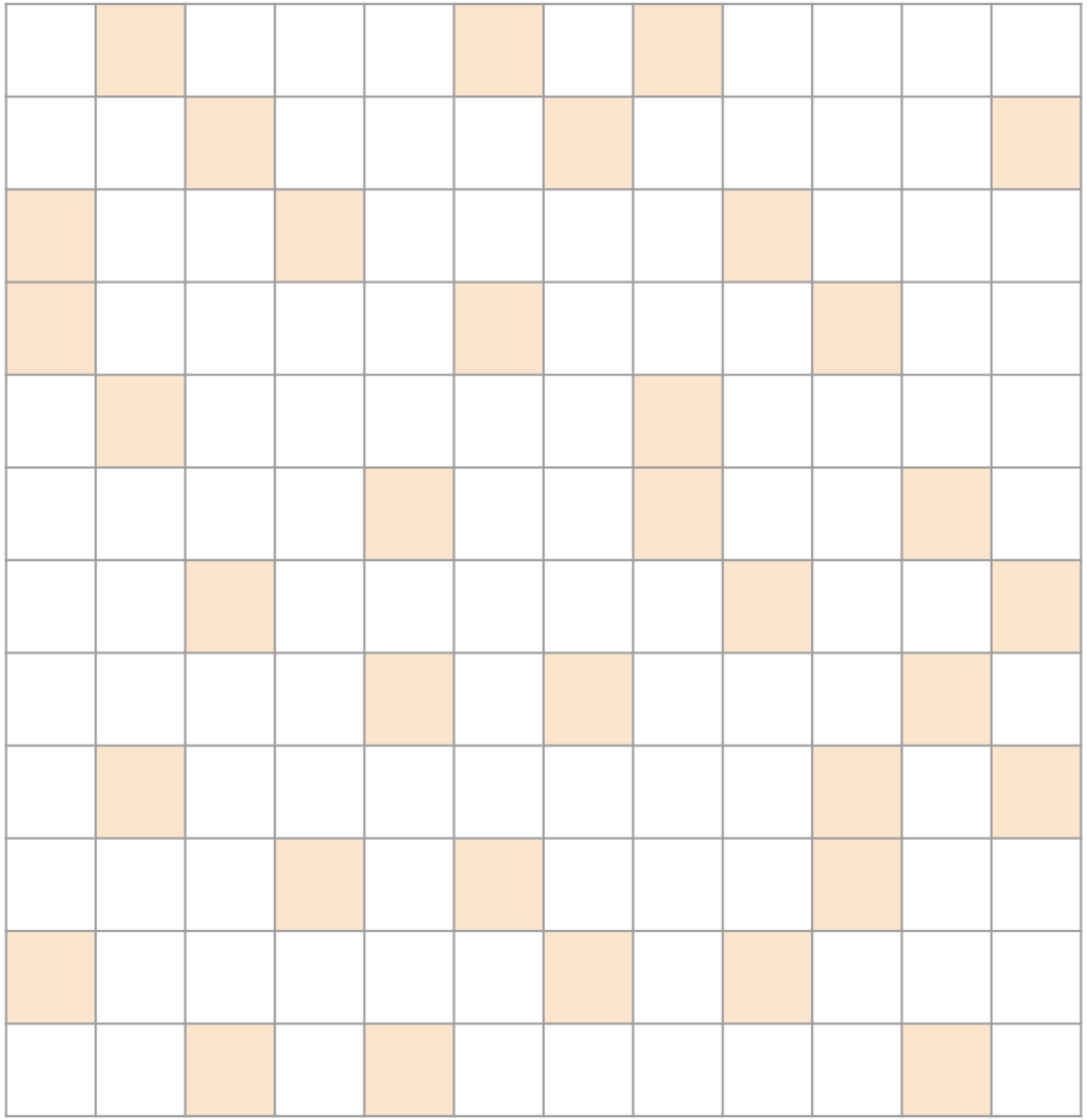
Lab 7 Variable Names

JDS_T Length of Cols matRows[4] {3, 2, 2, 0 }

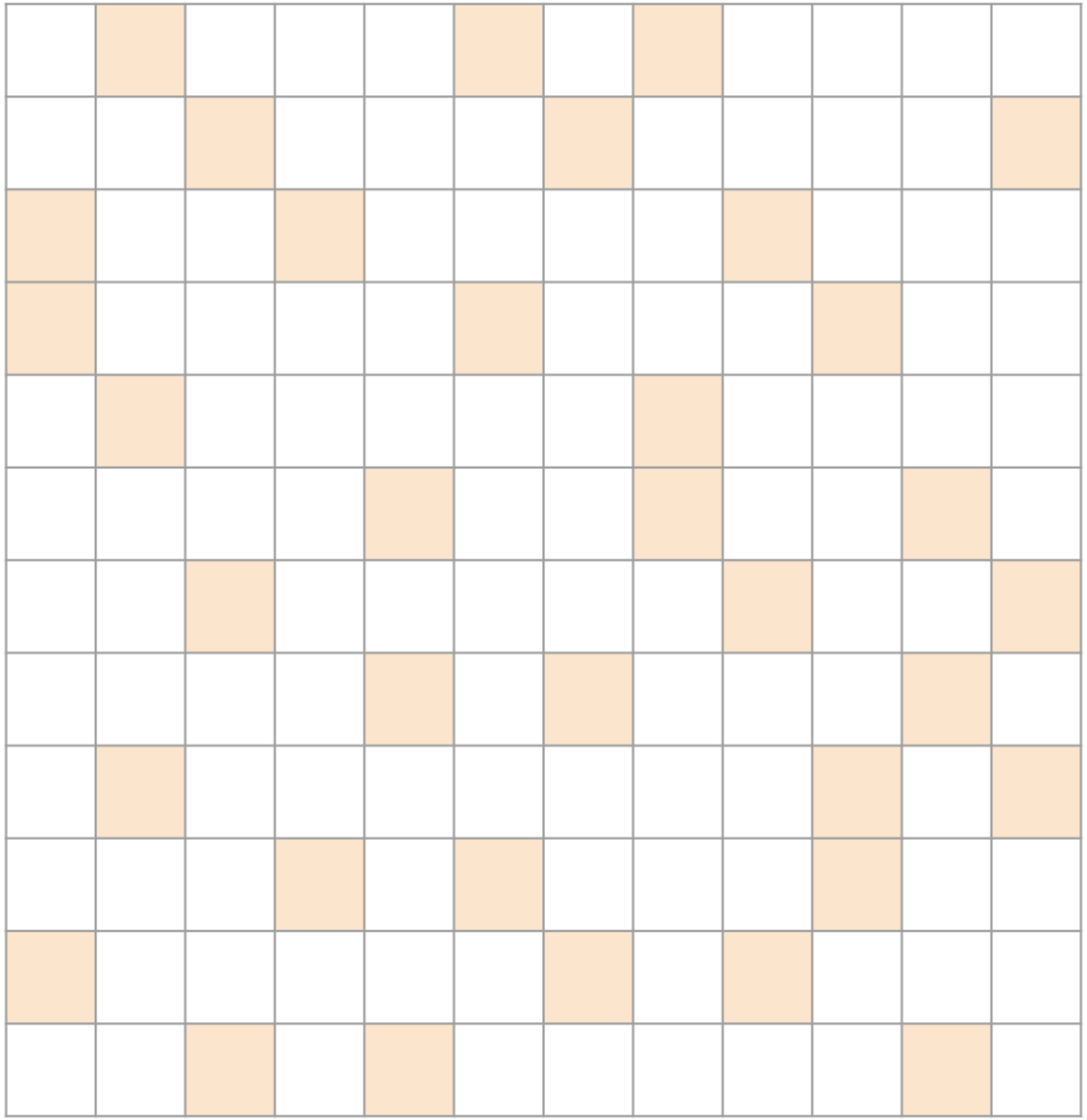
		Sec 0	Sec 1	Sec 2	
Nonzero values matData[7]	{	2, 3, 1,	4, 1, 1	1	}
Column indices matCols[7]	{	1, 0, 3,	2, 2, 3	3	}

JDS_T Column Pointers matColStart[4] {0, 3, 6, 7 }

JDS Row Indices matRowPerm[4] {2, 0, 3, 1 }



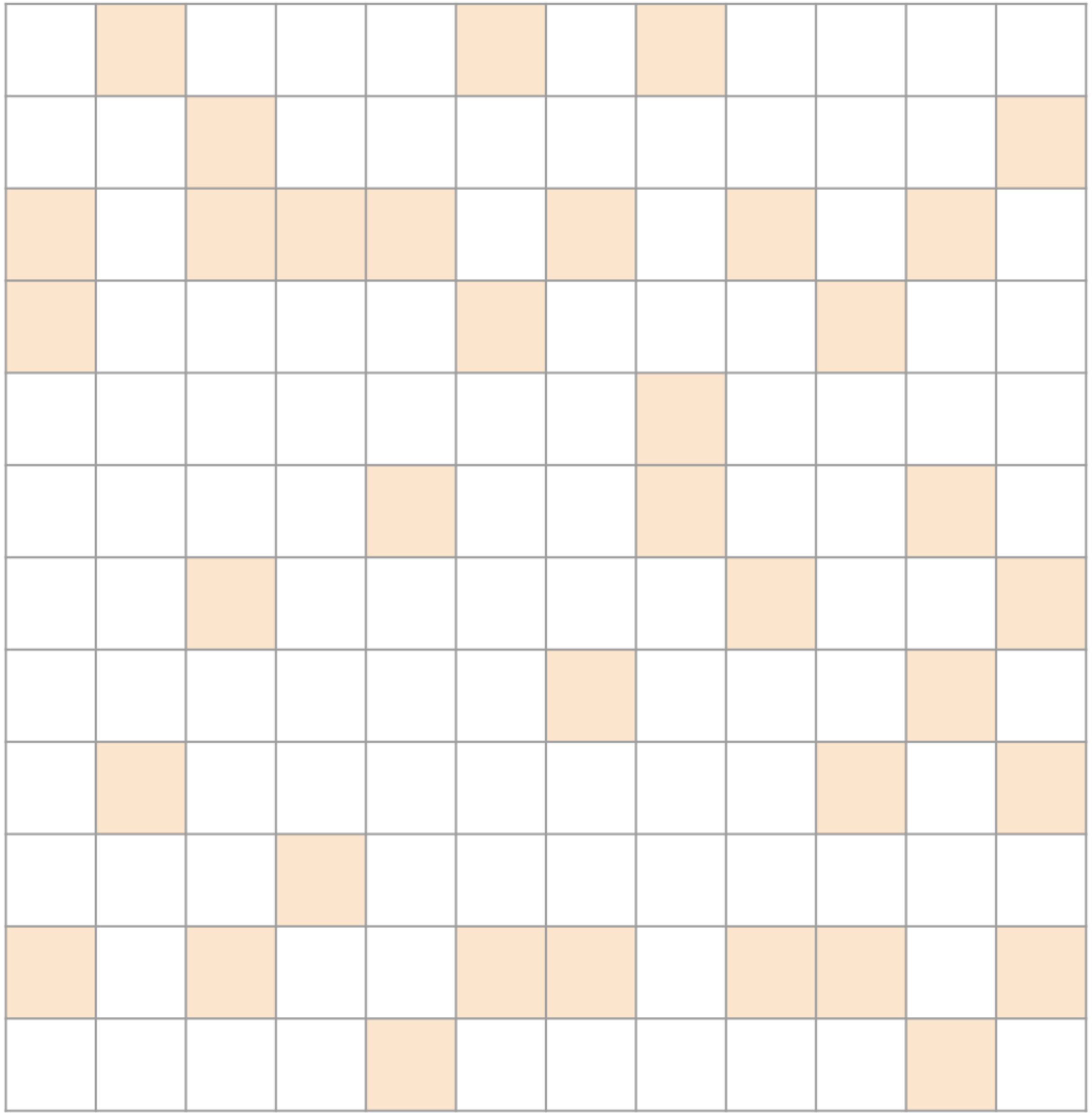
Roughly Random…



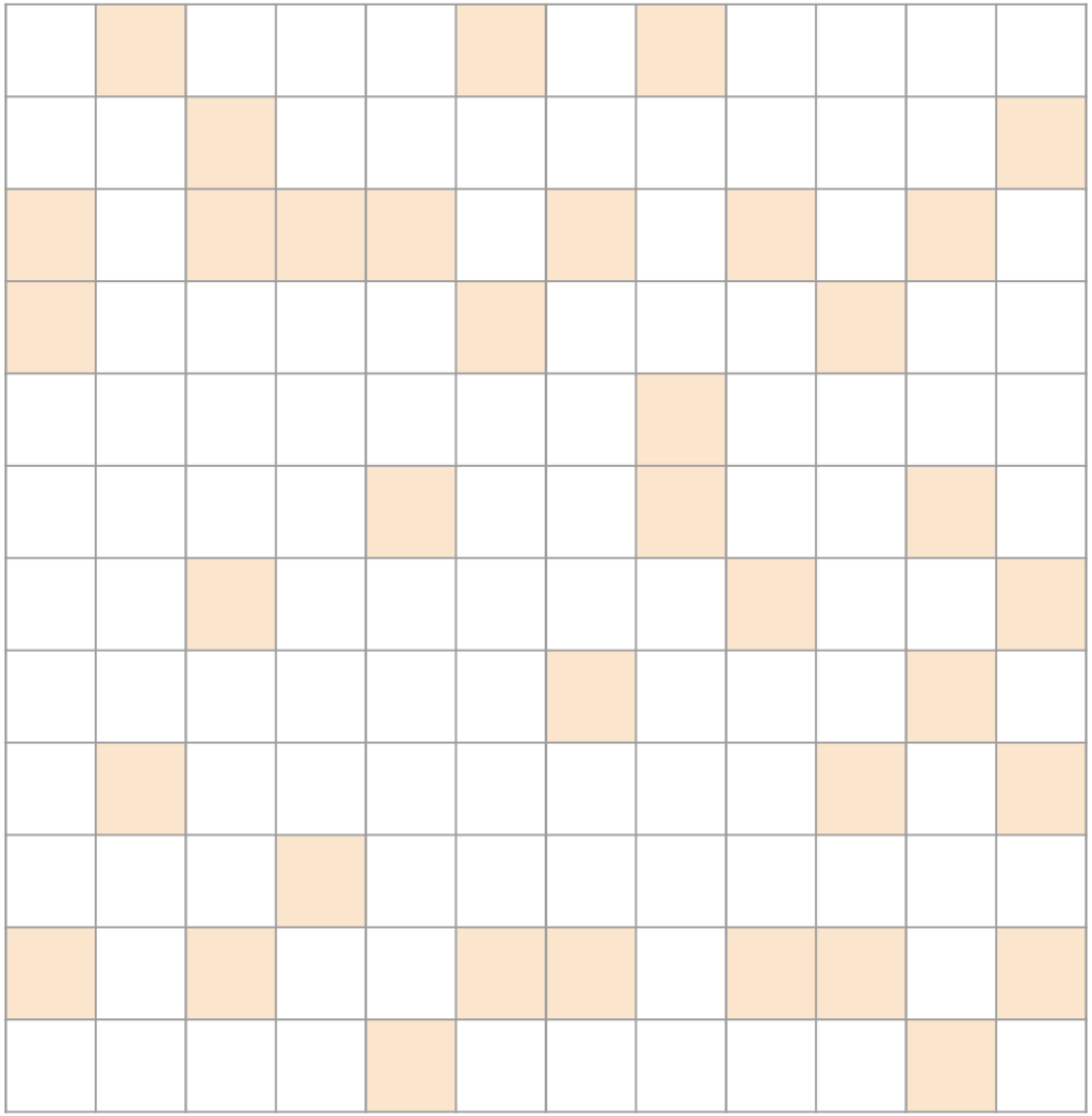
Roughly Random…

Probably best with ELL.

- Padding will be uniformly distributed
- Sparse representation will be uniform



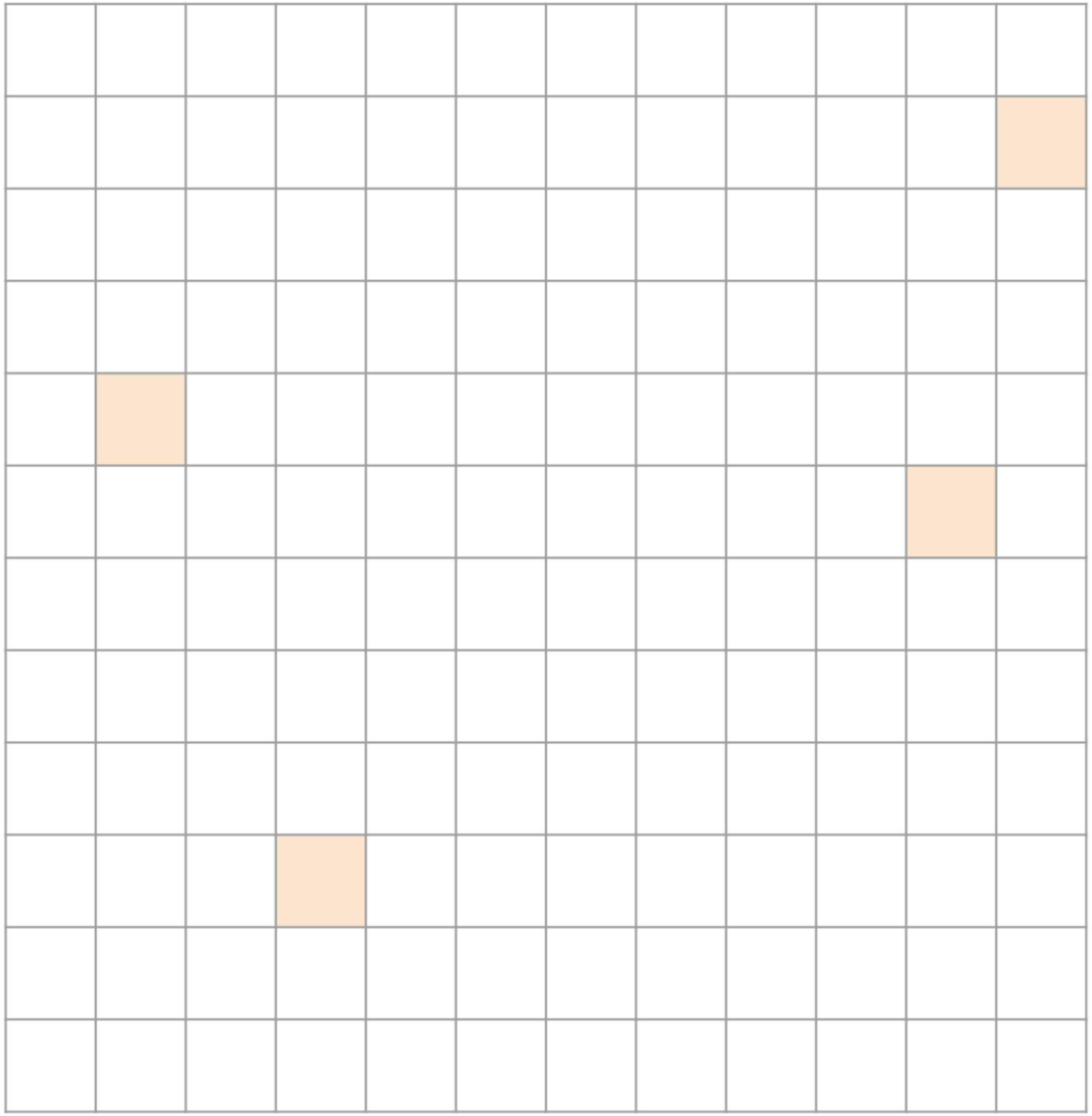
High variance in rows…



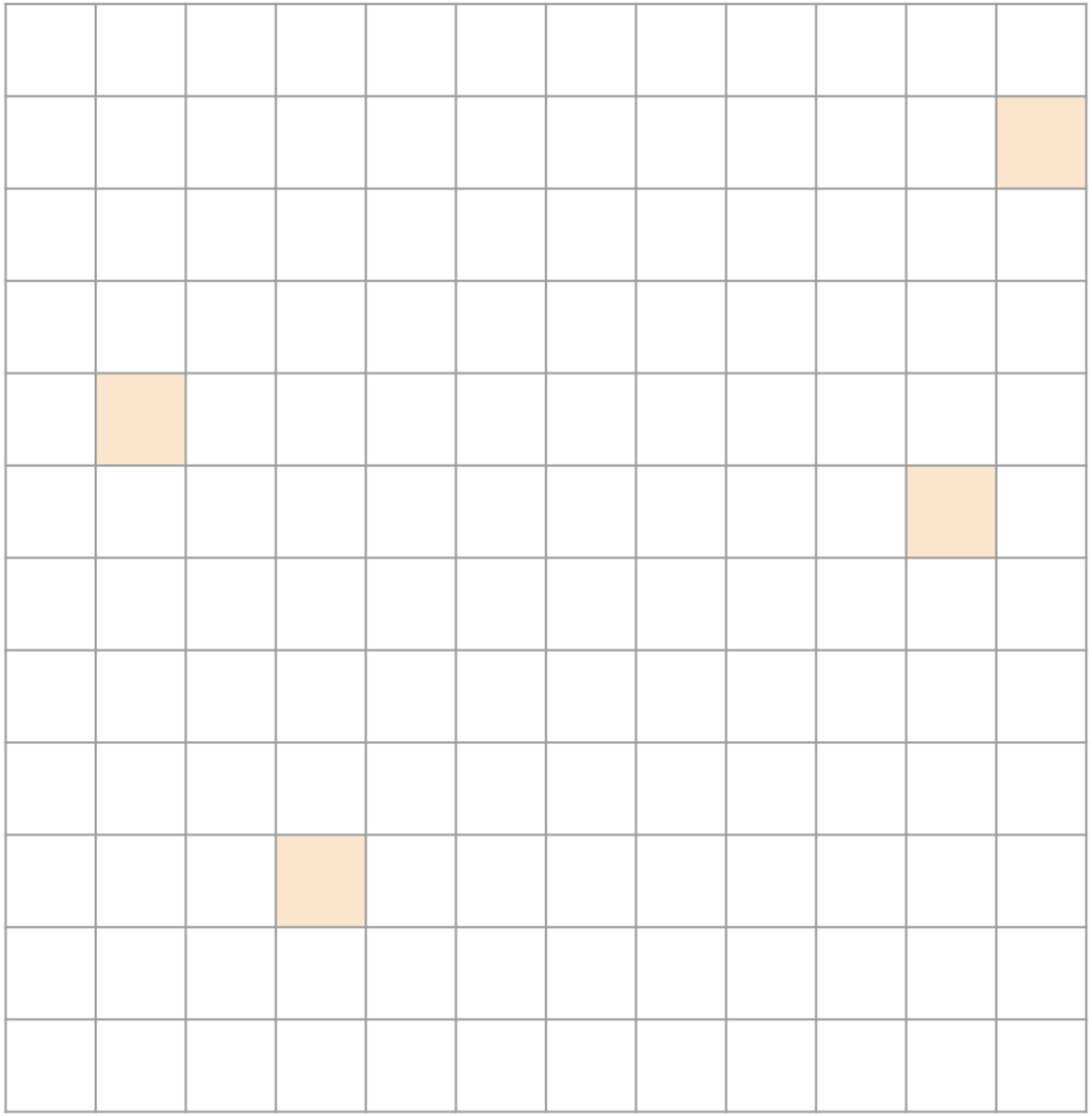
High variance in rows

Probably best with ELL/COO

- Benefit of ELL for most cases
- Outliers are captured with COO



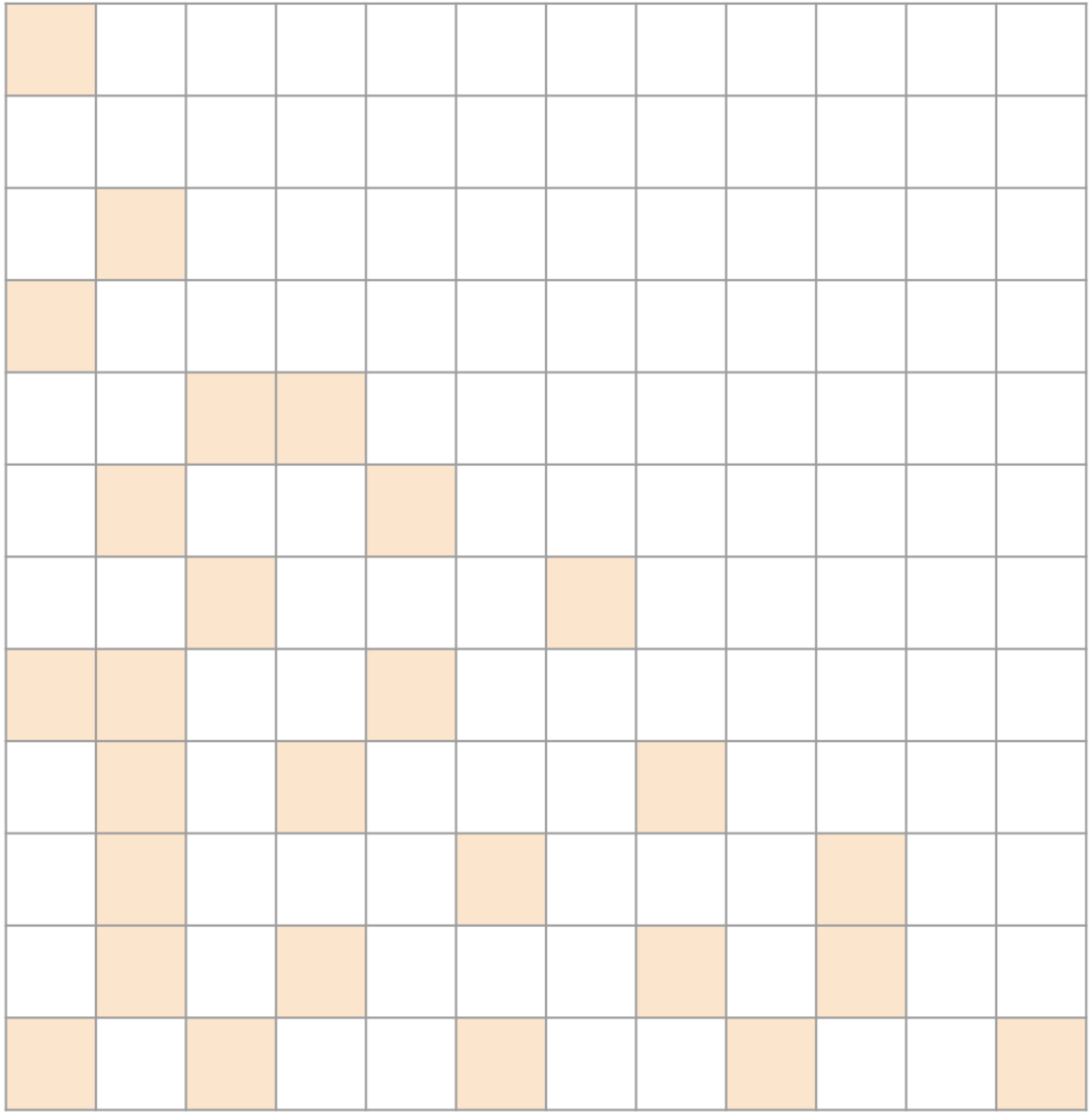
Very sparse…



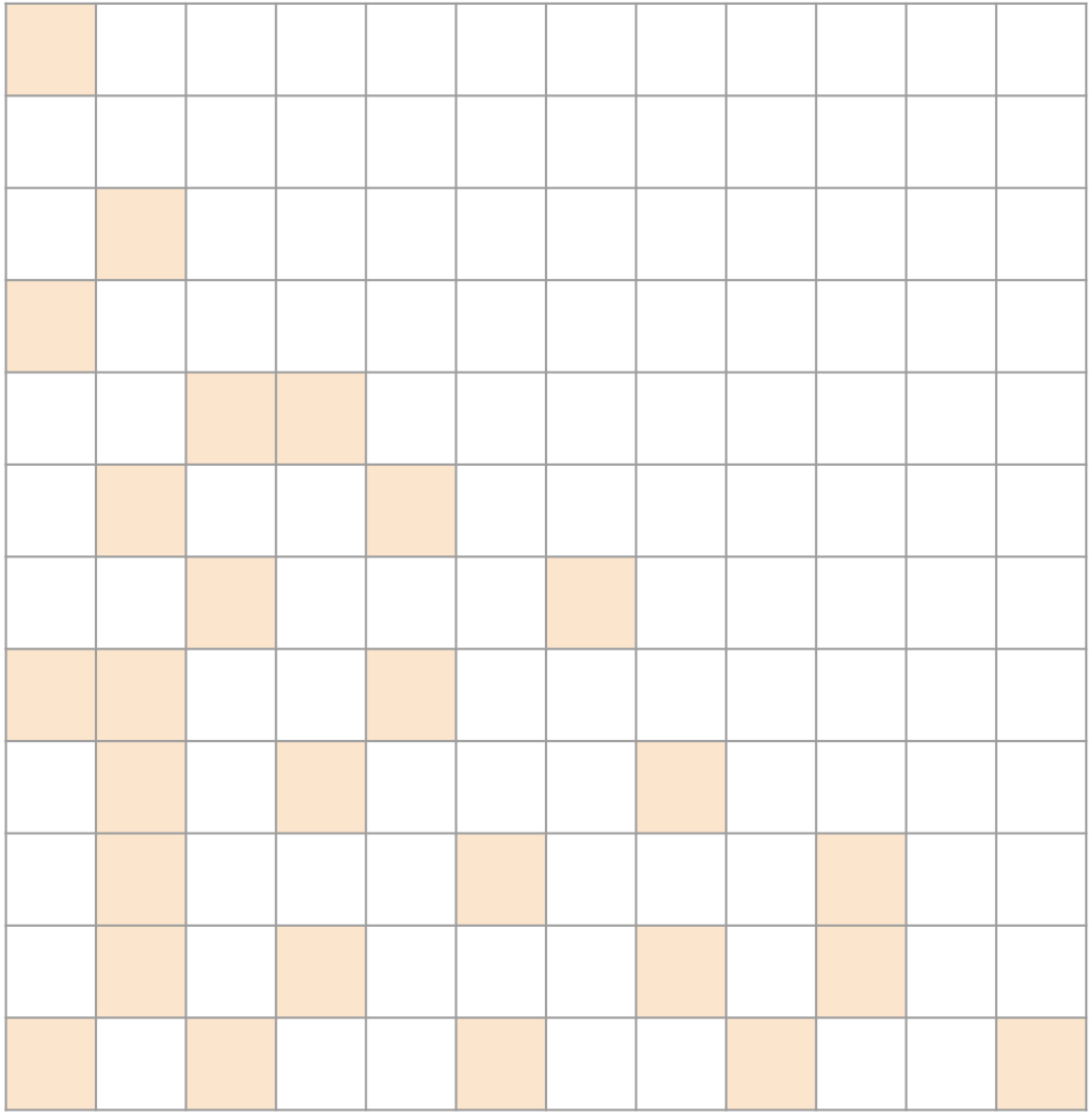
Very sparse

Probably best with COO

- Not a lot of data, compute is sparse



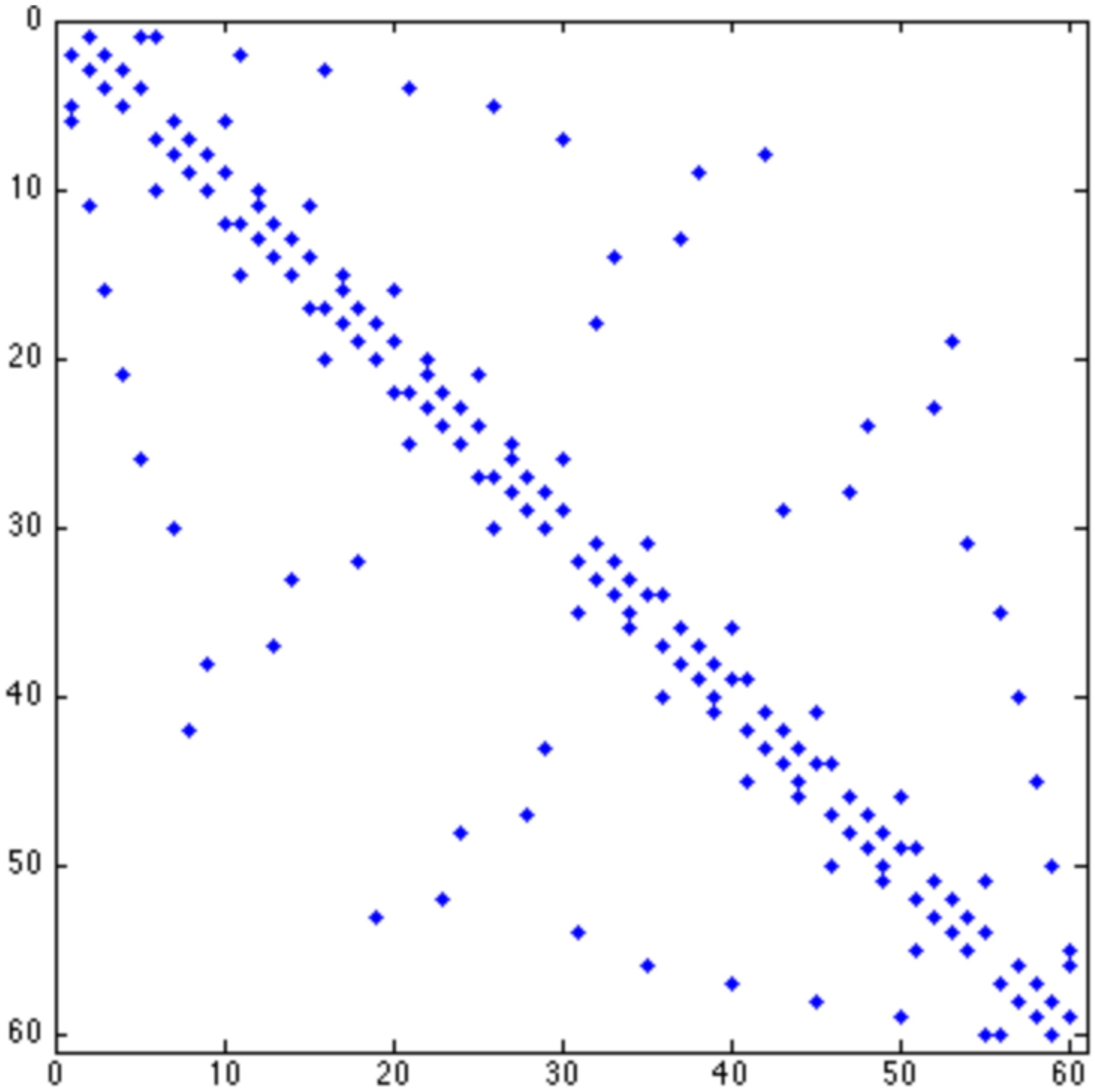
Roughly triangular…



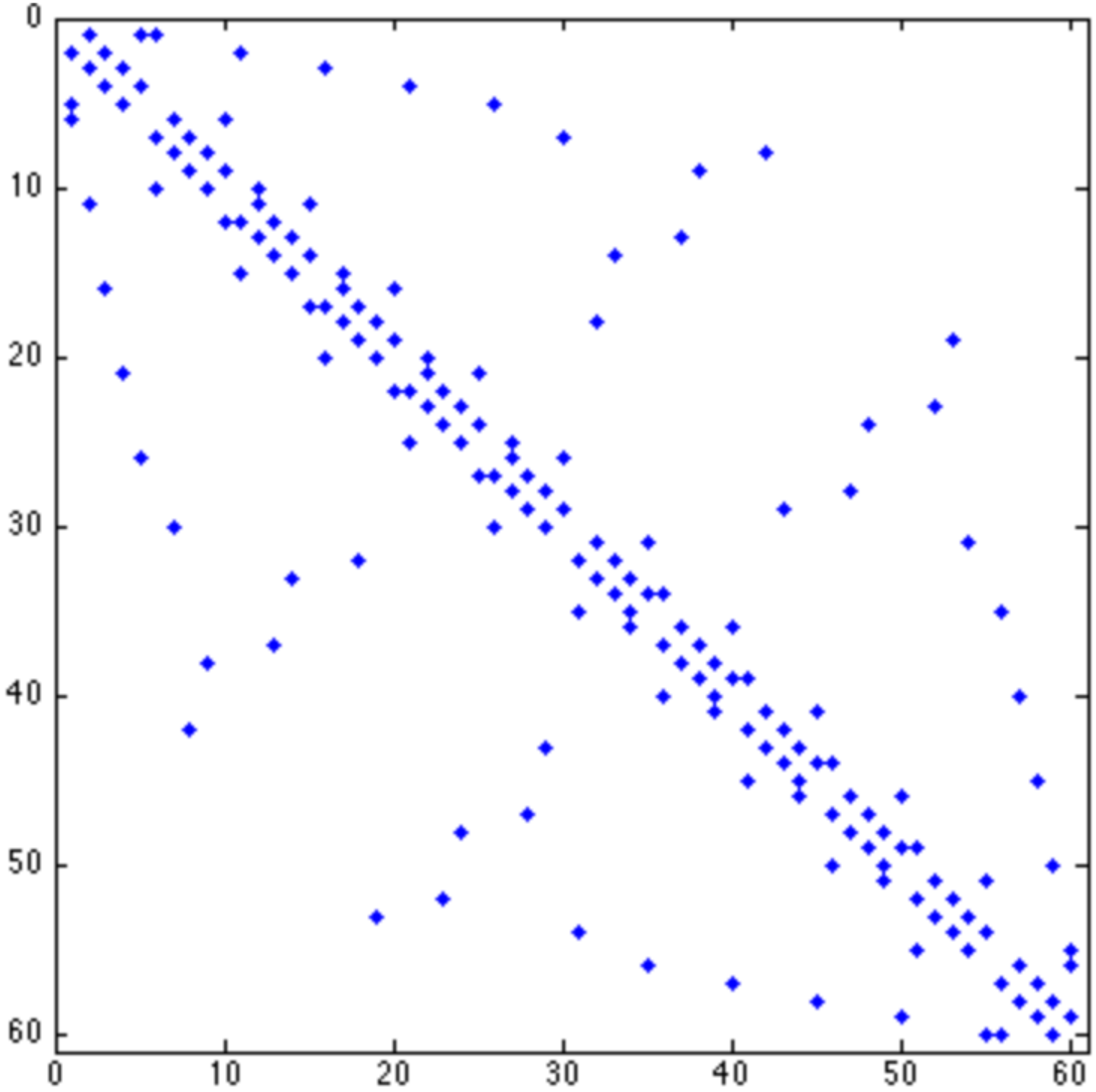
Roughly triangular…

Probably best with JDS

- Takes advantage of sparsity structure



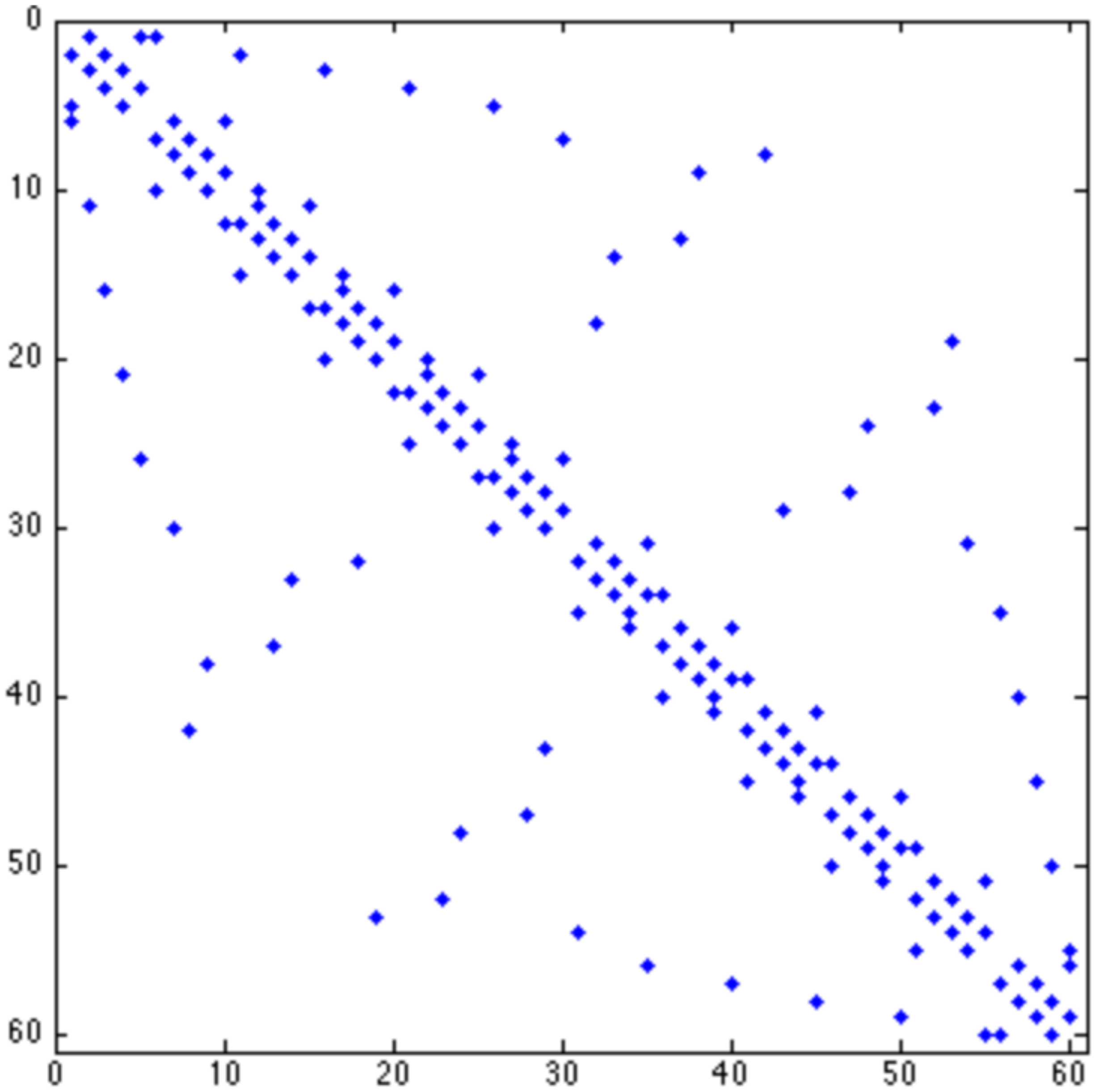
Banded Matrix…

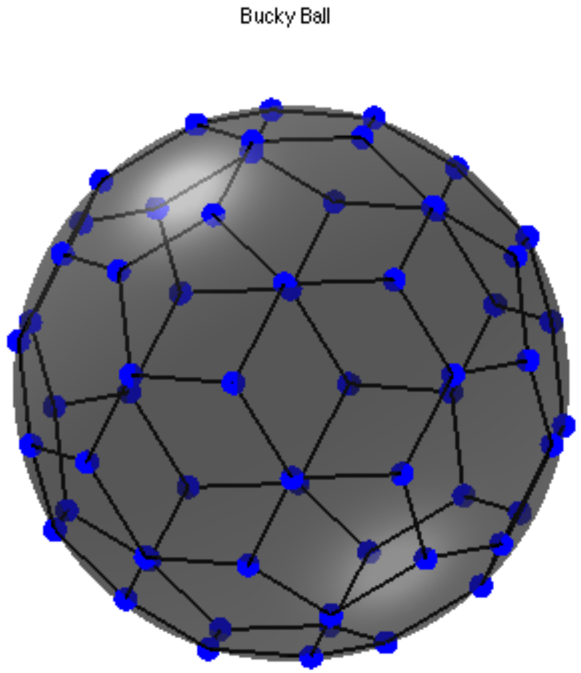


Banded Matrix…

Probably best with ELL

- Small amount of variance in rows


0
10
20
30
40
50
60
0
10
20
30
40
50
60


Bucky Ball

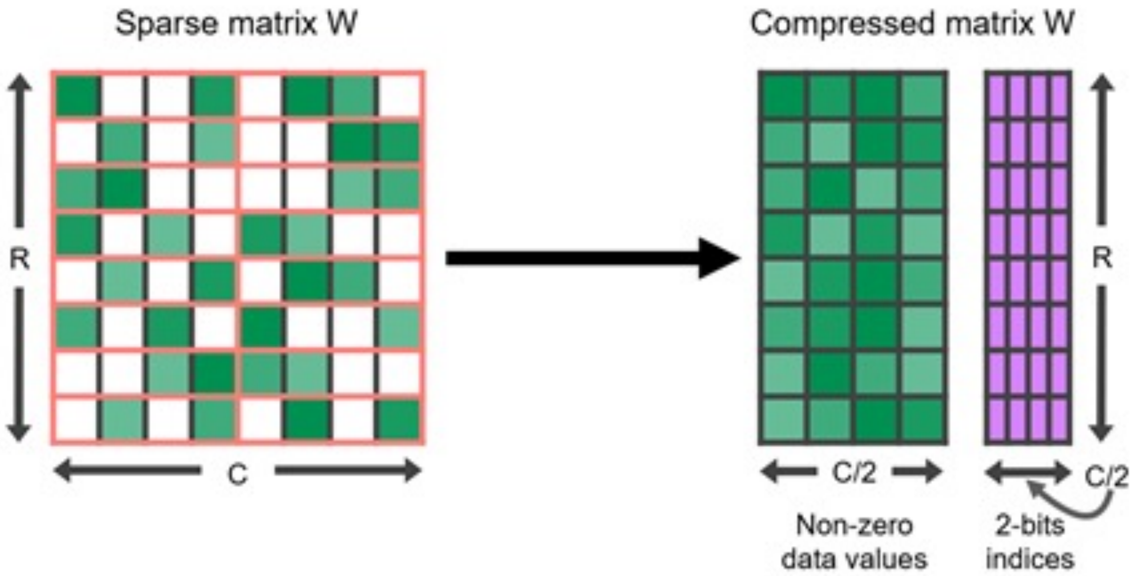
Other formats

- Diagonal (DIA): for strictly banded/diagonal matrices
- Packet (PKT): create diagonal submatrices by reordering rows/cols
- Dictionary of Keys (DOK): map of (row/col) to data
- Compressed Sparse Column (CSC): when to use over CSR?
- Blocked CSR: useful for block sparse matrices

- What about situations where sparsity is dynamic, i.e., the large sparse systems are dynamically generated at run-time?

Sparsity in Deep Neural Networks

- Quasi-uniform distribution of zeros
- Sometimes >50%, but rarely 90%
- Weight matrices are Large!
- Metadata and overhead are important considerations



2:4 Compression

- Either a block is compressed or it isn't
- Compressed blocks store 4 words in the space of 2

Sparse Matrices as Foundation for Advanced Algorithm Techniques

- Graphs are often represented as sparse adjacency matrices
  - Used extensively in social network analytics, natural language processing, etc.
- Binning techniques often use sparse matrices for data compaction
  - Used extensively in ray tracing, particle-based fluid dynamics methods, and games
- These will be covered in ECE508/CS508

ANY MORE QUESTIONS
READ CHAPTER 10