ECE408/CS483/CSE408 Fall 2022

Applied Parallel Programming

Lecture 19
Parallel Sparse Methods

Course Reminders

- MP5.2 is due this week
- Project Milestone 2: Baseline Convolution Kernel
 - Due November 4th

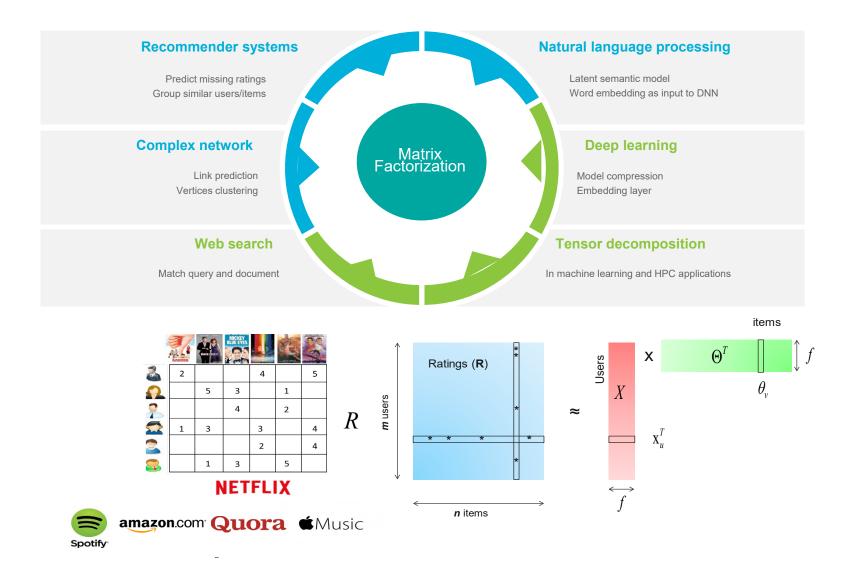
Objective

- To learn the key techniques for compacting input data in parallel sparse methods for reduced consumption of memory bandwidth
 - better utilization of on-chip memory
 - fewer bytes transferred to on-chip memory
 - Better utilization of global memory
 - Challenge: retaining regularity

Sparse Matrix

- Many real-world systems are sparse in nature
 - Linear systems described as sparse matrices
- Solving sparse linear systems
 - Iterative Conjugate Gradient solvers based on sparse matrix-vector multiplication is a common method
- Solution of PDE systems can be formulated into linear operations expressed as sparse matrix-vector multiplication

Sparse Matrix in Analytics and Al

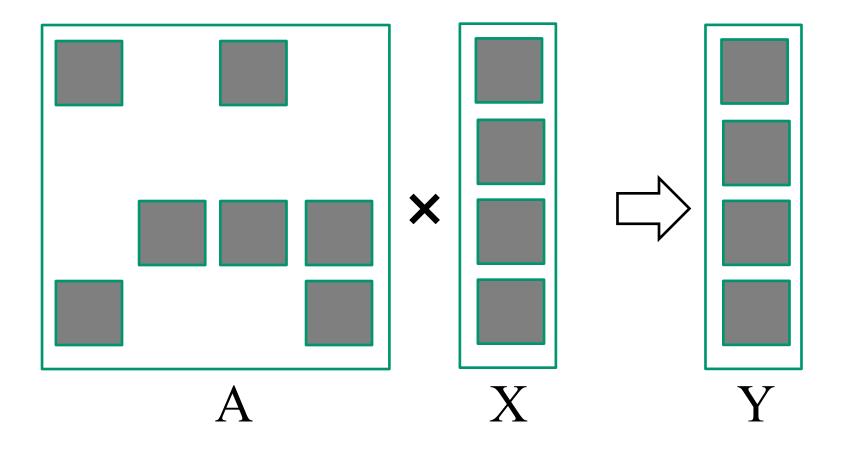


Sparse Matrix in Scientific Computing

Science Area	Number of Teams	Codes	Struct Grids	Unstruct Grids	Dense Matrix	Sparse Matrix	N- Body	Monte Carlo	FFT	PIC	Sig I/O
Climate and Weather	3	CESM, GCRM, CM1/WRF, HOMME	Χ	X		X		X			Χ
Plasmas/Magnetosphere	2	H3D(M),VPIC, OSIRIS, Magtail/UPIC	X				Х		Χ		Χ
Stellar Atmospheres and Supernovae	5	PPM, MAESTRO, CASTRO, SEDONA, ChaNGa, MS-FLUKSS	X			X	Х	X		X	X
Cosmology	2	Enzo, pGADGET	X			X	Х				
Combustion/Turbulence	2	PSDNS, DISTUF	X						Χ		
General Relativity	2	Cactus, Harm3D, LazEV	X			X					
Molecular Dynamics	4	AMBER, Gromacs, NAMD, LAMMPS				X	Х		Χ		
Quantum Chemistry	2	SIAL, GAMESS, NWChem			Х	X	Х	X			Χ
Material Science	3	NEMOS, OMEN, GW, QMCPACK			Х	X	Х	X			
Earthquakes/Seismology	2	AWP-ODC, HERCULES, PLSQR, SPECFEM3D	X	X			Х				X
Quantum Chromo Dynamics	1	Chroma, MILC, USQCD	X		Х	X					
Social Networks	1	EPISIMDEMICS									
Evolution	1	Eve									
Engineering/System of Systems	1	GRIPS,Revisit						X			
Computer Science	1			X	Х	X			Χ		Χ

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Sparse Matrix-Vector Multiplication (SpMV)



Challenges

- Compared to dense matrix multiplication, SpMV
 - Is irregular/unstructured
 - Has little input data reuse
 - Benefits little from compiler transformation tools
- Key to maximal performance
 - Maximize regularity (by reducing divergence and load imbalance)
 - Maximize DRAM burst utilization (layout arrangement)

A Simple Parallel SpMV

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

Each thread processes one row

Compressed Sparse Row (CSR) Format

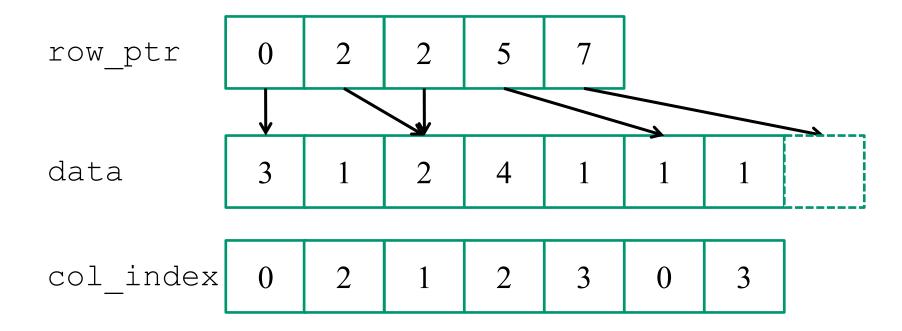
CSR Representation

	Ro		≤ 0	R	OW	2	Rov	v3	
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	}		

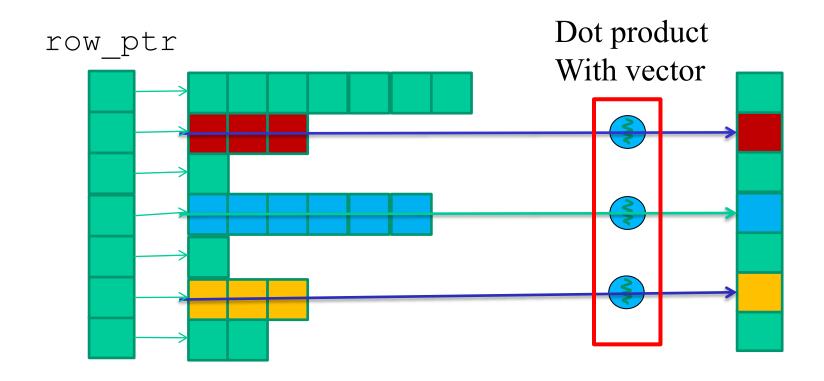
Dense representation

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

CSR Data Layout



CSR Kernel Design



A Parallel SpMV/CSR Kernel (CUDA)

```
1. global void SpMV CSR (int num rows, float *data, int
  *col index, int *row ptr, float *x, float *y)
     int row = blockIdx.x * blockDim.x + threadIdx.x;
3.
     if (row < num rows) {</pre>
       float dot = 0;
       int row start = row ptr[row];
5.
6. int row end = row ptr[row+1];
  for (int elem = row start; elem < row end; elem++)
7.
8.
           dot += data[elem] * x[col index[elem]];
9.
       y[row] = dot;
```

```
      Row 0
      Row 2
      Row 3

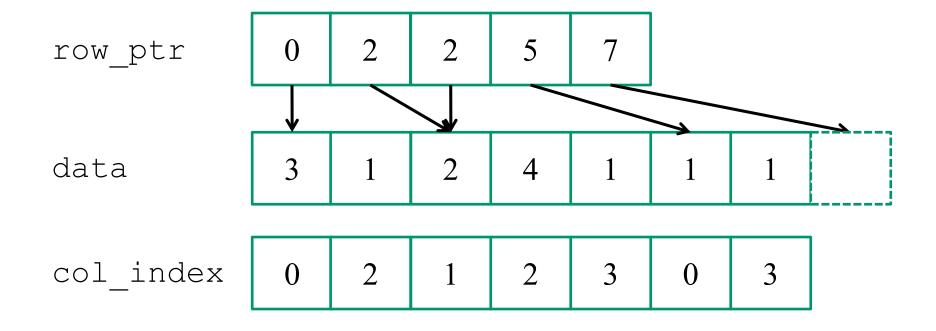
      Nonzero values
      data[7]
      { 3, 1, 2, 4, 1, 1, 1 }

      Column indices
      col_index[7]
      { 0, 2, 1, 2, 3, 0, 3 }

      Row Pointers
      row_ptr[5]
      { 0, 2, 2, 5, 7 }
```

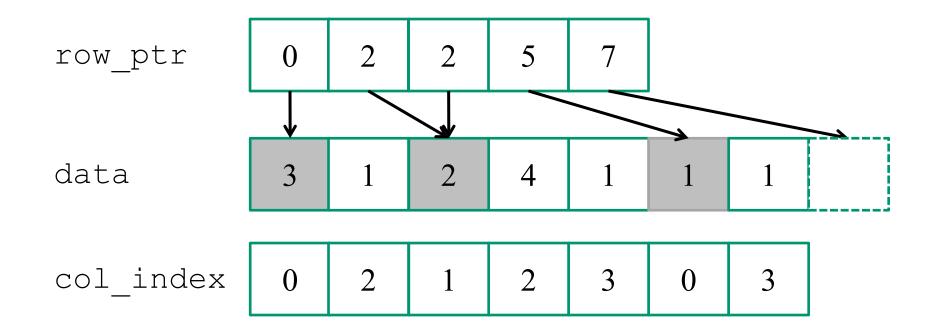
CSR Kernel Control Divergence

Threads execute different number of iterations

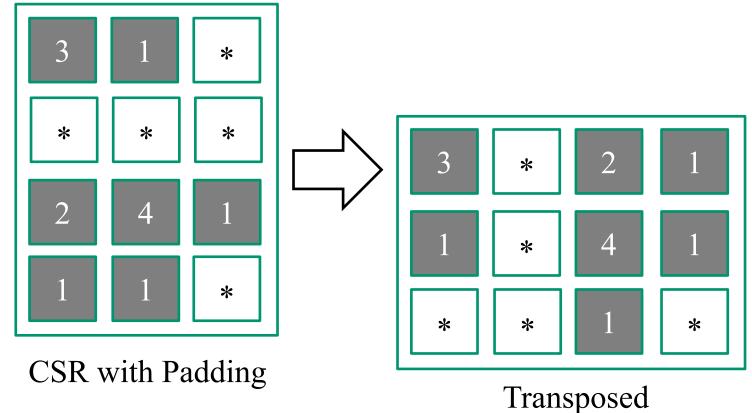


CSR Kernel Memory Divergence (Uncoalesced Accesses)

- Adjacent threads access non-adjacent memory locations
 - Grey elements are accessed by all threads in iteration 0

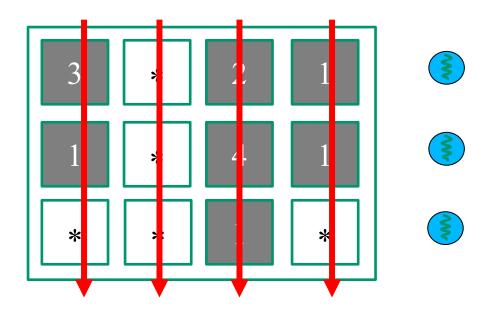


Regularizing SpMV with ELL(PACK) Format



- 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

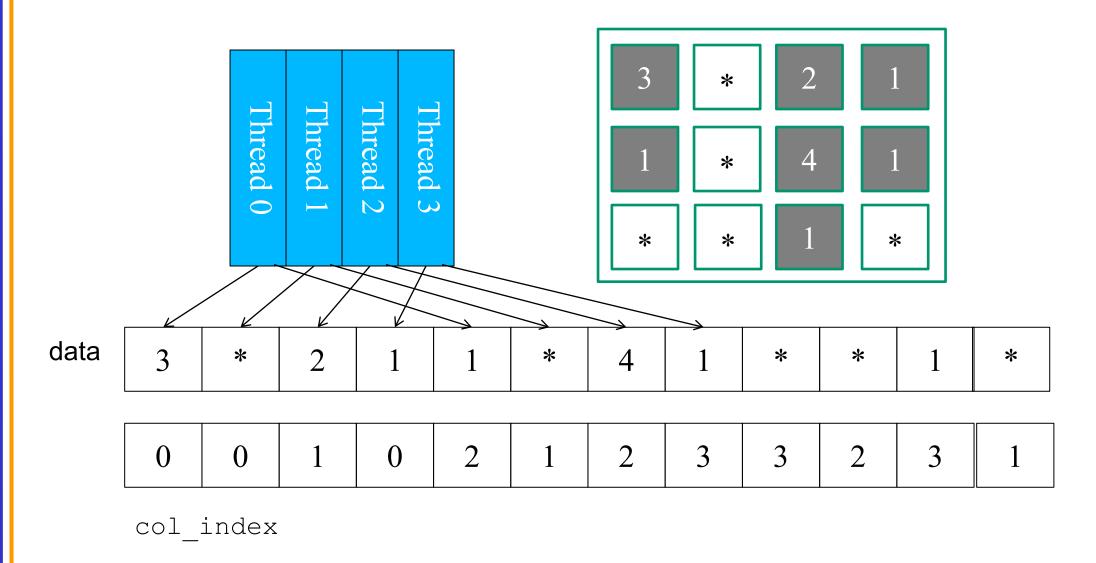
ELL Kernel Design



A parallel SpMV/ELL kernel

```
global void SpMV ELL(int num rows, float *data,
     int *col index, int num elem, float *x, float *y)
   int row = blockIdx.x * blockDim.x + threadIdx.x;
   if (row < num rows) {
     float dot = 0;
5.
    for (int i = 0; i < num elem; i++)
6.
         dot += data[row+i*num rows]*x[col index[row+i*num rows]];
7.
     y[row] = dot;
```

Memory Coalescing with ELL



Coordinate (COO) format

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

	Rov		$\mathbf{W} 0$		Row 2			Row 3				
Nonzero values	data[7]	{	3,	1,	1	2,	4,	1,		1,	1	}
Column indices	col_index[7]	{	0,	2,	1	1,	2,	3,		0,	3	}
Row indices	<pre>row_index[7]</pre>	{	0,	0,	1	2,	2,	2,		3,	3	}

COO Allows Reordering of Elements

```
      Row 0
      Row 2
      Row 3

      Nonzero values data[7]
      { 3, 1, 2, 4, 1, 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, 2, 3, 3 }
```

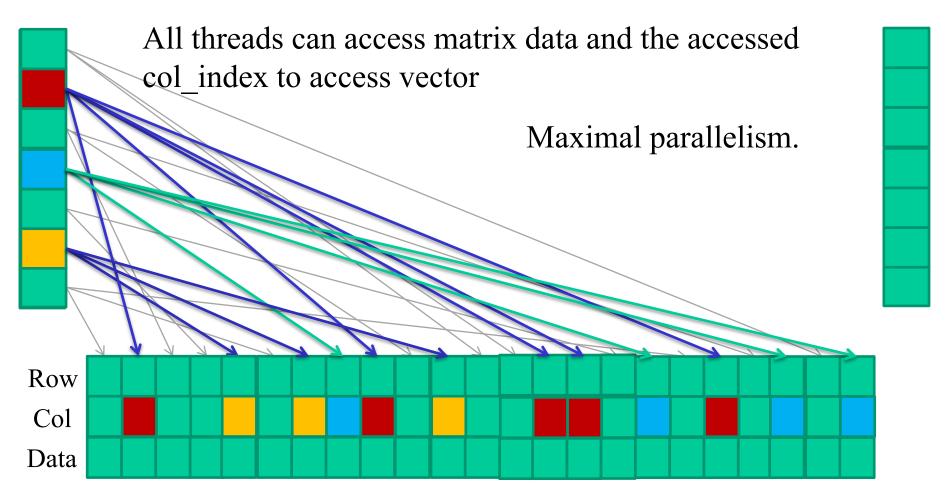
```
Nonzero values data[7] { 1 1, 2, 4, 3, 1 1 }
Column indices col_index[7] { 0 2, 1, 2, 0, 3, 3 }
Row indices row_index[7] { 3 0, 2, 2, 0, 2, 3 }
```

COO Kernel

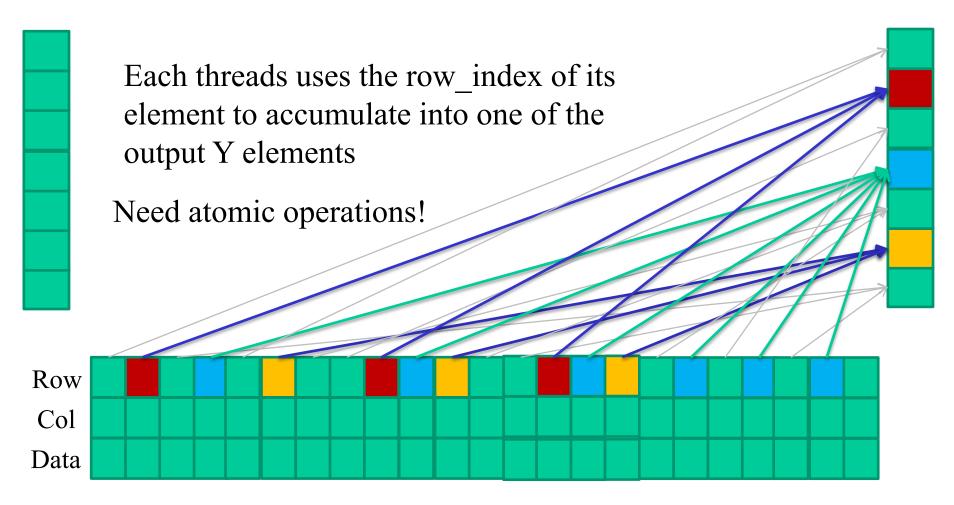
```
for (int i = 0; i < num_elem; i++)
    y[row_index[i]] += data[i] * x[col_index[i]];</pre>
```

a sequential loop that implements SpMV/COO

COO Kernel Design Accessing Input Matrix and Vector

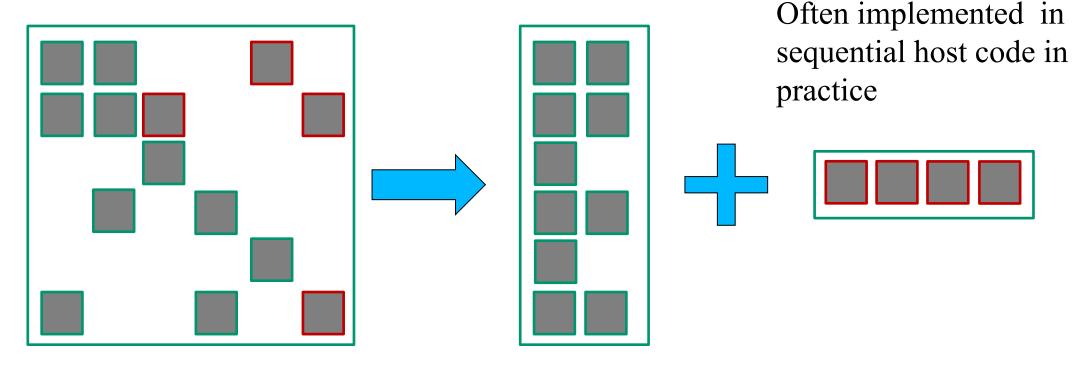


COO kernel Design Accumulating into Output Vector

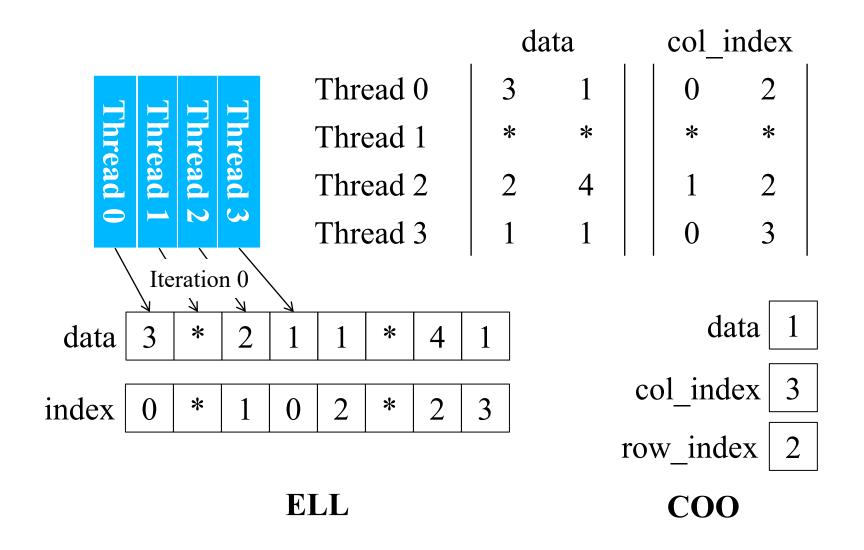


Hybrid Format (ELL + COO)

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



Reduced Padding with Hybrid Format



ANY MORE QUESTIONS READ CHAPTER 10