Berkeley Winter School

Advanced Algorithmic Techniques for GPUs

Lecture 7: Input Compaction

Objective

- To learn the key techniques for compacting input data for reduced consumption of memory bandwidth
 - Via better utilization of on-chip memory
 - As well as fewer bytes transferred to on-chip memory
- To understand the tradeoffs between input compaction and input binning/regularization

Sparse Data Motivation for Compaction

- Many real-world inputs are sparse/non-uniform
- Signal samples, mesh models, transportation networks, communication networks, etc.



Sparse matrix-vector multiplication



• Compute $y \leftarrow Ax + y$

where A is sparse and x, y are dense



Unlike dense methods, SpMV is generally

- unstructured / irregular
- entirely bound by memory bandwidth

Parallelizing CSR SpMV



Compressed Sparse Row

Straightforward approach

one thread per matrix row

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

CSR SpMV Kernel (CUDA)



```
int row = blockDim.x * blockIdx.x + threadIdx.x;
if ( row < num_rows ) {
   float dot = 0;
    int row_start = ptr[row];
    int row_end = ptr[row + 1];
   for (int jj = row_start; jj < row_end; jj++)
        dot += data[jj] * x[indices[jj]];
   y[row] += dot;
}</pre>
```

				Row 0		Row 2			Rov		
Nonzero values	data[7]	Π	{	З,	1,	2,	4,	1,	1,	1	};
Column indices	<pre>indices[7]</pre>	=	{	Ο,	2,	1,	2,	з,	Ο,	3	};
Row pointers	ptr[5]	=	{	Ο,	2,	2,	5,	7	};		

Problems with simple CSR kernel



Execution divergence varying row lengths

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

Memory divergence

minimal coalescing

				#0	#1	#0	#1	#0	#2	#1	Iteration
Nonzero values	data[7]	=	ł	з,	1,	2,	4,	1,	1,	1	};
Column indices	<pre>indices[7]</pre>	=	{	ο,	2,	1,	2,	з,	ο,	3	};
Row pointers	ptr[5]	=	{	Ο,	2,	2,	5,	7	};		





Memory divergence

minimal coalescing



Regularizing SpMV with ELL format



Storage for K nonzeros per row

- pad rows with fewer than K nonzeros
- inefficient when row length varies







Quantize each row to a fix length K

	\	/alue	S	С	olum	ns
Thread 0	3	1	*	0	2	*
Thread 1	*	*	*	*	*	*
Thread 2	2	4	1	1	2	3
Thread 3	1	1	*	0	3	*

Layout in column-major order

yields full coalescing

Memory Coalescing with ELL



Exposing maximal parallelism



Use COO (Coordinate) format

list row, column, and value for every non-zero entry

Nonzero values	data[7]	Π	{	З,	1,	2,	4,	1,	1,	1	};
Column indices	cols[7]	=	{	0,	2,	1,	2,	З,	0,	3	};
Row indices	rows[7]	=	{	0,	0,	1,	1,	1,	2,	2	};

Assign one thread to each non-zero entry

- each thread computes an A[i,j]*x[j] product
- sum products with segmented reduction algorithm
- Iargely insensitive to row length distribution

Hybrid Format



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



Any More Ideas?

- JDS format
 - Sort rows according to their number of non-zero elements
- Can use Hybrid with JDS and and launch multiple kernels

Sparse formats for different matrices







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Structured Matrices





Unstructured Matrices





Performance Comparison





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Binning of Sample Points

- For simplicity, we will use 1D gridding examples
- Each sample point has
 - S.x (will be represented with Bin#)
 - S.value (will be omitted unless necessary)



A Binned Gather Parallelization



A Tiled Gather Implementation



More on Tiled Gather

- Threads cooperate to load all the relevant bins from Global Memory to Shared Memory
- Each thread accesses relevant bins from Shared Memory
- Uniform binning for Non-uniform distribution
 - Large memory overhead for dummy cells
 - Reduced benefit of tiling
 - Many threads spend much time on dummy sample points

Compact Binning for Gather Parallelization

- Avoid pre-allocated fixed capacity bins (multidimensional array)
- Sort samples into bins of varying sizes in input array instead
 - Bins 5, 6, 8 are implicit, zero-sample



GPU Binning - Use Scatter to Generate Bin Capacities



Need to use atomic operations for counting the capacity

Determine Start and End of Bins

 Use parallel scan operations on the bin capacity array to generate an array of starting points of all bins (CUDPP)



Actual Binning

• All inputs can now be placed into their bins in parallel, using atomic operations





Controlling Load Balance (done during capacity generation)

- Limit the size of each bin
 - When counter exceeds limit for a bin, the input samples are placed into a "CPU" overflow bin
 - CPU places excess sample points into a CPU list
 - CPU does gridding on the excess sample points in parallel with GPU
 - Eventually merge





When a bin capacity reaches a preset limit, do not further increment the capacity counter But place the excess input into an overflow bin

Determine Start and End of Bins

 Use parallel scan operations on the bin capacity array to generate an array of starting points of all bins (CUDPP)



Actual Binning

• All inputs can now be placed into their bins in parallel



Note the similarity

- Compact bins CSR
- Overflow bins COO

 One could use ELL or JDS type of optimization on bins if desired

Hybrid Format



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



ANY FURTHER QUESTION?