## AM 148 Lecture 6

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## Overview

(1) Histogram

- Atomics
- Generating Color Distributions from an image
(2) Segmented Scan
(3) Sort

4 Sparse Matrix Vector Product

## What is a Histogram?

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- Histogram gives a representation of the distribution of numerical data
- Its an estimate of the true PDF
- Based on binning
- Algorithm classifies data based on a bin and collects the binned data


## How can we make one?

A serial implementation is straightforward

```
void histogram(unsigned int *histo, type *measurements, int
    bin_count, int array_length)
            for(int i = 0; i < bin_count; i++)
            histo[i] = 0;
            for(int i = 0; i <array_length; i++)
                        histo[computeBin(measurements[i])]++;
```

$\}$

Here your data could be integers, floats, or strings e.g. "Green", "Blue", etc

## First Try Parallel Histogram

```
_-global__ void first_hist(unsigned int *histo, type *data,
    int n)
{
    int tid = threadIdx.x + blockDim.x*blockIdx.x;
        if(tid > n)
        return;
    histo[computeBin(data[tid])]++;
//Where computeBin is a __device__ function!
}
```


## Why didn't this work?

- The source of our issues is with the d_bins[myBin]++ line


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(1) Read bin Value from global memory to a register
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(3) Write Bin Value from register to global memory


## Why didn't this work?

- The source of our issues is with the d_bins[myBin]++ line
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(1) Read bin Value from global memory to a register
(2) Increment Bin Value
(3) Write Bin Value from register to global memory
- Race condition!


## Fixing the issue

- Atomics are built in CUDA pragmas that serialize memory transactions/operations
- Locks a locale in memory so that no other thread can read/write to it until current thread is done
- We'll use atomicAdd


## Issue with Atomics

- Serialized access to memory location


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- Serialized access to memory location
- Creates a performance bottleneck


## Thought experiment

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(3) A histogram with 1000 bins

## A Shared Memory Approach

- Create block local histogram
- Use atomics


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- Create block local histogram
- Use atomics
- Combines block local histograms into global histogram


## Application of Histogram

- Generating Color distributions of an image


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- Generating Color distributions of an image
- Generating frequency/probability distributions from raw data


## Code

## Segmented Scan

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- Launching many separate scans is inefficient
- Combine Arrays as segments, use a flagging array to mark segments.


## Exclusive sum scan:

$$
(1,2,3,4,5,6,7,8,) \Longrightarrow(0,1,3,6,10,15,21,28)
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\begin{aligned}
(1,2,3,4,5,6,7,8,) & \Longrightarrow(0,1,3,6,10,15,21,28) \\
(1,2|3,4,5| 6,7,8) & \Longrightarrow(0,1|0,3,7| 0,6,13)
\end{aligned}
$$

using

$$
(1,0,1,0,0,1,0,0)
$$

## Compact

Before we begin a sort, let's talk about an algorithm called compact

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- Input data $\rightarrow$ smaller partition of input data
- Compacting the larging input set into something smaller


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- Compact is an algorithm to partition data
- Input data $\rightarrow$ smaller partition of input data
- Compacting the larging input set into something smaller
- If we only want to do computation on a subset of data


## Compact Continued

- Input

$$
\left[S_{0}, S_{1}, S_{2}, S_{3}, S_{4}, \ldots\right]
$$

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- Output

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$$

- To generate the output we need to compute the scatter address of each output element


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- we compute addresses

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[0-,-, 1,2,-, 3,-]
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- Change predicates

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[1,0,0,1,1,0,1,0]
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And generate

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- This is a Scan operation!


## Sorting an array

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- Keep Hardware busy (lots of threads)
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- Prefer Coalesced Memory Access


## Radix Sort

Radix sort relies on sorting using the binary notation of a number. Here are a number of steps for a basic Radix sort algorithm:
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(1) Start with least signicant bit
(2) Split Input into 2 sets based on bit, otherwise preserve order
(3) Move to next most significant bit, rinse and repeat.

## Radix Sort Example

Lets suppose we have the following array of unsigned integers.
$[0,5,2,7,1,3,6,4] \Longrightarrow[000,101,010,111,001,011,110,100]$

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group least significant bit
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move to next bit

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group least significant bit

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$$

move to next bit

$$
[000,100,101,001,010,110,111,011]
$$

finally
$[000,001,010,011,100,101,110,111] \Longrightarrow[0,1,2,3,4,5,6,7]$

## Underlying Primitives

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- Then (inclusive) scan over the one bit predicates added with the last address of zero bits
- This algorithm can be optimized by increasing the number of bits per compaction (more subsets)


## CUDA Example

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- Dense Matrices are Matrices with little to no 0 entries
- We have done Dense Matrix-vector multiplication $\approx \mathcal{O}\left(N^{2}\right)$ operations
- If we can leverage sparsity, we save computation.


## Types of Sparse Matrix Representations

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- Coordinate List (COO)
- Stores a list (row,column, value) tuples of nonzero entries
- Compressed Sparse Row (CSR, "Yale Format)
- Represents the matrix by 3 one dimensional arrays
- Value array
- Column index
- Row pointer
(CSR Format)
- Value Array contains non-zero values
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- Column index contains the column index of the non-zero values
(CSR Format)
- Value Array contains non-zero values
- Column index contains the column index of the non-zero values
- The row pointer array contains the compressed index of the value that starts a new row
- Row Pointer contains $M+1$ entries, defined as $R[0]=0$, $R[i]=R[I-1]+\#$ of nonzero elements in row $i-1$


## Example

$$
\mathbf{A}=\left(\begin{array}{llll}
0 & 0 & 0 & 0 \\
5 & 8 & 0 & 0 \\
0 & 0 & 3 & 0 \\
0 & 6 & 0 & 0
\end{array}\right)
$$

## Example

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0 & 0 & 0 & 0 \\
5 & 8 & 0 & 0 \\
0 & 0 & 3 & 0 \\
0 & 6 & 0 & 0
\end{array}\right)
$$

Then the CSR format is

$$
\begin{gathered}
\mathbf{v}=[5,8,3,6] \\
\mathbf{c}=[0,1,2,1] \\
\mathbf{r}=[0,0,2,3,4]
\end{gathered}
$$

## SpMV

- Best Use of CSR format is Sparse Matrix Dense Vector multiplication (SpMV)


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- Best Use of CSR format is Sparse Matrix Dense Vector multiplication (SpMV)
(1) Create a segmented representation of matrix from value and row pointer vectors
(2) Gather vector values using column indices
(3) Pairwise multiply 1 and 2
(9) Inclusive segmented sum scan on 3


## SpMV Example

Suppose we wish to do

$$
\left(\begin{array}{lll}
a & 0 & b \\
c & d & e \\
0 & 0 & f
\end{array}\right)\left(\begin{array}{l}
x \\
y \\
z
\end{array}\right)
$$

## SpMV Example

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\end{array}\right)\left(\begin{array}{l}
x \\
y \\
z
\end{array}\right)
$$

- Value vector

$$
\mathbf{v}=[a, b, c, d, e, f]
$$

## SpMV Example

Suppose we wish to do

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- Value vector

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\mathbf{v}=[a, b, c, d, e, f]
$$

- Column

$$
\mathbf{c}=[0,2,0,1,2,2]
$$

## SpMV Example

Suppose we wish to do

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\left(\begin{array}{lll}
a & 0 & b \\
c & d & e \\
0 & 0 & f
\end{array}\right)\left(\begin{array}{l}
x \\
y \\
z
\end{array}\right)
$$

- Value vector

$$
\mathbf{v}=[a, b, c, d, e, f]
$$

- Column

$$
\mathbf{c}=[0,2,0,1,2,2]
$$

- Rowptr

$$
\mathbf{r p}=[0,0,2,5]
$$

## SpMV Example Continued

(1) Segmented representation

$$
[a, b|c, d, e| f]
$$

## SpMV Example Continued

(1) Segmented representation

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[a, b|c, d, e| f]
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(2) vector values using column

$$
[x, z, x, y, z, z]
$$

## SpMV Example Continued

(1) Segmented representation

$$
[a, b|c, d, e| f]
$$

(2) vector values using column

$$
[x, z, x, y, z, z]
$$

(3) Pairwise multiplication

$$
[a x, b z|c x, d y, e z| f z]
$$

(1) Segmented scan

$$
[a x+b z|c x+d y+e z| f z]
$$

$$
\left(\begin{array}{lll}
a & 0 & b \\
c & d & e \\
0 & 0 & f
\end{array}\right)\left(\begin{array}{l}
x \\
y \\
z
\end{array}\right)=\left(\begin{array}{l}
a x+\theta y+b z \\
c x+d y+e z \\
\theta x+\theta y+f z
\end{array}\right)
$$

In this simple case we save 3 multiplications and 3 adds. On large scale matrices the savings will be more substantial.

## CUDA Example



Multiplied by a vector of 1 s of size 1024

## Kernel

## Timing vs Dense MatVec

