Parallel Computation Patterns (Histogram)
Histogram

- A method for extracting notable features and patterns from large data sets
  - Feature extraction for object recognition in images
  - Fraud detection in credit card transactions
  - Correlating heavenly object movements in astrophysics
  - ...

- Basic histograms - for each element in the data set, use the value to identify a “bin counter” to increment
A Text Histogram Example

- Define the bins as four-letter sections of the alphabet: a-d, e-h, i-l, n-p, ...
- For each character in an input string, increment the appropriate bin counter.
- In the phrase “Programming Massively Parallel Processors” the output histogram is shown below:
A simple parallel histogram algorithm

- Partition the input into sections
- Have each thread to take a section of the input
- Each thread iterates through its section.
- For each letter, increment the appropriate bin counter
Sectioned Partitioning (Iteration #1)
Sectioned Partitioning (Iteration #2)

programming
massively
parallel processors

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

a-d e-h i-l m-p q-t u-x y-z
Input Partitioning Affects Memory Access Efficiency

- Sectioned partitioning results in poor memory access efficiency
  - Adjacent threads do not access adjacent memory locations
  - Accesses are not coalesced
  - DRAM bandwidth is poorly utilized
Input Partitioning Affects Memory Access Efficiency

- Sectioned partitioning results in poor memory access efficiency
  - Adjacent threads do not access adjacent memory locations
  - Accesses are not coalesced
  - DRAM bandwidth is poorly utilized

- Change to interleaved partitioning
  - All threads process a contiguous section of elements
  - They all move to the next section and repeat
  - The memory accesses are coalesced
Interleaved Partitioning of Input

- For coalescing and better memory access performance
Interleaved Partitioning (Iteration 2)
Are threads able to write to the same memory address? What happens when they do?
Data races
Objective

– To understand data races in parallel computing
  – Data races can occur when performing read-modify-write operations
  – Data races can cause errors that are hard to reproduce
  – Atomic operations are designed to eliminate such data races
Read-modify-write in the Text Histogram Example

- For coalescing and better memory access performance
Read-Modify-Write Used in Collaboration Patterns

- For example, multiple bank tellers count the total amount of cash in the safe
- Each grab a pile and count
- Have a central display of the running total
- Whenever someone finishes counting a pile, read the current running total (read) and add the subtotal of the pile to the running total (modify-write)
- A bad outcome
  - Some of the piles were not accounted for in the final total
A Common Parallel Service Pattern

- For example, multiple customer service agents serving waiting customers
- The system maintains two numbers,
  - the number to be given to the next incoming customer (I)
  - the number for the customer to be served next (S)
- The system gives each incoming customer a number (read I) and increments the number to be given to the next customer by 1 (modify-write I)
- A central display shows the number for the customer to be served next
- When an agent becomes available, he/she calls the number (read S) and increments the display number by 1 (modify-write S)
- Bad outcomes
  - Multiple customers receive the same number, only one of them receives service
  - Multiple agents serve the same number
A Common Arbitration Pattern

- For example, multiple customers booking airline tickets in parallel
  - Each
    - Brings up a flight seat map (read)
    - Decides on a seat
    - Updates the seat map and marks the selected seat as taken (modify-write)

- A bad outcome
  - Multiple passengers ended up booking the same seat
Data Race in Parallel Thread Execution

Old and New are per-thread register variables.

Question 1: If Mem[x] was initially 0, what would the value of Mem[x] be after threads 1 and 2 have completed?

Question 2: What does each thread get in their Old variable?

Unfortunately, the answers may vary according to the relative execution timing between the two threads, which is referred to as a data race.
### Timing Scenario #1

<table>
<thead>
<tr>
<th>Time</th>
<th>Thread 1</th>
<th>Thread 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(0) Old $\leftarrow$ Mem[x]</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>(1) New $\leftarrow$ Old + 1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>(1) Mem[x] $\leftarrow$ New</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>(1) Old $\leftarrow$ Mem[x]</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>(2) New $\leftarrow$ Old + 1</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>(2) Mem[x] $\leftarrow$ New</td>
</tr>
</tbody>
</table>

- Thread 1 Old = 0
- Thread 2 Old = 1
- Mem[x] = 2 after the sequence
### Timing Scenario #2

<table>
<thead>
<tr>
<th>Time</th>
<th>Thread 1</th>
<th>Thread 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>(0) Old ← Mem[x]</td>
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<td></td>
</tr>
<tr>
<td>6</td>
<td>(2) Mem[x] ← New</td>
<td></td>
</tr>
</tbody>
</table>

- Thread 1 Old = 1
- Thread 2 Old = 0
- Mem[x] = 2 after the sequence
Timing Scenario #3

<table>
<thead>
<tr>
<th>Time</th>
<th>Thread 1</th>
<th>Thread 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(0) Old ← Mem[x]</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>(1) New ← Old + 1</td>
<td></td>
</tr>
<tr>
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<td></td>
<td>(0) Old ← Mem[x]</td>
</tr>
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</tr>
<tr>
<td>5</td>
<td></td>
<td>(1) New ← Old + 1</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>(1) Mem[x] ← New</td>
</tr>
</tbody>
</table>

- Thread 1 Old = 0
- Thread 2 Old = 0
- Mem[x] = 1 after the sequence
# Timing Scenario #4

<table>
<thead>
<tr>
<th>Time</th>
<th>Thread 1</th>
<th>Thread 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(0) Old ← Mem[x]</td>
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</tr>
<tr>
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<td>(1) New ← Old + 1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>(1) Mem[x] ← New</td>
<td></td>
</tr>
</tbody>
</table>

- Thread 1 Old = 0
- Thread 2 Old = 0
- Mem[x] = 1 after the sequence
Purpose of Atomic Operations
– To Ensure Good Outcomes

thread1:  \[ \begin{align*}
\text{Old} & \leftarrow \text{Mem}[x] \\
\text{New} & \leftarrow \text{Old} + 1 \\
\text{Mem}[x] & \leftarrow \text{New}
\end{align*} \]

thread2:  \[ \begin{align*}
\text{Old} & \leftarrow \text{Mem}[x] \\
\text{New} & \leftarrow \text{Old} + 1 \\
\text{Mem}[x] & \leftarrow \text{New}
\end{align*} \]

Or

thread1:  \[ \begin{align*}
\text{Old} & \leftarrow \text{Mem}[x] \\
\text{New} & \leftarrow \text{Old} + 1 \\
\text{Mem}[x] & \leftarrow \text{New}
\end{align*} \]

thread2:  \[ \begin{align*}
\text{Old} & \leftarrow \text{Mem}[x] \\
\text{New} & \leftarrow \text{Old} + 1 \\
\text{Mem}[x] & \leftarrow \text{New}
\end{align*} \]
What can we do to overcome data races?
Atomic operations in cuda
Data Race without Atomic Operations

Mem[x] initialized to 0

thread1: Old $\leftarrow$ Mem[x]
New $\leftarrow$ Old + 1
Mem[x] $\leftarrow$ New

thread2: Old $\leftarrow$ Mem[x]
New $\leftarrow$ Old + 1
Mem[x] $\leftarrow$ New

- Both threads receive 0 in Old
- Mem[x] becomes 1
Key Concepts of Atomic Operations

- A read-modify-write operation performed by a single hardware instruction on a memory location *address*
  - Read the old value, calculate a new value, and write the new value to the location
  - The hardware ensures that no other threads can perform another read-modify-write operation on the same location until the current atomic operation is complete
    - Any other threads that attempt to perform an atomic operation on the same location will typically be held in a queue
    - All threads perform their atomic operations *serially* on the same location
Atomic Operations in CUDA

- Performed by calling functions that are translated into single instructions (a.k.a. *intrinsic functions* or *intrinsics*)
  - Atomic add, sub, inc, dec, min, max, exch (exchange), CAS (compare and swap)
  - Read CUDA C programming Guide 4.0 or later for details

- Atomic Add

  ```c
  int atomicAdd(int* address, int val);
  ```

  reads the 32-bit word `old` from the location pointed to by `address` in global or shared memory, computes `(old + val)`, and stores the result back to memory at the same address. The function returns `old`. 
More Atomic Adds in CUDA

- **Unsigned 32-bit integer atomic add**
  
  ```c
  unsigned int atomicAdd(unsigned int* address, unsigned int val);
  ```

- **Unsigned 64-bit integer atomic add**
  
  ```c
  unsigned long long int atomicAdd(unsigned long long int* address, unsigned long long int val);
  ```

- **Single-precision floating-point atomic add (capability > 2.0)**
  
  ```c
  float atomicAdd(float* address, float val);
  ```
A Basic Text Histogram Kernel

- The kernel receives a pointer to the input buffer of byte values
- Each thread process the input in a strided pattern

```c
__global__ void histo_kernel(unsigned char *buffer,
                              long size, unsigned int *histo)
{
    int i = threadIdx.x + blockIdx.x * blockDim.x;

    // stride is total number of threads
    int stride = blockDim.x * gridDim.x;

    // All threads handle blockDim.x * gridDim.x
    // consecutive elements
    while (i < size) {
        int alphabet_position = buffer[i] - "a";
        if (alphabet_position >= 0 && alphabet_position < 26)
            atomicAdd(&histo[alphabet_position/4]), 1);
        i += stride;
    }
}
```
A Basic Histogram Kernel (cont.)

- The kernel receives a pointer to the input buffer of byte values
- Each thread process the input in a strided pattern

```c
__global__ void histo_kernel(unsigned char *buffer,
                              long size, unsigned int *histo)
{
    int i = threadIdx.x + blockIdx.x * blockDim.x;

    // stride is total number of threads
    int stride = blockDim.x * gridDim.x;

    // All threads handle blockDim.x * gridDim.x
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    while (i < size) {
        int alphabet_position = buffer[i] - "a";
        if (alphabet_position >= 0 && alphabet_position < 26)
            atomicAdd(&histo[alphabet_position/4]), 1);
        i += stride;
    }
}
```
What overheads may be associated with atomics?
Atomic operation performance
Atomic Operations on Global Memory (DRAM)

• An atomic operation on a DRAM location starts with a read, which has a latency of a few hundred cycles

• The atomic operation ends with a write to the same location, with a latency of a few hundred cycles

• During this whole time, no one else can access the location
Atomic Operations on DRAM

- Each Read-Modify-Write has two full memory access delays
  - All atomic operations on the same variable (DRAM location) are serialized
Latency determines throughput

- Throughput of atomic operations on the same DRAM location is the rate at which the application can execute an atomic operation.

- The rate for atomic operation on a particular location is limited by the total latency of the read-modify-write sequence, typically more than 1000 cycles for global memory (DRAM) locations.

- This means that if many threads attempt to do atomic operation on the same location (contention), the memory throughput is reduced to < 1/1000 of the peak bandwidth of one memory channel!
You may have a similar experience in supermarket checkout

- Some customers realize that they missed an item after they started to check out
- They run to the isle and get the item while the line waits
  - The rate of checkout is drastically reduced due to the long latency of running to the isle and back.
- Imagine a store where every customer starts the check out before they even fetch any of the items
  - The rate of the checkout will be $1 / (\text{entire shopping time of each customer})$
Hardware Improvements

- Atomic operations on Fermi L2 cache
  - Medium latency, about 1/10 of the DRAM latency
  - Shared among all blocks
  - “Free improvement” on Global Memory atomics
Hardware Improvements

- Atomic operations on Shared Memory
  - Very short latency
  - Private to each thread block
  - Need algorithm work by programmers (more later)
Privatization Technique for Improved Throughput
Privatization

Heavy contention and serialization

Block 0 → Block 1 → ... → Block N

Final Copy

Atomic Updates
Privatization (cont.)

less contention and serialization
Privatization (cont.)

Block 0  Block 1  ...  Block N

Copy 0  Copy 1  ...  Copy N

Final Copy

Atomic Updates

less contention and serialization

Final Copy
Cost and Benefit of Privatization

- **Cost**
  - Overhead for creating and initializing private copies
  - Overhead for accumulating the contents of private copies into the final copy

- **Benefit**
  - Much less contention and serialization in accessing both the private copies and the final copy
  - The overall performance can often be improved more than 10x
Shared Memory Atomics for Histogram

- Each subset of threads are in the same block
- Much higher throughput than DRAM (100x) or L2 (10x) atomics
- Less contention – only threads in the same block can access a shared memory variable
- This is a very important use case for shared memory!
Shared Memory Atomics Requires Privatization

– Create private copies of the histo[] array for each thread block

```c
__global__ void histo_kernel(unsigned char *buffer,
    long size, unsigned int *histo)
{
    __shared__ unsigned int histo_private[7];
```
Shared Memory Atomics Requires Privatization

- Create private copies of the histo[] array for each thread block

```c
__global__ void histo_kernel(unsigned char *buffer,
                              long size, unsigned int *histo)
{
    __shared__ unsigned int histo_private[7];

    if (threadIdx.x < 7) histo_private[threadIdx.x] = 0;
    __syncthreads();
}
```

Initialize the bin counters in the private copies of histo[]
int i = threadIdx.x + blockIdx.x * blockDim.x;
// stride is total number of threads
int stride = blockDim.x * gridDim.x;
while (i < size) {
    atomicAdd(&private_histo[buffer[i]/4], 1);
    i += stride;
}
Build Final Histogram

    // wait for all other threads in the block to finish
    __syncthreads();
    
    if (threadIdx.x < 7) {
        atomicAdd(&histo[threadIdx.x]), private_histo[threadIdx.x] );
    }
    
    }
More on Privatization

- Privatization is a powerful and frequently used technique for parallelizing applications

- The operation needs to be associative and commutative
  - Histogram add operation is associative and commutative
  - No privatization if the operation does not fit the requirement

- The private histogram size needs to be small
  - Fits into shared memory

- What if the histogram is too large to privatize?
  - Sometimes one can partially privatize an output histogram and use range testing to go to either global memory or shared memory