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Module 7.1 – Parallel Computation Patterns (Histogram)

Histogramming

Objective

- To learn the parallel histogram computation pattern
  - An important, useful computation
  - Very different from all the patterns we have covered so far in terms of output behavior of each thread
  - A good starting point for understanding output interference in parallel computation

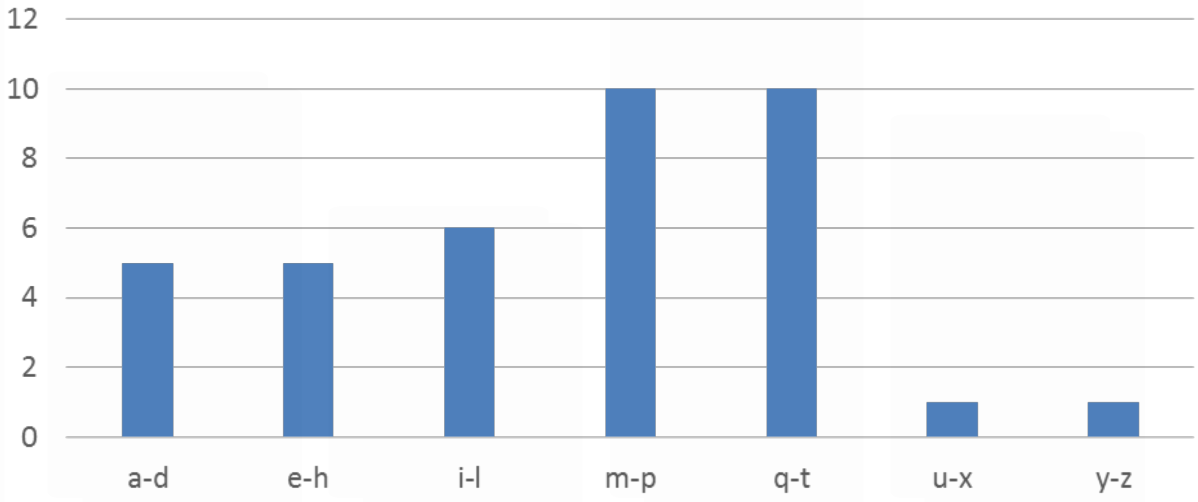
Histogram

- 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

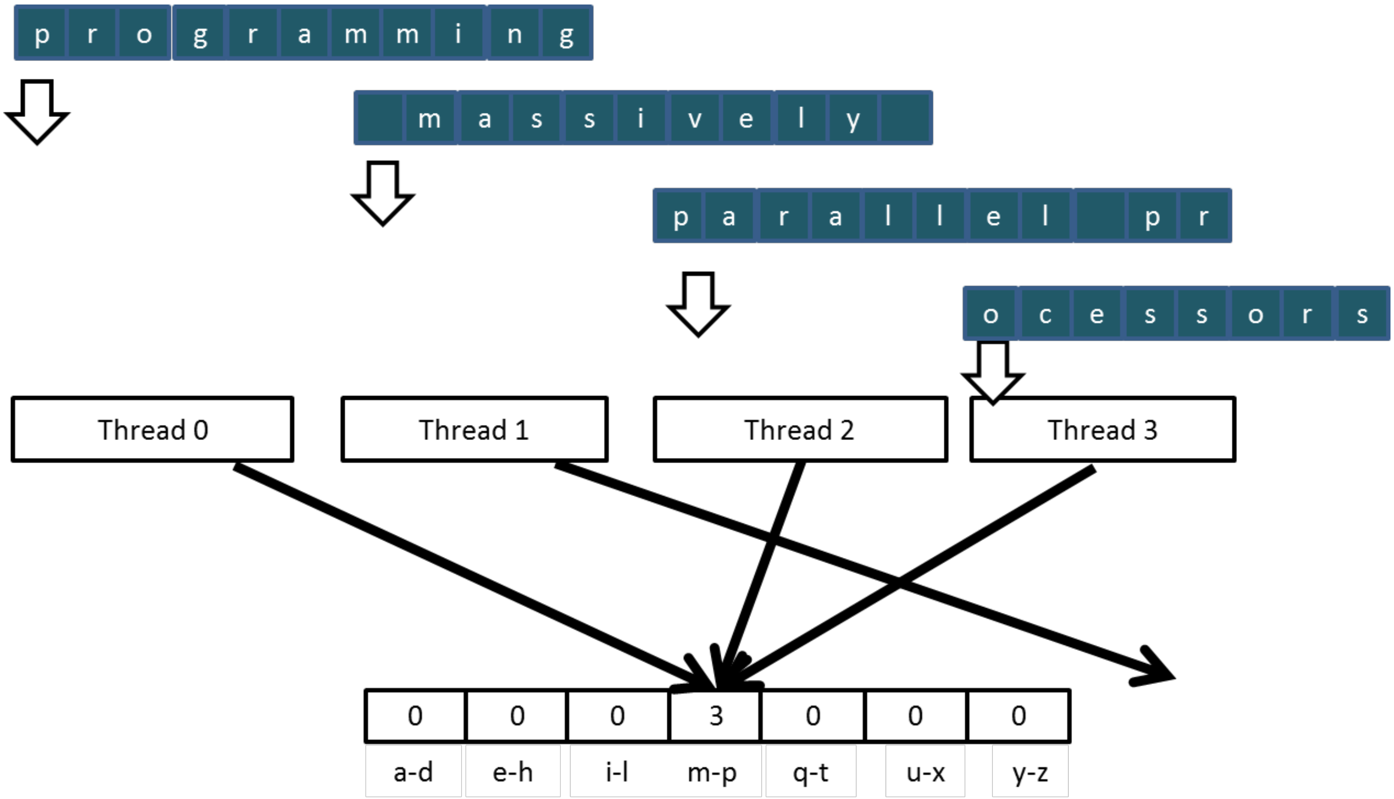
- Define the bins as four-letter sections of the alphabet: a-d, e-h, i-l, n-p, …
- For each character in an input string, increment the appropriate bin counter.
- In the phrase “Programming Massively Parallel Processors” the output histogram is shown below:



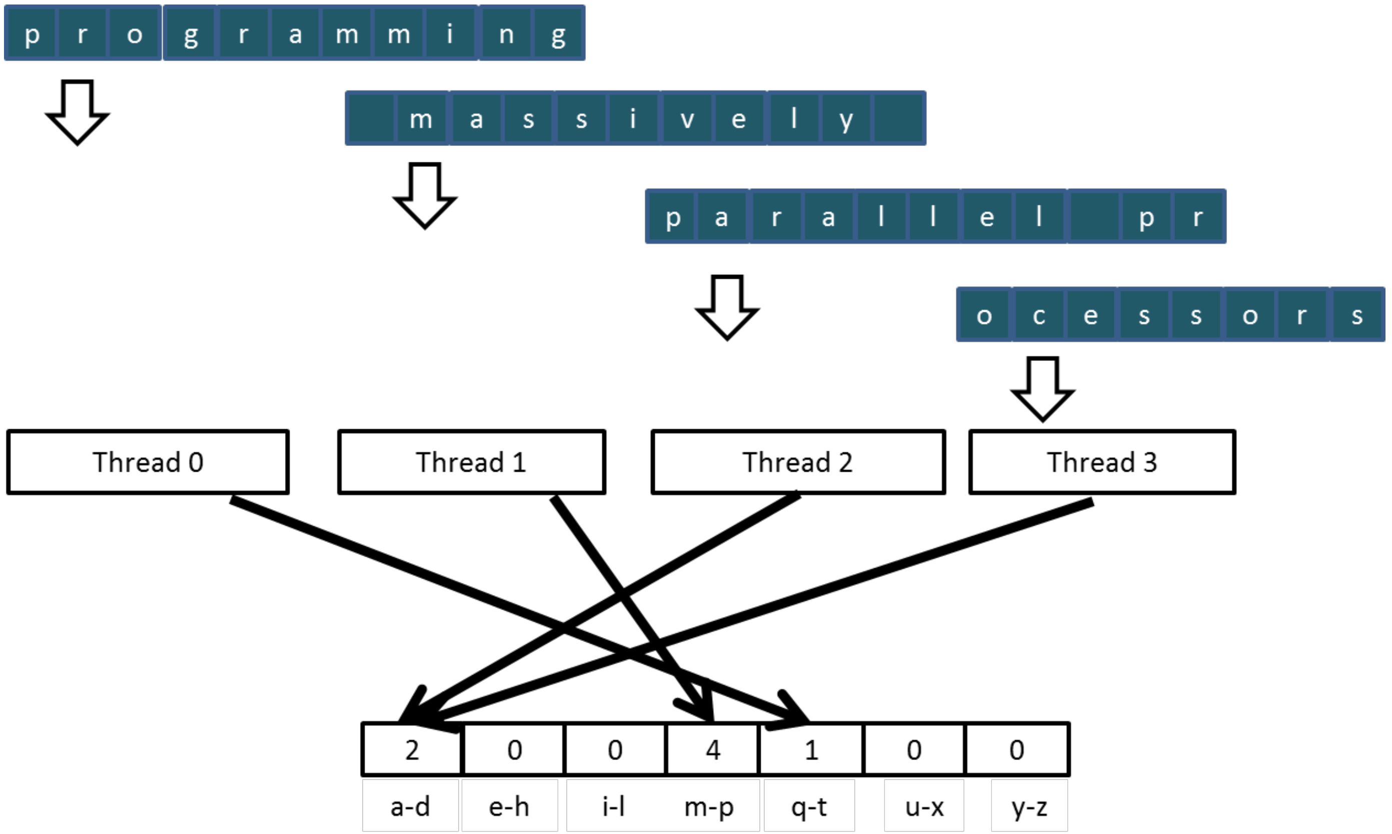
A simple parallel histogram algorithm

- 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)

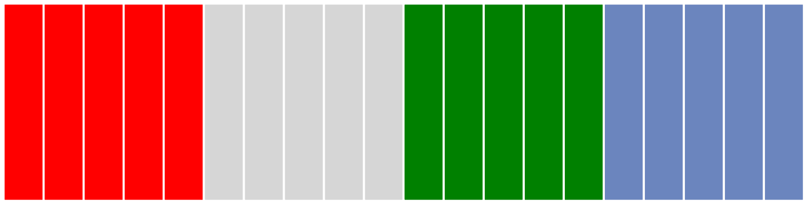


Sectioned Partitioning (Iteration #2)



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



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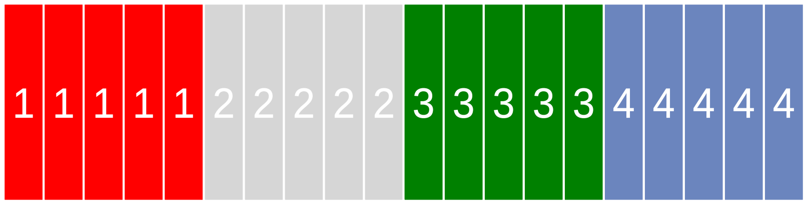
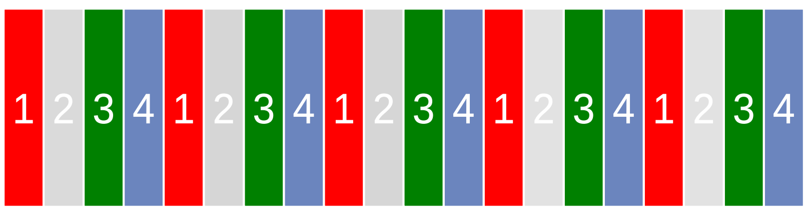
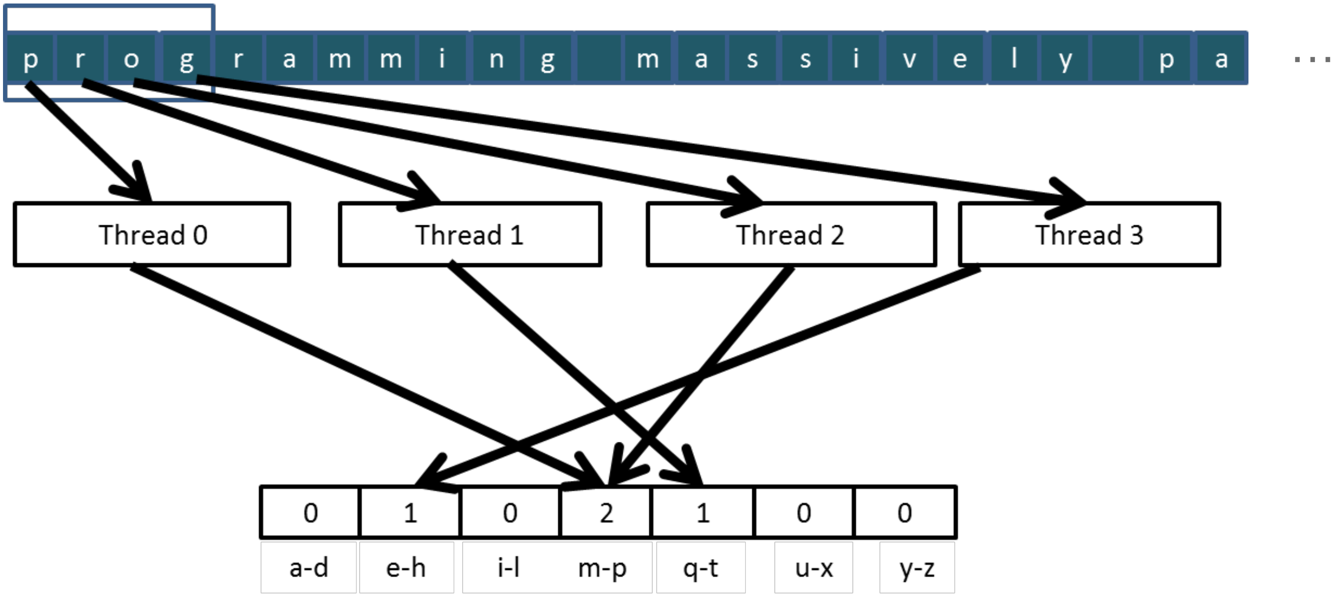


- Change to interleaved partitioning
  - All threads process a contiguous section of elements
  - They all move to the next section and repeat
  - The memory accesses are coalesced

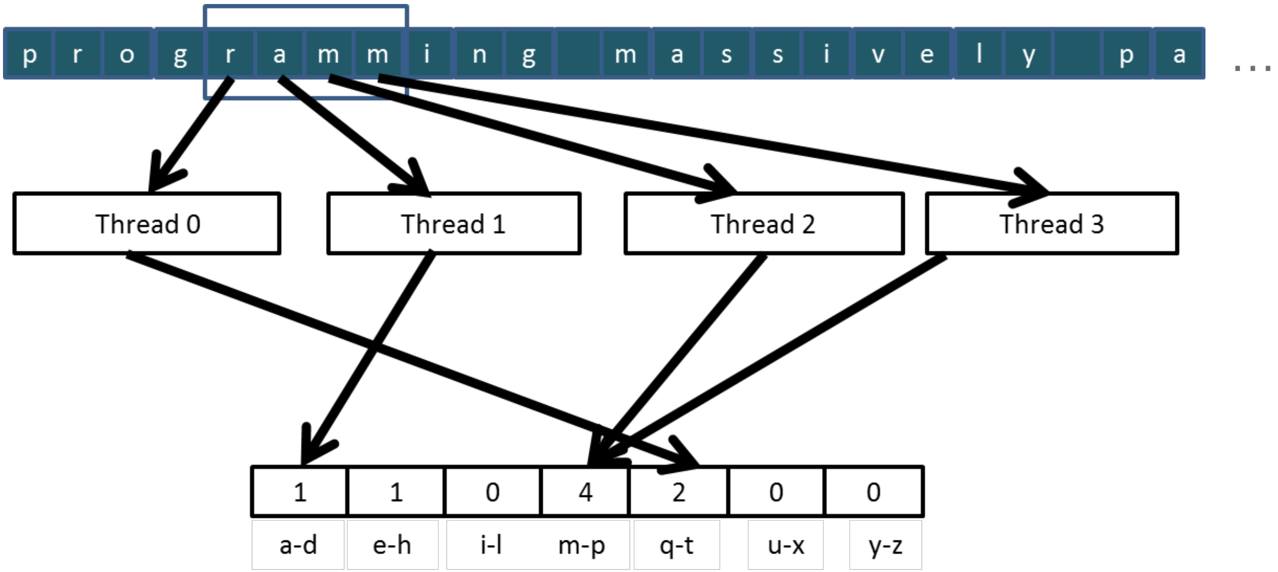


Interleaved Partitioning of Input

– For coalescing and better memory access performance



Interleaved Partitioning (Iteration 2)



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Module 7.2 – Parallel Computation Patterns (Histogram)

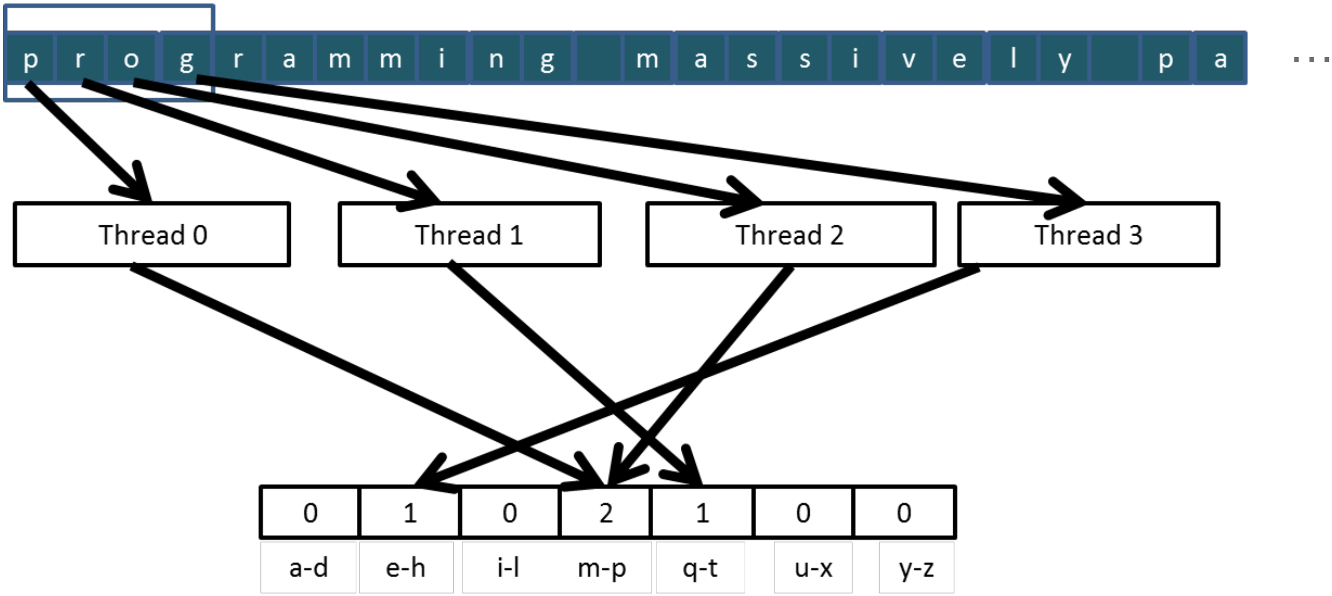
Introduction to Data Races

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

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

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

Time	Thread 1	Thread 2
1	(0) Old ← Mem[x]	
2	(1) New ← Old + 1	
3	(1) Mem[x] ← New	
4		(1) Old ← Mem[x]
5		(2) New ← Old + 1
6		(2) Mem[x] ← New

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

Timing Scenario #2

Time	Thread 1	Thread 2
1		(0) Old ← Mem[x]
2		(1) New ← Old + 1
3		(1) Mem[x] ← New
4	(1) Old ← Mem[x]	
5	(2) New ← Old + 1	
6	(2) Mem[x] ← New	

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

Timing Scenario #3

Time	Thread 1	Thread 2
1	(0) Old ← Mem[x]	
2	(1) New ← Old + 1	
3		(0) Old ← Mem[x]
4	(1) Mem[x] ← New	
5		(1) New ← Old + 1
6		(1) Mem[x] ← New

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

Timing Scenario #4

Time	Thread 1	Thread 2
1		(0) Old ← Mem[x]
2		(1) New ← Old + 1
3	(0) Old ← Mem[x]	
4		(1) Mem[x] ← New
5	(1) New ← Old + 1	
6	(1) Mem[x] ← New	

– Thread 1 Old = 0
– Thread 2 Old = 0
– Mem[x] = 1 after the sequence

Purpose of Atomic Operations – To Ensure Good Outcomes

thread1: Old ← Mem[x]
New ← Old + 1
Mem[x] ← New

thread2: Old ← Mem[x]
New ← Old + 1
Mem[x] ← New

Or

thread2: Old ← Mem[x]
New ← Old + 1
Mem[x] ← New

thread1: Old ← Mem[x]
New ← Old + 1
Mem[x] ← New

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Module 7.3 – Parallel Computation Patterns (Histogram)

Atomic Operations in CUDA

Objective

- To learn to use atomic operations in parallel programming
  - Atomic operation concepts
  - Types of atomic operations in CUDA
  - Intrinsic functions
  - A basic histogram kernel

Data Race Without Atomic Operations

Mem[x] initialized to 0

thread1: Old ← Mem[x]

time

New ← Old + 1

Mem[x] ← New

thread2: Old ← Mem[x]

New ← Old + 1

Mem[x] ← 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 Arithmetic 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 for details

- Atomic Add

```
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. These three operations are performed in one atomic transaction. The function returns **old**.

More Atomic Adds in CUDA

– Unsigned 32-bit integer atomic add

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

– Unsigned 64-bit integer atomic add

```
unsigned long long int atomicAdd(unsigned long long
    int* address, unsigned long long int val);
```

– Single-precision floating-point atomic add (Compute capability 2.x+)

```
float atomicAdd(float* address, float val);
```

– Double-precision floating-point atomic add (Compute capability 6.x+)

```
double atomicAdd(double* address, double val);
```

– 16-bit floating-point atomic add (Compute capability 7.x+)

```
__half atomicAdd(__half* address, __half 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

```
__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) {
       atomicAdd( &(histo[buffer[i]]), 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

```
__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 && alpha_position < 26)
       atomicAdd(&(histo[alphabet_position/4]), 1);
       i += stride;
   }
}
```

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Module 7.4 – Parallel Computation Patterns (Histogram)

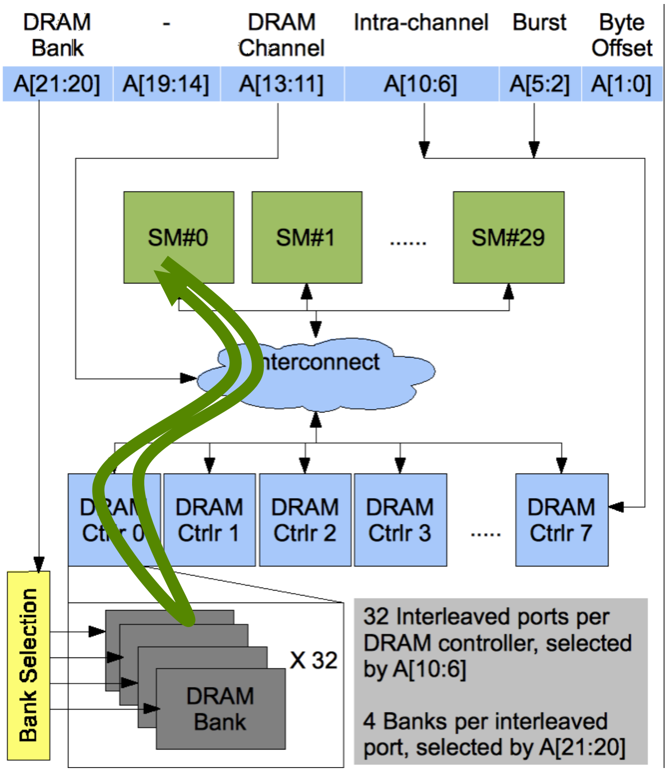
Atomic Operation Performance

Objective

- To learn about the main performance considerations of atomic operations
  - Latency and throughput of atomic operations
  - Atomic operations on global memory
  - Atomic operations on shared L2 cache
  - Atomic operations on shared memory

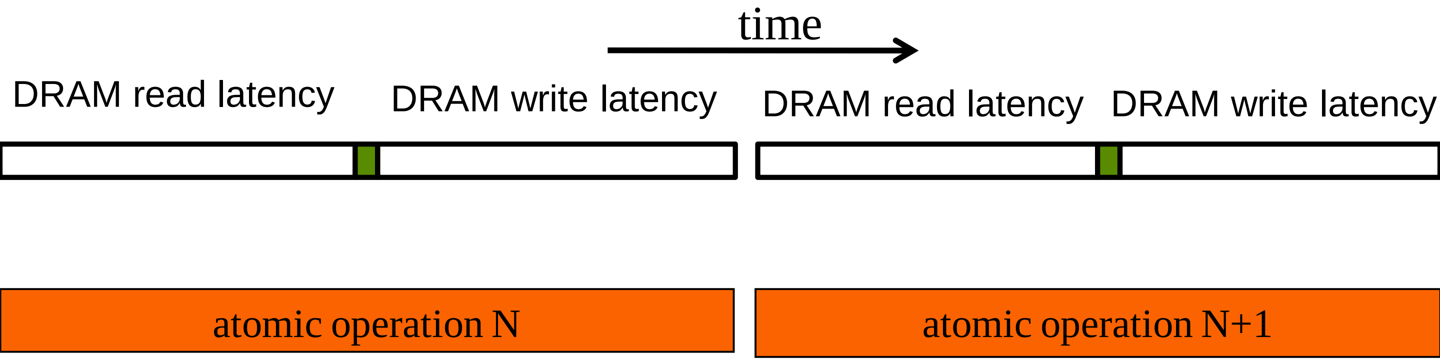
Atomic Operations on Global Memory (DRAM)

- 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

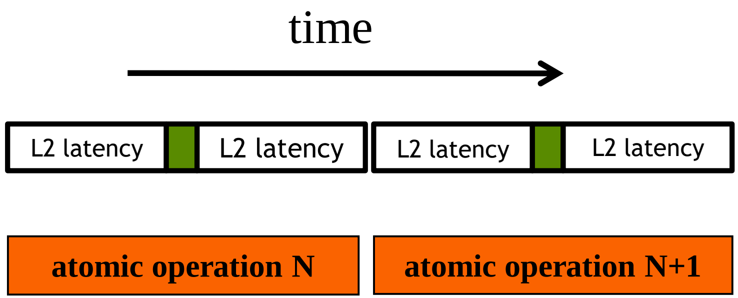
- Throughput of atomic operations on the same DRAM location is the rate at which the application can execute an atomic operation.
- The rate for atomic operation on a particular location is limited by the total latency of the read-modify-write sequence, typically more than 1000 cycles for global memory (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 / (entire shopping time of each customer)

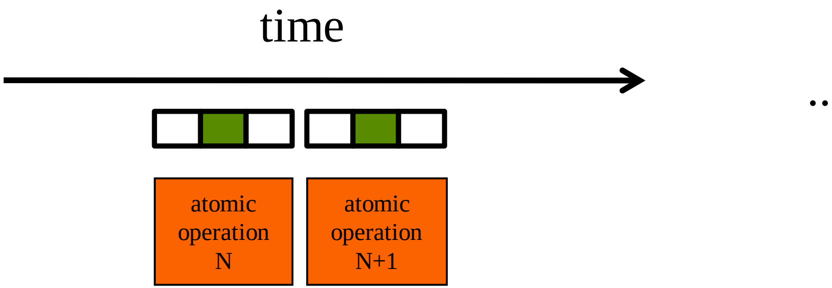
Hardware Improvements

- 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)



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Module 7.5 – Parallel Computation Patterns (Histogram)

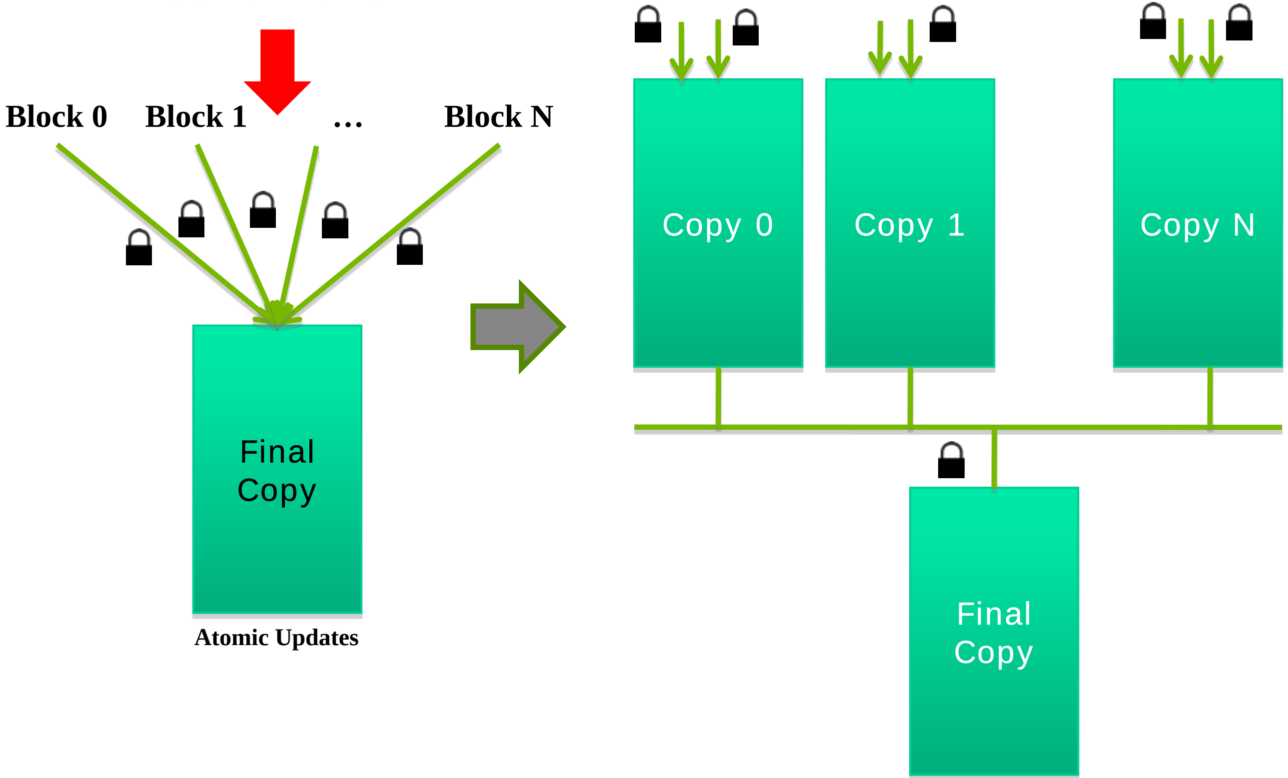
Privatization Technique for Improved Throughput

Objective

- Learn to write a high performance kernel by privatizing outputs
  - Privatization as a technique for reducing latency, increasing throughput, and reducing serialization
  - A high performance privatized histogram kernel
  - Practical example of using shared memory and L2 cache atomic operations

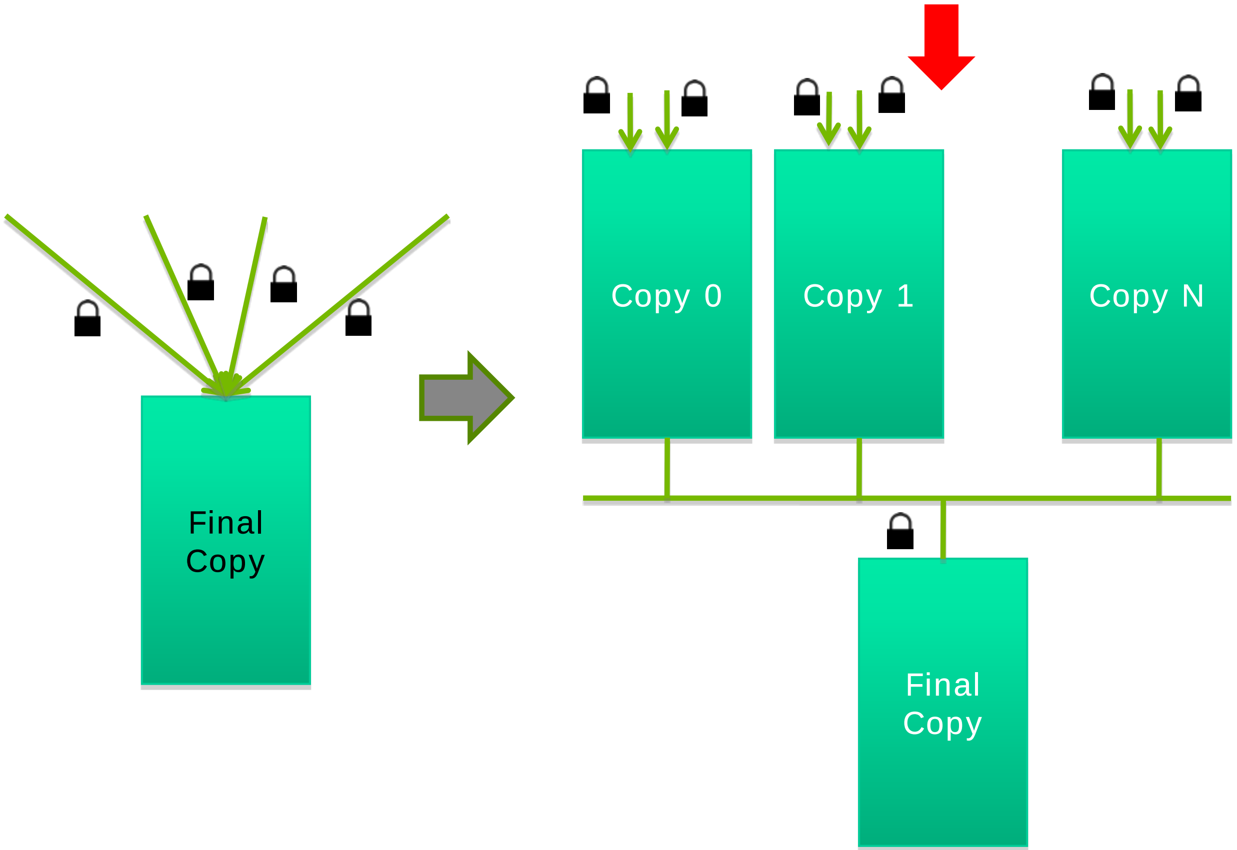
Privatization

Heavy contention and serialization

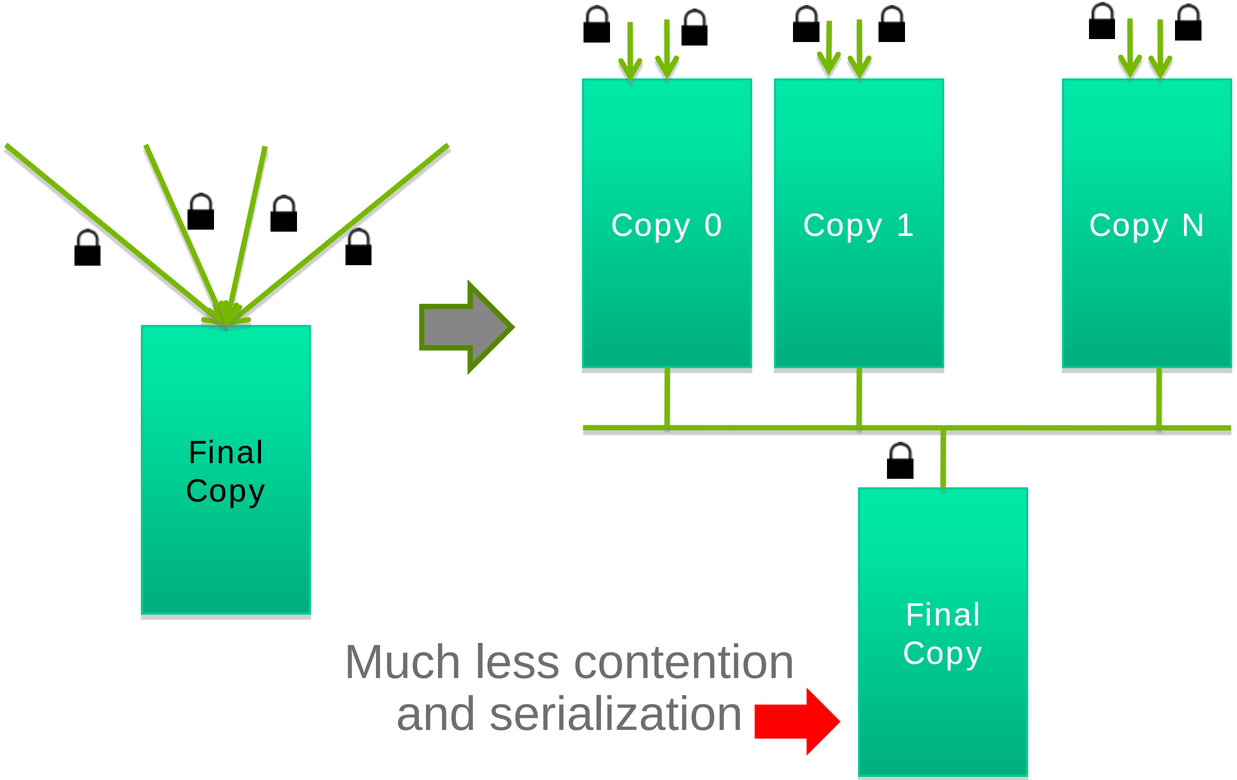


Privatization (cont.)

Much less contention and serialization



Privatization (cont.)



Much less contention and serialization

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

```
__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

```
__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[]

Build Private Histogram

```
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

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