

CME213/ME339

Lecture 9

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Lecture Overview

- Reduction implementations
 - Warp
 - Block
 - Multi-Block
- Reductions and floating point
- Atomic Operations
- Matrix-Vector Product
- Matrix-Matrix Product



Non-type Template Parameters

- Template parameters can also be integers, not just types
- Useful for specifying block size, shared memory size
- Size of statically declared shared memory must be known at compile time

```
1  template<int N>
2  int add(const int &x) {
3      return x + N;
4  }
5
6  int x;
7  add<3>(x);
8  add<5>(x);
```



Warp Reduce

```
1  for (int shift = 4; shift > 0; shift >= 1) {  
2      if (lane < shift) {  
3          smem[lane] += smem[lane + shift];  
4      }  
5      __syncthreads();  
6  }
```

0	1	2	3	4	5	6	7
---	---	---	---	---	---	---	---

4	6	8	10	4	5	6	7
---	---	---	----	---	---	---	---

12	16	8	10	4	5	6	7
----	----	---	----	---	---	---	---

28	16	8	10	4	5	6	7
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Block Reduce

- Similar idea to Warp Reduce
- Need to handle arbitrary block sizes, not just power of 2
- Bump loop limit up to next power of 2 and add conditional to avoid going past edge
- Alternatively, can make smem array larger and fill with identity value



Reducing Arbitrary Sizes with One Block

- Before block reduce, loop through the array
- Each thread does a local accumulation of:
`val[threadIdx.x] + val[threadIdx.x + blockSize] + ...`
- After local accumulation the block does a tree reduction
- Calculating performance - how much memory do we read?
- Every item is read from memory once
- $N * \text{sizeof}(\text{int})$ bytes
- We can ignore the write of one value



Reducing with Multiple Blocks

- Each block can reduce the values at:
 $[bId * blockDim.x, (bId + 1) * blockDim.x) +$
 $[bId * blockDim.x + blockDim.x, (bId + 1) * blockDim.x + blockDim.x)$
- But then what to do about combining the values from each block?
- Multi-pass
 - Write each block's value to memory
 - Launch one more kernel of only one block to reduce these values
- Use Atomic Operations to combine the value from each block



Atomic Operations

- Used to serialize updates to the same memory location and prevent race conditions
- Thread 1 in block 0 and Thread 4 in block 1 both want to add to output[5]
- If they both operate as below, the final value of output[5] will have either the accumulation of thread 1 or thread 4, but not both

```
1  int gval = output[5];  
2  myVal += output[5];  
3  output[5] = myVal;  //race condition!
```



Atomic Operations

- The hardware serializes the access from different threads
- Ensures correctness
- But isn't fast and isn't really parallel code
- Used carefully and sparingly, can simplify algorithms and sometimes even boost performance

```
1  int oldVal = atomicAdd(output + 5, myVal);
```



Atomic Operations

- Atomic Operations can operate on locations in both shared and global memory
- Operations in shared memory are about an order of magnitude faster than global memory
- Operations supported on latest hardware:
 - Add supported for ints, unsigned ints, longs and floats (but not doubles)
 - Sub, Min, Max supported only for integer types
 - Bitwise And, Or, Xor support only for integer types
- Atomic Compare and Swap can be used to implement any atomic operation
- `T oldVal = atomicOp(Mem Address, val);`



Atomic CAS

- If oldVal is the same as what is in memory then newVal replaces oldVal
- Whatever was at the memory address is returned
- If you understand this, you understand atomics

```
1  int memoryVal = memory[10];
2  int newVal = myVal + memoryVal;
3  int oldVal = memoryVal
4  while(memoryVal = atomicCAS(memory + 10, oldVal, newVal)
5          != oldVal) {
6      newVal = myVal + memoryVal;
7      oldVal = memoryVal;
8  }
```



Back to Reductions

- We use atomic operations to reduce the values of different blocks
- *One* thread from each block performs the atomic add
- How does performance change with a different number of blocks?
- Each SM can have maximum 8 resident blocks
- There are 16 SMs on this GPU = 128 blocks to completely fill GPU
- Expect max performance at multiples of 128 blocks



More about SM Occupancy

- In addition to 8 block limit
- 1536 thread limit
- $8 * 192 = 1536$, called 100% Occupancy
- $6 * 256 = 1536$
- $8 * 128 = 1024$; $1536 = 66\%$ Occupancy
- Blocks of 128 have lower performance because there are less threads available to hide latency

