



CSE 746 - Parallel and High Performance Computing Lecture 4 - Reduction with CUDA

Pawel Pomorski, *HPC Software Analyst* SHARCNET, University of Waterloo

ppomorsk@sharcnet.ca
http://ppomorsk.sharcnet.ca/

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#### Reductions in CUDA

- Reductions: min/max, average, sum, ...
- Can be a significant bottleneck for the performance, because it breaks pure data parallelism.
- There is no perfect way to do reductions in CUDA. The two commonly used approaches (each with its own set of constraints) are:

Binary reductions

## Binary reductions

- The most universal type of reductions (e.g., the only way to do double precision reductions)
- Even when using single precision (which is faster than double precision), binary summation will be more accurate than atomic summation, because it employs more accurate pairwise summation.
- Usually the more efficient way to do reductions

## Binary reductions

- But: typically relies on (very limited) shared memory placing constraints on how many reductions per kernel one can do
- Relies on thread synchronization, which can only be done within a single block places constraints on how many threads can participate in a binary reduction (usually 64 ... 256; maximum 1024)
- For a large number of data elements (>1024), this leads to the need to do multi-level (multi-kernel) binary reductions, with storing the intermediate data in device memory; this can reduce the performance
- Can be less efficient for small number of data elements (<64)
- Significantly complicates the code

- Very simple and elegant code
  - Almost no change compared to the serial code
  - A single line code: much better for code development and maintenance
  - No need for multiple intermediate kernels (saves on overheads related to multiple kernel launches)
  - Requires no code changes when dealing with any number of data elements from 2 to millions
- Usually more efficient when the number of data elements is small (<64)

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- But: atomic operations are serialized, which usually means worse performance
- Only single precision accuracy can become really bad for summation and averaging when the number of elements is large (many thousands) because it uses sequential summation.
- All the above means that to find the right way to carry out a reduction in CUDA, with the right balance between code readability, efficiency, and accuracy, one often has to try both binary and atomic ways, and choose the best.



# Binary summation with number of elements being a power of 2

```
shared double sum[BLOCK SIZE];
syncthreads(); // Required if there were prior computations in the kernel
int nTotalThreads = blockDim.x; // Total number of active threads;
// only the first half of the threads will be active.
while(nTotalThreads > 1)
 int halfPoint = (nTotalThreads >> 1); // divide by two
  if (threadIdx.x < halfPoint)</pre>
    int thread2 = threadIdx.x + halfPoint;
    sum[threadIdx.x] += sum[thread2]; // Pairwise summation
syncthreads();
nTotalThreads = halfPoint; // Reducing the binary tree size by two
```



# Binary averaging with number of elements being a power of 2

```
__shared__ double avg[BLOCK_SIZE];
...
__syncthreads(); // Required if there were prior computations in the kernel
int nTotalThreads = blockDim.x;

while(nTotalThreads > 1)
{
   int halfPoint = (nTotalThreads >> 1); // divide by two
   if (threadIdx.x < halfPoint)
   {
     int thread2 = threadIdx.x + halfPoint;
     avg[threadIdx.x] += avg[thread2]; // First sum
     avg[threadIdx.x] /= 2; // and then divide
   }
   __syncthreads();
nTotalThreads = halfPoint; // Reducing the binary tree size by two
}</pre>
```



# Binary min/max with number of elements being a power of 2

```
__shared__ double min[BLOCK_SIZE];
syncthreads(); // Required if there were prior computations in the kernel
int nTotalThreads = blockDim.x:
while(nTotalThreads > 1)
  int halfPoint = (nTotalThreads >> 1); // divide by two
  if (threadIdx.x < halfPoint)</pre>
    int thread2 = threadIdx.x + halfPoint;
    double temp = min[thread2];
    if (temp < min[threadIdx.x])</pre>
       min[threadIdx.x] = temp;
  syncthreads();
 nTotalThreads = halfPoint; // Reducing the binary tree size by two
```



### Multiple binary reductions

```
shared double min[BLOCK SIZE], sum[BLOCK SIZE];
syncthreads(); // Required if there were prior computations in the kernel
int nTotalThreads = blockDim.x;
while(nTotalThreads > 1)
  int halfPoint = (nTotalThreads >> 1); // divide by two
  if (threadIdx.x < halfPoint)</pre>
    int thread2 = threadIdx.x + halfPoint;
    sum[threadIdx.x] += sum[thread2]; // First reduction
    double temp = min[thread2];
    if (temp < min[threadIdx.x])</pre>
       min[threadIdx.x] = temp; // Second reduction
__syncthreads();
nTotalThreads = halfPoint; // Reducing the binary tree size by two
```



### Two-step binary reduction

```
// Host code
#define BSIZE 1024 // Always use a power of two; can be 32...1024
// Total number of elements to process: 1024 < Ntotal < 1024^2

int Nblocks = (Ntotal+BSIZE-1) / BSIZE;

// First step (the results should be stored in global device memory):
x_prereduce <<<Nblocks, BSIZE >>> ();

// Second step (will read the input from global device memory):
x_reduce <<<1, Nblocks >>> ();
```



# Binary reduction with an arbitrary number of elements (BLOCK\_SIZE)

```
shared double sum[BLOCK SIZE];
 syncthreads(); // Required if there were prior computations in the kernel
int nTotalThreads = blockDim_2; // Total number of threads, rounded up to the next
                                //power of two
while(nTotalThreads > 1)
  int halfPoint = (nTotalThreads >> 1); // divide by two
  if (threadIdx.x < halfPoint)</pre>
    int thread2 = threadIdx.x + halfPoint;
    if (thread2 < blockDim.x) // Skipping the fictitious threads
                              // blockDim.x ...blockDim 2-1
       sum[threadIdx.x] += sum[thread2]; // Pairwise summation
 syncthreads();
nTotalThreads = halfPoint; // Reducing the binary tree size by two
```



# Binary reduction with an arbitrary number of elements (BLOCK\_SIZE)

• You will have to compute blockDim\_2 (blockDim.x rounded up to the next power of two), either on device or on host (and then copy it to device). One could use the following function to compute blockDim\_2, valid for 32-bit integers:

```
int NearestPowerOf2 (int n)
{
  if (!n) return n; // (0 == 2^0)

  int x = 1;
  while(x < n)
    {
     x <<= 1;
    }
  return x;
}</pre>
```



```
// In global device memory:
   __device__ float xsum; __device__ int isum, imax;

// In a kernel:
float x;
int i;
   __shared__ imin;
   ...
atomicAdd (&xsum, x);
atomicAdd (&isum, i);
atomicMax (&isum, i);
atomicMax (&imax, i);
atomicMin (&imin, i);

//see CUDA specification for full list of atomic operations available
```



### Writing your own atomic operations in CUDA

- Possible, but this is a more advanced topic
- Any atomic operation can be implemented based on **atomicCAS**() (Compare and Swap)
- Performance may be very poor
- Here is what a double precision atomicAdd would look like



#### atomicCAS

- reads the 32-bit or 64-bit word **old** located at the address **address** in global or shared memory
- computes (old == compare ? val : old), stores the result back to memory at the same address
- returns old

### Exercise - implement reduction via 3 approaches

Can be found in:

/home/ppomorsk/CSE746 lec4/Reduction

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### Exercise - implement largest prime search

Can be found in:

/home/ppomorsk/CSE746 lec4/Primes

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