



GPUs and CUDA 3 Intrinsics

CS121 Parallel Computing
Spring 2018

Race conditions

- Race condition: Different outcomes depending on execution order.
- Race conditions can occur in any concurrent system, including GPUs.
 - Code should print $a = 1,000,000$.
 - But actually printed $a = 88$.
- GPUs have atomic intrinsics for simple atomic operations.
- Hard to implement general mutex in CUDA.
 - Codes using critical sections don't perform well on GPUs anyway.

```
__global__ void raceKernel(int *d_a) {  
    *d_a += 1;  
}  
  
void main() {  
    int a = 0; *d_a;  
  
    cudaMalloc((void **) &d_a,  
        sizeof(int));  
    cudaMemcpy(d_a, &a, sizeof(int),  
        cudaMemcpyHostToDevice);  
  
    raceKernel<<<1000, 1000>>>(d_a);  
  
    cudaMemcpy(&a, d_a, sizeof(int),  
        cudaMemcpyDeviceToHost);  
    printf("a = %d\n", a);  
    cudaFree(d_a);  
}
```



CUDA atomics

- Can perform atomics on global or shared memory variables.
- `int atomicInc(int *addr)`
 - Reads value at `addr`, increments it, returns old value.
 - Hardware ensures all 3 instructions happen without interruption from any other thread.
- `int atomicAdd(int *addr, int val)`
 - Reads value at `addr`, adds `val` to it, returns old value.
- `int atomicMax(int *addr, int val)`
 - Reads value at `addr`, sets it to max of current value and `val`, returns old value.
- `int atomicExch(int *addr1, int val)`
 - Sets `val` at `addr` to `val`, returns old value at `val`.
- `int atomicCAS(int *addr, old, new)`
 - “Compare and swap”, a conditional atomic.
 - Reads value at `addr`. If value equals `old`, sets value to `new`. Else does nothing.
 - Indicates whether state changed, i.e. if your view is up to date.
 - Universal operation, i.e. can be used to perform any other kind of synchronization.



Finding max of array

- A grid of threads computes the max of an array in global memory.

```
__global__ void max(int *vals, int* global_max) {  
    int i = threadIdx.x + blockDim.x * blockIdx.x;  
    int val = vals[i];  
    atomicMax(global_max, val);  
}
```

- Works correctly, no race conditions.
- **Ex** Thread 1 tries to set global_max to 4, thread 2 tries to set it to 5.
 - ☐ If thread 1 goes, then thread 2, global_max becomes 4 then 5.
 - ☐ If thread 2 goes, then thread 1, global_max becomes 5, stays 5.



Atomics performance

```
__global__ void max(int *vals, int* global_max) {  
    int i = threadIdx.x + blockDim.x * blockIdx.x;  
    int val = vals[i];  
    atomicMax(&global_max, val);  
}
```

- Problem is this code is really slow.
- When multiple threads perform atomic operation on same variable, they get serialized.
 - Many threads may update `global_max` at same time. Execution becomes sequential instead of parallel.
 - Even with no contention, atomic operation somewhat slower than regular operation.



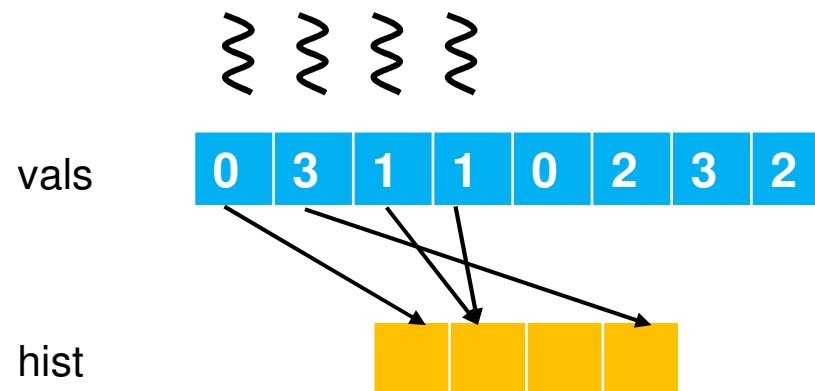
Improving performance

```
__global__ void max(int *vals, int* global_max, int
    *local_max, int num_locals) {
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    int val = vals[i];
    int local_i = i % num_locals;
    int old_max = atomicMax(&local_max[local_i], val);
    if (old_max < val) {
        atomicMax(&global_max, val);
    }
}
```

- Split the single global max into num_locals number of local max values.
- Thread i atomically maxes with its local max, local_max[local_i].
- Only if it increased the local max does thread try to increase the global max.
 - Local max usually won't increase, so rarely need to update global max.
- Spread out contention to the local maxes, reduce frequency of updates to global max.
- Still doesn't perform that well. A reduction tree is more efficient.

Computing a histogram

- Given an array of values from 0 to k, count the number of each value.
- Ex [0,0,1,0,1] \Rightarrow [3,2], i.e. three 0's and two 2's.



```
__global__ void hist(unsigned char *vals, int size, int *hist) {  
    int i = threadIdx.x + blockIdx.x * blockDim.x;  
    int stride = blockDim.x * gridDim.x;  
    while (i < size) {  
        atomicAdd(&(hist[vals[i]]), 1);  
        i += stride;  
    }  
}
```

Improving performance

- Hist array stored in global memory, so access is slow.
- Since all threads write to same array, contention can be high.
- Better to make local histogram in shared memory for each thread block, add result to global histogram at the end.
 - Atomic ops on shared memory faster.
 - Fewer threads per block so less contention on local_hist.
 - Only one atomic op on global histogram per value instead of many increments.

```
__global__ void hist(unsigned char *vals,  
                     int size, int *hist) {  
  
    // Assume 256 different vals  
    __shared__ int local_hist[256];  
    if (threadIdx.x < 256)  
        local_hist[threadIdx.x] = 0;  
    __syncthreads();  
  
    int i = threadIdx.x + blockIdx.x *  
            blockDim.x;  
    int stride = blockDim.x * gridDim.x;  
    while (i < size) {  
        atomicAdd(&(local_hist[vals[i]]), 1);  
        i += stride;  
    }  
    __syncthreads();  
    if (threadIdx.x < 256)  
        atomicAdd(&(hist[threadIdx.x]),  
                  local_hist[threadIdx.x]);  
}
```


Aggregation and atomics

- Want threads to aggregate data into a shared structure.
- **Ex** Filtering. Given a source array `src` with `n` elements, and a predicate, copy all elements of `src` satisfying predicate into destination `dst`.
 - In our examples, we copy all positive values.
- Consider four methods
 - Global memory `atomicAdd`.
 - Shared memory `atomicAdd`.
 - Scan based filtering using Thrust's `copy_if()`.
 - Warp-aggregated filtering.

```
int filter(int *dst, const int *src,
          int n) {
    int nres = 0;
    for (int i = 0; i < n; i++)
        if (src[i] > 0)
            dst[nres++] = src[i];
    return nres; }
```

Sequential

```
__global__
void filter_k(int *dst, int *nres,
              const int *src, int n) {
    int i = threadIdx.x + blockIdx.x *
              blockDim.x;
    if(i < n && src[i] > 0)
        dst[atomicAdd(nres, 1)] = src[i]; }
```

Global memory atomics

Source: <https://devblogs.nvidia.com/parallelforall/cuda-pro-tip-optimized-filtering-warp-aggregated-atomics/>

Aggregation and atomics

```
__global__
void filter_shared_k(int *dst, int
    *nres, const int* src, int n) {
    __shared__ int l_n;
    int i = blockIdx.x * (NPER_THREAD *
        BS) + threadIdx.x;

    for (int iter = 0; iter < NPER_THREAD;
        iter++) {
        // zero the counter
        if (threadIdx.x == 0)
            l_n = 0;
        __syncthreads();

        // get the value, evaluate the
        // predicate, and increment the
        // counter if needed
        int d, pos;

        if (i < n) {
            d = src[i];
            if(d > 0)
                pos = atomicAdd(&l_n, 1);
        }
    }
```

```
__syncthreads();

// leader increments the global
// counter
if (threadIdx.x == 0)
    l_n = atomicAdd(nres, l_n);
__syncthreads();

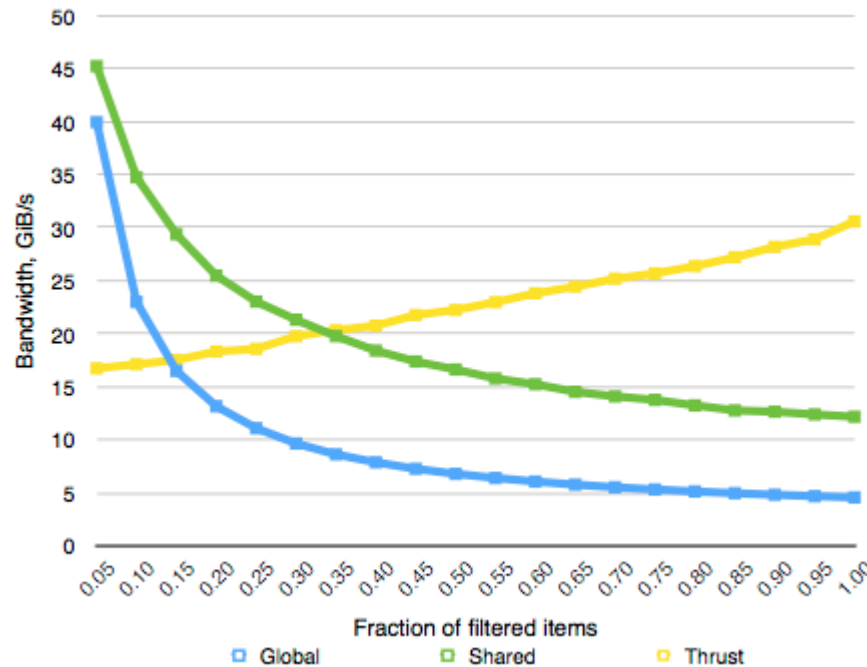
// threads with true predicates
// write their elements
if (i < n && d > 0) {
    pos += l_n; // increment local pos
                // by global counter
    dst[pos] = d;
}
__syncthreads();

i += BS;
}
```

Shared memory atomics

Each block uses local index `l_n`, then merges with global counter `nres`.

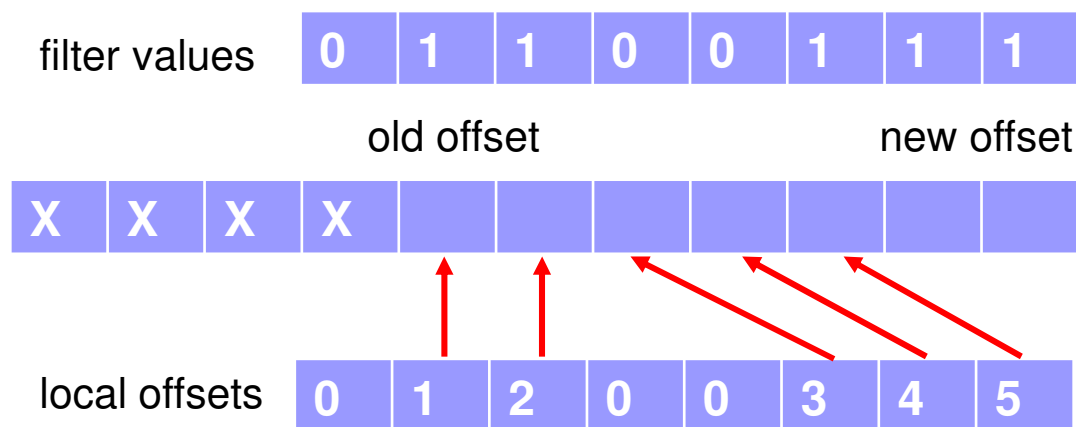
Aggregation and atomics



- Global memory atomics has very poor performance.
 - Performance degrades as more elements satisfy filter, due to conflicts.
- Shared memory over 2X better, but performance still degrades.
- Scan based filtering in Thrust has large up front cost.
 - But performance actually improves as filtered items increase, due to higher GPU utilization.

Warp-aggregated atomics

- Warp-based aggregation lets threads in a warp add their private values into a shared counter using fewer atomic adds.
 - Threads in the warp elect a leader.
 - Threads compute a total atomic increment for the warp.
 - Leader thread performs an atomic add, and gets the old global offset value.
 - Leader broadcasts global offset to all threads in warp.
 - Each thread adds its own local offset to global offset to get its final array index.



Warp-aggregated filtering

```
__device__
int atomicAggInc(int *ctr) {
    // mask of active lanes
    int mask = __ballot(1);

    // select the leader
    int leader = __ffs(mask) - 1;

    // leader does the update
    int res;
    if (lane_id == leader)
        res = atomicAdd(ctr, __popc(mask));

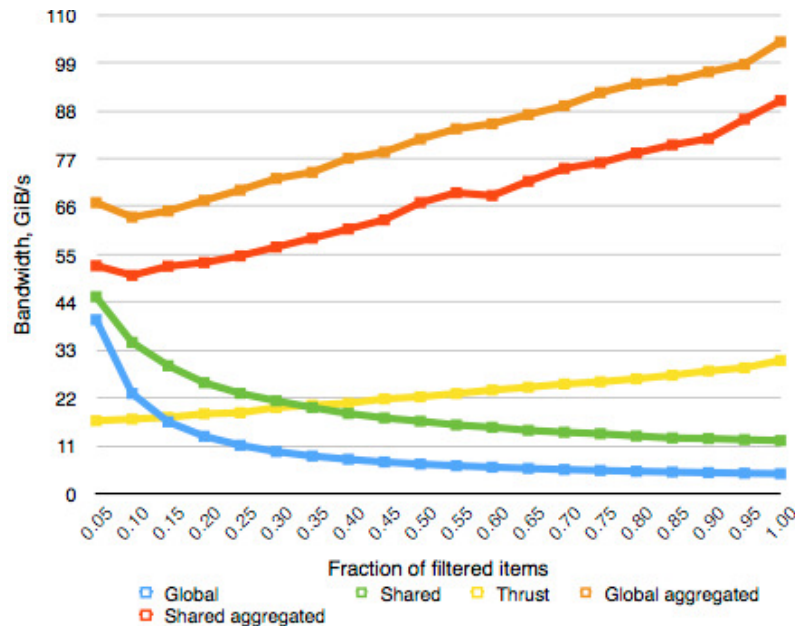
    // broadcast result
    res = __shfl(res, leader);

    // each thread computes its own value
    return res + __popc(mask & ((1 <<
        lane_id) - 1));
}
```

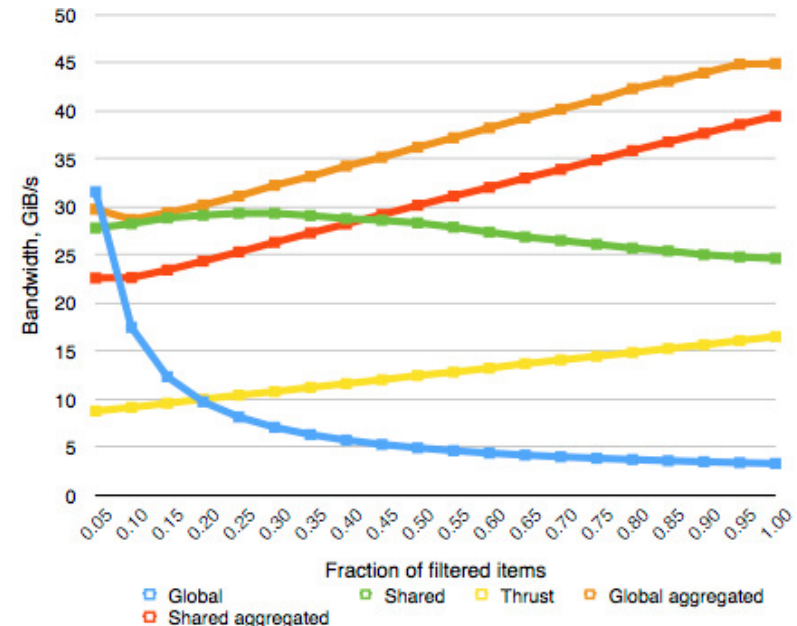
```
__global__ void filter_k(int *dst, const
    int *src, int n) {
    int i = threadIdx.x + blockIdx.x *
        blockDim.x;
    if (i >= n)
        return;
    if (src[i] > 0)
        dst[atomicAggInc(nres)] = src[i];
}
```

- Lane is a thread's index within warp (0 to 31).
 - Compute as $\text{threadIdx.x} \% 32$.
- Want lowest active lane (i.e. thread with positive src value) to be leader.
- `__ballot(v)` intrinsic returns a 32 bit mask indicating whether v is true at each lane.
 - So `__ballot(1)` selects the active lanes.
- `__ffs(mask)` intrinsic finds first set bit in mask.
- `__popc(mask)` intrinsic counts the number of set bits in mask.
- `__shfl(res, leader)` intrinsic lets leader broadcast res to all other threads in warp.
- `mask & ((1 << lane_id) - 1)` keeps only the set bits in mask before the `lane_id`'th bit.
 - Ex If mask = 10100110, lane_id = 4, then this sets mask to 0000110.
 - `__popc(mask & ((1 << lane_id) - 1))` counts number of threads satisfying predicate with lower ID.

Performance



Tesla K40 (Kepler)



GeForce GTX 750 Ti (Maxwell)

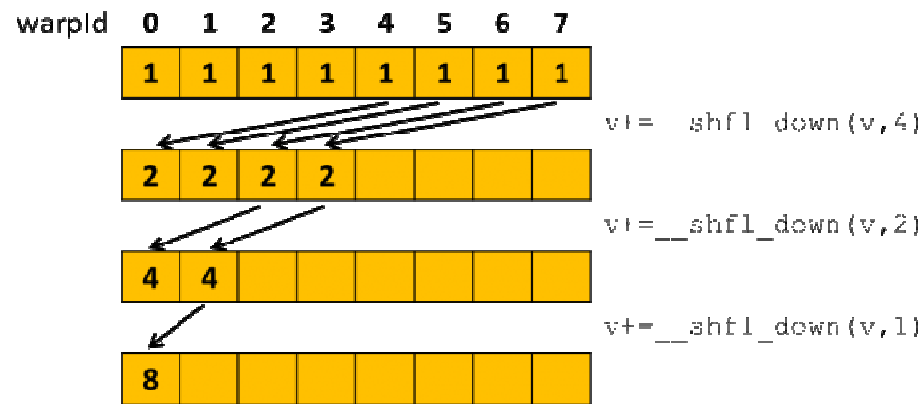
- Up to 100 GB/s bandwidth on Kepler (simply copying has 180 GB/s).
 - Performance improves with filter ratio, because more elements written.
 - Global memory aggregation even faster than shared memory.
- Maxwell provides very efficient shared memory atomics, so the atomicAdd method is competitive for small filter ratios.
 - This particular Maxwell only had 5 SMs, hence the low overall performance.



Shuffle intrinsics

- Starting from Kepler, shuffle operations allow very fast moving of data between threads in a warp.
- Again, let $\text{lane} = \text{threadIdx.x} \% 32$.
- Four shuffle operations.
 - `int __shfl_up(int var, int delta)`
 - `var` is a local register variable.
 - Copy value of `var` from a thread that's `delta` lanes higher to this thread.
 - Threads above lane 31-`delta` don't do anything.
 - `int __shfl_down(int var, int delta)`
 - `int __shfl_xor(int var, int laneMask)`
 - Do XOR of `laneMask` with this thread's lane to determine lane to copy `var` from.
 - `int __shfl(int var, int srcLane)`
 - Copy `var` from lane `srcLane`.
- Can only read value from an active thread doing the shuffle instruction.
 - Copying from inactive thread leads to undefined behavior.
 - Be careful using shuffle on branching code.

Shuffle warp reduce

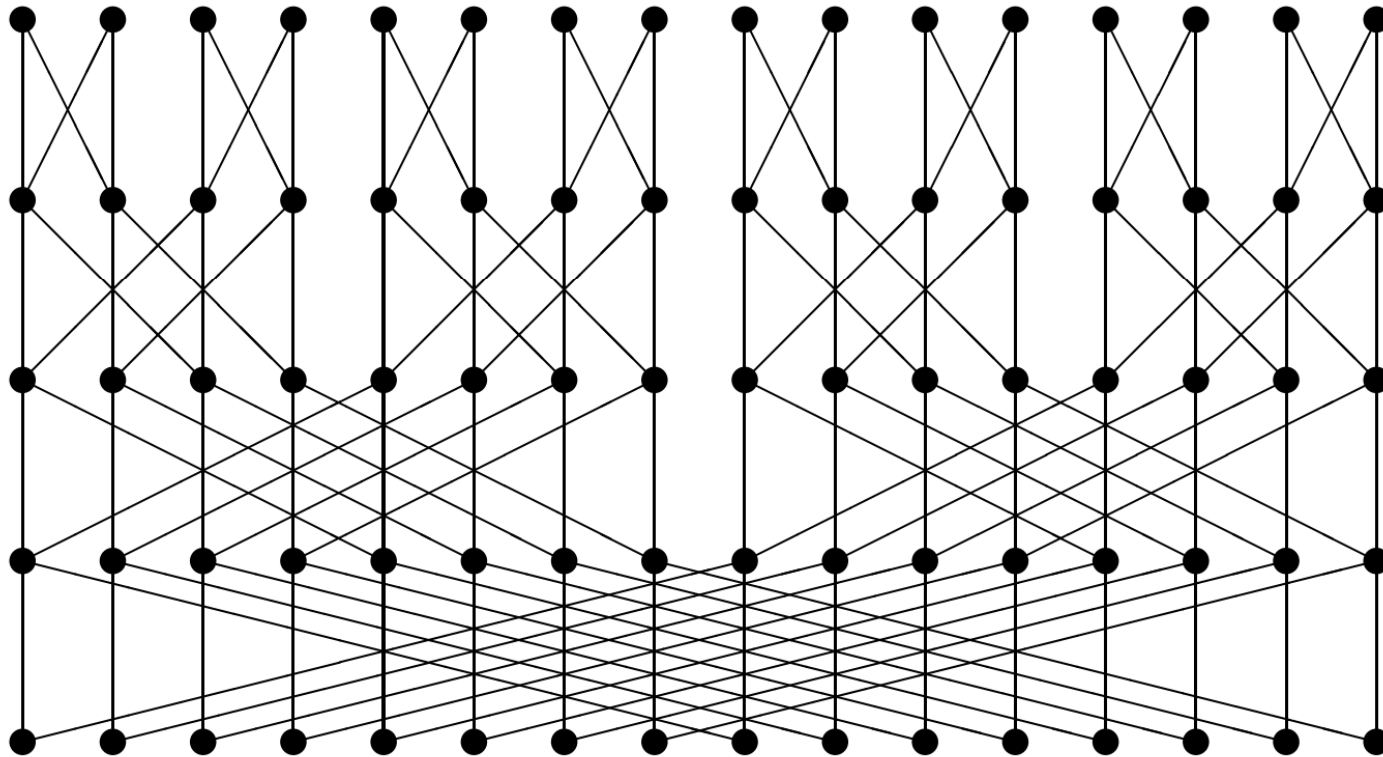


Source: <https://devblogs.nvidia.com/parallelforall/faster-parallel-reductions-kepler/>

- Can do reduce using shuffle instead of shared memory.
- Can be 2-3X faster than moving same data using shared memory.
- Also frees up shared memory for other uses.
- Since warp is SIMD, threads are automatically synchronized after shuffle, without need for `__syncthreads()`.

Shuffle warp all-reduce

```
for (int i=1; i<32; i*=2)
    value += __shfl_xor(value, i);
```



Source: <https://people.maths.ox.ac.uk/gilesm/cuda/lecs/lec4.pdf>

Block reduce

```
__inline__ __device__ int blockReduceSum(int val) {
    static __shared__ int shared[32];          // Shared mem for 32 partial sums
    int lane = threadIdx.x % warpSize;
    int wid = threadIdx.x / warpSize;

    val = warpReduceSum(val);                  // Each warp performs partial reduction
    if (lane==0) shared[wid]=val;              // Write reduced value to shared memory
    __syncthreads();                          // Wait for all partial reductions

    //read from shared memory only if that warp existed
    val = (threadIdx.x < blockDim.x / warpSize) ? shared[lane] : 0;
    if (wid==0) val = warpReduceSum(val);      // Final reduce within first warp
    return val;
}
```

- Assume we have at most 1024 threads in the block.
- First do reduction in each warp.
- Then first thread in each warp writes value to a size 32 (= block size / warp size) shared memory array.
- Then (a subset of) threads in the first warp read the array, then do another warp wide reduction.
 - This can reduce $32 \times 32 = 1024$ values.

Reducing larger arrays

```
__global__ void deviceReduceKernel(int *in,
    int* out, int N) {
    int sum = 0;
    //reduce multiple elements per thread
    for (int i = blockIdx.x * blockDim.x +
        threadIdx.x; i < N;
        i += blockDim.x * gridDim.x) {
        sum += in[i]; }
    sum = blockReduceSum(sum);
    if (threadIdx.x==0)
        out[blockIdx.x]=sum;
}
```

```
void deviceReduce(int *in, int* out, int N)
{
    int threads = 512;
    int blocks = min((N + threads - 1) /
        threads, 1024);

    deviceReduceKernel<<<blocks,
        threads>>>(in, out, N);
    deviceReduceKernel<<<1, 1024>>>(out, out,
        blocks);
}
```

- Run two kernels, first in which every block produces a sum, and the second to add up the block sums.
 - Assume at most 1024 thread blocks.
- Each thread in grid first sums array elements in strides of the grid size.
 - Number of threads in the grid is $T = \text{blockDim.x} * \text{gridDim.x}$.
 - Each thread sums every T 'th array element.
- First thread in each block writes block sum to array out.
- Run second kernel with one thread block to sum up the ≤ 1024 block sums.