CUDA Threads

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- saxpy: hello-world for GPUs
- Threads organization: grids, blocks, threads, and warps.
- Synchronization
- Examples

Example: saxpy

- saxpy = "single-precision a times x plus y".
- The device code.
- The host code.
- The running saxpy

saxpy: device code

```
__global__ void saxpy(uint n, float a, float *x, float *y) {
  uint i = blockIdx.x*blockDim.x + threadIdx.x; // nvcc built-ins
  if(i < n)
    y[i] = a*x[i] + y[i];
}
```

- Each thread has `x`, `y`, and `z` indices.
    - We'll just use `x` for this simple example.
- Note that we are creating one thread per vector element:
    - Exploits GPU hardware support for multithreading.
    - We need to keep in mind that there are a large, but limited number of threads available.

saxpy: host code (part 1 of 5)

```
int main(int argc, char **argv) {
  uint n = atoi(argv[1]);
  float *x, *y, *yy;
  float *dev_x, *dev_y;
  int size = n*sizeof(float);
  x = (float *)malloc(size);
  y = (float *)malloc(size);
  yy = (float *)malloc(size);
  for(int i = 0; i < n; i++) {
    x[i] = i;
    y[i] = i*i;
  }
  ...
}
```

- Declare variables for the arrays on the host and device.
- Allocate and initialize values in the host array.

saxpy: host code (part 2 of 5)

```
int main(void) {
  ...
  cudaMalloc((void**)(&dev_x), size);
  cudaMalloc((void**)(&dev_y), size);
  cudaMemcpy(dev_x, x, size, cudaMemcpyHostToDevice);
  cudaMemcpy(dev_y, y, size, cudaMemcpyHostToDevice);
  ...
}
```

- Allocate arrays on the device.
- Copy data from host to device.

saxpy: host code (part 3 of 5)

```
int main(void) {
   ...
   float a = 3.0;
   saxpy<<<ceil(n/256.0),256>>>(n, a, dev_x, dev_y);
   cudaMemcpy(yy, dev_y, size, cudaMemcpyDeviceToHost);
   ...
}
```

- Invoke the code on the GPU:
  - `saxpy<<<ceil(n/256.0),256>>>(...)` says to create $\lceil n/256 \rceil$ blocks of threads.
  - Each block consists of 256 threads.
  - See slide 10 for an explanation of threads and blocks.
  - The pointers to the arrays (in device memory) and the values of `n` and `a` are passed to the threads.
- Copy the result back to the host.

saxpy: host code (part 4 of 5)

```
  ...
  for(int i = 0; i < n; i++) { // check the result
    if(yy[i] != a*x[i] + y[i]) {
      fprintf(stderr,
              "ERROR: i=%d, a[i]=%f, b[i]=%f, c[i]=%f\n",
              i, a[i], b[i], c[i]);
      exit(-1);
    }
  }
  printf("The results match!\n");
  ...
}
```

- Check the results.

saxpy: host code (part 5 of 5)

```
int main(void) {
  ...
  free(x);
  free(y);
  free(yy);
  cudaFree(dev_x);
  cudaFree(dev_y);
  exit(0);
}
```

- Clean up.
- We're done.

Launching Kernels

- Terminology
  - Data parallel code that runs on the GPU is called a **kernel**.
  - Invoking a GPU kernel is called **launching** the kernel.
- How to launch a kernel
  - The host CPUS invokes a `__global__` function.
  - The invocation needs to specify how many threads to create.
  - Example:
    - `saxpy<<<ceil(n/256.0),256>>>(...)`
    - creates $\lceil \frac{n}{256} \rceil$ **blocks**
    - with 256 **threads** each.

Threads and Blocks

- The GPU hardware combines threads into **warps**
  - Warps are an aspect of the hardware.
  - All of the threads of warp execute together – this is the SIMD part.
  - The functionality of a program doesn't depend on the warp details.
  - But understanding warps is critical for getting good performance.
- Each warp has a "next instruction" pending execution.
  - If the dependencies for the next instruction are resolved, it can execute for all threads of the warp.
  - The hardware in each streaming multiprocessor dispatches an instruction each clock cycle if a ready instruction is available.
  - The GPUs in the `lin??.ugrad.cs.ubc.ca` machines support 48 such warps of 32 threads each in a "thread block."
- What if our application needs more threads?
  - Threads are grouped into "thread blocks".
  - Each thread block has up to 1024 threads (the HW limit).

Compiling and running

```
lin25$ nvcc saxpy.cu -o saxpy
lin25$ ./saxpy 1000
The results match!
```

But is it fast?

- For the `saxpy` example as written here, not really.
  - Execution time dominated by the memory copies.
- But, it shows the main pieces of a CUDA program.
- To get good performance:
  - We need to perform many operations for each value copied between memories.
  - We need to perform many operations in the GPU for each access to global memory.
  - We need enough threads to keep the GPU cores busy.
  - We need to watch out for thread divergence:
    - If different threads execute different paths on an if-then-else,
    - Then the else-threads stall while the then-threads execute, and vice-versa.
  - And many other constraints.
- GPUs are great if your problem matches the architecture.

Thread organization: grids, blocks and threads

- Lots of nVidia jargon here.
  - When a kernel is launched, it creates an array of threads.
  - This array is called a **grid**.
- A grid is organized as an array of **blocks**
- Each block is an array of **threads**
- Why so many details?
  - A block must have all execution resources it needs before it is launched:
    - A block runs on a single SM.
    - The execution model suggests that blocks run to completion (i.e. they are not swapped-out during execution).
  - Switching between threads in a block is done by hardware.
  - By distinguishing blocks from threads, the CUDA model exposes the performance issues to the programmer.

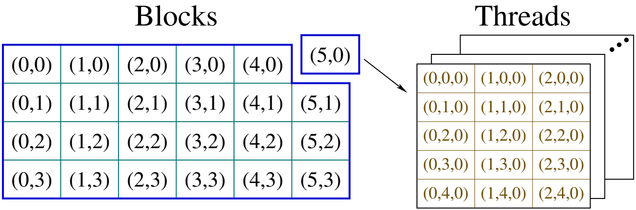
A grid is an array of blocks

(0,0)	(1,0)	(2,0)	(3,0)	(4,0)	(5,0)
(0,1)	(1,1)	(2,1)	(3,1)	(4,1)	(5,1)
(0,2)	(1,2)	(2,2)	(3,2)	(4,2)	(5,2)
(0,3)	(1,3)	(2,3)	(3,3)	(4,3)	(5,3)

A grid

- Blocks are scheduled by the GPU **software**.
- Blocks can be arranged as a 1D, 2D, or 3D array.
- There can be **lots** of blocks:
  - There can be up to $2^{31} = 2,147,483,648$ blocks in the x-dimension.
  - There can be up to $2^{16} = 65536$ blocks in the y- and z-dimensions.

Each block is an array of threads



Where do they put all those threads?

- Threads are scheduled by the GPU **hardware**.
- Threads can be arranged as a 1D, 2D, or 3D array.
- There are a limited number of threads per block:
  - The total number of threads (product of all dimensions) is at most 256 to 1024, depending on the GPU.

Threads and blocks: launching a kernel

- Let's say we have:

  `__global__ void kernel_fun(`*args*`)`

- To launch this kernel, we execute a statement like:

  `kernel_fun<<<`*dimGrid*`, `*dimBlock*`>>>(`*actuals*`);`

  where
  - *dimGrid* is specifies the dimension(s) of the grid (an array of blocks):
    - *dimGrid* can be an `int`, in which case the array is one dimensional of that size.
    - or, *dimGrid* can be a `dim3`, for example:

      `dim3(6,4,1)`
    - The last component of the `dim3` is the z-dimension, which is ignored when describing a grid. To avoid confusion, the standard practice it to use a value of `1`.
  - *dimBlock* is specifies the dimension(s) of each block (an array of threads):
    - *dimGrid* can be an `int` or a `dim3`.
    - If *dimGrid* is a `dim3`, all three dimensions are used.

Threads and blocks: within a kernel

- With a kernel, CUDA-C provides four variables to determine the position of a thread within the grid: `blockDim`, `blockIdx`, `threadDim`, and `threadIdx`.
- `blockDim.x` and `blockDim.y` give the size of the grid in the `x`- and `y`-dimensions.
- `threadDim.x`, `threadDim.y`, and `threadDim.z` give the size of each block.
- `blockIdx.x` and `blockIdx.y` give the indices of the thread's block within the grid. Note that:
  - $0 \leq$ `blockIdx.x` $<$ `BlockDim.x`, and
  - $0 \leq$ `blockIdx.y` $<$ `BlockDim.y`.
- Likewise, `threadIdx.x`, `threadIdx.y`, and `threadIdx.z` give the indices of the thread within its block.
- Because the size of blocks are limited, it is common to use code such as:

```
uint my_idx = blockDim.x*blockIdx.x + threadIdx.x;
```

  to combine the block and thread indices into a single index.

Bounds checking: launching kernels

- Consider executing `kernel_fun` on an array of `n` elements.
- Because `n` might be large, we'll use `n/256` blocks of 256 threads.
  - THINK: what if `n` is not a multiple of 256?
  - We'll round up to make sure we have enough threads.
- The kernel launch looks like:

```
kernel_fun<<<ceil(n/256.0), 256>>>(n, myArray);
```

  - Why divide by `256.0` instead of `256`?
  - Why use `ceil`?

Bounds checking: in the kernel

- The kernel launch looks like:

```
kernel_fun<<<ceil(n/256.0), 256>>>(n, myArray);
```

- THINK: what if `n` is not a multiple of 256?
  - We'll launch more than `n` threads?
  - For example, if `n==1000`, then we'll launch 4 blocks of 256 threads. A total of 1024 threads.
  - What will the last 24 threads do?
- Add a test:

```
uint my_idx = blockDim.x*blockIdx.x + threadIdx.x;
if(my_idx < n) {
  ...
}
```

Warps

- Warps refer to how the hardware executes threads.
  - The programmer writes code with grid consisting of blocks of threads.
  - You can write **correct** code without paying attention to warps.
  - But you need to think about warps to write `fast` code.
- Each streaming multiprocessor (SM) in the GPU executes threads in SIMD fashion.
  - A warp is a collection of threads that execute together on the same SM.
- Why we care:
  - It helps performance to make the number of threads in a block a multiple of the warp size.
  - Thread divergence is an issue when different threads in the same warp follow different control paths.
- Etymology: “warp” is a term from weaving:

> *“the threads on a loom over and under which other threads (the weft) are passed to make cloth”*

From the *New Oxford American Dictionary* (on my laptop).

A Warped Example: Reduce (part 1 of 2)

- Consider a reduce of an array, `data`, of `n` elements using `n/2` threads. Assume `n` is power of 2.
- Simple code:

```
for(int stride = 1; stride < n; stride += stride) {
  if((my_idx & (stride-1)) == 0)
    data[2*my_idx] += data[2*my_idx + stride];
  __syncthreads(); % see slide 24
}
```

- Consider `n == 16`
  - First iteration, for `i` in 0, . . . , 7, `data[2*i] += data[2*i]+1`. Now, all the even indexed elements have their sum with their odd counterpart.
  - Second iteration, for `i` in 0, 2, 4, 6, `data[2*i] += data[2*i]+2`. All elements with indices that are multiples of four, have their sum with the next three elements.
  - Third iteration leads with `data[0]` and `data[8]` holding sums for their halves of the array.
  - The fourth iteration puts the complete sum into `data[0]`.
- What if `n==1024`? See the next slide.

A Warped Example: Reduce (part 2 of 2)

- What if `n==1024`?
  - We have 512 threads: 16 warps of 32 threads.
  - In the first iteration, all threads are active.
  - In the next iteration, each warp has 16 active threads – the GPU has to execute the code for all 16 warps, even though half the threads do nothing.
  - In subsequent iterations, the warps are more and more poorly utilized.
- We would like to pack the busy threads into the minumum number of warps.

Faster Warps

```
for(int stride = n/2; stride > 0; stride >>= 1) {
  if(my_idx < stride)
    data[my_idx] += data[my_idx] + stride;
  __syncthreads();
}
```

- Consider `n == 1024`.
- In the first iteration, there are 16 active warps – all threads in each warp are busy.
- In the second iteration, there are 8 active warps – all threads in each active warp are busy.
- Similarly, for the 3rd through 5th iterations:
  - The number of active warps decreases.
  - All threads in each active warp are busy.

Synchronization

- The reduce example used `__syncthreads()`: all the threads in the block must execute this statement before any continue beyond it.
  - Be **very** careful about thread divergence.
  - All threads in the block must meet at the barrier.
  - They must all meet at the **same** barrier.
- We'll have more examples of synchronization next week.

Some examples

See examples.cu.

Preview

November 14: GPU Mamory: Part 1	
Reading:	Kirk & Hwu – Chapter 4
November 16: GPU Mamory: Part 2	
November 19: GPU Performance: Part 1	
Reading:	Kirk & Hwu – Chapter 5
November 21: GPU Performance: Part 2	
November 23: GPU Performance: Part 3	

- Kirk & Hwu = *Programming Massively Parallel Computers*
- On-line here – where "here" means `https://www.sciencedirect.com/book/9780128119860/programming-massively-parallel-processors`
- Free access from UBC (use the UBC library ezproxy from off-campus).

Review

- In CUDA, what is a grid, a block, and thread?
- Why does CUDA allow millions of thread blocks but only 256 to 1024 threads per block?
- How does a programmer specify the number of thread blocks and number of threads when launching a CUDA kernel?
- How does a thread determine its position within the thread grid? "global memory" in CUDA programming.
- Why do threads need to check their indices against array bounds?
- What is a warp? Why does it matter?