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ETH zürich



Writing GPU Kernels

Sebastian Keller, Prashanth Kanduri
and Ben Cumming, CSCS



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Going Parallel : Kernels and Threads

Threads and Kernels

- **Threads** are streams of execution, run simultaneously on GPU.
- A **kernel** is the function run by each thread.
- CUDA provides language support for:
 - writing kernels;
 - launching many threads to execute a kernel in parallel.
- CUDA hides the low-level details of launching threads.

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- A **kernel** is the function run by each thread.
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 - launching many threads to execute a kernel in parallel.
- CUDA hides the low-level details of launching threads.

The process for developing CUDA kernels

1. Formulate algorithm in terms of parallel work items.
2. Write a kernel implementing a work item on one thread.
3. Launch the kernel with the required number of threads.

Scaled Vector Addition (axpy)

We have used CUBLAS to perform scaled vector addition:

$$\mathbf{y} = \mathbf{y} + \alpha \mathbf{x}$$

- \mathbf{x} and \mathbf{y} are vectors of length n ;

$$x, y \in \mathbb{R}^n$$

- α is scalar.

$$\alpha \in \mathbb{R}$$

Applying `axpy` requires n operations:

$$y_i \leftarrow y_i + a * x_i, \quad i = 0, 1, \dots, n - 1$$

which can be performed **independently** and **in any order**.

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axpy implemented on CPU with a loop

```
void axpy(double* y, const double* x, double a, int n) {  
    for(int i=0; i<n; ++i)  
        y[i] = y[i] + a*x[i];  
}
```

Kernels

A **kernel** defines the work item for a single thread

- The work is performed by many threads executing the same kernel **simultaneously**.
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host : add two vectors

```
void add_cpu(int* a, int* b, int n){  
    for(auto i=0; i<n; ++i)  
        a[i] = a[i] + b[i];  
}
```

CUDA : add two vectors

```
--global--  
void add_gpu(int* a, int* b, int n){  
    auto i = threadIdx.x;  
    a[i] = a[i] + b[i];  
}
```

- **--global--** keyword indicates a kernel
- **threadIdx** used to find unique id of each thread

Launching a kernel

- Host code launches a kernel on the GPU **asynchronously**.
- CUDA provides the “triple chevron” `<<<_,_>>>` syntax for launching a kernel.

host : add two vectors

```
auto n = 1024;  
auto a = host_malloc<int>(n);  
auto b = host_malloc<int>(n);  
add_cpu(a, b, n);
```

CUDA : add two vectors

```
auto n = 1024;  
auto a = device_malloc<int>(n);  
auto b = device_malloc<int>(n);  
add_gpu<<<1,n>>>(a, b, n);
```

- `add_gpu<<<1, num_threads>>>(args...)` launches the kernel `add_gpu` with `num_threads` parallel threads.

Exercise: My First Kernel

Open `axpy/axpy.cu`

1. Write a kernel that implements `axpy` for `double`
 - `axpy_kernel(double* y, double* x, double a, int n)`
 - **extra:** can you write a C++ templated version for any type?
2. launch the kernel (look for `TODO`)
3. Compile the test and run
 - it will pass with no errors on success
 - first try with small vectors of size 8
 - try increasing launch size... what happens?
4. **extra:** can you extend the kernel to work for larger arrays?



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Scaling Up : Thread Blocks

In the **axpy** exercises we were limited to 1024 threads for a kernel launch

- but we need to scale beyond 1024 threads for the **massive parallelism** we were promised!

Thread blocks and grids



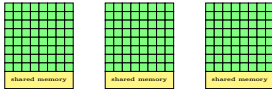
kernels are executed in groups of threads called **thread blocks**

- the launch configuration `axpy<<<grid_dim, block_dim>>>(...)`
 - launch a **grid** of `grid_dim` **blocks**
 - each **block** has `block_dim` **threads**
 - for a total of `grid_dim × block_dim` threads
- previously we launched just one thread block
`axpy<<<1, n>>>(...)`

Why the additional complexity?

Coordination between threads doesn't scale:

- Threads in a block can synchronize and share resources
- This does not scale past a certain number of cores/threads
- EACH P100 GPU **streaming multiprocessor** (SMX) has 64 CUDA cores, and can run 2048 threads
- Threads in a block run on the same SMX, with shared resources and thread cooperation
- Work is broken into blocks, which are distributed over the 56 SMXs on the GPU.

| concept | hardware | |
|---------|---|--|
| thread |  | <ul style="list-style-type: none"> each thread executed on one core |
| block |  | <ul style="list-style-type: none"> block executed on 1 SMX multiple blocks per SMX if sufficient resources threads in a block share SMX resources |
| grid |  | <ul style="list-style-type: none"> kernel is executed in grid of blocks blocks distributed over SMXs multiple kernels can run at same time |

Calculating thread indexes

A kernel has to calculate the index of its work item

- In `axpy` we used `threadIdx.x` for the index.
- With multiple blocks, we need more information, which is available in the following **magic variables**:

| | |
|------------------------|--|
| <code>gridDim</code> | : total number of blocks in the grid |
| <code>blockDim</code> | : number of threads in a thread block |
| <code>blockIdx</code> | : index of block <code>[0, gridDim-1]</code> |
| <code>threadIdx</code> | : index of thread in thread block <code>[0, blockDim-1]</code> |

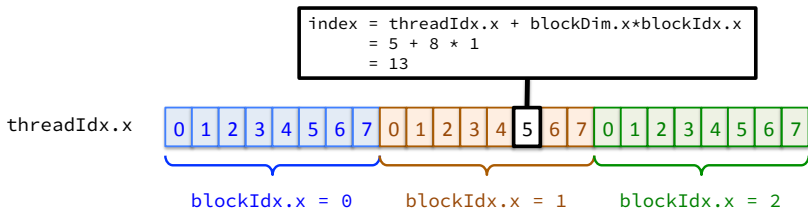
Calculating thread indexes

Consider accessing an array of length 24 with 8 threads per block. The **dimensions** of the kernel launch are:

- `blockDim.x == 8` (8 threads/block)
- `gridDim.x == 3` (3 blocks)

We calculate the index for our thread using the formula

```
auto index = threadIdx.x + blockIdx.x*blockDim.x
```



Calculating grid dimensions

The number of thread blocks and the number of threads per block are parameters for the kernel launch:

```
kernel<<<blocks, threads_per_block>>>(...)
```

Remember to guard against overflow when the number of work items is not divisible by the thread block size

vector addition with multiple blocks

```
__global__  
void add_gpu(int* a, int* b, int n){  
    auto i = threadIdx.x + blockIdx.x*blockDim.x;  
    if(i<n) { // guard against access off end of arrays  
        a[i] += b[i];  
    }  
}  
  
// in main()  
auto block_size = 512;  
auto num_blocks = (n + (block_size-1)) / block_size;  
add_gpu<<<num_blocks, block_size>>>(a, b, n);
```

Calculating grid dimensions

We have to take care when calculating the number of blocks in the grid, i.e. `blocks`:

```
kernel<<<blocks, threads_per_block>>>(...)
```

Most likely, the number of work items `n` is not a multiple of `threads_per_block`

- some threads in the last thread block will be idle.

Calculating grid dimensions

```
// in main()
auto block_size = 512;
auto num_blocks = (n + block_size - 1) / block_size;
add_gpu<<<num_blocks, block_size>>>(a, b, n);
```

How many threads per block?

The number of threads per block has an impact on performance

- The optimal number depends on resources required by the kernel (registers, shared memory, computational intensity, etc).

The short answer is 64 or 128 on P100.

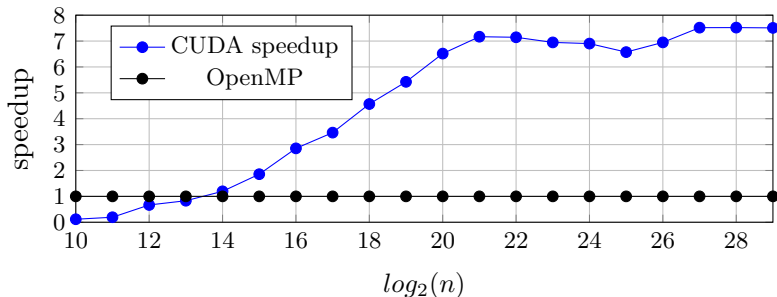
- For the main kernels in your application, perform experiments to find the ideal block size.

Exercise: Blocks

Open `axpy/axpy.cu` from the last exercise

1. Extend the `axpy` kernel for arbitrarily large input arrays (any `n`)
2. Update the call site to calculate the grid configuration
3. Compile the test and run
 - it will pass with no errors on success
4. Experiment with varying the size of the arrays (scaling)
 - start small and increase
5. finish the `newton.cu` example
 - how do the h2d, d2h and kernel timings compare?
6. **extra:** Compare scaling with the `axpy_omp` benchmark
7. **extra:** Experiment with varying the block size

Exercise: Results



The GPU is a throughput device:

- CUDA breaks even for $n \geq 2^{14} \approx 16,000$
- requires $2^{21} \approx 2,000,000$ to gain “full” $7\times$ speedup

You have to provide enough parallelism to exploit many cores