# XJCO3221 Parallel Computation

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Lecture 15: GPU threads and kernels

# Previous lecture

In the last lecture we started looking at General Purpose GPU programming, or GPGPU:

- **Device** contains a number of **SIMD processors**, each containing some number of **cores**.
- Thread scheduling is performed **in hardware**.
- Programmable using **OpenCL** (this course), CUDA, and others.
- Device discovery performed at run time (*cf.* the `displayDevices.c` example).

# This lecture

Next we will see how to perform vector addition on a GPU:

- **Communicating** data between the device (GPU) and the host (CPU) using the **command queue**.
- Compiling and executing **kernels** on the device.
- **Work items** are the basic unit of concurrency.
- Arranged into **work groups** for **scalability**.
- How to set the work group size.

# Vector addition

Code on Minerva: `vectorAddition.c`, `vectorAddition.cl` and `helper.h`

Once again use **vector addition** as our first worked example:

$$\mathbf{c} = \mathbf{a} + \mathbf{b} \quad \text{or} \quad c_i = a_i + b_i \ , \ i = 1 \ldots N.$$

In serial code:

```
1 for( i=0; i<N; i++ )
2   c[i] = a[i] + b[i];
```

where vectors **a**, **b** and **c** all have $N$ elements *(as before, mathematical and computer indexing differ by one)*.

This is a **map**/**data parallel** problem with no **data dependencies**.

# Host and device

The CPU is the **host**, and the GPU is the **device**:

| Host | CPU |
|---|---|
| Device | GPU, accelerator, FPGA, ... |

Assume that CPU and GPU memory are **separate**[1].

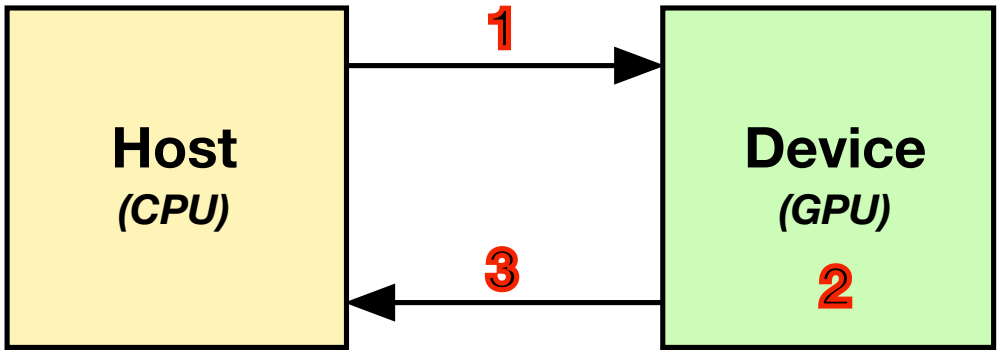
If the initial data is only accessible to the CPU, must **transfer** to the GPU to perform the calculations, then **transfer** the result back to the CPU.

- This requires **explicit communication**, somewhat similar to the distributed memory model.

[1] Some modern GPUs support **unified memory** — see next lecture.

# Typical program structure

1. **Send** problem data from host to the device.
2. **Perform** calculations on the device.
3. **Return** results from device to the host.



# Contexts and command queues

Recall from last lecture that to use OpenCL we first need to:

1. Identify the **platform** and a suitable **device**.
2. For each device, initialise a **context** and **command queue**.

The routine `simpleOpenContext_GPU()` in `helper.h` helps:

```
1 cl_device_id device;
2 cl_context context = simpleOpenContext_GPU(&device);
3
4 cl_int status;
5 cl_command_queue queue = clCreateCommandQueue(context,
      device,0,&status);
6 ...     // Use the GPU.
7 clReleaseCommandQueue(queue);
8 clReleaseContext(context);
```

# Device memory allocation

Suppose arrays a, b and c initialised on the **host**:

```
1 float *host_a = (float*) malloc(N*sizeof(float));
```

Similar for host_b, host_c.

Can allocate **device** memory for this array **and copy from the host array** using clCreateBuffer:

```
1 cl_mem device_a = clCreateBuffer(
2   context,
3   CL_MEM_READ_ONLY|CL_MEM_COPY_HOST_PTR, // Flags.
4   N*sizeof(float),          // Size in bytes.
5   host_a,                   // Copy from this host array.
6   &status                   // Error status.
7 );
```

Similar for device_b, device_c.

# clCreateBuffer() usage

- The `context` has been initialised for the GPU.
- The flag `CL_MEM_READ_ONLY` refers to how the **device** accesses the memory.
  - Specifying 'read only' allows the runtime system to optimise execution — see next lecture.
- The flag `CL_MEM_COPY_HOST_PTR` automatically copies from an existing **host** array (the $4^{\text{th}}$ argument).
- For `device_c`, where no host data (yet) exists, the flag is just `CL_MEM_WRITE_ONLY` and the $4^{\text{th}}$ argument is `NULL`.
- `status` is set to `CL_SUCCESS` if the operation was successful, otherwise some other error code.

# GPU kernel

## Definition

**Kernels** are functions that execute on the device.
**Each thread** within the SIMD cores executes the kernel.

Use standard C syntax:

```
1 __kernel
2 void vectorAdd(__global float *a,__global float *b,
      __global float *c)
3 {
4   int gid = get_global_id(0);
5   c[gid] = a[gid] + b[gid];
6 }
```

# OpenCL kernels

- All kernels[1] preceded with `__kernel`.
- Must return `void` — otherwise which thread's return value would be returned to the host?
- `__global` refers to the device memory we have just allocated.
  - More on this next lecture.
- `get_global_id()` returns the (global) index for 'this' thread.
  - For this problem it is the index of the vector.
  - See later.

[1] CUDA kernels are preceded `__global__` (if they are callable by the host).

# Building a kernel

OpenCL kernels are compiled **at run time** (of the C code).

- Allows optimisation for the device that executes it.

Requires a series of API calls. Typically:

1. Start with the program as a `char*` **string** (typically read from file ending in `.cl`).
2. Create the **program** for the context with `clCreateProgramWithSource()`.
3. **Build** (compile and link) using `clBuildProgram()`.
4. Create a **kernel** using `clCreateKernel()`.

# Building a kernel with `helper.h`

To simplify this process, the file `helper.h` contains the routine `compileKernelFromFile()`.

For this vector addition example:

```
cl_kernel kernel = compileKernelFromFile(
  "vectorAddition.cl",  // File with kernel code.
  "vectorAdd",          // Name of function.
  context,              // Same as before.
  device                // Same as before.
);

... // Use kernel.

clReleaseKernel(kernel);
```

It also includes some basic error handling.

# Setting kernel arguments

Each kernel argument must be set by using `clSetKernelArg()`:

```
status = clSetKernelArg(
  kernel,              // The kernel object.
  0,                   // The argument number.
  sizeof(cl_mem),      // The size of the argument.
  &device_a            // The value.
);
```

This is repeated for argument 1 ($\rightarrow$`device_b`) and argument 2 ($\rightarrow$`device_c`) for the vector addition example.

# Starting a kernel in OpenCL[1]

To start a kernel, you place it on the **command queue** using `clEnqueueNDRangeKernel()`:

```
1 // Will cover this later.
2 size_t indexSpaceSize[1], workGroupSize[1];
3 indexSpaceSize[0] = N;
4 workGroupSize [0] = 128;
5
6 // Place the kernel onto the command queue.
7 status = clEnqueueNDRangeKernel(queue,kernel,1,NULL,
      indexSpaceSize,workGroupSize,0,NULL,NULL);
```

There are many arguments; we will cover some later.

Note that `size_t` is an **unsigned integer**.

[1] In CUDA: `kernel<<<workGroupSize,indexSpaceSize>>>(...)`.

# Copying data between device and host[1]

To get the result (`device_c`) back to the host (`host_c`), enqueue a **read buffer** command:

```
status = clEnqueueReadBuffer(
  queue,              // The command queue.
  device_c,           // Device memory.
  CL_TRUE,            // Blocking.
  0,                  // Offset; must be zero.
  N*sizeof(float), // Data size.
  host_c,             // Host memory.
  0, NULL, NULL       // Events; ignore for now.
);
```

Note this is a **blocking** communication call - **it will not return until the copy has finished** — like `MPI_Send()`/`MPI_Recv()`.

[1] In CUDA: `cudaMemcpy(...,cudaMemcpyDeviceToHost)`.

# Copying data from host to device[1]

If we had *not* used `CL_MEM_COPY_HOST_PTR` earlier, we would need two calls to `clEnqueueWriteBuffer()`:

```
1 status = clEnqueueWriteBuffer(queue,device_a,CL_FALSE
      ,0,N*sizeof(float),host_a,0,NULL,NULL);
2 status = clEnqueueWriteBuffer(queue,device_b,CL_FALSE
      ,0,N*sizeof(float),host_b,0,NULL,NULL);
```

- Copies **from** host **to** device.
- `CL_FALSE` used for **non-blocking** communication.
- The device memory **always** comes before host memory in the argument list.

[1] In CUDA: `cudaMemcpy(...,cudaMemcpyHostToDevice)`.

# Work items

**Definition**

The **work item** is the unit of concurrent execution. It usually maps onto a single **hardware thread**.

As thread scheduling on a GPU is implemented in hardware, there is (essentially) **no overhead** in launching/destroying threads.

- No problem **oversubscribing**, *i.e.* issuing more threads than there are physical cores.

**Normally issue as many threads as the problem requires**.

# Work item hierarchy

To remain **scalable**, the hardware does not allow communication (including synchronisation) between *all* threads at once.

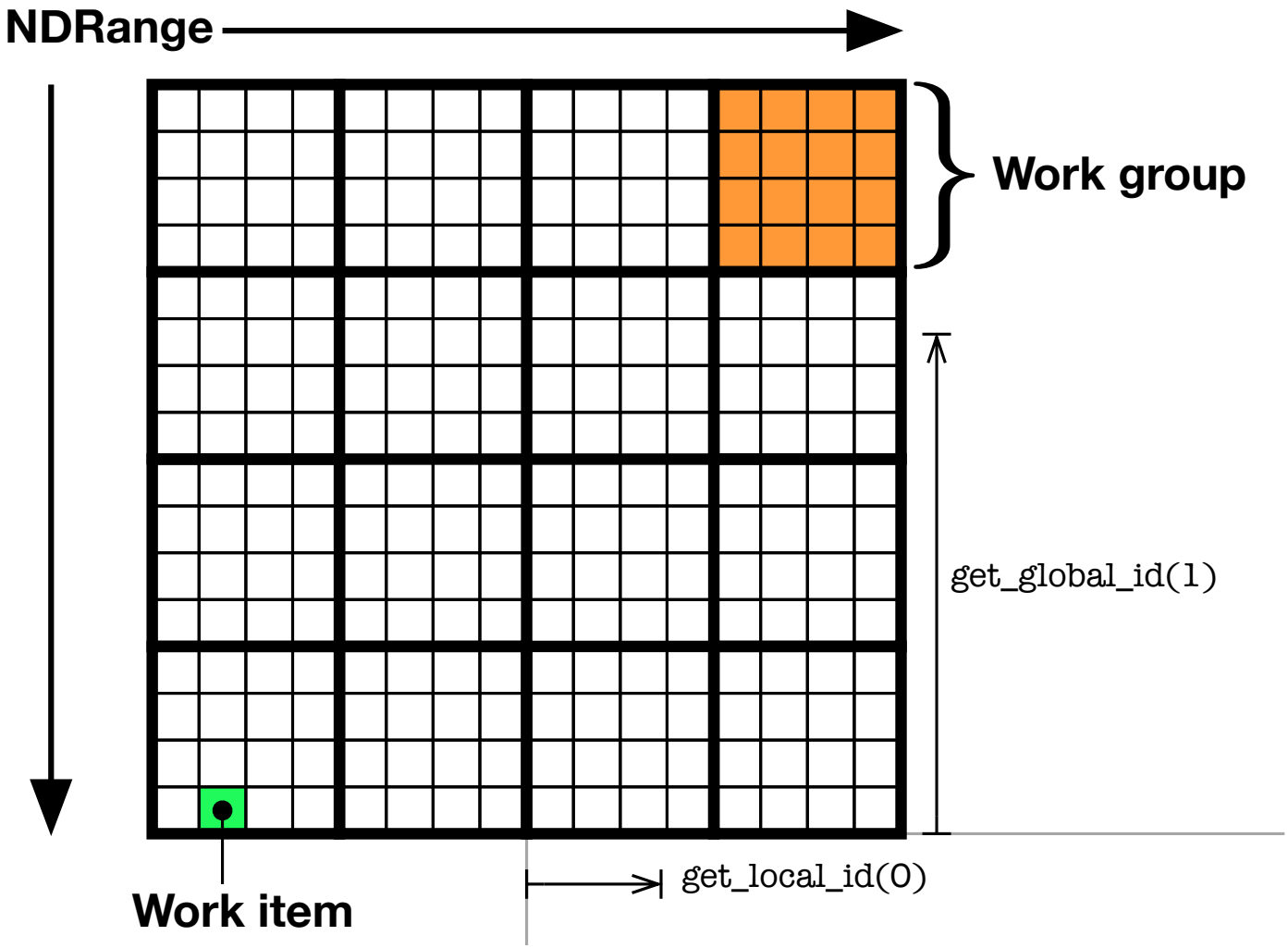
Instead employs a **hierarchy**:

- **Work items** belong to **work groups**[1].
- Communication (including synchronisation) only possible **within** a work group.

The full range of all threads is called **NDRange** in OpenCL, for *n*-dimensional range[2].

[1] *Threads* and *thread blocks* in CUDA.
[2] *Grid* in CUDA.

# Hierarchy of work items: 2D example



# Specifying the *n*-dimensional range NDRange

The NDRange must be 1, 2 or 3 dimensions.

A 2-dimensional example:

```
1 size_t globalSize    [2] = {X,Y };
2 size_t workGroupSize[2] = {8,16};
3
4 status = clEnqueueNDRangeKernel(queue,kernel,2,0,
    globalSize,workGroupSize,0,NULL,NULL);
```

- Launches `X*Y` kernels in total (one per work item).
- In work groups of 8*16.

OpenCL 2.0 allows `X` and `Y` to be arbitrary, but in earlier versions they must be multiples of the work group size (8 and 16 here).

Once in a kernel, can get the **global** indices using `get_global_id()`. For this 2D example:

```
get_global_id(0);  // Varies from 0 to X-1 inc.
get_global_id(1);  // Varies from 0 to Y-1 inc.
```

Similarly can get the indices **within** the work group using `get_local_id()`:

```
get_local_id(0);  // Varies from 0 to 7 inc.
get_local_id(1);  // Varies from 0 to 15 inc.
```

Can also get the number of work items in a group or in the NDRange using `get_local_size()` and `get_global_size()`:

```
get_local_size (1);  // Returns 16.
get_global_size(0);  // Returns X.
```

# What group size to use?

Devices have a **maximum work group size** they can support. This can be determined at run time as follows:

```
1 size_t maxWorkItems;
2 clGetDeviceInfo(device,CL_DEVICE_MAX_WORK_GROUP_SIZE,
      sizeof(size_t),&maxWorkItems,NULL);
```

Note this refers to **all** items in a group (*i.e.* 8*16=128).

Other factors may suggest using work group sizes less than this maximum.

- We will look at one of these next time.

Passing `NULL` as the work group argument lets OpenCL try to determine a suitable size **automatically**.

# Summary and next lecture

Today we have looked at a complete GPGPU solution:

- **Communication** between **host** and **device**.
- **Kernels** that execute on the device.
- Basic unit of concurrency is the **work item**.
- Group into **work groups**, within which communication is possible.

In the following lecture we will look at the different memory types on a GPU.