A QUICK INTRODUCTION TO SYCL

LEARNING OBJECTIVES

- Quick SYCL introduction
- Writing a one-page application

WHAT IS SYCL?

SYCL is a single source, high-level, standard C++ programming model, that can target a range of heterogeneous platforms

WHAT IS SYCL?

A first example of SYCL code.

```
1  #include <sycl/sycl.hpp>
2
3  int main(int argc, char *argv[]) {
4    std::vector<float> dA{2.3}, dB{3.2}, dO{7.9};
5
6    try {
7      auto asyncHandler = [&](sycl::exception_list eL) {
8        for (auto &e : eL)
9          std::rethrow_exception(e);
10     };
11     sycl::queue gpuQueue{sycl::default_selector{}, asyncHandler};
12
13     sycl::buffer bufA{dA.data(), sycl::range{dA.size()}};
14     sycl::buffer bufB{dB.data(), sycl::range{dB.size()}};
15     sycl::buffer bufO{dO.data(), sycl::range{dO.size()}};
16
17     gpuQueue.submit([&](sycl::handler &cgh) {
18       sycl::accessor inA(bufA, cgh, sycl::read_only);
19       sycl::accessor inB(bufB, cgh, sycl::read_only);
20       sycl::accessor out(bufO, cgh, sycl::write_only);
21
22       cgh.parallel_for(sycl::range{dA.size()},
23                        [=](sycl::id<1> i) { out[i] = inA[i] + inB[i]; });
24     });
25
26     gpuQueue.wait_and_throw();
27
28   } catch (sycl::exception &e) {
                                  YCL exception */
31 }
```

Managing the data

Work unit

Device code

SYCL KEY CONCEPTS

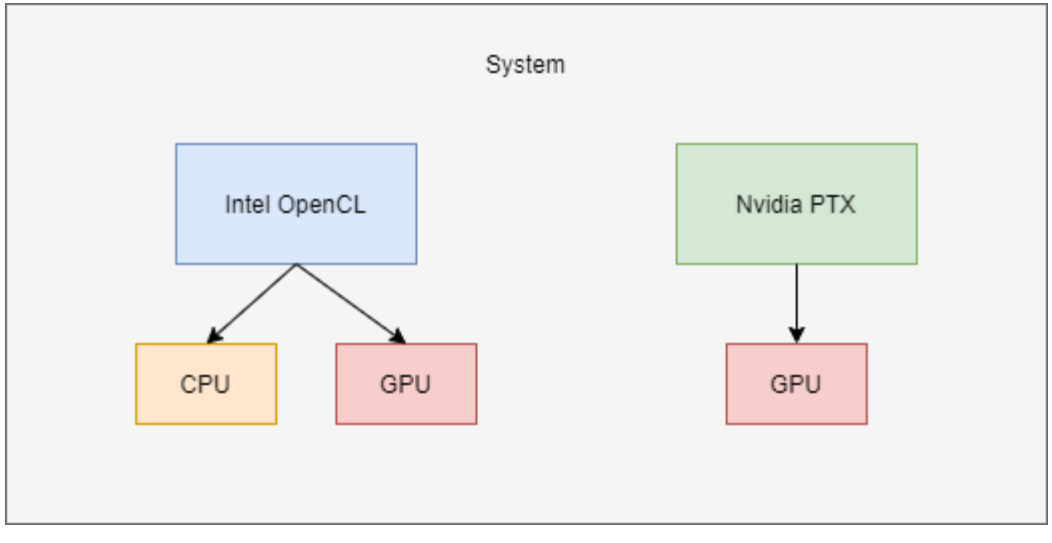
- SYCL is a C++-based programming model:
  - Device code and host code exist in the same file
  - Device code can use templates and other C++ features
  - Designed with "modern" C++ in mind
- SYCL provides high-level abstractions over common boilerplate code
  - Platform/device selection
  - Buffer creation and data movement
  - Kernel function compilation
  - Dependency management and scheduling

SYCL SYSTEM TOPOLOGY

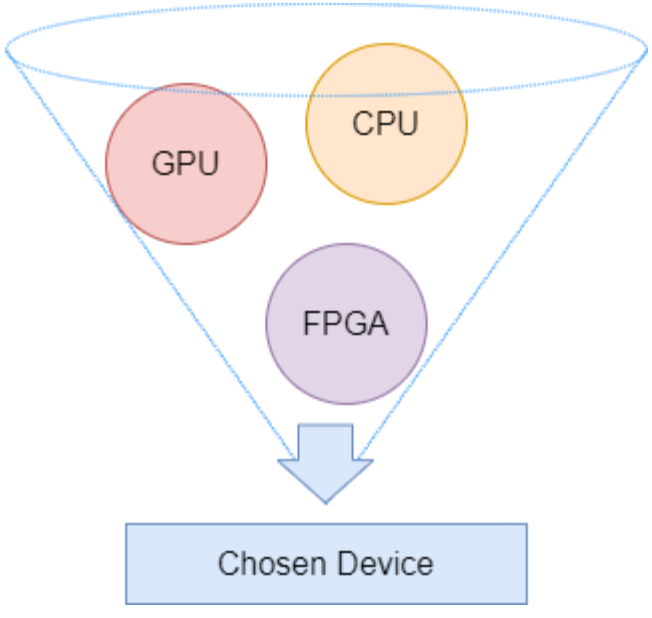
- A SYCL application can execute work across a range of different heterogeneous devices.
- The devices that are available in any given system are determined at runtime through topology discovery.

PLATFORMS AND DEVICES

- The SYCL runtime will discover a set of platforms that are available in the system.
    - Each platform represents a backend implementation such as Intel OpenCL or Nvidia CUDA.
- The SYCL runtime will also discover all the devices available for each of those platforms.
    - CPU, GPU, FPGA, and other kinds of accelerators.



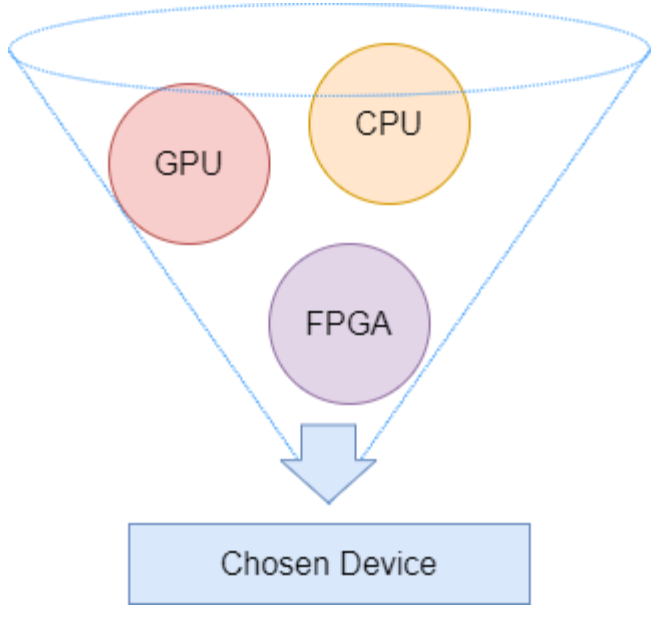
QUERYING WITH A DEVICE SELECTOR



- To simplify the process of traversing the system topology SYCL provides device selectors.
- A device selector is is a callable C++ object which defines a heuristic for scoring devices.
- SYCL provides a number of standard device selectors, e.g. `default_selector_v`, `gpu_selector_v`, etc.
- Users can also create their own device selectors.

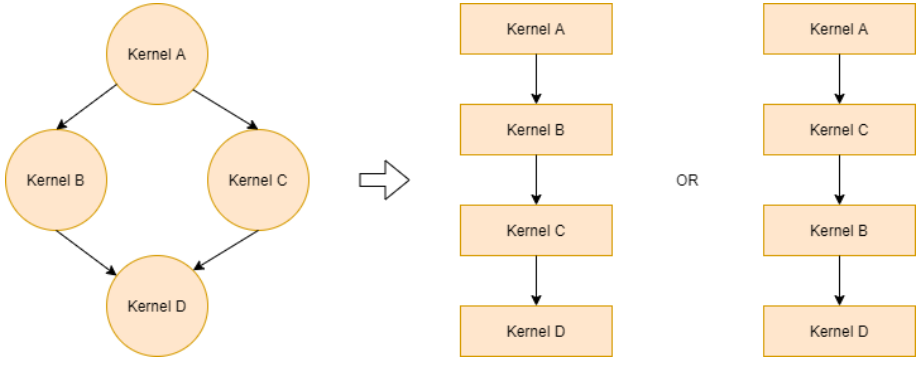
QUERYING WITH A DEVICE SELECTOR

```
auto gpuDevice = device(gpu_selector_v);
```



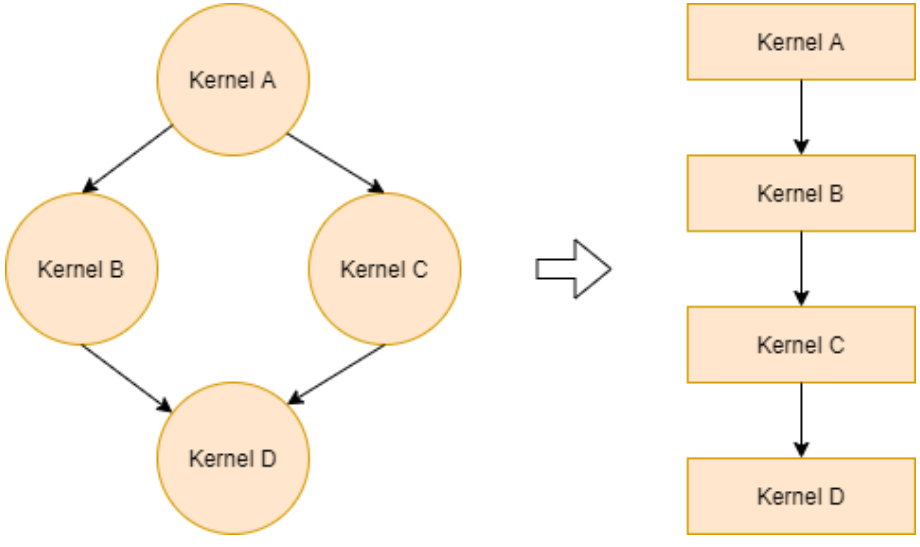
- A device selector takes a parameter of type `const device &` and gives it a "score".
- Used to query all devices and return the one with the highest "score".
- A device with a negative score will never be chosen.

SYCL QUEUES



- Commands are submitted to devices in SYCL by means of a Queue
- SYCL queues are by default out-of-order.
- This means commands are allowed to be overlapped, re-ordered, and executed concurrently, providing dependencies are honoured to ensure consistency.

IN-OF-ORDER EXECUTION



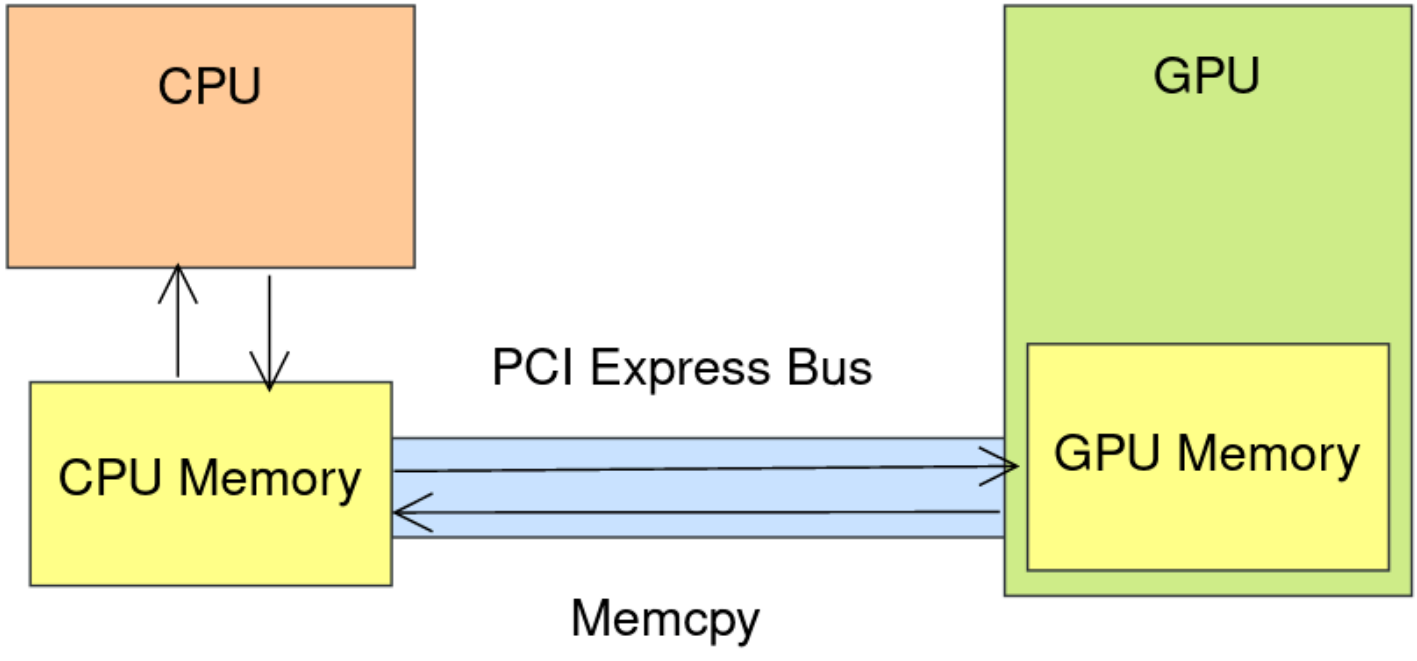
- SYCL queues can be configured to be in-order.
- This mean commands must execute strictly in the order they were enqueued.

MEMORY MODELS

- In SYCL there are two models for managing data:
  - The buffer/accessor model.
  - The USM (unified shared memory) model.
- Which model you choose can have an effect on how you enqueue kernel functions.

CPU AND GPU MEMORY

- A GPU has its own memory, separate to CPU memory.
- In order for the GPU to use memory from the CPU, the following actions must take place (either explicitly or implicitly):
    - Memory allocation on the GPU.
    - Data migration from the CPU to the allocation on the GPU.
    - Some computation on the GPU.
    - Migration of the result back to the CPU.

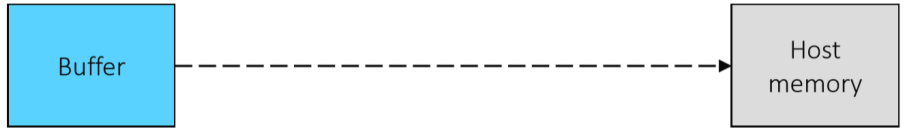


SYCL BUFFERS & ACCESSORS

- The buffer/accessor model separates the storage and access of data
  - A SYCL buffer manages data across the host and any number of devices
  - A SYCL accessor requests access to data on the host or on a device for a specific SYCL kernel function
- Accessors are also used to access data within a SYCL kernel function
  - This means they are declared in the host code but captured by and then accessed within a SYCL kernel function

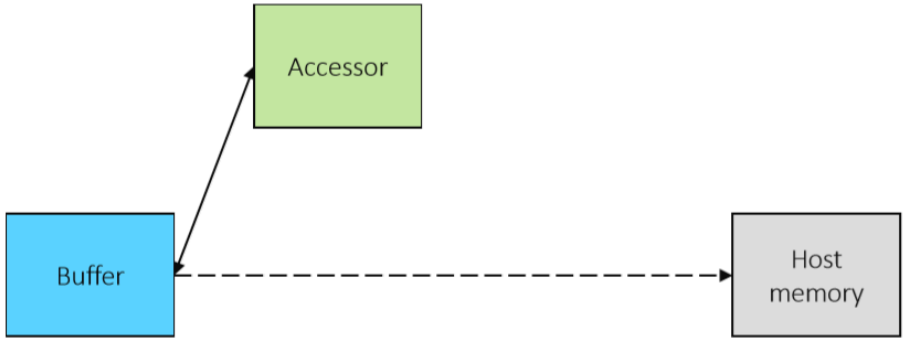
SYCL BUFFERS & ACCESSORS

- When a buffer object is constructed it will not allocate or copy to device memory at first
- This will only happen once the SYCL runtime knows the data needs to be accessed and where it needs to be accessed



SYCL BUFFERS & ACCESSORS

- Constructing an accessor specifies a request to access the data managed by the buffer
- There are a range of different types of accessor which provide different ways to access data



ACCESSING DATA WITH ACCESSORS

```
buffer<float, 1> bufA(dA.data(), range<1>(dA.size()));
buffer<float, 1> bufB(dB.data(), range<1>(dB.size()));
buffer<float, 1> bufO(dO.data(), range<1>(dO.size()));

gpuQueue.submit([&](handler &cgh){
  sycl::accessor inA{bufA, cgh, sycl::read_only};
  sycl::accessor inB{bufB, cgh, sycl::read_only};
  sycl::accessor out{bufO, cgh, sycl::write_only};
  cgh.parallel_for<add>(range<1>(dA.size()),
    [=](id<1> i){
    out[i] = inA[i] + inB[i];
  });
});
```

- Here we access the data of the `accessor` by passing in the `id` passed to the SYCL kernel function.

USM: MALLOC_DEVICE

```
void* malloc_device(size_t numBytes, const queue& syclQueue, const property_list &propList = {});

template <typename T>
T* malloc_device(size_t count, const queue& syclQueue,  const property_list &propList = {});
```

- A USM device allocation is performed by calling one of the `malloc_device` functions.
- Both of these functions allocate the specified region of memory on the `device` associated with the specified queue.
- The pointer returned is only accessible in a kernel function running on that `device`.
- Synchronous exception if the device does not have aspect::usm_device_allocations
- This is a blocking operation.

USM: FREE

```
void free(void* ptr, queue& syclQueue);
```

- In order to prevent memory leaks USM device allocations must be free by calling the `free` function.
- The `queue` must be the same as was used to allocate the memory.
- This is a blocking operation.

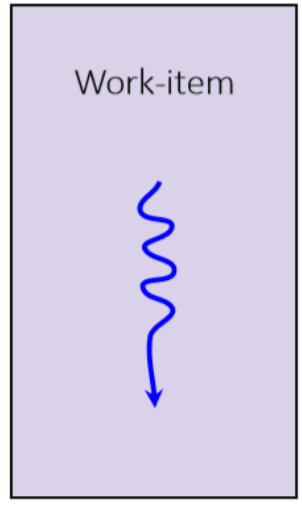
USM: MEMCPY

```
event queue::memcpy(void* dest, const void* src, size_t numBytes, const std::vector &depEvents);
```

- Data can be copied to and from a USM device allocation by calling the queue's `memcpy` member function.
- The source and destination can be either a host application pointer or a USM device allocation.
- This is an asynchronous operation enqueued to the queue.
- An `event` is returned which can be used to synchronize with the completion of copy operation.
- May depend on other events via `depEvents`

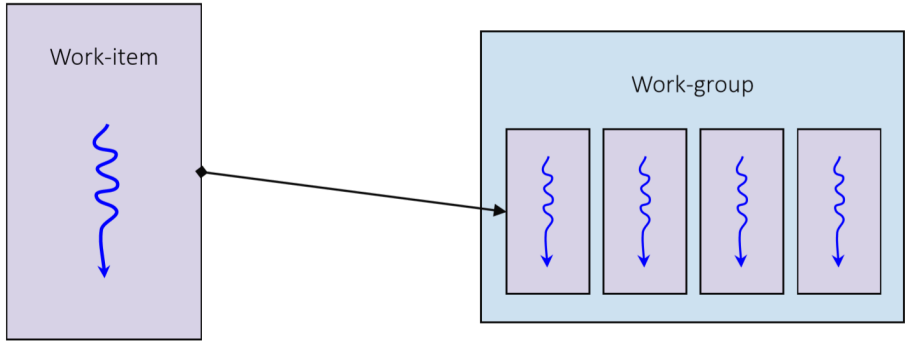
SYCL EXECUTION MODEL

- SYCL kernel functions are executed by **work-items**
- You can think of a work-item as a thread of execution
- Each work-item will execute a SYCL kernel function from start to end
- A work-item can run on CPU threads, SIMD lanes, GPU threads, or any other kind of processing element



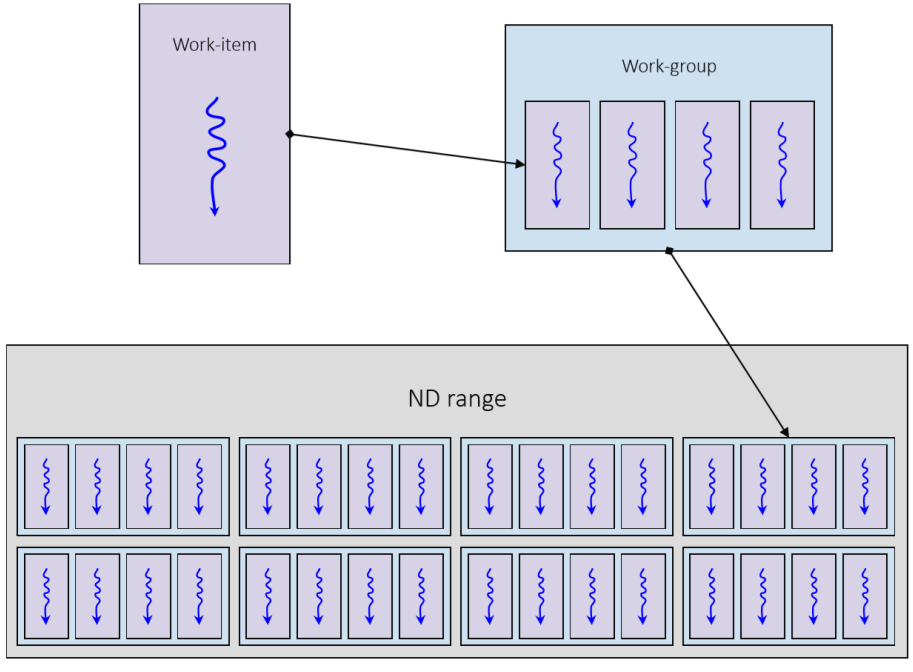
SYCL EXECUTION MODEL

- Work-items are collected together into **work-groups**
- The size of work-groups is generally relative to what is optimal on the device being targeted
- It can also be affected by the resources used by each work-item



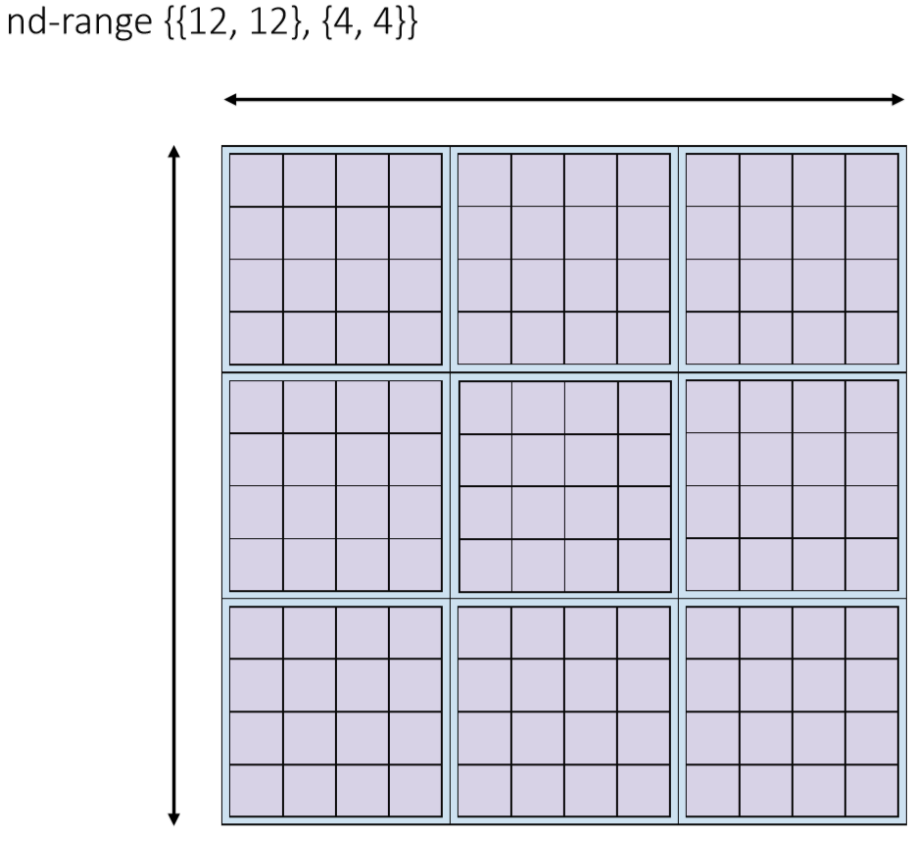
SYCL EXECUTION MODEL

- SYCL kernel functions are invoked within an **nd-range**
- An nd-range has a number of work-groups and subsequently a number of work-items
- Work-groups always have the same number of work-items



SYCL EXECUTION MODEL

- The nd-range describes an **iteration space**: how it is composed in terms of work-groups and work-items
- An nd-range can be 1, 2 or 3 dimensions
- An nd-range has two components
  - The **global-range** describes the total number of work-items in each dimension
  - The **local-range** describes the number of work-items in a work-group in each dimension



EXPRESSING PARALLELISM

```
cgh.parallel_for<kernel>(range<1>(1024),
  [=](id<1> idx){
    /* kernel function code */
});
```

- Overload taking a **range** object specifies the global range, runtime decides local range
- An **id** parameter represents the index within the global range

---

```
cgh.parallel_for<kernel>(range<1>(1024),
  [=](item<1> item){
    /* kernel function code */
});
```

- Overload taking a **range** object specifies the global range, runtime decides local range
- An **item** parameter represents the global range and the index within the global range

---

```
cgh.parallel_for<kernel>(nd_range<1>(range<1>(1024),
  range<1>(32)),[=](nd_item<1> ndItem){
    /* kernel function code */
});
```

- Overload taking an **nd_range** object specifies the global and local range
- An **nd_item** parameter represents the global and local r

SYCL KERNELS

- SYCL kernels (i.e. the device function the programmer wants executed) are expressed either as C++ function objects or lambdas.
- Comparing with other GPU paradigms, kernel arguments are either data members or lambda captures, respectively
- For function objects, the member function `operator()(sycl::id)` is the compute function, which is equivalent to the lambda style

```
// then add slides explaining the practical work and how to
// glue it all together from scratch
```

FUNCTION OBJECT

```
class MyKernel {
  sycl::accessor input_;
  float* output_;

  MyKernel(sycl::buffer buf, float* output, sycl::handler& h)
    : input{buf.get_access(h)}, output_{output} {}

  // const is required
  void operator()(sycl::item<1> i) const {
    ; // computation here
  }
};
```

The members are accessible on the device inside the function call operator.

LAMBDA FUNCTION

```
sycl::buffer buf = /* normal init */;
float * output = sycl::malloc_device(/* params */);

... queue submit as normal ...

auto acc = buf.get_access(h);
auto func = [=](sycl::item<1> i) {
  acc[i] = someVal;
  output[i.get_global_linear_id()] = someOtherVal;
});
handler.parallel_for(range, func);
```

The variables used implicitly are captured by value and are usable in the kernel.

SYCL KERNELS

- These forms are equivalent (as in normal C++) and which one to use depends on preference and use case
- Each instance of the kernel has a uniquely valued `sycl::item` describing its position in the iteration space as covered in "SYCL execution model"
- Can be used to index into accessors, pointers etc.

FIRST EXERCISE

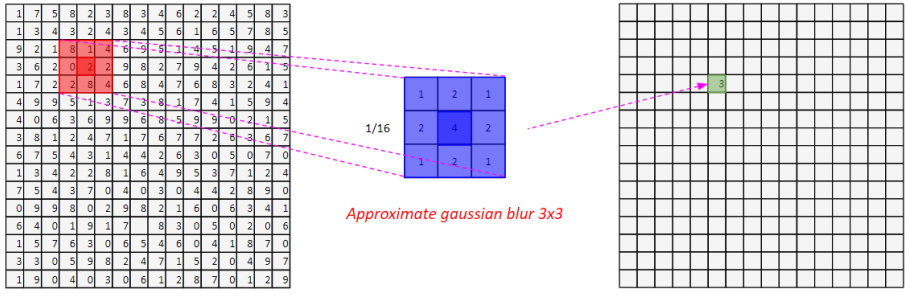
- Use Data Parallelism and write a SYCL kernel
- The exercise README is in the "Code_Exercises/Introduction_to_SYCL" folder
- Follow the guidelines in the README and comments in the source.cpp file
    - There is a solution file but only use it if you need to

IMAGE CONVOLUTION SAMPLE APPLICATION

- The algorithm is **embarrassingly parallel**.
- Each work-item in the computation can be calculated entirely independently.
- The algorithm is computation heavy.
- A large number of operations are performed for each work-item in the computation, particularly when using large filters.
- The algorithm requires a large bandwidth.
- A lot of data must be passed through the GPU to process an image, particularly if the image is very high resolution.

IMAGE CONVOLUTION DEFINITION

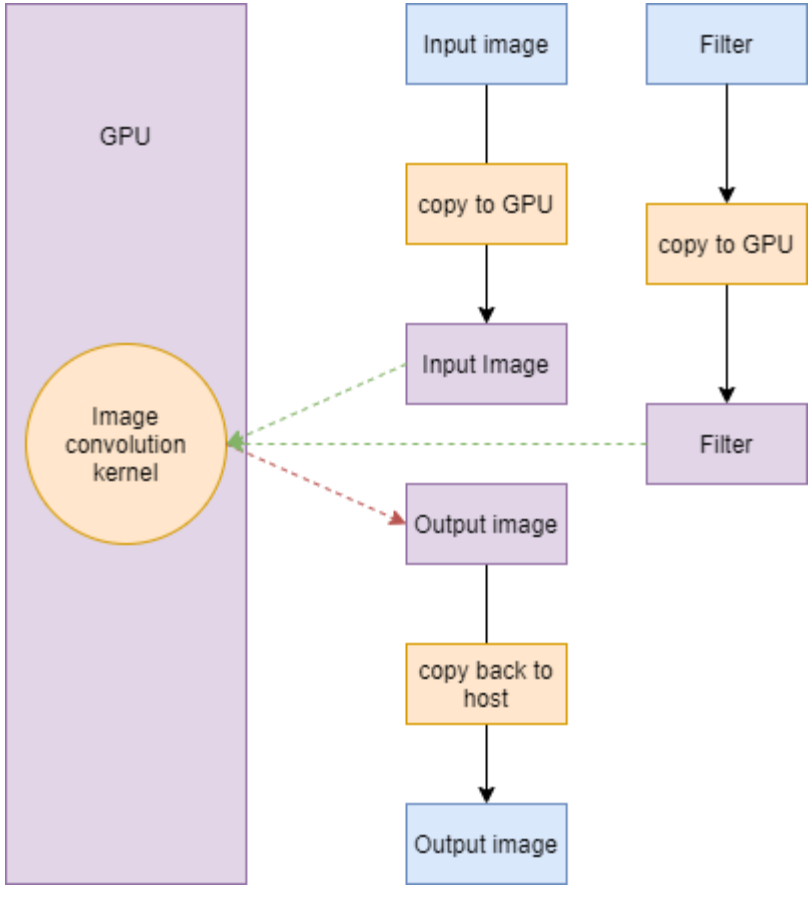
$$G = h \otimes F \qquad G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} h[u,v]F[i+u, j+v]$$



- A filter of a given size is applied as a stencil to the position of each pixel in the input image.
- Each pixel covered by the filter is then multiples with the corresponding element in the filter.
- The result of these multiplications is then summed to give the resulting output pixel.
- Here we have a 3x3 gaussian blur approximation as an example.

IMAGE CONVOLUTION EXAMPLE

IMAGE CONVOLUTION DATA FLOW



- The kernel must read from the input image data and writes to the output image data.
- It must also read from the filter.
- The input image data and the filter don't need to be copied back to the host.
- The output image data can be uninitialized.

GAUSSIAN BLUR

- The blur is implementable in two passes: one vertical, one horizontal
- Each item in the iteration space would load a series of pixels to the left and right (or top and bottom) of its position in the image
- Then, multiply with the corresponding element in the filter
- Then sum these intermediate results and store them to the output
- A dscrete convolution, in other words

WALKTHROUGH

- Explain a more complex example through image convolution
- Solution available in `Code_Exercises/Image_Convolution_Functors/solution.cpp`

REFERENCE IMAGE

- We provide a reference image to use in the exercise.
- This is in Code_Exercises/Images
- This image is a 512x512 RGBA png.
- Feel free to use your own image but we recommend keeping to this format.
- The read and write functions can be found in `image_conv.h`.

CONVOLUTION FILTERS

- `auto filter = util::generate_filter(util::filter_type filterType, int width);`
- The utility for generating the filter data takes a `filter_type` enum which can be either `identity` or `blur` and a width.
- Feel free to experiment with different variations.
- Note that the filter width should always be an odd value.
- The function can be found in `image_conv.h`