GPU Programming Using CUDA

Samuli Laine

NVIDIA

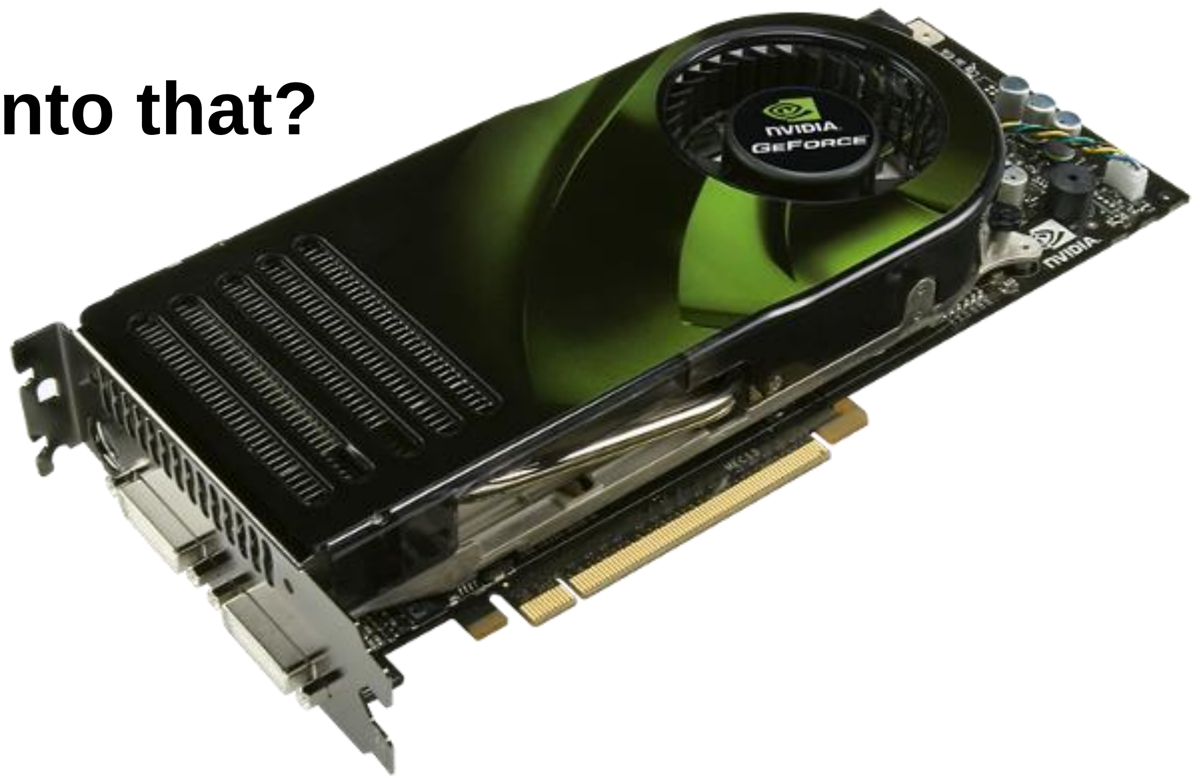
Today

- Brief history of CUDA
- Machine and execution model
- Writing CUDA kernels
- Using the API

- Will not look at the hardware yet
  - That's for next week

Motivation for GPU programming

- This thing packs a lot FLOPs and memory bandwidth
- How to tap into that?



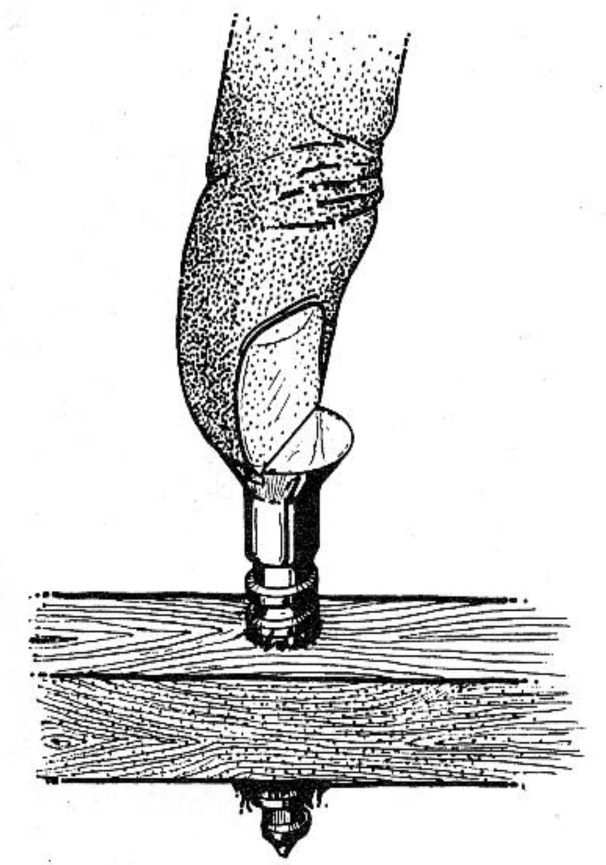
Early days: GPGPU

- General-Purpose GPU programming
  - The craze around 2004 – 2006
- Trick the GPU into general-purpose computing by casting problem as graphics
  - Turn data into images (textures)
  - Turn algorithms into image synthesis (rendering passes)
- Many attempts to handle these automatically
  - Brook, Sh, PeakStream, MS Accelerator, …
  - Take a "program", somehow convert to shaders

Problems with GPGPU

- Constrained memory access model
  - No scattered writes, no generic read/write
- Split computation into multiple passes
  - Limited by what shaders can do
  - Must understand graphics HW to understand the limitations
  - Trickery to circumvent the rigidity of hardware
- Overhead of graphics API

GPGPU: An illustrated guide



The road to CUDA

- Okay, this GPGPU thing has potential
  - The only problem is that it sucks
- Let’s design the right tool for the job
- Need new hardware capabilities? → Build it
  - We are a hardware company, after all
- Develop a better API for poking the GPU
  - Extend C++, don’t invent a new language
- CUDA 1.0 released in June 2007
  - An established and mature platform by now

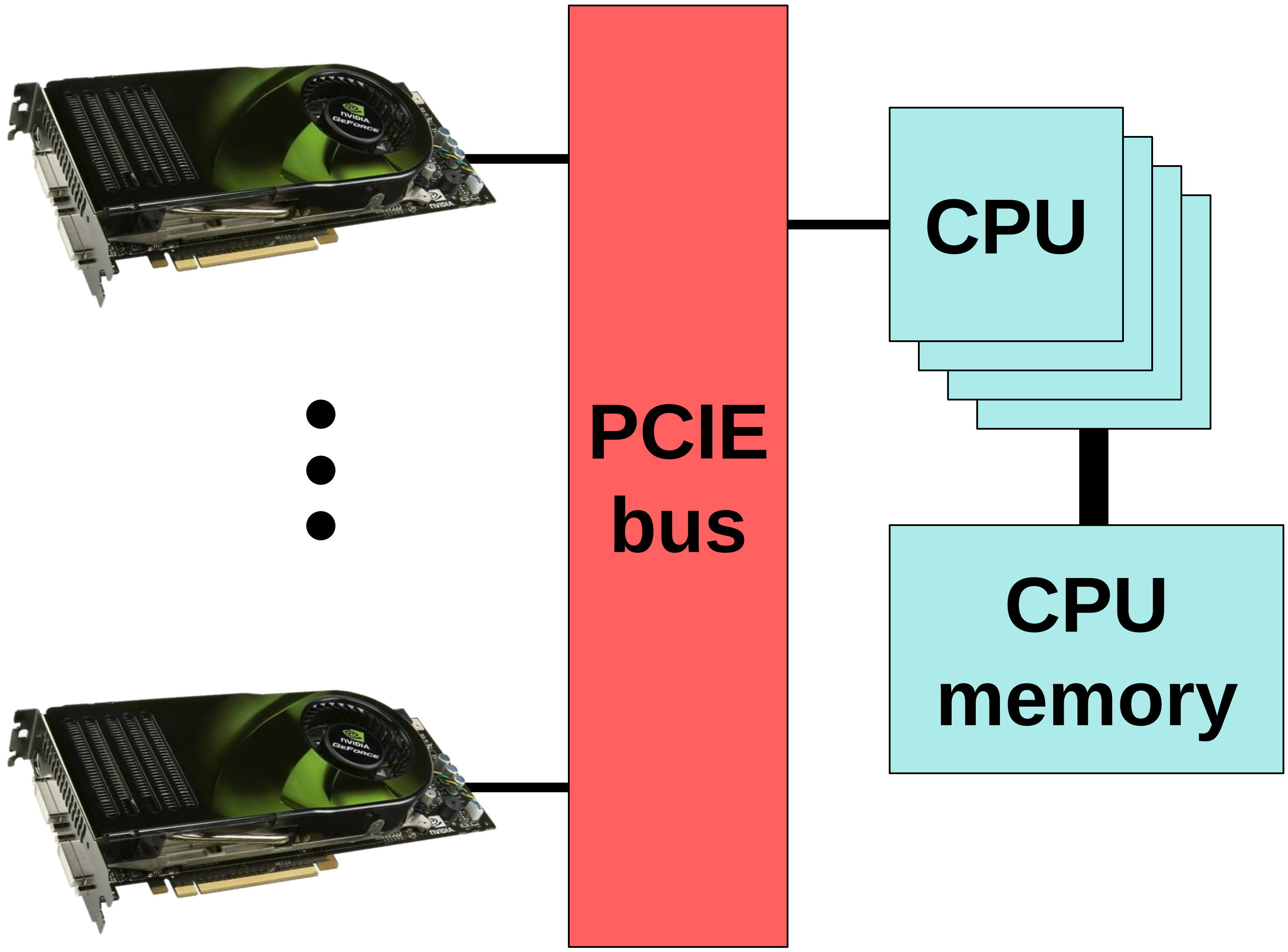
What is CUDA

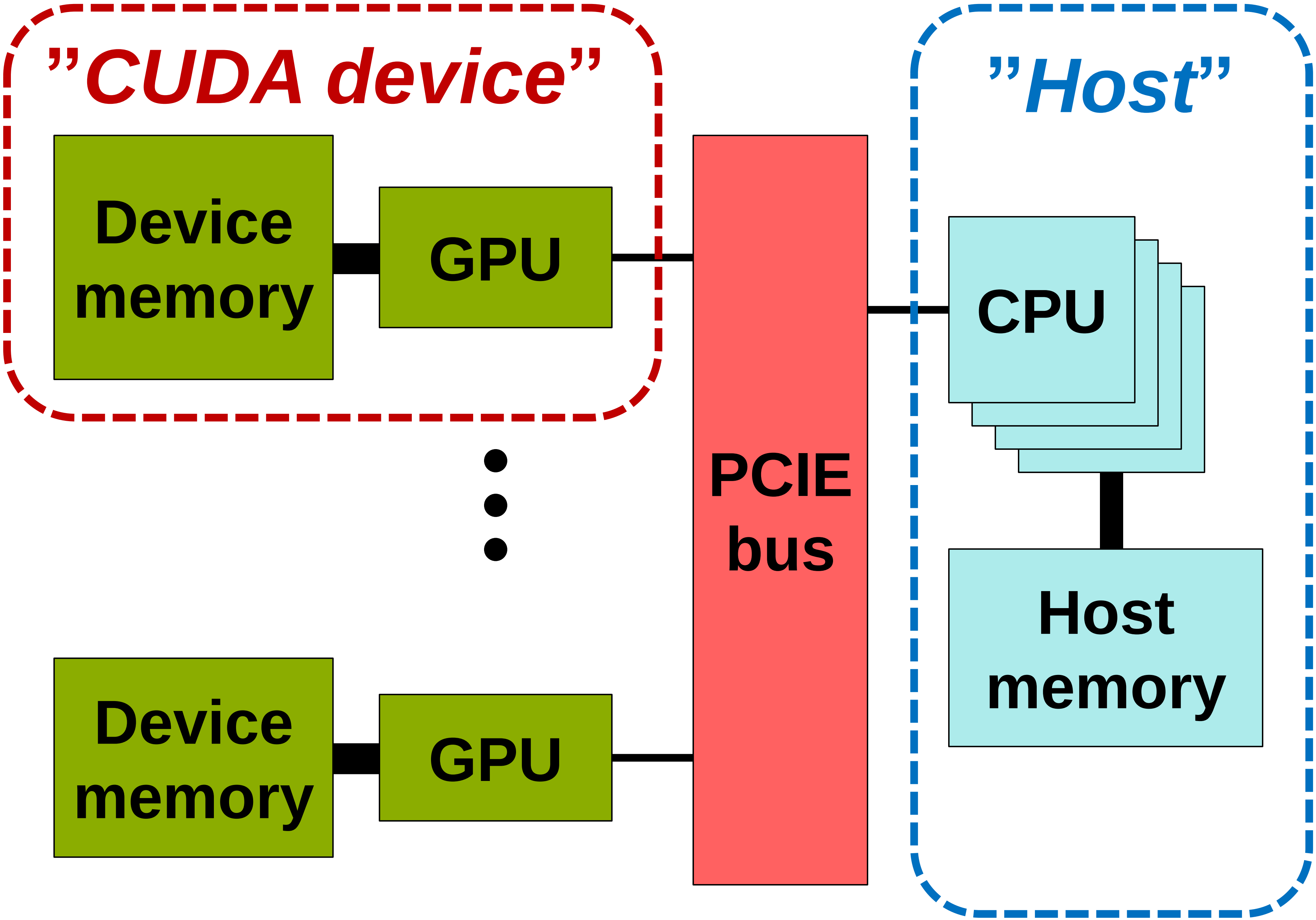
- A set of C/C++ language extensions that allow writing programs that run on GPUs
- C/C++ API for configuring and managing GPU execution, memory, etc.

- Tools for compiling, profiling and debugging your code
- Libraries for common tasks (FFT, BLAS, …)
- Documentation

Machine and execution model

CUDA machine model




"CUDA device"
Device memory
GPU
Device memory
GPU
PCIE bus
"Host"
CPU
Host memory

CUDA execution model

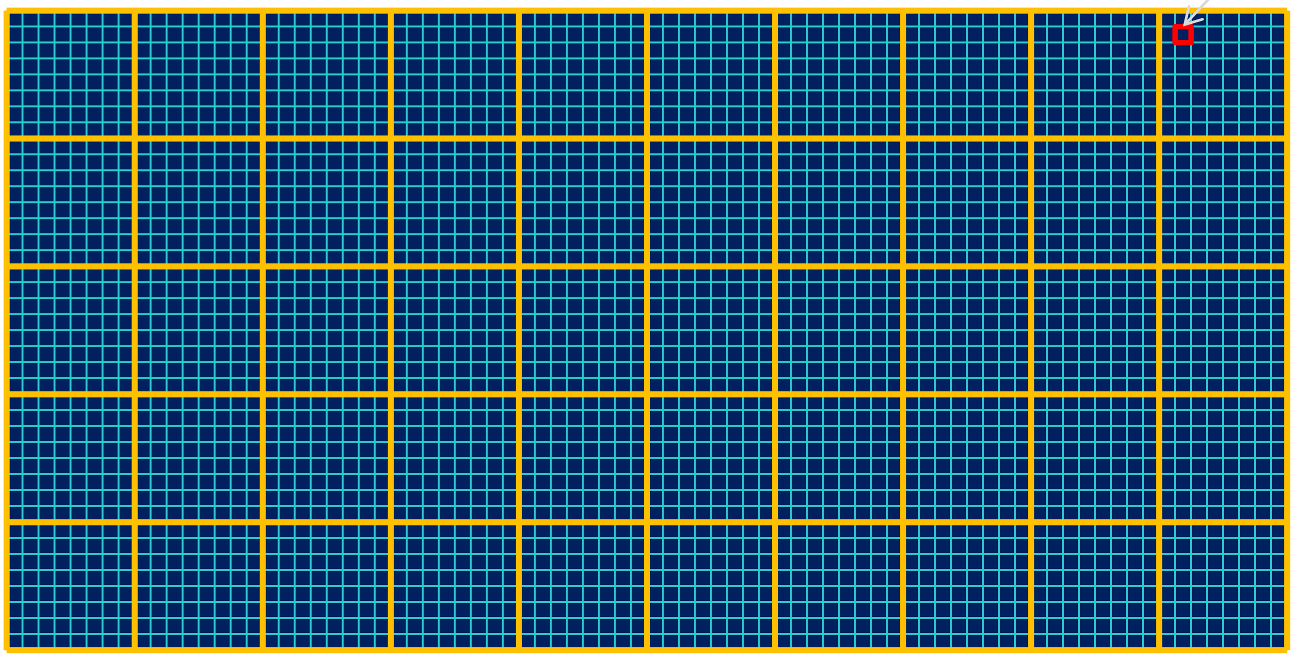
- **Kernel ≈ A function executed over a large number of threads on a GPU**
- **A kernel is launched over a grid of blocks**
  - **Blocks and grid can be 1D, 2D or 3D**
  - **Extra dimensions are really just syntactic sugar but convenient if the data lives in a 2D or 3D domain**
- **Every thread can query its**
  - **Thread location within the block (`threadIdx`)**
  - **Block location within the grid (`blockIdx`)**
  - **Block and grid dimensions (`blockDim`, `gridDim`)**

Example

- **Use blocks with 8 × 8 threads**
- **Launch a grid of 10 × 5 blocks**
- **Total = 8 × 8 × 10 × 5 = 3200 threads**

```
threadIdx.x = 1
threadIdx.y = 1
blockIdx.x = 9
blockIdx.y = 0

blockDim.x = 8
blockDim.y = 8
gridDim.x = 10
gridDim.y = 5
```



Why blocks?

- Why do we have blocks, instead of just a flat gigantic grid of threads?
  - Block is guaranteed to be localized
    - All threads of a block run at the same time
- Threads of a block can use fast shared memory
  - Load common data together and work on it
- Threads of a block can synchronize efficiently
- Individual blocks must be truly independent
  - No guarantees about execution order or parallelism

Writing CUDA kernels

Digression: CUDA API flavors

- **Driver API** **(function prefix `cu`, e.g., `cuMemcpy`)**
  - **Low-level → lots of control for programmer**
  - **E.g., explicit uploading of kernel binaries**
- **Runtime API** **(function prefix `cuda`, e.g., `cudaMemcpy`)**
  - **High-level → easy to use**
  - **Automatic mixed C/C++/CUDA compilation**
  - **Automatic management of kernel binaries**
  - **Syntactic sugar for ease of use**
  - **We will be using this**

Code organization

- Source files may contain a mixture of host and device code
  - Recommended to use extension `.cu` for these
- These are compiled with Nvidia's NVCC
  - Host code gets compiled with `gcc`
  - Device code gets compiled with Nvidia tools
    - Produce device binaries for multiple platforms
  - CUDA kernel launches from host code are patched to upload the relevant binaries to GPU, etc.
  - Everything is linked together in a single `.o` file

CUDA language extensions

- These are understood by NVCC
- Function and variable decorators
  - `__device__`: Executes on GPU, callable from GPU
  - `__global__`: Executes on GPU, callable from CPU (= kernel)
    - Callable from GPU as well on modern hardware
  - `__host__`: Ordinary CPU function (default, can be omitted)
- Storage specifiers
  - `__shared__`: Block-wide shared memory
  - `__constant__`: Constant memory
- Special variables in device code
  - `threadIdx`, `blockIdx`, `blockDim`, `gridDim`, etc.

Kernel launch

`kernelFunc<<<Dg, Db>>>(parameters)`

- `kernelFunc` has to be a `__global__` function
- `Dg` and `Db` are grid and block dimensions
  - Type either `int` or `dim3`
    - Which is just a struct of `unsigned int x, y, z;`
    - Components initialized to 1 by default

Example kernel and launch

```
// Device code
__global__ void my_kernel(int size_x, int size_y,
                          const float* input, float* output)
{
    int x = threadIdx.x + blockIdx.x * blockDim.x;
    int y = threadIdx.y + blockIdx.y * blockDim.y;
    if (x >= size_x || y >= size_y)
        return;
    output[x + size_x * y] = 2.0 * input[x + size_x * y];
}

// Host code
    ...
    dim3 szBlock(16, 16);
    dim3 szGrid((size_x + szBlock.x - 1) / szBlock.x,
                (size_y + szBlock.y - 1) / szBlock.y);
    my_kernel<<<szGrid, szBlock>>>(size_x, size_y, ...);
    ...
```

Shared memory

- Specified using the `__shared__` keyword
- Unlike normal variables, not a per-thread resource but a per-block resource
  - All threads in a block see the same variable / array
- To cooperate, threads usually must synchronize between shared writes and reads
  - `__syncthreads()`
  - Does not proceed until all treads in block have reached this point
  - Synchronizing in conditional code → trouble

Shared memory, continued

- Shared memory is close to the execution units
  - Much faster than ordinary device memory
- It is also a limited resource
  - Basically limits how many threads the GPU can have resident
    - Somewhat complex issue, will go into more details in the next lecture
  - If you use *way* too much (over 48 KB per block), the kernel cannot be launched at all

Shared memory, example

1. Each thread moves a piece of data from device memory into shared memory
2. All threads call `__syncthreads()`
3. Each thread looks at a window of data in shared memory (read-only)
4. Each thread writes its result into its own location in device memory

Runtime API

Calling CUDA API functions

- In addition to declaring and launching kernels, a program typically performs CUDA API calls to, e.g.,
  - Select the CUDA device
  - Allocate / free / copy memory
  - Manage events for benchmarking
  - Synchronize between host and device
- These are plain old library function calls
  - If a file does not contain device code, can be compiled with `gcc`

Error codes

- Every function returns an error code
  - Type `cudaError_t`
  - Value is `cudaSuccess` (= 0) if no error occurred
- Helpers to convert error code to string
  - `const char* cudaGetErrorName(cudaError_t error)`
  - `const char* cudaGetErrorString(cudaError_t error)`
- To get last error (e.g., from kernel launch)
  - `cudaError_t cudaGetLastError(void)`

- If something doesn't work, check errors first!

Parts of the API covered

- Device management
- Memory management
- Basic synchronization
- Events

- This is only a small subset of the API, but should be enough for this course

Device management

```
cudaGetDeviceCount(int* count)
cudaGetDeviceProperties(cudaDeviceProp* prop,
                        int device)
cudaSetDevice(int device)
```

- Device 0 is selected by default
  - Driver always places the ”best” device to slot 0
  - So, often no need to call `cudaSetDevice` at all
- Device selection is a low-overhead call
  - Using multiple GPUs from same CPU thread

Memory management

- Host and device memories are separate
- But device can access host memory directly
  - So-called ”zero-copy” memory
  - Slow, but sometimes the best choice

- Basic pattern: Allocate memory on device and copy data between host and device explicitly
  - This is usually the fastest option

Memory allocation on device

```
cudaMalloc(void** devPtr, size_t size)
cudaFree(void* devPtr)
```

- `cudaMalloc` gives a C/C++ pointer that CANNOT be dereferenced on the host
  - Mixing up host and device pointers → crash
- Valid uses for the device pointer:
  - CUDA API calls (e.g. `cudaMemcpy`)
  - Passing it as parameter in a kernel launch

Memory allocation on host

```
cudaMallocHost(void** ptr, size_t size)
cudaFreeHost(void* ptr)
```

- Returns host pointer to *page-locked* memory
  - Whenever copying data between host and device, the memory has to be page-locked
  - If copying from/to ordinarily allocated memory (from `malloc` / `new[]`), must page-lock and unlock at every copy, which takes time
  - Page-locked memory cannot be swapped out by the operating system

Mapping host memory on device

```
cudaHostAlloc(void** pHost, size_t size,
              unsigned int flags)
cudaHostRegister(void* ptr, size_t size,
                 unsigned int flags)
cudaHostGetDevicePointer(void** pDevice,
    void* pHost, unsigned int flags)
cudaHostUnregister(void* ptr)
cudaFreeHost(void* ptr)
```

- Allocate mapped, page-locked memory <u>or</u> register (page-lock + map) an existing range
  - Set `flags` = `cudaHostAllocMapped`
- Query a device pointer to that range

Copying memory

```
cudaMemcpy(void* dst, const void* src,
           size_t count,
           cudaMemcpyKind kind)
```

- One function for all directions
  - Plain `memcpy` is of course fine for host→host copy
- `dst` and `src` must be either host or device pointers depending on usage
- `kind` is `cudaMemcpyHostToHost`, `cudaMemcpyHostToDevice`, `cudaMemcpyDeviceToHost`, or `cudaMemcpyDeviceToDevice`
- Fully synchronous: Waits until device is idle, returns after copy is complete *

Note on API asynchronicity

- Many CUDA calls are in reality asynchronous
  - Place a request in command stream, return immediately
- Also true for kernel launches
  - Control returns to host thread immediately
  - Kernel starts running when the device frees up
- Implicit synchronization at certain points
  - E.g., memory transfers
- Explicit synchronization also possible
- This matters when benchmarking

API asynchronicity: Example 1

1. Start CPU timer
2. Copy data from host to device
3. Launch kernel
4. Copy results from device to host
5. Stop CPU timer

- Stop works, because step 4 forces synchronization between host and device
- Start does not: timer may include previously issued GPU operations

API asynchronicity: Example 2

1. **Copy data from host to device**
2. **Start CPU timer**
3. **Launch kernel**
4. **Stop CPU timer**
5. **Copy results from device to host**

- **This does not give the kernel execution time**
- **For correct results, must either synchronize explicitly, or use *events***

Explicit synchronization

`cudaDeviceSynchronize(void)`

- **Returns after all kernel launches and API calls issued so far have been completed**

Synchronization example

1. Copy data from host to device
2. Call `cudaDeviceSynchronize()`
3. Start CPU timer
4. Launch kernel
5. Call `cudaDeviceSynchronize()`
6. Stop CPU timer
7. Copy results from device to host

- Gives a rough estimate of kernel execution time

Events

```
cudaEventCreate(cudaEvent_t* event)
cudaEventDestroy(cudaEvent_t event)
cudaEventRecord(cudaEvent_t event)
cudaEventElapsedTime(float* ms,
        cudaEvent_t start, cudaEvent_t end)
cudaEventSynchronize(cudaEvent_t event)
```

- **Best way to benchmark what happens in the GPU**
- **When GPU *records* an event, internal clock is stored**
- **Time between two recorded events can be queried**

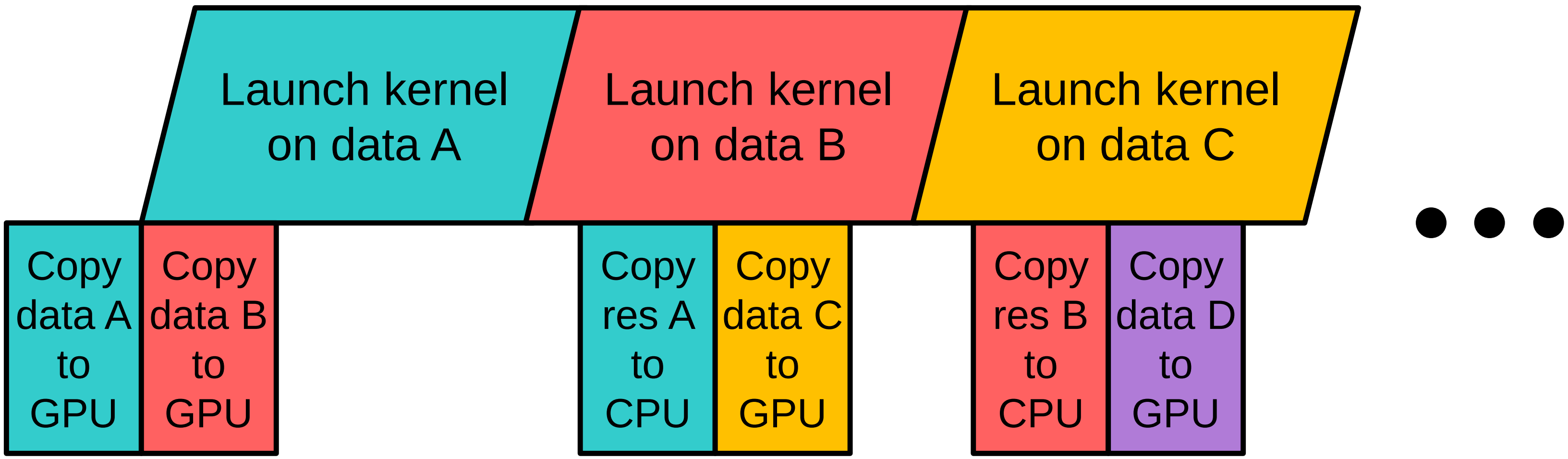
Events, example

1. Create two events: `evStart` and `evEnd`
2. Record `evStart`
3. Launch kernel
4. Record `evEnd`
5. Call `cudaDeviceSynchronize()`
   - None of the preceding calls were synchronous
6. Query time between `evStart` and `evEnd`
7. Destroy the events

Asynchronous programming

- Advanced technique
- Asynchronous memory copies (`cudaMemcpyAsync`)
  - Do not wait until device idle, return immediately
- Kernel launches are already asynchronous with host code
  - Kernel launches can be overlapped with each other and with async memory transfers by using *streams*
- Best case: Memory transfers can be hidden completely

Asynchronous example



- **Double-buffering on GPU side**
- **Streams to allow concurrent kernel execution and memory transfers**
  - **Indicates which operations are independent**
  - **Will skip details now**

Digging deeper

What's in the .o

- Final binaries for multiple architectures
  - In SASS = architecture-specific assembly
  - Known architectures: pick the compiled SASS
- Intermediate-language code for the latest architecture
  - In PTX = architecture-independent assembly
  - Future architectures: driver compiles into SASS at load time

- Both PTX and SASS can be extracted from the object file and examined

PTX vs SASS

- PTX is a very simple translation from source
  - No optimizations, no register allocation
  - Stays fixed between architectures
  - Not useful when trying to optimize code
- SASS is compiled for a specific architecture
  - Exactly what the GPU will run
  - Register allocation and all optimizations done
  - All ”smartness” in the compilation is in PTX→SASS phase

Extracting PTX and SASS

`cuobjdump -ptx foo.o`

- Typically only a single PTX representation for each kernel is found

`cuobjdump -sass foo.o`

- Find the correct SASS for your device
  - Can also extract SASS for a specific architecture using the `-arch` option
  - E.g., for Quadro K2000, specify `-arch sm_30`

Documentation

- `docs.nvidia.com/cuda`
- Main document: Programming Guide
  - Language extensions, special functions you can call in kernels, execution model, etc.
- API reference: CUDA Runtime API

- PTX documentation: PTX ISA
- SASS instruction set: CUDA Binary Utilities → Instruction Set Reference
- Plus a lot more – Best Practices Guide, Tuning Guides, etc.

Thank you

- Questions