
Programming in
OpenCL
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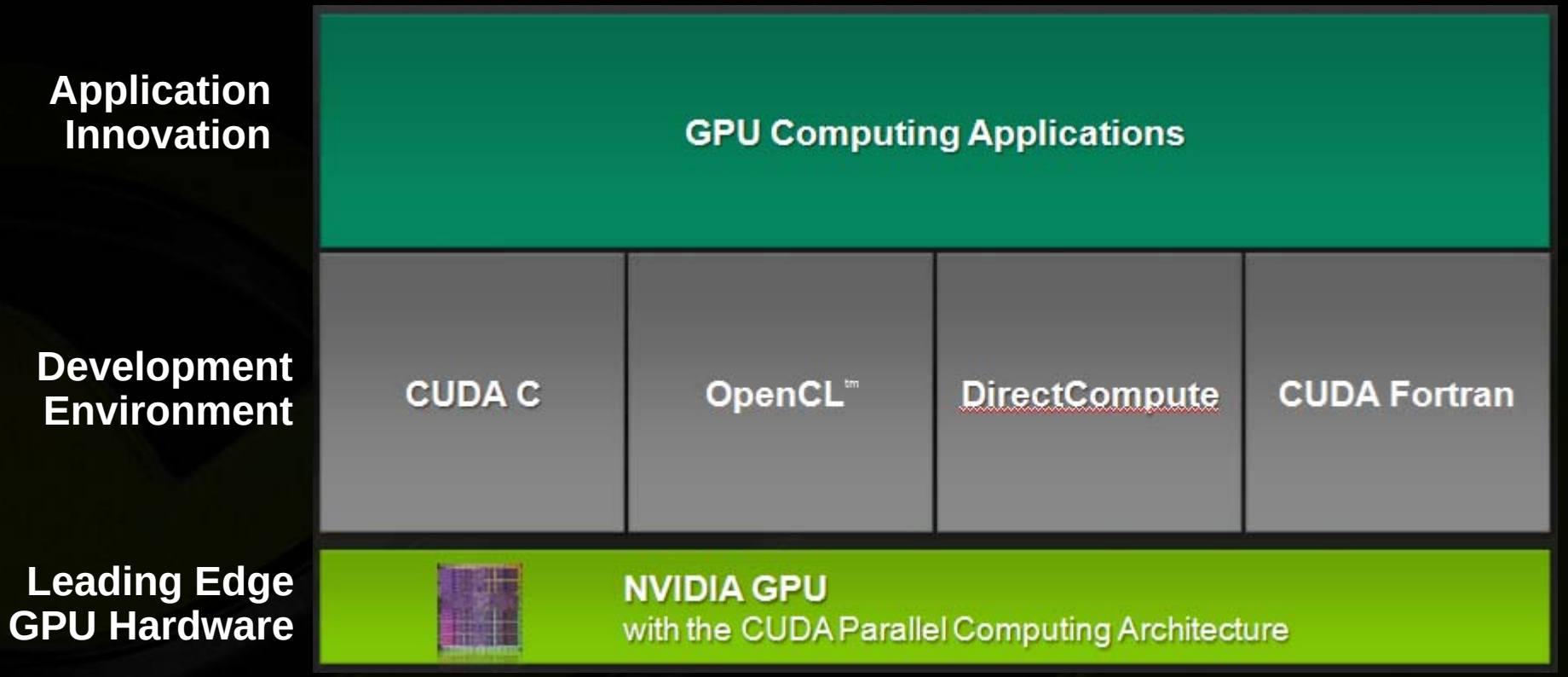
Outline

- Introduction to OpenCL
- OpenCL API Overview
- Performance Tuning on NVIDIA GPUs
- OpenCL Programming Tools & Resources

OpenCL and the CUDA Architecture



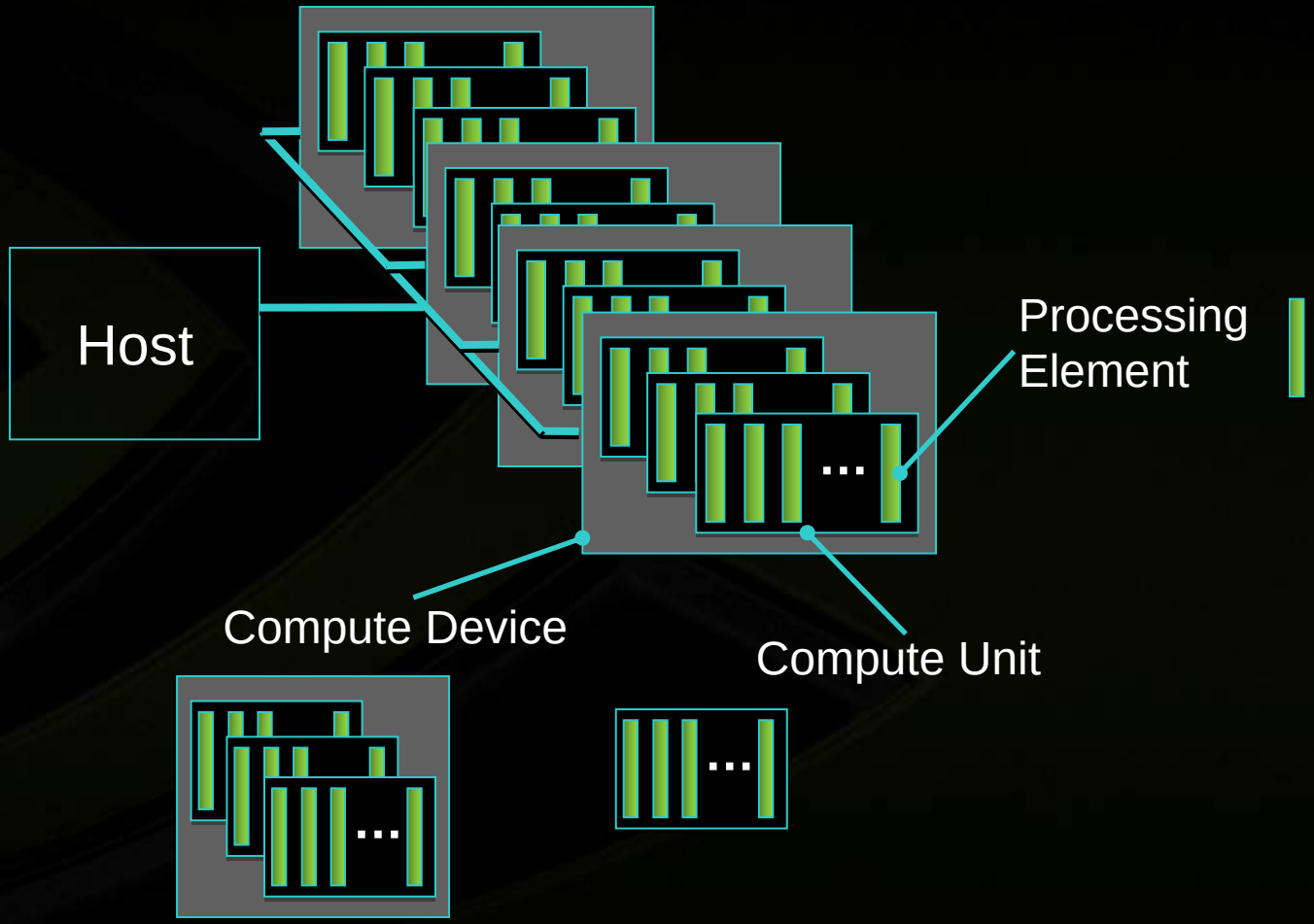
OpenCL Portability

- Portable code across multiple devices
  - GPU, CPU, Cell, mobiles, embedded systems, …
- NOTE:

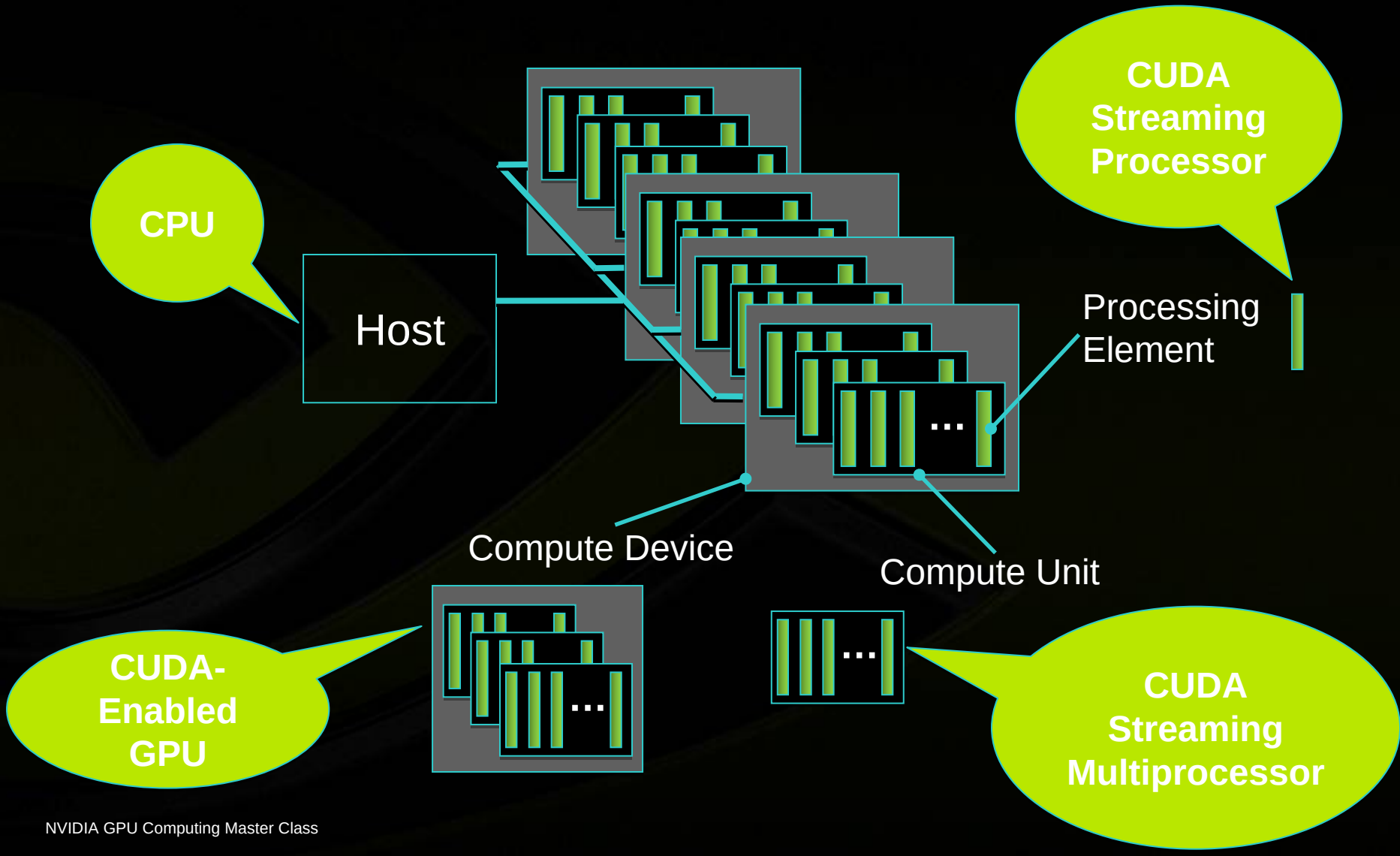
  functional portability != performance portability

  - Different code for each device is necessary to get good performance
  - Even for GPUs from different vendors!

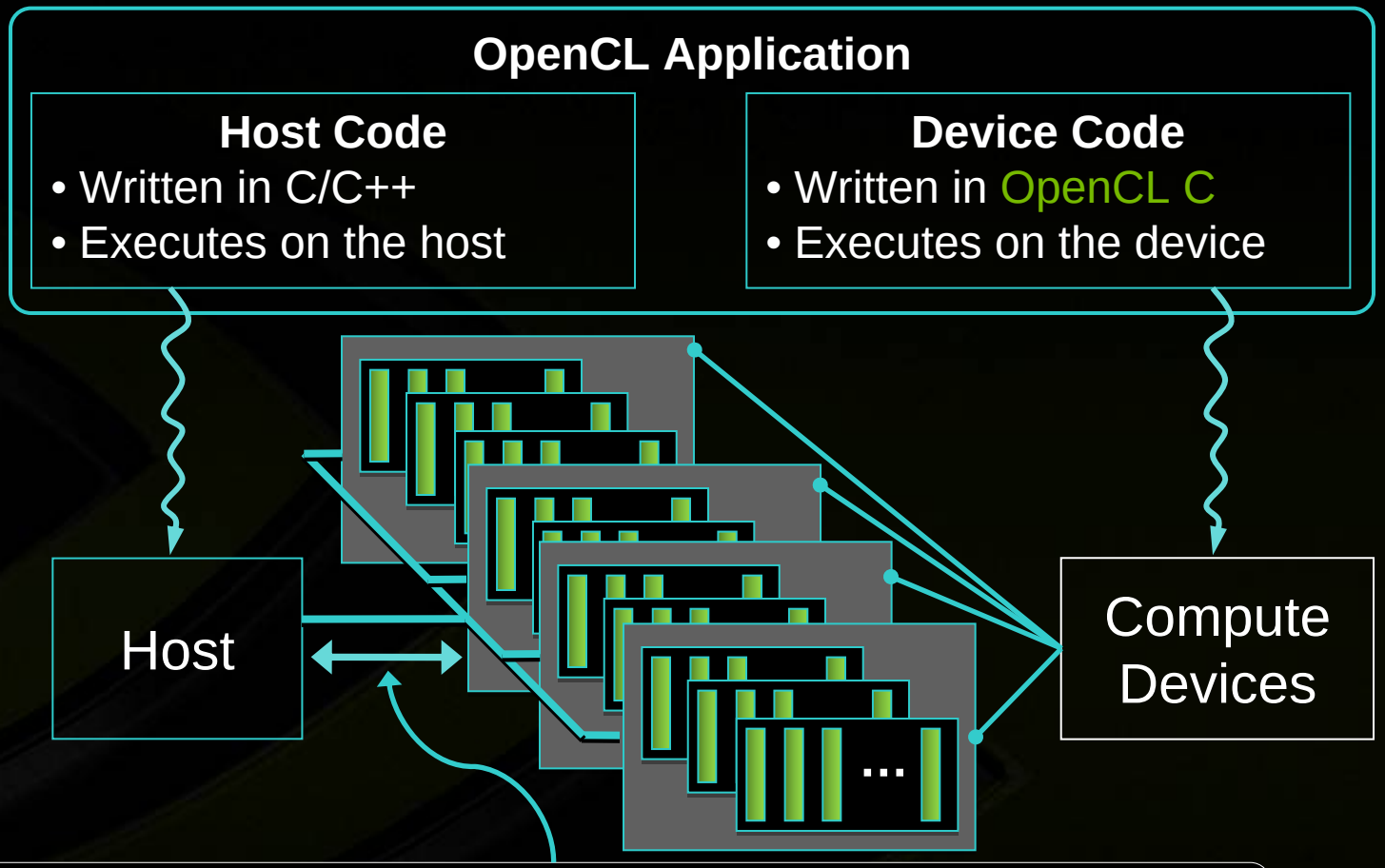
OpenCL Platform Model



OpenCL Platform Model on the CUDA Architecture



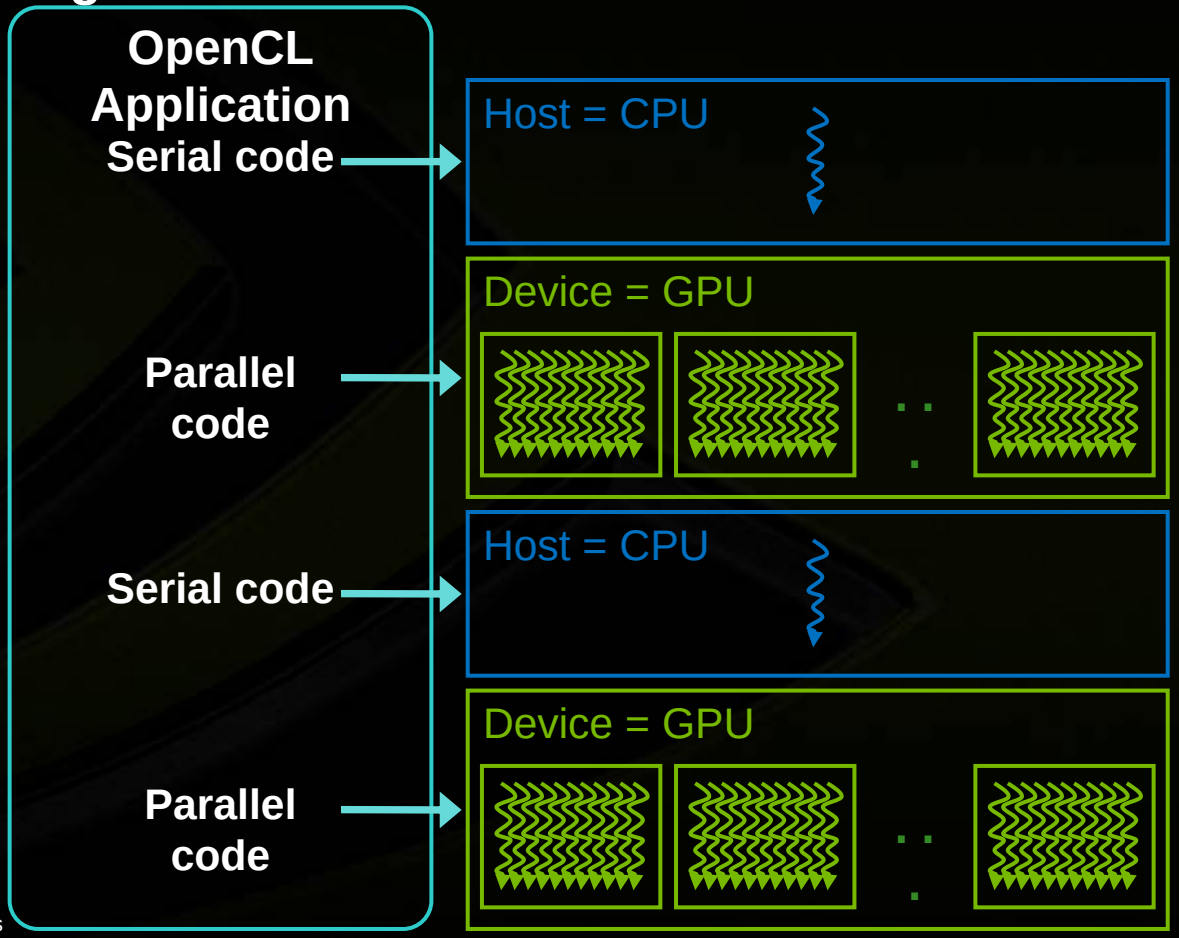
Anatomy of an OpenCL Application



Host code sends commands to the devices:
- to transfer data between host memory and device memories
- to execute device code

Heterogeneous Computing

- **Serial** code executes in a **CPU** thread
- **Parallel** code executes in many **GPU** threads across multiple processing elements

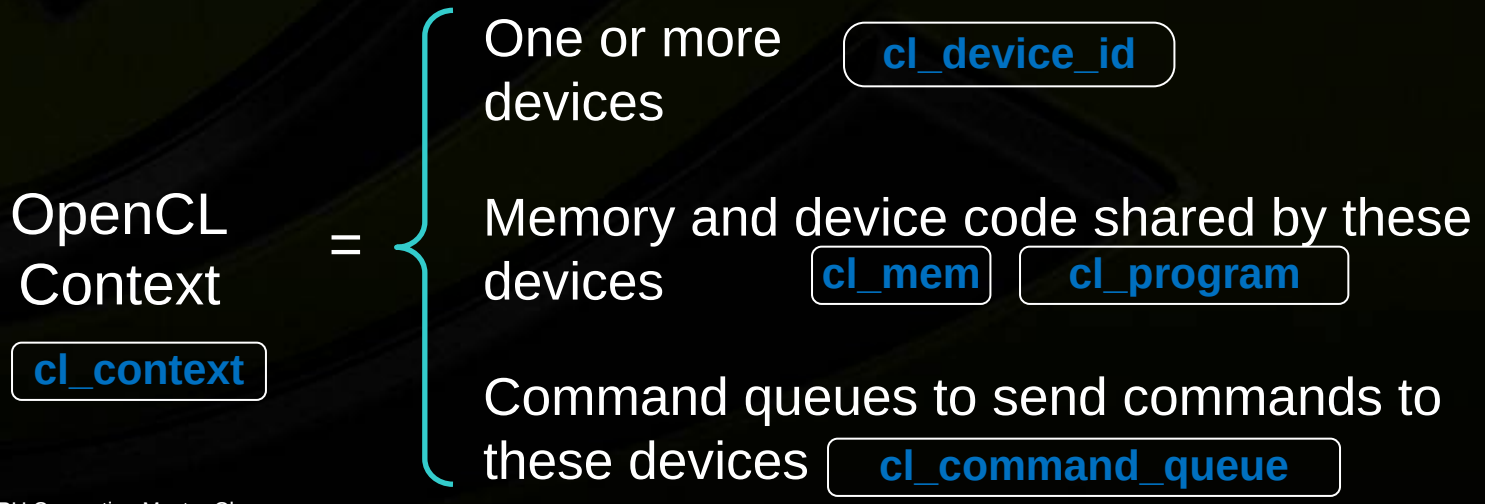


OpenCL Framework

- Platform layer
  - Discover OpenCL devices and their capabilities and create contexts
- Runtime layer
  - Memory management and command execution within a context
- OpenCL C Compiler
  - Creates program executables that contain OpenCL kernels

Platform Layer

- Query platform information
  - clGetPlatformIDs(): list of platforms
  - clGetPlatformInfo(): profile, version, vendor, extensions
  - clGetDeviceIDs(): list of devices
  - clGetDeviceInfo(): type, capabilities
- Create OpenCL context on one or more devices of one platform



Error Handling, Resource Deallocation

- Error handling:
  - All host functions return an error code
  - Context error callback can be specified
- Resource deallocation
  - Reference counting API: clRetain*(), clRelease*()
- Both are removed from code samples for clarity
  - Please see SDK samples for complete code

Context Creation

```
// Create an OpenCL context for all GPU devices on the first Platform
cl_context* CreateContext() {
    cl_platform_id platform_id;
    clGetPlatformIDs(1, &platform_id, NULL);

    return clCreateContextFromType(
    {CL_CONTEXT_PLATFORM, platform_id, 0},
    CL_DEVICE_TYPE_GPU,
    NULL, NULL, NULL);
}
// Get the list of GPU devices associated with a context
cl_device_id* GetDevices(cl_context context) {
    size_t size;
    clGetContextInfo(context, CL_CONTEXT_DEVICES, 0, NULL, &size);
    cl_device_id* device_id = malloc(size);
    clGetContextInfo(context, CL_CONTEXT_DEVICES, size, device_id,
    NULL);
    return device_id;
}
```

Runtime

- Command queues creation and management
- Memory allocation and management
- Device code compilation and execution
- Event creation and management (synchronization, profiling)

Command Queue

- Sequence of commands scheduled for execution on a specific device
  - Enqueuing functions: clEnqueue*()
  - Multiple queues can execute on the same device
- Two modes of execution:
  - In-order: Each command in the queue executes only when the preceding command has completed
    - Including all memory writes, so memory is consistent with all prior command executions
  - Out-of-order: No guaranteed order of completion for commands

Commands

- Memory copy or mapping
- Device code execution
- Synchronization point

Command Queue Creation

```
// Create a command-queue for a specific device
cl_command_queue CreateCommandQueue(cl_context context,
    cl_device_id device_id)
{
    return clCreateCommandQueue(context, device_id, 0, NULL);
}
```

Command Synchronization

- Some clEnqueue*() calls can be optionally blocking
- Queue barrier command
  - Any commands after the barrier start executing only after all commands before the barrier have completed
- An event object can be associated to each enqueued command
  - Any commands (or clWaitForEvents()) can wait on events before executing
  - Can be queried to track execution status and get profiling information

Memory Objects

- Two types of memory objects (cl_mem):
  - Buffer objects
  - Image objects
- Associated with context, only implicitly with device
- Memory objects can be copied to host memory, from host memory, or to other memory objects
- Regions of a memory object can be accessed from host by mapping them into the host address space

Buffer Object

- One-dimensional array
- Elements are scalars, vectors, or any user-defined structures
- Accessed within device code via pointers

```
__kernel void myKernel(__global int* buffer) {
  <...>
  // Access element in buffer object
  int v = buffer[get_global_id(0)];
  <...>
}
```

Image Object

- Two- or three-dimensional array
- Elements are 4-component vectors from a list of predefined formats
- Accessed within device code via built-in functions
  (storage format not exposed to application)
  - Sampler objects are used to configure how built-in functions sample images (addressing modes, filtering modes)
- Can be created from OpenGL texture or renderbuffer

Data Transfer between Host and Device

```
int main() {
    cl_context context = CreateContext();
    cl_device_id* device_id = GetDevices(context);
    cl_command_queue command_queue =
    CreateCommandQueue(context, device_id[0]);
    size_t size = 100000 * sizeof(int);
    int* h_buffer = (int*)malloc(size);
    cl_mem* d_buffer = clCreateBuffer(context,
    CL_MEM_READ_WRITE, size, NULL, NULL);
    …    // Initialize host buffer h_buffer
    clEnqueueWriteBuffer(command_queue,
                         d_buffer, CL_FALSE, 0, size, h_buffer, 0, NULL,
    NULL);
    …    // Process device buffer d_buffer
    clEnqueueReadBuffer(command_queue,
                         d_buffer, CL_TRUE, 0, size, h_buffer, 0, NULL,
    NULL);
}
```

Device Code in OpenCL C

- Derived from ISO C99
  - A few restrictions: recursion, function pointers, functions in C99 standard headers
  - Some extensions: built-in variables and functions, function qualifiers, address space qualifiers, e.g:

```
__global float* a; // Pointer to device memory
```

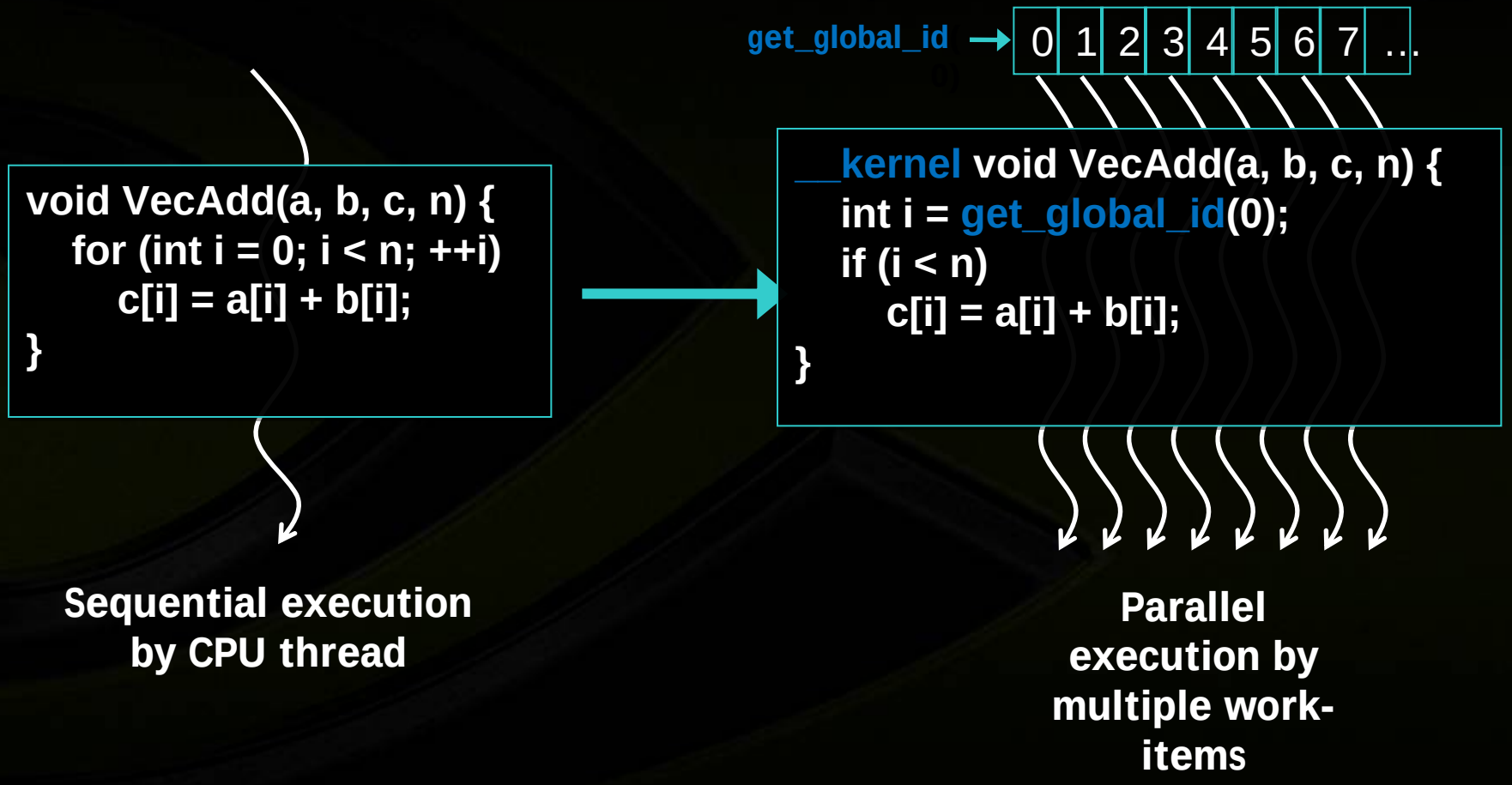
- Functions qualified by __kernel keyword (a.k.a kernels) can be invoked by host code

```
__kernel void MyKernel() { … }
```

Kernel Execution: NDRange and Work-Items

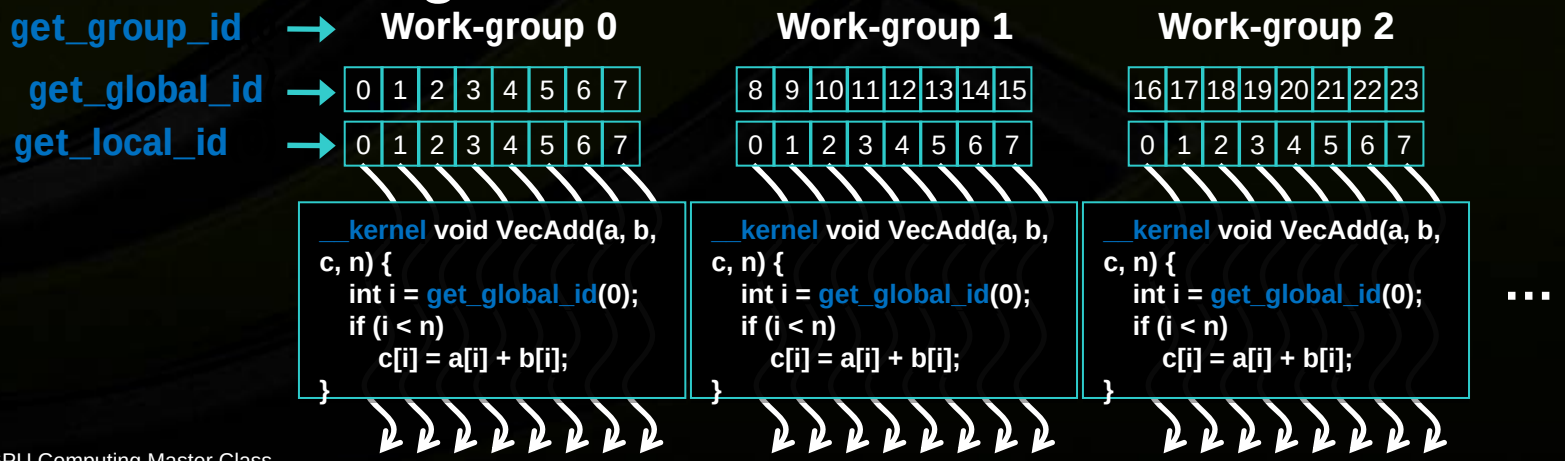
- Host code invokes a kernel over an index space called an *NDRange*
  - NDRange = “N-Dimensional Range”
  - NDRange can be a 1-, 2-, or 3-dimensional space
- A single kernel instance at a point in the index space is called a *work-item*
  - Each work-item has a unique global ID within the index space (accessible from device code via get_global_id())
  - Each work-item is free to execute a unique code path

Example: Vector Addition



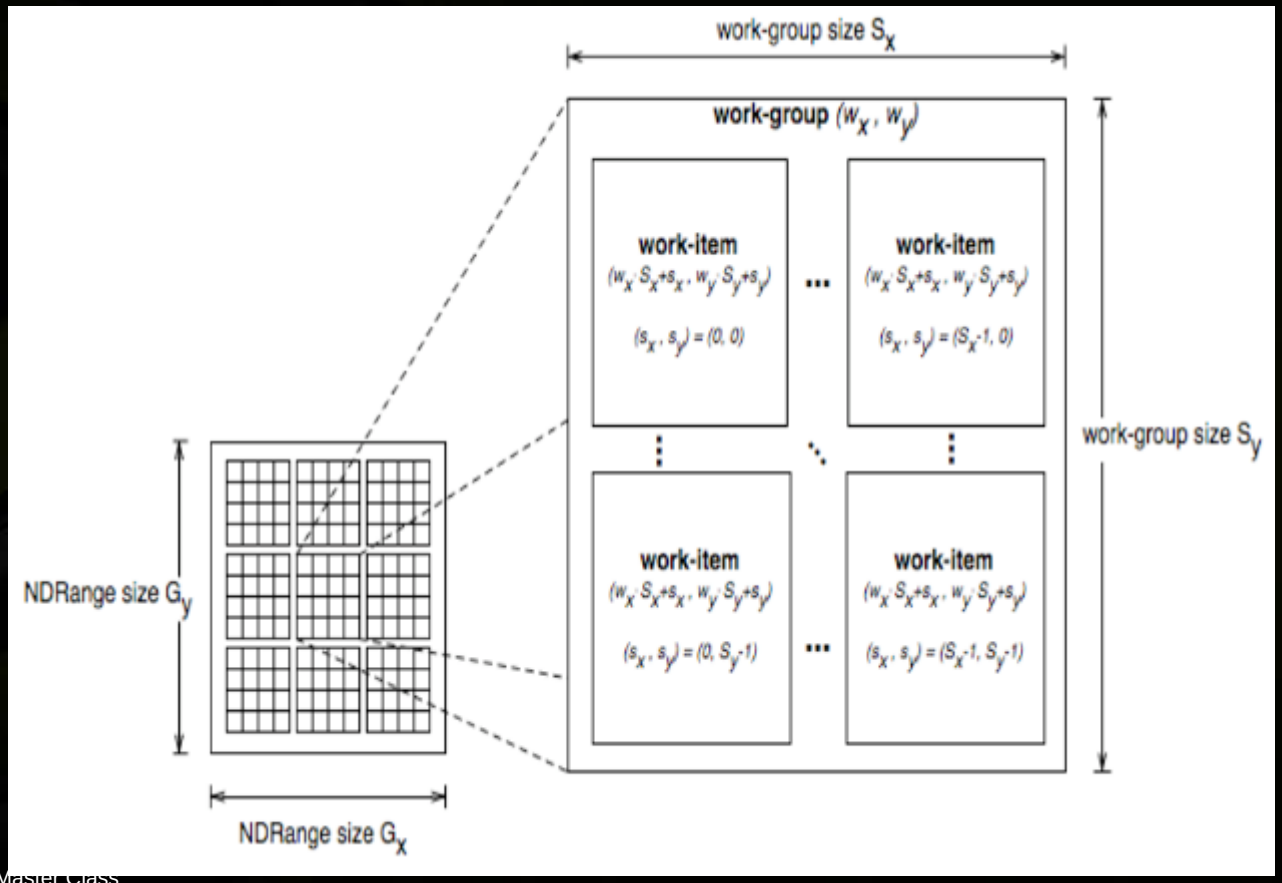
Kernel Execution: Work-Groups

- Work-items are grouped into *work-groups*
  - Each work-group has a unique work-group ID (accessible from device code via get_group_id())
  - Each work-item has a unique local ID within a work-group (accessible from device code via get_local_id())
  - Work-group has same dimensionality as NDRange

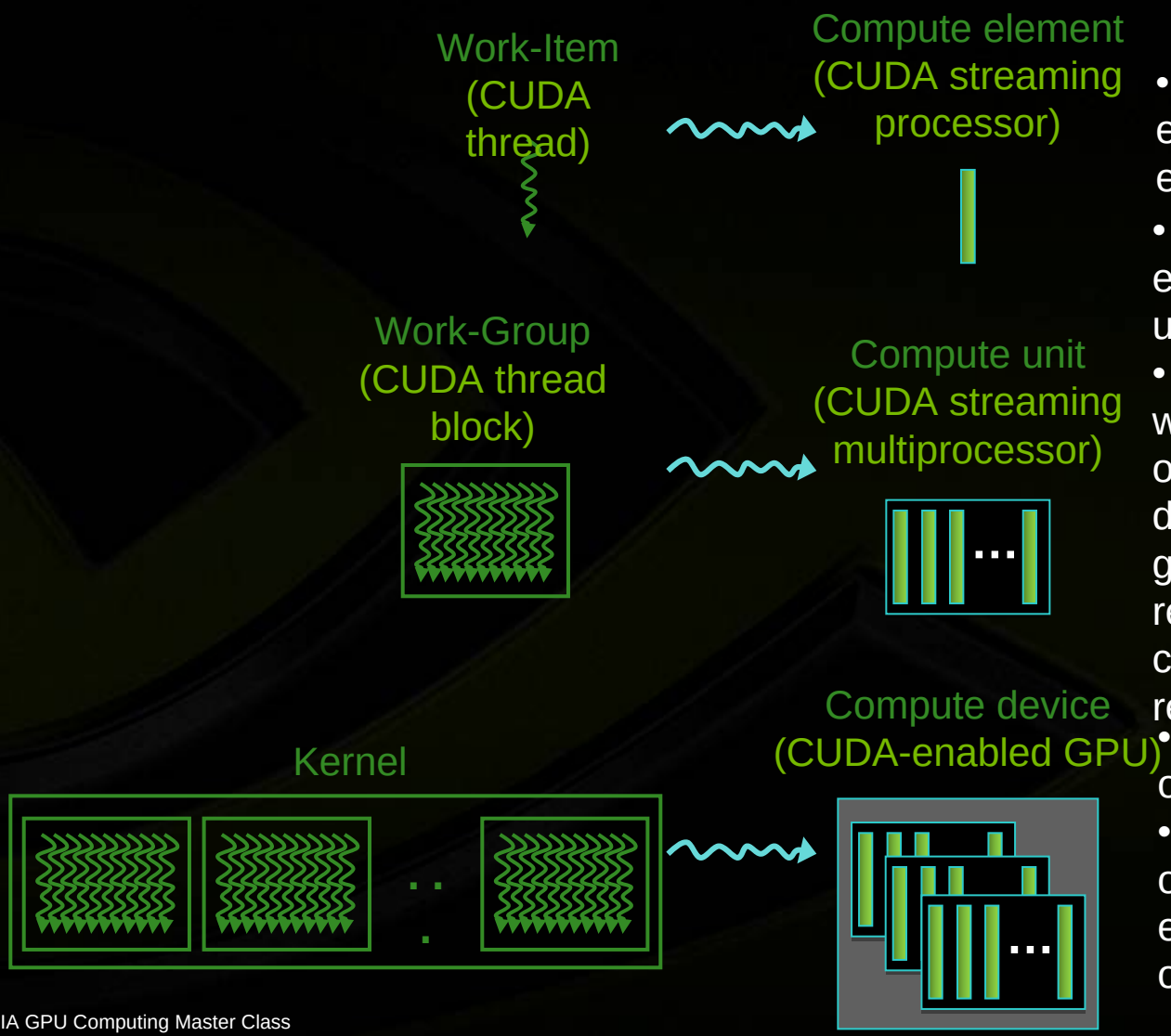


Example of 2D NDRange

- Total number of work-items = G_x x G_y
- Size of each work-group = S_x x S_y
- Number of work-groups = (G_x / S_x) x (G_y / S_y) (must be dividable)



Kernel Execution on Platform Model



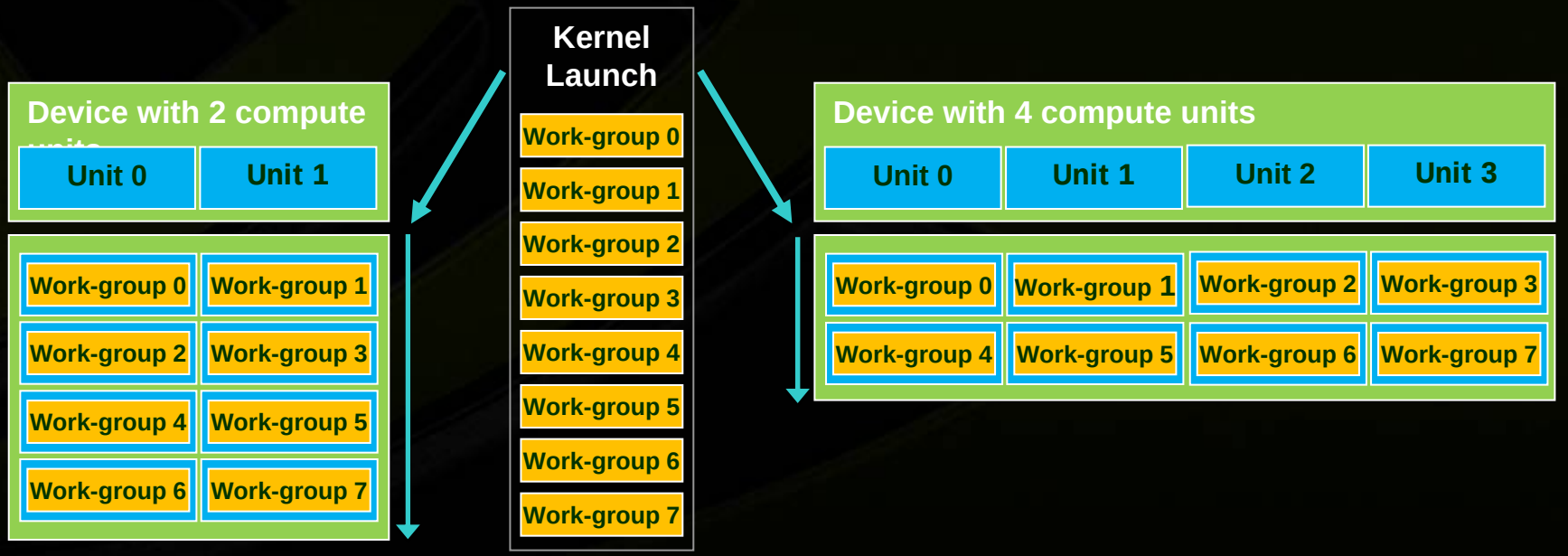
- Each work-item is executed by a compute element
- Each work-group is executed on a compute unit
- Several concurrent work-groups can reside on one compute unit depending on work-group's memory requirements and compute unit's memory resources
- Each kernel is executed on a compute device
- On Tesla architecture, only one kernel can execute on a device at one time

Benefits of Work-Groups

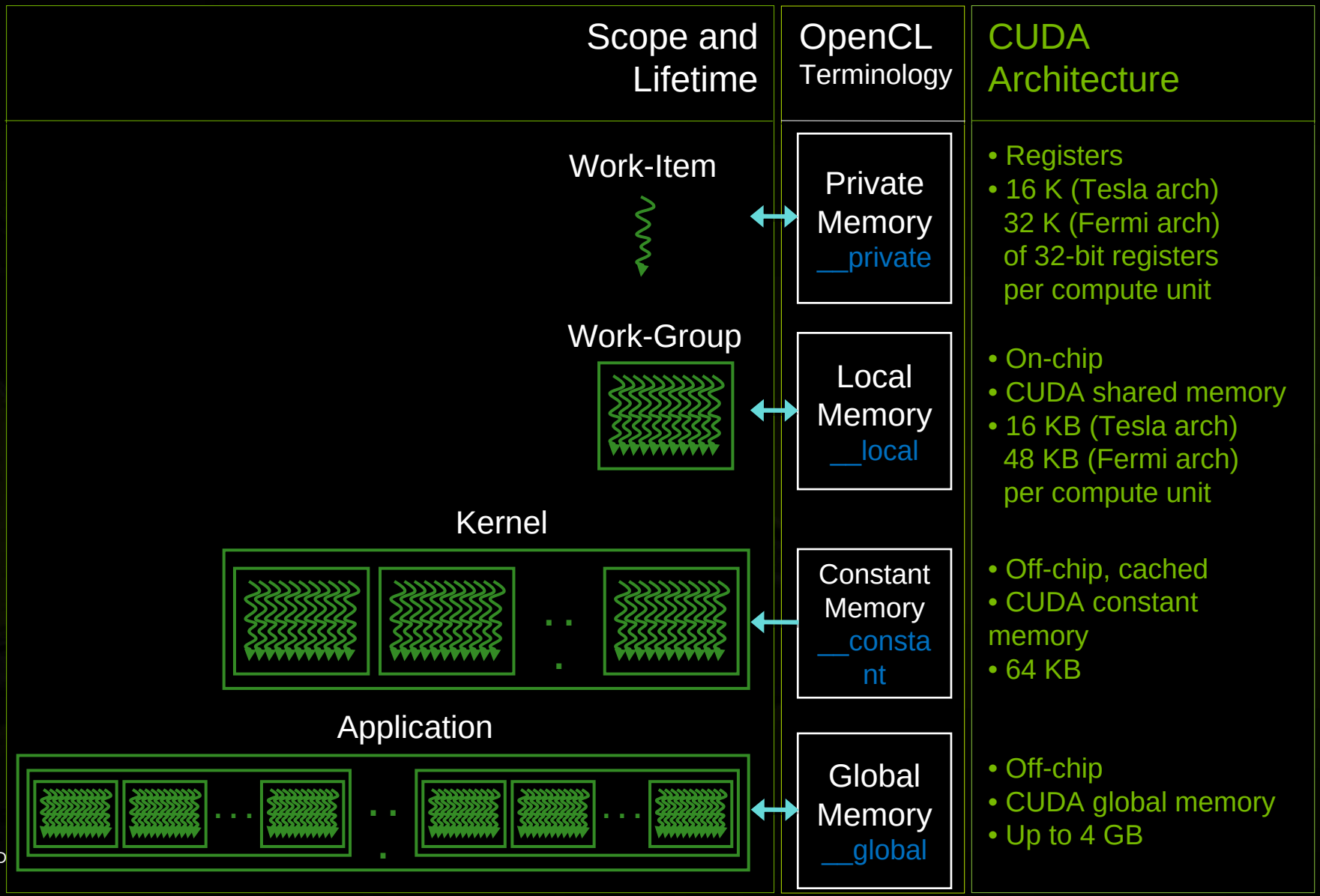
- Automatic scalability across devices with different numbers of compute units
- Efficient cooperation between work-items of same work-group
  - Fast shared memory and synchronization

Scalability

- Work-groups can execute in any order, concurrently or sequentially
- This independence between work-groups gives scalability:
  - A kernel scales across any number of compute units



Memory Spaces



Cooperation between Work-Items of same Work-Group

- Built-in functions to order memory operations and synchronize execution:
  - mem_fence(CLK_LOCAL_MEM_FENCE and/or CLK_GLOBAL_MEM_FENCE): waits until all reads/writes to local and/or global memory made by the calling work-item prior to mem_fence() are visible to all threads in the work-group
  - barrier(CLK_LOCAL_MEM_FENCE and/or CLK_GLOBAL_MEM_FENCE): waits until all work-items in the work-group have reached this point and calls mem_fence(CLK_LOCAL_MEM_FENCE and/or CLK_GLOBAL_MEM_FENCE)
- Used to coordinate accesses to local or global memory shared among work-items

Program and Kernel Objects

- A program object encapsulates some source code (with potentially several kernel functions) and its last successful build
  - clCreateProgramWithSource() // Create program from source
  - clBuildProgram() // Compile program
- A kernel object encapsulates the values of the kernel's arguments used when the kernel is executed
  - clCreateKernel() // Create kernel from successfully compiled
    // program
  - clSetKernelArg() // Set values of kernel's arguments

Kernel Invocation

```
int main() {
    …    // Create context and command queue, allocate host and device
    buffers of N elements
    char* source = "__kernel void MyKernel(__global int* buffer, int N) {\n"
                   "    if (get_global_id(0) < N) buffer[get_global_id(0)] = 7;\n"
                   "}\n ";
    cl_program program = clCreateProgramWithSource(context, 1, &source,
    NULL, NULL);
    clBuildProgram(program, 0, NULL, NULL, NULL, NULL);
    cl_kernel kernel = clCreateKernel(program, "MyKernel", NULL);
    clSetKernelArg(kernel, 0, sizeof(cl_mem), (void*)&d_buffer);
    clSetKernelArg(kernel, 1, sizeof(int), (void*)&N);
    size_t localWorkSize = 256; // Number of work-items in a work-group
    int numWorkGroups = (N + localWorkSize – 1) / localWorkSize;
    size_t globalWorkSize = numWorkGroups * localWorkSize;
    clEnqueueNDRangeKernel(command_queue, kernel,
                           1, NULL, &globalWorkSize, &localWorkSize, 0,
    NULL, NULL);
    …    // Read back buffer
}
```

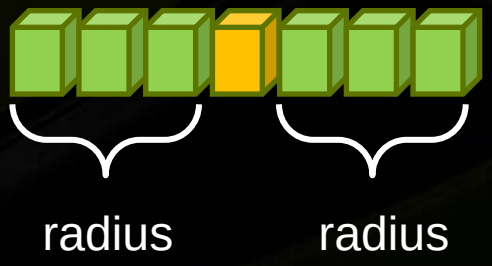
NDRange dimension

OpenCL Local Memory on the CUDA Architecture

- On-chip memory (CUDA shared memory)
  - 2 orders of magnitude lower latency than global memory
  - Order of magnitude higher bandwidth than global memory
  - 16 KB per compute unit on Tesla architecture (up to 30 compute units)
  - 48 KB per compute unit on Fermi architecture (up to 16 compute units)
- Acts as a user-managed cache to reduce global memory accesses
- Typical usage pattern for work-items within a work-group:
  - Read data from global memory to local memory; synchronize with barrier()
  - Process data within local memory; synchronize with barrier()
  - Write result to global memory

Example of Using Local Memory

- Applying a 1D stencil to a 1D array of elements:
  - Each output element is the sum of all elements within a radius
- For example, for radius = 3, each output element is the sum of 7 input elements:

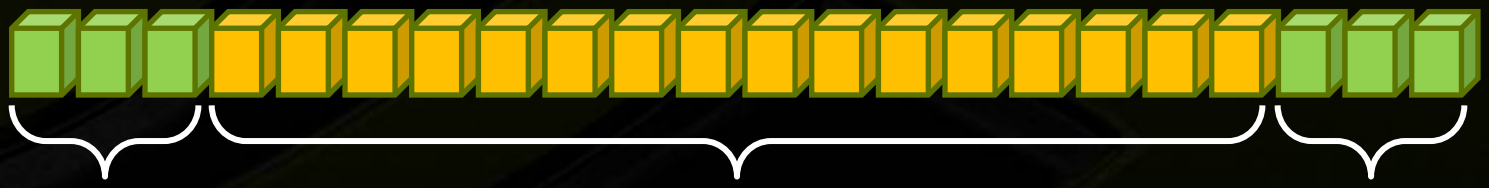


Implementation with Local Memory

- **Each work-group outputs one element per work-item, so a total of WG_SIZE output elements**

  (WG_SIZE = number of work-items per work-group):

  - **Read (WG_SIZE + 2 * RADIUS) elements from global memory to local memory**
  - **Compute WG_SIZE output elements in local memory**
  - **Write WG_SIZE output elements to global memory**



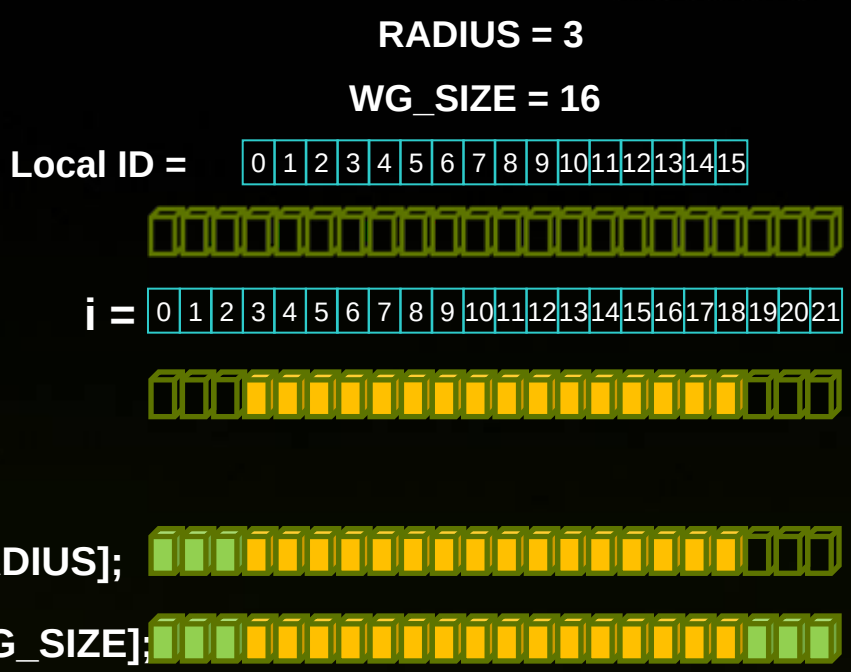
"halo" = RADIUS elements on the left

The WG_SIZE input elements corresponding to the output elements

"halo" = RADIUS elements on the right

Kernel Code

```
__kernel void stencil(__global int* input,
                      __global int* output) {
  __local int local[WG_SIZE + 2 * RADIUS];
  int i = get_local_id(0) + RADIUS;
  local[i] = input[get_global_id(0)];
  if (get_local_id(0) < RADIUS) {
     local[i - RADIUS]    = input[get_global_id(0) – RADIUS];
     local[i + WG_SIZE] = input[get_global_id(0) + WG_SIZE];
  }
  barrier(CLK_LOCAL_MEM_FENCE); // Blocks until work-items are done writing to local
    memory
  int value = 0;
  for (offset = - RADIUS; offset <= RADIUS; ++offset) value += local[i + offset]; // Sum
  output[get_global_id(0)] = value;          }
```



OpenCL C Language Restrictions

- Pointers to functions are not allowed
- Pointers to pointers allowed within a kernel, but not as an argument
- Bit-fields are not supported
- Variable length arrays and structures are not supported
- Recursion is not supported
- Writes to a pointer of types less than 32-bit are not supported
- Double types are not supported, but reserved
- 3D Image writes are not supported

- Some restrictions are addressed through extensions

Optional Extensions

- Extensions are optional features exposed through OpenCL
- The OpenCL working group has already approved many extensions that are supported by the OpenCL specification:
  - Double precision floating-point types (Section 9.3)
  - Built-in functions to support doubles
  - Atomic functions (Section 9.5, 9.6, 9.7)
  - 3D Image writes (Section 9.8)
  - Byte addressable stores (write to pointers with types < 32-bits) (Section 9.9)
  - Built-in functions to support half types (Section 9.10)

Performance Overview

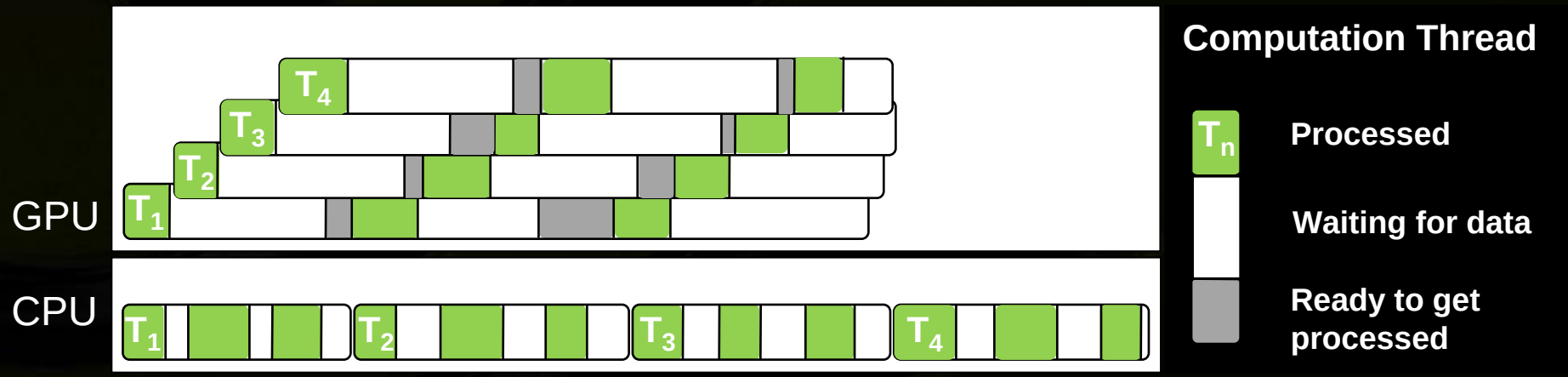
- OpenCL is about performance
  - Standard to make use of the massive computing power of parallel processors like GPUs
- But, performance is generally not portable across devices:
  - There are multiple ways of implementing a given algorithm in OpenCL. Each can have vastly different performance characteristics for a given compute device!
- Achieving good performance on GPUs requires a basic understanding of GPU architecture

Heterogeneous Computing

- Host + multiple devices = heterogeneous platform
- Distribute workload to:
  - Assign to each processor the type of work it does best
    - CPU = serial, GPU = parallel
  - Keep all processors busy at all times
  - Minimize data transfers between processors or hide them by overlapping them with kernel execution
    - Overlapping requires data allocated with CL_MEM_ALLOC_HOST_PTR

GPU Computing: Highly Multithreaded

- GPU compute unit “hides” instruction and memory latency with computation
  - Switches from stalled threads to other threads at no cost (lightweight GPU threads)
  - Needs enough concurrent threads to hide latency
  - Radically different strategy than CPU core where memory latency is “reduced” via big caches

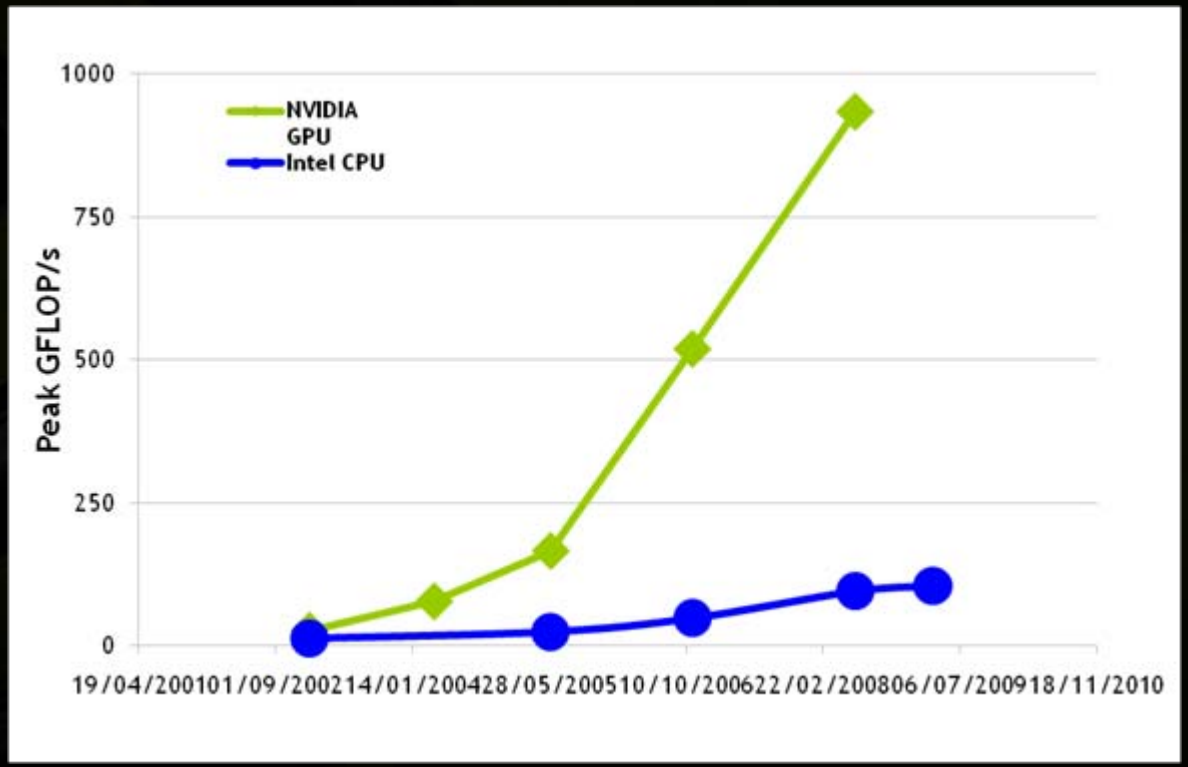


GPU Computing: Highly Multithreaded

- Latency hiding is only possible if there is other work that can be done in parallel
- Therefore, kernels **must** be launched with hundreds of work-items per compute unit for good performance
  - Minimal work-group size of 64; higher is usually better (typically 1.2 to 1.5 speedup)
  - Number of work-groups is typically 100 or more

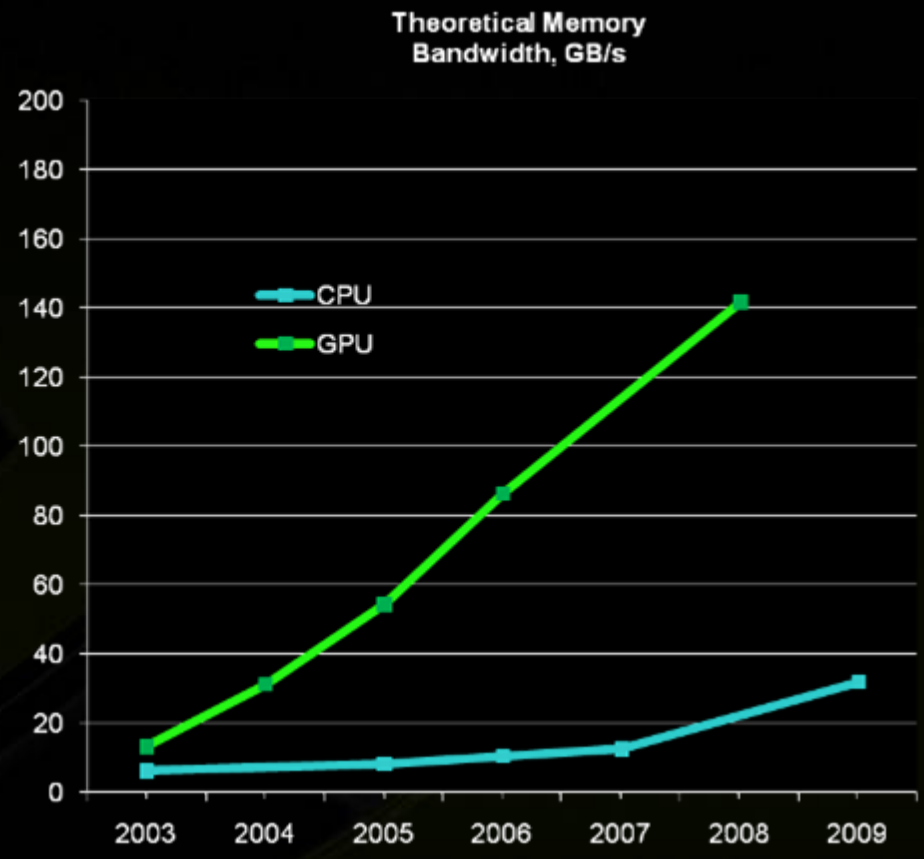
GPU Computing: High Arithmetic Intensity

- GPU devotes many more transistors than CPU to arithmetic units ⇒ high arithmetic intensity



GPU Computing: High Memory Bandwidth

- GPUs offer high memory bandwidth, so applications can take advantage of high arithmetic intensity and achieve high arithmetic throughput



CUDA Memory Optimization

- Memory bandwidth will increase at a slower rate than arithmetic intensity in future processor architectures
- So, maximizing memory throughput is even more critical going forward
- Two important memory bandwidth optimizations:
  - Ensure global memory accesses are coalesced
    - Up to an order of magnitude speedup!
  - Replace global memory accesses by shared memory accesses whenever possible

CUDA = SIMT Architecture

- Same Instruction Multiple Threads
  - Threads running on a compute unit are partitioned into groups of 32 threads (warps) in which all threads execute the same instruction simultaneously
- Minimize divergent branching within a warp
  - Different code paths within a warp get serialized
- Remove barrier calls when only threads within same warp need to communicate
  - Threads within a warp are inherently synchronized

CUDA = Scalar Architecture

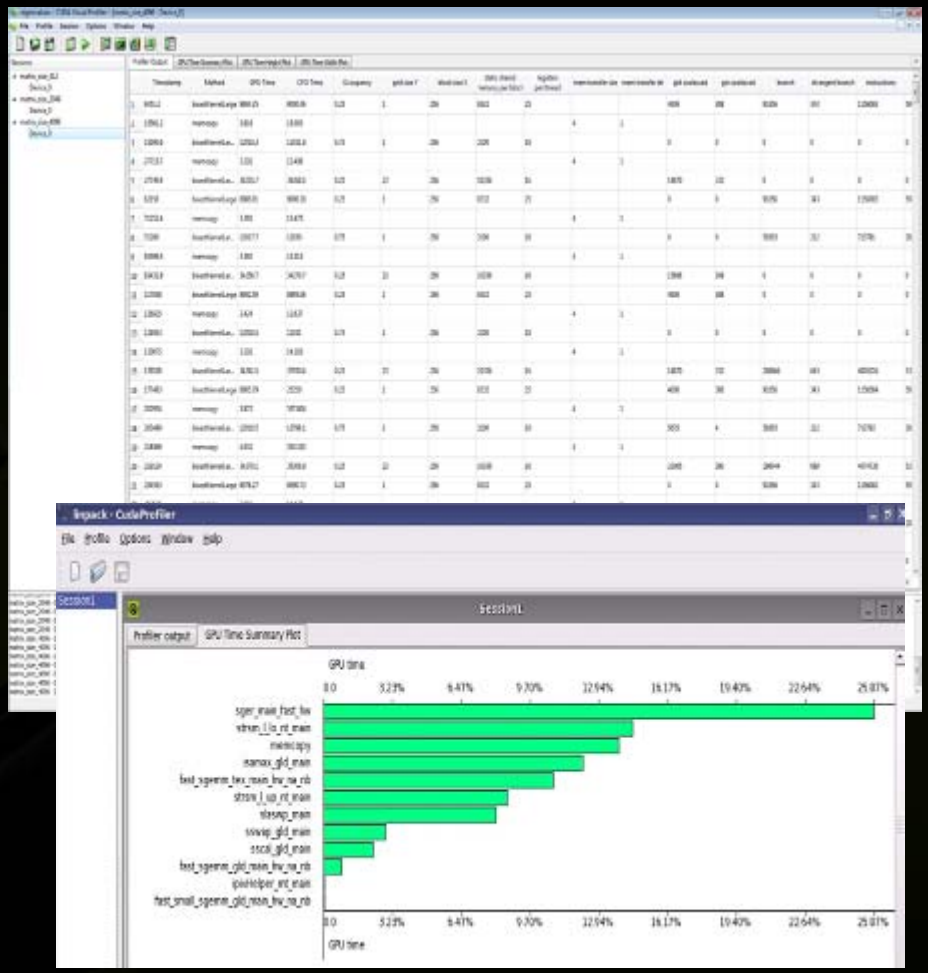
- **Use vector types for convenience, not performance**
- **Generally want more work-items rather than large vectors per work-item**

Maximize Instruction Throughput

- Favor high-throughput instructions
- Use native_*() math functions whenever speed is more important than precision
- Use -cl-mad-enable compiler option
  - Enables use of FMADs, which can lead to large performance gains
- Investigate using the -cl-fast-relaxed-math compiler option
  - Enables many aggressive compiler optimizations

OpenCL Visual Profiler

- Analyze GPU HW performance signals, kernel occupancy, instruction throughput, and more
- Highly configurable tables and graphical views
- Save/load profiler sessions or export to CSV for later analysis
- Compare results visually across multiple sessions to see improvements
- Supported on Windows and Linux
- Included in the CUDA Toolkit



OpenCL Information and Resources

- NVIDIA OpenCL Web Page:
  - http://www.nvidia.com/object/cuda_opencl.html
- NVIDIA OpenCL Forum:
  - http://forums.nvidia.com/index.php?showforum=134
- NVIDIA driver, profiler, code samples for Windows and Linux:
  - https://nvdeveloper.nvidia.com/object/get-opencl.html
- Khronos (current specification):
  - http://www.khronos.org/registry/cl/specs/opencl-1.0.48.pdf
- Khronos OpenCL Forum:
  - http://www.khronos.org/message_boards/viewforum.php?f=28