CUDA C/C++ Basics

Supercomputing 2011 Tutorial

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What is CUDA?

- CUDA Architecture
    - Expose GPU computing for general purpose
    - Retain performance

- CUDA C/C++
    - Based on industry-standard C/C++
    - Small set of extensions to enable heterogeneous programming
    - Straightforward APIs to manage devices, memory etc.

- This session introduces CUDA C/C++

Introduction to CUDA C/C++

- What will you learn in this session?

    - Start from "Hello World!"

    - Write and execute C code on the GPU

    - Manage GPU memory

    - Manage communication and synchronization

Prerequisites

- You (probably) need experience with C or C++

- You don't need GPU experience

- You don't need parallel programming experience

- You don't need graphics experience

CONCEPTS

Heterogeneous Computing

Blocks

Threads

Indexing

Shared memory

__syncthreads()

Asynchronous operation

Handling errors

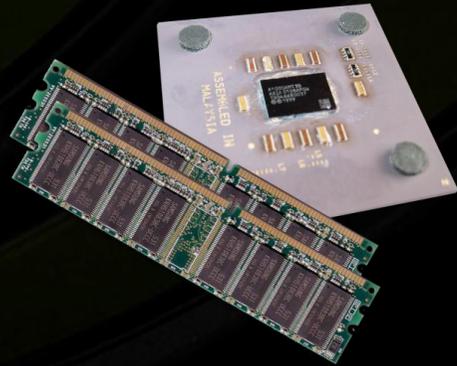Managing devices

HELLO WORLD!

CONCEPTS

Heterogeneous Computing

- Terminology:
  - *Host*   The CPU and its memory (host memory)
  - *Device* The GPU and its memory (device memory)

Host

Device

Heterogeneous Computing

device code

host code

parallel function

serial function

serial code

parallel code

serial code

```cpp
#include <iostream>
#include <algorithm>

using namespace std;

#define N        1024
#define RADIUS    3
#define BLOCK_SIZE 16

__global__ void stencil_1d(int *in, int *out) {
    __shared__ int temp[BLOCK_SIZE + 2 * RADIUS];
    int gindex = threadIdx.x + blockIdx.x * blockDim.x;
    int lindex = threadIdx.x + RADIUS;

    // Read input elements into shared memory
    temp[lindex] = in[gindex];
    if (threadIdx.x < RADIUS) {
        temp[lindex - RADIUS] = in[gindex - RADIUS];
        temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
    }

    // Synchronize (ensure all the data is available)
    __syncthreads();

    // Apply the stencil
    int result = 0;
    for (int offset = -RADIUS ; offset <= RADIUS ; offset++)
        result += temp[lindex + offset];

    // Store the result
    out[gindex] = result;
}

void fill_ints(int *x, int n) {
    fill_n(x, n, 1);
}

int main(void) {
    int *in, *out;           // host copies of a, b, c
    int *d_in, *d_out;       // device copies of a, b, c
    int size = (N + 2*RADIUS) * sizeof(int);

    // Alloc space for host copies and setup values
    in = (int *)malloc(size); fill_ints(in,  N + 2*RADIUS);
    out = (int *)malloc(size); fill_ints(out, N + 2*RADIUS);

    // Alloc space for device copies
    cudaMalloc((void **)&d_in,  size);
    cudaMalloc((void **)&d_out, size);

    // Copy to device
    cudaMemcpy(d_in,  in,  size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_out, out, size, cudaMemcpyHostToDevice);

    // Launch stencil_1d() kernel on GPU
    stencil_1d<<<N/BLOCK_SIZE,BLOCK_SIZE>>>(d_in + RADIUS, d_out + RADIUS);

    // Copy result back to host
    cudaMemcpy(out, d_out, size, cudaMemcpyDeviceToHost);

    // Cleanup
    free(in); free(out);
    cudaFree(d_in); cudaFree(d_out);
    return 0;
}
```
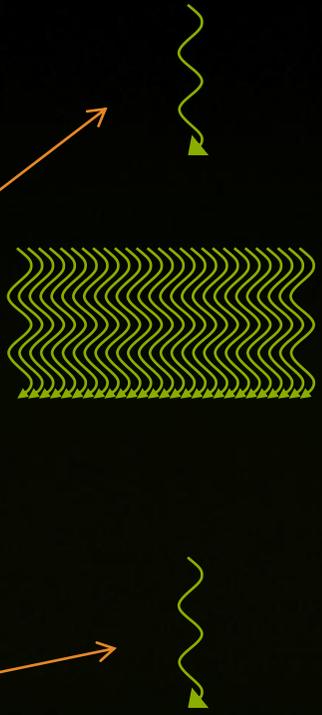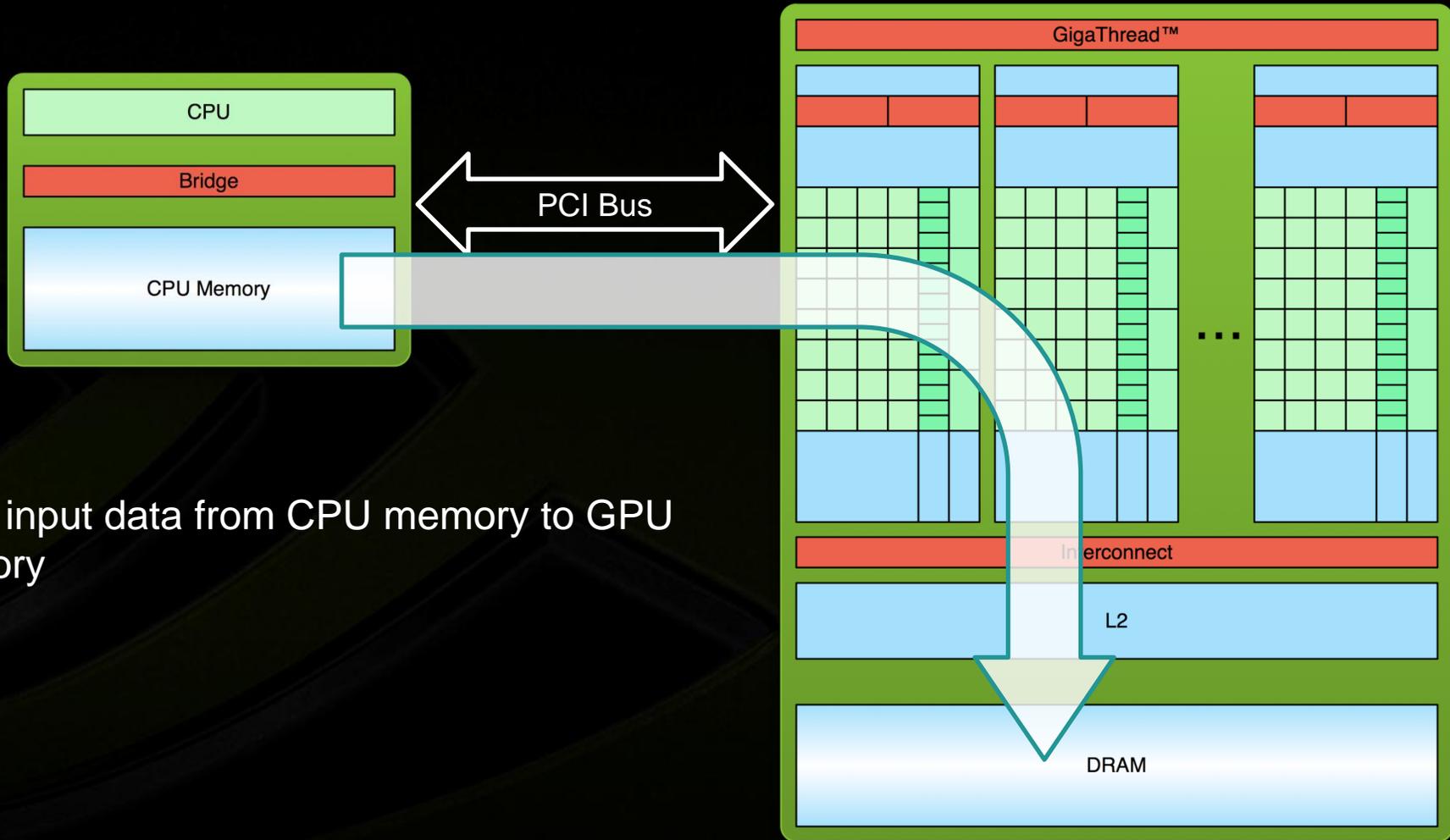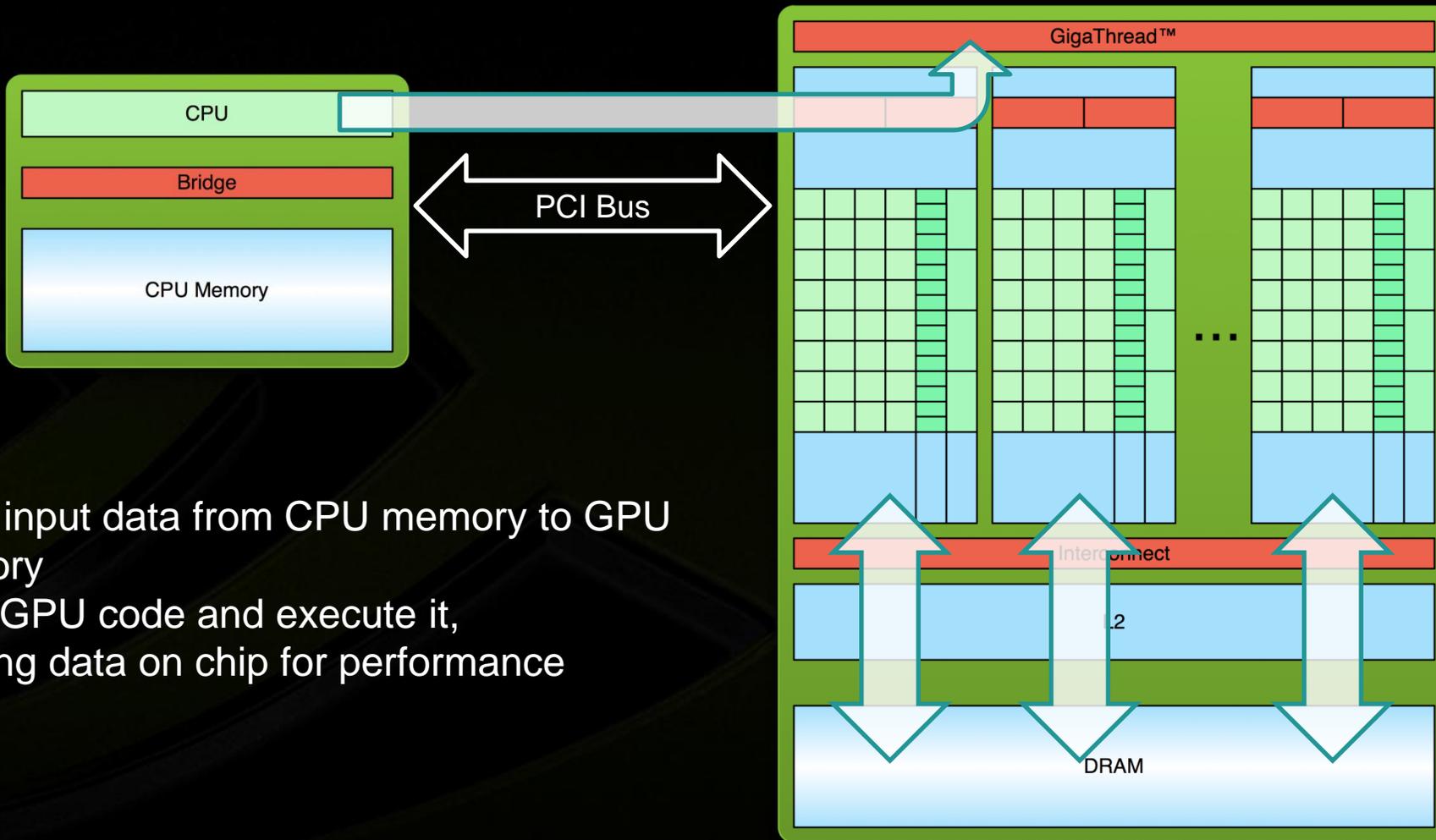
Simple Processing Flow
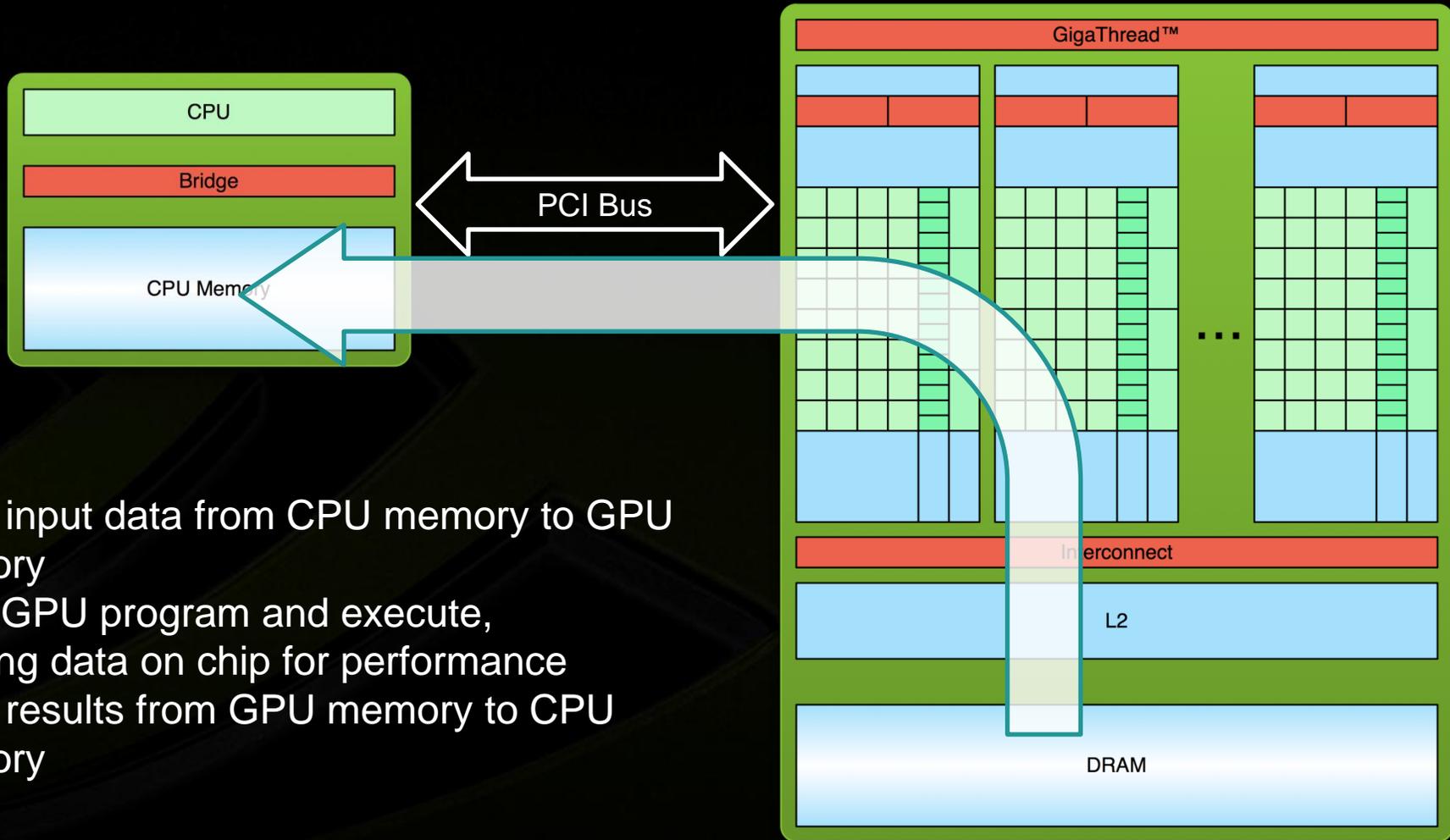

1. Copy input data from CPU memory to GPU memory

Simple Processing Flow

1. Copy input data from CPU memory to GPU memory
2. Load GPU code and execute it, caching data on chip for performance

Simple Processing Flow

1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance
3. Copy results from GPU memory to CPU memory

Hello World!

```c
int main(void) {
        printf("Hello World!\n");
        return 0;
}
```

- Standard C that runs on the host

- NVIDIA compiler (nvcc) can be used to compile programs with no *device* code

Output:

```
$ nvcc
hello_world.cu
$ a.out
Hello World!
$
```

```
__global__ void mykernel(void) {

}


int main(void) {
        mykernel<<<1,1>>>();
        printf("Hello World!\n");
        return 0;

}
```

- Two new syntactic elements…

Hello World! with Device Code

```
__global__ void mykernel(void) {
}
```

- CUDA C/C++ keyword `__global__` indicates a function that:
  - Runs on the device
  - Is called from host code

- `nvcc` separates source code into host and device components
  - Device functions (e.g. `mykernel()`) processed by NVIDIA compiler
  - Host functions (e.g. `main()`) processed by standard host compiler
    - `gcc, cl.exe`

Hello World! with Device Code

```
mykernel<<<1,1>>>();
```

- Triple angle brackets mark a call from *host* code to *device* code
  - Also called a "kernel launch"
  - We'll return to the parameters (1,1) in a moment

- That's all that is required to execute a function on the GPU!

Hello World! with Device Code

```
__global__ void mykernel(void) {
}


int main(void) {
    mykernel<<<1,1>>>();
    printf("Hello World!\n");
    return 0;
}
```

Output:

```
$ nvcc hello.cu
$ a.out
Hello World!
$
```

- `mykernel()` does nothing, somewhat anticlimactic!

Parallel Programming in CUDA C/C++

- But wait… GPU computing is about massive parallelism!

- We need a more interesting example…

- We'll start by adding two integers and build up to vector addition

a   b   c
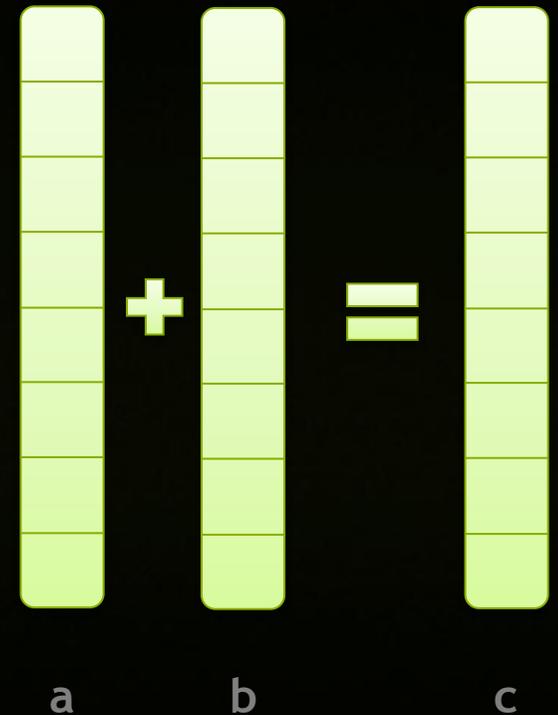
Addition on the Device

- A simple kernel to add two integers

```
__global__ void add(int *a, int *b, int *c) {
        *c = *a + *b;
}
```

- As before __global__ is a CUDA C/C++ keyword meaning
  - `add()` will execute on the device
  - `add()` will be called from the host

Addition on the Device

- Note that we use pointers for the variables

```
__global__ void add(int *a, int *b, int *c) {
        *c = *a + *b;
    }
```

- `add()` runs on the device, so `a`, `b` and `c` must point to device memory

- We need to allocate memory on the GPU

Memory Management

- Host and device memory are separate entities
  - *Device* pointers point to GPU memory
    May be passed to/from host code
    May *not* be dereferenced in host code
  - *Host* pointers point to CPU memory
    May be passed to/from device code
    May *not* be dereferenced in device code

- Simple CUDA API for handling device memory
  - `cudaMalloc(), cudaFree(), cudaMemcpy()`
  - Similar to the C equivalents `malloc(), free(), memcpy()`

Addition on the Device: `add()`

- Returning to our `add()` kernel

```
__global__ void add(int *a, int *b, int *c) {
    *c = *a + *b;
}
```

- Let's take a look at main()…

Addition on the Device: `main()`

```c
int main(void) {
    int a, b, c;                    // host copies of a, b, c
    int *d_a, *d_b, *d_c;           // device copies of a, b, c
    int size = sizeof(int);

    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    // Setup input values
    a = 2;
    b = 7;
```

```
    // Copy inputs to device
    cudaMemcpy(d_a, &a, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU
    add<<<1,1>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(&c, d_c, size, cudaMemcpyDeviceToHost);

    // Cleanup
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

CONCEPTS

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Blocks

Threads

Indexing

Shared memory

__syncthreads()

Asynchronous operation

Handling errors

Managing devices

RUNNING IN PARALLEL

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Moving to Parallel

- GPU computing is about massive parallelism

  - So how do we run code in parallel on the device?

```
add<<< 1, 1 >>>();

add<<< N, 1 >>>();
```

- Instead of executing `add()` once, execute N times in parallel

Vector Addition on the Device

- With `add()` running in parallel we can do vector addition

- Terminology: each parallel invocation of `add()` is referred to as a block
    - The set of blocks is referred to as a grid
    - Each invocation can refer to its block index using `blockIdx.x`

```
__global__ void add(int *a, int *b, int *c) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- By using `blockIdx.x` to index into the array, each block handles a different element of the array

Vector Addition on the Device

```
__global__ void add(int *a, int *b, int *c) {
        c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- On the device, each block can execute in parallel:

Block 0

```
c[0]   = a[0] + b[0];
```

Block 1

```
c[1]   = a[1] + b[1];
```

Block 2

```
c[2]   = a[2] + b[2];
```

Block 3

```
c[3]   = a[3] + b[3];
```

Vector Addition on the Device: `add()`

- Returning to our parallelized `add()` kernel

```
__global__ void add(int *a, int *b, int *c) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- Let's take a look at main()…

Vector Addition on the Device: `main()`

```c
#define N 512
int main(void) {
    int *a, *b, *c;            // host copies of a, b, c
    int *d_a, *d_b, *d_c;      // device copies of a, b, c
    int size = N * sizeof(int);

    // Alloc space for device copies of a, b, c
    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    // Alloc space for host copies of a, b, c and setup input values
    a = (int *)malloc(size); random_ints(a, N);
    b = (int *)malloc(size); random_ints(b, N);
    c = (int *)malloc(size);
```

Vector Addition on the Device: `main()`

```c
// Copy inputs to device
cudaMemcpy(d_a, a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, b, size, cudaMemcpyHostToDevice);

// Launch add() kernel on GPU with N blocks
add<<<N,1>>>(d_a, d_b, d_c);

// Copy result back to host
cudaMemcpy(c, d_c, size, cudaMemcpyDeviceToHost);

// Cleanup
free(a); free(b); free(c);
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
return 0;
}
```

Review (1 of 2)

- Difference between *host* and *device*
    - *Host*   CPU
    - *Device* GPU

- Using `__global__` to declare a function as device code
    - Executes on the device
    - Called from the host

- Passing parameters from host code to a device function

Review (2 of 2)

- Basic device memory management
  - `cudaMalloc()`
  - `cudaMemcpy()`
  - `cudaFree()`

- Launching parallel kernels
  - Launch `N` copies of `add()` with `add<<<N,1>>>(…);`
  - Use `blockIdx.x` to access block index

CUDA Threads

- Terminology: a block can be split into parallel threads

- Let's change `add()` to use parallel *threads* instead of parallel *blocks*

```
__global__ void add(int *a, int *b, int *c) {
        c[threadIdx.x] = a[threadIdx.x] + b[threadIdx.x];
}
```

- We use `threadIdx.x` instead of `blockIdx.x`

- Need to make one change in `main()`...

Vector Addition Using Threads: `main()`

```c
#define N 512
int main(void) {
    int *a, *b, *c;                    // host copies of a, b, c
    int *d_a, *d_b, *d_c;              // device copies of a, b, c
    int size = N * sizeof(int);

    // Alloc space for device copies of a, b, c
    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    // Alloc space for host copies of a, b, c and setup input values
    a = (int *)malloc(size); random_ints(a, N);
    b = (int *)malloc(size); random_ints(b, N);
    c = (int *)malloc(size);
```

```
// Copy inputs to device
cudaMemcpy(d_a, a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, b, size, cudaMemcpyHostToDevice);

// Launch add() kernel on GPU with N threads
add<<<1,N>>>(d_a, d_b, d_c);

// Copy result back to host
cudaMemcpy(c, d_c, size, cudaMemcpyDeviceToHost);

// Cleanup
free(a); free(b); free(c);
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
return 0;
}
```

CONCEPTS

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COMBINING THREADS AND BLOCKS

Combining Blocks *and* Threads

- We've seen parallel vector addition using:
  - Several blocks with one thread each
  - One block with several threads

- Let's adapt vector addition to use both *blocks* and *threads*

- Why? We'll come to that…

- First let's discuss data indexing…

Indexing Arrays with Blocks and Threads

- No longer as simple as using `blockIdx.x` and `threadIdx.x`

  - Consider indexing an array with one element per thread (8 threads/block)

threadIdx.x	threadIdx.x	threadIdx.x	threadIdx.x
0 1 2 3 4 5 6 7	0 1 2 3 4 5 6 7	0 1 2 3 4 5 6 7	0 1 2 3 4 5 6 7
blockIdx.x = 0	blockIdx.x = 1	blockIdx.x = 2	blockIdx.x = 3

- With M threads per block, a unique index for each thread is given by:

```
int index = threadIdx.x + blockIdx.x * M;
```

Indexing Arrays: Example

▪ Which thread will operate on the red element?

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 |

M = 8

threadIdx.x = 5

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

blockIdx.x = 2

```
int index = threadIdx.x + blockIdx.x * M;
          =      5       +     2      * 8;
          = 21;
```

Vector Addition with Blocks and Threads

- Use the built-in variable `blockDim.x` for threads per block

  ```
  int index = threadIdx.x + blockIdx.x * blockDim.x;
  ```

- Combined version of `add()` to use parallel threads *and* parallel blocks

  ```
  __global__ void add(int *a, int *b, int *c) {
      int index = threadIdx.x + blockIdx.x * blockDim.x;
      c[index] = a[index] + b[index];
  }
  ```

- What changes need to be made in `main()`?

Addition with Blocks and Threads: `main()`

```c
#define N (2048*2048)
#define THREADS_PER_BLOCK 512
int main(void) {
    int *a, *b, *c;                    // host copies of a, b, c
    int *d_a, *d_b, *d_c;              // device copies of a, b, c
    int size = N * sizeof(int);

    // Alloc space for device copies of a, b, c
    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    // Alloc space for host copies of a, b, c and setup input values
    a = (int *)malloc(size); random_ints(a, N);
    b = (int *)malloc(size); random_ints(b, N);
    c = (int *)malloc(size);
```

Addition with Blocks and Threads: `main()`

```c
// Copy inputs to device
cudaMemcpy(d_a, a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, b, size, cudaMemcpyHostToDevice);

// Launch add() kernel on GPU
add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a, d_b, d_c);

// Copy result back to host
cudaMemcpy(c, d_c, size, cudaMemcpyDeviceToHost);

// Cleanup
free(a); free(b); free(c);
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
return 0;
}
```

Handling Arbitrary Vector Sizes

- Typical problems are not friendly multiples of `blockDim.x`

- Avoid accessing beyond the end of the arrays:

```
__global__ void add(int *a, int *b, int *c, int n) {
    int index = threadIdx.x + blockIdx.x * blockDim.x;
    if (index < n)
        c[index] = a[index] + b[index];
}
```

- Update the kernel launch:

```
add<<<(N + M-1) / M,M>>>(d_a, d_b, d_c, N);
```

Why Bother with Threads?

- Threads seem unnecessary
  - They add a level of complexity
  - What do we gain?

- Unlike parallel blocks, threads have mechanisms to efficiently:
  - Communicate
  - Synchronize

- To look closer, we need a new example…

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Shared memory

__syncthreads()

Asynchronous operation

Handling errors

Managing devices

COOPERATING THREADS

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1D Stencil

- Consider applying a 1D stencil to a 1D array of elements
  - Each output element is the sum of input elements within a radius

- If radius is 3, then each output element is the sum of 7 input elements:

Implementing Within a Block

- Each thread processes one output element
  - `blockDim.x` elements per block

- Input elements are read several times
 - With radius 3, each input element is read seven times

Sharing Data Between Threads

- Terminology: within a block, threads share data via shared memory

- Extremely fast on-chip memory
  - By opposition to device memory, referred to as global memory
  - Like a user-managed cache

- Declare using __shared__, allocated per block

- Data is not visible to threads in other blocks

Implementing With Shared Memory

- Cache data in shared memory
    - Read `(blockDim.x + 2 * radius)` input elements from global memory to shared memory
    - Compute `blockDim.x` output elements
    - Write `blockDim.x` output elements to global memory

- Each block needs a halo of `radius` elements at each boundary

in

halo on left   halo on right

out

blockDim.x output elements
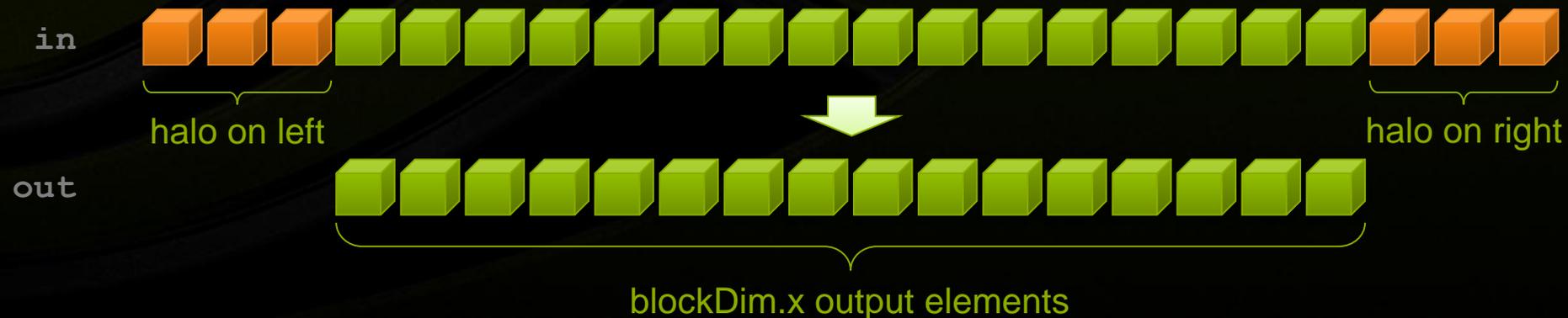
Stencil Kernel

```
__global__ void stencil_1d(int *in, int *out) {
    __shared__ int temp[BLOCK_SIZE + 2 * RADIUS];
    int gindex = threadIdx.x + blockIdx.x * blockDim.x;
    int lindex = threadIdx.x + RADIUS;

    // Read input elements into shared memory
    temp[lindex] = in[gindex];
    if (threadIdx.x < RADIUS) {
        temp[lindex - RADIUS] = in[gindex - RADIUS];
        temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
    }
```

Stencil Kernel

```
    // Apply the stencil
    int result = 0;
    for (int offset = -RADIUS ; offset <= RADIUS ; offset++)
        result += temp[lindex + offset];

    // Store the result
    out[gindex] = result;
}
```

Data Race!

- The stencil example will not work…

- Suppose thread 15 reads the halo before thread 0 has fetched it…

```
...
temp[lindex] = in[gindex];
if (threadIdx.x < RADIUS) {
    temp[lindex - RADIUS] = in[gindex - RADIUS];
    temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
}
int result = 0;
for (int offset = -RADIUS ; offset <= RADIUS ; offset++)
    result += temp[lindex + offset];
...
```

Store at temp[18]

Skipped since threadId.x > RADIUS

Load from temp[19]

__syncthreads()

- `void __syncthreads();`

- Synchronizes all threads within a block
  - Used to prevent RAW / WAR / WAW hazards

- All threads must reach the barrier
  - In conditional code, the condition must be uniform across the block

Stencil Kernel

```c
__global__ void stencil_1d(int *in, int *out) {
    __shared__ int temp[BLOCK_SIZE + 2 * RADIUS];
    int gindex = threadIdx.x + blockIdx.x * blockDim.x;
    int lindex = threadIdx.x + radius;

    // Read input elements into shared memory
    temp[lindex] = in[gindex];
    if (threadIdx.x < RADIUS) {
        temp[lindex - RADIUS] = in[gindex - RADIUS];
        temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
    }

    // Synchronize (ensure all the data is available)
    __syncthreads();
```

Stencil Kernel

```c
    // Apply the stencil
    int result = 0;
    for (int offset = -RADIUS ; offset <= RADIUS ; offset++)
        result += temp[lindex + offset];


    // Store the result
    out[gindex] = result;
}
```

Review (1 of 2)

- Launching parallel threads
  - Launch `N` blocks with `M` threads per block with `kernel<<<N,M>>>(…);`
  - Use `blockIdx.x` to access block index within grid
  - Use `threadIdx.x` to access thread index within block

- Allocate elements to threads:

```
int index = threadIdx.x + blockIdx.x * blockDim.x;
```

- Use `__shared__` to declare a variable/array in shared memory
  - Data is shared between threads in a block
  - Not visible to threads in other blocks

- Use `__syncthreads()` as a barrier
  - Use to prevent data hazards

Coordinating Host & Device

- Kernel launches are asynchronous
    - Control returns to the CPU immediately

- CPU needs to synchronize before consuming the results

`cudaMemcpy()`	Blocks the CPU until the copy is complete Copy begins when all preceding CUDA calls have completed
`cudaMemcpyAsync()`	Asynchronous, does not block the CPU
`cudaDeviceSynchronize()`	Blocks the CPU until all preceding CUDA calls have completed

Reporting Errors

- All CUDA API calls return an error code (`cudaError_t`)
    - Error in the API call itself
    OR
    - Error in an earlier asynchronous operation (e.g. kernel)

- Get the error code for the last error:
    ```
    cudaError_t cudaGetLastError(void)
    ```
- Get a string to describe the error:
    ```
    char *cudaGetErrorString(cudaError_t)

    printf("%s\n", cudaGetErrorString(cudaGetLastError()));
    ```

Device Management

- Application can query and select GPUs
    ```
    cudaGetDeviceCount(int *count)
    cudaSetDevice(int device)
    cudaGetDevice(int *device)
    cudaGetDeviceProperties(cudaDeviceProp *prop, int device)
    ```

- Multiple host threads can share a device

- A single host thread can manage multiple devices
    `cudaSetDevice(i)` to select current device

    `cudaMemcpy(…)` for peer-to-peer copies

Introduction to CUDA C/C++

- What have we learned?
  - Write and launch CUDA C/C++ kernels
    - `__global__`, `<<<>>>`, `blockIdx`, `threadIdx`, `blockDim`
  - Manage GPU memory
    - `cudaMalloc()`, `cudaMemcpy()`, `cudaFree()`
  - Manage communication and synchronization
    - `__shared__`, `__syncthreads()`
    - `cudaMemcpy()` **vs** `cudaMemcpyAsync()`, `cudaDeviceSynchronize()`

Topics we skipped

- We skipped some details, you can learn more:
    - CUDA Programming Guide
    - CUDA Zone – tools, training, webinars and more
      http://developer.nvidia.com/cuda

- Need a quick primer for later:
    - Compute capability
   - Multi-dimensional indexing
    - Textures

Compute Capability

- The compute capability of a device describes its architecture, e.g.
  - Number of registers
  - Sizes of memories
  - Features & capabilities

Compute Capability	Selected Features (see CUDA C Programming Guide for complete list)	Tesla models
1.0	Fundamental CUDA support	870
1.3	Double precision, improved memory accesses, atomics	10-series
2.0	Caches, fused multiply-add, 3D grids, surfaces, ECC, P2P, concurrent kernels/copies, function pointers, recursion	20-series

- The following presentations concentrate on Fermi devices
  - Compute Capability >= 2.0
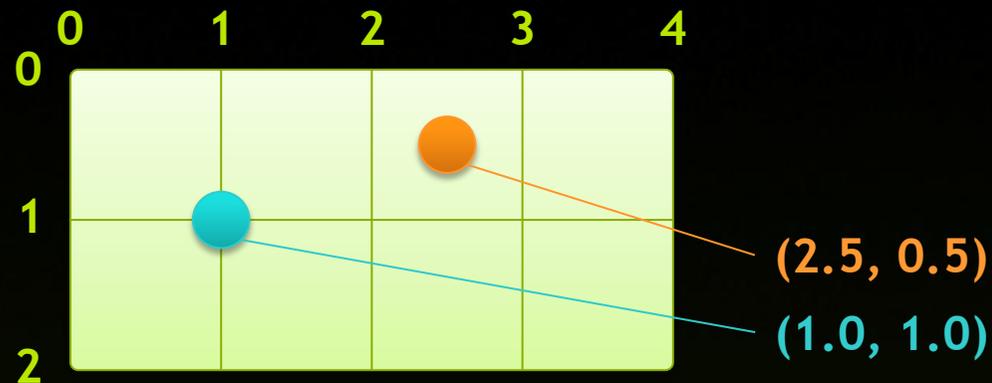
IDs and Dimensions

- A kernel is launched as a grid of blocks of threads
  - `blockIdx` and `threadIdx` are 3D
  - We showed only one dimension (`x`)

- Built-in variables:
  - `threadIdx`
  - `blockIdx`
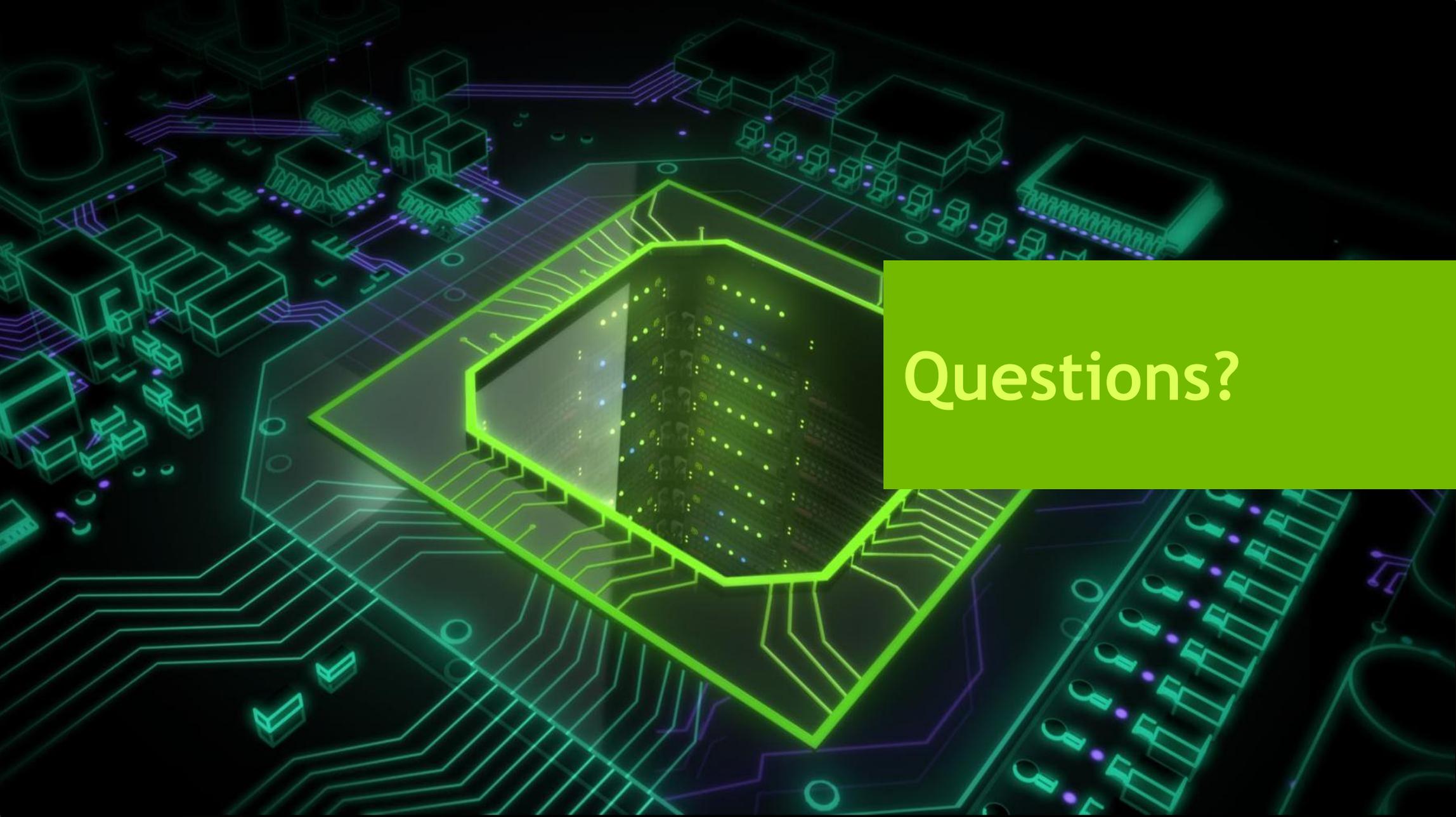 - `blockDim`
  - `gridDim`
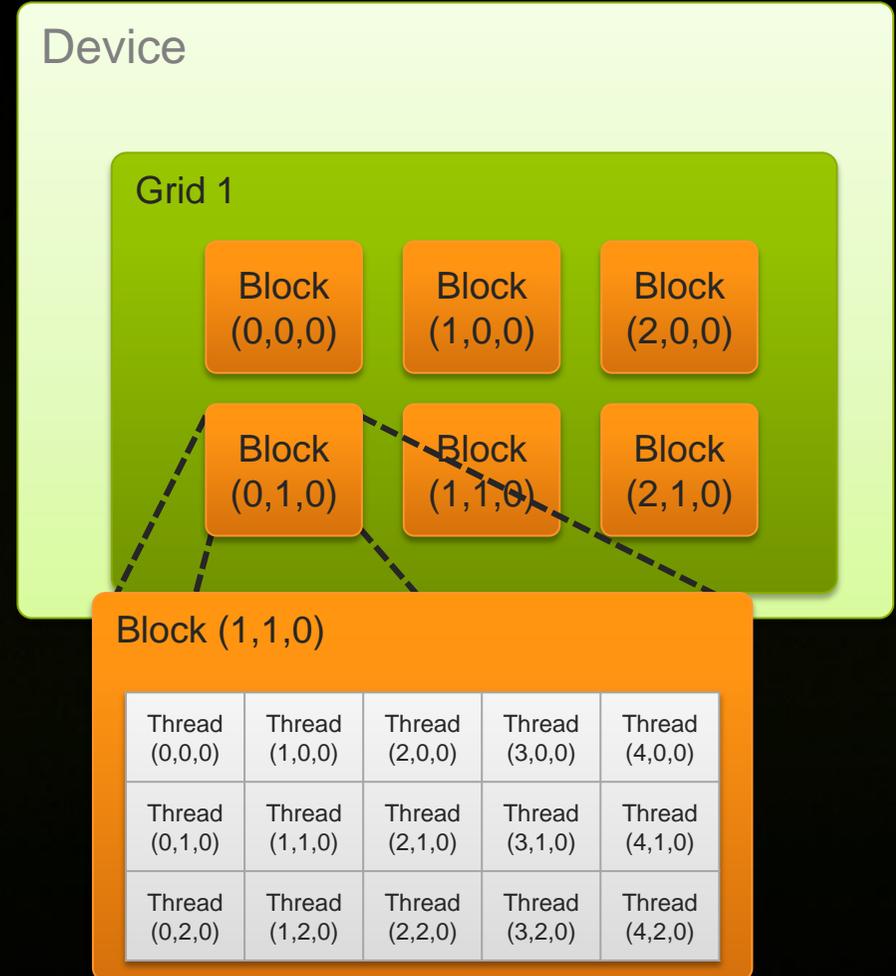
Textures

- ## Read-only object
  - Dedicated cache

- ## Dedicated filtering hardware
  (Linear, bilinear, trilinear)

- ## Addressable as 1D, 2D or 3D

- ## Out-of-bounds address handling
  (Wrap, clamp)

(2.5, 0.5)
(1.0, 1.0)

Questions?