

Introduction to CUDA Programming

An Introduction to CUDA

高性能计算机研究中心

What is CUDA?

■ CUDA Architecture

- Expose GPU parallelism for general-purpose computing
- 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 launch CUDA C/C++ kernels
 - 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

Blocks

Threads

Indexing

Shared memory

__syncthreads()

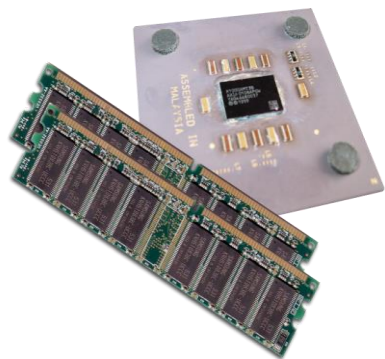
Asynchronous operation

Handling errors

Managing devices

Heterogeneous Computing

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



Host



Device

Heterogeneous Computing

```
#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);

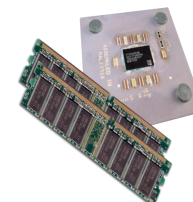
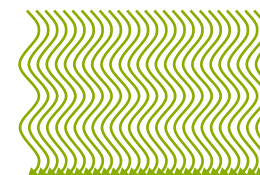
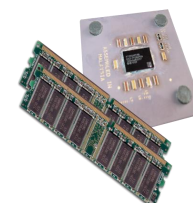
    // Copy result back to host
    cudaMemcpy(out, d_out, size, cudaMemcpyDeviceToHost);

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

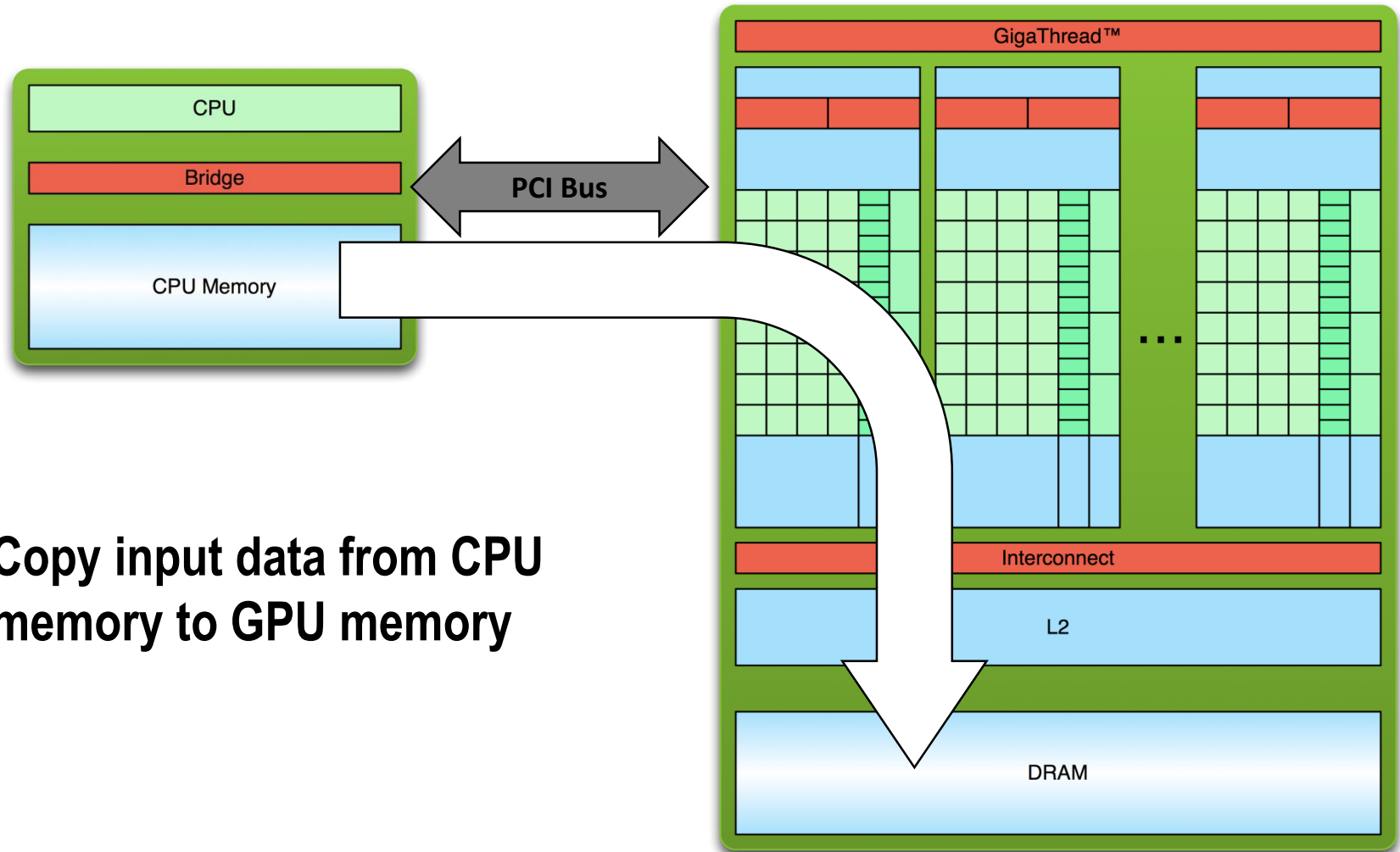
parallel fn

serial code

parallel code
serial code

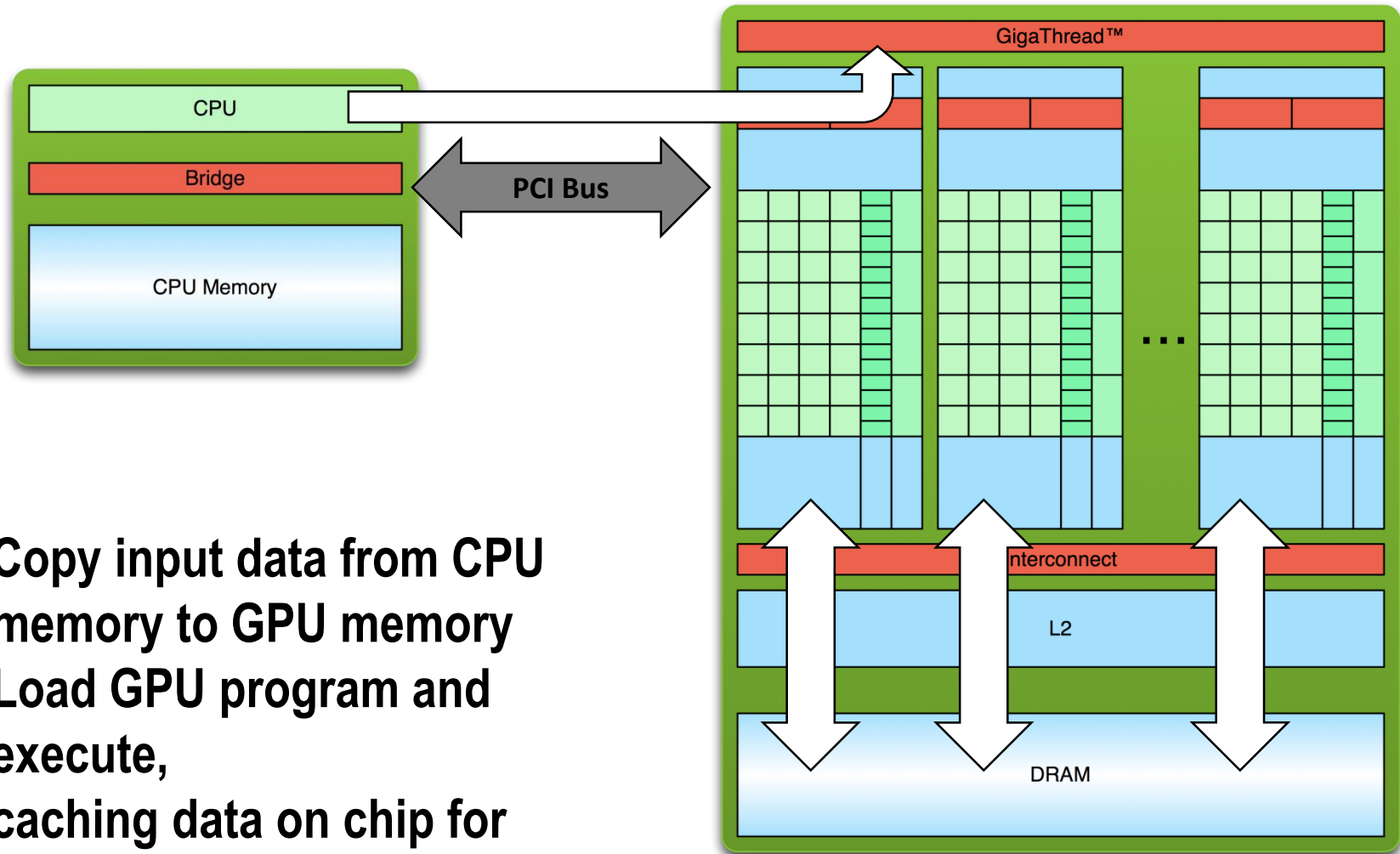


Simple Processing Flow



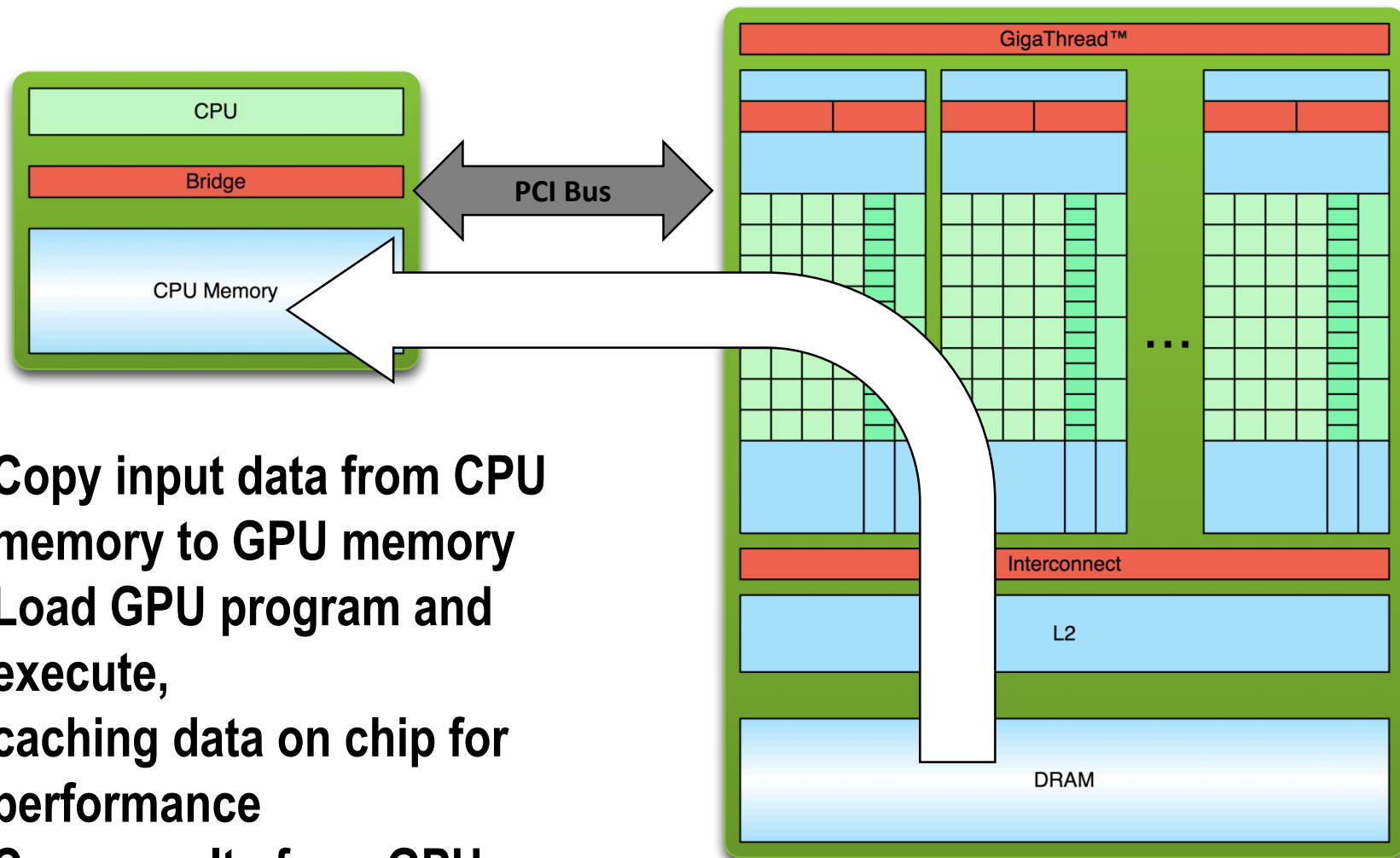
1. Copy input data from CPU memory to GPU memory

Simple Processing Flow



1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, 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!

```
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!  
$
```

Hello World! with Device Code

```
__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 C0de

```
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;  
}
```

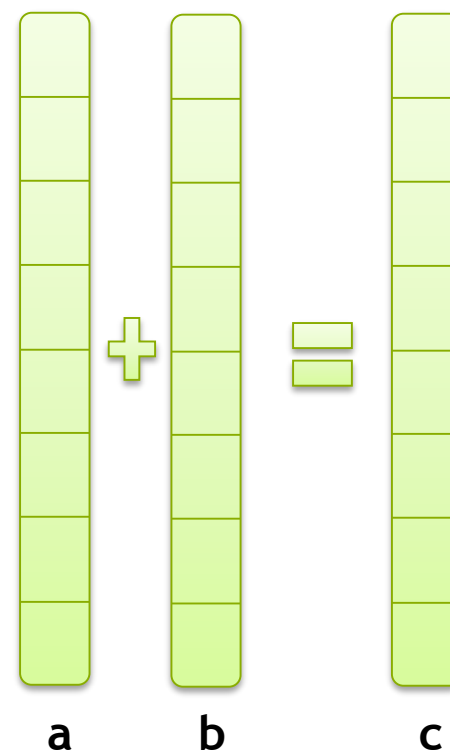
- `mykernel()` does nothing, somewhat anticlimactic!

Output:

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


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



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

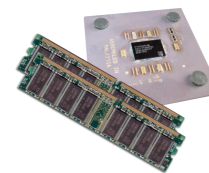
May be passed to/from host code

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()`

```
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;
```

Addition on the Device: `main()`

```
// 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;
}
```

RUNNING IN PARALLEL

CONCEPTS

Heterogeneous Computing

Blocks

Threads

Indexing

Shared memory

__syncthreads()

Asynchronous operation

Handling errors

Managing devices

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 index

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()

```
#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()

```
// 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

INTRODUCING THREADS

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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()

```
#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 Using Threads: main()

```
// 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;
}
```

COMBINING THREADS AND BLOCKS

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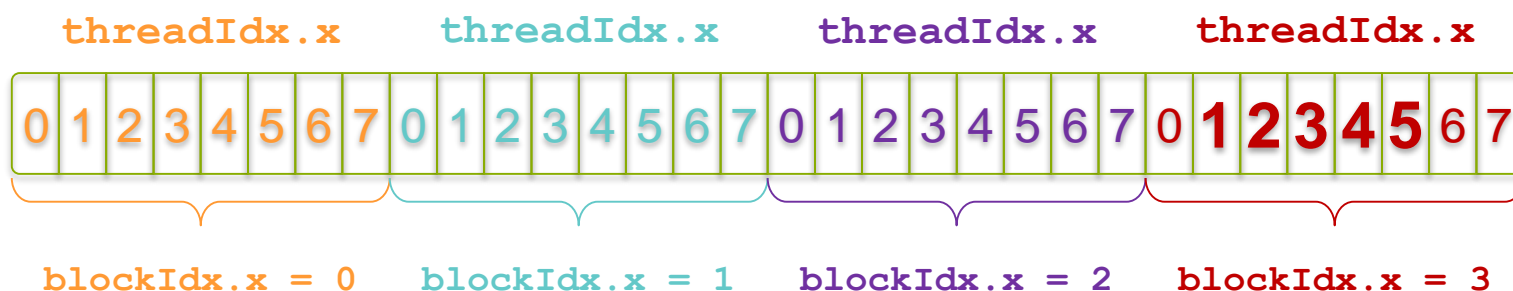
Managing devices

Combining Blocks and Threads

- We've seen parallel vector addition using:
 - Many blocks with one thread each
 - One block with many 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)

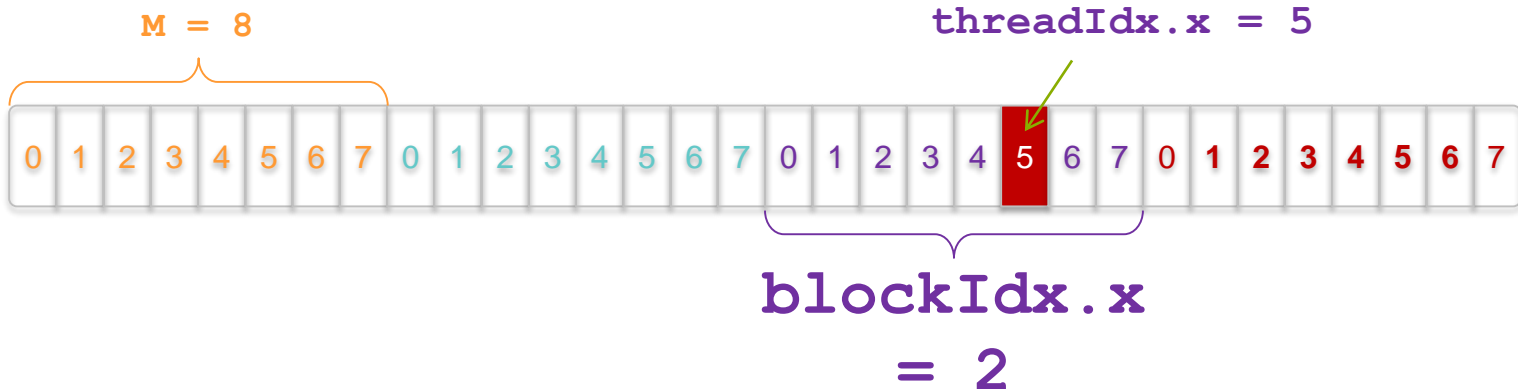


- With M threads/block a unique index for each thread is given by:

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

Indexing Arrays: Example

- Which thread will operate on the red element?



```

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()`

```
#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()`

```
// 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:**
 - Communicate
 - Synchronize
- **To look closer, we need a new example...**

COOPERATING THREADS

CONCEPTS

Heterogeneous Computing

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Shared memory

__syncthreads()

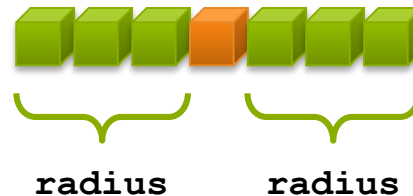
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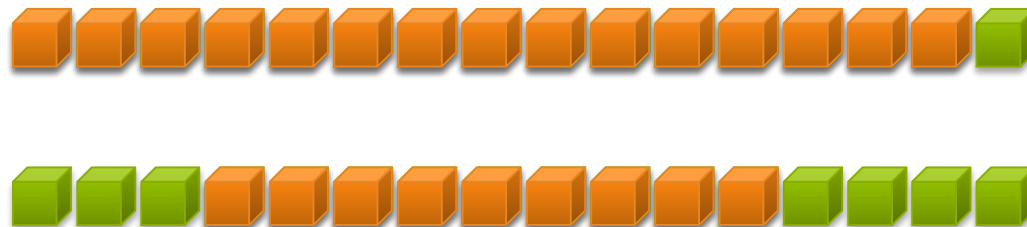
1D Stencil

- 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

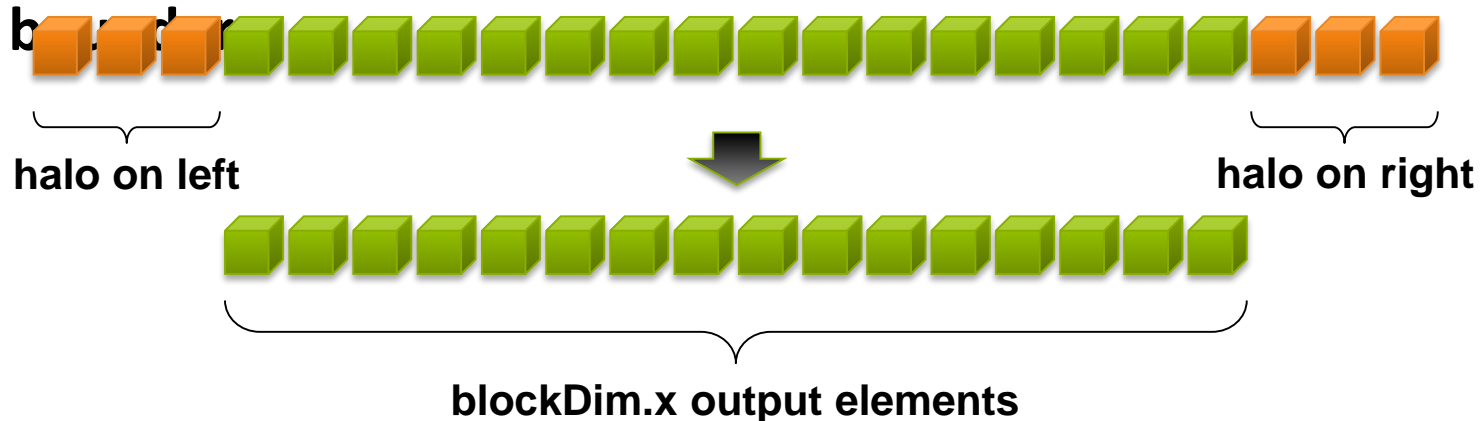


Sharing Data Between Threads

- **Terminology: within a block, threads share data via `shared memory`**
- **Extremely fast on-chip memory, user-managed**
- **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 ($\text{blockDim.x} + 2 * \text{radius}$) 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



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
    result = 0;
for (    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];           Store at temp[18] 
if (threadIdx.x < RADIUS) {
    temp[lindex - RADIUS] = in[gindex - RADIUS];    Skipped, threadIdx > RADIUS
    temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
}

int result = 0;
result += temp[lindex + 1];           Load from temp[19] 
```

__syncthreads()

- **__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

```
__global__ void stencil_1d(int *in, int *out) {
    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)
    ();
}
```

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;  
}
```


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
```

Review (2 of 2)

- 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

MANAGING THE DEVICE

CONCEPTS

Heterogeneous Computing

Blocks

Threads

Indexing

Shared memory

__syncthreads()

Asynchronous operation

Handling errors

Managing devices

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 threads can share a device

- A single thread can manage multiple devices

```
cudaSetDevice(i) to select current device
```

```
cudaMemcpy(...) for peer-to-peer copies†
```

[†] requires OS and device support

Introduction to CUDA C/C++

■ What have we learned?

- Write and launch CUDA C/C++ kernels
 - `__global__`, `blockIdx.x`, `threadIdx.x`, `<<<>>>`
- Manage GPU memory
 - `cudaMalloc()`, `cudaMemcpy()`, `cudaFree()`
- Manage communication and synchronization
 - `__shared__`, `__syncthreads()`
 - `cudaMemcpy()` VS `cudaMemcpyAsync()`,
`cudaDeviceSynchronize()`

Compute Capability

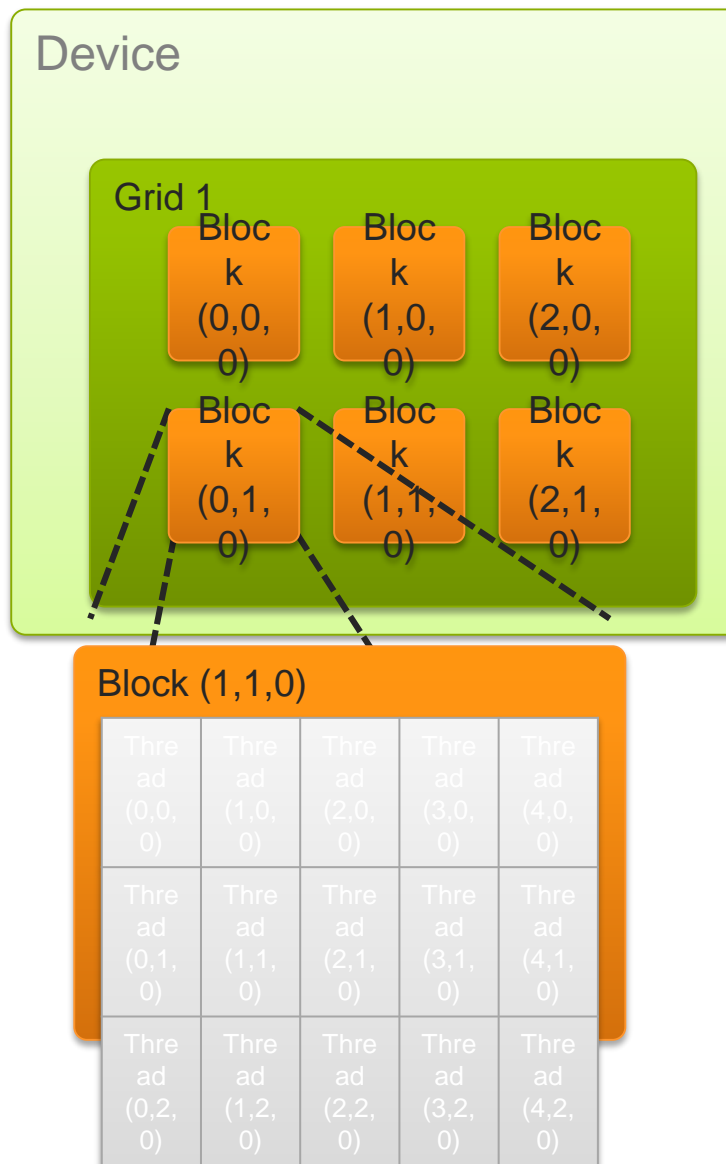
- The **compute capability** of a device describes its architecture, e.g.
 - Number of registers
 - Sizes of memories
 - Features & capabilities

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

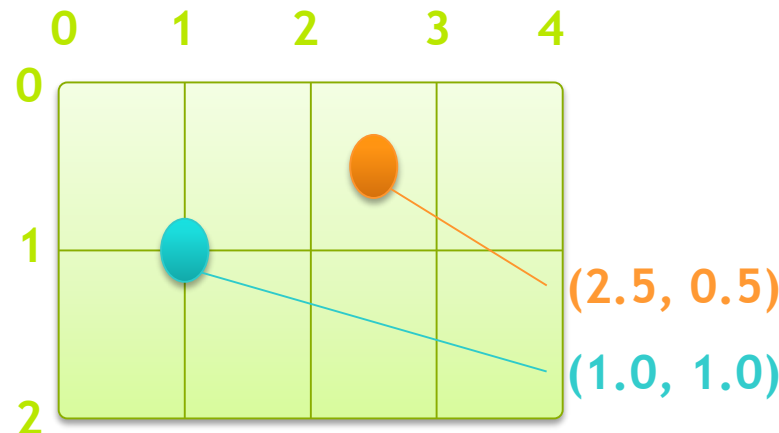
IDs and Dimensions

- 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)



Topics we skipped

- We skipped some details, you can learn more:
 - CUDA Programming Guide
 - CUDA Zone – tools, training, webinars and more
developer.nvidia.com/cuda
- Need a quick primer for later:
 - Multi-dimensional indexing
 - Textures

Practical 1

- start from code shown above (but with comments)
- learn how to compile / run code
- test error-checking and printing from kernel functions
- modify code to add two vectors together (including sending them over from the host to the device)
- if time permits, look at CUDA SDK examples

Practical 1

■ Things to note:

- memory allocation

```
cudaMalloc((void**) &dx, nbytes);
```

- data copying

```
cudaMemcpy(hx, dx, nbytes, cudaMemcpyDeviceToHost);
```

- reminder: prefix `h_` and `d_` to distinguish between arrays on the host and on the device is not mandatory, just helpful labelling
- kernel routine is declared by `__global__` prefix, and is
- written from point of view of a single thread

Practical 1

- Second version of the code is very similar to first, but uses an SDK header file for various safety checks – gives useful feedback in the event of errors.

- check for error return codes:

- `checkCudaErrors(...);` pages:

```
getLastCudaError( ... );
```

Practical 1

- **One thing to experiment with is the use of printf within a CUDA kernel function:**
 - **essentially the same as standard printf; minor difference in integer return code**
 - **each thread generates its own output; use conditional code if you want output from only one thread**
 - **output goes into an output buffer which is transferred to the host and printed later (possibly much later?)**
 - **buffer has limited size, so could lose some output if there's too much**
 - **need to use either `cudaDeviceSynchronize()`; or `cudaDeviceReset()`; at the end of the main code to make sure the buffer is flushed before termination**

Key reading

- **CUDA Programming Guide, version 5.5:**
 - Chapter 1: Introduction
 - Chapter 2: Programming Model
 - Appendix A: CUDA-enabled GPUs
 - Appendix B, sections B.1 – B.4: C language extensions
 - Appendix B, section B.17: printf output
 - Appendix G, section G.1: features of different GPUs