Heterogeneous programming

CUDA

Thierry Garcia

CY Tech

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Objectives

- acquire the basic training to analyse heterogeneous architectures with accelerators such as a GPU, as an alternative to multi-core systems of general purpose processors, and be able to compare their performance.
- develop efficient software for these platforms by means of languages.

Course Goals

- learn how to program heterogeneous computing systems.
- use parallel programming API, tools and techniques.

Contents

- Introduction and reminders (autonomous lessons).
- Structure of a heterogeneous system CPU-GPU.
- Introduction to CUDA programming.
- Optimization techniques.
- Programming on heterogeneous systems CPU-GPU.

Data parallelism

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- For example, in image processing, converting a color pixel to grayscale requires only the data of that pixel.
- A global operation, such as finding the average brightness of all pixels in an image, can be broken down into many smaller computations that can be executed independently.

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Figure: Conversion of a color image to a grayscale image.

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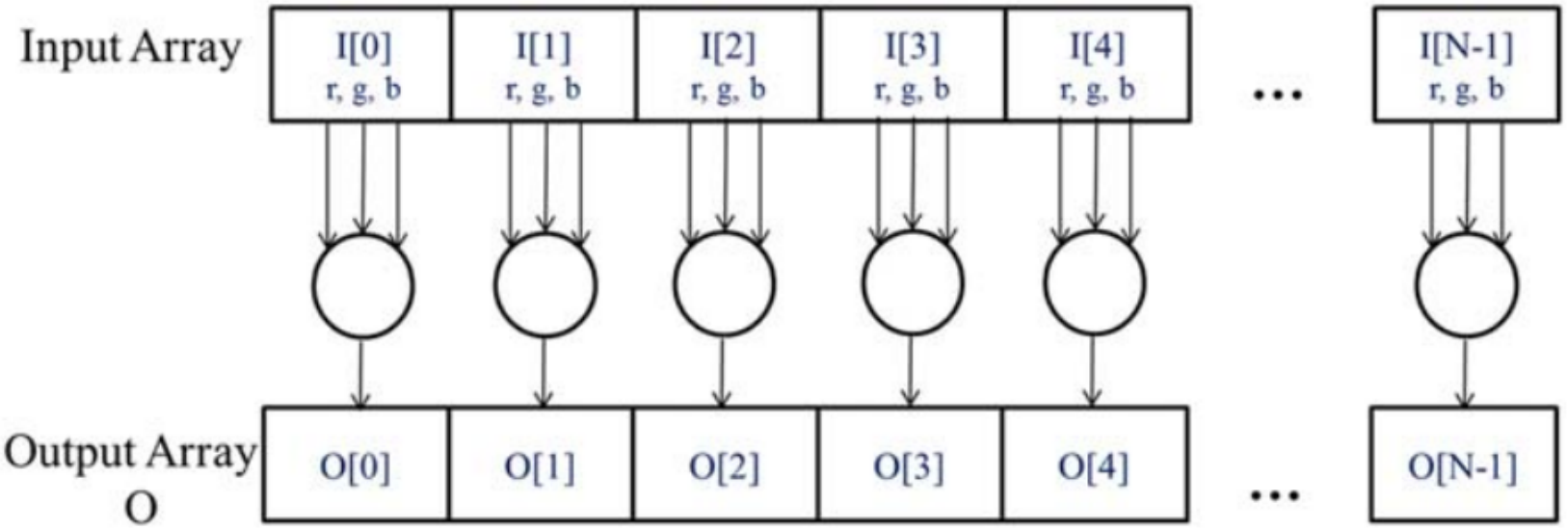

Figure: Data parallelism in image-to-grayscale conversion. Pixels can be calculated independently of each other.

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- Each CUDA C source file can have a mixture of host code and device code.

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- All the threads that are launched by a kernel call are collectively called a grid.These threads are the primary vehicle of parallel execution in a CUDA platform.

CUDA

What is CUDA?

- Figure 3 shows the execution of two grids of threads. When all threads of a grid have completed their execution, the grid terminates, and the execution continues on the host until another grid is launched.

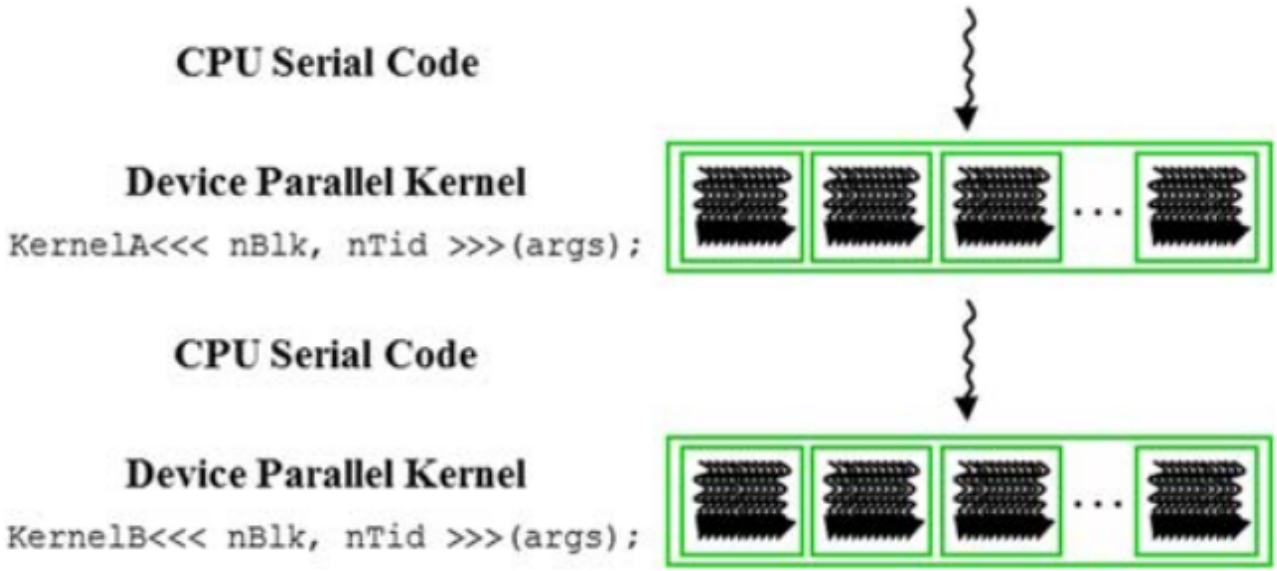

Figure: Execution of a CUDA program.

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  - Small set of extensions to enable heterogeneous programming
  - Direct APIs to manage devices, memory etc.

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- From 2007, NVidia made the CUDA (Compute Unified Device Architecture) available to programmers.
- Nvidia said : "CUDA is a parallel computing platform and programming model invented by NVIDIA. It enables dramatic increases in computing performance by harnessing the power of the graphics processing unit (GPU)."

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  - the organisation of threads in the form of a grid of thread blocks
- the physical model which is responsible for distributing and executing the threads on the GPU's execution cores

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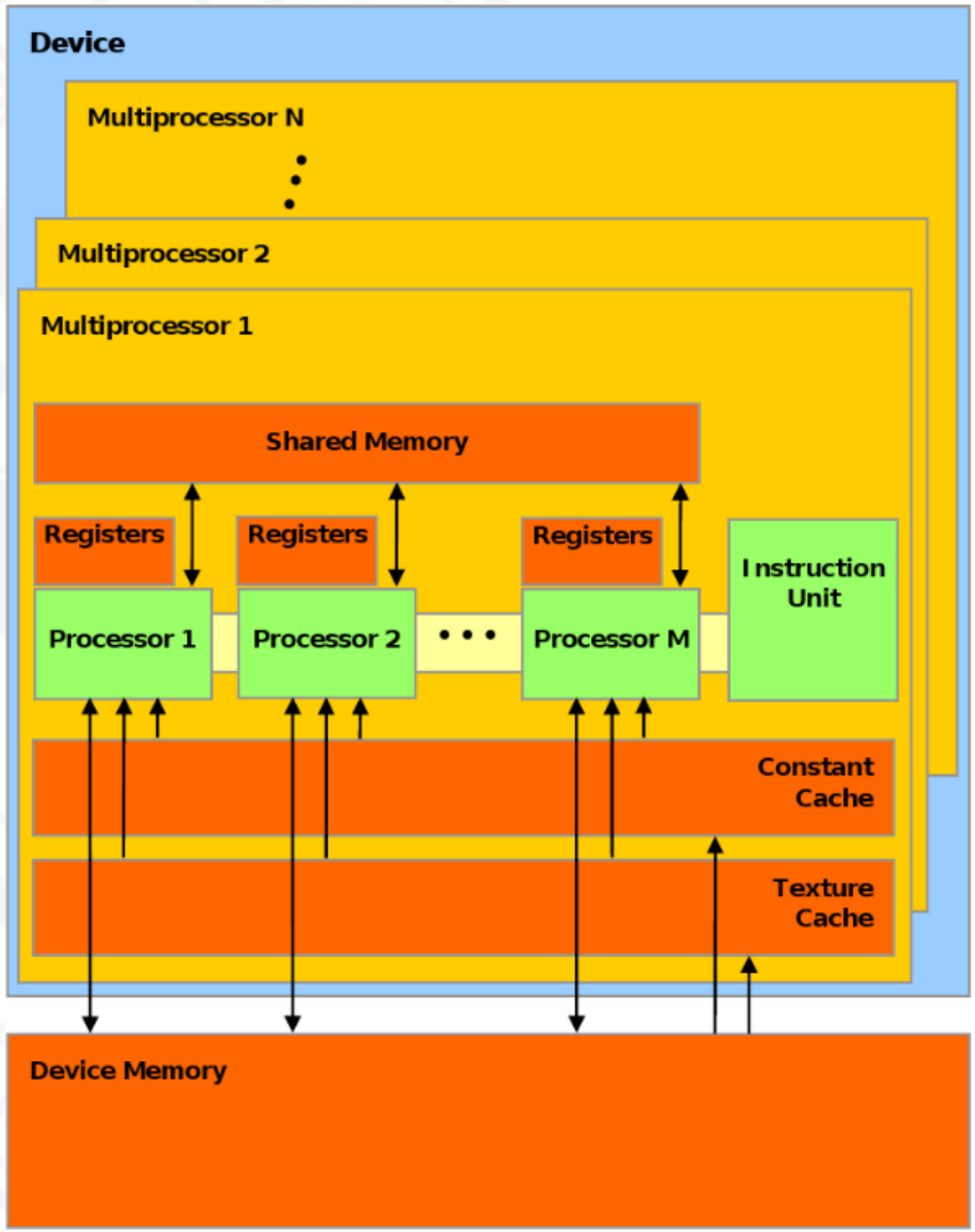

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  - Thousands of threads on hundreds of processors for optimal operation.

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- Threads all execute the same code

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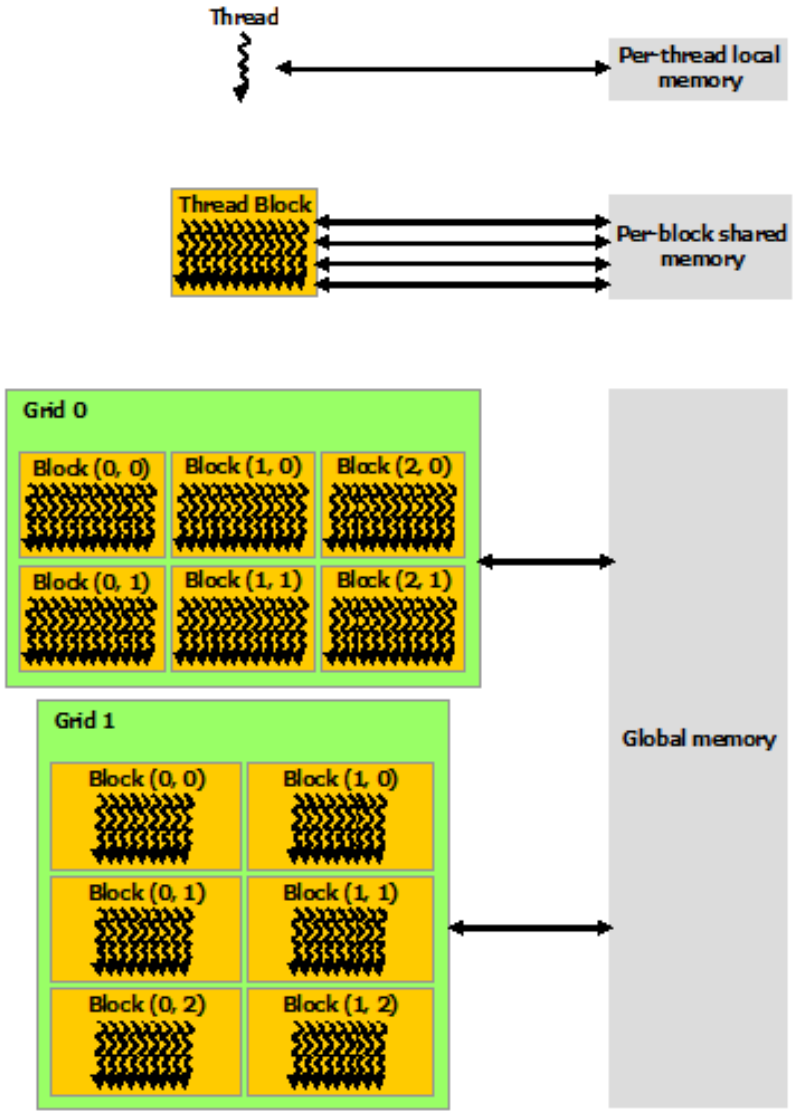

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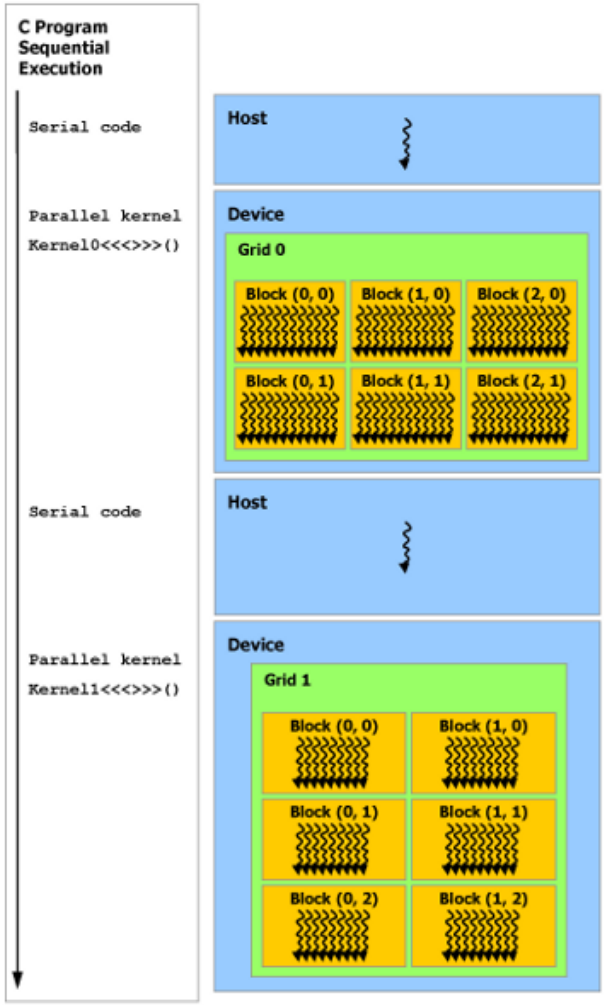
Heterogeneous Programming



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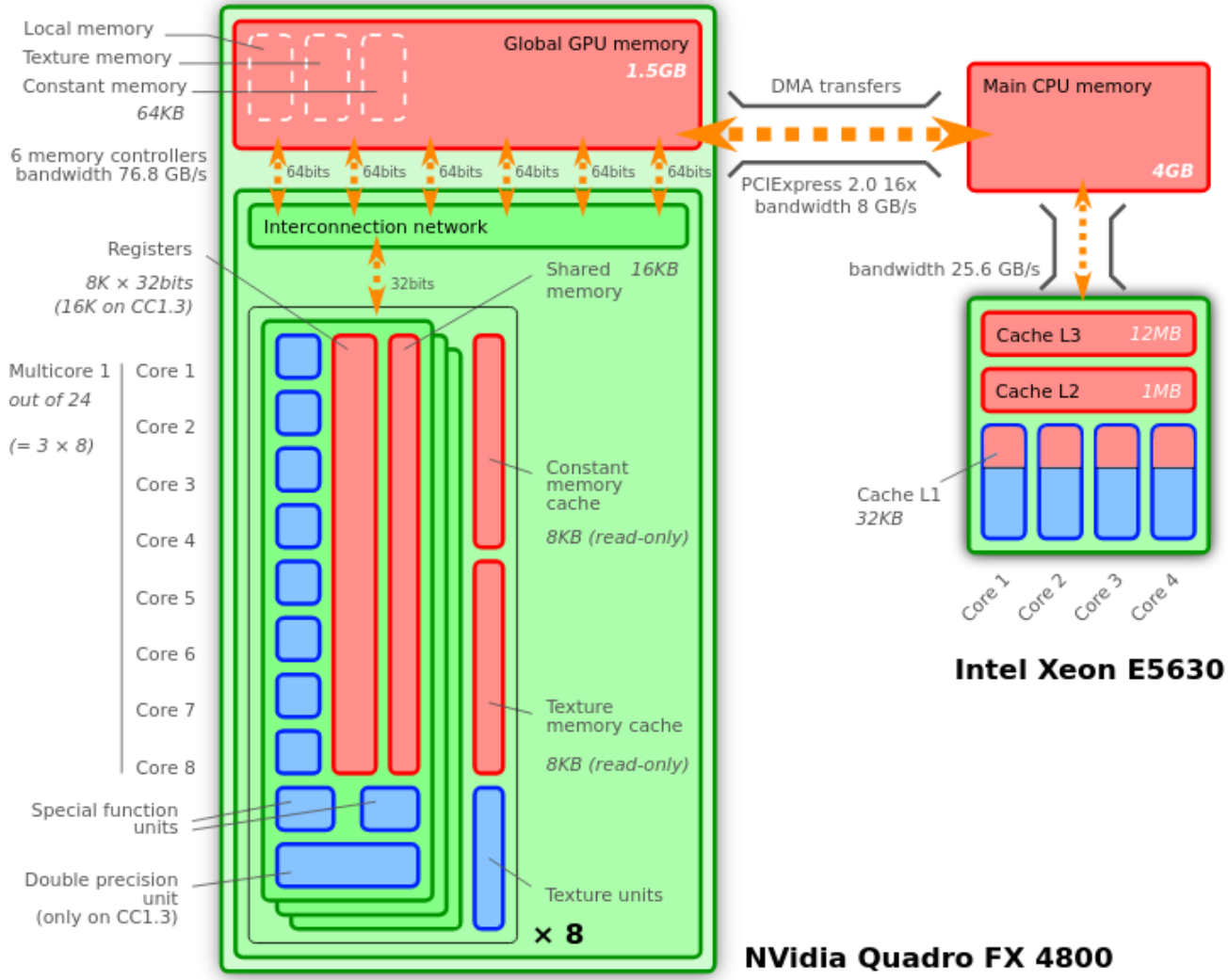
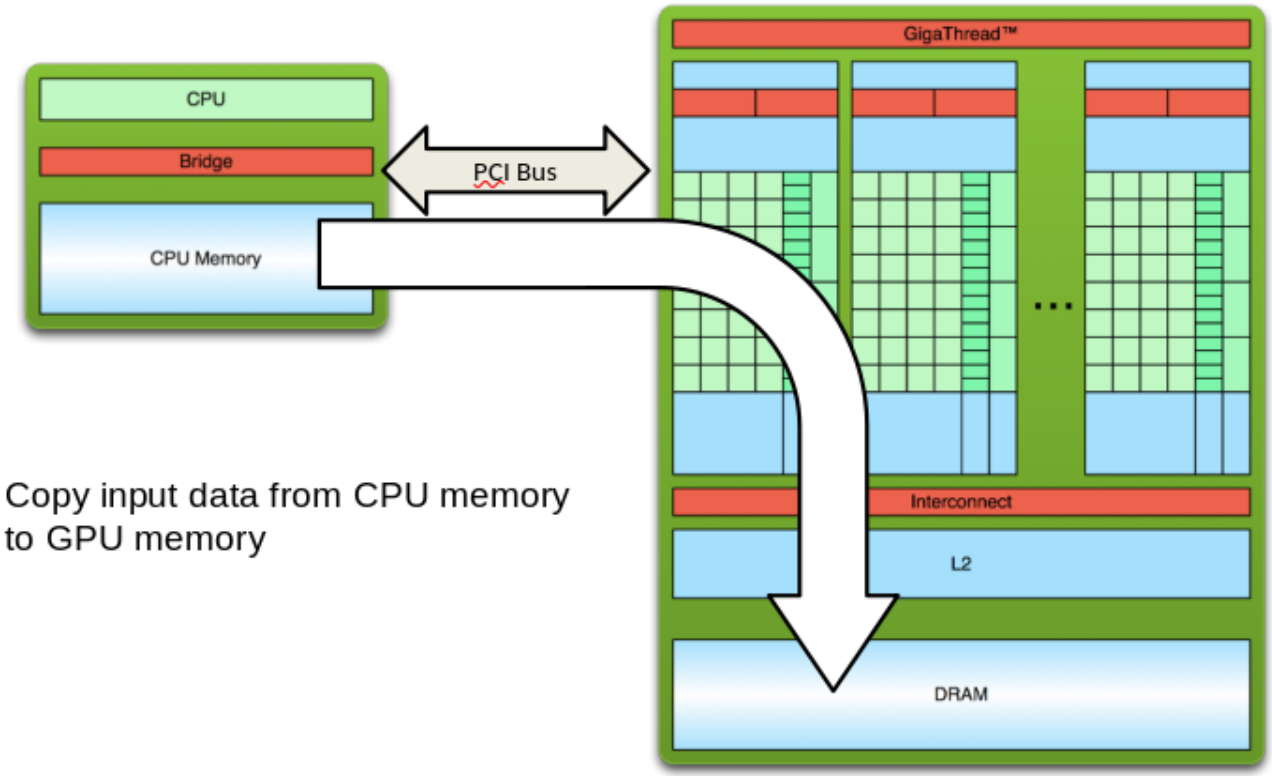
- A GPU is a set of N small independent SIMD machines sharing a memory: *N* multiprocessors



Example hardware of nVIDIA Tesla GPU architecture

Simple Processing Flow



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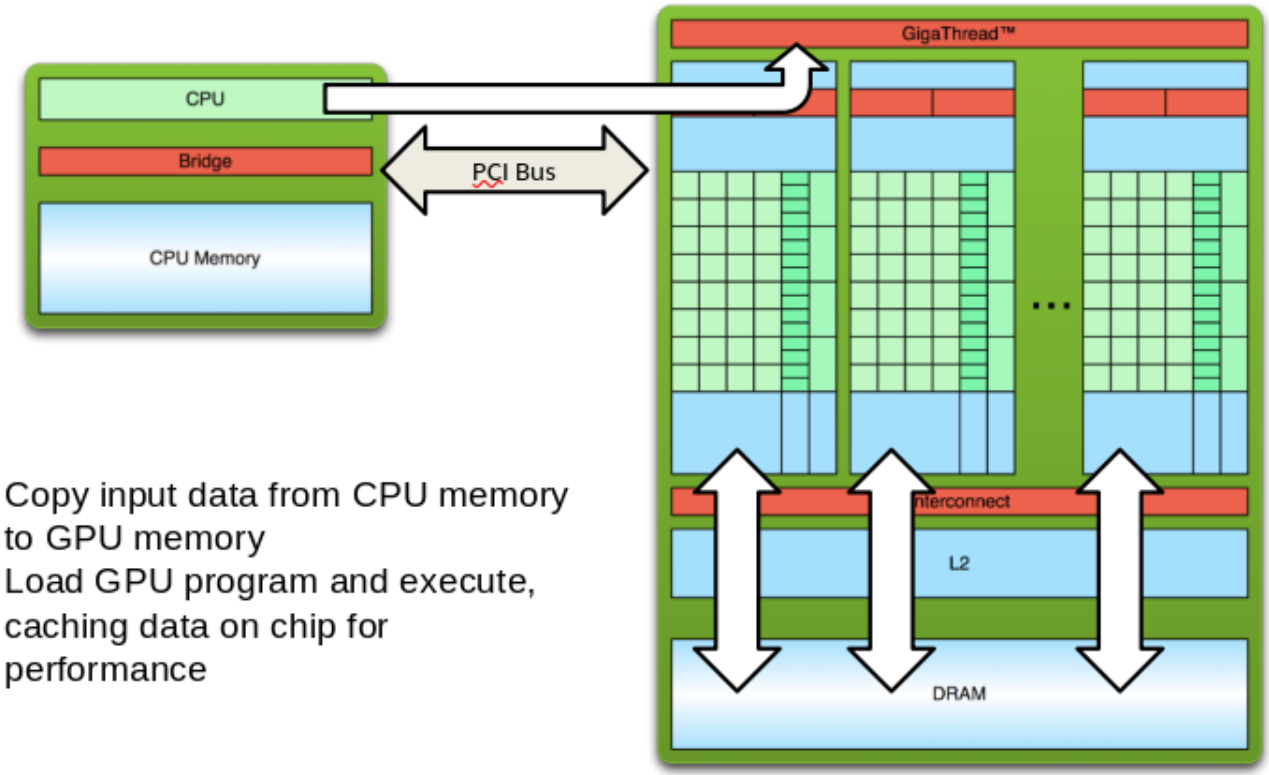

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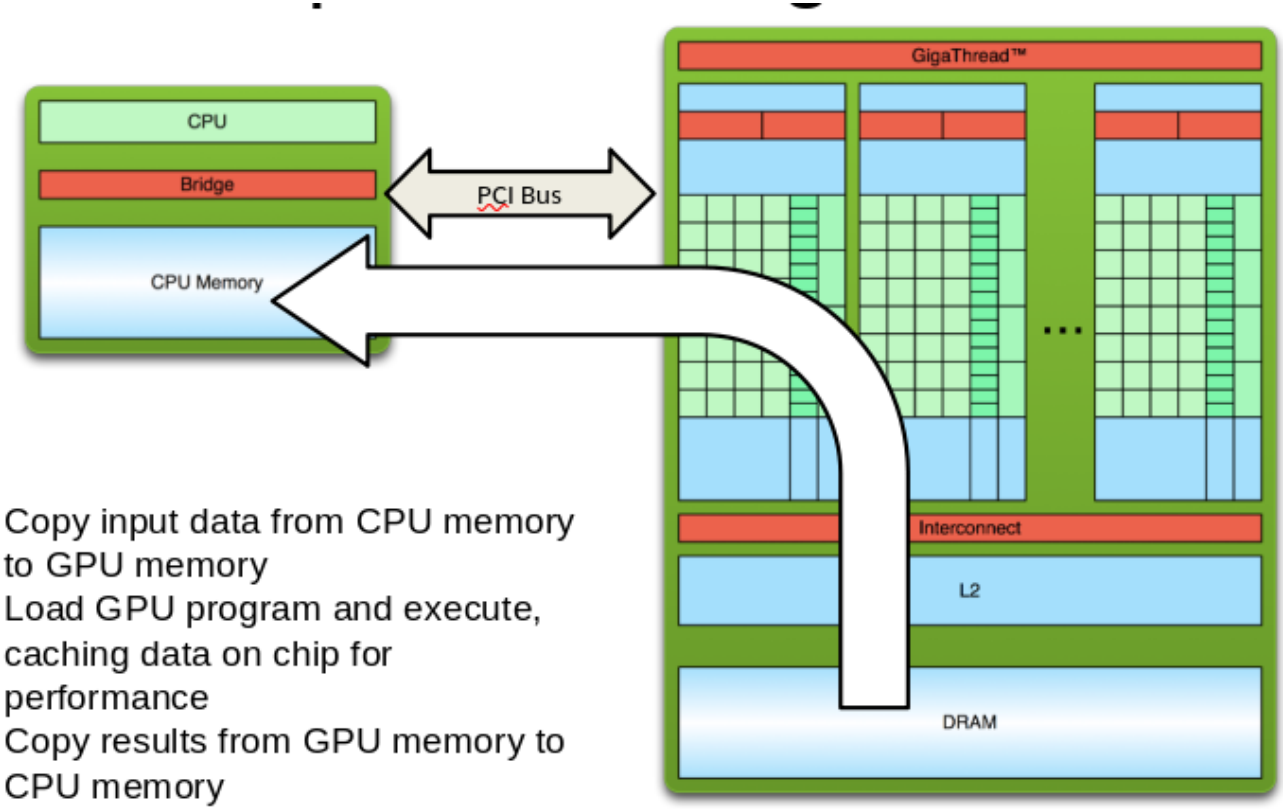

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2. Load GPU program and execute, caching data on chip for performance
3. Copy results from GPU memory to CPU memory

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- Communication intra-block by shared memory
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CUDA: First Program

Hello World!

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

- Standard C that runs on the host (CPU and system's memory)
- NVIDIA compiler (nvcc) can be used to compile programs with no device code

```
>nvcc hello_world.cu
>./a.out
Hello World!
>
```

CUDA: First Program

Hello World! with Device Code

```
#include <stdio.h>

__global__ void kernel(void) {
}

int main(void) {
        kernel<<<1,1>>>();
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- nvcc separates source code into host and device components

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- A call to this empty function embellished with $<<<1,1>>>$
- CUDA C adds __global__ qualifier to standard C and alerts the compiler that a function should be compiled to run on a device instead of the host.
- nvcc separates source code into host and device components
  - Device functions (kernel()) processed by NVIDIA compiler

CUDA: First Program

Hello World! with Device Code

```
#include <stdio.h>

__global__ void kernel(void) {
}

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

- A new empty function named kernel() qualified with __global__
- A call to this empty function embellished with $<<< 1, 1 >>>$
- CUDA C adds __global__ qualifier to standard C and alerts the compiler that a function should be compiled to run on a device instead of the host.
- nvcc separates source code into host and device components
  - Device functions (kernel()) processed by NVIDIA compiler
  - Host functions (main()) processed by standard host compiler gcc, cl.exe

CUDA : First Program

Hello World! with Device Code

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

- Triple angle brackets mark a call from host code to device code

CUDA : First Program

Hello World! with Device Code

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  - Also called a “kernel launch”

CUDA : First Program

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- 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

CUDA : First Program

Hello World! with Device Code

```
kernel<<<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!

First Program

Hello World! with Device Code

```
#include <stdio.h>

__global__ void kernel(void) {
}

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

- kernel() does nothing for the moment.

CUDA

How test code ?

CUDA

Connection CESGA

- On LINUX, install openfortivpn : sudo dnf install openfortivpn or sudo apt install openfortivpn
- In a terminal : sudo openfortivpn gateway.cesga.es:443 -u cursoxxx@ce
- In another terminal : ssh cursoxxx@ft3.cesga.es
- compute –mem 1 –gpu <– mem = 1 Go
- scontrol show node c7257 <– hostname
- module load cuda
- nano hello.cu <– copy or create code
- nvcc hello.cu -o hello
- ./hello

CUDA

Connection CESGA

- Guide FT-3 (`https://cesga-docs.gitlab.io/ft3-user-guide/gpu_nodes.html`)
- 2 types de GPU dans le FT-3 : Nvidia A100 et Tesla T4 .
- Accès à T4 interactif via la commande "compute –gpu". Il n'y a que 10 nœuds avec T4 disponibles via cette option. S'il y a 10 utilisateurs demandant un T4, le suivant devra attendre que l'un des autres libère une de ces sessions.
- Accès aux 64 nœuds avec 2 A100 chacun. L'accès à ces nœuds se fait en envoyant des travaux à la file d'attente avec l'option "–gres=gpu" sans interactivité.
- Option intermédiaire, en fonction de l'occupation des A100 à tout moment, serait d'utiliser : salloc -I600 –gres=gpu –mem-per-cpu=3G -c 32 -t 10:00 srun -c 32 –pty –preserve-env /bin/-bash -i

CUDA

Connection CESGA

- Download and test deviceprop.cu

CUDA

Measuring performance

```
int main ( void ) {
float elapsed=0;
clock_t cpu_startTime, cpu_endTime;
double cpu_ElapseTime=0;
cudaEvent_t start, stop;
cpu_startTime = clock();
cudaEventCreate(&start);
cudaEventCreate(&stop);
cudaEventRecord(start, 0);
kernel <<<1,1>>>() ;
cudaEventRecord(stop, 0);
cudaEventSynchronize (stop);
cudaEventElapsedTime(&elapsed, start, stop);
cudaEventDestroy(start);
cudaEventDestroy(stop);
printf("The elapsed time in gpu was %.8f ms\n", elapsed);
printf ( "Hello World ! \n" ) ;
cpu_endTime = clock();
cpu_ElapseTime = ((cpu_endTime - cpu_startTime)/(double)
    CLOCKS_PER_SEC);
printf("The elapsed time in cpu was %.8f ms\n",
    cpu_ElapseTime);
return 0;}
```

CUDA

Let's test the code : hello.cu

CUDA

Parallel Programming in CUDA C/C++

CUDA

Parallel Programming in CUDA C/C++

- But wait ... GPU computing is about massive parallelism!

CUDA

Parallel Programming in CUDA C/C++

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- We need a more interesting example ...

CUDA

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

CUDA

Parallel Programming in CUDA C/C++

- But wait ... GPU computing is about massive parallelism!
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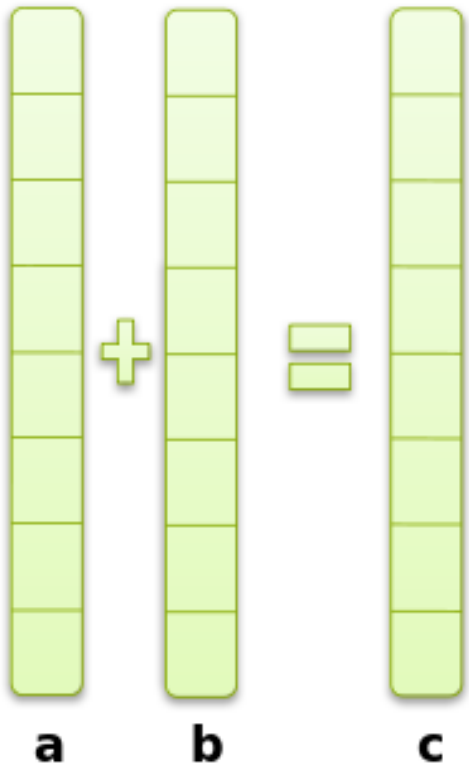
- We'll start by adding two integers and build up to vector addition



CUDA: First Program

```
#include <stdio.h>

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

CUDA: First Program

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#include <stdio.h>

__global__ void add(int *a, int *b, int *c) {
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- As before __global__ is a CUDA C/C++ keyword meaning

CUDA: First Program

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

CUDA: First Program

```
#include <stdio.h>

__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

CUDA: First Program

```
#include <stdio.h>

__global__ void add(int *a, int *b, int *c) {
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CUDA: First Program

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

CUDA: First Program

```
#include <stdio.h>

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

- add() run on the device, so a,b and c must point to device memory
- we need to allocate memory on GPU

CUDA: Memory management

- Host and device memory are separate entities

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  - Device pointers point to GPU memory

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  - cudaMalloc(), cudaFree(), cudaMemcpy()

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- Host and device memory are separate entities
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    - ★ 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()

CUDA: First Program

```
#include <stdio.h>

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

- Let's take a look at main()

CUDA: First Program

```
#include <stdio.h>

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

int main(void) {
    int h_a, h_b, h_c; // host copies of a,b,c
    int *d_a, *d_b, *d_c; //device copie 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
        h_a = 2;
        h_b = 7;
```

CUDA: First Program

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

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

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

    printf("Result = %d\n",h_c);

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

CUDA

Let's test the code addseq.cu with measuring performance

CUDA: Unified Memory (SCC K40m and P100)

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- The P100 will offer the best performance when using this feature.
- Unified Memory simplifies memory management in a CUDA code.
- For more details see: `https://devblogs.nvidia.com/unified-memory-cuda-beg`

CUDA: First Program

```
include <stdio.h>

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

int main(void) {
    int *a, *b, *c;  // host AND device
    int size = sizeof(int);
        // Allocate space for device copies of a, b, c
        cudaMallocManaged(&a, size);
            cudaMallocManaged(&b, size);
        cudaMallocManaged(&c, size);
        // Setup input values
        *a = 2; *b = 7;
    // Launch add() kernel on GPU. Data values are
    // sent to the host when accessed in the kernel
    add<<<1,1>>>(a,b,c);
    // Wait for GPU to finish before accessing on host
    cudaDeviceSynchronize();
    // access will auto-transfer data back to the host
    printf("%d %d %d\n",*a, *b, *c);
    cudaFree(a); cudaFree(b); cudaFree(c); // Cleanup
    return 0;
}
```

CUDA

Let's test the code addseqm.cu with measuring performance - compare with addseq.cu

CUDA: Moving to parallel

GPU computing is about massive parallelism

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

CUDA: Moving to parallel

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

```
add<<<1,1>>>();
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CUDA: Moving to parallel

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

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

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

CUDA: 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 !!

CUDA: Vector Addition on the Device

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

CUDA: Vector Addition on the Device

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- Terminology: each parallel invocation of add() is referred to as a block

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  - The set of blocks is referred to as a grid

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- 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];
}
```

CUDA: 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

CUDA: Vector Addition on the Device

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

CUDA: Vector Addition on the Device

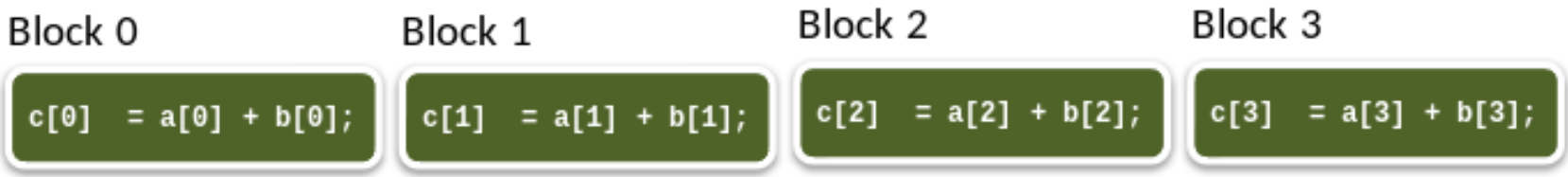
```
__global__ void add(int *a, int *b, int *c) {
        c[blockIdx.x] = a[blockIdx.x] +
            b[blockIdx.x];
}
```

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

CUDA: 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:



CUDA: Vector Addition on the Device

- Returning to our parallelized add() kernel

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

CUDA: Vector Addition on the Device

- 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() ...

CUDA: Vector Addition on the Device

```
#define N 512
int main(void) {
    int *h_a, *h_b, *h_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
    h_a = (int *)malloc(size); random_ints(h_a, N);
    h_b = (int *)malloc(size); random_ints(h_b, N);
    h_c = (int *)malloc(size);
```

CUDA: Vector Addition on the Device

```
// Copy inputs to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, h_b, size, cudaMemcpyHostToDevice);
```

CUDA: Vector Addition on the Device

```
// Copy inputs to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, h_b, size, cudaMemcpyHostToDevice);

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

CUDA: Vector Addition on the Device

```
    // Copy inputs to device
    cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
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    // Launch add() kernel on GPU with N blocks
    add<<<N,1>>>(d_a, d_b, d_c);

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

    // Cleanup
    free(h_a); free(h_b); free(h_c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

CUDA

Let's test the code vecaddpar.cu with measuring performance

```
void random_ints(int* a, int N)
{
        int i;
        for (i = 0; i < N; ++i)
        a[i] = rand();
}
```

CUDA

- Exit or Ctrl-D
- compute –mem 2 –gpu

Let's test the code vecaddpar.cu with measuring performance with N=1024, 10240, 102400, 1024000, 10240000 (user argv)

CUDA: Review

- Difference between host and device

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  - Host CPU

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  - Host CPU
  - Device GPU

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- Difference between host and device
  - Host CPU
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CUDA: Review

- 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

CUDA: Review

- Basic device memory management

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  - Launch N copies of add() with add$<<< N, 1 >>>$(...);

CUDA: Review

- 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

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

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

CUDA: Threads

- Terminology: a block can be split into parallel threads
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```
__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() ...

CUDA: Vector Addition on the Device

```
#define N 512
int main(void) {
    int *h_a *h_b, *h_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
    h_a = (int *)malloc(size); random_ints(h_a, N);
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    h_c = (int *)malloc(size);
```

CUDA: Vector Addition on the Device

```
// Copy inputs to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, h_b, size, cudaMemcpyHostToDevice);
```

CUDA: Vector Addition on the Device

```
// Copy inputs to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, h_b, size, cudaMemcpyHostToDevice);

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

CUDA: Vector Addition on the Device

```
    // Copy inputs to device
    cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
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    // Launch add() kernel on GPU with N threads
    add<<<1,N>>>(d_a, d_b, d_c);

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

    // Cleanup
    free(h_a); free(h_b); free(h_c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

CUDA

Let's test the code vecaddpartargt.cu with measuring performance with N=1024, 10240, 102400, 1024000, 10240000 (user argv)

CUDA: 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 ...
- Use blockIdx.x to access block index
- First let's discuss data indexing ...

CUDA: Indexing Arrays with Blocks and Threads

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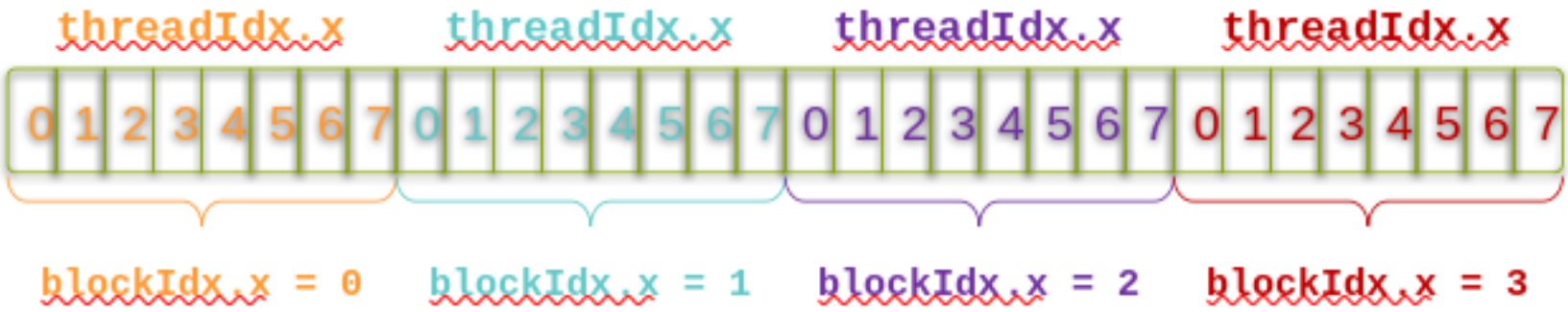

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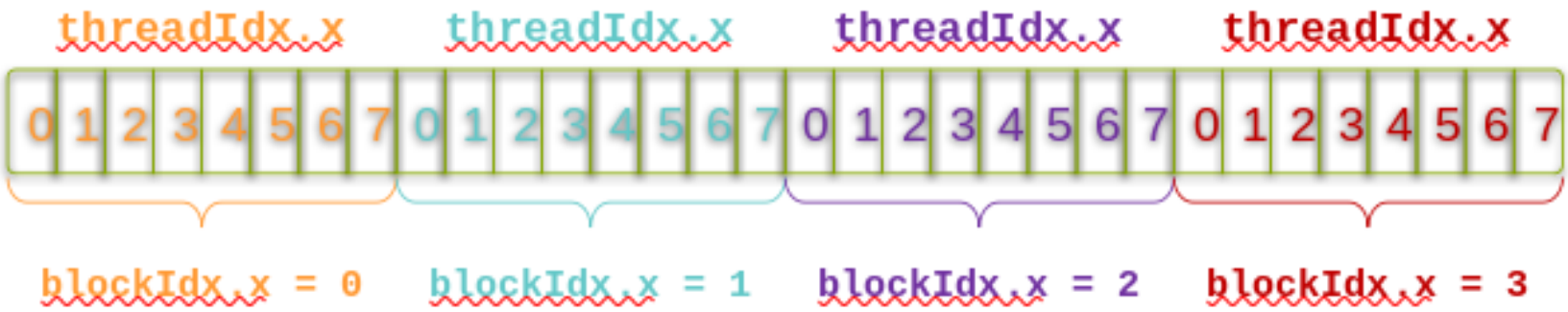

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int index = threadIdx.x + blockIdx.x * M;
```
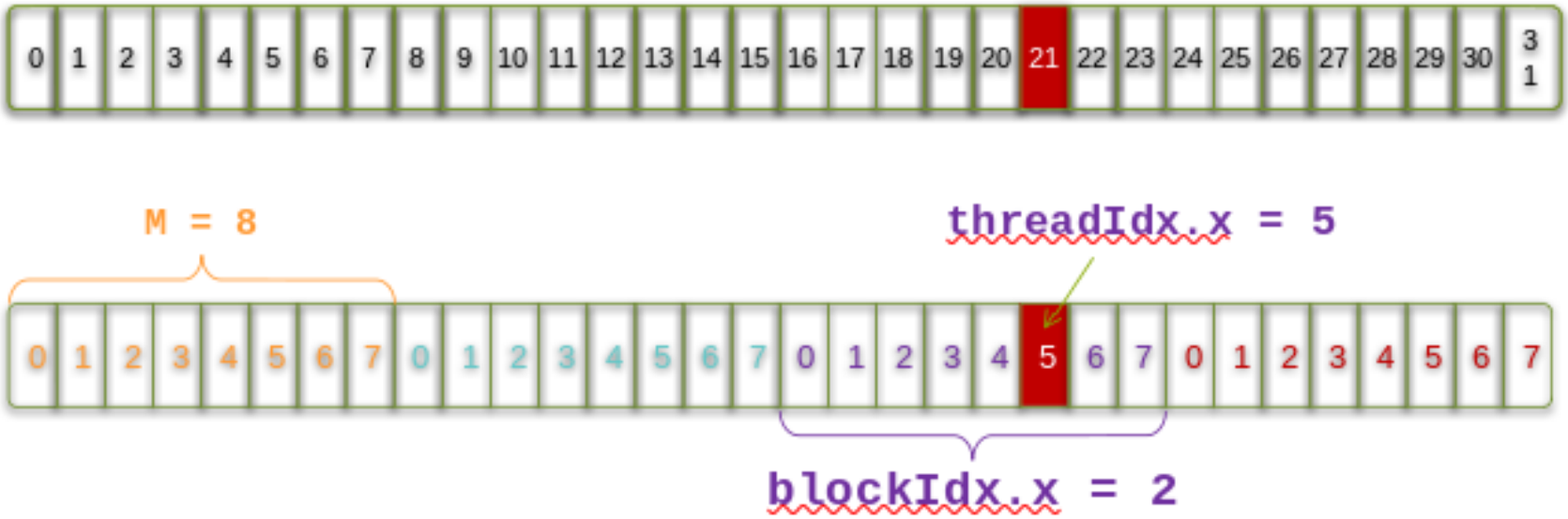

CUDA: Indexing Arrays - Example

- Which thread will operate on the red element?



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

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

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

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

CUDA: Addition with Blocks and Threads

```
#define N (2048*2048)
#define THREADS_PER_BLOCK 512
int main(void) {
    int *h_a, *h_b, *h_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
    h_a = (int *)malloc(size); random_ints(h_a, N);
    h_b = (int *)malloc(size); random_ints(h_b, N);
    h_c = (int *)malloc(size);
```

CUDA: Vector Addition on the Device

```
// Copy inputs to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
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// Copy inputs to device
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// Launch add() kernel on GPU
add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a,
    d_b, d_c);
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    // Launch add() kernel on GPU
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        d_b, d_c);

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

    // Cleanup
    free(h_a); free(h_b); free(h_c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

CUDA

Let's test the code vecaddpartargbt.cu with measuring performance with N=1024, 10240, 102400, 1024000, 10240000 (user argv)

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```
add<<<(N + M-1) / M,M>>>(d_a, d_b, d_c, N);
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- To look closer, we need a new example ...

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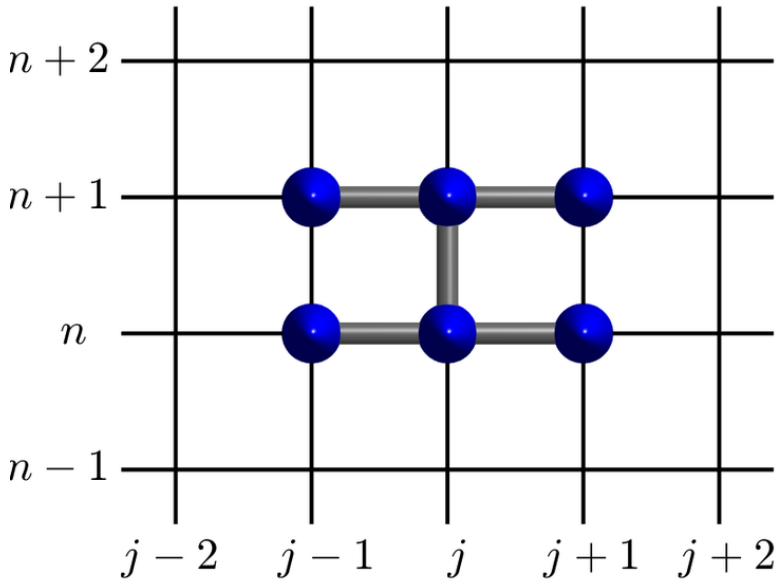
CUDA: Cooperating Threads

1D Stencil :

- In mathematics, especially the areas of numerical analysis concentrating on the numerical solution of partial differential equations, a stencil is a geometric arrangement of a nodal group that relate to the point of interest by using a numerical approximation routine.
- Stencils are the basis for many algorithms to numerically solve partial differential equations (PDE).



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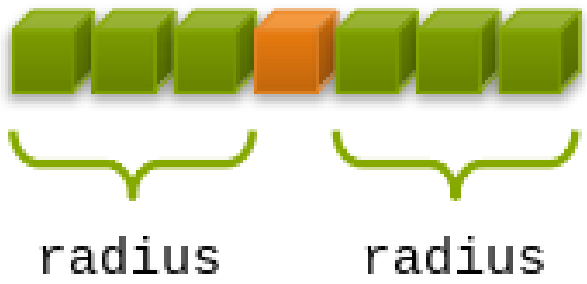

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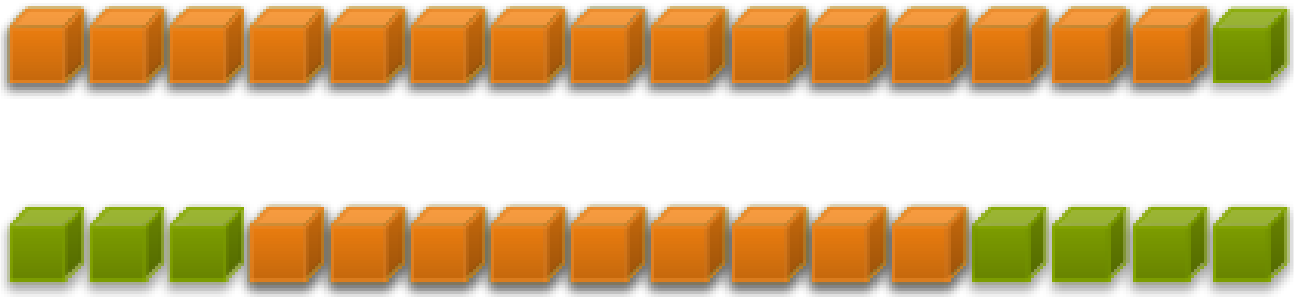

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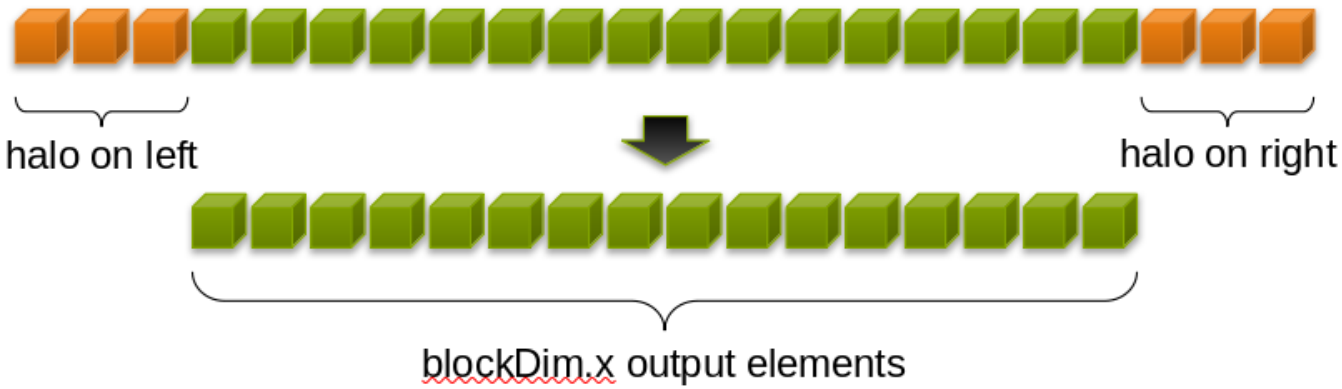
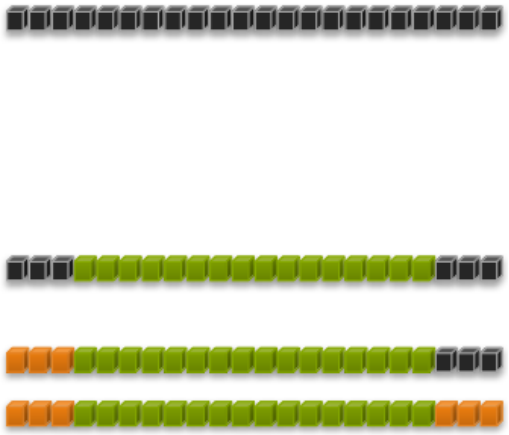


CUDA: Stencil Kernel

```
__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];
```



CUDA: 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;
}
```

CUDA: 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;
result += temp[lindex + 1];
```

Store at temp[18]

Skipped, threadIdx > RADIUS

Load from temp[19]

CUDA: Synchronize

- void __syncthreads();
- Synchronizes all threads within a block
  - Used to prevent RAW (Read after Write), WAR (Write after Read), WAW (Write after Write) hazards
- All threads must reach the barrier
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__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();
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CUDA: Stencil Kernel

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    int result = 0;
    for (int offset = -RADIUS ; offset <= RADIUS ;
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`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

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

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- Application can query and select GPUs

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```
cudaGetDeviceCount(int *count)
cudaSetDevice(int device)
cudaGetDevice(int *device)
cudaGetDeviceProperties(cudaDeviceProp
    *prop, int device)
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- Multiple threads can share a device

CUDA: Managing the device

Device Management

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```
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

CUDA: Managing the device

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)
```

CUDA: Review

- What have we learned?

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- What have we learned?
  - Write and launch CUDA C/C++ kernels

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- What have we learned?
  - Write and launch CUDA C/C++ kernels
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  - Manage GPU memory
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  - Manage communication and synchronization

CUDA: Review

- 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()

CUDA: Review

- 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()

CUDA: Compute Capability

- The compute capability of a device describes its architecture, e.g.
- Number of registers
- Sizes of memories
- Features & capabilities
- For an update-to-date list see Wikipedia:
- `https://en.wikipedia.org/wiki/CUDA#Version_features_and_specifications`
- Examples GPUs:

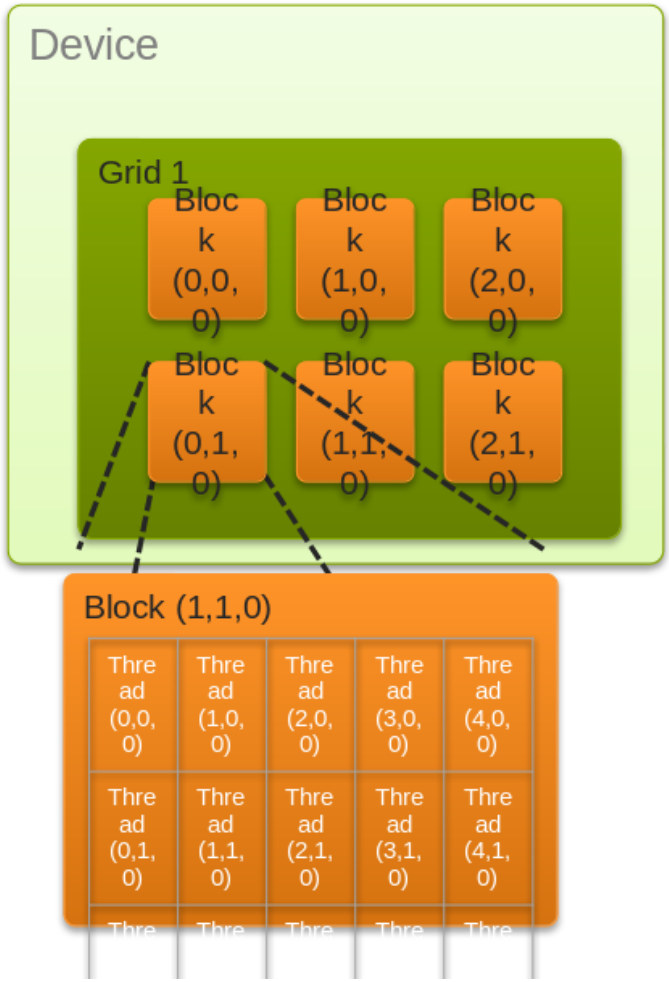
GPU	Compute Capability
M2050	2.0
M2070	2.0
K40m	3.5
P100	6.0

- Features & capabilities

This lesson has concentrated on Fermi devices with Compute Capability >= 2.0

CUDA: Stencil Kernel

- 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



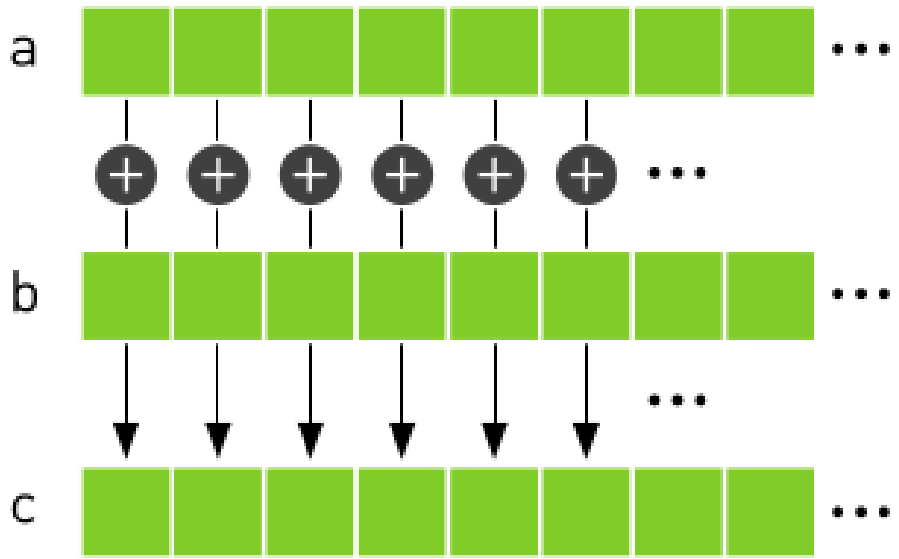
CUDA Parallel Programming

CUDA-Reminders

- Previously, we saw how easy it was to get a standard C function to start running on a device.
- By adding the __global__ qualifier to the function and by calling it using a special angle bracket syntax, we executed the function on a GPU.
- This was extremely simple but it can be also extremely inefficient.
- Why ? Because NVIDIA's hardware engineering have optimized graphics processors to perform hundreds of computations in parallel.
- However, thus far we have only ever launched a kernel that runs serially on the GPU.

CUDA-Parallel Programming

Summing vectors



CUDA-Parallel Programming

```
#define N 10
void add( int *a, int *b, int *c ) {
    for (i=0; i < N; i++) {
        c[i] = a[i] + b[i];
    }
}

int main( void ) {
    int a[N], b[N], c[N];
    // fill the arrays 'a' and 'b'
    for (int i=0; i<N; i++) {
        a[i] = -i;
        b[i] = i * i;
    }
    add( a, b, c );
    // display the results
    for (int i=0; i<N; i++) {
        printf( "%d + %d = %d\n", a[i], b[i], c[i] );
    }
    return 0;
}
```

CUDA-Parallel Programming

It's work on only one CPU

```
void add( int *a, int *b, int *c ) {
    for (i=0; i < N; i++) {
        c[i] = a[i] + b[i];
    }
}
```

CUDA-Parallel Programming

We propose to modify the function in the following way as follows

```
void add( int *a, int *b, int *c ) {
    int tid = 0; // ???
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 1; // ???
    }
}
```

CUDA-Parallel Programming

We compute the sum within a while loop where the index tid ranges from 0 to N-1 (processors number).

```
void add( int *a, int *b, int *c ) {
    int tid = 0; // this is CPU zero, so we start at zero
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 1; // ???
    }
}
```

CUDA-Parallel Programming

```
void add( int *a, int *b, int *c ) {
    int tid = 0; // this is CPU zero, so we start at zero
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 1; // we have one CPU, so we increment by
            one
    }
}
```

CUDA-Parallel Programming

For example, with a dual-core processor, one could change the increment to 2 and have one core initialize the loop with tid = 0 and another with tid = 1. The first core would add the even-indexed elements, and the second core would add the odd- indexed elements.

CPU CORE 1

```
void add( int *a, int *b, int *c )
{
    int tid = 0;
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 2;
    }
}
```

CPU CORE 2

```
void add( int *a, int *b, int *c )
{
    int tid = 1;
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 2;
    }
}
```

CUDA-Parallel Programming

- It is possible to make the same addition very similarly on a GPU by writing add() as a device function.
- This should look similar to previous code.

CUDA-Parallel Programming

```
define N 10
int main( void ) {
    int a[N], b[N], c[N], *dev_a, *dev_b, *dev_c;

    // allocate the memory on the GPU
    cudaMalloc((void**)&dev_a, N * sizeof(int));
    cudaMalloc((void**)&dev_b, N * sizeof(int));
    cudaMalloc((void**)&dev_c, N * sizeof(int));
    // fill the arrays 'a' and 'b' on the CPU
    for (int i=0; i<N; i++) { a[i] = -i;  b[i] = i * i; }
    // copy the arrays 'a' and 'b' to the GPU
    cudaMemcpy(dev_a,a,N*sizeof(int),cudaMemcpyHostToDevice);
    cudaMemcpy(dev_b,b,N*sizeof(int),cudaMemcpyHostToDevice);

    add<<<N,1>>>( dev_a, dev_b, dev_c );

    // copy the array 'c' back from the GPU to the CPU
    cudaMemcpy(c,dev_c,N*sizeof(int),cudaMemcpyDeviceToHost);
    // display the results
    for (int i=0; i<N; i++) { printf( "%d + %d = %d\n", a[i], b
    // free the memory allocated on the GPU
    cudaFree( dev_a ); cudaFree( dev_b ); cudaFree( dev_c );
    return 0; }
```

CUDA-Parallel Programming

- In this code, we allocate 3 arrays on the device with cudaMalloc().
- We clean up with cudaFree().
- We copy the input data to device and the result to the host.
- And we execute the device code in add() from the host.

CUDA-Parallel Programming

- But why we fill the input array on CPU ?
- Simply for performance on the GPU !

CUDA-Parallel Programming

- We use $add <<< N, 1 >>> (dev\_a, dev\_b, dev\_c)$;
- So N blocks with one thread !
- The GPU runs N copies of our kernel code.
- The block is used is referenced with the variable blockIdx.x

CUDA-Parallel Programming

```
__global__ void add( int *a, int *b, int *c ) {
    int tid = blockIdx.x; // handles the data at its
        thread id
    if (tid < N)
        c[tid] = a[tid] + b[tid];
```

CUDA-Parallel Programming

- When we launched the kernel, we specified N as the number of parallel blocks.
- We call the collection of parallel blocks a grid.
- This specifies to the runtime system that we want a one-dimensional grid of N blocks.
- These threads will have varying values for blockIdx.x, the first taking value 0 and the last taking value N-1.

CUDA-Parallel Programming

For example, on four blocks we obtain :

BLOCK 1

```
__global__ void
add( int *a, int *b, int *c ) {
    int tid = 0;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}
```

BLOCK 2

```
__global__ void
add( int *a, int *b, int *c ) {
    int tid = 1;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}
```

BLOCK 3

```
__global__ void
add( int *a, int *b, int *c ) {
    int tid = 2;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}
```

BLOCK 4

```
__global__ void
add( int *a, int *b, int *c ) {
    int tid = 3;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}
```

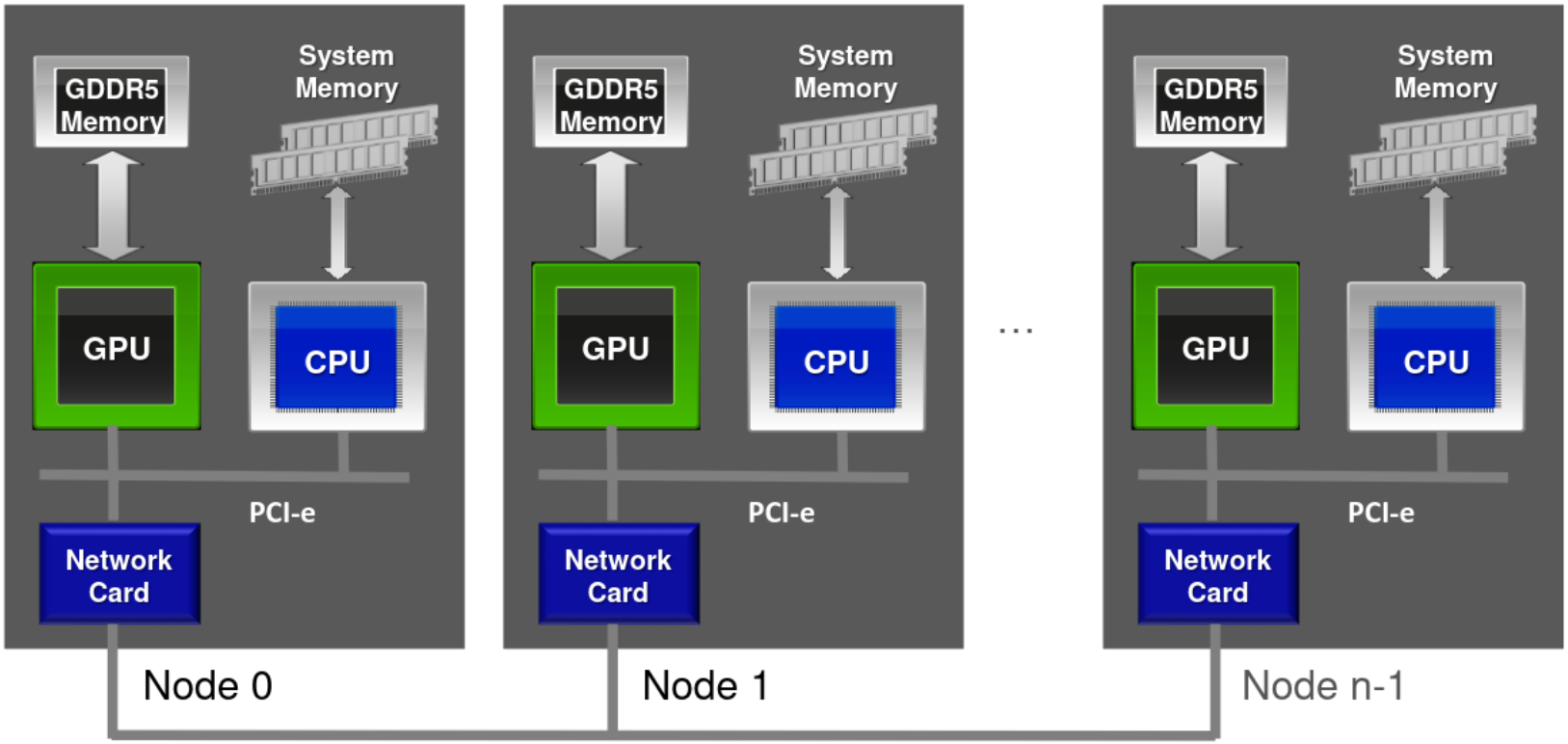
CUDA and MPI-Parallel Programming

MPI and CUDA

https://on-demand.gputechconf.com/gtc/2014/presentations/S4236-multi-gpu-programming-mpi.pdf

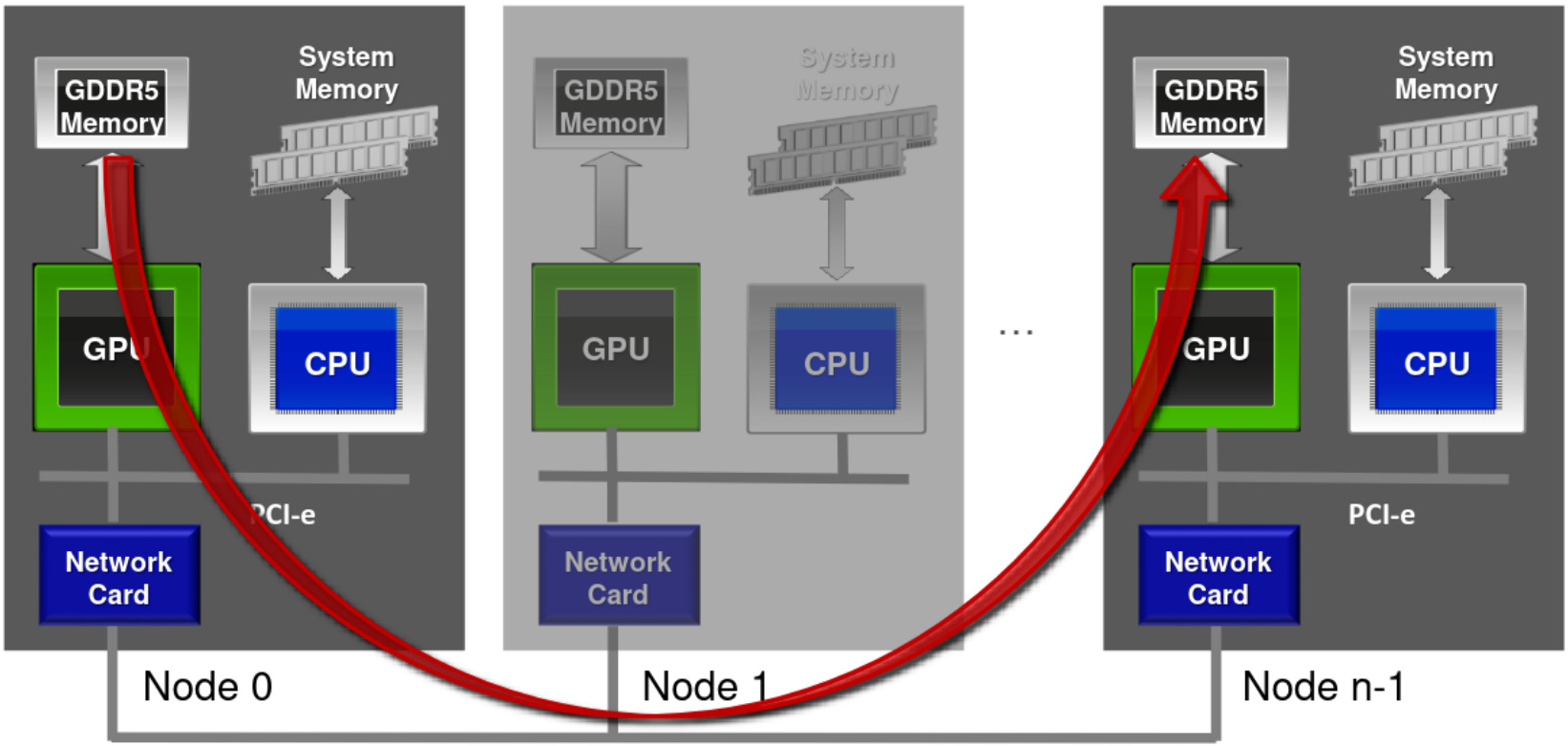
CUDA and MPI-Parallel Programming

MPI+CUDA



CUDA and MPI-Parallel Programming

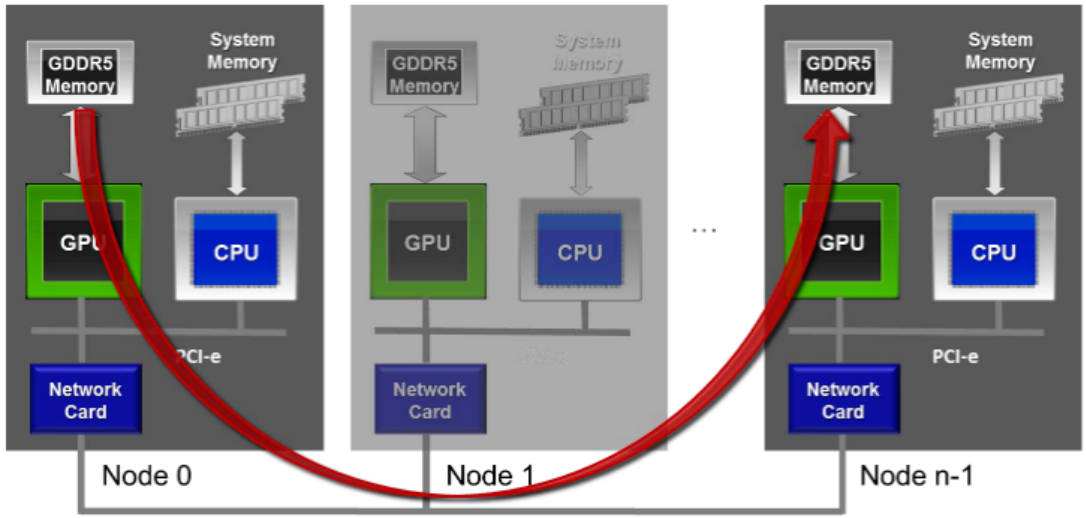
MPI+CUDA



WHAT YOU WILL LEARN

- What MPI is
- How to use MPI for inter GPU communication with CUDA an OpenACC
- What CUDA-aware MPI is
- What Multi Process Service is and how to use it
- How to use NVIDIA Tools in an MPI environment
- How to hide MPI communication times

MPI+CUDA

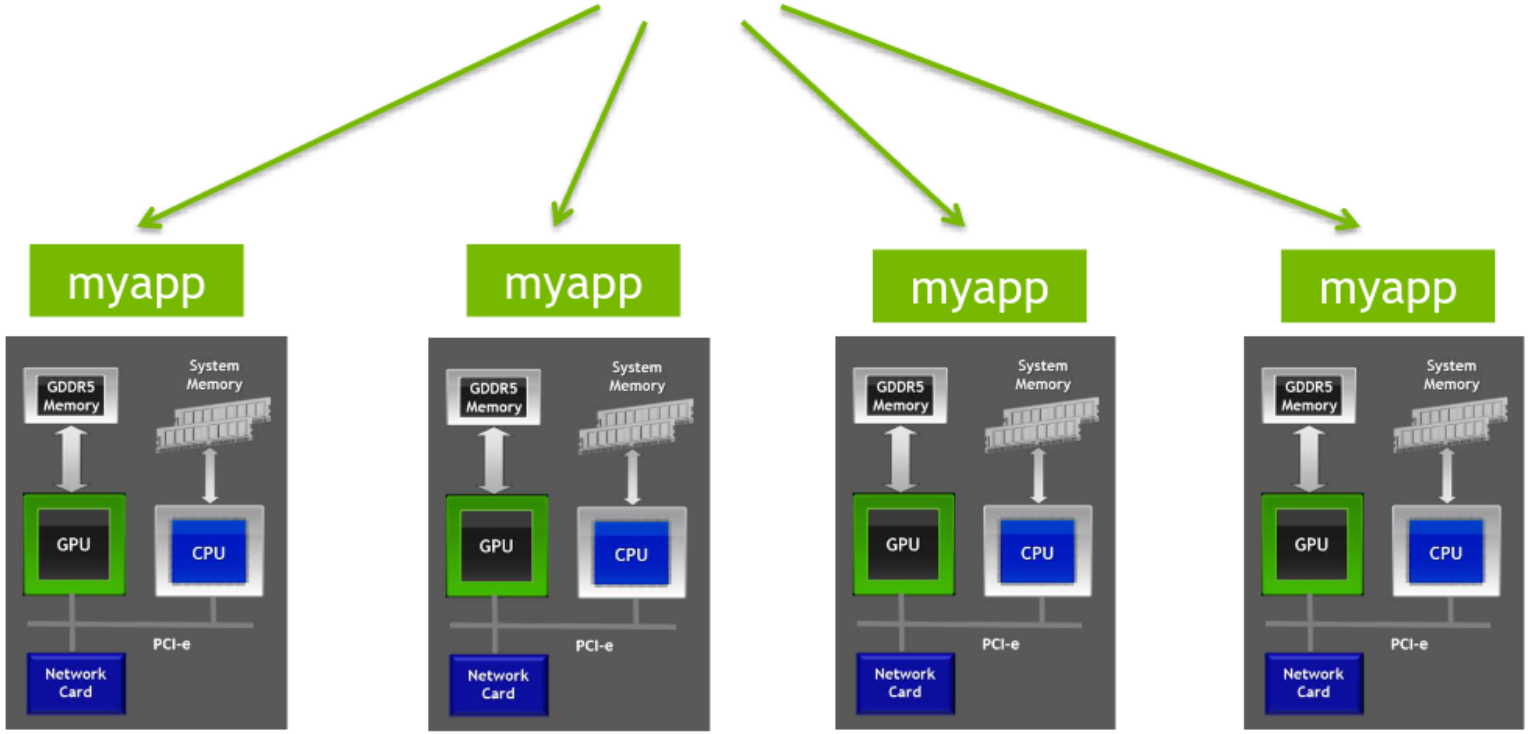



```
//MPI rank 0
MPI_Send(s_buf_d,size,MPI_CHAR,n-1,tag,MPI_COMM_WORLD);

//MPI rank n-1
MPI_Recv(r_buf_d,size,MPI_CHAR,0,tag,MPI_COMM_WORLD,&stat);
```

MPI - COMPILING AND LAUNCHING

```
$ mpicc -o myapp myapp.c
$ mpirun -np 4 ./myapp <args>
```

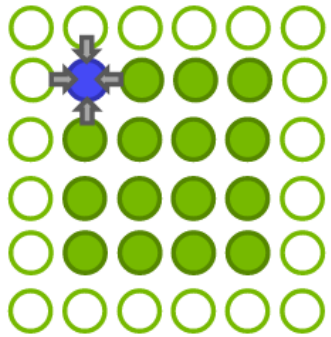


EXAMPLE: JACOBI SOLVER - SINGLE GPU

While not converged

- Do Jacobi step:

```
for (int i=1; i < n-1; i++)
  for (int j=1; j < m-1; j++)
    u_new[i][j] = 0.0f - 0.25f*(u[i-1][j] + u[i+1][j]
                              + u[i][j-1] + u[i][j+1])
```



- Swap `u_new` and `u`
- Next iteration

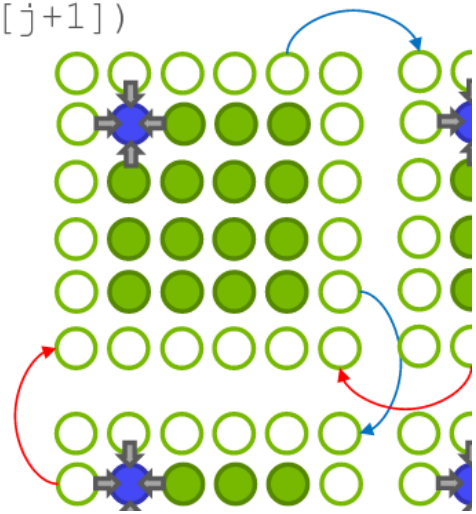
EXAMPLE: JACOBI SOLVER - MULTI GPU

While not converged

- Do Jacobi step:

```
for (int i=1; i < n-1; i++)
  for (int j=1; j < m-1; j++)
    u_new[i][j] = 0.0f - 0.25f*(u[i-1][j] + u[i+1][j]
                               + u[i][j-1] + u[i][j+1])
```

- Exchange halo with 2 4 neighbor
- Swap `u_new` and `u`
- Next iteration



EXAMPLE: JACOBI SOLVER

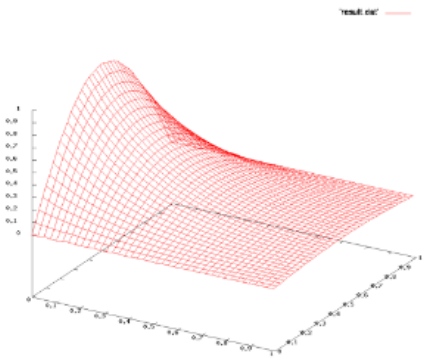
- Solves the 2D-Laplace equation on a rectangle

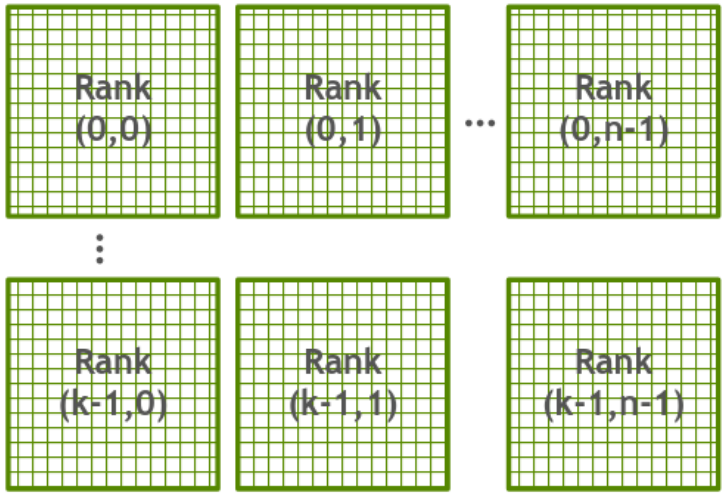
$$\Delta u(x,y) = 0 \; \forall \; (x,y) \in \Omega \backslash \delta\Omega$$

  - Dirichlet boundary conditions (constant values on boundaries)

$$u(x,y) = f(x,y) \in \delta\Omega$$

- 2D domain decomposition with n x k domains

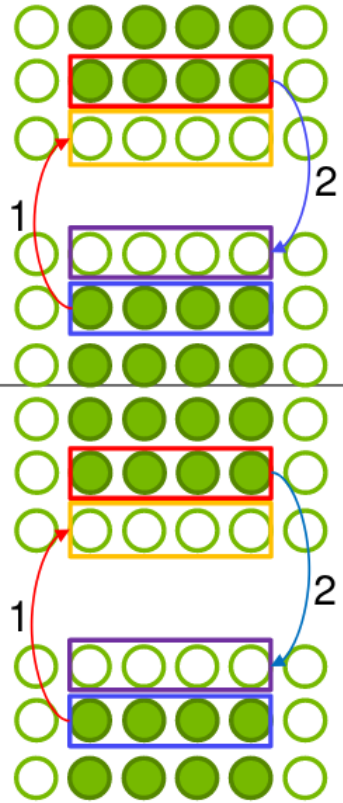




EXAMPLE: JACOBI - TOP/BOTTOM HALO UPDATE

```
MPI_Sendrecv(u_new+offset_first_row, m-2, MPI_DOUBLE, t_nb, 0,
             u_new+offset_bottom_bondary, m-2, MPI_DOUBLE, b_nb, 0,
             MPI_COMM_WORLD, MPI_STATUS_IGNORE);
```

```
MPI_Sendrecv(u_new+offset_last_row, m-2, MPI_DOUBLE, b_nb, 1,
             u_new+offset_top_bondary, m-2, MPI_DOUBLE, t_nb, 1,
             MPI_COMM_WORLD, MPI_STATUS_IGNORE);
```



CUDA and MPI-Parallel Programming

CUDA

```
MPI_Sendrecv(u_new_d+offset_first_row, m-2, MPI_DOUBLE, t_nb, 0,
             u_new_d+offset_bottom_bondary, m-2, MPI_DOUBLE, b_nb, 0,
             MPI_COMM_WORLD, MPI_STATUS_IGNORE);
MPI_Sendrecv(u_new_d+offset_last_row, m-2, MPI_DOUBLE, b_nb, 1,
             u_new_d+offset_top_bondary, m-2, MPI_DOUBLE, t_nb, 1,
             MPI_COMM_WORLD, MPI_STATUS_IGNORE);
```