



GPU Parallel Programming: CUDA

National Tsing Hua University
2018, Fall Semester



Outline

- Programming Model
- CUDA Language
- Example Code Study
- CPU & GPU Synchronization
- Multi-GPU
- Dynamic Parallelism

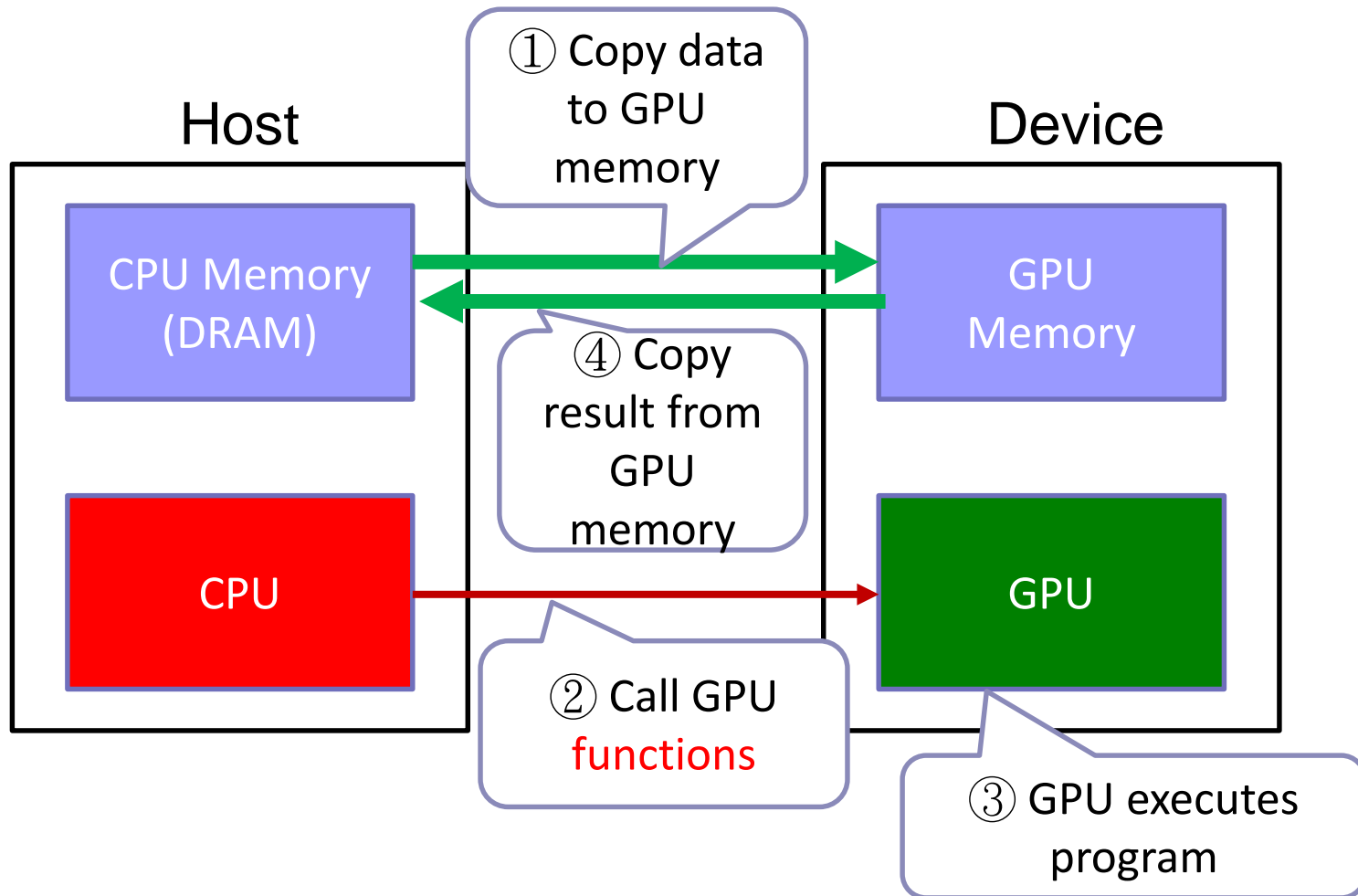
What is CUDA?

■ CUDA: Compute Unified Device Architecture

- CUDA is a **compiler** and **toolkit** for programming NVIDIA GPUs
- Enable heterogeneous computing and horsepower of GPUs
- CUDA API extends the C/C++ programming language
- Express SIMD parallelism
- Give a high level abstraction from hardware

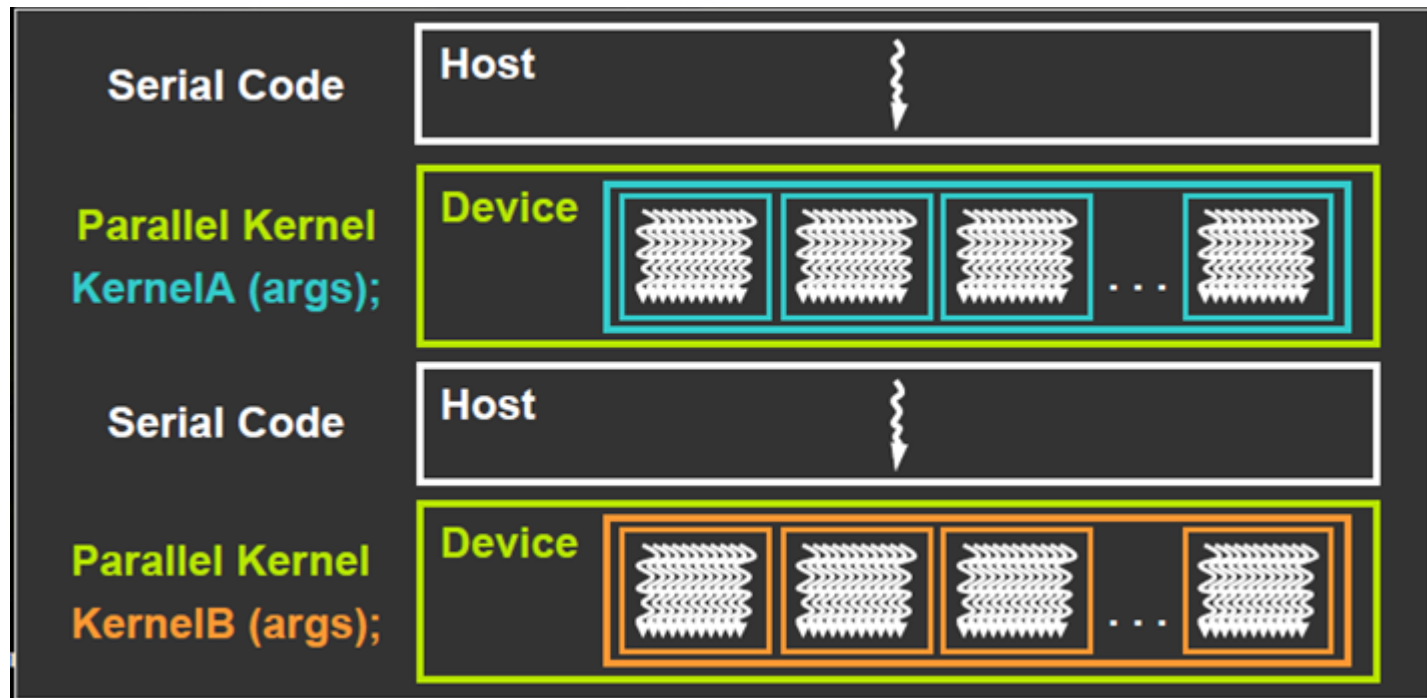
CUDA SDK Version	Compute Capability	Architecture
6.5	1.X	Tesla
7.5	2.0-5.x	Fermi, Kepler, Maxwell
8.0	2.0-6.x	Fermi, Kepler, Maxwell, Pascal
9.0	3.0-7.x	Kepler, Maxwell, Pascal, Volta

CUDA program flow



CUDA Programming Model

- CUDA = serial program with parallel kernels, all in C
 - Serial C code executes in a host thread (i.e. CPU thread)
 - Parallel kernel C code executes in many device threads across multiple processing elements (i.e. GPU threads)



CUDA program framework

GPU code
(parallel)

CPU code
(serial or
parallel if
p-thread/
OpenMP/T
BB/MPI is
used.)

```
#include <cuda_runtime.h>
```

```
__global__ void my_kernel(...) {  
    ...  
}
```

```
int main() {  
    ...  
    cudaMalloc(...)  
    cudaMemcpy(...)  
    ...  
    my_kernel<<<nblock,blocksize>>>(...)  
    ...  
    cudaMemcpy(...)  
    ...  
}
```

Kernel = Many Concurrent Threads

- One kernel is executed at a time on the device
- Many thread execute each kernel
 - Each thread executes the same code
 - ... on the different data based on its threadID

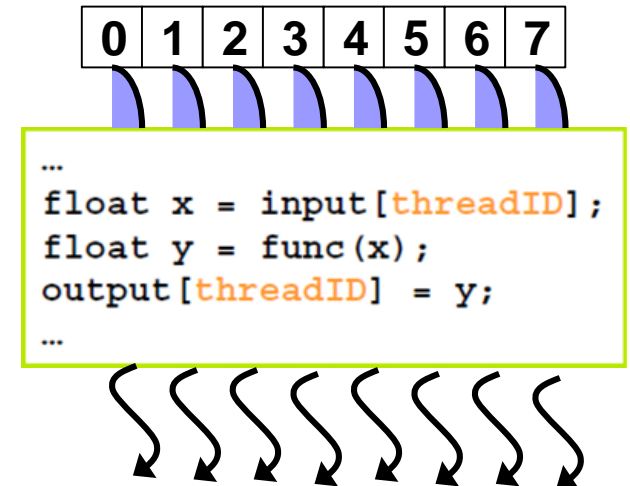
- CUDA thread might be

- Physical threads

- ◆ As on NVIDIA GPUs
 - ◆ GPU thread creation and context switching are essentially free

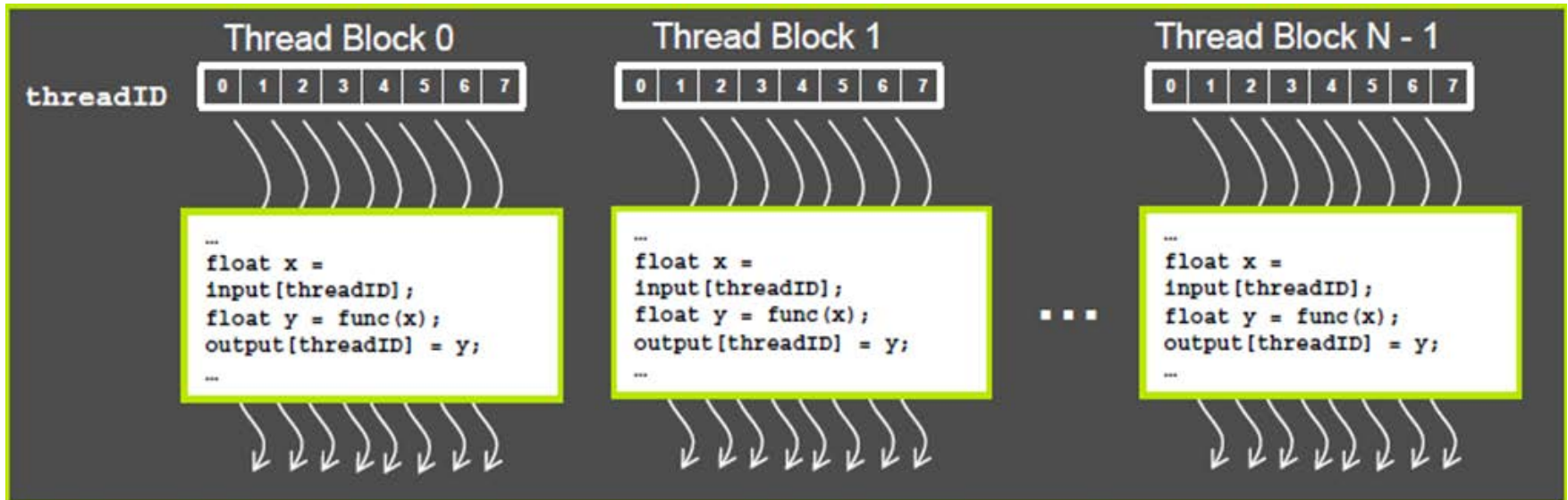
- Or virtual threads

- ◆ E.g. 1 CPU core might execute multiple CUDA threads



Hierarchy of Concurrent Threads

- Threads are grouped into thread blocks
 - Kernel = grid of thread blocks

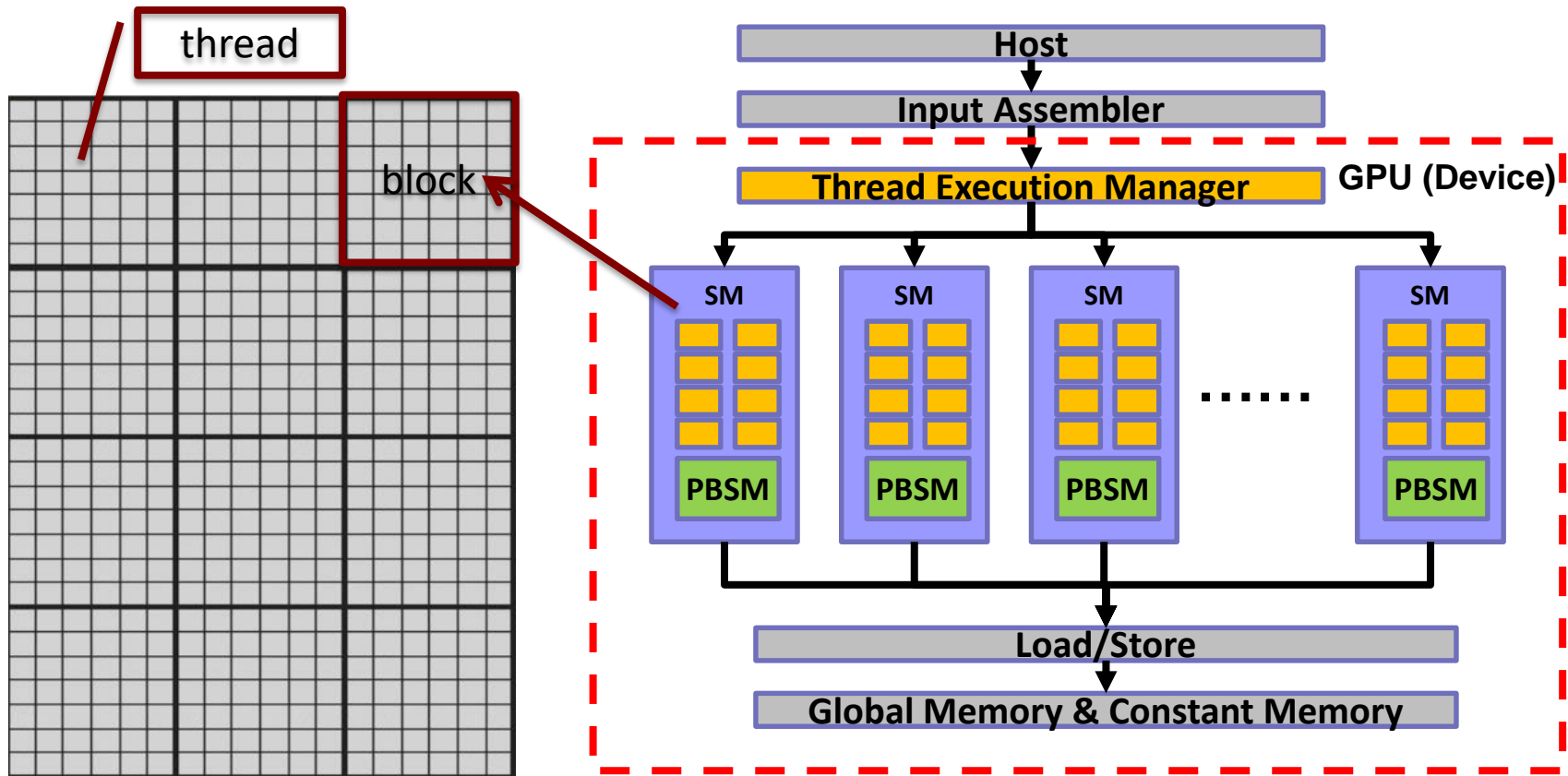


- By definition, threads in the same block may synchronized with barriers, but not between blocks

```
scratch[threadID] = begin[threadID];
__syncthreads();
int left = scratch[threadID - 1];
```

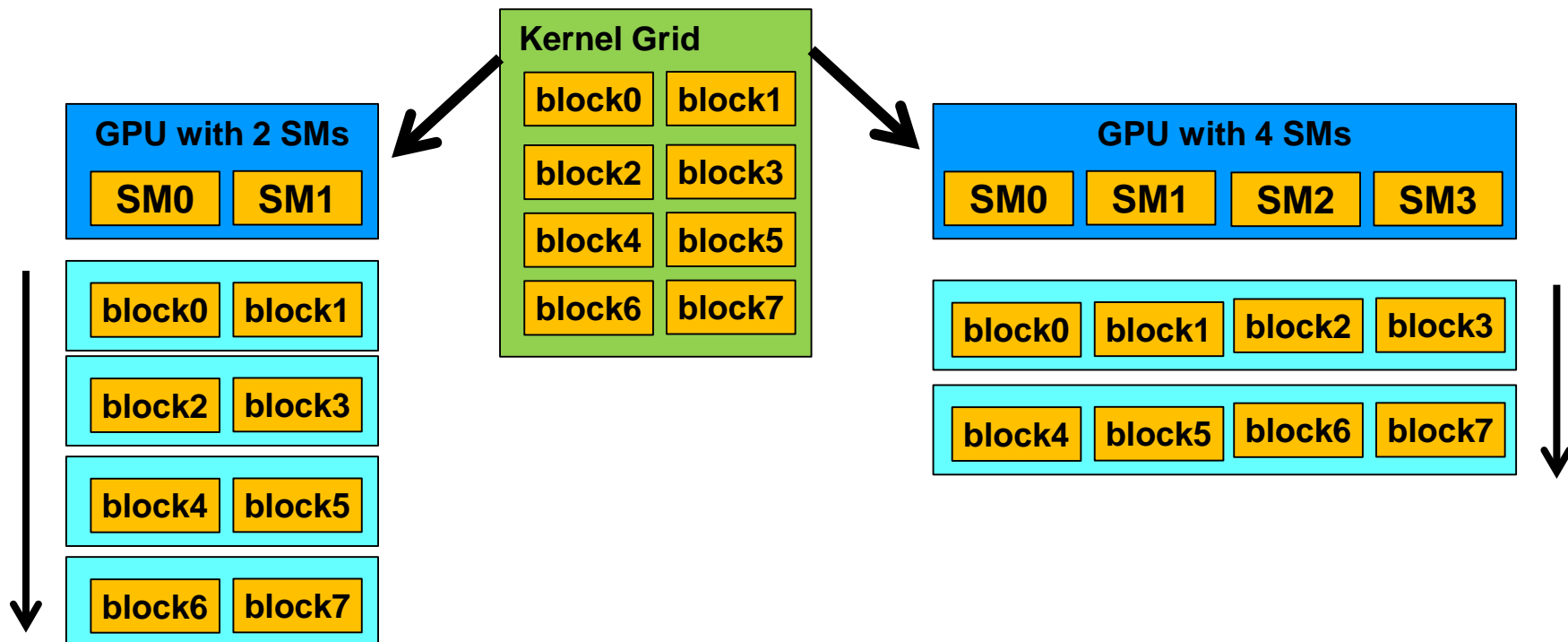

Software Mapping

- Software: grid → blocks → threads
- Hardware: GPU(device) → SM(multicore processor) → core



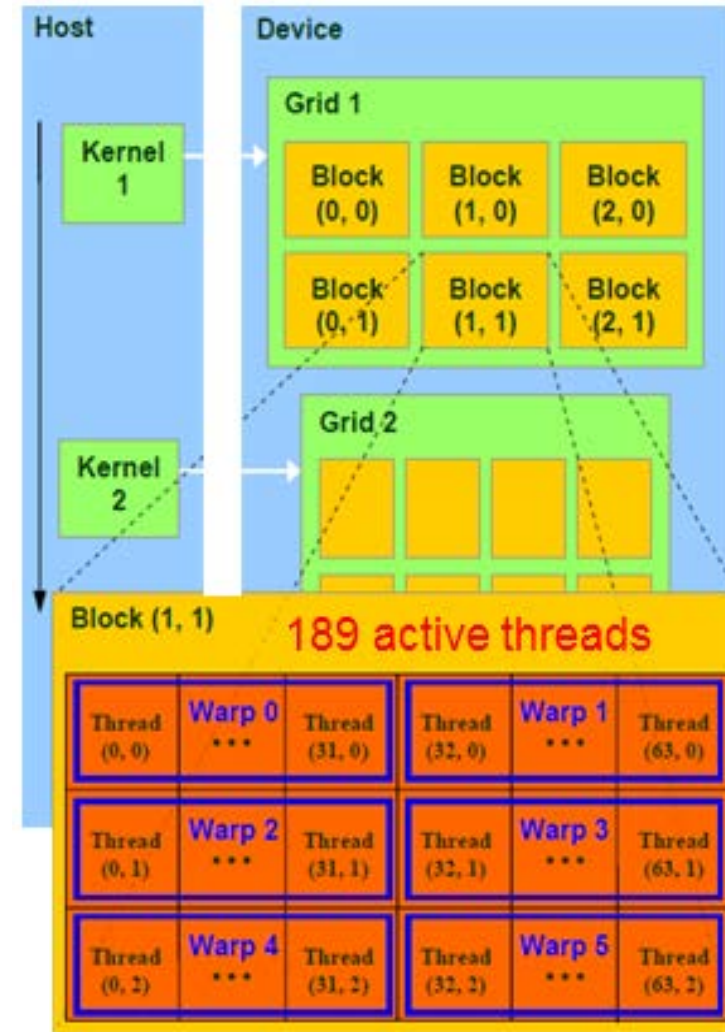
Block Level Scheduling

- Blocks are independent to each other to give scalability
 - A kernel scales across any number of parallel cores by scheduling blocks to SMs



Thread Level Scheduling - Warp

- **Inside the SM**, threads are launched in groups of 32, called **warps**
 - Warps share the control part (**warp scheduler**)
 - Threads in a warp will be executing the same instruction (SIMD)
- In other words ...
 - Threads in a warp execute **physically** in parallel
 - Warps and blocks execute **logically** in parallel



Thread group limits

■ GTX1080 CUDA Capability 6.1

➤ Use `deviceQuery.cpp` to find out your limits

■ Total number of threads per kernel = threads per block * number of blocks

➤ Max dimension size of a thread block (x,y,z): (1024, 1024, 64)

➤ Max dimension size of a grid size (x,y,z): ($2^{31}-1$, $2^{16}-1$, $2^{16}-1$)

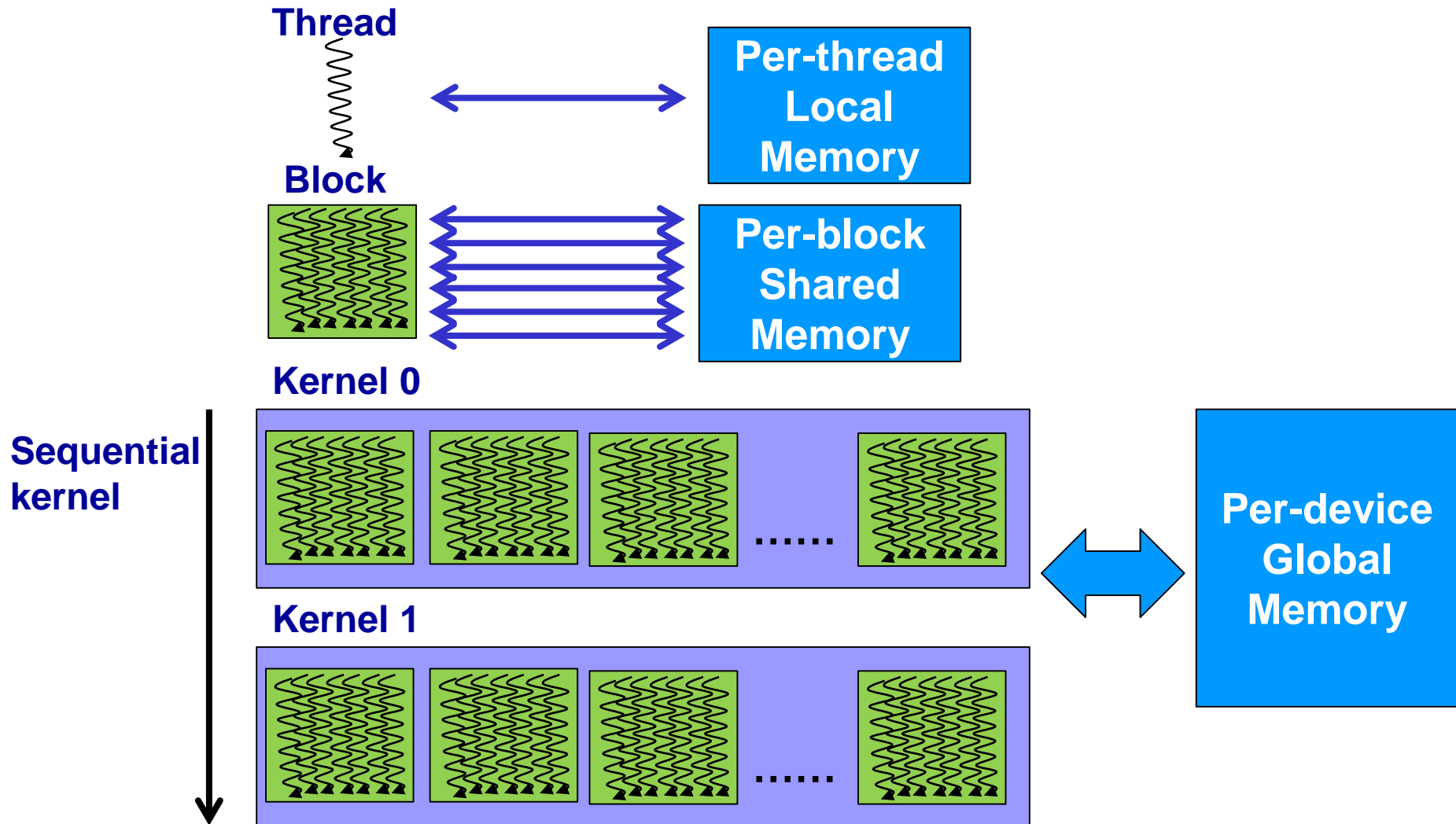
■ Maximum execution concurrency

➤ Maximum number of resident grids per device (Concurrent Kernel Execution): 32

➤ Maximum number of threads per multiprocessor: 2048

➤ Maximum number of threads per block: 1024

Memory Hierarchy



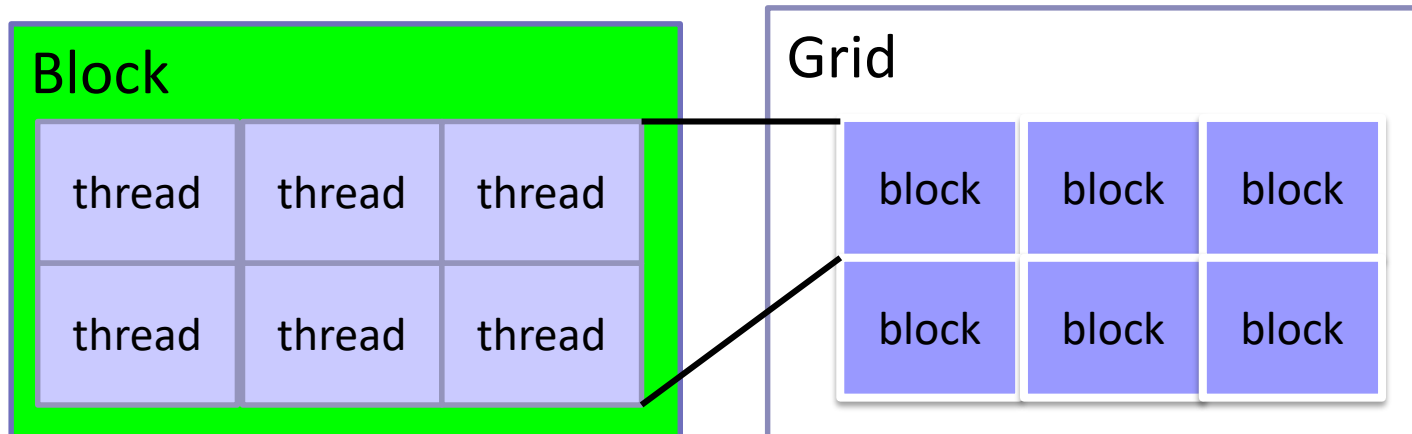
Memory size limits

■ GTX1080 CUDA Capability 6.1

- Use `deviceQuery.cpp` to find out your limits
- Total amount of global memory: 11171 MBytes
- Total amount of constant memory: 64 MBytes
- Total amount of shared memory per block: 48 MBytes
- Total number of registers available per block: 65536

CUDA Programming Terminology

- Host : CPU
- Device : GPU
- Kernel : functions executed on GPU
- Thread : the basic execution unit
- Block : a group of threads
- Grid : a group of blocks



Quiz

- Can a kernel run across multiple SM processors?
- Does the kernel below have to run on 10 different SM processors?
 - `my_kernel<<< 10, 10 >>>();`
- Can the threads from a same block run across multiple SM processors?
- What is the difference between the two kernels below?
 1. `my_kernel<<< 1, 100 >>>(A);`
 2. `my_kernel<<< 100, 1 >>>(A);`
- Why shared block memory can only be accessed by the threads in the same blocks?
- Why we have to call `__syncthreads()` within a block if there are data dependency between statements
- Why `__syncthreads()` is not supported across blocks?



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CUDA Language

Philosophy: provide minimal set of extensions necessary

■ Kernel launch

```
kernelFunc<<< nB, nT, nS, Sid >>>(...); // nS and Sid are optional
```

- nB : number of blocks per grid (grid size)
- nT : number of threads per block (block size)
- nS : shared memory size (in bytes)
- Sid : stream ID, default is 0

■ Build-in device variables

- threadIdx; blockIdx; blockDim; gridDim

■ Intrinsic functions that expose operations in kernel code

```
__syncthreads();
```

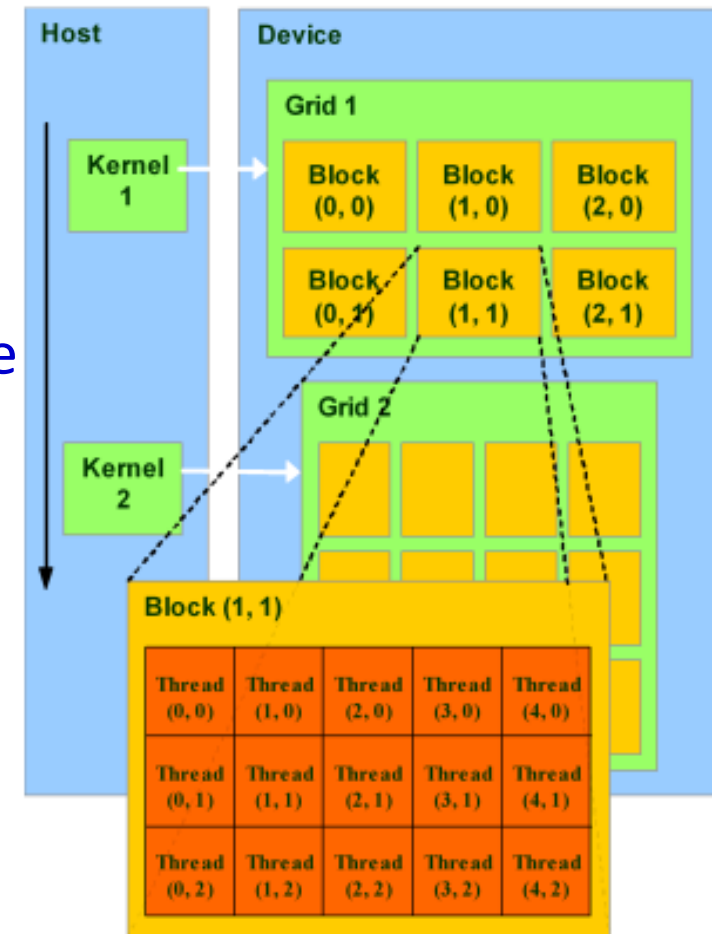
■ Declaration specifier to indicate where things live

```
__global__ void KernelFunc(...); // kernel function, run on device  
__device__ void GlobalVar;        // variable in device memory  
__shared__ void SharedVar;        // variable in per-block shared memory
```

Thread and Block IDs

- Build-in device variables
 - `threadIdx`; `blockIdx`; `blockDim`; `gridDim`
- The index of threads and blocks can be denoted by a 3 dimensional struct
 - `dim3` defined in `vector_types.h`

```
struct dim3 { x; y; z; };
```
- Example:
 - `dim3 grid(3, 2);`
 - `dim3 blk(5, 3);`
 - `my_kernel<<< grid, blk >>>();`
- Each thread can be uniquely identified by a tuple of index (x,y) or (x,y,z)



Q: When will we use multi-dimensional index?

Quiz

- How to index a 100 elements of an array under the following kernel launch setting?

```
// Kernel definition
__global__ void VecAdd(float* A)
{
    int i =           
    A[i] = A[i] + 1;
}
```

1. `my_kernel<<< 1, 100 >>>(A);`
2. `my_kernel<<< 100, 1 >>>(A);`
3. `my_kernel<<< 10, 10 >>>(A);`
4. `size=10; dim3 blk(size, size);`
`my_kernel<<< 1, blk >>>(A, size);`

Quiz

- How to index a 100 elements of an array under the following kernel launch setting?

```
// Kernel definition
__global__ void VecAdd(float* A)
{
    int i =           
    A[i] = A[i] + 1;
}
```

1. `my_kernel<<< 1, 100 >>>(A);` ➔ `int i = threadIdx;`
2. `my_kernel<<< 100, 1 >>>(A);` ➔ `int i = blockIdx;`
3. `my_kernel<<< 10, 10 >>>(A);`
➔ `int i=blockIdx*blockDim+threadIdx;`
4. `size=10; dim3 blk(size, size);`
`my_kernel<<< 1, blk >>>(A, size);`
➔ `int i = threadIdx.x * blockDim.x + threadIdx.y;`

Function Qualifiers

Function qualifiers	limitations
<code>__device__</code> function	Executed on the device Callable from the device only
<code>__global__</code> function	Executed on the device Callable from the host only (must have void return type!)
<code>__host__</code> function	Executed on the host Callable from the host only
Functions without qualifiers	Compiled for the host only
<code>__host__ __device__</code> function	Compiled for both the host and the device

Variable Type Qualifiers

Variable qualifiers	limitations
<code>__device__ var</code>	<ul style="list-style-type: none">• Resides in device's global memory space
<code>__constant__ var</code>	<ul style="list-style-type: none">• Has the lifetime of an application• Is accessible from all the threads within the grid and from the host through the runtime library• Resides in device's constant memory space
<code>__shared__ var</code>	<ul style="list-style-type: none">• Resides in the shared memory space of a thread block• Has the lifetime of the block• Is only accessible from all the threads within the block

Device memory operations

■ Three functions:

- `cudaMalloc()`, `cudaFree()`, `cudaMemcpy()`
- Similar to the C's `malloc()`, `free()`, `memcpy()`

1. `cudaMalloc(void **devPtr, size_t size)`

- `devPtr`: return the address of the allocated device memory
- `size`: the allocated memory size (**bytes**)

2. `cudaFree (void *devPtr)`

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

- `count`: size in **bytes** to copy

cudaMemcpyKind

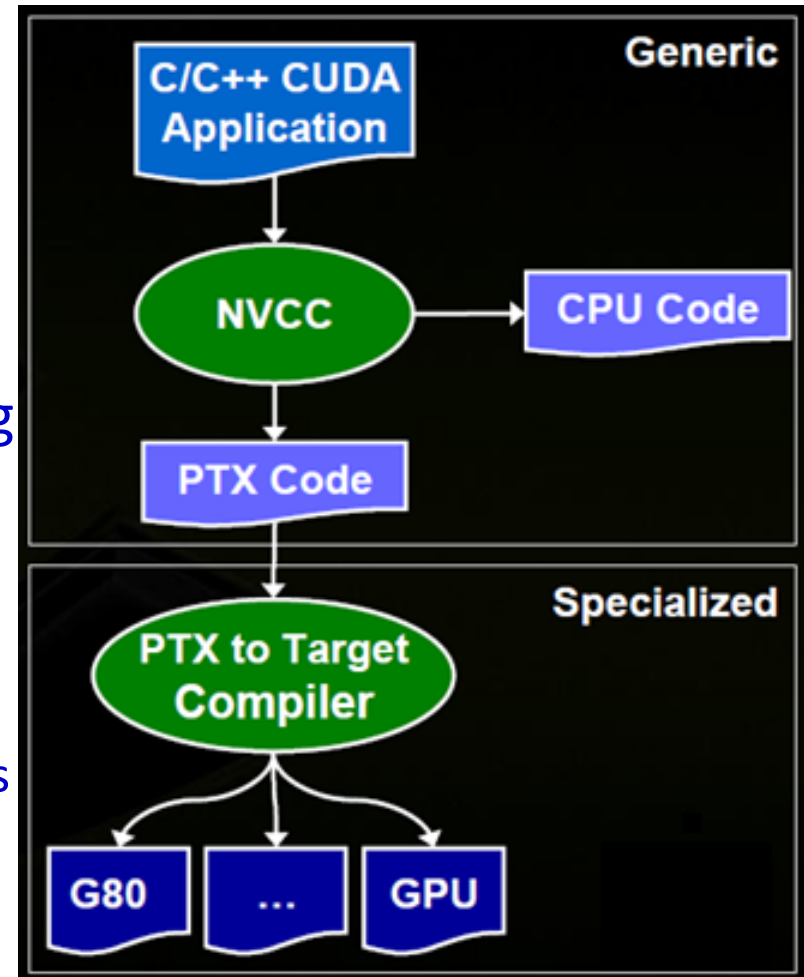
- one of the following four values

cudaMemcpyKind	Meaning	dst	src
cudaMemcpyHostToHost	Host → Host	host	host
cudaMemcpyHostToDevice	Host → Device	device	host
cudaMemcpyDeviceToHost	Device → Host	host	device
cudaMemcpyDeviceToDevice	Device → Device	device	device

host to host has the same effect as memcpy()

Program Compilation

- Any source file containing CUDA language must be compiled with NVCC
 - NVCC separates code running on the host from code running on the device
- Two-stage compilation:
 - Virtual ISA
 - ◆ PTX: Parallel Threads eXecutions
 - Device-specific binary object





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Example 1: Hello World!


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

■ Two new syntactic elements...

1. `__global__` indicates a function that runs on the device and is called from host code
2. `mykernel<<<1,1>>>()`;
Triple angle brackets mark a call from host code to device code, which is called a “kernel launch”.

Example 2: add 2 numbers

```
__global__ void add(int *a, int *b, int *c) {  
    *c = *a + *b;  
}  
int main(void) {  
    int ha=1,hb=2,hc;  
    add<<<1,1>>>(&ha, &hb, &hc);  
    printf("c=%d\n",hc);  
    return 0;  
}
```



- This does not work!!
- `int ha, hb, hc` are in the host memory (DRAM), which cannot be used by device (GPU).
- We need to allocate variables in “device memory”.

The correct main ()

```
int main(void) {
    int a=1, b=2, c; // host copies of a, b, c
    int *d_a, *d_b, *d_c; // device copies of a, b, c
    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, sizeof(int));
    cudaMalloc((void **)&d_b, sizeof(int));
    cudaMalloc((void **)&d_c, sizeof(int));
    // Copy inputs to device
    cudaMemcpy(d_a, &a, sizeof(int), cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, sizeof(int), 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;
}
```

Example 3: add 2 vectors

■ Let's first look at the sequential code!

```
// function definition
void VecAdd(int N, float* A, float* B, float* C)
{
    for(int i = 0; i<N; i++)
        C[i] = A[i] + B[i];
}

int main()
{ ...
    VecAdd (N, Ah, Bh, Ch);
    ...
}
```

Parallel CUDA code

- Use `blockIdx.x` as the index of the arrays
 - Each thread processes 1 addition, for the elements indexed at `blockIdx.x`.

```
// Kernel definition
__global__ void VecAdd(float* A, float* B, float* C)
{
    int i = threadIdx.x;
    C[i] = A[i] + B[i];
}

int main()
{ ...
    // Kernel invocation with N threads
    VecAdd<<<1, N>>>(Ah, Bh, Ch); ...
}
```


Alternative implementation

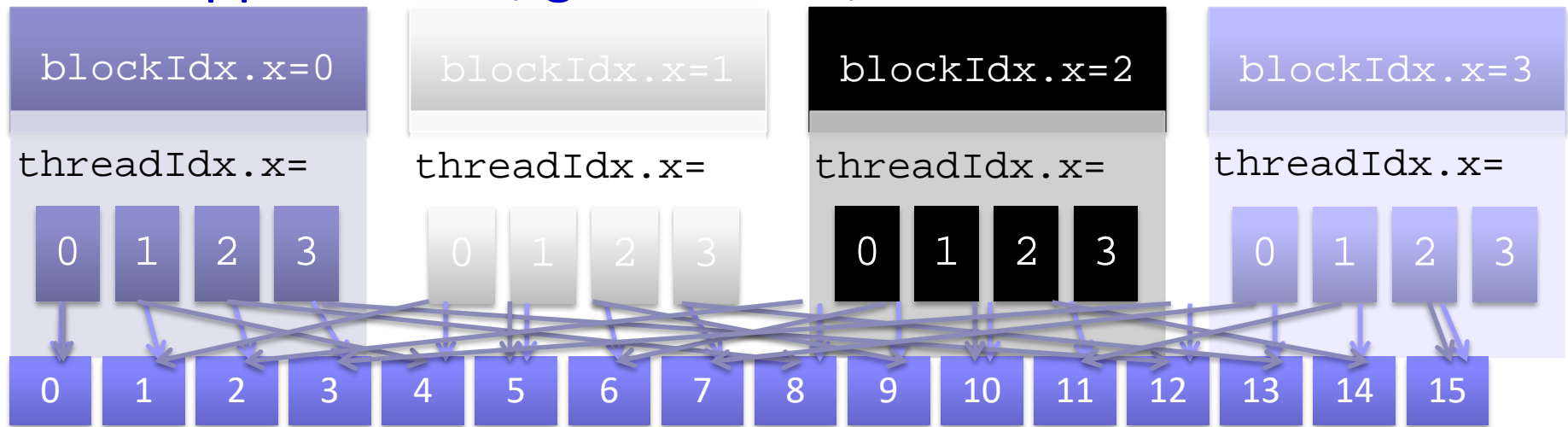
- Using parallel thread instead

```
__global__ void add(int *a, int *b, int *c) {  
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];  
}  
int main(void) {  
    int a[N], b[N], c[N];  
    int *d_a, *d_b, *d_c;  
    ...  
    add<<< N, 1 >>>(d_a, d_b, d_c);  
    ...  
}
```

- N blocks and each block has 1 thread.
- Which one is better?
 - Threads in the same block can communicate, synchronize with others, but the number of threads per block is limited.

3rd implementation

- Using multiple threads and multiple blocks
- Suppose $N=16$, grid size = 4, and block size = 4

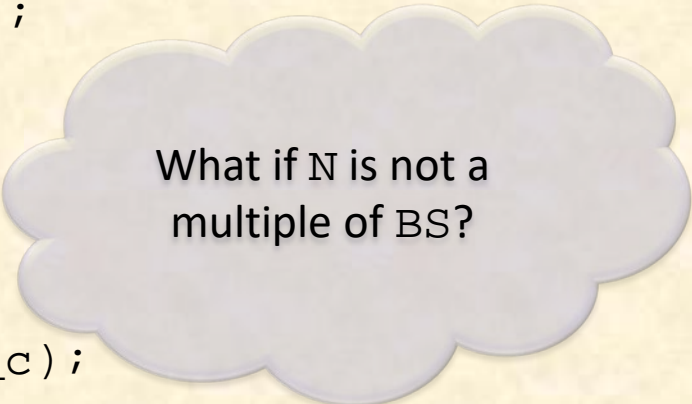


- How to index 16 elements of an array?
 - Method 1: $\text{index} = \text{blockIdx.x} * 4 + \text{threadIdx.x}$
 - Method 2: $\text{index} = \text{threadIdx.x} * 4 + \text{blockIdx.x}$
- Which one is better?

The general case

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

```
__global__ void add(int *a, int *b, int *c) {  
    int index = threadIdx.x + blockIdx.x * blockDim.x;  
    c[index] = a[index] + b[index];  
}  
  
int main(void) {  
    int a[N], b[N], c[N];  
    int *d_a, *d_b, *d_c;  
    ...  
    add<<< N/BS, BS >>>>(d_a, d_b, d_c);  
    ...  
}
```



What if N is not a multiple of BS?

- BS is block size (number of threads per block)

A even more general case

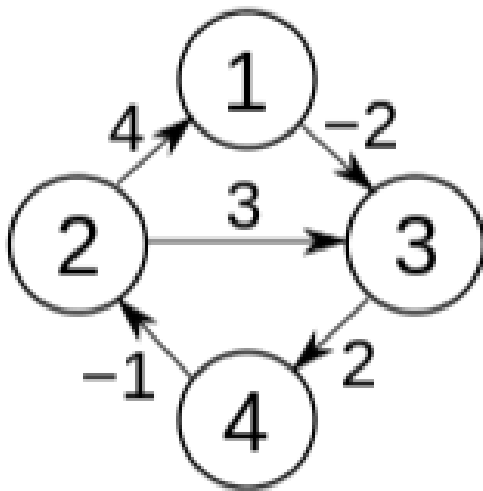
```
__global__ void add(int *a, int *b, int *c, int n) {  
    int index = threadIdx.x + blockIdx.x * blockDim.x;  
    if (index < n)  
        c[index] = a[index] + b[index];  
}  
int main(void) {  
    int a[N], b[N], c[N];  
    int *d_a, *d_b, *d_c;  
    ...  
    add<<< (N+BS-1)/BS, BS>>>(d_a, d_b, d_c, N);  
    ...  
}
```

- The kernel function can have branches, but with a price to pay...

Example4: APSP

- Given a weighted directed graph $G(V, E, W)$, where $|V| = n$, $|W| = m$, and $W > 0$, find the shortest path of all pairs of vertices (v_i, v_j) .

- Example:



0	INF	-2	INF
4	0	3	INF
INF	INF	0	2
INF	-1	INF	0

Initial
weight

0	-1	-2	0
4	0	2	4
5	1	0	2
3	-1	1	0

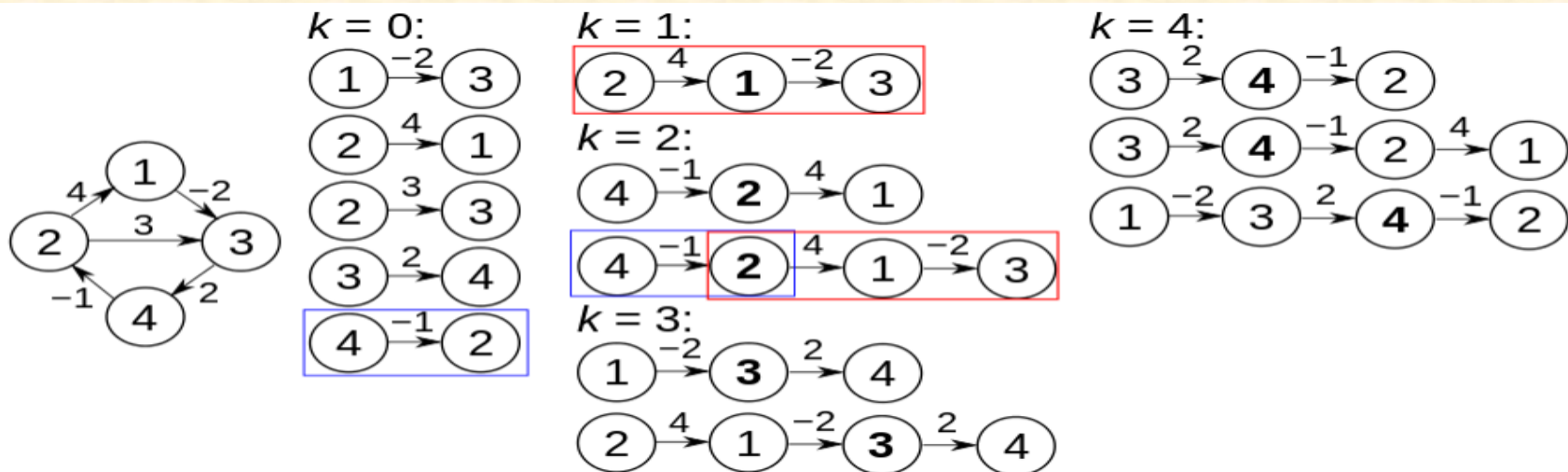
Final
result

Floyd-Warshall (Sequential code)

Floyd-Warshall(G, W)

```
{
   $n \leftarrow |V|$ 
   $D^{(0)} \leftarrow W$ 
  for  $k = 1$  to  $n$  do
    for  $i = 1$  to  $n$  do
      for  $j = 1$  to  $n$  do
        if  $D^{(k-1)}[i, j] > D^{(k-1)}[i, k] + D^{(k-1)}[k, j]$ 
        then  $D^{(k)}[i, j] \leftarrow D^{(k-1)}[i, k] + D^{(k-1)}[k, j]$ 
        else  $D^{(k)}[i, j] \leftarrow D^{(k-1)}[i, j]$ 
  return  $D^{(n)}$ 
}
```

How to parallelize it?



Implementation I

- 1 block and n threads.
- Thread i updates the SP for vertex i .

```
__global__ void FW_APSP(int k, int D[n][n]) {  
    int i = threadIdx.x;  
    for (int j = 0; j < n; j++)  
        if (D[i][j] > D[i][k] + D[k][j])  
            D[i][j] = D[i][k] + D[k][j];  
}  
  
int main() { ...  
    for (int k = 0; k < n; k++)  
        FW_APSP<<<1, n>>>(k, D);  
}
```

Simple! But can it be faster ?

Implementation 2

■ Each thread updates one pair of vertices

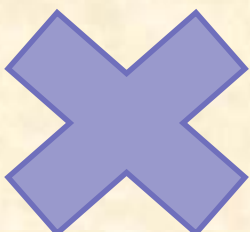
➤ Increase parallelism from n to n^2

```
__global__ void FW_APSP(int k, int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    if (D[i][j] > D[i][k] + D[k][j])  
        D[i][j] = D[i][k] + D[k][j];  
}  
  
int main() { ...  
    dim3 threadsPerBlock(n, n);  
    for (int k = 0; k < n; k++)  
        FW_APSP<<<1, threadsPerBlock >>>(k, D);  
}
```

■ How about the for-loop of k ?

Implementation 3

```
__global__ void FW_APSP(int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    for (int k = 0; k < n, k++)  
        if (D[i][j] > D[i][k] + D[k][j])  
            D[i][j] = D[i][k] + D[k][j];  
}  
int main() { ...  
    dim3 threadsPerBlock(n, n);  
    FW_APSP<<<1, threadsPerBlock >>>(D);  
}
```



- It is a synchronous computation
 - There are data dependency on k...

Add __syncthreads ()

```
__global__ void FW_APSP(int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    for (int k = 0; k < n, k++){  
        if (D[i][j] > D[i][k] + D[k][j])  
            D[i][j] = D[i][k] + D[k][j];  
        __syncthreads();  
    }  
}  
  
int main() { ...  
    dim3 threadsPerBlock(n, n);  
    FW_APSP<<<1, threadsPerBlock >>>(D);  
}
```



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Asynchronous Functions

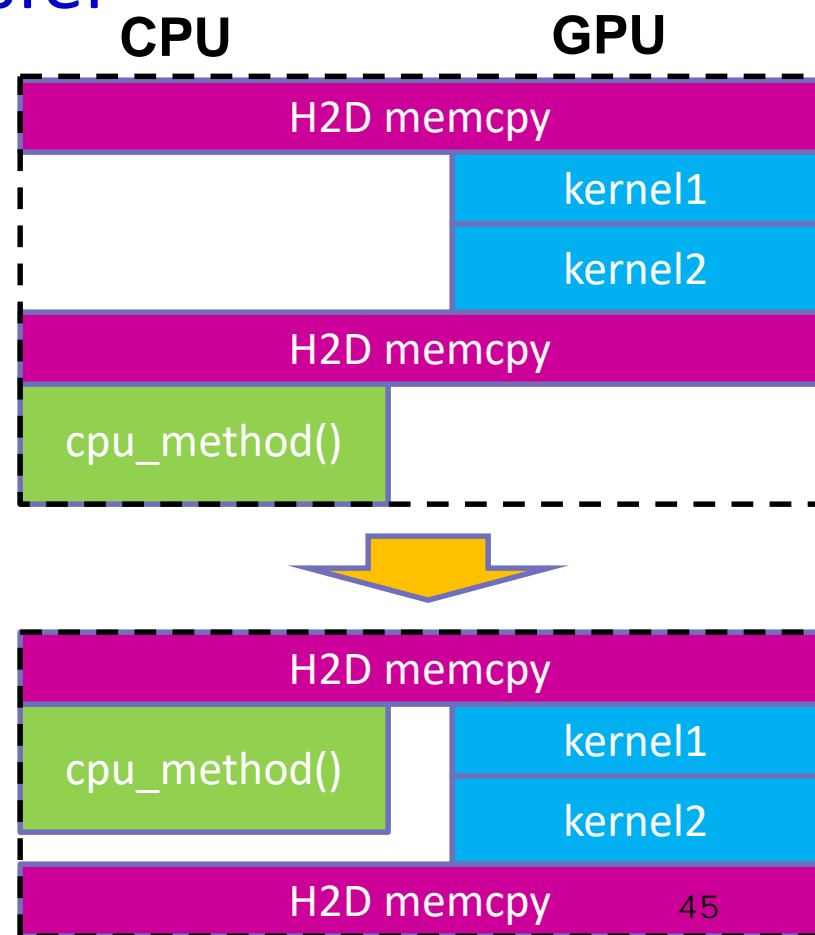
- To facilitate concurrent execution between **host** and **device**, **most CUDA function** calls are **asynchronous**:
 - Control is returned to the host thread before the device has completed the requested task.
 - **But function calls from a kernel are serialized on GPU**
- Asynchronous functions:
 - **Kernel launches**
 - Asynchronous memory copy and set options: **cudaMemcpyAsync, cudaMemcpyAsync**
 - **cudaMemcpy** within the **same device**
 - H2D cudaMemcpy of **64kB or less**
 - **cudaEvent functions**

Why Use Asynchronous Functions?

- Overlap CPU computation with the GPU computation or data transfer

```
void main() {  
    cudaMemcpy ( /**/, H2D ) ;  
    kernel2 <<< grid, block>>> ( ) ;  
    kernel3 <<< grid, block>>> ( ) ;  
    cudaMemcpy ( /**/, D2H ) ;  
    cpu_method() ;  
}
```

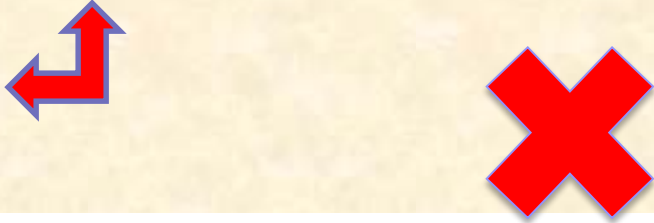
```
void main() {  
    cudaMemcpy ( /**/, H2D ) ;  
    kernel2 <<< grid, block>>> ( ) ;  
    kernel3 <<< grid, block>>> ( ) ;  
    cudaMemcpyAsync ( /**/, D2H ) ;  
    cpu_method() ;  
}
```



Risk of Using Asynchronous Functions

- Programmer must enforce synchronization between **GPU** and **CPU** when there is **data dependency**

```
void main() {  
    cudaMemcpyAsync ( d_a, h_a, count, H2D ) ;  
    kernel <<< grid, block>>> (d_a) ;  
    cudaMemcpyAsync ( h_a, d_a, count, D2H ) ;  
    cpu_method(h_a);  
}
```

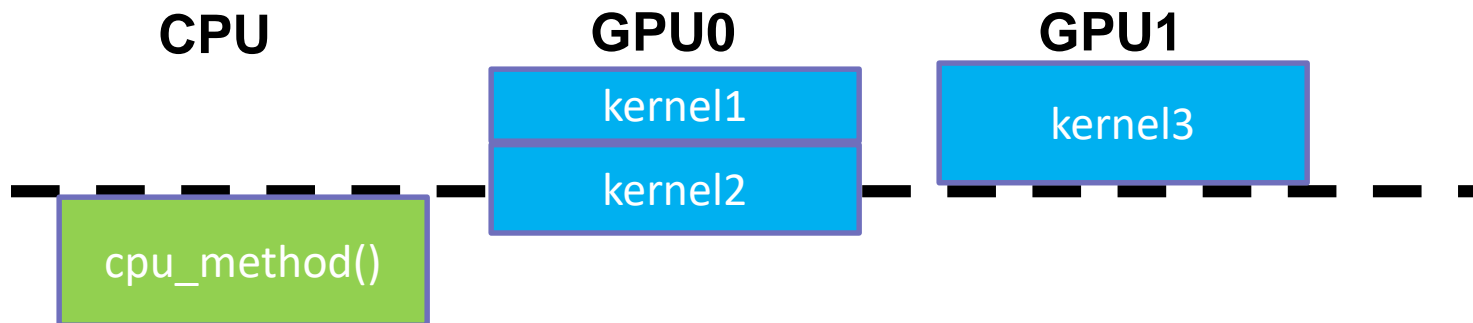


Synchronization between CPU & GPU

- Device based: `cudaDeviceSynchronize()`
 - Block a CPU thread until all issued CUDA calls to a device complete
- Context based: `cudaThreadSynchronize()`
 - Block a CPU thread until all issued CUDA calls from the thread complete
- Stream based: `cudaStreamSynchronize(stream-id)`
 - Block a CPU thread until all CUDA calls in stream stream-id complete
- Event based:
 - `cudaEventSynchronize(event)`
 - ◆ Block a CPU thread until event is recorded
 - `cudaStreamWaitEvent(stream-id, event)`
 - ◆ Block a GPU stream until event reports completion

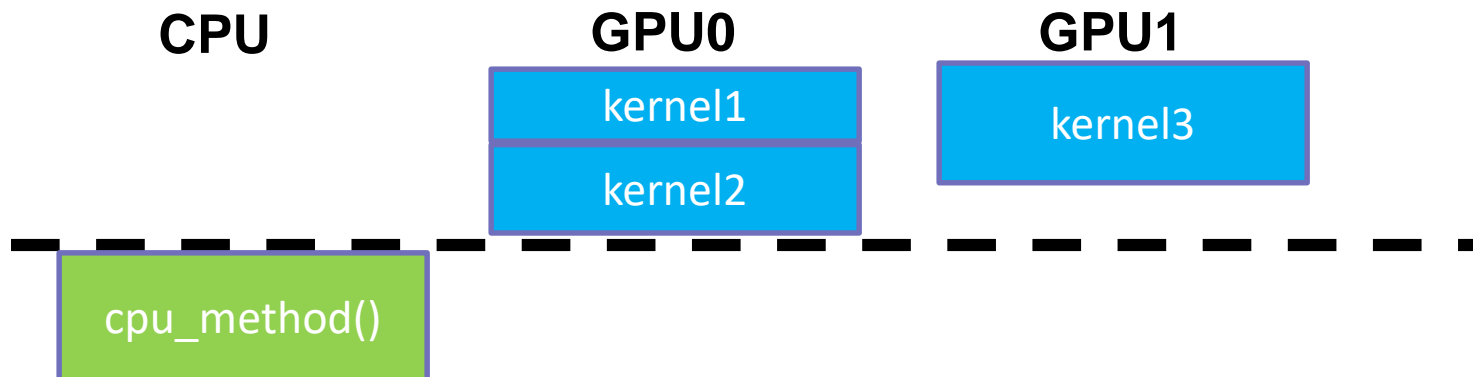
Device Synchronization Example

```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> ();  
    kernel2 <<< grid, block>>> ();  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> ();  
    cudaDeviceSynchronize()  
    cpu_method();  
}
```



Thread Synchronization Example

```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> ();  
    kernel2 <<< grid, block>>> ();  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> ();  
    cudaThreadSynchronize();  
    cpu_method();  
}
```

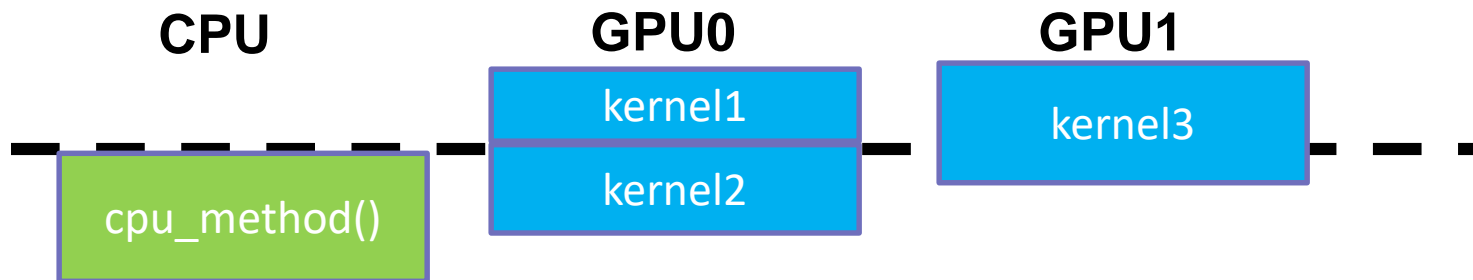


CUDA event

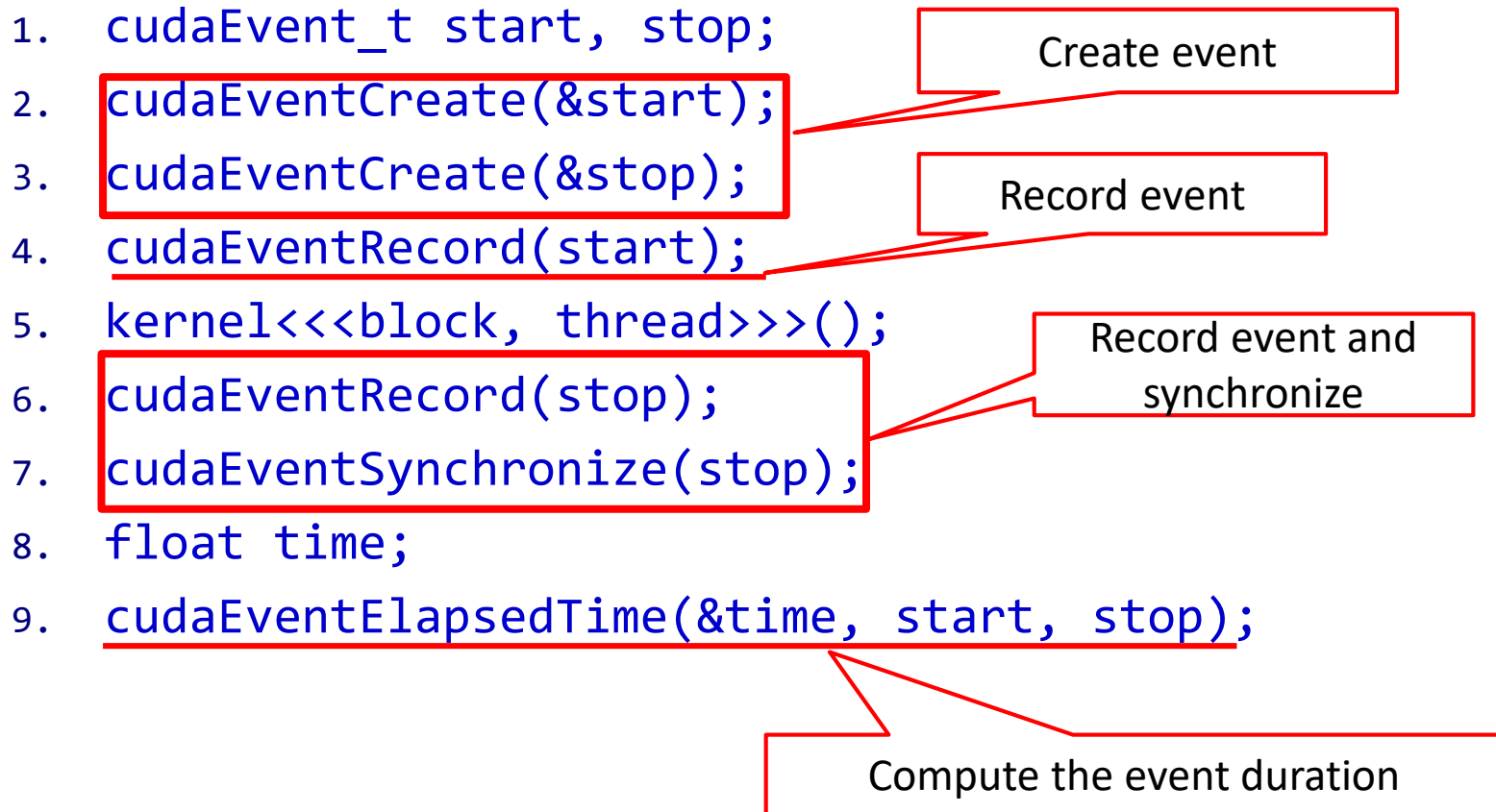
- Data type : `cudaEvent_t`
- `cudaError_t cudaEventCreate(cudaEvent_t* event)`
 - Create CUDA event
- `cudaError_t cudaEventRecord(cudaEvent_t event, cudaStream_t stream = 0)`
 - Record CUDA event
 - If stream is non-zero, the event is recorded after all preceding operations in the stream have been completed
 - Since operation is **asynchronous**, `cudaEventQuery()` and/or `cudaEventSynchronize()` must be used to determine when the event has actually been recorded
- `cudaError_t cudaEventSynchronize(cudaEvent_t event)`
 - Wait until the completion of all device work preceding the most recent call to **`cudaEventRecord()`**

Event Synchronization Example

```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> ();  
    cudaEventRecord(event)  
    kernel2 <<< grid, block>>> ();  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> ();  
    cudaEventSynchronize (event)  
    cpu_method();  
}
```



Kernel Time Measurement Example





Outline

- Programming Model
- CUDA Language
- Example Code Study
- CPU & GPU Synchronization
- **Multi-GPU**
- Dynamic Parallelism

Multi-GPUs

■ Multi-GPUs within a node

- A single CPU thread, multiple GPU
- Multiple CPU threads belonging to the **same process**, such as **pthread** or **openMP**

■ Multiple GPUs on multiple nodes

- Need to go through network API, such as **MPI**

Single thread multi-GPUs

- All CUDA calls are issued to the current GPU

➤ `cudaSetDevice()` sets the current GPU

```
// Run independent kernel on each CUDA device
int numDevs = 0;
cudaGetNumDevices(&numDevs);
for (int d = 0; d < numDevs; d++) {
    cudaSetDevice(d);
    kernel<<<blocks, threads>>>(args);
}
```

- Asynchronous calls (kernels, memcpy) don't block switching the GPU

```
cudaSetDevice( 0 );
kernel<<<...>>>(...);
cudaSetDevice( 1 );
kernel<<<...>>>(...);
```

Using CUDA with OpenMP

- Put CUDA functions inside the parallel region
- General setting:
 - The number of CPU threads is the same as the number of CUDA devices. Each CPU thread controls a different device, processing its portion of the data.
- It's possible to use more CPU threads than there are CUDA devices.
 - Several CPU threads will be allocating resources and launching kernel on the same device, which will slow down the performance.

Example: cudaOMP.cu

```
...
cudaGetDeviceCount(&num_gpus);
...
omp_set_num_threads(num_gpus);
// create as many CPU threads as there are CUDA devices
#pragma omp parallel
{
    unsigned int cpu_thread_id = omp_get_thread_num();
    unsigned int num_cpu_threads = omp_get_num_threads();
    cudaSetDevice(cpu_thread_id);
    int gpu_id = -1;
    cudaGetDevice(&gpu_id);
    printf("CPU thread %d (of %d) uses CUDA device %d\n",
          cpu_thread_id, num_cpu_threads, gpu_id);
    ...
}
```

Using CUDA with MPI

```
int main(int argc, char* argv[]){
    int rank, size;
    int A[32];
    int i;
    MPI_Init(&argc, &argv);
    MPI_Comm_rank(MPI_COMM_WORLD, &rank);
    MPI_Comm_size(MPI_COMM_WORLD, &size);
    printf("I am %d of %d\n", rank, size);
    for(i = 0; i < 32; i++) A[i] = rank+1;
    launch(A); // a call to launch CUDA kernel
    MPI_Barrier(MPI_COMM_WORLD);
    MPI_Finalize();
    return 0;
}
```

Example: **launch(A)**

```
extern "C"
void launch(int *A){
    int *dA;
    cudaMalloc((void**)&dA, sizeof(int)*32);
    cudaMemcpy(dA, A, sizeof(int)*32,
               cudaMemcpyHostToDevice);
    kernel<<<1, 32>>>(dA);
    cudaMemcpy(A, dA, sizeof(int)*32,
               cudaMemcpyDeviceToHost);
    cudaFree(dA);
}
```

Sharing data between GPUs

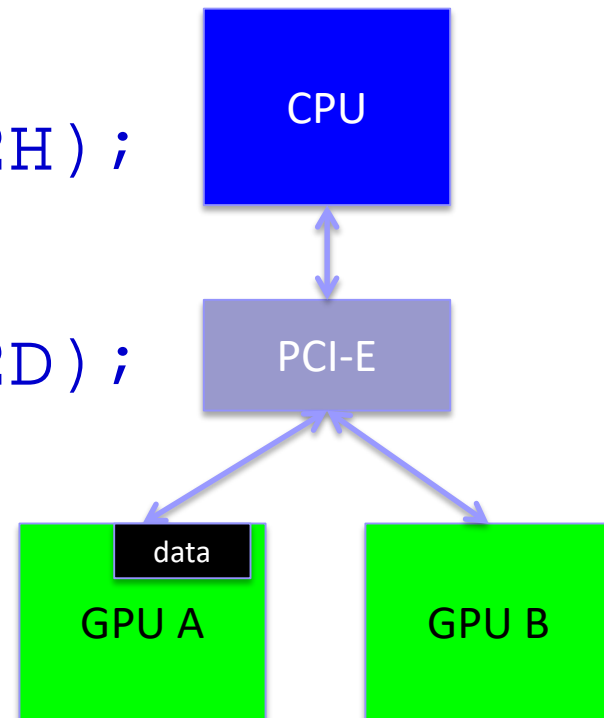
■ Options

1. Explicit copies via host
2. Zero-copy shared host array
3. Peer-to-peer memory copy

1. Explicit copies via host

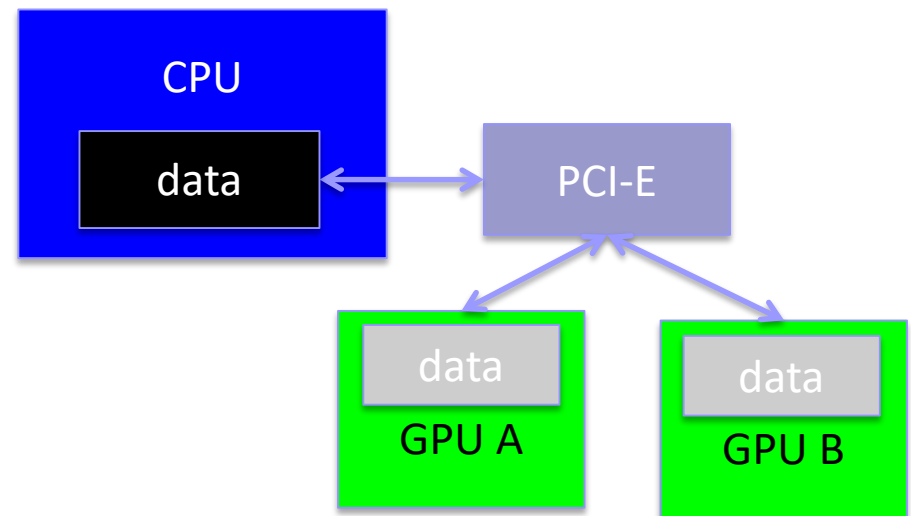
- CPU explicitly copies data from device A to device B
- Example:

```
cudaSetDevice(0);  
cudaMemcpy(DM1, HM, n, D2H);  
cudaSetDevice(1);  
cudaMemcpy(HM, DM2, n, H2D);
```



2. Using zero-copy

- “Zero-copy” refers to direct device access to host memory
- Device threads can read directly from host memory over PCI-e without using cudaMemcpy H2D or D2H
- The host memory must be pinned (page-locked)
 - Pageable memory cannot be directly accessed by the GPU because of the OS virtual memory mechanism



Host Memory Allocation

■ `malloc()`

- Regular C library memory allocation
- Managed by host
- Cannot be directly accessed by GPUs
- Must be copied to device memory via `cudaMemcpy()`

■ `cudaMallocHost(void ** hostPtr, size_t size)`

- Allocate **pinned** (page-locked) host memory for higher `cudaMemcpy` performance
- Used with `cudaMemAsync()` for **async memory copy** or **CUDA stream**

■ `cudaHostAlloc(void ** hostPtr, size_t size, unsigned int flags)`

- Add the flag ***“cudaHostAllocMapped”*** to allocate **pinned** host memory for higher `cudaMemcpy` performance
- Add the flag ***“cudaHostAllocPortable”*** to allocate **shared** host memory for **“Zero copy”**

➔ **All these functions return host memory pointer**

Zero Copy via `cudaHostAlloc()`

- Allocate **host memory** using `cudaHostAlloc()`
 - It returns a **host pointer**. It can enable faster host memory access.
 - **Must** add flag `cudaHostAllocMapped` for **page-locked**
 - Add flag `cudaHostAllocPortable` for **sharing among all devices**
- Bind host pointer to device pointer using `cudaHostGetDevicePointer(void**, void*, 0)`

```
int *hostPtr, *dev0Ptr, *dev1Ptr;
cudaHostAlloc(&hostPtr, 10, cudaHostAllocMapped |
cudaHostAllocPortable);
cudaSetDevice(0);
cudaHostGetDevicePointer(&devPtr0, hostPtr, 0);
kernel<<1,10>>(devPtr0);
cudaSetDevice(1);
cudaHostGetDevicePointer(&dev1Ptr, hostPtr, 0);
kernel<<1,10>>(devPtr1);
```


Pitfalls of using zero-copy

- PCI-e is lower in bandwidth and higher in latency than **GPU global memory**
 - ➔ access speed is slower than global memory
- Use zero-copy if:
 - The data is **only accessed once** or few times
 - Generate data on the device and copy back to host **without reuse**
 - Kernel(s) that access the memory are **compute bound**

3. Peer-to-Peer Memcpy

- Direct copy from pointer on GPU A to pointer on GPU B
- Using two functions

```
cudaError_t cudaMemcpyPeer(void *dst, int  
dstDevice, const void* src, int srcDevice,  
size_t count)
```

```
cudaError_t cudaMemcpyPeerAsync(void *dst,  
int dstDevice, const void* src, int  
srcDevice, size_t count, cuda_stream_t  
stream=0)
```

Example: P2P memcpy

```
cudaSetDevice(0);      //set device 0 as current
float *p0;
size_t size = 1024*sizeof(float);
cudaMalloc(&p0, size); //allocate mem on device 0
cudaSetDevice(1);      //set device 1 as current
float *p1;
cudaMalloc(&p1, size); //allocate mem on device 1

cudaSetDevice(0);      //set device 0 as current
Kernel1<<<1000,128>>>(p0); //launch on dev 0
cudaSetDevice(1);      //set device 1 as current
cudaMemcpyPeer(p1,1,p0,0,size); //copy p0 to p1
Kernel1<<<1000,128>>>(p1); //launch on dev 1
```

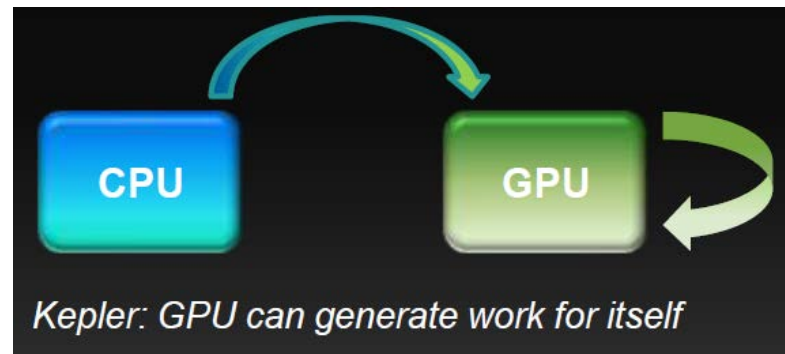
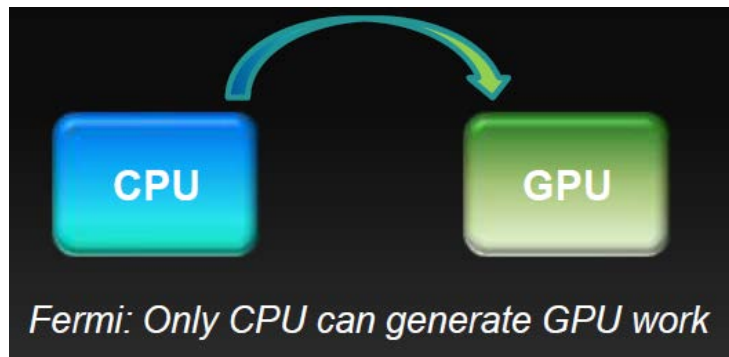


Outline

- Programming Model
- CUDA Language
- Example Code Study
- CPU & GPU Synchronization
- Multi-GPU
- **Dynamic Parallelism**

Dynamic parallelism

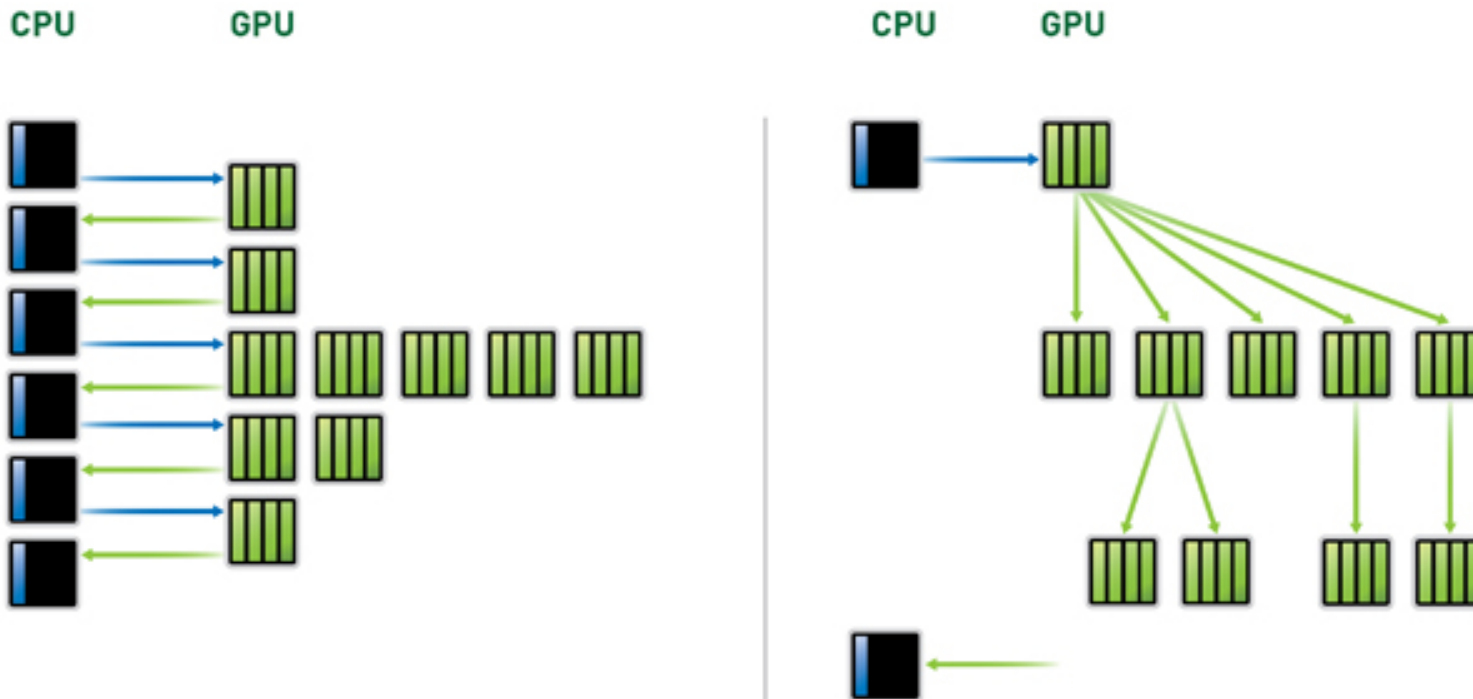
- The ability to launch new **grids** from the **GPU**
 - Dynamically
 - Simultaneously
 - Independently
- Supported from **CUDA5.0** on devices of **Compute Capability 3.5** or higher



What does it mean?

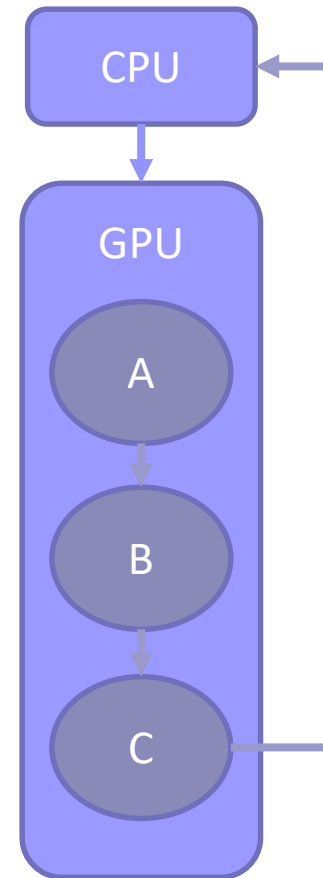
- Reduce the number of kernel launches

DYNAMIC PARALLELISM



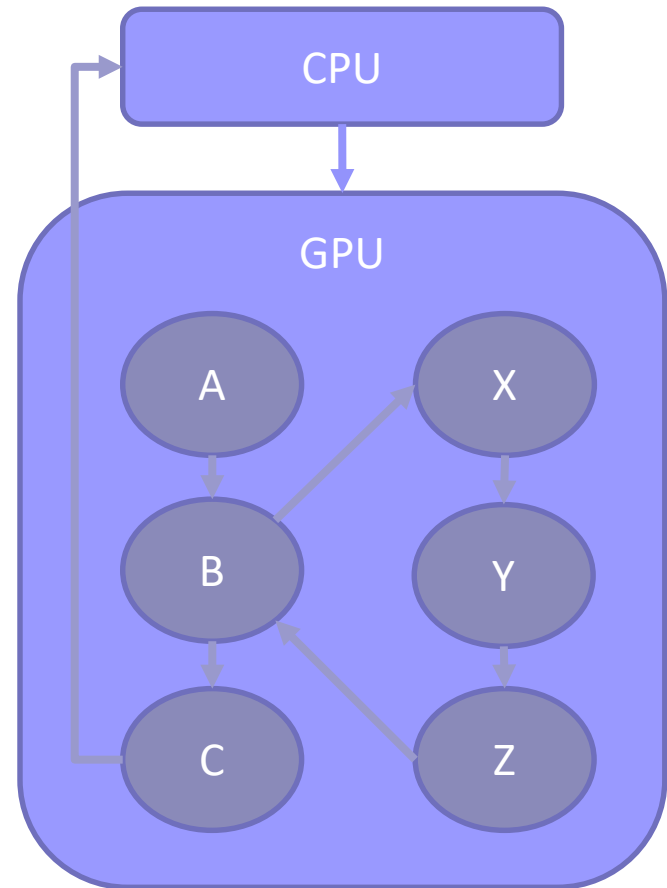
Dependency in CUDA

```
void main() {  
    float *data;  
    do_stuff(data);  
    A <<< ... >>> (data);  
    B <<< ... >>> (data);  
    C <<< ... >>> (data);  
    cudaDeviceSynchronize();  
    do_more_stuff(data);  
}
```



Nested dependency

```
void main() {  
    float *data;  
    do_stuff(data);  
    A <<< ... >>> (data);  
    B <<< ... >>> (data);  
    C <<< ... >>> (data);  
    cudaDeviceSynchronize();  
    do_more_stuff(data);  
}  
  
__global__ void B(float *data){  
    do_stuff(data);  
    X <<< ... >>> (data);  
    Y <<< ... >>> (data);  
    Z <<< ... >>> (data);  
    cudaDeviceSynchronize();  
    do_more_stuff(data);  
}
```

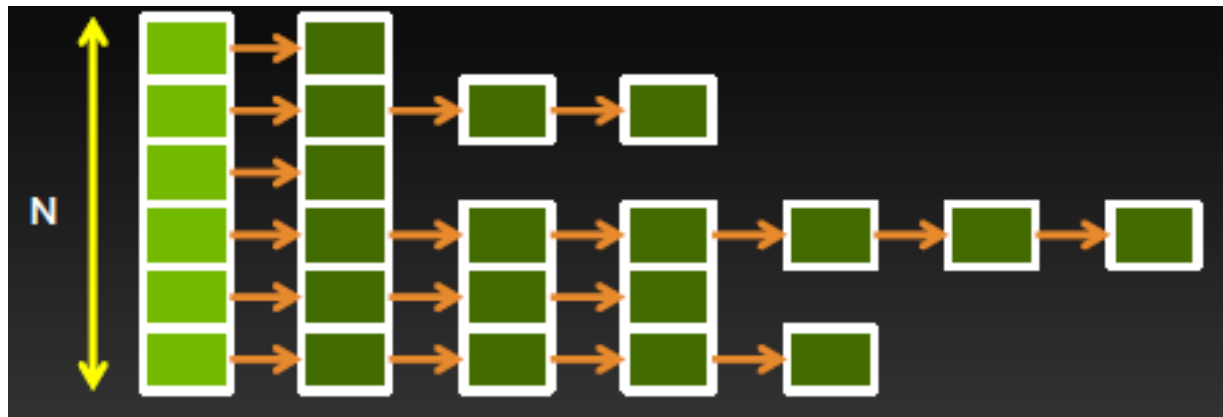


What is DP good for?

- Dynamic block size and grid size
- Dynamic work generation
- Nested parallelism
- Library calls
- Parallel recursion

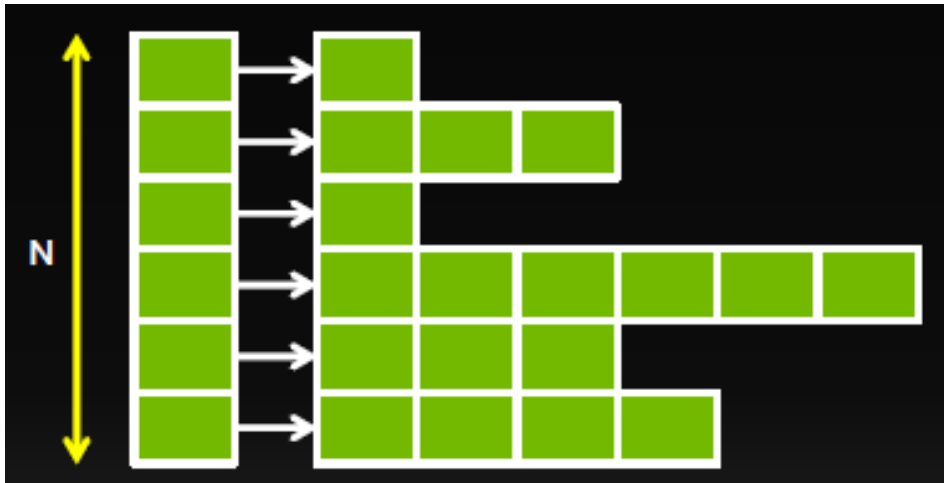
1. Dynamic block size and grid size

```
for i = 1 to N
  for j = 1 to x[i]
    convolution(i, j)
  next j
next i
```

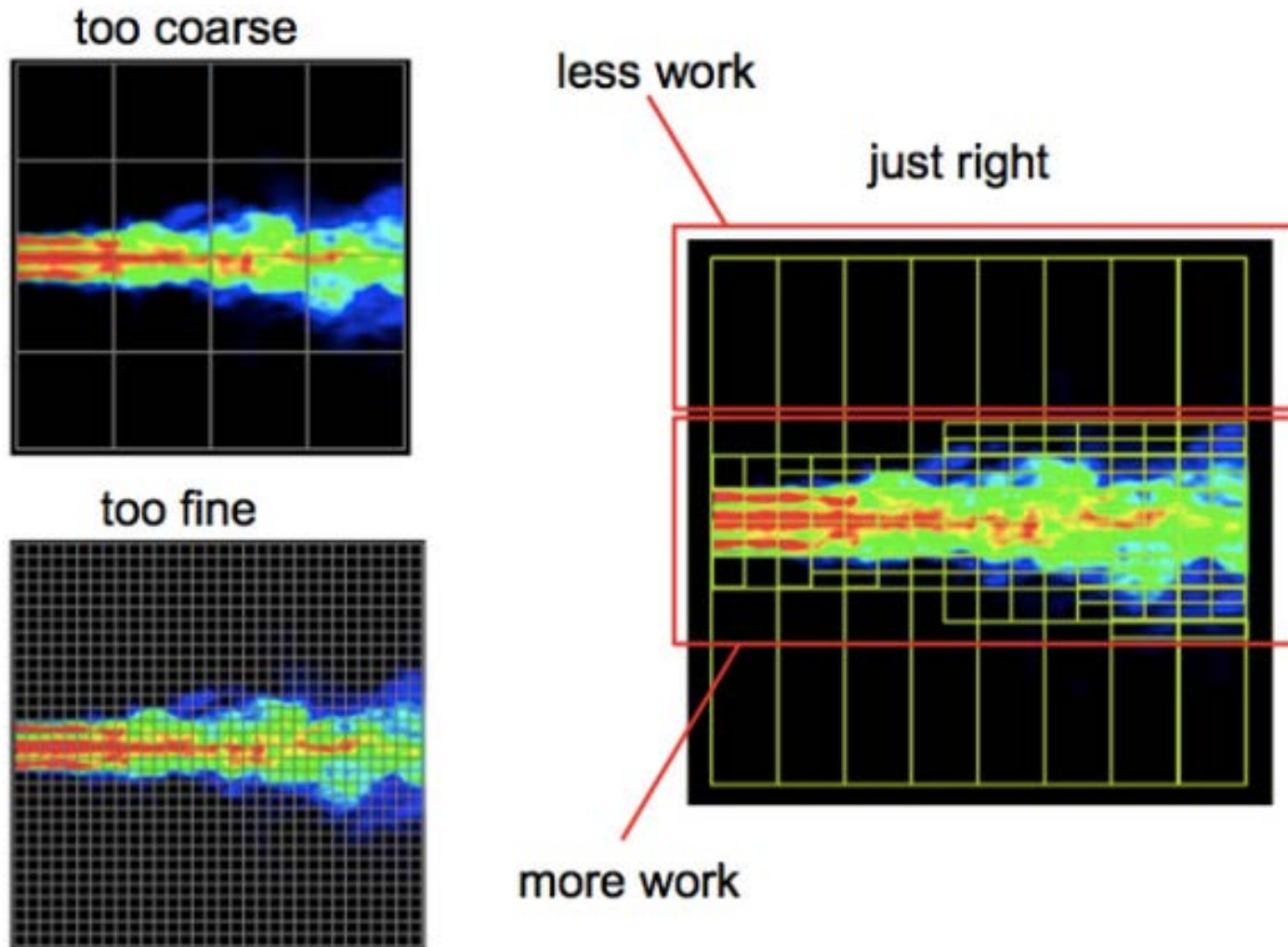


1. Dynamic block size with DP

```
__global__ void convolution(int x[]){  
    for j = 1 to x[blockIdx]  
        kernel<<< ... >>>(blockIdx, j)  
    }  
    ...  
    convolution<<< N, 1 >>>(x);  
}
```



2. Dynamic work generation



3. Nested Parallelism

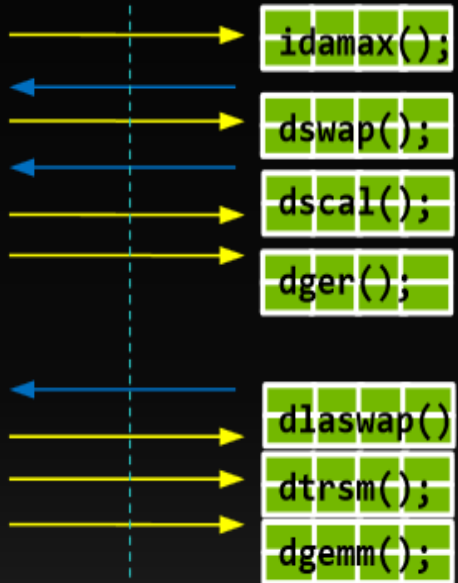
LU decomposition (Fermi)

```

dgetrf(N, N) {
  for j=1 to N
    for i=1 to 64
      idamax<<<>>
      memcpy
      dswap<<<>>
      memcpy
      dscal<<<>>
      dger<<<>>
    next i

    memcpy
    dlaswap<<<>>
    dtrsm<<<>>
    dgemm<<<>>
  next j
}
    
```

CPU Code



GPU Code

LU decomposition (Kepler)

```

dgetrf(N, N) {
  dgetrf<<<>>
}
    
```

CPU Code

```

dgetrf(N, N) {
  for j=1 to N
    for i=1 to 64
      idamax<<<>>
      dswap<<<>>
      dscal<<<>>
      dger<<<>>
    next i
    dlaswap<<<>>
    dtrsm<<<>>
    dgemm<<<>>
  next j
}
    
```

GPU Code

```

synchronize();
}
    
```

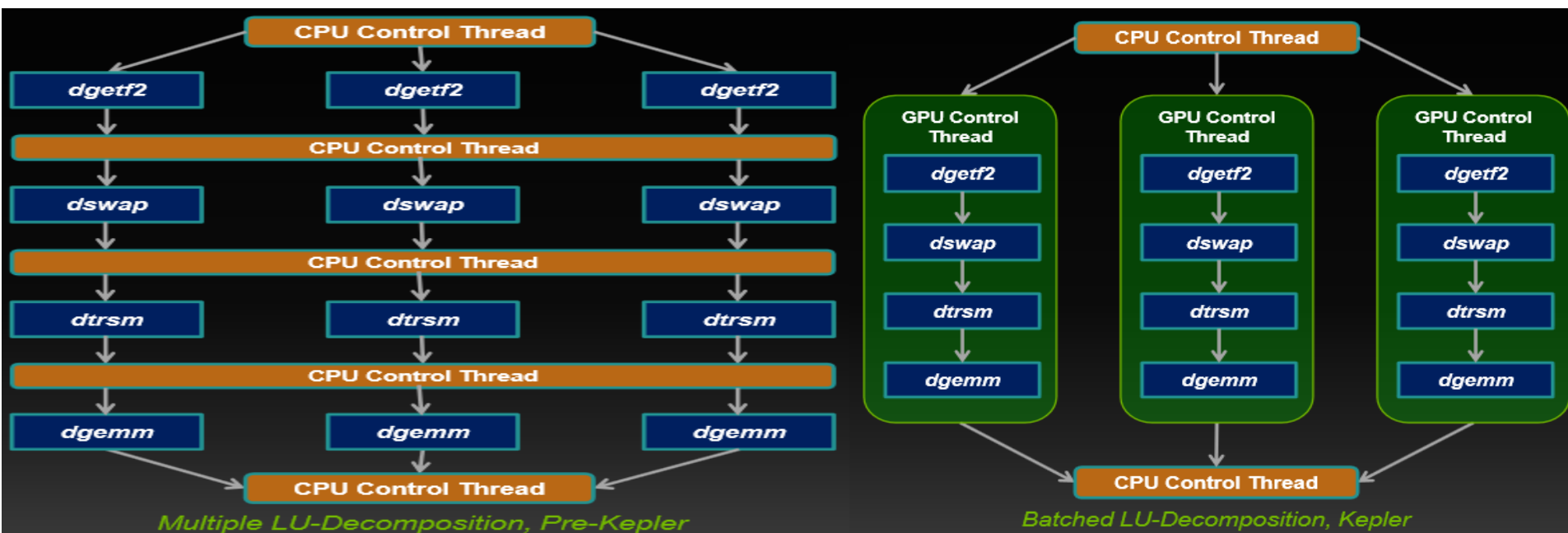
LU Decomposition

■ CPU controlled batching

- Limited by single point control
- Can run at most 10s of threads
- CPU is fully consumed with controlling launches

■ Batching via DP

- Move top loop to GPU
- Run thousands of independent tasks
- Release CPU for other work



4. Library call

```
__global__ void libraryCall(float *a, float *b, float *c){
    // All threads generate data
    createData(a, b);
    __syncthreads();
    // Only one thread calls library
    if(threadIdx.x == 0) {
        cublasDgemm(a, b, c);
        cudaDeviceSynchronize();
    }
    // All threads wait for dtrsm
    __syncthreads();
    // Now continue
    consumeData(c);
}
```

5. Parallel Recursion

■ Quick sort

```
__global__ void qsort(int *data, int l, int r) {  
    int pivot = data[0];  
    int *lptr = data+l, *rptr = data+r;  
  
    // Partition data around pivot value  
    partition(data, l, r, lptr, rptr, pivot);  
  
    // Launch next stage recursively  
    if(l < (rptr-data))  
        qsort<<< ... >>>(data, l, rptr-data);  
    if(r > (lptr-data))  
        qsort<<< ... >>>(data, lptr-data, r);  
}
```


Reference

- **NVIDIA CUDA Library Documentation**

http://developer.download.nvidia.com/compute/cuda/4_1/rel/toolkit/docs/online/index.html

- **NVIDIA, Introduction to Dynamic Parallelism**

<http://on-demand.gputechconf.com/gtc/2012/presentations/S0338-GTC2012-CUDA-Programming-Model.pdf>