



# GPU Parallel Programming: CUDA Summary

National Tsing-Hua University  
2017, Summer Semester



# Outline

- Execution
- Memory
- Synchronization
- Stream

# 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(...)  
    ...  
}
```

# Function Qualifiers

Function qualifiers	limitations
<code>__device__</code> function	
<code>__global__</code> function	
<code>__host__</code> function	
Functions without qualifiers	
<code>__host__ __device__</code> function	

# 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 <b>void</b> 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

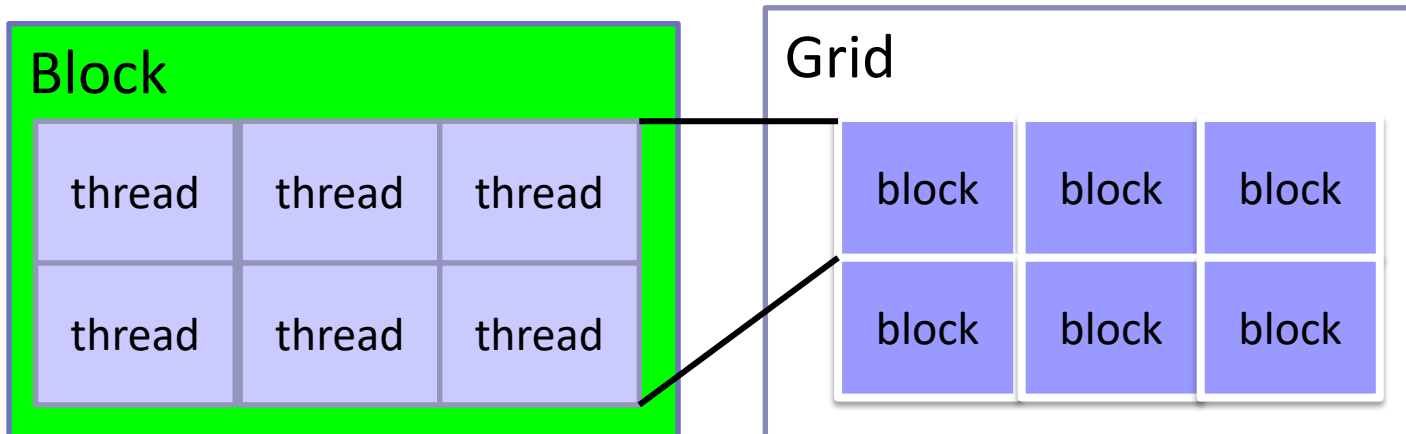


# CUDA Programming Terminology

- Host?
- Device?
- Kernel?
- Thread?
- Block is a group of what?
- Grid is a group of what?

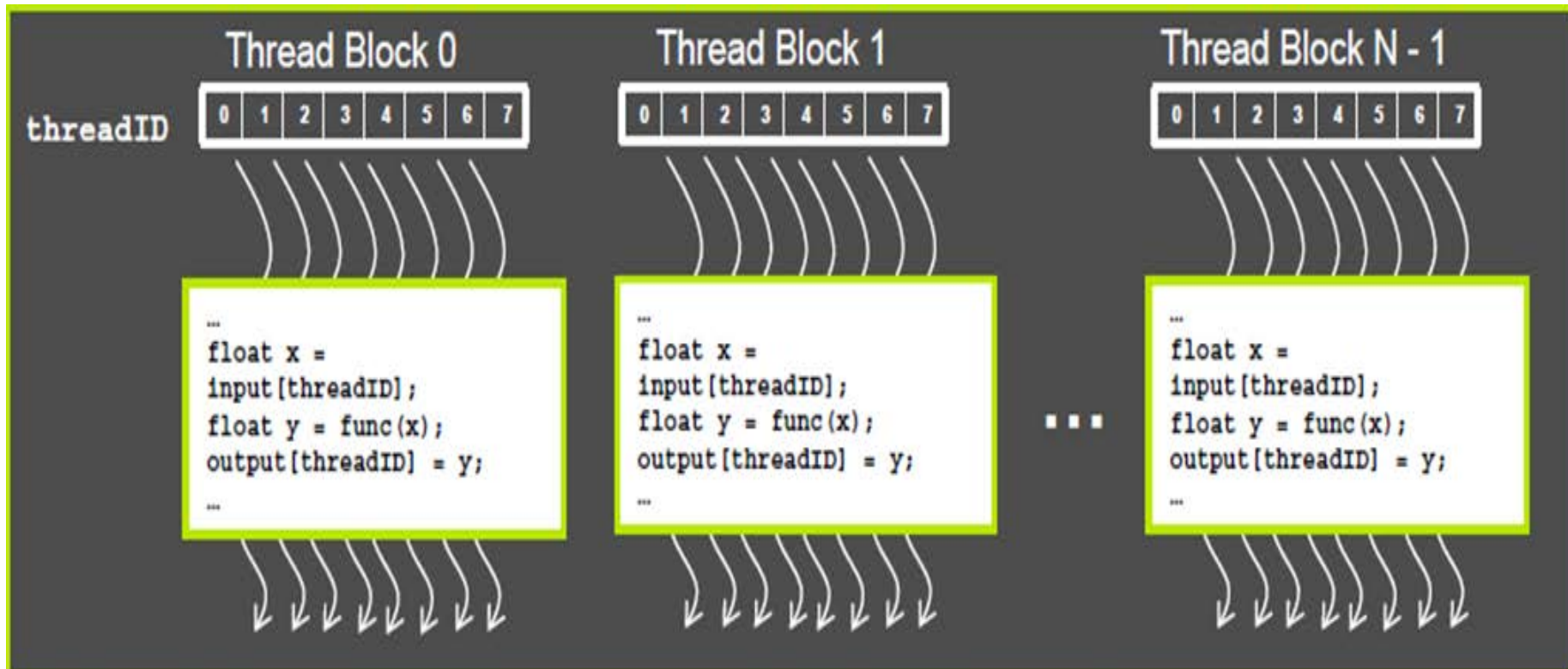
# CUDA Programming Terminology

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



# Hierarchy of Concurrent Threads

- Threads are grouped into thread blocks
  - Kernel = grid of thread blocks
  - Each thread has a unique **threadIdx** and **blockIdx** identifier

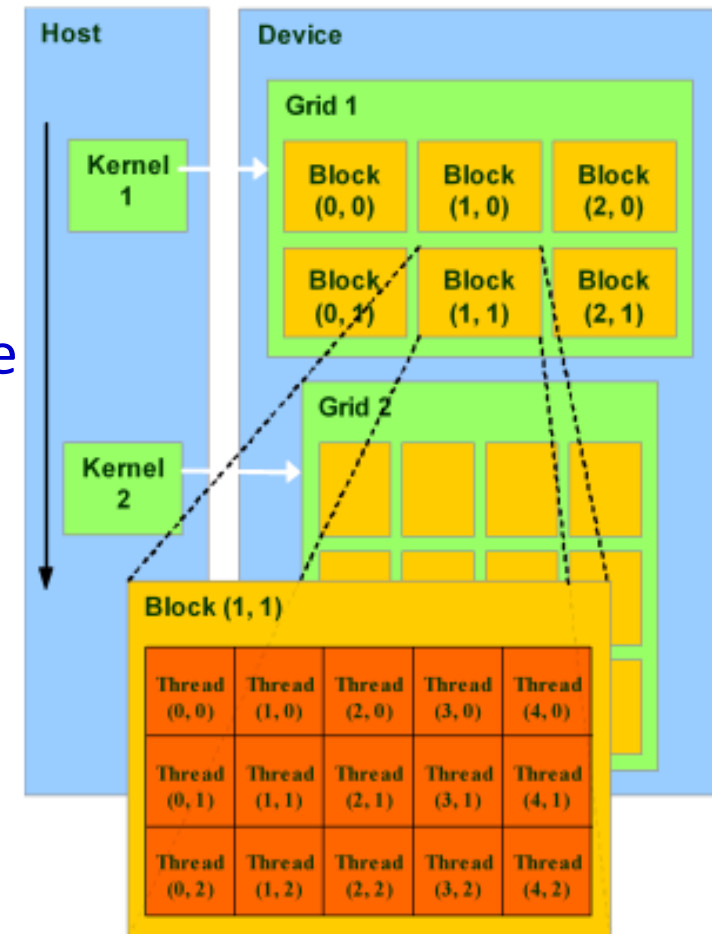




# Thread and Block IDs

- 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?

# Thread and Block IDs

- 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);`

# Thread and Block IDs

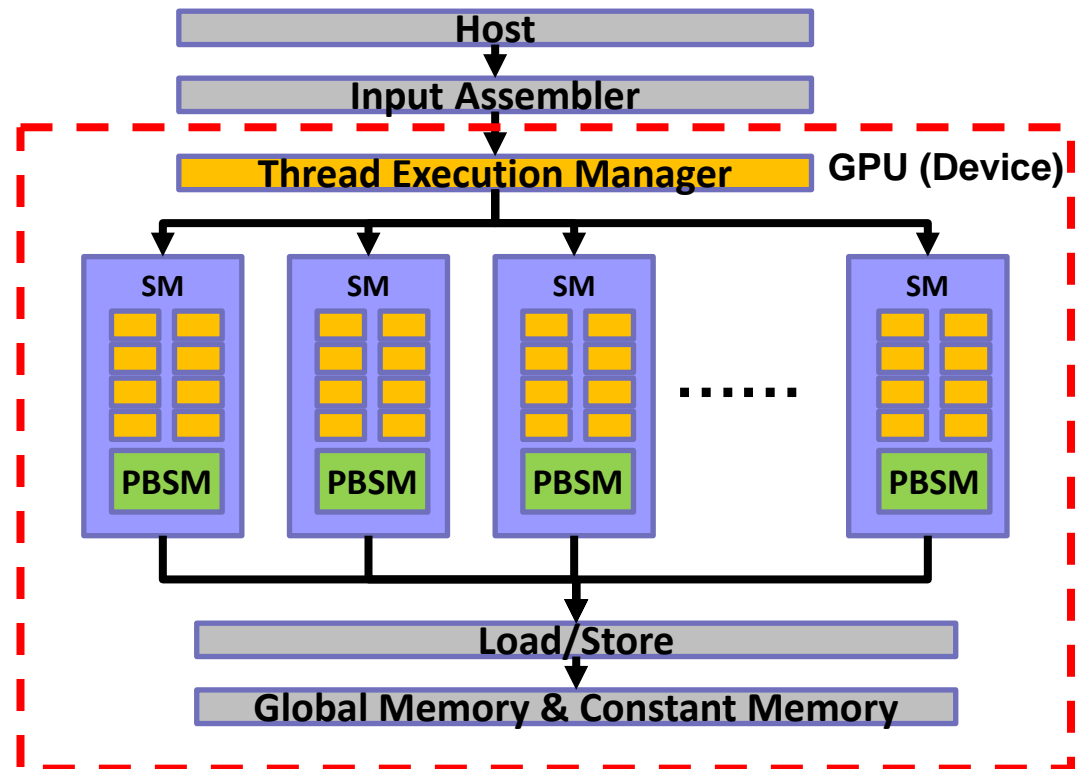
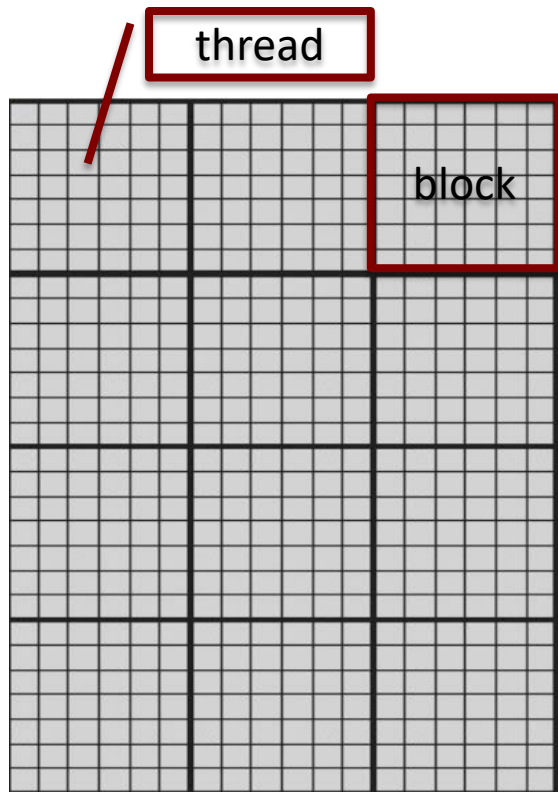
- How to index a 100 elements of an array under the following kernel launch setting?

```
// 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;`

# Software to Hardware Mapping

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



# Software to Hardware Mapping

- Can a kernel run on two different devices at the same time?
- Can a kernel run across multiple SM processors?
- 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);`
- Wshared block memory can only be accessed by the threads in the same blocks?
- Why `__syncthreads()` is not supported across blocks?

# Software to Hardware Mapping

- Can a kernel run on two different devices at the same time?

No

- Can a kernel run across multiple SM processors? Yes

- Can the threads from a same block run across multiple SM processors? No

- What is the difference between the two kernels below?

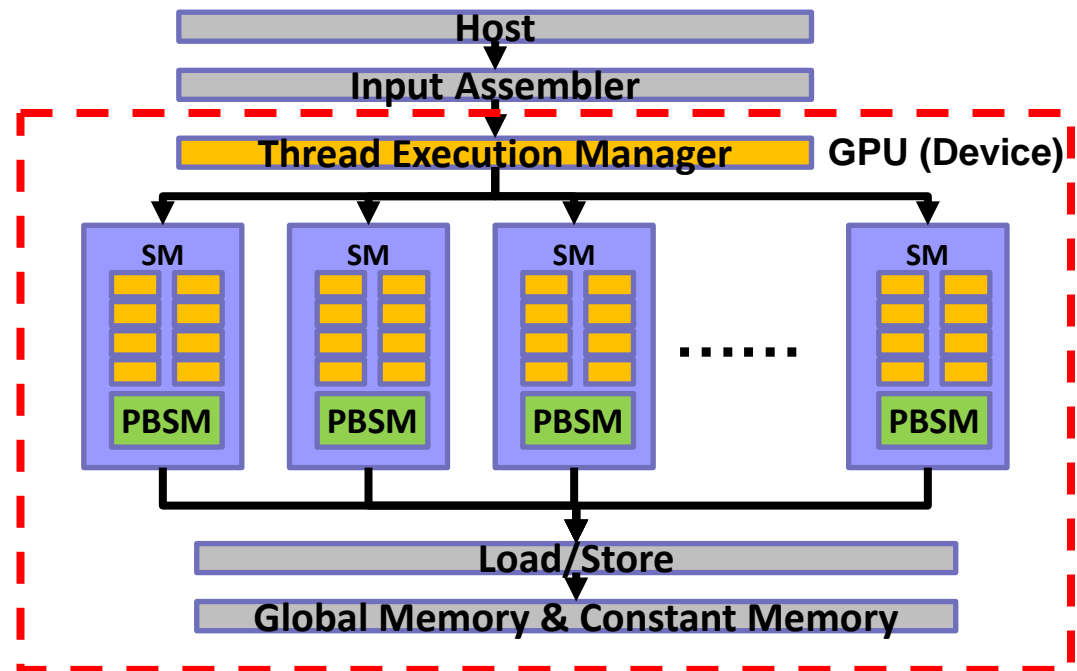
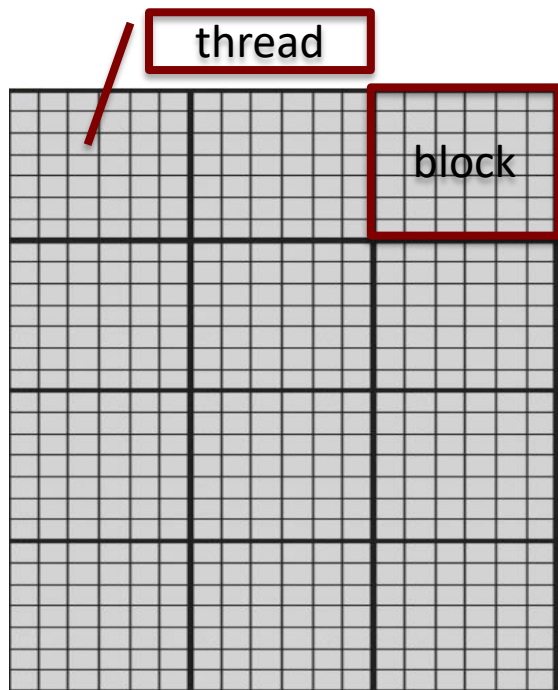
1. `my_kernel<<< 1, 100 >>>(A);`

2. `my_kernel<<< 100, 1 >>>(A);`

- Why shared block memory can only be accessed by the threads in the same blocks?
- Why `__syncthreads()` is not supported across blocks?

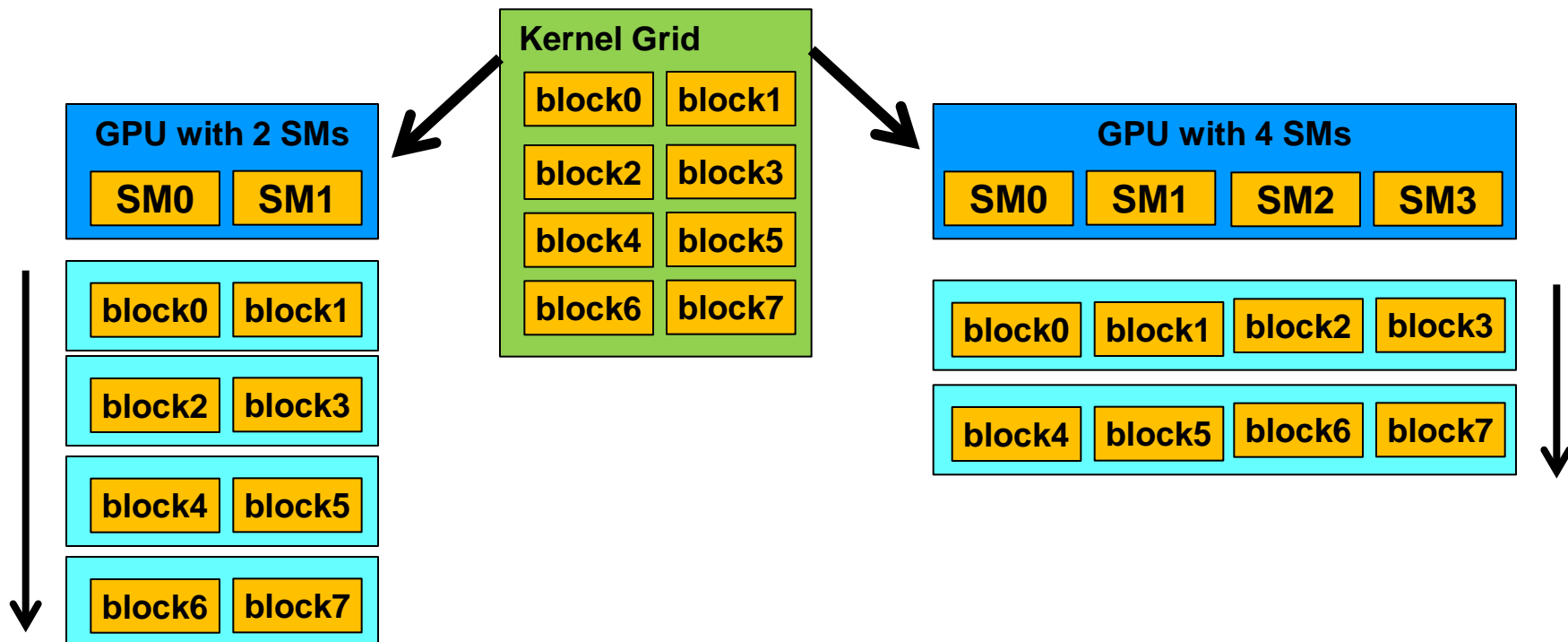
# Software to Hardware Mapping

- The actual **software running instances** to **hardware computing unit** mapping is done by the hardware thread execution manager **at runtime**



# Block Level Scheduling

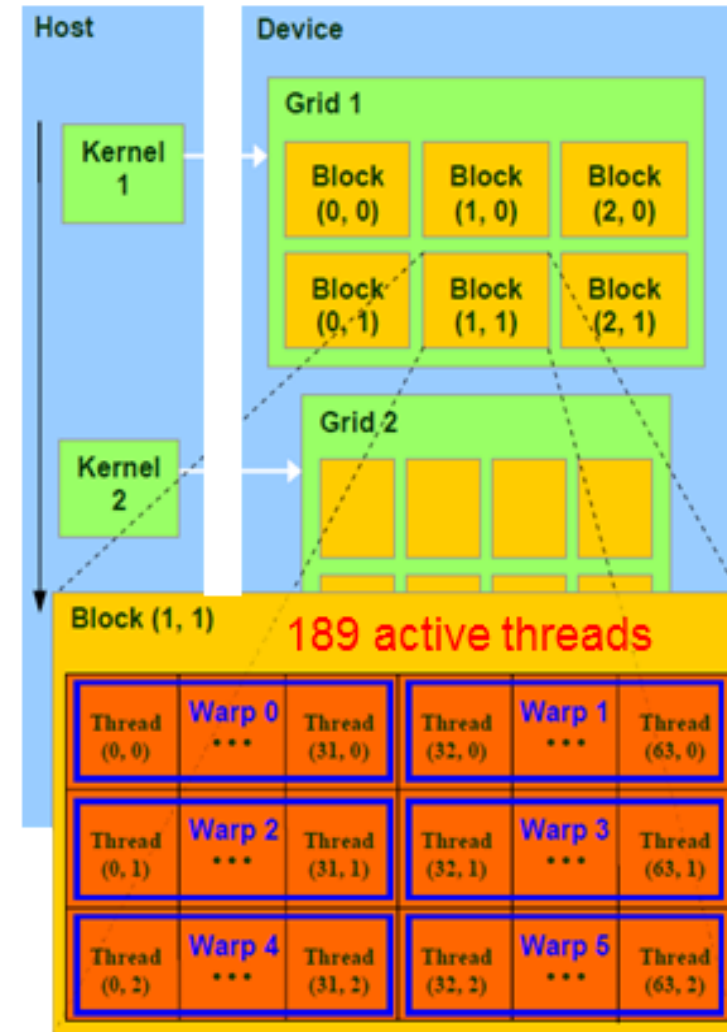
- Blocks are independent to each other to give scalability
  - A kernel scales across any number of parallel cores by scheduling blocks to SMs





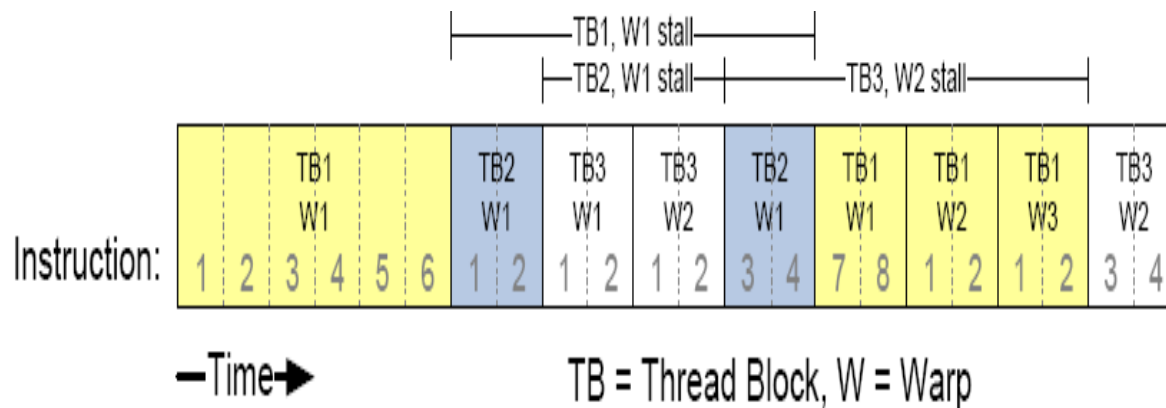
# Thread Level Scheduling - Warp

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



# Thread Level Scheduling - Warp

- Hardware implements **zero-overhead Warp scheduling**
  - Warps whose next instruction has its **operands ready for consumption** are eligible for execution
  - Warps are **switched when memory stalls**
- There are limited number of active blocks & warps
  - Maximum number of active blocks per SM is 8 (Fermi)
  - Maximum number of active warps per SM is 48 (Fermi)
  - **Maximum number of active threads per SM is  $48 \times 32 = 1,536$**

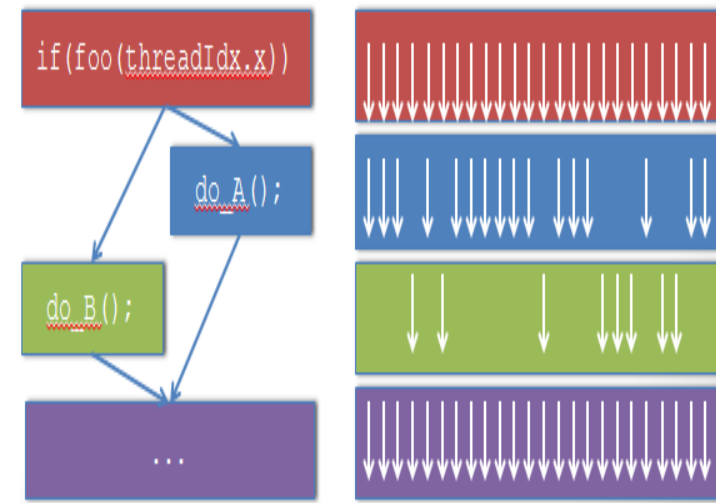


# Software to Hardware Mapping

- Does the kernel below have to run on 10 different SM processors?
  - `my_kernel<<< 10, 10 >>>();`
- Can multiple blocks run on a single SM processors?
- If a SM only has 128 cores, does it mean there can only be 128 active threads on the SM?
- Why we have to call `__syncthreads()` within a block if there are data dependency between statements
  - `A[threadIdx] = threadIdx; A[threadIdx] += A[threadIdx/2];`
- Why branch will cause divergence?
  - `If (A[threadIdx] > 0) A[threadIdx]=1; else A[threadIdx]=-1;`

# Software to Hardware Mapping

- Does the kernel below have to run on 10 different SM processors? **No**
  - `my_kernel<<< 10, 10 >>>();`
- Can multiple blocks run on a single SM processors? **Yes**
- If a SM only has 128 cores, does it mean there can only be 128 active threads on the SM? **No**
- Why we have to call `__syncthreads()` within a block if there are data dependency between statements
  - `A[threadIdx] = threadIdx;`
  - `A[threadIdx] += A[threadIdx/2];`
- Why branch will cause divergence?
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# Outline

- Execution
- **Memory**
- Synchronization
- Stream

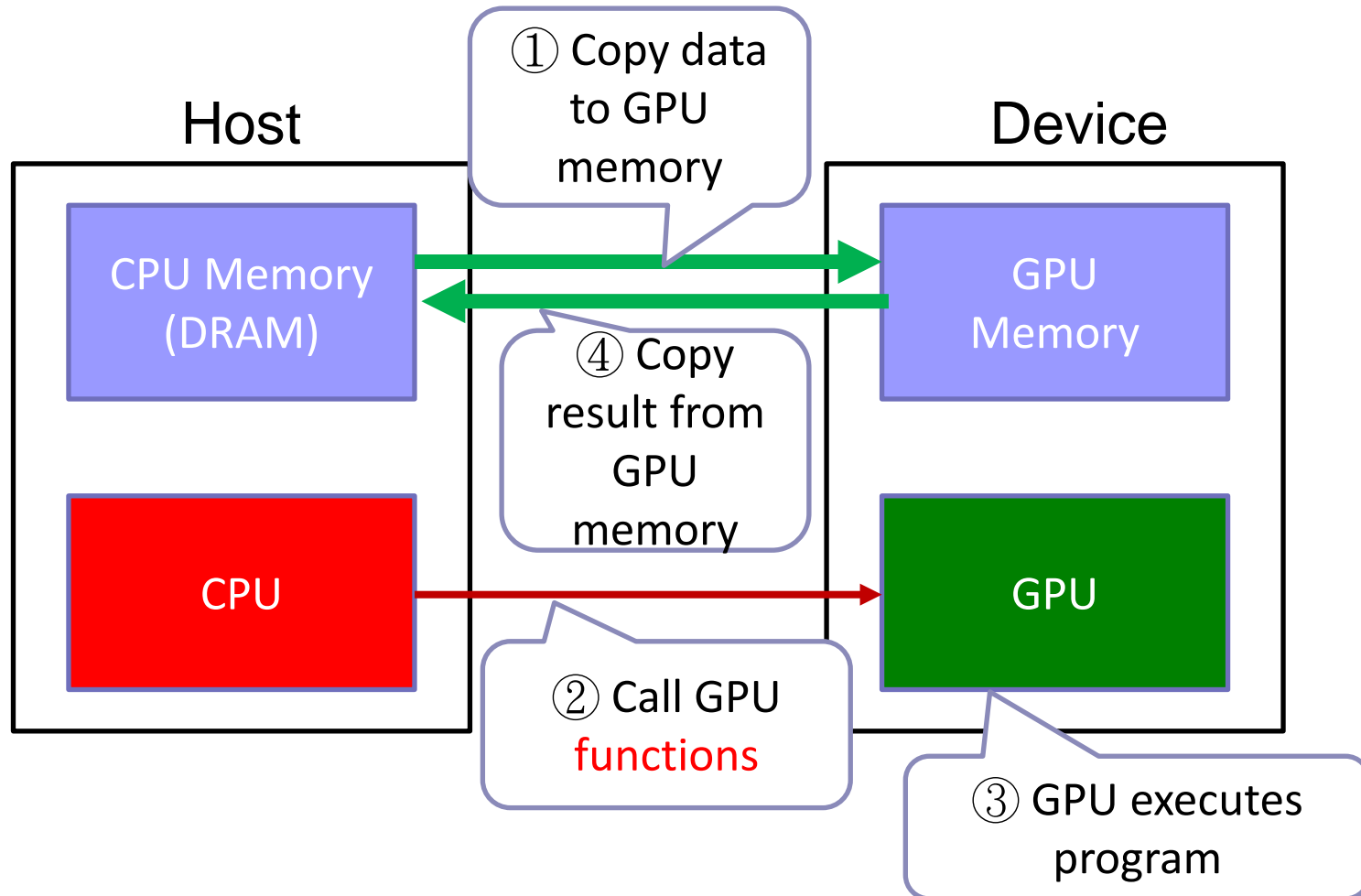


# Outline

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# CUDA program flow

Q: Why we have to copy the memory content?

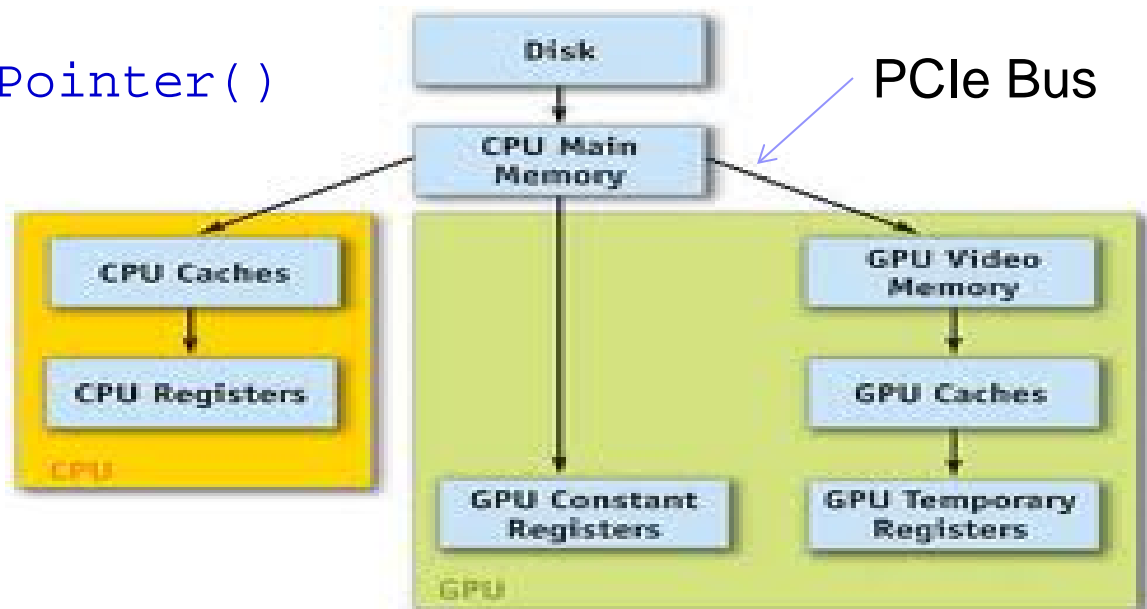
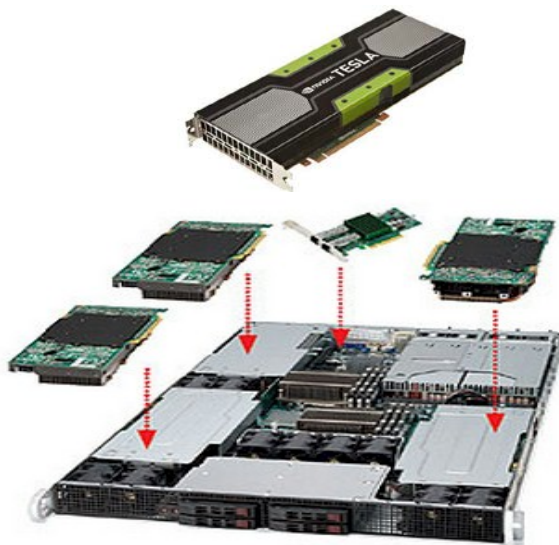


# GPU Servers

Device pointer & host pointer are in two different **address space**!

- Device memory is controlled by GPU
  - Must use **device pointer**
- Host memory is controlled by CPU
  - Must use **host pointer**
- **Zero copy** can allow GPU directly access host memory, but GPU still use the **device pointer not host pointer**

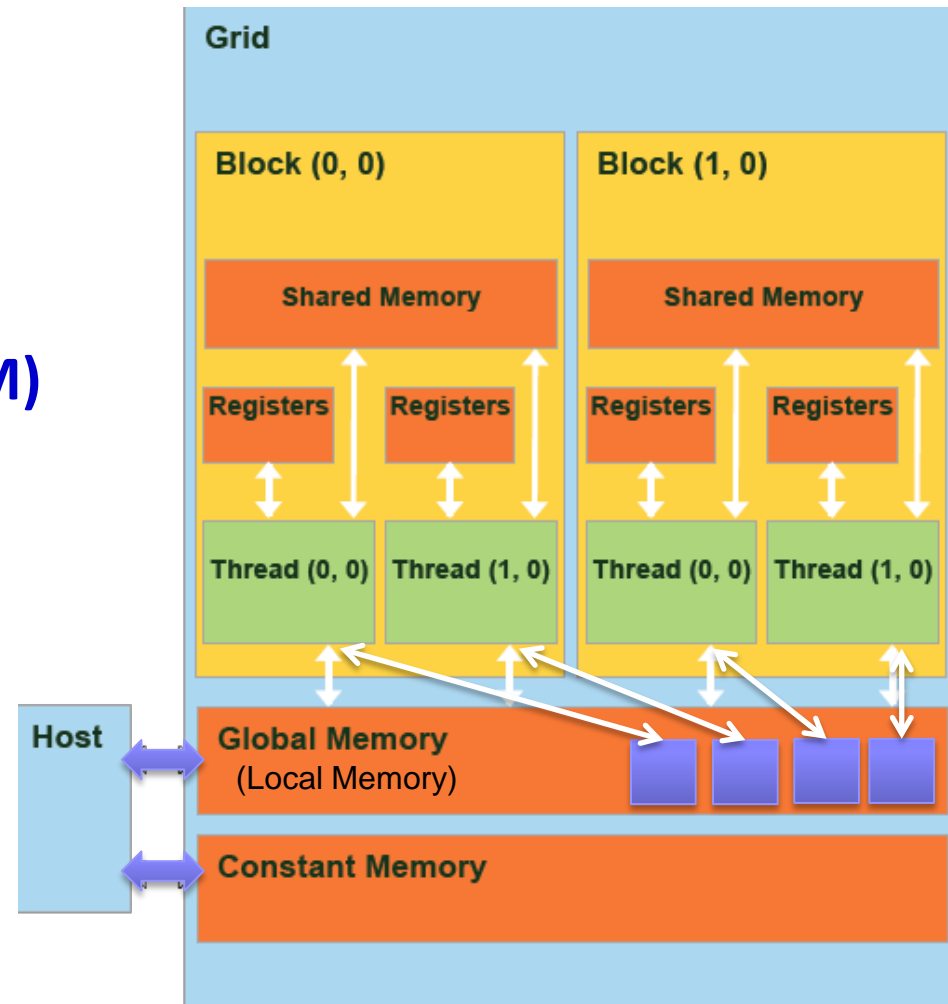
`cudaHostAlloc()`  
`cudaHostGetDevicePointer()`





# GPU Memory Hierarchy

- Registers
- Shared memory
- Global/Local memory (DRAM)
- Constant memory



# Software to Hardware Mapping

## CUDA Variables within a Kernel

Local  
variable

Shared  
variable

Global  
variable

Register

Local  
Memory

Shared  
Memory

Global  
Memory

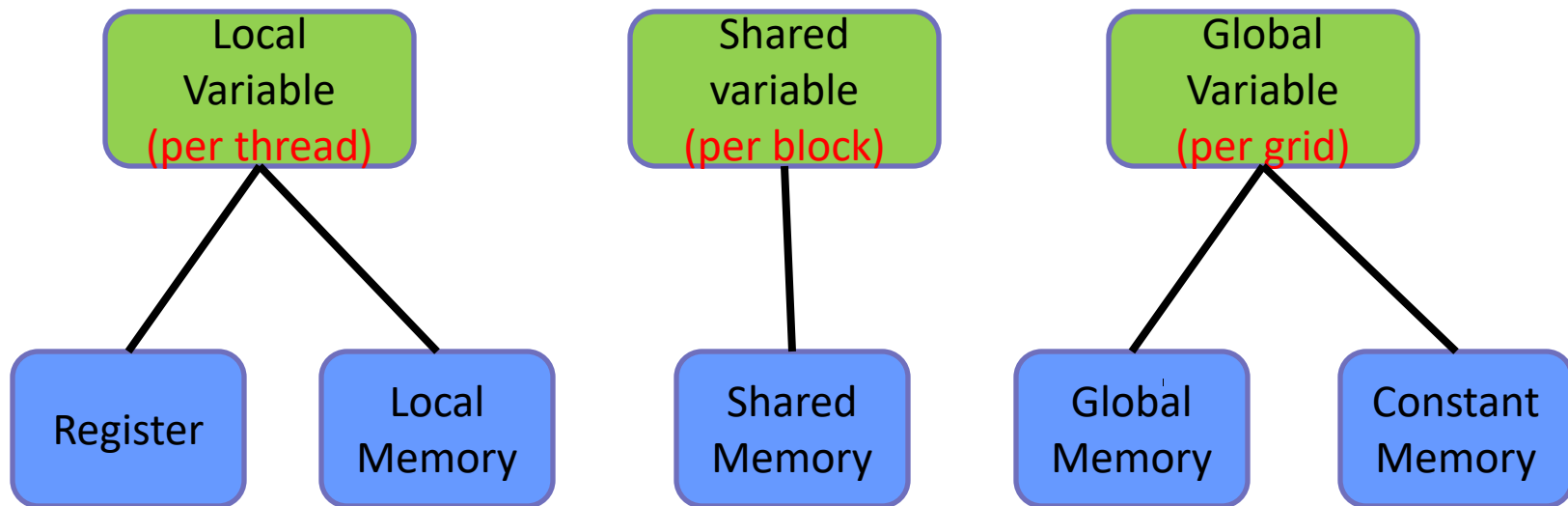
Constant  
Memory

## GPU Memory Hierarchy

Q: What is the data scope of each variable, and what is the mapping between software and hardware?

# Software to Hardware Mapping

## CUDA Variables within a Kernel



## GPU Memory Hierarchy

Q: What is the data scope of each variable, and what is the mapping between software and hardware?

# Outline

- Execution
- **Memory**
  - Local variable
  - Global variable
  - Shared variable
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# Local Variable: Register vs Local Memory

- A local variable declared in a kernel function can be reside in **register** (on chip memory) or **local memory** (off chip memory). What are the differences between them?
  - When will a local variable be stored in local memory? (hint: only in 2 situations)

```
__global__ void distance(int *m, int *n, int *V){  
    int i, j, k;  
    int a[10], b[10], c[10];  
}
```

Q: Where are the variables (i, j, k, a, b, c, m, n, V) stored (register, local memory, global memory, shared memory)?

# Local Memory

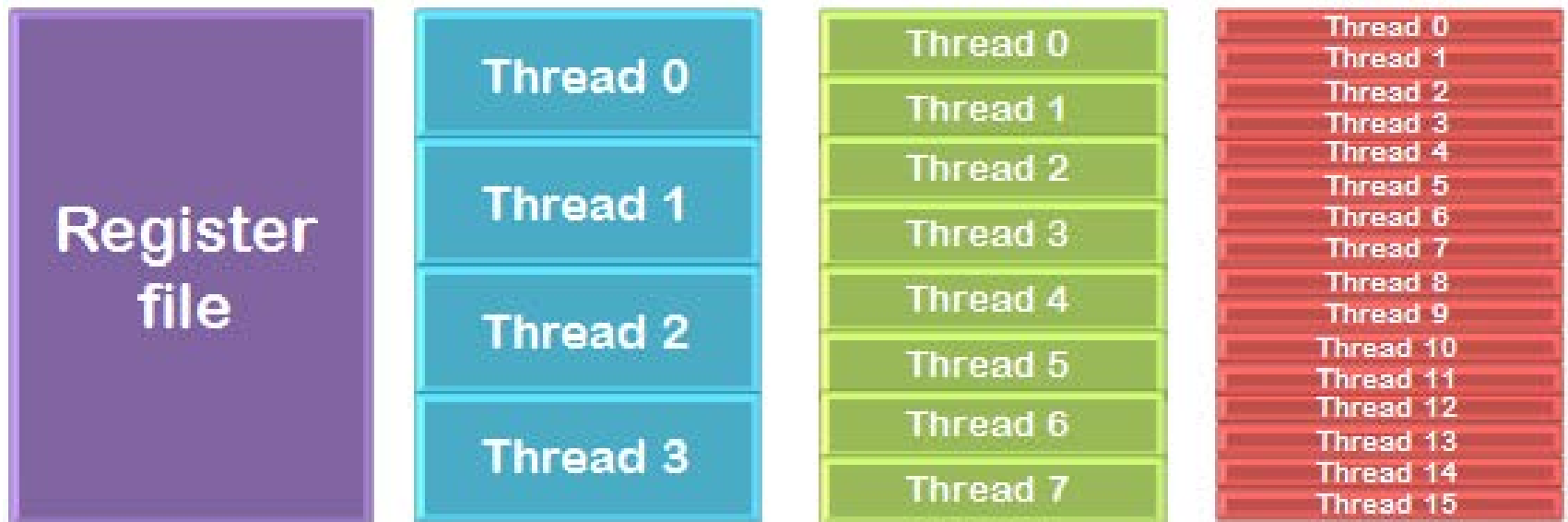
Q: What is register pressure?

- Name refers to memory where registers and other thread-data (**array**) is spilled
  - Runs out of SM resources due to **register pressure**
  - **Registers aren't indexable**, so arrays have to be placed in local memory
  - “**Local**” because each thread has its own **private access scope**
- Details:
  - Not really a “memory” – bytes are stored in **global memory (DRAM)**
- Differences from global memory:
  - Addressing is resolved by the **compiler**
  - Stores are **cached in L1**

Q: Where is L1 cache?

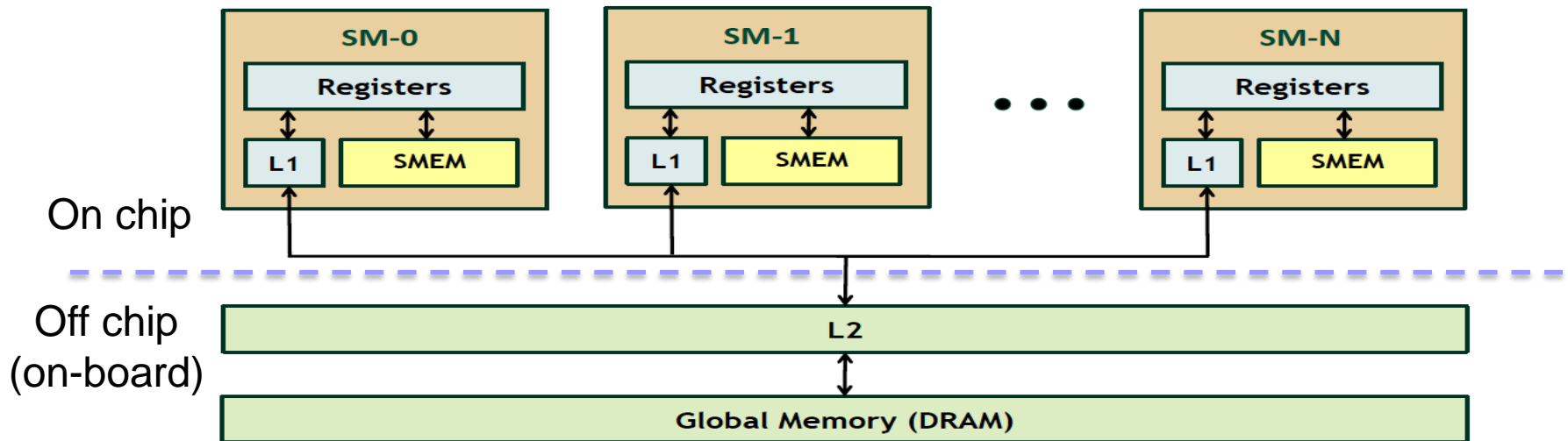
# Register Pressure

- Too few threads
  - can't hide pipeline / memory access latency
- Too many threads
  - register pressure
  - Limited number of registers among concurrent threads
  - Limited shared memory among concurrent blocks



# Memory Cache

- L1 & L2 are used to cache **local memory** contents
  - L1: On chip memory. Same as **share memory**
    - ◆ Programmers can decide the ratio of shared memory and L1 cache
  - L2: Off chip memory Cache. Same as **global memory**



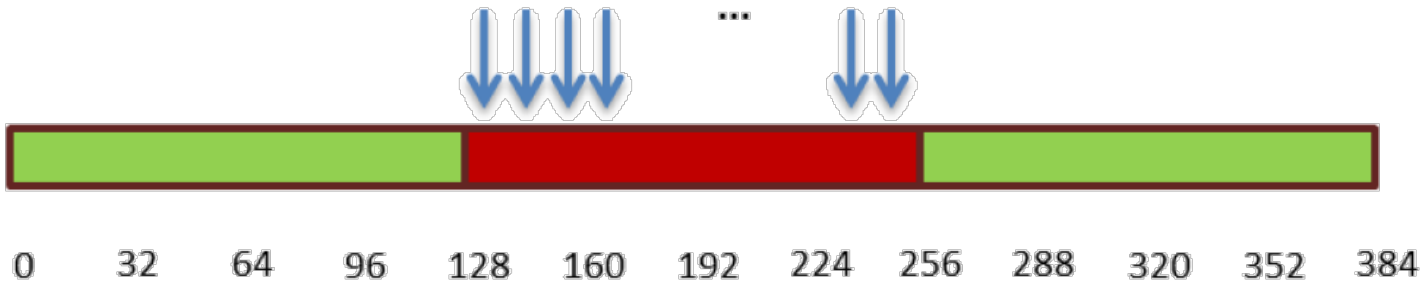


# Coalesced Memory Access Problem

## ■ Coalesced access

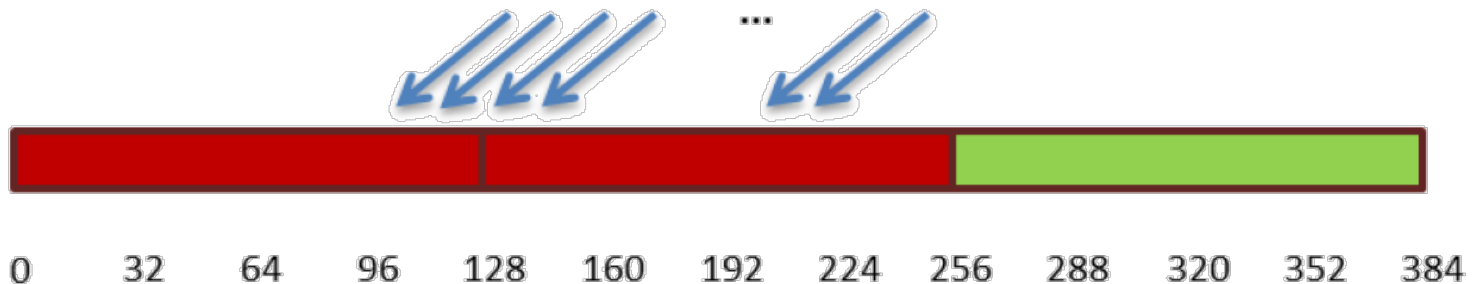
addresses from a warp

Prefer linear and aligned memory access pattern



## ■ Unaligned sequential addresses that fit into two 128-byte L1-cache lines

addresses from a warp



# Outline

- Execution

- **Memory**

  - Local variable

  - **Global variable**

  - Shared variable

- Synchronization

- Stream



# Global Variable:

## Global Memory vs Constant Memory

- What are the two key differences between them?



# Global Variable:

## Global Memory vs Constant Memory

- What are the two key differences between them?

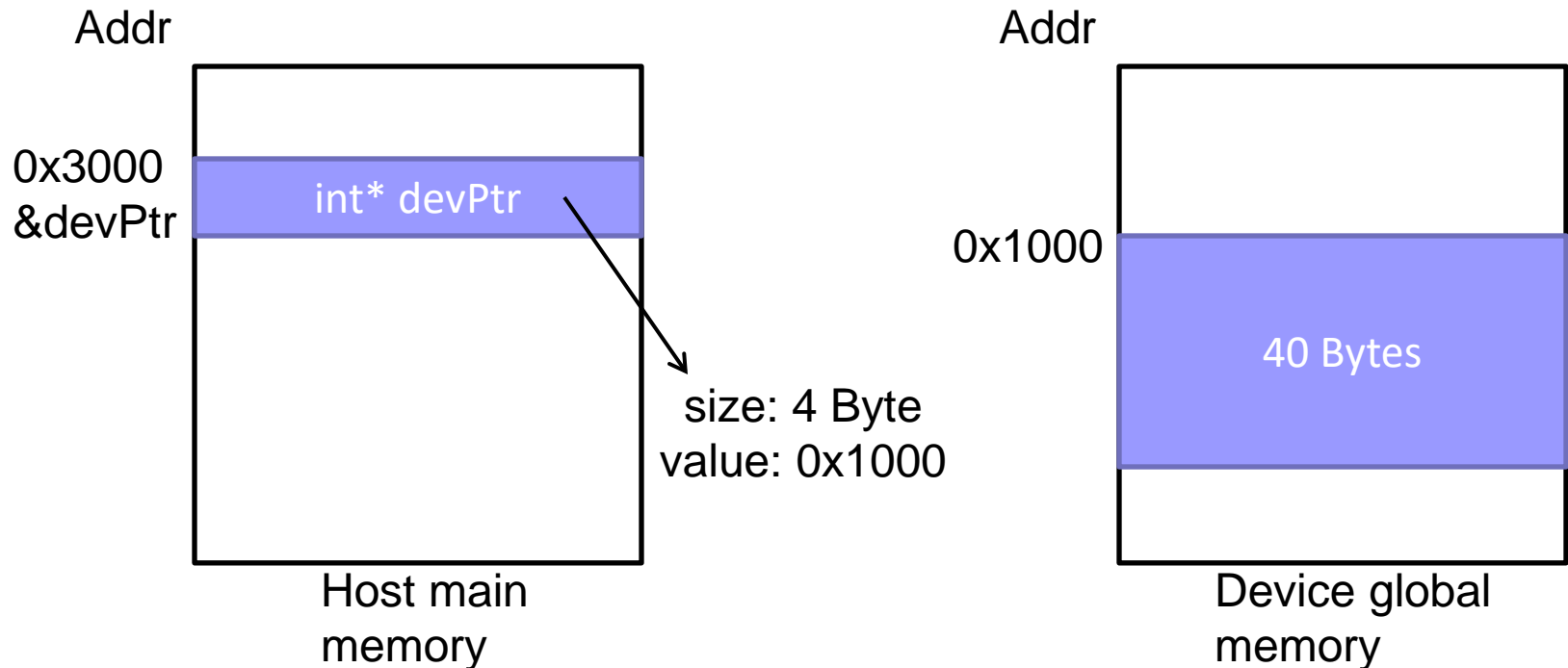
- Constant memory is read only
- Constant memory can be cached

# How to Allocate Device (Global) Memory

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

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

2. `cudaFree (void *devPtr)`



# Synchronous Global Memory Copy

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

➤ count: size in **bytes** to copy

<code>cudaMemcpyKind</code>	Meaning	dst	src
<code>cudaMemcpyHostToHost</code>	Host → Host	host	host
<code>cudaMemcpyHostToDevice</code>	Host → Device	device	host
<code>cudaMemcpyDeviceToHost</code>	Device → Host	host	device
<code>cudaMemcpyDeviceToDevice</code>	Device → Device	device	device

host to host has the same effect as `memcpy()`

Compiler does not distinguish between the device pointer & host pointer.  
You have to check by yourself very carefully.

# Copy 3 Int between Device & Host

```
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, sizeof(int), cudaMemcpyDeviceToHost);  
    // Cleanup  
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);  
    return 0;  
}
```

# Asynchronous Global Memory Copy

- `cudaMemcpyAsync`: the **host** memory must be pinned using `cudaMallocHost()` or `cudaHostAlloc()` with the flag **`cudaHostAllocMapped`**

```
int main(void) {
    int *in, out;
    int *d_in, *d_out;
    cudaMallocHost(&in, sizeof(int));
    int* = 1;
    cudaMalloc((void **)&d_in, sizeof(int));
    cudaMalloc((void **)&d_out, sizeof(int));
    cudaMemcpyAsync(d_in, in, sizeof(int), cudaMemcpyHostToDevice);
    add<<<1,1>>>(d_in, d_out);
    cudaMemcpyAsync(&out, d_out, sizeof(int),
    cudaMemcpyDeviceToHost);
    cudaFree(d_in); cudaFree(d_out);
    return 0;
}
```

If host memory is not pinned, error may occur at runtime when the memory is swapped by OS



# Host Memory $\leftrightarrow$ Constant Memory

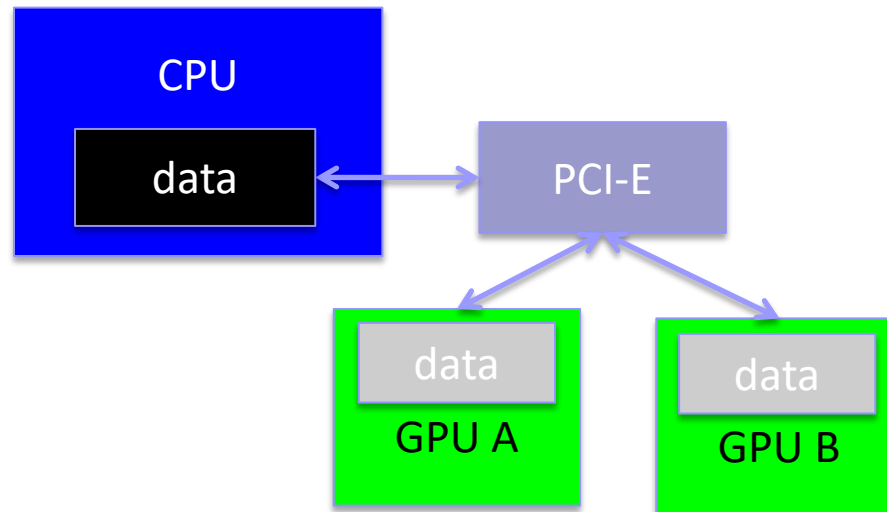
- Use `cudaMemcpyToSymbol()` & `cudaMemcpyFromSymbol()`

```
__constant__ int constData[100];
int main(void) {
    int A[100];
    cudaMemcpyToSymbol(constData, A, sizeof(A));
    add<<<grid_size,blk_size>>>();
    cudaMemcpyFromSymbol(A, constData, sizeof(A));
}
__global__ kernel() {
    int v = constData[threadIdx];
}
```

# Page-Locked Data Transfers (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

Q: What are the two purposes of using zero-copy?



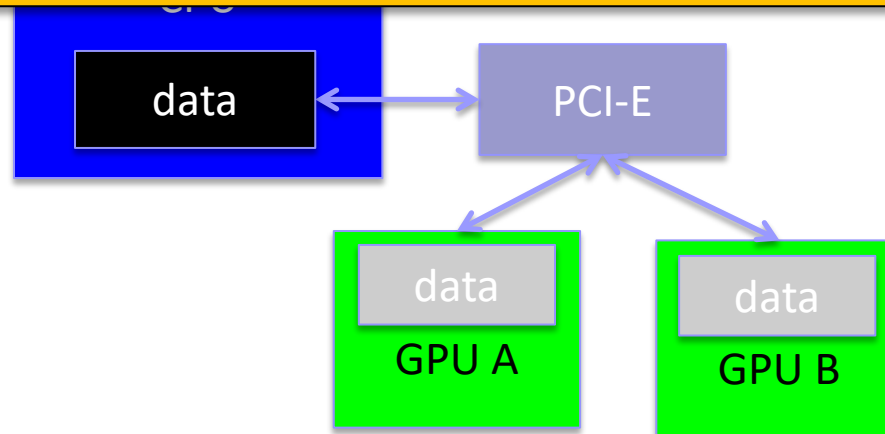
# Page-Locked Data Transfers (Zero-copy)

- “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

Q: What are the two purposes of using zero-copy?

Ans: (1) avoid the overhead of memory copy

(2) used as a shared memory between 2 GPU devices



# Page-Locked Data Transfers (Zero-copy)

- 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);
```

# cudaHostAlloc() vs cudaMallocHost()

## ■ Both allocate memory on **host**

- cudaMalloc() allocate memory on device

## ■ Page-locked

- cudaMallocHost() pins memory by default
- cudaHostAlloc() has to use the flag **cudaHostAllocMapped** to pin the memory

## ■ Page-shared

- cudaMallocHost() doesn't support
- cudaHostAlloc() has the flag **cudaHostAllocPortable**

\*cudaHostAlloc() is only supported after CUDA2.2

# Outline

- Execution
- **Memory**
  - Local variable
  - Global variable
  - **Shared variable**
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# Shared Variable: Shared Memory

- What is the difference between shared memory and global memory?
  - Data scope?
  - Speed?
  - Size?

# Using Shared Memory for Optimization

```
__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];  
}
```

Q: How many global memory accesses?

```
extern __shared__ int S[][];  
__global__ void FW_APSP(int k, int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    S[i][j] = D[i][j]; // move data to shared memory  
    __syncthreads();  
    // do computation  
    if (S[i][j] > S[i][k] + S[k][j])  
        D[i][j] = S[i][k] + S[k][j];  
}
```



# Using Shared Memory for Optimization

```
__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];  
}
```

Q: Why only move 1 element, and need sync?

```
extern __shared__ int S[][];  
__global__ void FW_APSP(int k, int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    S[i][j] = D[i][j]; // move data to shared memory  
    __syncthreads();  
    // do computation  
    if (S[i][j] > S[i][k] + S[k][j])  
        D[i][j] = S[i][k] + S[k][j];  
}
```

# When to Synchronize between Threads

- When there is data dependency between threads, `__syncthreads()` is required

```
__global__ void FW_APSP(int* A, int* B) {  
    int i = threadIdx;  
    __shared__ S[10];  
    S[i] = A[i];  
    // do computation  
    int V = S[i] + S[i+1];  
    S[10-i] = V;  
    B[i]=V;  
}
```

Q: Where to add `__syncthreads()`?

# When to Synchronize between Threads

- When there is data dependency between threads, `__syncthreads()` is required

```
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    int i = threadIdx;  
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    S[i] = A[i];  
    __syncthreads();  
    // do computation  
    int V = S[i] + S[i+1];  
    __syncthreads();  
    S[10-i] = V;  
    B[i]=V;  
}
```

# Using Shared Memory for Optimization

```
__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];  
}
```

Q: Why declare shared variable using extern?

```
extern __shared__ int S[][];  
__global__ void FW_APSP(int k, int D[n][n]) {  
    int i = threadIdx.x;  
    int j = threadIdx.y;  
    S[i][j] = D[i][j]; // move data to shared memory  
    __syncthreads();  
    // do computation  
    if (S[i][j] > S[i][k] + S[k][j])  
        D[i][j] = S[i][k] + S[k][j];  
}
```

# Dynamic Allocate Shared Memory

- Use extern variable, and 3<sup>rd</sup> kernel launch argument
- Limitation: All shared variables point to the same memory buffer address

```
extern __shared__ int S[];
__global__ void FW_APSP(int* k, int* D, int* n) {
    int i = threadIdx.x;
    int j = threadIdx.y;
    S[i*(*n)+j]=D[i*(*n)+j]; //move data to shared memory
    __syncthreads();
    // do computation
    if (S[i*(*n)+j]>S[i*(*n)+k]+S[k*(*n)+j])
        D[i*(*n)+j]= S[i*(*n)+k]+S[k*(*n)+j];
}
void main(){
    FW_APSP<<<1,n*n, n*n*sizeof(int)>>> (...);
}
```

Q: Why the massy index for shared variable?

# Address Issue of Dynamic Allocation

- If you have multiple extern declaration of shared:

```
extern __shared__ float As[];
```

```
extern __shared__ float Bs[];
```

this will lead to As pointing to the same address as Bs.

- Solution: keep As and Bs inside the 1D-array.

```
extern __shared__ float smem[];
```

- Need to do the memory management yourself

- When calling kernel, launch it with size of  $sAs + sBs$ , where  $sAs$  and  $sBs$  are the size of As and Bs respectively.
- When indexing elements in As, use `smem[ 0 :  $sAs - 1$  ]` ;  
when indexing elements in Bs, use `smem[  $sAs$  :  $sAs + sBs$  ]`.

# Shared memory address translation

- `Mul(<<<1, N, N>>>(A, B, C, N); //C=A*B`
  - The third parameter is the size of shared memory.

```
extern __shared__ int S[];
inline int Addr(int matrixIdx, int i, int N) {
    return (N*matrixIdx + i);
}
__global__ void Mul(int* A, int* B, int* C, int* N) {
    int i = threadIdx.x;
    //move data to shared memory
    S[Addr(0, i)]=A[i];
    S[Addr(1, i)]=B[i];
    __syncthreads();
    // do computation
    C[i]=S[Addr(0, i)]*S[Addr(1, i)];
}
```

# Static Shared Memory Allocation

- `Mul<<<1, N>>>(A, B, C); //C=A*B`
  - The third parameter is the size of shared memory.

```
__global__ void Mul(int* A, int* B, int* C) {  
    int N=10;  
    int i = threadIdx.x;  
    __static__ int SA[10]; //static allocation  
    __static__ int SB[10]; //static allocation  
    //move data to shared memory  
    SA[i]=A[i];  
    SB[i]=B[i];  
    __syncthreads();  
    // do computation  
    C[i]=SA[i]*SB[i];  
}
```



# Summary of CUDA Variables in Kernel

Static Variable declaration	Memory	Scope	Lifetime	Speed	Total # of variables	Visible by # of threads
<code>int var</code>	Register	Thread	Thread	1x	100,000	1
<code>int array_var[10]</code>	Local	Thread	Thread	100x	100,000	1
<code>__shared__ int shared_var</code>	Shared	Block	Block	1x	100	100
<code>__device__ int global_var</code>	Global	Grid	App	100x	1	100,000
<code>__constant__ int constant_var</code>	Constant	Grid	App	1x	1	100,000



# Outline

- Execution
- Memory
- Synchronization
- Stream

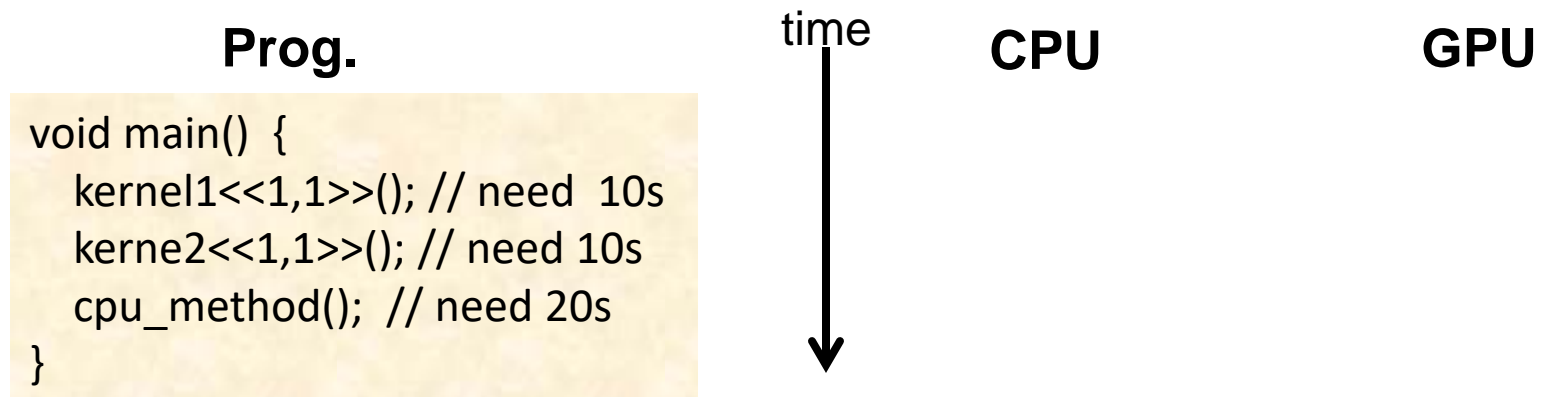


# Asynchronous Functions

- What does asynchronous function mean in CUDA programming?

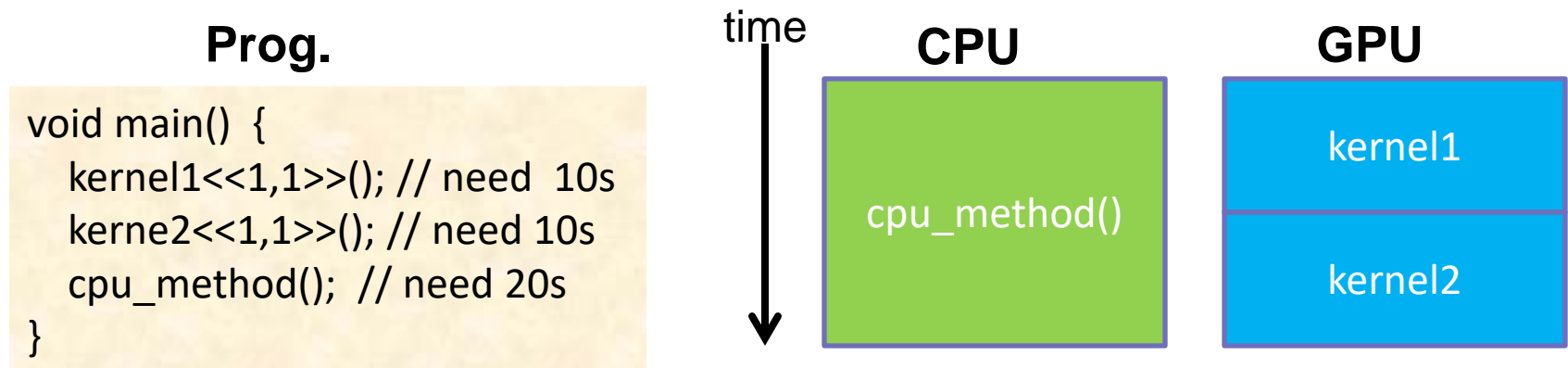
# Asynchronous Functions

- What does asynchronous function mean in CUDA programming?
  - Functions that can facilitate **concurrent execution** between **host** and **device**
  - Control is returned to the host thread **before the device has completed the requested task**



# Asynchronous Functions

- What does asynchronous function mean in CUDA programming?
  - Functions that can facilitate **concurrent execution** between **host** and **device**
  - Control is returned to the host thread **before the device has completed the requested task**



# Asynchronous Functions

## ■ What are the asynchronous functions?

- kernel launch?
- cudaMemcpy?
- cudaMemcpyAsync?
- cudaMalloc?
- cudaFree?
- cudaEventRecord?
- cudaEventElapsedTime?

# Asynchronous Functions

## ■ What are the asynchronous functions?

- kernel launch? **Yes**
- cudaMemcpy? **No**
- cudaMemcpyAsync? **Yes**
- cudaMalloc? **No**
- cudaFree? **No**
- cudaEventRecord? **Yes**
- cudaEventElapsedTime? **Yes**

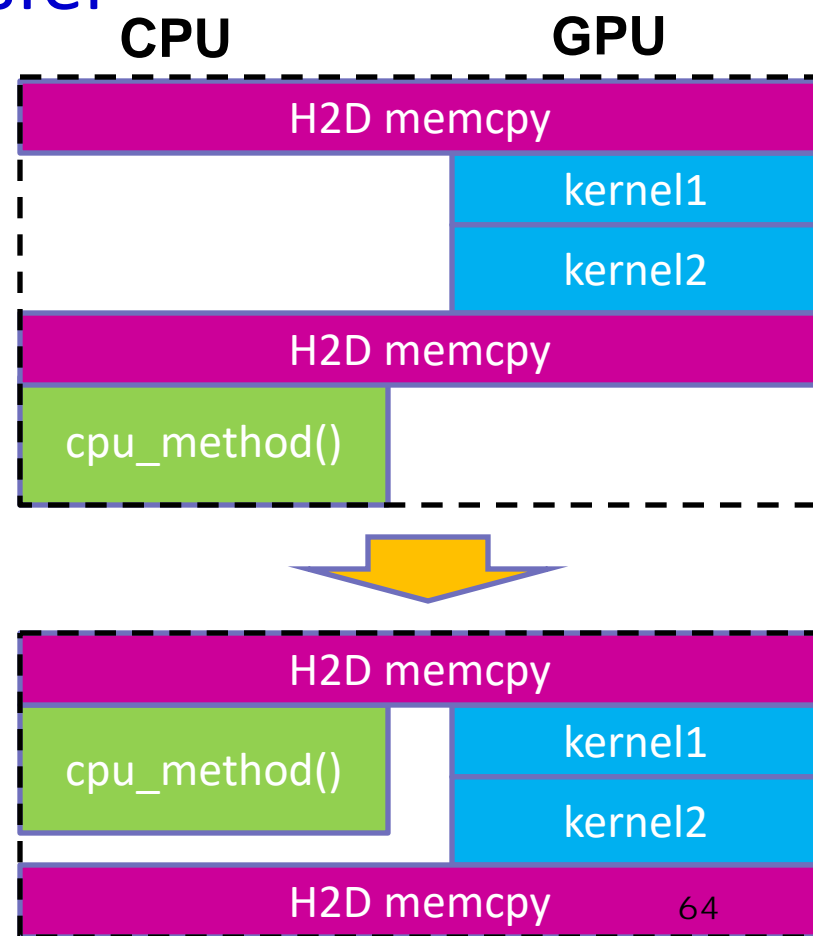
- Check CUDA API reference.
- Think about whether the operations need to involve both CPU and GPU cooperation together.

# 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() ;  
}
```

Q: How to overlap the time?

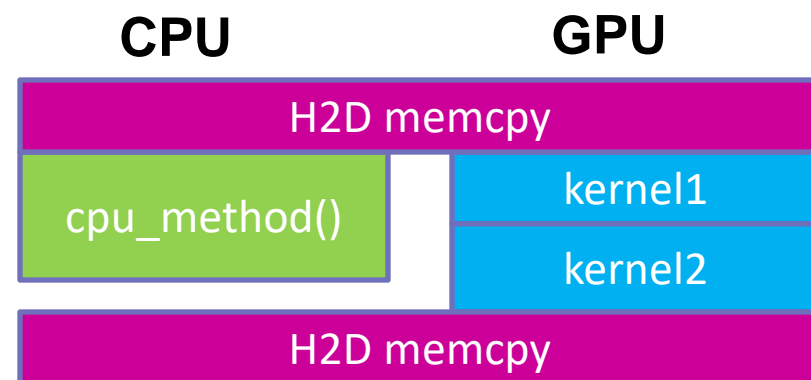




# Why Use Asynchronous Functions?

- Overlap CPU computation with the GPU computation or data transfer

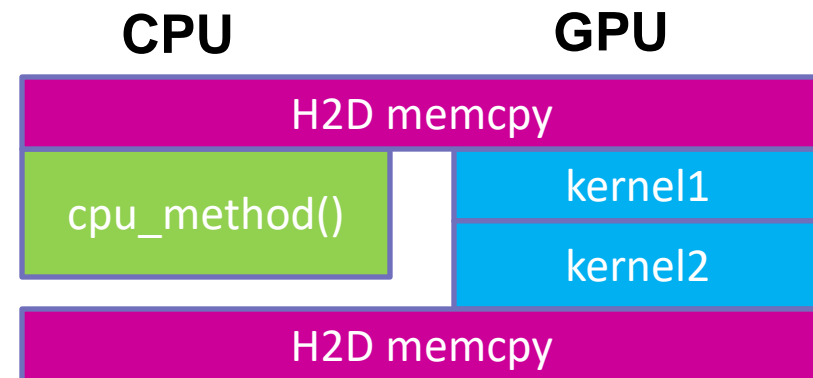
```
void main() {  
    cudaMemcpy ( /**/, H2D ) ;  
    kernel2 <<< grid, block>>> ( ) ;  
    kernel3 <<< grid, block>>> ( ) ;  
    cudaMemcpyAsync ( /**/, D2H ) ;  
    cpu_method( ) ;  
}
```



# Why Use Asynchronous Functions?

- Overlap CPU computation with the GPU computation or data transfer

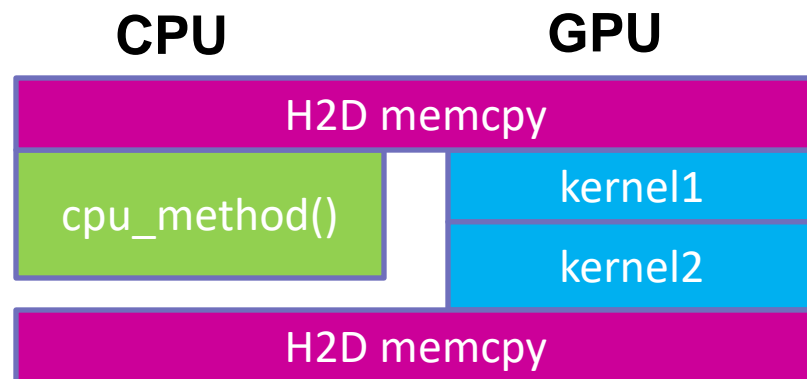
```
void main() {  
    cudaMemcpy ( /**/, H2D ) ;  
    kernel2 <<< grid, block>>> ( ) ;  
    kernel3 <<< grid, block>>> ( ) ;  
    cpu_method ( ) ;  
    cudaMemcpy ( /**/, D2H ) ;  
}
```



# Why Use Asynchronous Functions?

- Overlap CPU computation with the GPU computation or data transfer

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



# 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) ;  
}
```

Q: Is it correct? What's wrong?

# 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) ;  
}
```

Q: Is it correct? What's wrong?

Ans: "h\_a" has data dependency

# Risk of Using Asynchronous Functions

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

```
void main() {  
    cudaEventRecord(start);  
    kernel<<<block, thread>>>();  
    cudaEventRecord(stop);  
    cudaEventElapsedTime(&time, start, stop);  
}
```

Q: Is it correct? What's wrong?

# Risk of Using Asynchronous Functions

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

```
void main() {  
    cudaEventRecord(start);  
    kernel<<<block, thread>>>();  
    cudaEventRecord(stop);  
    cudaEventElapsedTime(&time, start, stop);  
}
```

Q: Is it correct? What's wrong?

Ans: "stop" has data dependency

# How to Synchronize 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



# How to Synchronize CPU & GPU?

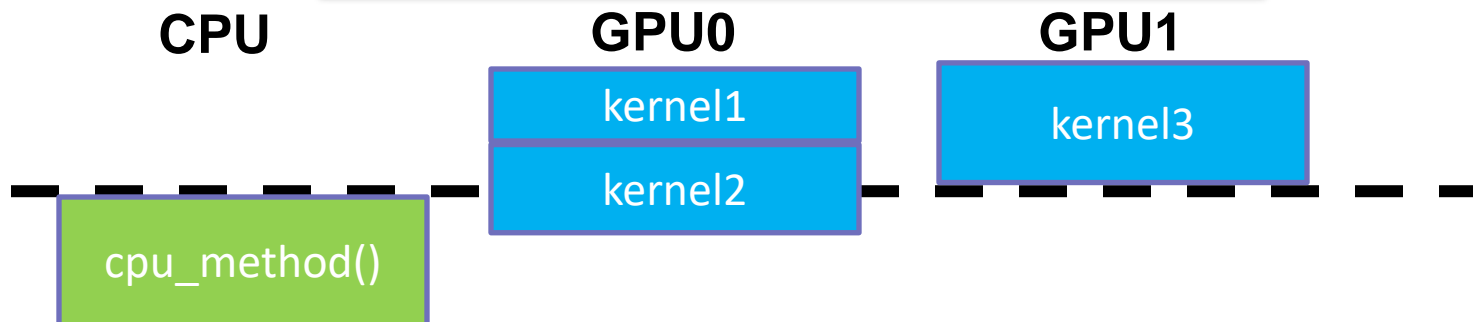
```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> ();  
    kernel2 <<< grid, block>>> ();  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> ();  
    cudaDeviceSynchronize()  
    cpu_method();  
}
```

Q: What happens?

# How to Synchronize CPU & GPU?

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

Q: What happens?



# How to Synchronize CPU & GPU?

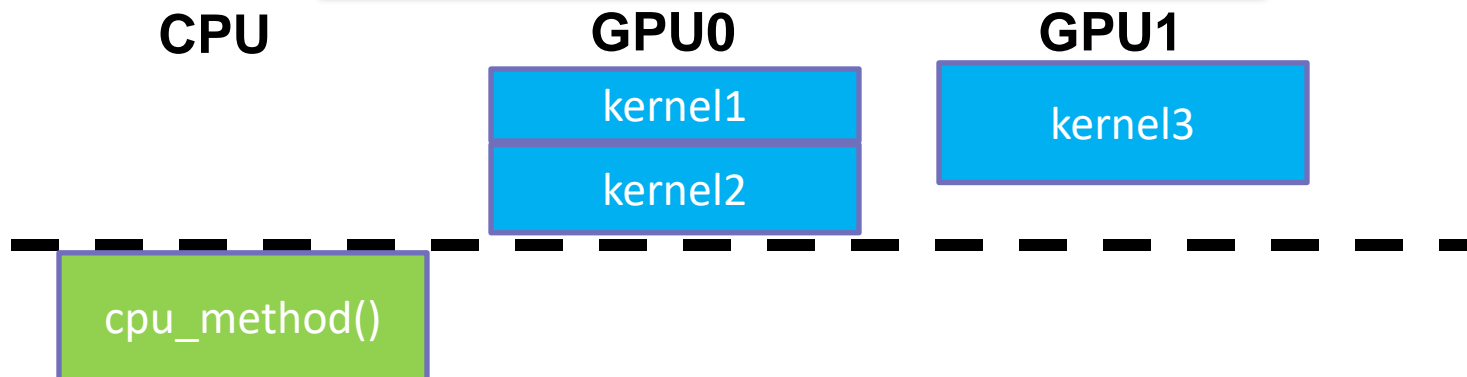
```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> ();  
    kernel2 <<< grid, block>>> ();  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> ();  
    cudaThreadSynchronize()  
    cpu_method();  
}
```

Q: What happens?

# How to Synchronize CPU & GPU?

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

Q: What happens?



# How to Synchronize CPU & GPU?

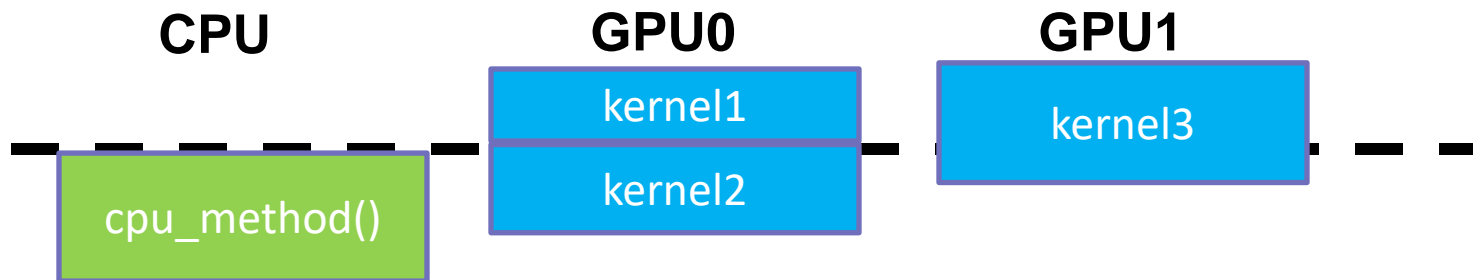
```
void main() {  
    cudaSetDevice(0);  
    kernel1 <<< grid, block>>> () ;  
    cudaEventRecord(event)  
    kernel2 <<< grid, block>>> () ;  
    cudaSetDevice(1);  
    kernel3 <<< grid, block>>> () ;  
    cudaEventSynchronize (event)  
    cpu_method() ;  
}
```

Q: What happens?

# How to Synchronize CPU & GPU?

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

Q: What happens?





# Outline

- Execution
- Memory
- Synchronization
- Stream

# CUDA Function Execution on GPU

- All the CUDA functions (**regardless asynchronous or not**) issued from the **same CPU thread** on the **same device** is serialized and executed in order

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

## GPU





# CUDA Function Execution on GPU

- CUDA functions from **different CPU threads/processes** can always be **executed in parallel** as long as the **device has sufficient resources**

```
#pragma omp parallel  
{  
    kernel <<< grid, block>>> ( ) ;  
}
```

GPU

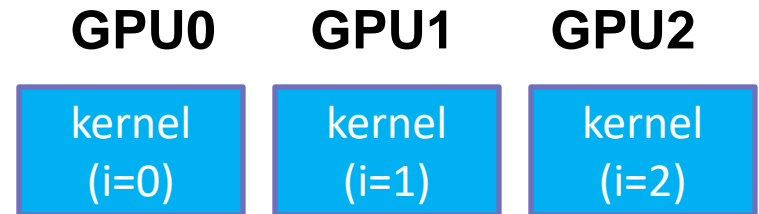
kernel (thread1)	kernel (thread2)	kernel (thread3)
kernel (thread4)	kernel (thread5)	kernel (thread6)

.....

# CUDA Function Execution on GPU

- CUDA functions issued from the **same CPU thread**, but on **different devices** can be executed at the same time

```
for(int i=0; i<3; i++) {  
    cudaSetDevice(i);  
    kernel <<< grid, block>>> ();  
}
```

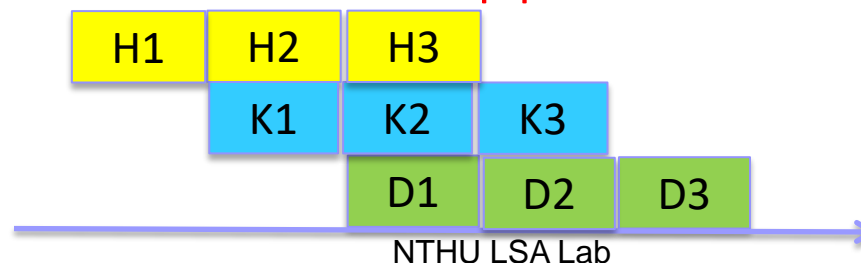


# CUDA Streams

- CUDA Stream is a technique to **overlap the execution of a kernel**, and **hide data transfer delay from computations**
  - Operations in **different streams** can be interleaved and, when possible, they can even **run concurrently**
  - **Operations in the same stream are still serialized and executed in order**
- Consider a kernel process a huge dataset
  - Without stream, the kernel computation can only start after the dataset is transferred



- With stream, we can partition the dataset, assign each partition to a stream, and execute them in a **pipeline**



# CUDA Streams

- kernel launch

- `kernel<<<grid,block,0,stream-id>>> ( /*...*/ );`

- Stream-id must be allocated and destroyed

- `cudaStream_t *stream;`

- `cudaStreamCreate(&stream);`

- `cudaStreamDestroy(stream);`

- Memory copy can be either synchronous or asynchronous. **But synchronous memcpy prevents streams from running in parallel**

- **If asynchronous copy is used, host memory must be pinned**

# CUDA Streams

```
cudaStream_t stream[2];
cudaStreamCreate(&stream[0]);
cudaStreamCreate(&stream[1]);
cudaMallocHost(&hostPtr, 2 * size); // pinned(page
locked mem)
for (int i = 0; i < 2; ++i) {
    cudaMemcpyAsync(/*...*/,          // async memcpy
        cudaMemcpyHostToDevice, stream[i]);
    kernel<<<100,512,0,stream[i]>>>(/*.../);
    cudaMemcpyAsync(/*...*/,
        cudaMemcpyDeviceToHost, stream[i]);
}
cudaStreamDestroy(stream[0]);
cudaStreamDestroy(stream[1]);
```

# CUDA Stream Synchronization

- Operations in **different streams** can be interleaved and, when possible, they can even **run concurrently**
- **Operations in the same stream are still serialized and executed in order**

```
cudaMemcpyAsync(d_A, A, H2D, stream[0]);  
cudaMemcpyAsync(d_B, B, H2D, stream[0]);  
kernel<<<n,m,0,stream[0]>>>(d_A, d_B, d_C);  
cudaEventRecord(event, stream[0]);  
cudaMemcpyAsync(C, d_C, D2H, stream[0]);  
cudaMemcpyAsync(d_D, D, H2D, stream[1]);  
cudaStreamWaitEvent ( stream[1], event );  
kernel<<<n,m,0,stream[1]>>>(d_C, d_D, d_E);  
cudaMemcpyAsync(E, d_E, D2H, stream[1]);  
cudaDeviceSynchronize();  
print(E);
```

