

# Lec12 Synchronize threads within Block and Device Memories

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CSCD 439/539 GPU Computing

# Summary We Learned

- GPU computing history and GPU device evolution.
- Programming model
  - Global memory
  - Host memory vs. Device Memory
  - Map Thread Grid to 1D and 2D dataset
  - Simple Kernel with 1D and 2D grid
- Hardware features
  - Architecture of modern GPUs
- `cuPrintf()` and error handling
- Pointers to pointers on device

# Recall Some Details

- Recall that threads:
  - Execute within blocks
  - Grouped into warp of 32 threads within blocks
  - Block warps are executed in turn on a multiprocessor
    - can have more than 32 threads per block
    - more is often better (1024 is max for new hardware now per block)
  - Threads in same block can all access global memory and a small fast **shared memory** (used to be 16KB, newer cards 48KB/block)

# Outline for Today

- Synchronize threads within a block
- Different GPU memory types

# Memory Model

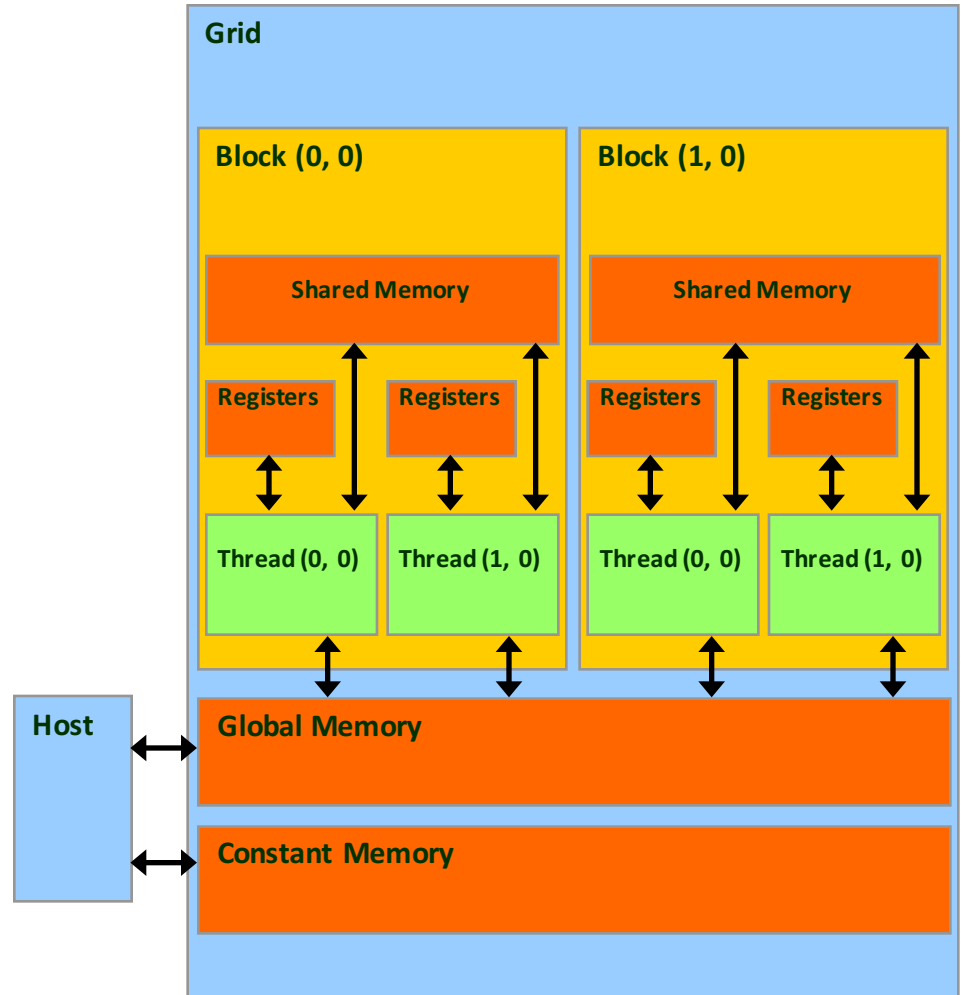
- Recall host responsibility
  - allocate global memory on card device,  
float \*d\_dataB  
cudaMalloc(&d\_dataB, numDeviceBytes)
  - copy required data from host to device and vice versa.
  - choose block dimensions:
    - dim3 threads(blockwidth, blockheight, 1)

# Memory Model

- Recall host responsibility
  - choose grid dimensions:
    - `dim3 grid(1, numBlocks, 1)`
  - compute total dynamic shared memory needed by a block, `int sharedMemorySize = ??`
  - execute kernel:
    - `kernel_2<<<grid, threads, sharedMemorySize>>>(d_dataA, d_dataB)`

# Hardware Implementation of CUDA Memories

- Each thread can:
  - Read/write per-thread **registers**
  - Read/write per-thread **local memory**
  - Read/write per-block **shared memory**
  - Read/write per-grid **global memory**
  - Read/only per-grid **constant memory**



# CUDA Variable Type Qualifiers

Variable declaration	Memory	Scope	Lifetime
<code>int var;</code>	register	thread	thread
<code>int array_var[10];</code>	local	thread	thread
<code>__shared__ int shared_var;</code>	shared	block	block
<code>__device__ int global_var;</code>	global	grid	application
<code>__constant__ int constant_var;</code>	constant	grid	application

- **“automatic” scalar variables without qualifier** reside in a register
  - compiler will spill to thread local memory
- **“automatic” array variables without qualifier** reside in thread-local memory. But physically use a piece of global memory.



# CUDA Variable Type Performance

Variable declaration	Memory	Penalty
<code>int var;</code>	register	1x
<code>int array_var[10];</code>	local	100x
<code>__shared__ int shared_var;</code>	shared	1x
<code>__device__ int global_var;</code>	global	100x
<code>__constant__ int constant_var;</code>	constant	1x

- scalar variables reside in fast, on-chip registers
- shared variables reside in fast, on-chip memories
- thread-local arrays & global variables reside in uncached off-chip memory
- constant variables reside in cached off-chip memory

# CUDA Variable Type Scale

Variable declaration	Instances	Visibility
<code>int var;</code>	100,000s	1
<code>int array_var[10];</code>	100,000s	1
<code>__shared__ int shared_var;</code>	1000s	100s
<code>__device__ int global_var;</code>	1	100,000s
<code>__constant__ int constant_var;</code>	1	100,000s

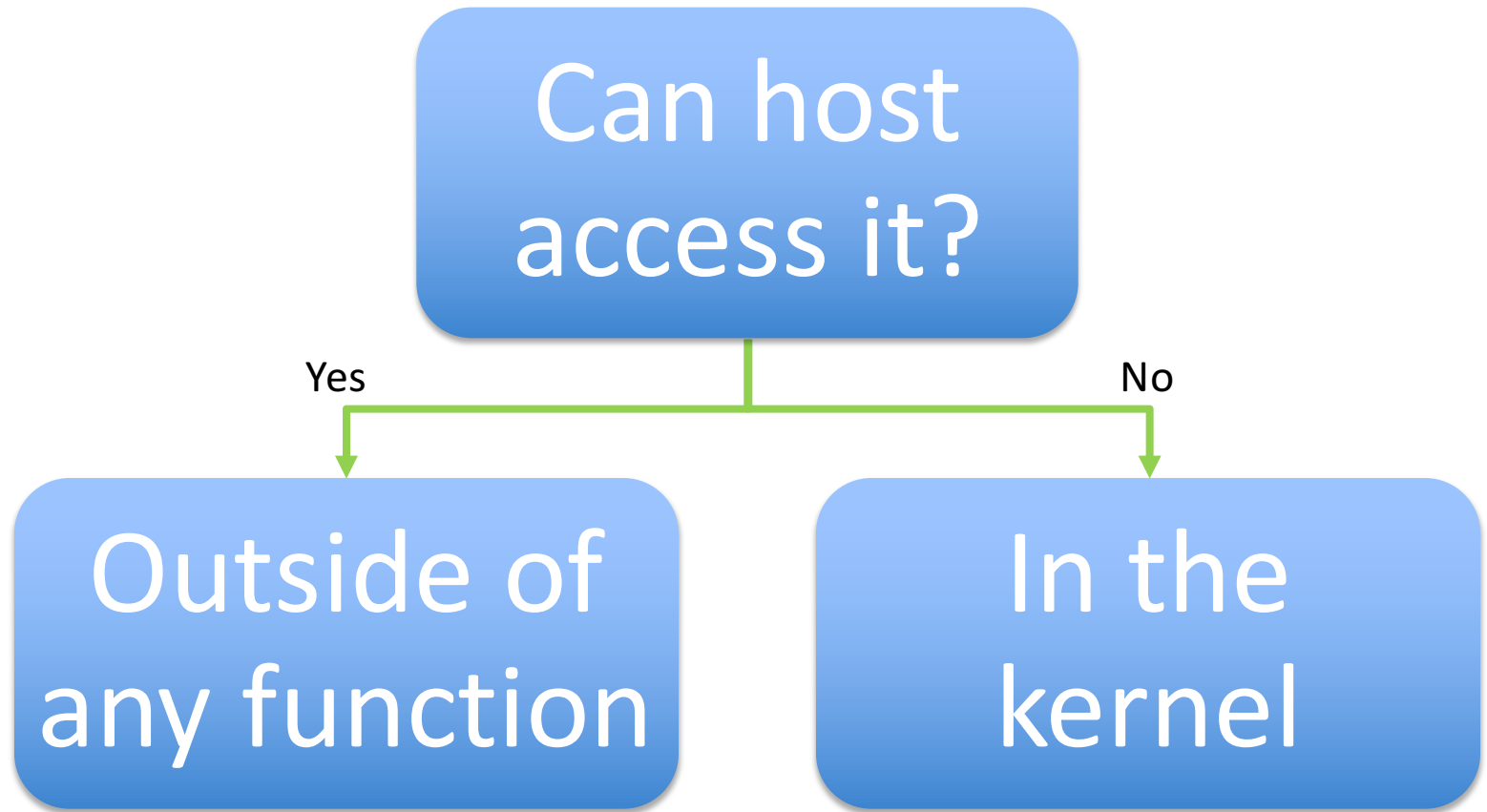
If we have 1000 blocks and each block has 100 threads.

- 100Ks per-thread variables, R/W by 1 thread
- 1000s shared variables, each R/W by 100s of threads
- 1 global variable is R/W by 100Ks threads
- 1 constant variable is readable by 100Ks threads

# Constant Memory

- <http://cuda-programming.blogspot.com/2013/01/what-is-constant-memory-in-cuda.html>
- Ideally, for threads in a warp(or half), reading from the constant cache is as fast as reading from a register as long as all threads read the **same or nearby addresses**.
- Cost scales linearly with the number of different addresses read by all threads within a warp(half).
- Demo of Constant Memory

# Where to declare variables?



`__constant__ int constant_var;`

`int var;`

`__device__ int global_var;`

`int array_var[10];`

`__shared__ int shared_var;`

# Shared Memory

- Per-Block Shared memory
  - global memory is very slow, costs 100-200 simple instructions to access.
  - shared memory costs only 1 or 2 single instruction.
  - Threads within a block can be synchronized with a barrier.

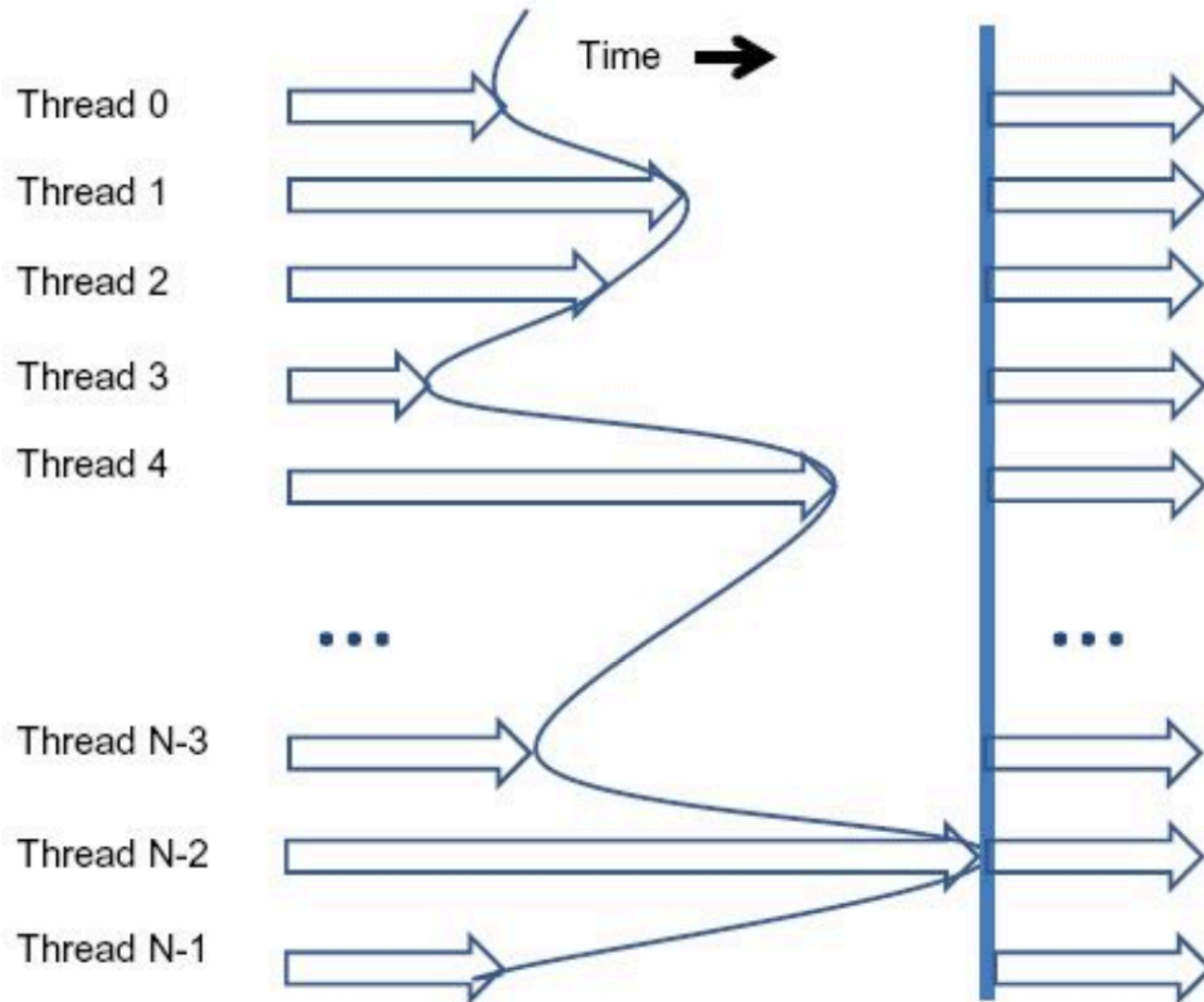
# Shared Memory

- Synchronization of threads within a block  
`__syncthreads();`
  - barrier synchronization between all threads in a block.
  - This does not apply between blocks.
  - Remember how to synchronize threads between blocks?
    - No built-in mechanism in Cuda for threads from different blocks waiting for each other.
    - Decompose one kernel into multiple ones.
    - Launch them one after another.

# syncthreads()

- Barrier synchronization for threads within a block.
- Allows threads in a block to wait for each other until **all** threads in that block reached that barrier points, then they can move forward.
- Acts like Barrier Object in Pthread and Java threads.

# syncthreads()



**FIGURE 4.11**

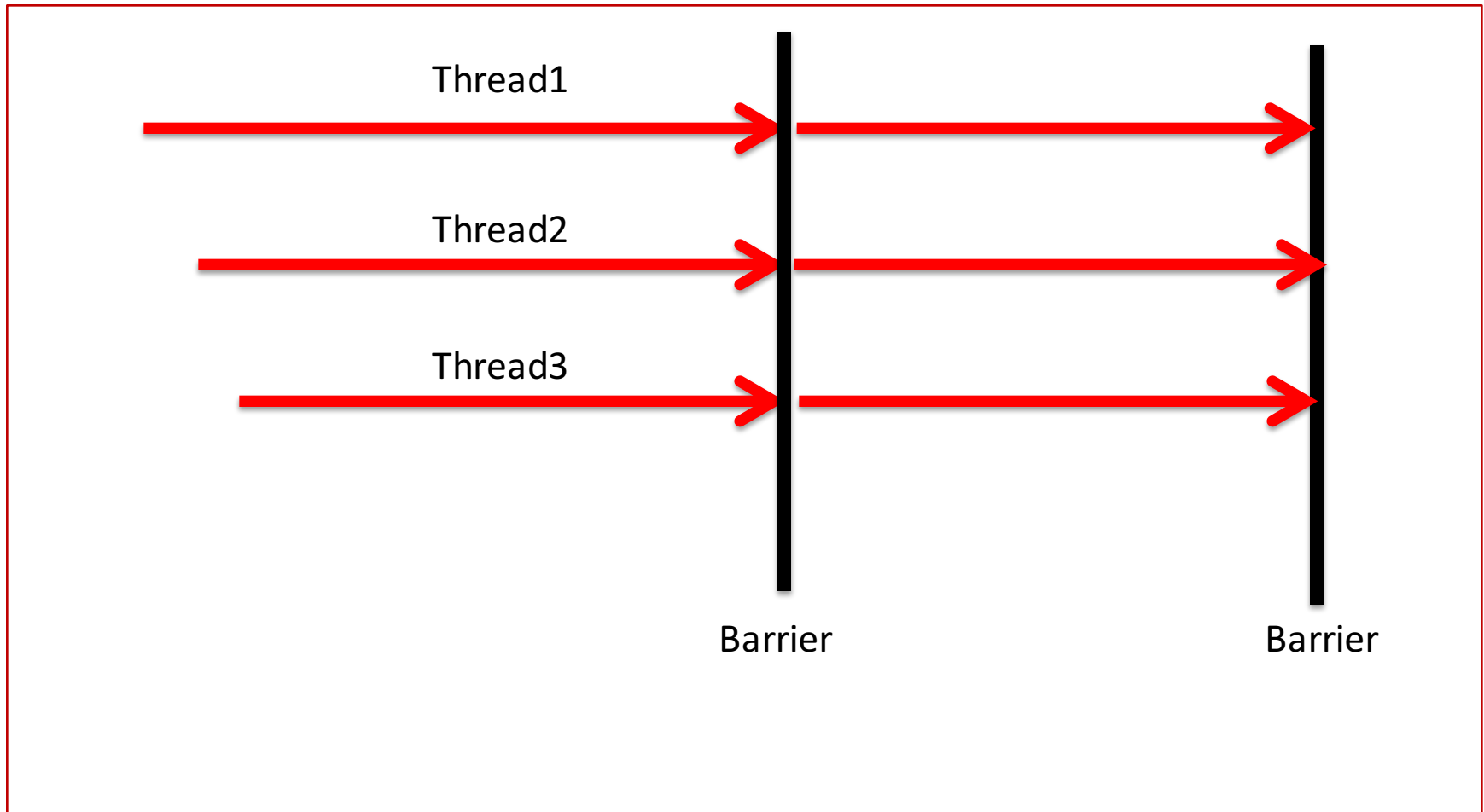
An example execution timing of barrier synchronization.



# Barrier Synchronization

```
//inside kernel method shared by multiple threads
for(int i = 0; i < 500; i ++) {
    //do work here
    //
    if( i == 100) {
        __syncthreads(); //barrier pointer
    }
}
```

# Barrier Synchronization



# syncthreads()

- **All** threads in that block **must** execute `__syncthreads()`, or we will deadlock.
  - makes sure all threads involved in the barrier eventually get the resources and arrive at the barrier.
- Be careful when use it inside if statement
  - You have to make sure ALL threads will evaluate the if condition either true or false.
  - If some threads go true branch and some go false branch,
    - Deadlock, Why?

# syncthreads()

```
//inside a kernel
if ( a[idx] % 2 == 0 )
{
    dowork1();
    __syncthreads();
}
else
{
    dowork2();
    __syncthreads();
}
//what will happen?
```

We have two barrier points, all threads have to go either if true branch and dowork1, Or all threads have to go else branch dowork2(). Otherwise, we deadlock.

# syncthreads()

- When is `__syncthreads()` necessary or useful?

**When one thread needs a result computed by another thread.**

**This thread has to wait until the result is ready.**

- **Note:** There is a natural synch happening after an if-statement or similar conditional.

# Wrap Up

- Different types of GPU memory
- `__syncthreads()` for threads within blocks.
- Next Class, case study of shared memory and why we use shared memory?