



Master Informatics Eng.

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Programming GPUs with CUDA *(most slides are borrowed)*

The CUDA programming model



- **Compute Unified Device Architecture**
- **CUDA** is a programming model, designed for
 - a multicore CPU **host** coupled to a many-core **device**, where
 - **devices** have wide SIMD/SIMT parallelism, and
 - the **host** and the **device** do not share memory
- **CUDA** provides:
 - a thread abstraction to deal with SIMD
 - synchronization & data sharing between small groups of threads
- **CUDA** programs are written in **C** with extensions
- **OpenCL** inspired by **CUDA**, but hw & sw vendor neutral
 - programming model essentially identical

CUDA Devices and Threads

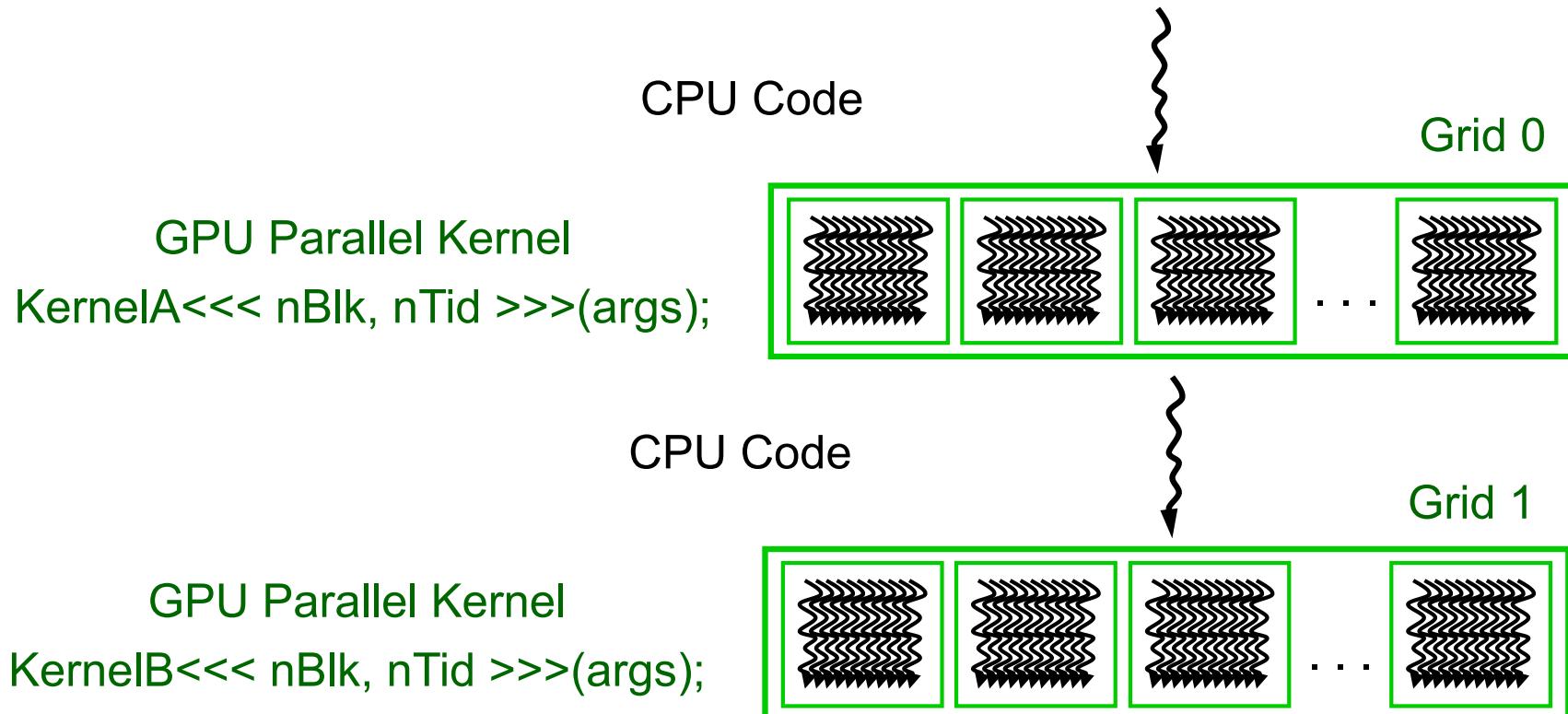


- A compute **device**
 - is a coprocessor to the CPU or **host**
 - has its own DRAM (**device memory**)
 - runs many **threads in parallel**
 - is typically a **GPU** but can also be another type of parallel processing device
- Data-parallel portions of an application are expressed as device **kernels** which run on many threads - **SIMT**
- Differences between GPU and **CPU** threads
 - GPU threads are extremely lightweight
 - very little creation overhead, requires **LARGE** register bank
 - GPU needs 1000s of threads for full efficiency
 - multi-core **CPU** needs only a few

CUDA basic model: *Single-Program Multiple-Data (SPMD)*



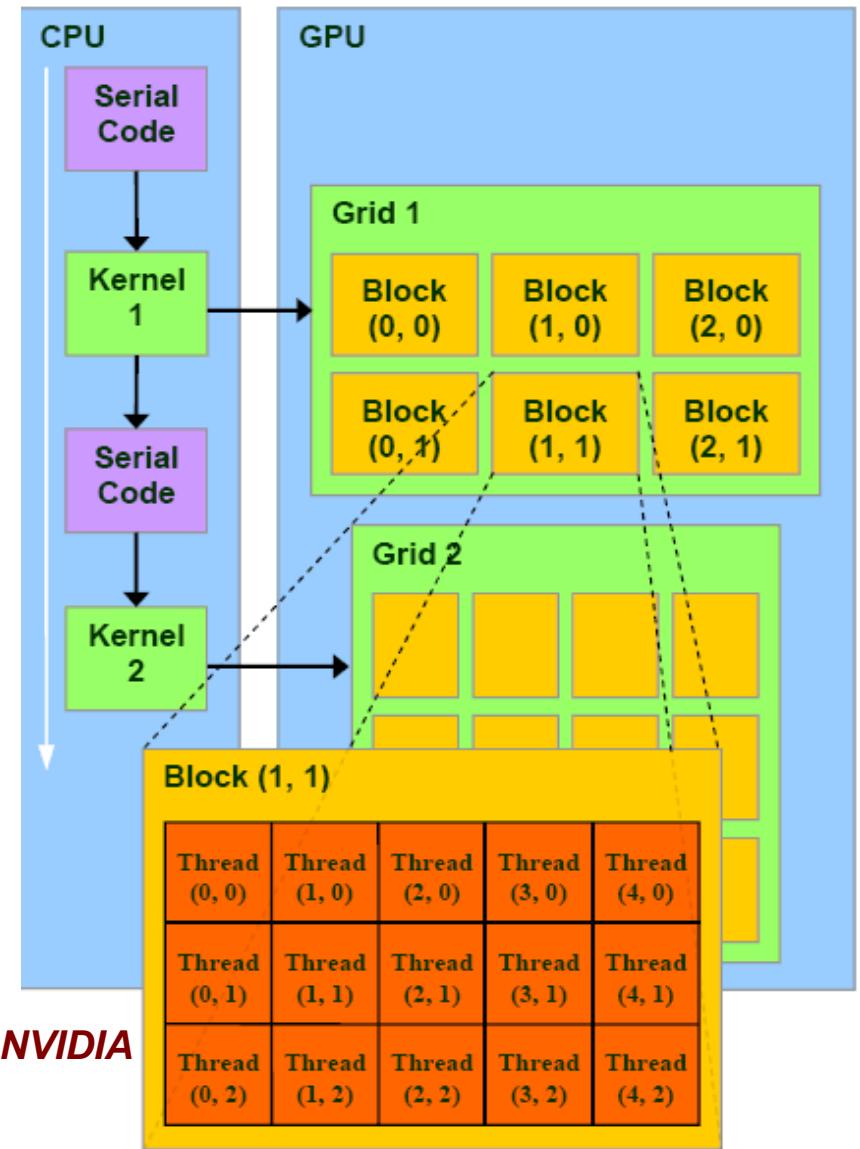
- CUDA integrates **CPU+GPU** code in a **C** program
 - Serial C code executes on **CPU**
 - Parallel **Kernel** C code executes on GPU **thread blocks**



Programming Model: SPMD + SIMT/SIMD



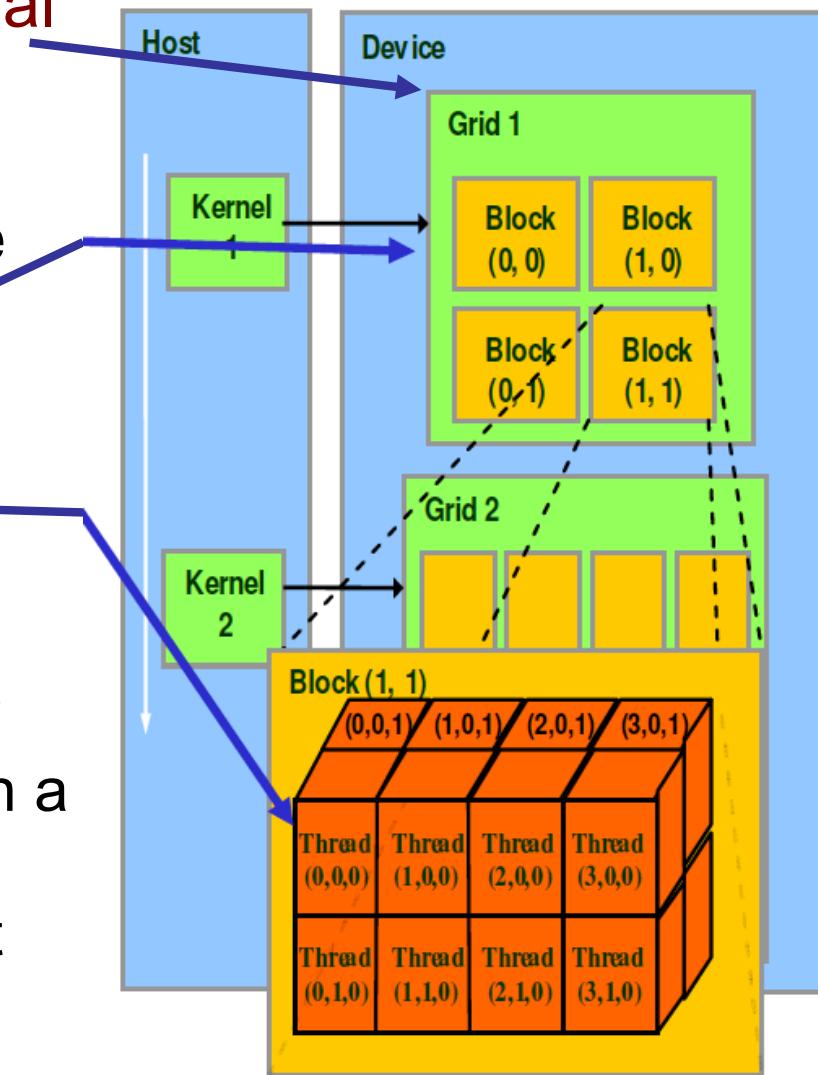
- Hierarchy
 - Device => Grids
 - Grid => Blocks
 - Block => Warps
 - Warp => Threads
- Single kernel runs on multiple blocks (SPMD)
- Threads within a warp are executed in a lock-step way called single-instruction multiple-thread (SIMT)
- Single instruction are executed on multiple threads (SIMD)
 - Warp size defines SIMD granularity (32 threads)
- Synchronization within a block uses shared memory



Courtesy NVIDIA

The Computational Grid: Block IDs and Thread IDs

- A kernel runs on a computational grid of thread blocks
 - Threads share global memory
- Each thread uses IDs to decide what data to work on
 - Block ID: 1D or 2D
 - Thread ID: 1D, 2D, or 3D
- A thread block is a batch of threads that can cooperate by:
 - Sync their execution w/ barrier
 - Efficiently sharing data through a low latency shared memory
 - Two threads from two different blocks cannot cooperate



Example



- Multiply two vectors of length 8192
 - Code that works over all elements is the grid
 - Thread blocks break this down into manageable sizes
 - 512 threads per block
 - SIMD instruction executes 32 elements at a time
 - Thus, grid size = 16 blocks
 - Block is analogous to a strip-mined vector loop with vector length of 32
 - Block is assigned to a *multithreaded SIMD processor* by the *thread block scheduler*
 - SM in NVidia terminology...
 - ... or simply a CPU-type core
 - Current-generation NVidia GPU (GA100 Ampere) has 128 *multithreaded SIMD processors*

Strip-mining and Cleanup

Strip-mining, also known as loop sectioning, is a loop transformation technique for enabling SIMD-encodings of loops, as well as a means of improving memory performance. By fragmenting a large loop into smaller segments or strips, this technique transforms the loop structure in two ways:

- It increases the temporal and spatial locality in the data cache if the data are reusable in different passes of an algorithm.
- It reduces the number of iterations of the loop by a factor of the length of each vector, or number of operations being performed per SIMD operation. In the case of Streaming SIMD Extensions, this vector or strip-length is reduced by 4 times: four floating-point data items per single Streaming SIMD Extensions single-precision floating-point SIMD operation are processed.

First introduced for vectorizers, this technique consists of the generation of code when each vector operation is done for a size less than or equal to the maximum vector length on a given vector machine.

The compiler automatically strip-mines your loop and generates a cleanup loop. The following examples demonstrate strip mining and cleaning up loops.

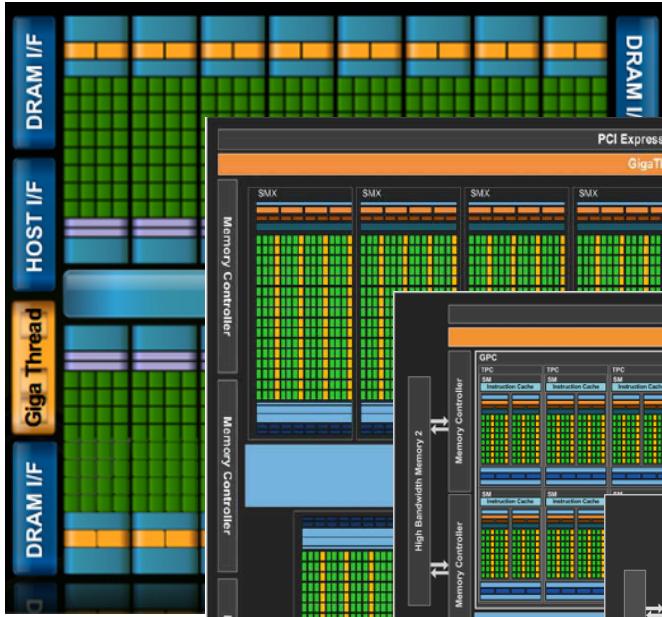
Example1: Before Vectorization

```
i = 1
do while (i<=n)
a(i) = b(i) + c(i) ! Original loop code
i = i + 1
end do
```

Example 2: After Vectorization

```
!The vectorizer generates the following two loops
i = 1
do while (i < (n - mod(n,4)))
! Vector strip-mined loop.
a(i:i+3) = b(i:i+3) + c(i:i+3)
i = i + 4
end do
do while (i <= n)
a(i) = b(i) + c(i)      !Scalar clean-up loop
i = i + 1
end do
```

Generations of NVidia GPUs



Fermi:
16 SM
Jul'11

Kepler:
15 SMX
Oct'13

Pascal:
60 SM
Nov'15

Volta:
84 SM
Jun'17

Each block is assigned to a SM



Ampere:
128 SM
May'20



C with CUDA Extensions: C with a few keywords

```
void saxpy_serial(int n, float a, float *x, float *y)
{
    for (int i = 0; i < n; ++i)
        y[i] = a*x[i] + y[i];
}
// Invoke serial SAXPY kernel
saxpy_serial(n, 2.0, x, y);
```

Standard C Code

```
__global__ void saxpy_parallel(int n, float a, float *x, float *y)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    if (i < n) y[i] = a*x[i] + y[i];
}
// Invoke parallel SAXPY kernel with 256 threads/block
int nbBlocks = (n + 255) / 256;
saxpy_parallel<<<nbBlocks, 256>>>(n, 2.0, x, y);
```

Parallel C Code

NVIDIA Confidential

Terminology (and in NVidia)



- Threads of SIMD instructions (**warps**)
 - Each has its own IP (up to 48/64 per SIMD processor, Fermi/after-Kepler)
 - Thread scheduler uses scoreboard to dispatch
 - No data dependencies between threads!
 - Threads are organized into blocks & executed in groups of 32 threads (**thread block**)
 - Blocks are organized into a grid
- The thread block scheduler schedules blocks to SIMD processors (**Streaming Multiprocessors, SM**)
- Within each SIMD processor:
 - 32 SIMD lanes (**thread processors**)
 - Wide and shallow compared to vector processors

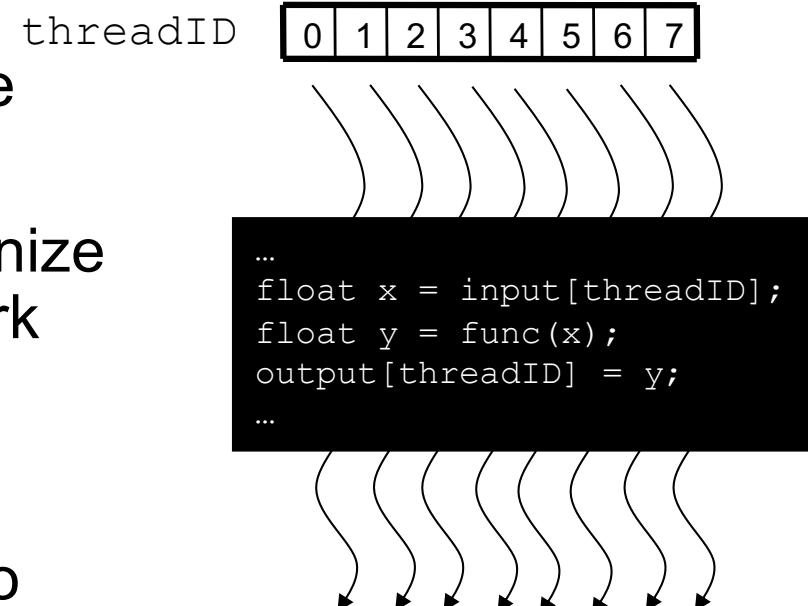
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CUDA Thread Block

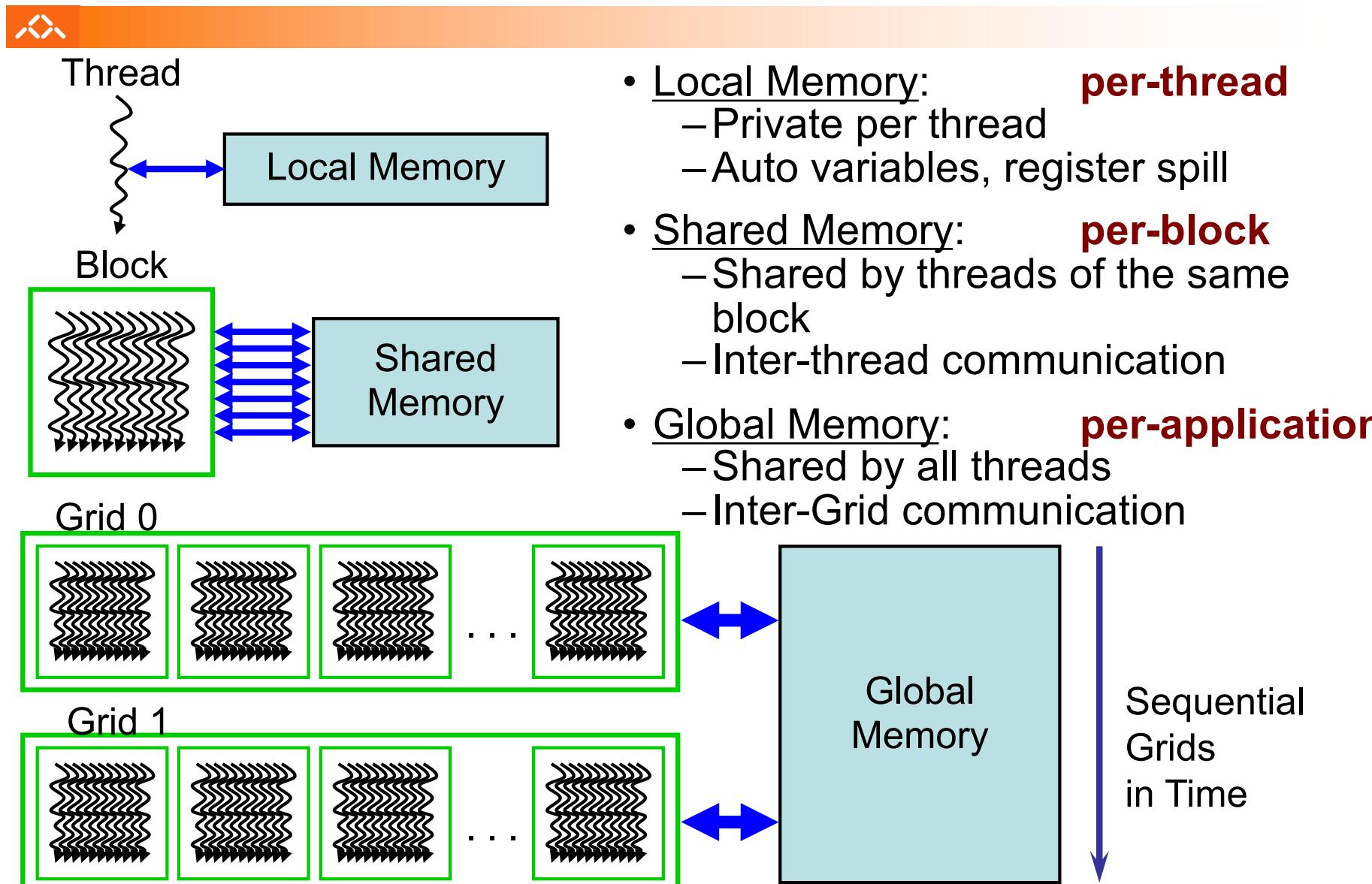


- Programmer declares (Thread) Block:
 - Block size **1** to **512** concurrent threads
 - Block shape **1D**, **2D**, or **3D**
 - Block dimensions in threads
- All threads in a Block execute the same thread program
- Threads share data and synchronize while doing their share of the work
- Threads have **thread id** numbers within Block
- Thread program uses **thread id** to select work and address shared data

CUDA Thread Block



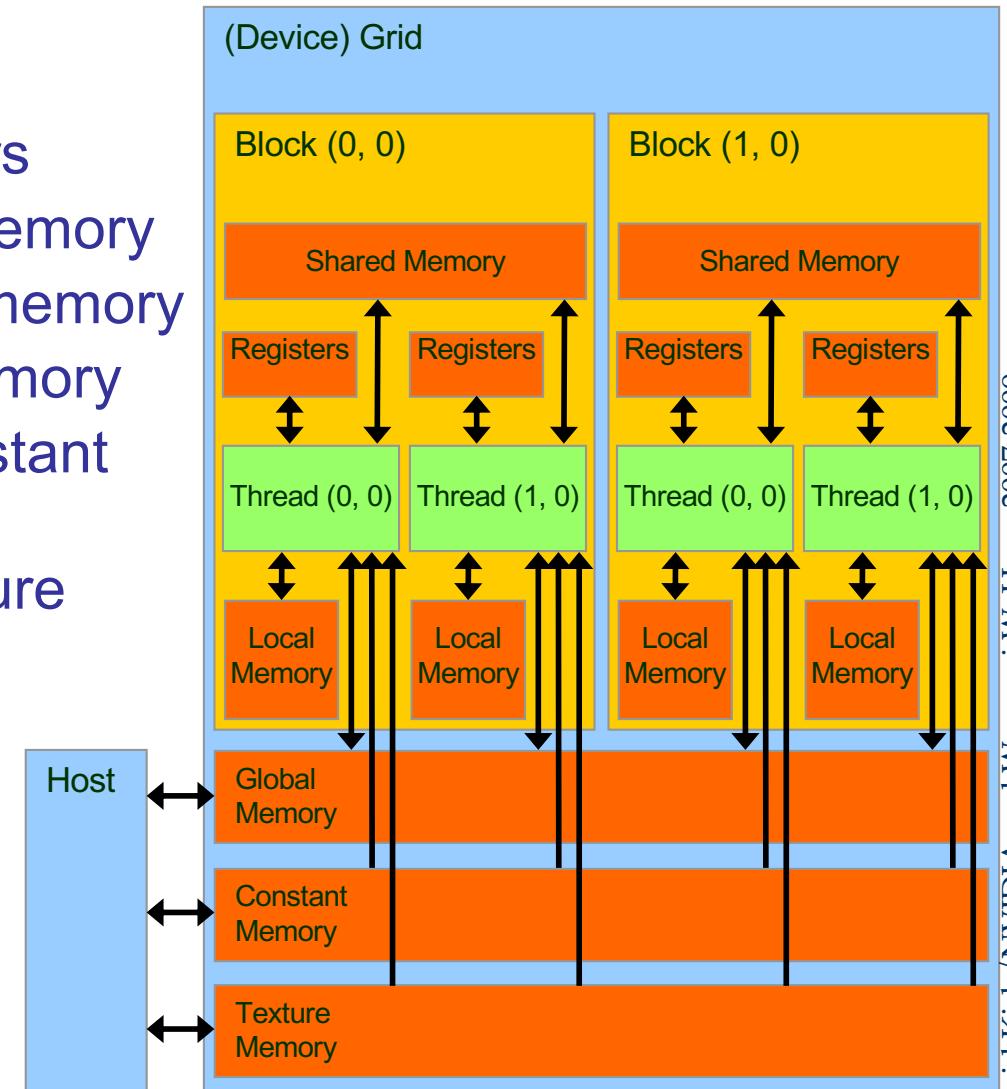
Parallel Memory Sharing



CUDA Memory Model Overview



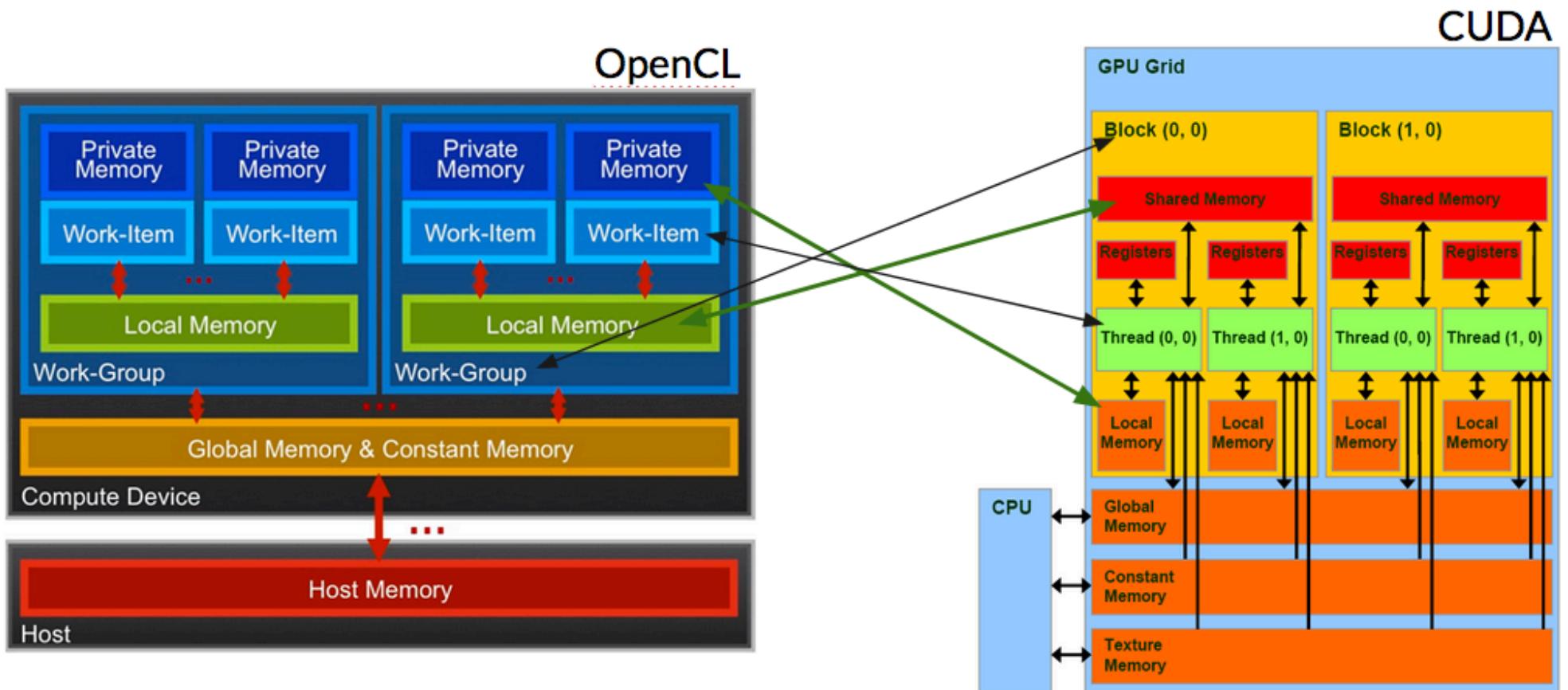
- Each thread can:
 - R/W per-thread registers
 - R/W per-thread local memory
 - R/W per-block shared memory
 - R/W per-grid global memory
 - Read only per-grid constant memory
 - Read only per-grid texture memory
- The host can R/W global, constant, and texture memories



Terminology: CUDA and OpenCL



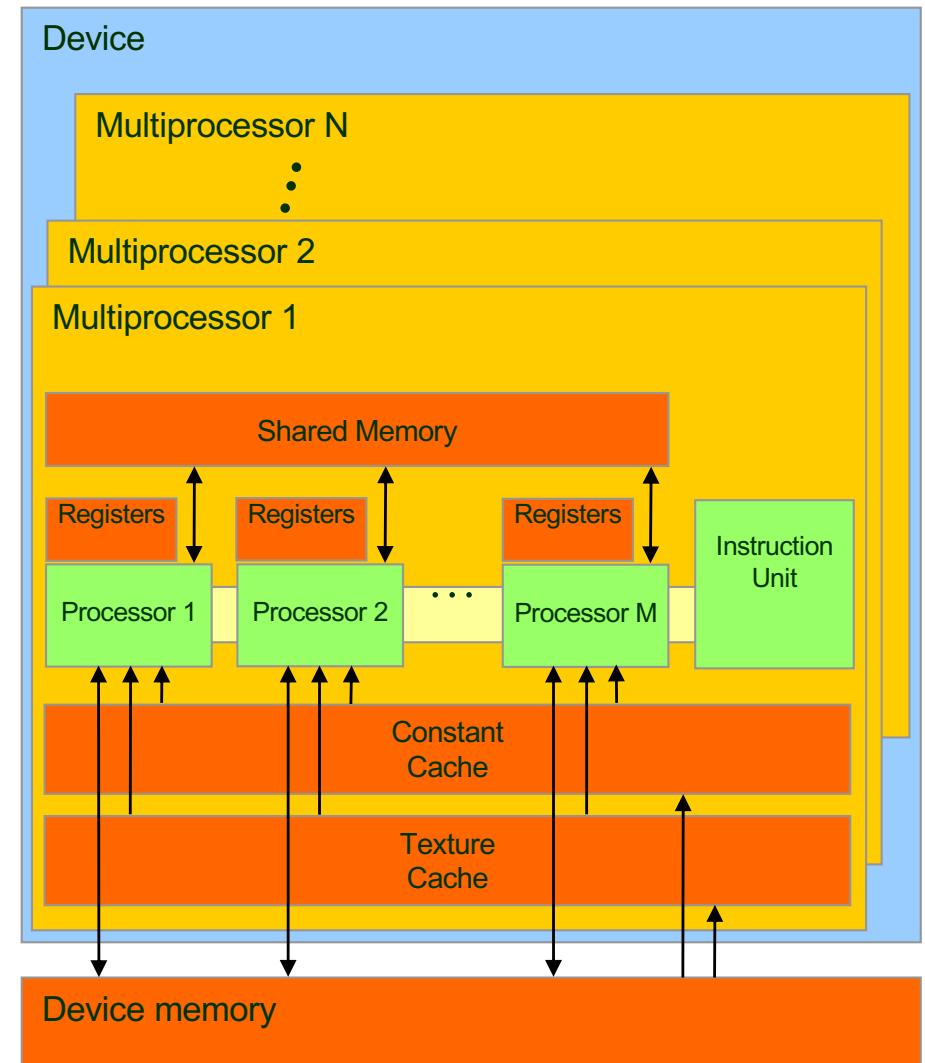
CUDA and OpenCL



Hardware Implementation: Memory Architecture

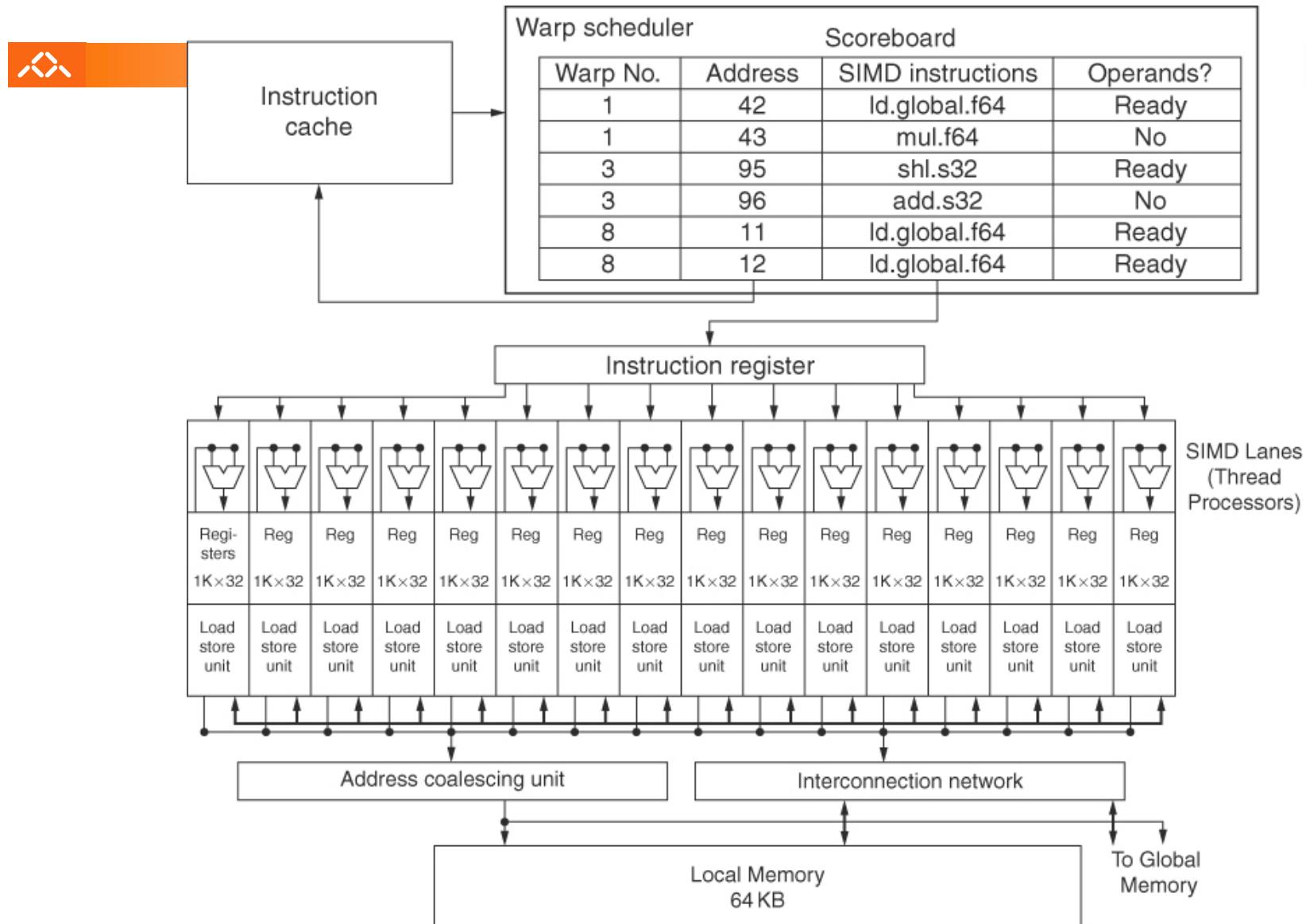


- Device memory (DRAM)
 - Slow (2~300 cycles)
 - Local, global, constant, and texture memory
- On-chip memory
 - Fast (1 cycle)
 - Registers, shared memory, constant/texture cache



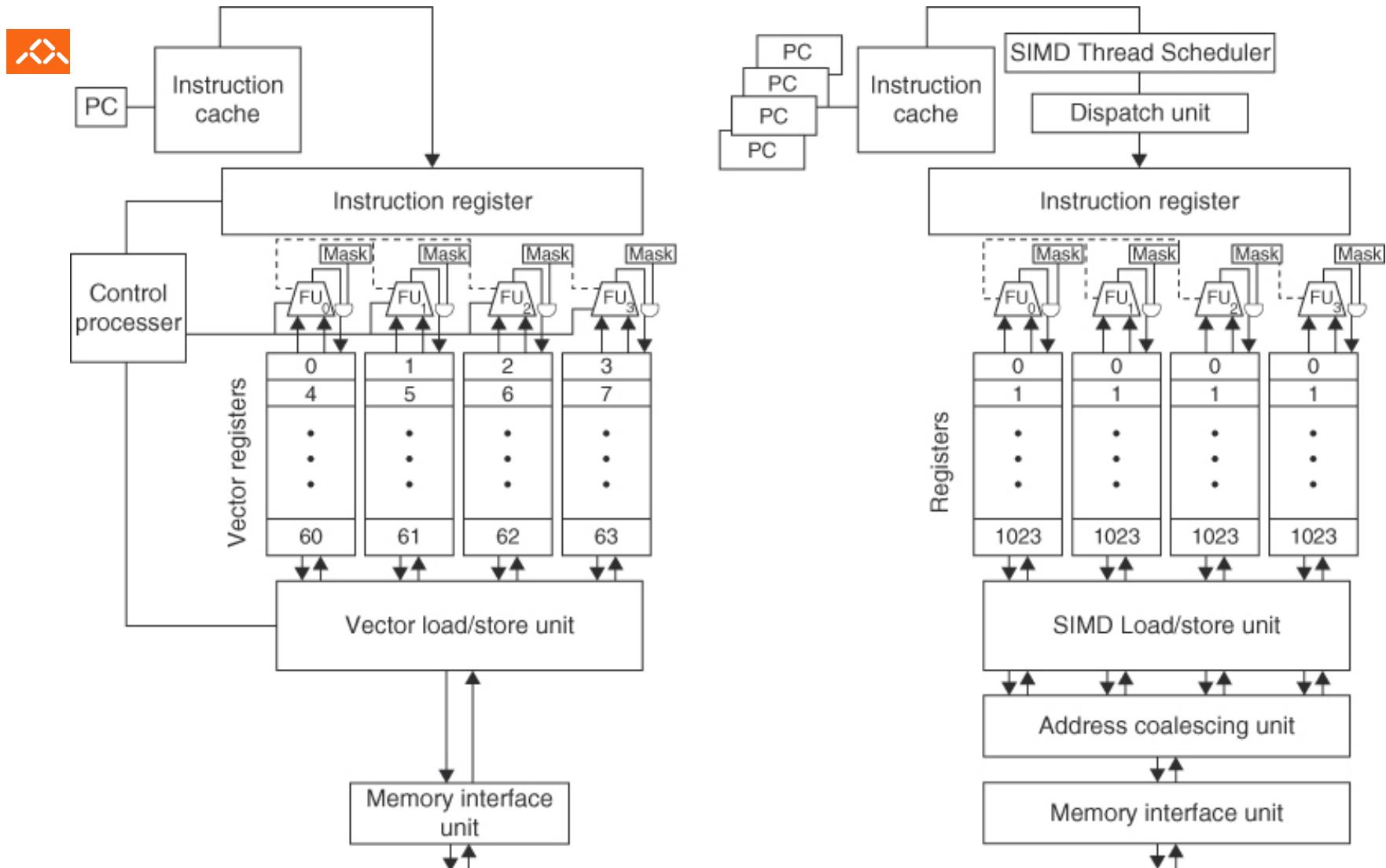
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Example



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Vector Processor versus CUDA core



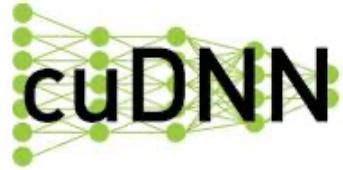
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Conditional Branching



- Like vector architectures, GPU branch hardware uses internal masks
- Also uses
 - Branch synchronization stack
 - entries consist of masks for each SIMD lane
 - i.e. which threads commit their results (all threads execute)
 - Instruction markers to manage when a branch diverges into multiple execution paths
 - push on divergent branch
 - ...and when paths converge
 - act as barriers
 - pops stack
- Per-thread-lane 1-bit predicate register, specified by programmer

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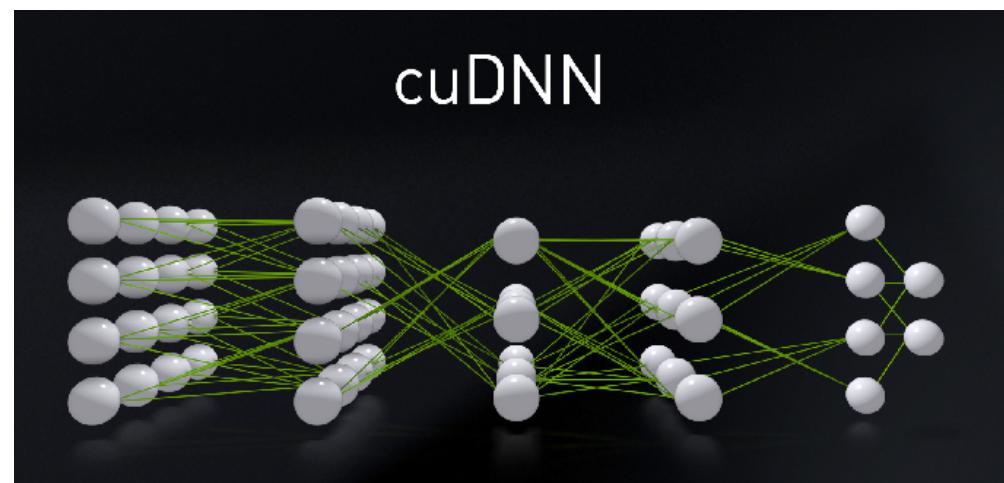
cuDNN: CUDA for Deep Neural Nets



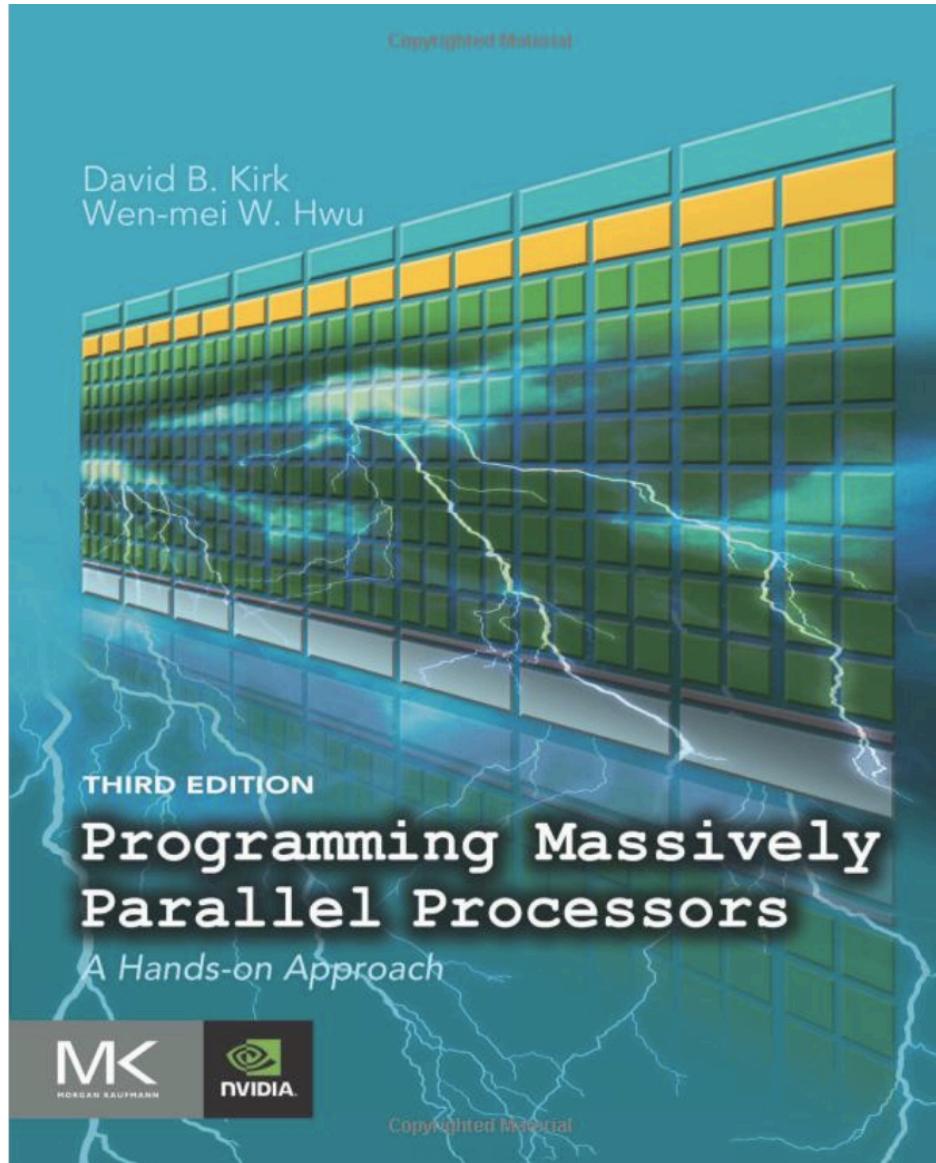
cuDNN: a GPU-accelerated library of primitives for deep neural networks

cuDNN contains:

- common training and inference routines,
- tensor utility routines,
- routines for CNN for training and inference time,
- ...



Recommended textbook (2)



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