

GPU

Computation

CSCI 4239/5239

Advanced Computer Graphics

Spring 2016

Solutions to Parallel Processing

- Message Passing (distributed)
 - MPI (library)
- Threads (shared memory)
 - pthreads (library)
 - OpenMP (compiler)
- GPU Programming (shared bus)
 - CUDA (compiler)
 - OpenCL (library)
 - OpenACC (compiler)
 - GLSL Compute Shader

Using the GPU for Computation

- The GPU is very good at floating point. How can we use that to do computations?
 - Write a shader and be the result be a pseudo-color
 - Use CUDA with nVidia hardware
 - Use OpenCL with general hardware
 - Use an OpenGL 4.3 Compute Shader
- Issues
 - Getting instructions and data to the GPU
 - Precision of computations

Text/Notes

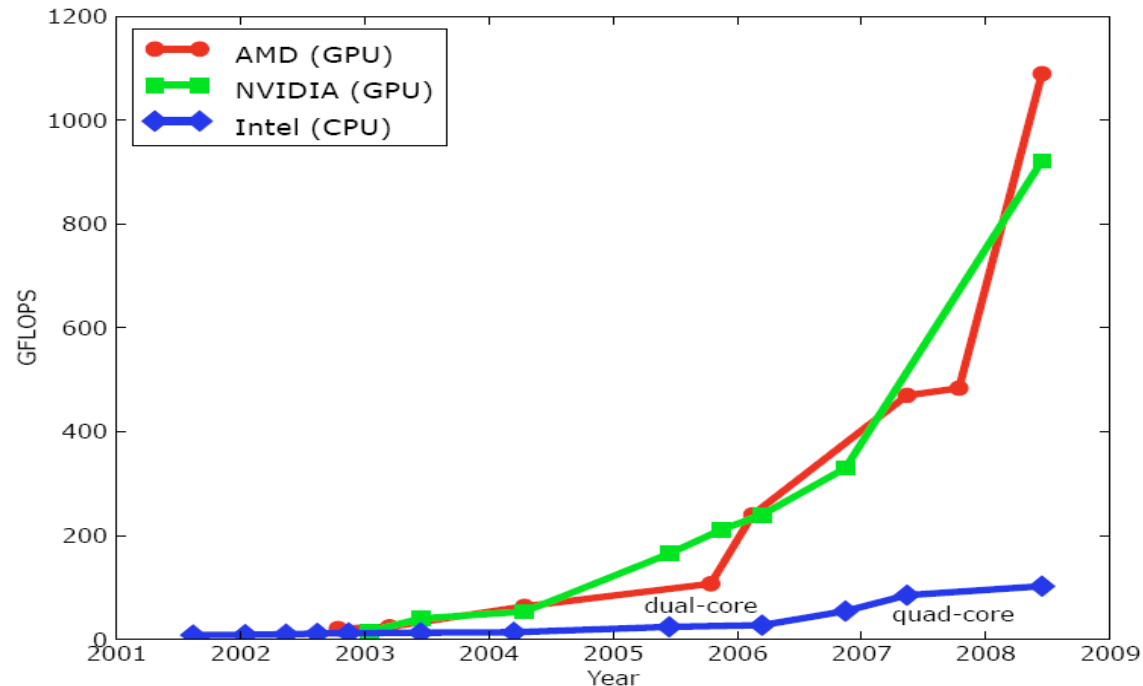
- Programming massively Parallel Processors
 - *Kirk and Hwu*
 - Good introduction to CUDA and OpenCL
 - Examples, tips and Tricks
 - Most slides taken from their lecture notes
- CUDA by Example
 - *Sanders and Kandrot*
 - CUDA only
 - Examples

History of Coprocessors

- Floating point option
 - 8087, 80287, Weitek
- Floating Point Systems Array Processors
 - Attaches to VAX
- DSP chips
- Analog and special purpose CPUs
- Graphics Processors

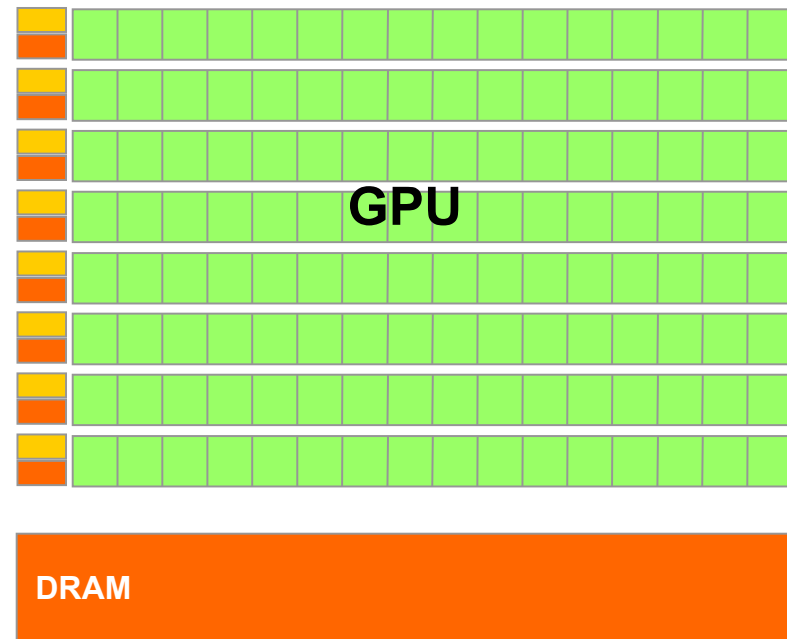
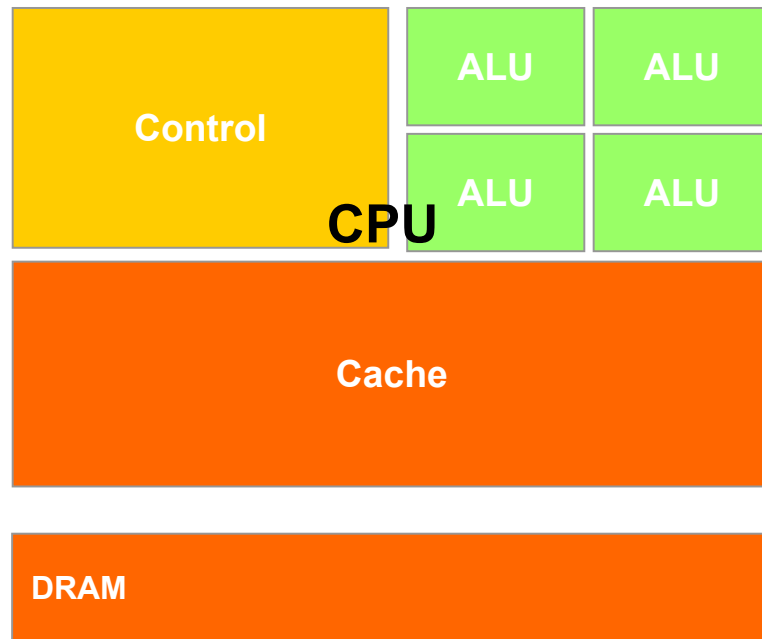
Why Massively Parallel Processor

- A quiet revolution and potential build-up
 - Calculation: 367 GFLOPS vs. 32 GFLOPS
 - Memory Bandwidth: 86.4 GB/s vs. 8.4 GB/s
 - Until 2006, programmed through graphics API

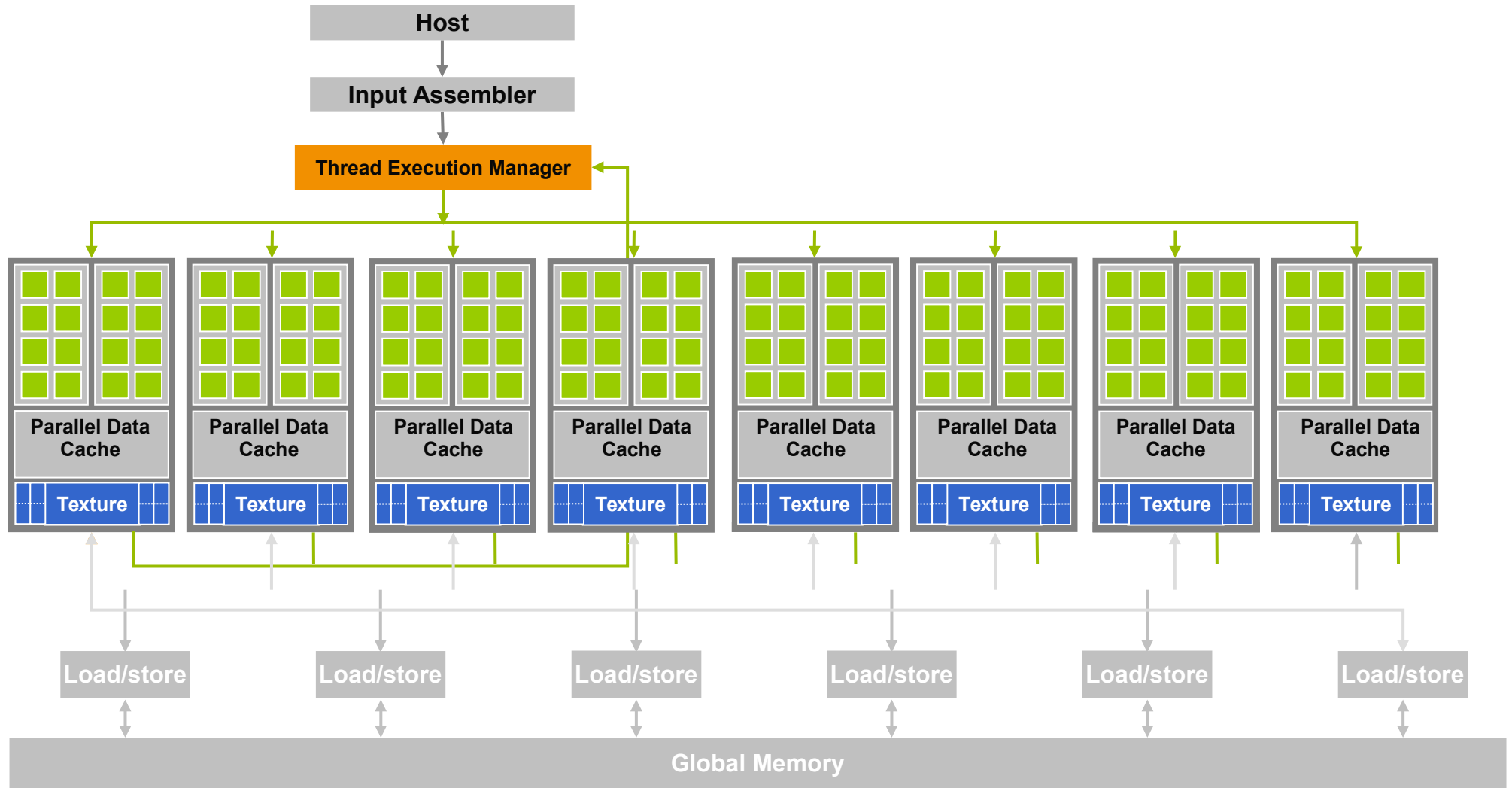


- GPU in every PC and workstation – massive volume and potential impact

CPUs and GPUs have fundamentally different design philosophies



Architecture of a CUDA-capable GPU

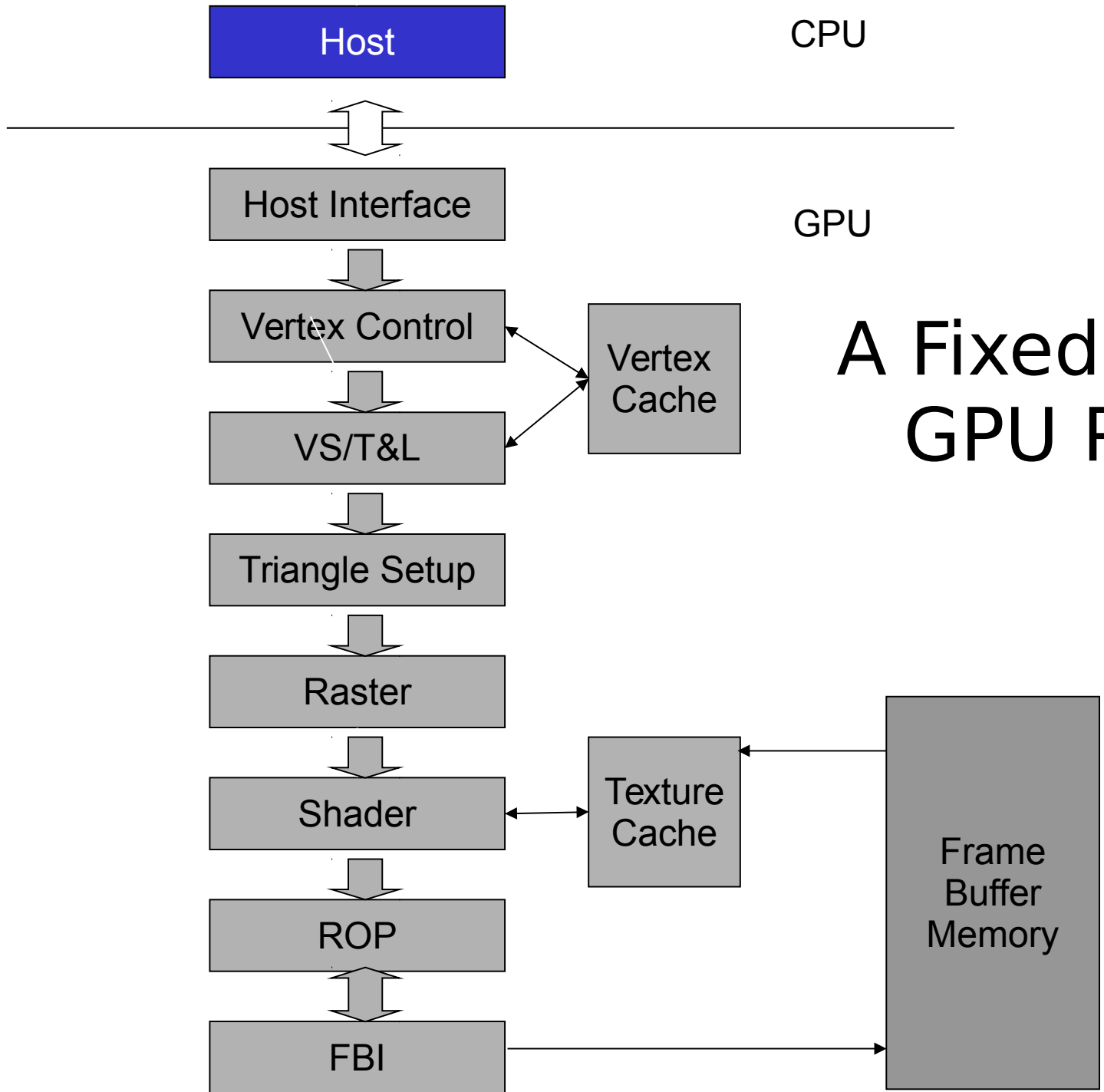


GT200 Characteristics

- 1 TFLOPS peak performance (25-50 times of current high-end microprocessors)
- 265 GFLOPS sustained for apps such as VMD
- Massively parallel, 128 cores, 90W
- Massively threaded, sustains 1000s of threads per app
- 30-100 times speedup over high-end microprocessors on scientific and media applications: medical imaging, molecular dynamics

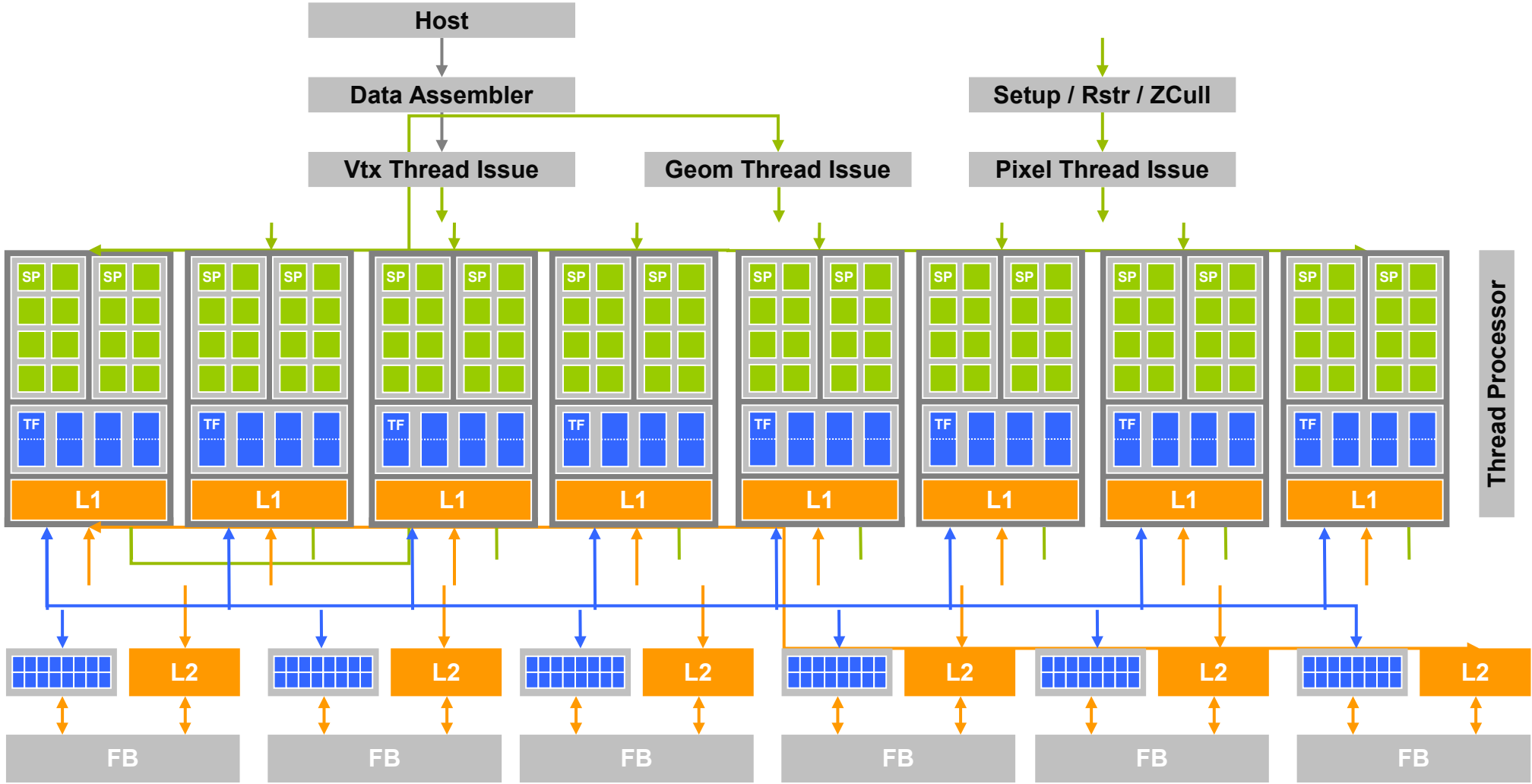
“I think they're right on the money, but the huge performance differential (currently 3 GPUs \sim 300 SGI Altix Itanium2s) will invite close scrutiny so I have to be careful what I say publically until I triple check those numbers.”

-John Stone, VMD group, Physics UIUC



A Fixed Function GPU Pipeline

Unified Graphics Pipeline



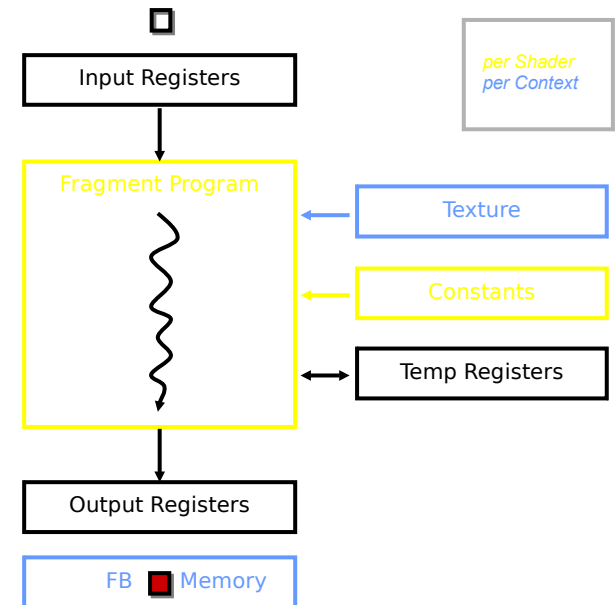
What is (Historical) GPGPU ?

- General Purpose computation using GPU and graphics API in applications other than 3D graphics
 - GPU accelerates critical path of application
- Data parallel algorithms leverage GPU attributes
 - Large data arrays, streaming throughput
 - Fine-grain SIMD parallelism
 - Low-latency floating point (FP) computation
- Applications – see GPGPU.org
 - Game effects (FX) physics, image processing
 - Physical modeling, computational engineering, matrix algebra, convolution, correlation, sorting



Previous GPGPU Constraints

- Dealing with graphics API
 - Working with the corner cases of the graphics API
- Addressing modes
 - Limited texture size/dimension
- Shader capabilities
 - Limited outputs
- Instruction sets
 - Lack of Integer & bit ops
- Communication limited
 - Between pixels
 - Scatter $a[i] = p$



Compute Shaders

- Shader buffers for memory access
- Shader has access to entire array for both read and write
- Compute shader compiled using OpenGL
- Requires OpenGL 4.3

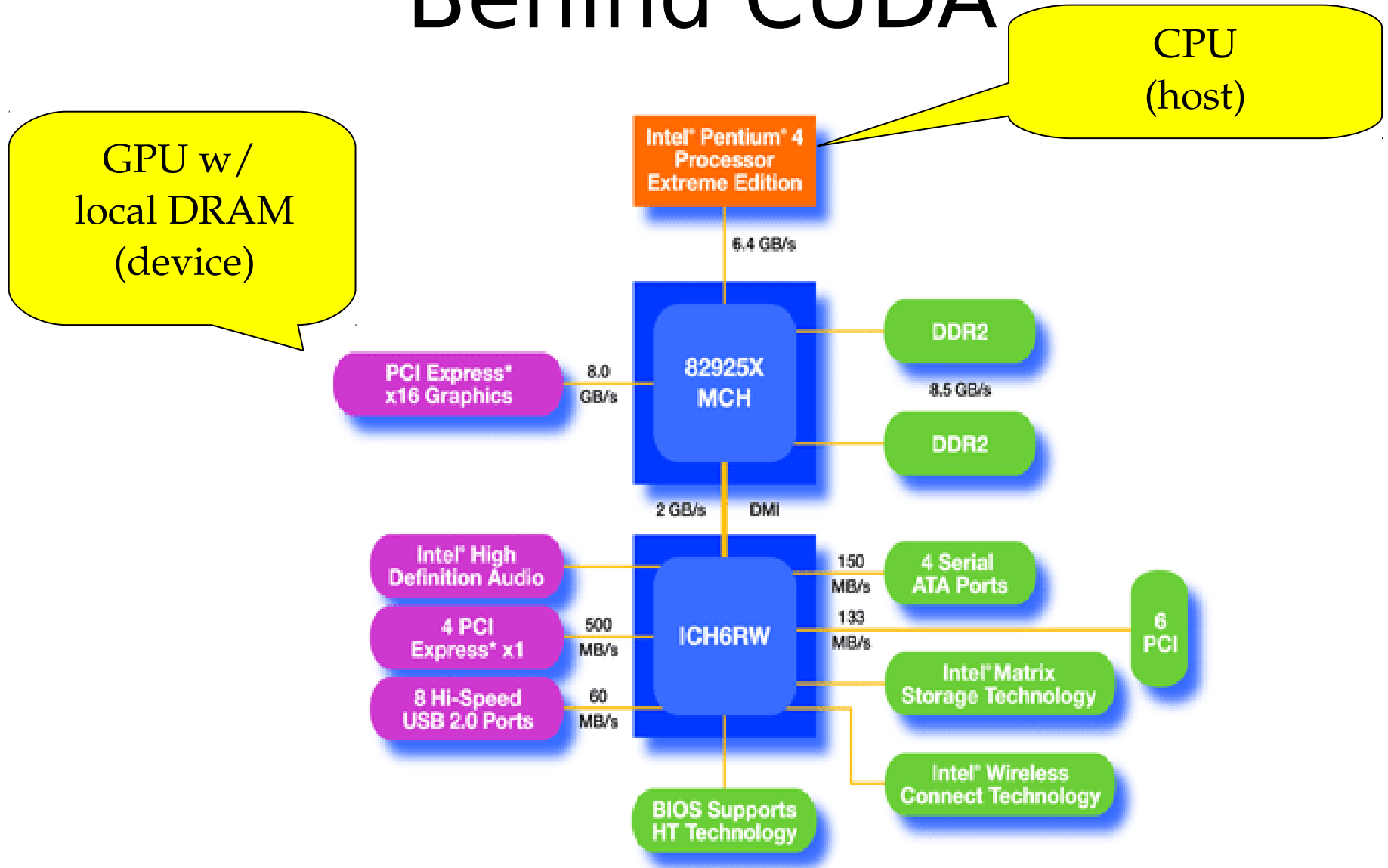


CUDA

- “Compute Unified Device Architecture”
- General purpose programming model
 - User kicks off batches of threads on the GPU
 - GPU = dedicated super-threaded, massively data parallel co-processor
- Targeted software stack
 - Compute oriented drivers, language, and tools
- Driver for loading computation programs into GPU
 - Standalone Driver - Optimized for computation
 - Interface designed for compute – graphics-free API
 - Data sharing with OpenGL buffer objects
 - Guaranteed maximum download & readback speeds
 - Explicit GPU memory management



An Example of Physical Reality Behind CUDA



Parallel Computing on a GPU

- 8-series GPUs deliver 25 to 200+ GFLOPS on compiled parallel C applications
 - Available in laptops, desktops, and clusters
- GPU parallelism is doubling every year
- Programming model scales transparently
- Programmable in C with CUDA tools
- Multithreaded SPMD model uses application data parallelism and thread parallelism



GeForce 8800



Tesla D870



Tesla S870

Overview

- CUDA programming model – basic concepts and data types
- CUDA application programming interface – basic
- Simple examples to illustrate basic concepts and functionalities
- Performance features will be covered later

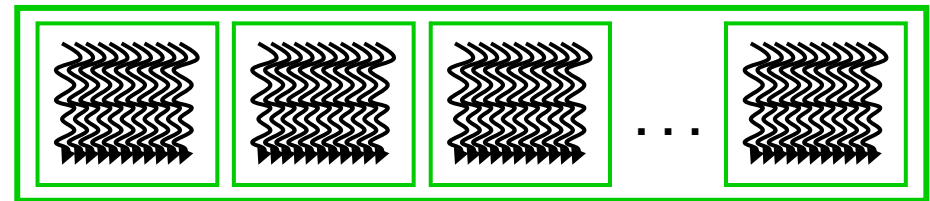
CUDA - C with no shader limitations!

- Integrated host+device app C program
 - Serial or modestly parallel parts in **host** C code
 - Highly parallel parts in **device** SPMD kernel C code

Serial Code (host)

Parallel Kernel (device)

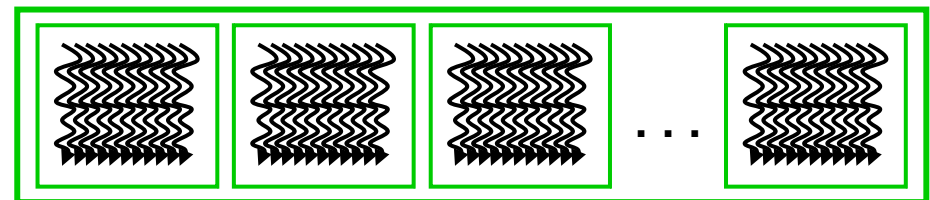
```
KernelA<<< nBlk, nTid >>>(args);
```



Serial Code (host)

Parallel Kernel (device)

```
KernelB<<< nBlk, nTid >>>(args);
```



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
- Differences between GPU and CPU threads
 - GPU threads are extremely lightweight
 - Very little creation overhead
 - GPU needs 1000s of threads for full efficiency
 - Multi-core CPU needs only a few

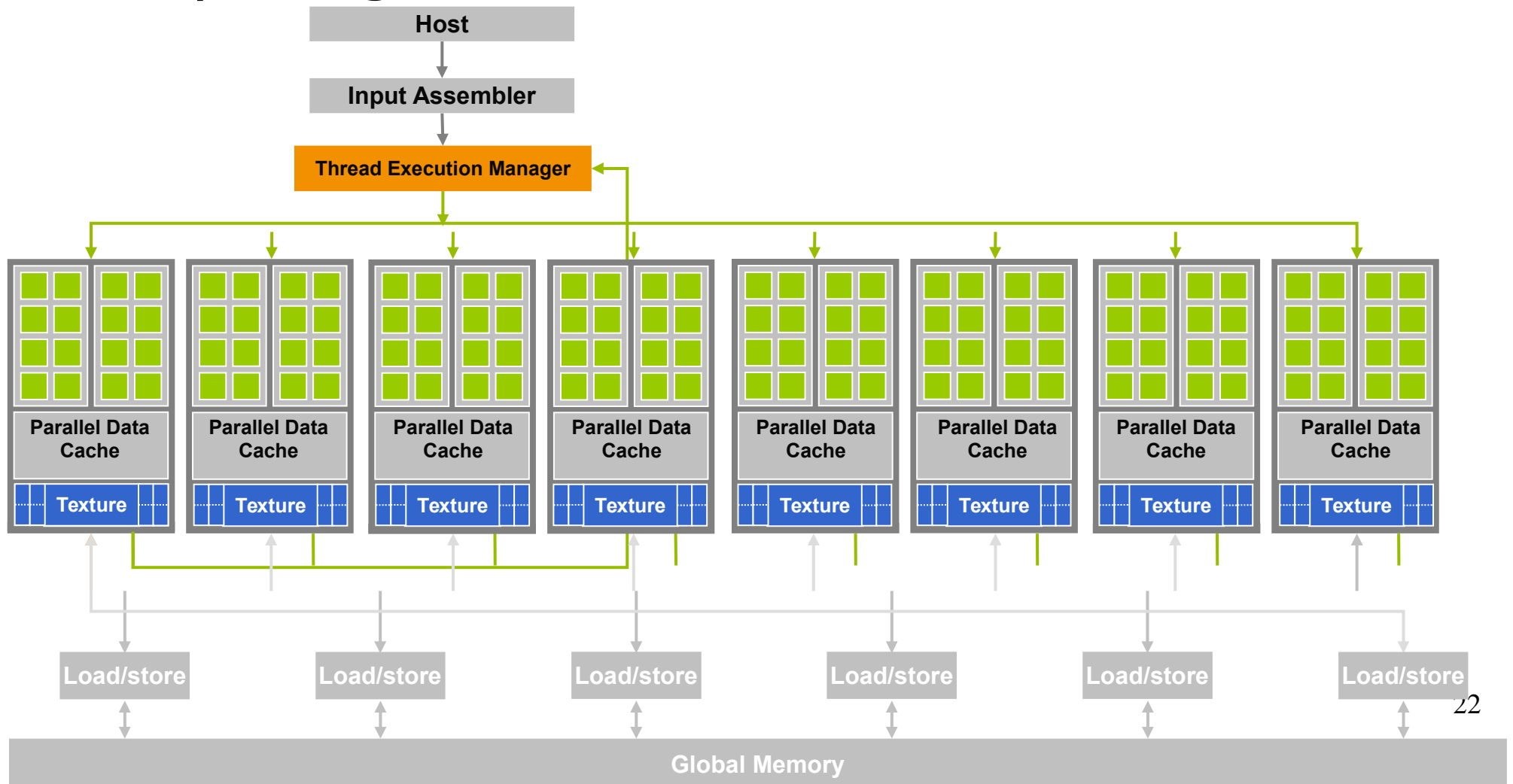
G80 - Graphics Mode

- The future of GPUs is programmable processing
- So - build the architecture around the processor



G80 CUDA mode - A **Device** Example

- Processors execute computing threads
- New operating mode/HW interface for computing



Extended C

- **Declspecs**

- **global, device, shared, local, constant**

```
__device__ float filter[N];  
__global__ void convolve (float *image) {  
    __shared__ float region[M];  
    ...  
  
    region[threadIdx] = image[i];  
  
    __syncthreads()  
    ...  
  
    image[j] = result;  
}
```

- **Keywords**

- **threadIdx, blockIdx**

- **Intrinsics**

- **__syncthreads**

- **Runtime API**

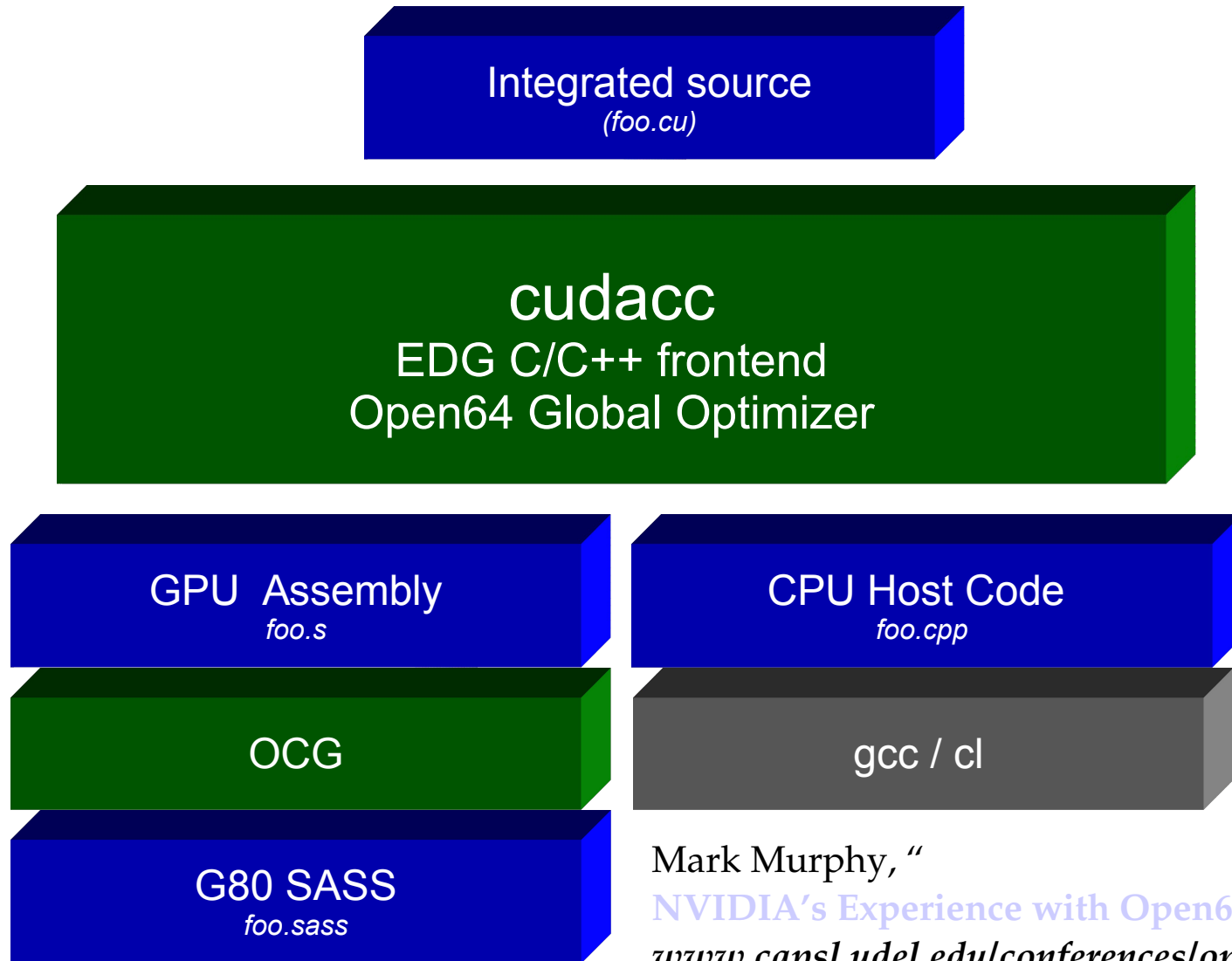
- **Memory, symbol, execution management**

```
// Allocate GPU memory  
void *myimage = cudaMalloc(bytes)
```

```
// 100 blocks, 10 threads per block  
convolve<<<100, 10>>> (myimage);
```

- **Function launch**

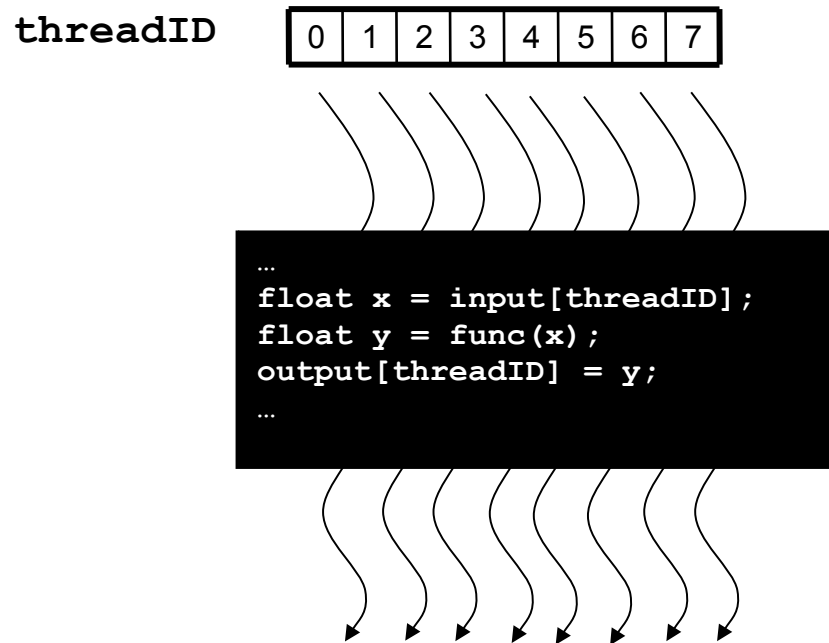
Extended C



Mark Murphy, “
NVIDIA’s Experience with Open64,”
[www.capsl.udel.edu/conferences/open64/2008/
Papers/101.doc](http://www.capsl.udel.edu/conferences/open64/2008/Papers/101.doc)

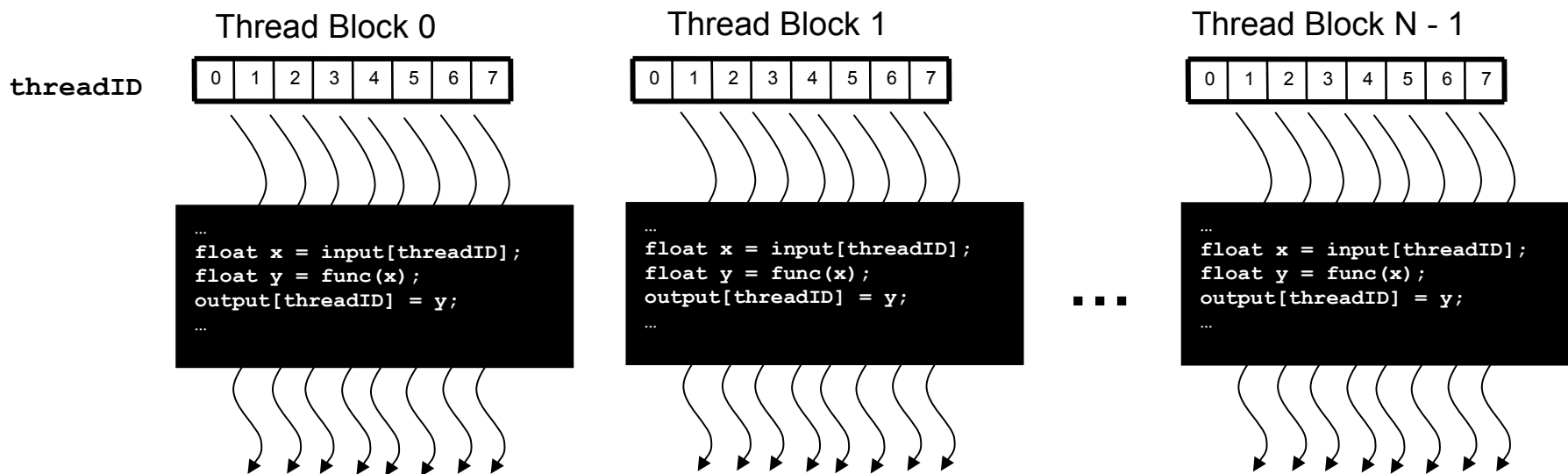
Arrays of Parallel Threads

- A CUDA kernel is executed by an array of threads
 - All threads run the same code (SPMD)
 - Each thread has an ID that it uses to compute memory addresses and make control decisions



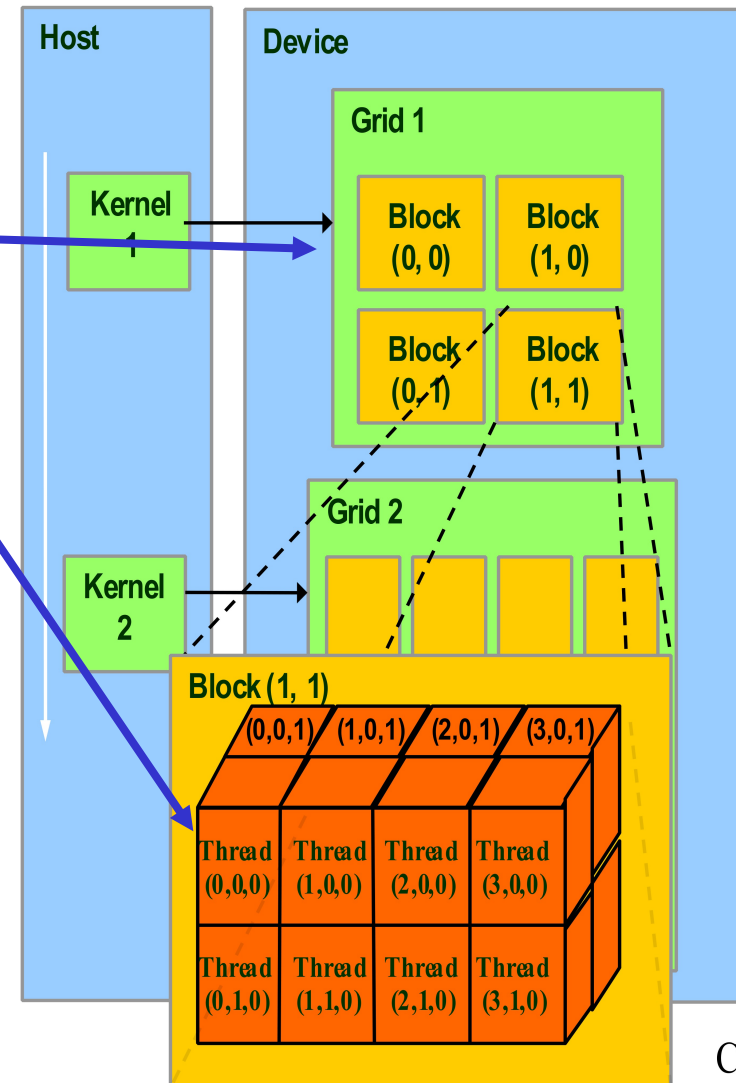
Thread Blocks: Scalable Cooperation

- Divide monolithic thread array into multiple blocks
 - Threads within a block cooperate via **shared memory, atomic operations** and **barrier synchronization**
 - Threads in different blocks cannot cooperate



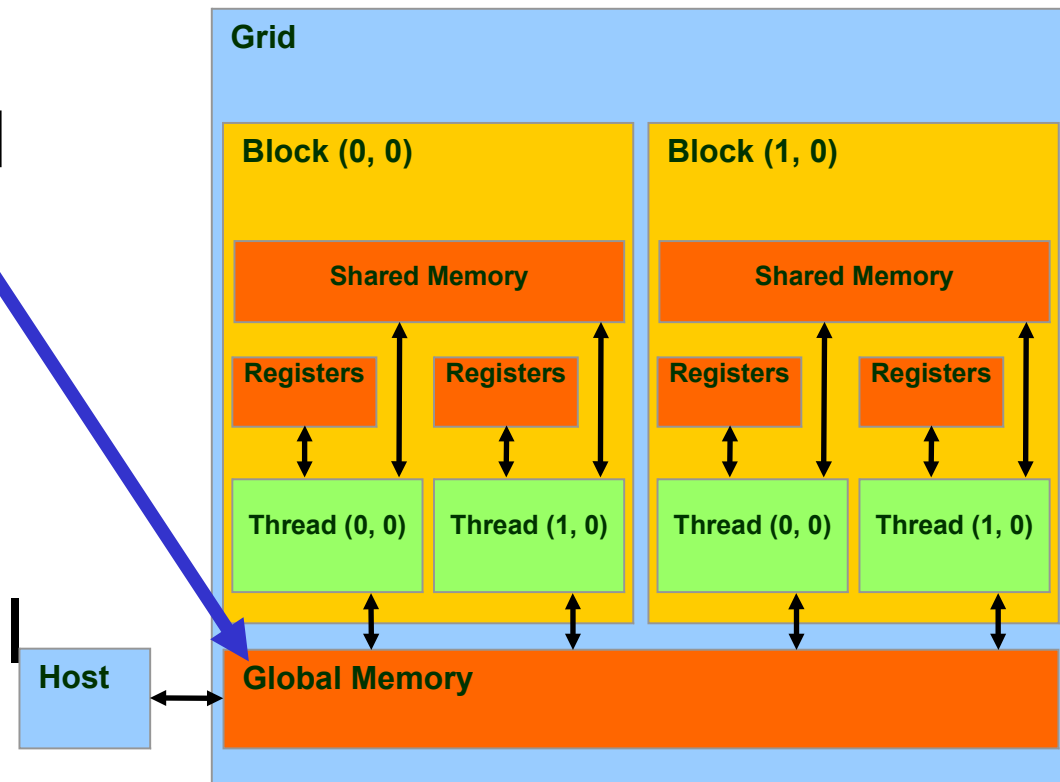
Block IDs and Thread IDs

- Each thread uses IDs to decide what data to work on
 - Block ID: 1D or 2D
 - Thread ID: 1D, 2D, or 3D
- Simplifies memory addressing when processing multidimensional data
 - Image processing
 - Solving PDEs on volumes
 - ...



CUDA Memory Model Overview

- Global memory
 - Main means of communicating R/W Data between **host** and **device**
 - Contents visible to all threads
 - Long latency access
- We will focus on global memory for now
 - Constant and texture memory will come later

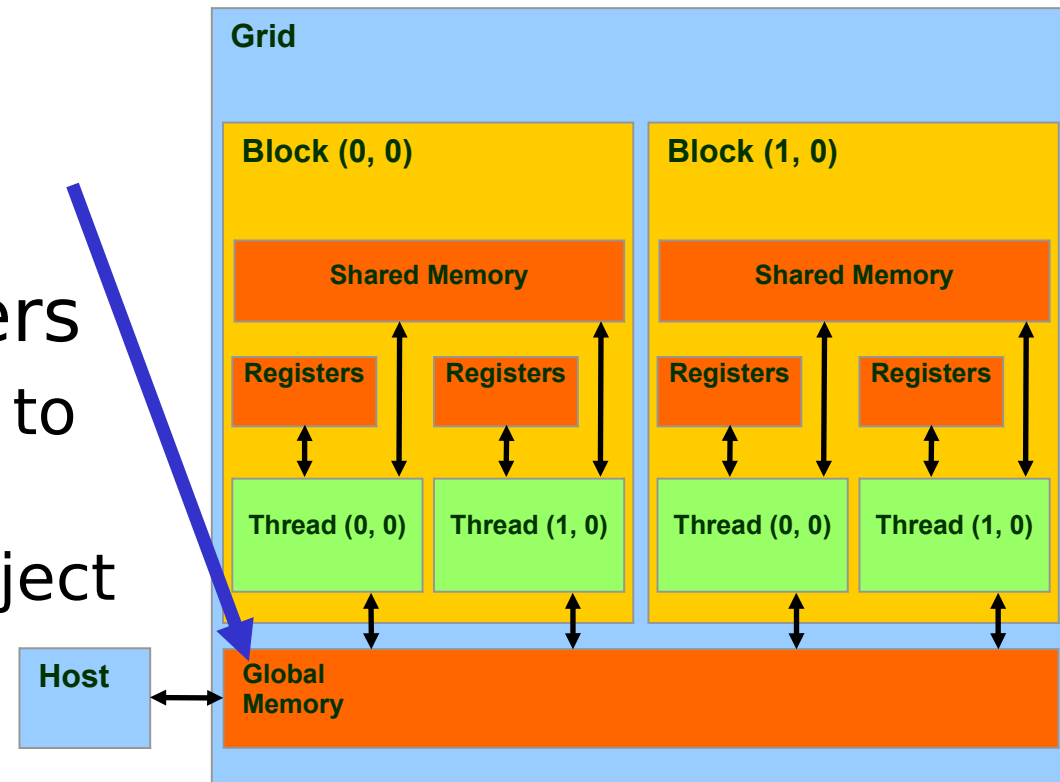


CUDA API Highlights: Easy and Lightweight

- The API is an **extension to the ANSI C programming language**
 - ➔ Low learning curve
- The hardware is **designed to enable lightweight runtime and driver**
 - ➔ High performance

CUDA Device Memory Allocation

- `cudaMalloc()`
 - Allocates object in the device Global Memory
 - Requires two parameters
 - **Address of a pointer** to the allocated object
 - **Size of** allocated object
- `cudaFree()`
 - Frees object from device Global Memory
 - Pointer to freed object



CUDA Device Memory Allocation (cont.)

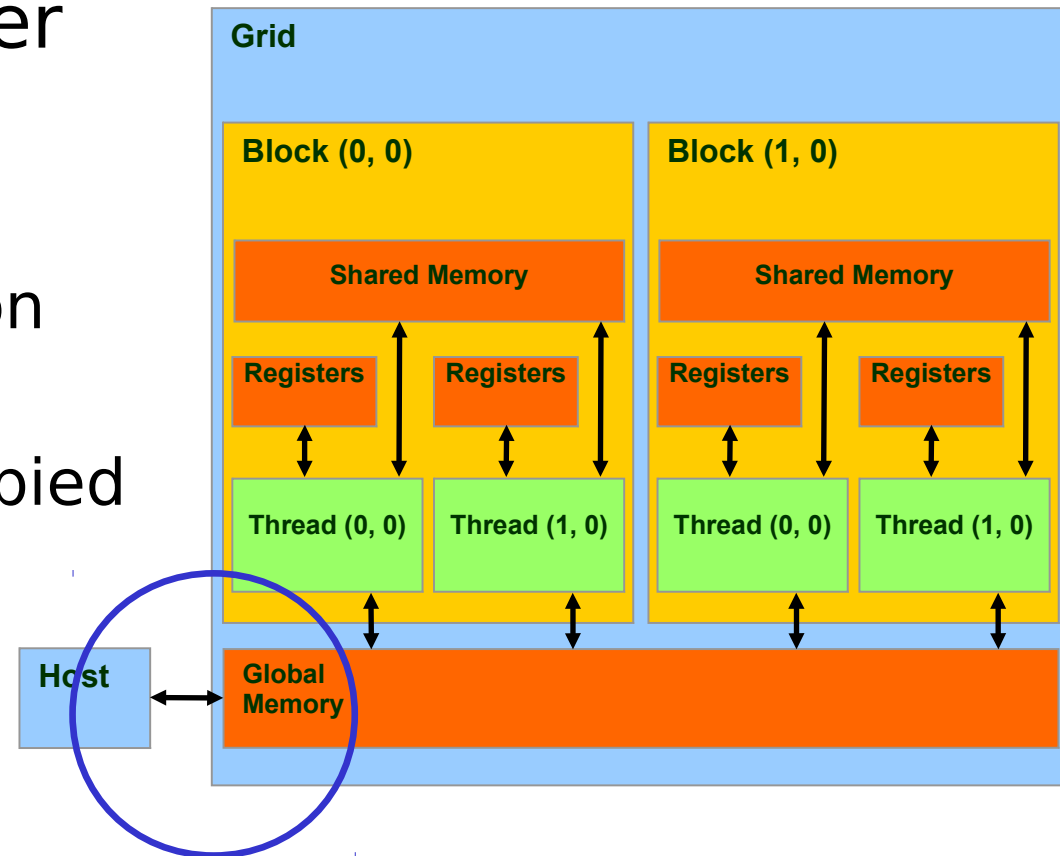
- Code example:
 - Allocate a $64 * 64$ single precision float array
 - Attach the allocated storage to Md
 - “d” is often used to indicate a device data structure

```
TILE_WIDTH = 64;  
Float* Md  
int size = TILE_WIDTH * TILE_WIDTH * sizeof(float);
```

```
cudaMalloc((void**)&Md, size);  
cudaFree(Md);
```

CUDA Host-Device Data Transfer

- `cudaMemcpy()`
 - memory data transfer
 - Requires four parameters
 - Pointer to destination
 - Pointer to source
 - Number of bytes copied
 - Type of transfer
 - Host to Host
 - Host to Device
 - Device to Host
 - Device to Device
- Asynchronous transfer



CUDA Host-Device Data Transfer (cont.)

- Code example:
 - Transfer a $64 * 64$ single precision float array
 - M is in host memory and Md is in device memory
 - `cudaMemcpyHostToDevice` and `cudaMemcpyDeviceToHost` are symbolic constants

```
cudaMemcpy(Md, M, size, cudaMemcpyHostToDevice);
```

```
cudaMemcpy(M, Md, size, cudaMemcpyDeviceToHost);
```

CUDA Function Declarations

	Executed on the:	Only callable from the:
<code>__device__ float DeviceFunc()</code>	device	device
<code>__global__ void KernelFunc()</code>	device	host
<code>__host__ float HostFunc()</code>	host	host

- `__global__` defines a kernel function
 - Must return `void`
- `__device__` and `__host__` can be used together

CUDA Function Declarations (cont.)

- __device__ functions cannot have their address taken
- For functions executed on the device:
 - No recursion
 - No static variable declarations inside the function
 - No variable number of arguments

Calling a Kernel Function - Thread Creation

- A kernel function must be called with an **execution configuration**:

```
__global__ void KernelFunc(...);  
dim3      DimGrid(100, 50);      // 5000 thread blocks  
dim3      DimBlock(4, 8, 8);     // 256 threads per block  
size_t    SharedMemBytes = 64;  // 64 bytes of shared memory  
KernelFunc<<< DimGrid, DimBlock, SharedMemBytes >>>(...);
```

- Any call to a kernel function is asynchronous from CUDA 1.0 on, explicit synch needed for blocking

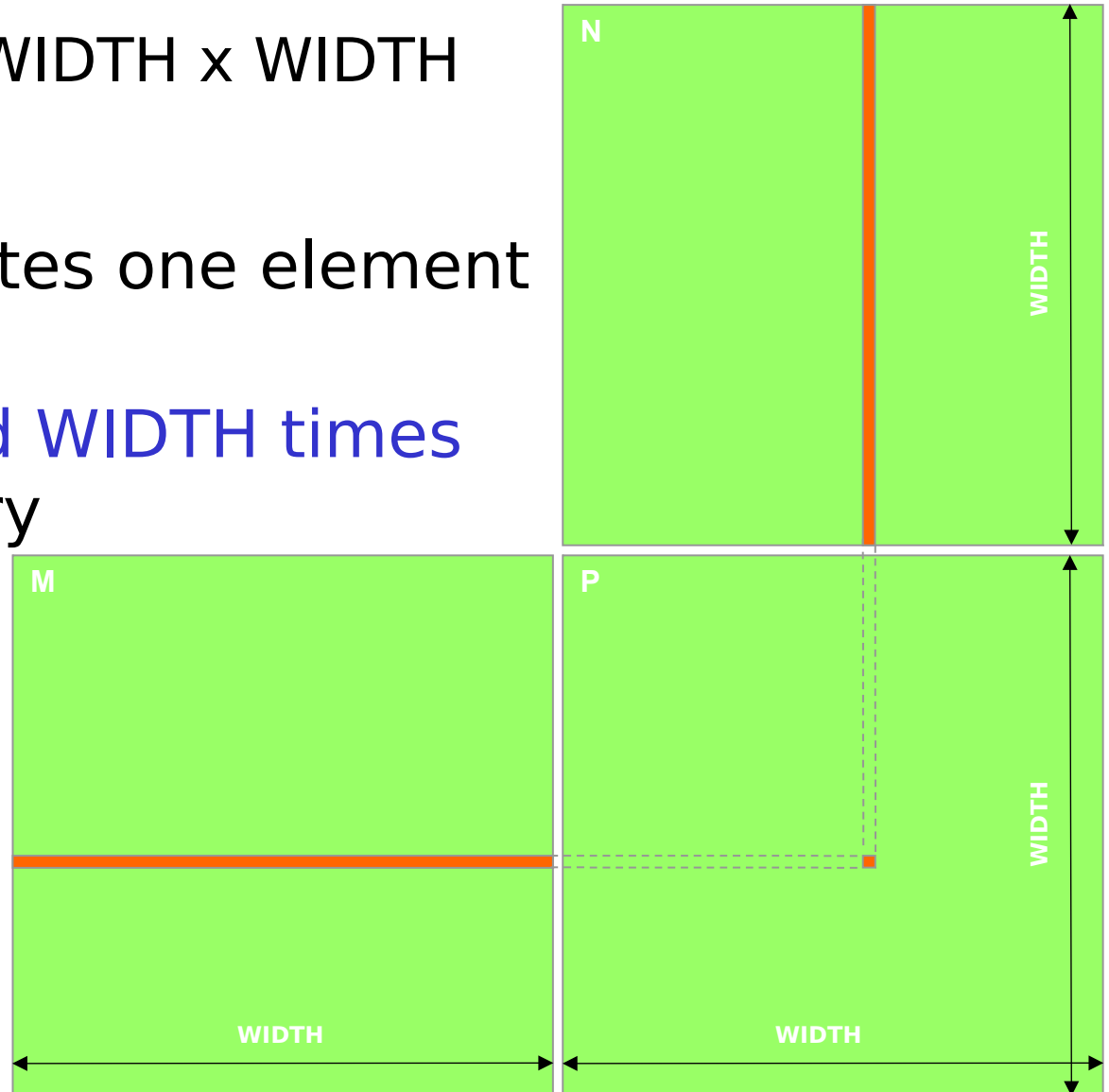
A Simple Running Example

Matrix Multiplication

- A simple matrix multiplication example that illustrates the basic features of memory and thread management in CUDA programs
 - Leave shared memory usage until later
 - Local, register usage
 - Thread ID usage
 - Memory data transfer API between host and device
 - Assume square matrix for simplicity

Programming Model: Square Matrix Multiplication Example

- $P = M * N$ of size $WIDTH \times WIDTH$
- Without tiling:
 - One **thread** calculates one element of P
 - M and N are loaded $WIDTH$ times from global memory



Memory Layout of a Matrix in C

$M_{0,0}$	$M_{1,0}$	$M_{2,0}$	$M_{3,0}$
$M_{0,1}$	$M_{1,1}$	$M_{2,1}$	$M_{3,1}$
$M_{0,2}$	$M_{1,2}$	$M_{2,2}$	$M_{3,2}$
$M_{0,3}$	$M_{1,3}$	$M_{2,3}$	$M_{3,3}$

M



$M_{0,0}$	$M_{1,0}$	$M_{2,0}$	$M_{3,0}$	$M_{0,1}$	$M_{1,1}$	$M_{2,1}$	$M_{3,1}$	$M_{0,2}$	$M_{1,2}$	$M_{2,2}$	$M_{3,2}$	$M_{0,3}$	$M_{1,3}$	$M_{2,3}$	$M_{3,3}$
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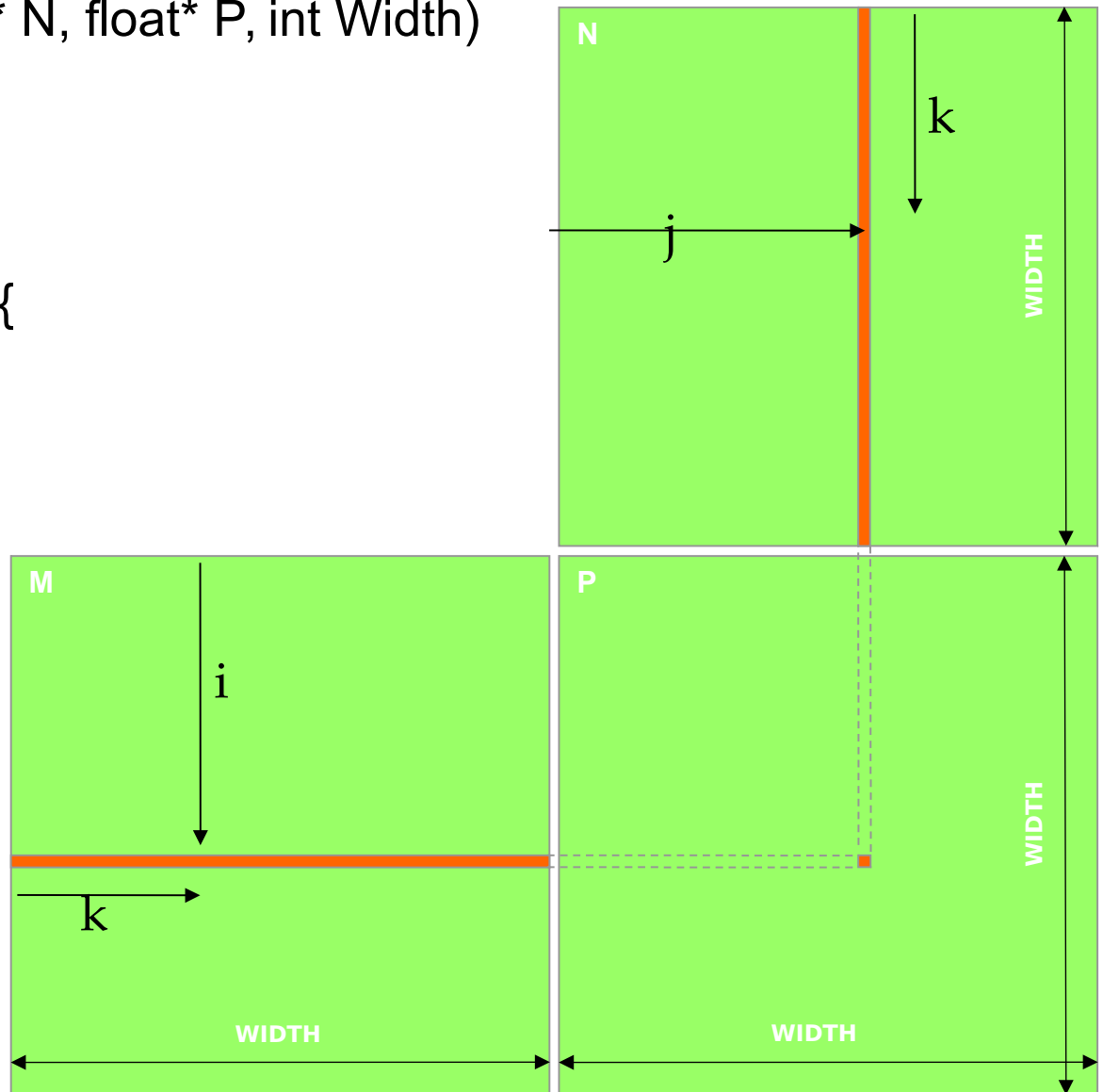
Matrix Multiplication

A Simple Host Version in C

```
// Matrix multiplication on the (CPU) host in double precision
```

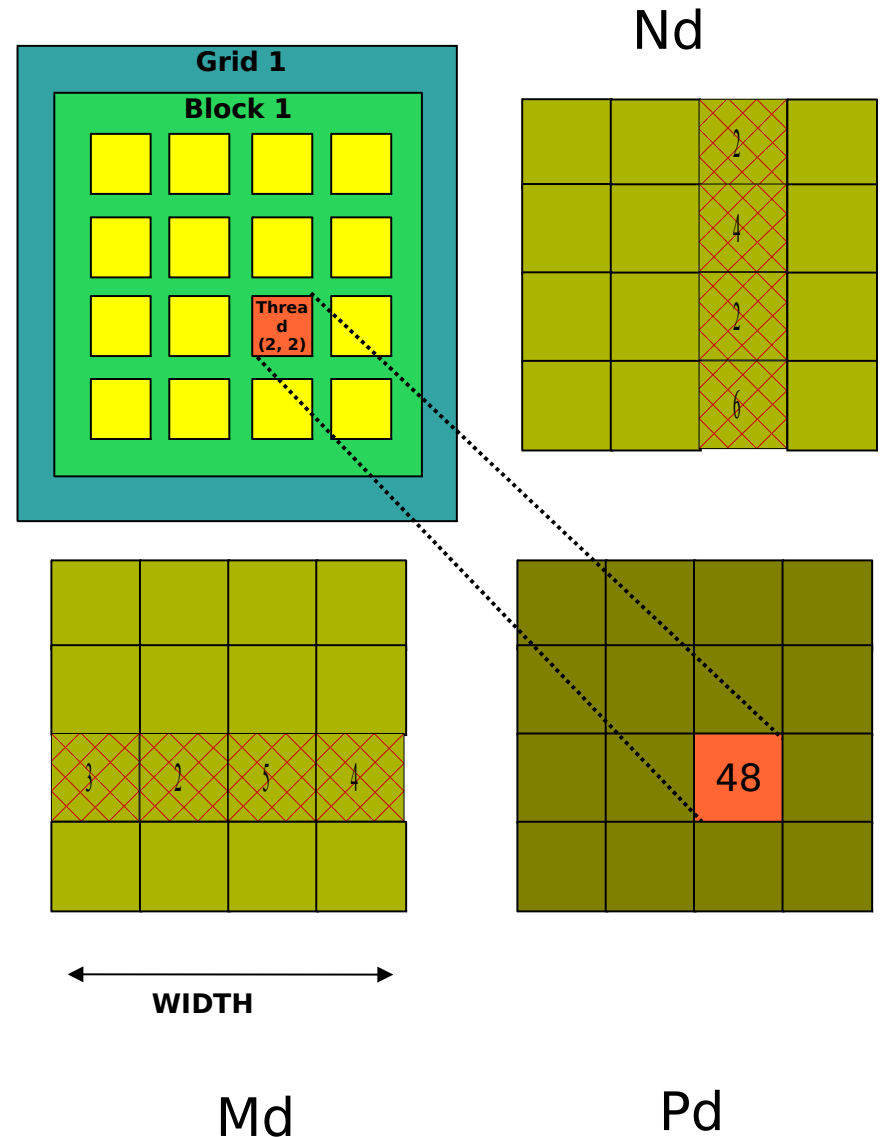
```
void MatrixMulOnHost(float* M, float* N, float* P, int Width)
```

```
{  
  for (int i = 0; i < Width; ++i)  
    for (int j = 0; j < Width; ++j) {  
      double sum = 0;  
      for (int k = 0; k < Width; ++k) {  
        double a = M[i * width + k];  
        double b = N[k * width + j];  
        sum += a * b;  
      }  
      P[i * Width + j] = sum;  
    }  
}
```



Threads and Blocks

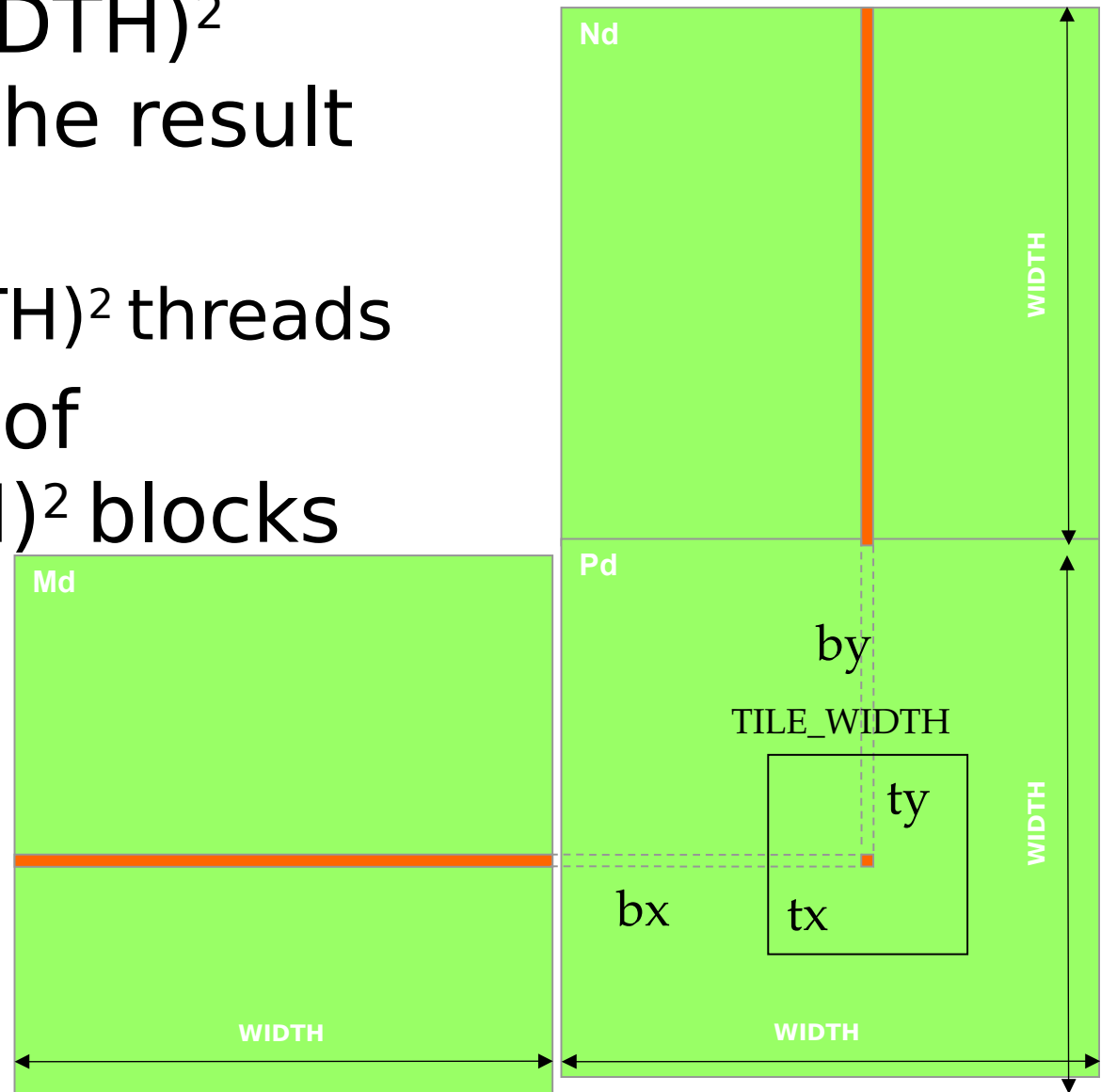
- One Block of threads compute matrix Pd
 - Each thread computes one element of Pd
- Each thread
 - Loads a row of matrix Md
 - Loads a column of matrix Nd
 - Perform one multiply and addition for each pair of Md and Nd elements
 - Compute to off-chip memory access ratio close to 1:1 (not very high)
- Size of matrix limited by the number of threads allowed in a thread block



Tiled Kernel Function

- Have each 2D thread block to compute a $(\text{TILE_WIDTH})^2$ sub-matrix (tile) of the result matrix
 - Each has $(\text{TILE_WIDTH})^2$ threads
- Generate a 2D Grid of $(\text{WIDTH}/\text{TILE_WIDTH})^2$ blocks

You still need to put a loop around the kernel call for cases where $\text{WIDTH}/\text{TILE_WIDTH}$ is greater than max grid size (64K)!



Kernel Function Code

```
// Matrix multiplication kernel
```

```
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{

    // Index of thread
    unsigned int j = blockIdx.x*blockDim.x+threadIdx.x;
    unsigned int i = blockIdx.y*blockDim.y+threadIdx.y;

    // Calculate element value
    float sum = 0;
    for (int k=0;k<n;k++)
        sum += A[i*n+k] * B[k*n+j];

    // Store element value
    C[i*n+j] = sum;
}
```

Step 1: Copy Input Data

```
void MatrixMulOnDevice(float* M, float* N, float* P, int Bw, int Bn)
{
    int Width = Wb*Bn;
    int size = Width * Width * sizeof(float);
    float* Md, Nd, Pd;

    // Allocate and Load M, N to device memory
    cudaMalloc(&Md, size);
    cudaMemcpy(Md, M, size, cudaMemcpyHostToDevice);
    cudaMalloc(&Nd, size);
    cudaMemcpy(Nd, N, size, cudaMemcpyHostToDevice);
    // Allocate P on the device
    cudaMalloc(&Pd, size);
```

Step 2: Kernel Invocation

```
// Setup the execution configuration
dim3 dimGrid(Bw, Bw);
dim3 dimBlock(Bn, Bn);

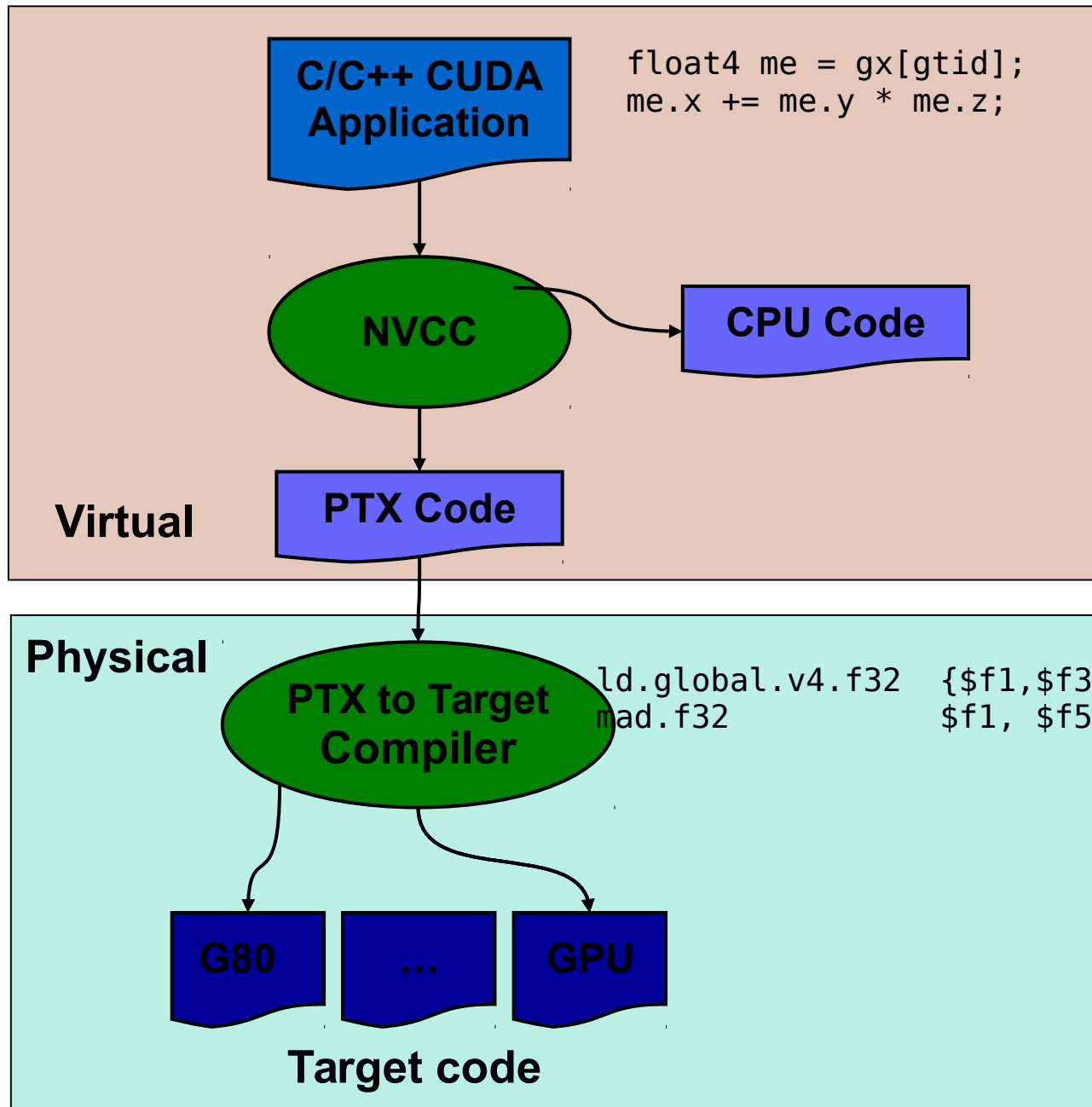
// Launch the device computation threads!
MatrixMulKernel<<<dimGrid, dimBlock>>>(Md, Nd, Pd, Bw*Bn);
```

Step 3: Copy Output Data

```
// Read P from the device
cudaMemcpy(P, Pd, size, cudaMemcpyDeviceToHost);

// Free device matrices
cudaFree(Md); cudaFree(Nd); cudaFree (Pd);
}
```

Compiling a CUDA Program



- Parallel Thread eXecution (PTX)
 - Virtual Machine and ISA
 - Programming model
 - Execution resources and state

Compilation

- Any source file containing CUDA language extensions must be compiled with NVCC
- NVCC is a compiler driver
 - Works by invoking all the necessary tools and compilers like cudacc, g++, cl, ...
- NVCC outputs:
 - C code (host CPU Code)
 - Must then be compiled with the rest of the application using another tool
 - PTX
 - Object code directly
 - Or, PTX source, interpreted at runtime

Linking

- Any executable with CUDA code requires two dynamic libraries:
 - The CUDA runtime library (`cudaart`)
 - The CUDA core library (`cuda`)

Debugging Using the Device Emulation Mode

- An executable compiled in **device emulation mode** (`nvcc -deviceemu`) runs completely on the host using the CUDA runtime
 - No need of any device and CUDA driver
 - Each device thread is emulated with a host thread
- Running in device emulation mode, one can:
 - Use host native debug support (breakpoints, inspection, etc.)
 - Access any device-specific data from host code and vice-versa
 - Call any host function from device code (e.g. `printf`) and vice-versa
 - Detect deadlock situations caused by improper usage of `__syncthreads`

Device Emulation Mode Pitfalls

- Emulated device threads execute sequentially, so **simultaneous accesses of the same memory location by multiple threads** could produce different results.
- **Dereferencing device pointers** on the host or host pointers on the device can produce correct results in device emulation mode, but will generate an error in device execution mode

Floating Point

- Results of floating-point computations will slightly differ because of:
 - Different compiler outputs, instruction sets
 - Use of extended precision for intermediate results
 - There are various options to force strict single precision on the host