

CS 380 - GPU and GPGPU Programming

Lecture 12: GPU Compute APIs, Pt. 2

Markus Hadwiger, KAUST

Reading Assignment #7 (until Oct 18)



Read (required):

- Programming Massively Parallel Processors book, 3rd edition, Chapter 7 (*Parallel Patterns: Convolution*)
- PTX Instruction Set Architecture 7.4 (https://docs.nvidia.com/cuda/pdf/ptx_isa_7.4.pdf)
Read Chapters 1 – 3; get an overview of Chapter 12;
browse through the other chapters to get a feeling for what PTX looks like
- CUDA SASS, Chapter 4: https://docs.nvidia.com/cuda/pdf/CUDA_Binary_Utils.pdf

Read (optional):

- Inline PTX Assembly in CUDA (CUDA SDK: [Inline_PTX_Assembly.pdf](#))
- Dissecting GPU Architecture through Microbenchmarking:

Volta: <https://arxiv.org/abs/1804.06826>

Turing: <https://arxiv.org/abs/1903.07486>

<https://developer.download.nvidia.com/video/gputechconf/gtc/2019/presentation/s9839-discovering-the-turing-t4-gpu-architecture-with-microbenchmarks.pdf>

Ampere: <https://www.nvidia.com/en-us/on-demand/session/gtcspring21-s33322/>



CUDA Software Development

CUDA Optimized Libraries:
math.h, FFT, BLAS, ...

Integrated CPU + GPU
C Source Code

NVIDIA C Compiler

NVIDIA Assembly
for Computing (PTX)

CPU Host Code

CUDA
Driver

Profiler

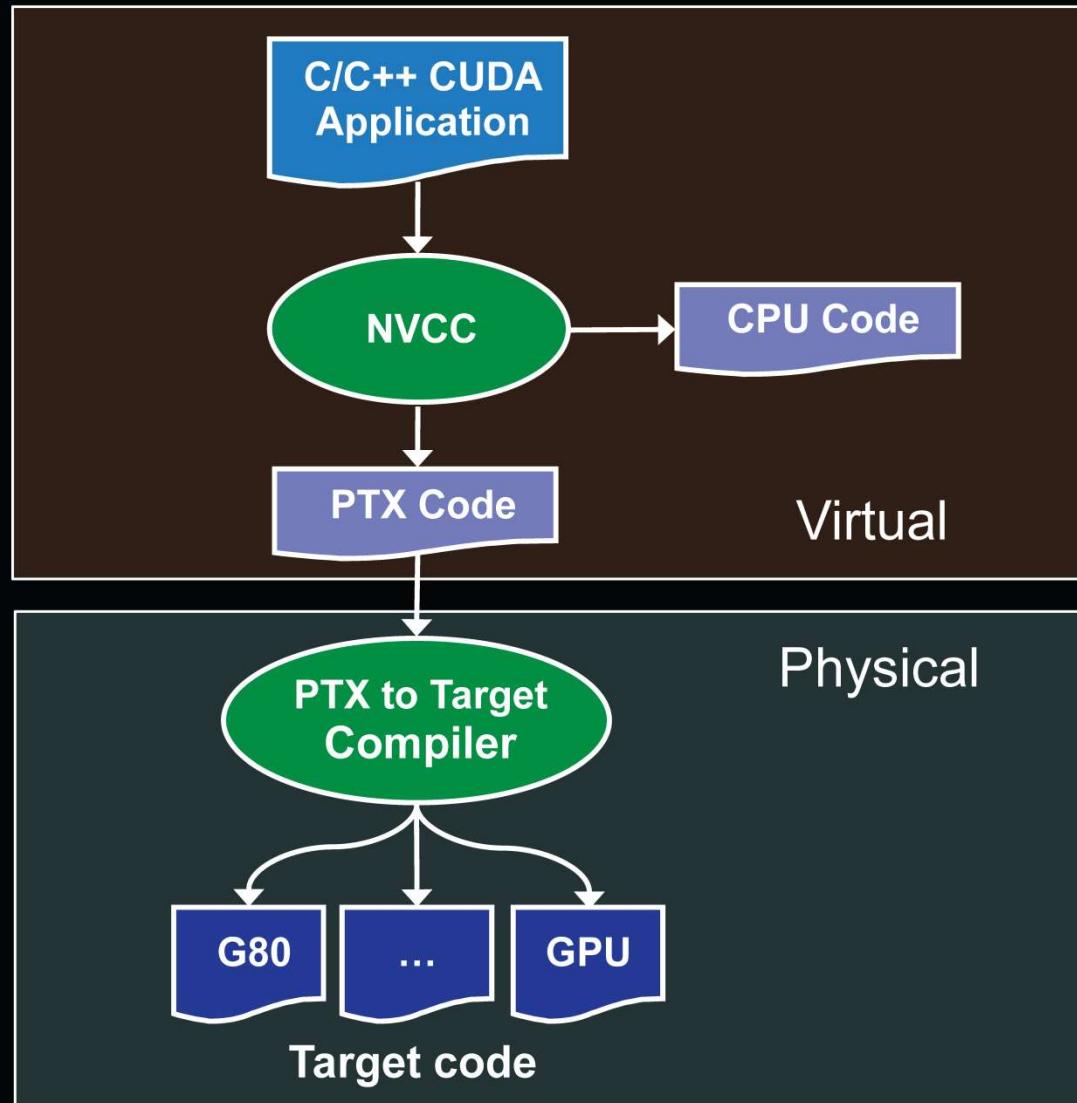
Standard C Compiler

GPU

CPU



Compiling CUDA Code



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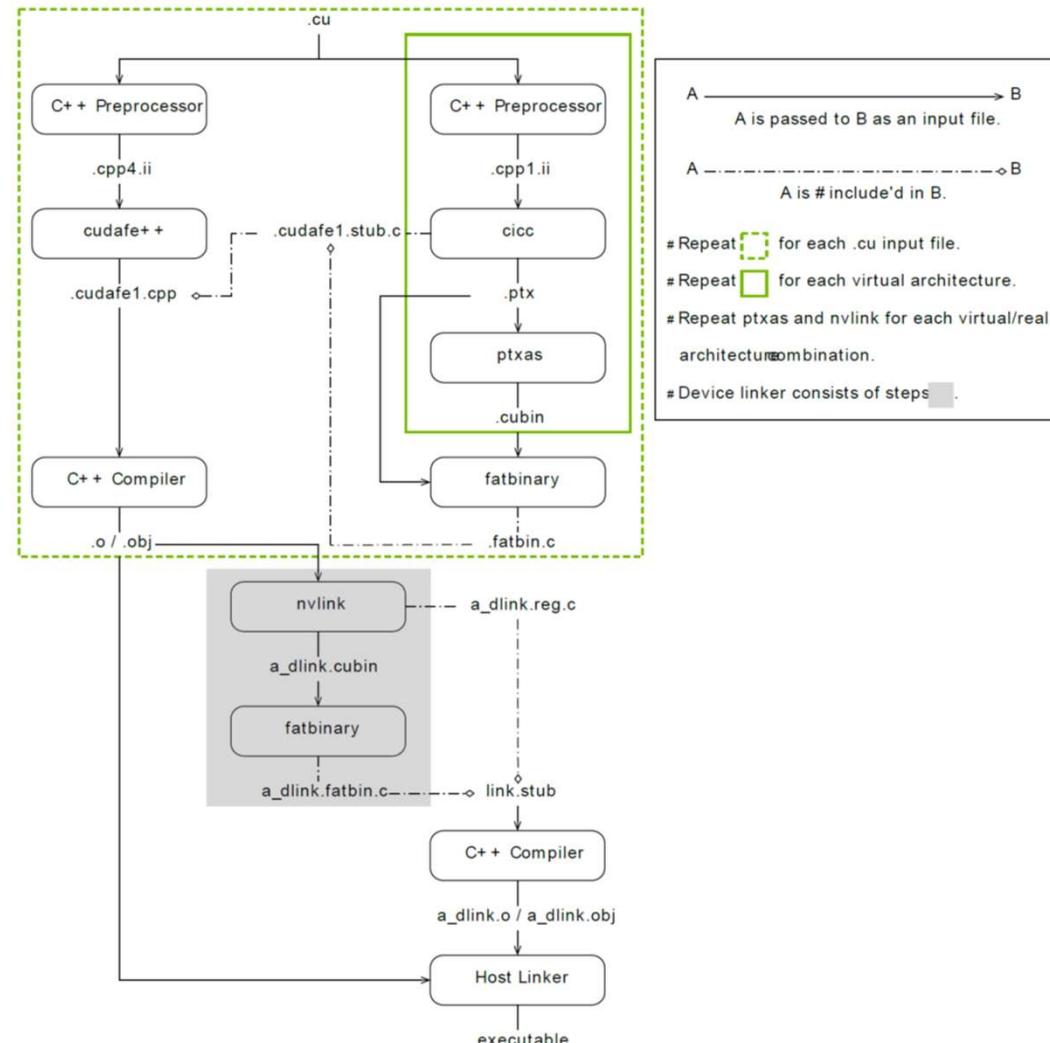
NVIDIA



CUDA Compilation Trajectory

CUDA Compiler Driver
(NVCC) docs:

[CUDA_Compiler_Driver_NVCC.pdf](#)





4.2.7. Options for Steering GPU Code Generation

4.2.7.1. `--gpu-architecture arch` (`-arch`)

Specify the name of the class of NVIDIA virtual GPU architecture for which the CUDA input files must be compiled.

With the exception as described for the shorthand below, the architecture specified with this option must be a *virtual* architecture (such as `compute_50`). Normally, this option alone does not trigger assembly of the generated PTX for a *real* architecture (that is the role of `nvcc` option `--gpu-code`, see below); rather, its purpose is to control preprocessing and compilation of the input to PTX.

For convenience, in case of simple `nvcc` compilations, the following shorthand is supported. If no value for option `--gpu-code` is specified, then the value of this option defaults to the value of `--gpu-architecture`. In this situation, as only exception to the description above, the value specified for `--gpu-architecture` may be a *real* architecture (such as a `sm_50`), in which case `nvcc` uses the specified *real* architecture and its closest *virtual* architecture as effective architecture values. For example, `nvcc --gpu-architecture=sm_50` is equivalent to `nvcc --gpu-architecture=compute_50 --gpu-code=sm_50,compute_50`.

See [Virtual Architecture Feature List](#) for the list of supported *virtual* architectures and [GPU Feature List](#) for the list of supported *real* architectures.

CUDA Compilation Trajectory / Code Gen



4.2.7.2. `--gpu-code code, ... (-code)`

Specify the name of the NVIDIA GPU to assemble and optimize PTX for.

nvcc embeds a compiled code image in the resulting executable for each specified *code* architecture, which is a true binary load image for each *real* architecture (such as sm_50), and PTX code for the *virtual* architecture (such as compute_50).

During runtime, such embedded PTX code is dynamically compiled by the CUDA runtime system if no binary load image is found for the *current* GPU.

Architectures specified for options `--gpu-architecture` and `--gpu-code` may be *virtual* as well as *real*, but the *code* architectures must be compatible with the *arch* architecture.

When the `--gpu-code` option is used, the value for the `--gpu-architecture` option must be a *virtual* PTX architecture.

For instance, `--gpu-architecture=compute_60` is not compatible with `--gpu-code=sm_52`, because the earlier compilation stages will assume the availability of `compute_60` features that are not present on `sm_52`.

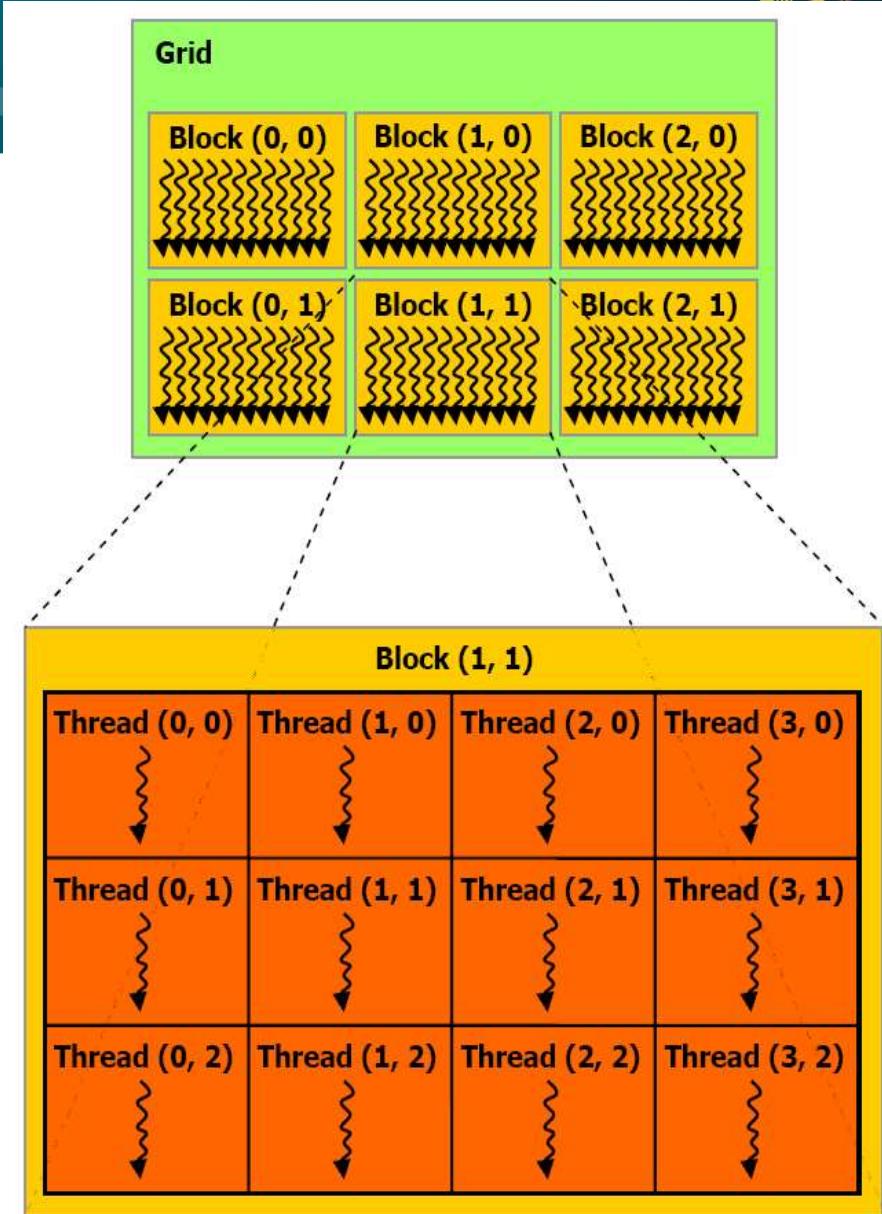
See [Virtual Architecture Feature List](#) for the list of supported *virtual* architectures and [GPU Feature List](#) for the list of supported *real* architectures.

Look at compatibility guides:

https://docs.nvidia.com/cuda/pdf/NVIDIA_Ampere_GPU_Architecture_Compatibility_Guide.pdf

CUDA Multi-Threading

- CUDA model groups threads into blocks; blocks into grid
- Execution on actual hardware:
 - Block assigned to SM (up to 8, 16, or 32 blocks per SM; depending on compute capability)
 - 32 threads grouped into warp





CUDA Kernels and Threads

- Parallel portions of an application are executed on the device as **kernels**
 - One **kernel** is executed at a time
 - Many threads execute each **kernel**
- Differences between CUDA and CPU threads
 - CUDA threads are extremely lightweight
 - Very little creation overhead
 - Instant switching
 - CUDA uses 1000s of threads to achieve efficiency
 - Multi-core CPUs can use only a few

Definitions

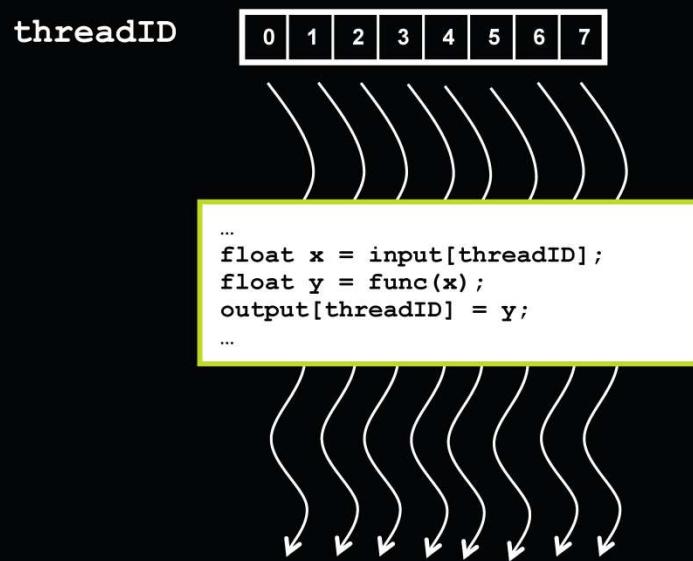
Device = GPU

Host = CPU

Kernel = function that runs on the device

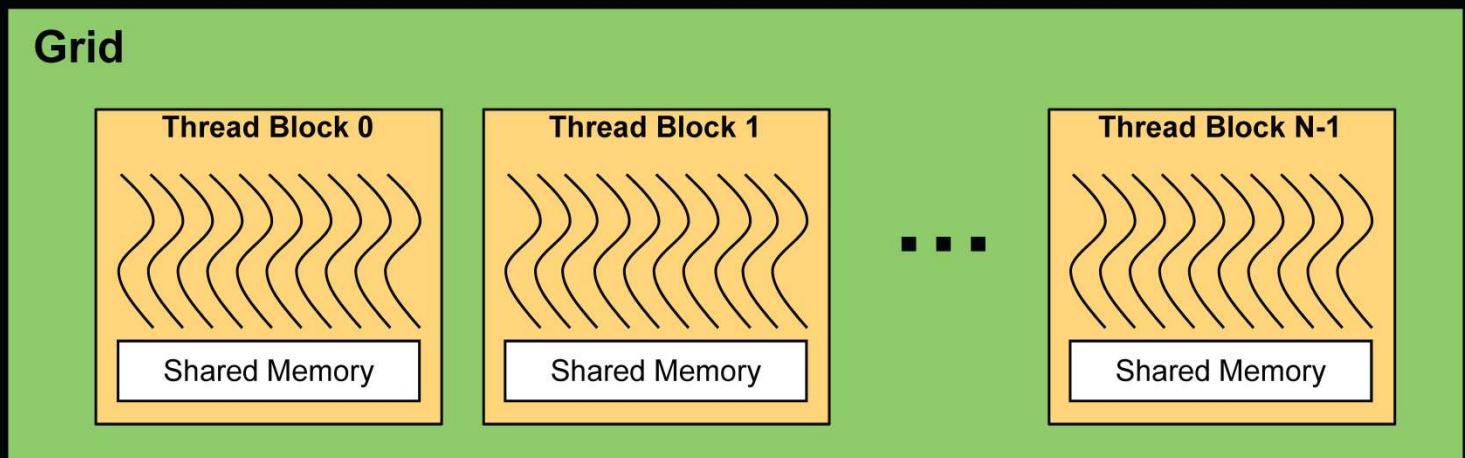
Arrays of Parallel Threads

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



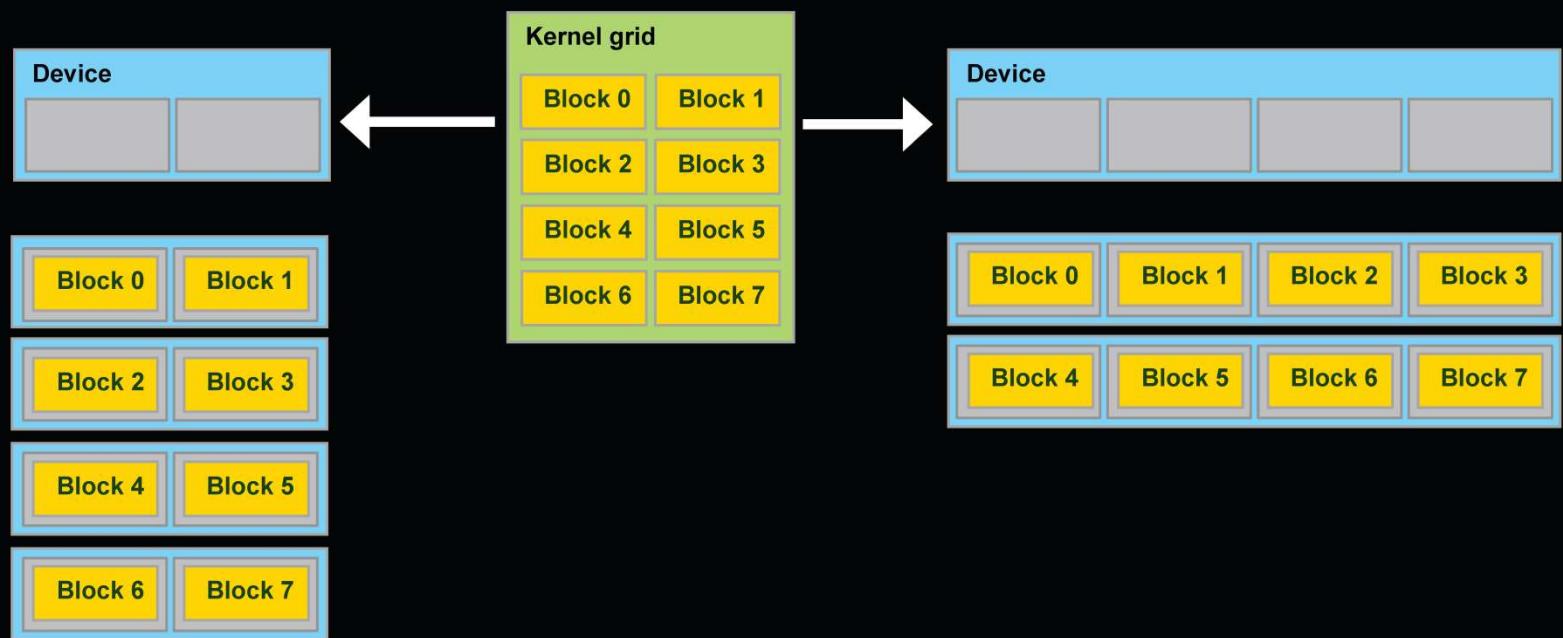
Thread Batching

- Kernel launches a **grid of thread blocks**
 - Threads within a block cooperate via shared memory
 - Threads within a block can synchronize
 - Threads in different blocks cannot cooperate
- Allows programs to *transparently scale to different GPUs*



Transparent Scalability

- Hardware is free to schedule thread blocks on any processor
 - A kernel scales across parallel multiprocessors

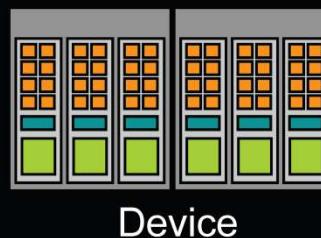
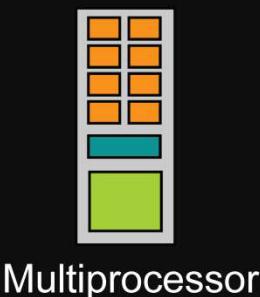


Execution Model

Software



Hardware



Threads are executed by thread processors

Thread blocks are executed on multiprocessors

Thread blocks do not migrate

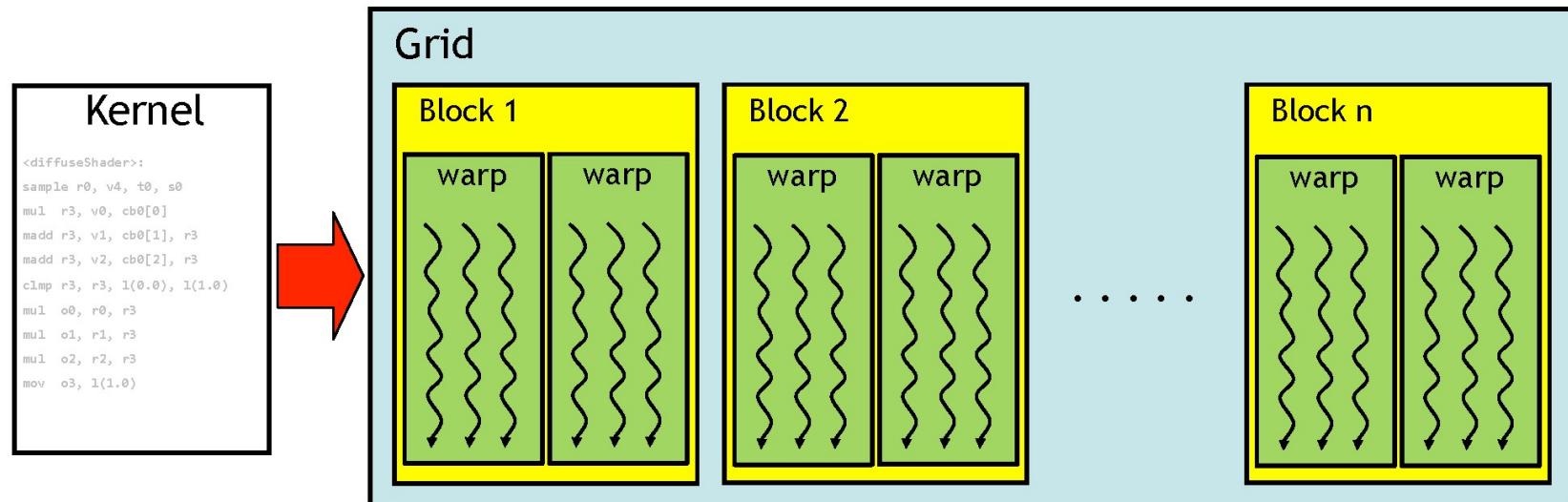
Several concurrent thread blocks can reside on one multiprocessor - limited by multiprocessor resources (shared memory and register file)

A kernel is launched as a grid of thread blocks

Only one kernel can execute on a device at one time

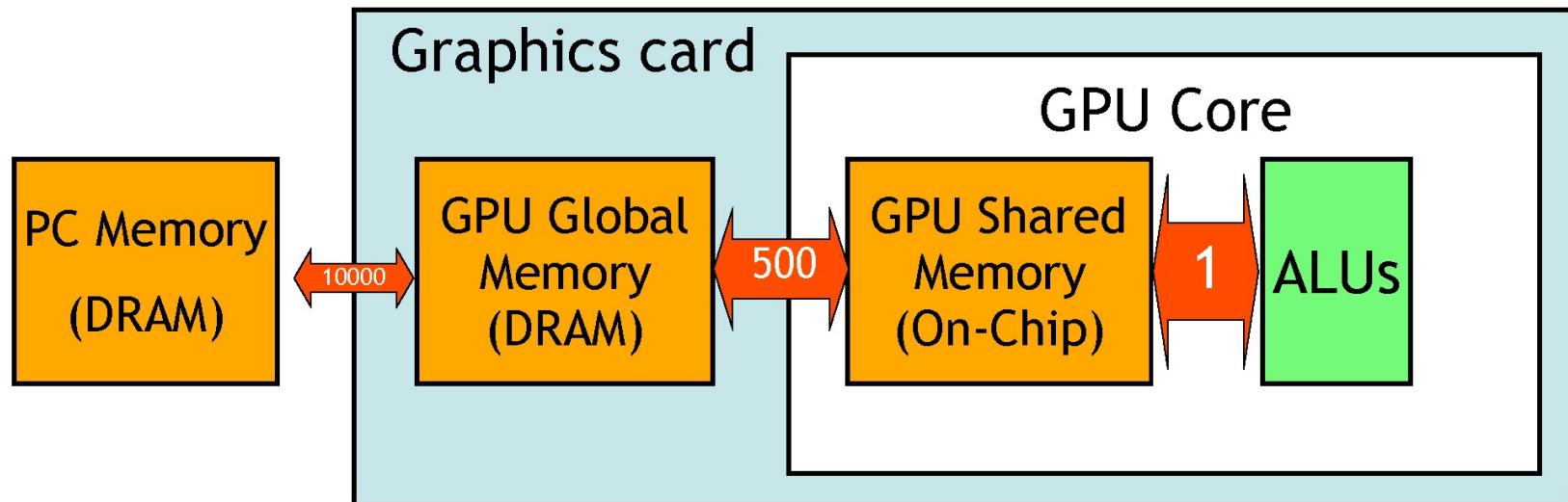
CUDA Programming Model

- Kernel
 - GPU program that runs on a thread grid
- Thread hierarchy
 - Grid : a set of blocks
 - Block : a set of warps
 - Warp : a SIMD group of 32 threads
 - Grid size * block size = total # of threads



CUDA Memory Structure

- Memory hierarchy
 - PC memory : off-card
 - GPU global : off-chip / on-card
 - GPU shared/register/cache : on-chip
- The host can read/write global memory
- Each thread communicates using shared memory

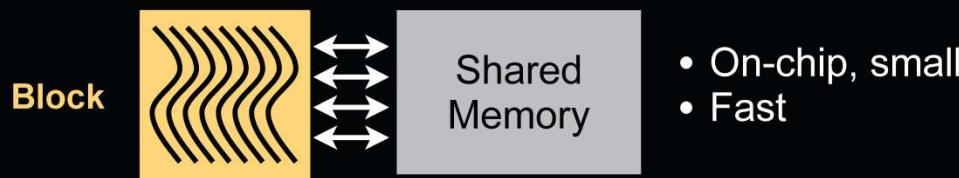


Kernel Memory Access

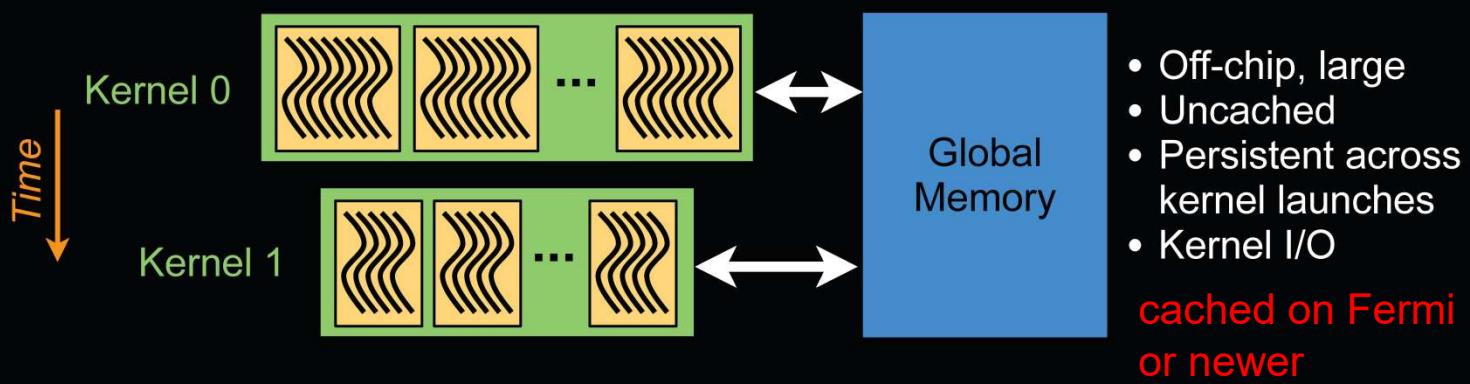
- **Per-thread**



- **Per-block**



- **Per-device**



Memory Architecture



Memory	Location	Cached	Access	Scope	Lifetime
Register	On-chip	N/A	R/W	One thread	Thread
Local	Off-chip	No*	R/W	One thread	Thread
Shared	On-chip	N/A	R/W	All threads in a block	Block
Global	Off-chip	No*	R/W	All threads + host	Application
Constant	Off-chip	Yes	R	All threads + host	Application
Texture	Off-chip	Yes	R	All threads + host	Application

* cached on Fermi or newer



(Memory) State Spaces

PTX ISA 7.4 (Chapter 5)

Name	Addressable	Initializable	Access	Sharing
.reg	No	No	R/W	per-thread
.sreg	No	No	RO	per-CTA
.const	Yes	Yes ¹	RO	per-grid
.global	Yes	Yes ¹	R/W	Context
.local	Yes	No	R/W	per-thread
.param (as input to kernel)	Yes ²	No	RO	per-grid
.param (used in functions)	Restricted ³	No	R/W	per-thread
.shared	Yes	No	R/W	per-CTA
.tex	No ⁴	Yes, via driver	RO	Context

Notes:

¹ Variables in .const and .global state spaces are initialized to zero by default.

² Accessible only via the ld.param instruction. Address may be taken via mov instruction.

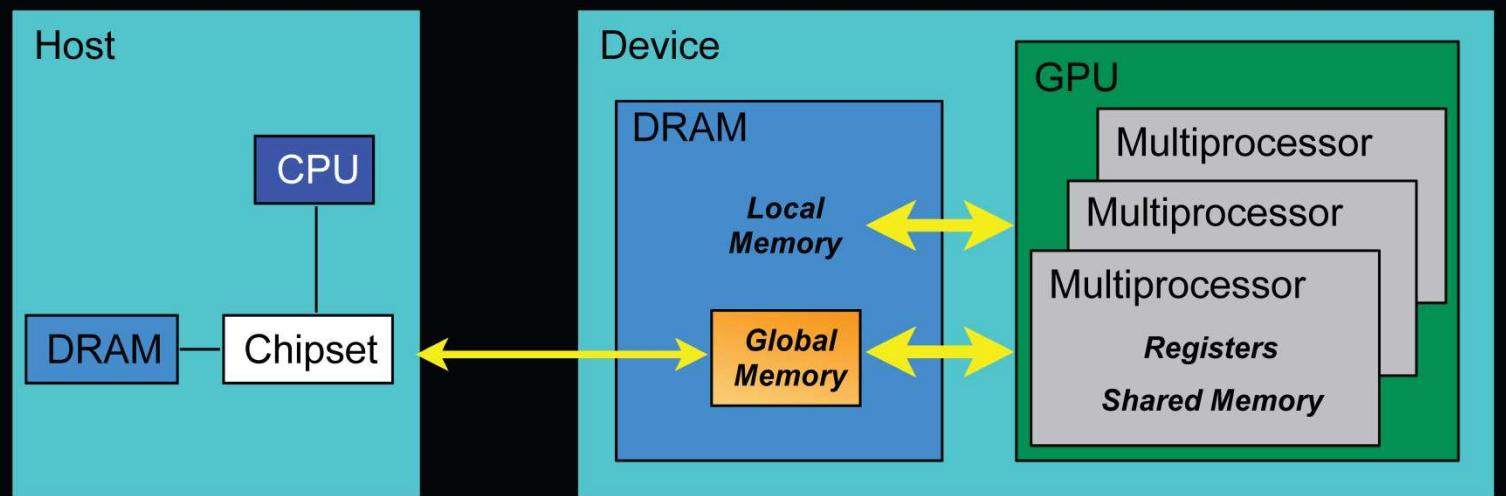
³ Accessible via ld.param and st.param instructions. Device function input and return parameters may have their address taken via mov; the parameter is then located on the stack frame and its address is in the .local state space.

⁴ Accessible only via the tex instruction.

Managing Memory

Unified memory space can be enabled on Fermi / CUDA 4.x and newer

- CPU and GPU have separate memory spaces
- Host (CPU) code manages device (GPU) memory:
 - Allocate / free
 - Copy data to and from device
 - Applies to *global* device memory (DRAM)



GPU Memory Allocation / Release

- **cudaMalloc(void ** pointer, size_t nbytes)**
- **cudaMemset(void * pointer, int value, size_t count)**
- **cudaFree(void* pointer)**

```
int n = 1024;
int nbytes = 1024*sizeof(int);
int *a_d = 0;
cudaMalloc( (void**) &a_d, nbytes );
cudaMemset( a_d, 0, nbytes );
cudaFree(a_d);
```

Data Copies

- **cudaMemcpy(void *dst, void *src, size_t nbytes, enum cudaMemcpyKind direction);**
 - **direction** specifies locations (host or device) of **src** and **dst**
 - Blocks CPU thread: returns after the copy is complete
 - Doesn't start copying until previous CUDA calls complete
- **enum cudaMemcpyKind**
 - **cudaMemcpyHostToDevice**
 - **cudaMemcpyDeviceToHost**
 - **cudaMemcpyDeviceToDevice**



Data Movement Example

```
int main(void)
{
    float *a_h, *b_h; // host data
    float *a_d, *b_d; // device data
    int N = 14, nBytes, i ;

    nBytes = N*sizeof(float);
    a_h = (float *)malloc(nBytes);
    b_h = (float *)malloc(nBytes);
    cudaMalloc((void **) &a_d, nBytes);
    cudaMalloc((void **) &b_d, nBytes);

    for (i=0, i<N; i++) a_h[i] = 100.f + i;

    cudaMemcpy(a_d, a_h, nBytes, cudaMemcpyHostToDevice);
    cudaMemcpy(b_d, a_d, nBytes, cudaMemcpyDeviceToDevice);
    cudaMemcpy(b_h, b_d, nBytes, cudaMemcpyDeviceToHost);

    for (i=0; i< N; i++) assert( a_h[i] == b_h[i] );
    free(a_h); free(b_h); cudaFree(a_d); cudaFree(b_d);
    return 0;
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```

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```

Host

a_h

b_h

Data Movement Example

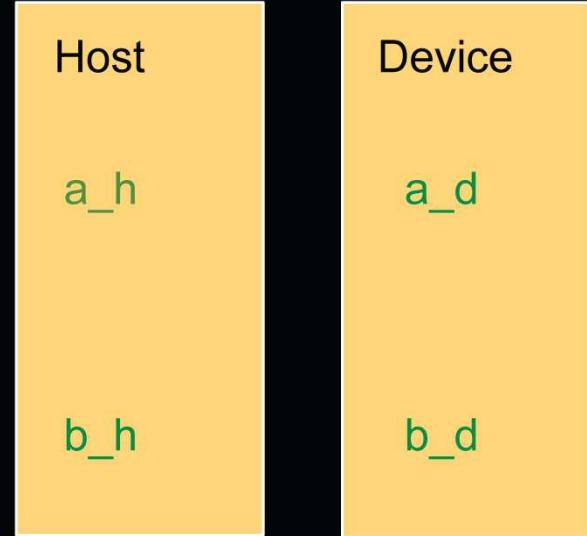
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Data Movement Example

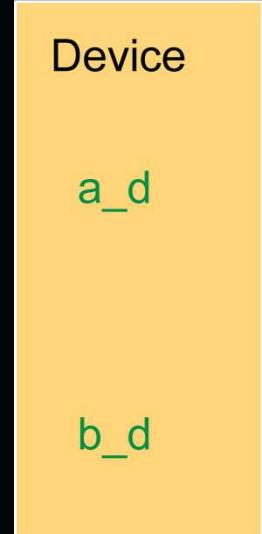
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Data Movement Example

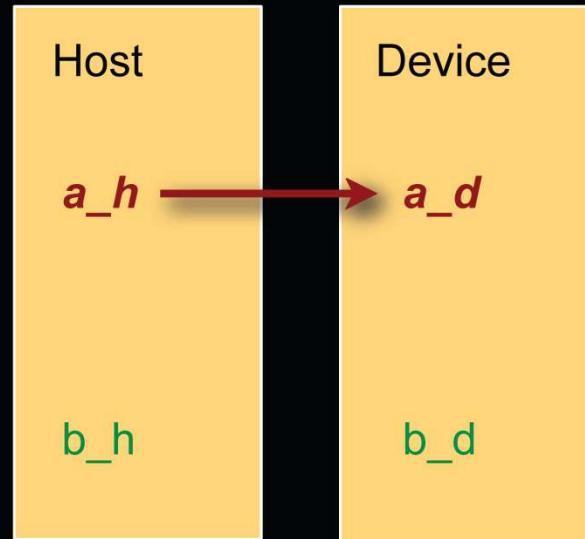
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Data Movement Example

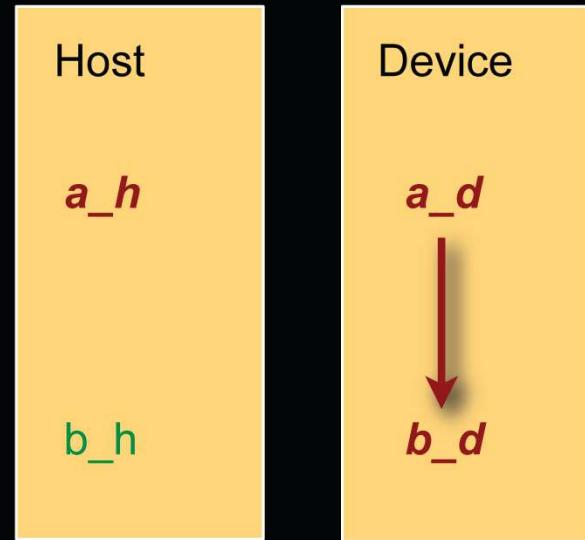
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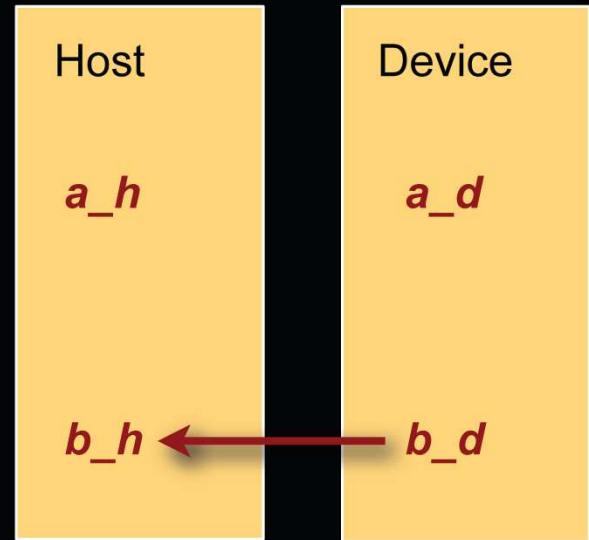
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Data Movement Example

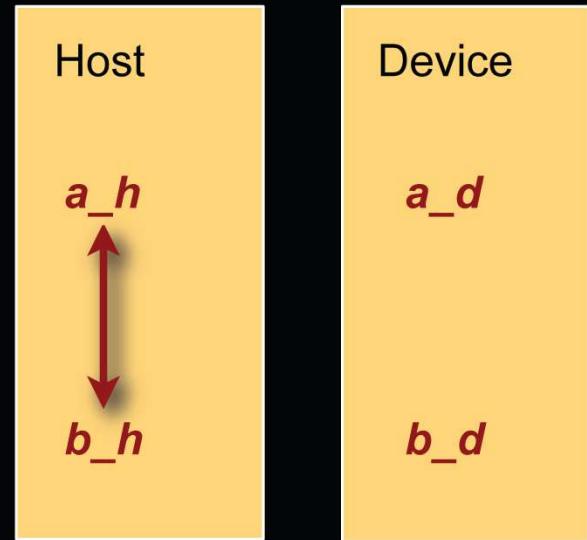
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    free(a_h); free(b_h); cudaFree(a_d); cudaFree(b_d);
    return 0;
}
```





Executing Code on the GPU

- Kernels are C functions with some restrictions
 - Cannot access host memory except: (*) and (**)
 - Must have **void** return type
 - No variable number of arguments (“varargs”)
 - (Not recursive) recursion supported on **__device__** functions from cc. 2.x (i.e., basically on **all** current GPUs)
 - No static variables

- Function arguments automatically copied from host to device

(*) “unified memory programming” introduced with CUDA 6 (cc. 3.x +):
allocate memory with **cudaMallocManaged()**; uses automatic migration

(**) also: mapped pinned (page-locked) memory (“zero-copy memory”):
allocate memory with **cudaMallocHost()**; beware of low performance!!

Note: UVA (“unified virtual addressing”; cc. 2.x +) is something different!!
just pertains to unified pointers (see **cudaPointerGetAttributes()**, ...) NVIDIA

Function Qualifiers

- Kernels designated by function qualifier:
 - **`_global_`**
 - Function called from host and executed on device
 - Must return void
 - Other CUDA function qualifiers
 - **`_device_`**
 - Function called from device and run on device
 - Cannot be called from host code
 - **`_host_`**
 - Function called from host and executed on host (default)
 - **`_host_`** and **`_device_`** qualifiers can be combined to generate both CPU and GPU code

Variable Qualifiers (GPU code)

- **__device__**
 - Stored in global memory (large, high latency, no cache)
 - Allocated with `cudaMalloc` (**__device__** qualifier implied)
 - Accessible by all threads
 - Lifetime: application
- **__shared__**
 - Stored in on-chip shared memory (very low latency)
 - Specified by execution configuration or at compile time
 - Accessible by all threads in the same thread block
 - Lifetime: thread block
- **Unqualified variables:**
 - Scalars and built-in vector types are stored in registers
 - What doesn't fit in registers spills to “local” memory

CUDA 6+: **__managed__** (with **__device__**) for managed memory (unified memory programming)



Launching Kernels

- Modified C function call syntax:

```
kernel<<<dim3 dG, dim3 dB>>>(...)
```

- Execution Configuration (“<<< >>>”)
 - **dG** - dimension and size of grid in blocks
 - Two-dimensional: **x** and **y**
 - Blocks launched in the grid: **dG.x * dG.y**
 - **dB** - dimension and size of blocks in threads:
 - Three-dimensional: **x**, **y**, and **z**
 - Threads per block: **dB.x * dB.y * dB.z**
 - Unspecified **dim3** fields initialize to 1

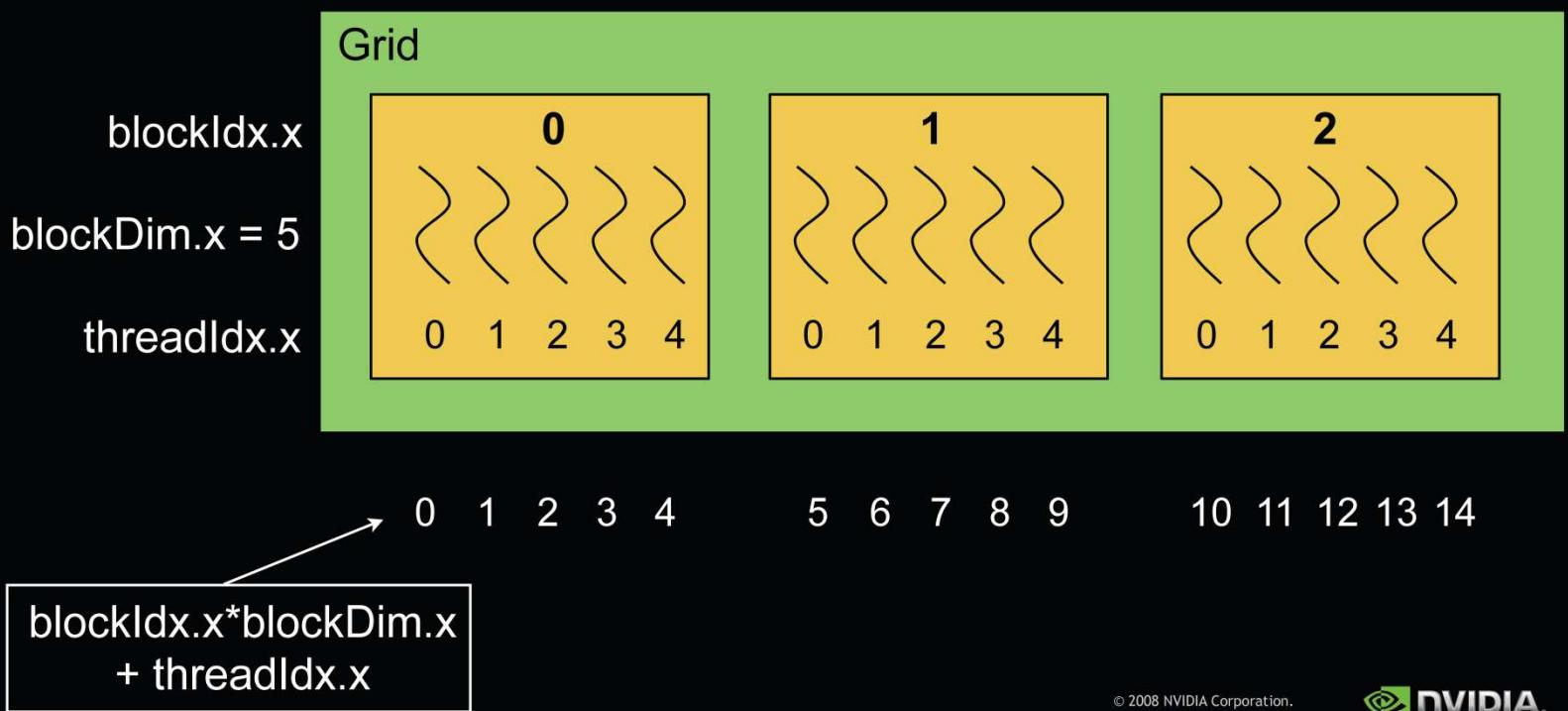
CUDA Built-in Device Variables

- All **`_global_`** and **`_device_`** functions have access to these automatically defined variables
 - **`dim3 gridDim;`**
 - Dimensions of the grid in blocks (at most 2D)
 - **`dim3 blockDim;`**
 - Dimensions of the block in threads
 - **`dim3 blockIdx;`**
 - Block index within the grid
 - **`dim3 threadIdx;`**
 - Thread index within the block



Unique Thread IDs

- Built-in variables are used to determine unique thread IDs
 - Map from local thread ID (`threadIdx`) to a global ID which can be used as array indices



Increment Array Example

CPU program

```
void inc_cpu(int *a, int N)
{
    int idx;

    for (idx = 0; idx < N; idx++)
        a[idx] = a[idx] + 1;
}

int main()
{
    ...
    inc_cpu(a, N);
}
```

CUDA program

```
__global__ void inc_gpu(int *a, int N)
{
    int idx = blockIdx.x * blockDim.x
              + threadIdx.x;
    if (idx < N)
        a[idx] = a[idx] + 1;
}

int main()
{
    ...
    dim3 dimBlock (blocksize);
    dim3 dimGrid( ceil( N / (float)blocksize ) );
    inc_gpu<<<dimGrid, dimBlock>>>(a, N);
}
```

Thread Cooperation

- The Missing Piece: threads may need to cooperate
- Thread cooperation is valuable
 - Share results to avoid redundant computation
 - Share memory accesses
 - Drastic bandwidth reduction
- Thread cooperation is a powerful feature of CUDA
- Cooperation between a monolithic array of threads is not scalable
 - Cooperation within smaller **batches** of threads is scalable



Host Synchronization

- All kernel launches are asynchronous
 - control returns to CPU immediately
 - kernel executes after all previous CUDA calls have completed
 - `cudaMemcpy()` is synchronous
 - control returns to CPU after copy completes
 - copy starts after all previous CUDA calls have completed
 - `cudaThreadSynchronize()`
 - blocks until all previous CUDA calls complete
- CUDA 4.x or newer:
`cudaDeviceSynchronize()` and
`cudaStreamSynchronize()`

Host Synchronization Example

```
// copy data from host to device  
cudaMemcpy(a_d, a_h, numBytes, cudaMemcpyHostToDevice);  
  
// execute the kernel  
inc_gpu<<<ceil(N/(float)blocksize), blocksize>>>(a_d, N);  
  
// run independent CPU code  
run_cpu_stuff();  
  
// copy data from device back to host  
cudaMemcpy(a_h, a_d, numBytes, cudaMemcpyDeviceToHost);
```



Device Runtime Component: Synchronization Function

- `void __syncthreads();`
- **Synchronizes all threads in a block**
 - Once all threads have reached this point, execution resumes normally
 - Used to avoid RAW / WAR / WAW hazards when accessing shared
- **Allowed in conditional code only if the conditional is uniform across the entire thread block**

Synchronization

- Threads in the same block can communicate using shared memory
- No HW global synchronization function yet
 - `__syncthreads()`
 - Barrier for threads only within the current block
 - `__threadfence()`
 - Flushes global memory writes to make them visible to all threads

Plus newer sync functions, e.g., from compute capability 2.x:

`__syncthreads_count()`, `__syncthreads_and/or()`,
`__threadfence_block()`, `__threadfence_system()`, ...

Now: Must use versions with `_sync` suffix, because of
Independent Thread Scheduling (compute capability 7.x and newer)!

COOPERATIVE GROUPS

Kyrylo Perelygin, Yuan Lin
GTC 2017



COOPERATIVE GROUPS VS BUILT-IN FUNCTIONS

Example: warp aggregated atomic

```
// increment the value at ptr by 1 and return the old value
__device__ int atomicAggInc(int *p);

coalesced_group g = coalesced_threads();
int res;
if (g.thread_rank() == 0)
    res = atomicAdd(p, g.size());
res = g.shfl(res, 0);
return g.thread_rank() + res;
```

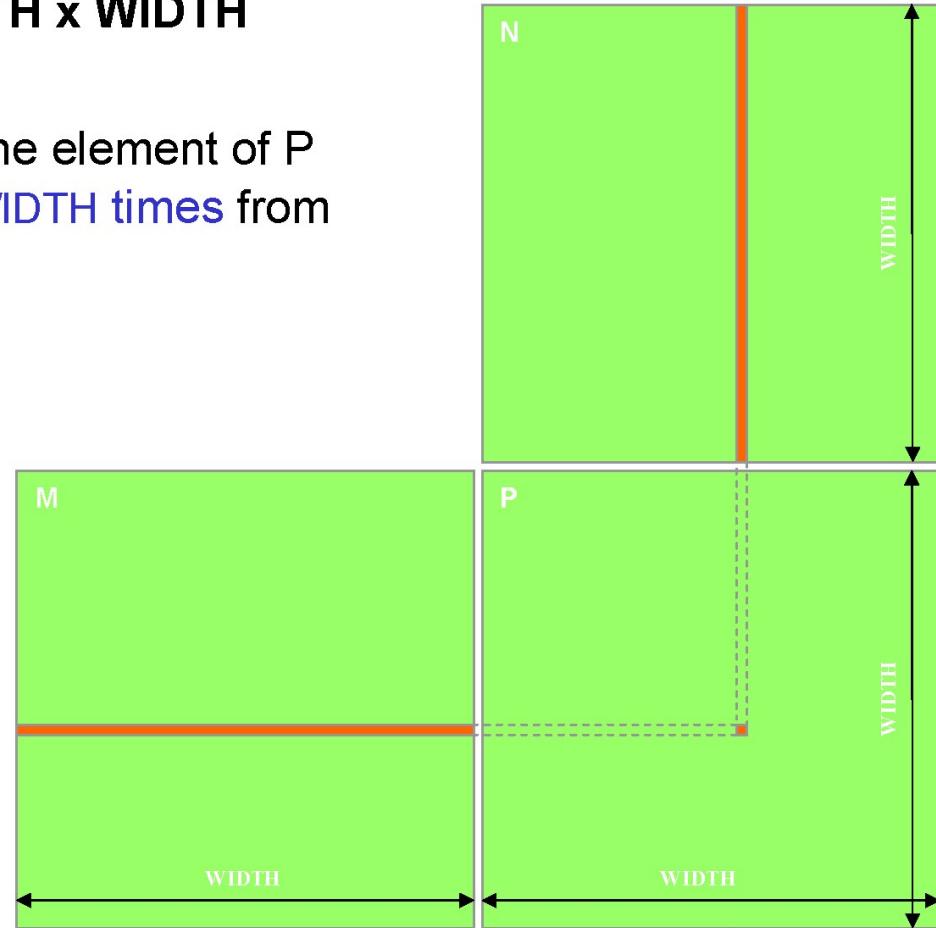
```
int mask = __activemask();
int rank = __popc(mask & __lanemask_lt());
int leader_lane = __ffs(mask) - 1;
int res;
if (rank == 0)
    res = atomicAdd(p, __popc(mask));
res = __shfl_sync(mask, res, leader_lane);
return rank + res;
```

Matrix-Matrix Multiplication

$$\mathbf{P} = \mathbf{M} \mathbf{N}$$

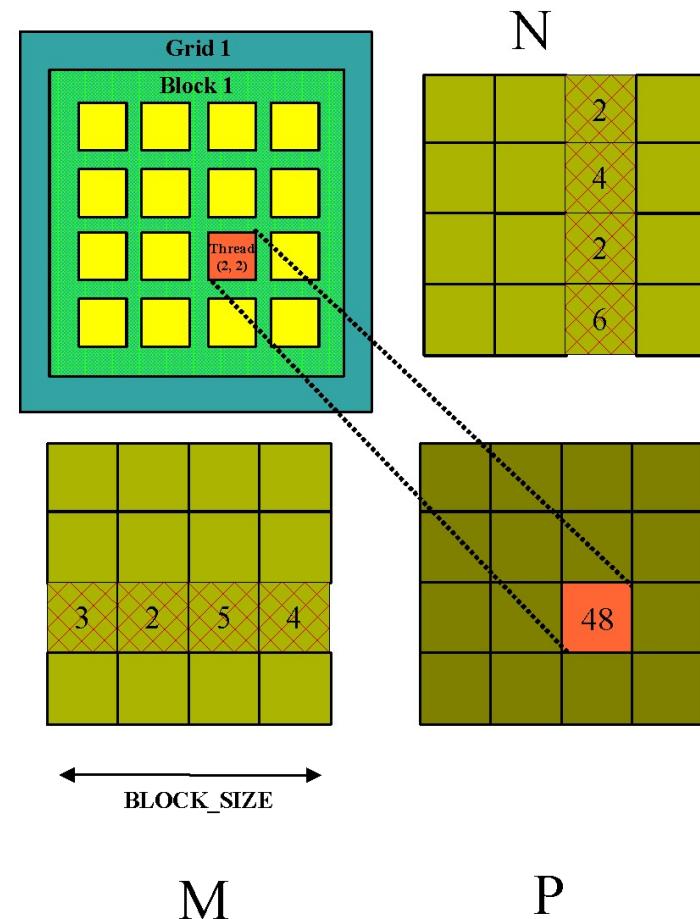
Programming Model: Square Matrix Multiplication

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



Multiply Using One Thread Block

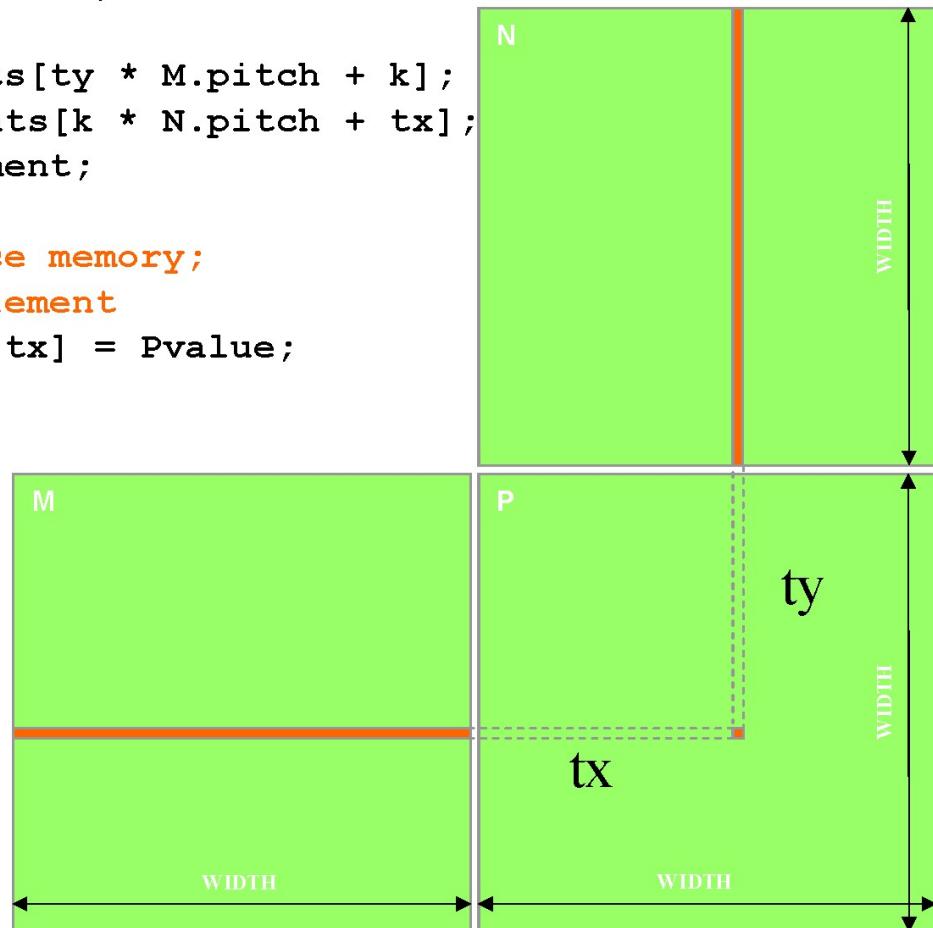
- **One block of threads computes matrix P**
 - Each thread computes one element of P
- **Each thread**
 - Loads a row of matrix M
 - Loads a column of matrix N
 - Perform one multiply and addition for each pair of M and N elements
 - Compute to off-chip memory access ratio close to 1:1 (not very high)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



Matrix Multiplication

Device-Side Kernel Function (cont.)

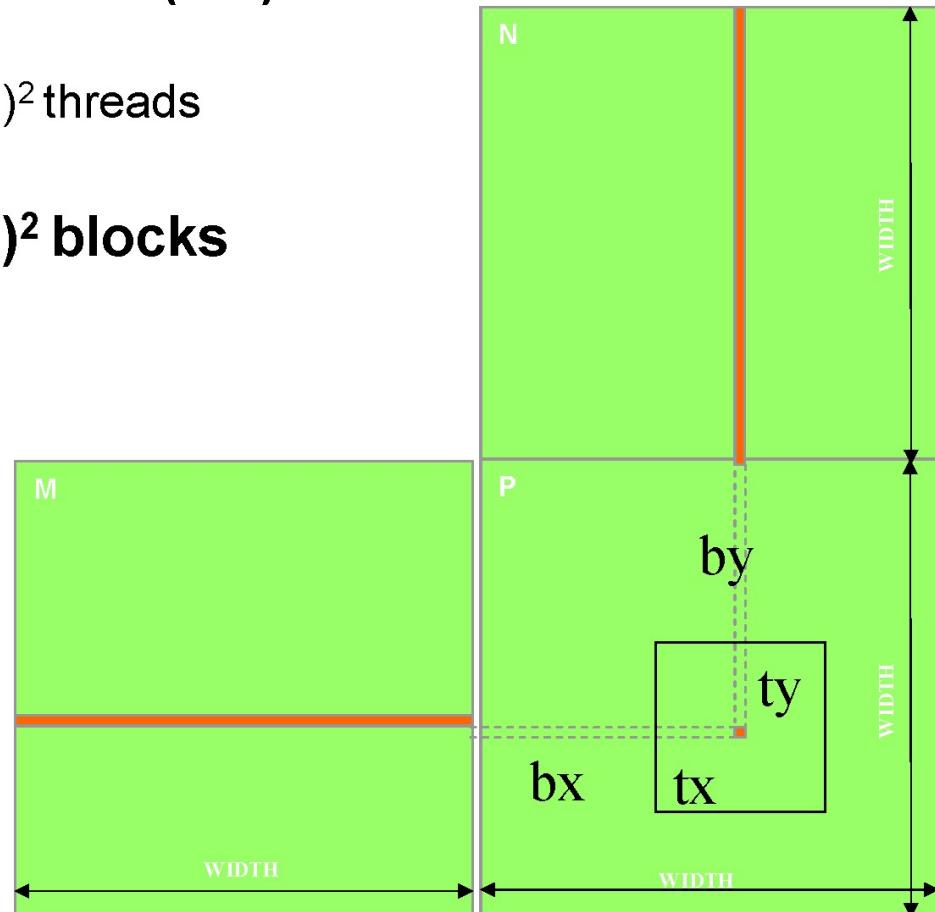
```
...  
for (int k = 0; k < M.width; ++k)  
{  
    float Melement = M.elements[ty * M.pitch + k];  
    float Nelement = Nd.elements[k * N.pitch + tx];  
    Pvalue += Melement * Nelement;  
}  
// Write the matrix to device memory;  
// each thread writes one element  
P.elements[ty * blockDim.x+ tx] = Pvalue;  
}
```



Handling Arbitrary Sized Square Matrices

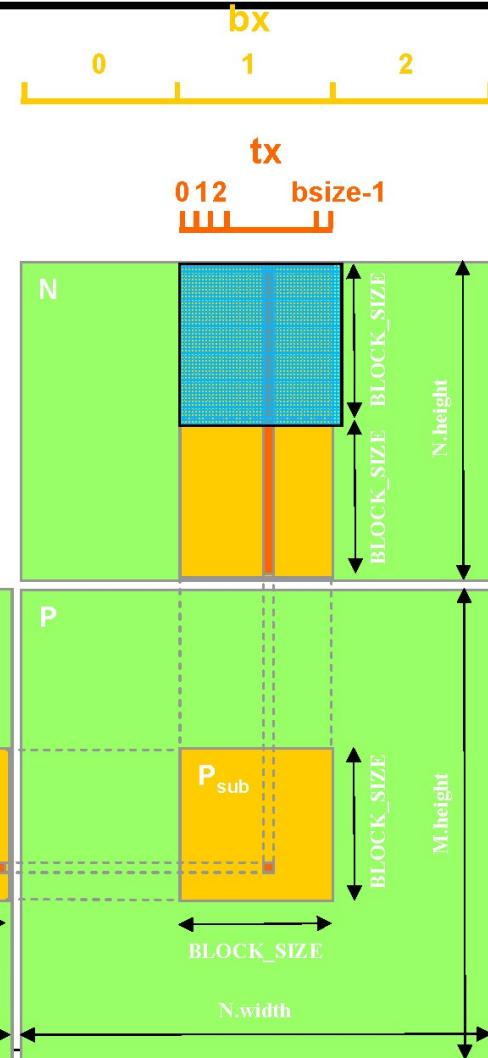
- Have each 2D thread block to compute a $(BLOCK_WIDTH)^2$ sub-matrix (tile) of the result matrix
 - Each has $(BLOCK_WIDTH)^2$ threads
- Generate a 2D Grid of $(WIDTH/BLOCK_WIDTH)^2$ blocks

You still need to put a loop around the kernel call for cases where WIDTH is greater than Max grid size!



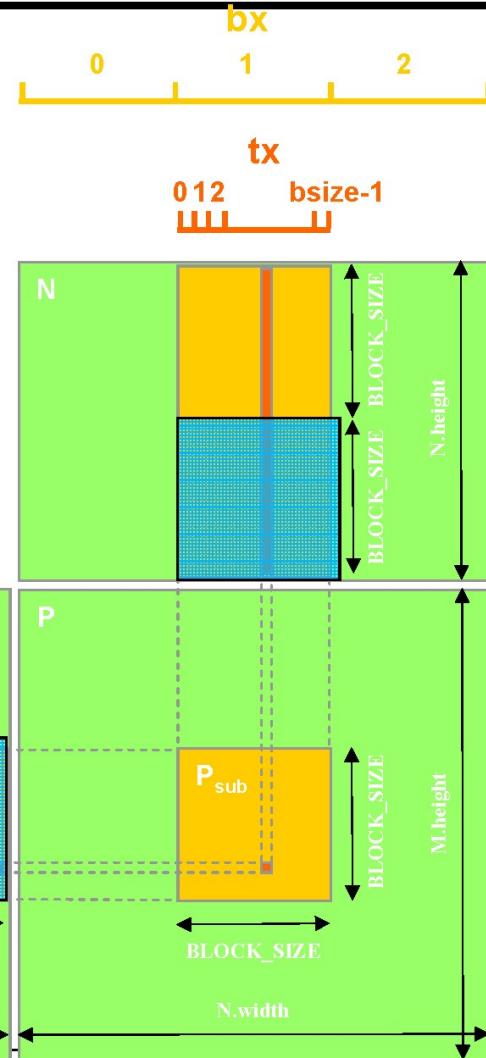
Multiply Using Several Blocks - Idea

- One thread per element of P
- Load sub-blocks of M and N into shared memory
- Each thread reads one element of M and one of N
- Reuse each sub-block for all threads, i.e. for all elements of P
- Outer loop on sub-blocks



Multiply Using Several Blocks - Idea

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Example: Matrix Multiplication (1)

- Copy matrices to device; invoke kernel; copy result matrix back to host

```
// Matrix multiplication - Host code
// Matrix dimensions are assumed to be multiples of BLOCK_SIZE
void MatMul(const Matrix A, const Matrix B, Matrix C)
{
    // Load A and B to device memory
    Matrix d_A;
    d_A.width = d_A.stride = A.width; d_A.height = A.height;
    size_t size = A.width * A.height * sizeof(float);
    cudaMalloc((void**)&d_A.elements, size);
    cudaMemcpy(d_A.elements, A.elements, size,
               cudaMemcpyHostToDevice);

    Matrix d_B;
    d_B.width = d_B.stride = B.width; d_B.height = B.height;
    size = B.width * B.height * sizeof(float);
    cudaMalloc((void**)&d_B.elements, size);
    cudaMemcpy(d_B.elements, B.elements, size,
               cudaMemcpyHostToDevice);
```



Example: Matrix Multiplication (2)

```
// Allocate C in device memory
Matrix d_C;
d_C.width = d_C.stride = C.width; d_C.height = C.height;
size = C.width * C.height * sizeof(float);
cudaMalloc((void**)&d_C.elements, size);

// Invoke kernel
dim3 dimBlock(BLOCK_SIZE, BLOCK_SIZE);
dim3 dimGrid(B.width / dimBlock.x, A.height / dimBlock.y);
MatMulKernel<<<dimGrid, dimBlock>>>(d_A, d_B, d_C);

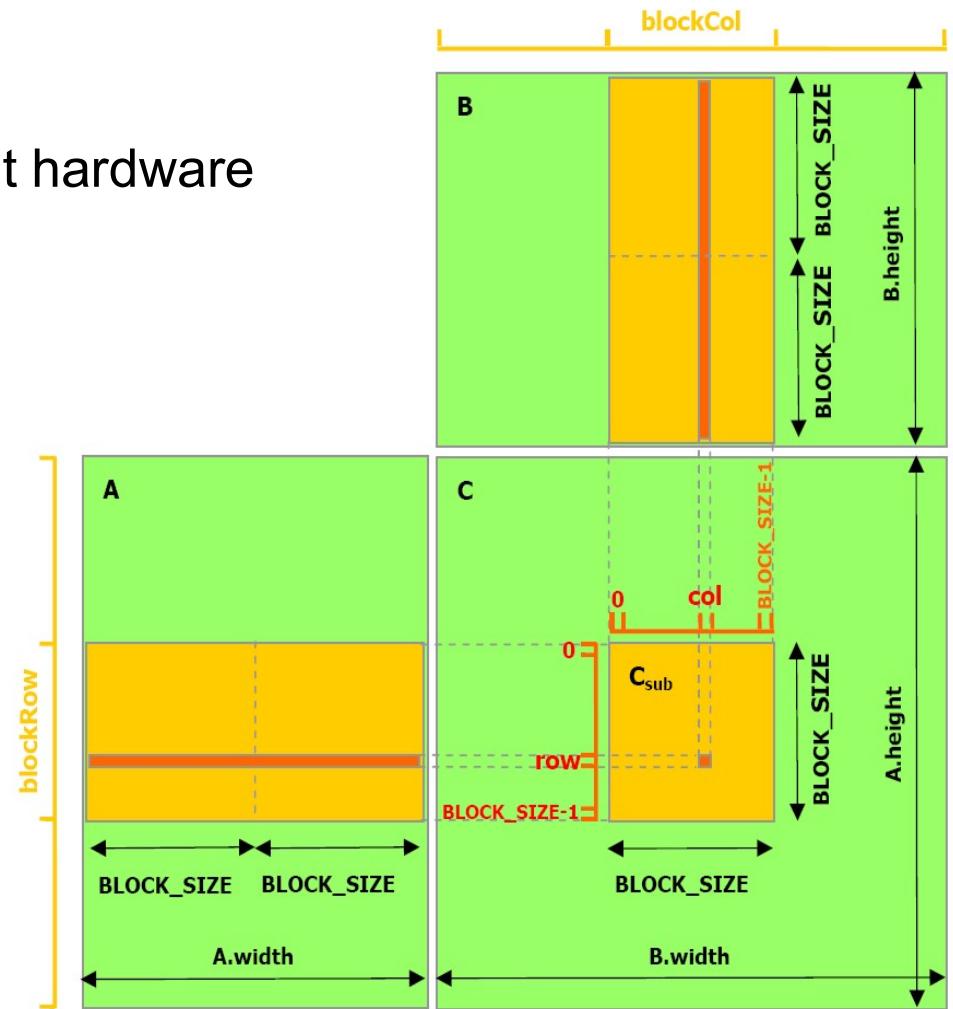
// Read C from device memory
cudaMemcpy(C.elements, d_C.elements, size,
           cudaMemcpyDeviceToHost);

// Free device memory
cudaFree(d_A.elements);
cudaFree(d_B.elements);
cudaFree(d_C.elements);
}
```

Example: Matrix Multiplication (3)



- Multiply matrix block-wise
- Set BLOCK_SIZE for efficient hardware use, e.g., to 16 on cc. 1.x or 16 or 32 on cc. 2.x +
- Maximize parallelism
 - Launch as many threads per block as block elements
 - Each thread fetches one element of block
 - Perform row * column dot products in parallel





Example: Matrix Multiplication (4)

```
__global__ void MatrixMul( float *matA, float *matB, float *matC, int w )
{
    __shared__ float blockA[ BLOCK_SIZE ][ BLOCK_SIZE ];
    __shared__ float blockB[ BLOCK_SIZE ][ BLOCK_SIZE ];

    int bx = blockIdx.x; int tx = threadIdx.x;
    int by = blockIdx.y; int ty = threadIdx.y;

    int col = bx * BLOCK_SIZE + tx;
    int row = by * BLOCK_SIZE + ty;

    float out = 0.0f;
    for ( int m = 0; m < w / BLOCK_SIZE; m++ ) {

        blockA[ ty ][ tx ] = matA[ row * w + m * BLOCK_SIZE + tx ];
        blockB[ ty ][ tx ] = matB[ col + ( m * BLOCK_SIZE + ty ) * w ];
        __syncthreads();

        for ( int k = 0; k < BLOCK_SIZE; k++ ) {
            out += blockA[ ty ][ k ] * blockB[ k ][ tx ];
        }
        __syncthreads();
    }

    matC[ row * w + col ] = out;
}
```

Caveat: for brevity, this code assumes matrix sizes are a multiple of the block size (either because they really are, or because padding is used; otherwise guard code would need to be added)

Thank you.