CUDA/GPU Programming(2)

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Acknowledgement

- Some Slides are from David Kirk Wen-mei Hwu’s UIUC GPU Course

- Some Slides are from Patrick Cozzi University of Pennsylvania CIS 565

Contents

- Built-ins and functions
- Memory model Recall
- Synchronizing threads
- Matrix multiply revisited

Functional Declarations

	Executed on the:	Only callable from the:
`__global__ void KernelFunc()`	device	host
`__device__ float DeviceFunc()`	device	device
`__host__ float HostFunc()`	host	host

See Appendix B.1 in the NVIDIA CUDA C Programming Guide for more details

Functional Declarations

- __global__
  - Must return void
- _device_
  - Used to be Inlined by default
  - Think as it is.

See Appendix B.1 in the NVIDIA CUDA C Programming Guide for more details

Functional Declarations

- What do these do?
  - `__global__ __host__ void func()`
  - `__device__ __host__ void func()`

Functional Declarations

- What do these do?
  - `__global__ __host__ void func()`
  - `__device__ __host__ void func()`

```
__host__ __device__ func()
{
#if __CUDA_ARCH__ == 100
    // Device code path for compute capability 1.0
#elif __CUDA_ARCH__ == 200
    // Device code path for compute capability 2.0
#elif !defined(__CUDA_ARCH__)
    // Host code path
#endif
}
```


Code from http://developer.download.nvidia.com/compute/cuda/3_2_prod/toolkit/docs/CUDA_C_Programming_Guide.pdf

Functional Declarations

- Global and device functions
  - Less recursion (ok with Fermi, kepler, Maxwell)
  - OK with malloc() but be cautious
  - Careful with function calls through pointers

- Consider thousands of threads following the same
- Instruction stream

Vector Types

- char[1–4], uchar[1–4]
- short[1–4], ushort[1–4]
- int[1–4], uint[1–4]
- long[1–4], ulong[1–4]
- longlong[1–4], ulonglong[1–4]
- float[1–4]
- double1, double2

Vector Types

- Available in host and device code
- Construct with `make_<type name>`

```
int2 i2 = make_int2(1, 2);
float4 f4 = make_float4(
  1.0f, 2.0f, 3.0f, 4.0f);
```

Vector Types

- Access with `.x`, `.y`, `.z`, and `.w`

```
int2 i2 = make_int2(1, 2);
int x = i2.x;
int y = i2.y;
```

  - No `.r`, `.g`, `.b`, `.a`, `etc.` like GLSL

Math Functions

- `double` and `float` overloads
  - No vector overloads
- On the host, functions use the C runtime implementation if available

See Appendix C in the NVIDIA CUDA C Programming Guide for a complete list of math functions

Math Functions

- Partial list:
  - `sqrt`, `rsqrt`
  - `exp`, `log`
  - `sin`, `cos`, `tan`, `sincos`
  - `asin`, `acos`, `atan2`
  - `trunc`, `ceil`, `floor`

See Appendix C in the NVIDIA CUDA C Programming Guide for a complete list of math functions

Math Functions

- *Intrinsic* function
  - Device only
  - Faster, but less accurate
  - Prefixed with `__`
  - `__exp`, `__log` , `__sin` , `__pow` , …

See Appendix C in the NVIDIA CUDA C Programming Guide for a complete list of math functions

Memory Model Recall

Recall:

- Device code 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
- Host code can
  - R/W per grid global and constant memories

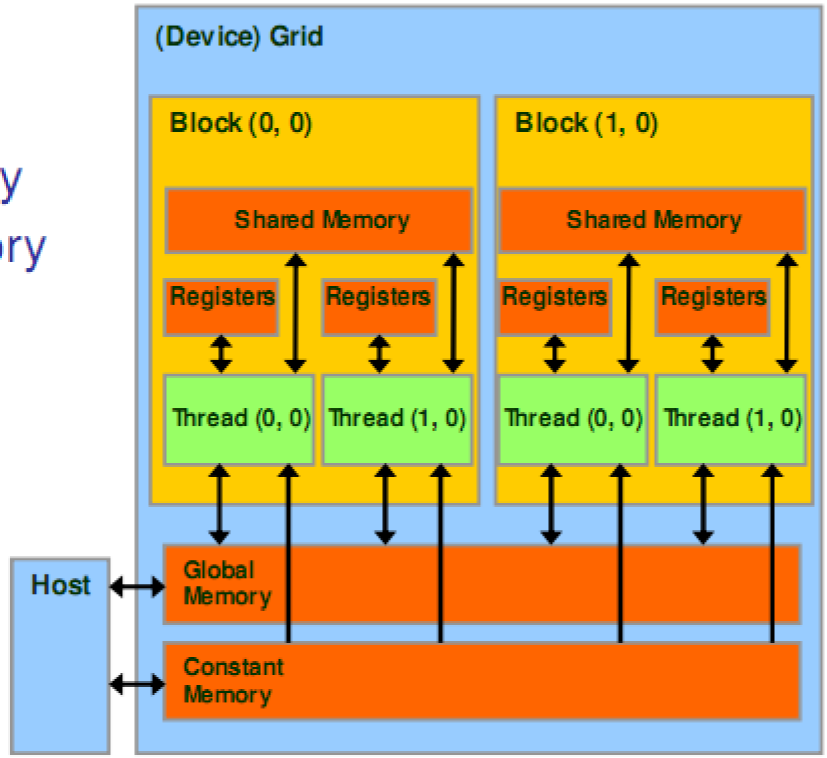
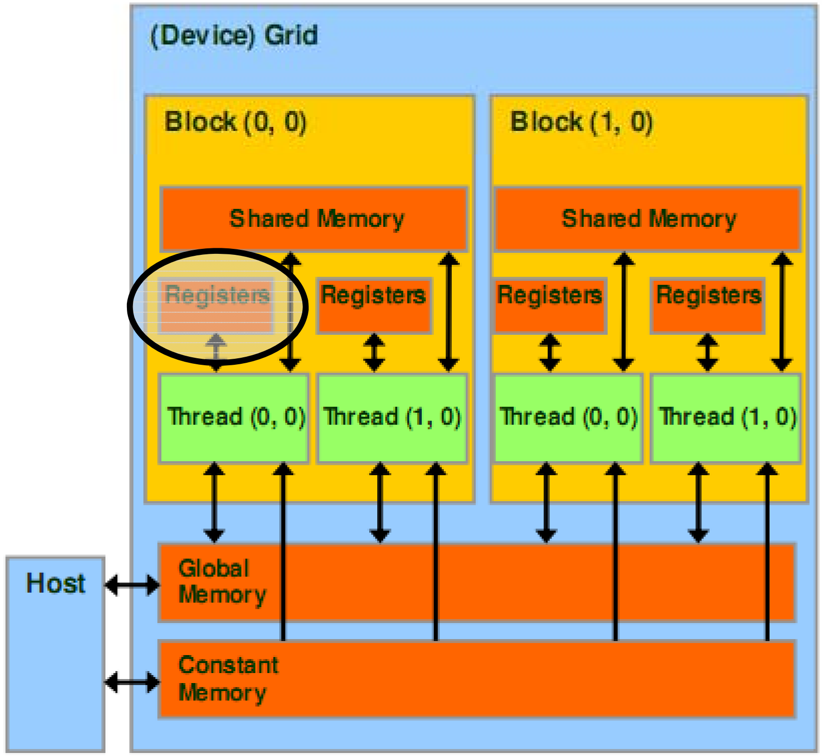


Image from: http://courses.engr.illinois.edu/ece498/al/textbook/Chapter2-CudaProgrammingModel.pdf

Memory Model

- Registers
  - Per thread
  - Fast, on-chip, read/wri
    access
  - Increasing the number o
    registers used by a ker
    has what affect?



Memory Model

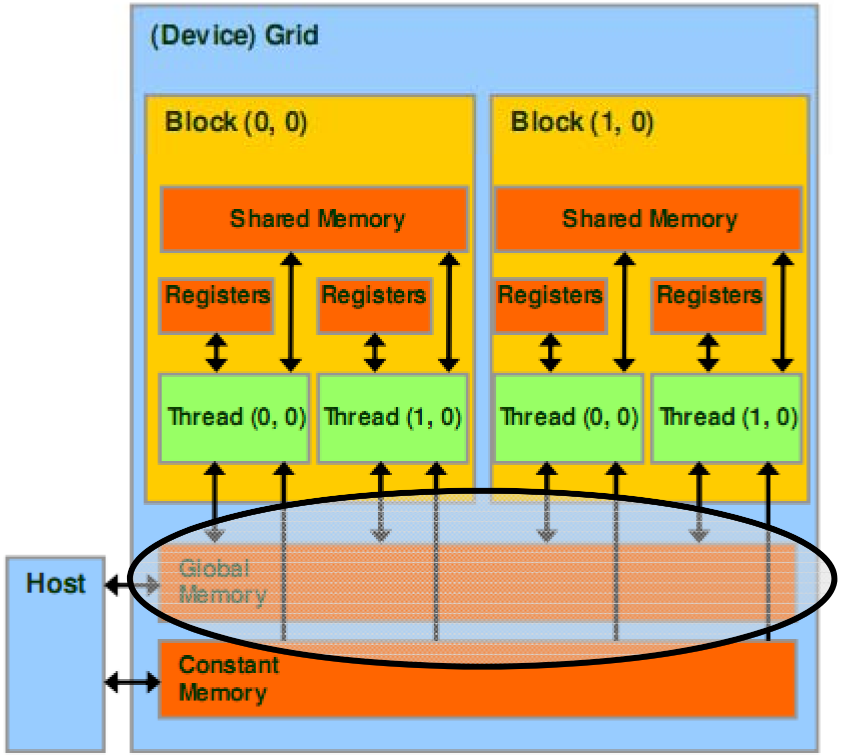
- Registers – G80
  - Per SM
    - Up to 768 threads
    - 8K registers
  - How many registers per thread?
- Registers – Kepler – Per SM
    - Up to 2048 threads
    - 64K Registers
- Registers –Maxwell– Per SM
    - Up to 2048 threads
    - 64K Registers

Memory Model

- Registers – G80
  - 8K / 768 = 10 registers per thread
  - Exceeding limit reduces threads by the block
  - Example: Each thread uses 11 registers, and each block has 256 threads
    - How many threads can a SM host?
    - How many warps can a SM host?
    - What does having less warps mean?

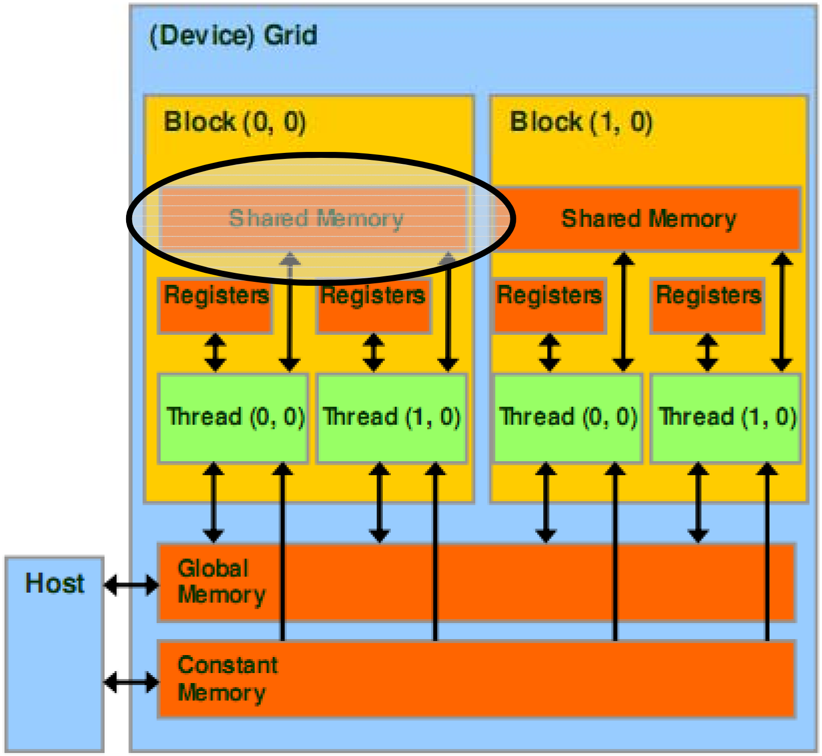
Memory Model

- Local Memory
  - Stored in global memory
    - Copy per thread
  - Used for automatic arra
    - Unless all accessed with constant indices



Memory Model

- Shared Memory
  - Per block
  - Fast, on-chip, read/wri
    access
  - Full speed random acces



Memory Model

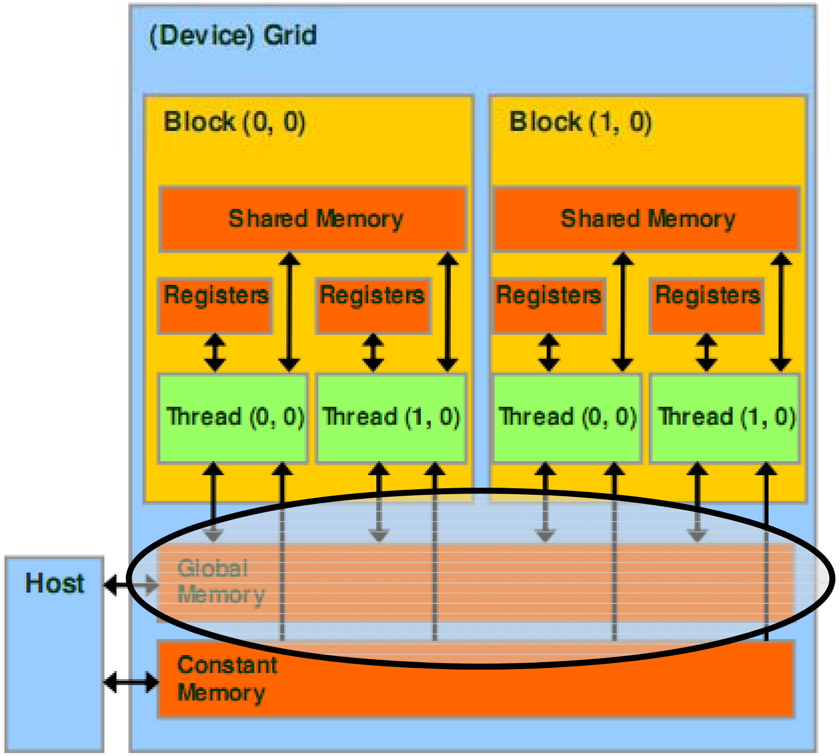
- Shared Memory – G80
  - Per SM
    - Up to 8 blocks
    - 16 KB
  - How many KB per block
- Shared Memory – Maxwell
  - Per SM
    - Up to 32 blocks
    - 96 KB
  - How many KB per block

Memory Model

- Shared Memory - G80
  - 16 KB / 8 = 2 KB per block
  - Example
    - If each block uses 5 KB, how many blocks can a SM host?

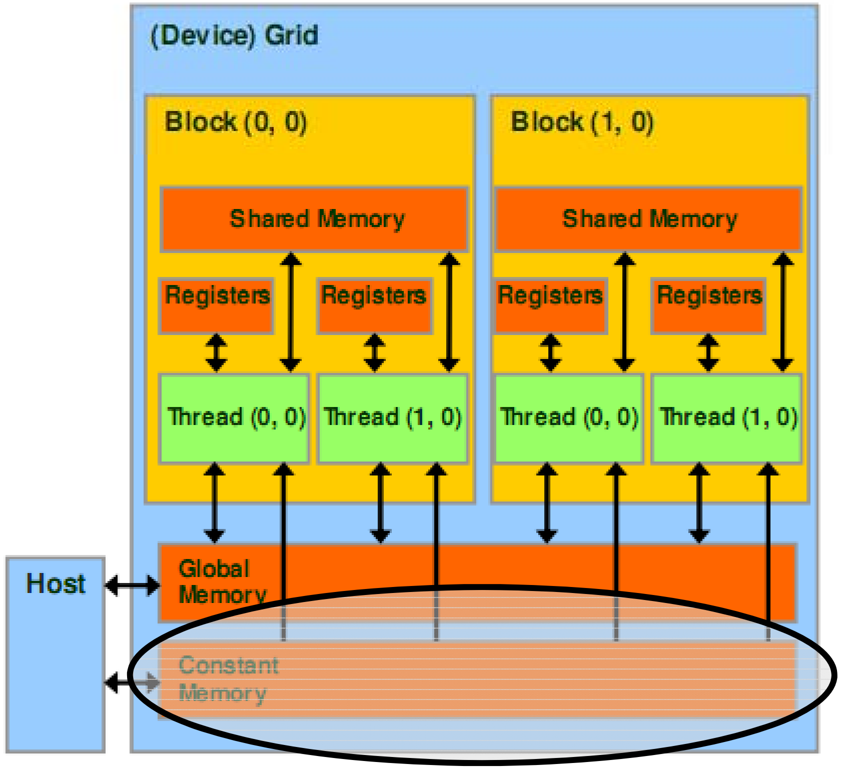
Memory Model

- Global Memory
  - Long latency (100s cycles)
  - Off-chip, read/write access
  - Random access causes performance hit
  - Host can read/write
  - GT200
    - 150 GB/s
    - Up to 4 GB
  - G80 - 86.4 GB/s



Memory Model

- Constant Memory
  - Short latency, high bandwidth, read only access when all threads access the same locatio
  - Stored in global memory but cached
  - Host can read/write
  - Up to 64 KB



Memory Model

Variable Declaration	Memory	Scope	Lifetime
`Automatic variables other than arrays`	register	thread	kernel
`Automatic array variables`	local	thread	kernel
`__shared__ int sharedVar;`	shared	block	kernel
`__device__ int globalVar;`	global	grid	application
`__constant__ int constantVar;`	constant	grid	application

See Appendix B.2 in the NVIDIA CUDA C Programming Guide for more details

Memory Model

- Global and constant variables
  - Host can access with
    - `cudaGetSymbolAddress()`
    - `cudaGetSymbolSize()`
    - `cudaMemcpyToSymbol()`
    - `cudaMemcpyFromSymbol()`
  - Constants must be declared outside of a function body

Review: Thread Hierarchies

```
int threadID = blockIdx.x *
  blockDim.x + threadIdx.x;
float x = input[threadID];
float y = func(x);
output[threadID] = y;
```

Review: Thread Hierarchies

```
int threadID = blockIdx.x *
  blockDim.x + threadIdx.x;
float x = input[threadID];
float y = func(x);
output[threadID] = y;
```

Use grid and block position to compute a thread id

Review: Thread Hierarchies

```
int threadID = blockIdx.x *
  blockDim.x + threadIdx.x;
float x = input[threadID];
float y = func(x);
output[threadID] = y;
```

Use thread id to read from input

Review: Thread Hierarchies

```
int threadID = blockIdx.x *
  blockDim.x + threadIdx.x;
float x = input[threadID];
float y = func(x);
output[threadID] = y;
```

Run function on input: data-parallel!

Review: Thread Hierarchies

```
int threadID = blockIdx.x *
  blockDim.x + threadIdx.x;
float x = input[threadID];
float y = func(x);
output[threadID] = y;
```

Use thread id to output result

Thread Synchronization

- Threads in a block can synchronize
  - call __syncthreads to create a barrier
  - A thread waits at this call until all threads in the block reach it, then all threads continue

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i + 1]);
```

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Time: 0

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Time: 1

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Threads 0 and 1 are blocked at barrier

Time: 1

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Time: 2

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Time: 3

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

All threads in block have reached barrier, any thread can continue

Time: 3

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Time: 4

Thread Synchronization

Thread 0

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 1

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 2

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```

Thread 3

```
Mds[i] = Md[j];
__syncthreads();
func(Mds[i], Mds[i+1]);
```


Time: 5

Thread Synchronization

- Why is it important that execution time be similar among threads?
- Why does it only synchronize within a block?

Thread Synchronization

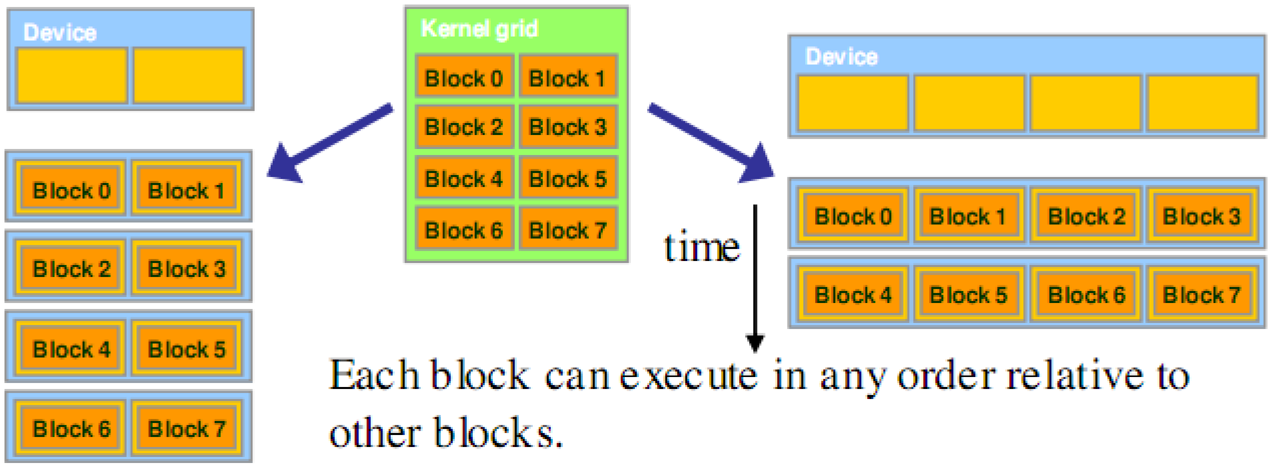


Figure 3.5 Lack of synchronization across blocks enables transparent scalability of CUDA programs

Image from http://courses.engr.illinois.edu/ece498/al/textbook/Chapter3-CudaThreadingModel.pdf

Thread Synchronization

- Can `__syncthreads()` cause a thread to hang?

Thread Synchronization

```
if (someFunc())
{
  __syncthreads();
}
// ...
```

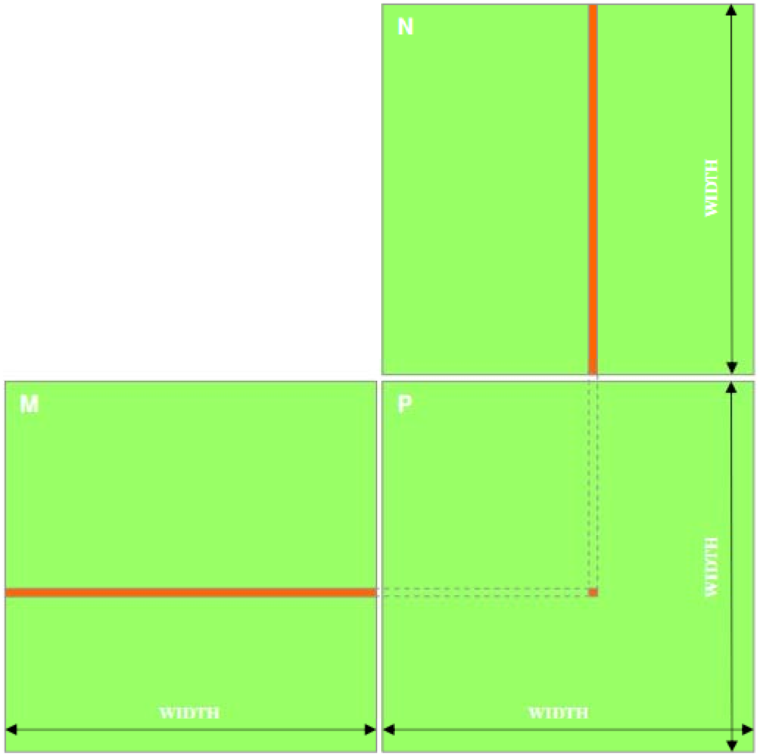
Thread Synchronization

```
if (someFunc())
{
  __syncthreads();
}
else
{
 __syncthreads();
}
```

Let’ s revisit matrix multiple

Matrix Multiply: CPU Implementation

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



Code from: http://courses.engr.illinois.edu/ece498/al/lectures/lecture3%20cuda%20threads%20spring%202010.ppt

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
   // 2D Thread ID
   int tx = threadIdx.x;
   int ty = threadIdx.y;

   // Pvalue stores the Pd element that is computed by the thread
   float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
       float Mdelement = Md[ty * Md.width + k];
       float Ndelement = Nd[k * Nd.width + tx];
       Pvalue += Mdelement * Ndelement;
     }

   // Write the matrix to device memory each thread writes one element
   Pd[ty * Width + tx] = Pvalue;
}
```

Accessing a matrix, so using a 2D block

Code from: http://courses.engr.illinois.edu/ece498/al/textbook/Chapter2-CudaProgrammingModel.pdf

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
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   float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
       float Mdelement = Md[ty * Md.width + k];
       float Ndelement = Nd[k * Nd.width + tx];
       Pvalue += Mdelement * Ndelement;
    }

   // Write the matrix to device memory each thread writes one element
   Pd[ty * Width + tx] = Pvalue;
}
```

Each kernel computes one output

Code from: http://courses.engr.illinois.edu/ece498/al/textbook/Chapter2-CudaProgrammingModel.pdf

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
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    // 2D Thread ID
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    int ty = threadIdx.y;

    // Pvalue stores the Pd element that is computed by the thread
    float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
        float Mdelement = Md[ty * Md.width + k];
        float Ndelement = Nd[k * Nd.width + tx];
        Pvalue += Mdelement * Ndelement;
    }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

Where did the two outer for loops in the CPU implementation go?

Code from: http://courses.engr.illinois.edu/ece498/al/textbook/Chapter2-CudaProgrammingModel.pdf

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
    // 2D Thread ID
    int tx = threadIdx.x;
    int ty = threadIdx.y;

    // Pvalue stores the Pd element that is computed by the thread
    float Pvalue = 0;

     for (int k = 0; k < Width; ++k)
     {
         float Mdelement = Md[ty * Md.width + k];
         float Ndelement = Nd[k * Nd.width + tx];
         Pvalue += Mdelement * Ndelement;
      }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

No locks or synchronization, why?

Code from: http://courses.engr.illinois.edu/ece498/al/textbook/Chapter2-CudaProgrammingModel.pdf

Matrix Multiply

- Problems
  - Limited matrix size
    - Only uses one block
    - G80 and GT200 – up to 512 threads per block
    - Fermi, Kepler, Maxwell – up to 1024 threads per block
  - Lots of global memory access

Matrix Multiply

- Remove size limitation
  - Break **Pd** matrix into tiles
  - Assign each tile to a block
  - Use **threadIdx** and **blockIdx** for indexing

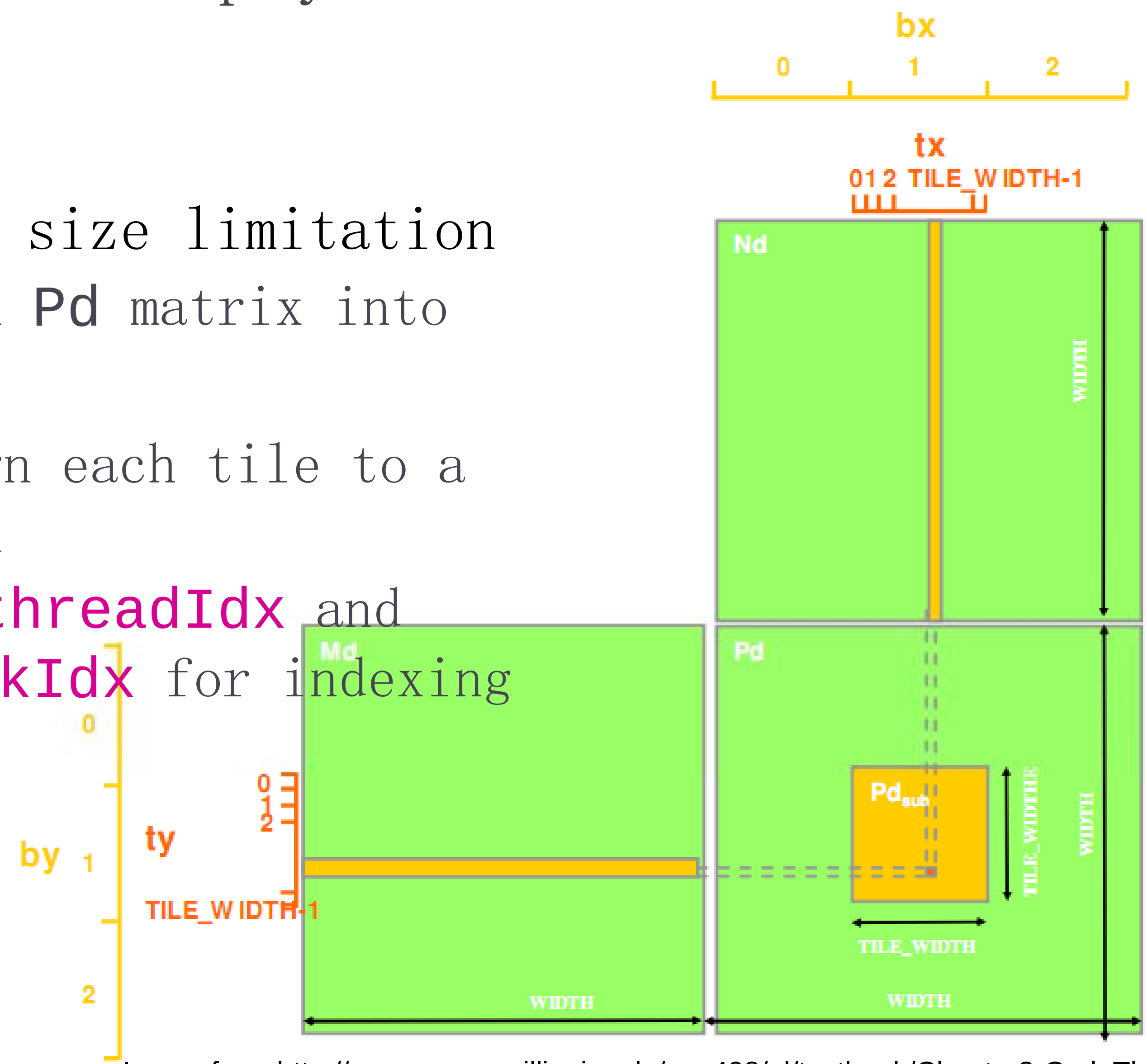

Image from http://courses.engr.illinois.edu/ece498/al/textbook/Chapter3-CudaThreadingModel.pdf

Matrix Multiply

- Example
  - Matrix: 4x4
  - TILE_WIDTH = 2
  - Block size: 2x2

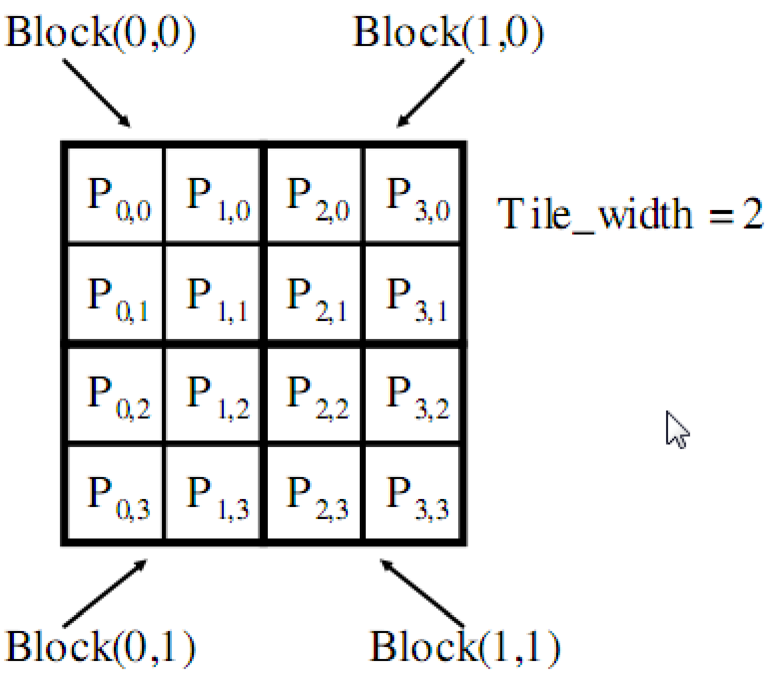

Image from http://courses.engr.illinois.edu/ece498/al/textbook/Chapter3-CudaThreadingModel.pdf

Matrix Multiply

- Example
  - Matrix: 4x4
  - `TILE_WIDTH` = 2
  - Block size: 2x2

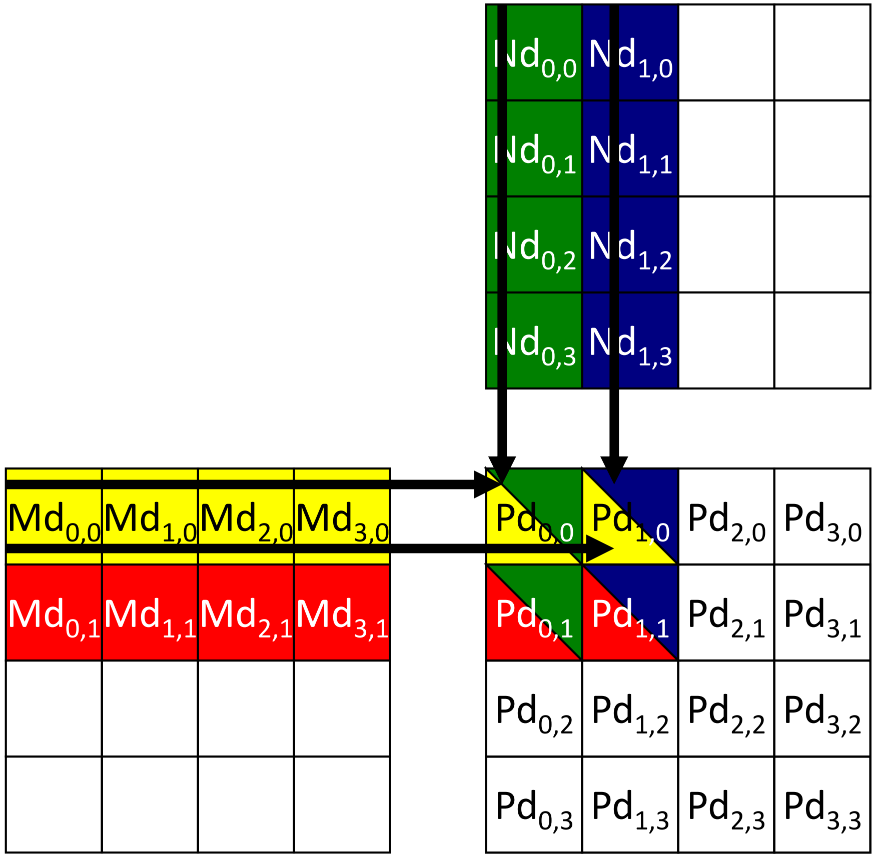

Image from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  int Row = blockIdx.y * blockDim.y + threadIdx.y;
  int Col = blockIdx.x * blockDim.x + threadIdx.x;

  float Pvalue = 0;
  for (int k = 0; k < Width; ++k)
    Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];

  Pd[Row * Width + Col] = Pvalue;
}
```


Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

Calculate the row index of the Pd element and M

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  int Row = blockIdx.y * blockDim.y + threadIdx.y;
  int Col = blockIdx.x * blockDim.x + threadIdx.x;

  float Pvalue = 0;
  for (int k = 0; k < Width; ++k)
    Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];

  Pd[Row * Width + Col] = Pvalue;
}
```


Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

Calculate the column index of Pd and N

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  int Row = blockIdx.y * blockDim.y + threadIdx.y;
  int Col = blockIdx.x * blockDim.x + threadIdx.x;

  float Pvalue = 0;
  for (int k = 0; k < Width; ++k)
    Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];

  Pd[Row * Width + Col] = Pvalue;
}
```


Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

Each thread computes one element of the block sub-matrix

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  int Row = blockIdx.y * blockDim.y + threadIdx.y;
  int Col = blockIdx.x * blockDim.x + threadIdx.x;

  float Pvalue = 0;
  for (int k = 0; k < Width; ++k)
    Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];

  Pd[Row * Width + Col] = Pvalue;
}
```


Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

- Invoke kernel:

```
dim3 dimGrid(Width / TILE_WIDTH, Height / TILE_WIDTH);
dim3 dimBlock(TILE_WIDTH, TILE_WIDTH);

MatrixMulKernel<<<dimGrid, dimBlock>>>(
  Md, Nd, Pd, TILE_WIDTH);
```

What about global memory access?

Matrix Multiply

- Limited by global memory bandwidth
  - Tesla K40 peak GFLOPS(SP): 5000
  - Require 20000 GB/s to achieve this
  - G80 memory bandwidth: 288 GB/s
    - Limits code to 72 GFLOPS
    - In practice, code runs at 60 GFLOPS

  - Must drastically reduce global memory access

Matrix Multiply

- Each input element is read by `Width` threads
- Use shared memory to reduce global memory bandwidth

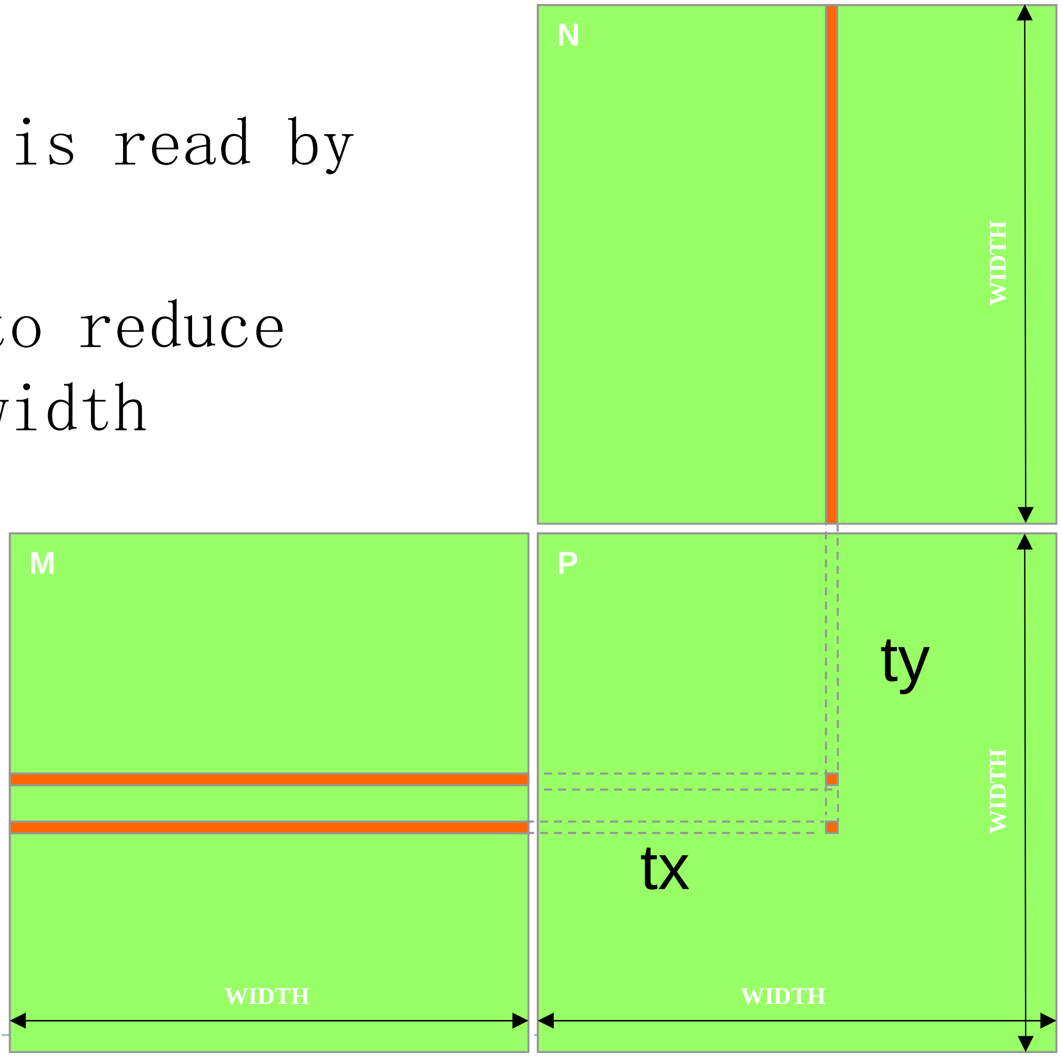

Image from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

- Break kernel into phases
  - Each phase accumlates **Pd** using a subset of **Md** and **Nd**
  - Each phase has good data locality

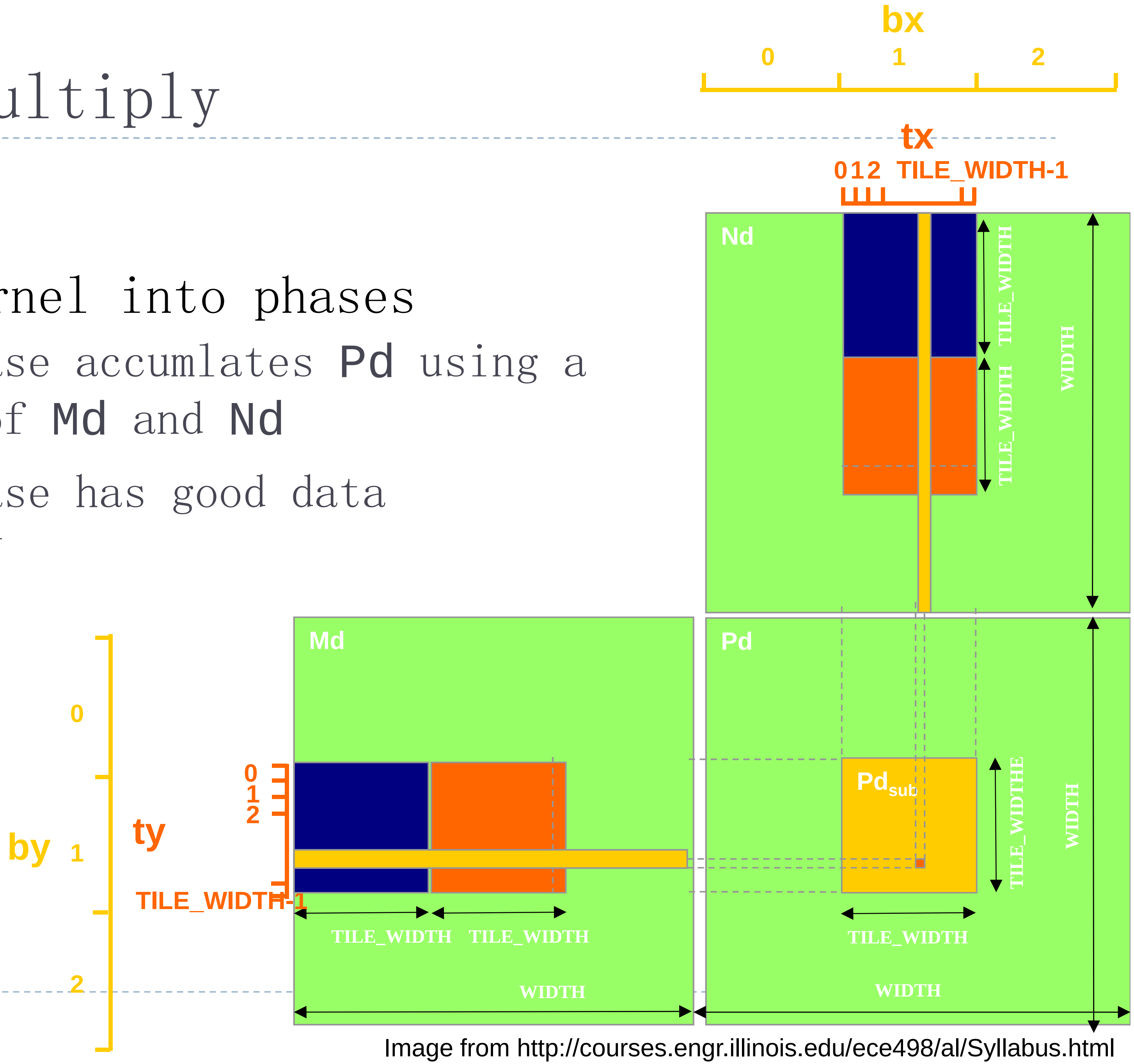

Image from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

- Each thread
  - loads one element of **Md** and **Nd** in the tile into shared memory

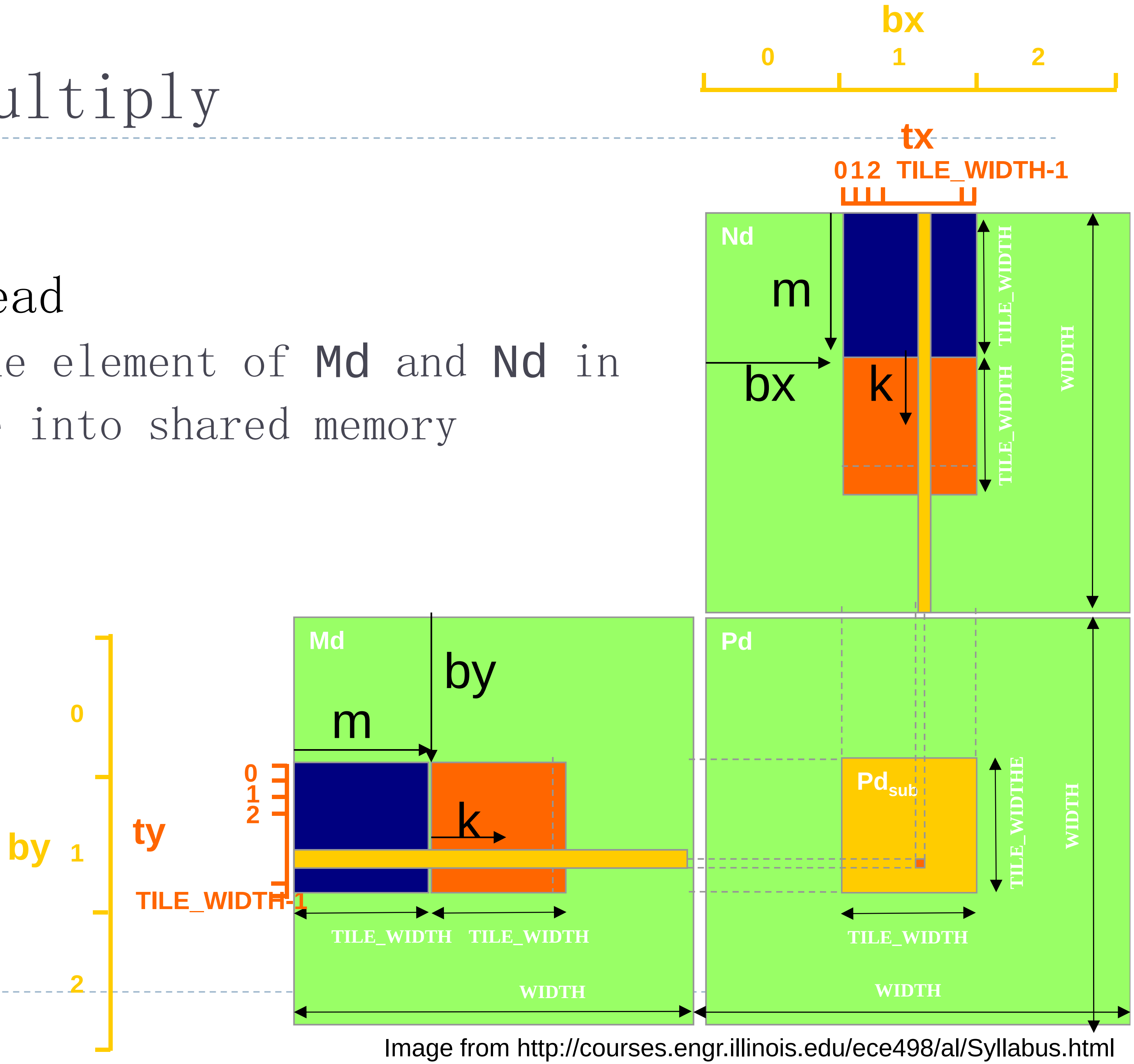

Image from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```


Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Shared memory for a subset of Md and Nd

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

`Width/TILE_WIDTH`
- Number of phases

`m`
- Index for current phase

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Bring one element each from Md and Nd into shared memory

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Wait for every thread in the block, i.e., wait for the tile to be in shared memory

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Accumulate subset of dot product

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Why?

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

```
__global__ void MatrixMulKernel(
  float* Md, float* Nd, float* Pd, int Width)
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

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

  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __synchthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
```

Write final answer to global memory

Code from http://courses.engr.illinois.edu/ece498/al/Syllabus.html

Matrix Multiply

- How do you pick `TILE_WIDTH`?
  - How can it be too large?

Matrix Multiply

- How do you pick `TILE_WIDTH`?
  - How can it be too large?
    - By exceeding the maximum number of threads/block
      - G80 and GT200 – 512
      - Fermi – 1024

Matrix Multiply

- How do you pick **`TILE_WIDTH`**?
  - How can it be too large?
    - By exceeding the maximum number of threads/block
      - G80 and GT200 – 512
      - Fermi – 1024
    - By exceeding the shared memory limitations
      - G80: 16KB per SM and up to 8 blocks per SM
        - 2 KB per block
        - 1 KB for **`Nds`** and 1 KB for **`Mds`** (16 * 16 * 4)
        - **`TILE_WIDTH`** = 16
        - A larger **`TILE_WIDTH`** will result in less blocks

Matrix Multiply

- Shared memory tiling benefits
  - Reduces global memory access by a factor of `TILE_WIDTH`
    - 16x16 tiles reduces by a factor of 16
  - G80
    - Now global memory supports 345.6 GFLOPS
    - Close to maximum of 346.5 GFLOPS

First-order Size Considerations in G80

- Each thread block should have many threads
  - TILE_WIDTH of 16 gives 16*16 = 256 threads
- There should be many thread blocks
  - A 1024*1024 Pd gives 64*64 = 4K Thread Blocks
- Each thread block perform 2*256 = 512 float loads from global memory for 256 * (2*16) = 8K mul/add operations.
  - Memory bandwidth no longer a limiting factor