Advanced Threads





In This Lecture

- Matrix Multiplication Review
- Reduce memory traffic: tiling
- Tiling Matrix Multiplication
- Memory Coalescing
- Boundary Checks

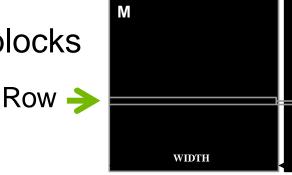
Matrix Multiplication Review

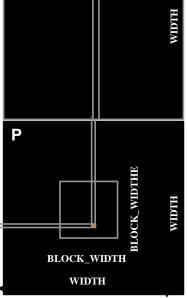
Basic problem: matrix multiplication

 When performing a matrix multiplication, each element of the output matrix P is an inner (dot) product of a row of M and a column of N.

 Similarly to previous examples each thread will compute a single value of the output matrix P

We organize threads as blocks



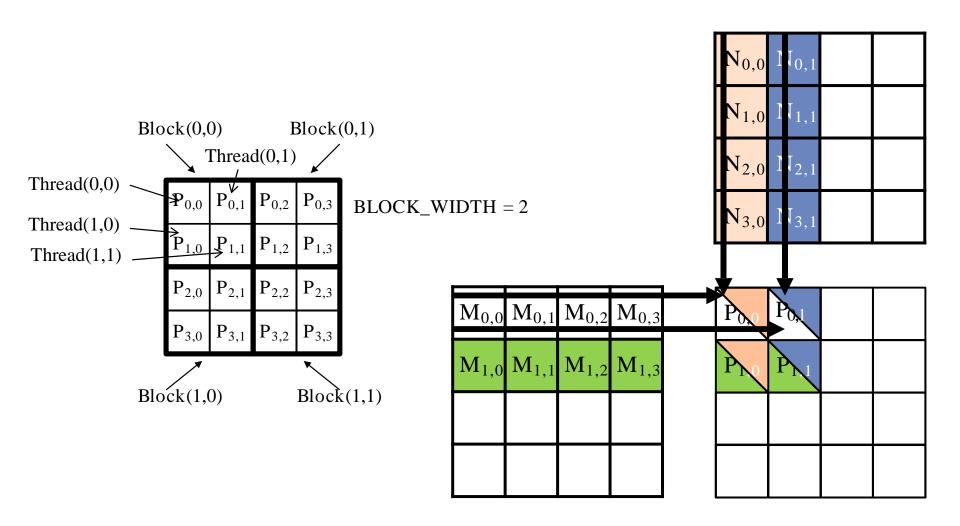


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Basic Matrix Multiplication

```
__qlobal void MatrixMulKernel(float* M, float* N, float* P, int Width)
 // Calculate the row index of the P element and M
 int Row = blockIdx.y*blockDim.y + threadIdx.y;
 // Calculate the column index of P and N
 int Col = blockIdx.x*blockDim.x + threadIdx.x;
 if ((Row < Width) && (Col < Width)) {
   float Pvalue = 0;
   // each thread computes one element of the block sub-matrix
   for (int k = 0; k < Width; ++k) {
     Pvalue += M[Row*Width+k]*N[k*Width+Col];
   P[Row*Width+Col] = Pvalue;
```

Toy example visualization

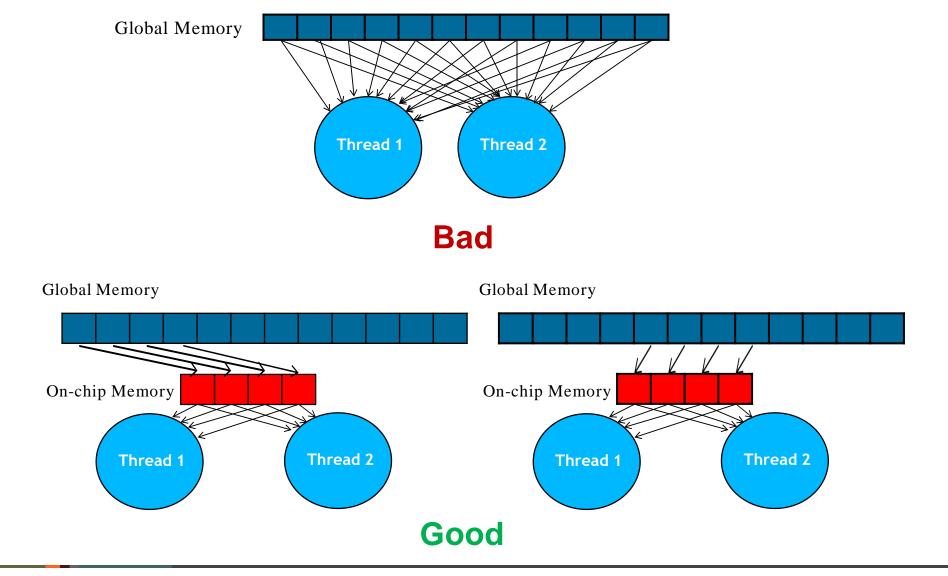


Reduce memory traffic: Tiling

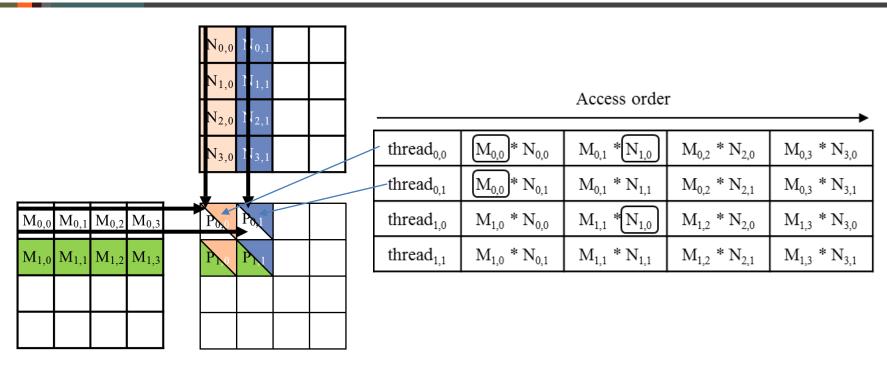
Tiling and CUDA memories

- Remind the tradeoffs of CUDA memories:
 - the global memory is large but slow;
 - the shared memory is small but fast. (100X low latency)
- A common strategy is to partition the data into subsets called tiles so that each tile fits into the shared memory.
 An important criterion is that the kernel computation on these tiles can be done independently of each other.
 - Note that not all data structures can be partitioned into tiles given an arbitrary kernel function.

Global vs. shared memory access



Repeated Global Memory Access



- Each thread accesses four elements of M and four elements of N during its execution.

 Among the four threads highlighted, there is a significant overlap in the M and N elements they access. For example, thread_{0.0} and thread_{0.1} both access M_{0.0} as well as the rest of row 0 of M.
- If we can somehow manage to have thread_{0,0} and thread_{0,1} to collaborate so that these M elements are only loaded once from global memory, we can reduce the total number of accesses to the global memory by half.
- In fact, we can see that every M and N element is accessed exactly twice during the execution of block_{0,0}. (If block size is 4x4, then 4 accesses on a SM)

Memory access patterns

Good: when threads have similar access timing Bad: when threads have very Thread 1 Time Thread 1 Time Thread 1 Time Thread 2

With tiling we are going to transform a program to localize memory locations accessed among threads and timing of their access.

Long access sequences of each thread are broken into phases, using barriers to synchronize access times to each section by the threads.

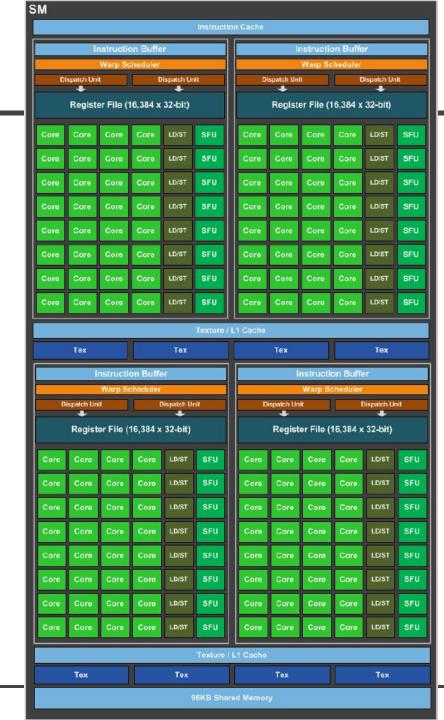
different timing

Tiling in General: how?

- Identify a tile of global memory contents that are accessed by multiple threads
- Load the tile from global memory into on-chip memory
- Have the multiple threads to access their data from the on-chip memory
- Use barrier synchronization to make sure that all threads have completed the current phase (tile)
- Move on to the next tile

On-Chip Memory in SM

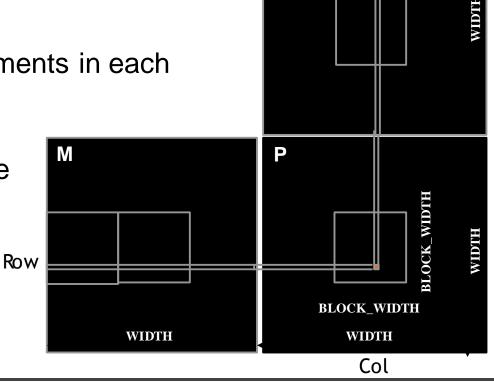
- A SM of NVIDIA GTX 1080
 - Registers
 - Shared Memory (96Kb)



Tiling Matrix Multiplication

Tiling matrix multiplication

- Break up the execution of each thread into phases
- so that the data accesses by the thread block in each phase are focused on one tile of M and one tile of N
- The tile is of BLOCK_SIZE elements in each dimension
- All threads in a block participate
- Each thread loads one M element and one N element in tiled code



Shared Memory Preparation

- → In reality M, N, P are 1D arrays in Global Memory
- → Shared Memories for M and N are allocated as 2D arrays

 No,0
 No,1
 No,2
 No,3

 No,1
 No,2
 No,3

 No,1
 No,2
 No,3

 No,3
 No,3
 No,3

 No,3
 No,3
 No,3

 No,3
 No,3
 No,3

Shared Memory

M

M _{0,0}	M _{0,1}	M _{0,2}	M _{0,3}
M _{1,0}	M _{1,1}	M _{1,2}	M _{1,3}
M _{2,0}	M _{2,1}	M _{2,2}	M _{2,3}
M _{3,0}	M _{3,1}	M _{3,2}	M _{3,3}

Shared Memory

P _{0,0}	P _{0,1}	P _{0,2}	P _{0,3}
P _{1,0}	P _{1,1}	P _{1,2}	P _{1,3}
n	9	,	
P _{2,0}	P _{2,1}	P _{2,2}	P _{2,3}

Phase 0 Load for Block (0,0)

→ Copy data to Shared Memory

 N_{0,0}
 N_{0,1}
 N_{0,2}
 N_{0,3}

 N_{1,0}
 N_{1,1}
 N_{1,2}
 N_{1,3}

 N_{2,0}
 N_{2,1}
 N_{2,2}
 N_{2,3}

 N_{3,0}
 N_{3,1}
 N_{3,2}
 N_{3,3}

Shared Memory

N

N_{0,0} N_{0,1} N_{1,1}

M

M _{0,0}	M _{0,1}	M _{0,2}	M _{0,3}		M _{0,0}	M _{0,1}
M _{1,0}	M _{1,1}	M _{1,2}	M _{1,3}		M _{1,0}	M _{1,1}
M _{2,0}	M _{2,1}	M _{2,2}	M _{2,3}	S	hared N	Memor
M _{3,0}	M _{3,1}	M _{3,2}	M _{3,3}			

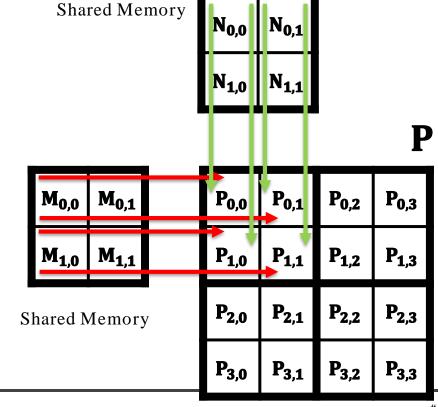
P _{0,0}	P _{0,1}	P _{0,2}	P _{0,3}
P _{1,0}	P _{1,1}	P _{1,2}	P _{1,3}
P _{2,0}	P _{2,1}	P _{2,2}	P _{2,3}
P _{3,0}	P _{3,1}	P _{3,2}	P _{3,3}

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Phase 0 Use for Block (0,0) (iteration 0)

→ Calculate dot product

N _{0,0}	N _{0,1}	N _{0,2}	N _{0,3}
N _{1,0}	N _{1,1}	N _{1,2}	N _{1,3}
N _{2,0}	N _{2,1}	N _{2,2}	N _{2,3}
N _{3,0}	N _{3,1}	N _{3,2}	N _{3,3}



N

M

 $M_{0,2}$

 $M_{0,1}$

 $M_{0,3}$

Phase 0 Use for Block (0,0) (iteration 1)

M_{0,2}

 $M_{1,2}$

 $M_{2,2}$

M_{3,2}

 $M_{0,1}$

M_{1,1}

 $M_{2,1}$

 $M_{3,1}$

M_{1,0}

 $M_{2,0}$

M_{3,0}

 $M_{0,3}$

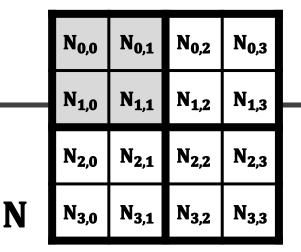
 $M_{1,3}$

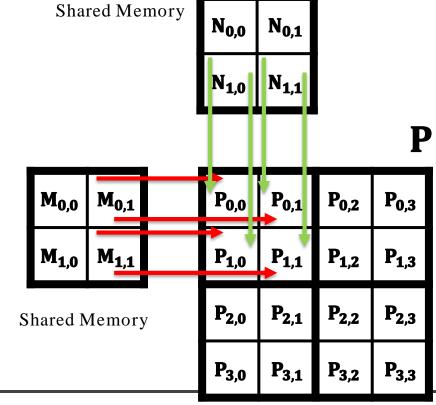
 $M_{2,3}$

 $M_{3,3}$

→ Calculate dot product

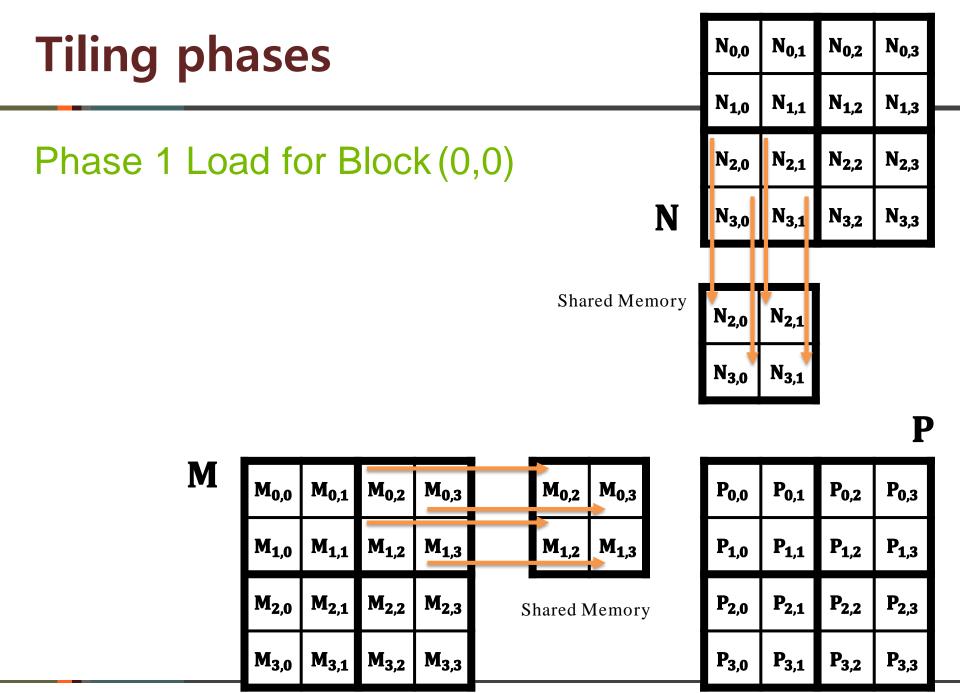
M



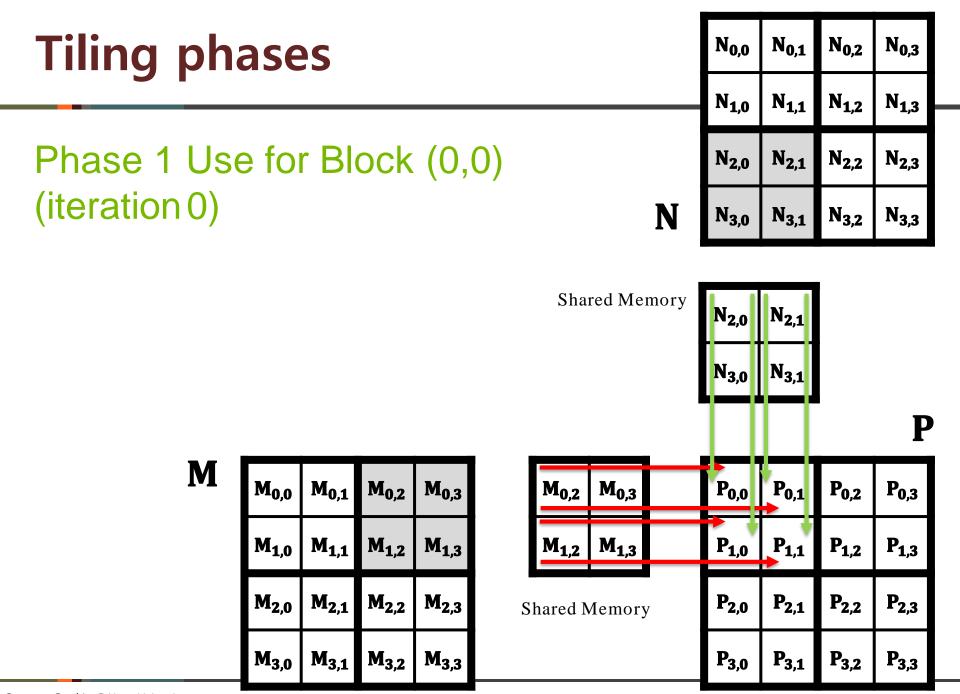


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Phase 1 Use for Block (0,0) (iteration 1)

→ Result for Block (0,0) is finished

 $M_{0,1}$

M_{1,1}

 $M_{2,1}$

 $M_{3,1}$

M_{1,0}

 $M_{2,0}$

 $M_{3,0}$

M_{0,2}

M_{1,2}

 $M_{2,2}$

M_{3,2}

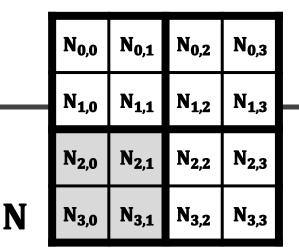
 $M_{0,3}$

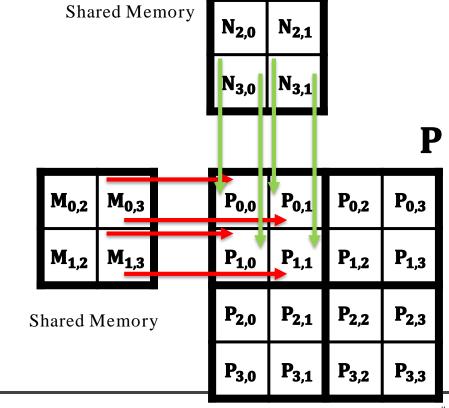
 $M_{1.3}$

 $M_{2,3}$

 $M_{3,3}$

M





Execution Phases of Toy Example

Time	<u> </u>

	Phase	0		Phase 1			
thread _{0,0}	$M_{0,0}$ \downarrow $Mds_{0,0}$	$N_{0,0}$ \downarrow $Nds_{0,0}$	$PValue_{0,0} += \\ Mds_{0,0}*Nds_{0,0} + \\ Mds_{0,1}*Nds_{1,0}$	$\mathbf{M}_{0,2}$ \downarrow $\mathbf{M}ds_{0,0}$	$egin{array}{c} \mathbf{N_{2,0}} \\ \downarrow \\ \mathrm{Nds}_{0,0} \end{array}$	$PValue_{0,0} += \\ Mds_{0,0}*Nds_{0,0} + \\ Mds_{0,1}*Nds_{1,0}$	
thread _{0,1}	$\mathbf{M}_{0,1}$ \downarrow $\mathbf{Mds}_{0,1}$	$N_{0,1}$ \downarrow $Nds_{1,0}$	$\begin{array}{c} PValue_{0,1} += \\ Mds_{0,0}*Nds_{0,1} + \\ Mds_{0,1}*Nds_{1,1} \end{array}$	$\mathbf{M}_{0,3}$ \downarrow $\mathbf{M}ds_{0,1}$	$N_{2,1}$ \downarrow $Nds_{0,1}$	$PValue_{0,1} += \\ Mds_{0,0}*Nds_{0,1} + \\ Mds_{0,1}*Nds_{1,1}$	
thread _{1,0}	$M_{1,0}$ \downarrow $Mds_{1,0}$	$N_{1,0}$ \downarrow $Nds_{1,0}$	$PValue_{1,0} += \\ Mds_{1,0}*Nds_{0,0} + \\ Mds_{1,1}*Nds_{1,0}$	$\mathbf{M}_{1,2}$ \downarrow $\mathbf{M}ds_{1,0}$	$N_{3,0}$ \downarrow $Nds_{1,0}$	$PValue_{1,0} += \\ Mds_{1,0}*Nds_{0,0} + \\ Mds_{1,1}*Nds_{1,0}$	
thread _{1,1}	$\mathbf{M}_{1,1}$ \downarrow $\mathbf{M}_{1,1}$	$N_{1,1}$ \downarrow $Nds_{1,1}$	$PValue_{1,1} += \\ Mds_{1,0}*Nds_{0,1} + \\ Mds_{1,1}*Nds_{1,1}$	$\mathbf{M}_{1,3}$ \downarrow $\mathbf{M}_{1,1}$	$N_{3,1}$ \downarrow $Nds_{1,1}$	$PValue_{1,1} += \\ Mds_{1,0}*Nds_{0,1} + \\ Mds_{1,1}*Nds_{1,1}$	

Shared memory allows each value to be accessed by multiple threads

Execution Phases of Toy Example

Tim	Time								
		Phase	0		Phase 1				
	thread _{0,0}	$M_{0,0}$ \downarrow $Mds_{0,0}$	$N_{0,0}$ \downarrow $Nds_{0,0}$	$\begin{array}{c} \text{PValue}_{0,0} += \\ \text{Mds}_{0,0} * \text{Nds}_{0,0} + \\ \text{Mds}_{0,1} * \text{Nds}_{1,0} \end{array}$	$\mathbf{M}_{0,2}$ \downarrow $\mathbf{M}ds_{0,0}$	$N_{2,0}$ \downarrow $Nds_{0,0}$	$PValue_{0,0} += \\ Mds_{0,0}*Nds_{0,0} + \\ Mds_{0,1}*Nds_{1,0}$		
	thread _{0,1}	$M_{0,1}$ \downarrow $Mds_{0,1}$	$N_{0,1}$ \downarrow $Nds_{1,0}$	$PValue_{0,1} += Mds_{0,0}*Nds_{0,1} + Mds_{0,1}*Nds_{1,1}$	$\mathbf{M}_{0,3}$ \downarrow $\mathbf{Mds}_{0,1}$	$N_{2,1}$ \downarrow $Nds_{0,1}$	$\begin{array}{l} PValue_{0,1} += \\ Mds_{0,0}*Nds_{0,1} + \\ Mds_{0,1}*Nds_{1,1} \end{array}$		
	thread _{1,0}	$\mathbf{M}_{1,0}$	$N_{1,0}$	$PValue_{1,0} += Mds_{1,0}*Nds_{0,0} +$	$\mathbf{M}_{1,2}$	N _{3,0}	PValue _{1,0} += Mds _{1,0} *Nds _{0,0} +		

- In general, if an input matrix is of dimension Width and the tile size is TILE_WIDTH, the dot product would be performed in Width/TILE_WIDTH phases (num of blocks to process).
- With each phase focusing on a small subset of the input matrix values, the threads can collaboratively load the subset into the shared memory and use the values in the shared memory to satisfy their overlapping input needs in the phase.
- Mds and Nds are re-used to hold the input values in different phases:
 reducing need of the amount of shared memory.

Execution Phases of Toy Example

Time	me			Barrier Barrier		Barrier	Barrier
	Phase ()		Phase 1			
thread _{0,0}	$egin{array}{ c c c c } \mathbf{M_{0,0}} \\ \downarrow \\ \mathbf{Mds_{0,0}} \\ \end{array}$	$N_{0,0}$ \downarrow $Nds_{0,0}$	$PValue_{0,0} += \\ Mds_{0,0}*Nds_{0,0} + \\ Mds_{0,1}*Nds_{1,0}$	$\mathbf{M_{0,2}}$ \downarrow $\mathbf{Mds_{0,0}}$	$N_{2,0}$ \downarrow $Nds_{0,0}$	PValue _{0,0} += Mds _{0,0} *Nds _{0,0} + Mds _{0,1} *Nds _{1,0}	
$thread_{0,1}$	$M_{0,1}$ \downarrow $Mds_{0,1}$	$N_{0,1}$ \downarrow $Nds_{1,0}$	$PValue_{0,1} += \\ Mds_{0,0}*Nds_{0,1} + \\ Mds_{0,1}*Nds_{1,1}$	$\mathbf{M}_{0,3}$ \downarrow $\mathbf{Mds}_{0,1}$	$N_{2,1}$ \downarrow $Nds_{0,1}$	$PValue_{0,1} += \\ Mds_{0,0}*Nds_{0,1} + \\ Mds_{0,1}*Nds_{1,1}$	
thread _{1,0}	$M_{1,0}$ \downarrow $Mds_{1,0}$	$N_{1,0}$ \downarrow $Nds_{1,0}$	$PValue_{1,0} += \\ Mds_{1,0}*Nds_{0,0} + \\ Mds_{1,1}*Nds_{1,0}$	$M_{1,2}$ \downarrow $Mds_{1,0}$	$N_{3,0}$ \downarrow $Nds_{1,0}$	$PValue_{1,0} += \\ Mds_{1,0}*Nds_{0,0} + \\ Mds_{1,1}*Nds_{1,0}$	
$thread_{1,1}$	$\begin{matrix} \mathbf{M_{1,1}} \\ \downarrow \\ \mathbf{Mds_{1,1}} \end{matrix}$	$N_{1,1}$ \downarrow $Nds_{1,1}$	$PValue_{1,1} += \\ Mds_{1,0}*Nds_{0,1} + \\ Mds_{1,1}*Nds_{1,1}$	$\mathbf{M}_{1,3}$ \downarrow $\mathbf{M}ds_{1,1}$	$N_{3,1}$ \downarrow $Nds_{1,1}$	$PValue_{1,1} += \\ Mds_{1,0}*Nds_{0,1} + \\ Mds_{1,1}*Nds_{1,1}$	
			time -			•	

Both the data loading and calculation have to be Synchronized

Barrier Synchronization

- Synchronize all threads in a block
 - __syncthreads()
- All threads in the same block must reach the
 syncthreads() before any of the them can move on.
- Best used to coordinate the phased execution for tiled algorithms
 - To ensure that all elements of a tile are loaded at the beginning of a phase
 - To ensure that all elements of a tile are consumed at the end of a phase

Loading Input Tile 0 of M (Phase 0)

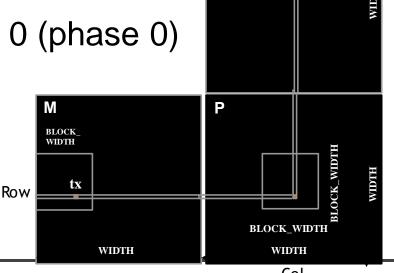
 Have each thread load an M element and an N element at the same relative position as its P element.

```
int Row = by * blockDim.y + ty;
```

int Col = bx * blockDim.x + tx;

2D indexing for accessing Tile 0 (phase 0)

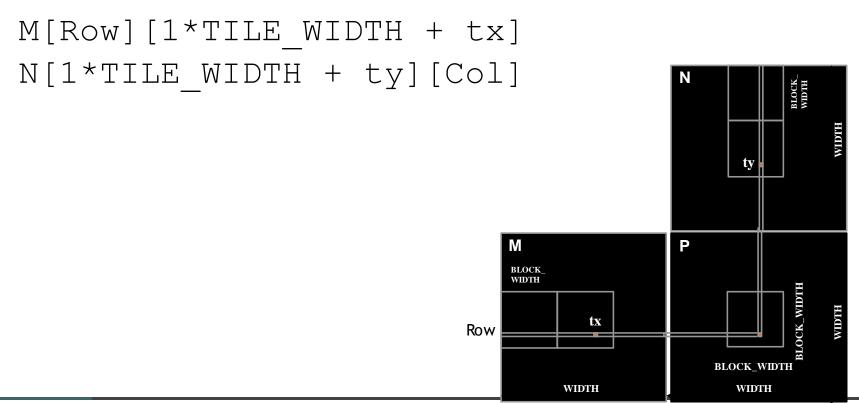
M[Row][tx] N[ty][Col]



Col

Loading Input Tile 1 of M (Phase 1)

2D indexing for accessing Tile 1 (phase 1)



Col

Allocating M and N

 M and N can be allocated dynamically, using 1D indexing

```
M[Row] [ph*TILE_WIDTH+tx]
M[Row*Width + ph*TILE_WIDTH + tx]
N[ph*TILE_WIDTH+ty] [Col]
N[(ph*TILE_WIDTH+ty)*Width + Col]
```

where ph is the sequence number of the current phase

Tiled Matrix Multiplication Kernel

```
global void MatrixMulKernel(float* M, float* N, float* P, 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 * blockDim.y + ty;
 int Col = bx * blockDim.x + tx;
 float Pvalue = 0;
// Loop over the M and N tiles required to compute the P element
for (int ph = 0; ph < Width/TILE WIDTH; ++ph) {</pre>
   // Collaborative loading of M and N tiles into shared memory
  Mds[ty][tx] = M[Row*Width + ph*TILE WIDTH+tx];
  Nds[ty][tx] = N[(t*TILE WIDTH+ty)*Width + Col];
   syncthreads();
   for (int i = 0; i < TILE WIDTH; ++i)</pre>
     Pvalue += Mds[ty][i] * Nds[i][tx];
     synchthreads();
 P[Row*Width+Col] = Pvalue;
```

Tiled Matrix Multiplication Kernel

```
global void MatrixMulKernel(float* M, float* N, float* P, int Width) {
  _shared__ float Mds[TILE WIDTH][TILE WIDTH];
                                                 Shared variables: block scope
 <u>__shared__</u> 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 * blockDim.y + ty;
                                               Automatic scalar variables: registers
 int Col = bx * blockDim.x + tx;
 float Pvalue = 0;
 / Loop over the M and N tiles required to compute the P element
                                                                   iterates over phases
for (int ph = 0; ph < Width/TILE WIDTH; ++ph) {</pre>
   // Collaborative loading of M and N tiles into shared memory
  Mds[ty][tx] = M[Row*Width + ph*TILE WIDTH+tx];
                                                     load into shared memory
  Nds[ty][tx] = N[(t*TILE WIDTH+ty)*Width + Col];
                      assures that all threads have loaded the data into shared mem.
   __syncthreads();
   for (int i = 0; i < TILE WIDTH; ++i)</pre>
     Pvalue += Mds[ty][i] * Nds[i][tx];
   __synchthreads();
                             assures that all threads have finished using the data into
                                                   shared mem.
 P[Row*Width+Col] = Pvalue;
```

Tile (Thread Block) Size Considerations

- Each thread block should have many threads
 - TILE_WIDTH of 16 gives 16*16 = 256 threads
 - TILE_WIDTH of 40 gives 40*40 = 1600 threads
- For 16, in each phase, each block performs 2*256 = 512 float loads from global memory for 256 * (2*16) = 8,192 mul/add operations. (16 floating-point operations for each memory load)
- For 40, in each phase, each block performs 2*1600 = 3,200 float loads from global memory for 1600 * (2*40) = 1,280,000 mul/add operations. (40 floating-point operation for each memory load)

Shared Memory and Threading

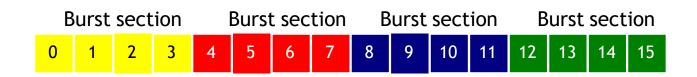
- For an SM with 96 KB shared memory (GTX 1080)
 - Shared memory size is implementation dependent!
 - For TILE_WIDTH = 16, each thread block uses 2*256*4B = 2KB of shared memory.
 - For 96KB shared memory, one can potentially have up to 48 thread blocks executing on a SM (fully occupied)
 - This allows up to 48*256*2 = 24,576 pending loads.
 (2 per thread, 256 threads per block)
 - In case of TILE_WIDTH 40 would lead to 2*40*40*4 Byte= 12.5KB shared memory usage per thread block, allowing 7 thread blocks (1600*7=11200 threads) active at the same time
 - However, the thread count limitation of 2048 threads per SM in current GPUs will reduce the number of blocks per SM to one! (2048-1600=448 threads unoccupied)
- Each __syncthreads() can reduce the number of active threads for a block

Memory Coalescing

Memory bandwidth

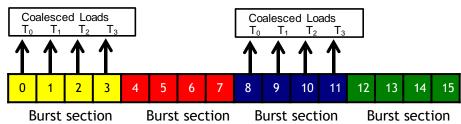
- One of the most important factors of CUDA kernel performance is accessing data in the global memory (a DRAM memory).
- The process of reading a the status of a single bit takes tenth of nanoseconds in modern DRAM chips. This is in sharp contrast with the sub-nanosecond clock cycle time of modern computing devices.
- Modern DRAMs use parallelism to increase their rate of data access: Each time a DRAM location is accessed, a range of consecutive locations that include the requested location are actually accessed (DRAM bursts).
- When all threads in a warp execute a load instruction, the hardware detects
 whether they access consecutive global memory locations. In this case,
 the hardware combines, or coalesces, all these accesses into a consolidated
 access to consecutive DRAM locations.
- Modern DRAM systems are designed to always be accessed in burst mode.
 Burst bytes are transferred to the processor but discarded when accesses are not to sequential locations.

DRAM Burst – A System View

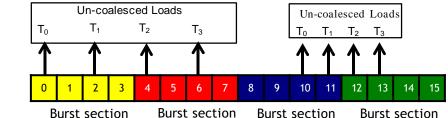


- Each address space is partitioned into burst sections
 - Whenever a location is accessed, all other locations in the same section are also delivered to the processor
- Basic example: a 16-byte address space, 4-byte burst sections
 - In practice, we have at least 4GB address space, burst section sizes of 128bytes or more

Coalesced access

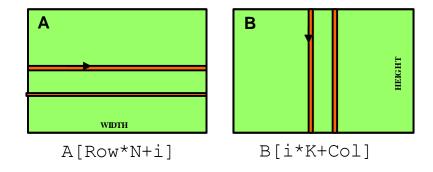


 When all threads of a warp execute a load instruction, if all accessed locations fall into the same burst section, only one DRAM request will be made and the access is fully coalesced.



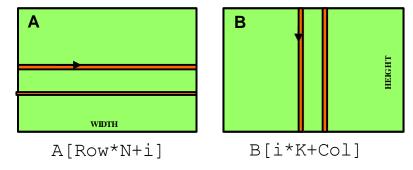
- When the accessed locations spread across burst section boundaries:
 - Coalescing fails
 - Multiple DRAM requests are made
 - The access is not fully coalesced.
- Some of the bytes accessed and transferred are not used by the threads

Two Access Patterns of Basic Matrix Multiplication

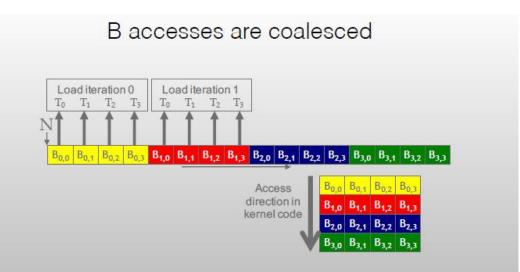


- i is the loop counter in the inner product loop of the kernel code
- A is M×N, B is N×K
- Col = blockIdx.x*blockDim.x + threadIdx.x

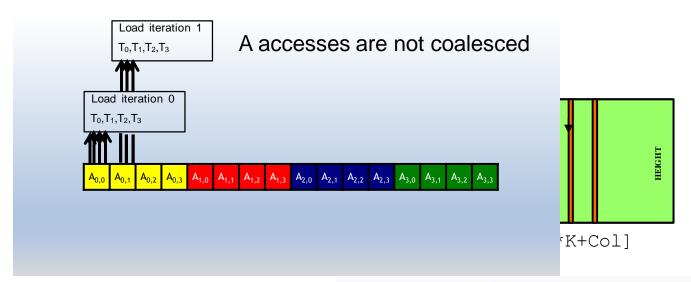
Two Access Patterns of Basic Matrix Multiplication



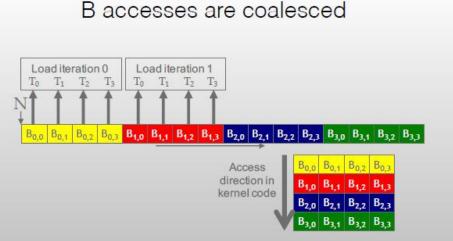
- i is the loop counter in the inne
- A is M×N, B is N×K
- Col = blockIdx.x*blockI



Two Access Patterns of Basic Matrix Multiplication



- i is the loop counter in the inne
- A is M×N, B is N×K
- Col = blockIdx.x*blockI



Non coalesced read

 If an algorithm intrinsically requires a kernel code to iterate through data along the row direction, one can use the shared memory to enable memory coalescing

-

- The technique is called corner turning
- A tiled algorithm can be used to enable coalescing
- Once the data is in shared memory, they can be accessed either on a row basis or a column basis

Loading Data from Global Memory

```
int Row = by * blockDim.y + ty;
int Col = bx * blockDim.x + tx;

for (int ph = 0; ph < Width/TILE_WIDTH; ++ph)
{
    Mds[ty][tx] = M[Row*Width + ph*TILE_WIDTH + tx];
    Nds[ty][tx] = N[(ph*TILE_WIDTH+ty)*Width + Col];
    ...
}</pre>
```

For Mds, adjacent threadIdx.x threads will access adjacent M elements. also,

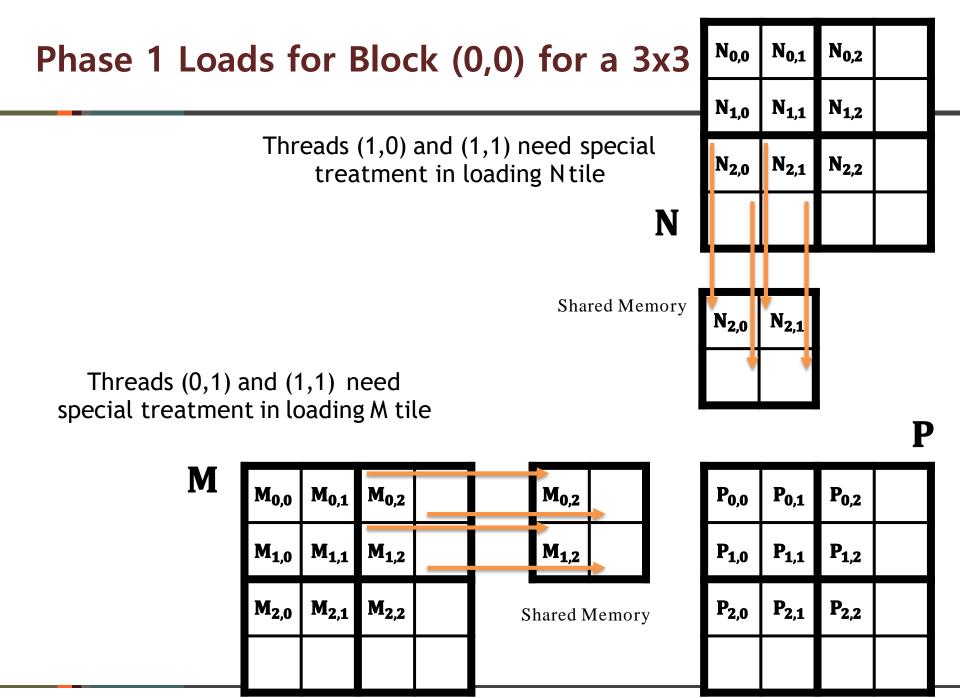
For Nds, adjacent threadIdx.x threads will access adjacent N elements.

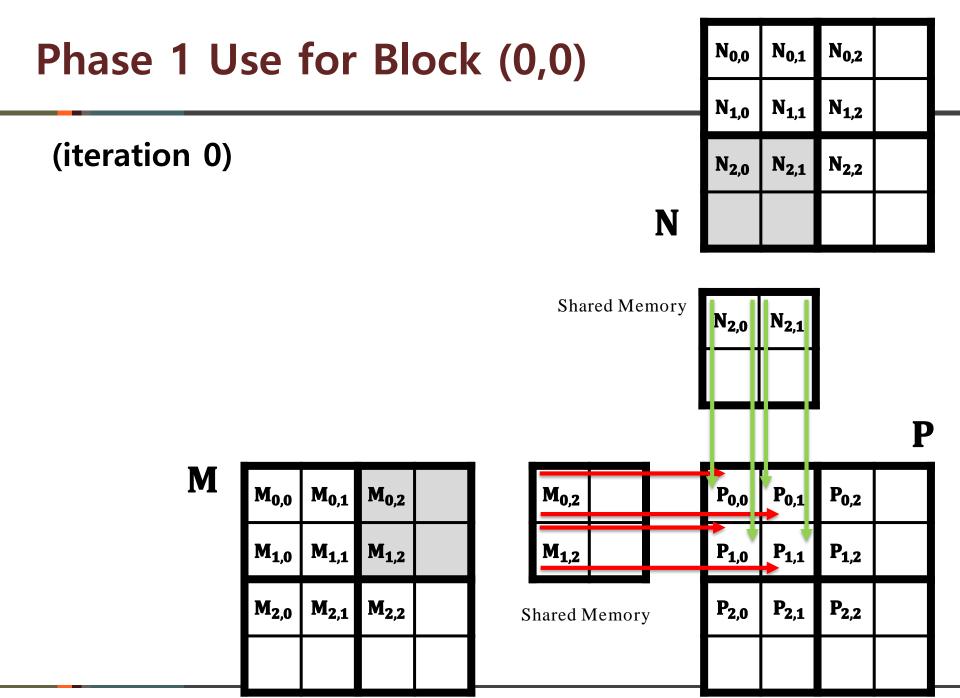
→ Both data loads are all coalesced, hence extra benefit for using Shared memory.

Boundary Checks

Boundary checks

- The previous code assumes that the matrix has a size (a width) that is an exact multiple of TILE_WIDTH.
- Let's extend the code to handle square matrices with an arbitrary width.





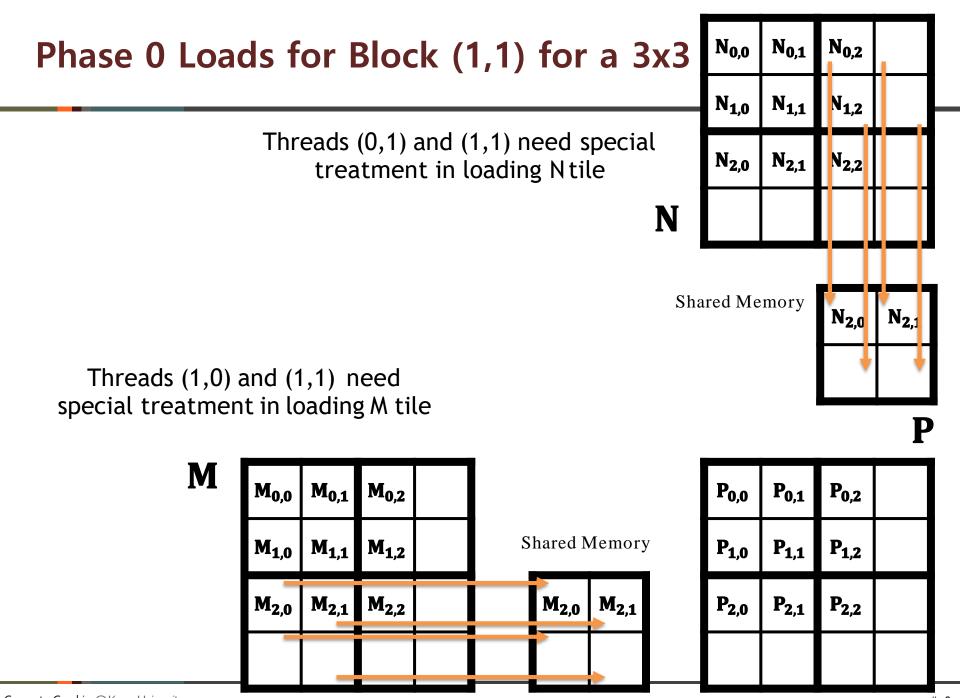


All Threads need special treatment. None of them should introduce invalidate contributions to their P elements.

Shared Memory N_{2,0} N_{2,1} M_{0,2} P_{0,0} | P_{0,1} P_{0,2} $M_{1.2}$ P_{1.2} $P_{2.0}$ $P_{2,1}$ $P_{2,2}$ **Shared Memory**

N

M _{0,0}	M _{0,1}	M _{0,2}	
M _{1,0}	M _{1,1}	M _{1,2}	
M _{2,0}	M _{2,1}	M _{2,2}	



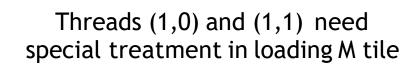


Threads (0,1) and (1,1) need special treatment in loading Ntile

N_{0,0} N_{0,1} N_{0,2}

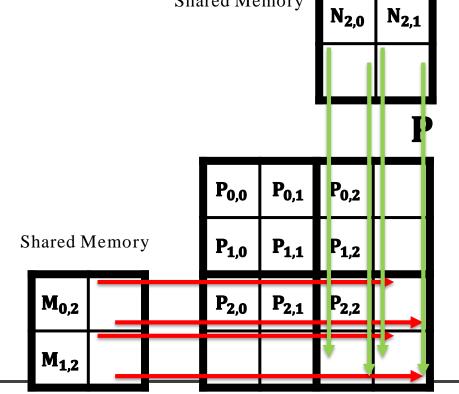
N_{1,0} N_{1,1} N_{1,2}

N_{2,0} N_{2,1} N_{2,2}



M

M _{0,0}	M _{0,1}	M _{0,2}	
M _{1,0}	M _{1,1}	M _{1,2}	
M _{2,0}	M _{2,1}	M _{2,2}	

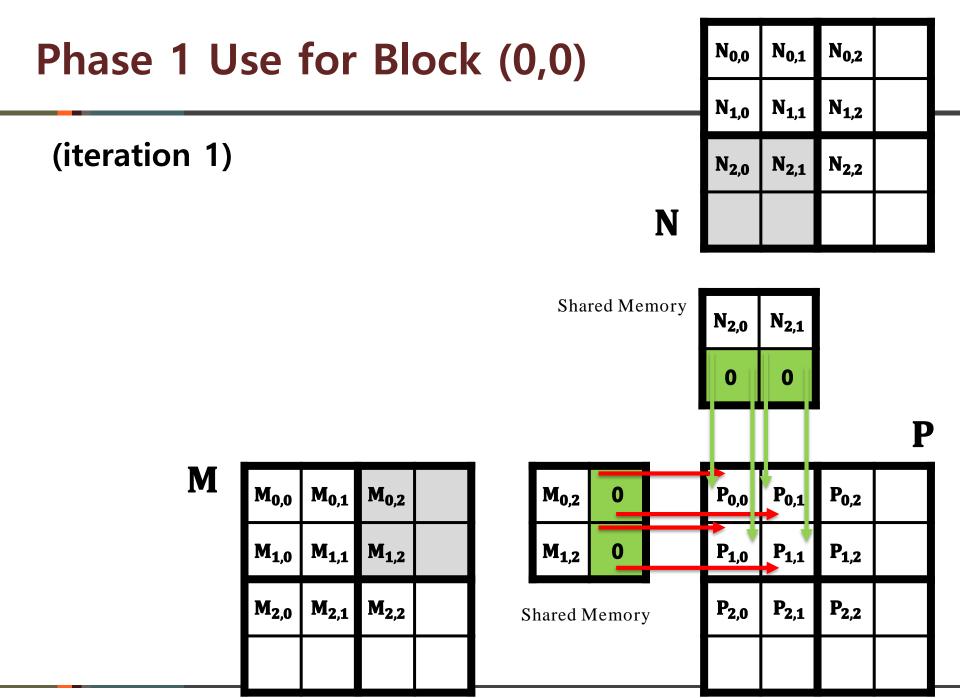


Shared Memory

N

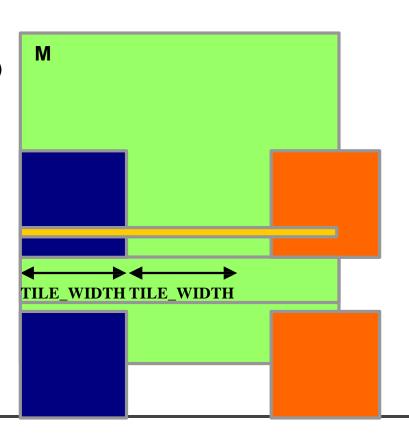
A solution

- When a thread is to load any input element, test if it is in the valid index range
 - If valid, proceed to load
 - Else, do not load, just write a 0
- Rationale: a 0 value will ensure that that the multiply-add step does not affect the final value of the output element
- The condition tested for loading input elements is different from the test for calculating output P element
 - A thread that does not calculate valid P element can still participate in loading input tile elements



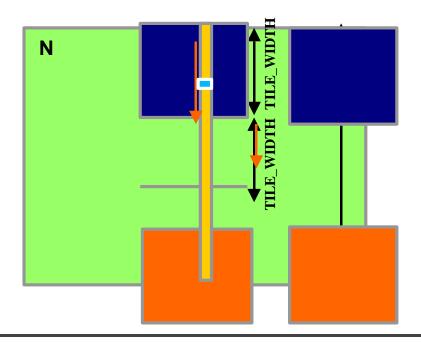
Boundary Condition for Input M Tile

- Each thread loads
 - M[Row][ph*TILE_WIDTH+tx]
 - M[Row*Width + ph*TILE_WIDTH+tx]
- Need to test
 - (Row < Width) && (ph*TILE_WIDTH+tx < Width)
 - · If true, load M element
 - Else, load 0



Boundary Condition for Input N Tile

- · Each thread loads
 - N[ph*TILE_WIDTH+ty][Col]
 - N[(ph*TILE_WIDTH+ty)*Width+ Col]
- Need to test
 - (ph*TILE_WIDTH+ty < Width) && (Col< Width)
 - If true, load N element
 - Else, load 0



Practice: Tiled Matrix Multiplication

- Copy Sample Skeleton Code
 - cp -r /home/share/18_Shared ./[FolderName]
 - cd [FolderName]
- Notepad: MatrixMulti.cu 코드 Kernel function 완성
- Compile & run program
 - make
 - ./EXE

Matrix Multiplication – with boundary check

```
//Continued from Tiled Matrix Multiplication Kernel
  for (int ph = 0; ph < NUM PHASE; ++ph) {
    if (Row < Width && ph*TILE WIDTH + tx < Width) {
     Mds[ty][tx] = M[Row*Width + ph*TILE WIDTH + tx];
    }else{
     Mds[ty][tx] = 0.0;
    if (ph*TILE WIDTH + ty < Width && Col < Width) {
     Nds[ty][tx] = N[(ph*TILE WIDTH + ty)*Width + Col];
    }else{
     Nds[ty][tx] = 0.0;
    }
     syncthreads();
    if (Row < Width && Col < Width) {
      for (int i = 0; i < TILE WIDTH; ++i) {
        Pvalue += Mds[ty][i] * Nds[i][tx];
      syncthreads();
 if (Row < Width && Col < Width) P[Row*Width + Col] = Pvalue;
} /* end of kernel */
```

Some Important Points

- For each thread the conditions are different for
 - Loading M element
 - Loading N element
 - Calculating and storing output elements for P
- The effect of control divergence should be small for large matrices

Handling General Rectangular Matrices

- In general, the matrix multiplication is defined in terms of rectangular matrices
 - A (J×K) M matrix multiplied with a (K×L) N matrix results in a (J×L) P matrix
- So far we have seen square matrix multiplication, a special case
- The kernel function needs to be generalized to handle general rectangular matrices
 - The Width argument is replaced by three arguments: J, K, L
 - When Width is used to refer to the height of M or height of P, replace it with J
 - When Width is used to refer to the width of M or height of N, replace it with K
 - When Width is used to refer to the width of N or width of P, replace it with L

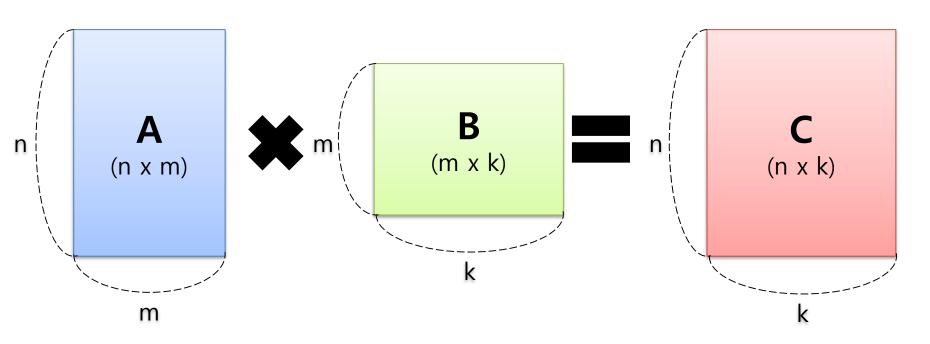
Assignment #4

Purpose of Assignment

Purpose

- Programming "Matrix Multiplication Program" on the GPU
 - Skeleton Code is given.
 - Skeleton Code is in the GPU Server.
 Path: /home/share/Assignment4/
 - Requires Arbitrary Sized Matrices
 - Requires Matrix Tiling
 - Compile and Run on the GPU Server
 - Print Results to Text File

Arbitrary size Matrix Multiplication



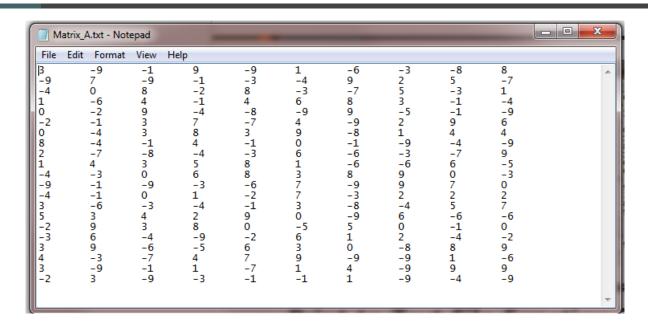
- Implement routine to define Matrix Size
 - n, m and k
- Input Elements of A and B are Random Variables
 - Integers in a range (-10, 10)

Parameters input

- Input Parameters with Console Commands
 - Matrix Size

```
penorchid@ubuntu:~/cuda$ ./EXE
Input the Value of n:16
Input the Value of m:13
Input the Value of k:7
```

Results Print



- Routine for File I/O is given.
- Write Matrices A,B and C.
 - 1 text file per Matrix

Submit the Assignment

Submit the zip file @ Blackboard

- File name must be "Assignment4_StudentID_Name.zip"
 - Ex. Assignment4_2015000000_박지혁.zip
- Zip file must include
 - Src files
 - Result running Image file
 - Result printed text files

History of Matrix Multiplication

Previous Matrix Multiplication @ CPU

C Function

```
void matrixMult (int a[N][N], int b[N][N], int c[N][N], int width)
{
  for (int i = 0; i < width; i++) {
    for (int j = 0; j < width; j++) {
      int sum = 0;
      for (int k = 0; k < width; k++) {
        int m = a[i][k];
        int n = b[k][j];
        sum += m * n;
      }
      c[i][j] = sum;
  }
}</pre>
```

N

N _{0,0}	N _{0,1}	N _{0,2}	N _{0,3}
N _{1,0}	N _{1,1}	N _{1,2}	N _{1,3}
N _{2,0}	N _{2,1}	N _{2,2}	N _{2,3}
N _{3,0}	N _{3,1}	N _{3,2}	N _{3,3}

M

M _{0,0}	M _{0,1}	M _{0,2}	M _{0,3}
M _{1,0}	M _{1,1}	M _{1,2}	M _{1,3}
M _{2,0}	M _{2,1}	M _{2,2}	M _{2,3}
M _{3,0}	M _{3,1}	M _{3,2}	M _{3,3}

P

P _{0,0}	P _{0,1}	P _{0,2}	P _{0,3}
P _{1,0}	P _{1,1}	P _{1,2}	P _{1,3}
P _{2,0}	P _{2,1}	P _{2,2}	P _{2,3}
P _{3,0}	P _{3,1}	P _{3,2}	P _{3,3}

Previous Matrix Multiplication @ GPU

CUDA Kernel

```
__global___ void matrixMult (int *a, int *b, int *c, int width) {
  int k, sum = 0;

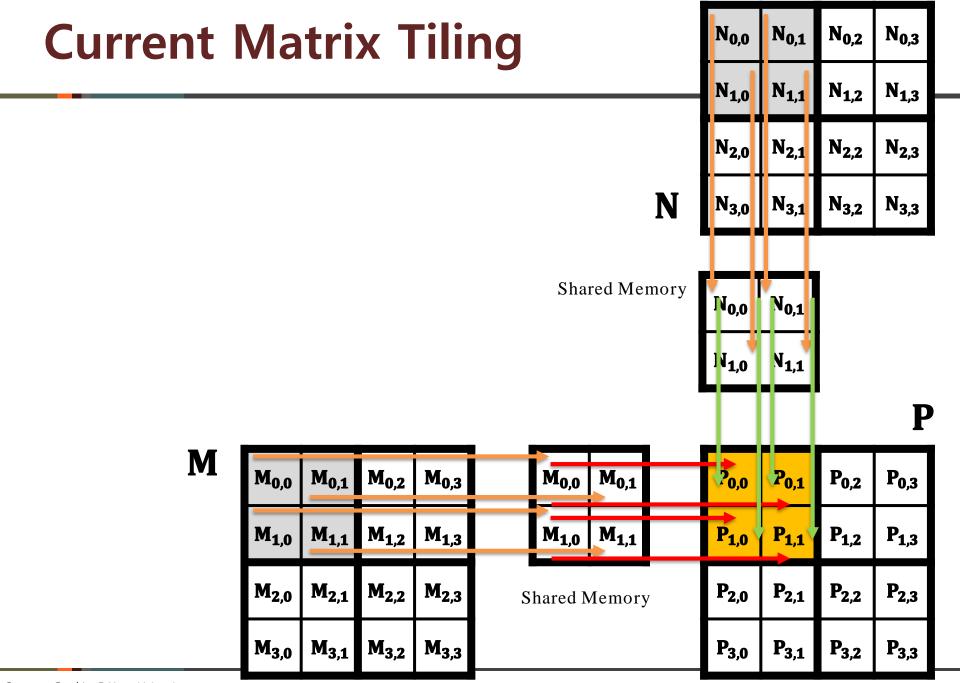
int col = threadIdx.x + blockDim.x * blockIdx.x;
  int row = threadIdx.y + blockDim.y * blockIdx.y;

if(col < width && row < width) {
  for (k = 0; k < width; k++)
     sum += a[row * width + k] * b[k * width + col];
     c[row * width + col] = sum;
  }
}</pre>
```

N ₁	N _{0,1}	N _{0,2}	Nod
111,0	N . ,	N _{1,2}	N _{.,}
1112,0	N 2, 1	N 2,22	N _{2,3}
1113,0	N :, 1	N _{3,2}	N;,;
			-111

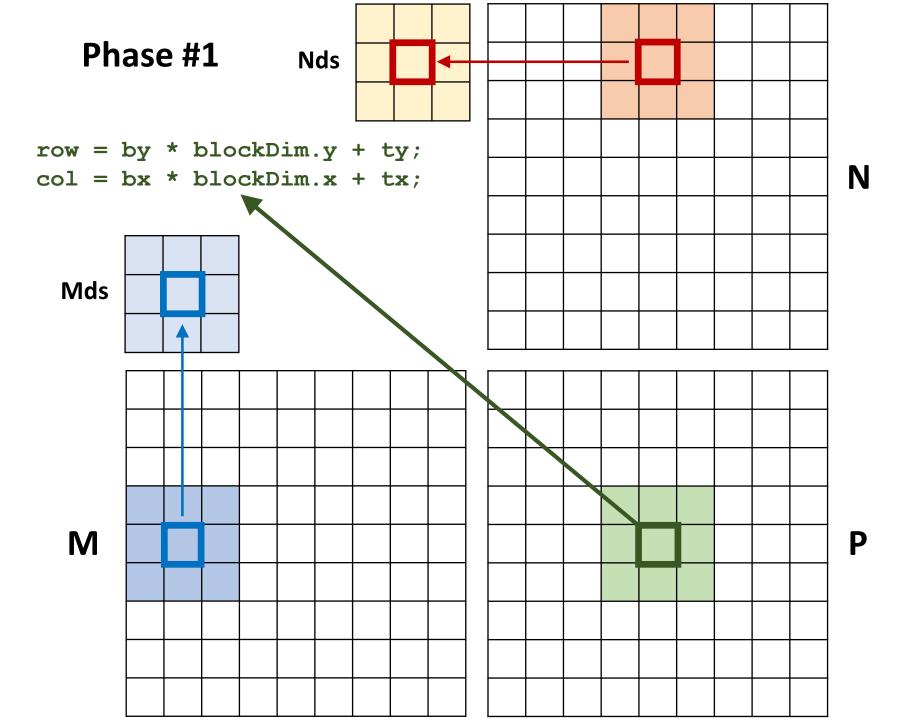
N

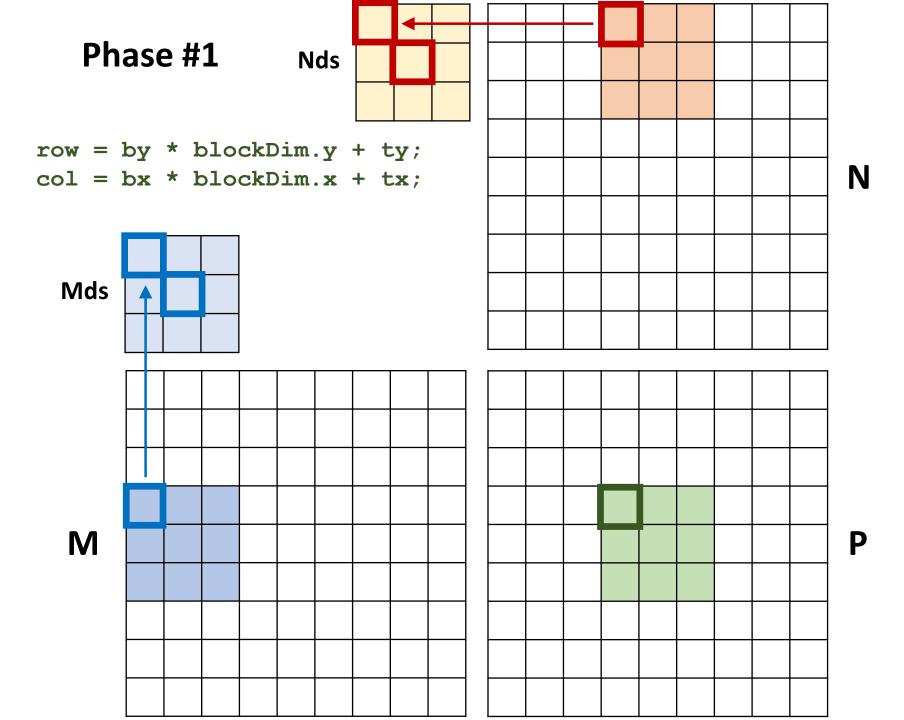
Ma na na	
1410,0 1-10,1 1-10,2 1-10,3	
M _{1,0} M _{1,1} M _{1,2} M _{1,3}	
M _{2,U} M, M, M,	P, 2 P,
M _{3,0} W _{3,1} W _{3,2} W _{3,3}	72.1 P.2 P.3

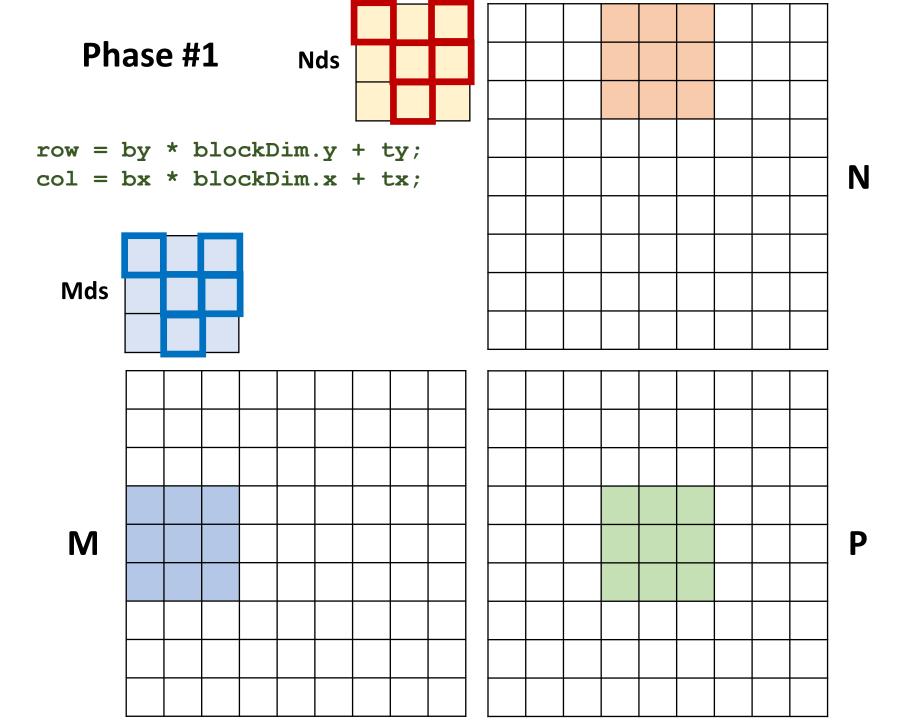


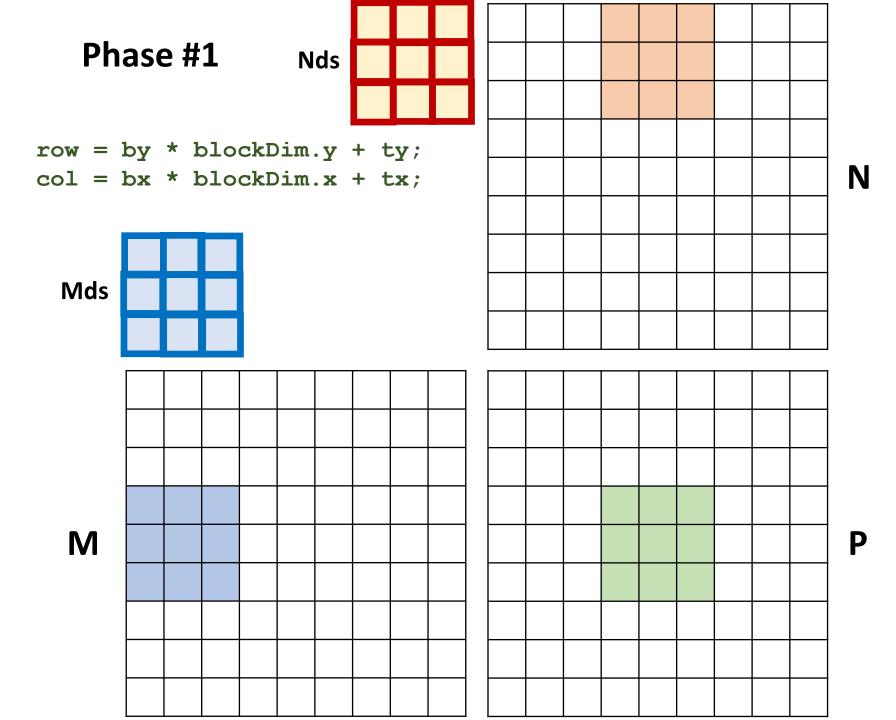
ComputerGraphics @ Korea University

Tiling Animation

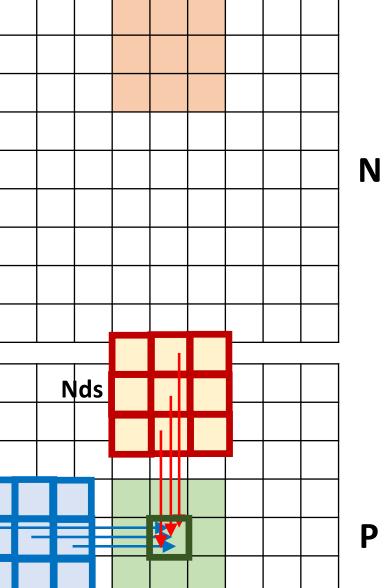


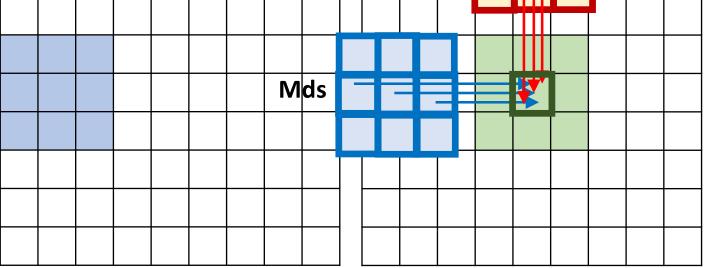






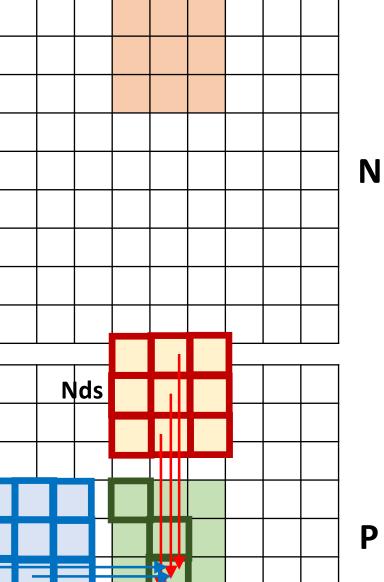
```
row = by * blockDim.y + ty;
col = bx * blockDim.x + tx;
```

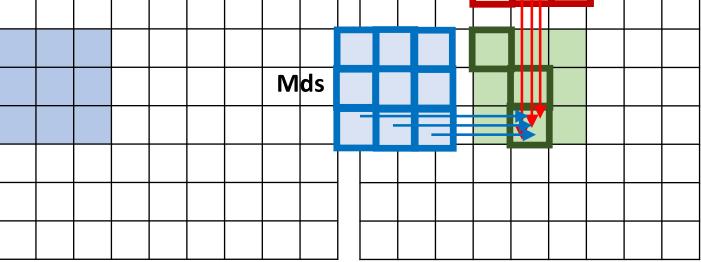




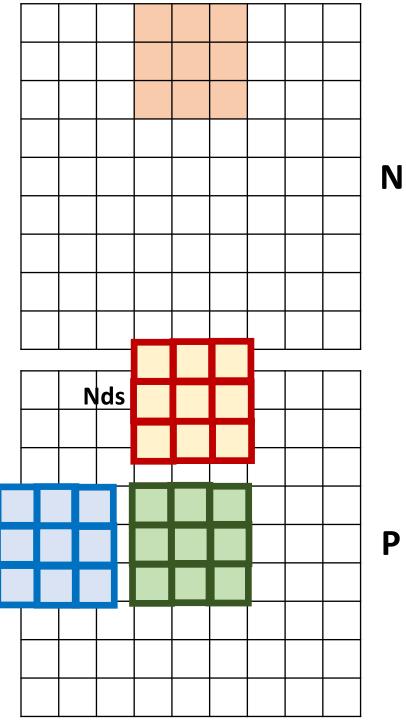
Phase #1 row = by * blockDim.y + ty; N col = bx * blockDim.x + tx; Nds Mds M P

```
row = by * blockDim.y + ty;
col = bx * blockDim.x + tx;
```



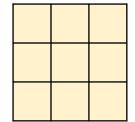


```
row = by * blockDim.y + ty;
col = bx * blockDim.x + tx;
```



Mds

Nds

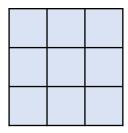


```
row = by * blockDim.y + ty;
col = bx * blockDim.x + tx;
```

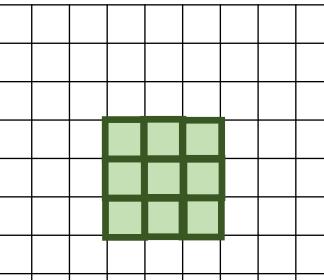
N

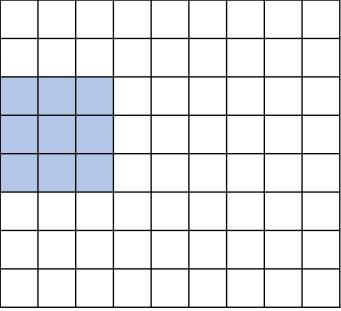
P

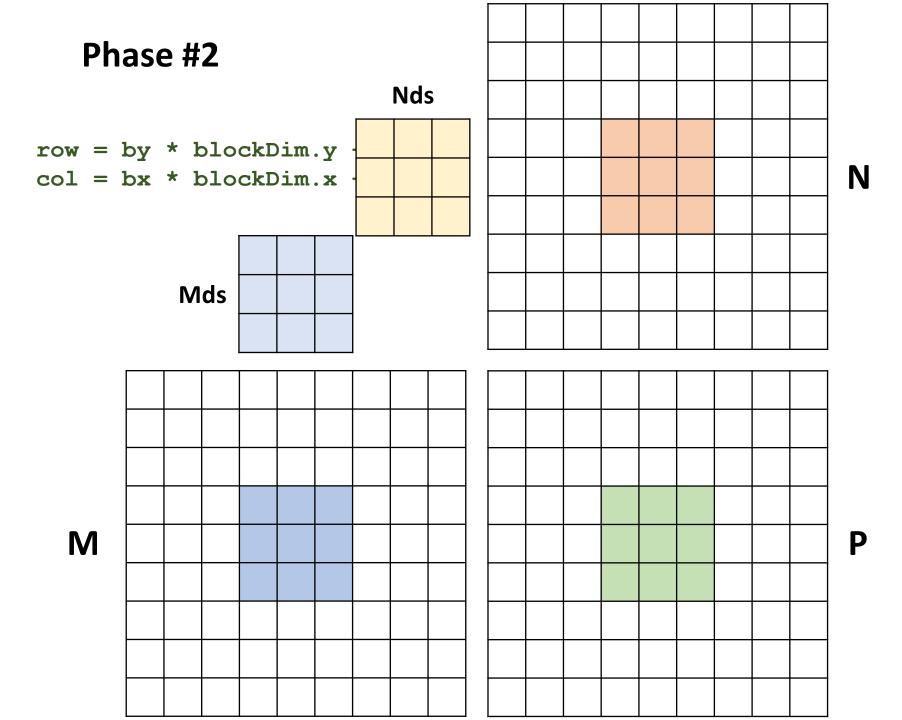






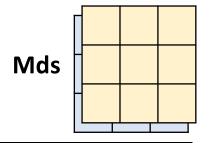






```
row = by * blockDim.y + ty;
col = bx * blockDim.x + tx;
```

Nds



N

P

