

# Memory and Data Locality

CUDA Memories

## Objective

- To learn to effectively use the CUDA memory types in a parallel program
  - Importance of memory access efficiency
  - Registers, shared memory, global memory
  - Scope and lifetime

# Review: Image Blur Kernel.

→

```
// Get the average of the surrounding 2xBLUR_SIZE x 2xBLUR_SIZE box
for(int blurRow = -BLUR_SIZE; blurRow < BLUR_SIZE+1; ++blurRow) {
    for(int blurCol = -BLUR_SIZE; blurCol < BLUR_SIZE+1; ++blurCol) {

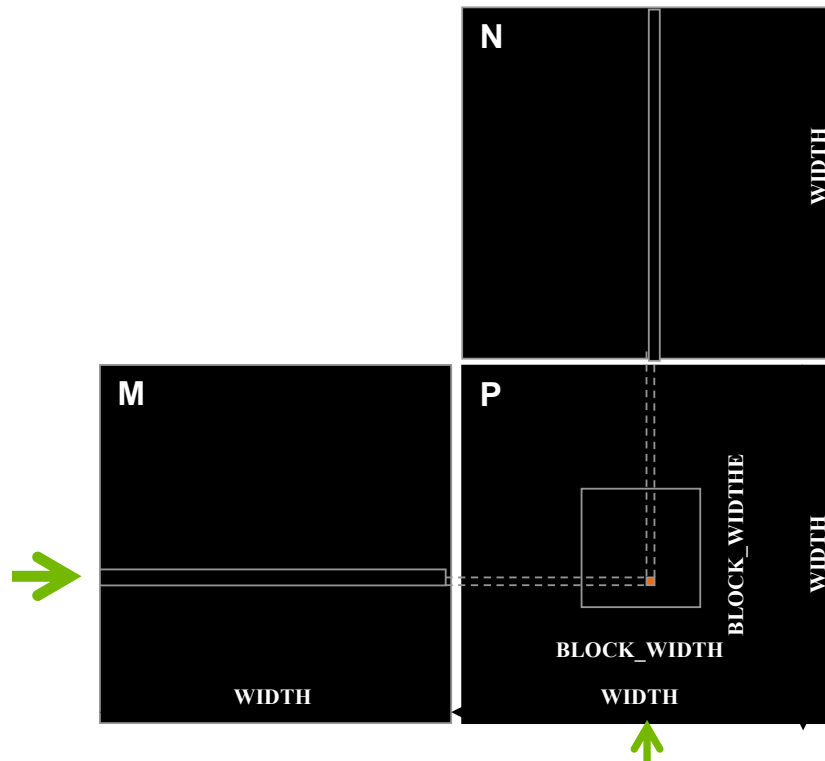
        int curRow = Row + blurRow;
        int curCol = Col + blurCol;
        // Verify we have a valid image pixel
        if(curRow > -1 && curRow < h && curCol > -1 && curCol < w) {
            pixVal += in[curRow * w + curCol];
            pixels++; // Keep track of number of pixels in the accumu
        }
    }
}

// Write our new pixel value out
out[Row * w + Col] = (unsigned char)(pixVal / pixels);
```

## How about performance on a GPU

- All threads access global memory for their input matrix elements
  - One memory accesses (4 bytes) per floating-point addition
  - 4B/s of memory bandwidth/FLOPS
- Assume a GPU with
  - Peak floating-point rate 1,600 GFLOPS with 600 GB/s DRAM bandwidth
  - $4 \times 1,600 = 6,400$  GB/s required to achieve peak FLOPS rating
  - The 600 GB/s memory bandwidth limits the execution at 150 GFLOPS
- This limits the execution rate to 9.3% (150/1600) of the peak floating-point execution rate of the device!
- Need to drastically cut down memory accesses to get close to the 1,600 GFLOPS

# Example – Matrix Multiplication



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## A Basic Matrix Multiplication

```
__global__ 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;  
    }  
}
```

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# Example – Matrix Multiplication

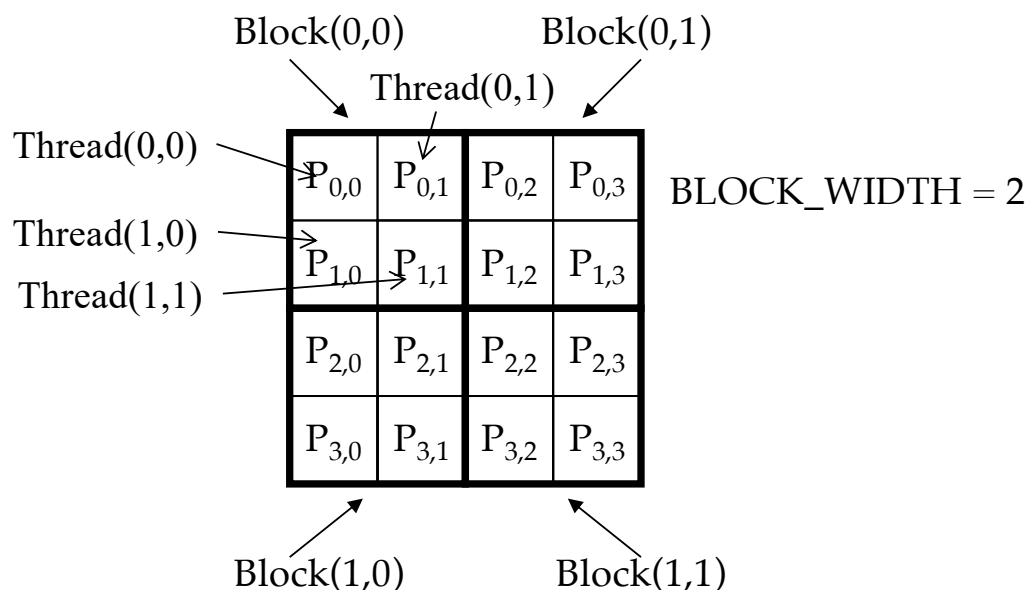
```
__global__ void MatrixMulKernel(float* M, float* N, float* P, int Width) {  
  
    // Calculate the row index of the P element and M  
    int Row = blockIdx.y*blockDim.y+threadIdx.y;  
  
    // Calculate the column index of P and N  
    int Col = blockIdx.x*blockDim.x+threadIdx.x;  
  
    if ((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;  
    }  
}
```

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## A Toy Example: Thread to P Data Mapping

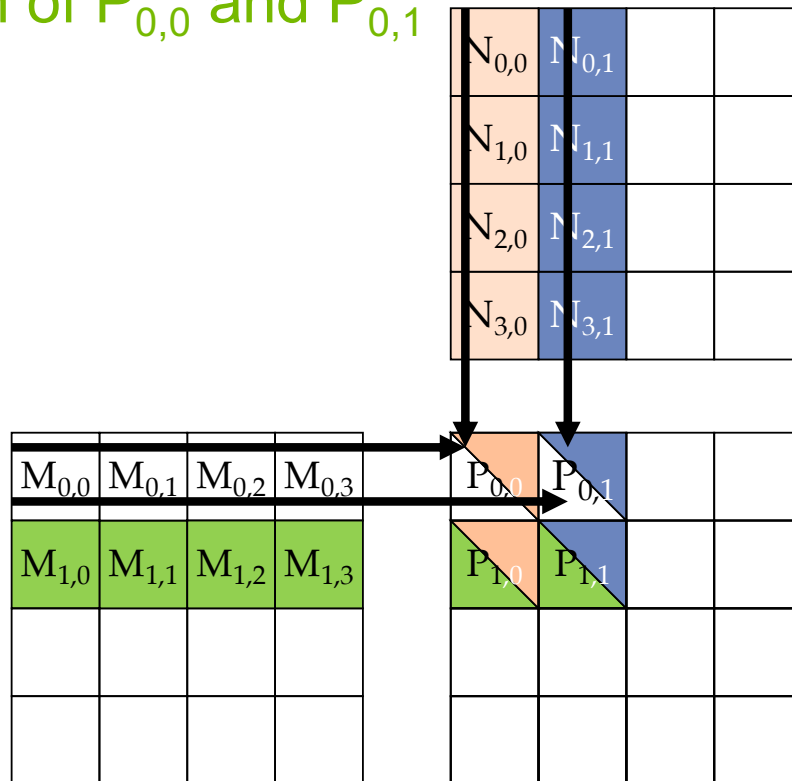


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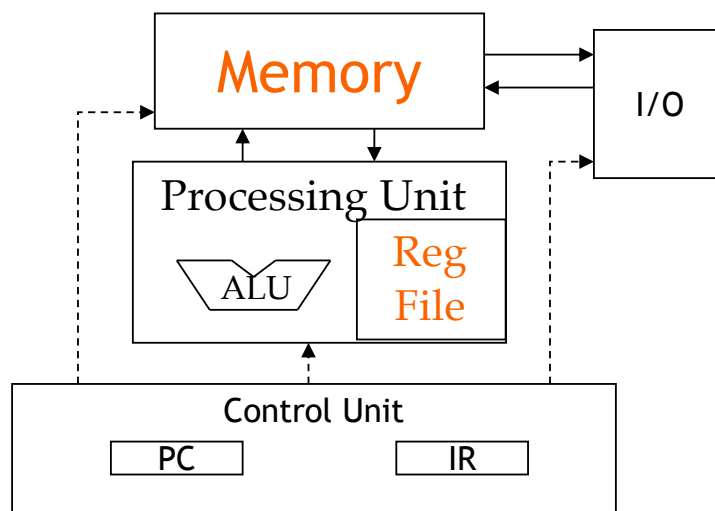
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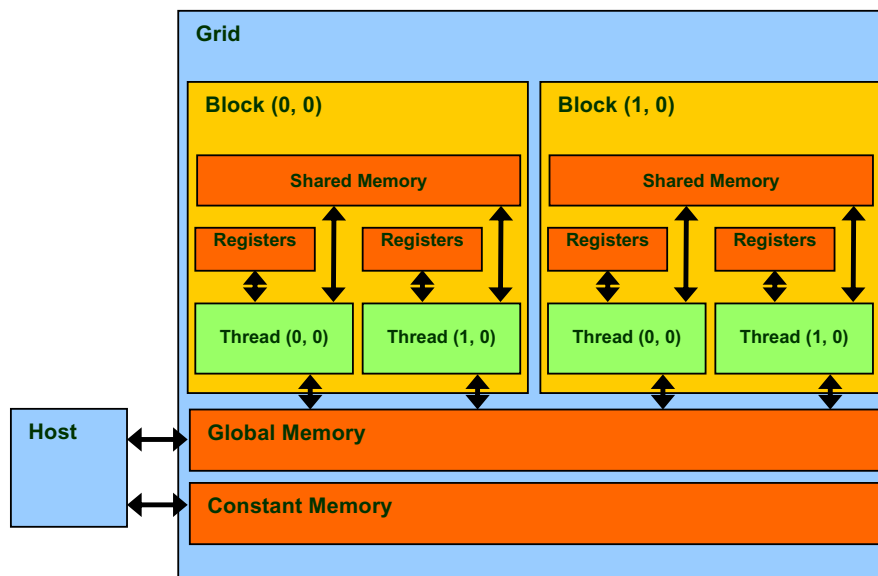
## Calculation of $P_{0,0}$ and $P_{0,1}$



## Memory and Registers in the Von-Neumann Model



# Programmer View of CUDA Memories



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## Declaring CUDA Variables

Variable declaration	Memory	Scope	Lifetime
<code>int LocalVar;</code>	register	thread	thread
<code>__device__ __shared__ int SharedVar;</code>	shared	block	block
<code>__device__ int GlobalVar;</code>	global	grid	application
<code>__device__ __constant__ int ConstantVar;</code>	constant	grid	application

- `__device__` is optional when used with `__shared__`, or `__constant__`
- Automatic variables reside in a register
  - Except per-thread arrays that reside in global memory

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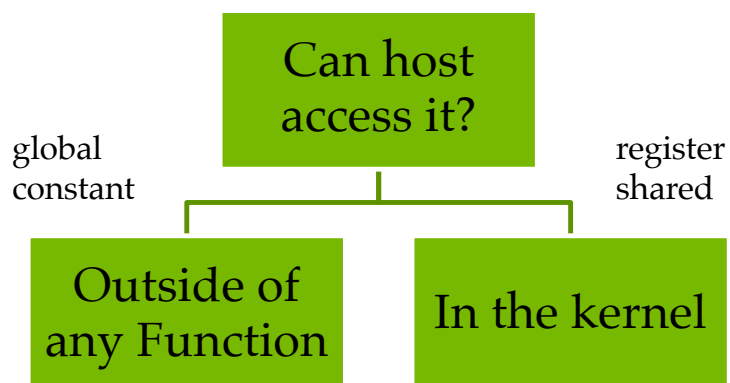
## Example: Shared Memory Variable Declaration

```
void blurKernel(unsigned char * in, unsigned char * out,  
int w, int h)  
{  
    __shared__ float ds_in[TILE_WIDTH][TILE_WIDTH];  
    ...  
}
```

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## Where to Declare Variables?



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# Shared Memory in CUDA

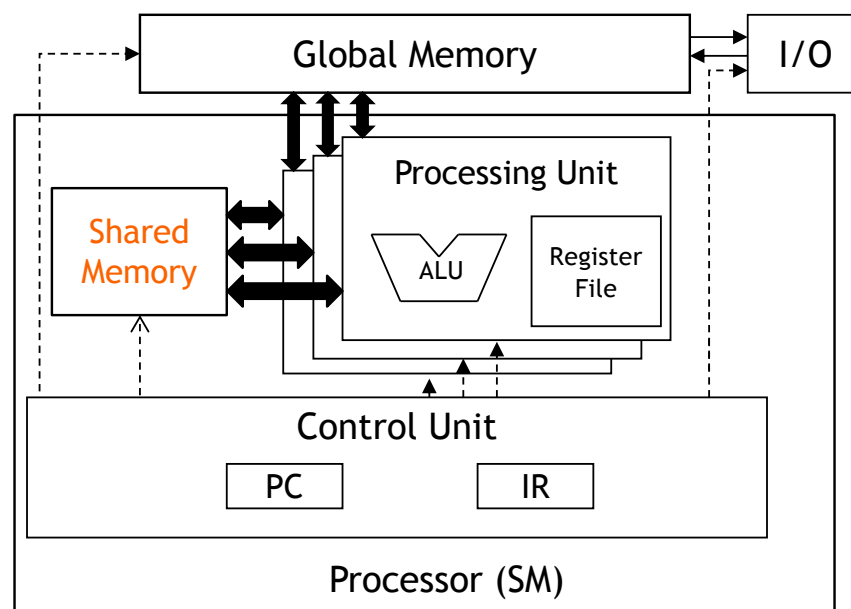
- A special type of memory whose contents are explicitly defined and used in the kernel source code
  - One in each SM
  - Accessed at much higher speed (in both latency and throughput) than global memory
  - Scope of access and sharing - thread blocks
  - Lifetime – thread block, contents will disappear after the corresponding thread finishes terminates execution
  - Accessed by memory load/store instructions
  - A form of scratchpad memory in computer architecture

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## Hardware View of CUDA Memories



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## Module 4.2 – Memory and Data Locality

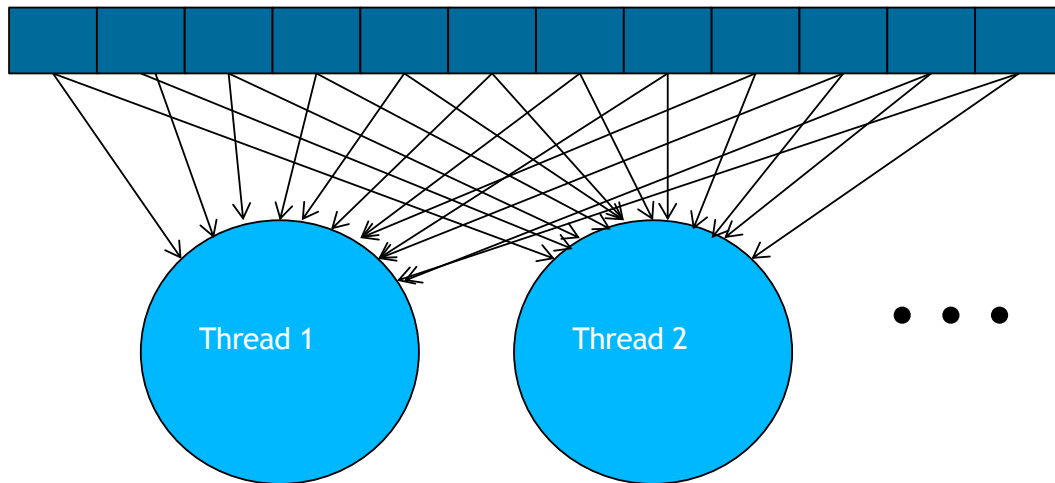
Tiled Parallel Algorithms

### Objective

- To understand the motivation and ideas for tiled parallel algorithms
  - Reducing the limiting effect of memory bandwidth on parallel kernel performance
  - Tiled algorithms and barrier synchronization

# Global Memory Access Pattern of the Basic Matrix Multiplication Kernel

Global Memory



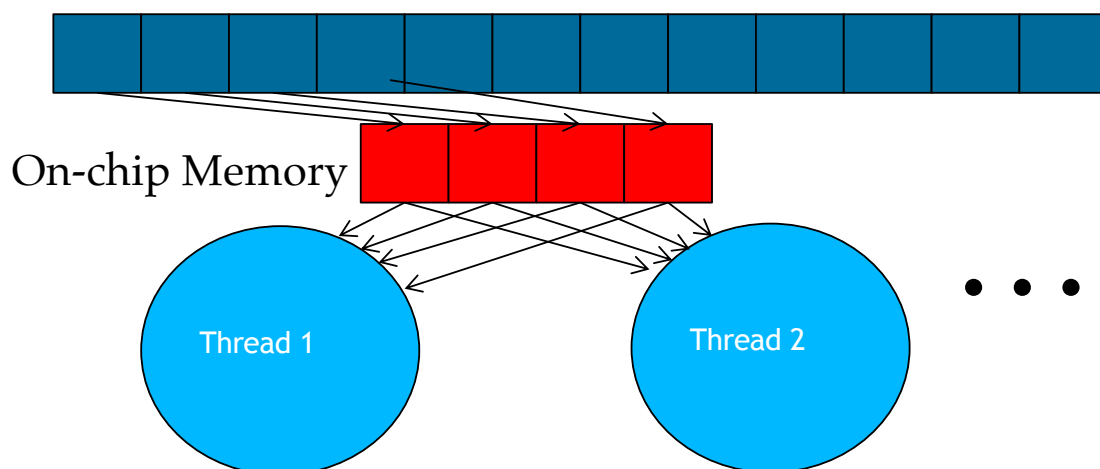
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## Tiling/Blocking - Basic Idea

Global Memory



Divide the global memory content into tiles

Focus the computation of threads on one or a small number of tiles at each point in time

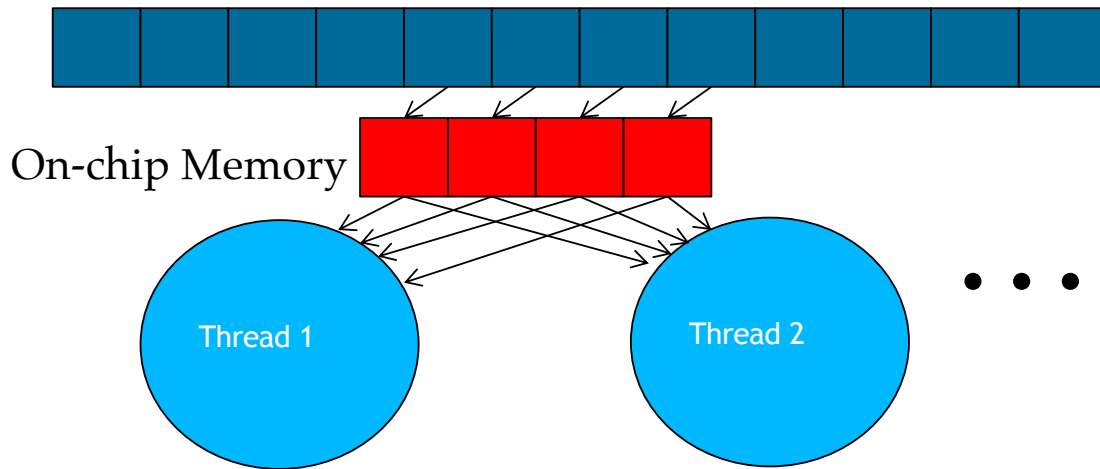
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# Tiling/Blocking - Basic Idea

Global Memory



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## Basic Concept of Tiling

- In a congested traffic system, significant reduction of vehicles can greatly improve the delay seen by all vehicles
  - Carpooling for commuters
  - Tiling for global memory accesses
    - drivers = threads accessing their memory data operands
    - cars = memory access requests



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## Some Computations are More Challenging to Tile

- Some carpools may be easier than others
  - Car pool participants need to have similar work schedule
  - Some vehicles may be more suitable for carpooling
- Similar challenges exist in tiling



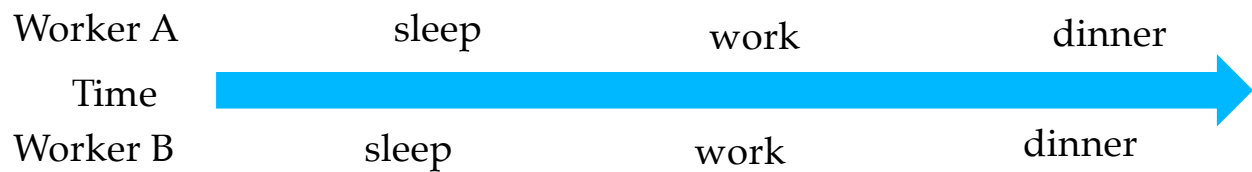
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## Carpools need synchronization.

- Good: when people have similar schedule



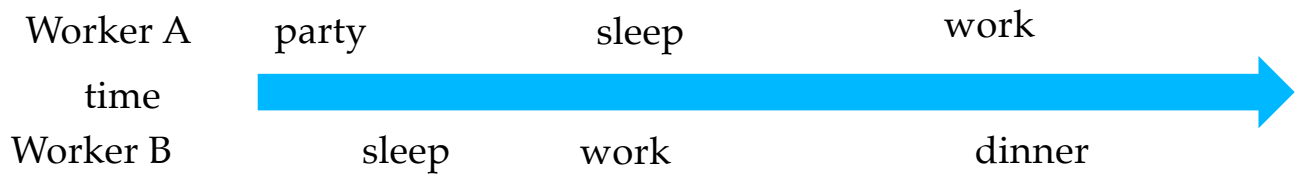
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## Carpools need synchronization.

- Bad: when people have very different schedule



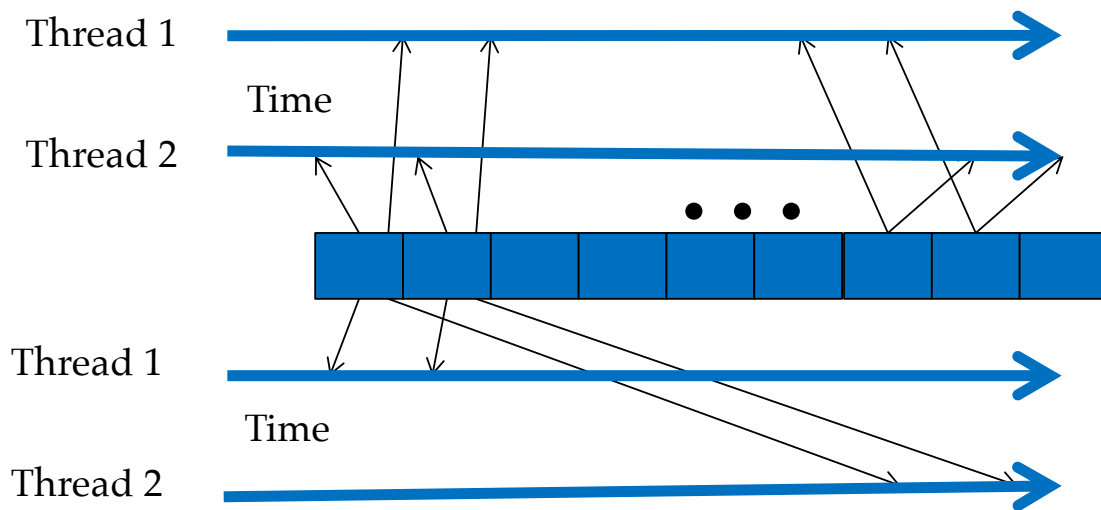
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## Same with Tiling

- Good: when threads have similar access timing



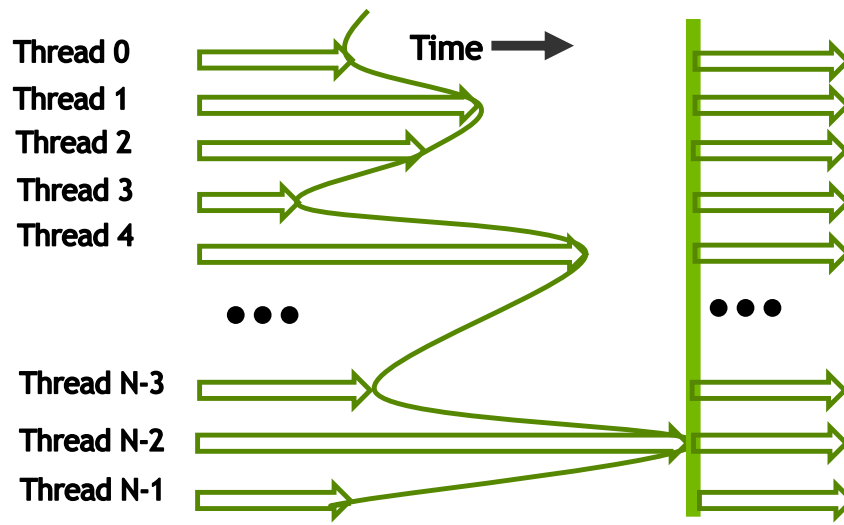
- Bad: when threads have very different timing

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# Barrier Synchronization for Tiling



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## Outline of Tiling Technique

- Identify a tile of global memory contents that are accessed by multiple threads
- Load the tile from global memory into on-chip memory
- Use barrier synchronization to make sure that all threads are ready to start the phase
- 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
- Move on to the next tile

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# Memory Model and Locality

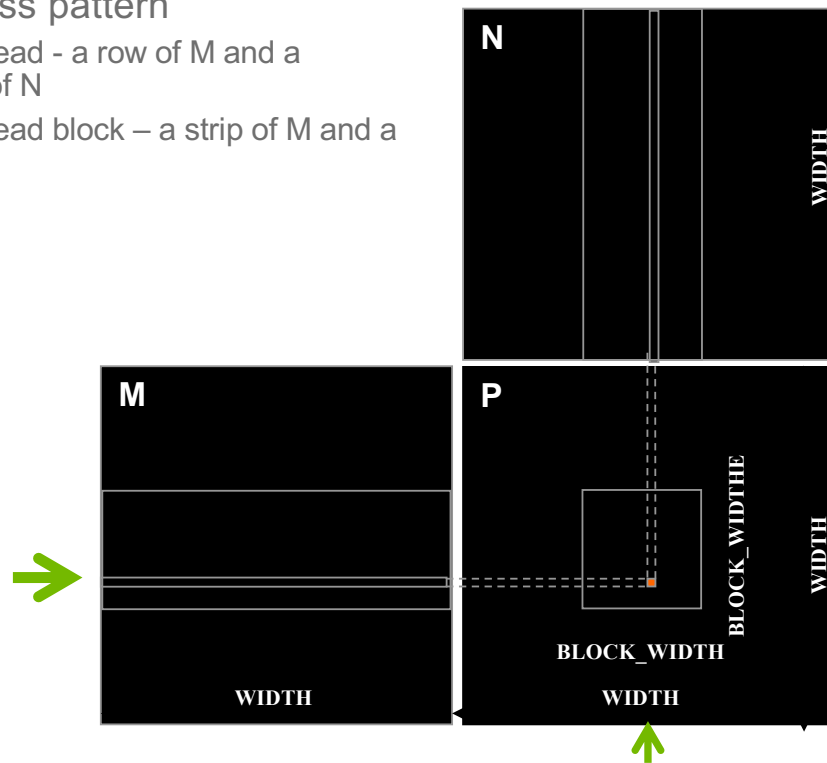
Tiled Matrix Multiplication

## Objective

- To understand the design of a tiled parallel algorithm for matrix multiplication
  - Loading a tile
  - Phased execution
  - Barrier Synchronization

# Matrix Multiplication

- Data access pattern
  - Each thread - a row of M and a column of N
  - Each thread block – a strip of M and a strip of N



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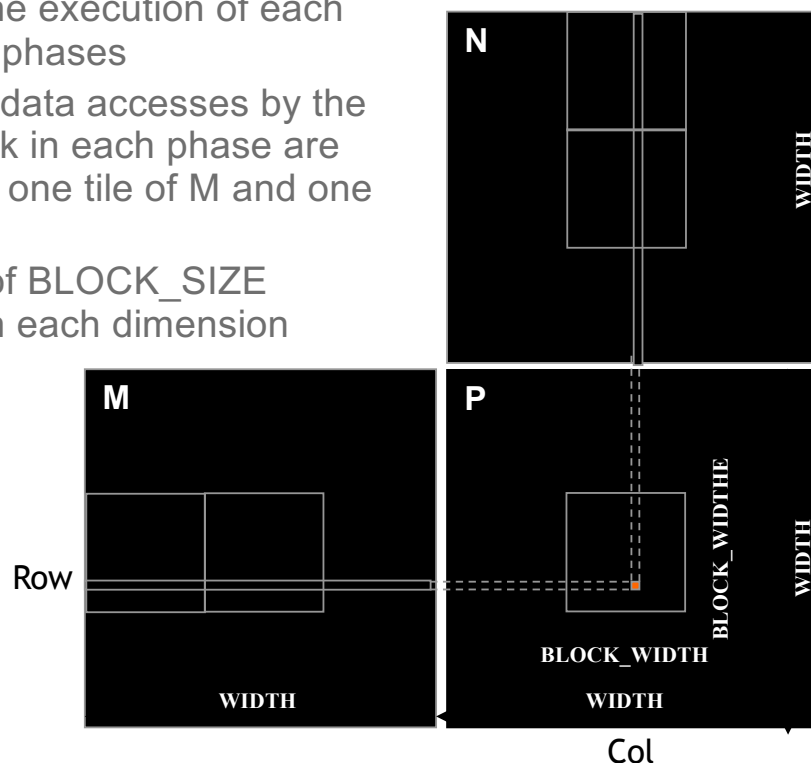
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# Tiled Matrix Multiplication

- 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



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Col

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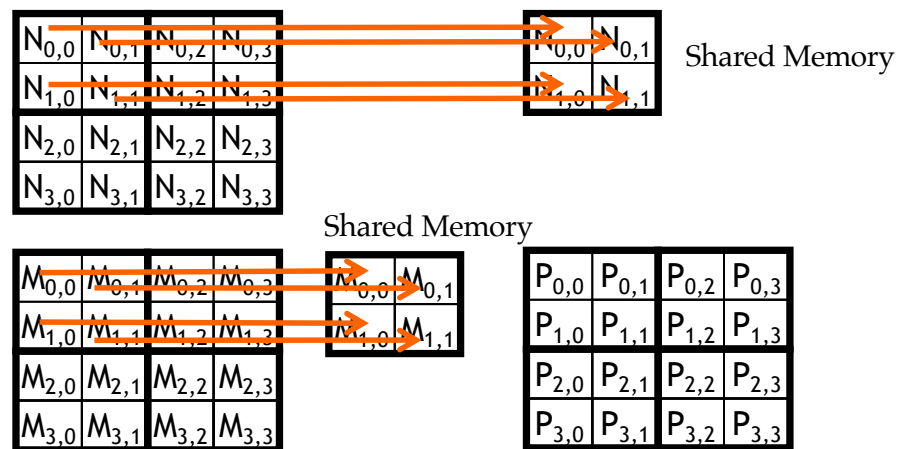
# Loading a Tile

- All threads in a block participate
  - Each thread loads one M element and one N element in tiled code

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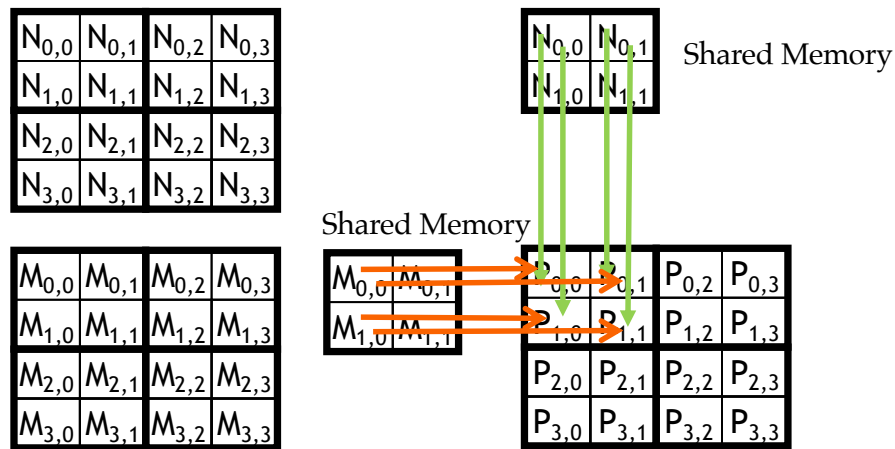
## Phase 0 Load for Block (0,0)



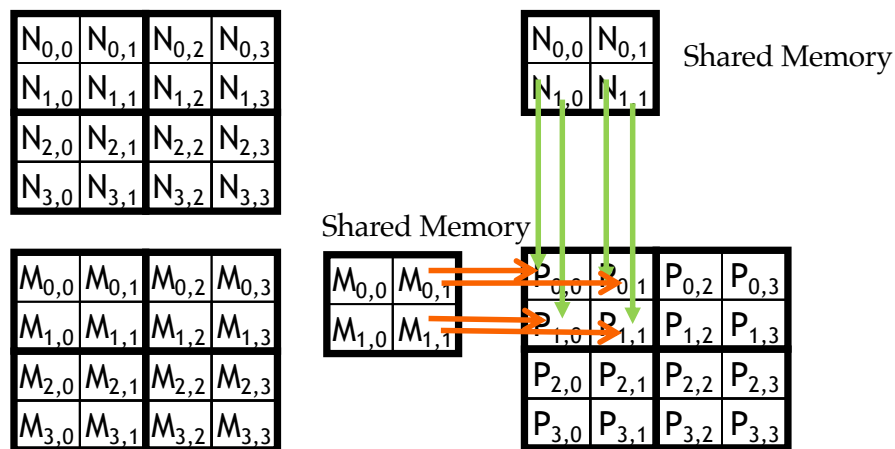
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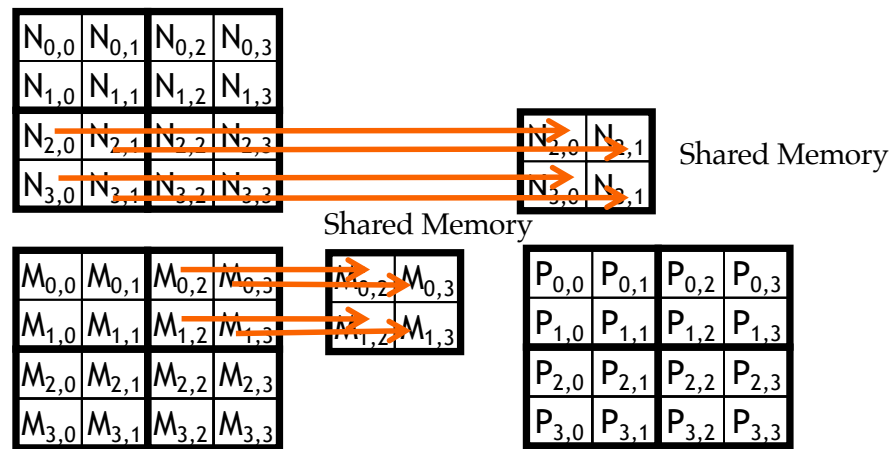
## Phase 0 Use for Block (0,0) (iteration 0)



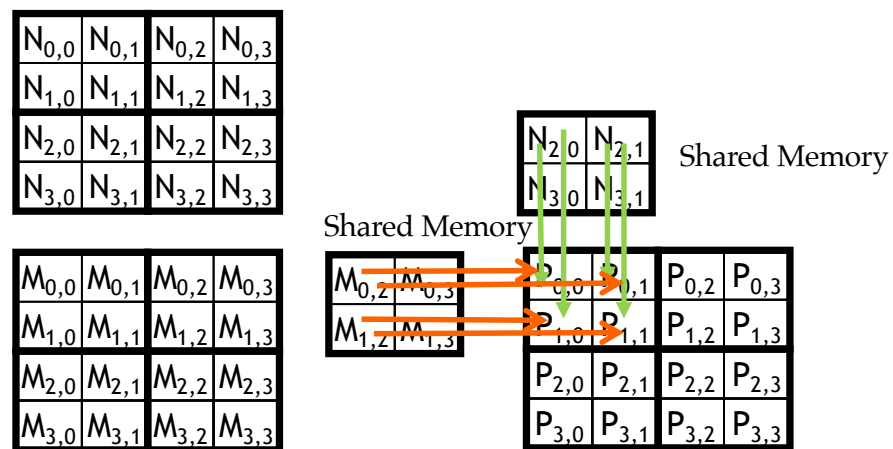
## Phase 0 Use for Block (0,0) (iteration 1)



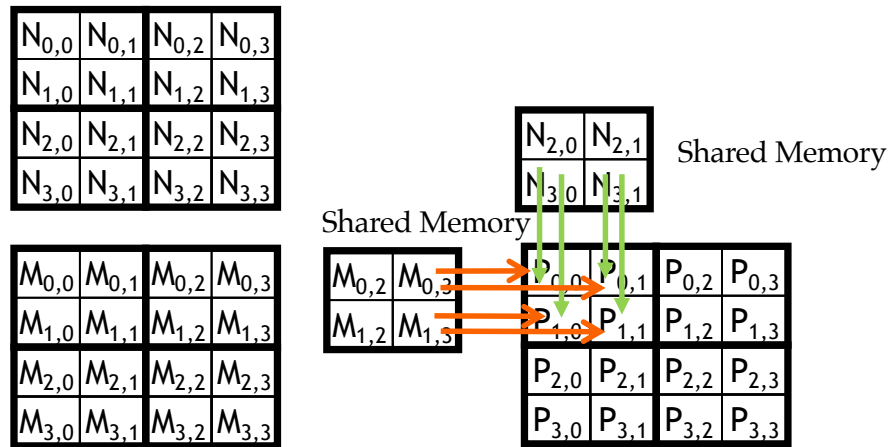
## Phase 1 Load for Block (0,0)



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



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



## Execution Phases of Toy Example

	Phase 0			Phase 1		
thread <sub>0,0</sub>	$M_{0,0}$ ↓ $Mds_{0,0}$	$N_{0,0}$ ↓ $Nds_{0,0}$	$PValue_{0,0} +=$ $Mds_{0,0} * Nds_{0,0} +$ $Mds_{0,1} * Nds_{1,0}$	$M_{0,2}$ ↓ $Mds_{0,0}$	$N_{2,0}$ ↓ $Nds_{0,0}$	$PValue_{0,0} +=$ $Mds_{0,0} * Nds_{0,0} +$ $Mds_{0,1} * Nds_{1,0}$
thread <sub>0,1</sub>	$M_{0,1}$ ↓ $Mds_{0,1}$	$N_{0,1}$ ↓ $Nds_{1,0}$	$PValue_{0,1} +=$ $Mds_{0,0} * Nds_{0,1} +$ $Mds_{0,1} * Nds_{1,1}$	$M_{0,3}$ ↓ $Mds_{0,1}$	$N_{2,1}$ ↓ $Nds_{0,1}$	$PValue_{0,1} +=$ $Mds_{0,0} * Nds_{0,1} +$ $Mds_{0,1} * Nds_{1,1}$
thread <sub>1,0</sub>	$M_{1,0}$ ↓ $Mds_{1,0}$	$N_{1,0}$ ↓ $Nds_{1,0}$	$PValue_{1,0} +=$ $Mds_{1,0} * Nds_{0,0} +$ $Mds_{1,1} * Nds_{1,0}$	$M_{1,2}$ ↓ $Mds_{1,0}$	$N_{3,0}$ ↓ $Nds_{1,0}$	$PValue_{1,0} +=$ $Mds_{1,0} * Nds_{0,0} +$ $Mds_{1,1} * Nds_{1,0}$
thread <sub>1,1</sub>	$M_{1,1}$ ↓ $Mds_{1,1}$	$N_{1,1}$ ↓ $Nds_{1,1}$	$PValue_{1,1} +=$ $Mds_{1,0} * Nds_{0,1} +$ $Mds_{1,1} * Nds_{1,1}$	$M_{1,3}$ ↓ $Mds_{1,1}$	$N_{3,1}$ ↓ $Nds_{1,1}$	$PValue_{1,1} +=$ $Mds_{1,0} * Nds_{0,1} +$ $Mds_{1,1} * Nds_{1,1}$
	time →					

## Execution Phases of Toy Example (cont.)

	Phase 0			Phase 1		
thread <sub>0,0</sub>	<b>M<sub>0,0</sub></b> ↓ Mds <sub>0,0</sub>	<b>N<sub>0,0</sub></b> ↓ Nds <sub>0,0</sub>	PValue <sub>0,0</sub> += <b>Mds<sub>0,0</sub></b> *Nds <sub>0,0</sub> + Mds <sub>0,1</sub> *Nds <sub>1,0</sub>	<b>M<sub>0,2</sub></b> ↓ Mds <sub>0,0</sub>	<b>N<sub>2,0</sub></b> ↓ Nds <sub>0,0</sub>	PValue <sub>0,0</sub> += Mds <sub>0,0</sub> *Nds <sub>0,0</sub> + Mds <sub>0,1</sub> *Nds <sub>1,0</sub>
thread <sub>0,1</sub>	<b>M<sub>0,1</sub></b> ↓ Mds <sub>0,1</sub>	<b>N<sub>0,1</sub></b> ↓ Nds <sub>1,0</sub>	PValue <sub>0,1</sub> += <b>Mds<sub>0,0</sub></b> *Nds <sub>0,1</sub> + Mds <sub>0,1</sub> *Nds <sub>1,1</sub>	<b>M<sub>0,3</sub></b> ↓ Mds <sub>0,1</sub>	<b>N<sub>2,1</sub></b> ↓ Nds <sub>0,1</sub>	PValue <sub>0,1</sub> += Mds <sub>0,0</sub> *Nds <sub>0,1</sub> + Mds <sub>0,1</sub> *Nds <sub>1,1</sub>
thread <sub>1,0</sub>	<b>M<sub>1,0</sub></b> ↓ Mds <sub>1,0</sub>	<b>N<sub>1,0</sub></b> ↓ Nds <sub>1,0</sub>	PValue <sub>1,0</sub> += Mds <sub>1,0</sub> *Nds <sub>0,0</sub> + Mds <sub>1,1</sub> *Nds <sub>1,0</sub>	<b>M<sub>1,2</sub></b> ↓ Mds <sub>1,0</sub>	<b>N<sub>3,0</sub></b> ↓ Nds <sub>1,0</sub>	PValue <sub>1,0</sub> += Mds <sub>1,0</sub> *Nds <sub>0,0</sub> + Mds <sub>1,1</sub> *Nds <sub>1,0</sub>
thread <sub>1,1</sub>	<b>M<sub>1,1</sub></b> ↓ Mds <sub>1,1</sub>	<b>N<sub>1,1</sub></b> ↓ Nds <sub>1,1</sub>	PValue <sub>1,1</sub> += Mds <sub>1,0</sub> *Nds <sub>0,1</sub> + Mds <sub>1,1</sub> *Nds <sub>1,1</sub>	<b>M<sub>1,3</sub></b> ↓ Mds <sub>1,1</sub>	<b>N<sub>3,1</sub></b> ↓ Nds <sub>1,1</sub>	PValue <sub>1,1</sub> += Mds <sub>1,0</sub> *Nds <sub>0,1</sub> + Mds <sub>1,1</sub> *Nds <sub>1,1</sub>

time →

Shared memory allows each value to be accessed by multiple threads

## 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 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



# GPU Teaching Kit

Accelerated Computing



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