



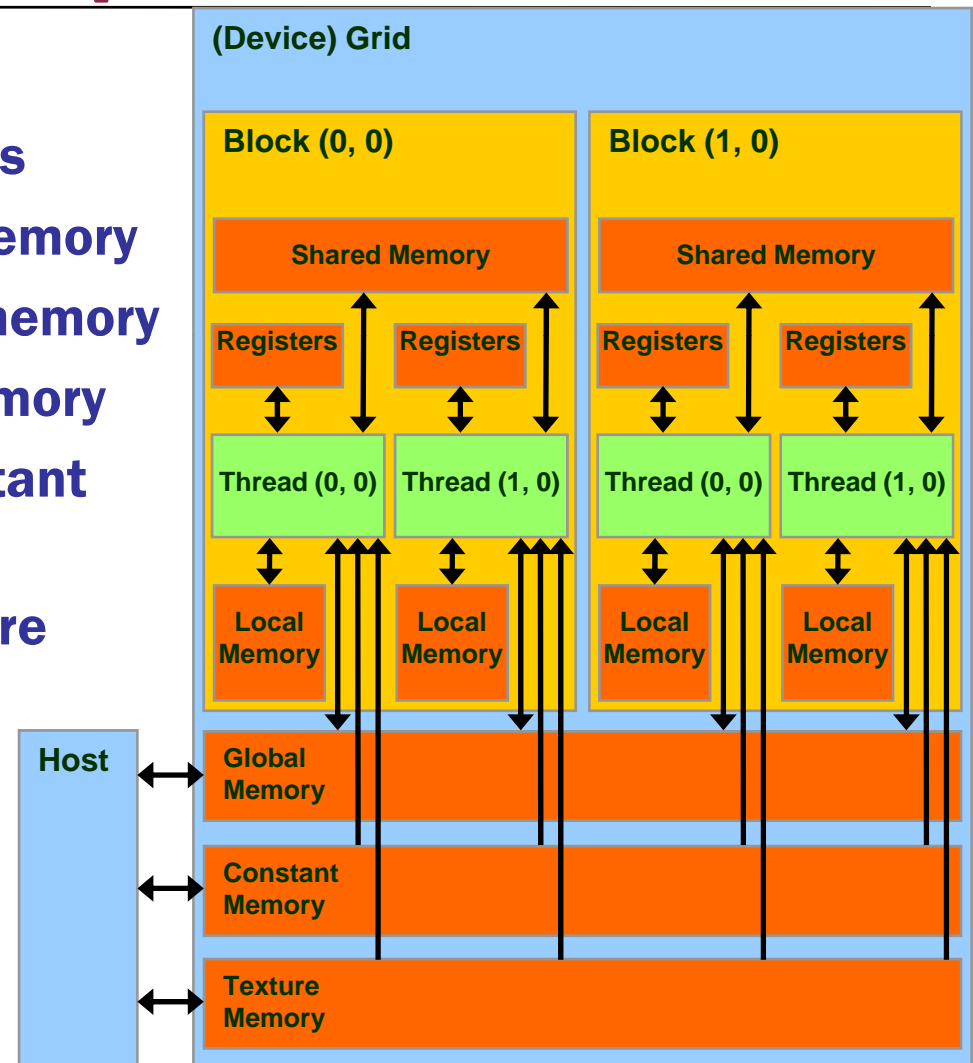
GPU Memory II

— Memory Hardware and Bank Conflict

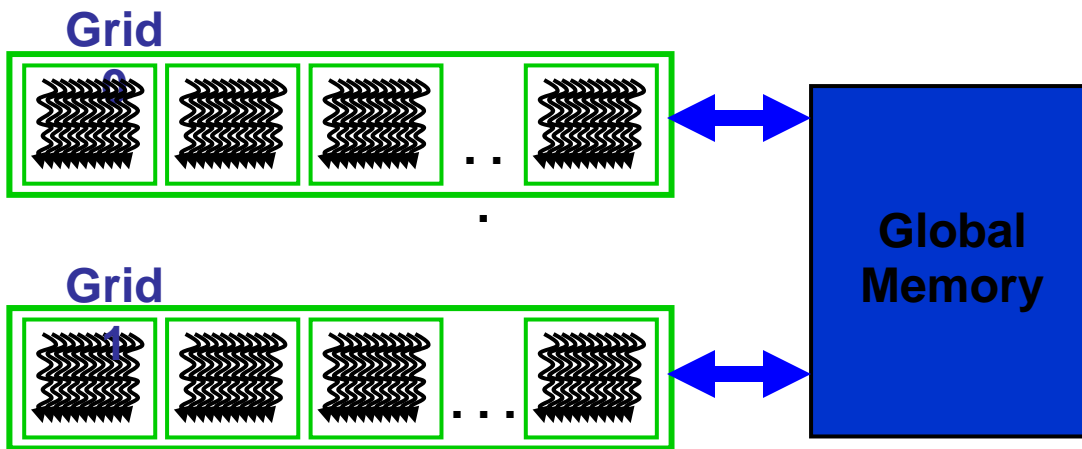
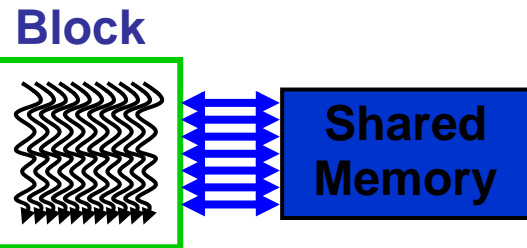
CUDA Device Memory Space: Review

- **Each thread 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**
 - Read only per-grid **texture memory**

- **The host can R/W global, constant, and texture memories**

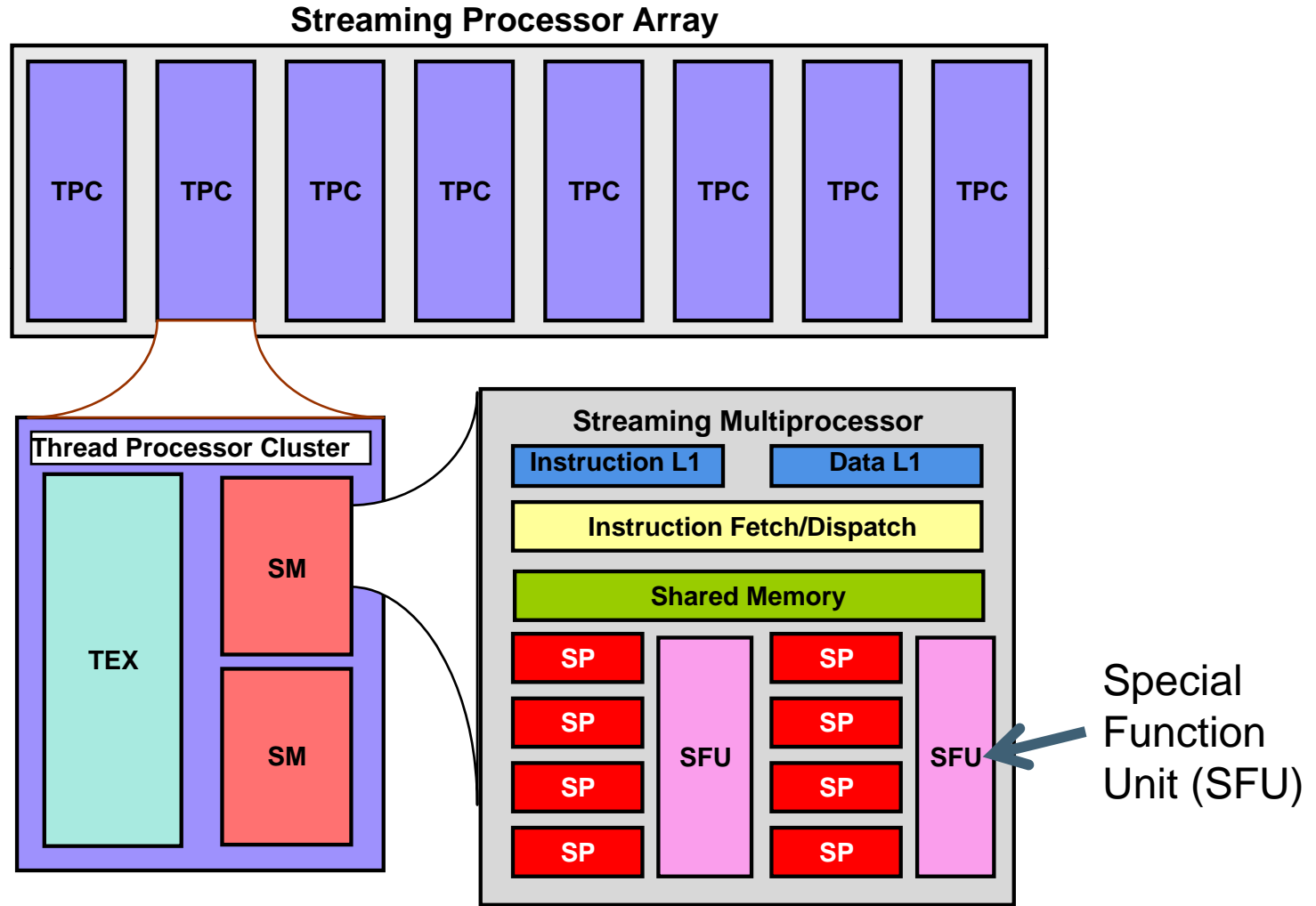


Parallel Memory Sharing



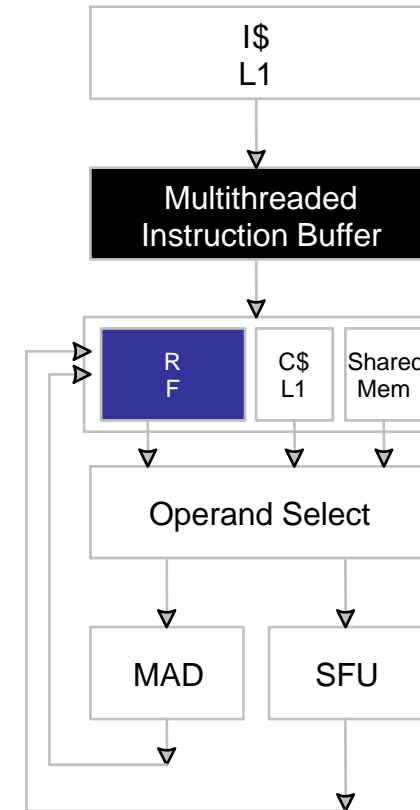
- **Local Memory:** per-thread
 - Private per thread
 - Auto variables, register spill
- **Shared Memory:** per-Block
 - Shared by threads of the same block
 - Inter-thread communication
- **Global Memory:** per-application
 - Shared by all threads
 - Inter-Grid communication

Hardware Overview



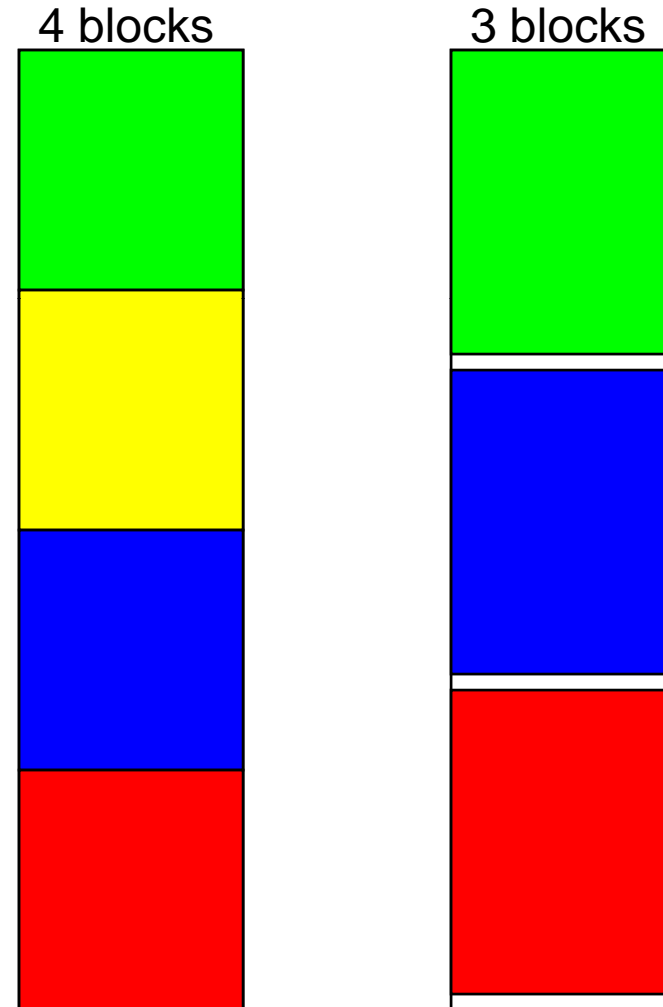
Register File

- **Register File (RF)**
 - **32 KB**
 - **Provides 4 operands/clock**
- **Texture pipe can also read/write RF**
 - **2 SMs share 1 TEX**
- **Load/Store pipe can also read/write RF**



Programmer View of Register File

- **There are 8192 registers in each SM in G80**
 - **Registers are dynamically partitioned across all Blocks assigned to the SM**
 - **Once assigned to a Block, the register is NOT accessible by threads in other Blocks**
 - **Each thread in the same Block only access registers assigned to itself**



Matrix Multiplication Example

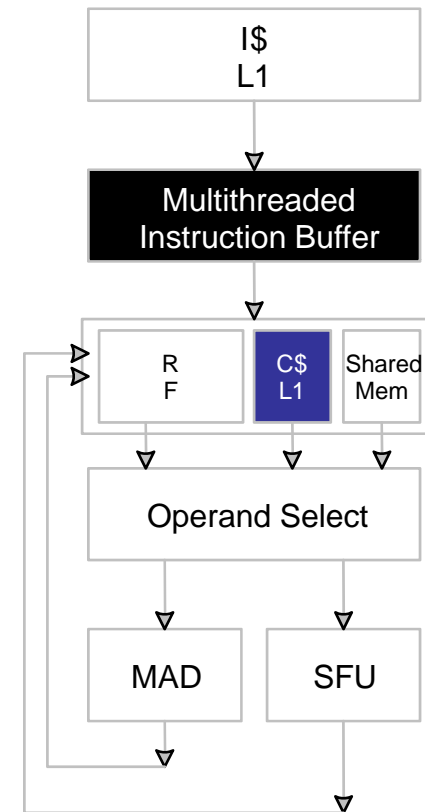
- **If each Block has 16X16 threads and each thread uses 10 registers, how many thread can run on each SM?**
 - Each Block requires $10 * 256 = 2560$ registers
 - $8192 = 3 * 2560 + \text{change}$
 - So, three blocks can run on an SM as far as registers are concerned
- **How about if each thread increases the use of registers by 1?**
 - Each Block now requires $11 * 256 = 2816$ registers
 - $8192 < 2816 * 3$
 - Only two Blocks can run on an SM, **1/3 reduction of parallelism!!!**

More on Dynamic Partitioning

- **Dynamic partitioning gives more flexibility to compilers/programmers**
 - **One can run a smaller number of threads that require many registers each or a large number of threads that require few registers each**
 - **This allows for finer grain threading than traditional CPU threading models.**
 - **The compiler can tradeoff between instruction-level parallelism and thread level parallelism**

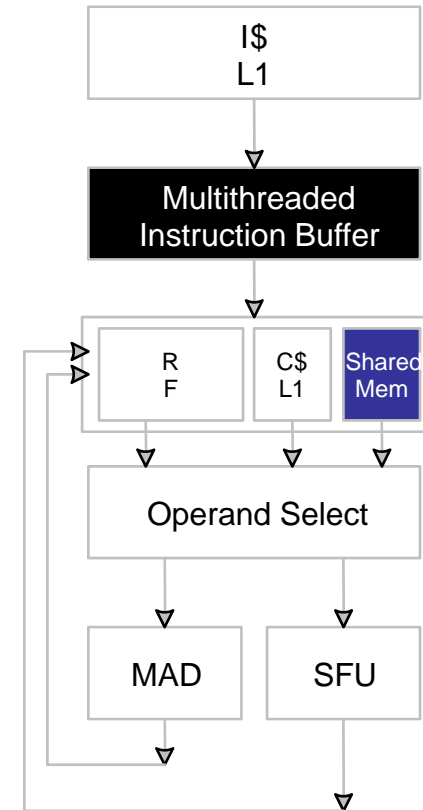
Constant

- **Immediate address constants**
- **Indexed address constants**
- **Constants stored in DRAM, and cached on chip**
 - **L1 per SM**
- **A constant value can be broadcast to all threads in a Warp**
 - **Extremely efficient way of accessing a value that is common for all threads in a Block!**



Shared Memory

- **Each Multi-processor has 16 KB of Shared Memory**
 - **16 banks of 32bit words**
 - **Will discuss about accessing pattern later**
- **Visible to all threads in a thread block**
 - **read and write access**

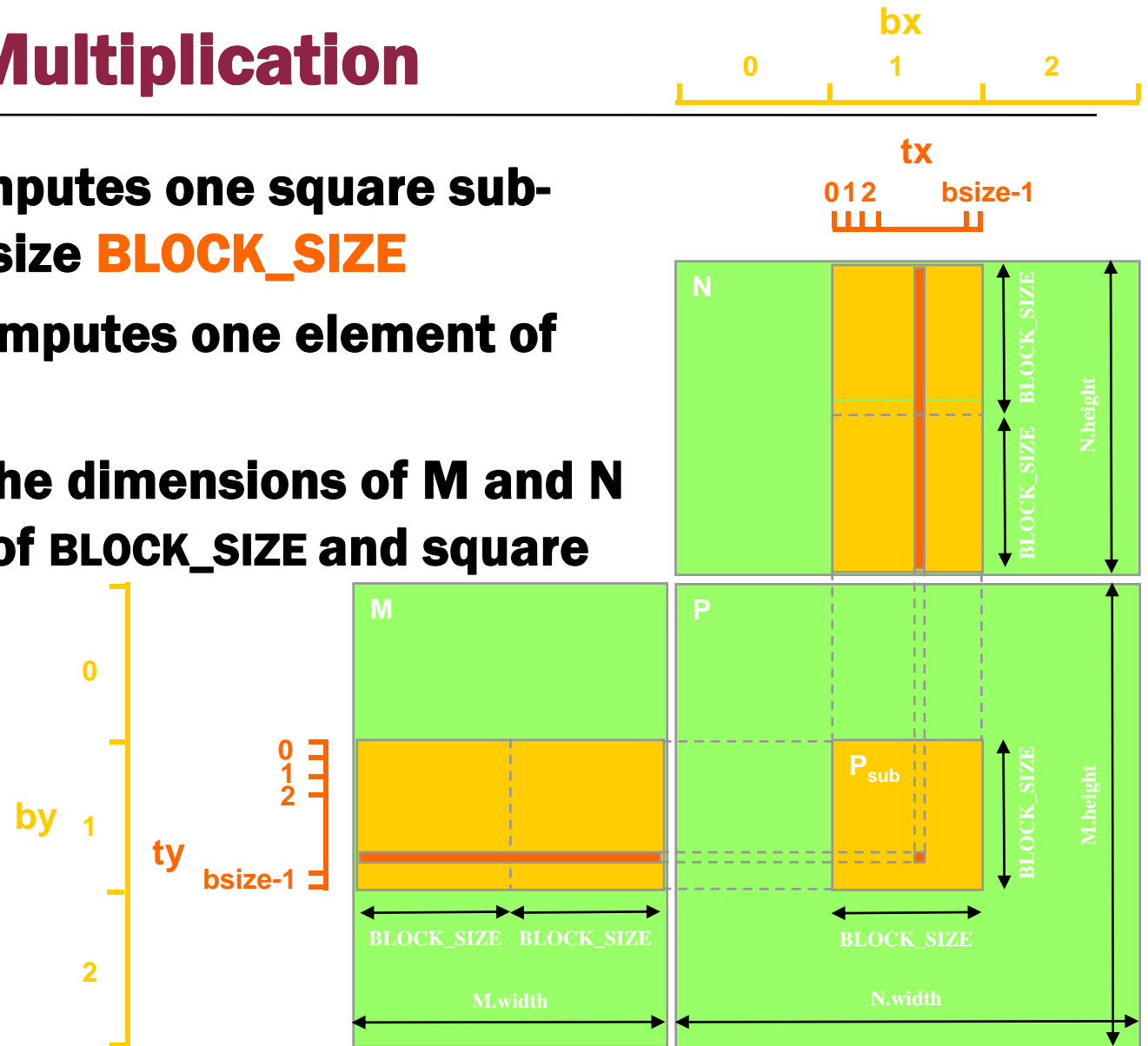


Matrix Multiplication Example

- **Explore Tile-based implementation with *Shared Memory*.**
- **Question:**
 - **How is shared memory organized?**
 - **What are the issues when accessing shared memory?**

Tile Based Multiplication

- One **block** computes one square sub-matrix P_{sub} of size **BLOCK_SIZE**
- One **thread** computes one element of P_{sub}
- Assume that the dimensions of M and N are multiples of **BLOCK_SIZE** and square shape



Tiled Matrix Multiplication Kernel – Review

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

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

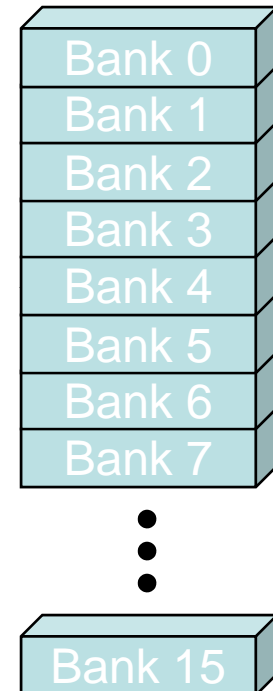
5.  int Row = by * TILE_WIDTH + ty;
6.  int Col = bx * TILE_WIDTH + tx;

7.  float Pvalue = 0;
8.  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    // Collaborative loading of Md and Nd tiles into shared memory
9.    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
10.   Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
11.   __syncthreads();

12.   for (int k = 0; k < TILE_WIDTH; ++k) {
13.     Pvalue += Mds[ty][k] * Nds[k][tx];
14.     Syncthreads();
15.   }
16.   Pd[Row*Width+Col] = Pvalue;
}
```

Shared Memory Organization

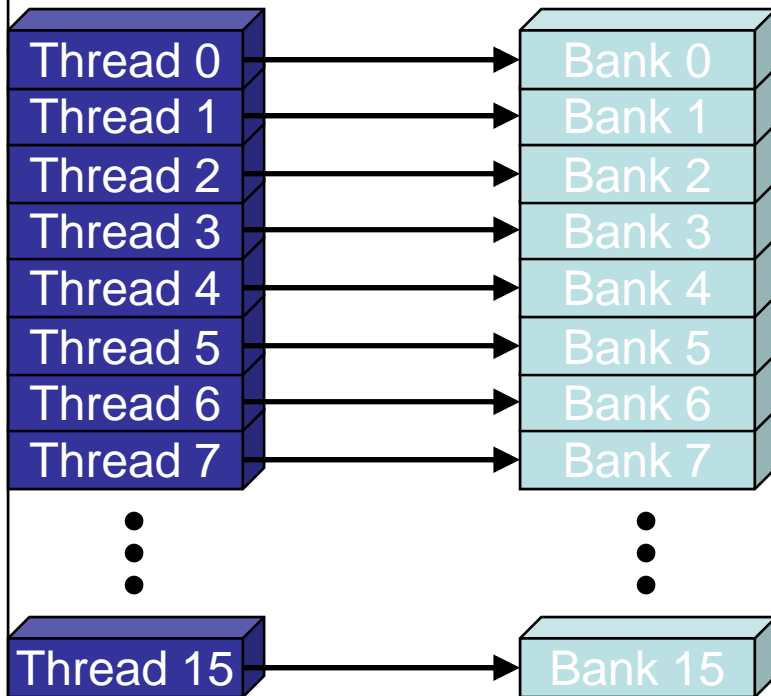
- **Parallel Memory Architecture:**
 - Memory is divided into **banks**
 - Essential to achieve high bandwidth
- **Each bank can service one address per cycle**
 - A memory can service as many simultaneous accesses as it has banks
- **Multiple simultaneous accesses to a bank result in a **bank conflict****
 - **Conflicting accesses are serialized**



Share Memory Access Issue

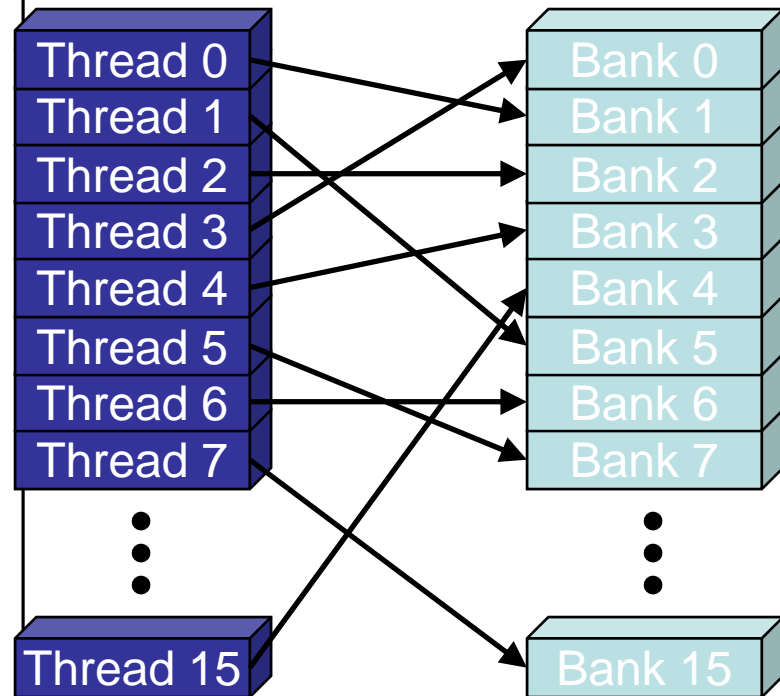
➤ **No Bank Conflicts**

- **Linear addressing
stride == 1**

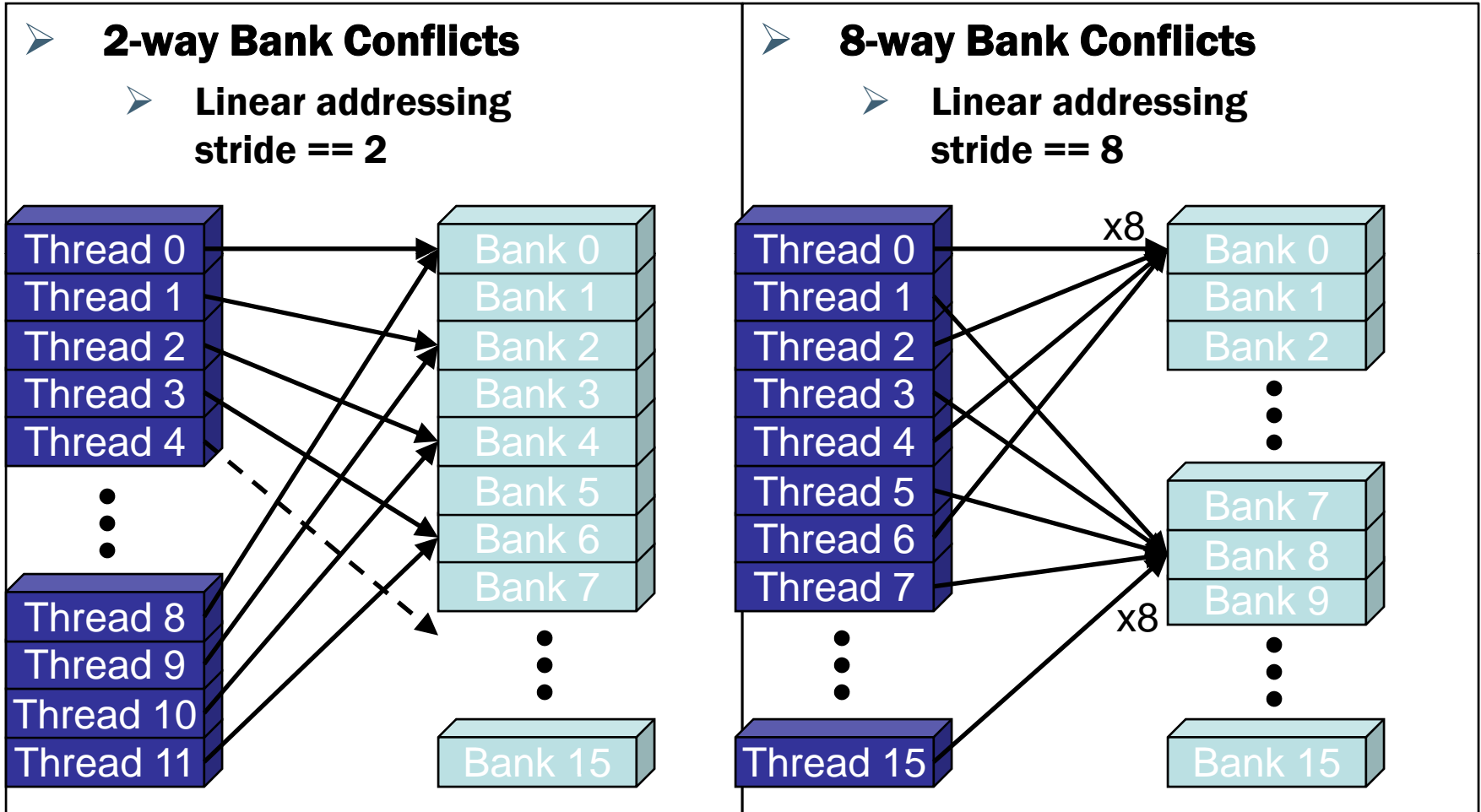


➤ **No Bank Conflicts**

- **Random 1:1 Permutation**



Share Memory Access Issue



How addresses map to banks in CUDA

- **Each bank has a bandwidth of 32 bits per clock cycle**
- **Successive 32-bit words are assigned to successive banks**
- **G80 has 16 banks**
 - **So bank = address % 16**
 - **Same as the size of a half-warp**
 - **No bank conflicts between different half-warps, only within a single half-warp**

Share Memory Performance

- **Shared memory is as fast as registers if there are no bank conflicts**
- **The fast case:**
 - **If all threads of a half-warp access different banks, there is no bank conflict**
 - **If all threads of a half-warp access the identical address, there is no bank conflict (**broadcast**)**
- **The slow case:**
 - **Bank Conflict: multiple threads in the same half-warp access the same bank**
 - **Must serialize the accesses**
 - **Cost = max # of simultaneous accesses to a single bank**

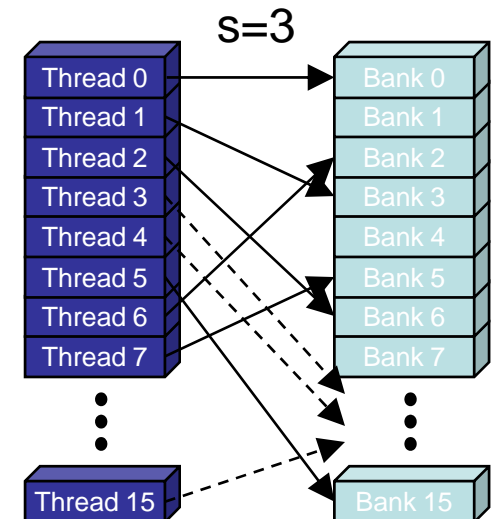
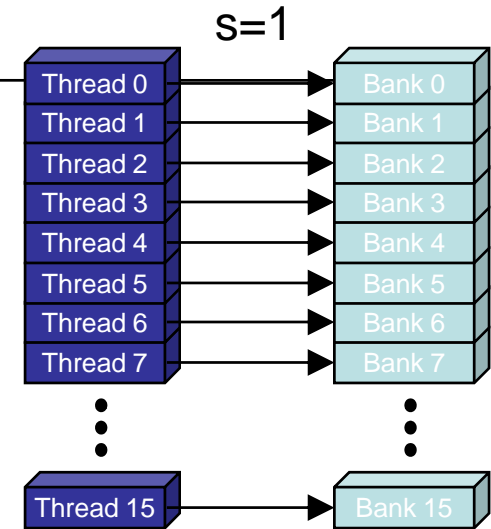
Linear Addressing (1D)

➤ **Given:**

```
__shared__ float shared[256];
float foo = shared[baseIndex + s * threadIdx.x];
```

➤ **This is only bank-conflict-free if s shares no common factors with the number of banks**

➤ **16 on G80, so s must be odd**



Data types and bank conflicts

- This has no conflicts if type of shared is 32-bits:

```
foo = shared[baseIndex + threadIdx.x]
```

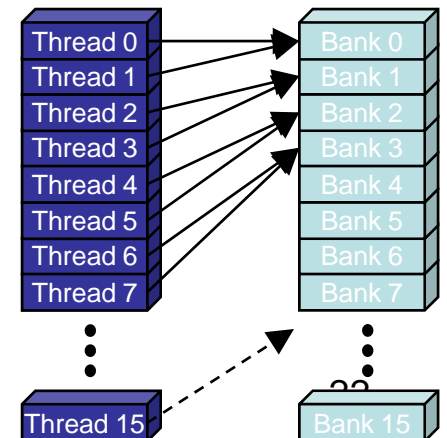
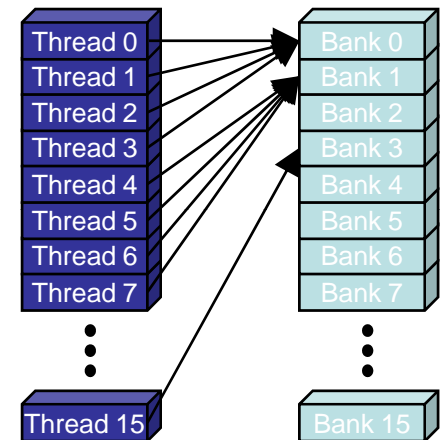
- But not if the data type is smaller

- 4-way bank conflicts:

```
__shared__ char shared[];  
foo = shared[baseIndex + threadIdx.x];
```

- 2-way bank conflicts:

```
__shared__ short shared[];  
foo = shared[baseIndex + threadIdx.x];
```

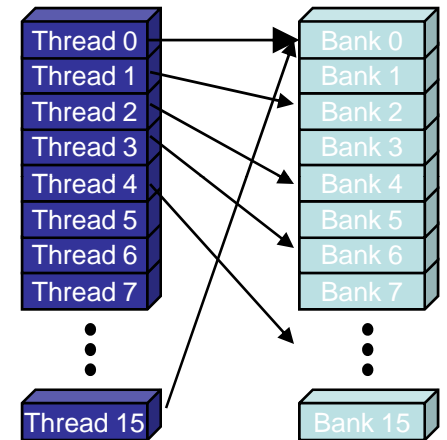


Structs and Bank Conflicts

- **Struct assignments compile into as many memory accesses as there are struct members:**

```

struct vector { float x, y, z; };
struct myType {
    float f;
    int c;
};
__shared__ struct vector vectors[64];
__shared__ struct myType myTypes[64];
    
```



- **This has no bank conflicts for vector; struct size is 3 words**
 - **3 accesses per thread, contiguous banks (no common factor with 16)**

```
struct vector v = vectors[baseIndex + threadIdx.x];
```

- **This has 2-way bank conflicts for my Type; (2 accesses per thread)**

```
struct myType m = myTypes[baseIndex + threadIdx.x];
```

Common Array Bank Conflict Patterns 1D

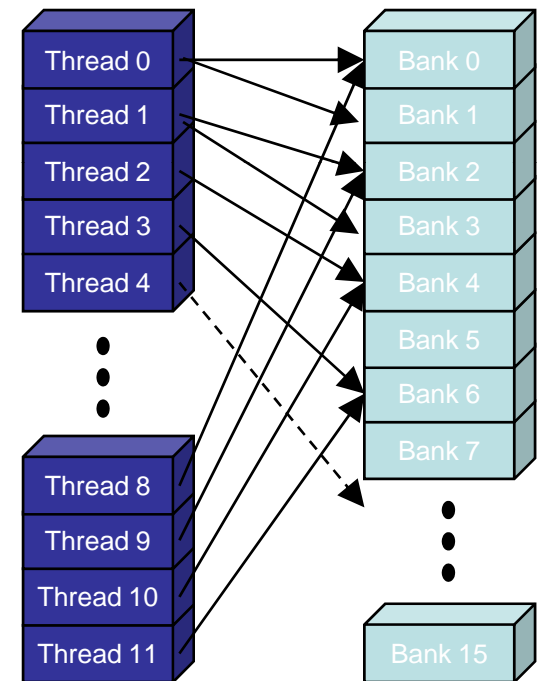
- **Each thread loads 2 elements into shared memory:**

- **2-way-interleaved loads result in 2-way bank conflicts:**

```

int tid = threadIdx.x;
shared[2*tid] = global[2*tid];
shared[2*tid+1] = global[2*tid+1];
    
```

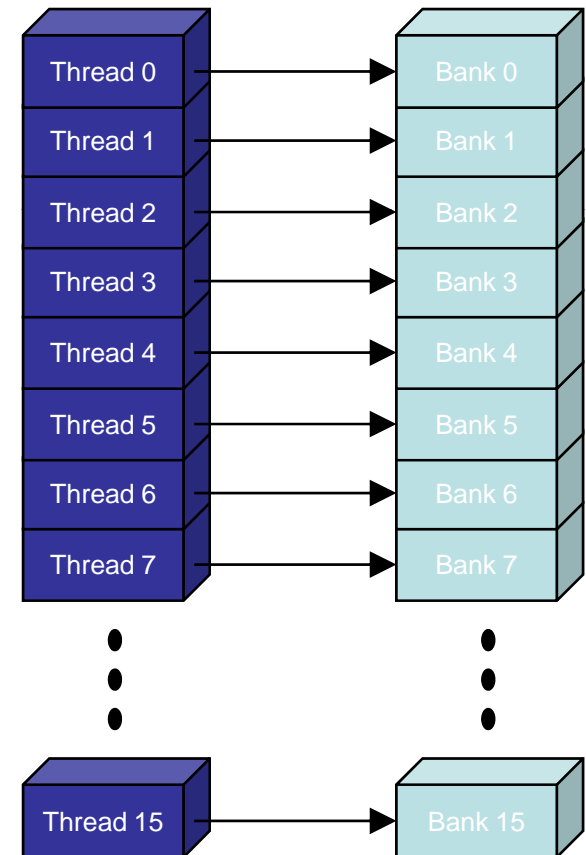
- **This makes sense for traditional CPU threads, locality in cache line usage and reduced sharing traffic.**
 - **Not in shared memory usage where there is no cache line effects but banking effects**



A Better Array Access Pattern

- Each thread loads one element in every consecutive group of `blockDim` elements.

```
shared[tid] = global[tid];  
shared[tid + blockDim.x] =  
    global[tid + blockDim.x];
```



Common Bank Conflict Patterns (2D)

- **Operating on 2D array of floats in shared memory**
 - e.g. image processing
- **Example: 16x16 block**
 - Each thread processes a row
 - So threads in a block access the elements in each column simultaneously (example: row 1 in purple)
 - 16-way bank conflicts: rows all start at bank 0
- **Solution 1) pad the rows**
 - Add one float to the end of each row
- **Solution 2) transpose before processing**
 - Suffer bank conflicts during transpose

Bank Indices without Padding

0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0	1	2	3	4	5	6	7	...	15

Bank Indices with Padding

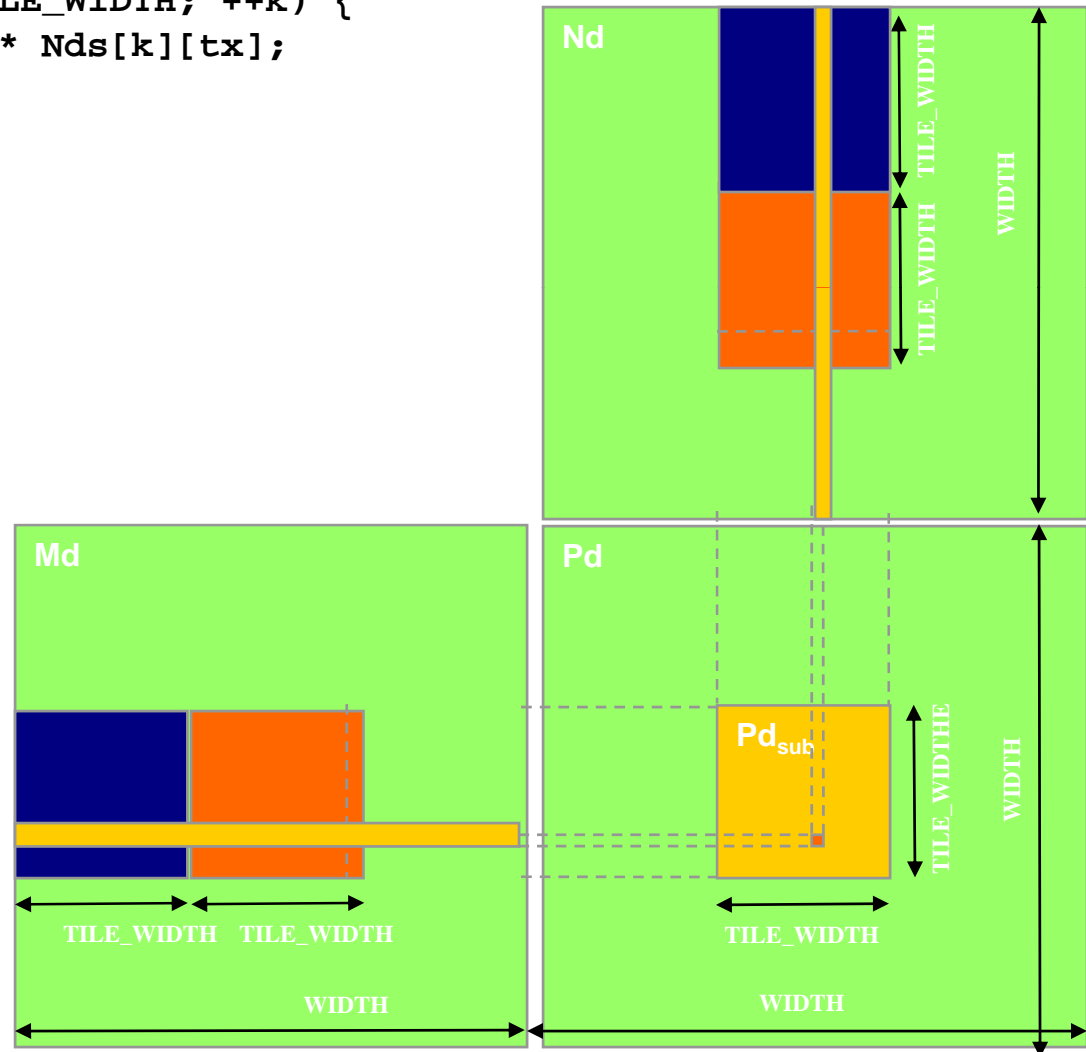
0	1	2	3	4	5	6	7	...	15	0
1	2	3	4	5	6	7	8	...	0	1
2	3	4	5	6	7	8	9	...	1	2
3	4	5	6	7	8	9	10	...	2	3
4	5	6	7	8	9	10	11	...	3	4
5	6	7	8	9	10	11	12	...	4	5
6	7	8	9	10	11	12	13	...	5	6
7	8	9	10	11	12	13	14	...	7	8
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0	1	2	3	4	5	6	...	14	15

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Synchthreads();
15. }

```



Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```
12. for (int k = 0; k < TILE_WIDTH; ++k) {  
13.   Pvalue += Mds[ty][k] * Nds[k][tx];  
14.   Synchthreads();  
15. }
```

$Mds[ty * TILE_WIDTH + k]$

$Nds[k * TILE_WIDTH + tx]$

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

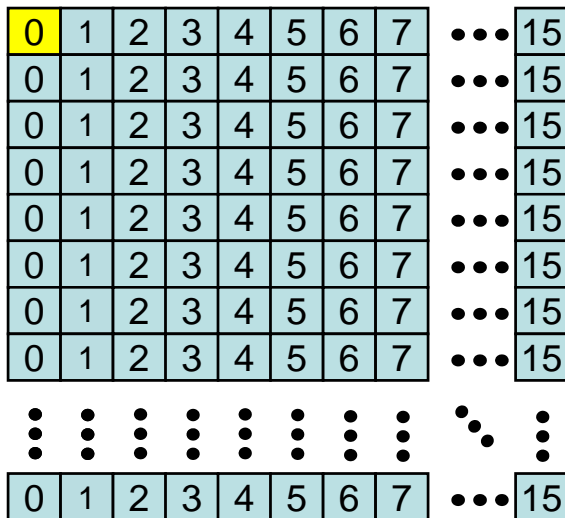
```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Synchthreads();
15. }

```

$Mds[ty * TILE_WIDTH + k]$

$Nds[k * TILE_WIDTH + tx]$



- For **TILE_WIDTH** = 16
 - The whole half-warp is accessing the same shared memory location.
 - Conflict. But, GPU support **broadcasting**.

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Syncthreads();
15. }
  
```

Mds[ty * TILE_WIDTH + k]

Nds[k * TILE_WIDTH + tx]

0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15

- For **TILE_WIDTH = 8**
 - The first half-warp and the second half-warp are accessing two different shared memory location.
 - 8-way bank conflict.

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Synchthreads();
15. }

```

$Mds[ty * TILE_WIDTH + k]$

$Nds[k * TILE_WIDTH + tx]$

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

- For **TILE_WIDTH** = 4
- 4-way bank conflict.

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Synchthreads();
15. }

```

$Mds[ty * TILE_WIDTH + k]$

$Nds[k * TILE_WIDTH + tx]$

- For **TILE_WIDTH** = 16
 - Each thread in a half-warp is accessing different shared memory location.
 - No conflict.

0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
0	1	2	3	4	5	6	7	...	15
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0	1	2	3	4	5	6	7	...	15

Does Matrix Multiplication Incur Shared Memory Bank Conflicts?

```

12. for (int k = 0; k < TILE_WIDTH; ++k) {
13.   Pvalue += Mds[ty][k] * Nds[k][tx];
14.   Synchthreads();
15. }

```

$Mds[ty * TILE_WIDTH + k]$

$Nds[k * TILE_WIDTH + tx]$

- For **TILE_WIDTH** = 8
 - Since the memory storage organization is row-major for 2D array, so it's the same with **TILE_WIDTH** = 16.
 - No conflict.

0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15