

Performance Consideration 1

Prof. Seokin Hong

Agenda

- **Memory Optimizations**

- **More about Global Memory**
- **Memory Coalescing** to fully utilize global memory bandwidth
- **Reducing Bank Conflict** to fully utilize shared memory bandwidth

- **Considering Control-Flow Divergence**

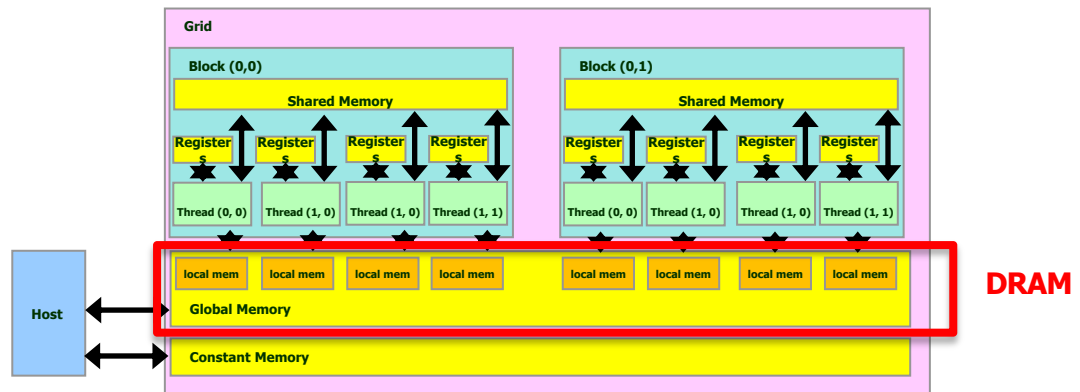
- Warps and SIMD Hardware

- **Considering Occupancy**

- Dynamic Partitioning of Resources

- **Considering Thread Granularity**

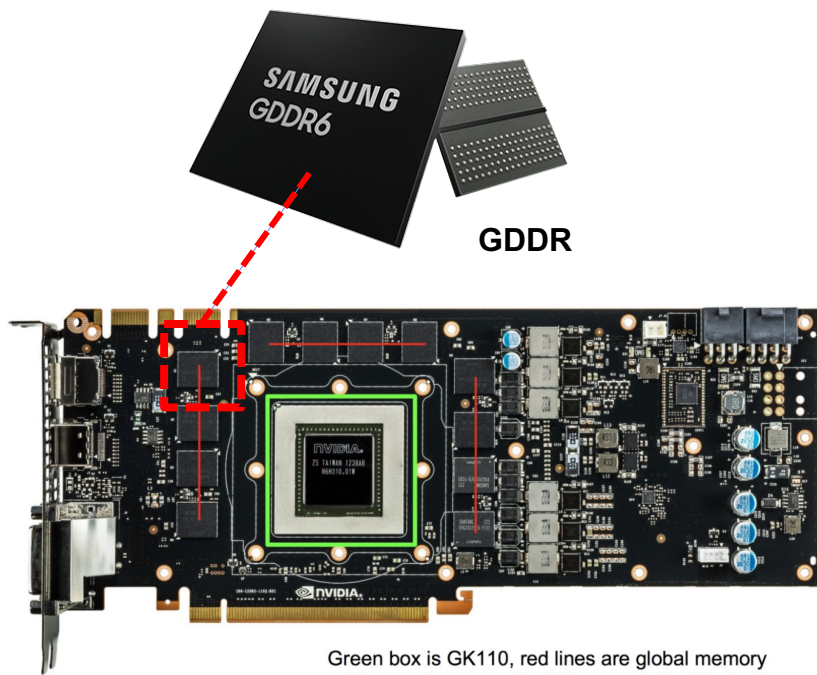
More about Global Memory



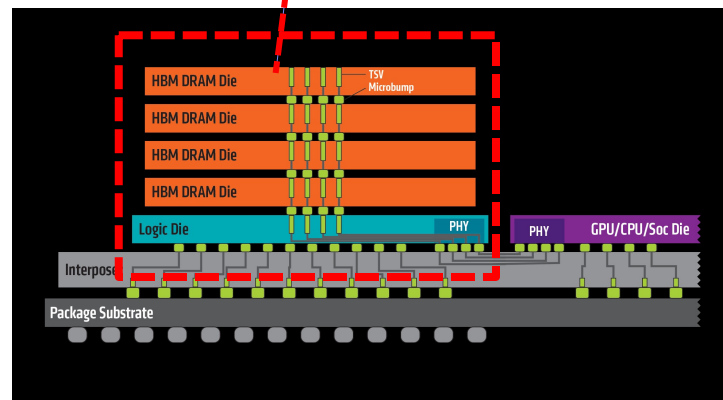
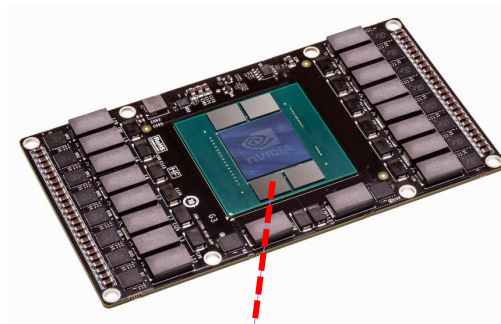
DRAM

CUDA Global Memory = DRAM

- The global memory of a CUDA device is implemented with DRAM (Dynamic Random Access Memory)
 - Graphic DRAM is built for much **higher bandwidth**
 - GDDR (Graphic DDR)
 - HBM (3D-stacked High Bandwidth Memory)

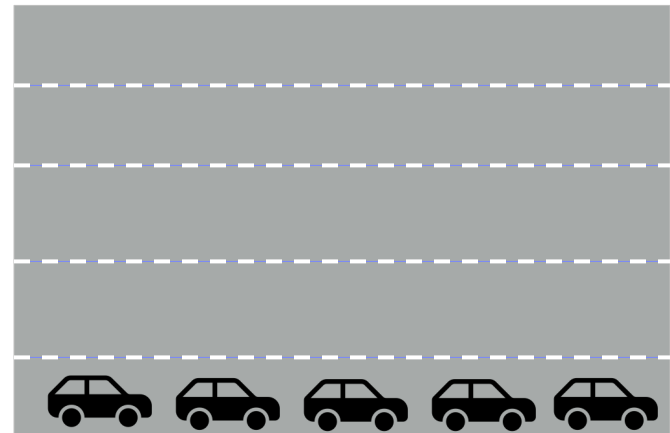
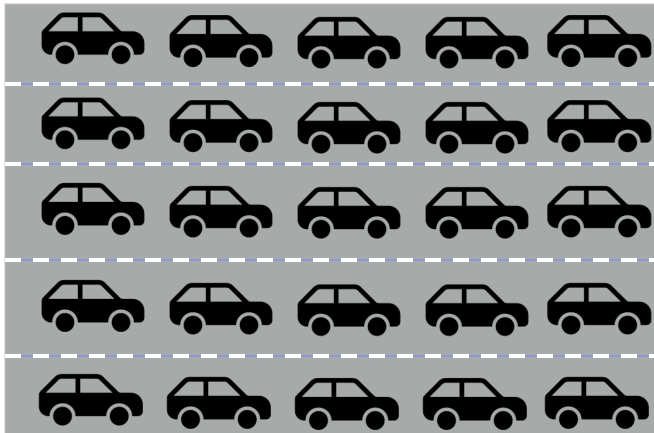


Green box is GK110, red lines are global memory

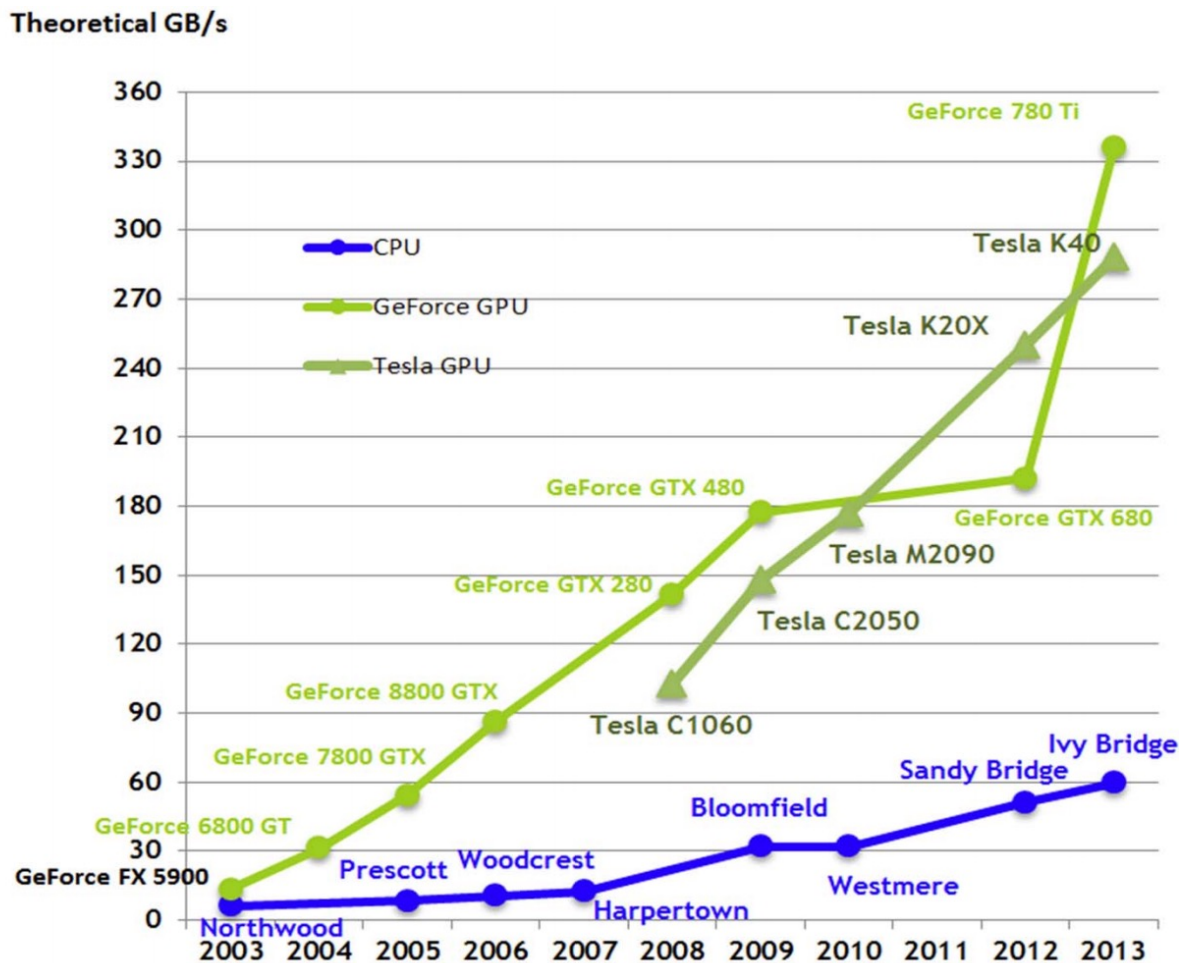


Global Memory is a major bottleneck

- DRAM is slow → long access latency (~ 300 cycles)
- Graphic DRAM has much higher bandwidth than standard DRAM
 - E.g., P100 with 4 HBM : 1TB /s
- So, programming techniques are required to fully utilize the DRAM bandwidth!!
- Need to understand DRAM to know **causes of the DRAM bandwidth problem** in CUDA programming



Memory Bandwidth Comparison



P100 with 4 HBM : 1TB /s

Why do GPUs need higher bandwidth DRAM?

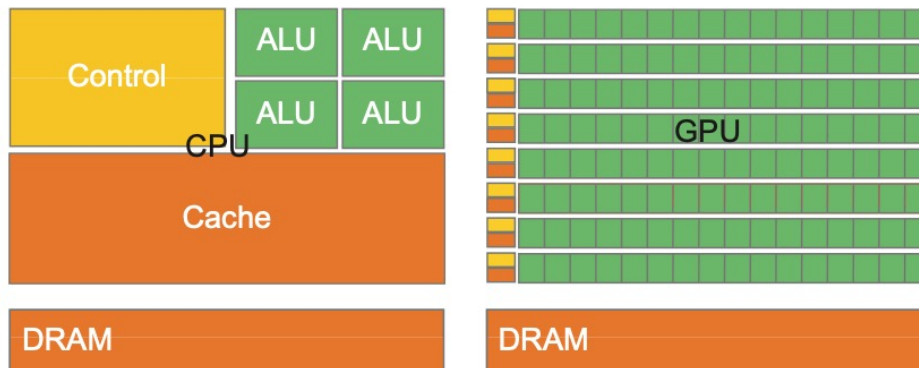
- **Lots of compute**

- 24 Streaming Multiprocessors, each with 128 execution units

- **Lots of threads**

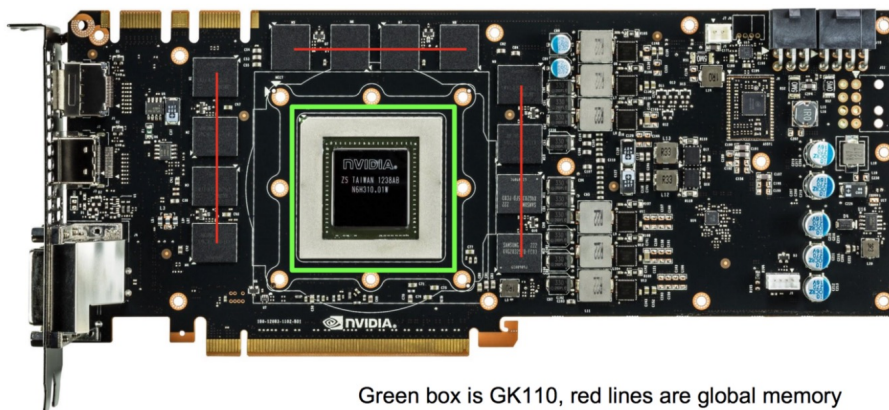
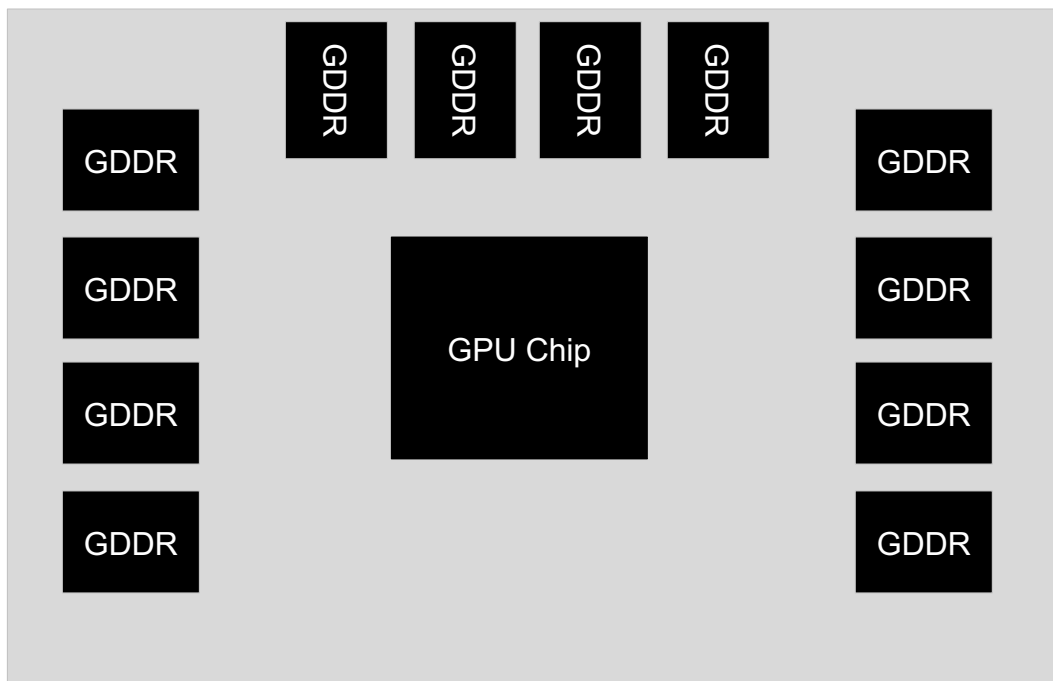
- 64 warps of 32 threads per Streaming Multiprocessors
→ 49,152 threads executing simultaneously on 3072 execution units

→ To feed the threads, GPU must be capable of moving extremely large amount of data in and out of Global memory



DRAM Subsystem Organization

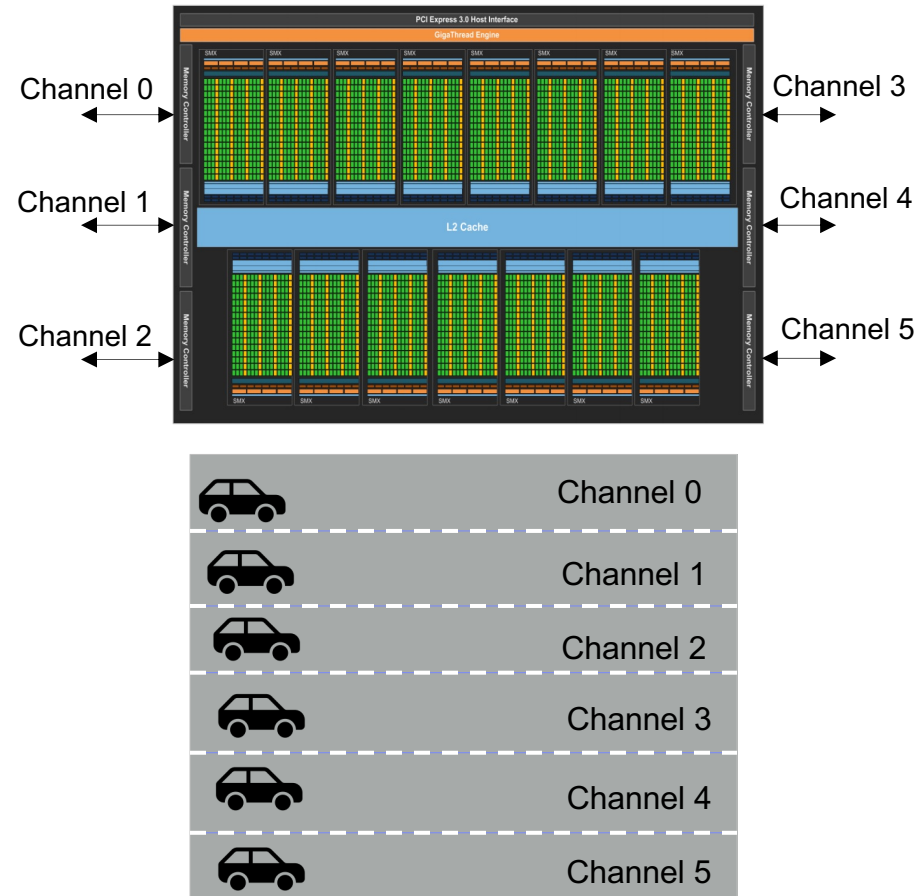
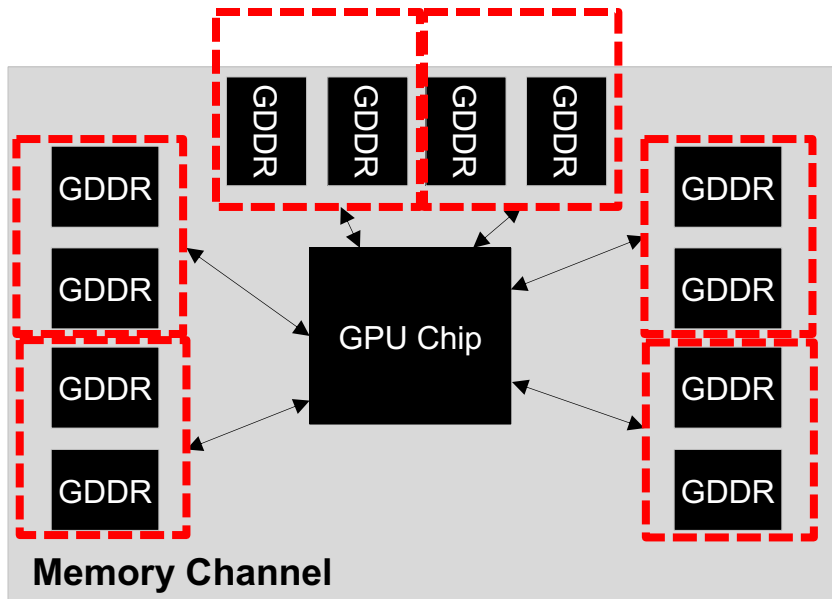
- Channel
- Chip
- Bank
- Row/Column



Green box is GK110, red lines are global memory

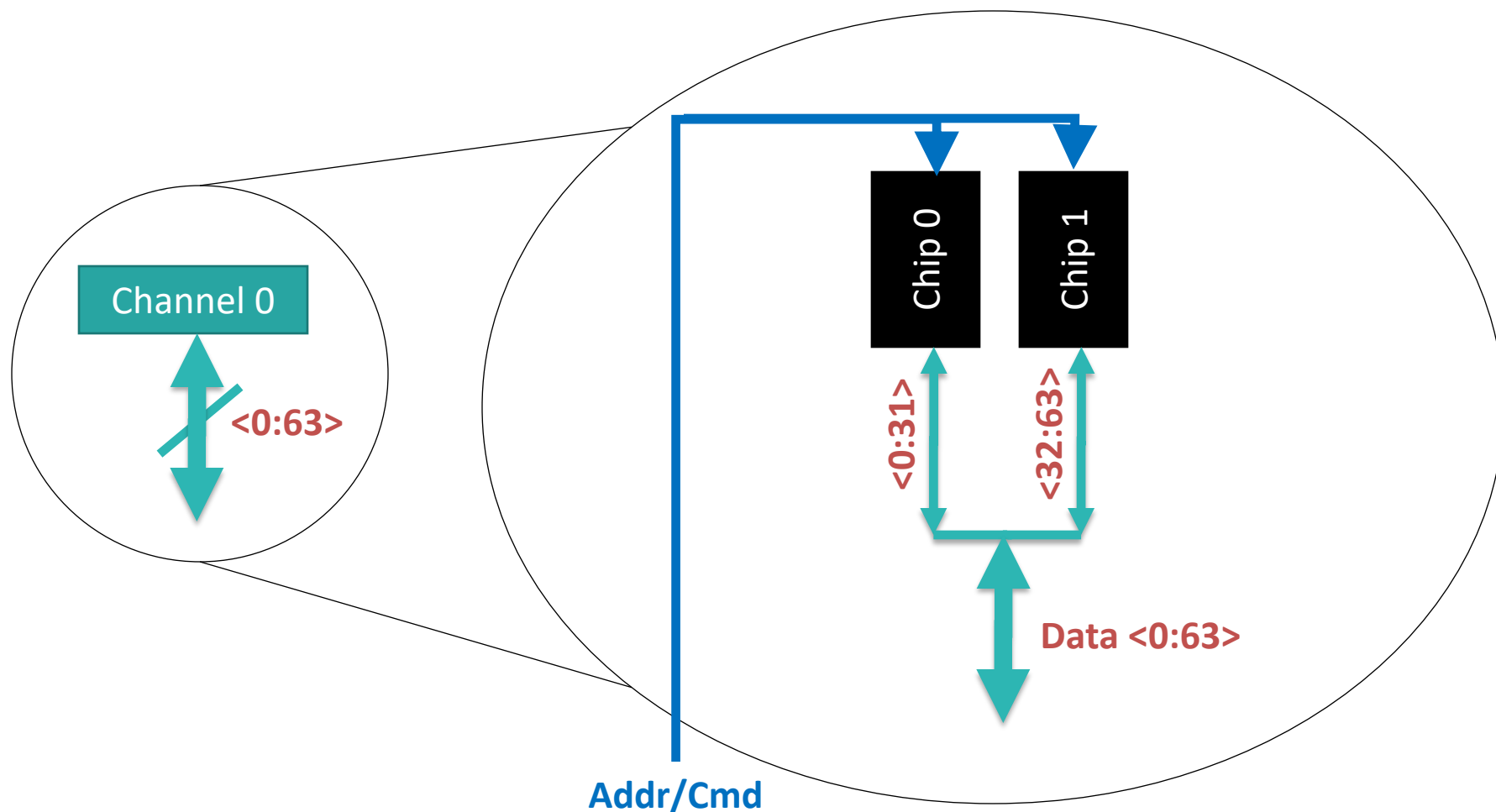
Channel

- Each **memory channel** operates **independently**
 - Can serve memory requests independently to read or write cache blocks (32B or 64B)
 - Typically 64-bits wide with the command and address bus
 - It is important to exploit **channel-level parallelism** by uniformly distributing memory requests across memory channels

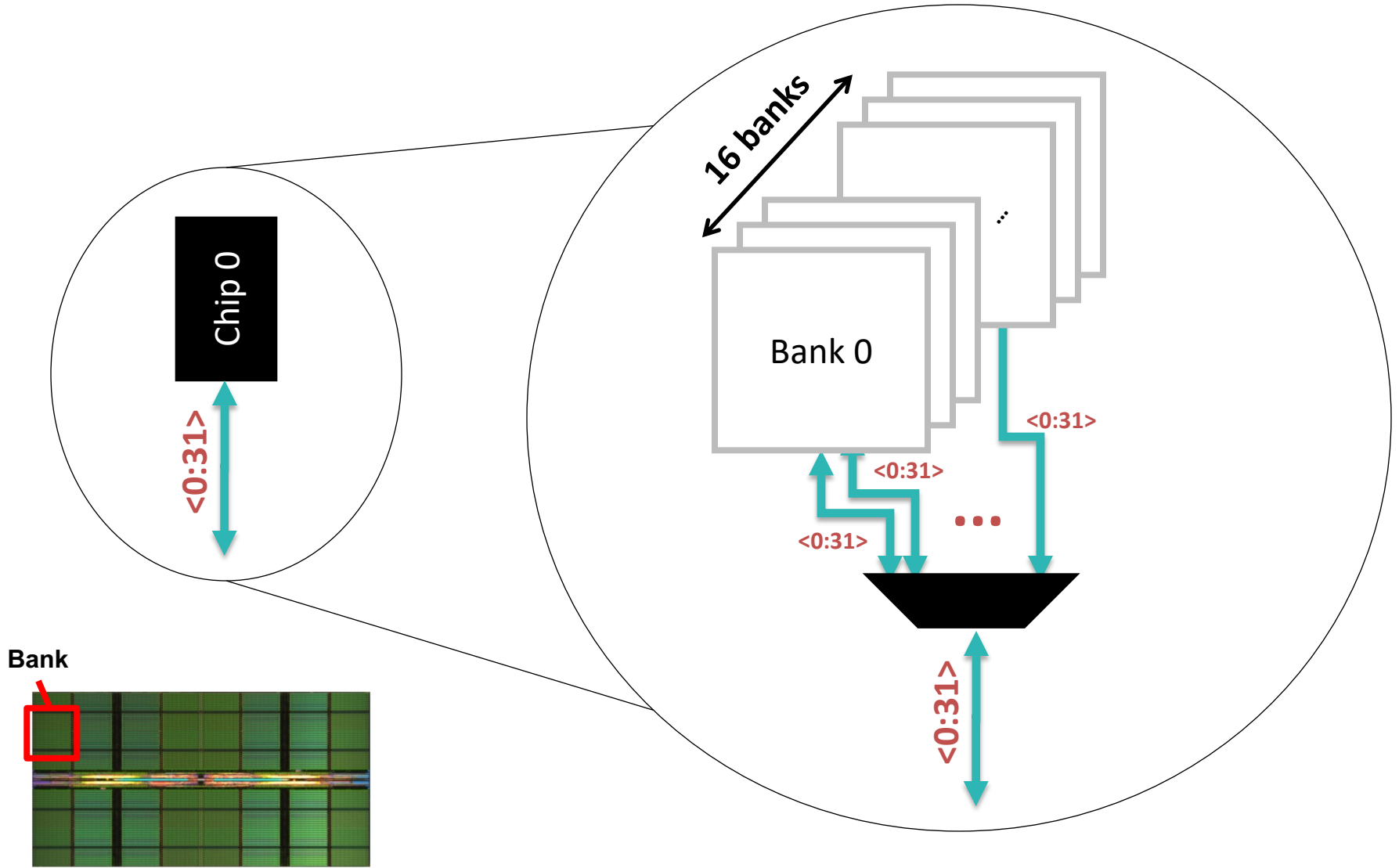


Chip

- **All chips comprising a channel are controlled at the same time**
 - Respond to a single command
 - Share address and command buses, but provide different data

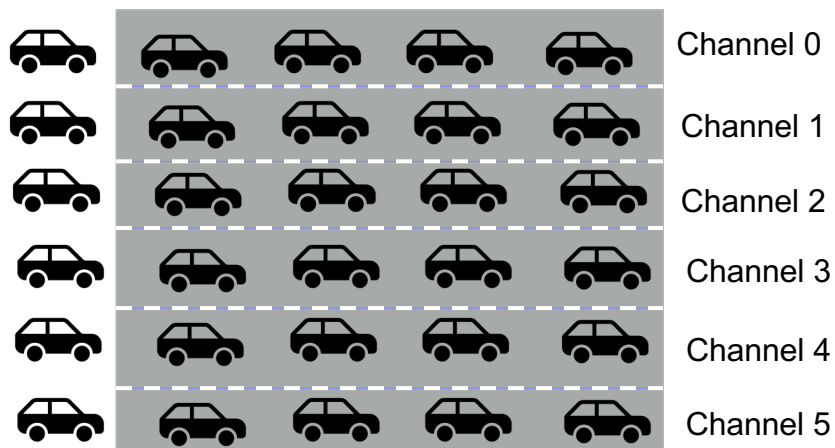
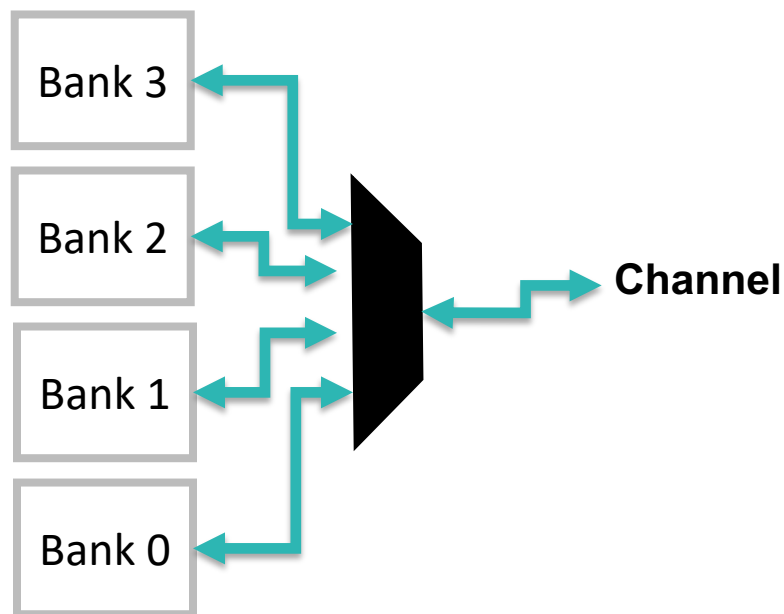


Bank

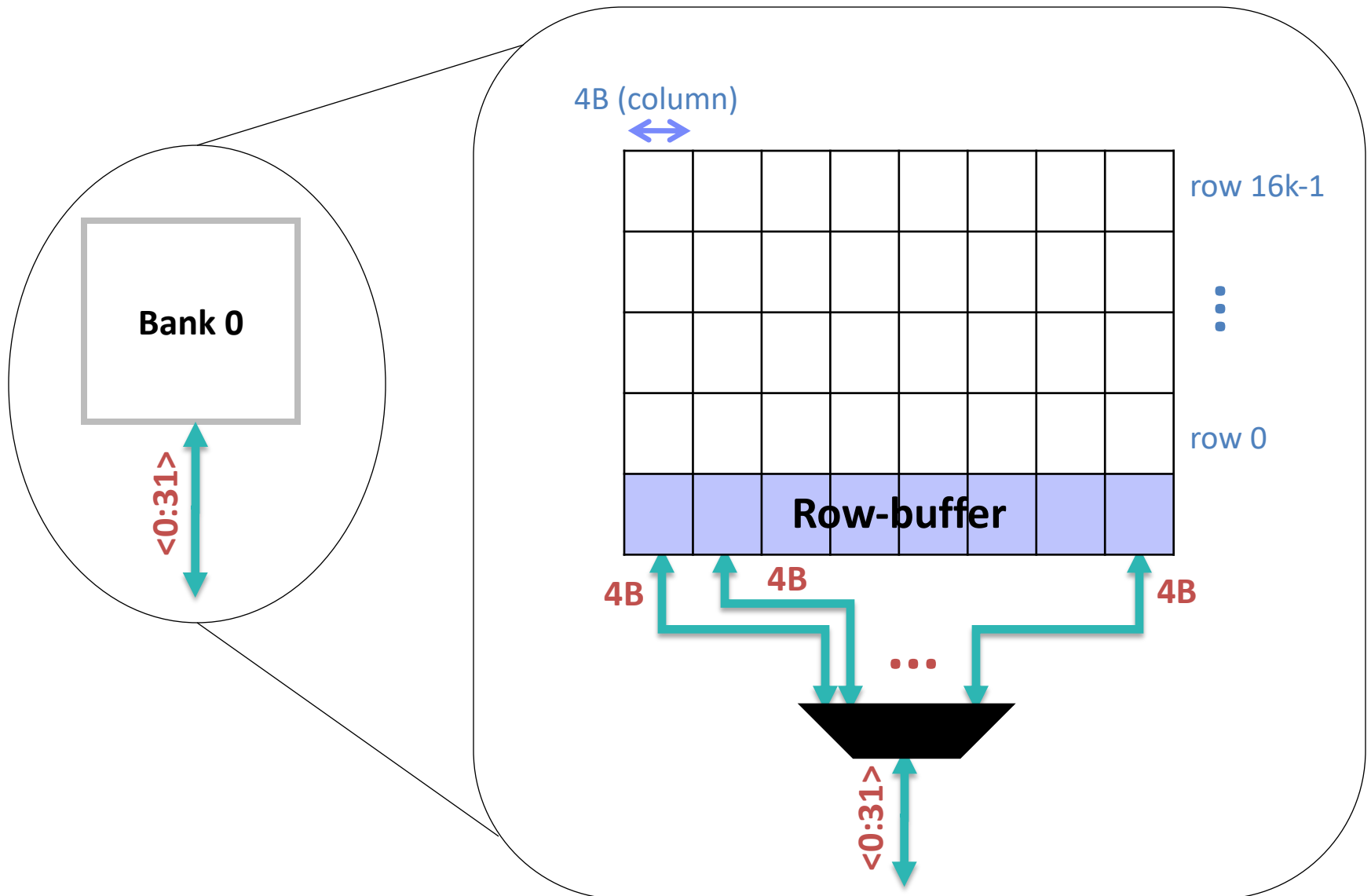


Bank (cont'd)

- A chip consists of multiple banks
- Banks share command/address/data buses
- **Each bank operate independently**
- It is important to exploit **bank-level parallelism** by uniformly distributing memory requests across banks

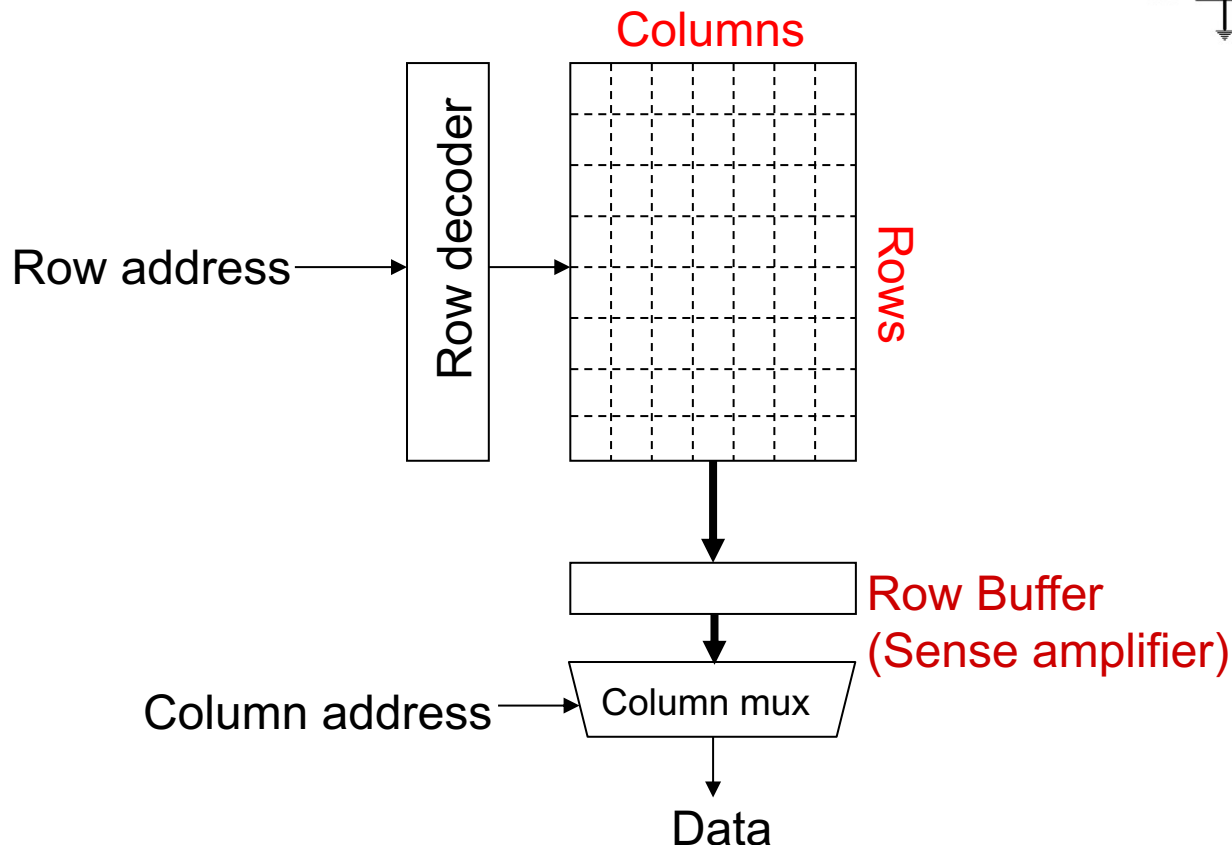
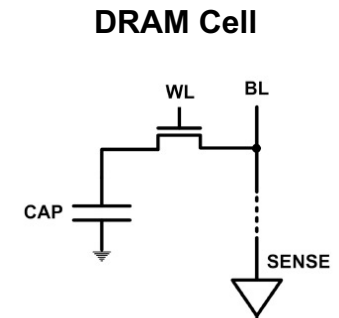


Breaking down a Bank



Breaking down a Bank

- A DRAM bank is a 2D array of cells: rows x columns
- A “DRAM row” is also called a “DRAM page”
- “Sense amplifiers” is also called “row buffer”

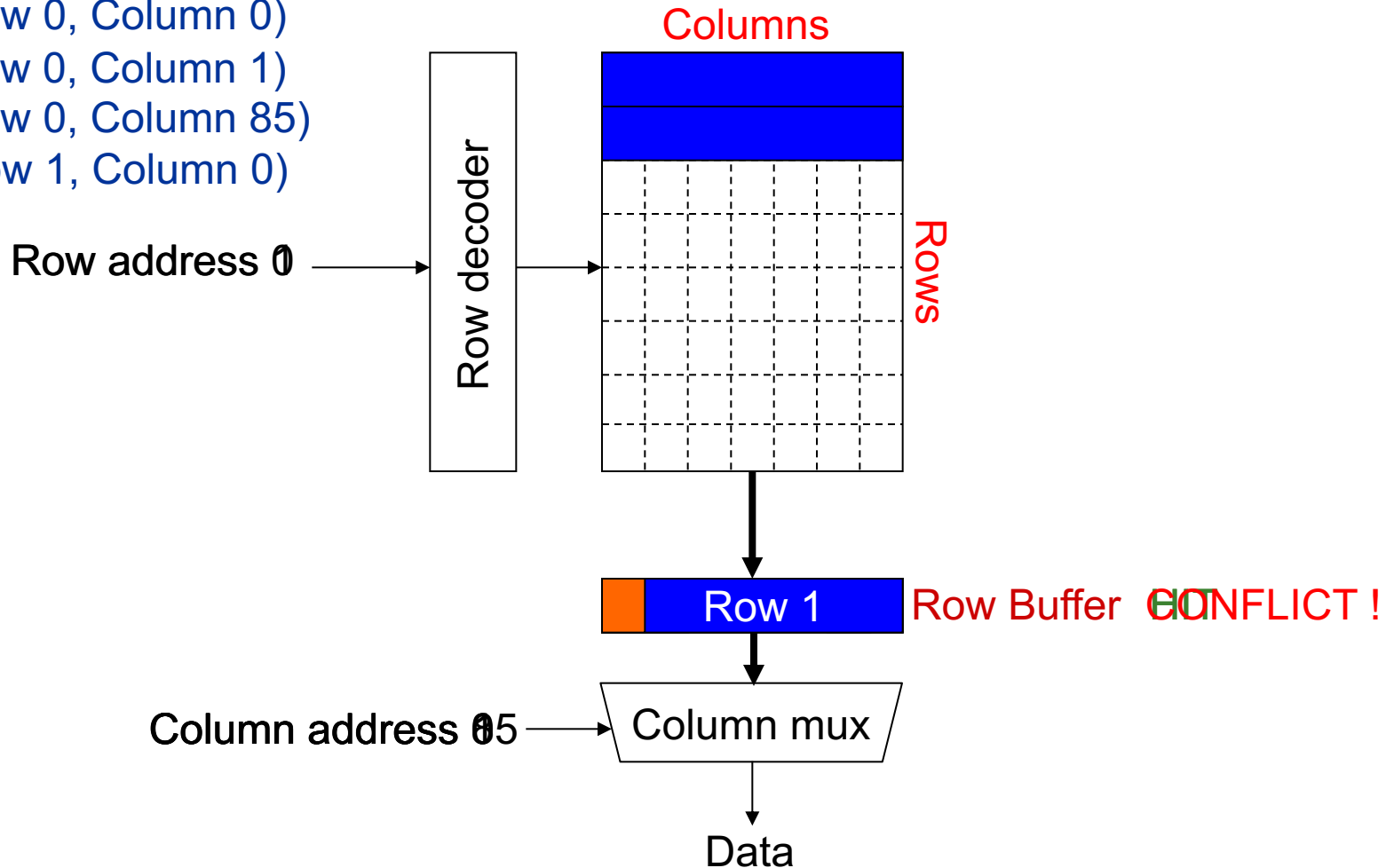


DRAM Bank Operation

- Each address is a <row, column> pair
- Access to an “close row”
 - **Activate** command opens row (placed into row buffer)
 - **Read/write** command reads/writes column in the row buffer
 - **Precharge** command closes the row and prepares the bank for next access
- Activation and Precharge are very slow!!!
- Access to an “open row”
 - No need for activation → **Fast**

DRAM Bank Operation

Access Address:
(Row 0, Column 0)
(Row 0, Column 1)
(Row 0, Column 85)
(Row 1, Column 0)

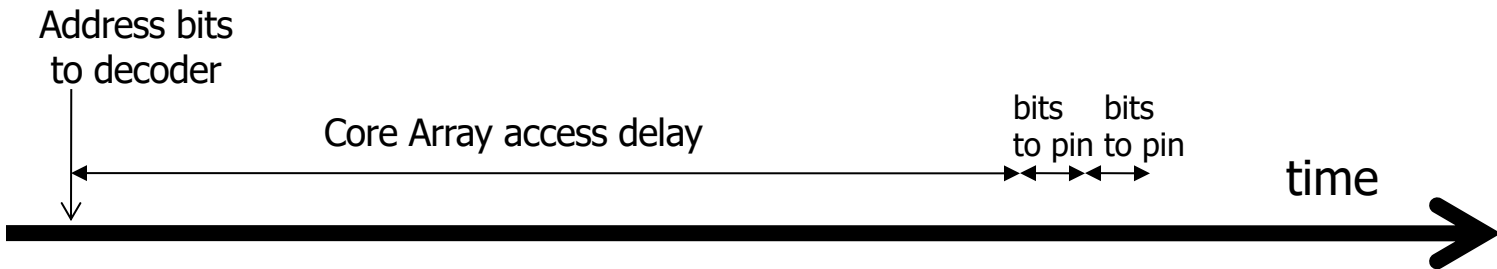


It is important to maximize the row buffer hit !!

Accesses on consecutive memory address → High row buffer hit rate!

DRAM Bursting

- **DRAM Bursting:** transfer a block (e.g., 64B) in N steps through a memory channel
- Modern DRAM systems are designed to be always accessed in **burst mode**. Burst bytes are transferred but discarded when accesses are not to sequential locations.



Burst timing



Non-burst timing

DRAM Bursting with Banking



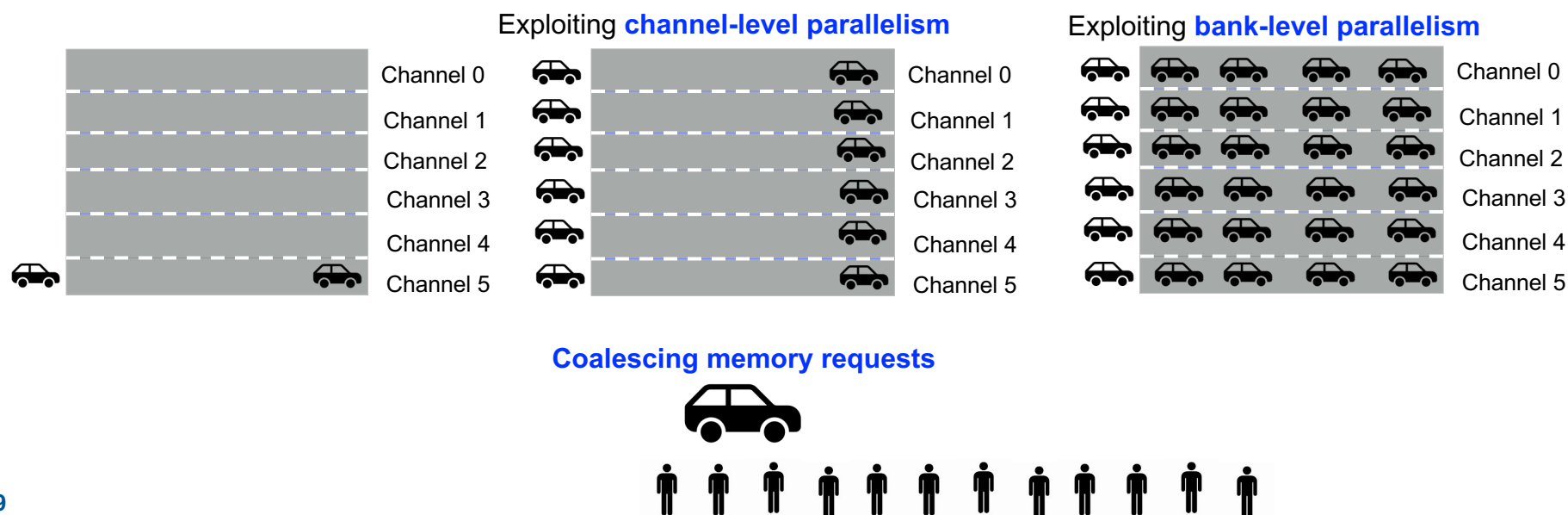
Single-Bank burst timing, dead time on interface



Multi-Bank burst timing, reduced dead time

Summary: To fully utilize the DRAM bandwidth

- Exploit **channel-level parallelism** by uniformly distributing memory requests across memory channels
- Exploit **bank-level parallelism** by uniformly distributing memory requests across banks
- Maximize the row buffer hit rate by referencing consecutive memory addresses
- **Coalescing memory requests**

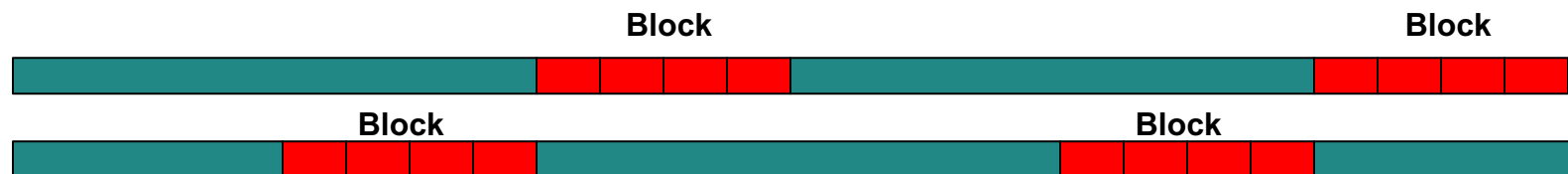


Memory Coalescing to fully utilize global memory bandwidth

Coalesce: 합체하다

Memory Coalescing

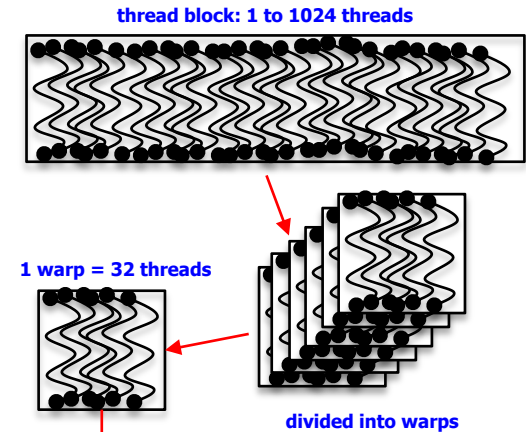
- If an kernel uses data from **consecutive memory addresses**, the DRAMs work close to the peak memory bandwidth!!
- **Off-chip memory is accessed in chunks** (aka. Cache block)
 - **Even if you read only a single word**
 - If you don't use whole chunk, bandwidth is wasted
- **Chunks are aligned to multiples of 32/64/128 bytes**
 - Unaligned accesses will cost more !!



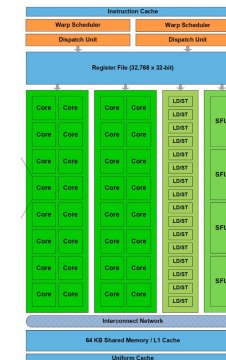
Multi-Bank burst timing, reduced dead time

Memory Coalescing (Cont'd)

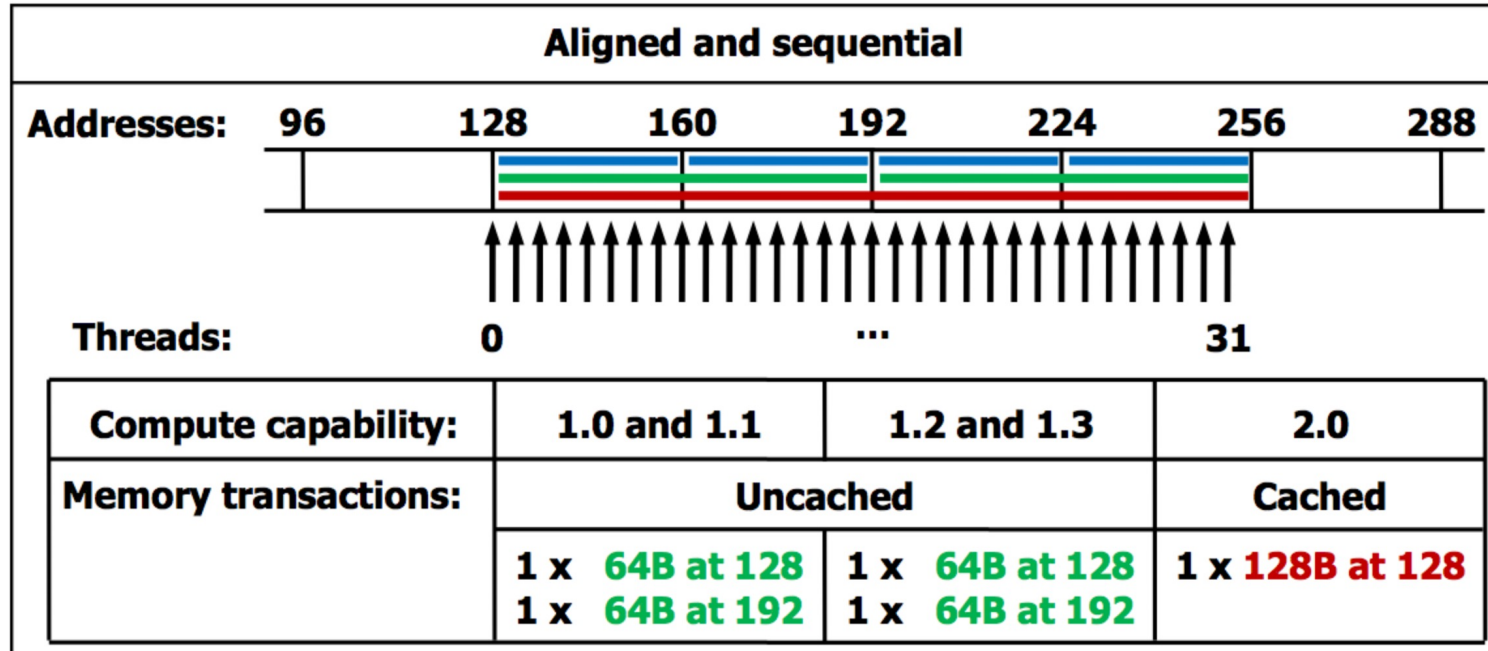
- Recall, all threads in a warp execute the same instruction
- When all threads in a warp execute a load instruction, the hardware detects whether the threads access consecutive memory addresses
 - If so, the hardware **coalesces** all memory accesses into **a consolidated access** to consecutive DRAM locations
 - $32 \text{ threads} \times 4\text{B} = 128\text{B}$
 - With Coalescing \rightarrow 1 memory requests
 - Without Coalescing \rightarrow 32 memory requests



divided into warps



Memory Coalescing (Cont'd)

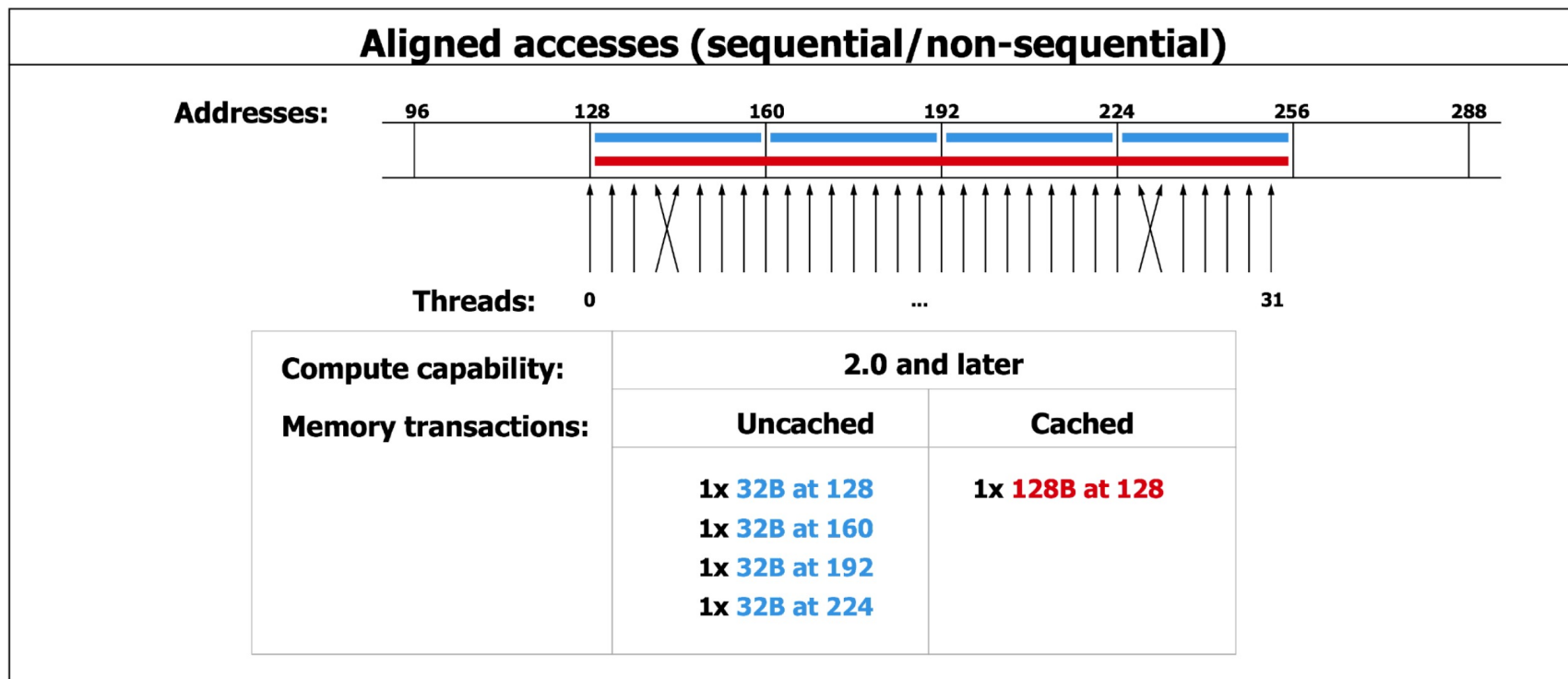


From NVIDIA Programming Guide

If thread 0 accesses location 128, thread 1 accesses location 132, ... thread 31 accesses location 255, then all these accesses are **coalesced**, that is: combined into **one single access**



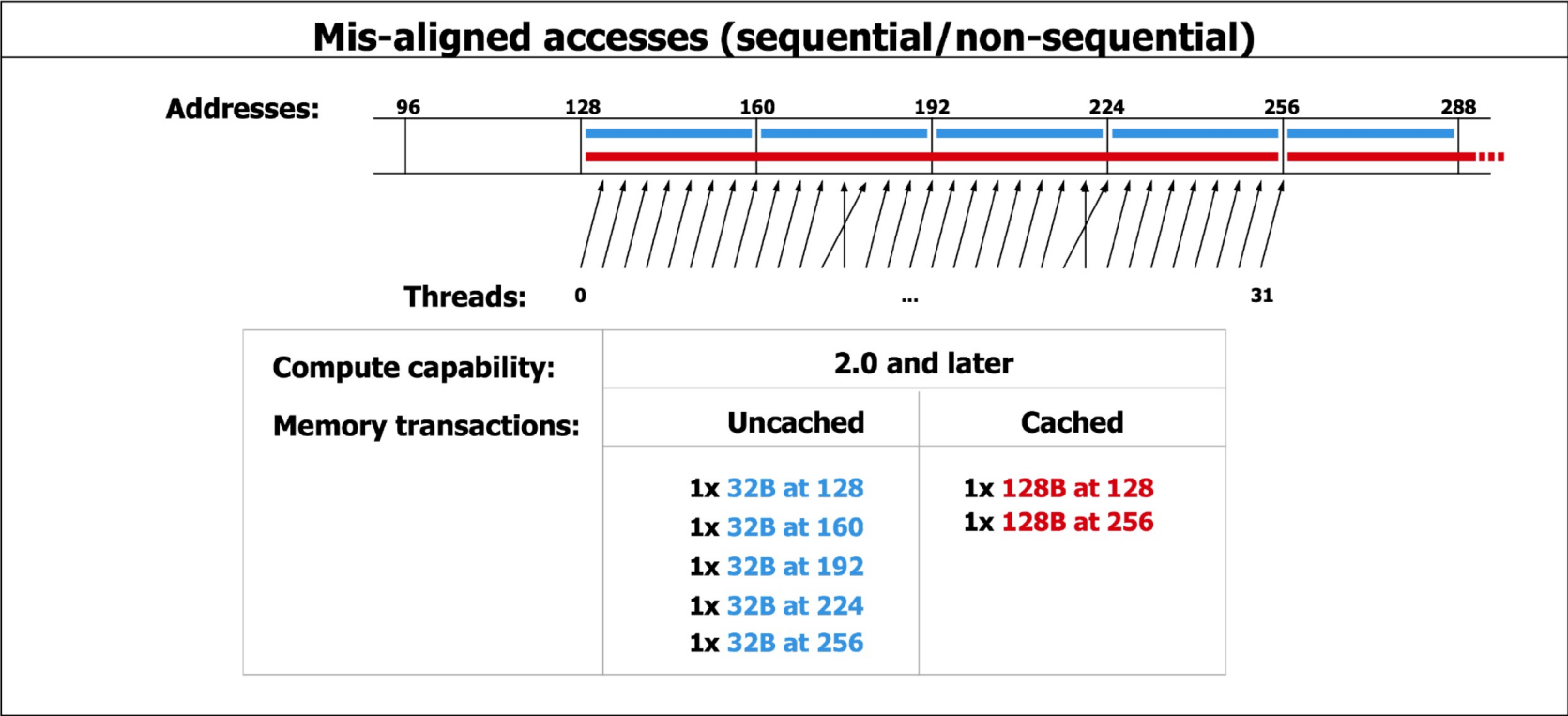
Memory Coalescing (Cont'd)



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If thread 0 accesses location 128, thread 1 accesses location 132, ... thread 31 accesses location 255, then all these accesses are **coalesced**, that is: combined into **one single access**

Memory Coalescing (Cont'd)

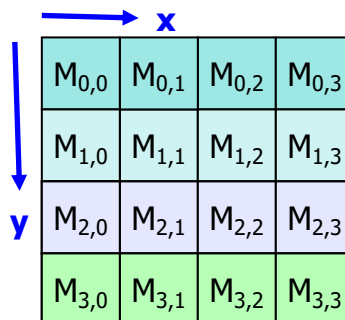


From NVIDIA Programming Guide

If thread 0 accesses location 129, thread 1 accesses location 133, ... thread 31 accesses location 256, then all these accesses are **coalesced**, that is: combined into **two accesses**

Review: Row-major Matrix Layout in C/C++

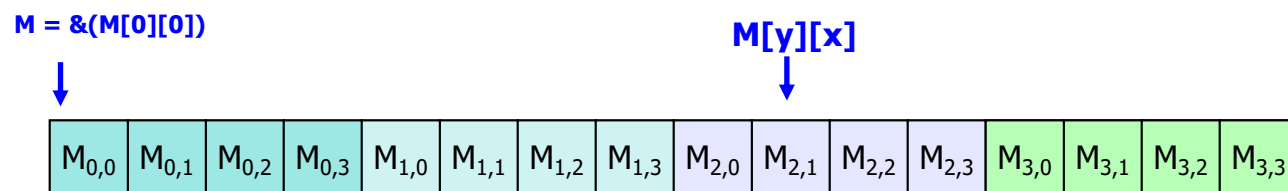
- logical layout:



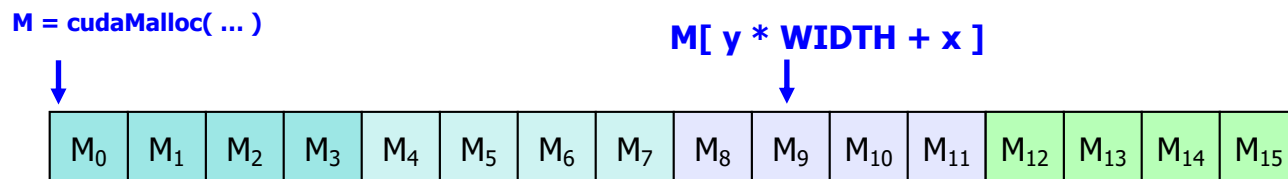
A 4x4 matrix with rows indexed 0 to 3 and columns indexed 0 to 3. The elements are labeled $M_{i,j}$. A blue arrow labeled 'x' points to the right above the matrix, and a blue arrow labeled 'y' points downwards to the left of the matrix.

$M_{0,0}$	$M_{0,1}$	$M_{0,2}$	$M_{0,3}$
$M_{1,0}$	$M_{1,1}$	$M_{1,2}$	$M_{1,3}$
$M_{2,0}$	$M_{2,1}$	$M_{2,2}$	$M_{2,3}$
$M_{3,0}$	$M_{3,1}$	$M_{3,2}$	$M_{3,3}$

- physical layout: 1D array



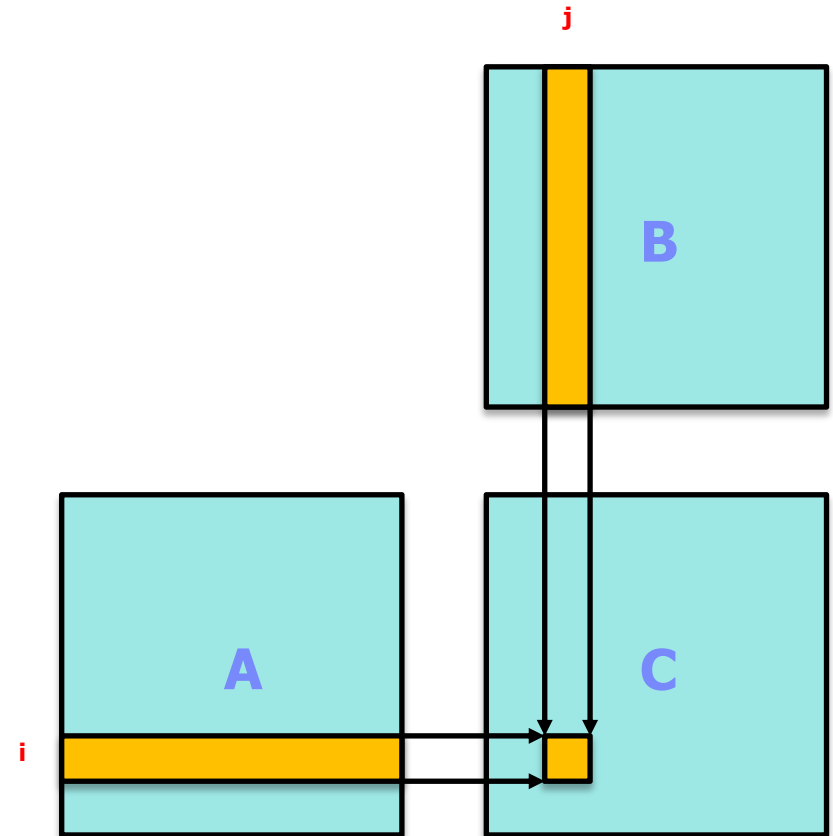
- re-interpret:



Review: CUDA Matrix Multiplication

- One block of threads compute matrix C
 - Each thread computes one element of C
- Each thread
 - loads a row of matrix A
 - loads a column of matrix B
 - Perform one multiply and addition for each pair of A and B elements

$$c_{ij} = \sum_{k=1}^n a_{ik} b_{kj}$$

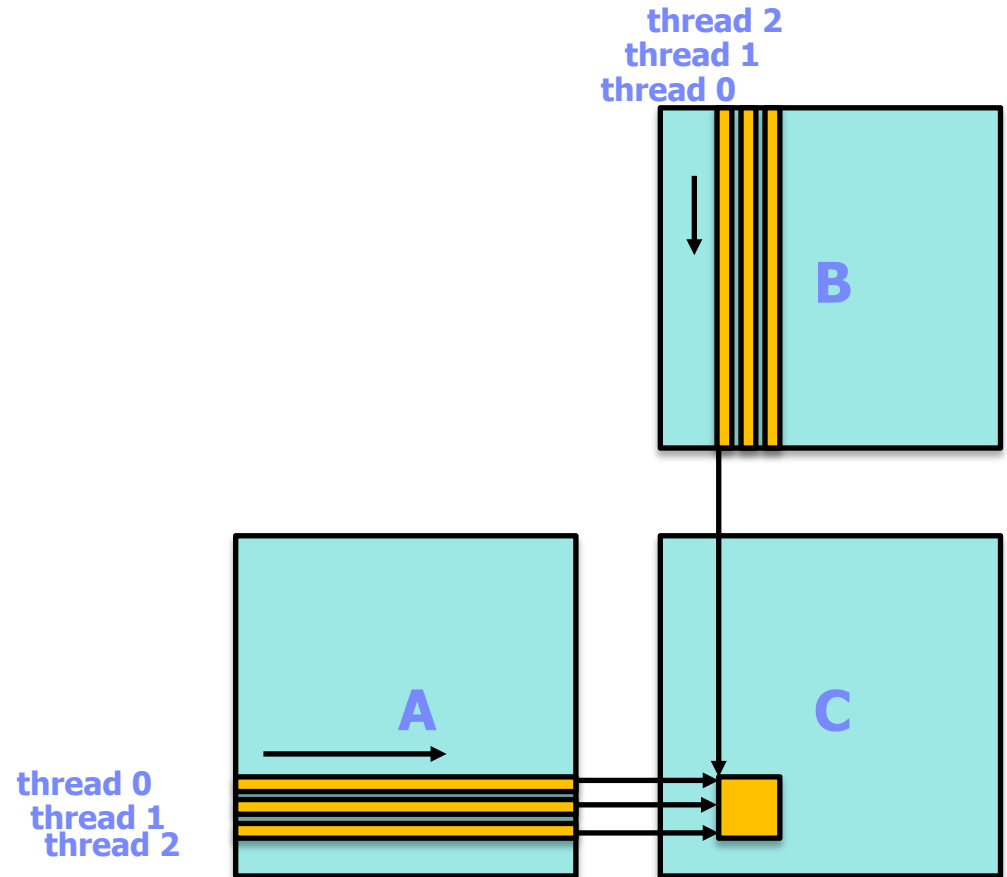


CUDA Matrix Multiplication Kernel

```
// kernel program for the device (GPU): compiled by NVCC
__global__ void addKernel(int* c, const int* a, const int* b, const int WIDTH) {
    int x = threadIdx.x;
    int y = threadIdx.y;
    int i = y * WIDTH + x;    // [y][x] = y * WIDTH + x;
    int sum = 0;
    for (int k = 0; k < WIDTH; ++k) {
        sum += a[y * WIDTH + k] * b[k * WIDTH + x];
    }
    c[i] = sum;
}
```

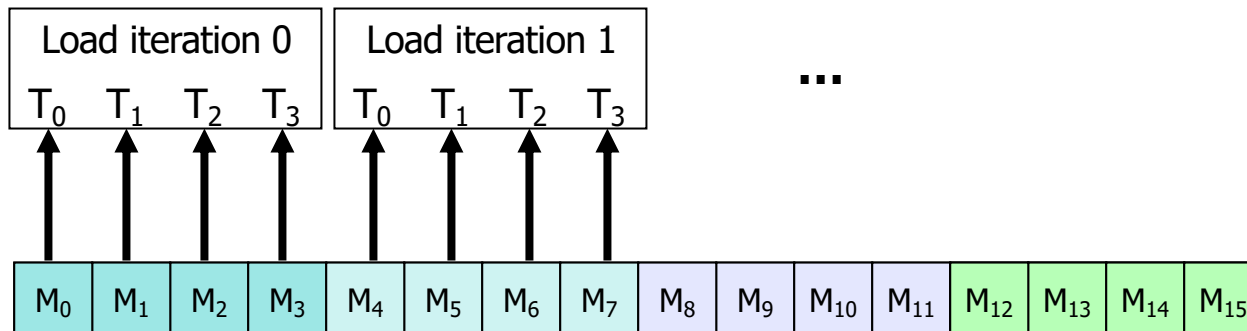
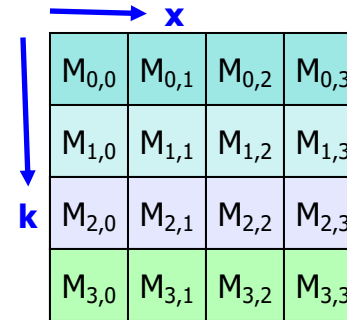
DRAM Access Patterns

- Multiple threads are working in a warp
- for A matrix,
 - $a[y * \text{WIDTH} + k]$
- for B matrix,
 - $b[k * \text{WIDTH} + x]$



B accesses are coalesced

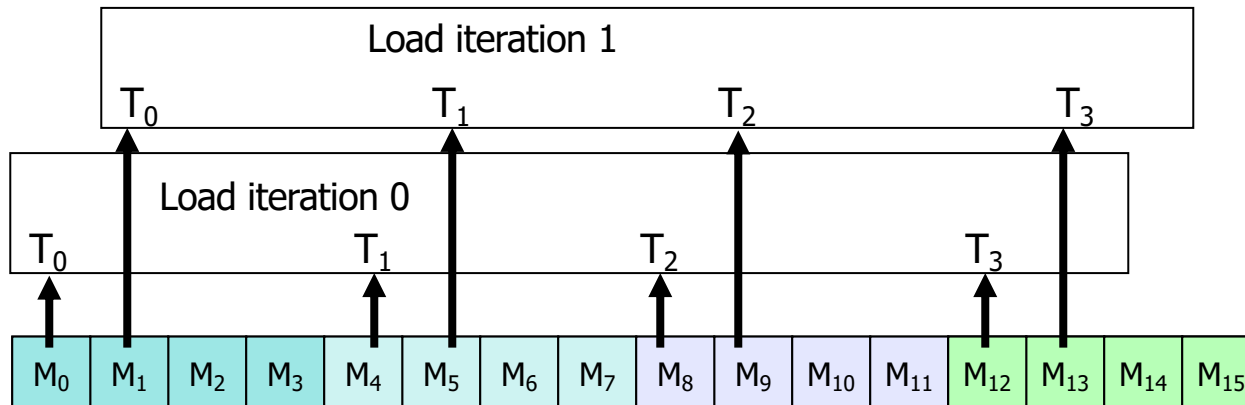
- $b[k * \text{WIDTH} + x]$
- $k = 0, 1, 2, \dots$
 - thread 0: $b[k * \text{WIDTH} + 0]$
 - thread 1: $b[k * \text{WIDTH} + 1]$
 - thread 2: $b[k * \text{WIDTH} + 2]$
 - thread 3: $b[k * \text{WIDTH} + 3]$



A accesses are not coalesced

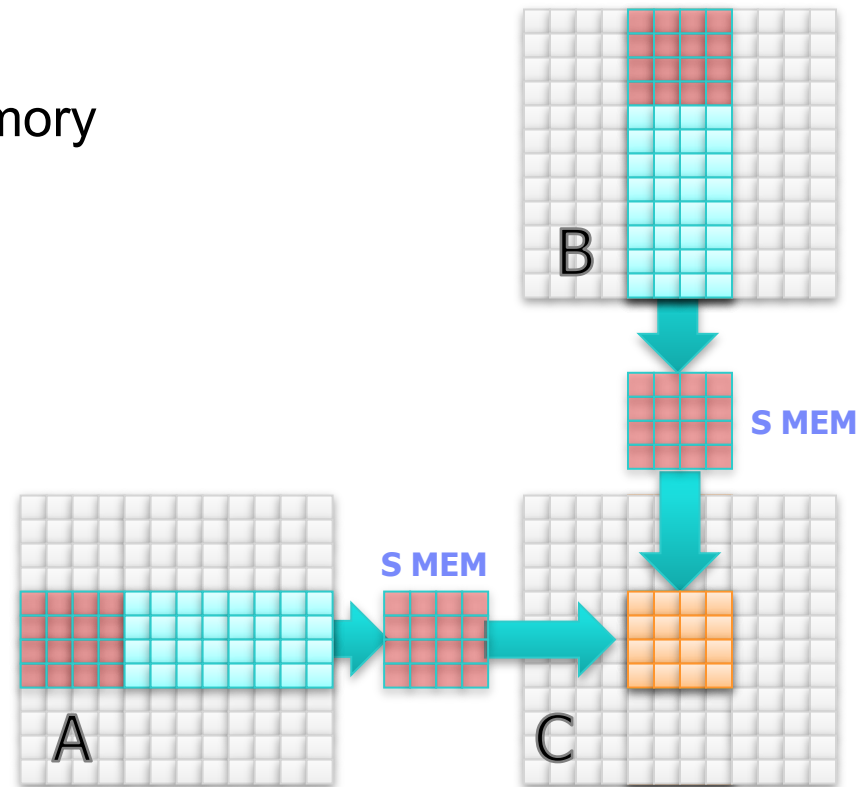
- $a[y * \text{WIDTH} + k]$
- $k = 0, 1, 2, \dots$
 - thread 0: $a[0 * \text{WIDTH} + k]$
 - thread 1: $a[1 * \text{WIDTH} + k]$
 - thread 2: $a[2 * \text{WIDTH} + k]$
 - thread 3: $a[3 * \text{WIDTH} + k]$

$M_{0,0}$	$M_{0,1}$	$M_{0,2}$	$M_{0,3}$
$M_{1,0}$	$M_{1,1}$	$M_{1,2}$	$M_{1,3}$
$M_{2,0}$	$M_{2,1}$	$M_{2,2}$	$M_{2,3}$
$M_{3,0}$	$M_{3,1}$	$M_{3,2}$	$M_{3,3}$



Shared Memory Matrix Multiplication

- make a thread block as a tile
- partition the global memory into tiles
- then, load it to the shared memory



Tiled Matrix Multiplication Kernel

```
__global__ void matmul(float* g_C, const float* g_A, const float* g_B, const int width) {
    __shared__ float s_A[TILE_WIDTH][TILE_WIDTH];
    __shared__ float s_B[TILE_WIDTH][TILE_WIDTH];

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

    int gy = by * TILE_WIDTH + ty; // global y index
    int gx = bx * TILE_WIDTH + tx; // global x index

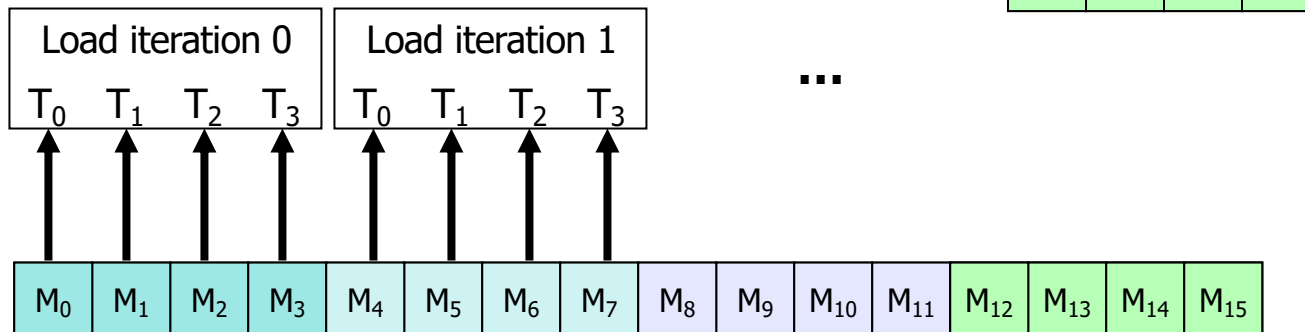
    float sum = 0.0F;

    for (register int m = 0; m < width / TILE_WIDTH; ++m) {
        // read into the shared memory blocks
        s_A[ty][tx] = g_A[gy * width + (m * TILE_WIDTH + tx)];
        s_B[ty][tx] = g_B[(m * TILE_WIDTH + ty) * width + gx];
        __syncthreads();

        // use the shared memory blocks to get the partial sum
        for (register int k = 0; k < TILE_WIDTH; ++k) {
            sum += s_A[ty][k] * s_B[k][tx];
        }
        __syncthreads();
    }
    g_C[gy * width + gx] = sum;
}
```

B accesses are coalesced

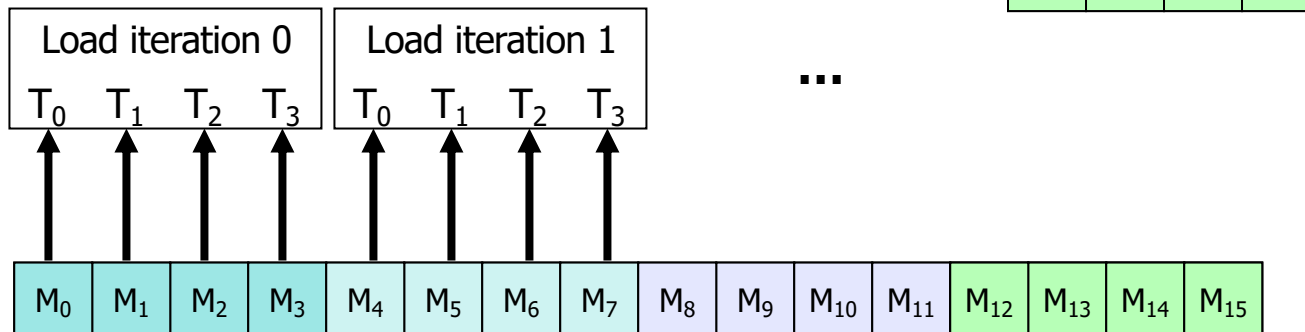
- $gx = bx * TILE_WIDTH + tx$
- $s_B[ty][tx] = g_B[(m * TILE_WIDTH + ty) * width + gx];$
- $tx = 0, 1, 2, \dots$
 - thread 0: $b[\dots + 0]$
 - thread 1: $b[\dots + 1]$
 - thread 2: $b[\dots + 2]$
 - thread 3: $b[\dots + 3]$



	x			
k	$M_{0,0}$	$M_{0,1}$	$M_{0,2}$	$M_{0,3}$
	$M_{1,0}$	$M_{1,1}$	$M_{1,2}$	$M_{1,3}$
	$M_{2,0}$	$M_{2,1}$	$M_{2,2}$	$M_{2,3}$
	$M_{3,0}$	$M_{3,1}$	$M_{3,2}$	$M_{3,3}$

A accesses are coalesced

- $s_A[ty][tx] = g_A[gy * width + (m * TILE_WIDTH + tx)];$
- $tx = 0, 1, 2, \dots$
 - thread 0: $b[\dots + 0]$
 - thread 1: $b[\dots + 1]$
 - thread 2: $b[\dots + 2]$
 - thread 3: $b[\dots + 3]$



	x			
k	$M_{0,0}$	$M_{0,1}$	$M_{0,2}$	$M_{0,3}$
	$M_{1,0}$	$M_{1,1}$	$M_{1,2}$	$M_{1,3}$
	$M_{2,0}$	$M_{2,1}$	$M_{2,2}$	$M_{2,3}$
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Next?

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