

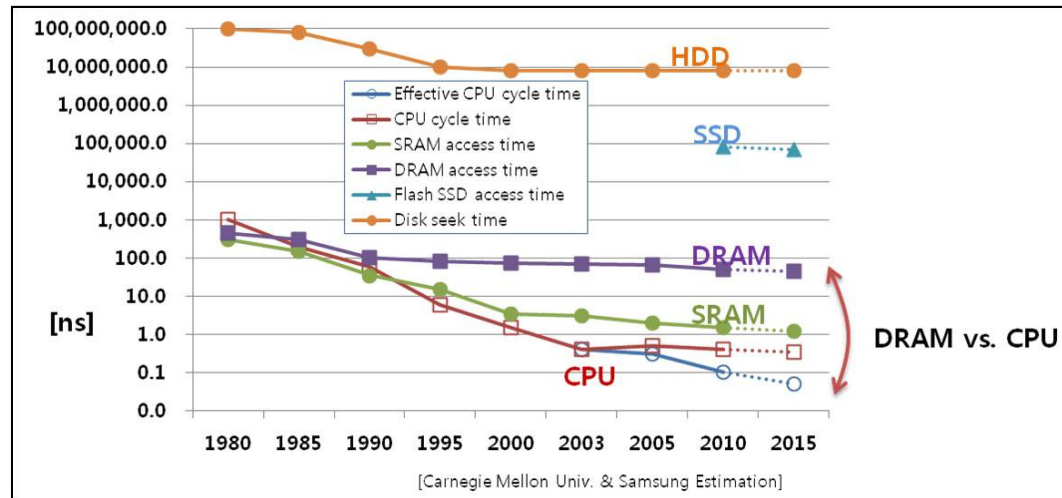


GPUs and CUDA 2

Memory and Warps

CS121 Parallel Computing
Spring 2018

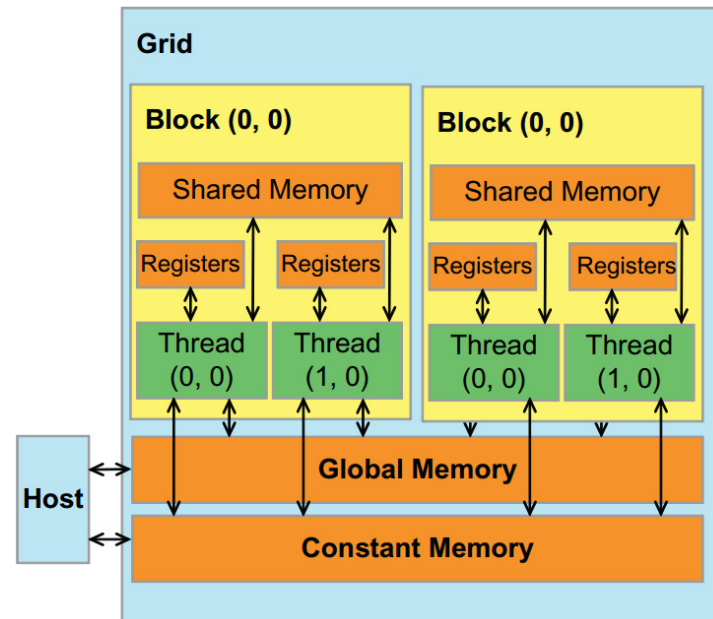
Need for speed



- Speed of code determined by amount of computation and memory accesses.
- Computation speed has been improving much faster than memory latency and bandwidth.
- Today, the main bottleneck is high memory latency and low memory bandwidth relative to CPU.
- But processors can access many different types of memory.
- Can write fast code if use right memory at right time.

GPU memory organization

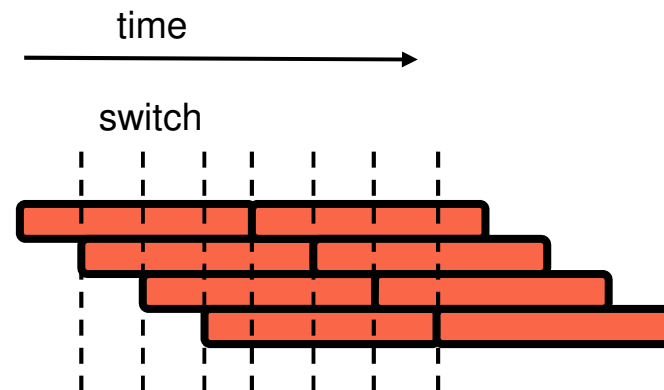
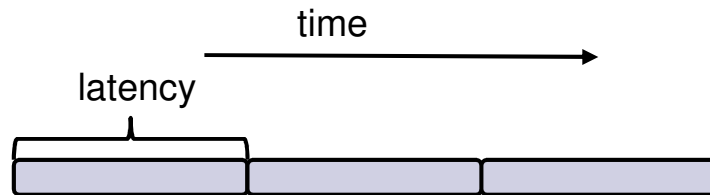
- GPU has several types of memory.
 - Different size, latency, bandwidth and scope.
 - Generally, the larger the size and scope, the slower and less bandwidth.
- Registers, shared memory, L1 cache are on-chip, much faster and higher bandwidth than global memory.
- L1 cache is controlled by hardware.
- In contrast, programmer controls what's stored in shared memory.
- Shared memory size + L1 cache size = 64KB. User configurable.



Type	Size	Latency (cycles)	Bandwidth	Visibility
Global	1-12 GB	400-800	150 GB/s	grid
Constant	64KB	cached		grid, read-only
Shared	48KB/16KB per SM	~20	1,500 GB/s	block
L1 cache	16KB/48KB per SM	~20	1,500 GB/s	block
Registers	64K per SM	~1	8,000 GB/s	thread

Global memory latency

- Global memory has very high latency.
- If each thread waits (blocks) for a global memory operation to finish before doing the next operation, performance is very poor.
- Solution is to keep large pool of active threads.
- When one thread blocks doing a memory operation, switch to another thread.
 - “Massive multi-threading” (MMT).
- Total throughput high, even though each thread has high latency.





Global memory latency

- Each SM has own scheduler to do thread switching.
 - Different from device Gigathread scheduler, which allocates thread blocks to SMs.
- Each thread's context (program counter, registers) always maintained in the SM.
 - SM has ~64K registers to allocate to ~1000 threads in a thread block.
 - Very fast, “zero overhead” thread switching.
- SM scheduler has “scoreboard” to keep track of which threads assigned to the SM are blocked / unblocked.
 - Keeps picking unblocked threads to run.
- Only effective if SM has many threads, so that there always exists some unblocked threads.
 - This is why SM can run ~1000 threads, though it only has ~30 cores.
- For high performance need many threads per SM.
 - High “occupancy”.



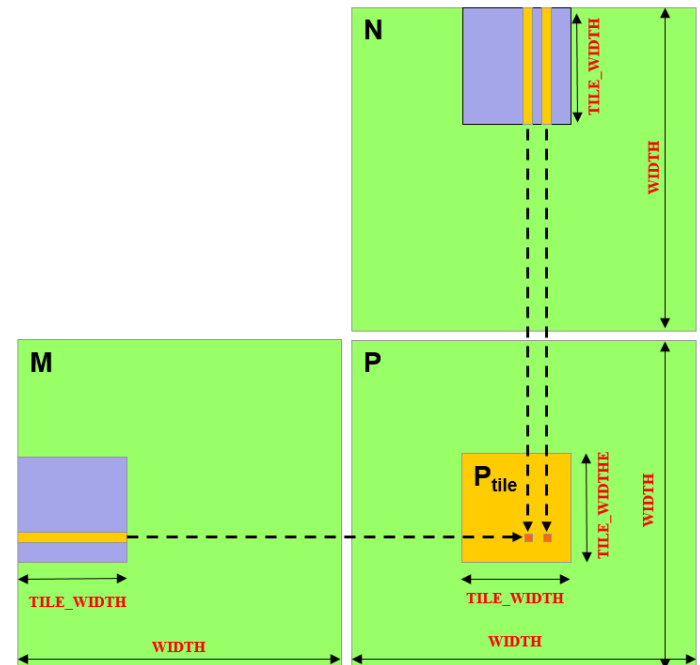
Global memory bandwidth

- Massive multithreading not enough for performance.
 - Only addresses latency.
 - But doesn't help with other bottleneck, bandwidth.
- GPU's computing power is much higher than its global memory bandwidth.
 - Ex Compute: 1.5 TFLOPS. Bandwidth: 200 GB/s.
- Recall matrix multiplication
$$P_{\text{value}} += M[\text{Row} * \text{Width} + k] * N[k * \text{Width} + \text{Col}]$$
- 6 floating point ops (+, *) for 2 memory ops (read M and N).
 - Compute to global memory access (CGMA) ratio 3:1.
- 200 GB/s = 50G floating point vals / sec \Rightarrow 150 GFLOPS.
 - 1/10 of theoretical peak!

Exploiting data reuse

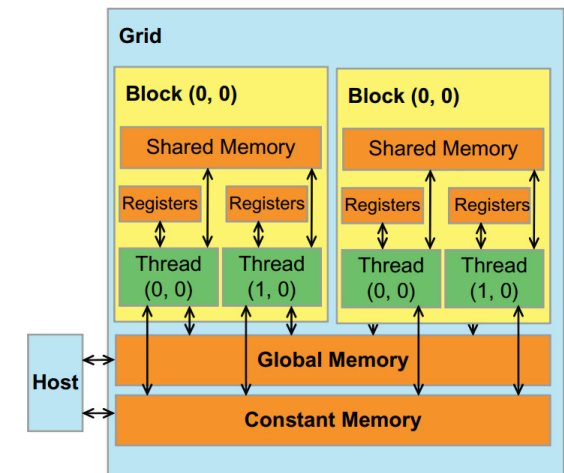
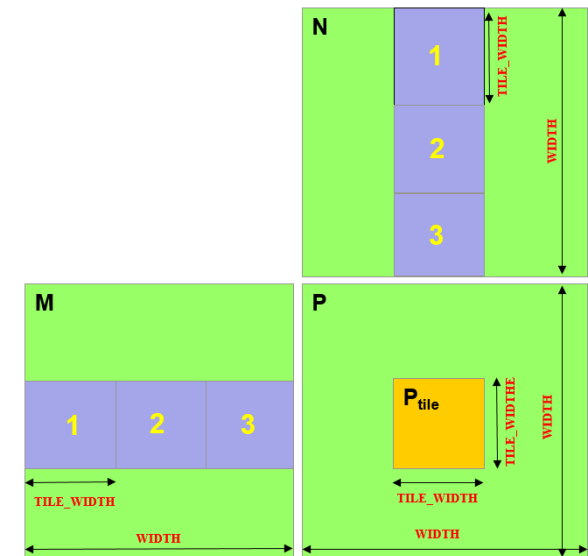
```
__global__ void MatrixMulKernel(float* d_M, float* d_N, float* d_P, int Width) {  
    int Row = blockIdx.y*blockDim.y+threadIdx.y;  
    int Col = blockIdx.x*blockDim.x+threadIdx.x;  
  
    if ((Row < Width) && (Col < Width)) {  
        float Pvalue = 0;  
        for (int k = 0; k < Width; ++k)  
            Pvalue += d_M[Row*Width+k] * d_N[k*Width+Col];  
        d_P[Row*Width+Col] = Pvalue; } }
```

- P_{tile} contains a block of TILE_WIDTH^2 threads.
- Every thread loads all data it needs by itself.
 - TILE_WIDTH^2 threads in P_{tile} each loads $2 * \text{TILE_WIDTH}$ data $\Rightarrow 2 * \text{TILE_WIDTH}^3$ global memory reads.
- But notice all threads in P_{tile} need data from purple tiles.
 - Purple data can be reused!
- Threads in P_{tile} cooperate to load purple tiles, eliminating redundant global memory reads.
 - Only $2 * \text{TILE_WIDTH}^2$ global memory reads in total. A factor of TILE_WIDTH less!



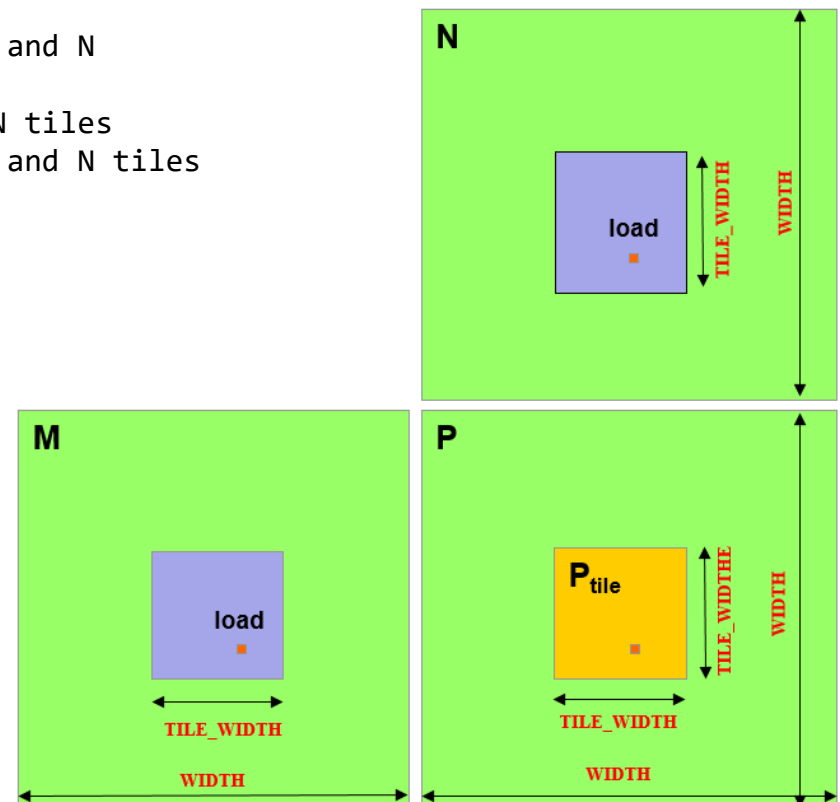
Shared memory and tiled MM

- Tiled MM is a memory efficient method of performing matrix multiplication using shared memory.
- Break M, N into tiles and multiply tile by tile.
 - Work in phases.
 - Exploit data reuse in each phase.
- $\# \text{ phases} = \text{WIDTH} / \text{TILE_WIDTH}$
- In phase i , threads in P_{tile} cooperatively load i^{th} tile from M, N in global memory into shared memory.
- Then each thread reads a row and column of data from shared memory.
- After all threads finished with the tiles, next two tiles loaded, overwriting current ones.



Tiled matrix multiplication

```
__global__ void MatrixMulKernel(float* d_M, float* d_N, float* d_P, int Width) {  
    // Allocate space for M and N block in shared memory  
  
    // Thread in block (bx, by) works on (bx, by)'th  $P_{tile}$   
    // Thread with ID (tx, ty) works on element (tx, ty) in its  $P_{tile}$   
  
    // Loop over the M and N tiles required to compute the P element  
    for (int m = 0; m < WIDTH/TILE_WIDTH; m++) {  
        // Load one element from M and N into shared memory  
        // How do we calculate which elements to load?  
        // Wait till all threads finished loading from M and N  
  
        // Compute dot product from shared memory M and N tiles  
        // Wait till all threads in block finish using M and N tiles  
    }  
    // Write value of P element back to global memory  
}
```



Tiled matrix multiplication

```
__global__ void MatrixMulKernel(float* d_M, float* d_N, float* d_P, int Width) {
    __shared__ float ds_M[TILE_WIDTH][TILE_WIDTH];
    __shared__ float ds_N[TILE_WIDTH][TILE_WIDTH];

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

    // Thread identifies row and column of P element to work on
    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

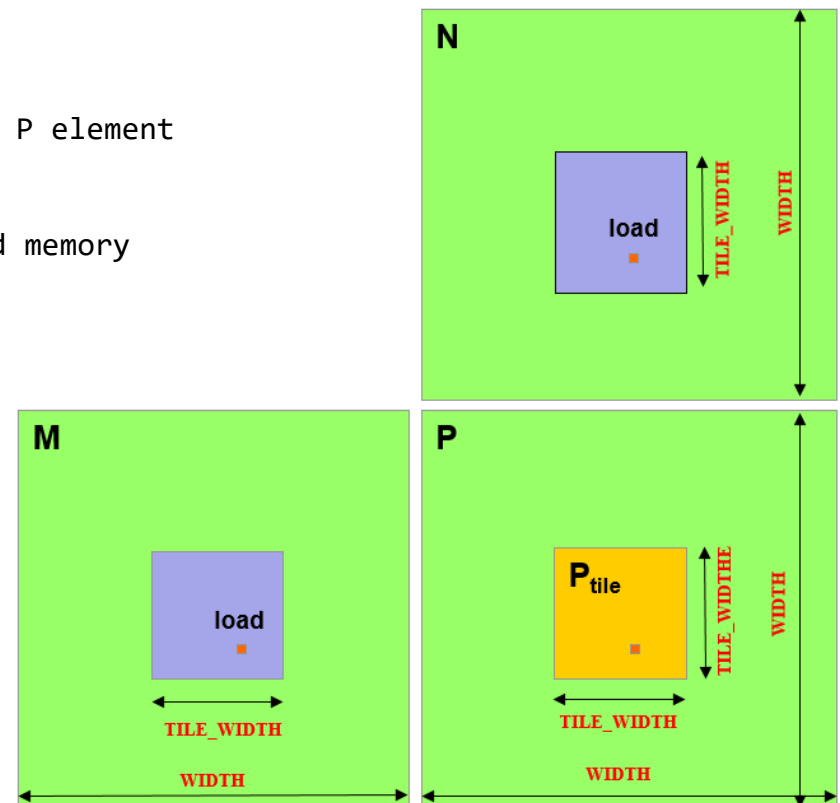
    float Pvalue = 0;
    // Loop over the M and N tiles required to compute the P element
    for (int m = 0; m < WIDTH/TILE_WIDTH; m++) {

        // Collaboratively load M and N tiles into shared memory
        ds_M[ty][tx] = d_M[Row*WIDTH + m*TILE_WIDTH+tx];
        ds_N[ty][tx] = d_N[Col+(m*TILE_WIDTH+ty)*WIDTH];

        // Wait till all threads finished loading tiles
        __syncthreads();

        // Compute dot product from tiles
        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += ds_M[ty][k] * ds_N[k][tx];

        __syncthreads();
    }
    d_P[Row*Width+Col] = Pvalue;
}
```





Shared memory and tiled MM

- Decreases total number of reads from global memory compared to naive algorithm.
- Consider an $n \times n$ matrix with $m \times m$ blocks.
- Naive algorithm
 - n^2 elements each require $2n$ global memory reads. $2n^3$ total.
- Shared memory algorithm
 - $(n/m)^2$ blocks in total.
 - Each block does n/m phases.
 - In each phase, block does $2m^2$ reads from global memory.
 - Total $(n/m)^2 * (n/m) * 2m^2 = 2n^3/m$ accesses.
 - A factor of m less!
- Doesn't decrease overall number of memory accesses.
 - Threads do $2n^3$ reads to shared memory instead of global memory.
- But get much better performance, because shared memory bandwidth is 10X global memory bandwidth.



Tiled matrix multiply performance

- With 16x16 tiles, decrease global memory usage by factor of 16.
- Can get $(200\text{GB}/4\text{B}) \cdot (3 \text{ FLOP} / 1\text{B}) \cdot 16 = 2400$ GFLOPS, compared to 150 GFLOPS from before!
- Each thread block uses $16 \times 16 \times 4\text{B} \times (2 \text{ matrices}) = 2\text{KB}$ of shared memory.
- Even if only 16KB shared memory, can still run 8 blocks per SM, which is enough to achieve full occupancy.
 - Each block has 256 threads, so 6 blocks enough to saturate SM with 1536 thread capacity.
- If use 32x32 tiles, then 1024 threads per tile / thread block, so only one thread block per SM.
 - Only 2/3 occupancy if SM can run 1536 threads.
 - Note the tradeoff between improving bandwidth and occupancy.



Effective use of shared memory

- General strategy is to find reused data and load it into fast, high bandwidth memory.
 - Very effective in practice.
 - Same principle as caches, except that programmer controls what's in shared memory.
 - Data reuse is also called temporal locality.
- Using shared memory is sometimes hard, since it's so small.
 - 48KB shared mem / SM, vs. 6 GB global mem.
 - On a CPU, 32KB L1 cache vs 8GB main mem.
- Designing algorithms with high temporal locality is one of main techniques for getting fast code.



CUDA Variable Type Qualifiers

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 without any qualifier reside in a register.
 - Except per-thread arrays, which reside in global memory.

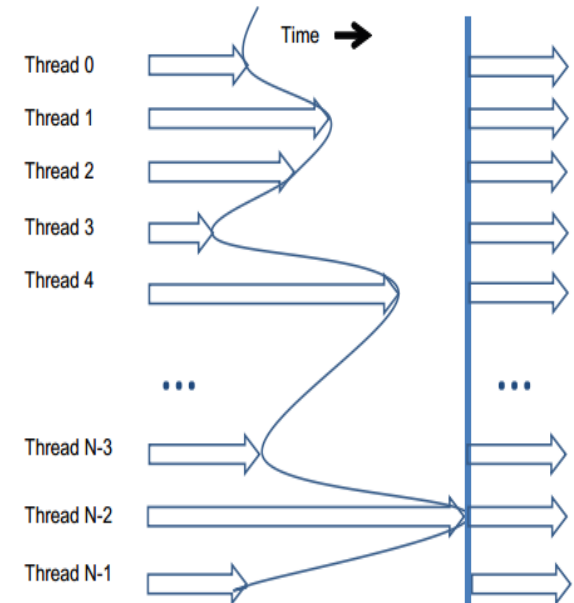


Synchronization

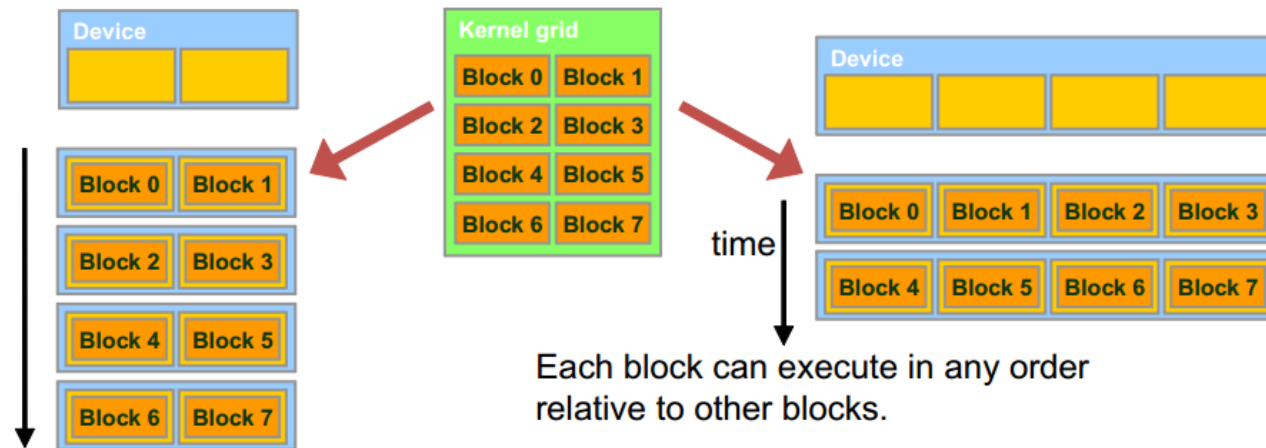
- In algorithms up to now, threads mostly worked independently.
 - E.g. it's ok if say thread 1 took 3 steps but thread 2 took 7.
- Sometimes threads need to coordinate. I.e. they must all finish some step before any thread can go on to next step.
 - **Ex** In MM, threads must finish loading M, N tiles into shared mem before any thread can start its dot product.
- Threads within a block can synchronize using `__syncthreads()`.
 - Scheduler ensures a thread reaching `__syncthreads()` statement blocks until all threads in block also reach that `__syncthreads()`.
 - This is a barrier synchronization.

Synchronization

- Must be careful with synchronization.
- **Ex** If code has `__syncthreads()` but some thread in block goes into infinite loop, block will never finish!
- **Ex** If `__syncthreads()` occurs in `if` block, then all threads must go through the `if`, or none do. Otherwise block never finishes.
- **Ex** If `__syncthreads()` occurs in both branches of `if-then-else` code block, all threads must go through same branch, or block never finishes.
- `__syncthreads()` can also cause wasted work. Threads arriving earlier at the barrier wait for later threads.
 - Decreases number of schedulable threads. May hurt latency hiding.
- Avoid synchronization if possible.



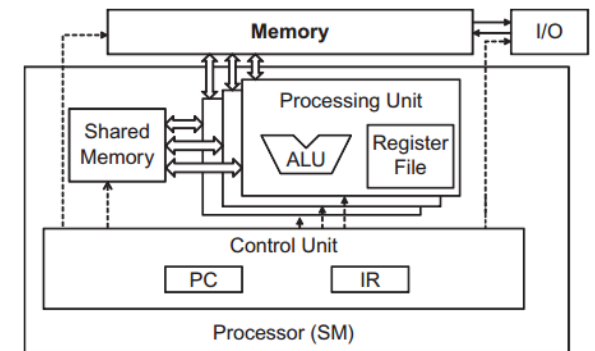
Synchronization



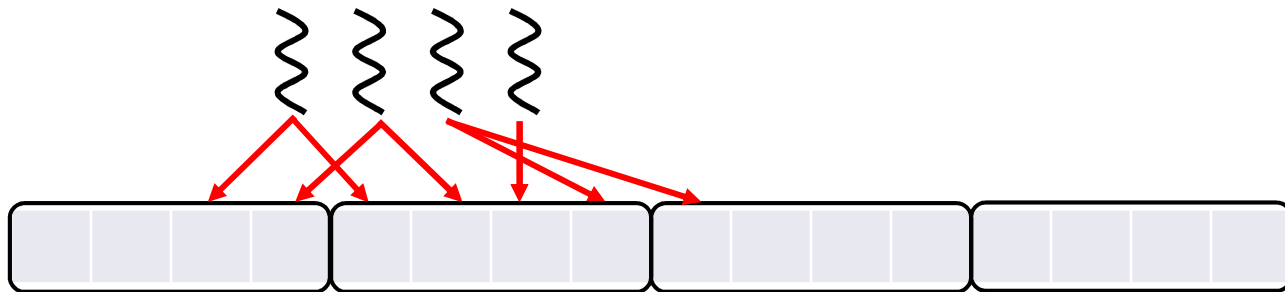
- Threads in different blocks can't synchronize.
- This allows blocks to execute in any order, and scale transparently to GPUs with more SMs.
- Downside is if need inter-block synchronization, must wait till all blocks in kernel finish, then start a new kernel.

Thread warps

- An SM contains one or more SIMD (single instruction multiple data) processors.
 - Each SIMD processor contains multiple cores that run the same command on different data.
- The unit of “SIMDness” is a warp of 32 threads.
 - An entire warp of threads runs at a time.
 - A thread block is divided into warps with consecutive threadIdx.x values.
- Execution is fast when entire warp “does the same thing”.
 - Different warps can do different things without performance loss.
- It's much slower when there's non-coalesced memory accesses, control flow divergence or bank conflicts.

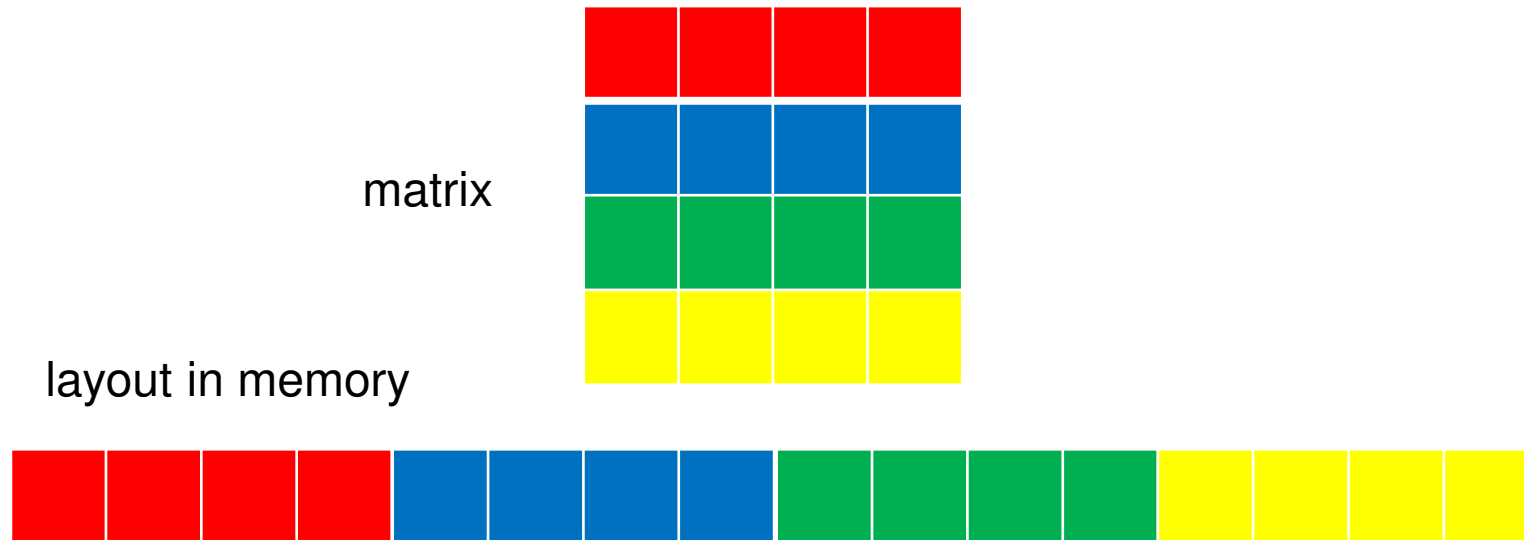


Memory coalescing



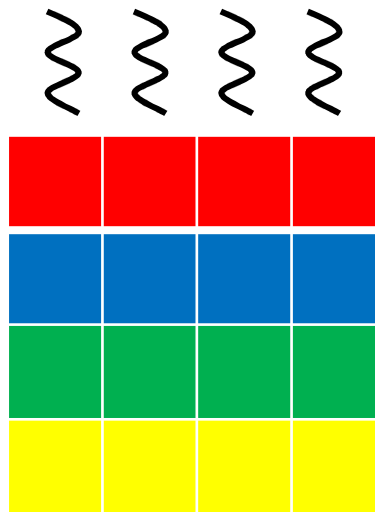
- Global memory divided into segments of 128 B (= 32 floats).
- Suppose SM executes a warp of 32 threads all executing a SIMD instruction reading from global memory.
 - If all 32 locations being read lie in one segment, hardware detects this and only transfers one segment (128 B) from global memory to SM.
 - Access is coalesced.
 - If locations lie in k different segments, $k \cdot 128$ B are transferred.
 - Access is uncoalesced.
 - In worst case, transfer $32 \cdot 128$ B = 4KB to read 32 floats!
 - Huge waste of limited global memory bandwidth.
- For good performance, make global memory accesses as coalesced as possible.

Coalescing example



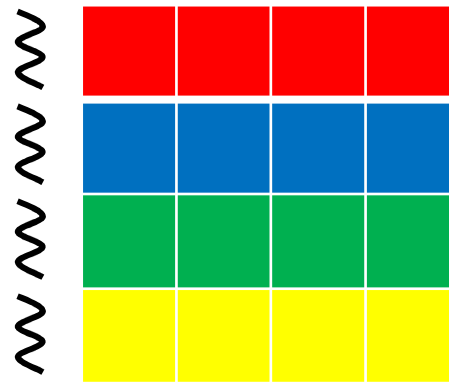
- Say we have 4x4 matrix, stored in row major format.
- Suppose segments are 4 elements wide.
 - I.e. can transfer 4 consecutive elements in one step.
- We have warp of 4 threads, and want to iterate through matrix either row by row, or column by column.

Coalescing example



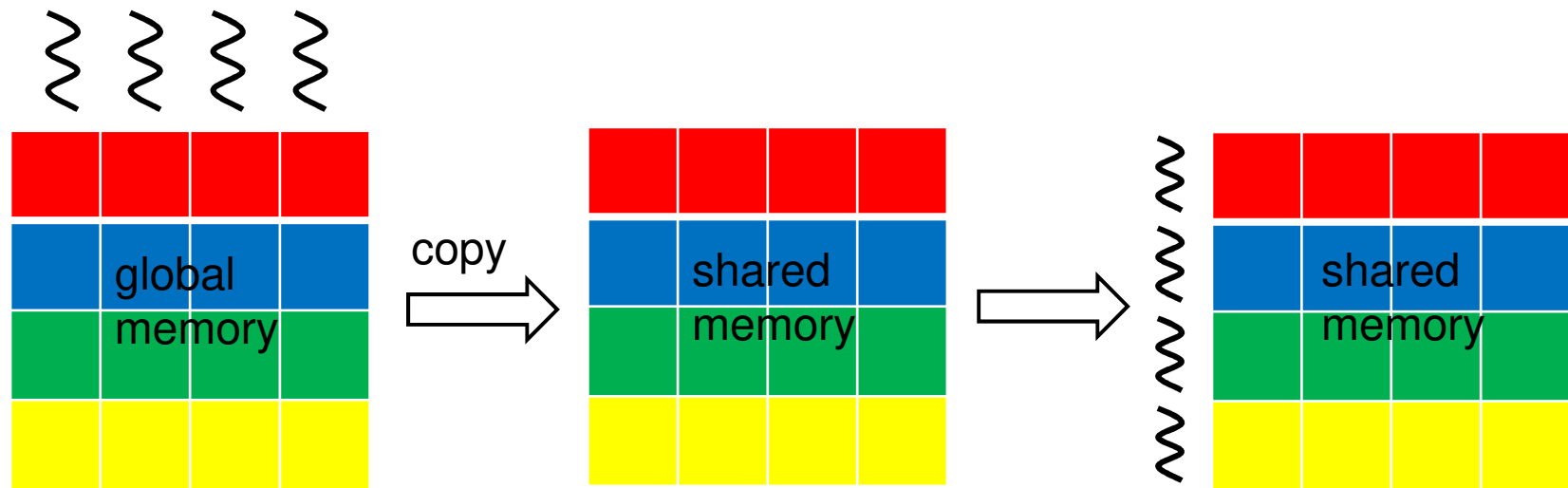
- When iterating by row, we naturally map one thread to each column.
 - Need 4 iterations in total.
- Numbers show locations accessed each iteration.
 - Locations all consecutive. All iterations coalesced.

Coalescing example



- When iterating by column, map one thread per row.
 - In iteration 1, access locations 0,4,8,12.
 - In iteration 2, access locations 1,5,9,13. Etc.
 - Each iteration accesses nonconsecutive locations.
 - All accesses noncoalesced.

Improving coalescing



- Only global memory has bandwidth penalty for noncoalesced accesses.
- Shared memory has much smaller penalty for scattered accesses.
- To improve coalescing, first do coalesced read from global to shared memory. Then make scattered accesses to shared memory.
- **Ex** To read matrix by column, first read it by row and copy to matrix in shared memory. Then read shared memory matrix by column.
- Once again shows flexibility of shared memory vs global memory.



Warp divergence

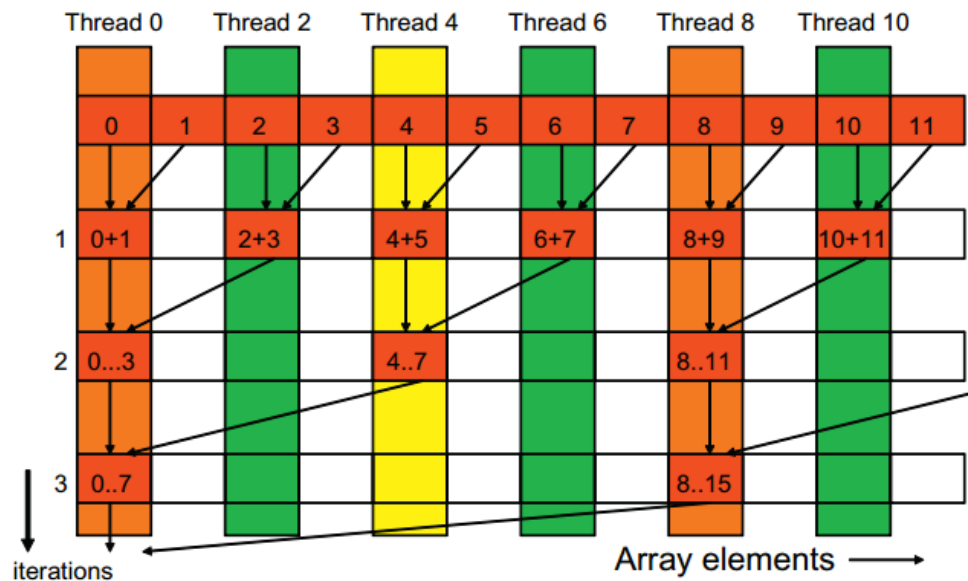
- Since SM is SIMD, efficient when all threads run same instruction.
 - SM finishes a warp in one pass.
- But if code has branches, threads can run different instructions.

```
if (threadIdx.x % 3 == 0) i += 1;  
else if (threadIdx.x % 3 == 1) i -= 1;  
else i *= 2;
```

- Called warp divergence.
- If threads have k branches, SM takes k passes to run warp.
 - In each pass, runs all threads of one branch, which all run same instruction.
- In worst case, SM takes 32 passes to run one warp!

Divergence example

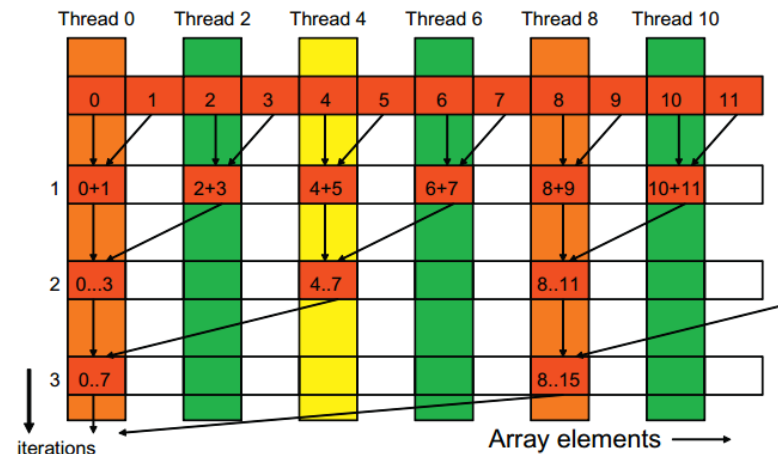
- Reduction produces single number from array of numbers.
 - Ex Returns sum, max, or min of array.
 - Very commonly used operation.
- Can be computed in parallel using reduction tree.
 - With n values and n threads, do $O(n)$ additions, take $O(\log n)$ iterations.



Divergence example

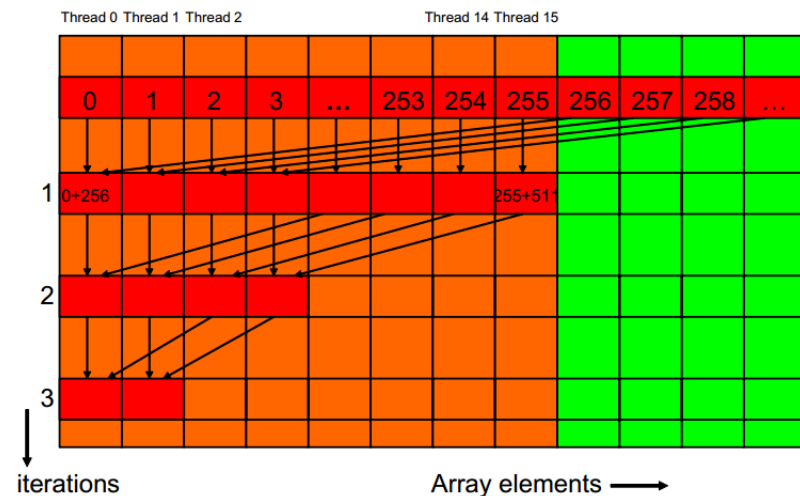
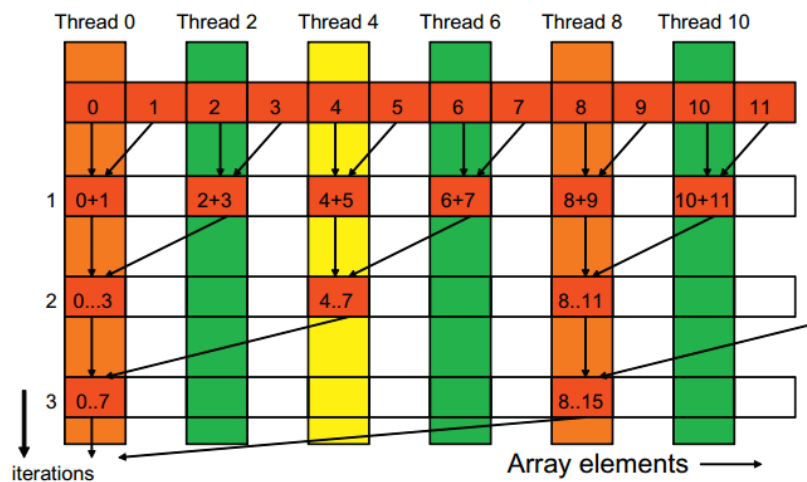
```
int t = threadIdx.x;
for (int stride = 1; stride < blockDim.x; stride *= 2) {
    __syncthreads();
    if (t % (2*stride) == 0)
        partialSum[t] += partialSum[t+stride];
}
```

- Number of threads working halves every iteration.
- Each working thread adds value from stride away into its location in output array.
 - stride=1 in iteration 1, then 2, 4, 8, etc.
- `__syncthreads()` ensures all values from one iteration complete before computing next iteration.



Reducing divergence

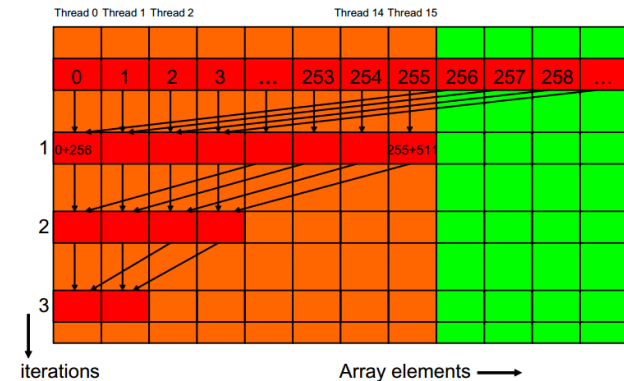
- Each iteration has 2 branches, the threads with $(t \% (2 * \text{stride})) == 0$, and the other threads.
 - Each iteration takes 2 passes to complete.
- Can modify algorithm to decrease amount of divergence.
 - Still tree based, but first add values from far away.
 - Iter 1: first 256 threads add value from 256 away.
 - Iter 2: first 128 threads add value from 128 away.
 - Iter 3: first 64 threads add value from 64 away. Etc.
 - Work, time complexity same as before.



Reducing divergence

```
int t = threadIdx.x;
for (int stride = blockDim.x; stride > 1; stride /= 2) {
    __syncthreads();
    if (t < stride)
        partialSum[t] += partialSum[t+stride];
}
```

- Why is divergence reduced?
 - In first iteration, first 256 threads = 8 warps all do if, last 8 warps all don't.
 - In second iteration, first 128 threads = 4 warps do if, last 12 don't.
 - No divergence till 5th iteration.
- From 5th iteration on, 16, 8, 4, 2 threads from first warp do if.
- 8 iterations, only 4 have divergence.
- Can you get rid of the 4 iterations with divergence?



Bank conflicts

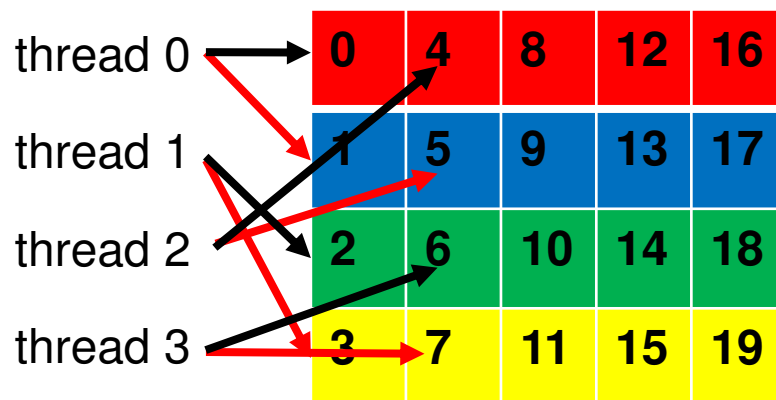
- Shared memory is arranged in banks.
 - A bank stores a set of 4B data.
 - Allows parallel accesses. Threads can access different banks at same time.
- If n banks, then address x is stored in bank $x \% n$.
 - Current GPUs have 32 banks.
- If threads in a warp access different banks, completes in one pass.
- If $k > 1$ threads access different addresses in same bank, get k -way bank conflict.
 - Accesses serialize, takes k passes to complete accesses.
 - Unless all threads access same value, which then gets broadcast in one pass.
- Different warps don't have bank conflicts.

bank 0	0	4	8	12	16
bank 1	1	5	9	13	17
bank 2	2	6	10	14	18
bank 3	3	7	11	15	19

Bank conflict example

- Suppose 4 banks, warp size = 4 and block size = 4.
- Want each thread to load two values from global memory into shared memory.
- If thread loads consecutive locations, 2 way bank conflict.
- If thread loads locations block size apart, no bank conflicts!

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



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

