



Introduction to CUDA II

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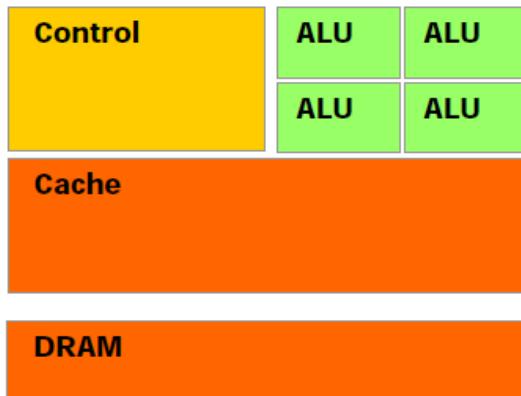
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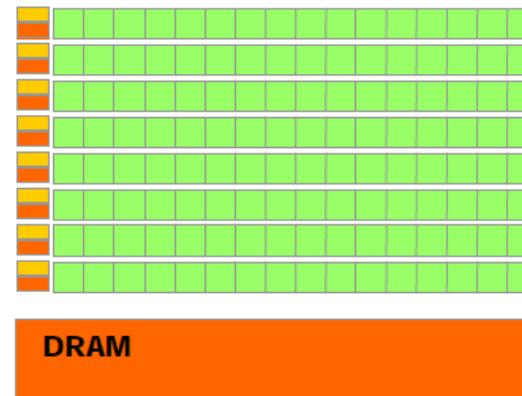
GPU Work Abstraction

- CUDA Kernels can be thought of as telling a GPU to compute all iterations of a set of nested loops concurrently
- Threads are dynamically scheduled onto hardware according to a hierarchy of thread groupings

CPU: Cache heavy, focused on individual thread performance

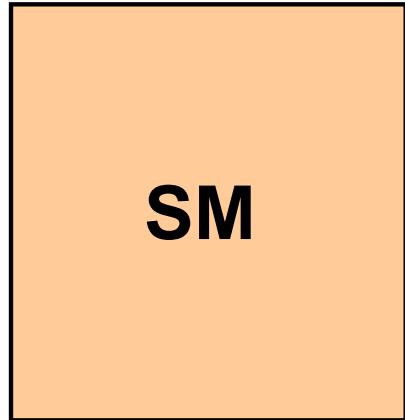


GPU: ALU heavy, massively parallel, throughput oriented

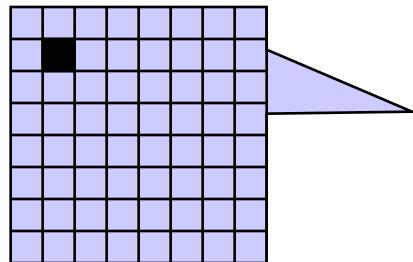


Grids, Thread Blocks, Threads

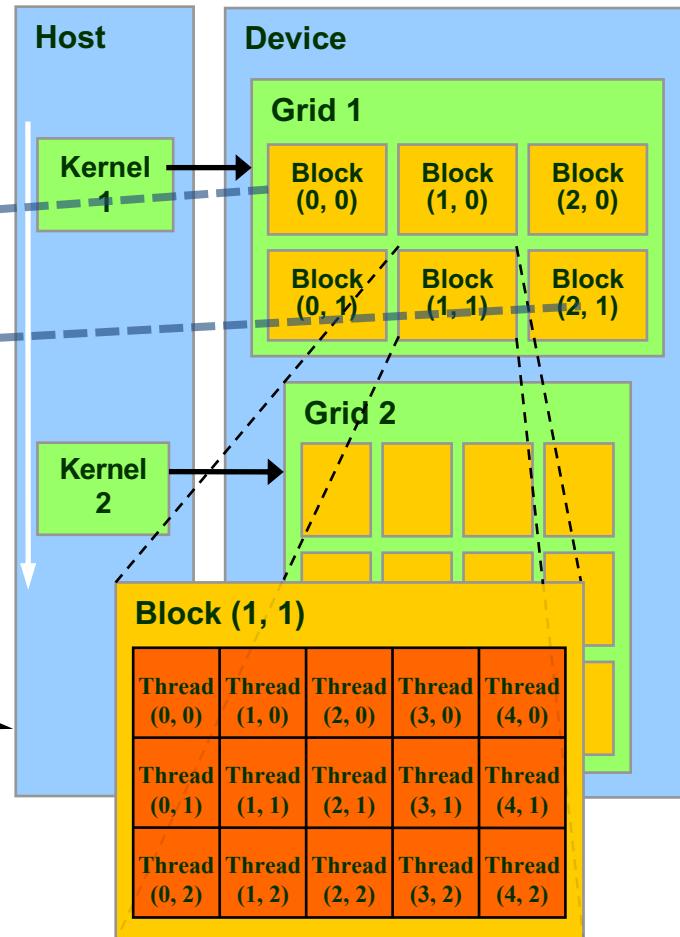
Thread blocks are scheduled onto pool of GPU SMs...



1-D, 2-D, 3-D thread block:



1-D, 2-D, or 3-D Grid of Ths blocks:



Built-in Variables to manage grids and blocks

dim3 => a new datatype defined by CUDA:

- **struct dim3 { unsigned int x, y, z };**
 - three unsigned ints where any unspecified component defaults to 1.
-
- **dim3 gridDim;**
 - Dimensions of the grid in blocks
 - **dim3 blockDim;**
 - Dimensions of the block in threads
 - **dim3 blockIdx;**
 - Block index within the grid
 - **dim3 threadIdx;**
 - Thread index within the block

Bi-dimensional threads configuration: set the elements of a square matrix

```
__global__ void kernel( int *a, int dimx, int dimy ) {
    int ix = blockIdx.x*blockDim.x + threadIdx.x;
    int iy = blockIdx.y*blockDim.y + threadIdx.y;
    int idx = iy*dimx + ix;

    a[idx] = idx+1;
}
```

```
int main() {
    int dimx = 16;
    int dimy = 16;
    int num_bytes = dimx*dimy*sizeof(int);

    int *d_a=0, *h_a=0; // device and host pointers

    h_a = (int*)malloc(num_bytes);
    cudaMalloc( (void**)&d_a, num_bytes );

    dim3 grid, block;
    block.x = 4;
    block.y = 4;
    grid.x = dimx / block.x;
    grid.y = dimy / block.y;

    kernel<<<grid, block>>>( d_a, dimx, dimy );

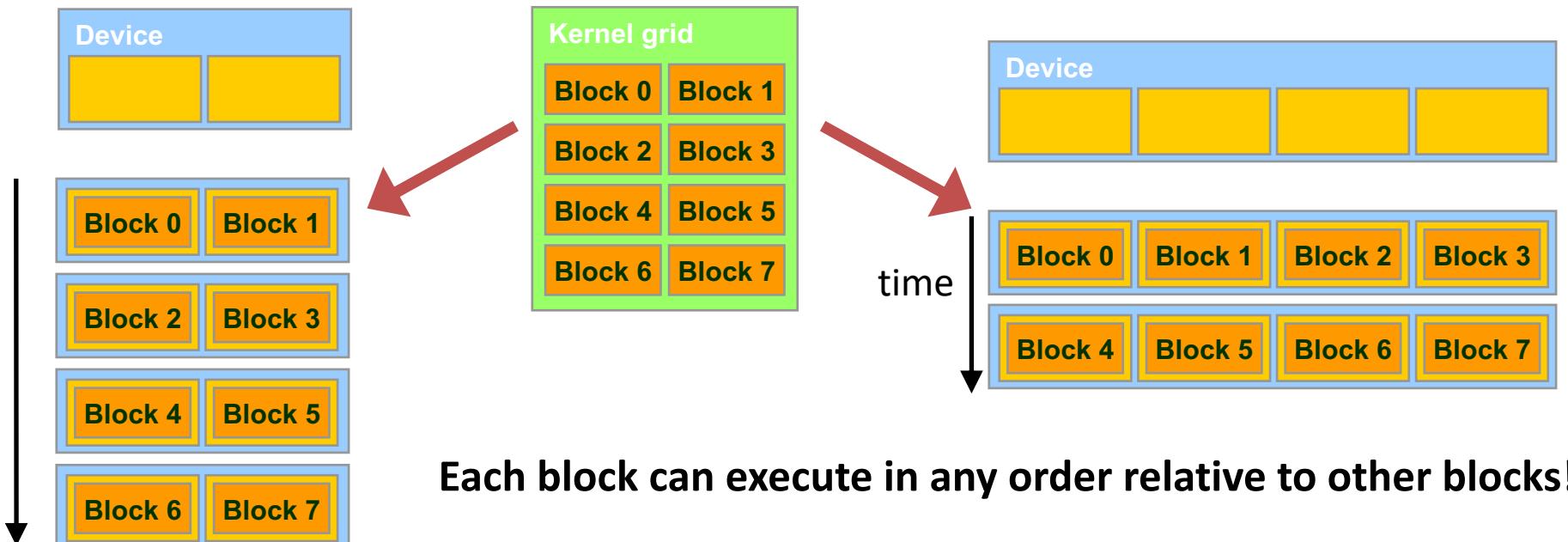
    cudaMemcpy(h_a,d_a,num_bytes,
              cudaMemcpyDeviceToHost);

    for(int row=0; row<dimy; row++) {
        for(int col=0; col<dimx; col++)
            printf("%d ", h_a[row*dimx+col] );
        printf("\n");
    }

    free( h_a );
    cudaFree( d_a );
    return 0;
}
```

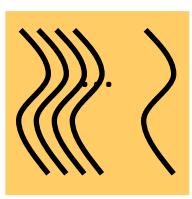
Transparent Scalability

- Hardware is free to assigns blocks to any processor at any time
 - A kernel scales across any number of parallel processors

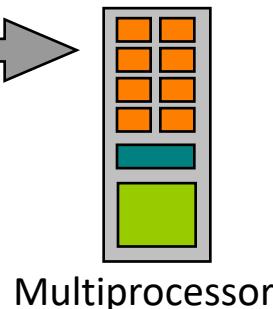
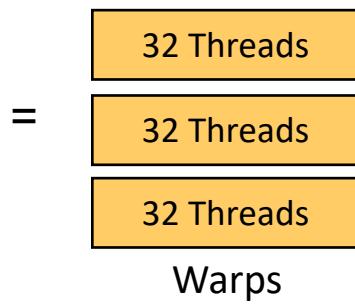


GPU Thread Block Execution

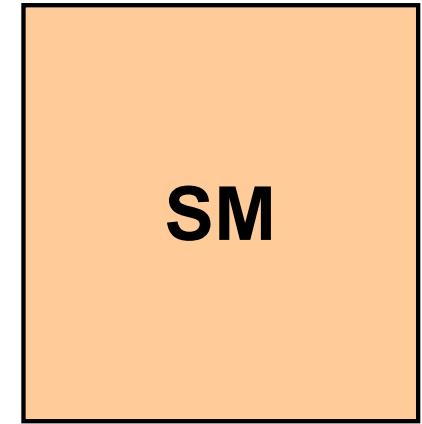
- Thread blocks are decomposed onto hardware in **32-thread “warps”**
- Hardware execution is scheduled in units of **warps**
 - an SM can execute warps from several thread blocks
- **Warps** run in SIMD-style execution:
 - All threads execute the same instruction in lock-step
 - If one thread stalls, the entire warp stalls...
 - A branch taken by a thread has to be taken by all threads...
(divergence is bad)



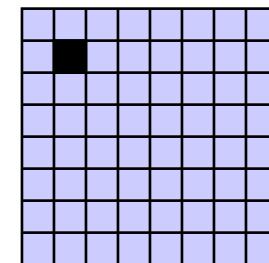
Thread
Block



Thread blocks are multiplexed onto pool of GPU SMs...



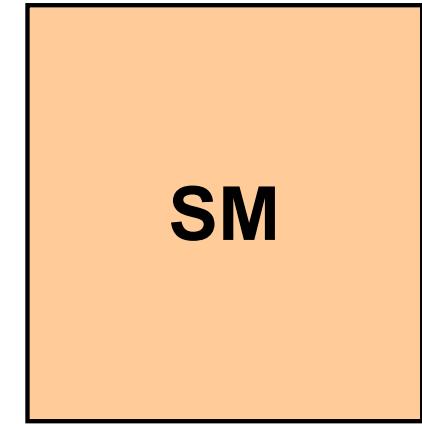
1-D, 2-D, 3-D
thread block:



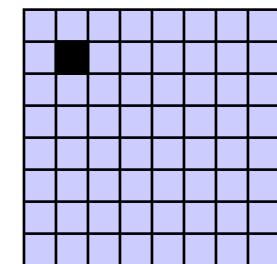
GPU Warp Branch Divergence

- Branch divergence: when not all threads take the same branch, the entire warp has to **execute both sides of the branch**
- Branch divergence issue not unique to GPUs, affects **all SIMD hardware platforms...**
- On GPUs, we get fast **hardware-based** implementation of predication/masking/etc...
- GPU blocks memory writes from disabled threads in the “if then” branch, then inverts all thread enable states and runs the “else” branch
- GPU hardware detects warp re-convergence and then runs with all threads enabled...

Thread blocks are multiplexed onto pool of GPU SMs...



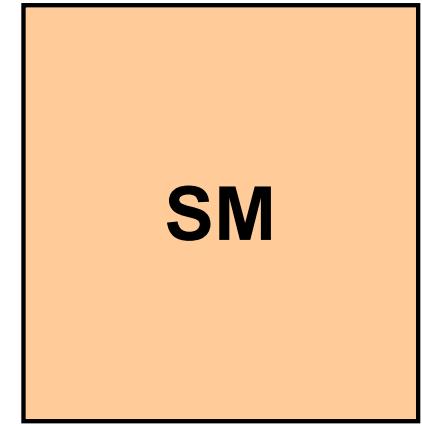
1-D, 2-D, 3-D
thread block:

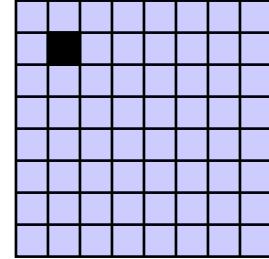


GPU Warp Branch Divergence

- Threads within the same thread block can communicate with each other in fast on-chip shared memory
- Once scheduled on an SM, thread blocks run until completion
- Because the order of thread block execution is arbitrary and blocks cannot be stopped, they cannot communicate or synchronize with other thread blocks (*)
- (*) Atomic memory ops are an exception wrt/ communication

Thread blocks are multiplexed onto pool of GPU SMs...



1-D, 2-D, 3-D
thread block:




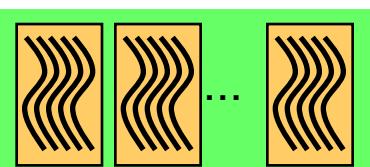
Execution Model

Software

Thread



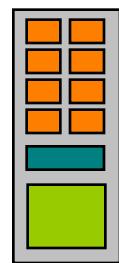
Thread Block



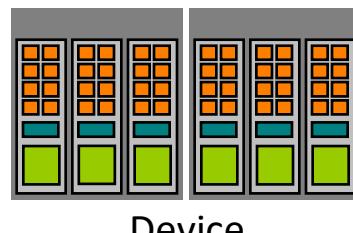
Grid

Hardware

Scalar Processor



Multiprocessor



Threads are executed by scalar processors

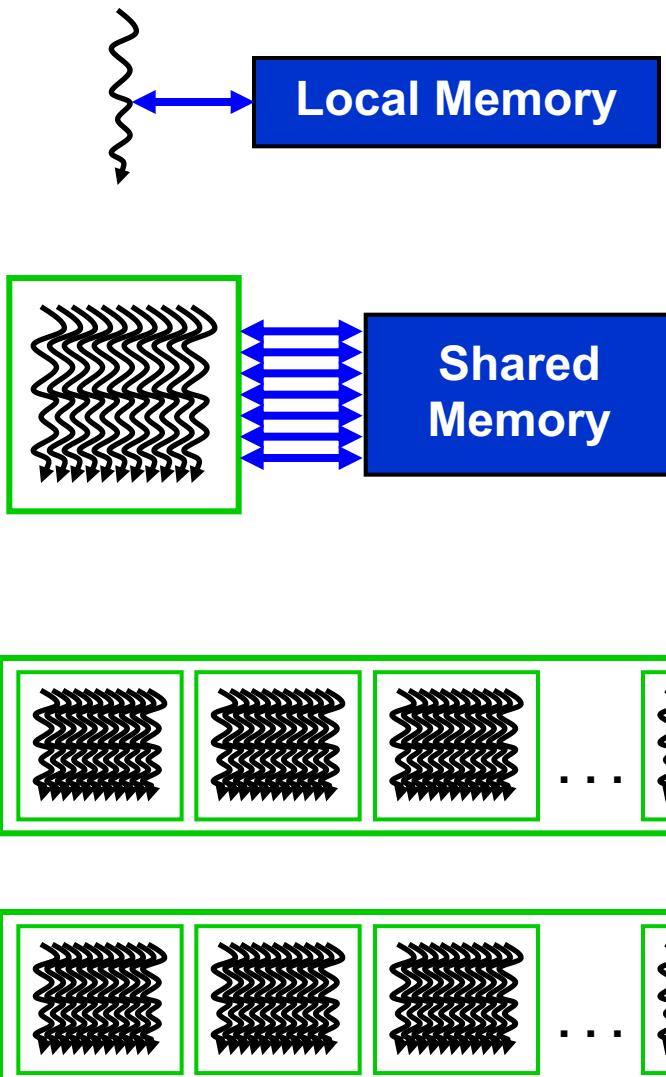
Thread blocks are executed on multiprocessors

Thread blocks **do not migrate**

Several concurrent thread blocks can reside on one multiprocessor - limited by multiprocessor resources (shared memory and register file)

A kernel is launched as a grid of thread blocks

Memory Hierarchy



- Registers (fast up to availability)
 - Limited num. registers available per block
- Shared Memory: per-block
 - Shared by threads of the same block
 - *Fast* inter-thread communication
- Global Memory: per-application
 - Shared by all threads
 - Inter-Grid communication

**Sequential Grids
Execution in
Time**



Synchronization

- GPU blocks do not synchronize each other (except using atomic operations)
- Threads within a block can cooperate by sharing data through some shared memory and by synchronizing their execution to coordinate memory accesses
- one can specify synchronization points in the kernel by calling the `__syncthreads()` intrinsic function
- `__syncthreads()` acts as a barrier at which all threads in the block must wait before any is allowed to proceed
- `cudaDeviceSynchronize()` can be used on host to synchronize the host with a GPU.
- Kernels are asynchronous to the host, `cudaMemcpy` is not (blocking)

Atomic Operations

- Terminology: Read-modify-write uninterruptible when *atomic*
- Many *atomic operations* on memory available with CUDA C
 - `atomicAdd()`
 - `atomicSub()`
 - `atomicMin()`
 - `atomicMax()`
 - `atomicInc()`
 - `atomicDec()`
 - Other `atomic` ...
- Predictable result when simultaneous access to memory required

Multiblock Dot Product: dot ()

```
__global__ void dot( int *a, int *b, int *c ) {  
  
    __shared__ int temp[THREADS_PER_BLOCK];  
  
    int index = threadIdx.x + blockIdx.x * blockDim.x;  
  
    temp[threadIdx.x] = a[index] * b[index];  
  
    __syncthreads();  
  
    if( 0 == threadIdx.x ) {  
        int sum = 0;  
        for( int i = 0; i < THREADS_PER_BLOCK; i++ ) sum += temp[i];  
        atomicAdd( c, sum );  
    }  
}
```

- We need to atomically add **sum** to **c** in our multiblock dot product



GPU On-Board Global Memory

GPU arithmetic rates dwarf memory bandwidth

For Kepler K40 hardware:

~4.3 SP TFLOPS vs. ~288 GB/sec

The ratio is roughly **60 FLOPS per memory reference**
for single-precision floating point

Peak performance achieved with “**coalesced**” memory access patterns –
patterns that result in a single hardware memory transaction for a SIMD
“warp” – a contiguous group of 32 threads



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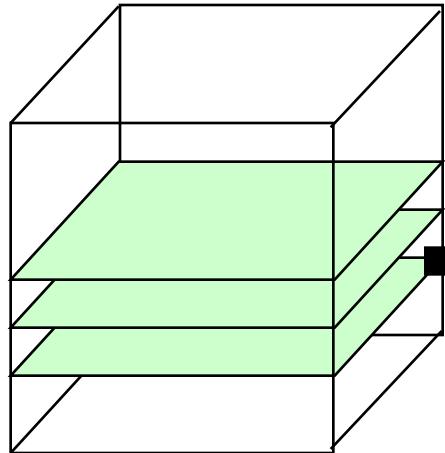


Memory Coalescing (Oversimplified explanation)

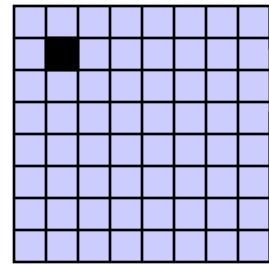
- Threads in a warp perform a read/write operation that can be serviced in a single hardware transaction
- Rules vary slightly between hardware generations, but new GPUs are much more flexible than old ones
- If all threads in a warp read from a contiguous region that's 32 items of 4, 8, or 16 bytes in size, that's an example of a coalesced access
- Multiple threads reading the same data are handled by a hardware broadcast
- Writes are similar, but multiple writes to the same location yields undefined results

CUDA Grid/Block/Thread Decomposition

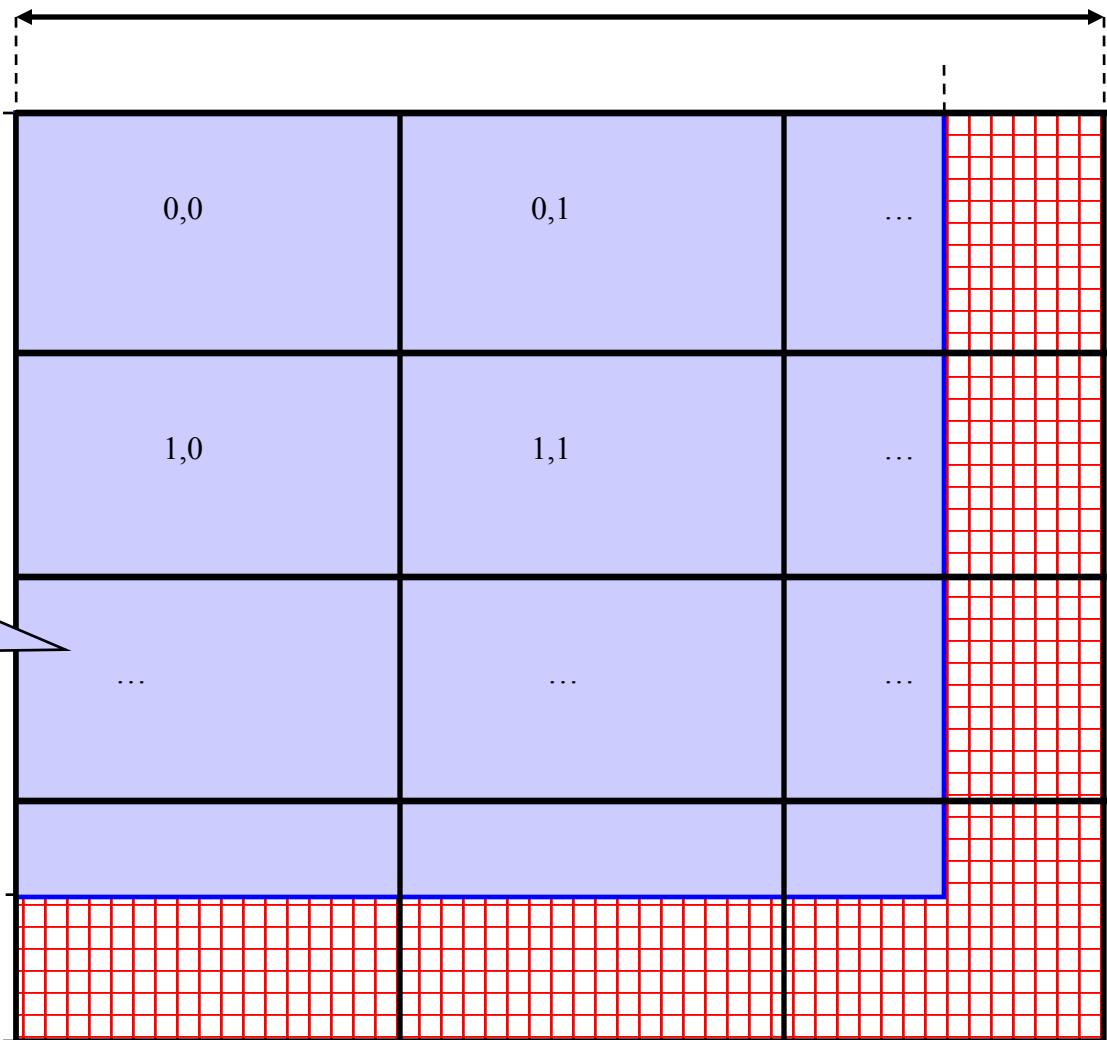
**1-D, 2-D, or 3-D
Computational Domain**



**1-D, 2-D, 3-D
thread block:**



**1-D, 2-D, or 3-D (SM $\geq 2.x$)
Grid of thread blocks:**



Padding arrays out to full blocks
optimizes global memory performance
by guaranteeing memory coalescing

CUDA Compiler: nvcc basic options

- **-arch=sm_35 →** enable code for a given capability
- **-G →** enable debug for device code
- **--ptxas-options=-v →** show register and memory usage
- **--maxrregcount <N> →** limit the number of registers
- **-use_fast_math →** use fast math library
- **-O3 →** Enables compiler optimization
- **-ccbin *compiler_path* →** use a different C compiler
- **--compiler-options →** Specify options directly to the compiler/preprocessor.



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Getting Performance From GPUs

- Don't worry (much) about counting arithmetic operations...at least until you have nothing else left to do
- GPUs provide tremendous memory bandwidth, but even so, **memory bandwidth often ends up being the performance limiter**
- Keep/reuse data in **registers** as long as possible
- The main consideration when programming GPUs is **accessing memory efficiently**, and storing operands in the **most appropriate memory system** according to data size and access pattern



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Why Does GPU Accelerate Computing?

Highly scalable design

Higher aggregate memory bandwidth

Huge number of low frequency cores

Higher aggregate computational power

Massively parallel processors for data processing



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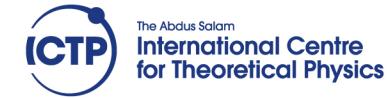
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Why Does GPU Not Accelerate Computing?

PCI Bus bottleneck

Synchronization weakness

Extremely slow serialized execution

High complexity, SPMD + SIMD + Memory Model

People forget about the Amdahl's law: accelerating only the 50% of the original code, the expected speedup can get at most a value of 2!!



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CPU & GPU



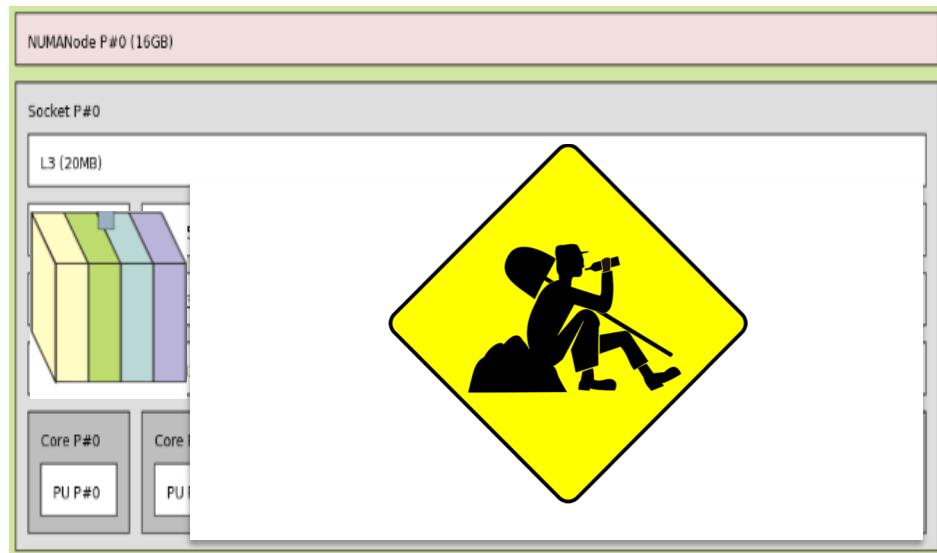
The Intel Xeon E5-2665
Sandy Bridge-EP 2.4GHz

~ 8 GBytes



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CPU & GPU

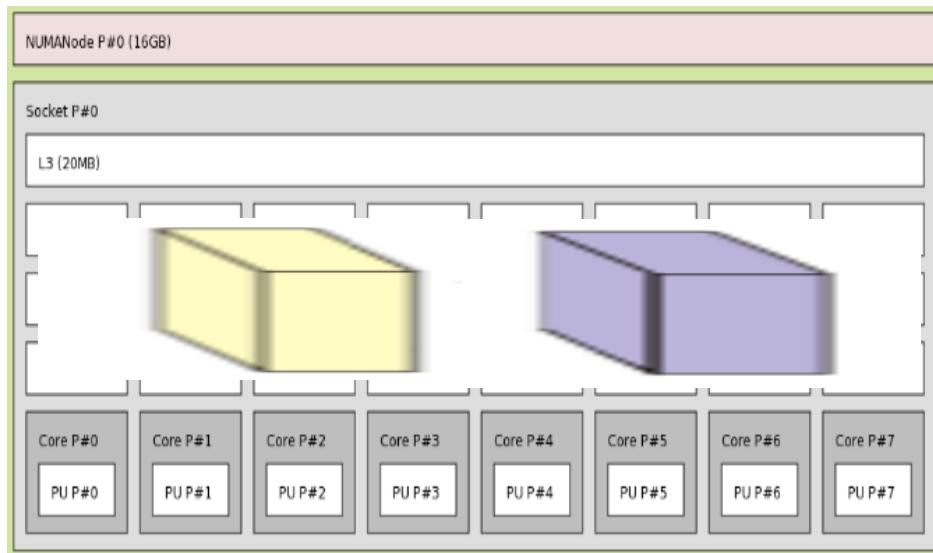


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References

- <http://www.ks.uiuc.edu/Research/gpu/>
- <http://indico.ictp.it/event/a14302/other-view?view=ictptimetable> (ICTP - SMR2760)
- <http://www.iac.rm.cnr.it/~massimo/PMC.html>
- CUDA Zone: <https://developer.nvidia.com/cuda-zone>
- CUDA by Example



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