GPU Programming Using CUDA

Gregory G. Howes
Department of Physics and Astronomy
University of Iowa

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Outline

- Concepts for GPU Computing
- Programming Model for GPU Computing using CUDA C
- CUDA C Programming
- Advanced CUDA Capabilities

GPU Computing

Graphics Processing Units (GPUs) have been developed in response to strong market demand for realtime, high-definition 3D graphics (video games!)

GPUs are highly parallel,
multithreaded,
manycore processors

- Tremendous computational horsepower
- Very high memory bandwidth

We hope to access this power for scientific computing

GPU Programming Languages

- CUDA (Compute Unified Device Architecture) is the proprietary programming language for NVIDIA GPUs

- OpenCL (Open Computing Language) is portable language standard for general computing that can exploit capabilities of GPUs from any manufacturer.

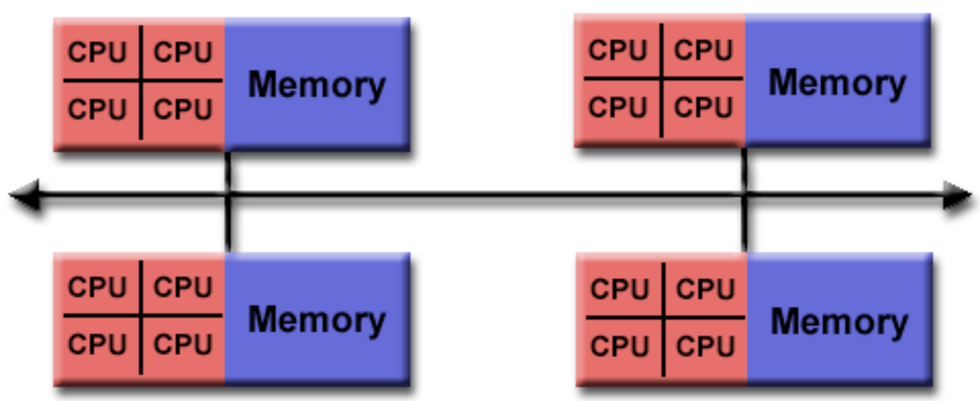
Both languages provide extensions to C (as well as other languages) that enable the programmers to access the powerful computing capability for general-purpose computing on GPUs (GPGPU)

Today we will focus on the basics of CUDA C programming

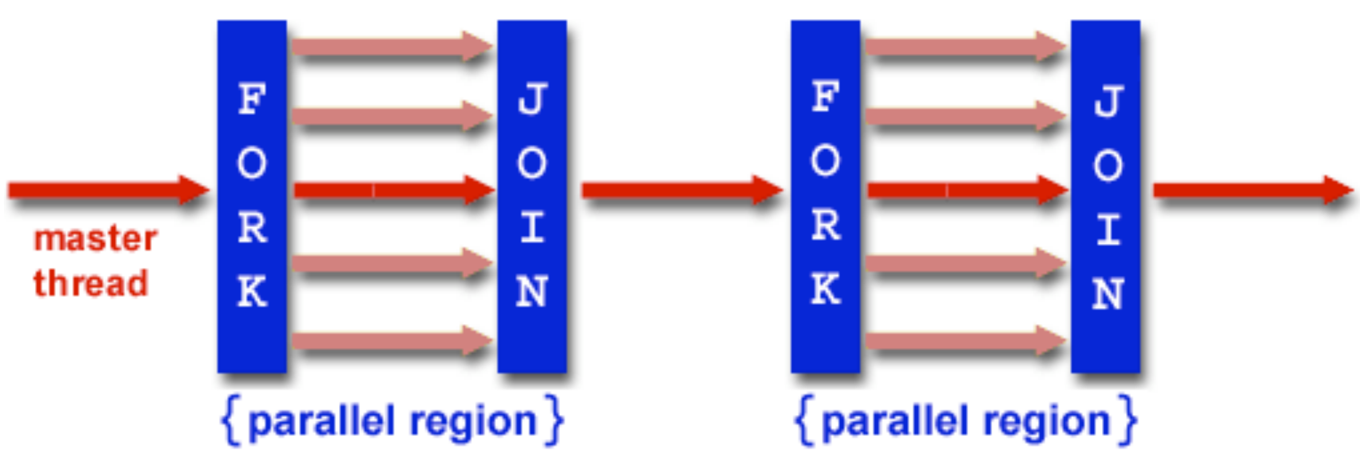
Parallel Computing Architectures

Different computer architectures suggest three approaches to parallel computing:

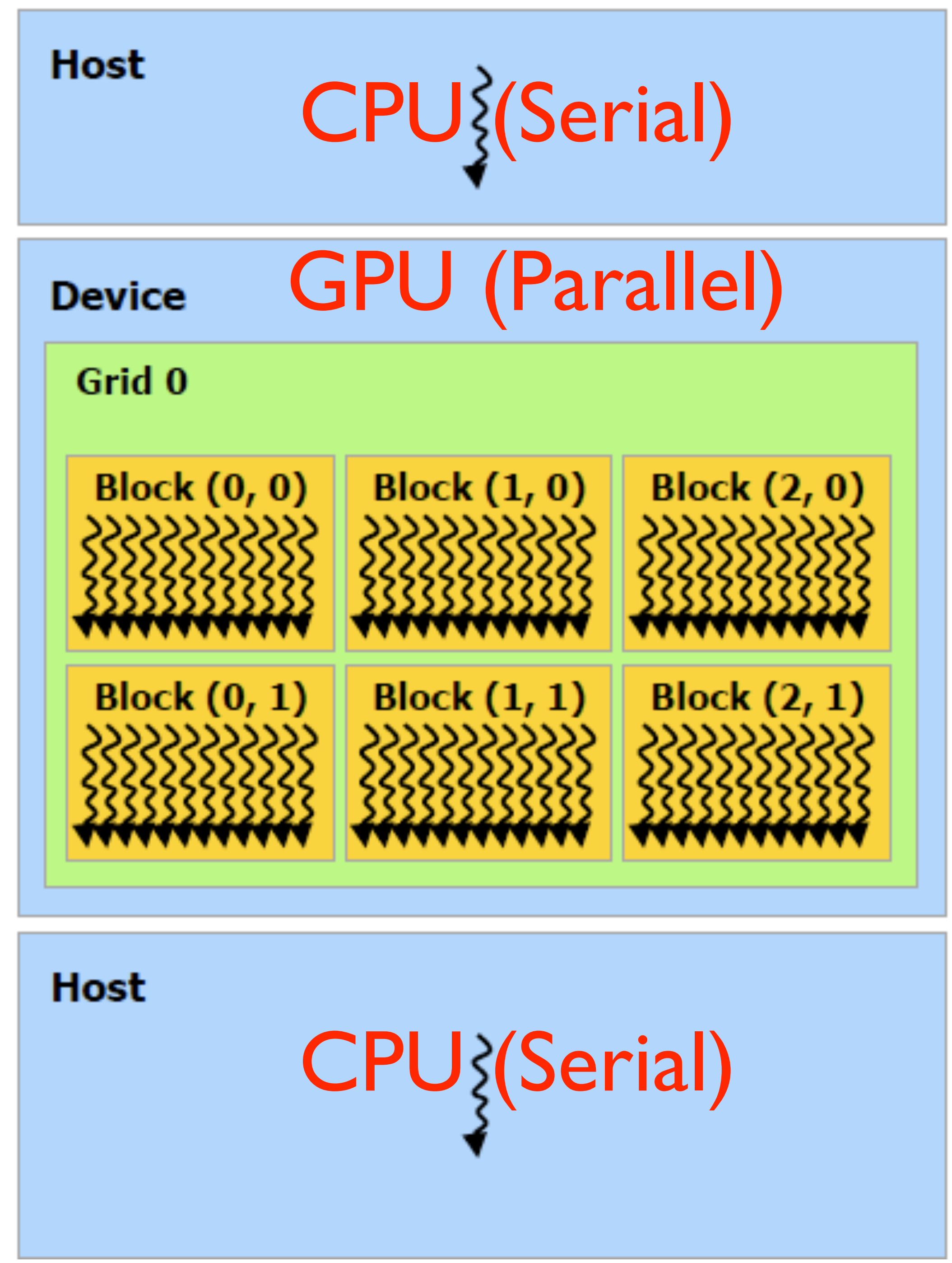
1) Message Passing (MPI)



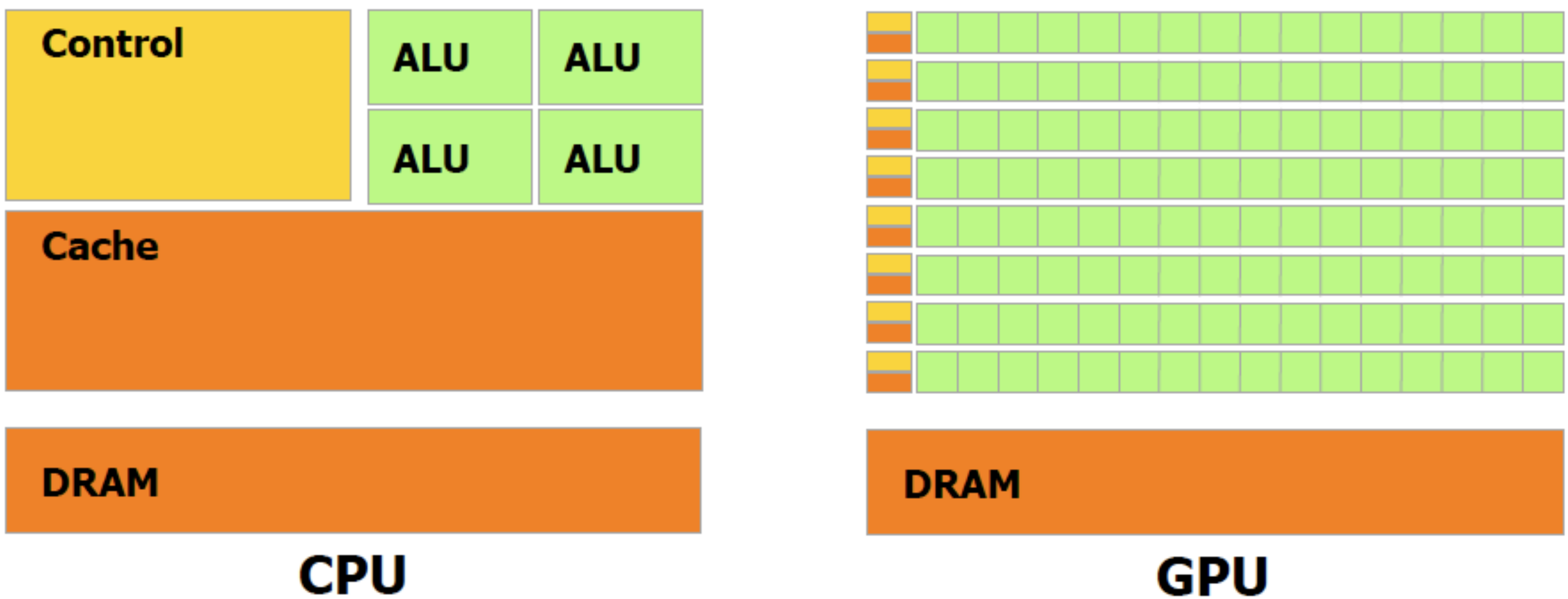
2) Multithreading (OpenMP)



3) GPU (CUDA)



More Transistors to Data Processing



CPUs devote a significant fraction of transistors to data caching and flow control

GPUs devote more transistors to data processing (arithmetic and logic units, ALU)

GPU vs. CPU Peak Performance

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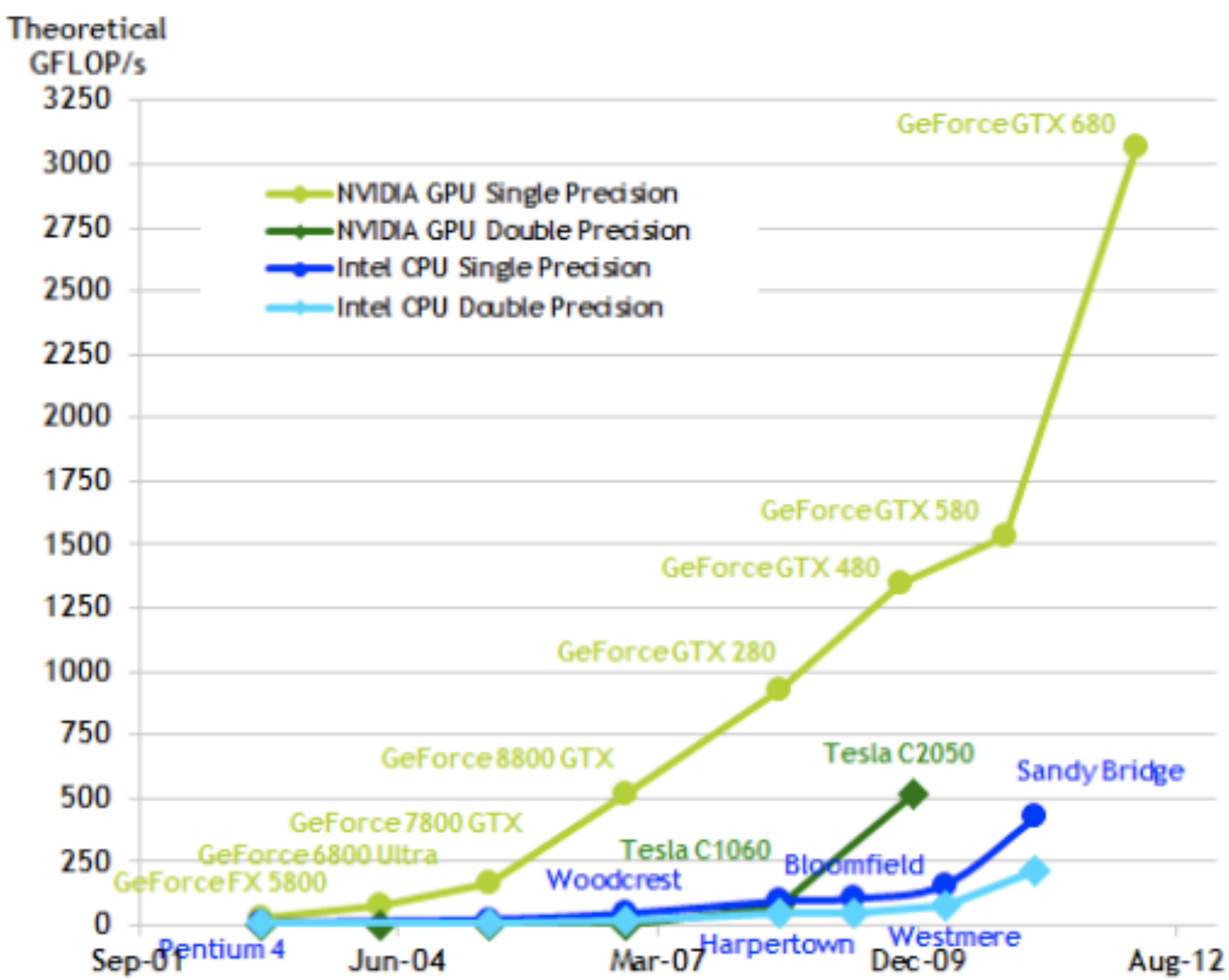
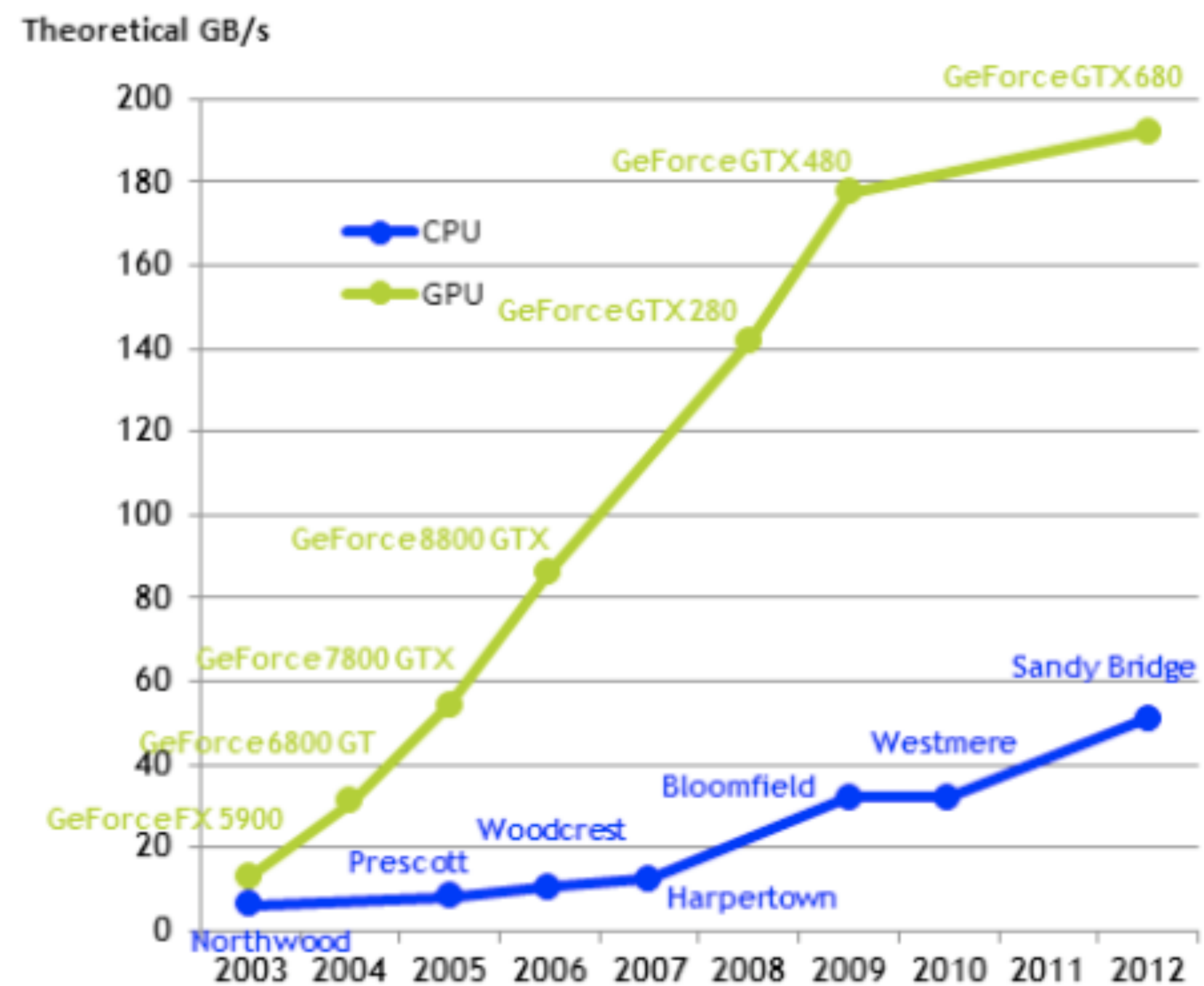
FLoating point Operations Per Second (FLOPS)



Memory Access Bandwidth (GB/s)



Many Languages for GPU Computing

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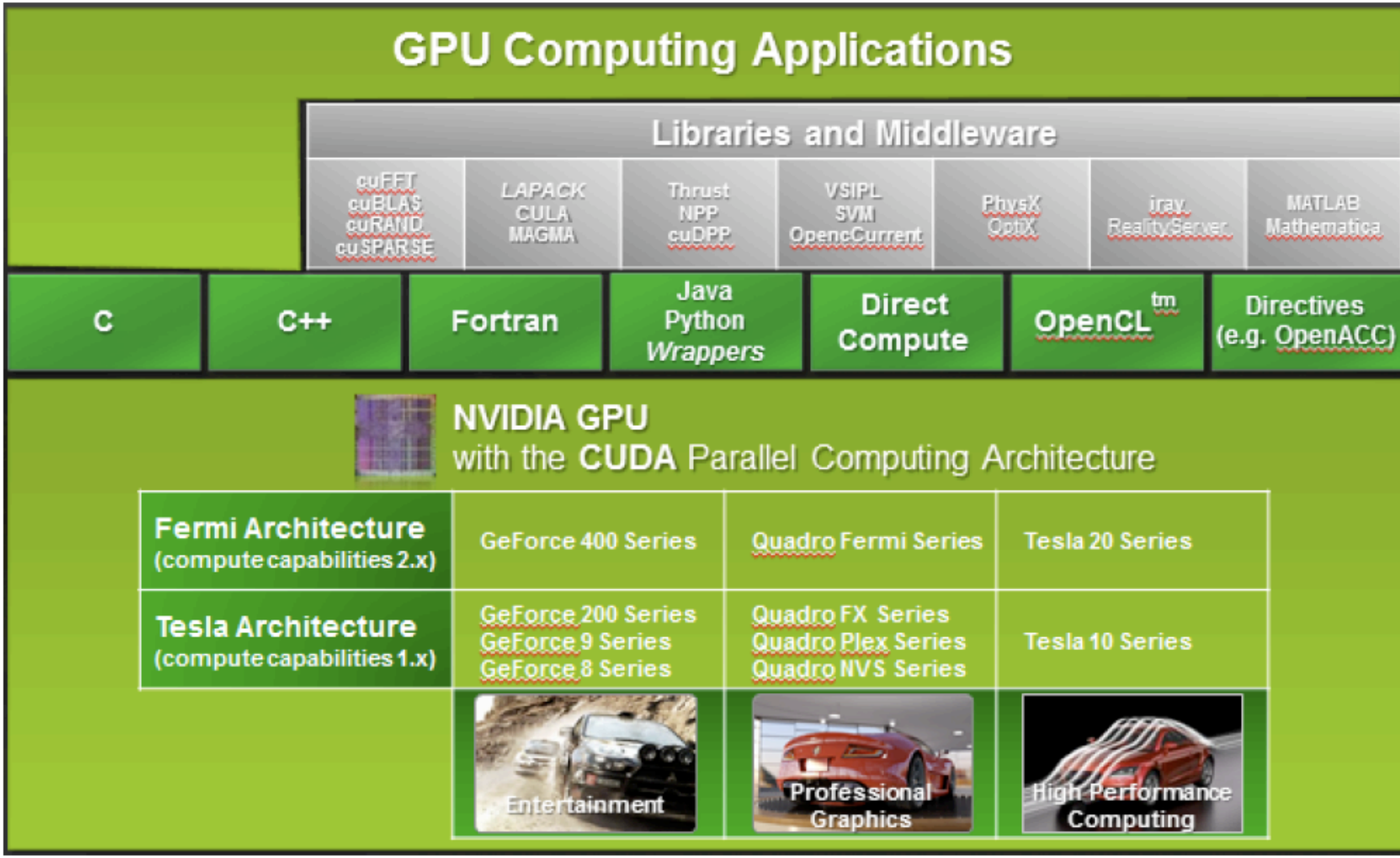
NVIDIA's diverse offerings for GPU Computing



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CUDA C Programming

CUDA C Programming Language

- Minimal set of extensions to the C programming language
- Core concepts:
  - Hierarchy of thread groups
  - Shared memory
  - Barrier synchronization

1) Kernel:

- C function executed *N* times in parallel by *N* CUDA threads
- Called by the Host (CPU) but executed on the Device (GPU)

2) Thread Hierarchy:

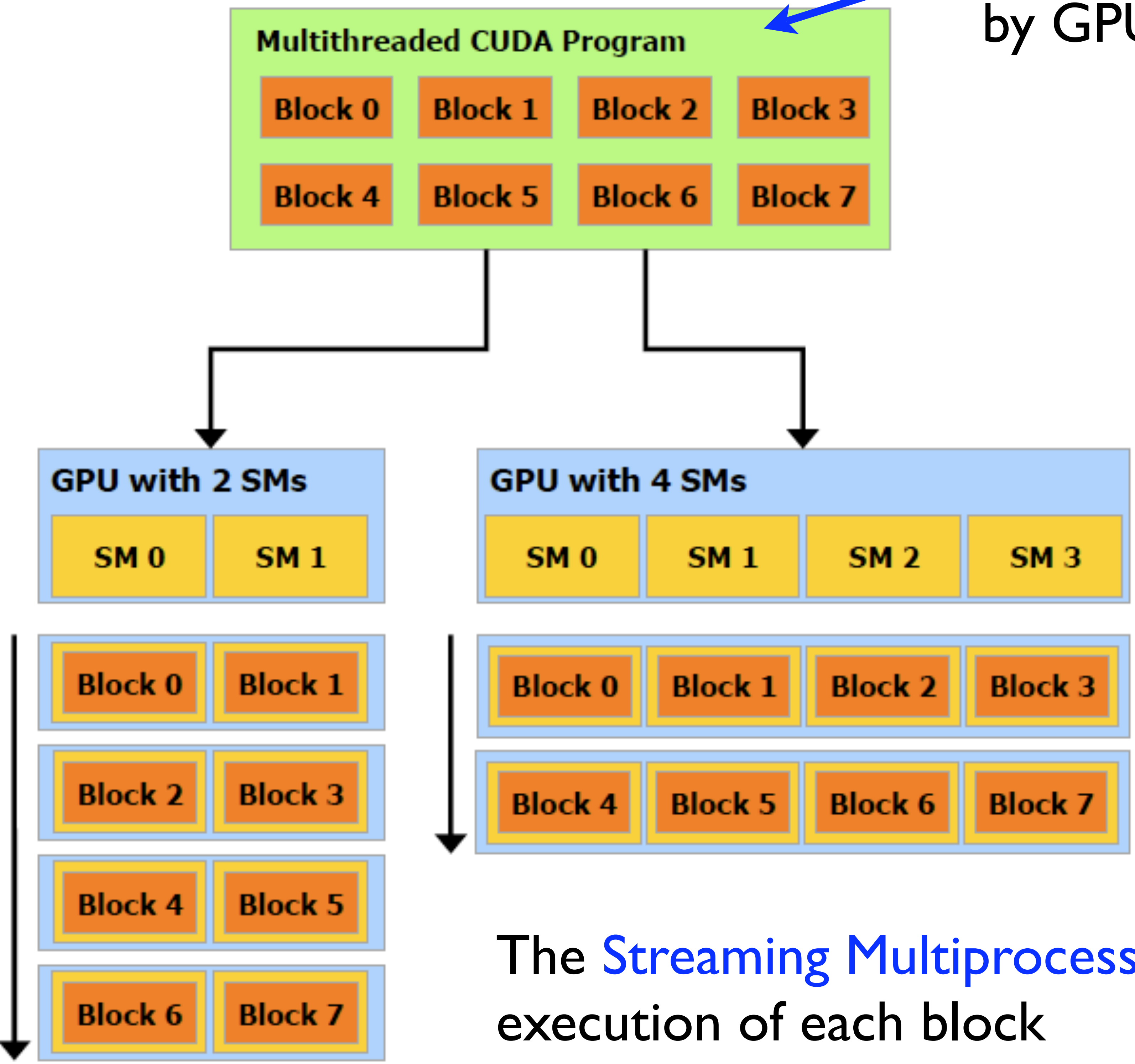
- Grid: Contains many blocks that can be solved independently in parallel
- Block: Contains many threads that can be solve cooperatively in parallel

3) Memory Functions:

- Allocate and Free memory space on Device (GPU),
- Copy data from Host (CPU) to Device (GPU), and vice versa

Thread Hierarchy: Grid of Blocks

Grid: Full problem to be solved by GPU is broken into blocks

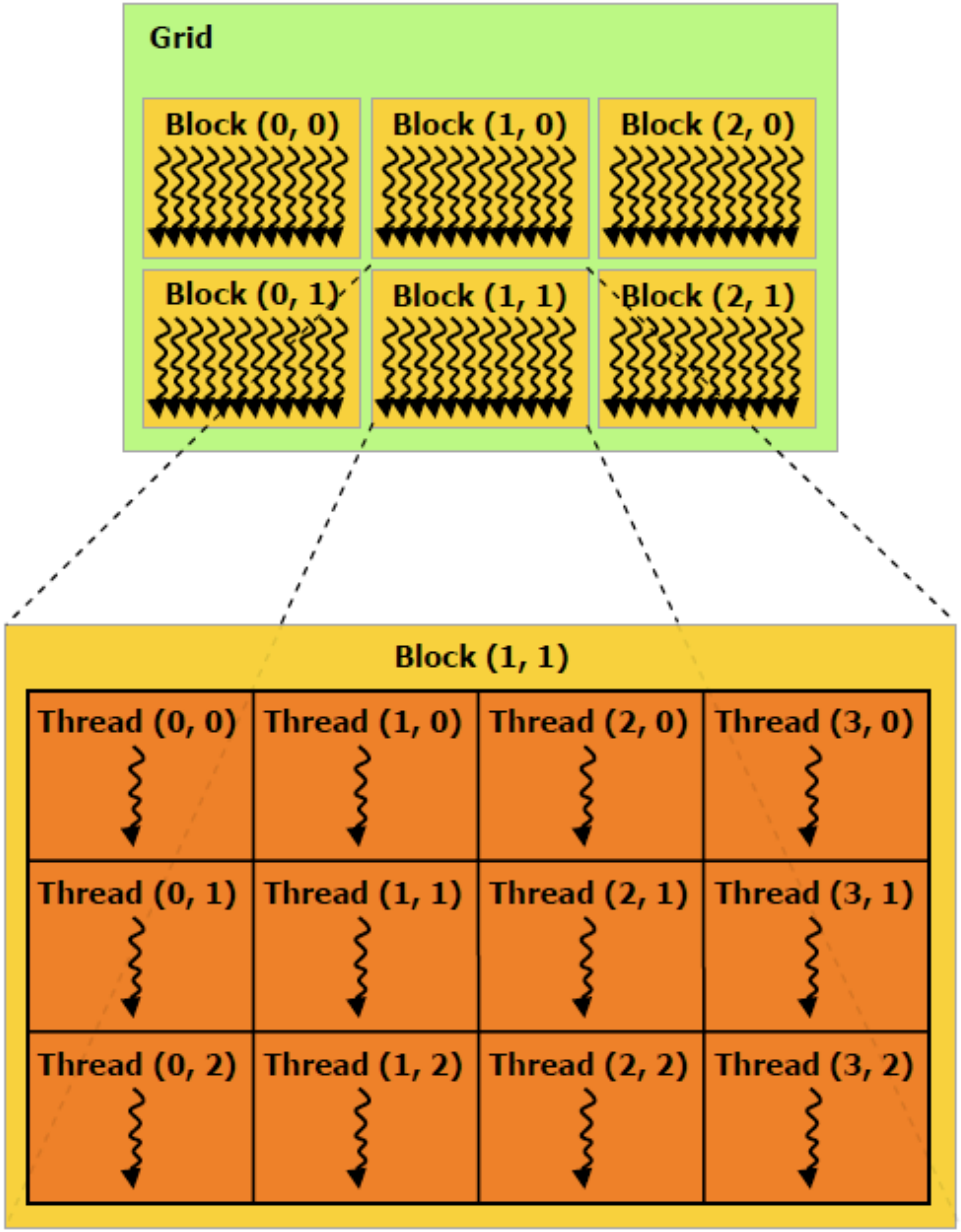


Each block is independent. The blocks can be executed, in any order, concurrently or sequentially

The Streaming Multiprocessors (SMs) control the execution of each block

This model enables excellent scalability for a varying number of cores per GPU

Thread Hierarchy: Block of Threads



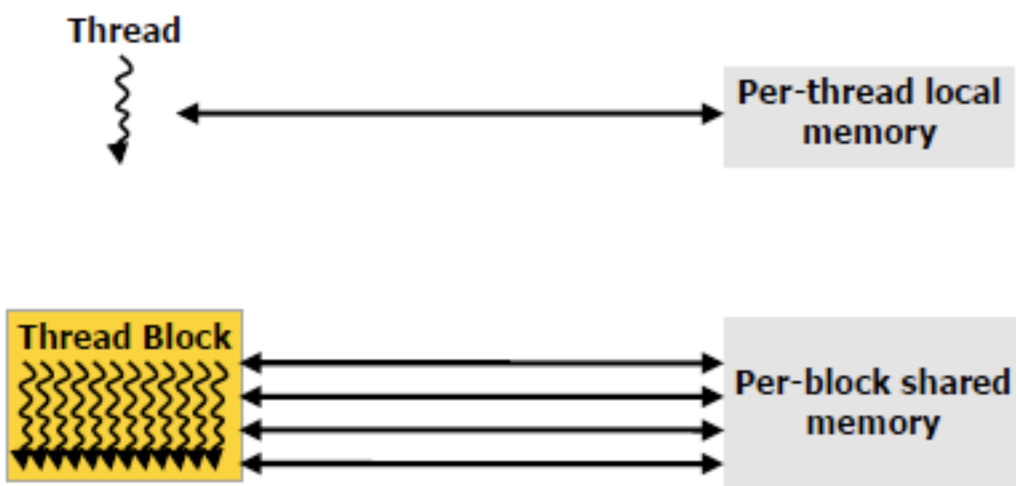
Each block contains many threads

Threads within a block are executed in parallel, either cooperatively or independently

Memory Hierarchy

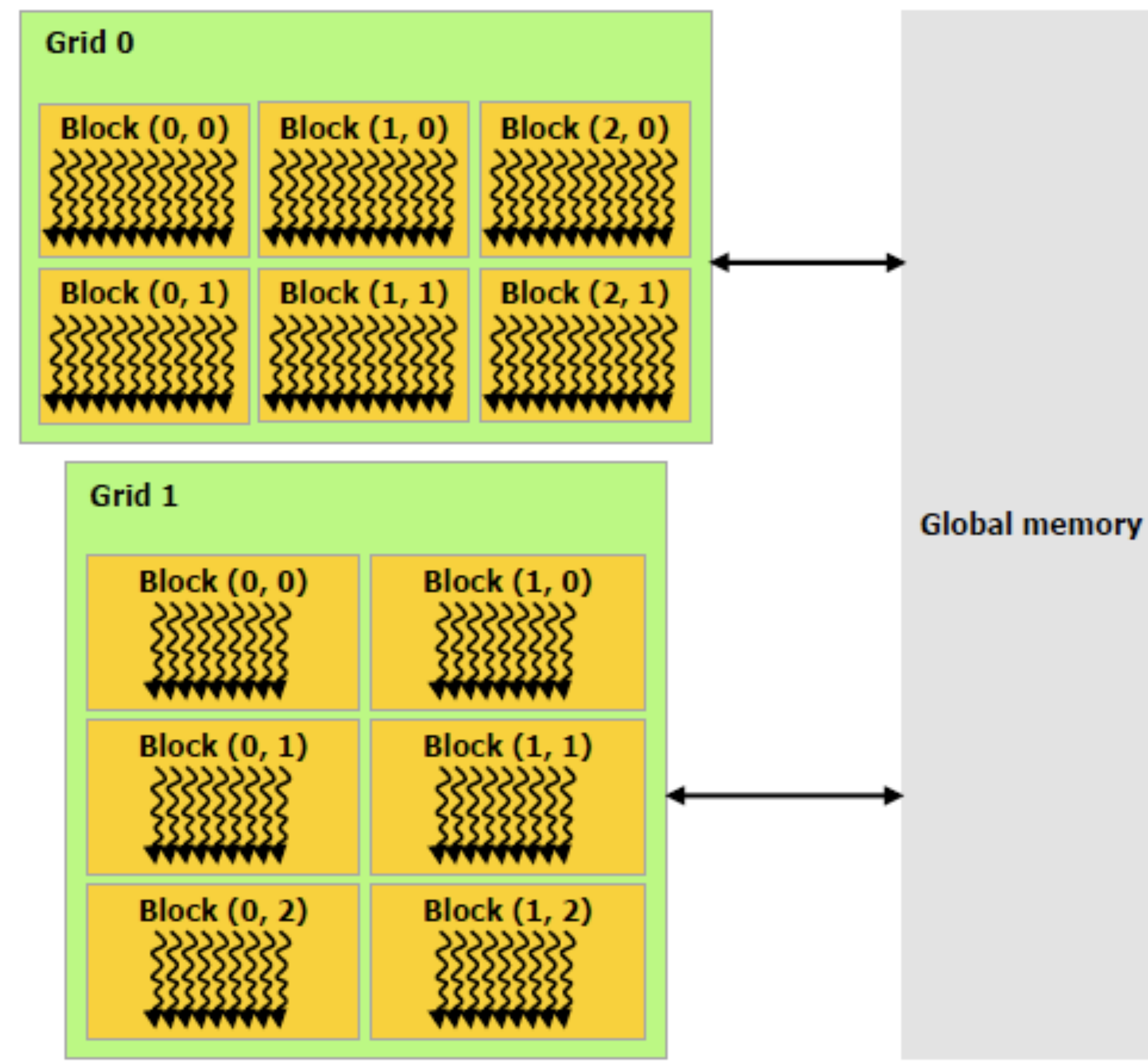
Very high memory bandwidth can be achieved using a hierarchy of memory

Each thread has private local memory



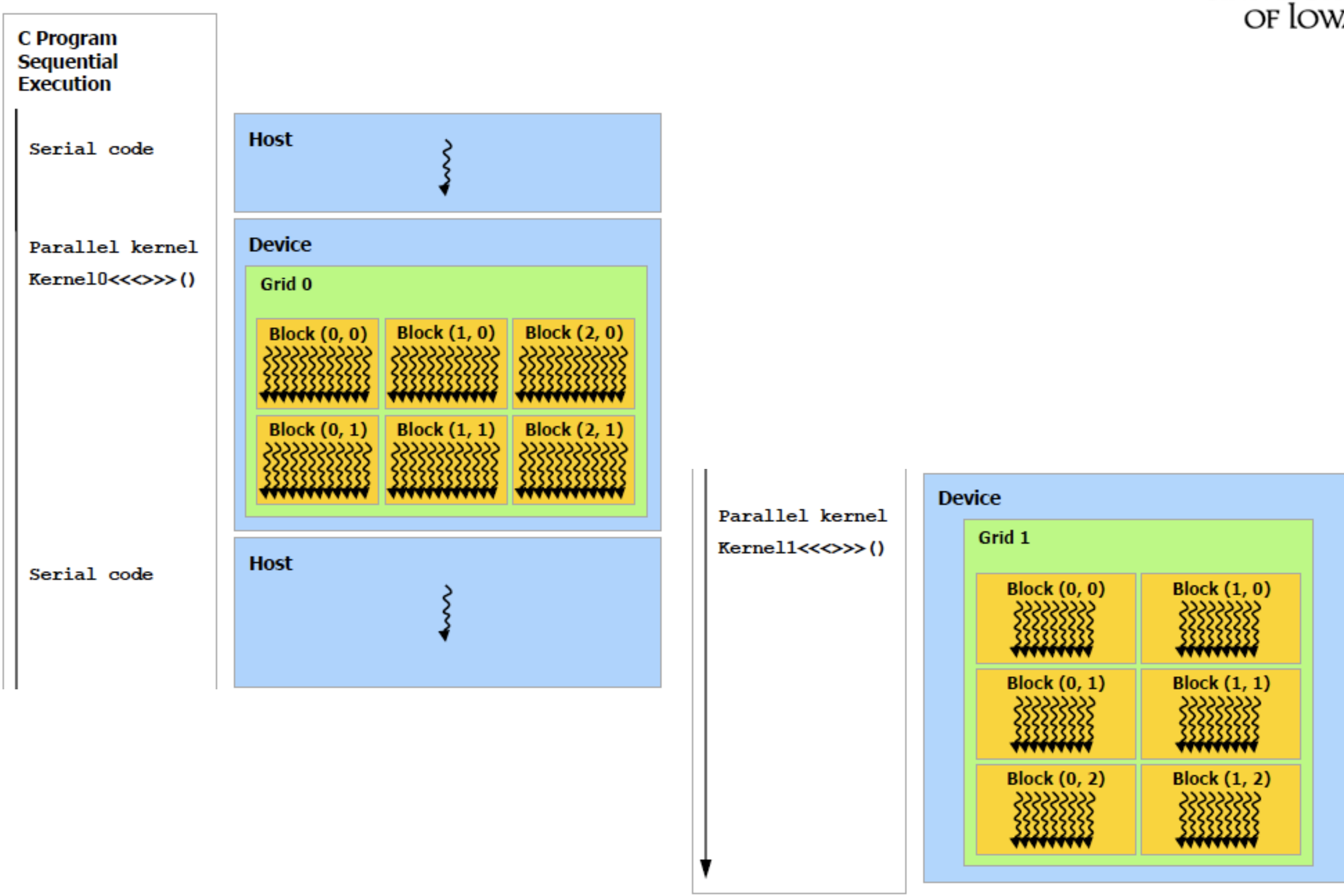
Each thread block has fast access to shared memory

All threads have slower access to global memory



All threads can also access read-only Constant and Texture memory, optimized for different memory usages

General Flow of CUDA C Program



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Programming in CUDA C

- Comparison of Multithreading and GPU Computing

- The Kernel
  - Thread Hierarchy

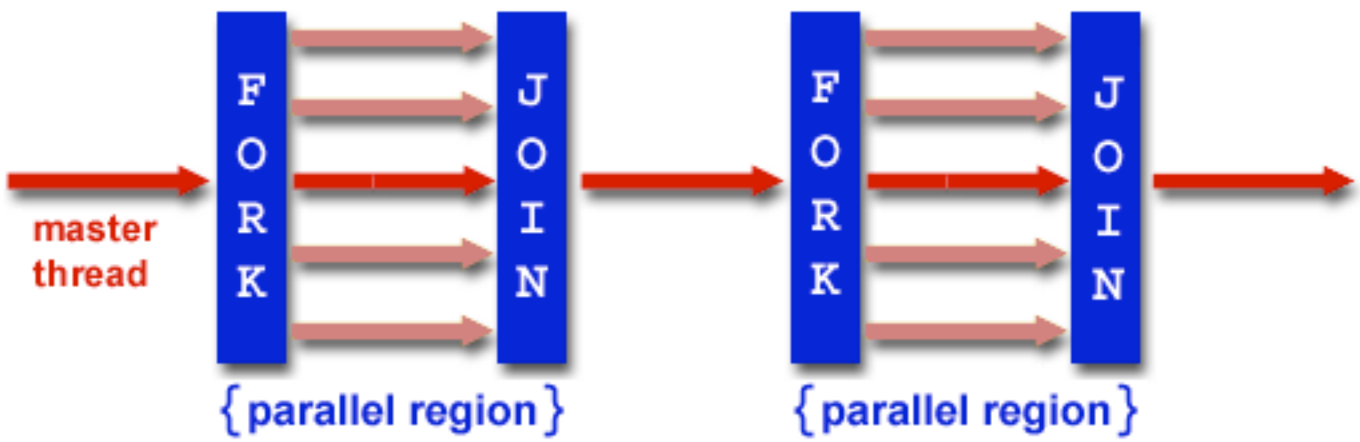
- Memory Functions

- Examples

Comparison to OpenMP Multithreading

General Implementation:

- Multithreading using OpenMP



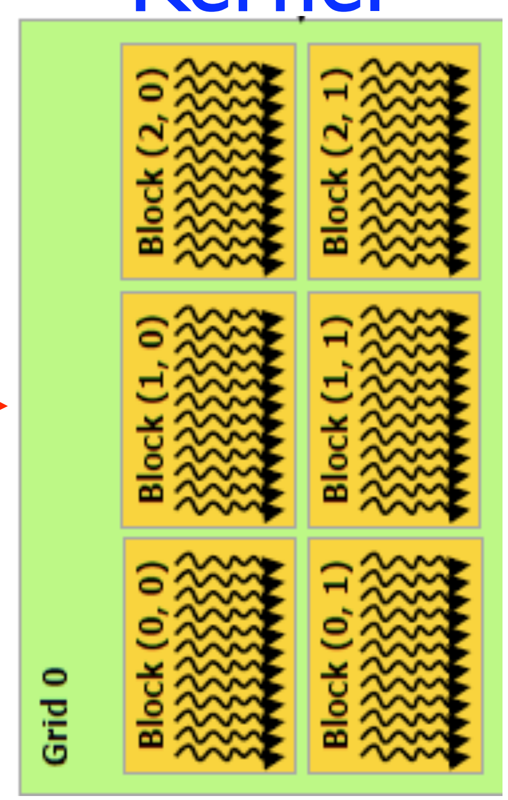
All of this executes on the multicore host CPU with access to shared memory

- Parallel Computation on GPU device

Host → Copy data from host memory to device memory → Kernel → Copy data from device memory to host memory → Host

Host → Device

Kernel



Device

Device → Host

The Kernel in CUDA C

Kernels:

- CUDA C enables the programmer to define C functions, called kernels, that are executed N times in parallel on the GPU device

- Declaration specifier: Kernels are defined using `__global__`

```
__global__ void VecAdd(int *a, int *b, int *c)
```

- Kernels are called from the host (CPU) using a new execution configuration syntax,

```
<<<blocksPerGrid,threadsperBlock>>>
```

```
VecAdd<<<blocksPerGrid,threadsperBlock>>>(d_a,d_b,d_c);
```

NOTE: Kernel functions are called from the host, but executed on the device!

Blocks and Threads

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Thread Hierarchy:

- The execution configuration specifies:

  `blocksPerGrid`

  `threadsperBlock`

- These variables are 3-component integer vectors of type `dim3`

- For example,

```
dim3 threadsperBlock(N,N);
```

defines 2D thread blocks of size *N* by *N*

- In the kernel function, the thread ID is accessed through the variable `threadIdx`, where the two dimensions are given by `threadIdx.x` and `threadIdx.y`

Blocks and Threads

Blocks:

- The block ID and block dimensions are similarly accessed through
  `blockIdx` giving `blockIdx.x` and `blockIdx.y`
  `blockDim` giving `blockDim.x` and `blockDim.y`

- A general formula for computing the appropriate index based on multiple blocks is

```
int i = blockIdx.x*blockDim.x + threadIdx.x;
```

Limitations:

- The maximum number of threads per block is the number of GPU cores, 512 for the GeForce GTX580.
- The number of blocks per grid is unlimited, and is determined by the number of blocks required to do the entire calculation.

- For a 2D computation of size *N* by *N*

```
dim3 numBlocks(N/threadsPerBlock.x,N/threadsPerBlock.y);
```

CUDA Kernel

Standard serial C function

```
/*  Function to compute y=a*x+y */
void saxpy_serial(int n, float a, float *x, float *y)
{
  for (int i=0; i < n; i++)
    y[i]= a*x[i] + y[i];
}

/* Call Function from main() */
saxpy_serial(4096*256, 2.0, x, y);
```

Parallel CUDA C kernel

```
__global__ void saxpy_parallel(int n, float a, float *x, float *y)
{
  int i=blockIdx.x*blockDim.x + threadIdx.x;
  if (i < n)  y[i]= a*x[i] + y[i];
}

/* Call Function from main() */
saxpy_parallel<<<4096,256>>>(4096*256, 2.0, x, y);
```

CUDA Kernel

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General Comments:

- The kernel contains only the commands within the loop
- The kernel call is asynchronous
  - After the kernel is called, the host can continue processing before the GPU has completed the kernel computation

	Executed on the:	Only callable from the:
`__device__ float DeviceFunc()`	device	device
`__global__ void KernelFunc()`	device	host
`__host__ float HostFunc()`	host	host

- The computations in the kernel can only access data in device memory

Therefore, a critical part of CUDA programming is handling the transfer of data from host memory to device memory and back!

CUDA Memory Functions

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- Device memory is allocated and freed using
  `cudaMalloc()`
  `cudaFree()`

  Example:

```
size_t size = N * sizeof(float);
float* d_A;
cudaMalloc(&d_A, size);
```

- Data is transferred using
  `cudaMemcpy()`

  Example:

```
/* Allocate array in host memory */
float* h_A = (float*)malloc(size);
/* Copy array from host memory to device memory */
cudaMemcpy(d_A, h_A, size, cudaMemcpyHostToDevice);
```

Example CUDA code for Vector Addition

```
#include<stdio.h>
#include<cuda.h>
#define N 100 /* Size of vectors */

/* Define CUDA kernel */
__global__ void add( int *a, int *b, int *c ) {
  int tid = blockIdx.x*blockDim.x+threadIdx.x;
  if (tid < N)
    c[tid] = a[tid] + b[tid];
}
```

Example CUDA code for Vector Addition

```
int main() {
  int a[N], b[N], c[N];
  int *dev_a, *dev_b, *dev_c;

  /* allocate the memory on the GPU  */
  cudaMalloc( (void**)&dev_a, N * sizeof(int) );
  cudaMalloc( (void**)&dev_b, N * sizeof(int) );
  cudaMalloc( (void**)&dev_c, N * sizeof(int) );

  /* Copy the arrays 'a' and 'b' from CPU host to GPU device*/
  cudaMemcpy( dev_a, a, N * sizeof(int), cudaMemcpyHostToDevice );
  cudaMemcpy( dev_b, b, N * sizeof(int), cudaMemcpyHostToDevice );

  int threadsPerBlock=512;
  int blocksPerGrid=(N+threadsPerBlock-1)/threadsPerBlock;
  add<<<blocksPerGrid,threadsPerBlock>>>( dev_a, dev_b, dev_c );

  /* Copy the array 'c' back from GPU device to CPU host*/
  cudaMemcpy( c, dev_c, N * sizeof(int), cudaMemcpyDeviceToHost );

  /* Free the memory allocated on the GPU device*/
  cudaFree( dev_a );
  cudaFree( dev_b );
  cudaFree( dev_c );
}
```

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Advanced CUDA Capabilities

- Shared Memory
- Concurrent memory copy and kernel execution
- Asynchronous concurrent execution
- Lower-level CUDA driver API
- Multiple devices on host system with peer-to-peer memory access
- Texture and surface memory
- Graphics functions with OpenGL and Direct3D Application Programming Interfaces (APIs)