High Performance Computing and GPU Programming

Lecture 2: GPU Core

GPU Intro Cont.

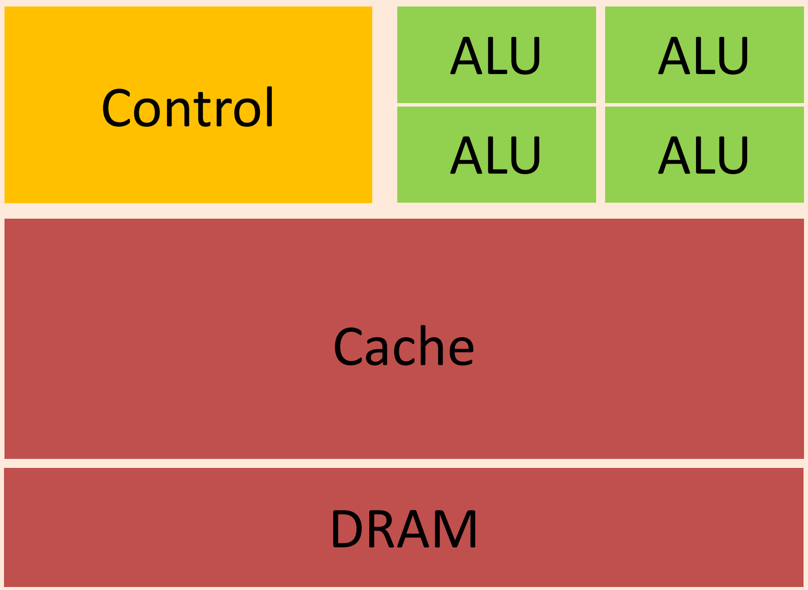
Programming Model

GPU Memory

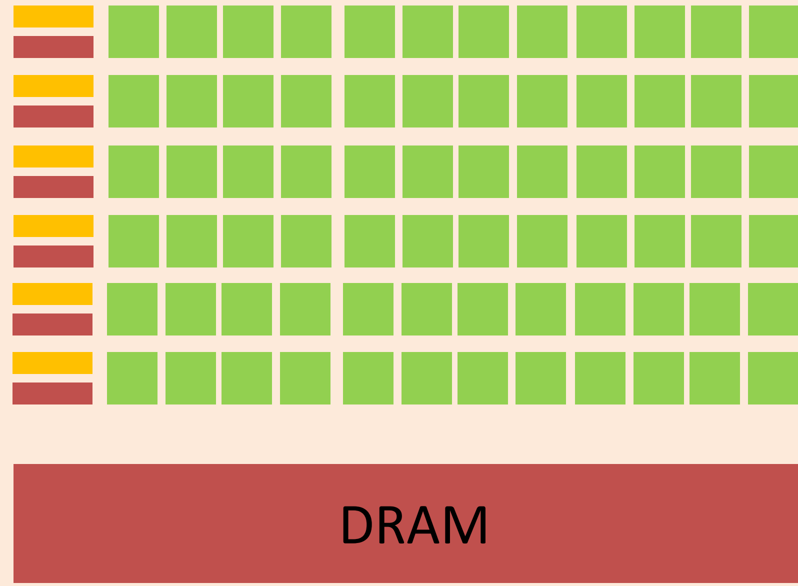
GPU Intro

GPU Intro

- CPU vs. GPU



CPU
SIMD – Single instruction multiple data vector units



GPU
SIMT – Single instruction multiple threads

GPU Intro

- CPU vs. GPU

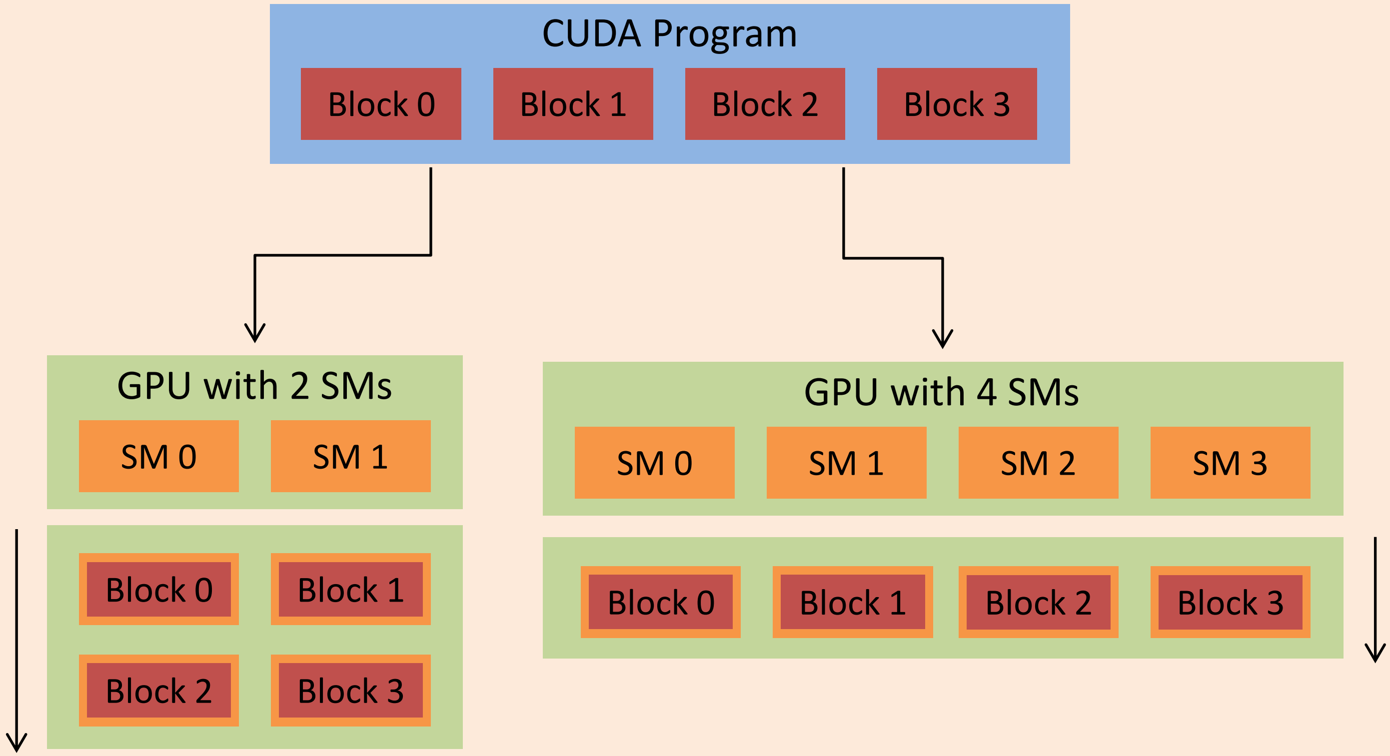
	GPU – Tesla K20	CPU – Intel I7
Cores	Main memory	4 (8)
Memory	5 GB	32 KB L1 cache / core 256 KB L2 cache / core 8 MB L3 shared
Clock Speed	2.6 GHz	3.2 GHz
Bandwidth	208 GB/s	25.6 GB/s
FLOPS	1.17 x 10^12	70 x 10^9

Programming Model

Programming Model

- Three major topics in GPU computing
  - Architecture Management
    - Threads and blocks – How to set-up?
  - Memory Management
    - This is where you get speed!
  - Algorithm Management
    - Optimization and massive parallelism

Programming Model

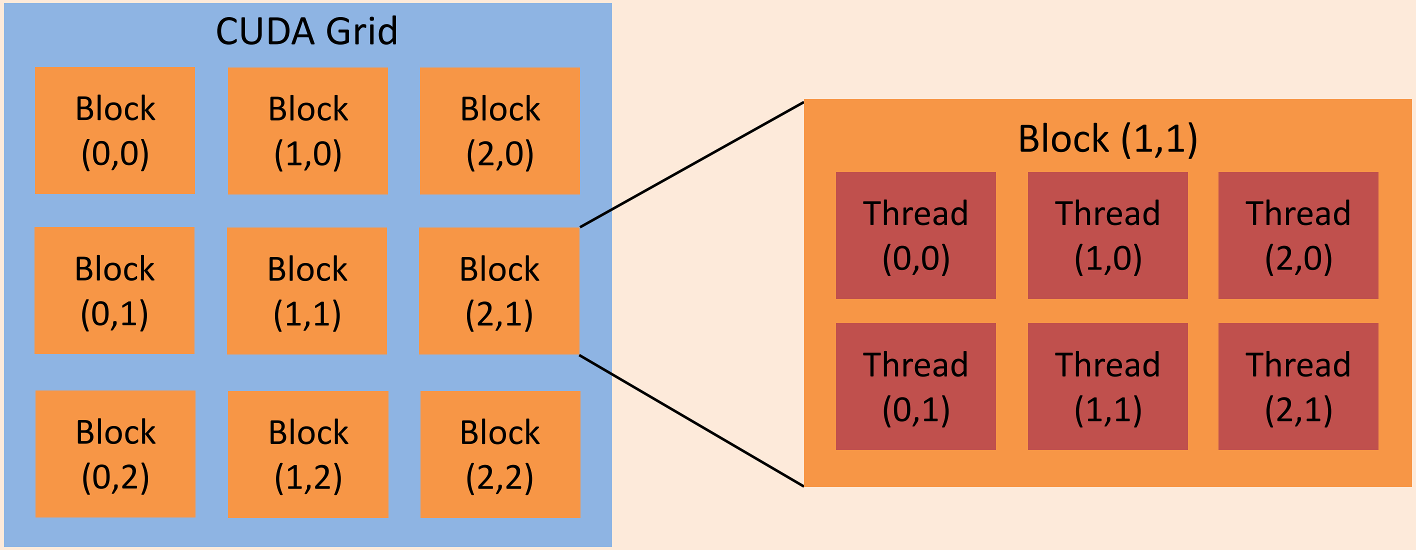


- SM creates, manages, schedules, and executes threads in groups of parallel threads - Warps

Programming Model

- Warps are not easy
  - Warp size is 32 threads on current GPUs
  - Threads in a warp start together
  - When an SM has a task or block:
    - The threads are split into warps
    - A sort of “scheduling” is done
- Most of the time we have to ignore this
  - Not all problems fit into a multiple of 32!
  - Many papers claim 500x speed-up for matrix operations
    - The cases are for sizes of 32x32, 256x256, 512x512, ect…

Programming Model




```
// Kernel definition
__global__ void VecAdd(float* A, float* B, float* C)
{
    int i = threadIdx.x;
    C[i] = A[i] + B[i];
}

int main()
{
    ...
    // Kernel invocation with N threads
    VecAdd<<<1, N>>>(A, B, C);
    ...
}
```

Programming Model

- Memory must be allocated

```
// Host code
int main()
{
    // Allocate input vectors in host memory
    float* A_h = (float*)malloc(N * sizeof(float));
    float* B_h = (float*)malloc(N * sizeof(float));

    // Initialize input vectors
    ...

    // Allocate vectors in device memory
    float* A_d, B_d, C_d;
    cudaMalloc(&A_d, N * sizeof(float));
    cudaMalloc(&B_d, N * sizeof(float));
    cudaMalloc(&C_d, N * sizeof(float));

    // Copy vectors from host memory to device memory
    cudaMemcpy(A_d, A_h, N * sizeof(float), cudaMemcpyHostToDevice);
    cudaMemcpy(B_d, B_h, N * sizeof(float), cudaMemcpyHostToDevice);

    // Invoke kernel
    VecAdd<<<1, N>>>(A_d, B_d, C_d, N);

    // Copy result from device memory to host memory
    cudaMemcpy(C_h, C_d, N * sizeof(float), cudaMemcpyDeviceToHost);

    // Free device memory
    cudaFree(d_A); cudaFree(d_B); cudaFree(d_C);
}
```

```
// Device code
__global__ void VecAdd(float* A, float* B, float* C, int N)
{
    int i = blockDim.x * blockIdx.x + threadIdx.x;
    if (i < N)
        C[i] = A[i] + B[i];
}
```

Programming Model

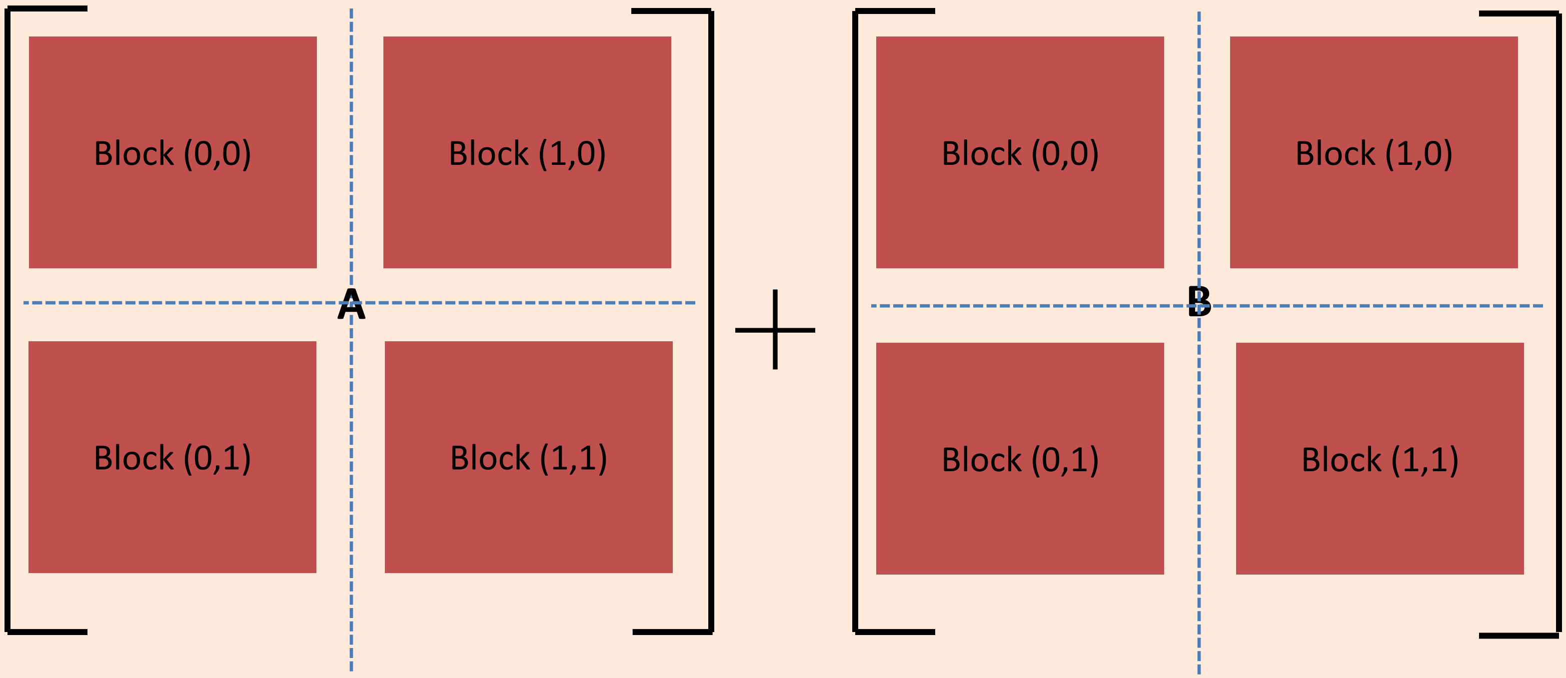
- Thread Hierarchy
  - Controlled by “dim3” declaration
  - Threads have a limit!

```
// Kernel definition
__global__ void MatAdd(float A[N][N], float B[N][N],
                       float C[N][N])
{
    int i = threadIdx.x;
    int j = threadIdx.y;
    C[i][j] = A[i][j] + B[i][j];
}

int main()
{
    ...
    // Kernel invocation with one block of N * N * 1 threads
    int numBlocks = 1;
    dim3 threadsPerBlock(N, N);
    MatAdd<<<numBlocks, threadsPerBlock>>>(A, B, C);
    ...
}
```

Programming Model

- Now consider a multi-block multi-thread problem

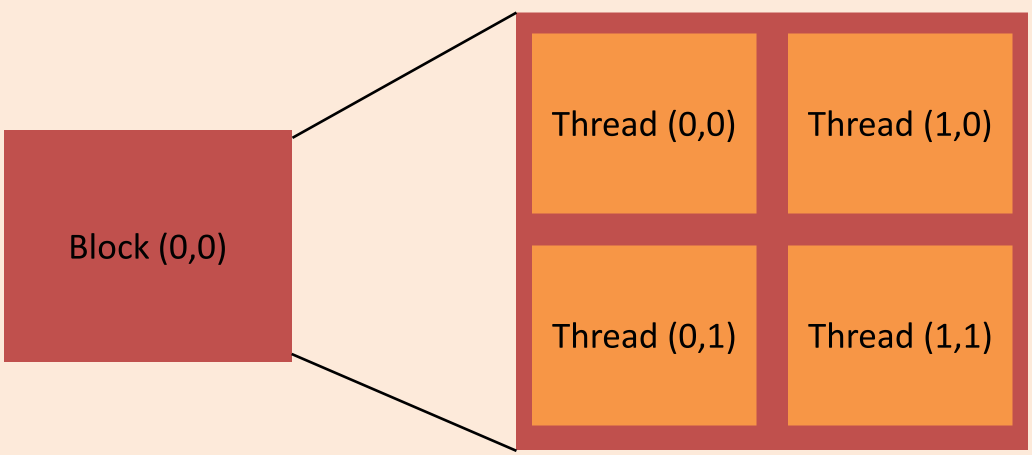


- Break it up!

Programming Model

```
// Kernel definition
__global__ void MatAdd(float A[N][N], float B[N][N], float C[N][N])
{
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    int j = blockIdx.y * blockDim.y + threadIdx.y;
    if (i < N && j < N)
        C[i][j] = A[i][j] + B[i][j];
}

int main()
{
    ...
    // Kernel invocation
    dim3 threadsPerBlock(2, 2);
    dim3 numBlocks(N / threadsPerBlock.x, N / threadsPerBlock.y);
    MatAdd<<<numBlocks, threadsPerBlock>>>(A, B, C);
    ...
}
```

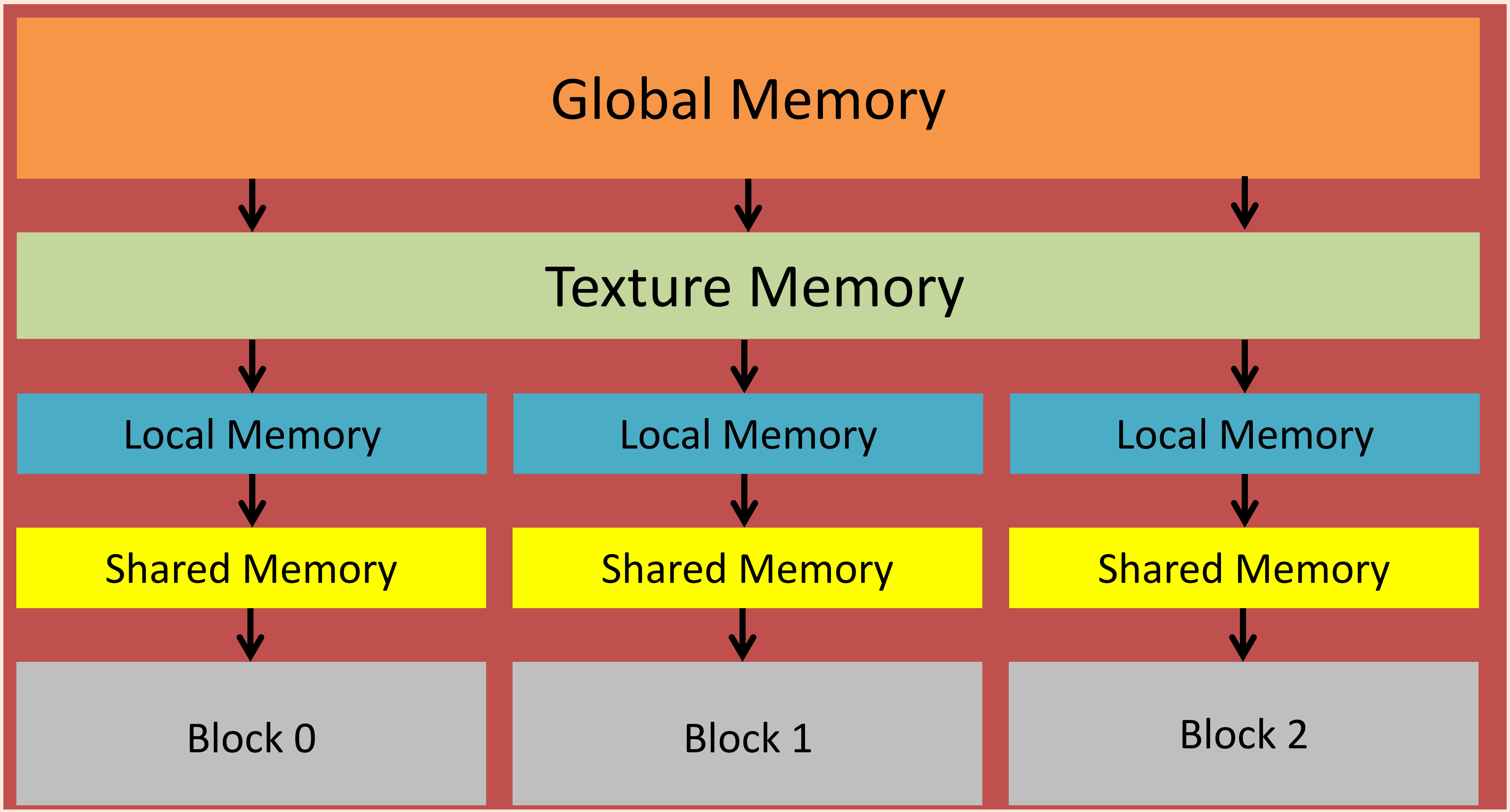


	Threads	Blocks	Grid
Idx.x	0,1	0,1	-
Idx.y	0,1	0,1	-
Dim.x	-	2	2
Dim.y	-	2	2

GPU Memory

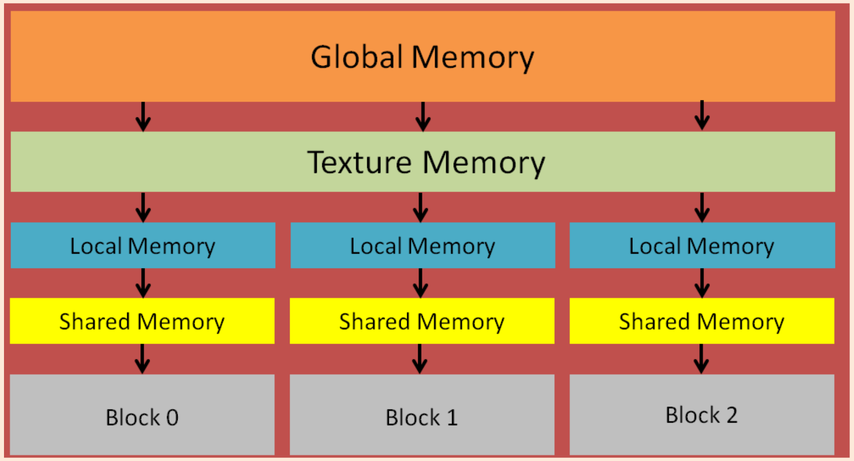
GPU Memory

- We will discuss more on threads later
- Introduce memory – Diagram!



GPU Memory

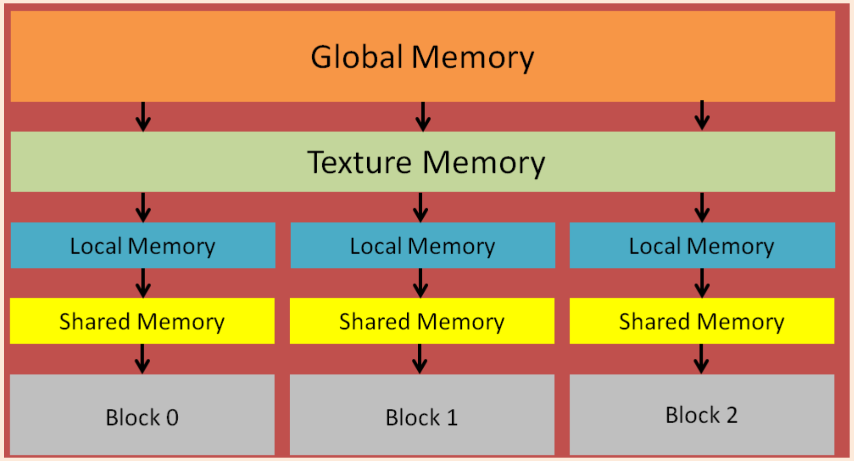
- Global Memory
  - Main GPU memory – but also slow!
  - Try to never run computations here – only in some situations
  - All blocks and all threads



- Texture Memory
  - A little complicated to explain
  - You can read data from here fast!
  - But cannot write data directly
  - All blocks and all threads

GPU Memory

- Local Memory
  - Local to each thread in the block
  - Able to communicate – but never do it!
  - Registers are here
  - Very fast



- Shared Memory
  - Difficult to use correctly – but very powerful
  - 150x faster than global memory
  - Local to the block

GPU Memory

- Starting an application – We must …

Global Memory

1. Allocate everything we need to the GPU into global memory
2. You must decide what goes into the texture cache

Texture Memory

3. Now execute a CUDA kernel – everything we need is there
4. Decide what memory you need and where you need it from
5. Run computations – store result into global memory when done
6. Use this memory in other kernels

- There are several deciding factors on where you get you memory and where you store it

GPU Memory

Where to get it?

Global Memory

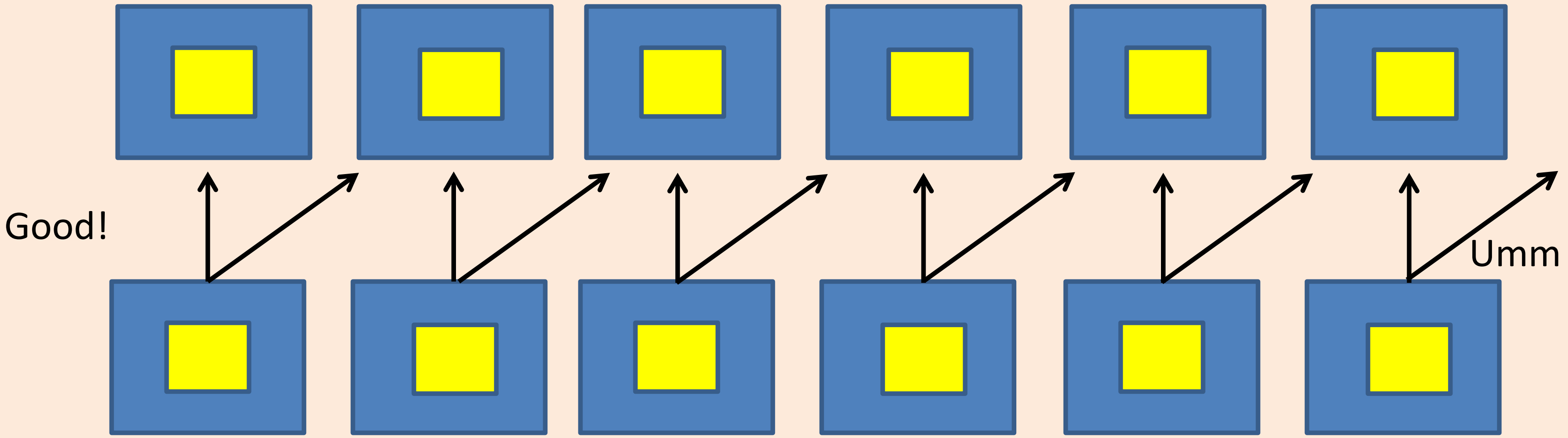
- Coalesced
- That’s it!

Texture Memory

- Non-Coalesced
- That’s it!

GPU Memory

- What is Coalesced?
  - The single most important thing you can do
  - All threads in a HALF Warp access global memory at the same time
    - Again…Warps…
    - How about simple!
  - Neighboring threads access neighboring cells in memory



GPU Memory

Where to put it?

Local Memory

- Coalesced access
- One access by thread – then move on!
- Huge performance
- Basically do I need…
  - Coalesced computations?
  - No sharing data?

Shared Memory

- for/do loops
- Required by other blocks
- Required by other threads
- Basically do I need …
  - Repeated access?
  - Shared access?

Wrap Up

- Next time…
  - CUDA for you
    - What you need, where to get it, how to install it
  - Thread index mapping
    - 2-D or 3-D to 1-D
  - Introduce CUDA memory types
    - Texture, local, global, shared
  - Program interpolation function (if time permits it)
    - CPU vs. GPU implementation