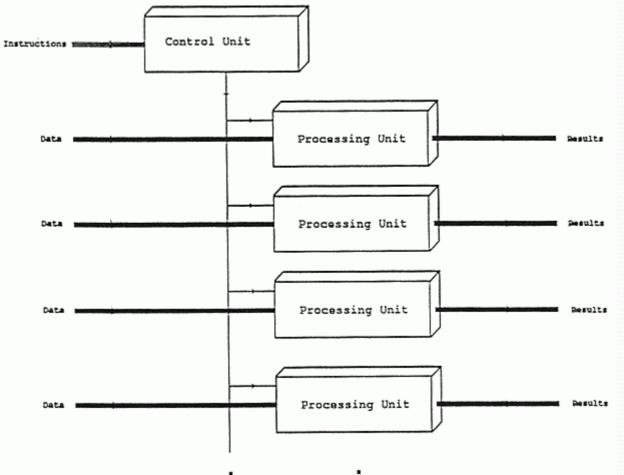
IHPC 2011, June 1-3rd 2011 Parallel Programming with GPUs

Professor S. Oliveira, University of Iowa. Computer Science and Mathematics Departments and AMCS program member.

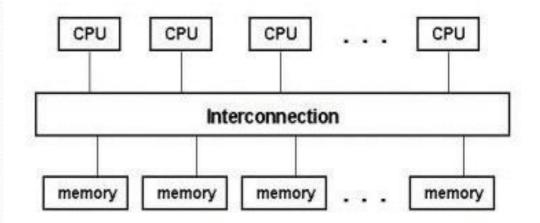
SIMD



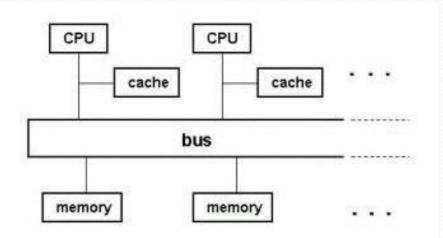
.

MIMD Shared Memory

- Virtual view single globally addressable memory
- May be a single memory or several memories
- Access time can vary (NUMA) based on how close a memory is to the referencing processor



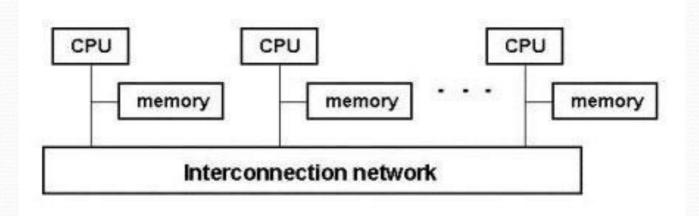
Shared-memory MIMD architecture



Bus-based shared-memory MIMD architecture

MIMD Distributed Memory

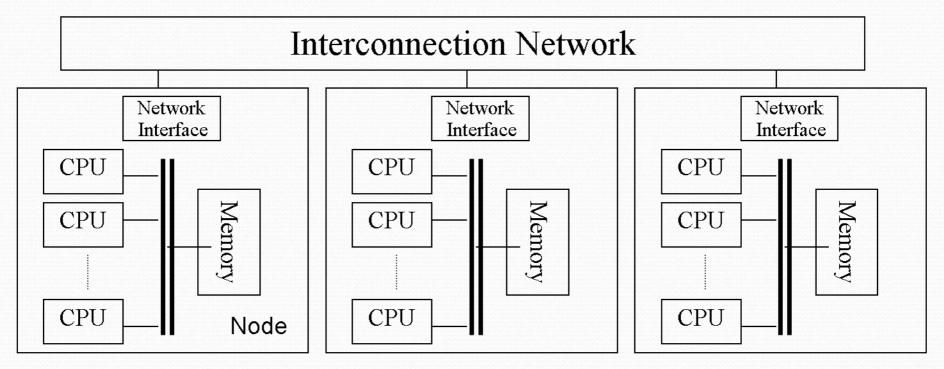
- Each processor has its own private memory
- Data must be explicitly sent from one processor to another over the network to share data



Symmetric Multi-Processing

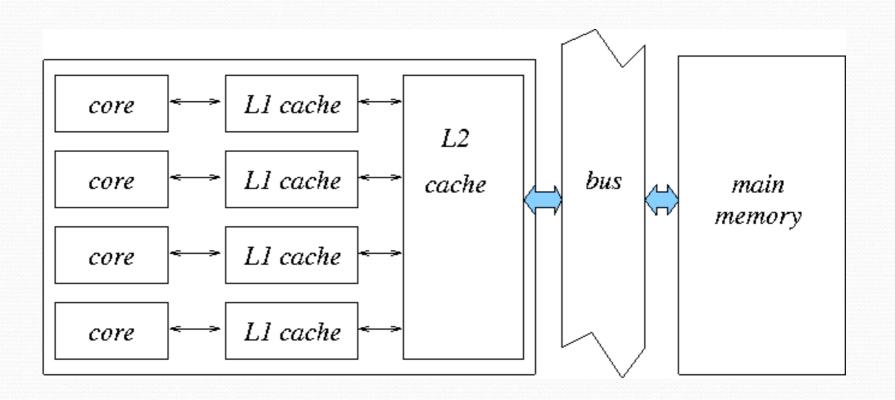
• Shared memory within a node

- Multiple sockets
- Multicore chip in each socket
- Distributed memory across nodes



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Multicore Processor

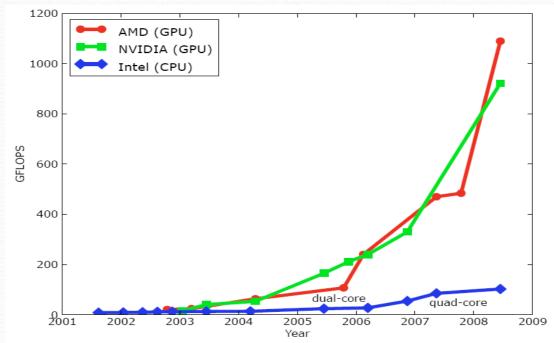


Tools for parallel Programming

- In 1997 MPI (message Passing Interface) for distributed memory systems. In 2008 OpenMPI (open source version) was made available.
- Pthreads or OpenMP (1997) for shared memory programming on computers and processors. OpenMP application programming interface (API) was developed by the OpenMP ARB (arch. Review board)
- CUDA (2003) for host-device architectures GPU's and also recently Intel's OpenCL. Graphics GPU's used OpenGL which is good for graphics application but very difficult for numerical software development.

Massively Parallel Processor with GPUs

A quiet revolution and potential build-up Calculation: 367 GFLOPS vs. 32 GFLOPS Memory Bandwidth: 86.4 GB/s vs. 8.4 GB/s Until 2007, programmed through graphics API



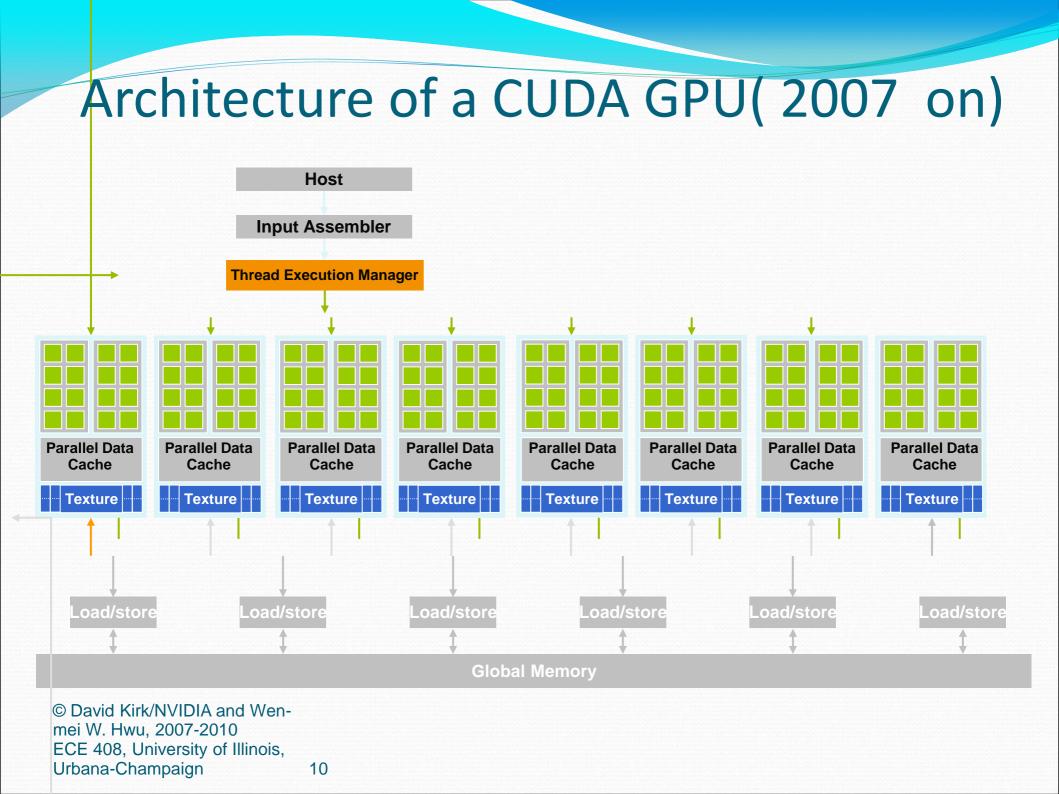
GPU in every PC and workstation – massive volume and potential impact

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CPUs and GPUs have fundamentally different design philosophies

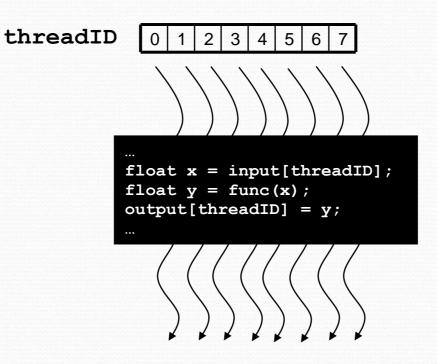


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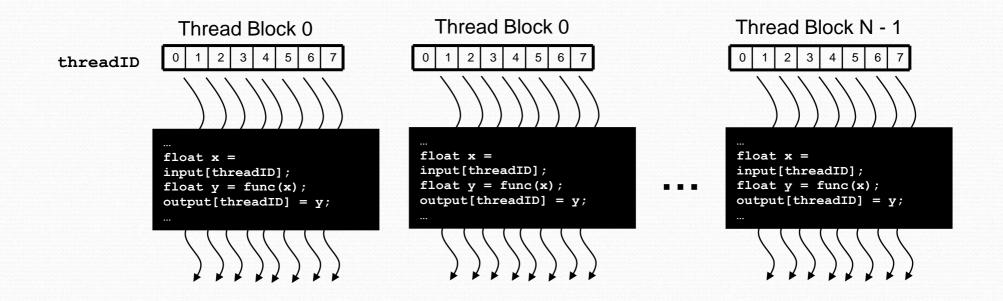
Arrays of Parallel Threads

- A CUDA kernel is executed by an array of threads
 - All threads run the same code (SPMD)
 - Each thread has an ID that it uses to compute memory addresses and make control decisions



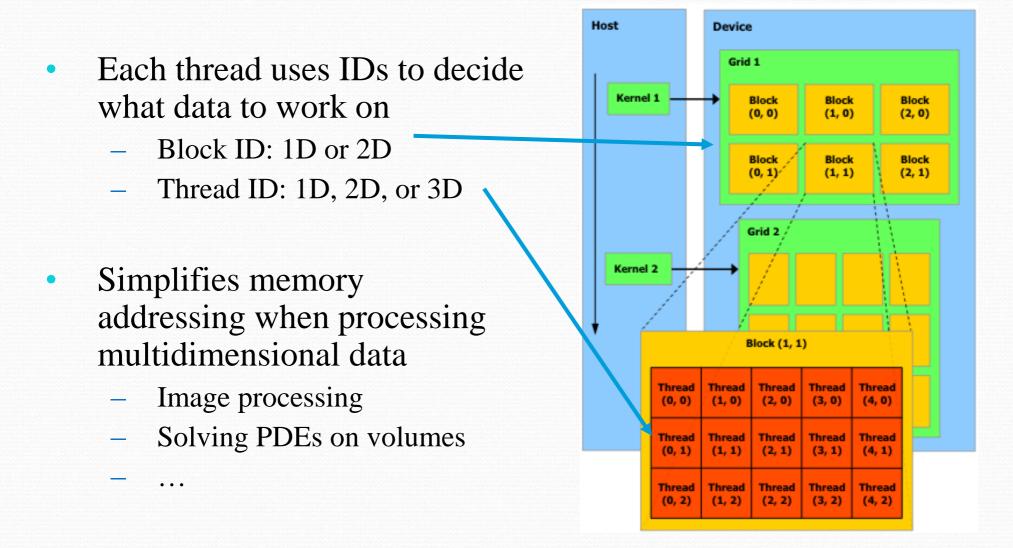
Cooperation

- Divide monolithic thread array into multiple blocks
 - Threads within a block cooperate via **shared memory**, **atomic operations** and **barrier synchronization**
 - Threads in different blocks cannot cooperate



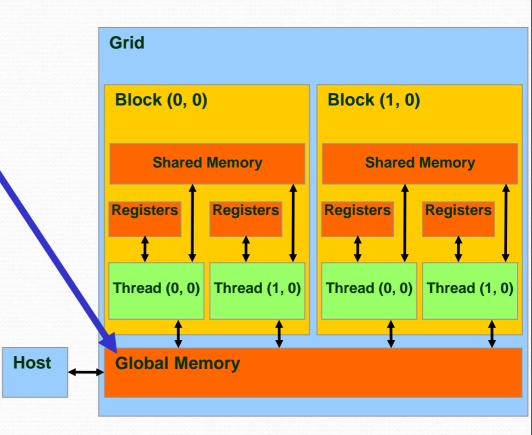
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Block IDs and Thread IDs



CUDA Memory Model Overview

- Global memory
 - Main means of communicating R/W Data between host and device
 - Contents visible to all threads
 - Long latency access
- We will focus on global memory for now



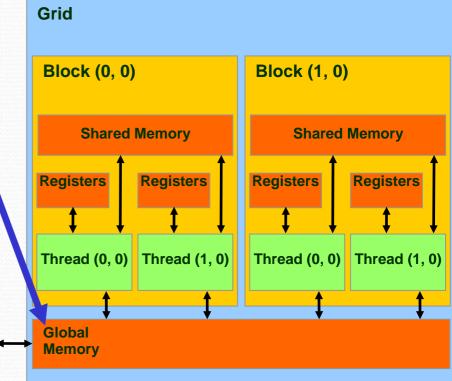
CUDA Device Memory

cudaMalloc()

- -Allocates object in the device <u>Global Memory</u>
- Requires two parameters
 - Address of a pointer to the allocated object

Host

- Size of of allocated object
- cudaFree()
 - Frees object fromdevice
 Global Memory



CUDA Device Memory Allocation (cont.)

• Code example:

- Allocate a 64 * 64 single precision float array
- Attach the allocated storage to Md
- "d" is often used to indicate a device data structure

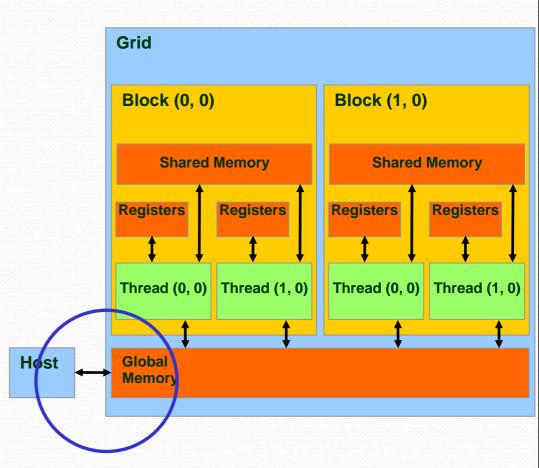
```
TILE_WIDTH = 64;
Float* Md;
int size = TILE_WIDTH * TILE_WIDTH * sizeof(float);
cudaMalloc((void**)&Md, size);
cudaFree(Md);
```

CUDA Host-Device Data Transfer

• cudaMemcpy() - synchronous

- memory data transfer
- Requires four parameters
 - Pointer to destination
 - Pointer to source
 - Number of bytes copied
 - Type of transfer
 - Host to Host
 - Host to Device
 - Device to Host
 - Device to Device
- Asynchronous transfer
 - cudaMemcpyAsync()

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CUDA Host-Device Data Transfer

• Code example:

- Transfer a 64 * 64 single precision float array
- M is in host memory and Md is in device memory
- cudaMemcpyHostToDevice and cudaMemcpyDeviceToHost are symbolic constants

cudaMemcpy(Md, M, size, cudaMemcpyHostToDevice);

cudaMemcpy(M, Md, size, cudaMemcpyDeviceToHost);

- Declspecs
 - global, device, shared, constant
- Keywords
 - threadIdx, blockIdx
- Intrinsics
 - __syncthreads
- Runtime API
 - Memory, symbol, execution management
- Function launch

```
device float filter[N];
 global void convolve (float *image)
                                         {
  shared float region[M];
  . . .
  region[threadIdx] = image[i];
  syncthreads()
  image[j] = result;
}
// Allocate GPU memory
cudaMalloc((void **) & myimage, bytes);
```

```
// 100 blocks, 10 threads per block
convolve<<<100, 10>>> (myimage);
```

- <u>device</u> functions cannot have their address taken
- For functions executed on the device:
 - No recursion
 - No static variable declarations inside the function
 - No variable number of arguments

CUDA Function Declarations

	Executed on the:	Only callable from the:
<pre>device float DeviceFunc()</pre>	device	device
	device	host
<pre>host float HostFunc()</pre>	host	host

- <u>device</u> and <u>host</u> can be used together

Calling a Kernel Function – Thread Creation A kernel function must be called with an execution configuration:

____global___ void KernelFunc(...);

dim3 DimGrid(100, 50); // 5000 thread blocks

- dim3 DimBlock(4, 8, 8); // 256 threads per block
- size_t SharedMemBytes = 64; // 64 bytes of shared
 memory

KernelFunc

<<< DimGrid, DimBlock, SharedMemBytes >>>(...);

 Any call to a kernel function is asynchronous – host can continue processing after the kernel call

Choosing the GPU

int main(void) {
 cudaDeviceProp prop;
 int dev;

```
cudaGetDevice( &dev );
printf( "ID of current CUDA device: %d\n", dev );
```

```
memset( &prop, o, sizeof( cudaDeviceProp ) );
prop.major = 1;
prop.minor = 3;
cudaChooseDevice( &dev, &prop );
printf( "ID of CUDA device closest to revision 1.3: %d\n", dev );
```

```
cudaSetDevice( dev );
```

Adding two vectors on GPU

// Example 1: Uses 1 thread per block
#define N 100 // size of vectors

```
__global__ void add( int *a, int *b, int *c ) {
    int tid = blockIdx.x; // tid = block index for 1 thread/block (N blocks)
    int tid = threadIdx.x; // tid = thread index for 1 block kernel launch
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}</pre>
```

int main(void) {
 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' to the GPU
cudaMemcpy(dev_a, a, N * sizeof(int), cudaMemcpyHostToDevice);
cudaMemcpy(dev_b, b, N * sizeof(int), cudaMemcpyHostToDevice);

add<<<N,1>>>(dev_a, dev_b, dev_c); // kernel launch: 1 thread/block, N blocks add<<<1,N>>>(dev_a, dev_b, dev_c); // kernel launch: N threads/block, 1 block

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

// and display the results...

```
// free the memory allocated on the GPU
cudaFree( dev_a );
cudaFree( dev_b );
cudaFree( dev_c );
```

return o;

General case: B blocks, T threads/block

```
#define N (32 * 1024)
```

```
#define B 128
```

```
#define T 128
```

```
__global__ void add( int *a, int *b, int *c ) {
    int tid = threadIdx.x + blockIdx.x*blockDim.x;
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += blockDim.x*gridDim.x;
    }
}</pre>
```

Max # blocks = 65,535 Max # threads/block usually = 512 Choosing 128 threads/block: B = (N+127)/128

Using the kernel

int main(void) {
 int a[N], b[N], c[N];
 int *dev_a, *dev_b, *dev_c;
 // allocate memory on device
 cudaMalloc((void**)&dev_a, N * sizeof(int));
 cudaMalloc((void**)&dev_b, N * sizeof(int));
 cudaMalloc((void**)&dev_c, N * sizeof(int));

// initialize vectors a & b...

// copy a & b to device (dev_a & dev_b)
cudaMemcpy(dev_a, a, N * sizeof(int), cudaMemcpyHostToDevice);
cudaMemcpy(dev_b, b, N * sizeof(int), cudaMemcpyHostToDevice);

add<<<B,T>>>(dev_a, dev_b, dev_c); // kernel launch: T threads/block, B blocks

// copy from device and use results
cudaMemcpy(c, dev_c, N * sizeof(int), cudaMemcpyDeviceToHost);

Inner products

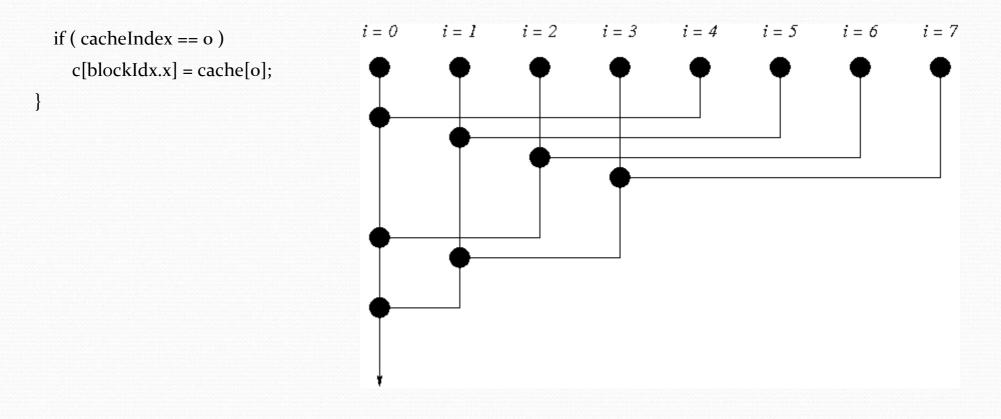
```
__global__ void dot(float *a, float *b, float *c) {
    __shared__ float cache[threadsPerBlock];
    int tid = threadIdx.x + blockIdx.x*blockDim.x;
    int cacheIndex = threadIdx.x;
```

```
float temp = o;
while ( tid < N ) {
  temp += a[tid]*b[tid];
  tid  += blockDim.x * gridDim.x;
}
cache[cacheIndex] = temp;
```

```
__syncthreads();
```

// parallel reduction: threadsPerblock must be a power of two!

// cache[o] is now the sum of a[i]*b[i] for all i for this thread block



More on this...

22C:177 High performance and Parallel Computing (cross-listed with 22M:178) Fall 2011

Covers:

- MPI
- OpenMP
- CUDA (OpenCL?)

See http://www.cs.uiowa.edu/~oliveira/C177-F11/C177-F11-description.html

Dr. Oliveira Current Research

- Granular flow simulation on GPU's simulating interactions between rocks or balls as they slide and roll; highly dynamic sparse interact'ns
- Clustering for large databases: algorithms for grouping PPN functional modules, grouping genes activated simultaneously in CNS of rats
- Issues about GPUs Redesigning algorithms; ML algorithms
- Other applications using MPI and OpenMP Applications involving PDEs, ODEs, linear and no linear solvers, preconditioners (recursive algorithms)

Some references.....

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- Art of Concurrency, Clay Breshears (2009)
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- Programming Massively Parallel Computers, Kirk & Hwu, Morgan Kauffman (2010)
- Writing Scientific Software, Oliveira & Stewart, Cambridge University Press (2006)
- *Parallel Programming with MPI*, Pacheco, Morgan Kauffman (1996)