CSC266 Introduction to Parallel Computing using GPUs
Introduction to CUDA

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URCS

Outline

Background

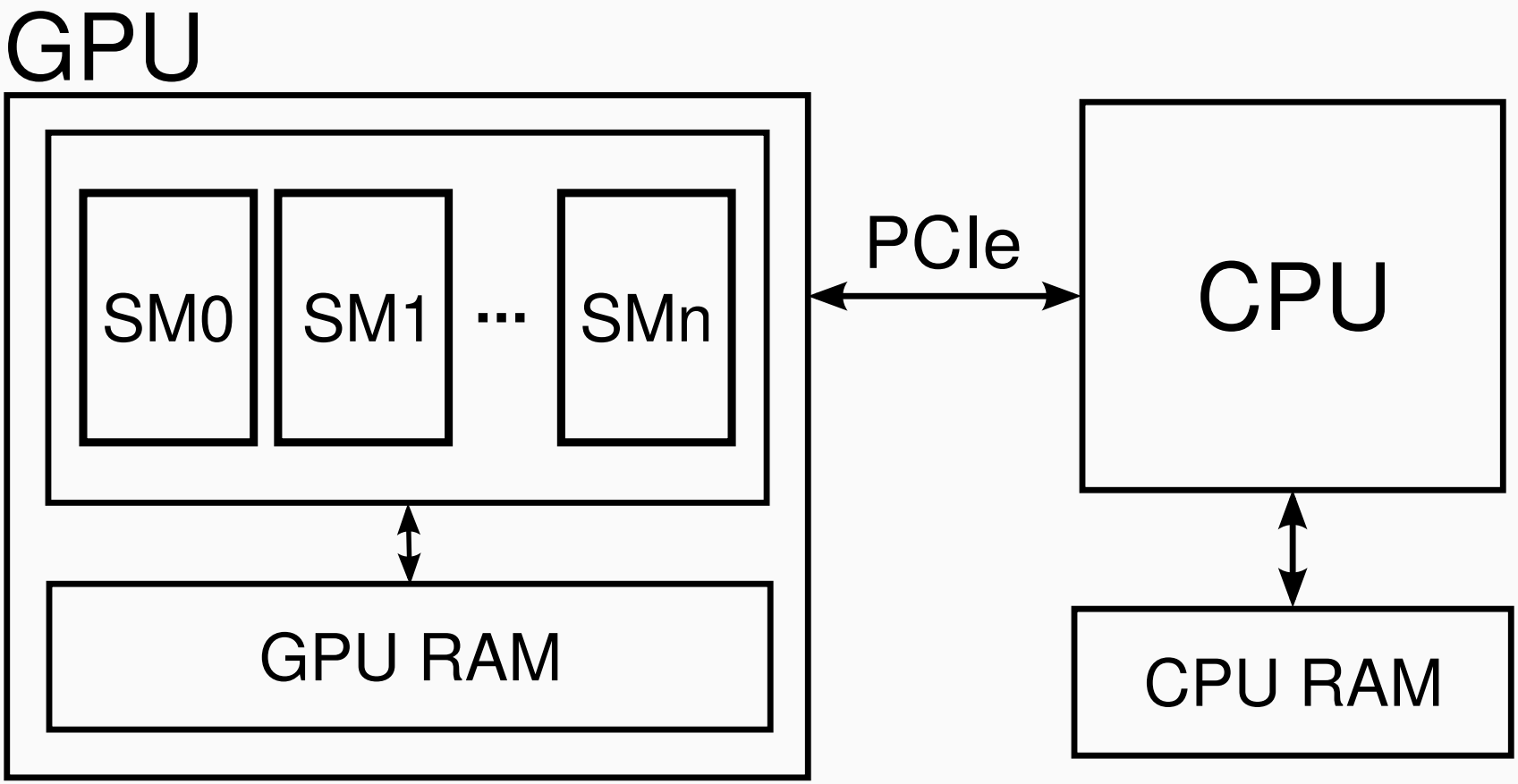
Memory

Code

Execution Model

Outline

CUDA programmer's view of the system



Data access in Shared memory vs Distributed systems

- Shared Memory system
  - Same address space
  - Data in the system accessed through load/store instructions
  - E.g., multicore
- Distributed Memory System (e.g. MPI)
  - (Usually) different address space
  - Data in the system accessed through message-passing
  - E.g., clusters

Is a GPU-containing system a distributed system?

- Does data live in the same address space?
- Is data in the entire system accessed through load/store instructions?

Outline

Pointers

- Addresses are contained in pointers
- GPU addresses are C/C++ pointers in CPU code
  - True, in CUDA
  - False, in OpenCL (`cl::Buffer` in CPU)

Allocating Host Memory

- Data lives in CPU memory
- Read/Written by CPU using load/store instructions
- Allocated by `malloc` (or equivalent)
- Freed by `free` (or equivalent)
- Pointers cannot be deferenced by GPU

Allocating GPU Memory

- Data lives in GPU memory
- Read/Written by GPU using load/store instructions
- Allocated by `cudaMalloc` (or `cudaMallocManaged`)
- Freed by `cudaFree`
- Pointers cannot be deferenced by CPU
- Data transferred using copies (`cudaMemcpy`)

Allocating Pinned Memory

- Data lives in CPU memory
- Read/Written by CPU using load/store instructions
- Read/Written by GPU using load/store instructions over PCIe bus
- Same pointer value
- Allocated by `cudaMallocHost` (or `cudaHostMalloc`)
- Freed by `cudaFree`
- No transfers needed!

Mapping Host-allocated Memory to GPUs

- Data lives in CPU memory
- Read/Written by CPU using load/store instructions
- Read/Written by GPU using load/store instructions over PCIe bus
- Allocated by `malloc`
- Mapped by `cudaHostRegister`
- GPU uses different pointer (`cudaHostGetDevicePointer`)
- Freed by `free`
- No transfers needed!

Managed Memory

- Data lives in CPU memory or GPU memory
- Read/Written by CPU using load/store instructions
- Read/Written by GPU using load/store instructions
- But not by both at the same time!
- Same pointer value
- Freed by `cudaFree`
- No manual transfers needed!
- Data transferred "automagically" behind scenes

Summary

Pointer from	Host	GPU	Same Pointer
CPU `malloc`	Y	N	N
`cudaMalloc`	N	Y	N
`cudaHostMalloc`	Y	Y	Y
`cudaHostRegister/GetDevicePointer`	Y	Y	N
`cudaMallocManaged`	Y	Y	Y

Outline

Host code and device code

- CPU code callable from CPU (`__host__`)
- GPU code callable from CPU (`__global__`)
- GPU code callable from GPU (`__device__`)
- Code callable from both CPU and GPU (`__host__`, `__device__`)
- CPU code callable from GPU (N/A)

CUDA source code layout

```
__global__
void vector_add(int *a, int *b, int *c, int N) {
    ...
}

int main(void) {
   ...
   vector_add<<<...>>>(a, b, c, N);
}
```

CUDA Compilation Model (Simple)

- All code lives in CUDA source files (`.cu`)
- `nvcc` compiler separates GPU and CPU code
  - Inserts calls to appropriate CUDA runtime routines
- GPU code is compiled to PTX or binary
  - PTX code will be compiled to binary at runtime
- CPU code is compiled by GCC (or clang)

Fat binary

- End result of `nvcc` run is a single executable
  - On Linux, standard ELF executable
- Contains code for both CPU and GPU
- CUDA automatically sets up everything
  - OpenCL does not
  - No OpenCL equivalent of `nvcc`

Outline

Vector Addition again

```
__global__
void vector_add(int *a, int *b, int *c, int N) {
    ...
}

int main(void) {
   ...
   vector_add<<<...>>>(a, b, c, N);
}
```

Execution starts on the CPU

- Program starts in `main`, as usual
- On first call to CUDA library, a GPU context is created
  - GPU Context == CPU Process
  - Can also create one automatically
- Default GPU is chosen automatically *per thread*
  - If multiple GPUs
  - Usually the newest, ties broken by the fastest
  - This is where default allocations and launches occur
  - Can be changed *per thread* (`cudaSetDevice`)

Memory Allocation and Copies

- `cudaMalloc`, etc. used to allocate memory
  - CPU waits for allocation
- `cudaMemcpy`, etc. used to copy memory across
  - CPU waits by default for copy to finish
  - LATER LECTURES: non-blocking copying APIs

Launch

- Determine a thread block size: say, 256 threads
- Divide work by thread block size
  - Round up
  - $\lceil N/256 \rceil$
- Configuration can be changed *every* call

```
int threads = 256;
int Nup = (N + threads - 1) / threads;
int blocks = Nup / threads;

vector_add<<<blocks, threads>>>(...)
```

Kernel Launch Configuration

- GPU kernels are SPMD kernels
  - Single-program, multiple data
  - All threads execute the same code
- Number of threads to execute is specified at launch time
  - As a *grid* of B *thread blocks* of T threads each
  - Total threads: $B \times T$
- Reason: Only threads within the same thread block can communicate with each other (cheaply)
  - Other reasons too, but this is the only algorithm-specific reason

Distributing work in the kernel

```
__global__
vector_add(int *a, int *b, int *c, int N) {
   int tid = threadIdx.x + blockIdx.x * blockDim.x;

   if(tid < N) {
      c[tid] = a[tid] + b[tid];
   }
}
```

- Maximum 2^{32} threads supported
- *gridDim*, *blockDim*, *blockIdx* and *threadIdx* are CUDA-provided variables

Blocking and Non-blocking APIs

- Blocking API (or operation)
  - CPU waits for operation to finish
  - e.g. simple `cudaMemcpy`
- Non-blocking API (or operation)
  - CPU does not wait for operation to finish
  - e.g. kernel launches
  - You can wait explicitly using special CUDA APIs

Helpful Tips

- Each CUDA API call returns a status code
  - Check this *always*
  - If an error occurred, this will contain error code
  - Error may be related to this API call or *previous non-blocking API calls!*
- Use `cuda-memcheck` tool to detect errors
  - Slows down program, but can tell you of many errors