CSC266 Introduction to Parallel Computing using GPUs
Introduction to CUDA

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URCS
Outline

Background

Memory

Code

Execution Model
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Execution Model
CUDA programmer’s view of the system

![Diagram showing the CUDA programmer's view of the system, with CPU, PCIe, GPU, SMs, and RAM connections.](image-url)
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

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• 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 dereferenced 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
<table>
<thead>
<tr>
<th>Pointer from</th>
<th>Host</th>
<th>GPU</th>
<th>Same Pointer</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU malloc</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>cudaMalloc</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>cudaHostMalloc</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>cudaHostRegister/GetDevicePointer</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>cudaMallocManaged</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>
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Execution Model
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`
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__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

```c
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

```c
__global__
void 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