Chip Multiprocessors
COMP35112

Lecture 14 - GP-GPUs and CUDA

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Today’s Lecture

- General purpose graphical processing units (GP-GPUs) provide cheap access to parallel computing resources
- They have been used successfully for some applications
- Need to talk about:
  - Hardware characteristics
  - How to program applications to use them
GPU Characteristics

- History: an ‘attached processor’ designed to reduce load on CPU caused by need to draw sophisticated images many times per second – driven by games…

- Characteristics therefore:
  - Multi-core, usually an entirely separate memory
  - Good Floating Point performance
  - High Memory Bandwidth: ~3 × that of CPUs (in 2008)
    - Not changed much since

- NVidia GeForce GTX 280 GPU
  - had 240 cores - ~933GFlop/s (2008)

- NVidia Titan X has 3584 cores – 11TFlop/s (2016)
GPU Instruction Set

- In 1980s and 1990s, graphics hardware was configurable (via API calls from CPU), but not programmable – matched to algorithms used in the graphics pipeline
- In 2001-2, application developers got access to the actual instruction set used
- Still more restricted than CPU
- Massive SIMD data parallelism built in!
- GP-GPU = general purpose GPU – can be used via an API for stream computing
The Graphics Pipeline

- The early fixed-function pipelines (e.g. NVIDIA GeForce) contained, in order:
  - Host interface (DMA bulk data)
  - Vertex Control (loads vertex cache)
  - Vertex shading/transformation & lighting
  - Triangle setup
  - Raster
  - Shader (using a Texture cache) ! Lots of floating point here
  - Raster Operations
  - Frame Buffer Interface
Writing General Purpose Applications for a GPU

- To compute a function, it could be written as a *pixel shader*
- Input data would be stored as a *texture image*
- Output had to be cast as *pixels*
- Constraints on data structure and data transfer
  - To “fit” in with the graphics pipeline view
- To use outputs from one phase of the program, they had to be written to the pixel frame buffer, which could then be used as a texture map input to the next phase
- Heroic efforts were made to go general purpose using OpenGL and DirectX …quite low level APIs
Later Developments

- Using more general purpose units, the pipeline is implemented by recycling through these units
  - i.e. no longer have dedicate h/w per pipeline stage
- e.g. in the GeForce 8800 GPU, the first to use the Tesla architecture, the processors are visited 3 times
Tesla Architecture

Figure 1. Tesla unified graphics and computing GPU architecture. TPC: texture/processor cluster; SM: streaming multiprocessor; SP: streaming processor; Tex: texture, ROP: raster operation processor.
Tesla Design

- More ‘general purpose’ programmable architecture
- Multiple independent processor ‘clusters’
- Each cluster has 2 ‘streaming multiprocessors’ (SMs)
- Each SM has 8 ‘streaming processors’ (SPs) (cores)
  - Plus two Special Function Units (SFU) for sin/cos etc.
  - Plenty of registers supporting fast context switch
- SIMD execution: all cores in a SM execute the same instruction but on different data
  - Care needed to ensure cost of loading data minimised (e.g. “coalesced” memory accesses)
Tesla Principles

- Re-circulating data, so variable (algorithm) pipeline length – flexible for new algorithms
  - Keep data on devices and transform with multiple “kernels”
- Clusters allocated dynamically to different processing stages (“kernels”)
- Cluster computations can be totally different threads
  - E.g. from multiple kernels, even applications
- Need lots of independent work in applications to keep the clusters busy
Stream Multiprocessor Cluster

Figure 2: Texture/processor cluster (TPC).
The next generation Tesla architecture was called Fermi (then Kepler, Maxwell, Pascal)

- It had much more hardware parallelism

- And more sophisticated functionality is included, such as virtual memory management, better f.p. support

- Recent (2017) is the Pascal architecture
  - NVIDIA Titan X

See:

www.nvidia.com/object/tesla_computing_solutions.html

http://www.geforce.co.uk/hardware/10series/titan-x/
NVIDIA Titan X Architecture - 2017
NVIDIA Titan X

- 12 Billion transistors
- 3584 CUDA cores
- 1.5GHz
- 12GB memory
- 11 Tflop/s performance
- 480 GB/s bandwidth
The CUDA Programming Language

- CUDA = ‘Compute Unified Device Architecture’
  - Specific to NVIDIA hardware
- Essentially heterogeneous
  - Host = CPU
  - Device = GPU
- Program (in C) has code for both host and device(s), and compiler separates it
- Device code is data-parallel *kernels* generating a large number of threads
- Note that these threads are very lightweight
Example: Matrix Multiplication

- This is a typical data-parallel application
- Basic operations are floating-point multiply-adds
- These are done in the kernels
- Host code has to organise things, copy data values to and from device memory, handle the answer when produced, etc.
- This is an example of a single kernel
  - But think in context of an application with multiple kernels
  - Data sent to device and transformed by multiple kernels
void MatMul (float *M, float *N, float *P, int width) {

    // allocate device memory for M, N, P
    // copy values of M and N to allocated locations
    // invoke kernel code to perform the calculation
    // copy P back from device memory
    // free device memory
}

Outline of CUDA Code: P=M*N
Detail: Allocate Device Memory

```c
float *Md;

int size = width * width * sizeof(float);
cudaMalloc((void **)&Md, size);

....

cudaFree(Md);
```
Detail: Copying Values

... 

cudaMemcpy(Md, M, size, cudaMemcpyHostToDevice) ;

...

cudaMemcpy(P, Pd, size, cudaMemcpyDeviceToHost) ;
__global__ void MMkernel(float *Md, float *Nd, float *Pd, int width)
{
    int tx = threadIdx.x; int ty = threadIdx.y;
    float Pvalue = 0;
    for (int k = 0; k < width; k++)
    {
        float Mdel = Md[ty*width + k];
        float Ndel = Nd[k*width + tx];
        Pvalue += Mdel * Ndel;
    }
    Pd[ty*width + tx] = Pvalue;
}
Three CUDA Function Declaration Prefixes

- __device__ executed on device, called from device
- __global__ executed on device, called from host
- __host__ executed on host and called from host
- Note: a function can be both __host__ and __device__, generating 2 versions of the code!
  - Enables heterogeneous execution – part on CPU, part on GPU
- Compile using nvcc – the NVIDIA compiler
Kernel Execution

- When invoked (*launched*), the kernel is executed as a Cartesian **grid** of parallel threads ("**thread blocks**")
- The host has control over how many threads there are, and how they are organised
- Launch code is therefore slightly complicated
- A thread block is executed to completion on the SM on which it runs
- Multiple thread blocks can be allocated to an SM
  - to help hide memory latency (by switching between thread blocks on a memory stall)
- Thread blocks are split into “warps”, related to the number of cores in an SM, for execution
- One block may consist of many warps
dim3 dimBlock(width, width) ; // size of thread block

dim3 dimGrid(1,1) ; // configuration of thread … … blocks in the grid

// … blocks in the grid

MMkernel<<dimGrid, dimBlock>>>(Md, Nd, Pd, width) ;

Where: <<<<…>>> is the “execution configuration”,

<<<< number of blocks, threads per block >>>>
CUDA Memory model

- Total number of active threads limited by per-thread local memory (e.g. registers)
- Need to choose thread block sizes to best share the limited block resources
- Other perf. issues exist…
- Programming Guide gives tips, and helpful tools exist to tune codes.
OpenCL, OpenMP and OpenACC

- Standardised languages for GP-GPUs, cross-platform
- OpenCL development was initiated by Apple, but done by Khronous Group (OpenGL people!)
  - Derives heavily from CUDA
- OpenMP4.x has pragma-based support for executing code on accelerators, intended to satisfy needs across a broader range of GP-GPU and attached processor architectures
- OpenACC is another design, based on pragmas – closely related to (and works together with) OpenMP
  - Ideally OpenACC and OpenMP will converge in future…
Next and Final Lecture

- Programming for the kinds of multi-core architectures we have described is certainly challenging.
- There has been long-standing dissatisfaction about this state of affairs, especially in academia.
- The next, and final, lecture surveys alternative approaches (for both languages and hardware) that live on now and were studied in the 1970s -1990s, particularly here in Manchester:
  - Functional Programming and Dataflow Principles
  - A current resurgence of interest in the form of “task-based” programming for heterogeneous systems