HOW AND WHEN TO USE

GPUS

WHAT IS A GPU?



- Few processing cores
- Highly flexible
- Low latency, moderate throughput



DRAM

GPU

- Many processing cores
- Limited flexibility
- High latency, High throughput

AMDAHL'S LAW

- The more of your problem that is parallel the faster a GPU will make it.
- The more data you have to process, the more likely it is to be paralleliseable.
- Good examples: FFTs, particle simulations, linear algebra, etc.
- Bad examples: Unknown problem in CS, does NC=P?



OVERVIEW

- In this tutorial you will learn:
 - How to check the GPUs on a node
 - How to write a CUDA kernel
 - How GPU memory management works
 - How CUDA threads, blocks and grids are arranged
 - Memory access rules
 - Tools that make it all easy

GLOSSARY

- Host: The server that hosts the GPU
- Device: The GPU accelerator card
- Kernel: A program that is executed by the GPU
- Profiler: A tool for measuring the performance of a piece of code

HELLO WORLD

- Log into Numerix0
- Add CUDA bin/ to PATH
 - export PATH=\$PATH:/usr/ local/cuda/bin/
- Make yourself a working directory
- Run nvidia-smi to check GPUs
- Open editor of your choice...

+ NVIDIA-SMI 418.39 Driver Version: 418.39	CUDA Version: 10.1
GPU Name Persistence-M Bus-Id Disp.A Fan Temp Perf Pwr:Usage/Cap Memory-Usage	Volatile Uncorr. ECC GPU-Util Compute M.
I 0 Tesla K20m 0n I 00000000:04:00.0 Off I N/A 23C P8 13W / 225W 00000 0MiB / 4743MiB	0 61/cb/f50%453359Default01
I Tesla K20m 00.0 0ff N/A 29C P8 14W 225W 000000:09:00.0 0ff	al/lib/python3.6/dist-0al cll/lib/0%thon3.Defaultol
I 2 Tesla K40m 00 0n I 0000000:83:00.0 Off I N/A 26C P8 21W / 235W I 00MiB / 11441MiB	0 0% Default
I	0 0% Default
root@c2aa77c9b7a8n/#_bgr <nnb-< td=""><td></td></nnb-<>	
IoProcesses: Bb703: /#content of the content of the	GPU Memory 1340104.18422Usaget222:pl
No running processes found	

HELLO WORLD	
C	CUDA
<pre>void c_hello(){ printf("Hello World!\n"); } int main() { c_hello(); return 0; }</pre>	<pre>global void cuda_hello(){ printf("Hello World from GPU!\n"); } int main() { cuda_hello<<<1,1>>>(); return 0; }</pre>

nvcc -o hello_world hello_world.cu

https://cuda-tutorial.readthedocs.io/en/latest/tutorials/tutorial01/



https://cuda-tutorial.readthedocs.io/en/latest/tutorials/tutorial01/

GPU ASYNCHRONISITY

- Host and Device code are asynchronous
- Good because GPU can do work at the same time as CPU does work
- CUDA kernel launches return immediately
- It is users responsibility to synchronise and to check errors
- Do this using
 cudaDeviceSynchronise()

.7		
.8	gl	.obal <i>void</i> cuda_hello(){
.9		<pre>printf("Hello World from GPU!\n");</pre>
20	}	
21		
22	int	<pre>main() {</pre>
.3		cuda_hello<<<1,1>>>();
24		<pre>cudaDeviceSynchronise();</pre>
25		return 0;
26	}	

MEMORY MANAGEMENT

- new: Allocates memory on host
- cudaMalloc: Allocates memory on device
- cudaMemcpy: Copies data to/from host/device
- cudaFree: Free memory on the device
- delete: Free memory on the host

ADDING TWO VECTORS

Worked example

ERROR HANDLING

- CUDA code can fail silently at runtime: VERY BAD, WTF IS HAPPENING, WHY DOES IT NOT WORK!
- Users have responsibility to check for errors
- Many CUDA functions return cudaError_t values
- When error == cudaSuccess everything is good
- The rest of the time us cudaGetErrorString() to find out what went wrong
- Copy /media/scratch/gpu-tutorial/examples/errors/error_checker.cu into all your codes and use the CUDA_ERROR_CHECK macro.

BENCHMARKING

Use NVPROF (command line) or NVVP (GUI) to benchmark code

(py3) ebarr@numer ==1852== NVPROF i Hello world!	ix0:/medi s profili	a/scratch/ ng process	gpu-tutori 1852, com	al/example mand: ./he	s/hello_wo llo_world	rld\$ nvpro	f ./hello_world rom reikna) from reikna)			
==1852==dProfilingLapplication:up./hello_world/usr/local/Lib/python3.6/dist-packages (from mako>=0.8.0->re										
==1852== Profiling result: plckages: neikna										
Runninghsetu Type nt	Time(%)	for Time	Calls	A∨g	Min	Max	Name			
GPU activities:	100.00%	100.71us	heels/c5/91/	100.71us	100.71us	100.71us	hello_world(void)			
API calls:	96.71%	313.61ms	1	313.61ms	313.61ms	313.61ms	cudaLaunchKernel			
	1.94%	6.2803ms	388	16.186us	312ns	655.13us	cuDeviceGetAttribute			
	1.13%	3.6717ms	4	917.91us	584.01us	1.2852ms	cuDeviceTotalMem			
	0.21%	665.27us	4	166.32us	132.66us	258.91us	cuDeviceGetName			
	0.01%	22.135us	for more 4 f	5.5330us	3.9950us	7.5830us	cuDeviceGetPCIBusId			
	0.00%	8.9100us	onnection810	1 31130us 8	226 434ns 2	2.0600us	pcuDeviceGet			
	0.00%	4.0870us	3	1.3620us	327ns	2.0800us	cuDeviceGetCount			
	0.00%	2.1250us	at 19130 4	531ns	443ns	753ns	cuDeviceGetUuid			

Try testing the vector addition code...

CUDA ARCHITECTURE

- GPU has many processing threads available, but they do not all work independently.
- Threads are mapped into blocks, which are in turn mapped into grids.
- One grid per kernel
- Blocks and grids can be 3D (X, Y, Z indexing)
- We write general code that is parameterised by the thread and block coordinates
- Groups of 32 threads (a warp) work in lockstep



MEMORY HIERARCHY

- Different types of memory available (fastest to slowest):
 - **Registers:** 256 kB, thread local
 - Shared memory: 64 kB, block local
 - Constant memory: 64 KB, global, read-only, broadcast
 - Texture memory: Huge, global, read-only, hardware interpolation
 - Global memory: Huge, global



MAPPING A CODE TO CUDA THREADS

- Which parts of the code are independent?
- Can the code be broken up into separate tasks?
- Can I do the most work possible per byte of memory at one time?
- Can I write code that doesn't care how many threads or blocks I have?

MAPPING A CODE TO CUDA THREADS

How do I map the following?



- **Clue:** CUDA will tell me which thread is executing the code by the following variables:
 - **gridDim.x,** gridDim.y, gridDim.z (how many blocks in each grid axis)
 - blockIdx.x, blockIdx.y, blockIdx.z (the block index)
 - blockDim.x, blockDim.y, blockDim.z (how many threads in each block axis)
 - threadIdx.x, threadIdx.y, threadIdx.z (the block index)
- Consider only the X axis

MAPPING A CODE TO CUDA THREADS

```
___global__
86
    void vector_add(float *out, float *a, float *b, int n)
87
88
      int total_threads = gridDim.x * blockDim.x;
89
      int n_per_thread = (n / total_threads) + 1;
90
      int idx = n_per_thread * (blockDim.x * blockIdx.x + threadIdx.x);
91
      for (int ii = idx;
92
            (ii < idx + n_per_thread) \&\& (ii < n);
93
94
           ++ii)
95
          out[ii] = a[ii] + b[ii];
96
97
98
    }
\sim
```

- Here each thread does n_per_thread calculations
- Code works, but it has problems: unnecessary calculations, and a uncoalesced memory access pattern

MEMORY ACCESS PATTERNS

- CUDA likes it when neighbouring threads read neighbouring data
- Threads in same half-warp (16 threads) should try to read data in 32-, 64- or 128byte aligned cache lane
- Can affect per performance



MAPPING A CODE TO CUDA THREADS

```
73
     __global__
74
    void vector_add(float *out, float *a, float *b, int n)
75
76
    {
         for (idx = blockDim.x * blockIdx.x + threadIdx.x;
77
             idx < n:
78
             idx += gridDim.x * blockDim.x)
79
80
         {
             out[idx] = a[idx] + b[idx];
81
82
         }
    }
83
84
```

- Memory access is now coalesced (neighbouring threads access neighbouring data)
- Threads still do multiple indices, but without unnecessary extra calculations

KERNEL LAUNCHING

- CUDA uses <<<>>> triple angle bracket notation for kernel launches
- Arguments are:
 - 1. Grid dimensions
 - 2. Block dimensions
 - 3. Size of desired dynamic shared memory (optional)
 - 4. Stream ID (optional)
- Dimensions can be described with a dim3 struct
 - e.g. <<<dim3(4,4,4), dim3(5,5,5)>>> would give a 4 by 4 by 4 grid of blocks (64), each with 5 by 5 by 5 threads (125)
- Maximum number of threads per block is 1024 (there are also limits for each dimension and the same for blocks)

KERNEL LAUNCHING

- As we have written our vector_add code to be threadblock agnostic, we can choose any combination of threads and blocks (but only x-axis).
 - vector_add<<<1024,128>>>(d_out, d_a, d_b, N);
 - vector_add<<<dim3(1024,1,1), dim3(128,1,1)>>>(d_out, d_a, d_b, N);
- After the kernel call we can synchronise to wait for it to finish (and we should check the error code returned)
 - CUDA_ERROR_CHECK(cudaDeviceSynchronize());

TOOLS

- Lots of libraries for CUDA:
 - Mathmatical functions with CUDA Math Library
 - Fast Fourier Transforms with cuFFT
 - Deep Neural Networks with cuDNN
 - Linear algebra with cuBLAS, cuSPARSE, cuSOLVER and cuTENSOR
 - Random number generators with **cuRAND**

MAKING THINGS EASY

- Lots of high-level language abstractions:
 - Thrust: C++ STL-like library that provides easy interface for people already familiar with C++
 - PyCUDA: Python wrappers for CUDA Driver API that provide extensive functionality with the ability to embed raw CUDA code that can be JIT compiled.

THRUST: VECTOR ADD

```
#include <thrust/device_vector.h>
101
     #include <thrust/host_vector.h>
102
     #include <thrust/transform.h>
103
104
     #define N 1000000
105
106
     int main()
107
     Ł
       thrust::host_vector<float> a(N);
108
       thrust::host_vector<float> b(N);
109
       thrust::device_vector<float> d_a = a;
110
       thrust::device_vector<float> d_b = b;
111
       thrust::device_vector<float> d_out(N);
112
       thrust::transform(d_a.begin(), d_a.end(), d_b.begin(),
113
                          d_out.begin(), thrust::plus<float>());
114
       thrust::host_vector<float> out = d_out;
115
116
        return 0;
117
     }
```

PYCUDA: VECTOR ADD

```
import pycuda.gpuarray as gpuarray
120
     import pycuda.driver as cuda
121
     import pycuda.autoinit
■ 122
123
      import numpy as np
124
      a = np.random.normal(0, 1, 1000000)
125
      b = np.random.normal(0, 1, 1000000)
126
      a_gpu = gpuarray.to_gpu(a.astype(np.float32))
127
      b_gpu = gpuarray.to_gpu(b.astype(np.float32))
128
      a_plus_b = (a_gpu + b_gpu).get()
129
130
```