Topics: GPUs

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GPU-based computing appears strongly in the Top 500 largest computers in the world

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Graphics libraries (like OpenGL and DirectX) that were originally developed to draw pictures eventually supported programmable sequences of operations via *shader languages* such as GLSL and HLSL (aka Cg)

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This means putting in hardware to support generic computation, not just graphics oriented stuff

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OpenCL is strong, and is supported by NVIDIA, AMD, Intel and ARM amongst others

GPUs
CUDA

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In contrast, OpenCL is a library that runs on plain C or C++ (and any other language that can call C functions)

GPUs
Architecture

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Memory access in GPUs is relatively **very slow**, so there would be a lot of waiting otherwise

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Exercise Why don't normal CPUs do the same: have hardware support for threads?

GPUs

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OpenCL has a separate set of words for the same things

GPUs

CUDA

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NVIDIA calls this “Single Instruction Multiple Thread” (SIMT)

GPUs
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CUDA

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CUDA

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Warps are the basic SIMD chunk

This means it is better to gather threads that take the same branches of an if or loop as they will be processed together:

```
if (threadid < 32) {...} else {...}
```

is better than

```
if (threadid % 2 == 0) {...} else {...}
```

GPUs
CUDA

A block (of multiple warps) is the basic chunk that gets scheduled on a multiprocessor; the multiprocessor then executes the warps, as many as it can at a time as the hardware permits

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Warps within a block might be executed at the same time or at different times depending on the number of cores per multiprocessor and the number of schedulers per multiprocessor

Having many warps and many blocks means the system can adapt at runtime to the number of multiprocessors available in the hardware

GPUs
CUDA

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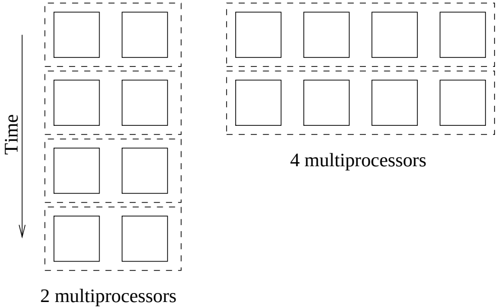
Suppose we have 8 blocks in our grid

GPUs

CUDA



Processing CUDA blocks

This naturally and automatically obtains more parallelism when there are more multiprocessors. So it makes sense to have lots more blocks than multiprocessors

GPUs
CUDA

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GPUs

CUDA

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Registers are what you need to use if you want fast access, but registers are limited in number, and `__local__` memory might be needed if the compiler can't fit the data into registers

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GPUs

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GPUs
CUDA

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So you need to take care on where you place data

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Values are passed from CPU to GPU as arguments of CUDA kernel calls; or as explicit cpu-memory-to-gpu-memory copies

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Just use an integer for 1D

GPUs

CUDA

If `fun` is a kernel (i.e., GPU function), we can call it from the CPU code by

```
fun<<<G,B>>>(arg1, arg2, ...);
```

to run `fun` on a grid containing blocks arranged as `G`; the blocks containing threads arranged as `B`

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(And copies the code for the kernel to the GPU; copies the argument values to the GPU; starts the GPU scheduler; and so on)

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In fact, one of the issues when writing a CUDA program is figuring how to choose your blocks and distribute your data amongst them

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In fact, one of the issues when writing a CUDA program is figuring how to choose your blocks and distribute your data amongst them

For example, the amount of shared memory per block is very limited, so this may affect how you choose blocks

GPUs

Properties of a typical gamer's card (2020):

name	'GeForce RTX 3080'
totalGlobalMem	10GB
maxThreadsPerBlock	1024
maxRegistersPerBlock	65536
clockRate	1.44 GHz
multiProcessorCount	68 processors
CoreCount	8704 (128 per multiprocessor)
warp size	32 threads
processing:	25 TFlop single
	783 GFlop double (1/32)
power	320W

GPUs

Properties of a compute oriented GPU card (2015):

name	'GeForce GTX K20X'
totalGlobalMem	6039339008
sharedMemPerBlock	49152
maxThreadsPerBlock	1024
maxRegistersPerBlock	65536
maxThreadsDim	1024 x 1024 x 64
maxGridSize	2147483647 x 65535 x 65535
clockRate	0.73 GHz
multiProcessorCount	14 processors
CoreCount	2688 (192 per multiprocessor)
warp size	32 threads
processing:	3935 GFlop single
	1310 GFlop double (1/3)
power	235W

GPUs

December 2017: NVIDIA Titan V

CUDA Cores	5120
Tensor Cores	640
Transistors	21.1 billion
Power	250W
Single precision	12.4 TFLOPS
Double precision	6.1 TFLOPS
Half precision	24.6 TFLOPS

Half precision they call “deep learning FLOPS”

Tensor cores are specialised to 4×4 matrix half-precision fused multiply add ($AB + C$) computations, also for AI

The main point of GPUs is they have a large number of cores: the RTX 3080 above has 8704 cores in 68 multiprocessors

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There is also a chunk of global *constant* memory (`__constant__`), which is read-only but faster to access than the read-write global memory

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And some read-only *texture* memory, whose development arose from the needs of graphics

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A texture reference can be associated with an area of global memory and then that memory is read via the reference

GPUs

CUDA

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- the index into the texture memory is a floating point number: the value at index 3.14142, say, is interpolated appropriately by the hardware between the values for indices 3 and 4

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It is possible to ignore the clever stuff and just use textures as a fast(er) way to read global memory

GPUs

CUDA

	Speed	Access	Scope	Size	Lifetime
register	v fast	r/w	thread	10s	thread
local	slow	r/w	thread	GBs	thread
shared	fast	r/w	block	KBs	block
global	slow	r/w	grid	GBs	application
constant	cached	r	grid	KBs	application
texture	cached	r	grid	KBs	application

N.B. the thread, block and grid/kernel lifetimes are typically all the same; a typical application will have many kernel calls