An Introduction to GPUs and their Applicability to MC Internal Seminar at 27th GEANT4 Collaboration Meeting

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- ... condensed into 30 minutes
 - (will focus on GPUs by NVIDIA, but similar concepts apply to AMD)

Contents

Strengths of GPUs

Peculiarities of GPUs

Applicability for Monte Carlo simulations

What exactly IS a GPU?

- ► GPU = **Graphics** Processing Unit
 - ► CPU = **Central** Processing Unit



(humorous video)

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- Create images for output to display device
 - ► Today's hardware: programmable shaders
 - ► Highly-parallel architecture, efficient for its task



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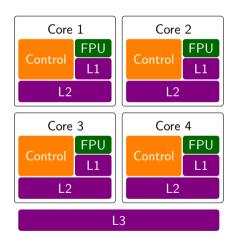


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- ► GPGPU = General-purpose GPU
 - or "General-purpose computing on GPUs" (according to Wikipedia)

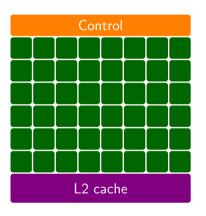
High-level comparison with (modern) CPUs

- Current CPUs have few cores
 - ► At least compared to current GPUs
- Instead optimized for sequential programs (or "mildly" threaded)
 - ► Hierarchy of cashes
 - Complex control logic, branch prediction
 - Out-of-order execution
 - **.**...



High-level comparison with (modern) CPUs

- ► GPUs have many "dumb" cores
- No focus on a single thread
 - Optimize throughput of all cores
- Hide latencies via scheduling
 - Oversubscribe hardware, more threads than cores
 - Efficiently switch between threads (for example if waiting for memory)



Massive data parallelism

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- GPUs have to be efficient at their task
 - ► For graphics, throughput is measured in "frames per second" (FPS)...
- Need to process millions of triangles for millions of pixels
 - Computations are independent, can be parallelized
 - Simply not important how long a single triangle / pixel would take...

(Ab)using GPUs for science

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 - ▶ They began writing graphics pipelines to "offload" parts of their applications.
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 - ▶ Effectively abusing the programmable vertex and pixel shaders
- ► In 2007, NVIDIA introduced the CUDA platform
 - Explicit APIs for compute kernels with less overhead
 - Proprietary interface, defined by NVIDIA
- ► Since then: number of standards for using GPUs (OpenCL, OpenACC, OpenMP)









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- ▶ Prime use case for science: linear algebra
 - Vectors similar to lists of vertices, matrices represented as arrays...
 - Anyway: transformations are core tasks of GPUs for graphics
- Traditionally important for simulations in HPC

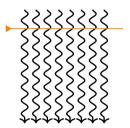
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- One example: general matrix-matrix multiplication, gemm
 - Also at the core of neural networks!

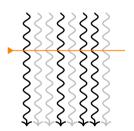
Thread divergence

► GPUs are less good at non-uniform workloads

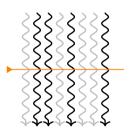
- ► GPUs are less good at non-uniform workloads
- ► Hardware is optimized to work in "lockstep"
 - ▶ Initially program counter was per warp (= 32 threads)!



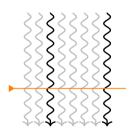
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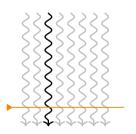
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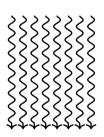
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- Hardware is optimized to work in "lockstep"
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 - Extreme case: only one thread executing at a time
- Somewhat relaxed / improved in recent generations
 - ► Still, strictly uniform code is fastest



Memory coalescencing

► Related optimization: memory coalescing

Memory coalescencing

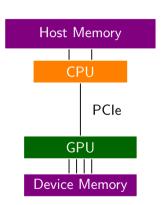
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 - ▶ Put related values close together, if accessed together
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- On CPUs, improved performance by optimizing for caches
 - Put related values close together, if accessed together
 - Keyword: Array of Structures, AoS
- On GPUs, best to have threads load adjacent values
 - For example, make 32 threads load entries 0 to 31 of an array
 - ► Hardware will optimize by "coalescing" loads
 - Keyword: Structure of Arrays, SoA

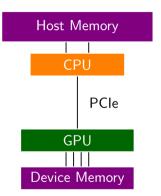
Separate memory spaces and data transfer

► GPU memory is (usually) separate from main memory



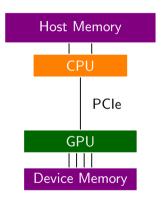
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 - Does your problem size fit into GPU memory?



Separate memory spaces and data transfer

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- ▶ It is faster than main memory, but limited in capacity
 - Does your problem size fit into GPU memory?
- ▶ Data must be transferred via interconnect (PCIe)
 - Much slower than memory bandwidths
 - ▶ Affects both directions: input data and simulation result



A quick note on floating point precision

- ► (Consumer) GPUs are sold and optimized for graphics output
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 - ightarrow Performance ratio 1:32 for double precision computations!
- ▶ Data center GPUs for HPC are optimized for simulation
 - ► Ratio 1:2 for double precision

Natural parallelism and computations

- Particle transport is embarrassingly parallel
 - lacktriangle Tracks are simulated independently ightarrow good for GPU simulation
 - ▶ However, leads to very different tracking than GEANT4 (stack-based)
 - Secondary and stopped tracks need to be handled (changing population)

Natural parallelism and computations



- Particle transport is embarrassingly parallel
 - ightharpoonup Tracks are simulated independently \rightarrow good for GPU simulation
 - ► However, leads to very different tracking than GEANT4 (stack-based)
 - Secondary and stopped tracks need to be handled (changing population)
- Many computations and mathematical functions
 - Logarithms, square roots, exponential, sin & cos
 - ► GPUs can provide higher throughput for these

Applicability for Monte Carlo simulations Non-uniformity



- Monte Carlo simulations governed by random numbers
 - ► Many interactions require rejection-based sampling
 - $\,\rightarrow\,$ Thread divergence, bad for performance on GPUs

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- Monte Carlo simulations governed by random numbers
 - Many interactions require rejection-based sampling
 - → Thread divergence, bad for performance on GPUs
- GEANT4 simulates many different particle types
 - Many different physics processes and models
 - → Thread divergence, bad for performance on GPUs
- ▶ Divergence also comes from geometry and field propagation

Data lookup and requirements



- Cross sections require data lookup by kinetic energy
 - ▶ Depends on simulation history, which is random
 - $\,\rightarrow\,$ No memory coalescing, bad for performance on GPUs



Data lookup and requirements

- Cross sections require data lookup by kinetic energy
 - Depends on simulation history, which is random
 - ightarrow No memory coalescing, bad for performance on GPUs
- ► GEANT4 almost exclusively uses doubles
 - ► Required in some places a unit vector must be unit!
 - Care must be taken when reducing precision...

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- ▶ GPUs provide great processing power, but are very different from CPUs
 - Designed for massive data parallelism
- ► As with any application, performance depends on many factors
 - Some positive characteristics of MC, but many challenges