

High Performance
Computing in Julia
from the ground up.

**Introduction to GPU Programming &
CUDA.jl**

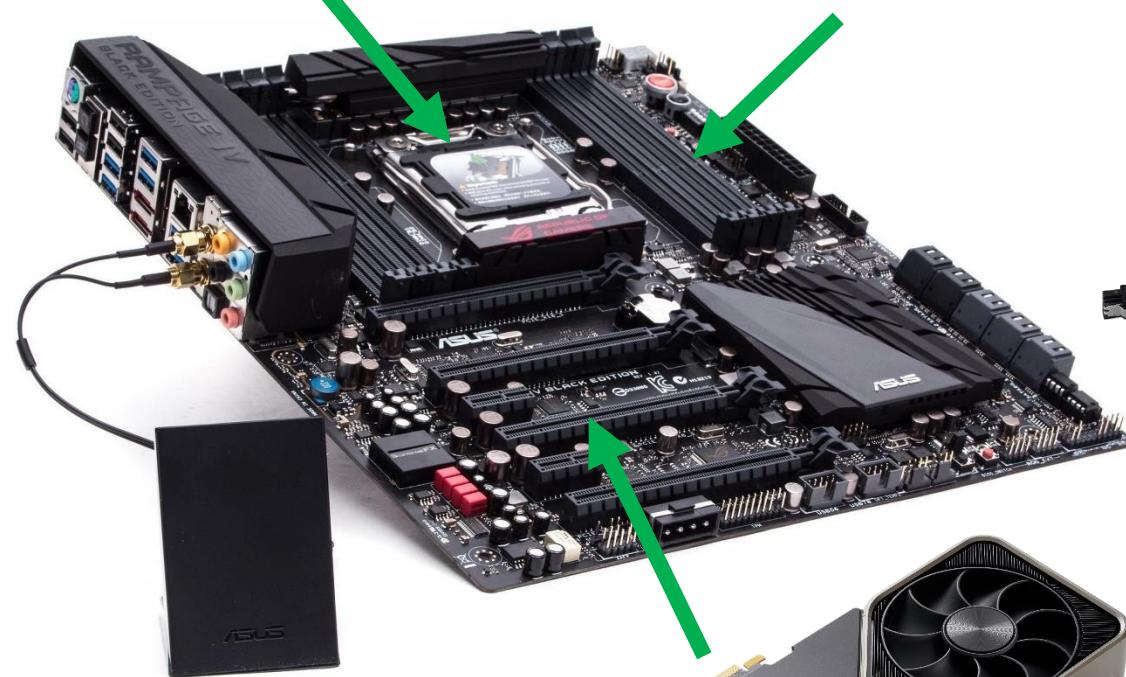
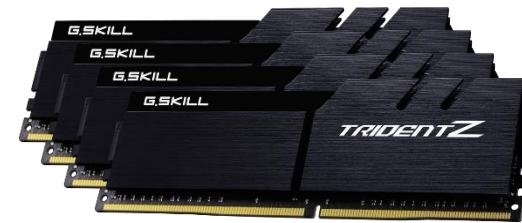
Aims

- To introduce GPU hardware
- To discuss the different options for GPU programming
- To introduce array-based GPU programming with CUDA

Central Processing Unit (CPU)
e.g. Intel or AMD CPUs



Random Access Memory (RAM)
e.g. DDR3, DDR4, DDR5



Graphics Processing Unit (GPU)
e.g. NVIDIA/AMD

Storage
e.g. HDD/SSD

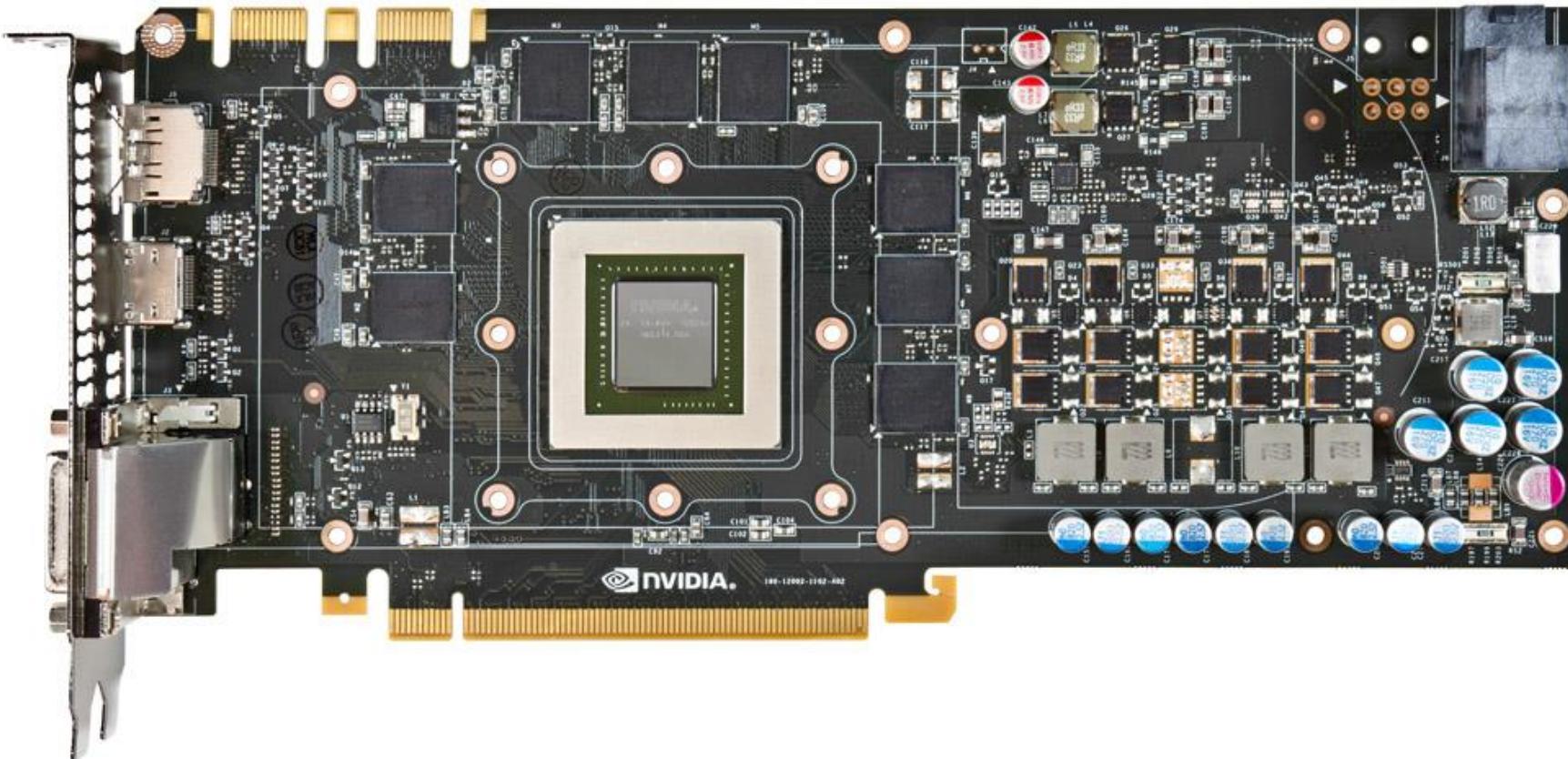


General-Purpose Graphics Processing Unit (GPGPU)

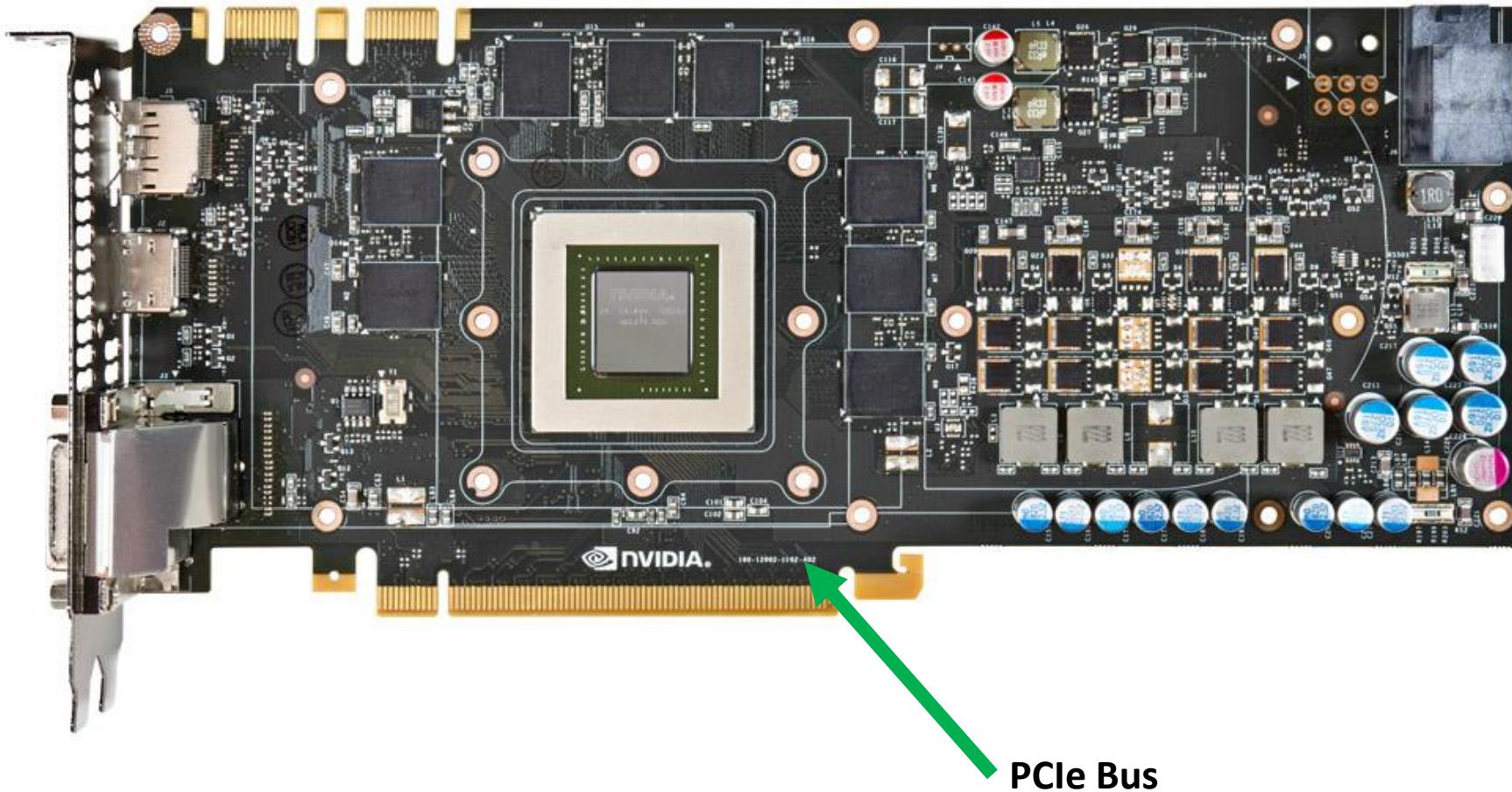
- Massively parallel co-processors which work alongside the CPU
- Traditionally used to accelerate graphics workloads
- Hardware is also useful for accelerating many modern workloads (e.g. AI/ML/Fluid dynamics etc)
- While CPUs has 10s of cores, GPUs have 10,000s of cores



Anatomy of a GPU

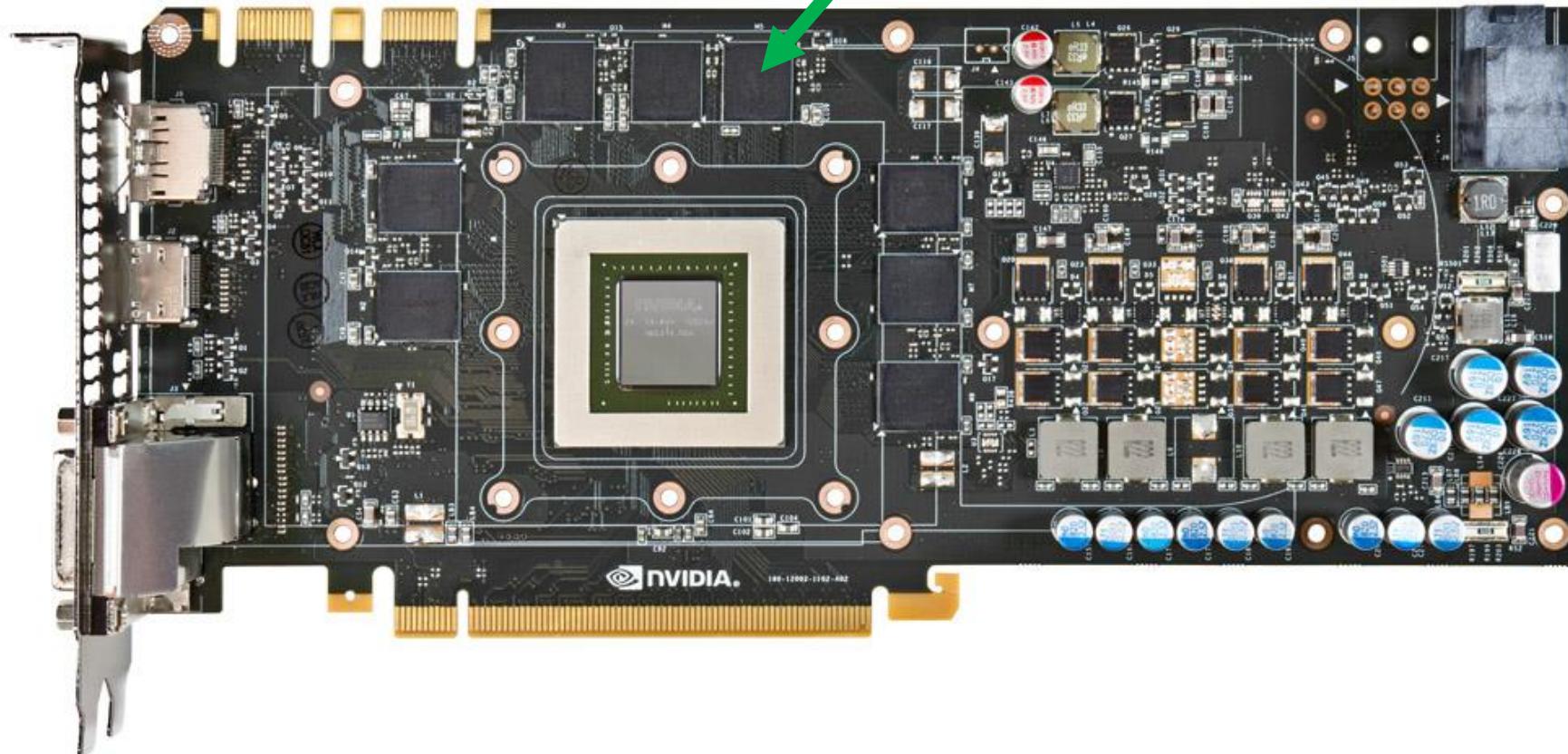


Anatomy of a GPU

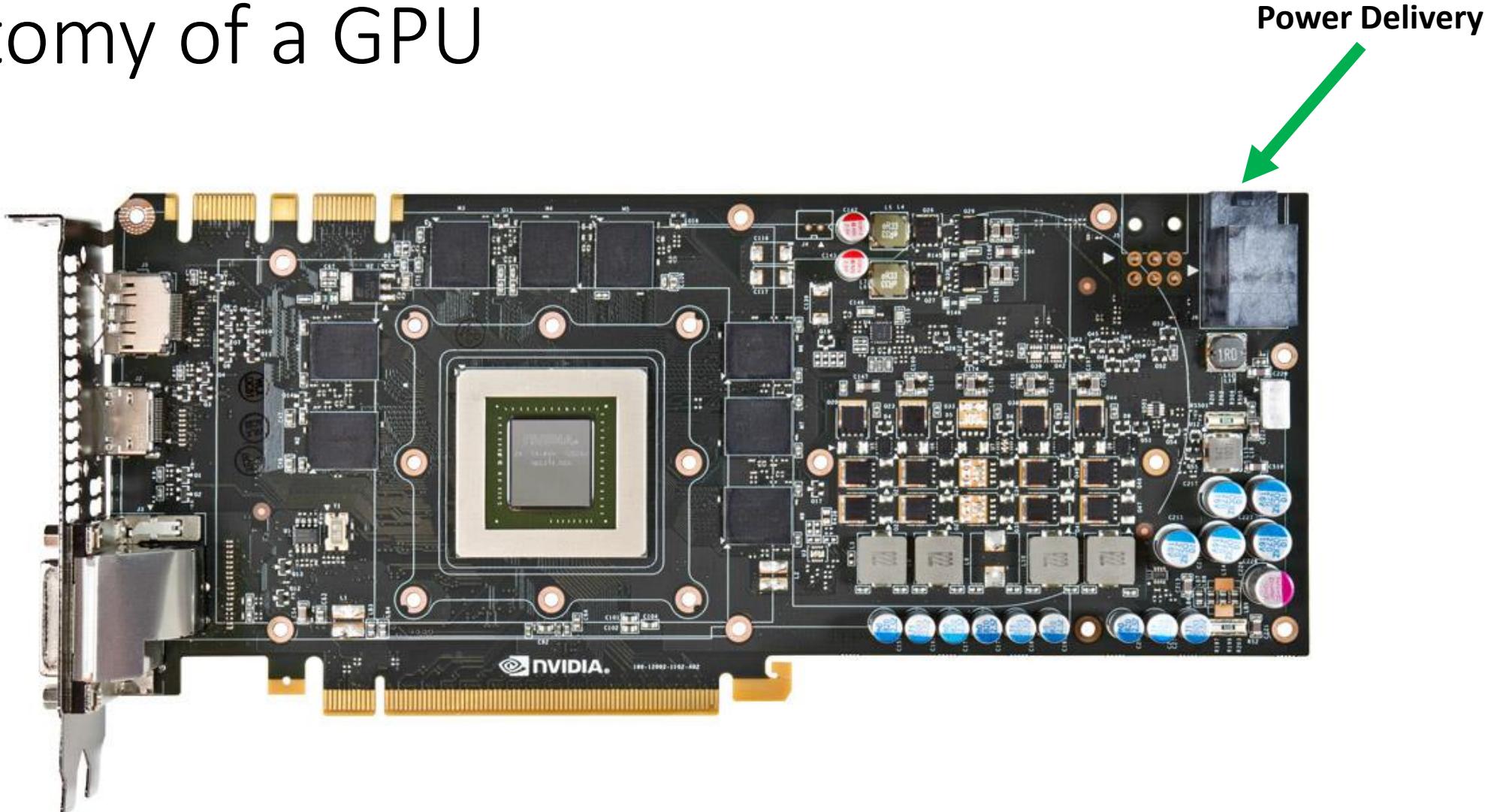


Anatomy of a GPU

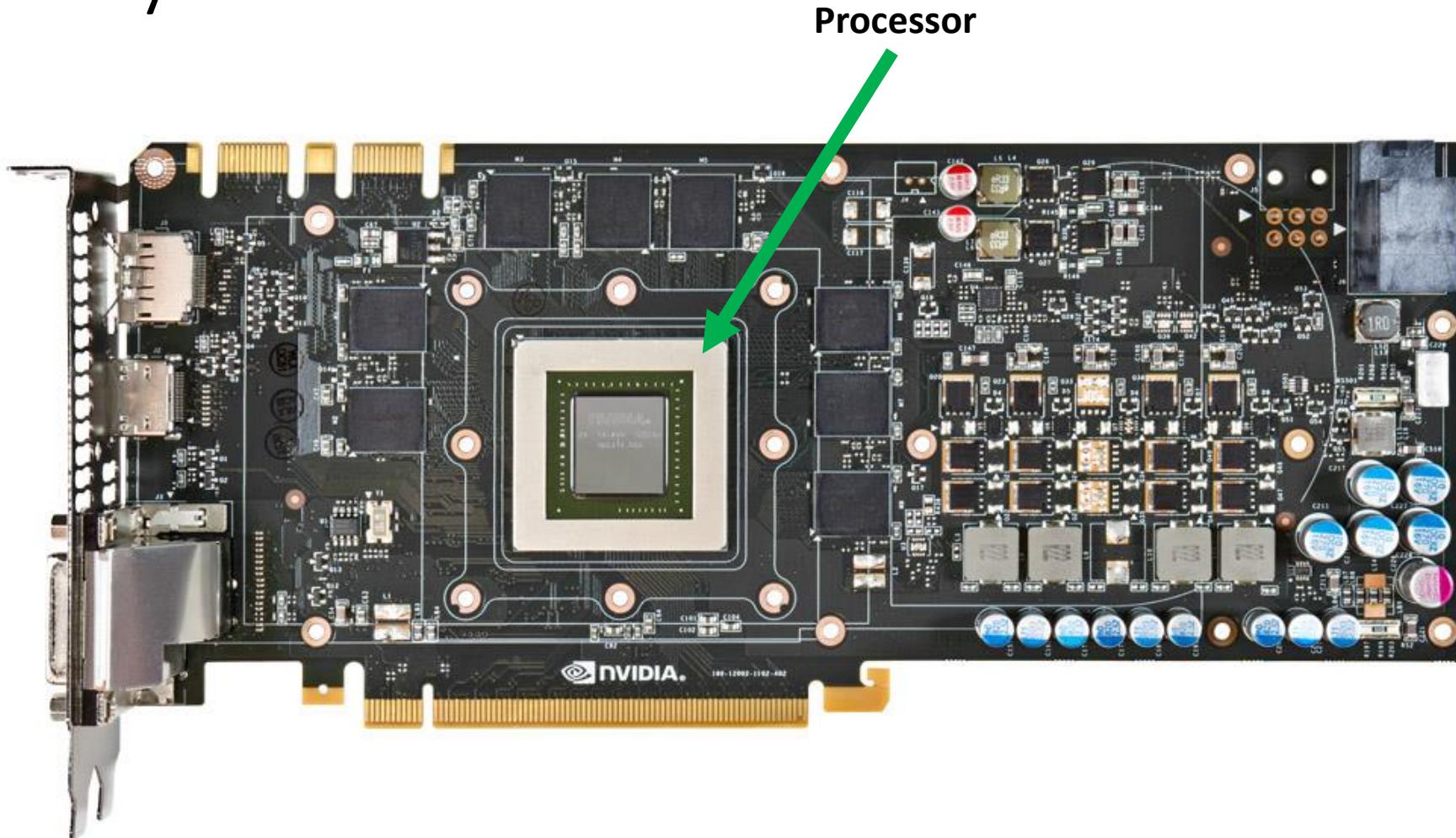
DRAM
e.g. GDDR6/HBM2



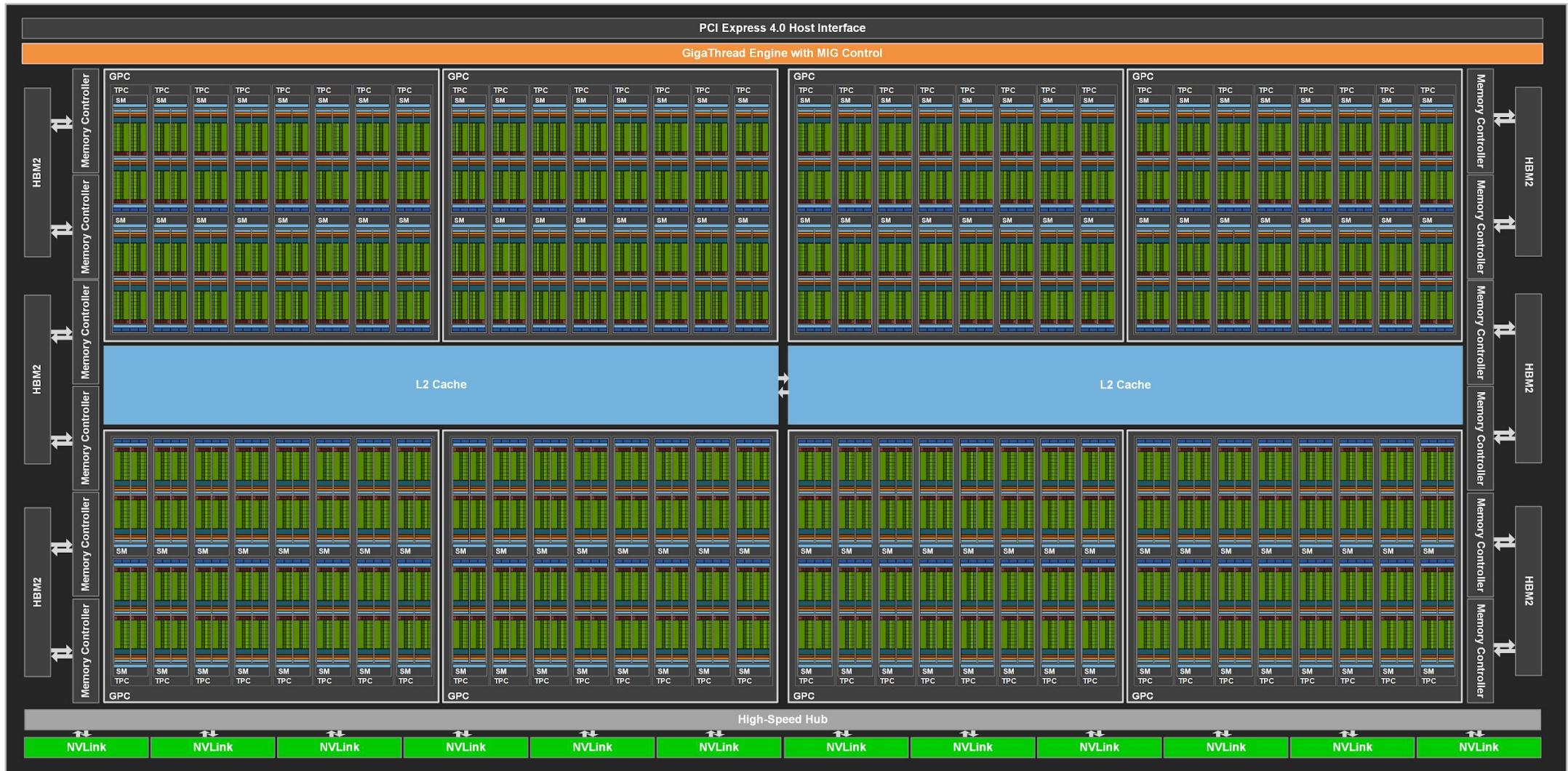
Anatomy of a GPU



Anatomy of a GPU



Anatomy of a GPU: A100

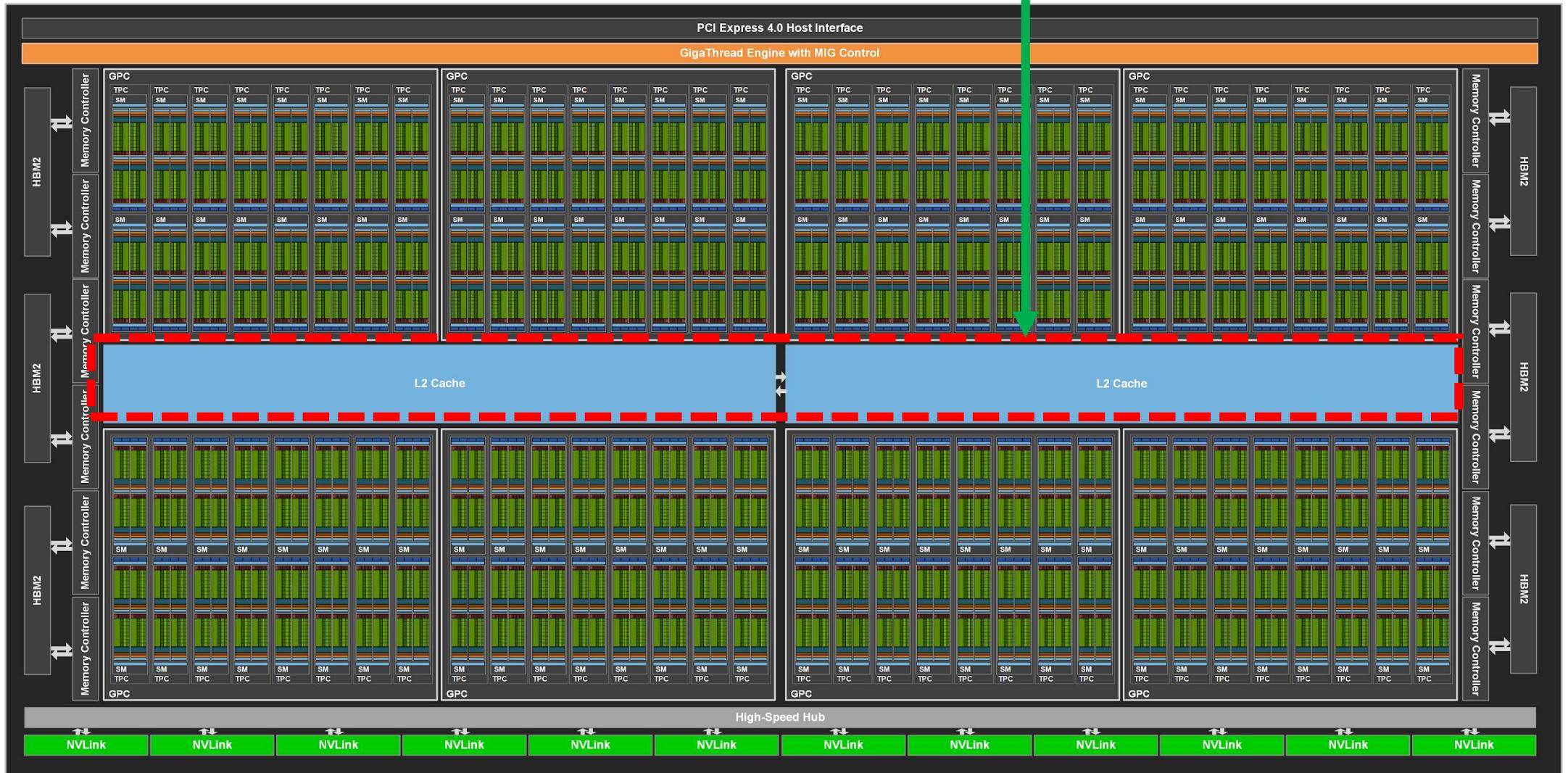


Anatomy of a GPU: A100

HBM2
Memory



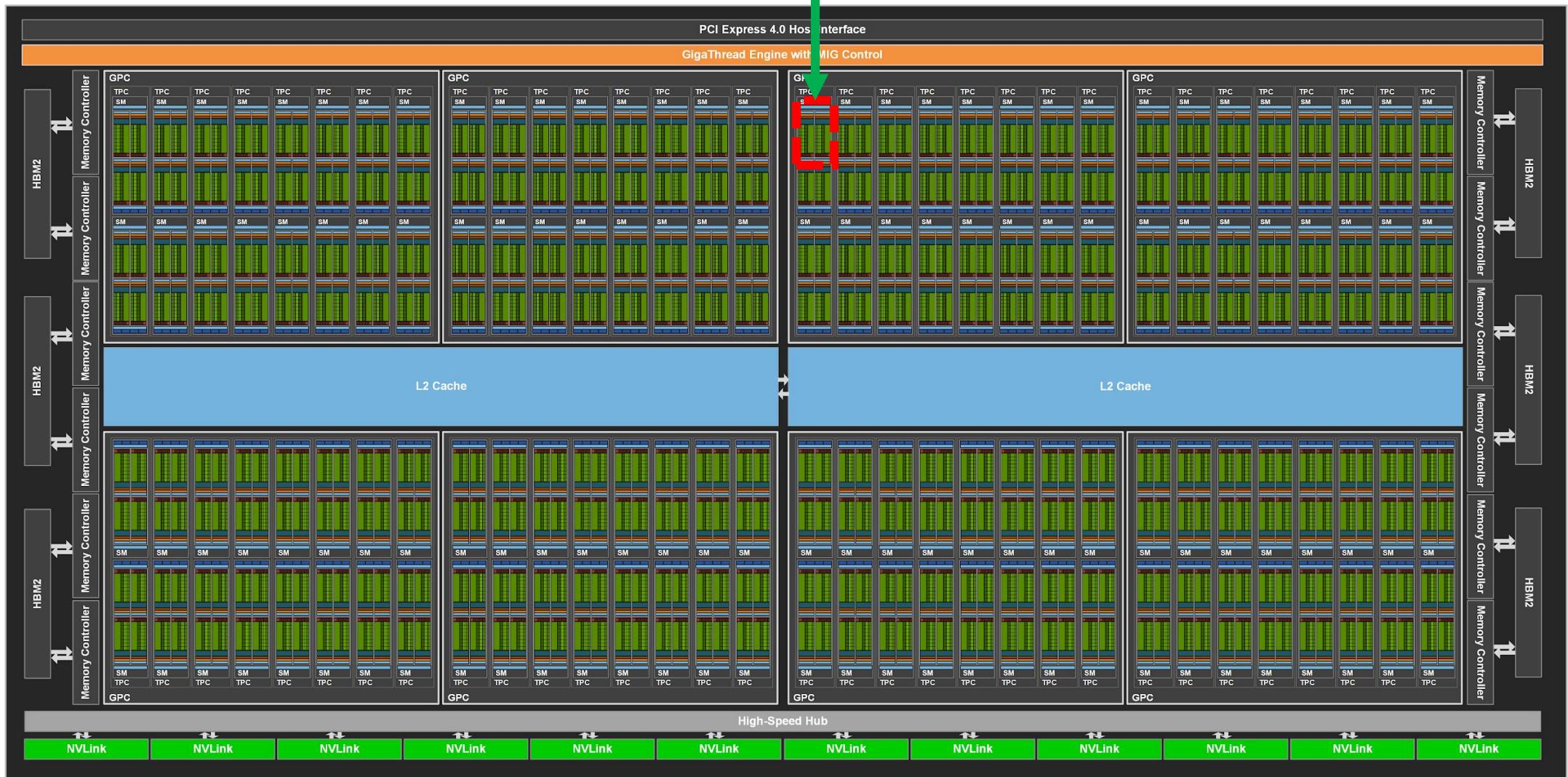
Anatomy of a GPU



<https://developer.nvidia.com/blog/nvidia-ampere-architecture-in-depth/>

Anatomy of a GPU

Streaming Multiprocessor (SM)



GPU Cores

- Contains many “cores” which can be used to perform math operations
- Less general purpose and slower than a CPU “core”
- Focuses on floating-point and integer math (32 bits)
- Has a much smaller cache than a CPU core





GPU Platforms

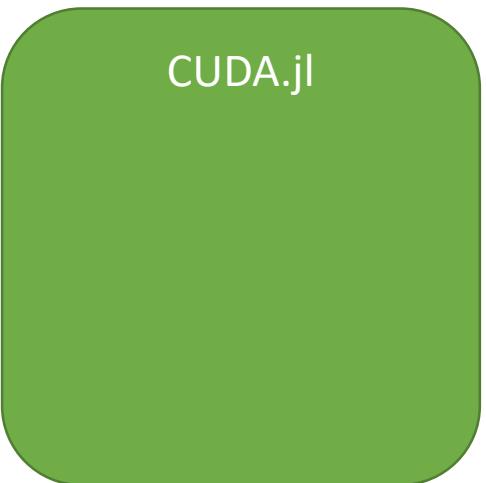
CUDA

- NVIDIA has the most market share in HPC GPU applications (especially in AI/ML)
- CUDA is the most popular **hardware platform** and **API** for programming GPUs
- Provides an **abstraction** to allow programming for many different GPU models, providing a virtual instruction set to the programmer
- Has GPU implementations of common algorithms such including **BLAS**, **FFT**, **RNG** and **linear solvers**
- More recently, has **CUDNN** for machine learning acceleration

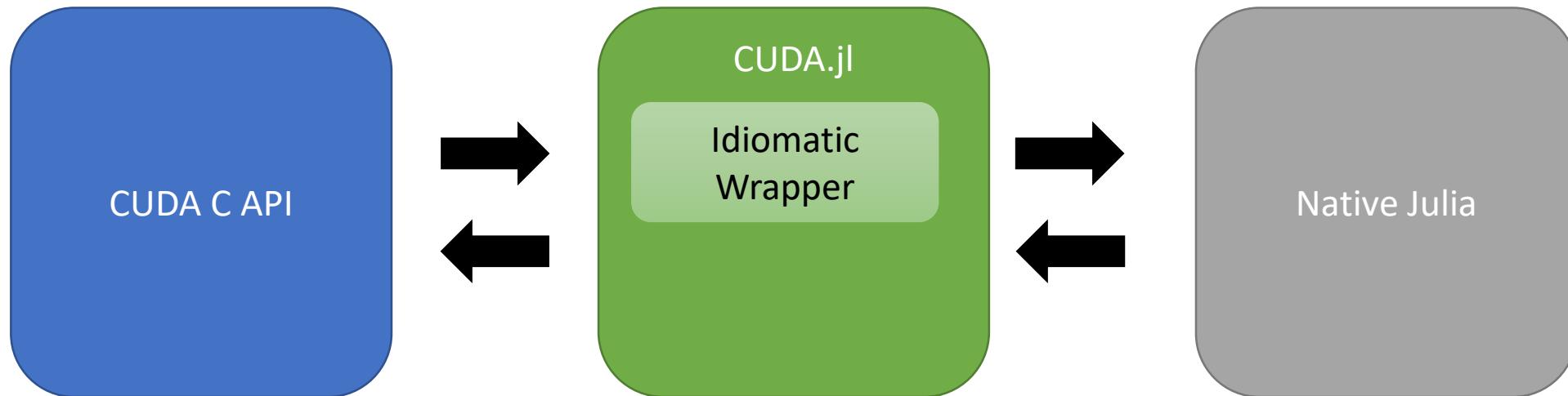
CUDA.jl



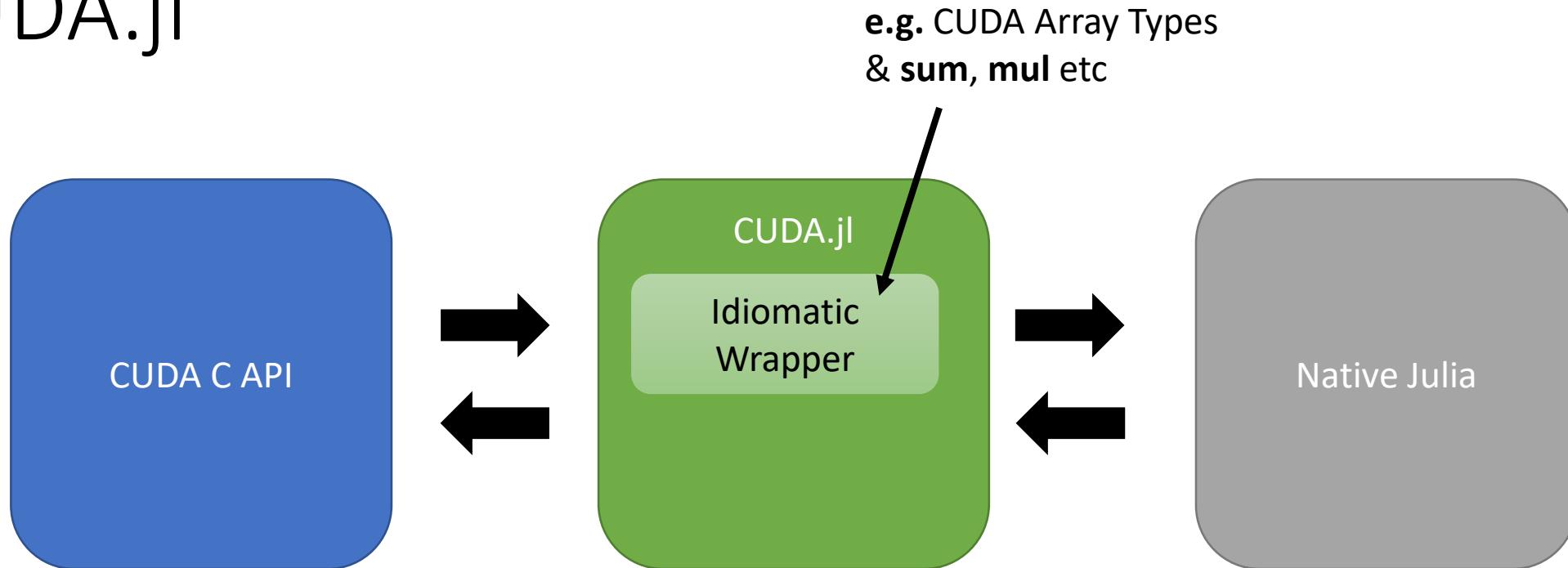
CUDA.jl



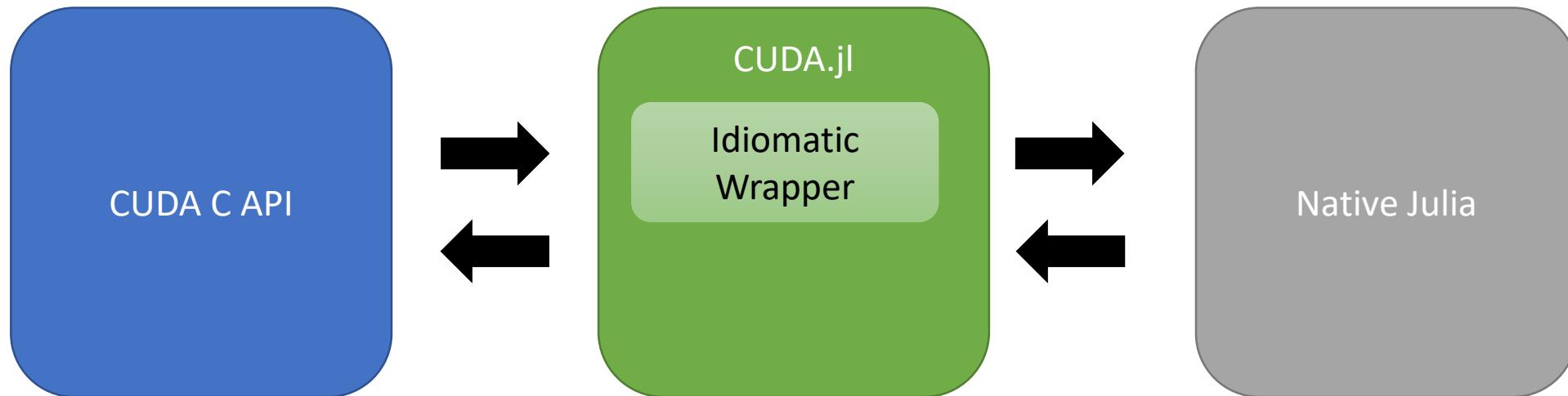
CUDA.jl



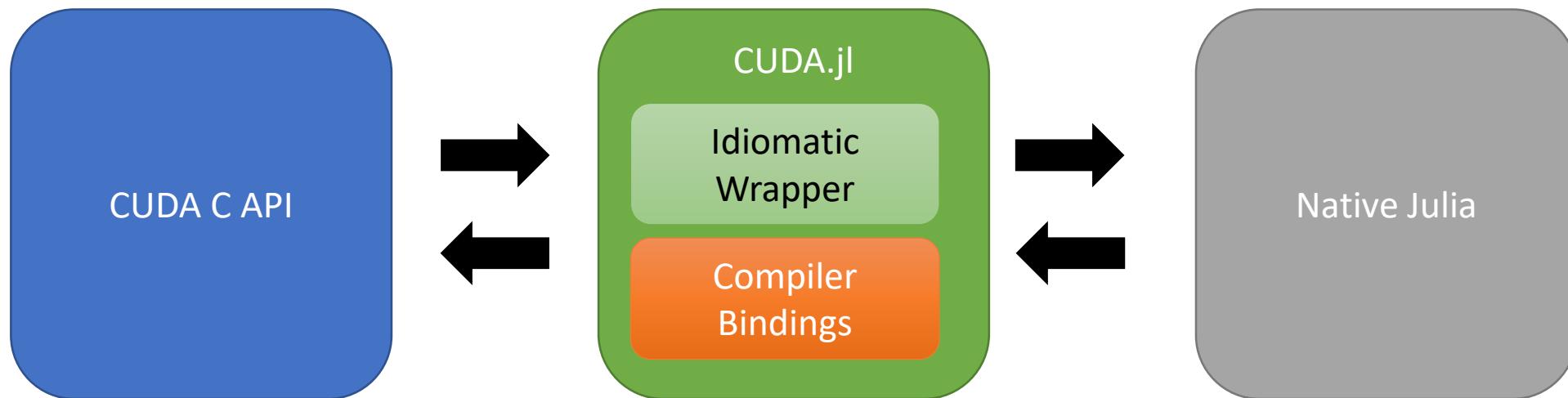
CUDA.jl



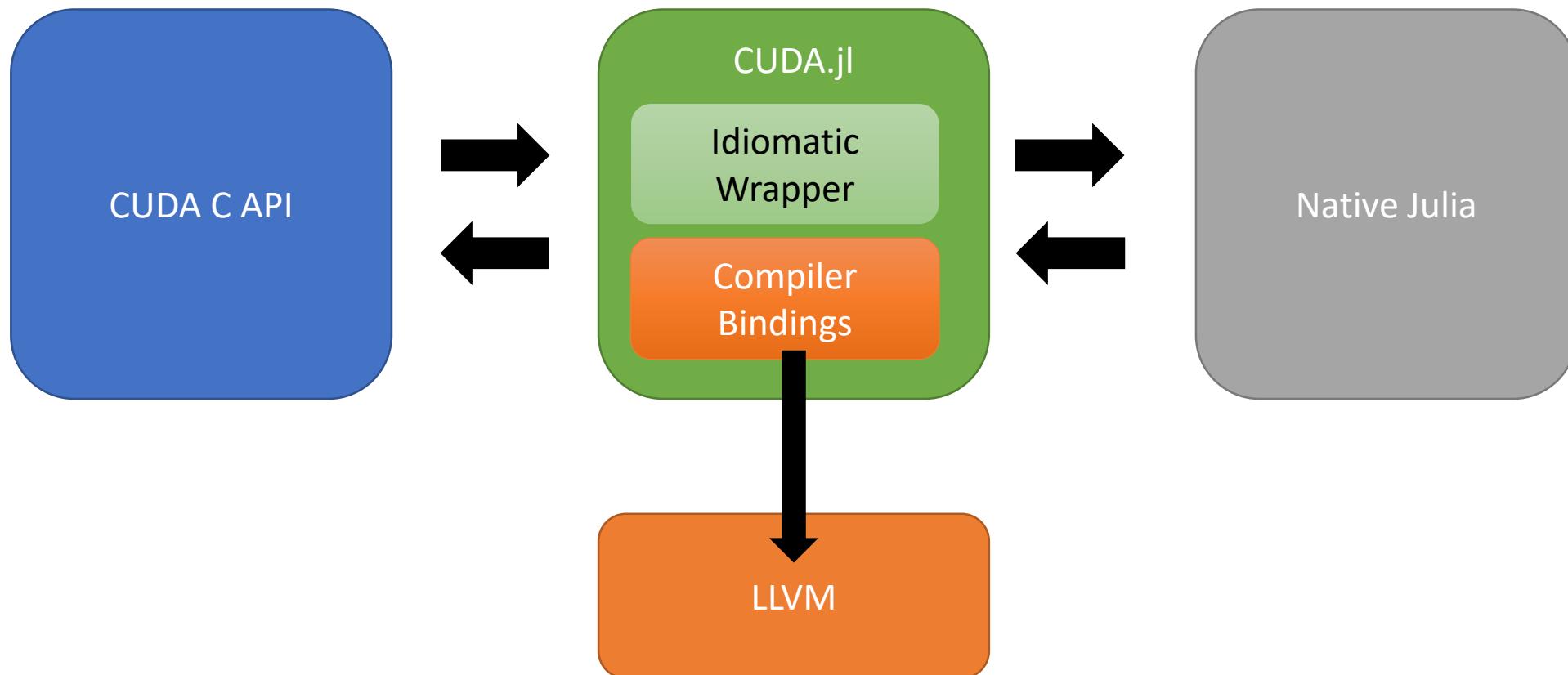
CUDA.jl



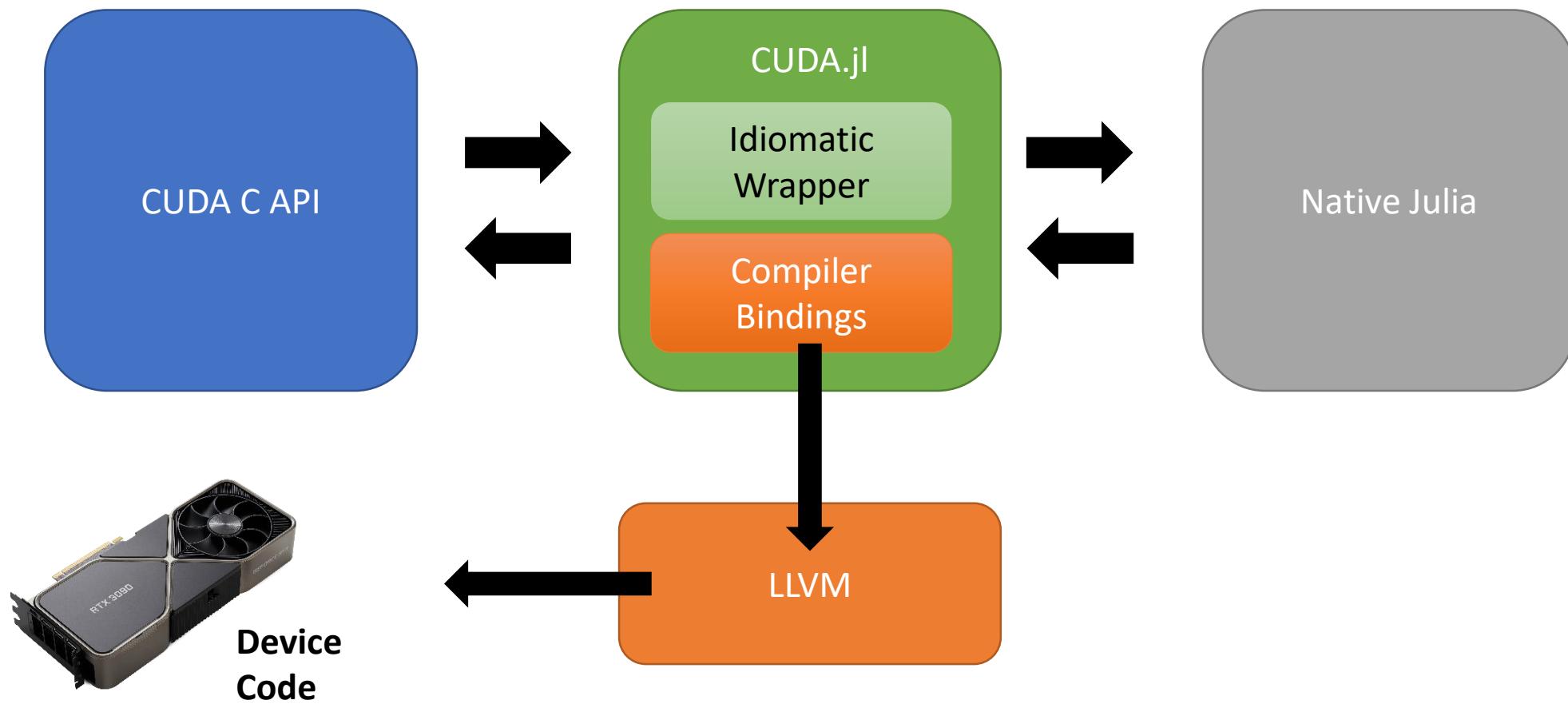
CUDA.jl



CUDA.jl



CUDA.jl

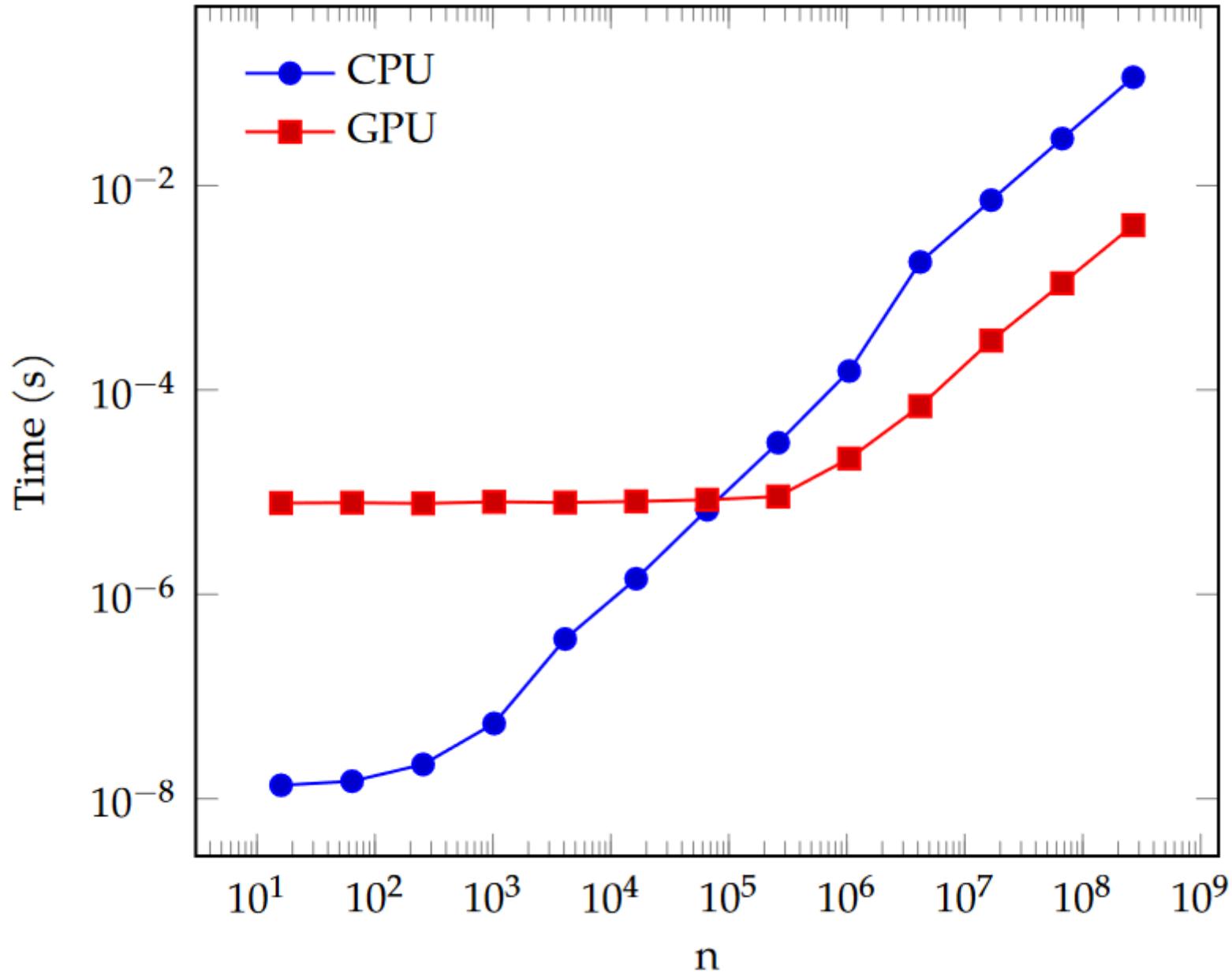


CUDA.jl

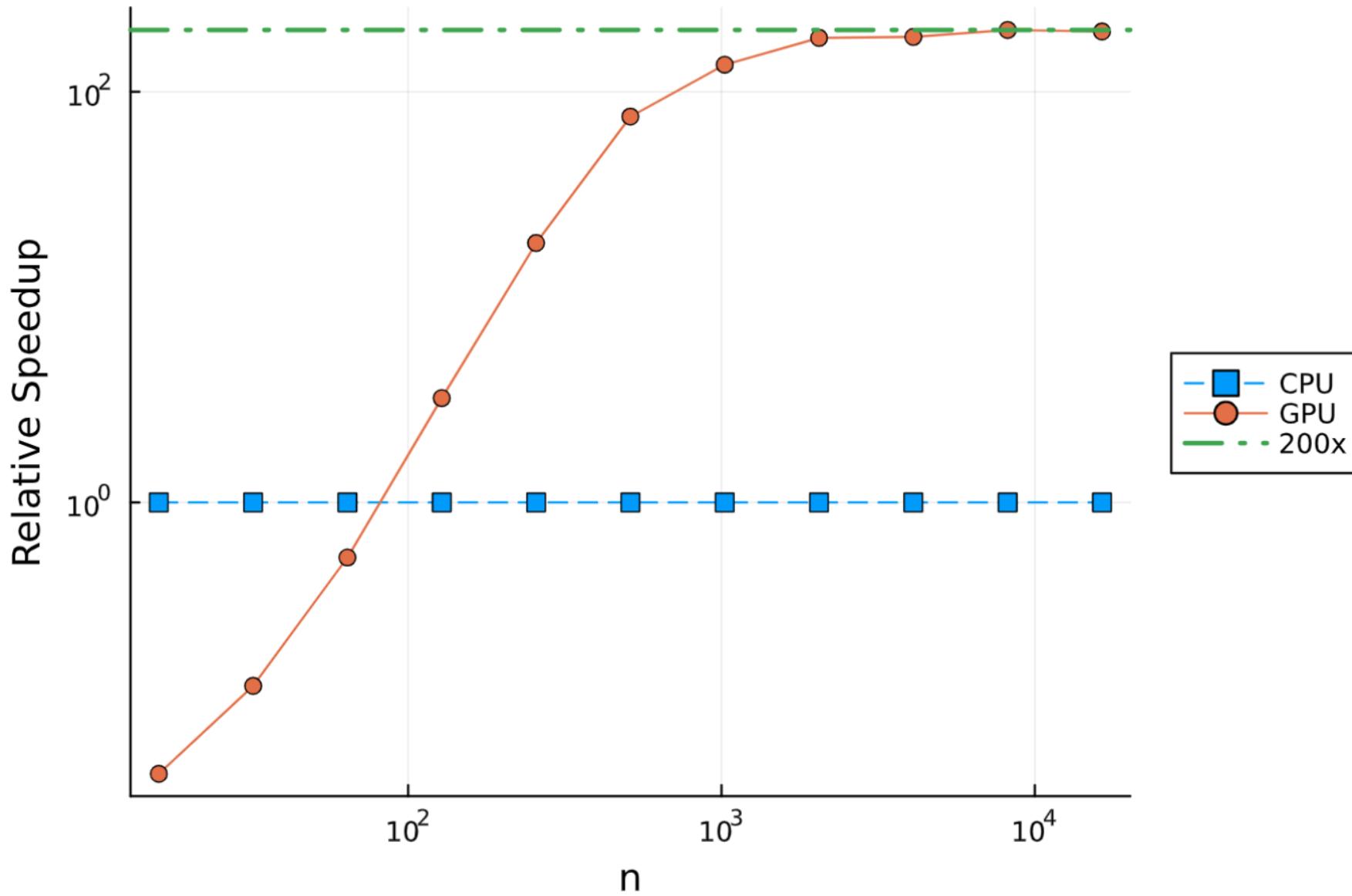
Array Programming

<https://github.com/MPAGS-HPC-in-Julia/gpu-demo>

Vector Addition: $\mathcal{O}(n)$



Matrix Multiplication: $\mathcal{O}(n^3)$



Array Programming with CUDA.jl

Restriction

- Scalar indexing on GPU transfers data between GPU and CPU and is **very slow**
- All memory required by the computation on the GPU **must** already exist on the GPU
- Broadcasted functions must be **type stable** to be successfully compiled into native GPU code

Tip

- Avoid “**for**” loops and use broadcasting and generic functions
- Use in-place operations where possible to avoid excessive allocation & copying
- Use the “**@code_warntype**” macro to make sure the function is type safe

Generic GPU Programming

- Stick to broadcasting and functions with GPU specialisations such as “**map**”, “**reduce**”, “**sum**” etc
- This allows code to work with both CPU and GPU arrays
- If code is more complex, and requires a “**for**” loop, you must write a custom GPU program – called a **kernel**
- **CUDA.jl** allows us to write kernels in pure Julia, which can get compiled to native device code
- Packages like **KernelAbstractions.jl** can help to write generic device-independent code

Next Session – CUDA.jl Kernel Programming

Assignment

<https://classroom.github.com/a/q9ycWkI6>

Task:

- Calculate the visualisation for the Julia set fractal using the GPU

Julia Set

