An introduction to

The CUDA programming environment

- Introduction : the rise of GPUs
- NVIDIA GPUS and CUDA
- Basic syntax
- Memory organization
- Examples

GPUs and the CUDA environment

➤ GPUs [Graphics Processing Units] are very powerful co-processors for graphics.

➤ Idea: why not use them for numerical computing?

➤ GPUs are present in every workstation - for graphics processing

✍1 Find out what graphics card you have on your desktop computer or laptop..

➤ Characteristics:

–large data arrays, streaming data

–fine-grain SIMD computations

–single precision floating point computation

- Difficulty: software.
- Solution: CUDA
- CUDA = Compute Unified Device Architecture
- Introduced in 2006 for NVIDIA GPUs
- Idea of attached processor [or co-processor]– Not new [e.g. FPS AP-120B 'array processor' unveiled in 1981]

Terminology

- GPGPU : General purpose GPU
- GPU-accelerated computing: use GPUs along a CPU to speed-up computing

GPUs and the CUDA environment

- Currently a very popular approach to: inexpensive supercomputing
- See a series of articles in 2008 - when this whole thing started: *CUDA - supercomputing for the masses* by Rob Farber in 'Dr. Dobbs'
- You can buy a Teraflop peak power for around $1,500.
- Amazingly this price has remained ∼ the same – Difference: you get more from one GPU Example Tesla Products

Megatrend: GPU Performance being tuned for Deep Learning (single precison 'tensor-flops', vs FP64 teraflops).

GPU model	Price	FP64 Perf.	$ / TFLOPS	DL (FP32) Perf.	$/ TensFPS
V100 16GB	$10,664*	7 TFLOPS	$1,523	112 TFLOPS	$95.21
32GB	$11,458*		$1,637		$102.3
P100 (16GB)	$ 7,374	4.7 TFLOPS	$ 1,569	18.7 TFLOPS	$394.33

* Note the huge jump in performance for Deep learning made in recent generation GPUs (Tesla V100).

* $\sim$ 10 years ago: 1 TFLOPS for approximately $1,350 (Tesla C2050) [see that Dr. Dobbs article]

The NVIDIA products

4 families

• **Tegra:**	Mobile and embedded devices (e.g., phones)
• **GeForce:**	Consumer graphics, gaming
• **Quadro:**	High-performance visualization
• **Tesla:**	High performance computing (Tesla M2050)

Example: The'cudaxx' cluster in cselabs

✍2 To do in class: Look at the 'cudaxx' cluster – Analyze one node: "cuda01.cselabs.umn.edu" –

➤ What GPU?

➤ Use the command *lspci*: Explore the unix command *lspci* before class. Look for "GPU" or "Graphics"

➤ PCI: Peripheral Component Interconnet [bus that attaches peripheral devices, e.g., USB, audio, RAID, Ethernet, ...]

➤ Another (unix) command: *nvidia-smi* (Nvidia System Management Interface) – For nvidia GPUs only

✍3 Read about *compute capability* in Nvidia Documentation. What is it for the nodes of the cudaxx cluster?

https://www.techpowerup.com/gpu-specs/geforce-gtx-470.c267

The new: The'veggie' cluster in cselabs

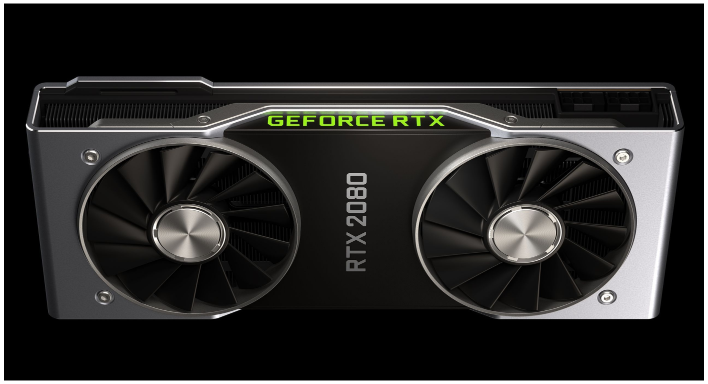
- Recall: each node has 80 cores
- + Equipped with NVIDIA Tesla T4

For details see:

[Tesla T4 @ NVIDIA]

CUDA Cores	2560
NVIDIA Turing Tensor Cores	320
Memory	16 GB GDDR6 w. ECC
Memory Interface	256-bit
Memory Bandwidth	320 GB/s
Single Precision Floating Point Perf.	8.1 TFLOPS (w. GPU Boost Clock)
Mixed Precision (FP16 / FP32)	65 TFLOPS
INT8-Precision	130 TOPS
INT4-Precision	260 TOPS
System Interface	PCI-Express 3.0 x16
Max. Power Consumption	70 Watt

Example: NVIDIA GeForce RTX 2080 Ti



- CUDA cores: 4,352
- Base Clock speed: 1350MHz
- Boosted Clock speed: 1545MHz
- FP32 peak speak: 13.44 TFlops

- RTX-OPS : 76T
- Memory capacity: 11GB GDDR6
- Memory bandwidth: 616 GB/sec
- Memory speed: 14 Gbps
- Memory interface width: 352-bit
- Memory bandwidth: 616GBps

See Comparisons

CUDA environment: Device and Host

- Host processor (CPU) and Device (GPU)
- Model built around many threads executed on the device

SIMT: Single Instuction Multiple Threads

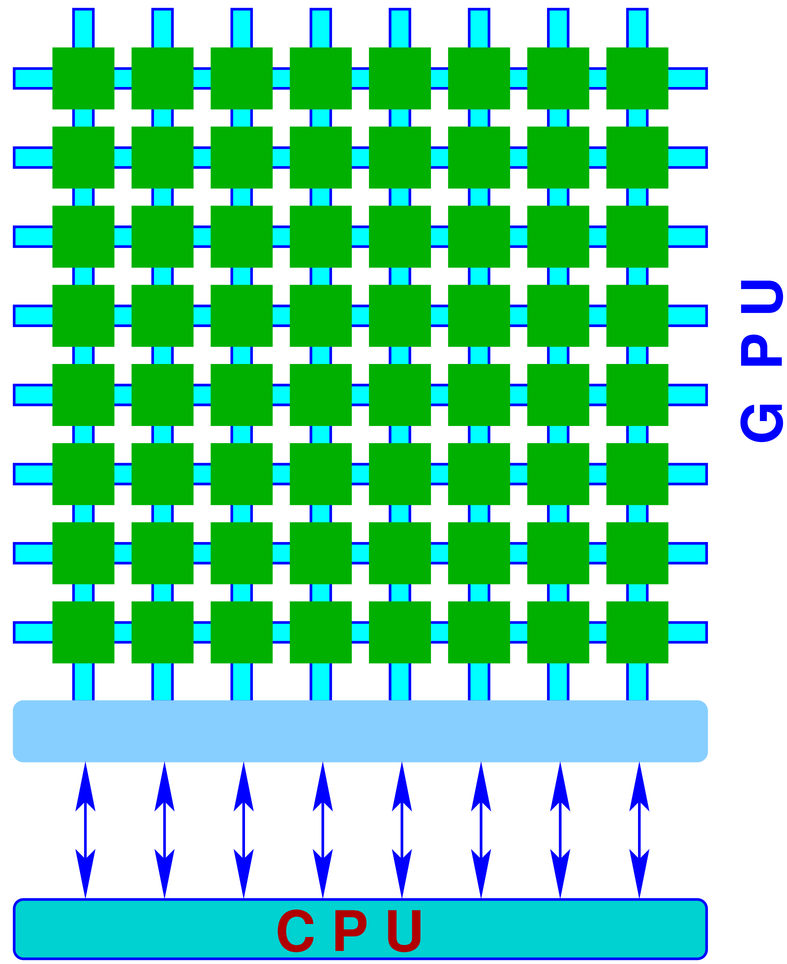
- A Kernel == a piece of code executed on the device
- Each kernel is run in a thread. Blocks of threads are executed on a Streaming Multiprocessor (SM). Details later.
- Idea: generate many threads (in the form of an SIMT code) which will be run on the GPU
- Host code may be C, C++, fortran90, ..
- Kernels are in C with CUDA syntax extensions

The CUDA environment: The big picture

➤ A host (CPU) and an attached device (GPU)

Typical program:

1. Generate data on CPU
2. Allocate memory on GPU
   `cudaMalloc(...)`
3. Send data Host → GPU
   `cudaMemcpy(...)`
4. Execute GPU 'kernel':
   `kernel <<<(...)>>>(..)`
5. Copy data GPU →CPU
   `cudaMemcpy(...)`

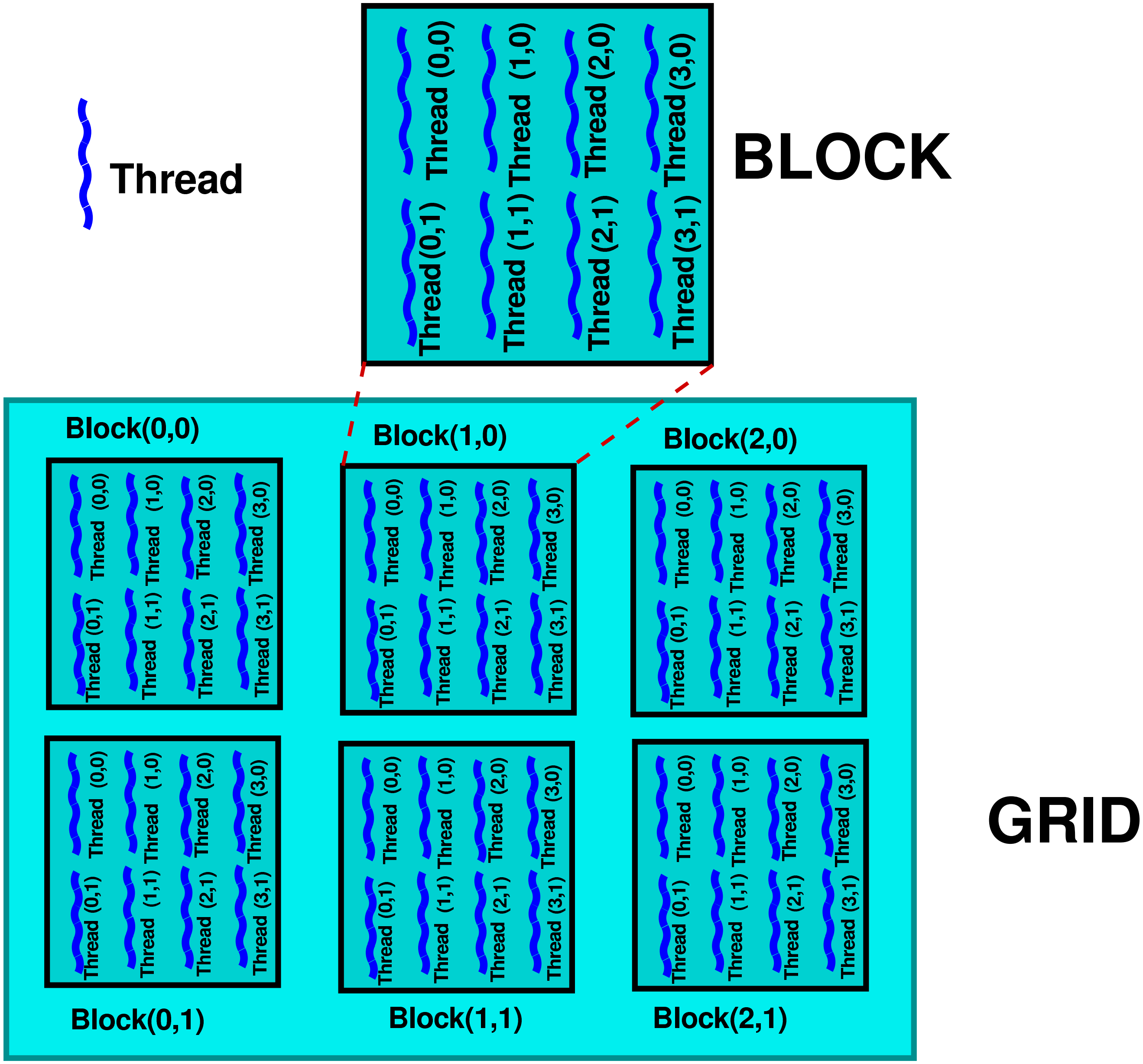


Threads, Warps, Blocks, and Grids

- A group of 32 Threads is a Warp
- Warps grouped into thread Blocks
- Blocks have $\leq \mathbf{1,024}$ threads
- Thread blocks are grouped into grids.

Thread $\longrightarrow$ Block of Threads $\longrightarrow$ Grid of Blocks

- Lots of flexibility in selecting block/grid shapes and dimensions
- Documentation


Thread
BLOCK
Thread (0,0)
Thread (1,0)
Thread (2,0)
Thread (3,0)
Thread (0,1)
Thread (1,1)
Thread (2,1)
Thread (3,1)
Block(0,0)
Block(1,0)
Block(2,0)
Block(0,1)
Block(1,1)
Block(2,1)
GRID

- Blocks may be 1-D, 2-D, or 3-D,
- Grids can also be 1-D, 2-D, or 3-D
- Related kernel variables:

  Grid: gridDim, blockIdx,   Block: blockDim, threadIdx

blockIdx, threadIdx are 3-Dimensional - can invoke

blockIdx.x, blockIdx.y, blockIdx.z

and:

threadIdx.x, threadIdx.y, threadIdx.z

Function Type Qualifiers

`__device__` : declares a function which executes on device. [Callable from the device only.]

`__global__` declares a *kernel* function - which is Executed on device, Callable from host only.

`__host__` declares a host function [executed on host, callable from host only]

If no qualifiers → considered *host* [but can also combine __host__ and __device__]

➤ There are some restrictions – see docs. For example recursion not supported on device. ...

Hello World in Cuda-ish:

```
#include <stdio.h>
__global__ void helloFromGPU(){
  printf("Hello World-Thread: %d\n",threadIdx.x);
}

int main(void) {
  helloFromGPU<<<1,16>>>();
  cudaDeviceSynchronize();
  return(0);
}
```

Example:

```
// Kernel definition:
__global__ void vecAdd(float *x,float *y,float *z)
{
   int i = threadIdx.x;
    z[i] = x[i] + y[i];
 }
```

```
    int main {
      ...
      /*  Kernel call:  [1 Block of $n$ threads] */
      vecAdd <<<1, n>>> (xd, yd, zd);
    }
```

CUDA environment: Basic syntax

Kernels are called with the $<<<\ >>>$ construct:

some_kernel_fun $<<<$ Dg, Db, Ns$>>>$

```
-   Dg = dimensions of the grid (type dim3 )
-   Db = dimensions of the block (type dim3 )
-   Ns = number of bytes shared memory dynamically
         allocated / block (type size_t). 0 default
```

➤ What is type `dim3`? An integer vector type [uint3] - used to specify dimensions

➤ Declare as: `dim3 var(dimx, dimy, dimz),`

➤ ... retrieve components as: `var.x, var.y, var.z`

➤ Unspecified components set to 1

Built-in variables

- `gridDim` is of type dim3. Contains dimension of grid. Similarly for `blockDim`
- Can retrieve block dimensions from

`blockDim.x, blockDim.y, blockDim.z`

- `blockIdx` (type: `uint3`) contains block ID within grid
- `threadIdx` (type: uint3) contains thread index within block.

Example:

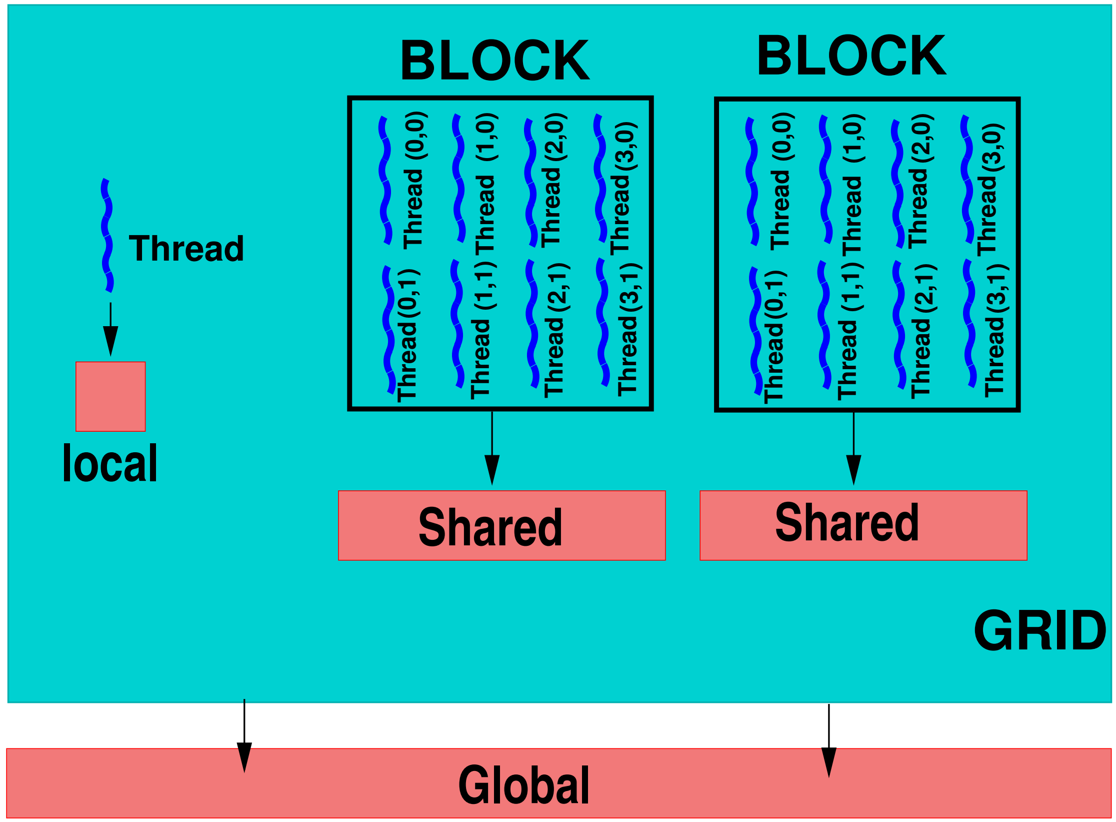
```
// Kernel definition:

__global__ void MatAdd(float A[N][N]),
             float B[N][N],float C[N][N]) {
  int i = threadIdx.x ;
  int j = threadIdx.y ;
  C[i][j] = A[i][j] + B[i][j]};
}
int main() {
  ...
// Kernel invocation
  dim3 dimBlock(N, N)};
  MatAdd<<<1, dimBlock>>>(A, B, C);
}
```

Example:

```
  __global__ void KernelFun(..)
//host:
 dim3  DimGrid(200,10);     //2000 thread blocks
 dim3  DimBlock(4,8,8);     //256  threads per block
 size_t SharedMemBytes=64;//shared mem. per block
 KernelFun<<<DimGrid,DimBlock,SharedMemBytes>>>(..)
```

- How to get index of a thread?
- For a 1-D block: Index of a thread & its thread ID are the same
- For a 2-D block of size `(Dx, Dy)`: thread ID of a thread of index `(x, y)` is `(x + y*Dx)`;
- For 3-D blocks of size `(Dx, Dy, Dz)`: thread ID of a thread of index `(x, y, z)` is `(x + y*Dx + z*Dx*Dy)`.

CUDA environment: Memory Hierarchy



Threads can access their local memories, shared memroy of their block, and global memory.

CUDA environment: Device & Host Memory

- Device (GPU) memory distinct from that of host.
- Kernels operate only on device memory
- Also: Texture memory [called CUDA arrays] –
- Can allocate device memory with `cudaMalloc()`
- Copy from host to device with `cudaMemcpy()`
- Can also use `cudaMallocPitch()`,`cudaMalloc3D()`, `cudaMemcpy2D()`, `cudaMemcpy3D()`, [see prog. guide]

CUDA environment: Shared vs. Global Memory

➤ By default, the kernel will use global memory

➤ However, shared memory is *much* faster and should be used when possible

➤ Declarations:

```
__shared__ float, int,..
```

CUDA documentation, resources

- Main document from the CUDA main site
- A PDF document also available [short-cut available in Canvas]
- General documentation site: Here
- CUDA sample source codes: Here

New: openACC

- Note: Under development.
- Main Idea: use directives – Very similar to openMP
- Supported by vendors: there is a chance it will replace CUDA (?)

Importantly: it is now part of gcc.7.xx

Example: : *product of two vectors*

- Much simpler than under CUDA [used to be test1.cu]
- Available and works on *Veggie* cluster [gcc version 9.xx installed]
- Docs: See this page → https://gcc.gnu.org/wiki/OpenACC for status and the openACC homepage → https://www.openacc.org/

```
int main(void){
  float *x, *y;
/*-------------------- size of arrays */
  const int N = 20;
  size_t size = N * sizeof(float);
/*-------------------- Allocate array and set
 values */
  y = (float *)malloc(size);
  x = (float *)malloc(size);
  for (int i=0; i<N; i++) {
    y[i] = (float) (i+1);
    x[i] = (float) (i-1);
  }
#pragma acc parallel loop
  for (int i=0; i<N; i++)
     y[i] = y[i]*x[i];
/*-------------------- print result */
  for (int i=0; i<N; i++)
     printf("%d %8.2f\n", i, y[i]);
/* -------------------- free memory */
   free(x); free(y);
 }
```

openACC: A few important directives

- *#pragma acc parallel* Defines a parallel region
- *#pragma acc kernels* Gives hint to compiler that a block that can 'kernelized'
- *#pragma acc loop* defines the type of parallelism in parallel or kernels region.
- *#pragma acc data* defines and copies data to / from device

➤ On Canvas: full documentation from openACC-standard.ORG

➤ Book by Kirk and Hwu (see syllabus): Chapter 19

➤ See sample code VecAdd on Canvas for illustration

➤ Group assignment: Mat-Add in openACC $\longrightarrow$ with a goal of getting best performance.

Run-time functions

```
int acc_get_num_devices( acc_device_t );
void acc_set_device_type( acc_device_t );
acc_device_t acc_get_device_type( void );
int acc_get_device_num( acc_device_t );
void acc_set_device_num( int, acc_device_t );

...
```

Some of these can also be set via environment variables

```
tcsh:
 setenv ACC_DEVICE_TYPE NVIDIA
bash:
 export ACC_DEVICE_TYPE=NVIDIA

tcsh:
 setenv ACC_DEVICE_NUM 1
bash:
 export ACC_DEVICE_NUM=1
 ...
```