GPU Intro and Python AI + GPU

High-Performance Computing

Summer 2021 at GIST

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Jupyter Notebook

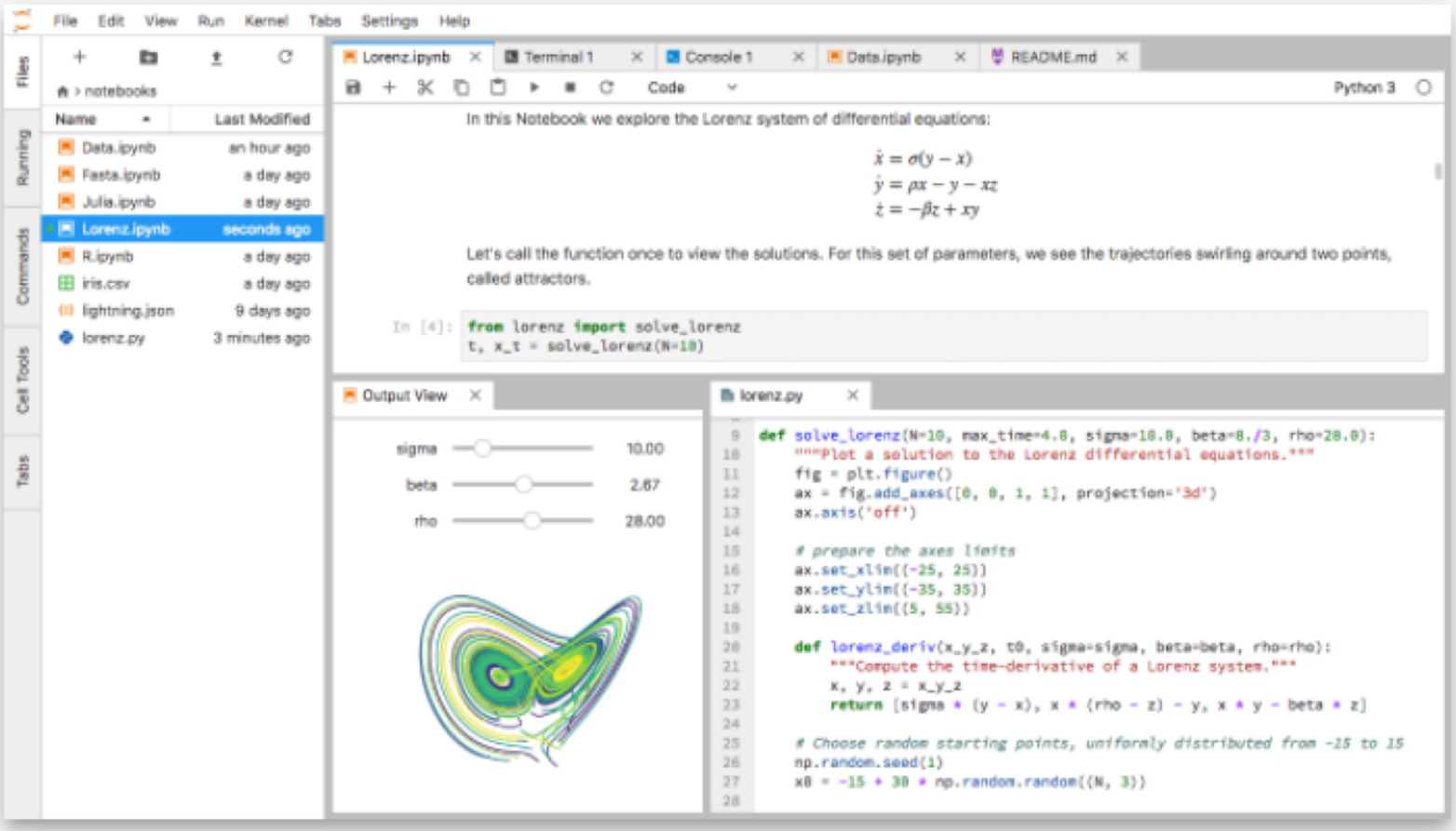
- https://jupyter.org/

Project Jupyter exists to develop open-source software, open-standards, and services for interactive computing across dozens of programming languages.

Jupyter Lab

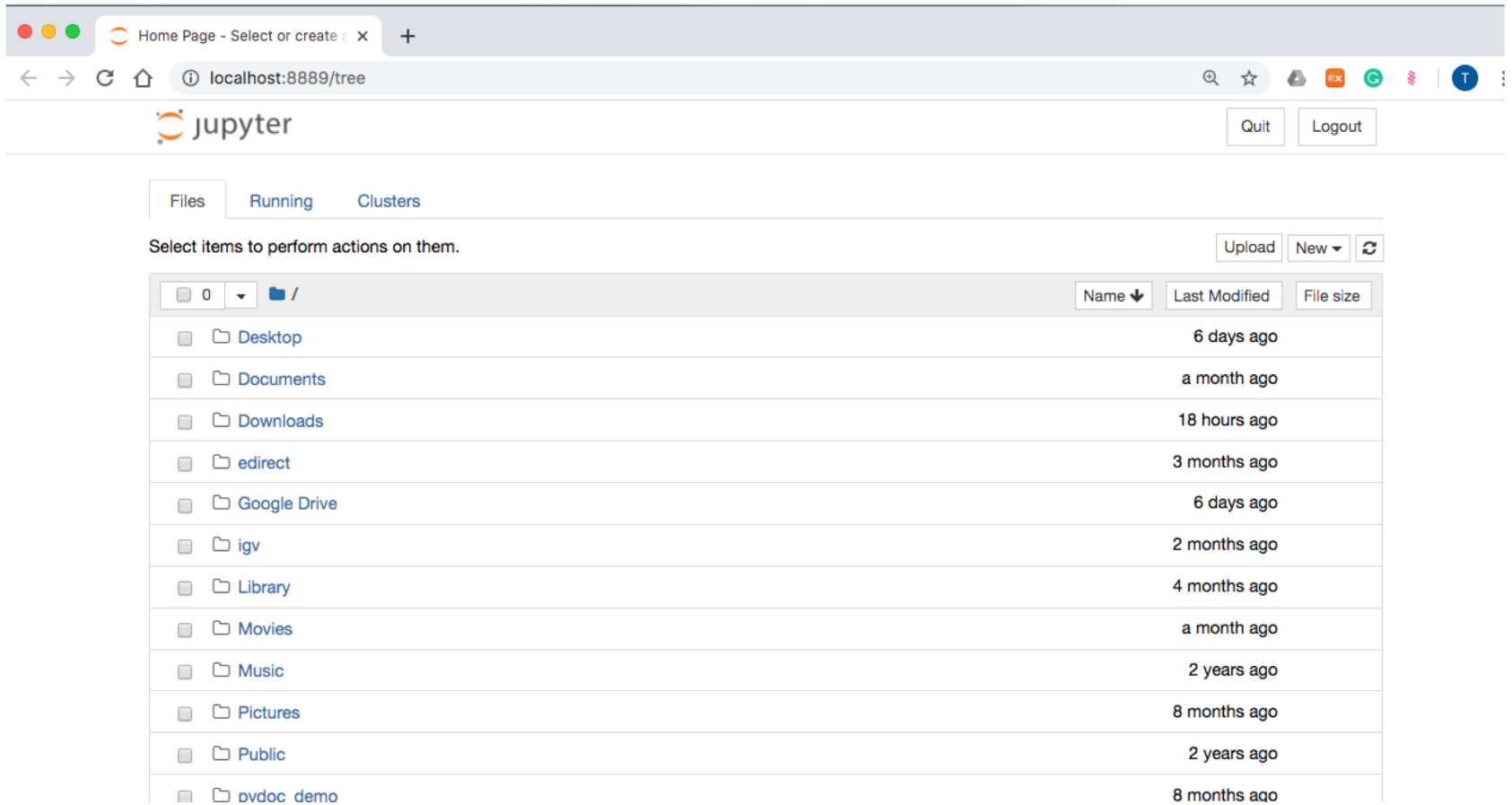
- https://jupyterlab.readthedocs.io/en/stable/

JupyterLab is the next-generation web-based user interface for Project Jupyter. Try it on Binder.
JupyterLab follows the Jupyter Community Guides.



Run Jupyter Notebook (Jupyter Lab)

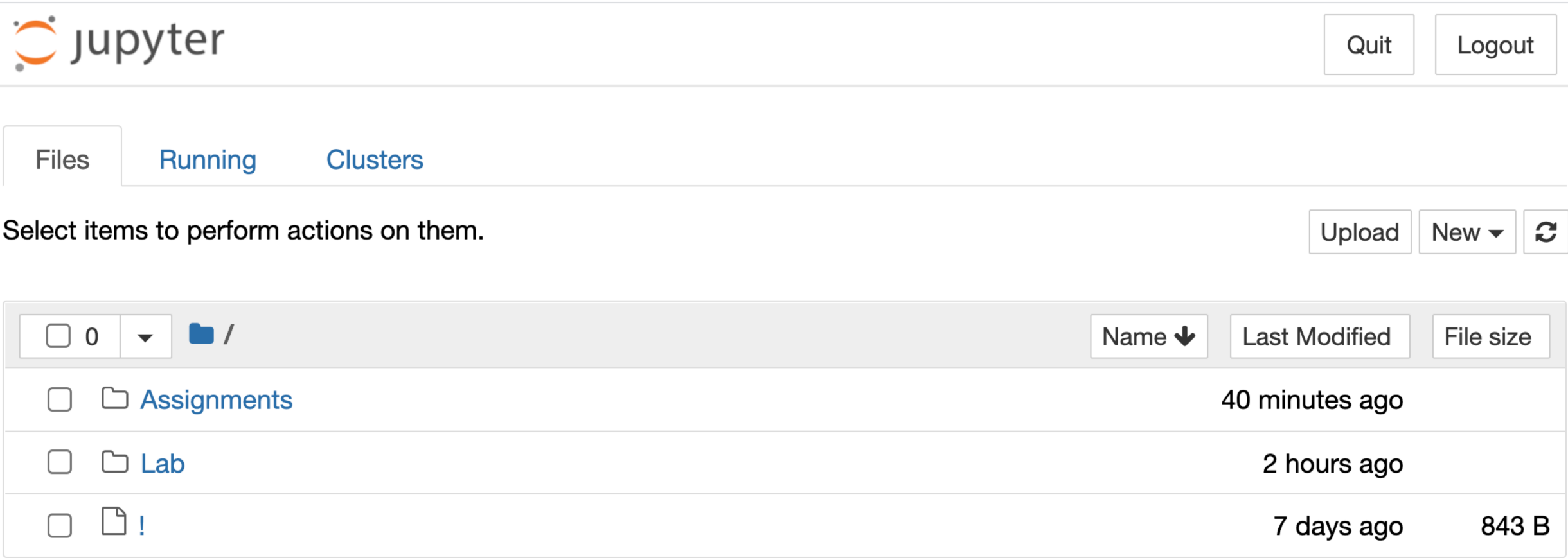
- Install and run
  - Jupyter notebook: just type “jupyter notebook” and it will open a default web browser



How to run the program on GIST VM via Jupyter Notebook?

- https://techtalktone.wordpress.com/2017/03/28/running-jupyter-notebooks-on-a-remote-server-via-ssh/
- Remote (Server: our case is GIST VM):
  - $ jupyter notebook password
  - $ jupyter notebook --no-browser --port=8887
    - Be careful: Each user will use a unique port. If someone is using the port, change the 8887 to something else.
- Local (Mac or Windows):
  - $ ssh -N -L localhost:8888:localhost:8887 ai@210.125.85.148
  - Open a browser and type localhost:8888

How to run a program on GIST VM via Jupyter Notebook?



GPU

- GPU: Graphics Processing Unit
  - Designed for real-time graphics
  - Present in almost every PC
  - Increasing realism and complexity

What is GPU?

- It is a processor optimized for 2D/3D graphics, video, visual computing, and display.
- It is highly parallel, highly multithreaded multiprocessor optimized for visual computing.
- It provide real-time visual interaction with computed objects via graphics images, and video.
- It serves as both a programmable graphics processor and a scalable parallel computing platform.
- Heterogeneous Systems: combine a GPU with a CPU

Nvidia GPU

The Best Budget Graphics Cards in 2021

Featured

NVIDIA GEFORCE RTX 3070

- Cooling System: Fan
- Boost Clock Speed: 1.73 GHz
- GPU Memory Size: 8 GB

$499.99

CHECK AVAILABILITY

+ Compare

Featured

NVIDIA GEFORCE RTX 3060 TI

- Cooling System: Fan
- Boost Clock Speed: 1.67 GHz
- GPU Memory Size: 8 GB

$399.99

CHECK AVAILABILITY

+ Compare

NVIDIA GEFORCE RTX 3080

- Cooling System: Fan
- Boost Clock Speed: 1.71 GHz
- GPU Memory Size: 10 GB

$699.99

CHECK AVAILABILITY

+ Compare

RTX 3080


GEFORCE RTX 3080
THE ULTIMATE PLAY
The GeForce RTX™ 3080 delivers the ultra performance that gamers crave, powered by Ampere—NVIDIA's 2nd gen RTX architecture. It's built with enhanced RT Cores and Tensor Cores, new streaming multiprocessors, and superfast G6X memory for an amazing gaming experience.
STARTING AT $699.00
2ND GENERATION
RT CORES
2X THROUGHPUT
3RD GENERATION
TENSOR CORES
UP TO 2X THROUGHPUT
NEW
SM
2X FP32 THROUGHPUT


RTX 3080

RTX 3080

- Specs (https://www.nvidia.com/en-us/geforce/graphics-cards/30-series/rtx-3080/)

GEFORCE RTX 3080

GPU Engine Specs:	NVIDIA CUDA® Cores	8704
	Boost Clock (GHz)	1.71
	Base Clock (GHz)	1.44
Memory Specs:	Standard Memory Config	10 GB GDDR6X
	Memory Interface Width	320-bit
Technology Support:	Ray Tracing Cores	2nd Generation
	Tensor Cores	3rd Generation
	NVIDIA Architecture	Ampere
	Microsoft DirectX® 12 Ultimate	Yes

RTX 3080

What is RTX?

- RTX stands for Ray Tracing Texel eXtreme and is also a variant under GeForce.
- The RTX cards were specially designed to support real-time ray tracing which made the video looked more beautiful.
- They were first announced in 2018 and uses Turing architecture.
- These cards support the DXR extension in Microsoft's DirectX12 and also DLSS (Deep Learning Super Sampling).

NVIDIA's Ampere architecture is an evolution of Turing, which powered the RTX 20 series. The new architecture includes huge gains in three key areas: streaming multiprocessors (SM) with double the throughput of their predecessors, second-gen RT cores that deliver significantly better performance, and third-gen Tensor cores that offer sizable gains in AI-based tasks.

https://www.windowscentral.com/nvidia-geforce-rtx-3080-review

RTX 3080

Graphics Card	RTX 3080 FE
Architecture	GA102
Process (nm)	Samsung 8N
Transistors (Billion)	28.3
Die size (mm^2)	628.4
GPCs	6
SMs	68
FP32 CUDA Cores	8704
Tensor Cores	272
RT Cores	68
Boost Clock (MHz)	1710
VRAM Speed (Gbps)	19
VRAM (GB)	10
VRAM Bus Width	320
ROPs	96
TPCs	34

https://www.tomshardware.com/reviews/nvidia-geforce-rtx-3080-review

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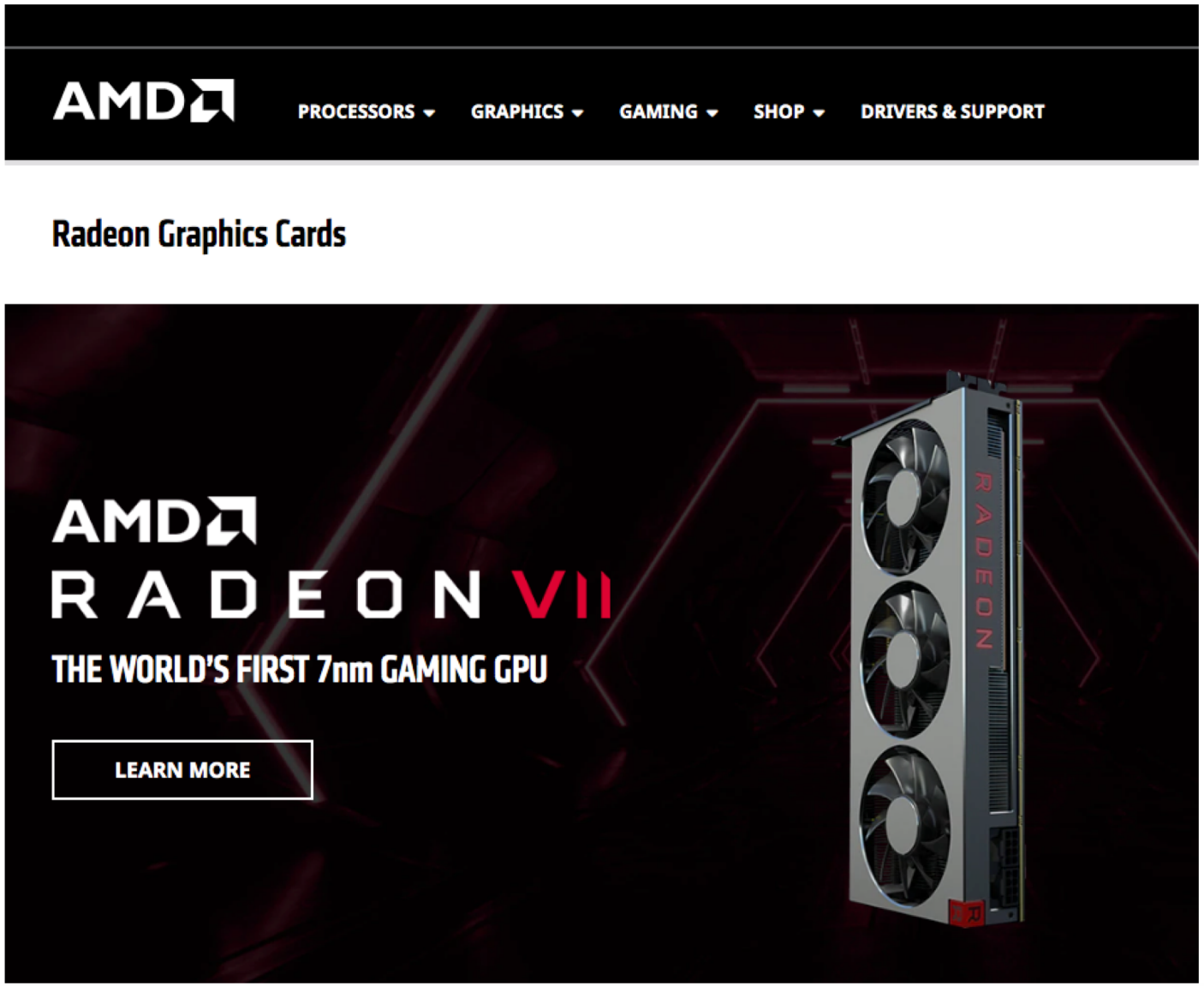
ROPs	96
TPCs	34

- Nvidia GPUs consist of several GPCs (Graphics Processing Clusters), each of which has some number of SMs (Streaming Multiprocessors). Nvidia splits each SM into four partitions that can operate on separate sets of data. With Ampere, each SM partition now has 16 FP32 CUDA cores, 16 FP32/INT CUDA cores, a third-gen Tensor core, load/store units, and a special function unit. The whole SM has access to shared L1 cache and memory, and there's a single second-gen RT core. In total, that means 64 FP32 cores and 64 FP32/INT cores, four Turing cores, and one RT core.
- https://www.tomshardware.com/reviews/nvidia-geforce-rtx-3080-review

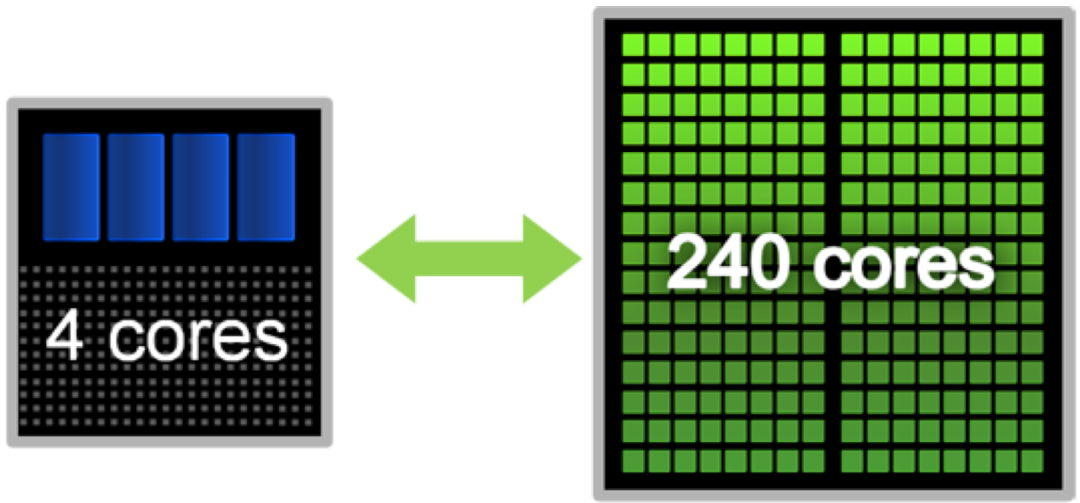
AMD Radeon



- My MacBook Pro has Radeon Pro 560

GPU and CPU

- Typically GPU and CPU coexist in a heterogeneous setting
- "Less" computationally intensive part runs on CPU (coarse-grained parallelism), and more intensive parts run on GPU (fine-grained parallelism)
- NVIDIA's GPU architecture is called CUDA (Compute Unified Device Architecture) architecture, accompanied by CUDA programming model, and CUDA C/C++ language



Difference among CPU, GPU, APU, FPGA, DSP, and Intel MIC?

- https://www.quora.com/What-is-the-difference-among-CPU-GPU-APU-FPGA-DSP-and-Intel-MIC

  - CPU
    - CPU is a general purpose processor. General Purpose in the sense that it is designed to perform a number of operations but the way these operations are performed may not be best for all applications. Graphics or Video Processing is one such example. Although a CPU can perform these tasks (which involve repeated additions/multiplications which may be performed in parallel) , the performance achieved is not good enough for modern applications.
  - GPU
    - Graphics processing Unit or GPU is designed to accelerate creation of images for a computer display. A CPU consists of a few cores optimized for sequential serial processing while a GPU consists of thousands of smaller, more efficient cores designed for handling multiple tasks simultaneously. They are designed to perform functions such as texture mapping, image rotation, translation, shading, etc. They may also support operations such as motion compensation, calculation of inverse DCT, etc. for accelerated video decoding.
  - Intel MIC
    - Intel Many Integrated Core or Intel MIC Architecture combines many Intel cores onto a single chip. Unlike its competitor in HPC market, NVidia TESLA GPU, it provides up to 61 cores. One of the key advantages that Intel MIC offers over NVidia GPUs is that it runs same instruction set as 64-bit Pentium. Standard C, C++ can be used for writing source codes to program these cores.
  - APU
    - APU stands for Accelerated Processing Unit which refers to the main processor of system which has additional functionality for accelerating execution of certain operations. This additional capability may be provided by an on chip graphics processing unit. In simple terms APU is CPU + GPU on a single chip.
  - DSP
    - Digital Signal Processor or DSP is optimized for high speed processing of numeric data representing the analog signals in real time. They are designed for quickly performing large number of numeric operations repeatedly on a series of data samples and are ideal for processing streaming digital signals. They provide functionalities that are helpful for DSP applications such as bit reverse addressing which is helpful for FFT computation, architectural support for very tight extremely low overhead loops, saturation arithmetic, etc.
  - FPGA
    - An FPGA (Field Programmable Gate Array) is entirely different from CPU, GPU, DSP, etc. in the sense that it is not a processor in itself i.e. it does not run a program stored in the program memory. In layman's terms, an FPGA is nothing but a bulk of reconfigurable digital logic suspended in a sea of programmable inter-connects. A typical FPGA may also have dedicated memory blocks, digital clock manager, IO banks and several other features which vary across different vendors and models. Since they can be configured after manufacturing at costumer's end, they can be used to implement any logic function (including but not limited to a processor core). This makes them ideal for re-configurable computing and application specific processing. Intel has recently announced a new range of Xeon Processors with integrated FPGA so that each chip can be configured at run type depending upon application needs.

GIST AI-X Cluster System

Computing

DGX A100

8x NVIDIA A100 GPUs

320 GB GPU Memory

1 TB System Memory

Dual AMD Rome
2.25 GHz (64-Core) CPU
9x 200Gb/s NIC

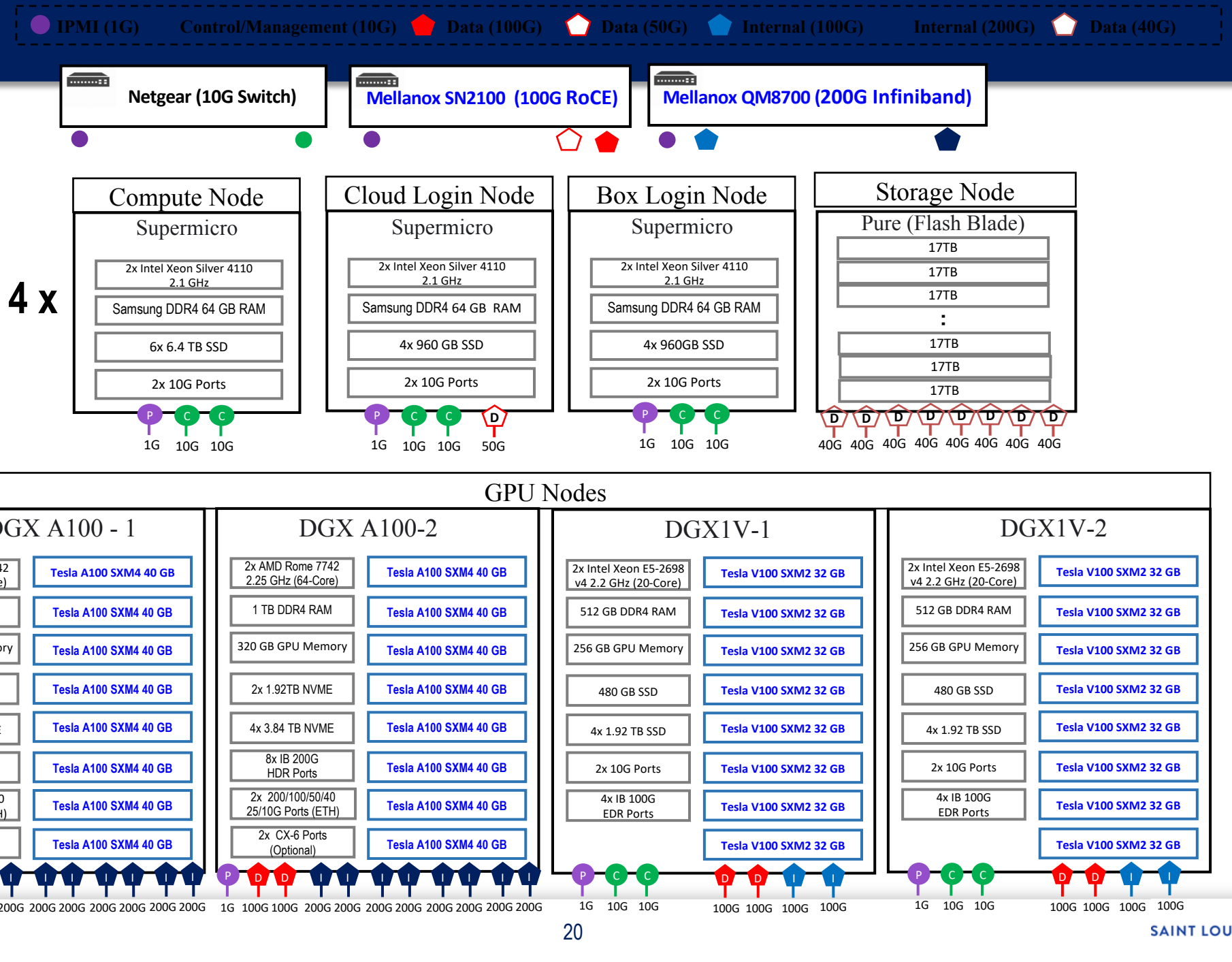
DGX-1V

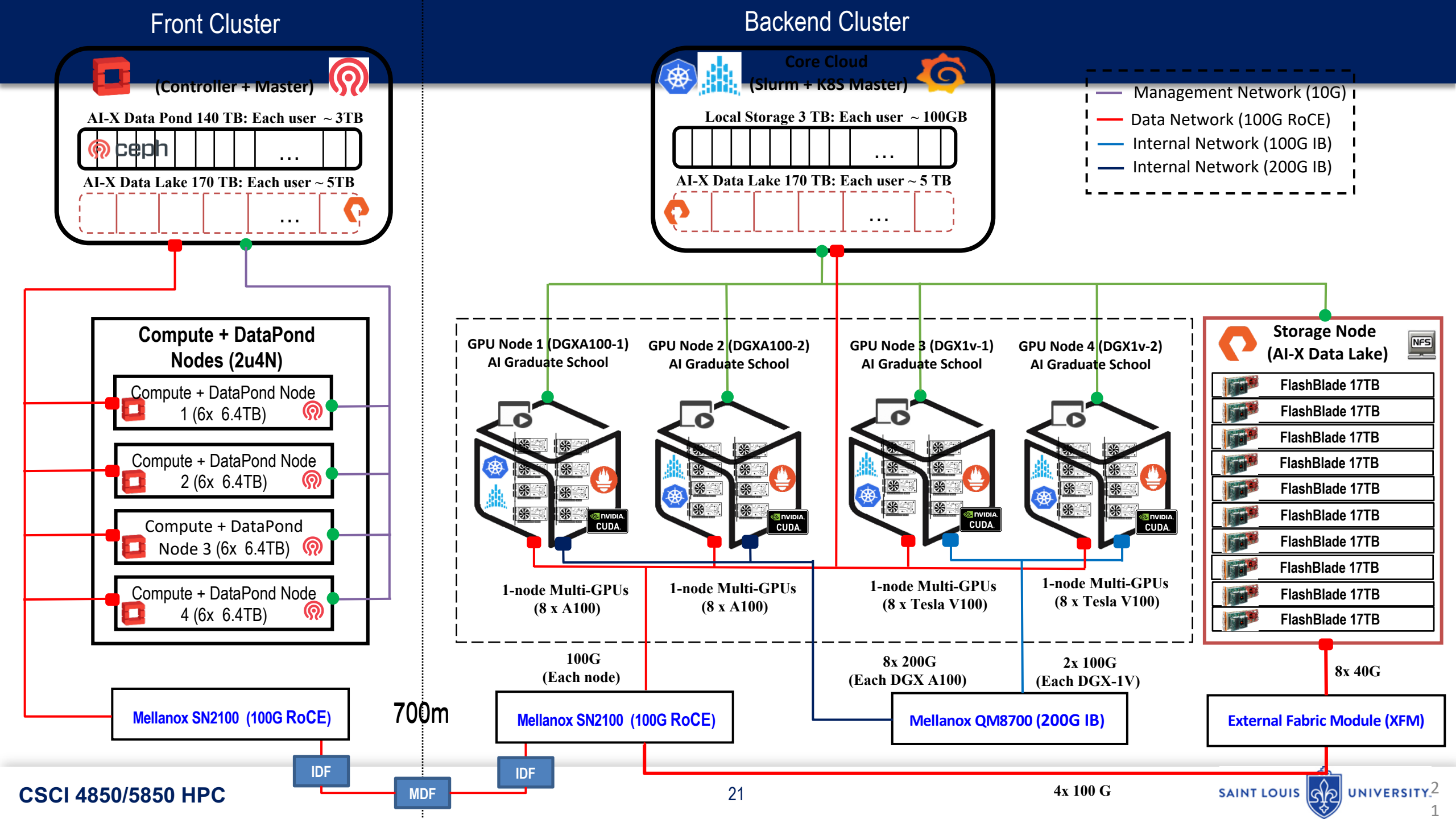
8x NVIDIA V100 GPUs

256 GB GPU Memory

512 GB System Memory

Dual Intel Xeon E5-2698 v4
2.2 GHz (20-Core) CPU
4x 100Gb/s NIC


IPMI (1G)
Control/Management (10G)
Data (100G)
Data (50G)
Internal (100G)
Internal (200G)
Data (40G)
Netgear (10G Switch)
Mellanox SN2100 (100G RoCE)
Mellanox QM8700 (200G Infiniband)
4 x
Compute Node
Supermicro
2x Intel Xeon Silver 4110 2.1 GHz
Samsung DDR4 64 GB RAM
6x 6.4 TB SSD
2x 10G Ports
P C C
1G 10G 10G
Cloud Login Node
Supermicro
2x Intel Xeon Silver 4110 2.1 GHz
Samsung DDR4 64 GB RAM
4x 960 GB SSD
2x 10G Ports
P C C D
1G 10G 10G 50G
Box Login Node
Supermicro
2x Intel Xeon Silver 4110 2.1 GHz
Samsung DDR4 64 GB RAM
4x 960GB SSD
2x 10G Ports
P C C
1G 10G 10G
Storage Node
Pure (Flash Blade)
17TB
17TB
17TB
:
17TB
17TB
17TB
D D D D D D D D
40G 40G 40G 40G 40G 40G 40G 40G
GPU Nodes
DGX A100 - 1
2x AMD Rome 7742 2.25 GHz (64-Core)
1 TB DDR4 RAM
320 GB GPU Memory
2x 1.92TB NVME
4x 3.84 TB NVME
8x IB 200G HDR Ports
2x 200/100/50/40 25/10G Ports (ETH)
2x CX-6 Ports (Optiona)
Tesla A100 SXM4 40 GB
P D D I I I I I I I I
1G 100G 100G 200G 200G 200G 200G 200G 200G 200G 200G
DGX A100-2
2x AMD Rome 7742 2.25 GHz (64-Core)
1 TB DDR4 RAM
320 GB GPU Memory
2x 1.92TB NVME
4x 3.84 TB NVME
8x IB 200G HDR Ports
2x 200/100/50/40 25/10G Ports (ETH)
2x CX-6 Ports (Optional)
Tesla A100 SXM4 40 GB
P D D I I I I I I I I
1G 100G 100G 200G 200G 200G 200G 200G 200G 200G 200G
DGX1V-1
2x Intel Xeon E5-2698 v4 2.2 GHz (20-Core)
512 GB DDR4 RAM
256 GB GPU Memory
480 GB SSD
4x 1.92 TB SSD
2x 10G Ports
4x IB 100G EDR Ports
Tesla V100 SXM2 32 GB
P C C D D I I
1G 10G 10G 100G 100G 100G 100G
DGX1V-2
2x Intel Xeon E5-2698 v4 2.2 GHz (20-Core)
512 GB DDR4 RAM
256 GB GPU Memory
480 GB SSD
4x 1.92 TB SSD
2x 10G Ports
4x IB 100G EDR Ports
Tesla V100 SXM2 32 GB
P C C D D I I
1G 10G 10G 100G 100G 100G 100G


Front Cluster
Backend Cluster
(Controller + Master)
AI-X Data Pond 140 TB: Each user ~ 3TB
ceph
AI-X Data Lake 170 TB: Each user ~ 5TB
Core Cloud
(Slurm + K8S Master)
Local Storage 3 TB: Each user ~ 100GB
AI-X Data Lake 170 TB: Each user ~ 5 TB
Management Network (10G)
Data Network (100G RoCE)
Internal Network (100G IB)
Internal Network (200G IB)
Compute + DataPond Nodes (2u4N)
Compute + DataPond Node 1 (6x 6.4TB)
Compute + DataPond Node 2 (6x 6.4TB)
Compute + DataPond Node 3 (6x 6.4TB)
Compute + DataPond Node 4 (6x 6.4TB)
GPU Node 1 (DGXA100-1) AI Graduate School
GPU Node 2 (DGXA100-2) AI Graduate School
GPU Node 3 (DGX1v-1) AI Graduate School
GPU Node 4 (DGX1v-2) AI Graduate School
1-node Multi-GPUs (8 x A100)
1-node Multi-GPUs (8 x A100)
1-node Multi-GPUs (8 x Tesla V100)
1-node Multi-GPUs (8 x Tesla V100)
Storage Node (AI-X Data Lake)
NFS
FlashBlade 17TB
100G (Each node)
8x 200G (Each DGX A100)
2x 100G (Each DGX-1V)
8x 40G
Mellanox SN2100 (100G RoCE)
700m
Mellanox SN2100 (100G RoCE)
Mellanox QM8700 (200G IB)
External Fabric Module (XFM)
IDF
MDF
IDF
4x 100 G

GPU Programming Option

CUDA Versus OpenCL Versus OpenACC

NVIDIA. ACCELERATED COMPUTING Downloads Training Ecosystem Forums Join Login

CUDA Zone

CUDA® is a parallel computing platform and programming model developed by NVIDIA for general computing on graphical processing units (GPUs). With CUDA, developers are able to dramatically speed up computing applications by harnessing the power of GPUs.

In GPU-accelerated applications, the sequential part of the workload runs on the CPU – which is optimized for single-threaded performance – while the compute intensive portion of the application runs on thousands of GPU cores in parallel. When using CUDA, developers program in popular languages such as C, C++, Fortran, Python and MATLAB and express parallelism through extensions in the form of a few basic keywords.

The CUDA Toolkit from NVIDIA provides everything you need to develop GPU-accelerated applications. The CUDA Toolkit includes GPU-accelerated libraries, a compiler, development tools and the CUDA runtime.

Download Now ›

What is OpenACC?

OpenACC is a user-driven directive-based performance-portable parallel programming model designed for scientists and engineers interested in porting their codes to a wide-variety of heterogeneous HPC hardware platforms and architectures with significantly less programming effort than required with a low-level model.

Get Started or take the next steps

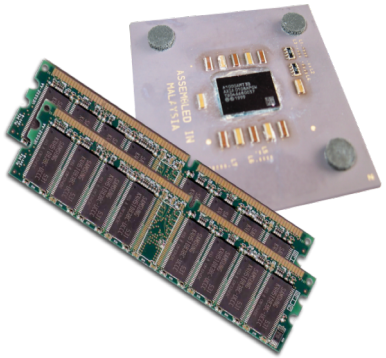
```
#pragma acc data copy(A) create(Anew)
while ( error > tol  &&  iter  <  iter_max )  {
  error = 0.0;
#pragma acc kernels {
#pragma acc loop independent collapse(2)
  for (  int  j = 1; j < n-1;  j++ )  {
    for (  int  i = 1; i < m-1; i++ )  {
      Anew [j] [i] = 0.25 * ( A [j] [i+1] + A [j] [i-1] +
                              A [j-1] [i] + A [j+1] [i]);
      error = max ( error, fabs (Anew [j] [i] - A [j] [i]));
    }
  }
}
```

What is CUDA?

- NVIDIA CUDA Architecture
  - Expose GPU computing for general purpose
  - Retain performance
- CUDA C/C++
  - Based on industry-standard C/C++
  - Small set of extensions to enable heterogeneous programming
  - Straightforward APIs to manage devices, memory etc.
- This session introduces CUDA C/C++

Heterogeneous Computing

- Terminology:
  - *Host* The CPU and its memory (host memory)
  - *Device* The GPU and its memory (device memory)



Host

Device

https://developer.nvidia.com/cuda-education

Heterogeneous Computing

```
#include <iostream>
#include <algorithm>

using namespace std;

#define N          1024
#define RADIUS     3
#define BLOCK_SIZE 16

__global__ void stencil_1d(int *in, int *out) {
        __shared__ int temp[BLOCK_SIZE + 2 * RADIUS];
        int gindex = threadIdx.x + blockIdx.x * blockDim.x;
        int lindex = threadIdx.x + RADIUS;

        // Read input elements into shared memory
        temp[lindex] = in[gindex];
        if (threadIdx.x < RADIUS) {
                temp[lindex - RADIUS] = in[gindex - RADIUS];
                temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
        }

        // Synchronize (ensure all the data is available)
        __syncthreads();

        // Apply the stencil
        int result = 0;
        for (int offset = -RADIUS ; offset <= RADIUS ; offset++)
                result += temp[lindex + offset];

        // Store the result
        out[gindex] = result;
}

void fill_ints(int *x, int n) {
        fill_n(x, n, 1);
}

int main(void) {
        int *in, *out;          // host copies of a, b, c
        int *d_in, *d_out;      // device copies of a, b, c
        int size = (N + 2*RADIUS) * sizeof(int);

        // Alloc space for host copies and setup values
        in  = (int *)malloc(size); fill_ints(in,  N + 2*RADIUS);
        out = (int *)malloc(size); fill_ints(out, N + 2*RADIUS);

        // Alloc space for device copies
        cudaMalloc((void **)&d_in,  size);
        cudaMalloc((void **)&d_out, size);

        // Copy to device
        cudaMemcpy(d_in,  in,  size, cudaMemcpyHostToDevice);
        cudaMemcpy(d_out, out, size, cudaMemcpyHostToDevice);

        // Launch stencil_1d() kernel on GPU
        stencil_1d<<<N/BLOCK_SIZE,BLOCK_SIZE>>>(d_in + RADIUS,
d_out + RADIUS);

        // Copy result back to host
        cudaMemcpy(out, d_out, size, cudaMemcpyDeviceToHost);

        // Cleanup
        free(in); free(out);
        cudaFree(d_in); cudaFree(d_out);
        return 0;
}
```

parallel fn

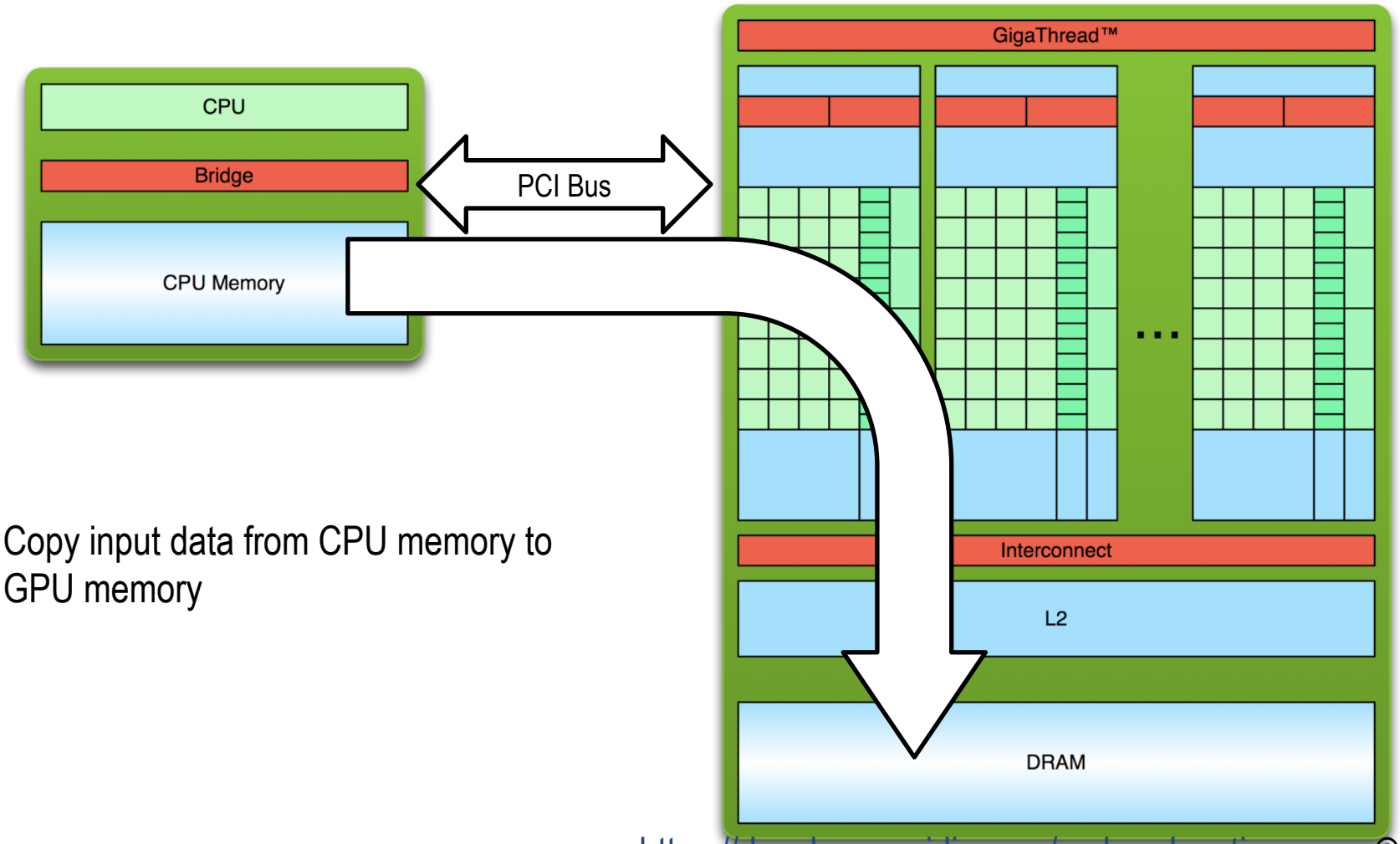
serial code

parallel code

serial code

https://developer.nvidia.com/cuda-education

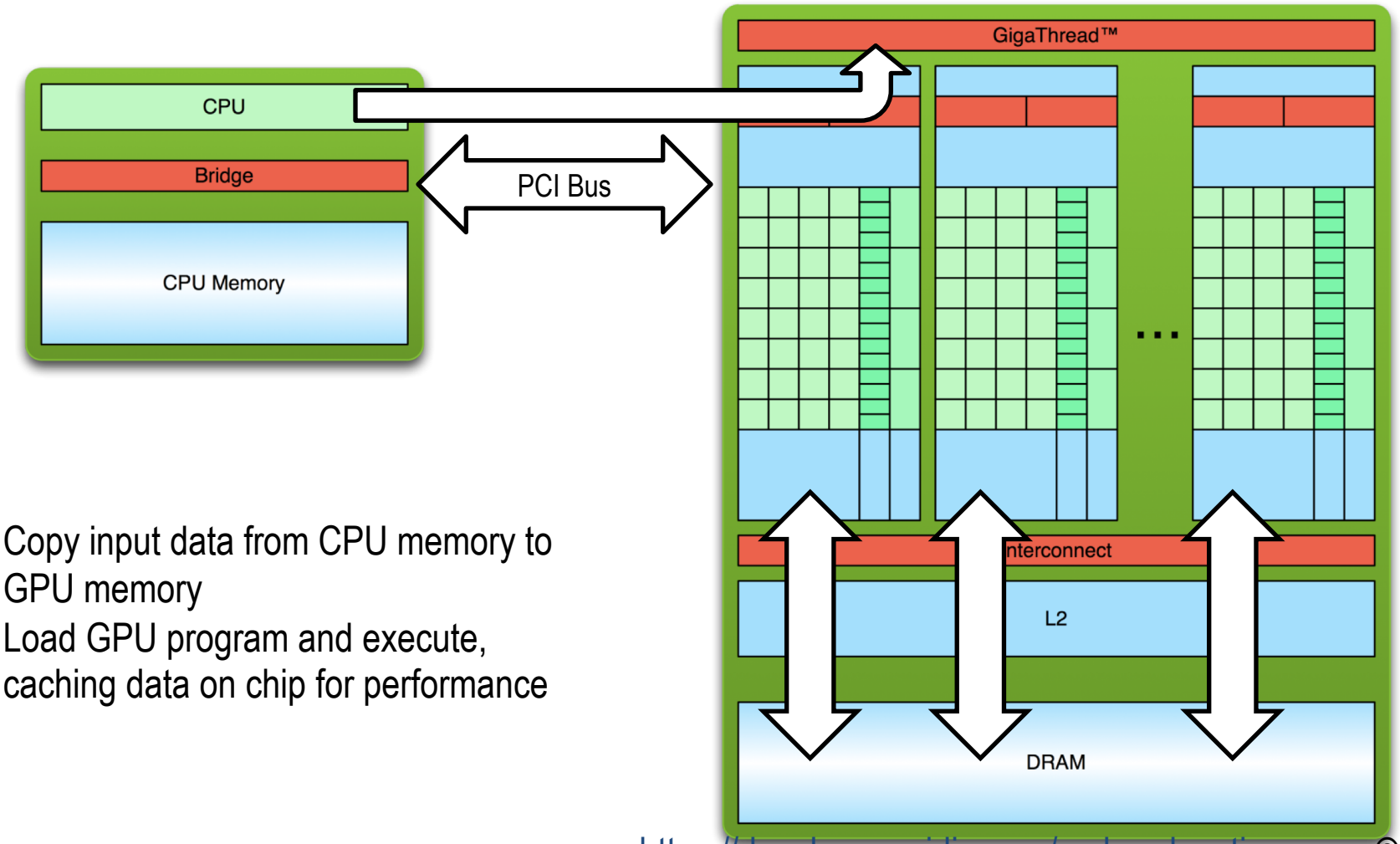
Simple Processing Flow



1. Copy input data from CPU memory to GPU memory

https://developer.nvidia.com/cuda-education

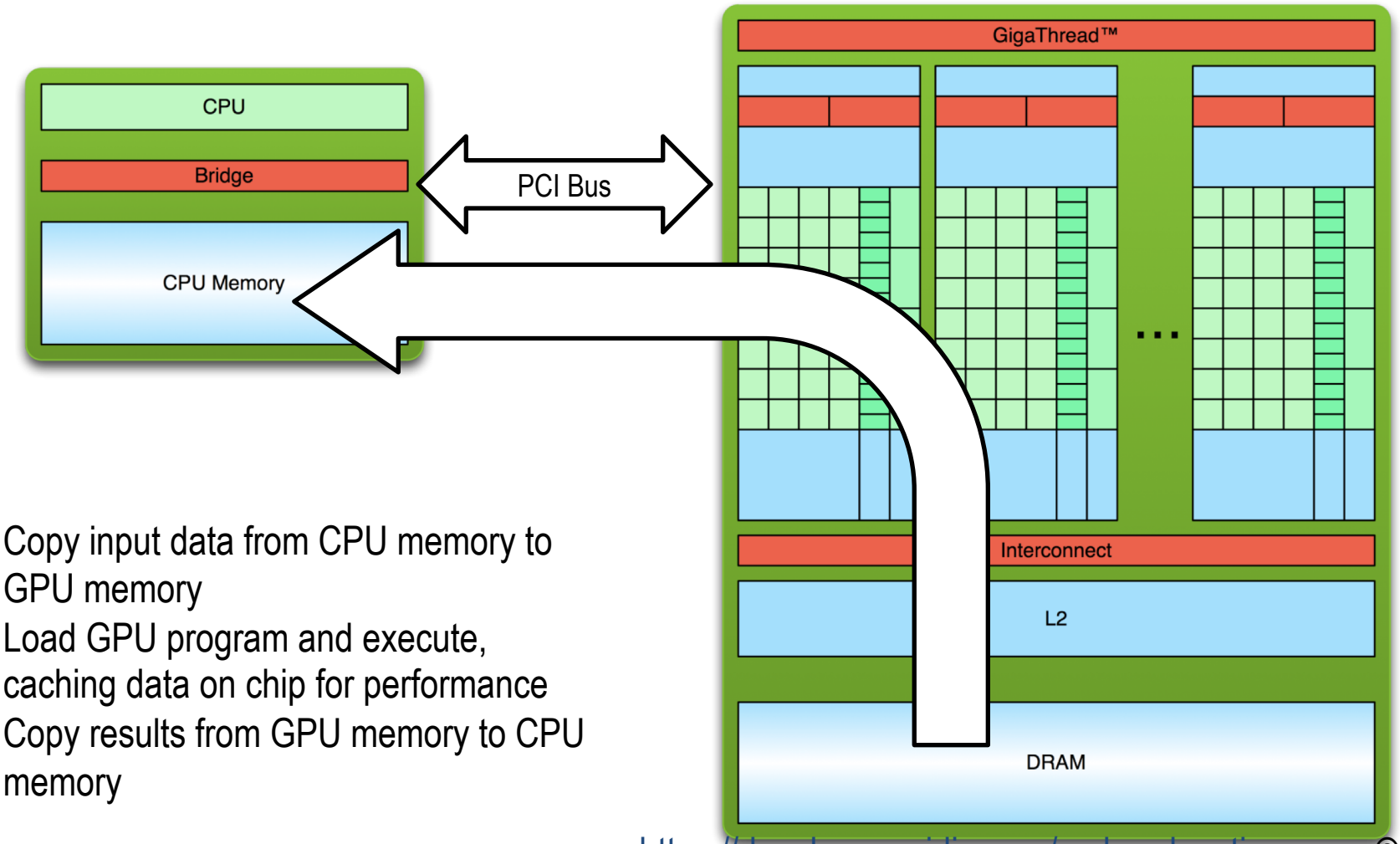
Simple Processing Flow



1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance

https://developer.nvidia.com/cuda-education

Simple Processing Flow



1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance
3. Copy results from GPU memory to CPU memory

https://developer.nvidia.com/cuda-education

NVIDIA CUDA Toolkit

https://developer.nvidia.com/cuda-toolkit

CUDA Toolkit

Develop, Optimize and Deploy GPU-Accelerated Apps

The NVIDIA® CUDA® Toolkit provides a development environment for creating high performance GPU-accelerated applications. With the CUDA Toolkit, you can develop, optimize, and deploy your applications on GPU-accelerated embedded systems, desktop workstations, enterprise data centers, cloud-based platforms and HPC supercomputers. The toolkit includes GPU-accelerated libraries, debugging and optimization tools, a C/C++ compiler, and a runtime library to build and deploy your application on major architectures including x86, Arm and POWER.

Using built-in capabilities for distributing computations across multi-GPU configurations, scientists and researchers can develop applications that scale from single GPU workstations to cloud installations with thousands of GPUs.

Download Now

A Quick Comparison between CUDA and C

C

```c
void c_hello(){
    printf("Hello World!\n");
}

int main() {
    c_hello();
    return 0;
}
```

CUDA

```c
__global__ void cuda_hello(){
    printf("Hello World from GPU!\n");
}

int main() {
    cuda_hello<<<1,1>>>();
    return 0;
}
```

CUDA

- https://developer.nvidia.com/cuda-toolkit
- https://devblogs.nvidia.com/even-easier-introduction-cuda/
- https://cuda-tutorial.readthedocs.io/en/latest/tutorials/tutorial01/
- https://www.nvidia.com/docs/IO/116711/sc11-cuda-c-basics.pdf

OpenCL

- https://www.khronos.org/opencl/

OpenCL for Low-level Parallel Programing

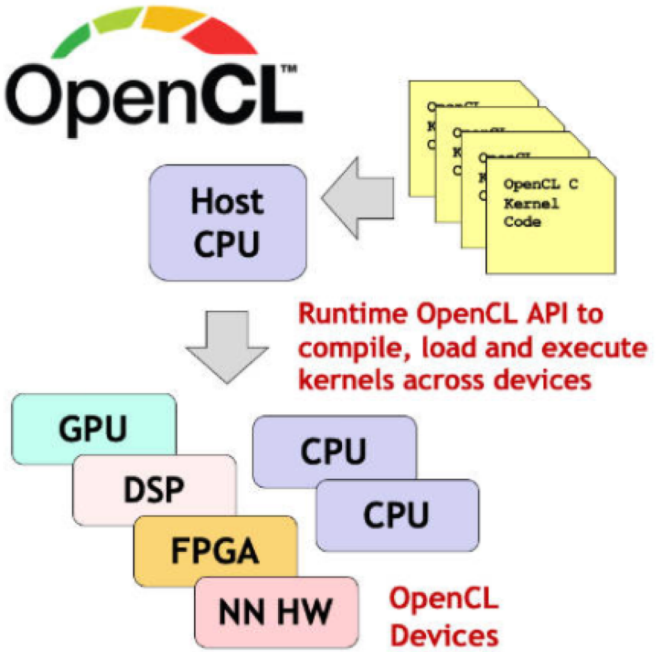
OpenCL speeds applications by offloading their most computationally intensive code onto accelerator processors - or devices. OpenCL developers use C or C++-based kernel languages to code programs that are passed through a device compiler for parallel execution on accelerator devices.

Programming and Runtime Framework for Application Acceleration
Offload compute-intensive kernels onto parallel heterogeneous processors
CPUs, GPUs, DSPs, FPGAs, Tensor Processors
OpenCL C or C++ kernel languages

Platform Layer API
Query, select and initialize compute devices

Runtime API
Build and execute kernels programs on multiple devices

Explicit Application Control
Which programs execute on what device
Where data is stored in memories in the system
When programs are run, and what operations are dependent on earlier operations



Complements GPU-only APIs
Simpler programming model
Relatively lightweight run-time
More language flexibility, e.g., pointers
Rigorously defined numeric precision

OpenACC

- https://www.openacc.org/

What is OpenACC?

The OpenACC Organization is dedicated to helping the research and developer community advance science by expanding their accelerated and parallel computing skills. We have 3 areas of focus: participating in computing ecosystem development, providing training and education on programming models, resources and tools, and developing the OpenACC specification.

Get Started or take the next steps

```
#pragma acc data copy(A) create(Anew)
while ( error > tol  &&  iter  <  iter_max )  {
  error = 0.0;
#pragma acc kernels
  {
#pragma acc loop independent collapse(2) reduction(max:error)
  for (  int  j = 1; j < n-1;  j++ )  {
    for (  int  i = 1; i < m-1; i++ )  {
      Anew [j] [i] = 0.25 * ( A [j] [i+1] + A [j] [i-1] +
                              A [j-1] [i] + A [j+1] [i]);
      error = max ( error, fabs (Anew [j] [i] - A [j] [i]));
    }
  }
  ...
  }
}
```

Popular Deep Learning Framework

TensorFlow

Keras

PyTorch

Caffe

Deep Learning with Fast.Ai

fast.ai

APACHE mxnet

Microsoft CNTK

Paddle (Baidu)

CNTK (Microsoft)

MXNet (Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc but main framework of choice at AWS

C++, Python, R, Julia, Perl Scala

Caffe (UC Berkeley) → Caffe2 (Facebook)

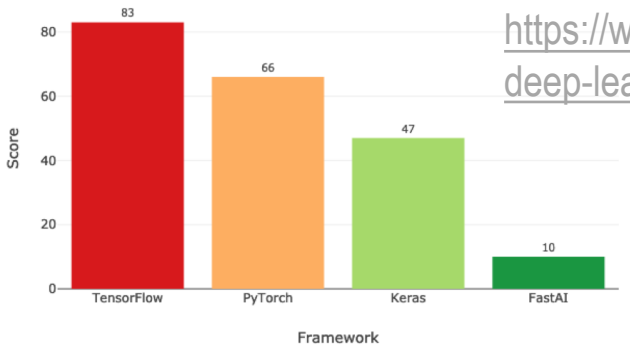
lua Torch (NYU / Facebook) → PyTorch (Facebook)

Theano (U Montreal) → TensorFlow (Google)

And others...

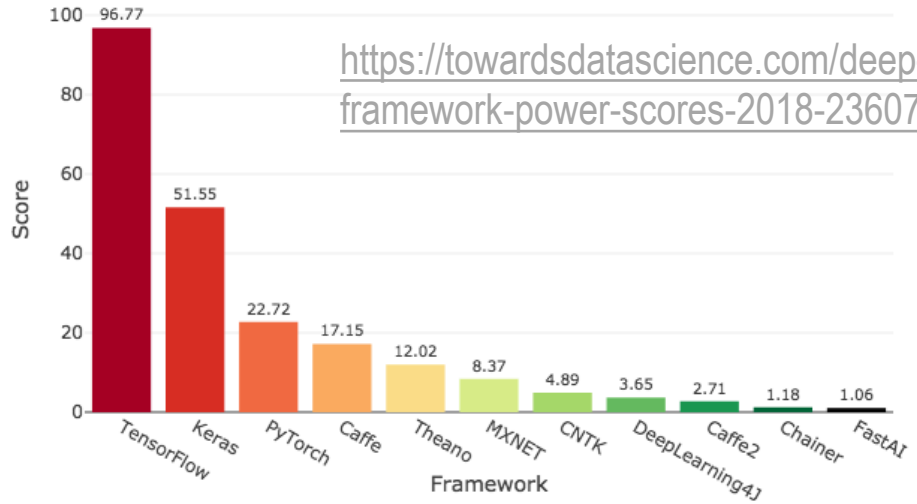
https://web.cs.ucdavis.edu/~yjlee/teaching/ecs289g-winter2018/Pytorch_Tutorial.pdf

Deep Learning Framework Six-Month Growth Scores 2019



https://www.kdnuggets.com/2019/05/which-deep-learning-framework-growing-fastest.html

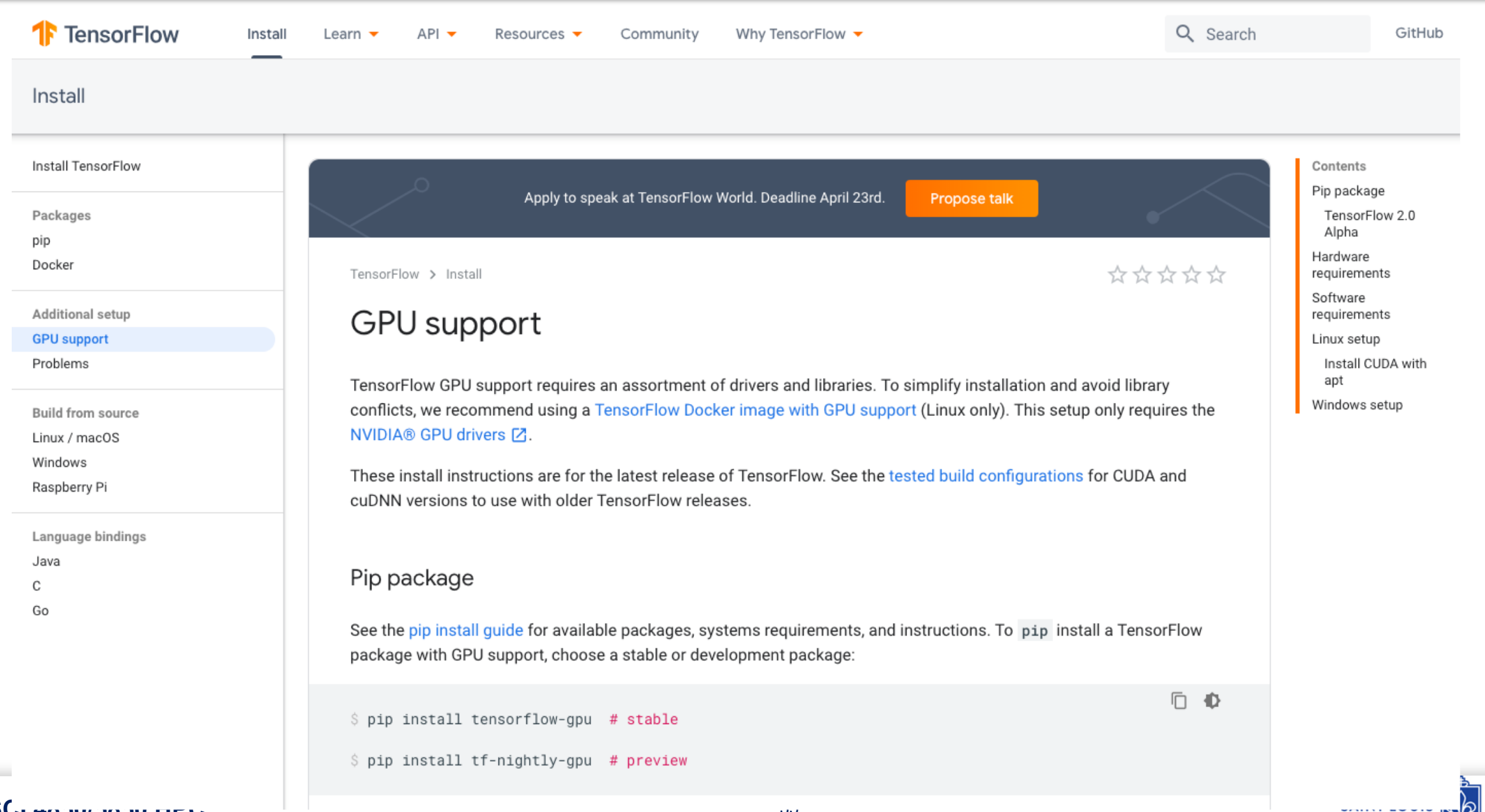
Deep Learning Framework Power Scores 2018



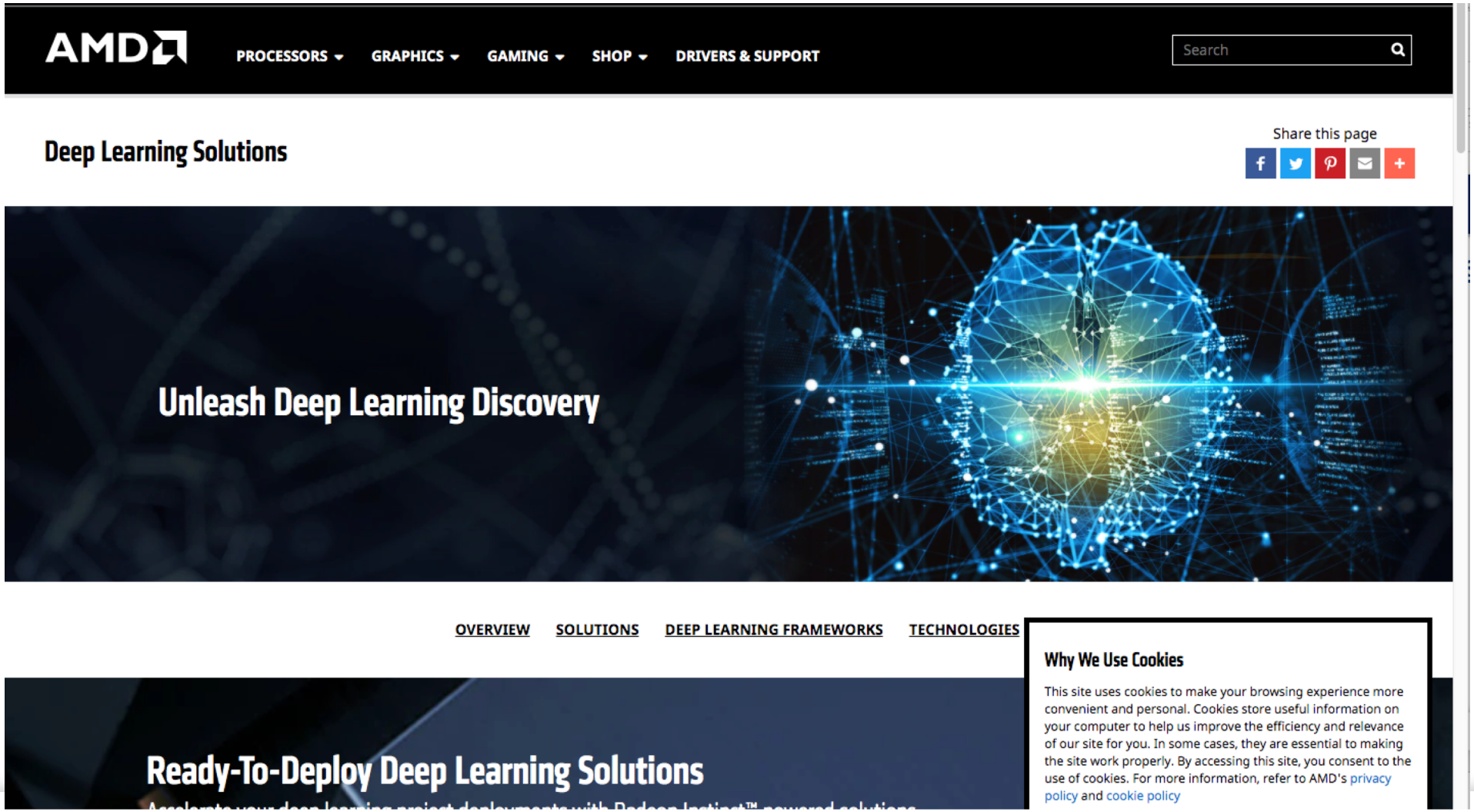
https://towardsdatascience.com/deep-learning-framework-power-scores-2018-23607ddf297a

VERSITY.

Machine/Deep Learning + GPU

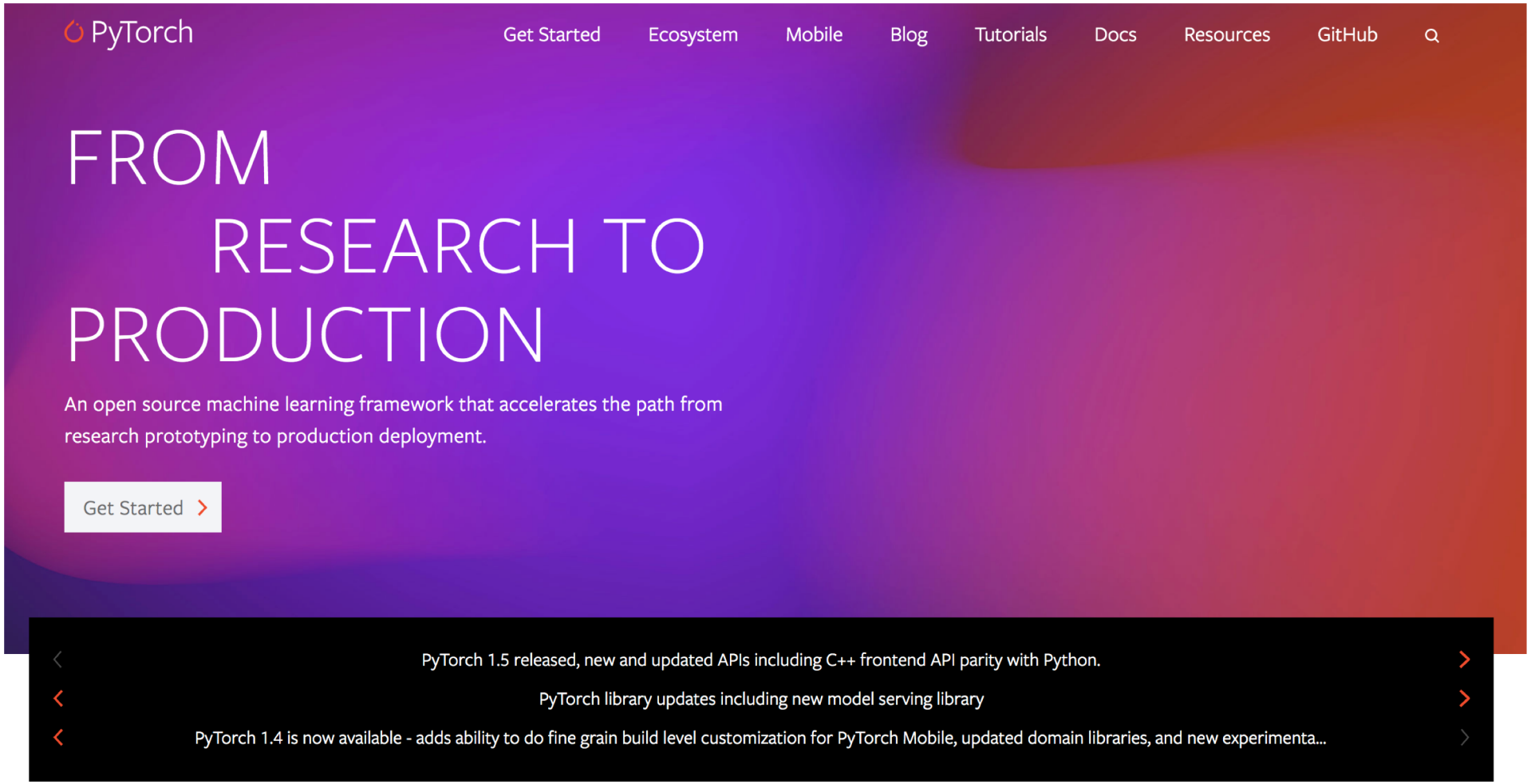


- https://www.amd.com/en/graphics/servers-radeon-instinct-deep-learning



PyTorch + GPU

- https://pytorch.org/



PyTorch and PyCUDA

- What is PyTorch?
  - https://pytorch.org/
  - Open source machine learning library
  - Developed by Facebook's AI Research lab
  - It leverages the power of GPUs
  - Automatic computation of gradients
  - Makes it easier to test and develop new ideas.
- What is PyCUDA?
  - https://documen.tician.de/pycuda/
  - Pythonic access to Nvidia's CUDA parallel computation API.
  - Convenience. Abstractions like pycuda.compiler.SourceModule and pycuda.gpuarray.GPUArray make CUDA programming even more convenient than with Nvidia's C-based runtime.

Again, this course is not a Machine Learning, Deep Learning, or Natural Language Processing. course. If you are interested in ML/DL/NLP, consider to take the course coming soon.

Multi-GPU Framework Comparison

Train+Val w/ data-loader + data-augmentation on real-data on SSD

DL Library	1xV100/CUDA 9/CuDNN 7	4xV100/CUDA 9/CuDNN 7
Pytorch	27min	10min
Keras(TF)	38min	18min
Tensorflow	33min	22min
Chainer	29min	8min
MXNet(Gluon)	29min	10min

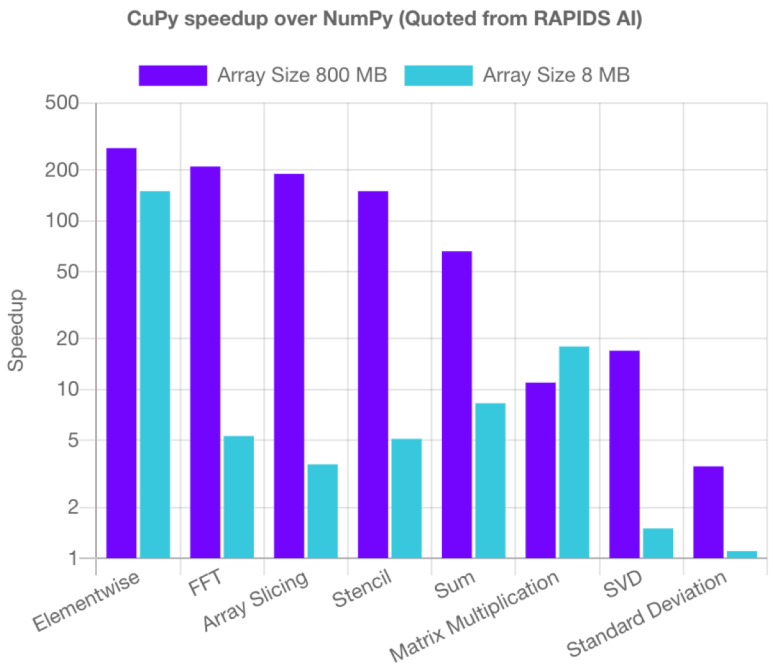
Train w/ synthetic-data in RAM

DL Library	1xV100/CUDA 9/CuDNN 7	4xV100/CUDA 9/CuDNN 7
Pytorch	25min	8min
Keras(TF)	36min	15min
Tensorflow	25min	14min
Chainer	27min	7min
MXNet(Gluon)	28min	8min

https://medium.com/@iliakarmanov/multi-gpu-rosetta-stone-d4fa96162986

Numpy vs CuPy

- https://cupy.dev/



HIGH PERFORMANCE WITH GPU

CuPy is an open-source array library for GPU-accelerated computing with Python. CuPy utilizes CUDA Toolkit libraries including cuBLAS, cuRAND, cuSOLVER, cuSPARSE, cuFFT, cuDNN and NCCL to make full use of the GPU architecture.
The figure shows CuPy speedup over NumPy. Most operations perform well on a GPU using CuPy out of the box. CuPy speeds up some operations more than 100X. Read the original benchmark article Single-GPU CuPy Speedups on the RAPIDS AI Medium blog.

- https://towardsdatascience.com/heres-how-to-use-cupy-to-make-numpy-700x-faster-4b920dda1f56

Here's How to Use CuPy to Make Numpy Over 10X Faster

GPU CUDA

High-Performance Computing

Summer 2021 at GIST

Tae-Hyuk (Ted) Ahn
Department of Computer Science
Program of Bioinformatics and Computational Biology
Saint Louis University

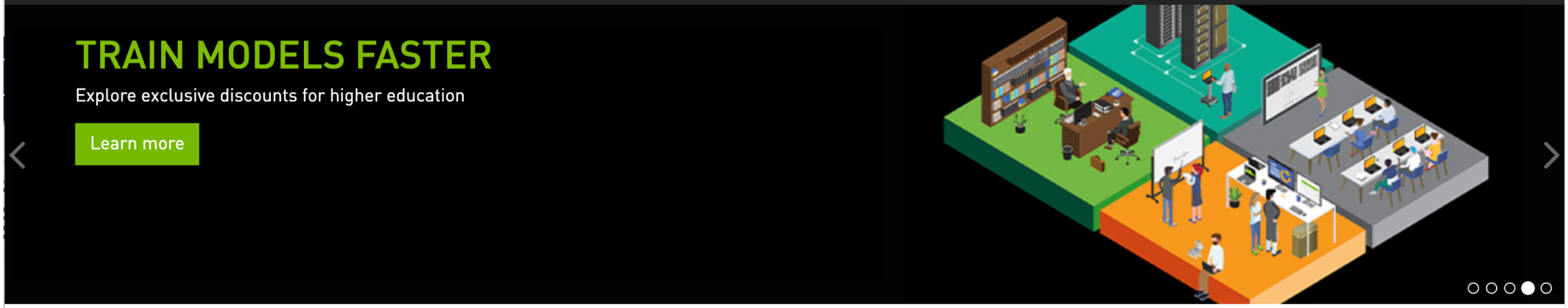
SAINT LOUIS
UNIVERSITY
EST. 1818

CUDA

developer.nvidia.com/cuda-zone

NVIDIA DEVELOPER HOME BLOG FORUMS DOCS DOWNLOADS TRAINING ACCOUNT

DOWNLOADS TRAINING ECOSYSTEM FORUMS



CUDA® is a parallel computing platform and programming model developed by NVIDIA for general computing on graphical processing units (GPUs). With CUDA, developers are able to dramatically speed up computing applications by harnessing the power of GPUs.

In GPU-accelerated applications, the sequential part of the workload runs on the CPU – which is optimized for single-threaded performance – while the compute intensive portion of the application runs on thousands of GPU cores in parallel. When using CUDA, developers program in popular languages such as C, C++, Fortran, Python and MATLAB and express parallelism through extensions in the form of a few basic keywords.

The CUDA Toolkit from NVIDIA provides everything you need to develop GPU-accelerated applications. The CUDA Toolkit includes GPU-accelerated libraries, a compiler, development tools and the CUDA runtime.

Download Now ›

How to compile?

```
1 #include <stdio.h>
2
3 int main() {
4   printf("Hello, world!\n");
5   return 0;
6 }
```

- $ nvcc hello.cu -o hello
- ./hello

```
[ahnt@gpu1:CUDA]$ nvcc hello.cu -o hello
[ahnt@gpu1:CUDA]$ ./hello
Hello, world!
```

A Quick Comparison between CUDA and C

C

```c
void c_hello(){
    printf("Hello World!\n");
}

int main() {
    c_hello();
    return 0;
}
```

CUDA

```c
__global__ void cuda_hello(){
    printf("Hello World from GPU!\n");
}

int main() {
    cuda_hello<<<1,1>>>();
    return 0;
}
```

Compiling CUDA Program

- Compiling a CUDA program is similar to C program. NVIDIA provides a CUDA compiler called nvcc in the CUDA toolkit to compile CUDA code, typically stored in a file with extension .cu. For example

```
$ nvcc cuda_helloworld.cu -o cuda_helloworld
```

Hello World!

```
1 #include <stdio.h>
2
3 __global__ void mykernel() {
4   printf("Hello World from GPU!\n");
5 }
6
7 int main() {
8   mykernel<<<1,1>>>();
9   return 0;
10 }
```

Output:

```
[ahnt@gpu1:CUDA]$ nvcc hello_cuda.cu -o hello_cuda
[ahnt@gpu1:CUDA]$ ./hello_cuda
[ahnt@gpu1:CUDA]$
```

NO Output.. ??

Hello World! with Device Code

```
__global__ void mykernel(void) {
}

int main(void) {
        mykernel<<<1,1>>>();
        cout << "Hello CUDA World!" << endl;
        return 0;
}
```

- Two new syntactic elements…

Hello World! with Device Code

```
__global__ void mykernel(void) {
}
```

- CUDA C/C++ keyword `__global__` indicates a function that:
  - Runs on the device
  - Is called from host code

- `nvcc` separates source code into host and device components
  - Device functions (e.g. **`mykernel()`**) processed by NVIDIA compiler
  - Host functions (e.g. **`main()`**) processed by standard host compiler
    - **`gcc`**, **`cl.exe`**

Hello World! with Device Code

```
mykernel<<<1,1>>>();
```

- Triple angle brackets mark a call from *host* code to *device* code
  - Also called a “kernel launch”
  - We’ll return to the parameters (1,1) in a moment

- That’s all that is required to execute a function on the GPU!

Vector addition using CUDA

vector_add.c

```c
#include <math.h>
#include <assert.h>

#define N 10000000
#define MAX_ERR 1e-6

void vector_add(float *out, float *a, float *b, int n) {
    for(int i = 0; i < n; i++){
        out[i] = a[i] + b[i];
    }
}

int main(){
    float *a, *b, *out;

    // Allocate memory
    a   = (float*)malloc(sizeof(float) * N);
    b   = (float*)malloc(sizeof(float) * N);
    out = (float*)malloc(sizeof(float) * N);

    // Initialize array
    for(int i = 0; i < N; i++){
        a[i] = 1.0f;
        b[i] = 2.0f;
    }

    // Main function
    vector_add(out, a, b, N);

    // Verification
    for(int i = 0; i < N; i++){
        assert(fabs(out[i] - a[i] - b[i]) < MAX_ERR);
    }

    printf("out[0] = %f\n", out[0]);
    printf("PASSED\n");
}
```

Converting vector addition to CUDA

- Copy vector_add.c to vector_add.cu
- Convert vector_add() to GPU kernel

```
__global__ void vector_add(float *out, float *a, float *b, int n) {
    for(int i = 0; i < n; i++){
        out[i] = a[i] + b[i];
    }
}
```

- Change vector_add() call in main() to kernel call

```
    // Main function
    vector_add<<<1,1>>>(out, a, b, N);
```

- Compile and run the program

Converting vector addition to CUDA

- You will notice that the program does not work correctly.
- The reason is CPU and GPUs are separate entities.
- Both have their own memory space. CPU cannot directly access GPU memory, and vice versa.
- In CUDA terminology, CPU memory is called host memory and GPU memory is called device memory. Pointers to CPU and GPU memory are called host pointer and device pointer, respectively.

Converting vector addition to CUDA

For data to be accessible by GPU, it must be presented in the device memory. CUDA provides APIs for allocating device memory and data transfer between host and device memory. Following is the common workflow of CUDA programs.

1. Allocate host memory and initialized host data
2. Allocate device memory
3. Transfer input data from host to device memory
4. Execute kernels
5. Transfer output from device memory to host

So far, we have done step 1 and 4. We will add step 2, 3, and 5 to our vector addition program and finish this exercise.

Device memory management

- CUDA provides several functions for allocating device memory. The most common ones are cudaMalloc() and cudaFree(). The syntax for both functions are as follow

```
cudaMalloc(void **devPtr, size_t count);
cadaFree(void *devPtr);
```

- cudaMalloc() allocates memory of size count in the device memory and updates the device pointer devPtr to the allocated memory.
- cudaFree() deallocates a region of the device memory where the device pointer devPtr points to.
- They are comparable to malloc() and free() in C, respectively

Memory transfer

- Transfering date between host and device memory can be done through cudaMemcpy function, which is similar to memcpy in C. The syntax of cudaMemcpy is as follow

```
cudaMemcpy(void *dst, void *src, size_t count, cudaMemcpyKind kind)
```

- The function copy a memory of size count from src to dst.
- kind indicates the direction. For typical usage, the value of kind is either cudaMemcpyHostToDevice or cudaMemcpyDeviceToHost. There are other possible values but we will not touch them in this course.

Completing vector addition

- Allocate and deallocate device memory for array a, b, and out.
- Transfer a, b, and out between host and device memory.

```
// Allocate device memory
cudaMalloc((void**)&d_a, sizeof(float) * N);
cudaMalloc((void**)&d_b, sizeof(float) * N);
cudaMalloc((void**)&d_out, sizeof(float) * N);

// Transfer data from host to device memory
cudaMemcpy(d_a, a, sizeof(float) * N, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, b, sizeof(float) * N, cudaMemcpyHostToDevice);

// Executing kernel
vector_add<<<1,1>>>(d_out, d_a, d_b, N);

// Transfer data back to host memory
cudaMemcpy(out, d_out, sizeof(float) * N, cudaMemcpyDeviceToHost);

// Verification
for(int i = 0; i < N; i++){
    assert(fabs(out[i] - a[i] - b[i]) < MAX_ERR);
}
printf("out[0] = %f\n", out[0]);
printf("PASSED\n");

// Deallocate device memory
cudaFree(d_a);
cudaFree(d_b);
cudaFree(d_out);

// Deallocate host memory
free(a);
free(b);
free(out);
}
```

Compile and measure performance.

```
$ nvcc vector_add.cu -o vector_add
$ time ./vector_add
$ nvprof ./vector_add
```

- Using time does not give much information about the program performance. NVIDIA provides a commandline profiler tool called nvprof, which give a more insight information of CUDA program performance.

```
ubuntu@ip-172-31-5-141:~/cuda_lab/instructor$ time ./vector_add
out[0] = 3.000000
PASSED

real    0m3.189s
user    0m2.012s
sys     0m1.172s
ubuntu@ip-172-31-5-141:~/cuda_lab/instructor$ nvprof ./vector_add
==2117== NVPROF is profiling process 2117, command: ./vector_add
out[0] = 3.000000
PASSED
==2117== Profiling application: ./vector_add
==2117== Profiling result:
            Type  Time(%)      Time     Calls       Avg       Min       Max  Name
 GPU activities:   99.28%  4.22754s         1  4.22754s  4.22754s  4.22754s  vector_add(float*, float*, float*, int)
                    0.41%  17.392ms         1  17.392ms  17.392ms  17.392ms  [CUDA memcpy DtoH]
                    0.31%  13.405ms         2  6.7026ms  6.6934ms  6.7118ms  [CUDA memcpy HtoD]
```

Going Parallel

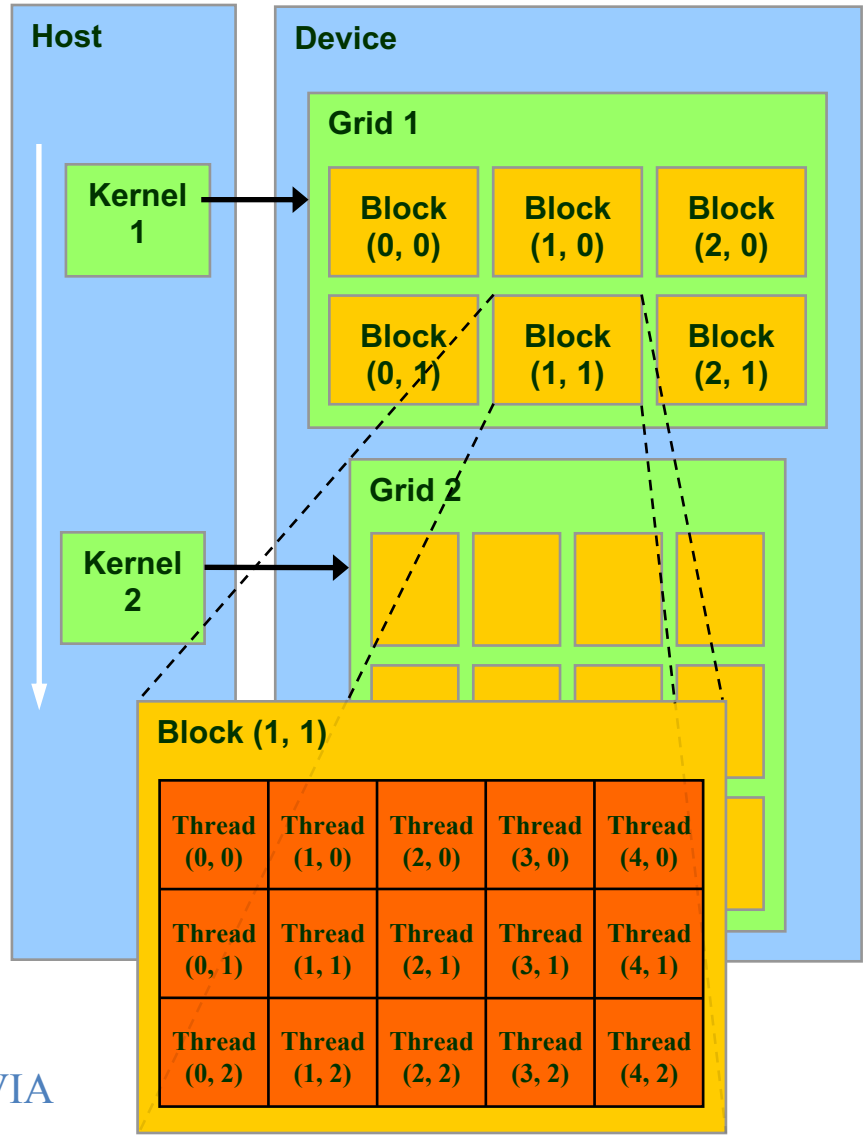
- CUDA use a kernel execution configuration <<<...>>> to tell CUDA runtime how many threads to launch on GPU. CUDA organizes threads into a group called "thread block". Kernel can launch multiple thread blocks, organized into a "grid" structure.

```
<<< M , T >>>
```

- Which indicate that a kernel launches with a grid of *M* thread blocks. Each thread block has *T* parallel threads.

Thread Batching: Grids and Blocks

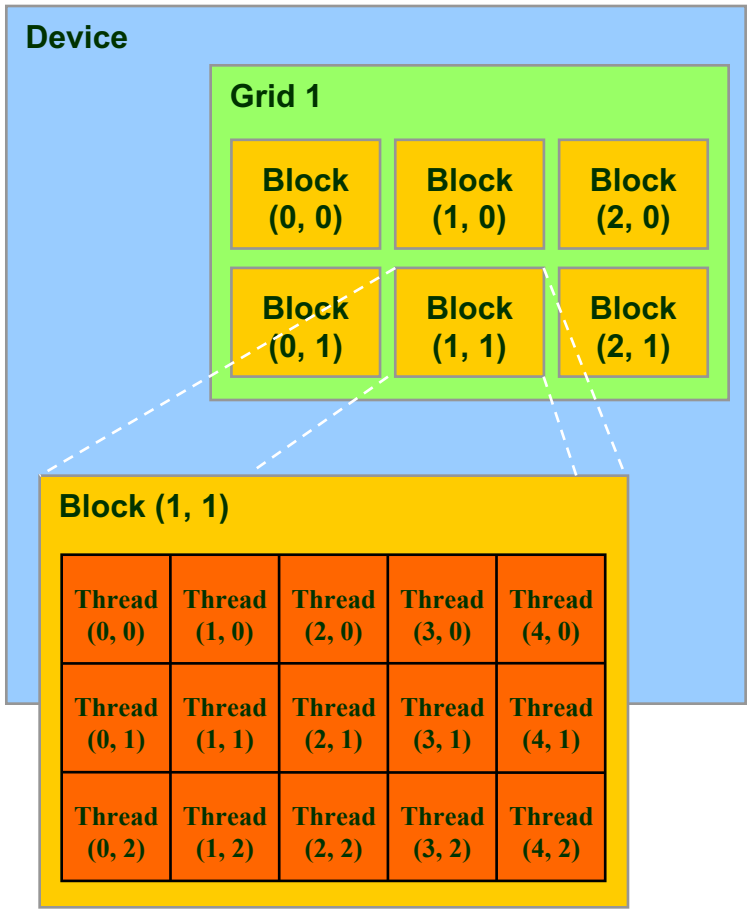
- A kernel is executed as a grid of thread blocks
  - All threads share data memory space
- A thread block is a batch of threads that can cooperate with each other by:
  - Synchronizing their execution
    - For hazard-free shared memory accesses
  - Efficiently sharing data through a low latency shared memory
- Two threads from two different blocks cannot cooperate



Courtesy: NDVIA

Block and Thread IDs

- Threads and blocks have IDs
  - So each thread can decide what data to work on
  - Block ID: 1D, 2D, or 3D (blockIdx.{x,y,z})
  - Thread ID: 1D, 2D, or 3D (threadIdx.{x,y,z})
- Simplifies memory addressing when processing multidimensional data
  - Image processing
  - Solving PDEs on volumes
  - …



Courtesy: NDVIA

Built-in Variables for Block and Thread

Built-in variables:

- threadIdx.{x,y,z} – thread ID within a block
- blockIDx.{x,y,z} – block ID within a grid
- blockDim.{x,y,z} – number of threads within a block
- gridDim.{x,y,z} – number of blocks within a grid

kernel<<<nBlocks,nThreads>>>(args)

- Invokes a parallel kernel function on a grid of nBlocks where each block instantiates nThreads concurrent threads

Parallelizing vector addition using multithread

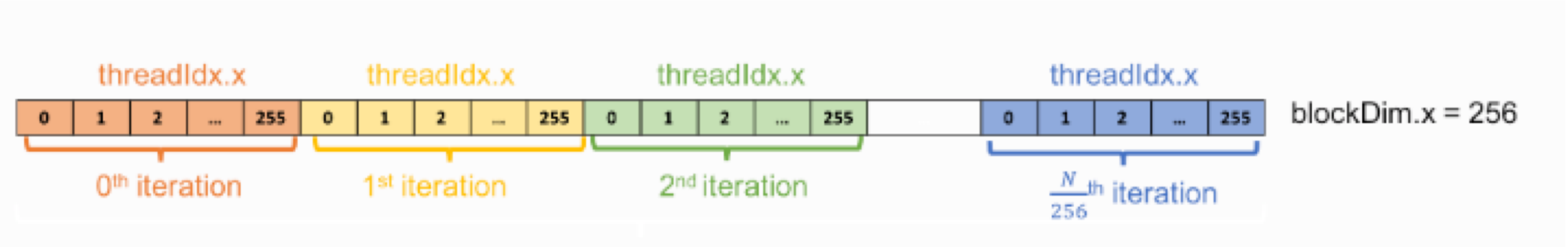
```
vector_add <<< 1 , 256 >>> (d_out, d_a, d_b, N);
```

- threadIdx.x contains the index of the thread within the block
- blockDim.x contains the size of thread block (number of threads in the thread block).
- For the vector_add() configuration, the value of threadIdx.x ranges from 0 to 255 and the value of blockDim.x is 256.

Parallelizing vector addition using multithread

```
vector_add <<< 1 , 256 >>> (d_out, d_a, d_b, N);
```

Parallelizing vector addition using multithread



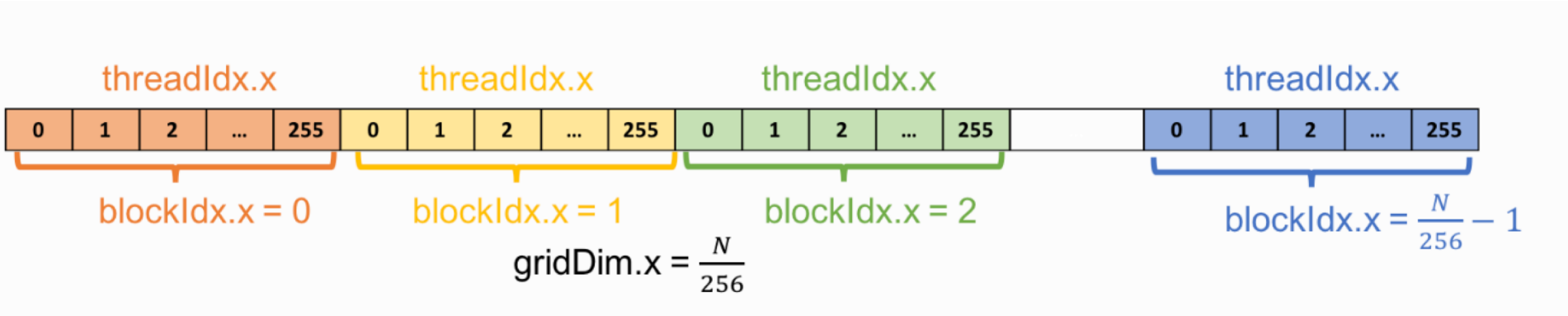
- For the k-th thread, the loop starts from k-th element and iterates through the array with a loop stride of 256.
- For example, in the 0-th iteration, the k-th thread computes the addition of k-th element.
- In the next iteration, the k-th thread computes the addition of (k+256)-th element, and so on.

vector_add_thread.cu

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include <math.h>
4  #include <assert.h>
5  #include <cuda.h>
6  #include <cuda_runtime.h>
7
8  #define N 10000000
9  #define MAX_ERR 1e-6
10
11 __global__ void vector_add(float *out, float *a, float *b, int n) {
12     int index = threadIdx.x;
13     int stride = blockDim.x;
14
15     for(int i = index; i < n; i += stride){
16         out[i] = a[i] + b[i];
17     }
18 }
19
```

```
44      // Executing kernel
45      vector_add<<<1,256>>>(d_out, d_a, d_b, N);
46
```

Adding more threads blocks

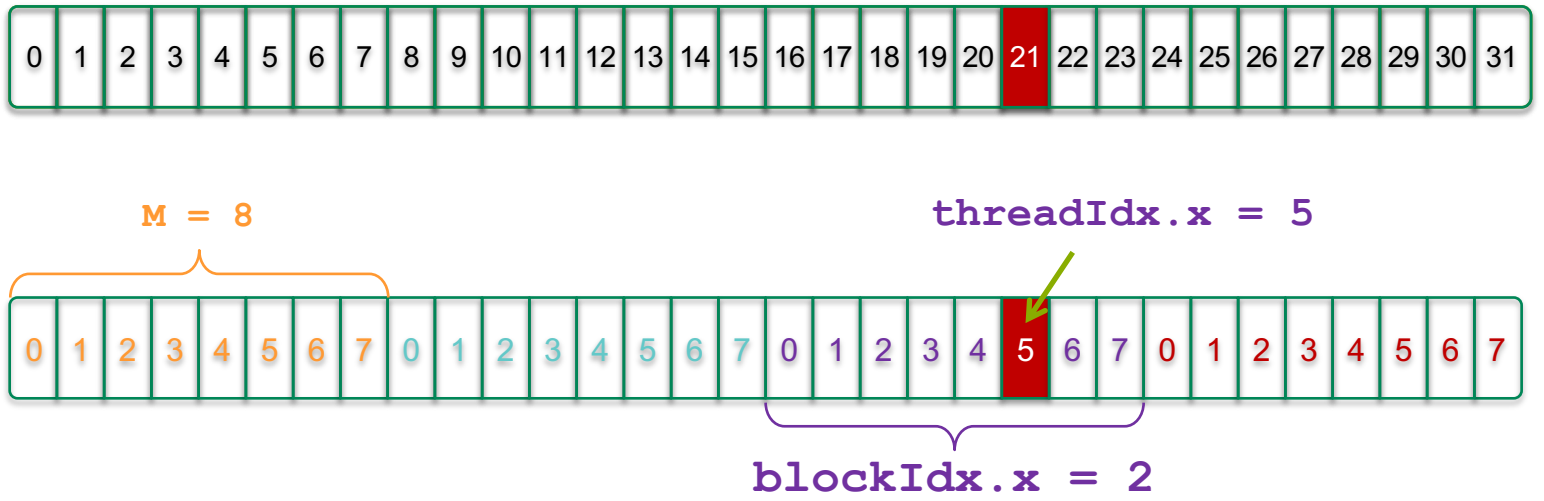


- We will use two of them: blockIdx.x and gridDim.x.
- blockIdx.x contains the index of the block with in the grid
- gridDim.x contains the size of the grid
- With 256 threads per thread block, we need at least N/256 thread blocks to have a total of Nthreads. To assign a thread to a specific element, we need to know a unique index for each thread. Such index can be computed as follow

```
int tid = blockIdx.x * M + threadIdx.x;
```

Indexing Arrays: Example

- Which thread will operate on the red element?




```
int index = threadIdx.x + blockIdx.x * M;
          =      5      +     2       * 8;
          = 21;
```

Vector Addition with Blocks and Threads

- Use the built-in variable `blockDim.x` for threads per block

```
int index = threadIdx.x + blockIdx.x * blockDim.x;
```

- Combined version of `add()` to use parallel threads *and* parallel blocks

```
__global__ void add(int *a, int *b, int *c) {
    int index = threadIdx.x + blockIdx.x * blockDim.x;
    c[index] = a[index] + b[index];
}
```

- What changes need to be made in `main()`?

main ()

```
// Launch add() kernel on GPU
add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a, d_b, d_c);
```

vector_sum_bt.cu

```
#include <iostream>
#include <cstdlib>

#define N (4*8)
#define THREADS_PER_BLOCK 8

using namespace std;

__global__ void add(int *a, int *b, int *c)
{
    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}

int main(int argc, char *argv[])
{
    int a[N], b[N], c[N];          // host copies of a, b, c
    int *d_a, *d_b, *d_c;          // device copies of a, b, c
    int size = sizeof(int);

    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, N*size);
    cudaMalloc((void **)&d_b, N*size);
    cudaMalloc((void **)&d_c, N*size);

    // Setup input values
    for (int i=0; i<N; i++) {
        a[i] = -i;
        b[i] = i * i;
    }
```

```
    // Copy inputs to device
    cudaMemcpy(d_a, &a, N*size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, N*size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU
    add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a, d_b,
d_c);
    //add<<<4,8>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(&c, d_c, N*size, cudaMemcpyDeviceToHost);

    // Display the results
    for (int i=0; i<N; i++) {
        printf("%d + %d = %d\n", a[i], b[i], c[i]);
    }

    // Free the memory allocated on the GPU
    cudaFree(d_a);
    cudaFree(d_b);
    cudaFree(d_c);

    return 0;
```

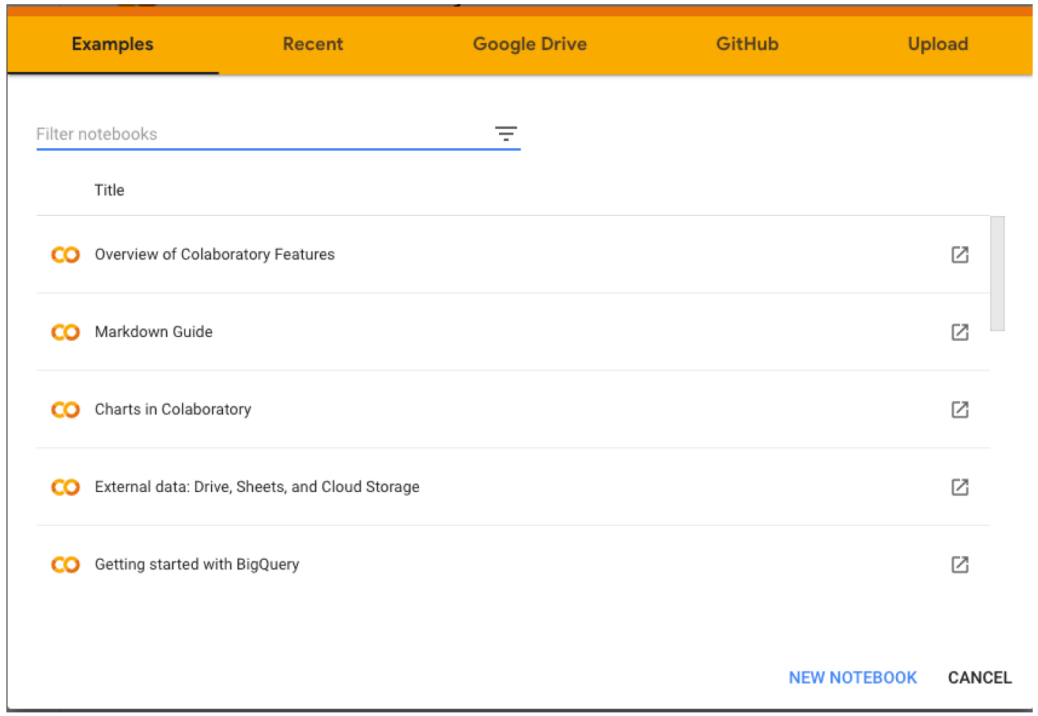
CUDA Thread Indexing Cheatsheet

- http://cs.calvin.edu/curriculum/cs/374/CUDA/CUDA-Thread-Indexing-Cheatsheet.pdf

Google Colab

Colaboratory, or "Colab" for short, allows you to write and execute Python in your browser, with

- Zero configuration required
- Free access to GPUs
- Easy sharing
- Built on top of Jupyter Notebook
- Google Colab notebooks are stored on the drive



Google Colab Let's Begin!

Create a Colab Notebook

- 1. Open Google Colab.
- 2. Click on 'New Notebook'.

OR

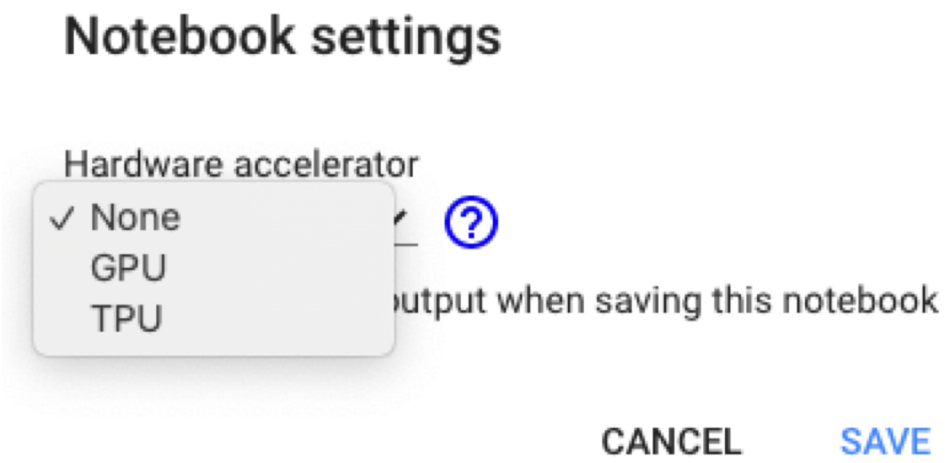
1. Open Google Drive.
2. Create a new folder for the project.
3. Click on 'New' > 'More' > 'Colaboratory'.

I have below default Colab Notebooks directory. Check it on your Google Drive and create HPC_Lab

Setting GPU Accelerator

The default hardware of Google Colab is CPU or it can be GPU.

1. Click on ‘Edit’ > ‘Notebook Settings’ > ‘Hardware Accelerator’ > ‘GPU’.

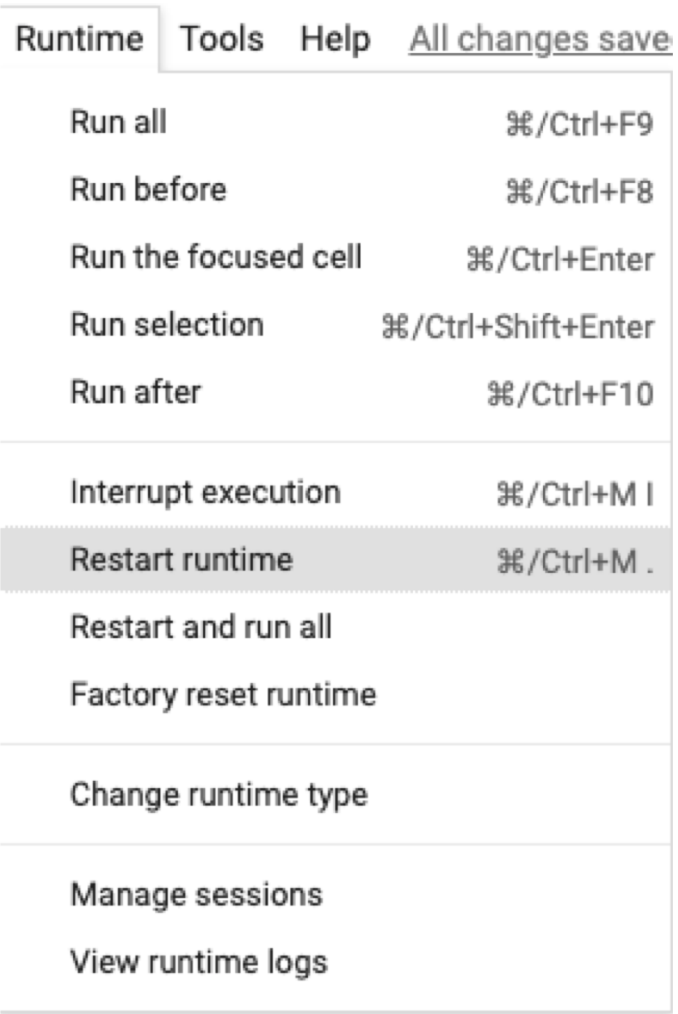


Running a Cell

- Make sure the runtime is connected. The notebook shows a green check and 'Connected' on the top right corner.
- There are various runtime options in 'Runtime'.

OR

- To run the current cell, press SHIFT + ENTER.



Running a Cell

- Bash commands can be run by prefixing the command with '!'.

```
[1]  !ls

     sample_data
```

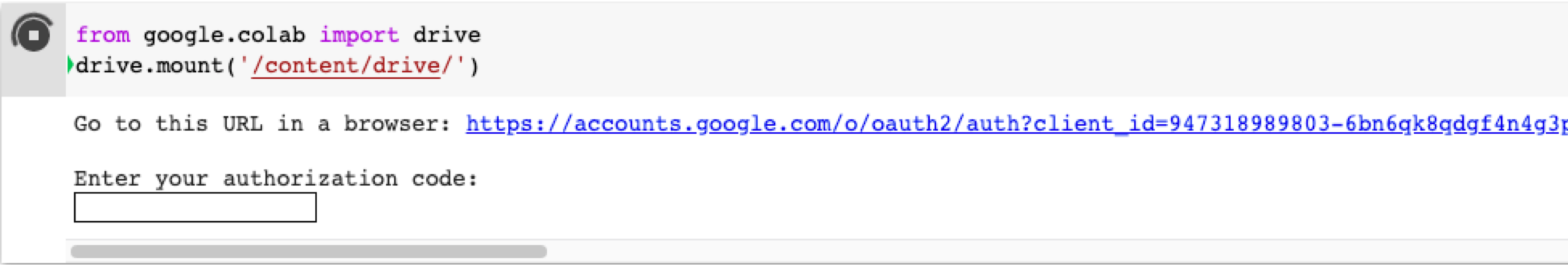
```
     !ls sample_data/

     anscombe.json                    mnist_test.csv
     california_housing_test.csv      mnist_train_small.csv
     california_housing_train.csv     README.md
```

Connect to your Google Drive

```
1  from google.colab import drive
2  drive.mount('/content/drive/')
```

- When you run the code above, you should see a result like this:



- **Click** the link, **copy** verification code and **paste** it to text box. Then, it will be

```
[5]  from google.colab import drive
     drive.mount('/content/drive/')

     Mounted at /content/drive/
```

Connect to your Google Drive

```
[6]  !ls

     drive  sample_data
```

```
[8]  !ls drive/MyDrive/

      22.160P_A_Tilt_FPS26_Live5
      23.160M_S_Automotive_Live5
     'BCB-5250 Spring 2021 Survey.gform'
      Career
     'Colab Notebooks'
      ColabTest
      Commitment
     'CSCI-2100 5002 Final Exam Schedule Voting.gform'
     'CSCI-4850 5850 HPC Spring 2021 Survey.gform'
      EBSCO
      Kirmizis_2007_Sir2_wildtype_histone_H3.merge.bw
      PersonalDocuments
      Research
      Software
      Teaching
     '~$ummary.docx'
     'Worksheet (1).gform'
      Worksheet.gform
```

Check CPU and RAM specifications

```
!cat /proc/cpuinfo
!cat /proc/meminfo
```

```
processor       : 0
vendor_id       : GenuineIntel
cpu family      : 6
model           : 63
model name      : Intel(R) Xeon(R) CPU @ 2.30GHz
stepping        : 0
microcode       : 0x1
cpu MHz         : 2299.998
cache size      : 46080 KB
physical id     : 0
siblings        : 2
core id         : 0
cpu cores       : 1
apicid          : 0
initial apicid  : 0
fpu             : yes
fpu_exception   : yes
cpuid level     : 13
wp              : yes
flags           : fpu vme de pse tsc msr pae mce cx8
bugs            : cpu_meltdown spectre_v1 spectre_v2
bogomips        : 4599.99
clflush size    : 64
cache_alignment : 64
address sizes   : 46 bits physical, 48 bits virtual
power management:

processor       : 1
vendor_id       : GenuineIntel
cpu family      : 6
model           : 63
```

```
MemTotal:       13333564 kB
MemFree:        10529740 kB
MemAvailable:   12432924 kB
Buffers:           85436 kB
Cached:          1958172 kB
SwapCached:            0 kB
Active:          1025112 kB
Inactive:        1462468 kB
Active(anon):     409852 kB
Inactive(anon):      360 kB
Active(file):     615260 kB
Inactive(file):  1462108 kB
Unevictable:           0 kB
Mlocked:               0 kB
SwapTotal:             0 kB
SwapFree:              0 kB
Dirty:               372 kB
Writeback:             0 kB
AnonPages:        443960 kB
Mapped:           245996 kB
Shmem:              1012 kB
Slab:             170776 kB
```

Check GPU

```
!nvidia-smi
```

```
Thu Apr 29 13:36:22 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 465.19.01    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P4            Off  | 00000000:00:04.0 Off |                    0 |
| N/A   39C    P0    23W /  75W |    199MiB /  7611MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
+-----------------------------------------------------------------------------+
```

- https://developer.nvidia.com/blog/nvidia-tesla-p4-gpus-available-now-on-the-google-cloud-platform/

Tesla P4 Specs

- https://www.nvidia.com/content/dam/en-zz/Solutions/design-visualization/solutions/resources/documents1/Tesla-P4-Product-Brief.pdf

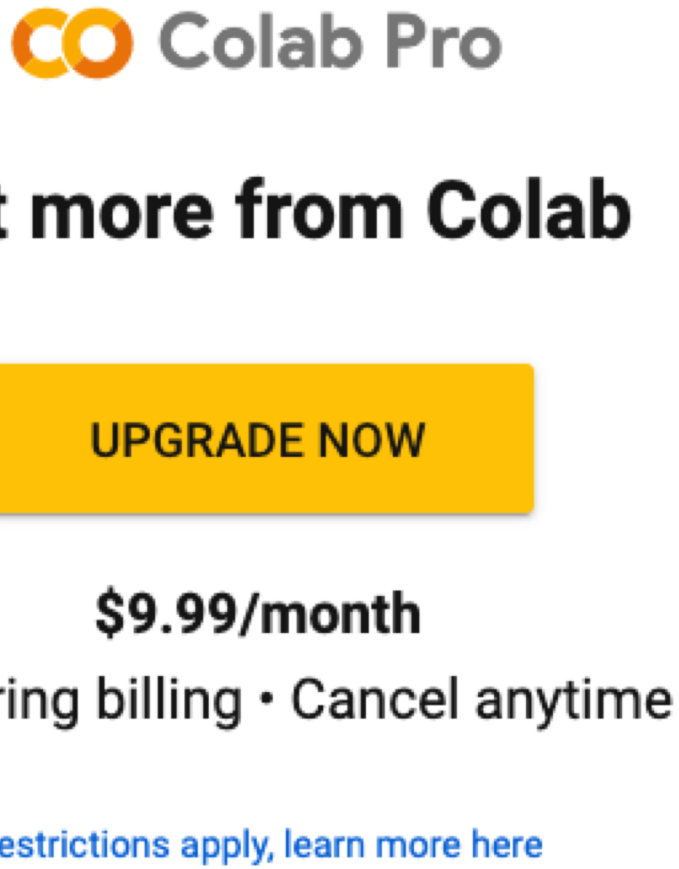
Table 1. Product Specifications

Specification		Description
Product SKUs		PG414 SKU 200; NVPN: 699-2G414-0200-100 PG414 SKU 201; NVPN: 699-2G414-0201-100
Total board power		PG414 SKU 200: 75 Watts PG414 SKU 201: 50 Watts
GPU SKU		GP104-895-A1
PCI Device ID		0x1BB3
SSID		SKU 200: 0x11D8 SKU 201: 0x11E0
Board ID		0x10DE
NVIDIA® CUDA® cores		2560
GPU clocks	Base	885 MHz
	Maximum boost	1531 MHz (1113 MHz default)
	Idle	405 MHz
VBIOS	EEPROM size	4 Mbit
	UEFI	Supported
PCI Express interface		PCI Express 3.0 ×16 Lane and polarity reversal supported
Weight	Board	240 Grams
	Bracket with screws	9.7 Grams (low-profile bracket)
		15.6 Grams (ATX bracket)

Table 2. Memory Specifications

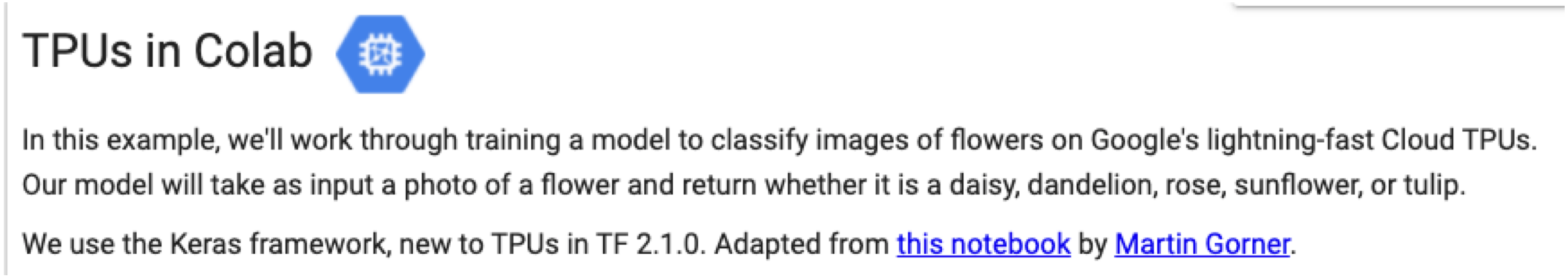
Specification		Description
Memory clocks	Performance	2.8 GHz
	Idle	324 MHz
Memory size		8 GB
Memory bus width		256-bit
Memory configuration		8 pcs 256M × 32 GDDR5
Peak memory bandwidth		Up to 192 GBytes/s

Need more powerful GPUs on Google Colab?



Google Colab TPUs

- https://colab.research.google.com/notebooks/tpu.ipynb



Tensorflow with GPU

- https://colab.research.google.com/notebooks/gpu.ipynb
- Open https://colab.research.google.com/notebooks/gpu.ipynb copy to your Drive and move it to your working directory!
- First, you'll need to enable GPUs for the notebook:
  - Navigate to Edit→Notebook Settings
  - select GPU from the Hardware Accelerator drop-down
- Next, we'll confirm that we can connect to the GPU with tensorflow:

```
%tensorflow_version 2.x
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
Found GPU at: /device:GPU:0
```

Tensorflow with GPU

- Observe TensorFlow speedup on GPU relative to CPU

```
%tensorflow_version 2.x
import tensorflow as tf
import timeit

device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  print(
      '\n\nThis error most likely means that this notebook is not '
      'configured to use a GPU.  Change this in Notebook Settings via the '
      'command palette (cmd/ctrl-shift-P) or the Edit menu.\n\n')
  raise SystemError('GPU device not found')

def cpu():
  with tf.device('/cpu:0'):
    random_image_cpu = tf.random.normal((100, 100, 100, 3))
    net_cpu = tf.keras.layers.Conv2D(32, 7)(random_image_cpu)
    return tf.math.reduce_sum(net_cpu)

def gpu():
  with tf.device('/device:GPU:0'):
    random_image_gpu = tf.random.normal((100, 100, 100, 3))
    net_gpu = tf.keras.layers.Conv2D(32, 7)(random_image_gpu)
    return tf.math.reduce_sum(net_gpu)

# We run each op once to warm up; see: https://stackoverflow.com/a/45067900
cpu()
gpu()

# Run the op several times.
print('Time (s) to convolve 32x7x7x3 filter over random 100x100x100x3 images '
      '(batch x height x width x channel). Sum of ten runs.')
print('CPU (s):')
cpu_time = timeit.timeit('cpu()', number=10, setup="from __main__ import cpu")
print(cpu_time)
print('GPU (s):')
gpu_time = timeit.timeit('gpu()', number=10, setup="from __main__ import gpu")
print(gpu_time)
```

```
Time (s) to convolve 32x7x7x3 filter over random 100x100x100x3 images (batch x height x width x channel). Sum of ten runs.
CPU (s):
3.042170389000006
GPU (s):
0.04080971800001976
GPU speedup over CPU: 74x
```

Running CUDA in Google Colab

- **CUDA** comes already pre-installed in **Google Colab**.

```
!nvidia-smi
```

```
Thu Apr 29 14:38:42 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 465.19.01    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla K80           Off  | 00000000:00:04.0 Off |                    0 |
| N/A   73C    P8    32W / 149W |      0MiB / 11441MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

Running CUDA in Google Colab

- **CUDA** comes already pre-installed in **Google Colab**.

```
[2]  !nvcc --version

     nvcc: NVIDIA (R) Cuda compiler driver
     Copyright (c) 2005-2020 NVIDIA Corporation
     Built on Wed_Jul_22_19:09:09_PDT_2020
     Cuda compilation tools, release 11.0, V11.0.221
     Build cuda_11.0_bu.TC445_37.28845127_0
```

- As it can be seen, the installation regards CUDA 11.0.

Running CUDA in Google Colab

- To enable CUDA **programming** and **execution** directly under Google Colab, you can install the nvcc4jupyter plugin as

```
!pip install git+git://github.com/andreinechaev/nvcc4jupyter.git
```

```
!pip install git+git://github.com/andreinechaev/nvcc4jupyter.git

Collecting git+git://github.com/andreinechaev/nvcc4jupyter.git
  Cloning git://github.com/andreinechaev/nvcc4jupyter.git to /tmp/pip-req-build-ugiskyks
  Running command git clone -q git://github.com/andreinechaev/nvcc4jupyter.git /tmp/pip-req-
Building wheels for collected packages: NVCCPlugin
  Building wheel for NVCCPlugin (setup.py) ... done
  Created wheel for NVCCPlugin: filename=NVCCPlugin-0.0.2-cp37-none-any.whl size=4307 sha256
  Stored in directory: /tmp/pip-ephem-wheel-cache-lrani5l9/wheels/10/c2/05/ca241da37bff77d60
Successfully built NVCCPlugin
Installing collected packages: NVCCPlugin
Successfully installed NVCCPlugin-0.0.2
```

Running CUDA in Google Colab

- After that, you should load the plugin as

  %load_ext nvcc_plugin

```
%load_ext nvcc_plugin

created output directory at /content/src
Out bin /content/result.out
```

Now it is ready to run CUDA code!!

Running CUDA in Google Colab

- Write and run CUDA code by adding below prefix

  %%cu

- Compilation and execution occurs when pressing the play button to run a code cell.
- Test below Hello World again!

```
%%cu
#include <iostream>
int main()
{
    std::cout << "Hello World CUDA on Google Colab GPU!\n";
    return 0;
}
```

```
Hello World CUDA on Google Colab GPU!
```

Running CUDA in Google Colab

- Run the code that I provided in the last lecture

```
%%cu
#include <iostream>
#include <cstdlib>

#define N (4*8)
#define THREADS_PER_BLOCK 8

using namespace std;

__global__ void add(int *a, int *b, int *c)
{
    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}

int main()
{
    int a[N], b[N], c[N];       // host copies of a, b, c
    int *d_a, *d_b, *d_c;       // device copies of a, b, c
    int size = sizeof(int);

    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, N*size);
    cudaMalloc((void **)&d_b, N*size);
    cudaMalloc((void **)&d_c, N*size);

    // Setup input values
    for (int i=0; i<N; i++) {
        a[i] = -i;
        b[i] = i * i;
    }

    // Copy inputs to device
    cudaMemcpy(d_a, &a, N*size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, N*size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU
    add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a, d_b, d_c);
    //add<<<4,8>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(&c, d_c, N*size, cudaMemcpyDeviceToHost);

    // Display the results
    for (int i=0; i<N; i++) {
        printf("%d + %d = %d\n", a[i], b[i], c[i]);
    }

    // Free the memory allocated on the GPU
    cudaFree(d_a);
    cudaFree(d_b);
    cudaFree(d_c);

    return 0;
}
```

Running CUDA in Google Colab

- Results! ??

```
0 + 0 = 0
-1 + 1 = 0
-2 + 4 = 0
-3 + 9 = 0
-4 + 16 = 0
-5 + 25 = 0
-6 + 36 = 0
-7 + 49 = 0
-8 + 64 = 0
-9 + 81 = 0
-10 + 100 = 0
-11 + 121 = 0
-12 + 144 = 0
-13 + 169 = 0
-14 + 196 = 0
-15 + 225 = 0
-16 + 256 = 0
-17 + 289 = 0
-18 + 324 = 0
-19 + 361 = 0
-20 + 400 = 0
-21 + 441 = 0
-22 + 484 = 0
-23 + 529 = 0
-24 + 576 = 0
-25 + 625 = 0
-26 + 676 = 0
-27 + 729 = 0
-28 + 784 = 0
-29 + 841 = 0
-30 + 900 = 0
-31 + 961 = 0
```

```
[ahnt@gpu1:CUDA]$ ./vector_sum_bt
0 + 0 = 0
-1 + 1 = 0
-2 + 4 = 2
-3 + 9 = 6
-4 + 16 = 12
-5 + 25 = 20
-6 + 36 = 30
-7 + 49 = 42
-8 + 64 = 56
-9 + 81 = 72
-10 + 100 = 90
-11 + 121 = 110
-12 + 144 = 132
-13 + 169 = 156
-14 + 196 = 182
-15 + 225 = 210
-16 + 256 = 240
-17 + 289 = 272
-18 + 324 = 306
-19 + 361 = 342
-20 + 400 = 380
-21 + 441 = 420
-22 + 484 = 462
-23 + 529 = 506
-24 + 576 = 552
-25 + 625 = 600
-26 + 676 = 650
-27 + 729 = 702
-28 + 784 = 756
-29 + 841 = 812
-30 + 900 = 870
-31 + 961 = 930
```

Running CUDA in Google Colab

- Notice that Google Colab currently provides the newer **T4** or **P100** GPU or the older **K80** if other GPUs are not available. CUDA 11 is not compatible with those!
- Let's change to CUDA 10.1

```
!rm -rf cuda
!ln -s /usr/local/cuda-10.1 /usr/local/cuda
!stat cuda
```

```
  File: cuda -> /usr/local/cuda-10.1
  Size: 20              Blocks: 0          IO Block: 4096   symbolic link
Device: 32h/50d Inode: 4207961     Links: 1
Access: (0777/lrwxrwxrwx)  Uid: (    0/    root)   Gid: (    0/    root)
Access: 2021-04-29 15:07:24.122422198 +0000
Modify: 2021-04-29 15:07:24.021422297 +0000
Change: 2021-04-29 15:07:24.021422297 +0000
 Birth: -
```

Running CUDA in Google Colab

- Run again! It works!!

```
0 + 0 = 0
-1 + 1 = 0
-2 + 4 = 2
-3 + 9 = 6
-4 + 16 = 12
-5 + 25 = 20
-6 + 36 = 30
-7 + 49 = 42
-8 + 64 = 56
-9 + 81 = 72
-10 + 100 = 90
-11 + 121 = 110
-12 + 144 = 132
-13 + 169 = 156
-14 + 196 = 182
-15 + 225 = 210
-16 + 256 = 240
-17 + 289 = 272
-18 + 324 = 306
-19 + 361 = 342
-20 + 400 = 380
-21 + 441 = 420
-22 + 484 = 462
-23 + 529 = 506
-24 + 576 = 552
-25 + 625 = 600
-26 + 676 = 650
-27 + 729 = 702
-28 + 784 = 756
-29 + 841 = 812
-30 + 900 = 870
-31 + 961 = 930
```

Lab Assignment

- Run below CUDA code in Google Colab and get the correct results

```
%%cu
#include <iostream>
#include <cstdlib>

#define N (4*8)
#define THREADS_PER_BLOCK 8

using namespace std;

__global__ void add(int *a, int *b, int *c)
{
    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}

int main()
{
    int a[N], b[N], c[N];       // host copies of a, b, c
    int *d_a, *d_b, *d_c;       // device copies of a, b, c
    int size = sizeof(int);

    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, N*size);
    cudaMalloc((void **)&d_b, N*size);
    cudaMalloc((void **)&d_c, N*size);

    // Setup input values
    for (int i=0; i<N; i++) {
        a[i] = -i;
        b[i] = i * i;
    }

    // Copy inputs to device
    cudaMemcpy(d_a, &a, N*size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, N*size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU
    add<<<N/THREADS_PER_BLOCK,THREADS_PER_BLOCK>>>(d_a, d_b, d_c);
    //add<<<4,8>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(&c, d_c, N*size, cudaMemcpyDeviceToHost);

    // Display the results
    for (int i=0; i<N; i++) {
        printf("%d + %d = %d\n", a[i], b[i], c[i]);
    }

    // Free the memory allocated on the GPU
    cudaFree(d_a);
    cudaFree(d_b);
    cudaFree(d_c);

    return 0;
}
```

```
0 + 0 = 0
-1 + 1 = 0
-2 + 4 = 2
-3 + 9 = 6
-4 + 16 = 12
-5 + 25 = 20
-6 + 36 = 30
-7 + 49 = 42
-8 + 64 = 56
-9 + 81 = 72
-10 + 100 = 90
-11 + 121 = 110
-12 + 144 = 132
-13 + 169 = 156
-14 + 196 = 182
-15 + 225 = 210
-16 + 256 = 240
-17 + 289 = 272
-18 + 324 = 306
-19 + 361 = 342
-20 + 400 = 380
-21 + 441 = 420
-22 + 484 = 462
-23 + 529 = 506
-24 + 576 = 552
-25 + 625 = 600
-26 + 676 = 650
-27 + 729 = 702
-28 + 784 = 756
-29 + 841 = 812
-30 + 900 = 870
-31 + 961 = 930
```