Introduction to GPU Acceleration on Alpine

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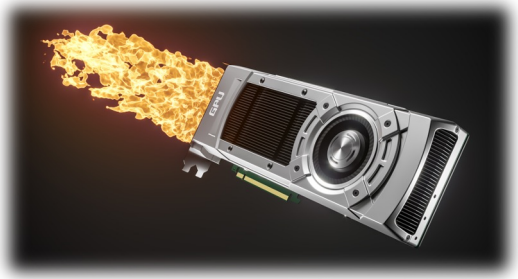

Computing and Data Beyond the Desktop

- large-scale computing resources
- storage of research data
- high-speed data transfer
- data sharing support
- consultation in computational science and data management

Main Page:
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RMACC Cyber Infrastructure

https://ask.cyberinfrastructure.org/c/rmacc/65

- Provides opportunity for RMACC members to converse amongst themselves and with the larger research computing community
- The “go to” general Q&A platform for the global research computing community - researchers, facilitators, research software engineers, CI engineers, sys admins and others.

Overview

- Intro to Alpine's Heterogeneous Architecture
- Criteria for GPU Acceleration
- Factors Affecting GPU Speedup
- GPU Programming Tools
- Requesting GPUs on Alpine with Slurm
- GPU Monitoring on Alpine
- Hands-on Example: matmul with TensorFlow

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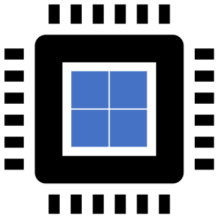
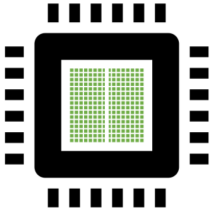
CPUs vs GPUs

Central Processing Unit



- General workhorse
- Contains dozens of cores
- Good for serial processing and handling multiple

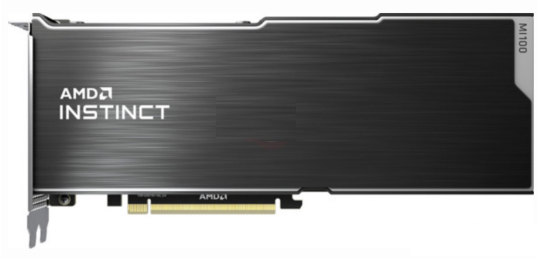
Graphics Processing Unit



- Specialized
- Contains thousands of cores
- Good for parallel processing and handling specific tasks quickly

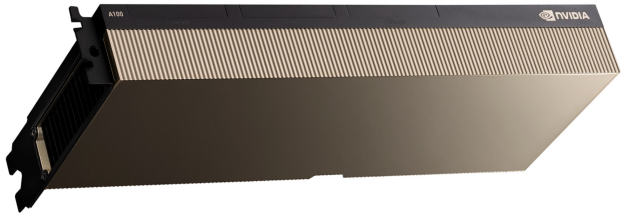
Alpine's Heterogeneous Architecture

A100 GPU



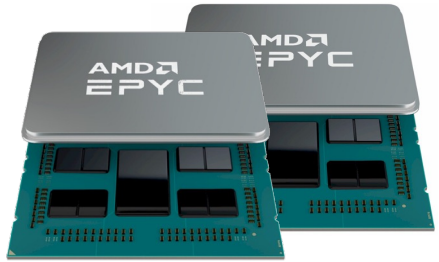
8 nodes x 3 GPUs /node

MI100 GPU



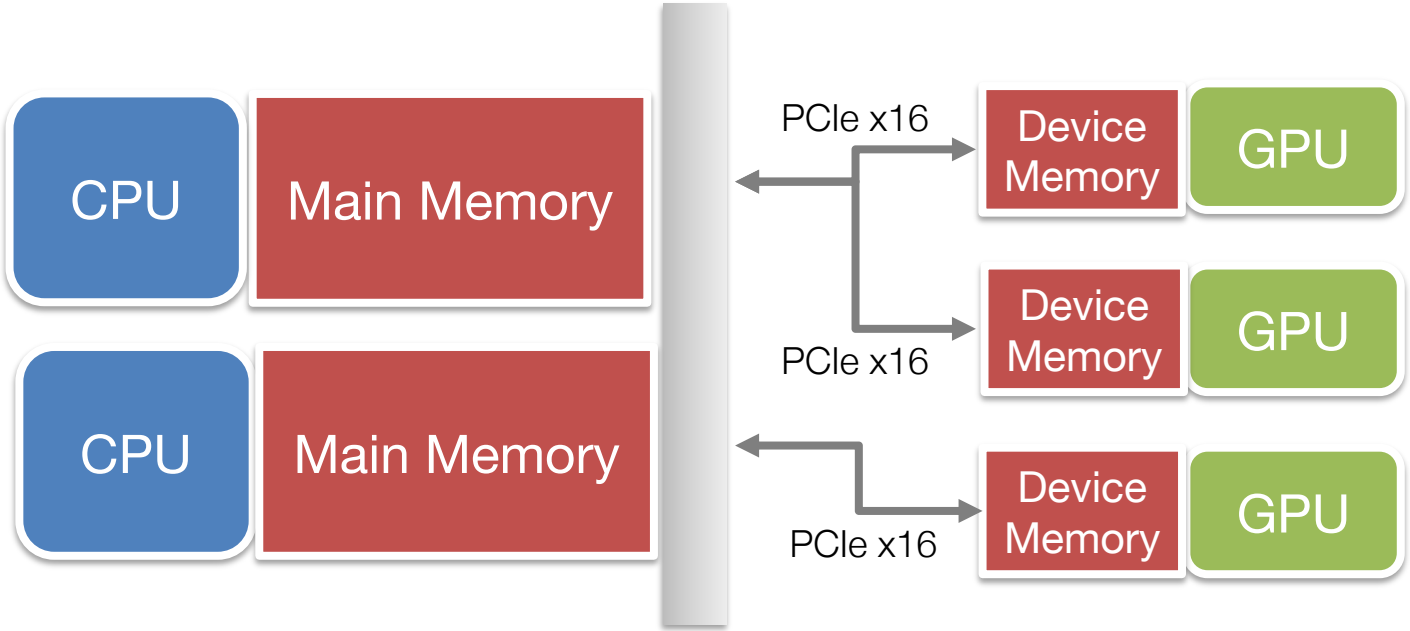
8 nodes x 3 GPUs /node

Milan CPU



64 nodes with 64 cores per node

Alpine's Heterogeneous Architecture

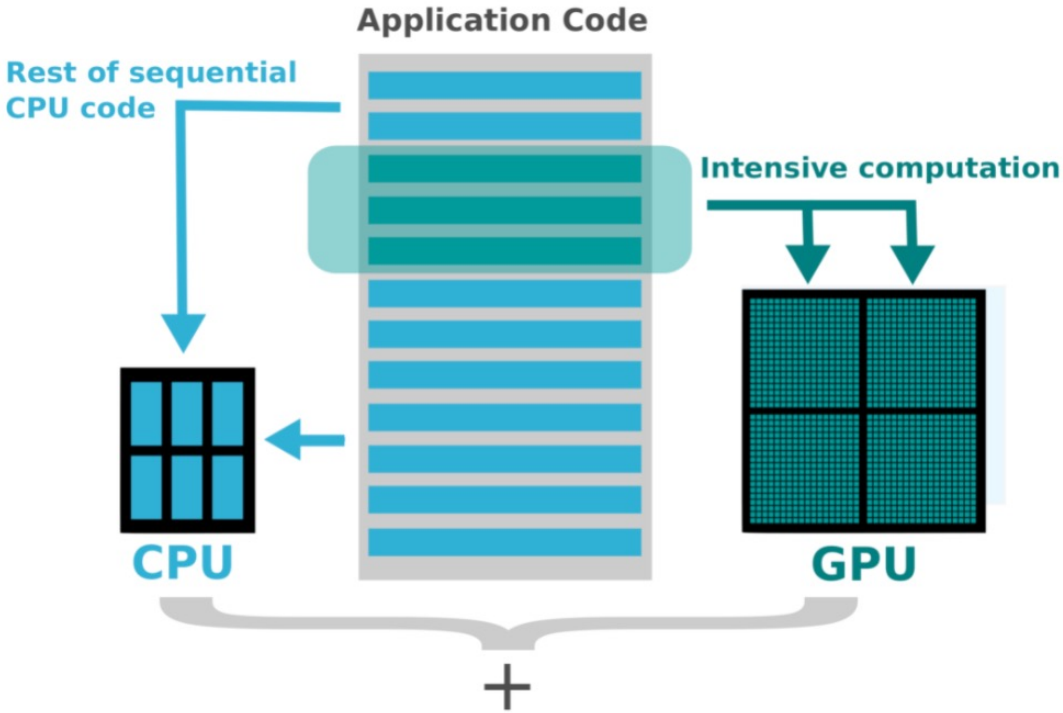


Combines main processors and accelerators, e.g., CPUs and GPUs

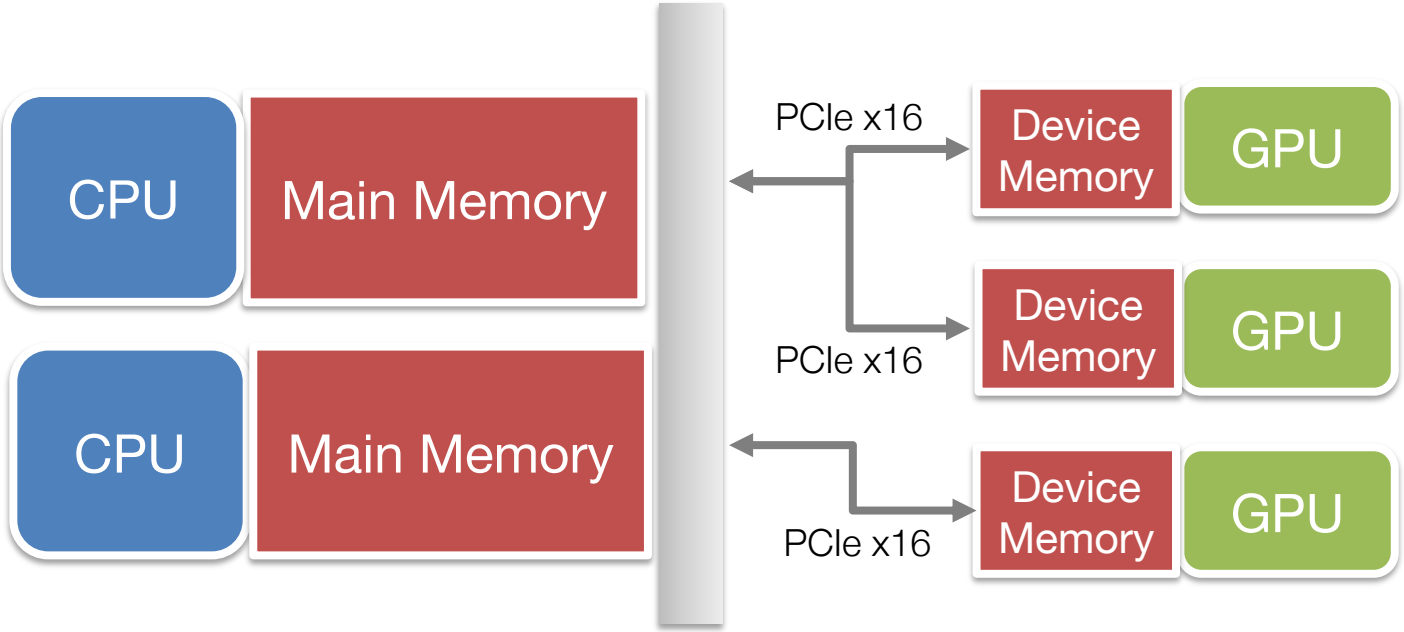
GPU-Accelerated Code

Offloading model

- Increased speed can be achieved by porting computationally intensive parts of code to GPU(s)



GPU-Accelerated Code



Data needs to be copied from CPU to GPU, computation is performed on the GPU, then output is transferred back to CPU.

Get Started on Alpine

Log in:

```
ssh <username>@login.rc.colorado.edu
```

Load the Alpine Slurm module:

```
module load slurm/alpine
```

Confirm the module is loaded:

```
module list
```

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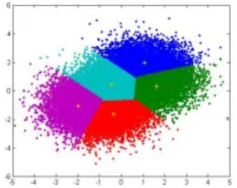
Criteria for GPU Acceleration

1. The time spent on computationally intensive parts of the workflow **exceeds** the time spent transferring data to and from GPU memory
2. Computations are **massively parallel**- the computations can be broken down into hundreds or thousands of independent units of work

Common GPU-Accelerated Workflows

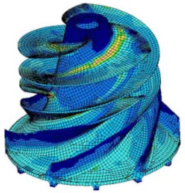
- Floating-point operations
- Operations that involve running the exact same code on a huge number of different data points at once.

Common GPU-Accelerated Workflows



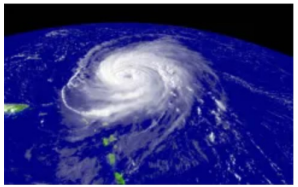
1. Dense Linear Algebra

vector and matrix operations, e.g. clustering algorithms, K-means



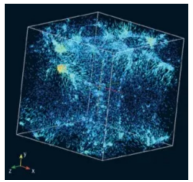
2. Sparse Linear Algebra

matrix multiplication matrices composed mostly of 0s, e.g. finite element analysis



3. Spectral Methods

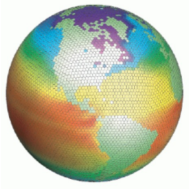
solving differential equations, e.g. fluid dynamics, quantum mechanics, weather prediction



4. N-Body Methods

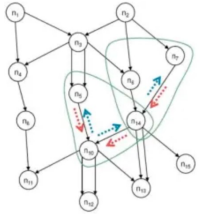
simulation of dynamical system of particles, e.g. astronomy, computational chemistry, physics

Common GPU-Accelerated Workflows



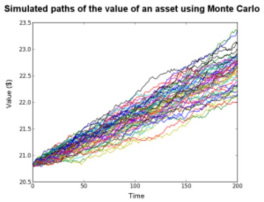
5. Structured Grids

computations that depend on neighbors in an irregular grid, e.g. image processing, physics simulations



6. Unstructured Grids

Grids with different elements that have a different number of neighbors, e.g. computational fluid dynamics



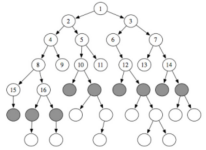
7. Map-Reduce & Monte Carlo

Each process runs completely independent from one another, e.g. Monte-Carlo, Distributed Searching

8. Combinational Logic

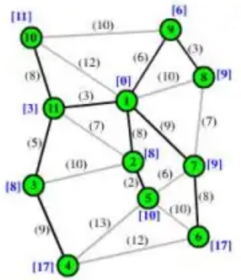
Usually involve performing simple operations on large amounts of data, e.g. hashing, encryption, checksums

Common GPU-Accelerated Workflows



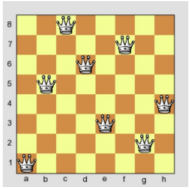
9. Graph Traversal

Problem of visiting all the nodes in a graph, updating and checking values along the way, e.g. search, sorting, serialization



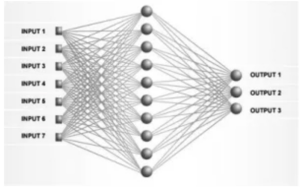
10. Dynamic Programming

Algorithmic technique to compute solutions by solving overlapping subproblems, e.g. graph problems, sequence alignment



11. Backtracking

Build all possible solutions, usually branch-and-bound solution approach, e.g. puzzles, traveling salesman

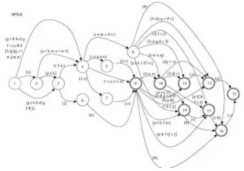


12. Probabilistic Graphical Models

e.g. Bayesian networks, hidden Markov models, neural networks

Shamelessly borrowed from StreamHPC.com

Common GPU-Accelerated Workflows



13. Finite State Machines

Mathematical model of computation used to design computer programs and sequential logic circuits, e.g. data mining, video compression

Further Reading

- Geng et al. **OpenCL and the 13 dwarfs: a work in progress**
- Asanovic et al. **The landscape of parallel computing research: A view from Berkeley**
- Vincent Hindriksen's blog post **The 13 application areas where OpenCL and CUDA can be used**

Poll

What statement best describes your experience with GPU Acceleration?

sli.do: #8229141

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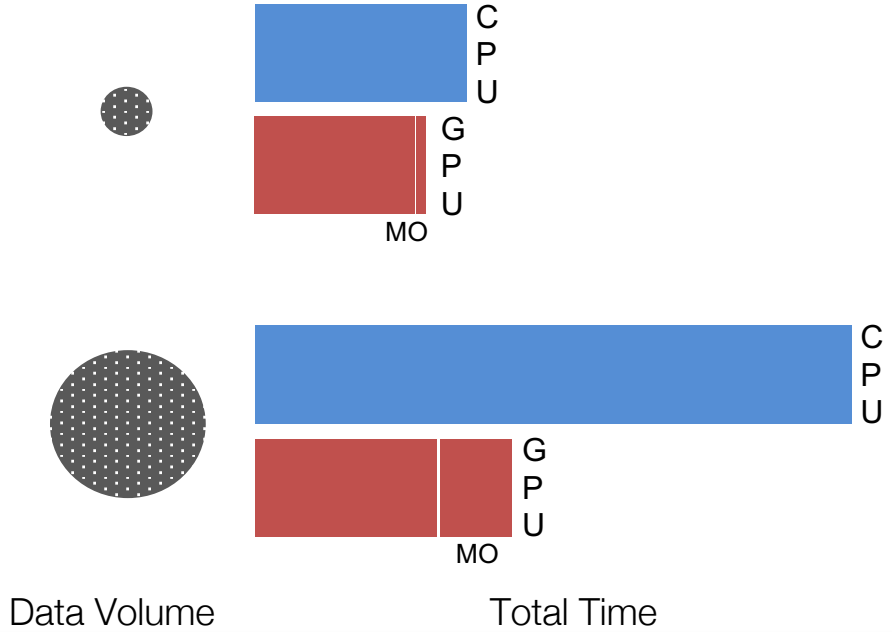
Factors Affecting GPU Speedup

1. Data Volume
2. Data Dependency
3. Data Processing Order
4. Data Type
5. Code/Algorithmic Complexity
6. Computational Intensity

Factors Affecting GPU Speedup

1 Data Volume

- The time spent transferring data to/from CPU to GPU is worthwhile for high data volumes



Factors Affecting GPU Speedup

2 Data Dependency

- Processing a data point depends on previous data points.
  - This should be avoided!

```
for (i=1; i<1000; i++){
    sum = sum + a[i]; /* S1 */
}
```

```
for (i=1; i<1000; i++){
    a[i] = 2 + a[i]; /* S1 */
}
```

Factors Affecting GPU Speedup

3 Data Processing Order

- Data should be written and read in a continuous order for maximum utilization of a GPU.
  - May require adjustments to algorithm

Factors Affecting GPU Speedup

4 Data Type

- Operations on strings are slow unless they can be treated as numbers.
- Performance per GPU can vary quite a bit if workflows include16-bit and 64-bit floats.

Factors Affecting GPU Speedup

5 Code/Algorithmic Complexity

- ‘Simple’ code is better ported to GPUs
  - Deeply branched code and while-loops perform poorly on GPUs
  - Recursive functions need rewriting

Factors Affecting GPU Speedup

6 Computational Intensity

- GPUs perform best when there is a lot of processing compared to loading and storing data (FLOP per Byte ratio)

Factors Affecting GPU Speedup

Performance increases from GPUs depend on several factors related to the data and algorithm.

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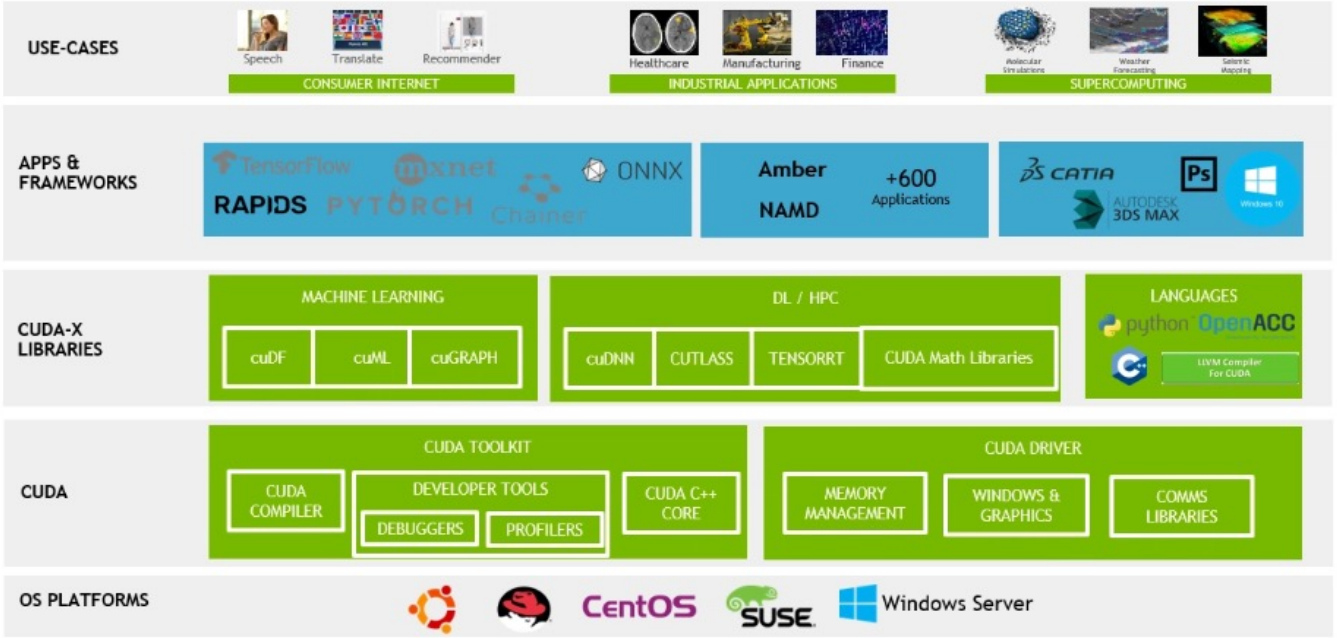
GPU Programming Tools

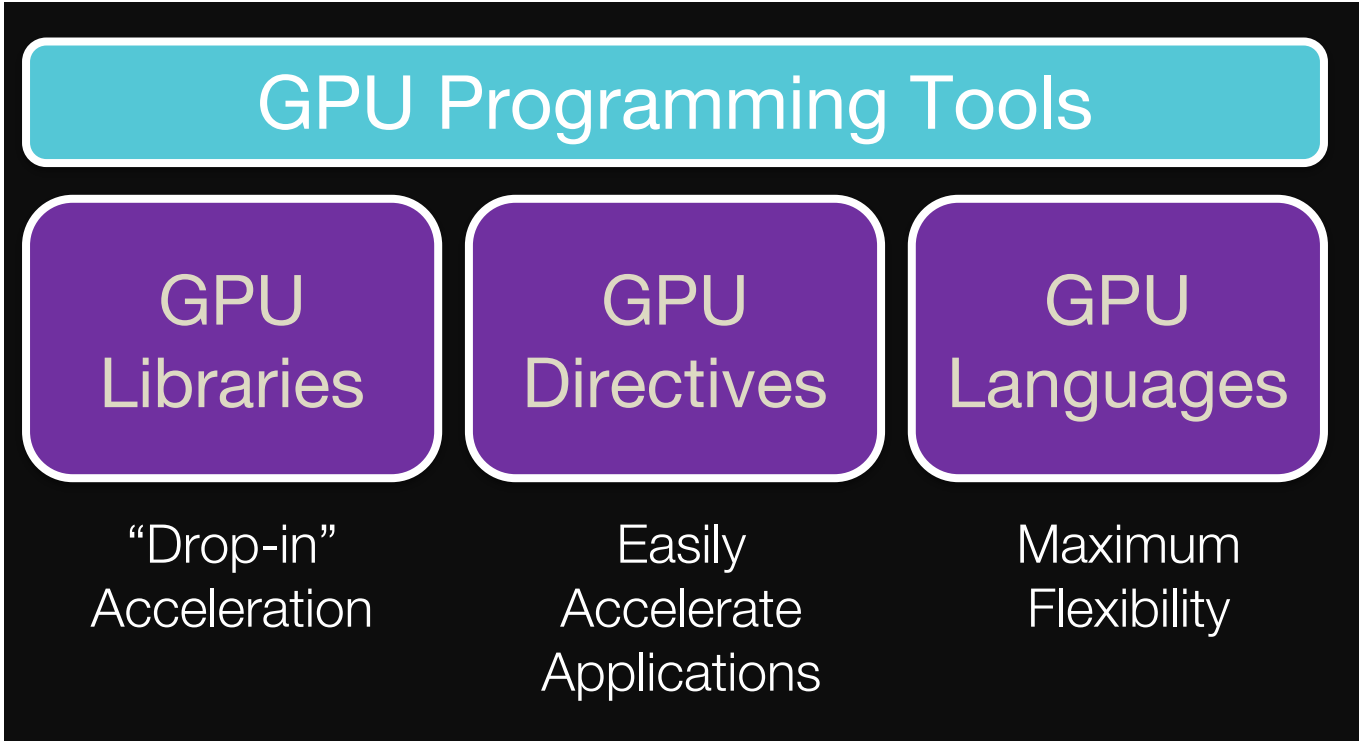
CUDA - a parallel computing platform and programming model



blogs.nvidia.com

GPU Programming Tools

More than CUDA!



GPU Programming Tools

GPU Libraries

- Require little understanding of GPU hardware
- Usually involve minor changes to code
- Accelerated versions of many scientific libraries are available, e.g.
  - LAPACK → MAGMA, libFLAME
  - BLAS → cuBLAS, clBLAS
  - NumPy & SciPy → cuPy

GPU Programming Tools

DBSCAN on CPU

```
#create dataset with 100,000 points using make_circles function
from sklearn.datasets import make_circles
X, y = make_circles(n_samples=int(1e5), factor=.35, noise=.05)

#run DBSCAN clustering algorithm
from sklearn.cluster import DBSCAN
db = DBSCAN(eps=0.6, min_samples=2)
y_db = db.fit_predict(X)
```

DBSCAN with RAPIDS on GPU

```
#convert data to pandas.DataFrame then create cudf.DataFrame
import pandas as pd
import cudf
X_df = pd.DataFrame({'fea%d'%i: X[:, i] for i in range(X.shape[1])})
X_gpu = cudf.DataFrame.from_pandas(X_df)

#use GPU-accelerated version of DBSCAN from cuML
from cuml import DBSCAN as cuml
DBSCANdb_gpu = cumlDBSCAN(eps=0.6, min_samples=2)
y_db_gpu = db_gpu.fit_predict(X_gpu)
```

GPU Programming Tools

GPU Directives

- Easier to learn and involve fewer changes to code that GPU programming languages
- Better portability among devices and platforms
- Compiler directives, e.g. OpenACC, are the most commonly used

GPU Programming Tools

GPU Directives

- Require little understanding of GPU hardware, but more than GPU libraries
  - Host- CPU
  - Device- GPU
  - Kernel- functions launched to the GPU

GPU Programming Tools

OpenACC

- A collection of compiler directives that specify loops and regions of code in standard C, C++, and Fortran to be offloaded from a host CPU to an attached parallel accelerator (developer.nvidia.com)
- Let compiler guess data allocation and movement or control it with directive clauses
- Can be used with GPU libraries, OpenMP

Basic Program Structure (C/C++)

```
#include "openacc.h"
#pragma acc <directive> [clauses [[,] clause] . . .] new-line
<code>
```

Compiling (C/C++) for NVIDIA GPU

```
nvcc --acc -Minfo=accel your_program_acc.c
pgcc –acc –ta=nvidia –c your_program_acc.c
```

GPU Programming Tools

Kernel directives tell the compiler to generate parallel accelerator kernels for the loop nests following the directive.

Example Kernel Directive (C/C++)

```
//Hello_World_OpenACC.c
void Print_Hello_World()
{
#pragma acc kernels
      for(int i = 0; i <  5; i++)
        {
           printf("Hello World!\n");
         }
}
```

Data directives tell the compiler to create code that performs specific data movements and provides hints about data usage.

Example Data Directive (C/C++)

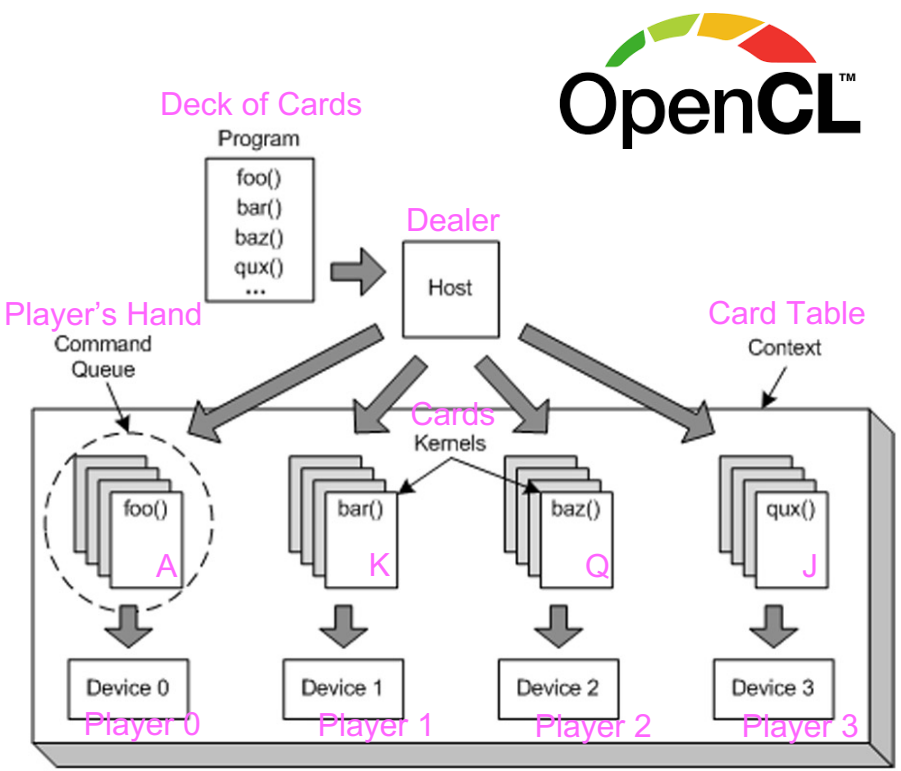
```
#pragma acc data copy(a)
{
    #pragma acc kernels
    {
       for(int i = 0; i <  n; i++)
      {
          a[i] = 0.0
      }
    }
}
```

GPU Programming Tools

GPU Languages (Language Extensions)

- Require in-depth knowledge of hardware
- May involve substantial changes to code
- Code must be maintained to keep up with hardware changes & performance guidelines
- Alpine supports OpenCL (NVIDIA & AMD GPUs), HIP (NVIDIA & AMD), & CUDA (NVIDIA only)

GPU Programming Tools



Dealer distributes cards to players.
Host distributes kernels to devices.

Player receives cards from dealer.
Device receives kernels from host.

Dealer selects cards from a deck.
Host selects kernels from a program

Each player receives cards as part of a hand.
Each device receives kernels through the command queue.

Card table makes it possible for players to transfer cards to each other.
OpenCL Context allows devices to receive kernels and transfer data.

	Description	Code Example
1	Obtain OpenCL platform	clGetPlatformIDs(1, &platform, NULL)
2	Obtain device id for at least one device (accelerator)	clGetDeviceIds(platform, CL_DEVICE_TYPE_GPU, 1, &device, NULL)
3	Create context for device	context = clCreateContext(NULL, 1, &device, NULL, NULL, &err)
4	Create accelerator program from source code	program = clCreateProgramWithSource (context, 1, (const char**) &program_buffer, &program_size, &err)
5	Build the program	clBuildProgram(program, 0,..)
6	Create kernel(s) from program functions	kernel = clCreateKernel(program, "kernel_name", &err)
7	Create command queue for target device	queue = clCreateCommandQueue(context, device, 0, &err)
8	Allocate device memory / move input data to device memory	memObject = clCreateBuffer (context, NULL, SIZE_N, NULL, &err) clEnqueueWriteBuffer(command_queue, memObject, ..., TOTAL_SIZE, hostPointer, ...)
9	Associate arguments to kernel with kernel object	cl_int clSetKernelArg (kernel, arg_index, arg_size, *arg_value)

10	Deploy kernel for device execution	global_size = TOTAL_NUM_THREADS;
		local_size = WORKGROUP_SIZE;
		clEnqueueNDRangeKernel(command_queue, kernel, 1, NULL, &global_size, &local_size, 0, NULL, NULL);

11	Move output data to host memory	clEnqueueReadBuffer(command_queue, memObject, blocking_read, offset, TOTAL_SIZE, hostPointer, 0, NULL, NULL)
12	Release context/program/kernels/memory	clReleaseMemObject(memObject) / clReleaseKernel(kernel) / clReleaseProgram(program) / clReleaseContext(context)

GPU Programming Tools

GPU Frameworks

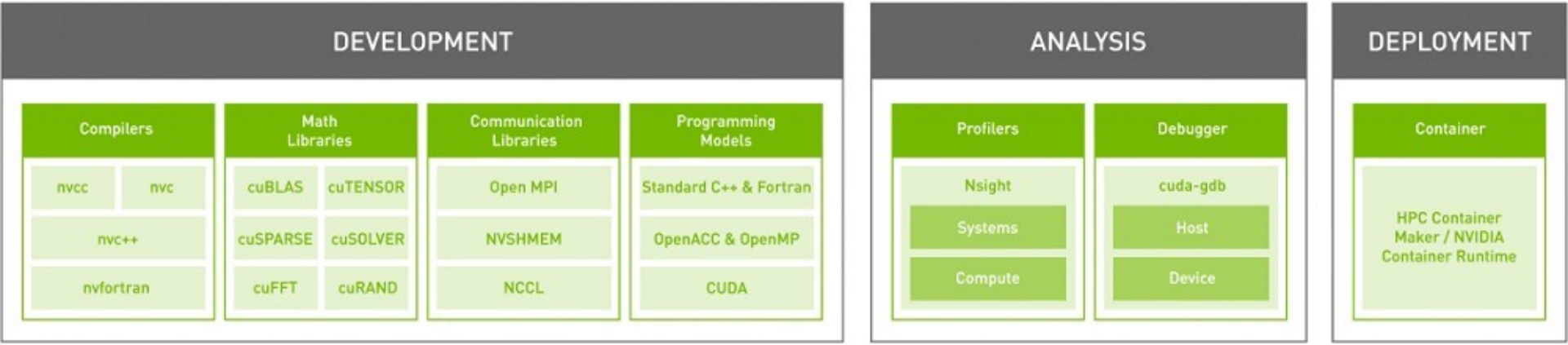
- Offer building blocks for designing, training, and validating workflows (like deep learning)
  - e.g. PyTorch, TensorFlow, Keras, Apache MXNet
- Rely on GPU-accelerated libraries

GPU Programming Tools

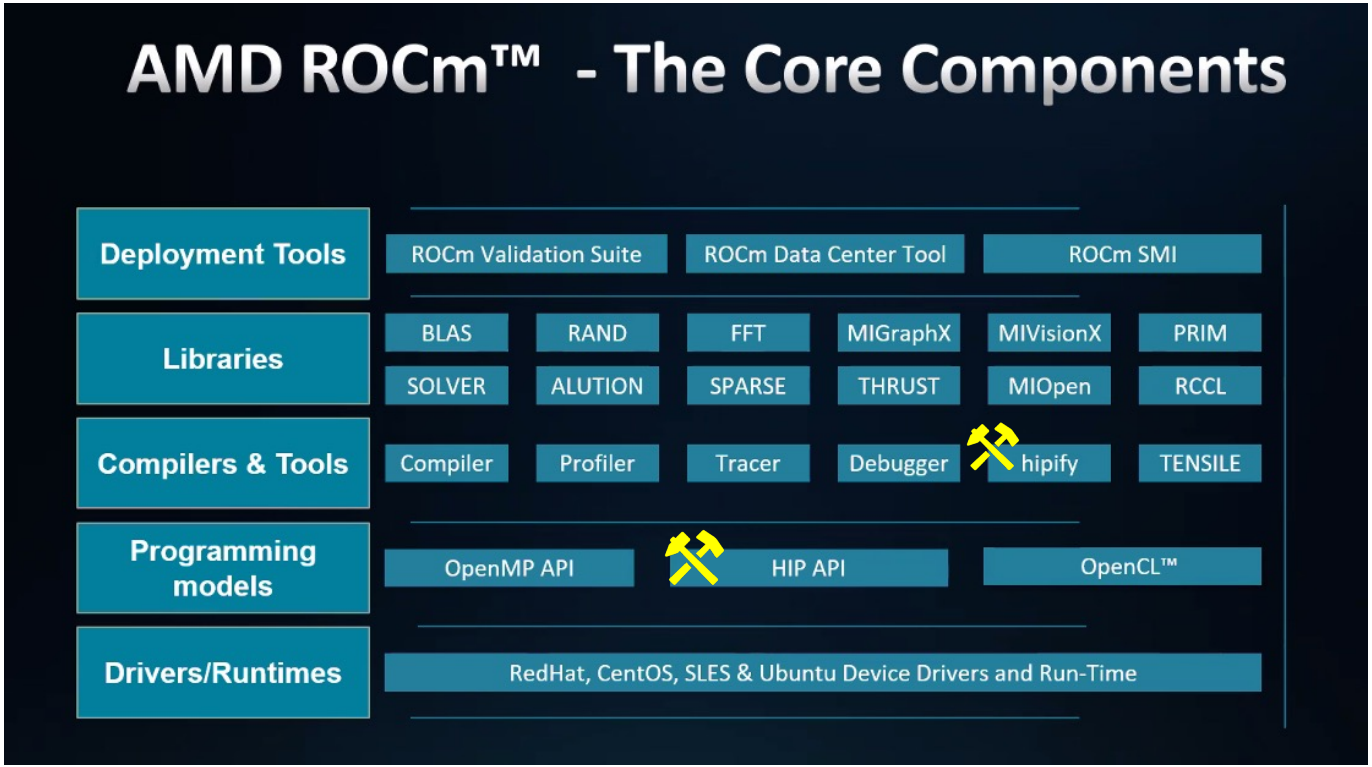
GPU programming tools vary in terms of ease of implementation, portability, and flexibility.

GPU Programming Tools

NVIDIA SDK



GPU Programming Tools



The Heterogeneous Computing Interface for Portability (HIP) is a vendor-neutral C++ programming model for implementing highly tuned workload for GPUs. HIP (like CUDA) is a dialect of C++ supporting templates, classes, lambdas, and other C++ constructs.

A “hipify” tool is provided to ease conversion of CUDA codes to HIP, enabling code compilation for either AMD or NVIDIA GPU (CUDA) environments. The ROCm™ HIP compiler is based on Clang, the LLVM compiler infrastructure, and the “libc++” C++ standard library.

Poll

Rank the GPU programming tools by how likely you are to use them, from most (1) to least likely (6).

sli.do: #8229141

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Requesting GPUs on Alpine with Slurm

Access Slurm job scheduler from login node

```
module load slurm/alpine
```

View Alpine GPU resources and configurations

```
sinfo --Format NodeList:30,Partition,Gres |grep gpu |grep -v "mi100|a100"

c3gpu-c2-u[1,3,5,7,9,11,13,15]aa100          gpu:a100:3
c3gpu-c2-u[1,3,5,7,9,11,13,15]aa100-ucb      gpu:a100:3
c3gpu-c2-u[1,3,5,7,9,11,13,15]aa100-csu      gpu:a100:3
c3gpu-c2-u[1,3,5,7,9,11,13,15]aa100-amc      gpu:a100:3
c3gpu-c2-u[17,19,21,23,25,27,2ami100         gpu:mi100:3
c3gpu-c2-u[17,19,21,23,25,27,2ami100-ucb     gpu:mi100:3
c3gpu-c2-u[17,19,21,23,25,27,2ami100-csu     gpu:mi100:3
c3gpu-c2-u[17,19,21,23,25,27,2ami100-amc     gpu:mi100:3
c3gpu-c2-u[17,19,21,23,25,27,2atesting       gpu:mi100:3
c3gpu-c2-u[1,3,5,7,9,11,13,15]atesting       gpu:a100:3
```

Nvidia A100s
partition=aa100-<institution>
e.g. partition=aa100-ucb

AMD A100s
partition=ami100-<institution>
e.g. partition=ami100-ucb

Requesting GPUs on Alpine with Slurm

Request a compile node

```
acompile --help
acompile --ntasks=4 --gpu=amdgpu --time=2:00:00
acompile --ntasks=4 --gpu=nvidia --time=2:00:00
```

Start an interactive job

```
sinteractive --ntasks=64 --gres=gpu:3 --partition=aa100-ucb --time=1:00:00
sinteractive --ntasks=20 --gres=gpu:1 --partition=ami100-ucb
sinteractive  --gres=gpu:1 --partition=ami100-ucb --qos=long --time=7-00:00:00
sinteractive  --gres=gpu:1 --nodes=2 --partition=ami100-ucb
```

Overview

- Intro to Alpine's Heterogeneous Architecture
- Criteria for GPU Acceleration
- Factors Affecting GPU Speedup
- GPU Programming Tools
- Requesting GPUs on Alpine with Slurm
- **GPU Monitoring on Alpine**
- Hands-on Example: matmul with TensorFlow

GPU Monitoring & Performance Profiling Tools

nvidia-smi

- Command-line utility tool for monitoring NVIDIA GPUs
- Returns device- and process-level information
- Available on Alpine Nvidia nodes without loading any modules

GPU Monitoring & Performance Profiling Tools

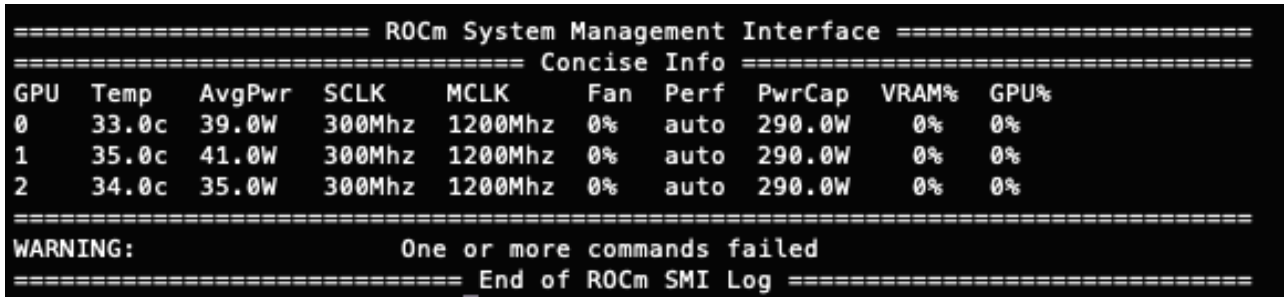
```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 510.47.03    Driver Version: 510.47.03    CUDA Version: 11.6     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA A100-PCI...  Off  | 00000000:21:00.0 Off |                    0 |
| N/A   36C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   1  NVIDIA A100-PCI...  Off  | 00000000:81:00.0 Off |                    0 |
| N/A   36C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   2  NVIDIA A100-PCI...  Off  | 00000000:E2:00.0 Off |                    0 |
| N/A   37C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+

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

GPU Monitoring & Performance Profiling Tools

rocm-smi

- Command-line utility tool for monitoring AMD GPUs
- Returns extensive information
- Available on Alpine AMD nodes without loading any modules

GPU Monitoring & Performance Profiling Tools



More Information:

```
rocm-smi --help
```

Documentation available at
https://rocmdocs.amd.com/en/latest/ROCm_System_Managment/ROCm-SMI-CLI.html

Quiz

Quick Quiz!

sli.do: #8229141

Overview

- Intro to Alpine's Heterogeneous Architecture
- Criteria for GPU Acceleration
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- GPU Monitoring on Alpine
- **Hands-on Example: matmul with TensorFlow**

GPU Speedup Example: Matrix Multiplication with Tensorflow

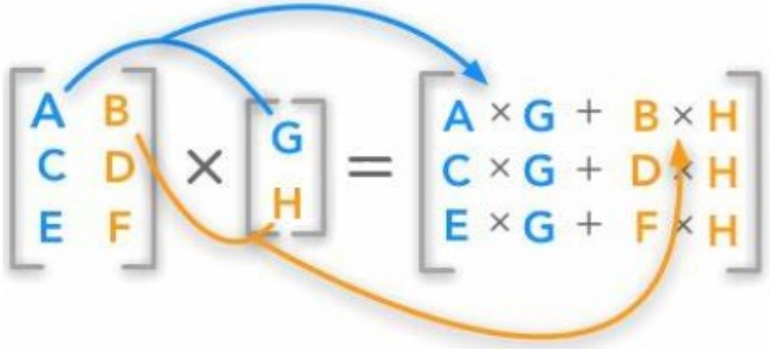
- A matrix is a rectangular array of numbers arranged in rows and columns.
- The order of a matrix is the number of rows and columns.

$$\begin{pmatrix} 6 & 2 & 4 \\ 2 & 1 & 6 \end{pmatrix}$$

order = 2x3

GPU Speedup Example: Matrix Multiplication with Tensorflow

Matrix multiplication is used in many ML algorithms.



We will use Tensorflow's tf.matmul function.

GPU Speedup Example: Matrix Multiplication with Tensorflow

Navigate to your preferred working space (projects, scratch, etc.):

```
cd /projects/$USER/
```

Git the repository:

```
git clone https://github.com/ResearchComputing/Intro_GPU_Acceleration.git
```

Make the scripts executable:

```
cd Intro_GPU_Acceleration
chmod u+x tf*
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

tf.matmul-cpu.py

```
import os
import numpy as np
import tensorflow as tf
import time

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3’
os.environ['CUDA_VISIBLE_DEVICES'] = ‘-1’
if tf.test.gpu_device_name():
       print(“GPU found”)
else:
      print(“Tensorflow is using only CPUs.”)

numpy_start = time.time()
a = np.random.rand(10000,70000)
print(“Numpy generated a random 10000x70000 matrix, matrix a”)
b = np.random.rand(70000,10000)
print(“Numpy generated a random 70000x10000 matrix, matrix b”)
numpy_end = time.time()
print(“It took numpy”, numpy_end-numpy_start, “seconds to generate matrices a and b.”
print(“Tensorflow is beginning matrix multiplication.”
tf_start = time.time()
tf.matmul(a,b)
tf_end=time.time()
print(“Tensorflow multiplied matrices a and b in”, tf_end-tf_start,”seconds.”)
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

tf.matmul-gpu.py

```
import os
import numpy as np
import tensorflow as tf
import time

os.environ['CUDA_VISIBLE_DEVICES'] = ‘0’
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3’

numpy_start = time.time()
a = np.random.rand(10000,70000)
print(“Numpy generated a random 10000x70000 matrix, matrix a”)
b = np.random.rand(70000,10000)
print(“Numpy generated a random 70000x10000 matrix, matrix b”)
numpy_end = time.time()
print(“It took numpy”, numpy_end-numpy_start, “seconds to generate matrices a and b.”
print(“Tensorflow is beginning matrix multiplication.”
tf_start = time.time()
tf.matmul(a,b)
tf_end=time.time()
print(“Tensorflow multiplied matrices a and b in”, tf_end-tf_start,”seconds.”)
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

Start an interactive node on Alpine with 1 A100 as follows:

```
sinteractive --time=01:00:00 --ntasks=20 --gres=gpu:1 --partition=aa100-ucb --reservation=gpuclass
```

Activate the conda environment:

```
module load anaconda
conda activate /curc/sw/conda_env/tf-gpu-cuda11.2
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

Run CPU-only script:

```
python tf.matmul-cpu.py
```

```
Tensorflow is using only CPUs.
Numpy generated a random 10000x70000 matrix, matrix a.
Numpy generated a random 70000x10000 matrix, matrix b.
It took numpy 6.565369129180908 seconds to generate matrices a and b.
Tensorflow is beginning matrix multiplication.
Tensorflow multiplied matrices a and b in 45.82650423049927 seconds.
```

Run GPU-accelerated script:

```
python tf.matmul-gpu.py
```

```
Numpy generated a random 10000x70000 matrix, matrix a.
Numpy generated a second random 70000x10000 matrix, matrix b.
It took numpy 6.620205402374268 seconds to generate the matrices.
Tensorflow is beginning matrix multiplication.
Tensorflow multiplied matrices a and b in 3.0970964431762695 seconds.
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

```
import os
import numpy as np
import tensorflow as tf
import time

os.environ["CUDA_VISIBLE_DEVICES"]="0"
os.environ["TF_CPP_MIN_LOG_LEVEL"]="3"

numpy_start=time.time()
a = np.random.rand(50000, 20000)
print("Numpy generated a random 50000x20000 matrix, matrix a.")
b = np.random.rand(20000, 50000)
numpy_end=time.time()
print("Numpy generated a second random 20000x50000 matrix, matrix b.")
print("It took numpy", numpy_end-numpy_start, "seconds to generate the matrices.")
print("Tensorflow is beginning matrix multiplication.")
tf_start = time.time()
c = tf.matmul(a,b)
tf_end  = time.time()
print("Tensorflow multiplied matrices a and b in", tf_end-tf_start, "seconds.")
quit()
```

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 510.47.03    Driver Version: 510.47.03    CUDA Version: 11.6     |
|-------------------------------+----------------------+----------------------+
| 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  NVIDIA A100-PCI...  Off  | 00000000:21:00.0 Off |                    0 |
| N/A   36C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   1  NVIDIA A100-PCI...  Off  | 00000000:81:00.0 Off |                    0 |
| N/A   36C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   2  NVIDIA A100-PCI...  Off  | 00000000:E2:00.0 Off |                    0 |
| N/A   37C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+

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

GPU Speedup Example: Matrix Multiplication with Tensorflow

```
import os
import numpy as np
import tensorflow as tf
import time

os.environ["CUDA_VISIBLE_DEVICES"]="0"
os.environ["TF_CPP_MIN_LOG_LEVEL"]="3"

numpy_start=time.time()
a = np.random.rand(50000, 20000)
print("Numpy generated a random 50000x20000 matrix, matrix a.")
b = np.random.rand(20000, 50000)
numpy_end=time.time()
print("Numpy generated a second random 20000x50000 matrix, matrix b.")
print("It took numpy", numpy_end-numpy_start, "seconds to generate the matrices.")
print("Tensorflow is beginning matrix multiplication.")
tf_start = time.time()
c = tf.matmul(a,b)
tf_end  = time.time()
print("Tensorflow multiplied matrices a and b in", tf_end-tf_start, "seconds.")
quit()
```

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 510.47.03    Driver Version: 510.47.03    CUDA Version: 11.6     |
|-------------------------------+----------------------+----------------------+
| 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  NVIDIA A100-PCI...  Off  | 00000000:21:00.0 Off |                    0 |
| N/A   36C    P0    40W / 250W |  38819MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   1  NVIDIA A100-PCI...  Off  | 00000000:81:00.0 Off |                    0 |
| N/A   35C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   2  NVIDIA A100-PCI...  Off  | 00000000:E2:00.0 Off |                    0 |
| N/A   37C    P0    40W / 250W |      0MiB / 40960MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A   3447060      C   python                          38817MiB |
+-----------------------------------------------------------------------------+
```

GPU Speedup Example: Matrix Multiplication with Tensorflow

- How could we speed this up even further?
- How would matrix size affect the observed speed up?

Thank you!

Survey: http://tinyurl.com/curc-survey18

Alpine Documentation:
https://curc.readthedocs.io/en/latest/clusters/alpine/index.html

Ask for Help: colorado.edu/rc/userservices/contact

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