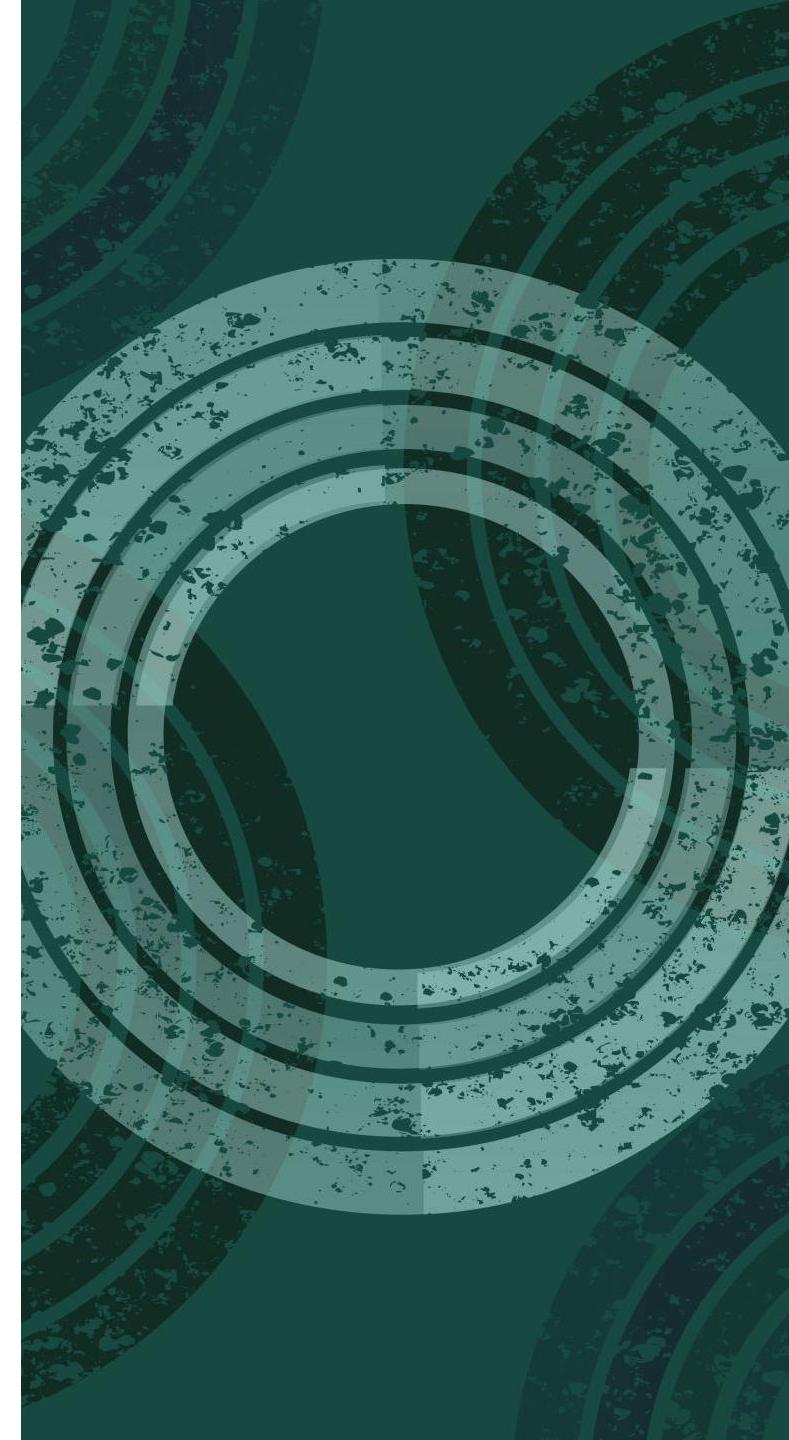
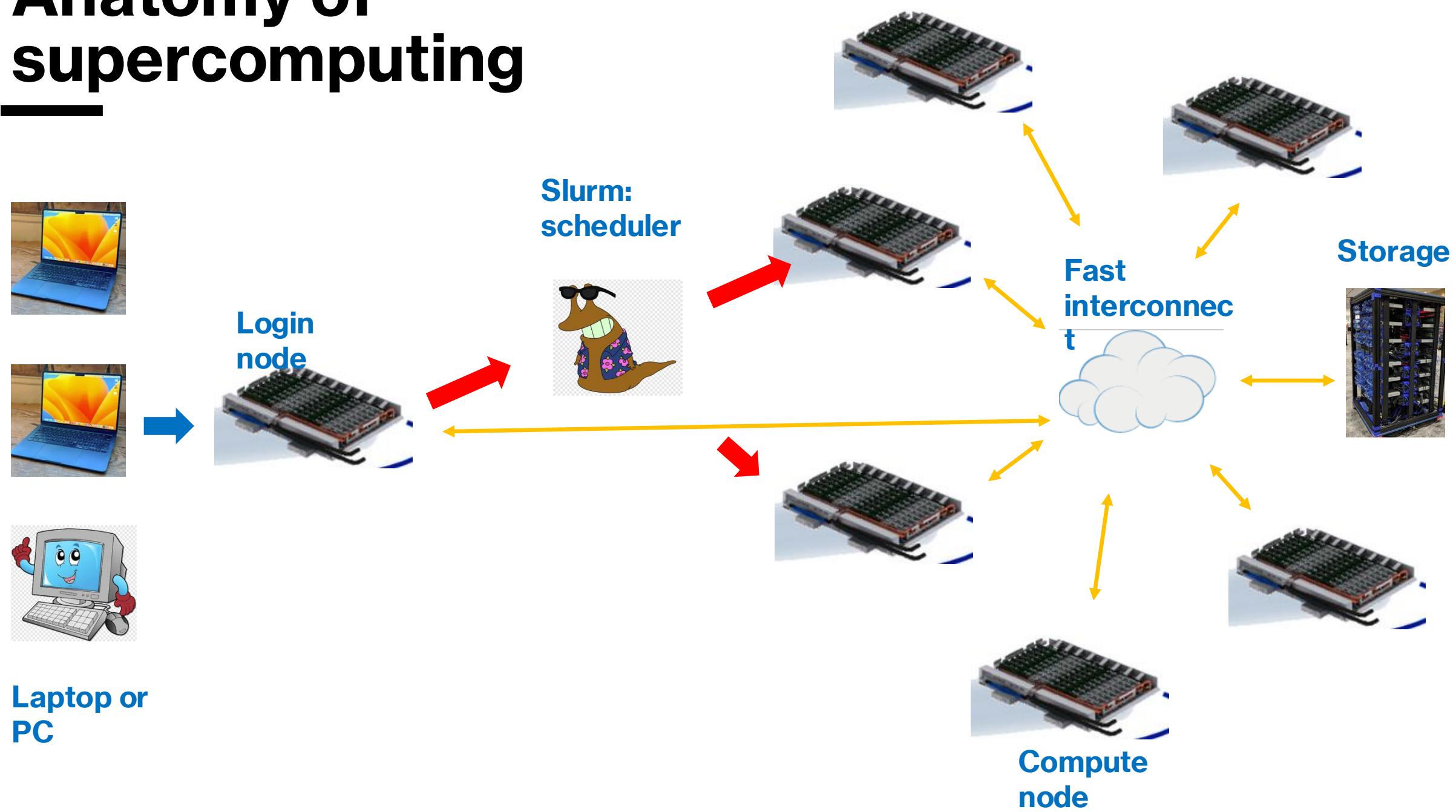


INTRODUCTION TO GPU PARTITIONS ON ALPINE

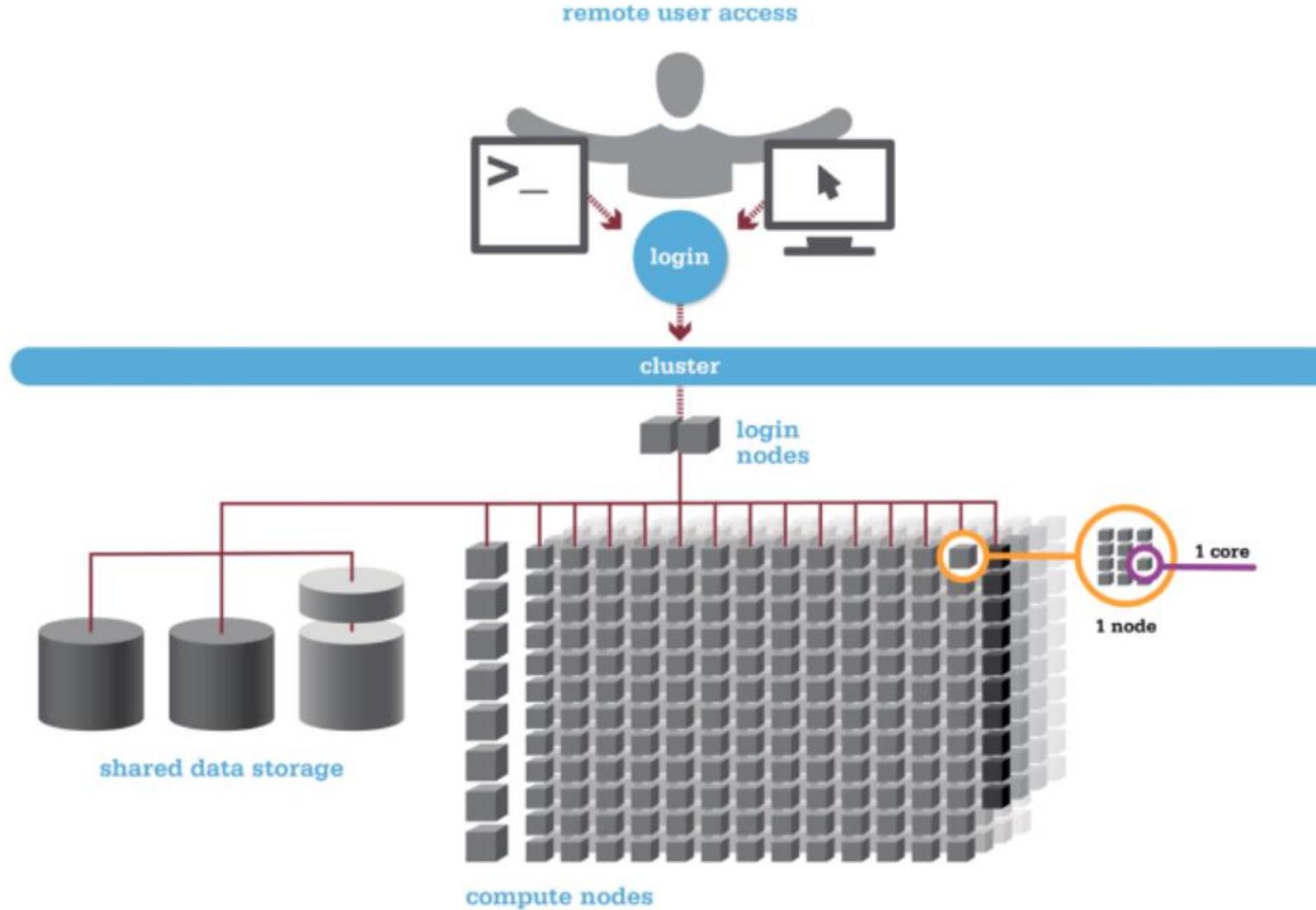
By Kevin Fotso



Anatomy of supercomputing



Architechture of a supercomputer

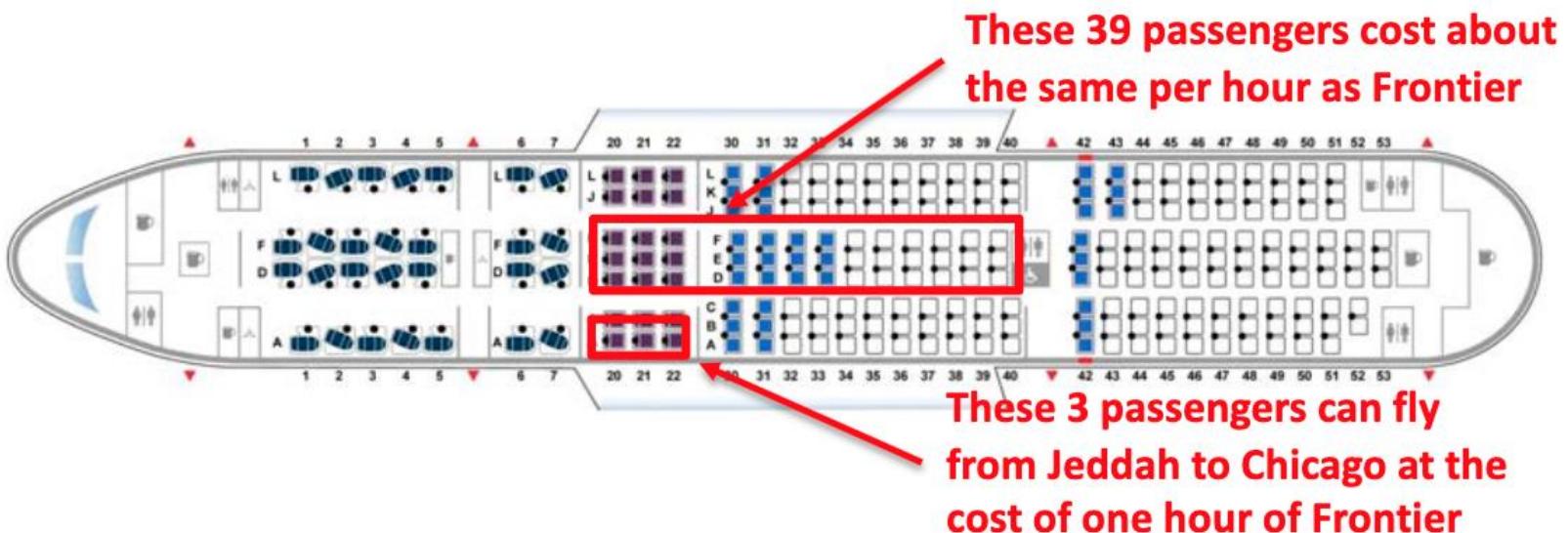


- Login nodes. To log into the system, cd into directories, look at files etc ...
- Compute node. Dedicated to do the computation
- The slurm scheduler controls access to the compute nodes to avoid a tragedy of the commons ...

Why Slurm?

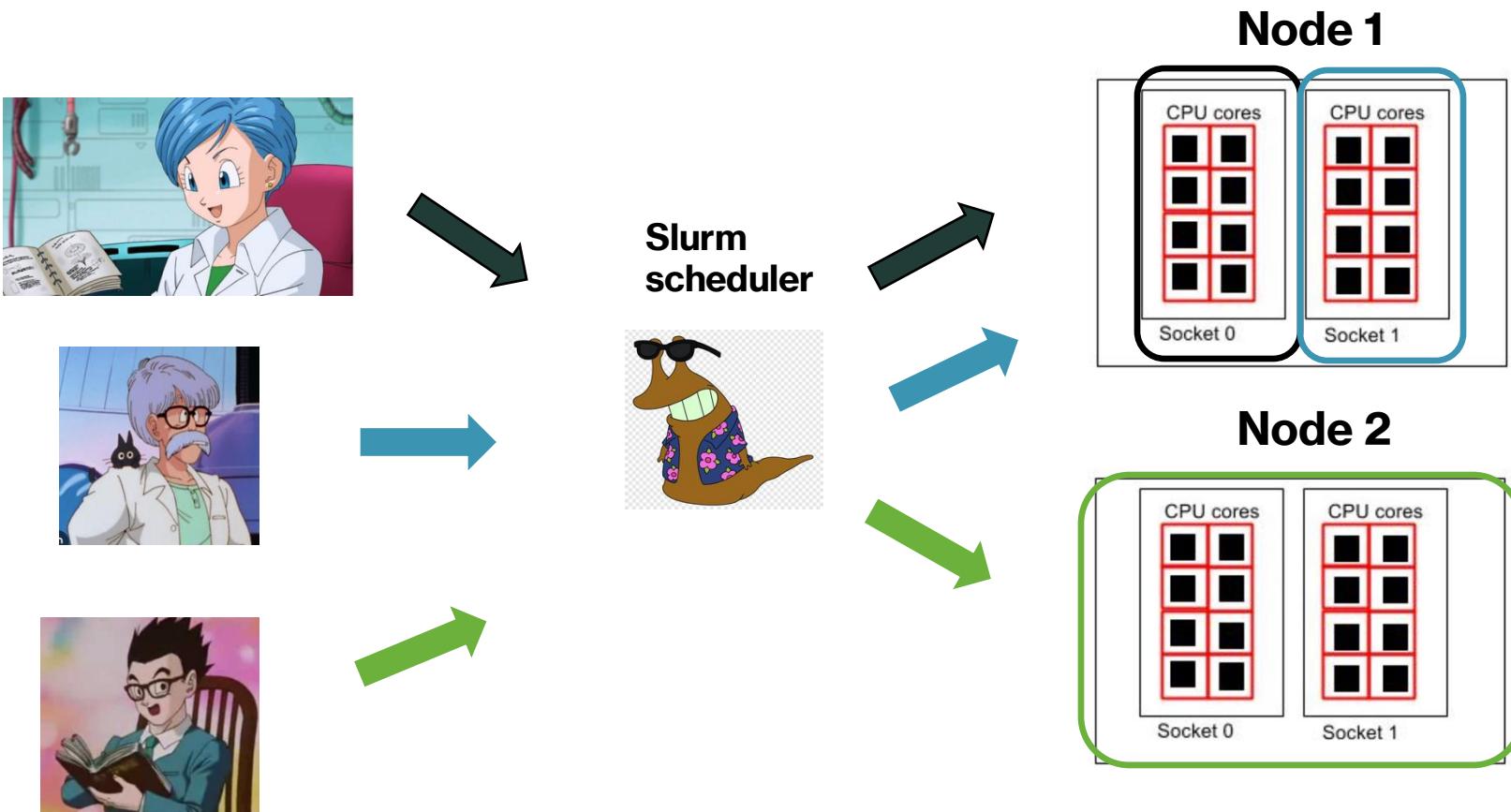


- Allows for better tracking of resource used per user
- Better management of resource across user base
- More sustainable and less tragedy of the commons
- Widely used and supported by applications in case of bugs.



Why Slurm?

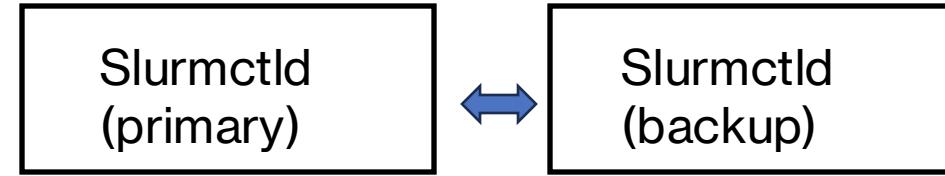
- Bulma request 8 cores from Node 1
- Dr. Brief requests 8 cores as well from Node 1
- Gohan requests 16 cores from Node 2
- No tragedy of the common!!!



Slurm architecture

Controller daemons

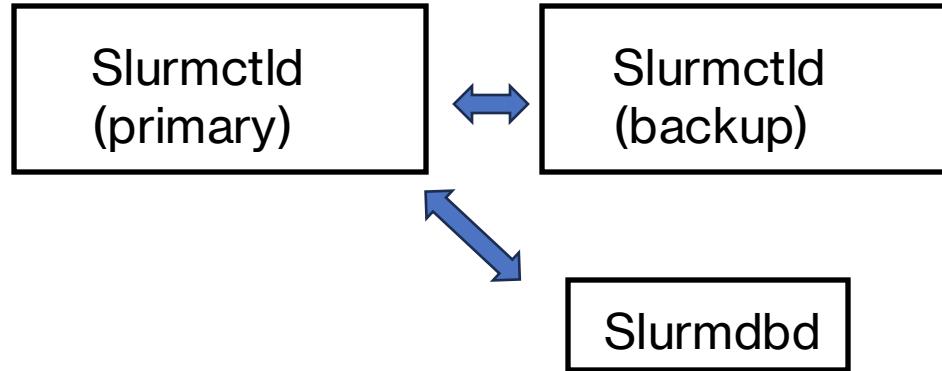
- Slurmctld are daemons that monitor the state of resources, decide when to initiate job states and process users command.



Slurm architecture

Controller daemons

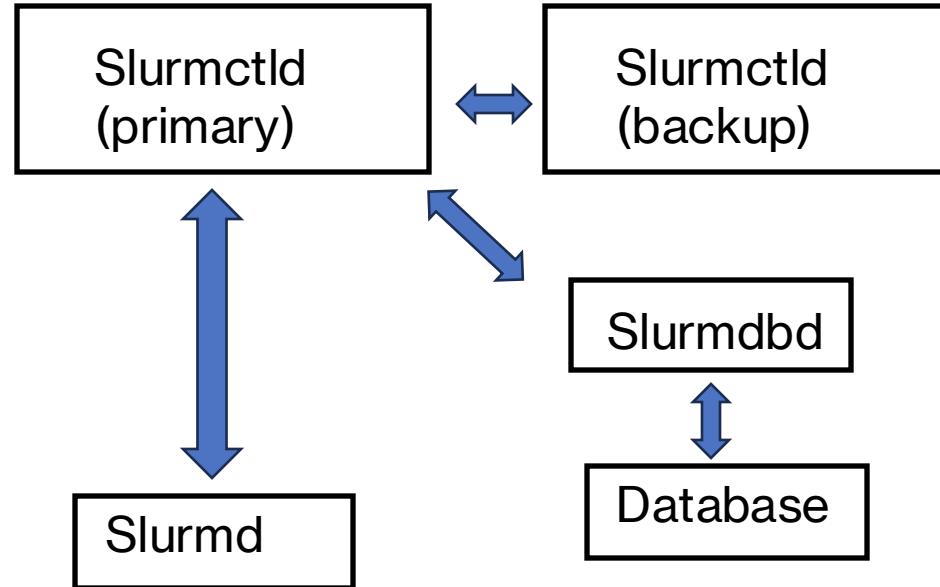
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- Slurmdbd is the database daemon and records accounting information and manages some other config (qos, fair share ...)



Slurm architecture

Controller daemons

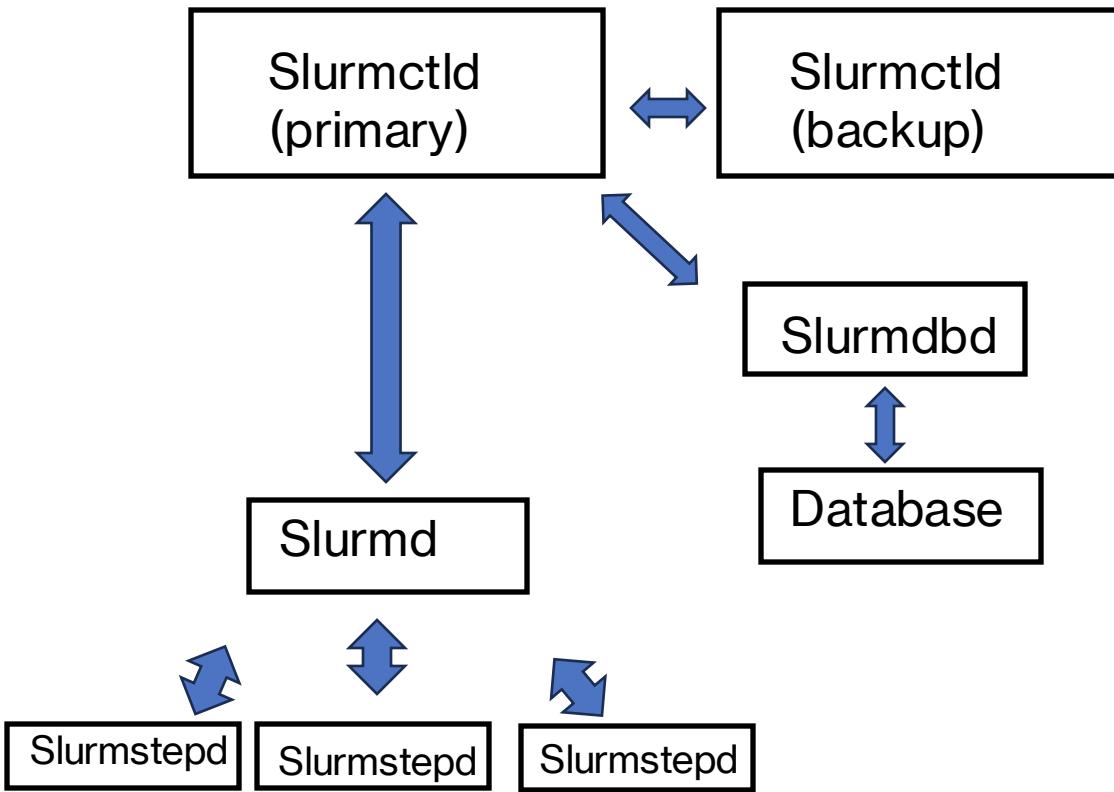
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Slurm architecture

- Slurmctld are daemons that monitor the state of resources, decide when to initiate job states and process users command.
- Slurmdbd is the database daemon and records accounting information and manages some other config (qos, fair share ...).
- Slurmd is the slurm compute daemon on compute nodes. Spawn processes on behalf of users
- Slurmstepd are processes spawned by Slurmd that launch user's batch script, manage accounting, I/O, signals during compute.

Controler daemons

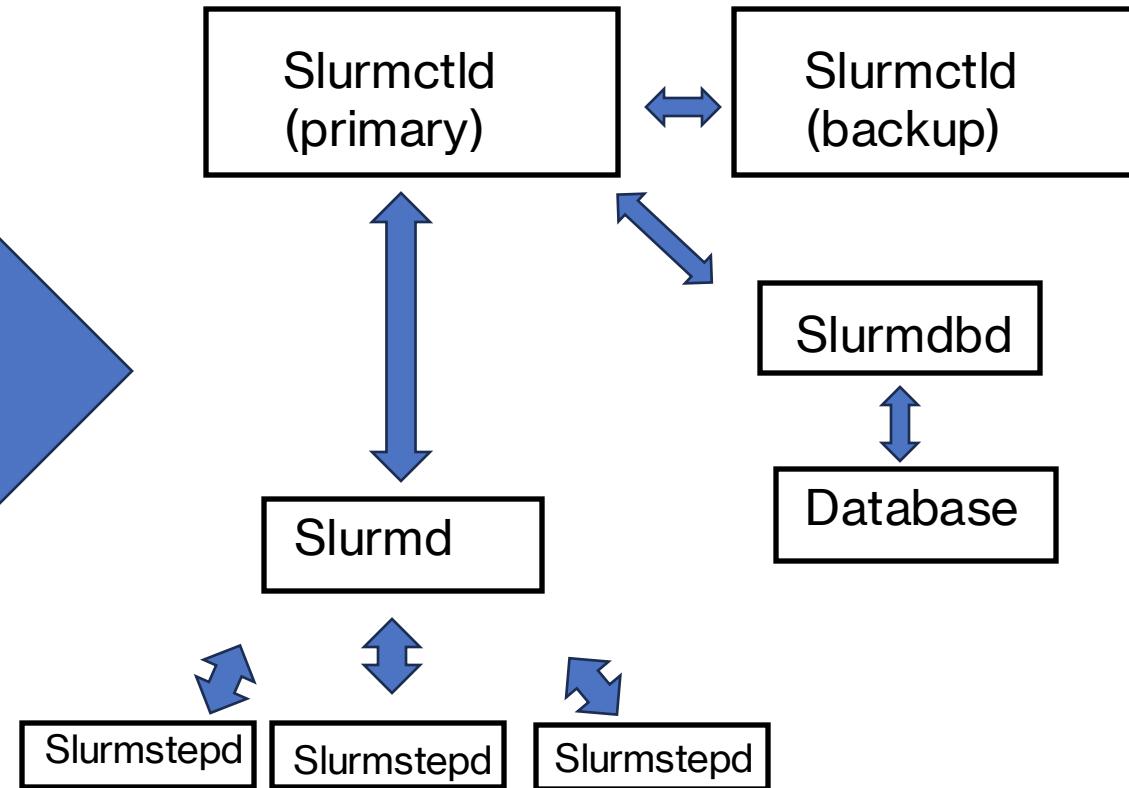


Slurm architecture

User's commands

- scontrol
- sinfo
- squeue
- scancel
- sacct
- srun
- scontrol

Controller daemons



— Context[1]

- Our cluster named Alpine is made of 26,032 cores and 439 compute nodes

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- Our cluster named Alpine is made of 22,180 cores and 382 compute nodes.
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- Each GPU node is 2x25 Gb Ethernet+RoCE interconnected.
- 3 gpus per node.
- The OS is RedHat 8.8
- One needs to submit a proposal to access Grace Hopper. Let me know if interested!

Software stack

- Our software versions on the cuda side are: [cuda/11.2](#), [cuda/11.3](#), [cuda/11.4](#), [cuda/11.8](#) and [cuda/12.1.1](#)

Software stack

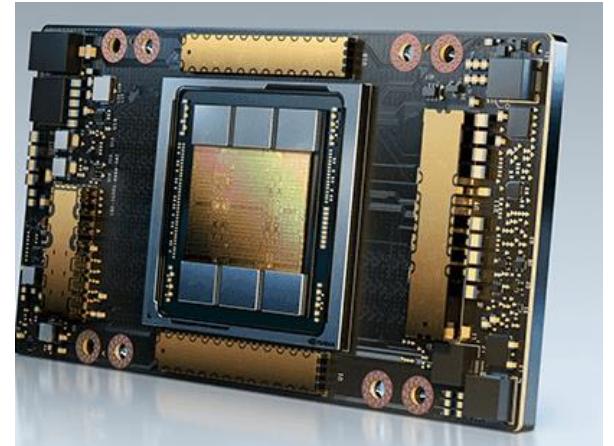
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- Our software versions on the AMD side are: [rocm/5.2.3](#), [rocm/5.3.0](#), [rocm/5.5.0](#), [rocm/6.1.0](#)

— Computing situation

- Our users on the Medical Campus side have been used to computation on the A100 nodes, and recently L40 nodes.

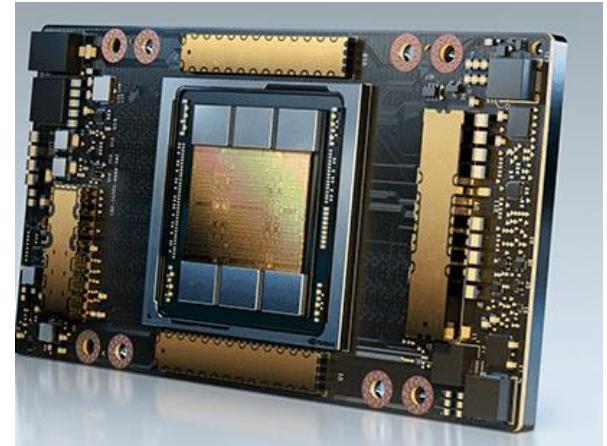
Alpine NVIDIA A100 Specs

- 40GB or 80 GB global memory for each gpu.



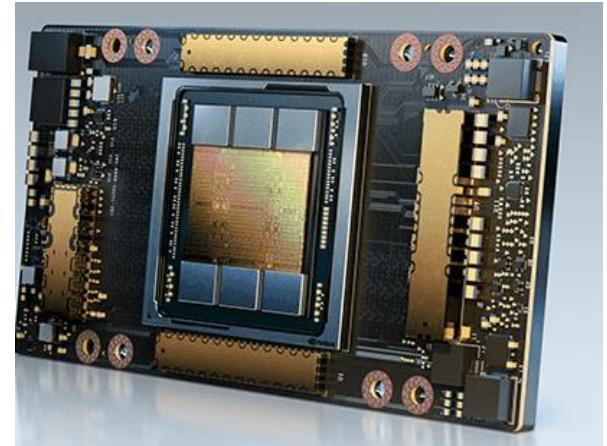
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- Peak memory bandwidth is >2TB/s.



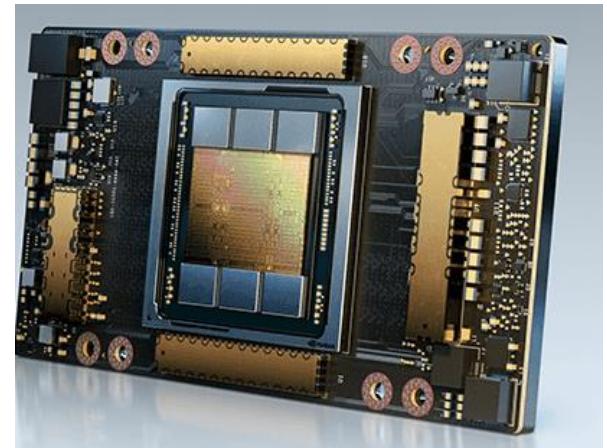
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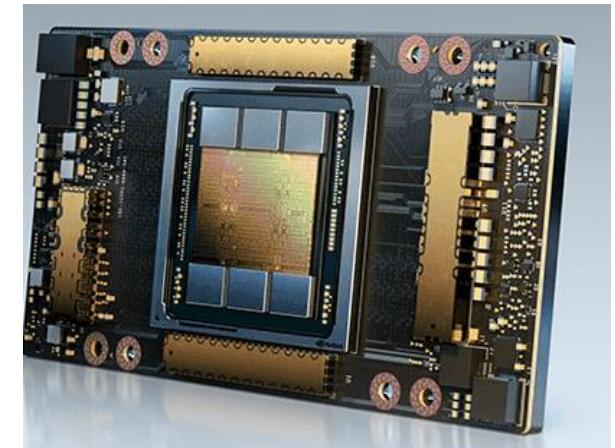
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- Two partition names on Alpine: aa100 for batch submission and atesting_a100 as a debugging partition

To access the A100 compute node with 80G please include

the following below in your slurm script:

- **#SBATCH --partition=aa100**
#SBATCH --constraint=gpu80



Alpine NVIDIA L40 Specs

- 48GB global memory for each gpu.
- Peak memory bandwidth is 864 GB/s.
- 3 NVIDIA gpus per node
- One partition names on Alpine: al40 for batch submission



Alpine AMD MI100 Specs

- 32 GB global memory for each gpu (80 GB memory for the NVIDIA A100 gpu)



Alpine AMD MI100 Specs

- 32 GB global memory for each gpu (80 GB memory for the NVIDIA A100 gpu)
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- Peak memory bandwidth is 1.2 TB/s (>2TB/s for NVIDIA A100)
- 3 AMD gpus per node
- Two partition names on Alpine: ami100 for batch submission and atesting_mi100 as a debugging partition



Slurm & GPU partitions

Alpine GPU Partitions

Try these commands.

```
1 ssh <username>@login.rc.colorado.edu
2 sinfo --Format Partition
3 sinfo --partition aa100,ami100,atesting_a100,atesting_mi100      --Format
   Partition,Nodes,Time
4 scontrol show partition aa100
5 scontrol show partition atesting_a100
6 scontrol show partition ami100
7 scontrol show partition atesting_mi100
8 scontrol show node c3gpu-c2-u17
9 scontrol show node c3gpu-a9-u29-1
```



Shows partition name, total nodes, and time limit

Slurm & GPU partitions

Alpine GPU Partitions

Try these commands.

```
1 ssh <username>@login.rc.colorado.edu
2 sinfo --Format Partition
3 sinfo --partition aa100,ami100,atesting_a100,atesting_mi100      --Format
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6 scontrol show partition ami100
7 scontrol show partition atesting_mi100
8 scontrol show node c3gpu-c2-u17
9 scontrol show node c3gpu-a9-u29-1
```

Shows current State, Default walltime,
Billing, type of nodes etc ...

Slurm & GPU partitions

Requesting Alpine GPUs with Slurm

Slurm flags needed to request 1 AMD GPU node with 2 GPUs and 20 CPU cores

File display
--partition=ami100
--gres=gpu:2
--ntasks=20

in a job script submitted with **sbatch** command

```
#SBATCH --partition=ami100
#SBATCH --gres=gpu:2
#SBATCH --ntasks=20
#SBATCH --job-name=gpu_test
#SBATCH --output=gpu_test_%j.out
#SBATCH --error=gpu_test_%j.err
#SBATCH --mail-type=ALL
#SBATCH --mail-user=<email>
```

in an interactive job

```
sinteractive --partition=ami100 --gres=gpu:2 --ntasks=20
```

Slurm & GPU partitions

Requesting Alpine GPUs with Slurm

```
#request one AMD GPU with default time and default CPU cores  
sinteractive --partition=ami100 --gres=gpu:1  
  
#request two AMD GPUs with 64 CPU cores for 24 hours  
sinteractive --partition=ami100 --gres=gpu:2 --ntasks=64 --time=24:00:00  
  
#request one AMD GPU for 7 days (requires long QoS)  
sinteractive --partition=ami100 --gres=gpu:1 --time=7-00:00:00 --qos=long  
  
#request three 80GB NVIDIA A100 GPUs with 20 CPU cores for default time  
sinteractive --partition=aa100 --ntasks=20 --gres=gpu:3 --constraint=gpu80
```

To access 80G on debug mode!!



File display



Pay attention to defaults!

Slurm & GPU partitions

Alpine GPU Partitions- Defaults and Limits

```
sinteractive --partition=<ami100 or aa100> --gres=gpu
```

| | Default | Minimum | Maximum |
|-----------|---------------------|----------------|---|
| ntasks | 1 | 1 | 64 per node |
| GPU cards | 1 GPU (- -gres=gpu) | 1 GPU per node | Users are limited to their jobs collectively using up to 2/3 of the total GPUs in the partition. Once all running jobs exceed 2/3 of total GPUs, jobs will be queued with the reason QOSMaxGRESPerUser and will eventually run. File display |
| Nodes | 1 | 1 | 12 for --partition=aa100, but see above 8 for --partition=ami100, but see above |
| Time | 12:00:00 | time > 0:00 | 24:00:00 with --qos=normal 7-00:00:00 with --qos=long |

There are rules with how much GPUs you can get

Slurm & GPU partitions

Alpine GPU Testing Partitions- Defaults and Limits

```
sinteractive --partition=<atesting_a100 or atesting_mi100> --gres=gpu
```

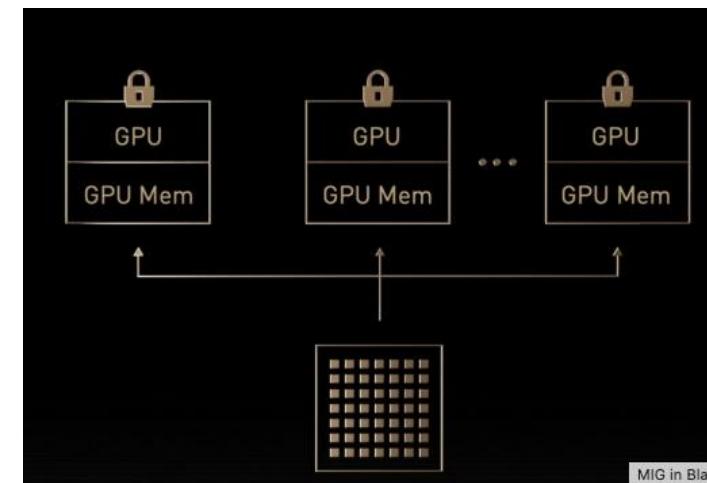
| | Default | Minimum | Maximum |
|-----------|----------------------|-------------|-----------------------------|
| ntasks | 1 | 1 | 16 |
| GPU cards | 0 without --gres=gpu | 1 | 3 |
| | | | <small>File display</small> |
| Nodes | 1 | 1 | 1 |
| Time | 1:00:00 | time > 0:00 | 1:00:00 |



There are rules with how much GPUs you can get

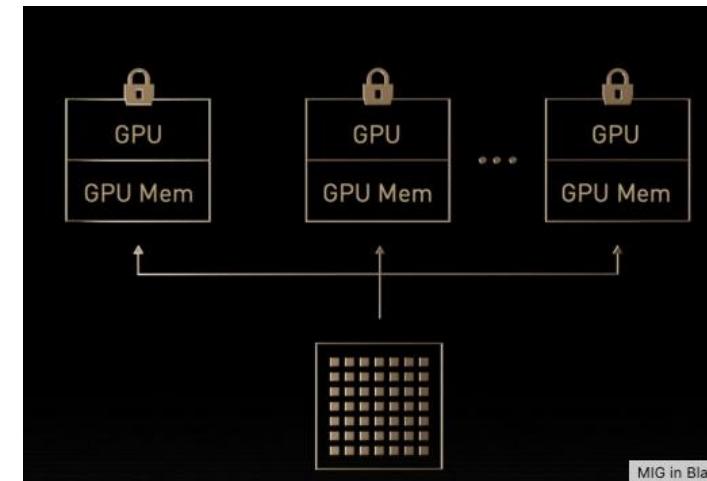
NVIDIA MIG

- The `atesting_a100` partition utilizes NVIDIA's Multi-Instance GPU (MIG) feature, which can "slice" GPUs into multiple GPU instances.



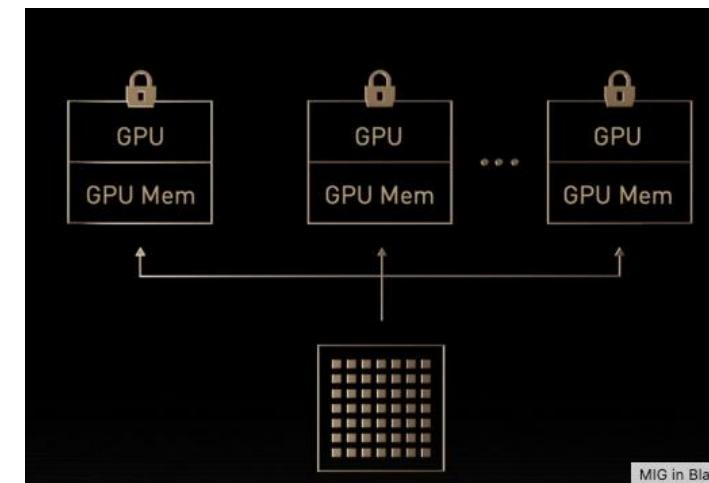
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NVIDIA MIG

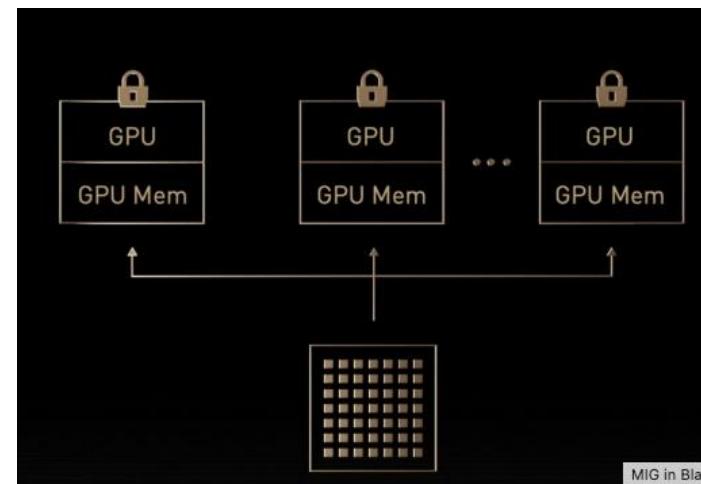
- The `atesting_a100` partition utilizes NVIDIA's [Multi-Instance GPU \(MIG\)](#) feature, which can "slice" GPUs into multiple GPU instances.
- These GPU instances can be treated as a single GPU.
- One important limitation is that MIG does not allow for multiple GPU instances to communicate with each other.



NVIDIA MIG

- sinteractive --partition=atesting_a100 --gres=gpu --ntasks=10 --time=30:00

(Request 1 A100 MIG slice with 10 CPU cores for 30 minutes)



IV- Intro to GPU profiling NVIDIA

—

3 steps

- Analyze code: for assessing the blocks that need optimization

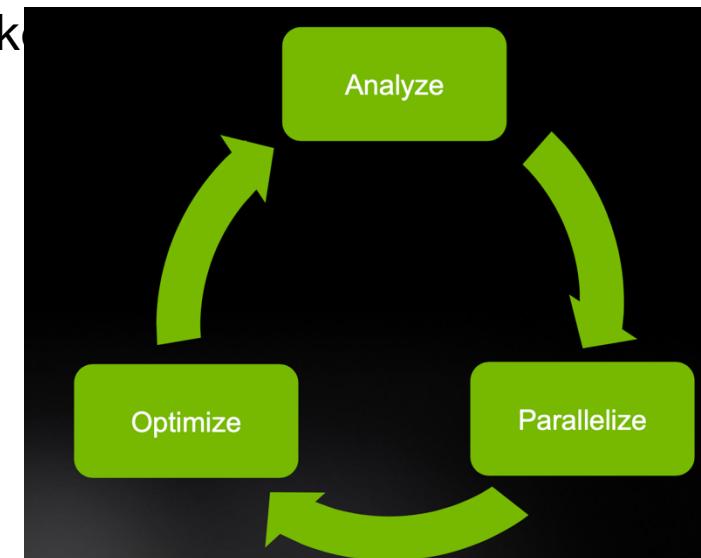
—

3 steps

- Analyze code: for assessing the blocks that need optimization
- Then parallelize the further by rewriting the parts that take the most time

3 steps

- Analyze code: for assessing the blocks that need optimization
- Then parallelize the further by rewriting the parts that take
- Optimize the code
- Repeat



Benefits of nsights

- Allows to measure the bottlenecks of the pipeline to improve efficiency
- Allows to avoid work based on intuition or guess (is the pipeline CPU or GPU bound?)
- See how asynchronous the software is interacting.

— 2 things necessary to profile

- You need to have nsys on the hpc
`module load cuda/11.8`
- When running your GPU pipeline run it with nsys and it will create an output
- Export that output profile to your local laptop where you downloaded the nsight app.
- You may profile for a 30s to 2 min to get an idea of the bottleneck.
You do not need to profile for the entire time if you have a heavy run

nsys command

```
nsys profile --trace=cuda,nvtx,osrt,cudnn,cublas --backtrace=dwarf  
--capture-range=cudaProfilerApi --gpu-metrics-devices=all -output=oft-profile-dwarf4  
sh scripts/expt-singleGPU.sh --profile 50 --profile_start 5000 --profile_epoch 1
```

Nsight Systems CLI command

Select APIs to trace

Enable GPU memory use tracking (but there is extra overhead)

Collect thread call-stack sample backtraces via DWARF info - deeper but more expensive to collect

Trigger collection on cudaProfilerStart API in application, or consider timer-based options

GPU metrics sampling at default 10khz

Name the report file

Application command - plus arguments for when to start profiling

<https://docs.nvidia.com/nsight-systems/UserGuide/index.html#cli-profile-command-switch-options>

srun nsys profile ... required on multi-node or multi-container

nsys profile mpirun ... optional on single node to produce a single report

Nsys with Deep learning Horovod on Alpine (Slurm script)

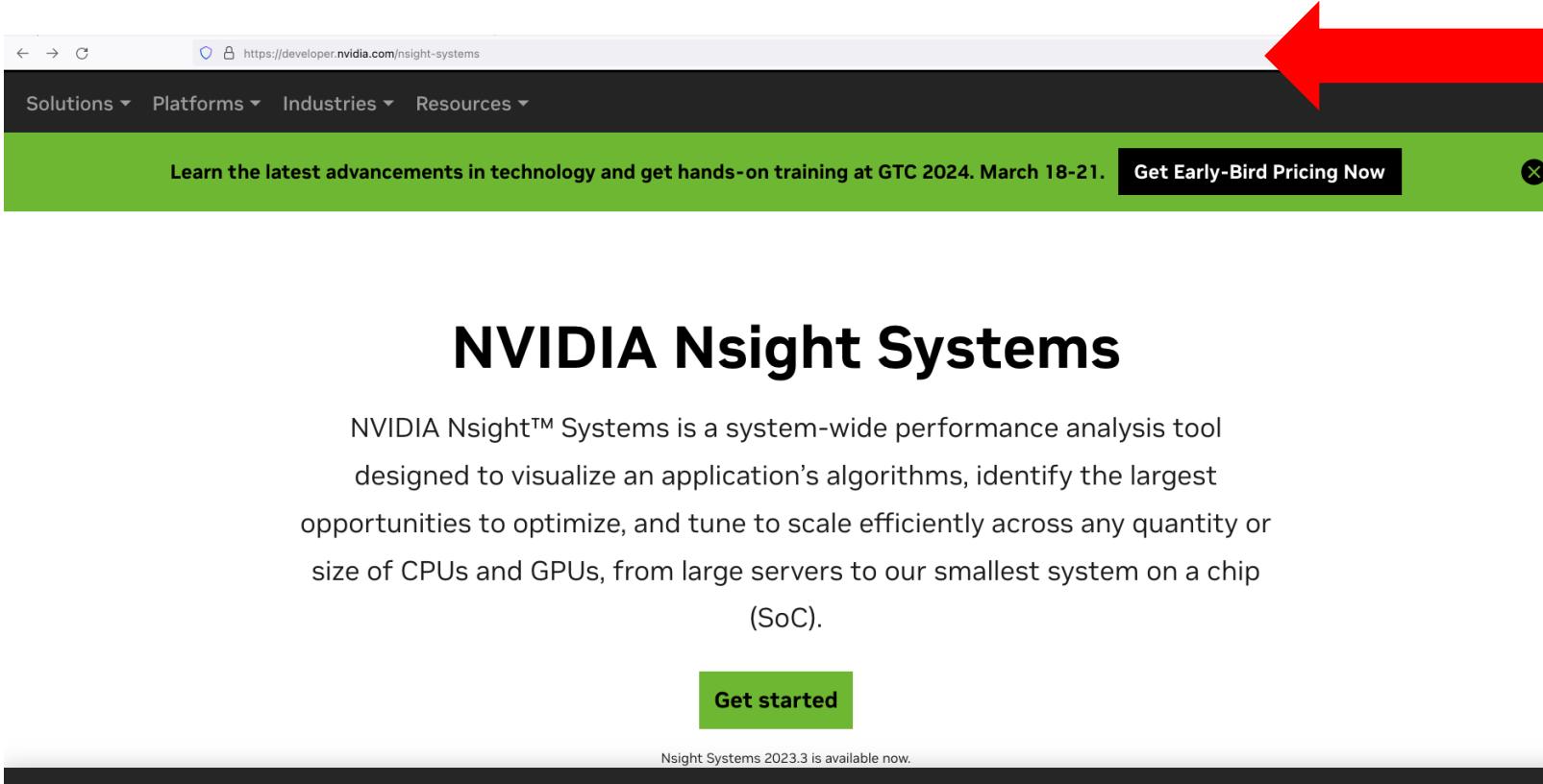
```
# We test it with 4 GPUs
echo "Testing it with 4 GPUs"
nsys profile --trace=cuda,nvtx,osrt,cudnn,cublas \
    --capture-range=cudaProfilerApi \
    --gpu-metrics-device=all \
    --output=horovod_profile \
    horovodrun -np 4 -H $node1:2,$node2:2
horovod_housing_tf.py
```



We use 2 GPUs
on node 1 and 2
on node 2

NVIDIA Nsight

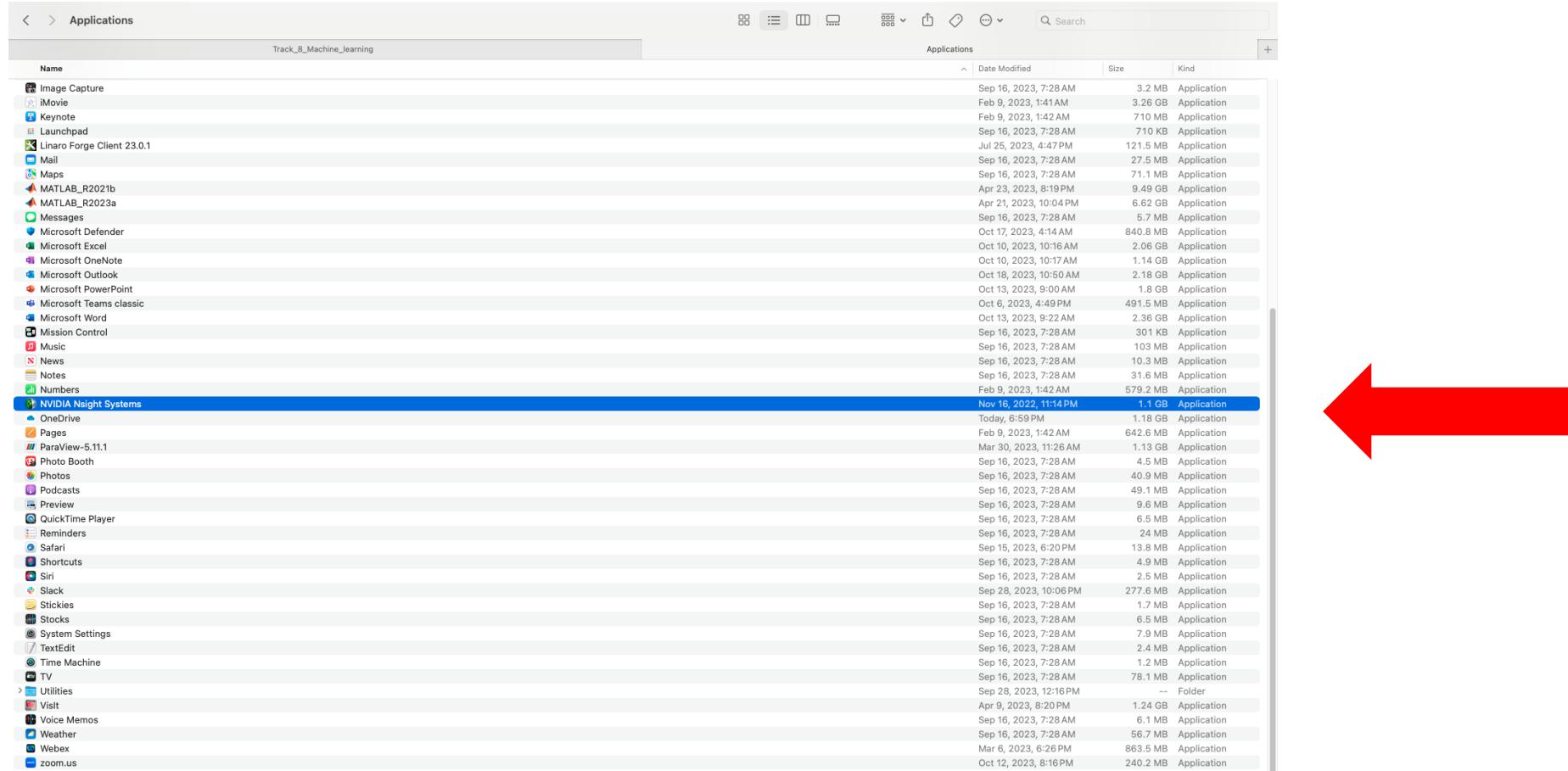
- Download the NVIDIA Nsight system client tool to your local computer



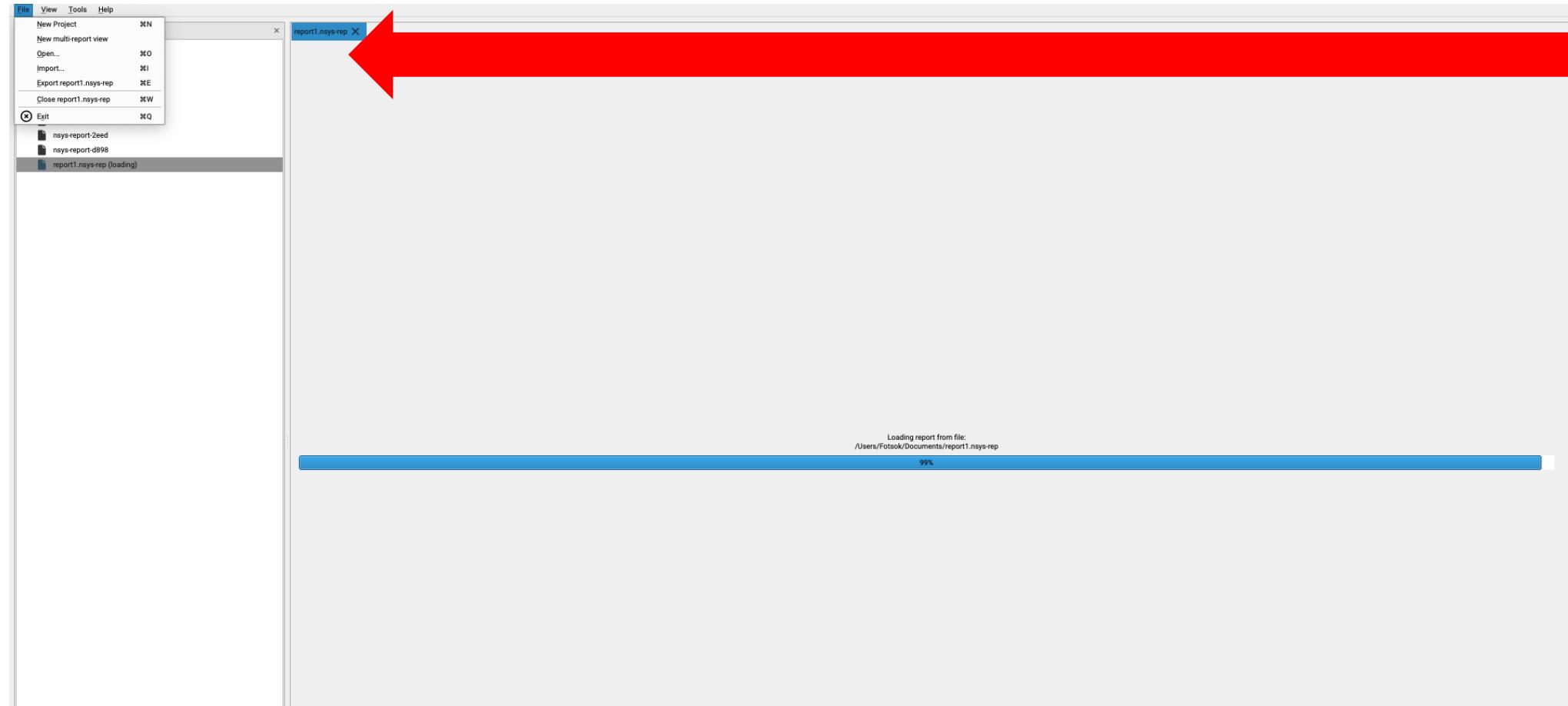
A screenshot of a web browser displaying the NVIDIA developer website at <https://developer.nvidia.com/nsight-systems>. The page features a dark header with navigation links for Solutions, Platforms, Industries, and Resources. A green banner at the top promotes GTC 2024 training from March 18-21, with a 'Get Early-Bird Pricing Now' button. A large red arrow points to the top of the page, specifically to the URL in the address bar. The main content area is titled 'NVIDIA Nsight Systems' and describes it as a system-wide performance analysis tool. It highlights its ability to visualize algorithms, identify optimization opportunities, and tune efficiently across various hardware components. A 'Get started' button is located at the bottom of the main content section.

<https://developer.nvidia.com/nsight-systems>

NVIDIA Nsight (2)



NVIDIA Nsight (3)

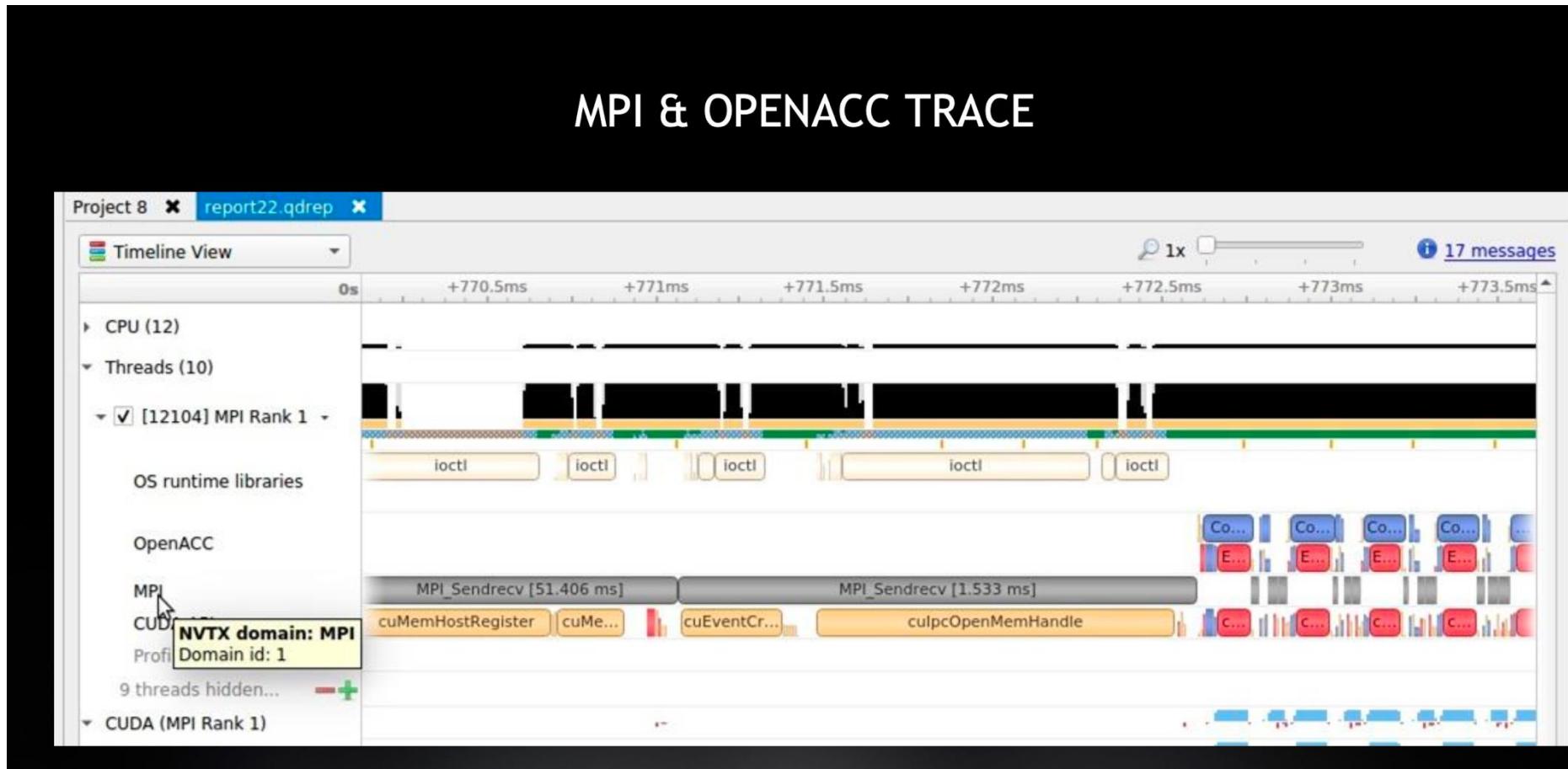


Click on open

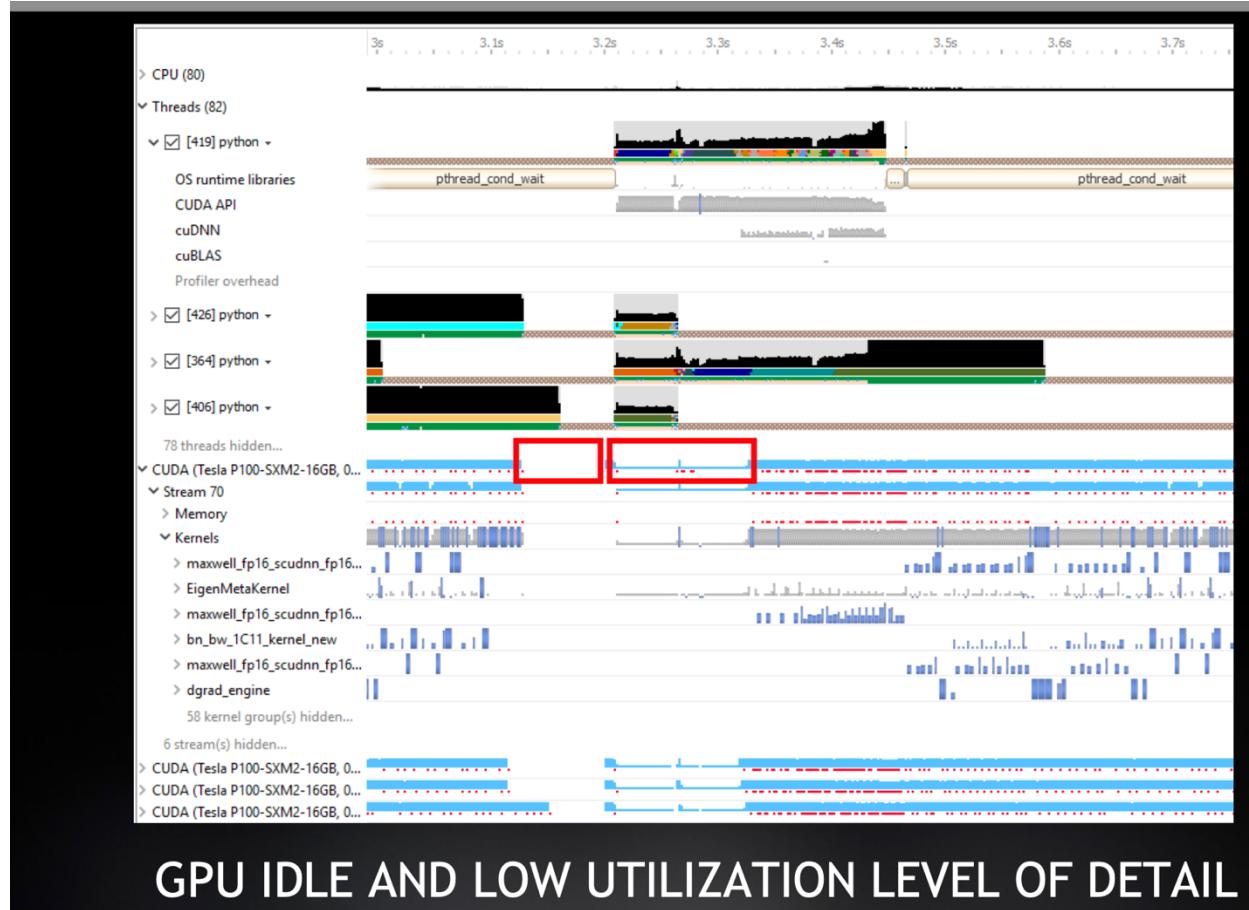
What can be visualize with nsys



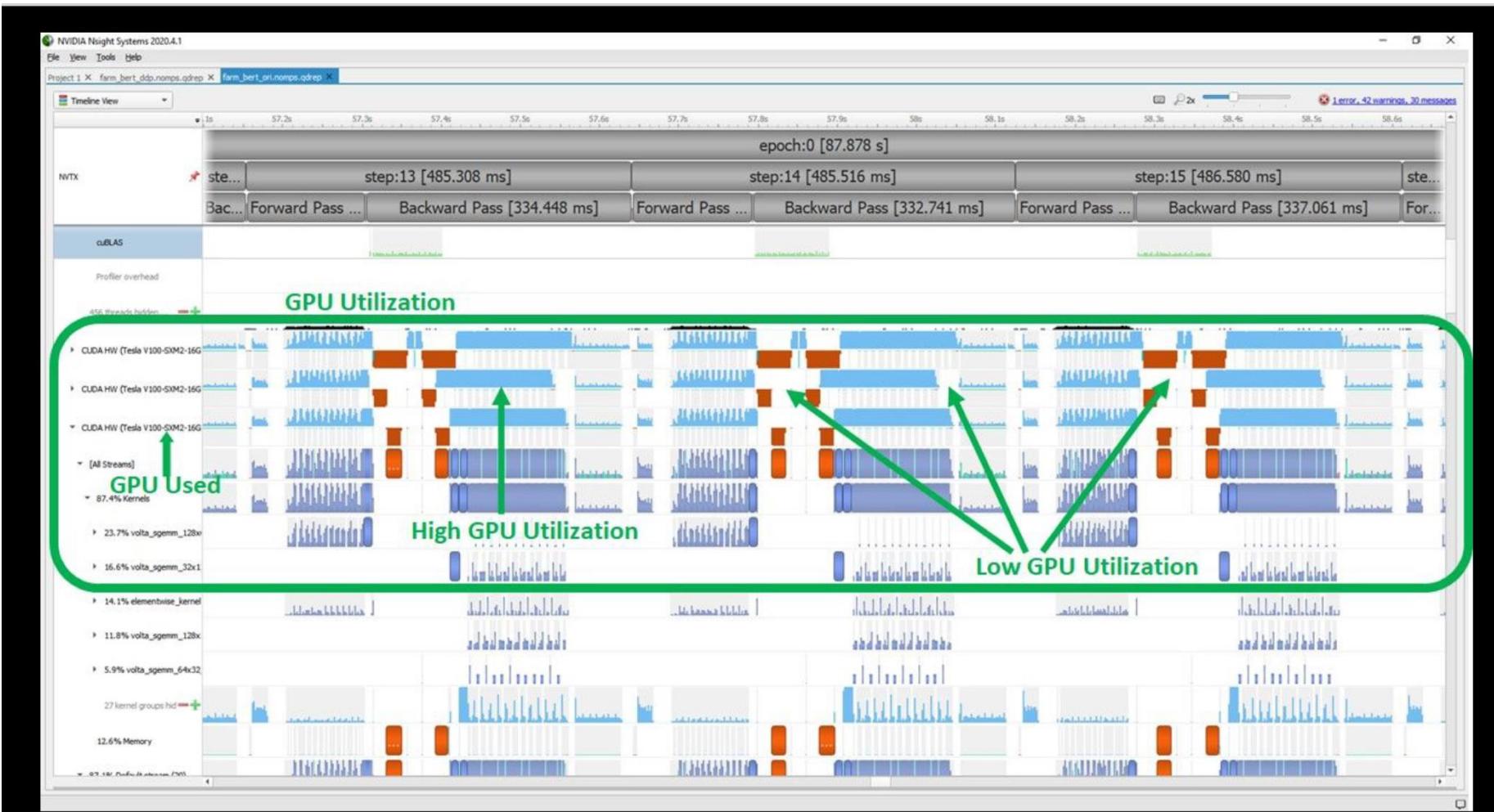
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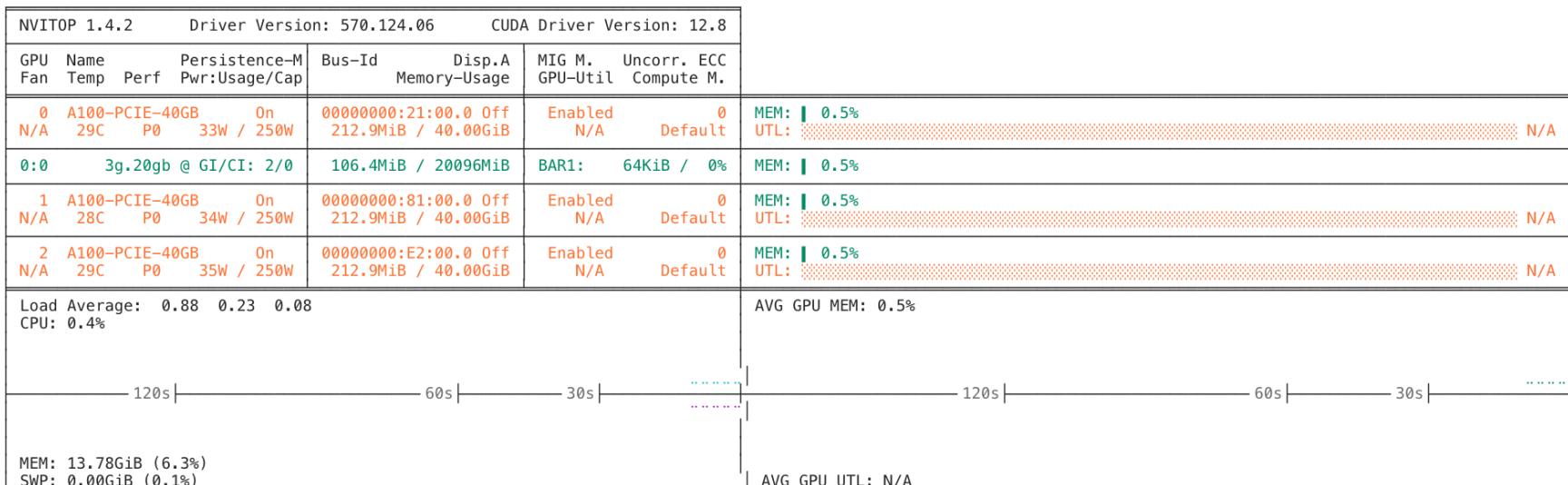
High vs low GPU utilization



Source: <https://alcf.anl.gov/sites/default/files/2022-07/Nsight%202022.pdf>

Other monitoring tools

- Nvtop (pip install nvtop)
 - gpustats (pip install gpustats)



```
Processes: kfotso@xsede.org@c3gpu-c2-u13.rc.int.colorado.edu
GPU    PID   USER GPU-MEM %SM  %CPU  %MEM  TIME  COMMAND
No running processes found
```

AMD GPU software stack

- Heterogeneous Computing interface (Hip) is a C++ software stack API and kernel language to automatically run, convert or create code on AMD or NVIDIA GPUs.

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AMD GPU software stack

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- Its equivalent with NVIDIA is cuda.
- Radeon Open Compute (ROCM) is an ensemble of software stack that incorporates HIP.
- It allows to port CUDA code, supports deep learning pipelines (Pytorch, Tensorflow) and math libraries (Blas, FFT, Sparse etc ...)

AMD GPU computing on Alpine

- Make sure that you are in the video group to use AMD GPUs!!!

AMD GPU computing on Alpine

- Make sure that you are in the video group to use AMD GPUs!!!
- Without the video group you will not be able to see the AMD GPUs

sinteractive --partition=ami100 --time=02:00:00 --ntasks=4 --gres=gpu:1

- groups \$USER

AMD GPU computing on Alpine

- ROCMinfo gives information about the GPU model. If when running it you do not see anything then you will not be able to use the GPU

AMD GPU computing on Alpine

- ROCMinfo gives information about the GPU model. If when running it you do not see anything then you will not be able to use the GPU

```
root@pptainer:~# rocminfo  
Inable to open /dev/kfd read-write: Permission denied
```

AMD GPU computing on Alpine

- Your output should look more like this!

```
[kfotso@xsede.org@c3gpu-c2-u17 workshop_amd_gpu]$ rocminfo

=====
HSA System Attributes
=====
Runtime Version:      1.1
System Timestamp Freq.: 1000.000000MHz
Sig. Max Wait Duration: 18446744073709551615 (0xFFFFFFFFFFFFFF) (timestamp count)
Machine Model:        LARGE
System Endianness:    LITTLE

=====
HSA Agents
=====
*****
Agent 1
*****
  Name:          AMD EPYC 7543 32-Core Processor
  Uuid:          CPU-XX
  Marketing Name: AMD EPYC 7543 32-Core Processor
  Vendor Name:   CPU
```

AMD GPU computing on Alpine

- Hipconfig provides useful information about the hip library

```
[kfotso@xsede.org@c3gpu-c2-u17 workshop_amd_gpu]$ hipconfig
HIP version : 5.4.22801-aaa1e3d8

== hipconfig
HIP_PATH      : /opt/rocm-5.4.0
ROCM_PATH    : /opt/rocm-5.4.0
HIP_COMPILER  : clang
HIP_PLATFORM  : amd
HIP_RUNTIME   : rocclr
CPP_CONFIG    : -D__HIP_PLATFORM_HCC__= -D__HIP_PLATFORM_AMD__= -I/opt/rocm-5.4.0/include -I/opt/rocm-5.4.0/llvm/bin/../lib/clang/15.0.0 -I/opt/rocm-5.4.0/hsa/include

== hip-clang
HSA_PATH      : /opt/rocm-5.4.0/hsa
HIP_CLANG_PATH: /opt/rocm-5.4.0/llvm/bin
```

Running our first model

- This example shows how we fit a 3rd order polynomial to a sine function
- Example from https://pytorch.org/tutorials/beginner/pytorch_with_examples.html
- Make sure that you are logged out from the interactive session

Running our first model

```
#!/bin/bash
#SBATCH --job-name=run_amd_gpu_standard
#SBATCH --output=run_amd_gpu_standard.%j.out
#SBATCH --error=run_amd_gpu_standard.%j.err
#SBATCH --partition=ami100
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=6
#SBATCH --gres=gpu:1
#SBATCH --account=amc-general
#SBATCH --reservation=amc_workshop
#SBATCH --time=00:10:00

# We make sure that the user can run mambaforge
cp ~/.condarc ~/.mambarc

echo "***** Loading ROCM and pytorch + exporting useful paths *****"
# We load ROCM which is the collection of drivers, libraries, tools and API to run
# on an AMD GPU : https://rocm.docs.amd.com/en/latest/what-is-rocm.html
# For NVIDIA it is NVIDIA CUDA
module load rocm/5.2.3

# We load pytorch 1.13.0 that has been built for the ROCM,
# which is compatible with ROCM5.2.X : https://pytorch.org/get-started/previous-versions/
module load pytorch/1.13.0
```



We give
job name,
output
and error

Running our first model

```
#!/bin/bash
#SBATCH --job-name=run_amd_gpu_standard
#SBATCH --output=run_amd_gpu_standard.%j.out
#SBATCH --error=run_amd_gpu_standard.%j.err
#SBATCH --partition=ami100
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=6
#SBATCH --gres=gpu:1
#SBATCH --account=amc-general
#SBATCH --reservation=amc_workshop
#SBATCH --time=00:10:00

# We make sure that the user can run mambaforge
cp ~/.condarc ~/.mambarc

echo "***** Loading ROCM and pytorch + exporting useful paths *****"
# We load ROCM which is the collection of drivers, libraries, tools and API to run
# on an AMD GPU : https://rocm.docs.amd.com/en/latest/what-is-rocm.html
# For NVIDIA it is NVIDIA CUDA
module load rocm/5.2.3

# We load pytorch 1.13.0 that has been built for the ROCM,
# which is compatible with ROCM5.2.X : https://pytorch.org/get-started/previous-versions/
module load pytorch/1.13.0
```

Name of
the AMD
GPU
partition

Running our first model

```
#!/bin/bash
#SBATCH --job-name=run_amd_gpu_standard
#SBATCH --output=run_amd_gpu_standard.%j.out
#SBATCH --error=run_amd_gpu_standard.%j.err
#SBATCH --partition=ami100
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=6
#SBATCH --gres=gpu:1
#SBATCH --account=amc-general
#SBATCH --reservation=amc_workshop
#SBATCH --time=00:10:00

# We make sure that the user can run mambaforge
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echo "***** Loading ROCM and pytorch + exporting useful paths *****"
# We load ROCM which is the collection of drivers, libraries, tools and API to run
# on an AMD GPU : https://rocm.docs.amd.com/en/latest/what-is-rocm.html
# For NVIDIA it is NVIDIA CUDA
module load rocm/5.2.3

# We load pytorch 1.13.0 that has been built for the ROCM,
# which is compatible with ROCM5.2.X : https://pytorch.org/get-started/previous-versions/
module load pytorch/1.13.0
```

We ask for 1 node and a few cores since most computation will be on the gpu

Running our first model

```
#!/bin/bash
#SBATCH --job-name=run_amd_gpu_standard
#SBATCH --output=run_amd_gpu_standard.%j.out
#SBATCH --error=run_amd_gpu_standard.%j.err
#SBATCH --partition=ami100
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=6
#SBATCH --gres=gpu:1
#SBATCH --account=amc-gener...
#SBATCH --reservation=amc_workshop
#SBATCH --time=00:10:00

# We make sure that the user can run mambaforge
cp ~/.condarc ~/.mambarc

echo "***** Loading ROCM and pytorch + exporting useful paths *****"
# We load ROCM which is the collection of drivers, libraries, tools and API to run
# on an AMD GPU : https://rocm.docs.amd.com/en/latest/what-is-rocm.html
# For NVIDIA it is NVIDIA CUDA
module load rocm/5.2.3

# We load pytorch 1.13.0 that has been built for the ROCM,
# which is compatible with ROCM5.2.X : https://pytorch.org/get-started/previous-versions/
module load pytorch/1.13.0
```

We ask
for 1 GPU



Running our first model

```
#!/bin/bash
#SBATCH --job-name=run_amd_gpu_standard
#SBATCH --output=run_amd_gpu_standard.%j.out
#SBATCH --error=run_amd_gpu_standard.%j.err
#SBATCH --partition=ami100
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=6
#SBATCH --gres=gpu:1
#SBATCH --account=amc-general
#SBATCH --reservation=amc_workshop
#SBATCH --time=00:10:00

# We make sure that the user can run mambaforge
cp ~/.condarc ~/.mambarc

echo "***** Loading ROCM and pytorch + exporting useful paths *****"
# We load ROCM which is the collection of drivers, libraries, tools and API to run
# on an AMD GPU : https://rocm.docs.amd.com/en/latest/what-is-rocm.html
# For NVIDIA it is NVIDIA CUDA
module load rocm/5.2.3

# We load pytorch 1.13.0 that has been built for the ROCM,
# which is compatible with ROCM5.2.X : https://pytorch.org/get-started/previous-versions/
module load pytorch/1.13.0
```

We load
the
modules

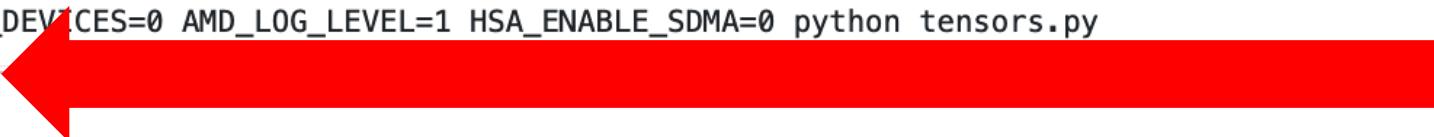
Running our first model

```
echo "***** Running the models *****"  
# We want to make sure that we can profile what is going on  
# We want to set AMD_LOG_LEVEL for profiling and debugging  
#CODE 0 means No log  
#CODE 1 means log the error  
#CODE 2 means log warnings  
#CODE 3 means log information  
#CODE 4 means debug mode  
# More information here: https://rocm.docs.amd.com/projects/HIP/en/develop/developer\_guide/logging.html  
  
HIP_VISIBLE_DEVICES=0 ROCR_VISIBLE_DEVICES=0 AMD_LOG_LEVEL=1 HSA_ENABLE_SDMA=0 python tensors.py
```

Here is a way we can debug our code or even profile what is going on

Running our first model

```
echo "***** Running the models *****"  
# We want to make sure that we can profile what is going on  
# We want to set AMD_LOG_LEVEL for profiling and debugging  
#CODE 0 means No log  
#CODE 1 means log the error  
#CODE 2 means log warnings  
#CODE 3 means log information  
#CODE 4 means debug mode  
# More information here: https://rocm.docs.amd.com/projects/HIP/en/develop/developer\_guide/logging.html  
  
HIP_VISIBLE_DEVICES=0 ROCR_VISIBLE_DEVICES=0 AMD_LOG_LEVEL=1 HSA_ENABLE_SDMA=0 python tensors.py
```



AMD_LOG_LEVEL variable is very useful

While the job is running ...

```
[kfotso@xsede.org@login-ci1 workshop_amd_gpu]$ squeue --me
  JOBID PARTITION      NAME      USER ST      TIME  NODES NODELIST(REASON)
  5187143  acompile acompile kfotso@x  R      10:03      1 c3cpu-c11-u3-4
  5187117    ami100 sinterac kfotso@x  R      20:16      1 c3gpu-c2-u17
[kfotso@xsede.org@login-ci1 workshop_amd_gpu]$ █
```



We look
for node
where
the GPU
job is
running

While the job is running ...

```
[kfotso@xsede.org@login-ci1 workshop_amd_gpu]$ squeue --me
  JOBID PARTITION      NAME      USER ST      TIME  NODES NODELIST(REASON)
  5187143  acompile acompile kfotso@x  R      10:03      1 c3cpu-c11-u3-4
  5187117    ami100 sinterac kfotso@x  R      20:16      1 c3gpu-c2-u17
[kfotso@xsede.org@login-ci1 workshop_amd_gpu]$ ssh c3gpu-c2-u17
```



We ssh to
the node

While the job is running ...

```
[kfotso@xsede.org@c3gpu-c2-u17 ~]$ watch -n 1 rocm-smi --showmeminfo vram
```



This
shows
that we
are on
the gpu
node

While the job is running ...

```
[kfotso@xsede.org@c3gpu-c2-u17 ~]$ watch -n 1 rocm-smi --showmeminfo vram
```



rocm-smi
is the
equivalen
t of
nvidia-
smi

While the job is running ...

```
every 1.0s: rocm-smi --showmeminfo vram
```

```
=====ROCM System Management Interface=====
GPU[1]      : vram Total Memory (B): 34342961152
GPU[1]      : vram Total Used Memory (B): 2590732288
GPU[2]      : vram Total Memory (B): 34342961152
GPU[2]      : vram Total Used Memory (B): 7012352
GPU[3]      : vram Total Memory (B): 34342961152
GPU[3]      : vram Total Used Memory (B): 7012352
=====
End of ROCm SMI Log =====
```



We are
on GPU 1
and we
can tell
that the
job is
using the
GPU
memory

Now we run the job with LOG_LEVEL_4

- Only use this if your script is failing
- It is for debugging purpose

Now we run the job with LOG_LEVEL 4 or 5

- Only use this if your script is failing
- It is for debugging purpose

```
export PYTHONPATH=$PIP_INSTALL_DIR:$PIP_INSTALL_DIR/bin:$PYTHONPATH
export PATH=$PIP_INSTALL_DIR:$PATH
#export DEVICE_LIB_PATH=/curc/sw/install/rocm/5.2.3/amdgcn/bitcode
#export ROCM_DEVICE_LIB_PATH=/curc/sw/install/rocm/5.2.3/amdgcn/bitcode

# We need to specify the HIP platform
HIP_PLATFORM=amd
USE_ROCM=1
# We may now install the additional pytorch AMD compatible packages:
export PATH=$PATH:$PIP_INSTALL_DIR/bin

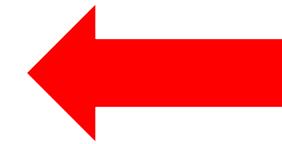
# Running the vision transformer example
# This example shows a simple implementation of Vision Transformer on the CIFAR-10 dataset.
# Original code from https://github.com/pytorch/examples/tree/main/vision_transformer

echo "***** Running the models *****"
# We want to make sure that we can profile what is going on
IP_VISIBLE_DEVICES=0 ROCR_VISIBLE_DEVICES=0 AMD_LOG_LEVEL=5 HSA_ENABLE_SDMA=0 python vision_transformer_example.py
```



Now we run the job with LOG_LEVEL 4 or 5

```
Extracting ./dataset/cifar-10-python.tar.gz to ./dataset
Files already downloaded and verified
:3:hip_device_runtime.cpp :515 : 10340869225183 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount ( 0x7ffea9cabfa8 )
:3:hip_device_runtime.cpp :517 : 10340869225203 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount: Returned hipSuccess :
:3:hip_device_runtime.cpp :515 : 10340869225229 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount ( 0x7f78970657f4 )
:3:hip_device_runtime.cpp :517 : 10340869225233 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount: Returned hipSuccess :
:3:hip_device.cpp :346 : 10340869225240 us: 3360697: [tid:0x7f790645a280] hipGetDeviceProperties ( 0x7ffea9cabcb0, 0 )
:3:hip_device.cpp :348 : 10340869225248 us: 3360697: [tid:0x7f790645a280] hipGetDeviceProperties: Returned hipSuccess :
:3:hip_device_runtime.cpp :500 : 10340869225360 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cac2ac )
:508 : 10340869225367 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225406 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab7ec )
:508 : 10340869225411 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225415 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab70c )
:508 : 10340869225419 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225424 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab5bc )
:508 : 10340869225429 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:3:hip_error.cpp :27 : 10340869225442 us: 3360697: [tid:0x7f790645a280] hipGetLastError ( )
:3:hip_memory.cpp :493 : 10340869225454 us: 3360697: [tid:0x7f790645a280] hipMalloc ( 0x7ffea9cab138, 2097152 )
:4:rocdevice.cpp :2054: 10340869225580 us: 3360697: [tid:0x7f790645a280] Allocate hsa device memory 0x7f7649e00000, size 0x200000
:3:rocdevice.cpp :2093: 10340869225585 us: 3360697: [tid:0x7f790645a280] device=0x55d237eaf930, freeMem_ = 0xfee00000
:495 : 10340869225593 us: 3360697: [tid:0x7f790645a280] hipMalloc: Returned hipSuccess : 0x7f7649e0000: duration: 139 us
:530 : 10340869225602 us: 3360697: [tid:0x7f790645a280] hipSetDevice ( 0 )
:535 : 10340869225606 us: 3360697: [tid:0x7f790645a280] hipSetDevice: Returned hipSuccess :
:530 : 10340869225609 us: 3360697: [tid:0x7f790645a280] hipSetDevice ( 0 )
:535 : 10340869225612 us: 3360697: [tid:0x7f790645a280] hipSetDevice: Returned hipSuccess :
:500 : 10340869225636 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab54c )
:508 : 10340869225639 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225643 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab56c )
:508 : 10340869225644 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:566 : 10340869225661 us: 3360697: [tid:0x7f790645a280] hipMemcpyWithStream ( 0x7f7649e00000, 0x55d238356fc0, 12288, hipMemcpyHostToDevice, stream:<null> )
:2686: 10340869225670 us: 3360697: [tid:0x7f790645a280] number of allocated hardware queues with low priority: 0, with normal priority: 0, with high priority: 0, maximum per priority is: 4
```



Hip can
see the
gpu

Now we run the job with LOG_LEVEL 4 or 5

```
Extracting ./dataset/cifar-10-python.tar.gz to ./dataset
Files already downloaded and verified
:3:hip_device_runtime.cpp :515 : 10340869225183 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount ( 0x7ffea9cabfa8 )
:3:hip_device_runtime.cpp :517 : 10340869225203 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount: Returned hipSuccess :
:3:hip_device_runtime.cpp :515 : 10340869225229 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount ( 0x7f78970657f4 )
:3:hip_device_runtime.cpp :517 : 10340869225233 us: 3360697: [tid:0x7f790645a280] hipGetDeviceCount: Returned hipSuccess :
:3:hip_device.cpp :346 : 10340869225240 us: 3360697: [tid:0x7f790645a280] hipGetDeviceProperties ( 0x7ffea9cabcb0 )
:3:hip_device.cpp :348 : 10340869225248 us: 3360697: [tid:0x7f790645a280] hipGetDeviceProperties: Returned hipSuccess :
:3:hip_device_runtime.cpp :500 : 10340869225360 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cac2ac )
:508 : 10340869225367 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225406 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab7ec )
:508 : 10340869225411 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225415 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab70c )
:508 : 10340869225419 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225424 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab5bc )
:508 : 10340869225429 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:27 : 10340869225442 us: 3360697: [tid:0x7f790645a280] hipGetLastError ( )
:493 : 10340869225454 us: 3360697: [tid:0x7f790645a280] hipMalloc ( 0x7ffea9cab138, 2097152 )
:2054: 10340869225580 us: 3360697: [tid:0x7f790645a280] Allocate hsa device memory 0x7f7649e00000, size 0x200000
:2093: 10340869225585 us: 3360697: [tid:0x7f790645a280] device=0x55d237eaf930, freeMem_ = 0xfee00000
:495 : 10340869225593 us: 3360697: [tid:0x7f790645a280] hipMalloc: Returned hipSuccess : 0x7f7649e00000: duration: 139 us
:530 : 10340869225602 us: 3360697: [tid:0x7f790645a280] hipSetDevice ( 0 )
:535 : 10340869225606 us: 3360697: [tid:0x7f790645a280] hipSetDevice: Returned hipSuccess :
:530 : 10340869225609 us: 3360697: [tid:0x7f790645a280] hipSetDevice ( 0 )
:535 : 10340869225612 us: 3360697: [tid:0x7f790645a280] hipSetDevice: Returned hipSuccess :
:500 : 10340869225636 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab54c )
:508 : 10340869225639 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:500 : 10340869225643 us: 3360697: [tid:0x7f790645a280] hipGetDevice ( 0x7ffea9cab56c )
:508 : 10340869225644 us: 3360697: [tid:0x7f790645a280] hipGetDevice: Returned hipSuccess :
:566 : 10340869225661 us: 3360697: [tid:0x7f790645a280] hipMemcpyWithStream ( 0x7f7649e00000, 0x55d238356fc0, 12288, hipMemcpyHostToDevice, stream:<null> )
:2686: 10340869225670 us: 3360697: [tid:0x7f790645a280] number of allocated hardware queues with low priority: 0, with normal priority: 0, with high priority: 0, maximum per priority is: 4
```

Hip can see the gpu

We get information about runtime libraries, and data movement.

Now we want to introduce rocprof

- You may use rocprof to profile your job as well.
- It will output a file that you can upload into chrome.

Now we want to introduce rocprof

- You may use rocprof to profile your job as well.
- It will output a file that you can upload into chrome.

```
[kfotso@xsede.org@c3gpu-c2-u17 workshop_amd_gpu]$ rocprof --stats --basenames --hip-trace python vision_transformer_example.py
RPL: on '240229_074832' from '/curc/sw/install/rocm/5.2.3' in '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu'
RPL: profiling "python" "vision_transformer_example.py"
RPL: input file ''
RPL: output dir '/tmp/rpl_data_240229_074832_3367074'
RPL: result dir '/tmp/rpl_data_240229_074832_3367074/input_results_240229_074832'
Files already downloaded and verified
Files already downloaded and verified
EPOCH[TRAIN]1/10: 4%|| | 486/12500 [00:35<12:48, 15.63it/s, Loss=4.853929]
```

Now we want to introduce rocprof

- You may use rocprof to profile your job as well.
- It will output a file that you can upload into chrome.

```
1799 10.972630500793457
1899 10.250618934631348
1999 9.770797729492188
Result: y = 0.00992796290665865 + 0.8281400203704834 x + -0.001712737255729735 x^2 + -0.0892621725
hsa_copy_deps: 0
scan ops data 62009:62010
e.org/workshop_amd_gpu/results.copy_stats.csv' is generating
dump json 2003:2004
File '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu/results.json' is generating
File '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu/results.hip_stats.csv' is generating
dump json 628111:628112
File '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu/results.json' is generating
File '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu/results.stats.csv' is generating
dump json 60005:60006
File '/scratch/alpine/kfotso@xsede.org/workshop_amd_gpu/results.json' is generating
```



Can upload
JSON file
into chrome

Let's run more ambitious models

- Let's try a more ambitious model
- We run an example shows a simple implementation of Vision Transformer on the CIFAR-10 dataset.
- Feel free to use rocm-smi

```
# This example shows a simple implementation of Vision Transformer on the CIFAR-10 dataset.  
# Original code from https://github.com/pytorch/examples/tree/main/vision_transformer  
python vision_transformer_example.py
```

Now let's see how to build a container that can run on AMD GPU

- Make sure that your `~/.bashrc` does not contain any `$TMP_DIR` variables
- The call below is intended to be run interactively after you've logged into a gpu node

```
sinteractive --partition=atesting_mi100 --qos=testing --time=01:00:00 --gres=gpu:1 --ntasks=4
```

```
sinteractive --partition=ami100 --nodes=1 --ntasks=4 --gres=gpu:1 --time=00:10:00
```

Now let's see how to build a container that can run on AMD GPU

- |

```
#I am putting in comment the command I used to download and run the container:  
# Make sure to comment all the export TMP in your ~/.bashrc  
# apptainer build dev-ubuntu-20.04_latest.sif docker://rocm/dev-ubuntu-20.04  
# apptainer overlay create --fakeroot --sparse --size 100000 sparse_3_simple_overlay.img  
# Make sure to comment all the export TMP in your ~/.bashrc
```

```
export ALPINE_SCRATCH=/gpfs/alpine1/scratch/$USER  
export APPTAINER_TMPDIR=$ALPINE_SCRATCH/singularity/tmp  
export APPTAINER_CACHEDIR=$ALPINE_SCRATCH/singularity/cache  
mkdir -pv $APPTAINER_CACHEDIR $APPTAINER_TMPD
```



To build the container we had to create an overlay

Now let's see how to build a container that can run on AMD GPU

- |

```
#I am putting in comment the command I used to download and run the container:  
# Make sure to comment all the export TMP in your ~/.bashrc  
# apptainer build dev-ubuntu-20.04_latest.sif docker://rocm/dev-ubuntu-20.04  
# apptainer overlay create --fakeroot --sparse --size 100000 sparse_3_simple_overlay.img  
# Make sure to comment all the export TMP in your ~/.bashrc  
  
export ALPINE_SCRATCH=/gpfs/alpine1/scratch/$USER  
export APPTAINER_TMPDIR=$ALPINE_SCRATCH/singularity/tmp  
export APPTAINER_CACHEDIR=$ALPINE_SCRATCH/singularity/cache  
mkdir -pv $APPTAINER_CACHEDIR $APPTAINER_TMPD
```



An overlay allows to create a filesystem on top of the immutable .sif container

Now let's see how to build a container that can run on AMD GPU

- |

```
#I am putting in comment the command I used to download and run the container:  
# Make sure to comment all the export TMP in your ~/.bashrc  
# apptainer build dev-ubuntu-20.04_latest.sif docker://rocm/dev-ubuntu-20.04  
# apptainer overlay create --fakeroot --sparse --size 100000 sparse_3_simple_overlay.img  
# Make sure to comment all the export TMP in your ~/.bashrc
```

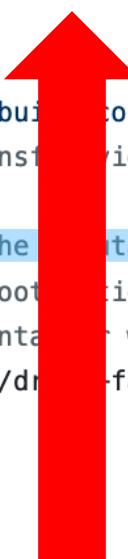
```
export ALPINE_SCRATCH=/gpfs/alpine1/scratch/$USER  
export APPTAINER_TMPDIR=$ALPINE_SCRATCH/singularity/tmp  
export APPTAINER_CACHEDIR=$ALPINE_SCRATCH/singularity/cache  
mkdir -pv $APPTAINER_CACHEDIR $APPTAINER_TMPD
```



Make sure to
export the
apptainer
related tmp and
cache dir

Now let's see how to build a container that can run on AMD GPU

```
echo "***** Copying the .sif and .img files *****"  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/sparse_3_simple_overlay.img .  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/build-dev-ubuntu-20.04_latest.sif .  
export CONTAIN_DIR=${PWD}  
  
echo "***** Running the build container *****"  
# --containall is very important as it allows to transfer video permission to the container  
# Otherwise you will not see the AMD GPU  
#--overlay allows to create a filesystem on top of the immutable .sif container  
# so that you can modify it at will with the --fakeroot option  
# To install packages and run pipeline inside the container we run:  
apptainer shell -H $CONTAIN_DIR --bind=/dev/kfd,/dev/dri --fakeroot --rocm --containall --overlay sparse_3_simple_overlay.img build-dev-ubuntu-20.04
```



Copy the container related images and overlay to the directory where you cloned the repo

Now let's see how to build a container that can run on AMD GPU

```
echo "***** Copying the .sif and .img files *****"  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/sparse_3_simple_overlay.img .  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/build-dev-ubuntu-20.04_latest.sif .  
export CONTAIN_DIR=${PWD}  
  
echo "***** Running the built container *****"  
# --contain_dir is very important as it allows to transfer video permission to the container  
# Otherwise you will not see the AMD GPU  
#--overlay allows to create a filesystem on top of the immutable .sif container  
# so that we can modify it at will with the --fakeroot option  
# To install packages and run pipeline inside the container we run:  
apptainer -c -H $CONTAIN_DIR --bind=/dev/kfd,/dev/dri --fakeroot --rocm --containall --overlay sparse_3_simple_overlay.img build-dev-ubuntu-20.04
```



Export the
current
directory env

Now let's see how to build a container that can run on AMD GPU

```
echo "***** Copying the .sif and .img files *****"  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/sparse_3_simple_overlay.img .  
cp /scratch/alpine/kfotso@xsede.org/test_container_docker/build-dev-ubuntu-20.04_latest.sif .  
export CONTAIN_DIR=${PWD}  
  
echo "***** Running the built container *****"  
# --containall is very important as it allows to transfer video permission to the container  
# Otherwise you will not see the AMD GPU  
#--overlay allows to create a filesystem on top of the immutable .sif container  
# so that you can modify it at will with the --fakeroott option  
# To install packages and run pipeline inside the container we run:  
apptainer shell -H $CONTAIN_DIR --bind=/dev/kfd,/dev/dri --fakeroott --rocm --containall --overlay sparse_3_simple_overlay.img build-dev-ubuntu-20.04
```



Call the container

Now let's see how to build a container that can run on AMD GPU

- In the apptainer folder go to /usr/bin and run the tensor.py model

```
[kfotso@xsede.org@c3gpu-c2-u17 test_container_docker]$ apptainer shell -H $CONTAIN_DIR --bind=/dev/kfd,/dev/dri --fakeroot --rocm --contain  
e_3_simple_overlay.img build-dev-ubuntu-20.04_latest.sif  
]INFO: User not listed in /etc/subuid, trying root-mapped namespace  
INFO: Using fakeroot command combined with root-mapped namespace  
WARNING: Skipping /dev/kfd bind mount: already mounted  
WARNING: Skipping /dev/dri bind mount: already mounted  
INFO: unknown argument ignored: lazytime  
Apptainer> ] ds  
Apptainer>  
Apptainer> cp tensors.py /usr/bin/█
```

Notes:

- Although the AMD GPU computation has been demonstrated with pytorch, there is a high chance that it can be done with tensorflow as well.
- You can also use other pytorch ROCM compatible versions to install packages:
<https://pytorch.org/get-started/previous-versions/>

Notes:

- Although the AMD GPU computation has been demonstrated with pytorch, there is a high chance that it can be done with tensorflow as well.
- When investigating, we found that Princeton supports it.

What happens if my gpu deep learning job runs out of memory?

- Assess your network size based on the number of parameters and the batch size, then multiply it by the precision type.

What happens if my gpu deep learning job runs out of memory?

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- For example, if your network is using **271,210** parameters with **float64** precision and **1** batch size, the calculation goes as follows:

[Mem_size= **271,210** parameters **X 8** bytes **X 1** batch size]

What happens if my gpu deep learning job runs out of memory?

- Assess your network size based on the number of parameters and the batch size, then multiply it by the precision type.
- For example, if your network is using **271,210** parameters with **float64** precision and **1** batch size, the calculation goes as follows:

[Mem_size= **271,210** parameters **X 8** bytes **X 1** batch size]

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- Consider as well reducing the precision, for instance from float64 to float32

What happens if my gpu deep learning job runs out of memory?

- Consider as well reducing the precision, for instance from float64 to float32.
- Reduce batch size.

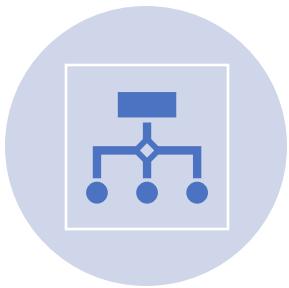
What happens if my gpu deep learning job runs out of memory?

- Consider as well reducing the precision, for instance from float64 to float32.
- Reduce batch size.
- Consider doing distributed computing.

What happens if my gpu deep learning job runs out of memory?

- Consider as well reducing the precision, for instance from float64 to float32.
- Reduce batch size.
- Consider doing distributed computing.
- Consider doing feature selection prior to running your model in order to reduce the size of your data.

What is Horovod? (1)



A distributed deep learning training framework for Tensorflow, Keras, Pytorch, and Apache MXNet.



Originally developed by Uber to train ML models in hours and mins instead of days and weeks.



What is Horovod? (2)



WITH HOROVOD, ML ALGORITHM CAN
BE SCALED TO RUN ON 100 OF GPUS
WITH JUST FEW LINE OF PYTHON CODE.



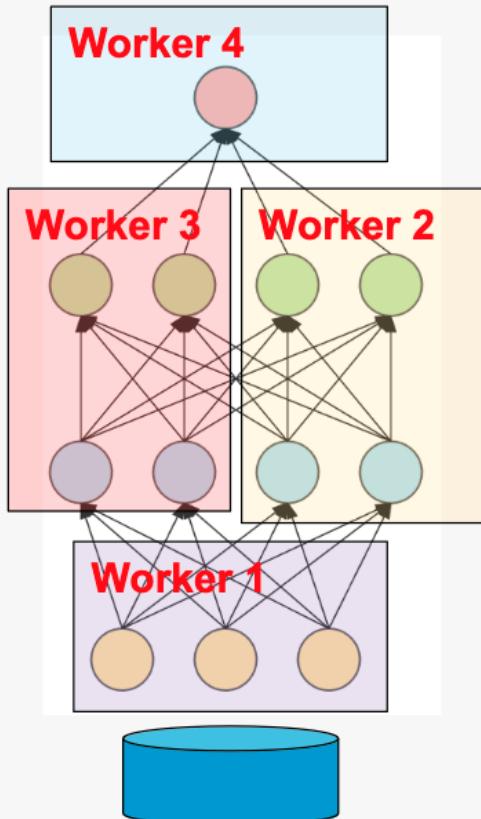
PORTABLE, RELATIVELY EASY AND
FAST.



IT IS HOSTED UNDER THE LINUX
FOUNDATION

Parallelization schemes (1)

Parallelization schemes – Model Parallelism (MP)



```
import torch
import torch.nn as nn
import torch.optim as optim

class ToyModel(nn.Module):
    def __init__(self):
        super(ToyModel, self).__init__()
        self.net1 = torch.nn.Linear(10, 10).to('cuda:0')
        self.relu = torch.nn.ReLU()
        self.net2 = torch.nn.Linear(10, 5).to('cuda:1')

    def forward(self, x):
        x = self.relu(self.net1(x.to('cuda:0')))
        return self.net2(x.to('cuda:1'))

model = ToyModel()
loss_fn = nn.MSELoss()
optimizer = optim.SGD(model.parameters(), lr=0.001)

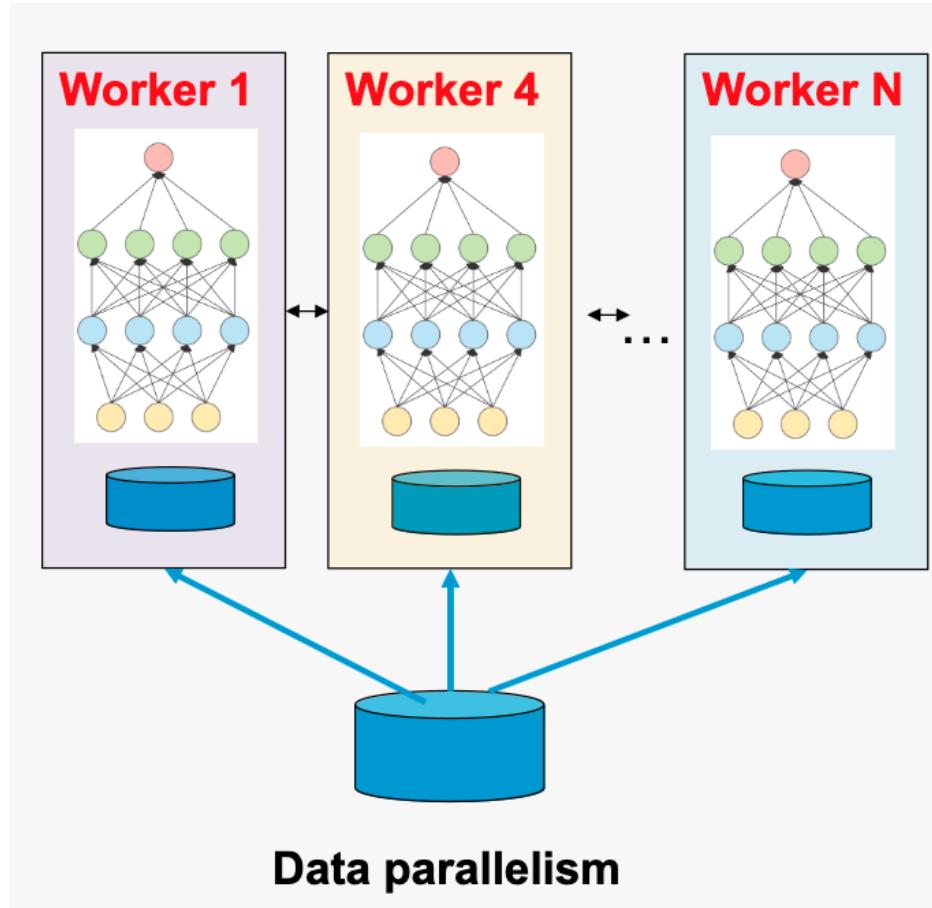
optimizer.zero_grad()
outputs = model(torch.randn(20, 10))
labels = torch.randn(20, 5).to('cuda:1')
loss_fn(outputs, labels).backward()
optimizer.step()
```

PyTorch multiple GPU model parallelism within a node

Worker 1

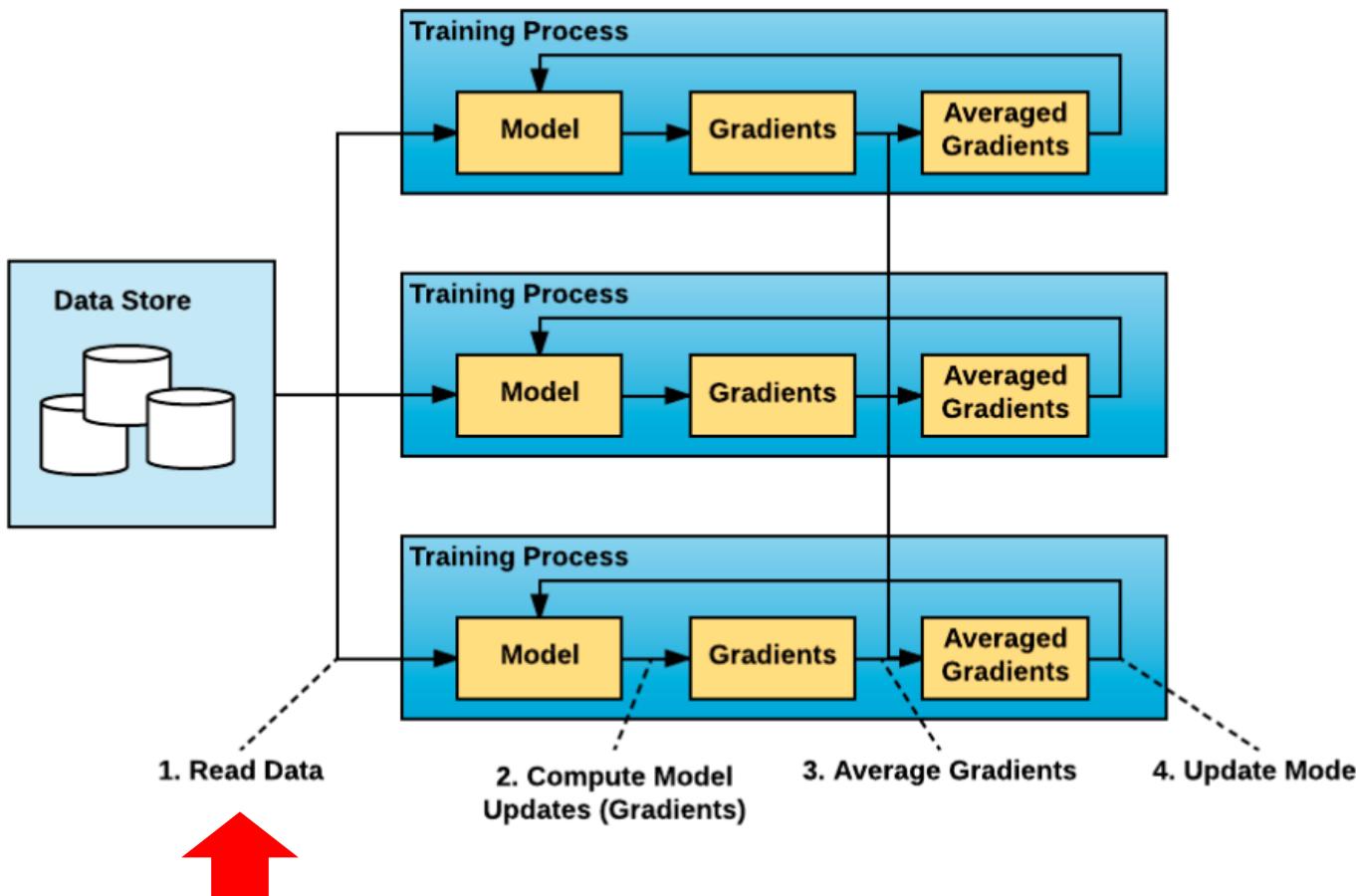
Worker 2

Parallelization schemes (2)



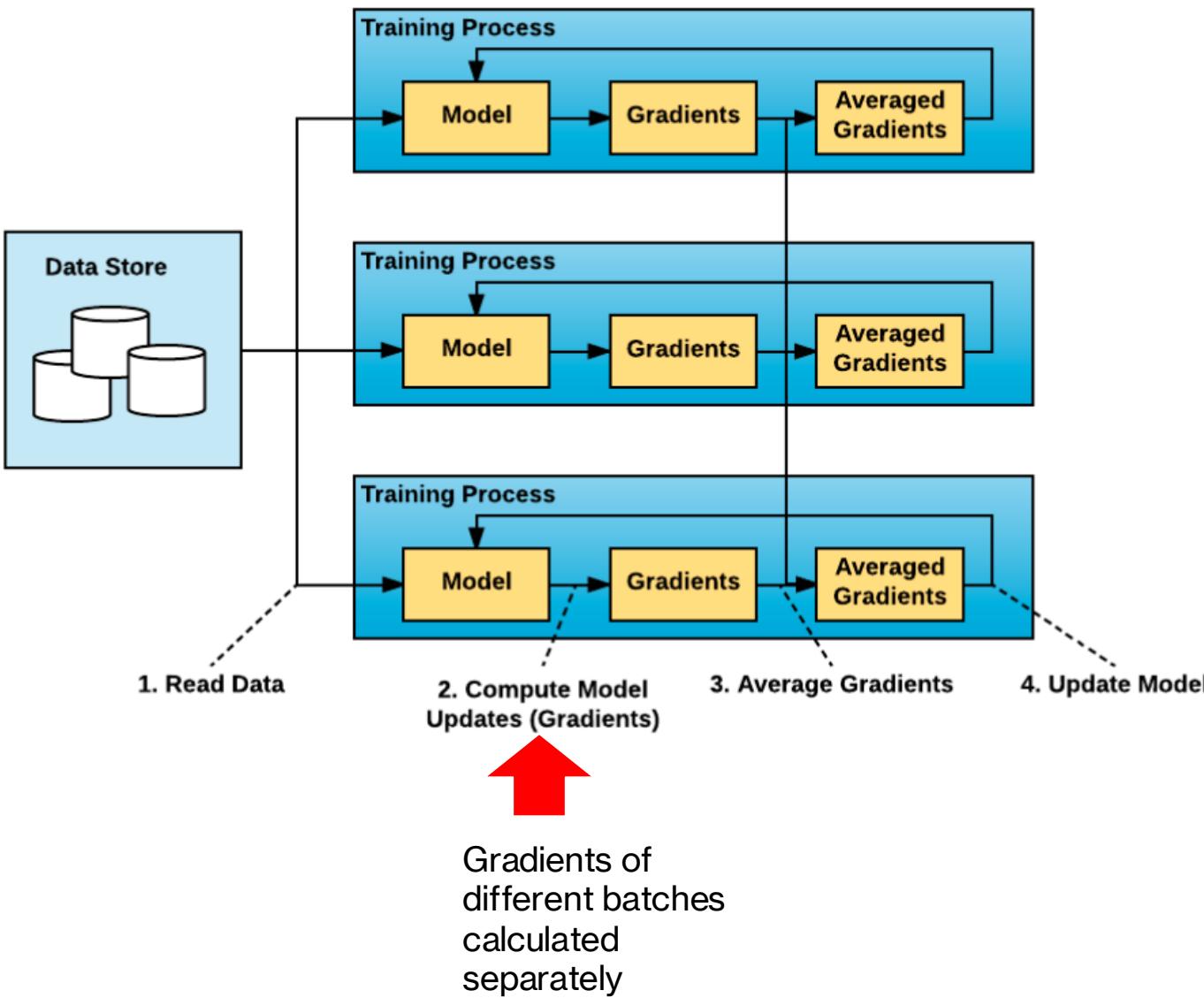
- Data parallelism
- Model is replicated on each worker
- Each worker processes a subset of the minibatch
- Weights are synchronized before updating the model
- Widely supported.

Overview of the Horovod training model

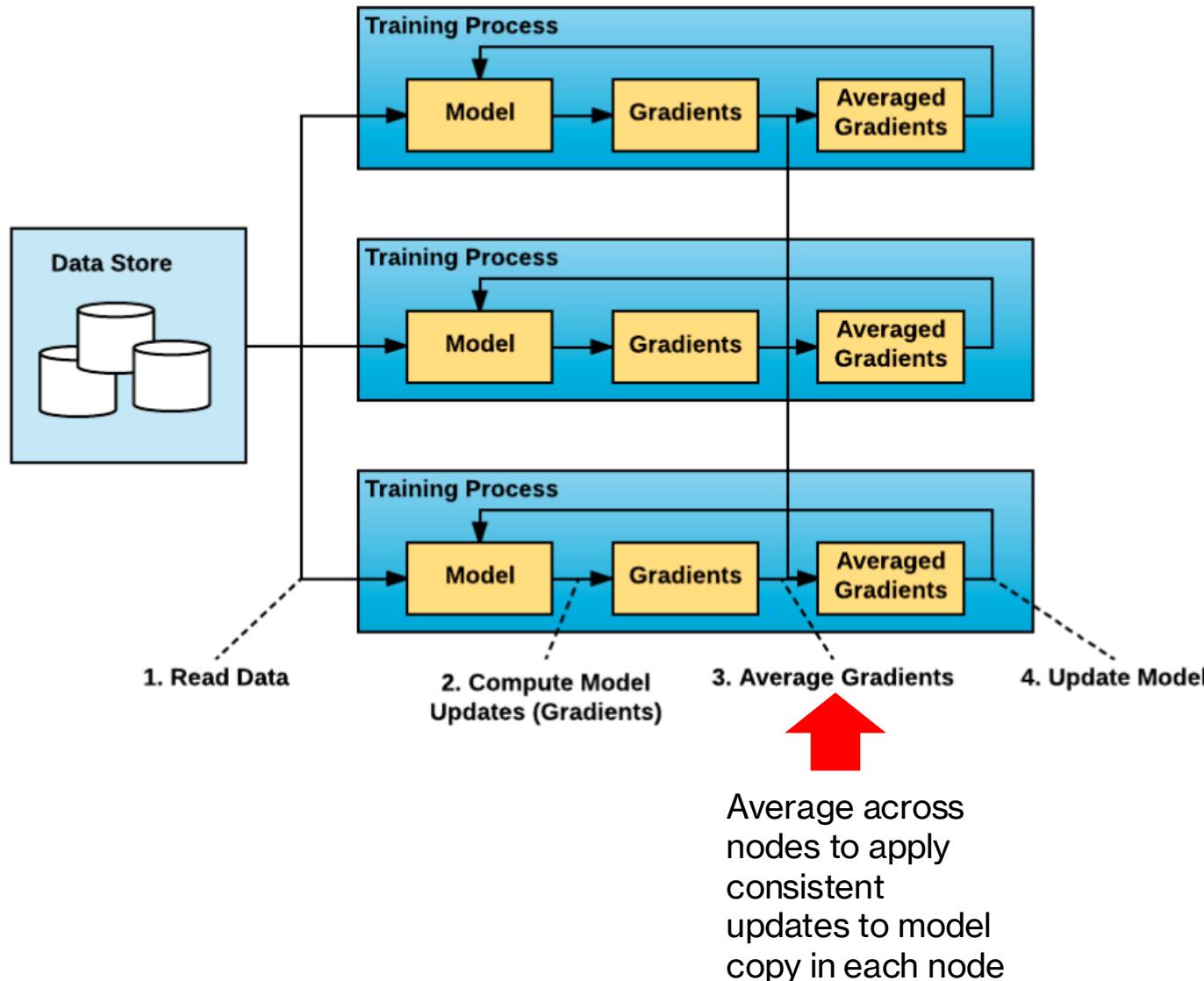


Reads chunk
of data
(batch)

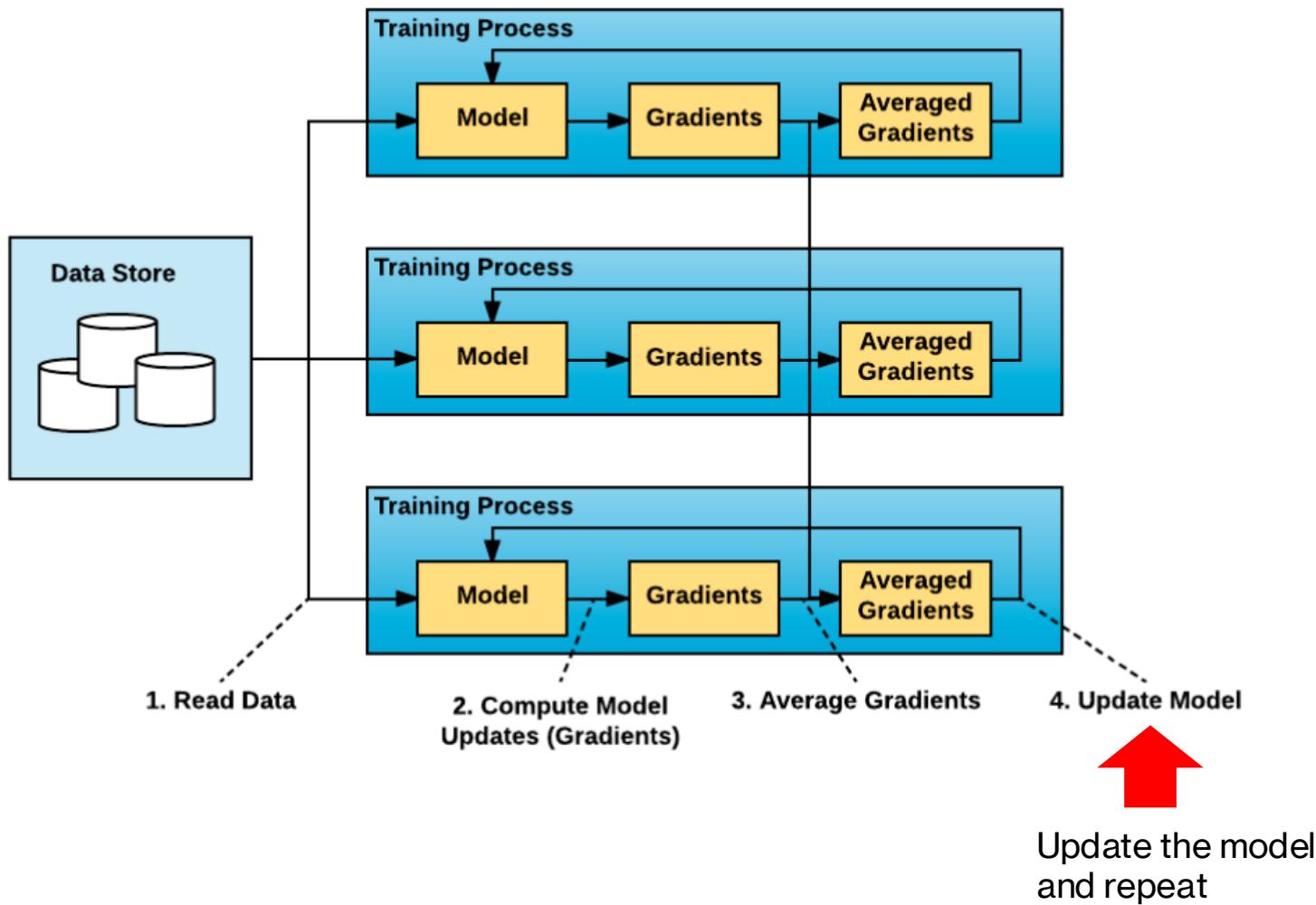
Overview of the Horovod training model (1)



Overview of the Horovod training model(1)



Overview of the Horovod training model (1)



Snippet of Horovod basic code

```
import tensorflow as tf  
import horovod.tensorflow as hvd
```

Import horovod & tensorflow

```
# Initialize Horovod  
hvd.init()
```

```
# Pin GPU to be used to process local rank (one GPU per process)  
config = tf.ConfigProto()  
config.gpu_options.visible_device_list = str(hvd.local_rank())
```

```
# Build model...  
loss = ...  
opt = tf.train.AdagradOptimizer(0.01)
```

```
# Add Horovod Distributed Optimizer  
opt = hvd.DistributedOptimizer(opt)
```

```
# Add hook to broadcast variables from rank 0 to all other processes  
# during initialization.  
hooks = [hvd.BroadcastGlobalVariablesHook(0)]
```

```
# Make training operation  
train_op = opt.minimize(loss)
```

```
# The MonitoredTrainingSession takes care of session initialization,  
# restoring from a checkpoint, saving to a checkpoint, and closing  
# when done or an error occurs.
```



Snippet of Horovod basic code

```
import tensorflow as tf
import horovod.tensorflow as hvd

# Initialize Horovod
hvd.init()

# Pin GPU to be used to process local rank (one GPU per process)
config = tf.ConfigProto()
config.gpu_options.visible_device_list = str(hvd.local_rank())

# Build model...
loss = ...
opt = tf.train.AdagradOptimizer(0.01)

# Add Horovod Distributed Optimizer
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# Add hook to broadcast variables from rank 0 to all other processes
# during initialization.
hooks = [hvd.BroadcastGlobalVariablesHook(0)]

# Make training operation
train_op = opt.minimize(loss)

# The MonitoredTrainingSession takes care of session initialization,
# restoring from a checkpoint, saving to a checkpoint, and closing
# when done or an error occurs.
```

Wraps any regular Tensorflow opt with Horovod optimizer which will take care of averaging the gradients automatically

Snippet of Horovod basic code

```
import tensorflow as tf
import horovod.tensorflow as hvd

# Initialize Horovod
hvd.init()

# Pin GPU to be used to process local rank (one GPU per process)
config = tf.ConfigProto()
config.gpu_options.visible_device_list = str(hvd.local_rank())

# Build model...
loss = ...
opt = tf.train.AdagradOptimizer(0.01)

# Add Horovod Distributed Optimizer
opt = hvd.DistributedOptimizer(opt)

# Add hook to broadcast variables from rank 0 to all other processes
# during initialization.
hooks = [hvd.BroadcastGlobalVariablesHook(0)]  
# Make training operation
train_op = opt.minimize(loss)

# The MonitoredTrainingSession takes care of session initialization,
# restoring from a checkpoint, saving to a checkpoint, and closing
# when done or an error occurs.
```

Broadcast variable across all ranks to ensure consistent initialization

Snippet of Horovod basic code

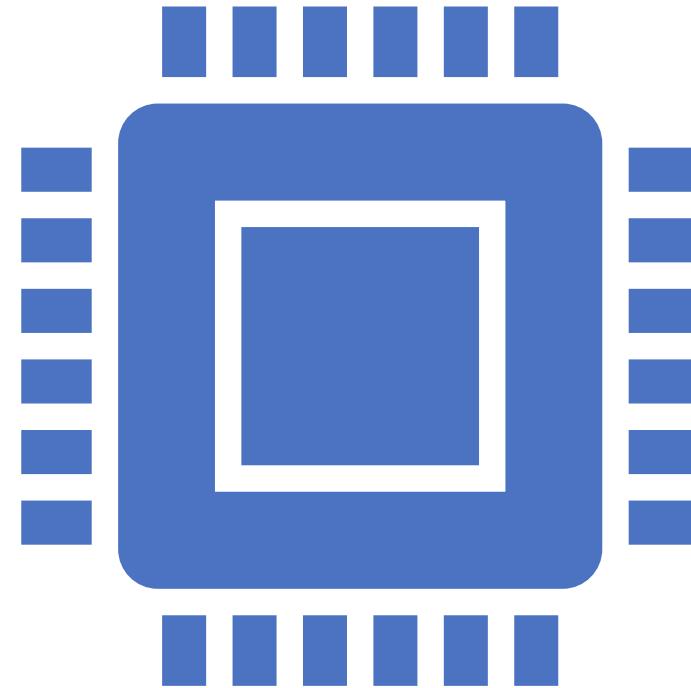
```
with tf.train.MonitoredTrainingSession(checkpoint_dir="/tmp/train_logs",
                                         config=config,
                                         hooks=hooks) as mon_sess:
    while not mon_sess.should_stop():
        # Perform synchronous training.
        mon_sess.run(train_op)
```



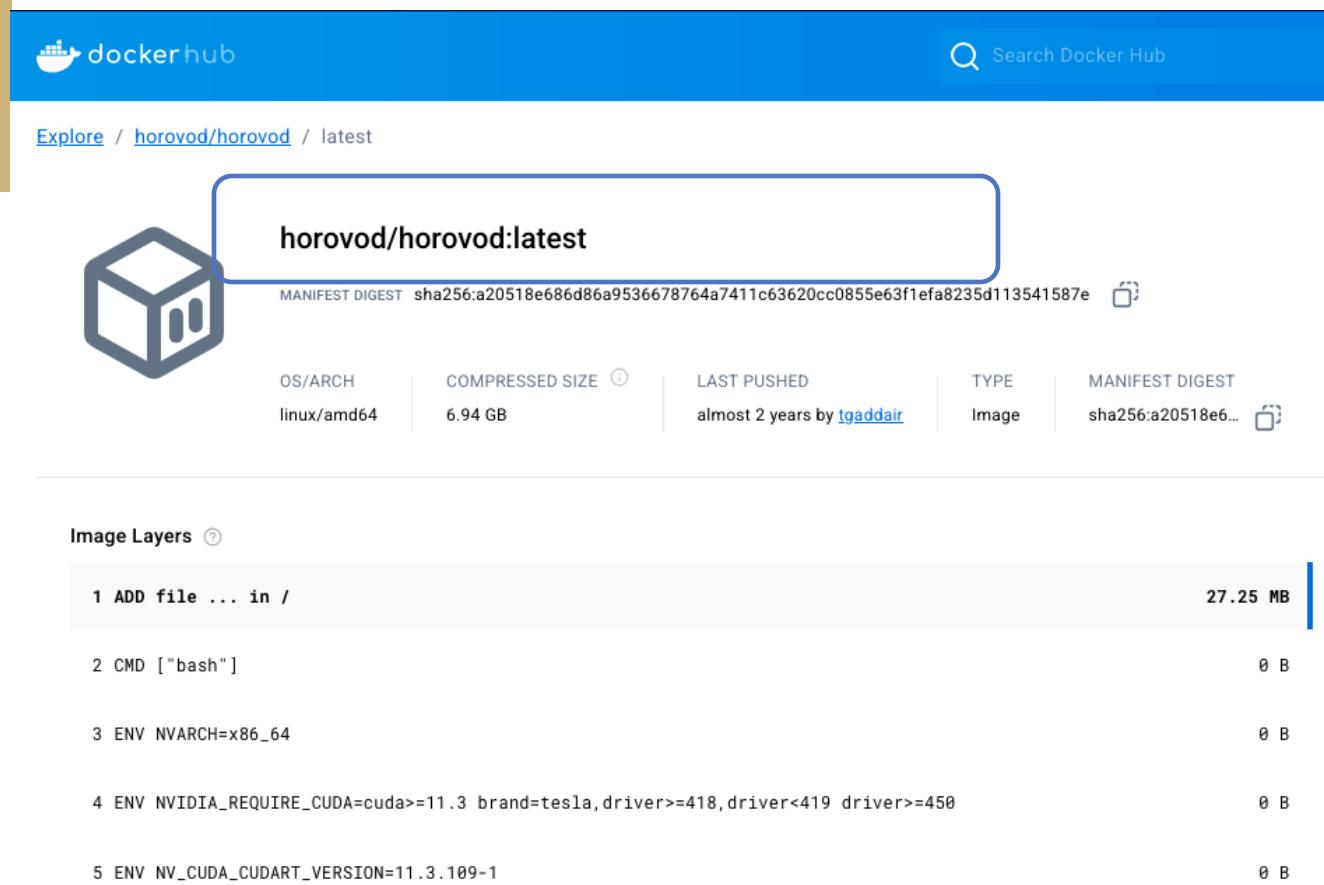
Monitoring session for
automatic session init,
checkpoint
accommodation & closing

Collective communication with Horovod

- Message Passing Interface (MPI) for CPUs and GPUs in general.
- NVIDIA Collective Communication Library (NCCL) with multi-node & multi GPU.
- GLOO developed by Facebook AI
- Allow to average the gradients automatically (ring-allreduce operation)



Let's install Horovod!

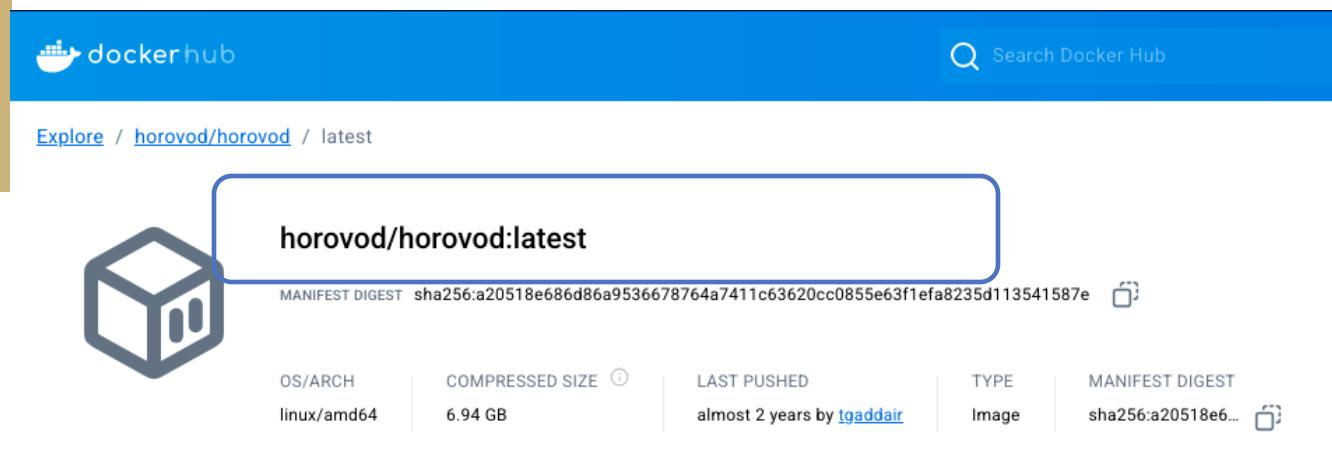


- Horovod allows run distributed deep learning on multiple cpus, gpus and nodes.

Source:

<https://hub.docker.com/layers/horovod/horovod/latest/images/sha256-a20518e686d86a9536678764a7411c63620cc0855e63f1efa8235d113541587e?context=explore>

Let's use a Docker container!



- Horovod allows run distributed deep learning on multiple cpus, gpus and nodes.

- Please refer to our workshop here:
https://github.com/kf-cuanschutz/CU-Anschutz-HPC-documentation/blob/main/Workshops/Introduction_to_Horovod_102423_part1_official_v2.pdf

Source:

<https://hub.docker.com/layers/horovod/horovod/latest/images/sha256-a20518e686d86a9536678764a7411c63620cc0855e63f1efa8235d113541587e?context=explore>

Let's use a Docker container!

- We make sure to go to a compute node on Alpine

```
@login-ci1 ~]$ acompile -ntasks=4 -time=12:00:00
```

```
@c3cpu-a2-u32-2 ~]$
```

Let's use a Docker container!

- We make sure to go to a compute node on Alpine

```
@login-ci1 ~]$ acompile -ntasks=4 -time=12:00:00
```

```
@c3cpu-a2-u32-2 ~]$
```

- Because the filesystem /tmp is small on Alpine, we probably want to export tmp directories to the scratch filesystem.

```
@c3cpu-a2-u32-2 ~]$ export ALPINE_SCRATCH=/gpfs/alpine1/scratch/$USER  
@c3cpu-a2-u32-2 ~]$ export APPTAINER_TMPDIR=$ALPINE_SCRATCH/apptainer/tmp  
@c3cpu-a2-u32-2 ~]$ export APPTAINER_CACHE=$ALPINE_SCRATCH/apptainer/cache  
@c3cpu-a2-u32-2 ~]$ mkdir -pv $APPTAINER_TMPDIR $APPTAINER_TMPDIR
```

We convert the docker img into apptainer

- We use the build command, which works equally for apptainer or singularity.

```
@c3cpu-a2-u32-2 ~]$ apptainer build horovod.sif docker://horovod/horovod:latest  
INFO: Starting build...  
Copying blob 326d76058f67 skipped: already exists  
Copying blob 846c0b181fff skipped: already exists  
Copying blob 6fc9dd88827c skipped: already exists
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash
```

```
#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

Job name, output and error

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100 ← NVIDIA partition name
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2 ← We ask for 2 nodes
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```



We ask for 30 CPU cores total.
NOT GPU cores !!!

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

We ask for 2 GPUs per node



```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```



Anschutz users account

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```



Walltime

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

Load gcc to load OpenMPI

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
```

```
ml cuda/11.8
```

Load cuda to use nsys

```
module load anaconda
conda activate prs_gpu
```

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```

Load anaconda

Horovod on Alpine (Slurm script)

```
#!/bin/bash

#SBATCH --job-name=horovod_mult_gpu_
#SBATCH --output=horovod_mult_gpu_.%j.out
#SBATCH --error=horovod_mult_gpu_.%j.err
#SBATCH --partition=aa100
#SBATCH --nodes=2
#SBATCH --ntasks=30
#SBATCH --gres=gpu:2
#SBATCH --account=amc-general
#SBATCH --time=00:20:00
```

```
ml gcc openmpi/4.1.1
ml cuda/11.8
```

```
module load anaconda
conda activate prs_gpu
```



Activate environment

Horovod on Alpine (Slurm script)

NCCL library
export

```
# We export the NCCL library
export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:/projects/kefo9343/software/spack/opt/spack/linux-rhel8-zen/gcc-8.4.1/nccl-2.18.3-1-2pmue

# We want the XLA flags and tensorrt for optimization
export XLA_FLAGS=--xla_gpu_cuda_data_dir /projects/kfotso@xsede.org/software/anaconda/envs/prs_gpu

] export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:$CONDA_PREFIX/lib/python3.8/site-packages/tensorrt

# If I want to run on multiple nodes, I will need to know their hostnames
scontrol show hostname > ${SLURM_SUBMIT_DIR}/nodelist.txt
node1=`sed -n 1p ${SLURM_SUBMIT_DIR}/nodelist.txt`

# An example in case you want to add a new node, corresponding to the line number
node2=`sed -n 2p ${SLURM_SUBMIT_DIR}/nodelist.txt`
```

Horovod on Alpine (Slurm script)

```
# We export the NCCL library
export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:/projects/kefo9343/software/spack/opt/spack/linux-rhel8-zen/gcc-8.4.1/nccl-2.18.3-1-2pmuetqeeecftln5wn6jqy6xcvyzak6d/lib

# We want the XLA flags and tensorrt for optimization
export XLA_FLAGS=--xla_gpu_cuda_data_dir /projects/kfotso@xsede.org/software/anaconda/envs/prs_gpu
export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:$CONDA_PREFIX/lib/python3.8/site-packages/tensorrt

# If I want to run on multiple nodes, I will need to know their hostnames
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node1=`sed -n 1p ${SLURM_SUBMIT_DIR}/nodelist.txt`

# An example in case you want to add a new node, corresponding to the line number
node2=`sed -n 2p ${SLURM_SUBMIT_DIR}/nodelist.txt`
```

XLA flags and
tensorRT for
optimization



Horovod on Alpine (Slurm script)

```
# We export the NCCL library
export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:/projects/kefo9343/software/spack/opt/spack/linux-rhel8-zen/gcc-8.4.1/nccl-2.18.3-1-2pmuetqeeecftln5wn6jqy6xcvyzak6d/lib

# We want the XLA flags and tensorrt for optimization
export XLA_FLAGS=--xla_gpu_cuda_data_dir /projects/kfotso@xsede.org/software/anaconda/envs/prs_gpu

export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:$CONDA_PREFIX/lib/python3.8/site-packages/tensorrt

# If I want to run on multiple nodes, I will need to know their hostname:
scontrol show hostname > ${SLURM_SUBMIT_DIR}/nodelist.txt
node1=`sed -n 1p ${SLURM_SUBMIT_DIR}/nodelist.txt`  

# An example in case you want to add a new node, corresponding to the line number
node2=`sed -n 2p ${SLURM_SUBMIT_DIR}/nodelist.txt`
```

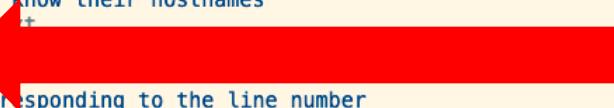
We create a
nodelist with
scontrol that we
store in nodelist.txt

Horovod on Alpine (Slurm script)

```
# We export the NCCL library
export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:/projects/kefo9343/software/spack/opt/spack/linux-rhel8-zen/gcc-8.4.1/nccl-2.18.3-1-2pmuetqeeecftln5wn6jqy6xcvyzak6d/lib

# We want the XLA flags and tensorrt for optimization
export XLA_FLAGS=--xla_gpu_cuda_data_dir /projects/kfotso@xsede.org/software/anaconda/envs/prs_gpu

export LD_LIBRARY_PATH=$LD_LIBRARY_PATH:$CONDA_PREFIX/lib/python3.8/site-packages/tensorrt

# If I want to run on multiple nodes, I will need to know their hostnames
scontrol show hostname > $SLURM_SUBMIT_DIR/nodelist.txt
node1=`sed -n 1p $SLURM_SUBMIT_DIR/nodelist.txt`
```

We assign the content of nodelist.txt into variables

Horovod on Alpine (Basic Neural Net)

- California housing dataset
- Target variable is the median house value for California districts
- Simple regression neural network
- Code adapted from the Hands On Machine learning book chapter 10.

Horovod on Alpine (Python script)

```
# This horovod test comes from the original chapter 10 of Hands on Machine learning
# https://github.com/ageron/handson-ml3/blob/main/10_neural_nets_with_keras.ipynb
print(4)
# Get the current timestamp
timestamp1 = time.time() ←
# Horovod: initialize Horovod.
hvd.init()

# Selecting the GPU devices on the node
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
if gpus:
    tf.config.experimental.set_visible_devices(gpus[hvd.local_rank()], 'GPU')
```

Timestamp to
measure the
duration

Horovod on Alpine (Python script)

```
# This horovod test comes from the original chapter 10 of Hands on Machine learning
# https://github.com/ageron/handson-ml3/blob/main/10_neural_nets_with_keras.ipynb
print(4)
# Get the current timestamp
timestamp1 = time.time()

# Horovod: initialize Horovod.
hvd.init()

# Selecting the GPU devices on the node
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
if gpus:
    tf.config.experimental.set_visible_devices(gpus[hvd.local_rank()], 'GPU')
```

Initialize Horovod
and set multi GPUs



Horovod on Alpine (Python script)

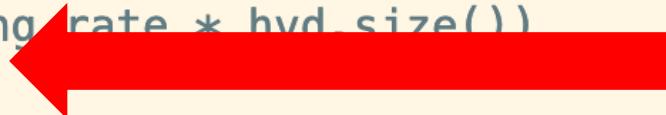
```
tf.random.set_seed(42)
norm_layer = tf.keras.layers.Normalization(input_shape=X_train.shape[1:])
model = tf.keras.Sequential([
    norm_layer,
    tf.keras.layers.Dense(50, activation="relu"),
    tf.keras.layers.Dense(50, activation="relu"),
    tf.keras.layers.Dense(50, activation="relu"),
    tf.keras.layers.Dense(1)
])
```



Simple Neural Net

Horovod on Alpine (Python script)

```
# Tune the learning rate
learning_rate = 1e-3

#K.set_value(model.optimizer.learning_rate, learning_rate)
# Horovod: adjust learning rate based on number of GPUs.
opt = tf.keras.optimizers.Adadelta(learning_rate * hvd.size())

# Horovod: add Horovod Distributed Optimizer.
opt = hvd.DistributedOptimizer(opt)
# Horovod: add Horovod Distributed Optimizer.

model.compile(loss="mse", optimizer=opt, metrics=["RootMeanSquaredError"])
norm_layer.adapt(X_train)

# Defining batch size and epochs as a function of horovod
batch_size = 8
```

Learning rate is scaled by
the number of GPUs

Horovod on Alpine (Python script)

```
total_epochs_ = int(math.ceil(6.0 / hvd.size()))

callbacks = [
    # Horovod: broadcast initial variable states from rank 0 to all other processes.
    # This is necessary to ensure consistent initialization of all workers when
    # training is started with random weights or restored from a checkpoint.
    hvd.callbacks.BroadcastGlobalVariablesCallback(0),
]

# Horovod: save checkpoints only on worker 0 to prevent other workers from corrupting them.
if hvd.rank() == 0:
    callbacks.append(tf.keras.callbacks.ModelCheckpoint('./checkpoint-{epoch}.h5'))

# Model fitting across multiple GPUs
model.fit(X_train,
           y_train,
           epoch=total_epochs_,
           verbose=1,
           callbacks=callbacks,
           validation_data=(X_valid, y_valid))
```



We scale the number of epoch by the number of GPUs

Horovod on Alpine (Python script)

```
total_epochs_ = int(math.ceil(6.0 / hvd.size()))

callbacks = [
    # Horovod: broadcast initial variable states from rank 0 to all other processes.
    # This is necessary to ensure consistent initialization of all workers when
    # training is started with random weights or restored from a checkpoint.
    hvd.callbacks.BroadcastGlobalVariablesCallback(0),
]
# Horovod: save checkpoints only on worker 0 to prevent other workers
if hvd.rank() == 0:
    callbacks.append(tf.keras.callbacks.ModelCheckpoint('./checkpoint-{epoch}.h5'))

# Model fitting across multiple GPUs
model.fit(X_train,
           y_train,
           epochs=total_epochs_,
           verbose=1,
           callbacks=callbacks,
           validation_data=(X_valid, y_valid))
```

checkpointing

Run slurm script

- sbatch **horovod_mpi.sh**
- Check the nodes where the job is running

```
e.org@login-ci2 : ~ ~ ~ ~ ~  
JOBID PARTITION      NAME      USER ST  
481362      aa100 horovod_ kfotso@x R  
479946      acompile acompile kfotso@x R  
481778      atesting_ sinterac kfotso@x R  
e.org@login-ci2
```

```
]$ squeue --me  
TIME      NODES NODELIST(REASON)  
2:34        2 c3gpu-a9-u31-1,c3gpu-a9-  
2:03:48      1 c3cpu-c9-u5-2  
7:56        1 c3gpu-a9-u29-1  
]$ ssh c3gpu-a9-u29-1^C
```



We have a GPU
node that we can
ssh to:
c3gpu-a9-u29-1

GPU monitoring

ssh to a that node on a different screen and run:

```
nvidia-smi -l
```

| NVIDIA-SMI 525.85.12 Driver Version: 525.85.12 CUDA Version: 12.0 | | | | | | | |
|---|--------------------|---------------|------------------|--------------------|--------------|------------------|----------|
| 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. |
| <hr/> | | | | | | | |
| 0 | NVIDIA A100 80G... | On | 00000000:25:00.0 | Off | 26% | 0 | Disabled |
| N/A | 33C | P0 | 80W / 300W | 1869MiB / 81920MiB | | | |
| <hr/> | | | | | | | |
| 1 | NVIDIA A100 80G... | On | 00000000:81:00.0 | Off | 25% | 0 | Default |
| N/A | 32C | P0 | 81W / 300W | 1869MiB / 81920MiB | | | Disabled |
| <hr/> | | | | | | | |
| Processes: | | | | | | | |
| GPU | GI | CI | PID | Type | Process name | GPU Memory Usage | |
| ID | ID | | | | | | |
| 0 | N/A | N/A | 569301 | C | python | 1866MiB | |
| 1 | N/A | N/A | 569302 | C | python | 1866MiB | |

We can confirm
that we are using
2 GPUs!!!

GPU monitoring

ssh to a that node on a different screen and run:

```
nvidia-smi -l
```

| NVIDIA-SMI 525.85.12 Driver Version: 525.85.12 CUDA Version: 12.0 | | | | | | | |
|---|--------------------|---------------|------------------|--------------------|----------|------------|----------|
| 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. |
| <hr/> | | | | | | | |
| 0 | NVIDIA A100 80G... | On | 00000000:25:00.0 | Off | 26% | 0 | Disabled |
| N/A | 33C | P0 | 80W / 300W | 1869MiB / 81920MiB | | | |
| <hr/> | | | | | | | |
| 1 | NVIDIA A100 80G... | On | 00000000:81:00.0 | Off | 25% | 0 | Default |
| N/A | 32C | P0 | 81W / 300W | 1869MiB / 81920MiB | | | Disabled |
| <hr/> | | | | | | | |

Percentage GPU usability. That is the portion of time 1 or more kernels were used

| Processes: | | | | | |
|------------|-----|-----|--------|------|------------------|
| GPU | GI | CI | PID | Type | Process name |
| ID | ID | | | | GPU Memory Usage |
| <hr/> | | | | | |
| 0 | N/A | N/A | 569301 | C | python |
| 1 | N/A | N/A | 569302 | C | python |
| <hr/> | | | | | |

GPU monitoring

ssh to a that node on a different screen and run:

```
nvidia-smi -l
```

| NVIDIA-SMI 525.85.12 Driver Version: 525.85.12 CUDA Version: 12.0 | | | | | | | |
|---|--------------------|---------------|------------------|--------------------|--------------|------------------|----------|
| 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. |
| <hr/> | | | | | | | |
| 0 | NVIDIA A100 80G... | On | 00000000:25:00.0 | Off | 0 | | |
| N/A | 33C | P0 | 80W / 300W | 1869MiB / 81920MiB | 26% | Default | Disabled |
| <hr/> | | | | | | | |
| 1 | NVIDIA A100 80G... | On | 00000000:81:00.0 | Off | 0 | | |
| N/A | 32C | P0 | 81W / 300W | 1869MiB / 81920MiB | 25% | Default | Disabled |
| <hr/> | | | | | | | |
| Processes: | | | | | | | |
| GPU | GI | CI | PID | Type | Process name | GPU Memory Usage | |
| ID | ID | | | | | | |
| 0 | N/A | N/A | 569301 | C | python | 1866MiB | |
| 1 | N/A | N/A | 569302 | C | python | 1866MiB | |

How much
memory is used.

GPU monitoring

nvidia-smi has more parameters that can be used. Cheatsheet here:

<https://www.docs.arc.vt.edu/usage/gpumon.html>

```
[kfotso@xsede.org@c3gpu-a9-u29-1 ~]$ nvidia-smi --query-gpu=timestamp,name,pci.bus_id,driver_version,temperature.gpu,utilization.gpu,utilization.memory --format=csv -l 5
timestamp, name, pci.bus_id, driver_version, temperature.gpu, utilization.gpu [%], utilization.memory [%]
2023/10/23 21:42:45.228, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 32, 0 %, 0 %
2023/10/23 21:42:45.230, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 31, 0 %, 0 %
2023/10/23 21:42:50.233, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 33, 7 %, 0 %
2023/10/23 21:42:50.234, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 32, 5 %, 0 %
2023/10/23 21:42:55.236, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 34, 25 %, 2 %
2023/10/23 21:42:55.237, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 32, 23 %, 1 %
2023/10/23 21:43:00.238, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 34, 25 %, 2 %
2023/10/23 21:43:00.240, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 33, 25 %, 1 %
2023/10/23 21:43:05.241, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 34, 25 %, 2 %
2023/10/23 21:43:05.243, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 33, 24 %, 1 %
2023/10/23 21:43:10.244, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 35, 26 %, 2 %
2023/10/23 21:43:10.246, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 33, 25 %, 2 %
2023/10/23 21:43:15.247, NVIDIA A100 80GB PCIe, 00000000:25:00.0, 525.85.12, 35, 26 %, 2 %
2023/10/23 21:43:15.248, NVIDIA A100 80GB PCIe, 00000000:81:00.0, 525.85.12, 33, 26 %, 2 %
```

Slurm job (2 GPUs)

```
tput=horovod_profile horovodrun -np 2 -H localhost:2 horovod_cnn_mnist.py
GPU 0: General Metrics for NVIDIA GA100 (any frequency)
GPU 1: General Metrics for NVIDIA GA100 (any frequency)
2023-10-23 21:47:46.810582: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,0]<stderr>:2023-10-23 21:47:52.457092: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,0]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stderr>:2023-10-23 21:47:52.485600: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,1]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stdout>:4
[1,0]<stdout>:4
[1,0]<stderr>:2023-10-23 21:47:57.693575: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 0, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:25:00.0, compute capability: 8.0
[1,1]<stderr>:2023-10-23 21:47:57.708825: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 1, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:81:00.0, compute capability: 8.0
[1,0]<stdout>:Epoch 1/3
[1,1]<stdout>:Epoch 1/3
[1,0]<stderr>:2023-10-23 21:48:01.104191: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,1]<stderr>:2023-10-23 21:48:01.117719: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,0]<stderr>:2023-10-23 21:48:01.793663: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.813954: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.846349: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f6a85723010 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,1]<stderr>:2023-10-23 21:48:01.846381: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,0]<stderr>:2023-10-23 21:48:01.854430: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f0deed4b800 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,0]<stderr>:2023-10-23 21:48:01.854486: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,1]<stderr>:2023-10-23 21:48:01.857037: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,0]<stderr>:2023-10-23 21:48:01.861230: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,1]<stderr>:2023-10-23 21:48:02.027518: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
[1,0]<stderr>:2023-10-23 21:48:02.034153: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
```

The profiling sees
the 2 GPUs.

Slurm job (2 GPUs)

```
tput=horovod_profile horovodrun -np 2 -H localhost:2 horovod_cnn_mnist.py
GPU 0: General Metrics for NVIDIA GA100 (any frequency)
GPU 1: General Metrics for NVIDIA GA100 (any frequency)
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[1,0]<stderr>:2023-10-23 21:47:52.457092: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,0]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stderr>:2023-10-23 21:47:52.485600: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,1]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stdout>:4
[1,0]<stdout>:4
[1,0]<stderr>:2023-10-23 21:47:57.693575: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 0, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:25:00.0, compute capability: 8.0
[1,1]<stderr>:2023-10-23 21:47:57.708825: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 1, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:81:00.0, compute capability: 8.0
[1,0]<stdout>:Epoch 1/3
[1,1]<stdout>:Epoch 1/3
[1,0]<stderr>:2023-10-23 21:48:01.104191: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,1]<stderr>:2023-10-23 21:48:01.117719: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,0]<stderr>:2023-10-23 21:48:01.793663: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.813954: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.846349: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f6a85723010 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,1]<stderr>:2023-10-23 21:48:01.846381: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,0]<stderr>:2023-10-23 21:48:01.854430: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f0deed4b800 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,0]<stderr>:2023-10-23 21:48:01.854486: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,1]<stderr>:2023-10-23 21:48:01.857037: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
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[1,1]<stderr>:2023-10-23 21:48:02.027518: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
[1,0]<stderr>:2023-10-23 21:48:02.034153: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
```

2 GPU got assigned

Slurm job (2 GPUs)

```
tput=horovod_profile horovodrun -np 2 -H localhost:2 horovod_cnn_mnist.py
GPU 0: General Metrics for NVIDIA GA100 (any frequency)
GPU 1: General Metrics for NVIDIA GA100 (any frequency)
2023-10-23 21:47:46.810582: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
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[1,0]<stderr>:2023-10-23 21:47:52.457092: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,0]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stderr>:2023-10-23 21:47:52.485600: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
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[1,1]<stdout>:4
[1,0]<stdout>:4
[1,0]<stderr>:2023-10-23 21:47:57.693575: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 0, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:25:00.0, compute capability: 8.0
[1,1]<stderr>:2023-10-23 21:47:57.708825: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 1, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:81:00.0, compute capability: 8.0
[1,0]<stdout>:Epoch 1/3
[1,1]<stdout>:Epoch 1/3
[1,0]<stderr>:2023-10-23 21:48:01.104191: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,1]<stderr>:2023-10-23 21:48:01.117719: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,0]<stderr>:2023-10-23 21:48:01.793663: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.813954: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.846349: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f6a85723010 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,1]<stderr>:2023-10-23 21:48:01.846381: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,0]<stderr>:2023-10-23 21:48:01.854430: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f0deed4b800 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,0]<stderr>:2023-10-23 21:48:01.854486: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,1]<stderr>:2023-10-23 21:48:01.857037: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,0]<stderr>:2023-10-23 21:48:01.861230: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,1]<stderr>:2023-10-23 21:48:02.027518: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
[1,0]<stderr>:2023-10-23 21:48:02.034153: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
```

CUDNN gets loaded for each

Slurm job (2 GPUs)

```
tput=horovod_profile horovodrun -np 2 -H localhost:2 horovod_cnn_mnist.py
GPU 0: General Metrics for NVIDIA GA100 (any frequency)
GPU 1: General Metrics for NVIDIA GA100 (any frequency)
2023-10-23 21:47:46.810582: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,0]<stderr>:2023-10-23 21:47:52.457092: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,0]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stderr>:2023-10-23 21:47:52.485600: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
[1,1]<stderr>:To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
[1,1]<stdout>:4
[1,0]<stdout>:4
[1,0]<stderr>:2023-10-23 21:47:57.693575: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 0, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:25:00.0, compute capability: 8.0
[1,1]<stderr>:2023-10-23 21:47:57.708825: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1635] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 78916 MB memory: --> device: 1, name: NVIDIA A100 80GB PCIe, pci bus id: 0000:81:00.0, compute capability: 8.0
[1,0]<stdout>:Epoch 1/3
[1,1]<stdout>:Epoch 1/3
[1,0]<stderr>:2023-10-23 21:48:01.104191: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,1]<stderr>:2023-10-23 21:48:01.117719: I tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:424] Loaded cuDNN version 8600
[1,0]<stderr>:2023-10-23 21:48:01.793663: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.813954: I tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:637] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
[1,1]<stderr>:2023-10-23 21:48:01.846349: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f6a85723010 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,1]<stderr>:2023-10-23 21:48:01.846381: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,0]<stderr>:2023-10-23 21:48:01.854430: I tensorflow/compiler/xla/service/service.cc:169] XLA service 0x7f0deed4b800 initialized for platform CUDA (this does not guarantee that XLA will be used). Devices:
[1,0]<stderr>:2023-10-23 21:48:01.854486: I tensorflow/compiler/xla/service/service.cc:177] StreamExecutor device (0): NVIDIA A100 80GB PCIe, Compute Capability 8.0
[1,1]<stderr>:2023-10-23 21:48:01.857037: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,0]<stderr>:2023-10-23 21:48:01.861230: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var 'MLIR_CRASH_REPRODUCER_DIRECTORY' to enable.
[1,1]<stderr>:2023-10-23 21:48:02.027518: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
[1,0]<stderr>:2023-10-23 21:48:02.034153: I ./tensorflow/compiler/jit/device_compiler.h:180] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.
```

XLA opt is initialize and the stream is executed

Special Thanks

- Special thanks to Brandon Reyes from the Boulder team for his contribution on the container aspect of AMD GPU computation

Questions?