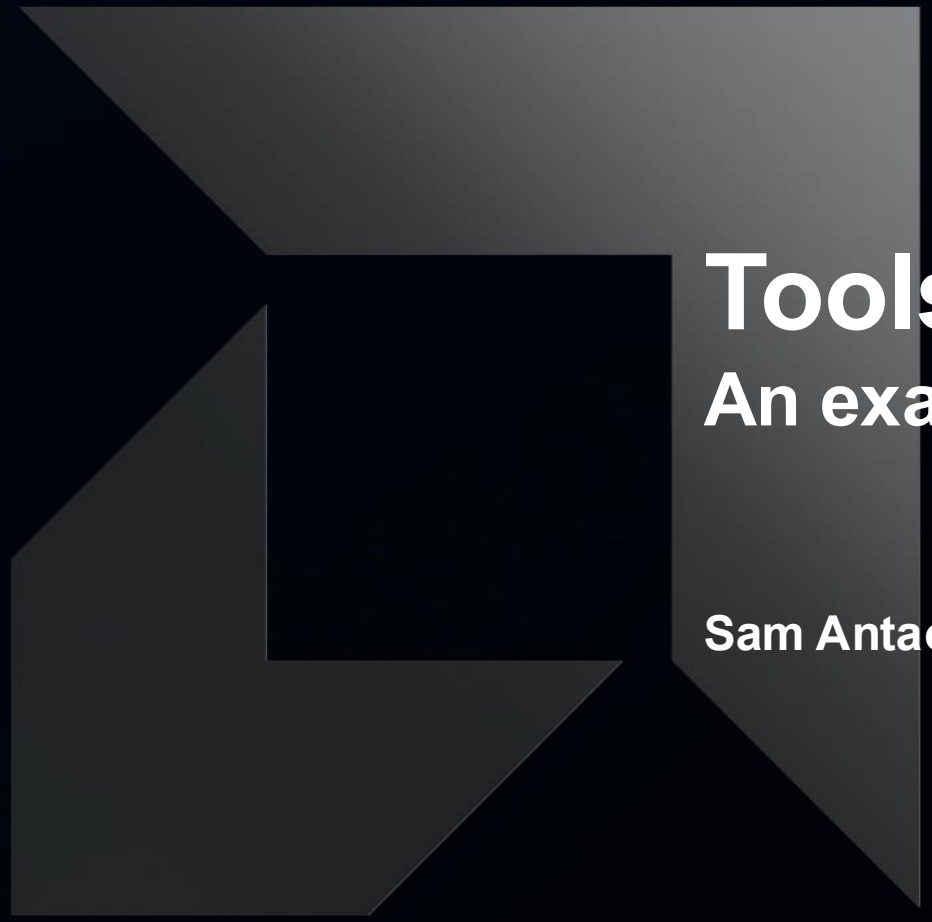

Tools in action

An example with Pytorch

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LUMI Advanced Training
Oct. 24th 2025

AMD
together we advance_

slides on LUMI in /project/project_465002175/Slides/AMD/

hands-on exercises: https://hackmd.io/@sfantao/lumi-training-tal-2025#Pytorch-example

hands-on source code: /project/project_465002175/Exercises/AMD/Pytorch

Agenda

1. Intro to Pytorch and its dependencies
2. Controlling affinity
3. Profiling – rocprof and omnitools.

All suggestions presented here are transversal to any AI or HPC application!

Python applications can leverage the same tooling as non-python applications!

Scripting examples are suggestions and can always be adapted!

Pytorch highlight

- Official page: https://pytorch.org/
- Code: https://github.com/pytorch/pytorch
- Python™-based framework for machine learning
  - Auto-differentiation on tensor types
- GPU-enabled
  - ROCm support for MI250x (and others)
  - Hipification as part of the build system
    - C/C++ libraries with proper bindings for Python
  - Python code does **NOT** need changing – using the same CUDA conventions
- Other related packages:
  - Torch vision/audio, triton, many others
- Many more build on it
  - vLLM, Deepspeed, Megatron-LM

Pytorch install – our base environment

```
module purge
module load CrayEnv
module load PrgEnv-cray/8.5.0
module load craype-accel-amd-gfx90a
module load cray-python
```

Setup the GPU environment and the Cray Python environment

Recent Pytorch builds need recent user-level ROCm versions.

```
# This path provides more recent ROCm modules.
module use /appl/local/containers/test-modules
module load rocm/6.1.3.lua
```

We will be using 6.1.3 as it the oldest version for Pytorch 2.4.1 official releases

Pytorch install – running the examples

- For simplicity and improve the demonstration we leverage interactive runs on existing node allocation
- We run beforehand:

```
N=1 ; salloc -p standard-g \
        --threads-per-core 1 \
        --exclusive \
        -N $N \
        --gpus $((N*8)) \
        -t 4:00:00 --mem 0
```

We are reserving **N nodes**, in this case only one node, using **one of the two available hardware threads** per core. We we'll be using the **8 GCDs** available in each node.

- This is a good way to experiment and converge to the correct job description.
- Don't forget to release your allocations once you are done!
- Once you consolidate your job description you can leverage batch jobs.
  - Salloc options translate directly to sbatch options.

Pytorch install – system python

- Native install from Pytorch python wheels

Package install version can mix the Pytorch version as well as the ROCm it was build against.

Where do we want to install things - don't use your home folder!

This is where Pytorch project posts the wheel files - browse it to see what versions and ROCm combinations are available.

```
pip3 install -t $PWD/pip-installs --pre torch==2.4.1+rocm6.1       --index-url https://download.pytorch.org/whl/
```

```
Collecting torch==2.4.1+rocm6.1
  Downloading https://download.pytorch.org/whl/rocm6.1/torch-2.4.1%2Brocm6.1-cp311-cp311-linux_x86_64.whl (2662.0 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.9/2.7 GB 74.9 MB/s eta 0:00:24
```

Make the frershly install Pytorch available to your Python runs

```
PYTHONPATH=$PWD/pip-installs \
        srun --jobid=$jobid -n1 --gpus 8 \
        python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

```
> I have this many devices: 8
```

Should yield the number of GCDs in the node.

Example 01

Pytorch install – virtual environments

Example 02

- Virtual environments are convenient to manage python package installation in ones user-space

Leverage the venv module to create the virtual environment

We are happy to leverage system's already installed packages

The folder where the virtual environment will be installed

```
python -m venv --system-site-packages cray-python-virtualenv
```

```
source cray-python-virtualenv/bin/activate
```

Activate the environment. It will be leveraged by the install and run.

Install and run as before. No need to specify install location – the environment is doing it for you.

```
pip3 install --pre torch==2.4.1+rocm6.1 --index-url https://download.pytorch.org/whl/
srun --jobid=$jobid -n1 --gpus 8 \
  python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

Pytorch install – conda environment

- Conda environment adds the package-manager functionality to a virtual environment
- One can tune the Python version to use as we won't be leveraging the system one anymore.
  - No `module load cray-python` needed!

```
curl -LO https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh
bash ./Miniconda3-* -b -p miniconda3 -s
```

Download and install a minimal conda (miniconda).

```
source $PWD/miniconda3/bin/activate base
```

Activate the conda environment

```
conda create -y -n pytorch python=3.11
source $PWD/miniconda3/bin/activate pytorch
```

Create and activate a conda environment to install Pytorch based on Python 3.11

Install and run as before - Conda package manager doesn't have ROCm enabled Pytorch installs

```
pip3 install --pre torch==2.4.1+rocm6.1 --index-url https://download.pytorch.org/whl/
srun --jobid=$jobid -n1 --gpus 8 \
 python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

Pytorch install – conda environment install from source

- Installing Pytorch from source is not recommended on LUMI
  - Too old default ROCm to build against.
- It might be useful in some cases: builds with symbols for debugging.

```
# We need a recent enough compiler – we'll use gcc
module load PrgEnv-gnu/8.5.0 gcc/10.3.0

# Clone a given version of Pytorch and all its third_party components
git clone -b v2.4.1 --recursive \
  https://github.com/pytorch/pytorch pytorch-source

# Createand activate conda environment to manage the install
conda create -y -n pytorch-from-source python=3.11
source $wd/miniconda3/bin/activate pytorch-from-source

# Install requirements for Pytorch and some build tools.
pip install -r $wd/pytorch-source/requirements.txt
conda install -y cmake ninja

# Sometimes we need to solve some library clashes between conda and the system. We force the removal of the conda libstdc++ so that we use the system one.
rm -rf $wd/miniconda3/envs/pytorch-from-source/lib/libstdc++.so

# Point to our ROCM instalation that is not in a default path.
grep -rl /opt/rocm | \
  xargs sed  -I "s#/opt/rocm#$ROCM_PATH#g"

# Hipify source
nice python3 tools/amd_build/build_amd.py

# Build with debug symbols
CC=$(which gcc) \
  CXX=$(which g++) \
  CMAKE_PREFIX_PATH=$CONDA_PREFIX:$CMAKE_PREFIX_PATH \
  LDFLAGS="-L$ROCM_PATH/deps -lstdc++ -ltinfo" \
  USE_KINETO=0 BUILD_TEST=0 \
  PYTORCH_ROCM_ARCH=gfx90a \
  REL_WITH_DEB_INFO=1 \
  nice python3 setup.py bdist_wheel

pip install $wd/pytorch-source/dist/torch-*.whl
```

Enable/disable the packages you care about.

Build with debug symbols

Pytorch install – Singularity containers

- Control better the Pytorch environment
- Less strain on the filesystem
  - All application installation is loaded as a single file
- Enable more recent ROCm versions
- Transferable and arguably more portable
- Some containers available under:
  - `/appl/local/containers/sif-images/`

- Any cons?
  - Updating the environment and installing more packages may require rebuild the container
  - Containers can't currently be build on LUMI:
    - Needs containers to be built elsewhere and copied to the system
  - Submitting jobs has to be done more carefully.

```
SIF=<myimage.sif>

srun --jobid=$jobid -n1 \
singularity exec \
        -B /var/spool/slurmd \
        -B /opt/cray \
        -B /usr/lib64/libcxi.so.1 \
        -B $wd:/workdir \
        $SIF /workdir/run-me.sh
```

Make relevant pieces of native environment visible inside the container

Make my work directory visible inside the container

The container image

Use helper script to spin the application

Pytorch install – Singularity containers


```
SIF=/appl/local/containers/sif-images/lumi-pytorch-rocm-6.1.3-python-3.12-pytorch-v2.4.1.sif

rm -rf $wd/run-me.sh
cat > $wd/run-me.sh << EOF
#!/bin/bash -e

# Start conda environment inside the container
\$WITH_CONDA

# Run application
python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'

EOF
chmod +x $wd/run-me.sh

srun --jobid=$jobid -n1 --gpus 8 \
singularity exec \
 -B /var/spool/slurmd \
 -B /opt/cray \
 -B /usr/lib64/libcxi.so.1 \
-B $wd:/workdir \
 $SIF /workdir/run-me.sh
```

The container image to use: Pytorch 2.4.1 on top of ROCm 6.1.3

One could leverage a script to describe what is going to be executed inside the container.

This script has to load the container Conda environment. A special variable is set in the container to facilitate that.

Run as before.

Invoke singularity to start the container and execute the script created above.

Controlling device visibility

- Controlling visibility
  - HIP_VISIBLE_DEVICES=0,1,2,3 python -c 'import torch; print(torch.cuda.device_count())'
  - ROCR_VISIBLE_DEVICES=0,1,2,3 python -c 'import torch; print(torch.cuda.device_count())’
  - SLURM sets ROCR_VISIBLE_DEVICES
  - Implications of both ways of setting visibility – blit kernels and/or DMA

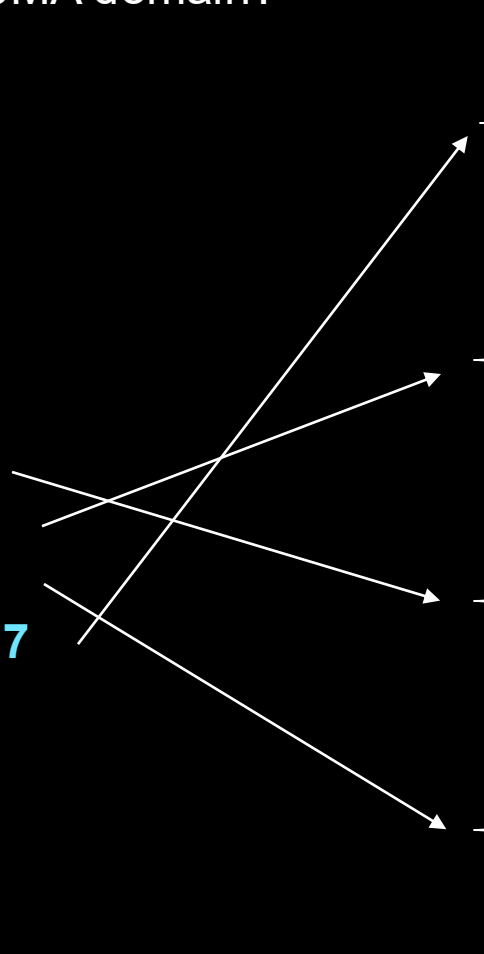
  - Considerations:
    - Does my app expects GPU visibility to be set in the environment?
    - Does my app expects arguments to define target GPUs
    - Does my app make any assumption on the device based on other information:
      - MPI rank
      - CPU-range
      - Auto-determined
    - How many processes using the same GPU:
      - Contention vs occupancy
      - Runtime scheduling limits
      - Increased scheduling complexity
      - Imbalance

Most Pytorch applications and driver scripts assume the GPU to be used corresponds to the local rank!!!

Testing affinity

- What CPUs I have available and their NUMA domain?
  - lscpu
- What GPUs I have
  - rocm-smi –showtopo

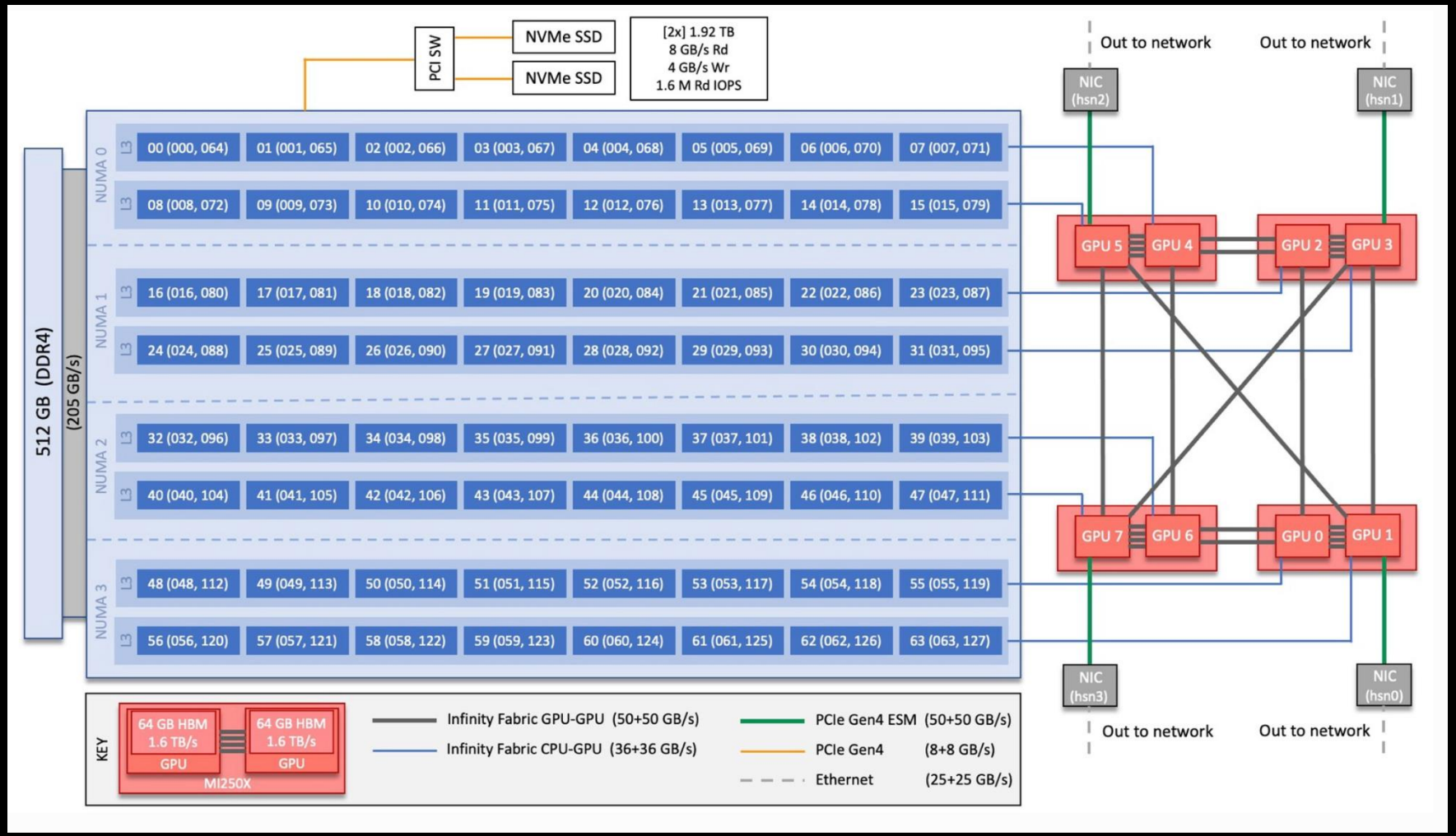
NUMA node0 CPU(s): 0-15,64-79
NUMA node1 CPU(s): 16-31,80-95
NUMA node2 CPU(s): 32-47,96-111
NUMA node3 CPU(s): 48-63,112-127



GPU[0] : (Topology) Numa Node: 3
GPU[0] : (Topology) Numa Affinity: 3
GPU[1] : (Topology) Numa Node: 3
GPU[1] : (Topology) Numa Affinity: 3
GPU[2] : (Topology) Numa Node: 1
GPU[2] : (Topology) Numa Affinity: 1
GPU[3] : (Topology) Numa Node: 1
GPU[3] : (Topology) Numa Affinity: 1
GPU[4] : (Topology) Numa Node: 0
GPU[4] : (Topology) Numa Affinity: 0
GPU[5] : (Topology) Numa Node: 0
GPU[5] : (Topology) Numa Affinity: 0
GPU[6] : (Topology) Numa Node: 2
GPU[6] : (Topology) Numa Affinity: 2
GPU[7] : (Topology) Numa Node: 2
GPU[7] : (Topology) Numa Affinity: 2

Testing affinity

- ORNL topology - https://docs.olcf.ornl.gov/systems/crusher_quick_start_guide.html



Testing affinity

- Check what SLURM is giving us:

```
srun -c 7 -N 2 -n 16 --gpus 16 \
 bash -c 'echo "$SLURM_PROCID -- GPUS $ROCR_VISIBLE_DEVICES -- $(taskset -p $$)"' \
 | sort -n -k1
```

```
0 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54249's current affinity mask: fe
1 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54250's current affinity mask: fe00
2 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54251's current affinity mask: fe0000
3 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54252's current affinity mask: fe000000
4 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54253's current affinity mask: fe00000000
5 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54254's current affinity mask: fe0000000000
6 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54255's current affinity mask: fe000000000000
7 -- GPUS 0,1,2,3,4,5,6,7 -- pid 54256's current affinity mask: fe00000000000000
8 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110083's current affinity mask: fe
9 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110084's current affinity mask: fe00
10 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110085's current affinity mask: fe0000
11 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110086's current affinity mask: fe000000
12 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110087's current affinity mask: fe00000000
13 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110088's current affinity mask: fe0000000000
14 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110089's current affinity mask: fe000000000000
15 -- GPUS 0,1,2,3,4,5,6,7 -- pid 110090's current affinity mask: fe00000000000000
```

Example 05

Careful! Allocations do not follow GPU ranking!!

Testing affinity

- Check what SLURM is giving us:

```
srun -N 2 -n 16 --gpus 16 \
 --cpu-bind=mask_cpu:0xfe000000000000,0xfe00000000000000,0xfe0000,0xfe000000,0xfe,0xfe00,0xfe00000000,0xfe0000000000 \
 bash -c 'echo "$SLURM_PROCID -- GPUS $ROCR_VISIBLE_DEVICES -- $(taskset -p $$)"' \
 | sort -n -k1
```

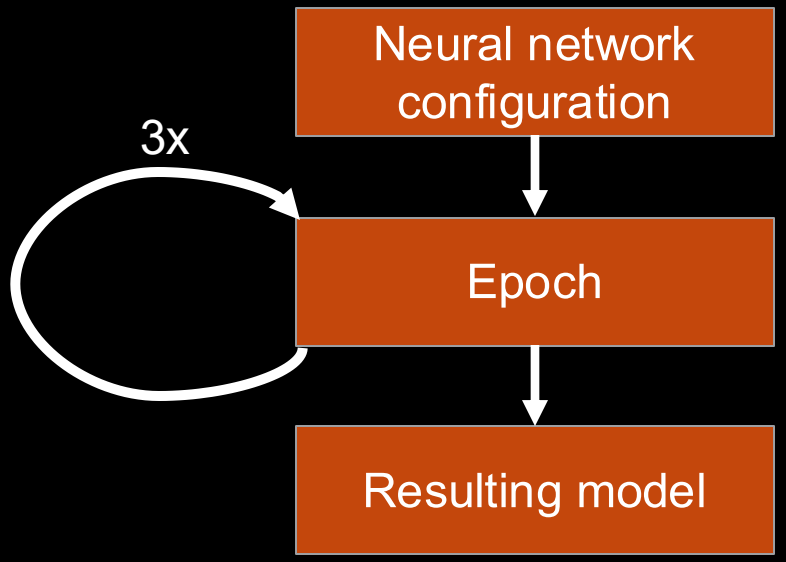
```
0 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13819's current affinity mask: fe000000000000
1 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13820's current affinity mask: fe00000000000000
2 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13821's current affinity mask: fe0000
3 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13822's current affinity mask: fe000000
4 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13823's current affinity mask: fe
5 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13824's current affinity mask: fe00
6 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13825's current affinity mask: fe00000000
7 -- GPUS 0,1,2,3,4,5,6,7 -- pid 13826's current affinity mask: fe0000000000
8 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94670's current affinity mask: fe000000000000
9 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94671's current affinity mask: fe00000000000000
10 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94672's current affinity mask: fe0000
11 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94673's current affinity mask: fe000000
12 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94674's current affinity mask: fe
13 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94675's current affinity mask: fe00
14 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94676's current affinity mask: fe00000000
15 -- GPUS 0,1,2,3,4,5,6,7 -- pid 94677's current affinity mask: fe0000000000
```

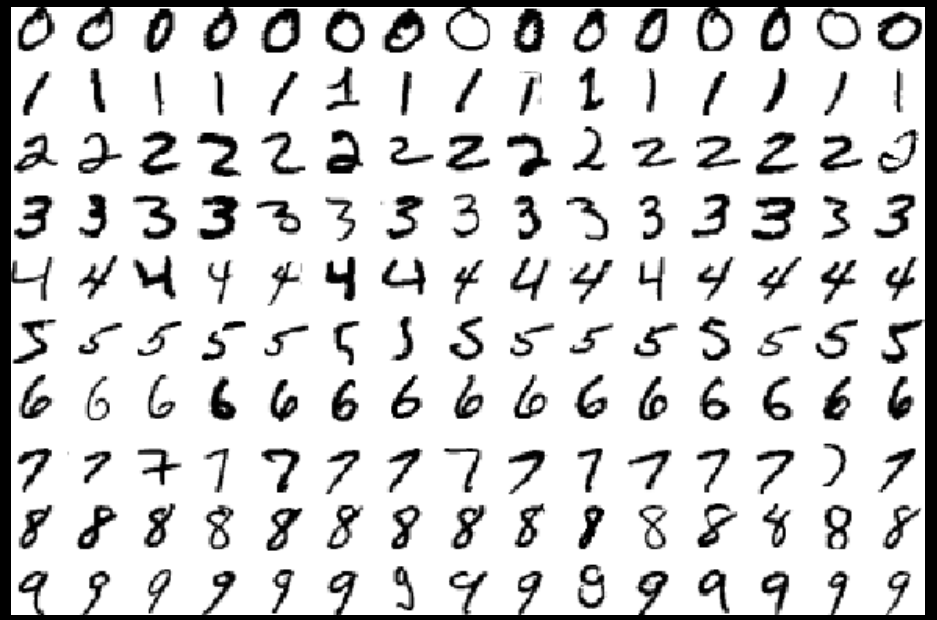
Great! CPUs are properly bound to the GPUs!

Example 05

Pytorch example app – MNIST distributed learning

- Popular computer vision training dataset
- AI training iterate over epochs and a given sample batch is considered in each epoch
- Provided example runs over 3 epochs (properly trained models need much more than than!)
- MNIST training considers number images with different formats.





Pytorch example app – MNIST distributed learning

Examples 06

- What provides distributed capability:
  - Pytorch Distribute Data Parallel (DDP) – Batches of different data run concurrently
  - Other more sophisticated methods available
  - Frameworks like Deepspeed and Horovod can also enable distributed training.

```
import torch.distributed as dist
…
dist.init_process_group(
 backend='nccl',
 init_method='env://',
 world_size=int(os.environ['WORLD_SIZE']),
 rank=int(os.environ['RANK']))
```

Let's use RCCL collectives library.

Well be learning about the distributed setting from the environment

Capture some env vars to adjust my distributed training

- … Epoch 0 Loss 0.148397 Global batch size 2048 on 16 ranks
- … Epoch 1 Loss 0.147906 Global batch size 2048 on 16 ranks
- … Epoch 2 Loss 0.147717 Global batch size 2048 on 16 ranks

Pytorch example app – MNIST distributed learning – RCCL

- RCCL should be set to use only high-speed-interfaces - Slingshot
- The problem one might see on startup:
- ***NCCL error in: /workdir/pytorch-example/pytorch/torch/csrc/distributed/c10d/ProcessGroupNCCL.cpp:1269, unhandled system error, NCCL version 2.12.12***
- Check error origin by setting RCCL specific debug environment variables:

```
export NCCL_DEBUG=INFO

NCCL INFO NET/Socket : Using [0]nmn0:10.120.116.65<0> [1]hsn0:10.253.6.67<0>
[2]hsn1:10.253.6.68<0> [3]hsn2:10.253.2.12<0> [4]hsn3:10.253.2.11<0>
NCCL INFO /long_pathname_so_that_rpms_can_package_the_debug_info/data/driver/rccl/src/init.cc:1292
```

Node has interfaces other than Slingshot

These are the correct ones.

- The fix:

```
export NCCL_SOCKET_IFNAME=hsn0,hsn1,hsn2,hsn3
```

Point RCCL to use all 4 high-speed interfaces. It will know how to bind them based on the node topology.

Pytorch example app – MNIST distributed learning - script

- What can/should I include in my start script:

Example 06

```
if [ \$SLURM_LOCALID -eq 0 ] ; then
  rocm-smi
fi

export MIOPEN_USER_DB_PATH="/tmp/$(whoami)-miopen-cache-\$SLURM_NODEID"
export MIOPEN_CUSTOM_CACHE_DIR=\$MIOPEN_USER_DB_PATH

# Report affinity
echo "Rank \$SLURM_PROCID --> \$(taskset -p \$\$)"

# Start conda environment inside the container
\$WITH_CONDA

# Set interfaces to be used by RCCL.
export NCCL_SOCKET_IFNAME=hsn0,hsn1,hsn2,hsn3

# Set environment for the app
export MASTER_ADDR=\$(python /workdir/get-master.py "\$SLURM_NODELIST")
export MASTER_PORT=29500
export WORLD_SIZE=\$SLURM_NPROCS
export RANK=\$SLURM_PROCID
export ROCR_VISIBLE_DEVICES=\$SLURM_LOCALID

# Run app
cd /workdir/mnist
python -u mnist_DDP.py --gpu --modelpath /workdir/mnist/model
```

Smoke test to confirm GPUs are available

Just-in-time compiles are a common technique in these applications. MIOpen leverages this functionality. Let's cache those builds in node-local storage instead of the default home folder. ROCm 6.2 may not need this.

Activate the container Conda environment that provides Pytorch

Point RCCL to use the high-speed network interfaces

Translate SLURM environment into something that Pytorch DDP understands

Run my model training

Pytorch example app – MNIST distributed learning - rocprof

Example 07

- Rocprof profiler client is the easiest way to get started with GPU profiling.
- It is available as part of the ROCm stack and, therefore, available in the containers
- It is seldomly useful to profile every single process/rank of your app:
  - Profilling more than needed = more potential profiling overhead
  - Misleading conclusions

Command to prepend to my application instantiation

```
pcmd=''
if [ $RANK -eq 2 ] ; then
  pcmd='rocprof --hip-trace'
fi
```

We want to profile only for one rank – in this case rank #2

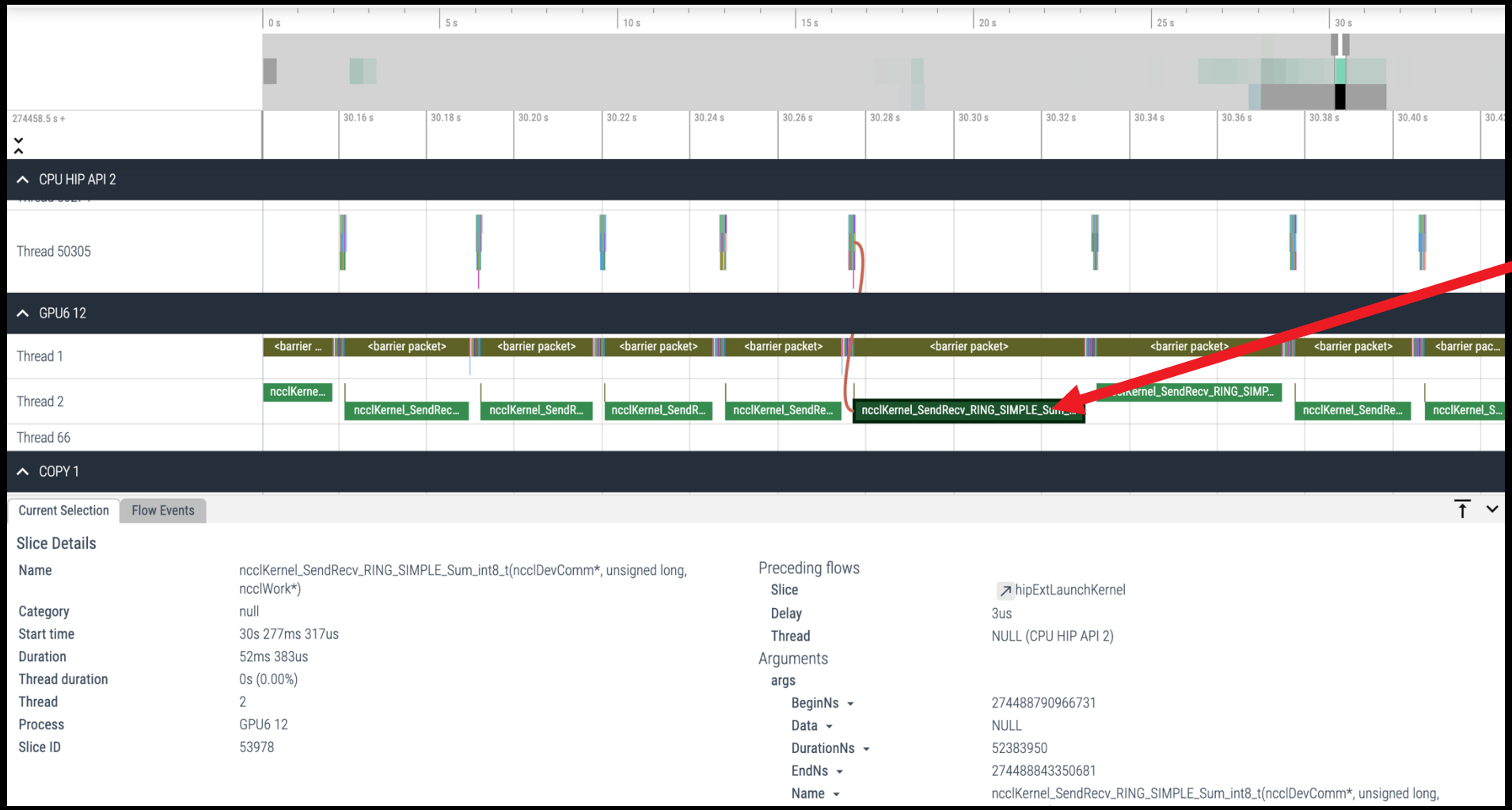
Run command as before except to the prepended profiling command

```
$pcmd python -u mnist_DDP.py --gpu --modelpath /workdir/mnist/model
```

More than one rank to be profiled? Use, –o myresults.$RANK.csv, to make sure sure there are no races generating the profile files

Pytorch example app – MNIST distributed learning - rocprof

- Bound by RCCL communication!

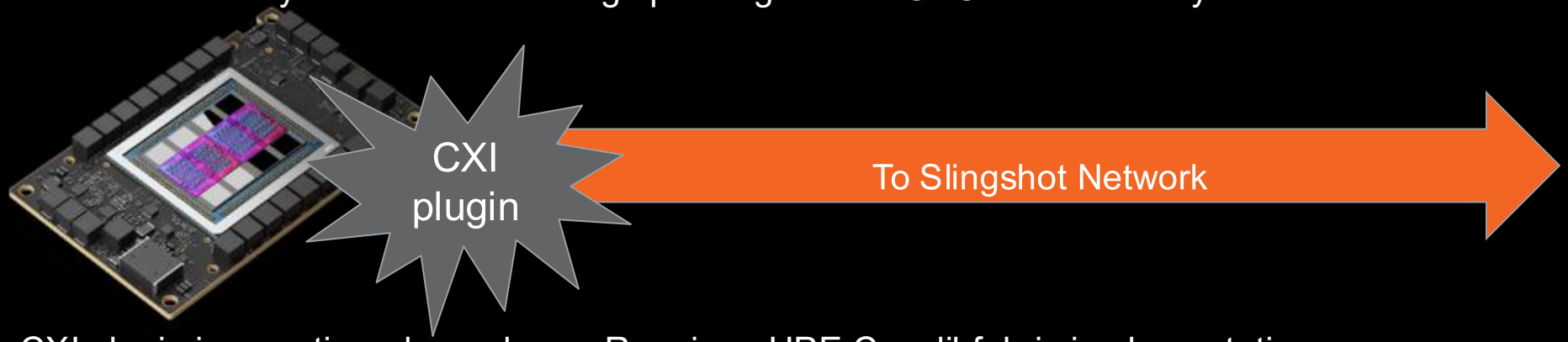


Example 07

Collectives kernels dominate profile

Comms are important! - RCCL AWS-CXI plugin

- LUMI, Frontier (and others) directly attaches AMD Instinct™ MI250x Accelerator to the Slingshot Network
  - Enable collectives computation on devices
  - Minimize the role of the CPU in the control path – expose more asynchronous computation opportunities
  - Lowest latency for network message passing is from GPU HBM memory



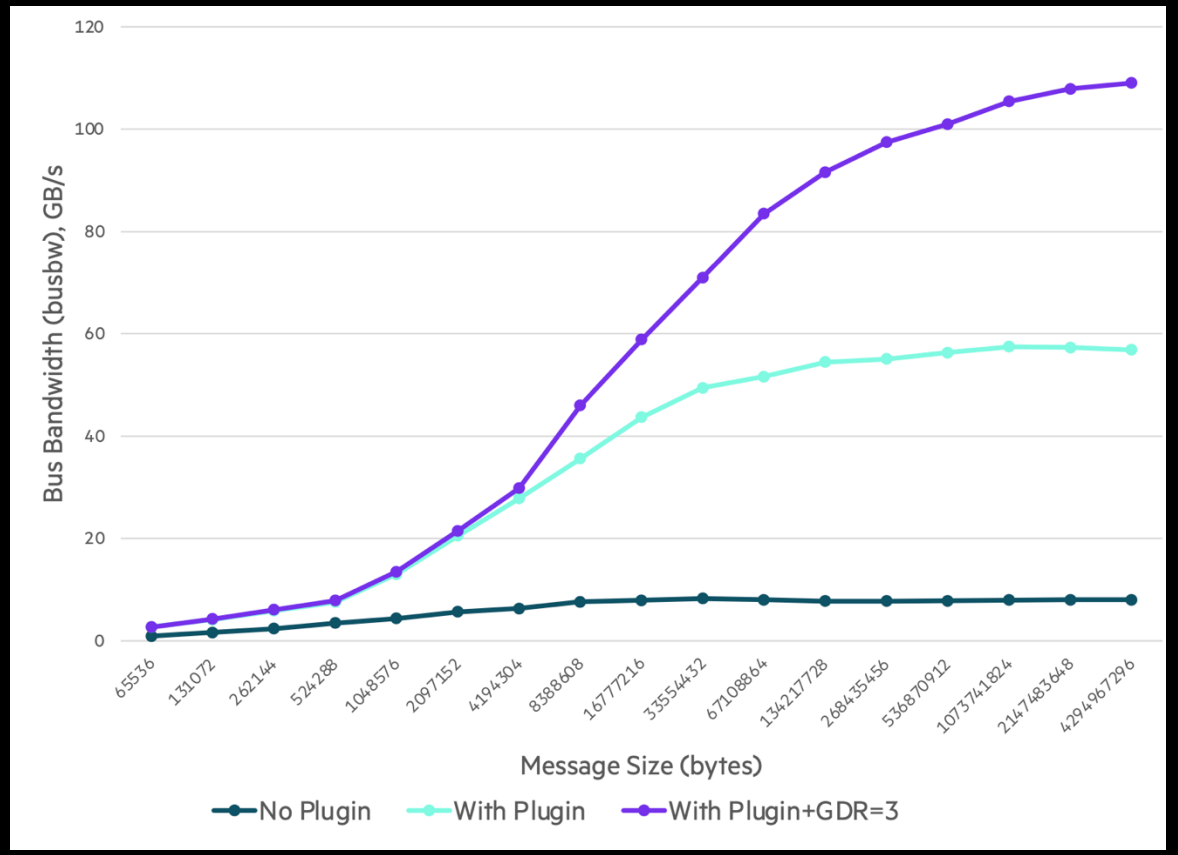
- CXI plugin is a runtime dependency. Requires: HPE Cray libfabric implementation
  - https://github.com/rocm/aws-ofi-rccl
  - 3-4x faster collectives
- **Included in the LUMI provided containers! If not using the LUMI containers make sure you have that in your environment:**

```
export NCCL_DEBUG=INFO
export NCCL_DEBUG_SUBSYS=INIT
# and search the logs for:
[0] NCCL INFO NET/OFI Using aws-ofi-rccl 1.4.0
```

Configuring RCCL environment (cont.)

- RCCL should be set configured to use GPU RDMA:
  - `export NCCL_NET_GDR_LEVEL=PHB`
- On upcoming ROCm versions (6.2) this won't be needed – it is default.
- Why should I spend time with all this?
  - 3-4x better bandwidth utilization with plugin
  - 2x better bandwidth utilization with RDMA
  - Can scale further!

- **Careful using external containers! You may need to be setting plugin yourself!**



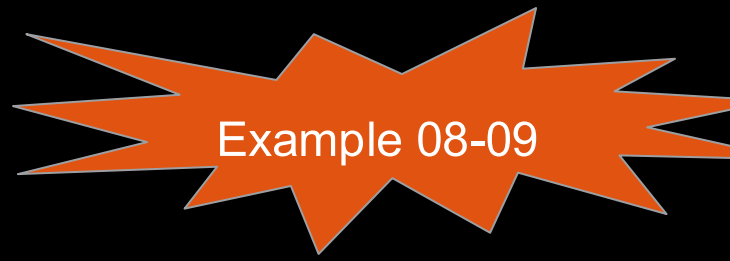
Pytorch example app – MNIST distributed learning – Omnitrace

- Obtain more thorough trace information and visualization
  - https://github.com/AMDResearch/omnitrace

- Omnitrace install outside the container can be used
  - The host/container ROCm levels should match

```
module use module use /appl/local/containers/test-modules
module load rocm/6.1.3.lua omnitrace/1.12.0-rocm6.1.x
SIF=/appl/local/containers/sif-images/lumi-pytorch-rocm-6.1.3-python-3.12-pytorch-v2.4.1.sif
```

- Configuration file:
  - omnitrace-avail -G omnitrace.cfg –all
  - `export OMNITRACE_CONFIG_FILE=/workdir/omnitrace-config.cfg`
  - Override environment with command line arguments if needed



Pytorch example app – MNIST distributed learning – Omnitrace

Example 08

- Sample – learn about the native stack trace along side GPU activity
- GPU activity is **never** sampled even in sampling mode
- Adjust configuration file according to the needs:

```
OMNITRACE_USE_SAMPLING = true
OMNITRACE_USE_ROCM_SMI = false
OMNITRACE_SAMPLING_CPUS = none
OMNITRACE_SAMPLING_GPUS = 2
```

Let's do sampling!
Not interested in sampling GPU hardware metrics (frequency, temperature…)
Not interested in sampling CPU hardware metrics
Targeting GPU #2 only used by Rank #2

- Execution similar to rocprof:

```
pcmd=''
if [ $RANK -eq 2 ] ; then
  pcmd='omnitrace-sample -- '
fi
$pcmd python -u mnist_DDP.py --gpu --modelpath /workdir/mnist/model
```

Prepend omnitrace sampling driver for rank #2

- We need to add a few more bindings to singularity:

```
srun --jobid=$jobid -N $((Nodes)) -n $((Nodes*8)) --gpus $((Nodes*8)) --cpu-bind=mask_cpu:$MYMASKS \
 singularity exec \
   …\
  -B $wd:/workdir \
  -B $OMNITRACE_dir/omnitools \
  -B /usr/lib64/libpciaccess.so.0 \
  $SIF /workdir/run-me.sh
```

Make omnitrace available in the container
Omnitrace does PCIe info loading – so we need to enable that

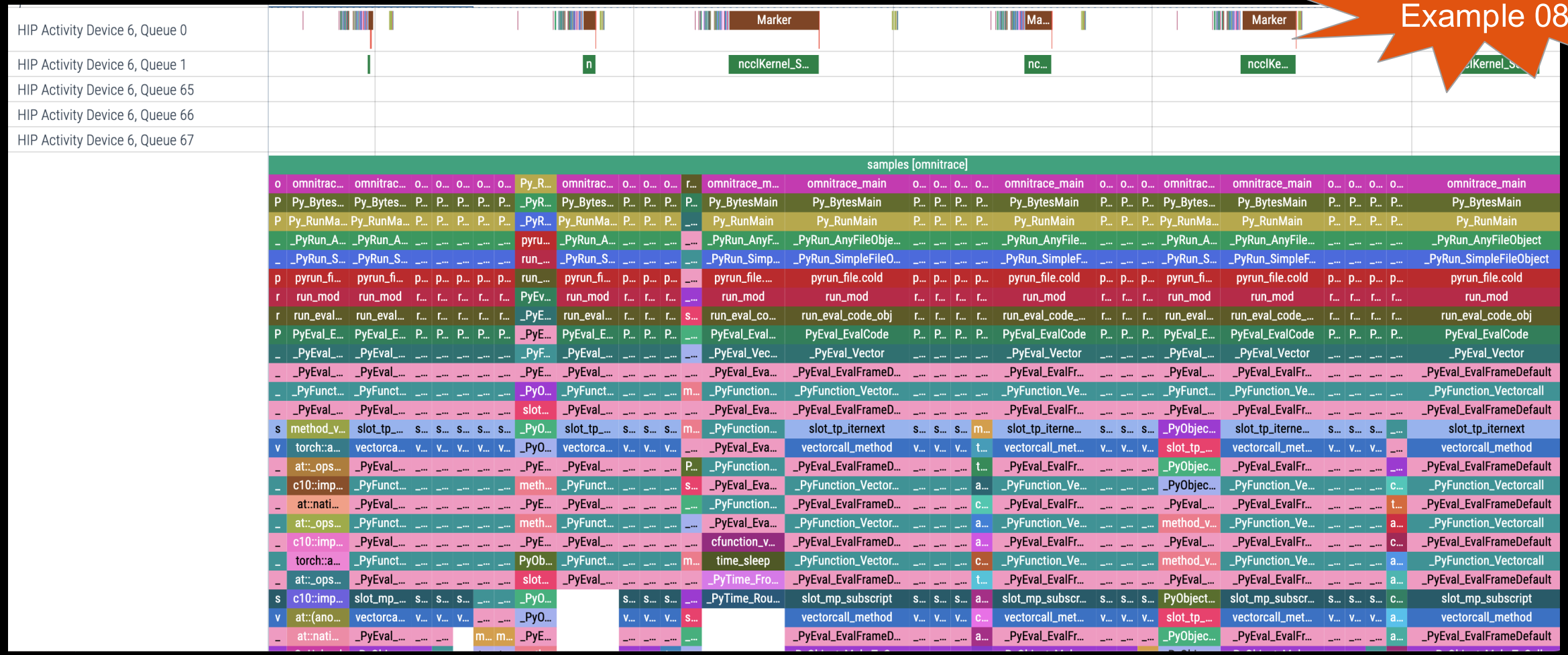
- …and make sure the environment inside the container is set accordingly:

```
export PATH=$OMNITRACE_dir/bin:$PATH
export LD_LIBRARY_PATH=$OMNITRACE_dir/lib:$LD_LIBRARY_PATH
export PYTHONPATH=$OMNITRACE_dir/lib/python/site-packages:$LD_LIBRARY_PATH
```

Makes sure all Omnitrace bits are available in my environment.

Pytorch example app – MNIST distributed learning – Omnitrace

- Native stack flame graph:



Pytorch example app – MNIST distributed learning – Omnitrace

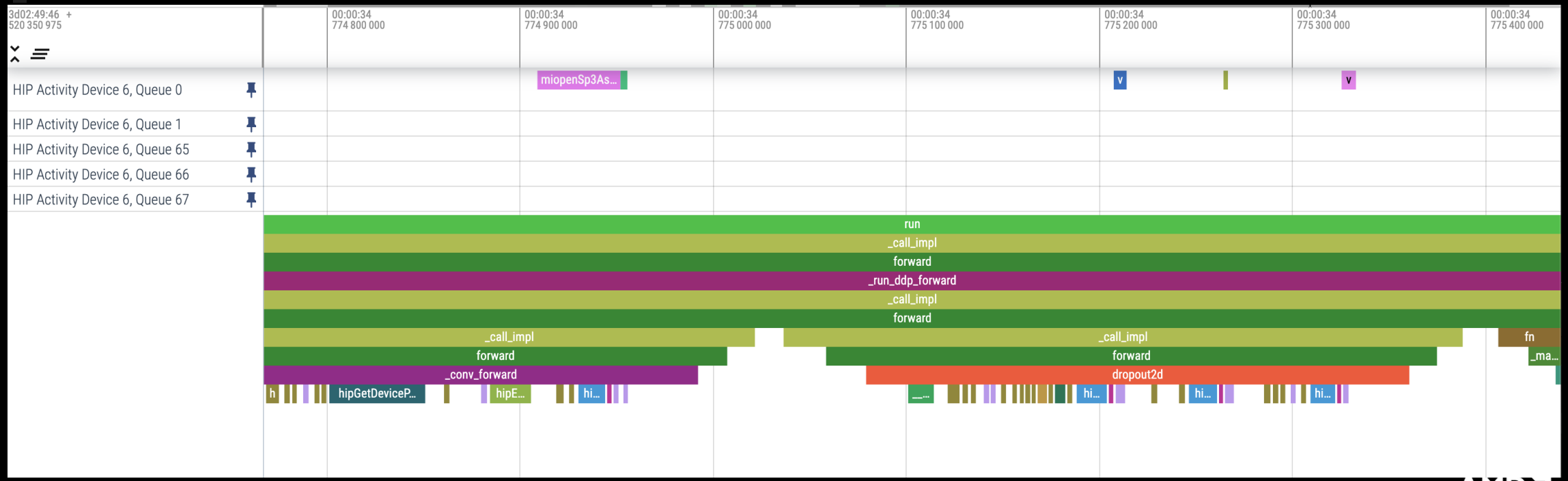
- Sampling the Python and C/C++ parts of the code – omnitrace-python

```
if [ \$RANK -eq 2 ] ; then
  omnitrace-python-3.10 -- mnist_DDP.py --gpu --modelpath /workdir/mnist/model
else
  python -u mnist_DDP.py --gpu --modelpath /workdir/mnist/model
fi
```

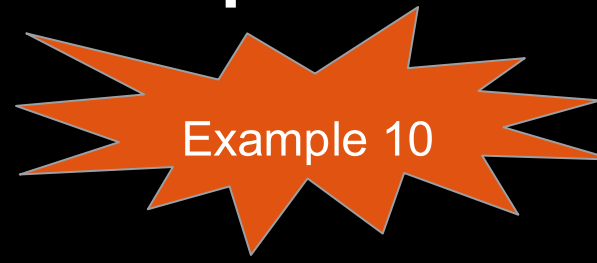
Example 9

Omnitrace expects the Python script as opposed to the Python executable

Match relevant python version



Pytorch example app – MNIST distributed learning – Omniperf



- Obtain detailed kernel performance counters
  - https://github.com/AMDResearch/omniperf

```
module use module use /appl/local/containers/test-modules
module load rocm/6.1.3.lua omniperf/2.1.0
```

- Virtual environment is used to extend the existing Python environment inside the container.
- Omniperf needs replaying the application many times
  - Could be challenging to profile individual ranks as all need replaying.

```
if [ $RANK -eq 0 ] ; then
  omniperf profile -n myprof --device 0 --roof-only -- $(which python) -u mnist_DDP.py …
else
  for i in {1..4} ; do
    sleep 10
    python -u mnist_DDP.py --gpu --modelpath /workdir/mnist/model
  done
fi
```

Collect roofline profile for rank #0 that uses device #0

Replay the app on the other ranks as many times as needed (5 times for roofline)

Pytorch example app – MNIST distributed learning – Omniperf

- Analyze in or outside the container):
  - omniperf analyze -p workloads/pytorch/MI200/ --gui

Example 10

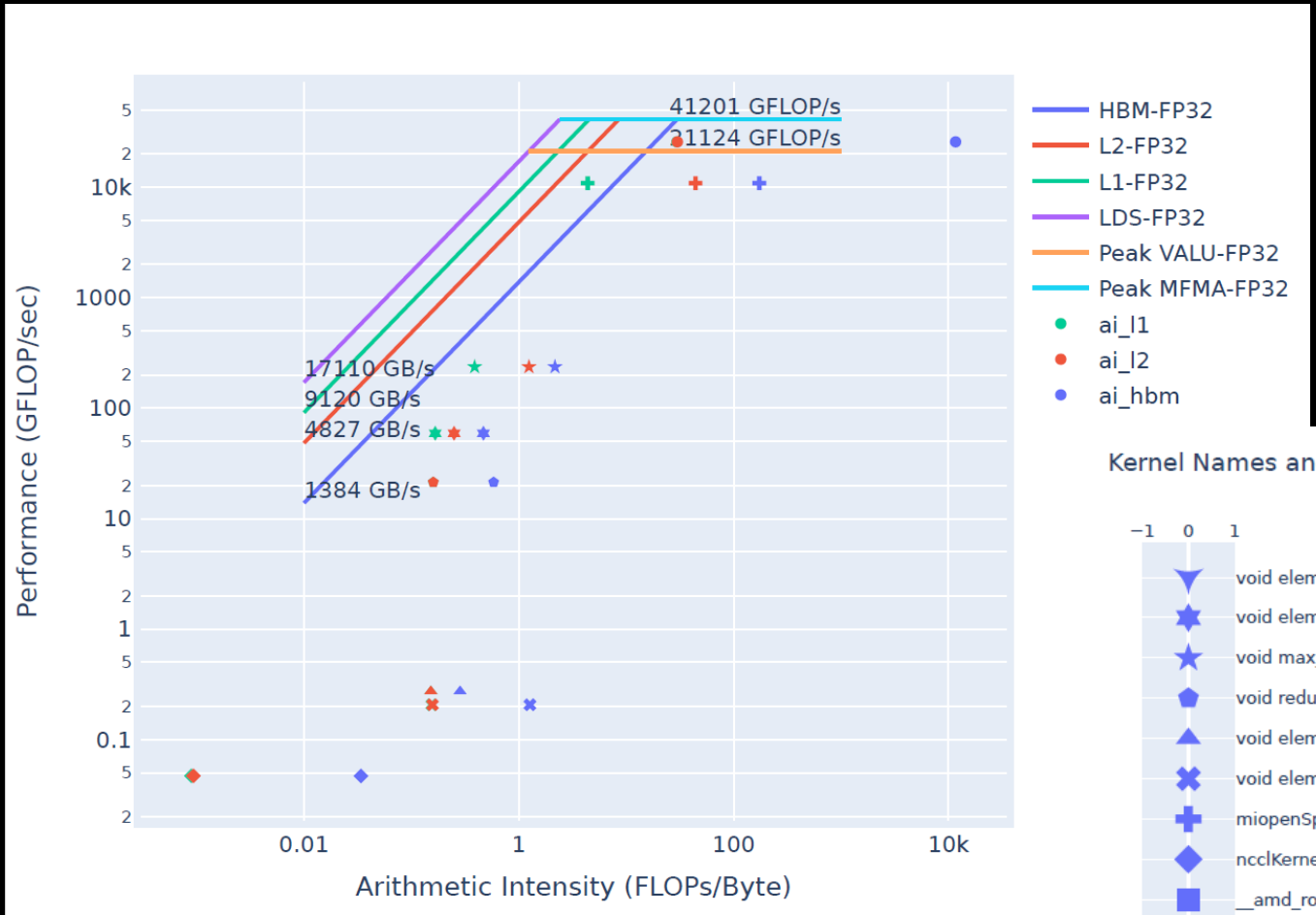
Select kernel of interest

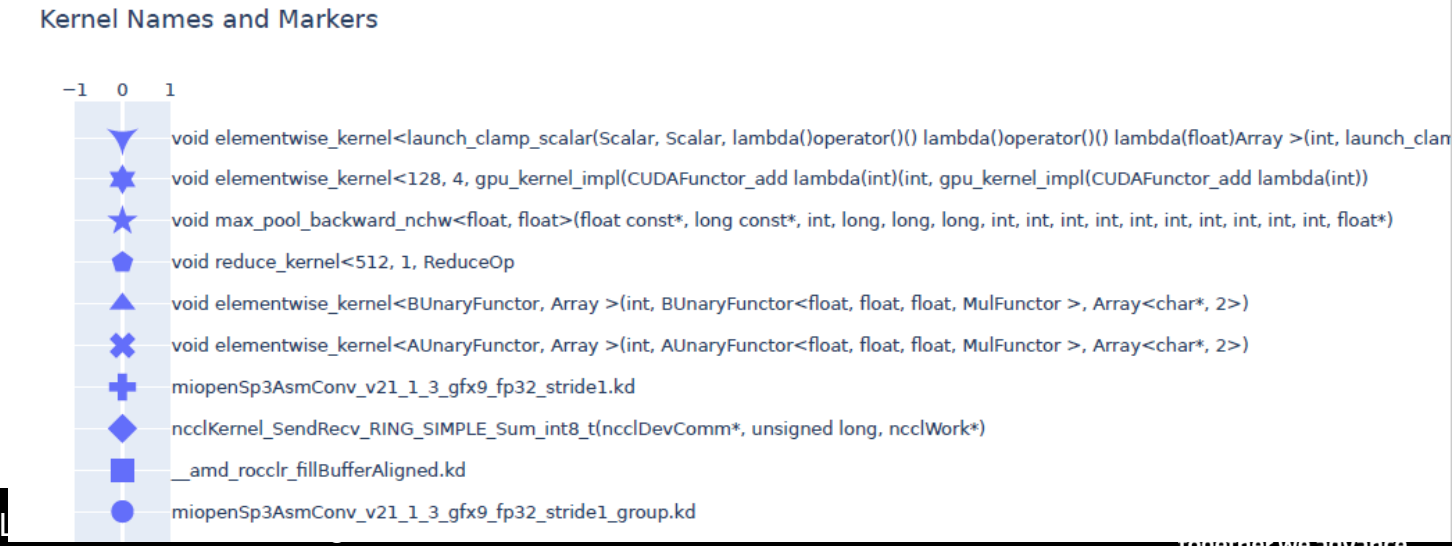
Pytorch example app – MNIST distributed learning – Omniperf

- Analyze in or outside the container):
  - Roofline PDFs

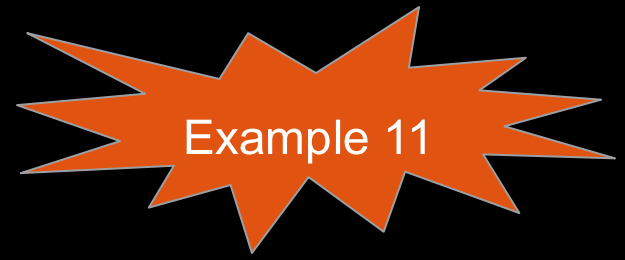
Example 10

Kernel names





Leveraging framework profiler infrastructure



- AI frameworks typically provide hooks for developers to gather profiling information
- An example with Pytorch:

```
from torch.profiler import profile, record_function, ProfilerActivity

for epoch in range(args.epochs):

    prof = None
    if epoch == 3:
        print("Starting profile...")
        prof = profile(activities=[ProfilerActivity.CPU, ProfilerActivity.CUDA])
        prof.start()

    for imgs, labels in dataloader:
        with torch.amp.autocast('cuda',enabled=args.amp):
            imgs, labels = imgs.cuda(), labels.cuda()
            outputs = model(imgs)
        loss = criterion(outputs, labels)
        loss = scaler.scale(loss)
        loss.backward()
        scaler.step(optimizer)
        scaler.update()

    if prof:
        prof.stop()
        prof.export_chrome_trace("trace.json")
```

Invoke the profiler

Enable profiling for epoch number 3

Training for an epoch

Finish profiling and generate trace

Trace file can be viewed in Perfetto UI tool

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