Extreme scale AI training on LUMI

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Controlling device visibility with multiple nodes

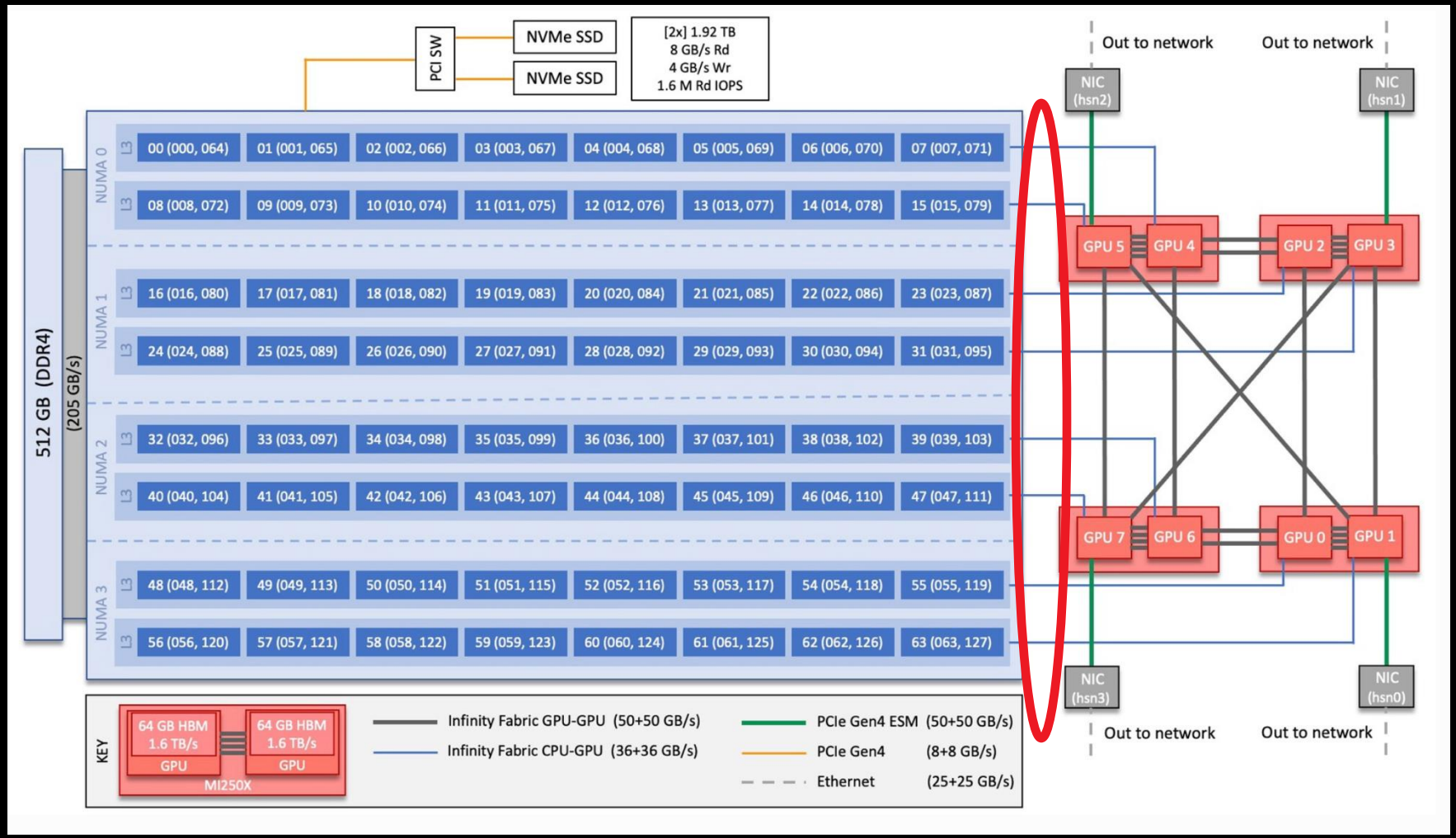
- Rank and global rank now mean different things!
- Controlling visibility
  - HIP_VISIBLE_DEVICES=0,1,2,3 python -c 'import torch; print(torch.cuda.device_count())'
  - ROCR_VISIBLE_DEVICES=0,1,2,3 python -c 'import torch; print(torch.cuda.device_count())’
  - SLURM sets ROCR_VISIBLE_DEVICES
  - Implications 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!!!

Checking GPU-CPU affinity

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



Testing affinity on multiple nodes

- 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
```

Careful! Allocations do not follow GPU ranking!!

Testing affinity on multiple nodes

- Check what SLURM is giving us:

Interpreted across nodes using a round-robin approach

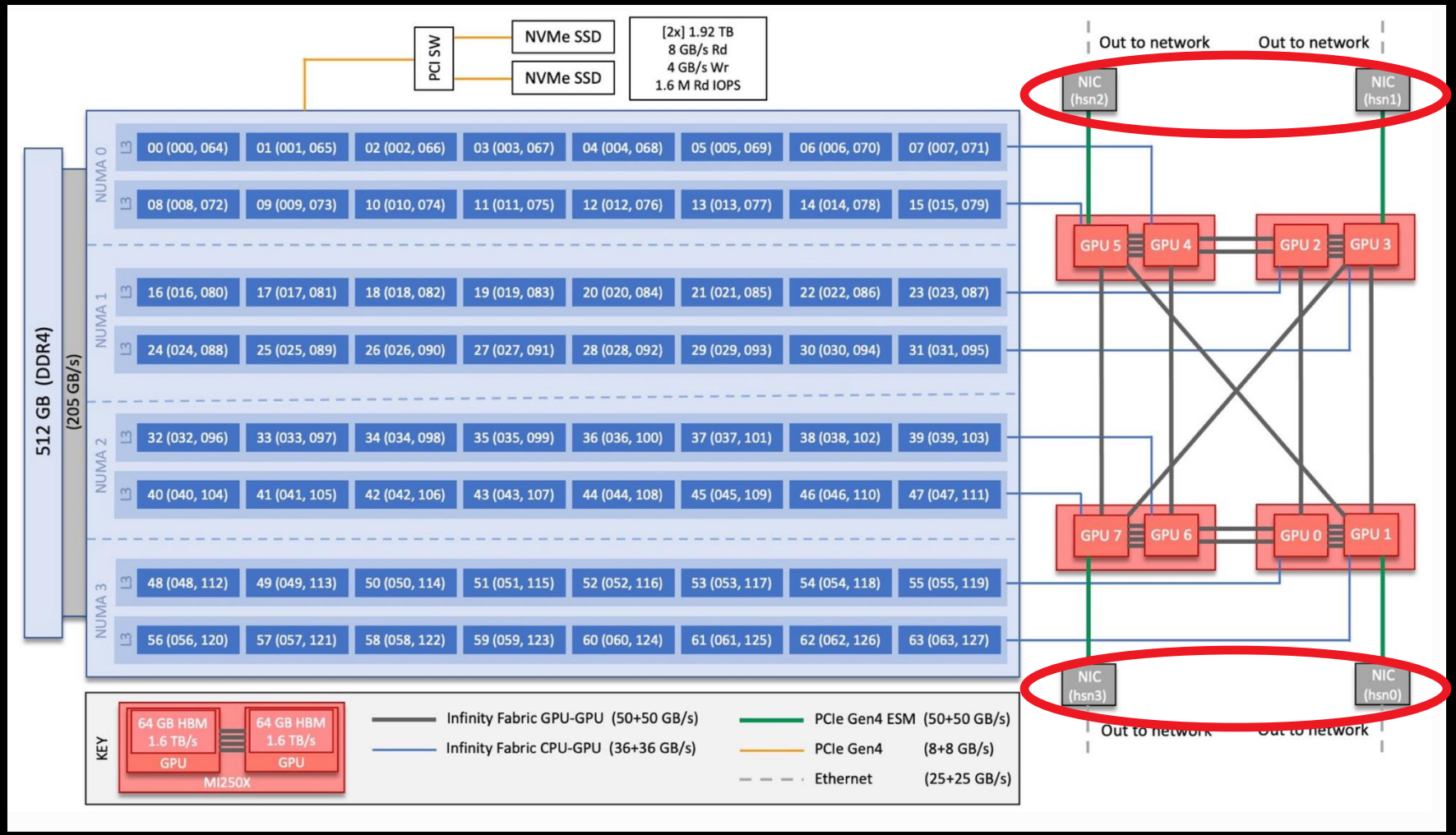
```
srun -N 2 -n 16 --gpus 16 \
 --cpu-bind=mask_cpu:0xfe000000000000,0xfe00000000000000,0xfe0000,0xfe000000,0xfe,0xfe00,0xfe00000000,0xfe0000000000 \
 bash -c 'echo "$SLURM_PROCID -- GPUS $ROCR_VISIBLE_DEVICES -- $(taskset -p $$)"' \
 | sort -n -k1
```

```
 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
```

Consider add an affinity check in your job scripts!

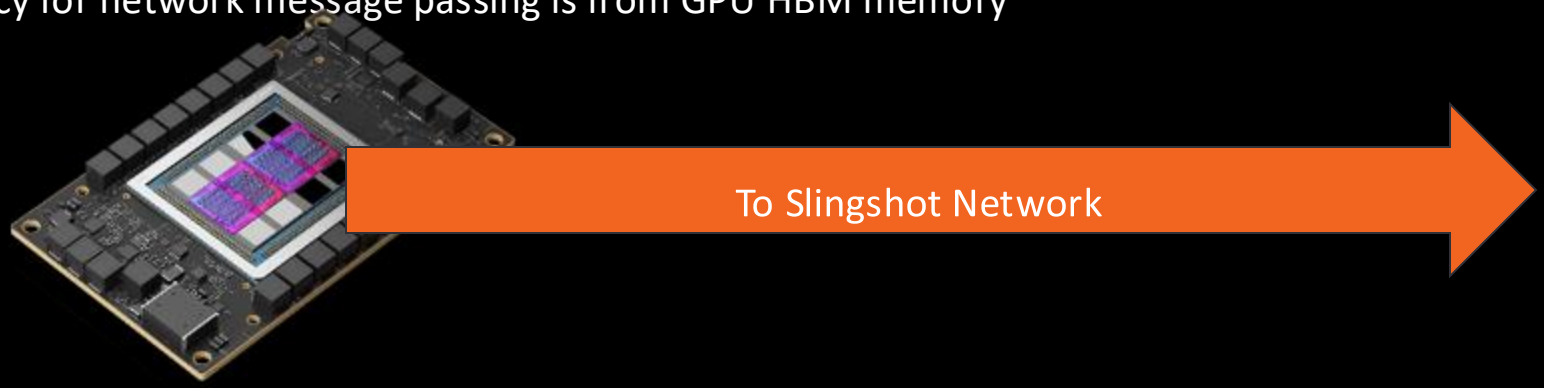
Checking GPU and NIC connection

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



Comms are important!

- LUMI, Frontier (and others) directly attaches AMD Instinct™ MI250x Accelerator to the Slingshot Network
  - Minimize the role of the CPU in the control path
  - Lowest latency for network message passing is from GPU HBM memory



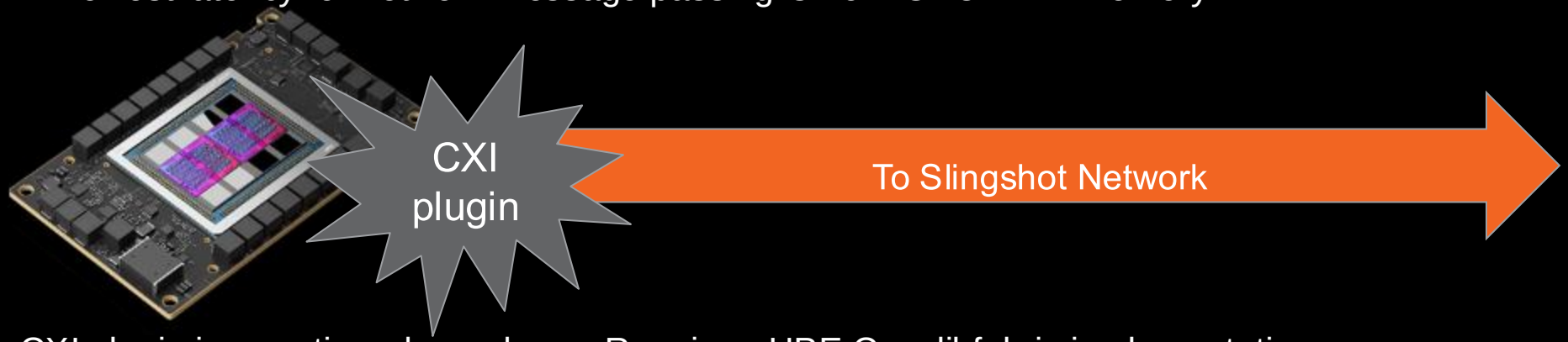
- For example,

```
hipMalloc(&device_buffer, Msize);
init_data<< >>(device_buffer, Msize);  // launch GPU kernel
hipDeviceSynchronize();
MPI_Sendrecv(&device_buffer, Msize, MPI_FLOAT, … , MPI_COMM_WORLD, MPI_STATUS_IGNORE);
```

- Requires: HPE Cray MPICH

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

- 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:

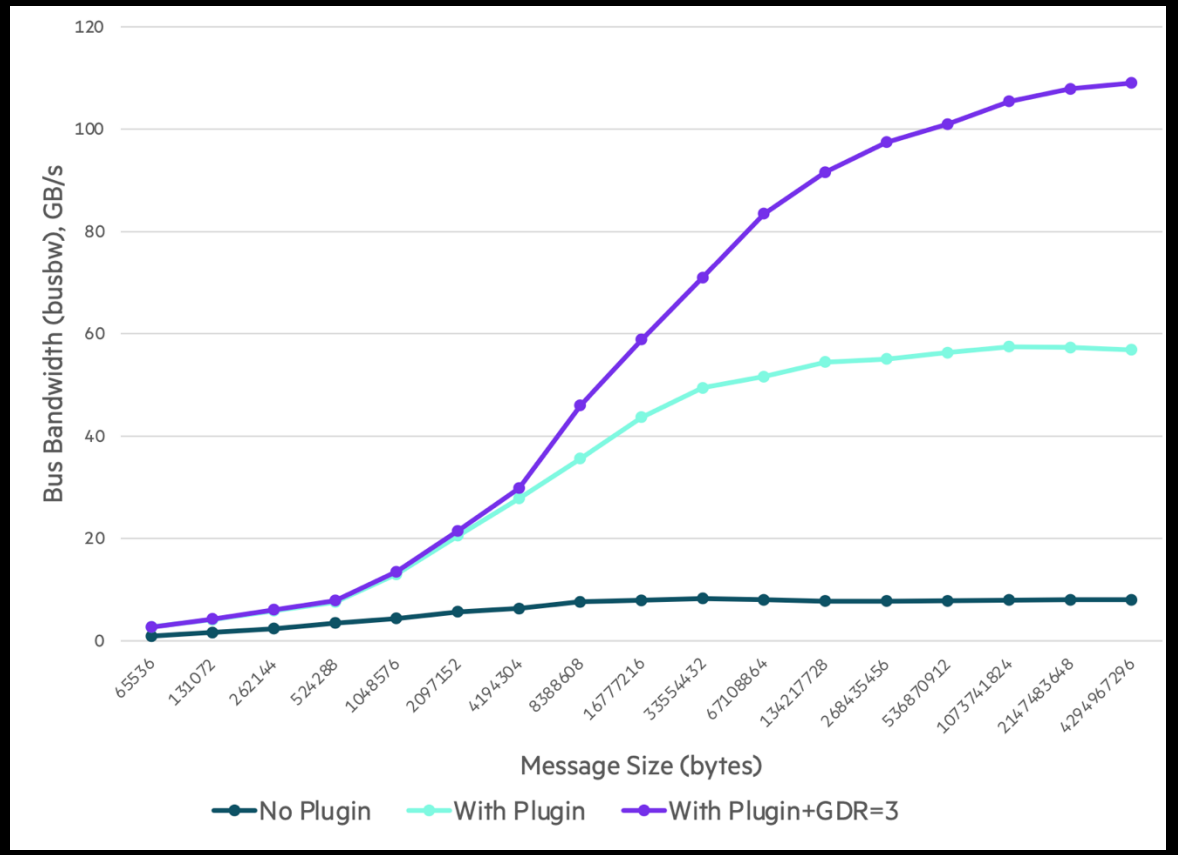
```
export NCCL_SOCKET_IFNAME=hsn0,hsn1,hsn2,hsn3
```

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

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!**



MIOpen configuration

- MIOpen is a library for high-optimized machine learning primitives
- Used on many models – not in our LLM example though
- It uses caches to enable just-in-time compilation organized as SQLite databases
- File system doesn’t deal well with SQLite locks when many processes are trying to access it.
- Solution? Setup individual caches for groups of ranks – we recommend per node:

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

- Want to check MIOpen activity – setup the following environment variable:

  export MIOPEN_ENABLE_LOGGING=1

Where’s the master???

- Ranks need to know where the master ranks is:

```
export MASTER_ADDR=$(hostname)
export MASTER_PORT=29500
```

- When using multiple nodes this is not good enough.
- We can leverage SLURM tools to query what the first node of an allocation is:

```
export MASTER_ADDR=$(scontrol show hostname "$SLURM_NODELIST" | head -n1)
export MASTER_PORT=29500
```

- There is no SLURM tools inside the containers:

```
srun singularity exec mycontainer.sif \
bash -c 'MASTER_ADDR=$(scontrol show hostname "$SLURM_NODELIST" | head -n1) ./myapp’
```

```
MASTER_ADDR=$(scontrol show hostname "$SLURM_NODELIST" | head -n1)
srun singularity exec mycontainer.sif \
bash -c './myapp'
```

Putting it all together

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

```
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
export NCCL_NET_GDR_LEVEL=PHB

# 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
python -u ./myapp
```

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.

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

Monitoring activity with multiple nodes

- rocm-smi can still be used to understand GPU activity.
- Using SLURM to access nodes other than the first one in the allocation can be challenged.
- You can chose to forward the relevant monitoring information to access from the login node.
- Pipe information to a port of your choosing in your launching script :

```
srun -N 2 -n 2 bash -c 'watch -n1 rocm-smi | nc -l 0.0.0.0 56789’
```

- Access the information from the login node:

```
nc nid007974 56789
```

```
======================= ROCm System Management Interface =======================
================================== Concise Info ==================================
GPU  Temp   AvgPwr  SCLK    MCLK     Fan  Perf    PwrCap  VRAM%  GPU%
0    46.0c  92.0W   800Mhz  1600Mhz  0%   manual  500.0W    0%   0%
1    52.0c  N/A     800Mhz  1600Mhz  0%   manual  0.0W      0%   0%
```

Monitoring activity with multiple nodes - profiling

- Profiling and logging can and (most of the time) should be target at specific ranks.
  - Overhead
  - Cluttered information

- Leverage the SLURM environment to tailor the application instantiation to activate profile or logging.

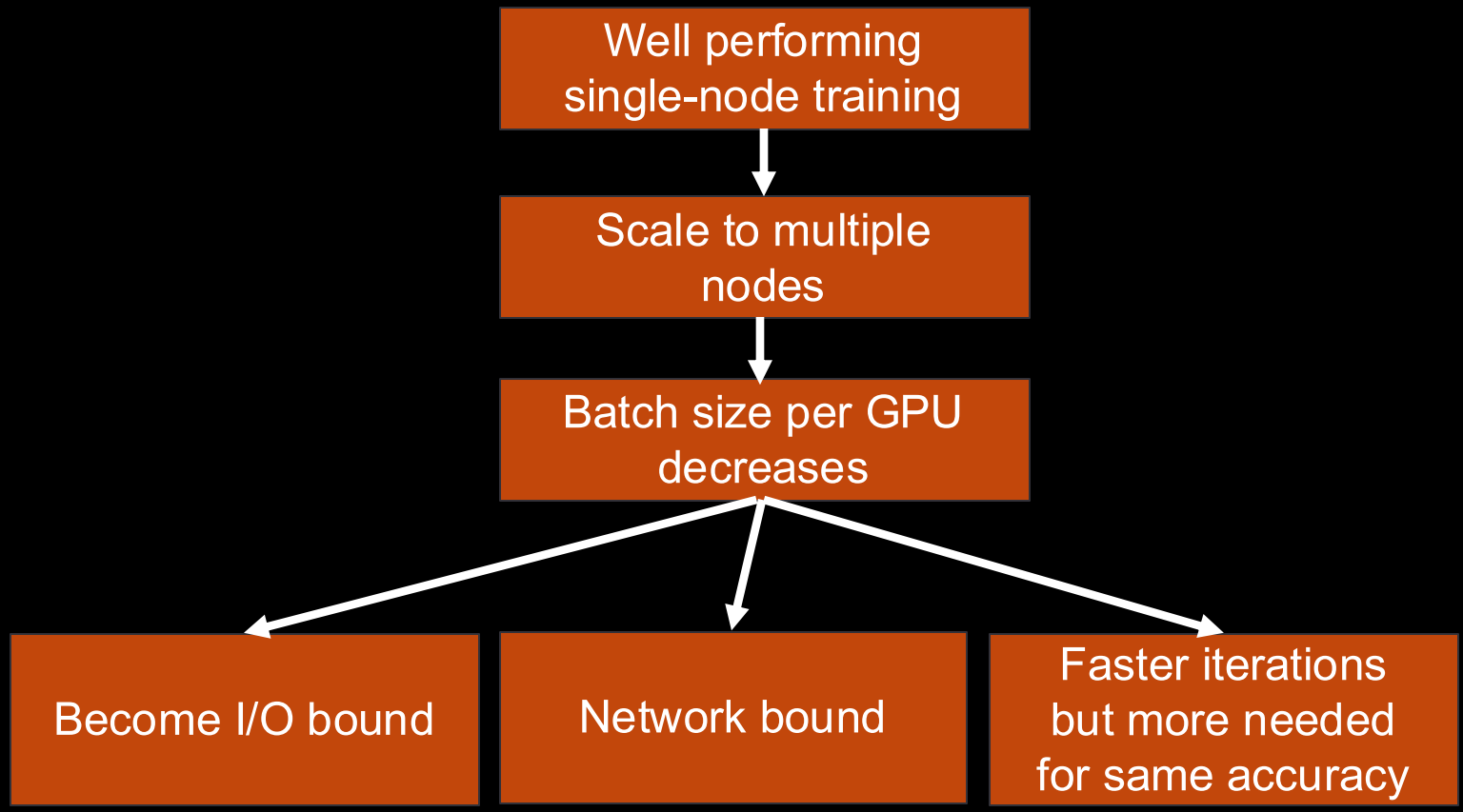
```
pcmd=''
if [ $SLURM_PROCID -eq 2 ] then
  pcmd='rocprof --hip-trace --stats’
fi
$pcmd ./myapp
```

- If profiling with more than one rank makes sure to define rank-specific output files to avoid corruption.

```
rocprof --hip-trace --stats -o myprofile-$SLURM_PROCID.csv ./myapp
```

Monitoring is your friend

- Why would I want to scale my model?
  - Train faster – strong-scaling
  - Train bigger – weak-scaling
  - My model doesn't fit in just a few GPUs
- How far can I go?
  - Depends on your model
  - Scaling can change the bottlenecks
  - Scaling can change convergence
- Monitor the regime in which your operating the GPUs at all times!



- You'll always be bound by some type of communication at some point!!!

Other ways to express parallelism - FSDP

- We talked mostly about Distribute Data Parallel (DDP) applications – there are others!
- Fully Sharded Data Parallel is another option.
  - Create shards out of the neural net model more likely to be activated together
  - Try keep less state in the GPU – could support larger models with less GPUs
  - More complexities in configuring the different knobs. Depending on the tunning may require more or less changes to your code.
  - https://pytorch.org/blog/introducing-pytorch-fully-sharded-data-parallel-api/
- Using FSDP requires wrapping your model into the relevant FSDP object.

```
wrapper_kwargs = Dict(cpu_offload=CPUOffload(offload_params=True))
with enable_wrap(wrapper_cls=FullyShardedDataParallel, **wrapper_kwargs):
 fsdp_model = wrap(model())
```

Your original model

- Some tools to control the wrapping in less intrusive ways have been created - ***accelerate***.
  - Enabling FSDP on transformers: https://huggingface.co/docs/transformers

Other ways to express parallelism - Horovod

- Horovod is a framework to enable distributed deep-learning training with TensorFlow, Keras, PyTorch, and Apache MXNet. The goal of Horovod is to make distributed deep learning fast and easy to use.

Step 1: configure ROCm details

```
# Configure for ROCm
export HOROVOD_WITHOUT_MXNET=1
export HOROVOD_WITHOUT_GLOO=1
export HOROVOD_GPU=ROCM
export HOROVOD_ROCM_HOME=$ROCM_PATH
export HOROVOD_GPU_OPERATIONS=NCCL
export HOROVOD_CPU_OPERATIONS=MPI
export HOROVOD_WITH_MPI=1
export HOROVOD_ROCM_PATH=$ROCM_PATH
export HOROVOD_RCCL_HOME=$ROCM_PATH/rccl
export RCCL_INCLUDE_DIRS=$ROCM_PATH/rccl/include
export HOROVOD_RCCL_LIB=$ROCM_PATH/rccl/lib
export HCC_AMDGPU_TARGET=gfx90a
export CMAKE_PREFIX_PATH=$MPICH_PATH
```

Step 2: configure for your favorite framework details

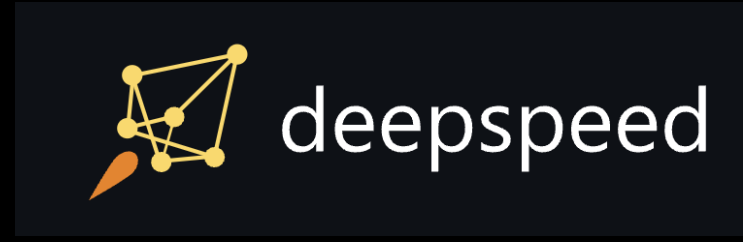
```
# Configure for TensorFlow
export HOROVOD_WITH_TENSORFLOW=1
export HOROVOD_WITHOUT_PYTORCH=1

# Configure for PyTorch
export HOROVOD_WITHOUT_TENSORFLOW=1
export HOROVOD_WITH_PYTORCH=1
```

Horovod needs MPI at launch

Step 3: install

```
# Install
pip install --no-cache-dir --force-reinstall --verbose horovod==$HOROVOD_VERSION
```

Other ways to express parallelism - DeepSpeed



- DeepSpeed is a framework to optimize distributed deep-learning training and inference

```
DS_BUILD_AIO=0 \
DS_BUILD_CCL_COMM=1 \
DS_BUILD_CPU_ADAM=0 \
DS_BUILD_CPU_LION=0 \
DS_BUILD_EVOFORMER_ATTN=0 \
DS_BUILD_FUSED_ADAM=1 \
DS_BUILD_FUSED_LION=1 \
DS_BUILD_CPU_ADAGRAD=0 \
DS_BUILD_FUSED_LAMB=1 \
DS_BUILD_QUANTIZER=0 \
DS_BUILD_RANDOM_LTD=0 \
DS_BUILD_SPARSE_ATTN=0 \
DS_BUILD_TRANSFORMER=0 \
DS_BUILD_TRANSFORMER_INFERENCE=0 \
DS_BUILD_STOCHASTIC_TRANSFORMER=1 \
pip install deepspeed==0.14.0 \
--global-option="build_ext" --global-option="-j32"

ds_report
```

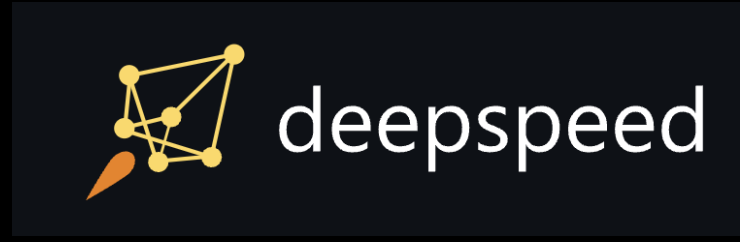
Select all the optimizations not all are enabled for GPUs.

Allow multiple process builds.

Utility to report supported capabilities.

```
--------------------------------------------------
op name ..... installed .. compatible
--------------------------------------------------
async_io ..... [NO] ..... [NO]
fused_adam ..... [YES] ..... [OKAY]
cpu_adam ..... [NO] ..... [OKAY]
cpu_adagrad ..... [NO] ..... [OKAY]
cpu_lion ..... [NO] ..... [OKAY]
evoformer_attn ..... [NO] ..... [NO]
fused_lamb ..... [YES] ..... [OKAY]
fused_lion ..... [YES] ..... [OKAY]
inference_core_ops ..... [NO] ..... [OKAY]
cutlass_ops ..... [NO] ..... [OKAY]
transformer_inference .. [NO] ..... [OKAY]
quantizer ..... [NO] ..... [OKAY]
ragged_device_ops ..... [NO] ..... [OKAY]
ragged_ops ..... [NO] ..... [OKAY]
random_ltd ..... [NO] ..... [OKAY]
sparse_attn ..... [NO] ..... [NO]
spatial_inference ..... [NO] ..... [OKAY]
transformer ..... [NO] ..... [OKAY]
stochastic_transformer . [YES] ..... [OKAY]
--------------------------------------------------
```

Other ways to express parallelism - DeepSpeed



- Again wrapping your model in the relevant object is the way to go!

```
import deepspeed

deepspeed.init_distributed()

model, optimizer, _, _ = deepspeed.initialize(
    model = model,
    optimizer = optimizer, #e.g. SGD
    args = args,
    dist_init_required=True
)
```

Original model

Original optimizers

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