

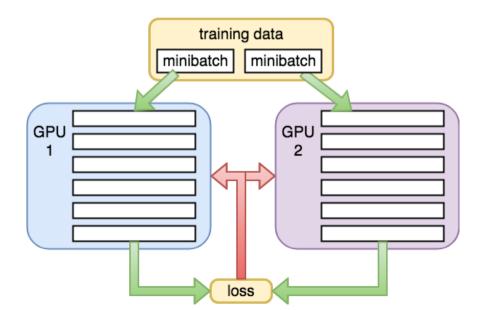
Scaling AI training to multiple GPUs

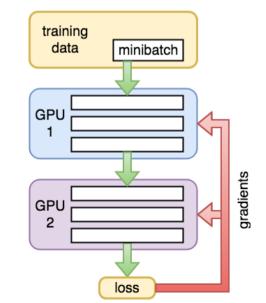
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Reasons to use multiple GPUs

LUMI

Training takes a long time and I have a lot of data → data parallelism My model is too big to fit into one GPU \rightarrow model parallelism





Using multiple GPUs

• Each node (computer) in LUMI has 8 GPUs (Actually 4 x MI250x, which is a dual chip card = 8 GCDs) ech

GPUO

GRU 3

CCD3

SCOL

GOI

GCDG

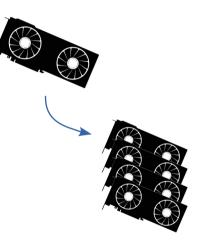
GOL -

ODE

For each GPU you use
 1-7 CPU cores for data
 loading and pre-processing

Using multiple GPUs

- Not automatic: your code needs to support multiple GPUs
- Frameworks like Hugging Face, Lightning or Accelerate *may* auto-detect multiple GPUs (with the right options)
- For pure PyTorch code, there are many options depending on the scenario:
 - DistributedDataParallel (DDP)
 - Hybrid approaches for models too big for a single GPU:
 - Fully-sharded Data Parallel (FSDP)
 - DeepSpeed



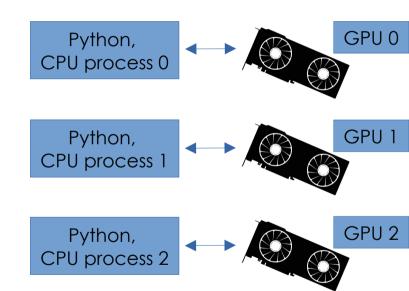
Multi-GPU resource allocation on LUMI

- Use --gpus-per-node=N where N=1,...,8 (--gpus-per-task option not currently recommended due to bug in Slurm)
- Allocate a maximum of 1/8 of resources per GPU:
 - 60 GB CPU memory (RAM) and 7 CPU cores per GPU
 - Full node: 480 GB and 56 cores (leaving some "slack" for the system)
 - Note: you always get the full GPU memory (VRAM) of 64 GB per GCD (no need to allocate that with Slurm options)
 - Resources billed in GPUh according to 1/8 slice

One Python CPU control process per GPU

- Torchrun can handle launching the processes. Launch single torchrun: --tasks-per-node=1
- Without torchrun, use Slurm tasks: --tasks-per-node=8
- Each process should know which GPU to use, e.g.

```
gpu_id = int(os.environ["LOCAL_RANK"])
device = torch.device("cuda", gpu_id)
```

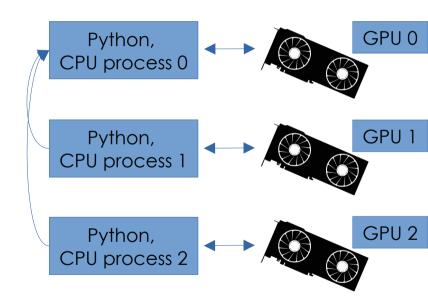


Set up communication between processes

- First process is the "master" and the others connect back to it
- Torchrun can handle this automatically: torchrun --standalone ...
- Without torchrun you need to set up environment variables:

MASTER_ADDR=\$(hostname)
MASTER_PORT=25900
WORLD_SIZE=\$SLURM_NPROCS
RANK=\$SLURM_PROCID

 Note: rank needs to be set differently for each process, see exercise for example



LUMI

#!/bin/bash Remember rule-of-thumb: #SBATCH -- account=project 465001958 • 1 GPU = 1/8 of node #SBATCH -- partition=small-g #SBATCH --gpus-per-node=2 • Use also $\leq 1/8$ of CPU #SBATCH -- ntasks-per-node=1 cores and memory #SBATCH -- cpus-per-task=14 per GPU #SBATCH -- mem=120G #SBATCH -- time=1:00:00 ## < module loading part as before - removed for readability> srun singularity exec \$CONTAINER \ torchrun will take care torchrun --standalone \ of launching one --nnodes=1 \setminus process per GPU --nproc-per-node=\${SLURM GPUS PER NODE} \ my python script.py

Example: 2 GPUs with torchrun

Example: 8 GPUs with torchrun

LUMI

#!/bin/bash

- #SBATCH --account=project_465001958
- #SBATCH --partition=standard-g
- #SBATCH --gpus-per-node=8
- #SBATCH --ntasks-per-node=1
- #SBATCH -- cpus-per-task=56

```
#SBATCH -- mem=480G
```

```
#SBATCH -- time=1:00:00
```

< module loading part as before - removed for readability>

```
srun singularity exec $CONTAINER \
    torchrun --standalone \
        --nnodes=1 \
        --nproc-per-node=${SLURM_GPUS_PER_NODE} \
        my_python_script.py
```

Full node = we can also use standard-g

Example: 8 GPUs <i>without</i> to	brchrun LUMI
<pre>m #!/bin/bash </pre>	Q = - • ×
<pre>#SBATCHaccount=project_465001958 #SBATCHpartition=standard-g #SBATCHgpus-per-node=8 #SBATCHntasks-per-node=8 #SBATCHcpus-per-task=7 #SBATCHcpus-per-task=7 #SBATCHtime=1:00:00 ## < module loading part as before - p</pre>	We use Slurm tasks to launch 8 Python processes
<pre>export MASTER_ADDR=\$(hostname) export MASTER_PORT=24500 export WORLD_SIZE=\$SLURM_NPROCS srun bash -c "RANK=\\$SLURM_PROCID LOCA</pre>	Where to connect to? How many processes are there? Which process am I? AL_RANK=\\$SLURM_LOCALID singularity exec "

Do we need to change the Python code?



- For plain PyTorch: yes, use DistributedDataParallel (DDP)
- For higher level frameworks, **mostly no:**
 - transformers.Trainer is automatically set up for distributed training when WORLD_SIZE & RANK environment variables are set
 - Similar for other high-level frameworks like PyTorch Lightning or Accelerate
- BUT: Pay attention to global batch size vs per device batch size!
 - Example: global batch size = 32 for one GPU, split over 8 GPUs, per-device batch size is 4
- Cosmetic: You might want to print some things only on rank 0

PyTorch DistributedDataParallel (DDP)

1) Initialize PyTorch distributed:

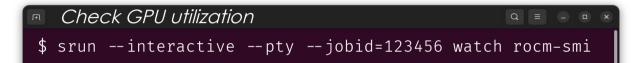
torch.distributed.init_process_group(backend='nccl')

2) Wrap your model:

model = torch.nn.parallel.DistributedDataParallel(model, ...)

3) Use the distributed sampler:

Check that you are actually using all GPUs!



- Utilization should be > 0% for all requested GPUs
- Note: showing high utilization is a necessary, but not sufficient condition for it actually doing something useful!
 - Refer back to lecture 4 yesterday Understanding GPU activity & checking jobs
 - Check GPU power and use profiling



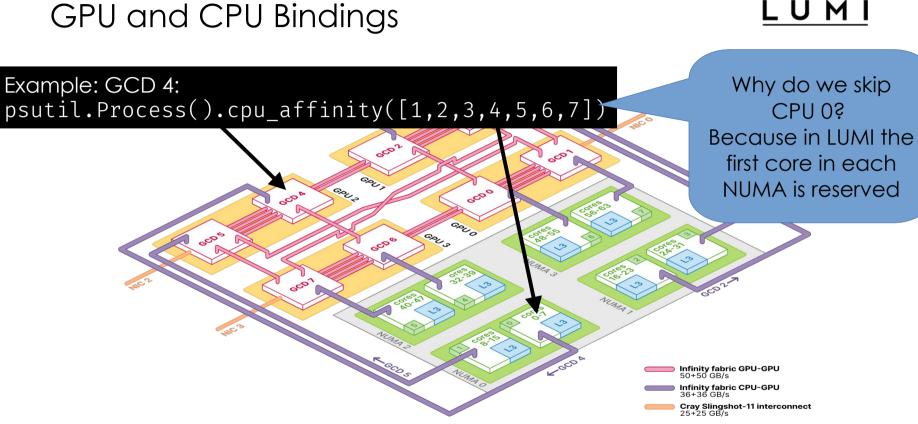


Multi-GPU tips & tricks

- Use RCCL and libfabric for efficient communication on LUMI
 - AWS OFI RCCL plugin for containers: https://github.com/ROCm/aws-ofi-rccl
- Add fault tolerance when possible, especially for huge jobs
 - Checkpointing!
- (Optionally) bind the processes to optimal CPU cores
 - Improves CPU-GPU I/O, might speed up cases with high I/O
- Issues with multi-worker data loaders segfaulting:

if __name__ = __main__:

multiprocessing.set_start_method("spawn")



https://docs.lumi-supercomputer.eu/runjobs/scheduled-jobs/distribution-binding/#gpu-binding