HPC.NRW

NATIONALES HOCHLEISTUNGS RECHNEN

EDIH Rheinland

WEST AI KI-Servicezentrum

PPCES: Machine and Deep Learning

Distributed Deep Learning + Case Study – PyTorch

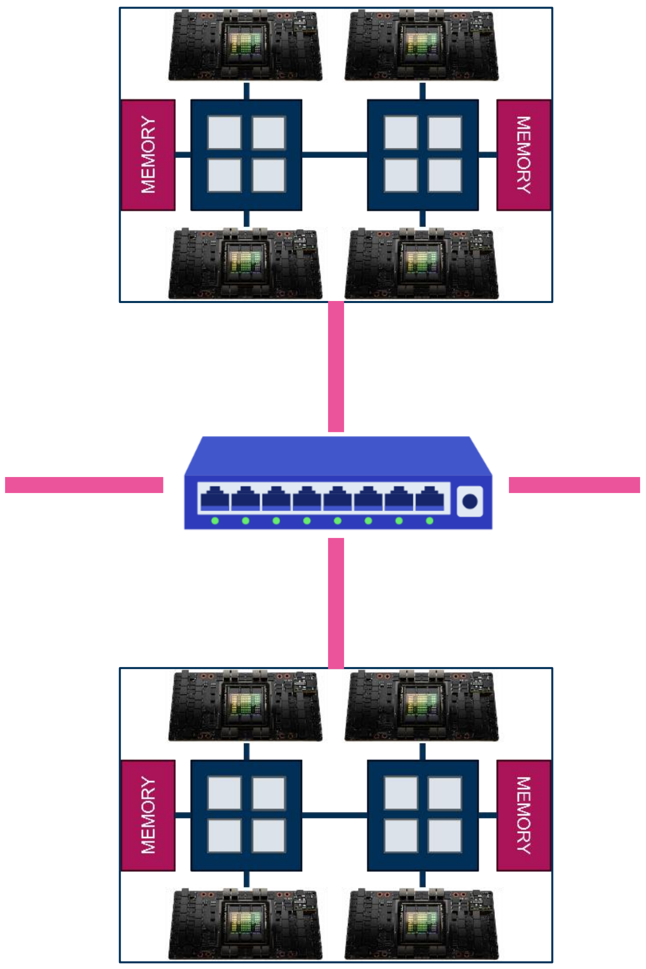
DAS KOMPETENZNETZWERK FÜR HOCHLEISTUNGSRECHNEN.

Distributed Deep Learning – Motivation

- **Why do we need distributed deep learning?**
  - One compute node or GPU is not enough
    - Limited host memory → dataset too large for single compute node
    - Limited GPU memory → model too large to fit into GPU memory
  - Speedup training (or inference)
    - Single GPU could run workload
    - But: Multiple GPUs can complete workload much faster

- **Challenges**
  - Communication necessary (data, parameters, weights)
    - Common backends: MPI, NCCL, Gloo (file-based)
  - Model consistency (centralized vs decentralized)
  - Learning rate scaling might be required

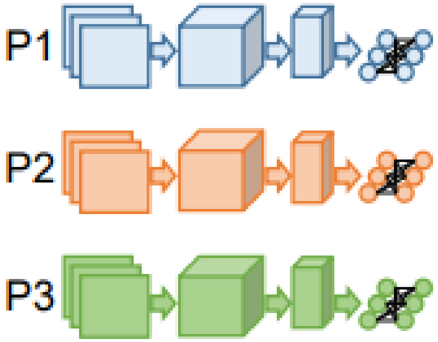
Compute Node 1

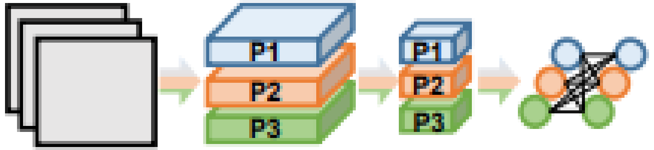


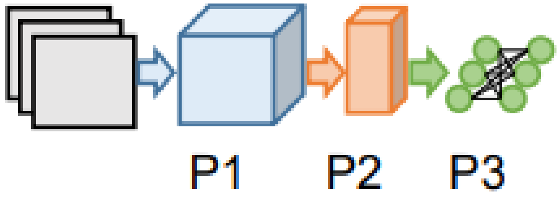
Compute Node 2

Parallelism Strategies for Distributed Deep Learning

– **Three most common strategies**







Data Parallelism

- Split data in micro-batches
- Easy to implement
- Best strong scalability
- Does not improve memory consumption

Model Parallelism

- Split layers in partitions
- Necessary for large layers
- Can improve load balancing
- Hard and time consuming to implement

Layer Pipelining

- Split DNN in partitions
- Improves memory consumption
- Hard to achieve good load balance
- Difficult to implement

➔ **Faster training**

➔ **Bigger models**

Images: Ben-Nun et al.

Example: Data Parallelism with 2 GPU Workers

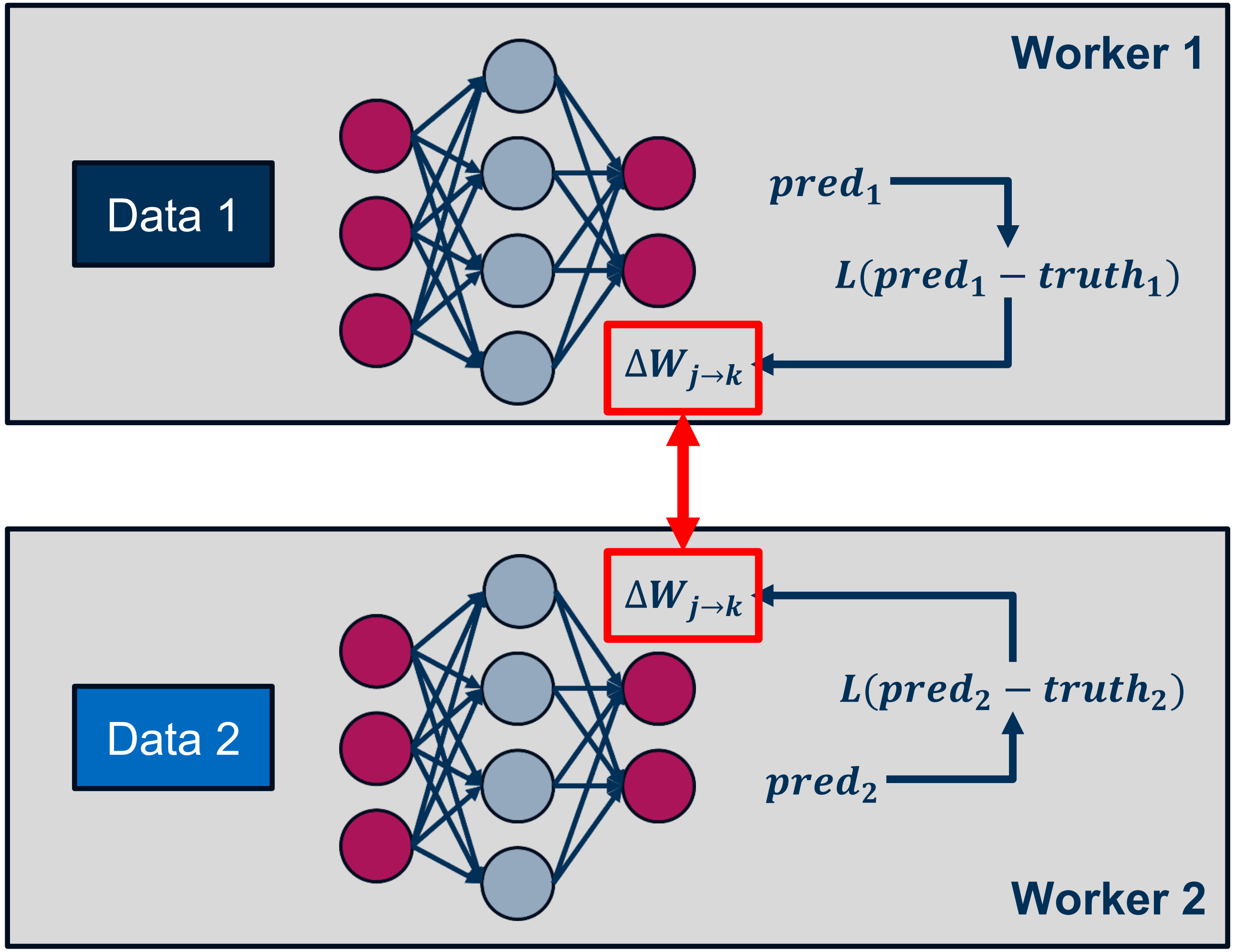
HPC.NRW

Batch #1 (e.g. 1024)

- Data 1 — **512 samples**
- Data 2 — **512 samples**

Batch #2 (e.g. 1024)

- Data 1 — **512 samples**
- Data 2 — **512 samples**



– **Note:**

- Batch size limits parallelism
- Scaling batch size requires scaling of learning rate (linearly)

Solutions for Distributed Deep Learning

- **Native support in frameworks**
  - TensorFlow: `tf.distribute.Strategy` (Documentation)
    - e.g., `MirroredStrategy`, `MultiWorkerMirroredStrategy`
  - PyTorch: `torch.distributed` (Documentation)
    - Especially: `torch.nn.parallel.DistributedDataParallel` (DDP)

- **Additional software such as Horovod**
  - Developed by Uber Engineering (Documentation)
  - Aiming at large scale workloads (MPI backend)
  - With only little code modification supports
    - TensorFlow
    - PyTorch
    - MXNet

PyTorch – Distributed DL with DDP

- **Step 1:** Spawn multiple processes
  - Represent workers (usually 1 per GPU)
  - Can be spread across multiple compute nodes
  - Examples: MPI, `torchrun`, …

Zsh

```
# execute with MPI/srun
srun ... python train_model.py <args>

# execute with MPI/srun
srun ... zsh -c '\
    source set_vars.sh && \
    apptainer exec -e --nv ${PYTORCH_IMAGE}
      bash -c "python train_model.py <args>"'
```

- **Step 2:** Initialize and destroy process group
  - Processes need to communicate and exchange data
  - Requires: $\#_{\text{procs}}$, ID_{proc}
  - Built-in `torch.distributed` package
  - Available backends: NCCL, MPI, Gloo, …
    - NCCL: Need to set MASTER_ADDR and MASTER_PORT

Python

```
# initialize process group
torch.distributed.init_process_group(
    backend='nccl', init_method="env://",
    world_size=args.world_size,
    rank=args.world_rank
)

# wait for completion
torch.distributed.barrier()
```

PyTorch – Distributed DL with DDP

- **Step 3:** Wrap your model
  - Use `DistributedDataParallel` (DDP)
  - Model parameters will be synchronized at creation
  - Specify the desired device

```
from torch.nn.parallel import
DistributedDataParallel

# wrap your model and specify device
model = DistributedDataParallel(
    model,
    device_ids=[args.local_rank]
)
```

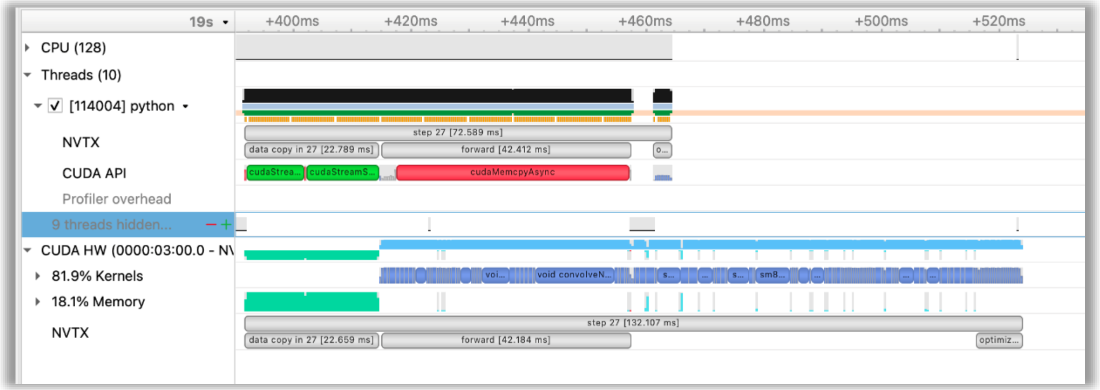
- **Step 4:** Distribute data across workers
  - Each worker will get a split of the batches
  - Idea: Extend loader with `DistributedSampler`
    - Number of Replicas
    - Current Proc ID
    - Shuffle or not?

```
from torch.utils.data import
DistributedSampler, DataLoader

# create sampler
sampler = DistributedSampler(
    dataset, shuffle=True,
    num_replicas=args.world_size,
    rank=args.world_rank
    )

# create data loader that is using the sampler
loader = DataLoader(dataset, sampler=sampler)
```

Identifying Resource Utilization and Efficiency

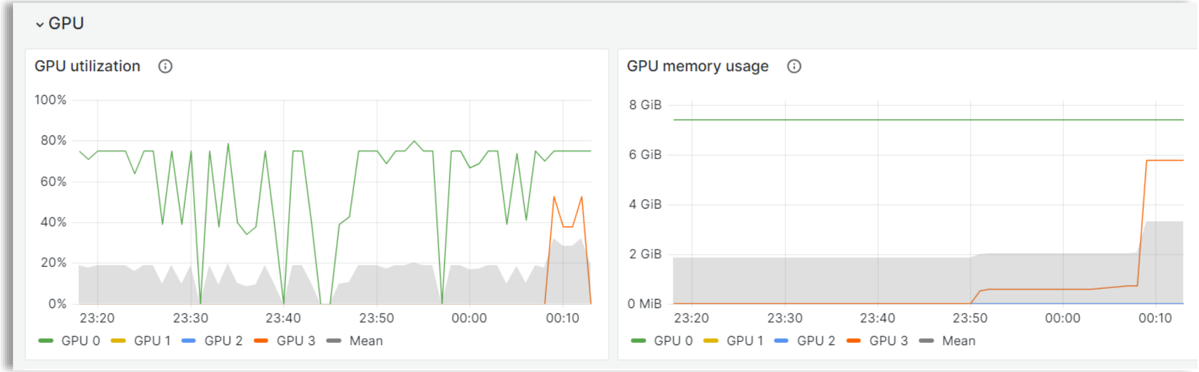
- **Question:** How do I know how much resources are used?
  - Compute vs. Memory
  - Does it make sense to scale to multiple GPU or even multipe nodes?

- **Various tools available**
  - Regular profiling / tracing tools
    - Score-P, CUBE, Vampire (Link)
    - Create detailed profiles and traces of your application
  - TensorBoard (Link) / NVIDIA Nsight Systems (Link)
    - Specifically designed for DL frameworks
    - Identify issues and receive recommendations
  - Easier: monitoring (e.g., with `nvidia-smi`)



Identifying Resource Utilization and Efficiency (on CLAIX)

- **Easy Option 1:** Review our continuous monitoring (in Grafana)
  - We collect several metrics every minute
  - https://perfmon.hpc.itc.rwth-aachen.de/
  - View monitoring data for your current / previous jobs
    - CPU / Memory / GPU / Power / Network



- **Easy Option 2:** NVIDIA System Management Interface (`nvidia-smi`)
  - Provides monitoring and management capabilities
  - Information about
    - Configuration (e.g., compute mode)
    - Clock speed, power draw & temperature
    - Utilization (GPU, memory, encoder / decoder)
  - Output can be configured and written to csv or stdout
    - e.g., filter what you want to see and in what interval

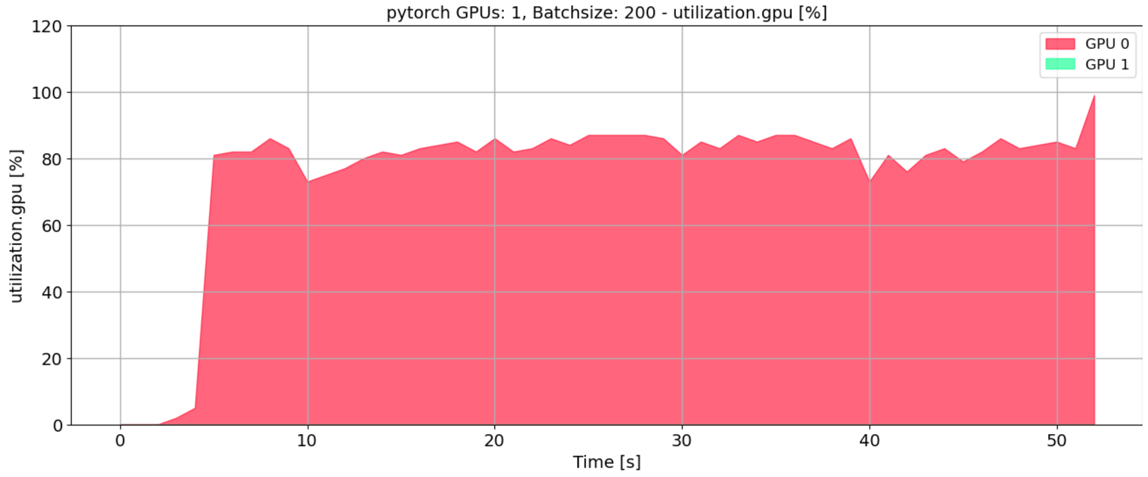
Basic Resource Utilization Checks with `nvidia-smi`

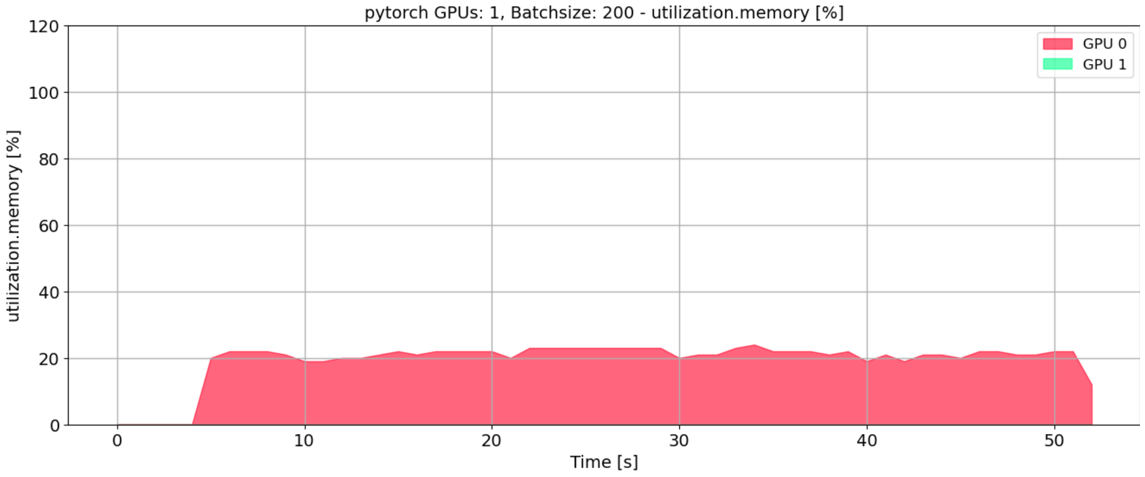
HPC.NRW

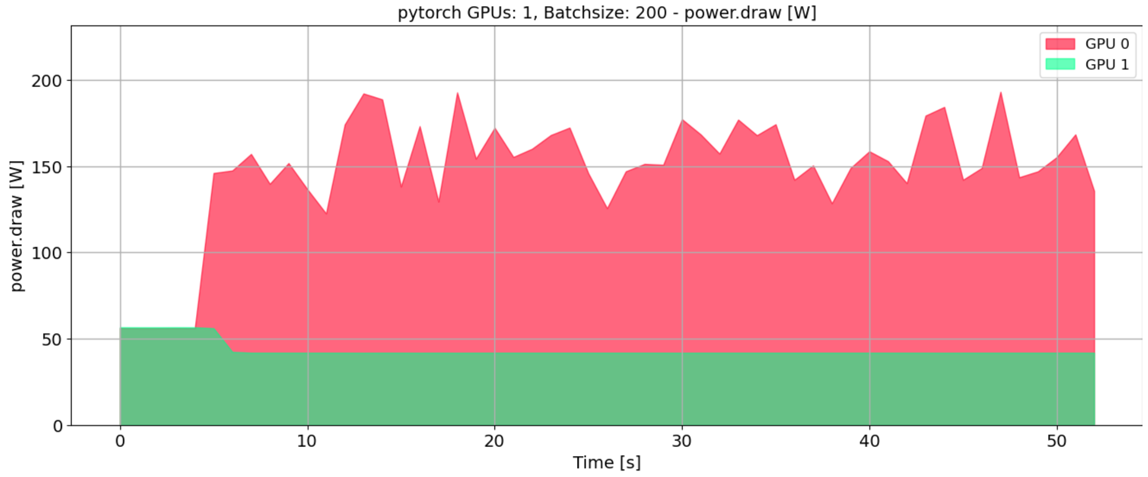
```
# repeat query every 2 second and pipe result to separate file
nvidia-smi –query-gpu=timestamp,index,compute_mode,pstate,utilization.gpu,utilization.memory,memory.used,temperature.gpu,power.draw --format=csv --loop=2 &> data.txt &

# remember ID of process that has just been started in background
export proc_id_monitor=$!

# execute your program
<exec statement> <params>

# stop monitoring again
kill -2 ${proc_id_monitor}
sleep 5
```

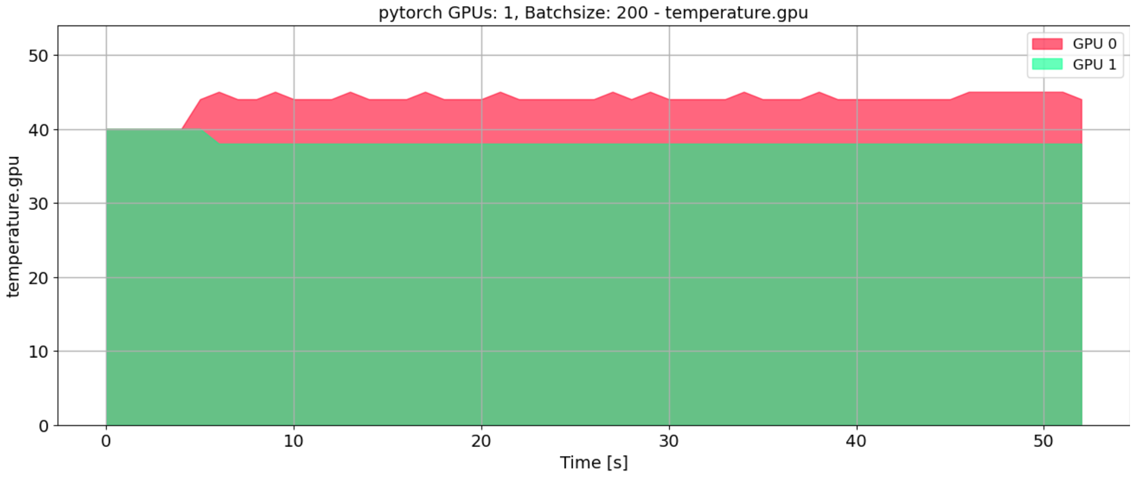
```
timestamp, index, compute_mode, pstate, utilization.gpu [%],
utilization.memory [%], ...
2021/11/12 14:24:52.010, 1, Default, P0, 0 %, 0 %, 0 MiB, 40, 56.54 W
2021/11/12 14:24:54.012, 0, Default, P0, 81 %, 20 %, 2758 MiB, 44, 145.93 W
2021/11/12 14:24:54.013, 1, Default, P0, 0 %, 0 %, 0 MiB, 40, 56.01 W
2021/11/12 14:24:56.015, 0, Default, P0, 82 %, 22 %, 2758 MiB, 45, 147.40 W
2021/11/12 14:24:56.016, 1, Default, P0, 0 %, 0 %, 0 MiB, 38, 42.31 W
2021/11/12 14:24:58.017, 0, Default, P0, 82 %, 22 %, 2758 MiB, 44, 156.98 W
2021/11/12 14:24:58.019, 1, Default, P0, 0 %, 0 %, 0 MiB, 38, 41.82 W
2021/11/12 14:25:00.020, 0, Default, P0, 86 %, 22 %, 2758 MiB, 44, 139.66 W
2021/11/12 14:25:00.022, 1, Default, P0, 0 %, 0 %, 0 MiB, 38, 41.82 W
2021/11/12 14:25:02.023, 0, Default, P0, 83 %, 21 %, 2758 MiB, 45, 151.70 W
```

Basic Resource Utilization Checks with `nvidia-smi`


pytorch GPUs: 1, Batchsize: 200 - utilization.gpu [%]
🟥 GPU 0
🟩 GPU 1
utilization.gpu [%]
Time [s]


pytorch GPUs: 1, Batchsize: 200 - utilization.memory [%]
🟥 GPU 0
🟩 GPU 1
utilization.memory [%]
Time [s]


pytorch GPUs: 1, Batchsize: 200 - power.draw [W]
🟥 GPU 0
🟩 GPU 1
power.draw [W]
Time [s]


pytorch GPUs: 1, Batchsize: 200 - temperature.gpu
🟥 GPU 0
🟩 GPU 1
temperature.gpu
Time [s]