Profiling AI Applications: Techniques and Best Practices

Giorgos Kosta

Research Engineer

CaSToRC

eurocc.cyi.ac.cy

A Bit About Myself

- Research Engineer at CaSToRC
- Works on DS and ML projects
- Awareness and Communications task leader for EuroCC2
- Email: g.kosta@cyi.ac.cy

Learning Objectives

- Understanding key metrics for AI application profiling.
- Introduction to PyTorch profiling and visualisation using Tensorboard.
- Interpreting profiling results.
- Optimizing your code by implementing changes based on profiling insights.

Why Profile AI Applications?

- Identification of underutilized resources:
  - Correct allocation in HPC environments.
  - Identification of bottlenecks
- It can also be a great when debugging:
  - Make informed decisions on model architecture and training.
- Scaling behavior - training larger datasets.

Key Performance Metrics - GPU metrics

- Core GPU Utilization (SM Activity):
  - Percentage of time GPU streaming multiprocessors are active.
  - Target: >80% during training indicates good compute utilization.
  - Common issues: Low utilization often indicates CPU bottlenecks or inefficient batching .

GPU Summary ⓘ

GPU 0:	
Name	Tesla V100-SXM2-32GB
Memory	31.74 GB
Compute Capability	7.0
GPU Utilization	58.85 %
Est. SM Efficiency	55.17 %
Est. Achieved Occupancy	54.37 %

VS

GPU Summary ⓘ

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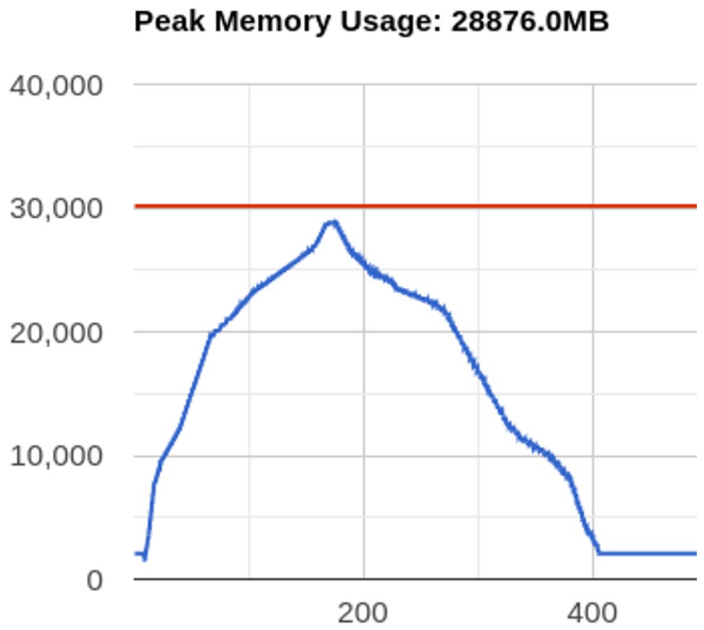
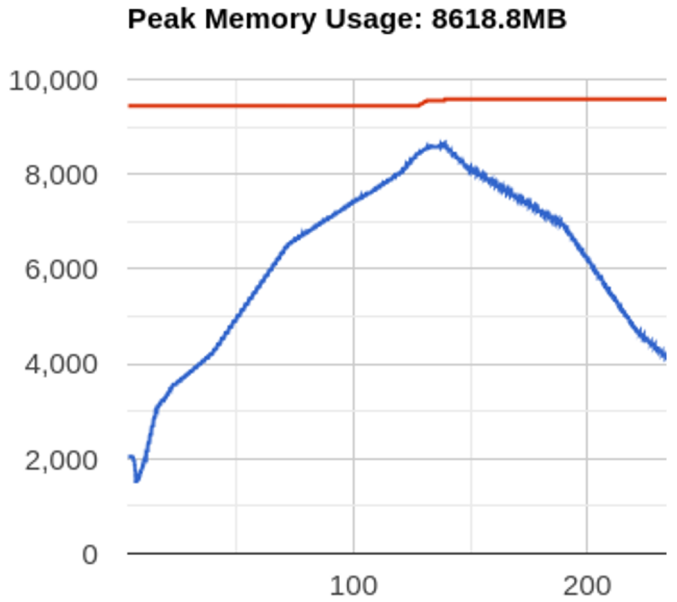
Key Performance Metrics - GPU metrics

- GPU Memory Utilization:
  - Percentage of allocated vs total GPU memory.
  - Optimal range: 80-90% (leaving headroom for spikes).



VS



Key Performance Metrics - GPU metrics

- Relationship between metrics:
  - High utilization + low memory utilisation = compute bound
  - Low utilization + high memory utilisation = memory bound
  - Low both = potential CPU/data loading bottleneck

Peak Memory Usage: 28876.0MB

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Peak Memory Usage: 8618.8MB

GPU Summary

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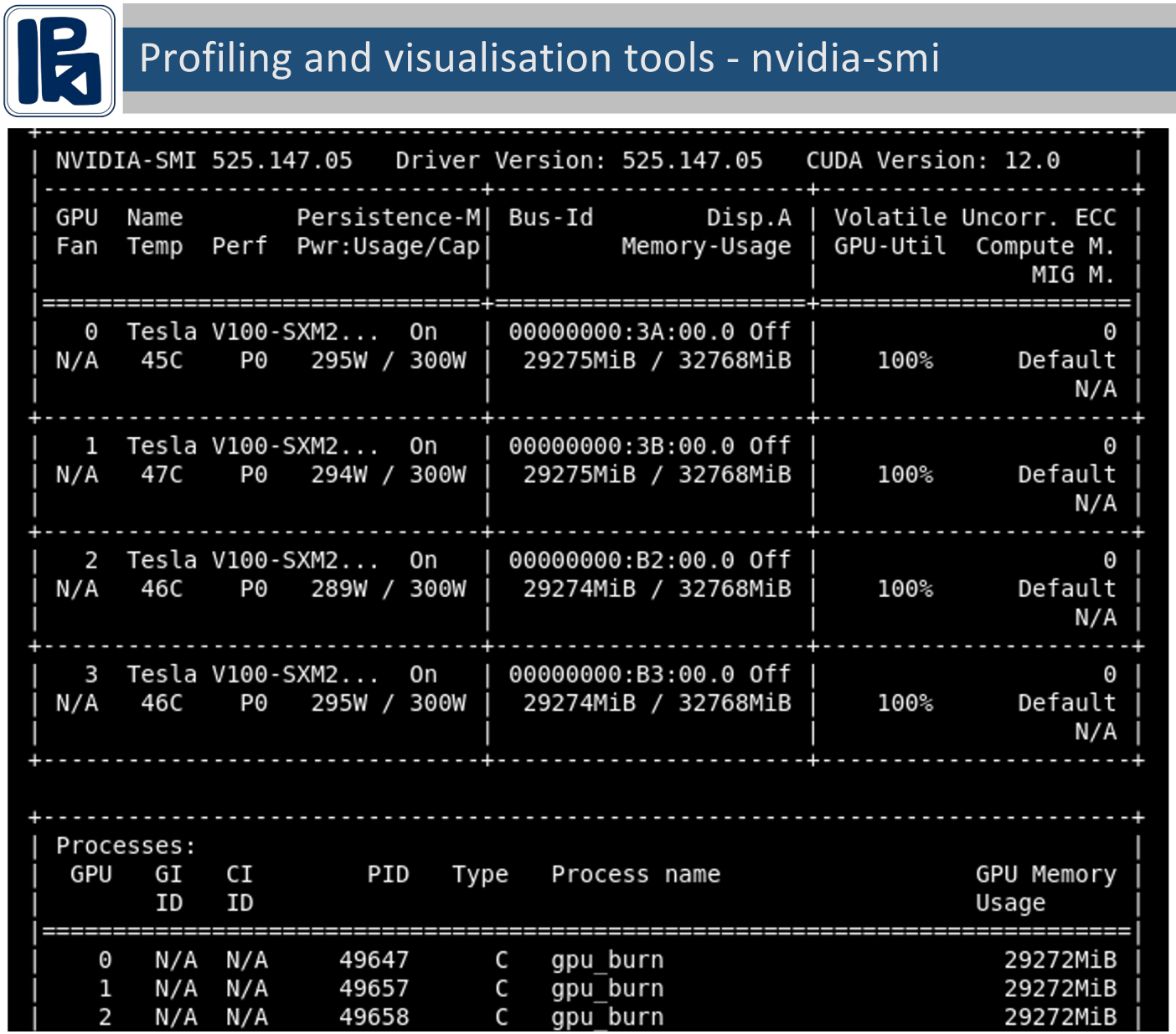
Key Performance Metrics - CPU metrics

- DataLoader Performance - time per batch retrieval

- Data Transformation Costs
  - Tokenization time (for NLP tasks)
  - Image preprocessing operations
  - Data augmentation computation time



Profiling and visualisation tools - nvidia-smi

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 525.147.05   Driver Version: 525.147.05   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. |
|===============================+======================+======================|
|   0  Tesla V100-SXM2...  On   | 00000000:3A:00.0 Off |                    0 |
| N/A   45C    P0   295W / 300W |  29275MiB / 32768MiB |    100%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
|   1  Tesla V100-SXM2...  On   | 00000000:3B:00.0 Off |                    0 |
| N/A   47C    P0   294W / 300W |  29275MiB / 32768MiB |    100%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
|   2  Tesla V100-SXM2...  On   | 00000000:B2:00.0 Off |                    0 |
| N/A   46C    P0   289W / 300W |  29274MiB / 32768MiB |    100%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
|   3  Tesla V100-SXM2...  On   | 00000000:B3:00.0 Off |                    0 |
| N/A   46C    P0   295W / 300W |  29274MiB / 32768MiB |    100%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A     49647      C   gpu_burn                        29272MiB |
|    1   N/A  N/A     49657      C   gpu_burn                        29272MiB |
|    2   N/A  N/A     49658      C   gpu_burn                        29272MiB |
```

Command:
$ nvidia-smi

Useful usage:
$ watch -n 2 nvidia-smi

Profiling and visualisation tools - torch profiler

Limits trace file size on long running jobs

```
with torch.profiler.profile(
    schedule=torch.profiler.schedule(
        wait=1,     # Number of steps to wait before profiling
        warmup=1,   # Number of warmup steps before recording
        active=3,   # Number of steps to record
        repeat=1    # Number of times to repeat the cycle
    ),
    on_trace_ready=torch.profiler.tensorboard_trace_handler(log_dir),
    record_shapes=True,
    profile_memory=True,
    with_stack=True
) as prof:
    for step, batch_data in enumerate(train_loader):
        loss = train_step(  model=model, data=batch_data, criterion=criterion,
                            optimizer=optimizer, scaler=scaler, device=device)
        prof.step()

        if step >= (1 + 1 + 3)*10:  # wait + warmup + active steps
            break
```

Records stack trace of program

Profiling and visualisation tools - torch profiler

```python
with record_function("batch_processing"):
    # Move data to GPU
    input_ids = batch['input_ids'].cuda()
    attention_mask = batch['attention_mask'].cuda()
    labels = batch['label'].cuda()

    # Simulate some computation
    with record_function("model_computation"):
        time.sleep(0.01)  # Simulate model forward pass

    # Ensure GPU operations are complete
    torch.cuda.synchronize()
```

Average time per batch: 18.07 ms

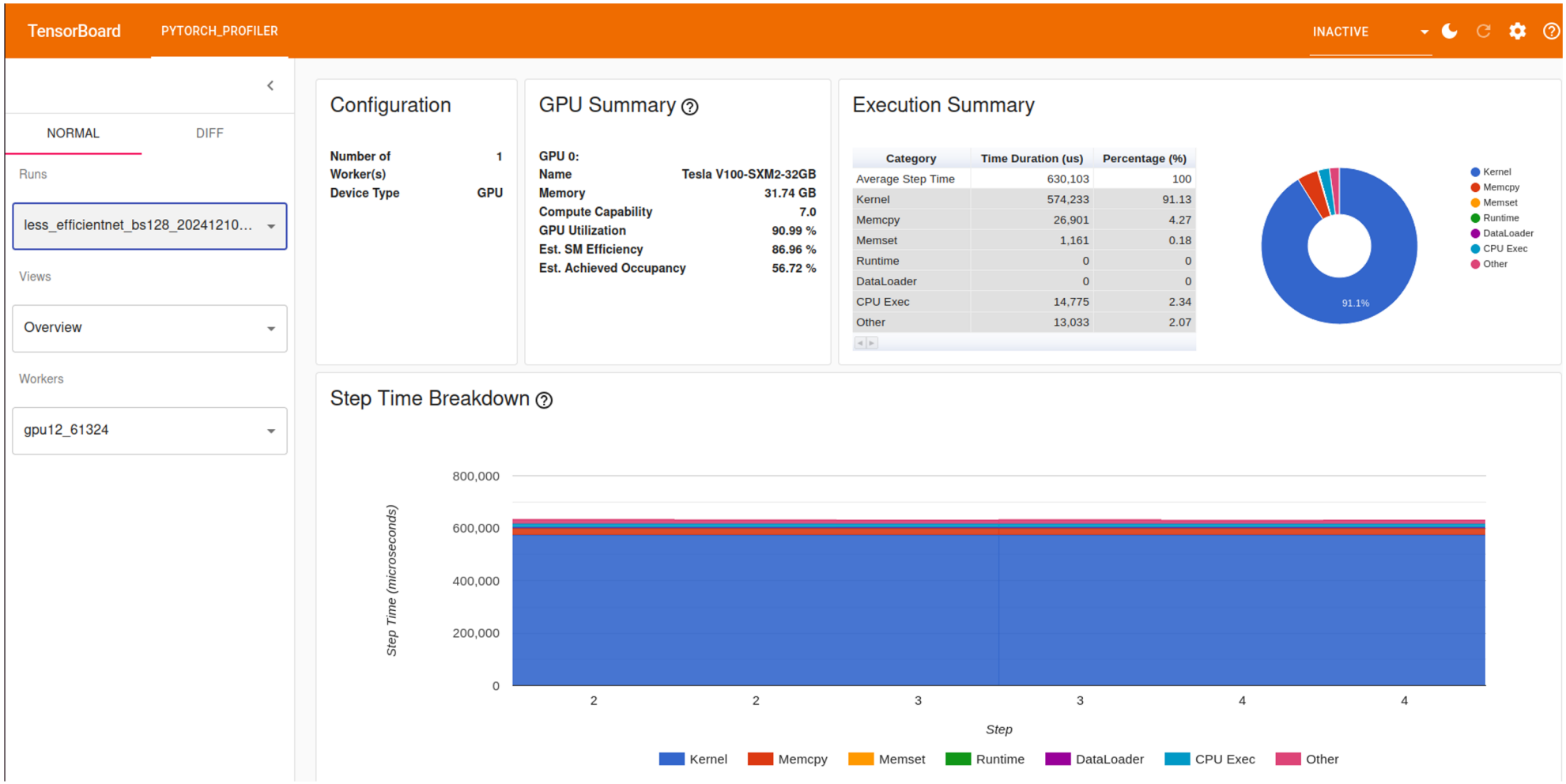
Detailed profile by operation type:

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time avg
ProfilerStep*	1.80%	606.000us	98.34%	33.187ms	11.062ms
batch_processing	2.54%	856.000us	94.02%	31.727ms	10.576ms
model_computation	90.13%	30.414ms	90.14%	30.417ms	10.139ms
enumerate(DataLoader)#_MultiProcessingDataLoaderIter...	2.28%	769.000us	2.31%	779.000us	259.667us
aten::zeros	1.35%	455.000us	1.73%	583.000us	48.583us
aten::to	0.07%	22.000us	1.25%	421.000us	46.778us
aten::_to_copy	0.32%	108.000us	1.18%	399.000us	44.333us
aten::copy_	0.15%	50.000us	0.73%	248.000us	27.556us
aten::empty	0.50%	170.000us	0.50%	170.000us	7.083us
cudaStreamSynchronize	0.41%	137.000us	0.41%	137.000us	15.222us

Profiling and visualisation tools - torch profiler

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time a
ProfilerStep*	0.19%	416.000us	99.97%	221.120ms	73.707
enumerate(DataLoader)#_MultiProcessingDataLoaderIter...	85.66%	189.461ms	85.72%	189.594ms	63.198
batch_processing	0.12%	264.000us	14.05%	31.082ms	10.361
model_computation	13.65%	30.197ms	13.65%	30.199ms	10.066
aten::to	0.02%	35.000us	0.27%	607.000us	25.292
aten::_to_copy	0.02%	38.000us	0.26%	572.000us	63.556
aten::copy_	0.02%	55.000us	0.22%	484.000us	53.778
cudaMemcpyAsync	0.13%	295.000us	0.13%	295.000us	32.778
cudaStreamSynchronize	0.06%	134.000us	0.06%	134.000us	14.889
aten::empty	0.05%	109.000us	0.05%	109.000us	2.795

Profiling and visualisation tools - Tensorboard - Overview

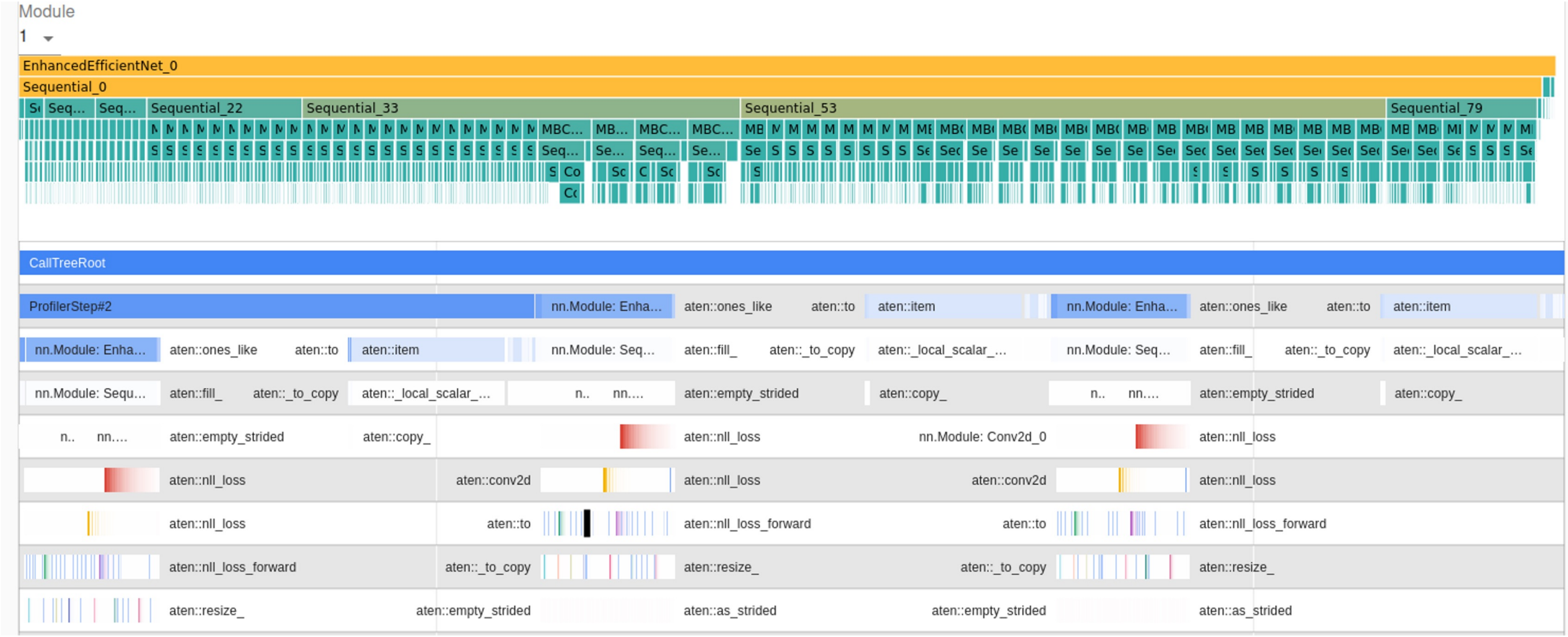


Profiling and visualisation tools - Tensorboard - Module view

Module View

Module Name	Occurences	Operators	Host Total Time	Host Self Time	Device Total Time	Device Self Time
CrossEntropyLoss_0	3	3	444.078125	98.3544921875	0	0
− EnhancedEfficientNet_0	3	9	482772.07421875	236.7734375	0	0
+ Sequential_0	3	0	478405.6484375	130.7431640625	0	0
AdaptiveAvgPool2d_61	3	3	147.2841796875	60.814453125	0	0
− Sequential_87	3	0	2499.5439453125	142.298828125	0	0
Linear_0	3	3	680.4931640625	53.5078125	0	0
ReLU_0	3	3	202.0869140625	53.4443359375	0	0
Dropout_0	3	3	341.5185546875	79.119140625	0	0

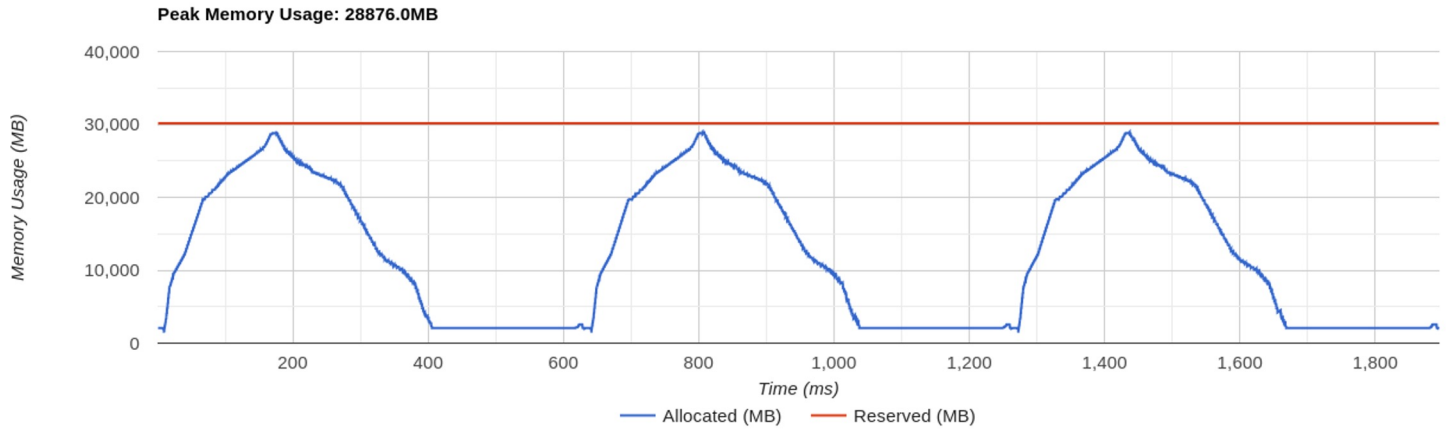
Profiling and visualisation tools - Tensorboard - Module view



Profiling and visualisation tools - Tensorboard - Module view

Memory View

Device
GPU0



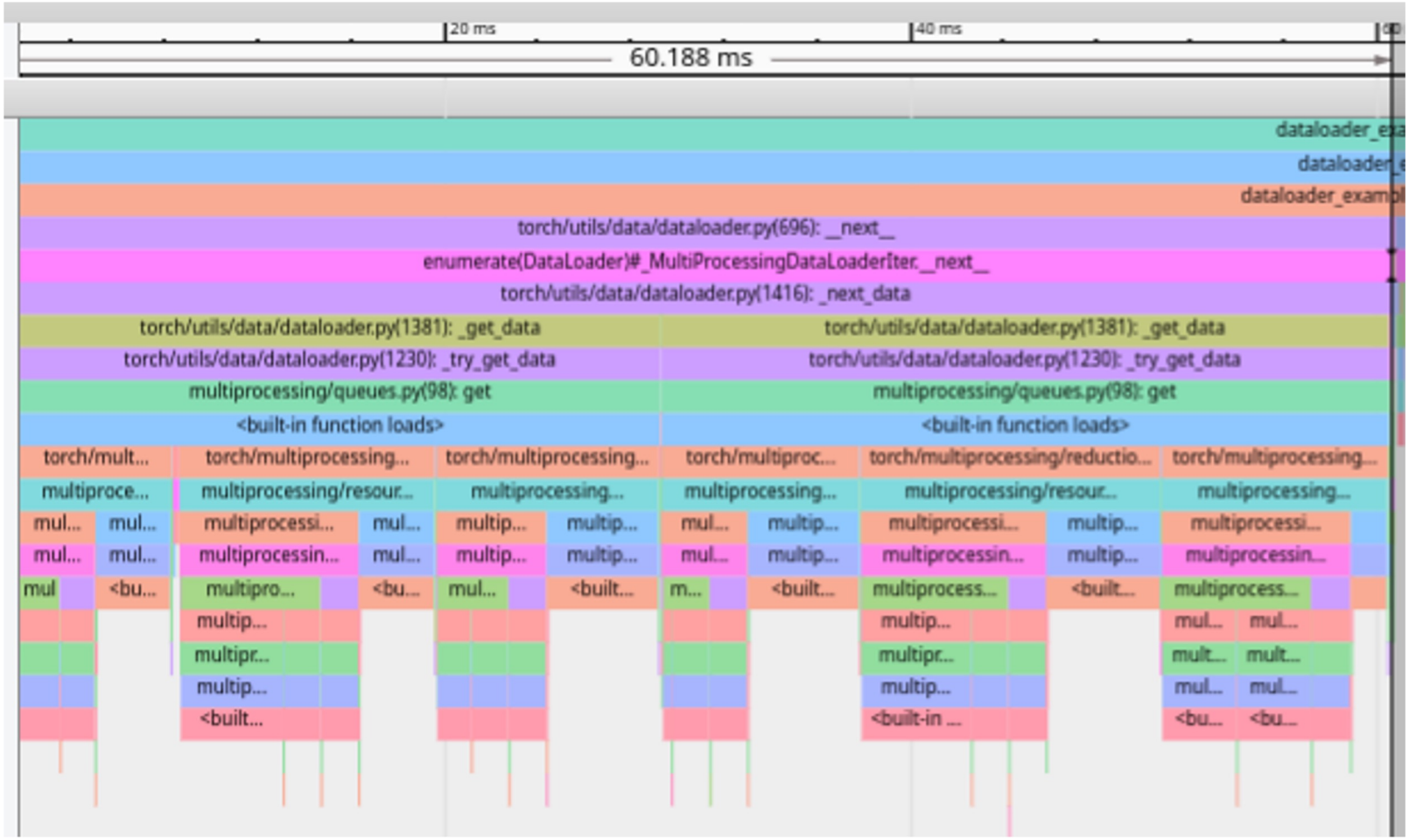
Search by Name

Min Size(KB) 64232.125

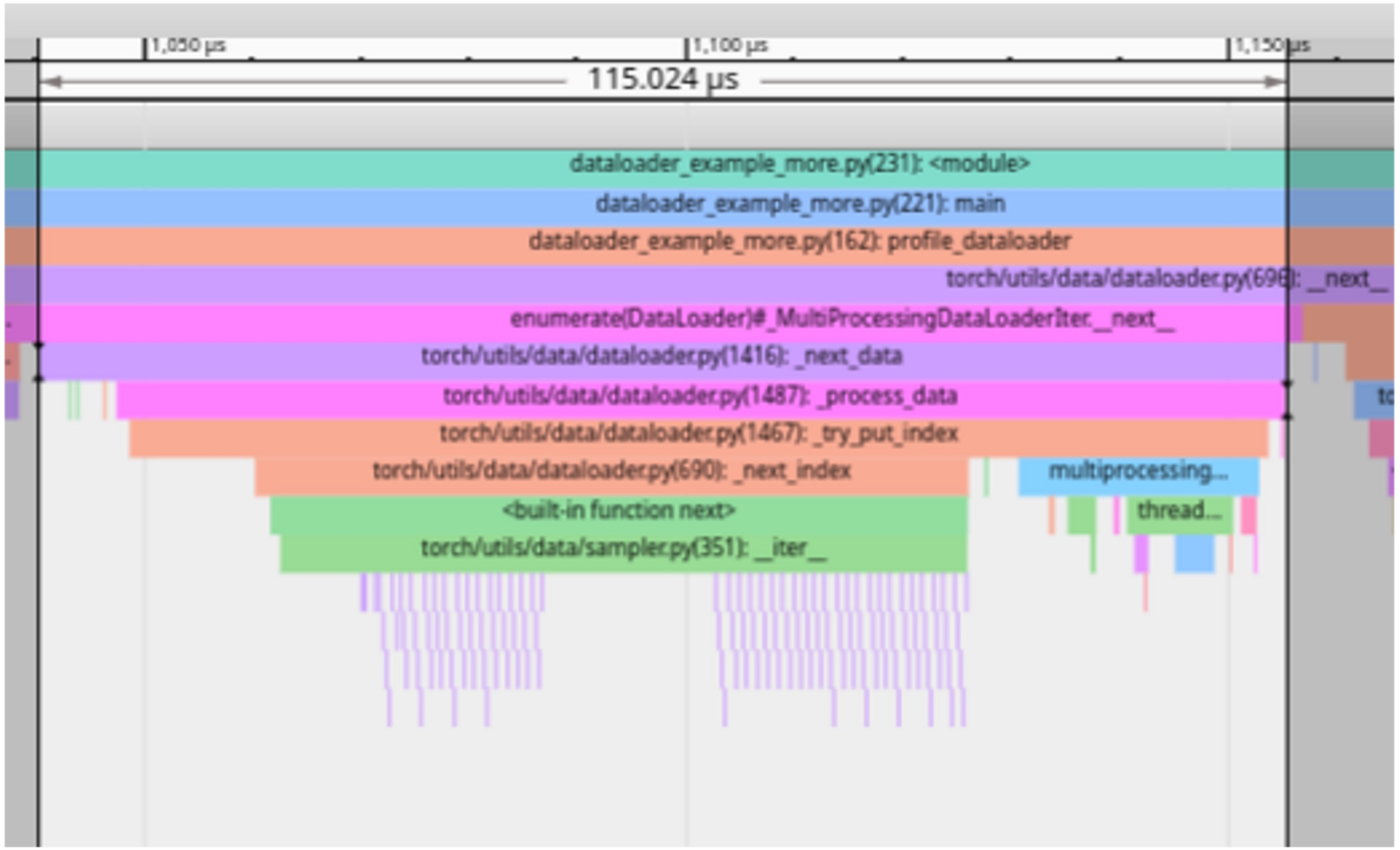
Max Size(KB) 256928.5

Operator	Size (KB)	Allocation Time (ms)	Release Time (ms)	Duration (ms)
aten::cudnn_convolution	100444	10.31	10.37	0.05
aten::cudnn_convolution	100444	10.84	10.88	0.04
aten::empty_like (aten::empty)	100352	10.98	11.27	0.29
aten::cudnn_convolution	100444	11.41	11.45	0.04
aten::empty_like (aten::empty)	100352	11.55	11.81	0.25
aten::cudnn_convolution	100444	11.96	12	0.04

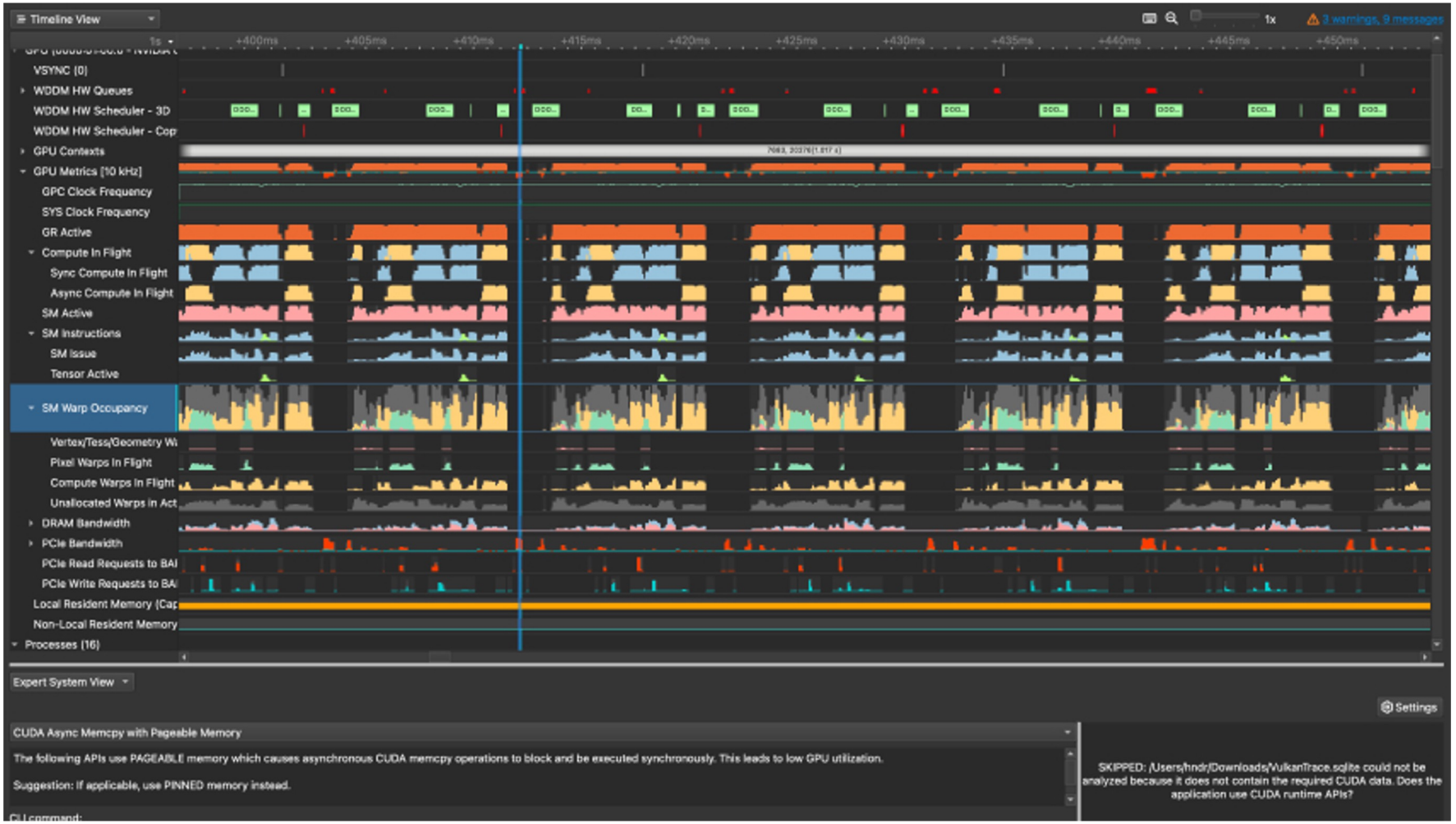
Profiling and visualisation tools - Tensorboard - Trace view (slow)



Profiling and visualisation tools - Tensorboard - Trace view (fast)



Profiling and visualisation tools - NSight



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

Thank you for the attention!

More information:

https://castorc.cyi.ac.cy/
https://eurocc.cyi.ac.cy/

Contact us at:
eurocc-contact@cyi.ac.cy

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Practical

1. Launch tensorboard:

```
$ cd edu26
$ cp -r logs_pactical1/ ~/
$ ./launch_tensorboard.sh
```

2. Launch python examples on compute nodes.

```
$ cp -r practical1/ ~/
$ cd ../practical1/
$ sbatch launch_dataloader.py
```

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