Monitoring GPU-accelerated Deep Learning models

NRIS

Norwegian research infrastructure services

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Motivation

- It does not seem that my code runs on **GPU** [Graphics Processing Unit].
- I don’t see any **performance gain** when running on GPU.
- It seems my code does something strange;
- How can I check what is going on ?
- How can I **identify ”hot spots”** in my code ?
- **Would it be relevant** to run my code on GPU?

Outline

I. **CPU vs GPU-architectures** [**GPU**: Graphics Processing Unit]

II. **Basic tools for GPU-usage**

III. **Profiling Deep Learning with PyTorch Profiler**

- What is PyTorch Profiler ?
- How to setup PyTorch Profiler?
- **Demo**: How to use PyTorch Profiler ?

Performance of a computer

- **The performance of a processor is measured by the quantity:**

FLOPS (**F**loiting-**P**oint of **O**pertaions **P**er **S**econd).

- It is a measure of the speed of a computer to perform arithmetic operations.

For a single processor:

FLOPS = (Clock speed)x(cores)x(FLOPs/cycle)

=Peak performance

FLOP is a way of encoding real numbers (i.e. FP64 or FP32, FP16…)

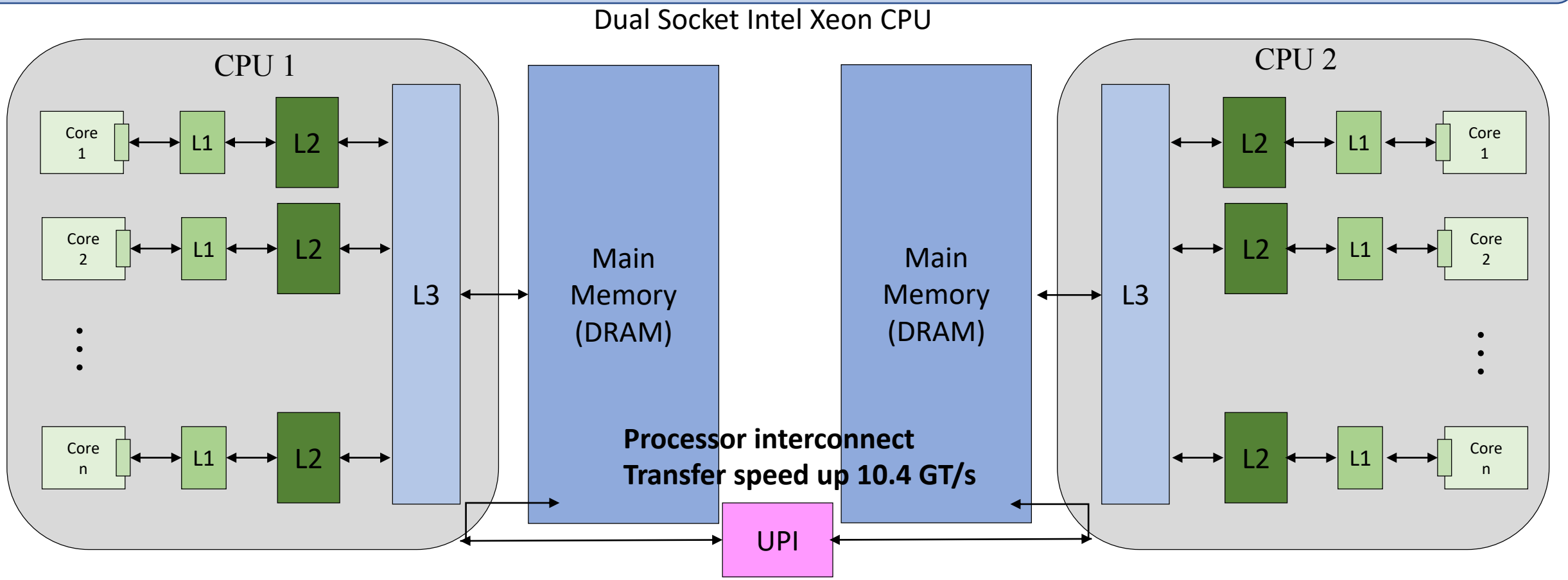
Exp**. 1 PetaFLOPS** = 10^15 calculations per second.

Supercomputer

Cluster

Computer (or node/server)

CPU-Architecture

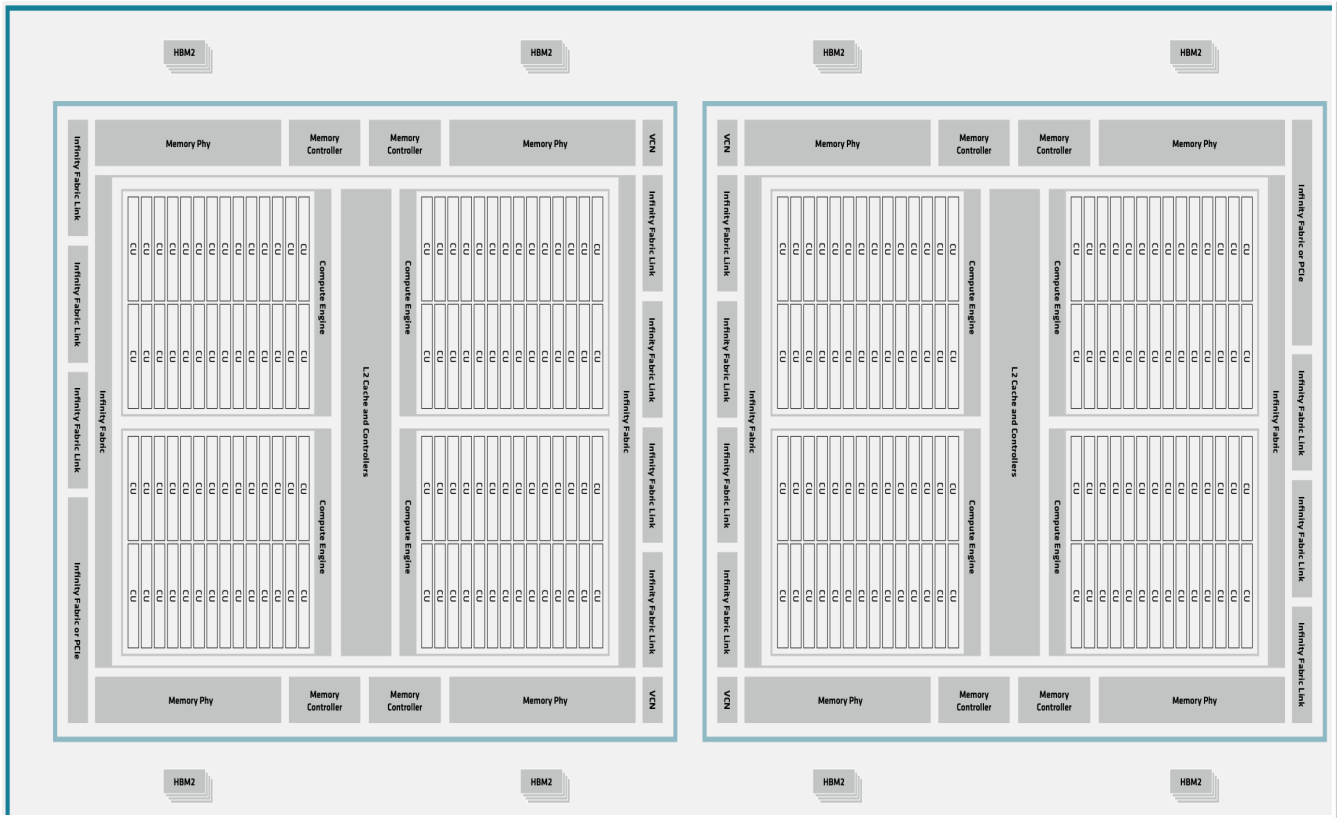


Access L1 Memory is Faster than L2

	Registers	L1 Cache	L2 Cache	L3 Cache	DRAM	Disk
Speed	1 cycle	~4 cycles	~10 cycles	~30 cycles	~200 cycles	10ms
Size	< KB per core	~32 KB per core	~256 KB per core	~35 MB per socket	~100 GB per socket	TB

https://indico.cern.ch/event/814979/contributions/3401193/attachments/1831477/3105158/comp_arch_codas_2019.pdf

GPU-Architecture



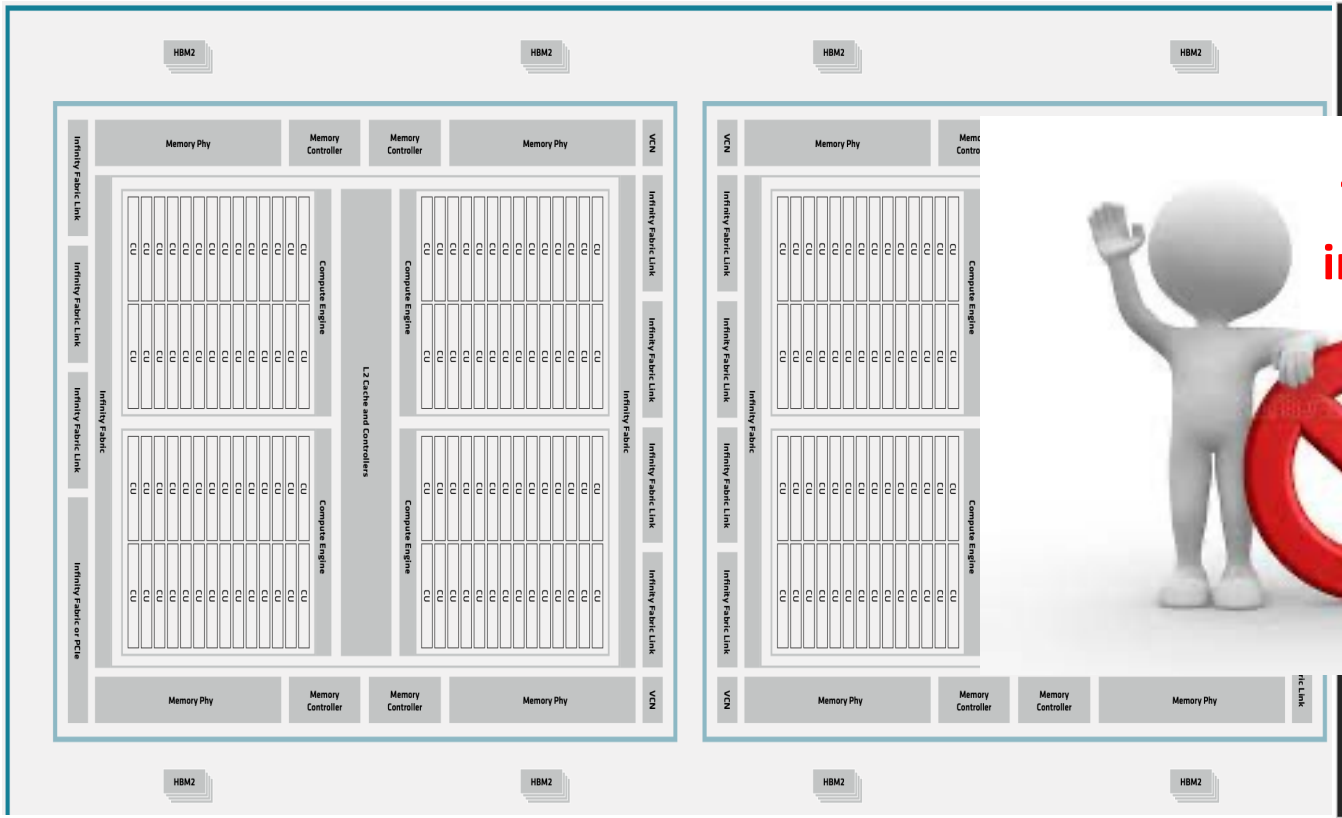
AMD GPU MI250X

NVIDIA GPU GA100

https://www.amd.com/system/files/documents/amd-cdna2-white-paper.pdf

https://images.nvidia.com/aem-dam/en-zz/Solutions/data-center/nvidia-ampere-architecture-whitepaper.pdf

GPU-Architecture



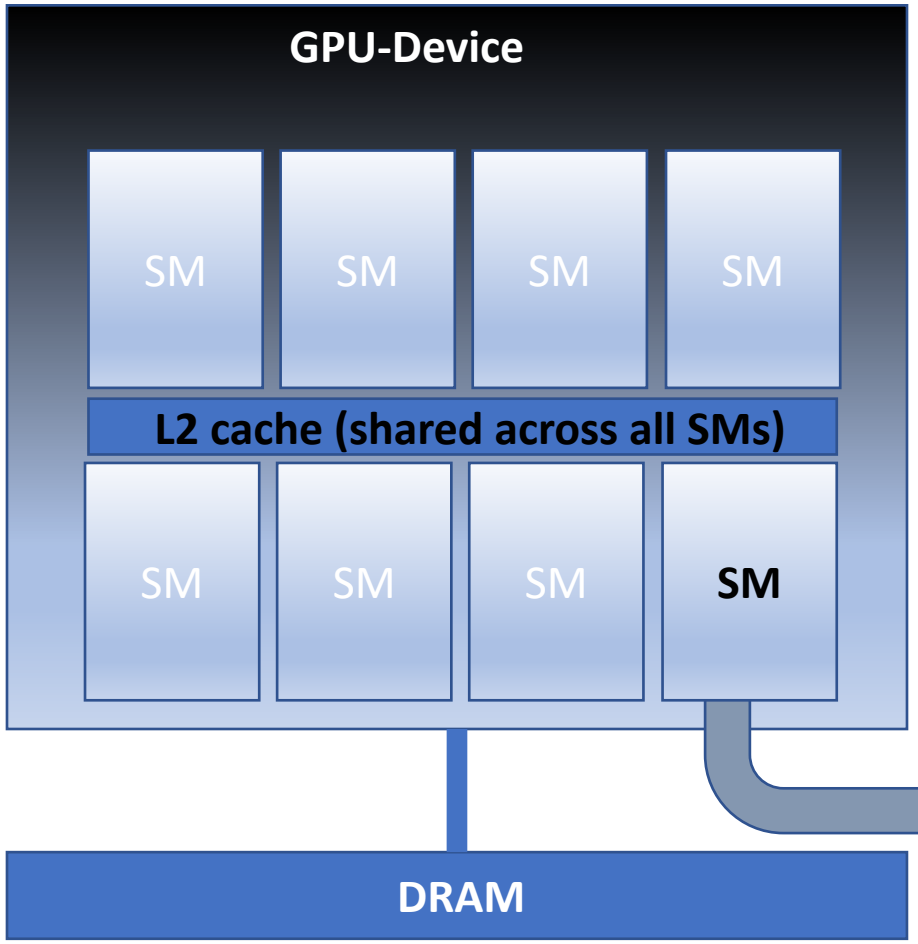
AMD GPU MI250X

NVIDIA GPU GA100

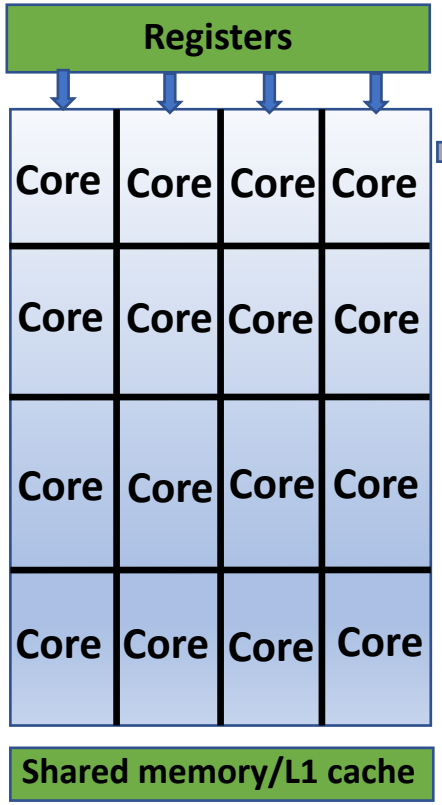
https://www.amd.com/system/files/documents/amd-cdna2-white-paper.pdf

https://images.nvidia.com/aem-dam/en-zz/Solutions/data-center/nvidia-ampere-architecture-whitepaper.pdf

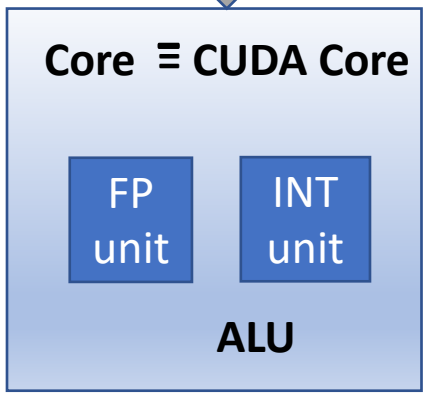
Architecture of NVIDIA-GPU devices (simplified version)



Streaming Multiprocessor (SM)



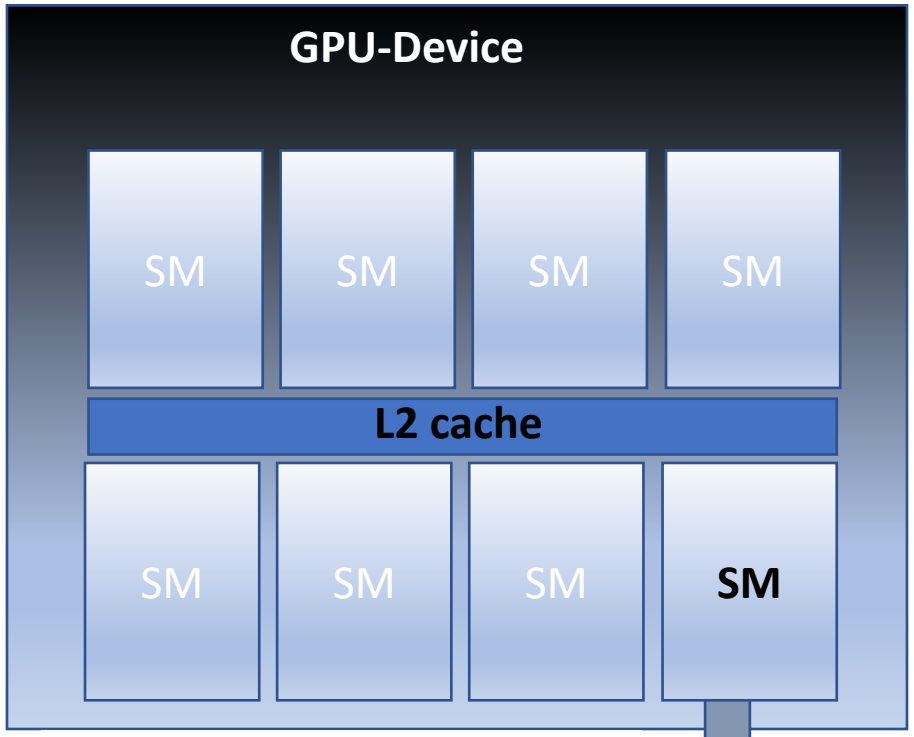
Data are stored temporarily. Registers are private to each thread.

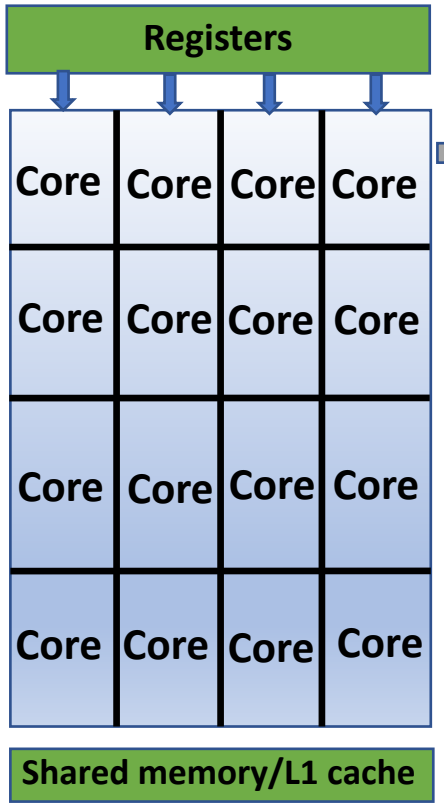


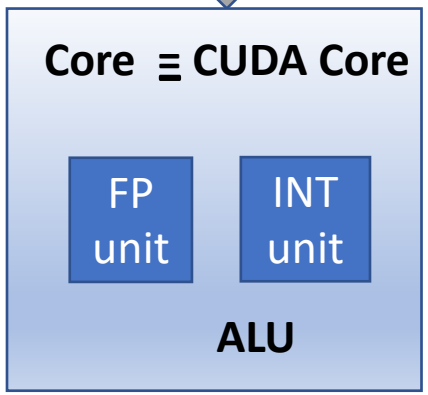
All threads share L1 cache.

- Core includes ALU. Various logical operations for computations (FP32, FP64,) e.g. addition, multiplication and …
- ALU executes SIMD instructions. (processing multiple data with the same operation concurently (in parallel))

Architecture of NVIDIA-GPU devices (simplified version)







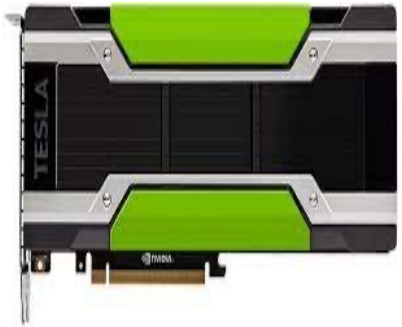
Streaming Multiprocessor (SM)

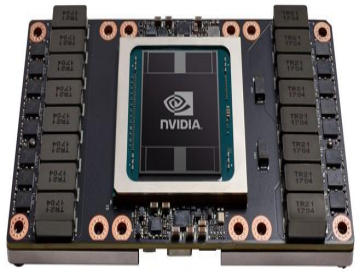
NVIDIA Tesla A100

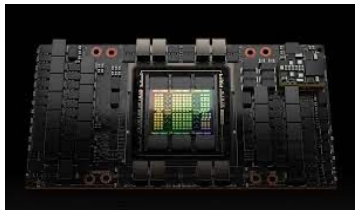
For Tesla A100 GPU: 108 SMs, each SM has:

64 FP32 cores ===== A total of 6912 FP32 CUDA cores
64 INT32 cores ===== A total of 6912 INT32 CUDA cores.

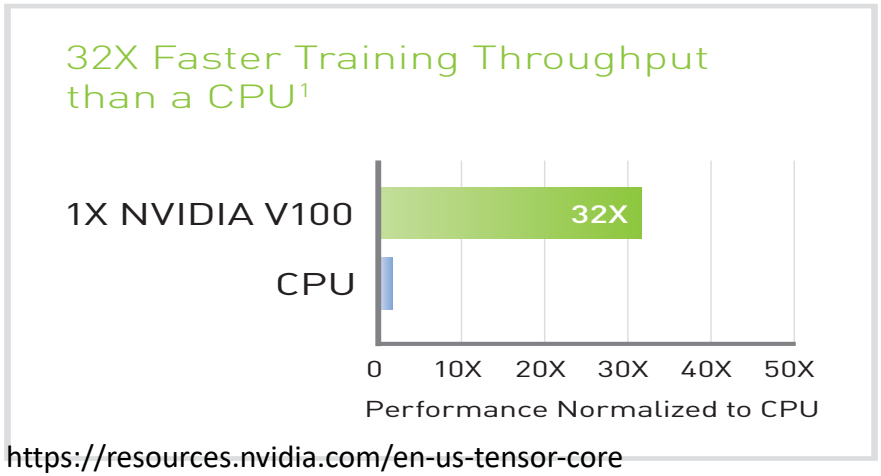
NVIDIA GPU charcteristics







Architecture	NVIDIA P100 (Pascal)	NVIDIA GV100 (Volta)	NVIDIA GA100	NVIDIA GH100
SMs	56	84	128	144
FP32 CUDA cores per SM	64	64	64	128
NVIDIA CUDA cores	3584	5376	8192	18432
Tensor cores/GPU	NA	672	512	576
Peak performance	9.3 TFLOPS	15.7 TFLOPS	39 TFLOPS	66.9 TFLOPS
Transistors	15.3 billion	21.1 billion	54.2 billion	80 billion



https://resources.nvidia.com/en-us-tensor-core

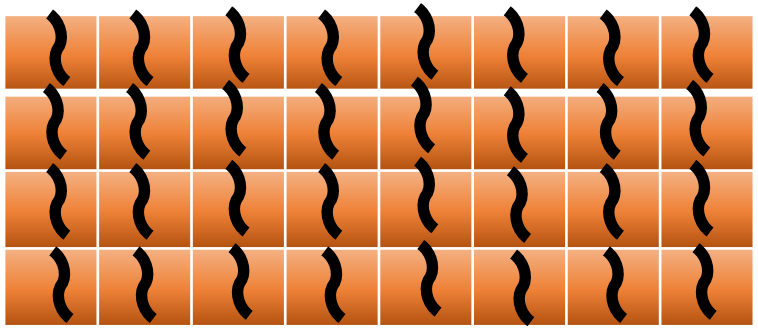
Execution on GPU

Software scheme

Hardware scheme

CUDA thread
(a full warp)

CUDA core



CUDA block

1024 threads

32 warps

is executed on

core core core
core core core

Streaming Multiprocessor (SM)

Grid of gangs
(CUDA kernel grid)

CUDA block | CUDA block | CUDA block | CUDA block

CUDA block | CUDA block | CUDA block | **CUDA block**

GPU-Device

SM SM SM SM

SM SM SM **SM**

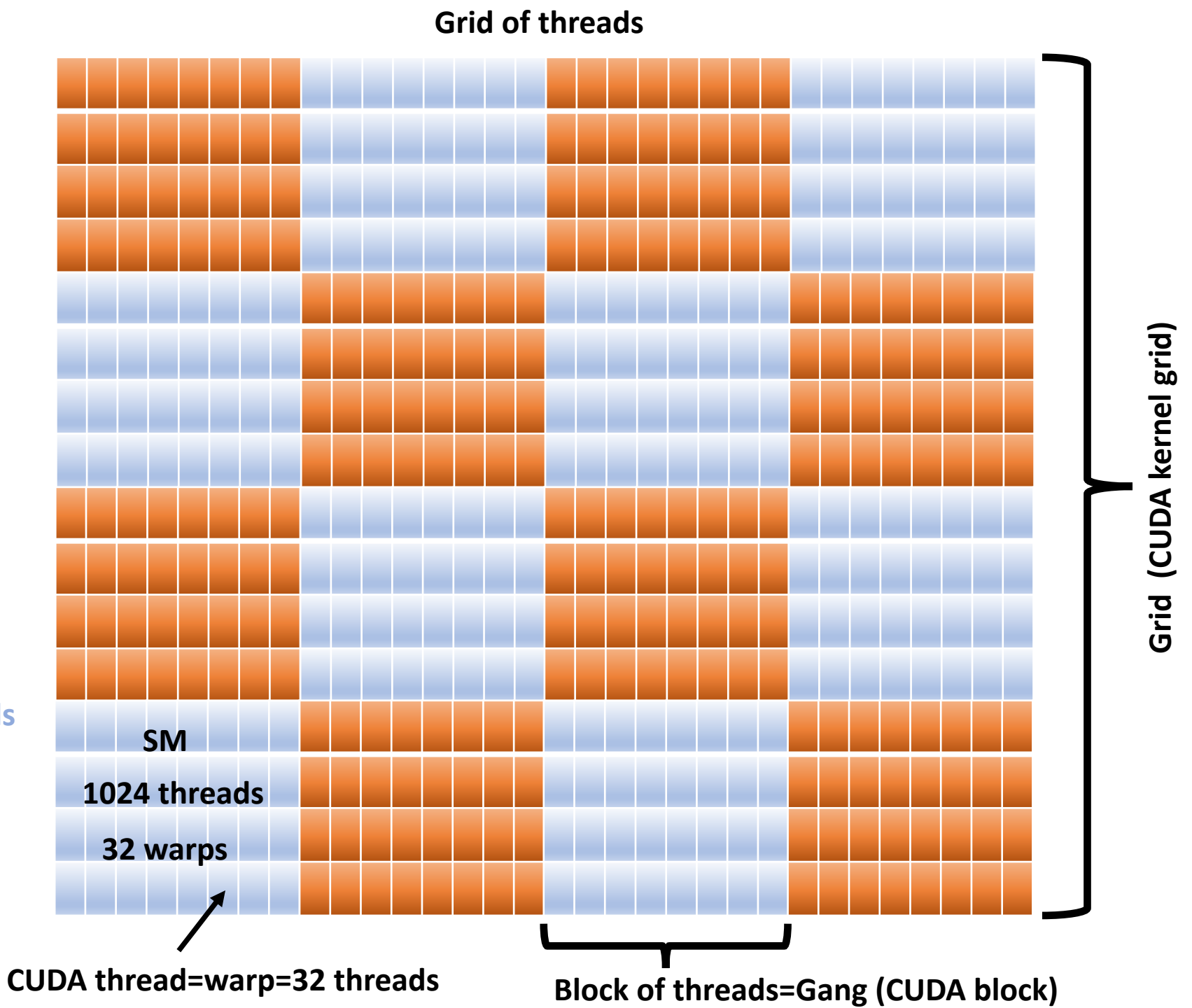
Mapping a matrix into a GPU-device

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

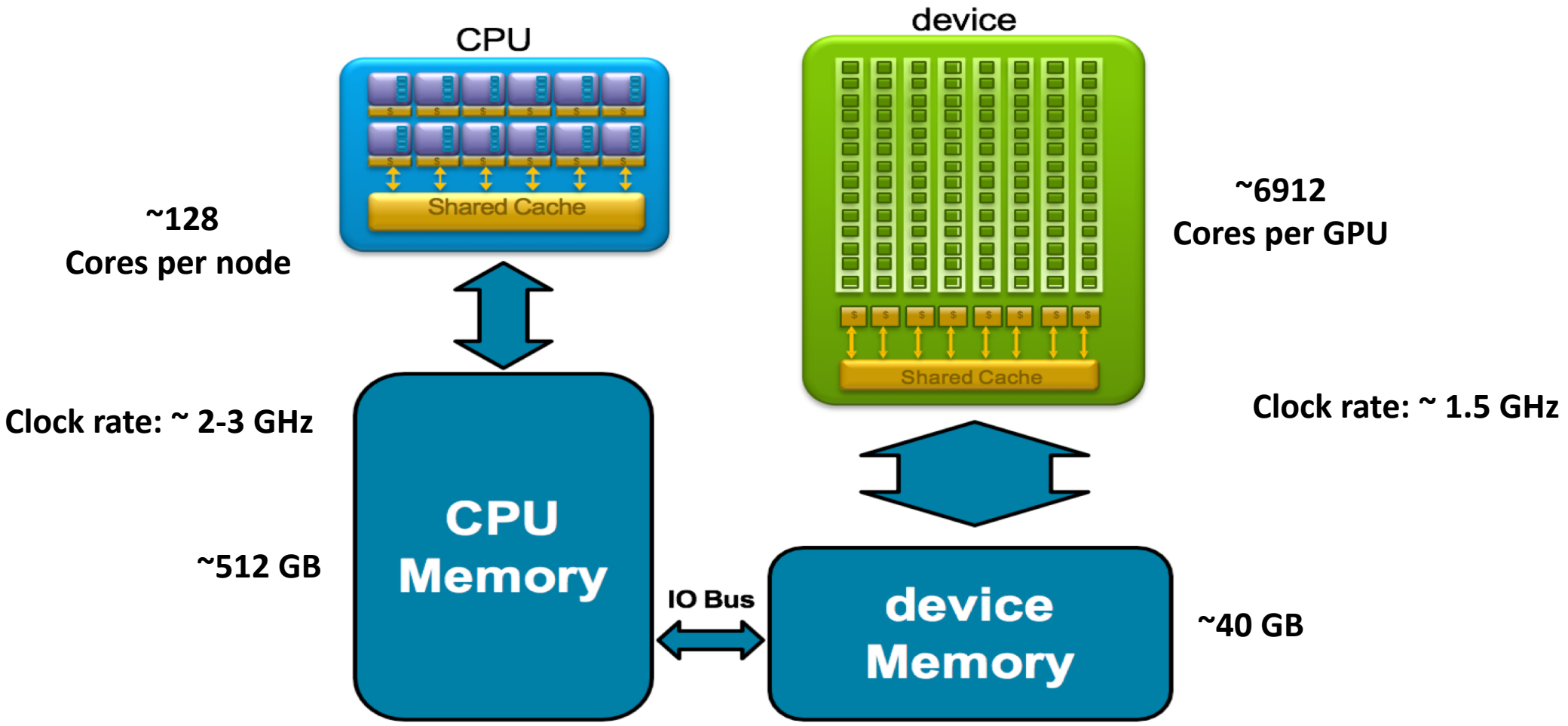
Each thread executes a different piece
Of data item (data parallelism).

Each CUDA block has 1024 threads
(32 warps. A warp=collection of 32 threads
are executed simultaneously by a SM)

Execution on hardware
CUDA thread
CUDA block
CUDA grid



CPU vs GPU



Adapted from NVIDIA

High troughput
Low latency

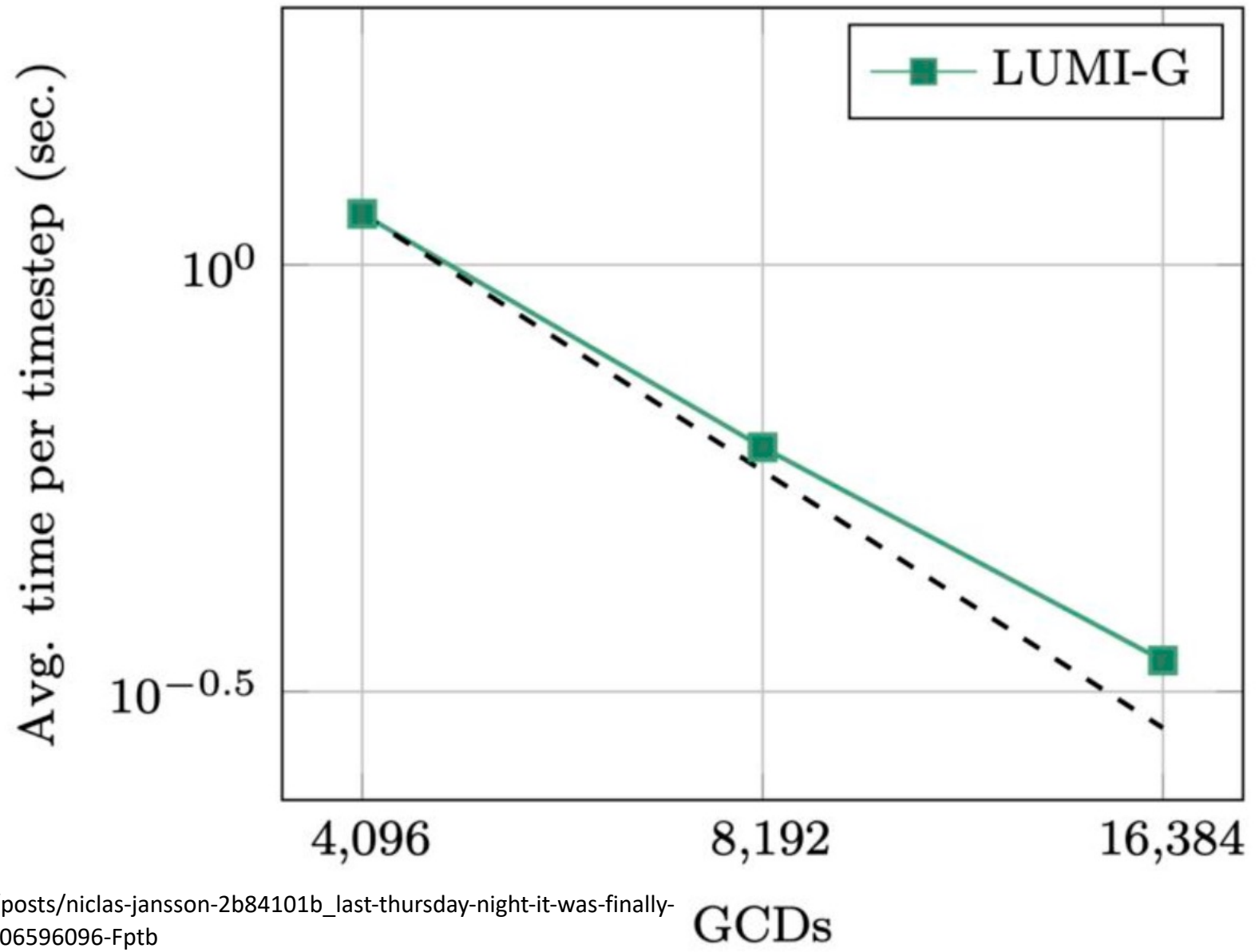
Scaling analysis

nodes	GPUs	execution time	speed-up ratio	parallel efficiency
1	1	212	1.0	100%
1	2	140	1.5	75%
1	3	110	1.9	64%
1	4	105	2.0	50%
2	8	145	1.5	18%

https://researchcomputing.princeton.edu/support/knowledge-base/scaling-analysis#gpus

Scaling analysis

nodes	G	ciency
1		
1		
1		
1		
2		



'scaling-analysis#gpus

https://www.linkedin.com/posts/niclas-jansson-2b84101b_last-thursday-night-it-was-finally-time-activity-7008055581806596096-Fptb

Basic tools for GPU-usage

Basic NVIDIA tools

$nvidia-smi

$nvidia-smi stats

$nvidia-smi dmon

Demo

Basic tools for viewing GPU-usage

Overview of GPU-usage: $nvidia-smi

```
[hicham@c7-8 ~]$ nvidia-smi
Sun Jan  8 17:53:37 2023
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 515.43.04    Driver Version: 515.43.04    CUDA Version: 11.7     |
|-------------------------------+----------------------+----------------------+
| 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 P100-PCIE...  Off  | 00000000:39:00.0 Off |                    0 |
| N/A   28C    P0    33W / 250W |    325MiB / 16384MiB |     39%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A     43560      C   python                           323MiB |
+-----------------------------------------------------------------------------+
```

	Value	Description
Driver Version	515.43.04	
CUDA Version	11.7	
GPU	0	GPU index
Name	Tesla P100	GPU name
Temp	28C	GPU-Temperature
Perf	P0	GPU-Performance
Persistance-M	Off	Persistance mode
Pwr:Usage/Cap	33W/250W	Ratio of GPU-Power usage
Bus-Id	00000000:39:00.0	
Disp.A	Off	Display active
Mem Usage	325/16384 MiB	Memory used
Volatile Uncorr.ECC	0	Counter Uncorrelated error
GPU-Util	39%	GPU utilisation
Compute M.	Default	Compute memory

See e.g. https://nvidia.custhelp.com/app/answers/detail/a_id/3751/~/useful-nvidia-smi-queries

https://medium.com/analytics-vidhya/explained-output-of-nvidia-smi-utility-fc4fbee3b124

Basic tools for viewing GPU-usage

Device statistic: $nvidia-smi stats

$nvidia-smi stats -d gpuUtil

```
0, gpuUtil , 1673214742538187, 0
0, gpuUtil , 1673214743709403, 0
0, gpuUtil , 1673214743876909, 0
0, gpuUtil , 1673214744044158, 0
0, gpuUtil , 1673214744211676, 8
0, gpuUtil , 1673214744379109, 4
0, gpuUtil , 1673214744546360, 0
0, gpuUtil , 1673214744713449, 13
0, gpuUtil , 1673214744880577, 57
0, gpuUtil , 1673214745047676, 46
0, gpuUtil , 1673214745214772, 0
0, gpuUtil , 1673214745381932, 60
0, gpuUtil , 1673214745549000, 68
0, gpuUtil , 1673214745716307, 0
0, gpuUtil , 1673214745883405, 0
0, gpuUtil , 1673214746050521, 69
0, gpuUtil , 1673214746217605, 59
0, gpuUtil , 1673214746384700, 0
0, gpuUtil , 1673214746551961, 9
0, gpuUtil , 1673214746718809, 87
0, gpuUtil , 1673214746885861, 32
0, gpuUtil , 1673214747052886, 0
0, gpuUtil , 1673214747219955, 22
0, gpuUtil , 1673214747387022, 82
0, gpuUtil , 1673214747554122, 23
0, gpuUtil , 1673214747721127, 0
0, gpuUtil , 1673214747888199, 65
0, gpuUtil , 1673214748055238, 62
0, gpuUtil , 1673214748222243, 0
0, gpuUtil , 1673214748389417, 0
0, gpuUtil , 1673214748556383, 80
```

To display

GPU utilisation
&
Memory utilisation

$nvidia-smi stats -d memUtil

```
0, memUtil , 1673214794670094, 0
0, memUtil , 1673214794837087, 0
0, memUtil , 1673214795004095, 0
0, memUtil , 1673214795171159, 0
0, memUtil , 1673214795338176, 3
0, memUtil , 1673214795505181, 0
0, memUtil , 1673214795672219, 0
0, memUtil , 1673214795839287, 8
0, memUtil , 1673214796006305, 25
0, memUtil , 1673214796175765, 11
0, memUtil , 1673214796342801, 0
0, memUtil , 1673214796509822, 26
0, memUtil , 1673214796676819, 20
0, memUtil , 1673214796843886, 0
0, memUtil , 1673214797010928, 0
0, memUtil , 1673214797177935, 30
0, memUtil , 1673214797344972, 16
0, memUtil , 1673214797511999, 0
0, memUtil , 1673214797679049, 6
0, memUtil , 1673214797846118, 29
0, memUtil , 1673214798013127, 10
0, memUtil , 1673214798180164, 0
0, memUtil , 1673214798347203, 15
0, memUtil , 1673214798514211, 31
0, memUtil , 1673214798681248, 0
0, memUtil , 1673214798848289, 4
0, memUtil , 1673214799015297, 30
0, memUtil , 1673214799182335, 11
0, memUtil , 1673214799349448, 0
0, memUtil , 1673214799516412, 11
0, memUtil , 1673214799683451, 30
```

To display more information: **”$nvidia-smi stats -h"**

Basic tools for viewing GPU-usage

Device monitoring: $nvidia-smi dmon

```
[hicham@c7-8 ~]$ nvidia-smi dmon
# gpu    pwr  gtemp  mtemp     sm    mem    enc    dec   mclk   pclk
# Idx      W      C      C      %      %      %      %    MHz    MHz
    0     31     28      -      9      0      0      0    715   1189
    0     31     28      -      0      0      0      0    715   1189
    0     31     28      -      0      0      0      0    715   1189
    0     26     28      -      0      0      0      0    715    455
    0     26     28      -      0      0      0      0    715    455
    0     30     28      -      2      0      0      0    715   1189
    0     31     28      -      8      4      0      0    715   1189
    0    173     30      -     32     13      0      0    715   1328
    0     36     30      -      3      1      0      0    715   1328
    0    164     31      -     77     31      0      0    715   1328
    0    137     30      -      0      0      0      0    715   1328
    0     37     30      -     43     17      0      0    715   1328
    0    183     32      -     46     19      0      0    715   1328
    0     36     30      -      0      0      0      0    715   1328
    0     37     31      -     88     35      0      0    715   1328
    0    157     33      -     34     14      0      0    715   1328
    0     36     31      -      0      0      0      0    715   1328
    0     37     32      -     84     34      0      0    715   1328
    0    160     33      -     36     14      0      0    715   1328
    0     37     31      -      0      0      0      0    715   1328
    0     37     32      -     84     33      0      0    715   1328
    0    109     33      -     83     32      0      0    715   1328
    0     36     31      -      0      0      0      0    715   1328
```

SM: Streaming Multiprocessor

Select GPU ultilisation

$**nvidia-smi pmon -s u**

Select memory usage

$**nvidia-smi pmon -s m**

Display more information

$**nvidia-smi pmon -h**

DEMO

How to access GPU metrics in **HPC systems** using the command-line **nvidia-smi**

Method 1

The command **nvidia-smi** is available from a **GPU node**:

- Login to Betzy cluster: **$ssh username@betzy.sigma2.no**
- Identify GPU partitions: **$sinfo –p accel**
- Submit a job: **$sbatch job.slurm**
- Which node: **$squeue –u username**
- ssh to the node e.g. **$ssh b5304**
- Run the command: **$nvidia-smi**
- For more options: **$nvidia-smi -h**

Method 2

Run the command **nvidia-smi** interactively

- Submit a job: **$sbatch job.slurm**
- Copy paste the **JobID** to the syntax below:

```
$for j in {1..10}; do srun --jobid=JobID
--interactive --pty nvidia-smi; sleep 2; done
```

Profiling Deep Learning with PyTorch Profiler

- What is PyTorch Profiler ?
- How to setup PyTorch Profiler

- **Demo**: How to use PyTorch Profiler?

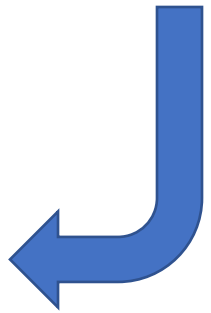
What is PyTorch Profiler ?

- Advanced tool for analysing Deep Learning models.
- Dynamical tool built inside PyTorch.
- Collection of metrics during training and inference.
  - GPU usage
  - Tensor cores usage
  - GPU Kernel view
  - Memory view
  - Trace view

View in a web browser

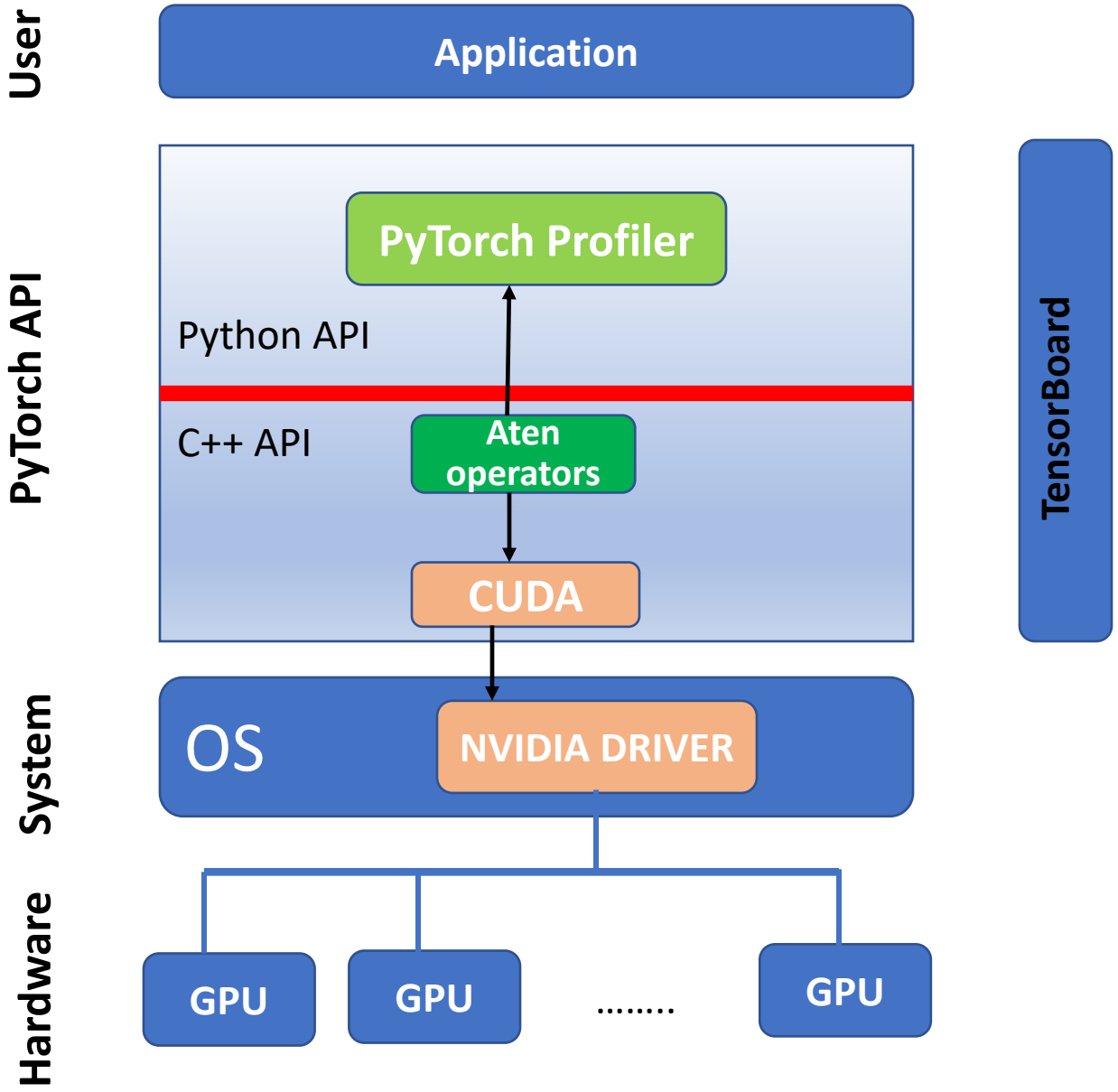
Identify bottelnecks [memory and GPU]

Identify functions that use the majority of time



Improve Performance

Architecture of PyTorch Profiler (simplified version)



Adapted from https://www.youtube.com/watch?v=m6ouC0XMYnc&ab_channel=PyTorch [see slide at 23:00 min]

Setup in HPC systems:

Setup in HPC systems:

Installing PyTorch

- **Method 1**: Loading a module
- **Method 2**: Virtual environment
- **Method 3**: Singularity container

Installing TensorBoard Plugin

```
$ python –m pip install torch_tb_profiler
```

Setup in HPC systems:

- **Method 3**: Singularity container

- **Pull the PyTorch container image**

e.g. from NVIDIA NGC container:
https://catalog.ngc.nvidia.com/orgs/nvidia/containers/pytorch
[the host system must have the CUDA driver installed and the container must have CUDA]

$singularity pull docker://nvcr.io/nvidia/pytorch:22.12-py3

- **Launch singularity container**

$singularity exec --nv pytorch_22.12-py3.sif python main.py

NVIDIA PyTorch container contains the following software:

- CUDA
- cuBLAS
- NVIDIA cuDNN
- NVIDIA NCCL (optimized for NVLink)
- RAPIDS
- NVIDIA Data Loading Library (DALI)
- TensorRT
- Torch-TensorRT

https://catalog.ngc.nvidia.com/orgs/nvidia/containers/pytorch

Setup in HPC systems:

Installating TensorBord in a virtual environment

Step0: load a python model, create & activate Virt. Env.

Find a python module: $module avail python

Load a python module .e.g.:

$module load Python/3.9.6-GCCcore-11.2.0

$mkdir Myenv

$python –m venv Myenv

$source Myenv/bin/activate

Step1: Install via pip wheel packages

Install PyTorch Profiler TensorBoard Plugin:

$python –m pip install torch_tb_profiler

DEMO:Profling a Resnet 18 model

DEMO:Profling a Resnet 18 model

```
with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA],
    schedule=torch.profiler.schedule(
        wait=1,
        warmup=1,
        active=2),
    on_trace_ready=torch.profiler.tensorboard_trace_handler('./out', worker_name='profiler'),
    record_shapes=True,
    profile_memory=True,
    with_stack=True
) as prof:
```

Lines of code to enable profiling with PyTorch Profiler

Output of profiling will be saved In ./out directory

```
#training step for each batch of input data
    for step, data in enumerate(trainloader):
        .
        .
        .
      if step +1>= 10:
          break
      prof.step()
```

Training loop

https://pytorch.org/tutorials/intermediate/tensorboard_profiler_tutorial.html

Submit an application: $sbatch job.slurm

```
#!/bin/bash -l
#SBATCH --job-name=pyt-profiler
#SBATCH --account=nn9987k
#SBATCH --time=00:10:00
#SBATCH --partition=accel
#SBATCH --nodes=1          #nbr of nodes
#SBATCH --ntasks=1         #nbr of tasks
#SBATCH --cpus-per-task=1 #nbr of threads (or cores)
#SBATCH --gpus=1           #total nbr of gpus
#SBATCH --gpus-per-node=1 #nbr of gpus per node
#SBATCH --mem=4G           #main memory
#SBATCH -o PyTprofiler.out

#define paths
Mydir=/cluster/projects/nn9987k/PyTorchProfiler
MyContainer=${Mydir}/Container/pytorch_22.12-py3.sif
MyExp=${Mydir}/examples

#specify bind paths by setting the environment variable
export SINGULARITY_BIND="${MyExp},$PWD"

#TF32 is enabled by default in the NVIDIA NGC TensorFlow and PyTorch containers
#To disable TF32 set the environment variable to 0
export NVIDIA_TF32_OVERRIDE=0

#to run singularity container
singularity exec --nv ${MyContainer} python3 ${MyExp}/resnet18_profiler_api.py

echo
echo "--Job ID:" $SLURM_JOB_ID
echo "--total nbr of gpus" $SLURM_GPUS
```

Viewing with Tensorboard plugin

Viewing with Tensorboard plugin

1- Load a python module, e.g.:

$module load Python/3.9.6-GCCcore-11.2.0

2- Activate the virtual environment:

$source Myenv/bin/activate

3- Launch the TensorBoard Plugin:

$tensorboard --logdir=./out --bind_all

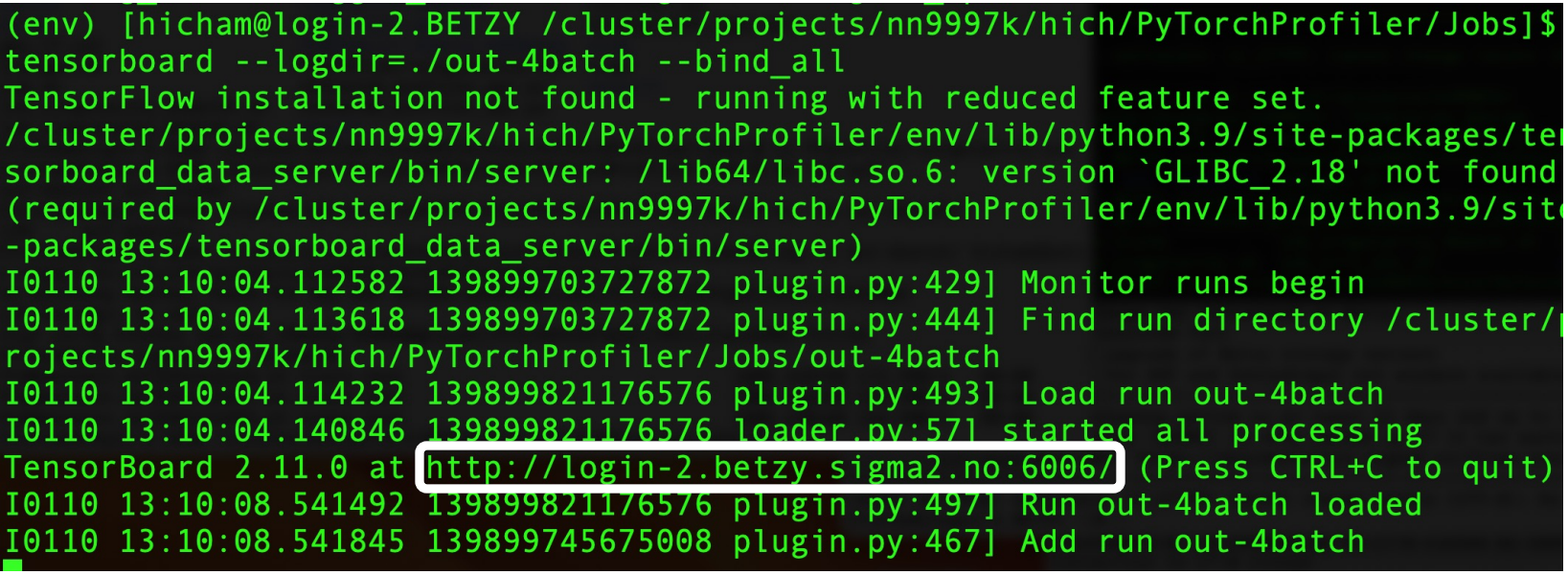
TensorBoard 2.11.0 at http://login-2.betzy.sigma2.no:6006/

4- Open a new terminal for local port forwarding

$ssh -L 6006:login-2.betzy.sigma2.no:6006 user@betzy.sigma2.no

5- View on a browser [chrome, firefox]

http://localhost:6006/



GPU Usage View

TensorBoard PYTORCH_PROFILER INACTIVE UPLOAD

NORMAL DIFF

Runs

Xresult

Views

Overview

Workers

worker0

Spans

1

Configuration

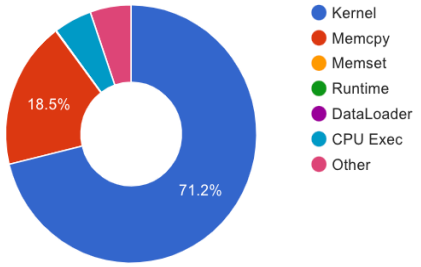
Number of Worker(s)	1
Device Type	GPU

GPU Summary

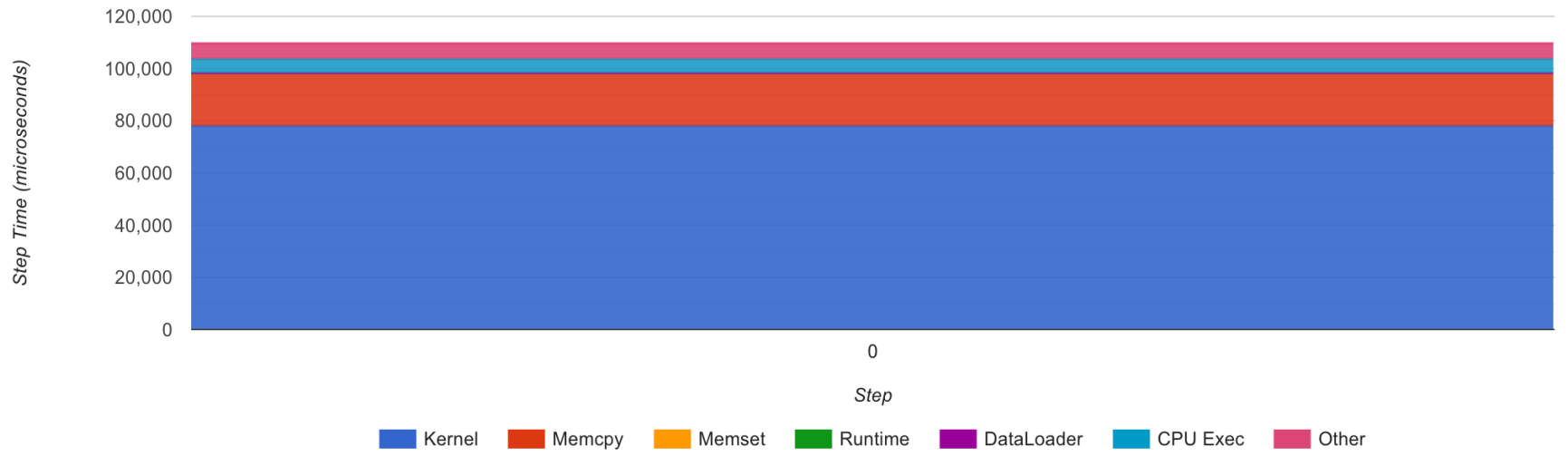
GPU 0:	
Name	Tesla P100-PCIE-16GB
Memory	15.9 GB
Compute Capability	6.0
GPU Utilization	71.23 %
Est. SM Efficiency	70.04 %
Est. Achieved Occupancy	44.79 %

Execution Summary

Category	Time Duration (us)	Percentage (%)
Average Step Time	109,570	100
Kernel	78,052	71.23
Memcpy	20,258	18.49
Memset	67	0.06
Runtime	0	0
DataLoader	0	0
CPU Exec	5,391	4.92
Other	5,802	5.3



Step Time Breakdown



GPU Kernel View

TensorBoard PYTORCH_PROFILER INACTIVE UPLOAD

NORMAL DIFF

Runs

Xresult

Views

GPU Kernel

Workers

worker0

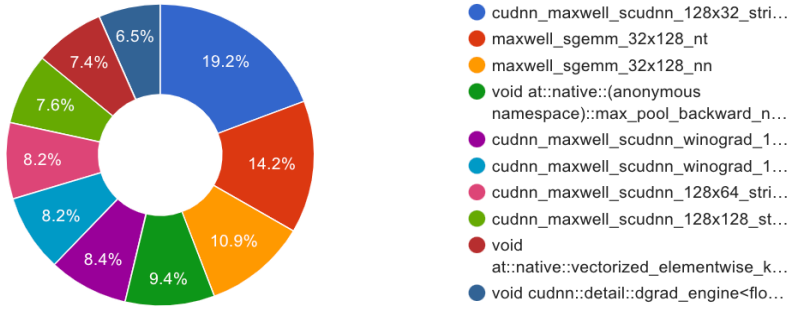
Spans

1

Kernel View

All kernels Top kernels to show 10

Total Time (us)



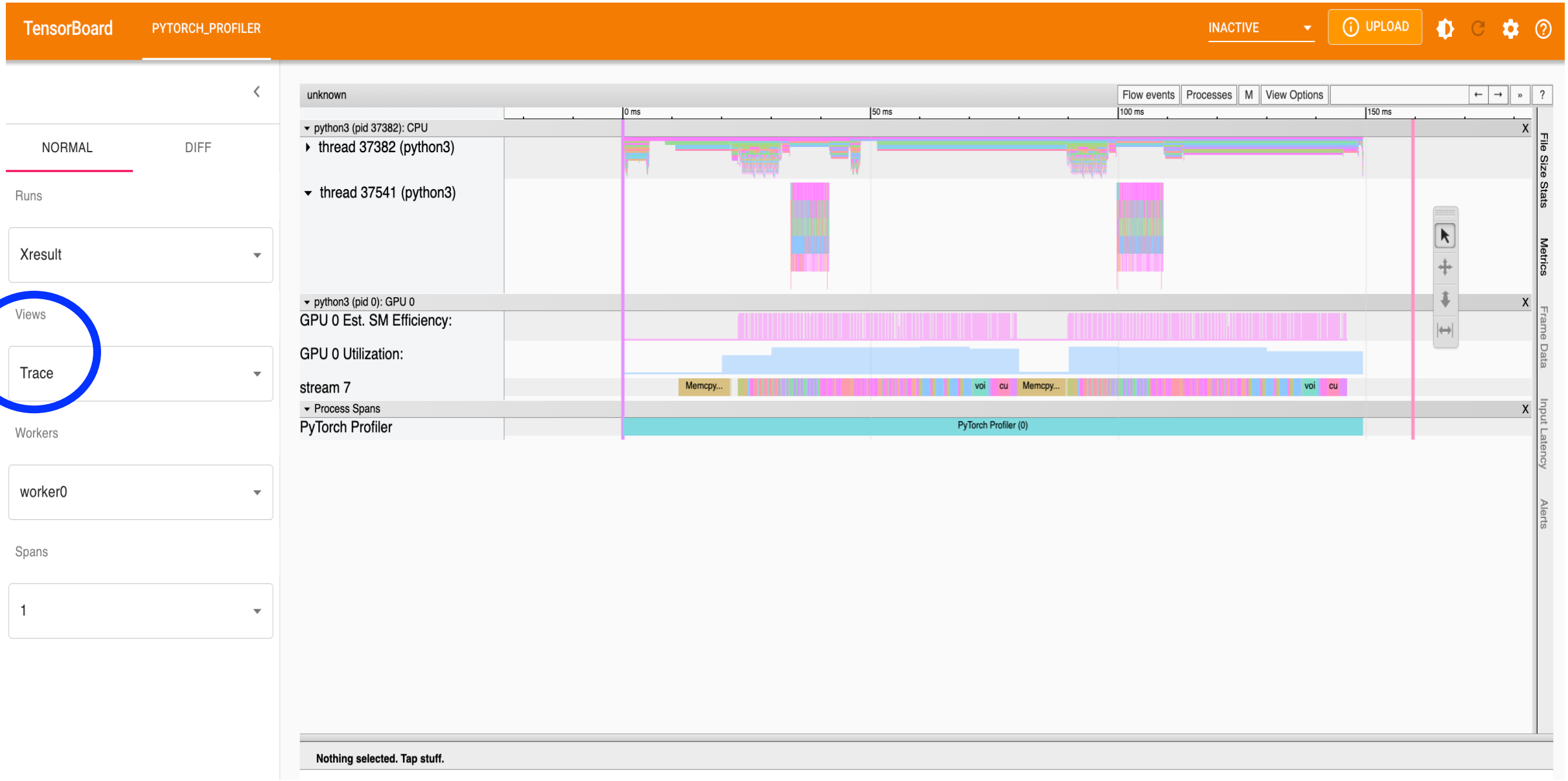
Tensor Cores Utilization

Group By Kernel Name

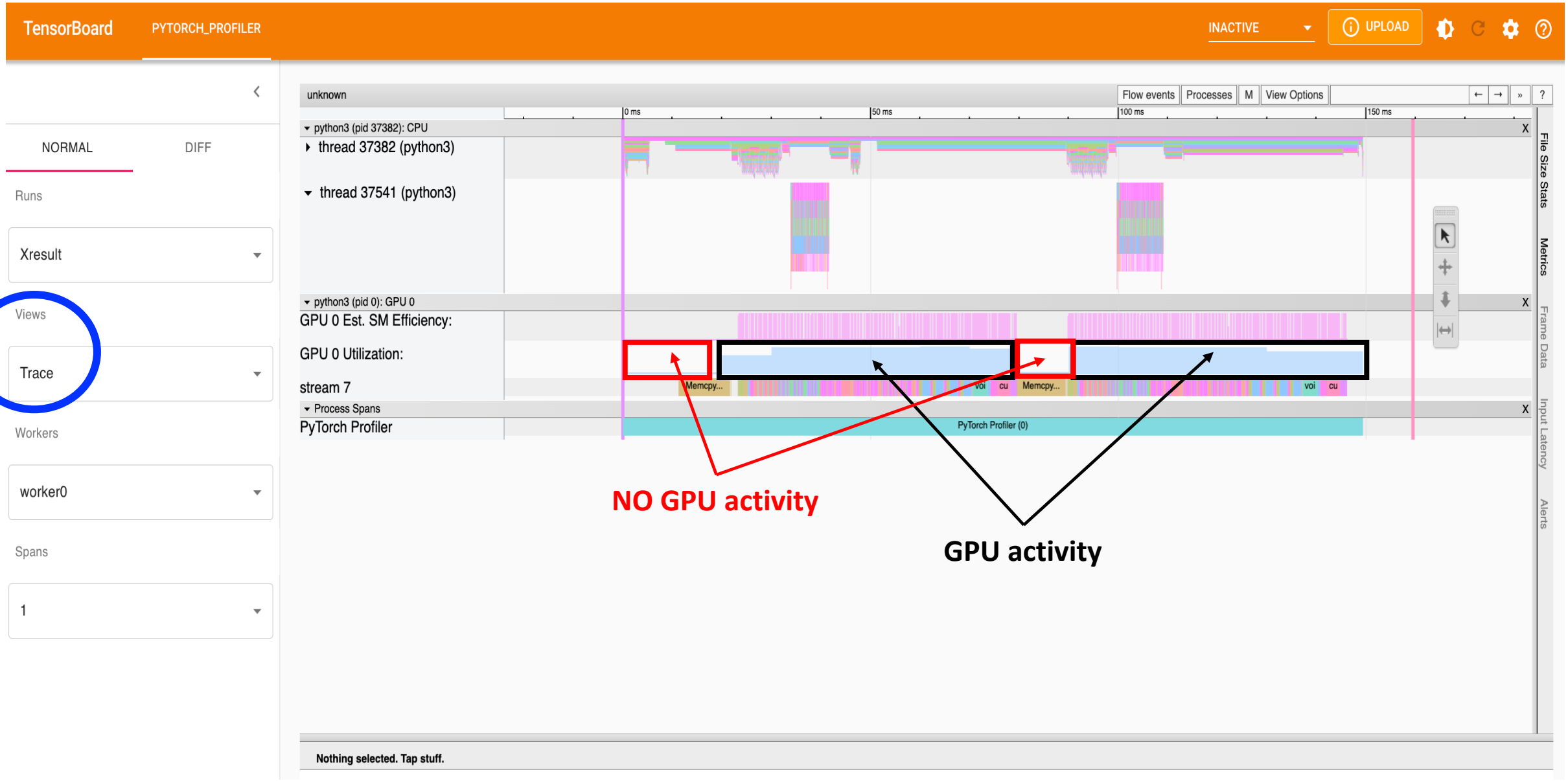
Search by Kernel Name

Name	Tensor Cores Used	Calls	Total Duration (us)	Mean Duration (us)	Max Duration (us)	Min Duration (us)	Mean Blocks Per SM	Mean Est. Achieved Occupancy (%)
cudnn_maxwell_scudnn_128x32_stridedB_splitK_medium_nn_v0	No	8	12302	1538	1548	1521	10	31
maxwell_sgemm_32x128_nt	No	24	9091	379	422	326	23.44	50
maxwell_sgemm_32x128_nn	No	18	6977	388	436	340	20.11	50
void at::native::(anonymous namespace)::max_pool_backward_nchw<float, float>(float const*, long const*, int, long, long, long, int, int, int, int, int, int, int, int, int, float*)	No	2	6009	3004	3005	3004	1792	100
cudnn_maxwell_scudnn_winograd_128x128_ldg1_ldg4_relu_tile148m_nt_v1	No	8	5373	672	681	657	32	25
cudnn_maxwell_scudnn_winograd_128x128_ldg1_ldg4_mobile_relu_tile148t_nt_v0	No	8	5282	660	671	646	32	25
cudnn_maxwell_scudnn_128x64_stridedB_splitK_large_nn_v0	No	2	5235	2618	2618	2617	4	25
cudnn_maxwell_scudnn_128x128_stridedB_splitK_medium_nn_v0	No	8	4888	611	736	413	4.43	11.81

Trace View


TensorBoard
PYTORCH_PROFILER
INACTIVE
UPLOAD
NORMAL
DIFF
Runs
Xresult
Views
Trace
Workers
worker0
Spans
1
unknown
Flow events
Processes
M
View Options
0 ms
50 ms
100 ms
150 ms
python3 (pid 37382): CPU
thread 37382 (python3)
thread 37541 (python3)
python3 (pid 0): GPU 0
GPU 0 Est. SM Efficiency:
GPU 0 Utilization:
stream 7
Memcpy...
voi
cu
Memcpy...
voi
cu
Process Spans
PyTorch Profiler
PyTorch Profiler (0)
File Size Stats
Metrics
Frame Data
Input Latency
Alerts
Nothing selected. Tap stuff.

Trace View


TensorBoard
PYTORCH_PROFILER
INACTIVE
UPLOAD
NORMAL
DIFF
Runs
Xresult
Views
Trace
Workers
worker0
Spans
1
unknown
Flow events
Processes
M
View Options
0 ms
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python3 (pid 37382): CPU
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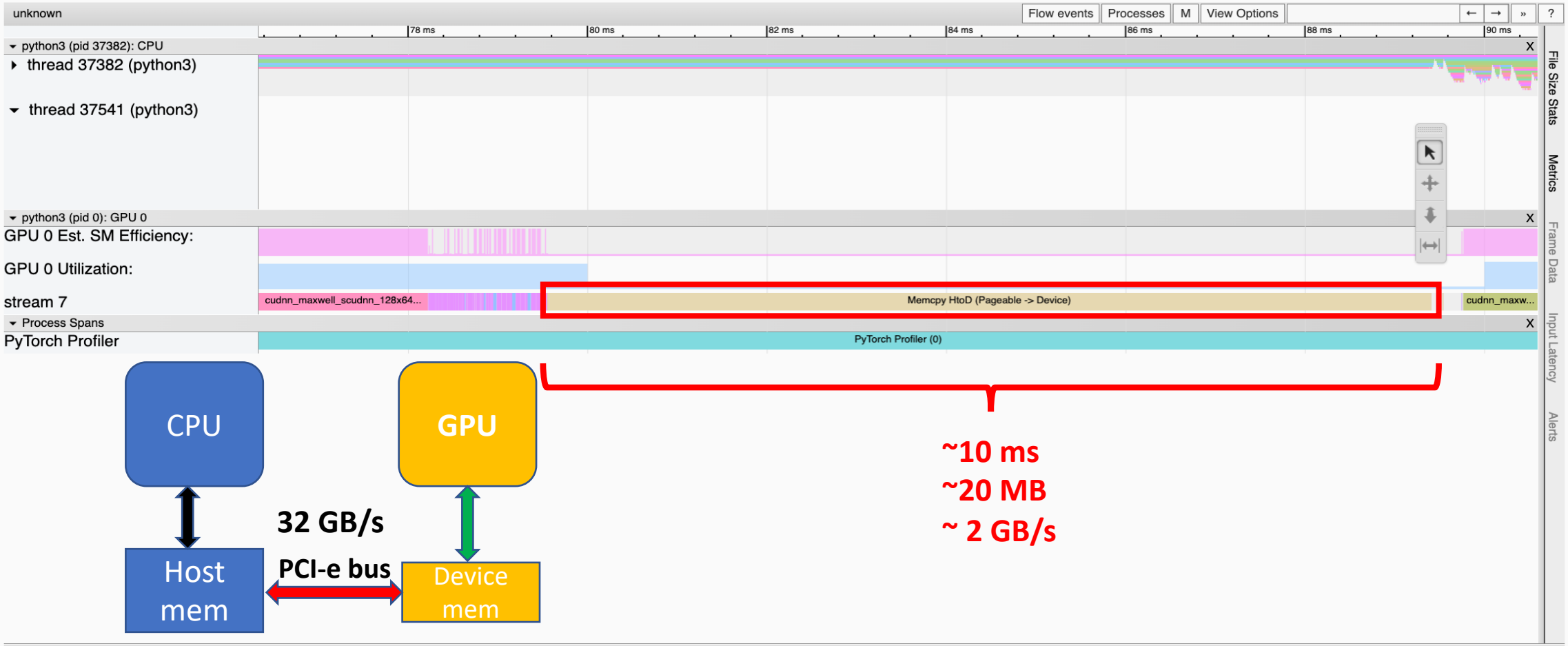
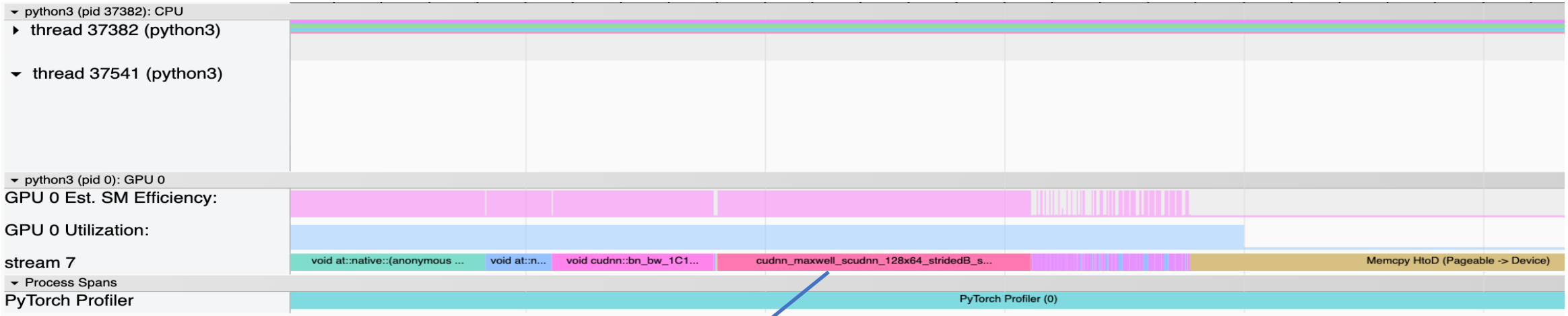
GPU 0 Est. SM Efficiency:
GPU 0 Utilization:
stream 7
Memcpy...
voi
cu
Process Spans
PyTorch Profiler
PyTorch Profiler (0)
File Size Stats
Metrics
Frame Data
Input Latency
Alerts
NO GPU activity
GPU activity
Nothing selected. Tap stuff.

Trace View

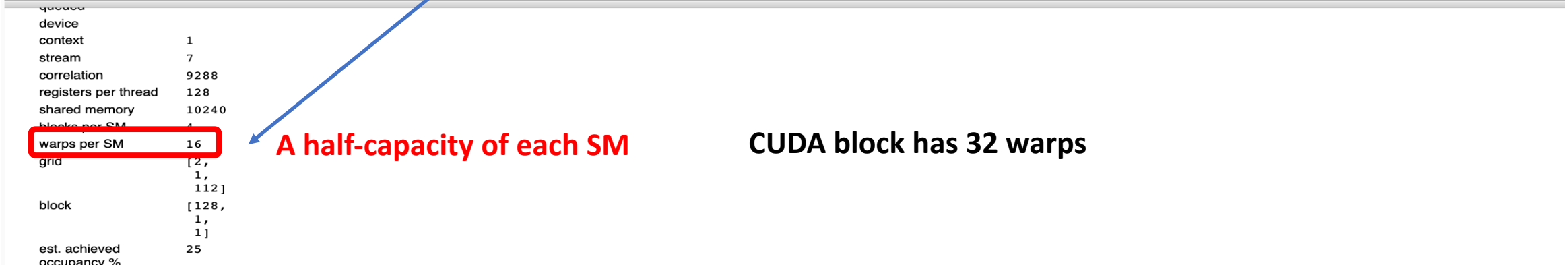


Title	Memcpy HtoD (Pageable -> Device)
Category	gpu_memcpy
User Friendly Category	other
Start	79.550 ms
Wall Duration	9.861 ms
▼Args	
External id	10236
device	
context	1
stream	7
correlation	10236
bytes	19267584
memory bandwidth (GB/s)	1.9537964022721233

Trace View



Cuda stream: a sequence of operations executed on a GPU (in the order)



A half-capacity of each SM

CUDA block has 32 warps

Memory View

TensorBoard PYTORCH_PROFILER INACTIVE UPLOAD

NORMAL DIFF

Runs

Xresult

Views

Memory

Workers

worker0

Spans

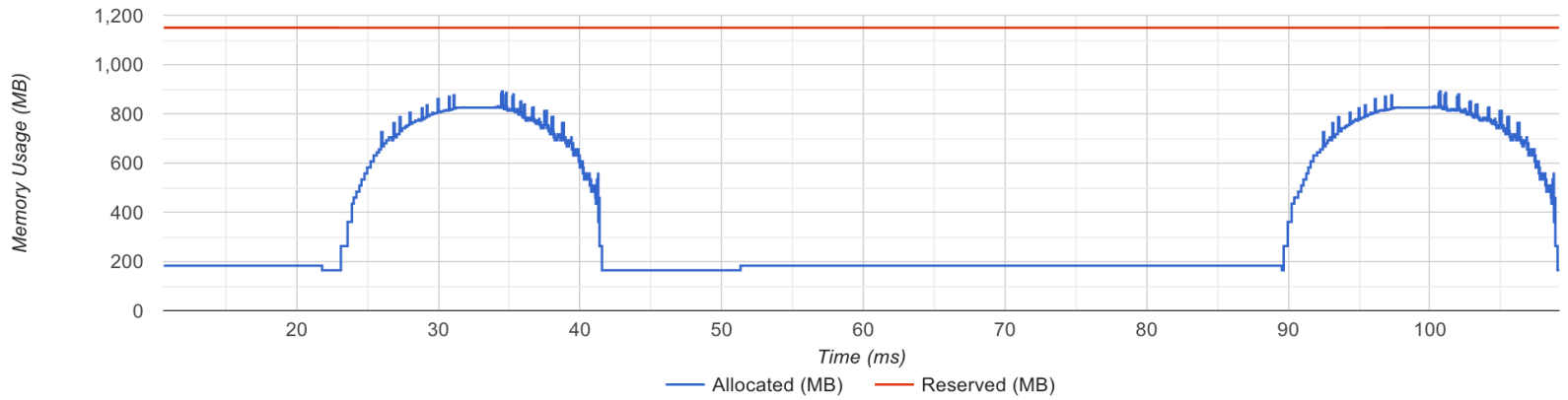
1

Memory View

Device

GPU0

Peak Memory Usage: 891.0MB



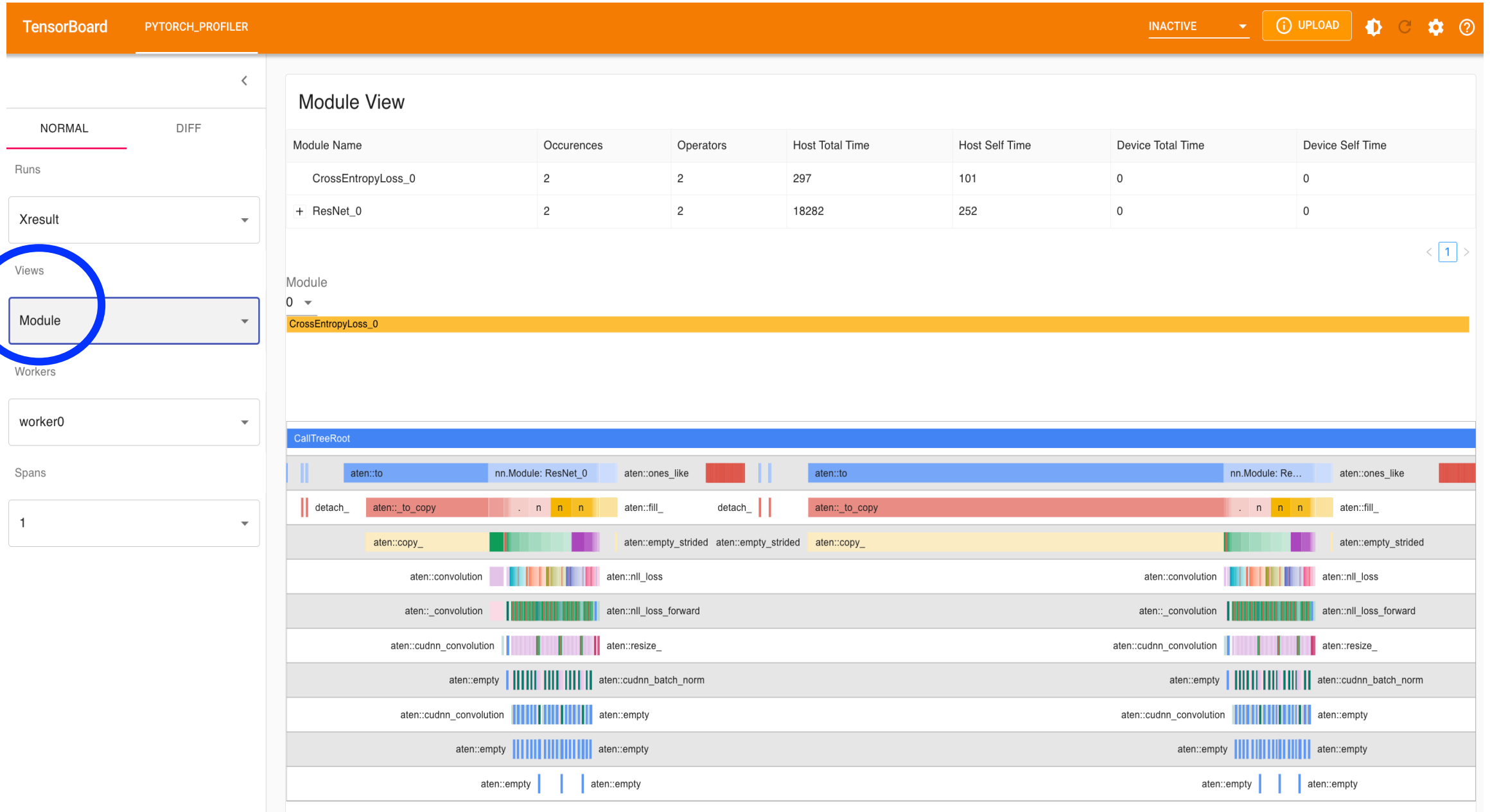
Search by Name

Min Size(KB) 25088

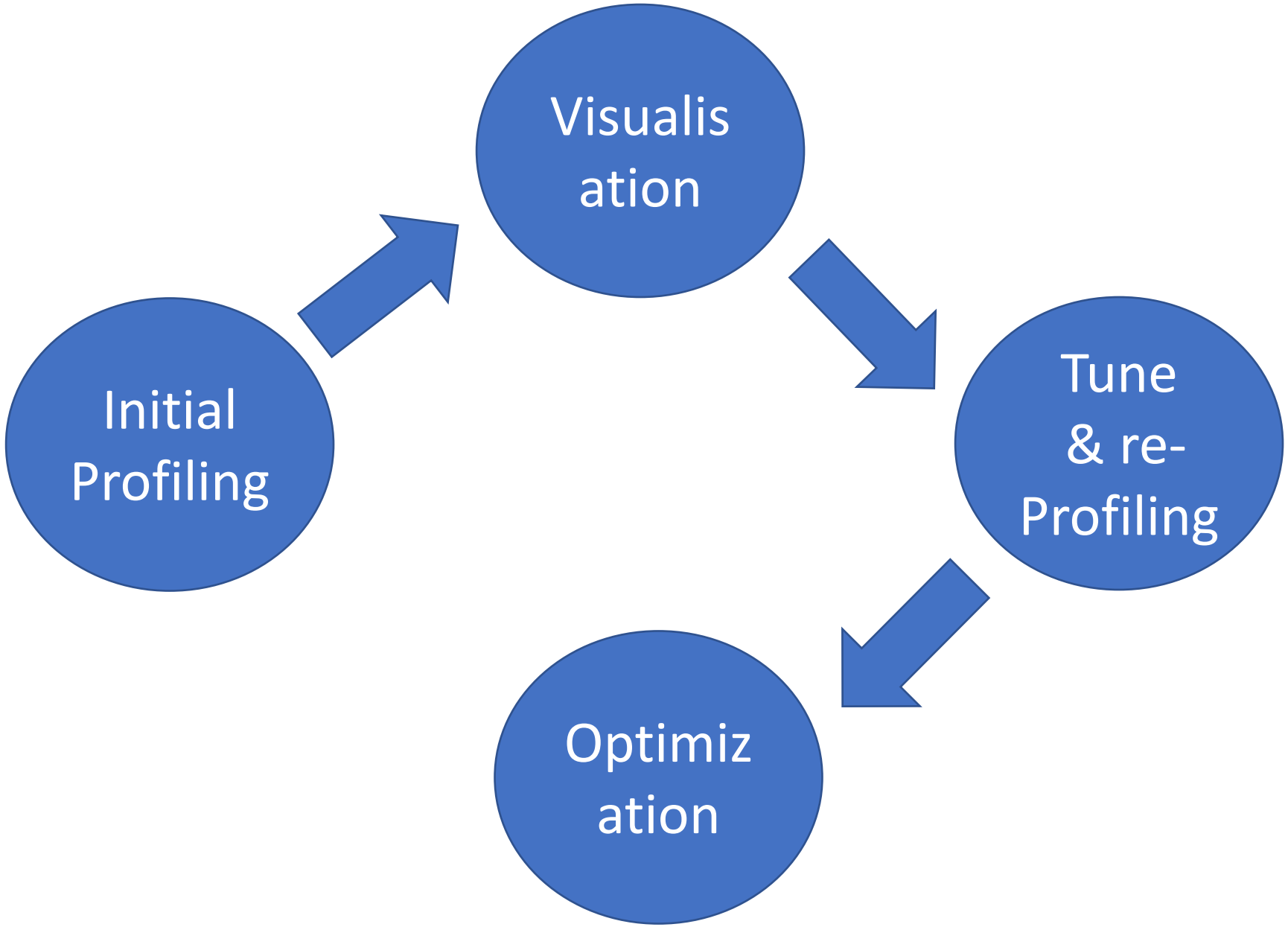
Max Size(KB) 100352

Operator	Size (KB)	Allocation Time (ms)	Release Time (ms)	Duration (ms)
aten::cudnn_convolution	59392	25.97	26.06	0.09
aten::cudnn_convolution	59392	26.84	26.93	0.09
aten::cudnn_convolution	59392	27.27	27.33	0.06
aten::cudnn_convolution	46080	27.97	28.04	0.07
aten::cudnn_convolution	46080	28.84	28.9	0.06
aten::cudnn_convolution	46080	29.18	29.23	0.05
aten::cudnn_convolution	55296	29.96	30.03	0.07
aten::cudnn_convolution	55296	30.75	30.8	0.05
aten::cudnn_convolution	55296	31.08	31.13	0.05

Module View


TensorBoard
PYTORCH_PROFILER
INACTIVE
UPLOAD
NORMAL
DIFF
Runs
Xresult
Views
Module
Workers
worker0
Spans
1
Module View
Module Name
Occurences
Operators
Host Total Time
Host Self Time
Device Total Time
Device Self Time
CrossEntropyLoss_0
2
2
297
101
0
0
ResNet_0
2
2
18282
252
0
0
Module
0
CrossEntropyLoss_0
CallTreeRoot
aten::to
nn.Module: ResNet_0
aten::ones_like
aten::to
nn.Module: Re...
aten::ones_like
detach_
aten::_to_copy
aten::fill_
detach_
aten::_to_copy
aten::fill_
aten::copy_
aten::empty_strided
aten::empty_strided
aten::copy_
aten::empty_strided
aten::convolution
aten::nll_loss
aten::convolution
aten::nll_loss
aten::_convolution
aten::nll_loss_forward
aten::_convolution
aten::nll_loss_forward
aten::cudnn_convolution
aten::resize_
aten::cudnn_convolution
aten::resize_
aten::empty
aten::cudnn_batch_norm
aten::empty
aten::cudnn_batch_norm
aten::cudnn_convolution
aten::empty
aten::cudnn_convolution
aten::empty
aten::empty
aten::empty
aten::empty
aten::empty
aten::empty
aten::empty

Cycle of Profiling



Conclusion

Conclusion

- Basic understanding of GPU architecture.
- Profiling analysis becomes necessary.
  - Identify bottlenecks.
  - Improve the performance.
  - Well-utilisation of GPUs.
- Scaling analysis.

I stop HERE