

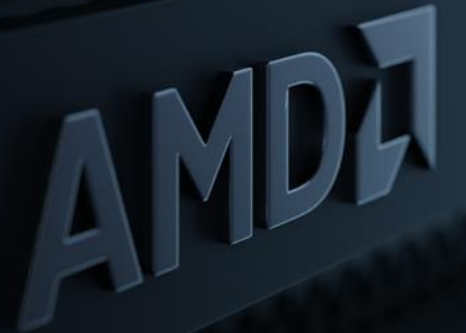


Understanding GPU activity & checking jobs

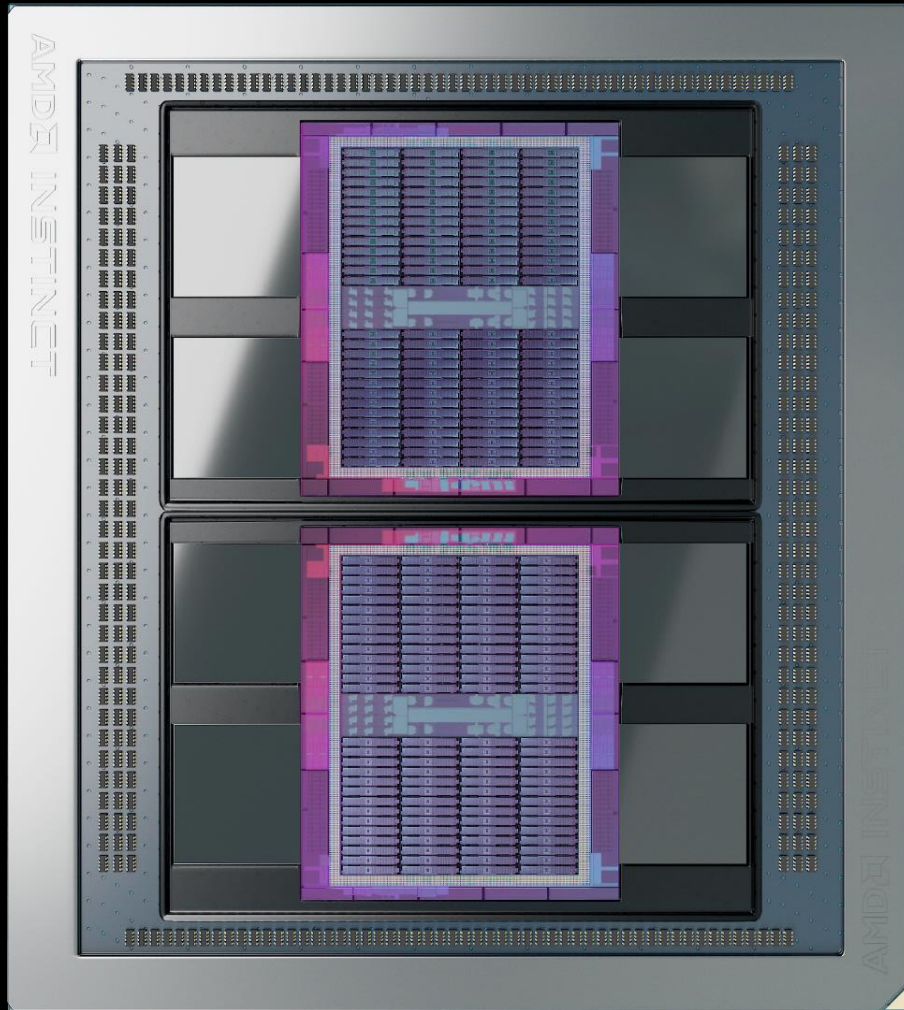
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LUMI AI Workshop

Helsinki, Finland, Feb. 4-5th, 2025



AMD Instinct™ GPUs



AMD INSTINCT™ MI250X

TWO COMPUTE CHIPLETS – 2 GCDs

58B

Transistors in 6nm

220

Compute Units

880

2nd Gen Matrix Cores

128

GB HBM2E @ 3.2 TB/s

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

AMD Instinct™ GPUs

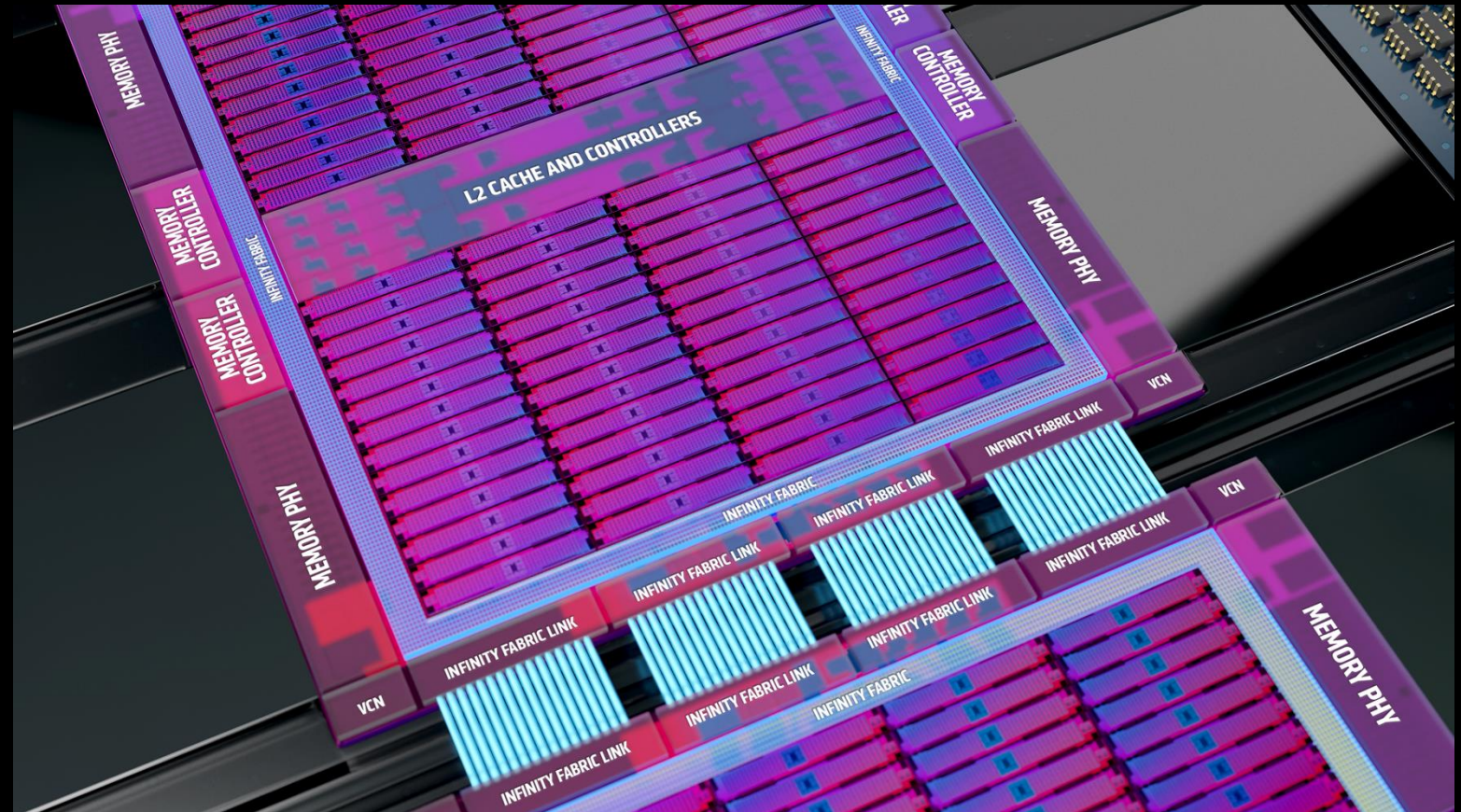
MULTI-CHIP DESIGN

TWO GPU DIES IN PACKAGE TO MAXIMIZE COMPUTE & DATA THROUGHPUT

INFINITY FABRIC FOR
CROSS-DIE
CONNECTIVITY

4 LINKS RUNNING
AT 25GBPS

400GB/S OF BI-
DIRECTIONAL BANDWIDTH



Multiple GCD design has implications on monitoring strategy!

- GPUs have a given power budget for the two GCDs
- What is happening in one GCD will limit power in the other
- Drawn power is the best indicator of GPU activity:
 - A kernel waiting idle for data shows in the driver as 100% GPU utilization
 - Drawn power oscillating around 500W indicates that compute capabilities in the full GPU are being leveraged
 - For single GCD, 300W should be a good indication
- rocm-smi is que easiest way to peek at GPU utilization – but not the most accurate!

As reported by the driver – doesn't indicate how well the resource is used

Average power consumption

```

===== ROCm System Management Interface =====
===== Concise Info =====
GPU   Temp   AvgPwr  SCLK   MCLK   Fan   Perf   PwrCap  VRAM%  GPU%
0     58.0c  324.0W  1650Mhz 1600Mhz 0%   manual 500.0W  98%   100%
1     49.0c  N/A     800Mhz 1600Mhz 0%   manual 0.0W   0%    0%
=====
===== End of ROCm SMI Log =====
  
```

Frequency will shift to observe GPU power/thermal budget

Starting a SLURM parallel session

- Starting session in specific nodes to monitor
 - For first node of allocation:

```
srun --interactive \  
--pty \  
/bin/bash
```

- For other nodes (GPU's won't be visible):

```
srun --pty \  
--jobid <jobid> \  
-w <target_node> \  
--overlap \  
/usr/bin/bash
```

Get your job ID and
allocated nodes
(`squeue -me`)

Start parallel session
(`srun -interactive...`)

Monitor node activity:
rocm-smi for GPU
top or similar to CPU

Logging from the environment

- HIP runtime and GPU dispatch information can be logged with `AMD_LOG_LEVEL=4`

```
:3:hip_module.cpp      :662 : 117659918626 us: 8088 : [tid:0x14b2015e9700]
  hipLaunchKernel ( 0x14b5ec183ed0, {32768,1,1}, {512,1,1}, 0x14b2015e71b0, 0, stream:<null> )
...
:3:rocvirtual.cpp      :786 : 117659918634 us: 8088 : [tid:0x14b2015e9700] Arg0: = val:16777216
:3:rocvirtual.cpp      :786 : 117659918636 us: 8088 : [tid:0x14b2015e9700] Arg1: = val:22689590804480
... ShaderName : _ZN2at6native6legacy18elementwise_kernelIli512ELi1EZNS0_15gpu_kernel_implIZZNS0_23direct_copy_kernel

:3:hip_module.cpp      :663 : 117659918649 us: 8088 : [tid:0x14b2015e9700] hipLaunchKernel: Returned hipSuccess :
```

Number of blocks and threads of the dispatch

Arguments

Kernel mangled name

Return error

AMD Profilers

ROC-profiler (rocprof)

Hardware Counters

Raw collection of GPU counters and traces

Counter collection with user input files

Counter results printed to a CSV

Traces and timelines

Trace collection support for

CPU copy

HIP API

HSA API

GPU Kernels

Visualisation

Traces visualized with Perfetto

	A	B	C	D	E
1	Name	Calls	TotalDura	AverageN	Percentage
2	hipMemcpyAsync	99	3.22E+10	3.25E+08	44.14872
3	hipEventSynchronize	330	2.42E+10	73394557	33.225
4	hipMemsetAsync	87	7.76E+09	89232696	10.64953
5	hipHostMalloc	9	5.41E+09	6.01E+08	7.415198
6	hipDeviceSynchronize	28	1.32E+09	47006288	1.805515
7	hipHostFree	17	1.05E+09	61534688	1.435014
8	hipMemcpy	41	8.11E+08	19791876	1.113161
9	hipLaunchKernel	1856	58082083	31294	0.079676
10	hipStreamCreate	2	46380834	23190417	0.063625
11	hipMemset	2	18847246	9423623	0.025854
12	hipStreamDestroy	2	15183338	7591669	0.020828
13	hipFree	38	8269713	217624	0.011344
14	hipEventRecord	330	2520035	7636	0.003457
15	hipMalloc	30	1484804	49493	0.002037
16	__hipPopCallConfigura	1856	229159	123	0.000314
17	__hipPushCallConfigur	1856	224177	120	0.000308
18	hipGetLastError	1494	100458	67	0.000138
19	hipEventCreate	330	76675	232	0.000105
20	hipEventDestroy	330	64671	195	8.87E-05
21	hipGetDevicePropertie	47	51808	1102	7.11E-05
22	hipGetDevice	64	11611	181	1.59E-05
23	hipSetDevice	1	401	401	5.50E-07
24	hipGetDeviceCount	1	220	220	3.02E-07

Omnitrace

Trace collection

Comprehensive trace collection

CPU

GPU

Supports

CPU copy

HIP API

HSA API

GPU Kernels

OpenMP®

MPI

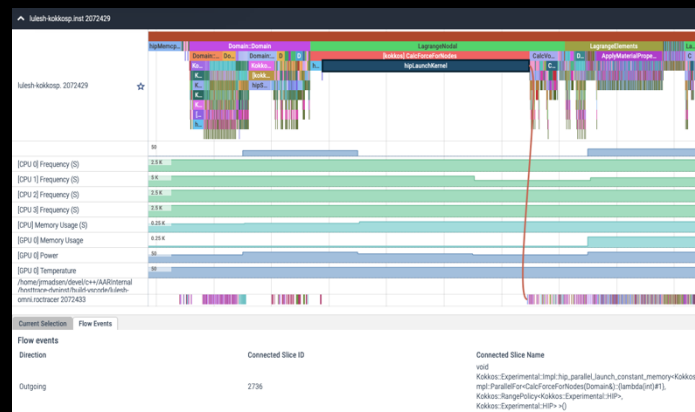
Kokkos

p-threads

multi-GPU

Visualisation

Traces visualized with Perfetto



Omniperf

Performance Analysis

Automated collection of hardware counters

Analysis

Visualisation

Supports

Speed of Light

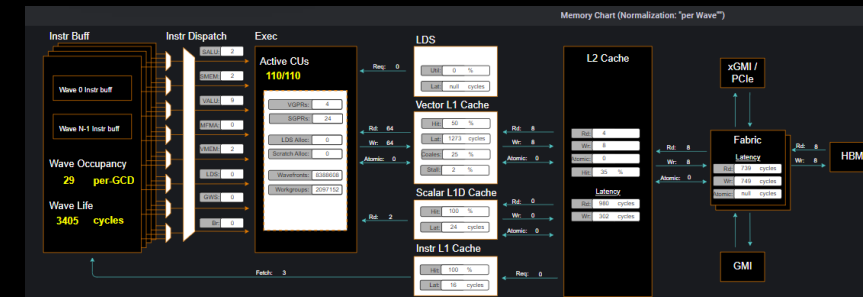
Memory chart

Rooflines

Kernel comparison

Visualisation

With Grafana or standalone GUI



Recent improvements to AMD profilers

	ROCm 6.1	ROCm 6.2	ROCm 6.3
GPU performance analysis for ROCm based apps	rocprof (rocprofv1)	rocprofv3 beta (new RocProfiler tool)	rocprov3 beta
Holistic overview of CPU, GPU and system activity	omnitrace stand-alone tool from AMD research	omnitrace integrated to official ROCm	omnitrace renamed to rocprof-sys
GPU kernel profiling	omniperf stand-alone tool from AMD research	omniperf integrated to official ROCm	omniperf renamed to rocprof-compute

Focus of this talk

Profiling with Rocprof

- Rocprof profiler client is the easiest way to get started with GPU profiling
- It is available as part of the ROCm stack and, therefore, available in the containers
- It is seldomly useful to profile every single process/rank of your app:
 - Profiling more than needed = more potential profiling overhead
 - Misleading conclusions



```
pcmd=""  
if [ $RANK -eq 2 ] ; then  
pcmd='rocprof --hip-trace'  
fi
```

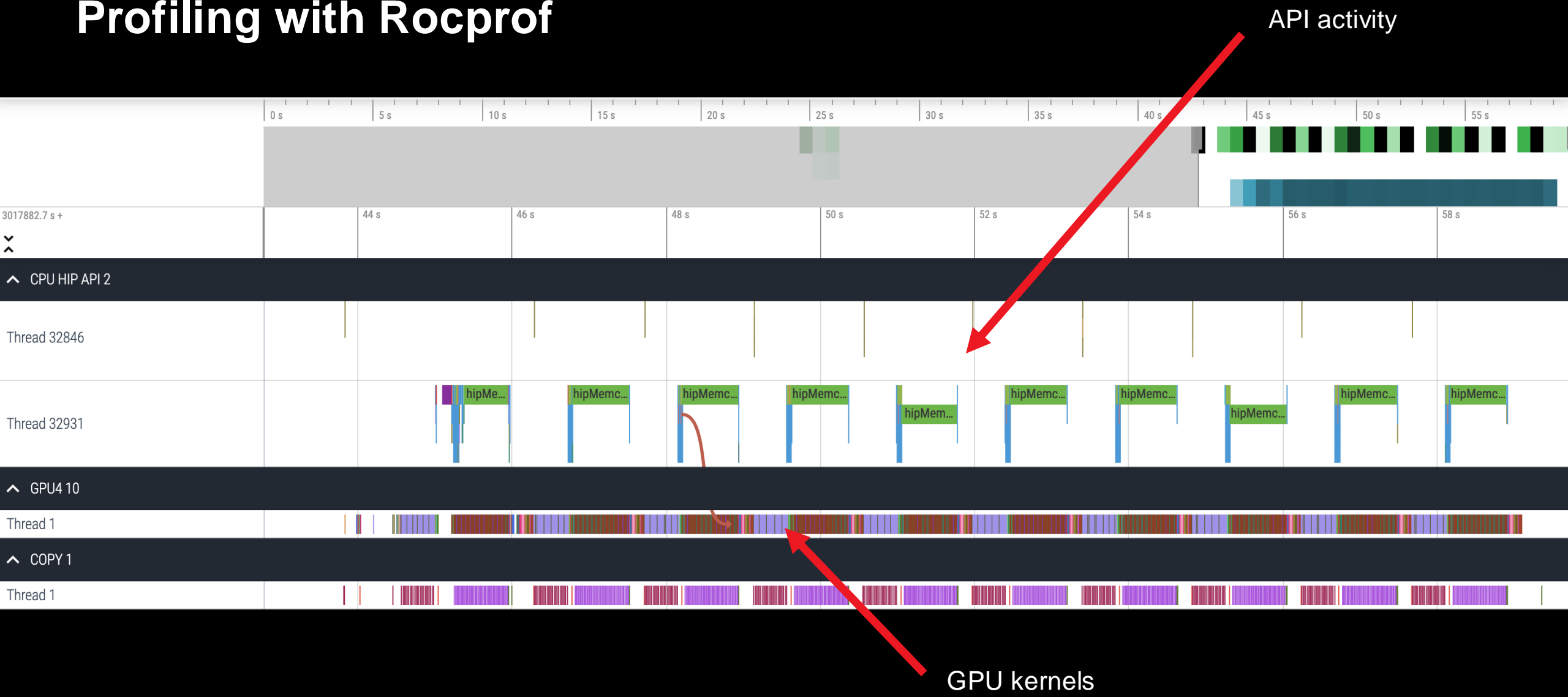
Command to prepend to my application instantiation

We want to profile only for one rank – in this case rank #2

Run command as before except to the prepended profiling command

```
$pcmd python -u myapp.py
```

Profiling with Rocprof



API activity

GPU kernels

Leveraging framework profiler infrastructure

- AI frameworks typically provide hooks for developers to gather profiling information
- An example with Pytorch:

```
from torch.profiler import profile, record_function, ProfilerActivity
```

```
for epoch in range(args.epochs):
```

```
    prof = None
```

```
    if epoch == 3:
```

```
        print("Starting profile...")
```

```
        prof = profile(activities=[ProfilerActivity.CPU, ProfilerActivity.CUDA])
```

```
        prof.start()
```

```
    for imgs, labels in dataloader:
```

```
        with torch.amp.autocast('cuda', enabled=args.amp):
```

```
            imgs, labels = imgs.cuda(), labels.cuda()
```

```
            outputs = model(imgs)
```

```
            loss = criterion(outputs, labels)
```

```
            loss = scaler.scale(loss)
```

```
            loss.backward()
```

```
            scaler.step(optimizer)
```

```
            scaler.update()
```

```
    if prof:
```

```
        prof.stop()
```

```
        prof.export_chrome_trace("trace.json")
```

Invoke the profiler



Enable profiling for epoch number 3



Training for an epoch



Finish profiling and generate trace



Trace file can be viewed in Perfetto UI tool



Comment about visualizing Rocprof traces

- We came across some visualization issues in the latest versions of Perfetto UI <https://ui.perfetto.dev/>
- We suggest using a previous release <https://ui.perfetto.dev/v46.0-35b3d9845/#/>

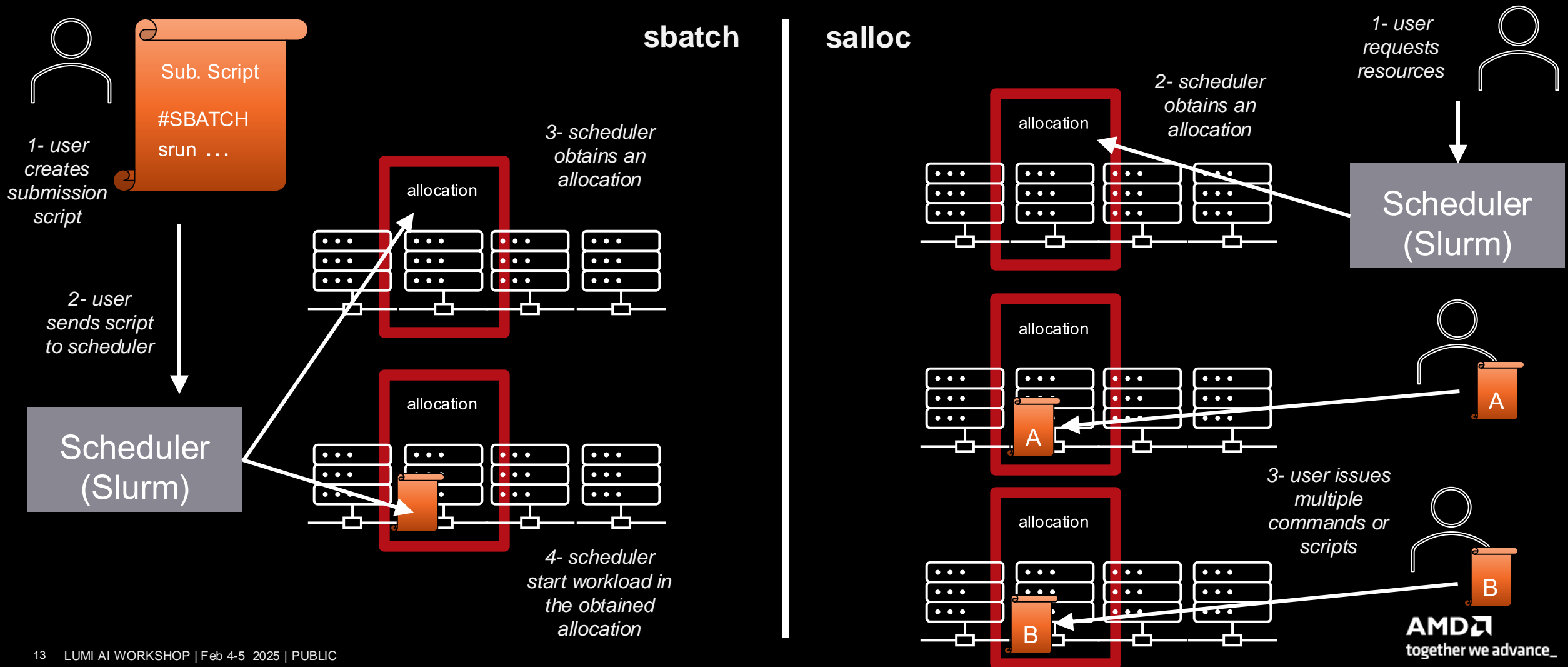
- Service of an older version of Perfetto known to be better compatible running on the login nodes:

```
ssh <your username>@lumi-uan01.csc.fi -L 10000:localhost:10000
```

- Then connect to <http://localhost:10000/> to access the service
- This is based on this dockerHUB project in case you want to run it on your machine:
 - <https://hub.docker.com/r/sfantao/perfetto4rocm>
- For large profiles consider using trace_processor to load the files outside the browser

Before jumping to the exercises... sbatch vs salloc

- In previous exercises you used batch jobs (with sbatch) – for this session we introduce interactive jobs (with salloc)



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