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CARMA: Collocation-Aware Resource Manager with GPU Memory Estimator

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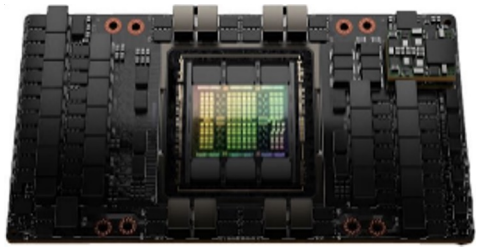
GPU Underutilization Challenge

An analysis of 100,000 jobs run by 100s of users for ~2 months on a real-world cluster shows ~52% GPU utilization on average ✷

Hardware problem

1. Compute/memory requirements of models don't always match with the GPUs
   - e.g., transfer learning, small models
2. No fine-grained sharing mechanism and virtual memory on GPUs



Mem: 141GB

BASIC-L: ~2.44billion params

MobileNetV2: ~3.4M params

Software problem

1. Exclusive GPU assignments
2. Mostly black-box view of tasks

kubernetes

hadoop YARN

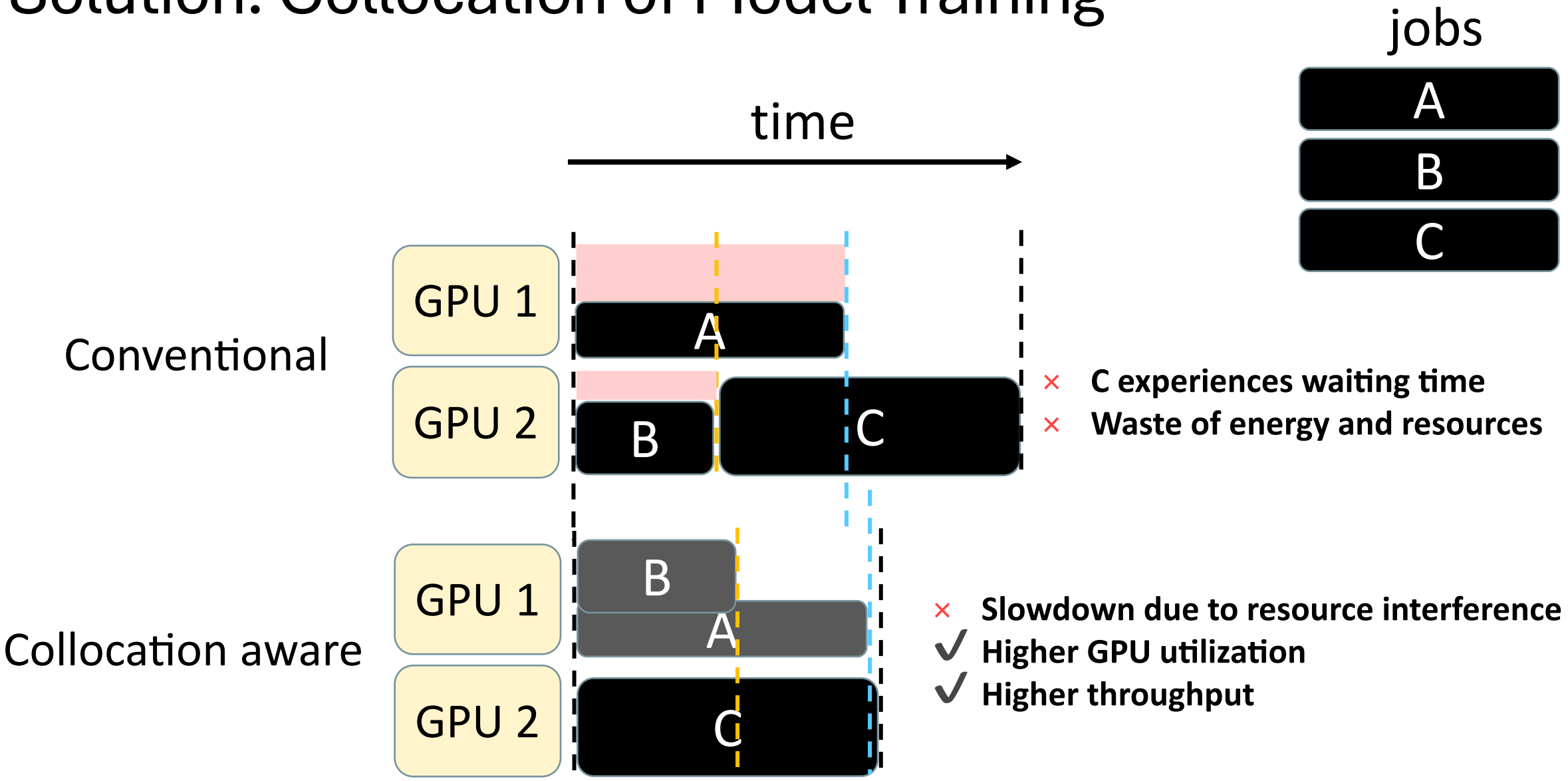
slurm workload manager

✷ Jeon, Myeongjae, et al. "**Analysis of Large-Scale Multi-Tenant GPU Clusters for DNN Training Workloads.**" USENIX Annual Technical Conference. 2019.
✷ Yanjie Gao et al. **"An Empirical Study on Low GPU Utilization of Deep Learning Jobs."** In: Proceedings of the IEEE/ACM 46th International Conference on Software Engineering. 2024.

Gefion AI Supercomputer

1528 NVIDIA H100
Tensor Core GPUs

Solution: Collocation of Model Training



Statement

Improving GPU Underutilization challenge and increasing GPU energy efficiency through task collocation.

Overview

Profiling & Monitoring (EuroMLSys'23) — 1

Collocation Analysis (EuroMLSys'24) — 2

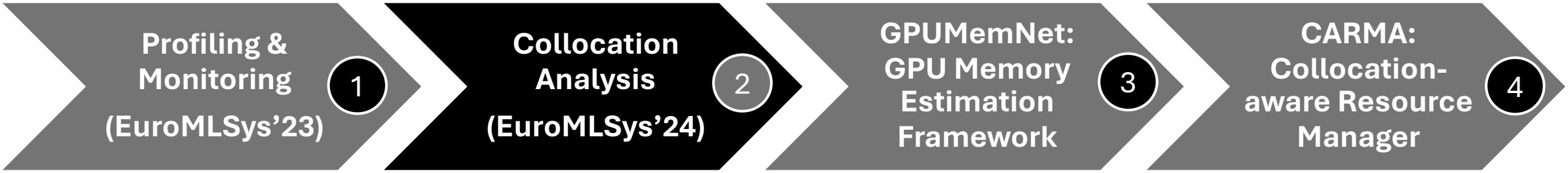
GPUMemNet: GPU Memory Estimation Framework — 3

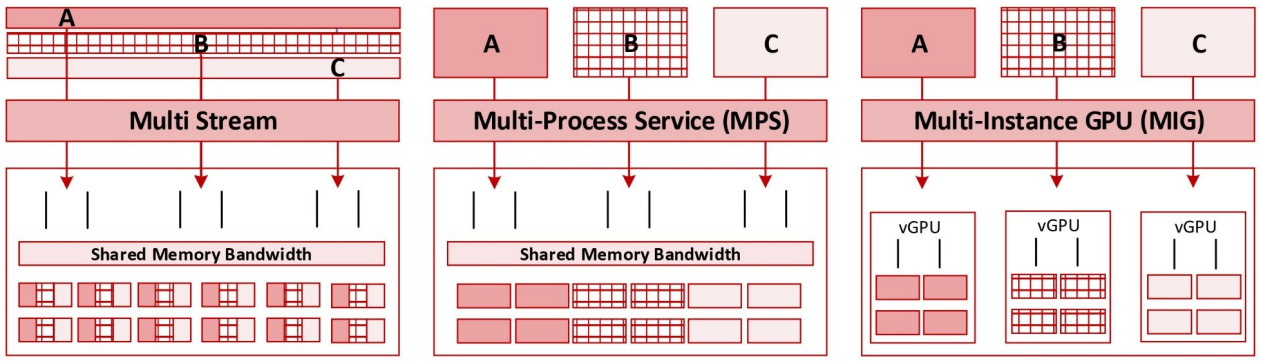
CARMA: Collocation-aware Resource Manager — 4

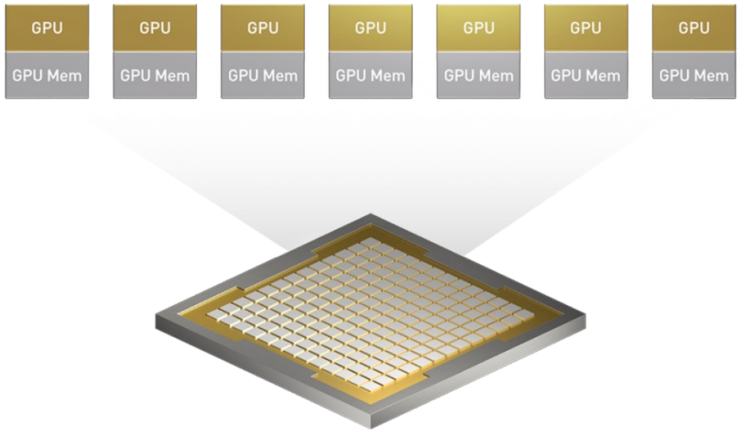
```
sh-4.2$ nvidia-smi
Wed Dec 11 09:52:10 2019
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 418.87.01    Driver Version: 418.87.01    CUDA Version: 10.1     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla K80           On   | 00000000:00:1E.0 Off |                    0 |
| N/A   44C    P0    60W / 149W |  11292MiB / 11441MiB |     13%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|    0      9389      C   ...naconda3/envs/tensorflow_p36/bin/python 11012MiB |
|    0     21268      C   ...naconda3/envs/tensorflow_p36/bin/python   267MiB |
+-----------------------------------------------------------------------------+
```

Overview



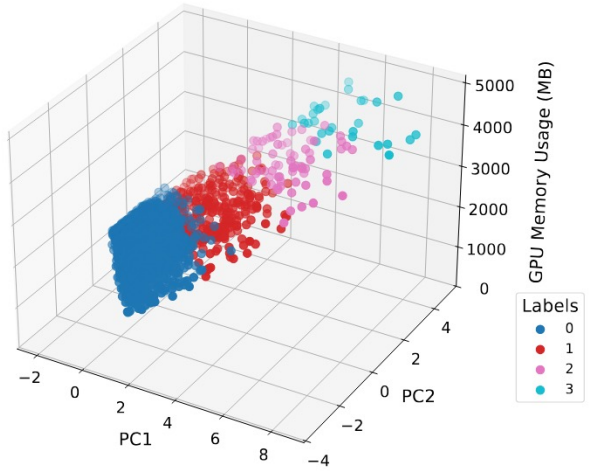




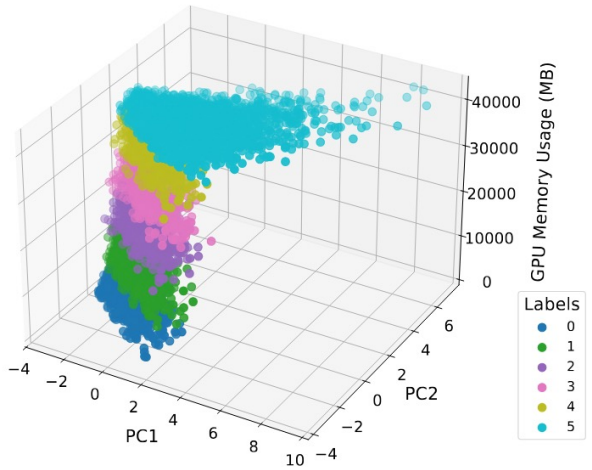
https://www.nvidia.com/en-us/technologies/multi-instance-gpu/

Overview

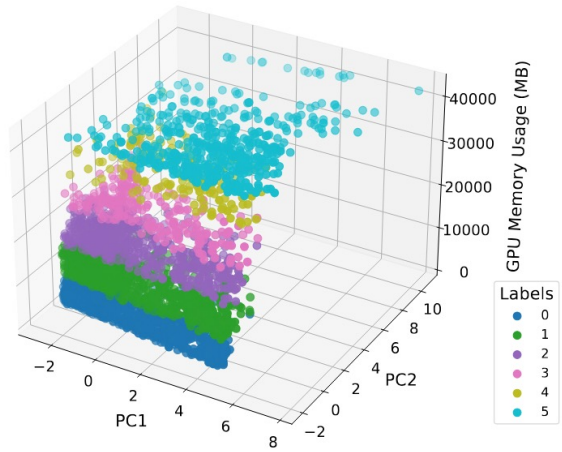
1. **Profiling & Monitoring (EuroMLSys'23)**
2. **Collocation Analysis (EuroMLSys'24)**
3. **GPUMemNet: GPU Memory Estimation Framework**
4. **CARMA: Collocation-aware Resource Manager**



MLPs



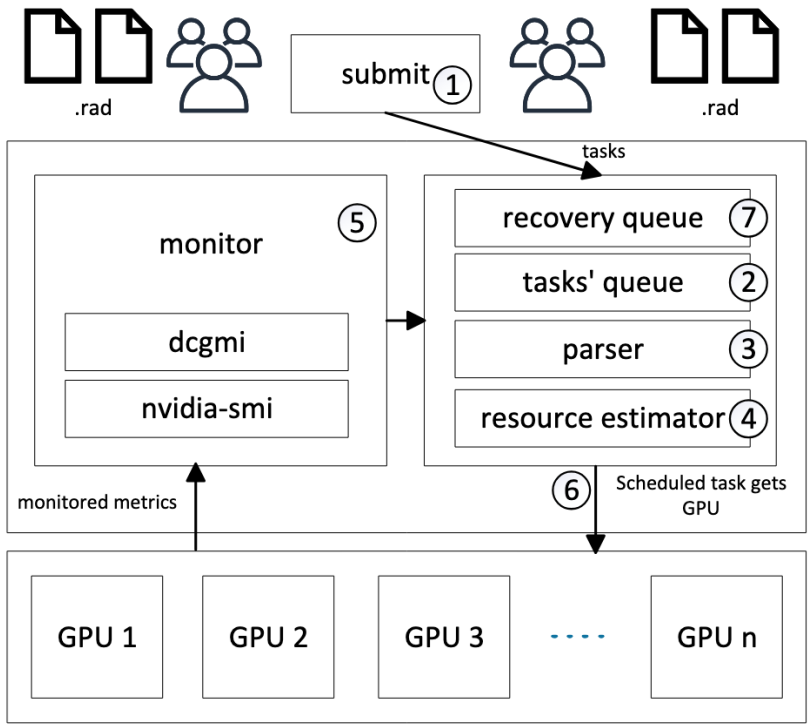
CNNs

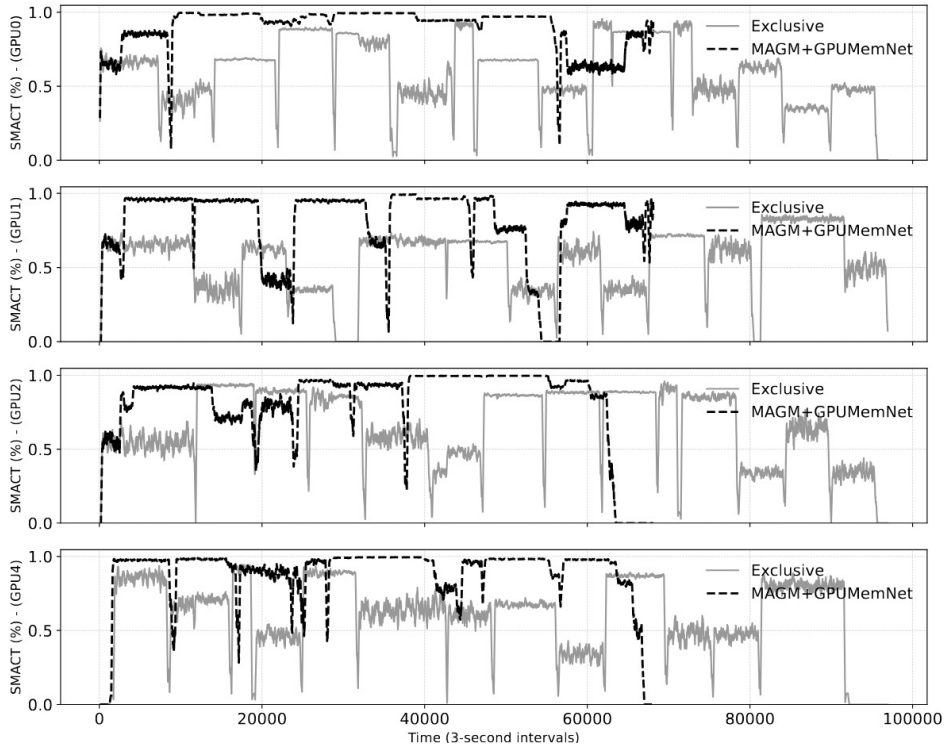


Transformers

Overview

Profiling & Monitoring (EuroMLSys'23) 1 → **Collocation Analysis (EuroMLSys'24)** 2 → **GPUMemNet: GPU Memory Estimation Framework** 3 → **CARMA: Collocation-aware Resource Manager** 4



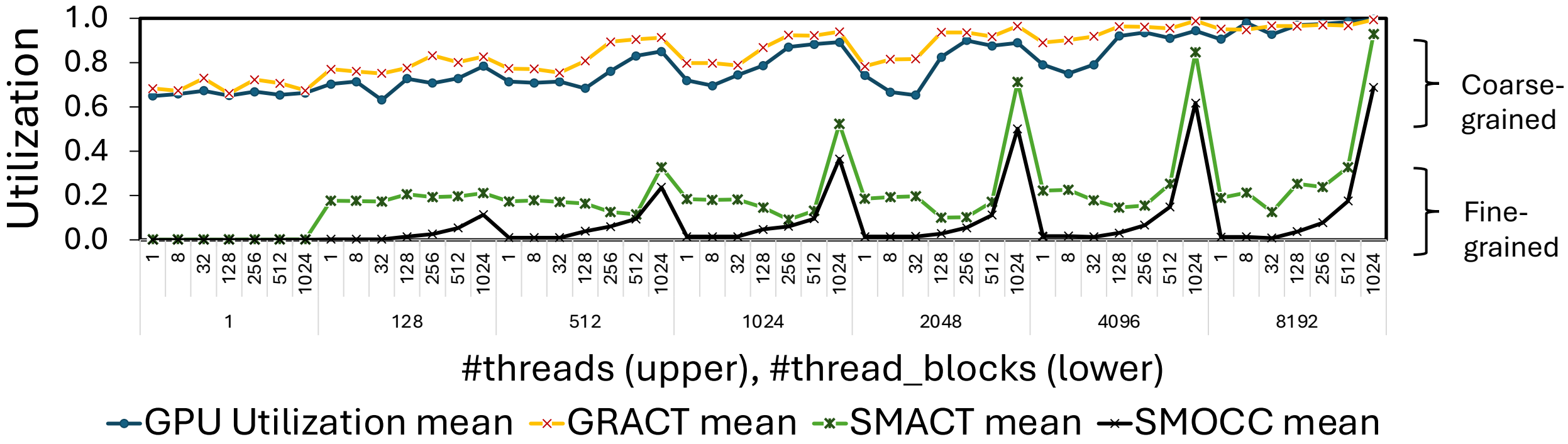


1

Profiling and Monitoring Deep Learning Training Tasks

GPU Utilization

- **GPU Utilization**: % of time one or more kernels were executing on the GPU
- **GRACT**: % of time any portion of the graphics or compute engines were active
- **SMACT:** the fraction of active time on an SM, averaged over all SMs
- **SMOCC**: degree of parallelism / max supported parallelism on SM



Coarser-grained utilization metrics can be misleading.

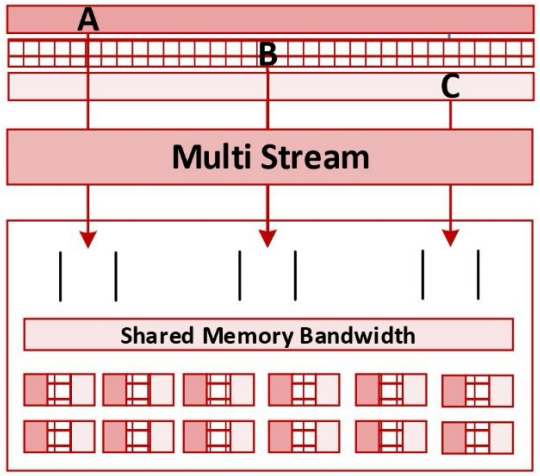
Digest

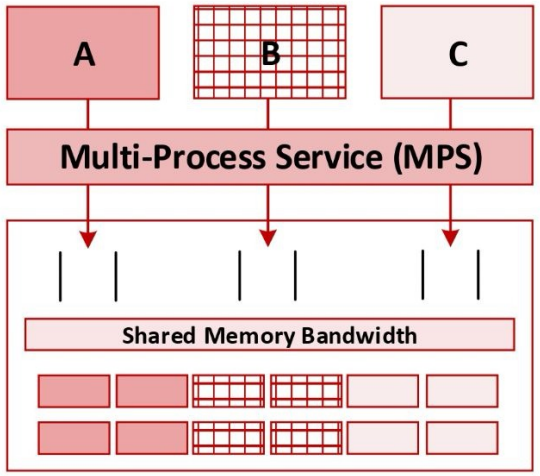
- For model level optimization purposes
  - Use framework specific profilers
- For digging deeper into OS and system
  - Use Nsight Systems
- For kernel-level optimizations
  - Use Nsight Compute
- Profile the needed amount of code for a reasonable range of time
  - Profiling for an iteration might be enough to show the behavior of training a model
- For online decision-making purposes
  - Use monitoring tools with representative fine-grained metrics

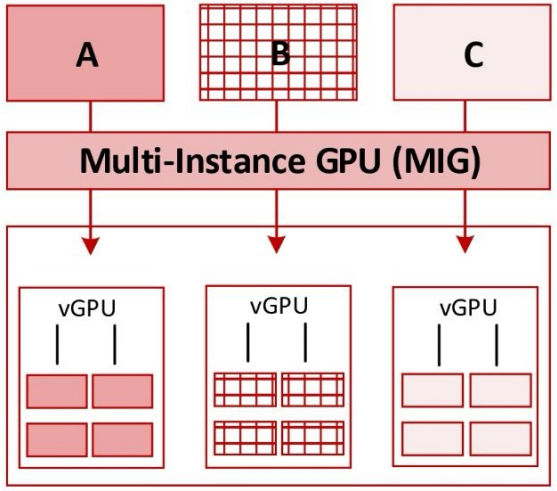
2

An Analysis of Collocation on GPUs for Deep Learning Training

Collocation on NVIDIA GPUs

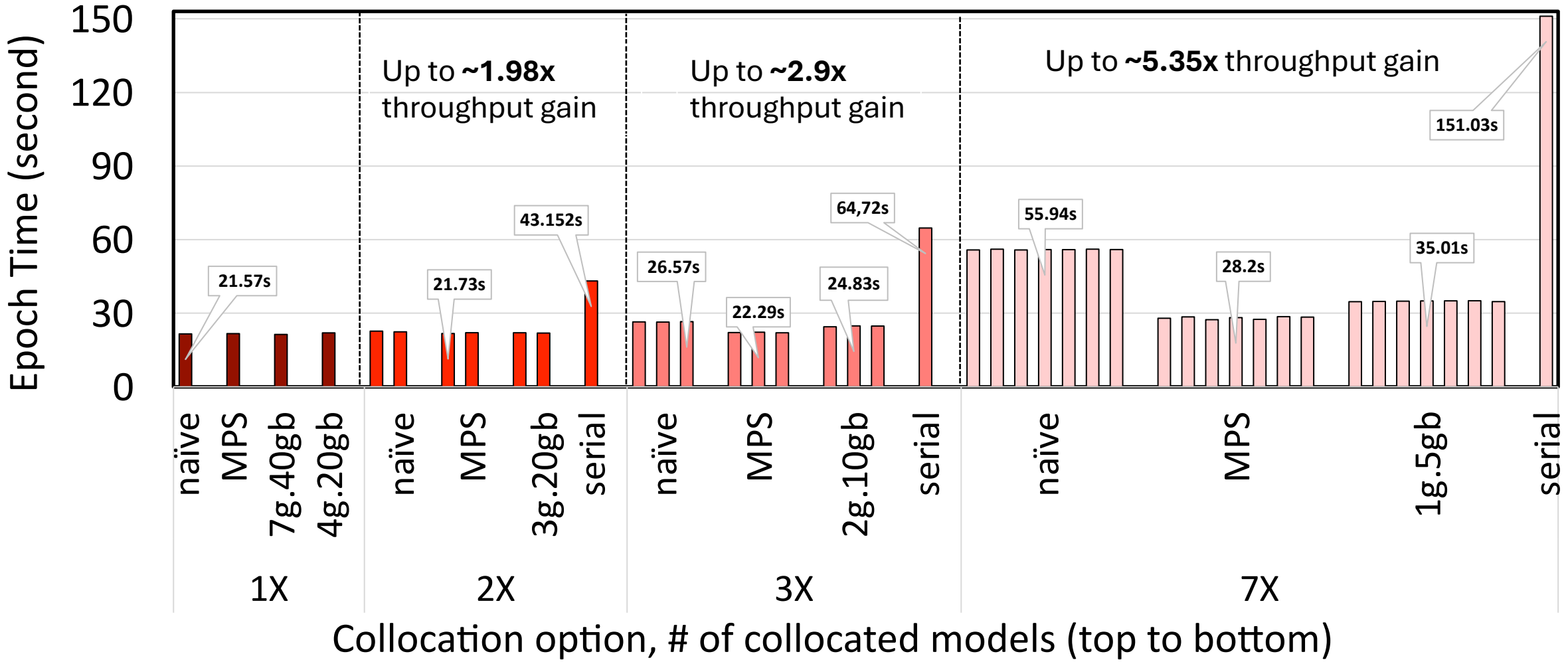






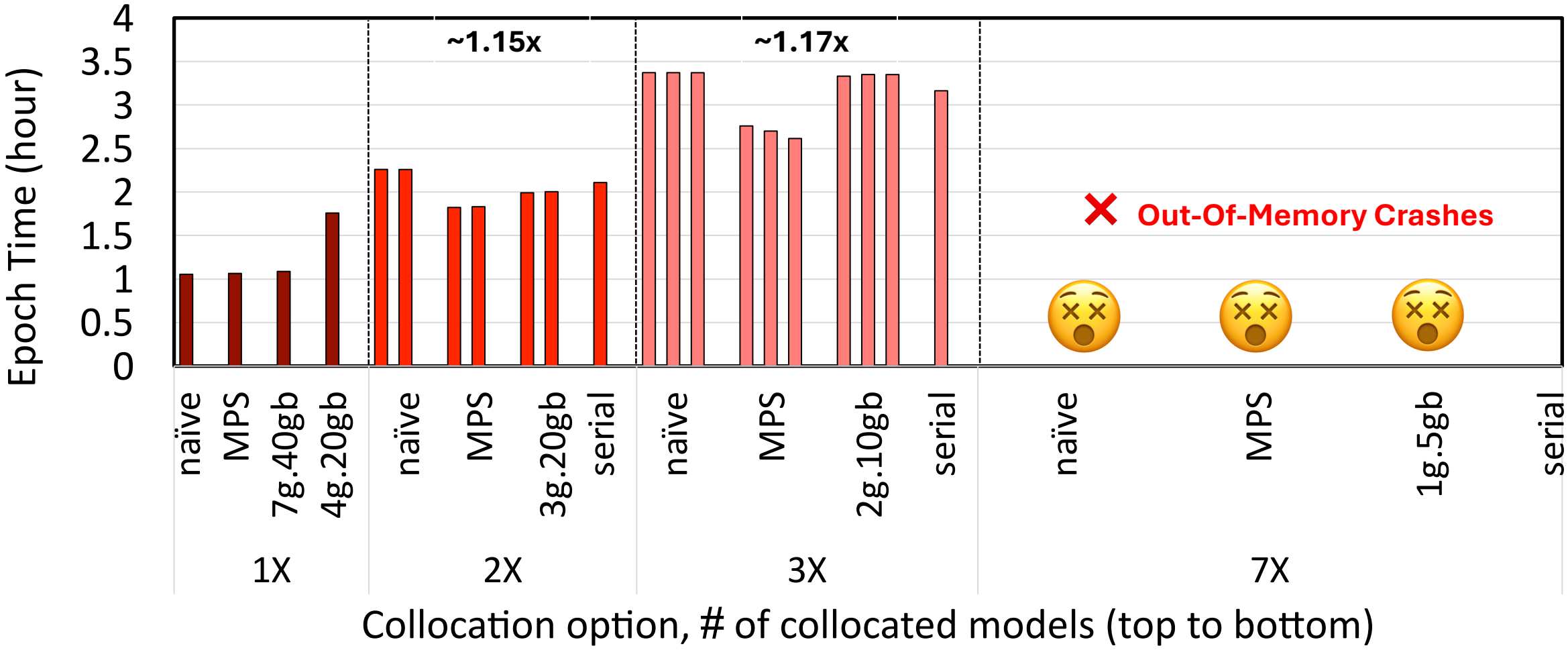
Streams (naïve)	Multi-Process Service (MPS)	Multi-Instance GPU (MIG)
➢ Easy to use	➢ Launching a daemon process	➢ Configuration overhead
False dependencies limit parallelism	➢ Takes care of false dependencies Interference still can degrade performance	➢ Complete isolation No interference
		✕ Fewer resources per instance may result in performance degradation

Small: ResNet26 on Cifar10 (batch size: 32)



Up to ~5.35x throughput gain despite increased epoch time
MPS > MIG > streams (naïve)

Large: ResNet152 on ImageNet (batch size: 32)



Negligible throughput gain with intolerable slow downs.

We cannot have 7X because of Out-Of-Memory (OOM) crashes.

Summary

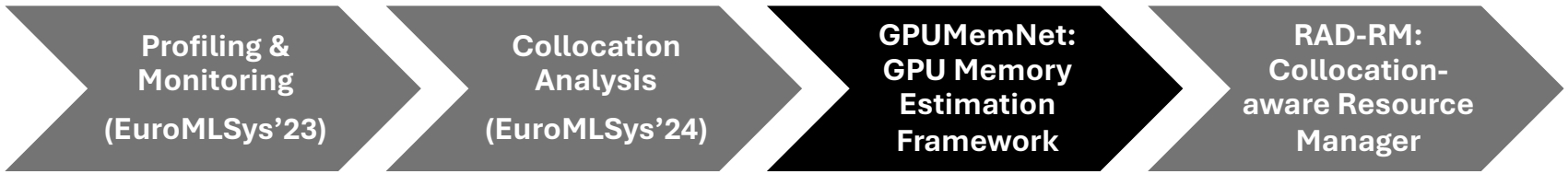
- Collocation is beneficial
  - Aggregate memory need of all collocated tasks is less than GPU memory
  - GPU utilization (SMACT) is less than 80%

- MPS offers higher performance

- MIG’s rigid partitioning may lead to sub-optimal performance!

3

GPUMemNet + Other Estimators



Having an estimation for GPU Memory => More Reliable Collocation

Estimating GPU Memory is challenging!

- Optimizations
  - Applied by Default:
    - Activation reuse, dynamic memory management
  - May be enabled by the user:
    - Layer fusion, gradient checkpointing, mixed precision, etc.

These introduce levels of unpredictability to GPU memory estimation.

Existing Estimators

1. Analytical
    1. Horus formula (***TPDS '21***)
    2. DNNMem, Microsoft's Analytical work (***ESEC/FSE '20***)
    3. LLMem (***IJCAI '24***)

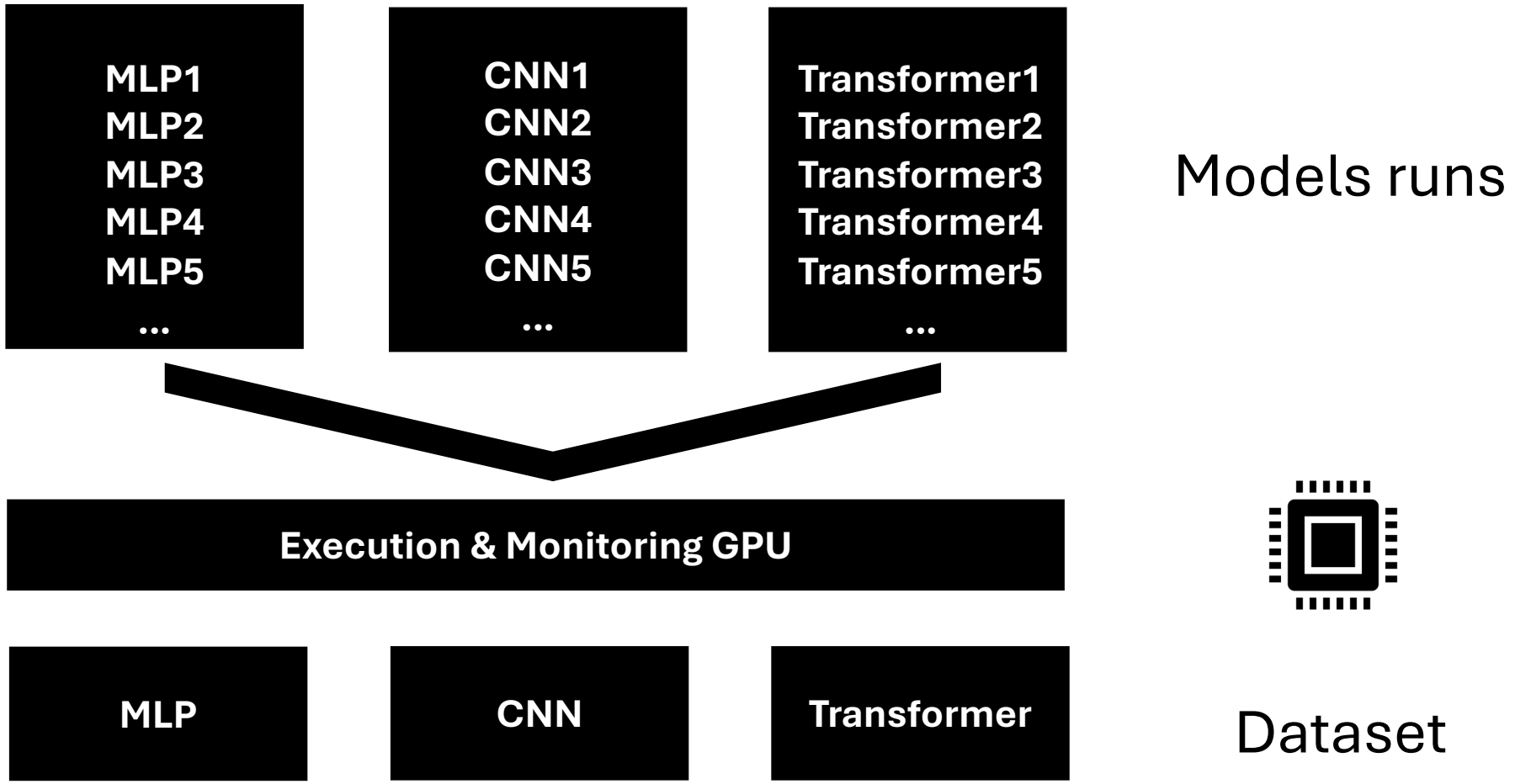
2. Libraries
    1. Fake Tensor
    2. DeepSpeed

3. ML-based approach
    - DNNPerf, graph neural networks (***ICSE-SEIP '23***)

https://pytorch.org/docs/stable/torch.compiler_fake_tensor.html
https://deepspeed.readthedocs.io/en/latest/memory.html

Challenges of Using ML for Estimation

Dataset

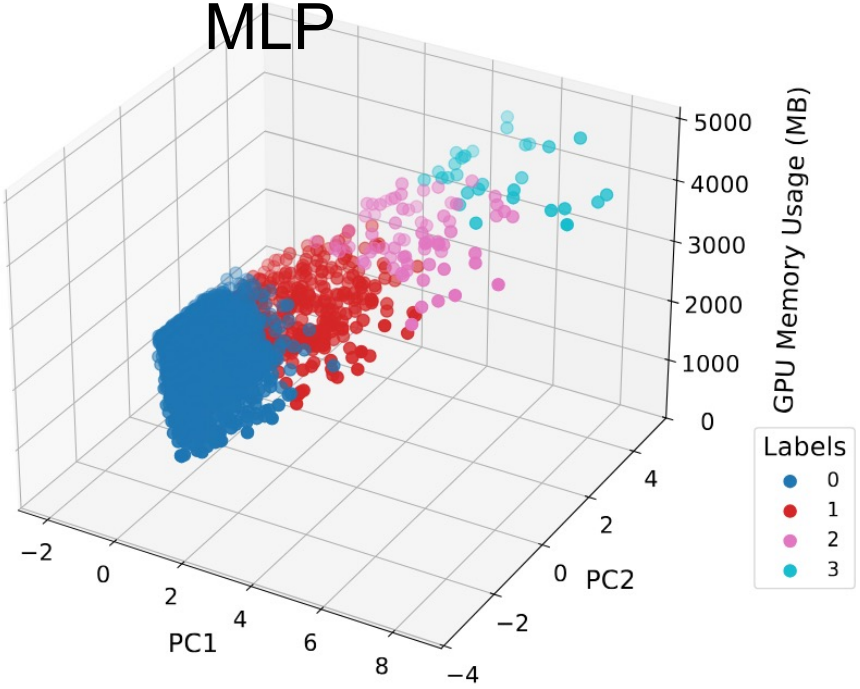


Classification Formulation

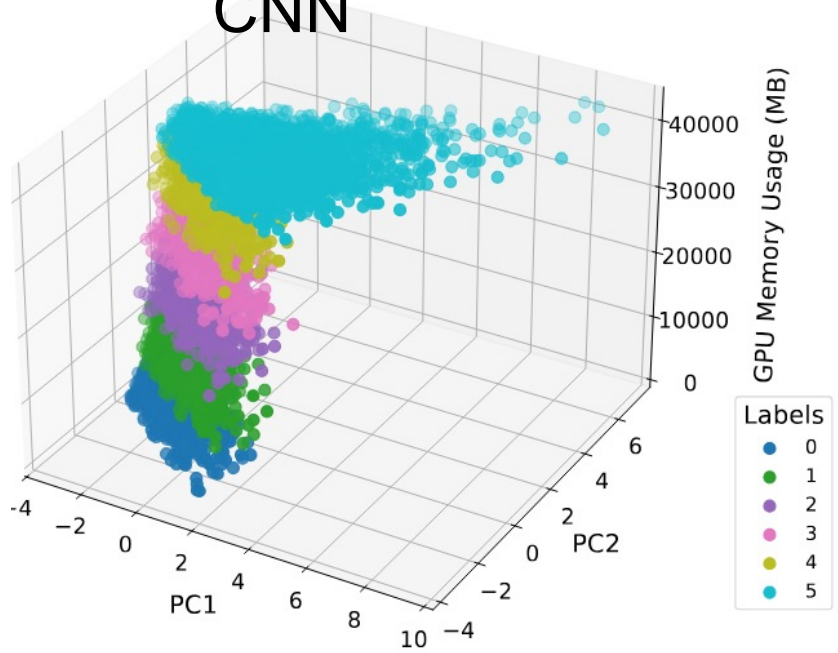
- Discretize data into same-GB classes
  - e.g., 0-1GB (1), 1GB-2GB (2), …

- Looked into the data through PCA and t-SNE
  - The classes are observable!

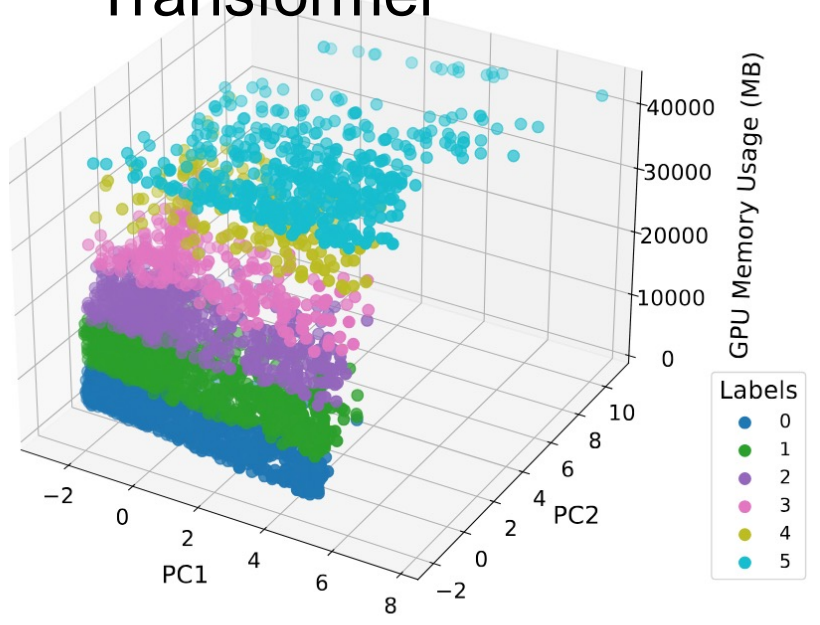
MLP



CNN

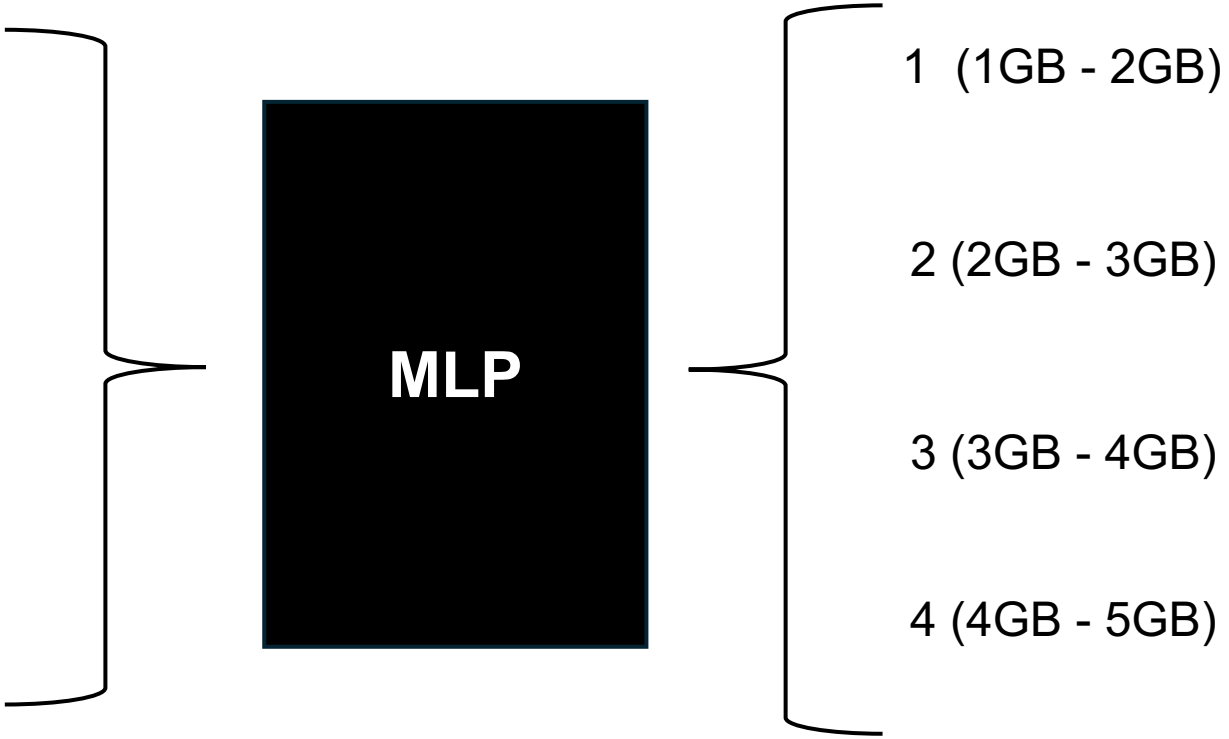


Transformer



Memory Estimator - MLP-based

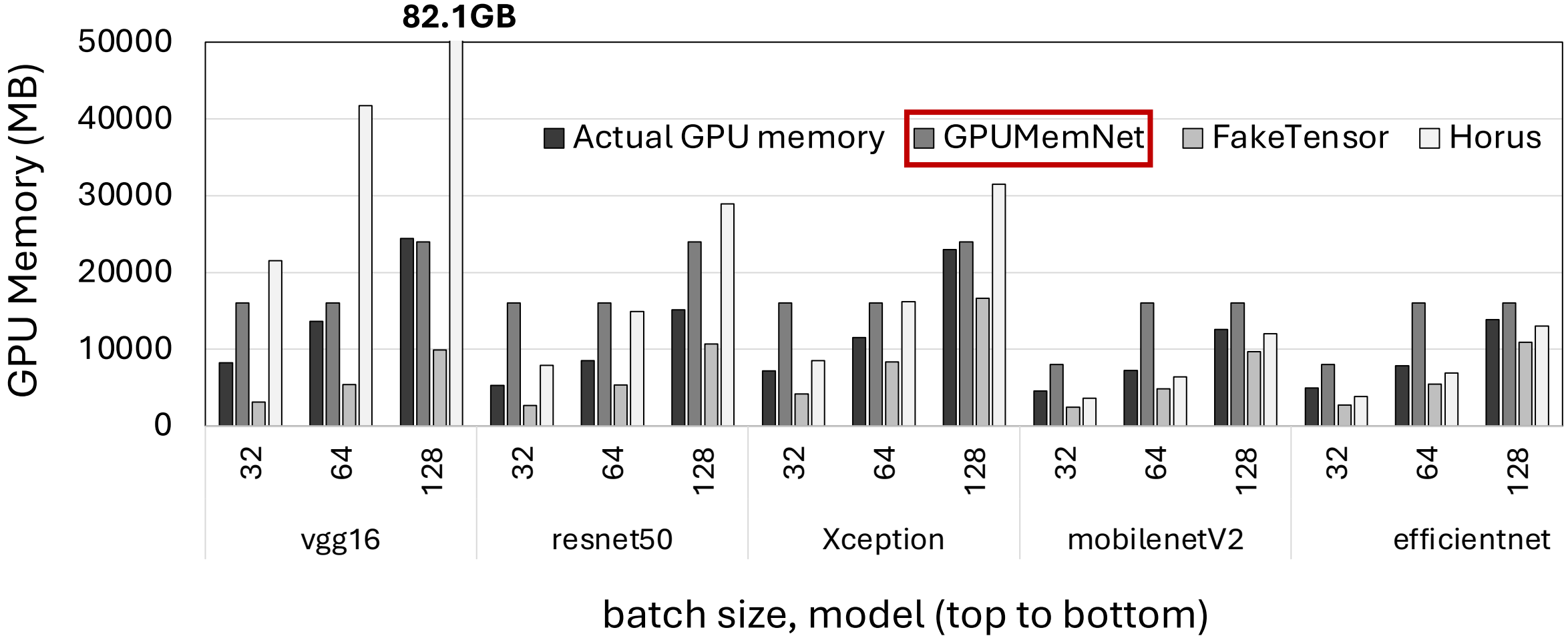
- #linear layers
- #batch normalization layers
- #dropout layers
- batch size
- #parameters
- #activations
- activation encoding cos/sin



Results

Dataset	Estimator	Class Range Size	#Classes	Accuracy
MLP	MLP	1GB	5	0.95
	MLP	2GB	4	0.97
	Transformer	1GB	5	0.97
	Transformer	2GB	4	0.98
CNN	MLP	8GB	6	0.82
	Transformer	8GB	6	0.81
Transformer	MLP	8GB	6	0.87
	Transformer	8GB	6	0.85

Unseen real-world models



GPUMemNet closest to actual GPU memory!
Almost never underestimates, preventing OOMs.

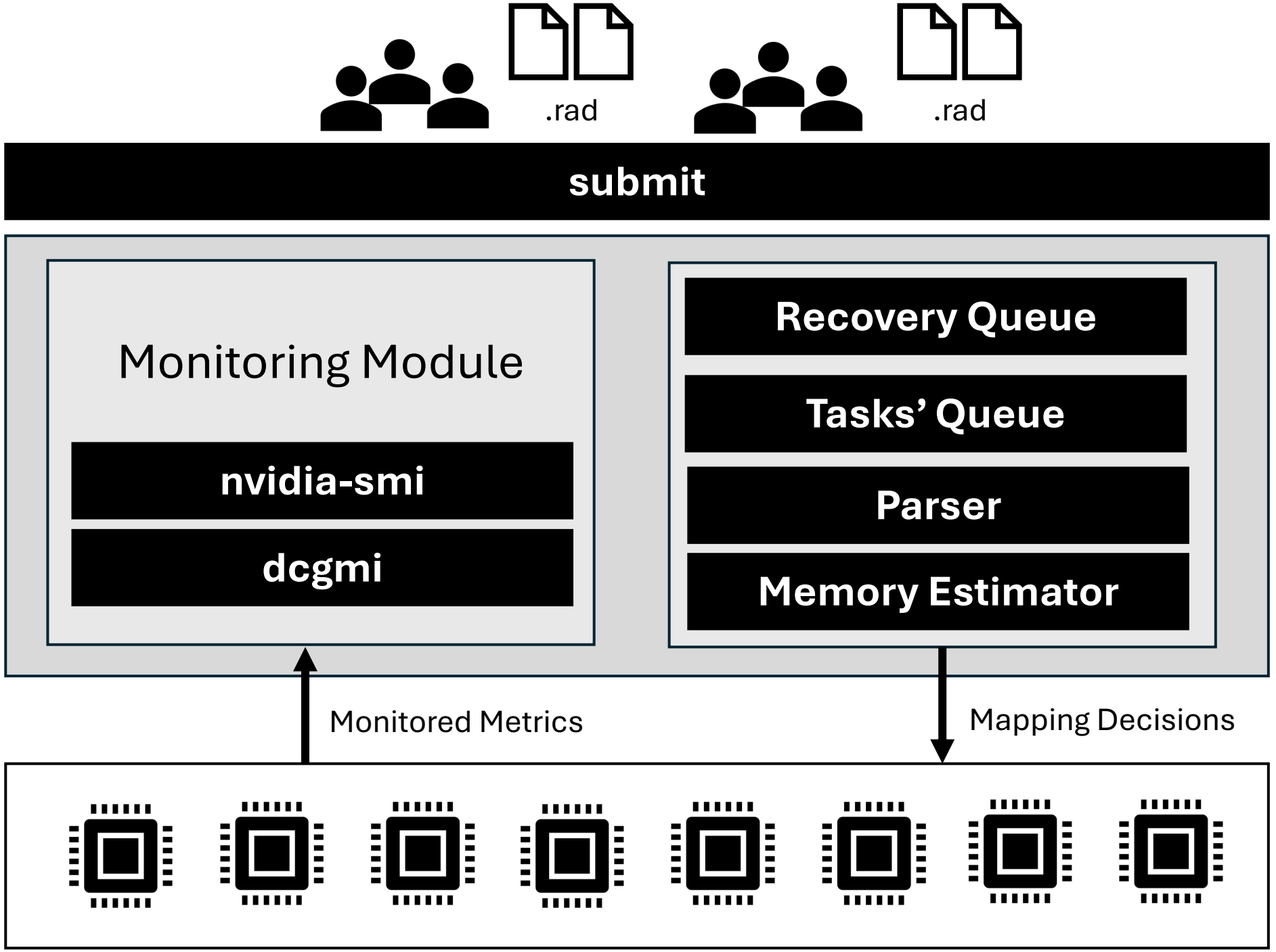
Summary

- GPUs are underutilized.
- Collocation can be an opportunity.
- GPU memory estimation is needed for more reliable collocation
- GPUMemNet
  - Dataset
  - Tools for extending the dataset

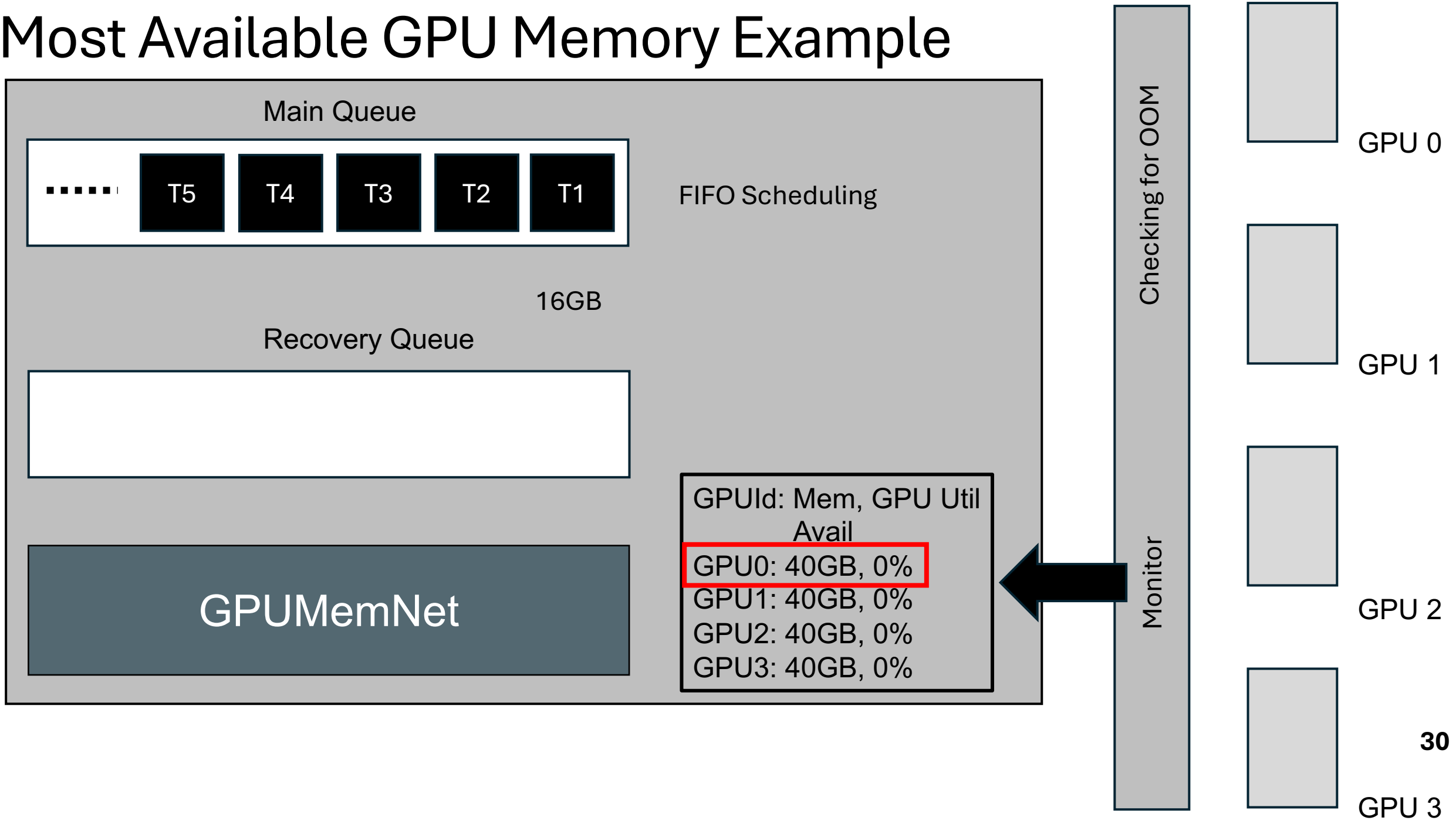
4

Resource-Aware Data systems-Resource Manager (RAD-RM)

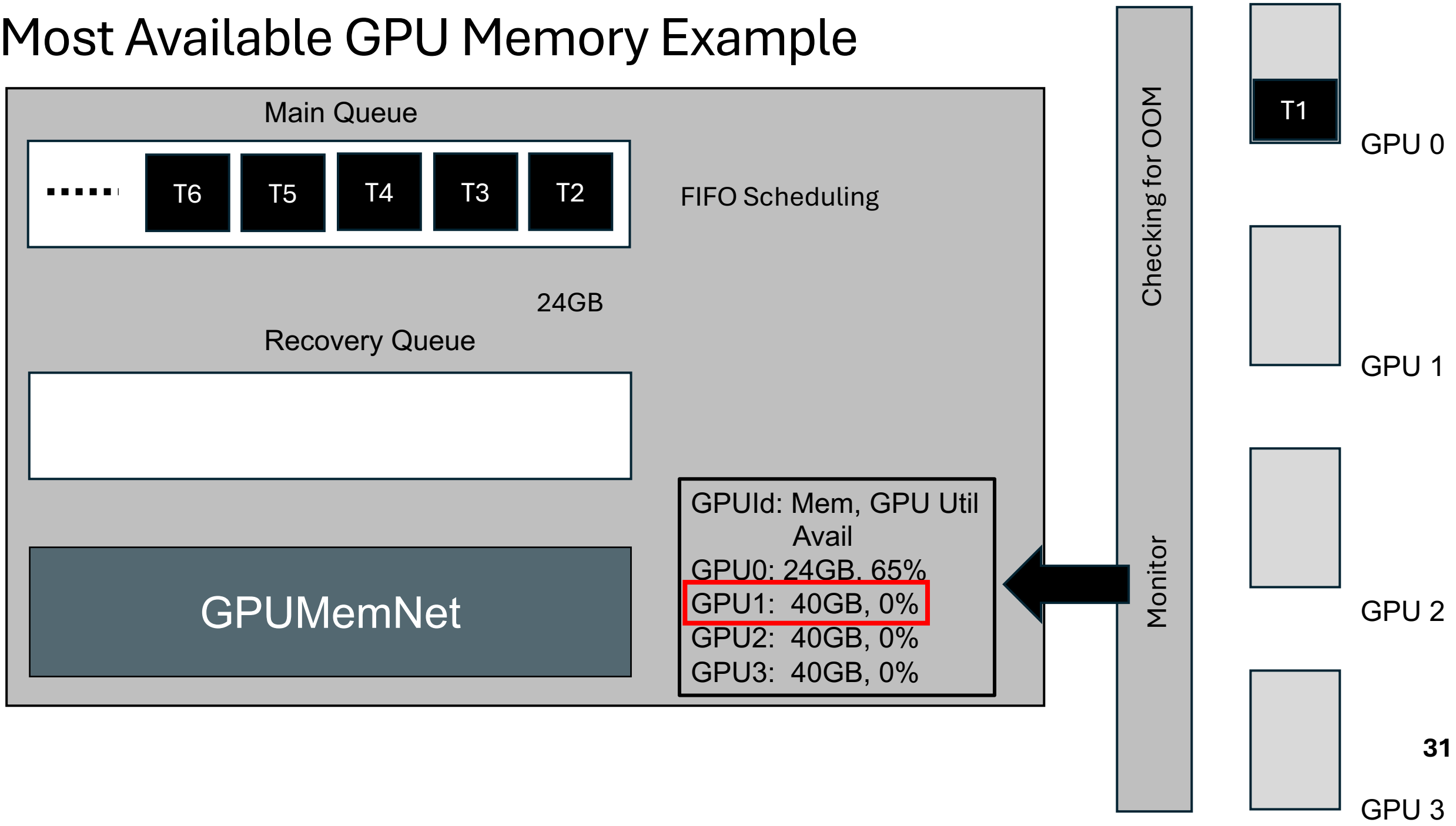
CARMA


.rad
.rad
submit
Monitoring Module
nvidia-smi
dcgmi
Recovery Queue
Tasks' Queue
Parser
Memory Estimator
Monitored Metrics
Mapping Decisions

Most Available GPU Memory Example



Most Available GPU Memory Example



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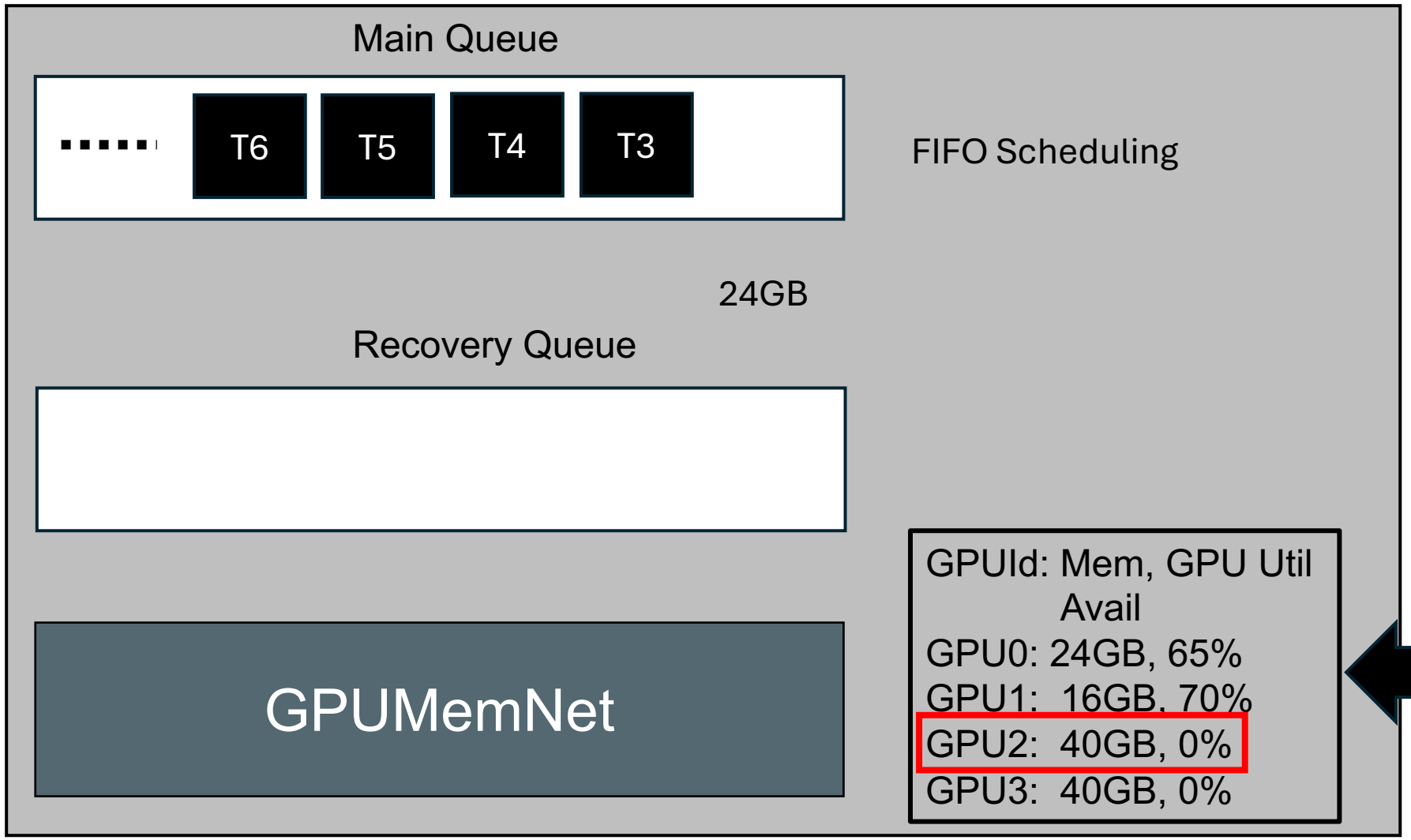
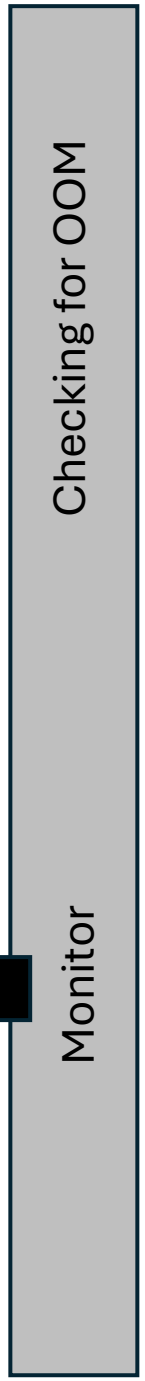
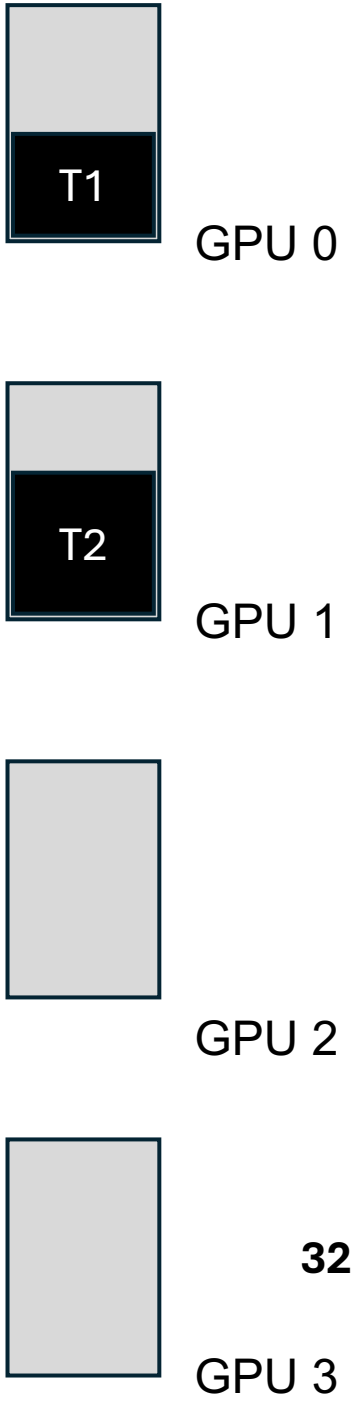
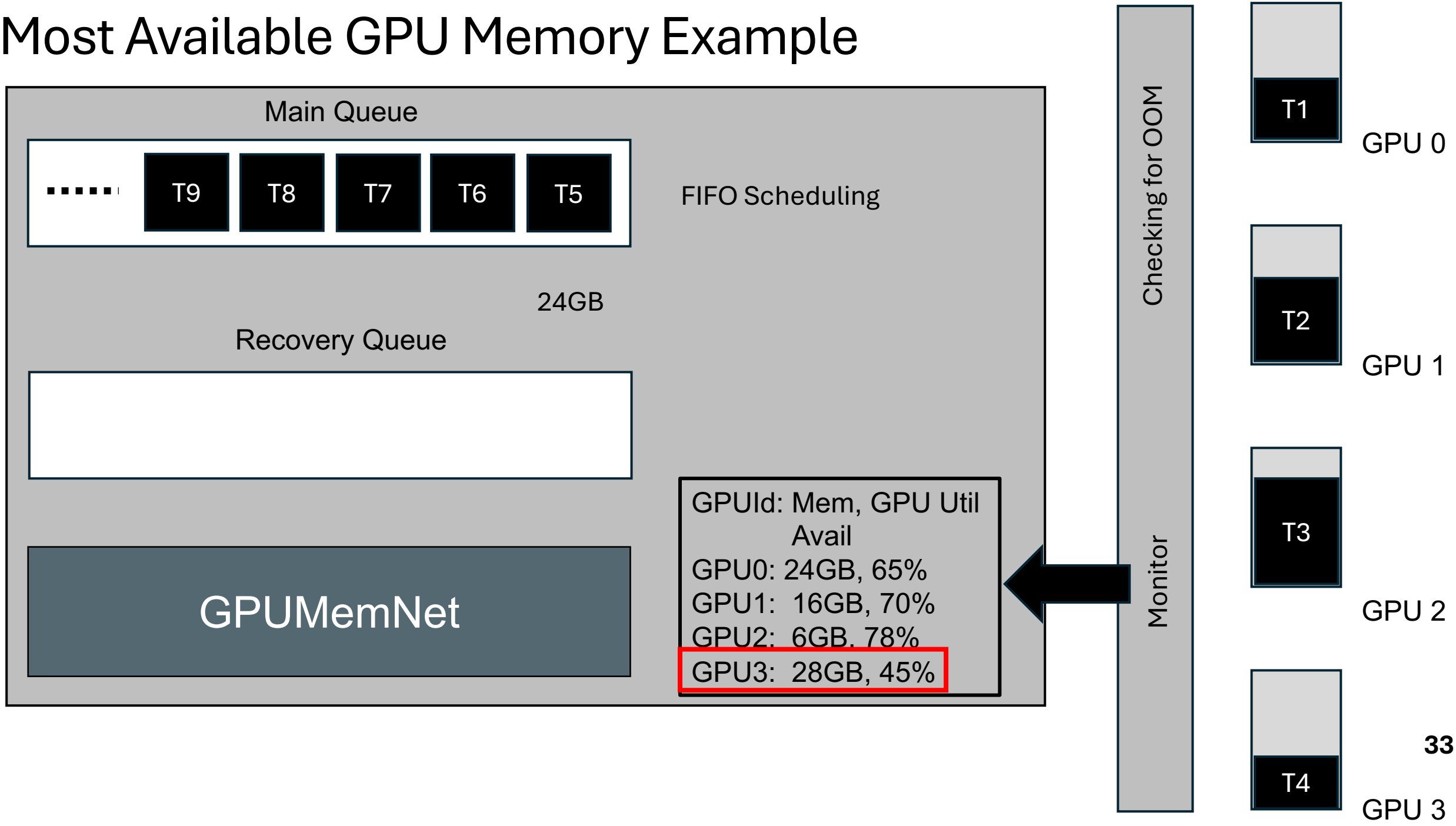


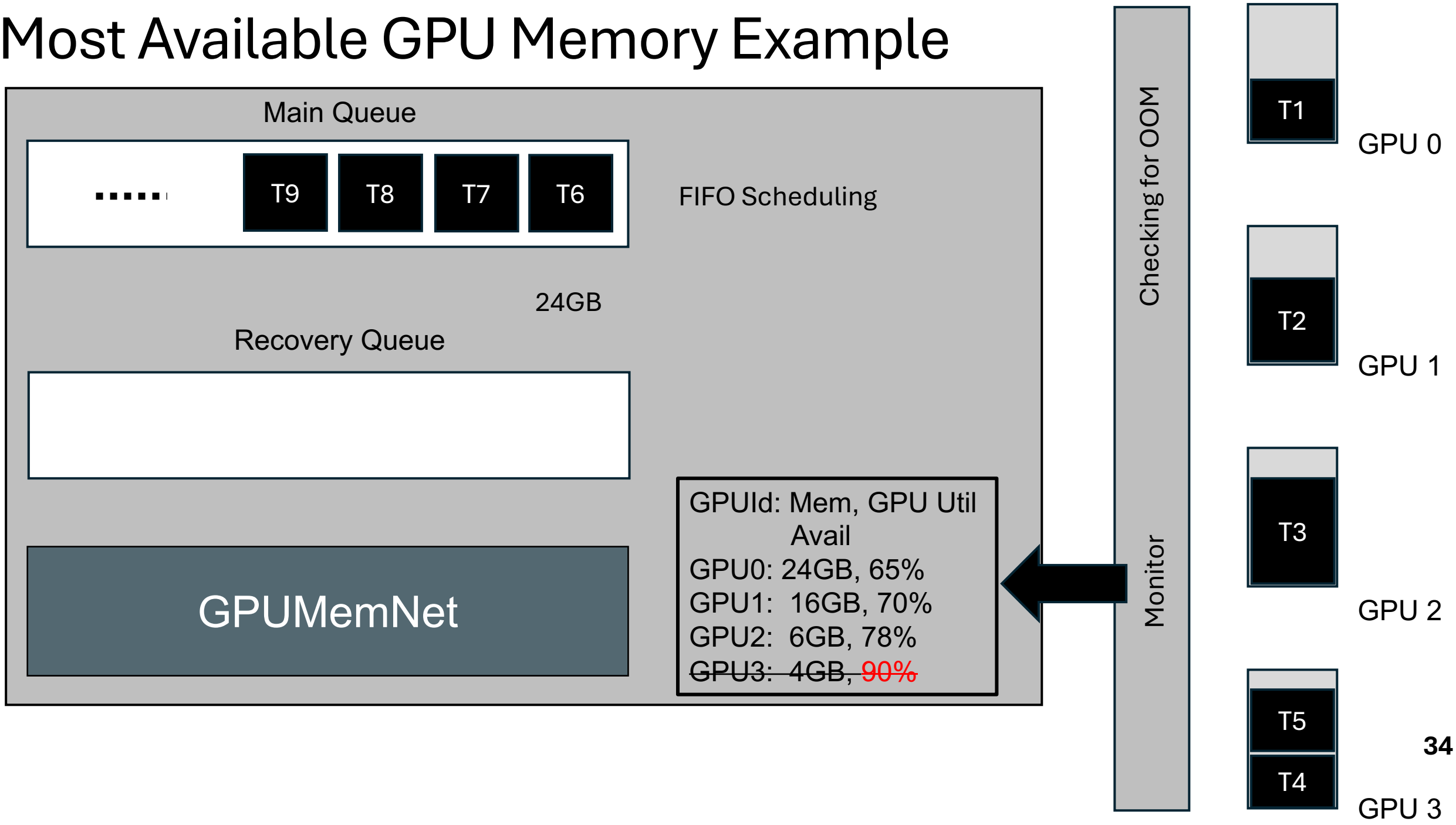




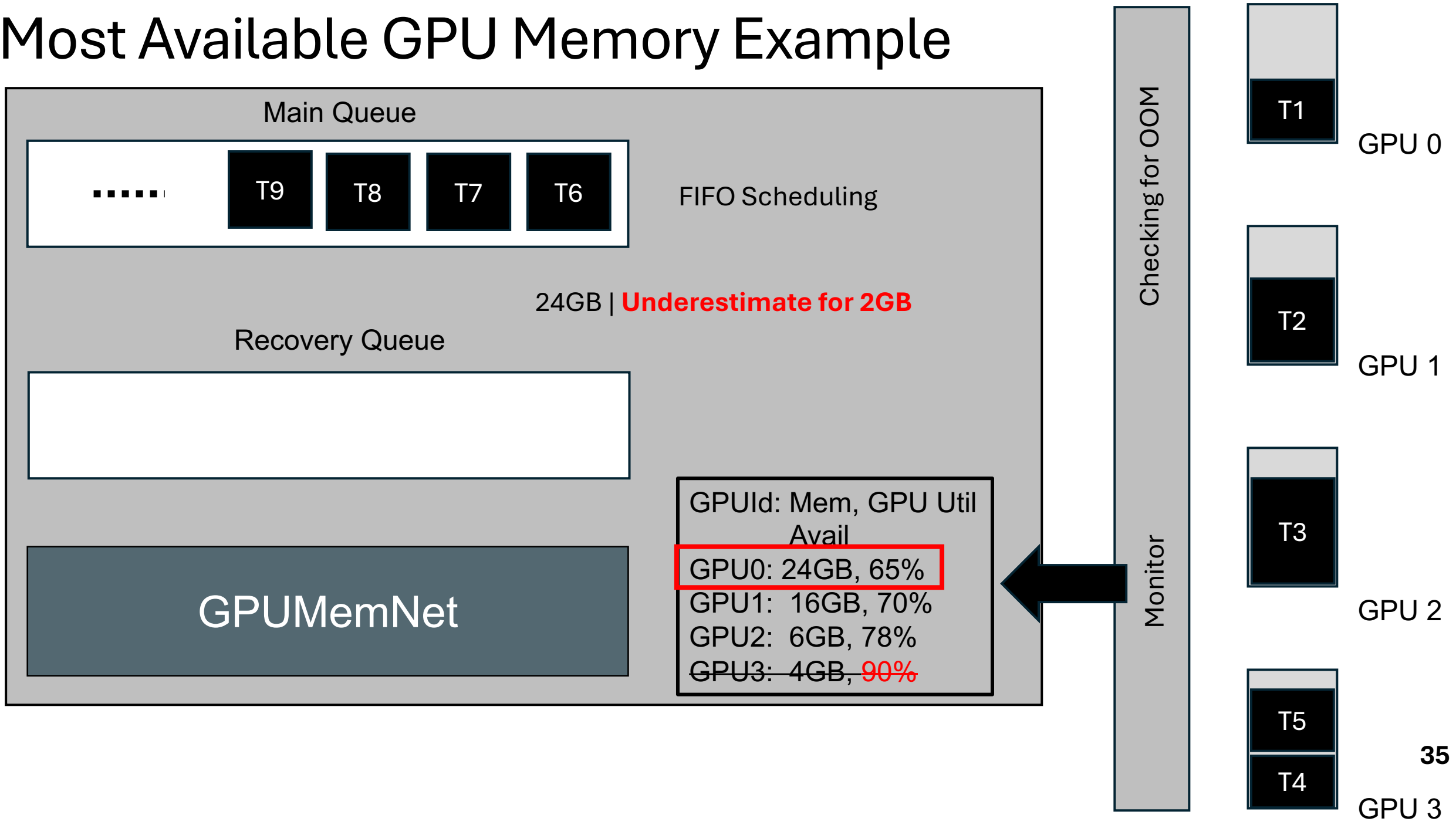
Most Available GPU Memory Example



Most Available GPU Memory Example



Most Available GPU Memory Example



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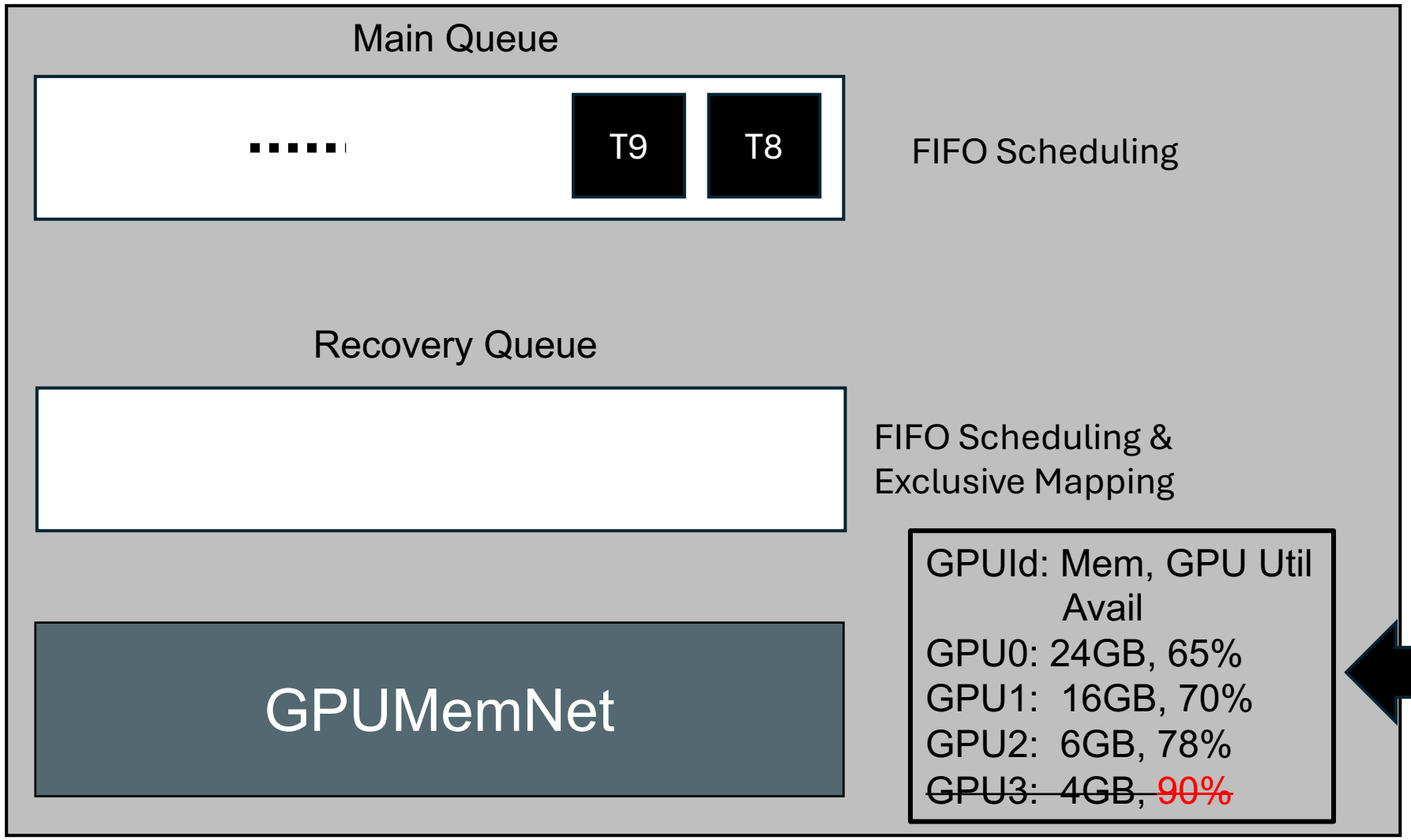
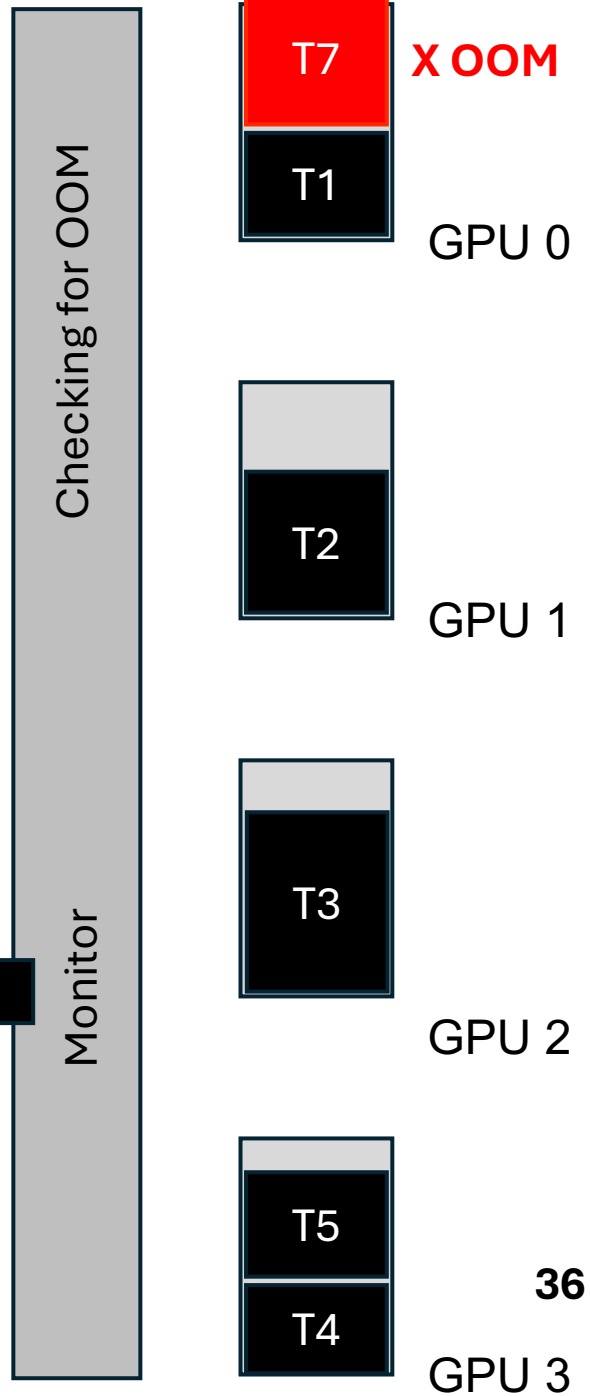




Evaluation Setup

- NVIDIA DGX Station A100
  - 4x 40GB A100 GPUs
  - 1x AMD EPYC 7742

- Mapped Training Tasks
  - A subset of Microsoft **Philly Trace** ✤ submission times

  - 90-tasks trace of light, medium and heavy tasks (65% light, 27% medium, 8% large) ♣
  - 60-task trace of medium and heavy tasks (83% medium and 17% large) ♣

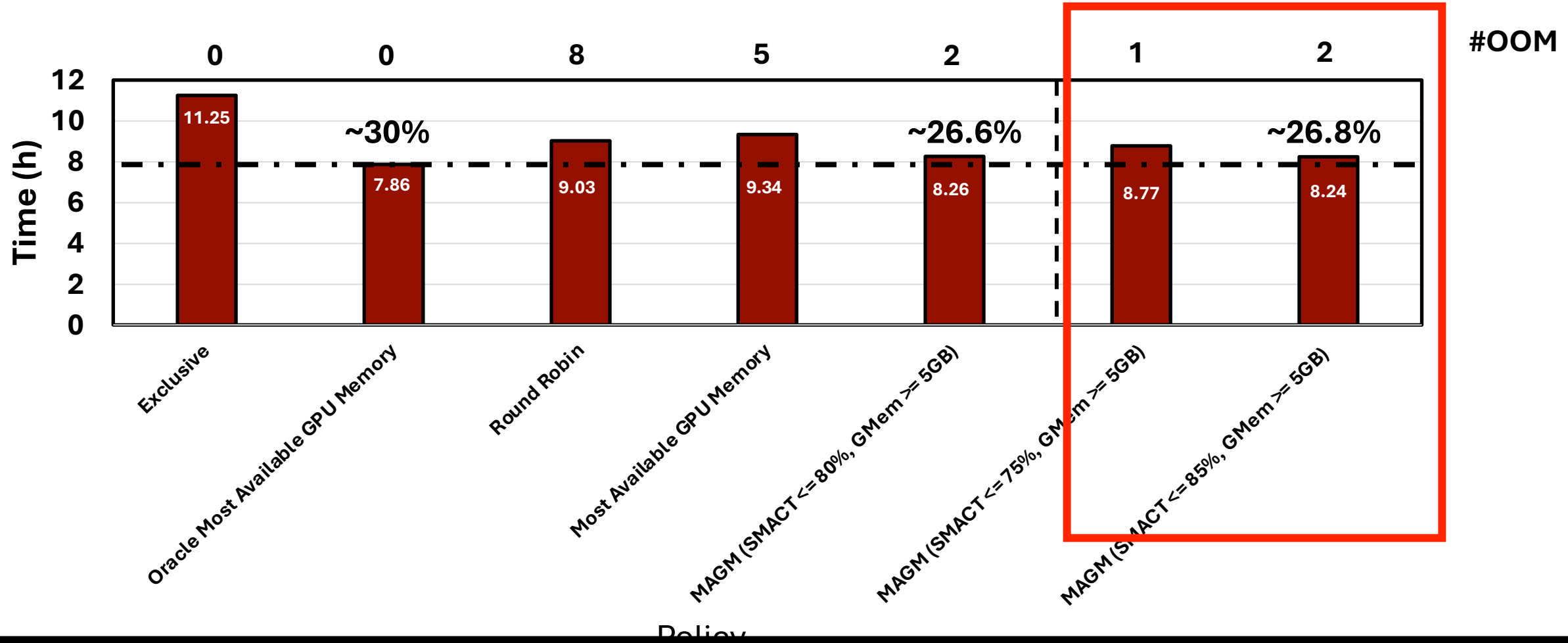
✤ Jeon, Myeongjae, et al. "**Analysis of Large-Scale Multi-Tenant GPU clusters for DNN training workloads**," *USENIX **ATC** 19*.

♣ Ye, Zhisheng, et al. "**Astraea: A fair deep learning scheduler for multi-tenant gpu clusters**," ***ITPDS*** 21.

A glimpse of 90-task trace!

```
python src/submit.py --task workloads/efficientNet3.rad
sleep 441
python src/submit.py --task workloads/resnet18_cifar100_20e_3.rad
sleep 52
python src/submit.py --task workloads/resnet18_cifar100_50e_1.rad
sleep 51
python src/submit.py --task workloads/resnet34_cifar100_20e_2.rad
sleep 365
python src/submit.py --task workloads/resnet34_cifar100_20e_1.rad
sleep 18
python src/submit.py --task workloads/resnet.rad
sleep 166
python src/submit.py --task workloads/resnet18_cifar100_20e_3.rad
sleep 439
python src/submit.py --task workloads/resnet18_cifar100_20e_1.rad
sleep 83
```

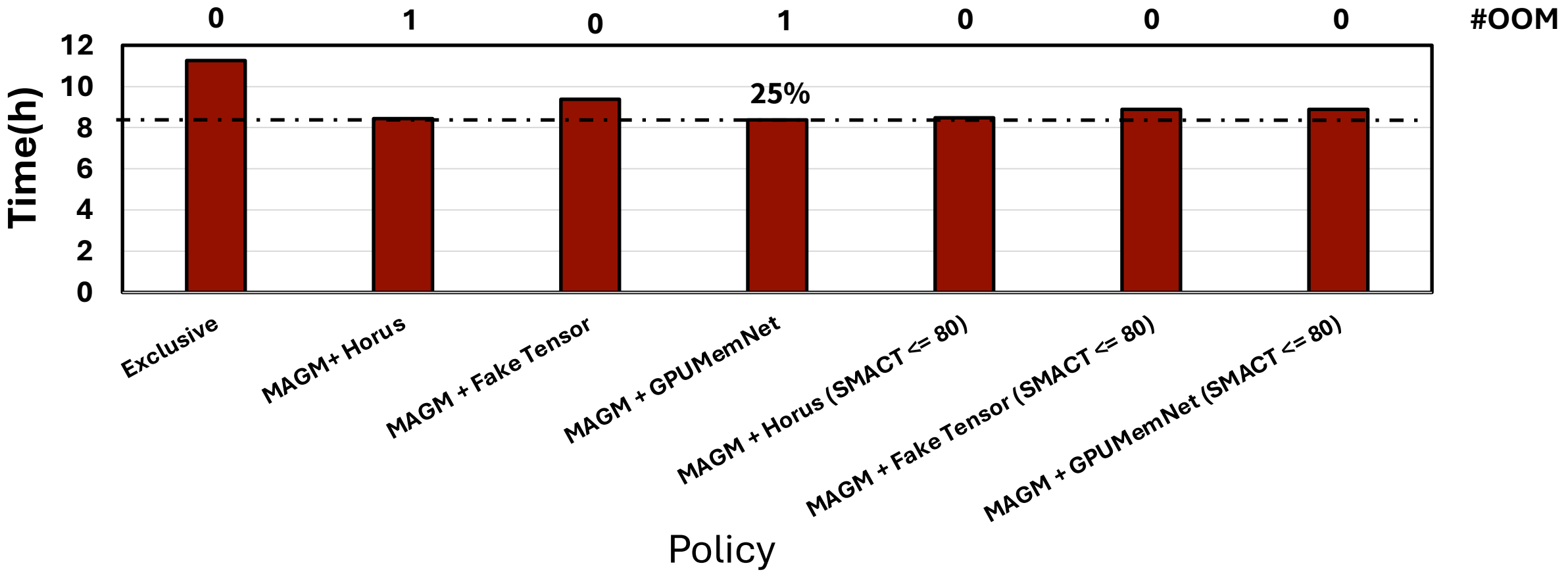
90-task trace relying on the recovery method scenarios



Collocation with least resource interference is beneficial!

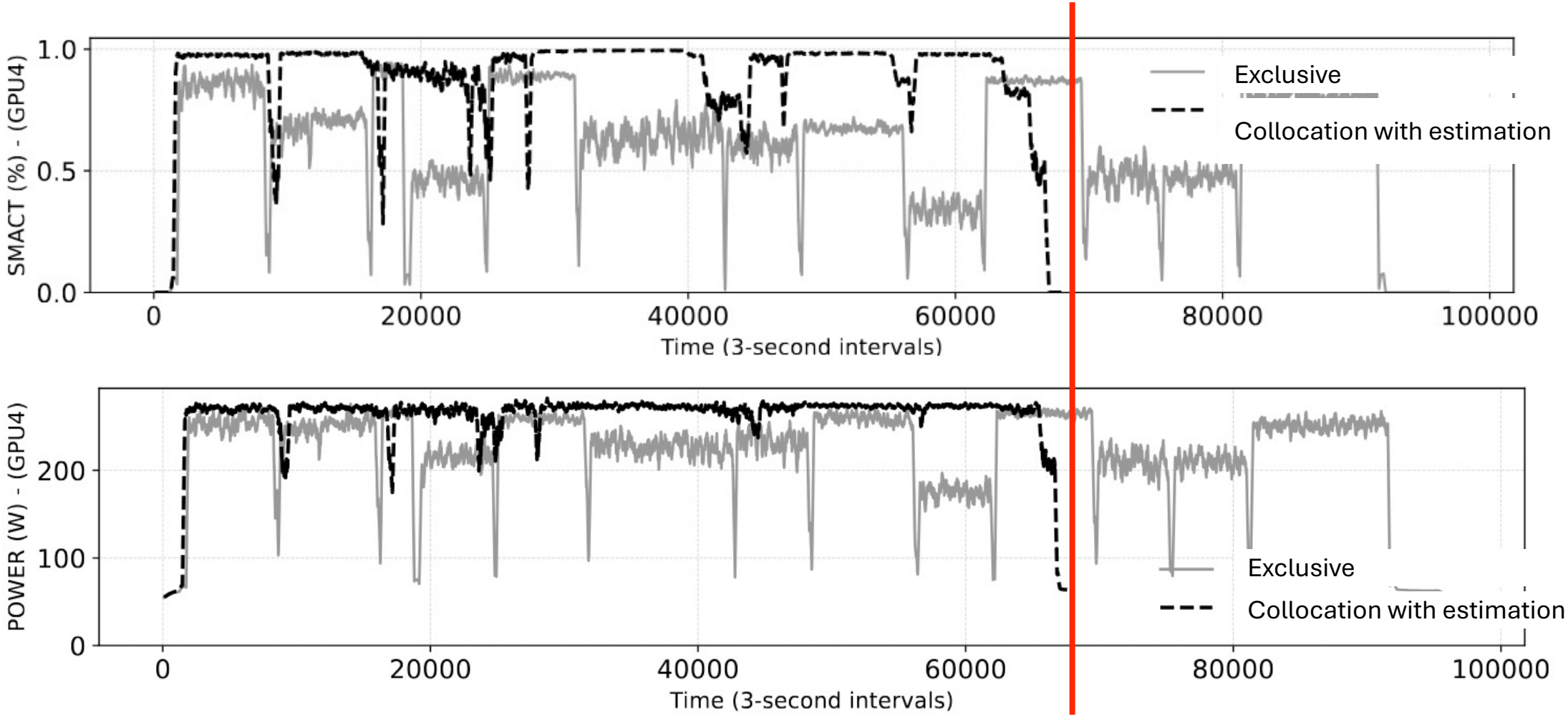
Preconditions coupled with collocation policies affect the number of OOM crashes.

90-task trace with integrated GMem Estimators



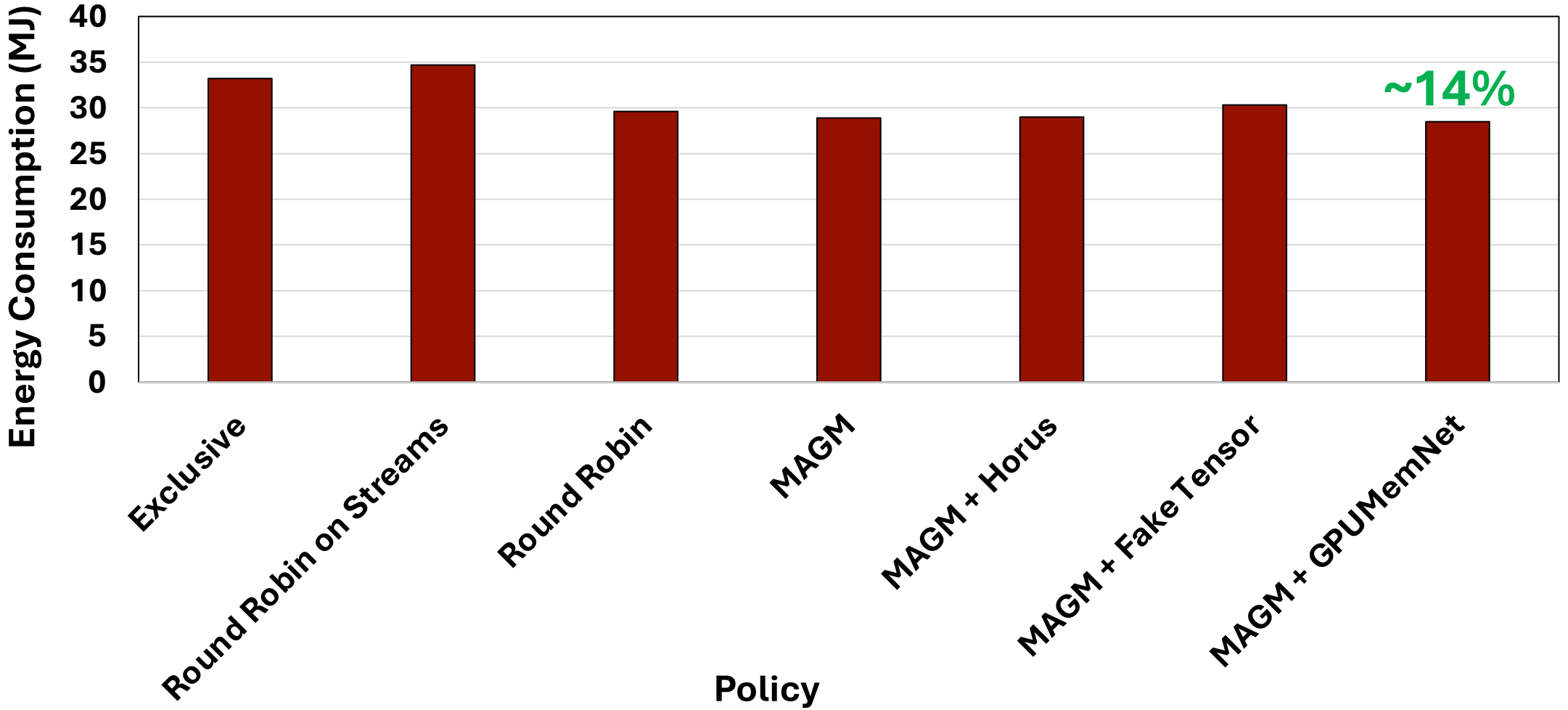
Having even inaccurate estimations help preventing OOMs!

GPU Utilization & Power over time



Collocation-aware resource management improves GPU Utilization.

Energy Consumption

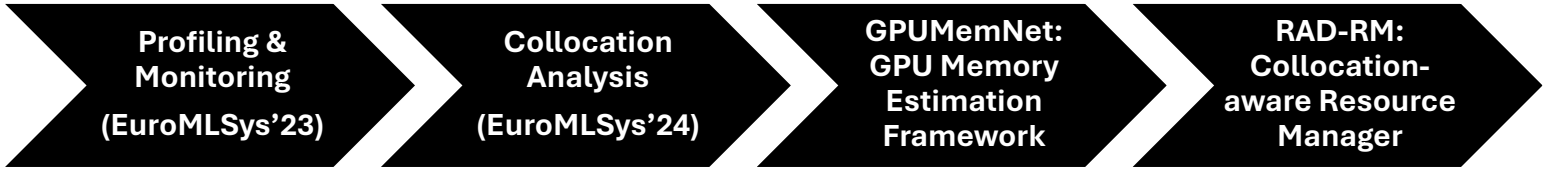


Collocation-aware resource management improves energy efficiency.

Summary

- Collocation policies and preconditions affect the number of OOMs.
- Least interference promises higher performance via throughput gain.
- The sequence of coming tasks also affects the number of OOMs.
- Collocation-aware resource managers improve GPU utilization and energy efficiency.

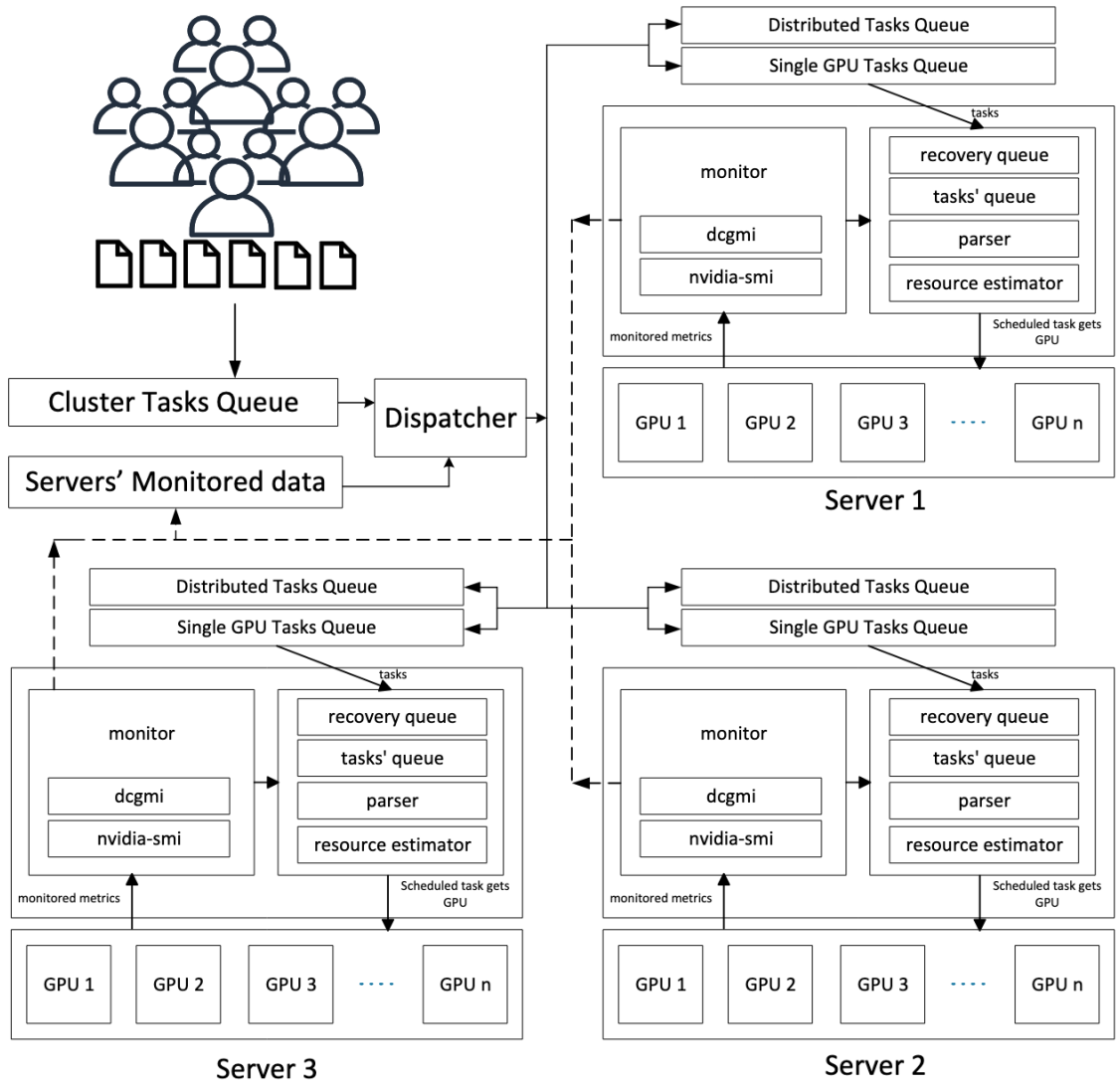
Conclusion



- Fine-grained metrics (SMACT for utilization) from monitoring tools
- Collocation is beneficial when applied carefully.
  - If aggregate SMACT <= ~80%
  - OOM crashes and performance degradation due to resource interference
- GPU Memory estimation is necessary for a more reliable collocation.
- Collocation-aware resource management improves GPU utilization and energy efficiency.

Future Directions

- GPU Utilization Estimation
  - and Integrating in the system
- Looser Recovery Method
- Fairness and Checkpointing
- Extending to cluster scale



Thanks ☺