DASYA

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peaceful sharing while training

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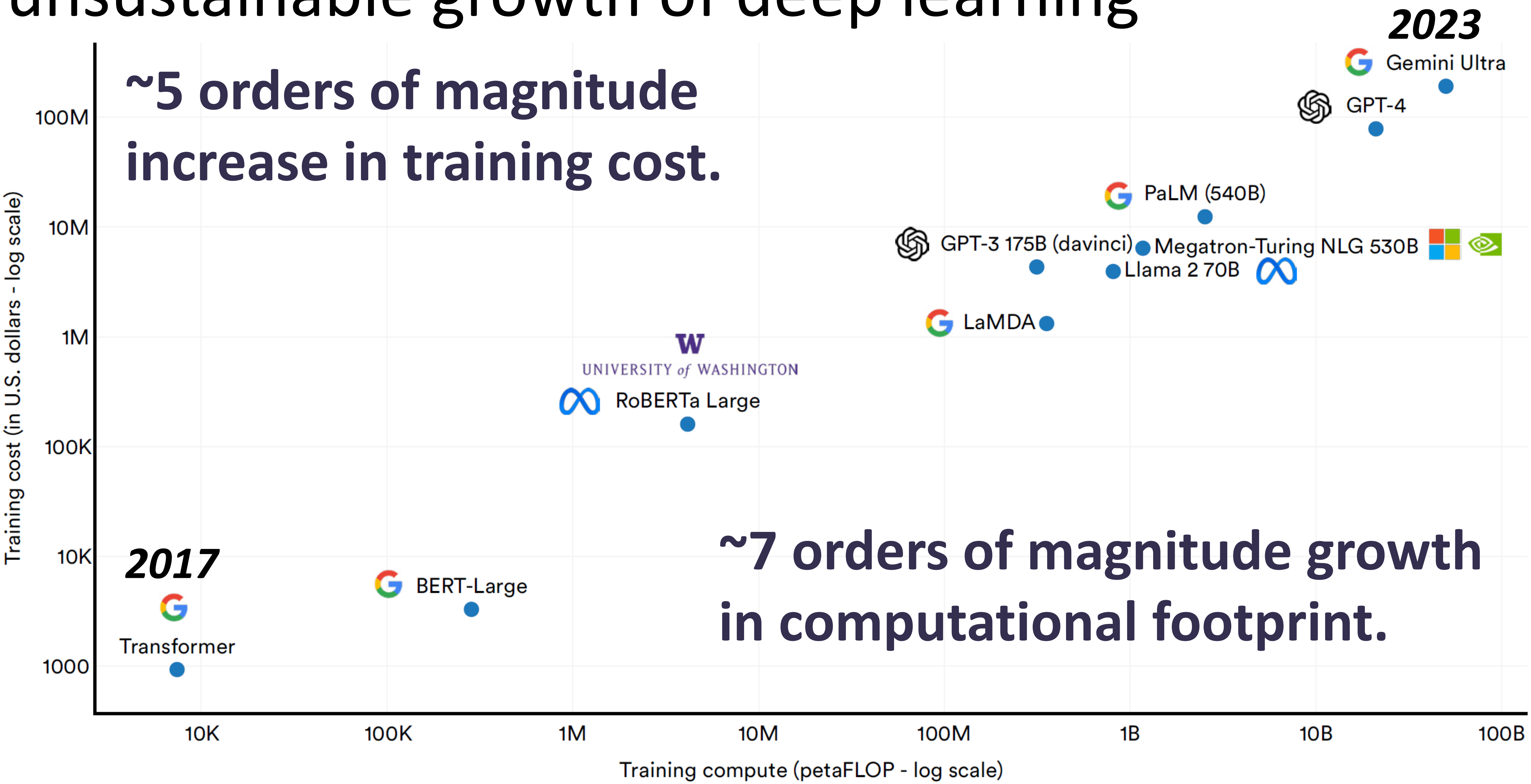
INDEPENDENT RESEARCH FUND DENMARK

novo nordisk foundation

CWI - DSDSD
04/10/2024

unsustainable growth of deep learning



source: [Stanford AI Index Report 2024]

hardware underutilization

NVIDIA H200

141GB memory

50MB L2 cache

4.8TB/s
memory bandwidth

in the meanwhile, on pre-H200 GPUs …

- ***@ITU***, many ML jobs utilize ***less than 50% of GPU resources*** e.g., transfer learning, small models
- ***in real-world*, ~52% GPU utilization*** on average for 100,000 jobs

can we do better while using fewer resources?

*Jeon et al. "Analysis of Large-Scale Multi-Tenant GPU Clusters for DNN Training Workloads." *ATC* 2019

sharing for deep learning training

- GPU sharing

[An Analysis of Collocation on GPUs for Deep Learning Training]
Ties Robroek, Ehsan Yousefzadeh-Asl-Miandoab, Pınar Tözün.
EuroMLSys 2024

- data & work sharing

[TensorSocket: Shared Data Loading for Deep Learning Training]
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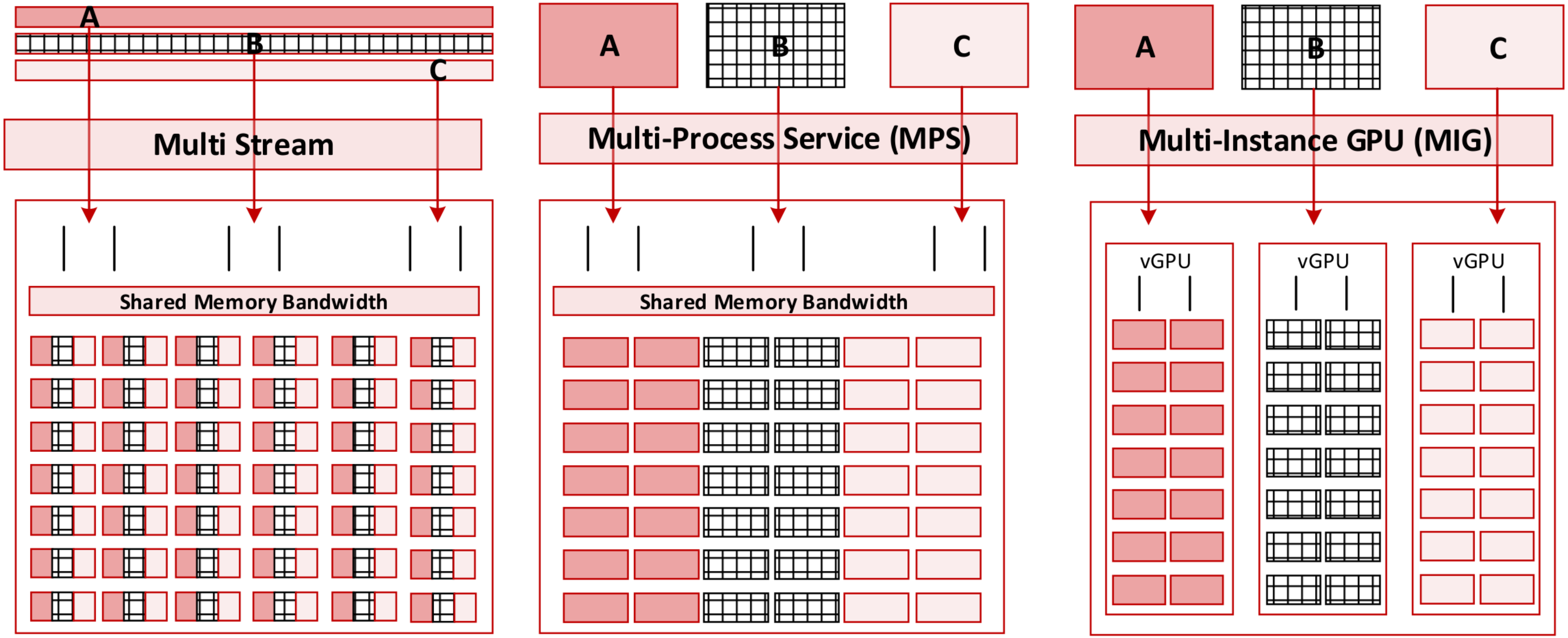
sharing resources on (NVIDIA) GPUs

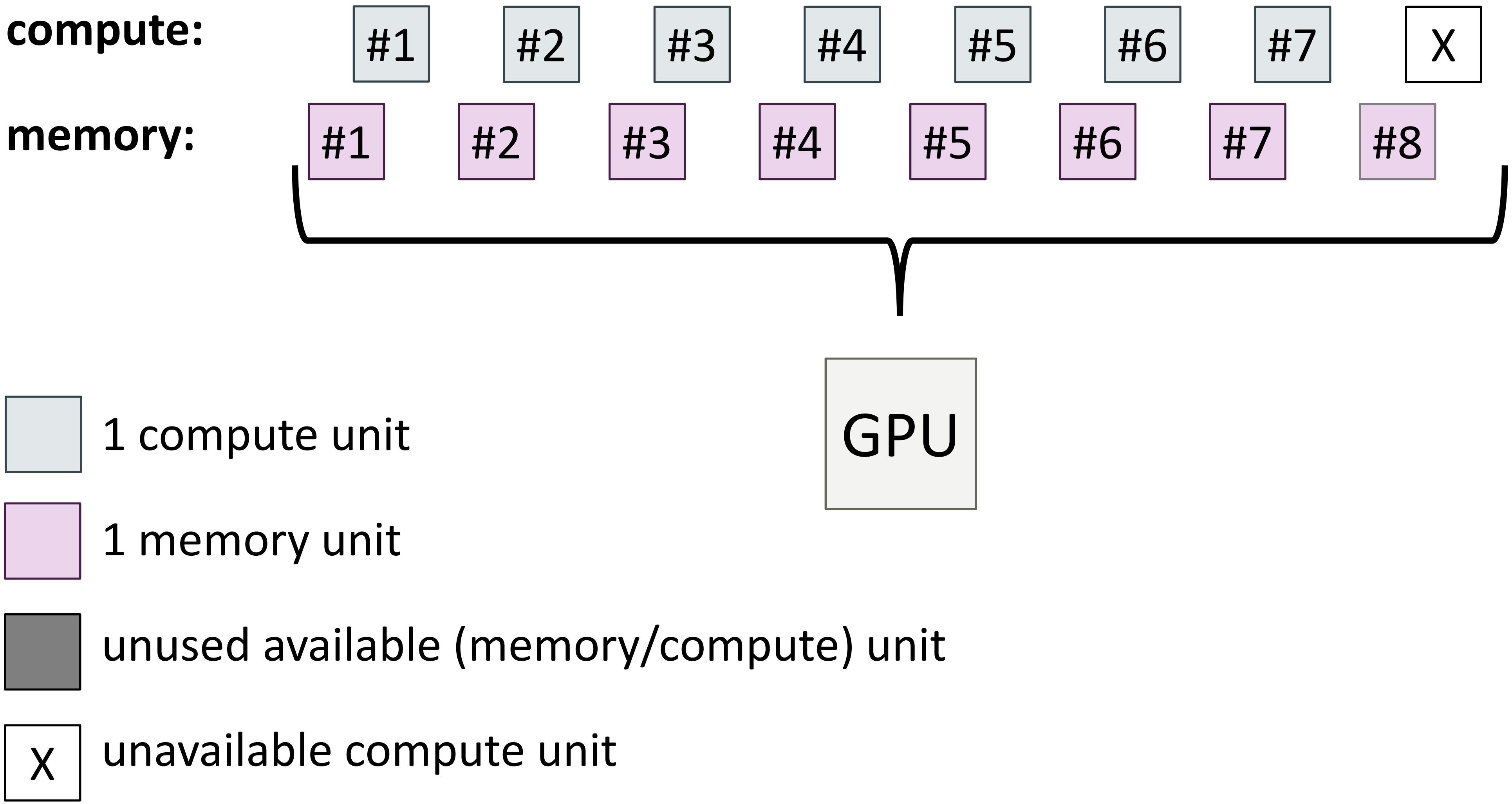


- most straightforward
- time-multiplexing
- ✕ limited parallelism

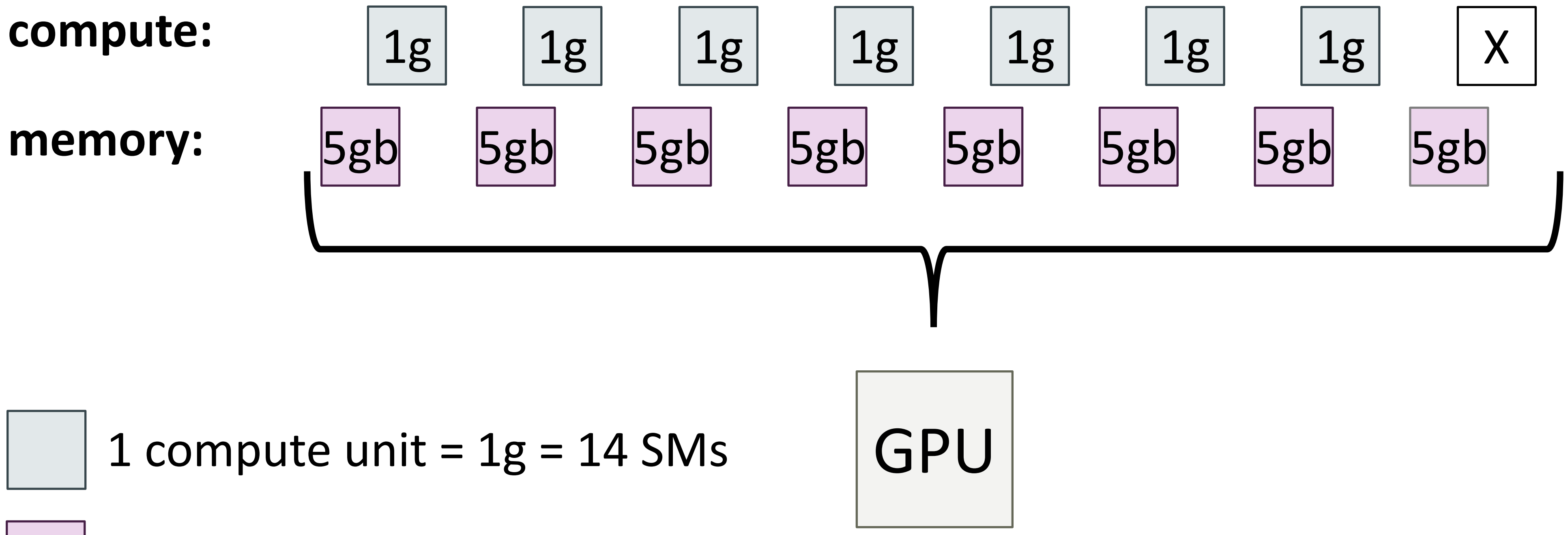
- finer-grained sharing
- ✕ single user (due to safety)

- hardware-support for resource split
- ✕ rigid partitioning

multi-instance GPU



multi-instance GPU on A100 (40GB)



1 compute unit = 1g = 14 SMs

1 memory unit = 5GB

unused available (memory/compute) unit

X unavailable compute unit = 10 SMs (streaming multiprocessor)

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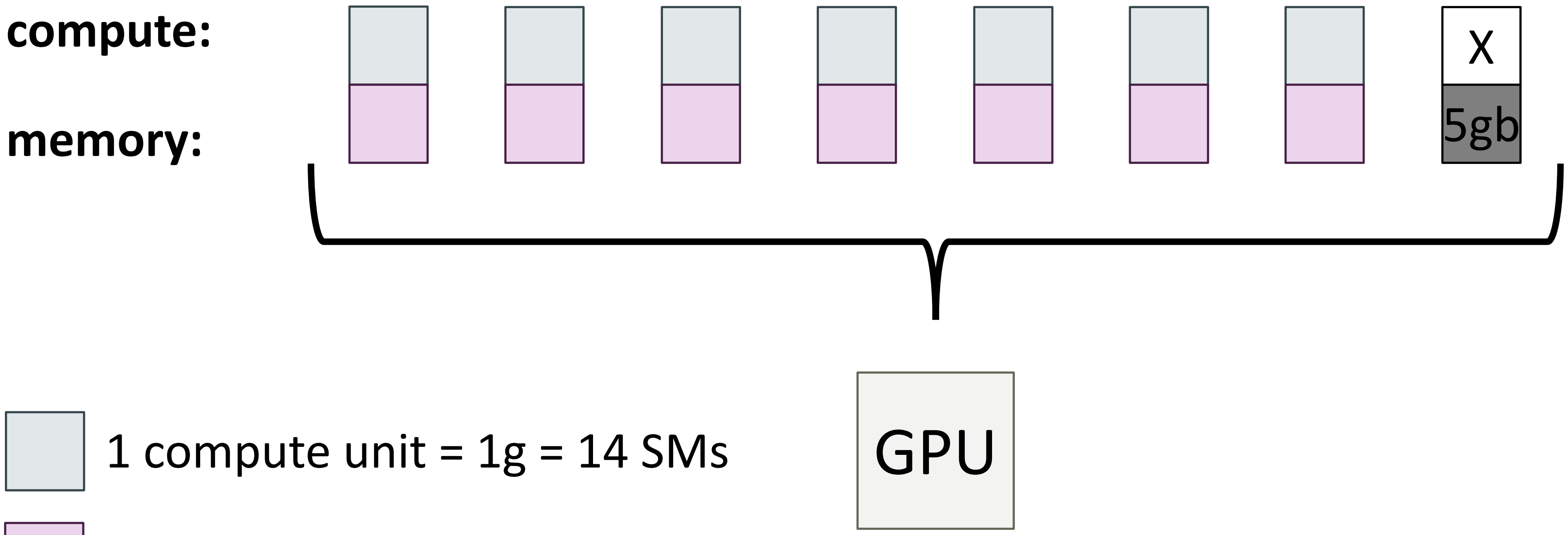

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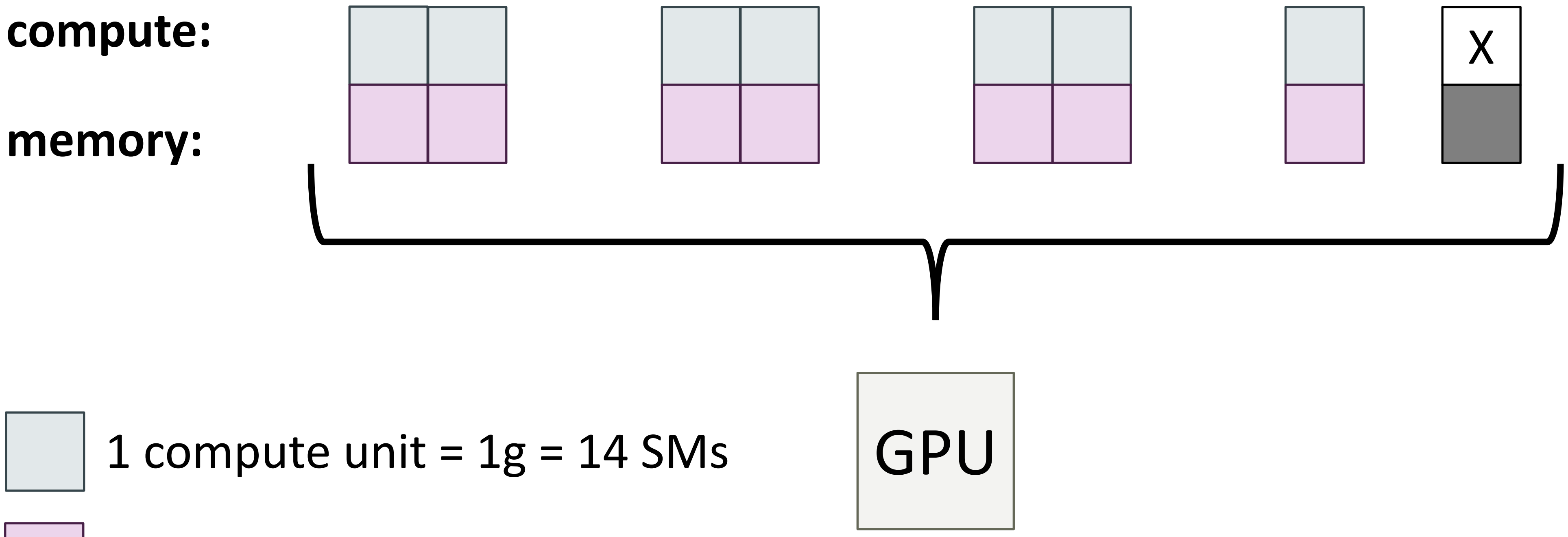

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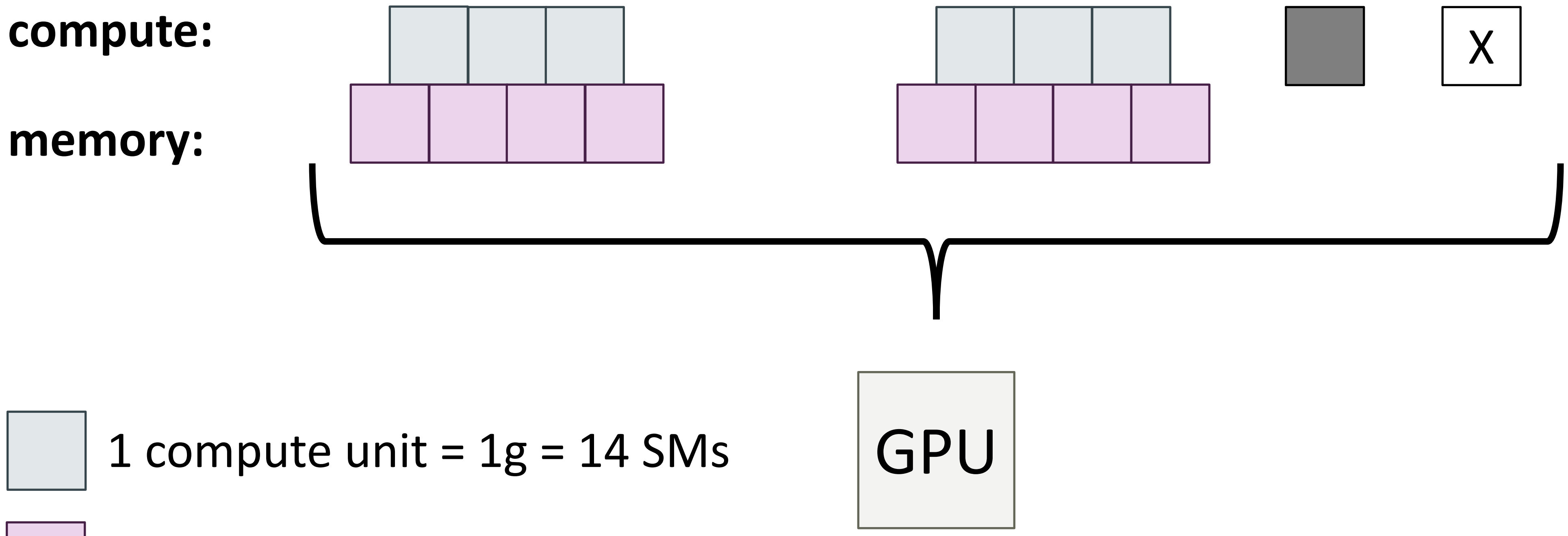

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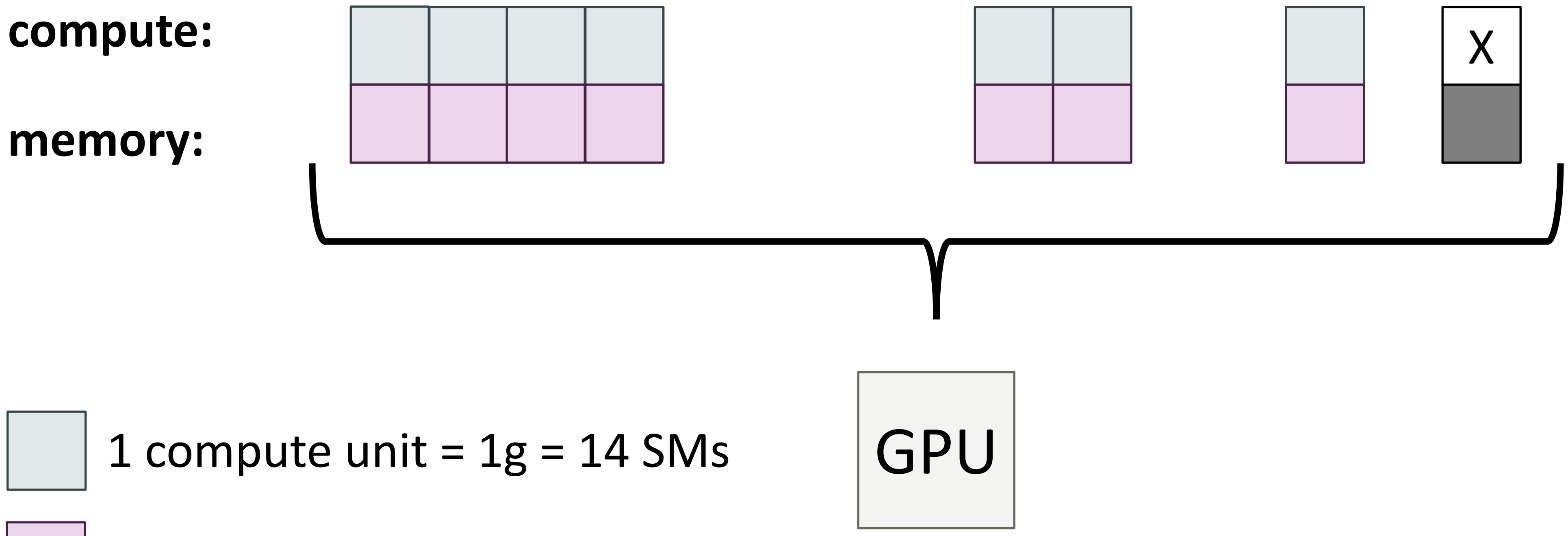

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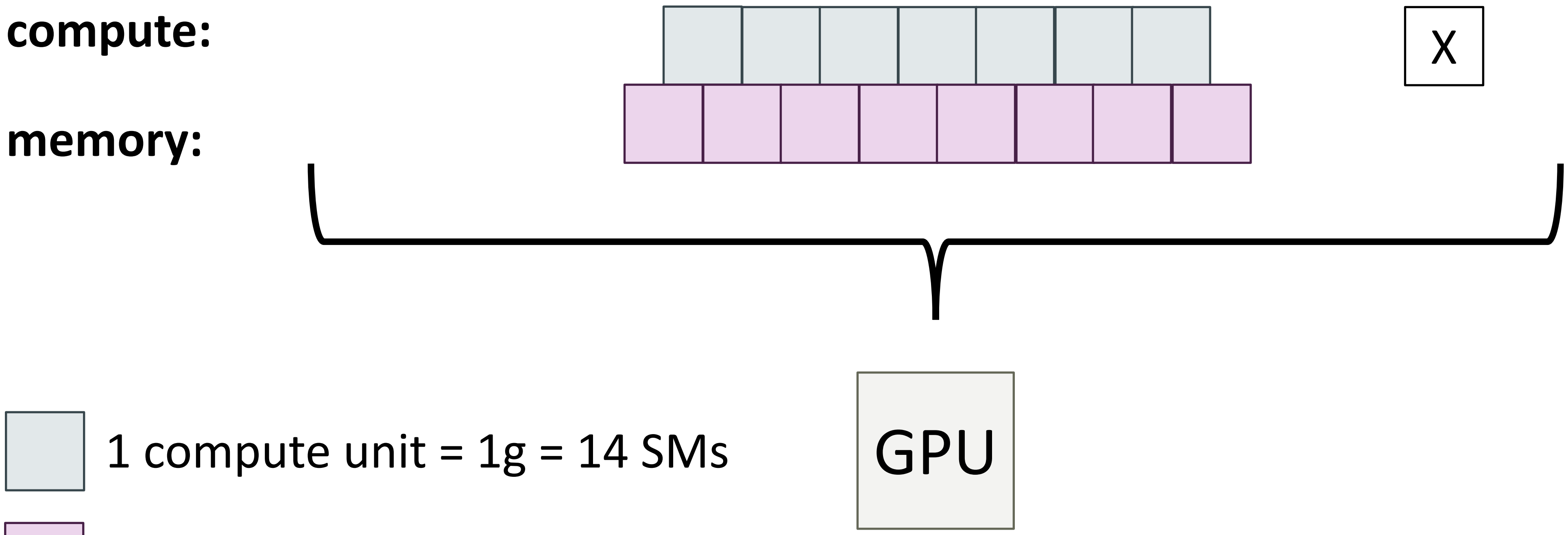

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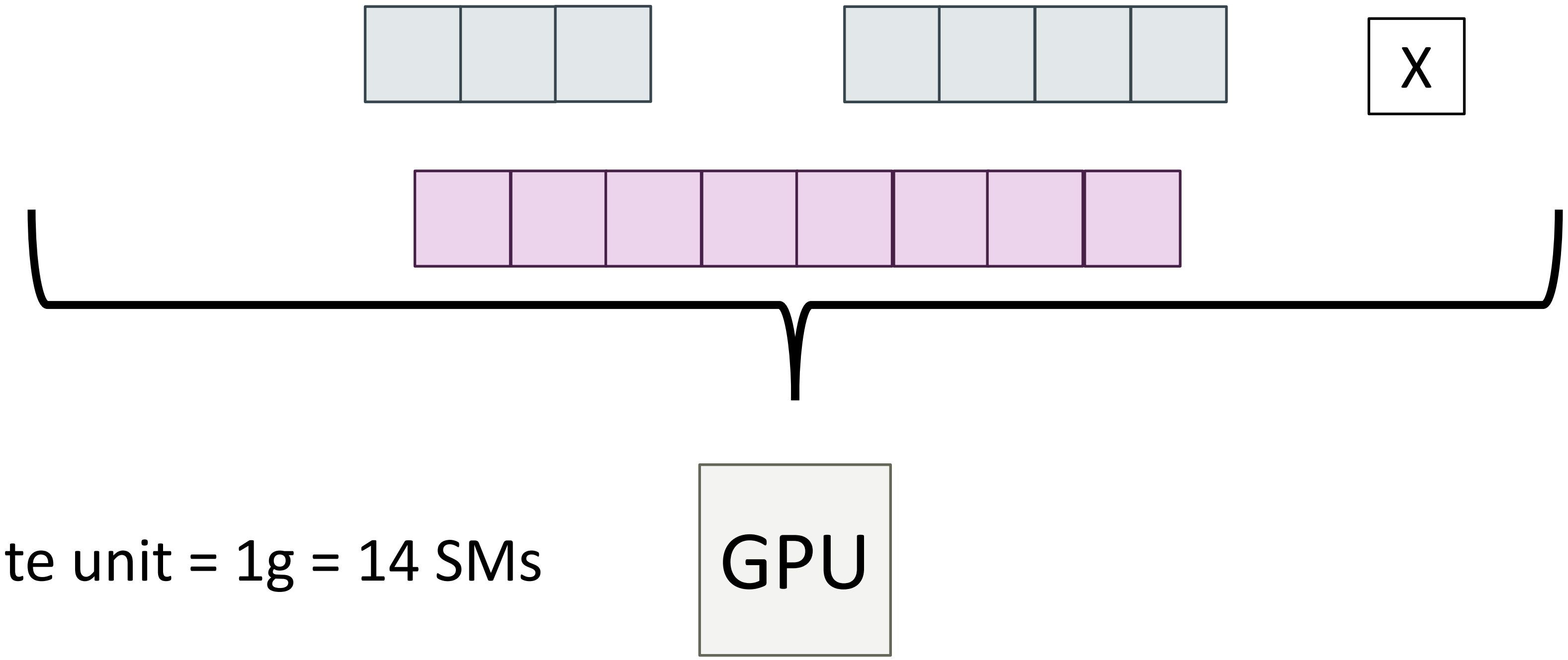
compute:

memory:



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performance impact of collocation

NVIDIA DGX Station A100

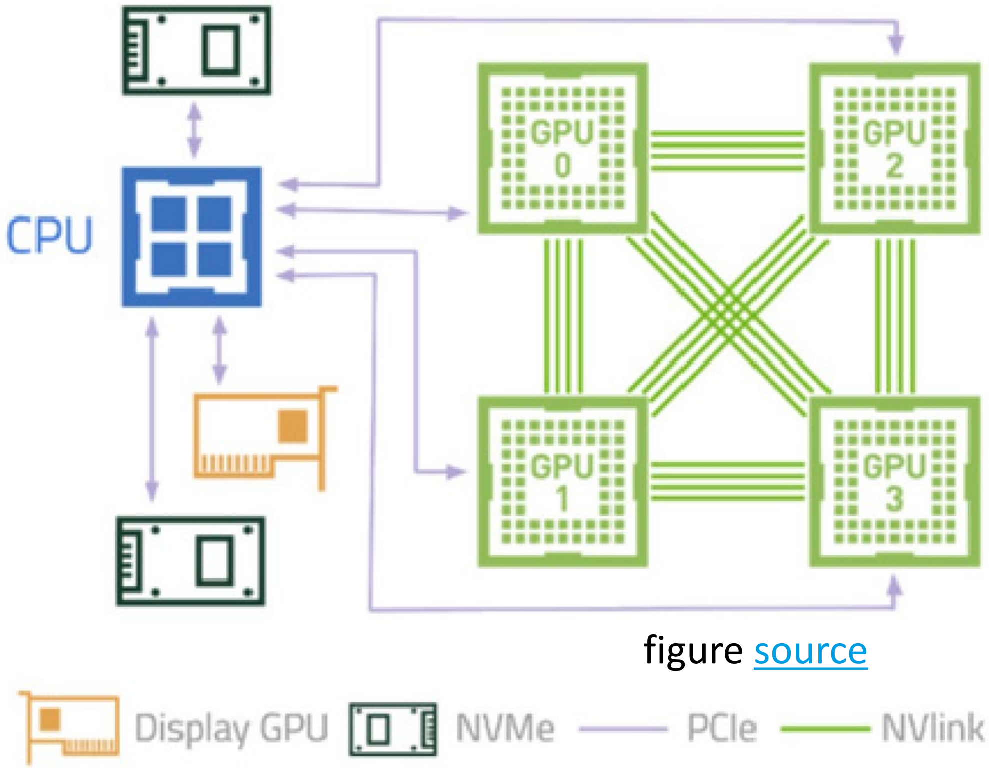


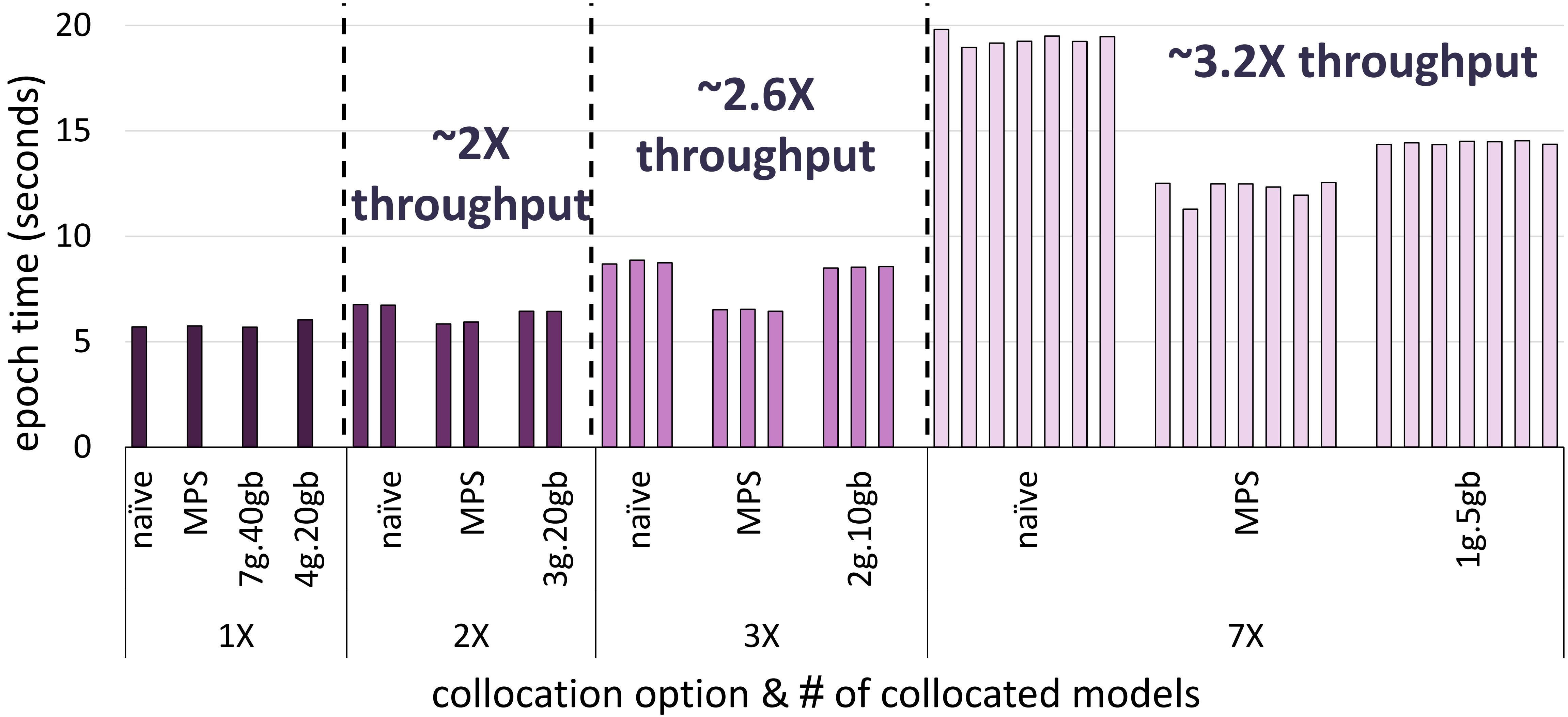
figure source

CPU = AMD 7742 – 512 GB RAM
64 physical cores
GPU = NVIDIA A100 – 40 GB RAM

workloads	model	batch size	dataset
small	**ResNet26** EfficientNet	128	CIFAR-10
medium	**ResNet50** EfficientNet	128	downsampled ImageNet*
large	**ResNet152** CaiT	32 128	ImageNet (2012)
xlarge	**DLRM**	1	Criteo Terabyte

- image models: CNN & transformers
  recommender model
- on single GPU with PyTorch v2.0
- results reported from 2nd epoch of training

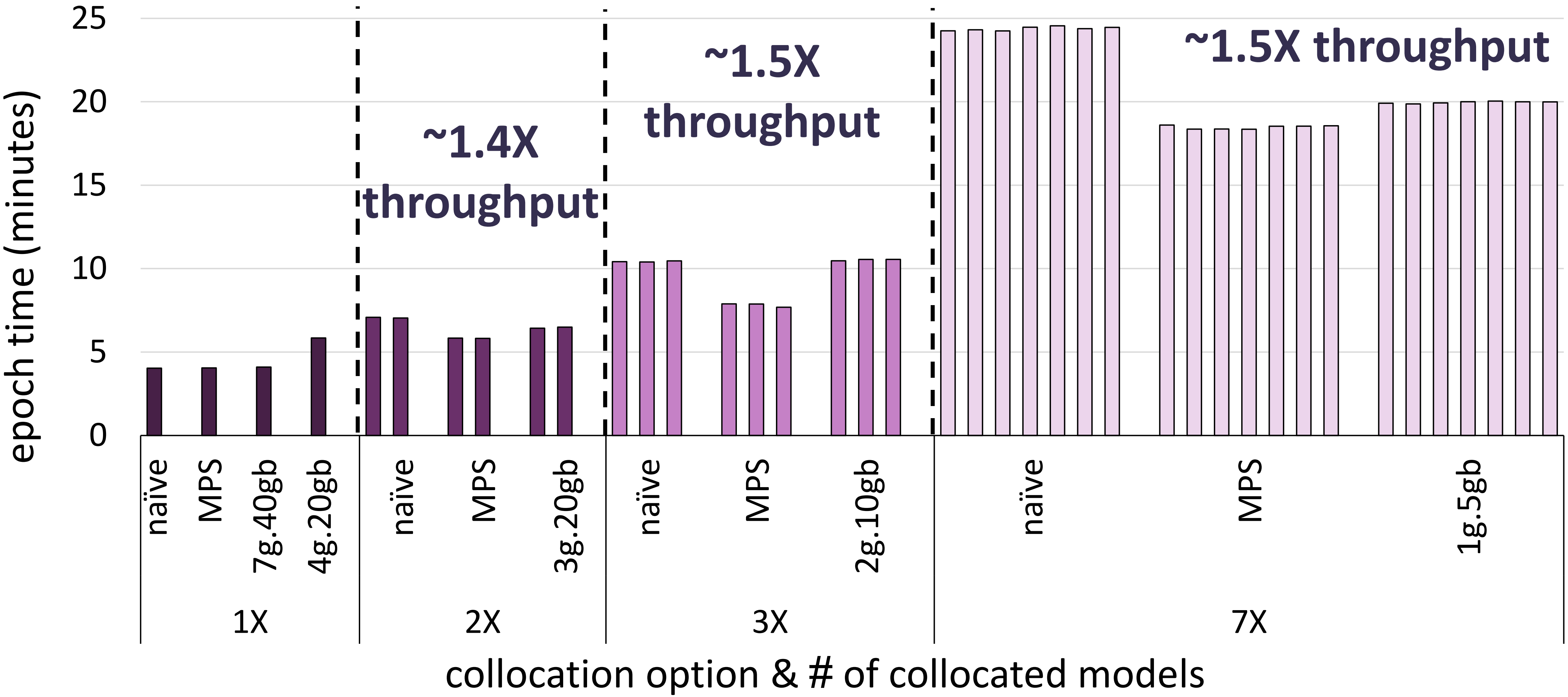
small case – ResNet26



collocation benefits despite increased epoch time

MPS > MIG > naïve

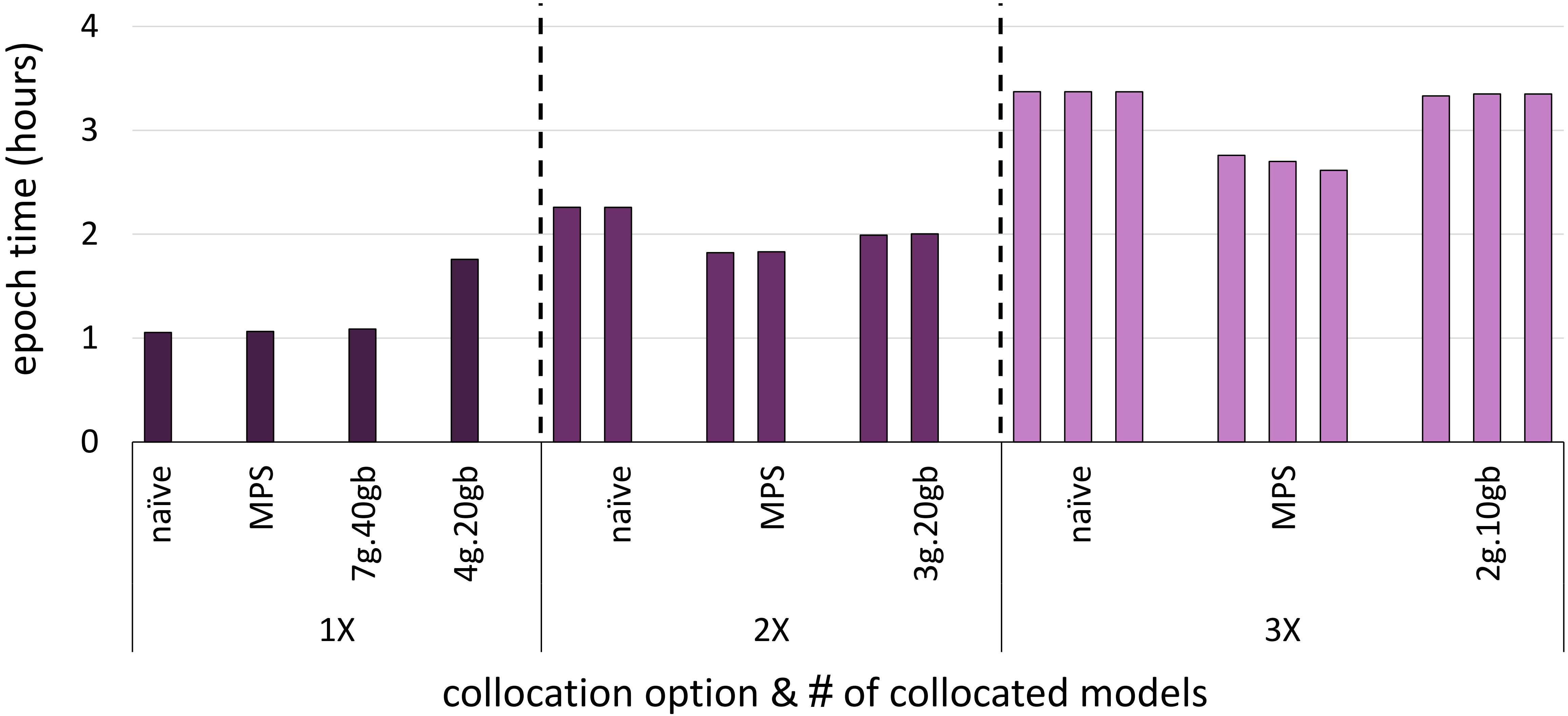
medium case – ResNet50



still some throughput benefits

but diminishing returns for increased collocation

large case – ResNet152



no more throughput benefits – 80% utilization when training alone

better to collocate with smaller or less compute heavy tasks

mixed workloads: compute- & memory-heavy

	DLRM – time per training block	ResNet152 – time per epoch	sm activity	memory footprint
DLRM alone			5%	29.14 GB
ResNet152 alone			82%	8.47 GB

mixed workloads: compute- & memory-heavy

	DLRM – time per training block	ResNet152 – time per epoch	sm activity	memory footprint
DLRM alone **ResNet152 alone**			5% 82%	29.14 GB 8.47 GB
naïve			81%	37.75 GB
MPS			81%	37.62 GB
MIG: **3compute – DLRM** **4compute – ResNet** **shared memory**			39%	37.86 GB

mixed workloads: compute- & memory-heavy

	DLRM – time per training block	ResNet152 – time per epoch	sm activity	memory footprint
DLRM alone **ResNet152 alone**	5.36 h -	- 1.05 h	5% 82%	29.14 GB 8.47 GB
naïve			81%	37.75 GB
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MIG: **3compute – DLRM** **4compute – ResNet** **shared memory**			39%	37.86 GB

mixed workloads: compute- & memory-heavy

	DLRM – time per training block	ResNet152 – time per epoch	sm activity	memory footprint
DLRM alone	5.36 h	-	5%	29.14 GB
ResNet152 alone	-	1.05 h	82%	8.47 GB
naïve	6.09 h (+14%)	1.11 h (+5%)	81%	37.75 GB
MPS	5.57 h (+5%)	1.10 h (+4%)	81%	37.62 GB
MIG: 3compute – DLRM 4compute – ResNet shared memory	5.60 h (+5%)	1.40 h (+33%)	39%	37.86 GB

collocation can lead to (almost) free lunch when workloads stress hardware different resources

sharing for deep learning training

- GPU sharing

[An Analysis of Collocation on GPUs for Deep Learning Training](#)
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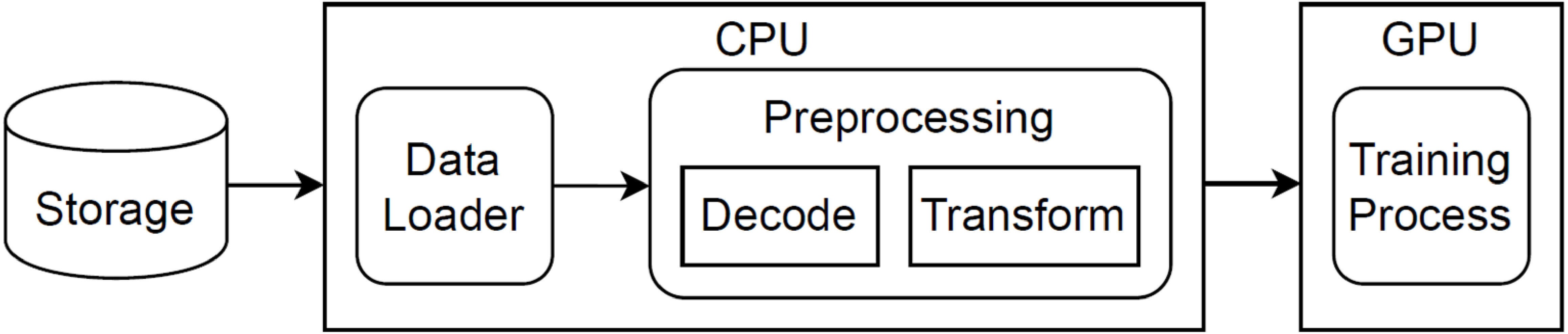
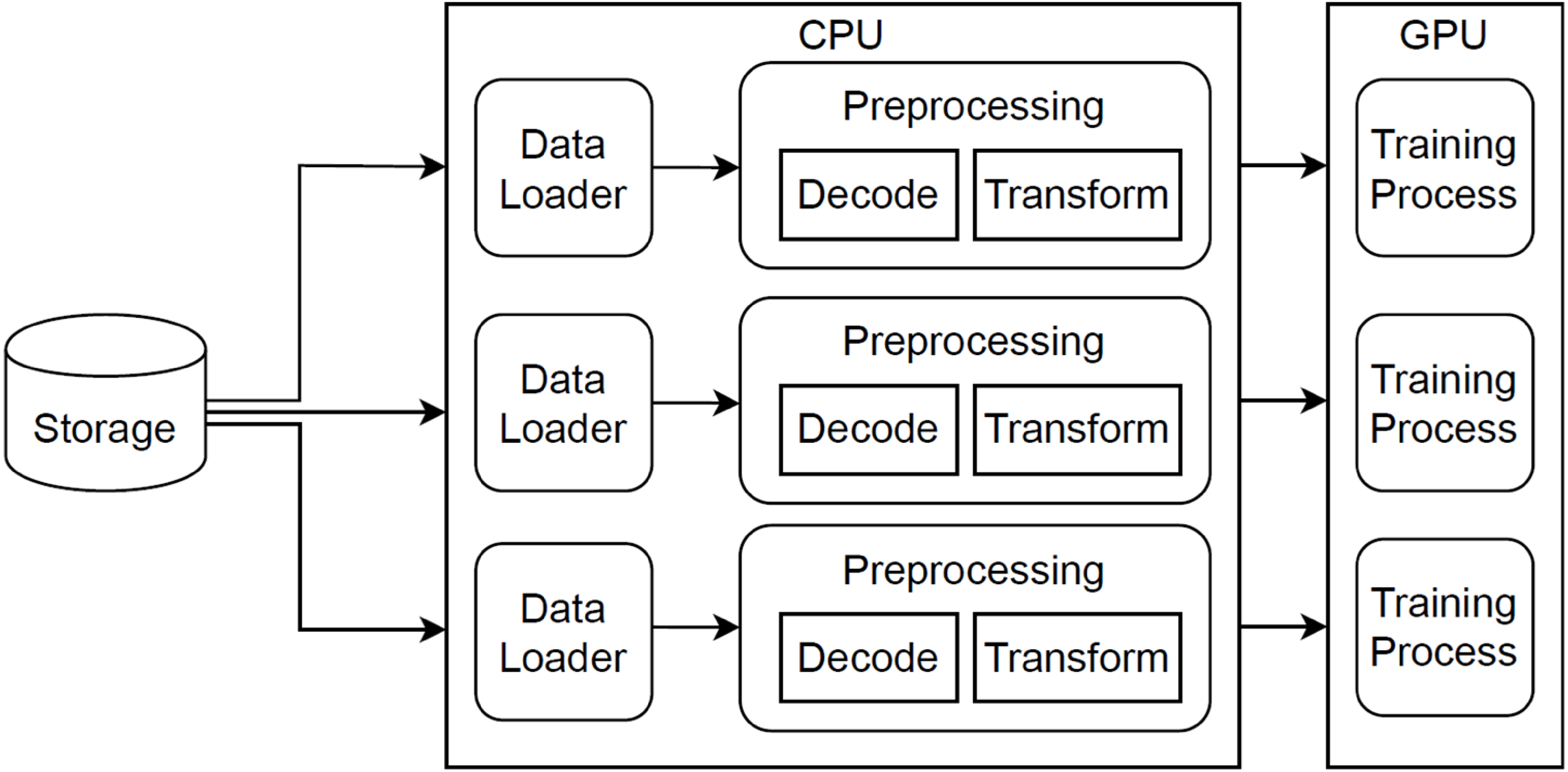
conventional journey of data while training



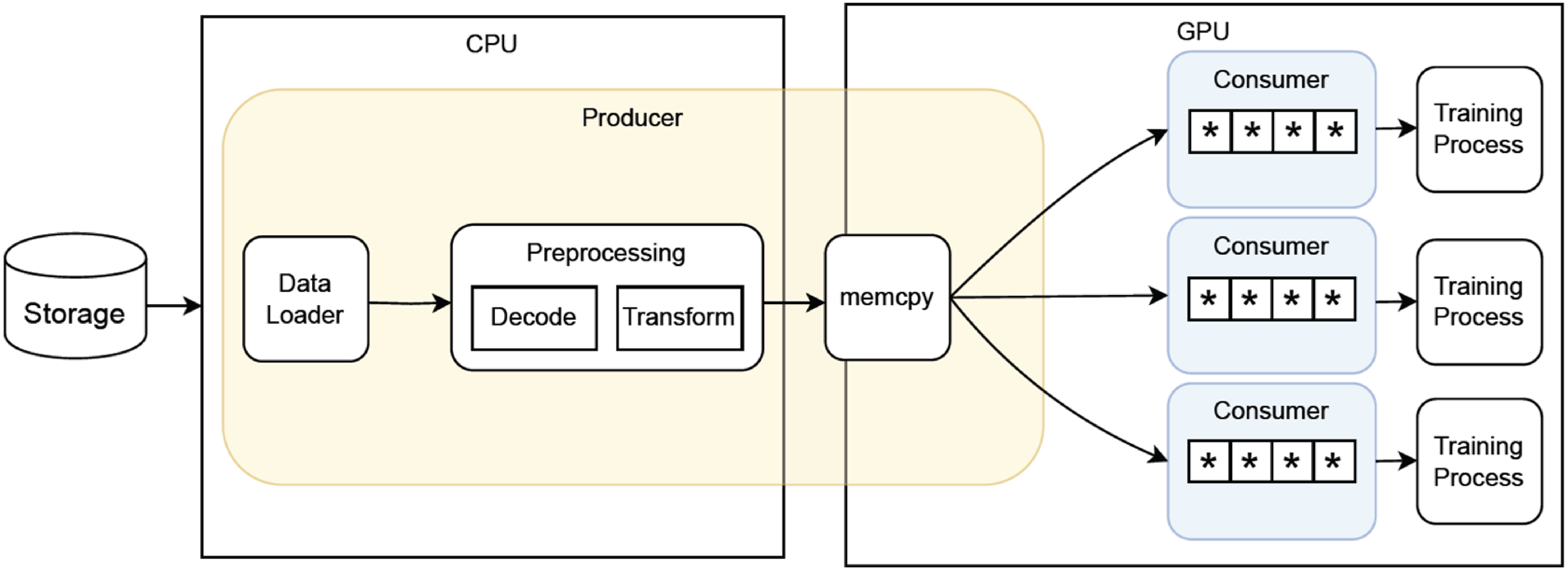
data journey in collocated training



redundant work & memory use!

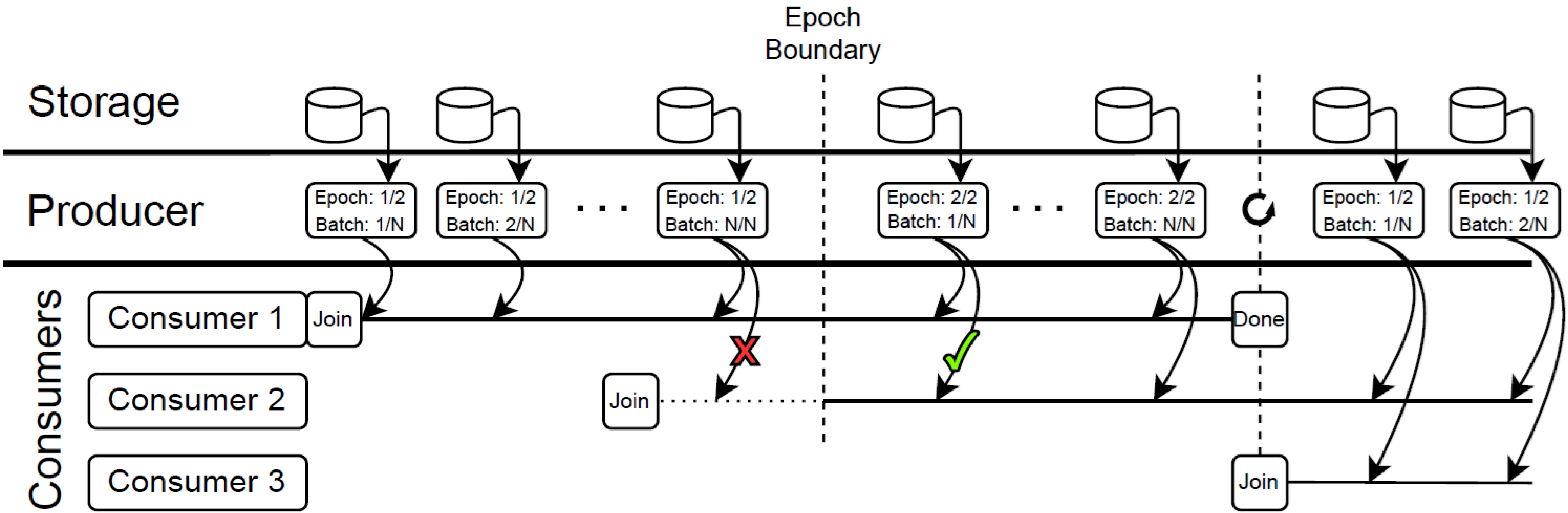
data sharing for collocated training

TensorSocket



eliminates redundant work on CPUs!

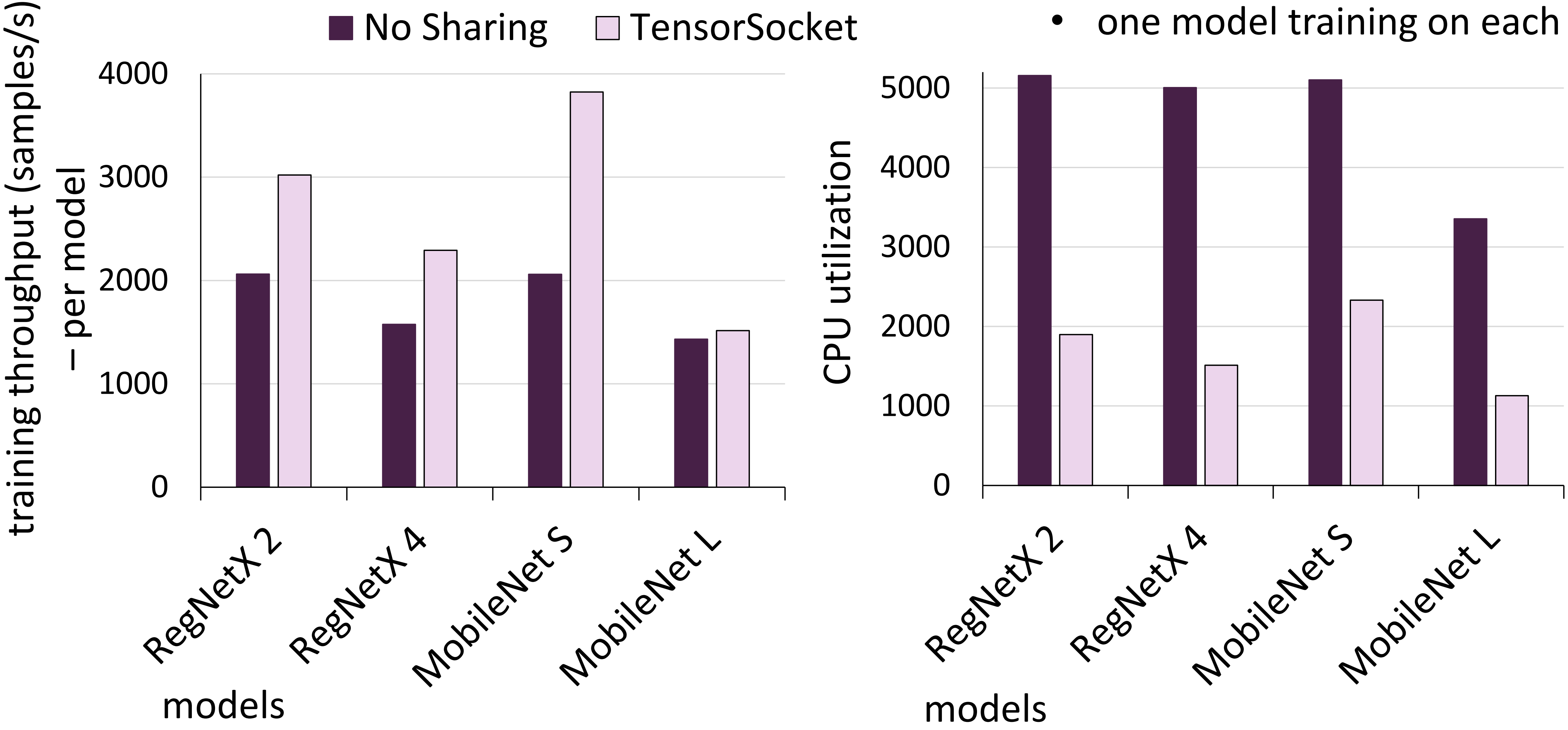
data loading server



consumers don't have to be in perfect sync.

impact of data sharing

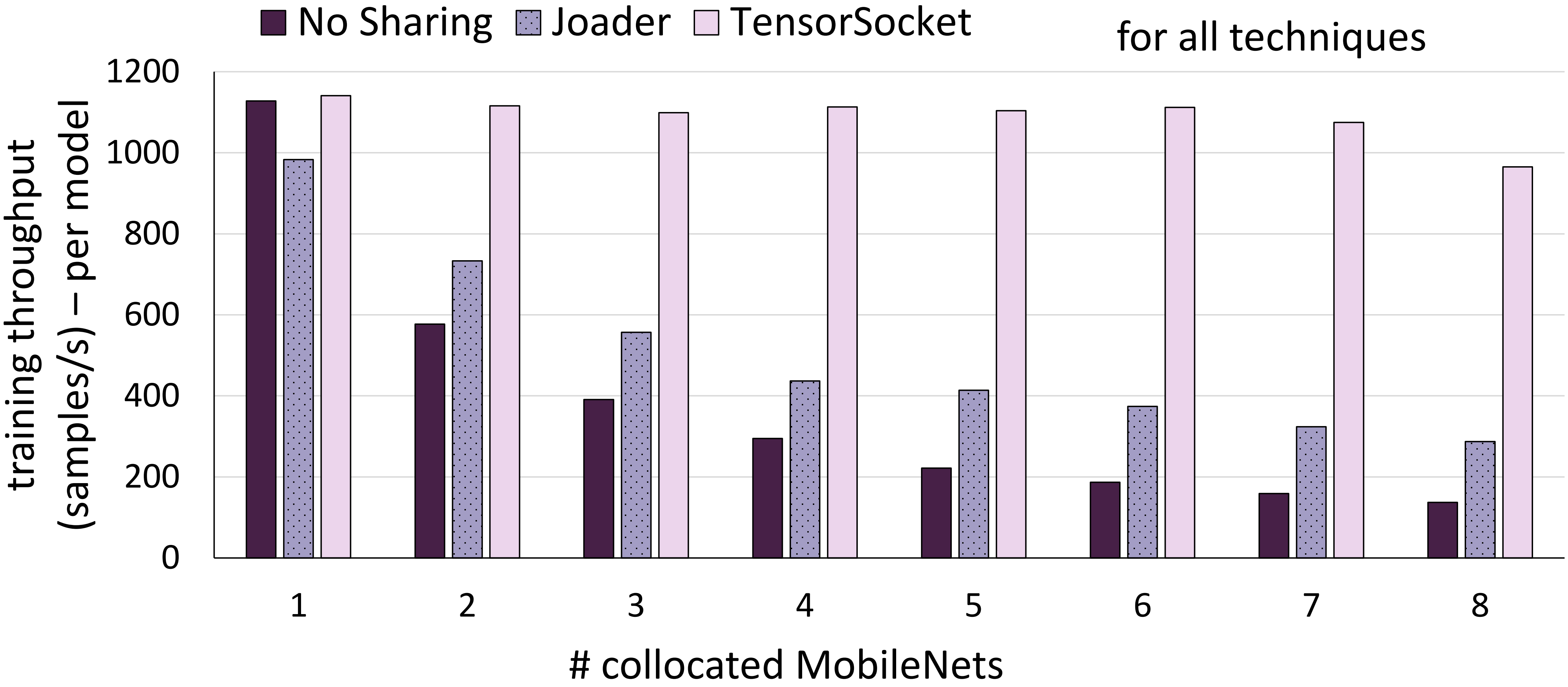
- 4 A100 GPUs
- one model training on each



higher overall throughput & reduced CPU need!

comparison to other techniques

- on a single H100 GPU (80GB)
- CPU resources are the same for all techniques



TensorSocket maintains throughput even under heavy collocation.

sharing for deep learning training

thank you!

- not all training needs all the resources of a single GPU

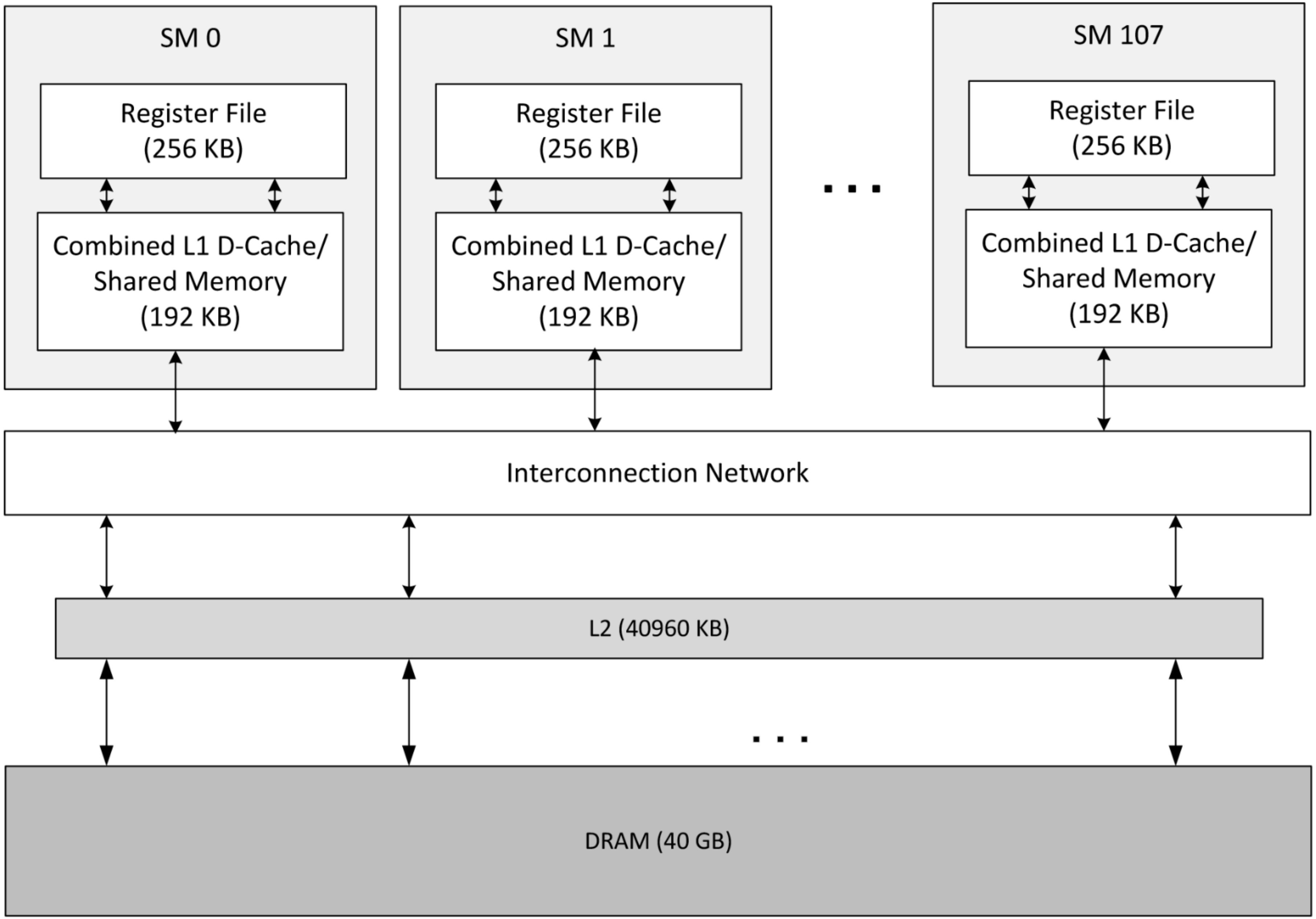
- collocation on GPUs benefits when the aggregate compute & memory needs of the collocated training runs fit in the GPU
  - MPS performs the best overall
  - MIG is the only option if more strict separation is needed

- data sharing can further reduce hardware resource needs while increasing training throughput

need to build schedulers that incorporate resource & data sharing for deep learning!

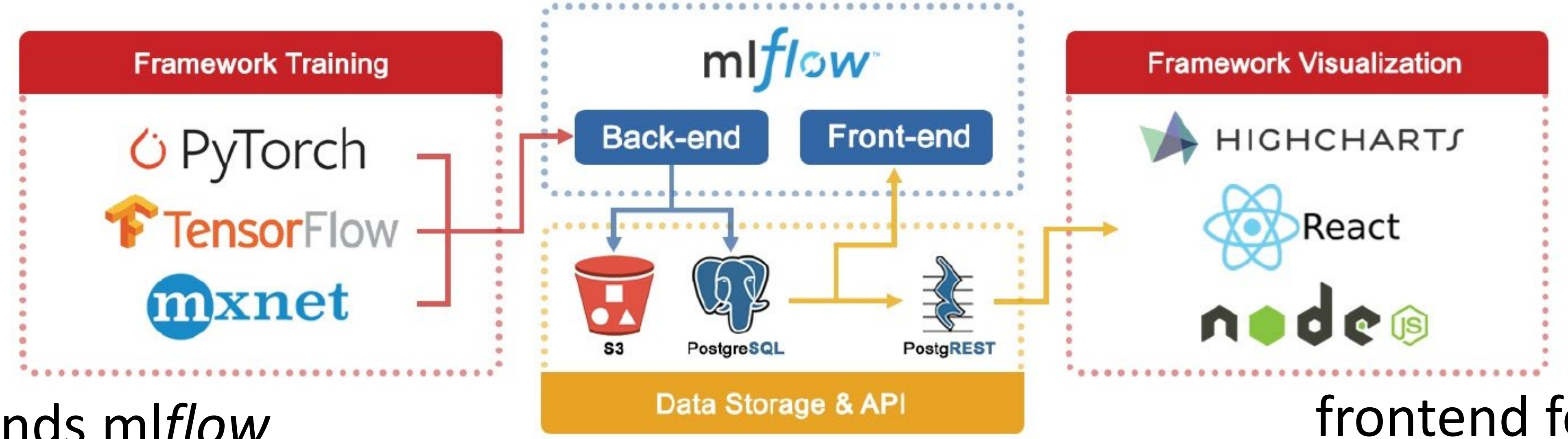
backup

A100



max threads per SM = 2048

radT



- extends ml*flow*
- incorporates collocation
- allows easy, extensible, and scalable tracking of hardware metrics on CPUs & GPUs
  - listeners for monitoring (dcgm, nvidia-smi, top) & profiling (nsys, ncu, pytorch profiler) tools

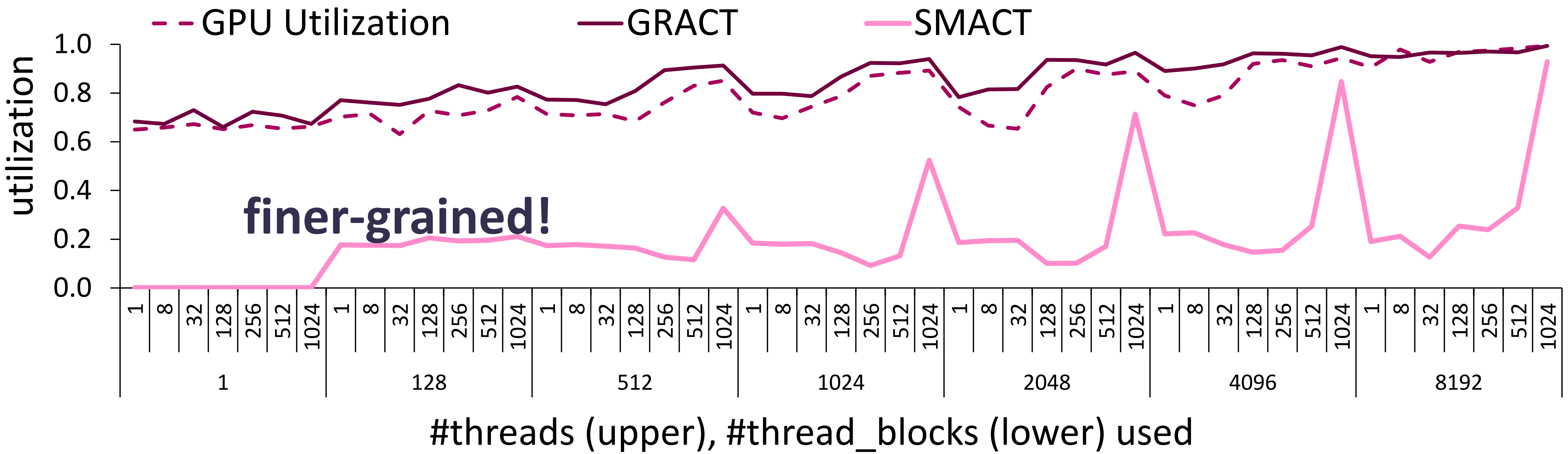
frontend for data exploration

used by several members of our group including data scientists for systematic benchmarking of deep learning training

Robroek et al. "Data Management and Visualization for Benchmarking Deep Learning Training Systems", DEEM 2023
https://github.com/Resource-Aware-Data-systems-RAD/radt & https://www.youtube.com/watch?v=oaGfzYjKJ1Q

GPU utilization

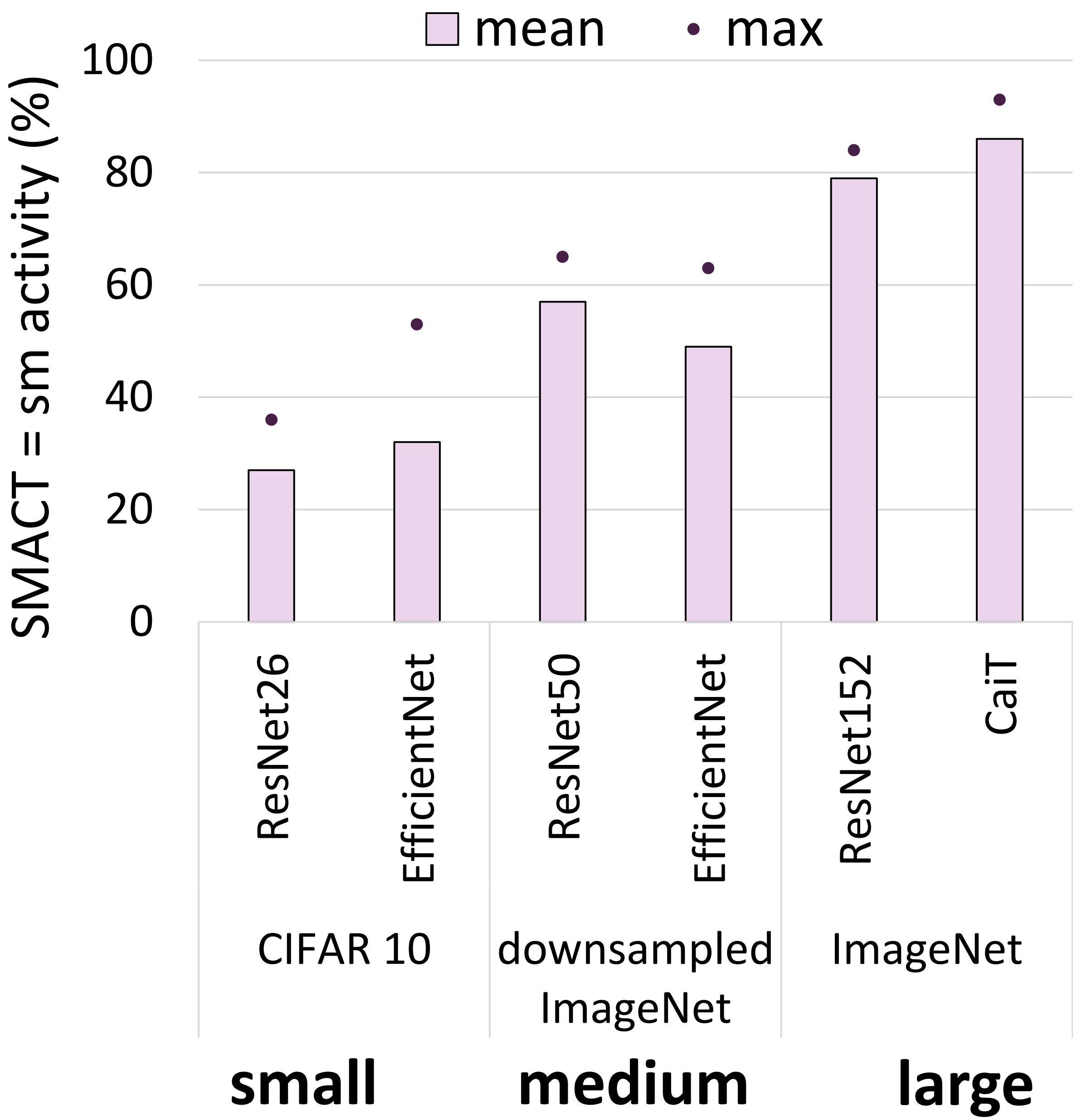
- **GPU utilization**: % of time one or more kernels were executing on the GPU
- **GRACT**: % of time any portion of the graphics or compute engines were active
- **SMACT:** the fraction of active time on an SM, averaged over all SMs = streaming multiprocessor

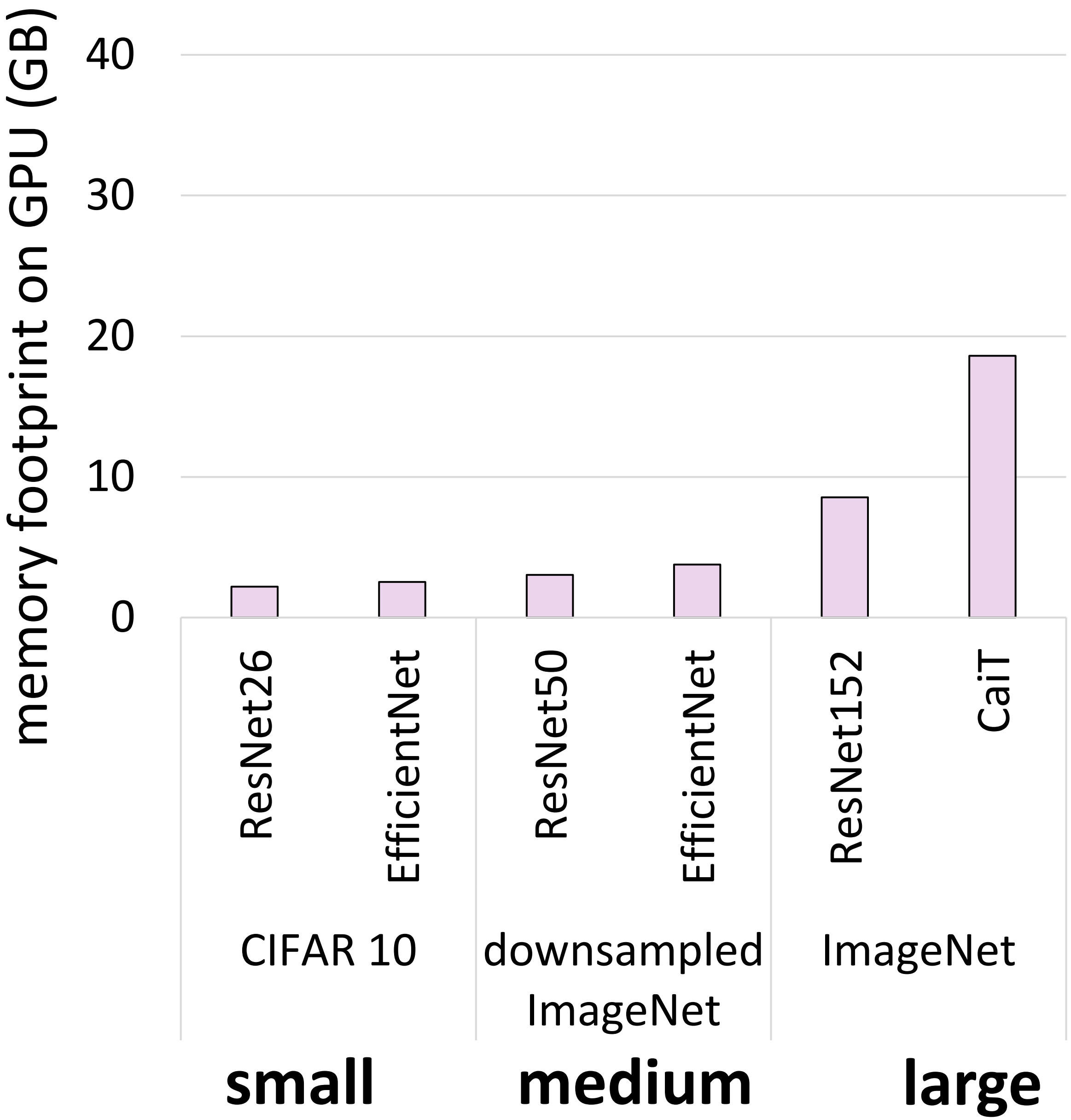


coarse-grained GPU utilization metrics could be misleading!

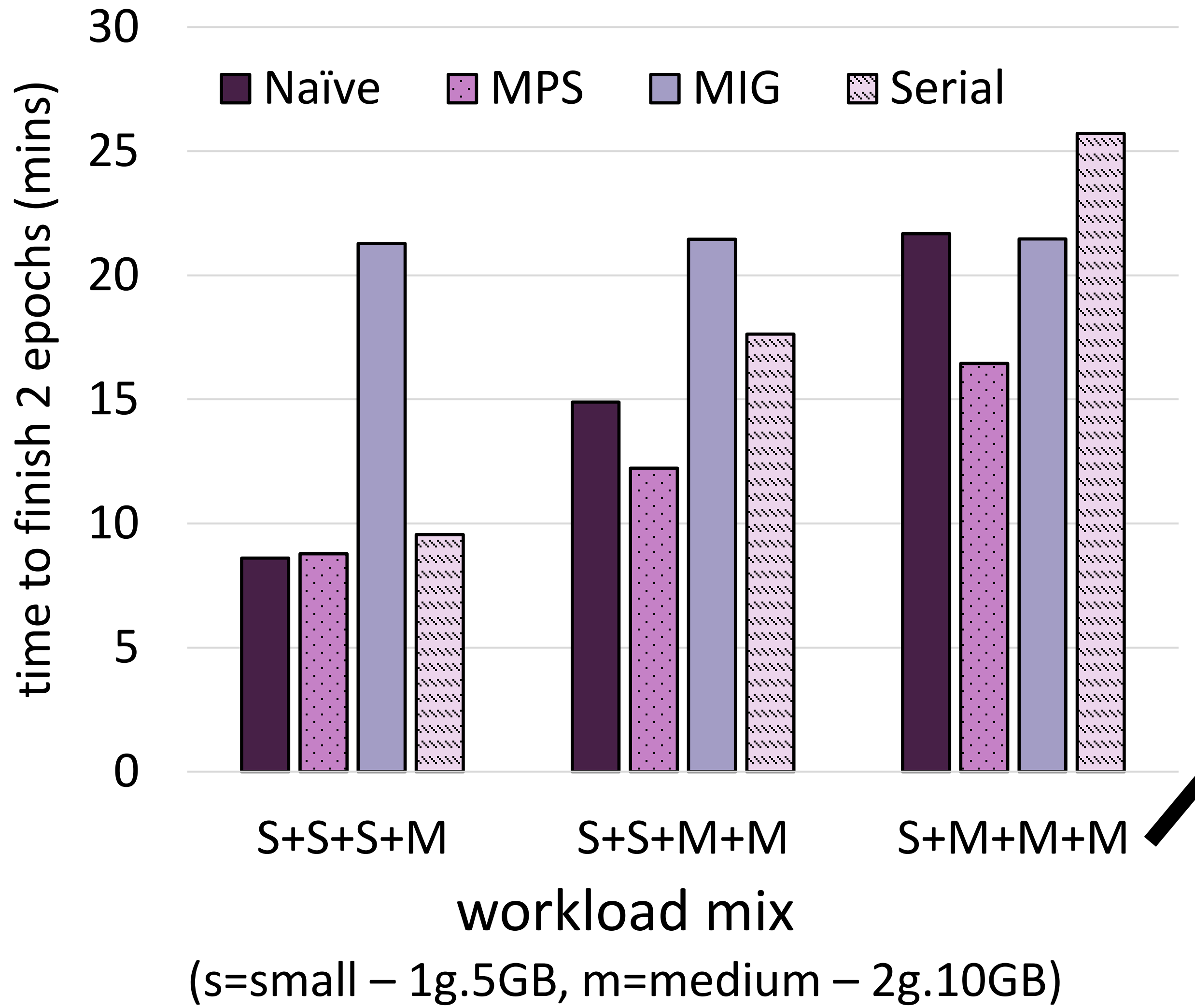
Yousefzadeh-Asl-Miandoab et al. "[Profiling and Monitoring Deep Learning Training Tasks]", EuroMLSys 2023

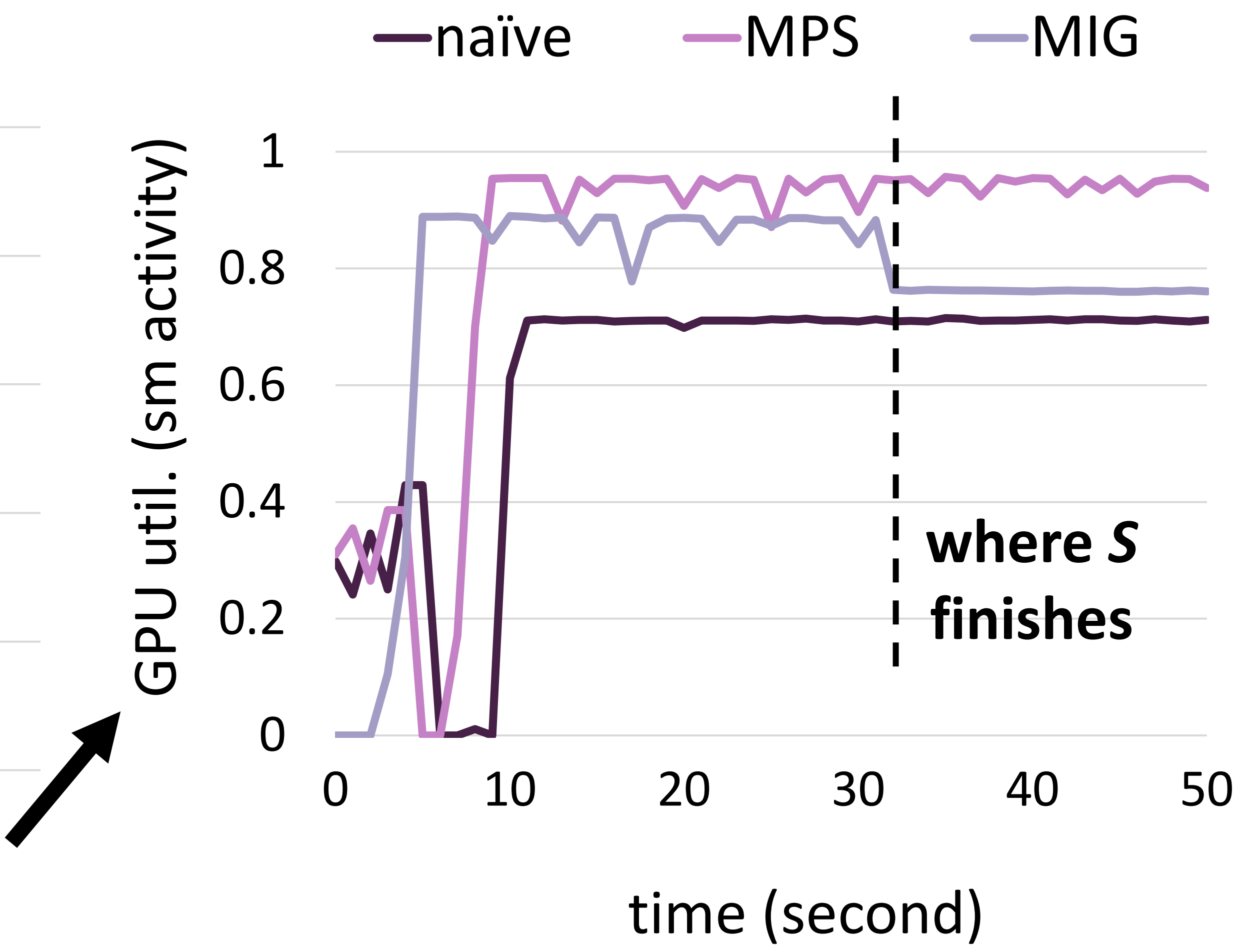
hardware utilization without collocation





mixed workloads: all compute-heavy



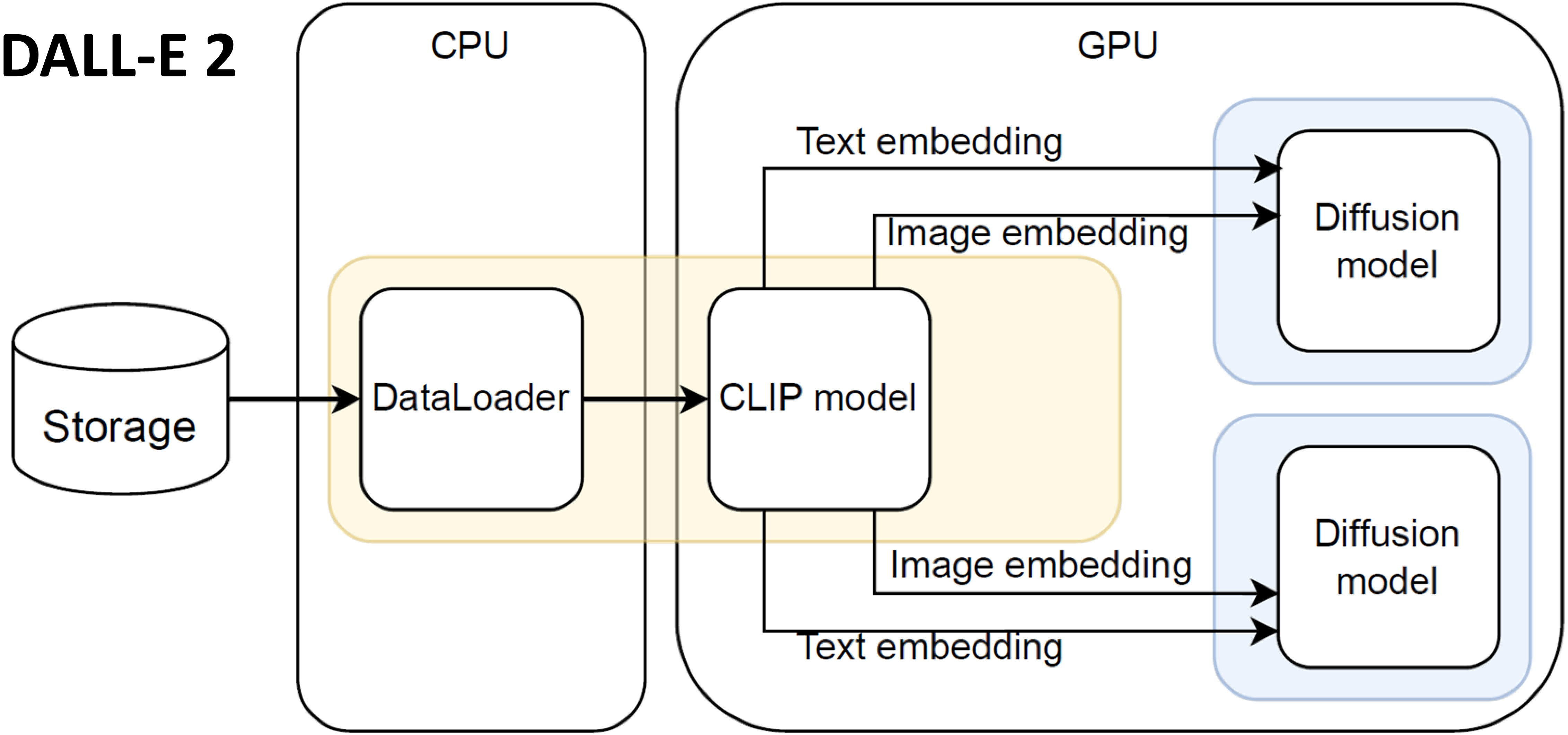


with MPS → the small training is for free near the medium one

with MIG → isolation at the cost of inflexible resource distribution

data sharing for collocated training

DALL-E 2



can also reduce work on GPUs!

teamRAD - resource-aware data systems

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