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satisfying the data monster with fewer resources

a quest to feed the GPU in deep learning training

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DEEM
27/06/2025

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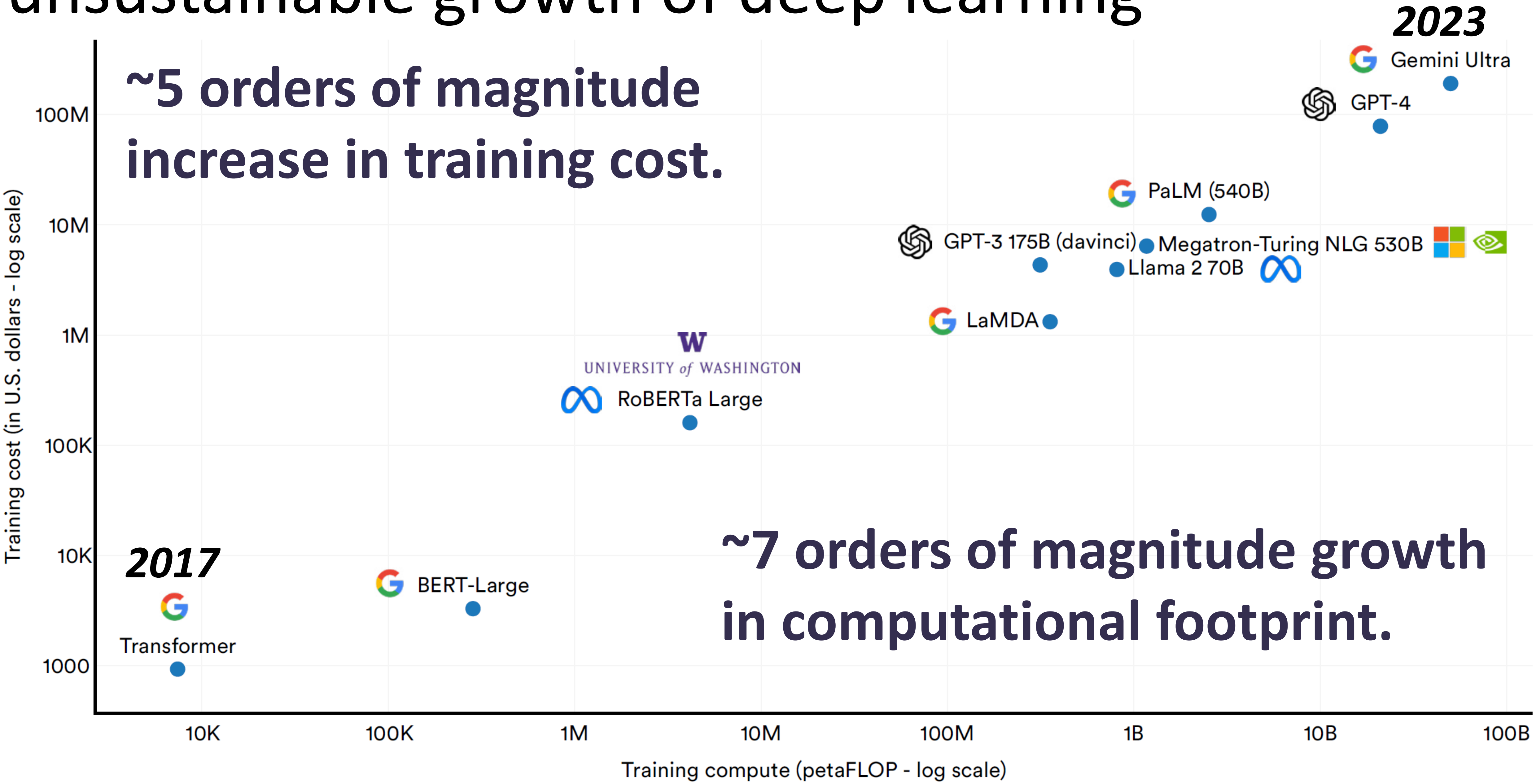
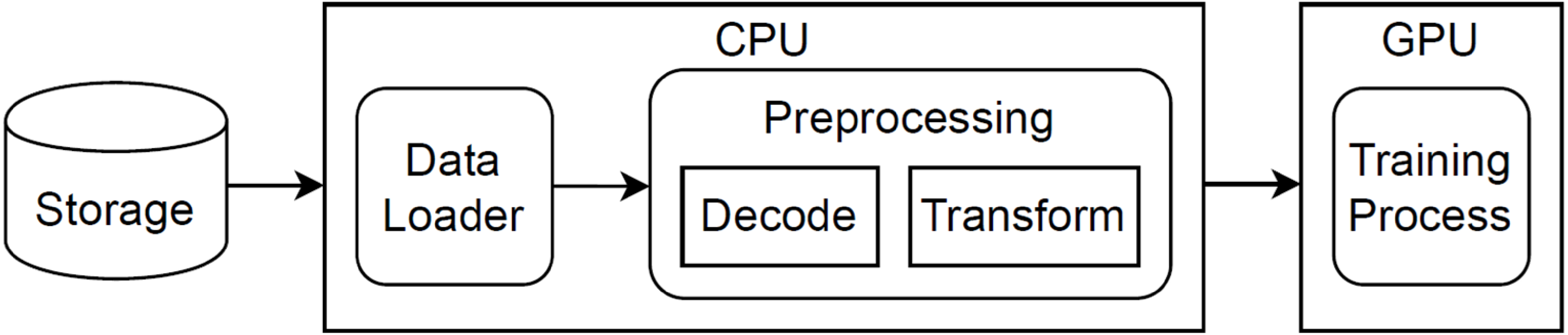
unsustainable growth of deep learning



source: [Stanford AI Index Report 2024]

journey of data in deep learning training



CPU feeds the accelerators

- 16-64 cores per GPU (recommended)
- 96 cores per TPU*

➔ **otherwise, accelerator may be underutilized**

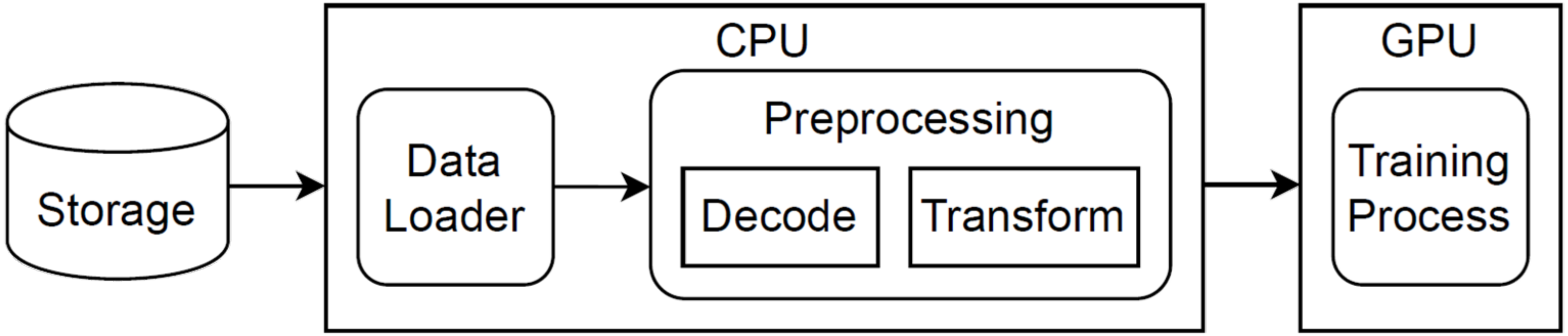
➔ **can we do more with fewer CPUs & less of the CPU?**

*Audibert et al., “tf.data service: A Case for Disaggregating ML Input Data Processing.” ACM SoCC 2023

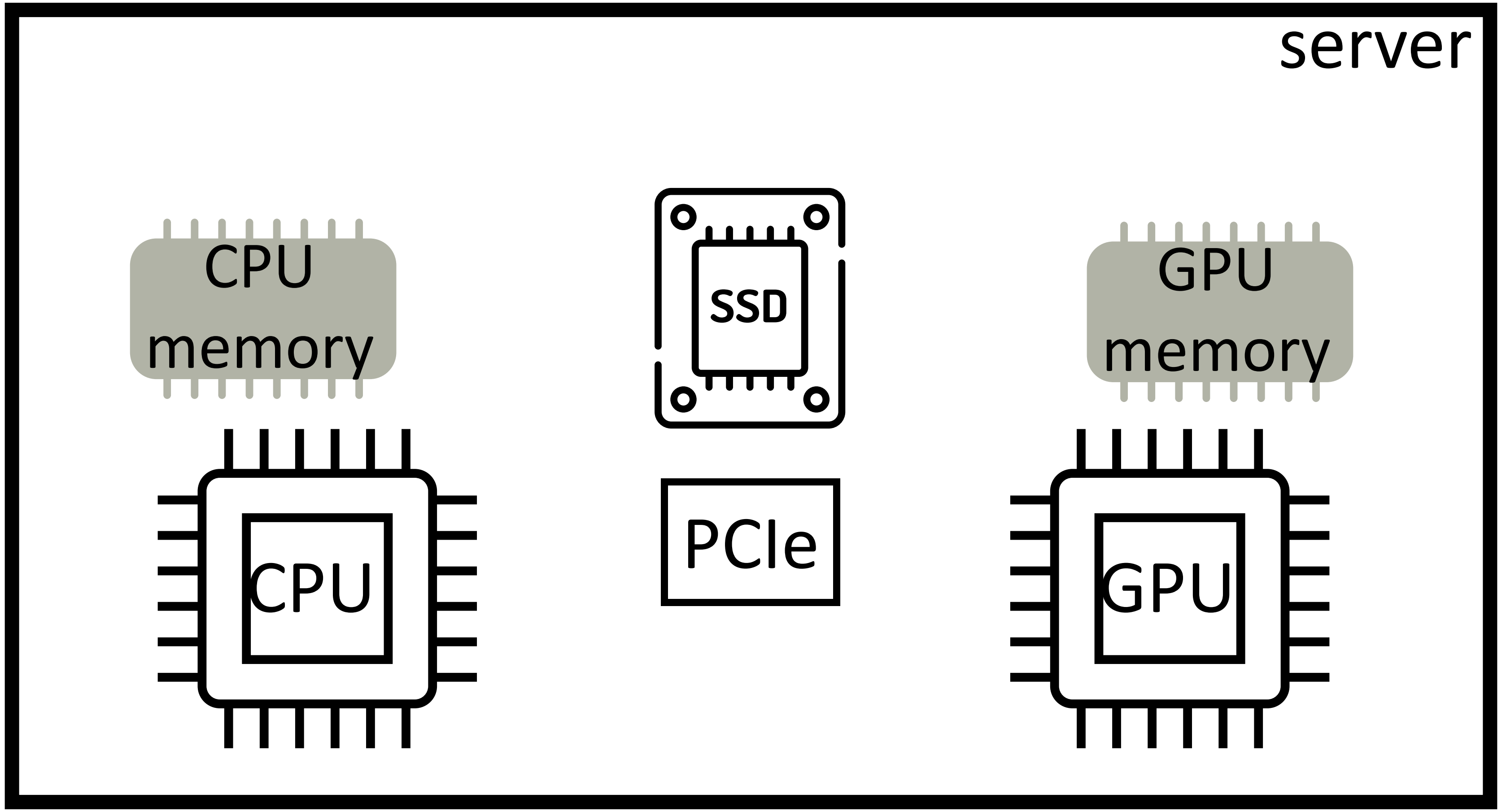
deep learning with less hardware

- GPU-centric I/O path
- data & work sharing
- impact of data selection

Path to GPU-Initiated I/O for Data-Intensive Systems
Karl B. Torp, Simon Lund, Pınar Tözün.
DaMoN 2025

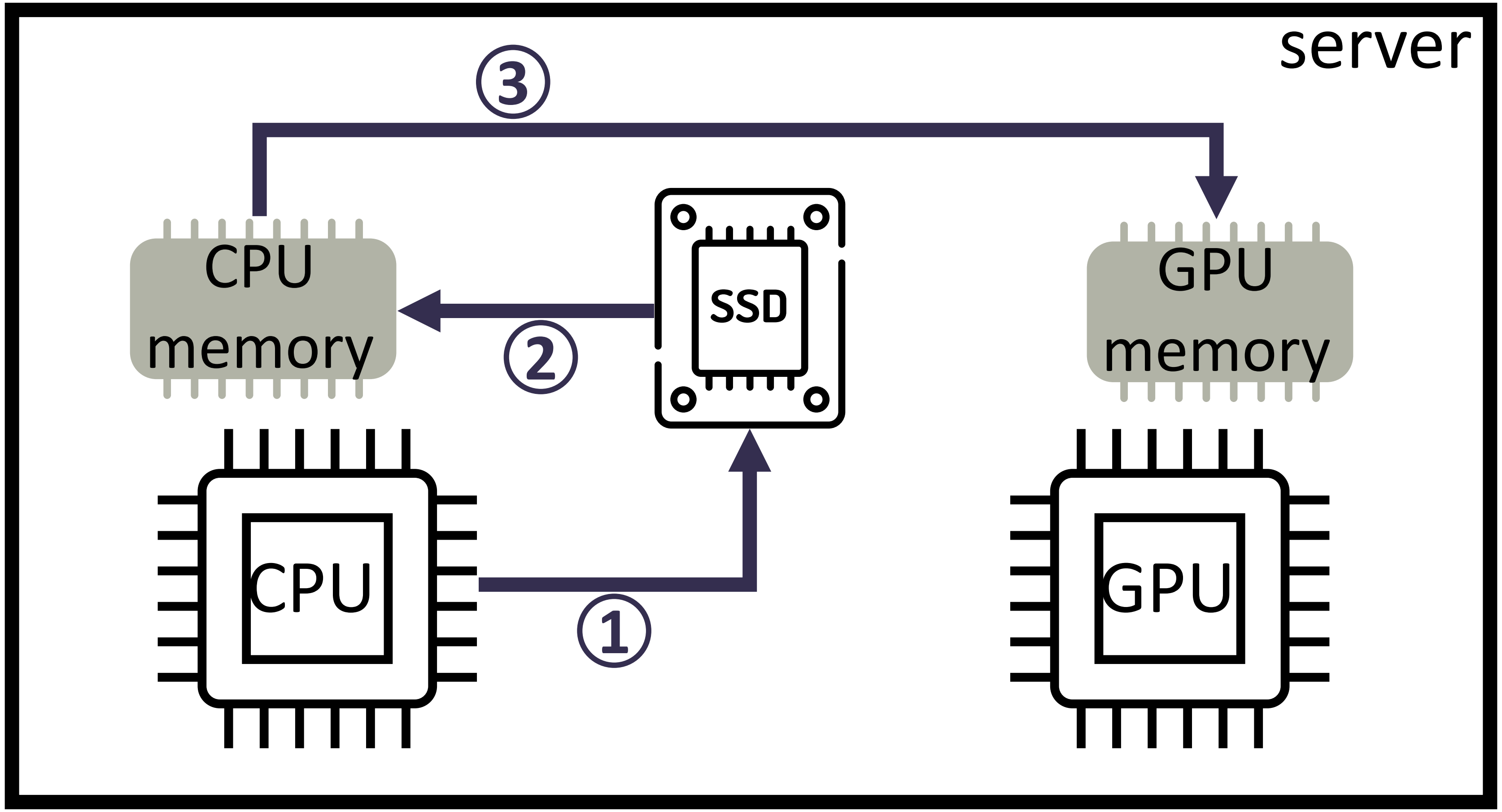


target hardware setup



* PCIe is dropped in the remaining figures for the sake of simplicity in illustrations.

conventional: CPU-centric I/O

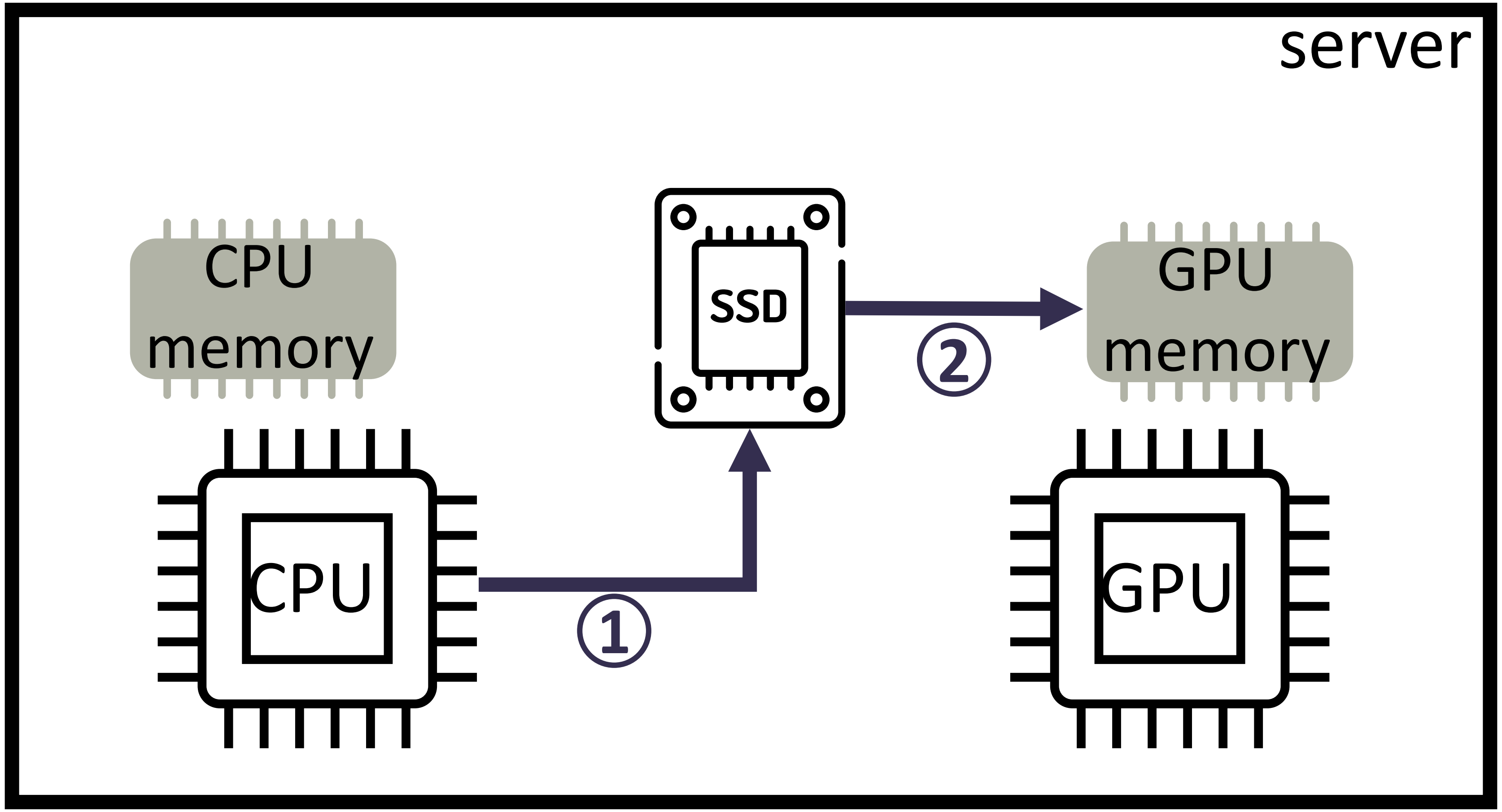


✓ **ecosystem support**

× **CPU-bound & overhead from memory copy**

GDS: GPU-centric & CPU-initiated

GPUDirect
[NVIDIA'19]

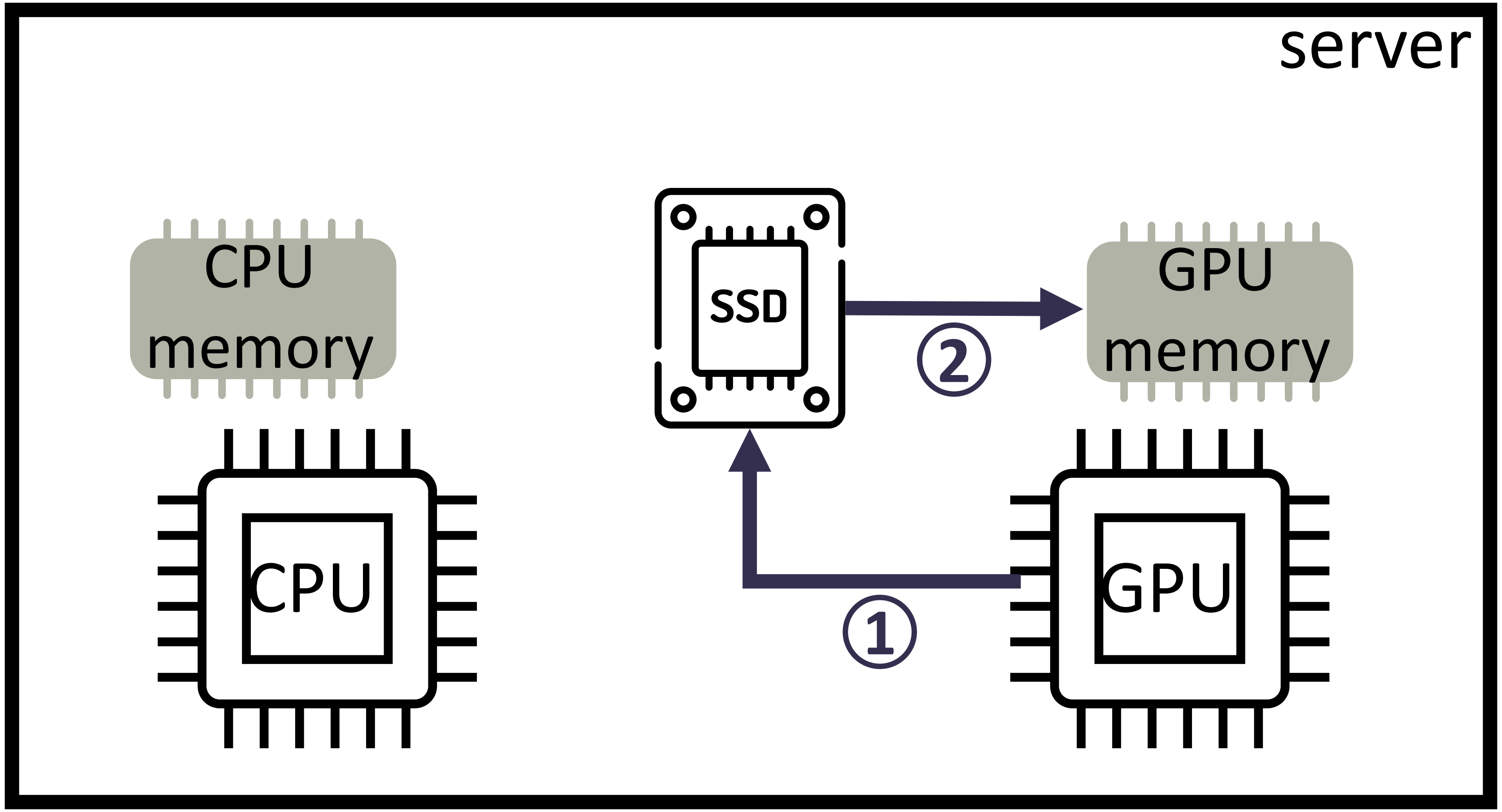


✓ **eliminates the extra memory copy**

× **still CPU-bound**

BaM: GPU-centric & GPU-initiated

Big
Accelerator
Memory
[ASPLOS'23]



✓ **eliminates the CPU on the path**

× **ecosystem missing & saturates GPU**

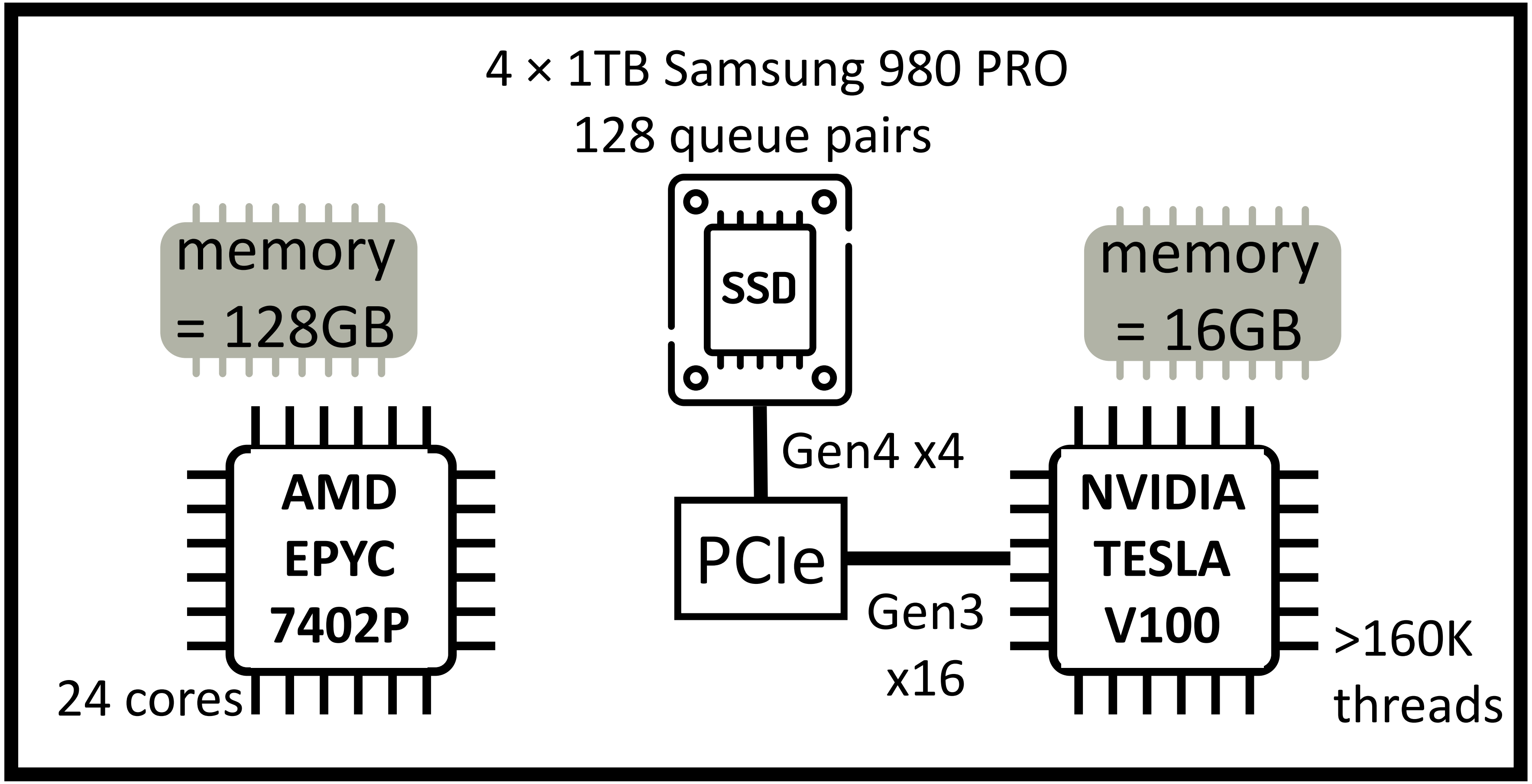
evaluation: CPU- vs GPU-centric I/O

mechanisms: CPU-centric: SPDK & GPU-centric: GDS, BaM

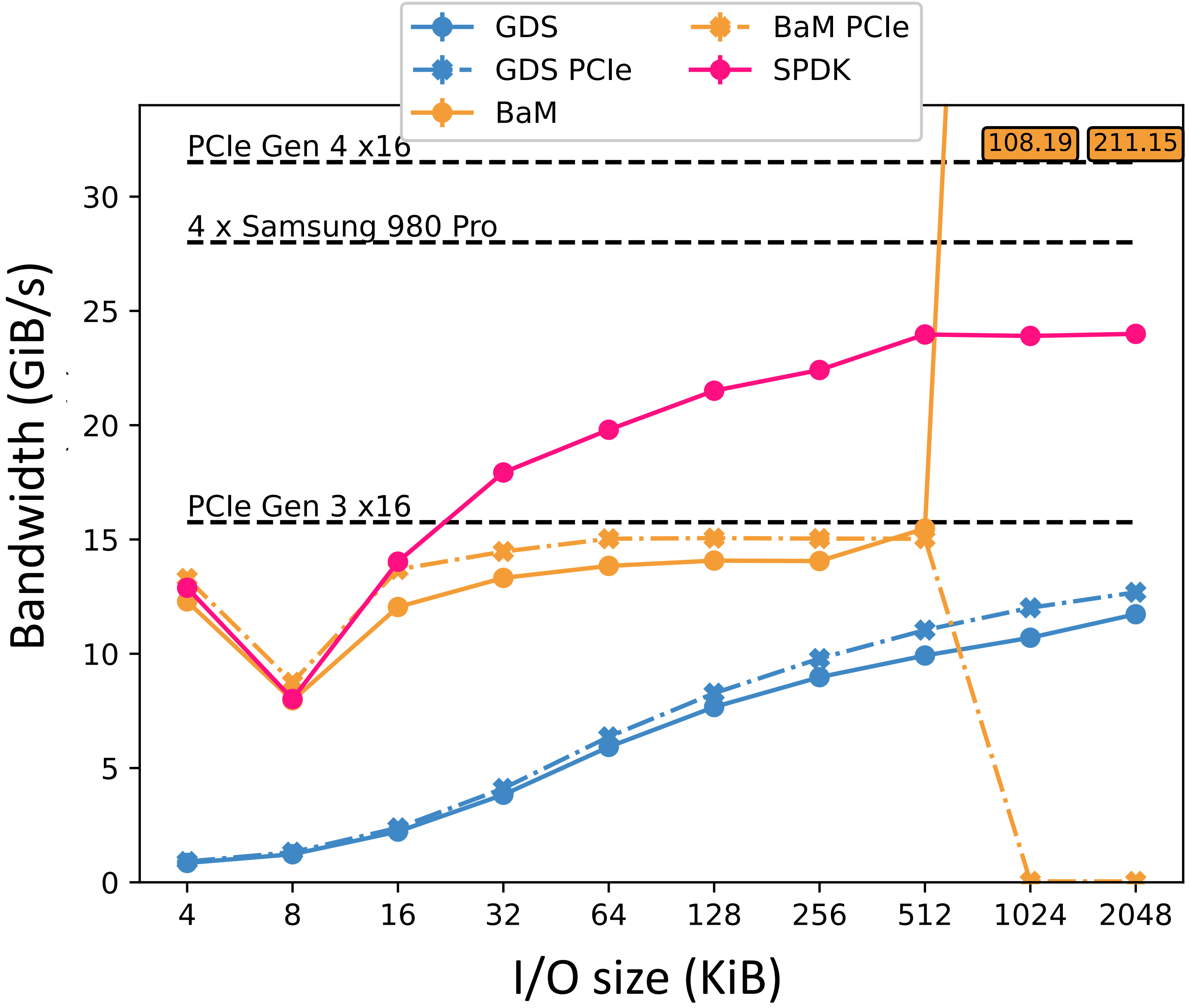
workload: random reads

→ each mechanism has their own tool for benchmarking

hardware



bandwidth utilization – 4 SSDs & PCIe



GDS is CPU-compute heavy.

➔ 16 logical cores utilized

BaM is limited by the PCIe Gen3 link & heavy on the GPU resources.

➔ whole GPU utilized

SPDK is the most resource-efficient but has a longer path to the GPU.

➔ 2 logical cores utilized

path to GPU-centric I/O

- need to reduce the dependency on CPUs for more efficient deep learning pipelines
- GPU-centric I/O is a way to do that & we have the mechanisms today (e.g., GDS, BaM)
  - GDS has dependency on CPUs still
  - BaM requires a lot of GPU resources

➔ **when to use which mechanism while being resource-aware?**

➔ **how to best integrate them into popular deep learning frameworks (or GPU databases) for wider-scale use?**

deep learning with less hardware

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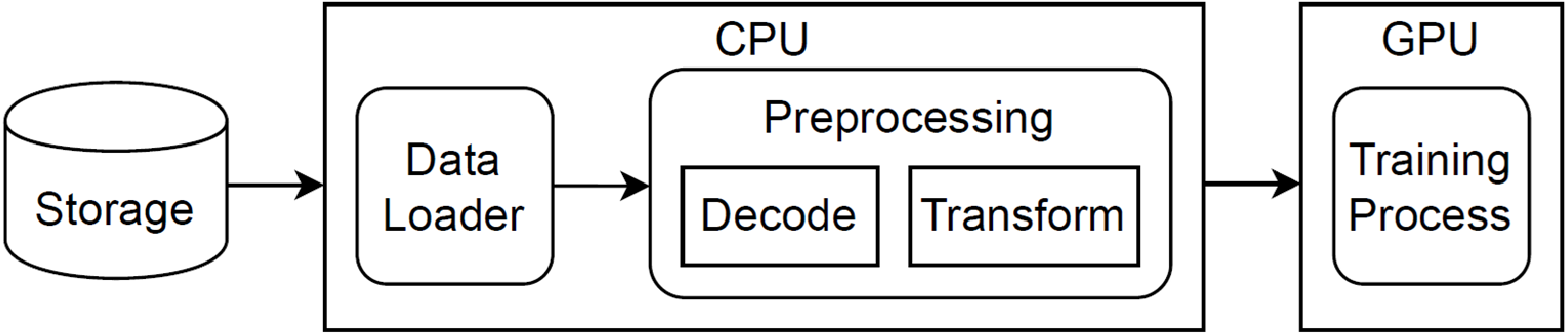
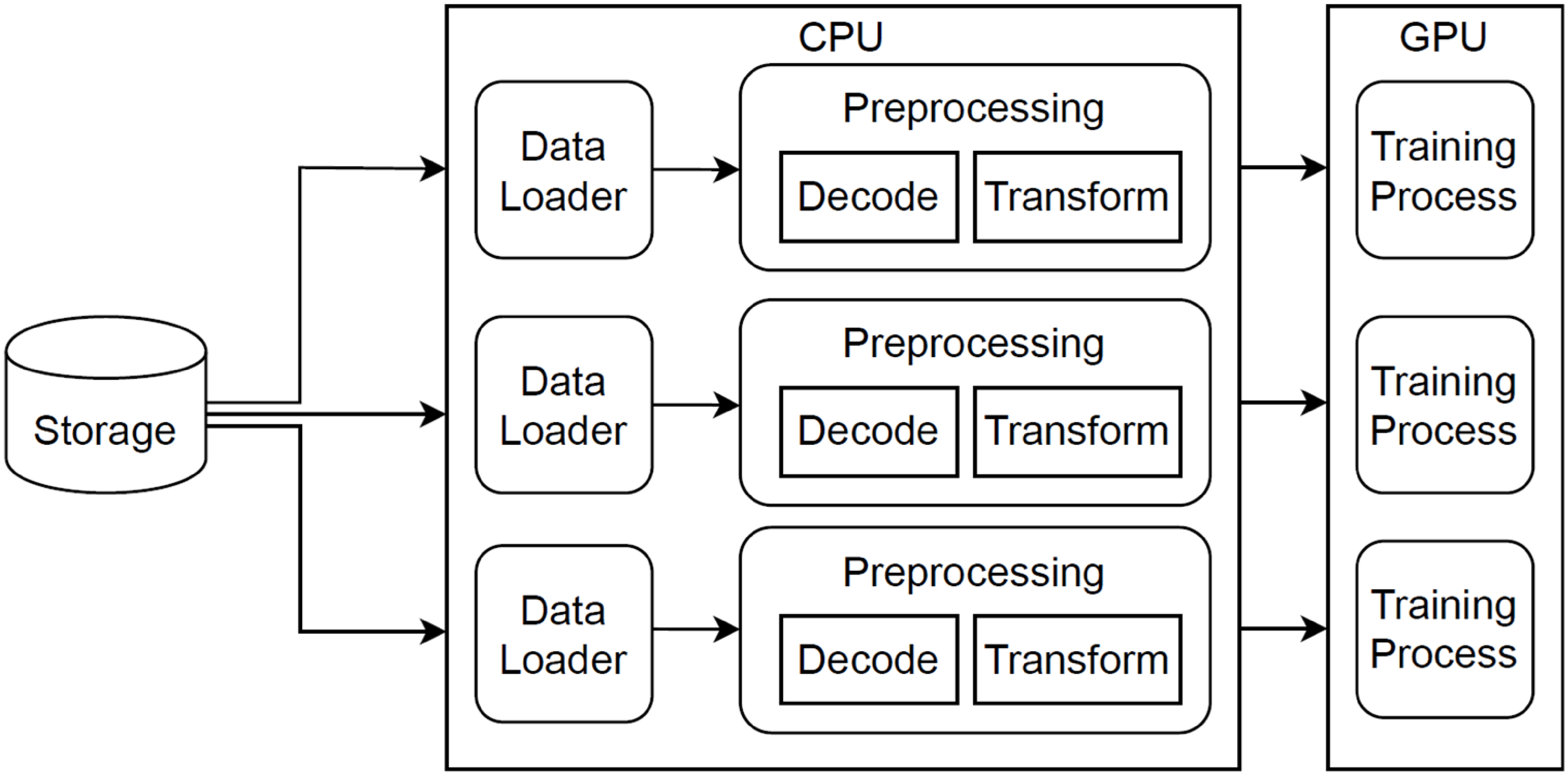
[TensorSocket: Shared Data Loading for Deep Learning Training]
Ties Robroek, Neil Kim Nielsen, Pınar Tözün.
SIGMOD 2026

conventional journey of data while training



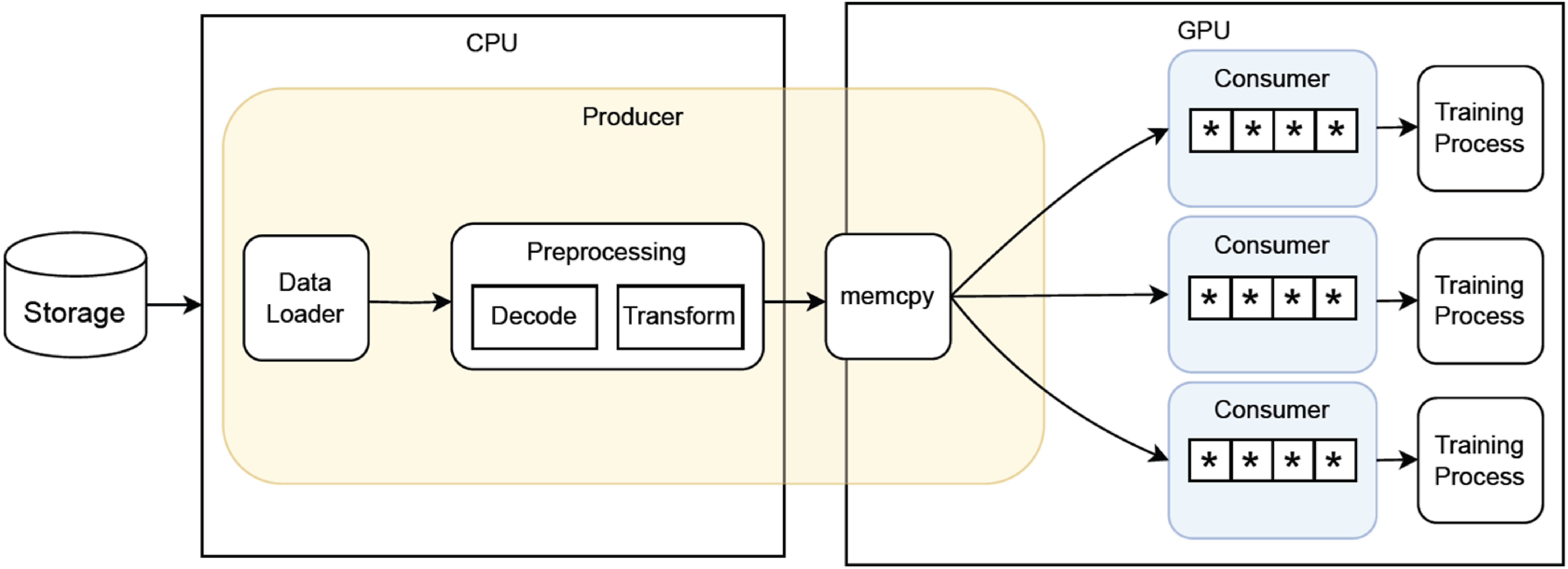
data journey in collocated training



redundant work & CPU use!

data sharing for collocated training

TensorSocket



minimize the redundancy!

TensorSocket requirements & limitations

➔ consumers go through the data at the same rate

doesn't mean that consumers …

- cannot join at different epochs of training
- train at differing speeds
- have different batch sizes

➔ target is smaller scale

- collocation of model training on a single server
- models can fit into the memory of a single GPU

not everyone needs "big" models & scale!

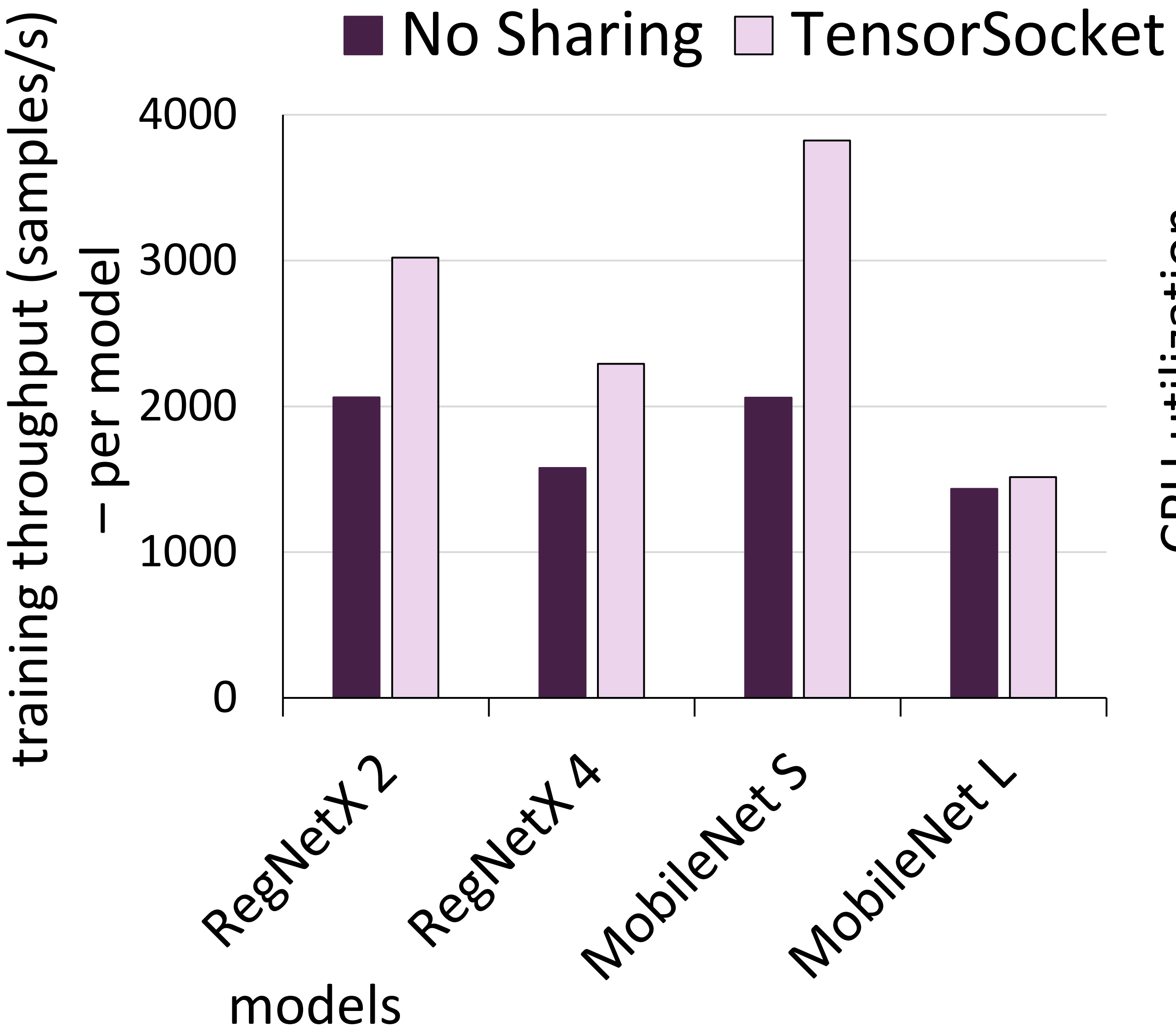
for larger scales, check out *tf.data service*, *CoorDL* …

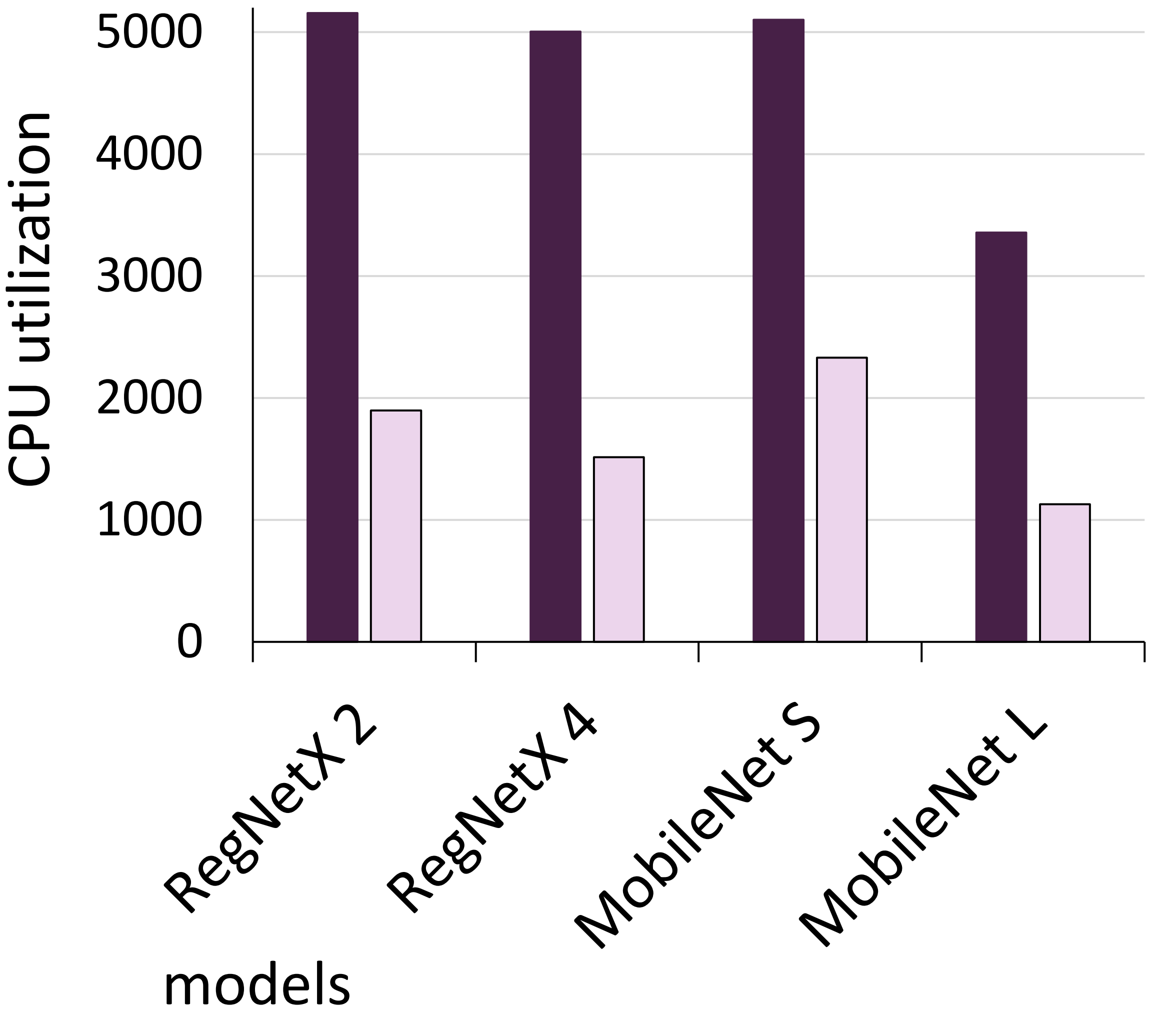
[SoCC'23] [PVLDB'21]

- Varoquaux et al. Hype, Sustainability, and the Price of the Bigger-is-Better Paradigm in AI
- Margot Seltzer, SIGMOD'25 keynote

impact of data sharing

- on PyTorch
- a server with 4 A100 (40GB) GPUs
- one model training on each

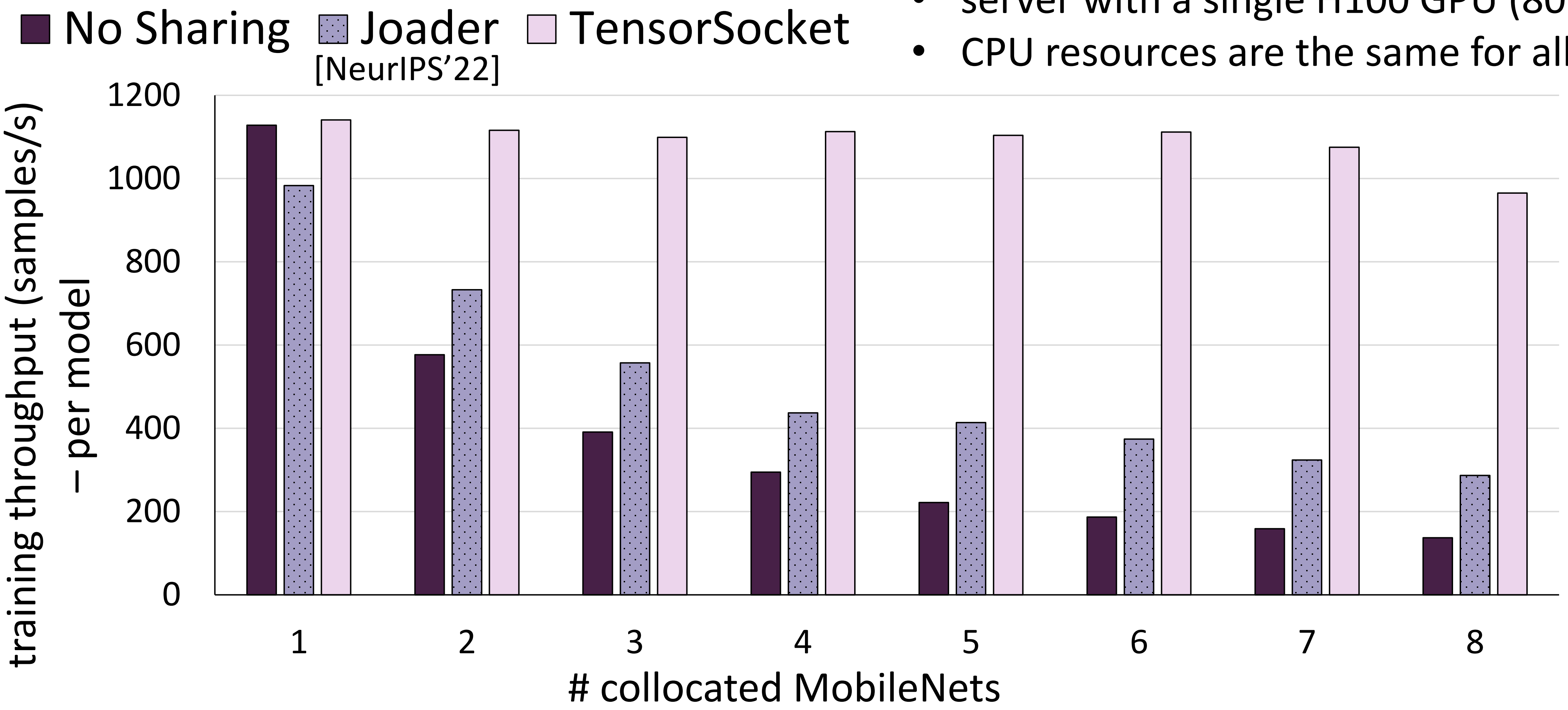




higher overall throughput & reduced CPU need!

comparison to other techniques

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



TensorSocket sustains throughput even with GPU collocation & reduces both CPU and GPU needs for the whole workload

sharing for deep learning training

- workload collocation allows data & work sharing

- ***TensorSocket*** enables data & work sharing for collocated training jobs on the same dataset

can reduce both the CPU & GPU needs of training while increasing training throughput

deep learning with less hardware

- GPU-centric I/O path
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- impact of data selection

Collaboration started at 2024 Dagstuhl seminar: Resource-Efficient Machine Learning.
Ties Robroek, Maximilian Böther, ***Niklas Christiansen, Daniel Sepehri***, Dagmar Kainmüller, Theo Rekatsinas, Stefanie Scherzinger, Ana Klimovic, Pınar Tözün.

why data selection?

- reduce the dataset size
- increase model accuracy
- fine-tuning

➔ **unclear impact on the end-to-end training time!**

➔ **trade-off: computational complexity vs “better” data selection**

preliminary results

base model = Llama-3.2-1B-Instruct
dataset = TruthfulQA

server with a single H100 GPU (80GB)

	duration (mins)	GPU energy use (Wh)	accuracy gain over base model
LESS (25%) [ICML'24]			
Full			
Random (50%)			
Random (25%)			

preliminary results

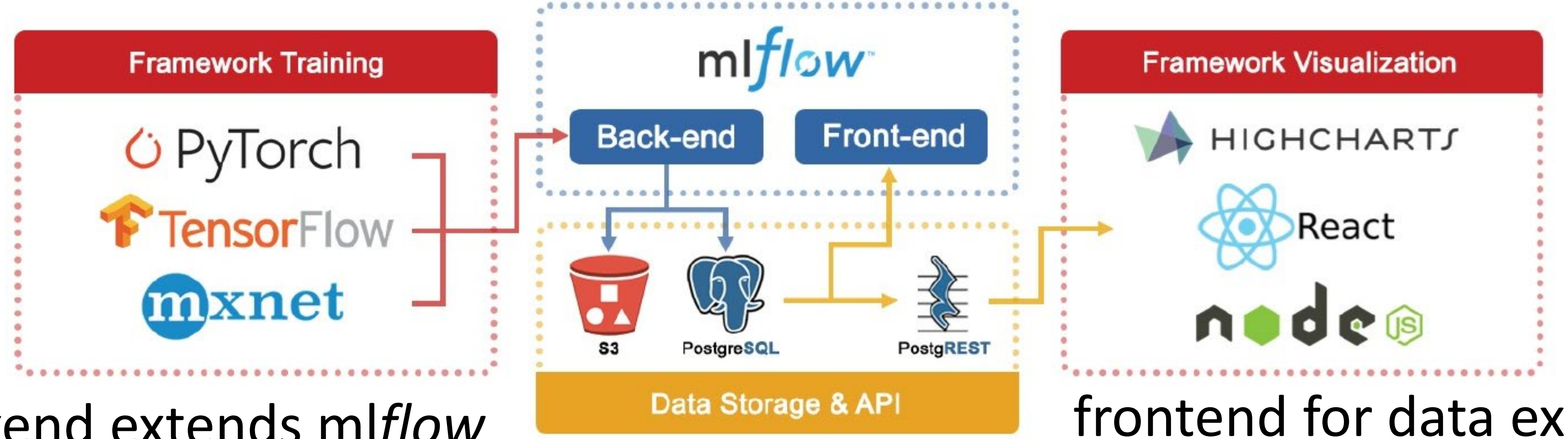
base model = Llama-3.2-1B-Instruct
dataset = TruthfulQA

server with a single H100 GPU (80GB)

	duration (mins)	GPU energy use (Wh)	accuracy gain over base model
LESS (25%) [ICML'24]	318	1099	80%
Full	84	417	84%
Random (50%)	43	215	63%
Random (25%)	23	118	39%

if the data selection can be used across different fine-tuning processes, the costs may amortize

radT
[DEEM'23]



- backend extends ml*flow*
- incorporates collocation
- allows easy, extensible, and scalable hardware monitoring
  (dcgm, nvidia-smi, top, iostat, carbontracker, nsight systems/compute, pytorch profiler …)

frontend for data exploration

used by our group & data scientists @ITU for systematic benchmarking of deep learning training

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thank you!