Characterizing Machine Learning I/O with MLPerf Storage

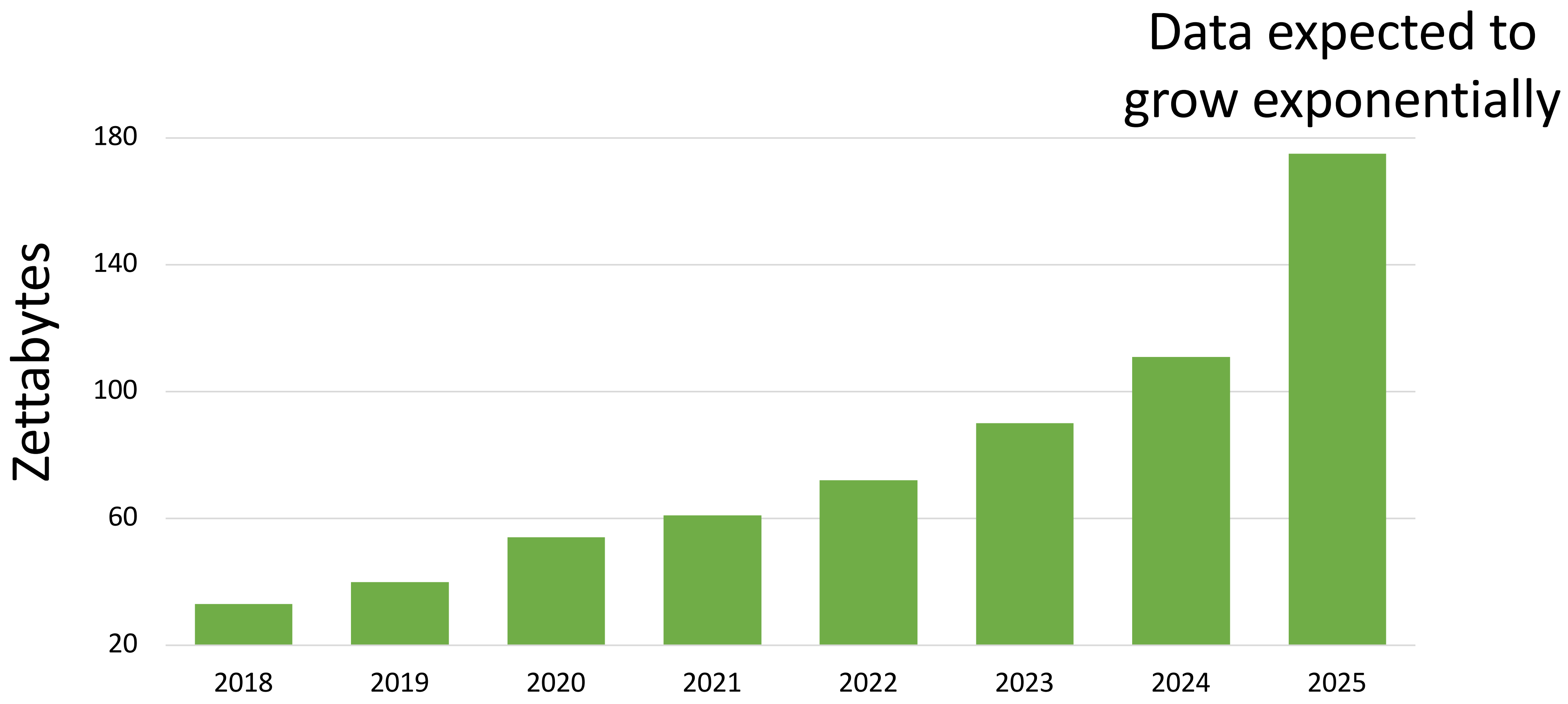
Oana Balmau

WoCC Keynote, December 12th, 2023

McGill

ML Commons

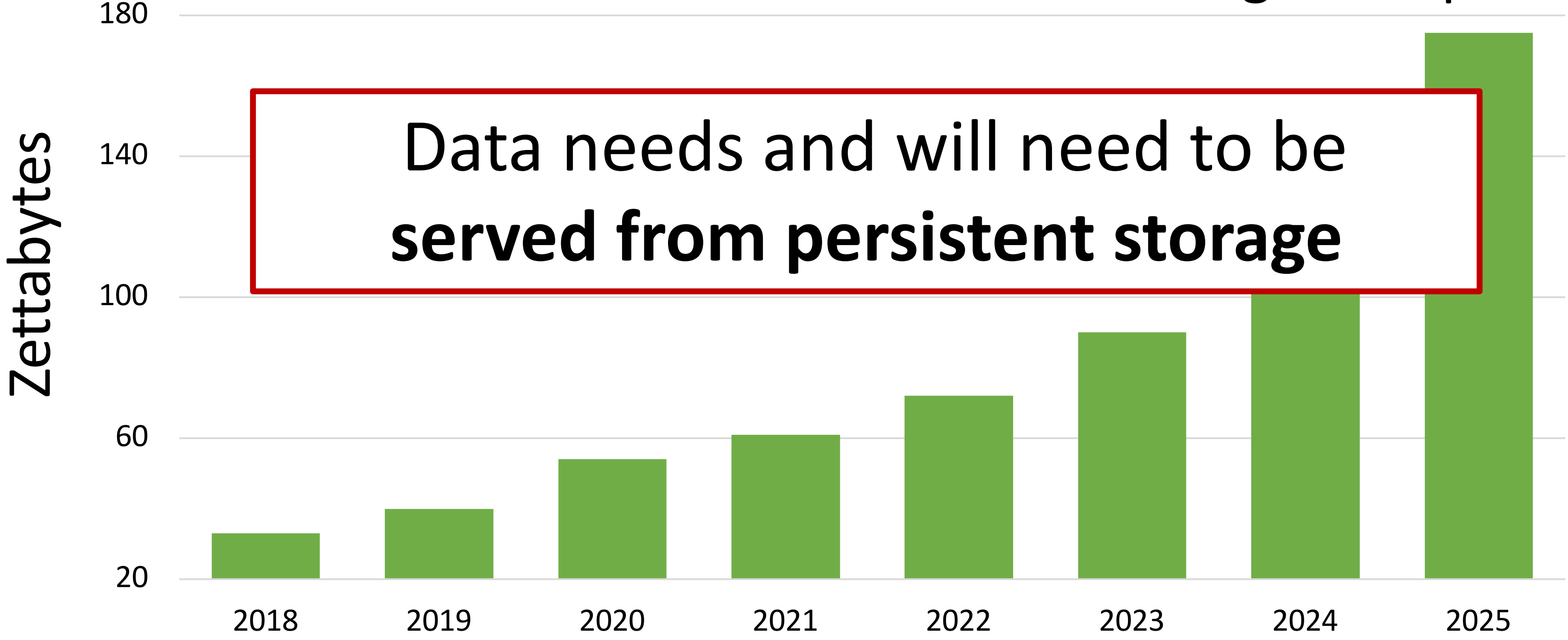
Humanity produces a lot of data



Source: IDC 2022

Humanity produces a lot of data

Data expected to
grow exponentially



Data needs and will need to be
served from persistent storage

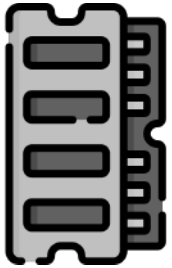
Source: IDC 2022

Data is the moving force of ML algorithms

… but in many projects the **storage decision is an afterthought**

Inefficient I/O can slow down ML Workloads

Dataset fits in system memory



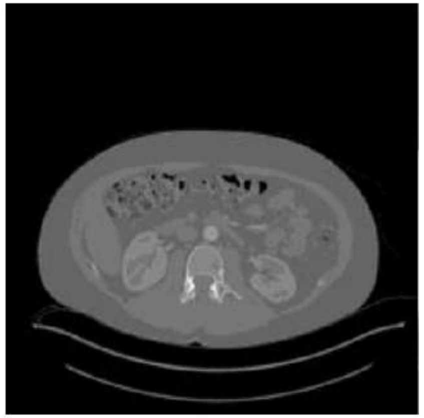
Dataset = 2x system memory

Training time increased by 3x

Example: Image Segmentation with 3D U-Net

An example of a coronal section of one of the training cases with its ground truth segmentation overlaid (kidney in red, tumor in blue).
Source https://arxiv.org/pdf/1912.01054.pdf

Medical image segmentation
2019 Kidney Tumor Segmentation Challenge (KiTS19)
CT scans from ~300 kidney tumor cases



Sample images from the KiTS19 dataset before (left) and after (right) preprocessing.
Source: https://arxiv.org/pdf/1908.02625.pdf

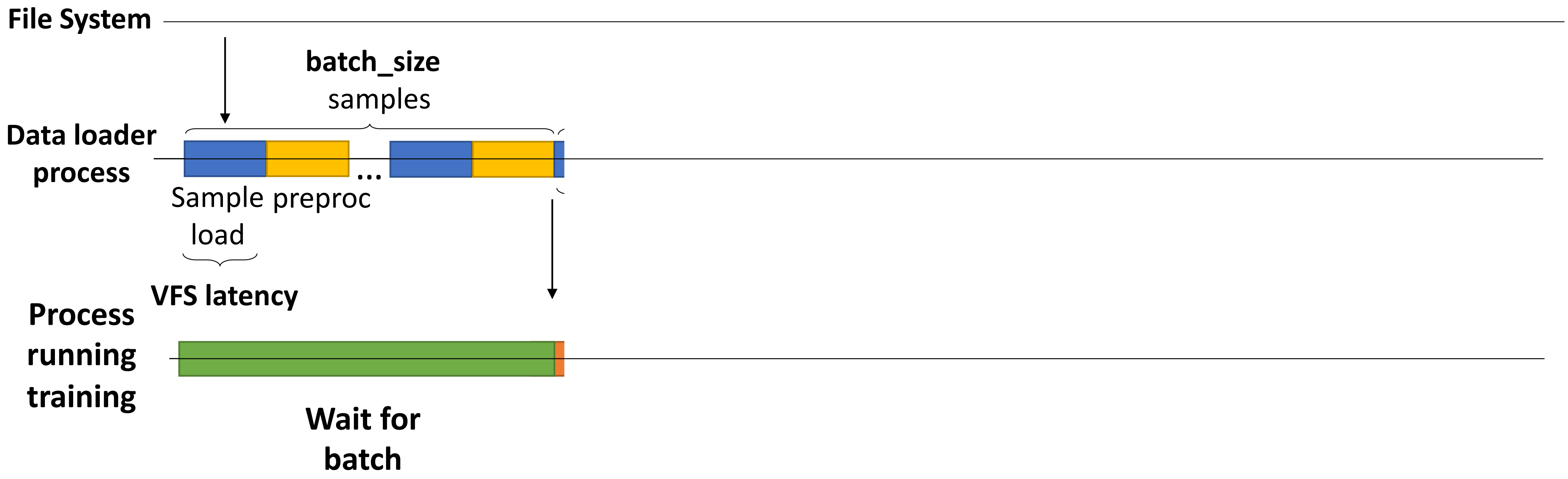
Example: Image Segmentation with 3D U-Net

File System

Data loader process

Process running training

Example: Image Segmentation with 3D U-Net



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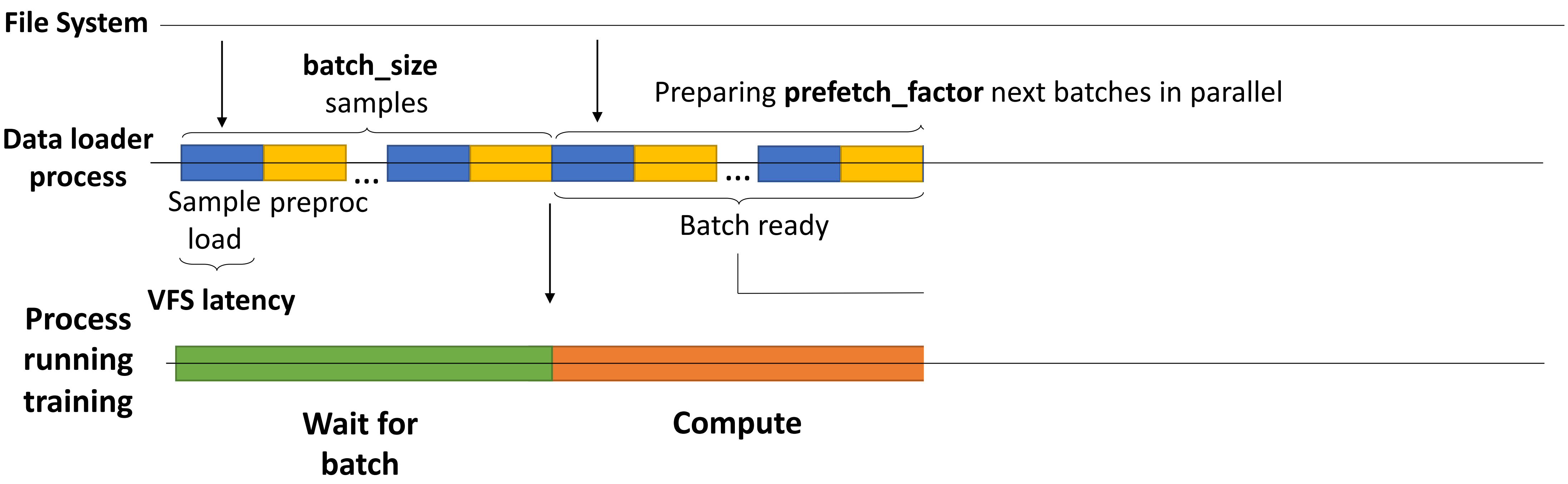

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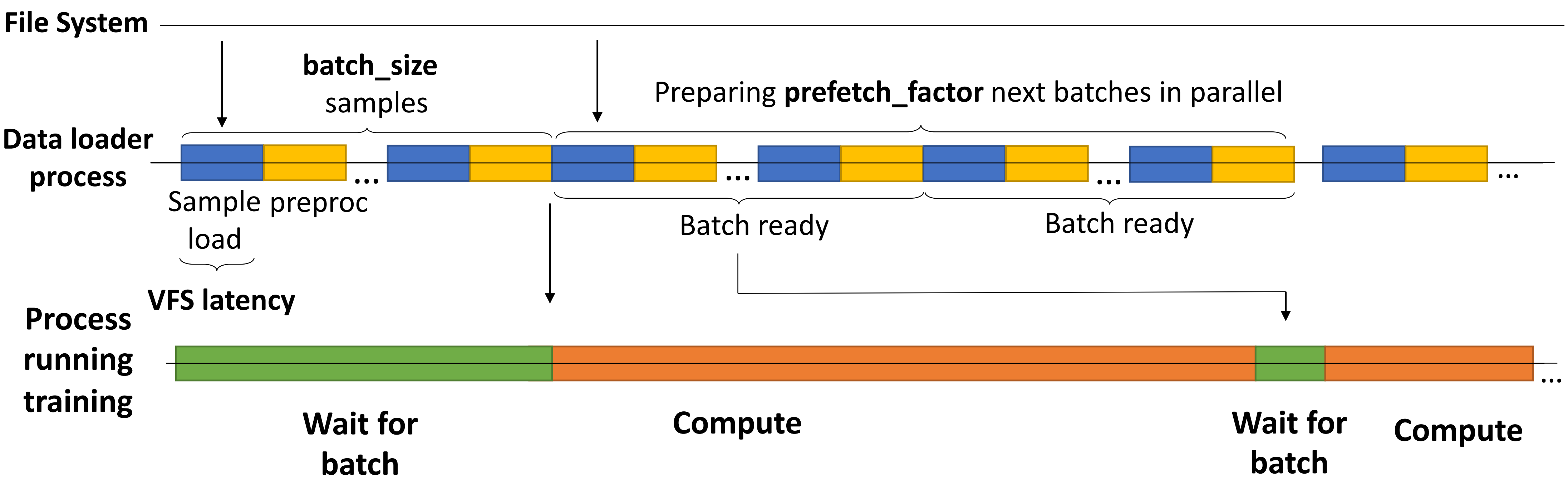
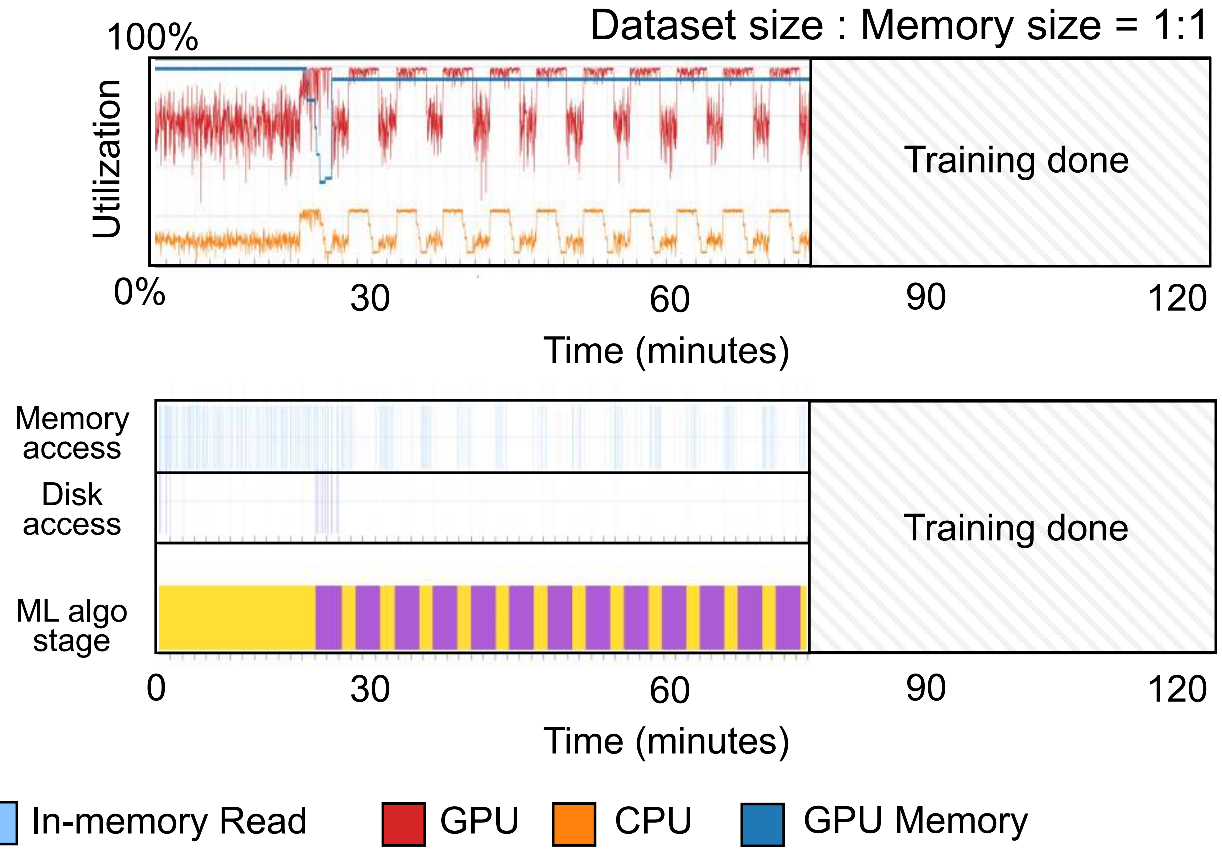


Inefficient I/O can slow down ML Workloads

Experiment setup

- DGX-1 server
  - 8 x V100 GPUs, 32GB GPU memory
  - 512GB DRAM
- Image segmentation workload:
  - Unet3D, Pytorch
  - MLPerf Training implementation
  - KiTS19 dataset

Dataset fits in system memory



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  - MLPerf Training implementation
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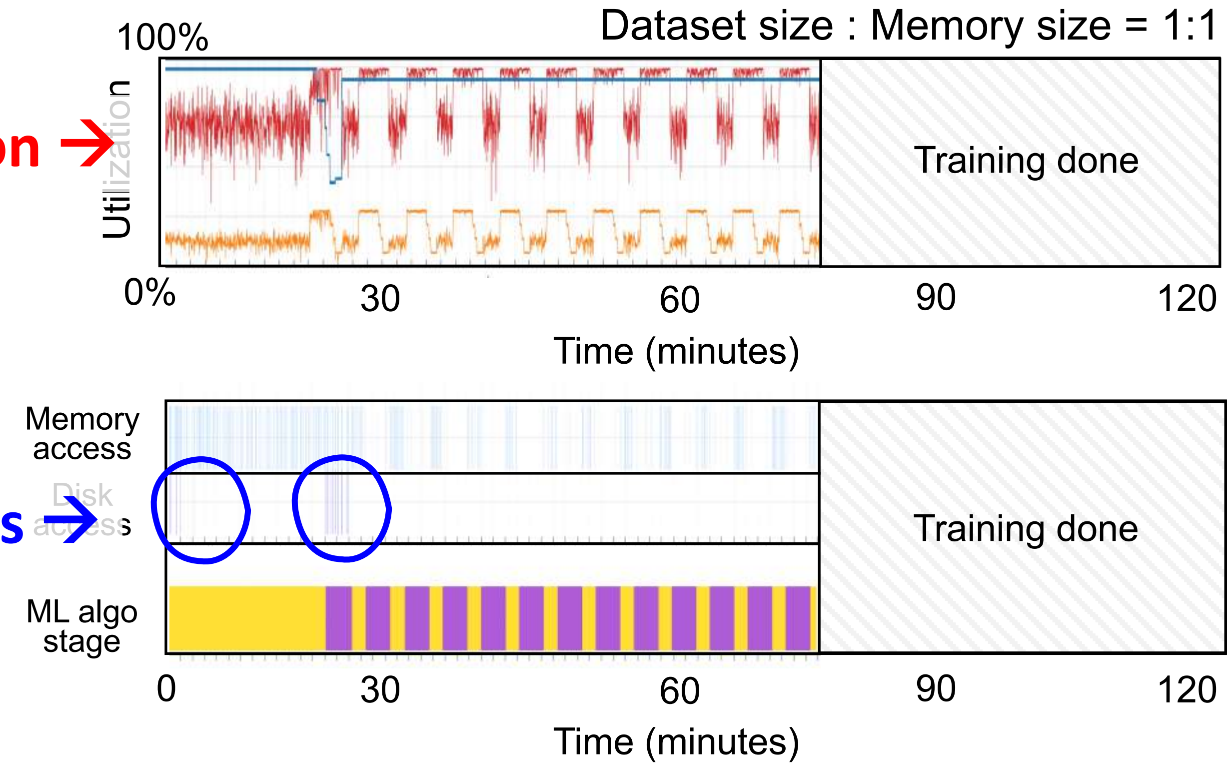
High GPU utilization →

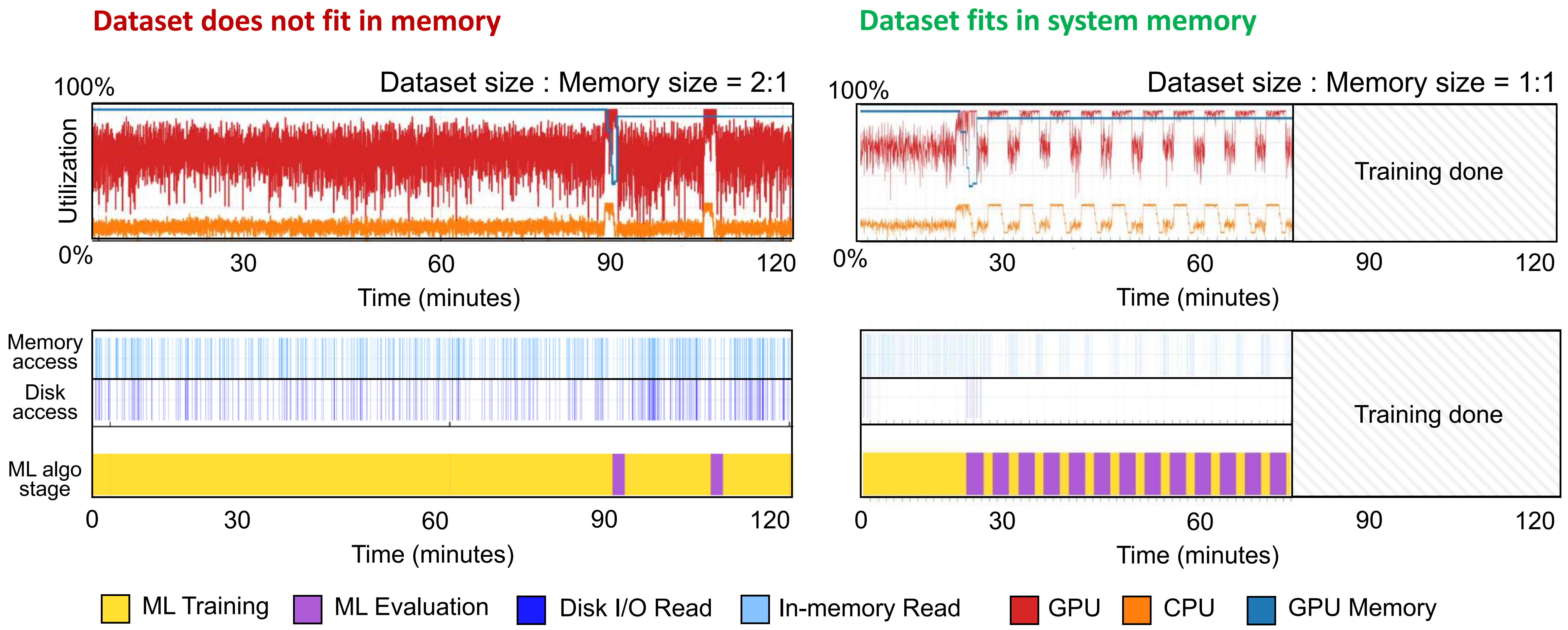
Little disk access →

Dataset fits in system memory



ML Training | ML Evaluation | Disk I/O Read | In-memory Read | GPU | CPU | GPU Memory

Inefficient I/O can slow down ML Workloads



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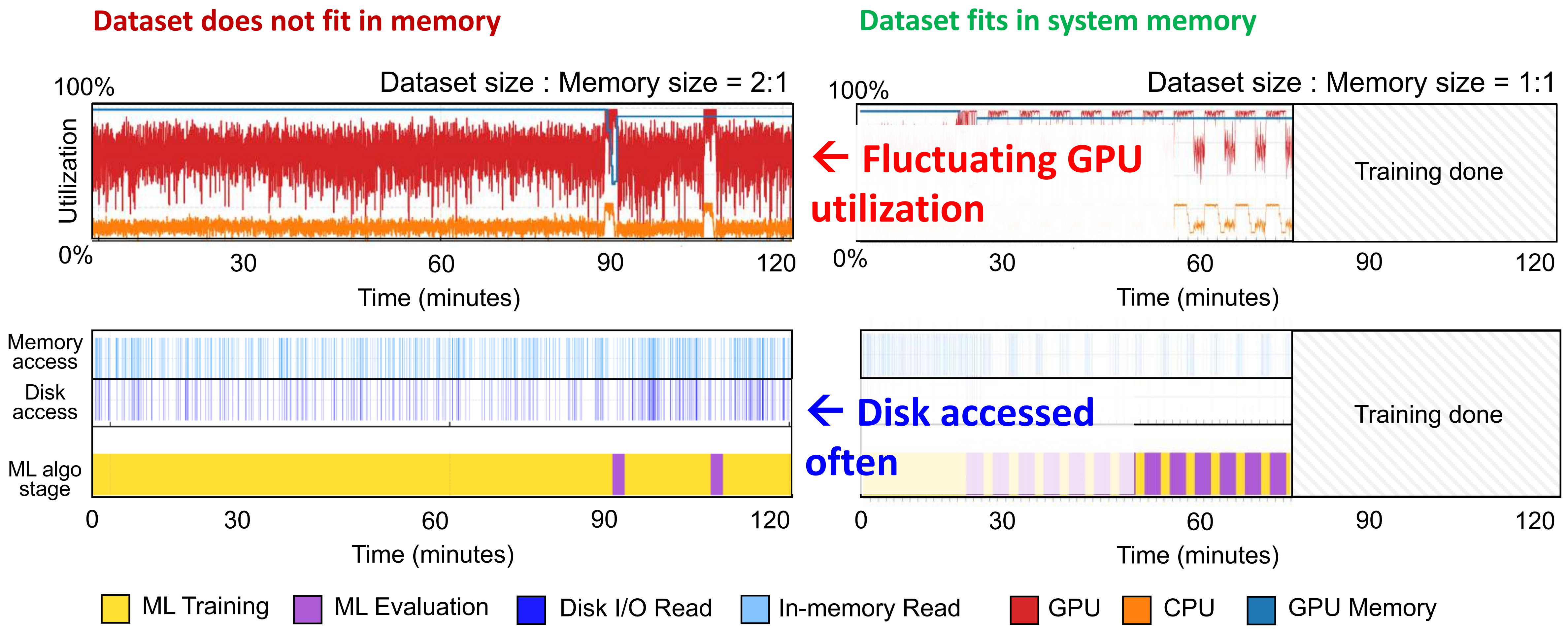

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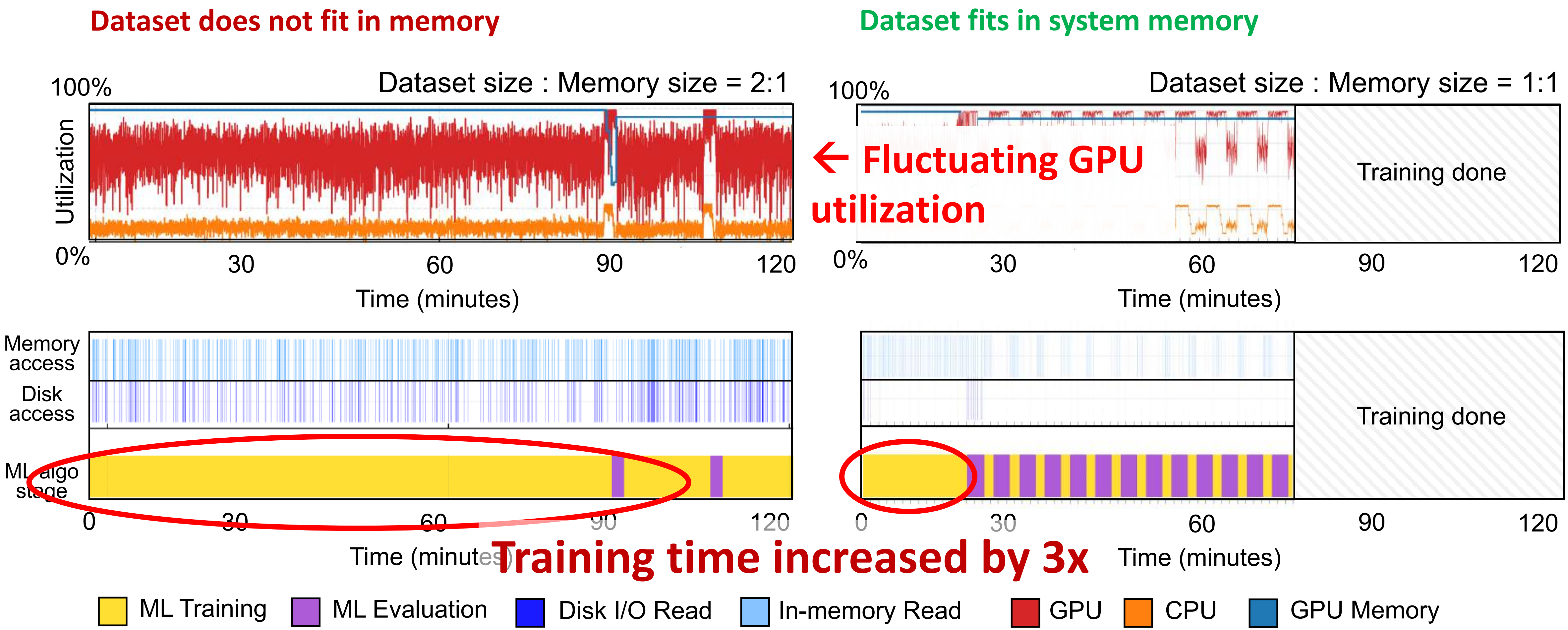


Data is the moving force of ML algorithms

… but in many projects the **storage decision is an afterthought**

Why create an ML Storage benchmark?

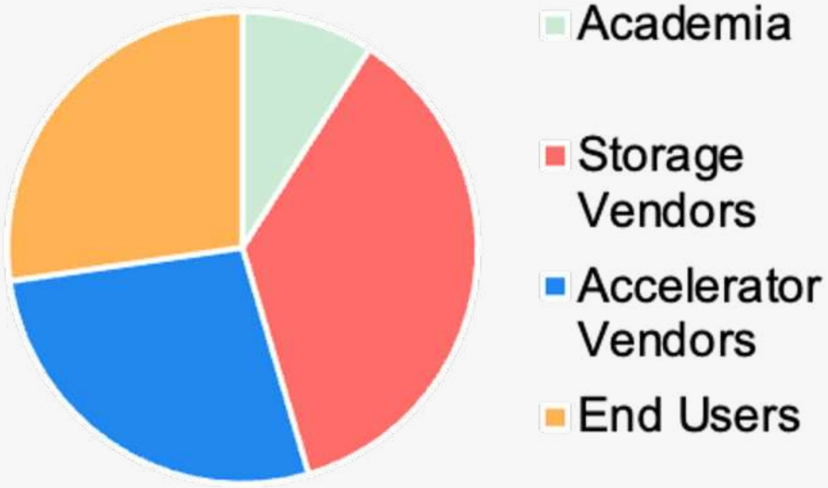
Why create an ML Storage benchmark?

- **Understand storage bottlenecks in ML workloads and propose optimizations**

- **Help AI/ML researchers and practitioners make an informed *storage* decision**

MLPerf Storage Working Group (132 members)

Who are we?



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Current ML/AI benchmarks

Many existing ML/AI benchmarks

DeepMind Lab

MLPerf

OpenAI

DLBT

PMLDB

DAWNBench

Current ML/AI benchmarks

- Focus on **end-to-end testing**

  → hard to isolate value of each component

- Insist on **training and inference** speed

  → tend to simplify storage

  → ignore pre-processing

- **Expensive accelerators** needed to run
- Require **extensive entry knowledge**

DeepMind Lab

MLPerf

OpenAI

DLBT

PMLDB

DAWNBench

Benchmark Vision

Existing benchmarks

Focus on **end-to-end testing**

Simplified storage setup

Expensive accelerators needed to run

Require **extensive entry knowledge**

Our work

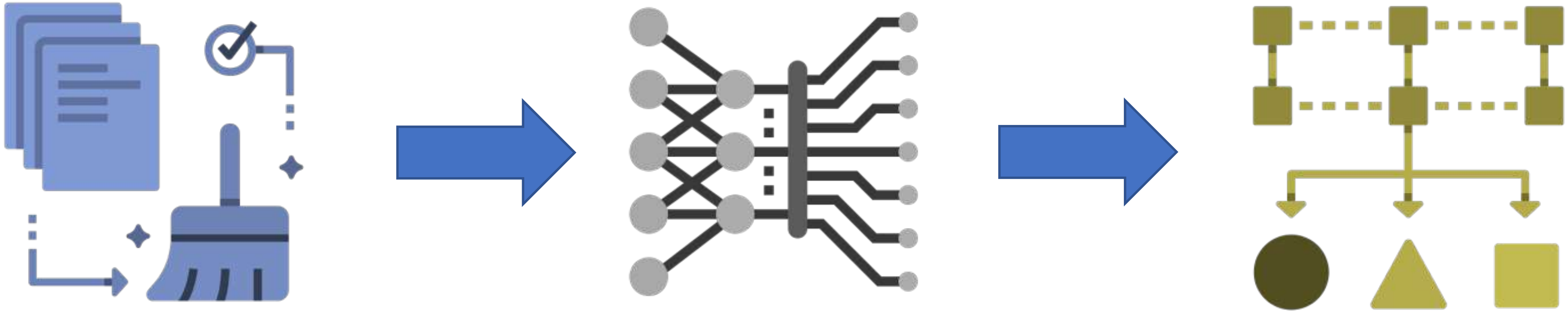
Focus on **storage impact in ML/AI**

Realistic **storage & pre-processing** settings

No accelerator required to run

Minimal AI/ML knowledge required

Stages of the ML Pipeline

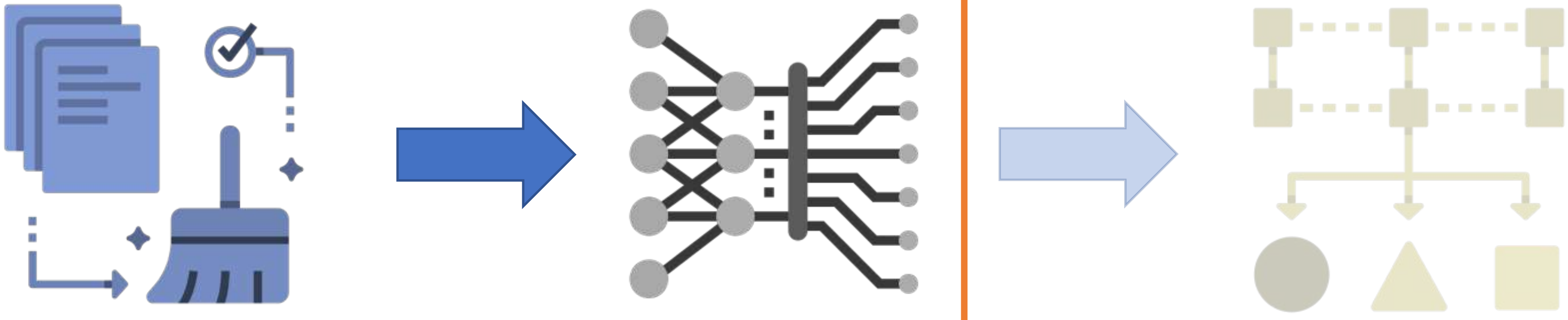


Data cleaning & pre-processing **Training** **Inference**

Stages of the ML Pipeline

I/O intensive [1,2] – Our focus

*As much as **50% of the Watts** can go into storage and data cleaning [2]*



Data cleaning & pre-processing

Training

Inference

*[1] Murray et al. **tf.data: A Machine Learning Data Processing Framework**, VLDB 21.*
*[2] Zhao et a. **Understanding Data Storage and Ingestion for Large-Scale Deep Recommendation Model Training** ISCA 22.*

Data Pipeline in ML: Pre-processing

Storage resources

Disk

Memory

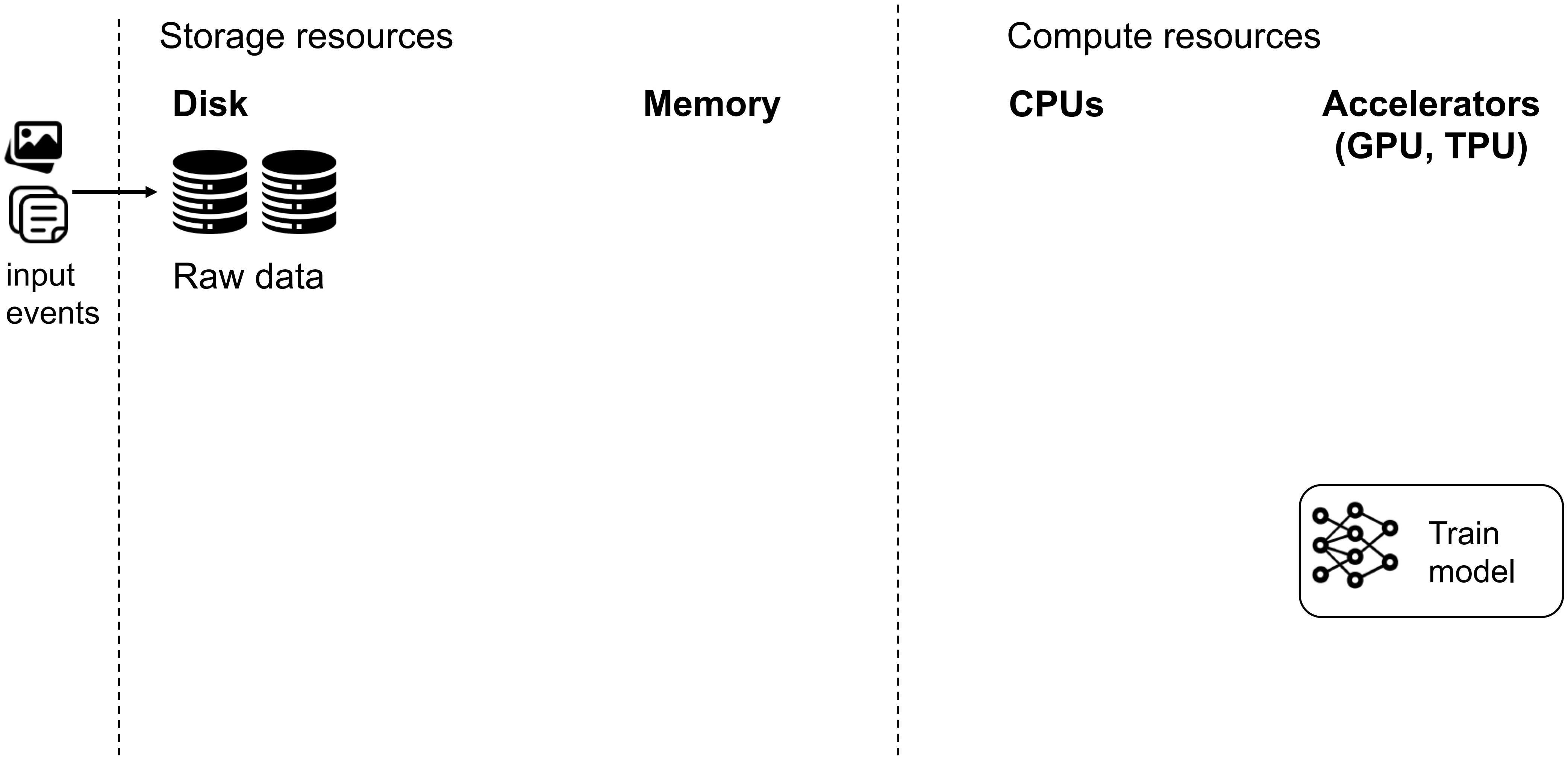
Compute resources

CPUs

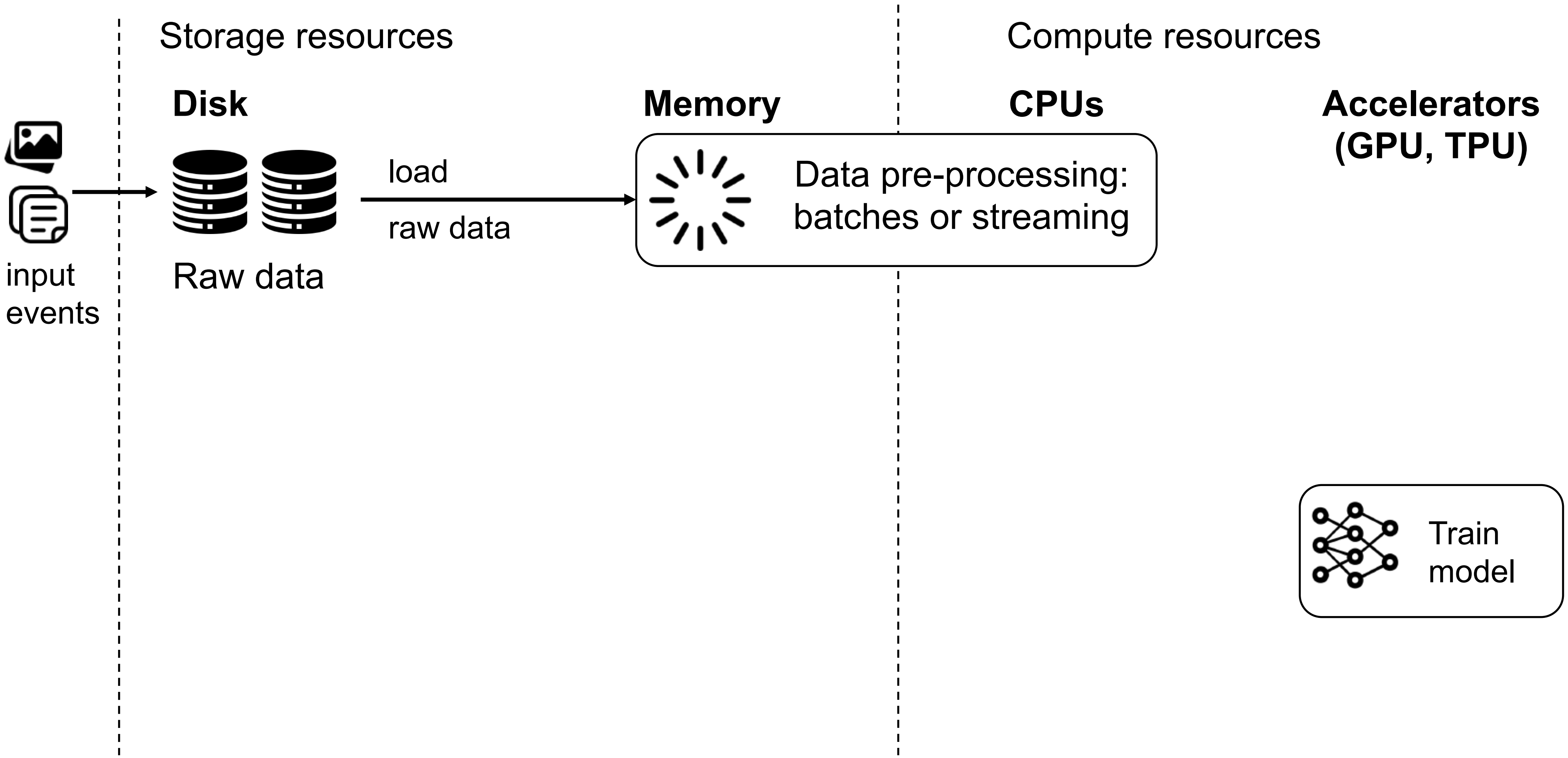
Accelerators (GPU, TPU)

Train model

Data Pipeline in ML: Pre-processing



Data Pipeline in ML: Pre-processing



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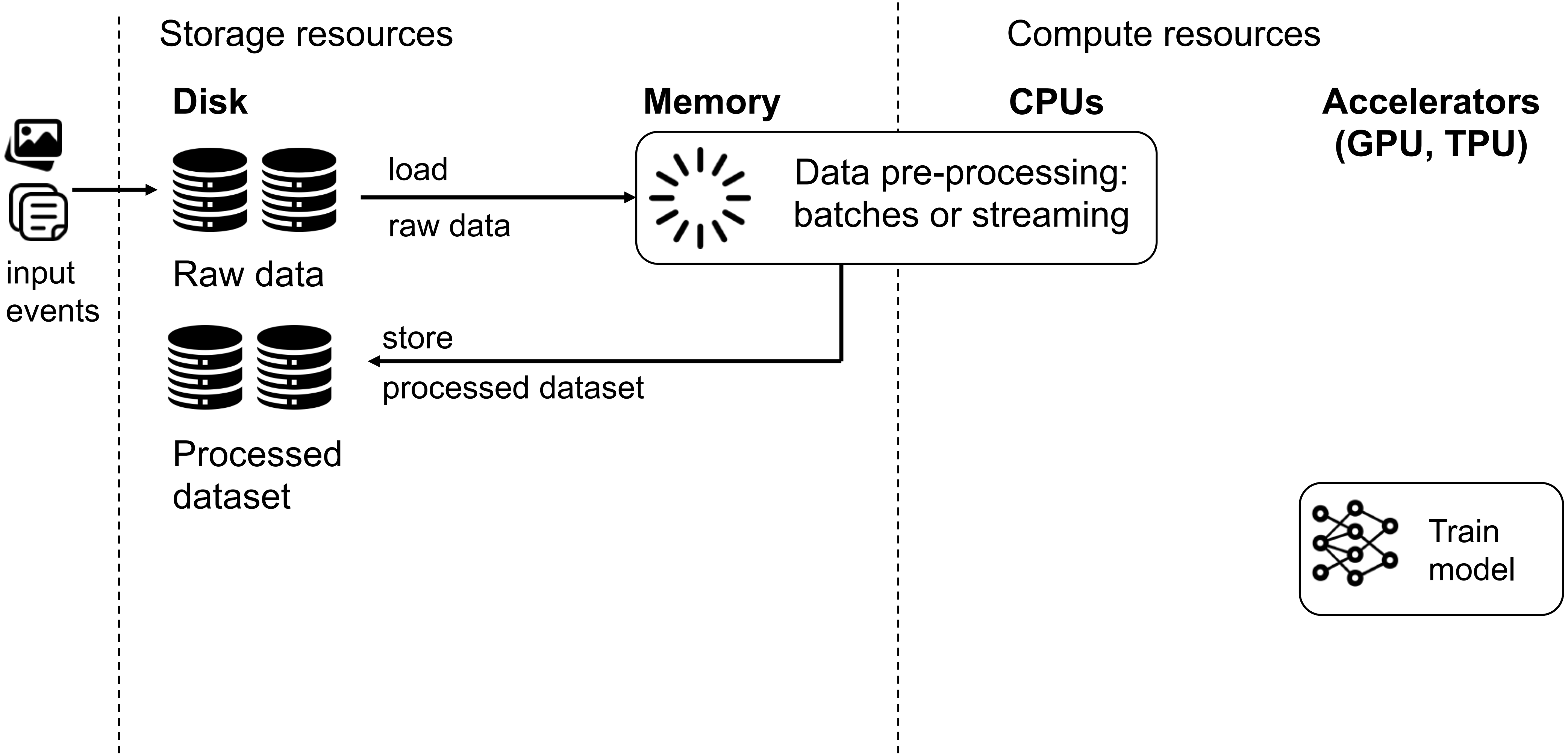

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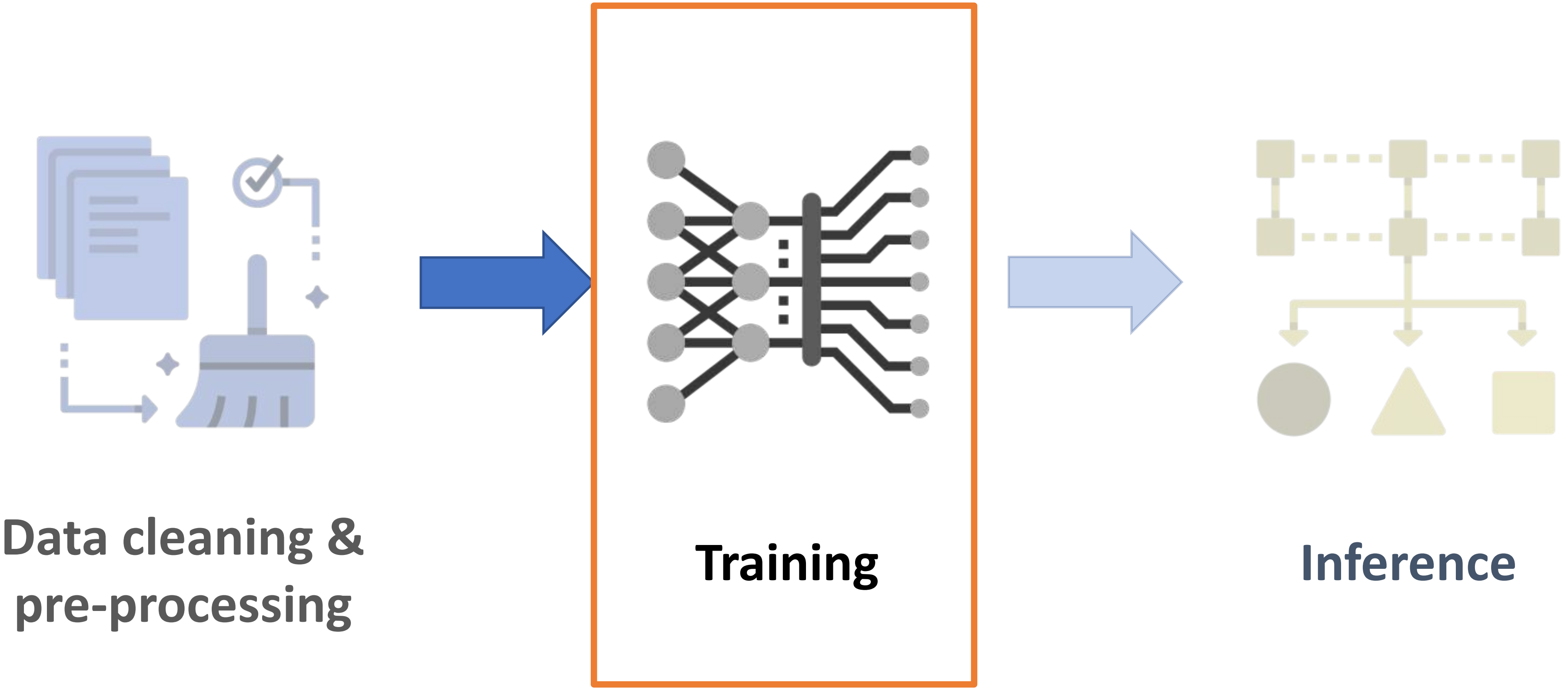

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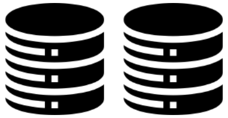
Data pipeline in ML: Training

Storage resources

Disk



Cleaned
dataset

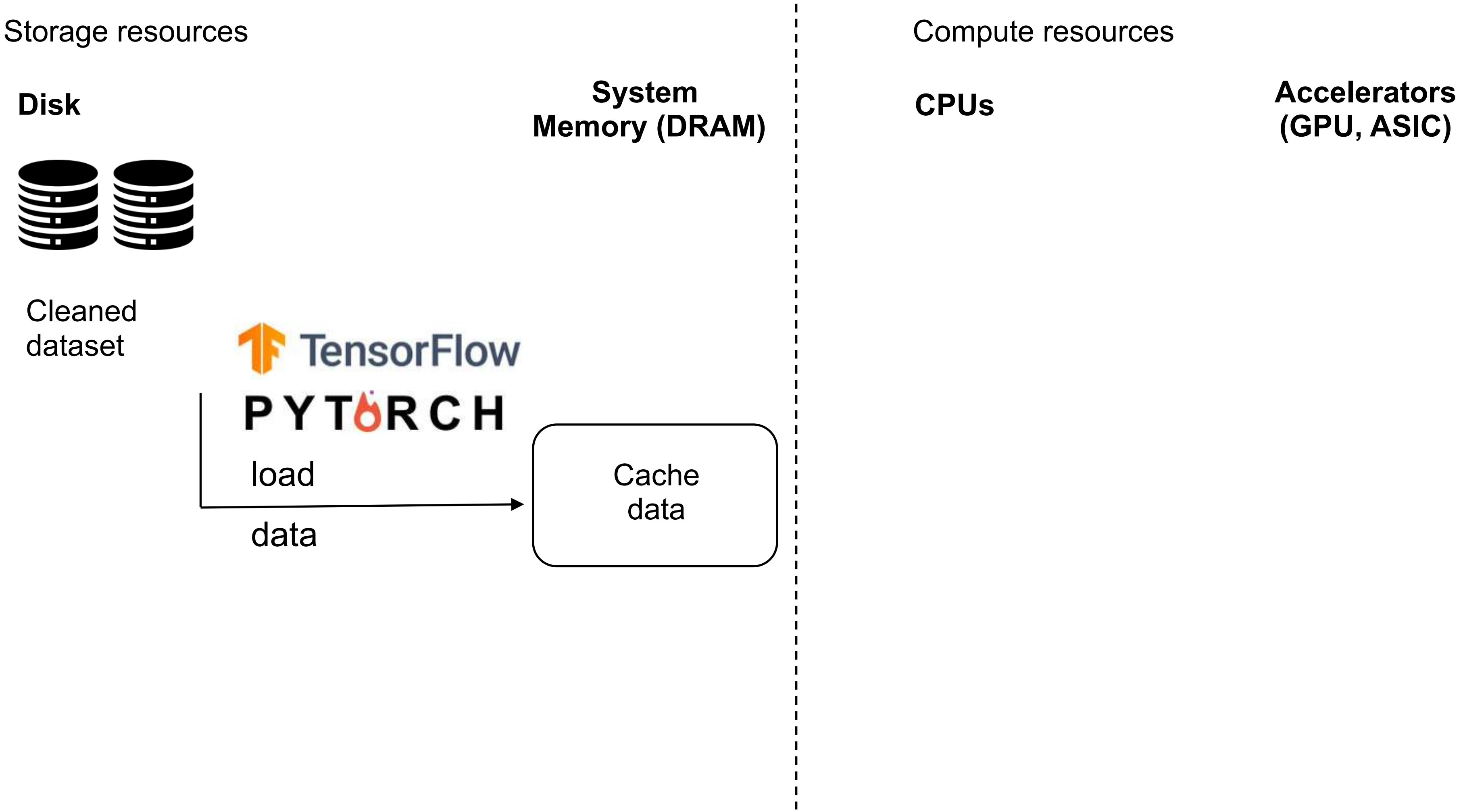
System Memory (DRAM)

Compute resources

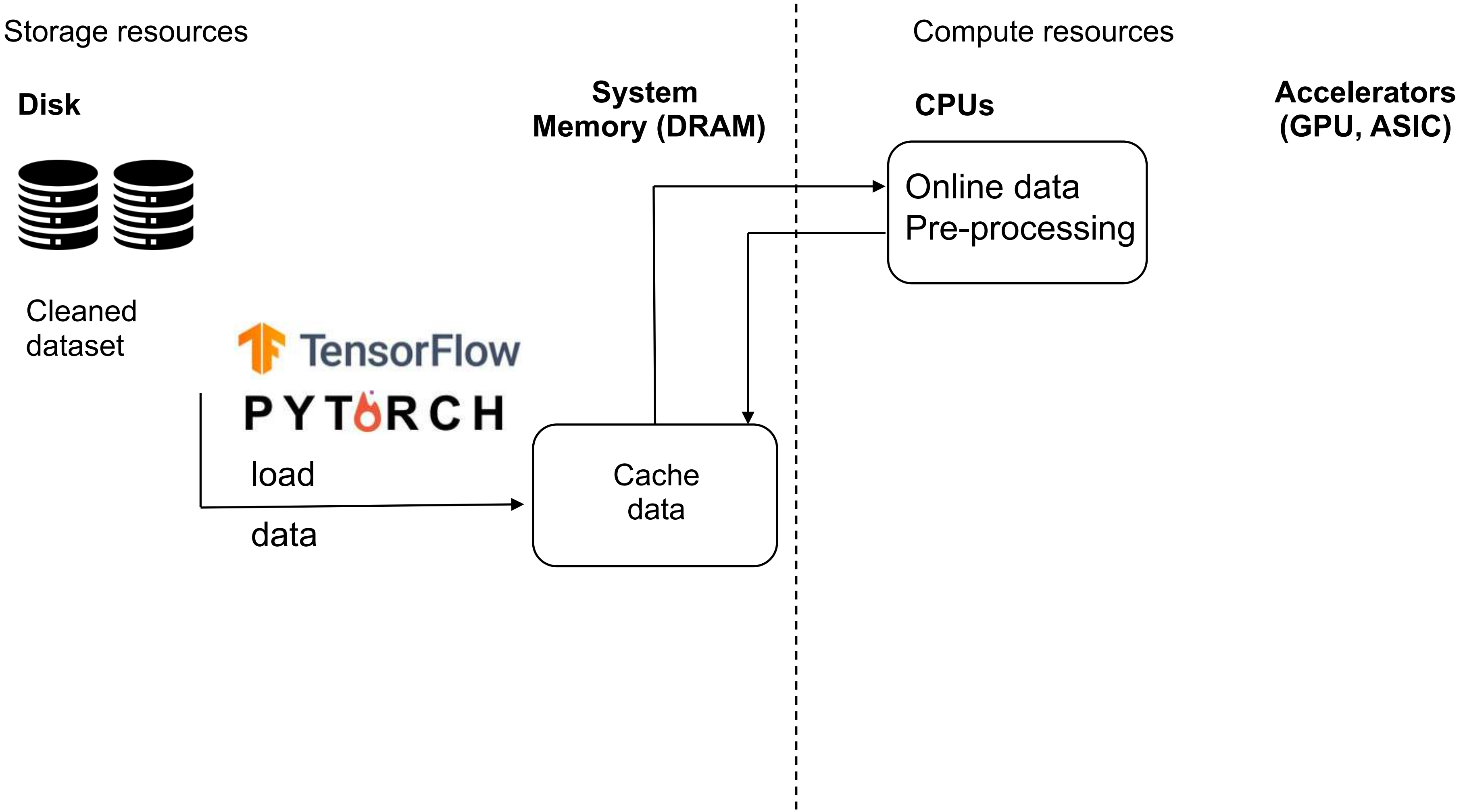
CPUs

Accelerators (GPU, ASIC)

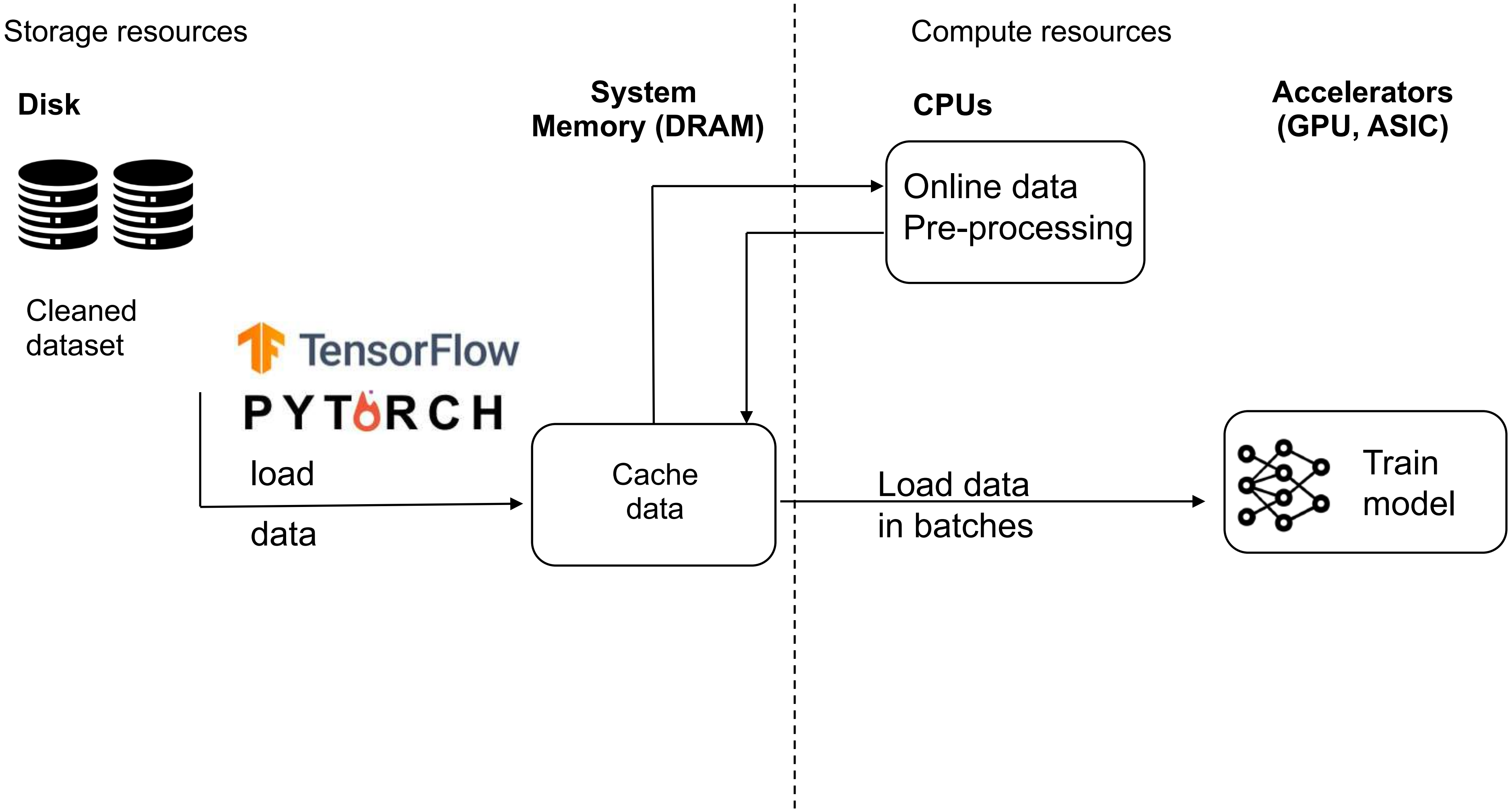
Data pipeline in ML: Training



Data pipeline in ML: Training



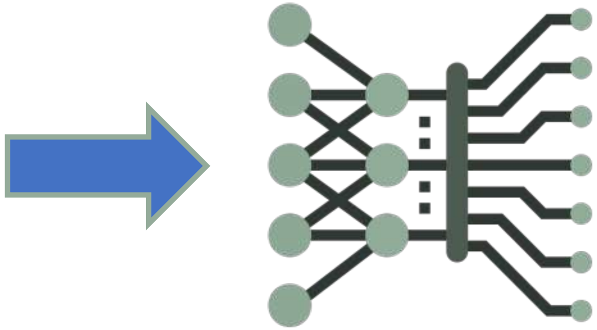
Data pipeline in ML: Training



MLPerf Storage

Data cleaning & pre-processing

MLPerf Storage V0.5



Training

Focus on **storage impact in ML/AI**

Realistic **storage** settings in

training phase

No accelerator required to run

Minimal AI/ML knowledge

MLPerf Storage – workloads

Workload	**Image segmentation**	**Natural language processing**	**Recommender Systems**
Model	3D U-Net	BERT	DLRM
Seed data	KiTS19 Set of images	Wikipedia 2020 Text	Criteo Terabyte Click logs
Framework	Pytorch	Tensorflow	Pytorch
I/O behavior	Random access inside many small files	Sequential access of small subset of files, streamed.	Random access inside one large file

https://github.com/mlcommons/storage

- **Single node**
- Many **simulated accelerators.**
- **Synthetic datasets** generated from real dataset seed.
- **Local storage**

MLPerf Storage – Benchmark metric

Must capture dynamics between storage and compute.

MLPerf Storage – Benchmark metric

Must capture dynamics between storage and compute.

Storage-centric metrics

- ✓ IOPS
- ✓ Latency
- ✓ Read/Write throughput
- ✓ Capacity

Compute-centric metrics

- ✓ Training time
- ✓ Trained model accuracy
- ✓ Accelerator utilization

☹Neither metric is enough to capture the storage-compute relationship

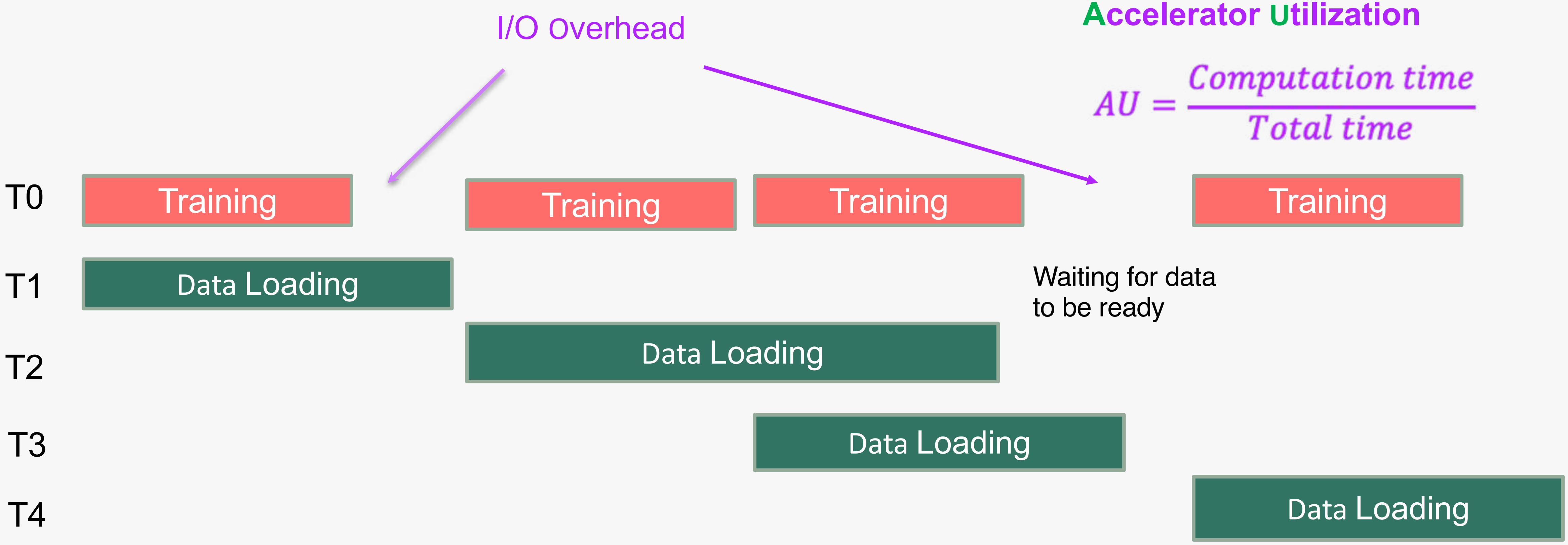
- Storage metrics too generic. Cannot capture dynamics of ML workloads.
- Compute-centric metrics too narrow (e.g., no notion of dataset size).

Proposed metric

$$Throughput = \frac{num\_samples}{Time\ per\ epoch}$$

Accelerator Utilization

$$AU = \frac{Computation\ time}{Total\ time}$$

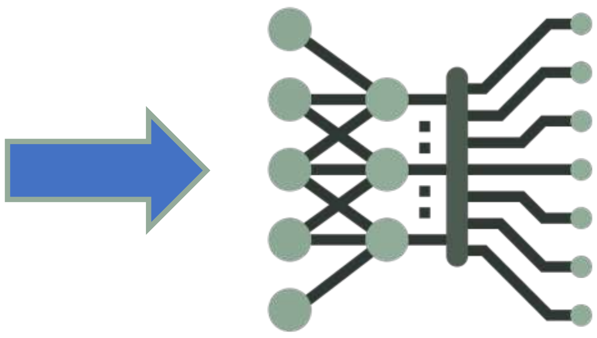


Goal of benchmark:
Maximize samples / second, given an **Accelerator Utilization > 90%** at a certain scale.

MLPerf Storage

Data cleaning & pre-processing

MLPerf Storage V1



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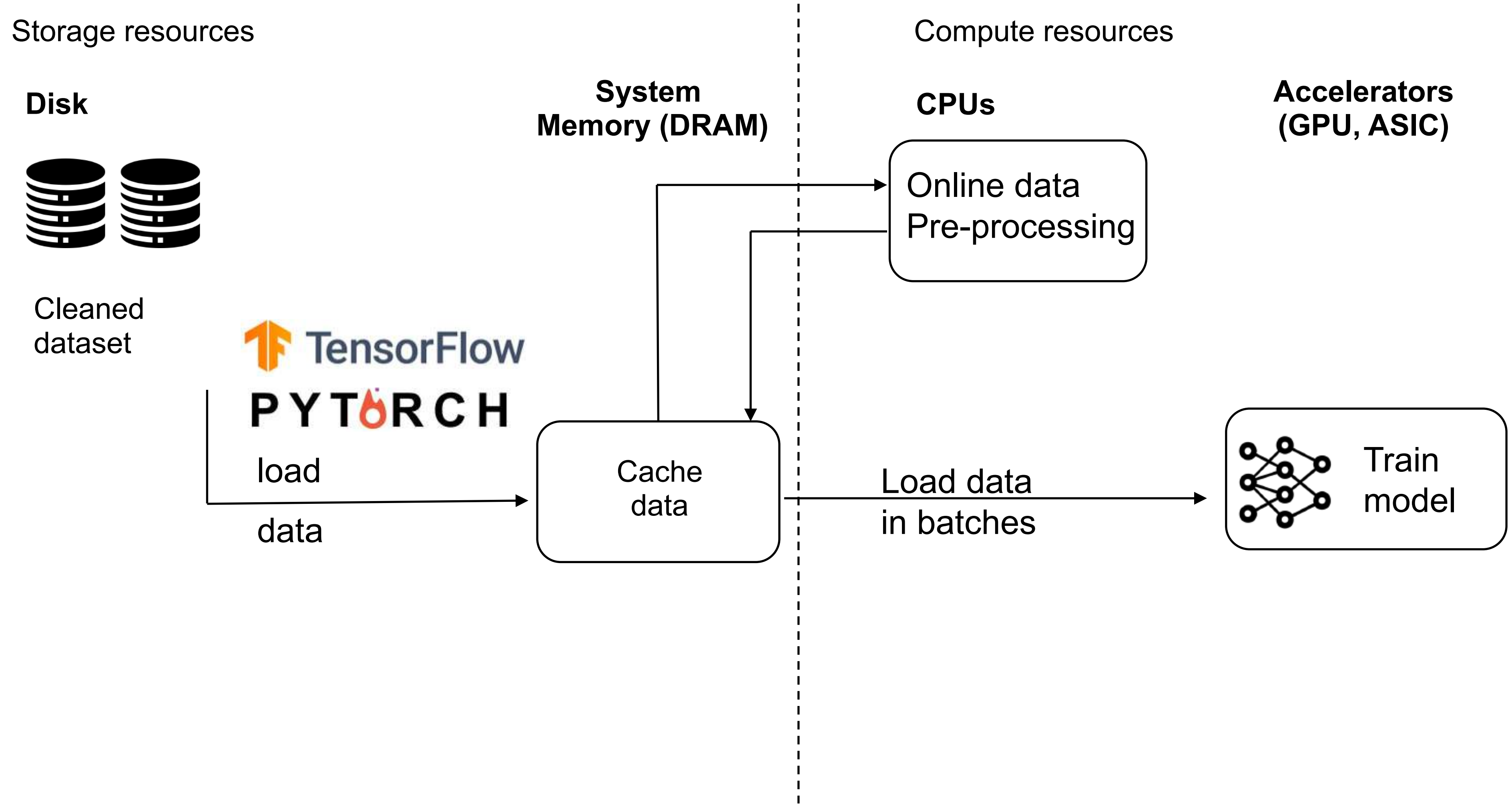
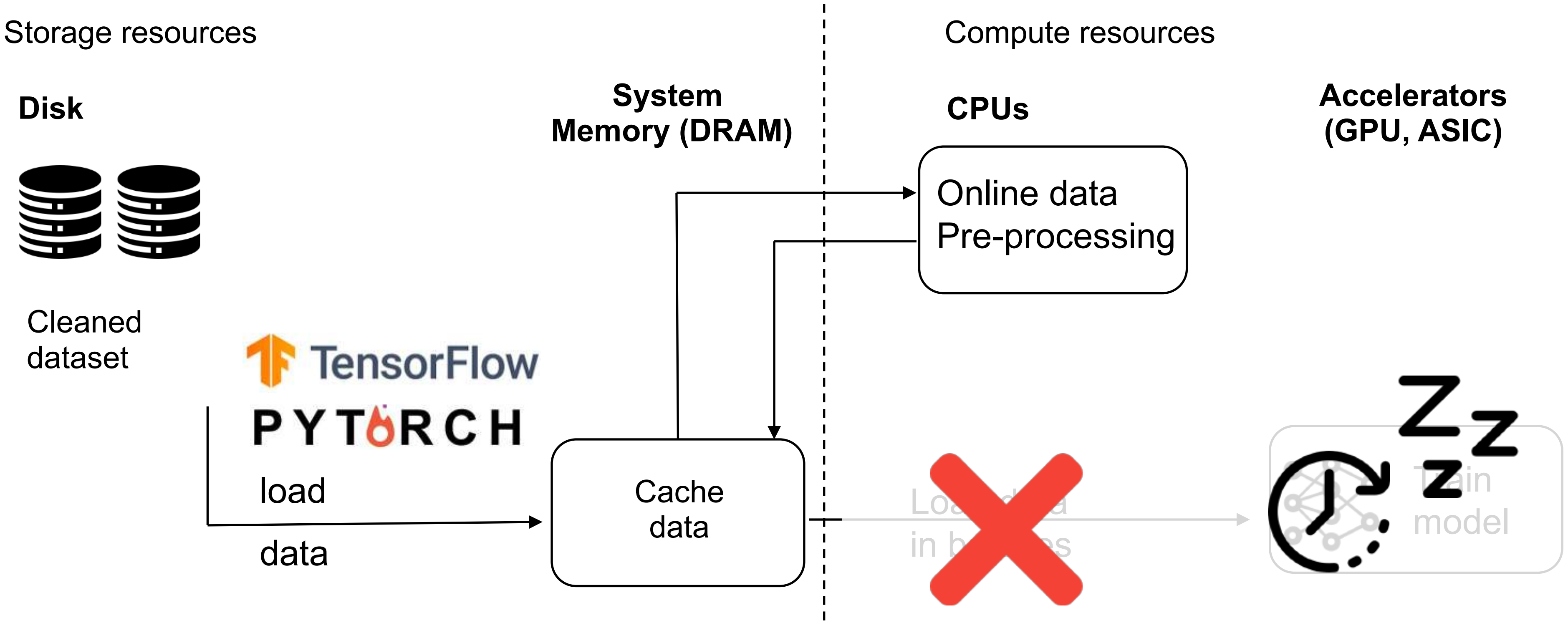
Data pipeline in ML: Training



Data pipeline in MLPerf Storage benchmark

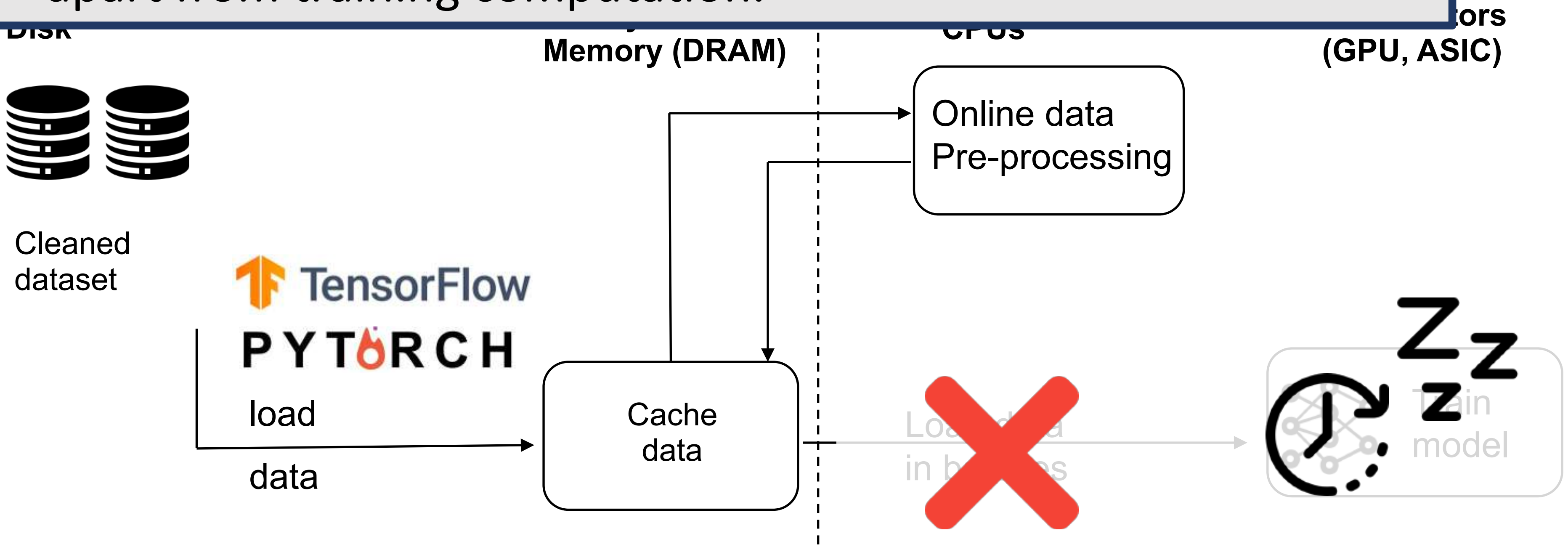


Benchmark is built as an extension of DLIO [1]

[1] H. Devarajan, H. Zheng, et al. DLIO: A Data-Centric Benchmark for Scientific Deep Learning Applications, CCGrid '21.

Data pipeline in MLPerf Storage benchmark

✓ Realistic storage settings: nothing changes in data pipeline, apart from training computation.



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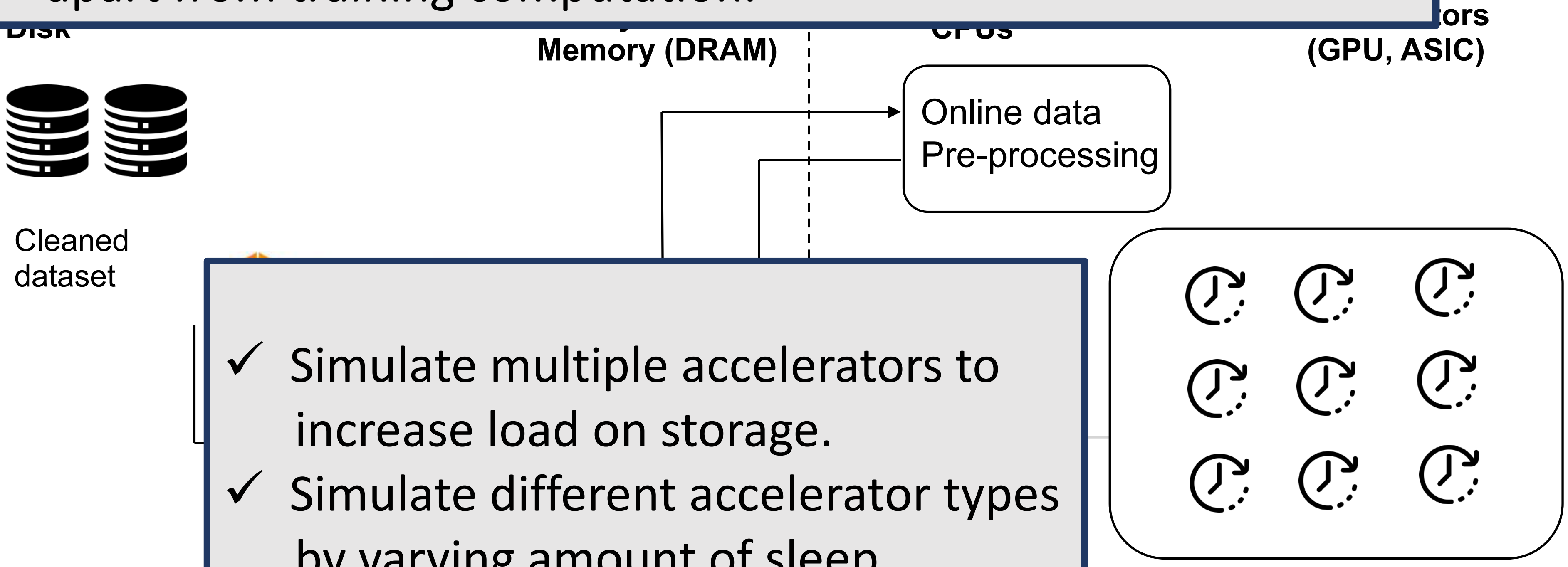

✓ Simulate multiple accelerators to increase load on storage.

✓ Simulate different accelerator types by varying amount of sleep

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Experimental Evaluation

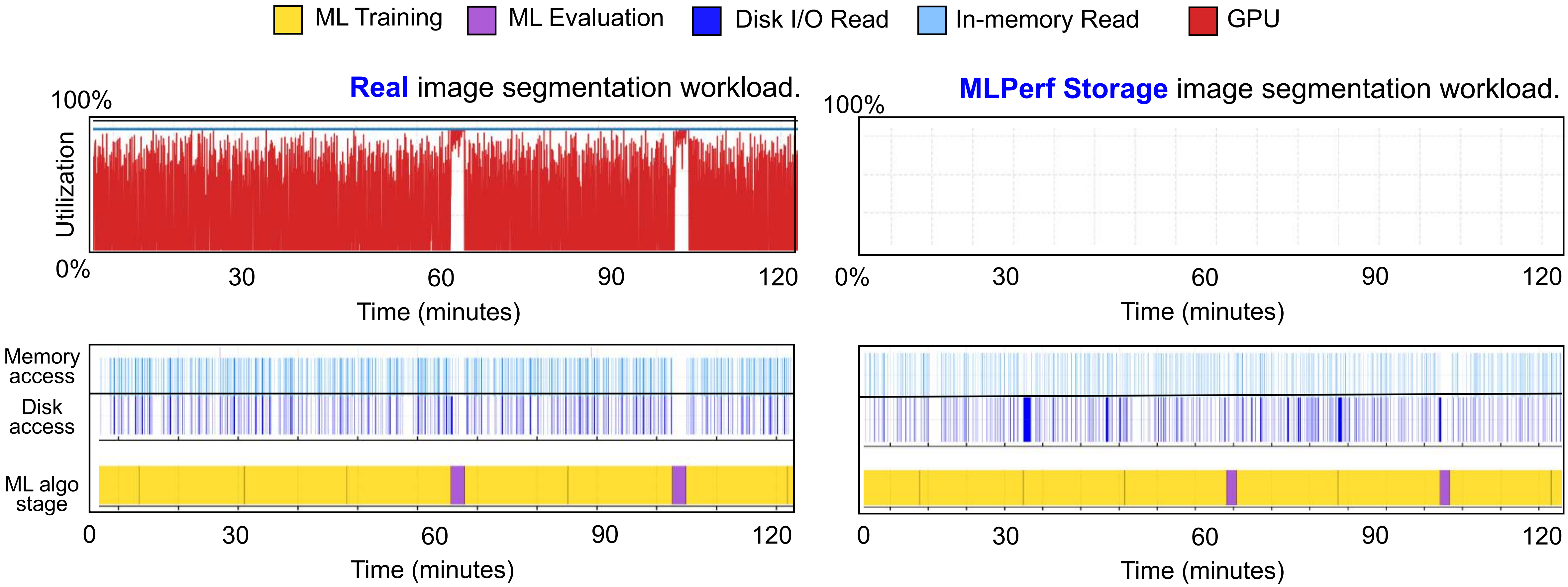
- DGX-1 server
  - 8 x V100 GPUs, 32GB GPU memory
  - 512GB DRAM

- Dataset size : Host memory size = 2:1

3D U-Net

- Pytorch, KiTS19 dataset seed
- Small model, large data.
  - 100s MB per sample
- One sample per file.

Simulating training time does not impact I/O patterns



Experiment setup: DGX-1 with 8xV100 GPUs, 512GB DRAM. Dataset : KiTS19, Dataset size:Memory size ratio 2:1

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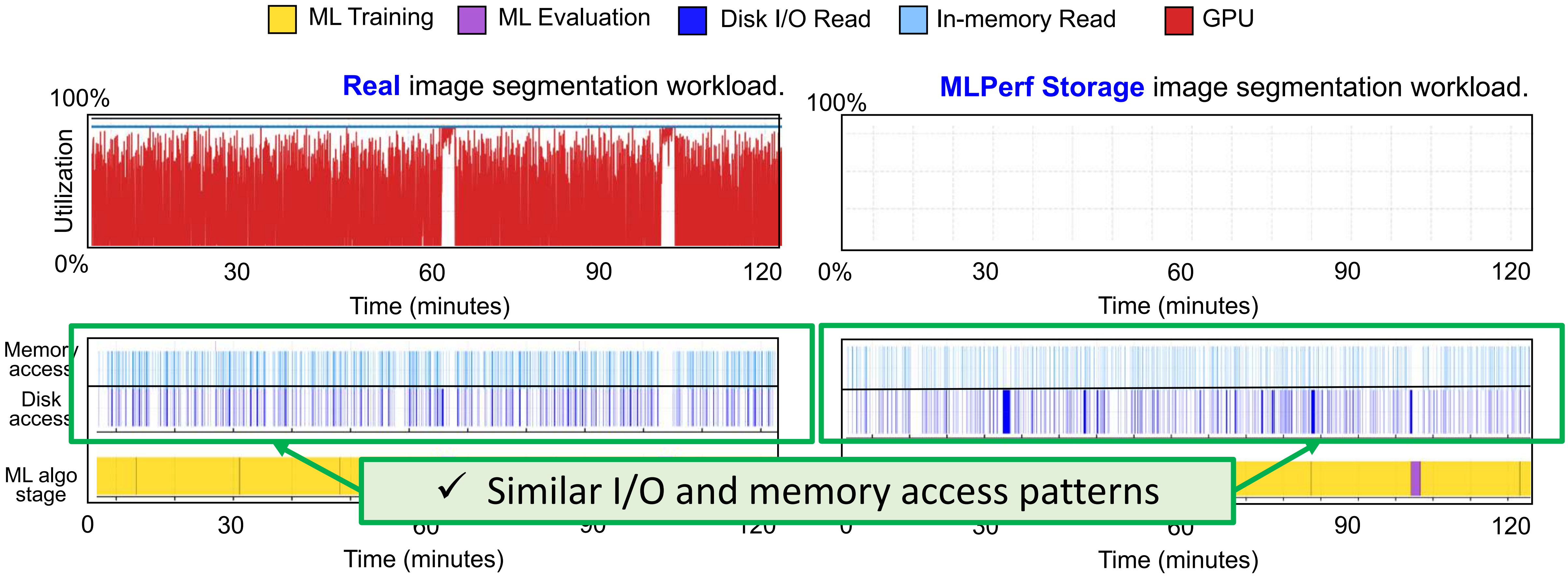

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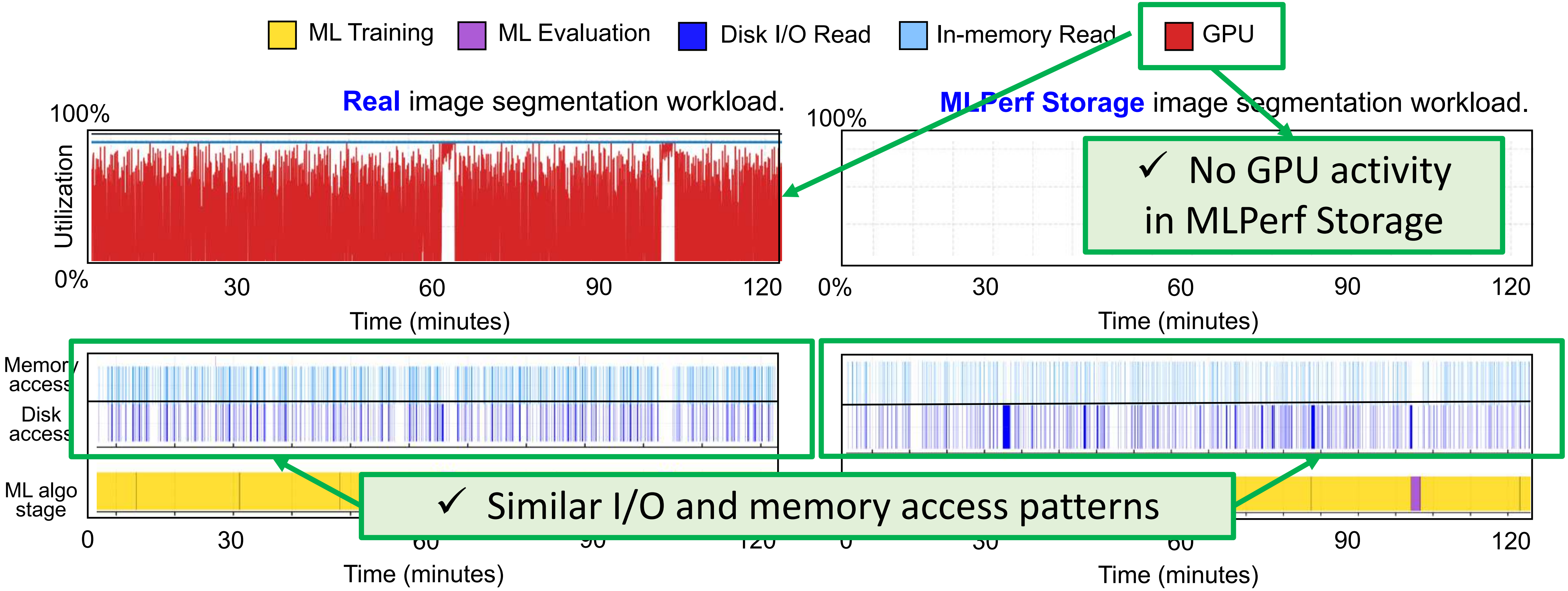

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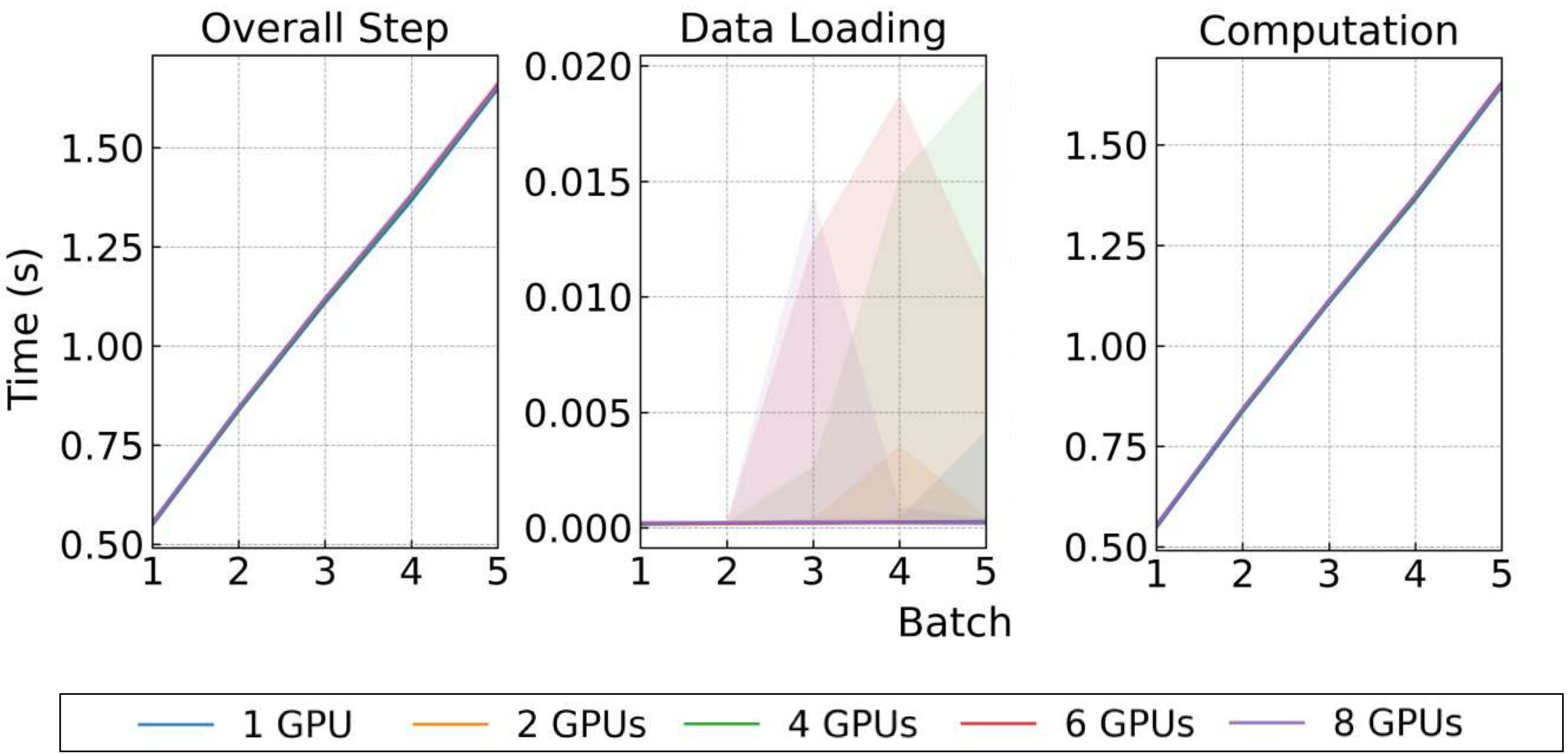
3D U-Net: Step Breakdown



Natural Language Processing: BERT

- Tensorflow implementation, Wikipedia dataset seed
- Large model, small data.
    - Model takes up most of GPU memory
- Many small samples per file
    - ~300K samples per file
- Sequential access inside the files
    - Prefetching

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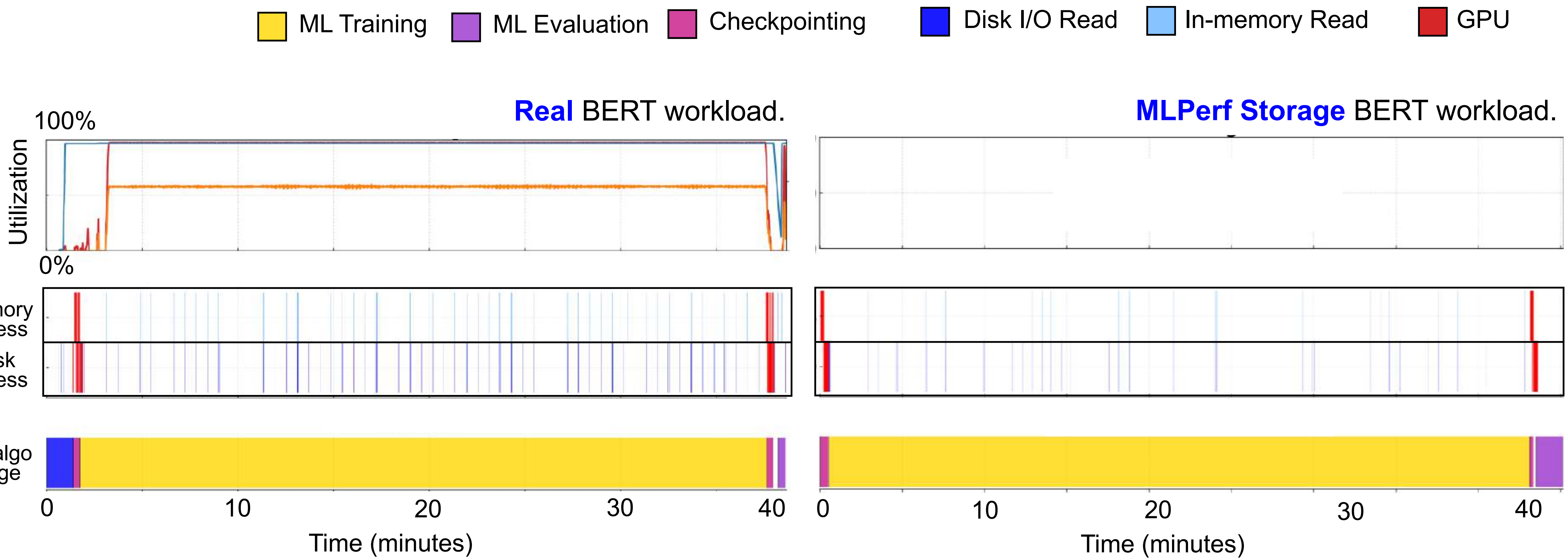
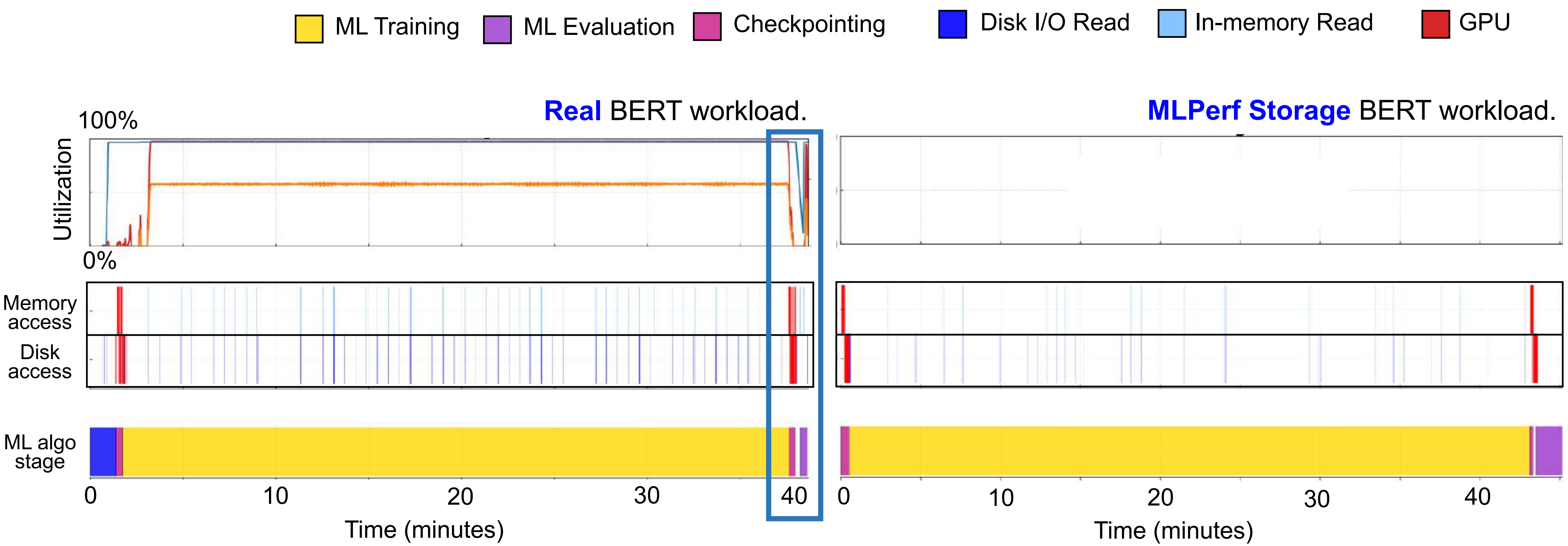
BERT



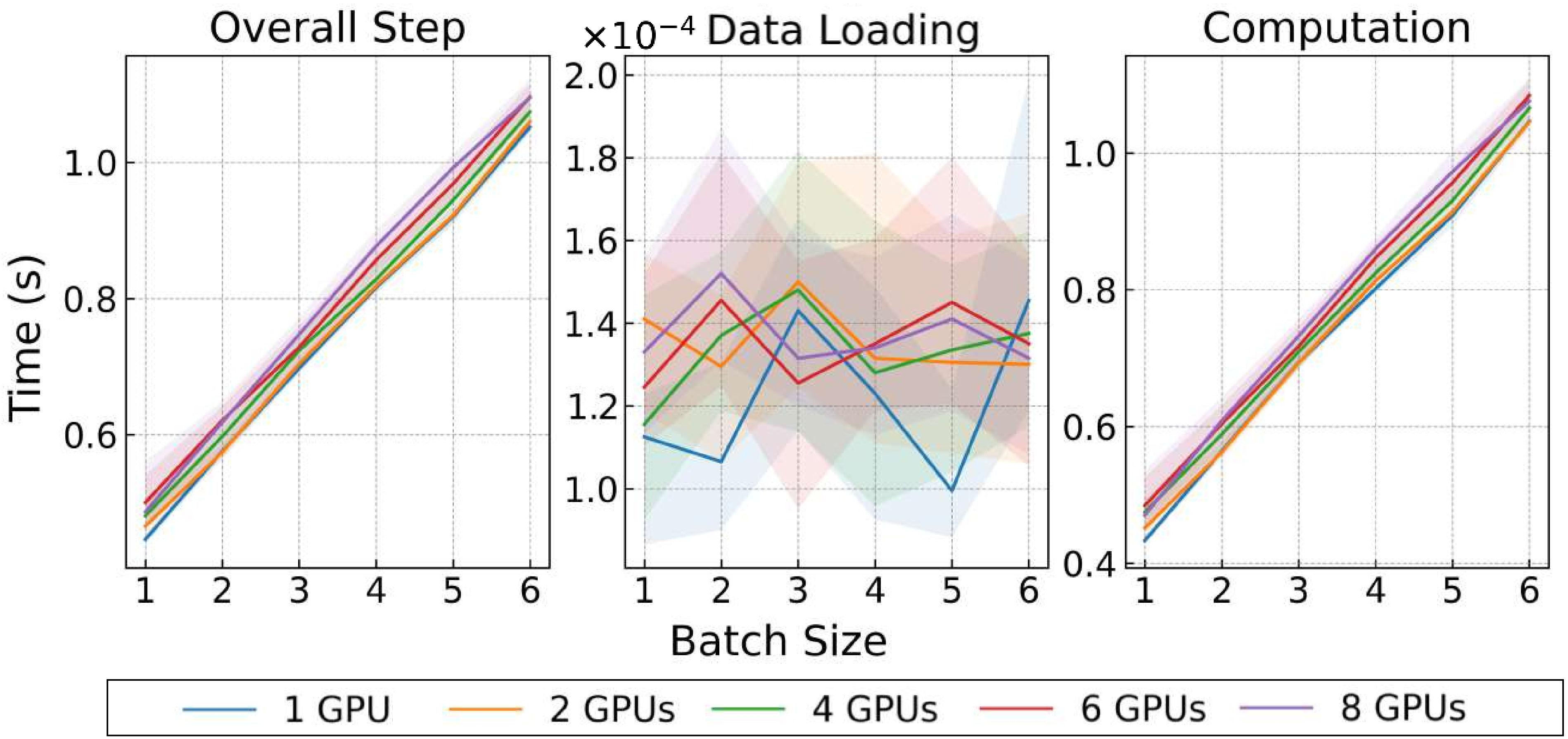
ML Training
ML Evaluation
Checkpointing
Disk I/O Read
In-memory Read
GPU
Real BERT workload.
MLPerf Storage BERT workload.
100%
0%
Utilization
Memory access
Disk access
ML algo stage
0
10
20
30
40
Time (minutes)

BERT



Checkpointing
is a bottleneck
GPU → 0% utilization during checkpoint

BERT: Step Breakdown



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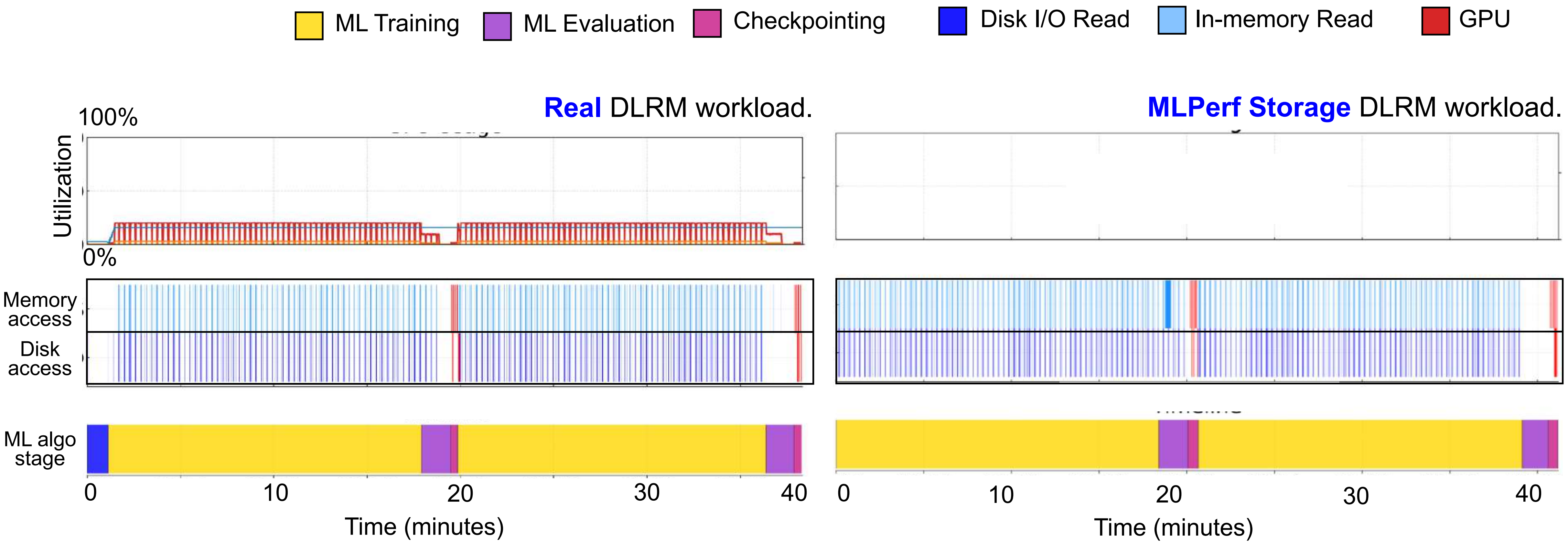
DLRM

- PyTorch implementation, Criteo dataset seed
- Large model, Large data.
  - Model and data parallelism
- Many small random accesses inside a large file

DLRM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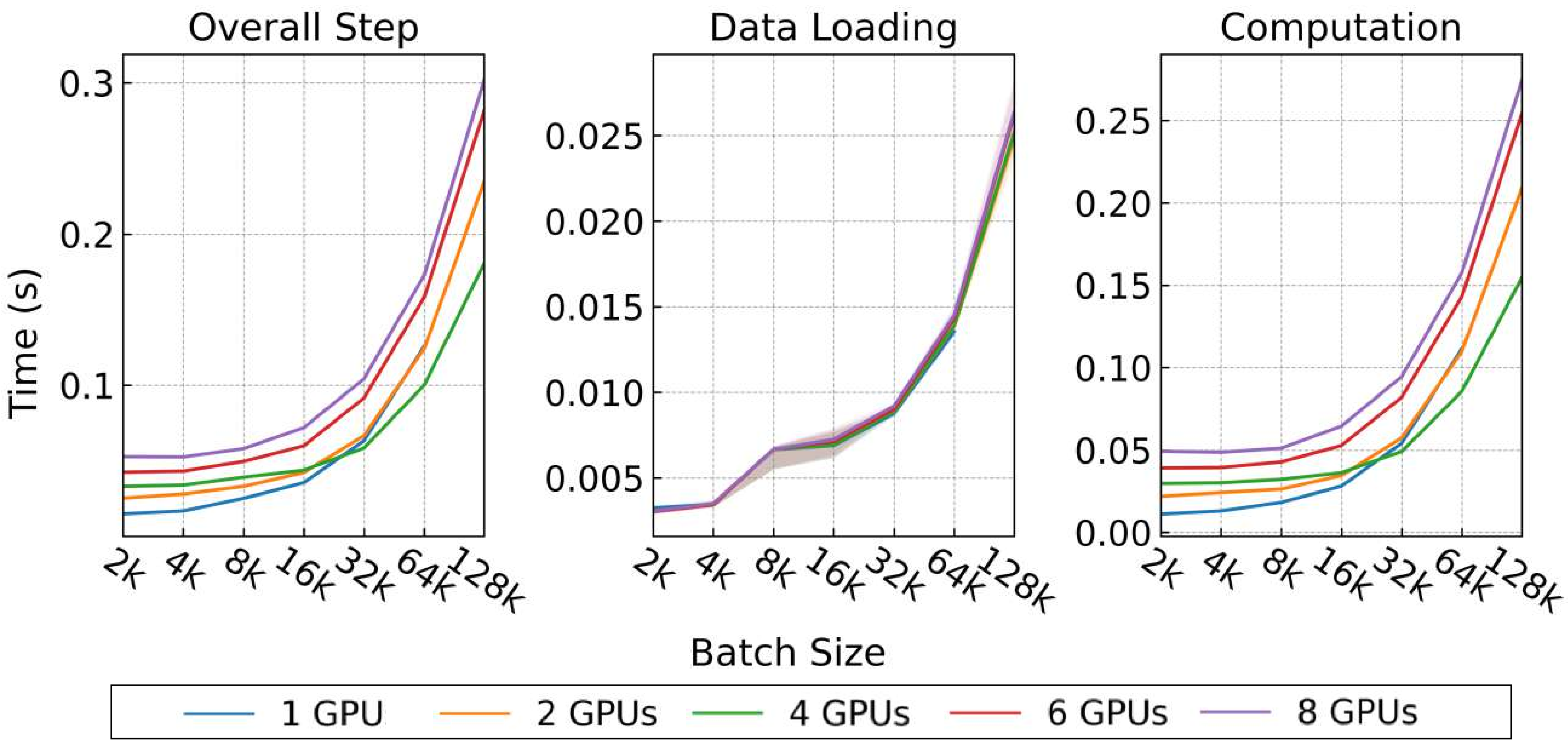


Lessons learned so far

- Storage on its own is not the main issue.

- Studying I/O patterns revealed opportunities for improvement:
  - In the data loaders (3D U-Net)
  - In the checkpointing (BERT)
  - In the algorithm (DLRM)

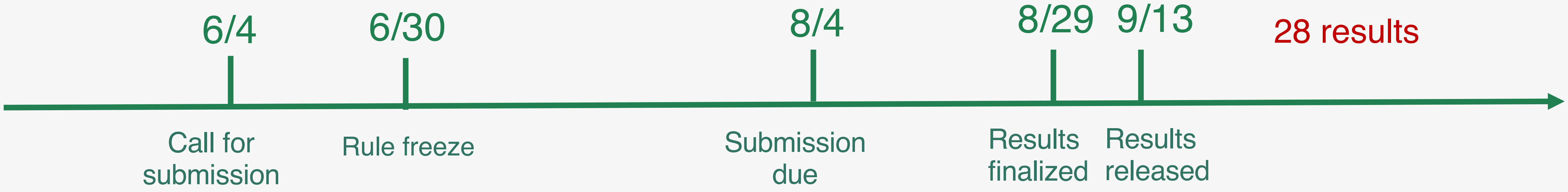
MLPerf Storage v0.5 results overview

Workload selected

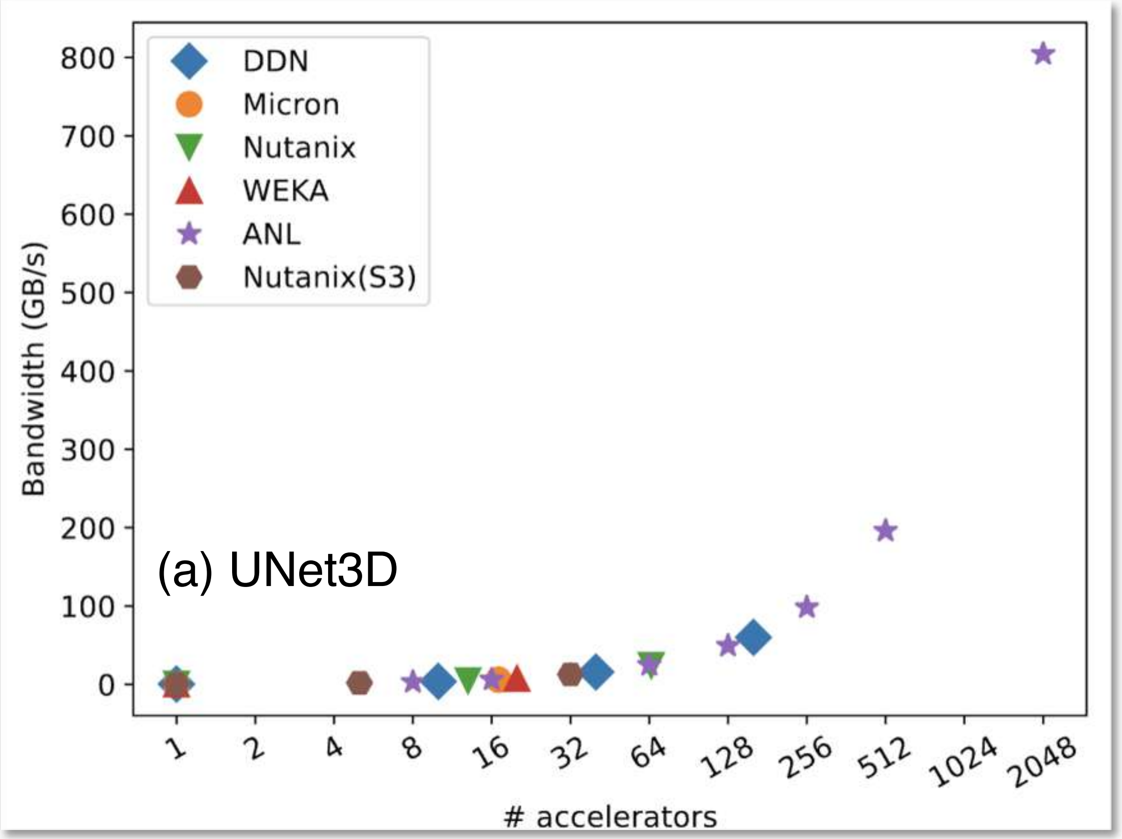
Workload	Image segmentation	Natural language processing
Model	UNet3D	BERT
Seed data	KiTS19 Set of images	Wikipedia 2020 Text
Sample size	~146 MB	~2.5 KB
Framework	Pytorch	Tensorflow
I/O behavior	Randomly select and read a file	Sequential access a subset of files, streamed

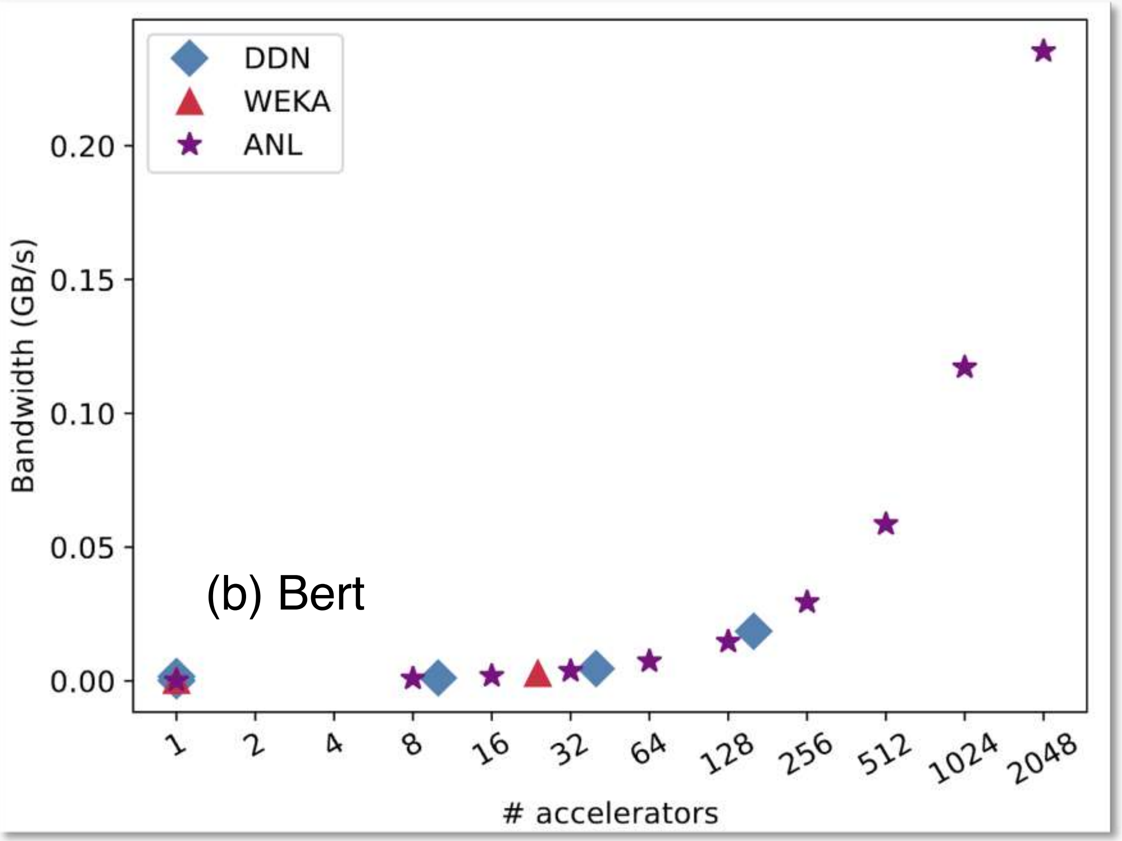
Timeline

5 submitters
28 results



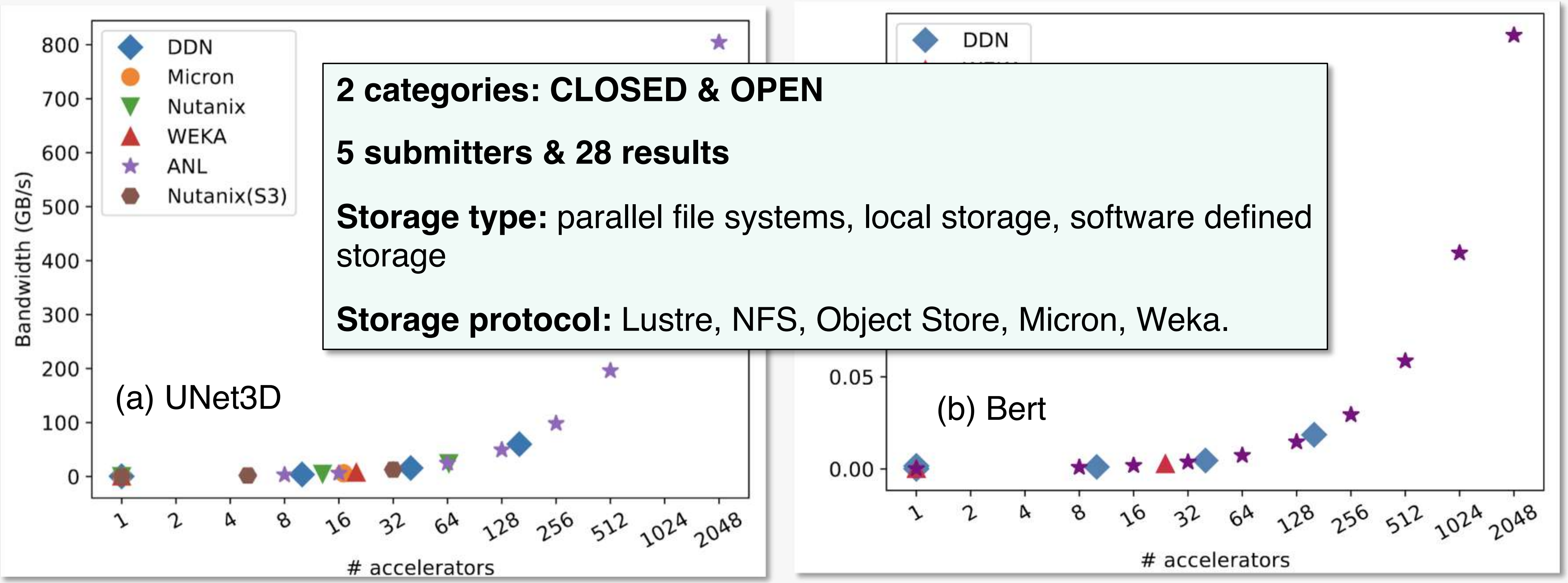
MLPerf Storage v0.5 results overview





Scatter plots of the results from the submitters: (a) UNet3D and (b) Bert. UNet3D is I/O intensive workload and Bert is compute intensive

MLPerf Storage v0.5 results overview



2 categories: CLOSED & OPEN

5 submitters & 28 results

Storage type: parallel file systems, local storage, software defined storage

Storage protocol: Lustre, NFS, Object Store, Micron, Weka.

Scatter plots of the results from the submitters: (a) UNet3D and (b) Bert. UNet3D is I/O intensive workload and Bert is compute intensive

Next Steps in MLPerf Storage

Collect **processing times** for different accelerator types: A100, H100.

Benchmark competition round 2: *https://github.com/mlcommons/storage*

I/O in distributed training

New workloads (LLM, text-to-image, HPC)

Workload collocation

Extend benchmark with **ML pre-processing phase.**

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McGill DISCS Lab

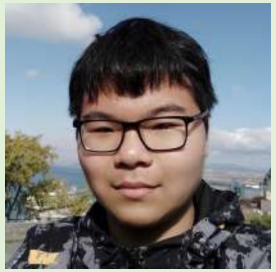
discslab.cs.mcgill.ca
gitlab.cs.mcgill.ca/discs-lab

Postdoctoral Researcher

Dr. Stella Bitchebe

PhD Candidates:

Nelson Bore



Jiaxuan Chen

Shubham Vashisth

Pritish Mishra

Rahma Nouaji

Masters Students

Zachary Doucet

Aayush Kapur

Aidan Goldfarb

Ruoyu Deng

Key Takeaways – MLPerf Storage

MLPerf Storage is a new benchmark

Realistic **storage** settings

No accelerators required to run

Follow MLPerf Storage repository for updates:

https://github.com/mlcommons/storage

Get involved
https://mlcommons.org/working-groups/benchmarks/storage/

Share your thoughts
Email oana.balmau@mcgill.ca

Thanks to all working group co-chairs!

Curtis Anderson
Panasas

Huihuo Zheng
Argonne National Labs

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