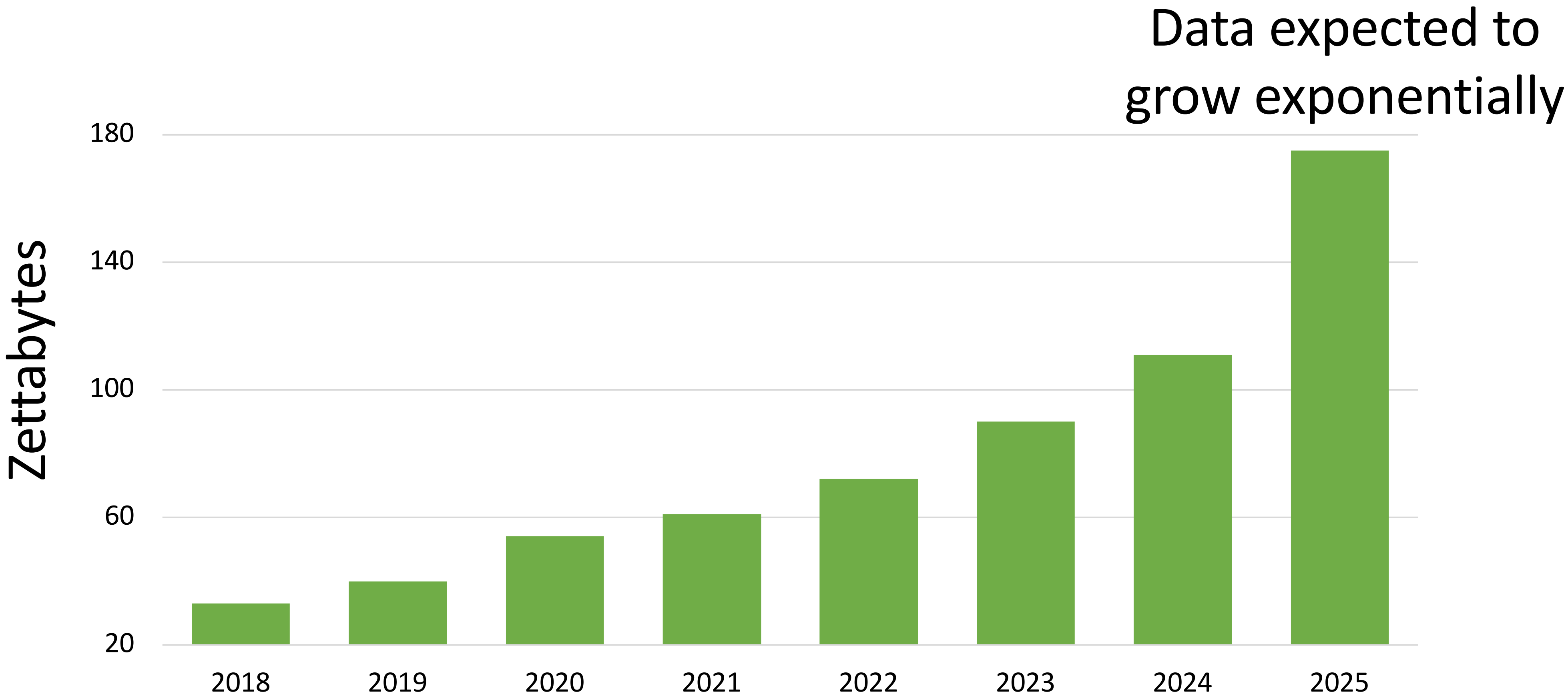
Characterizing Machine Learning I/O with MLPerf Storage

Oana Balmau

CHEOPS @ EuroSys, May 8th, 2023

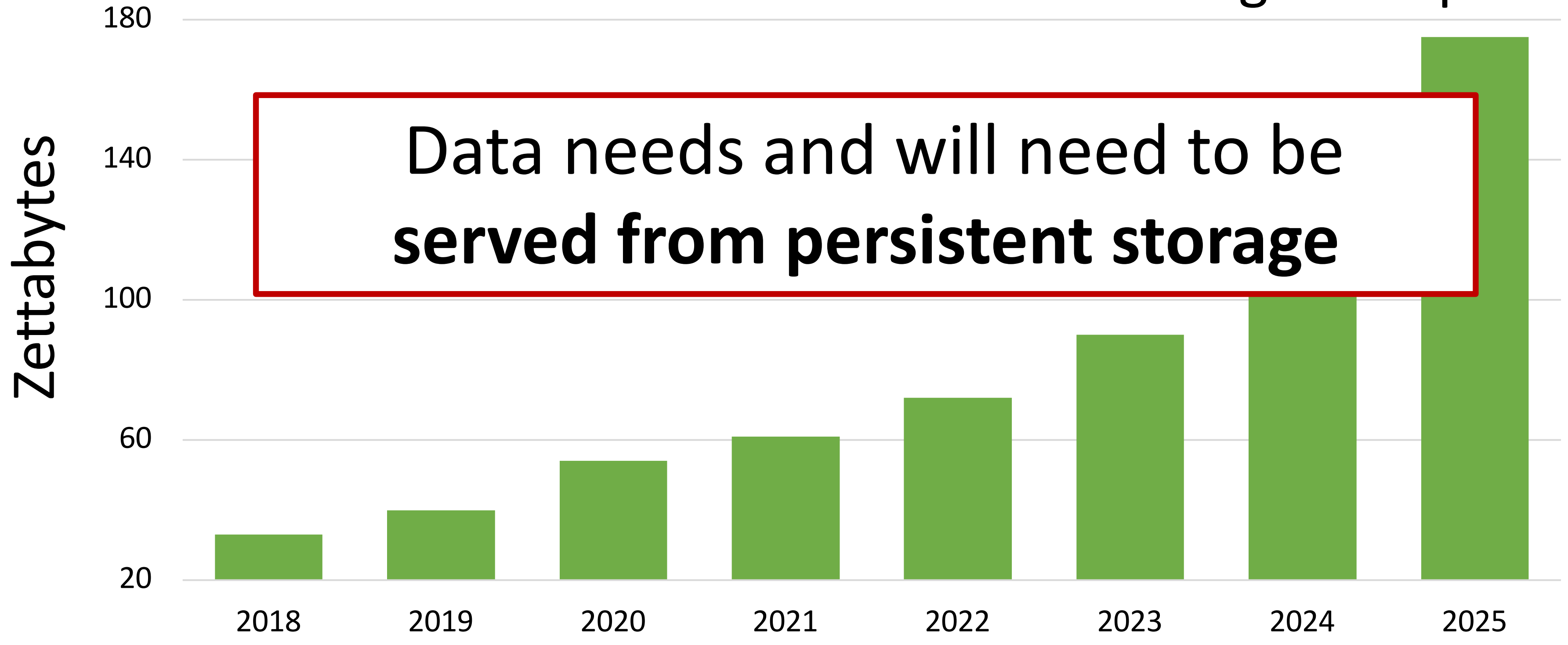
Humanity produces a lot of data



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

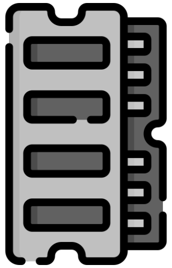
Source: IDC 2022

Data is the moving force of ML algorithms

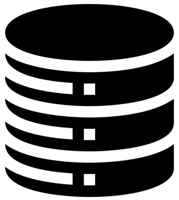
… but in many projects the **storage decision is an afterthought**

Inefficient I/O can slow down ML Workloads

Dataset fits in system memory



Dataset = 2x system memory

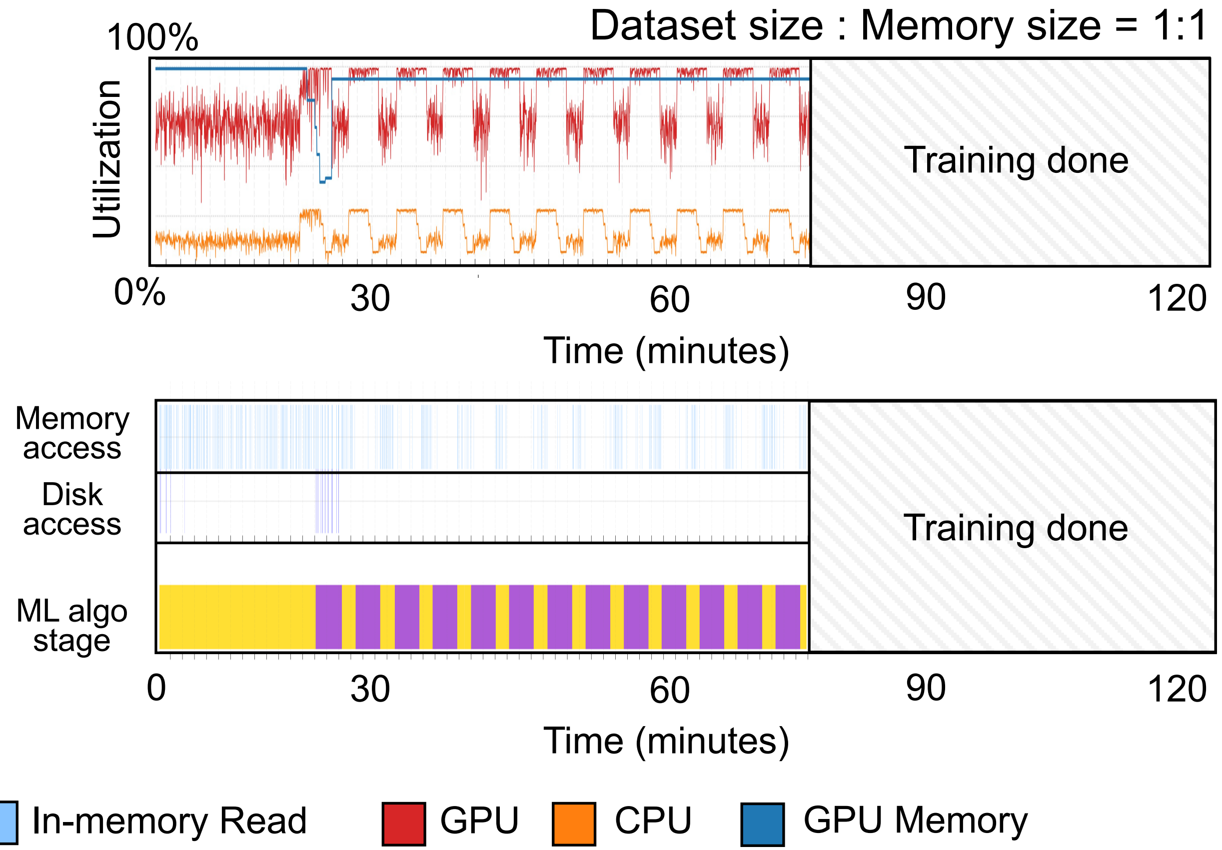


Training time increased by 3x

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



Inefficient I/O can slow down ML Workloads

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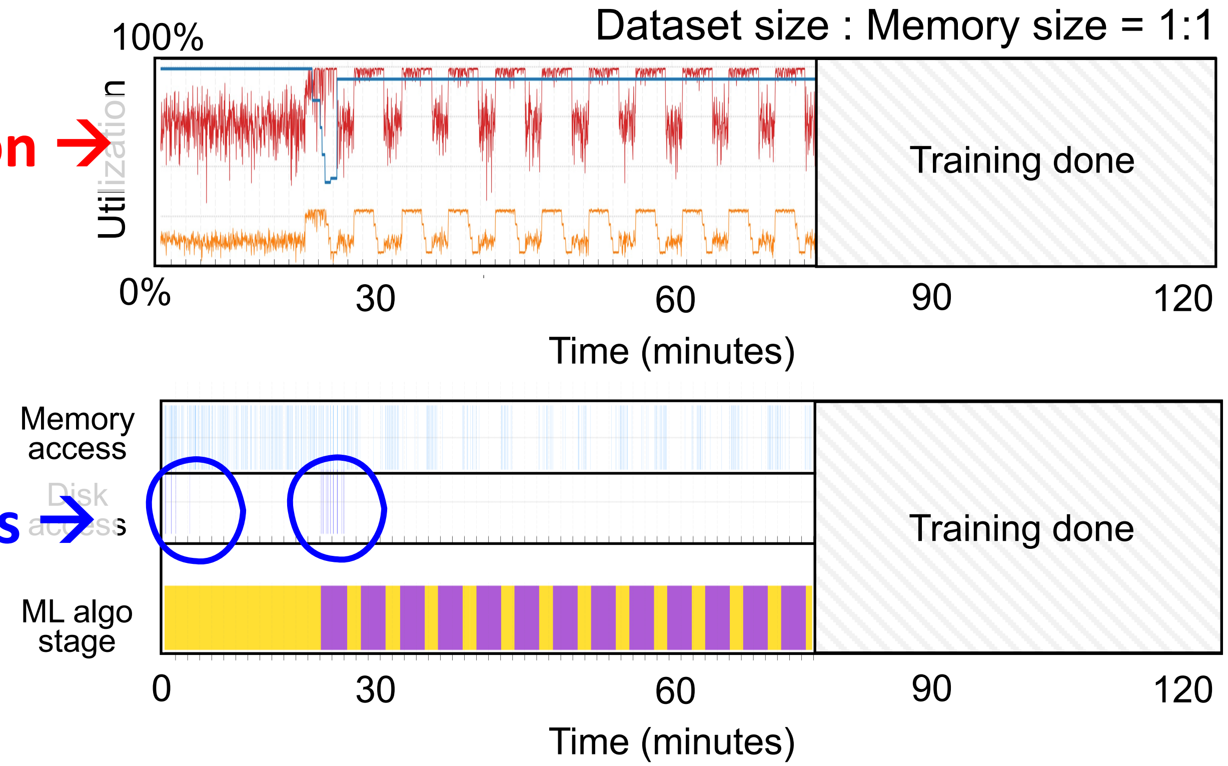
High GPU utilization →

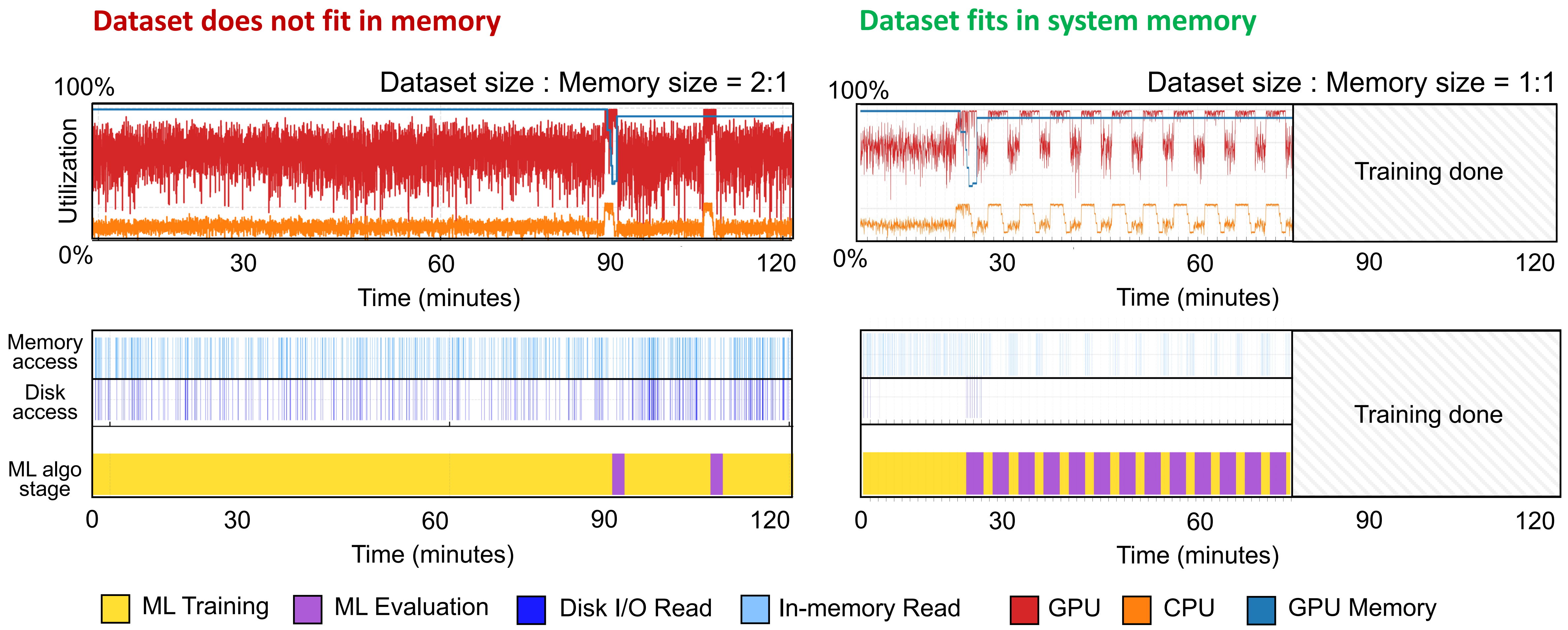
Little disk access →

Dataset fits in system memory



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

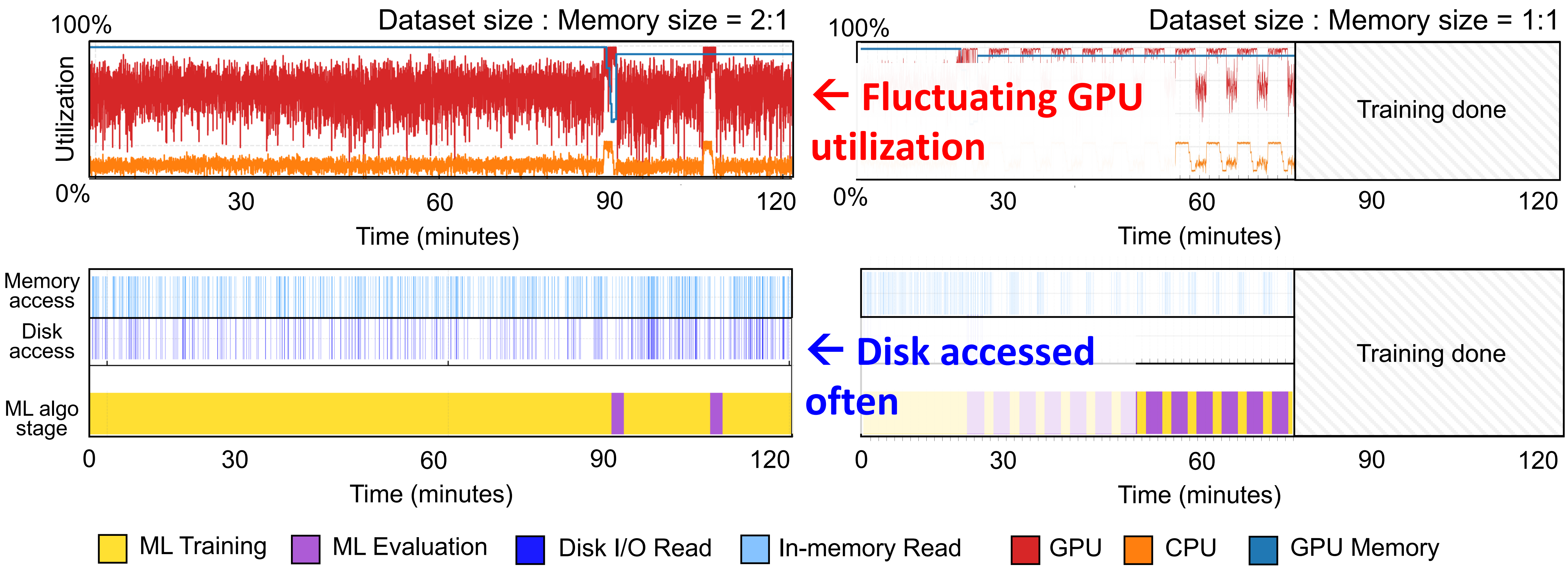
Inefficient I/O can slow down ML Workloads



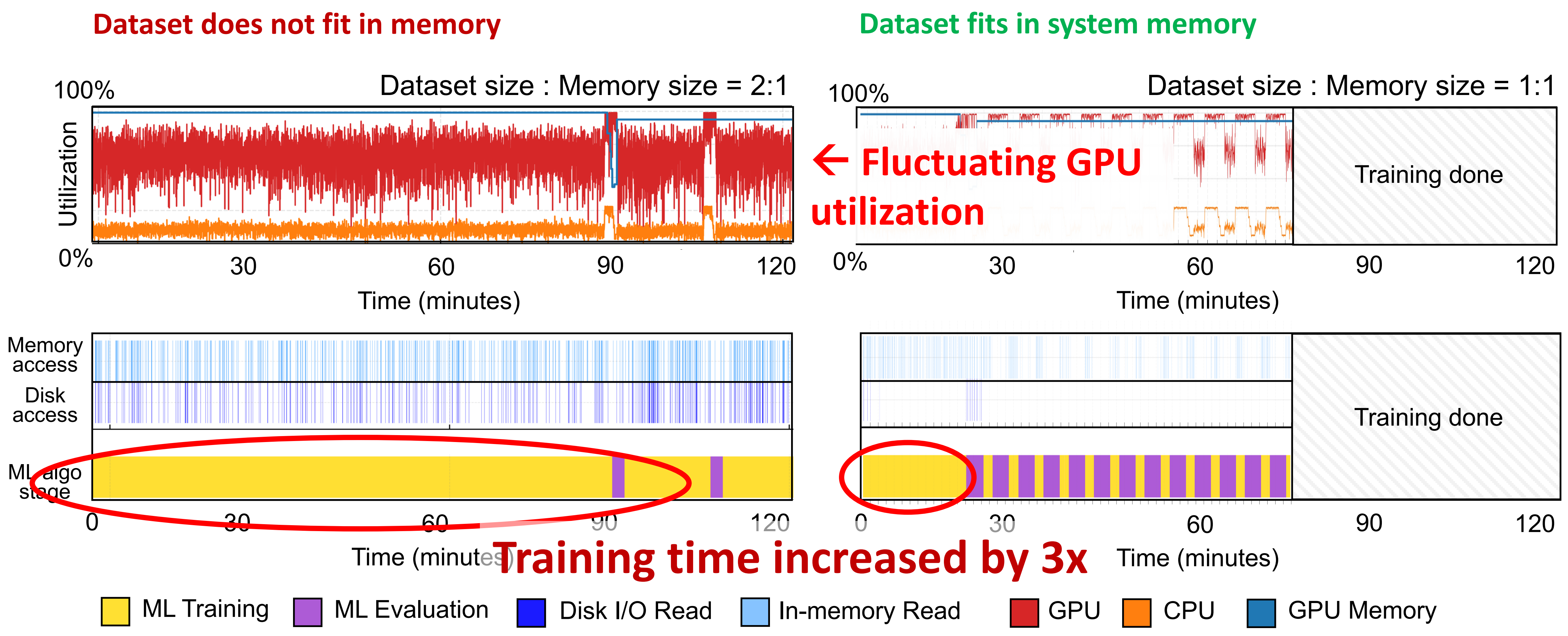
Inefficient I/O can slow down ML Workloads

Dataset does not fit in memory

Dataset fits in system memory



Inefficient I/O can slow down ML Workloads



Data is the moving force of ML algorithms

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

Why create an ML Storage benchmark?

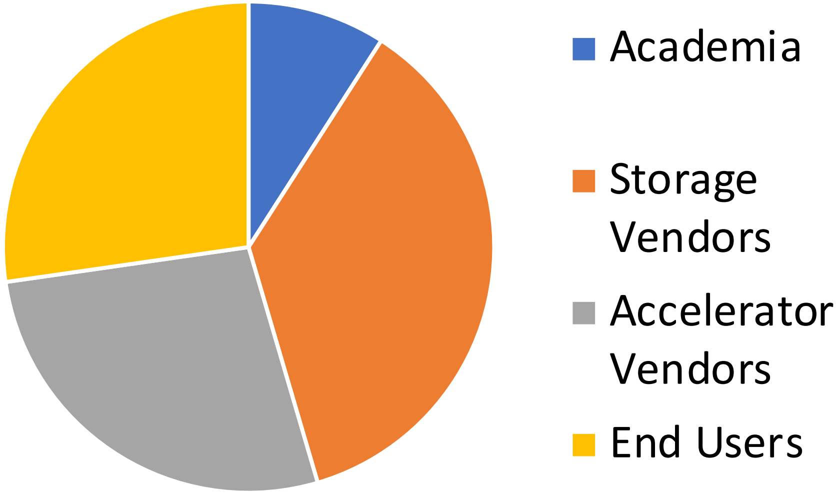
Why create an ML Storage benchmark?

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

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

MLPerf Storage working group

Mix of industry and academia



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tenstorrent

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

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Benchmark Vision

Existing benchmarks

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

Simplified storage setup

Expensive accelerators needed to run

Require **extensive entry knowledge**

Our work

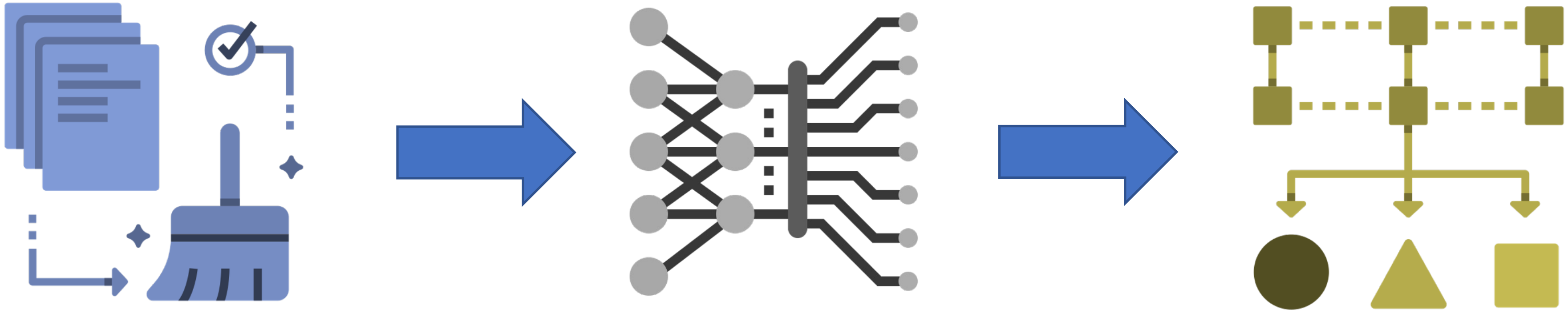
Focus on **storage impact in ML/AI**

Realistic **storage & pre-processing** settings

No accelerator required to run

Minimal AI/ML knowledge required

Stages of the ML Pipeline



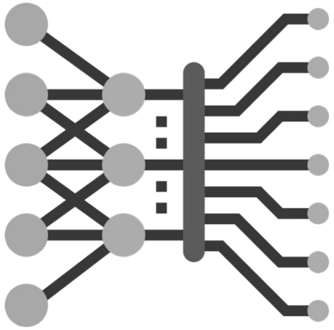
Data cleaning & pre-processing | **Training** | **Inference**

Stages of the ML Pipeline

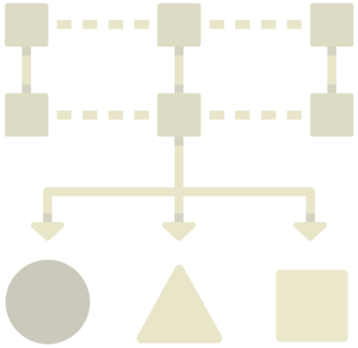
I/O intensive [1,2] – Our focus

*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

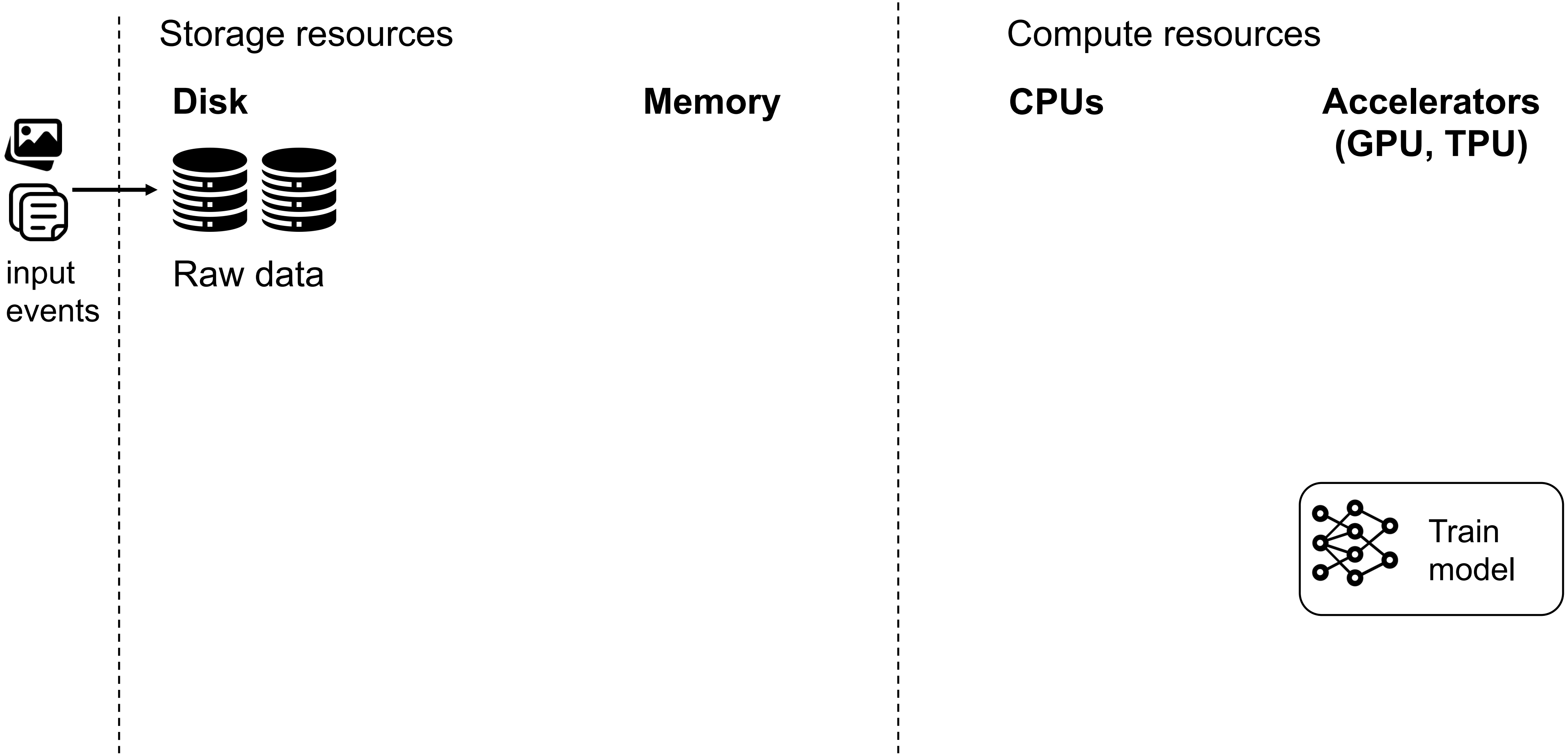
Compute resources

CPUs

Accelerators (GPU, TPU)

Train model

Data Pipeline in ML: Pre-processing



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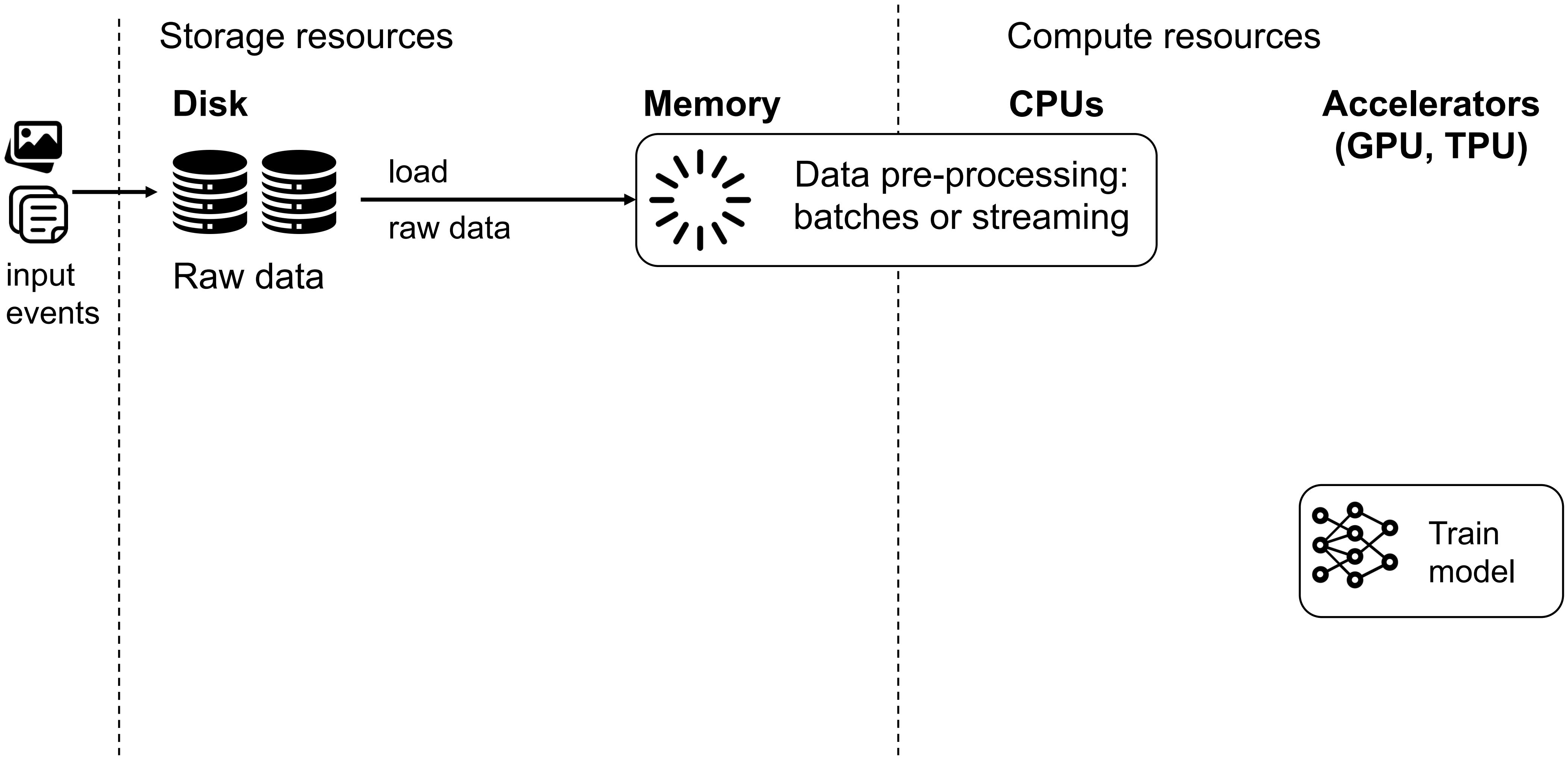

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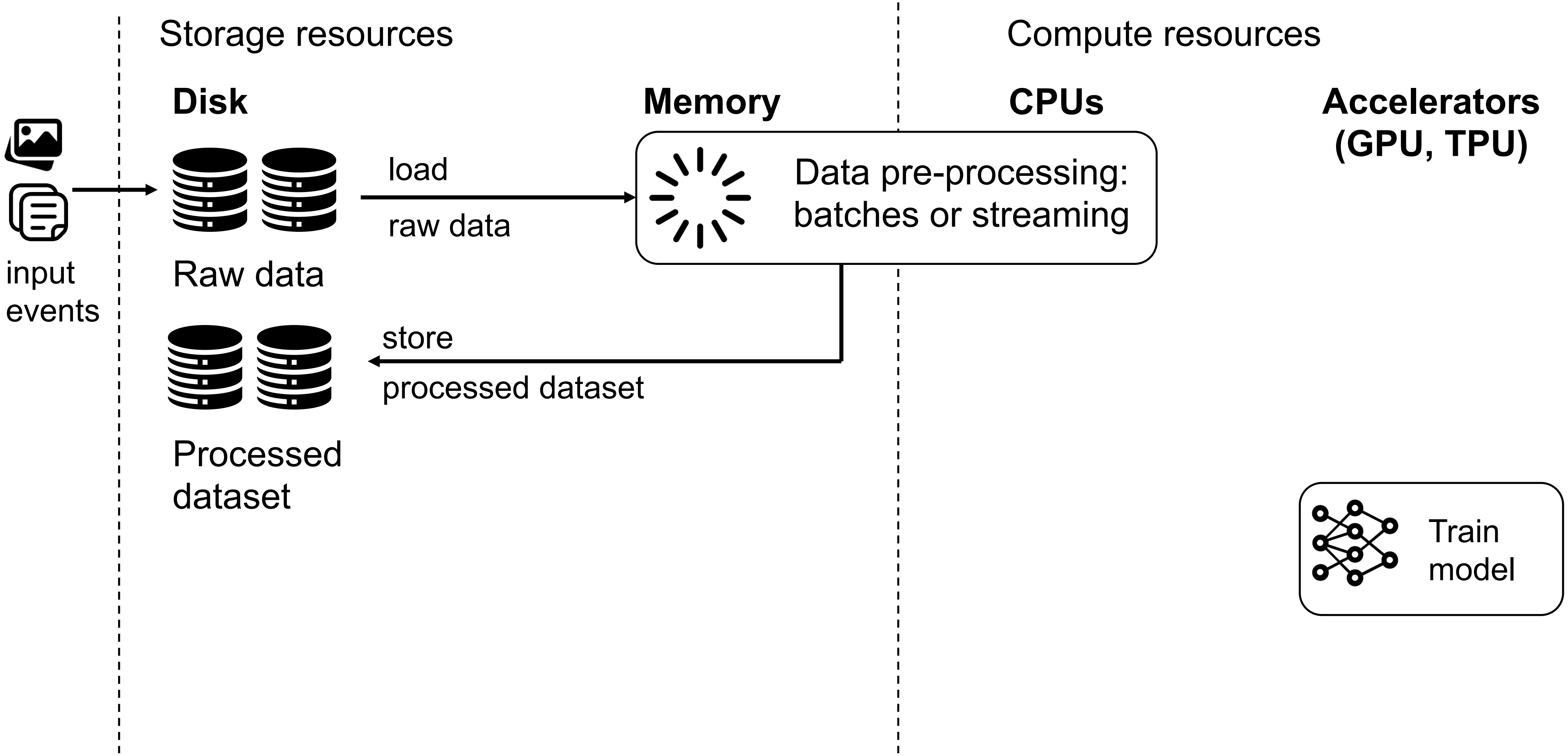

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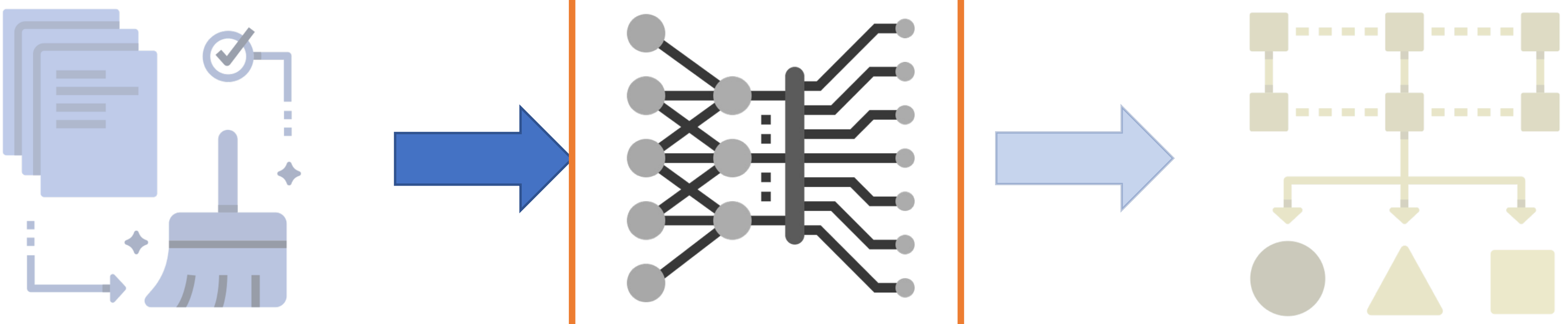

Data cleaning & pre-processing

Training

Inference

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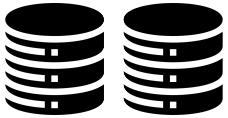
Data pipeline in ML: Training

Storage resources

Disk



Cleaned
dataset

System
Memory (DRAM)

Compute resources

CPUs

Accelerators
(GPU, ASIC)

Data pipeline in ML: Training

Storage resources

Disk

Cleaned
dataset

TensorFlow

PYTORCH

load

data

System Memory (DRAM)

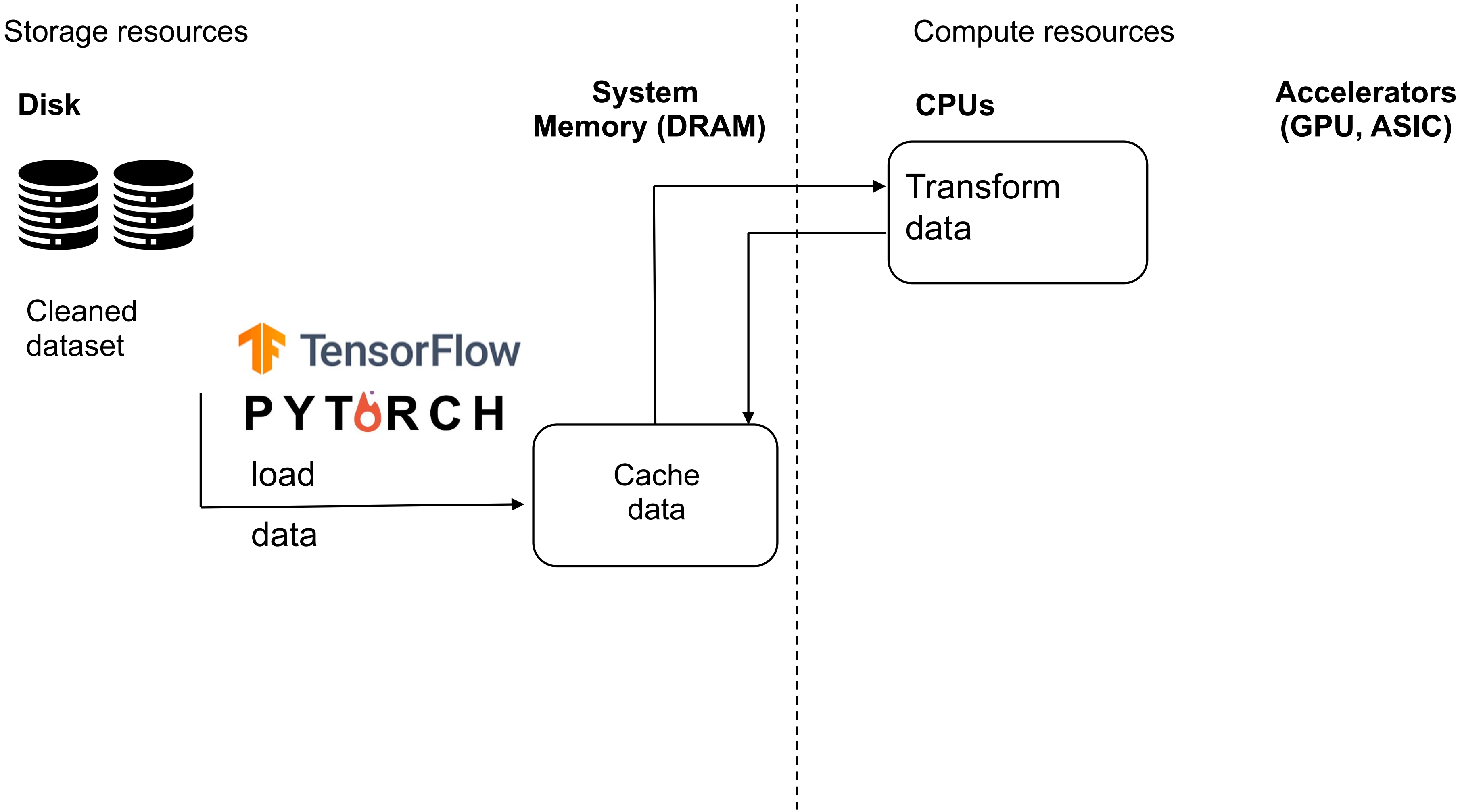
Cache
data

Compute resources

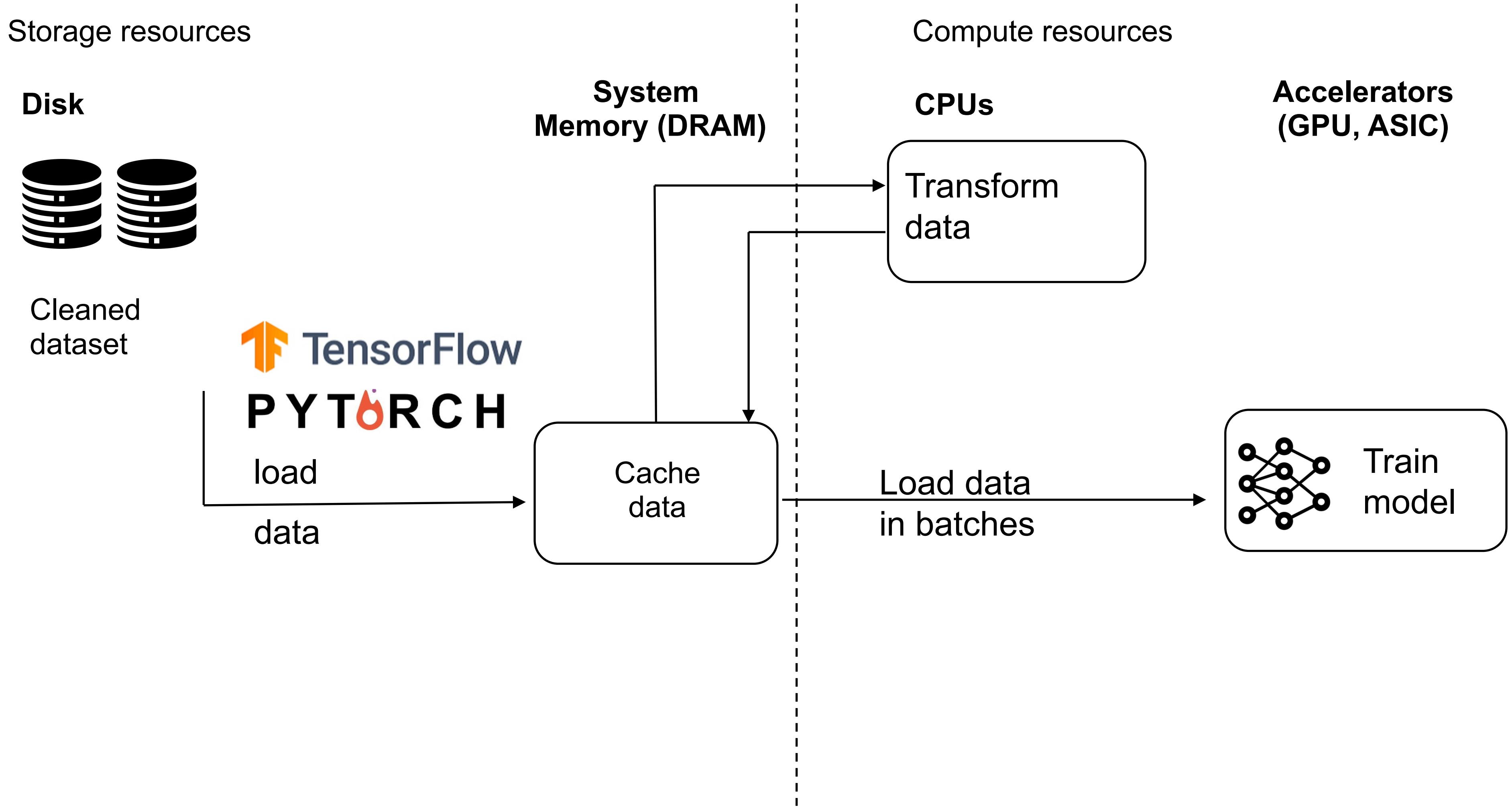
CPUs

Accelerators (GPU, ASIC)

Data pipeline in ML: Training



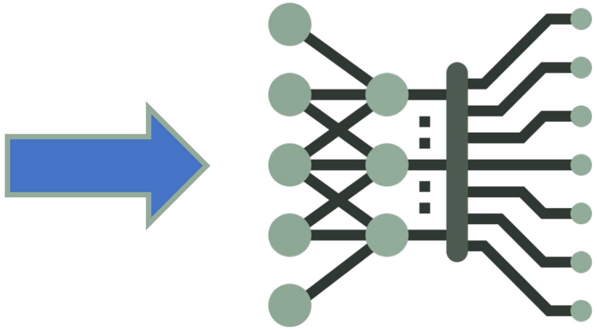
Data pipeline in ML: Training



MLPerf Storage

Data cleaning &
pre-processing

MLPerf Storage V1



Training

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

Realistic **storage** settings in

training phase

No accelerator required to run

Minimal AI/ML knowledge

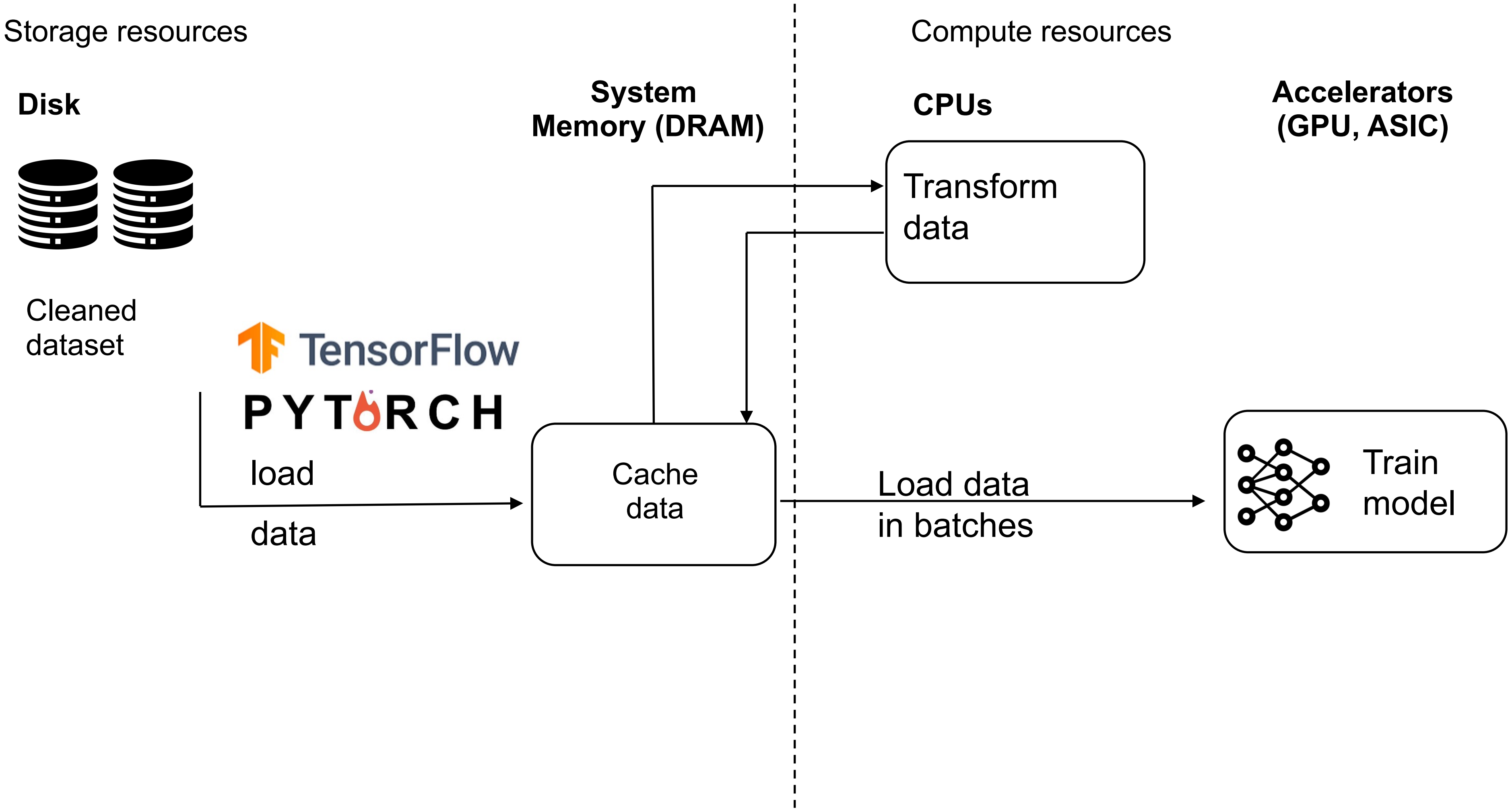
MLPerf Storage – workloads

Workload	Image segmentation	Natural language processing	Recommender Systems
Model	Unet3D	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

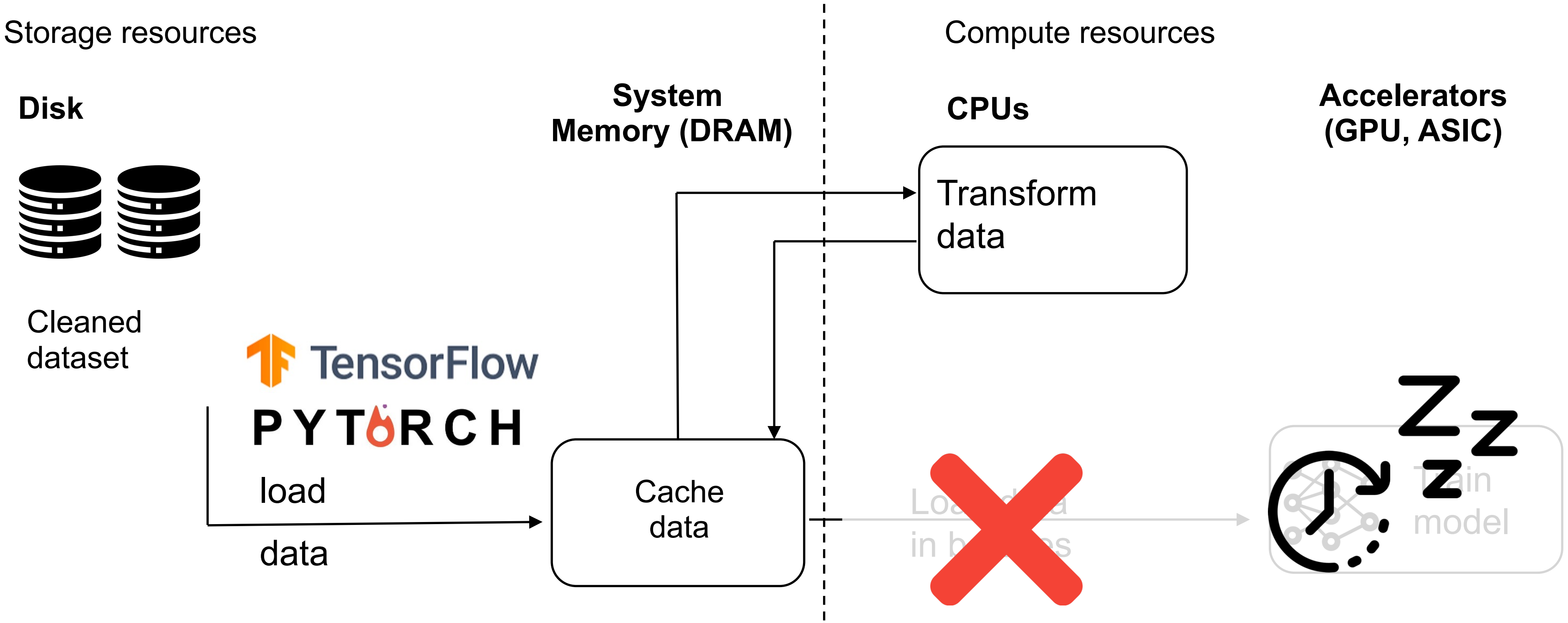
https://github.com/mlcommons/storage

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

Data pipeline in ML: Training



Data pipeline in MLPerf Storage benchmark

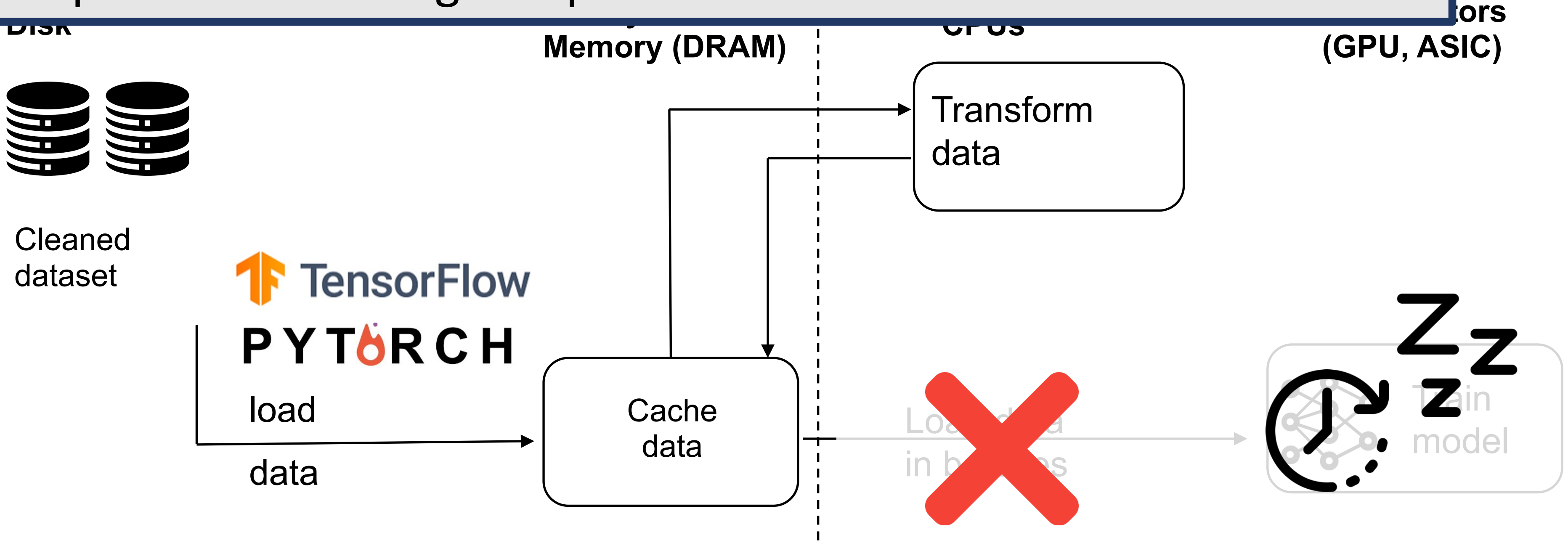


Benchmark is built as an extension of DLIO [1]

[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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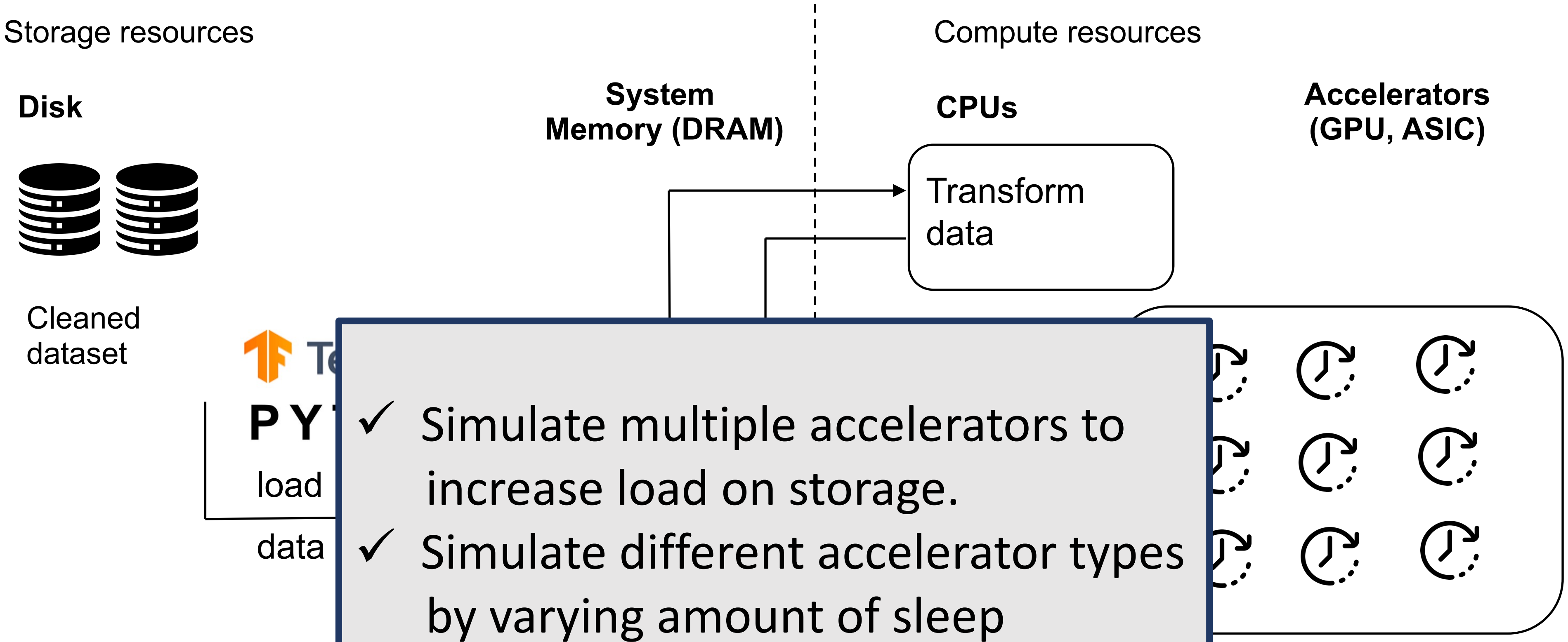

✓ Simulate multiple accelerators to increase load on storage.

✓ Simulate different accelerator types by varying amount of sleep

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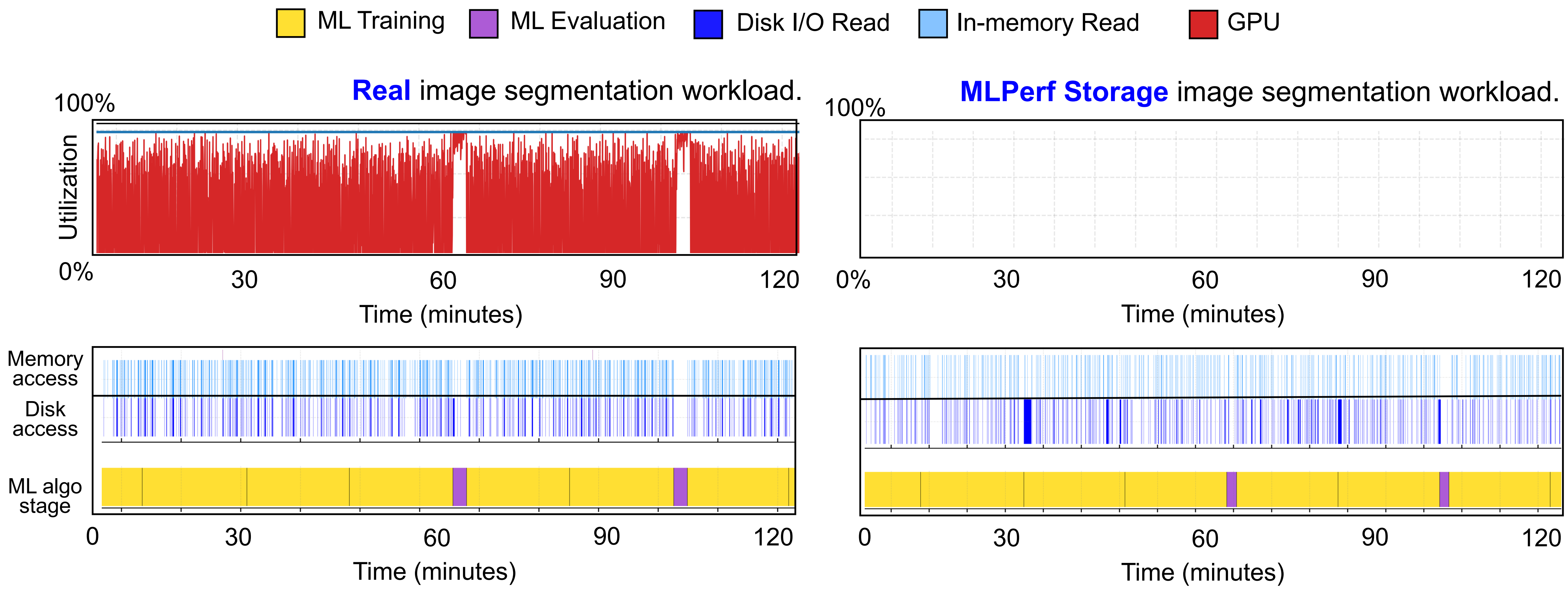
Simulating training time does not impact I/O patterns



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

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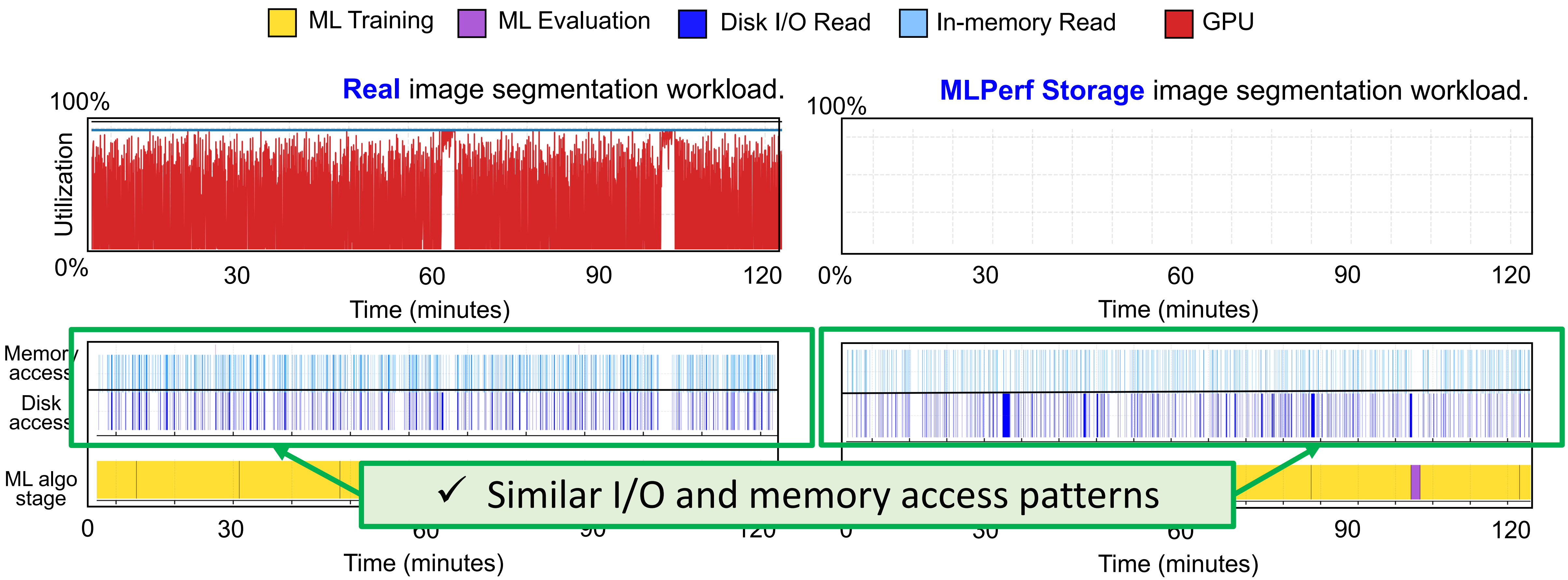

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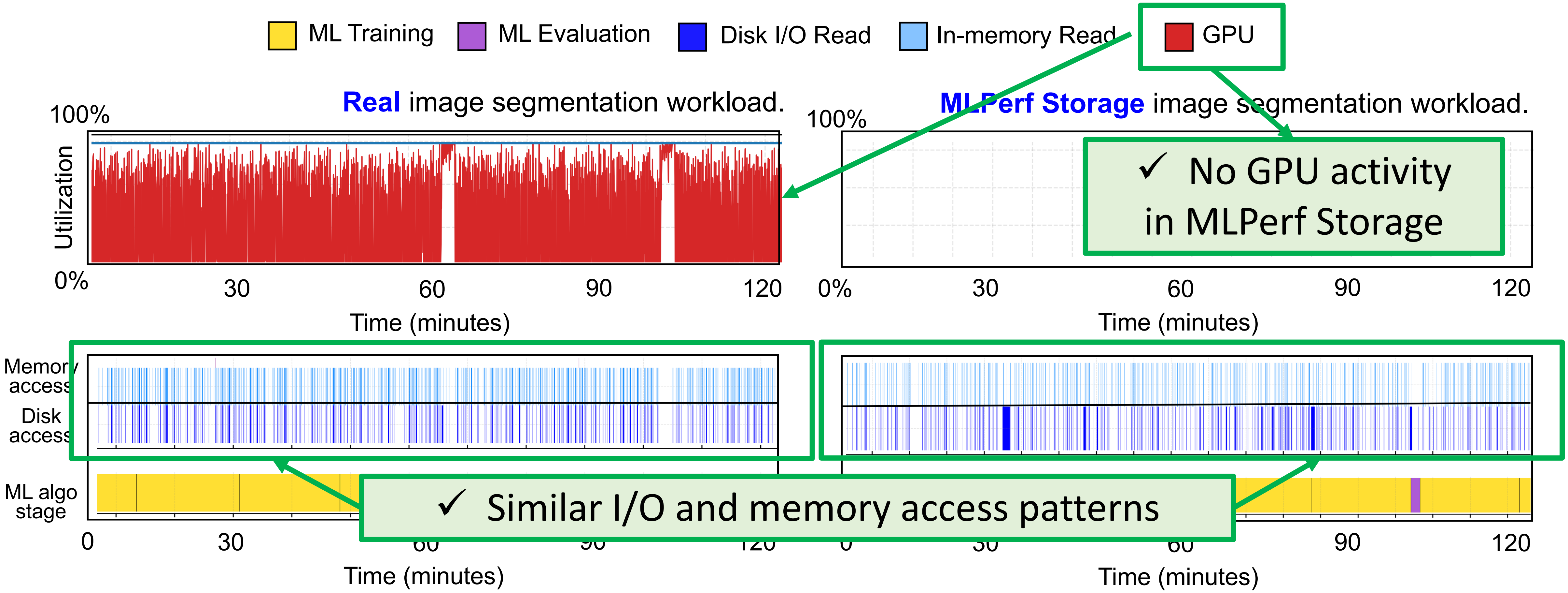

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Next Steps

Collect **processing times** for different accelerator types.

Open benchmark for submissions.

→ *https://github.com/mlcommons/storage*

I/O in distributed training

Trace and benchmark **ML pre-processing phase.**

McGill DISCS Lab

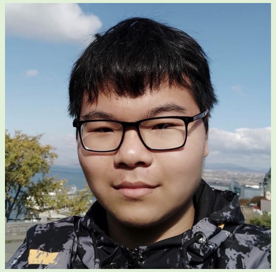
discslab.cs.mcgill.ca
gitlab.cs.mcgill.ca/discs-lab

Postdoctoral Researcher

Dr. Stella Bitchebe

PhD Candidates:

Nelson Bore



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Aidan Goldfarb

Rahma Nouaji

Undergraduate Students

Zachary Doucet

Zhongjie Wu

Olivier Michaud

Key Takeaways – MLPerf Storage

MLPerf Storage is a new benchmark

Realistic **storage** settings

No accelerators required to run

Follow MLPerf Storage repository for updates:

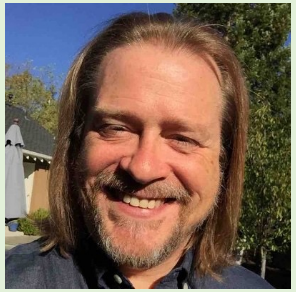
https://github.com/mlcommons/storage

Get involved
mlcommons.org/en/get-involved/

We appreciate your feedback

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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ML
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