

I/O Patterns and Bottlenecks in Deep Learning Workloads

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Related Works

Methodology (so far)

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Context

- ▶ Recent growing interest in optimizations for Machine Learning/Deep Learning training and inference methods.
- ▶ Used in various fields: LLMs, Image recognition and classifications, and so on.
- ▶ Large models often need very large HPC infrastructures for processing the insane amount of training data.
- ▶ The performance of the storage and I/O subsystem of HPC systems is critical

Context

- ▶ Traditional HPC workloads are characterized by large, sequential data access (PAUL; KARIMI; WANG, 2021).
 - ▶ Simulations which saves the state at the end or in checkpoints
- ▶ In contrast, ML workloads generate small, random reads across numerous files (PAUL; KARIMI; WANG, 2021).
- ▶ Large amounts of data (far greater than system memory) + random read pattern = lot of page faults and cache misses (VERY BAD)

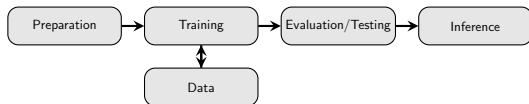
Context

Table 2.2 Example Time Scale of System Latencies

Event	Latency	Scaled
1 CPU cycle	0.3 ns	1 s
Level 1 cache access	0.9 ns	3 s
Level 2 cache access	2.8 ns	9 s
Level 3 cache access	12.9 ns	43 s
Main memory access (DRAM, from CPU)	120 ns	6 min
Solid-state disk I/O (flash memory)	50–150 μ s	2–6 days
Rotational disk I/O	1–10 ms	1–12 months
Internet: San Francisco to New York	40 ms	4 years
Internet: San Francisco to United Kingdom	81 ms	8 years
Internet: San Francisco to Australia	183 ms	19 years
TCP packet retransmit	1–3 s	105–317 years
OS virtualization system reboot	4 s	423 years
SCSI command time-out	30 s	3 millennia
Hardware (HW) virtualization system reboot	40 s	4 millennia
Physical system reboot	5 m	32 millennia

Context

- ▶ At Large Scale Distributed DL Workloads, IO can take roughly 85% of the *training* time (DRYDEN et al., 2021).
- ▶ And training is often one of the most expensive parts of the pipeline (LEWIS; BEZ; BYNA, 2025).



Objectives

General:

Understand **patterns in I/O operations and possible bottlenecks** in common Machine Learning workloads

Especifics:

- ▶ **Disk throughput:** Understand how disk throughput varies in training between epochs, checkpoints and when the number of training processes varies.
- ▶ **GPU usage:** Know how the GPU usage (%) behaves in those scenarios.

Justification

- ▶ By understanding those patterns and possible bottlenecks I hope to **find some ideas and directions for further work.**

Related Work

Lewis, Bez e Byna (2025)

Surveys literature from 2019 to 2024 on the I/O challenges, patterns, and optimizations for machine learning applications on high-performance computing systems to identify gaps for future research.

Párraga et al. (2021)

This paper presents a methodology for analyzing the input/output (I/O) patterns of deep learning applications on high-performance computing (HPC) systems, applying it to codes using TensorFlow2 and PyTorch with the MNIST and CIFAR-10 datasets to understand performance bottlenecks.

Related Work

Gainaru et al. (2022)

This paper discusses the complex I/O patterns and challenges of emerging machine learning workflows used for large-scale scientific data analysis, proposes methods to optimize data transfers, and demonstrates performance gains with a medical application case study.

Paul, Karimi e Wang (2021)

This paper presents an in-depth I/O characterization of over 23,000 machine learning jobs from a one-year period on the Summit supercomputer, using the Darshan tracing tool to analyze how their behavior varies across different scientific domains and workload scales.

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Methodology (so far)

- ▶ Simulation: dlio_benchmark (DEVARAJAN et al., 2021).
- ▶ The experiments are available at
⟨https://github.com/HpcResearchLaboratory/perf_2025⟩.
 - ▶ Custom workloads
 - ▶ dlio_benchmark (python venv :(, will try to use nix shell)
 - ▶ Slurm script to perform all benchmarks

Methodology (so far)

System

Table: System Specifications for 'tupi4'

Component	Specification
CPU	i9-14900KF, 3.20 GHz, 32 threads, 24 cores
Memory (RAM)	128 GB DDR5
GPU	NVIDIA GeForce RTX 4090
Storage	1.8 TB NVME
Motherboard	Gigabyte Technology Co., Ltd. Z790 UD AX

Methodology (so far)

Workloads

Table: Workflow Configuration Summary

Model Name	Framework Name	Epochs	Checkpoints Enabled
cosmoflow_h100_custom	tensorflow	1	No
default_custom	pytorch	10	No
megatron_deepspeed_LLNL_custom	pytorch	3	Yes (every 2 steps)
unet3d_h100_custom	pytorch	5	Yes (after epoch 5, then every 2)

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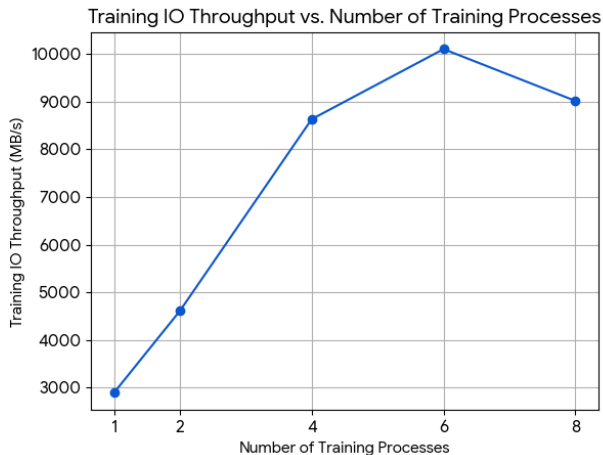
Related Works

Methodology (so far)

Results (so far)

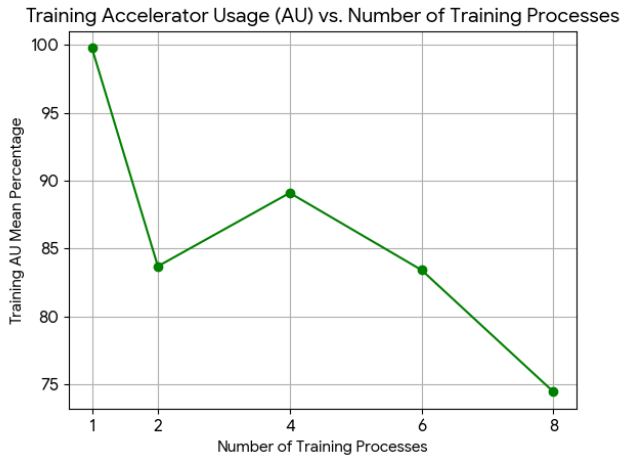
Results (so far)

Unet3d h100 custom: Training IO throughput(MB/s) x processes



Results (so far)

Unet3d h100 custom: Training AU (%) x processes



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