Accelerating I/O for Traditional HPC and Modern ML Workloads on Emerging HPC Systems

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The Problems and Motivation

- High-Performance Computing (HPC) systems emerged as a good choice for large-scale parallel Deep-Learning relative to cloud computing or locally setup clusters.
  - A lot of accelerators without virtualization
  - Fast interconnect for reduction
- Machine Learning (ML) workloads have very different data ingest patterns than HPC applications
  - Existing I/O infrastructures are optimized for HPC applications
  - Read intensive vs Write intensive
  - Independent I/O vs collective I/O
- HPC I/O subsystem is becoming **increasingly heterogeneous** and disaggregated.
  - It is unclear how both traditional and emerging workloads can take advantage of these systems.

Research Questions

We attack the problems from two angles:

- How do emerging workloads (ML/AI) differ from traditional HPC applications, what are the challenges and how to overcome them?
- How can HPC applications exploit emerging HPC systems with heterogeneous I/O?

What are the challenges of running modern AI workloads on HPC systems?

Characterizing I/O in DL workloads

- ML frameworks are optimized for the cloud without specific support to HPC I/O infrastructures (for example MPI-IO). **What are their techniques and how well do they perform?**

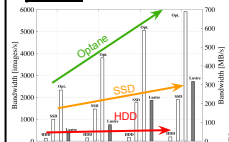


Fig.1

- **Optimization #1. Threading**
  - ML I/O pipelines are embarrassingly parallel. I.e. to fetch samples, preprocess them, and accumulate.
  - These pipelines (producers) can be executed in parallel independently.
- **Optimization #2. Prefetch**
  - Assuming the I/O pipeline (producer) on the CPU runs slower than the training on GPU (consumer), the GPU will be idle while the producer prepares a new batch of data.
  - By running the pipeline in parallel, the GPU can draw a new batch as soon as it has finished training the current batch.
  - **In certain cases, prefetch can result in a complete overlap of I/O and training (Fig.3).**
  - **Prefetching results in higher overall bandwidth and less idling time (Fig.2).**
  - **However, bandwidth contention can become a bottleneck** for both threading and prefetching, depending on the underlying hardware (Fig.1).

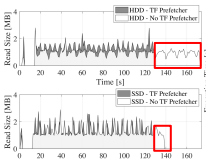


Fig.2

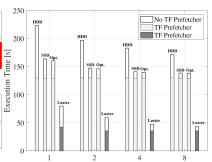


Fig.3

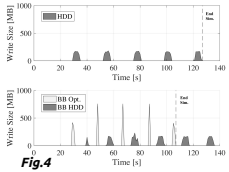


Fig.4

- **Optimization #3. Fast Checkpoint**
  - While ML I/O is read-intensive, blocking checkpointing of networks can also harm performance.
  - We create a prototype burst buffer that saves and sync a checkpoint to a fast Intel Optane SSD and asynchronously (through file system cache) copy the checkpoint to a hard disk. (Fig.4)
  - **We show that the burst buffer can effectively absorb the write I/O and significantly reduce the idle time (~2.6× improvement relative to a checkpoint in slower storage).**

tf-Darshan

- Our previous work gives coarse-grained characteristics of ML I/O workloads, but it does not answer the question on how the I/O is affected by the underlying workloads.
- To further understand the bottlenecks and ML workloads, **we develop a tf-Darshan, an I/O profiler that is tightly coupled with the new TensorFlow profiler** (Fig.5).
- We combine the data collection capability of the Darshan I/O profiler and compute information from tf.Profiler to give a fine-grained I/O characterization.

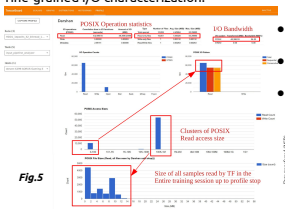


Fig.5

- **One major contribution of tf-Darshan is the ability to perform runtime instrumentation to allow snapshot profiling of a long training session** (Fig.7).
- The **lack of co-design between workloads and I/O (such as MPI-IO and PFS) can significantly hurt I/O** performance (e.g. only ~3 MB/s when reading a lot of small images from HDD).
- We find that TensorFlow performs a large number of small reads, and zero-sized reads to signal end of file (illustrated and annotated in red in the timeline in Fig.6 below), which translate to expensive POSIX I/O operations.

Fig.6

File name	Timeline (POSIX I/O Activity)
image_1.jpg	Read, Read
image_2.jpg	Read
image_3.jpg	Read, Read, Read

- We use the cluster of reading size collected from tf-Darshan to perform optimizations.
- **By staging a small portion of data with small file sizes to a fast storage device, we can improve bandwidth by up to 19%.**
- Our work highlights the importance of co-designing I/O and underlying workloads.

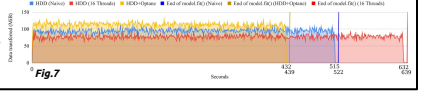


Fig.7

How can HPC applications take advantage of emerging I/O technologies?

Emulating Object Storage on HPC system

- POSIX I/O with strong consistency and coupled metadata management has long been considered a limiting factor for scalable I/O. *Object storage* has attractive characteristics that can potentially become a POSIX I/O replacement. However, it is unclear how HPC applications can exploit this. Here, we show how *object storage as an I/O semantic can bring immediate benefit even existing systems*.
- We design an object storage emulator to emulate the key characteristics of object stores: **immutability**, **flat namespace**, and **eventual consistency**. These are the key factors that leads to a high-performance in I/O.

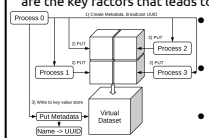


Fig.8

- To support HPC applications, we specifically support applications that use *domain decomposition* (Fig.8).
- **Our emulator allows applications to compose objects using one HDF5 file per process**, conceptually similar to the *subfiling* technique.
- To support object composition, **we use HDF5 Virtual Dataset (VDS) to link all objects together** to provide a global view.

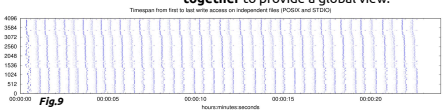


Fig.9

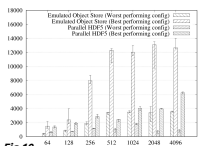
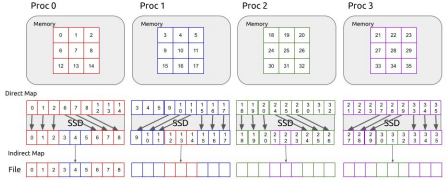


Fig.10

- We emulate metadata operations by writing serialized Protocol Buffers (protobuf).
- To simulate weak consistency, only root rank writes metadata through POSIX atomic rename. Processes do not need to synchronize after writing their partial objects (Fig.9).
- **We profile a benchmark application with Darshan and show significant bandwidth improvement relative to Parallel HDF5 (~80% reduction in time)** (Fig.10).

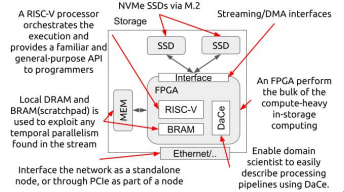
Work in Progress

A programming model for distributed I/O



- ***Research Question***: Existing parallel I/O models (such as MPI-IO) optimize the writing of shared files between processes (e.g. data sieving, non-contiguous access). These implementations are often co-designed with parallel file systems that are visible globally. *Yet, emerging I/O systems in the upcoming HPC systems are often local and disaggregated.* **How can applications use fast and distributed node-local storage to accelerate the writings of shared files?**
- ***Approach***: We envision a library that enables shared file I/O through distributed storage and global memory abstraction. By using a mmap-like memory allocator, we can translate memory operations into remote I/O that stage many files on node-local storage. They can be easily combined into a common file when staged to the parallel file system.

In-storage compute for ML preprocessing



- ***Research Question***: While existing I/O optimizations for ML (such as threading and prefetching) can partially mitigate I/O bottlenecks, issues such as small file sizes and bandwidth contention remain a problem. *At the same time, both I/O and preprocessing take up considerable CPU resources.* Our work highlighted the importance of co-designing I/O and workloads. **Can we co-design the hardware in a similar manner to also benefit preprocessing workloads?**
- ***Approach***: We propose a new kind of accelerator in form of FPGA that is attached directly to the storage system. Both I/O and preprocessing compute workloads can be offloaded accelerated by the FPGA. Data batches can be aggregated before being transferred to compute nodes for training.

Conclusions

- We researched and developed tools that characterize and explore ML I/O workloads that have very different I/O patterns comparing to traditional HPC applications.
- Our work highlights the importance of co-designing between I/O and underlying workloads and our tools provide the knowledge required to enable such optimizations.
- We also highlight the challenges of using emerging I/O technologies and how HPC applications can adapt to new programming models.

References

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