

Understanding I/O Behavior in Scientific Workflows on High Performance Computing Systems



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Overview

- ☐ Leadership high performance computing (HPC) infrastructures empower scientific, research or industry applications
- ☐ Heterogeneous storage stack is common in supercomputing clusters
- ☐ Project goals
- To extract the I/O characteristics of various HPC workflows
- To develop strategies to optimize overall application performance by improving the I/O behavior
- To leverage heterogeneous storage stack

☐ Initial steps

- To understand I/O behavior in scientific application workflow on HPC
- To perform systematic characterization and evaluation

I/O Workloads on HPC Workflow

- ☐ What is HPC Workflow?
- Pre-defined or random ordered execution of set of tasks
- Tasks performed by inter-dependent or independent applications
- ☐ Data transfer or dataflow in HPC Workflows can create bottleneck

□ Dataflow examples

- Huge metadata overhead on parallel file systems (PFS) by random tiny read requests in deep learning (DL) training workflow [1]
- Sequential write-intensive applications, e.g., CM1
- In-situ and in-transit analysis in applications, e.g., Montage
- Checkpoints and update-intensive applications, e.g., Hardware Accelerated Cosmology Code (HACC) [2]

Heterogeneous Storage Stack

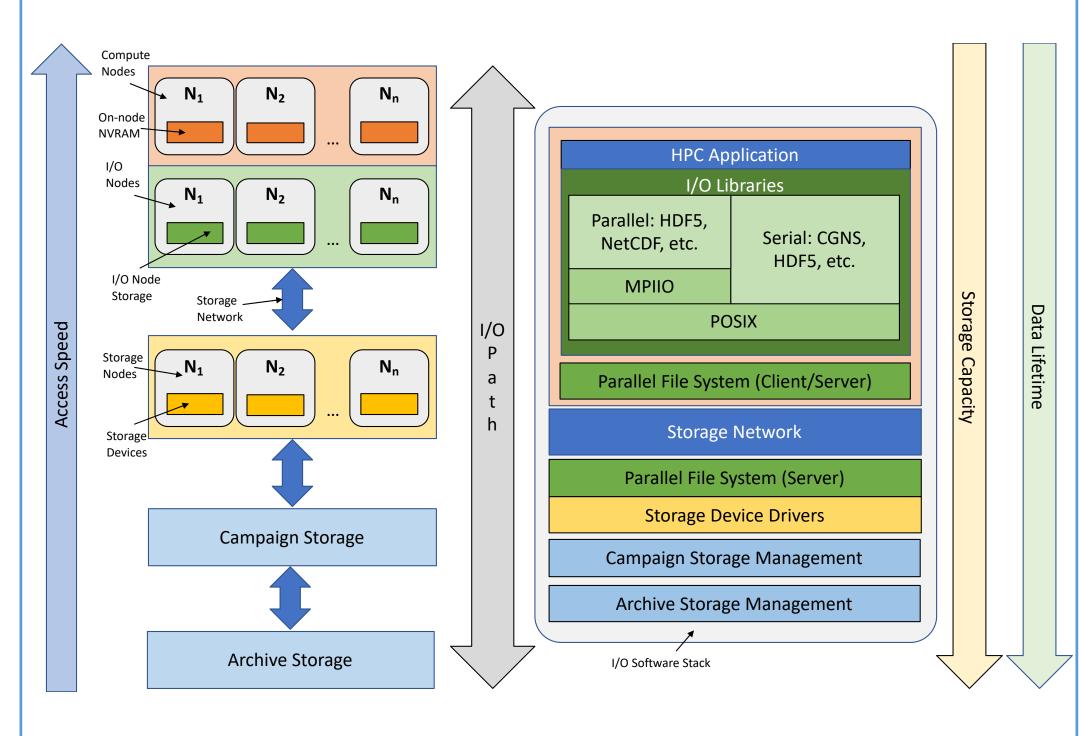


Fig. 1: Typical HPC I/O system architecture

Emulating Different Types of HPC I/O Patterns Randomiz File Range Read Files In Range Millions of Tiny Shared Burst Buffer, etc. Parallel File System (e.g. GPFS, Lustre, BeeGFS, etc.) (a) Node-local (b) Inter-node (c) I/O Chain Fig. 3: Producer-Consumer I/O Pattern Fig. 2: Deep Learning Training I/O Pattern ✓ MPI enabled C++ **Application to** Emulate HPC I/O dataflow emulator libaiori.a libkvtree.so ior_runner deep_learning | producer consumer checkpoint restart libaxl.so Local Storage Periodic Flushing Res deep learning:: dataflow emulator:: | io pattern:: ior runner:: Fig. 5: Class Diagram of Dataflow Emulator Parallel File System (PFS)

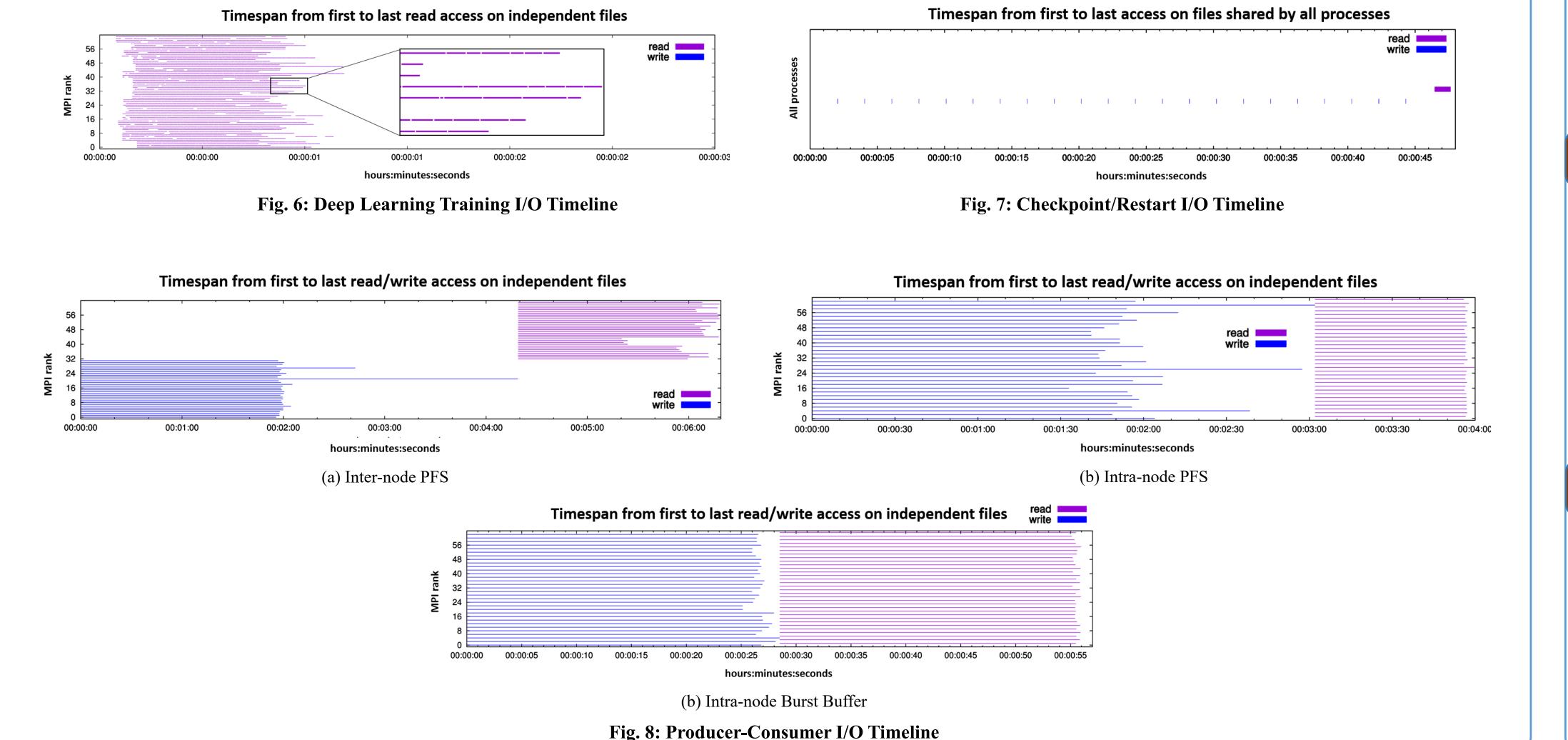
Experimental Results from Emulator

(a) I/O Operations

Fig. 4: Checkpoint/Restart I/O Pattern

✓ Usage: ./emulator --type data --subtype dl --input dir <dataset dir>

> Currently under active development



I/O Demands of Cancer Moonshot Pilot-2

- ☐ Cancer Moonshot Pilot2 (CMP2) [3] project
- Aims at using HPC for cancer research
- Seeks to simulate RAS protein and cell membrane interaction

☐ I/O behavior in CMP2

• Producer-consumer pattern between different submodules

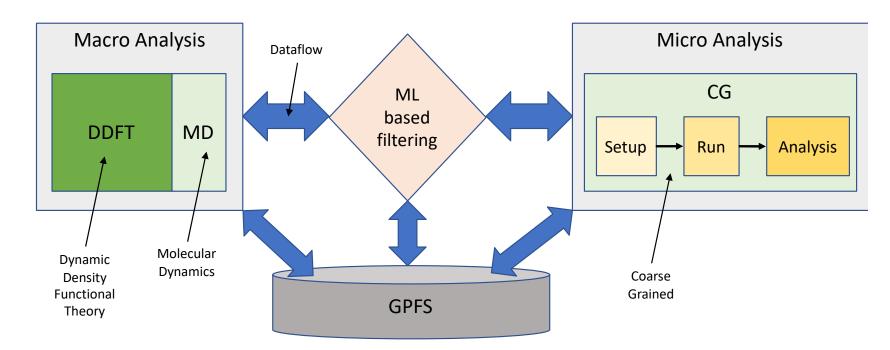


Fig. 9: Dataflow in CMP2 HPC implementation

Conclusion and Future Plans

- ☐ Handling dataflow in scientific applications' workflows is critical
- ☐ Effective I/O management system is necessary in workflow manager like MaestroWF [4]
- ☐ Intelligent data transfer among different units of heterogeneous storage resources in leadership supercomputers can improve performance
- Third party API libraries like Asynchronous Transfer Library (AXL) [5] can be leveraged

☐ Current Efforts

- ✓ Developing a Dataflow Emulator to generate different types of HPC I/O workloads
- ✓ Analyzing the CMP2 project to detect possible I/O vulnerabilities

☐ Future Plans

- To detect I/O behavior and dataflow by profiling CMP2 workflow
- To develop data management strategies to properly handle the dataflow in complicated and composite HPC workflows like CMP2

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