Towards Autonomous Storage and I/O Systems for Scientific Data

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Contributions from ExalO, ExaHDF5, and Proactive Data Containers (PDC) teams



Scientific data storage and access - Current scenario



Outline of this talk (focusing on HPC systems)

- Basics, trends, and challenges
- Recent optimization strategies we developed
 - Asynchronous I/O
 - Data caching
- Proactive Data Containers (PDC) data management runtime system
- Future research directions

I/O software stack - Several layers with inter-dependencies



Architectural trends impacting I/O - deep memory and storage hierarchy



Trends in computing devices

- Heterogeneous processing devices
 - CPUs
 - GPUs
 - FPGAs
 - Special purpose accelerators
 - ..
- Massive concurrency
- Locations of data generation and consumption
 - Traditional: In compute nodes
 - Trends: In network, in storage, and at the edge



Image from D. Vasudeven, via J. Shalf, Extreme Heterogeneity workshop report

Application I/O Trends

- HPC simulation and analysis
 - Parallel applications storing or retrieving data
 - checkpoint, restart, and analysis mostly defensive I/O
 - Partitioned regions of data in a large data object
 - Each process accesses (writes or reads) a single or multiple regions
 - Typically non-overlapping (there may be some overlapping at region boundaries)
 - Number of files: Single shared file (N-1), file-per-process (N-N), a few sub-files (M-N)
 - APIs: POSIX, MPI-IO, HDF5, etc.



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 - APIs: POSIX, MPI-IO, HDF5, etc.
- ML/AI
 - Read-heavy
 - Random accesses to different parts of a file or multiple files (due to shuffling between epochs)
 - Small I/O requests to batches of data, metadata accesses
 - Large numbers of files O (100,000)
 - APIs: Python, ML/AI frameworks (TensorFlow, PyTorch, Caffe, etc.)
- Experimental and observational facilities, Edge computing, etc.
 - Large numbers of small files, streaming data, sparse data, remote file accesses



What do users want?

Use case	Domain	Sim/EOD/analy sis	Data size	I/O Requirements			
FLASH	High-energy density physics	Simulation	~1PB	Data transformations, scalable I/O interfaces, correlation among			
E	Easy interfaces to complex systems						
CMB / Planck	Cosmology	Simulation,	10PB	Automatic data movement			
Autonomous data movement and performance tuning							
				transformations			
Inform	ation cap	ture, man	agem	ent, and search			
TECA	Climate	Analysis	~10PB	Data organization and efficient data movement			
HipMer	Genomics	EOD/Analysis	~100TB	Scalable I/O interfaces, efficient and automatic data movement			

Users:

- Scientists
- App developers
- Supercomputing facilities
- System designers

Storage and I/O challenges

- Poor performance
 - POSIX semantics
 - Tuning options at different software layers
- Complexity with deep storage hierarchy
 - Using the performance and capacity storage layers efficiently and transparently
- Heterogeneity of storage devices
 - From memory-class to hard-disks to tape
- Variability of performance on HPC systems
 - Some part of the storage system is concurrently shared by multiple users
- New classes of applications
 - ML / AI applications are read-heavy with random access patterns
 - EOD and Edge computing applications
- New high-level programming models
 - Performance & Productivity

A few recent I/O optimization methods and systems

- ExaHDF5 / ExalO
 - Asynchronous I/O
 - Using memory and storage hierarchy efficiently

- Proactive Data Containers (PDC)
 - Object-centric data management runtime system

HDF5 self-describing file format and API for science apps

- HDF5 is a self-describing file format, API, and tools designed to store, access, analyze, share, and preserve diverse, complex data in continuously evolving heterogeneous computing and storage environments
 - Maintained by The HDF Group (THG)

10000

100

unique us 1000

f

- Heavily used on DOE supercomputing systems and diverse science applications across the world
- Many ECP applications have dependency on HDF5-based I/O
 - 17 critical
 - 11 important
 - 8 interested



a. Number of linking instances on Edison (NERSC)

are interresting institutes when we we are b. Number of unique users on Edison (NERSC) ALCF Provided Library Usage for Mira

erage is ~53% of jobs between 08/15 to 08/







HDF5 Containers (Files)



¹² Adapted from THG and Quincey Koziol



<u>VOL Framework</u> is an abstraction layer within HDF5 Library

- Redirects I/O operations into VOL "connector", immediately after an API routine is invoked
- Pass-through VOL connector
 - Can be stacked on any other connector, to provide asynchronous operations to it
- Uses an "event set" to manage async operations
 - Can extract more performance, e.g., enable async read and write:



Slide from Houjun Tang

Async I/O VOL Connector

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Async I/O – Low overhead and efficient hiding of I/O latency

AMReX: A software framework for massively parallel, block-structured adaptive mesh refinement (AMR) applications



Number of nodes (6 process per node)

Nyx: An adaptive mesh, cosmological hydrodynamics simulation code (left)

Number of nodes (6 processes per node)

16

Castro: An adaptive mesh, astrophysical radiation/MHD/hydrodynamics simulation code

Async I/O VOL Connector

- Available now:
 - Source: <u>https://github.com/hpc-io/vol-async</u>
 - Docs: <u>https://hdf5-vol-async.readthedocs.io/en/latest</u>
- Future work:
 - Merge compatible VOL operations
 - If two async dataset write operations are putting data into same dataset, can merge into only one call to underlying VOL connector
 - Turn multiple 'normal' group create operations into a single 'multi' group create operation
 - Use multiple background threads
 - Needs HDF5 library thread-safety work, to drop global mutex
 - Switch to TaskWorks thread engine
 - A portable, high-level, task engine designed for HPC workloads
 - Task dependency management, background thread execution.

Cache VOL Connector - Integrating node-local storage into parallel I/O

Typical HPC storage hierarchy



Node-local storage (SSD, NVMe, etc)

Theta @ ALCF: Lustre + SSD (128 GB / node), ThetaGPU (DGX-3) @ ALCF: NVMe (15.4 TB / node) Summit @ OLCF: GPFS + NVMe (1.6 TB / node)

Cache VOL

- Using node-local storage for caching / staging data for fast and scalable I/O.
- Data migration to and from the remote storage is performed in the background.
- Managing data movement in multi-tiered memory / storage through stacking multiple VOL connectors (*async -> cache -> async*)
- All complexity is hidden from the users

Repo: <u>https://github.com/hpc-io/vol-cache</u>

Parallel Write (H5Dwrite) with cache VOL



Details are hidden from the application developers.

Parallel Read (H5Dread) w/ cache VOL

First time reading the data



Reading the data directly from node-local storage

One-sided communication for accessing remote

HDF5 Cache VOL uses node-local SSDs as cache \rightarrow 2X to 3X faster



1250 Baseline w/ Cache VOL 1000 Time (sec) Lustre and node-local SSDs on Theta 750 500 250 0 2 3 8 5 6 Epoch

VPIC-IO is a kernel derived from a plasma physics simulation of solar weather interacting with the earth's magnetosphere. The simulation writes particle data to HDF5 file, where each variable is mapped to a HDF5 dataset CosmoFlow is a 3D convolutional neural network model for learning the universe at scale. The model is implemented in TensorFlow with Horovod for data parallel training at scale.

Huihuo Zheng, Venkat Vishwanath, Quincey Koziol, Houjun Tang, John Ravi, John Mainzer, Suren Byna, "HDF5 Cache VOL: Efficient and Scalable Parallel I/O through Caching Data on Node-local Storage", Accepted to CCGrid 2022

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Object-centric data management



Proactive Data Containers (PDC) - An object-centric data movement runtime system





- Advantages with PDC
 - Application-level object abstractions Freedom from file management
 - Transparent utilization of storage hierarchy and data movement
 - Superior and scalable performance
 - Live system for data management services
 - Metadata management, analysis, indexing and querying services, consistency, data placement, etc.

Object-centric PDC Abstractions

- Container special case of object, metadata only
 - For grouping objects
- Object metadata and data payload
 - Multi-dimensional arrays
- Regions
 - A logical region in a multi-dimensional array
 - expressed with offsets, sizes, and strides
 - multi-dimensional



PDC metadata management

- Metadata is critical for finding objects previously written
- Predefined tags must be filled either by users (using API) or by extracting from system
- User-defined tags improve findability of objects
 KV pairs
- Unique IDs for metadata objects
- Querying for objects using tags
 - Exact match
 - Partial match

Pre-defined Tag	User-defined Tag		
 Object ID Data Location System Info ID Attributes Object Name Object Name -Timestep 	 (Tag Name0, Value0) (Tag Name1, Value1) (Tag Name2, Value2) 		



Metadata

Flat Namespace

Object-centric PDC API

- No explicit data movement
- Container
 - <u>create container</u>
 - delete container
 - add / delete objects
- Objects
 - <u>create object</u>
 - add metadata
 - <u>create regions</u>
 - <u>map objects / regions</u> from source to destination
 - Source and destinations can be memory or PDC spaces
 - lock when updating an object
 - <u>release</u> informs PDC runtime for implicit data movement
 - <u>find object</u> (followed by "map" for reading)
 - Explicit <u>put</u> and <u>get</u> object functions are also available



Transparent data movement in storage hierarchy

- Usage of compute resources for I/O
 - Shared mode Compute nodes are shared between applications and I/O services
 - Dedicated mode I/O services on separate nodes
- Users start PDC server and application links with the PDC client library
 - Set environment variables for informing PDC about the memory and storage locations
- Transparent data movement by PDC servers
 - Apps map data buffers to objects and PDC servers place and manage data
 - Apps query for data objects using attributes



Experimental setup

- Cori at NERSC
 - 1600 "Haswell" compute nodes
 - 128 GB DRAM/node
 - 32 cores/node
- SSD-based "Burst Buffer"
- HDD-based shared file system Lustre
 - *Shared* mode: One PDC server on each node, the remaining 31cores for user application execution.
 - *Dedicated* mode: PDC servers and user's application are on separate nodes
- Mercury Remote Procedure Calls (RPCs), as the communication mechanism between client and server and between servers - TCP and Cray GNI
- Benchmarks
 - VPIC-IO: I/O of a large-scale plasma physics simulation code
 - BD-CATS-IO: I/O kernel of a big data clustering analysis code

VPIC-IO (Weak Scaling) Multi-timestep Write



Total time to write 5 timesteps from the VPIC-IO kernel to Lustre and Burst Buffer on Cori. PDC is up to 5x faster than HDF5 and 23x over PLFS.

BD-CATS-IO (Weak scaling) Multi-timestep Read



Total time for reading data of 5 timesteps from the BD-CATS-IO kernel from the Lustre and from the burst buffer. PDC is up to **11X** faster than PLFS and HDF5.

Current status of PDC



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Data object

Metadata Manager

Lustre

manager

file

Data transform

and

GPFS

PDC client interface

. . .



- Current achievements in a next generation intelligent data management framework
 - Transparent
 - Asynchronous
 - High performance and scalable
 - Partial autonomy in utilizing storage hierarchy

Source code:

https://github.com/hpc-io/pdc

Publications

https://sdm.lbl.gov/pdc/

Proactive Data Containers (PDC) - Ongoing and future work



- Interface with Python and object (put and get) interfaces
- Extend to KV stores abstractions
- Data reorganization and placement based on access history
- Dynamic consistency
- Byte address mapping with PDC storage objects - working with John Shalf et al.
- Analysis on storage and network computing resources
- Federated data objects remote access across multiple file systems at a site, multiple HPC sites, and cloud environments

Scientific data storage and access - Looking into future



Future research to achieve autonomous storage and I/O management

* High-productivity interfaces for accessing data fast and easy

Interfaces

libraries

management

Information

- * Support for heterogeneous data models
- * Unified access to memory and storage system access
 - (in-system and remote)



* In-flight data transformations feature extraction using instorage, in-network computing * Quantitative metrics for the FAIR principles and data quality * Recommendation systems for relevant data using AI methods

* Autonomic and reconfigurable storage and I/O systems based on application needs * Lightweight monitoring of storage systems

Conclusions

- Trends
 - Architecture deepening hierarchy, high concurrency
 - Applications increasing diversity (exascale, EOD, ML/AI, etc.)
 - User requirements productivity and performance, knowledge management
- Our recent solutions at the I/O software level
 - Asynchronous I/O
 - Caching
 - Object-centric data management runtime system
- Domain scientists should not be burdened with data (I/O and other data movement) and metadata management tasks
 - Achieving autonomous storage and I/O requires novel high-productivity interfaces, information extraction and management, automatic data movement, reconfigurable storage, etc.



Thanks and Questions

- Contributions from:
 - PDC project team
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 - ExaHDF5 / ExalO team
 - Suren Byna, Scot Breitenfeld, Venkat Vishwanath, Houjun Tang, Qiao Kang, Jean Luca Bez, Huihuo Zheng, John Mainzer, Neil Fortner, Dana Robinson, Jordan Henderson, Jerome Soumagne, Richard Warren, Neelam Bagha, Elena Pourmal, Michela Becchi, John Ravi, Wei Zhang, Yong Chen, Kathryn Mohror, Sarp Oral, Adam Moody, Cameron Stanavige, Michael Brim, Seung-Hwan Lim, Ross Miller, Swen Boehm



