Exascale Storage Systems the Sirius way [4 pages]

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*Abstract*— As the exascale computing age emerges, data become one of the critical factors in how and where we do computing. Popular approaches in the past for I/O and storage libraries become increasingly bottlenecked by their past assumptions on data movement, re-arrangement, and storage. New technologies of today such as “bust buffers” will help address some of the short-term performance problems, but the underlying storage and I/O infrastructure needed to address the exascale age must be re-examined. Our approach is to make an important distinction between the data, metadata, and the knowledge contained therein and to understand it’s utility as the data ages in time. We formulate a new approach to the exascale Storage System and I/O (SSIO) allowing users to place their application knowledge into the system to better manage, store, and access the knowledge contained in the voluminous data.

# Introduction

The purpose of computing is insight, not numbers [3], a remark Richard Hamming made over 50 years ago at the dawning of the age of large scale scientific computing. The central objective of our next-generation storage and I/O system (Sirius) is to minimize the time to insight with respect to scientific computing. This means that we need research into managing, storing, and retrieving the large data volumes produced by simulations and analyzed for months afterwards. To motivate the research necessity for eliminating much of the current and future problems, we will first give an illustrative example describing the different research concentration areas. Later, we will discuss a new approach to refactoring data that can eliminate much of the current and future bottlenecks in knowledge discovery. However, this generates new challenges for both applied mathematics and computer science computers. Finally, we will discuss the auditor approach to help refactor the data and the additional meta challenges this creates for exascale storage systems.

## Illustrative Example

The motivating use case is a series of simulations of the ITER fusion experiments using the XGC1 application. XGC1 is one of the largest applications used at the Department of Energy's (DOE's) Leadership Class Facilities with an allocation of over 300M hours. These simulations were scheduled to produce 100 PB of data over ten days of total runtime on the Titan system at the Oak Ridge Leadership Computing Facility (OLCF) and required a team of experts, including the user group and I/O and storage personnel, to help ensure that the maximum amount of information would be saved. Due to physical resource limitations, the simulation was immediately restricted to write about 10 PB. However, when the time to write and read, together with the financial cost to archive this volume of data was fully explored, the data size goal was further reduced to only 5 PB total.

This forced a careful scrutiny of the data to be generated and restriction of the output to only the most important pieces. Further, this reduced data set had to be divided into two categories: the data that would be accessed while the simulation was running or shortly thereafter and the data that would be needed after the whole campaign was finished. The former category of data would be stored on disk and the latter would be archived. Additionally, the entire team needed to figure out how to efficiently retrieve these different categories of data for post-processing, analysis and visualization.

To accomplish this, the application and storage teams developed new application specific data reduction techniques and added them to the ADIOS I/O middleware layer. A rudimentary discovery system was also created to track what data was on disk and what was on tape. Initially this solution was sufficient, but eventually a new problem was discovered. Although the team had reserved compute resources for the run, the entire file system was shared resulting in very high I/O variability. Addressing this variability, caused by contention on shared resources, is an ongoing concern. Earlier efforts [11] are insufficient due to the immense data volumes, limited time available, and the number of other users of the shared storage array.

The problems faced by this user workflow motivate our research here. The use case demonstrated three tiers of solutions are required: application level knowledge of data and how it will be used, middleware management of data and resources, and storage system level scheduling of resources. It also provided us with new insights. First, the users and developers of the application data can, without a great loss of encoded knowledge, reduce the size of data that needs to be stored. Second, data storage must be managed with input from the users to correctly decide the target of storage operations. Third, shared resources must be managed in a way that provides sufficient performance to all applications without encumbering the applications with high variability in performance. These insights drive our work.

## Two guiding principles of Sirius

The exascale storage and I/O community must overcome the challenges described above for both the application scientist trying to write data and those trying to read data. This must be done such that the SSIO system can fairly share the resources among the users while helping enable exascale science by prioritizing and understanding the application level data requirements. We are ultimately guiding by our two basic principles:

Principle 1**:** **A knowledge-centric system design** that allows user knowledge to define data policies. Today, SSIO layers are written in a stovepipe fashion and quite often do not allow optimizations. We are re-designing the layers in a highly integrated fashion where users express their intentions into the system and actions will statically and dynamically optimize for both the system and for individual requests.

Principle 2: **Predictable performance and data quality in the SSIO layers** needs to be established to maximize the information (rather than raw data) generated on the exascale systems. Without predictable performance, runs be slowed down because of shared resource contention and it affects key science decisions, e.g., how much data reduction should be performed. To have confidence sufficient output time is available, a conservative estimate, rather than nearly accurate, must be used.

ADIOS can alleviate the need for “magic” and “tricks” to optimize application I/O performance on today's file systems by placing extra annotations in the metadata to better understand the underlying storage system. In SIRIUS, we are extending this by providing a systematic approach for combining intentions and other knowledge from the *user* with performance estimations and guarantees from the underlying storage.

By capturing user intentions and acting upon them in the middleware, we free the user from polluting application code with system specific optimizations. We have successfully employed this separation of concerns in ADIOS and believe it will become increasingly important because saving all data may not be possible and users want the ability to describe and prioritize different chunks of data.

These techniques will be further integrated in combing ADIOS with RADOS-Ceph, which is a distributed object store and file system. Ceph offers both a POSIX and object interface including features typically found in parallel file systems.

# Data Refactoring

The classical workflow where the entire dataset is written to storage for later analysis will no longer be viable in exascale simply because the amount of generated data will be too large due to capacity and performance limitations.

In the future, it will be vital to take advantage of *a priori* information when (1) writing and reading from the storage system to gain higher performance and predictability and prioritize the most useful data for end users so that I/O can be finished in the time available and (2) performing *in situ* operations and analysis before storing the information.

The fusion use case described earlier shares commonalities with many other DOE applications. *A priori* information can be provided by application scientists regarding which data should be sent to the storage system (e.g., SIRIUS) so that minimally, the most science relevant data can be available for subsequent analysis. This allows the science to be done even when the storage is busy servicing other users. It occurs often and causes high performance variability. Data refactoring generates the data prioritization. This refactoring includes data re-organization and reductions. There are many data refactoring techniques and the best choice will generally be application dependent. However, our observation is that, once the choice is settled for an application, it will not typically change from run to run. **[ref?]**

One research challenge for refactoring data effectively and efficiently is to understand when the time and resources required identifying and performing the “best methods” exceeds the intended gains. Another critical research question concerns quantifying and controlling information loss from refactoring the data and using a reduced dataset. A basic issue allied to refactoring is to understand how much information is actually present in a dataset and whether a refactoring based on a reduced order representation might prove effective. It is useful to classify scientific data into *regular* and *irregular* data. *Regular* data satisfies a known or relatively simple model and *irregular* data follows no obvious or explicit model. Although scientific data generally contains random components due to finite precision and measurement and calibration effects, useful scientific data is never purely random. Broadly speaking, the path from data to knowledge consists of extracting underlying models or patterns from the datasets and interpreting the resulting models.

Ideally, scientists would like to perform the entire analysis stage *in situ* effectively circumventing the large data issue completely. The catch, of course, is that thisis unlikely to be possible since, by their nature, large scale simulations aimto discover new information often hidden in the form of higher ordereffects amongst the data deluge. In particular, this means if data thinning ortruncation is applied haphazardly, the higher order effects may be eliminated.Theentire data set cannot be stored in an easily accessible source due to sheer size. Yet, the data cannotbe reduced prior to archiving without risking losing the desired information.Viewed in this way, the problem would appearintractable. However, much of thedata is redundant in an information theoretic sense. That is, theamount of information contained in the dataset is often significantly less thanthe amount of data. The difficulty stems from not knowing about this redundancy in advance *without the benefit of a priori knowledge.* This knowledge can often be provided by the user or can be acquiredthrough experience of dealing with differing runs of the same code.

Deep application knowledge means one can sometimes achieve dramatically superior data reduction compared with what one might achieve otherwise. However, even in the absence of such high level knowledge, SIRIUS must offer generic data reduction and re-organization techniques. For instance, certain basic data semantics information is needed and must be supported by the overall infrastructure. Currently we are studying three generic and one application specific refactoring methods: 1) Precision based, 2) Frequency-based, 3) Linear Auditing, and 4) Application aware histogramming. Each of these is described below.

**Precision based refactoring** groups together the most significant data bytes from each object. This data generally has a higher “utility” than data with the least significant bytes. The data needs to be re-arranged potentially involving memory intensive operations and needs to be done *in* situ as much as possible specifically avoiding the slow storage systems and inter-processor communications network. At most, this requires two copies of an individual dataset in memory. We are investigating techniques to allocate and deallocate this memory if the user will specify that the data will be overwritten after it is written to the storage system. This is often the case for many of the quantities written from the simulation, but there are many cases where, for example, we want to write all of the particles from a Particle-In-Cell (PIC) simulation. Since the particles will be used later in the calculation, we need to duplicate the storage. Our observation with working with the XGC1, GTC, and PIConGPU simulations is that we can temporary increase the storage of the particles and then release them since the temporary arrays used in the calculations are often freed when a PIC iteration is finished. Another challenge is that when data is read back, there is a serious potential cost in data reconstruction. In our example, we can imagine that the most significant bits are written to the parallel storage system. We see that the cost savings to store …

**Frequency-based refactoring** re-organizes data according to how often it appears. This is commonly used in streaming data and data reduction techniques such as those used JPEG-2000. These mechanisms support spatial random access or region of interest access at varying degrees of granularity. It demonstrates the possibility of storing the same data using different quality. In relation to this project, this capability allows us to place the lowest frequency chunks in the fastest storage and the highest frequency chunks on either the slowest storage tiers, or if writing out the data sizes are prohibitively costly, not even write out these pieces. In order to fully take advantage of frequency based re-organization, the data pre-conditioner first sorts the data in bins with fixed length and then wavelets and spline fits are used to re-organize the values. This re-organization effectively produces smoother data allowing for much better reduction later.

**Linear Auditor** uses a delta compression algorithm in time to perform lossless or lossy data compression. This technique has its basis in information theory where we understand that smooth data has low entropy and noisy data has high entropy. The thought is to separate the low entropy part of the data from the high entropy part. **We can have about ½ of a page on this linear auditor/. Mark can you put in some preliminary result for this as well**

**Application Aware Auditor** contains a class of techniques which have more domain knowledge than the generic techniques described above. One algorithm combines continuum based physics knowledge into Particle-In-Cell particle data to create a two-dimensional data histogram. In the XGC1 case, we will histogram in the particle velocity dimensions and then overlay a Maxwellian distribution to this to see the deviations and keep the differences of the deviations greatly reduce the number of particles. We have been working with C. S. Chang group at PPPL to achieve this histogram approach for the XGC1 code and have seen that we can reduce the data by 100X while retaining over 90% accuracy for all of known analytics we have worked on.

# Computer science challenges in refactoring

**Hasan’s section**

# metadata challenges

The challenge when applying refactoring techniques, particularly application aware techniques, is how to incorporate sufficient knowledge in the storage system such that an arbitrary future client has sufficient information to recreate the desired information. Additionally, by spreading data across multiple different kinds of storage media that typically have independent namespaces, locating any particular data will be challenging.

SIRIUS will provide sufficient built-in and extensible metadata services to support efficient data access. First, detailed data metadata, such as array dimensions and other similar data, must be visible within the metadata for any effective data selection. Second, each data chunk stored within the storage hierarchy must have some way to address it. As data utility forces data migration within SIRIUS, the metadata must either dynamically track data as it moves or offer a search feature to discover where data currently resides. Which approach is superior and under what conditions still needs to be determined.

# Conclusion

None yet

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Sirius project….

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