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HEP Software Foundation Community White Paper Working Group – Data Organization, Management and Access (DOMA)

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ABSTRACT: Without significant changes to data organization, management, and access (DOMA), HEP experiments will find scientific output limited by how fast data can be accessed and digested by computational resources. In this white paper we discuss challenges in DOMA that HEP experiments, such as the HL-LHC, will face as well as potential ways to address them. A research and development timeline to assess these changes is also proposed.

Contents

1   Introduction

The coming decade will bring HEP to the exabyte scale with the expected data volumes of the HL-LHC [1–3] experiments, the DUNE [4] experiment, and even non-HEP experiments such as the Square Kilometre Array (SKA) [5] entering this regime. In devising computing models for this era, many factors have to be taken into account. In particular, the increasing availability of very high-speed networks may reduce the need for CPU and data co-location. Such networks may allow for more extensive use of data access over the wide-area network (WAN) while providing fail-over capabilities, global and federated data namespaces, and will have an impact on data caching. Shifts in the data presentation and analysis models, such as a potential move to event-based or sub-event-based data streaming from the more traditional dataset-based or file-based data access, will be particularly important for optimizing the utilization of opportunistic computing cycles on HPC facilities, commercial cloud resources, and campus clusters, and can potentially resolve currently limiting factors such as job eviction.

Planned analysis of HL-LHC data and data analysis from other international collaborations will need to adopt a distributed computing model due to their scope. The data management systems that will enable this type of analysis will need to provide cost-based optimization of the data locations and delivery mechanisms.

2   Challenges and Opportunities

The LHC experiments currently collectively provision and manage about an Exabyte of storage of which approximately half is archival and half is traditional disk storage. The annual storage requirements are expected to jump by a factor of 10 for the HL-LHC. This increase is faster than projected density gains in current storage technologies and thus will present major challenges. Storage will remain one of the visible cost drivers for HEP computing. The projected growth and cost of the computational resources needed to analyze the data is expected to grow even faster than the base storage costs. The combination of storage and analysis computing costs may restrict scientific output and potential physics reach of the experiments. Thus, new techniques and algorithms are likely to be required.

The three main challenges for data in the HL-LHC era can be summarized as:

1. **Big Data:** The expected data volume will significantly increase in the HL-LHC era. Computing systems will need to handle this without significant cost increases and within evolving storage technology limitations.

2. **Dynamic Distributed Computing:** In addition, the significantly increased computational requirements for the HL-LHC era will also place new requirements on data. Specifically, the use of new types of compute resources (e.g.,

cloud, HPC) with different dynamic availability and characteristics will require more dynamic DOMA systems.

3. **New Applications:** New applications, such as machine learning training or high-rate data-query systems for analysis, will likely be employed to meet the computational constraints and to extend the physics reach of the HL-LHC. These new applications will place new requirements on how and where data is accessed and produced. For example, specific applications (e.g., training for machine learning) may require use of specialized processor resources, such as GPUs.

The rapid increase in recent years of data-intensive problems in both the commercial world and in the rest of the research world also provides a number of opportunities and solutions to tackle these challenges.

3 Current Approaches

The original LHC computing models (developed circa 2005) were built up from simpler models used before distributed computing was a central part of HEP computing. This allowed for a reasonably clean separation between three different aspects of interacting with data: organization, management and access.

- **Data Organization:** This is essentially how data is structured as it is written. Most data is written in the ROOT [6] file format. ROOT serializes data objects, compresses, and writes them in a column-wise manner. The data written in this way can only be meaningfully read by a software that includes data object libraries.

- **Data Management:** The key challenge here was the transition to the use of distributed computing in the form of the grid. To tackle this, the experiments developed dedicated data catalog, transfer and placement systems. To first order, the computing models were rather static: data was placed at sites and the relevant compute jobs were sent to the right locations.

- **Data Access:** Various protocols are used for direct reads (RFIO, dCap, XRootD, etc.) within a given computer center and/or explicit local stage-in and caching for read by jobs. Application access may use different protocols than those used by the data transfers between sites.

Before the LHC turn-on and in the first years of data taking, these three areas were, to first order, optimized independently. Many of the challenges were in the area of "Data Management" (DM) as the Worldwide LHC Computing Grid [7] was commissioned. As the LHC experiments' computing matured through Run1 and

Run2, interest has turned to optimizations spanning these three areas. For example, the recent use of "Data Federations" must consider together both Data Management and Access. As we will see below, some of the foreseen opportunities towards HL-LHC may require global optimizations.

Thus, in this document we take a broader view than traditional DM, and consider the combination of "Data Organization, Management and Access " together. We believe that this full picture of data needs in HEP will provide important opportunities for efficiency and scalability as we enter the many-Exabyte era.

3.1   HEP Workflow in Context

HEP data transfer and access patterns require network and storage architectures to be able to sustain a large dynamic range in IOPS. The primary data analysis workflows that drive these bandwidth requirements can be categorized into four main activities:

1) **Reconstruction:** Event reconstruction is CPU limited, due to the complexity of detector data and the computational algorithms needed to associate and disentangle the data. This is true of reconstruction methods used today at the LHC and throughout the HEP community and will continue to be the driving characteristic of reconstruction at the HL-LHC and for liquid argon TPC experiments. The CPU-bound nature of the algorithms and the ratio of event size to network bandwidth make the option of streaming individual events records (e.g., full collision events or beam spill triggers) across the WAN to compute elements a feasible strategy. The requirements of event streaming can be satisfied by a wide range of storage solutions.

2) **Simulation:** HEP event simulation strategies focus on transforming a small set of key input parameters into event and detector response information that is representative of what would be seen in the physical detector systems. Simulation processes are typically characterized by highly asymmetric IO. They typically have very small data ingest (typically just the key input parameters), while output data are similar in size and structure to real detector data. Due to their similar characteristics, output data from simulation processes share the requirements and associated challenges of detector data. The primary drivers that differentiate this type of HEP workflow from the other categorizations are the increased complexities that the simulation stages often require. These simulations often rely on auxiliary event generation mechanisms and can, in some HEP domains, require large external data sets representing interaction cross sections or detector response functions to be available to each instance of the event simulation. This type of common input and overlay data may present a challenge in relation to its scaling to the runtime environments of future HPC facilities and to the design of caching layers at computing site.

3) **Analysis:** Analysis level datasets and subsets are typically comprised of refined or reduced information that is most pertinent to the extraction of physics quantities. These analysis-focused event records can often be accepted or rejected through fast pre-filtered methods which do not require the reading and retrieval of the full event record. This fundamental difference in the way that the analysis data is consumed makes it more susceptible to storage bandwidth limitations and to IOPS transaction limits that underlying technologies can have. In particular, the internal structure of the event data can dramatically impact the efficiency of data retrieval and favor different access models and protocols while the actual analysis calculations being performed can dramatically affect the CPU-to-IO ratios. These factors make this categorization of data the most challenging to project to future storage needs and models.

4) **Replication:** Data replication, whether within a site or across multiple sites, is performed to enable efficient data access by improving data locality (the proximity of the data to compute resources) and exploiting the available data bandwidth between the storage and the compute locations. Data replication also serves to guard against data loss. Data replication places modest requirements on the IOPS that need to be supported, but drives the bandwidth requirements that are needed in enacting site-to-site data transfers between WAN endpoints (e.g., 10-100 Gbps). This requirement on the available WAN bandwidth provides a corresponding performance requirement on on the underlying storage systems to match network performance. Satisfying both requirements is necessary to provide efficient point-to-point data flow.

In addition to the characteristics described above, HEP workflows in each category exhibit a high degree of parallelism, which allow the work to map readily into both high throughput computing (HTC) and HPC environments. These domains span wide dynamic ranges in their requirements for concurrent data access. If the experiments of the HL-LHC, DUNE and other international projects are to utilize these facilities, they will need the ability to integrate with multiple storage technologies. The storage technologies will need to be tuned or matched to the corresponding computing resources that the experiments are targeting.

These storage models will also need to be designed and optimized for cost, in the context of the scientific workflows that they are enabling. Simultaneously, these storage models must remain flexible enough to support evolving physical storage options similar to the the shifts that have occurred in recent years between NVMe, SSDs, shingled disks, tapes, and other technologies.

4 Data Organization Models

The HEP community has long-established data organization patterns that have shaped the prevailing data access and storage models that are in use today. Today's HEP data organization is file-centric with sets of events stored in a given file. Alternative data organization models could yield gains depending on their respective data access and storage models. These alternative designs should be evaluated for the HL-LHC era, as they may produce cost reduction, better network utilization, and efficiency gains.

There are two main avenues that these organizational changes can follow, each with different impacts on the analysis methodologies. First, we should reconsider the structure of the data, which can be row-oriented, column-oriented, have varying levels of granularity, or represent larger or smaller aggregations of objects, boosting the efficiency of particular applications.

Secondly, we should reconsider the granularity at which data management systems operate. This is currently at aggregations of events (files, or larger sets, such as blocks or datasets), and could shift towards being the event (or even sub-event), potentially reducing storage volumes. In that case, other types of "containers" beyond files could be considered (e.g. objects).

Design decisions will be subject to competing requirements from data management and access optimization, and will have consequences throughout the system. We have to tackle a global optimization problem, taking into account all use cases and their respective frequencies to further optimize application performance for a given resource investment.

4.1 Optimizing Data Access

4.1.1 Data structures

The structure of data has to be adapted to application requirements. At one limit, the data could be organized simply as events, while the other extreme is to organize the data as columns which represent sub-event level objects such as particles. Event-based organization favors applications like event displays while column-based organization favors large statistical analysis. Our current system of data tiers in files draws intermediate (and overlapping) rectangles between these two extremes. Finding the right balance will be an important factor in efficient data analysis.

While it appears that organizing data in a more fine-grained fashion, as events or columns, has the potential of opening additional avenues for cost-savings and flexibility, the implications of such an organizational shift are still not well understood and need to be investigated.

4.1.2 Object and Cloud Storage systems

Decisions on granularity and structure have the potential of broadening the scope of technologies that can be used to store the data; for example, exploiting object stores (such as AWS S3 or Ceph [8]) as event stores. Such an approach would support parallel reading and writing of events as event objects from applications. This could allow applications to better scale to large numbers of CPU cores whereas in current models application concurrency is limited by the requirement to sequentially write events to files. Currently, the efficiency of of reading and writing events from object stores is sensitive to the size of the event— the smaller the event, the worse the efficiency is. Some of these potential inefficiencies may be mitigated by creating event bundles (i.e. several events in one object). The evolution of the ATLAS Event Service may provide some of the answers and should be supported. As a parallel effort, the ROOT team is also looking into increasing concurrency within the ROOT framework. This effort should also be supported as it may have more immediate success in the near term.

Commercial providers offer innovative storage services ("cloud storage") which may fit certain use cases well. The relevance of these solutions to HEP computing models must be understood, not only through technical metrics such as performance, but with an understanding of the underlying cost structure and the risks associated with such procurements. Reliance on commercially procured cloud storage as a core component of data organizational models would require a potential fundamental shift in user policies and discussion with funding agencies.

4.2 Optimizing Data Management

Data Management policy will directly affect data access. For example, the decision to distribute multiple enriched data-samples optimized for different use cases would improve data access and thus compute efficiency, at the expense of larger volumes transferred and stored. Similarly, the unit of data management could be changed, and become the event, which promises to reduce storage volumes and promote the use of opportunistic resources through enabling pre-emptibility in jobs. This would have cascading effects on data catalogs, data distribution and storage systems, and would affect data access. Where an experiment positions itself amongst all these possibilities will be dictated by its policy. Thus the potential gains in terms of efficient use of resources should be realized through data management systems which allow this policy to be expressed and implemented.

4.2.1 Data catalog models

A key requirement in devising data catalog models is understanding the required granularity of data to be cataloged and what data for an experiment needs to be centrally cataloged or tracked, and for what purpose (accounting, metadata, location). Analysis access to the data, for instance, may benefit from being below the

event level (e.g. physics object). Any such catalogs may have to be external to the primary data store (e.g., relational databases that work with metadata in the primary data store). If cataloging requirements for production and reconstruction differ considerably from analysis, an approach with multiple, complementary catalogs can also be considered. The cataloging schemes chosen will be tightly coupled with the data organization models. For example, in the case where data organization is object-based or content-addressable storage is used, the catalogs need only a single handle to have a fully descriptive location of a given event or other object being sought.

Our concern is that the size and complexity of a data catalog is proportional to the granularity of the data organization. Given that the organization is still in a state of flux (see previous section) it is difficult to judge the impact of future dataset sizes on data catalog models other than the simple fact that catalog sizes are likely to grow. It does seem clear, however, that data catalog models need to evolve in lockstep with the evolution of data organization models. A large and diverse set of foundational technologies exist upon which such future catalogs could be built. An informed technology choice which supports the anticipated catalog use cases will be crucial in enabling future scalability.

4.2.2 Data delivery methods

Data delivery models can become a limiting factor in performance, especially as they heavily depend on shared resources such storage systems and the network. Caching has to be considered to avoid data delivery bottlenecks and unnecessary transfers. At present, HEP data delivery models are designed solely with the traditional sequential processing paradigm used in reconstruction in mind. Computing models where the only form of persistent storage is on tape and all, or nearly all, disk-based storage is considered as a caching layer should also be considered, in which case work on optimizing workflows for cache efficiency and exploiting data popularity metrics would be valuable.

A useful analogy for data delivery methods might be content delivery network services (CDNs) such as the one offered by Akamai. Without CDNs, on-demand streaming of movies over the Internet or even the delivery of the web sites of major news outlets like CNN or BBC would quickly collapse. What is the equivalent of content delivery for accessing huge datasets over distance where a particular analysis might only require a fraction of the dataset? CDNs use, to great benefit, highly sophisticated proprietary naming, caching, and placement techniques that are customized to particular types of data and what is known about their access patterns. Similarly intelligent techniques could be used to place, compose, and deliver scientific data products, minimizing data movement, latency, and other costs, taking advan-

tage of data semantics and information about the location of reusable intermediate results. This is not unlike query planning in relational databases, except for the scale and the different data type of scientific data: a query optimizer might be able to recognize that data can be filtered remotely, or combined from data products cached in the neighborhood instead of having to fetch everything across continents. New approaches, like Named Data Networking (NDN), could play a role. NDNs allow the naming, at the network level, of the data you are looking for rather than its location, which opens the paths for many optimizations behind the scenes based on factors such as the client application location or the data type.

Currently, new data-caching strategies are being deployed (e.g., XRootD caching proxy servers, server-less caching, ARC-style caching) and may provide sufficient information on how such strategies can optimize mammoth data delivery task for HL-LHC event reconstruction and analysis. However, without a global view on how these strategies are used, they will likely have a limited impact on improving data delivery efficiency.

5   New Analysis Paradigms

Data analysis in most of HEP is currently tied to ROOT-based formats. In many currently-used paradigms, physicists consider all events at an equivalent level of detail and in the format offering the highest level of detail that needs to be considered in an analysis. However, not every event considered in analysis requires the same level of detail. One consideration to improve event access throughput is to design event tiers with different abstractions, and thus data sizes. All events can be considered at a lighter-weight tier while events of interest only can be accessed with a more information-rich tier.

For more scalable analysis, another opportunity to evaluate is how much work can be offloaded to a storage system, for example caching uncompressed or reordered data for fast access. The idea can be extended to virtual data and to query interfaces which would perform some of the transformation logic currently executed on CPU workers. Interactive querying of large datasets is an active field in the Big Data industry; examples include Spark-SQL, Impala, Kudu, Hawq, Apache Drill, and Google Dremel/BigQuery. A key question is about the usability of these techniques in HEP and we need to assess if our data transformations are not too complex for the SQL-based query languages used by these products. We also need to take into account that the adoption of these techniques, if they prove to be beneficial, would represent a disruptive change which directly impacts the end user and therefore promoting acceptance through intermediate solutions would be desirable. One such solution - "Service X" - has been proposed in Organizing Data Lakes. The service would start with the data in its persistent format, perform one or more operations on

it (e.g. joins, query, decompression, filtering to sub-event level), and finally deliver a data stream to a client.

Many analyses may benefit from column-based data access instead of the more traditional row-based access. Enabling data queries that consider histogram indexing is another feature that could provide performance increases in analysis.

When evaluating the potential benefits of moving to new techniques, for analysis in particular but not only, we should not forget that some techniques, like machine learning-based techniques, may have contradictory requirements. On one end, machine learning should dramatically reduce the pressure on the storage at the cost of using more CPU but it requires a learning phase which, even if it is shorter compared to the exploitation phase, can require a significant amount of resources with a non-typical, iterative, data access pattern. Thus, the challenge remains to find a good compromise to efficiently support a large variety of access patterns.

In addition to assessing the techniques that could improve the performance for the various use cases that we have, it is also important to ensure that the resources required by these techniques are in line with expected budget scenarios. Many of these techniques may imply shifting some of the storage resource usage to CPU usage or vice-versa. We need to ensure that the global cost will remain similar to what it is today and that the resulting computing model evolution is compatible with other constraints.

6   Performance: Tools and Metrics

As the size of available datasets grows, we must allow for the possibility of increased user-driven selection and dataset generation. In terms of reducing the strain on data access mechanisms, techniques such as data augmentation can prove useful. Cluster-computing frameworks (e.g., Spark) can also be leveraged to reduce the time of dataset reduction and access. It will be necessary to study and classify I/O patterns in applications used in order to understand how data access methods can be optimized across prevalent access patterns. Pattern data can then be used in algorithms resulting from active research in computer science that studies trade-offs between storage and CPU in various computing models.

A first correlated analysis of the I/O patterns of different computational tasks has already started at the CERN Data Centre and within several experiments. In particular, the combination of infrastructure and experiment information (e.g. detailed knowledge of hardware capabilities and network topology, per job CPU and storage metrics) may allow us to define more meaningful performance metrics than the traditionally-used raw data rate and CPU utilization which both have their limitations. These metrics should enable a joint quantitative comparison of different storage and computing approaches across individual system boundaries and thus lead to a more effective resource investment.

7 Common Challenges

The projected event complexity of data from future LHC runs and from high resolution liquid argon detectors will require advanced reconstruction algorithms and analysis tools to understand. The precursors of these tools, in the form of new machine learning paradigms and pattern recognition algorithms, already are proving to be drivers for the CPU needs of the HEP community. As these techniques continue to gain traction in our field and evolve, they will place new requirements on the computational resources that need to be leveraged by all of HEP. The storage systems that are developed and the data management techniques that are employed will need to directly support this wide range of computational facilities, and will need to be matched to the changes in the computational work so as not to impede the improvements that they are bringing.

Storage will remain one of the visible cost drivers for HEP computing, but the projected growth and cost of the computational resources needed to analyze the data are expected to grow faster than the base storage costs. The combination of storage and analysis computing costs may restrict scientific output and potential physics reach of the experiments. There must be R&D efforts in data management on how to minimize the impact of the data access and storage model on the overall cost of doing scientific analysis. This R&D should include an optimization of both the capital costs of storage as well as the potential impacts the storage systems can have on the CPU requirements for the experiments and their costs.

The ability to leverage new storage technologies, as they become available, into existing data delivery models is a challenge that we must be prepared for. New storage systems will present new interfaces and new behavior. A key decision in their successful exploitation will be whether to encapsulate this within a more familiar service or whether to present the new interface directly to applications which will thus have to be adapted. As discussed in the preceding sections, much of this change can be aided by active R&D into our own IO patterns; an approach which has not yet been adopted widely by the field.

HEP experiments should be prepared to leverage "tactical storage". Such storage may be provisioned only when it becomes cost-effective (e.g., from a cloud provider) and have a data management and provisioning system that can exploit such resources on short notice. Volatile data sources would impact many aspects of the system; catalogs, job brokering, monitoring/alerting, accounting, the applications themselves.

On the hardware side, R&D is needed in alternative approaches to data archiving to determine the possible cost/performance trade-offs. Currently, tape is extensively used to hold data that cannot economically be made available online. While the tape-stored data is still accessible, it comes with a high latency penalty and thus

limiting possible analysis. We suggest investigating either separate direct-access-based archives (e.g. disk or optical) or new models that overlay online direct-access volumes with archive space. This is especially relevant when access latency is proportional to storage density. Either approach would need to also evaluate reliability risks and the effort needed to provide data stability.

Cost reductions in maintenance and operation of the storage infrastructure can be realized through convergence of the major experiments and resource providers on shared solutions. This does not necessarily mean promoting a monoculture, as different solutions will be adapted to certain major classes of use-case, type of site or funding environment. Indeed, there will always be a judgment to make on the desirability of using a variety of specialized systems, or abstracting the commonalities through a more limited but common interface (the SRM story illustrates this point). Reduced costs and improved sustainability will be further promoted by extending these concepts of convergence beyond HEP and into the other large-scale scientific endeavors that will share the infrastructure in the coming decade. Efforts must be made as early as possible, during the formative design phases of such projects, to create the necessary links.

Finally, any and all changes undertaken must not make the ease of access to data any worse than it is under current computing models. We must also be prepared to accept the fact that the best possible solution may require significant changes in the way data is handled and analyzed. What is clear is that what is being done today will not scale to the needs of HL-LHC experiments.

8 Research and Development Roadmap and Goals

8.1 Sub-file granularity

Sub-file granularity (*e.g.* sub-event-based or event-based granularity) should be studied to see whether it can be implemented efficiently and in a scalable, cost-effective manner for all use cases that rely on event selection and whether it offers an advantage over the current paradigm of file-based granularity. Proposed actions are:

- Quantify impact on performance and resource utilization (storage, network) for the main type of access patterns (*i.e.* simulation, reconstruction, analysis).

- Assess the impact on catalogs and data distribution.

- Assess whether event-granularity makes sense in object stores that tend to require large chunks of data for efficiency.

- Test for improvement in recoverability from preemption, in particular when using cloud spot resources and/or dynamic HPC resources.

The above tasks should be completed by 2020 (and can be performed in parallel).

8.2 Data organization and analysis technologies

Data organization and analysis technologies in use by other big data users should be studied to glean whether we can benefit from them. Proposed actions are:

- Evaluate row-based versus column-based data organization on the performance of each type of access used.

- Investigate data storage and access solutions that support the use of map-reduce or Spark-like analysis tools and their adaptability to HEP analysis needs.

- Evaluate new compression schemes, just-in-time decompression schemes and mappings onto hardware architectures considering the flow of data from spinning disk to memory and application.

- Evaluate possible alternative storage formats to the ROOT format, especially storage formats optimized for storage efficiency and/or data filtering through metadata

The proposed proof-of-concept involves the above tasks that should be completed by 2020. If successful, implementation as a production system will be done in the following years.

8.3 Data caching

Investigate the role that data placement optimizations, such as caching, can play in optimizing the use of computing resources as well as the technologies that can be used for this. Proposed actions are:

- Quantify the benefit of caching for reconstruction, analysis, and simulation.

- Assess the benefit of caching for Machine Learning-based applications, in particular for the learning phase.

- Evaluate the benefits of using different approaches to data delivery from what is currently in use in HEP. Namely, Content Delivery Networks (CDN) and Named Data Networking (NDN) should be studied.

The first two actions should be completed by 2020 but evaluation of CDN/NDN is more long-term

8.4 Getting the most out of the storage diversity

The landscape of increasing diversity in storage service offerings and technologies should be studied and exploited in order to reduce HEP infrastructure costs. The proof-of-concept phase involves the following tasks:

- Understand what role tactical or opportunistic (potentially short-term) storage can play in HEP.

- Re-evaluate the role of archival storage solutions for HEP.

- Evaluate the role of "newer" storage architectures, such as object stores or key-value stores

The proof-of-concept should be completed by 2020 and, if successful, implementation in production will be done in the following years.

8.5 Global optimization of efficiency and latency

The inherent trade-offs between data access latency and efficiency of CPU use need to be studied and optimized on a global scale across the HEP infrastructure. The proof-of-concept phase involves the following tasks:

- Understand the impact of concentrating the data in fewer, larger locations (the "data-lake" approach).

- Understand the impact of an increased use of opportunistic compute resources, specifically those further from where data are stored.

The proof-of-concept should be completed by 2020 and, if successful, implementation in production will be done in the following years.

8.6 Data Access and Data Access Patterns

The data access needs and patterns should inform the the choice of storage media and data location. Proposed areas of inquiry are:

- Understand data access patterns, including investigating frequency of access of data

- Exploring ways to ease preliminary data filtering steps

- Exploring commercially-popular data transfer methods (e.g. HTTP)

The proof-of-concept should be completed by 2020 and, if successful, implementation in production will be done in the following years.

9 Conclusions

This document presents several areas pertaining to data access and management in HEP that will need to be re-examined in the coming decade before the expected volume and complexity of data becomes prohibitively expensive to store, access, and analyze. Extending current data handling methods and methodologies will prove intractable in the HL-LHC and DUNE era. The development and adoption of new data analysis paradigms gives the field, as a whole, a window in which to adapt our data access and data management schemes to ones which are more suited and optimally matched to a wide range of advanced computing models and analysis applications. This type of shift has the potential for enabling new analysis methods and allowing for an increase in scientific output.

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