

## **Parallel Writing of Nested Data in Columnar Formats**

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**Motivation**



- Large Hadron Collider at CERN
	- More than 2 exabytes since 2010
	- Stored in binary columnar format



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**Motivation**



- Large Hadron Collider at CERN ◦ More than 2 exabytes since 2010
	- Stored in binary columnar format
- High-Luminosity LHC (from 2029) ◦ Further increase of data rate
- RNTuple: evolution of the currently used TTree columnar format
	- Opportunity to include parallel writing from the start





[RNTuple Overview](#page-5-0)

[Concepts for Parallel Writing of Columnar Data](#page-14-0)

[Evaluation of Parallel RNTuple Writing](#page-19-0)

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# <span id="page-5-0"></span>**[RNTuple Overview](#page-5-0)**



- Serialize acyclic  $C++$  data structures into a columnar format
	- Important to support nested collections for HEP use cases

```
struct Event {
  int fld ;
  std :: vector<Track> fTracks;
} ;
                                            struct Track {
                                              float fEnergy;
                                              std :: vector<int> flds;
                                           } ;
```
<span id="page-6-0"></span>**Figure 1:** Simplified example of nested data structures. Real-world HEP data models often have thousands of fields.



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	- Columns at leafs of field tree: primitive, fixed-size types



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	- Columns at leafs of field tree: primitive, fixed-size types
- Columns partitioned into pages
	- Transparently compressed (default for RNTuple: Zstandard)
- Cluster: all pages of a consecutive range of rows, or entries















**Table 1:** Example of columnar representation for the nested data structure shown in Figure [1.](#page-6-0)

fId	fTracks	fTracks._0.fEnergy	fTracks._0.fIds	fTracks._0.fIds._0	
6873	$\mathcal{P}$	25.4f		42	
				27	
		32.8f		16	page
6874	२	14.7f	5	21	
				8	
			entry		
		column			



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## <span id="page-14-0"></span>**[Concepts for Parallel Writing of Columnar Data](#page-14-0)**



- Support for nested data implies variable row sizes
	- Transparent compression leads to variable page sizes
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	- Serialization and compression without synchronization
	- Then: final size is known, can be written into binary file format



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	- Serialization and compression without synchronization
	- Then: final size is known, can be written into binary file format
- Metadata updated in critical section





**Figure 2:** Illustration of filling three RNTuple clusters in parallel. After buffering in memory (top), entries are appended into a sequential file (bottom).

## <span id="page-19-0"></span>**[Evaluation of Parallel RNTuple Writing](#page-19-0)**



- Evaluate weak scaling behavior for a synthetic benchmark
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	- Two top-level fields: "event ID" and a vector of floats



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- Write data on Samsung PM1733 NVMe SSD formatted with ext4
	- Measured bandwidth with [Flexible I/O Tester](https://github.com/axboe/fio) (fio): 768 MB/s
	- Possible optimization: pre-allocate file with fallocate
	- Increases bandwidth to 1062 MB/s





Figure 4: Bandwidth measured with the synthetic benchmark writing on a server SSD.<sup>1</sup>

<sup>&</sup>lt;sup>1</sup>Figure adapted from the paper, see Backup Slide [3](#page-34-0) for the original plot.



- [Analysis Grand Challenge:](https://agc.readthedocs.io/) test workflows at scales required for HL-LHC
	- "ttbar" analysis, input dataset derived from 2015 Open Data of the CMS experiment
	- Conversion to RNTuple: 969 GB across 787 files, divided into nine partitions



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	- "ttbar" analysis, input dataset derived from 2015 Open Data of the CMS experiment
	- Conversion to RNTuple: 969 GB across 787 files, divided into nine partitions
- Evaluation benchmark: reduce size of the dataset by *skimming* 
	- Retain only fields used by analysis, filter events (entries) based on coarse cuts
	- Output: nine files, total size of 19 GB

### **Dataset Skimming of the Analysis Grand Challenge**





**Figure 6:** Speedup of the AGC dataset skimming benchmark compared to a full sequential run.

 $1$ ROOT's *implicit multithreading* (IMT) used to parallelize compression of pages.

 $^2$ TBufferMerger merges files in memory. It is the current way of parallel writing in <code>ROOT</code>.

# <span id="page-27-0"></span>**[Conclusions and Future Work](#page-27-0)**



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- Synthetic benchmark scales up to storage bandwidth limit
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- Extend parallel writing to process-level parallelism
- Distributed parallelism with MPI and writing to cluster filesystems

# **Backup Slides**





### **Writing to /dev/null**





### <span id="page-34-0"></span>**Writing to SSD (original plot from the paper)**





## **Writing to HDD**





### **Direct I/O – Writing to SSD, no compression – preliminary**



