# Exploiting Domain-Specific Data Properties to Improve Compression for High Energy Physics Data

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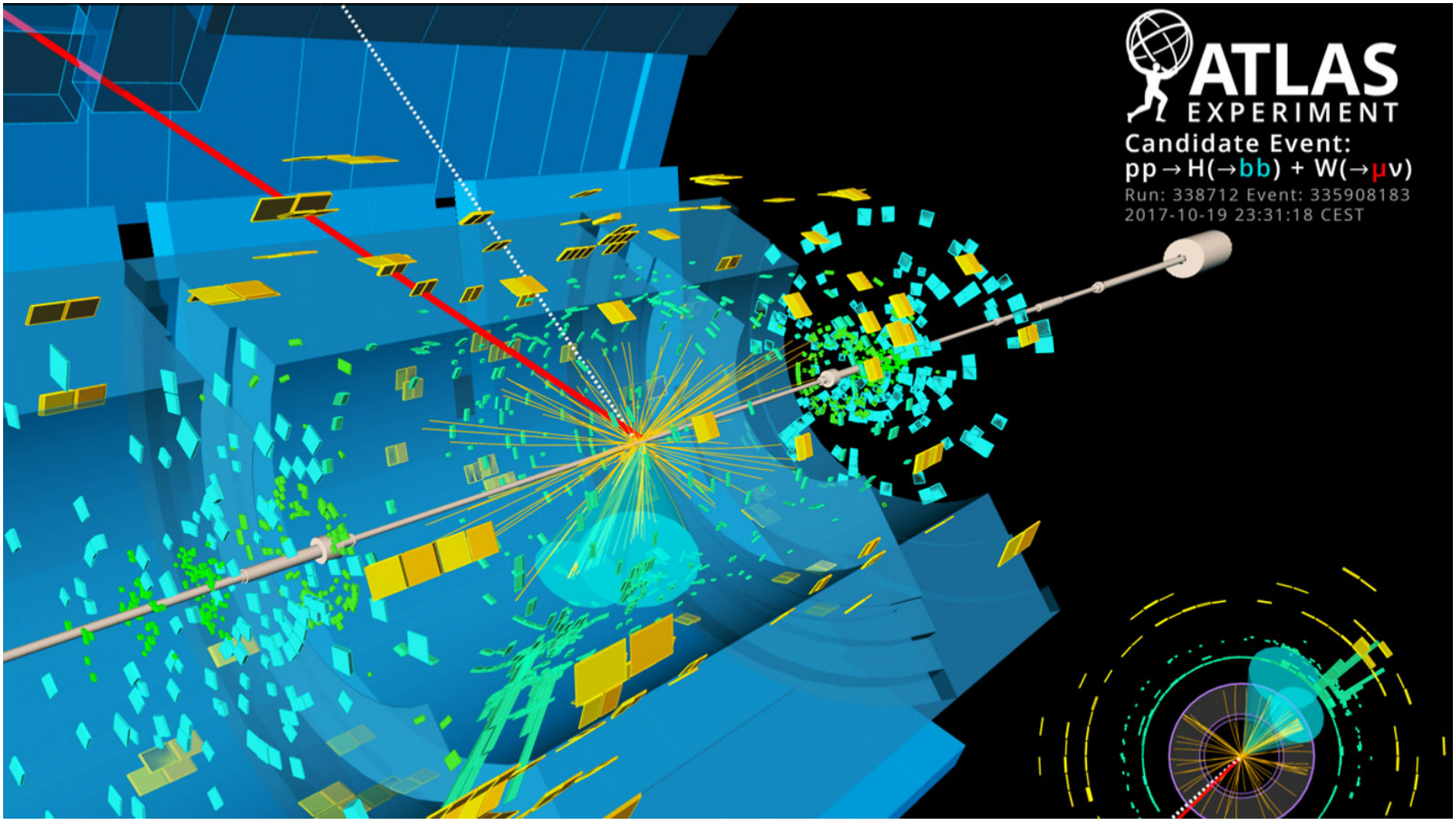
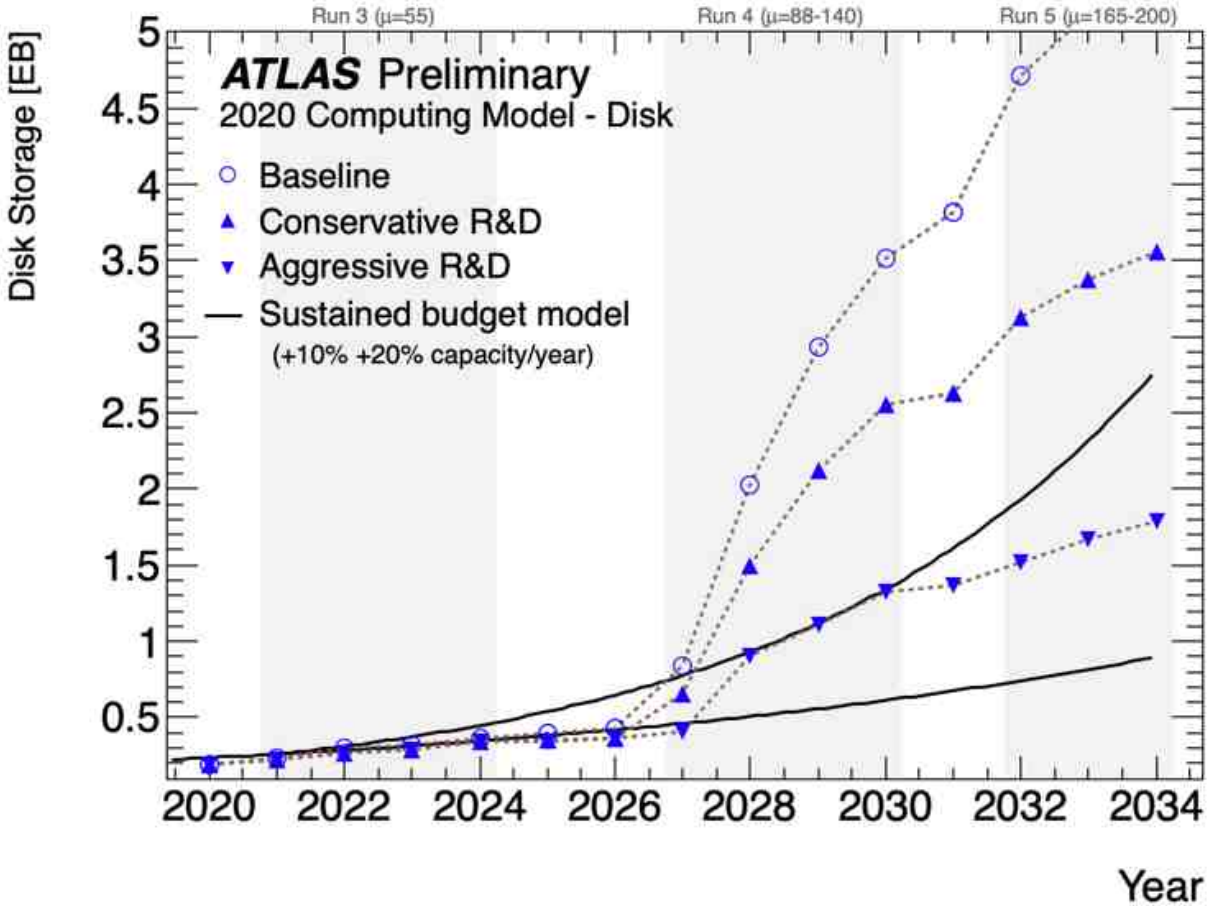
# Context

# High Energy Physics in a Nutshell




Less than $0.1\%$ of data recorded, but still more than $100$ PB per year!

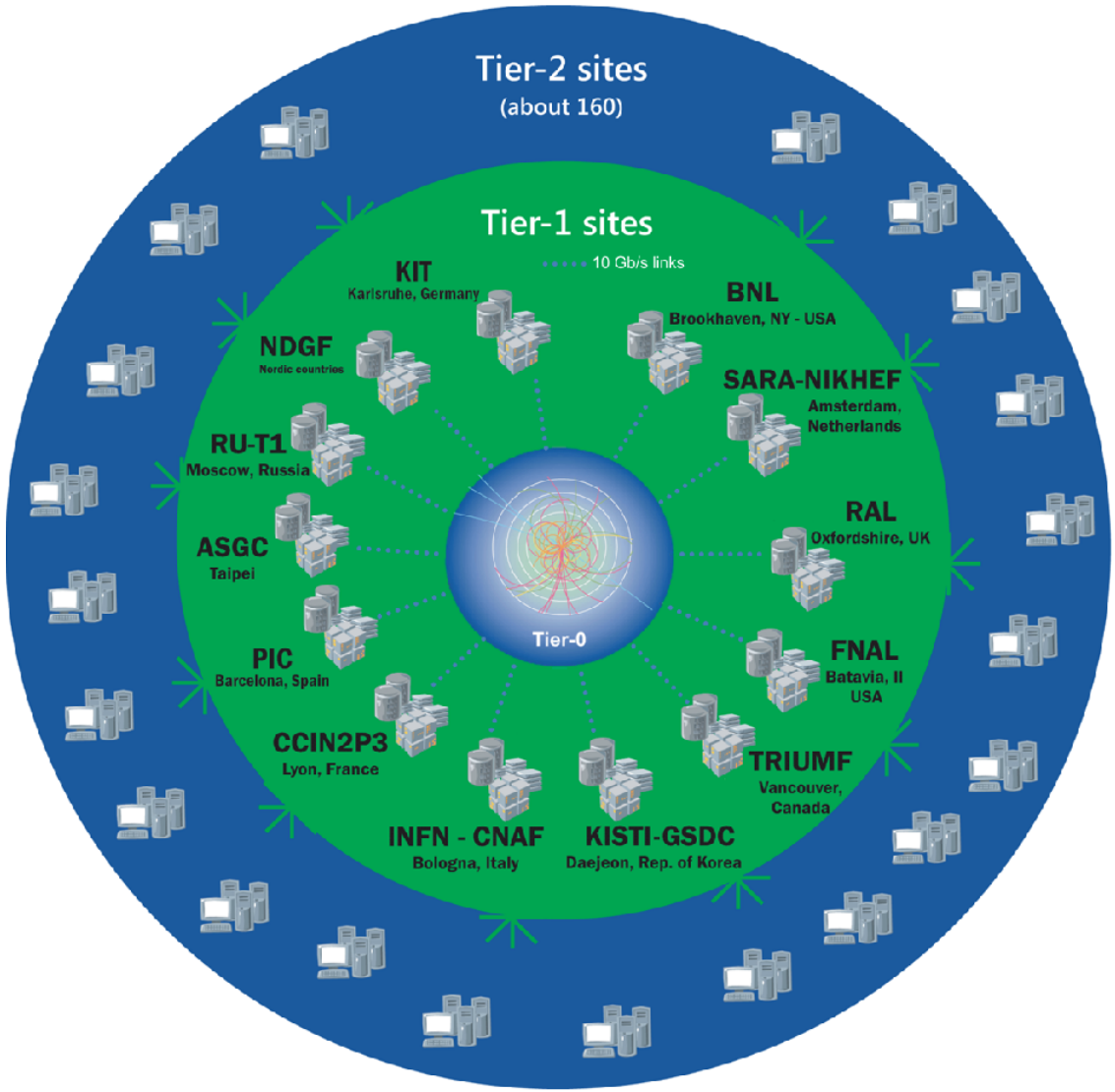
# Projected Data Growth




- Data storage requirements quickly outpace budget constraints.

# How Does CERN Store Data?

- Replicated for reliability and access speed
- Data moves from Tier-1 to Tier-2 for analysis and simulation
- Stored using



# How Does CERN Store Data?

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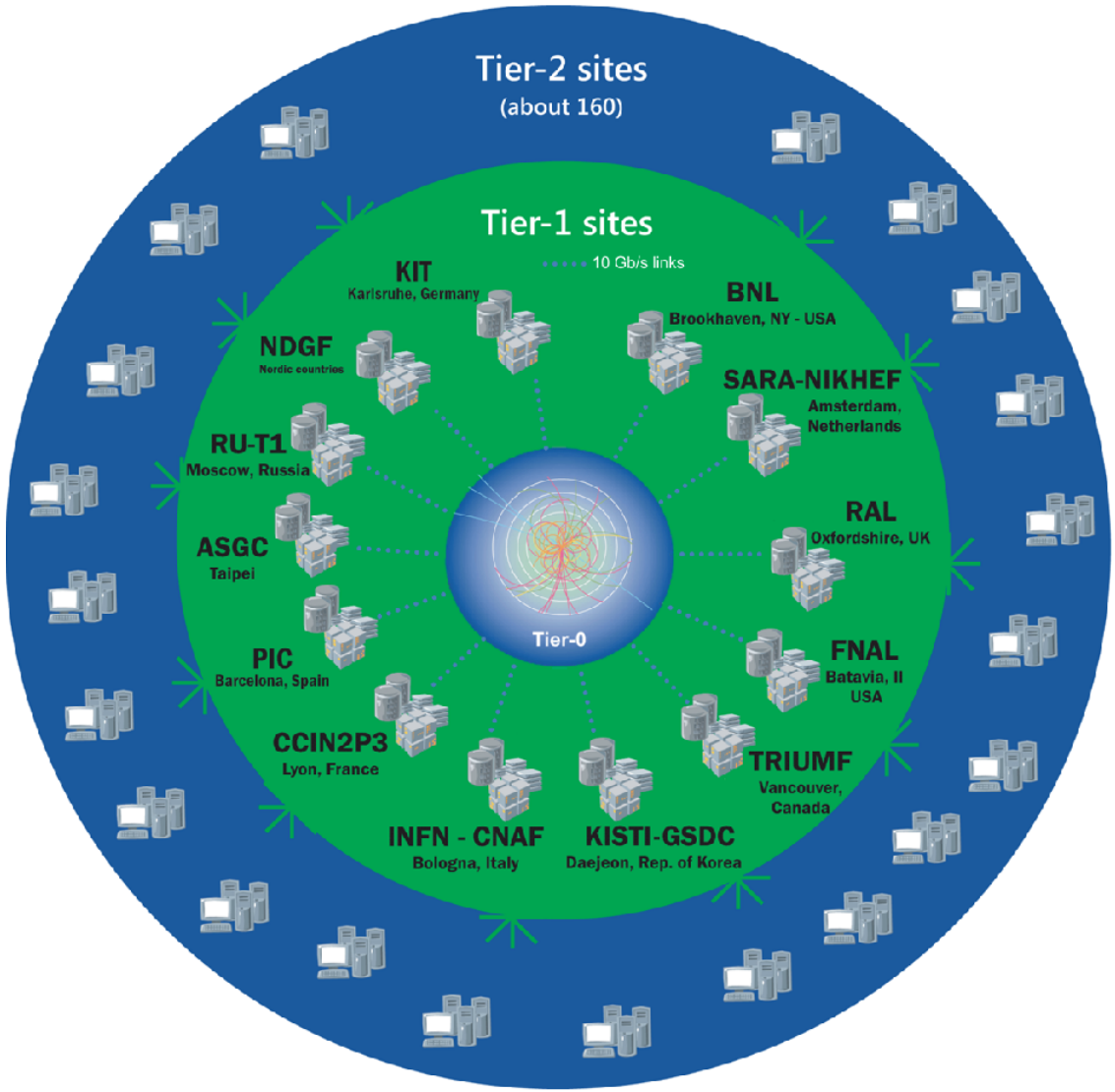
- Stored using
  - Tape (350PB)
  - HDD (280PB)
  - SSD (40PB)



# Problem Statement

- High energy physics data is costly to store (exabytes of data, millions of $)
- Current formats prioritize analysis performance over storage size

# Our Approach

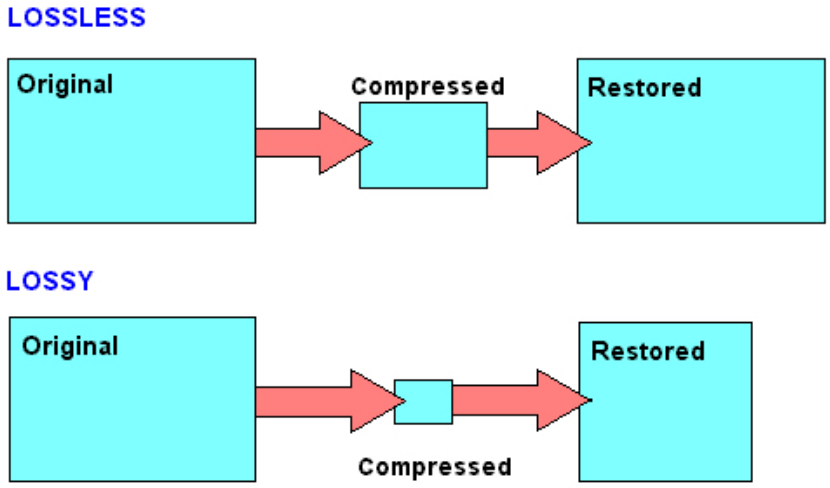
We utilize modern compression algorithms, domain-specific techniques, and aggregated storage to reduce storage requirements for archived high energy physics data.

Furthermore, we show that compression focused storage in a production environment can save petabytes of disk space while only requiring a minimal increase in computational resources.

# Data Compression

# Data Compression Overview

- **Lossless** vs. Lossy



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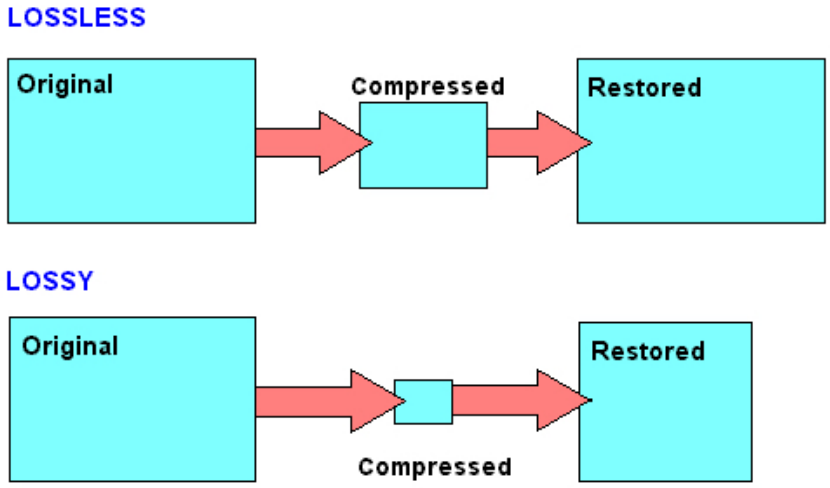

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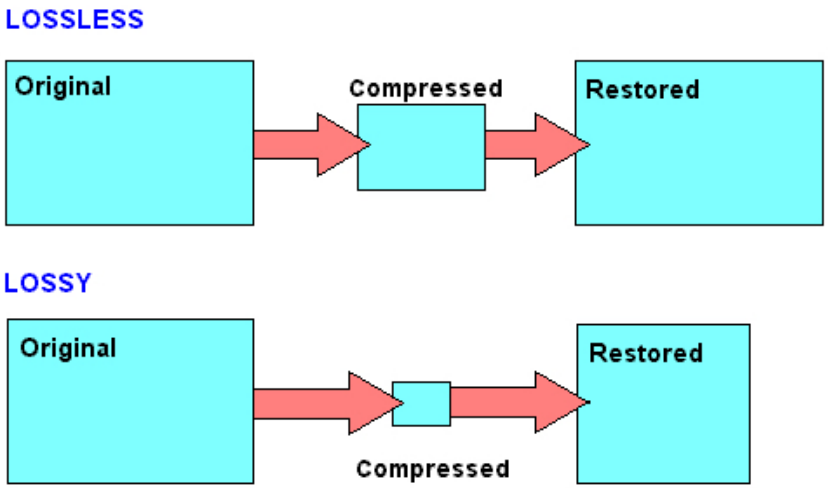
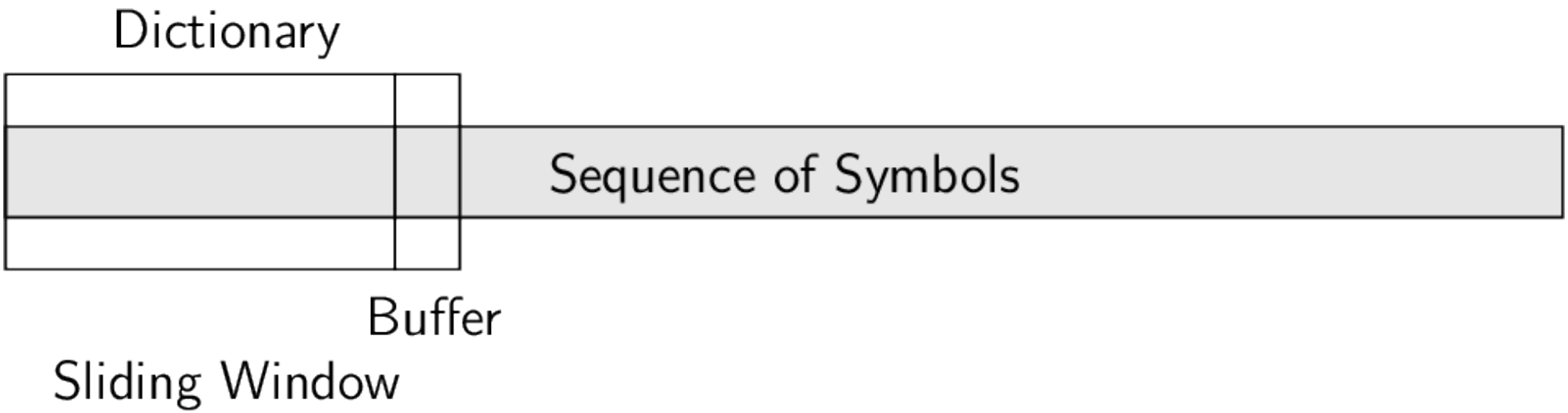



- **Lossless** vs. Lossy
- Tradeoff between speed & reduction in size
- Common general purpose software
  - **snappy**
  - **zlib**
  - **zstd**
  - lz4
  - lzma
  - brotli

# What Enables Good Compression?

- Repeated Patterns



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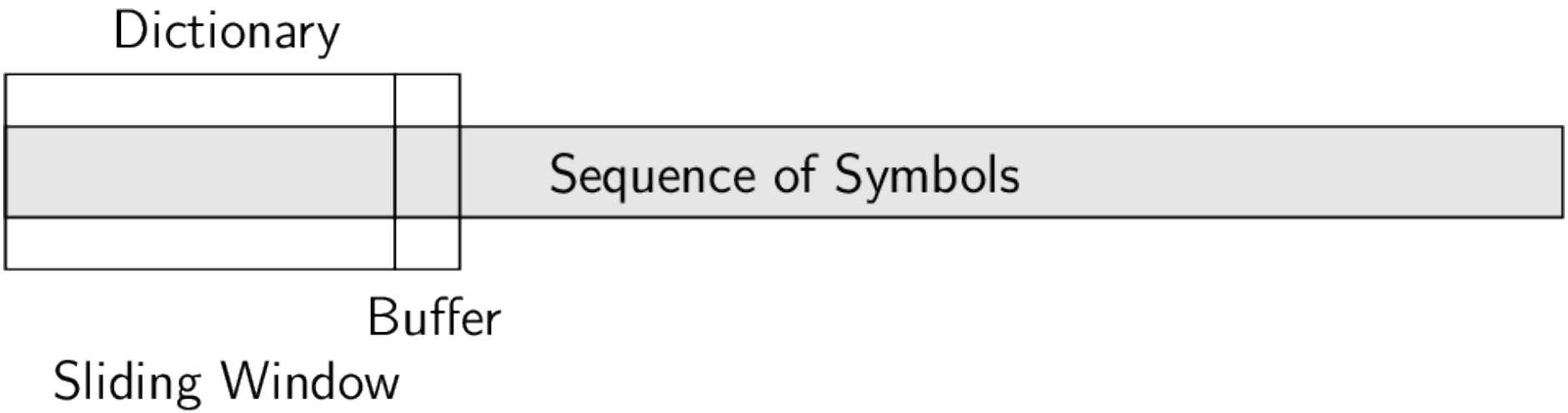
- Large Windows



# HEP Data Storage

# The ROOT Framework

- Massive scientific toolkit written in C++
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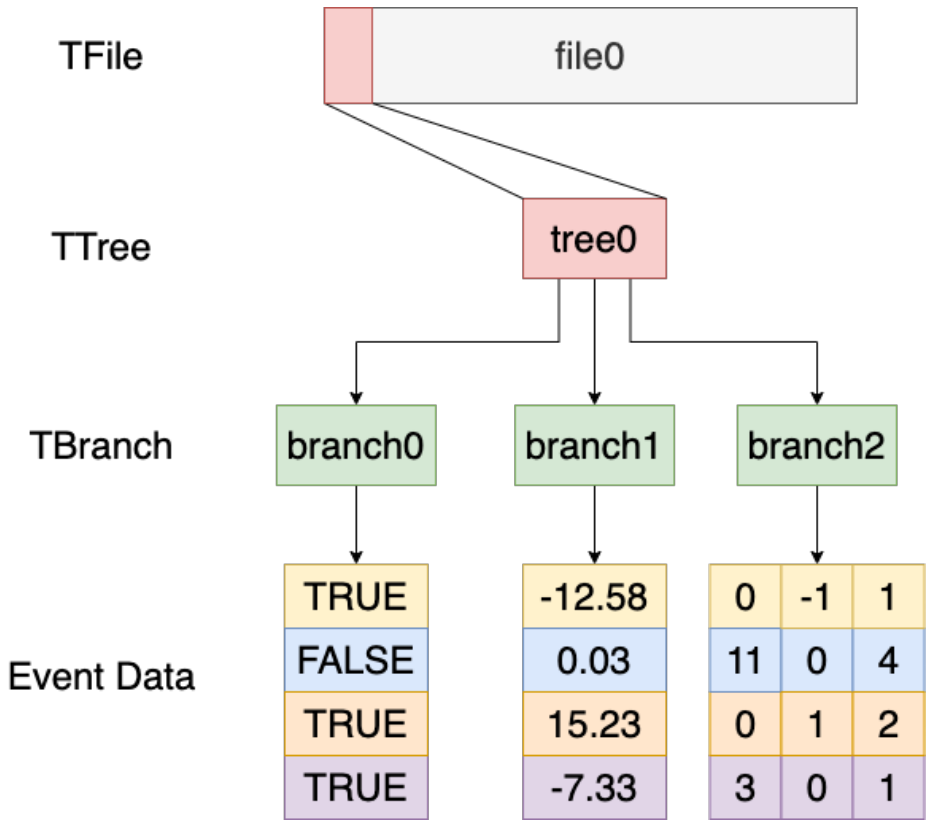
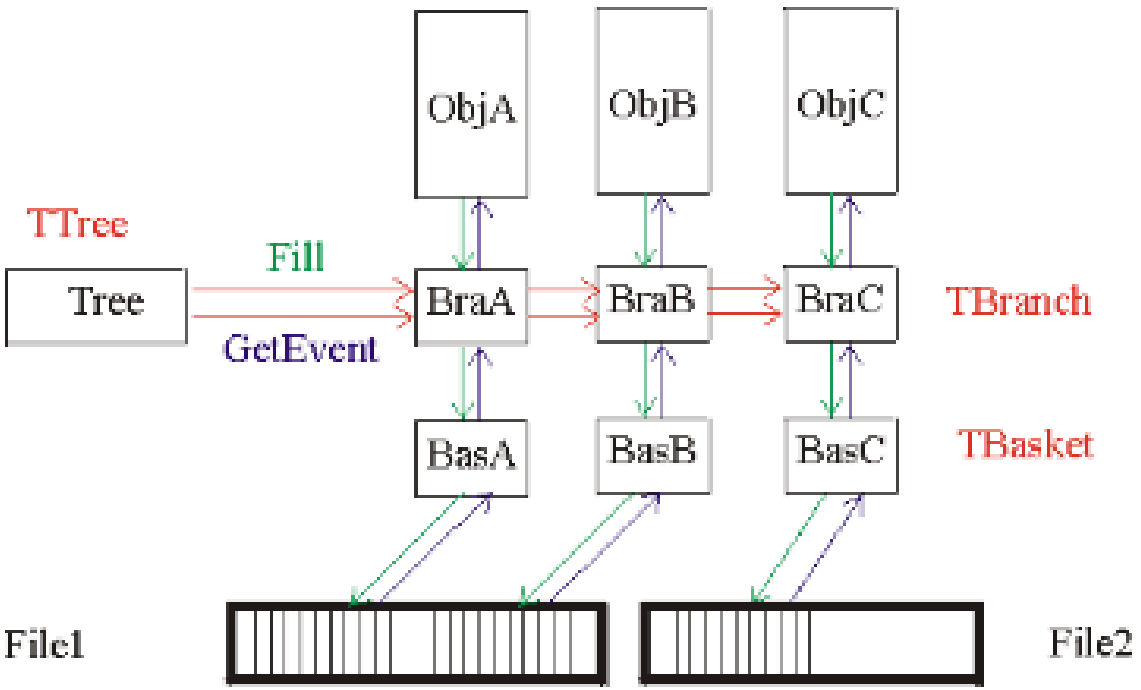
- Used for data processing, statistical analysis, visualisation, and storage
- Tree structure for storing data



# How Does ROOT Compress Data?

- Basket level compression (`zlib`)
- **Optimized for analysis workloads!**



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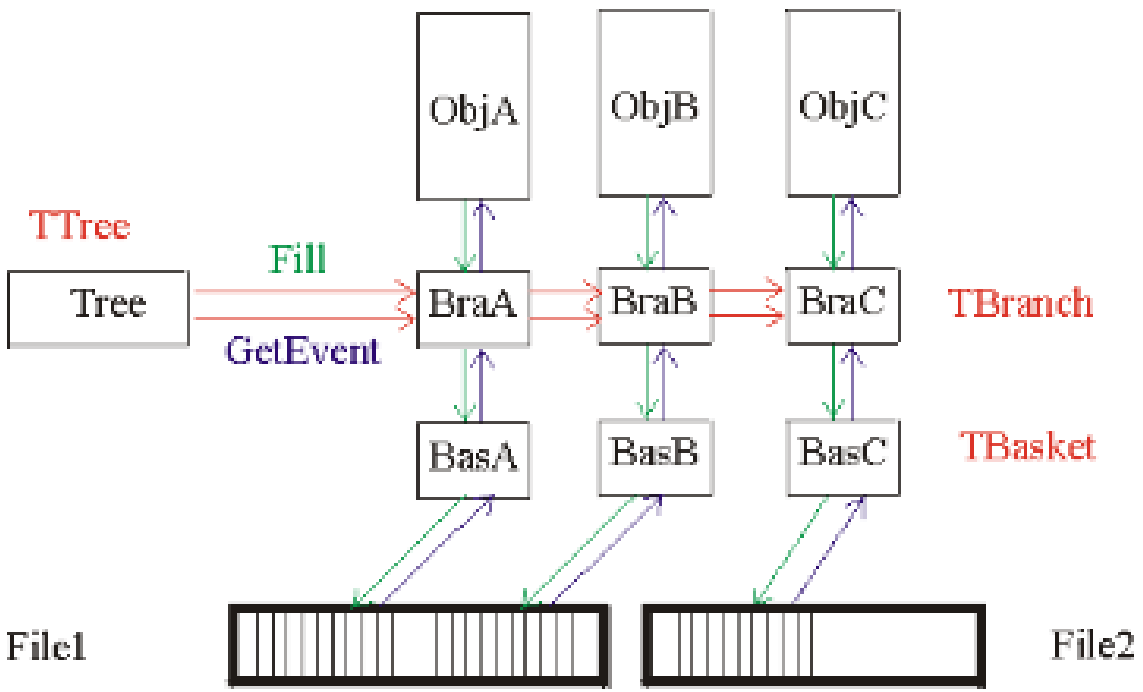
- Dozens of papers on providing "balance" between size and analysis performance



# What "Kind" of Data is Being Stored?

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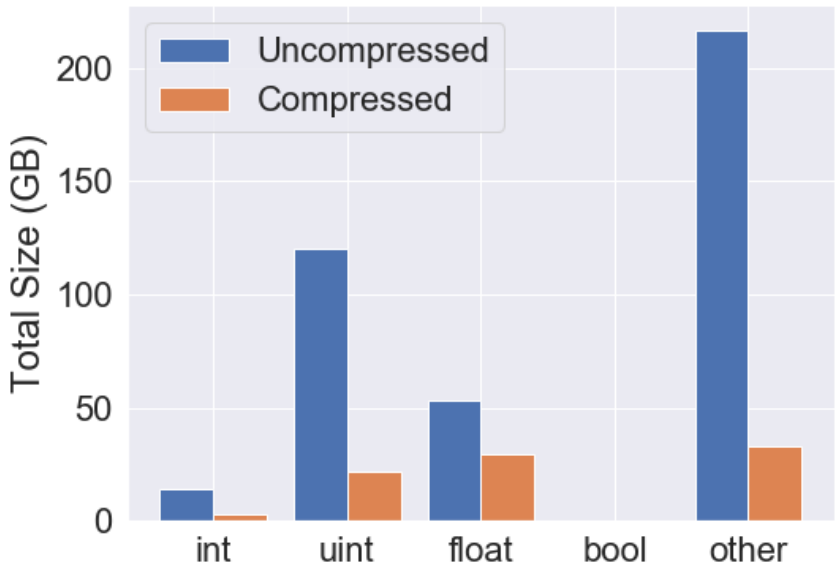
- Metadata and structured objects are hard to analyze and easy to compress.




ATLAS Data

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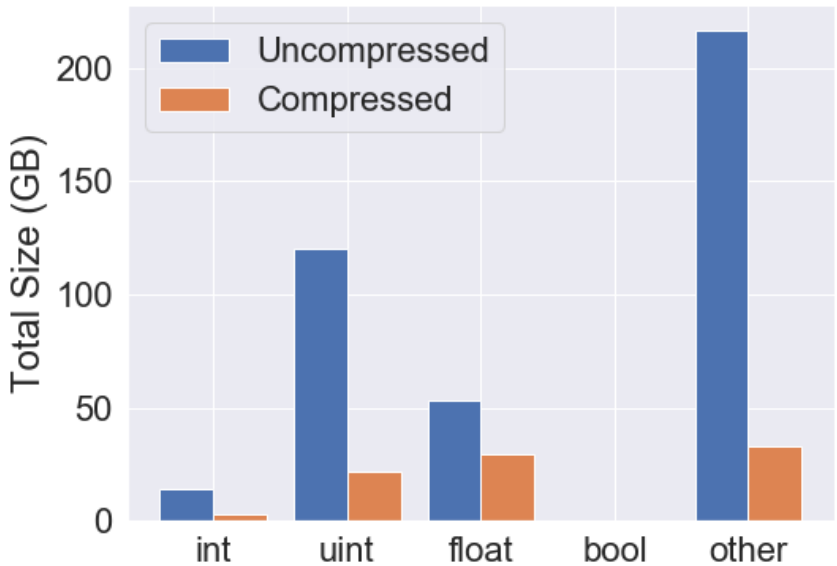
- Metadata and structured objects are hard to analyze and easy to compress.
- Therefore, we focus on floating point and integer data.




ATLAS Data

# Key Questions

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2. How much storage space can we save by applying these techniques?
3. Can this be implemented in a cost effective and scalable way for HEP experiments?

# Approach

# How Do We Reduce Data Storage Needs?

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## Key Insight

Larger windows only provide an advantage if data is stored in large enough blocks.

# Insight 2: Exploit Patterns and Repetition

- If we know the type or distribution of a dataset, we can use that information to aid in compression or to pre-train an algorithm.
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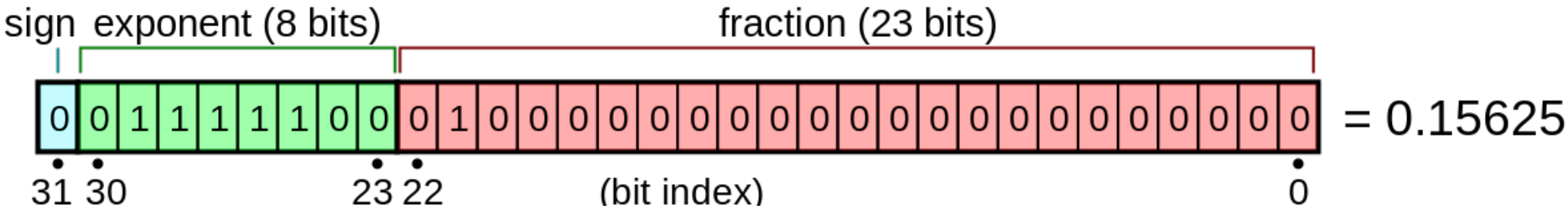
## Delta Encoding

Take the difference between successive elements:

Original Datastream: `[1,2,3,4,5,7,9,8,...]`

$\delta$-encoded Datastream: `[1,1,1,1,1,2,2,-1,...]`

# Insight 2: Exploit Patterns and Repetition

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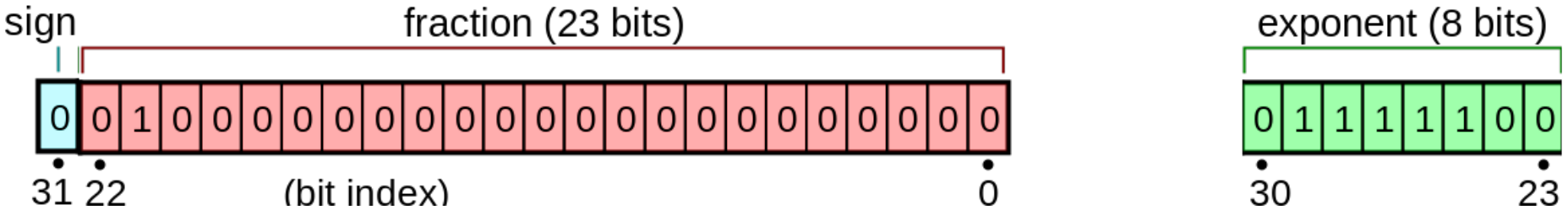


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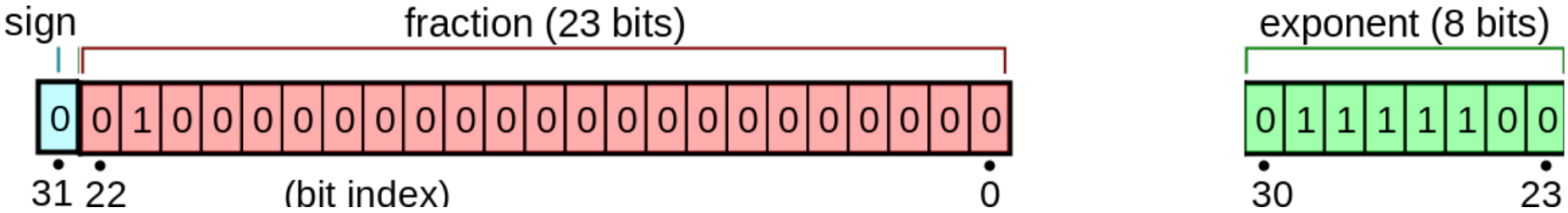


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## Key Insight

By aligning the same components across values, we increase the similarity within blocks.

# Improving CR (Specified)

## Approach

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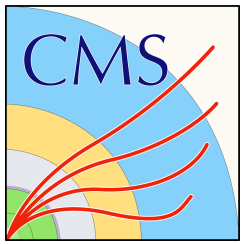
2. Delta encoding and float splitting
3. Compress on branch level granularity
4. Pretrain compression dictionaries

# Evaluation

# CMS+ATLAS Experiments/Methodology





- Largest HEP data release in history (1PB)
- Mix of end user data and analysis objects

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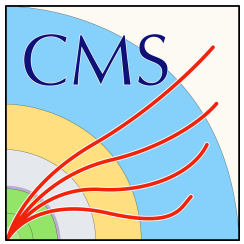



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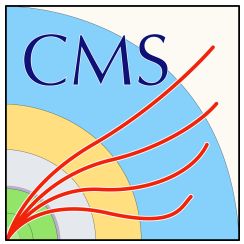



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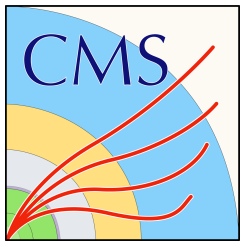



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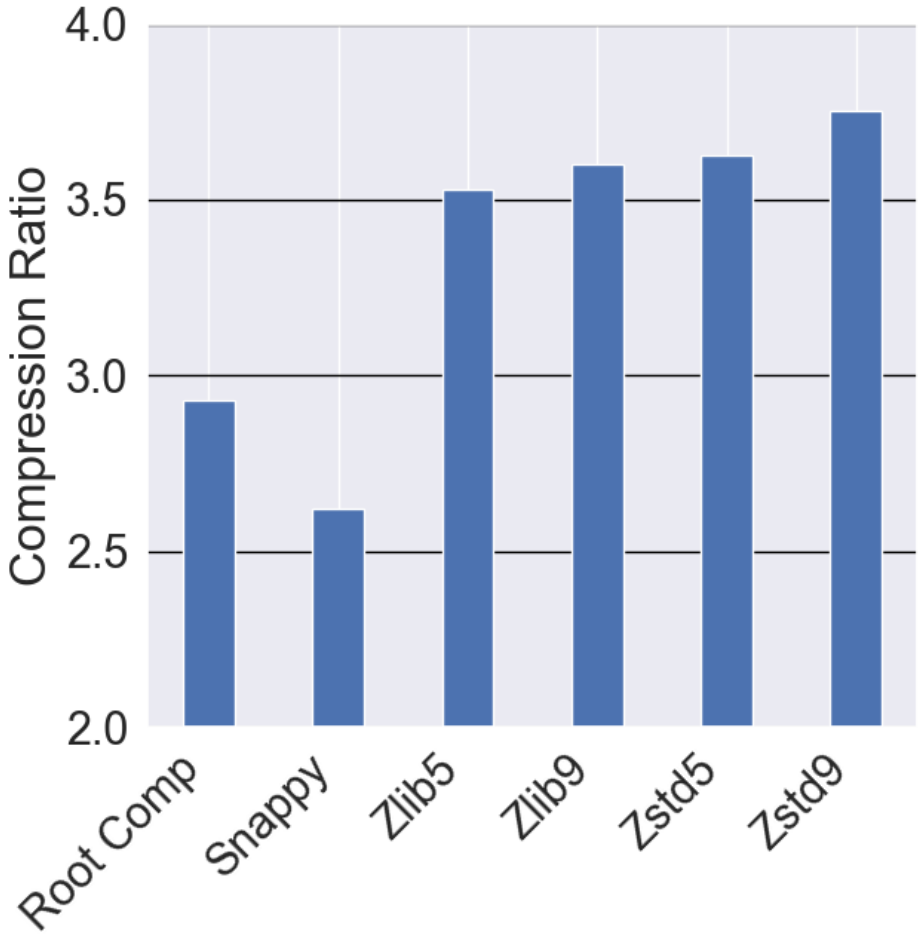
- **Extract** data and then evaluate compression
- **Compression Ratio (CR)**: $\frac{\text{Uncompressed Size}}{\text{Compressed Size}}$, reflects how compressed data is from the original.

# Better Compression Algorithms

- Compression level is a proxy for resource utilization (higher = more resources)
- `zstd` delivers $> 5\%$ better compression ratio than `zlib`



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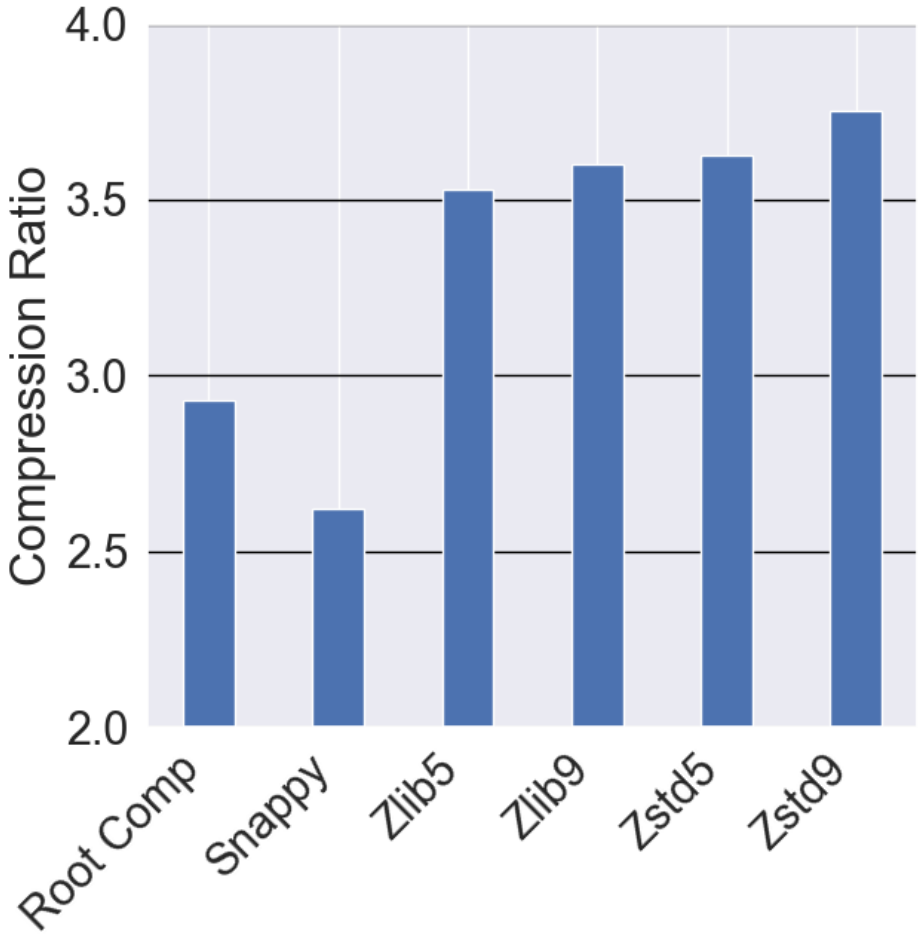

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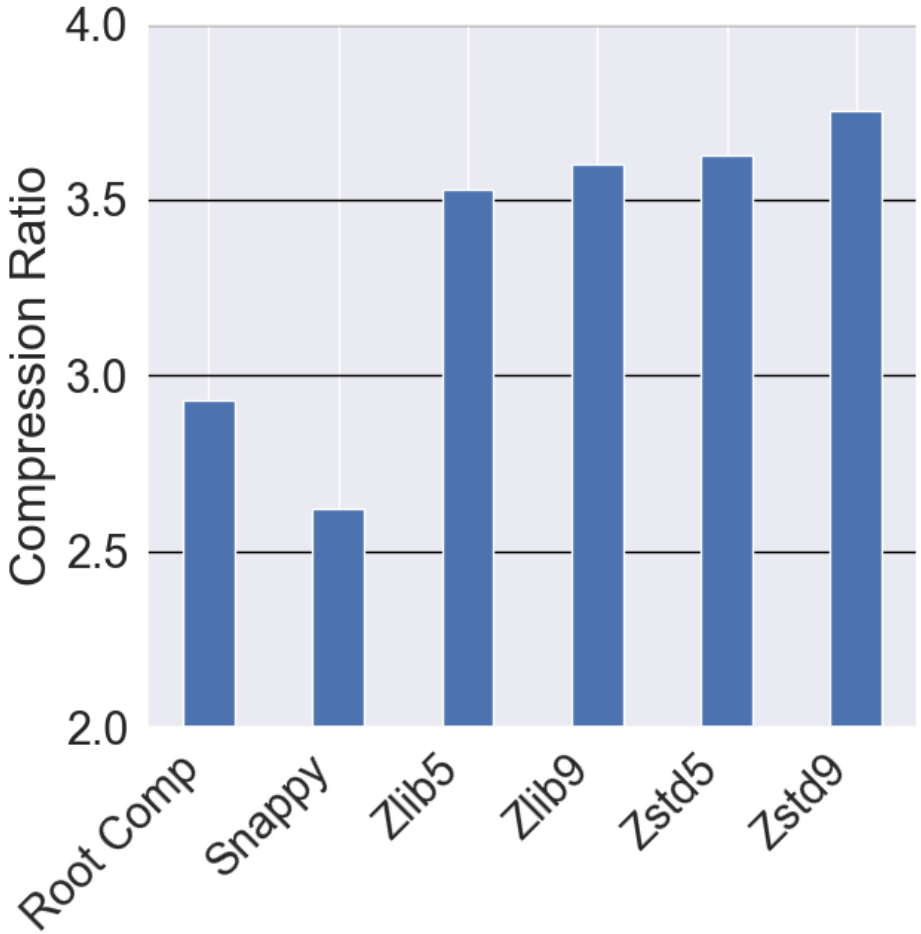

# Exploit Data Layout

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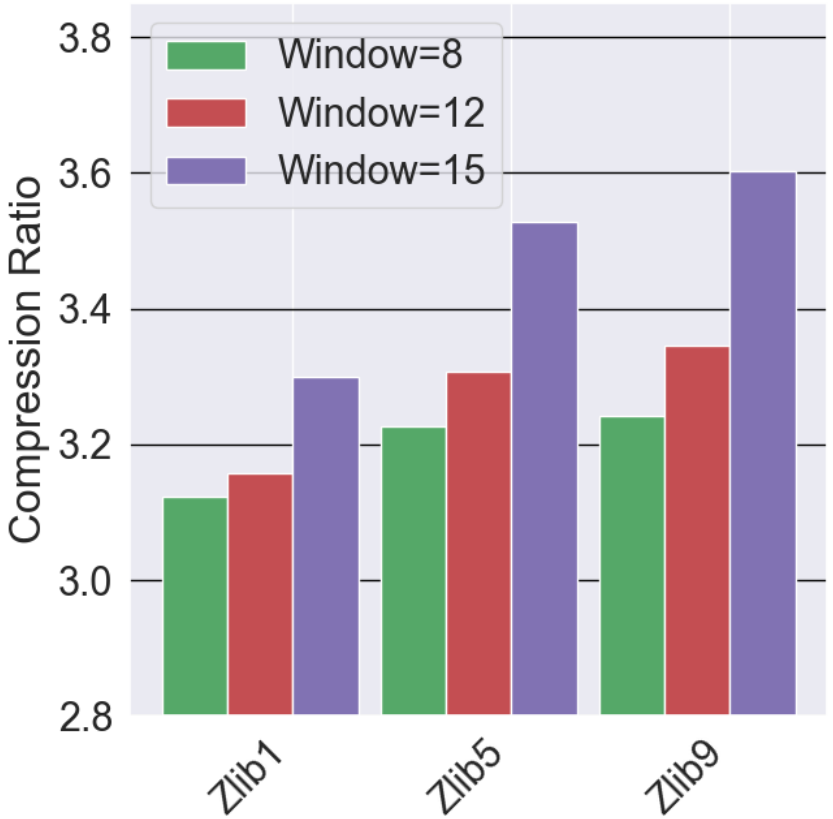

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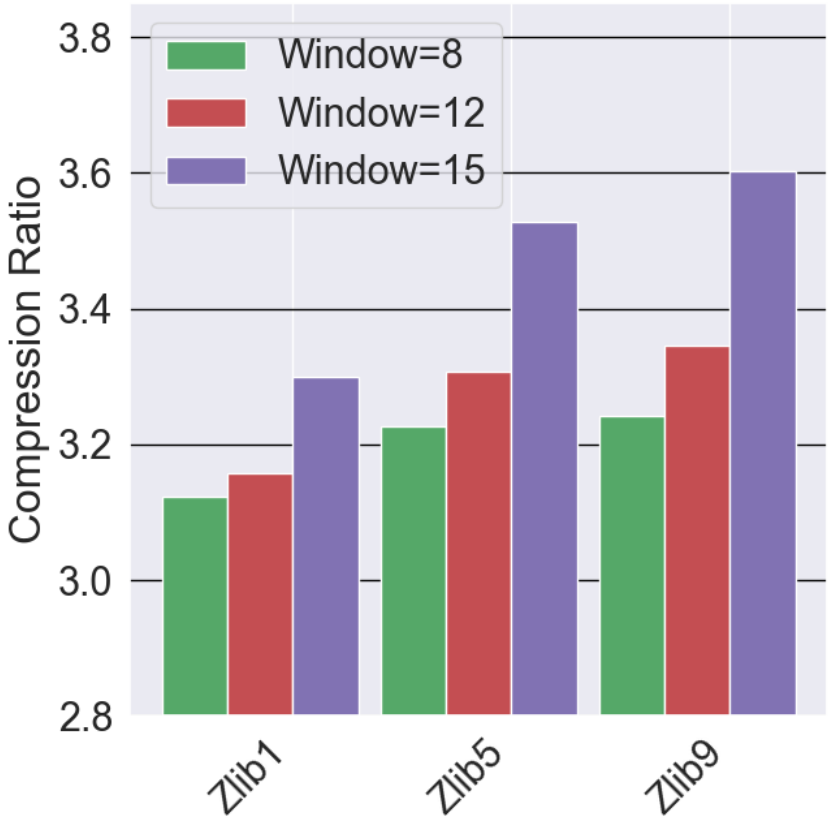

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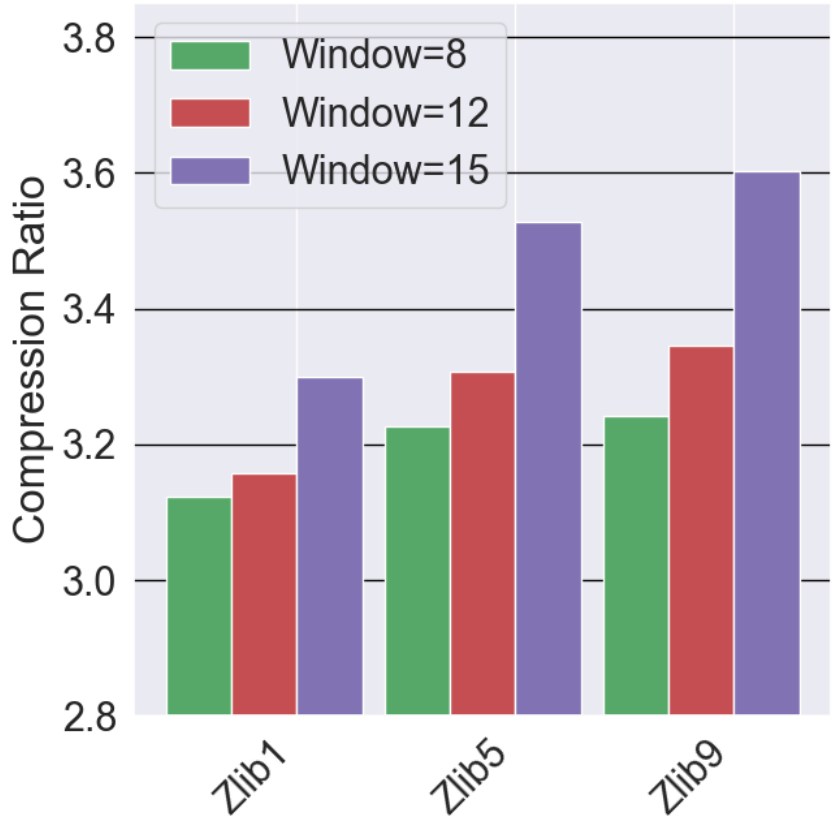
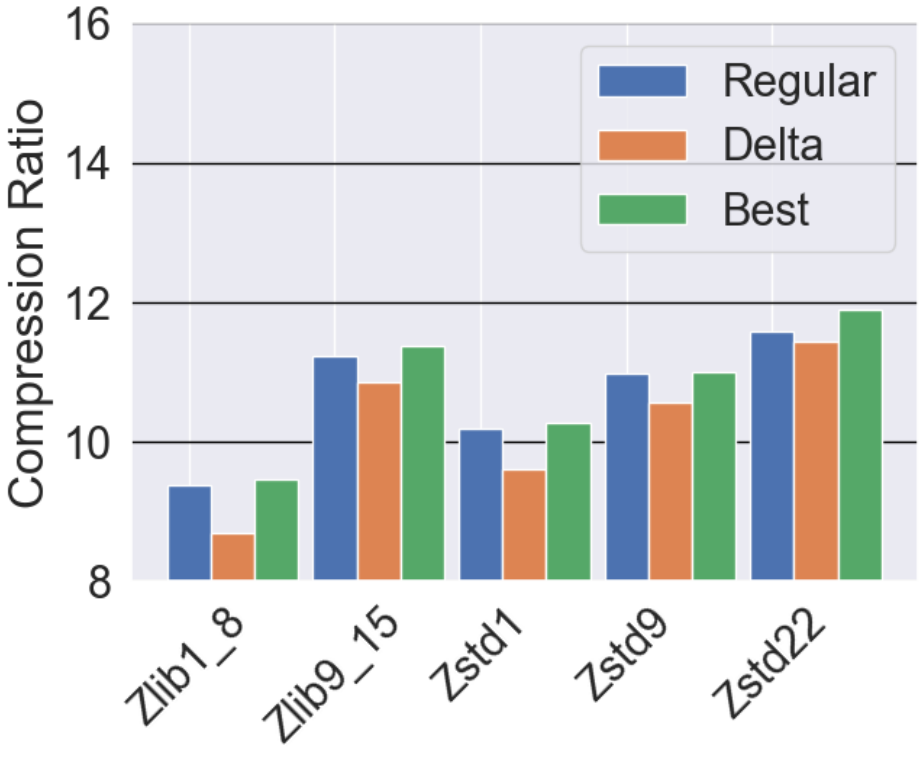


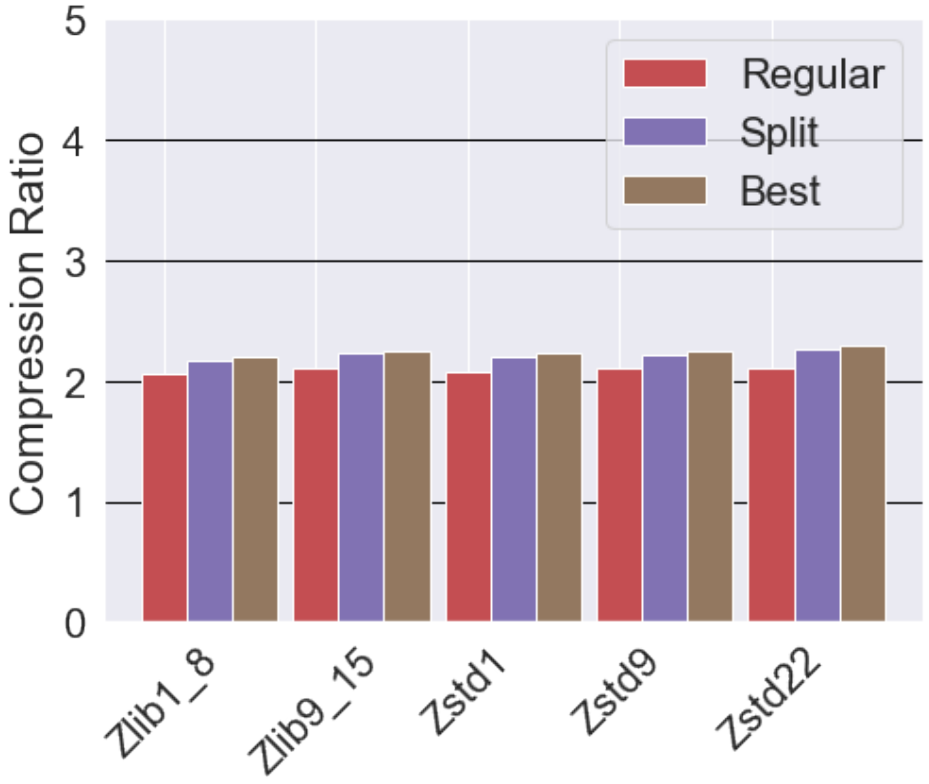

## Conclusion

Compressing at the granularity of branches enables better CR (full windows).

# Delta Encoding and Float Splitting




Integer data

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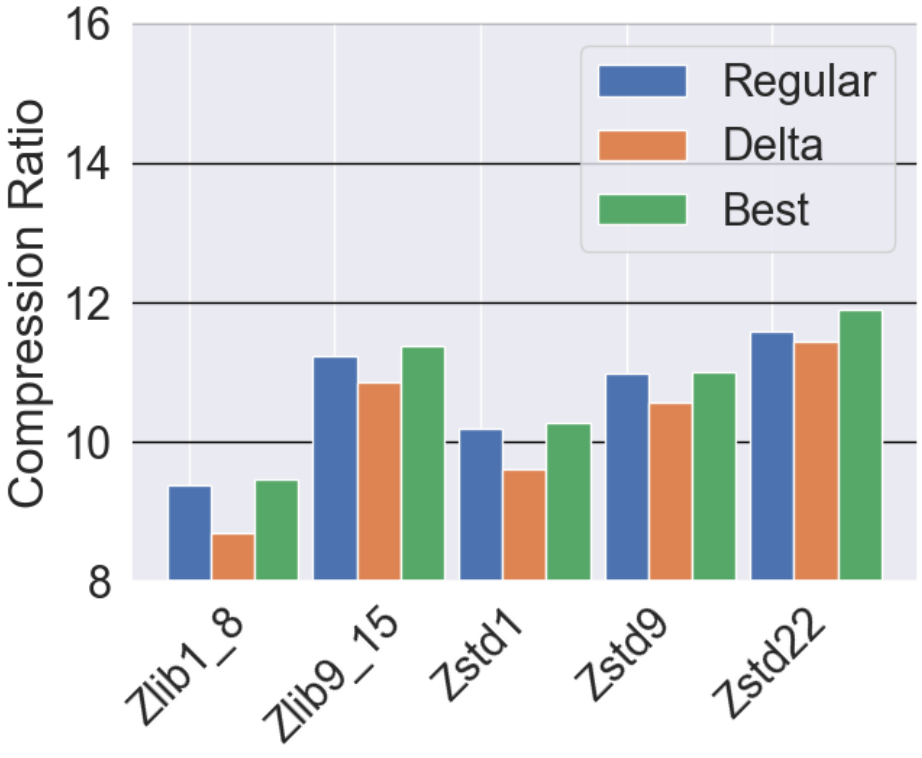


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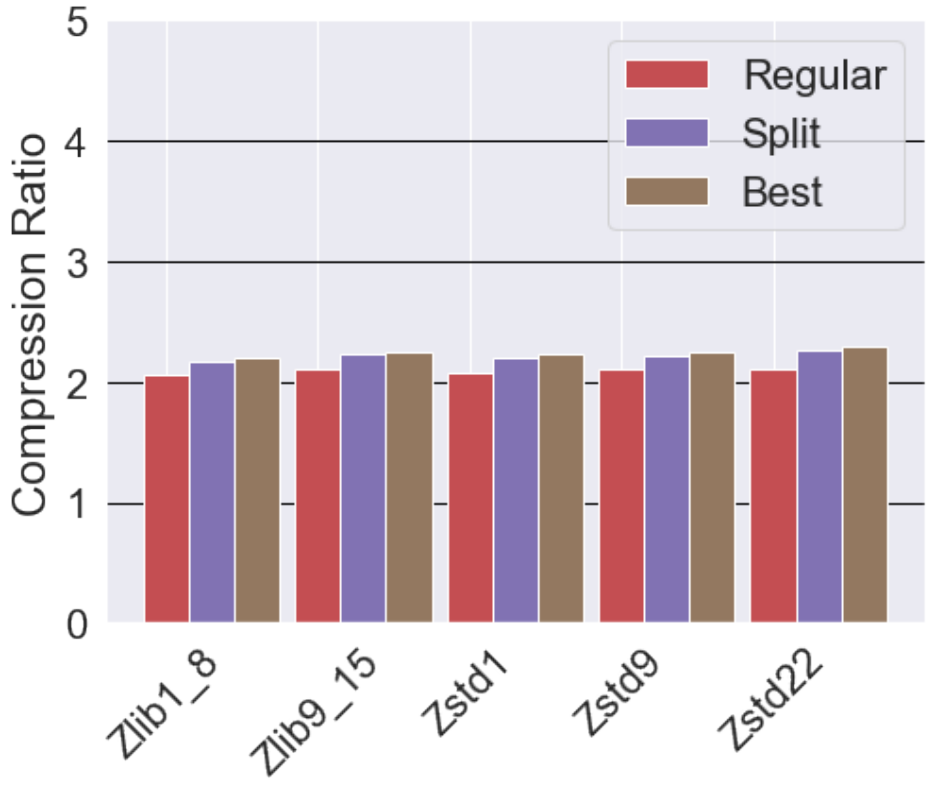
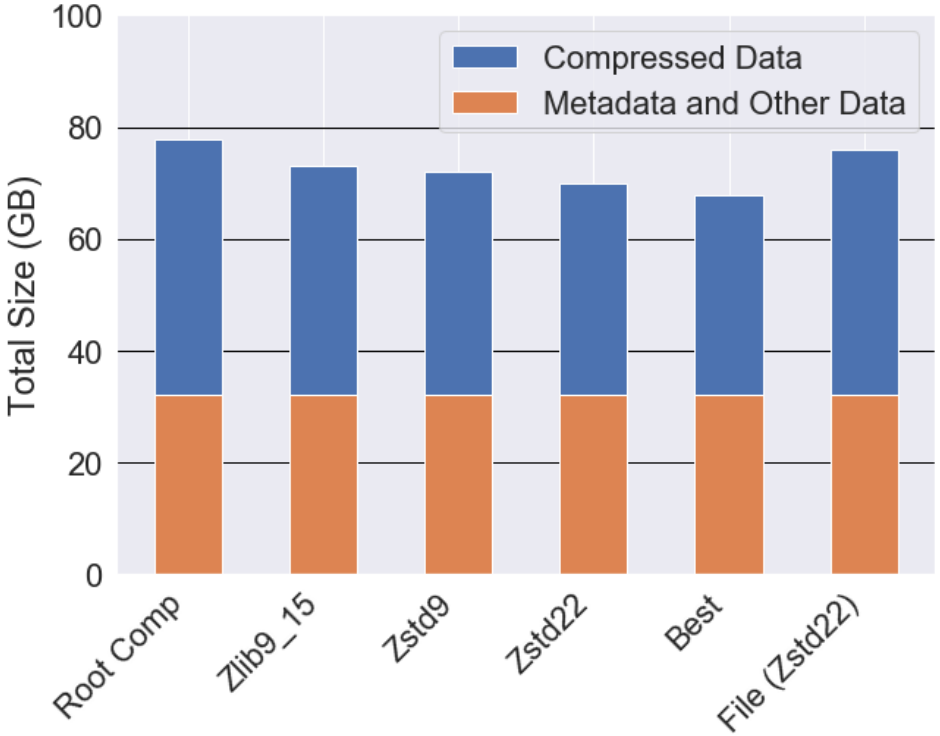



Floating point data

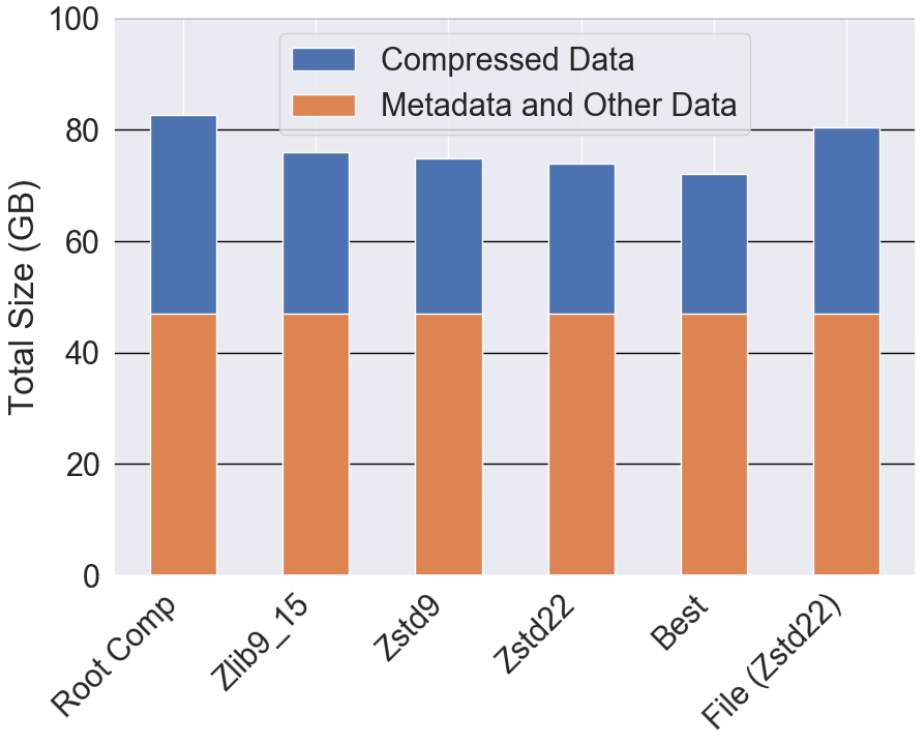
## Conclusion

Delta compression, used selectively, improves integer CR by 5%.
Floating point splitting, used selectively, improves float CR by 4%.

# General Takeaway




CMS Data




ATLAS Data

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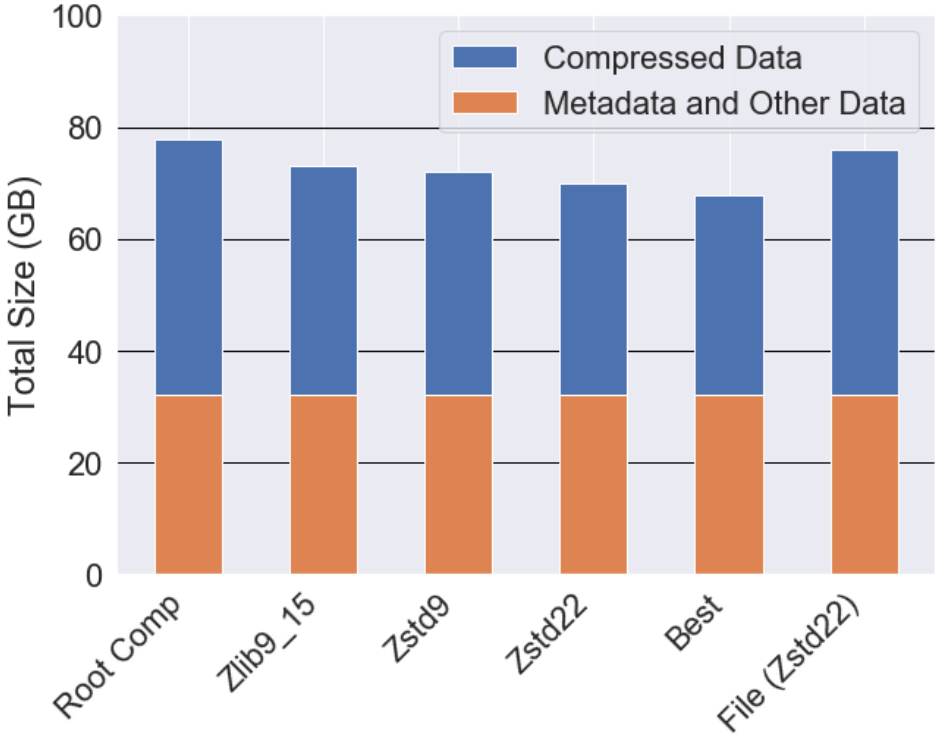


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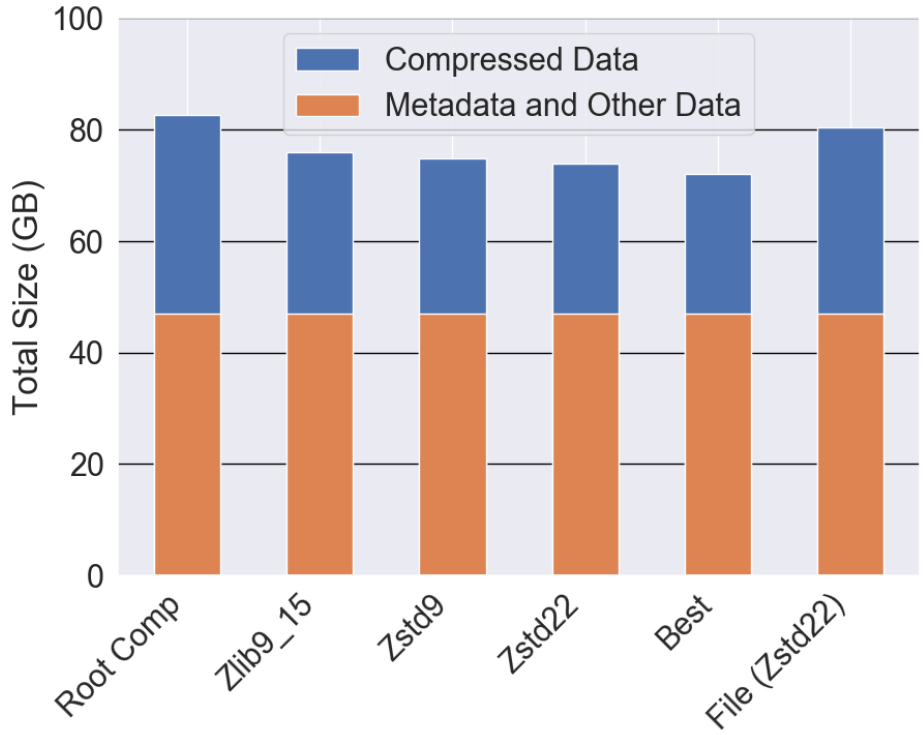


ATLAS Data

## Conclusion

We reduce data storage usage by up to 10% with `zstd`, level=9 and 15% with `zstd`, level=22.

# Compression at Production Scale

# Insight: Decompression >> Compression

- Common data use case is Filtering $\rightarrow$ Selection $\rightarrow$ Visualization
- HEP data access is mainly $> 95\%$ **reads**.
- Data can be compressed offline, but **must** be decompressed immediately when needed for analysis.

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## Key Insight

As long as decompression is done quickly, slower compression is not a barrier to analysis performance.

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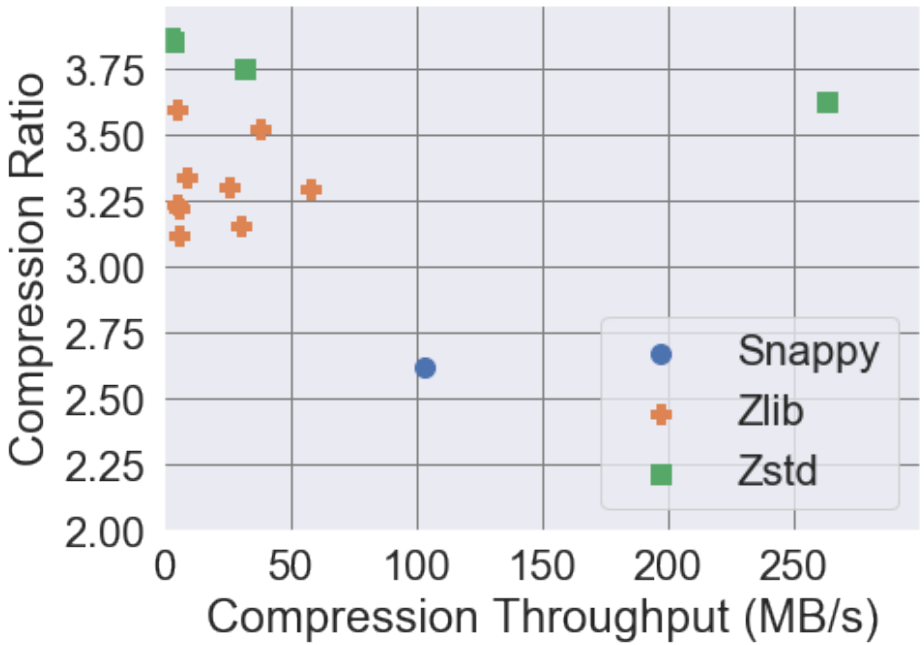
## Scaling Up to Production

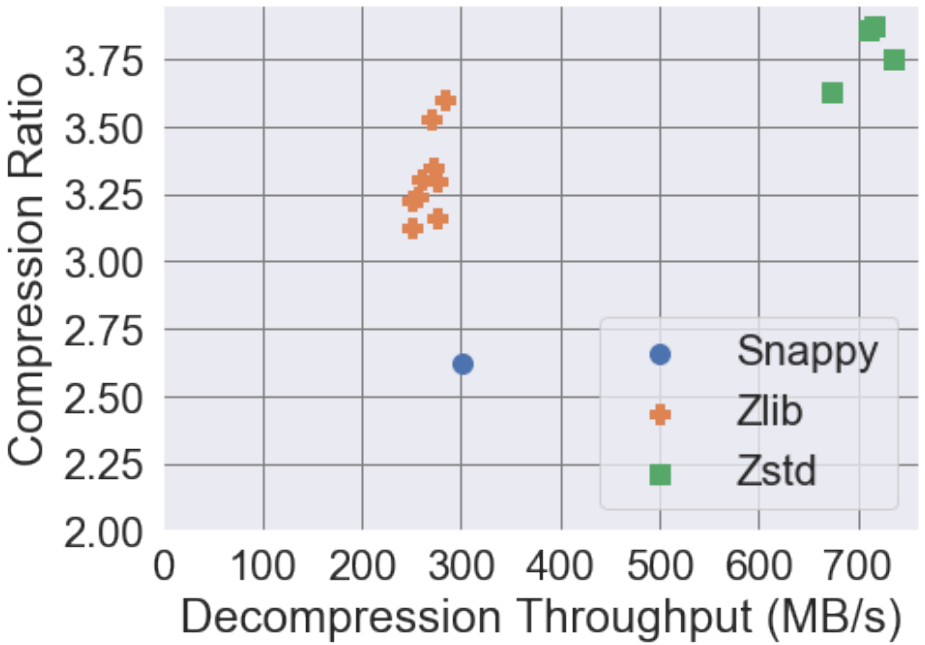
Design compression strategies to reduce data storage requirements, while delivering good read performance.

# Metrics

- **Compression Throughput**: $\frac{\text{Uncompressed Size}}{\text{Time to Compress}}$, shows single core throughput.
- **Core-Hour**: The amount of work done in one hour by a single core on the evaluation system (2.8 GHz Intel Xeon).

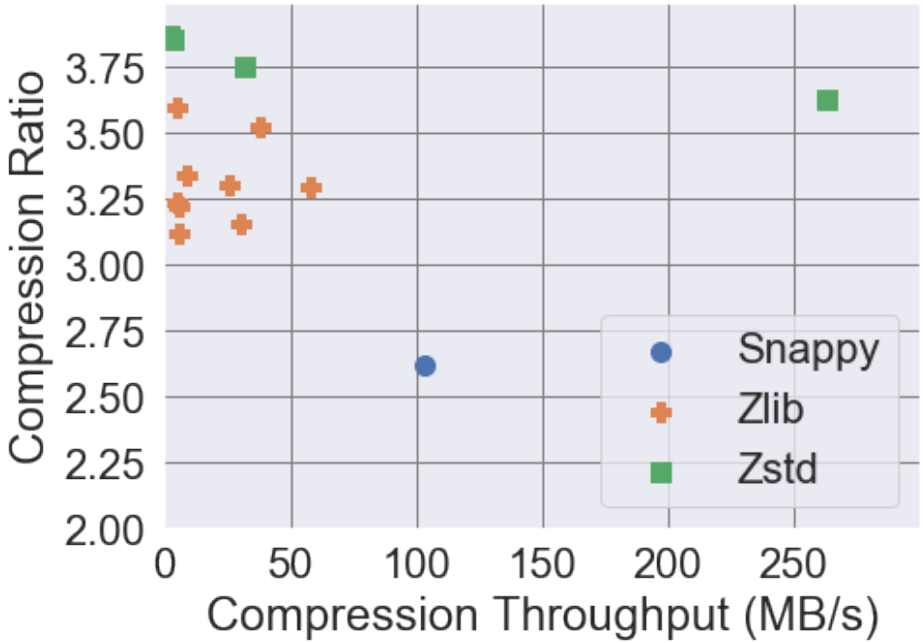
# Compression and Decompression Throughput

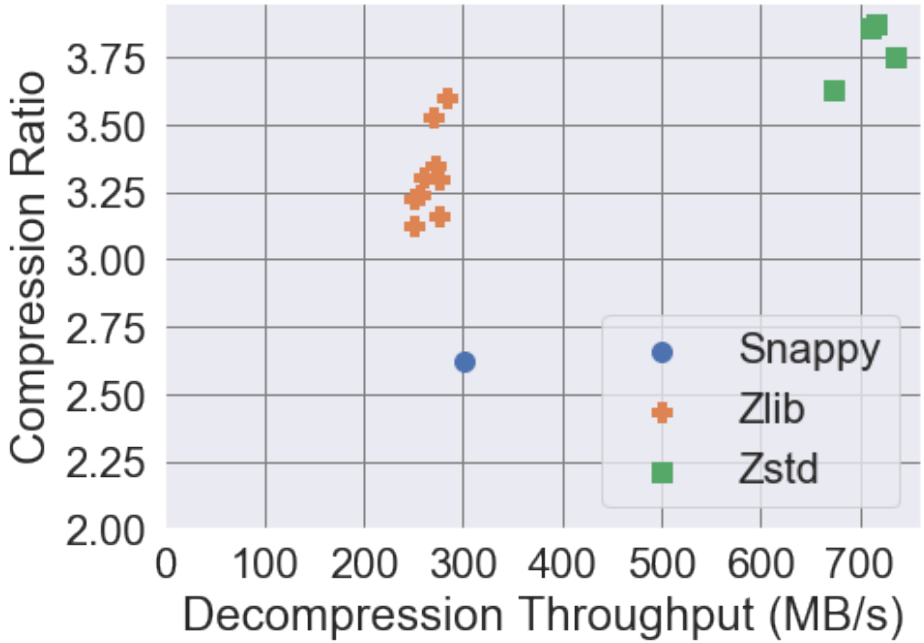



Each dot represents a different configuration for each algorithm.

# Compression and Decompression Throughput




Each dot represents a different configuration for each algorithm.

## Conclusion

Decompression performance is constant regardless of compression settings.

# 2 Selected Strategies

ROOT Configuration Changes

Extracted Branch-Level Storage

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## ROOT Configuration Changes

- Switch compression algorithms to `zstd`, level=9
- Add delta encoding and float splitting to ROOT library
- Minimal computational overhead

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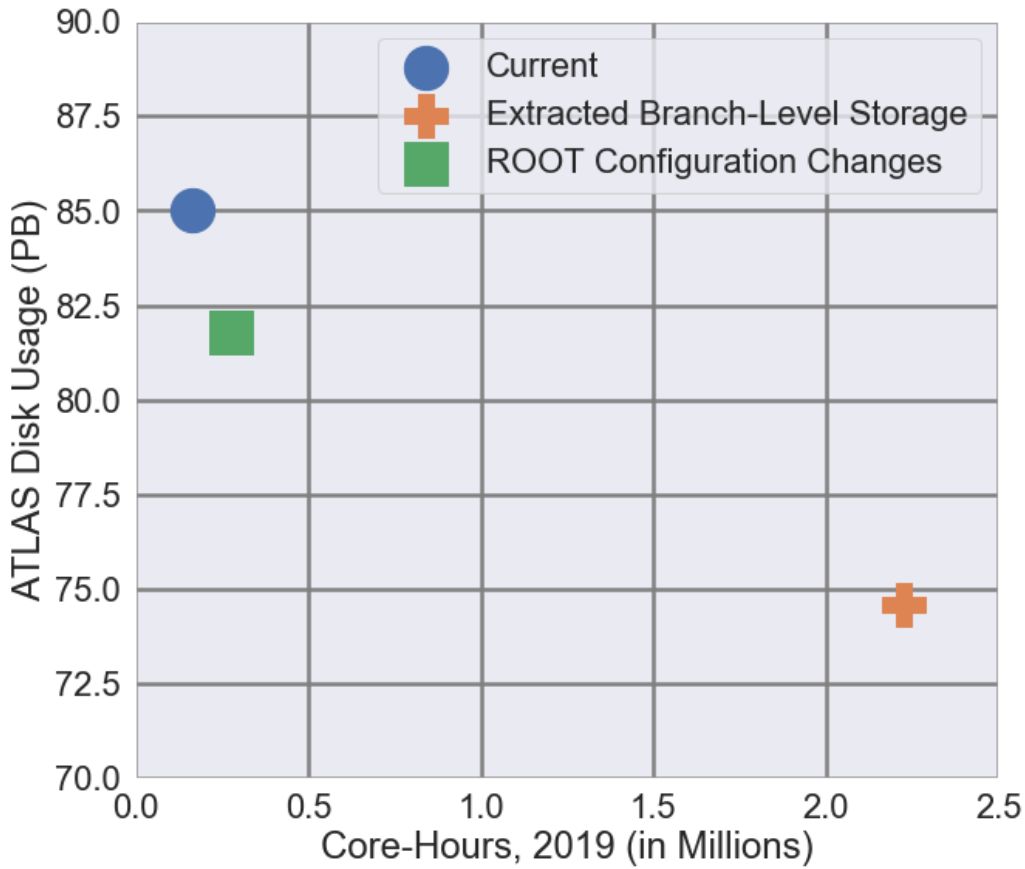
## Extracted Branch-Level Storage

- Compress and store in aggregate blocks
- Use `zstd`, level=22 and other techniques
- Need additional cores to handle reads and writes

# Saving Storage Space (2019)

- Save up to **12 PB** (15%)



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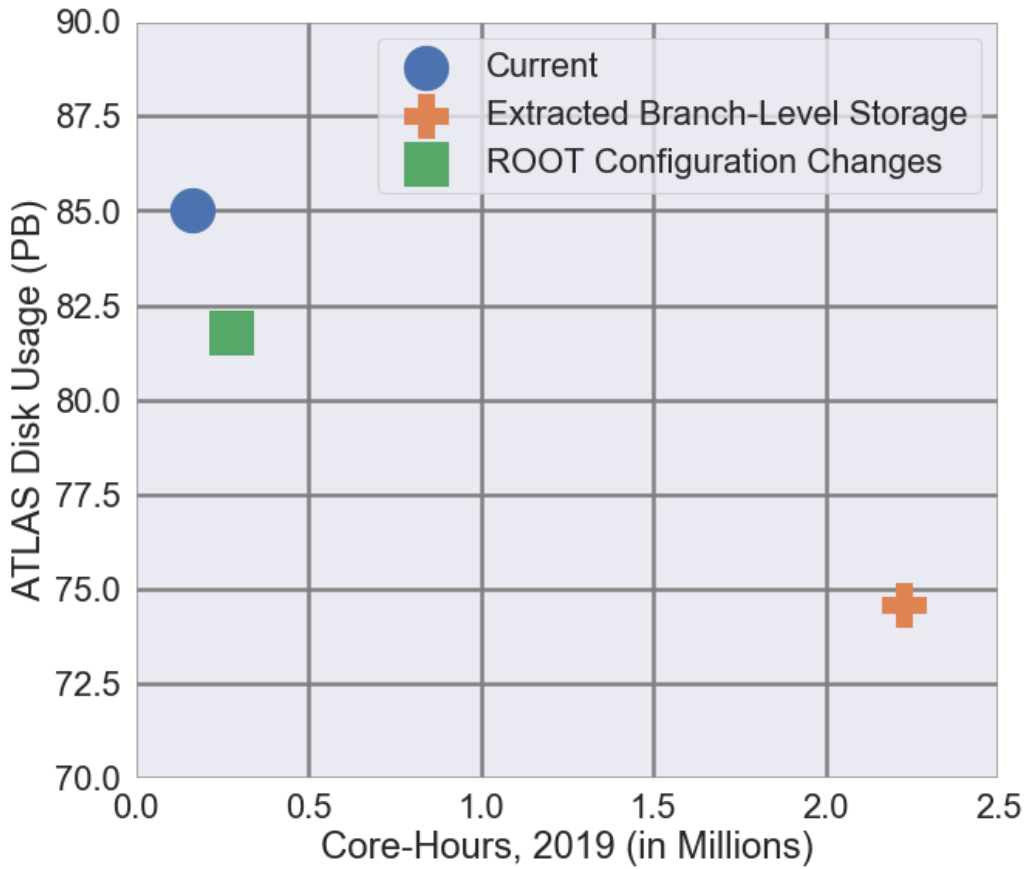

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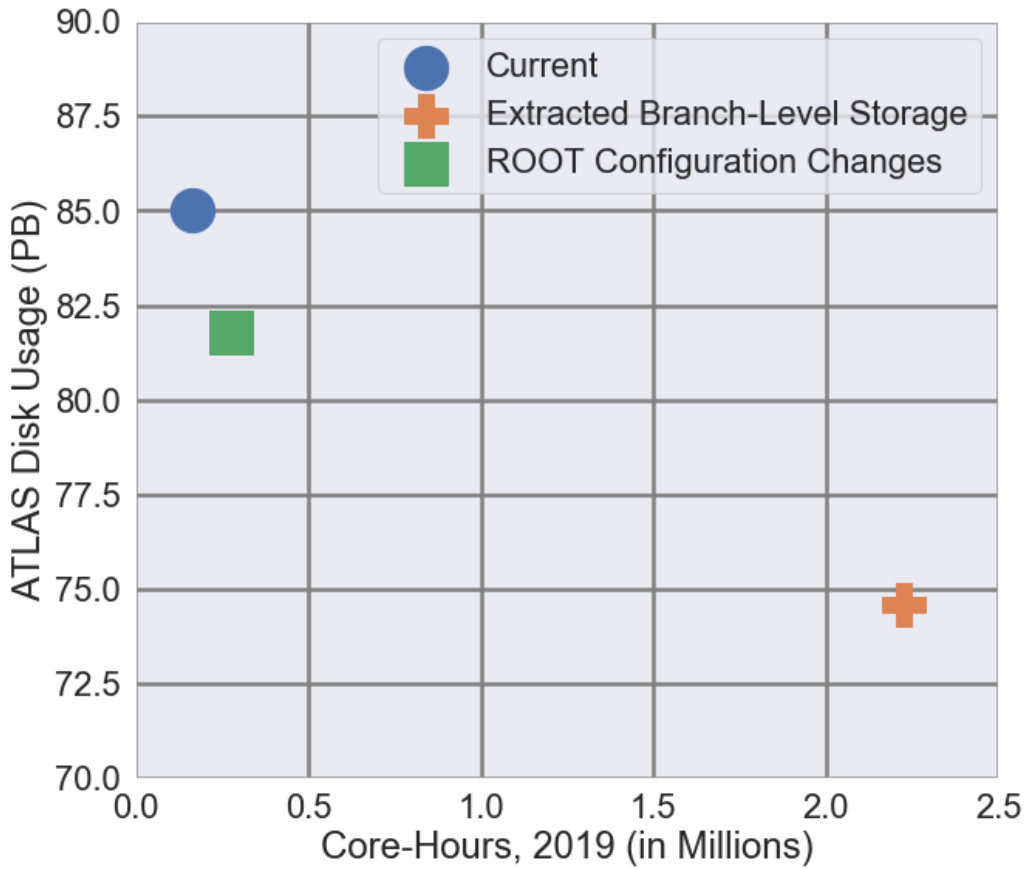
- Exchange storage size for computation
- Many future areas for exploration



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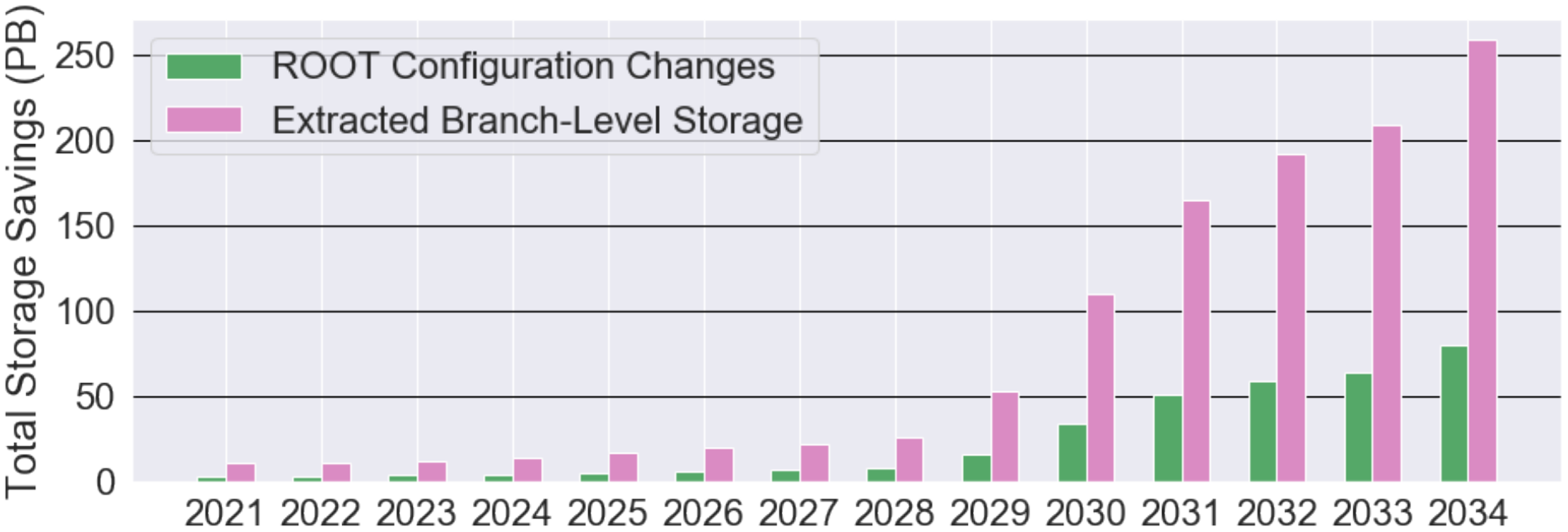


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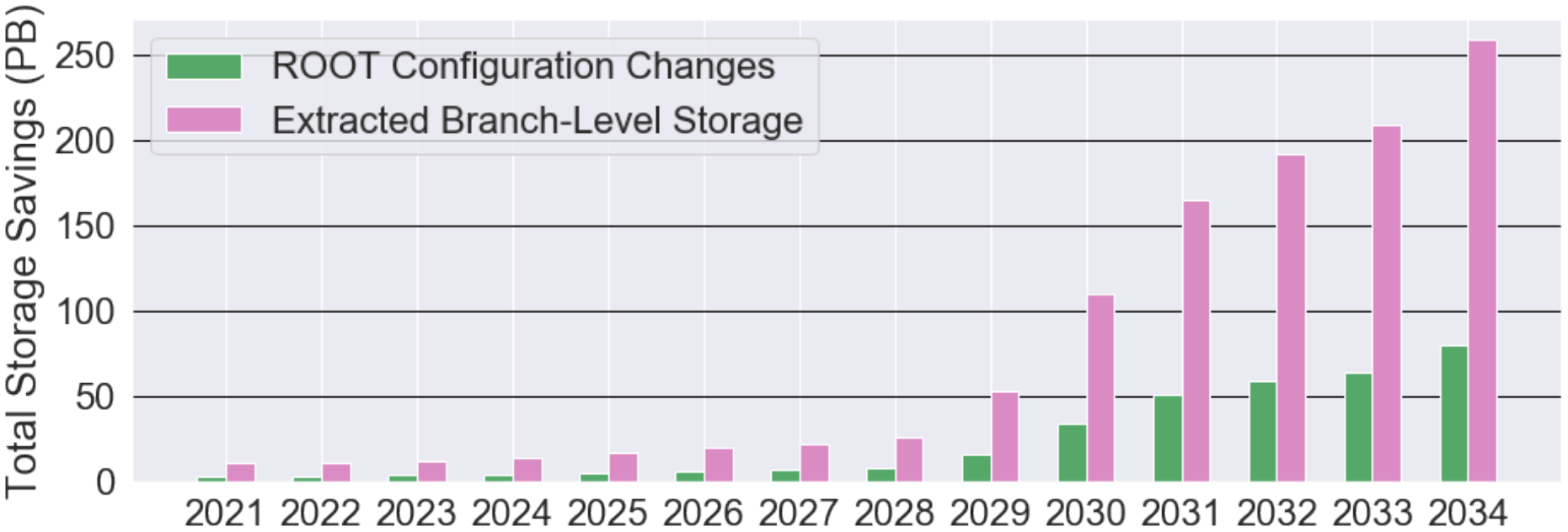


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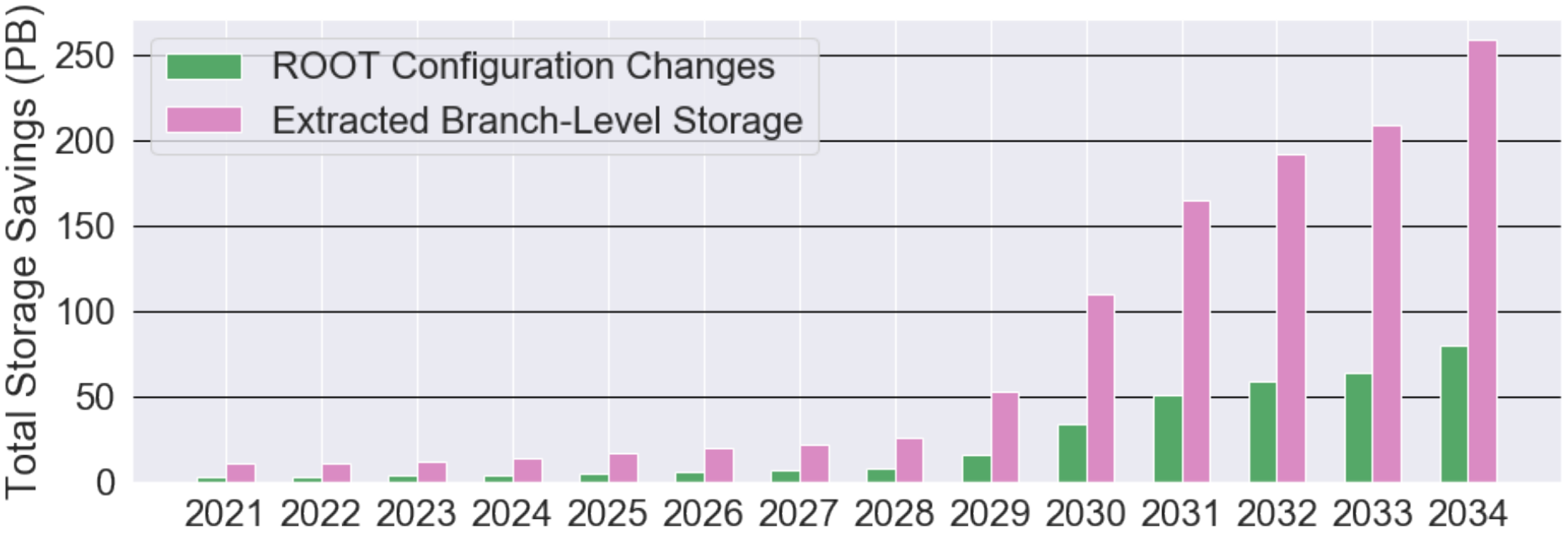


- Total savings of more than 250 PB of data in 2034
- Even with CPU costs, still represents savings of millions of dollars
- Better savings if analysis designed to work outside of ROOT

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3. Achieved data storage reduction of 15% on ATLAS DAOD (82 GB $\rightarrow$70 GB)
4. Modeled scale-up for ATLAS (Save $>$250 PB by 2035)

# Future Work

1. Can strategies like float splitting be generated automatically for any datatype/distribution?

2. Could data access patterns inform compression strategy choices?

3. Can storage acceleration be used to offload computational cost to accelerators?

# Acknowledgements

Prof. Andrew A. Chien

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Ilija Vukotic

Prof. Rob Gardner

Large-Scale Systems Group

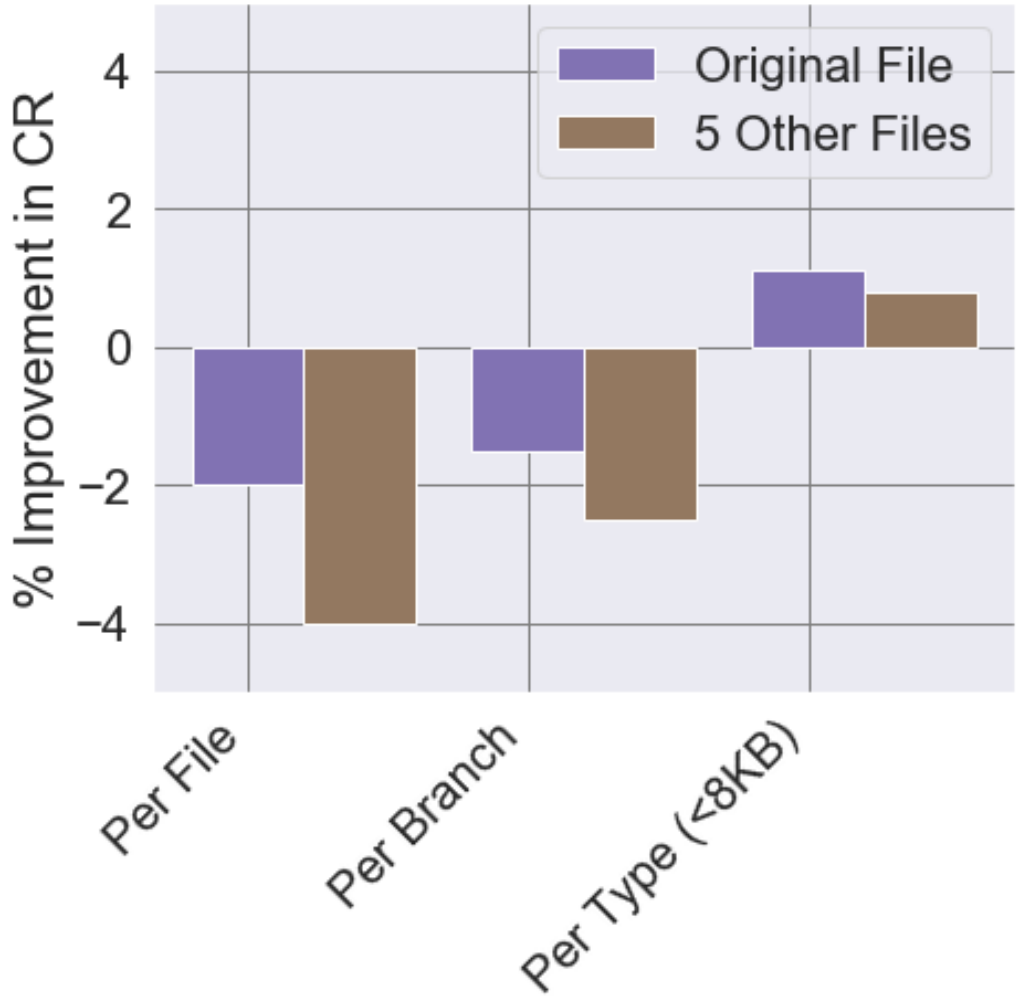
MANIAC Lab

# Questions?

# Backup Slides

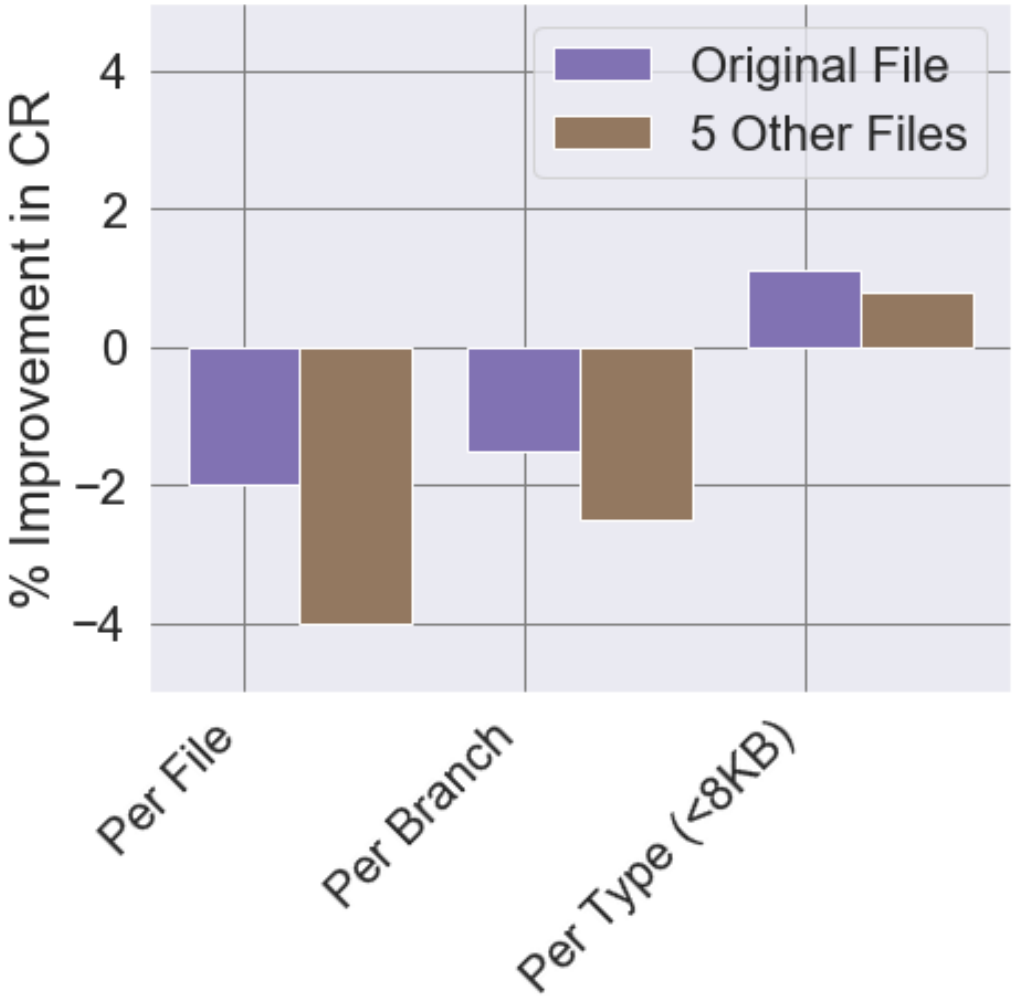
# Pretraining Dictionaries

- Train 1 dictionary per datatype with `zstd`

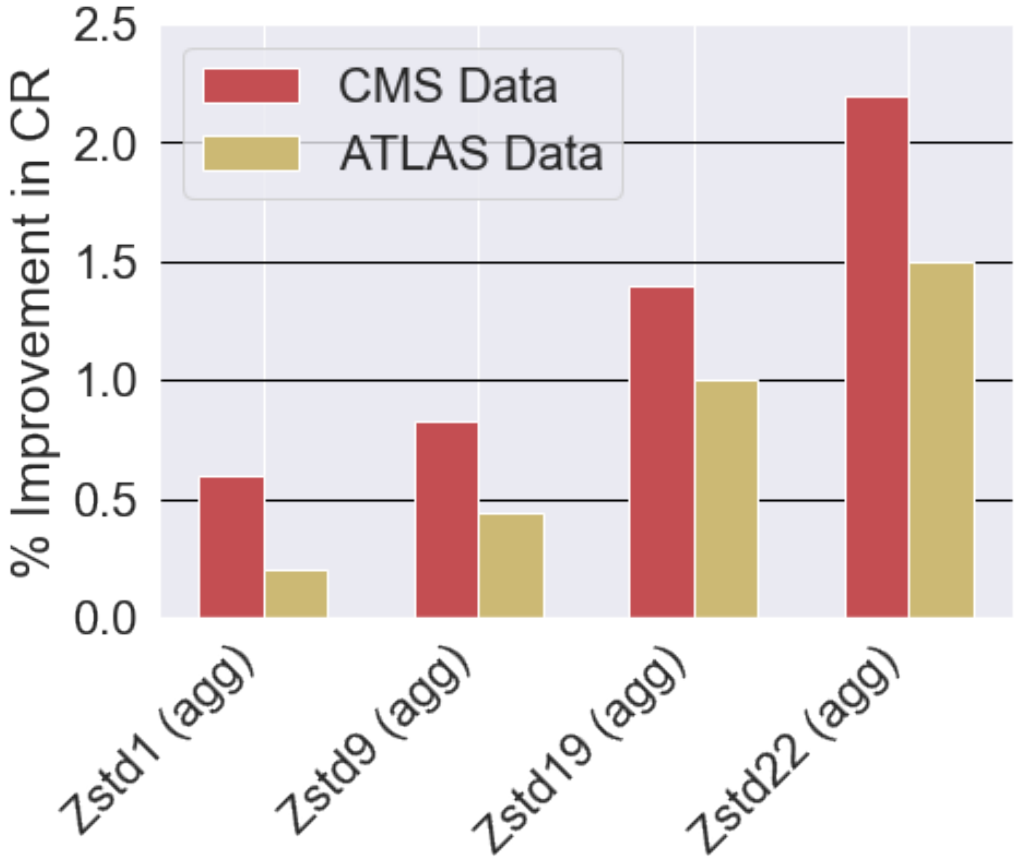


# Pretraining Dictionaries

- Train 1 dictionary per datatype with `zstd`
- Dictionary training does not universally improve compression ratio
- However, we realize a 1% improvement in CR when pretraining on small branches ($< 8$KB)



# Aggregate Strategies (Across Files)

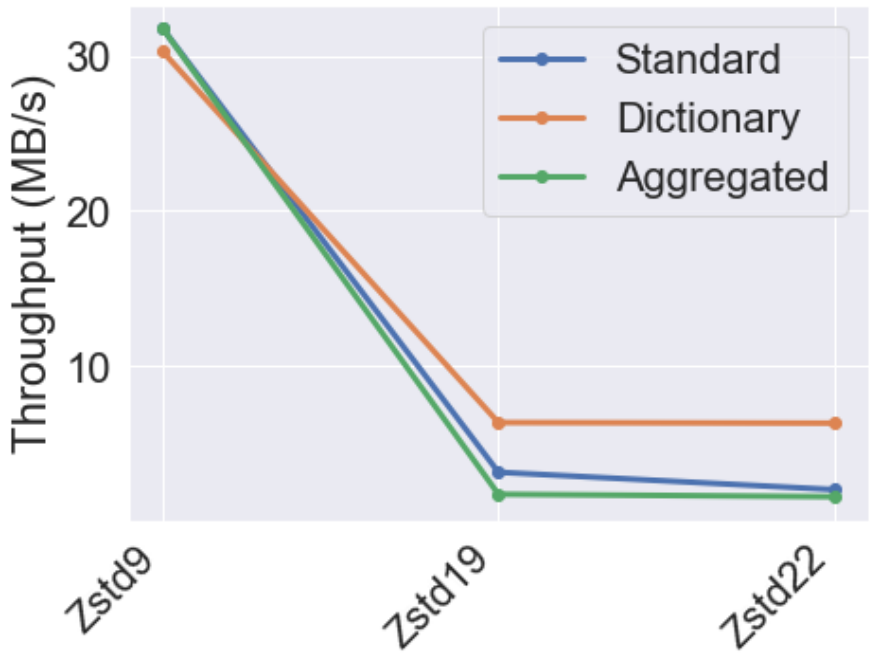



## Key Insight

Aggregating across files can improve compression ratio by up to 2%.

# Other Techniques Can Improve Throughput

- Pretraining improves compression throughput by **3x**



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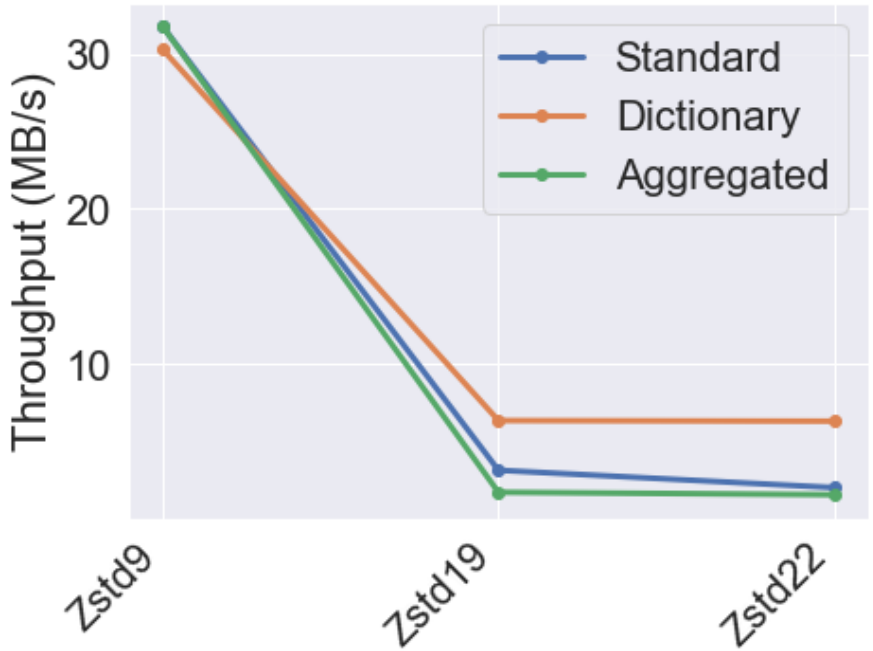

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- Pretraining improves compression throughput by **3x**
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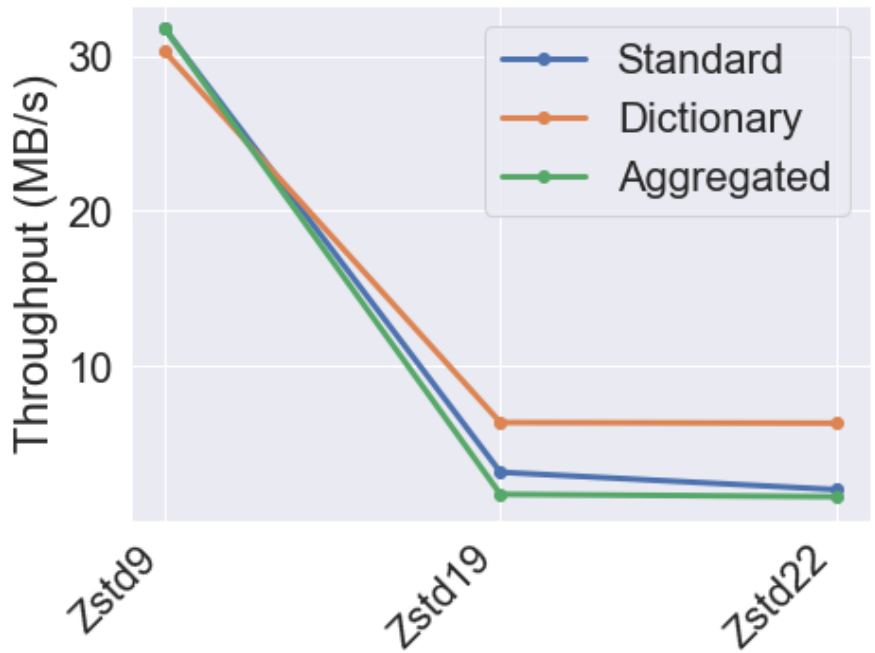
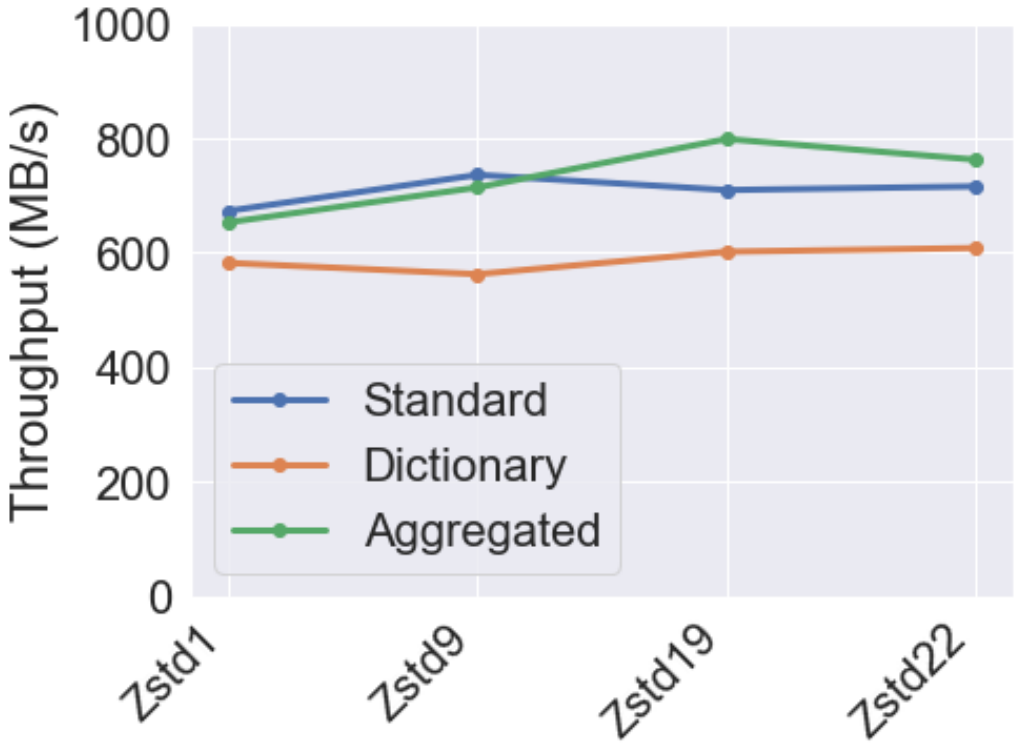
- Creating large baskets is not expensive (100 MB/s)



# Decompression Throughput for Zstd Variations




## Key Insight

`zstd` with aggregation and dictionary do not have a significant effect on decompression throughput, all still >575 MB/s.