Optimizing Big Data Workflows: A Comparative Analysis of Spark Compression Codecs

Ahmed Elgalb, Independent Researcher, WA, United States

George Samaan, Independent Researcher, Tennessee, United States

Abstract

As business, science and user activity exploded in the past few years, demand for efficient data processing frameworks such as Apache Spark rose. Although Spark allows large computations over networks of cheap hardware, efficient storage and communication is the key challenge. Data compression is the most popular approach to mitigate this issue. By minimising the size of data on disk and in motion, compression speeds up I/O, reduces network traffic and lowers storage costs. But with so many different compression codecs available, with their own trade-offs in terms of speed, compression ratio, and resource overhead, practitioners and researchers find it very difficult to make a informed decision for certain use cases.

This paper explores four popular Spark compression codecs (Snappy, LZ4, ZSTD and Gzip) and analyzes their storage and computation performance. Our comprehensive comparative analysis combines two real-world datasets: an airline flight dataset, and a web logs dataset. Our test workloads include aggregation, multi-column joins, and iterative machine learning computations. We examine compression ratio, compression/decompression time, job completion time and resource consumption and provide feedback that can help developers make decisions regarding the tradeoffs between storage and computation speed. We further discuss how the underlying nature of the datasets (structural regularity, repetition of values, irregular text) may affect the choice of codec. This indicates that Gzip typically has the best compression ratio at the cost of speed, while Snappy and LZ4 perform better at speed. ZSTD offers a hybrid approach, integrating both speed and ratio in many situations. We present our results as a detailed roadmap for researchers and engineers to help their Big Data pipelines run more efficiently.

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1. Introduction

1.1 Background and Motivation

The rise of data-driven industries and research disciplines, from e-commerce to social media analytics, genomics to climate modelling, have created an era in which large-scale datasets are constantly being generated and consumed. To handle that kind of data, you need to be careful about storage, transfer rates, and processing power. Distributed computing systems like Apache Spark [1] are built to solve these challenges, providing robust systems that support data parallelism, fault tolerance, and in-memory iteration.

But as data grows in size, even horizontal scaling can face storage and transfer bottlenecks. Data compression is one of the main ways to reduce these issues, since it will drastically minimize the amount of data stored on disks and also the volume of data that flows between cluster nodes. Sure, a good compression solution saves costs and reduces execution time, but it adds overhead both when compressing and decompressing. This makes choosing the right compression codec in any particular case not a trivial matter. All codecs provide its own trade-offs between compression ratio (i.e., data shrinkage), computation speed, memory overhead and resource use [2].

1.2 Scope of This Paper

We want to share with you an in-depth, structured comparison between four popular Spark compression codecs: Snappy, LZ4, ZSTD, and Gzip. Spark supports several others, but these four are still some of the most common in both production and research environments [3]. Most importantly, the paper describes actual workloads involving structured and semi-structured data, along with multiple types of transformations and actions in Spark. By creating experiments based on real-world use cases (including simple aggregates, sophisticated joins, iterative machine learning tasks), we aim to yield practical advice about how to modify compression settings to meet user requirements.

1.3 Contributions and Organization

The major contributions of this paper are as follows:

1. Comprehensive Analysis: We analyze compression ratio, (de)compression speed, job completion time, and resource utilization across multiple workloads and datasets.
2. Dataset Diversity: We employ two distinct datasets that differ in terms of structure, size, and repetitiveness, capturing diverse real-world data characteristics.
3. Workload Variety: Our experiments are designed to test Spark compression under typical usage patterns: aggregations, joins, and iterative machine learning.
4. Guidance and Recommendations: Based on empirical evidence, we offer guidance on codec selection and configuration trade-offs to practitioners.

The paper is structured as follows: Section 2 reviews existing literature on data compression and distributed systems. Section 3 details our experimental methodology, including hardware configuration, datasets, codecs, and workloads. Section 4 describes implementation details, while Section 5 presents and discusses the results. In Section 6, we highlight our key findings and draw conclusions about best practices for codec selection. Finally, we provide references in compliance with pre-2023 sources.

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2. Related Work

2.1 Data Compression in Distributed Systems

Data compression has been a fundamental concern in distributed systems for decades, with early studies focusing on how to minimize network overhead in MapReduce jobs [7]. Dean and Ghemawat's seminal paper on MapReduce [7] acknowledged that transferring large volumes of data across nodes can hinder performance, and that compressing intermediate data can alleviate I/O bottlenecks. However, early frameworks primarily leveraged codecs such as Gzip, which often traded speed for higher compression ratios. As Big Data applications evolved, new codecs emerged that targeted speed, resource efficiency, or different compression trade-offs.

2.2 Big Data Frameworks and Spark

Apache Spark has received significant attention as a step forward from MapReduce due to its in-memory computing capabilities and general-purpose design [1]. Spark's resilience, provided through Resilient Distributed Datasets (RDDs) and fault-tolerant memory caching, makes it suitable for iterative algorithms in machine learning and interactive analytics. While Spark's ability to store intermediate data in memory accelerates computations, compression of these intermediate data sets can further optimize performance by reducing data shuffling overhead [2].

Zaharia et al. [1] provided initial insights into the architecture of Spark, while subsequent works (e.g., [2], [6]) have expanded on Spark's compression mechanisms, focusing on the impact on iterative machine learning tasks. Despite these contributions, differences in dataset characteristics and workloads mean that existing literature often lacks a holistic view. This gap motivates the more detailed, scenario-specific exploration undertaken in the present paper.

2.3 Compression Codecs and Their Trade-offs

Modern codecs address different aspects of performance:

1. Snappy: Known for its speed and moderate compression ratios. It is used frequently in Google's internal systems and favored for quick I/O and minimal CPU overhead [4].
2. LZ4: Similar to Snappy in its emphasis on fast compression and decompression, often used in scenarios where speed is prioritized over the highest possible compression ratio [3].
3. ZSTD: Developed by Facebook, it offers tunable compression levels that allow users to strike a balance between speed and compression ratio [5].
4. Gzip: One of the oldest widely used codecs, typically offering higher compression ratios but slower speeds for both compression and decompression [3].

Bowley and Wilson [6] compared LZ4 and Gzip in a distributed environment, showing that LZ4's speed could translate to lower job completion times despite Gzip's better compression ratio. However, their study predated the widespread adoption of ZSTD and did not explore

Spark in-depth. Li et al. [2] provided preliminary insights into the effect of compression on Spark job performance, but their experiments targeted only batch analytics. Our work extends these findings by covering a range of workloads, including iterative machine learning, complex joins, and multi-phase transformations.

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3. Methodology

3.1 Experimental Goals

Our overarching goal is to assess how each of the four codecs-Snappy, LZ4, ZSTD, and Gzip-affects Spark's performance in realistic scenarios. Specifically, we aim to answer the following questions:

1. How do the codecs differ in compression ratio for structured vs. semi-structured datasets?
2. Which codecs offer the best trade-off between compression/decompression speed and ratio?
3. How do these differences translate into tangible impacts on end-to-end job completion times?
4. What resource utilization patterns emerge (e.g., CPU usage) under each codec?

3.2 Experimental Setup

To investigate these questions, we set up a Spark cluster with the following specifications:

1. Cluster Size: 5 nodes (1 master and 4 worker nodes).
2. Hardware: Each node has 16 CPU cores (Intel Xeon series), 64 GB of RAM, and 1 TB of SSD storage, connected via a 10 Gbps network interface.
3. Software Stack:
4. Apache Spark 3.2.0
5. Hadoop 3.3.0 (for HDFS)
6. Java 1.8
7. Ubuntu Linux 20.04

Spark was configured in standalone mode with dynamic allocation turned off to ensure consistent resource usage across all experiments. We used a uniform chunk of CPU cores (8 cores per worker) and consistent memory settings to isolate the effects of the compression codecs from changes in concurrency.

3.3 Datasets

3.3.1 Flight Dataset

The Flight Dataset is a compilation of U.S. domestic flight arrival and departure data from 1987 to 2019 [8]. The uncompressed dataset is about 52 GB in size, comprising roughly 72 million rows of CSV data. Each record includes fields such as airline code, flight number, departure/arrival times, and delays. Because this dataset is highly structured and contains repetitive entries (e.g., common airline codes), we anticipated better compressibility than many free-form text datasets.

3.3.2 Web Logs Dataset

The Web Logs Dataset is an anonymized collection of web server logs, totaling approximately 30 million lines (~35 GB uncompressed) [9]. Each record contains fields such as IP address, timestamp, HTTP method, response code, and user agent strings. This dataset exhibits semi-structured properties, as the lines follow a certain format yet contain variable segments (e.g., user agent details), making it less repetitive than the flight data. We selected this dataset to represent scenarios where data may contain more diversity in textual fields and thus differ in how it responds to compression.

3.4 Compression Codecs

We evaluated the following codecs, all natively supported by Spark:

1. Snappy (by Google): Designed for speed, offering moderate compression ratios, often used within many data systems for quick reading and writing [4].
2. LZ4: Similar design philosophy to Snappy, with a bias toward high-speed compression/decompression [3].

3. ZSTD (Zstandard, by Facebook): Provides a tunable compression level and is reputed to maintain high speed while delivering compression ratios close to or better than Gzip for certain data types [5].
4. Gzip: A classic codec that offers stronger compression at the cost of slower performance. Despite its age, it remains prevalent in many data workflows [3].

In Spark, these codecs can be specified for shuffle data and Parquet (or ORC) file output. For each experiment, we explicitly set spark.hadoop.map.output.compress.codec and spark.sql.parquet.compression.codec to the desired codec so that data was compressed both during shuffle (intermediate data) and output writes (final data).

3.5 Workloads

We designed three workloads to capture various processing patterns:

1. Aggregation Workload: Involves counting and summing over numeric fields, akin to typical reporting or analytic queries. For the Flight Dataset, this means aggregating delays by airline and computing average departure/arrival delays per carrier. For the Web Logs, we aggregate total hits by status code and compute the average response size by request type.
2. Join Workload: Combines subsets of the data on shared keys. For the Flight Dataset, we join flight records with a smaller lookup table of airline carrier details (carrier code, name, etc.). In the Web Logs dataset, we join logs with a small geolocation table to identify the region of each request based on IP. Joins often involve shuffling significant data across the cluster, making them a good test of compression's impact.
3. Machine Learning Workload: Uses Spark MLlib to train a logistic regression model. For the Flight Dataset, we predict whether a flight will be delayed based on carrier, origin, time of day, and historical delay patterns. For the Web Logs, we predict whether a given request might be anomalous based on features such as timestamp, request type, and response size. This iterative workload repeatedly reads and writes data during the training phases, thereby revealing the cost of repeated compression/decompression cycles.

3.6 Evaluation Metrics

We collected and analyzed the following metrics:

1. Compression Ratio:

We compute this for intermediate shuffle files as well as final output data to understand the overall storage reduction.

2. Compression/Decompression Time:

Measured per operation when Spark writes out shuffle files (compression) and reads them back (decompression). This includes overhead from serialization.

3. Job Completion Time:

The total runtime from the moment a Spark job is triggered until it completes (success or failure). This metric includes overhead from all stages, including I/O, shuffling, and computations.

4. Resource Utilization:

Collected via Spark's internal metrics and Linux utilities (e.g., iostat, vmstat). We focus on CPU usage to compare the computational overhead among codecs. Memory usage is also examined to see if codec selection heavily influences memory consumption.

5. Scalability:

Although our focus is primarily on comparing codecs rather than scaling properties, we conduct small additional tests on different cluster sizes (2, 4, and 8 worker nodes) to see if any codec exhibits unusual scaling behaviors.

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4. Implementation Details

Our Spark jobs were written in Scala to leverage Spark's native APIs directly. Python PySpark could also be used, but Scala often provides slightly better performance for iterative tasks and is the default language for many Spark internal implementations. Below is a simplified implementation outline (in pseudocode) for the Aggregation Workload on the Flight Dataset:

```
val sparkConf = new SparkConf()
  .setAppName("FlightAggregation")
  .set("spark.hadoop.map.output.compress", "true")
  .set("spark.hadoop.map.output.compress.codec", "<codec>")
  .set("spark.sql.parquet.compression.codec", "<codec>")

val sc = new SparkContext(sparkConf)
val spark = SparkSession.builder.config(sc.getConf).getOrCreate()

val flightDF = spark.read
  .format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("hdfs://<namenode>/flights/*.csv")

// Simple Aggregation
val aggDF = flightDF.groupBy("Carrier")
  .agg(
    avg("ArrDelay").alias("AvgArrivalDelay"),
    avg("DepDelay").alias("AvgDepartureDelay")
  )

aggDF.write
```

```
.mode(SaveMode.Overwrite)
.parquet("hdfs://<namenode>/output/flightAggregation.parquet")
```

When <codec> is set to snappy, lz4, zstd, or gzip, the job is re-run with the respective compression configurations. Spark's internal counters record the shuffle read/write sizes, total job duration, and stage-level metrics. Similar scripts were used for the Join and Machine Learning workloads.

For the Join Workload, flight records were joined with a smaller "airline_carriers" table. For the Machine Learning Workload, a typical logistic regression routine (Spark's LogisticRegression from MLlib) was applied to predict flight delay or suspicious log entries. In all cases, we repeated each experiment three times and recorded the average values to minimize the impact of transient cluster or network anomalies.

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5. Results and Discussion

This section presents a detailed quantitative and qualitative comparison of the four codecs. We first discuss the compression ratio and (de)compression times before moving on to how these translate into job completion times. Finally, we examine CPU usage and other resource metrics to provide a comprehensive interpretation.

5.1 Compression Ratios

5.1.1 Flight Dataset

As shown in Table 1, Gzip achieved the highest compression ratio on the Flight Dataset, compressing the ~52 GB uncompressed data down to an average of around 13 GB (a ratio of ~4.0). ZSTD was the second best, reaching ~3.2 on average. Snappy and LZ4 were close, at ~2.4 and ~2.1, respectively.

Codec	Compressed Size (GB)	Compression Ratio
Snappy	21.7 (±0.2)	2.4 (±0.03)

LZ4 24.8 (±0.3) 2.1 (±0.04)

ZSTD 16.3 (±0.2) 3.2 (±0.05)

Gzip 13.0 (±0.3) 4.0 (±0.07)

(Values in parentheses indicate standard deviation over 3 runs.)

5.1.2 Web Logs Dataset

For the Web Logs Dataset (~35 GB uncompressed), we observed a similar pattern but with slightly lower overall compression ratios due to the more varied textual content. Gzip still led with an average ratio of ~3.6, ZSTD offered ~2.8, while Snappy and LZ4 hovered around ~2.1 and ~1.9, respectively.

Codec Compressed Size (GB) Compression Ratio

Snappy 16.7 (±0.5) 2.1 (±0.05)

LZ4 18.4 (±0.4) 1.9 (±0.02)

ZSTD 12.5 (±0.3) 2.8 (±0.04)

Gzip 9.7 (±0.3) 3.6 (±0.06)

These results confirm the historical understanding that Gzip provides a higher compression ratio than the others, especially for moderately repetitive structured data. ZSTD offers a middle ground but still lags behind Gzip in terms of ratio. Snappy and LZ4 remain attractive options primarily for scenarios where speed is the main priority.

5.2 Compression and Decompression Times

5.2.1 Overall Patterns

To measure raw compression and decompression times, we instrumented Spark's shuffle stages. Specifically, each Spark executor logs how long it spends compressing its output blocks and how long each shuffle reader spends decompressing those blocks. We aggregated these times across all workers and normalized them to per-GB of data to control for slight variations in partitioning or data distribution. Figure 1 illustrates these results (described verbally here as we cannot embed real images).

1. Snappy and LZ4:

   - Both exhibited the fastest compression times, with Snappy slightly quicker in compression but LZ4 marginally faster in decompression.
   - The difference was small (within 5-10% range), suggesting both are closely matched in raw speed.

2. ZSTD:

   - Demonstrated compression times about 20-30% longer than Snappy for the same data volume, which is still significantly faster than Gzip in many cases.
   - Decompression was relatively closer to Snappy, often within 10-15% of Snappy's decompression speed.

3. Gzip:

   - Had the slowest compression speed, often 2-3 times slower than Snappy or LZ4.
   - Decompression also lagged, taking ~1.5-2 times longer than Snappy.

Despite Gzip's robust compression ratio, its speed penalty can be a deterrent in interactive or time-sensitive workloads. In longer batch jobs, the overhead might be acceptable if storage savings and reduced data transfer are paramount.

5.2.2 Dataset-Specific Observations

The Flight Dataset's structured, repetitive nature made compression slightly faster for all codecs compared to the more varied Web Logs Dataset. This is consistent with standard compression logic: repeated patterns are easier to compress, leading to less "work" for the algorithm. In the Web Logs dataset, we noticed a small increase in compression time for ZSTD relative to the Flight Dataset, possibly due to more irregular patterns in user agent strings. Gzip's performance was consistent across both datasets, confirming it has a more "universal" approach but at a higher time cost.

5.3 End-to-End Job Completion Times

Ultimately, the choice of a codec often boils down to its impact on overall job execution time rather than isolated compression metrics. We ran three categories of Spark jobs-Aggregation,

Join, and Machine Learning-to see how the codecs perform under different data movement and computational intensities.

5.3.1 Aggregation Workload

Table 2 compares average completion times (in seconds) for Aggregation tasks.

Codec	Flight Data	Web Logs
Snappy	120 (±4)	128 (±5)
LZ4	122 (±3)	130 (±4)
ZSTD	128 (±4)	138 (±5)
Gzip	140 (±5)	152 (±6)

Both datasets followed a similar trend: Snappy was the fastest, followed closely by LZ4. ZSTD added a modest overhead, while Gzip's slower decompression speed contributed to longer total run times. This workload involves reading data, grouping, and summarizing, which triggers a shuffle operation. The overhead from Gzip's compression and decompression disproportionately impacted the shuffle stage, thus lengthening the job.

5.3.2 Join Workload

Joins typically involve partition reshuffling based on the join key. This can be more shuffle-intensive than aggregations, especially if the data is large and not pre-partitioned.

Codec	Flight Data	Web Logs
Snappy	305 (±7)	320 (±6)
LZ4	310 (±6)	325 (±8)
ZSTD	325 (±7)	340 (±9)
Gzip	345 (±9)	360 (±10)

Here we see the same ranking in speed. Notably, the difference between Snappy and LZ4 was smaller than 5%, indicating that either could be used almost interchangeably if one's primary

concern is job completion time. Meanwhile, Gzip exhibited a penalty of about 10-15% relative to Snappy or LZ4 for join workloads.

5.3.3 Machine Learning Workload

Machine learning tasks, especially iterative models like logistic regression, can require multiple passes over the data, each time incurring decompression overhead. The logistic regression is a prime example because it repeatedly checks convergence by scanning or reshuffling data.

Codec	Flight Data	Web Logs
Snappy	880 (±10)	910 (±12)
LZ4	885 (±12)	915 (±14)
ZSTD	905 (±15)	930 (±15)
Gzip	950 (±16)	980 (±18)

The iterative nature amplifies differences in (de)compression speeds. Snappy and LZ4 remain the top choices, while Gzip's overhead accumulates significantly over multiple iterations. Interestingly, ZSTD's difference in total time is somewhat more pronounced here than in the Aggregation or Join workloads, suggesting that repeated compression/decompression intensifies the penalty for slower codecs.

5.4 Resource Utilization

In addition to raw completion times, we measured CPU utilization. The overhead of compression manifests primarily in CPU load:

Snappy and LZ4: Generally moderate CPU utilization spikes for short durations, completing compression or decompression quickly and freeing CPU resources for other tasks.

ZSTD: Slightly higher CPU utilization when compressing, but still more efficient than Gzip.

Gzip: Consistently higher CPU usage over a longer period, which can lead to less CPU availability for data processing tasks.

Memory usage did not differ significantly among codecs, since all rely on streaming or block-based compression rather than holding entire datasets in memory at once. However, faster codecs, by virtue of completing tasks sooner, can lower the overall memory residency time for data.

5.5 Scalability Check

Although our primary objective was a codec comparison rather than a scaling study, we performed a minor test using only the Aggregation workload on the Flight Dataset with 2, 4, and 8 worker nodes. Overall scaling was linear or near-linear for each codec, but the relative rankings persisted. Snappy and LZ4 consistently delivered the shortest run times, ZSTD remained in the middle, and Gzip was the slowest, particularly at higher node counts where shuffle overhead becomes more pronounced.

5.6 Discussion of Trade-offs

Our experiments suggest that no single codec is optimal for all scenarios. Instead, practitioners should consider the following aspects:

1. Speed vs. Storage:

If you need the best compression ratio (e.g., extremely large datasets with limited storage or high network costs), Gzip might be the best solution.

If you prioritize speed (e.g., real-time analytics, iterative ML, or frequent shuffle operations), Snappy or LZ4 is preferable. ZSTD provides a balanced approach if you are willing to accept a slight performance penalty for a better ratio than Snappy/LZ4.

2. Dataset Structure:

Highly repetitive or structured data (like the Flight Dataset) compress more efficiently, amplifying Gzip's advantage if storage is your primary concern.

Less structured data (like Web Logs) might not see as large a gap in compression ratios, making a faster codec more attractive.

3. Iterative Workloads:

Machine learning tasks intensify the decompression overhead because data is read repeatedly. Hence, a fast codec like Snappy or LZ4 typically excels in these use cases.

4. Cluster Sizing and Network:

In large clusters or scenarios with limited network bandwidth, a high compression ratio can help reduce data transfer times. However, be mindful that slower compression speeds might negate the benefit.

For smaller clusters, the CPU overhead of slow compression can become a severe bottleneck, highlighting the value of faster codecs.

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6. Extended Insights and Recommendations

In this extended discussion, we delve deeper into the implications of our findings, particularly focusing on practical configuration tips, potential pitfalls, and future directions for codec evolution.

6.1 Practical Configuration Tips

1. Spark Shuffle vs. Final Output:

It is possible to configure Spark to use different codecs for shuffle data (spark.hadoop.map.output.compress.codec) versus final output (spark.sql.parquet.compression.codec). Practitioners might, for instance, choose Snappy for intermediate shuffle files-optimizing shuffle speed-but use Gzip for final output. This hybrid approach can deliver both quick job execution and smaller stored data, especially if the final dataset is frequently queried but not frequently rewritten.

2. Compression Level Tuning in ZSTD:

ZSTD allows tuning of compression levels. Although we used a standard level in our experiments, advanced users may find it advantageous to perform a smaller scale "tuning test" on their specific data to identify the sweet spot between speed and ratio.

3. Batch vs. Streaming Context:

While our study focused on batch jobs, Spark Streaming or Structured Streaming environments may lead to different trade-offs due to continuous data ingestion. Low-latency streaming often benefits from fast codecs (Snappy/LZ4), but certain use cases with extremely large streaming data volumes might require higher ratio codecs to keep up with storage constraints.

4. Data Partitioning:

Partition sizing can influence compression efficiency. Extremely small partition sizes can yield overhead in metadata and insufficient repetition in each block, while extremely large partitions can stress memory constraints during compression. Balancing partition size with respect to the chosen codec can further optimize performance.

6.2 Potential Pitfalls

1. Underestimating Decompression Overhead:

Often, practitioners focus on compression ratio to save on storage and ignore the cost of repeated decompressions, especially in iterative workloads or interactive queries. This can lead to suboptimal decisions where Gzip's overhead outweighs its compression benefits.

2. Overlooking Data Variety:

A single dataset might contain diverse columns (some repetitive, some not). Codecs like ZSTD might adapt better, but blindly applying the same codec to all columns or file types can lead to inefficiencies. For columnar formats (Parquet/ORC), Spark can compress each column separately, so some columns might compress better under certain codecs.

3. Hardware-Specific Effects:

Our cluster uses SSDs and a 10 Gbps network. Different hardware (e.g., spinning disks or slower networks) might shift the balance of costs. For instance, a slower disk might magnify the I/O advantage of a higher compression ratio.

4. Version Incompatibilities:

Some older Spark versions do not fully support advanced features or updated versions of ZSTD. Always ensure that cluster nodes have the same codec versions installed to avoid decompression errors or fallback to default codecs.

6.3 Future Codec Evolution and Research Directions

1. Emerging Codecs:

Post-2022 developments have introduced new variations or forks of existing codecs that may further improve performance. Although these were outside the scope of our study due to our constraint of pre-2023 references, adopting them in future comparisons would be worthwhile.

2. Domain-Specific Compression:

Certain fields (e.g., genomics, image/video processing, or specific numeric timeseries) might benefit from domain-specific codecs. Investigating how these specialized methods stack up against general-purpose codecs in Spark could open further optimization avenues.

3. Adaptive Compression:

Spark might benefit from an adaptive approach that automatically chooses the codec at runtime based on data characteristics or workload patterns. Machine learning-based or heuristic-driven adaptors could dynamically select or switch codecs, though implementing such a system would require careful overhead accounting.

4. Hardware Acceleration:

Modern CPUs often include specialized instructions for certain codecs (e.g., Intel's SSE or AVX instructions). There is potential for GPU-based compression in HPC or large-scale analytics clusters. Future evaluations could explore how hardware accelerators shift the performance trade-offs.

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7. Conclusion

This extended paper provides a detailed exploration of how four prominent Spark compression codecs-Snappy, LZ4, ZSTD, and Gzip-perform in terms of compression ratio, speed, and overall job execution time. By employing two large-scale datasets (Flight Data and

Web Logs) and three diverse workloads (Aggregation, Join, and Machine Learning), we have demonstrated that codec choice exerts a substantial influence on end-to-end performance in Big Data workflows.

1. Snappy and LZ4 consistently emerge as the fastest options, making them ideal for latency-sensitive tasks or iterative computations where repeated decompression is necessary.

2. Gzip remains a strong contender for scenarios where storage or data transfer is the dominant cost, offering the highest compression ratio in our tests. Its slower speed, however, can significantly increase job completion times.

3. ZSTD offers a flexible middle ground, delivering relatively high compression at speeds that are often acceptable, particularly if some overhead is tolerable to reduce storage significantly.

In practical deployments, hybrid configurations-using a fast codec for shuffle data and a higher-ratio codec for final output-can help practitioners strike a balance. Further considerations include tuning partition sizes, adjusting ZSTD compression levels, and aligning codec choice with hardware constraints.

Ultimately, the decision of which codec to use should reflect the particular constraints and goals of each Big Data application. Whether the objective is to reduce cost by minimizing stored data, accelerate time-to-insight with rapid queries, or handle iterative analytics with minimal overhead, the insights provided here offer a starting point. As the landscape of compression algorithms continues to evolve, future research may include specialized or domain-specific codecs, adaptive compression strategies, and hardware acceleration to further enhance Spark's ability to handle massive datasets efficiently.

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