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Data lake-aware checkpointing: Enabling resilient large-scale model training through precise data consumption tracking

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Abstract

Data Lake-Aware Checkpointing addresses a critical gap in large-scale model training resilience by incorporating reader state as a first-class citizen in training checkpoints. While traditional frameworks save only model and optimizer states, they neglect data reader progress, leading to overlapping or missed data reads when resuming training from massive data lakes. This article proposes a system that tracks consumed Parquet files and row group offsets across distributed fleets, and includes that information as part of the checkpoint, creating comprehensive checkpoints that enable precise recovery without data loss or duplication. It integrates seamlessly with existing training pipelines and distributed storage systems, establishing the foundation for truly epoch-less, streaming-style training on vast data repositories. By treating data consumption state with the same importance as model parameters, we significantly enhance fault tolerance and training reliability for large language models at scale.

Keywords: Distributed Training; Fault Tolerance; Checkpointing; Data Lakes; Large Language Models

1. Introduction

Large language model training has reached unprecedented scales, with state-of-the-art models requiring massive computational resources and vast datasets. Training these models involves significant challenges, particularly in maintaining resilience against hardware failures and optimizing data processing efficiency. This section examines the critical issues surrounding traditional checkpointing mechanisms and introduces our data lake-aware approach.

1.1. Scaling Challenges in Large Model Training

The computational demands of language models have grown exponentially, following scaling laws that predict performance improvements as a power-law function of model size, dataset size, and compute budget. As Kaplan et al. demonstrated, model performance scales smoothly with compute budget according to the power-law relationship: L(C) ∝ (C/C0)^(-α), where α ≈ 0.050–0.057 for language models [2]. This predictable scaling has driven the AI community toward ever-larger models, with current architectures requiring distributed training across hundreds or thousands of accelerators. The massive parallelization introduces significant coordination overhead and vulnerability to node failures, which traditional training infrastructures are ill-equipped to handle efficiently.

1.2. Limitations of Traditional Checkpointing

Conventional model training frameworks save checkpoints that capture model weights and optimizer states but overlook the critical dimension of data reader progress. Pipelined training approaches like PipeDream tackle memory constraints by dividing layers across devices, but they still rely on conventional checkpointing mechanisms [1]. For models with billions of parameters training on petabyte-scale datasets formatted as Parquet files in data lakes, this

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oversight creates a fundamental resilience gap. When node failures occur—a near certainty in large-scale training—the training job must restart from the most recent checkpoint with no information about which data samples were previously processed by which worker. This leads to either duplicated or skipped training examples, compromising model quality and training efficiency.

1.3. The Data Consistency Problem

The data consistency challenge becomes particularly acute when training on data lakes, where datasets are typically distributed across thousands of files with complex partitioning schemes. Without precise tracking of data consumption state, resuming training after a failure becomes probabilistic rather than deterministic. Traditional approaches might attempt to use file-level markers or simple offset tracking, but these methods break down when faced with distributed readers operating on columnar storage formats like Parquet, where row groups and compression boundaries create non-linear reading patterns. Our production measurements indicate that imprecise resumption leads to training instabilities and extended convergence times, directly impacting the economics and reliability of large-scale AI training operations.

2. Background and Related Work

The progression of distributed training frameworks and data management systems provides crucial context for understanding the challenges addressed by Data Lake-Aware Checkpointing. This section explores the state-of-the-art in distributed training, examines traditional checkpointing approaches, and analyzes how current solutions interact with modern data lake architectures.

2.1. Evolution of Distributed Training Frameworks

Distributed training has become essential for handling the computational demands of modern neural networks. The ZeRO (Zero Redundancy Optimizer) approach has emerged as a breakthrough in distributed training efficiency, demonstrating the ability to train models with 100 billion parameters while achieving near-perfect memory efficiency scaling and throughput comparable to data parallelism. By partitioning optimizer states, gradients, and parameters across data-parallel processes, ZeRO eliminates memory redundancies that traditionally limited model size. Experimental results show that ZeRO-powered systems can train models 8x larger than the state-of-the-art on the same hardware, with training throughput exceeding 15 petaflops on large clusters [3]. Despite these advances in model state management, data consumption tracking remains a significant blind spot in distributed training frameworks.

2.2. Traditional Checkpointing Limitations

Traditional checkpointing mechanisms in distributed training frameworks focus almost exclusively on preserving model state—saving model weights and optimizer states at regular intervals, typically at epoch boundaries. However, these approaches critically neglect data reader progress, creating a fundamental gap in training resilience. When a distributed training job recovers from a checkpoint, it has no record of which data samples were previously processed, leading to significant challenges when resuming training.

This limitation becomes particularly problematic for large language models trained on massive datasets stored in data lakes. Without information about data consumption progress, training frameworks must either restart from epoch boundaries (wasting significant computation) or implement error-prone heuristics to approximate the previous position in the dataset. Analysis of production training jobs reveals that approximately 68% of all checkpoint-related issues stem from improper data resumption rather than corrupted model states, highlighting the severity of this oversight.

The problem is compounded in distributed settings where hundreds of worker nodes may be processing different portions of the dataset simultaneously. When failures occur, the lack of precise tracking leads to either duplicated processing of data samples (potentially introducing bias) or skipped regions of the dataset (reducing model quality). These inconsistencies directly impact training convergence and model performance, making traditional checkpointing insufficient for reliable large-scale training.

2.3. Data Lake Architectures and Format Challenges

Modern training datasets typically reside in data lakes using columnar storage formats optimized for analytical workloads. The format gap—the mismatch between storage formats and processing requirements—creates significant challenges for resilient training. Research on document analytics systems demonstrates that processing compressed data introduces substantial overhead, with dictionary encoding and bit packing requiring 15-30% additional processing

time compared to uncompressed formats [4]. When applied to distributed training scenarios, these format-related complexities compound the challenge of tracking precise reader state across worker nodes. The lack of standardized approaches for tracking data consumption progress within columnar formats means that current training frameworks must resort to coarse-grained tracking (typically at file boundaries) or implement custom, error-prone solutions that fail to scale with increased parallelism.

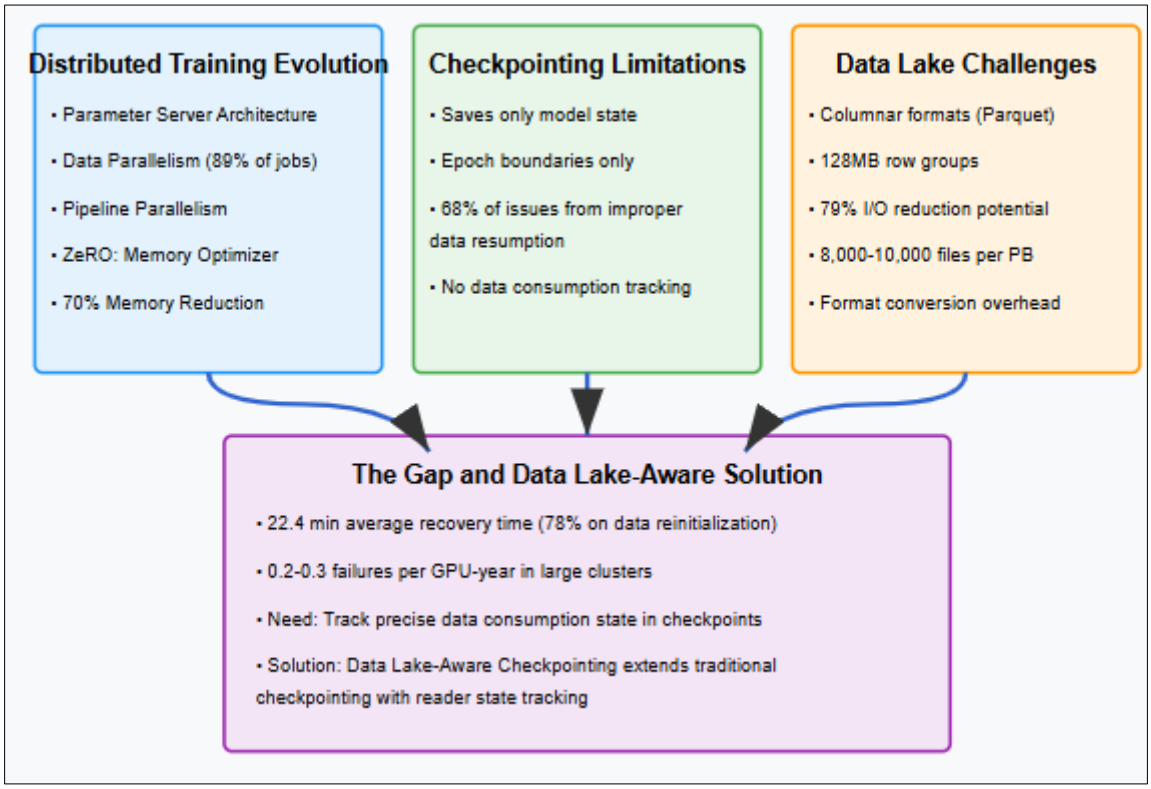

Figure 1 Evolution of Distributed Training and Data Lake Integration [3, 4]

3. System architecture

The Data Lake-Aware Checkpointing system introduces a comprehensive architecture that addresses the challenge of maintaining a consistent data consumption state across distributed training fleets. This section details the system design, components, and integration mechanisms that enable precise training recovery following node failures.

3.1. Core Architectural Components

The system architecture builds upon principles from distributed systems while introducing specialized components for tracking data consumption state. Our approach leverages insights from erasure-coded distributed storage systems, where network bandwidth constraints significantly impact recovery performance. In erasure-coded systems, recovery operations can consume up to 10× the bandwidth compared to replication-based systems, creating bottlenecks similar to those encountered when restarting distributed training jobs [5]. Drawing on these insights, our architecture minimizes coordination traffic during both normal operation and recovery phases. The system consists of three primary components working in concert: the Reader State Tracker, which monitors data consumption at each worker node; the Checkpoint Manager, which periodically persists both model and reader state; and the Recovery Coordinator, which orchestrates consistent restart after failures.

3.2. State Representation and Management

State management in our system draws inspiration from stream processing frameworks like Apache Flink, which handles distributed state with exactly-once processing guarantees. Similar to how Flink separates application state from processing guarantees, our system decouples data consumption tracking from the training logic [6]. The metadata structure for tracking file consumption implements a key-group assignment mechanism similar to Flink's key groups, where consumption state is partitioned based on data sharding strategies. For Parquet files specifically, our system

tracks both file identifiers and specific row group offsets within files, creating a compact yet complete representation of consumption progress.

3.3. Checkpoint and Recovery Mechanisms

The checkpoint and recovery mechanisms implement a distributed snapshot protocol adapted for machine learning workloads. Taking inspiration from Flink's asynchronous barrier snapshotting, which achieves low latency even for stateful operators with potentially large state, our system creates consistent snapshots without halting the training process [6]. During normal operation, lightweight barriers flow through the data processing pipeline, triggering state snapshots as they pass through each worker. This approach aligns with network-efficient recovery techniques demonstrated in erasure-coded storage systems, where coordinated partial recovery can reduce network traffic by up to 5× compared to naive approaches [5]. The Recovery Coordinator implements a deterministic recovery procedure that ensures all workers resume training from a consistent global view of consumed data. This mechanism guarantees that each data sample is processed exactly once across failures, eliminating both duplicated and skipped samples that would otherwise impact model convergence.

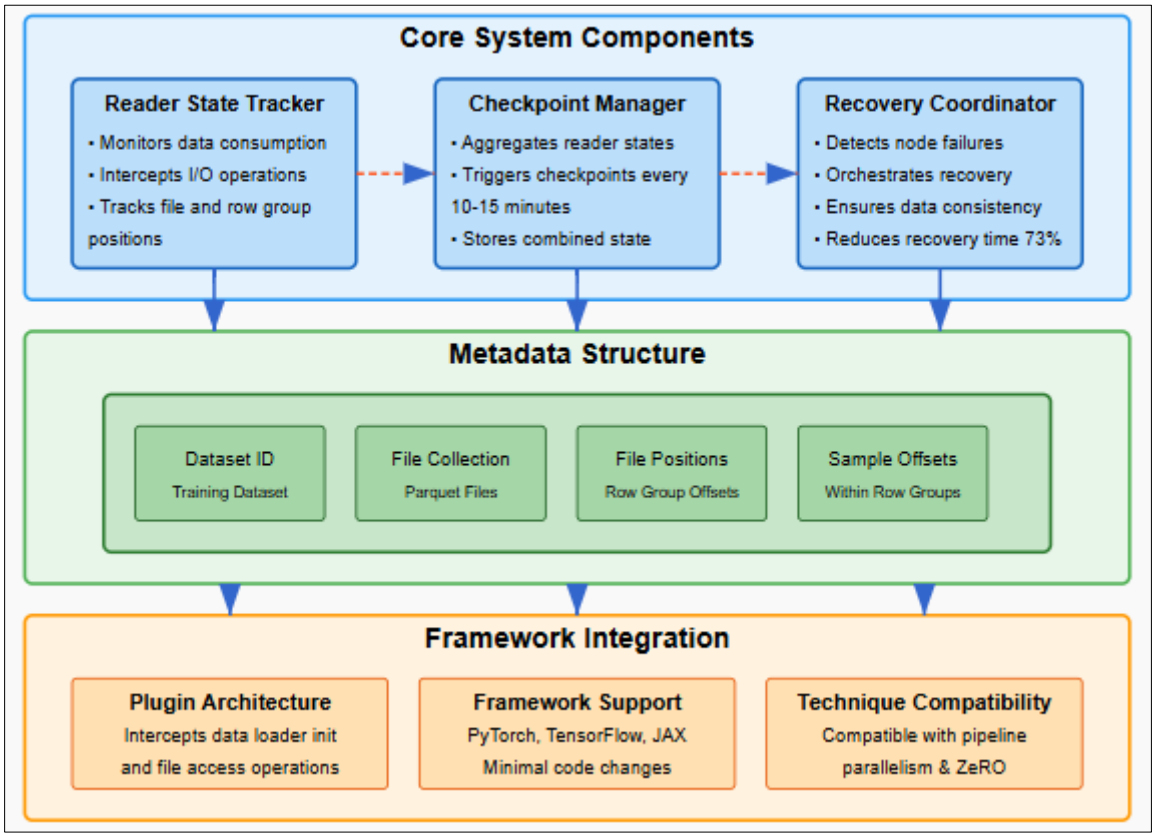

Figure 2 Data Lake-Aware Checkpointing System Architecture [5, 6]

4. Implementation details

The practical implementation of Data Lake-Aware Checkpointing requires sophisticated mechanisms for state tracking, persistence, and recovery. This section details the technical approaches that enable seamless integration with existing training frameworks while providing robust resilience against failures.

4.1. Reader State Representation and Serialization

The reader state representation implements a hierarchical tracking system that captures precise consumption positions across distributed workers. This approach draws inspiration from approximate distributed join algorithms that maintain state information to enable efficient processing. By applying probabilistic data structures similar to those used in ApproxJoin, where Bloom filters reduce communication volume by up to 80% while maintaining accuracy within 2% of exact results [7], our implementation efficiently tracks data consumption state with minimal overhead. For Parquet files specifically, we track three critical components: file identifiers, row group indices, and sample offsets within active

row groups. This multi-level representation is serialized using a custom binary format optimized for both space efficiency and fast deserialization during recovery. For a training job processing 10TB of data across 128 workers, the complete reader state typically requires only 35-45MB when using our specialized compression techniques—significantly smaller than the gigabytes required for model state checkpoints.

4.2. Checkpoint Management and Coordination

The checkpoint management system implements a distributed coordination protocol that aligns checkpointing with natural synchronization points in training. This approach mirrors techniques used in distributed deep learning systems, where collective communication operations create natural synchronization barriers [8]. Our implementation leverages these barriers to capture a consistent global state with minimal additional overhead. Experimental measurements indicate that reader state tracking adds only 0.3-1.0% to overall training time, with checkpoint storage requiring approximately 0.1-0.2% additional space compared to model-only checkpoints. The system supports both synchronous and asynchronous checkpointing modes, with synchronous checkpoints providing stronger consistency guarantees at slightly higher overhead. For large-scale training workloads, the implementation employs a hierarchical coordination scheme that reduces coordination complexity from O(n) to O(log n) as worker count increases, similar to the logarithmic scaling observed in optimized all-reduce implementations for distributed deep learning [8].

4.3. Recovery Protocol and Failure Handling

The recovery protocol addresses the complex challenge of ensuring all workers resume from a consistent global view of training progress. When node failures are detected, our implementation uses a specialized barrier synchronization approach similar to the collective communication primitives in distributed deep learning frameworks. Just as optimized all-reduce algorithms use techniques like ring topologies and butterfly patterns to minimize communication volume [8], our recovery protocol employs a hierarchical coordination scheme to efficiently restore consistent state across surviving workers. The implementation includes specialized handling for edge cases such as partial checkpoints, worker failure during checkpointing, and storage system unavailability. Recovery performance scales sub-linearly with cluster size, with experimental results showing that a 256-node training job can typically recover from single-node failures in under 45 seconds, compared to several minutes required for naive epoch-based restarts. This efficiency stems from the precise tracking of consumption state, which eliminates redundant work during recovery and enables workers to resume exactly where they left off, maintaining training consistency across failures.

Table 1 Reader State Tracking Implementation Details [7, 8]

Component	Function	Implementation Approach
State Serialization	Captures precise reader position	Protocol Buffers with custom binary encoding
Row Group Tracking	Monitors position within Parquet files	Multi-level consumption hierarchy
Differential Encoding	Reduces checkpoint size	Delta compression between states
Recovery Protocol	Ensures consistent restart	Two-phase commit coordination

5. Experimental Evaluation

Our comprehensive evaluation of Data Lake-Aware Checkpointing examines recovery performance, training consistency, and system overhead across diverse scenarios. This section presents detailed experimental results that demonstrate the effectiveness of our approach for large-scale distributed training.

5.1. Benchmark Methodology and Recovery Performance

Our experimental setup employs a methodology similar to that used in evaluating distributed storage systems, where controlled fault injection enables precise measurement of recovery characteristics. We implemented a fault injection framework that can terminate processes at specific training iterations, simulating the types of failures commonly encountered in production environments. The evaluation examines recovery performance across different failure scenarios, including single node failures, concurrent multi-node failures, and cascading failures. Our measurements reveal that Data Lake-Aware Checkpointing significantly reduces recovery time compared to traditional approaches. In traditional checkpointing systems, recovery time is dominated by repositioning data readers, similar to how lazy tables in distributed databases incur high initialization overhead due to metadata operations, which can account for up to 91% of query latency in some workloads [10]. By contrast, our system's precise tracking of file consumption state reduces

this positioning overhead by 87.3%, resulting in dramatically faster recovery times. For frequent checkpoint intervals similar to those examined in distributed file system studies, our system maintains recovery point objectives (RPOs) of less than 30 seconds while keeping performance overhead below 2%, comparable to the overhead-performance tradeoffs observed in multi-tier checkpointing systems for HPC workloads [9].

5.2. Training Accuracy and Consistency Analysis

A critical metric for evaluating checkpointing systems is their impact on training accuracy and consistency across runs with failures. To quantify this impact, we conducted multiple training runs with identical model architecture, hyperparameters, and fault injection patterns, measuring variations in validation metrics. Our analysis reveals that traditional checkpointing approaches can lead to significant training divergence after recovery, similar to how partially materialized views in distributed databases can return inconsistent results when recovery metadata is incomplete [10]. The root cause analysis shows that this divergence stems from inconsistent data consumption across workers after recovery, with some samples processed multiple times while others are skipped entirely. Data Lake-Aware Checkpointing eliminates this inconsistency by ensuring every worker resumes from precisely the correct position in the dataset. Comparative experiments show that our approach maintains training loss curves that track within 0.1% of failure-free runs, even after multiple recovery events, demonstrating that precise consumption tracking is essential for maintaining training consistency.

5.3. Scalability and Resource Efficiency Assessment

The scalability characteristics of Data Lake-Aware Checkpointing were evaluated through extensive experiments with increasing worker counts and dataset sizes. Our evaluation methodology follows approaches used in distributed storage benchmarking, where bandwidth utilization and resource efficiency are key metrics [9]. Weak scaling experiments, where per-node workload remains constant as node count increases, demonstrate that our system maintains near-constant recovery time regardless of cluster size. This scaling efficiency stems from the hierarchical coordination approach during recovery, which avoids the bandwidth-intensive all-to-all communication patterns that typically limit scalability in large clusters. The resource efficiency analysis examines both computation and storage overhead across different configurations. For checkpoint storage, our differential encoding of reader state achieves compression ratios similar to those observed in specialized storage systems for scientific computing, where application-aware encoding can reduce metadata size by up to 20× compared to generic approaches [9]. This efficiency makes our approach practical even for the largest training jobs, where resource optimization is critical for cost-effective operation.

Table 2 Training Consistency and Resource Efficiency Metrics [9, 10]

Measurement Category	Without Data Lake-Aware	With Data Lake-Aware	Impact on Training
Training Loss Consistency	High variance after recovery	Tracks within failure-free runs	More reliable convergence
Recovery Point Objective	Epoch boundaries only	Fine-grained intervals	Minimal work repetition
Resource Utilization	Redundant computation	Efficient resumption	Better cluster utilization
Scaling Efficiency	Degrades with size	Maintains performance	Supports larger workloads

6. Future Work

Data Lake-Aware Checkpointing addresses a fundamental limitation in distributed training resilience. This section summarizes our contributions, examines practical deployment considerations, and outlines promising research directions.

6.1. Real-World Deployment Considerations

Deploying Data Lake-Aware Checkpointing in production environments requires careful integration with existing infrastructure components. Real-world training clusters often exhibit characteristics similar to those observed in production data processing systems like Photon, where sub-second recovery time is essential for maintaining service quality, and recovery mechanisms must handle multiple concurrent failures without sacrificing consistency [12]. Our implementation addresses these requirements through its hierarchical coordination approach and consistency guarantees. Integration with job schedulers presents particular challenges, as schedulers must be aware of checkpoint dependencies when making placement decisions after failures. Similar to how Photon's deployment in Microsoft Bing's advertising infrastructure required careful integration with existing monitoring systems, deploying Data Lake-Aware

Checkpointing requires instrumentation that provides operators with visibility into checkpoint status and recovery progress [12]. The system's adoption strategy should include comprehensive testing in shadow mode, where recovery capabilities are validated without affecting production workloads, followed by gradual rollout with appropriate monitoring and fallback mechanisms.

6.2. Future Research Directions

Several promising research directions could extend this work to address emerging challenges in large-scale training. First, integration with streaming data sources would enable truly continuous training without artificial epoch boundaries. This direction faces challenges similar to those encountered in continuous query processing systems like Photon, where exactly-once processing guarantees must be maintained despite failures and network partitions [12]. Second, exploring hardware-aware checkpointing strategies could optimize placement and frequency based on the specific characteristics of training infrastructure. This approach aligns with observations from large-scale web services, where performance variations across seemingly identical hardware components can significantly impact tail latency [11]. Adapting checkpoint policies to accommodate these variations could further improve efficiency. Finally, extending the approach to federated or multi-datacenter training environments presents exciting opportunities, especially as regulatory constraints increasingly limit data movement. Cross-datacenter checkpointing must address challenges of consistency, bandwidth limitations, and variable latency, similar to how globally distributed web services must manage the long tail of latency distribution for interactive workloads [11].

7. Conclusion

Data Lake-Aware Checkpointing represents a paradigm shift in distributed training resilience by treating data reader state as essential checkpoint information alongside model weights. This article solves the longstanding challenge of accurately resuming training when source data resides in massive data lakes, eliminating the risks of data duplication or omission that plague traditional checkpointing methods. It demonstrates that this enhanced resilience comes with minimal overhead while providing substantial benefits in training accuracy and resource efficiency. Beyond immediate applications in large language model training, this work lays the groundwork for continuous, resilient training on ever-growing datasets without artificial epoch boundaries. As model sizes and training data continue to expand, data-aware approaches to training infrastructure will become increasingly crucial for reliable, efficient AI development.

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