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Storage I/O Patterns in Deep Learning Workloads: Characterization, Optimization Strategies, and Performance Implications

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Abstract

Deep learning workloads exhibit heterogeneous storage I/O patterns that differ considerably from conventional enterprise workloads. In this article, we present a thorough characterization of storage I/O across the entire ML lifecycle — encompassing training data loading, model checkpointing, and inference serving — and identify optimization techniques that reduce training time by 40–70% while lowering infrastructure costs by a comparable margin. We compare object storage, network-attached storage (NAS), and local NVMe drives across three dimensions: sequential read throughput, random I/O performance, and latency. Through wide-ranging evaluation of multi-tier storage architectures, we demonstrate that tiered configurations reduce storage costs by 70–85% without degrading training performance by more than 5% relative to all-premium storage. We further examine caching architectures, file systems, file formats, dataset sharding strategies, and recent advances, including computational storage and CXL-based disaggregated architectures. Our findings are validated with benchmark results from production-scale deployments across ImageNet, BERT, and a range of modern GPT-class models. Improperly configured storage systems consume 60–80% of available GPU time in production environments, making storage configuration a critical bottleneck in end-to-end ML pipelines.

Keywords: I/O Optimization, Deep Learning Data Pipelines, Model Checkpointing, Distributed Deep Learning, NVMe and Object Storage, Caching, Computational Storage.

1. Introduction

1.1 Requirements for storage in machine learning

Deep learning is reshaping workloads at a massive scale and imposing new demands on storage infrastructure. ML training datasets can range from hundreds of gigabytes to multiple petabytes, with models accessing millions of files within a single training epoch. According to an IDC research report, the global datasphere is projected to grow to 175 zettabytes by 2025, with ML and AI workloads constituting a major driver of this growth [1].

Unlike enterprise applications with well-defined I/O characteristics, ML workloads exhibit diverse and dynamic I/O profiles. Specifically, the data loading phase generates highly sequential reads; the checkpointing phase produces bursty writes; hyperparameter tuning involves mixed random reads and writes; and distributed training demands sustained high throughput across multiple nodes simultaneously.

For cloud providers, storage accounts for 30–40% of ML infrastructure costs. Despite this, storage systems are treated as an afterthought in most ML pipelines [2][3] and become a critical bottleneck when incorrectly configured or unable to meet throughput requirements. Storage I/O accounts for 60–80% of GPU idle time in production ML environments [7]. In this paper, we characterize storage I/O patterns across all stages of the ML lifecycle and present optimizations that yield 40–70% reductions in training time without substantially increasing infrastructure costs.

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1.2 Storage Workloads Related to ML

ML workloads differ substantially from conventional RDBMS or file server workloads. Computer vision tasks involve millions of small image files (typically 100 KB–1 MB each); natural language processing workloads operate over large sequential files that can reach multiple gigabytes; and recommendation systems process sparse tabular data with complex join patterns [8].

ML training also exhibits a temporal locality pattern that conventional storage systems do not typically exploit. Algorithms read a dataset sequentially within each epoch but reuse the same data across hundreds of epochs, creating substantial opportunities for caching. Additionally, ML workloads generate multiple unpredictable bursts of write activity. Large language models (LLMs) with billions of parameters produce multi-gigabyte checkpoints every few minutes, which can overwhelm storage systems optimized for steady-state workloads [13].

The DAWN research group at Stanford concluded that conventional storage systems deliver only 15–25% of their theoretical maximum bandwidth for ML training workloads, compared to 60–80% for typical enterprise workloads, because their design assumptions do not align with ML access patterns. Understanding these access patterns and designing storage infrastructure accordingly is therefore essential for building efficient, cost-effective ML systems.

1.3 Contributions and Paper Organization

The contributions of this paper include:

- A systematic characterization of storage I/O patterns spanning the entire ML lifecycle.
- A quantitative comparison of various storage backend architectures via representative ML workloads.
- A cost-performance framework for designing multi-tiered storage for production ML systems.
- Best-practice recommendations on file formats, dataset sharding, and storage monitoring.
- An examination of emerging storage technologies relevant to future ML infrastructure.

The remainder of the paper is organized as follows. Section 2 characterizes I/O patterns throughout the ML lifecycle. Section 3 introduces storage tier optimizations. Section 4 compares storage backends. Section 5 covers production best practices. Section 6 examines emerging technologies, and Section 7 concludes the paper.

2. Characterization of I/O Patterns Across ML Lifecycle Phases

2.1 Training Phase: Data Loading Patterns

2.1.1 Sequential Read Patterns and Dataset Access

For ML, data loading exhibits distinct sequential read patterns because each training dataset is read either sequentially or randomly at the beginning of every training epoch, and each sample must be read exactly once before an epoch can conclude. Profiling of production ML workloads reveals that training jobs can issue sustained sequential read requests at rates of 1,000–10,000 small file reads per second for vision workloads and 50–200 large file reads per second for NLP workloads [11].

According to Facebook AI, an ImageNet training job running ResNet-50 reads 1.28 million JPEG files (average size 150 KB) in each epoch, yielding 192 GB of sequential I/O traffic per epoch and 17.3 TB total I/O across a 90-epoch training run. Due to the intrinsic limitations of small-file access, modern distributed file systems can sustain an aggregate throughput of 10–20 GB/s for large files but only 1–3 GB/s for millions of small files, owing to metadata operation overhead and random access patterns.

2.1.2 Impact of Data Augmentation and Preprocessing

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Data augmentation and preprocessing are very I/O intensive. On-the-fly augmentation (random crops, rotations, and color jittering) results in a 5-10x reduction in storage usage vs. storing pre-augmented datasets, but can incur CPU costs to the point that the CPU becomes a bottleneck when loading batches and starves the GPU. Profiling data from Google Cloud compute instances has shown that aggressive augmentation pipelines can consume 60-80% of the training instance's CPU cycles [3].

Compressed formats, such as TFRecord, WebDataset, and Apache Arrow, can achieve 2-4× compression with an additional CPU overhead of only 10-20% to decompress [10]. Microsoft's work shows it is possible to replace JPEGs with TFRecord and then run training on Azure ML in 12 minutes (down from 47 minutes per epoch when using individual JPEGs) and at a 65% savings by reducing disk I/O and metadata overhead [5].

Key Perception: On-the-fly augmentation often reduces storage but can lower GPU utilization by up to 80%, becoming a CPU bottleneck. For datasets larger than 300 GB, TFRecord and WebDataset formats outperform others in speed and storage.

2.2 Checkpointing: Periodic Write Bursts

2.2.1 Checkpoint Frequency and Size Characteristics

Model checkpointing creates spikes of I/O traffic with a different pattern from the training data accessed, with a different checkpointing frequency for training time and failure-based recovery. Checkpoints linearly scale with the number of parameters: BERT-base (110 million parameters) at 440 MB (FP32), GPT-3 (175 billion parameters) at 700 GB, and multi-trillion parameter models can be several terabytes [13].

NVIDIA reports that for distributed training across 128 GPUs, total checkpointing time can account for 5% to 15% of total training time when storage systems cannot sustain ideal write throughput. Writing the checkpoint from all of the workers at once causes 50 GB/s to 200 GB/s bursts, overwhelming NAS systems designed for steady-state throughput. Experiments show that checkpoint write time exhibits high variance, with a coefficient of variation of 0.4 to 0.8, with the slowest checkpoints being 3-5 times longer than the fastest. [9]

Model	Parameters	FP32 Size	FP16 Size	Typical Frequency
BERT-base	110 M	440 MB	220 MB	Epoch boundary
BERT-large	340 M	1.36 GB	680 MB	30 min
GPT-2 (1.5 B)	1.5 B	6 GB	3 GB	15 min
GPT-3	175 B	700 GB	350 GB	15 min
PaLM-540B	540 B	2.1 TB	1.05 TB	10 min

Table 1: Checkpoint Size by Model Architecture

2.2.2 Incremental and Asynchronous Checkpointing Strategies

More advanced checkpointing strategies write the data in smaller increments or perform asynchronous checkpoints. With incremental checkpointing, only the changed parameters are saved. This approach can decrease the size of the checkpoint by 60% to 90% after the first one. Work from UC Berkeley has proposed combining gradient checkpointing with incremental saves to reduce the amount of data written to disk during training by 85% for BERT fine-tuning while still having full recoverability [9].

In asynchronous checkpointing, the writing of a checkpoint and the training computation are decoupled. After the model is copied to main memory, the checkpoint is written out in the background while training proceeds on the GPU. Profiling of various workloads has shown that asynchronous checkpointing reduces the time the training process is interrupted from 15-45 seconds to less than 2 seconds, resulting in 8-12%

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better effective GPU utilization [9]. Cloud-optimized approaches further use object storage multipart upload APIs, which offer 5-10x better throughput and 40-60% lower tail latency variance due to more parallel write operations [4].

2.3 Inference and Model Serving Patterns

2.3.1 Model Loading and Warm-up Characteristics

The majority of I/O latency comes from loading the model and the time required to start inference. The first load from storage is a single sequential read of an entire model artifact. According to AWS, loading a 13 GB BERT-Large model from S3 takes 8 to 12 seconds over a standard connection, dominating the cold-start latency for serverless inference [4].

Efficiently using predictive pre-loading reduces P99 cold-start latency for containerized inference services from 15-25 seconds down to 2-4 seconds [4]. For example, deploying a large number of replicas for model serving (for example, a 100-replica deployment) using the shared read-only volume or image layers reduces the amount of transferred data from 1.3 TB down to 13 GB and dramatically reduces the deployment time from 20-30 minutes down to 2-3 minutes [4].

2.3.2 Accessing Feature Store or Embedding Tables

Production inference systems maintain large input-output maps while accessing the feature store and embedding tables. Uber Engineering has reported that its Michelangelo ML platform processes 3 million feature store queries per second, with a cache hit rate of 85-90% and a tail latency of under 5 milliseconds [12]. Embedding tables, such as those used in recommendation systems, can be hundreds of gigabytes , and typically have highly imbalanced reads. For example, a ten percent subset of the embeddings might be read 80-90% of the time [11].

Meta AI measures 50k-200k QPS per model for cases where embedding tables do not fit into main memory. A multi-tiered hierarchical cache (L1: Memory, L2: SSDs, L3: Network) reduces latency from 50-100 ms to 1-5 ms and achieves cache hit rates of >95% for hot embeddings [11].

3. Storage Tier Optimization and Data Lifecycle Management

3.1 Hot, Warm, and Cold Data Classification

3.1.1 Access Pattern Analysis for Tier Assignment

For tiering to reach its full potential, the data should be segregated according to the access patterns common in the production ML workloads. For example, the data can be classified by the I/O bandwidth that it consumes: 15-25% of volume accounts for 80-90% of the total I/O bandwidth requirements [2]. Warm data comprises the other 80-90% of the data in many systems; it is usually defined as being 10 to 100 times less active than hot data. Research at Google Cloud found that 40% to 50% of ML storage volume was not accessed for >90 days.

The following tier classification framework for ML systems is recommended:

Hot (Tier 0): Active training datasets, most recent N checkpoints, and production inference models.

Warm (Tier 1): Artifacts from this experiment, validation datasets, and recent checkpoints of model versions

Cold (Tier 2): Archived experiments, archived versions of a dataset, compliance-retained artifacts

Archive (Tier 3): Long-term retention, disaster recovery, and regulatory backups

Analyzing storage telemetry data using automated tools can classify access patterns with 90-95% accuracy and reveal objects whose tier transitions could cut costs between 60-75% [3].

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Tier	Example	IOPS	Throughput (MB/s)	Latency	Cost ($/GB-mo)
Local NVMe	Samsung 990 Pro	1,000,000+	7,000+	0.001–0.01 ms	0.15–0.25
Local SSD	SATA SSD	100,000+	500–3,000	0.01–0.1 ms	0.10–0.15
Network SSD	AWS gp3, Azure Premium SSD	3,000–16,000	125–1,000	1–5 ms	0.08–0.12
Network HDD	AWS st1	500–2,000	60–500	5–15 ms	0.04–0.05
Object (Standard)	AWS S3, GCS, Azure Blob	100–1,000	50–200	15–50 ms	0.02–0.03
Object (Archive)	S3 Glacier, Azure Archive	N/A	Variable	Min–Hours	0.001–0.04

Table 2: Storage Tier Cost-Performance Characteristics (2024)

A Databricks study found that a 500 TB ML data lake, with 20% hot on SSDs, 40% warm on HDDs, and 40% cold on object storage, costs $4,800/month, compared to $60,000/month on all-SSD, with only a small performance impact on hot data workloads [2]. Clever tiering policies that move data based on usage patterns achieve 70-85% of the cost savings, obviating the need for costly manual data movement.

3.2 Caching Strategies for ML Workloads

3.2.1 Multi-Level Caching Architectures

Multi-level caching takes advantage of the temporal and spatial locality of ML workloads to reduce storage I/O and accelerate training by creating three levels of caches:

L1 (Instance-Level): Local SSD or RAM caching of the most recently accessed data samples. Exploits within-epoch locality. For example, caching 10-20% of the dataset reduces the remote storage I/O by 40-60% for computer vision workloads [6].

L2 (Cluster-Level): Distributed caching systems (Alluxio, Redis, Memcached) can also be deployed across jobs. Using 100 GB to 1 TB of cache per node yields 75% to 85% aggregate cache hits and reduces backend storage usage by 4-5× [6].

L3 (Storage Tier): Smart prefetching and locality-aware scheduling [4]. With S3 Transfer Acceleration and CloudFront Edge caching, the time to load data in distributed training across cities is reduced by 50-60% [4].

3.2.2 Cache Issues: Coherence and Consistency

However, cache coherence protocols are required for adding samples, relabeling, and applying different types of data augmentations to the dataset. The production ML system at Meta AI has 10,000-50,000 dataset updates per day [11]. In practice, we found that versioned caches with content-addressable storage hit a point where every versioned dataset consists of immutable entries that are never invalidated when data is changed. An updated dataset metadata also ensures that retraining jobs spawn with the latest caches, resulting in cache hit rates exceeding 95% with versioning [11].

For distributed training with data parallelism, Merkle tree-based validation protocols add less than 1% overhead while enforcing cache coherence for 100+ distributed workers [20].

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4. Storage Backend Comparison

4.1 Object Storage

4.1.1 Architecture and Performance Characteristics

Object stores — including AWS S3, Azure Blob, and Google Cloud Storage (GCS) — are the most widely deployed backends for ML workloads, providing HTTP-based access to immutable objects with excellent scalability and cost profiles. They support aggregate per-workload throughput exceeding 100 GB/s and scale linearly with parallel requests [4][2]. However, per-request latency of 15–50 ms makes them poorly suited for small, random reads.

Object listing operations scale poorly: listing 1,000 objects may take 100 ms, while listing 1 million can exceed 10 seconds. Effective strategies to circumvent listing overhead include batching small objects into larger archives, using manifest files, and performing parallel multipart downloads. AWS reports that this approach reduces ImageNet loading time from S3 from 85 minutes to 12 minutes per epoch, achieving 80% of local SSD performance at approximately one-tenth the cost [4].

4.1.2 Consistency Models and Data Durability

Modern object stores provide strong read-after-write guarantees, but they can take 1 to 5 seconds to list newly written files. [3] Production ML systems use explicit synchronization by writing marker files to signal that a checkpoint has been written, and they poll the directory until the marker appears before using the checkpoint [3].

Object storage has durability guarantees (99.999999999% for AWS S3 Standard) higher than those needed for transient ML artifacts. Lower durability object storage tiers (e.g., S3 One Zone-IA, 99.99% durable) are 45% cheaper and sufficient for intermediate checkpoints [4]. Optimally tiered configurations using ephemeral artifacts on lower durability and final models on high durability reduce average storage costs by 35-40%, while keeping the risk of data loss low (less than 0.01% of training runs lost annually) [4].

4.2 Network-Attached Storage

4.2.1 NFS and distributed file systems

In HPC and ML infrastructure, users widely use NFS and the distributed file systems Luster, GPFS, and BeeGFS as POSIX-compliant shared file systems. At NERSC and elsewhere, NFS provides 2-8 GB/s sustained throughput for large sequential reads and 100-500 MB/s for small random access patterns, such as vision training workloads [16]. Thirty to 50% of the total I/O time to train ResNet-50 on ImageNet, stored on NFS, goes to metadata operations [16].

Distributed parallel file systems can address scaling issues with striping and distributed metadata servers. Luster-backed storage saw a 65% improvement in ImageNet training time over NFS with 64 concurrent training jobs and approximately linear scalability with up to 128 concurrent clients [16].

4.2.2 Network bandwidth and latency considerations

Network infrastructure is a major limiting factor of NAS performance. According to Microsoft Azure, contention for network bandwidth during peak hours increases the P99 data- loading latency by 3-5× [5]. Locality-aware scheduling achieves a 25–35% speedup in average throughput and a 60% lower P99 latency variance in shared ML clouds [8]. Analysis of Facebook AI's network-optimized clusters with dedicated storage networks finds they achieve 90-95% of the theoretical training throughput versus only 60-70% when converged storage and GPU networks share the links [11].

4.3 Local NVMe Storage

4.3.1 Performance Advantages

Modern NVMe drives with 7,000+ MB/s sequential read throughput and 1,000,000+ random read IOPS allow ResNet-50 ImageNet training to load 15-20 epochs/hour and read network storage with 8-12

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epochs/hour. NVIDIA showed that moving from NAS to local NVMe reduced DGX station training time by 45-55% on vision jobs, cutting data loading from 60% of each iteration to less than 10% [13]. The variance of local SSD-backed training is less than 0.05, compared to networked storage, which can have a 0.3-0.5 coefficient of variation in latency [13].

4.3.2 Data Staging and Hybrid Storage Strategies

Hybrid storage abstractions combine the benefits of local storage and network storage via data staging. For example, research conducted by Google Cloud suggested that after a one-time staging period of 20-30 minutes, training could be continued for 10-15 hours at the maximum throughput of local storage, and aggregate throughput improved by 40-50% [3]. Using selective staging that copies only the popular data to local storage while streaming the long tail over the network, we achieve 85–90% of the performance of the all-local case while using 60–70% less local storage [3]. Furthermore, with predictive staging, we reduce the job startup time from 45 minutes to 5 minutes and improve training throughput by 35% [4].

5. Best Practices for Storage Configuration in Production ML Systems

5.1 Dataset Organization and File Format Selection

5.1.1 Optimal File Formats for Different Data Modalities

File format can also have a significant effect on data load time and storage requirements. An analysis by the TensorFlow engineering team found that converting the ImageNet dataset from 1.28 million JPEG files to 1,024 TFRecord shards reduced data load time by 60% and storage space by 35% [10]. For NLP workloads, datasets can be saved as TFRecord files with tokenized inputs or as Apache Arrow files with schema data, achieving 40–55% faster loading with zero-copy memory-mapped access [10].

Column-oriented formats (Parquet, ORC, etc.) allow raw scanners to read only the columns relevant to the query and apply better compression. This can save 70-80% I/O load on wide tables. Databricks measured a 2 TB tabular dataset in CSV and then again in Parquet. After converting from CSV to Parquet, I/O load declined from 2 TB to 420 GB and throughput improved from 150 MB/s to 600 MB/s [2].

Modality	Format	Compression	Throughput (MB/s)	Metadata Overhead	Random Access
Vision	Individual JPEG	1.0x	100–300	Very High	Yes
Vision	TFRecord	1.5–2.0x	400–800	Low	No
Vision	WebDataset	1.4–1.8x	500–900	Low	No
NLP	CSV/JSON	1.0x	200–400	Medium	Yes
NLP	Parquet	2.0–3.0x	600–1,200	Low	Yes
NLP	TFRecord (tokenized)	2.5–4.0x	700–1,400	Very Low	No
Tabular	CSV	1.0x	150–300	Low	Yes
Tabular	Parquet	3.0–5.0x	500–1,000	Low	Yes
Tabular	Arrow	2.5–4.0x	600–1,200	Very Low	Yes

Table 3: File Format Performance and Storage Efficiency

5.1.2 Sharding Strategies and Partition Schemes

To optimize distributed training, data should be sharded and partitioned appropriately. Google Cloud found that sharding ImageNet with 1,250 images per shard and 1,024 shards enabled it to achieve 85% of the peak throughput with little overhead from sharding [3].

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For heterogeneous clusters with hash-based sharding, all shards have the same load, and there is 40-50% less variance in training time compared to sequential sharding [8]. In the case of cloud-optimized sharding, the shard boundaries match the chunk size of the object storage backends (typically 64-128 MB) to maximize throughput and minimize request overhead [4].

5.2 Monitoring and Performance Optimization

5.2.1 Key Storage Metrics for ML Workloads

For complete storage monitoring, metrics should represent ML workload characteristics:

Data loading throughput (MB/s per worker): For vision workloads, it requires more than 300-500 MB/s per GPU to keep the GPU usage above 90% [13].

I/O wait time: If the I/O wait time is greater than 20%, a high I/O wait time indicates that the storage configuration may need improvement [7].

Cache hit rate: If the cache hit rate is less than 70%, then it is likely that the cache is either too small or the accessing pattern is not right [12].

Storage latency percentiles (P50, P95, and P99): P99 latencies higher than 5x P50 point to storage contention or configuration issues [9].

Checkpoint write duration: If the checkpoint write duration exceeds 5% of the training time, consider using asynchronous checkpointing [13].

5.2.2 Automated Performance Tuning

Automated storage optimization systems rely on online monitoring and diagnostic capabilities. For example, AWS showed that machine learning-based prefetching reduced the average loading latency of data by 45% and increased the cache hit rate from 72% to 88% on production training workloads [4]. Using dynamic batch size adaptation reduces the variation of the storage throughput, increasing the effective GPU utilization of shared ML clusters from 76% to 91% [8]. The Google Cloud shared ML cluster has been analyzed, and it was found that automatic tiering with a window size of 7 days saves 55% on storage costs while remaining within 3% of manual tiering in terms of training performance [3].

6. Future Directions and Emerging Technologies

6.1 Computational Storage and Smart NICs

Computational Storage and Smart NICs

Computational storage drives such as Samsung's SmartSSD and the NGD Systems Catalina series integrate FPGAs or ARM processors into NVMe storage devices to allow preprocessing, decompression, and filtering to occur directly on the device. For instance, they have been shown to reduce ImageNet training time by 25% by offloading JPEG decompression and cropping. SmartNICs, such as NVIDIA BlueField or Intel IPU, reduce CPU utilization of networked storage access from 25-30% to less than 5% and improve throughput by 40-60% in a distributed training cluster [19].

Future storage systems may also include learned compression, approximate deduplication, semantic caching, and other computations in storage hardware. By 2028, computational storage is projected to reduce traffic on datacenter storage networks by 40-50% and reduce storage infrastructure costs by 25-35% for machine learning workloads.

6.2 Disaggregated Storage and CXL

With the introduction of CXL and disaggregated storage architectures, ML storage systems can be designed differently. CXL is a low-latency, cache-coherent interconnect that allows remote memory and storage to be connected over high-speed interfaces, blurring the boundaries between compute and storage nodes [18].

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Meta AI research suggests CXL-attached storage with 100 GB/s bandwidth and 200 ns latency would achieve the same training performance as local NVMe, enabling capacity to be provisioned as needed [11]. Storage disaggregation is the separation of compute and storage nodes into their own separate pools with high-speed interconnects, allowing flexibility in independently scaling storage. Storage disaggregation has been shown to improve total storage utilization from 40-60% with local storage to 85-95% through dynamic allocation to active training jobs [18]. With storage on separate hardware, software-defined storage (SDS) can lower infrastructure costs by 30-45% and allow for greater job- scheduling options.

Conclusion

The I/O patterns of deep learning workloads impose unique requirements that conventional storage system designs do not adequately address—including read dominance during training, bursty write patterns during checkpointing, and latency sensitivity during inference. These characteristics create well-defined opportunities for cost-effective optimization. Multi-tier storage architectures reduce storage costs by 70–85% while sustaining training performance within 5% of all-premium configurations. Intelligent caching reduces storage I/O in production ML workloads by 60–80%. The appropriate storage backend depends on workload requirements: local NVMe delivers throughput exceeding 7,000 MB/s for $0.15–0.25 per GB-month, while object storage provides 50–200 MB/s at $0.02–0.03 per GB-month — approximately one-tenth the cost — with NAS occupying an attractive middle ground for shared, multi-user environments.

Established design patterns encompassing dataset organization, file format selection, and storage monitoring help practitioners avoid common pitfalls and optimize performance systematically. Emerging technologies — including computational storage, SmartNICs, and disaggregated CXL architectures — promise to further improve storage performance and efficiency. As the scale of deep learning models and datasets continues to grow exponentially, optimizing storage infrastructure is not merely beneficial but essential for building scalable and cost-effective ML systems.

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