Analyzing and Mitigating Data Stalls in DNN Training

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Abstract

We present the first comprehensive analysis of how the data pipeline affects the training of the widely used Deep Neural Networks (DNNs). We analyze nine models and four datasets while varying factors such as the amount of memory, number of CPU threads, etc. We find that in many cases, DNN training time is dominated by data stall time: time spent waiting for data to be fetched from storage and pre-processed. Based on our insights, we build CoorDL1, a novel data-loading library that accelerates DNN training by minimizing data stalls. CoorDL introduces three core techniques: coordinated pre-processing, partitioned caching, and DNN-aware software caching policy (minIO). CoorDL does not affect training accuracy, and does not require special hardware support. CoorDL accelerates multiple aspects of DNN training: hyperparameter search, single-server training, and multi-server training. Our experiments on a range of DNN tasks, models, datasets, and hardware configurations show that CoorDL accelerates hyperparameter search by up to 5.7×, single-server training by up to 2×, and multi-server training by up to 15× compared to the state-of-the-art data loading library DALI on PyTorch.

1 Introduction

Machine learning has become pervasive in our lives. It is used both in user-facing applications and in the backend infrastructure. One class of machine-learning models, Deep Neural Networks (DNN), have gained importance as they allow us to tackle problems that were previously intractable, such as image classification [37, 53, 78], translation [84], speech recognition [35], video captioning [82], and even predictive health-care [80].

Training DNNs is resource-intensive and time-consuming. During training, the model predicts the output given training data; based on the output, the model’s weights are tuned. This happens iteratively, in many rounds called epochs. The training process uses configuration options called hyperparameters (HP) that influence the speed and quality of the learning process. So the first step in training a model is finding the optimal set of HP. HP search is typically performed by launching several parallel jobs with different hyperparameters, monitoring their progress, and replacing poorly performing ones with new values, until the best hyperparameters are found. Once the hyperparameters are decided, DNN training is performed on a single GPU, single server with multiple GPUs, or across multiple servers in a cluster.

Training a DNN, especially in the distributed setting, involves all the different resources in a server from GPUs to networking. Researchers have tackled how to efficiently use these resources to reduce DNN training time, such as reducing communication overhead [36, 44, 59, 62, 85], GPU memory optimizations [24, 43, 72], and compiler-based operator optimizations [23, 46, 81]. However, the impact of storage systems, specifically the data pipeline, on DNN training has been relatively unexplored.

During DNN training, the data pipeline works as follows. Data items are first fetched from storage and then pre-processed. For example, for many important and widely-used classes of DNNs that work on images, audio, or video, there are several pre-processing steps: the data is first decompressed, and then random perturbations such as cropping the image or rotating it are performed to improve the model’s accuracy [68]. Pre-processing with the required random transformations has to be done for each epoch, while ensuring that each item in the dataset is processed exactly once per epoch. Once pre-processed, the data items are sent to the GPUs for processing. This data fetch and pre-processing is normally pipelined with the GPU computation. Ideally, the data pipeline should keep the GPUs continuously busy processing data; we term this GPU-bound. Unfortunately, DNN training is often IO-bound, bottlenecked by fetching the data from storage, or CPU-bound, bottlenecked by pre-processing data in memory. Collectively, we term these bottlenecks data stalls and differentiate between prep stalls (time spent pre-processing) and fetch stalls (time spent on IO).

Contributions. We present the first comprehensive analysis of data stalls across nine popular DNN models from three domains (image classification, object detection, and audio classification) and four datasets. We vary factors such as the storage media (hard disks and SSDs), amount of data that can be cached in memory, the number of CPU threads used to fetch and pre-process data, the number of GPUs, and GPU

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generation. We then analyze how these factors affect the data pipeline and DNN training. We find that the data pipelines in popular training frameworks like PyTorch and TensorFlow are inefficient, despite using state-of-the-art data-loading libraries like DALI [17] that reduce prep stalls using GPU-accelerated data pre-processing. We present CoorDL, a novel data loading library that accelerates DNN training by minimizing data stalls. CoorDL does not impact accuracy; training can sample as usual from the entire dataset, regardless of what is cached. CoorDL does not require specialized hardware, and runs over commodity networking and storage hardware. CoorDL addresses both fetch and prep stalls and accelerates several common training scenarios: HP search (by upto 5.7×), single-server DNN training (by upto 2×), and multi-server DNN training (by upto 15×).

Performing an analysis of how the data pipeline impacts DNN training is challenging since DNN training has a high degree of concurrency; it is hard to isolate the time taken to perform a single task especially as data loading and preparation are pipelined with GPU computation. We develop a tool, DS-Analyzer, that uses differential analysis between runs (e.g., comparing a run where data is completely cached vs when data needs to be fetched from storage) to accurately identify data-stall bottlenecks.

Our analysis yields several interesting insights. First, a large number of DNN models, even computationally expensive ones like ResNet50 [37] and VGG11 [78], have data stalls. Second, these data stalls occur across frameworks such as PyTorch and TensorFlow. Third, some models like ResNet18 require more than three cores per GPU for pre-processing; these models have prep stalls even on ML-optimized hardware like DGX-2 [7]. Fourth, there is a large amount of redundant work done by the data pipeline during HP search and distributed training where the same data items are fetched and pre-processed by multiple jobs or multiple servers. Finally, when the dataset is larger than available memory, current caching policies used by DNN training frameworks are inefficient, resulting in high disk I/O with unwanted evictions in the Page Cache.

For example, consider a cluster of ML-optimized cloud servers with V100 GPUs and 500 GiB of memory [1]; 400GiB is allocated to cache the input dataset. We would like to train ResNet50 [37] using the 645 GiB OpenImages [55, 76] dataset in PyTorch with DALI. When we perform HP Search for this model with eight jobs on a single server, a staggering 1.7 TiB of data (2.8× the size of the entire dataset) is fetched from storage during each epoch because the data pipeline of each of the eight jobs fetches and pre-processes the dataset independently. After determining the hyperparameters, when we perform distributed training on 16 GPUs across two servers, in each epoch of training both servers process a random disjoint half of the dataset (so that they collectively process the entire dataset once per epoch). Despite enough memory across two servers (800 GiB) to cache the entire dataset, each server fetches 119 GiB (from storage) per epoch when training, as the random data items being requested may not be cached locally at each server. If the server uses hard drives for storage, training incurs fetch stalls, causing the expensive GPU to be idle for 75% of the total training time.

Using the insights from our analysis as opportunities for improvement, we design and build CoorDL, a novel data loading library that accelerates DNN training by minimizing data stalls. CoorDL introduces three techniques to overcome data stall overheads. First, it introduces coordinated prep, which coordinates data fetch and pre-processing among concurrent HP search jobs. Coordinated prep takes advantage of the fact that all HP jobs are operating on the same data; all concurrent jobs can share one epoch’s worth of pre-processed data. In each epoch, data is fetched and pre-processed exactly once for all concurrent HP jobs, eliminating a significant amount of redundant work. Second, CoorDL introduces the novel MinIO software cache that is specialized for DNN training. MinIO exploits the unique data access pattern in DNN training to minimize the amount of data fetched from storage for training on a single server. Third, CoorDL introduces partitioned caching, where the dataset is partitioned and cached among the servers involved in distributed training for each job. On a local MinIO cache miss, data is fetched from the memory of a remote server (over the commodity TCP stack) rather than from local storage. The dataset is thus fetched from storage exactly once for the entire distributed training job.

We evaluate CoorDL on hyperparameter tuning, single-server, and multi-server distributed training scenarios. We compare CoorDL against PyTorch using DALI. We use cloud servers specialized for machine learning: 500 GB of DRAM, 24 CPU cores, 40Gbps Ethernet, eight GPUs (V100/1080Ti) and either SSD or hard disk. We use the Open-Images dataset [55, 76] for image classification and FMA dataset [29] for audio classification. For HP search on a single server with SSD, CoorDL accelerates training by 5.6× for the M5 audio model [27] and 1.9× for ResNet50. On a single server with SSDs and eight GPUs, CoorDL accelerates training of models such as ShuffleNet by up-to 1.8×. For distributed training with 16 GPUs across two servers, CoorDL accelerates training AlexNet by 15× on hard drives, and the M5 audio model training by 2.9× on SSDs.

The techniques in CoorDL can only help if the training is IO-bound or CPU-bound. If the model is GPU compute-intensive (e.g., language models such as Bert-L [31]), IO and CPU may not be the bottleneck, thus leaving little for CoorDL to do. Despite this limitation, we show via extensive experimentation on a wide range of DNN tasks, models, datasets, and hardware configurations that CoorDL significantly accelerates DNN training on commonly available ML optimized cloud servers. The problem of data stalls will only worsen with time as the size of data sets increase [15, 21, 55] and GPUs become faster [50]. To help practitioners predict and analyze data stalls, we extend DS-Analyzer to answer what-if
questions about data stalls in DNN training (e.g., What would be the impact on data stalls if GPU compute speeds increase by 2×?).

In summary, this paper makes the following contributions:

- The first comprehensive analysis of how the data pipeline affects DNN training (§3)
- The DS-Analyzer tool for performing differential analyses and answering what-if questions about the impact of the data pipeline on DNN training (§3.2)
- The design and implementation of the novel CoorDL data loading library (§4)
- Evaluation showing the efficacy of CoorDL in mitigating data stalls across a range of 3 tasks, 9 models, 4 datasets, and 2 different server configurations (§5)

2 Background

Deep Neural Networks (DNNs) are a class of ML models that automatically extract higher level features from the input data. The DNN is trained over multiple rounds termed epochs. Each epoch processes all items in the dataset exactly once, and consists of multiple iterations; each iteration processes a random, disjoint subset of the data termed a minibatch. The DNN is trained until a target accuracy is reached.

Training a DNN model to reach a given accuracy consists of two steps: (i) finding the optimal set of hyperparameters for the learning process, and (ii) running the learning algorithm until the desired accuracy is reached.

Hyperparameter (HP) search. There are many parameters for the learning algorithm that must be provided before the start of training. These hyperparameters influence the speed and quality of learning. Examples of hyperparameters are learning rate, its decay, dropout, and momentum. During the search process, we start several training jobs; each job trains the model with different hyperparameters, on each available GPU (or a distributed job across several GPUs); progress is checked after a few epochs and the worst-performing candidates are killed and replaced by new jobs with different hyperparameters that are chosen algorithmically [22, 32, 42, 56]. Tuning hyperparameters is crucial for generating DNN models that have high accuracy [69].

Training the model to target accuracy. The second step is to obtain models with high accuracy by training it with input data. The training process executes the following steps in each iteration of an epoch: 1) A minibatch of data items is fetched from storage. 2) The data items are pre-processed: e.g., in image classification, data items are decompressed, and then randomly cropped, resized, and flipped. 3) The minibatch is then processed at the GPU to obtain the model’s prediction in a forward pass. 4) A loss function is used to determine how much the prediction deviates from the right answer; both weight and activation gradients are computed across the different layers of the DNN. 5) Weights in the model’s layers are updated using gradients computed in the backward pass.

Figure 1: Data Pipeline for ResNet18. This figure shows the data pipeline with DALI for the ResNet18 model along with the throughput of each component in the pipeline. On a server with 8 V100 GPUs and 24 physical CPU cores, the overall throughput of the data pipeline is lower than the expected ingestion rate at the GPU, resulting in data stalls.

Ideally, most of the time in each epoch should be spent on Steps 3–5 (which we collectively term the GPU compute time), i.e., training is GPU bound. When performing multi-GPU training, individual GPUs (workers) exchange weight gradients with other workers before performing weight update. For this work, we roll the communication time for gradient exchange during multi-GPU training into computation time.

In most frameworks, data preparation (Steps 1 and 2) and GPU computation execute in a pipelined fashion; i.e., subsequent minibatches are prefetched and pre-processed by data preparation threads, using multiple CPU cores on the machine, as the GPU computes on the current minibatch of data. If the GPU is waiting for Steps 1–2 to happen, we term it a data stall. Specifically, if training is blocked on Step 1, we call it a fetch stall; the training is I/O bound in this case. Training blocked due to Step 2 is termed prep stall; this causes the training to be CPU bound. Data stalls cause the GPU to be idle, and must be minimized to increase GPU utilization.

The rate at which data items can be fetched from storage (Step 1) depends primarily on the storage media. The rate at which data items can be pre-processed (Step 2) depends upon the pre-processing operations and the number of CPU cores available for pre-processing.

DALI: Fast Data Pipelining. State-of-the-art data loading and pre-processing libraries like DALI can be used as a drop in replacement for the default dataloaders in frameworks like PyTorch, TensorFlow, or MxNet. DALI can accelerate data pre-processing operations on Nvidia GPUs using the NVJpeg image decoding library, and by GPU-accelerated data augmentation operations. DALI also prefetches and pipelines the data fetch and pre-processing with the GPU compute, similar to the default dataloader in PyTorch.

Example. Let us examine the data pipeline for the ResNet18 model. Figure 1 shows the data fetching and pre-processing pipeline for ResNet18, along with the throughput of various components in the pipeline. This experiment is run on a machine with eight V100 GPUs, and 24 CPU cores, a typical configuration for training machine-learning models. The raw data can be fetched from hard drives at 15 MB/s or from solid state drives at 530 MB/s. If we assume that 35% of the dataset is cached in DRAM, then the effective throughput
from the storage stack (assuming 35% of dataset fetched at memory bandwidth, and 65% fetched at disk bandwidth) is 802 MB/s. Pre-processing with 24 GPUs provides an overall throughput of 735 MB/s using DALI (or 1062MB/s if some pre-processing is offloaded to the GPU), far short of the 2283 MB/s required by the GPUs. As a result, the GPUs stall waiting for data to be fetched and pre-processed. In general, if we prefetch data at rate $F$, pre-process it at rate $P$ and perform GPU computation on it at rate $G$, then data stalls appear if $G > \min(F, P)$, i.e., GPU processes data at a rate faster than it can be prefetched or pre-processed. The fetch and prep stalls reported in this work are unmasked stall time; i.e., the stall time that shows up in the critical path, inspite of being pipelined with compute. From now on, we call data prefecching simply $\textit{fetch}$, and pre-processing $\textit{prep}$.

### 3 Analyzing Data Stalls

To understand data stalls in DNN training and the fundamental reasons why data stalls exist, we perform a comprehensive analysis on several DNNs by varying a number of factors, such as the number of GPUs, GPU generation, the size of the DRAM cache, the number of CPU threads etc. We present our major findings in this section, and show more analysis such as impact of batch size and higher CPU cores in Appendix.

#### 3.1 Methodology

**Models and Datasets.** We analyze nine state-of-the-art DNN models across three different tasks and four different datasets as shown in Table 1. This section focuses on the smaller ImageNet-1K dataset for image classification models. Evaluation with large datasets like ImageNet-22k and OpenImages is presented in Section §5. The image and audio classification models are taken from TorchVision [14] and TorchAudio [13] respectively; for object detection, we use NVIDIA’s official release of SSD300 v1.1 [9]. For all DNNs, we use the same pre-processing as in the original papers. Additionally, we evaluated data stalls on two language models; Bert-Large [31] on Wikipedia & BookCorpus dataset [89] for language modeling and GNMT [84] on WMT16 [20] (EN-De) dataset for translation. These models are GPU compute heavy and do not exhibit data stalls in our training environment (hence, results excluded from analysis); data stalls may show up in these models if GPUs get faster or the computation requirements for these models gets lower due to compact representations.

**Training environment.** All experiments are performed on PyTorch 1.1.0 using the state-of-the-art NVIDIA data loading pipeline, DALI. We have empirically verified that DALI’s performance is strictly better than PyTorch’s default data loader. We use two distinct server configurations for our analysis as shown in Table 2. Config-SSD-V100 has configuration closest to AWS p3.16xlarge [1] with gp2 storage [4], while Config-HDD-1080Ti is closest to AWS p2.8xlarge [2] with st1 storage [4]. Both our servers have 500GB DRAM, 24 physical CPU cores, and 8 GPUs per server. Both these server types are a part of internal clusters at a large cloud provider; they resemble publicly available cloud GPU SKUs [1,2] as well as publicly available information on typical production cluster SKUs [6,45].

**Training parameters.** For experiments on Config-SSD-V100, we use a batch size of 512 per GPU for all image classification models, 128 per GPU for SSD-Res18, 16 per GPU for M5 and perform weak scaling for distributed training (while ensuring that the global batch size is consistent with those widely used in the ML community). Since V100 GPUs have tensor cores, we use Apex mixed precision training with LARC (Layer-wise Adaptive Rate Clipping), and state-of-the-art learning rate warmup schedules [34]. On Config-HDD-1080Ti, we use the maximum batch size that fits the GPU memory (less than 256 for all models) and perform full-precision training.

**Training metrics.** We run all the experiments presented here for three epochs, and report the average epoch time (or throughput in samples per second), ignoring the first epoch. Since we start with a cold cache in our experiments, first epoch is used for warmup. Measuring data stall time does not require training to accuracy; per-epoch time remains stable.

### 3.2 Measuring data stalls using DS-Analyzer

We develop a standalone tool, DS-Analyzer that profiles data stalls in DNN training. Frameworks like PyTorch and TensorFlow provide an approximate time spent on data loading and pre-processing per minibatch, by simply placing timers in the training script. This is insufficient and inaccurate for two reasons. First, this technique cannot accurately provide

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### Table 1: Models and datasets used in this work.

| Task                  | Model                  | Dataset (Size)     |
|-----------------------|------------------------|--------------------|
| Image Classification  | ShuffleNetv2 [86]      | ImageNet-22k [5]   |
|                       | AlexNet [53]           |                    |
|                       | ResNet18 [37]          | (1.3TB)            |
| Obj Detection         | SSD+Res18 [60]         | Free Music [29]    |
|                       | M5 [27]                | (950GB)            |
| Audio Classify        | VGG11 [78]             | Imagenet-1k [73]   |
|                       | (146GB)                |                    |

### Table 2: Server configurations used in this work.

| Server Configuration | GPU Config | GPU Mem(GB) | Storage Media | Rand Read (MBps) |
|----------------------|------------|-------------|---------------|-----------------|
| SSD-V100             | 8xV100     | 32          | SSD           | 530             |
| HDD-1080Ti           | 8x1080Ti   | 11          | HDD           | 15 - 50         |

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the split up of time spent in data fetch (from disk or cache) and pre-processing operations. To understand if the training is bottlenecked on I/O or CPU, it is important to know this split.

Second, frameworks like PyTorch and libraries like DALI use several concurrent processes (or threads) to fetch and pre-process data; for a multi-GPU data parallel training job, a data stall in one of the data loading processes may reflect as GPU compute time for the other processes, because all GPU processes wait to synchronize weight updates at batch boundaries. Naively adding timers around data path does not provide accurate timing information. Therefore, DS-Analyzer uses a differential approach. DS-Analyzer runs in three phases;

1. **Measure ingestion rate.** First, DS-Analyzer pre-populates synthetic data at the GPUs and runs the job for a fixed number of epochs. This identifies the max data ingestion rate at the GPUs, with no fetch or prep stalls.

2. **Measure prep stalls.** Next, DS-Analyzer executes the training script with the given dataset by ensuring that the subset of data used is cached in memory, using all available CPU cores, and estimates the training speed. Since this run eliminates fetch stalls, any drop in throughput compared to (1) is due to prep stalls.

3. **Measure fetch stalls.** Finally, DS-Analyzer runs the training script by clearing all caches, and setting maximum cache size to a user-given limit, to account for fetch stalls. The difference between (2) and (3) is the impact of fetch stalls.

Additionally, DS-Analyzer collects low level metrics such as the throughput of the storage device, memory and network bandwidth, cache size, and memory utilization.

### 3.3 Data Stalls in DNN Training

Our analysis aims to answer the following questions:

- **Fetch Stalls.** When does the storage device (SSD/HDD) become a bottleneck for DNN training? (§3.3.1)
- **Prep Stalls.** When does data augmentation at the CPU become a bottleneck for DNN training? (§3.3.2)
- **Generality.** Do fetch and prep stalls exist in other training platforms like TensorFlow? (§3.3.3)

#### 3.3.1 When datasets cannot be fully cached

Datasets used for training DNNs are growing in size [15, 21, 55]. Even the ML-optimized cloud servers with 500GB DRAM can only cache 35% of ImageNet-22K, or 45% of the FMA dataset, or 65% of the OpenImages dataset. Popular datasets like ImageNet-1K cannot be fully cached on commonly used cloud SKUs like AWS p3.2xlarge, which has 61 GiB DRAM. When datasets don’t fit in memory, and the fetch rate ($F < \text{compute rate (min}(P, G))$, fetch stalls occur.

**Fetch stalls are common if the dataset is not fully cached in memory.** Figure 2 shows the percentage of per epoch time spent on I/O for nine different DNNs when 35% of their respective datasets can be cached in memory on Config-SSD-V100. DNNs spend 10 –70% of their epoch time on blocking I/O, despite pipelining and prefetching, simply because the compute rate is higher than fetch rate.

**OS Page Cache is inefficient for DNN training.** DNN training platforms like PyTorch, TensorFlow and libraries like DALI, rely on the operating system’s Page Cache to cache raw training data in memory. Unfortunately, the OS Page Cache leads to thrashing as it is not efficient for DNN training. If 35% of the data can be cached, then an effective cache should provide 35% hits; instead, the Page Cache provides a lower hit rate. For a 146 GiB data set, each epoch should see only 65% of the dataset, or 95GiB, fetched from storage. Instead, we observe 85% of the dataset fetched from storage every epoch; the 20% difference is due to thrashing. Figure 3 shows the fetch stalls, including those due to thrashing, when using PyTorch with DALI. An effective cache for DNN training must eliminate thrashing to reduce fetch stalls to the minimum shown in Figure 3.

**Lack of coordination among caches leads to redundant I/O in distributed training.** In distributed training jobs, the data to be fetched and processed is divided randomly among servers. The division is random and changes every epoch. As a result, each server often has to fetch data from storage every epoch; this is done even if the required data item is cached in another server that is a part of the distributed training job. This lack of coordination among caches makes dis-
Figure 4: Impact of CPU cores on training. DNNs need between 3 – 24 cores per GPU to mask prep stalls.

Distributed training storage I/O-bound. When training Resnet50 on ImageNet-1K (146GiB) across two servers having a total cache size of 150GiB, each server fetches 45GiB from storage in each epoch (despite the fact that the other server might have this data item in its cache). On Config-HDD-1080Ti, this leaves ResNet50 stalled on I/O for 75% of its epoch time.

Lack of coordination in HP search results in redundant I/O. HP search is performed by launching several parallel jobs with different HP on all available GPUs in a server [57]. All HP jobs access the same dataset in a random order in each epoch, resulting in cache thrashing and read amplification. When 8 single-GPU jobs are run in a server (35% cache), there is 7× read amplification per epoch (984 GiB read off storage compared to 125 GiB for one job), which slows down HP search on ResNet18 by 2× on Config-SSD-V100.

3.3.2 When datasets fit in memory

We now analyze the impact of CPU pre-processing on DNN training in the scenario where the entire dataset is cached in memory, thus eliminating fetch stalls due to storage I/O.

DNNs need 3–24 CPU cores per GPU for pre-processing.

Figure 4 shows how DNN training throughput changes as we vary the number of CPU pre-processing threads (per V100 GPU) for four models. For computationally complex models like ResNet50, 3 – 4 CPU cores per GPU is enough to prevent prep stalls; for computationally lighter models like ResNet18 or AlexNet, as many as 12 – 24 CPUs per GPU are needed to mask prep stalls. Since prep is CPU-intensive, using more threads (vCPUs) than the number of physical CPU cores does not help much; For a 8-GPU server with 32 CPU cores (64vCPUs), ResNet18 spends 37% of the epoch time on prep stalls (Appendix). Even on NVIDIA’s AI-optimized DGX-2, there are only three CPU cores per GPU; many models will have prep stalls on the DGX-2.

DALI is able to reduce, but not eliminate prep stalls.

DALI uses the GPU for pre-processing operations, and is thus able to reduce prep stalls, as shown in Figure 5 (a). The effectiveness of DALI depends on the GPU speed; for example, on the slower 1080Ti, DALI is able to eliminate prep stalls using three CPU threads and the GPU. On the faster

V100 though, DALI still results in 50% prep stalls when using three CPU threads and the GPU. Figure 6 shows that our observations hold across different DNNs when training with eight GPUs each with 3 CPUs.

Redundant pre-processing in HP search results in high prep stalls. During HP search, concurrent jobs process the same data. Currently, there is no coordination; if there are 8 HP jobs, the same data item is processed eight times. This is made worse by the fact that all HP jobs share the same set of CPU threads, leading to fewer CPU threads per GPU, and higher prep stalls. When 8 single-GPU ResNet18 HP jobs run on Config-SSD-V100, each job gets 3 CPU for prep and incurs a 50% prep stall as shown in Figure 6. Coordinating these HP search jobs on a single server can potentially eliminate prep stalls, as all available CPU (24 cores) can be used to prep the dataset exactly once per epoch and reused across jobs (Figure 4 shows ResNet18 requires 12 CPUs per GPU to eliminate prep stalls).
### 3.3.3 Data stalls exist across training frameworks

To generalize our findings on data stalls across different training platforms and data formats, we analyze the prep and fetch stalls in TensorFlow using the binary TFRecord format. Unlike PyTorch, TensorFlow does not store training data as small individual raw files. Instead, it shuffles the small random files, serializes them, and stores them as a set of files (100-200MB each) called TFRecords. TFRecords make reads more sequential. Training platforms like MXNet also use a similar serializing technique for data called RecordIO [61].

Table 3 shows the percentage of misses in the Page Cache for a 8-GPU training job and the IO amplification due to lack of coordination in HP search. Similar to PyTorch, TensorFlow can also use DALI’s GPU based pre-processing and exhibit prep stalls similar to PyTorch. TensorFlow’s TFRecord format results in 40% higher cache misses than the ideal because, the sequential access nature of TFRecords is at odds with LRU cache replacement policy of the Page Cache, resulting in a pathological case for LRU. The lack of co-ordination in HP search leads to redundant I/O & prep for a 8-GPU training job and the IO amplification due to lack of coordination in HP search.

### 3.3.4 Analysis summary

Table 4 summarizes our key findings pertaining to data stalls across DNN training frameworks, models, and hardware configurations. Our analysis also highlights that data stalls are a consistent problem across both TensorFlow and PyTorch.

### 3.4 What-if analysis with DS-Analyzer

While all the experiments in §3.3 are run on physical servers, we extend DS-Analyzer to help a user simulate these experiments without having to run all different configurations on physical servers. DS-Analyzer profiles the given model once on the server; using the metrics collected, it can answer what-if questions such as, how much cache does the model need to mask fetch stalls, how many CPU cores should each GPU use to eliminate prep stalls, and so on. This is a powerful means of analyzing whether throwing more hardware at the problem will solve the issue of data stalls. For instance, if training is dominated by fetch stalls (bottlenecked on disk bandwidth), then increasing the number of CPU cores on the machine has no benefit; either DRAM capacity has to be increased, or the disk must be replaced with a higher bandwidth one. Similarly, if the training job is bottlenecked on prep, then increasing DRAM has no effect on training time. DS-Analyzer is useful in scenarios like this, to predict the performance of a model as we scale up CPU, memory, or storage.

| Finding | CoorDL Insights |
|---------|-----------------|
| OS Page Cache is inefficient for DNN training due to thrashing | Optimize DNN cache to eliminate thrashing across epochs (MinIO §4.1) |
| Lack of coordination among local caches lead to redundant I/O in distributed training across servers | Local caches of servers can be coordinated to fetch data from the remote cache to overcome storage I/O bottlenecks (Partitioned Cache §4.2) |
| No coordination in HP search leads to redundant I/O & prep | HP search jobs must coordinate data fetch & prep (Coordinated Prep §4.3) |

Table 4: Key findings and implications of our analysis of data stalls

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**Figure 7: Architecture of CoorDL.** Raw data items from the local storage are cached in the MinIO cache. Multiple CPU threads fetch items from the local (or remote) MinIO cache, pre-process and create minibatches, which are then staged for sharing across jobs, if there are multiple jobs.

We evaluate DS-Analyzer’s what-if analysis on both our server configurations with image classification models for different cache sizes. The recommendations made by DS-Analyzer were within 4% of the empirical results (detailed example in Appendix).

### 4 CoorDL: Coordinated Data Loader

We present the design and implementation of CoorDL, a coordinated data loading library for DNN training on commodity servers. CoorDL uses available CPU and memory resources efficiently to reduce DNN training time by minimizing data stalls.

**Overview.** CoorDL coordinates fetching data from storage, pre-processing data, and creating minibatches for DNN training. Using insights from our analysis (Table 4), CoorDL minimizes fetch and prep stalls using three core techniques. First, CoorDL uses the novel MinIO software cache that exploits the data-access pattern of DNN training workloads to eliminate cache thrashing. Second, CoorDL coordinates the local MinIO caches of individual servers during distributed training; if there is a cache miss in a server’s MinIO cache, CoorDL fetches data preferentially from a remote MinIO cache rather than local storage. Finally, CoorDL introduces the novel coordinated-prep technique, that coordinates fetch and prep of data items across all concurrent jobs in a server, if they operate on the same dataset (such as in HP search).

The overall architecture of CoorDL is shown in Figure 7. The training dataset resides on a local storage device like SSD or HDD. If the data resides on a remote storage service, the data is cached in local storage when it is first accessed [54].
For all later epochs, the data is fetched from local storage. In each training iteration, a minibatch of data must be fetched from disk (or cache), pre-processed to apply random transformations and collated into a tensor that can be copied over to the GPU for DNN computation. CoorDL manages its own MinIO cache of the raw data items (before any stochastic pre-processing and randomization that can be applied over the GPU for DNN computation). The data sampling and randomization is unmodified; in each epoch, every minibatch is sampled randomly from the dataset. Every data item is then subjected to the random pre-processing pipeline specified in the training workload. The prepared minibatch is then placed in a cross-job staging area for consumption by the GPU. If a single data-parallel job is running across multiple GPUs in a server, then the minibatches in the staging are used exactly once per epoch and discarded; if there are concurrent HP jobs on a server, then the staging area retains minibatches until each concurrent job has used it exactly once in the current epoch. Any minibatch that satisfies this criteria is evicted from the staging area to make way for newer batches.

We now discuss CoorDL’s three core techniques in detail.

4.1 The MinIO cache

DNNs suffer from fetch stalls if the dataset cannot be fully cached in memory and has to be fetched from the storage during training (§3.3). Recall from Fig 1 that fetch stalls occur when the rate of data fetch is lower than the rate of compute (despite prefetching and pipelining data fetch with compute). When fetch stalls occur, compute proceeds at the rate at which uncached data items can be fetched from storage; therefore it is important to minimize the amount of data fetched from storage in each epoch. MinIO tackles this problem by ensuring that every item in the cache is used effectively in each epoch; thereby minimizing the amount of disk I/O per epoch to the ideal minimum.

DNN training has a unique data access pattern: it is repetitive across epochs and random within an epoch. Training is split into epochs: each epoch accesses all the data items in the dataset exactly once in a random order.

Currently, DNN training platforms rely on the OS Page Cache to cache training data. Every data item read from the storage device is cached in the Page Cache to speed up future accesses. When the Page Cache reaches its capacity, a cache replacement policy decides which of the existing items to evict to make space for the new one. Linux uses a variant of Least Recently Used (LRU) for cache replacement [33].

However, we make a key observation about the DNN access pattern that is at odds with such cache replacement policies. All data items in the dataset have equal probability of access in an epoch. Therefore, it is not important which data item is cached. Instead, it is crucial that cached items are not replaced before they are used, to minimize storage I/O per epoch.

Therefore, MinIO recommends a simple and unintuitive solution; items, once cached, are never replaced in the DNN cache. MinIO works as follows. In the first epoch of the training job, MinIO caches random data items as they are fetched from storage, to populate the cache. Once the cache capacity is reached, MinIO will not evict any items in the cache; instead, the requests to other data items default to storage accesses. The items in the MinIO cache survive across epochs until the end of the training job. Every epoch beyond the first gets exactly as many hits as the number of items in the cache; this reduces the per-epoch disk I/O to the difference in the size of the dataset and the cache.

Figure 8 contrasts the caching policy of the OS Page Cache and MinIO. Consider a dataset of size 4 (with items A – D) and a cache of size 2 (50% cache). Let’s say after warmup, the cache has two items D and B. Figure 8 shows the state of the cache for two training epochs. MinIO only incurs capacity misses per epoch (here 2); the Page Cache on the other hand, can result in anywhere between 2-4 misses per epoch because of thrashing. For instance, in the first epoch, D is in the cache to begin with, but kicked out to make way for a new item C, and later in the same epoch it is requested again (thrashing). We empirically verified this using large datasets and varying cache sizes (§5) and found that Page Cache results in close to 20% more misses than MinIO due to thrashing.

MinIO’s no replacement policy simplifies the design of the cache as we do not need bookkeeping about the access time or frequency of data items; if we were to implement a replacement policy, such metadata needs to be tracked. The strength of MinIO thus lies in its simplicity and effectiveness.

4.2 Partitioned Caching

MinIO reduces the amount of disk I/O (fetch stalls) in single-server training. In distributed training, the dataset is partitioned and processed by a group of servers. Each server operates on a random shard of the dataset per epoch.

The MinIO cache is not efficient in this setting. For example, consider a distributed training job across two servers, each of which can cache 50% of the dataset. In every epoch, each server has to process a random 50% partition of the dataset, some of which may be hits in the local MinIO cache but the misses result in storage I/O, which is expensive and results in fetch stalls.

We observe that the cross-node network bandwidth in publicly available cloud GPU instances and our clusters(10-40 Gbps) is up to 4× higher than the read bandwidth of local SATA SSDs (530 MBps). Data transfer over commodity TCP stack is much faster than fetching a data item from its lo-
Partitioned caching works as follows. In the first epoch, the dataset is sharded across all servers, and each server populates its local MinIO cache with data items in the shard assigned to it. At the end of the first epoch, CoorDL collectively caches a part of the dataset of size equal to the sum of capacities of individual MinIO caches. To route data fetch requests to the appropriate server, CoorDL maintains metadata about data items present in each server’s cache. Whenever a local cache miss happens in the subsequent epoch at any server, the item is first looked up in the metadata; if present, it is fetched from the respective server over TCP, else from its local storage.

If the aggregate memory on the participating servers is large enough to cache the entire dataset, then partitioned caching ensures that there is no storage I/O on any server beyond the first epoch; the entire dataset is fetched exactly once from disk in the duration of distributed training. Partitioned caching scales well as we distribute training across a large number of servers, by caching replicas of the dataset if there is more distributed memory than required for the dataset.

4.3 Coordinated Prep

Hyperparameter (HP) search for a model involves running several concurrent training jobs, each with a different value for the HP and picking the best performing one. Our analysis shows that co-locating HP search jobs on the same server results in both fetch and prep stalls (§3) due to lack of coordination in data fetch and prep among these jobs.

CoorDL introduces coordinated prep to address this issue. Each job in the HP search operates on the same data; hence, instead of accessing data items independently for each job, they can be coordinated to fetch and prep the dataset exactly once per epoch. Each epoch is completed in a synchronized fashion by all HP jobs; as a result, pre-processed minibatches created by one job can be reused by all concurrent jobs.

Coordinating HP search jobs must be done carefully to ensure this invariant holds: each job processes the entire dataset exactly once per epoch. A naive way of doing this is to pre-process the dataset once and reuse across all HP jobs and all epochs. This approach will not work for two reasons. First, reusing pre-processed data across epochs may result in lower accuracy, as the random transformations are crucial for learning. Second, the pre-processed items are 5–7× larger in size when compared to the raw data items. Caching pre-processed items will overflow the system memory capacity quickly. If we store them on storage, we may incur fetch stalls.

Coordinated prep addresses these challenges by staging pre-processed minibatches in memory for a short duration within an epoch. Since each job has identical per-minibatch processing time, the minibatch is short lived in the staging area. Coordinated prep works as follows.

Each HP search job on a server receives a random shard of the dataset when they start. Each job fetches and pre-processes the assigned shard, creating minibatches as they would normally do. When ready, these minibatches are exposed to the other jobs in the cross-job staging area. This is a memory region that is accessible to all running jobs on the server. Additionally, each minibatch has a unique ID and an associated atomic counter that tracks how many jobs have used this minibatch so far in the current epoch. When a job needs a minibatch for GPU processing, it retrieves it from the staging area and updates its usage counter. A minibatch is deleted from the staging area when it is used exactly once by all running jobs, as we want to ensure that it is not used across epochs. We empirically show in §5 that the addition of cross-job staging area does not introduce additional memory overhead.

Thus, coordinated prep ensures one sweep over the dataset per epoch for both data fetch and pre-processing, eliminating redundant work. Note that coordinated prep allows addition or removal of jobs only at epoch boundaries; this is not an issue because popular HP search algorithms evaluate the objective function (for e.g., accuracy), and make decisions on terminating or continuing the job at epoch boundaries [42, 56].

Handling job failures and terminations. The progress of each HP search job in CoorDL is dependent on the progress of all other running jobs, because each job is responsible for pre-processing a shard of the dataset. Therefore, if one of the jobs is killed by the user in the middle of an epoch, or terminates abruptly, all other jobs may stall waiting for minibatches that the job was responsible for preparing. To address this, CoorDL uses a failure detection module to monitor the status of running jobs.

Every prepared minibatch fetched from the staging area has an associated timeout. If any job times out waiting for a minibatch in the staging area, it notifies the driver process of a possible failure. All the jobs can deterministically identify which job failed to populate the batch it is waiting on. CoorDL’s failure detection module verifies if the reported job is alive or dead; if alive, it issues a broadcast to all the jobs to retry fetching the minibatch from staging area, else it spawns a new process to resume data loading for the shard that failed.

4.4 Implementation

We implement CoorDL by adding 1.5K lines of C++ code to DALI. Cross-batch staging is implemented as a binding between DALI and PyTorch in 935 lines of Python code. We implement DS-Analyzer in Python with 1.1K LOC. We have also implemented our techniques in the native PyTorch data loader (Py-CoorDL- details and evaluation in Appendix).

CoorDL uses file-backed shared memory to share data among jobs. The partitioned cache uses TCP connections to fetch data; connections are created on startup and kept alive for the duration of the job. The job failure detection module
uses an initial timeout that is 10 times the duration of an iteration (batch). Empirically, for all models we tested on, this duration was sufficient to mask the minor differences in the per-batch duration across jobs.

CoorDL can be used as a drop-in replacement to either native PyTorch dataloader, or DALI, with no modifications to the training script. Using DS-Analyzer requires about 10 – 15 lines of additions to the DNN training script.

5 Evaluation

We now evaluate the efficacy of CoorDL on three different aspects of the training process: hyperparameter tuning, multi-GPU training on a single server, and distributed training across multiple servers. We evaluate our techniques on nine models, performing three different ML tasks (image classification, object detection and audio classification) on four different datasets, each over 500GB as shown in Table 1. Since DALI strictly outperforms PyTorch DL, we use DALI (best of CPU or GPU based prep) as the baseline in our experiments.

Experimental setup. We evaluate CoorDL on two representative server configurations (Tbl 2) each with 500 GiB DRAM, 24 CPU cores, 40 Gbps Ethernet, eight GPUs, and 1.8 TiB of storage space. Config-SSD-V100 uses V100 GPUs and a SATA SSD, while Config-HDD-1080Ti uses 1080Ti GPUs and a magnetic hard drive. Config-SSD-V100 is similar to the AWS p3.16xlarge instance [1], while Config-HDD-1080Ti is similar to the AWS p2.8xlarge instance [2]. We use the same training methodology we used for analysis (§3.1).

We seek to answer the following questions:

- How does the MinIO cache affect multi-GPU training on a single server? (§5.1)
- How does partitioned caching improve training time for jobs distributed across multiple servers? (§5.2)
- How does coordinated prep benefit HP search? (§5.3)
- Does CoorDL affect DNN training accuracy? (§5.4)
- Does CoorDL enable better resource utilization compared to DALI? (§5.5)

While we present our main results in this section, more evaluation including the scalability of coordinated prep, and HP search with more CPU cores are available in the Appendix.

5.1 Single-server Multi-GPU training

CoorDL speeds up a single-server training job by reducing fetch misses using the MinIO cache. Figure 9(a) plots the relative speedup with respect to DALI while training the image classification and object detection models on the OpenImages dataset, and audio classification on FMA dataset. We evaluate MinIO against two modes of DALI. DALI’s default mode is DALI-seq, where it reads data sequentially off storage and shuffles them in memory [65]. DALI-shuffle accesses the dataset in a randomized order (doing random reads, similar to the native dataloader of PyTorch).

MinIO results in up to 1.8× higher training speed compared to DALI-seq by eliminating thrashing on Config-SSD-V100.

When the image classification models are trained with ImageNet-22k dataset, CoorDL results in up to 1.5× speedup. On Config-HDD-1080Ti, CoorDL accelerates ResNet50 training on OpenImages by 2.1× compared to DALI-seq and 1.53× compared to DALI-shuffle respectively.

Reduction in cache misses. We measure the disk I/O and number of cache misses when training ShuffleNet on OpenImages dataset on Config-SSD-V100. This server can cache 65% of the dataset. CoorDL reduces misses to the minimum number of 35%, resulting in 225 GB of I/O. In contrast, DALI-Seq results in 66% cache misses, increasing I/O by 87% to 422 GB; DALI-shuffle results in 53% cache misses, increasing I/O by 50% compared to CoorDL to 340 GB.

Note that, when the whole dataset does not fit in memory, DALI-shuffle performs better than DALI-seq (because sequential access is a pathological case for the Linux LRU page cache). Therefore, our evaluation in the rest of this section compares CoorDL to the stronger baseline, DALI-shuffle.

5.2 Multi-Server Distributed Training

We now evaluate CoorDL on a distributed training scenario. The lack of cache co-ordination between the participating servers results in fetch misses that lead to disk I/O. CoorDL uses partitioned caching to avoid redundant I/O.

Figure 9(b) shows that CoorDL improves the throughput of distributed training jobs by up to 15× (AlexNet on OpenImages) when trained across two Config-HDD-1080Ti servers (16 GPUs). On Config-HDD-1080Ti servers, 65% of the OpenImages dataset can be cached on a single server; and it can be fully cached in the aggregated memory of two servers. Therefore, CoorDL moves the training job from being I/O bound to GPU bound.

When trained across two servers on Config-SSD-V100, CoorDL accelerates ShuffleNet on ImageNet-22k by 1.3×, and Audio-M5 on FMA by 2.9×. The relative gains are lower on Config-SSD-V100 because the cost of a fetch miss is lower on SSDs due to its high random read throughput, as compared to HDDs on Config-HDD-1080Ti.

5.3 Hyperparameter Search

Figure 9(d) plots the relative increase in throughput of individual jobs across several models when eight concurrent HP search jobs are run on a Config-SSD-V100 server. On less computationally complex models like AlexNet and ShuffleNet, CoorDL increases training speed by 3×, because these models are originally CPU bound due to prep.

For the audio model, CoorDL increases the training speed by 5.6×. CoorDL reduces the total disk I/O from 3.5TB to 550GB, moving the job from being I/O bound to GPU bound. The reduced I/O results from CoorDL avoiding cache thrashing using coordinated prep. Similarly, on Config-HDD-1080Ti, CoorDL results in 5.3× faster training on the audio model, and 4.5× faster training on ResNet50.

On Config-HDD-1080Ti, CoorDL results in 5.3× faster
training on the audio model, and 4.5× faster training on ResNet50 by coordinating data fetch and prep.

Multi-GPU HP search jobs. Figure 9 (e) evaluates the efficacy of CoorDL for different configurations of HP search jobs on a machine; 8 1-GPU jobs, 4 2-GPU jobs, 2 4-GPU jobs, or 1 8-GPU job for AlexNet on OpenImages. For a single job case, the benefit is due to the MinIO cache; in other configurations, it is due to coordinated prep. When there are a lot of concurrent jobs, pre-processing becomes the bottleneck; coordinated prep is able to improve performance significantly.

HP search with fully cached dataset. CoorDL’s ability to speed up HP search jobs comes from coordinating pre-processing to overcome the imbalance in the ratio of CPU cores to GPU. We perform HP search with 8 jobs on Config-SSD-V100 with ImageNet-1k dataset that fits entirely in memory. CoorDL sped up HP search by 1.9× on AlexNet and 1.2× on ResNet50 by eliminating redundant prep.

5.4 Training to Accuracy with CoorDL

CoorDL does not change the randomness of data augmentation techniques involved. Its techniques do not affect the learning algorithm. To demonstrate this, we train ResNet50 to accuracy on ImageNet-1K using 16 GPUs across two Config-HDD-1080Ti servers, where each server is capable of caching 50% of the dataset. Figure 10 shows that CoorDL reduces the time to target accuracy (75.9%) from two days to just 12 hours (4× better), due to partitioned caching.

5.5 Resource Utilization

MinIO results in lower disk I/O and better CPU utilization. Figure 11 shows the I/O for two epochs of training ResNet18 on OpenImages on Config-SSD-V100. The I/O behavior is similar across models and server configurations.

DALI observes cache hits at the beginning of the epoch, but soon becomes I/O bound (disk bandwidth: 530 MB/s). Since MinIO is caching a random subset of the dataset, cache hits
in training ResNet50 with ImageNet-1K on 16x 1080Ts across 2 servers, CoorDL reduces the time to accuracy by 4× by coordinating the caches across the job’s individual servers. This results in a predictable I/O access pattern and faster training (epochs end earlier in Figure 11).

Profiling the CPU during training shows that the pre-processing threads in DALI are often stalled waiting for I/O. Since MinIO reduces the total disk I/O, CoorDL is able to better utilize the CPU threads for pre-processing. The combination of lower disk I/O and better CPU utilization leads to shorter training times when using CoorDL.

**CoorDL uses a fraction of available network bandwidth.** CoorDL shards the dataset equally among all servers in distributed training to ensure load balancing. We track the network activity during the distributed training for ResNet50 on OpenImages across two, three, and four servers with DALI and CoorDL. CoorDL used 5.7 Gbps per server of network bandwidth (14% of the 40 Gbps available). DALI used 1.18 Gbps of network bandwidth per server. CoorDL used 4.8× higher network bandwidth to train 4.3× faster than DALI.

**Co-ordinated prep has low memory overhead.** By design, co-ordinated prep has the same memory requirements as DALI. To experimentally validate this, we track the memory utilization of running hyperparameter search on AlexNet on OpenImages on a Config-SSD-V100 server using eight concurrent jobs. CoorDL uses 5 GB of extra process memory to store prepared mini-batches in memory until all hyperparameter jobs consume it. We reduce the cache space given to CoorDL by 5 GB (keeping the total memory consumption same for CoorDL and DALI). Despite the lower cache space, CoorDL still accelerated training by 2.9×.

6 Related Work

To the best of our knowledge, this paper presents the first comprehensive analysis of data stalls in DNN training. We place our work in the context of prior work.

**Optimizing DNN training time.** A number of solutions have been proposed to reduce the training time for DNNs including specialized hardware [16, 18, 45, 48, 64, 67, 71, 77], parallel training [25, 28, 39, 47, 52, 53, 62], GPU memory optimizations [24, 43, 72], lowering communication overhead [36, 44, 59, 85], faster communication libraries [19, 83], and compiler-based operator optimizations [23, 46, 81]. This paper presents a new point in this spectrum, data stalls.

**Hardware solutions to fetch stalls.** New hardware like NVIDIA’s Magnum IO [66], and PureStorage’s AIRI [70] provide high throughput storage solutions to address fetch stalls. While these fast hardware may mask fetch stalls in some models, they may not help if the model is bottlenecked on prep stalls. CoorDL accelerates DNN training by mitigating data stalls with existing commodity servers as opposed to relying on expensive hardware solutions.

**Redundancy in DNN training.** Prior work like Model Batch-Mining [63] has identified redundancy in model search; where an algorithm automatically searches for a model architecture for a given task. However, it optimizes for running multiple DNNs together on a single GPU, by sharing GPU computation across jobs. CoorDL on the other hand accelerates training in the more common setting where GPUs are not shared between jobs. OneAccess [49] is a preliminary study that uses reservoir sampling to generate uniformly random samples of data while accessing pre-processed data sequentially. In a departure from the state-of-the-art, OneAccess stores pre-processed data across epochs to reduce prep stalls; however such an approach precludes online data-augmentation techniques commonly used today such as rescaling, translations, flipping, and randomization (hue, saturation, brightness, and contrast), and this can affect model convergence adversely. Furthermore, OneAccess limits itself to a PyTorch baseline with no more than 2 CPU cores used per GPU and very small datasets such as CIFAR-10 (340MB) [51] and MS-COCO (20GB) [58].

**Distributed DNN caching.** Prior work like Quiver [54] and DeepIO [88] have looked at distributed caching techniques for specific DNN training settings such as multi-tenant clusters and HPC clusters with specialized hardware like RDMA. While both these works aim at reducing fetch stalls in specific scenarios, unlike CoorDL, they neither accelerate common-case single server training, nor eliminate prep stalls.

Quiver is distributed storage (SSD) cache that uses a new
substitutable sampling technique co-designed with the PyTorch framework, which restricts randomness in the creation of minibatches to a subset of cached items. Unlike CoorDL that accelerates a variety of training settings, Quiver is specifically designed for HP search when the dataset is too large to fit on the local storage device (> 3TB). DeepIO also proposes an entropy-aware sampling technique, and RDMA based data shuffling for distributed training across servers. However, when the entire dataset does not fit in memory, DeepIO cache suffers from thrashing unlike MinIO. Unlike DeepIO, CoorDL does not require any specialized hardware support.

7 Conclusion

We present the first detailed study of data stalls in several DNNs, and show that it accounts for up to 70% of the training time. The insights from our study, guide the design of CoorDL, a coordinated caching and pre-processing library for DNN training. CoorDL accelerates training by $15 \times$ for distributed training of AlexNet across two servers, and $5.2 \times$ for HP search on the audio model, by coordinating data fetch and prep across jobs. The techniques behind CoorDL are simple and intuitive, easing adoption into production systems.

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A Overview

This document contains supplementary material to the main submission, describing experiments that were omitted in the paper for brevity. This document discusses the following primary points.

- Analysis of prep stalls on servers with a large number of CPU cores, and evaluation of coordinated prep on such a server
- Evaluation results of CoorDL against DALI with ImageNet-22k
- Detailed evaluation of resource utilization by CoorDL
- A prototype implementation and evaluation of Py-CoorDL in the native PyTorch framework (without DALI)

B Analysis of Data Stalls

Our paper shows the analysis of data stalls in DNN training across various models, datasets, and hardware configurations. Here, we provide additional analysis of prep stalls such as increasing the number of CPU cores per GPU beyond 3, and the impact of batch size.

B.1 Training on servers with high CPU count

Typically, servers optimized for ML training (for example, NVIDIA DGX-2) have 3 CPU cores per GPU [7]. However, some cloud providers like AWS have servers with 8 GPUs.
Figure 13: **Epoch time with PyTorch and DALI.** This graph plots the epoch time for various image classification models with native PyTorch DL and DALI (CPU-prep and GPU-prep) on Config-SSD-V100. DALI provides significant speedup over PyTorch even in its CPU mode due to the optimized nvJPEG decoding library. For compute heavy models like ResNet50, GPU based pipeline hurts performance because there is no idle time at the GPU that can be used for pre-processing, and thus interferes with GPU computation.

Figure 14: **Impact of batch size on prep.** This graph plots the epoch time for MobileNetv2 on Config-SSD-V100 with 8-GPUs as we vary the per-GPU batch size. As batch size increases, the compute time at the GPU drops due to reduced communication overhead. However, the epoch time does not improve because training is bottlenecked by prep.

and 32 CPU cores (64 vCPUs), that results in 4 cores (or 8 vCPUs) per GPU. We analyze prep stalls in one such server with 8 V100 GPUs, 64 vCPUs, and 500GiB DRAM. Figure 12 shows the training speed for a Resnet18 training job as we vary the number of vCPUs per GPU for both CPU-based and GPU-based prep pipeline with DALI. Note that the dataset is fully cached in memory and there are no fetch stalls in this experiment. Resnet18 has 50% prep stall for 3 CPU cores per GPU, when GPU-based prep is used (shown by the GPU ingestion rate in Figure 12). With 8 vCPUs per GPU, prep stalls reduced to 37%, but did not vanish. Note that, pre-processing with CPU scales linearly up to the number of cores (here 4 per GPU), beyond that, hyperthreading does not result in linear gain in performance. Increasing the number of pre-processing threads in the server from 32 to 64 increased pre-processing speed only by 30%. In this experiment, we did not increase pre-processing threads per GPU beyond 5 in the GPU-prep mode of DALI, as it resulted in higher GPU memory consumption for prep and hence OOM. All the experiments presented in our main submission used 3 physical CPU cores per GPU (with GPU-prep of DALI where beneficial). This is only 25% slower than using 8 vCPUs per GPU (as shown in Figure 12). Additionally, the prep stall shown here is for ImageNet-1K; with richer datasets like OpenImages (higher per-image size), prep stalls increase further.

**B.2 Comparing PyTorch DL with DALI**

PyTorch has two different native modes for data parallel training; DataParallel (DP) and DistributedDataParallel (DDP). DP is usually slower than DDP even on a single server due to the Global Interpreter Lock (GIL) contention across threads, and additional overhead introduced by scattering inputs and gathering outputs across GPUs [12]. Figure 13 shows the epoch time for 7 different image classification models using the ImageNet-1K dataset (fully cached in memory) using native PyTorch DL with the faster DDP mode and DALI. PyTorch DL uses the Pillow library [26] and TorchVision [14] for image decoding and pre-processing while DALI uses the optimized nvJPEG library [8], therefore resulting in faster pre-processing even when using only CPU. When the GPU based DALI pipeline is used, training time further drops due to reduction in prep stalls. However, note that there are two downsides to using DALI’s GPU based prep. First, it takes up 2-5GB of additional GPU memory for pre-processing, the luxury of which may not be available for all models and GPUs, as GPU memory is limited. Second, scheduling pre-processing on the GPU hurts models like ResNet50, as they are already heavy on GPU computation. In all our analysis and evaluation presented in the paper, we run with both GPU and CPU based DALI pipeline and present the best of the two results (CPU-based prep was faster on ResNet-50 and VGG11).

**B.3 Impact of batch size on data stalls**

The impact of batch size on GPU computational efficiency is well studied [38, 79]; larger batch sizes utilize the massive GPU parallelism better, and also reduce the number of weight updates (inter-GPU communication) per epoch, resulting in faster training. Figure 14 shows the impact of varying the
We built DS-Analyzer to aid our analysis of data stalls and collects these metrics for a model as follows. Is required for this model to eliminate fetch stalls? What answer what-if questions such as, how much DRAM cache does the DNN need to eliminate data stalls to reap the benefits of faster compute. While this experiment considered a fully cached dataset, similar trends exist with fetch stalls as well.

C Predictive analysis with DS-Analyzer

We built DS-Analyzer to aid our analysis of data stalls and enable predictive analysis of performance implications of data pipeline on DNN training. While there exists prior work that profile the performance of a DNN, they focus on profiling the layer-wise performance of DNN [3, 11], low level performance counters for accelerators [10, 41], or finding optimization opportunities at the neural network layer level [87]. In contrast, DS-Analyzer analyzes the performance implications of CPU, memory, and storage on the performance of a DNN and answers questions such as, how much DRAM does the model need to avoid fetch stalls, how many CPU cores should each GPU use for pre-processing to eliminate prep stalls, and so on.

C.1 Estimating data stalls

Figure 15 shows the components involved in a typical DNN data pipeline; data is fetched from cache (and store) with an effective prefetch rate $F$, pre-processed at the CPU at a rate $P$ and processed at the GPU at a rate $G$. To perform predictive analysis, DS-Analyzer measures several metrics related to the data pipeline of the model; the maximum ingestion rate at the GPU ($G$), the rate of CPU prep ($P$), the rate of cache fetch ($C$), and the rate of storage fetch ($S$). These quantities are measured in samples per second. Using these metrics, DS-Analyzer can estimate the effective prefetch rate ($F$), and answer what-if questions such as, how much DRAM cache is required for this model to eliminate fetch stalls? What happens if the GPU compute is 2× faster?, etc. DS-Analyzer collects these metrics for a model as follows.

- **Fetch Rate ($F$)**: The maximum rate at which data can be fetched from cache, DS-Analyzer uses a microbenchmark to measure memory bandwidth and uses it as an approximation for $F$.

- **Prep Rate ($P$)**: The rate of CPU prep, pre-processed at the CPU at a rate $P$ and processed at the GPU at a rate $G$. To perform predictive analysis, DS-Analyzer measures several metrics related to the data pipeline of the model; the maximum ingestion rate at the GPU ($G$), the rate of CPU prep ($P$), the rate of cache fetch ($C$), and the rate of storage fetch ($S$). These quantities are measured in samples per second. Using these metrics, DS-Analyzer can estimate the effective prefetch rate ($F$), and answer what-if questions such as, how much DRAM cache is required for this model to eliminate fetch stalls? What happens if the GPU compute is 2× faster?, etc. DS-Analyzer collects these metrics for a model as follows.

- **GPU Rate ($G$)**: The rate at which data is processed at the GPU at a rate $G$.

- **Storage Rate ($S$)**: The rate of storage fetch.

- **Cache Rate ($C$)**: The rate of cache fetch.

- **CPU pre-processing**

- **GPU processing**

Table 5: Training speed (samples/s) predicted by the DS-Analyzer is almost 4% different from empirical values.

| % dataset cached (x) | 25% | 35% | 50% |
|----------------------|-----|-----|-----|
| $F_{\text{predicted}}$ | 6226 | 7164 | 9225 |
| $F_{\text{empirical}}$ | 6130 | 7118 | 9022 |

(i) **Measure ingestion rate ($G$)**. To find the maximum possible speed at which the DNN can train, DS-Analyzer first runs the job script for a fixed number of iterations (default: 100) with synthetic data that is pre-populated at the GPUs. It then calculates $G$ as,

$$G = \frac{\text{Total samples processed in (i)}}{\text{Time for (i)}}$$

Samples processed = #iterations $\times$ global batch size

(ii) **Measure prep rate ($P$)**. Next, DS-Analyzer executes the training script with the given dataset by ensuring that the subset of data used is cached in memory, using all available CPU cores. Additionally, the GPU computation is disabled to only run the data loader. This is required because, if $P \geq G$, then we cannot measure $P$ using the knowledge of runs (i) and (ii), as prep will be pipelined with GPU compute. Therefore, DS-Analyzer disables GPU computation and estimates $P$ in the same way as Eq (1).

(iii) **Measure storage fetch rate ($S$)**. Rate of fetch from storage is the maximum random read throughput of the storage device. To measure this, DS-Analyzer runs the data loader (with a cold cache, disabling both pre-processing and GPU compute), with all CPU cores.

(iv) **Measure cache fetch rate ($C$)**. To measure the rate at which data can be fetched from cache, DS-Analyzer uses a microbenchmark to measure memory bandwidth and uses it as an approximation for $C$. Note that run (ii) actually includes the time to fetch cached items as well; however we see that the cache fetch rate is very high (few tens of GBps), and does not add noise to the measurement of prep rate.

C.2 Example: Predicting optimal cache size

We now describe an example of what-if analysis with DS-Analyzer. We show how DS-Analyzer answers the question: **how much DRAM cache does the DNN need to eliminate fetch stalls?**

To predict the implication of cache size, DS-Analyzer calculates the effective prefetch rate ($F$) for a given cache size ($x\%$ of the dataset). Here, we assume that the cache implements an efficient policy like MinIO; i.e., a cache of size $x$ items has at least $x$ hits per epoch.

$F$ is computed as follows. Say the size of the dataset is $D$ samples, and cache is $x\%$ of the dataset. Therefore, in an
Figure 16: Estimating optimal cache size with DS-Analyzer.

epoch, the total time to read the dataset is given by

\[ T_f = \frac{D}{C} + \frac{D \times (1-x)}{S} \]  

(3)

The fetch rate is then calculated as,

\[ F = \frac{D}{T_f} = \frac{D}{\frac{D}{C} + \frac{D \times (1-x)}{S}} \]  

(4)

Since \( C >> D \), \( F \approx \frac{1}{\frac{1}{C} + \frac{1}{S} x} \), i.e, the effective fetch rate increases, as the number of uncached items per epoch decreases.

Since DS-Analyzer has already estimated values of \( D, C \), and \( S \), given a cache percentage \( x \), DS-Analyzer can predict the fetch rate using Eq (4).

Then, using \( F, P, \) and \( G \), it is easy to see where the bottleneck in training is:

- If \( \min(F, P, G) = G \), then the training is GPU-bound
- If \( \min(F, P, G) = P \), then the training is CPU-bound
- If \( \min(F, P, G) = F \), then the training is IO-bound

To evaluate how accurately DS-Analyzer can answer this question, we run the actual experiment by varying cache size on a physical server (\( F_{\text{empirical}} \)), and comparing it to the predictions of DS-Analyzer (\( F_{\text{predicted}} \)) for AlexNet on Config-SSD-V100 with Imagenet-1K as shown in Table 5. The predictions were a maximum of 4% off the empirical results. Using these predictions, DS-Analyzer can estimate the optimal cache size for the model by comparing it with prep rate (\( P \)) and GPU ingestion rate (\( G \)) as shown in Figure 16. At lower cache sizes, training is IO-bound, however, a cache that is 55% of the dataset size is sufficient to eliminate fetch stalls; larger cache (more DRAM) is not beneficial beyond this point, as training becomes CPU-bound. Figure 16 shows that empirical training speed observed from experiments with varying cache sizes on real hardware shows the same trend predicted by DS-Analyzer.

Note that the prep rate is much lower than the GPU ingestion rate; to eliminate this prep stall, we either need to add more CPU cores, or use techniques like coordinated prep to inch closer to the GPU ingestion rate.

Table 6: Impact on fetch misses and disk IO. When training ResNet18 on OpenImages (645GB), CoorDL reduces cache misses from 66% to 35%. Config-SSD-V100 caches 65% of the dataset, so this is the minimum miss rate.

D.1 Evaluation with ImageNet22k

ImageNet-22k is the extended version of the popular ImageNet-1K dataset, and contains about 14 million images that belong to 21841 different categories [30]. The average size of an image in this dataset is about 90KB, much smaller than the average image size in OpenImages dataset (300KB), as well as ImageNet-1K (150KB).

When we train the image classification models with ImageNet-22k on Config-SSD-V100, MinIO results in 20% higher cache hits than DALI-shuffle that resulted in 1.5x faster training on Shufflenet, and 1.4x faster on AlexNet and ResNet18.

Next, when we perform distributed training on these models on Config-SSD-V100 with 2 servers, AlexNet trained 1.3x faster, Shufflenet trained 1.33x faster and ResNet18 achieved 1.12x speedup. The fetch stalls with ImageNet-22k was lower than a more complex dataset like OpenImages because of the low per-image size that increased the the number of samples the storage can deliver per second.

Finally, we perform HP search with 8 concurrent jobs on Config-SSD-V100 on 7 image classification models. As shown in Figure 17, CoorDL results in up to 2.5x speedup.

D.2 Cache misses with CoorDL

CoorDL’s MinIO cache is designed to minimize the amount of storage I/O per epoch, by efficiently utilizing the all the items in cache. Table 6 enumerates the fetch misses and total disk I/O for DALI-seq, DALI-shuffle and CoorDL when training Shufflenetv2 on OpenImages dataset on Config-SSD-V100. This server can cache 65% of the dataset. CoorDL is able to reduce disk I/O by 47% compared to DALI-seq and 33% compared to DALI-shuffle, by reducing thrashing by 47% and 33% respectively. MinIO cache is able to reduce the cache misses down to capacity misses.

D.3 Scalability of partitioned caching

Our paper shows that when training is distributed across just enough servers that can cache the entire dataset in mem-
D.4 HP search with fully cached dataset

The core of CoorDL’s ability to speed up HP search jobs comes from coordinating pre-processing to overcome the imbalance in the ratio of CPU cores to GPU. We perform HP search with 8 jobs on Config-SSD-V100 with ImageNet-1k dataset that fits entirely in memory. As shown in Table 7, CoorDL sped up HP search by 1.9× on AlexNet and 1.2× on ResNet50 by eliminating redundant pre-processing operations.

D.5 HP search on servers with high CPU count

Config-SSD-V100 has 3 CPU cores per V100 GPU. To understand if servers like AWS p3.16xlarge with more CPU cores exhibit data stalls due to lack of co-ordination in pre-processing, we perform HP search with 8 1-GPU jobs on a server with 64 vCPUs and 8 V100s. Our experiment considers a fully-cached dataset to eliminate any I/O stalls. When training ResNet18 with OpenImages, CoorDL’s co-ordinated prep accelerated training by 2× even when a total of 64vCPUs are used (8vCPUs per GPU).
D.6 Resource utilization with CoorDL

**CPU utilization with CoorDL.** The paper showed how MinIO reduces the amount of data fetched from storage in each epoch and regularizes the data access pattern. Profiling the CPU during training of ResNet18 on OpenImages shows that the pre-processing threads in DALI are often stalled waiting for I/O as in Figure 19. Since MinIO reduces the total disk I/O, CoorDL is able to better utilize the CPU threads for pre-processing. The combination of lower disk I/O and better CPU utilization leads to shorter training times when using CoorDL.

**Low memory overhead of co-ordinated prep.** By design, co-ordinated prep has the same memory requirements as DALI. To experimentally validate this, we track the memory utilization of running hyperparameter search on AlexNet on OpenImages on a Config-SSD-V100 server using eight concurrent jobs. Figure 20 plots the memory utilization over time for both the process working memory, and the cache. CoorDL uses 5 GB of extra process memory to store prepared mini-batches in memory until all hyperparameter jobs consume it. We reduce the cache space given to CoorDL by 5 GB (keeping the total memory consumption same for CoorDL and DALI). Despite the lower cache space, CoorDL still accelerated training by 2.9×.

E Building Py-CoorDL in native PyTorch

As a proof of concept, we implemented two of the techniques behind CoorDL, MinIO and coordinated prep as a pluggable module to the native PyTorch DL (without DALI). This section briefly describes the implementation and presents the evaluation of Py-CoorDL against the native PyTorch DL.

**E.1 Implementation**

Py-CoorDL is implemented as a pluggable DataLoader module for PyTorch with minimal changes to its current DataLoader API. Py-CoorDL is implemented in 650 lines of Python code. Py-CoorDL is implemented using Python’s shared memory abstraction because PyTorch spawns multiple processes instead of threads to parallelize data fetch and prep (due to Python’s Global Interpreter Lock limiting concurrency of threads).

**E.2 Evaluation**

We evaluate Py-CoorDL on a server with 8 V100 GPUs, each with 16GB of GPU DRAM. Our server is 2 socket, 14-core Intel Xeon E5-2690@2.6GHz, with 500GB DRAM, and 2 different storage devices (SSD and HDD). We evaluate Py-CoorDL on five image classification models: AlexNet [53], ResNet18 [37], ShuffleNetv2 [86], SqueezeNet [40] and MobileNetv2 [75]. We set the batch size to the maximum that fits the GPU (512 for Alexnet, Shufflenet and ResNet18, 256 for the others). We train the model for 5 epochs and report the average epoch time excluding the first warmup epoch. We use the ImageNet 1K dataset of size 146GiB [74] and PyTorch 1.1. To evaluate the benefits of Py-CoorDL, we run our jobs in a Docker container with restricted memory to mimic the scenario where the dataset does not entirely fit in DRAM. This is equivalent to running the full ImageNet dataset (22K classes - 1.3TB) on our server.

**E.2.1 Multi-GPU training in a server**

**Hard drives.** Figure 21a plots the stabilized per epoch time as a function of cache size for ResNet18. In this experiment, DataParallel training is performed on 8 GPUs, each with a batch size of 512 and a total of 24 data workers pre-processing in parallel. Py-CoorDL brings down the per-epoch training
time by $2.1 \times 3.3 \times$. This is due to two reasons. First, Py-CoorDL increases the sequentiality of reading data items from the disk by indexing the entire data item instead of individual pages. Each data item in the ImageNet dataset is on average 150KB, which spans about 28 pages on disk. The native PyTorch DL fetches the pages of data items on demand, whenever the CPU thread requires to decode the item. As multiple data workers decode images in parallel, the pages from different images were requested randomly. Py-CoorDL reduces this randomness by reading the entire data item into memory, before decoding it. Second, MinIO caching policy results in 20% lower cache misses as compared to the page cache’s LRU scheme. Given the low throughput of disks (15MBps), this translates to a high savings in training time.

**Solid state drives.** Figure 21b shows the variation in training time for different cache sizes, when the dataset is accessed from a fast solid state drive (SSD). The throughput of the SSD is 500MBps. Reduction in cache trashing does not reduce the training time significantly because we are bottlenecked on pre-processing at the CPU (pre-processing throughput is around 327MBps). Therefore, the 20% reduction in store misses translates to a mere 7% lower training time. Note that when an optimized library like DALI is used for pre-processing, the CPU prep rate increases, making storage the bottleneck; this makes MinIO’s savings more significant with DALI.

**E.2.2 HP Search**

To evaluate the benefits of coordinated prep, we construct a microbenchmark where each job trains the ResNet18 model on a single GPU in a server, when the entire dataset is cached in memory. We evaluate two scenarios; 4 jobs, each using 6 data workers for pre-processing (4 GPU and 24 CPU), and 8 jobs with 3 data workers each (8 GPU and 24 CPU). The per-epoch time for these scenarios is shown in Figure 22. As the number of concurrent jobs increase, the data stall time increases because each job gets fewer CPU cores for pre-processing. Py-CoorDL reduces the data stall time close to 0 in both cases. It does so by launching a unified data loading process that pre-processes the dataset exactly once per epoch using all 24 CPUs, and shares the prepared batches across all the jobs. This technique results in $1.8 \times$ lower training time when 8 jobs are run concurrently on a single server.

**E.2.3 End-to-end benefit of Py-CoorDL**

We now evaluate the end-to-end benefit of CoorDL using a macrobenchmark; HP search using Ray Tune [57] when dataset does not fit entirely in memory.

**Ray Tune.** Ray Tune [57] is a HP optimization framework that provides the flexibility of using various search algorithms such as Population Based Training (PBT), Median Stopping Rule, and HyperBand. Ray Tune uses one of these algorithms to pick a unique value for the HP, and launches a training job on one of the available GPUs. We modified Ray Tune’s job executor to use Py-CoorDL and launch training jobs one on each available GPU in a server. We used the Hyperband search algorithm to sample 16 values of (learning rate, momentum) pairs and set the stopping criteria to be the completion of one epoch for brevity. The trends remain the same if the stopping criteria is set to a target accuracy.

**Experiment setting.** We run this macrobenchmark on a machine with 8 GPUs (8 samples are trained in parallel). For the PyTorch DL, we set the number of data workers to 3 for
Dataset resides on hard drive. As shown in Figure 23a, coordinated prep alone results in up to $2.5 \times$ speedup in total search time by reducing the total disk accesses by $2.5 \times$. The savings in time comes directly from the reduced disk accesses because the DataLoader in this case is bottlenecked on I/O rather than pre-processing. When MinIO caching policy is enabled, the effective speedup is close to $5.5 \times$ due to reduced storage miss and reduction in random accesses.

Dataset resides on solid state drive. When the dataset is on a faster medium like SSD, whose throughput is higher than that of pre-processing, the bottleneck in the DataLoader shifts to CPU. In this scenario, as shown in Figure 23b, coordinated prep reduces the overhead of pre-processing and speeds up search time by reusing prepared minibatches across jobs. With the addition of MinIO policy, the search does not speed up significantly due to cheap IO.

**E.3 Summary**

Py-CoorDL speeds up DNN training jobs by $2 \times - 5.7 \times$ by enabling efficient reuse of both raw data items and pre-processed batches. Although Py-CoorDL has marginal gains when dataset resides on SSD, the reason was the slow pre-processing rate of data augmentation operations used by PyTorch DL. If prep rate goes up, fetch stalls become prominent, and MinIO comes to the rescue, which is the case when using DALI for pre-processing [17].