Hoard: A Distributed Data Caching System to Accelerate Deep Learning Training on the Cloud

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ABSTRACT

Deep Learning system architects strive to design a balanced system where the computational accelerator – FPGA, GPU, etc, is not starved for data. Feeding training data fast enough to effectively keep the accelerator utilization high is difficult when utilizing dedicated hardware like GPUs. As accelerators are getting faster, the storage media & data buses feeding the data have not kept pace and the ever increasing size of training data further compounds the problem.

We describe the design and implementation of a distributed caching system called Hoard that stripes the data across fast local disks of multiple GPU nodes using a distributed file system that efficiently feeds the data to ensure minimal degradation in GPU utilization due to I/O starvation. Hoard can cache the data from a central storage system before the start of the job or during the initial execution of the job and feeds the cached data for subsequent epochs of the same job and for different invocations of the jobs that share the same data requirements, e.g. hyper-parameter tuning. Hoard exposes a POSIX file system interface so the existing deep learning frameworks can take advantage of the cache without any modifications. We show that Hoard, using two NVMe disks per node and a distributed file system for caching, achieves a 2.1x speed-up over a 10Gb/s NFS central storage system on a 16 GPU (4 nodes, 4 GPUs per node) cluster for a challenging AlexNet ImageNet image classification benchmark with 150GB of input dataset. As a result of the caching, Hoard eliminates the I/O bottlenecks introduced by the shared storage and increases the utilization of the system by 2x compared to using the shared storage without the cache.

1 INTRODUCTION

Recent advancements in artificial intelligence are fueled by deep learning techniques. Deep Learning (DL) is a class of machine learning (ML) techniques that achieved notable success in speech recognition, visual recognition, and language understanding. This success is due to three main advancements: availability of massive amounts of data, commodity accelerator hardware that can process this data faster such as FPGA, and GPUs, and the advancements in the neural network models and programming frameworks.

DL system architects strive to design a balanced system where the computational accelerators, e.g., GPUs, can achieve high utilization. While the GPUs provide the computational capability, data is the fuel that propels the DL training operations and keeps these GPUs busy. With growing training dataset sizes, especially in video and image processing, and increasing GPU speeds with every new generation of GPUs (NVidia P100, 2018; NVidia V100, 2018), feeding the training data fast enough to keep the GPUs busy is an increasingly difficult problem. There are two popular design patterns to overcome this problem but both of them have shortcomings.

In the first design pattern, DL systems are built with high performance storage, e.g. Solid State Drives (SSDs), or Non-Volatile Memory express (NVMe) drives on the GPU nodes (Amazon Inc., 2018; Bhattacharjee et al., 2017; IBM Corp., 2018a; Meng, 2018; Nvidia DGX, 2018; Paperspace, 2018). On these systems, users copy the training data from central storage systems, e.g. NFS, GPFS, Cloud Object Store into these high performance drives to feed the GPUs more efficiently. This is the most common approach we find today on-prem and in the cloud. In this model, additional compute nodes can be added incrementally, for example by renting more servers on the cloud, and newer hardware such a recent versions of GPU or CPU systems can be added to the DL system. It works well for many cases but its scalability suffers from the dependency on the central storage systems and the drives on the nodes pose operational problems.

There are several problems with this approach: the data is
copied from the central storage into these local disks and deleted as soon as the job is terminated to make room for new jobs. As a result, the data is copied at the start of every job and in large hyper-parameter tuning experiments, where tens to hundreds of parallel jobs are started on different nodes, the data copy is extremely taxing on the shared storage servers. In addition, these high performance storage drives on the nodes tend to be limited in capacity (typically 1TB) so jobs with large datasets fail to run because the data does not fit on the disks. Since the GPU systems, in general, are expensive and consist of multiple GPUs per node, they are often multi-tenant where storage and compute time is shared. In space sharing, different GPUs of the node are allocated to different user jobs and the data for all the jobs running on the node must fit in the limited capacity of the underlying storage on the node. When one job takes a subset of the GPUs on the node but takes up most of the disk space, other jobs taking free GPUs on the node fail to start because their data cannot be copied to the disk. In any case, every time a job starts, its data must be copied which could take many hours depending on the size of the input dataset, the network bandwidth, contention on the network and the disk bandwidth. This gets worse when a user needs to use more than one system to train a model with multiple GPUs using a data parallel approach, most common approach in DL training. In a data parallel approach, DL training on each node typically accesses all of the dataset, albeit in random order, but multiple times during the training process. This requires that each node has the entire dataset to train the model. For these reasons, the high performance drives on different nodes hold copies of the entire dataset, which is not an efficient use of their limited capacity.

In the second design pattern, DL systems are built with high performance computing (HPC) like dedicated storage systems connected to GPU clusters with high-end networking gear such as Infiniband or 100Gbps Ethernet (Belgodere, 2018; Meng, 2018; Sundar & Santosh, 2018; Zou et al., 2017). In this design, a small set of GPU nodes (typically <10) are connected to a dedicated storage server (see Sundar & Santosh, 2018) as an example). While this design addresses the I/O bottleneck problem and keeps the GPUs busy, and it supports larger datasets, it is expensive to scale such a solution to thousands of users and hundreds of servers with thousands of GPUs. This solution also does not give the flexibility to expand the cluster capability incrementally based on the workload and user demand, and seamlessly transition to newer hardware such as new versions of the GPUs and CPUs.

In this paper, we propose Hoard, a distributed caching system to address the limitations of the first design pattern for DL training on cloud environments. Hoard takes advantage of the unique access patterns of large-scale deep learning training and it is designed to address the needs of a multi-user, multi-tenant large scale training environment. The main contributions include:

- Design of a distributed cache management system that uses the fast local disks of compute nodes and stripes the job’s data across a subset of nodes in a configurable fashion. Data striping and holding data across multiple disks on multiple nodes allows the system to feed the GPUs at the rate they can consume the data. We use a distributed file system for the data caching after careful evaluation of a number of them against the requirements for DL workloads. Although we use a particular file system, the implementation is flexible enough to integrate a different file system backend for the distributed caching logic. By aggregating the space across multiple nodes, users can run jobs with much larger datasets than those that fit in the disks of a single node.

- Development of a simplified usage model so users can create cache objects that refer to their datasets in remote storage such as NFS and Object store and control their life cycle such a prefetch into the cache or delete from the cache independent of the job life cycle. This takes DL developer training work-flow into account. This model allows for users to cache datasets and run hyper-parameter experiments using that data without the overhead of copying the data for each job and for each hyper-parameter experiment.

- Demonstrating that Hoard can achieve the same performance as the local disk, that it adds minimal overhead, it achieves at least 2x speed-up over jobs that access data from remote storage and because of Hoard, the cluster can support 2x more jobs without taxing the shared storage system. Since the number of local disks scale with the number of nodes, Hoard can cache more data as more nodes are added to the cluster and as a result it can support larger datasets with the increasing scale of the system. As systems get larger, aggregate throughput of the system increases so the performance efficiency of cluster to run multiple jobs increases over using a shared storage system.

The problems we discussed with the DL system architectures and our results suggest that deep learning workload and developer work-flow aware distributed caches that leverage compute node local storage, memory and more modern memories like storage class memories (SCM) are necessary to ensure that the next generation faster accelerators can be feed with the data necessary for them to make forward progress. Such cache systems allow for better scalability of the DL systems on commodity hardware, more...
so in public cloud environments, without the need for HPC like storage and networking solutions.

The rest of the paper is organized as follows: Section 2 further describes the challenges with the first DL system design pattern and presents the requirements that drove the design of Hoard. Section 3 describes the user experience of Hoard and the underlying design of the caching system. Section 4 presents a comprehensive performance evaluation of Hoard across multiple dimensions. We present related work in Section 5 and describe our conclusions and future work in Section 6.

2 Requirements for large-scale deep learning data acceleration

Caching “far” data to closer and faster storage is, per se, an idea probably as old as computer science (Nelson et al., 1987). For what concerns file system data, which is the type of data we are concerned with in this work, most modern operating systems transparently use free main memory to cache “hot” file blocks (e.g., the buffer-cache mechanism in Linux (Linux Buffer Cache documentation, 2018)). We argue, however, that existing mechanisms do not match the requirements imposed by the unique access patterns of large-scale deep learning training.

First, the size of training datasets can easily exceed that of any individual server’s main memory; although it is not uncommon to see high end servers with few TBs of RAM but such servers are not common in cloud environments. Also, the amount of training data is deemed to increase at a much faster pace (some open datasets are already over the TB barrier (Krasin et al., 2017), with private datasets possibly growing even faster); increasing the amount of server memory at the same pace is clearly not economically viable, also considering that memory dedicated to caching is usually only a portion of the total server memory. Caching on local secondary storage (e.g., NVMes, SSDs or spinning disks - each with its own speed/cost trade-offs) is a more viable solution (Bent et al., 2002; Byan et al., 2012; Li et al., 2014a; Makatos et al., 2010; Saxena et al., 2012). However, in the increasingly common case where entire datasets must be accessed by a training job in each node, for example, in the case of large distributed training or parallel model hyper-parameterization, replicating the whole dataset in each of the servers’ secondary storage cache is often infeasible because of size of data, costs, and can lead to quick exhaustion of cluster storage capacity. This drove our first requirement.

Requirement 1: The cache should be implemented as secondary storage-based distributed cache, and it must effectively leverage the aggregate storage capacity across a subset of the nodes.

This means that the dataset can be as big as the aggregate secondary storage of the entire DL system so the training job is no longer limited by the size of the secondary storage on a single node.

Second, existing cache systems normally consider the file or file-block as the unit of cache management granularity. For example, the Linux buffer-cache adopts a least-recently-used (LRU) cache replacement policy that keeps in cache the most recently accessed file blocks while evicting the oldest ones. This type of granularity does not fit the access patterns of deep learning training jobs. In fact, every epoch of a training job accesses the full dataset; this means that, in case of cache contention, evicting a fraction (only some files or file-blocks) of a dataset is as good as not having any part of the dataset in cache. This is because the next training epochs will have to access again the fraction of the dataset that was previously evicted, leading to further evictions and, fundamentally, to cache trashing effects. This leads to our second requirement:

Requirement 2: Cache management policies should operate at the granularity of the dataset. The life cycle of the dataset in the cache is decoupled from the life cycle of the job. A dataset may be in cache well after a job has completed the execution.

This ensures that the dataset is in the system so repeated executions of the job with think times (typically developers train a model for some time, observe the convergence, kill the job, restart the training with a different set of parameters and repeat) and hyper-parameter training where lots of jobs execute in parallel benefit from the cached data.

In a distributed cache, every training job will access data from possibly different nodes in the data-center. Accessing non-local data could have two related and non-negligible consequences: (i) non-local data access could be slower than local-data access and, most importantly, (ii) non-local data access will use part of the capacity of the data-center network to move cached data across servers. While state-of-the art data-center networks (e.g., 40 GbE and 100 GbE networks are increasingly common) arguably provide more bandwidth than modern GPUs can consume while training typical deep learning models (see Section 4), we expect that new deep learning accelerators (either new GPUs or special purpose chips) will soon push this limit. Also, since the data network is not dedicated to the distributed cache, and it is used for application-level traffic (communication, synchronization) as well, this cache usage may result in impacting the communication dominated applications. This results in our third requirement:

1 at least statistically, in case of random batch sampling
requirement 3: Caching and job scheduling should be done in synergy. The job scheduler should colocate cached data and training jobs taking into account the data-center network-topology to maximize access speed and minimize interference to application performance.

Lastly, we want Hoard to be fully transparent and agnostic to the specific deep learning framework used to program the training jobs (e.g., TensorFlow (Abadi et al., 2015) or Caffe (Jia et al., 2014)) so it could be used with any DL framework.

Requirement 4: Cached data should be exposed transparently using a POSIX-compatible file system interface.

The next section describes the architecture of Hoard and its implementation to satisfy the above four requirements.

3 Hoard Deep Learning Data Accelerator Architecture

Hoard assumes that there is a resource manager that can deploy and execute deep learning jobs and a distributed caching layer to create and delete the distributed data objects that correspond to user datasets. The architecture of Hoard with its components are shown in Figure 1. Hoard is designed as a collection of micro-services with clearly defined interfaces and well defined functional boundaries that interact with the scheduling layer and the caching layer. For our implementation, Hoard assumes that deep learning jobs are deployed as containers and that the available cluster resources are scheduled by the Kubernetes (Kubernetes, 2018) container orchestration system. It could be easily implemented on top of cluster resource schedulers like Mesos, Yarn, and IBM Spectrum Conductor. We will discuss the technology selected for the distributed caching layer in Section 3.3.

In the following subsections we provide an overview of how Hoard is designed and implemented by first introducing the desired end-user experience (Section 3.1) before documenting how this behavior is realized on our current implementation (Section 3.2).

3.1 User experience

As shown in Figure 1, Hoard API Server exposes two sets of APIs that provide two main functions. One set of APIs allows the user to create new datasets, query the cached datasets, and delete the cached datasets. The second set of APIs allows the user to tie the cached datasets to the jobs and allow them to deploy the jobs. Hoard integrates transparently with Kubernetes. Datasets are represented as Kubernetes custom resources and they are cached and made available to deep learning containers as persistent volume claims.

Users inform Hoard about available (remote) datasets by using the standard Kubernetes administration interface (i.e., kubectl) to create the dataset custom resource which collects dataset meta-data, a unique dataset name, the URL identifying the remote dataset location, and related access credentials (we currently support remote stores exposed via NFS or via S3-compatible APIs (S3 API Documentation, 2018) for an object store).

Deep learning jobs are also submitted to the system as custom resources. A DL job resource consists of the training job details such as the number of nodes and GPUs to use, the container image to use and additionally specifies the dataset to use by specifying its unique name and the path within the container where the dataset files should be mounted.

Combining the information about compute resource availability (i.e., CPU, memory and GPUs) and cache-dedicated storage availability, and if the dataset is not in the cache, Hoard selects a set of “cache-nodes” for the dataset and another set to run the training containers. These two sets are co-selected to maximize locality of containers and cache-nodes, also taking into account the data-center topology (for example, rack-locality is prioritized if node-locality cannot be satisfied). A detailed discussion of the topology optimized scheduling is outside the scope of this paper. Under the hood, the transparent cache will be automatically mounted inside the training containers at the path specified by the user. Remote data is fetched either at first access or (optionally) pre-fetched asynchronously as soon as the dataset resource is created.

Cache eviction is managed at dataset granularity. When the cache is full, we currently support two eviction options: (i) we do not cache new datasets until the user manually specified one or more existing dataset to evict and (ii) we evict full datasets on an LRU basis. As the analysis of optimal eviction policies would require a thorough discussion of its own, we leave it out of the scope of this paper.

3.2 Hoard system design and implementation

As shown in the architecture of Hoard Figure 1, it is implemented as a collection of micro-services.

The distributed cache layer at the bottom realizes the distributed cache on data-center nodes. It implements the transparent caching logic, handles cache hits and misses and exposes a view of the full dataset as a POSIX file system in coordination with the distributed cache layer. It accepts command on what and where to cache or eviction or
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**Figure 1.** Hoard architecture.

...pre-fetch, but it does not make these choices on its own. The **dynamic provisioner** micro-services creates data volumes for datasets not present in the cache. The **scheduling layer** at the top is responsible for listening to the creation of **DL job** and **dataset** custom resources; based on those and on current resources availability, it makes data and jobs scheduling decisions. In the middle of these two layers, sits the **dataset manager layer**. It acts on the decisions taken by the scheduling layer, and based on those decisions, it configures and issues commands to the **dynamic provisioner** and the **distributed cache layer**.

The scheduling layer combines a scheduler service with two Kubernetes **custom resource controllers** (i.e., one for the **DL jobs** and one for the **datasets**). After scheduling decisions are taken and the underlying cache is configured, the scheduler service encodes scheduling decisions by using Kubernetes labels and delegates the actual scheduling of pods to the default Kubernetes scheduler.

The dataset management layer features a dataset-control API service that accepts commands from the scheduling layer and translates them into configuration commands for the distributed cache layer. As mentioned above, it also includes a Kubernetes dynamic volume provisioner that exposes the cached datasets as **persistent volume claims** once the underlying distributed cache is set up.

Finally, the distributed cache layer exploits a distributed file system deployed across the nodes of the data-enter to exploit the storage devices available on each node as local cache.

| Table 1. Comparison of distributed file system solutions for DL training |
|-------------------------------------------------|
| **File system** | **Training duration(min)** |
| GlusterFS       | 28.9                     |
| Alluxio         | 28.6                     |
| Spectrum Scale  | 27.5                     |

### 3.3 Selection of file system for the distributed cache

A distributed file system is at the core of the **Hoard**, so we performed a comparison of some of the most promising and widely used file systems available today (either open source or proprietary) to satisfy the requirements stated above and achieve the best performance possible. We have compared the raw performance in a DL training application of GlusterFS (Boyer et al., 2012), Alluxio (Li et al., 2014b) and IBM Spectrum Scale (Schmuck & Haskin, 2002). GlusterFS and Alluxio are open source, while Spectrum Scale is a proprietary solution.

The benchmark for the comparison is a single epoch training of Resnet50 using 4 GPUs Nvidia P100 and a BS of 128 images per GPU. The results are shown in Table 1. As the table shows, the three file systems enable a similar training performance. Further analysis of GlusterFS showed that it does not support a cache mode out of the box, i.e., it can be used as a cache to store the data from another central storage system. We could modify the GlusterFS code so it can be a cache but we discarded GlusterFS because of this limitation.

Both Alluxio and Spectrum Scale are designed to be configured to cache a remote store, with Spectrum Scale performing slightly better. A key requirement for the cache (Requirement 1 above) is that it should allow us to specify a subset of the nodes of the cluster to cache a particular dataset. This will constrain the data to a set of nodes and allow for better co-location of the data and jobs. Unfortunately Alluxio does not allow us to define a set of nodes to cache the data, but rather it will use all nodes to cache every dataset. Fortunately, Spectrum Scale allows for such selection so we chose it to implement the cache layer. This feature is of utmost importance to enable coordinated scheduling of datasets and DL jobs. Spectrum Scale is deployed on the nodes of the data-center as a kubernetes service where it exposes a fully POSIX compliant distributed file system (satisfying our requirement 4). Active File Management (AFM) (Spectrum Scale AFM, 2018) is the extension that (among other things) allows to use the distributed storage provided by Spectrum Scale as a transparent cache to remote stores. Spectrum Scale (Schmuck & Haskin, 2002) exposes a fully POSIX compliant distributed file system on shared-nothing clusters.
Table 2. Experimental cluster nodes hardware/software configuration

| Hardware configuration | Software configuration |
|------------------------|------------------------|
| **CPU**                | **OS**                 |
| IBM Power S822LC dual socket (8 cores, 10 threads, NVLink) | Ubuntu 16.04 (Linux 4.4.0-128-generics) |
| **System Memory**      | **Kubernetes**         |
| 512GB DDR4            | v1.3.1-lcp-ee          |
| **Local Storage**      | **IBM Spectrum Scale** |
| Samsung NVMe SSD 960 Pro (4 x 512GB) | v5.0.0 |
| **GPU**                | **Benchmark**         |
| 4 x Nvidia Tesla P100  | AlexNet, BS=1536, 4xGPU |
| 100G Ethernet          |                        |

4 Evaluation

In this section, we evaluate Hoard and demonstrate how it solves the problems described earlier.

All the experiments were conducted on a 4 node POWER8™ cluster (Figure 2) using NVLink (NVLink Fabric, 2018) connected NVidia P100 GPUs. All the nodes feature PCIe-attached NVMe disks and reside on the same 100GBE network (see Table 2 for full node configuration). The system is managed under an IBM Cloud Private environment (IBM Corp., 2018b). We kept our datasets on a remote NFS server residing on a different network and delivering a maximum aggregated data bandwidth of ∼1.05 GB/s when measured from applications. Although the scale is evidently smaller compared to expected data center-wide deployments of our system, we argue that this set up is sufficient to validate our assumptions and to provide insights on our solution.

The experiments use 4 jobs (1 job per node) with 4 GPUs each, training AlexNet with a batch size of 1536 images per GPU. The training dataset is ImageNet (Deng et al., 2009) and it is ∼144GB on disk. The training script is part of TensorFlow CNN benchmarks suite. IBM Spectrum Scale with AFM is installed on each node of the cluster and uses 2 NVMe devices per node as the back-end for the cache.

Even though our experiments run 4 distinct DL training jobs, the results can be easily projected to a distributed training. From the perspective of storage the access throughput needed is driven by the number of GPUs of the job rather than by the number of nodes used or the number of training jobs in those GPUs. We run 4 jobs using 4 GPUs, for a total of 16 GPUs being serviced by the same storage; this could be mapped to a single training job distributed over 4 nodes with 4 GPUs each. A second note is related to the choice of the deep learning model, AlexNet. The decision was taken by considering the trade-off between ease of access to the model, reproducibility for community, and input requirements (i.e., number of input elements processed per second). That said, it can easily be shown in a distributed multi-accelerator environment, the source storage could be stressed in a similar fashion, or more, using a large number of worker nodes training ResNet50, e.g. ResNet50 running on 16 Tesla Volta100 requires 15.5k images per second (Nvidia HGX, 2018). The TensorFlow CNN benchmark suite is freely available and designed to measure the performance of a TensorFlow model. AlexNet, among the other networks available in the suite, is one requiring higher input data throughput per GPU and thus demanding in terms of storage. Our approach is not tied to TensorFlow, deep learning applied to computer vision or AlexNet. Any other network model, developed for any machine learning framework, with high storage throughput requirements can immediately benefit from using Hoard, e.g. multi-modal input sensors, high-fidelity sensors.

In light of the requirements introduced in Section 2, we use the experimental section to validate that existing OS based in-memory caching techniques cannot cope with the storage requirements of a deep learning training (Requirement 1 & 2). On the contrary, we expect our approach to be almost agnostic on the availability of memory on each node of the data-center. In addition we also aim at confirming that even though our distributed caching system is sharing the network with the rest of applications, the amount of network traffic introduced for coordination of the cache nodes is not interfering with applications data traffic. Finally, we give some insights on how scheduling of DL jobs in relation to datasets placement is affecting the usage of network at the data-center level (Requirement 3).

4.1 Baseline cache performance compared to remote and local storage

First we needed to ensure that our cache can perform as well as the remote store for epoch 1 and as well as the local disk for subsequent epochs. In this experiment our AlexNet benchmark is executed for a total of 2 epochs with remote storage alone, local disk alone and with Hoard.

Figure 3 compares the two solutions currently applied to deep learning in data-centers and our Hoard caching solution: reading data directly from remote storage (REM) and copying the dataset to the local storage (NVMe, SSD, etc) of each node before starting the DL Jobs (NVMe). As
epochs are often required during neural network training. Because Hoard places the data close to the compute, the jobs finish 2x faster that means at least 2x more jobs can completed with Hoard in the time 1x jobs complete with the shared storage. As the cluster size grows and it can run more jobs, these jobs will place bigger load on the shared storage so Hoard’s advantage over shared storage grows as well. Thus Hoard improves the utilization of the cluster by at least 2x.

4.2 Impact of system memory availability on the efficacy of Hoard cache

The previous section does not take into account possible memory-based caching done by the operating system that could improve the performance while accessing the datasets directly from the remote storage.

The most common memory caching technique is the Linux buffer-cache (Linux Buffer Cache documentation, 2018) that opportunistically caches frequently accessed files blocks (1KB is the default block size) into the free memory available. Having the whole dataset cached in memory would make every access being serviced from DRAM rather than network or local storage, greatly improving the storage throughput perceived by applications. In this experiment we evaluate the impact of OS memory-based caching by varying the ratio between free memory available on each of the nodes and size of the dataset used (or MDR for brevity). Hoard does not benefit from OS buffer cache because it uses a portion of memory dedicated to Spectrum Scale (pagepool). In the case of buffer cache the MDR is changed using the Linux stress tool that can be programmed to spawn a process allocating an arbitrary amount of memory, or other training jobs co-located on the same nodes and thus sharing the system memory available.

If we project the performance of the figure over a long training (Table 3) we can conclude that Hoard achieves a 2.1x improvement in execution over the shared storage.

| 2 epochs | 30 epochs | 60 epochs | 90 epochs |
|----------|-----------|-----------|-----------|
| REM      | 1 x       | 1 x       | 1 x       | 1 x       |
| Hoard    | 0.93 x    | 1.98 x    | 2.07 x    | 2.1 x     |
| NVMe     | 2.28 x    | 2.3 x     | 2.32 x    | 2.32 x    |

Table 3. Long training speedup projections with remote storage as baseline.
Scale pagepool to reach the desired MDR value.

Figure 4 shows the average training performance, in frames per second (fps), with different MDR values. When the MDR is $> 1.1$, the whole dataset is cached in memory after the first epoch and the three solutions show the same performance. In a real deployment this is an unlikely scenario as it would require enough memory to host a full dataset and should also consider memory used by other applications. However, it is still useful to show the effectiveness of in-memory caching. In all the following experiments we fix the MDR to 0.5 as it represents a more plausible, yet generous, scenario.

Reducing the MDR has a detrimental effect on the REM case, as more data starts being fetched from remote storage during all the epochs of the training. The OS likely starts trashing the buffer cache bringing in file blocks recently read from NFS evicting others that will be needed in the near future due to the repetitive nature of DL training. It is interesting to see how Hoard is almost completely agnostic to the amount of memory assigned for in-memory caching (pagepool) by still being able to deliver the same performance of local NVMe storage access (the one in the figure for NVMe during first epoch) even when the MDR is set to 0.5. For the NVMe case even the minimum amount of buffer cache available is beneficial as it adds on top of the already high performance of NVMe devices.

4.3 Impact of Hoard caching on remote storage bandwidth

Different users might use different remote storage solutions that mainly differ in their read/write bandwidth. The NFS server used in our experiments allows a maximum read bandwidth measured from application of 1.05GB/s (used for all previous experiments) that could be already representative of off-the-shelf cloud storage. However for the sake of better understanding the characteristics of our framework we conducted an experiment where the NFS read bandwidth is further scaled down. To decrease the remote storage bandwidth perceived by applications we act on the NFS server (Figure 2) using the Linux traffic control tool⁴ that allows setting limits on the bandwidth of a network interface.

The results in Figure 5 validate an already expected behavior. While accessing training data directly from remote storage is heavily dependent on the bandwidth, Hoard is linked to it only during the first epoch. Subsequent epochs get close to local storage access throughput and the performance of the training job goes again to its maximum. Our approach performs equally better regardless of the remote storage solution selected by the user.

4.4 Impact of Hoard cache on data-center network usage

Although an individual job’s performance is incredibly important, we must consider overall throughput of the entire system in a multi-tenant environment. Consider the impacts on network communication when using the distributed cache where this overhead could potentially degrade the overall performance because of the control mes-

⁴Linux tc command man page: https://linux.die.net/man/8/tc
Table 4. Network usage during training

|                 | Total data transmitted (TB) | Transmission rate (Gb/s sent) | Training duration (hours) |
|-----------------|----------------------------|-------------------------------|---------------------------|
| REM             | 8.1                        | 1.23                          | 14.90                     |
| Hoard           | 8.1                        | 2.7                           | 6.97                      |

sages associated with the distributed cache.

To understand where we stand with respect to network usage we monitored, during 60 epochs of training, the amount of data exchange rate sustained by each node of the Hoard cluster while communicating with its peers, together with the total amount of data exchanged. We performed the same monitoring also in the case when datasets are directly accessed from remote storage. We also measured the duration of the training itself. The results collected are reported in Table 4 and show the average network traffic generated for 1 training job using 4 GPUs.

As a first validation, the total amount of data transmitted over the network is matching in both the cases considered (∼8TB, roughly 144GB × 60 epochs). The second interesting value to observe is the transmission rate. In the Hoard case it is the aggregate bandwidth sent by each node to all its peers, averaged over the whole training. While for the REM case the value is the average data sent rate by the NFS server for each of the four jobs running. The data transmission rate is ∼2.1× higher in the Hoard case. This results is somewhat expected as the training took ∼2.1× less than the REM case. We can easily conclude that the higher network bandwidth usage is not due to any extra communication introduced by GPFS/AFM, but rather to a faster training where the GPUs were able to process a higher number of frames per second. There is minimal traffic generated to coordinate the cache nodes but it is, negligible and impossible to appreciate because hidden by the huge traffic generated to exchange the actual dataset data.

4.5 Do we need to co-schedule data and compute?

What if the DL Jobs are scheduled on nodes where data is not locally cached? This is a possibility and our distributed cache layer supports it. We have performed a simple experiment where datasets are cached on only two of the nodes in our cluster (recall Hoard support this), and compared two scenarios, if the jobs are scheduled on those nodes versus being scheduled on nodes where the data is not locally cached. Due to the scale of our test cluster, coupled with the storage bandwidth requested by AlexNet, we could not stress our cache enough and appreciate any significant difference in performance. Nonetheless we want to give the reader some insights on what could be the effect of scheduling of DL jobs and datasets at the data-center level.

Table 5. Percentage of rack up-link bandwidth (40G network) used by DL jobs that are scheduled on a rack where data is not cached

| Percentage of jobs misplaced | 20 | 40 | 60 | 80 |
|-----------------------------|----|----|----|----|
| up-link BW                  | 5% | 9% | 13%| 17%|

We have performed a rack-level analysis of the up-link bandwidth utilization in relation to the number of DL jobs that fetch data from a dataset cached on a different rack. The data-center model considered in this analysis is composed of a number of racks, each of which is equipped with a top of rack switch (TOR) with 32 ports and an oversubscription ratio of 3:1. The TOR switch ports work at 40G with an aggregated up-link bandwidth of 320Gbps.

In Table 5 we show the projection of the percentage of the rack up-link bandwidth used by a total of 24 DL jobs.
with a certain percentage of such jobs scheduled on a rack different from the ones where their datasets are cached. The higher the percentage of misplaced jobs in a rack, the higher is the portion of up-link bandwidth used to access the datasets and the lower is the bandwidth remaining for other applications potentially running on the same racks. The numbers in the table do not seem worrisome (5% of total up-link for 20% of jobs misplaced). So, the co-scheduling may not be necessary for small scale cluster with substantial backbone bandwidth. However, newer GPUs deliver already up-to 3× higher performance in deep learning applications than an NVidia P100 (NVidia V100, 2018) and future GPUs and accelerators are expected to further improve the performance of a DL training. A wise scheduling policy would first try to schedule jobs and datasets on the same node, and if not possible prefer scheduling on the same rack to avoid network interference with other applications. We speculate that rack-aware scheduling might be sufficient to achieve a balance between locality, performance, and flexibility in placement.

5 Prior Art

Caching network based file systems is not a new topic in computer science (Nelson et al., 1987). There have been multiple works since then using both Solid State Disks (SSDs) or spinning disks as a local caches, and considering both single node and distributed deployments (Bent et al., 2002; Byan et al., 2012; Ernst et al., 2001; Eshel et al., 2010; Li et al., 2014a; Makatos et al., 2010; Saxena et al., 2012).

The unique access patterns and usage models of DL applications offer new opportunities to design distributed caches to improve resource utilization and performance of these applications. Caching remote storage to target I/O bound Deep Learning training applications at a large scale is instead a relatively newer topic, but there are already a few related projects that are worth mentioning. The first is the Kubernetes Volumes Controller (KVC) (Balaji & Ajay, 2018). KVC shares some of the goals of Hoard, i.e., caching of data in local nodes and co-location of DL training jobs with datasets, but it does not rely on a distributed cache layer. In case of distributed jobs the dataset is replicated on each of the nodes involved in the computation, clearly wasting the local storage available on each node. The second interesting approach is (Fu, 2018), where the Alluxio file system is used as a cache for datasets stored on a remote S3-based bucket. Although Alluxio works as a distributed cache for a remote store, it does not allow for placing datasets on specific nodes. In addition, the document cited only considers the perspective of the cache, giving no insights on the user experience. Hoard is instead a turnkey solution that can be directly used by a data scientist. Users can in fact interact with Hoard as with any other cloud service they are familiar with, where no choices are to be made in terms of location of data, scheduling of applications on compute nodes, etc. The last interesting approach is (Haußmann, 2018), where datasets stored on a remote NFS server are cached on the local storage of a node using the Linux cachefs

6 Conclusions

In this paper, we show that the distributed caching as a middleware layer in deep learning systems can be used to feed the accelerators as fast as they consume the data. Hoard distributed caching is built using an existing distributed file system for caching the data and uses a collection of micro-services that provide the functions to create caches on subsets of DL system nodes, coordinate with the job scheduler to co-locate cache and DL training jobs on sets of nodes and manage the cached data life-cycles independently of the job life cycles. This way the cached data could be used between different invocations of the same job and between jobs that use the same datasets. We evaluated Hoard on a moderately sized cluster with 4 nodes and 16 GPUs and showed that it improves the system utilization by 2×. Our implementation allows for scaling Hoard to much larger scale systems and we expect even higher utilization improvements because of the increased load that would be placed on the shared central storage system which will be mitigated by Hoard. We believe that deep learning workload-aware caches like Hoard play an increasingly important role in enabling deep learning workloads on the cloud because they can bridge the growing I/O gap between the central storage systems and the faster accelerators combined with growing datasets.
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