Elastic Model Aggregation with Parameter Service

Juncheng Gu\(^1\), Mosharaf Chowdhury\(^1\), Kang G. Shin\(^1\), Aditya Akella\(^2\)

\(^1\)University of Michigan, \(^2\)University of Texas at Austin

Abstract

Model aggregation – the process that updates model parameters – is an important step for model convergence in distributed deep learning (DDL). However, the parameter server (PS), a popular paradigm of performing model aggregation, causes CPU underutilization in deep learning (DL) clusters, due to the bursty nature of aggregation and static resource allocation. To remedy this problem, we propose Parameter Service, an elastic model aggregation framework for DDL training, which decouples the function of model aggregation from individual training jobs and provides a shared model aggregation service to all jobs in the cluster. In Parameter Service, model aggregations are efficiently packed and dynamically migrated to fit into the available CPUs with negligible time overhead. Furthermore, Parameter Service can elastically manage its CPU resources based on its load to enhance resource efficiency. We have implemented Parameter Service in a prototype system called AutoPS and evaluated it via testbed experimentation and trace-driven simulations. AutoPS reduces up to 75% of CPU consumption with little or no performance impact on the training jobs. The design of Parameter Service is transparent to the users and can be incorporated in popular DL frameworks.

1 Introduction

Deep learning (DL) has become a major driving force in many application domains, including image classification, speech recognition, and machine translation [11, 12, 6]. With increasing model complexity and large training datasets, many DL models are trained distributedly. Distributed deep learning (DDL) is becoming popular [21, 14] to meet their ever-growing demands.

Although GPU scheduling has so far received the most attention in the context of DL clusters [26, 9, 39, 31] and rightly so, we observe that the impact of traditional cluster resources such as CPU can be significant (§2). This is especially true for DDL training jobs, where parameter servers run on traditional virtual machines (VMs) or containers. When running those jobs, up to 80% of the allocated CPUs may be wasted due to the bursty and periodic nature of model aggregation. Note that CPUs are not free to use; renting one CPU core in the cloud takes around $900/yr [7]. Given the increasing number of DDL training jobs, users spend a substantial amount of money on the rented-but-unused CPUs.

The root cause of this CPU under-utilization is the “blind” application of resource management techniques from big data clusters for emerging DDL jobs. A VM or container allocated to a parameter server has a fixed amount of CPU resource, which is exclusive (non-sharable) and provisioned for peak usage. However, a parameter server usually cannot always keep its assigned CPU fully utilized – CPU consumption by DDL training is inherently bursty. Parameter servers of a DDL job must idly wait for the model updates from workers which are generated layer by layer according to the progress of back-propagation.

To remedy this inefficiency, we propose Parameter Service, an elastic model aggregation framework for DDL training that aims to improve overall CPU utilization without sacrificing training performance. Unlike prior work on model aggregation [20, 2] where parameter servers are assigned to individual jobs, Parameter Service decouples model aggregation from training and exposes a shared model aggregation service to all training jobs for better CPU utilization. Parameter Service resides between the DL framework and the low-level infrastructure. Therefore, it is transparent to the users and only requires a few modifications to the DL framework.

The crux of the problem is answering: How to efficiently share CPU resources for model aggregation among DDL jobs without degrading their performance? Parameter Service relies on two key knobs to address this question: dynamic workload assignment and elastic resource management. It can flexibly pack the model aggregations from the same or different jobs onto a single server to fill its idle CPU cycles so as to avoid resource wastage. When any workload change occurs (e.g., job arrivals and/or exits), Parameter Service can dynamically update the assignments to enhance resource efficiency and preserve job performance. In addition,
Parameter Service manages CPU resource elastically at the server level. The number of servers for model aggregation can be seamlessly scaled up or down based on the change of load in Parameter Service.

Moreover, dynamic model aggregation management requires efficient orchestration among servers, which would otherwise elongate the execution of workers and waste their GPUs. Leveraging two unique characteristics of DDL training, Parameter Service can flexibly re-assign model aggregations with negligible time overhead. Model aggregations happen at the tensor level with no data dependencies among each other. Thus, Parameter Service can freely reassign a single model aggregation without interrupting other ones in the same job. Once a decision is made, the master copy of tensor data needs to be migrated from the original server to the new one. Because DDL training is done iteratively with a fixed execution pattern, Parameter Service hides the time overhead by only performing data migration when the job is in the training stage at the worker side.

We propose a heuristic for assignment of model aggregations and a simple feedback-based scheme for resource scaling. Relying on the iterative nature of DDL training, our assignment scheme finds proper servers and gets cyclic execution slots for model aggregations. Incorporating with model aggregation assignment, our resource scaling mechanism balances between resource utilization and job performance. We have implemented Parameter Service in a system called AutoPS and deployed it on a real DL cluster. We evaluated it using Apache MXNet [3] with multiple state-of-the-art DL models. AutoPS reduces up to 75% of CPU resource from workload packing, with very-limited performance impact on the training jobs.

Overall, we make the following contributions in this paper:

- Parameter Service decouples model aggregation from training jobs and elevates it as a shared cluster-wide service. This makes it easier for users to run DDL training without maintaining parameter servers for each job.
- Parameter Service resolves the mismatch between DDL training and the infrastructure. It improves CPU utilization by dynamic workload assignment and elastic resource management.
- Parameter Service is completely transparent to users and requires trivial modifications in DL frameworks.

2 Background and Motivation

In this work, we focus on the classic data-parallel DDL training using the parameter server (PS) architecture, where multiple workers work on their local copies of the DL model in parallel and the training dataset is partitioned across all the workers (Figure 1a). The server instance in PS is separated from the training workers. It hosts the most updated copy (i.e., master copy) of the model parameters, and updates the model parameters in the master copy using the aggregated result. For performance reasons, a single DDL job may have multiple PS instances, each of which host different parts (i.e., parameter) of the model (Figure 1a). In current PS design [20, 32], the assignment of model parameters is often static once the job starts. Thus, the workload on each PS instance will not be changed when the job is running.

2.1 CPU Underutilization

Most DDL training jobs run in shared clusters to attain cost-effectiveness. Despite its benefits, there is a crucial mismatch between DDL training and the resource management software of the infrastructure. Many CPU cores, that are statically assigned to parameters server containers or VMs, are wasted due to the bursty model aggregations.
In each training iteration, the aggregation of a tensor cannot start until the completion of backward computation on that tensor. Due to this dependency, the CPU resource reserved for model aggregation at server side is mostly idle when the job is in the forward-and-backward stage (Figure 1b). Besides, model aggregation is performed at tensor-scale. There will be a spike of CPU usage when a tensor is ready to be updated. Therefore, the CPU usage of model aggregation is a combination of sharp spikes and idle cycles (Figure 3a). In a shared cluster, CPU resource are assigned through the abstraction of VM or container for isolation. To achieve good performance, users often oversubscribe the CPU resource of their virtual machines (or containers) to satisfy the peak demand. Due to the mismatch between the dynamic CPU usage and the static CPU allocation, CPUs reserved for model aggregation remain underutilized.

Figure 2 shows the average CPU utilization of model aggregation when training different models. The number of reserved CPU cores for each job’s PS server is the same as its peak usage. Since there is only 1 PS server in each job, the CPU consumption of model aggregation is concentrated at the single PS server. Among all the jobs, more than a half of the CPU resource are left unused. For VGG19 (1s-2w), the average CPU utilization of its server is only 16%. This issue will get worse when multiple PS servers are used in a single training job. Since the workload of model aggregation is divided among those PS servers, the corresponding CPU consumption is also split (Figure 3). Users need to reserve plenty of CPU cores for each PS server without violating the spikes on each of them.

### 2.2 Opportunities Brought by DDL training

DDL training has unique characteristics that create opportunities to resolve the mismatch with infrastructure.

**Tensor-Based Model Structure.** Although tensors are layered in the model and have dependencies with their neighbors in forward-and-backward computation, they are independent of each other when they are getting aggregated. Each tensor can be managed individually at the server side. Based on this feature, it is possible to apply fine-grained and dynamic workload management. Model aggregations can be independently mapped to the proper CPU slots for execution. The CPU utilization could be improved by packing more model aggregations from multiple jobs in a single server instance.

**Iterative Training.** To handle the aforementioned mismatch, the information of the training job, especially model aggregation, is required. Relying on the iterative feature, the runtime information (e.g., CPU consumption) of the job measured in the previous iterations can be used as the input for making long-term decisions in workload management.

### 3 Parameter Service

Parameter Service is an elastic model aggregation framework for DDL training. It aims at enhancing CPU utilization for model aggregation without sacrificing job performance. In this section, we first present the overview of Parameter Service. We then illustrate how model aggregations are managed by Parameter Service which includes the schemes of workload assignment and resource scaling.

#### 3.1 System Overview

To achieve the aforementioned goals, Parameter Service introduces two features, dynamic workload assignment and elastic resource allocation, to the traditional parameter server-based approach. When the total load in Parameter Service changes (e.g., job arrival and completion), workload reassignment might be triggered if Parameter Service finds any CPU slots that fit better for some existing model aggregations. Meanwhile, incorporating with workload (re)assignment, the number of model aggregation servers will be scaled up or down based on demands.

With Parameter Service, model aggregation is decoupled from individual training jobs, whereby their workers only need to submit the model aggregation requests to Parameter Service through the unique interface and wait for the response, without worrying about where the requests are handled and how much of resource to be allocated (Figure 4).
In the backend, Parameter Service carefully assigns those requests to the available servers. In the Parameter Service design, model aggregations are not grouped by training job any longer; each one is independent and can share the aggregation server with the ones from other training jobs.

Parameter Service has three components (Figure 4):

1. **pMaster** is a centralized manager. It has a job profiler and a server profiler that keep monitoring the status of training jobs and resource availability (i.e., CPU) of each Aggregator, respectively. When anything is changed, it will adjust the workload assignment and resource allocation accordingly.

2. **Aggregator** holds the model tensors of jobs and handles their aggregation requests. Any two Aggregators can migrate the workload from one to the other, when pMaster reassigns the workload between them.

3. **Agent** is the interface that Parameter Service exposes to the workers. It maintains a table that keeps track of Aggregators for tensors in the job. When an aggregation request comes, it will forward the request from its worker to the destination by checking the table.

Details on the interactions among those components (e.g., interfaces, and messages) can be found in the appendix.

### 3.2 Tensor Migration

There is one challenge: the aggregation servers keep the master copy (latest version) of tensors for model updating (Figure 1). Blocked by this data dependency, model aggregations cannot be freely reassigned to different servers.

In the current PS systems [20, 2], reassigning a single model aggregation task will interrupt the entire training job. It needs to pause the training process, checkpoint the model parameters, and resume the job with the new assignment, which brings tens of seconds overhead to the training process. In Parameter Service, we propose a deep-learning-specific migration mechanism that migrates tensor data between the Aggregators and updates assignment information in Agents. It exploits the features of DDL training for migration overhead.

**Negligible Time Overhead.** In model aggregation, the master copy of tensor at the Aggregator side is only needed when it is being updated. There is a large time window (from the completion of the last *Pull* to the start of *Update*) in each iteration that the tensor copy hosted by Aggregator is not accessed (Figure 1b). The actual migration of tensor data is performed within this window to hide its time overhead as much as possible. In many cases, a tensor migration exposes negligible or even zero time overhead to the training job. The detailed design of tensor migration protocol can be found in the appendix.

### 3.3 Model Aggregation Management

The core of Parameter Service lies in its schemes of model aggregation assignment and resource scaling that aim at improving CPU utilization without losing job performance.

When assigning model aggregations, Parameter Service has to carefully balance the trade-off between job performance and resource utilization. Allocating too many Aggregators is good for the jobs because of less resource contention but sacrifices resource utilization; and vice versa. One extreme is the current parameter server solution that allocates individual parameter servers for each training job. When an Aggregator has surplus capacity, Parameter Service will opportunistically pack more model aggregations on it for resource efficiency. It follows the principle that a training job should not lose its performance when other jobs share Aggregators with it.

Parameter Service can elastically change the amount of resource (i.e., the number of Aggregators) according to the total load of model aggregation in the cluster. There are two events that may trigger Aggregator scaling: (1) new training job arrival; (2) existing job exit. When a new training job arrives, Parameter Service will assign its model aggregations onto the existing Aggregators as much as possible. If they do not fit, new Aggregators will be allocated for the extra workload. For job exit, Parameter Service will return the empty Aggregators back to the cluster manager to avoid wastage. Moreover, it explores the opportunity of freeing the least-loaded Aggregators by trying to reassign the model aggregations to other Aggregators.

#### 3.3.1 Model Aggregation Assignment

After collecting the characteristics of a new training job, Parameter Service needs to assign the model aggregations from the temporary Aggregators to the stable ones and allocate new ones if needed. The objectives here include minimizing the total number of Aggregator for resource efficiency,
Figure 5: Toy examples of cyclic execution of Aggregator. In the two figures at the top, the Aggregator only serves one job (J1 or J2). In the bottom one, it serves both J1 and J2. The iteration duration of J1 (J2) is 6 (12) units of time; its model aggregation takes 2 (3) units of time.

and balancing the load of each Aggregator for less resource contention among model aggregations

It is infeasible to tackle this assignment problem at scale in an online manner. When many DDL jobs are served by Parameter Service, the large number of tensors (parameters) in DL models and fast training speed generate high volume of model aggregation requests per second, which can easily overwhelm the scheduler and lead to non-negligible queuing delay. Based on the periodicity of model aggregation workload, we propose an offline approach that gets fixed and cyclic execution slots for model aggregations.

Cyclic Execution. Aggregator has an execution cycle that covers the execution slots of model aggregation tasks assigned to it. The execution cycle is determined by the model aggregations on it and is updated when the assignments change. When Aggregator serves model aggregations from one job, its execution cycle is simply the job’s (also those model aggregations’) iteration duration. When model aggregations from multiple jobs are packed together, Aggregator picks the largest iteration duration among those jobs as its execution cycle. With that, all the model aggregations can be executed within a single cycle. And the jobs with smaller iteration duration may gets executed for multiple iterations. In the toy examples of Figure 5, the execution cycle of Aggregator is 6 (12) units of time when only tasks of J1 (J2) are assigned to it. If the tasks of J1 and J2 are packed together, Aggregator will have an execution cycle for 12 units of time. The model aggregations from J1 will be executed twice within one cycle.

With this cyclic execution design, assigning a model aggregation task could change the execution cycle of Aggregator, which affects the execution of existing tasks. For example, there is an Aggregator serving a model aggregation task whose execution time (iteration duration) is 1 (5) unit of time. If the task of J2 in Figure 5 is assigned to it, then its execution cycle will be 12 units of time. Accordingly, the iteration duration of the existing task will be 6 units of time, since the task can run twice in one cycle. Theoretically, the job of the existing task may lose 17% of its training speed.

With the purpose of eliminating potential performance loss, the assignment problem can be expressed as an integer programming problem (IP) with the objective of minimizing the performance loss of all job (see Appendix). Due to the non-linear constraints and objective function, the problem is NP-hard and is infeasible to solve.

Here, we introduce a heuristic-based solution (Pseudocode 1). The first step of our scheme is to estimate the performance impact to the co-located jobs on each Aggregator (Line 1 - 10). Assuming the new task (t) is assigned to Aggregator n, it updates the execution cycle (C_{en}^{t}) of n (Line 2), and then, the iteration duration (D_{jn}^{t}) of jobs on n (Line 4). When any job’s (estimated) performance loss exceeds the predefined threshold (LossLimit, default is 0.1), Aggregator n will be remove from the list of assignment destination (Line 7). After examining all the Aggregators, if no Aggregator remains, the scheme will allocate a new one (Line 12) and assign the task there (Line 13). Meanwhile, how many free CPU slots (F_{en}^{t}) on each Aggregator is calculated with the updated execution cycle and task execution (Line 9). Among the qualified Aggregators, our scheme assigns the new task to the best-fit one who has sufficient but the least number of free CPU slots. (Line 16 - 21). In the end, if no one has enough free CPU to fit the new task, a new Aggregator will be allocated (Line 22 - 23). After assigning model aggregations to Aggregators, Parameter Service monitors the performance (i.e., training speed) of training jobs and compares with their standalone performance which is profiled at the beginning. If there is any performance loss that exceeds the threshold (LossLimit), the new assignments will be reverted.

Handling Outliers in Cyclic Execution. Due to random reasons (e.g., cache misses, and network variations), workers in a DDL training job may become transient stragglers [13, 4, 10], which makes some model aggregation requests miss their execution slots in the execution cycle. Parameter Service handles those delayed outliers in two different ways. When a request arrives late, Aggregator will check whether it has sufficient CPU slots for this delayed request after reserving enough slots for the remaining scheduled requests in current cycle. If so, then the outlier will get executed. Otherwise, the request will be postponed to the next cycle, so that the co-located model aggregations are not affected. In worst case, the job could be delayed by one iteration.

| Table 1: Notations in the assignment scheme. |
|---|---|
| Notation | Description |
| C_{en} | Execution cycle of Aggregator n |
| C_{en}^{t} | Estimated C_{en} |
| D_{jn}^{t} | Profiled iteration duration of job j |
| d_j | Current iteration duration of job j |
| F_{en}^{t} | Estimated free CPU slots on Aggregation |
| J_n | Set of jobs that have tasks on Aggregator n |
| T_{jn}^{est} | Set of tasks on Aggregator n that belong to job j |

1 Each model aggregation task has one request per iteration.
### 3.3.2 Aggregator Scaling

Other than the model aggregation assignment scheme, Parameter Service needs to scale up or down the number of Aggregators to balance the tradeoff between CPU utilization and job performance. Aggregator scaling can be triggered by two events: job arrival and exit.

When a new job arrives, all of its model aggregations will be assigned by the scheme (§3.3.1). After that, if its performance is worse than the standalone one, Parameter Service will add a new Aggregator and re-assign the entire job. This procedure will repeat until the performance loss of job is within the threshold (LossLimit).

Parameter Service opportunistically recycles some light-loaded Aggregators when there are Aggregators released because of job exit. Starting from the least-loaded Aggregator, Parameter Service reassigns its workload to other Aggregators without new allocations allowed. If it succeeds, Parameter Service will recycle that Aggregator and repeat the procedure on the next least-loaded one.

### 3.3.3 Aggregator Cluster

It is a common issue that having a single centralized resource manager (i.e., pMaster) may hurt the performance of system at scale. In Parameter Service, assigning one model aggregation needs pMaster to scan all available Aggregators in the server pool. One training job may have hundreds or even thousands of model aggregations (i.e., tensors) in its model. Assuming Parameter Service gets deployed in a large-scale cluster, the time complexity of assigning one training job will exponentially increase with large numbers of Aggregators and model aggregations. Additionally, it could take even longer if there are new Aggregator allocations triggered in the assignments. Therefore, pMaster can be easily overwhelmed by a burst of job arrivals. Moreover, on-demand resource scaling in Parameter Service could affect the execution of running jobs through workload reassignments. A sequence of job events may thrash the workload assignments in Parameter Service, which makes it hard to get stable execution for the running jobs.

To handle this issue in Parameter Service, we apply the idea of server (i.e., Aggregator) cluster that the pool of Aggregators is split into multiple independent clusters (Figure 6). Each cluster has a controller who is in charge of managing the Aggregator resource in its cluster. All cluster controllers are under the management of pMaster. Workload assignment is split into two steps. A new job is firstly forwarded from pMaster to a cluster controller, then the controller assigns model aggregations of the job to its Aggregators. Therefore, one job gets Aggregator resource from a single cluster. Each cluster works independently.

**Why Aggregator Cluster?** Splitting the pool of Aggregators into multiple clusters brings the following benefits in mitigating the scalability issue. First, it is the cluster controller that allocates Aggregator resource to model aggregations. The number of assignment destinations in a cluster is much fewer than the total number of Aggregators in Parameter Service. Second, model aggregations of a job get the Aggregator resource from a single cluster. Only the jobs that are served by the same Aggregator cluster may be affected by a job event (arrival or exit). The impact of workload reassignments is limited within a single cluster. Moreover, multiple cluster controllers could perform workload assignments in parallel when there are multiple job arrivals.

With Aggregator cluster design, Parameter Service assigns model aggregations of new jobs in two steps. First, pMaster decides which cluster should be chosen for placing the new job. pMaster keeps track of the remaining free CPU resource of each Aggregator cluster. According to the profiled job information, specially total CPU consumption of the job, pMaster selects the best-fit cluster, who has suffi-

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**Pseudocode 1** Model Aggregation Assignment Scheme

```plaintext
input: t is new model aggregation task of job k
       et is the execution (CPU) time of t
       N is the set of allocated Aggregators
1: for all Aggregator n ∈ N do
2:    C_n^\text{est} ← \max(C_n, D_n)
3: for all job j ∈ J_n do
4:    d_j ← \max(D_j, \frac{C_n^\text{est}}{C_n^\text{est} / n})
5: end for
6: if \frac{d_j / D_j} ≥ LossLimit then
7:    N ← N \ n, and skip
8: end if
9: F_n^\text{est} ← C_n^\text{est} – \sum_{k \in N} \left( \frac{C_n^\text{est}}{d_j} \right) \sum_{i \in C_n^\text{est}} e_i
10: end for
11: if N is ∅ then
12:    Allocate Aggregator s
13: T_s^k ← t, N ← N \ s
14: return s and N
15: end if
16: for Aggregator n ∈ N in descending order do
17: if \frac{F_n^\text{est} / D_n} ≥ et and is the best fit then
18:    T_k^s ← T_k^s \ t
19:    return n and N
20: end if
21: end for
22: Allocate Aggregator s
23: T_s^k ← t, N ← N \ s
24: return s and N
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**Figure 6:** Overview of Aggregator cluster.
cient but least amount of free CPU resource, and forwards the new job there. The complexity of this step is negligible compared to the assignment scheme in Pseudocode 1. Once the job is forwarded to a cluster, the cluster controller assigns model aggregations in this job to its Aggregators following the assignment scheme in §3.3.1. As discussed above, the time complexity in this step is greatly reduced because of much fewer assignment destinations. When a job exits, its cluster controller should report this event to pMaster. pMaster will update the status of the cluster on its side for future job forwarding.

**Hybrid Resource Scaling.** As mentioned above, on-demand resource scaling triggered by job arrivals or exits may jeopardize the execution of running jobs when there are too many workload reassignments generated. Although periodically resource scaling could reduce such disruptions, it cannot respond to the change of resource demand in real-time. Consequently, Parameter Service performs resource scaling in a hybrid manner. There is a predefined resource scaling period in Parameter Service. Parameter Service adjusts the number of clusters and the amount of Aggregators in each cluster according to the resource demand measured in the latest period. To avoid starvation, on-demand Aggregator allocation is also allowed when the demand of new Aggregator is higher than a threshold.

There are interactions between pMaster and cluster controllers when job events or resource scaling occurs. For a new job arrival, pMaster needs to forward the new job information to the chosen cluster controller for assigning model aggregations. When a job exit, the cluster controller sends job completion information to pMaster for bookkeeping. A cluster controller should send allocation or deallocation requests to pMaster when resource scaling is triggered by job events in it. Approval has to be received before the cluster controller can carry out the operation. The amount of those interaction messages is at the same order of magnitude of job arrival and exit rate. Therefore, these interactions will not be the bottleneck of Parameter Service.

**4 Implementation**

We have implemented the design of Parameter Service into a system named AutoPS. AutoPS is built on top of ps-lite [20] with about 5K lines of C++ code added.

In AutoPS, pMaster is a daemon process that serves the entire cluster. It opens a connection address to the DDL training jobs who want to use Parameter Service. A training job can connect to pMaster through the Agents that are colocated with its workers. Agent is a implemented as a Key-Value library that is loaded by the DL framework of worker. Agent exposes the standard Push and Pull APIs to the Key-Value store layer in DL framework for model aggregation requests and responses. Since RDMA network is widely deployed in many DL clusters, our current implementation uses RDMA ibverbs for communication. Every Agent and Aggregator has a control channel to the pMaster. Agent needs to send requests to pMaster for job registration and tensor initialization. In response, pMaster sends back the initial assignments of tensor. When re-assigning workload, pMaster sends the migration command to the Aggregator that is currently hosting the tensor, and waits completion notifications from the two related Aggregators. In addition, pMaster sends profiling commands to Agents and Aggregators when there are updates in workload assignment or Aggregator allocation.

**5 Evaluation**

We evaluated AutoPS in testbed experiments and trace-driven simulations, and highlight the results as follows:

- AutoPS improves the resource (CPU) efficiency with none or negligible performance loss to the training jobs. It can reduce up to 75% of CPU servers comparing to the traditional parameter server approach.
- AutoPS outperforms the traditional parameter server approach (up to $1.17 \times$) when a single job uses each of them in standalone mode.
- The CPU saving benefits of AutoPS hold for the large-scale cluster scenario in trace-driven simulation.

**5.1 Experimental Setup**

**Testbed.** Our testbed consists of 8 GPU machines and 8 CPU machines. All machines connect to a 100 Gbps RDMA network. Each GPU machine has 4 NVIDIA Telsa P100 GPUs with NVLink connections.

**Workload.** We train 4 classic and popular DL models using MXNet in the experiments. Two of them are CNN models (AlexNet [18], VGG19 [37]), which are trained with ImageNet [5] dataset. The other two are RNN models (AWD-LM [27], BERT [6]). AWD-LM is trained with WikiText-2 [28] dataset; BERT uses BookCorpus [40]. Batch size of each model is set to the maximum to fit into the GPU memory in our testbed. In this chapter, “1s-2w” means the job requires 1 parameter server and 2 workers. Parameter server (and Aggregator) uses CPU machine, and worker runs on

![Figure 7: Normalized performance of single job using AutoPS. The performance of each job is normalized by its performance when using ps-lite. For each job, it use the same number of Aggregators (AutoPS) and parameter servers (ps-lite).](#)

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*AlexNet*, *VGG19*, *AWD-LM*, *BERT*
Baseline. We compare AutoPS to the classic parameter server implementation (ps-lite [20], also using RDMA network). Using ps-lite, each training job has an individual group of parameter servers for model aggregation. AutoPS also takes the number of parameter servers of each job to profile the standalone performance of the job.

Simulator. We build an event-based simulator and use a real job trace from Microsoft to evaluate AutoPS when it gets deployed on a large scale cluster. It simulates all job events and resource scaling activities.

Metric. We use the training speed (i.e., samples per second) to represent job performance. AutoPS saves CPU resource through reducing the number of Aggregators allocated for model aggregation. In testbed experiments, we focus on how many CPU servers are reduced in AutoPS comparing to ps-lite under the same scenarios, and define:

\[
\text{CPU Reduction Ratio} = \frac{\text{# of param. servers} - \text{# of Agg.}}{\text{# of param. servers}}
\]

Larger value of this ratio means savings more CPU servers for model aggregation.

5.2 Evaluation Results

5.2.1 Single-Job Experiments

To verify the effectiveness of model aggregation function in AutoPS, we compare the performance of jobs when they are using AutoPS and ps-lite in standalone mode (Figure 7).

The performance of AutoPS is not worse than ps-lite, which means the extra operations (e.g., extra request mappings for decoupling model aggregation, and periodic job profiling) have negligible impact on the training job. In addition, AutoPS outperforms ps-lite by up to 1.17× in some cases. These performance improvements come from the better balanced load distribution in AutoPS, comparing to the round-robin distribution in ps-lite.

5.2.2 Multi-Job Experiments

When multiple jobs run on AutoPS, it can opportunistically shrink the number of allocated Aggregators for resource efficiency. Here, we run multiple training jobs (with the same DL model and distributed settings) together to see how jobs’ performance and CPU server allocation will be changed. Due to the limitation of machines, we can run up to 4 (2s-2w) jobs, or 2 (4s-4w) jobs.

Table 2: CPU reduction ratio when 2 (4s-4w) jobs use AutoPS.

| Model   | AlexNet | VGG19 | AWD-LM | BERT |
|---------|---------|-------|--------|------|
| Ratio   | 0.375   | 0.5   | 0.5    | 0.5  |

GPU machine. Each worker has 4 GPUs (from the one machine).

Figure 8: Number of Aggregators when multiple (2s-2w) jobs use AutoPS together. Each job requires 2 parameter servers when using ps-lite. 2-job means two jobs use AutoPS together. Jobs in the same group train the same model.

CPU Reduction. Figure 8 shows the number of allocated Aggregators in AutoPS when multiple (2s-2w) jobs runs together. The baseline here is the total number of required parameter servers in each scenario. For example, there are 6 parameter servers needed in total when 3 (2s-2w) jobs use ps-lite for model aggregation. Comparing to ps-lite, AutoPS can save 25% to even 75% of CPU servers. The AlexNet jobs need more Aggregators than the jobs of other models. AlexNet is the only model that requires one extra Aggregator to run 2 (2s-2w) jobs. That’s because of the very short iteration time of AlexNet jobs, which makes them have much higher frequency of model aggregation than others. In contrast, 2 Aggregators can serve 4 VGG19 jobs whose iteration time is much longer. Table 2 shows the CPU reduction ratio of AutoPS when there are 2 (4s-4w) jobs. Same as Figure 8, most of the “2-job” cases can run without allocating new Aggregator.

Impact on Job Performance. In Parameter Service, the performance of training jobs should not be sacrificed for improving resource efficiency. When any workload assignment makes the job performance lower than the threshold (LowPerf), AutoPS will revoke it and re-do the assignment with new Aggregator added. Figure 9 shows how job пер-
Performance is impacted when multiple jobs use AutoPS. The number of allocated Aggregators of each multi-job group can be found in Figure 8. The average performance is measured when all jobs in the group are in stable state. Because of the performance protection (LowPerf), the performance loss caused by resource contentions among jobs are limited and even negligible in AutoPS. Comparing to the performance from AutoPS (in standalone mode), sharing AutoPS among multiple jobs may lose up to 9% training speed in our experiments. In some cases, the averaged performance of multiple jobs using AutoPS is even better than the standalone performance from ps-lite.

To conclude, AutoPS can reduce the number of Aggregators allocated for model aggregation through packing workload from multiple jobs. Meanwhile, it imports negligible performance loss to the training jobs.

Case Study of Aggregator Scaling. We bring a case study with two jobs to show how AutoPS scales Aggregator when job events (i.e., arrival and exit) occur. Figure 10 shows how the performance of jobs and Aggregator allocation is changed when job events occur. There is a VGG19 (2s-2w) job that uses AutoPS for model aggregation and is already in steady state. Following its parameter server requirement, AutoPS allocates 2 Aggregators for it. A new AlexNet (2s-2w) job just completed its initial performance profiling, and gets its first assignments to the two existing Aggregators at 11th second. The performance of VGG19 job is slightly affected because of resource contentions on those two servers. However, the new AlexNet job loses up to 22% of its performance. After monitoring enough iterations (default is 100), AutoPS determines the assignments of AlexNet job should be revoked. At 27th second, AutoPS allocates a new Aggregator and reassigns the AlexNet job. Both of the two jobs get better performance after that. The AlexNet job completes at the 42nd second. Since the newest Aggregator only has the model aggregations from AlexNet, AutoPS releases it right after job exit.

5.2.3 Trace-Driven Simulation
We evaluate AutoPS’s performance in CPU saving using a real job trace. This is 10-week job trace from a 2000-GPU cluster in Microsoft [14]. We compare the CPU consumption of AutoPS against the CPU requirements of running jobs in the trace-driven simulation. The x-axis is the ratio of allocated CPU cores of AutoPS to total CPU requirements of running jobs. CPU consumption and CPU requirements are measured with 1-min interval.

CPU Savings. We verify that the CPU saving benefits of AutoPS still hold when it gets deployed in a large-scale cluster. Figure 11 compares the CPU consumption of AutoPS against total CPU requirements of running jobs in the trace-driven simulation. The x-axis in the figure is the ratio of allocated CPU servers of AutoPS to total CPU requirements of running jobs. Smaller value of this ratio means more CPU savings of AutoPS. Over 99% of the time, this ratio is lower than 1, which means AutoPS could save CPU resource for model aggregation for majority of the time. Very rarely, AutoPS consumes more CPU resource than the CPU requirements from users. In worst cases, the ratio can be even larger than 2.5. These come from the scenarios that some allocated CPU resource in AutoPS are idle because of recently-completed jobs. Due the periodical resource scaling in §3.3.3, AutoPS could not release the free CPU resource until the end of current period, which makes CPU consumption of AutoPS being higher than the CPU requirements of running jobs. Overall, AutoPS could reduce the CPU cost (i.e., CPU time) of model aggregations by 52.7% in the simulated scenario.

6 Discussion
Utilizing Transient Resource. The cloud clusters usually have some amount of transient resource that has short available time. Cloud providers often sell the transient resource to users as spot instances with discounted price [1]. With resource elasticity in Parameter Service, it is feasible to run model aggregations on spot instances for cost saving purpose. When the spot instance of a Aggregator is going to expire, other Aggregators could immediately take over the affect model aggregations through workload reassignment with negligible overhead.

Performance Isolation for Multitenancy. To pursue CPU efficiency, Aggregator may assign model aggregations from
different jobs to the same Aggregator where jobs interfere with each other. Using a feedback-based assignment scheme, Parameter Service limits performance degradation within a certain threshold (LossLimit). However, this mechanism is infeasible to the multi-tenant environment where jobs may have different performance requirements. Parameter Service needs an isolation scheme which can satisfy the requirements from different users.

7 Related Work

Priority-based Model Aggregation. ByteScheduler [32] is state-of-the-art data parallel training framework based on parameter server architecture. It optimizes the execution order of model aggregations according to the execution DAG of the training job and enforces their priorities in the data communication layer for less queuing delay. Parameter Service differs from ByteScheduler in two fundamental ways. First, the role of parameter server in ByteScheduler has been changed. The function of updating model parameters, which is originally executed by parameter server, is moved to the execution engine at worker side. Therefore, the parameter server in ByteScheduler is just a hub that redistributes local gradients from workers. Second, the two PS-based systems working on different problems. Parameter Service focuses on reducing CPU consumption without sacrificing training performance. ByteScheduler [32] aims at improving training performance without considering CPU consumption. Moreover, comparing to ByteScheduler, Parameter Service has two benefits that are originated from the design of decoupling model aggregation. First, Parameter Service is easy to use since it is transparent to DL frameworks. Second, Parameter Service can utilize the transient resource in the cloud through its elastic feature. ByteScheduler is incapable of dynamically changing its underlying resource. Actually, the priority-based aggregation scheme in ByteScheduler can be integrated into Parameter Service to improve training performance.

Alternatives for Model Aggregation. Horovod [36] applies bandwidth optimal ring-based AllReduce algorithms for model aggregation in DDL training. This approach can fully utilize the network bandwidth among the training nodes. But it requires homogeneous hardware (specially network links of equal bandwidth) which does not hold in the shared cluster. ParameterHub [25] is a physical machine designed for model aggregation. Similar to Parameter Service, ParameterHub provides a cluster-wise parameter hosting and aggregation function to multiple DDL training jobs. However, it is not cost-effective because it can not flexibly scale up or down according to change of its load.

In-Network Model Aggregation With the trend of deploying programmable network devices in the cluster, in-network model aggregation has been proposed in the recent years. SwitchML [34] uses programmable switch dataplane to execute model aggregations. It reduces the volume of exchanged data during model aggregation and network latency for accelerating the training speed. iSwitch [22] is an in-switch aggregation acceleration solution for distributed reinforcement learning training. Focusing on the smaller but more frequent aggregations in reinforcement learning training, it conduces network packet level aggregation rather than the entire gradient vectors to reduce the aggregation overhead. SHARP [8] is a collective technology from Mellanox that is commonly applied for in-network aggregation. It’s only available in certain InfiniBand switches and comes with fixed functions, which make it difficult to evolve to support new aggregation approaches.

Elastic Scaling on GPU Workers. Applying resource elasticity in GPU workers could significantly improve GPU efficiency and shorter job completion time. However, existing DL frameworks either apply a fixed number of GPU workers throughout the lifetime of jobs, or adjusts the number of workers with high overheads that counteracts the benefits from elasticity. Recent work [30, 38] has been proposed to cut down the overhead of scaling GPU workers. Furthermore, [30] has an autoscaling engine, which considers account cost, other than GPU efficiency and job performance. [38] develops an elasticity-aware DL scheduler that achieves various scheduling objectives in multi-tenant GPU clusters.

8 Conclusion

Parameter Service is an elastic and shared model aggregation service for emerging DDL training jobs. It could enhance the utilization of CPU resource for model aggregations without hurting job performance. In Parameter Service, multiple jobs can submit their model aggregations to the unique interface without allocating and managing their own parameter servers. Internally, Parameter Service balances the trade-off between resource efficiency and job performance through dynamic workload and elastic resource scaling. Our implementation of Parameter Service, called AutoPS, saves up to 75% of CPU servers when serving DDL training jobs. Its CPU saving benefits hold when it gets deployed in a large-scale cluster. More importantly, Parameter Service is totally transparent to user and can easily be adopted by popular DL frameworks.

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A Decoupled Model Aggregation

In order to manage model aggregations from multiple jobs, Parameter Service firstly decouples them from training jobs. Originally, each training job maintains a group of parameter servers (PS) of its own. The assignment of model aggregation is statically decided by local worker before the job starts. Model aggregation requests use a Key-Value format. The key field is filled with the tensor ID, so that the request can be easily identified at both worker and PS side.

As a major mechanism in Parameter Service, the function of workload assignment is moved from individual training job to pMaster (Figure 12). For each worker, there is one Agent that has a mapping table for tensor assignment. It can assist the worker to figure out where the requests should be forwarded. When an aggregation request of a new tensor arrives at Agent, it will send the initial request to pMaster for assignment. Other than tensor ID, the job information (i.e., job ID) also has to be kept for each model aggregation request in Parameter Service, since an Aggregator might be shared by multiple training jobs. Therefore, the key field of aggregation request is transferred to be a pair of job ID and tensor ID by Agent before sending to the destination.

B Tensor Migration

Figure 13 shows the procedure of tensor migration in our design. pMaster initiates a migration request when a model aggregation needs to be reassigned. At ①, Aggregator\textsubscript{old} receives the migration request (MIGRATE\_INIT) and keeps the information of the tensor and Aggregator\textsubscript{new}. When the tensor is needed (Pull) by the workers at the beginning of next iteration (②), Aggregator\textsubscript{old} embeds the information of Aggregator\textsubscript{new} into the response and sends to the workers. Once workers receive the information (③), their Agents update the mapping table for the tensor. Then, workers can continue the forward-backward computation. Meanwhile, Aggregator\textsubscript{old} copies the contents (e.g., metadata, and model parameters) of the tensor (TENSOR\_COPY) to Aggregator\textsubscript{new} once the response to workers completes (④). At Aggregator\textsubscript{new} side, it adds the incoming tensor into its tensor list (⑤). When the copy finishes (⑥), Aggregator\textsubscript{old} will notify pMaster (TENSOR\_COPY\_DONE) that the tensor data has arrived at Aggregator\textsubscript{new}. After getting the gradient...
of the tensor in backward computation, workers push their results to Aggregator\textsubscript{new}. Once those local results arrive (8), Aggregator\textsubscript{new} also notifies pMaster (WORKER\_DONE) that the workers have the updated tensor assignment. The migration request completes after pMaster receives notifications from both Aggregator\textsubscript{old} and Aggregator\textsubscript{new}.

**Negligible Time Overhead.** We measure the time overhead of migrating all tensors in a model from one group of Aggregators to the other when the job is running, and take the averaged value from 10 runs for each model. From the view of training jobs, they are only suspended for tens of milliseconds by the reassignment (Table 3). The actual durations of those migration operations are much longer, most of which are hidden under the computing time at worker side. Compared with the existing approach of migrating model aggregation (pause, checkpoint, and resume), which halts the training job for tens of seconds [39, 9], the migration operation in AutoPS has negligible time overhead. AutoPS uses protobuf library to format the data before sending to the network. It introduces unavoidable overhead (e.g., data copy) by several milliseconds to each reassignment. The migration operation in AutoPS could be further optimized if it directly applies remote data access feature from RDMA networks.

**Data Consistency.** There are two data consistencies that should be guaranteed during tensor migration: (1) the mapping table among Agents, and (2) the master copy of the migrating tensor between Aggregator\textsubscript{old} and Aggregator\textsubscript{new}. Parameter Service merges the procedure of tensor migration into the iterative training procedure. The information of Aggregator\textsubscript{new} is added into the response message of Pull request. The corresponding mapping table of each Agent can be updated, as long as its worker receives the updated tensor. Thus, the consistency of the mapping table among Agents is guaranteed. Besides, Aggregator\textsubscript{new} will not execute model update on the tensor that is under migration until the tensor data is completely copied (TENSOR\_COPY) from Aggregator\textsubscript{old}. This insures the right version of tensor at Aggregator\textsubscript{new} is used in the following model aggregation.

### Problem Definition of Model Aggregation Assignment

Given a set of training jobs (J) and a set of allocated Aggregators (N), how to assign the model aggregation tasks to the limited number of Aggregators with the minimal performance loss?

The variable in this problem is \( p_{tn} \). It is a binary variable, and indicates whether model aggregation task \( t \) is assigned to Aggregator \( n \) or not.

The objective function is to minimize the maximal perfor-
mance loss among all jobs, which is expressed as:

$$\text{minimize} \quad \max_{j \in J} \{ L_j \}$$

There are two constraints:

$$\sum_{n \in \mathbb{N}} p_{tn} = 1, \quad \forall j \in J, \forall t \in j$$  \hspace{1cm} (1)

$$W_n \leq C_n, \quad \forall n \in \mathbb{N}$$  \hspace{1cm} (2)

$$C_n = \max_{j \in J, t \in j} (p_{tn} \cdot D_j)$$

$$d_j = \max_{t \in J, n \in \mathbb{N}} \left( \frac{C_n}{D_j} \cdot p_{tn} \right)$$

$$W_n = \sum_{j \in J} \sum_{t \in j} (p_{tn} \cdot e \cdot \left\lfloor \frac{C_n}{d_j} \right\rfloor)$$

$$L_j = \frac{d_j - D_j}{d_j}$$

The first one means each model aggregation can only be assigned to a single Aggregator. The second one requires that Aggregators should not be overloaded within each execution cycle.

D  Mitigating Network Interference

D.1 Vulnerability to Network Interference

In current shared clusters, high-speed networks (e.g., RDMA, and DPDK) have been deployed to accommodate the increase of computing power (e.g., GPU accelerator) [14]. However, due to the dynamic network interferences, the performance benefit from the high-speed network is not always realized for DDL training jobs.

Source of Network Interference. First, DL training cannot individually run in the cluster. There are many other applications [33] running to prepare the datasets for those training jobs. The data-processing frameworks (e.g., Hadoop, and Spark) that those applications rely on have been built on high-speed networks [23, 24] for better performance. In addition, the cluster itself runs numerous background services to support those applications, such as distributed storage [35, 17, 29], key-value store [15, 16], and database systems [19]. All of them share the high-speed network, thus making network availability dynamic for DDL training.

The performance (i.e., training speed) of DDL training can be affected when the network becomes congested. Figure 14 shows the performance of DDL training jobs when running with network interferences. We ran experiments on a cluster with 100 Gbps RDMA network. Each model is trained on MXNet, a popular DL framework, with different number of workers (w) and PS servers (s). In each job, the most heavy-loaded PS server competes for use of egress band-width of the host NIC with other background flows. Most jobs suffer performance loss in the presence of network interferences, which becomes worse with the increase of the number of background flows. For example, the performance loss of AlexNet (2s-2w) rises from 50% to 90% when the number of background flows increases from 4 to 32. The jobs of ResNet152 are more robust than others. This is because most of the tensors in ResNet model are very small; as a result, their network flows are tiny and are not blocked in the network for a long time.

In DDL training, the network load in model aggregation is statically mapped to the physical machines once the job starts. First, which server instance should handle the aggregation of a tensor is determined by the tensor assignment scheme in the DL framework (e.g., MXNet, and TensorFlow). However, those schemes (e.g., round-robin) only make static decisions and have not yet placed infrastructure information into consideration. So, the amount of data transferred between each pair of worker and server is constant. In addition, the server placement also remains fixed once the resource assignment is made by the cluster manager. This static mapping between the network load and the physical resource makes DDL training vulnerable to the network interferences.

D.2 Experiments

AutoPS can mitigate the impact of non-transient network interferences through dynamic workload assignment. Once performance loss and network interferences are detected, it will migrate the model aggregations from the affected Aggregator to another one that has sufficient remaining resource.

To verify AutoPS’s ability of mitigating network interferences, we replace the parameter server system (pslite) with AutoPS, and rerun the experiments in Section D.1. The most heavily-loaded Aggregator is congested by synthetic network background flows (with 1 MB message size) in the egress port of the host NIC. Besides, one extra condition is added here. There in no additional Aggregator available for AutoPS to use, which is designed to see how AutoPS performs without allocating more resource. Figure 15 shows the performance improvement from AutoPS when a DDL training job is affected by network interferences. In general, AutoPS has larger improvements when the network gets more and more congested. When there are 32 background flows, AutoPS improves jobs’ performance from 5.6× to 14.3×.

Although, AutoPS uses fewer useable Aggregators because of network interferences, it can still deliver 100% of the job performance in some cases, such as VGG19 (4s-4w) and AWD-LM (8s-8w). This means there are free resources among the original Aggregators. As long as the performance of job is higher than the LowPerf limit, AutoPS will not reassign a job even if it detects network interferences. For ex-
Figure 14: Performance of DDL training jobs when running with network interferences. Each model is trained with multiple distributed settings. "2s-2w" means there are 2 PS servers and 2 workers. Each server and worker runs on an individual machine. In each job, one of its PS servers is interfered by the collocated egress bandwidth flows. The performance of each job is normalized to its original performance when running alone.

Figure 15: Performance Improvements from AutoPS when there are network interferences. No additional Aggregator is allowed to allocate when AutoPS re-assigns model aggregation workload.

ample, AutoPS does not migrate the workload of the VGG19 (2s-2w) job. Because it has 93% of its performance remaining when there are two background flows interfering.