A Quantitative Survey of Communication Optimizations in Distributed Deep Learning

Shaohuai Shi, Zhenheng Tang, Xiaowen Chu, Chengjian Liu, Wei Wang, and Bo Li

Abstract

Nowadays, large and complex deep learning (DL) models are increasingly trained in a distributed manner across multiple worker machines, in which extensive communications between workers pose serious scaling problems. In this article, we present a quantitative survey of communication optimization techniques for data parallel distributed DL. We first identify the major communication challenges and classify the existing solutions into three levels, namely the learning algorithm, the system architecture, and the network infrastructure. We present the state-of-the-art communication optimization techniques and conduct a comparative study of seven common lossless distributed DL methods on a 32-GPU cluster with 100Gb/s InfiniBand (IB). We show that the DL models with low model intensity (such as BERT and BERT-Large) are difficult to scale out even with the best available lossless algorithm over 100Gb/s IB; and the system architecture and scheduling algorithms have a critical impact on the scaling property. We conclude the article with discussions of open issues for further investigation.

Introduction

The remarkable technological advances of deep learning (DL) have enabled a multitude of practical AI applications, ranging from computer vision to natural language processing and to robotics. In a typical DL workflow, deep neural network models are trained to solve a learning problem (e.g., image classification) on a labeled dataset; the trained models can then be used to make an inference given a new input (e.g., predicting the image label). Popular DL training algorithms include the standard mini-batch stochastic gradient descent (SGD) and its variants. These algorithms minimize a pre-defined loss function by iteratively updating the model parameters with stochastic gradients, calculated by sampling a mini-batch of data from the training set.

According to a recent study from OpenAI, the computational complexity required in DL training has doubled every 3.4 months since 2012, outpacing Moore's Law. As the training data and the DL models grow exponentially larger (e.g., the BDD100K auto-driving dataset has 120 million images, and the BERT-xlarge language model has over 1 billion parameters), training deep models on a single GPU or TPU device results in an exceedingly long time. A common practice is to parallelize DL training across multiple processors[1] that collaboratively update the model parameters. However, such distributed training requires iterative communications between processors, creating a severe performance bottleneck as the improvement of device interconnections lags far behind the rapidly increased computing power of AI processors. The result is the limited system scalability, as suggested by the Amdahl's law. Therefore, how to address the communication bottlenecks in distributed DL has attracted great attention from both academia and industry in recent years.

Model parallelism and data parallelism are the two major parallelization schemes [1] that enable multiple processors to collaboratively train a single model. Model parallelism splits the set of model parameters and distributes them to all processors, but the high dependency between different neurons and the unbalanced parameter sizes in deep models make model parallelism difficult to scale out. Data parallelism, on the other hand, distributes the computational workload of different data samples to different processors that share the same set of model parameters. Compared with model parallelism, data parallelism is more appealing due to its improved scalability and simpler implementation. In this article, we mainly focus on data parallelism.

Figure 1a illustrates the popular synchronized SGD algorithm for distributed DL with data parallelism, which has the same convergence performance (in terms of the number of iterations) as SGD on a single worker. In this method, workers load different data samples to calculate the gradients independently; all gradients are aggregated to update the model parameters. Data parallel synchronous SGD can be modeled by a directed acyclic graph (DAG), as shown in Fig. 1b. The backpropagation computations of gradients are from the last layer to the first (denoted by b_{P-1}, ..., b_1, b_0), and the distributed gradients should be aggregated (denoted by c_{P-1}, ..., c_1, c_0) before going into the feed-forward computations (denoted by f_0, f_1,..., f_{P-1}) of the next iteration. The distributed synchronized SGD is also known as bulk synchronous parallel (BSP) SGD as it requires communication and synchronization in every iteration. The gradients can be aggregated through one or more dedicated parameter servers (PS) [2] or by all-to-all (A2A) communications [3].

Much work has been proposed recently to improve the scalability of distributed DL. In this article, we develop a taxonomy for describing communication-efficient techniques in distributed

[1] Throughout this article, worker and processor are used interchangeably.

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Shaohuai Shi, Wei Wang and Bo Li are with The Hong Kong University of Science and Technology; Zhenheng Tang and Xiaowen Chu (corresponding author) are with Hong Kong Baptist University; Chengjian Liu is with Shenzhen Technology University.

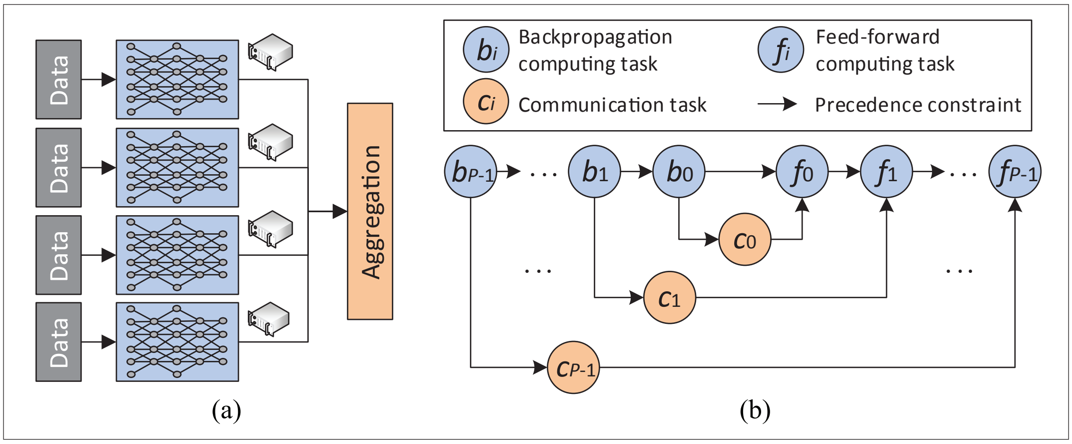


FIGURE 1. Data parallelism of distributed DL: a) data parallelism; b) a DAG example.

DL, and present a quantitative survey of communication optimization techniques for the BSP-style training algorithms. We identify the model intensity and batch size as two key factors that affect the system scalability, and conduct a quantitative study to compare seven state-of-the-art distributed training methods on a 32-GPU cluster with 100Gb/s IB. Our evaluation method and results can serve as a reference for practitioners to design their distributed DL platforms. (Our source code is publicly available at https://github.com/HKBU-HPML/ddl-benchmarks). Our main observations through this study are:

- A model with low model intensity and small batch size (thus a high communication-to-computation ratio) is difficult to scale out.
- The decentralized A2A architecture is more latency-sensitive than the centralized PS architecture, but the latter requires extra servers and network ports to achieve good performance.
- Scheduling algorithms can be useful to hide the communication costs in both PS and A2A architectures. In particular, tensor fusion is suitable for A2A, while tensor partition is more suitable for PS.

The remainder of this article is organized as follows. We first identify the communication issues and existing solutions in distributed DL. Then we elaborate commonly used communication optimization techniques, followed by our experimental study. Finally, we discuss the challenges and possible future research directions.

Communication Issues and Solutions

Scope, Assumptions, and Terminologies

In this article, we mainly discuss the communication issues in data parallel distributed DL, and focus on the data center or HPC environments where network speed is high and stable.

In a typical data parallel distributed DL (e.g., BSP-SGD), each training iteration consists of several steps. First, each worker loads a mini-batch of data as the input and performs feed-forward calculations to calculate the loss value against the corresponding labels. Next, each worker backpropagates the loss and calculates the first-order gradients of model parameters. The local gradients are aggregated among all workers, and the averaged gradients are finally used to update the model parameters. The algorithm proceeds to the next iteration, until a certain convergence condition is met. In this article, we assume data I/O can be overlapped with the computations, and hence will not consider the data I/O time.

Consider a training job of a deep model with D parameters that uses SGD with a mini-batch size of M. Assume the number of arithmetic operations required for a single data sample in each training iteration is C. A data parallelism solution with N workers will distribute the MC arithmetic operations to the N workers (e.g., each worker has a *local mini-batch size* of M/N). In the simplest case where communication tasks do not overlap with computing tasks, the speedup achieved by N workers is

$$\frac{t_s}{t_s/N + t_m},$$

where t_s is the computing time with a single worker, and t_m is the communication time of distributed training with N workers. As N becomes larger, the speedup approaches t_s/t_m, which explains the significance of communication optimization in distributed DL. To eliminate the impact of computing speed and communication speed on the analysis of speedup, we define the *communication-to-computation (C2C) ratio* of a distributed training job as the total amount of communication traffic divided by the total amount of computations. Due to the dependency between communication tasks and computation tasks (Fig. 1b), the C2C ratio is the key factor that affects the system scalability.

In practice, the total amount of communication traffic is linearly proportional to the model size D and also depends on the number of workers N. So we can use $D \cdot f(N)$ to model the amount of communication[2] where $f(N)$ depends on the communication scheme. The C2C ratio can then be calculated by

$$\frac{D \cdot f(N)}{M \cdot C}.$$

We define *model intensity*

$$I = \frac{C}{D},$$

which is the average number of arithmetic operations in an iteration per data sample per model parameter. Here, I is an intrinsic feature of the

[2] For simplicity, the unit of communication is the size of one model parameter or gradient. But in practice, the size of a model parameter could be different from the size of a gradient.

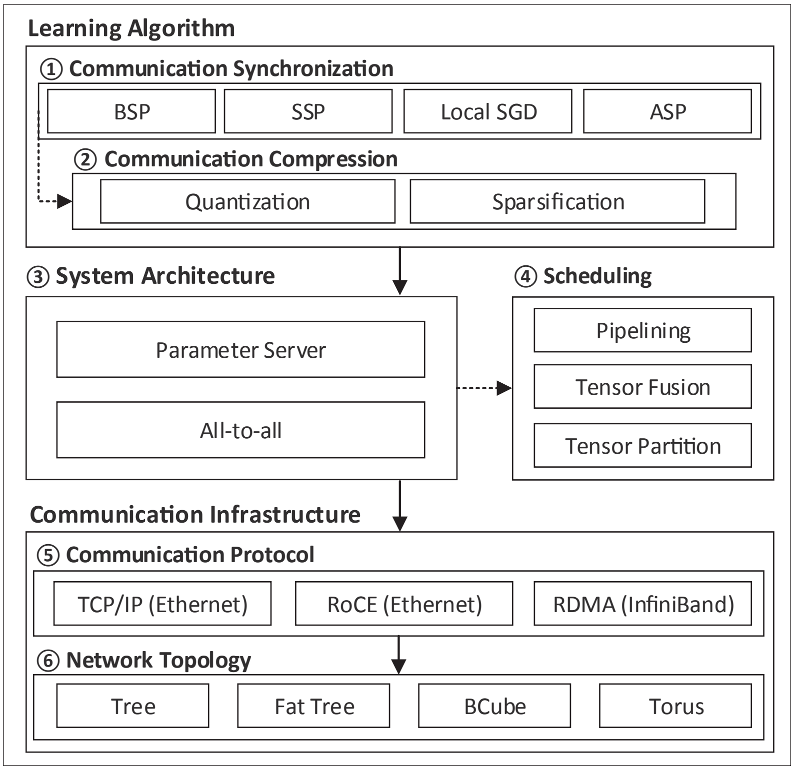


FIGURE 2. A three-level taxonomy of communication-efficient distributed DL.

model that captures the difficulty of parallelism. The C2C ratio can then be simplified as

$$\frac{f(N)}{M \cdot I}.$$

Our experimental results below verify that a model with low intensity I and/or small batch size M is difficult to scale. To reduce the C2C ratio of a given DL model, we need to design good communication schemes with small $f(N)$ and choose a large batch size M.

Communication Issues

We use the BERT-Large language model (with 336 million parameters) as an example to illustrate the communication challenges in distributed training. Given a local batch size of 8 (which is limited by the available GPU memory size), each iteration requires 597×10^9 floating point operations (FLOPs) which take 163ms on an Nvidia RTX2080Ti. There are several communication challenges that limit the system scalability of distributed training.

Communication Size: In each training iteration, the whole set of model parameters or their gradients should be exchanged across all workers. The BERT-Large model has a size of 1.34GB if the parameters are stored in a 32-bit format. Given N workers, finding the average of N sets of data and synchronizing the updated model within a short time period can be very challenging. For instance, when training BERT-Large on a server with 4 RTX2080Ti connected through PCIe 3.0, each iteration requires 441ms of communication time for the all-reduce operations, resulting in a poor speedup of 1.08×.

Communication Performance: Deep models have a layered structure, and the parameters and their corresponding gradients are typically stored as tens to hundreds of tensors. First of all, these tensors are calculated layer by layer on the fly, creating intrinsic time dependency that limits the design space of scheduling computing and communication tasks. Second, the tensor size ranges from kilobytes to mega-bytes. It is difficult to fully utilize the high network bandwidth when exchanging small messages [3]. For example, in our testbed, transmitting 1MB of message across the 10GbE (TCP/IP), 100GbE (TCP/IP), and 100GbIB (RDMA) achieves an effective throughput of 8.2Gb/s, 16.5Gb/s, and 83.2Gb/s, respectively, while transmitting a smaller message of 16KB across the 10GbE, 100GbE, and 100GbIB can only achieve much lower throughput of 1.2Gb/s, 4.6Gb/s, and 16.7Gb/s, respectively. Optimally exchanging various tensors among a set of workers requires a co-design of message exchange algorithm and network system architecture that considers both bandwidth and communication latency.

Solutions

There have been three different directions taken to address the above challenges: reducing the C2C ratio, overlapping the communication tasks with the computation tasks, and improving the communication performance by the advanced design of system architectures and communication primitives. In Fig. 2, we develop a three-level taxonomy to describe communication-efficient distributed DL.

Learning Algorithms: At the top, there are high-level learning algorithms with different communication complexity (aiming to reduce the C2C ratio), which can be classified into two types: increasing the workload of computation (e.g., large-batch training [4]), and reducing the communication complexity by quantization and/or sparsification. These algorithms are usually lossy in the sense that they generate inconsistent results with the single-worker SGD. Lossy algorithms may need more iterations to achieve the same level of convergence, though each iteration completes faster.

Large-batch training is an immediate way to reduce the C2C ratio by enlarging the batch size. With proper optimization tricks (e.g., layer-wise adaptive rate scaling), large-batch training can maintain the same generalization ability as single-worker SGD. However, the local batch size is limited by the memory size of the AI processor.

We can also relax the synchronization or reduce the communication frequency among workers (e.g., staled synchronized parallel (SSP) [5], local SGD [4], and asynchronous parallel (ASP) [6] SGD). SSP SGD allows some workers to run more iterations before synchronization, which is efficient in a heterogeneous environment where different workers have different computing horsepower. Local SGD allows all workers to run a specific number of local updates independently before synchronization. ASP SGD enables all workers to train the model without waiting for any other workers to update the model parameters. Compression techniques such as gradient quantization [7] and sparsification [8] are another thread of lossy algorithms. Gradient quantization quantifies each gradient into a few bits with little impact on the convergence, while gradient sparsification selects a small portion of the gradients for model updates.

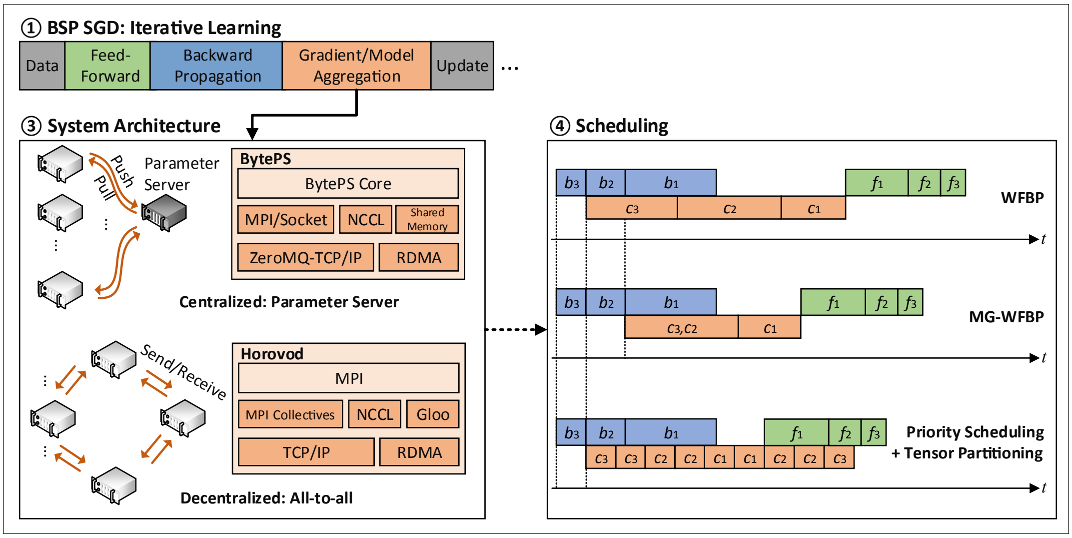


FIGURE 3. A communication optimization portfolio in distributed DL.

System Architectures: The middle level is the system architectures that define how the workers exchange the information. Parameter server (PS) (e.g., [2]) and all-to-all (A2A) (e.g., [3]) are the two most popular system architectures, and they can be equipped with different communication scheduling algorithms that can either overlap communication with computation or improve the communication performance by tensor fusion/partition. PS is a centralized architecture that requires one or more central servers to manage the model parameters, while A2A is a decentralized architecture that exploits message passing interface (MPI) or alike to perform data communication tasks. The optimization techniques in this level are usually lossless as they do not change the training results of the learning algorithms.

Communication Infrastructure: At the bottom level, there are diverse communication infrastructures offering fundamental data communication services, which include communication protocols and network topologies. The optimization techniques in this level are also *lossless*.

Popular communication protocols are TCP/IP, RDMA on InfiniBand, and RoCE. TCP/IP is widely supported by commodity Ethernet switches. However, it is inefficient for high-speed data communications due to the cost of data copy between the kernel buffer and the application buffer. RDMA can deliver lower latency and higher throughput than TCP/IP [9]. RDMA was originally run on InfiniBand, while RoCE (RDMA over converged Ethernet) enables the cheaper Ethernet to support RDMA. Network topology design is also important to improve the performance of distributed DL. For example, Wang *et al.* [10] showed that BCube is more suitable than Fat-tree for distributed DL.

In summary, a distributed training method may involve six different aspects: ① Communication Synchronization, ② Communication Compression, ③ System Architecture, ④ Scheduling, ⑤ Communication Protocol, and ⑥ Network Topology. This can be described as "it exploits ① with/without ②, running on ③ with/without ④ building on ⑤ and ⑥." In practice, BSP SGD with large-batch training is more popular than the other learning algorithms due to its good convergence property. Therefore, given a GPU cluster with a fixed communication infrastructure, the system architecture and scheduling algorithms become the key communication optimization techniques to improve the system scalability. In the next section, we continue to discuss the impact of system architectures and scheduling algorithms on the performance of distributed DL.

A Popular Communication Optimization Portfolio

In this section, we focus on the communication optimization techniques in system architecture design and scheduling algorithms. These techniques are lossless, making them particularly appealing to industry practitioners because model accuracy is the most important for many AI applications. Figure 3 gives an illustration of the communication optimization techniques.

System Architectures

PS and A2A represent two different design philosophies, with different communication properties.

Parameter Server (PS): In the PS architecture, a PS is logically a central server that aggregates the gradients from the workers, updates the model parameters, and sends back the latest model to the workers. It provides a simple and flexible framework for the system implementation. However, since PS needs to receive gradients from and send parameters (or averaged gradients) to all workers, it could easily become the system bottleneck in the BSP algorithm where all workers communicate with the PS almost simultaneously. With a single PS, the communication traffic is $2D$ for each worker and $2ND$ for the PS. To alleviate the communication pressure on a single PS, one can deploy multiple PSes.

Here we introduce a representative PS implementation called BytePS (https://github.com/bytedance/byteps), a highly optimized framework that supports multiple PSes by partitioning the gradient tensors in a load-balanced manner. Given S PSes, the D-dimensional gradient is partitioned into D/S parts so that each PS receives ND/S gradients from N workers. The received N gradient tensors are averaged on the server side and sent

Method	System architecture PS/All-to-all	Scheduling			Distributed software	Common libraries
		Pipelining	Tensor fusion	Tensor partition		
BSP-PS [13]	PS	×	×	×	BytePS	PyTorch-1.4 CUDA-10.1 NCCL-2.4.8
BSP-A2A [3, 11]	All-to-all	×	×	×	Horovod	
WFBP-PS [13]	PS	✓	×	×	BytePS	
WFBP-A2A [3, 11]	All-to-all	✓	×	×	Horovod	
MG-WFBP [3]	All-to-all	✓	✓	×	Horovod	
ByteScheduler-PS [14]	PS	✓	×	✓	BytePS	
ByteScheduler-A2A [14]	All-to-all	✓	×	✓	Horovod	

TABLE 1. Experimental settings for evaluation. For BytePS, as suggested by the official release, we use multiple PSes whose amount is the same as the number of worker servers. Each worker server has multiple workers (i.e., GPUs).

back to all N workers. Therefore, the communication traffic of each PS is reduced to $2ND/S$.

All-to-all (A2A): The average of the distributed gradient or parameter tensors can be calculated by an A2A operation, for example, the all-reduce primitive in MPI. The ring-based all-reduce collective is commonly used in distributed DL, which is bandwidth optimal by dividing the tensors into small messages and exchanging those messages simultaneously in a pipelined manner. However, ring-based all-reduce has a latency term that is linear to the number of workers, which becomes inefficient for large clusters. In the high-performance communication library (NCCL (https://developer.nvidia.com/nccl)), the double binary trees algorithm [11] is integrated for dense-GPU clusters, which delivers a logarithmic latency while preserving the bandwidth optimality. For some heterogeneous networking environments, using the hierarchy of communication bandwidths could further improve the communication efficiency [12].

Horovod (https://github.com/horovod/horovod) is a popular distributed DL framework built for the A2A architecture and supports many state-of-the-art distributed communication libraries (e.g., MPI, NCCL, and Gloo (https://github.com/facebookincubator/gloo)).

Scheduling

During the training process of distributed DL, the computing and communication tasks can be described by a DAG. The layer-wise (or tensor-wise) structure of deep models makes it possible to schedule different tasks intelligently so that part of the communication cost can be hidden, as shown in Fig.3 ④.

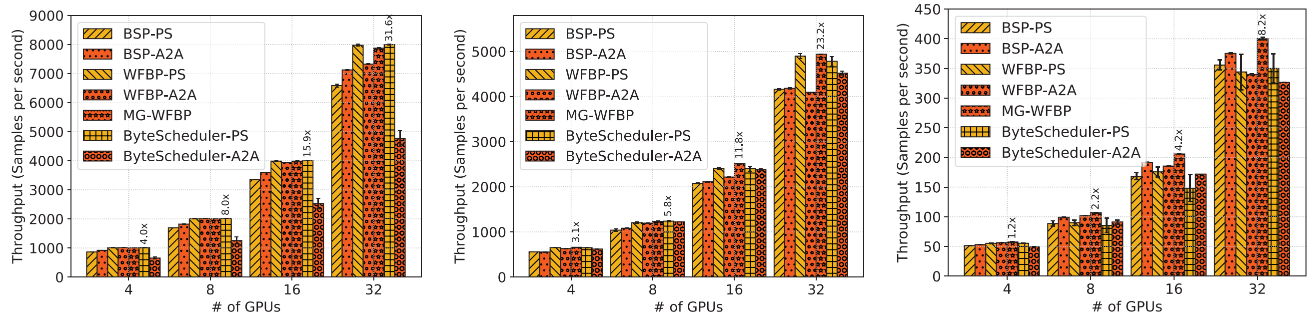
Layer-Wise Pipelining and Tensor Fusion: A deep model consists of a stack of layers, and the learnable parameters of each layer are generally represented by one or two tensors. During the backpropagation, if the gradients of layer P have been computed, then they can be immediately communicated so that the communication task can be pipelined with the computing task of layer $P - 1$. The naive pipelining between communications and computations during backpropagation is also called wait-free backpropagation (WFBP) [13], which can be applied to both PS and A2A architectures.

In A2A with pipelining, an all-reduce operation is required for each tensor, which usually divides the tensor into multiple small messages. Considering that transmitting two small messages together is generally faster than transmitting the two messages separately (e.g., in our 100Gb/s InfiniBand cluster, transmitting a 16KiB message takes 7.85us, while transmitting a 32KiB message takes 10.1us), the MG-WFBP algorithm adopts the idea of tensor fusion by optimally merging the gradients of several consecutive layers to minimize the iteration time [3]. Tensor fusion can effectively alleviate the negative impact of transmitting small messages.

Tensor Partitioning and Priority Scheduling: In the PS architecture, the communication happens between a worker and a PS and a tensor can be transmitted as a single message, making tensor fusion less beneficial than in A2A. Other than pipelining, there is another opportunity for performance improvement by priority scheduling. In PS, there are two directions of communications: push of gradients and pull of parameters. For each layer, the pull of parameters is commonly followed by the push of gradients. If the current layer has a large tensor, it would block other layers with small tensors. ByteScheduler [14] is the efficient scheduling strategy that partitions a large tensor into multiple smaller ones and allows the lower layers to be scheduled ahead of the higher layers. By using the priority scheduling, it is possible to overlap the communication tasks with both feed-forward and backpropagation computing tasks [14, 15].

Comparative Study

To demonstrate the key factors that affect the scalability of the optimization portfolio presented above, we evaluate and compare the system performance of seven representative distributed training methods listed in Table 1, which are widely used in practice and serve as good examples to quantitatively study different optimization techniques. BSP-PS and BSP-A2A are the baseline cases without special optimization, which are used to compare the efficiency of PS and A2A. WFBP-PS and WFBP-A2A are with WFBP scheduling, which can evaluate the effectiveness of WFBP on different architectures. MG-WFBP



(a) ResNet-50 (I = 470, LBS = 64) (b) BERT-Base (I = 249, LBS = 64) (c) BERT-Large (I = 248, LBS = 8)

FIGURE 4. System throughput comparison. I: model intensity. LBS: local batch size. The numbers on the top of the bars are the best speedups among the seven evaluated methods over the single-GPU SGD algorithm: a) ResNet-50 (I = 470, LBS = 64); b) BERT-Base (I = 249, LBS = 64); c) BERT-Large (I = 248, LBS = 8).

uses tensor fusion to address the latency problem of WFBP-A2A. ByteScheduler-PS and ByteScheduler-A2A are with both pipelining and tensor partition under PS and A2A architectures, respectively, which can show the performance of tensor partition.

We choose three representative deep models for evaluation, namely ResNet-50, BERT-Base, and BERT-Large, which are commonly used in image classification and natural language processing. Their model intensities are 470, 249, and 248, respectively. On RTX2080Ti, ResNet-50 and BERT-Base can support a local batch size of 64, while BERT-Large can only support 8. These three models can well illustrate the impact of model intensity and batch size on the system scalability.

Experimental Settings

Hardware: We conduct experiments on a GPU cluster with RDMA over 100Gb/s IB. The cluster consists of eight nodes (or worker servers). Each node has four Nvidia RTX2080Ti GPUs (11GB RAM) interconnected by PCIe3.0 x16, two Intel(R) Xeon(R) Gold 6230 CPUs, and 512GB memory.

Software: We exploit PyTorch-1.4 (https://pytorch.org/) as the backbone framework with GPU libraries of CUDA-10.1, cuDNN-7.6 and NCCL-2.4.8. We use the highly optimized libraries of BytePS-0.2.0 and Horovod-0.19.2 for PS and A2A architectures, respectively.

Measurements: We use the metric of system throughput (i.e., samples per second) in processing the data samples to evaluate the performance. For ResNet-50, a sample is an image with a resolution of 224 × 224 × 3; for BERT-Base and BERT-Large, a sample is a sentence with a length of 64 words. We use the SGD training with a single RTX2080Ti as the baseline to calculate the speedup. Note that when comparing the results between different number of workers, they have different effective batch sizes and their convergence might be different.

Experimental Results

Figure 4 depicts the experimental results, averaged over five independent experiments. For each run, we conduct 10 training iterations for warm-up, and another 100 iterations for measuring the average throughput. We summarize our major findings in Table 2.

Related factors	Major findings
Model intensity and batch size	1) The model with higher model intensity is easier to be parallelized. 2) Increasing the batch size to reduce the C2C ratio makes the parallelism easier, but the maximum local batch size is limited by GPU memory.
PS vs. A2A	3) There is no single winner in PS and A2A. Both can achieve comparable performance when enhanced with different optimization algorithms. But PS needs extra servers and network switch ports to be competitive with A2A.
Scheduling	4) Wait-free backpropagation (WFBP) can generally hide some communication costs. Scheduling is helpful when the communication time is comparable to the computing time per worker. 5) Tensor fusion (e.g., MG-WFBP) is suitable for A2A because it addresses the inefficiency of transmitting small messages in A2A. 6) Tensor partition (e.g., ByteScheduler) is suitable for PS, which makes communications better overlapped with computations.

TABLE 2. Major findings of experimental results.

Impact of Model Intensity and Batch Size:

ResNet-50 vs. BERT-Base: As the model intensity of ResNet-50 is about twice as large as BERT-Base, and their local batch sizes are both 64, the C2C ratio of ResNet-50 is around half of BERT-Base. Comparing Fig. 4a with Fig. 4b, we see that ResNet-50 has much better scalability than BERT-Base. For example, on the intra-node training with four GPUs, we can achieve an optimal speedup of 4× on ResNet-50, but only 3.1× on BERT-Base; with 32 GPUs, ResNet-50 has a speedup of 31.6×, while BERT-Base has only 23.2×. The results confirm that a model with higher intensity is easier to be parallelized.

BERT-Base vs. BERT-Large: The model intensities of BERT-Base and BERT-Large are very close, but the local batch size for BERT-Base is 8× larger than BERT-Large due to the smaller GPU memory footprint. Therefore, the C2C ratio of BERT-Large is about 8× higher than BERT-Base, which makes BERT-Large much more difficult to be parallelized, as confirmed by comparing Fig. 4c with Fig. 4b. The smaller speedups of BERT-Large are mainly due to the small batch size and limited bandwidth of PCIe3.0. For example, 4-GPU training on BERT-Large has a maximum of 1.2× speedup, while it is 3.1× for BERT-Base. The small GPU memory size of RTX2080Ti and the limited bandwidth of PCIe3.0 are not suitable for distributed training of BERT-Large. For comparison, when training BERT-Large on a much more expensive server with four Nvidia V100 GPUs (with 32GB memory) interconnected by NVLink (with more than 10× higher bandwidth than PCIe3.0), the local batch size can be as large as 128, and we achieved a speedup of 3.82×.

System Architecture–PS vs. A2A: It is well known that the PS architecture with a single PS does not scale well. In our evaluation on the PS architecture, we use the same number of PSes and worker servers [14]. Notice that in this setting, the PS architecture consumes more network switch ports and more total network bandwidth than A2A.

Regarding BSP-PS and BSP-A2A without pipelining, BSP-A2A outperforms BSP-PS in all cases. However, when exploiting WFBP [13] to pipeline communications with computations, WFBP-PS outperforms WFBP-A2A, especially on 32 workers. This is because the A2A architecture has a non-negligible latency term that is logarithmic/linear to the number of workers with tree/ring-based algorithms, and WFBP requires the gradients aggregated tensor-wisely, resulting in noticeable startup overheads [3]. The tensor fusion technique [3] can well address this startup problem. As we observe from Fig. 4, MG-WFBP achieves the best speedup on BERT-Base (except with the case of eight workers) and BERT-Large. But for ResNet-50 with higher model intensity, ByteScheduler-PS performs slightly better than MG-WFBP. In summary, there is no clear winner between PS and A2A. Both architectures can achieve comparable performance when equipped with suitable optimization techniques. However, PS needs extra servers and switch ports to keep the competitive edge with A2A.

Scheduling: The idea of scheduling is to overlap communication tasks with computing tasks. Regarding the WFBP algorithm, in most cases WFBP-PS and WFBP-A2A both run faster than BSP-PS and BSP-A2A, respectively. But WFBP-A2A sometimes suffers from the startup latency problem as many small messages need to be transferred, for example, under the case of BERT-Base and BERT-Large with 32 workers. MG-WFBP significantly improves the scalability of WFBP-A2A, especially with a large number of workers. ByteScheduler-A2A schedules the communications in the opposite direction with MG-WFBP by partitioning tensors instead of merging tensors, and its performance is not very promising. However, with the PS architecture, ByteScheduler-PS slightly outperforms WFBP-PS in ResNet-50. This indicates that without bringing extra heavy latency by partitioning tensors, communications of partitioned tensors can be better scheduled to overlap with backpropagation and feed-forward computations [14]. In summary, scheduling algorithms can improve the system scalability by hiding the communication overhead. However, when the communication time dominates the training time (e.g., BERT-Large), the overall speedup becomes rather limited and we need to either improve the network speed or consider lossy algorithms.

Challenges and Future Directions

Even though many techniques are proposed to address the communication problem in distributed DL, some technical challenges remain open to answer.

Communication Compression

As the model size increases, the communication cost grows, which could result in a very high C2C ratio. Lossless optimization algorithms in system architecture design and scheduling can only achieve marginal improvement since the communication cost dominates the training time. The communication compression techniques would be useful to significantly reduce the communication traffic in such cases. The primary challenge is how to maintain the model accuracy while keeping the convergence performance. Existing methods have proven that communication compression can achieve the same asymptotic convergence speed as vanilla SGD. Yet in practice, with a very high compression ratio, it generally requires more iterations to achieve the target loss value. One possible direction is to set different compression ratios for different layers to maximize the exchanged information. Another possibility is to dynamically set appropriate compression ratios at different training iterations.

Automatically Selected System Architecture

The PS and A2A architectures are widely deployed for the BSP algorithm in both industry and academia. Intuitively, the A2A architecture is more efficient than PS as it requires no central servers, but A2A is more latency-sensitive than PS. Furthermore, one can use multiple PSes to reduce the central server's network footprint. More uncertainly, with different hardware configurations, model properties, and scheduling algorithms, no solution is always better in all cases. An interesting yet challenging problem is to build mathematical performance models for both PS and A2A according to the training environments (e.g., the number of GPUs, network topology, link bandwidth and latency, model properties, and so on), so that a better architecture can be automatically chosen for training the target model.

Generic Scheduling

According to the characteristics of distributed DL, various scheduling algorithms try to maximize the parallelism of computing tasks and communication tasks. However, these algorithms were built upon the DAG of BSP with three types of tasks (i.e., feed-forward, backpropagation, and gradient communication). The scheduling algorithm only brings marginal improvement if the communication time is much longer than the computing time. Although communication compression can reduce the communication cost, current scheduling methods are not directly applicable to the BSP with gradient compression because compression introduces extra non-negligible computational costs and smaller communication traffic, which makes the scheduling more difficult. One possible solution is to design a generic scheduler for configured DAGs. The DAG would be changed due to tensor partition or fusion. For the configured DAG, the scheduler can use some heuristic algorithms to search for the configuration with better performance. Furthermore, current scheduling techniques such as MG-WFBP [3] and ByteScheduler [14] take two opposite directions (i.e., tensor fusion and tensor partition) for scheduling. In practice, no one is always better. An intelligent scheduler should be adaptive to the training environment and dynamically determine whether the tensors should be merged or partitioned to achieve higher performance.

Conclusion

In this article, we gave an overview of the techniques to address the communication challenges in distributed deep learning. We first analyzed the communication problems in distributed training of deep learning models, and then presented a taxonomy and survey of the existing state-of-the-art technologies. We particularly focused on the commonly used lossless methods and provided a quantitative analysis to these methods based on real-world experiments. Finally, we discussed the challenges and possible future research directions in this area.

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Biographies

Shaohuai Shi (shaohuais@cse.ust.hk) received a B.E. degree in software engineering from South China University of Technology, P.R. China, in 2010, an M.S. degree in computer science from Harbin Institute of Technology, P.R. China in 2013, and a Ph.D. degree in computer science from Hong Kong Baptist University in 2020. He is currently a research assistant professor in the Department of Computer Science and Engineering at the Hong Kong University of Science and Technology. His research interests include GPU computing and machine learning systems. He is a member of the IEEE.

Zhenheng Tang (zhtang@comp.hkbu.edu.hk) received a B.E. degree in communication engineering from Huazhong University of Science and Technology, P.R. China, in 2018. He is a Ph.D. student at Hong Kong Baptist University. His research interests include GPU computing and distributed deep learning.

Xiaowen Chu (chxw@comp.hkbu.edu.hk) received a B.E. degree in computer science from Tsinghua University, P.R. China, in 1999, and a Ph.D. degree in computer science from The Hong Kong University of Science and Technology in 2003. Currently, he is a full professor in the Department of Computer Science, Hong Kong Baptist University. His research interests include parallel and distributed computing, cloud computing and wireless networks. He is serving as an associate editor of *IEEE Access* and *IEEE Internet of Things Journal*. He is a senior member of the IEEE.

Chengjian Liu (liuchengjian@sztu.edu.cn) received his M.S. degree from the College of Computer Science and Software Engineering, Shenzhen University, P.R. China, in 2013, and his Ph.D. degree in computer science from the Hong Kong Baptist University in 2018. Currently, he is an assistant professor in the College of Big Data and Internet, Shenzhen Technology University. His research interests include distributed storage, blockchain, and general-purpose GPU computing.

Wei Wang (weiwa@cse.ust.hk) received his B.Eng. (Hons.) and M.Eng. degrees from Shanghai Jiao Tong University, and a Ph.D. degree from the University of Toronto in 2015, all in the Department of Electrical and Computer Engineering. He is an assistant professor in the Department of Computer Science and Engineering at the Hong Kong University of Science and Technology (HKUST). He is also affiliated with the HKUST Big Data Institute. His research interests cover the broad area of distributed systems, with special emphasis on big data and machine learning systems, cloud computing, and computer networks in general.

Bo Li (bli@cse.ust.hk) received a B.Eng. in computer science from Tsinghua University, Beijing and a Ph.D. degree in electrical and computer engineering from the University of Massachusetts at Amherst. He is a professor in the Department of Computer Science and Engineering, Hong Kong University of Science and Technology. He was the chief technical advisor of ChinaCache Corp. (NASDAQ CCIH), the largest CDN operator in China. He was a Cheung Kong visiting chair professor with Shanghai Jiao Tong University (2010-2013) and an adjunct researcher with Microsoft Research Asia (1999-2007) and with Microsoft Advance Technology Center (2007-2009). His current research interests include multimedia communications, Internet content distribution, datacenter networking, cloud computing, and wireless sensor networks. He made pioneering contributions in Internet video broadcast with the system Coolstreaming, which was credited as the world first large-scale peer-to-peer live video streaming system. The work appeared in IEEE INFOCOM (2005) and received the IEEE INFOCOM 2015 Test-of-Time Award. He has been an editor or a guest editor of more than a dozen IEEE journals and magazines. He was the co-TPC chair of IEEE INFOCOM 2004. He received five Best Paper Awards from the IEEE. He received the Young Investigator Award from Natural Science Foundation of China (NFSC) in 2005, and the State Natural Science Award (2nd Class) from China in 2011. He is a fellow of the IEEE.