A Distributed SGD Algorithm with Global Sketching for Deep Learning Training Acceleration

Lingfei Dai  
Institute of Computing Technology  
Chinese Academy of Sciences  
Beijing, China  
dailingfei20s@ict.ac.cn

Boyu Diao*  
Institute of Computing Technology  
Chinese Academy of Sciences  
Beijing, China  
diaoboyu2012@ict.ac.cn

Chao Li  
Institute of Computing Technology  
Chinese Academy of Sciences  
Beijing, China  
lichao@ict.ac.cn

Yongjun Xu  
Institute of Computing Technology  
Chinese Academy of Sciences  
Beijing, China  
xyj@ict.ac.cn

Abstract—Distributed training is an effective way to accelerate the training process of large-scale deep learning models. However, the parameter exchange and synchronization of distributed stochastic gradient descent introduce a large amount of communication overhead. Gradient compression is an effective method to reduce communication overhead. In synchronization SGD compression methods, many Top-k sparsification based gradient compression methods have been proposed to reduce the communication. However, the centralized method based on the parameter servers has the single point of failure problem and limited scalability, while the decentralized method with global parameter exchanging may reduce the convergence rate of training. In contrast with Top-k based methods, we proposed a gradient compression method with global gradient vector sketching, which uses the Count-Sketch structure to store the gradients to reduce the loss of the accuracy in the training process, named global-sketching SGD (gs-SGD). The gs-SGD has better convergence efficiency on deep learning models and a communication complexity of $O(\log d \times \log P)$, where $d$ is the number of model parameters and $P$ is the number of workers. We conducted experiments on GPU clusters to verify that our method has better convergence efficiency than global Top-k and Sketching-based methods. In addition, gs-SGD achieves 1.3-3.1× higher throughput compared with gTop-k, and 1.1-1.2× higher throughput compared with original Sketched-SGD.

Index Terms—Deep Learning Training; Distributed Stochastic Gradient Descent; Gradient Compression; Top-k Sparsification; Global Sketching

I. INTRODUCTION

In recent years, deep learning has been widely used in various fields, especially in Computer Vision, Natural Language Processing, and Speech Recognition [1] [2] [3]. Most deep learning networks have achieved state-of-art performance across various domains [4] [5] [6]. Stochastic gradient descent (SGD) and its various variants [7] are the main methods for training deep learning networks. However, the training process of deep learning models requires large-scale datasets, like ImageNet [8]. As the networks become deeper, the parameters of the model grow quickly results in a longer training time, even taking days to weeks [9].

To improve the training efficiency of deep learning models, high-performance acceleration hardware, like NVIDIA A100 [10], Google TPU [11] and Huawei Ascend910 [12], are applied to reduce training time. In addition, parallel training through multiple acceleration nodes is still one of the most effective ways to reduce training time [13] significantly. Whether it is synchronous training or asynchronous training, a large number of gradient parameters need to be transmitted between servers. Compared with the computing time, the data transmission time has a delay of orders of magnitude, especially for training models that require a large number of parameter interactions, such as RNN [14]. The network communication overhead of parameter information is the fatal bottleneck to the performance of distributed training [15].

In distributed deep learning, data parallelism, model parallelism, and hybrid parallelism [16] are three commonly used methods. Data parallelism randomly divides the entire datasets into several parts, then dispatches them to different nodes. Each node maintains a complete model replica with local parameters. Model parallelism split the model into several parts delivered on different nodes. Hybrid parallelism is a combination of data and model parallelism. In general, data parallelism is suitable for large training sets, and model parallelism is ideal for large-scale models. The distributed training discussed in this paper is mainly limited to data parallelism.

Recently, many gradient compression methods, including sparsification and quantization [7] [17] [18] [19] [20] have been proposed to reduce the communication overhead be-
tween workers in training large-scale DNNs by significantly reducing the size of the exchanged gradients. The most representative one is the Top-$k$ algorithm, which significantly reduces the communication overhead in the distributed training [21]. In addition, the Sketching sparsification method [22] based on the streaming algorithm is relatively novel, which can recover favorable convergence guarantees of vanilla SGD. But these two methods use the centralized method based on the parameter server (PS), which has the single point of failure problem and limited scalability. However, other methods with the decentralized method, such as gTop-$k$ [23], still have room for improvement in convergence efficiency when training deep learning models. In this paper, we use the Count Sketch to compress the gradient on the local workers, which is called a sketch. Then we first propose the tree structure All-Reduce algorithm to aggregate the sketches from workers. Compared with gTop-$k$ and Sketched-SGD, we reduce the communication complexity from $O(k \log P)$ and $O(\log d \times \log P)$ to $O(\log d \times \log P)$ respectively without affecting the convergence rate of the model. The gs-SGD achieves 1.3-3.1× acceleration effect compared with gTop-$k$, and 1.1-1.2× speedup than original Sketched-SGD. Our contributions are summarized as follows:

- We propose a global sketch sparsification algorithm on distributed synchronous SGD, called global-sketching SGD, to accelerate distributed training of deep neural networks.
- We implement the proposed gs-SGD atop popular framework PyTorch and Horovod, and evaluate the training efficiency on a 4-GPU cluster interconnected with 1Gbps Ethernet. Experiments result shows that our algorithm has significantly improved the convergence efficiency of training various CNNs, and reduces the communication time ratio among workers.
- gs-SGD achieves effectively improved training efficiency on the real-world applications with various CNNs under low-bandwidth networks (e.g., 1 Gig-Ethernet).

The rest of the paper is organized as follows. We introduce some related work in Section II, and then present our gs-SGD algorithm in Section III. Experimental results and discussions are presented in Section IV. Finally, we conclude the paper in Section V.

II. RELATED WORK

In general, data-parallel distributed SGD methods are divided into two categories: synchronous mode and asynchronous mode. This paper focuses on the gradient compression method in synchronous mode. In terms of gradient compression, sparsification and quantization are the two main methods [24] [25] [26]. Both centralized and distributed methods have been applied in different scenario [27] [28] [29].

The quantization method achieves a reduction in space occupancy by representing the gradient with a low-precision value. In 1-bit SGD [30], gradient quantization technology is used to reduce the communication overhead of distributed neural network training for the first time. In addition, the method also proposed an error feedback mechanism, which can alleviate the negative impact of gradient quantization and reduce the loss of model accuracy. signSGD [31] combined quantization with gradient direction. The paper demonstrated that it is the direction rather than the value that is significant for gradients. Therefore, even if only the sign of the gradient is kept to update the model, the training process can also converge. In some cases, this can reduce the noise of the gradient and make the convergence time shorter. A recent paper, based on previous work, realizes an adaptive quantization method [32]. In General, the value of the gradient is represented by a 32-bit variable. Therefore, there is an upper limit on the ratio of communication reduction for the quantification method, which is up to 32 times.

In contrast, the sparse method may achieve a gradient compression of hundreds of times [21]. The sparse methods reduce the space occupation by filtering some of the gradients, then discarding the remaining gradients. Filtering rules can be based on thresholds. For different models, how to determine the threshold to filter the gradient is a difficult problem. Therefore, some adaptive methods have also been proposed [33]. Besides thresholds, Top-$k$ compression is a widely used sparse method [34] [21]. DGD (Distributed Gradient Descent) [34] is an exploratory work. The training speed can be significantly improved by replacing dense updates in distributed SGD with sparse updates. It got 49% speedup on MNIST. DGC (Deep Gradient Compression) [21] applies momentum correction and local gradient clipping methods on top of gradient sparseness and achieves over 600 times compression. These sparse methods are mostly centralized, so there is a single point of communication bottleneck problem, especially in the harsh network communication environment. Although some methods have tried distributed gradient synchronization methods [23], they still have shortcomings in terms of convergence.

Beyond quantization and sparse methods, some vector mapping methods and data structures, like Count-Sketch [35], are applied to gradient compression [22]. The sketching data structure is mostly linear, both momentum and error accumulation can be carried out within the data. In the centralized topology, the error and momentum can be transmitted to the central node to eliminate errors and accelerate convergence [36]. This feature can also be applied to distributed gradient synchronization topology to reduce the convergence attenuation caused by gradient sparse. However, related research is rare.

Prior work has proposed applying sketching to compress the gradients on the workers in the distributed training. However, the communication complexity of these methods is high, which leads to large communication overhead. The AllReduce method used in the recently proposed gTop-$k$ effectively reduces the communication complexity of sparsification methods, but its convergence efficiency is still insufficient when training the model. The gs-SGD proposed
in this paper has the same low communication complexity as gTop-K and has higher convergence efficiency. The gs-SGD scheme effectively speeds up the training efficiency of various real-world applications of CNNs on GPU clusters under low-bandwidth networks (e.g., 1 Gig-Ethernet).

III. METHODS

A. SGD with Global Sketching

In general, synchronous distributed SGD algorithms are divided into centralized algorithms based on PSs and decentralized algorithms without PSs. In a decentralized scenario, the exchange and merging process of parameters is a typical all-reduce collective communications operation. Usually, we use the recursive halving and doubling method to all-reduce parameters among clusters. Recursive halving and doubling process is essentially constructing a binary tree to reduce all global parameters, then backtrack the results of the recursion to all leaf nodes along the binary tree.

Various Top-k compression techniques are widely used in gradient compression methods. However, when the compression ratio reaches a higher value, the Top-k method significantly attenuates convergence. In addition, the Top-k method must exchange both the gradient value and their coordinates i when synchronizing to ensure the correct execution of the reduction, which doubled the amount of communication.

In contrast with Top-k compression, there is a data structure named Count — Sketch. Count — Sketch can compress a gradient vector g into S(g) with a size of \( O(\frac{1}{\epsilon} \log d) \), where \( \epsilon \) is a parameter to select top-k largest gradient values, and d is the size of g. Count — Sketch finds all \((\alpha, \ell_2)\)-heavy coordinates and approximates their values with error \( \pm \epsilon \|g\|_2 \). It does so with a memory footprint of \( O(\frac{1}{\epsilon^2} \log d) \). In addition, Count — Sketch gained popularity in distributed systems primarily due to the merge ability property: given a sketch \( S(a) \) computed on the input vector \( a \) and a sketch \( S(b) \) computed on input \( b \), there exists a function \( S(a + b) \). Note that sketching the entire vector can be rewritten as a linear operation \( S(a) = Ca \), and therefore \( S(a + b) = S(a) + S(b) \). We take advantage of this crucial property in gs-SGD to aggregate sketches among workers.

In gs-SGD, each worker transmits a sketch instead of its gradient. Each worker needs to compress its gradient into a Count — Sketch structure locally. As shown in Lines 8 to 23 of Algorithm 1, in each iteration, two workers whose ranks are separated from each other by the value of the current iteration are taken in turn, and the latter transmits the local sketch to the former. After iterations are complete, we obtain the summed sketch on the first worker. And then, we recover the top-k largest gradient elements by magnitude from the summed sketch and use the exact value of the top-k to update the weight. This algorithm for recovering top-k elements from a summed sketch is summarised in Algorithm 2.

When \( P \) is not a power of 2, Algorithm 1 needs some minor improvements. In Fig. 1(a), \( P \) is power of two and Algorithm 1 works. In Fig. 1(b) and Fig. 1(c), \( P \) is not power of two. From the initial round, when the number of nodes participating in the reduce is odd, the node with the largest id goes directly to the next round without participating in this round of recursive halving. Through mathematical induction, we can get that no matter the initial value is odd or even, it will eventually reurse to a unique root node. Therefore, no matter whether \( P \) is a power of 2, we need at most \( 2\lceil \log P \rceil \) rounds to get all-reduce sketch results and pass them back to all workers.

B. Communication Complexity analysis

The communication nodes discussed in this article are all available GPU servers, which use the TCP/IP protocols to communicate to send and receive data simultaneously. For the communication complexity analysis, the cost of gradient exchanging between two nodes will be modeled by \( \alpha + \gamma \beta \) without considering network conflicts where \( \alpha \) is message startup time, and \( \beta \) is transmission time per data. Since
Algorithm 1 Global Sketching SGD

Input: The dataset: $D$
Input: The initialized weights: $w$
Input: The number of workers $P$
Input: The rank of worker $q$
Input: The number of iterations to train: $T$

1: initialize the stochastic gradient $G^0_0 = 0$
2: for $t = 1 \rightarrow T$ do
3: Sampling a mini-batch of data $D^i_0$ from $D$;
4: Compute stochastic gradient $G^g$;
5: Compute sketches $S^q_i$ of $G^g$
6: sends = $S^q_i$;
7: Initialize recvs with the same as sends;
8: nRounds = log $P$;
9: for $i = 1 \rightarrow n$Rounds do
10: pRanks = $[1 \rightarrow P, step = i]$;
11: if $i = 1 \rightarrow n$Rounds then
12: localRank = pRanks.index($g$);
13: if localRank$\%2 == 0$ then
14: source = pRanks[localRank + 1];
15: Recv(recvs, source=source);
16: sends = recvs + sends;
17: else
18: target = pRanks[localRank - 1];
19: Send(sends, dest=target);
20: end if
21: end if
22: $S_t =$ sends;
23: end for
24: $G_t = HEAVYMIX(S_t, k)$
25: Update $w_{t+1} = w_t - \eta G_t$
26: end for

Algorithm 2 HEAVYMIX [22]

Input: Sketch of gradient: $S$
Input: The number of non-zero elements: $k$
Input: The rank of worker: $g$

Output: $\tilde{g}: \forall i \in Top_k: \tilde{g}_i = g_i$ and $\forall i \notin Top_k: \tilde{g}_i = 0$

1: $\forall i$ query $\tilde{g}^2_i = \frac{1}{k\beta}||g_i||^2$ from sketch $S$
2: $H \leftarrow |\tilde{g}_i| \geq \frac{k}{2} / k$ and $NH \leftarrow |\tilde{g}_i| < \frac{k}{2} / k$
3: $Top_k = H \cup rand_l(NH)$, where $l = k - |H|$
4: second round of communication to get exact values of $Top_k$

IV. Experimental Results

We conduct extensive experiments to evaluate the effectiveness of our proposed gs-SGD by real-world applications on a 4-GPU cluster. We first compare the convergence efficiency with gs-SGD, gTop-k S-SGD and Sketched-SGD on ResNet-20 and VGG-16. Then we evaluate and compare the time performance with gs-SGD, gTop-k S-SGD and Sketched-SGD. After that, we run experiments on the convergence sensibility with different sparsity. We also make a comparison on scaling efficiency among the three algorithms.

All GPU machines are installed with Ubuntu-18.04, Nvidia GPU driver at version 460.56, and CUDA-11.2. The communication libraries are OpenMPI [39] at version 4.1.1 and NCCL [40] at version 2.4. We use the highly optimized distributed training library Horovod at version 0.22.1. The deep learning framework is PyTorch at version 1.8.0 with cuDNN-11.1. Details of the software are shown in Table I.

| Software   | Version          |
|------------|------------------|
| OS         | Ubuntu-18.04     |
| GPU driver | Nvidia GPU driver 460.56 |
| CUDA       | 11.2             |
| OpenMPI    | 4.1.1            |
| NCCL       | 2.4              |
| Horovod    | 0.22.1           |
| PyTorch    | 1.8.0            |

A. Convergence comparison

We compare our gs-SGD with the gTop-k S-SGD and the original Sketched-SGD with sparse gradients running on 4 workers. It should be noted that in order to improve the accuracy of our training, we used warmup for the first few epochs. To be specific, the first 4 epochs use the dynamic densities of [0.25, 0.0725, 0.015, 0.004] and small learning rates like [0.1, 0.03, 0.01].
The Convergences of ResNet-20 and VGG-16 models on the Cifar-10 data set are shown in Fig. 2 and Fig. 3. The results show that our gs-SGD basically converges at about 70 epochs, while gTop-k needs about 85 epochs. In other words, the convergence efficiency of gs-SGD on ResNet-20 and VGG-16 is slightly better than that of gTop-k, especially before 85 epochs, and almost consistent with the convergence efficiency of original Sketched-SGD.

It can be seen that our algorithm has a better convergence rate than gTop-k algorithm when training the above two models on the Cifar-10 data set, and does not lose the accuracy of the model.

B. Time performance analysis

We use the cases of 4 workers to analyze the time performance of gs-SGD. We break down the time of an iteration into three parts: GPU computation time (t_compu.), local sparsification time (t_compr.), and communication time (t_comm.). The results are shown in Fig. 4 and Fig. 5. It is obvious that the communication time of our algorithm is smaller than that of the original Sketched-SGD algorithm, especially on ResNet-20, because the AllReduce time complexity of our algorithm is $O(\log d \ast \log P)$ while the time complexity of the original Sketched-SGD algorithm is $O(\log d \ast P)$.

C. Convergence sensibility to the sparsity

To test the sensibility of convergence of gs-SGD to the sparsity, we run the experiments with different numbers of the parameters $k$ using VGG-16 and ResNet-20 on the Cifar-10 data set on 4 workers. The convergence curves are shown in Fig. 6 and Fig. 7. It can be seen that a very small value of $k$-parameter of 10000 will significantly damage the convergence and accuracy of both models. Therefore, there is a tradeoff between the high compression ratio and a stable convergence speed. In other words, the
higher compression ratio would bring lower communication overheads and higher scaling efficiency to a larger cluster. However, this indicates that we need to pay attention to the range of sparsity when training the model to avoid harming the convergence speed and accuracy of the model.

**Fig. 6.** Convergence curves for ResNet-20 trained on Cifar-10 data set with different k on 4 workers.

**Fig. 7.** Convergence curves for VGG-16 trained on Cifar-10 data set with different k on 4 workers.

**V. CONCLUSION**

Gradient compression is a promising method to solve the communication bottleneck in synchronous distributed training. In this paper, we propose gs-SGD, which uses Count-Sketch data structure to compress and transmit the gradients between workers, and improves convergence efficiency and system throughput while ensuring the communication complexity is $O(\log d \log P)$. We conducted experiments to compare the convergence efficiency and time performance of gs-SGD, gTop-$k$ and Sketched-SGD. The experimental results show that our algorithm has significantly improved the convergence efficiency of training various CNNs, and reduces the communication time ratio among workers. Experiments on different convolutional neural networks, including VGG-16 and ResNet-20, verify that gs-SGD can guarantee convergence efficiency without losing model accuracy. We have conducted experiments on a 4-GPU cluster interconnected with 1 Gbps Ethernet to confirm that the training throughput of gs-SGD proposed in this paper increased by 2.2x on average compared with gTop-$k$ S-SGD and 1.15x compared with Sketched-SGD.

For future work, we believe that scenarios with lower bandwidth network, more workers and more complex models are worth experimenting and researching.

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