EFFICIENT COMMUNICATIONS IN TRAINING LARGE SCALE NEURAL NETWORKS

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ABSTRACT

We consider the problem of how to reduce the cost of communication that is required for the parallel training of a neural network. The state-of-the-art method, Bulk Synchronous Parallel Stochastic Gradient Descent (BSP-SGD), requires many collective communication operations, like broadcasts of parameters or reductions for sub-gradient aggregations, which for large messages quickly dominates overall execution time and limits parallel scalability. To address this problem, we develop a new technique for collective operations, referred to as Linear Pipelining (LP). It is tuned to the message sizes that arise in BSP-SGD, and works effectively on multi-GPU systems. Theoretically, the cost of LP is invariant to P, where P is the number of GPUs, while the cost of more conventional Minimum Spanning Tree (MST) scales like $O(\log P)$. LP also demonstrate up to 2x faster bandwidth than Bidirectional Exchange (BE) techniques that are widely adopted by current MPI implementations. We apply these collectives to BSP-SGD, showing that the proposed implementations reduce communication bottlenecks in practice while preserving the attractive convergence properties of BSP-SGD.

1 INTRODUCTION

Scaling up neural networks with respect to parameter sizes, training sets, or both has drastically improved the state-of-the-art performance in several domains ranging from scene understanding, speech recognition, even to playing Go against professional players. Although training a large network saturated with nonlinearities is extremely time-consuming, the benefits brought forth by the large-scale sparks a surge of interests to parallelize the training on multi-GPUs. The parallelization of SGD demands synchronizations to exchange gradients and parameters per iteration, and this introduces the significant communication overhead. Previous studies have focused on trading the SGD convergence rate for fast gradient updates, such as stale or asynchronous SGD, 1-bit compressed gradient, etc. However, these methods are rarely adopted by Deep Learning frameworks as they depend on the balance between the enhanced iteration throughput and the decelerated convergence rate. Since BSP retains the convergence properties of SGD, the optimization of it should be interested.

The gradient aggregations and parameter exchanges in BSP SGD are typical operations of communication collectives (Chan et al., 2007). Messages in the large-scale neural networks training are dense, long, and fixed-length, while the performance of collective algorithms is drastically sensitive to these attributes. Besides, the processing speed is several orders of magnitude faster than the network unidirectional transmission rate. These prioritize the utilization of network bandwidth in the collective design. However, we have seen sub-optimal collective algorithms, e.g. MST and BE, widely adopted by the deep learning community (Agarwal et al., 2014) (Jia et al., 2014) (Duchi et al., 2011). MST only suits for the latency dominant case such as frequent short message exchanges, while the bandwidth term of BE can be further improved (Thakur et al., 2005).

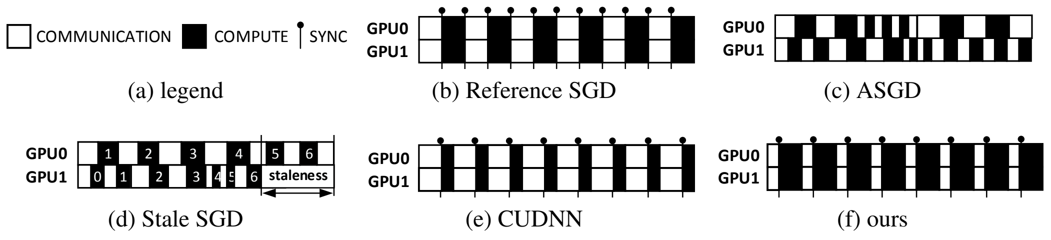


Figure 1: Illustrations of various methods to accelerate the training. Black blocks stands for computations, and white blocks stands for communications. CUDNN reduces the computation cost, while we reduce the communication cost.

In this paper, we introduce a new Linear Pipeline based collectives for the multiGPU training. The collectives demonstrate $\mathcal{O}(log(P))$ and up to 2 speedups, with respect to MST and BE based ones; and the bounds only hold in training large neural networks. In particular, the theoretical analysis and the implementation yield an interesting insight that ***the cost of our design is invariant to GPU numbers***, i.e., the cost of collective operations on 2 GPUs is similar to 20 GPUs. The design explores message granularity to maximize simultaneous bidirectional data exchanges. In specific, it divides a message into fine-grained blocks as the basic communication element. A GPU sends a block (via DMA 1) while receiving (via DMA 2) a new block from a neighbor. The copies are asynchronous launched on two GPU streams, and numerical operations further overlap data copies. As a result, our method renders a highly efficient pipeline to exchange messages for the neural network training.

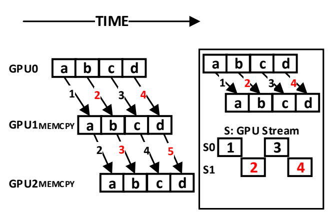
The proposed collective design achieves 2.3x to 360.55x speedups to Open MPI alternatives on 6 GPUs. In training GoogLeNet, we set up the same BSP SGD implementation but different underlying collectives. Our design demonstrates up to 1.7x convergence speedups to MST based Caffe.

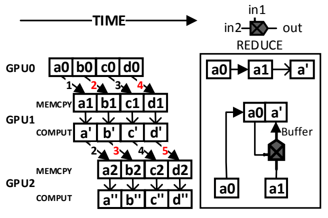
2 Related Work

The communication overhead has been widely identified as the major bottleneck to the data-parallel SGD (Shamir (2014), Li et al. (2014)). The data parallelism linearly adds the processing power by concurrent gradient computations with multiple GPUs. But it also requires synchronizations to collect sub-gradients or to broadcast parameters. In practice, the communication rate is several orders of magnitude slower than the computation (Coates et al., 2013). Various approaches have been proposed to debase the overhead.

The first group relaxes synchronous models of SGD to increase the iteration throughput (Dean et al. (2012), Zinkevich et al. (2010)). In this case, the relaxed SGD enables computations on a GPU to partially overlap with communications on others as demonstrated in Fig.1c and Fig.1d. Recht et al. (2011) proposed a lock free Asynchronous SGD (ASGD) that entirely gets rid of the synchronization requirement by allowing free concurrent parameters updates. But the relaxation only works well on sparse learning problems. In response, Ho et al. (2013) introduced the concept of staleness by bounding the fastest and the slowest machine within a few iterations apart to ensure the correctness. These relaxations claim to be effective as the enhanced iteration throughput offsets the disadvantages of degraded convergence rate. However, recent advances in deep learning frameworks (Cui et al. (2016)) have reestablished the advantages of BSP over relaxed ones in training neural networks. This reiterates the importances of studying BSP SGD.

The second group tries to reduce the overall communication volume. Seide et al. (2014) quantized gradients from 32 bits into 1 bit to reduce the message length, but the lost gradient information decelerates the convergence rate. Another approach is to accelerate the convergence with a large batch. Dekel et al. (2012) shows the convergence rate of mini-batch SGD is $\mathcal{O}(1/\sqrt{Tb} + 1/T)$ with b being the batch size. This result indicates a large batch needs fewer iterations to find a solution, thereby less overall synchronizations. However, unwieldy increasing the batch size is also unfavorable under limited computing resources demonstrated by Wang et al. (2016). Please note these methods still need synchronizations. Our work will further improve their performances.


(a) $broadcast$


(b) $reduce$

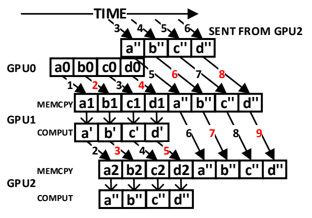

(c) $allreduce$

Figure 2: The data flow of $broadcast$, $reduce$ and $allreduce$ on 3 GPUs.

The third group conducts system optimizations to minimize the communication cost. Agarwal & Duchi (2011) andAgarwal et al. (2014) presented sub-gradient aggregations guided with a MST that takes $log(P)$ steps to fully synchronize the model. Deep learning frameworks such as Caffe (Jia et al., 2014) also adopt this approach. Unfortunately, MST only suits for latency dominant scenarios (i.e. high frequent short messages). Although collective algorithms have been thoroughly discussed in the HPC community (Almási et al. (2005), Gabriel et al. (2004), Shipman et al. (2006)), few studies their performances for the deep learning. Performances of collectives significantly vary w.r.t messages and network topologies, while messages in the network training are dense, long and fixed-length. Therefore, it is imperative to address such peculiarities in the collectives. Worringen (2003) proposed a pipeline collective model in shared memory environment for CPU data, but communications of different MPI processes sharing the same CPU memory bus within the same CPU socket. This causes bandwidth competition among different processes, thereby poor performance for the collective communication in shared memory environment for CPU data. In contrast, PCI-E is bi-directional. The latest GPUs also feature two independent DMA engines for simultaneous independent in/out communications. The hardware updates pave the way for LP based GPU communications.

3 Linear Pipeline based Collective Design Dedicated for Neural Network Training on Multi-GPUs

This section presents a new LP based MultiGPU collective design ensued by the concrete proof of its performance in training neural networks. The general idea of LP is as follows: a) we dissect a long message into fine-grained blocks. b) a GPU receives a block from the prior GPU via DMA1 while sending a block to the next one via DMA2. Please note each block exchange utilizes an independent physical link, and the entire network is fully utilized once the pipeline is filled.

Broadcast tackles the synchronizations of parameters among multiple GPUs. It copies the source vector to every GPUs. Fig.2a demonstrates the data flow of $broadcast$ collective on 3 GPUs. GPU0 is the source, and the rest are destinations. $Broadcast$ starts with filling the pipe by coping block a on GPU0 to GPU1 at the step 1. Let's focus on GPU1. At each step, GPU1 receives a block from GPU0 via DMA1, while GPU1 is also sending a block to GPU2 via DMA2. The data exchange in either way utilizes an independent link and DMA engine to achieve the maximal unidirectional rate. Hence, the bandwidth is fully exploited.

Reduce aggregates the sub-gradients to reconstruct the global one. It combines the elements provided in the vector of each GPU, and returns the combined value in the receive vector to a specific GPU. It supports basic arithmetic operations such as summations and multiplications. Fig.2b demonstrates the data flow of $reduce$ collective. GPU2 is the root that aggregates the vectors across all GPUs. $Reduce$ starts with filling the pipe by writing block $a0$ to a buffer on GPU1. Then, GPU1 reduces the received block $a0$ with $a1$ to yield a' (within the rectangle of Fig.2b). Please note the computation is much faster than the communication, we assume no latency on it. In practice, computations are further overlapped with communications. In the next time step, GPU1 retrieves $b0$ from GPU0 to reduce to b' via DMA 1, while GPU1 is also sending a' to GPU2 to reduce to a'' via DMA 2. b'', c'', d'' are reduced at the time step 3, 4, 5 in a similar fashion.

AllReduce enables us to collect sub-gradients and broadcast the latest parameters with only one synchronization point per SGD iteration. It combines vectors from all GPUs and distributes the result back to them. Mathematically, it is equivalent to a $reduce$ followed by a $broadcast$. However,

Table 1: The estimated costs of 3 collective communications.

	Bidirectional Exchange (BE)	Minimal Spanning Tree (MST)	Linear Pipeline (LP)
$broadcast$	$(\log p + p - 1)\alpha + 2(\frac{p-1}{p}n)\beta$	$\log p(\alpha + n\beta)$	$(p - 1 + \frac{n}{b})\alpha + (b(p-1) + n)\beta$
$reduce$	$(2\log p)\alpha + 2(\frac{p-1}{p}n)\beta + (\frac{p-1}{p}n)\gamma$	$\log p(\alpha + n\beta + n\gamma)$	$(p - 1 + \frac{n}{b})\alpha + (bp - b + n)(\beta + \gamma)$
$allreduce$	$(2\log p)\alpha + 2(\frac{p-1}{p}n)\beta + (\frac{p-1}{p}n)\gamma$	$\log p(2\alpha + 2n\beta + n\gamma)$	$2(p - 1 + \frac{n}{b})\alpha + (bp - b + n)(2\beta + \gamma)$

$allreduce$ is more efficient than two separate calls as it only needs to fill the pipeline once. For example, it takes 9 timesteps to $allreduce$ 4 message blocks, while $broadcast$ + $reduce$ will cost 10. Fig.2c demonstrates the data flow of $allreduce$ collective. It starts with reducing a'', after which a'' is broadcast to GPU1 and GPU2 at the timestep 5, 6 respectively. Please note $d0$ utilizes the outbound DMA at the timestep 4, therefore a'' has to wait tile timestep 5. b'', c'', d'' are $allreduce$ in a similar fashion.

Our collective is also specifically designed to accommodate GPU architecture features such as asynchronous kernel launches and the multi-stream processing. For example, the rectangle of Fig.2a demonstrates the data transfers are asynchronous launched on two separate streams. The copies happen at the red time steps are scheduled on the stream 0, while the black time steps are scheduled on the another stream. This overlaps the overhead of GPU kernel launches, further improving the pipeline. We demonstrate the data flow of collectives on 3 GPUs. If there are k GPUs, GPU n, $0 < n < k - 1$, duplicates the same pattern of GPU 1.

3.1 Architecture Analysis

LP is the optimal collective algorithm to fully exploit the network bandwidth of a MultiGPU system. Even though PCI-E supports full-duplex communication between any two endpoints, each PCI-E endpoint device only has one input and output port. This results in bandwidth competition if a GPU is receiving from multiple GPUs. Similarly, each PCI-E switch only contains one input and output port used for inter-switch communication, and inter-switch communications of the same direction also compete for the PCI-E bus. It is known that any delay in data movement between two GPUs interrupts the pipelining in the collectives. In such architecture, the communication from parent to children in MST based collective algorithm will compete the same PCI-E bus, and therefore breaks pipelining. The data exchange of BE also suffers from inter-switch communications congested in one direction. In contrast, LP connects all GPUs into a chain, and data always flow in one direction. Hence, data movements between two GPUs exclusively occupy the entire PCI-E bus and ensures the uninterrupted pipelining.

3.2 Theoretical Analysis

We adopt a cost model widely used by the MPI community to analyze collective operations (Thakur et al. (2005), Thakur & Gropp (2003)). The model assumes the time taken to send a message between two nodes follows:

$$T = \alpha + \beta n + \gamma n \tag{1}$$

where α is the latency or startup time of sending a message, β and γ is the transmission rate and reduce rate measured by time per byte, n is the message size in bytes. We also denote p as the node count, and b as the block size (in bytes) in the pipeline.

Proposition 1 *If the network latency $\alpha \to 0$, Linear Pipeline demonstrates $\mathcal{O}(\log p)$ and up to 2 times speedup w.r.t Minimal Spanning Tree and Bidirectional Exchange on a message of size $n \to \infty$, respectively.*

Proof. First, we derive the costs of 3 Linear Pipeline based collectives. According to Fig.2, the length of pipeline is $p - 1 + \frac{n}{b}$ blocks assuming each block to be b bytes. A block exchange takes $\alpha + \beta b + \gamma b$ (with reduce) or $\alpha + \beta b$ (without reduce). Consequently, $broadcast$ essentially costs $(\alpha + \beta b)(p - 1 + \frac{n}{b}) = (p - 1 + \frac{n}{b})\alpha + (b(p-1) + n)\beta$. Similarly $reduce$ costs $(\alpha + \beta b + \gamma b)(p - 1 + \frac{n}{b}) = (p - 1 + \frac{n}{b})\alpha + (b(p-1) + n)(\beta + \gamma)$. The cost of $allreduce$ is approximately equivalent with a $reduce$ followed by a $broadcast$. Therefore, the cost of $allreduce$ is $broadcast$ + $reduce$, $2(p-1+\frac{n}{b})\alpha + (bp-b+n)(2\beta+\gamma)$.

Secondly, we derive the costs of 3 MST based collectives. MPI adopts MST to $broadcast$ or $reduce$ short messages (Thakur et al. (2005)), the length of which is less than 12 KB. The core concept of MST is to organizes p GPUs into a balanced tree of height $\lceil logp \rceil$. Then, it takes $\lceil \log p \rceil$ steps to traverse all GPUs in the tree. Each step carries the message of length n, resulting in the cost of $broadcast$ to be the tree height times costs per step, i.e. $\log p(\alpha + n\beta)$ (we omit the ceiling for simplicity). Similarly, MST $reduce$ is $\log p(\alpha + n\beta + n\gamma)$, and $allreduce$ is a combination of $broadcast$ and $reduce$. Please note the latency term is $\log p\alpha$, which is the smallest among algorithms in Table.1. Therefore, MST only suits for high frequent short messages.

Finally, we present the costs of 3 BE based collectives. MPI $broadcast$ handles long messages with a MST based $scatter$ followed by a BE $allgather$. Please refer to Chan et al. (2007) for the analysis of BE collectives. Basically, $scatter$ costs $\sum_{k=1}^{\lceil logp \rceil}(\alpha + 2^{-k}n\beta) = \log p\alpha + \frac{p-1}{p}n\beta$, while $allgather$ costs $(p-1)\alpha + \frac{p-1}{p}n\beta$. The cost of $broadcast$ is the sum of these two. The MPI long message $reduce$ consists of a $reducescatter$ plus a $gather$, while $allreduce$ consists of a $reducescatter$ and a $allgather$. The cost for $reducescatter$ is $\log p\alpha + \frac{p-1}{p}n\beta + \frac{p-1}{p}n\gamma$, and both the costs of $gather$ and $allgather$ are $\log p\alpha + \frac{p-1}{p}n\beta$ (also in Chan et al. (2007)). TABLE 1 summarizes the costs of $broadcast$, $reduce$ and $allreduce$ under 3 different underlying algorithms.

The proposition holds under the assumptions of $\alpha \to 0$ and $n \to \infty$, and these assumptions are legitimate for the training of large scale neural networks on multiGPUs. Nowadays, the PCI Express x16 effectively reduces the latency α down to $10^{-7}s$ that is approximate to zero. The current two sockets shared memory machine supports up to 8 GPUs indicating p is limited. Let's take an appropriate block size b to ensure $\frac{n}{b} \ll \alpha$. This enables us to safely ignore the latency term, e.g. $\log p\alpha$ in MST $broadcast$. On the other hand, current deep convolutional neural network features tremendous parameters. For example, the parameter sizes of AlexNet is 50 MegaBytes. The transmission rate[1] $\beta \sim 10^9 Byte/Seconds$. In compared with the trivial latency term, the bandwidth term dominates the entire cost T. This result leads us to simplify the costs of BE, MST, and LP based $broadcast$ (table. 2) to be $2\frac{p-1}{p}n\beta$, $n\beta\log p$ and $(b(p-1)+n)\beta$, obtaining the following equations:

$$\frac{T_{broadcast\_BE}}{T_{broadcast\_LP}} \approx \frac{2(1-\frac{1}{p})}{1+\frac{b}{n}(p-1)} < 2 \tag{2}$$

$$\frac{T_{broadcast\_MST}}{T_{broadcast\_LP}} \approx \frac{\log p}{\frac{b(p-1)}{n}+1} < \log p \tag{3}$$

Compared with $broadcast$, $reduce$ has the additional γ term. Please note the processing speed of GPUs exceeds TFLOPs; the term $\gamma * n \to 0$. Therefore, it is also legitimate to ignore the γ term, yielding the same result $T_{reduce\_BE}/T_{reduce\_LP} < 2$ and $T_{reduce\_MST}/T_{reduce\_LP} < \log p$. We complete our proof to the proposition 1.

Another interesting point is the cost of ***Linear Pipeline is invariant to GPU count*** p ***regardless of message length*** n. This implies broadcasting a vector to 8 GPUs may cost same to 2 GPUs. In practice, we set the block size b around 64 KB, and p is within 10^1 These suggests the bandwidth term, e.g. the cost of LP $broadcast$ $(bp-p+n)\beta$, is identical to $n\beta$. Therefore, the cost of LP collectives are less likely to be affected by GPU counts p.

3.3 Deep Learning with Efficient BSP SGD

We formulate the neural network training as the following optimization problem. Let ψ be a loss function with weight vector $\mathbf{w}$ as function parameters that takes randomly sampled images $\mathbf{d_t}$ as the input. The objective of training is to find an approximate solution to the following problem:

$$\min_{\mathbf{w}} \quad E\{\psi_{\mathbf{w}}(\mathbf{d_t})\} = \int_{\Omega} \psi_{\mathbf{w}}(\mathbf{d_t})dP \tag{4}$$

[1]https://en.wikipedia.org/wiki/InfiniBand

Algorithm 1: BSP SGD with communications/computations overlapping.

```
while not converge do
    $broadcast(\mathbf{w}_t^0)$
    for $i \in [0, 1, ..., max\_layers]$ do
        $nonblocking\_broadcast(\mathbf{w}_t^{i+1})$
        Forward($i$)
        $sync\_broadcast()$
    Backward($max\_layers$)
    for $i \in [max\_layers - 1, ..., 1, 0]$ do
        $nonblocking\_reduce(\nabla\psi_{\mathbf{sub}}^{\mathbf{i+1}})$
        Backward($i$)
        $sync\_reduce()$
    $\mathbf{w_{t+1}}$ = GradientUpdate()
```

Algorithm 2: BSP SGD uses $broadcast$ + $reduce$.

```
while not converge do
    $\nabla\psi_{sub}$ = ForwardBackward($\mathbf{d_t}$)
    $\nabla\psi = reduce(\nabla\psi_{sub})$
    if $root$ then
        $\mathbf{w_{t+1}}$ = GradientUpdate()
    $broadcast(\mathbf{w_{t+1}})$
    $barrier$                /* sync new w */
```

Algorithm 3: BSP SGD uses allreduce.

```
while not converge do
    $\nabla\psi_{sub}$ = ForwardBackward($\mathbf{d_t}$)
    $\nabla\psi = allreduce(\nabla\psi_{\mathbf{sub}})$
    $barrier$      /* collect $\nabla\psi_{sub}$ */
    $\mathbf{w_{t+1}}$ = GradientUpdate()
    if $iter\%5 = 0$ then
        $broadcast(\mathbf{w_{t+1}})$
```

A typical training iteration of neural network consists of a Forward and Backward pass. Forward pass yields a loss that measures the discrepancy between the current predictions and the expected; Backward pass calculates the gradient, the negative of which points to the steepest descent direction. Gradient Descent updates the $\mathbf{w}$ as follows:

$$\mathbf{w}^t = \mathbf{w}^{t-1} - \eta_t \nabla\psi_{\mathbf{w}}(\mathbf{d_t}) \tag{5}$$

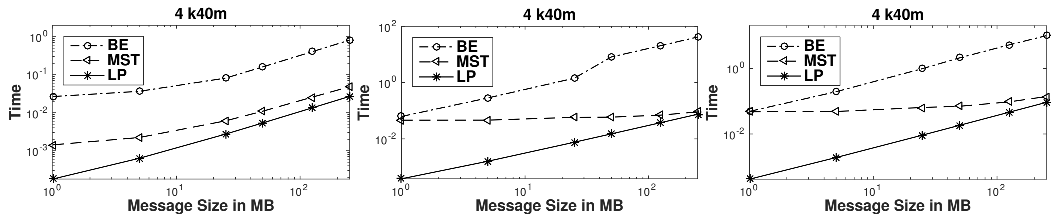
Guided with Data Parallelism, BSP SGD evenly divides $\mathbf{d_t}$ into p slices $\mathbf{d_t^1}, \mathbf{d_t^2}, ..., \mathbf{d_t^p}$ so that every GPU computes a sub-gradients toward $\mathbf{d_t^i}$ in parallel. The global gradient is equivalent to the average of sub-gradients. After finishing the gradient update, $\mathbf{w}^t$ is synchronized to all GPUs. We integrate the proposed collectives into this process to harness parallel processing capabilities of multiGPU system. In this paper, we discuss two ways of BSP SGD implementations.

•**fork and join**: This approach forks the gradient computations, and joins sub-gradients with communications. In this case, communications do not overlap with computations. Alg.2 and Alg.3 demonstrate two collective based implementations using 2 and 1 synchronization points.

In Alg.2, synchronizations rely on $broadcast$ and $reduce$. Each GPU calculates a sub-gradient referred to as $\nabla\psi_{sub}$. The master GPU reconstructs $\nabla\psi$ by reducing all $\nabla\psi_{sub}$. Then, GPUs synchronize latest weight $\mathbf{w}$ by broadcasting.

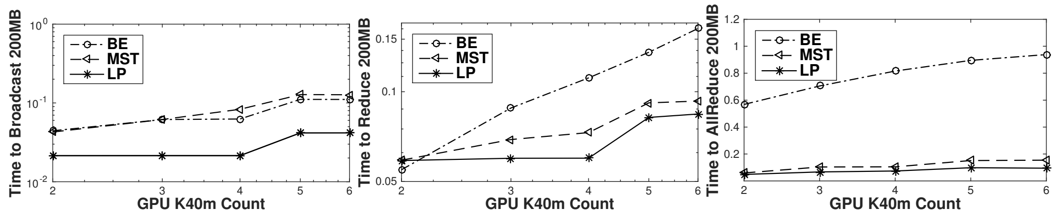
In Alg.3, synchronizations only rely on $allreduce$. The differences between this and Alg.2 are that 1) there is only 1 synchronization point; 2) every GPU computes the gradient update. However, the parameters are not consistent after several iterations due to the precision issues of float multiplications in $GradientUpdate$. We synchronize $\mathbf{w}$ every 5 iterations to eliminate such error while still retaining the benefit of using $allreduce$ (line 7-8 Alg.3).

•**overlapping communications with computations**: Another approach is to orchestra communications and computations overlapping at each network layer. In the forward pass, GPUs broadcast network parameters of layer t+1 amid forward computations at layer t. In the backward pass, GPUs all-reduce or reduce sub-gradients of layer t+1 amidst backward computations at layer t. As a result, layer-wise.computations partially overlap with communications further improving the SGD efficiency. Alg.1 outlines the general idea of communications and computations overlapping during the networks training. We use the nonblocking collective to achieve the overlapping. amidst backward computations at layer t.



(a) Broadcast (b) Reduce (c) AllReduce

Figure 3: The performance of different collective algorithms at different message sizes on 4 K40m.



(a) Broadcast (b) Reduce (c) AllReduce

Figure 4: The scalability experiment: it measures performance variations with increasing GPUs.

•**pros and cons of both approaches**: The cost of Alg.2 or Alg.**??** is $comm + compt$, while the overlapping is $max(comm, compt)$. If the network has over a few hundred MB of parameters, the overlapping will be significantly better than the fork and join approach. However, Alg.2 and Alg.3 are relatively easy to implement; the performance on networks < 100 MB is similar to that of overlapping.

4 Experiment

4.1 Collectives Evaluation

The MST and BE implementations used in benchmarks are Caffe [2] and OpenMPI. Caffe optimizes the GPU placement in an MST to fully utilize inter-GPU peer to peer (P2P) access. OpenMPI and our implementation, similar to Caffe, also take advantages of P2P. We setup AlexNet and GoogLeNet training using 3 kinds of BSP SGD proposed in section 3.3.

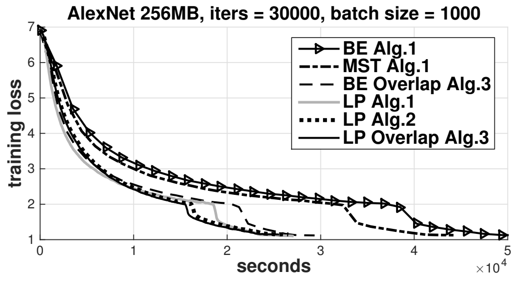
Fig.3 presents the performance of LP, MST, and BE based collectives at different message sizes on 4 K40m. The LP $broadcast$ demonstrates an average of 29.2x and 2.3x speedup over BE and MST based alternatives in Caffe and OpenMPI; the LP $reduce$ demonstrate an average of 360.55x and 8.7x speedup over BE and MST based reduce, and the LP AllReduce demonstrates an average of 109.2x and 7.9x speedup over BE and MST based $allreduce$. In theory, LP is approximately 2x faster than both the MST ($p = 4 \rightarrow logp = 2$) and BE. An extraordinary speedup against MPI is observable due to inefficient data movement in OpenMPI. It moves data to host RAM to perform reduce operations on the CPU before being copied to the target GPU. Instead, we perform reduce on the GPUs, and data blocks directly flow to the target GPU via P2P access. The overlapped $reduce$ computations with communications enables our $reduce$ and $allreduce$ to be 8x faster than that of MST. At each step of MST, GPUs reduce the incoming data only after the entire data is available. In contrast, our fine-grained block design enables communications and computations overlapping by reducing a block while receiving a new one in the pipeline. $broadcast$ only involves data copies, and both we and Caffe use P2P to transmit the data. Therefore, the speedup of MST $broadcast$ (2.3x), conforms to the 2.0x theoretical prediction.

The theoretical analysis indicates both the cost of LP and BE are invariant to the GPU count p, while the cost of MST increases with p by a factor of $logp$. This is also noticeable in the scalability experiment demonstrated in Fig.4. Please note there is a cost jump between 4 and 5 GPUs. Communications have to go through QPI after 4 GPUs, which incurs the additional cost of copying

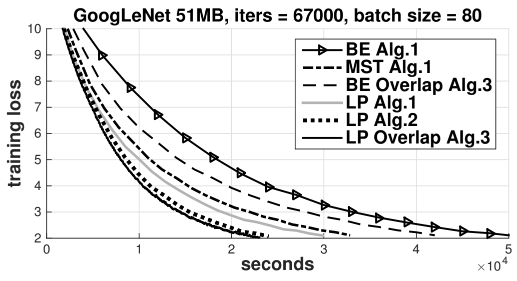
[2] Caffe implements an MST based broadcast and reduce for the multiGPU training.

Table 2: The iteration profile. comm stands for communications, and compt stands for computations. % represents the percentages of communications in an iteration. The statistics are the average of 30000 AlexNet iterations, and 67000 GoogLeNet iterations. We set the batch size of AlexNet to 1000, and GoogLeNet to 80. AlexNet and GoogLeNet are 256MB and 51MB, respectively.

	MST Alg.1			BE Alg.1			BE Alg.3			LP Alg.1			LP Alg.2			LP Alg.3		
	comm	compt	comm%	comm	compt	%	comm	compt	%	comm	compt	%	comm	compt	%	comm	compt	%
AlexNet	0.77s	0.92s	45.5%	1.05s	0.94s	52.7%	0.22s	0.93s	18.9%	0.084s	0.93s	8.3%	0.057s	0.94s	5.7%	0.011s	0.93s	1.2%
GoogLeNet	0.046s	0.267s	14.7%	0.334s	0.264s	55.9%	0.137s	0.263s	34.3%	0.02s	0.265s	7%	0.016s	0.26s	5.8%	0.01s	0.263s	3.7%



(a) AlexNet



(b) GoogLeNet

Figure 5: The training losses in fixed iterations on 4 K40m. We set GoogLeNet lr = 0.01. AlexNet starts at lr = 0.015, and set to 0.0015 after the average loss < 2. The solver is SGD + momentum, and the dataset is ImageNet.

through the host RAM. The cost of pipeline method robustly stays the same if GPU counts =[2,3,4] or [5,6], and QPI explains the inconsistency. The communication steps of MST for 2,3,4,5,6 GPUs are 1,2,2,3,3, respectively. The MST experiments verify the $logp$ cost increase w.r.t GPU counts by evident cost jumps at 3 and 5 GPUs. The data flow of OpenMPI between two GPUs follows GPU RAM$\rightarrow$host RAM$\rightarrow$GPU RAM. Therefore, OpenMPI costs linearly increase with GPU counts p.

4.2 Impact on the Neural Network Training

Fig.5 demonstrates LP collectives effectively reduce the total training time without affecting SGD's convergence properties in training large scale neural networks. We use inspurCaffe, Caffe and cuhk's Caffe branch to benchmark the performance of BE-Alg.1, MST-Alg.1 and BE-Overlap-Alg.3. We also implement Alg.1,2,3, integrated with LP collectives, in Caffe to ensure the consistency. Please note the model size affects the communication time, while the batch size affects the computation time. We carefully set these parameters to cover as many cases as possible. Please refer to the captions of TABLE.2 and Fig.5 for the experiment details. We assume these algorithms have similar convergence speeds in iterations as losses of AlexNet are approximate to 1 after 30000 iterations and losses of GoogLeNet are approximate to 2 after 67000 iterations. Whereas, the time taken to reach the target loss varies dramatically. For example, the speedups of LP-Overlap-Alg.3 over BE-Alg.1 in training AlexNet and GoogLeNet are 2.12x and 2.19x, respectively.

Under the same Alg.1 but different underlying collective algorithms, LP-Alg.1 presents 1.91x and 1.74x speedup over BE-Alg.1 and MST-Alg.1 in AlexNet, and 1.6x and 1.1x speedup over BE-Alg.1 and MST-Alg.1 in GoogLeNet. The iteration profiles of these 3 algorithms in TABLE.2 indicate the communication cost of LP-Alg.1 is only 10% of BE-Alg.1, and 11% of MST-Alg.1 in AlexNet; and 6% of BE-Alg.1, and 43% of MST-Alg.1 in GoogLetNet.

The experiments demonstrate that the speed of 3 proposed BSP SGD is Alg.3 $>$ Alg.2 $>$ Alg.1. The result conforms to our expectations as the cost of Alg.3 is $max(comm, compt)$, while the cost of Alg.1 and Alg.2 is $comm + compt$. However, the performance gain is quite limited from Alg.2 to Alg.3 as there is little room left for reducing communications from pipeline Alg.2 to Alg.3 demonstrated in table.2. If the model parameters keep increasing, we expect Alg.3 to be more efficient than Alg.2.

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