XPipe: Efficient Pipeline Model Parallelism for Multi-GPU DNN Training

Lei Guan, Wotao Yin, Dongsheng Li, Xicheng Lu
1College of Computer, National University of Defense Technology
2DAMO Academy, Alibaba Group (U.S.) Inc.
3Department of Mathematics, University of California, Los Angeles

Abstract—We propose XPipe, an efficient asynchronous pipeline model parallelism approach for multi-GPU DNN training. XPipe is designed to make use of multiple GPUs to concurrently and continuously train different parts of a DNN model. To improve GPU utilization and achieve high throughput, it splits a mini-batch into a set of micro-batches and allows the overlapping of the pipelines of multiple micro-batches, including those belonging to different mini-batches. Most importantly, the novel weight prediction strategy adopted by XPipe enables it to effectively address the weight inconsistency and staleness issues incurred by the asynchronous pipeline parallelism. As a result, XPipe incorporates the advantages of both synchronous and asynchronous pipeline model parallelism approaches. Concretely, it can achieve very comparable (even slightly better) model accuracy as its synchronous counterpart, while obtaining higher throughput than it. Experimental results show that XPipe outperforms other state-of-the-art synchronous and asynchronous model parallelism approaches.

Index Terms—asynchronous, pipeline, model parallelism, multi-GPU, micro-batch, weight prediction

I. INTRODUCTION

Deep Neural Networks (DNNs) have been recognized as one of the most effective tools for many machine learning tasks including image and video analysis [1], [2], language translation [3], [4], and speech recognition [5], [6]. Training a DNN model, however, often takes hours, days, and even weeks. The long training time of DNN models is mainly because the training always involves a huge amount of data and a large number of parameters (also known as weights) [7], [8].

In the past few years, there have been needs to quickly scale up DNNs. One comes from the fact that the image datasets to which we are applying DNNs have a larger number of images and always come in higher resolutions, for example, the ImageNet [9], JFT [10], and OpenImages [11] datasets. The need also arises as a DNN is used to simultaneously recognize more classes of subjects or objects [12], which requires many more layers and weights. Such increases inevitably create a higher demand for the memory of the training devices and the training throughput. Sometimes, breaking a DNN model into pieces and training them with multiple GPUs come to be the only choice for training a neural network with a huge amount of parameters.

Data parallelism is currently the most commonly used approach to utilize multiple GPU devices to accelerate DNN training. For data parallelism, each GPU holds a full copy of the DNN weights and is assigned with a subset of training data. Weight update happens only when the gradients on all GPUs are aggregated. Another orthogonal approach is model parallelism [13], where the DNN structure is divided into subsets of layers and each GPU only keeps a part of the DNN model (known as submodel). The naive model parallelism strategy is to divide the DNN into a set of submodels (each including one or more consecutive layers) and assign each submodel to a GPU device [14]. Each GPU only computes and transmits the activation to the next GPU in the forward direction, unless it owns the last layer, and computes and transmits gradients to the previous GPU in the backward direction unless it keeps the first layer. The inter-GPU communication overhead in model parallelism can be much less than that in data parallelism. However, the naive approach always works serially. That is, in each feedforward-backpropagation round, after a GPU completes its forward step, it waits until all its subsequent GPUs finish their forward and backward steps before it starts its backward step. This leads to that each GPU actives sequentially, one at a pipeline unit, causing serious under-utilization of the multi-GPU system.

To this end, we propose XPipe, an efficient asynchronous pipeline model parallelism approach. This work is motivated by the state-of-the-art synchronous pipeline approach GPipe [15] as well as asynchronous pipeline approaches PipeDream [16] and SpecTrain [17], which will be detailedly reviewed in the next section. XPipe inherits the pipeline structure of PipeDream and SpecTrain but uses a micro-batch as the basic processing unit, and adopts a more efficient strategy to address the weight inconsistency and staleness issues incurred by the asynchronous pipeline parallelism. Besides, adopting fine-grained micro-batch also makes XPipe easily scale up the mini-batch size. On the other hand, despite XPipe introduces micro-batches into the pipeline training as GPipe, XPipe allows the cross-training of these micro-batches from different mini-batches, giving rise to better GPU utilization and higher throughput than GPipe. In summary, XPipe incorporates the advantages of both synchronous and asynchronous pipeline model parallelism approaches. It provides high throughput, scales up mini-batch size easily, and achieves very compa-
rable (even slightly better) model accuracy as its synchronous counterpart (i.e., GPipe).

We evaluated XPipe using three popular Convolutional Neural Network (CNN) models on two different image datasets. The experimental results are detailedly reported, which demonstrate the effectiveness of our proposal. In comparison to PipeDream and SpecTrain, XPipe effectively alleviates the accuracy degradation and achieves very comparable (even slightly better) model accuracy as GPipe. At the same time, XPipe can obtain consistently higher throughput than GPipe, regardless of the number of mini-batch partitions. For example, when training Inception-V3 on Tiny ImageNet, XPipe provides an average of 20.0% (up to 31.9%) and 88.1% (up to 150.8%) throughput improvement over GPipe on 2-GPU and 4-GPU systems, respectively.

II. RELATED WORK

A great many works have explored model parallelism to accelerate DNN training using multiple GPUs [18]–[27]. Besides, pipelining has also been heavily studied and widely applied to speed up neural network training [22]–[25]. Combining the advantages of both model parallelism and pipelining, pipeline model parallelism has been recently proposed to efficiently train DNNs in a model-parallel manner [15], [16]. According to the way the weights updated, existing pipeline model parallelism approaches can be roughly classified into two categories: synchronous pipeline model parallelism and asynchronous pipeline model parallelism.

Synchronous pipeline model parallelism. The state-of-the-art synchronous approach is GPipe [15], which was proposed to address the low GPU-utilization problem of the naive model parallelism strategy and overcome the memory limitation for scaling up DNNs. The noteworthy feature of GPipe is that it first splits a mini-batch into a set of smaller micro-batches. Therefore the training has a finer data unit; each mini-batch is trained equally through the training of a set of micro-batches. Introducing micro-batches into the pipeline training makes GPipe pretty good at scaling up the mini-batch size. More importantly, GPipe trains each set of micro-batches in a pipelined manner, which, to some extent, allows the concurrent training of multiple GPUs. In this mean, GPU utilization is significantly improved compared to the naive model parallelism strategy. Meanwhile, GPipe belongs to synchronous-parallel approach and thus can train DNNs without degrading their model accuracy. However, since these micro-batches from the same mini-batch must flow through all the GPUs sequentially, GPipe is unable to always keep all GPUs being busy training the model in parallel and thus still suffers from load imbalance problem.

Asynchronous pipeline model parallelism. Asynchronous model-parallel (AMP) training [28] was proposed to overcome the low device-utilization problem in the naive model parallelism as well. AMP training allows asynchronous (thus faster) weight update as long as enough gradients are accumulated. However, AMP faces serious weight inconsistency and staleness issues due to the cross-training of multiple mini-batches. Besides that, another asynchronous pipeline parallel approach called PipeDream [16] was recently proposed. Similar to AMP training, PipeDream introduces multiple workers’ concurrent processing by simultaneously training multiple mini-batches in the pipeline. To address the weight inconsistency issue incurred by the cross-training of multiple mini-batches, PipeDream keeps a copy of the weights for each mini-batch active in the pipeline. However, keeping the weights wastes GPU memory especially for the case when a DNN model has a massive amount of model parameters. On the other hand, PipeDream suffers from staleness problem because it uses different versions of weights in the whole feedforward-backpropagation round [17]. The staleness issue slows down the convergence and degrades the model accuracy as well. To simultaneously alleviate the inconsistency and staleness issues in the asynchronous pipeline model parallelism, Chen et al. [17] proposed SpecTrain. It adopts the same pipeline structure as PipeDream, enables the cross-training of multiple mini-batches, and thus achieves high GPU utilization. Instead of storing the weights for each active mini-batch in the pipeline, SpecTrain addresses the weight inconsistency and staleness issues through weight prediction. Based on the observation that the smoothed gradients used in Momentum SGD [27] reflect the trend of weight updates, in both the forward and backward passes, SpecTrain uses the smoothed gradients time the weights version difference to predict the future weights. However, as shown in the experiments later, SpecTrain is still unable to completely solve the inconsistency and staleness issues and often incurs accuracy drop.

III. METHOD

A. Workflow

In XPipe, each mini-batch of size $N$ is split into $T$ smaller micro-batches. Thus a micro-batch of size $N/T$ becomes the basic data processing unit throughout the pipeline training. Figures 1(a) and 1(b) illustrate the workflow of XPipe on the 4-GPU system with $T = 2$ and $T = 4$, respectively. The number $i$ inside each box refer to the forward or backward pass of the $i$-th micro-batch. The white boxes denote the forward passes; grey boxes indicate the backward passes; orange boxes refer to the backward passes of the $T$-th micro-batches, at the end of which weights are updated. The grey dashed lines with arrows in Figure 1(a) depict the round trip of processing the third mini-batch (i.e., micro-batches 5 and 6); the grey dashed lines with arrows in Figure 1(b) depict the round trip of processing the second mini-batch (i.e., micro-batches 5, 6, 7 and 8). In the workflow of XPipe, each mini-batch is trained equally through the training of $T$ micro-batches. For example, in Figure 1(a) micro-batches 1 and 2 correspond to mini-batch 1, and so on. Similarly, for XPipe with $T = 4$ (as shown in the bottom figure of Figure 1(b)), micro-batches 1 to 4 correspond to mini-batch 1, and so on. The red arrowed lines in Figures 1(a) and 1(b) depict the weight prediction, which will be detailedly described later.

One noteworthy feature of XPipe is that the $T$ micro-batches corresponding to the same mini-batch should share the same
weights in their forward and backward passes. Weight update does not instantly happen when a micro-batch completes its backward pass. Instead, when performing the backward pass, the gradients are consistently accumulated across micro-batches, and applied to update model parameters only when the T-th micro-batch completes its backward pass (as shown by the orange boxes in Figure 1).

Beyond that, as depicted in Figures 1(a) and 1(b) XPipe intersects the execution order of micro-batches belonging to different mini-batches. That is, XPipe allows the cross-training of mini-batches, which is quite different to GPipe. In this way, all GPUs can continuously and concurrently train their submodels after the steady phase starts, giving rise to pretty high GPU utilization. Unfortunately, the cross-training of micro-batches results in weight inconsistency and staleness issues. For example, in Figure 1(a), GPU 0 uses the initial weights to perform the forward pass of the fifth micro-batch. However, when GPU 0 is ready to run the backward pass of it, the weights on GPU 0 have been updated twice, i.e., after the backward passes of micro-batches 2 and 4. Moreover, as shown in Figures 1(a) and 1(b) for each micro-batch, the number of weight updates happened between the forward pass and corresponding backward pass varies with the index of GPU. The GPUs with smaller index tend to use staler weights to perform the forward and backward passes. The staleness issue further slows down the convergence and hurts the model quality at the same time.

B. Weight Prediction

In this section, we propose an efficient weight prediction strategy to simultaneously address the weight inconsistency and staleness issues arising in the asynchronous pipeline training. Instead of using the smoothed gradients, XPipe performs weight prediction based on Adam [28] updates, where a running average of the first and second moment of the gradients are used.

For T micro-batches corresponding to a mini-batch, we refer to the micro-batch with the minimum index as a bellwether. Each mini-batch is allocated with a bellwether being in charge of doing weight prediction. For instance, the bellwether of the third mini-batch in Figure 1(a) is micro-batch 5 and the bellwether of the second mini-batch in Figure 1(b) is micro-batch 5 as well. The noteworthy feature of a bellwether is that it always comes in first to perform both forward and backward passes among the T micro-batches.

We use the weights version difference s to measure the amount of weight updates happened between the current pipeline unit and the pipeline unit at which the T-th micro-batch on GPU 0 completes its train round trip. The version difference s should always be calculated first when the bellwether is ready to perform weight prediction.

For forward pass, the bellwether calculates the version difference via

\[ s = \text{round}\left(\frac{\text{size} + T - \text{rank}/2 - 2}{T}\right), \]  

where size denotes the amount of weight updates happened between the forward pass and the corresponding backward pass of each micro-batch, T is the number of micro-batches, and rank denotes the rank of GPU.
where size refers to the amount of GPUs and rank is the index of each GPU.

At the backward pass, the version difference turns to

\[ s = \text{round} \left( \frac{T + |\text{rank}/2| - 1}{T} \right). \]  

(2)

For both forward and backward passes, the bellwether of the t-th mini-batch uses following formula to predict the corresponding future weights:

\[ \hat{W}_t = W_t - s \cdot lr \cdot \Delta W_t, \]  

(3)

where lr is the learning rate and \( \Delta W_t = \frac{\nabla_t}{\sqrt{m_t + \epsilon}} \) with

\[
\begin{align*}
  g_t &= \nabla(W_t), \\
  v_t &= \gamma \cdot v_{t-1} + (1 - \gamma) \cdot g_t, \\
  \overline{v}_t &= \frac{v_t}{\lambda}, \\
  m_t &= \lambda \cdot m_{t-1} + (1 - \lambda) \cdot g_t^2, \\
  \overline{m}_t &= \frac{m_t}{1 - \lambda}.
\end{align*}
\]

In (4), \( g_t \) refers to the gradients of stochastic objective corresponding to the t-th mini-batch; \( v_t \) is the biased first-moment estimate; \( m_t \) is the biased second raw moment estimate; \( \overline{v}_t \) is the bias-corrected first-moment estimate; \( \overline{m}_t \) is the bias-corrected second raw moment estimates; \( g_t^2 \) refers to elementwise square with \( g_t^2 = g_t \odot g_t \); \( \epsilon \), \( \gamma \) and \( \lambda \) are constant values.

Figures 1(a) and 1(b) illustrate the main idea of weight prediction by the bellwether on 4-GPU system with \( T = 2 \) and \( T = 4 \) respectively. The red arrows lined stand for the weight prediction performed by the bellwether. All of them start from the pipeline unit where the bellwethers start their forward passes and point to the pipeline unit at which their corresponding mini-batches on GPU 0 finish the whole train round. In Figures 1(a) and 1(b), \( \hat{W}_t \) denotes the predicted weights corresponding to the \( t \)-th mini-batch. On each GPU, when \( T \) micro-batches (i.e., a mini-batch) are ready to perform the forward pass or the backward pass in sequence, the bellwether will first calculate the version difference \( s \); then weight prediction is performed using the current weights \( W_t \) and version difference \( s \) to generate the future weights \( \hat{W}_t \) through (3). Following that, the other \( (T - 1) \) micro-batches will directly apply \( \hat{W}_t \) to perform their forward or backward passes.

In the following, we illustrate the weight prediction procedure of XPipe using the pipeline training procedure with \( T = 4 \) on the 4-GPU system. As shown in Figure 1(b) on GPU 0, when the second mini-batch (i.e., micro-batches 5, 6, 7 and 8) is ready to perform the forward pass, micro-batch 5 should first use formula (1) to calculate the version difference \( s \), and then apply formula (3) to calculate the future weights for the second mini-batch (i.e., \( \hat{W}_2 \)). After that, micro-batches 6, 7 and 8 directly make use of \( \hat{W}_2 \) to perform their forward passes. To avoid repeatedly doing weight predictions, the \( \hat{W}_2 \) generated by the bellwether (i.e., micro-batch 5) should be temporarily cached and then directly utilized by the following \( (T - 1) \) micro-batches.

Likewise, at the backward pass, a bellwether again takes charge of predicting future weights. As shown in Figure 1(b) when micro-batch 5 is ready to perform the backward pass, it will first use formula (2) to calculate the version difference \( s \), and then apply (3) to predict the future weights \( \hat{W}_2 \). As with the prediction in the forward pass, the generated weights via prediction are first cached, and then reused by the subsequent \( (T - 1) \) micro-batches for their backward passes in order to avoid repetitive weight predictions.

IV. EXPERIMENTAL RESULTS

A. Implementation Details

We implemented XPipe using PyTorch [29] of version 1.2.0. The code of XPipe will be released on Github. In the implementation of XPipe, each GPU was allocated with one process. Each process was in charge of managing the local memory, data transfer between the host and GPUs, gradients calculation, weight update, as well as communicating with other processes. PyTorch provides a package called torch.distributed for process-to-process message passing. In XPipe, each process used the MPI communication backend to realize inter-GPU communication. Non-block communication primitives (e.g., isend and irecv) were used to overlap inter-GPU communication and GPU computation.

B. Model Partition

The premise of pipeline model parallelism is to partition a DNN model into a set of submodels. A few prior works are concentrating on efficient partitioning [15], [16], [30]. Designing an efficient partitioning algorithm is beyond the focus of this paper. In the experiments, we always partition all the DNN layers across GPUs with roughly equal number of layers to balance their training time, while letting the latter GPUs have a slightly greater number of layers to achieve time/memory balance across GPUs.

C. Experiment Setup

We conducted all the experiments on a 4-GPU system, which is equipped with 4 GeForce RTX2080X Nvidia GPUs. The host CPU is an Intel i9-9940X (@3.30 GHz).

Three popular CNN models were chosen as the benchmark networks in our experiments: VGG-16 [31], ResNet-101 [32] and Inception-V3 [33], Two image datasets were used in the experiments. The first dataset is CIFAR-10 [34] which includes 60000 32×32 images in total, 50000 images for training and 10000 images for validation. The second dataset is Tiny ImageNet [35], which is categorized into 200 classes each having 500 training images and 50 validation images. Standard data augmentation schemes, including flipping, padding and random crop, were used in both of these two datasets. To be concrete, the CIFAR-10 images were normalized using mean \([0.4914, 0.4822, 0.4465]\) and std \([0.2023, 0.1994, 0.2010]\). For Tiny ImageNet, each \(64 \times 64 \times 3\) image was first scaled up to \(224 \times 224 \times 3\). Following that, the images were loaded into a range of \([0, 1]\) and then normalized using mean \([0.485, 0.456, 0.406]\) and std \([0.229, 0.224, 0.225]\).
In the experiments, we compared XPipe with following state-of-the-art pipeline model parallelism approaches: PipeDream (with weight stashing) [16], SpecTrain [17] and GPipe [15]. The following three measures were taken to ensure fair comparison. First, as with XPipe, we implemented PipeDream, SpecTrain, and GPipe using the PyTorch framework. Second, before the pipeline training starts, all the evaluated methods adopted the same model partitioning approach to split all the DNN layers across GPUs. Third, each evaluated approach took advantage of the same strategy (i.e., automatically reperformed the forward pass during the backward pass [15]) for better memory utilization. In all the experiments, we let the first GPU read the training data while letting the last GPU read the corresponding ground-truth labels. The seed was fixed with 1 for shuffling the data. For XPipe, we empirically set $\gamma = 0.9$, $\lambda = 0.999$ and $\epsilon = 1e-8$. Meanwhile, the elements of both $v_t$ and $m_t$ were initialized using $1e-4$ times randomly generated numerical values ranging from 0 to 1.

D. Results and Discussions

Comparison of XPipe, PipeDream, and SpecTrain In this section, we compared XPipe with PipeDream and SpecTrain in terms of convergence and model accuracy. Since GPipe without mini-batch partitioning automatically reduces to the naive pipeline approach, we trained GPipe with $T = 1$ to simulate the behavior of the naive approach and saw the learning results of it as the baseline. We also trained XPipe with $T = 1$ to isolate the effects of model partition. We selected VGG-16 and Inception-V3 as the benchmark network and used 4 GPUs to train them on CIFAR-10 for 90 epochs. The learning rate was initialized as 1e-2, and divided by 10 every 30 epochs. We trained the model using the Momentum SGD with the momentum factor $\gamma$ was set to 0.9 and weight decay was 5e-4. The mini-batch size for all the evaluated methods was 128.

Figure 2 depicts the learning curves for training VGG-16; Figure 3 shows the learning curves for training Inception-V3. Table I summarizes the obtained minimal validation loss and maximum validation top-1 accuracy. XPipe converges very fast, and its learning curves converges even slightly better than that of the baseline. Besides, the experimental results show that XPipe can always obtain the least validation loss value and very comparable validation top-1 accuracy as the baseline. On average, XPipe achieves 0.015% top-1 validation accuracy improvement over the baseline. In contrast, PipeDream and SpecTrain incurs an average of 0.265% and 0.51% top-1 accuracy drop respectively. Note that when running on the 4-GPU system, XPipe with $T = 1$ generates the same version differences as SpecTrain to do the weight prediction in both the forward and backward passes, but it converges faster and obtain better model accuracy than SpecTrain. The experiment results verify that the Adam-based weight prediction provides a more effective solution for weight prediction.

Comparison with GPipe In this section, we compared the convergence and model accuracy of XPipe with that of GPipe. We selected Inception-V3 and ResNet-101 as the benchmark network and used 4 GPUs to train them on Tiny ImageNet for 70 epochs. We compared XPipe and GPipe by running them with $T = 1$, $T = 2$ and $T = 4$ respectively. In all the experiments, we always set XPipe and GPipe with the same hyper-parameters to compare their performance. The mini-batch size for both of them was fixed with 100. The learning rate was initialized as 1e-2 and divided by 10 at the 40th and 60th epoch. We trained the models using the Momentum SGD with the momentum factor $\gamma$ was set to 0.9 and weight decay was 5e-4.

Figures 2 and 3 depict learning curves about the validation accuracy (top-1, in %) versus epochs.

![Figure 2](image2.png)

![Figure 3](image3.png)
top-1 accuracy are reported in Table II. For any setting of $T$, XPipe converges very fast and its learning curves on both Inception-V3 and ResNet-101 match well (even converge faster) with that of GPipe. This results again demonstrate the learning-effectiveness of XPipe. Table II shows that XPipe almost always achieves smaller validation loss value and higher validation top-1 accuracy than GPipe. On average, XPipe is able to obtain 0.26% and 0.67% top-1 validation accuracy improvement over GPipe for training Inception-V3 and ResNet-101 respectively.

### TABLE II
**RESULTS ON TINY IMAGENET:**
**TOP: RESULTS FOR INCEPTION-V3;**
**BOTTOM: RESULTS FOR RESNET-101.**

| Partition | Method   | Min. Val. Loss | Max. Val. Top-1 Acc. |
|-----------|----------|----------------|----------------------|
| $T = 1$   | GPipe    | 1.543          | 62.66% (~)          |
|           | XPipe    | 1.546          | 62.62% (-0.04%)     |
| $T = 2$   | GPipe    | 1.549          | 63.24% (~)          |
|           | XPipe    | 1.542          | 63.54% (+0.30%)     |
| $T = 4$   | GPipe    | 1.600          | 63.28% (~)          |
|           | XPipe    | 1.596          | 63.72% (+0.44%)     |

| Partition | Method   | Min. Val. Loss | Max. Val. Top-1 Acc. |
|-----------|----------|----------------|----------------------|
| $T = 1$   | GPipe    | 1.508          | 63.24% (~)          |
|           | XPipe    | 1.438          | 64.04% (+0.80%)     |
| $T = 2$   | GPipe    | 1.495          | 64.60%             |
|           | XPipe    | 1.459          | 65.06% (+0.46%)     |
| $T = 4$   | GPipe    | 1.560          | 64.08% (+0.74%)     |
|           | XPipe    | 1.540          | 64.82% (+0.74%)     |

**Throughput Study**

In this section, we compared the training speed of XPipe with that of PipeDream, SpecTrain and GPipe using 2 and 4 GPUs, respectively. Here training speed is measured through throughput which is defined by the number of training images per second. For PipeDream, SpecTrain and XPipe, the throughput measurement refers to the number of the per-second training images throughout the steady phase. We divided the comparison into two groups. For the first group, we compared the throughput of XPipe with that of PipeDream and SpecTrain. We selected VGG-16 and Inception-V3 as the benchmark network and trained them on the CIFAR-10 dataset for one epoch. The mini-batch size for all evaluated approaches was 128. In the first group, we always trained XPipe with $T = 1$ to isolate the effects of mini-batch partition. For the second group, we compared the throughput of XPipe with that of GPipe by considering different mini-batch partitions (i.e., $T = 1$, $T = 2$ and $T = 4$). We selected Inception-V3 and ResNet-101 as the benchmark network and trained them on the Tiny ImageNet for one epoch. The mini-batch sizes for both GPipe and XPipe on 2-GPU and 4-GPU systems were set to $50 \times T$ and $100 \times T$, respectively.

Figure 6 illustrates the throughput results of the first group; Figures 7 and 8 show the throughput results of the second group. It is worth noting that the experiments were conducted to compare the throughput of XPipe with that of other pipeline approaches under the same hyper-parameter setting. All the evaluated pipeline approaches can consistently obtain higher throughput when better model partition approach or elaborated hyper-parameter tuning (e.g., mini-batch size or $T$) is applied.

We can reach to following conclusions based on the observation of the throughput results. First, the throughput results in Figure 6 show that the throughput of XPipe is slightly...
inferior to that of PipeDream and SpecTrain despite all of them adopt the same pipeline structure. This is because XPipe takes advantage of a more computation-intensive weight prediction strategy to guarantee effective learning. Second, Figures 7 and 8 show that the throughput of GPipe is very sensitive to the choice of $T$ especially when training on the 4-GPU system. This is because the pipeline structure of GPipe varies with the setting of $T$, and different settings of $T$ give rise to different proportions of idle time. Contrastly, the pipeline structure of XPipe is independent of the setting of $T$. XPipe can always make all GPUs concurrently train the DNN model after the steady phase starts. Therefore, XPipe trains very fast and can consistently achieve high throughput, regardless of the setting of $T$. For Inception-V3, XPipe provides an average of 20.0% (up to 31.9%) and 88.1% (up to 150.8%) throughput improvement over GPipe on 2-GPU and 4-GPU systems, respectively. For ResNet-101, XPipe provides an average of 10.8% (up to 21.2%) and 84.6% (up to 142.7%) throughput improvement over GPipe on 2-GPU and 4-GPU systems, respectively.

**Robustness Study** In this section, we study the robustness of XPipe by using another two popular optimization methods for pipeline training: RMSProp [36] and Adam [28]. We again trained GPipe with $T = 1$ to simulate the behavior of the naive model parallel approach and regarded the results of it as the baseline. We selected VGG-16 as the benchmark network and trained it on CIFAR-10 for 50 epochs using 4 GPUs. The learning rate was fixed as 1e-4. The mini-batch size for all approaches was 128. For RMSProp, the value of momentum was set to 0.9; for Adam, the exponential decay rate for the
first and second momentum estimates were set to 0.9 and 0.999, respectively.

Figures 9 and 10 show the experimental results when using RMSProp and Adam as the optimization method, respectively. In both Figures 9 and 10, the left figure depicts the validation loss over epochs and the right figure shows the validation accuracy (top-1, in %) over epochs. The experimental results demonstrate the effectiveness of XPipe. For using either RMSProp or Adam as the optimization method, the learning curves of XPipe converge quickly and match well with that of the baseline. This demonstrates the robustness of Adam-based weight prediction strategy. XPipe can always guarantee learning-effective training, and the results of it are independent of the optimizer method used.

**Fig. 9.** Learning curves when using RMSProp optimizer.

**Fig. 10.** Learning curves when using Adam optimizer.

V. CONCLUSIONS

In this work, we propose an efficient asynchronous pipeline model parallelism method called XPipe. XPipe interweaves the pipeline training of micro-batches belonging to different mini-batches, so as to ensure that each GPU concurrently and continuously trains the DNN model, and thereby provide pretty high throughput. Most importantly, the novel weight prediction scheme makes XPipe effectively address the inconsistency and staleness issues in the asynchronous pipeline training. Overall, XPipe provides pretty high throughput, scales up mini-batch size easily, and achieves very comparable accuracy (even slightly better) as its state-of-the-art synchronous counterpart.

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