Reducing BERT Pre-Training Time from 3 Days to 76 Minutes

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Large-batch training is key to speeding up deep neural network training in large distributed systems. However, large-batch training is difficult because it produces a generalization gap. Straightforward optimization often leads to accuracy loss on the test set. BERT (*4*) is a state-of-the-art deep learning model that builds on top of deep bidirectional transformers for language understanding. Previous large-batch training techniques do not perform well for BERT when we scale the batch size (e.g. beyond 8192). BERT pre-training also takes a long time to finish (around three days on 16 TPUv3 chips). To solve this problem, we propose the LAMB optimizer, which helps us to scale the batch size to 65536 without losing accuracy. LAMB is a general optimizer that works for both small and large batch sizes and does not need hyper-parameter tuning besides the learning rate. The baseline BERT-Large model needs 1 million iterations to finish pre-training, while LAMB with batch size 65536/32768 only needs 8599 iterations. We push the batch size to the memory limit of a TPUv3 pod and can finish BERT training in 76 minutes (Table 1).

Table 1: We use the F1 score of SQuAD-v1 as the accuracy metric. The baseline F1 score is achieved by the pre-trained model (BERT-Large) provided by BERT's public github (as of February 1st, 2019). We use TPUv3s in our experiments. We use the same setting as the baseline: the first 9/10 of the total epochs used a sequence length of 128 and the last 1/10 of the total epochs used a sequence length of 512. All the experiments run the same number of epochs.

Solver	Batch Size	Iterations	F1 score on dev set	Hardware	Time
Baseline	512	1000k	90.395	16 TPUs	81.4h
Our Method	512	1000k	90.720	16 TPUs	82.8h
Our Method	1k	500k	90.377	32 TPUs	43.2h
Our Method	2k	250k	90.751	64 TPUs	21.4h
Our Method	4k	125k	90.548	128 TPUs	693.6m
Our Method	8k	62k	90.556	256 TPUs	390.5m
Our Method	16k	31k	90.679	512 TPUs	200.0m
Our Method	32k	15.6k	91.460	1024 TPUs	101.2m
Our Method	64k/32k	8599	90.584	1024 TPUs	76.19m

1 Introduction

Training deep neural networks is time-consuming. Currently, the most efficient way to reduce wallclock time is to use multiple chips (e.g. CPUs, GPUs, and TPUs) to parallelize the optimization process of SGD variants. Due to the data dependency between different layers in forward propagation and backward propagation, it is not efficient to parallelize across different layers. Instead, researchers parallelize the data points in the mini-batch at each iteration. If we fix the number of training epochs, linearly increasing the batch size means linearly decreasing the number of iterations (i.e. the number of weights updating). To minimize wall clock time, maximizing batch size would be ideal.

However, large-batch training is difficult. For example, by using a batch size of 512, AlexNet (*13*) is able to achieve 80+% top-5 testing accuracy for ImageNet training. A straightforward approach may only get 50% $\sim$ 60% top-5 accuracy or the divergence results when people scale the batch size beyond 4096. Keskar et al. (*10*) suggest there is a generalization gap in large-batch training. Hoffer et al. (*6*) suggest training longer may help to close the generalization gap. However, training longer means there is no benefit to doing large-batch training. Thus, the target of large-batch training is to achieve a comparable accuracy in a fixed number of epochs (*5*). By designing a series of learning rate schedules (*5, 12, 21*), researchers are able to scale the batch size in ImageNet training to 32K with minor accuracy loss. To the best of our knowledge, the fastest training result for 76+% top-1 accuracy is achieved by Ying et al. (*20*). By using the LARS optimizer (*21*) to scale the batch size to 32K, Ying et al. (*20*) are able to finish the ImageNet training with ResNet-50 in 2.2 minutes on a TPUv3 Pod.

BERT (*4*) is a state-of-the-art deep learning language model. It builds on top of deep bidirectional transformers for language understanding. The previous large-batch training techniques do not perform well when we scale the batch size to an extremely large case (e.g. beyond 8192). BERT pre-training takes a long time to finish (around three days on 16 TPUv3 chips). To scale up the batch size of BERT, we propose the LAMB optimizer in this paper. LAMB supports adaptive element-wise updating and accurate layer-wise correction. LAMB is a general optimizer works for both small and large batches. Users only need to tune the learning rate and no other hyper-parameters. By using LAMB, we are able to scale the batch size of BERT pre-training to 64K without losing accuracy. the BERT pre-training includes two stages: (1) the first 9/10 of the total epochs use a sequence length of 128 and (2) the last 1/10 of the total epochs use a sequence length of 512. The baseline needs 1 million iterations to finish the BERT pre-training, while we only need 8599 iterations which allows us to reduce the BERT-training time from 3 days to 76 minutes. We push the batch size to the hardware limit of a TPU Pod. A batch size larger than 32768 (with sequence length 512) runs out of memory. A batch size larger than 65536 (with sequence length 128) does not bring any speedup. Our optimizer may be able to scale the batch size to 128k or even larger. Due to the hardware limit, we stop at 32768 for sequence length 512 and 65536 for sequence length 128. All the BERT models in this paper denote the BERT-Large model. To conduct a fair comparison, all the experiments in this paper run the same number of epochs (i.e. fixed number of floating point operations). Our results are shown in Table 1.

2 Background and Related Work

The training of deep neural networks is based on Stochastic Gradient based methods. Let us use B as a batch of dataset and $|B|$ as batch size. At each step t a mini-batch of $|B|$ samples is selected from training set X. The gradients of loss function $\nabla L(x_i, w)$ are computed with respect to this subset of data, and weights w are updated based on the stochastic gradients (Equation (1)).

$$w_{t+1} = w_t - \eta \frac{1}{|B|} \sum\nolimits_{i \in B} \nabla L(x_i, w) \tag{1}$$

The computation of SGD optimization can be done with data-parallelism—each processor or machine computes its part of mini-batch. Increasing the mini-batch size allows scaling to more machines without reducing the workload on each machine. However, it was observed that training with extremely large batch is difficult (*6, 10*). The researchers need to carefully tune training hyper-parameters (like learning rate, momentum etc) to avoid losing test accuracy (*5, 14, 23*).

Krizhevsky (*12*) introduced some practical schemes for training with large batches. One important rule is to adjust the LR (learning rate) according to the batch size. When the batch $|B|$ is increased by k times, one should increase the LR by $\sqrt{k}$ to keep the variance of the gradient estimation at the same level. In practice he found that the **linear** scaling works better: when we increase $|B|$ by k, we should increase the LR by k while keeping other hyper-parameters (momentum, weight decay, etc) unchanged. Using this scheme Krizhevsky scaled up the batch size of AlexNet to 1024 with a minor (1%) loss in the accuracy comparing to baseline $|B|$=128.

By using either linear or square root LR scaling, large-batch training needs a large learning rate. However, a large initial learning rate usually leads to instability during the initial phase of training. To overcome this problem, Goyal et al. (*5*) proposed to use **learning rate warm-up**: training starts with a smaller LR and then gradually increases the LR to a larger value. After warm-up period (usually a few epochs) one switches to the regular LR policy (multi-steps, exponential or polynomial decay etc). Using LR warm-up and linear scaling Goyal (*5*) managed to train ResNet-50 with batch $|B|$=8K without loss in test accuracy.

Another problem in large batch training is the generalization gap, which is observed by Keskar et al. (*10*) during experiments on CIFAR-10 and CIFAR-100. They came to the conclusion that the generalization gap is due to the fact that large-batch methods tend to converge to the sharp minima of the training function. Large-batch training can easily achieve a high training accuracy but it is hard for the model to achieve a high test accuracy. They tried a few methods to improve generalization using data augmentation, warm-starting with small batch, but did not find a working solution.

There are several groups of researchers (*1–3, 7, 8, 16–19, 22, 23*) successfully scaling the batch size to large values and finishing the ImageNet training in minutes. To the best of our knowledge, the fastest training result for 76+% top-1 accuracy is achieved by Ying et al. (*20*). By using the LARS optimizer (*21*) to scale the batch size to 32K, Ying et al. (*20*) are able to finish ImageNet training with ResNet-50 in 2.2 minutes on a TPUv3 Pod. In this paper, our main task is BERT (*4*). BERT is an important technique that has achieved state-of-the-art results in several NLP tasks such as GLUE, MultiNLI, and SQuAD. This paper is the first report that scales the batch size of BERT training to extremely large (i.e. larger than 2K).

3 LAMB (Layer-wise Adaptive Moments optimizer for Batch training)

The baseline of BERT training uses Adam with weight decay as the optimizer (*15*), which is an variant of Adam optimizer (*11*). Another adaptive optimizer that has been successfully used in large-batch convolutional neural networks training is LARS (*21*). These optimizers inspired us to propose our new optimizer for large-batch BERT training. The overview of our proposed LAMB optimizer is shown in Algorithm 1.

3.1 Correcting the LARS trust ratio

In the LARS implementation[1], the authors define a coefficient $eeta$ to control the trust ratio. The authors use 0.001 as the default coefficient $eeta$. The coefficient $eeta$ is only used for the layer with a non-zero $|g|$ (L2 norm of the layer gradients) and a non-zero $|w|$ (L2 norm of the layer weights). For the layer with a zero $|w|$ or a zero $|g|$, LARS uses a trust ratio of 1.0. However, in some situations, this scheme may lead to a serious issue or divergence. For example, we assume that we use the default coefficient $eeta$ (0.001). The layer with a zero $|w|$ and a non-zero $|g|$ may get an extremely large trust ratio (e.g. 1000 times larger), which may lead to network divergence. We remove the coefficient $eeta$ in trust ratio computation. For the layer with a non-zero $|w|$ and a non-zero $|g|$, we use the regular LARS ratio without multiplying coefficient $eeta$. For the layer with a zero $|w|$ or a zero $|g|$, we use a trust ratio of 1.0. This correction avoids divergence in large-batch BERT training.

3.2 Fixing weight decay in trust ratio

In the LARS implementation, the authors used the weight decay in computing the trust ratio for accurate learning rate justification. Specifically, they use the rule in Equation (2). The LARS

[1] https://github.com/tensorflow/tensorflow/blob/r1.13/tensorflow/contrib/opt/python/training/lars_optimizer.py

trust ratio works well in the optimizers like momentum and SGD because they have a uniform learning rate for all weights.

$$lars\_trust\_ratio = \frac{|w|}{|g| + weight\_decay \times |w|} \tag{2}$$

However, for the adaptive optimizers like AdamW and Adam, the LARS ratio leads to inaccurate learning rate justification because these adaptive optimizers use element-wise updating scheme. Thus, we use a new way of computing trust ratio to make sure the weight decay term works in an element-wise way. The trust ratio of LAMB is defined in Equation (3), which computes the denominator in the element-wise way rather than the layer-wise way.

$$lamb\_trust\_ratio = \frac{|w|}{|g + weight\_decay \times w|} \tag{3}$$

3.3 Using more accurate information in gradient norm

In the LARS optimizer, the authors use the gradient norm and the weight decay as the denominator of the trust ratio. Specifically, they use $|g| = \|\nabla L(x_i, w)\|_2$. In practice, however, we find this information is not accurate in BERT training. LARS works well in ImageNet training (e.g. by ResNet-50 or AlexNet). Those models have far fewer parameters than BERT (61 million versus 300 million). For BERT training, the authors use the Adam with weight decay, which is an element-wise updating optimizer. We keep the feature of element-wise updates in the LAMB optimizer. The element-wise information comes from estimates of first and second moments of the gradients. Thus, we use the estimates of first and second moments of the gradients to conduct the layer-wise learning rate justification. Here, we use $g = \|\frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} + \lambda w_{t-1}\|_2$. The notations are defined in Algorithm 1. For an easier understanding, we use the same notation with the traditional Adam algorithm description. We use the trust ratio to update the global learning rate (detailed in Algorithm 1). Different layers will have different trust ratios. Our trust ratio is more accurate than that of LARS optimizer. In this way, we not only have the element-wise adaptive learning rate, but also have the scheme of layer-wise correction. We successfully scaled the batch size to 32K by LAMB optimizer for BERT training. In our experiments, LARS optimizer is able to scale the batch size of BERT to 8K.

3.3.1 Upper bound of trust ratio (a variant of LAMB)

Even when we use the element-wise updating based on the estimates of first and second moments of the gradients, we can still use $|g| = \|\nabla L(x_i, w)\|_2$ in the trust ratio computation. However, due to the inaccurate information, we observe that some of the LARS trust ratios are extremely large. Since the original LARS optimizer used momentum SGD as the base optimizer, the large trust ratio does not have a significant negative impact because all the elements in a certain layer use the same learning rate. However, for the adaptive optimizers like Adam and Adagrad, different elements will have different element-wise learning rates. In this situation, a large trust ratio may lead to the divergence of a weight with a large learning rate. One practical fix is to set an upper bound of the trust ratio (e.g. setting the bound as 10). By this way, we can still successfully scale the batch size of BERT training to 16K and will not add any computational and memory overhead to the LAMB optimizer.

Algorithm 1 The LAMB optimizer

Data: the number of iterations T; the number of layers L; the learning rate η; (the users only need to input η, default setting: weight decay rate λ=0.01, β_1=0.9, β_2=0.999, ϵ=1e-6)

Result: the trained model w

initialization

$t = 0$

while $t < T$ **do**

    ****** within each iteration ******

    Get a batch of data x_t

    $l = 0$

    while $l < L$ **do**

        ****** within each layer ******

        $g_t^l = \nabla L(w_{t-1}^l, x_t)$

        $m_t^l = \beta_1 m_{t-1}^l + (1 - \beta_1) g_t^l$

        $v_t^l = \beta_2 v_{t-1}^l + (1 - \beta_2) g_t^l \odot g_t^l$

        $\hat{m}_t^l = m_t^l / (1 - \beta_1^t)$

        $\hat{v}_t^l = v_t^l / (1 - \beta_2^t)$

        $r_1 = \|w_{t-1}^l\|_2$

        $r_2 = \|\frac{\hat{m}_t^l}{\sqrt{\hat{v}_t^l + \epsilon}} + \lambda w_{t-1}^l\|_2$

        $r = r_1 / r_2$

        $\eta^l = r \times \eta$

        $w_t^l = w_{t-1}^l - \eta^l \times (\frac{\hat{m}_t^l}{\sqrt{\hat{v}_t^l + \epsilon}} + \lambda w_{t-1}^l)$

    end

end

4 Experimental Results

4.1 Regular Training

The Tensor Processing Units (*9*) are powerful computational hardware for floating-point operations. We use TPUv3 in all the experiments. A TPUv3 Pod has 1024 chips and can provide more than 100 petaflops performance for mixed precision computing. Our results are shown in Table 1. The baseline uses the Wikipedia and BooksCorpus datasets (*24*) in the pretraining. We use the same dataset as the published BERT model, which is the concatenation of Wikipedia and BooksCorpus with 2.5B and 800M words respectively. The authors first conduct 900k iterations training for sequence length 128 and then conduct 100k iterations training for sequence length 512. The total training time is around three days on 16 TPUv3 chips. We use the F1 score of SQuAD-v1 as the accuracy metric. A higher F1 score means a better accuracy. Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset. It contains questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or span, from the corresponding reading passage, or the question might be unanswerable[2]. We downloaded the pre-trained model provided from the public BERT github[3]. By using the script provided by the authors, the baseline achieves a F1 score of 90.395. In our code, we use the dataset and baseline model provided by the authors of BERT and only changed the optimizer. By using the LAMB optimizer, we are able to achieve a F1 score of 91.460 in 15625 iterations for a batch size of 32768 (14063 iterations for sequence length 128 and 1562 iterations for sequence length 512). We reduce the BERT-training time from 3 days to around 100 minutes. We push the batch size to the hardware limit of a TPU Pod. A batch size larger than 32768 (with sequence length 512) would lead the TPU Pod to run out of memory.

We achieved 76.7% weak scaling efficiency (49.1 times speedup by 64 times computational resources). Because we use the synchronous data-parallelism for distributed training on the TPU Pod, there is communication overhead coming from transferring of the gradients over the interconnect. The gradients have the same size of the trained models. For ImageNet training with ResNet-50, researchers are able to achieve 90+% weak scaling efficiency because ResNet-50 has much fewer parameters than BERT (25 million versus 300 million). The LAMB optimizer does not expect the users to tune the hyper-parameters. Like Adam and AdamW, the users only need to input the learning rate. β_1 is used for decaying the running average of the gradient. β_2 is used for decaying the running average of the square of gradient. The default setting for other parameters in Algorithm 1: weight decay rate λ=0.01, β_1=0.9, β_2=0.999, ϵ=1e-6.

[2] https://rajpurkar.github.io/SQuAD-explorer/
[3] https://github.com/google-research/bert

4.2 Mixed-Batch Training

As mentioned previously, the BERT pre-training includes two stages: (1) the first 9/10 of the total epochs use a sequence length of 128 and (2) the last 1/10 of the total epochs use a sequence length of 512. For the second stage, due to memory limits, the maximum batch size on a TPUv3 Pod is 32768, so we stop at 32768 for stage 2. For the first stage, due to memory limits, the maximum batch size on a TPUv3 Pod is 131072. However, when we increased the batch size from 65536 to 131072, we did not observe a speedup, so we stopped at 65536 for stage 1. Previously, Smith et al. (*19*) also studied a mixed-batch training. However, they increase the batch size during training while we decrease the batch size. We are able to make full of the hardware resource from the starting point to the end. They only make full use of the hardware resource at the final stage. Increasing the batch size is able to warm-up and stabilize the optimization process, but decreasing the batch size brings chaos to the optimization process and can cause divergence. In our experiments, we found a technique that is useful to stabilize the second stage optimization. Because we switched to a different optimization problem, it is necessary to re-warm-up the optimization. Instead of decaying the learning rate at the second stage, we ramp up the learning rate from zero again in the second stage (re-warm-up). As with the first stage, we decay the learning rate after the re-warm-up phrase. With these changes, we only need 8599 iterations and can finish BERT training in around 76 minutes and achieve 101.8% weak scaling efficiency (65.2 times speedup by 64 times computational resources)

5 Conclusion and Future Work

Large batch techniques are key to speeding up deep neural network training. In this paper, we propose the LAMB optimizer, which supports adaptive element-wise updating and layer-wise correction. LAMB is a general optimizer works for both small and large batches. By using

LAMB, we are able to scale the batch size of BERT pre-training to 64K without losing accuracy. We reduce the BERT-training time from 3 days to around 76 minutes and push the batch size to the hardware limit of a TPU Pod. We are working on the theoretical analysis of the LAMB optimizer.

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