100-epoch ImageNet Training with AlexNet in 24 Minutes

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Abstract

Since its creation, the ImageNet 1-k benchmark set has played a significant role as a benchmark for ascertaining the accuracy of different deep neural net (DNN) models on the classification problem. Moreover, in recent years it has also served as the principal benchmark for assessing different approaches to DNN training. Finishing a 90-epoch ImageNet-1k training with ResNet-50 on a NVIDIA M40 GPU takes 14 days. This training requires $10^{18}$ single precision operations in total. On the other hand, the world’s current fastest supercomputer can finish $2 \times 10^{17}$ single precision operations per second. If we can make full use of the computing capability of a supercomputer for DNN training, we should be able to finish the 90-epoch ResNet-50 training in five seconds. Over the last two years a number of researchers have focused on how to close this significant performance gap through scaling DNN training to larger numbers of processors. Most successful approaches to scaling the training of ImageNet have used the approach of synchronous stochastic gradient descent. However, to scale synchronous stochastic gradient descent one must also increase the batch size used in each iteration. Thus, for many researchers, the focus on scaling DNN training has translated into a focus on developing approaches that enable increasing the batch size in data-parallel synchronous stochastic gradient descent without losing accuracy over a fixed number of epochs. As a result, we have seen the batch size and number of processors successfully utilized increase from 1K batch/128 processors to 8K batch/256 processors over the last two years. The recently published LARS algorithm increased batch size further to 32K for some DNN models. Following up on this work, we wished to confirm that LARS could be used to further scale the number of processors efficiently used in DNN training and, as a result, further reduce the total training time. In this paper we present the results of this investigation: using LARS we were able to efficiently utilize 512 KNL chips to finish the 90-epoch ImageNet training with AlexNet in 24 minutes, and we also matched Facebook’s prior result by finishing the 90-epoch ImageNet training with ResNet-50 in one hour. Furthermore, when we increase the batch size to above 20K, our accuracy is much higher than Facebook’s on corresponding batch sizes. (Figure 1).

Introduction

For deep learning applications, larger datasets and bigger models lead to significant improvements in accuracy (Amodei et al. 2015), but at the cost of longer training times. Moreover, many applications such as computational finance, autonomous driving, oil and gas exploration, and medical imaging, will almost certainly require training data-sets with billions of training elements and terabytes of data. This highly motivates the problem of accelerating the training time of Deep Neural Nets (DNN). For example, finishing 90-epoch ImageNet-1k training with ResNet-50 on a NVIDIA M40 GPU takes 14 days. This training requires $10^{18}$ single precision operations in total. On the other hand, the world’s current fastest supercomputer can finish $2 \times 10^{17}$ single precision operations per second (Dongarra et al. 2017). Thus, if we can make full use of the computing capability of a supercomputer for DNN training, we should be able to finish the 90-epoch ResNet-50 training in five seconds. So far, the best results on scaling ImageNet training have used synchronous stochastic gradient descent (synchronous SGD). The synchronous SGD algorithm has many inherent advantages, but at the root of these advantages is sequential consistency. Sequential consistency implies that all valid parallel implementations of the algorithm match the behavior of the sequential version. This property is invaluable during DNN design and during the debugging of optimization algorithms. Continuing to scale the synchronous SGD model to more
processors requires ensuring that there is sufficient useful work for each processor to do during each iteration. This, in turn, requires increasing the batch size used in each iteration. For example engaging 512 processors in synchronous SGD on a batch size of 1K would mean that each processor only processed a local batch of 2 images. If the batch size can be scaled up, the communication ratio can be more balanced.

As a result, over the last two years we have seen a focus on increasing the batch size and number of processors used in the DNN training for ImageNet-1K, with a resulting reduction in training time. In the following discussion we briefly review relevant work where all details of batch size, processors, DNN model, runtime, and training set are defined in the publications. All of the following refer to training on ImageNet.

FireCaffe (Iandola et al. 2015) demonstrated scaling the training of GoogleNet to 128 Nvidia K20 GPUs with a batch size of 1K for 72 epochs and a total training time of 10.5 hours. Although large batch size can lead to a significant loss in accuracy, using a warm-up scheme coupled with a linear scaling rule, researchers at Facebook (Goyal et al. 2017) were able to scale the training of ResNet 50 to 256 Nvidia P100’s with a batch size of 8K and a total training time of one hour. Using a more sophisticated approach to adapting the learning rate in a method they named the Layer-wise Adaptive Rate Scaling (LARS) algorithm (You, Gitman, and Ginsburg 2017), researchers were able to scale the batch size to very large sizes, such as 32K, although only 8 Nvidia P100 GPUs were employed. A 3.4% reduction in accuracy was attributed to the absence of data augmentation.

Given the large batch sizes that the LARS algorithm enables, it was natural to ask: how much further can we scale the training of DNNs on ImageNet? This is the investigation that led to this paper. In particular, we found that using LARS we could scale DNN training on ImageNet to 512 KNL nodes and finish the 100-epoch training with AlexNet in 24 minutes. Further, we were able to use the same 512 KNL nodes to match Facebook’s earlier result (Goyal et al. 2017), and we finish the 90-epoch ImageNet training with ResNet50 in one hour.

**Notes.** This paper is focused on training large-scale deep neural networks on $P$ machines/processors. We use $w$ to denote the parameters (weights of the networks), $w^j$ to denote the local parameters on $j$-th worker, $\bar{w}$ to denote the global parameter. When there is no confusion we use $\nabla w^j$ to denote the stochastic gradient evaluated at the $j$-th worker. All the accuracy means top-1 test accuracy. There is no data augmentation in all the results.

**Background and Related Work**

**Data-Parallelism SGD**

In data parallelism method, the dataset is partitioned into $P$ parts stored on each machine, and each machine will have a local copy of the neural network and the weights ($w^j$). In synchronized data parallelism, the communication includes two parts: sum of local gradients and broadcast of the global weight. For the first part, each worker computes the local gradient $\nabla w^j$ independently, and sends the update to the master node. The master then updates $\bar{w} \leftarrow \bar{w} - \eta / P \sum_{j=1}^P \nabla w^j$ after it gets all the gradients from workers. For the second part, the master broadcasts $\bar{w}$ to all workers. This synchronized approach is a widely-used method on large-scale systems (Iandola et al. 2016). Figure 2-(a) is an example of 4 worker machines and 1 master machine.

Scaling synchronous SGD to more processors has two challenges. The first is giving each processor enough useful work to do; this has already been discussed. The second challenge is the inherent problem that after processing each local batch all processors must synchronize their gradient updates via a barrier before proceeding. This problem can be partially ameliorated by overlapping communication and computation (Das et al. 2016) (Goyal et al. 2017), but the inherent synchronization barrier remains. A more radical approach to breaking this synchronization barrier is to pursue a purely asynchronous approach. A variety of asynchronous approaches have been proposed (Recht et al. 2011) (Zhang, Choromanska, and LeCun 2015a) (Jin et al. 2016) (Miliagkas et al. 2016). The communication and updating rules differ in the asynchronous approach and the synchronous approach. The simplest version of the asynchronous approach is a master-worker scheme. At each step, the master only communicates with one worker. The master gets the gradients $\nabla w^j$ from the $j$-th worker, updates the global weights, and sends the global weight back to the $j$-th worker. The order of workers is based on first-come-first-serve strategy. The master machine is also called as parameter server. The idea of a parameter server was used in real-world commercial applications by the Downpour SGD approach (Dean et al. 2012), which has successfully scaled to 16,000 cores. However, Downpour’s performance on 1,600 cores for a globally connected network is not significantly better than a single GPU (Seide et al. 2014b).

**Model Parallelism** Data parallelism replicates the neural network itself on each machine while model parallelism partitions the neural network into $P$ pieces. Partitioning the neural network means parallelizing the matrix operations on the partitioned network. Thus, model parallelism can get the same solution as the single-machine case. Figure 2-(b) shows an example of using 4 machines to parallelize a 5-layer DNN. Model parallelism has been studied in (Catanzaro 2013; Le 2013). However, since the input size (e.g. size of an image) is relatively small, the matrix operations are not large. For example, parallelizing a $2048 \times 1024 \times 1024$ matrix multiplication only needs one or two machines. Thus, state-of-the-art methods often use data-parallelism (Amodei et al. 2015; Chen et al. 2016; Dean et al. 2012; Seide et al. 2014a).

**Intel Knights Landing System**

Intel Knights Landing (KNL) is the latest version of Intel’s general-purpose accelerator. The major distinct features of KNL that can benefit deep learning applications include the following: (1) Self-hosted Platform. The traditional ac-
Figure 2: (a) is an example of data parallelism. Each worker sends its gradients $\nabla w_j$ to the master, and the master updates its weights by $\tilde{\omega} \leftarrow \tilde{\omega} - \eta / P \sum_{i=1}^{P} \nabla w_j$. Then the master sends the updated weights $\tilde{\omega}$ to all the workers. (b) is an example of model parallelism. A five layer neural network with local connectivity is shown here, partitioned across four machines (blue rectangles). Only those nodes with edges that cross partition boundaries (thick lines) will need to have their state communicated between machines (e.g. by MPI (Gropp et al. 1996)). Even in cases where a node has multiple edges crossing a partition boundary, its state is only sent to the machine on the other side of that boundary once.

Figure 3: In a certain range, large batch improves the performance of system (e.g. GPU). The data in this figure is collected from training AlexNet by ImageNet dataset on NVIDIA M40 GPUs. Batch=512 per GPU gives us the highest speed. Batch=1024 per GPU is out of memory.

Large-Batch DNN Training

Benefits of Large-Batch Training

The asynchronous methods using parameter server are not guaranteed to be stable on large-scale systems (Chen et al. 2016). As discussed in (Goyal et al. 2017), data-parallelism synchronized approach is more stable for very large DNN training. The idea is simple—by using a large batch size for SGD, the work for each iteration can be easily distributed to multiple processors. Consider the following ideal case. ResNet-50 requires 7.72 billion single-precision operations to process one 225x225 image. If we run 90 epochs for ImageNet dataset, the number of operations is $90 \times 1.28 \text{ Million} \times 7.72 \text{ Billion} (10^{18})$. Currently, the most powerful supercomputer can finish $200 \times 10^{15}$ single-precision operations per second (Dongarra et al. 2017). If there is an algorithm allowing us to make full use of the supercomputer, we can finish the ResNet-50 training in 5 seconds.

To do so, we need to make the algorithm use more processors and load more data at each iteration, which corresponds to increasing the batch size in synchronous SGD. Let us use one NVIDIA M40 GPU to illustrate the case of a single machine. In a certain range, larger batch size will make the single GPU’s speed higher (Figure 3). The reason is that low-level matrix computation libraries will be more efficient. For ImageNet training with Alexthe Net model the, optimal batch size per GPU is 512. If we want to use many GPUs and make each GPU efficient, we need a larger batch size. For example, if we have 16 GPUs, then we should set the batch size to $16 \times 512 = 8192$. Ideally, if we fix total number of data accesses and grow the batch size linearly...
Table 1: Train neural networks by ImageNet dataset. \( t_{\text{comp}} \) is the computation time and \( t_{\text{comm}} \) is communication time. We fix the number of epochs as 100. Larger batch size needs much less iterations. Let us set batch size=512 per machine. Then we increase the number of machines. Since \( t_{\text{comp}} \gg t_{\text{comm}} \), the single iteration time can be close to constant. Thus total time will be much less.

| Batch Size | Epochs | Iterations | GPUs | Iteration Time | Total Time |
|------------|--------|------------|------|----------------|------------|
| 512        | 100    | 250,000    | 1    | \( t_{\text{comp}} \) | 250,000 \times t_{\text{comp}} |
| 1024       | 100    | 125,000    | 2    | \( t_{\text{comp}} + \log(2)t_{\text{comm}} \) | 125,000 \times (t_{\text{comp}} + \log(2)t_{\text{comm}}) |
| 2048       | 100    | 62,500     | 4    | \( t_{\text{comp}} + \log(4)t_{\text{comm}} \) | 62,500 \times (t_{\text{comp}} + \log(4)t_{\text{comm}}) |
| 4096       | 100    | 31,250     | 8    | \( t_{\text{comp}} + \log(8)t_{\text{comm}} \) | 31,250 \times (t_{\text{comp}} + \log(8)t_{\text{comm}}) |
| 8192       | 100    | 15,625     | 16   | \( t_{\text{comp}} + \log(16)t_{\text{comm}} \) | 15,625 \times (t_{\text{comp}} + \log(16)t_{\text{comm}}) |
| ...        | ...    | ...        | ...  | ...            | ...        |
| 1,280,000  | 100    | 100        | 2500 | \( t_{\text{comp}} + \log(2500)t_{\text{comm}} \) | 100 \times (t_{\text{comp}} + \log(2500)t_{\text{comm}}) |

Table 2: Standard Benchmarks for ImageNet training.

| Model     | Epochs | Test Top-1 Accuracy |
|-----------|--------|---------------------|
| AlexNet   | 100    | 58% (Iandola et al. 2016) |
| ResNet-50 | 90     | 75.3% (He et al. 2016) |

with number of processors, the number of SGD iterations will decrease linearly and the time cost of each iteration remains constant, so the total time will also reduce linearly with number of processors (Table 1).

Model Selection
To scale up the algorithm to many machines, a major overhead is the communication among different machines (Zhang, Choromanska, and LeCun 2015b). Here we define scaling ratio, which means the ratio between computation and communication. For DNN models, the computation is proportional to the number of floating point operations required for processing an image. Since we focus on synchronous SGD approach, the communication is proportional to model size (or the number of parameters). Different DNN models have different scaling ratios. To generalize our study, we pick two representative models: AlexNet and ResNet50. The reason is that they have different scaling ratios. From Table 5, we observe that ResNet50’s scaling ratio is 12.5 \times larger than that of AlexNet. This means scaling ResNet50 is easier than scaling AlexNet. Generally, ResNet50 will have a much higher weak scaling efficiency than AlexNet.

In the fixed-epoch situation, large batch does not change the number of floating point operations (computation volume). However, large batch can reduce the communication volume. The reason is that the single-iteration communication volume is only related to the model size and network system. Larger batch size means less number of iterations and less overall communication. Thus, large batch size can improve the algorithm’s scalability.

Difficulty of Large-Batch Training
However, synchronous SGD with larger batch size usually achieves lower accuracy than when used with smaller batch sizes, if each is run for the same number of epochs, and currently there is no algorithm allowing us to effectively use very large batch sizes. (Keskar et al. 2016). Table 2 shows the target accuracy by standard benchmarks. For example, when we set the batch size of AlexNet larger than 1024 or the batch size of ResNet-50 larger than 8192, the test accuracy will be significantly decreased (Table 4 and Figure 4).

For large-batch training, we need to ensure that the larger batches achieve similar test accuracy with the smaller batches by running the same number of epochs. Here we fix the number of epochs because: Statistically, one epoch means the algorithm touches the entire dataset once; and computationally, fixing the number of epochs means fixing the number of floating point operations. State-of-the-art approaches for large batch training include two techniques:

1. **Linear Scaling** (Krizhevsky 2014): If we increase the batch size from \( B \) to \( kB \), we should also increase the learning rate from \( \eta \) to \( k\eta \).

2. **Warmup Scheme** (Goyal et al. 2017): If we use a large learning rate (\( \eta \)). We should start from a small \( \eta \) and increase it to the large \( \eta \) in the first few epochs.

The intuition of linear scaling is related to the number of iterations. Let us use \( B \), \( \eta \), and \( I \) to denote the batch size, the learning rate, and the number of iterations. If we increase the the batch size from \( B \) to \( kB \), then the number of iterations is reduced from \( I \) to \( I/k \). This means that the frequency of weight updating reduced by \( k \) times. Thus, we make the updating of each iteration \( k \times \) more efficient by enlarging the learning rate by \( k \) times. The purpose of a warmup scheme is to avoid the situation in which the algorithm diverges at the beginning because we have to use a very large learning rate based on linear scaling. With these techniques, researchers can use the relatively large batch in a certain range (Table 3). However, we observe that state-of-the-art approaches can only scale batch size to 1024 for AlexNet and 8192 for ResNet-50. If we increase the batch size to 4096 for AlexNet, we only achieve 53.1% in 100 epochs (Table 4). Our target is to achieve 58% accuracy even when using large batch sizes.
Table 3: State-of-the-art large-batch training and test accuracy.

| Team                     | Model | Baseline Batch | Large Batch | Baseline Accuracy | Large Batch Accuracy |
|--------------------------|-------|----------------|-------------|-------------------|----------------------|
| Google (Krizhevsky 2014) | AlexNet | 128           | 1024        | 57.7%             | 56.7%                |
| Amazon (Li 2017)         | ResNet-152  | 256           | 5120        | 77.8%             | 77.8%                |
| Facebook (Goyal et al. 2017) | ResNet-50  | 256           | 8192        | 76.40%            | 76.26%               |

Figure 4: The base learning rate of Batch 256 is 0.2 with poly policy (power=2). For the version without LARS, we use the state-of-the-art approach (Goyal et al. 2017): 5-epoch warmup and linear scaling for LR. For the version with LARS, we also use 5-epoch warmup. Clearly, the existing method does not work for Batch Size larger than 8K. LARS algorithm can help the large-batch to achieve the same accuracy with baseline in the same number of epochs.

Scaling up Batch Size

In this paper, we use LARS algorithm (You, Gitman, and Ginsburg 2017) together with warmup scheme (Goyal et al. 2017) to scale up the batch size. Using these two approaches, synchronous SGD with a large batch size can achieve the same accuracy as the baseline (Table 6). To scale to larger batch sizes (e.g. 32k) for AlexNet, we need to change the local response normalization (LRN) to batch normalization (BN). We add BN after each Convolutional layer. Specifically, we use the refined AlexNet model by B. Ginsburg\(^1\). From Figure 4, we can clearly observe the effects of LARS. LARS can help ResNet-50 to preserve the high test accuracy. The current approaches (linear scaling and warmup) has much lower accuracy for batch size = 16k and 32k (68% and 56%). The target accuracy is about 73%.

Experimental Results

Experimental Settings.

The dataset we used in this paper is ImageNet-1k (Deng et al. 2009). The dataset has 1.28 million images for training and 50,000 images for testing. Without data augmentation, the top-1 testing accuracy of our ResNet-50 baseline is 73% in 90 epochs. For versions without data augmentation, we achieve state-of-the-art accuracy (73% in 90 epochs). With data augmentation, our accuracy is 75.4%. In the original paper, the accuracy of ResNet-50 is 75.3% after 90 epochs (He et al. 2016). We use the same network as the original ResNet-50 paper. For the KNL implementation, we have two versions:

1. We wrote our KNL code based on Caffe (Jia et al. 2014) for single-machine processing and use MPI (Gropp et al. 1996) for the communication among different machines on KNL cluster.

2. We use Intel Caffe, which supports multi-node training by Intel MLSL (Machine Learning Scaling Library).

We use the TACC Stampede 2 supercomputer as our hardware platform\(^2\). All GPU-related data are measured based on B. Ginsburg’s nvcaffe\(^3\). The LARS algorithm is opened source by NVIDIA Caffe 0.16. We implemented the LARS algorithm based on NVIDIA Caffe 0.16.

\(^1\)https://github.com/borisgin/nvcaffe-0.16/tree/caffe-0.16/models/alexnet_bn
\(^2\)portal.tacc.utexas.edu/user-guides/stampede2
\(^3\)https://github.com/borisgin/nvcaffe-0.16
Table 4: Current approaches (linear scaling + warmup) do not work for AlexNet with batch size larger than 1024. We tune the warmup epochs from 0 to 10 and pick the one with highest accuracy. According to linear scaling, the optimal learning rate (LR) of batch size 4096 should be 0.16. We use poly learning rate policy, and the poly power is 2. The momentum is 0.9 and the weight decay is 0.0005.

| Batch Size | Base LR | warmup | epochs | test accuracy |
|------------|---------|--------|--------|---------------|
| 512        | 0.02    | N/A    | 100    | 0.583         |
| 1024       | 0.02    | no     | 100    | 0.582         |
| 4096       | 0.01    | yes    | 100    | 0.509         |
| 4096       | 0.02    | yes    | 100    | 0.527         |
| 4096       | 0.03    | yes    | 100    | 0.520         |
| 4096       | 0.04    | yes    | 100    | 0.530         |
| 4096       | 0.05    | yes    | 100    | 0.531         |
| 4096       | 0.06    | yes    | 100    | 0.516         |
| 4096       | 0.07    | yes    | 100    | 0.001         |
| ...        | ...     | ...    | ...    | ...           |
| 4096       | 0.16    | yes    | 100    | 0.001         |

Table 5: Scaling Ratio for AlexNet and ResNet50.

| Model       | communication | computation | comp/comm scaling ratio |
|-------------|---------------|-------------|--------------------------|
| AlexNet     | # 61 million  | # 1.5 billion | 24.6                     |
| ResNet50    | # 25 million  | # 7.7 billion | 308                      |

Fastest ImageNet training with AlexNet

Previously, NVIDIA reported that using one DGX-1 station they were able to finish 90-epoch ImageNet training with AlexNet in 2 hours. However, they used half-precision or FP16, whose cost is half of the standard single-precision operation. We run 100-epoch ImageNet training with AlexNet with standard single-precision. It takes 6 hours 9 minutes for batch size = 512 on one NVIDIA DGX-1 station. Because of LARS algorithm (You, Gitman, and Ginsburg 2017), we are able to have the similar accuracy using large batch sizes (Table 6). If we increase the batch size to 4096, it only needs 2 hour 10 minutes on one NVIDIA DGX-1 station. Thus, using large batch can significantly speedup DNN training.

Table 6: ImageNet Dataset with AlexNet Model. We use ploy learning rate policy, and the poly power is 2. The momentum is 0.9 and the weight decay is 0.0005. For batch size=32K, we changed local response norm in AlexNet to batch norm. Specifically, we use the refined AlexNet model by B. Ginsburg.

| Batch Size | LR rule | warmup | Epochs | test accuracy |
|------------|---------|--------|--------|---------------|
| 512        | regular | N/A    | 100    | 0.583         |
| 4096       | LARS    | 13 epochs | 100    | 0.584         |
| 8192       | LARS    | 8 epochs | 100    | 0.583         |
| 32768      | LARS    | 5 epochs | 100    | 0.585         |

For the AlexNet with batch size = 32K, we scale the algorithm to 512 KNL chips (about 32K processors or cores). The batch size per KNL is 64, so the overall batch size is 32678. We finish the 100-epoch training in 24 minutes. To the best of our knowledge, this is the fastest 100-epoch ImageNet training with AlexNet. The overall comparison is in Table 7.

ImageNet-1k training with ResNet-50

Facebook (Goyal et al. 2017) finishes the 90-epoch ImageNet training with ResNet-50 in one hour on 32 CPUs and 256 NVIDIA P100 GPUs (similar to 32 DGX-1 stations). After scaling the batch size to 32K, we are able to more KNLs. We use 512 KNL chips and the batch size per KNL is 64. We also finish the 90-epoch training in one hour. The version of our KNL chip is Intel Xeon Phi Processor 7250. Note that we are not affiliated to Intel or NVIDIA, and we do not have any a priori preference for GPUs or KNL. The overall comparison is in Table 8.

Codreanu et al. reported their experience on using Intel KNL clusters to speed up ImageNet training by a blog-post\(^4\). They reported that they achieved 73.78% accuracy (with data augmentation) in less than 40 minutes on 512 KNLs. Their batch size is 8k. However, Codreanu et al. only finished 37 epochs. If they conduct 90-epoch training, the time is 80 minutes with 75.25% accuracy. In terms of absolute speed (images per second), Facebook is faster than Codreanu. Since both Facebook and Codreanu used data augmentation, Facebook’s 90-epoch accuracy is higher than that of Codreanu.

\(^4\)https://blog.surf.nl/en/imagenet-1k-training-on-intel-xeon-phi-in-less-than-40-minutes/
Table 7: For batch size=32K, we changed local response norm in AlexNet to batch norm.

| Batch Size | epochs | Peak Top-1 Accuracy | hardware | time  |
|------------|--------|----------------------|----------|-------|
| 256        | 100    | 58.7%                | 8-core CPU + K20 GPU | 144h   |
| 512        | 100    | 58.8%                | DGX-1 station       | 6h 10m |
| 4096       | 100    | 58.4%                | DGX-1 station       | 2h 19m |
| 32K        | 100    | 58.5%                | 512 KNLs            | 24m    |

Table 8: ResNet50 Results. We use the same data augmentation with the original ResNet-50 model (He et al. 2016).

| Batch Size | Data Augmentation | epochs | Peak Top-1 Accuracy | hardware | time  |
|------------|-------------------|--------|----------------------|----------|-------|
| 256        | NO                | 90     | 73.0%                | DGX-1 station       | 21h    |
| 256        | YES               | 90     | 75.4%                | 16 KNLs                 | 45h    |
| 8192       | NO                | 90     | 72.7%                | DGX-1 station       | 21h    |
| 8192       | NO                | 90     | 72.7%                | 32 CPUs + 256 P100 GPUs | 1h     |
| 32K        | NO                | 90     | 72.6%                | 512 KNLs            | 1h     |
| 32K        | YES               | 90     | 74.7%                | 512 KNLs            | 1h     |

of Codreanu.

**ResNet-50 with Data Augmentation**

Based on the original ResNet50 model (He et al. 2016), we added data augmentation to our baseline. The top-1 val accuracy of original ResNet50 is 75.3% in 90 epochs. Our baseline achieves 75.4% top-1 val accuracy in 90 epochs. Because we do not have Facebook’s model file, we failed to reproduce full match their results of 76.24% top-1 accuracy. The model we used is available upon request. Codreanu et al. reported they achieved 75.81% top-1 accuracy in 90 epochs; however, they changed the model parameters (not only hyper-parameters). The overall comparison is in Table 9. We observe that our scaling efficiency is much higher than Facebook’s version. Even though our baseline’s accuracy is lower than Facebook’s, we achieve a correspondingly higher accuracy when we increase the batch size above 10K. The accuracy-epoch curve of our version is shown in Figure 5.

**NVIDIA P100 GPU and Intel KNL**

Because state-of-the-art models like ResNet50 are computational intensive, our comparison is focused on the computational power rather than memory efficiency. Since deep learning applications mainly use single-precision operations, we do not consider double-precision here. The peak performance of P100 GPU is 10.6 Tflops\(^5\). The peak performance of Intel KNL is 6 Tflops\(^6\). Based on our experience, the power of one P100 GPU is roughly equal to two KNLs. For example, we used 512 KNLs to match Facebook’s 256 P100 GPUs. However, using more KNLs still requires the larger batch size.

**Conclusion**

In recent years the ImageNet 1K benchmark set has played a significant role as a benchmark for assessing different approaches to DNN training. The most successful results on accelerating DNN training on ImageNet have used a synchronous SGD approach. To scale this synchronous SGD approach to more processors requires increasing the batch size. Using a warm-up scheme coupled with a linear scaling rule, researchers at Facebook (Goyal et al. 2017) were able to scale the training of ResNet 50 to 256 Nvidia P100’s with a batch size of 8K and a total training time of one hour. Using a more sophisticated approach to adapting the learning rate in a method they named the Layer-wise Adaptive Rate Scaling (LARS) algorithm (You, Gitman, and Ginsburg 2017), researchers were able to scale the batch size to 32K; however, the potential for scaling to larger number of processors was not demonstrated in that work, and only 8 Nvidia P100 GPUs were employed. Also, data augmentation was not used in that work, and accuracy was impacted. In this paper we confirmed that the increased batch sizes afforded by the LARS algorithm could lead to increased scaling. In particular, we scaled synchronous SGD batch size to 32K and using 512 Intel KNLs we were able to finish the 100-epoch ImageNet training with AlexNet in 24 minutes. We were also able to finish 90-epoch ImageNet training with ResNet-50 in one hour, which is similar to Facebook’s recent result. We also explored the impact of data augmentation in our work.

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Batch Size | 256 | 8K | 16K | 32K | 64K | note
--- | --- | --- | --- | --- | --- | ---
MSRA | 75.30% | 75.27% | — | — | — | original baseline
IBM | — | 75.01% | — | — | — | —
SURFarsa | — | 75.25% | — | — | — | —
Facebook | 76.30% | 76.20% | 75.20% | 72.40% | 66.04% | strong data augmentation
Our version | 73.00% | 72.70% | 72.70% | 72.60% | 70.00% | no data augmentation
Our version | 75.40% | 75.27% | 75.30% | 74.70% | 72.00% | weak data augmentation

The table above shows an overall comparison by 90-epoch ResNet50 Top-1 Val Accuracy.

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