ABSTRACT

Deep Learning (DL) models are widely used in machine learning due to their performance and ability to deal with large datasets while producing high accuracy and performance metrics. The size of such datasets and the complexity of DL models cause such models to be complex, consuming large amount of resources and time to train. Many recent libraries and applications are introduced to deal with DL complexity and efficiency issues. In this paper, we evaluated one example, Microsoft DeepSpeed library through classification tasks. DeepSpeed public sources reported classification performance metrics on the LeNet architecture. We extended this through evaluating the library on several modern neural network architectures, including convolutional neural networks (CNNs) and Vision Transformer (ViT). Results indicated that DeepSpeed, while can make improvements in some of those cases, it has no or negative impact on others.

Keywords  Machine Learning · Neural Networks · Deep Learning Models · Optimization Models

1 Introduction

The popularity of Neural Network and Deep Learning models is unprecedented. There are the prime choice for many machine learning models and applications. In comparison with traditional machine learning algorithms, Deep Learning algorithms perform better when datasets are large, [Mahapatra 2018]. However, the number of proposed neural network models and algorithms is large. In addition, these models can be trained with a wide range of hyperparameters, including the choice of learning rate, optimizer, length of training (i.e., number of epochs), etc. Finding the optimal model and hyperparameter for a particular dataset may not be straightforward without extensive evaluations. Besides, the complexity of models has been kept increasing due to the positive impact of complexity, such as including more layers may lead to a better accuracy. However, due to the large size and requirement for tremendous computational resources, such complex models may not be practical for many applications and limit their usage in production environments.

Large-scale distributed training improves the performance of training large and complex models. In those approaches, data parallelism is adopted and SGD is usually selected as the optimization method because of its high computation efficiency and well support by the DL tool-kits, such as TensorFlow, PyTorch and DeepSpeed [He et al. 2021]. In SGD, each worker processes a random mini-batch of training data. Quantized or sparcified SGD allows each worker to use fewer bits to pass gradients by sacrificing the convergence to a mild extent.

There are four stages during each in DL data parallel training, [Wang et al. 2021]:

- The model receives input data and then performs forward propagation.
- The model performs backward propagation using the loss calculated after forward propagation, generating the parameters gradients.
• The averaged gradients are computed and broadcast to each device.
• All parameters in each device are updated using the averaged gradients.

1.1 Distributed Deep Learning Frameworks

Besides, DeepSpeed, there are several other examples of distributed deep learning frameworks. These frameworks provide structured methods to define DL models using a collection of pre-built and pre-optimized components.

• TensorFlow, Abadi et al. [2016].
• Caffe and MPI Caffe, Vision and Center [2019]. Jia et al. [2014].
• Keras, Chollet et al. [2018].
• PyTorch DDP
• Microsoft Computational Network Toolkit, CNTK
• BigDL, Dai et al. [2019].
• SINGA, Ooi et al. [2015].
• MXNET-MPI, Chen et al. [2015].
• Horovod, Sergeev and Del Balso [2018].
• DeepSpeed, Rasley et al. [2020].

2 Related Work

2.1 Microsoft DeepSpeed: Evaluate models with a large number of parameters

DeepSpeed is a recent DL library made available to public by Microsoft in 2020. "DeepSpeed brings state-of-the-art training techniques, such as Zero Redundancy Optimizer (ZeRO): a novel memory optimization technology for large-scale distributed DL, optimized kernels, distributed training, mixed precision, and checkpointing, through lightweight APIs compatible with PyTorch", Rasley et al. [2020]. DeepSpeed is designed to enable a large set of input parameters. It is optimized for low latency and high throughput training. SEDONA. DeepSpeed implementation of 3D parallelism can scale to over a trillion parameters on 800 NVIDIA V100 GPUs by fully leveraging the aggregate GPU memory of a cluster, Branwen [2019]. The library is compatible with PyTorch in its current version. Examples of implementations of this library can be evaluated through https://github.com/microsoft/DeepSpeedExamples. In one example using BERT training dataset, the library showed a 34% efficiency improvement over the best published results. DeepSpeed main functions can be summarized into 3 major components:

• Zero: Zero, introduced by Rajbhandari et al. [2020] optimizes memory, which can improve training speed while increasing the model size that can be efficiently trained. This parallelized optimizer greatly reduces the resources needed for parallelism while increasing the number of parameters that can be trained, Rasley et al. [2020]. Data parallelism is not new in general as its already employed by High Performance Computing (HPC) systems that can employ parallelism not only in data, but also in the software, hardware and also the network.
• Sparse Attention: Attention-based DL models, such as Transformers, are effective in capturing relationships between input tokens. Sparse attention is an improvement of the attention mechanism to extract patterns from sequences longer than possible previously. In Transformers, it gets impractical to compute a single attention matrix, for very large inputs. Accordingly, and as an alternative to full attention, in sparse attention, each output position only computes weightings from a subset of input positions. Research papers showed that t sparse attention is sufficient to get state-of-the-art results in modeling long sequences over language modeling, image generation and music generation, Sukhbaatar et al. [2019].
• 1-bit Adam: State-of-the-art error compensation techniques only work with basic optimizers such as SGD, which are linearly dependent on the gradients. They do not work with non-linear gradient-based optimizers such as Adam, Tang et al. [2021]. 1-bit Adam is proposed to reduce the communication volume by up to 5x, offers better scalability, and provides the same sample-wise convergence speed as uncompressed Adam, Tang et al. [2021].

One limitation with DeepSpeed is that it can only support Transformer encoder layer, thus can only be used to train BERT-like models, Devlin et al. [2018]. DeepSpeed also requires the model to fit across the combined memory of all the GPU devices, Pudipeddi et al. [2020].
2.2 Models optimization and over-parameterized systems

DL models, often consist of huge amounts of parameters that far exceed the instance numbers, Bassily et al. [2018], Ma et al. [2018], Allen-Zhu et al. [2019], Oymak and Soltanolkotabi [2019]. Over-parameterization in DL networks has been shown to have advantages, where researchers indicated that wider networks train faster and have better generalization performance Neyshabur et al. [2014], Arpit et al. [2017]. Deep learning models are effective due to the effectiveness of local gradient-based optimization methods, such as Stochastic Gradient Descent (SGD), in training large neural networks. Liu et al. [2020]. Several publications (e.g. Jacot et al. [2018]) connected effective optimization of over-parameterized networks to properties of their linearizations.

3 Experiments and Discussion

This project tests seven neural network architectures, two optimizers, and two learning rate scheduling methods using the CIFAR-10 dataset Krizhevsky et al. [2009]. In total, 42 training trails of 21 unique combinations of the architecture, optimizer, and learning rate scheduling method are tested. Each unique combination is trained twice, with and without DeepSpeed, respectively.

We compare the performance between corresponding training trails in terms of classification accuracy and the training efficiency (i.e., seconds per epoch training). We start this section by giving an introduction to the experimental setup (Section 3.1). The detailed evaluation results are presented in Sections 3.2.1 and 3.2.2. Finally, this section ends with the discussion and limitation in Sections 3.3.

3.1 Experimental Setup

The Vision Transformer (ViT) Dosovitskiy et al. [2021] and six CNN architectures—namely LeNet LeCun et al. [1998], AlexNet Krizhevsky et al. [2012], VGG11 BN Simonyan and Zisserman [2014], ResNet-18 He et al. [2016], DenseNet-121 Huang et al. [2017], and SequeezeNet-v1.0 Iandola et al. [2016]—are tested on image classification tasks using CIFAR-10. The LeNet is implemented by ourselves, the ViT model is loaded from the timm library Wightman [2019], and the six CNNs are loaded from PyTorch. For all of the networks, we modify the output size of the last layer to be ten to match the number of classes in CIFAR-10. The input images are scaled to the proper size to match the input layer size of each model, ranging between $32 \times 32$ and $299 \times 299$.

Two optimizers, SGD and Adam Kingma and Ba [2014], and two learning rate scheduling methods (i.e., with or without learning rate scheduler) are also evaluated in this study. The WarmupLR learning rate scheduler is used for DeepSpeed models when a learning rate scheduler is used, and the CyclicLR Smith [2017] is used for the normal models (i.e., without using DeepSpeed) when a learning rate scheduler is used. The WarmupLR is adopted from the DeepSpeed examples. However, since PyTorch does not provide an implementation for WarmupLR, we decide to use CyclicLR instead. The base learning rate is set to $10^{-3}$ for all the training trials. If a learning rate scheduler is used, we set the minimum learning rate as 0 and maximum learning rate as $10^{-3}$.

All the experiments are conducted using a Linux workstation with two Nvidia 3090 GPU cards, with a 24 GB memory for each of them. The DeepSpeed training models are distributed to both of the GPUs, and the normal training models are trained using only one GPU card. Each model is trained for 25 epochs from scratch with a batch size of 16. Cross-entropy loss is used during the training. In addition, half-precision (FP16) is used for DeepSpeed training, and full precision (FP32) is used for normal training.

3.2 Experimental Results and Analysis

3.2.1 Classification Accuracy

With the architectures, optimizers, and learning rate scheduling methods mentioned above, 21 permutations are derived. We train each permutation twice, with or without DeepSpeed. Table 1 shows the best performance of 42 trained model. The words SGD and Adam indicate the optimizer used in the model training. The postfix *S shows whether a learning rate scheduler is used in training. The highest accuracy of each neural network architecture is highlighted in bold. The table reveals the best performance of different architectures is often coming from normal training.

To better analyze the result, we group the models into four different settings and present them in four plots:

- 1. Adam optimizer with learning rate scheduler for DeepSpeed models, and uses SGD without scheduler for normal models (Figure 1a):

1 https://github.com/microsoft/DeepSpeedExamples
Table 1: Classification Performance of Different Models

| Models      | DeepSpeed Training | Normal Training |
|-------------|--------------------|-----------------|
|             | SGD    | SGD+S   | Adam+S | SGD    | SGD+S   | Adam+S |
| LeNet       | 58.41  | 57.15   | 58.37   | 65.62  | 64.13   | 64.95  |
| AlexNet     | 60.39  | 61.64   | 62.56   | 82.60  | 80.54   | 70.61  |
| VGG11_BN    | 66.26  | 66.11   | 10.28   | 81.00  | 79.62   | 78.04  |
| ResNet-18   | 56.84  | 57.55   | 79.72   | 73.46  | 70.43   | 80.69  |
| DenseNet-121| 52.70  | 53.06   | 80.70   | 75.61  | 70.86   | 84.00  |
| SqueezeNet-v1.0 | 55.55 | 55.24   | 73.48   | 75.79  | 72.06   | 78.91  |
| ViT         | 58.87  | 59.40   | 13.15   | 61.22  | 63.45   | 20.20  |

- II. Adam optimizer with learning rate scheduler for all models (Figure 1b);
- III. SGD optimizer without learning rate scheduler for all models (Figure 1c);
- IV. SGD optimizer with learning rate scheduler for all models (Figure 1d).

Figure 1a shows the results of the models trained using Setting I, which is the original setting in the DeepSpeed CIFAR-10 example. We follow the example almost exactly, except we include six more neural network architectures. The figure shows that the DeepSpeed training models normally perform better when the training epoch is small, such as 1 or 2, except the VGG model. However, when the training epoch increases, the difference between normal and DeepSpeed training reduces. The normal training models might have a significant performance improvement than the corresponding counterpart over time, especially when the model capacity is small, such as LeNet and AlexNet. However, for models with larger capacity, such as ResNet and DenseNet, the performance of DeepSpeed training models are consistently better than the normal training models. It seems the experiment suggests DeepSpeed may be beneficial when the model capacity is larger. However, the comparison between the DeepSpeed and normal models could be biased because different optimizers were used in the example, especially given the fact that Adam optimizer is known for achieving a better performance in a shorter time frame.

To create a more fair comparison, we try to train both methods using the same hyperparameters or similar hyperparameters. Figure 1c shows the performance of models trained with SGD optimizer only (i.e., Setting III). No learning rate scheduler is used. The figure shows that all normal training models perform better than the corresponding DeepSpeed models. In addition, the performance difference between the two training methods (i.e., with or without DeepSpeed) could be as large as more than 20% for a particular architecture. For instance, DenseNet with DeepSpeed training is 52.70% accuracy. However, the performance of DenseNet with normal training is 75.61%.

Figure 1d shows the performance of models trained using SGD optimizer and learning rate scheduler (Setting IV). The result is very close to Figure 1c which uses SGD optimizer only. The WarmupLR scheduler does improve the performance of DeepSpeed models. However, the improvement is marginal, with an average of less than 1%. In general, DeepSpeed models still have significantly worse performance than normal training models.

Figure 1b shows the models trained using Adam optimizer with learning rate scheduler (Setting II). The figure reveals that the DeepSpeed models’ performance improved dramatically when using Adam optimizer. For instance, the performance of DeepSpeed trained ResNet is improved from about 57% accuracy to close to 80%, compared with SGD optimizer. However, this performance improvement is not limited to DeepSpeed models. The normal training ResNet model is also improved from lower 70% accuracy to 80%. Similarly, with SGD settings, the normal training models have better performance than the DeepSpeed training models.

3.2.2 Training Efficiency

Table 2 shows the training efficiency of each model with or without using DeepSpeed. We report the training efficiency in terms of seconds per epoch to train. For each pair of training, the one trained with less time is highlighted in bold. The table shows that normal training is faster for almost all of the convolutional neural network models, except DenseNet-121 with Adam optimizer. In addition, for almost all the convolutional neural network models, DeepSpeed training may take a significantly longer time, especially for AlexNet, the training time event got almost tripled. However,  

2https://github.com/microsoft/DeepSpeedExamples/tree/master/cifar
when evaluating the training time of ViT models, DeepSpeed shows a clear advantage, which usually takes only 2/3 of the training time compared with normal training.

### 3.3 Discussions and Limitations

The primary goal of this study is to evaluate the DeepSpeed library performance on classification models by extending the official example[3]. Initially, we want to use the example as-is to reduce the possibility of introducing bias to the experiences. However, we noticed that the official example uses different optimizers and learning rate scheduling methods to train the DeepSpeed and normal models. More specifically, the DeepSpeed model uses the Adam optimizer with a learning rate scheduler, and the normal model uses the SGD optimizer without a learning rate scheduler. Thus, we decided to expand our experiments to cover both Adam and SGD optimizers, as well as with and without a learning rate scheduler.

[3] https://github.com/microsoft/DeepSpeedExamples/tree/master/cifar
rate scheduler. However, our experiments may still be biased on some hyperparameters. For instance, all the models are initialized using random seedings, which may introduce uncertainty to each training trial. The DeepSpeed models are trained by distributing to two GPU cards for training; however, the normal models are trained using only one GPU card. Half-precision (FP16) is used for DeepSpeed training, and full precision (FP32) is used for normal training.

According to our experimental result, the DeepSpeed library does not be very helpful for CNNs, but it works well for ViT. This makes us wonder if the library is designed only for neural networks beyond the normal training scale. In addition, the official Github site\(^4\) of DeepSpeed claims to make distributed training easy, efficient, and effective. It may train 10x larger models and provide 10x faster training. Two particular observations from our experimental result may support this hypothesis.

For instance, Table 2 shows DeepSpeed reduces the training time of ViT models by up to 40%. However, it does not help for most CNN models. This result may show models with larger capacity may be benefited more from using DeepSpeed. In addition, if we compare the ViT classification performance against all other neural network architectures that trained using the same method, a bigger performance improvement is observed when using DeepSpeed. For instance, Table 1 shows that without using DeepSpeed, ViT has the worst performance regardless of the optimizer and scheduler. However, with using DeepSpeed, ViT performed the 3rd best amount of all the tested architectures when using SGD as the optimizer. This observation may also support our hypothesis that the DeepSpeed library is designed only for neural networks beyond the normal training scale. Thus, we would focus more on evaluating DeepSpeed on models with larger capacity in the future.

### 4 Summary and Conclusion

In this paper, we evaluated the performance of the DeepSpeed library on classification tasks across seven neural network architectures, two optimizers, and two learning rate scheduling methods. Our results demonstrate that DeepSpeed may improve model performance while reducing training time in cases where the model capacity is large. However, it has no or negative impact on those models with smaller capacity. It is important to mention, however, that our experiment may be limited by using a toy dataset (i.e., CIFAR-10) and some other factors. We are planning to expand our study to cross multiple datasets and more focus on models with larger capacity in terms of images, etc.

[^4]: https://github.com/microsoft/DeepSpeed

---

| Models     | Optimizer | Use Scheduler | DeepSpeed | Normal |
|------------|-----------|---------------|-----------|--------|
| LeNet      | SGD       | No            | 16.63     | 11.97  |
|            | Adam      | Yes           | 16.72     | 12.05  |
|            |           |               | 14.95     | 13.32  |
| AlexNet    | SGD       | No            | 101.41    | 35.72  |
|            | Adam      | Yes           | 101.46    | 35.56  |
|            |           |               | 97.95     | 48.61  |
| VGG11_BN   | SGD       | No            | 231.62    | 156.71 |
|            | Adam      | Yes           | 231.57    | 156.90 |
|            |           |               | 219.27    | 185.93 |
| ResNet-18  | SGD       | No            | 97.18     | 66.08  |
|            | Adam      | Yes           | 99.34     | 66.04  |
|            |           |               | 86.55     | 73.46  |
| DenseNet-121 | SGD  | No           | 346.94    | 273.53 |
|            | Adam      | Yes           | 348.22    | 275.50 |
|            |           |               | 288.87    | 318.77 |
| SqueezeNet-v1.0 | SGD | No        | 83.86     | 61.40  |
|            | Adam      | Yes           | 85.43     | 61.47  |
|            |           |               | 73.41     | 64.80  |
| ViT        | SGD       | No            | 259.05    | 354.91 |
|            | Adam      | Yes           | 259.56    | 384.52 |
|            |           |               | 225.54    | 376.50 |
References

Sambit Mahapatra. Why deep learning over traditional machine learning. *Towards Data Science*, 2018.

Xiaoxin He, Fuzhao Xue, Xiaozhe Ren, and Yang You. Large-scale deep learning optimizations: A comprehensive survey. *arXiv preprint arXiv:2111.00856*, 2021.

Xiaohui Wang, Ying Xiong, Xian Qian, Yang Wei, Lei Li, and Mingxuan Wang. Lightseq2: Accelerated training for transformer-based models on gpus. *arXiv preprint arXiv:2110.05722*, 2021.

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. *TensorFlow*: A system for *Large-Scale* machine learning. In *12th USENIX symposium on operating systems design and implementation (OSDI 16)*, pages 265–283, 2016.

Berkeley Vision and Learning Center. Caffe, 2019.

Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*, pages 675–678, 2014.

François Chollet et al. Keras: The python deep learning library. *Astrophysics source code library*, pages ascl–1806–1806, 2018.

Jeff Rasley, Samyam Rajbhandari, Olatunji Ruwase, and Yuxiong He. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, page 3505â–C3506. Association for Computing Machinery, New York, NY, USA, 8 2020. ISBN 978-1-4503-7998-4. URL https://doi.org/10.1145/3394486.3406703. [Online; accessed 2022-01-22].

ROCCO SEDONA. Scalable machine learning with high performance and cloud computing. Gwern Branwen. September 2020 news. 2019.

Sainbayar Sukhbaatar, Edouard Grave, Piotr Bojanowski, and Armand Joulin. Adaptive attention span in transformers. *arXiv preprint arXiv:1905.07799*, 2019.

Hanlin Tang, Shaoduo Gan, Ammar Ahmad Awan, Samyam Rajbhandari, Conglong Li, Xiangru Lian, Ji Liu, Ce Zhang, and Yuxiong He. 1-bit adam: Communication efficient large-scale training with adam’s convergence speed. *arXiv preprint arXiv:2102.02888*, 2021.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

Bharadwaj Pudipeddi, Maral Mesmakhosroshahi, Jinwen Xi, and Sujeeth Bharadwaj. Training large neural networks with constant memory using a new execution algorithm. *arXiv preprint arXiv:2002.05645*, 2020.

Siyuan Ma, Raef Bassily, and Mikhail Belkin. The power of interpolation: Understanding the effectiveness of sgd in modern over-parametrized learning. In *International Conference on Machine Learning*, pages 3325–3334. PMLR, 2018.

Zeyuan Allen-Zhu, Yuanzhi Li, and Zhao Song. A convergence theory for deep learning via over-parameterization. In *International Conference on Machine Learning*, pages 242–252. PMLR, 2019.
Samet Oymak and Mahdi Soltanolkotabi. Overparameterized nonlinear learning: Gradient descent takes the shortest path? In *International Conference on Machine Learning*, pages 4951–4960. PMLR, 2019.

Behnam Neyshabur, Ryota Tomioka, and Nathan Srebro. In search of the real inductive bias: On the role of implicit regularization in deep learning. *arXiv preprint arXiv:1412.6614*, 2014.

Devansh Arpit, Stanislaw Jastrzebski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, et al. A closer look at memorization in deep networks. In *International Conference on Machine Learning*, pages 233–242. PMLR, 2017.

Chaoyue Liu, Libin Zhu, and Mikhail Belkin. Toward a theory of optimization for over-parameterized systems of non-linear equations: the lessons of deep learning. *arXiv preprint arXiv:2003.00307*, 2020.

Arthur Jacot, Franck Gabriel, and Clément Hongler. Neural tangent kernel: Convergence and generalization in neural networks. *arXiv preprint arXiv:1806.07572*, 2018.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Alexey Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. *International Conference on Learning Representations*, 2021.

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25, 2012.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4700–4708, 2017.

Forrest N Iandola, Song Han, Matthew W Moskewicz, Khalid Ashraf, William J Dally, and Kurt Keutzer. Squeezenet: Alexnet-level accuracy with 50x fewer parameters and< 0.5 mb model size. *arXiv preprint arXiv:1602.07360*, 2016.

Ross Wightman. Pytorch image models. [https://github.com/rwightman/pytorch-image-models](https://github.com/rwightman/pytorch-image-models), 2019.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Leslie N Smith. Cyclical learning rates for training neural networks. In *2017 IEEE winter conference on applications of computer vision (WACV)*, pages 464–472. IEEE, 2017.