A Comparative Study between DeepSpeed and Horovod, two Distributed Deep Learning Frameworks

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Abstract. Large-scale computational resources are needed to run deep-learning models with huge parameters. The idea of distributed computing is becoming more and more significant as a result. In distributed deep learning, models are trained concurrently across numerous devices to shorten training times and enhance performance evaluation. There are several distributed deep learning frameworks available, which reduce training time and the need for significant computer resources. In this research, we have covered two distributed deep-learning frameworks-Horovod and DeepSpeed. We performed a comparative analysis between Horovd and DeepSpeed based on four factors: memory efficiency, speed, training time, and cost. According to our research, DeepSpeed is a more effective framework for distributed deep learning models than Horovod.

Keywords: Horovod · DeepSpeed · Distributed DL · Distributed Computing.

1 Introduction

Today's world is experiencing a significant rise in technology usage. Distributed systems are used more frequently due to the world's ever-expanding technical advancement. The term distributed system, also known as distributed computing is a collection of computers that enable users to do tasks more quickly and efficiently. Compared to other computing systems, distributed systems are more scalable and have better performance since they provide users with the results of a single integrated system.
It is challenging to process a huge amount of data in a short period of time and with low memory efficiency. With the help of distributed computing frameworks, we can easily process huge amounts of data in a concise time. Additionally, it enables memory-efficient processing of enormous amounts of data on a single computing platform. In distributed learning, tasks are split into smaller chunks

and performed on various computers to boost the effectiveness of the problem. Many researchers employ distributed deep learning frameworks to train various deep learning models while utilizing the advantages of distributed computing.
Frameworks are collections of libraries and classes that offer a wide range of functionality. There are numerous frameworks available for distributed deep learning. Some distributed deep learning frameworks like BigDL, TensorFlowOnSpark, Elephas, Mesh TensorFlow, Horovod, PyTorch, DeepSpeed, and many others exist. In this paper, we will compare the performance analysis of Horovod and DeepSpeed, two of the most well-known distributed learning frameworks. Future researchers will benefit from reading this paper to gain a thorough understanding of the two distributed frameworks and distinguish which framework will be more beneficial for developing which kind of deep learning models.
In the next section, Section 2 of the paper, we have described previously done works in distributed deep learning frameworks. In Section 3, we have discussed different deep learning frameworks. After that, the comparison between DeepSpeed and Horovod is briefly described in Section 4. Next, the result and analysis part of this research work is shown in Section 5. Finally, we conclude our paper by mentioning future works in Section 6.

2 Related Work

Comparative studies of various Distributed deep learning frameworks were only conducted by a few researchers. Lim et al. [1] proposed TFSM, a distributed deep learning framework, in their research paper. A Remote shared memory framework is used to build it, which offers shared space that can be accessed by several machines at fast speeds. They demonstrated through a comparison of their proposed framework with TensorFlow that TFSM outperforms existing deep learning frameworks in terms of training efficiency.

A research paper by Munjal et al. [2] conducted a comparative analysis of the performance of four deep learning frameworks PyTorch, TensorFlow, TensorFlow with Keras, and CNTK. Using different test datasets, the accuracy performance of the frameworks has been examined. According to the research, the Cognitive Toolkit (CNTK) performs the least accurately among the four frameworks as the difficulty of the datasets increases.

Bahrampour et al. [3] in their research work, showed a comparison based on the speed, hardware utilization, and extensibility between five deep learning frameworks: Neon, TensorFlow, Caffe, Torch, and Theano. They assess how well the aforementioned frameworks perform when used on a single system in CPU and GPU configurations. Theano and Torch are the frameworks that are most easily extensible, according to their experiments. Additionally, TensorFlow is another adaptable deep learning framework, however, its performance is poor than other frameworks.

A paper proposed by Goldsborough [4], reviewed a well-known deep learning framework, TensorFlow. In his paper, he highlighted the development history of deep machine-learning libraries. He concentrated on the outcomes and fundamental attributes of TensorFlow, including programming interfaces, and distributed models. Finally, he made qualitative and quantitative comparisons between TensorFlow and other deep learning frameworks like Torch, Theano, and Caffe.

Shatnawi et al. [5] present a comparative analysis of open-source deep learning frameworks in their research paper. Different deep learning frameworks including Theano, CNTK, and TensorFlow were compared both quantitatively and qualitatively. On a number of test datasets, they conducted the comparison using a range of algorithms. The datasets are MNIST and CIFAR-10, while the methods used are CNN, RNN, LSTM, etc. They concluded from their experiments that CNTK outperforms all other compared deep learning frameworks.

Comparative analysis between five deep learning frameworks: Theano, TensorFlow, Caffe, Torch, and Deeplearning4J is presented in Kovalev et al. paper [6]. They performed comparisons among the frameworks based on their performance accuracy, training, and classification time. They used the MNIST dataset to perform the comparison between the frameworks. Their study demonstrated that, when compared to other deep learning frameworks, Theano ranked top while Deeplearning4J came in last for speed and accuracy.

3 Distributed Deep Learning Frameworks

Distributed deep learning is a technique that enables researchers to run several tasks simultaneously across numerous devices and shorten task execution times by permitting task execution in different devices other than a single network. There are many distributed deep learning frameworks like BigDL, Horovod, DeepSpeed, Elephas, Mesh TensorFlow, and many others. Through these frameworks, distributed deep-learning tasks can be completed more quickly and effectively. The properties of two well-known distributed deep learning frameworks: Horovod and DeepSpeed are described below:

3.1 Horovod

Horovod is a distributed deep-learning framework introduced by Uber Technologies Inc. in 2017. It is a free and open-source framework used for PyTorch, Keras, TensorFlow, and Apache MXNet. It is designed to make it beneficial for the researchers by making it easier to use and decreasing the amount of time required to train a model from days to hours. Making it simple to scale a single-GPU training program to train on numerous GPUs simultaneously is the main reason behind developing this framework.

It is based on the concept of ring allreduce which allows it to be easier to use than other distributed frameworks. Allreduce, local rank, rank, size, broadcast, allgather, and alltoall are a few of the Message Passing Interface elements on which the main idea of Horovod is founded. This framework is designed for distributed training and with only five lines of python code, it can scale hundreds of GPUs. It is easy to learn and implement using Keras, PyTorch, Apache MXNet, and TensorFlow. All the processes can be combined into a single pipeline while using it in Apache Spark. Additionally, it can be set up on cloud computing systems like Azure, Amazon Web Services, and Databricks.

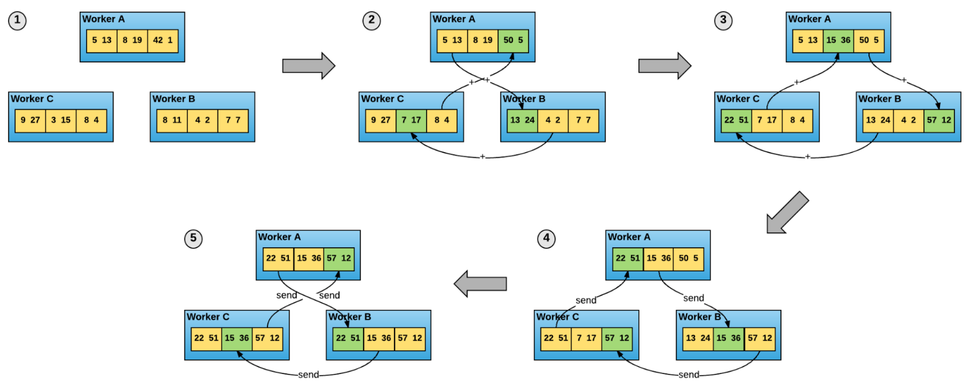

Fig. 1. Concept of Ring AllReduce [7]

3.2 DeepSpeed

DeepSpeed is another popular distributed deep learning framework. It is developed by Microsoft Research and released in May 2020. It is also an open-source optimized framework that is used for PyTorch. Deep learning models have some obstacles, such as model design and setting up modern training approaches including distributed training, mixed precision, and gradient accumulation, which make it exceedingly complex and time-consuming to train a large number of datasets in deep learning models. Furthermore, because training a huge dataset consumes a lot of time and memory, it is not always certain that the expected results will be obtained. DeepSpeed is designed in order to simplify the complexity involved in training big datasets for deep learning models.

Turing-NLG, one of the largest word embedding models with 17 billion parameters, has been developed as one of the most significant DeepSpeed appli-

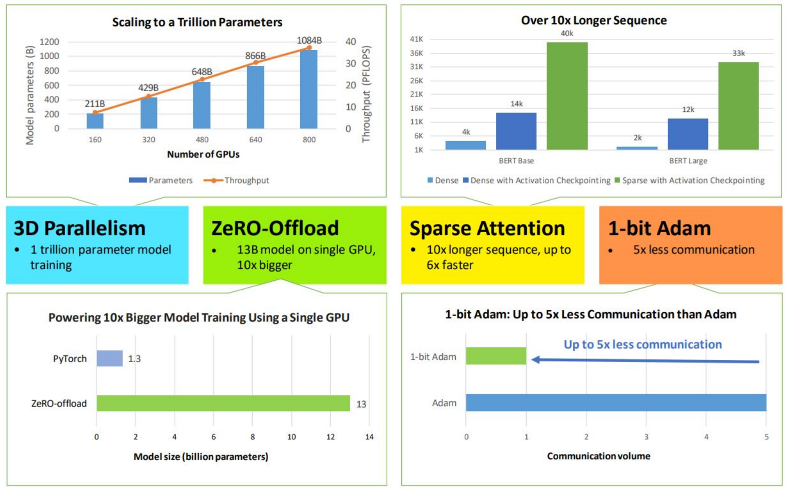

Fig. 2. DeepSpeed Performance [8]

cations. Using DeepSpeed we can train models with billions and trillions of parameters. Low latency and high throughput can be achieved by DeepSpeed as it allows scaling up to hundreds of GPUs. In order to increase the memory and computation efficiency of deep learning training, DeepSpeed offers pipeline parallelism, which divides a model's layers into phases that can be performed in parallel. Moreover, Microsoft has also released DeepSpeed Compression, a composable framework that combines compression techniques with extremely effective system optimizations to reduce deep learning model size and increase inference speed while maintaining significantly lower compression costs. The performance analysis of DeepSpeed in shown in Figure 2.

4 Comparative Analysis

Training deep learning models with a large number of parameters is quite difficult. To train these models, researchers need modern approaches like mixed precision, distributed computing, etc. However, due to a lack of memory, hardware limitations, and lengthy model training, predicted outcomes and accuracies are still not reached. Two distributed deep learning libraries, DeepSpeed and Horovod, are presented to address these problems.

Although DeepSpeed and Horovod are the most widely used distributed deep learning frameworks, each has a unique set of features. In this section of the study, we will compare the two libraries' memory capacity, speed, cost, and model training time.

4.1 Memory

DeepSpeed uses ZeRO optimizer stage one to train a model with billions of parameters. It has the capacity to support models with 100 billion parameters. Other frameworks, can train models with 1.5 billion to 11 billion parameters which are 10 times fewer than DeepSpeed can [9]. To train models with 200 billion to trillions of parameters, ZeRO optimizer stages two and three will also be implemented in the future. By combining three parallelism techniques (3D parallelism), pipeline parallelism, tensor-slicing model parallelism, and ZeRO-powered data parallelism, DeepSpeed can train large models with trillions of parameters. The memory usage of DeepSpeed with and without ZeRO optimizer is shown in Figure 3

Horovod is unquestionably easy to integrate into a codebase because the adjustments required are minimal and easy to understand, but it has some drawbacks too. The performance of the system significantly falls as the number of nodes is increased to scale it up. Additional hardware and networking setup are needed to set up multi nodes in Horovod [10].

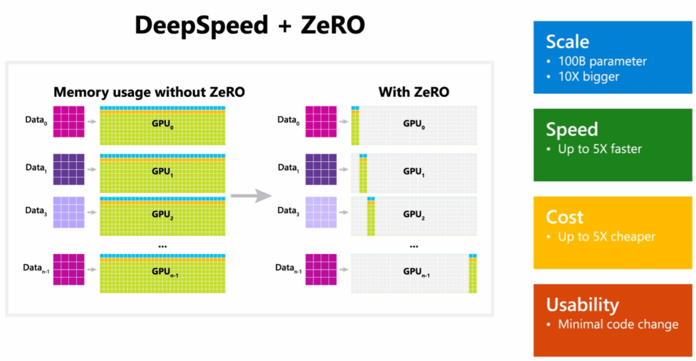

Fig. 3. DeepSpeed with ZeRO [11]

4.2 Speed

Compared to other libraries, DeepSpeed has a five times faster throughput on a variety of hardware. ZeRO and model parallelism are combined by DeepSpeed to train larger models with trillions of parameters, which results in greater throughput [9]. These throughput increases are the result of DeepSpeed's better memory performance, ability to fit these models with less parallelism and larger batch sizes, and better memory efficiency.

Horovod performs better when training a deep-learning model with just a single GPU. However, Horovod's performance decreases significantly—by a factor of about ten [10] when many GPUs are utilized to speed up training and reduce training time. Additionally, it took longer time to train than it would have on a single GPU.

4.3 Training Time

DeepSpeed recently achieved the fastest training time record of the BERT model on 1024 NVIDIA V100 GPUs [12]. It took 44 minutes to train which shows 34% improvement in training because previously it took 67 minutes to achieve the same result using the same number of GPUs [13].

When it comes to model training on a single device, Horovod outperforms alternative distributed deep learning frameworks. However, adding more devices to boost performance while cutting down on training time yields surprising consequences. The training time actually increases by around 10 times compared to using a single device.

4.4 Cost

In Horovod distributed systems, we train our model in different devices and GPUs parallelly. Different GPUs can be in a single device or in multiple devices. The training data is divided into different portions and each GPU trains on a unique batch of samples at each stage of the training process. Finally, it shares the resulting gradients with the rest of the workers. While training, if any of the devices is spot failed then the whole training will stop in the Horovod training system. Because the cost of a spot interruption is substantially larger in the case of N devices, it will increase the total cost of training models while using Horovod frameworks.

On the other hand, DeepSpeed is three times more affordable than the alternatives for training models. The higher memory efficiency of DeepSpeed and the capacity to fit models with a lower level of model parallelism and bigger batch sizes result in throughput gains. The cost of training can be greatly lowered as a result of increased throughput. For example, DeepSpeed uses three times fewer resources to train a model with 20 billion parameters.

5 Results and Discussion

DeepSpeed and Horovod are two well-known examples of popular distributed deep learning frameworks. From the above comparison, we saw that the memory efficiency of DeepSpeed is better than Horovod. While in the case of training time and speed, Horovod performs less well than the other one. In the case of cost efficiency, DeepSpeed is comparatively better than Horovod as it uses three times fewer resources than other DL libraries.

We can conclude from the comparative analysis that DeepSpeed outperforms Horovod in terms of training time, cost, memory efficiency, and speed.

Table 1. Comparative Analysis of DeepSpeed and Horovod

	Horovod	**DeepSpeed**
Memory Efficiency	Less Efficient	More Efficient
Speed	Slow	Fast
Training Time	Higher	Comparatively Lower
Cost	Costly	Less-Cost

6 Conclusion

Numerous difficulties, including hardware restrictions and trade-offs between computation and efficiency, arise when training models with a large number of parameters. The idea of distributed computing is very helpful in reducing the amount of memory needed for model training as well as increasing the speed and effectiveness of the models. Multiple devices collaborate in parallel in distributed computing systems, which helps to lessen the model's time complexity. Two distributed deep learning libraries—Horovod and DeepSpeed—were covered in this article. Four criteria are used in the comparison of Horovod and DeepSpeed: memory effectiveness, model training time, speed, and cost. According to the analysis, the DeepSpeed framework is superior to the other one for distributed deep learning model training in terms of effectiveness and utility. The results of this study will aid researchers in understanding distributed DL frameworks and in determining which framework is required for which models.In the future, we will compare other frameworks after applying them to different models and datasets.

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