A Snapshot of Parallelism in Distributed Deep Learning Training

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Abstract. The accelerated development of applications related to artificial intelligence has generated the creation of increasingly complex neural network models with enormous amounts of parameters, currently reaching up to trillions of parameters. Therefore, it makes your training almost impossible without the parallelization of training. Parallelism applied with different approaches is the mechanism that has been used to solve the problem of training on a large scale. This paper presents a glimpse of the state of the art related to parallelism in deep learning training from multiple points of view. The topics of pipeline parallelism, hybrid parallelism, mixture-of-experts and auto-parallelism are addressed in this study, which currently play a leading role in scientific research related to this area. Finally, we develop a series of experiments with data parallelism and model parallelism. The objective is that the reader can observe the performance of two types of parallelism and understand more clearly the approach of each one.

Keywords: deep learning, parallelism, artificial neural networks.

1 Introduction

Deep learning has shown great potential to solve complex problems in several areas, such as computer vision, natural language processing, and speech recognition (Hey, 2020). For this reason, the scientific community has implemented artificial intelligence approaches with great acceptance in many areas of science and engineering (Stevens, et al., 2020). However, as deep learning models have become larger and more complex, the training time required to obtain accurate results has increased significantly. To address this challenge and speed up the training process, parallelism techniques have been implemented and combined in the field of deep learning (DL) (Chen, M, 2023).

The goal of this paper is to provide an overview of the various parallelism techniques used in training DL (Ben-Nun & Hoefler, 2019; Verbraeken, et al., 2020). The current overview of the most important issues related to parallelism in deep learning is presented, including parallelism paradigms, techniques or approaches, optimizations and deep learning frameworks. Also, important concepts are described to support the theoretical basis of artificial neural networks and how they have evolved to reach the most advanced deep learning models used today.

This study focuses on the two main types of parallelism: data parallelism and model parallelism. Data parallelism executes the same task on multiple distributed nodes with a different data set and model parallelism changes the approach by partitioning the neural network model and distributing it across multiple accelerators (Rojas, Quirós-Corella, Jones, & Meneses, 2022). In addition, research related to various parallelism techniques and optimizations is described, such as pipeline parallelism that divides the training of deep learning models into stages and processes them in parallel, hybrid parallelism that takes advantage of the combination of several parallelism approaches (DP and MP) to speed up training, and mixture of experts (MoE) that uses multiple expert models to optimize training performance and learning. As an additional element, a brief description of the state of the research related to fault tolerance in parallel DL training is made.

Finally, through the execution of a series of experiments, a comparison of the training of DL models using two parallelism approaches is presented. The results obtained are analyzed and compared, in order to provide the reader with an experimental vision of the main approaches.
2 Important Topics in Deep Learning Parallelism

2.1 Artificial Neural Network and Deep Learning

Inspired by biological neural networks, Artificial Neural Network (ANN) are massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. All of these interconnections have a value, commonly called weight, that is adjusted to allow for learning. Some ANN architectures also have weighted connections not only from one layer to the next, but also to one or more layers below (Hopfield, 1988; Pouyanfar, et al., 2018). An ANN consists of an input layer of neurons (or nodes, units), one or two (or even more) hidden layers of neurons, and a final layer of output neurons and must be configured in such a way that the application of a set of inputs produces the desired set of outputs (Wang, 2003).

Deep learning algorithms are also a subset of ANNs when the use of multilayer structures (hidden layers) is preferred, since they can handle more than one problem at the same time to give a unique answer (Kukačka, Golkov, & Cremers, 2017). Deep learning uses multiple layers to represent data abstractions to build computational models. Deep learning algorithms are mainly based on the well-known Deep Neural Networks (DNN) or also called Convolutional Neural Networks (CNN) (Wu, 2017).

CNN is one of the largest networks in the field of deep learning. They are analogous to traditional ANNs in that they are composed of neurons that self-optimize through learning. The only notable difference between CNNs and traditional ANNs is that CNNs are mainly used in the field of pattern recognition within images (Albawi, Mohammed, & Al-Zawi, 2017; Li, Liu, Yang, Peng, & Zhou, 2022).

![DL Parallelism Diagram](image)

**Figure 1.** Deep Learning Parallelism

DL Frameworks DL uses multiple layers to represent the abstractions of data to build computational models. Different DL algorithms help to improve the learning performance, broaden the scopes of applications, and simplify the calculation process. DL frameworks (Abadi, et al., 2016; Batur Dinler, Şahin, & Abualigah, 2021; Chen, et al., 2015; Collobert, Bengio, & Mariéthoz, 2002; Jia, et al., 2014; Manaswi, 2018; Ravanelli, Parcollet, & Bengio, 2019) combine the implementation of modularized algorithms, optimization techniques, distribution techniques, and support to infrastructures (Pouyanfar, et al., 2018). In conclusion, the purpose of the DL Frameworks is to help developers and researchers to easily take advantage of the technologies (Mittal & Vaishay, 2019).

2.2 Parallelism Paradigms

Currently the components of high performance computing systems are dedicated to supporting parallelism. Neural network algorithms have been adapted for better use in parallelism paradigms. There are two main approaches to train deep neural network models in a distributed manner: data and model parallelism. The figure 1 shows in a general way the operation and relationship that exists between the 3 main DL paradigms that exist.
Data Parallelism Data parallelism is usually expressed as a single thread of control operating on data sets distributed over all nodes (Subhlok, Stichnoth, O’Hallaron, & Gross, 1993). Data parallelism divides the data set into partitions whose number is equal to the number of accelerators (GPUs, TPUs). According to the gradient update strategy, data parallelism can be divided into two categories, synchronous parallelism and asynchronous parallelism. In synchronous parallelism, the training rate is limited by the slowest accelerator because the parameter server needs to collect parameters from all accelerators each round. Asynchronous parallelism reduces the timeout of accelerators with an asynchronous gradient update strategy (Zhang, Lee, & Qiao, 2023).

In another study (Gholami, Azad, Jin, Keutzer, & Buluc, 2018), it is described other types of parallelism that are framed within DP and are related to the training input data: batch parallelism and domain parallelism. The first is related to the assignment of groups of input data as a whole to the processes that are executed (this is the option commonly studied in the literature). The second is based on the subdivision of individual input data to processes.

Model Parallelism Model parallelism partitions a model among multiple GPUs. Each GPU is responsible for the weight updates of the assigned model layers (Krizhevsky, 2014; Mirhoseini, et al., 2017). This scheme is used when the model is too large to fit in the memory of a single device, and hence data parallelism cannot be used. The model to train is partitioned and every device trains its own portion of the model using the same batch of examples (Harlap, et al., 2018; Moreno-Alvarez, Haupt, Paoletti, & Rico-Gallego, 2021).

According to Janbi, Katib and Mehmood (2023), Jiang et al. (2020), Kirby et al. (2020), and Shoeybi et al. (2020) there are several strategies for model partitioning, i.e., how a neural network model is divided into smaller parts for distributed processing across multiple devices. The most common strategy is (1) layer-wise, the model is partitioned by layers, assigning each layer to a different device. For example, in Jia, Lin and Aiken (2018) a layer-wise parallelism is proposed that allows each layer in the network to use an individual parallelization strategy. (2) fine-grained, the model is partitioned into smaller blocks, which allows more granularity in the distribution. This strategy can be subdivided into (2.1) grid-based, the model is divided into a matrix, distributing different sections of the model to separate devices. (2.2) tree-structured, the model is decomposed into a tree structure, where each node in the tree is assigned to a device, allowing a high degree of parallelism and efficient communication between neighboring nodes in the tree, in Wang et al. (2023) propose a system to accelerate communication and computation on multi GPU platforms.

It is necessary to mention the work carried out by Che, Yang and Cheng (2019), where a comparison is made between data parallel and model parallel. This work focuses on three aspects: inter-GPU load balancing, inter-GPU communication, and training efficiency. In the first aspect, with data parallelism, load balancing can be easily maintained, but with model parallelism it is more complex, by dividing the complexity into different layers. In the second aspect, both data parallelism and model parallelism require communications between the GPUs and according to Takisawa, Yazaki, and Ishihata (2020) due to the communication time between the nodes, the learning performance can degrade and overload the training. Finally, in the third aspect, both data parallelism and model parallelism affect the efficiency of DNN training, that is, the rate of convergence and the accuracy of the model.

### 3 Parallelism techniques and optimizations

#### 3.1 Pipeline Parallelism

Pipeline parallelism (PP) improves the efficiency of both memory consumption and computation of deep learning training by partitioning the layers of a model into stages that can be processed in parallel. With this technique it is possible to train large neural network models that do not fit into the memory of an accelerator. In a pipeline parallelism, each piece of data moves from stage to stage, eventually producing a final result (Harlap, et al., 2018; Huang, et al., 2019; Mastoras & Gross, 2018; Narayanan, et al., 2019; Yang, Zhang, Zhang, Yang, & Wei, 2022). PP takes advantage of a pipelined execution strategy across different accelerators. With the pipeline execution strategy, PP can get better performance by using accelerators more efficiently compared to the naive parallelism model (Hu, et al., 2021; Zhang, Lee, & Qiao, 2023). Several authors have indicated the challenge that exists between load balancing and the
communication overhead in PP. In Kamruzzaman, Swanson, and Tullsen (2013) is explained a technique used to balance both situations. This technique provides linear speedup for several applications and outperforms prior techniques to exploit pipeline parallelism.

Table 1. Pipeline libraries.

<table>
<thead>
<tr>
<th>Library</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>DeepSpeed</td>
<td>Library for training large models by improving scale, speed, cost and usability, unlocking the ability to train 100 billion parameter models.</td>
<td>(Aminabadi, et al., 2022; Li, et al., 2024; Rajbhandari, et al., 2022; Rasley, Rajbhandari, Ruwase, &amp; He, 2020)</td>
</tr>
<tr>
<td>GPipe</td>
<td>Optimization of pipeline parallelism training process. GPipe applies synchronous backward updates, and has been integrated into the PyTorch framework.</td>
<td>(Huang, et al., 2019; Tanaka, Taura, Hanawa, &amp; Torisawa, 2021; Zhang, Lee, &amp; Qiao, 2023)</td>
</tr>
<tr>
<td>PipeDream</td>
<td>Supports pipelined training, and automatically determines how to systematically split a given model across the available compute nodes</td>
<td>(Harlap, et al., 2018; Narayanan, et al., 2019; Zhang, Lee, &amp; Qiao, 2023)</td>
</tr>
<tr>
<td>Other pipeline libraries: EdgePipe (Hu, et al., 2021; Yoon, Byeon, Kim, &amp; Lee, 2022; Yuan, et al., 2023), BaPipe (Akintoye, Han, Zhang, &amp; Zhang, 2022; Zhao, et al., BaPipe: Exploration of Balanced Pipeline Parallelism for DNN Training, 2021; Zhao, et al., BaPipe: Balanced Pipeline Parallelism for DNN Training, 2022), XPipe (Guan, Yin, Li, &amp; Lu, 2020), vPipe (Zhao, et al., 2022; Zhao, et al., 2022; Zhu, 2023), PipeMare (Yang, et al., 2021), Chimera (Li &amp; Hoefler, 2021), TeraPipe (Li, et al., 2021), HetPipe (Park, et al., 2020), PipeTransformer (He, Li, Soltanolkotabi, &amp; Avestimehr, 2021; Miao, et al., 2022), AutoPipe (Liu, et al., 2022; Zhang, et al., 2023), Quantpipe (Wang, et al., 2023), PipePar (Zhang, et al., 2023)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Shows a summary of some of the main pipeline libraries that exist. The most important libraries are briefly described and other libraries of interest are included at the end of the table.

3.2 Hybrid Parallelism

The need to reduce the overhead of training large neural networks opened the possibility to implement approaches that involve more than one type of parallelism. Hybrid parallelism (HP) is one of the most recognized approaches today and that, due to the combination of strategies, is used to solve increasingly complex problems and with enormous volumes of computing. The HP is the combination of data parallelism and model parallelism (Howison, Bethel, & Childs, 2012). Current scientific work based on DL often requires training models with large dimensions which can make training much more expensive due to excessive memory usage (Oyama, et al., 2021).

Research to implement hybrid parallelism schemes to increase performance shows important advances. One of these advances is the combination of intralayer and interlayer parallelism to perform distributed training of DNN (Akintoye, Han, Zhang, & Zhang, 2022; Camp, Garth, Childs, Pugmire, & Joy, 2011; Oyama, et al., 2021; Song, et al., 2019; Zeng, Liu, Tang, Chang, & Li, 2021). These are investigations that describe optimizations on the parallel training of the models, demonstrating that despite the large volumes of data, memory costs can be improved. One of the reasons why it is necessary to optimize training is to be able to balance the memory capacity of the GPUs. This memory is limited by the number of computational operations required, which can result in excessively long training times (Narayanan, et al., 2021). Other investigations related to HP (Fan, et al., 2021; Li, S., et al., 2023) refer to optimization in processing times and synchronous frameworks that combine DP and Pipeline for large DNN models.

Recent research has focused on Hybrid Synchronous Parallelism (HSP), which alleviates communication contention without excessive speed degradation by removing network congestion and synchronizing all updated parameters after each iteration (Li, Mangoubi, Xu, & Guo, 2021; Li, Y., et al., 2023). In other investigations (Duan, et al., 2022; Liu, Chen, Zhou, & Ling, 2020; Song, et al., 2019; Zhou, et al., 2021) use heterogeneous Clustered HSPs (HPH) with the purpose of improving training by reducing communication time between layers and optimizing memory consumption.
3.3 Auto-parallelism

Auto-parallelism (AP) is a parallelization strategy that proposes to train DL models on a large scale in an efficient and practical way in several heterogeneous clusters, thus promoting an improvement in performance and memory consumption (Zheng, et al., 2022). Most efforts to improve model training have been manual. AP contributes to parallelization by developing strategies that provide improvements in the automatic conversion of sequential code into multithreaded or vectorized code to make use of available hardware devices (Liang, et al., 2023). One of these proposed models is Rhino (Zhang, et al., 2023) which is a tensor program acceleration system with AP on an Artificial Intelligence (AI) platform. Rhino efficiently searches for a parallel execution plan to speed up performance and communication within processing clusters. With AP many researchers try to avoid training algorithms that are not so highly personalized, since they contain many parameters and that these can be applied more generally (Liang, et al., 2023). Another proposed algorithm is Frontier Tracking (FT) (Cai, et al., 2022) which minimizes memory consumption when the number of devices is limited and uses the additional resources to reduce execution time. TensorOpt (Cai, et al., 2022) is based on FT and allows users to run distributed DNN training jobs without worrying about the details related to parallelization strategies for searching and encoding. Finally, there are also automation algorithms like Galvatron (Miao, et al., 2022) and Alpa (Zheng, et al., 2022). Galvatron is an algorithm that incorporates multiple dimensions of parallelism and automatically finds the most efficient hybrid parallelism strategy by automatically achieving distributed training with different GPU memory budgets. The other algorithm automates MP training of large DL models by generating execution plans that unify the DP, operators, and PP. Alpa distributes the training of large DL models in two hierarchical levels: inter-operator and intra-operator parallelism.

3.4 Mixture-of-Experts Parallelism

Mixture-of-Experts (MoE) models have become one of the most promising model architectures due to their significant reduction in training cost and improved performance compared to equivalent dense models. However, it presents a challenge due to the size of the models and the complex architecture (Rajbhandari, et al., 2022). MoE is an approach that has strong potential for training neural networks with up to trillions of parameters. A MoE layer contains many experts that share the same architecture and are trained by the same algorithm with a routing function that routes inputs to a few experts among all possible candidates (Chen, Deng, Wu, Gu, & Li, 2022). The huge number of parameters of current neural networks means that MoE is closely related to optimization and performance. Studies like Chen et al. (2022), Dai et al. (2022), Li, Jiang, Zhu, Wang, and Xu (2023), and Ma et al. (2018) focus on the optimization of different elements related to MoE. In Chen et al. (2022) a method for the progressive reduction of experts is proposed. The authors propose to progressively remove non-professional experts to reduce a MoE model to a single-expert dense model.

Other authors optimize based on the tasks that run the parallel application. In Ma et al. (2018) they adapt the MoE and propose a multi-task learning approach called MMoE (Multi-gate Mixture-Experts) to explicitly learn model relationships from data. So, they seek to build a single model that learns from multiple goals and tasks simultaneously. Other research (Dai, et al., 2022; Li, Jiang, Zhu, Wang, & Xu, 2023; Nie, et al., 2022) focuses on training. In the first work the authors divide the training in two stages to solve routing fluctuation problems with the implementation of StableMoE, in the second work they propose new communication scheduling schemes based on tensor partitioning and finally in Nie et al. (2022) an end-to-end MoE training framework called EvoMoE is proposed. This framework starts from training one single expert and gradually evolves into a large and sparse MoE structure. Furthermore, it is composed of two phases called expert-diversify phase and gate-sparsify phase. Regarding the need to increase performance, there are studies that modify the routing algorithms of MoE (Fedus, Zoph, & Shazeer, 2022; Riquelme, et al., 2024) or use up to a thousand feed-forward subnetworks contained in a layer (Sparsely-Gated Mixture-of-Experts layer) to determine a sparse combination of experts (Hazimeh, et al., 2024; Shazeer, et al., 2017).

Not only have new algorithms or optimization techniques been developed to increase performance. A large number of libraries and frameworks have also been proposed such as FastMoE (He, et al., 2021), DynaMoE (Kossmann, Jia, & Aiken, 2022), DSel ect-k (Harlap, et al., 2018), and Tutel (Hwang, et al., 2023), which are designed to solve specific problems that can influence performance and scalability. The FastMoE and Tutel libraries are more focused on the parallelism of the trainings. In the case of FastMoE,
it presents a distributed MoE training system for PyTorch with common accelerators and not relying on TPU s (Tensor Processing Units). On the other hand, Tutel is termed as a scalable stack for MoE. Tutel was designed to implement dynamic adaptive parallelism and pipelining without mathematical inequivalence or tensor migration overhead.

Table 2. Hardware configuration

<table>
<thead>
<tr>
<th>Item</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>System name</td>
<td>ThetaGPU</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>24</td>
</tr>
<tr>
<td>Number of CPU per node</td>
<td>2</td>
</tr>
<tr>
<td>CPU</td>
<td>ADM Rome</td>
</tr>
<tr>
<td>Number of CPU cores</td>
<td>64</td>
</tr>
<tr>
<td>Number of GPU per node</td>
<td>8</td>
</tr>
<tr>
<td>GPU</td>
<td>NVIDIA DGX A100</td>
</tr>
</tbody>
</table>

Table 3. Parallelism types performance: DDP and GPipe

<table>
<thead>
<tr>
<th>#GPU</th>
<th>Data parallel/DDP</th>
<th>Model parallel / GPipe</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy</td>
<td>Time (sec)</td>
</tr>
<tr>
<td>2</td>
<td>69.856</td>
<td>256.83</td>
</tr>
<tr>
<td>4</td>
<td>69.025</td>
<td>120.24</td>
</tr>
<tr>
<td>6</td>
<td>70.397</td>
<td>83.01</td>
</tr>
<tr>
<td>8</td>
<td>68.146</td>
<td>58.22</td>
</tr>
</tbody>
</table>

4 Assessing the parallelism of DL trainings

4.1 Experimental methodology

Hardware configuration: The system used to carry out the experiments is a supercomputer located at the Argonne Leadership Computing Facility (ALCF) called ThetaGPU. This system is part of a larger system called Theta. We use this system because it has the necessary GPUs to carry out the experiments presented in this study. Table 2 shows the characteristics of the high-performance computing system used in this study.

Methodology: In order to test some characteristics of the parallelism types, we decided to implement distributed training with the main types of parallelism in DL. Data parallelism via Horovod and model parallelism with the GPipe library. Both types of parallelism are implemented using the DL Pytorch framework.

It is important to clarify that the two types of parallelism have different characteristics. Model parallelism is used with neural network models that do not fit in the memory of an accelerator (GPU), since it is capable of training a neural network by dividing it into multiple partitions according to the number of GPUs available. In the following experiments, a small neural network (compared to trillion-parameter neural networks) is used with the sole intention of experimentally visualizing the differences between types of parallelism and laying the foundation for future studies.

All the experiments carried out used CIFAR100 as dataset and the ResNet18 neural network. This neural network is a reduced version of ResNet, which allows us to evaluate types of parallelism quickly, due to reasonable training times. In the case of training with model parallelism, the neural network used is transformed to a sequential structure so that it can be correctly computed. Additionally, pipeline parallelism is implemented by dividing batches into micro-batches to make the GPUs work in parallel as much as possible.

The results shown are generated by running 10 epochs. 10 repetitions of each experiment were carried out in order to obtain statistically acceptable results. Tables 3 and 4 show the results of these experiments. Table 3 shows the results of 32-bit training and table 4 shows the results of 16-bit training. To implement 16 bit training we use the NVIDIA APEX library activating the O3 mode (FP16).
4.2 Results analysis

The first experiment allows us to compare the performance of the two types of parallelism. Experiments were run on 2, 4, 6, and 8 GPUs. In the case of model parallel training we use an automatic layer distribution by time. This distribution traces the elapsed time of each layer to determine how many layers to allocate per GPU.

Both table 3 and table 4 show execution times of trainings. However, if we look only at the results of table 3 we can make some important observations: 1) The accuracy generated by the two types of parallelism is similar. This shows us that despite the fact that model parallelism is oriented to the training of large neural networks, the results are acceptable and comparable with those of data parallelism. 2) In the previous premise the accuracy is similar. However, the execution times are very different between both types of parallelism. The performance difference when comparing the time of 8 GPUs is noticeable. Data parallel shows a time of 58.22 seconds while model parallel reports a time of 1148.52 seconds. Clearly model parallel performance is degraded by data waiting between GPUs. Even though portions of the neural network run on different GPUs, the neural network is still a sequence of layers that must be respected. 3) Data parallel performance increases when scaling on GPUs. This is very different from model parallel where the time with 2 GPUs is similar to the time with 8 GPUs. It is interesting how with more GPUs a higher overhead is generated because the neural network is even more partitioned. With 2 GPUs the processing is slower, but there is less waiting for the GPUs.

Regarding the results of the table 4 we can highlight two important aspects: First, for both data parallel and model parallel there is a slight degradation of accuracy. This is generated by the reduction in training accuracy. This is generated by the reduction in training accuracy. This is generated by the reduction in training accuracy. Second, the results are similar to 32-bit training, taking into account the aforementioned aspects regarding the results of the table 3.

5 Concluding Remarks

Neural networks are gaining more and more popularity due to their great power to help solve complex problems in many fields of science. In parallel, the complexity of neural network models increases along with the hardware requirements. Due to how difficult and expensive the hardware is, many strategies have been developed to parallelize the processes involved in training neural networks.

In this study we tried to cover the most important concepts together with a large amount of research carried out in the field. The main types of parallelism (data and model parallelism) and the variants that exist, such as pipeline parallelism or hybrid parallelism, were taken into account. In addition, the topic of Mixture of Experts was addressed, which is relatively new in the field of deep learning. In this work, experimentation with the two main types of parallelism was presented and the result allowed us to contrast in a general and brief way some differences that exist between these types. Finally, it is clear that in this work it is not possible to cover all the research and developments that exist related to parallelism in DL. However, readers will be able to generate a very clear idea of the current panorama and the complexity that surrounds this field.

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