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Advancement Of Deep Learning In Big Data And Distributed Systems

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***Abstract*— Digital computing space has grown dramatically since the beginning of the 2000s to deal with an increase in data proliferation. These come from a wide variety area. For example, the number of connected devices explodes with the advent of the Internet of Things. These machines generate a growing number of data, which must be analyzed, by their interactions with the outside environment and its various sensors. Social networks are also another field in which various data has been used, interactive data and metadata that provide information on user profiles. All these data require the storage of large capacity and analysis of several data. In effect, if the arrival of this quantities of information demanded storage improvement, significant advances in processing and interpretation were also required and feasible. In this paper, the main contributions are summarized in a comparison table as detailed in Table 1, like the objectives, challenges, and novelty of each paper are clarified. The architecture or model and applications used—finally, the recommendations for each.**

Keywords: Deep Learning, big data, distributed systems.

I. Introduction

Because of the emergence of deep learning in 2012, the tools used for automated analysis of dealing with complicated problems could no longer be limited and thus provided a platform for such a great depth of complexity and number of degrees of organization, especially when the machine learning sector was unable to provide.

Machine learning tools are generally used to provide increasingly sophisticated services to users. For example, they are used to recommend movies or articles, but also personal assistant services, translation, fault diagnosis, or even automatic image analysis. Machine learning models enable knowledge to be extracted by analyzing large amounts of data. In recent years, deep learning algorithms have revolutionized this field, successfully performing tasks previously considered difficult. For example, in the area of an image, ImageNet's ILSVRC challenge involves classifying a wide variety of diverse images, found on the internet, with over a thousand different classes. In 2012, deep learning methods reached an average error of 16.42% [1] on the first 5 predictions (unlike conventional methods which obtained 26.17% that same year). Over the next five years, deep learning methods scored the highest scores each time, reaching an average error of 0.023% [2] (still on the top 5 predictions).

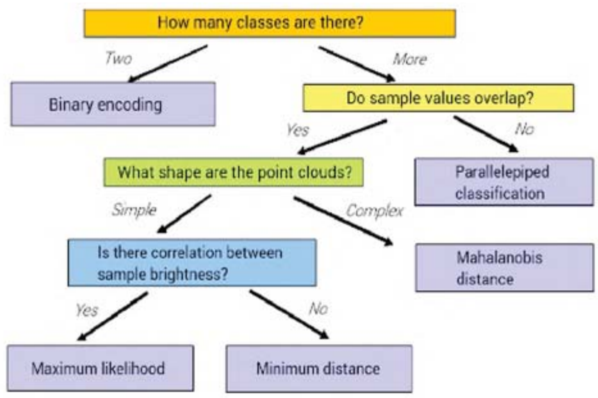

Fig.1 How classification works

In addition to the image field, deep learning methods have also enabled advances in the processing of natural languages [3], speech recognition [4], artificial intelligence for games, and many other areas such as online social media platforms or sensor-based data from smartphones and mobile devices [5-12]. Deep learning is based on models of neural networks with many hidden layers, known as deep neural networks. Learning these deep networks is particularly difficult because it requires the adjustment of many parameters[13]. Recent advances in neural networks as well as the appearance of increasingly large learning bases and progress in terms of hardware architecture (such as the use of graphics cards or dedicated card) have made it possible to popularize deep learning. Also, a lot of research has been done to speed up the learning of these models using parallel computing techniques[14, 15]. The main contributions are summarized in a comparison table as detailed in Table 1, like the objectives, challenges, and novelty of each paper are clarified. The architecture or model and applications used—finally, the recommendations for each.

II. RELATED WORK

1.1 Deep Learning

The author in [9, 16], the best/most predictive features are extracted from high-dimensional data to provide the most accurate predictions, such as classes. Non-linear features usually represent the more abstract aspects of deep architectures. Attempts and advances to collect big data in other disciplines, such as brain structure-function data, behavioral studies on cognitive tasks, and genetics. (for example, ENIGMA, ABIDE, ADNI, ADHD-200, OASIS, ABCD).

The Authors in [17, 18], Deep Learning, is a subset of machine learning that employs three types of learning techniques: supervised, semi-supervised, and unsupervised. It is composed of a large number of layers of artificial neural networks[19]. Each layer contains several neurons with activation functions capable of producing non-linear outputs. This methodology is said to be inspired by the human brain's neuron structure.

In [20], the authors have introduced a distributed platform for significant deep learning with Apache Spark, which has been using by numerous organizations in the use of big data projects.

The authors in [21] provided both the introduction of deep learning and several real-world use cases. They emerged from recent advances in bioinformatics, showing that deep learning can solve problems. Following that, an easy-to-to-follow demonstration of deep learning, has introduced neural network types such as shallow auto- and deep auto, generative and variational autoencoders, and the most recent state of the art architectures. The authors showed eight examples of research efforts that they believe could help improve the current understanding of bioinformatics, all of which spanned a variety of biomedical discovery areas. Concluded by answering questions and solutions about the types of challenges that users will face while implementing deep learning methods and made recommendations for resolving these problems.

In [22], the author applied deep learning to machine learning to general problem-solving in various ways, and a deep neural network forms these input layers into intermediate features.

The power of deep learning, which recently emerged, is due to its ability to learn complex, discriminating and compact features, activate successed prediction, etc. Such as in [6], [9], [16], [18], [20], [22], [23], [24] . Deep learning models are built in three stages, but the second stage can be implicitly dividing into two stages. The illustration in figure 2 illustrates the deep learning process.

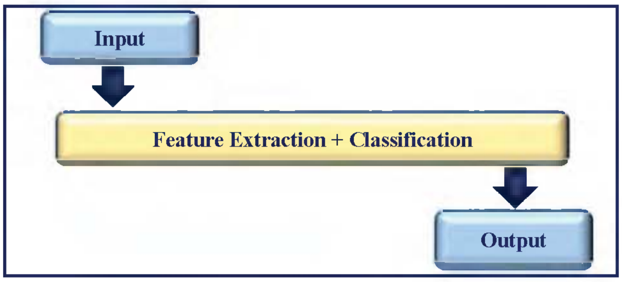

Fig.2 Deep Learning process

Thus, deep learning has gained popularity due to its capabilities for learning more abstract features, reduced model training complexity, good accuracy, ability to handle large datasets, support for transfer learning, and other characteristics [25-28].

1.2 Big Data

Big data is defined as a large volume, a high rate of change, and a wide variety of data that necessitates novel methods of information processing to gain insights and make decisions [9, 29].

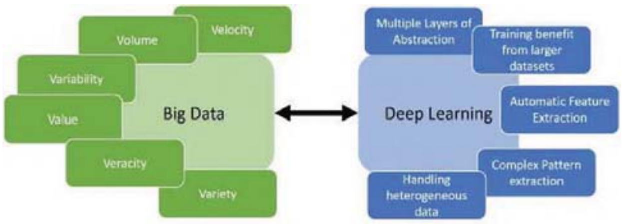

Fig.3 Big data 6 V's and connection with deep learning

Figure 3 above illustrates the 6V's, which are the fundamental characteristics of big data in general. However, data are considering big data if it meets the first three V's: volume, velocity, and variety. And how deep learning techniques' advantages can be leveraged to address these significant data challenges [22, 30, 31].

1.3 Model of Spark execution

As in other Big Data systems, a Spark cluster is comprised of a single driver node and several worker nodes. The driver node is responsible for task management (for example, task scheduling and dispatching) while the workers perform the actual computation [32, 33]. To perform the data processing in a fault-tolerant manner, Spark provides a working compute model. A Spark application possesses the Resilient Distributed Dataset and are immutable records distributed through a cluster, which cannot be further modified; additionally, these operations are both work on large scale RDDs (to specific datasets) and coarsely executed in parallel by various Spark tasks (for example, a single procedure is performed on all data objects at the same time) [34].

Table 1. A compilation of recent publications on deep learning and big data technologies

Author /Year	Objective	Limitations / Challenges	Significance	Deep Learning and Big Data Technologies	Architecture / Model	Application Area	Apache Spark Technique	Recommendation
[20] / 2019	Developed BigDL and Improving the accuracy	Real-time	Distributed deep learning	✓	Spark execut ion	SSD	✓	Comparison of a real-world object
[35] / 2021	Create different acoustic signatures in different environments and Evaluate the generated acoustic data	Frequency	Distributed environment transfer	✓	CNN	classificatio n	UrbanSou nd8K	an architecture different from CNN
[36] / 2017	Integrate a novel machine learning framework that allows Apache Spark to be distributed	• Accuracy and f1 score <75% • Limited big data technologies	Novel framework	✓	MLP	Healthcare & tourism	✓	Improve framework or develop it
[37] / 2018	Offers a distributed anomaly detection method for large-scale networks	Due to the other models, it was taking so much time to train and impact the accuracy	Abnormal behaviour detection	✓	DBN	Network abnormal behaviour detection	✓	Propose a new privacy mechanism to protect distributed IDS
[23] / 2016	Created and implemented a framework for deep neural network training	Small nodes, an extension of run time, and low error rate	HDFS	✓	DNN	Big data applications	✓	Increase the number of Deep Learning algorithms and tune the overall system to improve real-world applications
[38] / 2019	To provide knowledge on IoT security issues	Not discussed any big data technologies	Primarily discusses the usage of big data technologies	✓	IoT	OWASP	x	In order to investigate all possible threats, researchers must perform more research
[39] / 2019	A comprehensive survey and taxonomize existing in V2X	Not discussed big data technologies	Taxonomy of big data technologies	✓	RSU	V2X	Urban	Researchers must combine encryption strategies and trust to protect the network further
[40] / 2019	To provide comprehensive security analysis of IoT	Slight discussion of deep learning, despite big data	In-depth exploration of deep learning algorithms and big data technologies	✓	IoT	IDPs	Machine learning	Enhance the functionality of the IDPs, optimize their capabilities, and ward off potential attacks in real-time
[41] / 2017	Attacks in IoT	Big data and deep learning have not been discussed	In-depth exploration of deep learning and big data	✓	IoT	Compariso n of attacks	Attacks	Planning of each network layer with consideration of refinement in the safety seams
[42] / 2018	Discuss various security challenges and threats	Discussed deep learning and big data technologies insufficiently	In-depth exploration of deep learning and big data	✓	SGs	Classificati on	Security and Threats	A framework is proposed for achieving more secure SGs.

The above table can be summarized with the researchers' most important findings as they have devoted their articles to BigDL and Deep Learning in general, noting that [20] focused on developed BigDL and Improving the accuracy and distributed deep learning. While in [35] create different acoustic signatures in different environments and evaluate them. In [23], [36] focuses on a novel framework that allows Apache Spark to be distributed. But in [37] propose a new privacy mechanism to protect distributed IDS. In [38], [40], [41] focus on IoT in-depth exploration of deep learning and big data. Finally, in [42] a framework is proposed for achieving more security in SGs.

III. DISTRIBUTED SYSTEMS

As we have seen, deep neural networks can be used to provide many services to different users. Ideally, these models are learned using a set of data coming directly from these same users. In practice, this requires bringing all this data together on a machine or a server to train a deep neural network. There are some challenges with this gathering of data and learning within a data center. - In terms of hardware constraints, storing a large amount of data as well as learning a neural network require many resources. These architectures are therefore relatively expensive for the operator who wishes to offer a new service. - Grouping user data on a server also poses constraints in terms of respect for privacy[43]. Regulations regarding privacy are increasingly important in many countries and users are made aware of the use of their data by operators. This second point can be resolved in different ways.

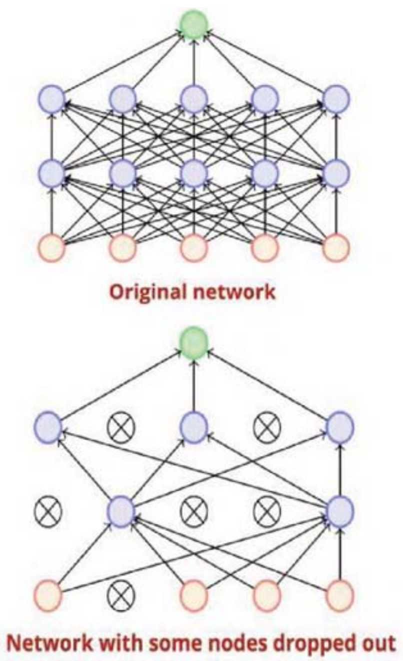

Fig.4 Before and after dropout in neural networks

While recent advances in Deep Neural Networks (DNNs) have been made in solving a variety of bigdata problems, DNNs are now widely used for this purpose. DNN is made up of the following areas of concern:

- Activation layer: This says whether or not the data is activated. in other words ("1" or "0") [44, 45].
- Pooling layer: In short, the aim of this layer is to reduce the volume of data [46].
- Fully-Connected Layer: It is named so because each neuron connects to the neurons of the previous layers, which means that they form an interconnected chain [47]. As shown in figure (4).

Dropout Layer: It is a solution which allows you to reduce over-fitting and subsequent shrinkage of the overall model fit by compensating for new, unique features that might be being mis-incorporated into the model by performing appropriate shrinkage on each existing layer.

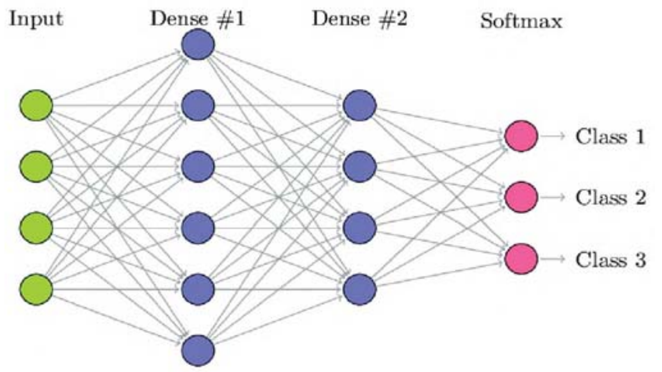

Fig.5 Example of fully-connected neural network

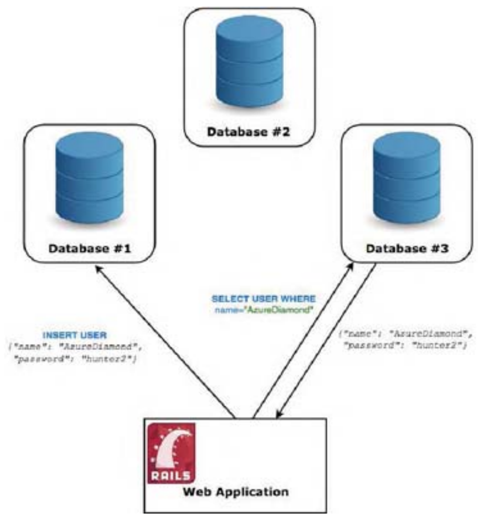

Fig.6 Distributed systems

It is possible to use a subset of user data (those who have authorized access to this data, for example) or to generate it artificially, or even experimentally. Another proposal is to divert an existing database from its original purpose to train the deep neural network to do another task. These solutions are not ideal in terms of learning and can remain relatively expensive for the operator. The objective of this thesis is to propose solutions to carry out the learning of deep neural networks directly on the users' machines in which the data is stored or acquired[48]. This solution has the advantage of not moving this data from the machines to a central server. The operator therefore no longer has direct access. Also, moving learning to users' machines reduces the resources required for the operator to learn the deep neural network. However, this method requires a large number of participants, both for the learning database (distributed among users) and for the necessary resources in terms of calculation. This, therefore, leads us to problems of calculations on distributed systems, applied to learning tasks of deep neural networks[49]. In this thesis, we present our contributions to perform deep learning on distributed systems to enable this type of collaborative learning. Researchers are also interested in this issue, such as Google engineers, authors of Federated Learning[50] [4].

There are mainly six aspects to be addressed on some of the conditions of expanding distributed systems. As listed below:

- Communication effective: The scalability of the distributed learning system is largely dictated by communication [24].
- Storage: Image resolution can slow-down commonly observed with model training.
- Resource scheduling, consistency, fault tolerance, etc.

IV. COMPARISON

Machine learning is motivated by completing tasks that are difficult to define exhaustively or by simple rules in traditional programs. Compared to developing an AI (Artificial Intelligence) to play the game of Go while respecting the rules of the game is relatively simple to program because the set of rules can easily be defined (Each player plays a single pawn in turn, he does not can only place his pawn on a valid square, etc.). However, optimally playing AI to achieve victory is impossible to define simply. This is because the game of Go does not have a known optimal strategy, which makes it difficult to create a series of rules for the AI to follow to win. Also, the number of possible states of the game, as well as the possibilities in each state, are so large that it is impossible to describe everything in a typical program for an AI. Let us take another example with computer vision. Recognizing the face of a human being in an image may seem like a simple task to us because we can do it without thinking. But when we combine the wide variety of possible faces with the set of all the layouts of these 9 Chapter 1 - State of the Art on Deep Learning Faces in an Image, it is impossible to simply describe these from the value of each pixel in the image. In both situations, machine learning can train statistical models so that they find on their own the knowledge necessary to perform these tasks using examples in our data.

A formal definition of machine learning has been proposed by T. Mitchell [51]: "A computer program is said to be capable of learning from an experience E while respecting a task class T with the measure of performance P if it accomplishes task T, measured by P, and improved by experiment E ". We will call this computer program capable of learning model (statistical model or learning model). Let's first see this model as a black box, capable of taking input data from the outside (for example, images from a camera, network traffic from a router, etc.) and returning an output (for example, AI decision making, description of an image, etc). This model has parameters θ which make it possible to influence its output as a function of the input As explained in Michell's definition, learning requires experience E. This typically consists of a Brain learning database that the model analyzes during the learning process. This learning of task T is done using a cost function J. This cost function is calculated on a Best test database, separate from Brain, to measure the performance of the learned model; it is the performance measure P. During training, the model must therefore be able to modify its parameters θ using the Brain training database to improve its performance measured by P. The fact that the performance is measured on a Best database separate from Brain implies a capacity for generalization of the model, that is to say, an ability to respond to cases that he did not see during his experience E. The goal of the model is to make its parameters θ tend towards an optimal $\theta *$ which minimizes J on Best (the measure P).

V. CONCLUSION

We have shown an interest in deep learning in distributed systems with the application of collaborative learning of a deep neural network. then, we proposed different methods to respond in part to the constraints exposed. Adatom allows you to perform asynchronous gradient descent to learn deep networks on many interconnected machines while increasing the costs in terms of communications. We have shown that this method was even able to achieve better results than standard asynchronous gradient descent and that it was able to cope with failures and the involvement of my heterogeneous machine (in terms of computing power). We then motivated, then studied, the possibility of model learning such as GANs in a decentralized distributed system. We have shown that methods that used rumor protocols approximated but did not exceed Federated Learning scores. in this paper, we summarized with the researchers' most important findings as they have devoted their articles to BigDL and Deep Learning in general, noting that [14] focused on developed BigDL and Improving the accuracy and distributed deep learning. While in [27], It created different acoustic signatures in different environments and evaluate them. In [17], [28] focuses on a novel framework that allows Apache Spark to be distributed. But in [29] propose a new privacy mechanism to protect distributed IDS. In [30], [32], [33] focus on IoT in-depth exploration of deep learning and big data. Finally, in [34] a framework is proposed for achieving more security in SGs.

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