State of the Art Artificial Neural Network, Deep Learning, and the Future Generation

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Abstract

The use of neural networks or artificial intelligence or deep learning in its broadest and most controversial sense has been a tumultuous journey involving three distinct hype cycles and a history dating back to the 1960s. Resurgent and enthusiastic interest in machine learning and its applications bolster the case for machine learning as a fundamental computational kernel. Furthermore, researchers have demonstrated that machine learning can be utilized as an auxiliary component of applications to enhance or enable new types of computation such as approximate computing or automatic parallelization. In our view, machine learning becomes not the underlying application, but a ubiquitous component of applications. In recent years, deep learning in artificial neural networks (ANN) has won numerous contests in pattern recognition and machine learning; this view necessitates a different approach towards the deployment of ANN and deep learning.

Keywords—Artificial neural network, deep learning, machine learning, neural network.

I. INTRODUCTION

Most times neural network architectures mimic the human mind and attempt to benefit from the features of nerve cells as much as possible. Deep neural networks (DNNs), like other neural networks, mostly use identical features rather than mimicking the human brain in making precise measurements. Deep learning (DL) is also known as deep machine learning, hierarchical learning or deep structured learning. It is used for the processing of nonlinear information using unsupervised or supervised features for classification and pattern analysis [1]. DLNNs with several layers are considered beneficial since the neural framework can be trained in the first layer to learn parts of the problem, while the neurons are trained in the second layer to learn a different part of the problem; as well as the third hidden layer and so on. So, DLNNs are considered more useful than the shallow networks. A DNN is an ANN which has input layer units and several hidden input and output layers and can be used to model and solve several complex nonlinear relationships. The feature of reducing layers can be configured by adding extra layers; and with a fewer number of units, can model difficult data with the same efficiency as the shallow networks [2]. Deep learning is a more effective approach than the traditional neural network in solving tasks that involve the availability of data [3]. It is used for solving problems on the MIC architecture without changing the baseline algorithm [4]. It is effective in facial expression recognition [5] and in solving many data stream mining tasks [6].

To fully understand the motivation behind this review, this paper is organized into sections as follows: the introduction has been made in the first section; section II presents the motivation for the study, while section III presents the recurring themes of deep learning (DL).In section IV, the supervised neural networks (NNs) is presented, while section V presents the unsupervised learning (UL).Section VI reviews the paradigms of learning; section VII presents the recurrent NNs; section VII presents backpropagation, and section IX discusses self-organizing networks. A conclusion from the review is presented in section X, which is followed by references.

II. THE MOTIVATION

Recently, DNNs have won several awards in the field of pattern recognition due to its flexibility and ability to

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solve many types of problems that cannot be solved using normal computation methods. It is widely used in the field of image and video processing and has shown amazing results in natural language processing. recurring themes of deep learning (DL) (Dynamic Programming (DP)): This is important in the presence of deterministic assumptions because it simplifies credit tasks [7]. Backpropagation is an example DP used in supervised learning. Hidden Markov Models (HMMs) are used in DP algorithms [8], and they are important when the neural network system contains additional ideas or concepts such as graphical models [9], [10].

1) Minimum Description Length (MDL): This means that the complexity of finding a solution by depending on the length of a program. The shortest programs are used in computing [11], [12]; some consider the program runtime [13]- [15] while others consider only constant runtime of the program [16]. MDL has been proposed to regularize and reduce the weight complexity of NNs [17].

2) Graphics Processing Units (GPU): There have been several previous attempts to fasten the GPUs used in NNs [18], [19], though a standard hardware has been introduced [20]. In recent years, GPUs have been widely used in video pl)ys and self-drive cars, leading to and reduction in their prices and improvement of their features in the aspects of training and speed [21], [22].

III. SUPERVISED NNS

1) Group Method of Data Handling (GMDH): This is a method used for training several NNs; some sources consider this method as the first that used multi-layer perception in deep learning system [23],[24],[25]. The polynomial activation functions may be used in the units of GMDH because this form of network has many applications [26],[27].

2) Convolutional Neural Networks (CNN): The CNN was first introduced by Fukushima [28] [29], [30], [31] who set the weights using spatial averaging (an unsupervised learning rule) [30], [31], instead of max-pooling.

IV. UNSUPERVISED LEARNING (UL)

Previously, several researchers have focused on learning without a teacher; among these researchers [32] [33], many have used several UL methods in the field of information theory [34]. Furthermore, UL has been proposed in automatic distribution [35], autoencoder, and linguistic structure encoding [36].

V. PARADIGMS OF LEARNING

Neural networks can be trained by providing it with a range of teaching patterns. These patterns should be carefully selected because they contribute to the speed of the network training, and by using some learning rules, the neural network can either change its training weight and be trained by the set weights.

1) Supervised learning: In supervised learning (SL), there are matching output patterns for each example offered to the neural network. Thus, the neural network can adjust its weight by knowing the difference between the current director and its goal [37], [38]. The most famous learning algorithms use supervised learning. Backpropagation [39], [40], [41], Delta rule, and supervised learning have many possible applications, as in speech recognition, automatic translation, hand-writing recognition, and stock market prediction [42], [43].

2) Unsupervised Learning: The unsupervised learning (UL) is the second type of learning paradigm used in classification networks.

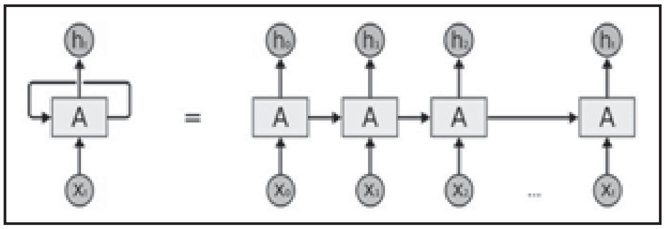
VI. RECURRENT NEURAL NETWORKS

Recurrent Neural Networks (RNNs) are considered as one of the fields of artificial neural networks similar to feedforward neural networks. The difference between them is that the forward data flow in the feedforward neural networks has no feedback nor cycle, but in the RNNs, there is at least one feedback. We can connect a hidden unit to the input units, itself orconnect all units with each other; thus, the internal state of the network enables it to learn sequences.

RNNs are powerful because of the distributed hidden state that makes it possible for them to efficiently retail their prior knowledge and the nonlinear dynamics that enables them to update their hidden state in intricate ways. There are several types of recurrent neural networks architectures. Fig. 1. illustrates an unrolled recurrent network, where A is a chunk of NN, Xj is the jth input of the NN, and h is the output at step j. The RNN is powerful in the fieldof speech [52] and handwriting recognition [53].

The Long Short-Term Memory (LSTM) is one of the important types of recurrent neural network architectures proposed by Jurgen Schmidhuber and Sepp Hoch Reiter in 1997 [54], [55].There are several types of LSTM that offer good solutions to problem-specific topologies [56] and in modifying self-connection [57]. Several tasks are solved by learning the rule of languages explained by

Fig. 1. An unrolled Recurrent Neural Network



deterministic finite state automata [58]-[60]. Free languages which cannot be represented by any other method [61], [62] can be handled with RNN [63], [64]. The result of HMM-based systems is comparable to that of LSTM [65]-[66]. LSTM is used in speech recognition [67], robot localization [68], online drive distraction detection [69], and robot control [70]. Other applications include voice detection [30], handwriting recognition [71], language identification [72], audio onset detection [64], machine translation [73], and social signal classification [74].

The depth of a feed-forward RNN does not apply to a recurrent RNN because it does not depend only on the number of layers in the network which must be multiple nonlinear layers but also because of its temporal structure. There are several types of depth of a recurrent neural network- from the input-to-hidden function and deep hidden-to-hidden function to the hidden-to-output function and stack of hidden states [75].

VII. BACKPROPAGATION

Backpropagation (BP) was first mentioned in a thesis submitted in 1970 by Linnainmaa, and maybe the first touch on the effectiveness of backpropagation [76],[77]. Control parameters were adapted by backpropagation, which is a way for multilayer thresholds using backpropagation [78]. A particular application for backpropagation in neural networks [79] also observed an increasing use of backpropagation for research [80], [81]. In convolutional NNs, [82], [83], backpropagation helped to improve the use of NNs to distinguish fingerprints [84]. Several types of researchers have used backpropagation in neural networks in the field of engineering [85], marketing [86], and medicine [87].

Back-propagation (BP) is an important area of NNs in which BP can be defined as a learning algorithm to reduce the error function. In BP, the errors in the neurons cannot be seen but can be known in the output layers. These errors can be calculated by finding the difference between the output and the desired output. The error in the hidden layers is also updated with the other parameters by depending on weight changes in the layer ahead. BP is a good method for training a multi-layered NN, and this is the motivation for developing BP [88].The NN is used to reduce the error in the gradient descent [89] where there are nonlinear, complex, differentiable and multi-layer parameters [90]-[92]; efficient error back propagation was first reported in a master thesis [76] by using adapting control parameters to minimize the cost functions [93]. A multi-layer threshold NNs [78] was first used with BP in computer programs for finding automatic implementation [94]. The application of BP in RNNs was reported by [95]-[100], and in convolutional Nns LeCun, Boser, Denker, Henderson, Howard, Hubbard, and Jackel [82] and Mohammed, Salih, Ţăpuş, and Hasan[101].

The advantages of BP are in its versatility and accuracy; however, it suffers from problems such as the length of time to resolve, not without complexity. There are many BP applications in medicine, bioinformatics, marketing, and others. BP has a high ability to solve problems that cannot be solved using traditional machine learning [39].

VIII. SELF-ORGANIZING NETWORKS

When we consider biological neural networks, several thoughts may come to mind; one is that our brain receives a lot of information ona daily basis and can recall impressions. The brain does not have any guidance, desired output or preparatory tests, but our cerebrum reacts to the external inputs by changing the state. Based on this basic thought of the biological neural networks and how they connect to the external world and organize themselves, Professor Teuvo Kohonen in the 80s, developed the self-organizing maps (SOM) which learn without a teacher, completely unsupervised [51], and hence, SOM is a type of artificial neural network (ANN).There are several types of self-organizing networks that have been used in a wide range of applications; Rumelhart and Zipser proposed the most basic schemes of SOM, which is a competitive learning algorithm [80].The earliest applications of SOM were in medicine, speech recognition, video and image processing, text or document mining, robotics, hardware implementation, and in computer animation.

IX. CONCLUSION

Neural Networks and Deep Neural Networks can be used for solving many problems that cannot be solved by any other method. Supervised and unsupervised learning have a strong relevance with deep learning in neural networks. GPU and convolutional NNs won competitions not only in pattern recognition but also in other fields like object detection and image segmentation. Backpropagation is used in training Neural Networks that have multilayers; hence, there is an increase in the research interest in this area of study. The Long Short-Term Memory is one of the important types of recurrent neural network architecture. As we know that the main task for recurrent neural networks is to use sequential information, with the output being based on prior computations. Another strategy to be considered about recurrent neural networks is that they have a memory that can capture previous calculations.

On the basis of the basic thought of the biological neural networks and how they are connected to the external world and organized, it becomes certain that self-organizing maps which are completely unsupervised can open a wide space for the development and use of this line of thought in several applications.

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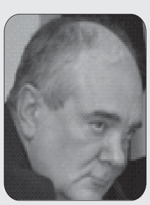

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