ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail
editor.ijmece@gmail.com
editor@ijmece.com

www.ijmece.com

ISSN2321-2152
www.ijmece .com
Vol 7, Issue.1 Jan 2019

An analysis of deep learning and a look forward to its potential

Y. Prasada Reddy

Abstract. This article provides an overview of deep learning algorithms and briefly discusses its potential for future advancements. The first section introduces the idea of deep learning and discusses its pros and cons. Part 2 showcases a number of deep learning methods. Areas of deep learning's application are introduced in the third half. The next step is to investigate deep learning's future advancements by combining the aforementioned techniques and applications. The last section provides a synopsis of the whole article.

1 Introduction

Arthur Samuel, an IBM employee, created a checkers-learning software as far back as 1952. By tracking the pieces' movements, it can create new models and train them to play better. The idea of machine learning as a discipline that might teach computers new skills outside of the realm of deterministic programming first arose in 1959. Several machine learning models, such as deep learning, have been suggested during the evolution of machine learning. There was a lack of initial focus on it because of the high computational cost caused by its complex structure and the enormous quantity of calculations required. Still, deep learning's stellar results have propelled it to the forefront of computer science and made it one of the most talked-about topics in the field. This article will provide a high-level overview of the most important deep learning models before diving into an analysis and discussion of the field's future possibilities.

Assistant professor[1,2,3],
Department of Computer Science and Engineering
KSRM College of Engineering (A)Kadapa

2 Introduction to deep learning

2.1 What is Deep Learning

3 One subfield of ML is known as "deep learning" [1]. In an effort to make advantage of data abstraction at a high level, this technique employs several nonlinear transformations or processing layers with complicated topologies. One kind of machine learning method is deep learning, which uses data characterization to make predictions. When compared to shallow learning, the idea of deep learning is contextual. Figure 1 shows that certain machine

learning models, such Support Vector Machines, are shallow since they only contain one layer or none at all. The foundation of deep learning is a network of hidden layers. A multi-layer neural network is the backbone of deep learning. To learn very abstract aspects of data, deep learning employs the input of one layer as the output of another.

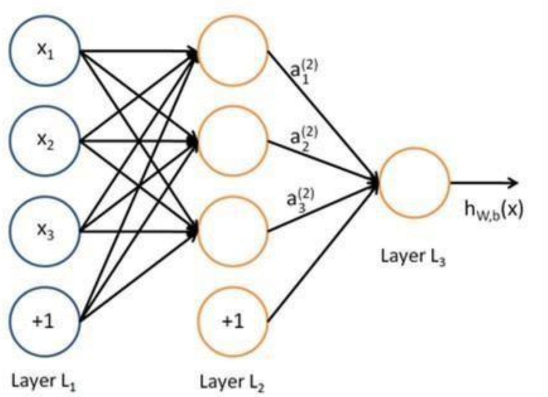

Fig. 1. A single-layer neural network

There are three main types of deep learning, similar to machine learning: supervised, semi-supervised, and unsupervised. A few examples of the current classical deep learning framework include recurrent neural networks, deep belief networks, restricted Boltzmann machines, and generative adversarial networks. These algorithms will be quickly presented in the section that follows.

3.1 Advantages and disadvantages of deep learning

4 Compared to more conventional neural networks, deep learning has shown superior performance. A deep neural network may do a great deal with little computational effort when it has been trained and fine-tuned for a specific purpose, such as picture categorization. Deep learning may also be changed. Modifying the model sometimes necessitates extensive code modifications for conventional techniques. Since deep learning relies on a predetermined network architecture, all that's needed to tweak the model is tweak the parameters, making it very versatile. It is possible to refine the deep learning framework until it is almost flawless. Also, unlike traditional methods, deep learning is not problem-specific and may instead be trained to solve a wide variety of real-world situations. There are also some limitations to deep learning. It has a somewhat high training expense, to begin with. Modern computer hardware has come a long way, and it is now possible to train basic neural networks on widely used computer modules. On the other hand, high-performance processing units may be rather expensive when training increasingly complicated neural networks.

Despite a significant decrease in the price compared to earlier versions, the training cost of deep learning is still very expensive due to the demand for such hardware. Additionally, there is the problem of obtaining enough data for neural network training, which adds to the already high economic expense of training these networks to an acceptable level. Second, deep learning isn't able to acquire new information by itself. Most deep learning systems still need human feature labeling for training, even though models like AlphaGo Zero have evolved that can learn without previous information. Training deep learning becomes more expensive due to the massive amount of labor involved in labeling large-scale datasets. Also, there isn't enough theory to back deep learning. Despite deep learning's impressive outcomes in several domains of application, ongoing research and advancements in deep learning are hindered by the lack of a comprehensive and robust theoretical elucidation for the model.

5 Main Deep Learning Algorithm Introduction

5.1 Convolutional Neural Network

6 As shown in Figure 2, a feedforward neural network known as a convolutional neural network (CNN) achieves remarkable results when processing huge images; its neurons are able to cover peripheral units inside the CNN via its convolution function. A fully connected layer, a pooling layer for integration, and a number of convolutional layers are the usual components of a convolutional neural network. When it comes to picture and voice recognition, convolutional neural networks do better. Its parameter considerations are more limited compared to other deep neural networks. Convolutional neural networks are among the most popular deep learning models due to their many benefits. Here we will quickly go over the fundamentals of a convolutional neural network.

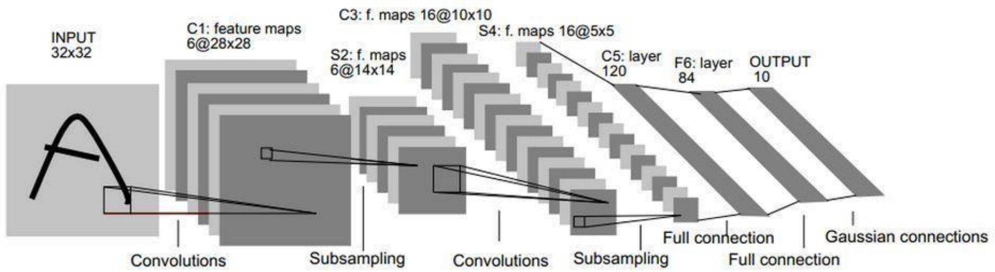

Fig. 2. Convolutional Neural Network, LeNet-5[5]

6.1.1 Convolutional layer.

The convolutional neural network convolves data using multiple convolution kernels in the convolutional layer to generate a plurality of feature maps corresponding to the convolutionkernel.

The convolution operation has the following advantages:

1. The weight sharing mechanism on the same feature map reduces the number ofparameters;
2. Local connectivity enables convolutional neural networks to take into account thecharacteristics of adjacent pixels when processing images;
3. There is no object in the image recognition due to the position of the object on theimage.

These advantages also make it possible to use a convolutional layer instead of a fullyconnected layer in some models to speed up the training process.

6.1.2 Pooling layer

After obtaining the features by convolution, we hope to use these features to do the classification. However, the amount of data that is often obtained is very large, and it is proneto over-fitting. Therefore, we aggregate statistics on features at different locations. This aggregation operation is called pooling. In the convolutional neural network, the pooling layer is used for feature filtering after image convolution to improve the operability of the classification.

6.1.3 Fully connected layer

After pooling layer is the fully connected layer, its role is to pull the feature map into a one-dimensional vector. The working mode of the fully connected layer is similar to that of a traditional neural network. The fully connected layer contains parameters in approximately 90% of the convolutional neural network, which allows us to map the neural network forwardinto a vector of fixed length. We can grant this vector to a particular image class or use it asa feature vector in subsequent processes.

6.2 Deep Belief Network

The deep belief network is a probability generation model. Compared with the neural networkwhich is a traditional discriminative model, the generated model is to establish a joint distribution between observation data and labels, and to evaluate both P (Observation|Label)and P (Label|Observation) while the discriminative model has only evaluated the latter, thatis, P (Label|Observation).

The deep confidence network consists of multiple restricted Boltzmann layers, a typical neural network type as shown. These networks are "restricted" to a visible layer and a hiddenlayer, with connections between the layers, but there are no connections between the cells within the layer. The hidden layer unit is trained to capture the correlation of higher order data represented in the visible layer.

6.3 Restricted Boltzmann Machine

7 To learn the probability distribution from the input data set, a Restricted Boltzmann Machine may be trained using a randomly generated neural

network. A bipartite graph is required for the qualifying model, while it is a Boltzmann machine issue. Both the input parameters and the training outcomes are represented in the model's visible and hidden cells, respectively. At least two units, one visible and one concealed, must be attached to each figure edge. On the other hand, the Boltzmann machine (unrestricted) is a recurrent neural network as it includes the connections between hidden cells. A more effective training procedure, particularly for the gradient divergence process, is achievable with the restricted Boltzmann machine due to this restriction compared to the generic Boltzmann machine. A number of applications have found success with the Boltzmann machine and its model, including classification, time series modeling, information processing, language processing, retrieval of images and information, collaborative filtering, and dimensionality reduction. Areas where restricted Boltzmann machines have found use include topic modeling, feature learning, collaborative filtering, dimensionality reduction, and classification. The limited Boltzmann machine may be taught using either supervised or unsupervised learning, depending on the job at hand.

7.1 Generative Adversarial Network

The Generated Adversarial Network was proposed in 2014. The Generative Adversarial Network uses two models, a generative model and a discriminative model. The discriminative model determines whether the given picture is a real picture, and the generative model creates a picture as close to the ground truth as possible. The generated model is designed to generate a picture that can spoof the discriminative model, and the discriminative model distinguishes the picture generated by the generated model from the real picture. The two models are trained at the same time, and the performance of the two models becomes stronger and stronger in the confrontation process between the two models,and will eventually reach a steady state.

The use of generating a network is very versatile, not only for the generation and discrimination of images, but also for other kinds of data.

8 Deep Learning Application

8.1 Image processing

9 Choosing characteristics by hand is a tedious process. It takes a long time to acclimate. We are thinking about letting the machine figure out the features on its own since manual selection is so unstable. In theory, deep learning can make computers -process, extract features from, and analyze features in pictures, deep learning employs patterns of multi-layer neural networks for image identification.

An example of a multi-layer neural network is the convolutional neural network,

ISSN2321-2152
www.ijmece .com
Vol 7, Issue.1 Jan 2019

which employs convolution operations to extract feature values in the convolutional layer, and then uses the pooling and fully connected layers to process and train data. Below, in the section titled "Technical Implementation of 2.2 Neural Network," the whole procedure is described in great depth.

Despite the fact that neural network image identification is still far from human-level accurate, it is much more efficient than manual recognition and can handle massive amounts of picture data. Applying the neural network approach will result in remarkable progress when confronted with massive amounts of data that cannot be handled manually. Furthermore, deep learning offers a potential solution for facial recognition software. One kind of biometric identification is face recognition, which uses data about a person's face to verify their identity. Numerous industries and fields have made extensive use of face recognition technology, including banking, law enforcement, the military, border patrol, government, aerospace, electric power, manufacturing, healthcare, education, and many more. Additionally, face recognition technology is expected to have promising growth prospects as technology continues to advance and social recognition capabilities improve. For hardware implementation-friendly face recognition, the neural network's properties allow for the avoidance of unduly complicated feature extraction.

9.1 Audio data processing

10 The field of voice processing is greatly affected by deep learning. One or more neural model-based embedding techniques may be included in almost all voice recognition solutions.

There are essentially three levels of speech recognition: signal, noise, and language. At the signal level, we improve and extract the voice signal, or we clean it up, extract its features, and preprocess it as needed. A variety of noises are produced by the various characteristics according to the noise intensity. Words are formed by combining the sounds at the language level, and subsequentlyVarious neural model–based methods exist at the signal level for improving and extracting the speech itself from the signal. Also, it can swap out the old-fashioned feature extraction approach with a neural network-based one, which is much more sophisticated and accurate. Both the noise and language levels make use of a wide range of deep learning approaches, and they use distinct neural model-based architectures for their respective categorization tasks.A

look on where deep learning may go from here

10.1 Representation Learning

11 Feature comprehension and abstraction is at the heart of deep learning. Consequently, deep learning relies heavily on feature learning. There is some wasted data during feature extraction and transmission to the lowest layer since deep learning relies on multi-layer neural networks. But over-fitting may happen if picture characteristics are removed too much. As a result, how to effectively extract the necessary features without over-fitting might be one of the primary research concerns in deep learning research pertaining to representational learning. Advancements in this area will greatly benefit neural networks' ability to classify and generalize.

11.1 Unsupervised Learning

12 We have established that a mountain of labeled data is needed to train a supervised neural network. There is a significant increase in the training cost of the neural network due to the enormous workload. Consequently, the expense of training a network will be substantially reduced if machines are used to do the task instead of humans. In addition to marker classification, Go assessment programs like AlphaGo Zero may make use of unsupervised learning. The rise of AlphaGo Zero demonstrates that robots may accomplish remarkable training outcomes in some domains, even in the absence of human- based previous knowledge. This is where unsupervised learning might help advance technology in some domains by automating machine learning using human knowledge bases beyond the constraints of the present state of the art. Additionally, most people are concentrating their research efforts on supervised learning at the moment, whereas unsupervised learning is receiving less attention. Thus, unsupervised learning offers a wealth of opportunities for study. One of the most popular fields of study right now is unsupervised learning. Another promising area for deep learning's future development is unsupervised learning, in my view.

12.1 Theory Complement

13 Much of the debate around deep learning centers on the fact that it lacks comprehensive theoretical backing, which in turn slows down the field's progress. Research into deep learning has become more thorough, and the theory behind deep learning is always evolving, thanks to the growing interest in deep learningthis year. Still, there isn't enough theory to definitively verify deep learning's underlying principles. Currently, the research is based on a combination of theory, practical testing, and experimentation. In the absence of new evidence, the hypothesis can only rely on tweaks to existing parameters in order to boost the models' efficiency, which might quickly become a research dead end. Hence, it seems that obtaining full theoretical foundation is crucial for the future growth of deep learning. Research into deep learning must progress toward a theory that can adequately describe the fundamental principle's structure, which will need constant refinement.

13.1 Perspective of Deep Learning Application

14 As mentioned in the paper's fourth section, the two primary use cases for deep learning are image identification and voice processing. Furthermore, natural language processing has also made use of deep learning in recent times. Autonomous vehicles, intelligent conversational robots like Siri, picture categorization, medical image processing, etc. are just a few examples of specific uses. For example, convolutional neural networks (CNNs) are primarily used in image processing, although other deep learning frameworks often have significantly different use cases. As an example, convolutional neural networks have been used to separate brain tumors with an accuracy of over 90% in medical image processing. Convolutional neural networks have further medical uses, such as the recognition of Alzheimer's disease brain images; when paired with human judgment, these networks provide more accurate diagnostic findings.

The medical field is only one area where deep learning has found use. By using deep learning, humans may save time and effort while getting higher-quality outcomes since well-trained computers can frequently calculate details that are impossible to achieve by hand. The standard procedure, for instance, involves taking a photo with the camera and then manually recognizing the license plate in order to administer penalty for further traffic signal violations at the junction. Viewing and capturing the photographs by hand is a tedious and inefficient process. Saving time and effort is just one of the many benefits that might accrue from implementing a system that automatically extracts license plate numbers from collected images using a deep neural network. My prediction is that many more fields, including as transportation, medicine, language, robotics, etc., will find uses for deep learning in the near future. While deep learning and artificial intelligence may not be able to fully replace humans just yet, they have the potential to significantly increase productivity.

Conclusion

Here we laid forth the groundwork for deep learning by introducing key algorithms and offering some speculation about its potential future evolution. The field of deep learning has already seen extensive study, a broad variety of application situations, and successful implementation in the real world. But deep learning and neural networks still have a lot of untapped potential; the field offers excellent opportunities for further study and has huge practical implications.

References

First, a review of deep learning for visual interpretation by Guo Y, Liu Y, Oerlemans A, and colleagues [J]. Publishing in 2016, Neurocomputing 187(C):27-48.
Guan-Wei W, Nan-Nan J I, and Chun-Xia Z. Boltzmann machines with restrictions [J]. Engineering and Mathematics in China, 2015.
3. A Rapid Learning Method for Deep Belief Networks[J] by Hinton, Osindero, and Teh. Presented in the journal Neural Computation, volume 18, issue 7, pages 1527– 1554.

4. The authors included are Goodfellow, Pouget-Abadie, Mirza, and others. Emerging Adversarial Networks [J]. The authors published their work in 2014 in the journal Advances in Neural Information Processing Systems, volume 3, pages 2672–2680.
P. Haffner, Y. Bengio, L. Bottou, and Y. LeCun (1998). "Recognition of

documents using gradient based learning". The source is the Proceedings of the IEEE, volume 86, issue 11, pages 2278–2324.