GLANCE ON VARIOUS DEEP LEARNING TECHNIQUES

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Abstract : Deep learning (DL) is an area of Artificial Intelligence which has been a part of digitalization solutions that has a major attention in the digital field. This review paper provides a brief overview of deep learning algorithms which are the most popular like, Auto-Encoders, Convolutional Neural Network (CNN), Deep Belief Networks (DBN), Long Short-Term Memory Networks (LSTMs), Restricted Boltzmann Machine (RBM) and Recurrent Neural Networks (RNNs), A brief account of their history, structure, advantages, and limitations is given, followed by a description of their applications, such as object detection, face recognition, action and activity recognition, and human pose estimation. Finally, a brief overview is given of future directions in designing deep learning schemes and the challenges involved within.

***IndexTerms* - AutoEncoders, Convolutional Neural Network, Deep Belief Networks, Long Short-Term Memory Networks, Restricted Boltzmann Machine and Recurrent Neural Networks.**

1. INTRODUCTION

Deep learning methods are mostly said to be developed since 2006(Deng, 2011). Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learn by example. Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a streetlamp. It is the key to voice control in consumer devices like phones, tablets, TVs, and hands-free speakers. Deep learning is getting lots of attention lately and for good reason. It's achieving results that were not possible before(https://in.mathworks.com). In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers(https://in.mathworks.com).

This paper is an overview of most recent techniques of deep learning, mainly recommended for upcoming researchers in this field. This article includes the basic idea of DL, major approaches and methods, recent step forward and applications. Overview papers are found to be very beneficial, especially for new researchers in a particular field. It is often hard to keep track with up to date advances in a research area, provided that field has great value in near future and related applications. Now-a-days, scientific research is an attractive profession since knowledge and education are more shared and available than ever.

2. RELATED WORKS

There lots of overview papers on Deep Learning (DL) in the past years. They described DL methods and their applications. Here, we are giving brief overview papers on deep learning. (Goodfellow et al., 2016) discussed deep networks and generative models in details. Starting from Machine Learning (ML) basics, pros and cons for deep architectures, they concluded recent DL researches and applications thoroughly. (Nielsen, 2015) described the neural networks in details along with codes and examples. He also discussed deep neural networks and deep learning to some extent. (Schmidhuber, J., 2014) covered history and evolution of neural networks based on time progression, categorized with machine learning approaches, and uses of deep learning in the neural networks. (Deng, 2011) gave an overview of deep structured learning and its architectures from the perspectives of information processing and related fields. (Arel et al.,2010) provided a short overview on recent DL techniques. (Bengio,2009) discussed deep architectures i.e. neural networks and generative models for AI. (Deng et al.,2014) described deep learning classes and techniques and applications of DL in several areas. (Wang et al.,2017) described the evolution of deep learning models in time-series manner. The briefed the models graphically along with the breakthroughs in DL research. This paper would be a good read to know the origin of the Deep Learning in evolutionary manner. They also mentioned optimization and future research of neural networks. (Wang et al., 2018)discussed state-of-the-art deep learning techniques for front-end and back-end speech recognition systems. (Zhang et al.,2016) did quick overview on DL algorithms i.e. supervised and unsupervised networks, optimization and training models from the perspective of representation learning. He focused on many challenges of Deep Learning e.g. scaling algorithms for larger models and data, reducing optimization difficulties, designing efficient scaling methods etc. along with optimistic DL researches.

(Bengio et al.,2013) discussed on Representation and Feature Learning aka Deep Learning. They explored various methods and models from the perspectives of applications, techniques and challenges. (Gary,2018) gave an important review on Deep Learning (DL), what it does, and its limits and its nature. He strongly pointed out the limitations of DL methods, i.e., requiring more data, having limited capacity, inability to deal with hierarchical structure, struggling with open-ended inference, not being sufficiently transparent, not being well integrated with prior knowledge, and inability to distinguish causation from correlation. All recent overview papers on Deep Learning (DL) discussed important things from several perspectives. It is necessary to go through them for a DL researcher. However, DL is a highly nourishing field right now.

3. EVOLUTION OF DEEP ARCHITECTURES

In this section, we will discuss the main recent Deep Learning (DL) approaches derived from Machine Learning and brief evolution of Artificial Neural Networks (ANN), which is the most common form used for deep learning.

Artificial Neural Networks (ANN) have come a long way, as well as other deep models. First generation of ANNs was composed of simple neural layers for Perception. They were limited in simple computations. Second generation used Back propagation to update weights of neurons according to error rates. Then Support Vector Machine (SVM) surfaced, and surpassed ANNs for a while. To overcome the limitations of backpropagation, Restricted Boltzmann Machine was proposed, making the learning easier. Other techniques and neural networks came as well e.g. Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) etc. From that point, ANNs got improved and designed in various ways and for various purposes. Some of the researchers provided detailed overview on the evolution and history of Deep Neural Networks (DNN) as well as Deep Learning (DL) (Schmidhuber,2014, Bengio,2009, Wang,20017, Goodfellow,2016, and Deng,2014).

4. DEEP LEARNING ALGORITHMS

Deep learning methods are a modern update to Artificial Neural Networks that develop plentiful computation. They are concerned with building much larger and more complex neural networks and, as commented on above, many methods are concerned with very large datasets of labelled analog data, such as image, text. audio, and video. The most popular deep learning algorithms are: Auto-Encoders, Convolutional Neural Network, Deep Belief Networks, Long Short-Term Memory Networks, Recurrent Neural Networks and Restricted Boltzmann Machine.

4.1 Autoencoders

Autoencoder is a three-layer neural network, Like feed forward neural network, autoencoder is typically trained using backpropagation algorithm. The training consists of two phases: Encoding and Decoding. In the encoding phase, the model tries to encode the input into some hidden representation using the weight metrics of the lower half layer, and in the decoding phase, it tries to reconstruct the same input from the encoding representation using the metrics of the upper half layer. Hence, weights in encoding and decoding are forced to be the transposed of each other(Moniz,2016).

Autoencoder has got immense popularity as generative model in recent years(Kingma,2013). Non Probabilistic and non-generative nature of conventional autoencoder has been generalized to generative modeling that can be used to generate the samples from the network meaningfully(Alain,2014 Bengio,2014 and Bengio,2013) Several variations of auto encoders are introduced with quite different properties and implementation to learn more efficient representation of data(Doersch, 2016).

4.2 Convolutional Neural Network (CNN)

(Moniz and Pal, 2016) proposed Convolutional Residual Memory Networks, which incorporates memory mechanism into Convolutional Neural Networks. It augments convolutional residual networks with a long short term memory mechanism. The convolutional neural network is a multilayer, feed-forward neural network that uses perceptrons for supervised learning and to analyze data. It is used mainly with visual data, such as image classification(https://pathmind.com). The massive advancements in deep learning are due in part to an exciting application of CNNs in a competition held in 2012. The success of a deep convolutional architecture called AlexNet, which was the basis for the ImageNet Large Scale Visual Recognition Competition (ILSVRC), was the primary reason for significantly accelerated research in the field of deep learning over the past several years. However, CNN's are not limited to image recognition. They have been applied directly to text analytics and can be applied to sound when it is represented visually as a spectrogram and graph data using graph convolutional networks.

CNN architecture is different from other neural networks. To better understand this distinction, consider images as data. Typically with computer vision, images are treated as two-dimensional matrices of numbers. However, in CNNs, an image is treated as a tensor or a matrix of numbers with additional dimensions. Tensors are formed y nesting arrays within arrays, with nesting potentially occurring infinitely. Images, in particular, are treated as four-dimensional tensors. If a scalar is a zero-dimensional object, a vector is one-dimensional, a matrices or collection of vectors is two-dimensional, and a stack of such matrices (pictured as a cube) is three-dimensional. Then a four-dimensional tensor consists of multiple such three-dimensional objects where each element in the cube has a stack of feature maps attached to it. The hidden layers in CNNs contain convolutional layers, normalization layers, pooling layers, and a fully connected layer. It takes an input image, assigns significant weights and biases to various aspects of the image to enable differentiation, and applies filters with minimum pre-processing. While the first convolution layer captures low-level features, the next layers extract higher-level features, creating a network with a sophisticated analysis of the images in the dataset. The CNN algorithm is efficient at recognition and highly adaptable. It's also easy to train because there are fewer training parameters, and is scalable when coupled with backpropagation. The CNN algorithm can be used with Image processing, recognition, and classification, Video recognition, Natural language-processing task, Pattern recognition, Recommendation engines, Medical image analysis(Bengio,2013, . LeCun, 2015 and . https://pathmind.com).

4.3 Deep Belief Network (DBN)

A Deep Belief Network is an unsupervised probabilistic deep-learning algorithm where the network has a generative learning model. It is a mix of directed and undirected graphical networks, with the top layer an undirected RBM and the lower layers directed downward. This enables a pre-training stage and a feed-forward network for the fine-tuning stage(Goodfellow,2016 and

Alain,2014). The DBN has multiple layers of hidden units, which are connected, and the learning algorithm is "greedy" from the stacked RBMs, meaning there is one layer at a time, sequentially from the bottom observed layer. DBNs offer energy-based learning and can benefit from unlabeled data. DBNs are useful for Image and face recognition, Video-sequence recognition, Motion-capture data, classifying high-resolution satellite image data(www.simplilearn.com). Some of the work on analysis of the features to understand what is lost and what is captured during its training is demonstrated in recognition (Ranzato,2011 and Ranzato,2013) computer vision where it is used for the training of higher order factorized Boltzmann machine, speech recognition, for pretraining DNN(Siniscalchi,2013, cS. M., et al. 2013 and Yu et al., 2012) for pretraining of deep convolutional neural network (CNN)(Lee,2011).

In most of the applications, this approach of pretraining a deep architecture led to the state of the performance in discriminative mode, like in recognizing handwritten digits, detecting pedestrians, time series prediction etc(Goodfellow,2016, Moniz,2016, Poultney,2007 and Sermanet, 2013). even when the number of labeled data was limited (Sermanet, 2013). It has got immense popularity in acoustic modeling 50 recently as the model could provide upto 20% improvement over state of the art models, Hidden Markov Model, Gaussian Mixture Model. The approach creates feature detectors hierarchically as features of features in pretraining that provide a good set of initialized weights to the discriminative model. The initialized weights are in a region near the optimal weights that can improve both modeling and the convergence in fine-tuning (Hinton,2005 and Erhan, 2010).

4.4 Long Short-Term Memory (LSTM)

The long short-term memory (LSTM) algorithm is a type of RNN that allows deep recurrent networks to be trained without making the gradients that update weights become unstable. Patterns can be stored in memory for more extended periods, with the ability to selectively recall or delete data. It uses backpropagation but is trained to learn sequence data using memory blocks connected into layers instead of neurons. As the information is processed through the layers, the architecture can add, remove, or modify data as needed. This algorithm is best suited for classification and prediction based on time series data, offering sophisticated results for diverse problems. These enable data scientists to create deep models using large stacked networks and handle complex sequence problems in machine learning more efficiently. LSTM is used for Captioning of images and videos, Language translation and modeling, Sentiment analysis, Stock market predictions(Doersch,2016, pathmind.com, www.simplilearn.com and www.deep-learning-site.com).

4.5 Recurrent Neural Network (RNN)

The recurrent neural network is designed to recognize a data set's sequential attribute and use patterns to predict the next likely scenario. It is a powerful approach to processing sequential data like sound, time series data, and written natural language. The stochastic gradient descent (SGD) is used to train the network along with a backpropagation algorithm. Unlike traditional networks, where inputs and outputs are independent of each other, in an RNN the hidden layer preserves sequential information from previous steps. This means the output from an earlier step is fed as the input to a current step, using the same weights and bias repeatedly for prediction purposes. The layers are then joined to create a single recurrent layer. These feedback loops process sequential data, allowing information to persist, as in memory, and inform the final output(ww.people.idsia.ch, www.simplilearn.com and www.deep-learning-site.com). If an RNN is tasked with guessing the next letter of a previous input letter, it can be trained by feeding letters of known words letter by letter, so it determines relevant patterns. RNNs are layered to process information in two directions: feed-forward (to process data from initial input to final output) and feedback loops using backpropagation (looping information back into the network). RNNs are different from feed-forward networks because feed-forward networks accept one input and give one output at a time. This one-to-one constraint does not exist with RNNs, which can refer to previous examples to form predictions based on their built-in memory. CNNs can learn the context in sequence-prediction problems, as well as process sequential and temporal data. They also can be used in a range of applications. CNNs are useful for sentiment classification, Image captioning, Speech recognition, Natural language processing, Machine translation, Search prediction, Video classification(pathmind.com and www.deep-learning-site.com).

Recurrent Neural Networks Although Hidden Markov Models (HMM) can express time dependencies, they become computationally unfeasible in the process of modelling long term dependencies which RNNs are capable of. (Sherstinsky, 2018) explained detailed derivation of Recurrent Neural Network from differential equations. RNNs are form of feed-forward networks spanning adjacent time steps such that at any time instant a node of the network takes the current data input as well as the hidden node values capturing information of previous time steps. During the backpropagation of errors across multiple timesteps the problem of vanishing and exploding gradients take place which can be avoided by Long Short Term Memory (LSTM) Networks introduced by (Hochreiter and Schmidhuber,1997). The amount of information to be retained from previous time steps is controlled by a sigmoid layer known as 'forget' gate whereas the sigmoid activated 'input gate' decides upon the new information to be stored in the cell followed by a hyperbolic tangent activated layer to produce new candidate values which is updated taking forget gate coefficient weighted old state's candidate value. Finally the output is produced controlled by output gate and hyperbolic tangent activated candidate value of the state. LSTM networks with peephole connections update the three gates using the cell state information. A single update gate instead of forget and input gate is introduced in Gated Recurrent Unit(GRU) merging the hidden and the cell state(Chung,2014). They presented a two layer deep LSTM architecture with each layer having a linear recurrent projection layer with more efficient use of the model parameters(Gers, 2000). Doetsch, P., et.al proposed a LSTM based training framework composed of sequence chunks forming mini batches for training for the purpose of handwriting recognition(Doetsch,,2014).

4.6 Restricted Boltzmann Machine (RBM)

The Restricted Boltzmann Machine (RBM) is a probabilistic graphical model or a type of stochastic neural network(www.simplilearn.com). It is a robust architecture for collaborative filtering and performs a binary factor analysis with restricted communication between layers for efficient learning. It is worth noting that RBMs have more or less been replaced by GANs or variational autoencoders by most machine learning practitioners. The network has one layer of visible units, one layer of hidden units, and a bias unit connected to all visible and hidden units. Hidden units are independent as a way to give unbiased samples. The neurons in the bipartite graph have a symmetric connection. However, there are no connections between the nodes within a group. RBM offers the advantages of energy-based learning like design flexibility, is useful for both probabilistic and non-probabilistic statistical models, restricts connectivity for easy learning, and is used with classification, regression, and generative models(Bengio,2013, Zhang, 2018,www.simplilearn.com and www.deep-learning-site.com). RBM is useful for Recommender systems, representation learning(Coates,2011), Dimensionality reduction(Hinton,2006), Topic modelling, prediction problems(Larochelle,2008). Recently RBM is getting immense popularity in the field of collaborative filtering due to the state of the art performance in Netflix(Salakhutdinov,2007).

Restricted Boltzmann Machine is a variation of Boltzmann machine with the restriction in the intra-layer connection between the units, and hence called restricted. It is an undirected graphical model containing two layers, visible and hidden layer, forms a bipartite graph. Different variations of RBMs have been introduced in literature in terms of improving the learning algorithms, provided the task. Temporal RBM(Sutskever,2007) and conditional RBM(Taylor,2007) proposed and applied to model multivariate time series data and to generate motion captures, Gated RBM(Memisevic,2007) to learn transformation between two input images, Convolutional RBM(Lee,2009) to understand the time structure of the input time series, mean-covariance RBM(Dahl,2010 and Mohamed,2012) to represent the covariance structure of the data, and many more like Recurrent TRBM (Sutskever,2008), factored conditional RBM (fcRBM)(Taylor, 2009). Different types of nodes like Bernoulli, Gaussian(Hinton,2012) are introduced to cope with the characteristics of the data used.

5. DEEP LEARNING FRAMEWORKS

There are a good number of open-source libraries and frameworks available for deep learning. Most of them are built for python programming language. Such as Theano21.Tensorow , PyTorch, PyBrain, Caffe , Blocks and Fuel , CuDNN,Honk, ChainerCV , PyLearn2, Chainer, torch,neon etc(Bahrampour,2015, Niitani,2017and https://github.com) did a comparative study of several deep learning frameworks.

6. CONCLUSION

Deep Learning (DL) has highly developed the world faster than ever, there are still ways to go. Your results are only as good as your data. We hope deep learning and AI will be much more devoted to the betterment of humanity, to carry out the hardest scientific researches, and last but not the least, to make the world a more better place for every single human.

Neural networks feed inaccurate or incomplete data will simply produce the wrong results We are still away from fully understanding of how deep learning works, how we can get machines more smarter, close to or smarter than humans, or learning exactly like human. DL has been solving many problems while taking technologies to another dimension. However, there are many complicated problems for humanity to deal with. For example, people are still dying from hunger and food crisis, cancer and other dangerous diseases etc.

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