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A Survey on Inferences from Deep Learning Algorithms

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Abstract: Deep learning, viewed as a part of machine learning is capable of learning the essence of data from a small data set by learning a nonlinear network structure. Deep learning algorithms have shown wide use in speech recognition, image processing, video processing and has wide application in various areas which uses any of these techniques. Still many application areas are emerging and are untouched by deep learning architectures. This study gives an overview of various application areas where deep learning algorithms or variants are applied and proved beneficial. As well it gives a summary of the top five popular deep learning tools available for research and implementation of deep learning algorithms.

Key words: Machine learning, deep learning, deep learning tools, beneficial, techniques, implementation

INTRODUCTION

Learning is required where we cannot directly write a computer program to do a task but the task is accomplished using the past experiences or history. Machine learning is nothing but writing an application which learns from past experiences. We require machine learning where we wish the system should adapt to changes in environment and act accordingly. Many such examples exist like conversion of speech into text, best path determination by the router based on quality of service, etc. Machine learning is that branch of computer science which focuses on development of programs that can learn by themselves (Alpaydin, 2004).

The digital data is increasing day by day thereby posing challenges to machine learning. The term big data has become buzzword because of its distinct characteristics as volume, veracity and velocity. The data collected today are complex, huge and unlabelled. To analyse such data simple machine learning algorithms are not sufficient. Deep learning algorithms are one of such avenues which helps in processing of complex, huge and unlabelled data (Bengio, 2009). Deep learning was first time proposed by Hinton *et al.* It is a new field of machine learning. Algorithms in deep learning aim at learning the features from the hierarchies of features which exists at various levels of abstraction (Najafabadi *et al.*, 2015), thus, making the analysis of complex and huge data possible.

MATERIALS AND METHODS

Deep learning and algorithms: Normal machine learning algorithms research on a neural network with 1 or 2 hidden layers. The network architecture in deep learning is created with the input layer, the hidden layers of which the number is normally 5 or 6 or even more and the output layer (Bengio, 2009) (Fig. 1).

The network transforms low-level features of images into high level features which are more abstract and thus makes classification and prediction easier. Generally, deep architectures have more units in hidden layers than normal shallow architectures.

Though the deep networks were available but were difficult to train. In 2007 a greedy layarwise training of deep network was proposed (Bengio *et al.*, 2007). This algorithms made deep architectures for use in real world scenarios.

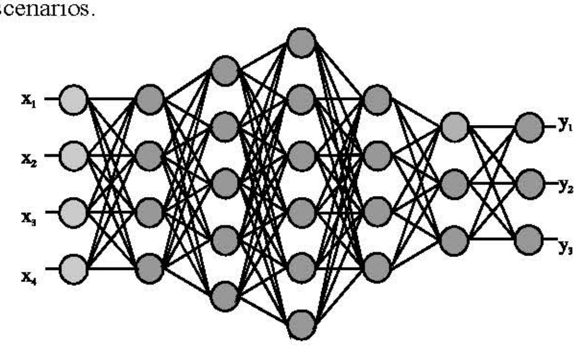

Fig. 1: A deep architecture

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Deep learning has numerous algorithms of machine learning. These algorithms attempts to model high-level abstractions in data. They create or design architectures which are composed of many non-linear transformations. Deep architectures can be modelled using any combinations of layers of network but still it has set traditional algorithms such as stacked autoencoder, deep Boltzman machines, deep convolutional networks and deep belief networks.

RESULTS AND DISCUSSION

Stacked auto-encoder: An auto-encoder is an artificial 3 or more layer neural network. It is used for unsupervised learning and output units are connected back to input units. The main purpose of an autoencoder is to learn a representation (encoding) for a set of data, typically for the purpose of dimensionality reduction. The other variant, called as stacked de-noising auto encoders, researches on cleaning (de-noising) the partially corrupted output. This algorithm was introduced in 2008 by Vincent *et al*. (2010) to provide a specific approach to good representation. If we can obtain output robustly from a corrupted input then it is termed as a good representation. Such a good representation is useful for recovering the corresponding clean input.

The auto-encoder network is trained to get the correct output. Now this cleaned output is used as a input to a supervised machine learning algorithm for example; Support vector machine or logistic regression or softmax layer. This is depicted clearly in Fig. 2 where x and y represent input and output and h represent the hidden autoencoder layers.

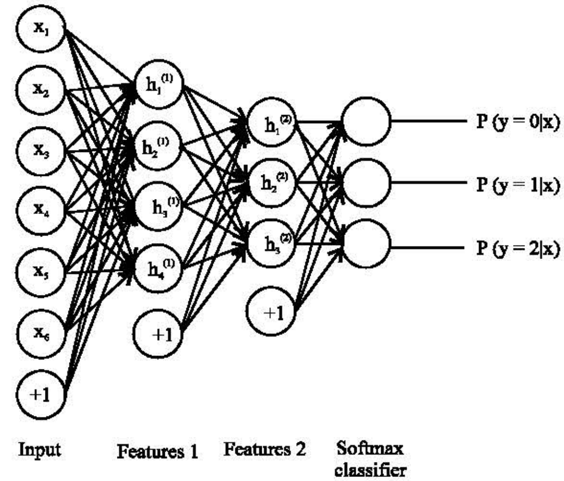

Fig. 2: Stacked autoencoder

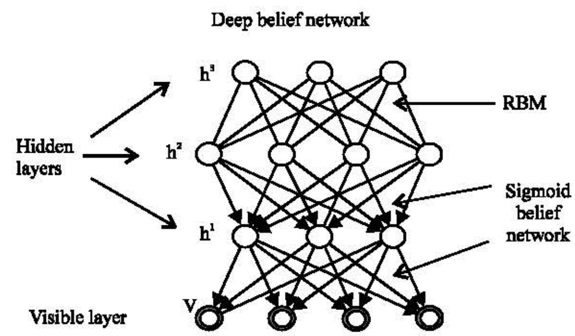

Fig. 3: Deep belief network

Deep Boltzmann machines: The basic unit of Deep Boltzmann Machines (DBM) are boltzmann machines which is constructed using stochastic binary nits. These units are symmetrically coupled and are stochastics. A deep Boltzmann machine is a created with layers of boltzmann machines. It is created with a set of visible units and many layers of hidden units. DBMs are very good in learning complex and abstract internal representations of the input. They can be effectively used in tasks such as object or speech recognition. One advantage of DBM is that they use limited labelled data. They canget the exact representations constructed using a very large supply of unlabelled sensory input data. The performance and functionality of DBMs are limited because of speed (Salakhutdinov and Hinton, 2009).

Deep belief networks: A Deep Belief Network (DBN) is a probabilistic and generative model. They are made up of multiple layers of latent units. The latent units are binary and input and output units are real or binary. One characteristics of BDN is that the layers are not intra connected. One layer units are connected with units of neighbouring layer. DBN has undirected connections in its deep layers while for the first two layers the connections are directed.

DBNs are useful when limited training data are available. Because of limited data weights can be poorly initialized and thus can significantly affect the model's performance. The weights obtained are in a region of the weight space that is near to the optimal weights. Thus, it is easy to have improved modelling and faster convergence of the model.

A DBN can be efficiently trained in an unsupervised, layer-by-layer manner. The layers here are made of Restricted Boltzmann Machines (RBM) (Larochelle and Bengio, 2008) (Fig. 3).

Deep convolutional networks: Deep Convolutional Networks (DCN) can be constructed using layers of convolutional restricted Boltzmann machines. These machines are stacked together to form the network. In recent research convolutional deep belief networks are used for deep learning. The recent research includes using these networks on standard datasets to achieve many good results. Convolutional neural networks are used for image processing, on the same line; DCN can be effectively used for the task of image processing and object recognition. Also, being a generative model it is used in other domains also to get best results. The main advantage of using DCN is scalability for high dimensional images and the processing is translation-invariant (Nguyen *et al*., 2015).

Application areas: Deep learning architectures and algorithms have wide application area right from computer vision, automatic speech recognition, audio recognition, bioinformatics, natural language processing, etc. These algorithms have shown remarkable results on various tasks. Table 1 gives a summary of various major application areas and deep learning algorithms used in these areas. Still there are many new areas where deep learning algorithms are not applied. The major research lies in testing these algorithms in these new area and finding out their usability.

Table 1: Deep learning in various application areas

Application area	Deep learning algorithms used	Paper	Inferences
Security	DBN with dropout	DeepSign: Deep learning for automatic Malware detection (David and Netanyahu, 2015)	Deep learning is applied mainly in speech, image and video domain. New domain is tried as malware detection
Image processing	CNN	Improving deep convolutional neural networks with unsupervised feature learning (Nguyen *et al*., 2015)	Worked on image dataset. Next step is to investigate the application to other network architectures to gain further insight into the proposed approach
	Stacked de-noising auto encoders	Stacked denoising autoencoders: learning useful representations in a deep network with a local denoising criterion (Vincent *et al*., 2008)	Classification error is reduced. Performance is equal to performance of DBN. Experimental results show that DAE are helpful for learning of higher level representations
	Autoencoder, deep SVM and GMM	A novel deep learning by combining discriminative model with generative model (Kim *et al*., 2015)	Output is created using SVM and GMM and then are combined and given to another layer. Easier classification of the uncertain data
	SVR with linear rectifier units	Estimating crop yields with deep learning and remotely sensed data (Kuwata and Shibasaki, 2015)	Using Satellite images crop yield estimation is done. Has better accuracy then normal SVM
	Deep nural network with SVM	Deep learning using linear support vector machines	On standard datasets like MINST, CIFAR-10 proved to be more accurate. Simple for implementation
	SDA and SVM	An introduction to deep learning (Lauzon, 2012)	Stacked auto encoder with SVM proved to be more accurate than SDA and logistic regression. Preprocessing is not required While in regular SVM and KNN the preprocessing is required
Regression analysis	Deep SVM	Deep support vector machines for regression problems	Experimented on 10 regression datasets performance and accuracy is improved
Finance	Deep SVM with fuzzy	A hierarchical fused fuzzy deep Neural network for data classification (Deng *et al*., 2016)	Deep learning SVM with fuzzy system is applied on financial trading system. Compared with normal SVM and normal fuzzy neural network accuracy and performance is improved
	Deep neural network with genetic algorithm	Genetic deep neural networks using different activation functions for financial data mining (Zhang *et al*., 2016)	Two different activation functions are used. Used optimization method as GA for activation functions, future work is to use ant colony optimization and Bee's algorithm. The system gave better accuracy
Big data: traffic Network analysis	SAE with logistic regression	Traffic flow prediction with big data: a deep learning approach (Lv *et al*., 2015)	Stacked auto encoders are used and compared with SVM, logistic regression is used for prediction. Other deep learning algorithms can be used. As well other prediction models can be used
Big data and image processing SVM. 8	SAE and SVM	A deep learning method combined sparse autoencoder with SVM (Ju *et al*., 2015)	SVM with Sparseautoencoder is used. Here, a 2 hidden layer network is used to determine the features and then output is given to SVM for classification. Better results than simple standard datasets were used for experimentation
Big data and education	SAE	Predicting students performance in education data mining (Guo *et al*., 2015)	Used deep learning to predict student's performance. Used sparse Auto Encoders and back propagation for learning. Applied to 9th school children data. Used 4 hidden layers and GPU processor
Music generel classification	Deep feed forward network and LRU	Deep neural networks: A case study for music genere classification (Rajanna *et al*., 2015)	Created a 2 hidden layer deep feed forward neural network for classification of music. Used rectifier linear units as the activation function. Used preprocessing on data to reduce the dimension
Handwritten character recognition	DBM	Comparison of different variants of restricted boltzmann machines (Guo *et al*., 2014)	DBM is the best RBM variant in terms of the classification errors. However, training a DBM is time consuming and the tuning of parameters is very difficult to the users

Table 1: Continue

Application area	Deep learning algorithms used	Paper	Inferences
Network analysis	Restricted boltzmann machines	LRBM: A restricted boltzmann machine based approach for representation learning on linked data (Li *et al*., 2014a, b)	RBM are used to do link prediction and node classification on linked data that is network data like Facebook network
Sentiment classification	Deep network using RBM	Active deep learning method for semi-supervised sentiment classification (Zhou *et al*., 2013)	Used RBM with unsupervised learning. The last layer is the linear RBM. The hidden layer with linear RBM has more nodes as compared to other hidden layers
Credit card analysis	Deep neural network and SVM	Deep learning for credit card data analysis (Niimi, 2015)	In this study, two major applications are introduced to develop advanced deep learning methods for credit-card data analysis The proposed methods are validated using various experiments with other machine learning algorithms. At the end it is observed that deep learning algorithms exhibits similar accuracy to the Gaussian kernel SVM
Big data	Tensor auto encoder	Deep computation model for unsupervised feature learning on big data (Zhang *et al*., 2016)	The tensor deep learning model takes more times to train the parameters than that of the stacked auto-encoder and the multimodal deep learning model, especially for feature learning on heterogeneous data
	Deep SVM	Deep twin support vector machine (Li *et al*., 2014)	Used twin SVM; that is first SVM for feature selection in hidden layer and another for classification as a main SVM. Accuracy is increased. Now these twin SVM are put in two layers-one in hidden layer whose output is given to main twin SVM
	Deep neural network	Big data and deep learning (Wilamowaski *et al*., 2016)	Common training algorithm for deep networks is suggested new visualization method is demonstrated
Time series	DBN with SVR	Ensemble deep learning for regression and time series forecasting (Qiu *et al*., 2014)	Ensemble deep belief network is proposed. Aggregated the forecasting outputs from various DBNs by a support vector regression model Provided best training construction result and most accurate prediction results. Standard power and time series dataset are used
Multimedia	DCNN	Describing multimedia content using Attention-based encoder-decoder networks (Cho *et al*., 2015)	Deep networks are used for structure output problem. The input is mapped to output which has its own structure. Encoder decoder architecture is used to describe multimedia content

Table 2: Summary of popular deep learning tools

	Tools				
Features	Pylearn 2	Theano	Caffe	Torch	Cuda-convnet
Hardware	CPU, GPU	CPU, GPU	CPU, GPU	CPU, GPU	GPU
Architecture	Three key components: dataset, model and training	Fairly Hacky	Standard layer wise design	Well designed with modular interface	Convolutional feed-forward algorithm classes neural networks
Ecosystem	Python	Python	C++	Lua	MATLAB, C++/CUDA
Platform	Cross platform	Cross platform	Cross platform	Linux based	Cross Platform
Performance	Good	Good	Good	Good	Best
Interfaces	Github	Python	Pycaffe	LuaJIT	CUDA
Advantages	Pylearn 2 is designed for flexibility and extensibility of achine learning algorithms	Quickest, computational graph is nice abstraction, high level wrappers ease the pain	Train models without writing any code, feedforward networks and image processing	Easy to write your own layer types and run on GPU, lots of pretrained models	Efficient implementation of convolution in CUDA
Disadvantages	Load all data set to main memory	Error messages can be unhelpful, large models can have long compile times	Need to write C++/CUDA for new GPU layers not good for recurrent networks not extensible	Not good for recurrent neural networks	It requires high performance GPU

Deep learning tools: While deep learning algorithms seem attractive; choosing the correct deep learning tool for implementation is important. There are various tools available. This section gives a comparative overview of top deep learning tools. All these tools are open source tools (Al-Rfou *et al*., 2016; Jia *et al*., 2014) (Table 2).

CONCLUSION

Though deep networks are proposed in 1996 their use has gained popularity from 2006. Because of advancements in processing capabilities of machine and parallel processing framework, implementation of deep networks and deep learning algorithms seems possible. Deep learning algorithms are found to be very useful in the area of image processing, Signal processing and natural language processing. But now there is a need to apply these concepts in new areas. With the advancement of big data new challenges are emerging and deep learning is proving useful in handling these challenges. It is evident that new application area challenges are solved effectively with the help of deep learning algorithms. It will be very interesting to test these algorithms in still more new areas to get accurate results and prediction.

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