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An Analysis on Deep Learning with its Advancements

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ABSTRACT

Most recently, Deep Learning being a part of wider area of Machine Learning plays a vital role of study from data representations. DL has been rapidly growing in several application domains by means of its different approaches, methods and tools. It is designed with a network of interconnected neuron units resembling the structure and function of bio neuron. Deep learning network has the ability of studying unsupervised from data collection which is not structured or labeled, supervised data containing labels, semi-supervised data which is partially supervised also known as Reinforcement data. Deep learning upgrades the concepts of machine learning to the next successive level. Deep learning algorithms has been constructed with multilayered connections, which makes use of artificial neural networks to study multiple levels related to the different levels of abstraction to solve complicated problems. Expected Outcomes have been shown that deep learning accurates the learning data features compared to traditional machine learning concepts in the various sectors. Deep learning architectures are Deep Neural Networks, Deep Belief Networks, Convolutional Neural Networks, AutoEncoders and so on. Every interconnected layer represents a depth of knowledge. This paper confers a brief study on Deep learning, its categories and its advanced features such as AutoEncoders, Generative Adversarial Networks and its types , Multi-view learning and Multi-task learning.

KEY WORDS: DEEP LEARNING, CATEGORIES OF DL, AUTOENCODERS, GAN, MULTI-VIEW LEARNING, MULTI-TASK LEARNING .

INTRODUCTION

Deep Learning is a method of machine-learning extremely based on its characterization such as an image expressed in different ways as a vector (or) series of edges using certain representations to soothe the tasks simpler Guo et al., (2017). Deep learning behaves as a class of Machine Learning algorithms which uses multiple layers to extract consecutively higher level features from the distributed input Zhaoet al., (2018). Being DL a part of Artificial Intelligence it consists of networks capable of learning unsupervised data or else unstructured or else unlabeled data which is also known as Deep Neural Learning (or) Deep Neural Network.

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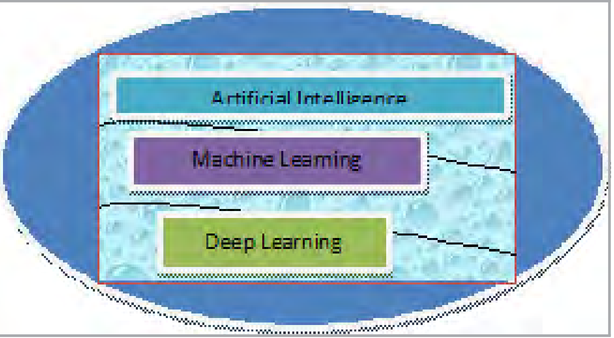
Pros and Cons of Deep Learning Process:
Pros and Cons of DL:
Pros:
1. DL promotes the complex relationships modeling and its concepts using multiple levels of representation
2. The use of supervised, unsupervised (or)semi-supervised learning features and its nature of

hierarchy supports to extract the higher levels of abstraction which are defined using the outcome values from its underneath levels.

Figure 1: Model of Deep Learning



Cons:

1. Modules designed in this learning usually contain repetitive connections intervening each pair of nodes which connects the next two layers of the neural network
2. Varied signal point interconnections are generally overlooked.
3. Enormous collection of layers are built on top of each module to extract the pyramid features from the extent bottom to top.

Why Deep Learning Is Favoured?: An advanced growing "Deep Learning" is a sub-field of machine-learning closely related to Artificial Intelligence. It promotes the modeling of difficult relationships and its concepts by using various levels of representations. It supports the following features.

Table 1. Differences between ML and DL

Concepts	Machine Learning	Deep Learning
Working Process	Different types of automated algorithms are used to predict future decisions and model the functions use the data fed to it	Combines data features and its relationships with use of neural networks that transforms the relevant information through the various stages of data processing
Management Process	Numerous algorithms are directed by the analysts to find the varying variables in datasets	After implementation, the algorithms are generally directed to itself for further analysis on data and its relationships
Data dependencies	Data requirement is smaller in size	Data requirement is larger in size
Problem Solving Method	-It breaks down the problem into multiple sub problems until it is solved to obtain the final outcome	It facilitates the direct point-to-point problem solving
Execution time	Less Parameters are used	Too many Parameters are used
Training	The training takes little time i.e, seconds to hours	The training requires more time possibly two weeks
Testing	It requires more time during testing which mainly depends on the amount of data	It requires very little time during testing
Interpretability	It is easier to understand and reasoning the result	It is difficult to understand and reasoning the result
Requirement of Data Points	Few thousand data points are usually used for analysis	Few million data points are allowed to run in program for the analysis
Outcome	It can be a numbered value such as a score or division	It can be any among the values such as a score, an element, text (or) sound

Universal learning approach: Deep Learning also called "Universal learning" since it can be applied to any kind of an application domain.

Strong and Powerful: Various approaches in Deep Learning does not require the design of features instantly, since the features are learned immediately optimum for the related tasks at time Chalapathy et al., (2019).

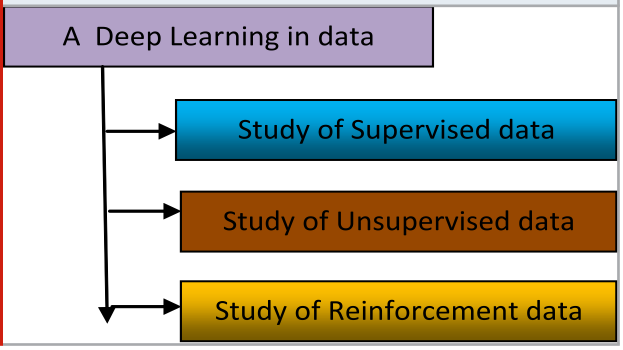
Conception: The deep learning approach similarities can be generated in different applications or else with different datatypes. This type of learning approach is called "Transfer Learning". Its advantage is useful in case the problem does not support sufficient available data.

Expandability: It is highly expanandable. A research paper published in year 2015 illustrates the network "ResNet" implementation with its concepts described by Microsoft to the networkers designed with 1202 layers which can be often implemented at a super computing scale Jinglin Xu et al,. (2019) Also, another initiative made at a superior level which leads a Lawrence Livermore National Laboratory (LCNL) in constructing frameworks to implement thousands of nodes in field of networks.

Machine Learning Vs Deep Learning

Categories of Deep Learning Approaches: Methods stated in both ML and DL are almost similar. The different studies on data are constructed under complicated learning structures which are entirely different.

Figure 2: Different approaches in DL



Supervised Learning: In Deep Learning, there are numerous learning algorithms available to update the weights of DNN. During the training process to represent an efficient function related to task. Supervised learning mainly concentrates on labeled data, where any expert can explain the chosen task performance. The data points added in the list includes an action pairs based on observations which points to the neural webwork models. In supervised learning approach, the environment has a number of inputs and its corresponding outputs as (At,Bt) ~ P. For example : Input -> At

Prediction -> B^t=f(At)
Loss value-> l (Bt, b^t)

The decision maker has the responsibility to consecutively update the network attributes for the better estimation of the intended outputs. Also, the decision maker should be capable to receive exact answers to the questions raised from different domains which are possible after every successful training.

There are various studies in supervised data learning approaches to show its usefulness in deep learning included with its types

- Deep Neural Networks [DNN]
- Convolutional Neural Networks [CNN]
- Recurrent Neural Networks[RNN]
- Long Short Term Memory [LSTM]
- Gated Recurrent Units [GRU]

Deep Neural Network: This neural network states the numerous layers through which data and its features are to be extracted. Deep Neural Networks contains its own class of Deep Belief Networks (DBN) which is made of multiple layers consisting visual designs recognised as Restricted Boltzmann Machine (RBMs) Qing Zhang et al., (2019). Either all (or) part of the parameters of DBN are smoothen to satisfy the certain criteria. Example: a supervised learning or a clustering loss.

Deep Belief Networks: DBN supports an aspect of random variation and its models which consists of multi layers holding random and hidden variables. The graphical pattern of Restricted Boltzmann Machine (RBM) and DBN are closely related due to framing and assembling a quite number of RBMs which enables the number of hidden layers to train the data more efficiently through RBM for remaining stages. Further, RBM is a well known special styled pattern of a Boltzmann Machine (BM). DBNetworks utitilizes the study of unsupervised learning to find numerous layers features used in a feed-forward neural network and properly processed to maximize the discrimination efficiently. Also, DBNs responses better classification results than broadly used learning techniques, outperforming SVM , KNN and a decision tree.

Convolutional Neural Network: This neural network is composed of single (or) multiple convolutional layers by means of subsampling steps and then followed by single (or) multiple with completion of connected layers similar to standard multilayer neural network. The calculation formula for the convolution layer is

$$Xn = f\,(\Sigma mW^{m}nX^{m}+bn)$$

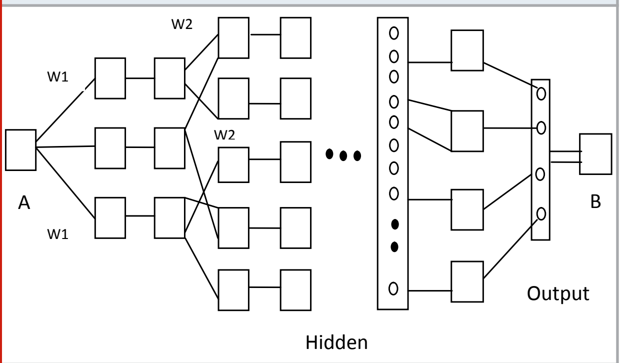
Where Xn represents the nth feature map
$W^{m}n$ represents the convolution kernel
m means the number of pixel channels
bn means the offset vector of the corresponding position map

In accordance with the configuration of deep learning, CNN is meant to reduce the data preprocessing steps.

The main sources for CNN to decrease its meshwork training parameters are Local receptivity, Weight Sharing and Pooling. The most highlighting part of CNN is its learning hierarchial features obtained from large collection of untagged values.

Unsupervised Learning: The systems processed with unknown labels known as unsupervised learning systems. In this system, the decision maker studies the internal (or) most vital features to find the relationships not known (or) its structures placed inside the input values. Mostly, unsupervised learning members are good in clustering based on its similarities, non-sequential dimensionality reduction which includes AutoEncoders, Restricted Boltzmann Machines and Generative techniques such as GAN. Additionally, Recurrent Neural Networks like LSTM and RL used in Unsupervised learning systems according to application areas.

Figure 3: Structure of CNN model



Semi-Supervised Learning: The study of data in Semi-Supervised Learning mainly concentrates on a part of labeled datasets often called Reinforcement Learning. In few cases, the semi-supervised learning techniques prefers the use of Deep Reinforcement Learning (DRL) and Generative Adversarial Networks. As like unsupervised learning, RNN includes LSTM and GRU in use of semi-supervised learning too.

Reinforcement Learning: The learning on reinforcement type of data allows the model to learn and execute the certain tasks through experimental process. This can be well modeled as Markov decision process which is properly illustrated as a record (S, A, P, R) where,

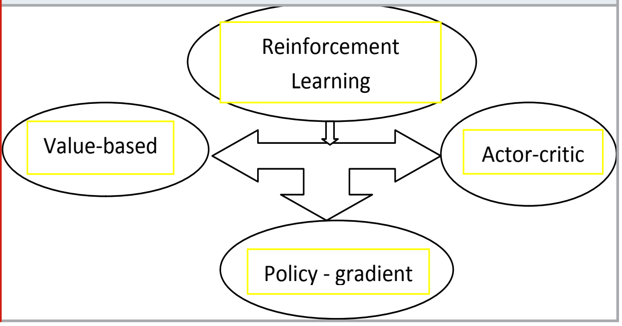
S->It is an attribute specifies state space
A->It is an action space of all possible actions applicable in data
P-> It is a state transition probability model
R-> It represents the reward function

Pros of RL:

- Unknown labeled datasets are required
- Advanced frameworks can be learned through RL.
- Cons of RL:
- Clustering the data to an optimal policy can be slower in process
- Needs time-consuming simulations (or) expensive training in theoretical data.

Classes of RL: Generally, algorithms framed in Reinforcement learning are classified into into three levels.

Figure 4: Algorithms in RL



Value- based algorithms: These algorithms generally rate the value on function F(V) which constitutes the value hold in a given state. In particular the state transition is known, the desired actions can be chosen by a policy to bring in a state so that the contemplated rewards are enlarged.

Benefit:

- The Optimum Policy is discovered greedily extending the "state-action" value function R(S, a)
- Non-Benefit:
- Assurance on the optimality cannot be predicted on the learned policy.

Policy-gradient algorithms: These algorithms cannot evaluate the value function whereas , it can restrict the policy and later update the necessary attributes to extend the awaited incentives. This process can be achieved by creating a reduction function and analyzing its slope in order to the network specification.

Benefit:

- During the period of training, the active network variables are modified in the determined way of the policy-gradient.

Non-Benefit:

- Extensive variance in the calculated policy-gradients.

Actor-critic algorithms: These algorithms are composite methods that integrates the usage of a value function with a limited policy functions, to build a exchange among the drawbacks of the extreme variation of policy grades and the angle of the value depends on its approaches. The reward function used in this algorithm has its following types:

a) Sparse reward function: The decision maker can only accept the perquisite which follows the certain events such as gain (or) loss in its related tasks.

b) Dense reward function: The decision maker will be given a perquisite at every time interval which is derived on the state it is in.

The type of reinforcement learning can be chosen to solve the task which depends on the problem scope (or) space.

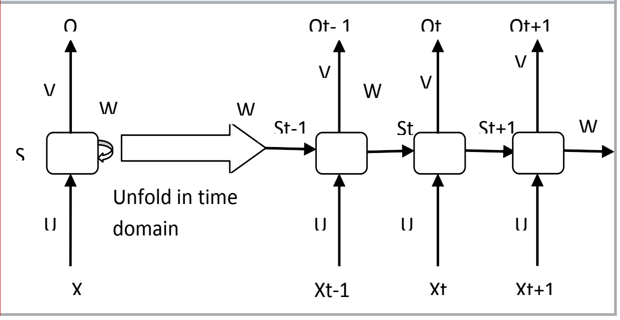
Examples: annealing, cross-entropy methods and SPSA.

Recurrent Neural NetworkS: In conventional type of networks , it prefers only complete connectivity between its adjacent layers, whereas nil connection exists between the nodes lies in the same layer. This occurrence may leads to failure of network especially in case of temporal –spatial problems. This drawback can be solved by receiving a feedback from previous state (hidden layer) to the current state.

The basic RNN architecture exhibits: (i)delay line and (ii) unfolded in time domain in series of two time steps.

Long-Short Term Memory: LSTM meshworks are capable of capturing the features of time series lies in the longer time span. Its network is most special kind of RNN. When considering the hidden layer as the unit of memory, LSTM network can manage with the connection lies in the time series in short as well as long term, which makes it is an extraordinary improvement compared with RNN. Moysset et.al. utilized the benefits of four directional two-dimensional LSTM memories to know the wide-ranging context exists intermediate to various local sectors and decreased tractable parameters within internal divided parameters.

Figure 5: Structure of RNN



Advanced Features In Deep Learning

Autoencoders: AutoEncoder(AE) is the most extensively manipulated procedures in illustration of unsupervised learning than others. This method is superior in training the mapping function to make sure the reduced reconstruction error lies among programmer layer and data layer Xin Y et al., (2018). Generally, the covered layer has less aspects compared to data layer which assists to find the important features of the data. The network comprises in following two parts namely

Encoder function => y = fw(x)
Decoder function => x'= gw'(y) generates a reconstruction.

Types of AutoEncoders:

1. **Under – Complete:** This learning representation makes the autoencoder to grab the most prominent features of the data, also it can control the proportion of inactive code 'z' lesser than the data 'x' acts as input.
2. **Denoising:** This learning representation can makes the encoder ew and decoder dw' to absolutely hold the form of data generating classification.
3. A denoising autoencoder reduces the following goal

$L = || x - dw'(ew(x^{-}))||^{2}2$
Where x^{-} is falsified in form of noise, copy of x.

Generative Adversarial Networks: GAN provides an unsupervised deep learning approach in estimation techniques whereby the two neural networks struggles to yield zero sum bias. In particular, the problems related to image creations, the originator is initiated with Gaussian noise to produce the images and its visibility is determined by the discriminator Tang et al., (2018). GANs have the two different areas in deep learning which comes under the following (i) semi-supervised 2) unsupervised.

Different types of GANs

1. **Deep Convolution GAN (DCGAN):** a semi-supervised learning representation proves the reliable results compared to unsupervised learning.
2. **Information – theoretic GAN (InfoGAN):** a better representation in complete unsupervised learning.
3. **Coupled Generative Adversarial Network (CoGAN):** It is a learned combined distribution of several domain images.
4. **Bidirectional Generative Adversarial Networks (BIGAN):** It is to be learned by mapping the characteristics reverse in process.
5. **Boundary Equilibrium Generative Adversarial Networks (BEGAN):** It is simple but its framework is strong in nature. It is a better training procedure because of its speed and stability.
6. **Wanserstein GAN (WGAN):** This improves the stability of optimization process.

Multi-View Learning: As like the view of different angles, Multi-view Learning plays an important role in enhancing the features discrimination by extracting inputs from various sources. The most important approach followed in learning representation is subspace learning exists among two input domains and its expansion in different views have been studied as a generalized usage of a higher-order correlation Qing Zhang et al., (2019). The learning of Multi-View Discriminant Analysis is used to reduce the number of aspects and its related features multiple views which utilizes the class information. Further, the related methods were designed in the same structure containing multiple views, its supervision and nonlinearity. The learning supports the subspace clustering methods to retrieve the low-dimensional data structures, multi-modal deep autoencoder was suggested to learn common characteristics in a pair's view of nonlinear representations. Also, Deep CCA – Canonical Correlation Analysis is a two-view method which increases the pair wise association while using neural networks.

Multi-view learning in classification and feature selection: This approach has its benefits in the combination of Multi-view learning with single-class Support Vector Machine (or) multi-class Support Vector Machines, where this method has its limitation to operate two classes of data with two views only. In the event of tracking the objects, the learning order can be directed by various types of features and know their similarities through the coordination of different plans along with entropy criterion.

Multi-Task Learning

- Different tasks in deep learning can be categorized under two groups ,
- Single-Task Learning (STL) also known as "Per-attribute classifier"
- Multi-Task Learning (MTL) also known as "Joint-attribute classifier"

In comparison of Single-Task Learning methods – every attribute is individually estimated by ignoring the correlations exists among the tasks, Multi-Task learning methods performs its learning multiple models to estimate multi-attribute using shared basis relationship. Example: Multi-Task learning networks in estimation of human pose ,prediction of required attributes to the problem, better alignment of face etc.

Multi-Task learning in object detection: In detecting objects, Multi-Task learning role in three stages namely Multi-Task Learning, Multi-scale representation and Conceptual Modeling.

Multi-Task Learning: The attitude of learning the multiple tasks provides a helpful representation for several connectivity tasks from the similar type of inputs, which are integrated on the basis of strongly supervised object division signals and region-based object discovery to fully utilize its features in multistage framework.

Multi-scale representation: It joins the activations processed from several layers along with the links passing output of previous layers as input to the next layers in framework by providing the attributes related information of various geographical designs.

Example; Cai et al., (2018) used the Multi-scale Convolutional Neural Network (MS-CNN) to make ease the variablility lies between the various sizes of entities and its receiving fields with several scale – individual output layers.

Contextual Modeling: This type of modeling maximizes the spotting performance by extracting the features from (or) about ROIs (Region of Interests) belongs to the various assisting parts in dealing with obstructions and its intra similarities.

Example: Zhu et al., (2018) suggested SegDeepM to explore the entity divisions, which mainly decreases the maximum dependent features on incipient candidate layers with the use of Markov random fields.

CONCLUSION

The paper reviews the prime differences between ML and DL, different approaches of DL and its usage along with its advancements such as Auto Encoders, GAN, Multi-view Learning and Multi-Task Learning. This concept can also be enhanced in the study of different data learning according to its originality and applying related patterns and tools to find the relevant outcomes.

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