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APPLICATION AND COMPARISON OF DEEPNET

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Abstract : This manuscript consists of the introduction to Machine Learning. How Machine learning has incorporated into all Social and technical field of everyday world . The concept is not a very new one but to which it has evolved till todays era is very powerful and spellbinding.
Additionally, Deep Learning concepts have also been discussed in this manuscript which explain abstraction layer-by-layer
Deep Learning has its very wide applications where amount of data is large. Not much details about the algorithms are known but in data science they form antidote. .(by Wikipedia)
Emergence of machine learning goes back to 1950 when statistical method was found and refined. Using simple algorithms, ground breaking machine learning research was carried out.
In 1980 rediscovery of back propagation (supervised learning) In machine learning resurgence is triggered.
In 1990s work of machine learning shifts from knowledge driven approach to data driven approach. Scientist started creating programs to analyse large amount of data and draw conclusion from it and learn from the result.

***IndexTerms* - . Machine learning, Deep Learning, Feature Extraction, Cross Validation**

I. INTRODUCTION

At first, we will survey Machine learning that has been incorporated in numerous fields for application and has emerged as new thought during this decade. Machine learning is causative most to business and technical world that it is getting used world wise.
The increase within the application Machine learning algorithms can be partially attributed to an unprecedented rise in growth of commercial web of things (IIoT).
IIoTs permit assortment of information for a given application through data-driven methodology to make another price value in diverse engineering fields
Very relevant example area are SIRI and ALEXA of virtual activities, without the need for human interference.
It is possible to review data gathered by the IIoTs by personal assistant in which the field of AI is employed. All we need to do is to activate them raise queries or instruct them to do certain

2.Machine Learning Applications.

Machine learning is in reality being used in many fields to revolutionized the existing scenario (machine learning applications information updated in 2019"- https://www.quora.com)
Some of the relevant field in which machine learning is applied are

1. Education
2. Search Engine
3. Health care
4. Digital Marketing
5. Engineering
6. Finance

Machine Learning in Education [1]

In education Machine learning handles numerous jobs that were tough to take care of antecedent Machine learning is employed to produce numerous data associated with education programme

6 ways are being discussed here which will revolutionize the education sector by the use of Machine learning

1.Increasing Efficiency-The educators can apply machine learning for management of classroom.scheduling etc. and focus on tasks which are beyond reach of AI.

2.learning Analytics-The ML can help educators to dive deep into data, shifting

through millions of pats of content which was not practically possible otherwise.

3.predictive Analytics-Educators can predict about the future events by the use of ML.for example by the present academic performance of the student future predictions of Academic Drop out can be predicted.

4.Adaptive Learning-Educators with the help of ML can analyse students performance and adapt the teaching method and curriculum accordingly.

5.Personalized Learning-Each student can be given unique teaching experience by the use of machine learning. Personalized learning is a education model where students guide their own learning going at their own pace and in some cases making their own decisions about what to learn.

6 Assessment-Educators can asses students exams and assignments more accurately using ML

Machine Learning in Search Engine [2]

The program use machine learning to gather information regarding user activity so they will counsel users regarding numerous topics in keeping with their demand. Google has introduced some wonderful services like voice recognition, image search and lots of it.

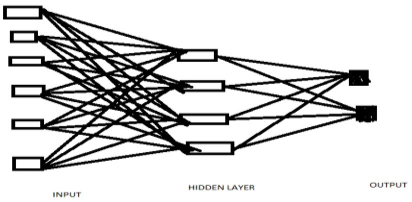
Search Engine are using machine learning to for pattern detection that help identify spam and duplicate content. In the paper "proposed efficient algorithm to filter spam using machine learning techniques by Ali Shafigh Aski and Navid Khalilzadeh Sourati (Pacific Science Review A:Natural Science and Engineering,2016 page no.145-149)" Three algorithm have been proposed to filter spam using ML.

1.Multilayer perceptron MLP-The model delivers information by activating input neurons containing values labelled on them.Activation function is applied on the middle or output layer of the perceptron neural net.

$$a_i = \sigma\left(\sum_j W_{ij} O_j\right)$$

a_i in (1) the value of activation level of the neuron i:j is the neuron set of the previous layer. W_{ij} is the weight attached to the link between iand j.o_j is the output of neuron j and $\rho(x)$ is the represent the transfer function.

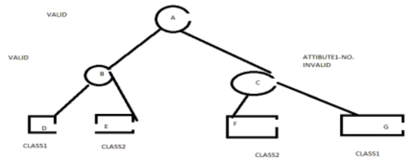
$$\rho(x) = \frac{1}{1+e^x} \qquad (2)$$



Fig(i) -Multilayer Perceptron(MLP)

An MLP is trained using error based back propagation strategy. An MLP(multi layer perceptron) indicates a nonlinear relationship between input and output vectors.The network weight is adjusted to reduce the error between predicted and targeted output. MLP is an in depth optimizer to solve many problems.

2.Decision tree classifier -The output of the Decision Tree is structural data in the form of binary tree.A training is a set of base tuples to determine classes related to these tuples. A tuple X is represented as X={x_1,x_2,x_3….x_n}.The tuple belong to predefined class called class label.The training set is randomly selected from the base this step is called learning step This techniques is very efficient and extensively uses classification .The structure is implemented with the following factors .A node represent adjective. Branch represent possible outputs. leaf represent class label. A Decision tree include a rule set by which objective functions can be predicted.The Greedy techniques is used here.



3.Naïve Bayesian classifier-It is Bayesian network it is acyclic directed graph indicating probability distribution in compressed way. A node is represented by Random variable X_i. A directed edge between parent and child shows interdependence between parent and child node. A Bayesian Classifier is simply a network used for classification including group C which indicates variable of class label and variable X_i which indicates feature. according to Bayes Theory

$$P(c=c_k/X=_x)=\frac{P(x=x(c=c_k)Pcc-=c_{1,2})}{P(x=x)} \qquad (3)$$

By assuming that random variable is independent conditionaly the above assumption can be written as

$$p(x = x|C = C_k) = \Pi_i P(x_i = x_i|C = C)k \qquad (4)$$

To clear the concept if we assume that word coca cola appears in 400 out of 3000 spams and given that would appears in only 5 of 300 valid emails the probability of email containing Coca-Cola is spam is p(coca cola /spam)= $\frac{\frac{400}{300}}{\frac{400}{3000}+\frac{5}{300}}$= 0/8889 (5)

The proposed model evaluated the system using set of rules. Each rule was assigned a score. The final score of the received email was compared with the threshold value. The received email was labelled junk and sent to the spam folder if the score more than the Threshold.

2.Identifying new signals -search engine teaches technology by the help of ML to identify new signals.

3. Weighted as small portion-search engine is applying in small portions not the entire search rankings

4. Custom signals based on specific query-Search engines are learning the customers preferences with the help of ML it give interesting experiences example Yandex search engine

5 Image search to identify photos-This task is done perfectly by ML as it analyses colours and shapes .It can search patterns and pair them with existing schema data and predict about the photo photographs.

6 Identifying similarities between words in search queries-It identifies the patterns and can predict meaning behind words better

7. Improving Add qualities-Ad ranks can be influenced by ML system

8. Synonym Identification-Snippets are recognised perfectly by ML system.

9. Query clarification-ML helps to understand user intent or search intent .University of Hon Kong did intensive study of search intent which can be fragmented into two segments that is specific or generalized information is being searched.

Machine Learning in Digital Marketing:[3]

Digital selling have its future in Machine Learning. Machine Learning tools have the flexibility to investigate extraordinarily massive sets of information and gift intelligible analytics that selling groups will use to their advantage. With the help of this system, we are able to predict the necessity of a client by analysing their previous activities then suggesting them new product. These techniques area unit employed by numerous e-commerce firms like Flip kart, Amazon, etc.

ML use in Digital marketing can help in

1. Better personalization

2 .Better customer service

3. Creating more precise content

4. Smart content creation

5. Stunning website design

6 Easier marketing Automation

7. Optimised Advertising

8. Automated email marketing campaigns

9. social media management

10. Transformative influencer marketing

11.We site SEO at scale

12 Improved PPC campaign

Machine Learning in Health Care: [4]

.("Citation from Science and health journal last modified in 2020"-https// www.sciencedirect.com)

In Health Care Machine Learning is employed to increase the diagnostic accuracy. By learning from previous case, we have a tendency to develop a system which may perform designation a lot of effectively. Also, we have a tendency to use this system to spot at-risk patients by learning behaviour and pattern of explicit sickness which may be a life saver.

In health care the use of ML is making miracles.(In a paper written by Dr.Kennedy and Dr.Tobias in international journal of Novel Research in computer science and software engineering ,volume 6,issue 3.pp-(1-11),2019) study has been conducted on how to predict demand for outpatient healthcare services using artificial neural network. Health care managers and planners must make future decisions about health care services delivery without knowing what will happen in the future .A neural network model was trained under the WEKA it is tool for data mining in machine learning enviroment and applied to predict the demand the result shows that the forecasts using neural network algorithm solves a more accurate result. for health services in various categories for private and public healthcare providers in Nairobi country Kenya.

e.g. Aircraft engines go through a range of challenging and changing environments in a number of cycles. They need a very comprehensive maintenance program to prevent catastrophic failures. Due to engine downtime and the time and effort involved, maintenance of engines is expensive.

The engines are fitted with a range of temperature and pressure measuring sensors at different locations, as well as other critical indicators, such as the fuel-to - air ratio and the speed of the fan. This sensor data can be used using machine learning algorithms to render engine health predictions based on the conditions it has been exposed to over its lifecycle.

Since the 1960s, machine learning has been around, so it is not a new phenomenon. However, only recently have all the elements needed for machine learning come together. More bandwidth access for data transfer over the internet, inexpensive data storage, and increasingly powerful computer resources are now widely accessible. More significantly, universal accessibility to robust algorithms is within easy reach of the use of machine learning. The synergy between design and operation can easily be generated and leveraged for better goods with the growth of IoT and access to field data. Our role as an engineer is to define and build easy-to-use processes for applications that can benefit from the use of machine learning.

Machine Learning in finance

Recently, due to huge data volumes as well as cheaper computing power, machine learning applications are in the forefront of financial sector. This helps to reshape the financial services industry, which explain why financial companies and banks look for candidates from a renowned upgrade course or some other financial institution with a diploma or certificate.

These businesses want to deploy Machine Learning technology for streamlining their processes, decreasing risks, optimizing portfolios, and underwriting loans. You should consider application of ML in finance before making a career move to this field.

Machine Learning in engineering:

The first things that come to mind when we think about machine learning applications are examples about daily life, such as spam filtering, various recommendation engines and fraud detection systems. These are direct machine learning implementations that simplify routine tasks, making our lives more efficient, enjoyable and safer. Applications of machine learning in engineering that are important in improving our efficiency and safeties are less well known.

Computer scientist Arthur Samuel first identified machine learning as a study area that enables computers to learn without being explicitly programmed in 1950s.This was different from existing conventional programming.

Inputs are system features and a program of rules that control the system; the output is traditionally the performance of the system.

Inputs are data in machine learning that contains both system features and performance for several system variations, and output is a program that can predict the output of the system based on system features.

As a consequence, the program evolves by fine-tuning the rules in conventional programming while the program fine-tunes with additional data in machine learning. Traditional programs are referred to as physics-based simulations in the scope of Computer Aided Engineering (CAE), and machine learning models as data-based predictive models.

- **Process Automation**

It is the deployment of software engineer to recognize patterns in an organization's workflow. Once a repetitive task has been identified, the RPA "bot" configures applications to trigger a response, coordinate transaction processing, and manipulate data, all while enabling interconnected communications within digitized systems.

- **Security**

Machine learning will, in theory, allow organisations to understand threats better and react to attacks and security incidents. It also automates more menial activities traditionally carried out by security teams that are stretched and often under-skilled.

As a consequence, the application of machine learning in security is a fast-growing trend. Market analysts (ABI) predict that cyber-security machine learning will increase spending on big data, artificial intelligence (AI) and analytics to $96 billion by 2021, while some of the global technology firms are already taking a stand to better protect their own customers.

Google uses machine learning algorithms to analyse threats to mobile endpoints operating on Android, as well as to recognise and uninstall malware from infected handsets, while the cloud computing giant Amazon has built the start-up. Launched Macie, a service that uses machine learning to discover, sort and classify data stored on the cloud storage service.

Under writing and credit scoring

There was a keen interest in using AI to automate processes from fraud detection to customer service following the advent of machine learning in finance. Our study leads us to believe that banks will continue to invest in machine learning for risk-related processes, including underwriting, in the coming five years.

Zest Finance CEO Jay Budzik addressed how entrepreneurs can use machine learning-based credit models to obtain more business and minimize risk by taking

Traditional Variables of Credit Score Vs. New data sources

Scores from FICO: Summary

The two scores FICO and credit scores have established themselves as the norm in credit modeling over the last thirty years. This has allowed banks, credit giving firms, and other lenders to determine credit applicants' credit eligibility objectively. Five factors determine the score, each of which have multiple weight-varying variables attached to them. These together when summed up gives total FICO score.

1. **Credit History (35 per cent):** The presence of bad and good accounts on one's credit report makes up one's credit history. Such defects summarise of late payments, bankruptcies, foreclosures, and similar instances that represent the inability of an entity to pay his or her debt.
2. **Credit Use (30 per cent):** FICO score means how much of a credit cap one uses in a given billing period, how many credit accounts one has opened, It also includes how much one's down payment is on instalment
3. **Credit history period (15 per cent):** The FICO score is higher if one keeps open credit accounts (as long as they use them), for longer time.
4. **Credit Categories (10 per cent):** The FICO score of one is determined by how varied their credit lines are. Credit forms include mortgages, car loans, credit cards.
5. **Recency (10 per cent):** Among other factors, FICO scores also considers how recently one applied for credit, paid off an account, or raised their balance.

6. The Intangible Credit and hence the Credit history Catch-22

7. The necessity of previously obtained lines of credit is what all these variables have in common. The conventional credit ratings are also obstacles to entry for the "credit invisible." In 2015, almost one out of ten Americans affiliated with the purchaser Financial Protection Bureau (CFPB) had 26 million invisible Americans in credit. The CFPB found, in addition, that "consumers have a loans history or a history of credit in which credit score in low-income communities is created more likely."

8. The most likely to require loans for large transactions are these segments of the population, They have no credit history which prevents them from being eligible for loans and credit when conventional credit ratings are used by underwriters to evaluate them: it's called catch-22.

9. Loans that do not exactly reflect the risk they pose to lenders are often available with credit ratings. Experian find that credit figures are on average around 638 for millenniums, below the national average in the US and well below the preceding centuries. The company admits that the company's credit histories are limited and 30 percent of FICO ratings have credit history, part of the age of these borrowers. As a result, lenders could not consider them as lending because they are just young when they may very well not be too risky

10. Although it was proven useful for older generations of middle class Americans to earn FICO and regular loan values, these scores can be less beneficial for thousands of American and low-income Americans who are used to debit card transactions

Inherently, these invisible lender are not risky, but they are rarely approved by lenders because their risk is unknown without a lending score.

The "Adapt Over Time" Challenge

The company states that FICO ratings change little over time. Zest Finance says that it would be difficult for FICO to differentiate between the following two people :

• someone with a few delayed payments from five years ago on their credit report, but who has not paid since then

• Somebody who never had a delayed payment on their credit report until the last few months during which many payments were made in a row,

The fact that the lives of these borrowers have changed over time and affected their ability to pay out their debts can be challenging for FICO and traditional credit models. In particular, this could prove disturbing for young people, many of whom struggle with debt.

Experian commented on a study about loans that found that approximately one in four millennials thought they were not adequately trained on how to establish good credit. 15 percent of millennial frequently skip master card fees, the same study showed.

They will find their financial status later in life, so that they simply pay on time, but traditional credit scores do not reflect this automatically. Owing to their poor credit background when they were younger, these borrowers fail to gain approval for a loan and their outcomes can be sustained if they don't open their credit accounts. This is another catch-22.

The solution could be new credit scoring data sources.

Latest Credit Scoring Data Sources.

Although a FICO score can include a dozen or two variables in its score .

The models we build for our customers seem to have hundreds or thousands of variables. We have one that runs an automobile loan business with 2200 variables.

More specifics mean more complicated credit models and these models offer a far more comprehensive picture as to whether a loan applicant could or could not pose a risk. New data sources could include:

- Pending court hearings Public information
- the manufacture and model of a vehicle for a car loan applicant.
- Satellite pictures of a property on which a borrower takes a mortgage.
- Articles the creditor purchases on his credit card.

Such categories of information would somewhat warn a lending applicant about the creditworthiness, but standard lending models do not recognize them.

II. The Machine Learning Advantage

The lenders need new solutions in the form of algorithms to handle them so that more variables can be taken into account. The dilemma is solved by machine learning. ML takes all those considerations into account, but does not make mistakes. Factors such as statistical similarities and drawbacks are the explanation for conventional scoring strategies.

There are countless numbers of data sources for machine learning that can be a component in a credit model. There are countless variables that could predict the willingness of an applicant to pay back their loan, and within massive data sets, machine learning is good at identifying trends. Credit models based on Machine learning can influence data points that are not yet known to predict a borrower 's probability of repaying his loan.

For example, Zest has partnered with Discover to tape the credit card company 's cache of client data to develop a new $7.5 billion personal credit model. Zest estimated that the model examined for applicants hundreds of information points up to 10 times as many as the previous Discover credit model had used.

The person developing models allegedly found that a record of discount-store shopping improved the likelihood of an applicant having a personal loan, while it would be diminished by an applicant writing an employer's full legal name on a loan application.

Applicants who called or explored on a fixed or mobile phone were considered better off bets than Skype or other Internet phone services because they were easier to follow anyone.

In addition, these sources mix themselves together to build data points of their own. For example, it does not happen that a borrower often buys accessories for his car affect their ability to repay their auto loan on their own.

However, in accordance with the vehicle composition, which the applicant needs to take out a loan, it is possible that the applicant will refund the loan less or more. These relationship forms are nearly difficult for contractors to figure out, but mostly machine learning benefits

Machine learning, which is much more adaptable than conventional credit models. It can take a year or more to create a new credit model, which can impede the ability of a bank to keep up with the evolving economic environment.

Relatively quickly, consumers and markets will shift. Some credit underwriting machine learning software has Automatic Automation risk management with them, which could allow lenders to refit models in less than a month to change their records of the underwriting as the economy evolves.

What ML-based Lenders Credit Models Mean

By accepting more invisible loan requests and more applicants whose credit scores paint an imperfect image of their credibility, machine learning enables banks and other lenders to increase revenue. For example, Zest Finance reported to have supported Prestige Financial Services with an ML-based credit model to increase loan approvals by 14 percent.

Without even raising risk, lenders can be able to raise revenue. At the same time, underwriters will begin to refuse loan request who are more riskier than their credit scores suggest. As a result, lenders will reduce the losses that they experience.

ML also allow risk-based pricing. Credit model based on ML can take into account far more data than conventional models, as previously mentioned, allowing for a more detailed image of the requester willingness to pay. As a result, with the interest rates they give borrowers, lenders can be even more discrete.

ML may pick up detailed variations between two very alike borrowers, and by providing a higher interest rate to one borrower, these variations could be worth capitalizing on. This could increase the profit obtained on each borrower without adding to the time of an underwriter scrutinizing the application of a requester. As a result, financer could see a noticeable rise in revenue on a scale.

For customers, what it means

Credit-invisible applicants canevaluate computer models through variables in new data sources in such a way as traditional models which are explicitly dependent on credit history. Applicants will find that lenders approve them if they do not have credit models based on machine learning. Building up its credit would be possible as lenders begin to invest in them, young people with thin credit histories.

Similarly, in coming days, millennial will find that when they are more likely to pay back their loans, the past wrong record of their past do not hold them from receiving a loan for large borrowing in the future. Therefore, the lenders would deter and avoid customers who will fail to pay by not offering loan to them. Lenders will discourage it and prevent it from happening .

Therefore, instead of accepting individuals who would default ,lenders would stop it and avoid it from happening to consumers by making a mess and providing loans to people who will not be able to pay. The score represents that. an applicant with a score of about 700 and in trouble with the law may be required over the course of a year to pay a fine in instalments. Such a decision may have an effect on the ability of the borrower to repay its loan, harm its credit score and do even greater long-term damage to its future.

A ML based credit model that considers pending court cases may suggest that an underwriter does not fully accept the loan request, even though their credit score would imply that they are eligible of loan. By not authorizing them in the first place, lenders will effectively hedge against riskier borrowers defaulting on their loans.

Portfolio Management

ML-powered applications are Robo advisors that offer automated financial services and guidance. They offer portfolio management services through statistics and algorithms that automatically establish and manage a customer's investment portfolio. Such digital investment platforms make the daunting investment process more straightforward for a lot of people.

Global Robo-Advisors Market: Overview

There has always been a strong demand for automation of complex activities that are handled by humans and hence are prone to errors by the use of machine learning algorithms. Primarily in the financial sector, the need to manage wealth in digital manners has paved to way an incrementing demand for robo-advisors, which use preset algorithms to sort consumers on the basis of their ability to manage risk and hence offer predefined and low-cost EMI. It has been observed that the coming of robo-advisors has reduced the cost of wealth management from 1.0% to 2.0% to 0.15% to 0.50% of the total assets. These advisors help in developing a portfolio for the clients, automates rebalancing, and tax-loss harvesting. It is working under a transparent technology and offers effective and unbiased financial advice, the demand in the global robo-advisors market will continue to increase during the forecast period of 2017 to 2025, according to this business and commerce study by Transparency Market Research.

Algorithmic Trading

Free trades are conducted by using Machine Learning Algorithms. It allows the execution of high orders by sending tiny increments of the law to the market at intervals. Hedge Fund Managers use these automated trading systems to integrate Machine Learning in finance.

HFT

HFT or High-Frequency Trading is algorithmic trading that occurs at rapid speeds beyond human capability. HFT makes use of algorithmic trading and is in demand among hedge funds and investment banks

Machine Learning involves digesting huge data chunks and learning how that data can be used to perform specific tasks, like separating authentic documents from fraudulent financial documents. ML utilizes different techniques for processing large, complex volumes of information, something the finance sector has more.

Decision support systems (DSSs) that ccontain large quantities of structured and unstructured data are fraud detection, A ML applications and Chabot, or health applications such as monitoring the COVID-19 pandemic. Experts expect that 79 trillion GB of data will have been produced globally by 2025. This avalanche of data makes data mining (DM) difficult for high-performance scalar-based computers to run a DSS for their intended applications effectively and efficiently. More powerful accelerator cards are proving to efficiently process enterprise data lakes to populate and upgrade data warehouses, such as vector processing engines backed by optimised middleware, from which concrete insights can be provided to the intended decision-makers

DEEP LEARNING

Till previous section we were discussing Machine learning. Now we will talk about Deep Learning subset of Machine learning.

Decision support systems (DSSs) that contain large quantities of structured and unstructured data are fraud detection, AML applications and chatbots, or health applications such as monitoring the COVID-19 pandemic. Experts expect that 79 trillion GB of data will have been produced globally by 2025. This avalanche of data makes data mining (DM) difficult for high-performance scalar-based computers to run a DSS for their intended applications effectively and efficiently. More powerful accelerator cards are proving to efficiently process enterprise data lakes to populate and upgrade data warehouses, such as vector processing engines backed by optimized middleware, from which concrete insights can be provided to the intended decision-maker.

With machine learning, less knowledge than deep learning is required to train the algorithm. To define the underlying structure, deep learning requires a comprehensive and diverse collection of data. Besides, a faster-trained model is given by machine learning. Most advanced architecture for deep learning with large amount of time to practice. The edge advantage of deep learning over machine learning is that it is extremely precise. We don't have to understand what the best data representation features are; the neural network has learned how to pick essential characteristics. In machine learning, you need to choose what features to implement in the model for yourself.

How Machine is made to Learn.

Imagine you can create a program to recognize objects. The model can be trained with a classifier. A classifier uses an object 's characteristics to try to classify the class to which it belongs.

In the example, the classifier will be trained to detect if the image is

- **tricycle**
- fleet
- four wheeler
- car

The above four objects are a class that the classifier must identify. To create a classifier and add a label, you need to provide some data as an input. The algorithm selects this data, a pattern is found and then classified in the respective category.

Supervised learning is called this job. The training data you feed to the algorithm contains a mark during supervised learning.

Training an algorithm follows these standard steps:

- the data collection
- Training the classifier
- Predicting

The first step is required to successfully select the algorithm or to fail to select the correct data. The expertise you use to train the model is a characteristic. In an object example, the features are the image pixels .

The first step is to build function columns. The next step is the selection of a model training algorithm. When the training has ended, the model predicts what picture would fit which object.

How to do Deep Learning Process (DL)

A neural network of deep learning is used to accomplish the learning process. A neural network is an architecture in which the layers are stacked.

Each input is converted into a neuron and multiplied by weight. The product of the multiplication flows to the next layer and is the entry. This process is repeated for each layer of the network. It gives an actual value for the regression task, and a probability for the classification task for each class. The output layer is called final layer A mathematical algorithm is used by the neural network to change the weights of all the neurons. If the value of the weights gives an output close to the fact, the neural network is fully trained. A well-trained neural network, for example, can identify the object in a picture with greater precision than the conventional neural network.

In machine learning, one way to perform this part is to use feature extraction. The extraction of features blends existing features to create a more appropriate collection of features. It can be done with PCA, T-SNE or any other reduction algorithms for dimensionality.

If we take an example, that practitioner needs to manually remove the role in the image, such as the eyes, nose, lips, and so on, in an image processing. The classification model feeds those extracted features to the model.

This problem is resolved by deep learning, particularly for a coevolutionary neural network. The first layer of a neural network learns small details from the image; the next layers add previous knowledge to complex information. The extraction of the function in the coevolutionary neural network is carried out by the filter. The network applies a filter to the picture to see if it's in match, i.e. the feature shape is close to a part of the image. When a contest takes place, the network can use the filter. The method of extraction of functions is thus automatically performed. Deep learning is an apprenticeship. Machine learning uses data to shape a model to simulate new data using a trained model. A predictor of output Y, given an input X, is a fundamental machine learning problem. An input / output mapping Y = F(X) determines the learning machine. Where X=(x1, x2,……………………………,xp)) .The output T may be continuous, discrete or mixed. .

Deep knowledge is hierarchical in that the algorithm removes variables in each layer, and the factors in a deeper level become the next level's characteristics.

The deep method, put differently, uses hierarchical predictors consisting of a set of nonlinear L transformations applied to X. The fundamental problem is to find the predictor of the output Y for the given input X .The learning machine is defined as input output pair Y=F(x)

Each L transformations are referred to as layers as the original input is X.The output of the first transformation is the first layer and ^y is output of (L+1)th layer where l€(1,2,3..L) are index depicting hidden layers.The number of L layers shows the

Deep Learning automatic feature extraction

A few hundred features in a dataset may be present. The computer will benefit from the significance of these features. However, not all of the functions of the algorithm are important. A main feature of machine learning is to find a relevant set of functionalities to make the system learn something.

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Deep knowledge is hierarchical in that the algorithm removes variables in each layer, and the factors in a deeper level become the next level's characteristics.

The deep method, put differently, uses hierarchical predictors consisting of a set of nonlinear L transformations applied to X. The fundamental problem is to find the predictor of the output Y for the given input X .The learning machine is defined as input output pair Y=F(x)

Each L transformations are referred to as layers as the original input is X.The output of the first transformation is the first layer and ^y is output of (L+1)th layer where l€(1,2,3..L) are index depicting hidden layers.The number of L layers shows the depth of the architecture(by J.B Heatson,N.G Pealson,J.H Witte 2018)

The common mathematical function used are:

Sigmoid function is used in Deep Learning. It is a mathematical function which has a characteristic S-shaped curve. There are a number of common sigmoid functions, such as the **logistic function(**1/(1 + exp(−x)),**)**, cosh(x), or tanh(x))

Heaviside is a step function denoted as H is a discontinuous function (e.g., (x > 0)), or

The Rectified Linear Unit (Re LU) is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value x it returns that value back. So it can be written as f(x)= max(0,x) ,f(x)=max(0,x).

(Re LU) max f(x); 0 g are widely used activation functions. In particular Re LU's have been found to lend themselves well to the rapid reduction of dimensions.

A deep learning predictor is a data reduction scheme that avoids series of dimensionality through the use of univariate activation functions. See Kolmorogov (1957), Lorenz (1976), Gallant and White (1988), Hornik et al. (1989), and Poggio and Girosi (1990) for further discussion.

How to train a Deep Architecture

It takes a number of steps to build a deep learner. Splitting the data set into three subsets, namely training, validation, and testing, is normal.

The training set is used for changing the network weights.

Once the Activation function size and depth of the learning routine is set we need to solve the training problem of finding (W,b) where W= (wo,…wL) and b=(b0….,bL) denote the learning parameters which we compute during training.

To minimize over fitting, the validation collection is used and applies to the architecture design (a.k.a. model selection).

Finally, research is used to validate a learner 's real predictive power. The training set is used for changing the network weights. To avoid over-fitting, the validation set is used and refers to the nature of the architecture.

Finally, research is used to validate a learner's real predictive power.

Cross validation

Cross validation is a technique by which we divide our training data into complementary subsets to then perform analysis and validation on various sets, aimed at reducing over-fitting and increasing out-of-sample efficiency. In particular, we can divide our training data into disjoint time periods of equal duration while training on time series, which is especially desirable in financial applications where accurate time-consistent predictors are difficult to come by and have to be extensively trained and tested.

The popular numerical approach to the solution is a method of stochastic gradient descent, which is usually called back-propagation, adapted to a deep learning environment.

The multi-modality of the system to be solved (and the resulting slow convergence properties) is one caveat of backpropagation in this context, which is the main reason why deep learning methods rely heavily on the availability of large computational power

Credit risk analysis is another field of great application of deep learning. A function representation of a high dimensional input space is the objective of a deep learning model.

In image processing, for example, one can think of layers as representing objects first, then parts of objects (faces), then edges, and finally pixels. For the credit-worthiness of businesses, a similar feature chart can be found. To obtain a picture of the health of a business, we can combine financial asset return data with text data (earnings calls) and accounting data (book values, etc.).

Other methods to train the DEEP NET are Back propagation network,Long Short term memory models etc (by J.B Heatson,N.G Pealson,J.H Witte 2018)

Finance applications of DEEP LEARNING

Deep learning applications in finance refer to Fama and French (1992, 2008), Engle (1982), Campbell, Lo, and MacKinley (1997), Singleton (2006), and Daniel and Titman

(2006). Hutchison, Lo, and Poggio (1994) provide a shallow learner for option pricing.

EVENT STUDIES

A deep learner can be build for event studies we can create a hidden factor $Z_j=W_1^TX_{j-1+l}$

We can construct the effect of l previous events on today turn

Where $X=(x_{1,\dots\dots,}x_n)$ are series of previous events and $W€R^l$ is the weighted matrix to extract l possible event.

If Max-pooling Activation function is used only largest Z value is considered rest ignored.

SMART INDEXING USING DEEP LEARNING TECHNIQUES

There are two conceptual methods we can choose from when attempting to reproduce (or approximate) a stock index through a subset of stocks through Deep Learning.

(i) Identify a select group of stocks that have traditionally provided a very similar output to that of the index observed.
(ii) Identify a small number of stocks that have historically accounted for an over-proportionate part of all the stocks that make up the index 's total aggregate results. On the face of things, while (i) and (ii) can seem very similar, they actually represent methodologies that are very different.

Many traditional index replication methods are basically rooted in linear regression, which is part of the community.

Sometimes, we try to find a small subset of stocks by trial and error, which provides a rational linear approximation of the considered index in the sample.

The deep learning version facilitates the transformation of the input data into a desired output through a hierarchical sequence of adaptive linear layers, which means that even non-linear relationships can be easily detected in training. Since a new understanding of the input features is given by any hidden layer, we refer to the resulting approximation (or prediction) strategy as a deep feature policy (DFP)

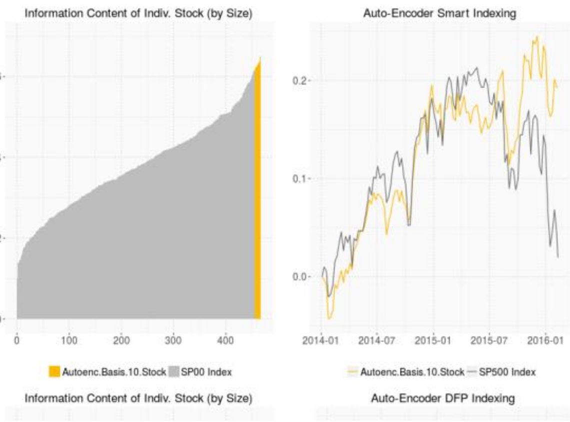

Fig IV (by J.B Heatson,N.G Pealson,J.H Witte 2018)

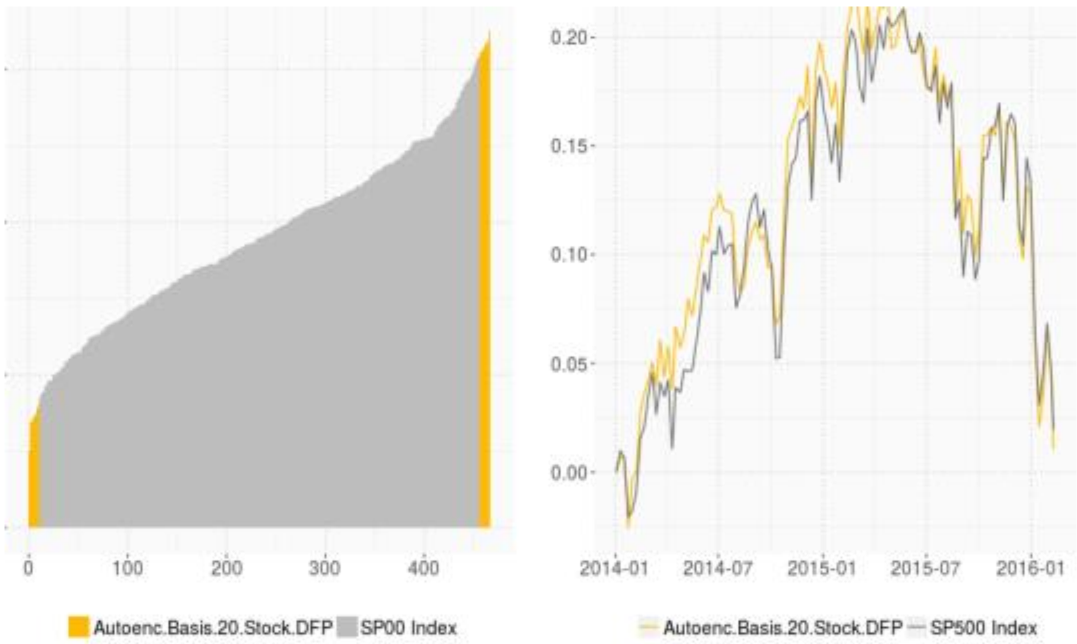

Fig V (by J.B Heatson,N.G Pealson,J.H Witte 2018)

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TECHINIQUES USED FOR PRICE FORCASTING

(by Manuel R. Vargas, Beatriz S. L. P. de Lima and Alexandre G. Evsukoff, "Deep learning prediction from financial news articles Pro 2017 IEEE International Conference)

- Recurrent Neural Network (RNN) — Short time horizon
- RNN is used for data with a sequential order, such as a time series database.
- Long, Short term Memory Models (LSTM) — Longer time horizon compared to RNN
- LSTM is a variation of RNN with added parameters in order to support longer memory so that the forecasted time horizon can be longer.
- Multilayer Perceptron (MLP)
- MLP is a class of feed-forward neural networks that consists of an Input layer, Hidden layer and Output layer. This is also suitable for time series forecasting because it is:
- Robust to outliers, noisy data and missing values

- Non-linear modelling
- Support for Multivariate forecasting
- Multi-step forecasting

Fraud Identification in Finance

The financial world is rife with fraud and deceit. Hackers and scammers often try to steal sensitive personal information and sell internal company data. In order to update their cyber security and fraud detection systems, companies are under significant scrutiny from governments worldwide. The process of scanning data streams for anomalies that mabe a security threat is now automated by machine learning and deep learning

Autoencoders

An Autoencoder is a Deep Learning algorithm for anomaly detection. An Autoencoder neural network is an unmonitored learning algorithm that uses back-propagation to set the target values equal to the inputs that basically encode and compress the data and recreate

the data as similar as possible to the original data representation. In auto encoder the training data set (X1,X2,…) we set the target as Yi=Xi .It is a static model with two linear layers

$z^{(2)} = W^{(1)}X + b^{(1)}$, $a^{(2)} = f2(z^{(2)})$,

$z^{(3)} = W^{(2)}a^{(2)} + b^{(2)}$, here $a(2)$ and $a(3)$ are activation levels

$Y = F_{W,b}(X) = a^{(3)} = f3(z^{(3)})$,

The goal is to learn the weight matrix for prediction at lower dimension level.

It demonstrate nicely that in deep learning we do not have to model Variance and Co variance Matrix explicitly as the model is itself in predictive form. .

An Autoencoder consists of 2 parts:

- **Encoder** — Takes input data and compresses it into a vector of quantities.
- **Decoder** — Takes the data from the encoder and reconstructs the original input.

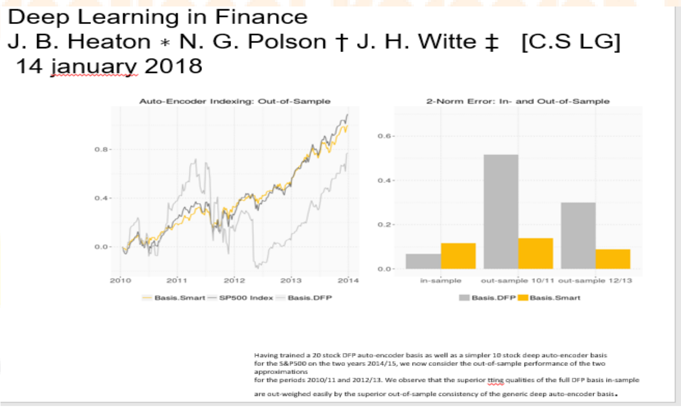

Fig VI

In this figure iii we find out that auto indexing replication auto indexing as suggested is more robust in out of sample performance.

IX. Conclusion

A general paradigm for using broad data sets to improve predictive output is provided by deep learning. As such, deep learning systems are well-suited in finance for many topics, both functional and theoretical. This chapter introduces hierarchical decision models for deep learning for financial prediction and classification problems. As we have seen before, deep learning has the ability to boost predictive efficiency in traditional applications, often dramatically. Our smart indexing example provides only one way of applying deep learning models in finance. For growth, several other applications remain. At the same time, deep learning is likely to pose major challenges to current financial thought, including, most importantly, the notion of market effectiveness. Deep learning could be capable of pricing assets within arbitrarily small pricing errors as it can model complex data non-linearities. This will suggest that markets are efficient in terms of information.

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