IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 4, Issue 2, April - May, 2016
ISSN: 2320 – 8791 (Impact Factor: 2.317)
www.ijreat.org

An Implementation Of Education System Through Deep And Deeper Learning Techniques

Dr.M. Kumarasamy
Professor, Villa College, Male, Maldives

Abstract

This paper describes that the application of deep learning to the deeper learning to improve the education system. In recent years, the popularity of deep learning has increased enormously in the machine learning community. Deep learning tries to model and extract high-level abstraction features in data using complex, multi-layer models and non-linear transformations. Deep learning methods are used in both supervised and unsupervised learning. Deep learning was successfully applied in multiple fields such as speech recognition, image recognition and classification, natural language processing, Education and many other tasks in machine learning. In all of these studies, the performance of the resulting algorithm was better than other machine learning approaches to these problems. In this paper we proposes how deeper learning enables students to transfer what they learn in school to solve problems they face in the future. In order to prepare young people to do the jobs computers cannot do all what the people requires. We must re-focus our education system around one objective that is giving students the foundational skills in problem-solving and communication that computers don't have. First part of this paper we deals with what is machine learning, supervised learning, future of deep learning. Second part of this paper we deals with the application of deep learning into deeper learning.

***Keywords** : Deep Learning, Deeper Learning, Machine Learning, Data Mining*

1.Introduction

In the current global economy, jobs increasingly require high skills. The education system needs to be aligned with these high-skilled jobs to ensure that today's students will be able to compete in tomorrow's job market. This requires that young people learn, process, and produce more than their parents and grandparents. To meet these demands, students will need "deep and deeper learning," a mix of knowledge, skills, and dispositions that includes critical thinking and problem solving, effective communication, collaboration, an academic mindset, and the ability to learn how to learn—all applied to the mastery of rigorous academic content. To succeed in the future, students will need to know how to analyze, collaborate, and innovate. But our education system isn't as effective at preparing them as it could be.

2.Machine Learning

Machine learning is a field of study that aims to design and implement algorithms that enable machines to learn from examples. The resulting algorithms allow us to recognize patterns in the data, extract knowledge from them, and make predictions for new, unseen examples. Given the limited number of training examples and also restricted computational resources, the key issue in machine learning is how to cope with complex variability's in the data efficiently. Machine learning has been applied to various areas including, but never limited to: object recognition, information extraction, recommendation systems, and so on. Machine learning models contain parameters to fit the data and thus they are often formulated as parameter optimization problems. This model fitting has two scenarios that should be avoided overfitting and underfitting. Overfitting occurs when the training data are not enough but the learning models are unnecessarly complex. As a result, the models even fit to irrelevant details of training examples and fail to generalize beyond them. In contrast, underfitting occurs when the models do not have enough capacities to cover the variability's in the examples and again, fail to generalize to test data. Hence, to strike a balance between these two extremes is an important challenge for machine learning.

3.Supervised Learning

The most common form of machine learning, deep or not, is supervised learning. Imagine that we want to build a system that can classify images as containing, say, a house, a car, a person or a pet. We first collect a large data set of images of houses, cars, people and pets, each labelled with its category. During training, the machine is shown an image and produces an output in the form of a vector of scores, one for each category. We want the desired category to have the highest score of all categories, but this is unlikely to happen before training. We compute an objective function that measures the error (or distance) between the output scores and the desired pattern of scores. The machine then modifies its internal adjustable parameters to reduce this error. These adjustable parameters, often called weights, are real numbers that can be seen as 'knobs' that define the input–output function of the machine. In a typical deep-learning system, there may be hundreds of millions of these adjustable weights, and hundreds of millions of labelled examples with which to train the machine.

To properly adjust the weight vector, the learning algorithm computes a gradient vector that, for each weight, indicates by what amount the error would increase or decrease if the weight were increased by a tiny amount. The weight vector is then adjusted in the opposite direction to the gradient vector.

4.Deep Learning in Data Mining

The main concept in deep leaning algorithms is automating the extraction of representations (abstractions) from the data. Deep learning algorithms use a huge amount of unsupervised data to automatically extract complex representation. These algorithms are largely motivated by the field of artificial intelligence, which has the general goal of emulating the human brain's ability to observe, analyze, learn, and make decisions, especially for extremely complex problems. Work pertaining to these complex challenges has been a key motivation behind Deep Learning algorithms which strive to emulate the hierarchical learning approach of the human brain. Models based on shallow learning architectures such as decision trees, support vector machines, and case-based reasoning may fall short when attempting to extract useful information from complex structures and relationships in the input corpus. In contrast, Deep Learning architectures have the capability to generalize in non-local and global ways, generating learning patterns and relationships beyond immediate neighbors in the data. Deep learning is in fact an important step toward artificial intelligence. It not only provides complex representations of data which are suitable for AI tasks but also makes the machines independent of human knowledge which is the ultimate goal of AI. It extracts representations directly from unsupervised data without human interference. A key concept underlying Deep Learning methods is distributed representations of the data, in which a large number of possible configurations of the abstract features of the input data are feasible, allowing for a compact representation of each sample and leading to a richer generalization. The number of possible configurations is exponentially related to the number of extracted abstract features. Noting that the observed data was generated through interactions of several known/unknown factors, and thus when a data pattern is obtained through some configurations of learnt factors, additional (unseen) data patterns can likely be described through new configurations of the learnt factors and patterns. Compared to learning based on local generalizations, the number of patterns that can be obtained using a distributed representation scales quickly with the number of learnt factors.

Deep learning algorithms lead to abstract representations because more abstract representations are often constructed based on less abstract ones. An important advantage of more abstract representations is that they can be invariant to the local changes in the input data. Learning such invariant features is an ongoing major goal in pattern recognition. Beyond being invariant such representations can also disentangle the factors of variation in data. The real data used in AI-related tasks mostly arise from complicated interactions of many sources. For example an image is composed of different sources of variations such a light, object shapes, and object materials. The abstract representations provided by deep learning algorithms can separate the different sources of variations in data. Deep learning algorithms are actually deep architectures of consecutive layers. Each layer applies a nonlinear transformation on its input and provides a representation in its output. The objective is to learn a complicated and abstract representation of the data in a hierarchical manner by passing the data through multiple transformation layers. The sensory data is fed to the first layer. Consequently the output of each layer is provided as input to its next layer.

Stacking up the nonlinear transformation layers is the basic idea in deep learning algorithms. The more layers the data goes through in the deep architecture, the more complicated the nonlinear transformations which are constructed. These transformations represent the data, so Deep Learning can be considered as special case of representation learning algorithms which learn representations of the data in a Deep Architecture with multiple levels of representations. The achieved final representation is a highly non-linear function of the input data.

5.Deep Learning in Big Data Analytics

Deep Learning algorithms extract meaningful abstract representations of the raw data through the use of an hierarchical multi-level learning approach, where in a higher-level more abstract and complex representations are learnt based on the less abstract concepts and representations in the lower level(s) of the learning hierarchy. While Deep Learning can be applied to learn from labeled data if it is available in sufficiently large amounts, it is primarily attractive for learning from large amounts of unlabeled/unsupervised data, making it attractive for extracting meaningful representations and patterns from Big Data.Once the hierarchical data abstractions are learnt from unsupervised data with Deep Learning, more conventional discriminative models can be trained with the aid of relatively fewer supervised/labeled data points, where the labeled data is typically obtained through human/expert input. Deep Learning algorithms are shown to perform better at extracting non-local and global relationships and patterns in the data, compared to relatively shallow learning architectures. Other useful characteristics of the learnt abstract representations by Deep Learning include: (1) relatively simple linear models can work effectively with the knowledge obtained from the more complex and more abstract data representations, (2) increased automation of data representation extraction from unsupervised data enables its broad application to different data types, such as image, textural, audio, etc., and (3) relational and semantic knowledge can be obtained at the higher levels of abstraction and representation of the raw data. While there are other useful aspects of Deep Learning based representations of data, the specific characteristics mentioned above are particularly important for Big Data Analytics.

Considering each of the four Vs of Big Data characteristics, i.e., Volume, Variety, Velocity, and Veracity, Deep Learning algorithms and architectures are more aptly suited to address issues related to Volume and Variety of Big Data Analytics. Deep Learning inherently exploits the availability of massive amounts of data, i.e. Volume in Big Data, where algorithms with shallow learning hierarchies fail to explore and understand the higher complexities of data patterns. Moreover, since Deep Learning deals with data abstraction and representations, it is quite likely suited for analyzing raw data presented in different formats and/or from different sources, i.e. Variety in Big Data, and may minimize need for input from human experts to extract features from every new data type observed in Big Data. While presenting different challenges for more conventional data analysis approaches, Big Data Analytics presents an important opportunity for developing novel algorithms and models to address specific issues related to Big Data.

6.Future of Deep Learning

Unsupervised learning had a catalytic effect in reviving interest in deep learning, but has since been overshadowed by the successes of purely supervised learning. We expect unsupervised learning to become far more important in the longer term. Human vision is an active process that sequentially samples the optic array in an intelligent, task-specific way using a small, high-resolution fovea with a large, low-resolution surround. We expect much of the future progress in vision to come from systems that are trained end-to-end and combine ConvNets with RNNs that use reinforcement learning to decide where to look. Systems combining deep learning and reinforcement learning are in their infancy, but they already outperform passive vision systems at classification tasks and produce impressive results in learning to play many different video games. Natural language understanding is another area in which deep learning is poised to make a large impact over the next few years. We expect systems that use RNNs to understand sentences or whole documents will become much better when they learn strategies for selectively attending to one part at a time. Ultimately, major progress in artificial intelligence will come about through systems that combine representation learning with complex reasoning. Although deep learning and simple reasoning have been used for speech and handwriting recognition for a long time, new paradigms are needed to replace rule-based manipulation of symbolic expressions by operations on large vectors.

7. Introduction : Deeper Learning

In classrooms where deeper learning is the focus, you find students who are motivated and challenged—who look forward to their next assignment. They apply what they have learned in one subject area to newly encountered situations in another. They can see how their classwork relates to real life. They are gaining an indispensable set of knowledge, skills, and beliefs, including:

- **Mastery of Core Academic Content:** Students build their academic foundation in subjects like reading, writing, math, and science. They understand key principles and procedures, recall facts, use the correct language, and draw on their knowledge to complete new tasks.
- **Critical Thinking and Problem Solving:** Students think critically, analytically, and creatively. They know how to find, evaluate, and synthesize information to construct arguments. They can design their own solutions to complex problems.
- **Collaboration:** Collaborative students work well in teams. They communicate and understand multiple points of view and they know how to cooperate to achieve a shared goal.
- **Effective Communication:** Students communicate effectively in writing and in oral presentations. They structure information in meaningful ways, listen to and give feedback, and construct messages for particular audiences.
- **Self-directed Learning:** Students develop an ability to direct their own learning. They set goals, monitor their own progress, and reflect on their own strengths and areas for improvement. They learn to see setbacks as opportunities for feedback and growth. Students who learn through self-direction are more adaptive than their peers.
- **An Academic Mindset:** Students with an academic mindset have a strong belief in themselves. They trust their own abilities and believe their hard work will pay off, so they persist to overcome obstacles. They also learn from and support each other. They see the relevance of their schoolwork to the real world and their own future success.

When students are developing knowledge, skills, and academic mindsets simultaneously, they learn more efficiently. They acquire and retain more academic knowledge when they are engaged, believe their studies are important, and are able to apply what they are learning in complex and meaningful ways.

7.1 Importance of Deeper Learning

We live in a world that is changing—and changing quickly. People and goods move around the world with unprecedented ease. The rapid advance of technology means that televisions, computers, and cell phones consume more than seven hours of the average children's day. Signs of our digital connectivity are all around us: every month, 100 billion searches are performed on Google. Every two years, the amount of digital information more than doubles. What is novel and revolutionary today is quickly outdated.
These changes pose important questions for education. How well will the students be able to use the information and technology at their fingertips, interpret the world around them, and adapt so that they can thrive in such a quickly changing environment? How well are we preparing them for a world that will look dramatically different when they graduate from high school?
Our students need a better education, one that gives them what they need to succeed.

8. Direct Instruction

Direct Instruction is a deductive teaching method where learning is viewed as a function of change in the students' long-term memory. Direct Instruction is the most-common teaching method in precollege institutions. Teachers provide students with elaborate presentations that fully explain the concepts of interest. Students then have the opportunity to practice and acquire skills or knowledge under the teacher's supervision in close-ended activities having a predicted outcome. Direct instruction is aimed at acquiring structured, factual, and algorithmic procedural knowledge. Therefore, its application is suitable when students are novices to a discipline and require strong instructional guidance to build a knowledge base that will allow them to effectively work in more autonomous ways. Although considered incompatible with constructivist learning theories and somehow overused, the unique advantages that deductive instruction offers to novice learners make it imperative to include Direct Instruction in our recommended approach to precollege engineering education.

8.1 Problem and Inquiry-based

Problem- and Inquiry-Based are two inductive teaching methods that share many traits when applied in precollege engineering, often making these methodologies indistinguishable. The underlying motivation of Problem- and Inquiry-Based methods is the acquisition and analysis of knowledge needed to understand complex concepts, providing learning experiences elicited by questions or problems. Knowledge is constructed through the process of finding a solution to the problem or an answer to a question. The solution to the problem is less important than the knowledge acquired by students through its construction. Oftentimes, the problem description is purposely ill-structured and open-ended. Problem- and Inquiry-Based methods stipulate no concrete subject matter learning objectives; students are not explicitly required to learn a specific set of facts or formulas. Rather, students perform a self-directed learning cycle where they determine the topics to be learned. First, by analyzing the problem or question at hand, then by identifying the corresponding learning issues that students perceive as relevant to determine a solution. The identification and attention to these learning issues are the essence of the self-directed learning cycle. Students are able to reexamine the problem with a new level of acquired knowledge, repeating this learning cycle whenever new learning issues arise. Because no explicit learning objectives exist, the problems proposed to students have to be designed in such way that they indirectly involve the learning of relevant subject matter concepts and principles. At the precollege level, problems are typically constructed to entail learning topics required in the state and federal education standards, with the identification of learning issues typically regulated by the instructors. Real-world problems are favored in Problem- and Inquiry-Based methods, as students are able to analyze these problems from a variety of perspectives without showing inconsistencies. Moreover, as opposed to fictional problems, real-world problems can provide a greater level of ownership and familiarity with students. Ownership of a problem arises when the proposed problem is personally relevant to the learner and not important just because it is a requirement to obtain a good grade. Educators recommend using problem statements that are ill-structured, avoiding inclusion of only key information, which would bias all learners to the same solution. Problem statements should also include information or questions that may not necessarily be relevant to determining a solution. Developing successful Problem- and Inquiry-Based learning activities can be one of the most challenging inductive methods to implement. Learning is directed by individuals who analyze the problem from their own perspective, as such, there is no guarantee that all the desired topics will be covered by everyone's experiences. While Problem- and Inquiry-Based methods can pose a number of challenges to educators and students the advantages are often greater, providing authentic experiences and increased interest and motivation.

8.2 Project Based

Project-Based is an inductive teaching method where students are driven by the application of knowledge. The learning activities are motivated by the creation of an end product which is the centerpiece of the curriculum, reflecting real production activities, excluding endeavors that are not directly related with the design and construction of the final products. From the instructor's perspective, the end product represents the students' resulting state of knowledge. Instructors examine the characteristics and behaviors of the students' final designs as well as observe how students improve upon defective products derived from wrong premises. Projects must have a large dynamic range of improvement where participants can clearly observe how the performance of prototypes improves dramatically between design iterations and can determine which designs are superior. The author identified five defining features of project-based methods: centrality, a driving question, constructive investigation, autonomy, and realism. The idea of centrality encompasses the in-depth exploration of a particular discipline's fundamental concepts, with the construction of the final product motivating all activities. Unlike Problem- and Inquiry-Based methods, intentional exposure to unrelated concepts and facts is not included. Rather, a driving question is posed that focuses the related concepts and principles of a discipline that students must understand. Development and implementation of a final product requires constructive investigation, entailing the acquisition of new knowledge and skills. Students have a high degree of autonomy and are not provided with a predetermined path or expected outcome. Projects involving cookbook style instructions, defining a step-by-step approach leaves little opportunity for students to develop their own solutions are considered an exercise rather than an instance of a project-based module. Finally, project goals should offer a level of authenticity or realism that expose students to the everyday challenges of working professionals, specifically the higher order cognitive skills required to generate new ideas, reflect on experience, and make project decisions. In summary, meaningful learning can be achieved in precollege engineering education by aligning curriculum goals to target each of the levels outlined in the Bloom Taxonomy, through integration of deductive and inductive teaching methods into precollege engineering curriculum. Based on the literature dictating how to mediate human activity for effective learning in precollege engineering, we additionally present an analysis of promising educational implements that have been specifically developed and/or proved to be effective in teaching engineering-related concepts to novice learners.

8.3 Software Based Educational Implements

Software-based implements are a popular choice for precollege engineering education and include design, modeling and simulation tools, introductory programming environments, and online engineering information resources. Software tools offer unique opportunities to institutions, instructors, and students. In many cases educational engineering software can be obtained at reduced prices or free of charge. Numerous applications have been designed to teach concepts that would traditionally depend on purchasing expensive or inaccessible hardware if implemented in nonsoftware environments. Instructors can effectively manage classrooms while students work at their own pace on a designated computer, while taking advantage of the embedded aides offered by many software tools. The effectiveness of software-based tools to teach engineering concepts is comparable to the effectiveness of teaching with hardware alternatives. Similarly the creativity, usefulness and originality of end products developed in a software-based environment can also matched those designed in physical environments. As with hardware-based educational implements, we have established a relationship between the different categories of software implements considered and the instruction methods that they most prominently facilitate. The technical expertise required by novice users to interact with software tools is usually modest in comparison to many of the hardware alternatives. New users are able to independently learn how to use software implements by following the tutorials distributed along with the tools. Additionally, during usage monitoring aides are also provided within the software environments to guide users. The accessibility of these software implements, however, should not be confused with simplicity, many software tools provide not only opportunities to engage in a wide range of learning experiences, but also the functionality to continually refine and elaborate artifacts in depth.

9. Conclusion

In this paper the author describes deep learning methodologies, machine learning, importance of deep learning in data mining, application of deep learning in big data analytics. There are many motivations to explore deep learning algorithms:

- the ability to learn complex functions,
- the ability to learn high-level, hierarchical abstractions,

• the ability to learn from a very large set of training data, and
• the ability to learn from unlabeled data.

In addition with deep learning the author further discusses deeper learning to improve the education system with problem and inquiry based, project based, hardware- and software-based educational implements, offering learning experiences for individuals with various learning preferences and accommodating a diversified number of teaching methods and engineering topics. As both deductive and inductive methods are essential for precollege engineering education, we argued that some educational technologies are more suitable to teach concepts through deductive methods, like direct instruction, while other technologies facilitate the implementation of the inductive methods of problem/ inquiry and project-based lessons. Software-based technologies encompass a rich number of engineering related topics. On the other hand, the most prominent engineering topics covered by hardware-based technologies are related to computer, electrical and mechanical engineering. The author concludes that education system with activity based, project based and inquiry based will induce and motivate the students community. Finally the author suggests to improve the education system and better employment opportunity, identifies the following skill sets (Employability Skills) need for the students:

i) High order thinking skills
ii) Creative and Innovative thinking
iii) Problem solving skills
iv) Technical skills
v) Positive attitude
vi) Willing to learn
viii) Be a proactive listener
ix) Be focused
x) Set specific goals

References

[1] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems, 2012.

[2] Andrew Ng. Unsupervised discovery of structure, succinct representations and sparsity. In International Conference on Machine Learning, 2009.

[3] Bishop, C. M. (2006). Pattern Recognition and Machine Learning (Information Science and Statistics). Springer.

[4] Darrin C Bentivegna, Aleš Ude, Christopher G Atkeson, and Gordon Cheng. Humanoid robot learning and game playing using pc-based vision. In Intelligent Robots and Systems, *2002.* IEEE/RSJ International Conference on, volume 3, pages 2449–2454. IEEE, 2002.

[5] UC Berkeley. New 'deep learning' technique enables robot mastery of skills via trial and error. http://news.berkeley.edu/2015/05/21/deep-learning-robot-masters-skills-via-trial-and-error/, 2015. [Online; accessed 12-September-2015]

[6] G. Desjardins, A. Courville, and Y. Bengio. Adaptive parallel tempering for stochastic maximum likelihood learning of RBMs. In *NIPS 2010 Workshop on* Deep Learning and Unsupervised Feature Learning, 2010a.

[7] J. Martens. Deep learning via Hessian-free optimization. In Proceedings of the 27th International Conference on Machine Learning (ICML), 2010.

[8] S. Haykin. Neural Networks and Learning Machines. Pearson Education, 3rd edition, 2009.

[9] Tieleman, T. (2008, July). Training restricted Boltzmann machines using approximations to the likelihood gradient. In Proceedings of the 25th international conference on Machine learning (pp. 1064-1071).

[10] Weinberger, K. Q. and Saul, L. K. (2009). Distance metric learning for large margin nearest neighbor classi_cation. Journal of Machine Learning Research.