NEURAL NETWORKS AND DEEP LEARNING CST 395 CS 5TH SEMESTER HONORS COURSE- Dr Binu V P, 9847390760

CS 5th Semester Honors course for the Computer Science at KTU- Dr Binu V P

Introduction to neural networks

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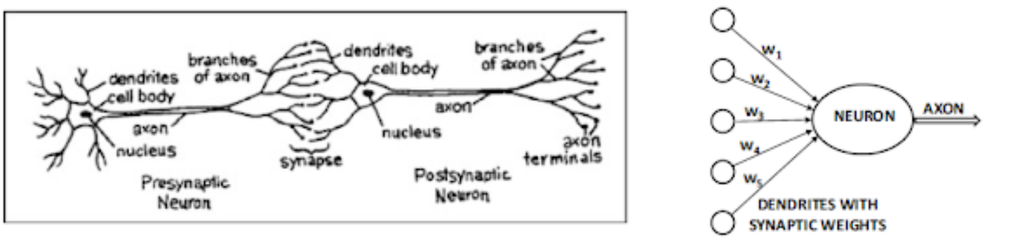
Artificial neural networks are popular machine learning techniques that simulate the mechanism of learning in biological organisms. The human nervous system contains cells, which are referred to as **neurons**. The neurons are connected to one another with the use of **axons and dendrites**, and the connecting regions between axons and dendrites are referred to as **synapses**.The strengths of synaptic connections often change in response to external stimuli. This change is how learning takes place in living organisms.

This biological mechanism is simulated in artificial neural networks, which contain computation units that are referred to as **neurons**. The computational units are connected to one another through weights, which serve the same role as the strengths of synaptic connections in biological organisms. Each input to a neuron is scaled with a weight, which affects the function computed at that unit. The following figure shows both the biological and artificial neural networks.

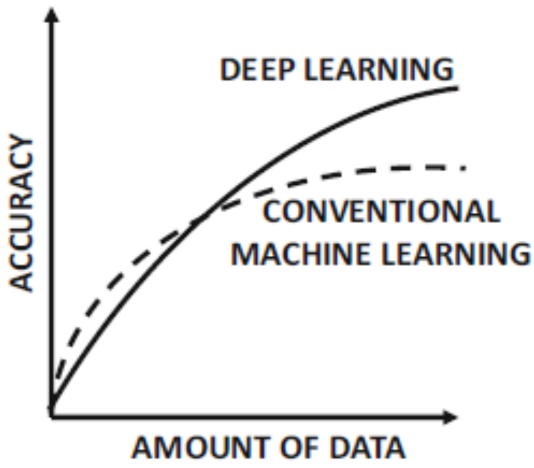


(a) Biological neural network (b) Artificial neural network

An artificial neural network computes a function of the inputs by propagating the computed values from the input neurons to the output neuron(s) and using the weights as intermediate parameters. Learning occurs by changing the weights connecting the neurons. Just as external stimuli are needed for learning in biological organisms, the external stimulus in artificial neural networks is provided by the training data containing examples of input-output pairs of the function to be learned. For example, the training data might contain pixel representations of images (input) and their annotated labels (e.g., carrot, banana) as the output. These training data pairs are fed into the neural network by using the input representations to make predictions about the output labels. The training data provides feedback to the correctness of the weights in the neural network depending on how well the predicted output (e.g., probability of carrot) for a particular input matches the annotated output label in the training data. One can view the errors made by the neural network in the computation of a function as a kind of unpleasant feedback in a biological organism, leading to an adjustment in the synaptic strengths. Similarly, the weights between neurons are adjusted in a neural network in response to prediction errors. The goal of changing the weights is to modify the computed function to make the predictions more correct in future iterations. Therefore, the weights are changed carefully in a mathematically justified way so as to reduce the error in computation on that example. By successively adjusting the weights between neurons over many input-output pairs, the function computed by the neural network is refined over time so that it provides more accurate predictions. Therefore, if the neural network is trained with many different images of bananas, it will eventually be able to properly recognize a banana in an image it has not seen before. This ability to accurately compute functions of unseen inputs by training over a finite set of input-output pairs is referred to as model **generalization**. The primary usefulness of all machine learning models is gained from their ability to generalize their learning from seen training data to unseen examples.

Neural networks are built as higher-level abstractions of the classical models that are commonly used in machine learning. In fact, the most basic units of computation in the neural network are inspired by traditional machine learning algorithms like least-squares regression and logistic regression.Neural networks gain their power by putting together many such basic units, and learning the weights of the different units jointly in order to minimize the prediction error. From this point of view, a neural network can be viewed as a computational graph of elementary units in which greater power is gained by connecting them in particular ways. When a neural network is used in its most basic form, without hooking together multiple units, the learning algorithms often reduce to classical machine learning models . The real power of a neural model over classical methods is unleashed when these elementary computational units are combined, and the weights of the elementary models are trained using their dependencies on one another. By combining multiple units, one is increasing the power of the model to learn more complicated functions of the data than are inherent in the elementary models of basic machine learning. The way in which these units are combined also plays a role in the power of the architecture, and requires some understanding and insight from the analyst. Furthermore, sufficient training data is also required in order to learn the larger number of weights in these expanded computational graphs.

An illustrative comparison of the accuracy of a typical machine learning algorithm with that of a large neural network is shown below. Deep learners become more attractive than conventional methods primarily when sufficient data/computational power is available. Recent years have seen an increase in data availability and computational power, which has led to a "Cambrian explosion" in deep learning technology.



Humans Versus Computers: Stretching the Limits of Artificial Intelligence

Humans and computers are inherently suited to different types of tasks. For example, computing the cube root of a large number is very easy for a computer, but it is extremely difficult for humans. On the other hand, a task such as recognizing the objects in an image is a simple matter for a human, but has traditionally been very difficult for an automated learning algorithm. It is only in recent years that deep learning has shown an accuracy on some of these tasks that exceeds that of a human. In fact, the recent results by deep learning algorithms that surpass human performance in (some narrow tasks on) image recognition would not have been considered likely by most computer vision experts as recently as 10 years ago.

Many deep learning architectures that have shown such extraordinary performance are not created by indiscriminately connecting computational units. The superior performance of deep neural networks mirrors the fact that biological neural networks gain much of their power from depth as well. Furthermore, biological networks are connected in ways we do not fully understand. In the few cases that the biological structure is understood at some level, significant breakthroughs have been achieved by designing artificial neural networks along those lines. A classical example of this type of architecture is the use of the **convolutional neural network** for image recognition. This architecture was inspired by Hubel and Wiesel's experiments in 1959 on the organization of the neurons in the cat's visual cortex. The precursor to the convolutional neural network was the neocognitron , which was directly based on these results.(https://journals.physiology.org/doi/pdf/10.1152/jn.1965.28.2.229)

The human neuronal connection structure has evolved over millions of years to optimize survival-driven performance; survival is closely related to our ability to merge sensation and intuition in a way that is currently not possible with machines. Biological neuroscience is a field that is still very much in its infancy, and only a limited amount is known about how the brain truly works. Therefore, it is fair to suggest that the biologically inspired success of convolutional neural networks might be replicated in other settings, as we learn more about how the human brain works .

A key advantage of neural networks over traditional machine learning is that the former provides a higher-level abstraction of expressing semantic insights about data domains by architectural design choices in the computational graph. The second advantage is that neural networks provide a simple way to adjust the complexity of a model by adding or removing neurons from the architecture according to the availability of training data or computational power. A large part of the recent success of neural networks is explained by the fact that the increased data availability and computational power of modern computers has outgrown the limits of traditional machine learning algorithms, which fail to take full advantage of what is now possible.

The performance of traditional machine learning remains better at times for smaller data sets because of more choices, greater ease of model interpretation, and the tendency to hand-craft interpretable features that incorporate domain-specific insights.With limited data, the best of a very wide diversity of models in machine learning will usually perform better than a single class of models (like neural networks). This is one reason why the potential of neural networks was not realized in the early years.

The “big data” era has been enabled by the advances in data collection technology; virtually everything we do today, including purchasing an item, using the phone, or clicking on a site, is collected and stored somewhere. Furthermore, the development of powerful Graphics Processor Units (GPUs) has enabled increasingly efficient processing on such large data sets. These advances largely explain the recent success of deep learning using algorithms that are only slightly adjusted from the versions that were available two decades back.Furthermore, these recent adjustments to the algorithms have been enabled by increased speed of computation, because reduced run-times enable efficient testing (and subsequent algorithmic adjustment). If it requires a month to test an algorithm, at most twelve variations can be tested in an year on a single hardware platform. This situation has historically constrained the intensive experimentation required for tweaking neural-network learning algorithms. The rapid advances associated with the three pillars of improved data, computation, and experimentation have resulted in an increasingly optimistic outlook about the future of deep learning. By the end of this century, it is expected that computers will have the power to train neural networks with as many neurons as the human brain. Although it is hard to predict what the true capabilities of artificial intelligence will be by then, our experience with computer vision should prepare us to expect the unexpected.

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