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# In Shortly about Neural Networks

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## Abstract

A neural network is a collection of neurons that are interconnected and interactive through signal processing operations. The traditional term "neural network" refers to a biological neural network, i.e., a network of biological neurons. The modern meaning of this term also includes artificial neural networks, built of artificial neurons or nodes. Machine learning includes adaptive mechanisms that allow computers to learn from experience, learn by example and by analogy. Learning opportunities can improve the performance of an intelligent system over time. One of the most popular approaches to machine learning is artificial neural networks. An artificial neural network consists of several very simple and interconnected processors, called neurons, which are based on modeling biological neurons in the brain. Neurons are connected by calculated connections that pass signals from one neuron to another. Each connection has a numerical weight associated with it. Weights are the basis of long-term memory in artificial neural networks. They express strength or importance for each neuron input. An artificial neural network "learns" through repeated adjustments of these weights.

## Keywords

Neural Network, Artificial Neural Network, Computer Vision, Robotics

## 1. Introduction

An Artificial Neural Network (ANN) model mimics the biological brain response to multisource inputs, e.g., sensory-motor stimuli [1]. ANNs simulate the brain using networks of interconnected neuron cells to create massively parallel processors. Of course, ANNs use networks of artificial nodes, not brain cells, to train data.

## 2. Neural Network

Neural networks are inspired by the working of cerebral cortex in mammals [2]. It is important to note, however, that these models do not closely resemble the working, scale and complexity of the human brain. Artificial neural network models can be understood as a set of basic processing units, which are tightly interconnected and operate on the given inputs to process the information and generate desired outputs. Neural networks can be grouped into two generic categories based on the way the information is propagated in the network.

### 2.1 Feed-forward networks

The information flow in a feed-forward network happens only in one direction. If the network is considered as a graph with neurons as its nodes, the connections between the nodes are such that there are no loops or cycles in the graph. These network architectures can be referred as Directed Acyclic Graphs (DAG). Examples include MLP and CNNs, which we will discuss in details in the upcoming sections.

### 2.2 Feed-back networks

As the name implies, feed-back networks have connections which form directed cycles (or loops). This architecture allows them to operate on and generate sequences of arbitrary sizes. Feed-back networks exhibit memorization ability and can store information and sequence relationships in their internal memory. Examples of such architectures include Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM).

Neural network-powered AI, with all its attendant benefits and risks, will be insinuating itself more and more into the healthcare endeavor [3]. There is a growing library of off-the-shelf software for doing machine learning. Here is a short list of where machine learning will be found, at ever higher levels of sophistication: direct voice-to-machine transcription; translation of patient information documents; navigating the insurance coverage quagmire; allocating professional staff; identifying dangerous combinations of drugs and laboratory findings; providing early notification of impending medical crises; recognizing abnormalities in radiologic studies; assisting decision-making for therapy of diseases like prostate and breast cancer; guiding driverless carts to deliver food trays and medical supplies to hospital patients; powering companion dolls, in the shape of babies or cuddly animals, for children and for the demented; interpreting electrocardiograms electroencephalograms, and all sorts of other grams; instructing an “artificial pancreas” when to deliver insulin, and how much; directing drones to pick up and deliver laboratory samples and medical supplies out in the community, etc. The sky is the limit. As always, it will take human intelligence to understand how best to use artificial intelligence.

## 3. Parameters

The weights of a neural network define the connections between neurons [2]. These weights need to be set appropriately so that a desired output can be obtained from the neural network. The weights encode the “model” generated from the training data that is used to allow the network to perform a designated task (e.g., object detection, recognition, and/or classification). In practical settings, the number of weights is huge which requires an automatic procedure to update their values appropriately for a given task. The process of automatically tuning the network parameters is called “learning” which is accomplished during the training stage (in contrast to the test stage where inference/prediction is made on “unseen data,” i.e., data that the network has not “seen” during training). This process involves showing examples of the desired task to the network so that it can learn to identify the right set of relationships between the inputs and the required outputs. For example, in the paradigm of supervised learning, the inputs can be media (speech, images) and the outputs are the desired set of “labels” (e.g., identity of a person) which are used to tune the neural network parameters.

## 4. CNN

CNNs (Convolutional Neural Network) are one of the most popular categories of neural networks, especially for high-dimensional data (e.g., images and videos) [2]. CNNs operate in a way that is very similar to standard neural networks. A key difference, however, is that each unit in a CNN layer is a two- (or high-) dimensional filter which is convolved with the input of that layer. This is essential for cases where we want to learn patterns from high-dimensional input media, e.g., images or videos. CNN filters incorporate spatial context by having a similar (but smaller) spatial shape as the input media, and use parameter sharing to significantly reduce the number of learn-able variables.

CNNs are a useful class of models for both supervised and unsupervised learning paradigms. The supervised learning mechanism is the one where the input to the system and the desired outputs (true labels) are known and the model learns a mapping between the two. In the unsupervised learning mechanism, the true labels for a given set of inputs are not known and the model aims to estimate the underlying distribution of the inputs data samples. The CNN learns to map a given image to its corresponding category by detecting a number of abstract feature representations, ranging from simple to more complex ones. These discriminative features are then used within the network to predict the correct category of an input image. The function of a CNN is similar to this pipeline, with the key difference being the automatic learning of a hierarchy of useful feature representations and its integration of the classification and feature extraction stages in a single pipeline which is trainable in an end-to-end manner. This reduces the need for manual design and expert human intervention.

## 5. Computer Vision

Computer Vision and Machine Learning have played together decisive roles in the development of a variety of image-based applications within the last decade (e.g., various services provided by Google, Facebook, Microsoft, Snapchat) [2]. During this time, the vision-based technology has transformed from just a sensing modality to intelligent computing systems which can understand the real world. Thus, acquiring computer vision and machine learning (e.g., deep learning) knowledge is an important skill that is required in many modern innovative businesses and is likely to become even more important in the near future.

Humans use their eyes and their brains to see and understand the 3D world around them. For example, humans can easily see a "cat" in the image and thus, categorize the image (classification task); localize the cat in the image (classification plus localization task); localize and label all objects that are present in the image (object detection task); and segment the individual objects that are present in the image (instance segmentation task). Computer vision is the science that aims to give a similar, if not better, capability to computers. More precisely, computer vision seeks to develop methods which are able to replicate one of the most amazing capabilities of the human visual system, i.e., inferring characteristics of the 3D real world purely using the light reflected to the eyes from various objects.

However, recovering and understanding the 3D structure of the world from twodimensional images captured by cameras is a challenging task [4]. Researchers in computer vision have been developing mathematical techniques to recover the three-dimensional shape and appearance of objects/scene from images. For example, given a large enough set of images of an object captured from a variety of views, computer vision algorithms can reconstruct an accurate dense 3D surface model of the object using dense correspondences across multiple views. However, despite all of these advances, understanding images at the same level as humans still remains challenging.

Commonly used machine-learning models are artificial neural networks, support-vector machines, Bayesian networks, and genetic algorithms. The most popular model approach in the field of machine learning is neural networks, often used in supervised learning. The idea behind this approach is to simulate aspect of the behavior of neurons in the human brain using the so-called perceptron algorithm. A perceptron or neural network consists of several artificial digital neurons that are networked along different layers: the input layer, hidden layer and output layer. This approach is also known as a black-box algorithm because interpretable information about the dynamics between input and output layer is not available. An artificial digital neuron is represented by a nonlinear function, the activation function and a weight function (transfer function) with variable weight parameters. The special feature of the nonlinear function is that it has a threshold. If this threshold value is exceeded by the input value of the function, the function outputs a one, and otherwise a zero. This behavior can be used to train a specific input-output mapping between the input and output layer of this type of network. If a specific network structure is then designed for a desired application, the network can be trained to a desired behavior, using the backpropagation algorithm and training data, by setting the parameters of the network accordingly. In this context, a deep neural network is a more complex variant of a normal neural network, where, for example, a higher number of hidden layers are used. The hidden layers can generally be seen as a not directly reachable layer with encoded information after the training phase. The dynamics and properties of these layers are not yet fully understood.

The first step in making an artificial intelligence system conscious would be a mutual simulation of high-level human cognitive functions, such as memory and imagination with large-scale neural networks [5]. Such a system will provide mapping between mental functions, combinations of the firing rate of the neurons, and the specific neuronal architecture; or even some biochemical features of the neuronal structures. The "Universal Grammar" optimal theory and A Theory of Cerebral Cortex demonstrate how discrete symbol structures can emerge from continuous dynamic systems such as neural networks. Those symbols can be represented as dynamic states over a set of distributed neurons where various symbols can be represented by various states in the same or different neural net.

Machine learning (ML) models themselves are numerous and varied; and our goal here is not to present a comprehensive library of models [6]. However, because of their increasing popularity in the field, artificial neural networks (ANNs) deserve special mention. ANNs belong to their own subset of ML methods known as Deep Learning. Deep Learning models are inspired by biological neural networks in that they are comprised of many connected nodes ('neurons'), with each connection transmitting 'signal' between nodes, like a synapse. Typically, this signal is a number, and each neuron performs some non-linear function of the sum of its inputs. As the network completes several attempts at 'learning' a task, the mathematical weighting of each nodal connection is determined based on that node's contribution to a successful outcome. In this way, the ANN is thought to resemble the function of biological synapse restructuring during a learning task. Unlike a biological brain, neurons in the ANN are arranged in layers, with each layer performing a specific task or data transformation. ANNs and Deep Learning in general have been successful in a variety of tasks, from computer vision and mobile advertising to cancer variant detection and patient outcome prediction.

## 6. ASM

Some methods used binary information, and some used regional information, but graph cut utilized both binary and regional information [7]. Another algorithm, in which contour was presented as a polygon with fixed labeled points. An ASM (active shape model) is a collection of landmark points and gray levels. Both the gray-level models and shape models were trained with the set of labeled images. In the improvement made in ASM, shape model was extracted from body location using thin spline method, and the Gaussian pyramid was used for quick iteration. Another technique named 4D lung segmentation, which is an extended form of ASM, was proposed in which 4D lung segmentation is refined by optimal surface finding algorithm and dataset was consisted of several volumes. Different masks were used to segment the lung region. For lung region segmentation, the average of intensity values of Gobar mask, intensity mask, and lung model mask was used. Intensity mask was used to highlight the dark part of the image, and it was the complement of X-ray, and lung model was computed from JSRT (Japanese Society of Radiological Technology) dataset. To map the model to the input image, bilinear alignment of the lung shape model is used, and a threshold was applied to get a lung region. Another technique was proposed, in which morphological operations, canny edge technique, and Euler number method were used to separate lung region from the input image. A methodology is proposed in which features comprised of Gabor wavelet transform and fractal dimension are extracted and fuzzy c-means clustering is used for initial contouring and deformable models based on level sets are used for final contour. Deep learning is also applied on chest radiographs. Convolutional Neural Network (CNN) framework is used for lung segmentation, which consists of seven layers, and it outperformed the manual segmentation. Another method is proposed in which Structure Correcting Adversarial Network (SCAN) framework is used. In this method, adversarial process is applied to create segmentation models for segmentation of chest radiographs.

## 7. Robotics

The goal of modern control in robotics is to develop approaches that enable the robot to act optimally on its own but also to handle potentially physical interactions with humans gently and in a human-centered way [4]. A very common approach to control physical interaction is impedance control or compliance control. This approach is based on controlling the connection between force and position on interaction ports, such that the robot has the ability to interact compliantly with the environment. For this purpose, the contact behavior between the robotic system and the object it is to interact with is modeled by a mass-spring-damper system, whereby the controller can adjust the stiffness and damping of this system. Classical impedance control quickly reaches its limits in dynamic, rapidly changing processes, which include human–robot interactions. The impedance control parameters must be known in advance and are usually set by experiments and calibration. In order to avoid this limitation, adaptive impedance control (AIC) was developed, whereby these parameters can also be changed online. New approaches combine AIC with approaches from machine learning to teach the robot certain impedance behaviors as well as how to deal with disturbances in the system. One example is the combined use of AIC and artificial neural networks to map complex disturbances that cannot be modeled analytically.

## 8. Artificial Intelligence

Computer-based systems are actually able to exhibit capabilities such as computational innovations, automated reasoning, assisted decision systems, data handling, language analysis and synthesis and, of course, direct control in robotics [8]. We are very busy teaching the machine how to understand humans, but at the same time the machine reciprocally and actively contributes to teaching humans! It is quite a feat, after all!

Neural networks can learn from experience: pattern recognition, classification of problems, better accuracy than human experts without the need for blocking initial definitions.

But, at the same time, over the years, human intelligence itself has been regularly improving. New solutions for accelerating the process are considered (which is as frightening as the growing AI). Genetic algorithms and programming are very promising; they generate randomly assembled new candidate solutions by mutating or recombining variants, following maximum likelihood estimation. Then selection criteria make it possible, over generations, to improve the quality. The changes could then be much more rapid than the natural random selection. Careful monitoring of the evolution would nevertheless be required, to prevent deviations. This approach, however, calls for a large computing capacity and must be agreed to be a transgression of our moral convictions.

Be that as it may, the outreach opportunities of human intelligence are significant when they are collectively organized with convenience; but this depends on the problem concerned. There still are talents that can only be solitary; they can never be replaced by an addition of mediocrities. Intelligence not only consists in solving complex problems…but, sometimes, inventing them. Human intelligence cannot be restricted to a unique criterion such as IQ or an exam; this is a common error.

## 9. Conclusion

An artificial neural network is a collection of artificial neurons (usually abstract concepts) that are interconnected and interactive through signal processing operations. It is modeled on the human brain. The network can have a series or one input of inputs and always one output, between which there is one or more so-called. hidden layers (so-called multilayer networks). Individual neurons, like layers, are interconnected by connections through which signals go. Connections between them are activated if the condition is set so-called activation function. The main application of artificial networks is in the search for dependencies between data that are not in a purely linear relationship, and yet can be combined into one complex input set. The aggregation of such data is the task of those skilled in the art in which neural networks are applied, while their analysis is later in the domain of the type of neural network selected. Today, there are several main types of networks, but the basic feature of all networks, regardless of the form and number of connections within them, is characterized by the property of "learning", ie training through a series of repetitive analysis procedures. Of the whole set of data, most were used for learning and less for re-predicting known values. Thus, it is possible to calculate the prediction error, which should be smaller with a larger number of attempts. Such a process of "learning" is similar to human learning from experience, hence the name "neural network".

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