Deep Learning Utilizing Supervised and Unsupervised Learning

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Overview

Although the concept of artificial intelligence began as early as 1300 CE, the field itself did not come to fruition until 1956, where, at the Dartmouth Summer Research Project on Artificial Intelligence, researchers convened to formulate the rubric for what would become arguably the most revolutionary field of computer science to date. By then, scientists had already proven that machines could outperform humans by means of calculation, programming, and automation. These achievements however were shadowed by the idea that machines have to be programmed to complete automated behaviors explicitly. The ultimate goal in automation however, is to remove those explicit instructions by means of calculated decision-making. Instead of a programmer inputting an explicit instruction, what if the machine could determine the instruction on its own? What if the machine could be trained, much like humans are, to make decisions based on existing patterns? If this could be accomplished, what applications would this type of intelligence have?

Patterns Are Everything

Human beings, although complex in their structure and behavior, can be reduced to one noticeable trait. All humans exhibit a psychological need for discernable patterns in everyday life. At the very basis of learning, are patterns of behavior, that once consistently repeated, become autonomous. The advent of relational databases, distributed computing, and data analytics has afforded science the ability to track these patterns. Through analysis, it has become quite evident that despite being incredibly complicated, humans can be incredibly predictable. Patterns of human behavior can be found in almost all data, the traces of which, can be used to train a machine to think as a human would. The algorithmical process of discovering these patterns and making automated decisions based on them is known as Deep Learning.

Supervised and Unsupervised Learning

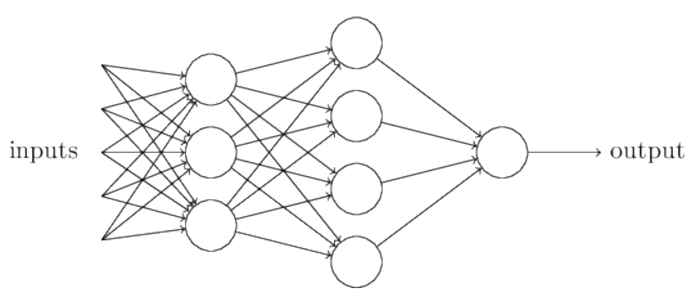
Deep learning algorithms can either learn by being provided a sample outcome, or a dataset for which no prior outcome has been defined. These learning classifications are known as Supervised and Unsupervised learning.

In a supervised learning environment, sample data is provided to the mathematical model for which outcomes are present. The model will then be trained to generate output based on the mathematical patterns present in the sample data. For example, if a teacher presents a child with a container of building blocks along with an example picture of a pre-assembled house, the child would then attempt to recreate the house based on the sample provided. The child might not have the exact instructions to build the house, but after many iterations of following the example, can accurately build one.

Alternatively, an unsupervised learning environment is not provided any sample output for which the network is trained. Instead, the algorithm seeks to discover patterns within the distribution of the data presented to it, resulting in classification and association of the underlying structure. Using the building block example, this would be akin to giving a child a container of blocks to use without any explicit instruction on how to use them. The child might begin by separating (classifying) each part and then possibly associating which parts might fit together. The result is not necessarily a house; rather, it is a grouping components, to build one.

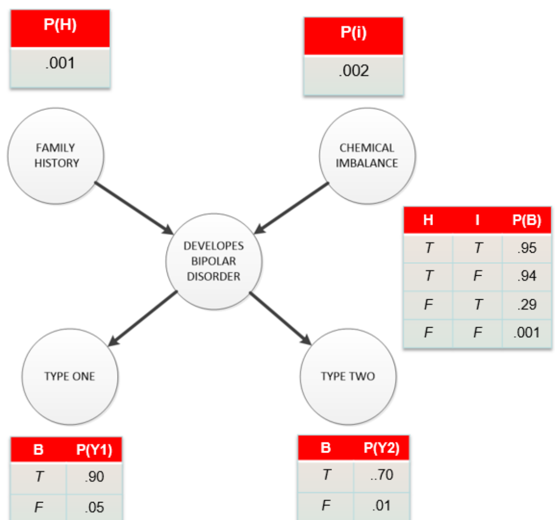
Deep Learning Networks

The human brain contains over 86 million specialized cells whose primary purpose is to communicate via electrical impulse. These cells, known as neurons, create networks for which all information in the human brain is processed. As such, deep learning and artificial intelligence begins with emulating this structure. In 1943, Warren McCulloch and Walter Pitts released a mathematical model to simulate this structure effectively creating the first Neural Network model. Artificial Neural Networks (ANNs) consist of nodes (neurons) which receive input and mathematically generate output based on interconnected layers for which mathematical weights can be modified. The network is effectively trained by presenting an input dataset compared against predetermined output. The resulting model can be used to predict outcomes in additional datasets presented to it. Artificial Neural Networks are used primarily for predictive analytics, that is, the learning method is applied in an effort to predict a given outcome based on inputs that the network was trained to receive.



Example of a Neural Network Structure

Whereas artificial neural networks perform predictive analysis, Bayesian networks utilize joint conditional probability distributions to perform causal analysis. They are also referred to as “belief networks” or “probabilistic networks”. They consist of a directed acyclic graph (DAG) representing variable relationships and associated conditional probability tables. Changes within the Bayesian network propagate throughout the network with network training. Nodes within the network represent variables in a child/descendent formality between each of the random variables, essentially mapping probabilistic relationships through a series of arcs. Arcs between random variables are known as edges and represent conditional dependencies. Nodes that are not connected via edges are considered to be conditionally independent of one another. Bayesian network graphs are usually presented with a set of conditional probability tables (CPTs) along with the acyclic graph.



Example of a Bayesian Network DAG with associated CPTs

Applications, Security, and Ethics

The ability to discover discernable patterns and train networks to infer outcomes accordingly is incredibly valuable. Neural networks for example are used extensively in finance to predict factors such as fraud and risk assessment. Bayesian networks are invaluable to the healthcare and pharmaceutical industry to map patient symptoms with possible causes. Automotive engineers utilize Bayesian inference in crash safety testing and manufacturing. Likewise insurance companies use the predictive power of neural networks to analyze claims.

Not all deep learning methodologies are inherently noble. The amount of data that can be analyzed leads to means of discovering data that would otherwise not be accessible. For example, researchers recently utilized a neural network to uncover unlock codes for mobile devices. By gathering sensor data from the devices' hardware, they were able to predict with 94% accuracy the unlock code for various mobile phones. Likewise, one could apply the methodologies of deep learning to discover a plethora of information about the users of a dataset, implying ethical concerns. For example, GPS location coupled with machine learning in social media leads to unethical friend suggestions between users and members of the professional community. (ie, doctors and patients).

As concerning as the ethical implications might be, the future of deep learning is bright. Artificial intelligence is fueled by deep learnings' multiple approaches to understanding the human condition. Although cognitive dissonance presents a challenge to deep learning, the ability to train and modify the networks yields a toolset sufficient for the revolution of computing. Deep learning will continue to grow exponentially as a result.

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