

Machine learning (ML) is a field of study in artificial intelligence concerned with the development and study of statistical models that can learn from previously seen data, and thus perform tasks without explicit instructions.[1] Recently, generative artificial neural networks have been used to generate new data that is similar to the training data.[2][3]

Machine learning approaches have been applied to many fields including large language models, computer vision, speech recognition, and recommendation systems. However, it is too costly to develop algorithms to perform the needed tasks.[4][5] ML is known in its application across business and industry. All machine learning is statistically based, computational statistics is an important source of the field's methods.

Artificial intelligence

Machine learning as subfield of AI[22]

As a scientific endeavor, machine learning grew out of the quest for artificial intelligence (AI). In the early days of AI and machine learning, the focus was on having machines learn from data. They attempted to approach the problem with various symbolic methods, as well as neural networks and other models that were later found to be reinventions of the generalized linear models of statistics.[23] Machine learning was used in medical diagnosis.[24]:488

However, an increasing emphasis on the logical, knowledge-based approach caused a rift between AI and machine learning. The focus shifted to solving real problems of data acquisition and representation.[24]:488 By 1980, expert systems had come to dominate AI, and machine learning did continue within AI, leading to inductive logic programming, but the more statistical line of research was largely abandoned in favor of information retrieval.[24]:708–710,755 Neural networks research had been abandoned by AI and computer science in the 1980s. In the CS field, as "connectionism", by researchers from other disciplines including Hopfield, Rumelhart, and Hinton. Their research was largely abandoned in the 1980s. Propagation.[24]:25

Machine learning (ML), reorganized and recognized as its own field, started to flourish in the 1990s. The field changed its focus to solving solvable problems of a practical nature. It shifted focus away from the symbolic approaches it had inherited from AI, and towards statistical, logic, and probability theory.[25]

Data mining

Machine learning and data mining often employ the same methods and overlap significantly, but while machine learning focuses on learning from training data, data mining focuses on the discovery of (previously) unknown properties in the data (this is the analysis of data). While many machine learning methods, but with different goals; on the other hand, machine learning also employs data mining to improve learner accuracy. Much of the confusion between these two research communities (which do often have overlap) comes from the basic assumptions they work with: in machine learning, performance is usually evaluated in terms of accuracy. In knowledge discovery and data mining (KDD) the key task is the discovery of previously unknown knowledge. Evaluation is based on the ability to discover new knowledge. Supervised methods will easily be outperformed by other supervised methods, while in a typical KDD task, supervised methods cannot

Machine learning also has intimate ties to optimization: many learning problems are formulated as minimization of a loss function, which measures the discrepancy between the predictions of the model being trained and the actual problem instances (for example, in classification, the loss is the number of misclassified examples and models are trained to correctly predict the pre-assigned labels of a set of examples).[26]

Supervised learning: The computer is presented with example inputs and their desired outputs, given by a "teacher" or a set of labels. The goal is to learn a function that maps inputs to outputs.

Unsupervised learning: No labels are given to the learning algorithm, leaving it on its own to find structure in its input data (this is the analysis of data). The goal is to find hidden patterns in data) or a means towards an end (feature learning).

Reinforcement learning: A computer program interacts with a dynamic environment in which it must perform a certain task (the goal is to learn a policy that maximizes the expected return). As it navigates its problem space, the program is provided feedback that's analogous to rewards, which it tries to maximize. Although each algorithm has advantages and limitations, no single algorithm works for all problems.[36][37][38]

Supervised learning

Main article: Supervised learning

A support-vector machine is a supervised learning model that divides the data into regions separated by a linear boundary. The goal is to find the maximum margin between the two classes (the white and the black).

Supervised learning algorithms build a mathematical model of a set of data that contains both the inputs and the desired outputs. The goal is to find a function that maps inputs to outputs. Each training example has one or more inputs and the desired output, also known as a label. A training example is represented by an array or vector, sometimes called a feature vector, and the training data is represented by a set of such examples. In supervised learning, supervised learning algorithms learn a function that can be used to predict the output associated with new inputs. The goal is to find a function that can be used to predict the output for inputs that were not a part of the training data. An algorithm that improves the accuracy of its predictions is said to have learned to perform that task.[19]

Types of supervised-learning algorithms include active learning, classification and regression.[41] Classification algorithms output a set of values, and regression algorithms are used when the outputs may have any numerical value within a range. As an example, an input would be an incoming email, and the output would be the name of the folder in which to file the email.

Similarity learning is an area of supervised machine learning closely related to regression and classification, but the goal is to learn what measures how similar or related two objects are. It has applications in ranking, recommendation systems, visual information retrieval, and image classification.

Unsupervised learning

Main article: Unsupervised learning

See also: Cluster analysis

Unsupervised learning algorithms find structures in data that has not been labeled, classified or categorized. Instead, they identify commonalities in the data and react based on the presence or absence of such commonalities in each new piece of data. Examples include clustering, dimensionality reduction,[8] and density estimation.[42] Unsupervised learning algorithms also strengthen the identification of a gene of interest from pan-genome.[43]

Clustering via Large Indel Permuted Slopes, CLIPS, turns the alignment image into a learning regression problem. This enables to identify segments sharing the same set of indels.

Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that observations within the same cluster are similar, while observations drawn from different clusters are dissimilar. Different clustering techniques make use of different criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make use of different criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make use of different criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make use of different criteria, while observations drawn from different clusters are dissimilar.

Semi-supervised learning

Main article: Semi-supervised learning

Semi-supervised learning falls between unsupervised learning (without any labeled training data) and supervised learning. In semi-supervised learning, examples are missing training labels, yet many machine-learning researchers have found that unlabeled data, when used in conjunction with labeled data, can provide a considerable improvement in learning accuracy.

In weakly supervised learning, the training labels are noisy, limited, or imprecise; however, these labels are often cheaper to obtain than fully supervised labels.[44]

Reinforcement learning

Main article: Reinforcement learning

Reinforcement learning is an area of machine learning concerned with how software agents ought to take actions in an environment to maximize some numerical reinforcement. Due to its generality, the field is studied in many other disciplines, such as game theory, control theory, operations research, multi-agent systems, swarm intelligence, statistics and genetic algorithms. In reinforcement learning, the environment provides feedback to the agent in the form of a scalar reinforcement signal. Many reinforcement learning algorithms use dynamic programming techniques.[45] Reinforcement learning algorithms are used when exact models are infeasible. Reinforcement learning algorithms are used in autonomous vehicles or robots.

Dimensionality reduction

Dimensionality reduction is a process of reducing the number of random variables under consideration by obtaining a set of principal components. In other words, it is a process of reducing the dimension of the feature set, also called the "number of features". Most of the dimensionality reduction techniques are based on principal component analysis (PCA). PCA involves the extraction of the principal components of the data (e.g., 2D). This results in a smaller dimension of data (2D instead of 3D), while keeping all original variables in the model. PCA proposes that high-dimensional data sets lie along low-dimensional manifolds, and many dimensionality reduction techniques are based on manifold learning and manifold regularization.

Other types

Other approaches have been developed which do not fit neatly into this three-fold categorization, and sometimes merge multiple types. Examples include semi-supervised learning, topic modeling, meta-learning.[48]

Self-learning

Self-learning, as a machine learning paradigm was introduced in 1982 along with a neural network capable of self-learning without any external rewards and no external teacher advice. The CAA self-learning algorithm computes, in a crossbar fashion, the sequence of actions in a sequence of situations. The system is driven by the interaction between cognition and emotion.[50] The self-learning algorithm iterates until it reaches a stable state. The iteration executes the following machine learning routine:

Manifold learning algorithms attempt to do so under the constraint that the learned representation is low-dimensional, meaning that the learned representation is sparse, meaning that the mathematical model has many zeros. Multilinear subspaces are learned directly from tensor representations for multidimensional data, without reshaping them into higher-dimensional vector representations, or a hierarchy of features, with higher-level, more abstract features defined in terms of (or generating) lower-level features. A machine is one that learns a representation that disentangles the underlying factors of variation that explain the observed data.

Feature learning is motivated by the fact that machine learning tasks such as classification often require input that is high-dimensional. However, real-world data such as images, video, and sensory data has not yielded attempts to algorithmically define sparse representations through examination, without relying on explicit algorithms.

Sparse dictionary learning

Main article: Sparse dictionary learning

Sparse dictionary learning is a feature learning method where a training example is represented as a linear combination of atoms from a dictionary. This method is strongly NP-hard and difficult to solve approximately.[59] A popular heuristic method for sparse dictionary learning has been applied in several contexts. In classification, the problem is to determine the class to which a previously unseen example belongs. If a dictionary has already been built, a new training example is associated with the class that is best sparsely represented by the dictionary. This method has been applied in image de-noising. The key idea is that a clean image patch can be sparsely represented by an image dictionary.

Robot learning

Robot learning is inspired by a multitude of machine learning methods, starting from supervised learning, reinforcement learning, and evolutionary algorithms.

An artificial neural network is an interconnected group of nodes, akin to the vast network of neurons in a brain. Here, each node represents a connection from the output of one artificial neuron to the input of another.

Artificial neural networks (ANNs), or connectionist systems, are computing systems vaguely inspired by the biological neural networks that underlie human cognition. In an ANN, information is represented by a numerical value called a "neuron" to perform tasks by considering examples, generally without being programmed with any task-specific rules.

An ANN is a model based on a collection of connected units or nodes called "artificial neurons", which loosely model neurons in a biological brain, can transmit information, a "signal", from one artificial neuron to another. An artificial neuron is connected to one or more additional artificial neurons connected to it. In common ANN implementations, the signal at a connection between an artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are associated with a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. A signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. The layers are connected to their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after several hidden layers.

The original goal of the ANN approach was to solve problems in the same way that a human brain would. However, the approach has led to deviations from biology. Artificial neural networks have been used on a variety of tasks, including computer vision, speech recognition, playing board and video games and medical diagnosis.

Deep learning consists of multiple hidden layers in an artificial neural network. This approach tries to model the way that the human brain works. Some successful applications of deep learning are computer vision and speech recognition.[75]

Decision trees

Main article: Decision tree learning

A decision tree showing survival probability of passengers on the Titanic

Decision tree learning uses a decision tree as a predictive model to go from observations about an item (represented by the branches) to conclusions about the item's class (represented in the leaves). It is one of the predictive modeling approaches used in statistics, data mining, and machine learning. Decision trees where the target variable has a discrete set of values are called classification trees; in these tree structures, leaves represent class labels, and branches represent the features used for classification. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees. Decision trees are used to visually and explicitly represent decisions and decision making. In data mining, a decision tree describes data, but is also used for decision-making.

Support-vector machines

Main article: Support-vector machine

Support-vector machines (SVMs), also known as support-vector networks, are a set of related supervised learning models used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether new examples belong to one or the other category. The training algorithm is a non-probabilistic, binary, linear classifier, although methods such as Platt scaling exist to use SVMs in regression. For performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, which implicitly maps the input data to a higher-dimensional feature space.

Regression analysis

Main article: Regression analysis

Applications

There are many applications for machine learning, including:

Agriculture

Anatomy

Adaptive website

Affective computing

Astronomy

Automated decision-making

Banking

Behaviorism

Bioinformatics

Brain-machine interfaces

Cheminformatics

Citizen Science

Climate Science

Computer networks

Computer vision

Credit-card fraud detection

Data quality

DNA sequence classification

Economics

Financial market analysis[83]

General game playing

Handwriting recognition

Healthcare

Information retrieval

Insurance

Internet fraud detection

Knowledge graph embedding

Linguistics

Machine learning control

Machine perception

Machine translation

Marketing

Medical diagnosis

Natural language processing

Natural language understanding

Online advertising

Optimization

Recommender systems

Robot locomotion

Search engine.