# FIRST SOURCE

# Machine Learning

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.

IBM has a rich history with machine learning. One of its own, Arthur Samuel, is credited for coining the term, “machine learning” with his research (PDF, 481 KB) (link resides outside IBM) around the game of checkers. Robert Nealey, the self-proclaimed checkers master, played the game on an IBM 7094 computer in 1962, and he lost to the computer. Compared to what can be done today, this feat almost seems trivial, but it’s considered a major milestone within the field of artificial intelligence. Over the next couple of decades, the technological developments around storage and processing power will enable some innovative products that we know and love today, such as Netflix’s recommendation engine or self-driving cars.

Machine learning is an important component of the growing field of data science. Through the use of statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects. These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics. As big data continues to expand and grow, the market demand for data scientists will increase, requiring them to assist in the identification of the most relevant business questions and subsequently the data to answer them.

## Machine Learning vs. Deep Learning vs. Neural Networks

Since deep learning and machine learning tend to be used interchangeably, it’s worth noting the nuances between the two. Machine learning, deep learning, and neural networks are all sub-fields of artificial intelligence. However, deep learning is actually a sub-field of machine learning, and neural networks is a sub-field of deep learning.

The way in which deep learning and machine learning differ is in how each algorithm learns. Deep learning automates much of the feature extraction piece of the process, eliminating some of the manual human intervention required and enabling the use of larger data sets. You can think of deep learning as "scalable machine learning" as Lex Fridman notes. Classical, or "non-deep", machine learning is more dependent on human intervention to learn. Human experts determine the set of features to understand the differences between data inputs, usually requiring more structured data to learn.

"Deep" machine learning can leverage labeled datasets, also known as supervised learning, to inform its algorithm, but it doesn’t necessarily require a labeled dataset. It can ingest unstructured data in its raw form (e.g. text, images), and it can automatically determine the set of features which distinguish different categories of data from one another. Unlike machine learning, it doesn't require human intervention to process data, allowing us to scale machine learning in more interesting ways. Deep learning and neural networks are primarily credited with accelerating progress in areas, such as computer vision, natural language processing, and speech recognition.

Neural networks, or artificial neural networks (ANNs), are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. The “deep” in deep learning is just referring to the depth of layers in a neural network. A neural network that consists of more than three layers—which would be inclusive of the inputs and the output—can be considered a deep learning algorithm or a deep neural network. A neural network that only has two or three layers is just a basic neural network.

## How machine learning works

UC Berkeley breaks out the learning system of a machine learning algorithm into three main parts:

* A Decision Process: In general, machine learning algorithms are used to make a prediction or classification. Based on some input data, which can be labelled or unlabeled, your algorithm will produce an estimate about a pattern in the data.
* An Error Function: An error function serves to evaluate the prediction of the model. If there are known examples, an error function can make a comparison to assess the accuracy of the model.
* An Model Optimization Process: If the model can fit better to the data points in the training set, then weights are adjusted to reduce the discrepancy between the known example and the model estimate. The algorithm will repeat this evaluate and optimize process, updating weights autonomously until a threshold of accuracy has been met.

## Machine learning methods

Machine learning classifiers fall into three primary categories.

### Supervised machine learning

Supervised learning, also known as supervised machine learning, is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately. This occurs as part of the cross validation process to ensure that the model avoids overfitting or underfitting. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox. Some methods used in supervised learning include neural networks, naïve bayes, linear regression, logistic regression, random forest, support vector machine (SVM), and more.

### Unsupervised machine learning

Unsupervised learning, also known as unsupervised machine learning, uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Its ability to discover similarities and differences in information make it the ideal solution for exploratory data analysis, cross-selling strategies, customer segmentation, image and pattern recognition. It’s also used to reduce the number of features in a model through the process of dimensionality reduction; principal component analysis (PCA) and singular value decomposition (SVD) are two common approaches for this. Other algorithms used in unsupervised learning include neural networks, k-means clustering, probabilistic clustering methods, and more.

### Semi-supervised learning

Semi-supervised learning offers a happy medium between supervised and unsupervised learning. During training, it uses a smaller labeled data set to guide classification and feature extraction from a larger, unlabeled data set. Semi-supervised learning can solve the problem of having not enough labeled data (or not being able to afford to label enough data) to train a supervised learning algorithm.

### Reinforcement machine learning

Reinforcement machine learning is a behavioral machine learning model that is similar to supervised learning, but the algorithm isn’t trained using sample data. This model learns as it goes by using trial and error. A sequence of successful outcomes will be reinforced to develop the best recommendation or policy for a given problem.

The IBM Watson® system that won the Jeopardy! challenge in 2011 makes a good example. The system used reinforcement learning to decide whether to attempt an answer (or question, as it were), which square to select on the board, and how much to wager—especially on daily doubles.

## Real-world machine learning use cases

**Speech recognition**: It is also known as automatic speech recognition (ASR), computer speech recognition, or speech-to-text, and it is a capability which uses natural language processing (NLP) to process human speech into a written format. Many mobile devices incorporate speech recognition into their systems to conduct voice search—e.g. Siri—or provide more accessibility around texting.

**Customer service**: Online chatbots are replacing human agents along the customer journey. They answer frequently asked questions (FAQs) around topics, like shipping, or provide personalized advice, cross-selling products or suggesting sizes for users, changing the way we think about customer engagement across websites and social media platforms. Examples include messaging bots on e-commerce sites with virtual agents, messaging apps, such as Slack and Facebook Messenger, and tasks usually done by virtual assistants and voice assistants.

**Computer vision**: This AI technology enables computers and systems to derive meaningful information from digital images, videos and other visual inputs, and based on those inputs, it can take action. This ability to provide recommendations distinguishes it from image recognition tasks. Powered by convolutional neural networks, computer vision has applications within photo tagging in social media, radiology imaging in healthcare, and self-driving cars within the automotive industry.

**Recommendation engines**: Using past consumption behavior data, AI algorithms can help to discover data trends that can be used to develop more effective cross-selling strategies. This is used to make relevant add-on recommendations to customers during the checkout process for online retailers.

**Automated stock trading**: Designed to optimize stock portfolios, AI-driven high-frequency trading platforms make thousands or even millions of trades per day without human intervention.

## Challenges of machine learning

As machine learning technology advances, it has certainly made lives easier. However, implementing machine learning within businesses has also raised a number of ethical concerns surrounding AI technologies. Some of these include:

* Technological singularity
  + While this topic garners a lot of public attention, many researchers are not concerned with the idea of AI surpassing human intelligence in the near or immediate future. This is also referred to as superintelligence, which Nick Bostrum defines as “any intellect that vastly outperforms the best human brains in practically every field, including scientific creativity, general wisdom, and social skills.” Despite the fact that Strong AI and superintelligence is not imminent in society, the idea of it raises some interesting questions as we consider the use of autonomous systems, like self-driving cars. It’s unrealistic to think that a driverless car would never get into a car accident, but who is responsible and liable under those circumstances? Should we still pursue autonomous vehicles, or do we limit the integration of this technology to create only semi-autonomous vehicles which promote safety among drivers? The jury is still out on this, but these are the types of ethical debates that are occurring as new, innovative AI technology develops.
* AI impact on jobs
  + While a lot of public perception around artificial intelligence centers around job loss, this concern should be probably reframed. With every disruptive, new technology, we see that the market demand for specific job roles shift. For example, when we look at the automotive industry, many manufacturers, like GM, are shifting to focus on electric vehicle production to align with green initiatives. The energy industry isn’t going away, but the source of energy is shifting from a fuel economy to an electric one. Artificial intelligence should be viewed in a similar manner, where artificial intelligence will shift the demand of jobs to other areas. There will need to be individuals to help manage these systems as data grows and changes every day. There will still need to be resources to address more complex problems within the industries that are most likely to be affected by job demand shifts, like customer service. The important aspect of artificial intelligence and its effect on the job market will be helping individuals transition to these new areas of market demand.
* Privacy
  + Privacy tends to be discussed in the context of data privacy, data protection and data security, and these concerns have allowed policymakers to make more strides here in recent years. For example, in 2016, GDPR legislation was created to protect the personal data of people in the European Union and European Economic Area, giving individuals more control of their data. In the United States, individual states are developing policies, such as the California Consumer Privacy Act (CCPA), which require businesses to inform consumers about the collection of their data. This recent legislation has forced companies to rethink how they store and use personally identifiable data (PII). As a result, investments within security have become an increasing priority for businesses as they seek to eliminate any vulnerabilities and opportunities for surveillance, hacking, and cyberattacks.
* Bias and discrimination
  + Instances of bias and discrimination across a number of intelligent systems have raised many ethical questions regarding the use of artificial intelligence. How can we safeguard against bias and discrimination when the training data itself can lend itself to bias? While companies typically have well-meaning intentions around their automation efforts, Reuters (link resides outside IBM) highlights some of the unforeseen consequences of incorporating AI into hiring practices. In their effort to automate and simplify a process, Amazon unintentionally biased potential job candidates by gender for open technical roles, and they ultimately had to scrap the project. As events like these surface, Harvard Business Review (link resides outside IBM) has raised other pointed questions around the use of AI within hiring practices, such as what data should you be able to use when evaluating a candidate for a role.
  + Bias and discrimination aren’t limited to the human resources function either; it can be found in a number of applications from facial recognition software to social media algorithms.
  + As businesses become more aware of the risks with AI, they’ve also become more active this discussion around AI ethics and values. For example, last year IBM’s CEO Arvind Krishna shared that IBM has sunset its general purpose IBM facial recognition and analysis products, emphasizing that “IBM firmly opposes and will not condone uses of any technology, including facial recognition technology offered by other vendors, for mass surveillance, racial profiling, violations of basic human rights and freedoms, or any purpose which is not consistent with our values and Principles of Trust and Transparency.”
* Accountability
  + Since there isn’t significant legislation to regulate AI practices, there is no real enforcement mechanism to ensure that ethical AI is practiced. The current incentives for companies to adhere to these guidelines are the negative repercussions of an unethical AI system to the bottom line. To fill the gap, ethical frameworks have emerged as part of a collaboration between ethicists and researchers to govern the construction and distribution of AI models within society. However, at the moment, these only serve to guide, and research (link resides outside IBM) (PDF, 984 KB) shows that the combination of distributed responsibility and lack of foresight into potential consequences isn’t necessarily conducive to preventing harm to society.1

# SECOND SOURCE

# Evolution of machine learning

Because of new computing technologies, machine learning today is not like machine learning of the past. It was born from pattern recognition and the theory that computers can learn without being programmed to perform specific tasks; researchers interested in artificial intelligence wanted to see if computers could learn from data. The iterative aspect of machine learning is important because as models are exposed to new data, they are able to independently adapt. They learn from previous computations to produce reliable, repeatable decisions and results. It’s a science that’s not new – but one that has gained fresh momentum.

While many machine learning algorithms have been around for a long time, the ability to automatically apply complex mathematical calculations to big data – over and over, faster and faster – is a recent development. Here are a few widely publicized examples of machine learning applications you may be familiar with:

* The heavily hyped, self-driving Google car? The essence of machine learning.
* Online recommendation offers such as those from Amazon and Netflix? Machine learning applications for everyday life.
* Knowing what customers are saying about you on Twitter? Machine learning combined with linguistic rule creation.
* Fraud detection? One of the more obvious, important uses in our world today.

## Machine Learning and Artificial Intelligence

While artificial intelligence (AI) is the broad science of mimicking human abilities, machine learning is a specific subset of AI that trains a machine how to learn. Watch this video to better understand the relationship between AI and machine learning. You'll see how these two technologies work, with useful examples and a few funny asides.

# Why is machine learning important?

Resurging interest in machine learning is due to the same factors that have made data mining and Bayesian analysis more popular than ever. Things like growing volumes and varieties of available data, computational processing that is cheaper and more powerful, and affordable data storage.

All of these things mean it's possible to quickly and automatically produce models that can analyze bigger, more complex data and deliver faster, more accurate results – even on a very large scale. And by building precise models, an organization has a better chance of identifying profitable opportunities – or avoiding unknown risks.

## What's required to create good machine learning systems?

* Data preparation capabilities.
* Algorithms – basic and advanced.
* Automation and iterative processes.
* Scalability.
* Ensemble modeling

## Who's using it?

**Financial services**

Banks and other businesses in the financial industry use machine learning technology for two key purposes: to identify important insights in data, and prevent fraud. The insights can identify investment opportunities, or help investors know when to trade. Data mining can also identify clients with high-risk profiles, or use cybersurveillance to pinpoint warning signs of fraud.

**Government**

Government agencies such as public safety and utilities have a particular need for machine learning since they have multiple sources of data that can be mined for insights. Analyzing sensor data, for example, identifies ways to increase efficiency and save money. Machine learning can also help detect fraud and minimize identity theft.

**Health** **care**

Machine learning is a fast-growing trend in the health care industry, thanks to the advent of wearable devices and sensors that can use data to assess a patient's health in real time. The technology can also help medical experts analyze data to identify trends or red flags that may lead to improved diagnoses and treatment.

**Retail**

Websites recommending items you might like based on previous purchases are using machine learning to analyze your buying history. Retailers rely on machine learning to capture data, analyze it and use it to personalize a shopping experience, implement a marketing campaign, price optimization, merchandise supply planning, and for customer insights.

**Oil and gas**

Finding new energy sources. Analyzing minerals in the ground. Predicting refinery sensor failure. Streamlining oil distribution to make it more efficient and cost-effective. The number of machine learning use cases for this industry is vast – and still expanding.

**Transportation**

Analyzing data to identify patterns and trends is key to the transportation industry, which relies on making routes more efficient and predicting potential problems to increase profitability. The data analysis and modeling aspects of machine learning are important tools to delivery companies, public transportation and other transportation organizations.

# What are some popular machine learning methods?

Two of the most widely adopted machine learning methods are supervised learning and unsupervised learning – but there are also other methods of machine learning. Here's an overview of the most popular types.

**Supervised learning** algorithms are trained using labeled examples, such as an input where the desired output is known. For example, a piece of equipment could have data points labeled either “F” (failed) or “R” (runs). The learning algorithm receives a set of inputs along with the corresponding correct outputs, and the algorithm learns by comparing its actual output with correct outputs to find errors. It then modifies the model accordingly. Through methods like classification, regression, prediction and gradient boosting, supervised learning uses patterns to predict the values of the label on additional unlabeled data. Supervised learning is commonly used in applications where historical data predicts likely future events. For example, it can anticipate when credit card transactions are likely to be fraudulent or which insurance customer is likely to file a claim.

**Unsupervised learning** is used against data that has no historical labels. The system is not told the "right answer." The algorithm must figure out what is being shown. The goal is to explore the data and find some structure within. Unsupervised learning works well on transactional data. For example, it can identify segments of customers with similar attributes who can then be treated similarly in marketing campaigns. Or it can find the main attributes that separate customer segments from each other. Popular techniques include self-organizing maps, nearest-neighbor mapping, k-means clustering and singular value decomposition. These algorithms are also used to segment text topics, recommend items and identify data outliers.

**Semisupervised learning** is used for the same applications as supervised learning. But it uses both labeled and unlabeled data for training – typically a small amount of labeled data with a large amount of unlabeled data (because unlabeled data is less expensive and takes less effort to acquire). This type of learning can be used with methods such as classification, regression and prediction. Semisupervised learning is useful when the cost associated with labeling is too high to allow for a fully labeled training process. Early examples of this include identifying a person's face on a web cam.

**Reinforcement learning** is often used for robotics, gaming and navigation. With reinforcement learning, the algorithm discovers through trial and error which actions yield the greatest rewards. This type of learning has three primary components: the agent (the learner or decision maker), the environment (everything the agent interacts with) and actions (what the agent can do). The objective is for the agent to choose actions that maximize the expected reward over a given amount of time. The agent will reach the goal much faster by following a good policy. So the goal in reinforcement learning is to learn the best policy.

# What are the differences between data mining, machine learning and deep learning?

Although all of these methods have the same goal – to extract insights, patterns and relationships that can be used to make decisions – they have different approaches and abilities.

**Data Mining**

Data mining can be considered a superset of many different methods to extract insights from data. It might involve traditional statistical methods and machine learning. Data mining applies methods from many different areas to identify previously unknown patterns from data. This can include statistical algorithms, machine learning, text analytics, time series analysis and other areas of analytics. Data mining also includes the study and practice of data storage and data manipulation.

**Machine Learning**

The main difference with machine learning is that just like statistical models, the goal is to understand the structure of the data – fit theoretical distributions to the data that are well understood. So, with statistical models there is a theory behind the model that is mathematically proven, but this requires that data meets certain strong assumptions too. Machine learning has developed based on the ability to use computers to probe the data for structure, even if we do not have a theory of what that structure looks like. The test for a machine learning model is a validation error on new data, not a theoretical test that proves a null hypothesis. Because machine learning often uses an iterative approach to learn from data, the learning can be easily automated. Passes are run through the data until a robust pattern is found.

**Deep learning**

Deep learning combines advances in computing power and special types of neural networks to learn complicated patterns in large amounts of data. Deep learning techniques are currently state of the art for identifying objects in images and words in sounds. Researchers are now looking to apply these successes in pattern recognition to more complex tasks such as automatic language translation, medical diagnoses and numerous other important social and business problems.

# How it works

To get the most value from machine learning, you have to know how to pair the best algorithms with the right tools and processes. SAS combines rich, sophisticated heritage in statistics and data mining with new architectural advances to ensure your models run as fast as possible – even in huge enterprise environments.

**Algorithms**: SAS graphical user interfaces help you build machine learning models and implement an iterative machine learning process. You don't have to be an advanced statistician. Our comprehensive selection of machine learning algorithms can help you quickly get value from your big data and are included in many SAS products. SAS machine learning algorithms include:

* Neural networks
* Decision trees
* Random forests
* Associations and sequence discovery
* Gradient boosting and bagging
* Support vector machines
* Nearest-neighbor mapping
* k-means clustering
* Self-organizing maps
* Local search optimization techniques (e.g., genetic algorithms)
* Expectation maximization
* Multivariate adaptive regression splines
* Bayesian networks
* Kernel density estimation
* Principal component analysis
* Singular value decomposition
* Gaussian mixture models
* Sequential covering rule building

**Tools and Processes**: As we know by now, it’s not just the algorithms. Ultimately, the secret to getting the most value from your big data lies in pairing the best algorithms for the task at hand with:

* Comprehensive data quality and management
* GUIs for building models and process flows
* Interactive data exploration and visualization of model results
* Comparisons of different machine learning models to quickly identify the best one
* Automated ensemble model evaluation to identify the best performers
* Easy model deployment so you can get repeatable, reliable results quickly
* An integrated, end-to-end platform for the automation of the data-to-decision process2

# THIRD SOURCE

# Overview

Machine learning (ML) is the study of computer algorithms that can improve automatically through experience and by the use of data.[3] It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, speech recognition, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.[4]

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning.[5] Some implementations of machine learning use data and neural networks in a way that mimics the working of a biological brain. In its application across business problems, machine learning is also referred to as predictive analytics.

Machine learning involves computers discovering how they can perform tasks without being explicitly programmed to do so. It involves computers learning from data provided so that they carry out certain tasks. For simple tasks assigned to computers, it is possible to program algorithms telling the machine how to execute all steps required to solve the problem at hand; on the computer's part, no learning is needed. For more advanced tasks, it can be challenging for a human to manually create the needed algorithms. In practice, it can turn out to be more effective to help the machine develop its own algorithm, rather than having human programmers specify every needed step.[6]

The discipline of machine learning employs various approaches to teach computers to accomplish tasks where no fully satisfactory algorithm is available. In cases where vast numbers of potential answers exist, one approach is to label some of the correct answers as valid. This can then be used as training data for the computer to improve the algorithm(s) it uses to determine correct answers. For example, to train a system for the task of digital character recognition, the MNIST dataset of handwritten digits has often been used[6].

## History and relationships to other fields

| **Decade** | **Summary** |
| --- | --- |
| <1950s | Statistical methods are discovered and refined. |
| 1950s | Pioneering [machine learning](https://en.wikipedia.org/wiki/Machine_learning) research is conducted using simple algorithms. |
| 1960s | [Bayesian methods](https://en.wikipedia.org/wiki/Bayesian_method) are introduced for [probabilistic inference](https://en.wikipedia.org/wiki/Bayesian_inference) in machine learning.[[1]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-1) |
| 1970s | '[AI Winter](https://en.wikipedia.org/wiki/AI_Winter)' caused by pessimism about machine learning effectiveness. |
| 1980s | Rediscovery of [backpropagation](https://en.wikipedia.org/wiki/Backpropagation) causes a resurgence in machine learning research. |
| 1990s | Work on Machine learning shifts from a knowledge-driven approach to a data-driven approach. Scientists begin creating programs for computers to analyze large amounts of data and draw conclusions – or "learn" – from the results.[[2]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-Marr-2) [Support-vector machines](https://en.wikipedia.org/wiki/Support-vector_machine) (SVMs) and [recurrent neural networks](https://en.wikipedia.org/wiki/Recurrent_neural_network) (RNNs) become popular.[[3]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-3) The fields of computational complexity via neural networks and super-Turing computation started.[[4]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-4) |
| 2000s | Support-Vector Clustering[[5]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-5) and other [kernel methods](https://en.wikipedia.org/wiki/Kernel_method)[[6]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-6) and unsupervised machine learning methods become widespread.[[7]](https://en.wikipedia.org/wiki/Timeline_of_machine_learning#cite_note-7) |
| 2010s | [Deep learning](https://en.wikipedia.org/wiki/Deep_learning) becomes feasible, which leads to machine learning becoming integral to many widely used software services and applications. |

The term machine learning was coined in 1959 by Arthur Samuel, an American IBMer and pioneer in the field of computer gaming and artificial intelligence.[7] A representative book of the machine learning research during the 1960s was the Nilsson's book on Learning Machines, dealing mostly with machine learning for pattern classification. Interest related to pattern recognition continued into the 1970s, as described by Duda and Hart in 1973. In 1981 a report was given on using teaching strategies so that a neural network learns to recognize 40 characters (26 letters, 10 digits, and 4 special symbols) from a computer terminal.

Tom M. Mitchell provided a widely quoted, more formal definition of the algorithms studied in the machine learning field: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E". This definition of the tasks in which machine learning is concerned offers a fundamentally operational definition rather than defining the field in cognitive terms. This follows Alan Turing's proposal in his paper "Computing Machinery and Intelligence", in which the question "Can machines think?" is replaced with the question "Can machines do what we (as thinking entities) can do?".

Modern day machine learning has two objectives, one is to classify data based on models which have been developed, the other purpose is to make predictions for future outcomes based on these models. A hypothetical algorithm specific to classifying data may use computer vision of moles coupled with supervised learning in order to train it to classify the cancerous moles. Where as, a machine learning algorithm for stock trading may inform the trader of future potential predictions.[8]

### Artificial intelligence

As a scientific endeavor, machine learning grew out of the quest for artificial intelligence. In the early days of AI as an academic discipline, some researchers were interested in having machines learn from data. They attempted to approach the problem with various symbolic methods, as well as what was then termed "neural networks"; these were mostly perceptron’s and other models that were later found to be reinventions of the generalized linear models of statistics. Probabilistic reasoning was also employed, especially in automated medical diagnosis.[10]

However, an increasing emphasis on the logical, knowledge-based approach caused a rift between AI and machine learning. Probabilistic systems were plagued by theoretical and practical problems of data acquisition and representation. By 1980, expert systems had come to dominate AI, and statistics was out of favor. Work on symbolic/knowledge-based learning did continue within AI, leading to inductive logic programming, but the more statistical line of research was now outside the field of AI proper, in pattern recognition and information retrieval. Neural networks research had been abandoned by AI and computer science around the same time. This line, too, was continued outside the AI/CS field, as "connectionism", by researchers from other disciplines including Hopfield, Rumelhart and Hinton. Their main success came in the mid-1980s with the reinvention of backpropagation.[10]

Machine learning (ML), reorganized as a separate field, started to flourish in the 1990s. The field changed its goal from achieving artificial intelligence to tackling solvable problems of a practical nature. It shifted focus away from the symbolic approaches it had inherited from AI, and toward methods and models borrowed from statistics and probability theory.

As of 2020, many sources continue to assert that machine learning remains a subfield of AI. The main disagreement is whether all of ML is part of AI, as this would mean that anyone using ML could claim they are using AI. Others have the view that not all of ML is part of AI where only an 'intelligent' subset of ML is part of AI.

The question to what is the difference between ML and AI is answered by Judea Pearl in The Book of Why. Accordingly, ML learns and predicts based on passive observations, whereas AI implies an agent interacting with the environment to learn and take actions that maximize its chance of successfully achieving its goals.

### Data mining

Machine learning and data mining often employ the same methods and overlap significantly, but while machine learning focuses on prediction, based on known properties learned from the training data, data mining focuses on the discovery of (previously) unknown properties in the data (this is the analysis step of knowledge discovery in databases). Data mining uses many machine learning methods, but with different goals; on the other hand, machine learning also employs data mining methods as "unsupervised learning" or as a preprocessing step to improve learner accuracy. Much of the confusion between these two research communities (which do often have separate conferences and separate journals, ECML PKDD being a major exception) comes from the basic assumptions they work with: in machine learning, performance is usually evaluated with respect to the ability to reproduce known knowledge, while in knowledge discovery and data mining (KDD) the key task is the discovery of previously unknown knowledge. Evaluated with respect to known knowledge, an uninformed (unsupervised) method will easily be outperformed by other supervised methods, while in a typical KDD task, supervised methods cannot be used due to the unavailability of training data.

### Optimization

Machine learning also has intimate ties to optimization: many learning problems are formulated as minimization of some loss function on a training set of examples. Loss functions express the discrepancy between the predictions of the model being trained and the actual problem instances (for example, in classification, one wants to assign a label to instances, and models are trained to correctly predict the pre-assigned labels of a set of examples).

### Generalization

The difference between optimization and machine learning arises from the goal of generalization: while optimization algorithms can minimize the loss on a training set, machine learning is concerned with minimizing the loss on unseen samples. Characterizing the generalization of various learning algorithms is an active topic of current research, especially for deep learning algorithms.

### Statistics

Machine learning and statistics are closely related fields in terms of methods, but distinct in their principal goal: statistics draws population inferences from a sample, while machine learning finds generalizable predictive patterns. According to Michael I. Jordan, the ideas of machine learning, from methodological principles to theoretical tools, have had a long pre-history in statistics. He also suggested the term data science as a placeholder to call the overall field.

Leo Breiman distinguished two statistical modeling paradigms: data model and algorithmic model, wherein "algorithmic model" means more or less the machine learning algorithms like Random forest.

Some statisticians have adopted methods from machine learning, leading to a combined field that they call statistical learning

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