What is Machine Learning?

Machine learning defined

Machine learning (ML) is the subset of artificial intelligence (AI) that focuses on building systems that learn—or improve performance—based on the data they consume. Artificial intelligence is a broad term that refers to systems or machines that mimic human intelligence. Machine learning and AI are often discussed together, and the terms are sometimes used interchangeably, but they don't mean the same thing. An important distinction is that although all machine learning is AI, not all AI is machine learning.

Today, machine learning is at work all around us. When we interact with banks, shop online, or use media, machine learning algorithms come into play to make our experience efficient, smooth, anc

Machine learning and the technology around it are developing rapidly, and we're just beginning to scratch the surface of its capabilities.

Learn more about machine learning solution

Types of Machine learning: two approaches to learning

Algorithms are the engines that power machine learning. In general, two major types of machine learning algorithms are used today: supervised learning and unsupervised learning. The difference between them is defined by how each learns about data to make predictions.

Supervised Machine Learning

Supervised machine learning algorithms are the most commonly used. With this model, a data scientist acts as a guide and teaches the algorithm what conclusions it should make. Just as a child learns to identify fruits by memorizing them in a picture book, in supervised learning, the algorithm is trained by a dataset that is already labeled and has a predefined output.

Examples of supervised machine learning include algorithms such as linear and logistic regression, multiclass classification, and support vector machines.

Unsupervised Machine Learning

Unsupervised machine learning uses a more independent approach, in which a computer learns to identify complex processes and patterns without a human providing close, constant guidance. Unsupervised machine learning involves training based on data that does not have labels or a specific, defined output.

To continue the childhood teaching analogy, unsupervised machine learning is akin to a child learning to identify fruit by observing colors and patterns, rather than memorizing the names with a teacher's help. The child would look for similarities between images and separate them into groups, assigning each group its own new label. Examples of unsupervised machine learning algorithms include k-means clustering, principal and independent component analysis, and association rules.

Choosing an Approach

Which approach is best for your needs? Choosing a supervised or unsupervised machine learning algorithm usually depends on factors related to the structure and volume of your data, and the use case to which you want to apply it. Machine learning has blossomed across a wide range of industries, supporting a variety of business goals and use cases including:

- Customer lifetime value

Anomaly detection

Dynamic pricing

Predictive maintenance

Image classification

Recommendation engines

Machine learning and developers

When getting started with machine learning, developers will rely on their knowledge of statistics, probability, and calculus to most successfully create models that learn over time. With sharp skills in these areas, developers should have no problem learning the tools many other developers use to train modern ML algorithms. Developers also can make decisions about whether their algorithms will be supervised or unsupervised. It's possible for a developer to make decisions and set up a model early on in a project, then allow the model to learn without much further developer involvement.

There is often a blurry line between developer and data scientist. Sometimes developers will synthesize data from a machine learning model, while data scientists will contribute to developing solutions for the end user. Collaboration between these two disciplines can make ML projects more valuable and useful.

Get started with ML

Machine learning business goal: model customer lifetime value

Customer lifetime value modeling is essential for ecommerce businesses but is also applicable across many other industries. In this model, organizations use machine learning algorithms to identify, understand, and retain their most valuable customers. These value models evaluate massive amounts of customer data to determine the biggest spenders, the most loyal advocates for a brand, or combinations of these types of qualities.

Customer lifetime value models are especially effective at predicting the future revenue that an individual customer will bring to a business in a given period. This information empowers organizations to focus marketing efforts on encouraging high-value customers to interact with their brand more often. Customer lifetime value models also help organizations target their acquisition spend to attract new customers that are similar to existing high-value customers.

Model customer churn through machine learning

Acquiring new customers is more time consuming and costlier than keeping existing customers s and loyal. Customer churn modeling helps organizations identify which customers are likely to sto engaging with a business—and why.

An effective churn model uses machine learning algorithms to provide insight into everything from churn risk scores for individual customers to churn drivers, ranked by importance. These outputs are key to developing an algorithmic retention strategy.

Gaining deeper insight into customer churn helps businesses optimize discount offers, email campaigns, and other targeted marketing initiatives that keep their high-value customers buying—and coming back for more.

Consumers have more choices than ever, and they can compare prices via a wide range of channels, instantly. Dynamic pricing, also known as demand pricing, enables businesses to keep pace with accelerating market dynamics. It lets organizations flexibly price items based on factors including the level of interest of the target customer, demand at the time of purchase, and whether the customer has engaged with a marketing campaign.

This level of business agility requires a solid machine learning strategy and a great deal of data about how different customers' willingness to pay for a good or service changes across a variety of situations. Although dynamic pricing models can be complex, companies such as airlines and ride-share services have successfully implemented dynamic price optimization strategies to maximize revenue.

Machine learning business goal: target customers with customer segmentation

Successful marketing has always been about offering the right product to the right person at the right time. Not so long ago, marketers relied on their own intuition for customer segmentation, separating customers into groups for targeted campaigns.

Today, machine learning enables data scientists to use clustering and classification algorithms to group customers into personas based on specific variations. These personas consider customer differences across multiple dimensions such as demographics, browsing behavior, and affinity. Connecting these traits to patterns of purchasing behavior enables data-savvy companies to roll out highly personalized marketing campaigns that are more effective at boosting sales than generalized campaigns are.

As the data available to businesses grows and algorithms become more sophisticated, personalization capabilities will increase, moving businesses closer to the ideal customer segment of one.

Machine learning business goal: tap the power of image classification

Machine learning supports a variety of use cases beyond retail, financial services, and ecommerce. It also has tremendous potential for science, healthcare, construction, and energy applications. For example, image classification employs machine learning algorithms to assign a label from a fixed set of categories to any input image. It enables organizations to model 3D construction plans based on 2D designs, facilitate photo tagging in social media, inform medical diagnoses, and more.

Deep learning methods such as neural networks are often used for image classification because th
most effectively identify the relevant features of an image in the presence of potential complicatio

example, they can consider variations in the point of view, illumination, scale, or volume of clutter in the image and offset these issues to deliver the most relevant, high-quality insights.

Blog: What's the Difference Between AI, Machine Learning, and Deep Learning?

Recommendation engines

Recommendation engines are essential to cross-selling and up-selling consumers and delivering a better customer experience.

Netflix values the recommendation engine powering its content suggestions at US$1 billion per year and Amazon claims that its system increases annual sales by 20 to 35 percent.

Recommendation engines use machine learning algorithms to sift through large quantities of data to predict how likely a customer is to purchase an item or enjoy a piece of content, and then make customized suggestions to the user. The result is a more personalized, relevant experience that encourages better engagement and reduces churn.

Machine learning use cases

Machine learning powers a variety of key business use cases. But how does it deliver competitive advantage? Among machine learning's most compelling qualities is its ability to automate and speed time to decision and accelerate time to value. That starts with gaining better business visibility and enhancing collaboration.

"Traditionally what we see is people not being able to work together," says Rich Clayton, vice president of product strategy for Oracle Analytics. "Adding machine learning to Oracle Analytics Cloud ultimately helps people organize their work and build, train, and deploy these data models. It's a collaboration tool whose value is in accelerating the process and allowing different parts of the business to collaborate, giving you better quality and models for you to deploy."

For example, typical finance departments are routinely burdened by repeating a variance analysis process —a comparison between what is actual and what was forecast. It's a low-cognitive application that can benefit greatly from machine learning.

"By embedding machine learning, finance can work faster and smarter, and pick up where the machine left off," Clayton says.

The power of prediction

Another exciting capability of machine learning is its predictive capabilities. In the past, business decisions were often made based on historical outcomes. Today, machine learning employs rich analytics to what will happen. Organizations can make forward-looking, proactive decisions instead of relying data.

For example, predictive maintenance can enable manufacturers, energy companies, and other industries to seize the initiative and ensure that their operations remain dependable and optimized. In an oil field with hundreds of drills in operation, machine learning models can spot equipment that's at risk of failure in the near future and then notify maintenance teams in advance. This approach not only maximizes productivity, it increases asset performance, uptime, and longevity. It can also minimize worker risk, decrease liability, and improve regulatory compliance.

The benefits of predictive maintenance extend to inventory control and management. Avoiding unplanned equipment downtime by implementing predictive maintenance helps organizations more accurately predict the need for spare parts and repairs—significantly reducing capital and operating expenses.

Webcast: Where Will Machine Learning Take You?

Machine learning potential

Machine learning offers tremendous potential to help organizations derive business value from the wealth of data available today. However, inefficient workflows can hold companies back from realizing machine learning's maximum potential.

To succeed at an enterprise level, machine learning needs to be part of a comprehensive platform that helps organizations simplify operations and deploy models at scale. The right solution will enable organizations to centralize all data science work in a collaborative platform and accelerate the use and management of open source tools, frameworks, and infrastructure.

Try an AI workshop

Machine learning topics

Machine learning defined
Machine learning: two approaches to learning
Machine learning and developers
Machine learning business goal: model customer lifetime value
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Machine learning business goal: target customers with customer segmentation
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Recommendation engines
Machine learning use cases
The power of prediction
Machine learning potential