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Origin, Development and Uses of Machine Learning

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Abstract
It is necessary to trace the studies made on any topic from the origin and the genesis so that, we can model the practical situations. The present overview of ML is a small attempt to trace the developments and applications, so that we can reduce the gap between theory and practice.

Keywords: machine learning, application in health care, time line of developments, supervised, unsupervised, reinforcement and semi supervised learning in machines

INTRODUCTION: Machine learning (**ML**) is a field of inquiry devoted to understanding and building methods that 'learn', methods that leverage data to improve performance on some set of tasks. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, called as training data, which allows us to make predictions or decisions. Machine learning algorithms are used in a wide variety of applications, related to medicine, email filtering, speech recognition, agriculture, and computer vision, when it is difficult to develop conventional algorithms to perform the tasks. A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers. The term machine learning was coined in 1959 by Arthur Samuel, an IBM employee and pioneer in the field of computer gaming and artificial intelligence.

By the early 1960s an experimental "learning machine" with punched tape memory, called Cybertron, had been developed by Raytheon Company to analyze sonar signals, electrocardiograms, and speech patterns using rudimentary reinforcement learning. It was repetitively "trained" by a human operator to recognize patterns to re-evaluate incorrect decisions. A representative book on research into machine learning during the 1960s by Nilsson's on Learning Machines, deals 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 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 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?"

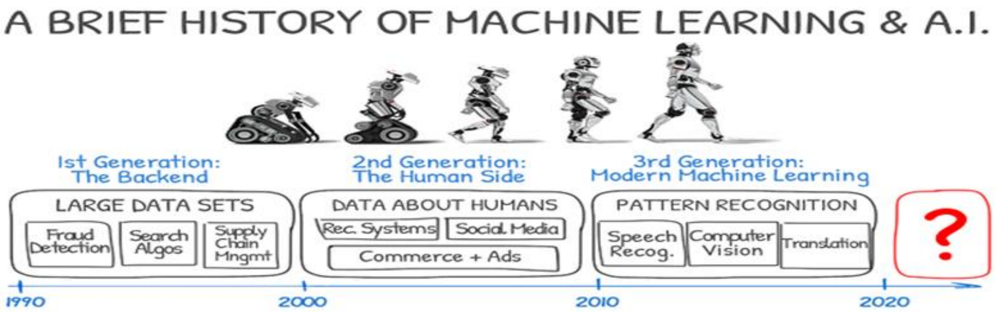
Modern-day machine learning has two objectives, one is to classify data based on models which have been developed, and the other purpose is to make predictions for future outcomes based on these models. A hypothetical algorithm to classifying data may use computer vision of moles coupled with supervised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

Machine learning programs 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 design algorithms. Thus telling the machine how to execute all steps required to solve the problem at hand; on the computer's. 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 step.

Machine Learning is a branch of the broader field of artificial intelligence that makes use of statistical models to develop predictions. In basic technical terms, machine learning uses algorithms that take empirical or historical data in, analyze it, and generate outputs based on that analysis.

Machine Learning is the field of study that gives computers the capability to learn without being explicitly programmed. ML is one of the most exciting technologies that one would have ever come across. Of course it is evident from the name, It gives the computer that makes it more similar to humans we call the ability to learn. Machine learning is actively used today, perhaps in many more situations than one would expect.

Machine learning (ML) is a field of inquiry devoted to understanding and building methods that 'learn', that is, methods that leverage data to improve performance on some set of tasks. Machine learning (ML) is a subset of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes.



In fact Artificial intelligence can enable systems to identify patterns in data, make decisions. and predict future outcomes. Whereas Machine learning can help companies determine the products you're most likely to buy and even the online content you're most likely to consume and enjoy. Machine learning makes it easier to analyze and interpret massive amounts of data, which would otherwise take decades. It can automate many tasks, especially the ones that only humans can perform with their innate intelligence. It also helps in automating and quickly creates models for data analysis. Various industries depend on vast quantities of data to optimize their operations and make intelligent decisions. It helps in creating models that can process and analyze large amounts of complex data to deliver accurate results.

These ML models are precise and scalable and function with less turnaround time. By building such precise Machine Learning models, businesses can leverage profitable opportunities and avoid unknown risks. Image recognition, text generation, and many other use-cases are finding applications in the real world, this is increasing the scope for machine learning experts.

Machine learning is incredibly complex and how it works varies depending on the task and the algorithms used to accomplish it. However, at its core, a machine learning model is a computer looking at data and identifying patterns, and then using those insights to complete its assigned task more effectively. Any task that relies upon a set of data points or rules can be automated using machine learning, including responding to customer service calls and reviewing CVs.

This pervasive and powerful ML of artificial intelligence is changing every industry. When companies today deploy artificial intelligence programs, they are most likely using machine learning — so much so that the terms are often used interchangeably. Machine learning is a subfield of artificial intelligence that gives computers the ability to learn without explicitly being programmed.

By applying machine learning techniques, companies are gaining significant competitive and financial advantages in delivering better customer experiences and reacting more swiftly to market shifts. Machine learning is widely used today in *web search, spam filters, recommender systems, ad placement, credit scoring, fraud detection, stock trading, drug design*, and many other applications.

Advantages of Machine Learning: The benefits businesses gain from machine learning are

*****Quickly discover specific trends, patterns and implicit relationships in vast, complex datasets
*Has the ability to learn and make predictions without human intervention
*Continuous improvement in accuracy, efficiency, and speed
*Good at handling multidimensional problems and multivariate data
*Help businesses make smarter and faster decisions in real-time
*Eliminate bias from human decision making
*Automate and streamline predictable and repetitive business processes
*Better use of data – both structured and unstructured.

HOW DOES IT WORK : Machine Learning is, undoubtedly, one of the most exciting subsets of Artificial Intelligence. It completes the task of learning from data with specific inputs to the machine. It's important to understand what makes Machine Learning work and, thus, how it can be used in the future.

The Machine Learning process starts with inputting training data into the selected algorithm. Training data being known or unknown is used to develop the final Machine Learning algorithm. The type of training data input does impact the algorithm, and that concept will be covered further momentarily.

New input data is fed into the machine learning algorithm to test whether the algorithm works correctly. The prediction and results are then checked against each other.

If the prediction and results don't match, the algorithm is re-trained multiple times until the data scientist gets the desired outcome. This enables the machine learning algorithm to continually learn on its own and produce the optimal answer, gradually increasing in accuracy over time.

TIME LINE OF STUDIES CARRIED OUT ON M.L.

We trace the origin and short history of machine learning and its most important milestones.

18th century —statistical methods: Several vital concepts in machine learning derive from probability theory and statistics, and they root back to the 18th century. In 1763, English statistician Thomas Bayes set out a mathematical theorem for probability, which came to be known as Bayes Theorem that a central concept of machine learning.

1950 — The Turing Test: mathematician Alan Turing's papers in the 1940s were full of ideas on machine intelligence. "Can machines think?", paving way for automata theory. In 1950, he suggested a test for machine intelligence, later known as the Turing Test, in which a machine is said to be "intelligent" if it could convince a human.

1952 — Game of Checkers: In 1952, researcher Arthur Samuel created an early learning machine, capable of learning to play checkers. It is an annotated guides to learn to distinguish right moves from bad.

1956 — The Dartmouth Workshop: The term 'artificial intelligence' was born during the Dartmouth Workshop in 1956, The workshop scientists, including computer scientist John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon.

1957 — The Perceptron: Noted American psychologist Frank Rosenblatt's Perceptron was an early attempt to create a neural network with the use of a rotary resistor (potentiometer) driven by an electric motor. The machine could create an output.

1967 — Nearest neighbor algorithm: The Nearest Neighbor (NN) rule in pattern recognition, which enabled article written by T. Cover and P. Hart in 1967. The algorithm gave an idea of solution to traveling sales problem.

1973 — The Light hill report and the AI winter: James Light hill in 1973, presented a very pessimistic forecast in the development of core aspects in AI research".

1979 — Stanford Cart: The students at Stanford University invented a robot called the Cart, radio-linked to a large mainframe computer, which can navigate obstacles in a room on its own. The invention was state of the art at the time.

1981 — Explanation Based Learning (EBL): Gerald Dejong introduced the concept of Explanation Based Learning (EBL), which analyses data and creates a general rule it can follow by discarding unimportant data.

1985 — Net Talk: Francis Crick Professor Terry Sejnowski invented NetTalk, NETtalk, a program that learns to pronounce written English text by being shown text as input and matching phonetic transcriptions for comparison. This has shed light on human learning.

1986 — Parallel Distributed Processing and neural network models: David Rumelhart and James McClelland published Parallel Distributed Processing, which advanced the use of neural network models for machine learning.

1992 — playing backgammon: Researcher Gerald Tesauro created a program based on an artificial neural network, which was capable of playing backgammon with abilities that matched top human players.

1997 — deep Blue: IBM's Deep Blue became the first computer chess-playing system to beat a reigning world chess champion. Deep Blue used the computing power in the 1990s to perform large-scale searches of potential moves and select the best move.

2006 — Deep Learning: Geoffrey Hinton created the term "deep learning" to explain new algorithms that help computers distinguish objects and text in images and videos.

2010 — Kinect: Microsoft developed the motion-sensing input device named Kinect that can track 20 human characteristics at a rate of 30 times per second. It allowed people to interact with the computer through movements and gestures.

2011 — Watson and Google Brain: IBM's Watson won a game of the US quiz show Jeopardy against two of its champions. In the same year, Google Brain was developed its deep neural network which could discover and categorize objects in the way a cat does.

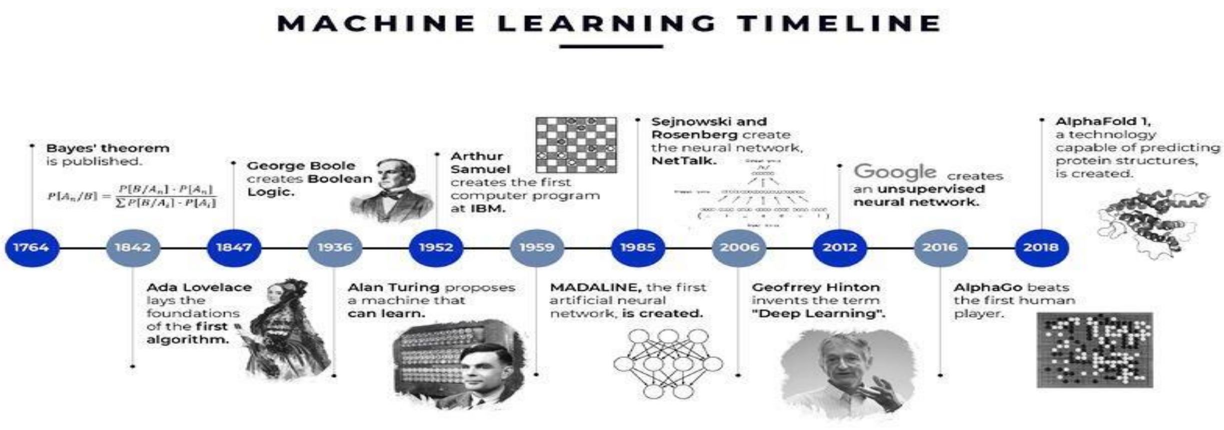
2012 — ImageNet Classification and computer vision: The year saw the publication of an influential research paper by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever, describing a model that can dramatically reduce the error rate in image recognition systems. Meanwhile, Google's X Lab developed a machine learning algorithm capable of autonomously browsing YouTube videos to identify the videos that contain cats.

2014 — Deep Face: Facebook developed a software algorithm Deep Face, which can recognize and verify individuals on photos with an accuracy of a human.

2015 — Amazon Machine Learning: AWS's Andy Jassy launched their Machine Learning managed services that analyze users' historical data to look for patterns and deploy predictive models. In the same year, Microsoft created the Distributed Machine Learning Toolkit, which enables the efficient distribution of machine learning problems across multiple computers.

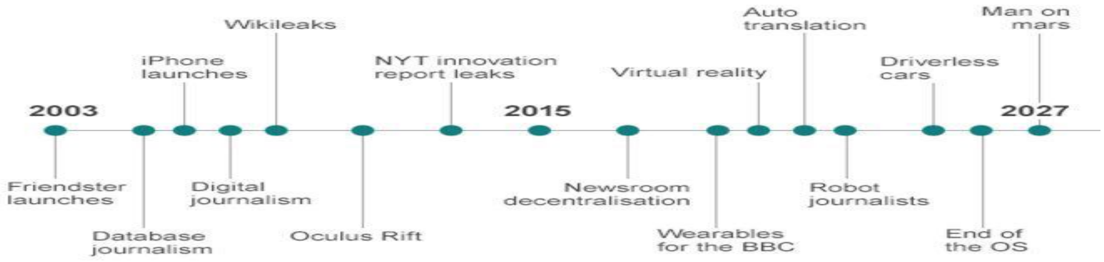
2016 — AlphaGo: AlphaGo, created by researchers at Google Deep Mind to play the ancient Chinese game of Go, won four out of five matches against Lee Sedol, who has been the world's top Go player for over a decade.

2017 — Libratus and Deepstack: Researchers at Carnegie Mellon University created a system named Libratus, and it defeated four top players at No Limit Texas Hold .



Machine learning time line from 18 th century

2017: Image Net Challenge – Milestone in the History of Machine Learning. The Image Net Challenge is a competition in computer vision that has been running since 2010. This challenge focuses on the abilities of programs to process patterns in images and recognize objects with varying degrees. In 2017, a milestone was reached. 29 out of 38 teams achieved 95% accuracy with their computer vision models. The improvement in image recognition is immense.



ML into the future

Present: State-of-the-art Machine Learning-- Machine learning is used in many different fields, from fashion to agriculture. Machine Learning algorithms are able to learn patterns and relationships between data, find predictive insights for complex problems and extract information that is otherwise too difficult to find. Today's Machine Learning algorithms are able to handle large amounts of data with accuracy in a relatively short amount of time.

Prerequisites for Machine Learning (ML) are, For those interested in learning beyond what is Machine Learning, a few requirements should be met to be successful in pursual of this field. These requirements include:

*Basic knowledge of programming languages such as Python, R, Java, JavaScript, etc

*Intermediate knowledge of statistics and probability

*Basic knowledge of linear algebra. In the linear regression model, a line is drawn through all the data *points, and that line is used to compute new values.

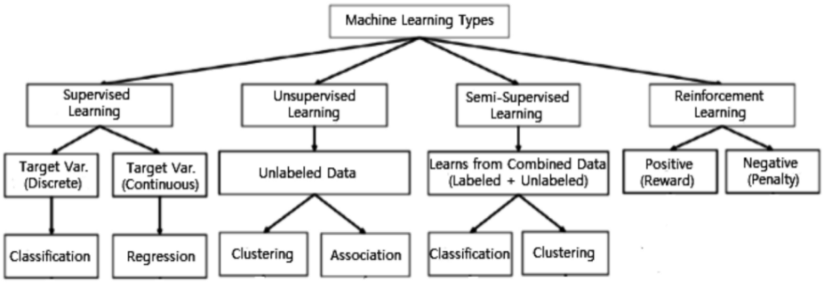
*Understanding of calculus

*Knowledge of how to clean and structure of raw data to the desired format to reduce the time taken for decision-making.

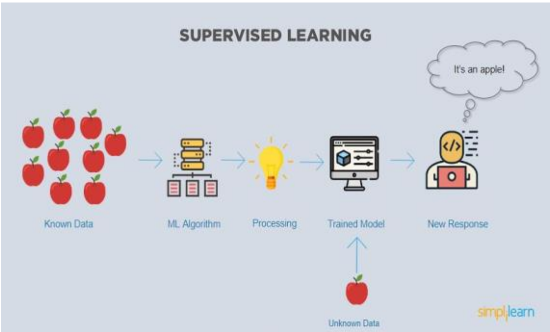
TYPES AND ALGORITHMS IN MACHINE LEARNING:

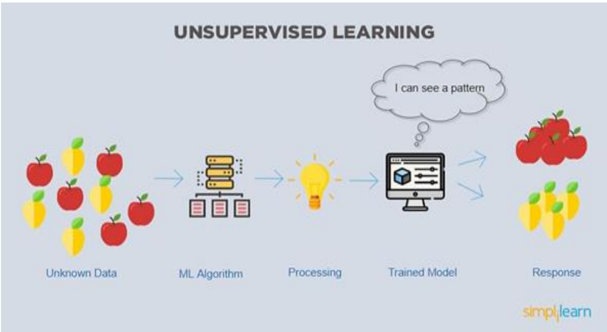
Depending on the situation, machine learning algorithms function using more or less human intervention/reinforcement. The four major machine learning models are *supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning.*

More specifically, Machine Learning is complex. Approximately 70 percent of machine learning is supervised learning, while unsupervised learning accounts for anywhere from 10 to 20 percent. The remainder is taken up by reinforcement learning.



1. Supervised Learning: In supervised learning, we use known or labeled data for the training data. Since the data is known, the learning is therefore, supervised, i.e., directed into successful execution. The input data goes through the Machine Learning algorithm and is used to train the model. Once the model is trained based on the known data, you can use unknown data into the model and get a new response.





In this case, the model tries to figure out whether the data is an apple or another fruit. Once the model has been trained well, it will identify that the data is an apple and give the desired response. The list of top algorithms currently being used for supervised learning are: *Polynomial regression; Random forest; Linear regression; Logistic regression; Decision trees; K-nearest neighbors; Naive Bayes; Now let's learn about unsupervised learning.*

2. Unsupervised Learning; In unsupervised learning, the training data is unknown and unlabeled - meaning that no one has looked at the data before. Without the aspect of known data, the input cannot be guided to the algorithm, which is where the unsupervised term originates from. This data is fed to the Machine Learning algorithm and is used to train the model. The trained model tries to search for a pattern and give the desired response. Here the algorithm is trying to break code like the Enigma machine but without the human mind directly.. There are many different ways that machine learning algorithms do this, including:

*Clustering, in which the computer finds similar data points within a data set and groups them accordingly (creating "clusters").

*Density estimation in which the computer discovers insights by looking at how a data set is distributed.

*Anomaly detection, in which the computer identifies data points within a data set that are significantly different from the rest of the data.

*Principal component analysis (PCA), in which the computer analyses a data set and summarises it so that it can be used to make accurate predictions

In this case, the unknown data consists of apples and pears which look similar to each other. The trained model tries to put them all together so that you get the same things in similar groups. Some of the top 7 algorithms currently being used for unsupervised learning are: *Partial least squares; Fuzzy means; Singular value decomposition; K-means clustering; Apriori; Hierarchical clustering; Principal component analysis*.

ML solves problems that cannot be solved by numerical means alone. Among the different types of ML tasks, a crucial distinction is drawn between supervised and unsupervised learning. **Supervised machine learning** is when the program is "trained" on a predefined set of "training examples," which then facilitate its ability to reach an accurate conclusion when given new data. **Unsupervised machine learning** is when the program is given a bunch of data and must find patterns and relationships therein.

With ***semi-supervised learning***, the computer is provided with a set of partially labeled data and performs its task using the labeled data to understand the parameters for interpreting the unlabeled data.

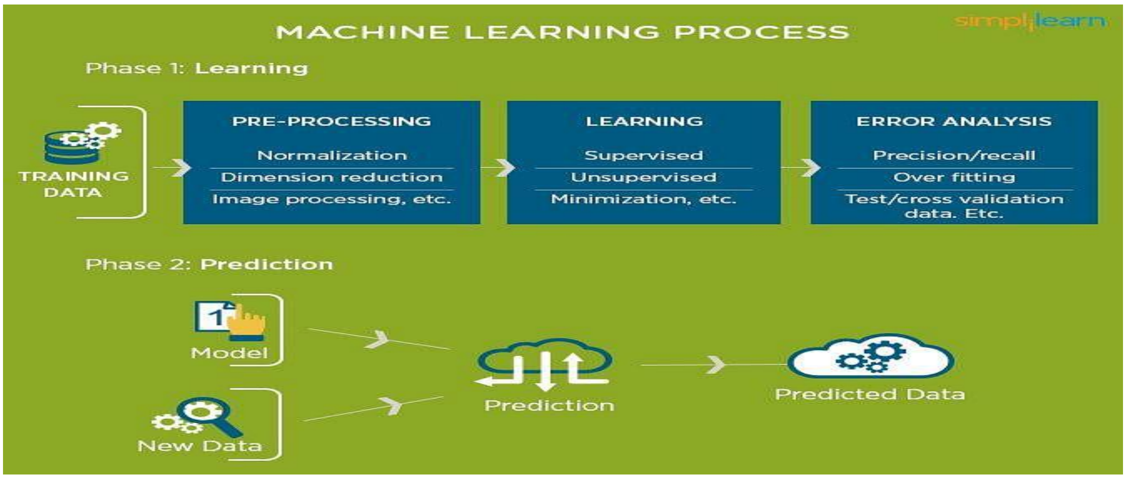
3. Reinforcement Learning: With *reinforcement learning*, the computer observes its environment and uses that data to identify *the ideal behavior that will minimizes risk* and/or maximizes reward. This is an iterative approach that requires some kind of reinforcement signal to help the computer better identify its best action.

On the whole Machine learning (ML) allows software applications to become more accurate at predicting outcomes, without being explicitly programmed. Machine learning algorithms use historical data as input to predict new output values. This machine learning is closely related to computational statistics, which focuses on making predictions using computers**.**

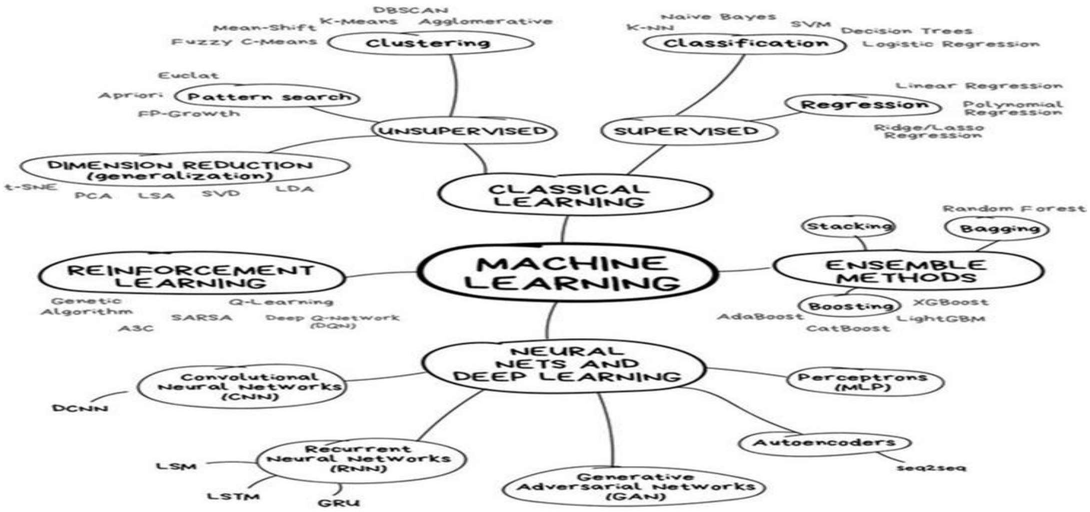
Like traditional types of data analysis, here, the algorithm discovers data through a process of trial and error and then decides what action results in higher rewards. Three major components make up reinforcement learning: the agent, the environment, and the actions. The agent is the learner or decision-maker, the environment includes everything that the agent interacts with, and the actions are what the agent does.

Reinforcement learning happens when the agent chooses actions that maximize the expected reward over a given time. This is easiest to achieve when the agent is working within a policy framework. Machine Learning is such a vital concept of modern times.

To better answer the question: what is machine learning" and understand the uses of Machine Learning we consider some of the applications of Machine Learning; *the self-driving Google car, cyber fraud detection, and online recommendation engines from Facebook, Netflix, and Amazon*. Machines make all these things possible by filtering useful pieces of information based on patterns to get accurate results.



The rapid evolution in Machine Learning (ML) has caused a subsequent rise in the use cases, demands, and the sheer importance of ML in modern life. Big Data has also become a well-used buzzword in the last few years. This may be due to the increased sophistication of Machine Learning, which enables the analysis of large chunks of Big Data. Machine Learning has also changed the way data extraction and interpretations are can be made by automating generic methods/algorithms, thereby replacing traditional statistical techniques.



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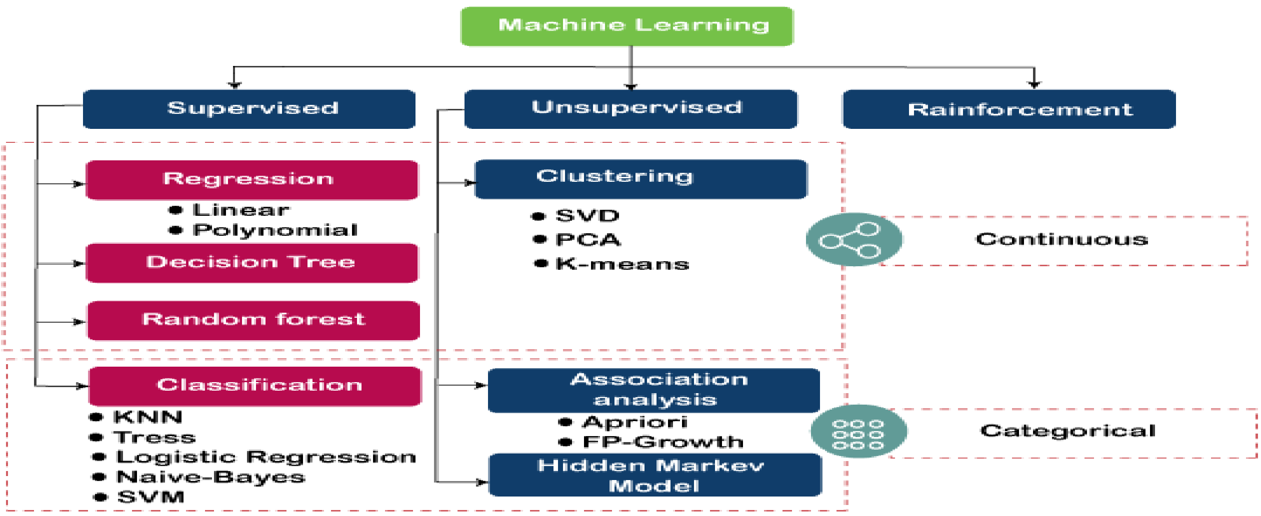
HOW TO DECIDE WHICH MACHINE LEARNING ALGORITHM SHOULD BE USED?

There are dozens of different algorithms to choose from, but there's no best choice or one that suits every situation. In many cases, you must resort to trial and error. But there are some questions we can ask that can help narrow down the choices.

*What's the size of the data you will be working with?
*What's the type of data you will be working with?
*What kinds of insights are you looking for from the data?
*How will those insights be used?
*What is the Best Programming Language for Machine Learning?

If we look at the choices based on sheer popularity, then Python gets the nod. Python is ideal for data analysis and data mining and supports many algorithms (*for classification, clustering, regression, and dimensionality reduction), and machine learning models.*



Enterprise Machine Learning and MLOps : Enterprise machine learning gives businesses important insights into customer loyalty and behavior, as well as the competitive business environment. Machine learning also can be used to forecast sales or real-time demand.

Machine learning operations (MLOps) is the discipline of Artificial Intelligence model delivery. It helps organizations scale production capacity to produce faster results, thereby generating vital business value.

Some Machine Learning Algorithms and Processes: In order to familiarize with standard Machine Learning algorithms and processes, we have to learn *neural networks, decision trees, random forests, associations, and sequence discovery, gradient boosting and bagging, support vector machines, self-organizing maps, k-means clustering, Bayesian networks, Gaussian mixture models, and more.* There are other machine learning tools and processes that leverage various algorithms to get the most value out of big data. These include:

*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 determine 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 process

MACHINE LEARNING STEPS : The task of imparting intelligence to machines seems daunting and impossible. But it is actually really easy. It can be broken down into 7 major steps:

1. Collecting Data: As you know, machines initially learn from the data that you give them. It is of the utmost importance to collect reliable data so that your machine learning model can find the correct patterns. The quality of the data that you feed to the machine will determine how accurate your model is. If you have incorrect or outdated data, you will have wrong outcomes or predictions which are not relevant.

Make sure you use data from a reliable source, as it will directly affect the outcome of your model. Good data is relevant, contains very few missing and repeated values, and has a good representation of the various subcategories/classes present.

2. Preparing the Data: After you have your data, you have to prepare it. You can do this by :

- Putting together all the data you have and randomizing it. This helps make sure that data is evenly distributed, and the ordering does not affect the learning process.
- Cleaning the data to remove unwanted data, missing values, rows, and columns, duplicate values, data type conversion, etc. You might even have to restructure the dataset and change the rows and columns or index of rows and columns.
- Visualize the data to understand how it is structured and understand the relationship between various variables and classes present.
- Splitting the cleaned data into two sets - a training set and a testing set. The training set is the set your model learns from. A testing set is used to check the accuracy of your model after training.

3. Choosing a Model: A machine learning model determines the output you get after running a machine learning algorithm on the collected data. It is important to choose a model which is relevant to the task at hand. Over the years, scientists and engineers developed various models suited for different tasks like speech recognition, image recognition, prediction, etc. Apart from this, you also have to see if your model is suited for numerical or categorical data and choose accordingly.

4. Training the Model: Training is the most important step in machine learning. In training, you pass the prepared data to your machine learning model to find patterns and make predictions. It results in the model learning from the data so that it can accomplish the task set. Over time, with training, the model gets better at predicting.

5. Evaluating the Model: After training your model, you have to check to see how it's performing. This is done by testing the performance of the model on previously unseen data. The unseen data used is the testing set that you split our data into earlier. If testing was done on the same data which is used for training, you will not get an accurate measure, as the model is already used to the data, and finds the same patterns in it, as it previously did. This will give you disproportionately high accuracy. When used on testing data, you get an accurate measure of how your model will perform and its speed.

6. Parameter Tuning: Once you have created and evaluated your model, see if its accuracy can be improved in any way. This is done by tuning the parameters present in your model. Parameters are the variables in the model that the programmer generally decides. At a particular value of your parameter, the accuracy will be the maximum. Parameter tuning refers to finding these values.
7. Making Predictions In the end, you can use your model on unseen data to make predictions accurately..
How to Implement Machine Learning Steps in Python?
In an example of data collected is from an insurance company, which tells you the variables that come into play when an insurance amount is set. Using this, you will have to predict the insurance amount for a person. This data was collected from Kaggle.com, which has many reliable datasets.

- You need to start by importing any necessary modules. Following this, you will import the data.
- Now, clean your data by removing duplicate values, and transforming columns into Numerical values to make them easier to work with.
- Now, split your dataset into training and testing sets.
- As you need to predict a numeral value based on some parameters, you will have to use Linear Regression. The model needs to learn on your training set. This is done by using the '.fit' command.
- Now, predict your testing dataset and find how accurate your predictions are.
- Now, get your parameters.
- The above picture shows the hyper-parameters which affect the various variables in your dataset.
- Stay ahead of the tech-game with our PG Program in AI and Machine Learning in partnership with Purdue and in collaboration with IBM.

To learn more about machine learning and how to make machine learning models, check out Simplilearn's AI and Machine Learning Course If you have any questions or doubts, mention them in this article's comments section, and we'll have our experts answer them for you at the earliest.

USES OF BAYES THEOREM IN MACHINE LEARNING: Developing classifier models may be the most common application on **Bayes Theorem in machine learning**. Of course there are many other applications. Two important examples are optimization and causal models.

I. Bayesian Optimization

Global optimization is a challenging problem of finding an input that results in the minimum or maximum cost of a given objective function. Typically, the form of the objective function is complex and intractable to analyze and is often non-convex, nonlinear, high dimension, noisy, and computationally expensive to evaluate.

Bayesian Optimization provides a principled technique based on Bayes Theorem to direct a search of a global optimization problem that is efficient and effective. It works by building a probabilistic model of the objective function, called the surrogate function that is then searched efficiently with an acquisition function before candidate samples are chosen for evaluation on the real objective function.

Bayesian Optimization is often used in applied machine learning to tune the hyperparameters of a given well-performing model on a validation dataset.

II. Bayesian Belief Networks:

Probabilistic models can define relationships between variables and be used to calculate probabilities.

Fully conditional models may require an enormous amount of data to cover all possible cases, and probabilities may be intractable to calculate in practice. Simplifying assumptions such as the conditional independence of all random variables can be effective, such as in the case of Naive Bayes, although it is a drastically simplifying step.

An alternative is to develop a model that preserves known conditional dependence between random variables and conditional independence in all other cases. Bayesian networks are a probabilistic graphical model that explicitly captures the known conditional dependence with directed edges in a graph model. All missing connections define the conditional independencies in the model. As such Bayesian Networks provide a useful tool to visualize the probabilistic model for a domain, review all of the relationships between the random variables, and reason about causal probabilities for scenarios given available evidence.

The networks are not exactly Bayesian by definition, although given that both the probability distributions for the random variables (nodes) and the relationships between the random variables (edges) are specified subjectively, the model can be thought to capture the "belief" about a complex domain.

1II. Bayesian Machine Learning Applications Examples

Bayesian machine learning is one of the most powerful tools in data analytics. Bayes' theorem, which was first introduced by Reverend Thomas Bayes in 1764, provides a way to infer probabilities from observations. Bayesian machine learning has become increasingly popular because it can be used for real-world applications such as credit card fraud detection and spam filtering. In this blog post, we will discuss Bayesian machine learning real-world examples to help you understand how Bayes' theorem works.

Bayesian machine learning utilizes Bayes' theorem to predict occurrences. Bayesian inference is grounded in Bayes' theorem, which allows for accurate prediction when applied to real-world applications. Here are some great examples of real-world applications of Bayesian inference:

1. **Credit card fraud detection**: Bayesian inference can identify patterns or clues for credit card fraud by analyzing the data and inferring probabilities with Bayes' theorem. Credit card fraud detection may have false positives due to incomplete information. After an unusual activity is reported to enterprise risk management, Bayesian neural network techniques are used on the customer profile dataset that includes each customer's financial transactions over time. With these analyses we can confirm whether there are any indications of fraudulent activities.

2. **Spam filtering**: Bayesian inference allows for the identification of spam messages by using Bayes' theorem to construct a model that can tell if an email is likely to be spam or not. The Bayesian model trained using the Bayesian algorithm will take each word in the message into account and give it different weights based on how often they appear in both spam and non-spam messages. Bayesian neural networks are also used to classify spam emails by looking at the probability of an email being spam.

3. **Medical diagnosis:** Bayes' theorem is applied in medical diagnoses to use data from previous cases and determine the probability of a patient having a certain disease. Bayesian inference allows for better prediction than traditional statistic methods because it can take into account all the factors that may affect an outcome and provide probabilities instead of just binary results. Bayes' theorem is used to compute posterior probabilities, which are combined with clinical knowledge about diseases and symptoms to estimate the likelihood of a condition. Bayesian inference is used in the diagnosis of Alzheimer's disease by analyzing past patient data and finding a pattern that can indicate whether a person has this condition. Bayes' theorem is especially useful for rare diseases that may occur infrequently and require a large amount of data to make accurate predictions.

4. **Patterns in customer dataset/marketing campaign performance**: Bayesian nonparametric clustering technique is used to find hidden patterns in data. Bayesian nonparametric clustering technique (BNC) is a powerful method that can be applied to various datasets such as customer datasets or marketing campaign performance. It helps find hidden patterns in data because Bayesian machine learning does not require any assumptions about the distribution of input variables. BNC enables you to find clusters that are statistically significant and can be generalized across other datasets as well.

5. **Help robots make decisions:** Bayesian inference is used in robotics to help robots make decisions. Bayes' theorem can be applied by using real-time sensor information from the robot's environment and inferring about its next move or action based on previous experiences. Robots will use Bayes' theorem for extracting relevant features such as speed, the direction of movement, obstacles, and other objects in the environment. Bayesian reinforcement learning can be applied to robot learning. Bayesian reinforcement learning (BRL) uses Bayes' theorem to compute the probability of taking a certain action based on previously learned experiences/knowledge and observations received from sensory information. BRL has been shown to outperform other machine learning algorithms such as *deep Q-learning, Monte Carlo Tree Search, and Temporal Difference Learning.*

6. **Reconstructing clean images from noisy images:** Bayes' theorem is used in Bayesian inverse problems such as Bayesian tomography. Bayesian inference can be applied to the problem of reconstructing images from noisy versions of those images using *Bayes' theorem and Markov Chain Monte Carlo (MCMC) algorithms*.

7. **Weather prediction**: Bayesian inference can be used in Bayesian machine learning to predict the weather with more accuracy. Bayes' theorem can be applied for predicting real-time weather patterns and probabilities of rain based on past data such as temperature, humidity, etc. Bayesian models compare favorably against classical approaches because they take into account the historical behavior of the system being modeled and provide a probability distribution over the possible outcomes of the forecast.

8. **Speech emotion recognition**: Nonparametric hierarchical neural network (NHNN), a lightweight hierarchical neural network model based on Bayesian nonparametric clustering (BNC), can be used to recognize emotions in speech with better accuracy. NHNN models generally outperform the models with similar levels of complexity and state-of-the-art models in within-corpus and cross-corpus tests. Through clustering analysis, is is shown that the NHNN models are able to learn group-specific features and bridge the performance gap between groups.

9. **Estimating gas emissions:** The recent findings suggest that a large fraction of anthropogenic methane emissions is represented by abnormal operating conditions of oil and gas equipments. As such, effective mitigation requires rapid identification as well as repairs for faulty sources controlled via advanced sensing technology or automatic fault detection algorithms based on recursive Bayes' techniques.

10. **Federated analytics (Faulty device detection, malfunctions) :** Bayesian approach can be applied to federated analytics, a new approach to data analytics involving an integrated pipeline of machine learning techniques. The Bayesian hierarchical model allows the user to interrogate the aggregated model and automatically detect anomalies that could indicate faulty devices, malfunctions, or other such problems with remote assets/sensor networks. Federated learning is the methodology that provides a means of decentralized computations for machine learning without a need for moving local data of users. In each round of the federated learning, the participating devices train a model on their respective local data and send only an encrypted update to the aggregator. The aggregator combines updates from all participants to improve a shared model followed by its distribution to all participants.

11. **Forensic analysis:** Bayesian inference can be used in Bayesian machine learning to infer the identity of an individual based on DNA evidence. Bayes' theorem is applied for forensic analysis, which involves reasoning about conditional probabilities and making statistical inferences from observed data (genetic marker alleles) with respect to one or more populations of possible genotypes under study.

12. **Optical character recognition (OCR):** Bayesian inference can be used in Bayesian machine learning to improve optical character recognition (OCR) performance. Bayes' theorem is applied for OCR, which involves the transformation of images captured on paper-based media into text strings that are computer-readable. Bayesian approaches have been shown to provide more accurate results compared with conventional machine learning algorithms.

Bayesian machine learning is a subset of Bayesian statistics that makes use of Bayes' theorem to draw inferences from data. *Bayesian inference can be used in Bayesian machine learning to predict the weather with more accuracy, recognize emotions in speech, estimate gas emissions,* and much more! If you're interested in learning more about how Bayes' theorem could help, let us know.

MAIN USES OF MACHINE LEARNING: Typical results from machine learning applications usually include web search results, real-time ads on web pages and mobile devices, email spam filtering, network intrusion detection, and pattern and image recognition. All these are the by-products of using machine learning to analyze massive volumes of data.

Traditionally, data analysis was trial and error-based, an approach that became increasingly impractical thanks to the rise of large, heterogeneous data sets. Machine learning provides smart alternatives for large-scale data analysis. Machine learning can produce accurate results and analysis by developing fast and efficient algorithms and data-driven models for real-time data processing.

Pro Tip: For more on Big Data and how it's revolutionizing industries globally, check out our "What is Big Data?" Article.

According to Market watch, the global machine learning market is expected to grow at a healthy rate of over 45.9 percent during the period of 2017-2025. If this trend holds, then we will see a greater use of machine learning across a wide spectrum of industries worldwide. Machine learning is here to stay. Some of the 10 Popular Machine Learning Algorithms are based on Linear regression; Logistic regression; Decision tree; SVM algorithm; Naive Bayes algorithm; KNN algorithm; K-means; Random forest algorithm; Dimensionality reduction algorithms; Gradient boosting algorithm and Ada-Boosting algorithm

Some Examples of Machine Learning Problems: Machine Learning problems are abound. They make up core or difficult parts of the software you use on the web or on your desktop every day. Think of the "do you want to follow" suggestions on twitter and the speech understanding in Apple's Siri. Given Below are 10 examples of machine learning that really ground what machine learning is all about.

a. Spam Detection: Given email in an inbox, identify those email messages that are spam and those that are not. Having a model of this problem would allow a program to leave non-spam emails in the inbox and move spam emails to a spam folder. We should all be familiar with this example.

b. Credit Card Fraud Detection: Given credit card transactions for a customer in a month, identify those transactions that were made by the customer and those that were not. A program with a model of this decision could refund those transactions that were fraudulent.

c. Digit Recognition: Given a zip codes hand written on envelops, identify the digit for each hand written character. A model of this problem would allow a computer program to read and understand handwritten zip codes and sort envelops by geographic region.

d. Speech Understanding: Given an utterance from a user, identify the specific request made by the user. A model of this problem would allow a program to understand and make an attempt to fulfil that request. The iPhone with Siri has this capability.

e. Face Detection: Given a digital photo album of many hundreds of digital photographs, identify those photos that include a given person. A model of this decision process would allow a program to organize photos by person. Some cameras and software like iPhoto has this capability. We study an example of face detection from a photo.

f. Product Recommendation: Given a purchase history for a customer and a large inventory of products, identify those products in which that customer will be interested and likely to purchase. A model of this decision process would allow a program to make recommendations to a customer and motivate product purchases. Amazon has this capability. Also think of Facebook, Google Plus and LinkedIn that recommend users to connect with you after you sign-up.

g. Medical Diagnosis: Given the symptoms exhibited in a patient and a database of anonymized patient records, predict whether the patient is likely to have an illness. A model of this decision problem could be used by a program to provide decision support to medical professionals.

h. Stock Trading: Given the current and past price movements for a stock, determine whether the stock should be bought, held or sold. A model of this decision problem could provide decision support to financial analysts.

i. Customer Segmentation: Given the pattern of behavior by a user during a trial period and the past behaviors of all users, identify those users that will convert to the paid version of the product and those that will not. A model of this decision problem would allow a program to trigger customer interventions to persuade the customer to covert early or better engage in the trial.

j. Shape Detection: Given a user hand drawing a shape on a touch screen and a database of known shapes, determine which shape the user was trying to draw. A model of this decision would allow a program to show the platonic version of that shape the user drew to make crisp diagrams. The Instaviz iPhone app does this.

These 10 examples give a good sense of what a machine learning problem looks like. There is a corpus of historic examples, there is a decision that needs to be modeled and a business or domain benefit to having that decision modeled and efficaciously made automatically.

Some of these problems are some of the hardest problems in Artificial Intelligence, such as Natural Language Processing and Machine Vision (doing things that humans do easily). Others are still difficult, but are classic examples of machine learning such as spam detection and credit card fraud detection.

Think about some of your interactions with online and offline software in the last week. I'm sure you could easily guess at another ten or twenty example of machine learning you have directly or indirectly used.

SOME CLASSES OF MACHINE LEARNING PROBLEMS: This is a valuable skill, because being good at extracting the essence of a problem will allow you to think effectively about what data you need and what types of algorithms you should try. There are common classes of problem in Machine Learning. The problem classes below are archetypes for most of the problems we refer to when we are doing Machine Learning.

- **Classification**: Data is labelled meaning it is assigned a class, for example spam/non-spam or fraud/non-fraud. The decision being modelled is to assign labels to new unlabelled pieces of data. This can be thought of as a discrimination problem, modelling the differences or similarities between groups.

- **Regression**: Data is labelled with a real value (think floating point) rather then a label. Examples that are easy to understand are time series data like the price of a stock over time, The decision being modelled is what value to predict for new unpredicted data.

- **Clustering**: Data is not labelled, but can be divided into groups based on similarity and other measures of natural structure in the data. An example from the above list would be organising pictures by faces without names, where the human user has to assign names to groups, like iPhoto on the Mac.

- **Rule Extraction**: Data is used as the basis for the extraction of propositional rules (antecedent/consequent aka if-then). Such rules may, but is typically not directed, meaning that the methods discover statistically supportable relationships between attributes in the data, not necessarily involving something that is being predicted. An example is the discovery of the relationship between the purchase of beer and diapers (this is data mining folk-law, true or not, it's illustrative of the desire and opportunity).

When you think a problem is a machine learning problem (a decision problem that needs to be modelled from data), think next of what type of problem you could phrase it as easily or what type of outcome the client or requirement is asking for and work backwards.

Machine Learning and Deep Learning: Machine Learning and Deep Learning algorithms are used to train models for data classification. This of the two to use depends on the kind of problem that is to be solved. Machine Learning and Deep Learning algorithms are also used in data analysis, processing and cleansing, more so where the data is unstructured and consists of pictures, video and voice. This has found critical application in Cyber security in today's digital age. Based on its ability to decipher patterns from humungous data volumes, these models assist in identifying and preventing threats.

Computer Vision: Computer Vision makes use of algorithms of Machine Learning in simple applications and Deep Learning for complex applications in detecting and then identifying objects. This is put to use in the facial recognition feature of smartphones and computers on the one hand and autonomous vehicles on the other hand. Some other examples of Computer Vision are bar coding, self-checkout kiosks and medical imaging.

CONCLUSIONS: Machine learning is the ability of a machine to improve its performance based on previous results. Machine learning methods enable computers to learn without being explicitly programmed and have multiple applications, for example The authorswhould like to thank the ae, in the improvement of data mining algorithms.

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