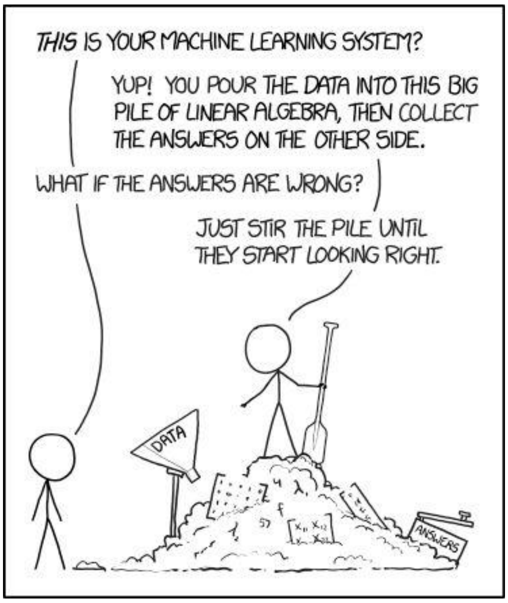
Machine Learning: A Primer


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

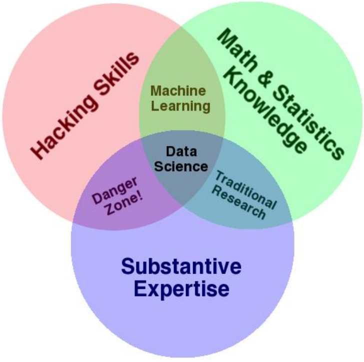
Do you use a personal assistant client like Siri or Alexa? Do you rely on a spam filter to keep your email inbox clean? Do you subscribe to Netflix and rely on its scarily-accurate suggestions to discover new movies to watch? If you said 'yes' to any of these questions, congratulations! You've made fine use of machine learning!

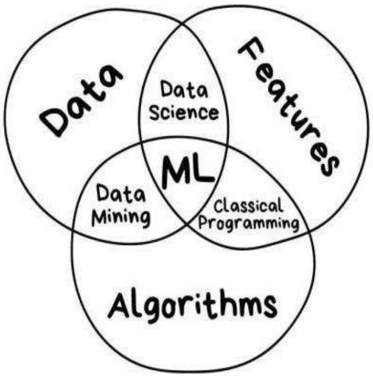
Although it sounds like a complicated idea that requires a lot of technical background, machine learning is actually a fairly simple concept.

To better understand it, let's go over the what, who, when, where, how, and why.

What is machine learning?

One day ladies will take their computers for walks in the park and tell each other, "My little computer said such a funny thing this morning". —Alan Turing

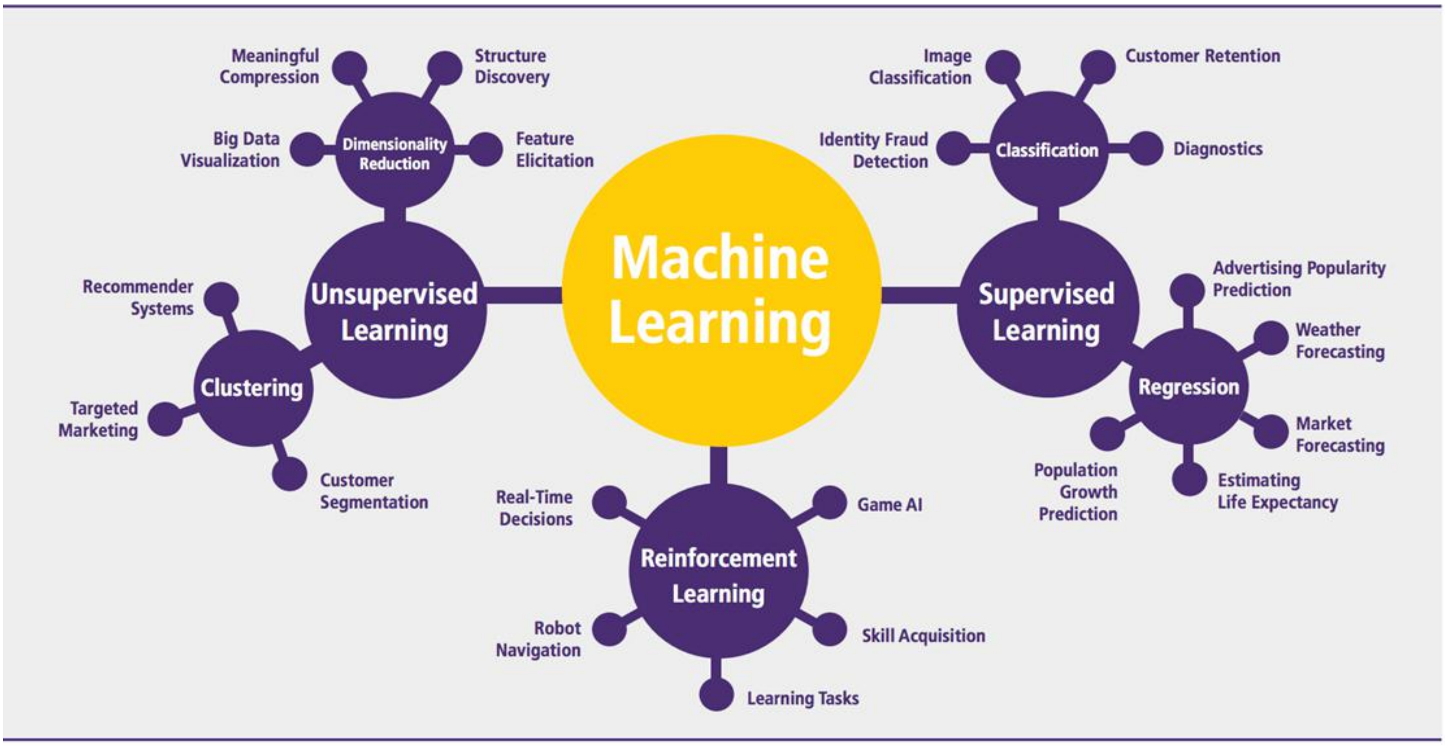




At its core, machine learning is "the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world." (Nvidia) This means that, rather than explicitly programming a computer to perform some task, you teach the computer how to develop an algorithm to complete the task.

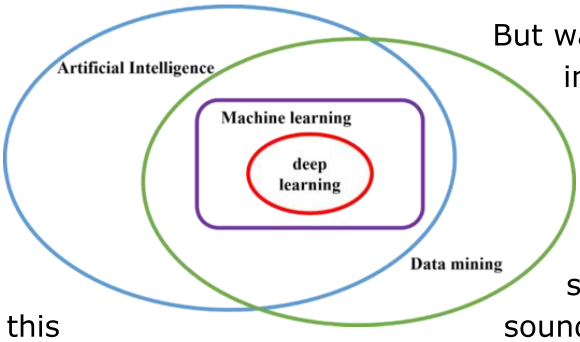
There are three major types of machine learning, all with specific advantages and disadvantages: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning involves sets of labeled data. The computer can use the provided data to recognize new instances of each labeled type using certain patterns. The two main types of supervised learning are classification and regression. In classification, a machine is trained to separate a group into specific classes. A simple example of classification is a spam filter on your email account. The filter analyzes the emails you've previously marked as spam and compares them to new emails. If they match to a certain percentage, these new emails are tagged as spam and sent to the appropriate folders. Emails are less similar are classified as normal and sent to your inbox. The second type of supervised learning is regression. In regression, a machine uses previous (labeled) data to make predictions about the future. Weather apps are good examples of regression. Using historical data about weather events (i.e. average temperature, humidity, and precipitation amounts), your phone's weather app can look at the current weather and make predictions about the weather in a future time frame.



In unsupervised learning, the data is unlabeled. As most real-world data is unlabeled, these algorithms are particularly useful. Unsupervised learning is divided into clustering and dimensionality reduction. Clustering is used to group objects based on properties and behaviors. This is different from classification because these groups are not provided to you. An example of clustering is dividing a group into different subgroups (say, based on age and marital status) to then send targeted marketing to. Dimensionality reduction, on the other hand, involves reducing the variables of a data set by finding commonalities. Most big data visualization uses dimensionality reduction to identify trends and rules.

Finally, reinforcement learning uses a machine's personal history and experiences to make decisions. The classic application of reinforced learning is game playing. As opposed to supervised and unsupervised learning, reinforcement learning is not concerned with providing "correct" answers or outputs. Instead, it focuses exclusively on performance. This mirrors how humans learn based on positive and negative consequences. If a child touches a hot stove, he quickly learns not to repeat that action. In this same vein, a chess-playing computer can learn not to move its King to a space accessible to an opponent's piece. This fundamental lesson of chess can then be expanded and extrapolated on until the machine is capable of playing (and eventually beating) top human players.

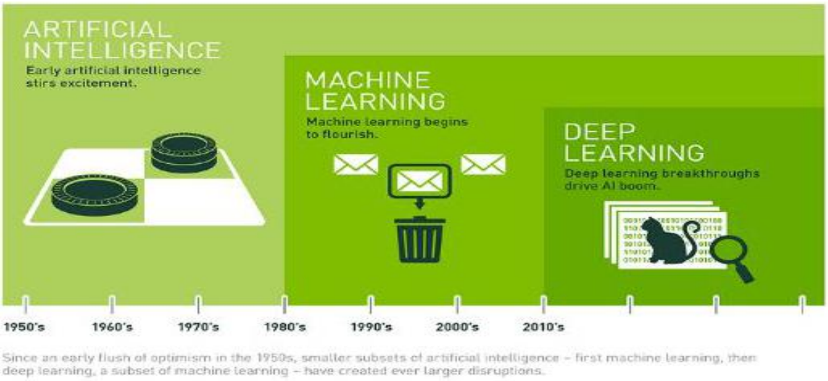


But wait, you might be saying. Are we talking about artificial intelligence? Sort of. Machine learning is a branch of artificial intelligence. Artificial intelligence is concerned with creating machines that can perform complex tasks as well (or better) than humans. These tasks often involve judgement, strategy, and cognitive reasoning, skills originally considered "off limits" to machines. While this sounds simple, the scope of these skills is immense—think language processing, image recognition, planning, and much more. Machine learning uses specific algorithms and programming approaches to achieve artificial intelligence. Without machine learning, our previously mentioned chess program would require millions and millions of lines of code, accounting for all edge cases and containing all possible moves from its opponents. With machine learning, we can reduce the code base into a fraction of its former self. Pretty nifty, huh?

There’s just one missing piece: deep learning and neural networks. We’ll go into them in more detail later, but for now, be aware that deep learning is a subset of machine learning focused on specifically mimicking the biology and process of the human brain.

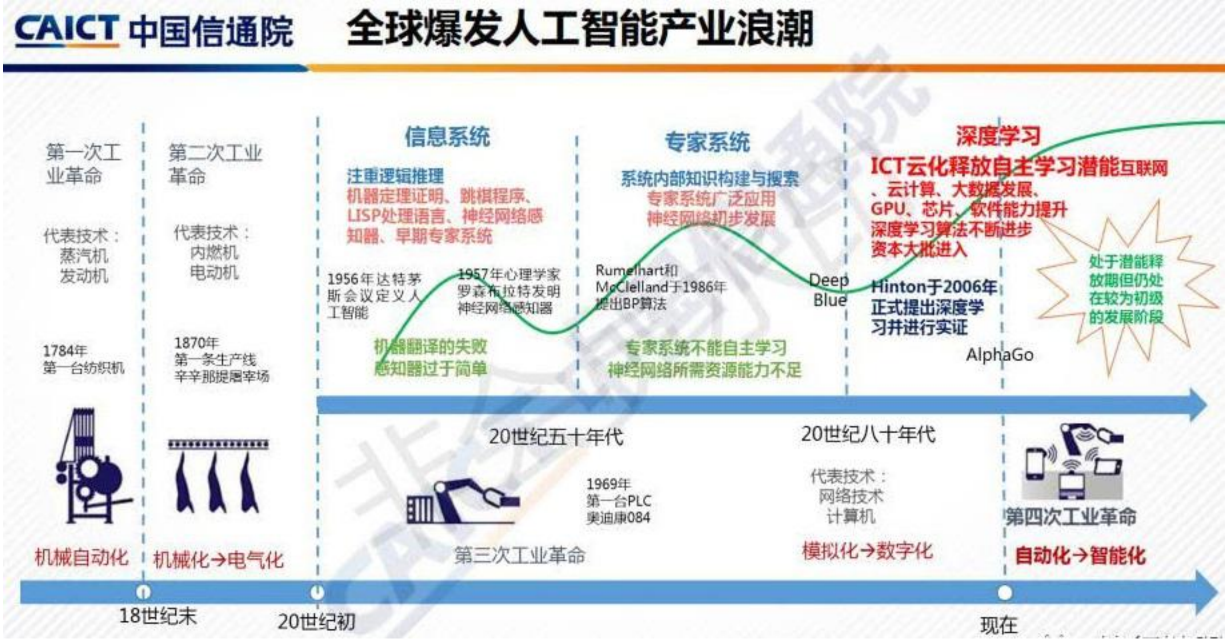
Who developed machine learning? Where and when?

A breakthrough in machine learning would be worth ten MicroSofts.—Bill Gates


ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.
MACHINE LEARNING
Machine learning begins to flourish.
DEEP LEARNING
Deep learning breakthroughs drive AI boom.
1950's
1960's
1970's
1980's
1990's
2000's
2010's

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

In my opinion, the earliest development in machine learning was Thomas Bayes’ 1783 publication of his eponymous theorem. Bayes’ theorem finds the probability of an event given historical data about similar events. It is, unsurprisingly, the basis of the Bayesian branch of machine learning which seeks to find the most likely occurence based on previous information. In other words, Bayes’ theorem is just a fancy schmancy math way of learning from experience, the fundamental idea of machine learning.



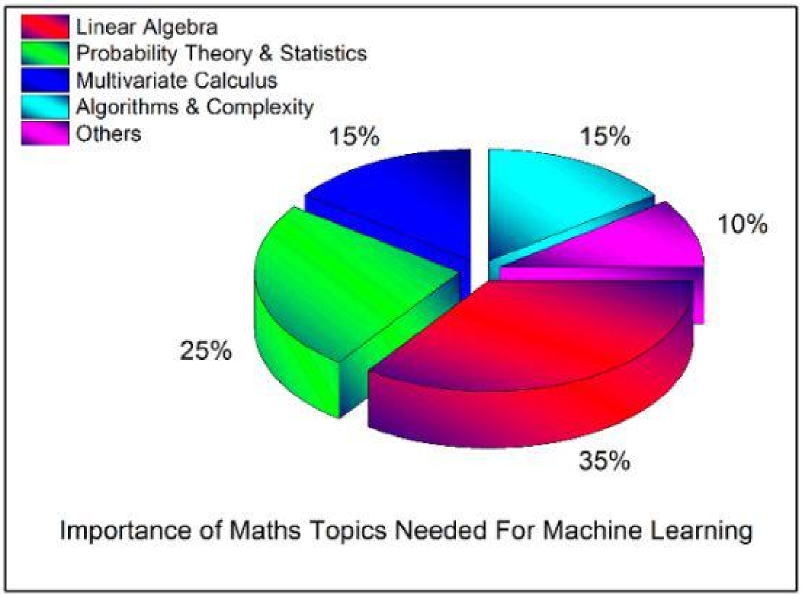
Centuries later, in 1950, computer scientist (and all-around badass) Alan Turing created the so-called Turing Test, where a computer must fool a human through text conversation into thinking she is speaking to another human. Turing argued that a machine could only be consider “intelligent” if it passed this test. Shortly after this, in 1952, Arthur Samuel created the first true machine learning program—a simple checkers game where the computer was able to learn strategy from previous plays and improve future performance. This was followed up with Donald Michie’s 1963 reinforcement learning-based tic-tac-toe program. For the next several decades, advances in machine learning followed the same general pattern—a technological breakthrough led to newer, more sophisticated computers, often tested by playing strategy games against professional human players. It hit its peak in 1997 when the IBM chess computer Deep Blue beat world champion Garry Kasparov in a chess match. More recently, Google developed AlphaGo focusing on the ancient Chinese board game Go, widely considered to be the hardest game in the world. Although Go was assumed to be too complex for a computer to master, AlphaGo finally prevailed in 2016, beating Lee Sedol in a five-game match.

The largest breakthrough in machine learning was the 2006 development of deep learning. Deep learning is a class of machine learning that aims to mimic the thought process of the human brain and is often used in image and speech recognition. The advent of deep learning led to many of the technologies we use (and possibly take for granted) today. Have you ever uploaded a picture to your Facebook account, only for it to suggest tagging the people in the picture? Facebook is using a neural network to recognize the faces in your photo. Or what about Siri? When you ask your iPhone about today's baseball scores, your speech is analyzed by a sophisticated speech-parsing algorithm. None of this would be possible without deep learning.

For a more thorough machine learning timeline, make sure to check out this great article by the Google cloud team!

How does machine learning work?

Attention all math shy readers: I regret to inform you that a basic understanding of some key mathematics concepts is required to fully comprehend most machine learning algorithms. But fear not! The required concepts are simple and draw on classes you've probably already taken. Machine learning uses linear algebra, calculus, probability and statistics.



Importance of Maths Topics Needed For Machine Learning

Top 3 linear algebra concepts:

1. matrix operations
2. eigenvalues/eigenvectors
3. vector spaces and norms

Top 3 calculus concepts:

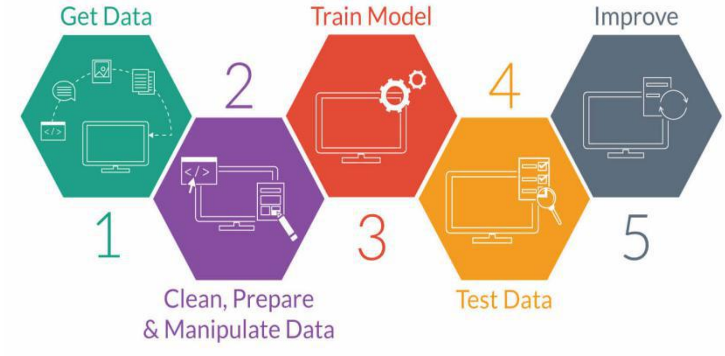
1. partial derivatives
2. vector-valued functions
3. directional gradients

Top 3 statistics concepts:

1. Bayes' theorem
2. combinatorics
3. sampling methods

Once you have a basic mathematical understanding, it's time to start thinking about the entire machine learning process. There are 5 main steps.

The left diagram explains the steps in a much clearer way than I could, so take a minute to study it before we focus on to the most crucial part: choosing the correct algorithm for the data and situation.

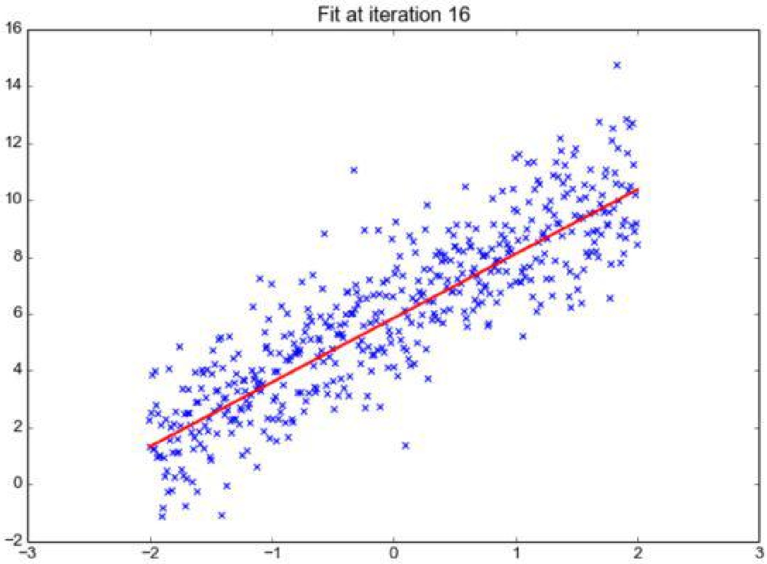


We don’t have better algorithms, we just have more data.—Peter Norvig

Let’s review some common groupings of algorithms:

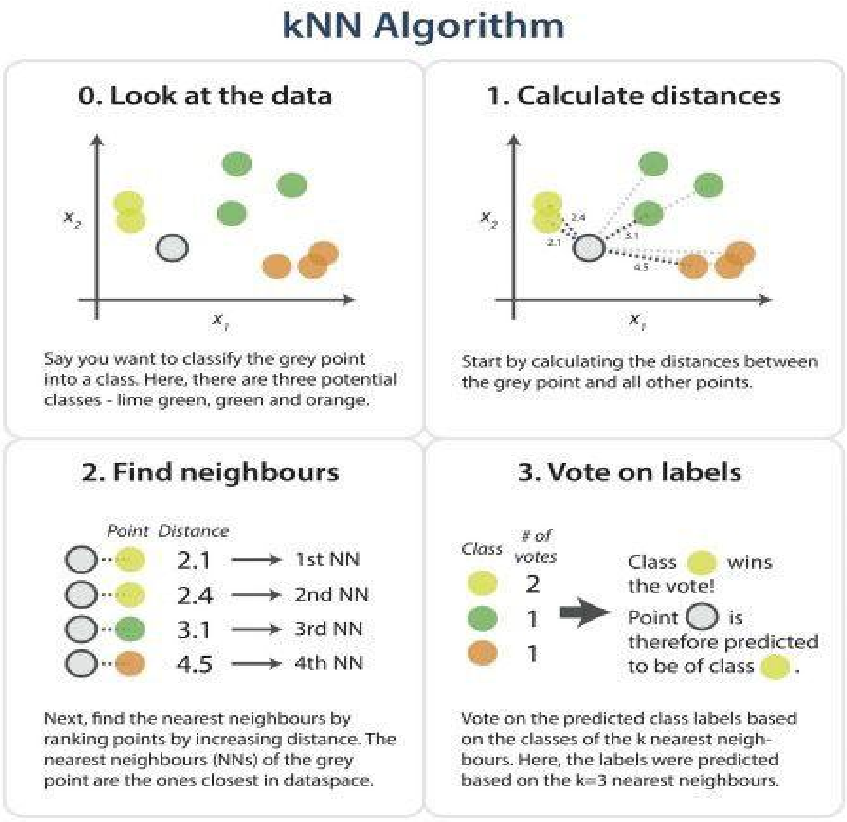
Supervised learning:

Linear Regression Algorithms (regression)



Possibly the most popular machine learning algorithms, linear regression algorithms are supervised learning algorithms that predict a specific outcome based on continous variables. Logistic regression, on the other hand, are used specifically to predict discrete values. Both these (and all other regression algorithms) are known for their speed; they are consistently ranked among the very fastest machine learning algorithms.

k-Nearest Neighbor(kNN)(classification)



Say you want to classify the grey point into a class. Here, there are three potential classes - lime green, green and orange.

Start by calculating the distances between the grey point and all other points.

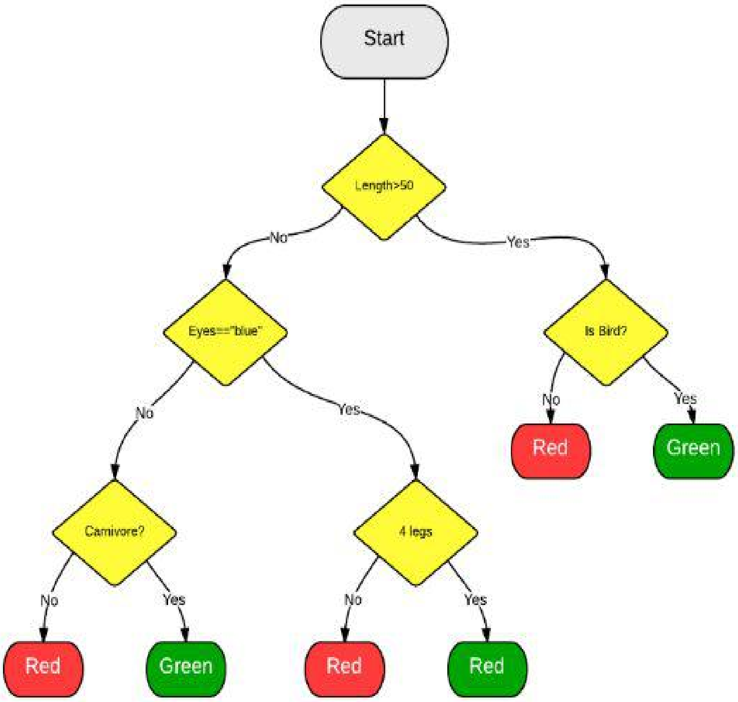
Next, find the nearest neighbours by ranking points by increasing distance. The nearest neighbours (NNs) of the grey point are the ones closest in dataspace.

Class ● wins the vote! Point ○ is therefore predicted to be of class ●.

Vote on the predicted class labels based on the classes of the k nearest neighbours. Here, the labels were predicted based on the k=3 nearest neighbours.

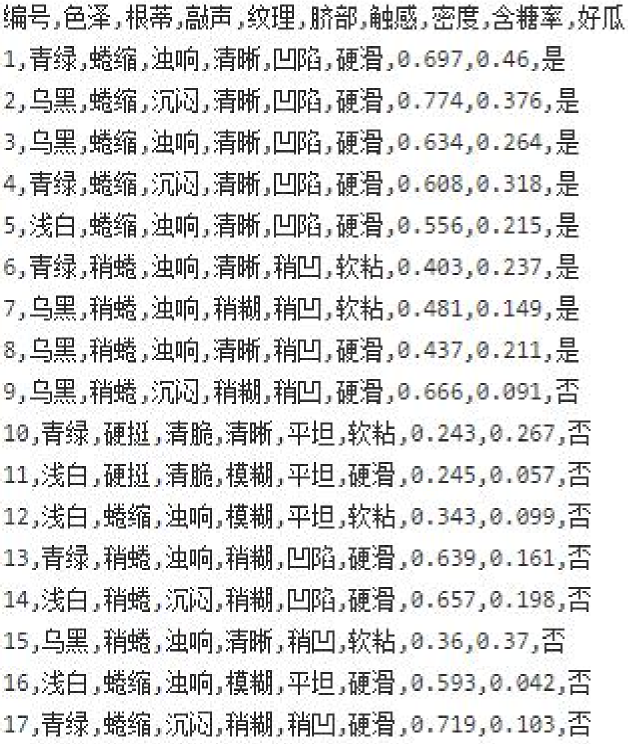
Instance-based analysis uses specific instances of provided data to predict an outcome. The most famous instance-based algorithm is k-Nearest Neighbor, also known as kNN. Used for classification, kNN compares the distance of data points and assigns each point to the group it is closest to.

Decision Tree Algorithms(classification)



Decision tree algorithms take groups of “weak” learners and have them work together to form one strong algorithm. These learners are organized in a tree-like structure, branching off one another. A popular decision tree algorithm is the Random Forest Algorithm. In this algorithm, the weak learners are randomly chosen. This tends to lead to a strong predictor. In the example below, we can discover numerous common traits (like eyes that are or are not blue), none of which would be enough on their own to identify the animal. When we put all these observations together, however, we are able to form a more complete picture and make a much more accurate prediction.

Bayesian Algorithms(classification)



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编号,色泽,根蒂,敲声,纹理,脐部,触感,密度,含糖率,好瓜
1,青绿,蜷缩,浊响,清晰,凹陷,硬滑,0.697,0.46,是
2,乌黑,蜷缩,沉闷,清晰,凹陷,硬滑,0.774,0.376,是
3,乌黑,蜷缩,浊响,清晰,凹陷,硬滑,0.634,0.264,是
4,青绿,蜷缩,沉闷,清晰,凹陷,硬滑,0.608,0.318,是
5,浅白,蜷缩,浊响,清晰,凹陷,硬滑,0.556,0.215,是
6,青绿,稍蜷,浊响,清晰,稍凹,软粘,0.403,0.237,是
7,乌黑,稍蜷,浊响,稍糊,稍凹,软粘,0.481,0.149,是
8,乌黑,稍蜷,浊响,清晰,稍凹,硬滑,0.437,0.211,是
9,乌黑,稍蜷,沉闷,稍糊,稍凹,硬滑,0.666,0.091,否
10,青绿,硬挺,清脆,清晰,平坦,软粘,0.243,0.267,否
11,浅白,硬挺,清脆,模糊,平坦,硬滑,0.245,0.057,否
12,浅白,蜷缩,浊响,模糊,平坦,软粘,0.343,0.099,否
13,青绿,稍蜷,浊响,稍糊,凹陷,硬滑,0.639,0.161,否
14,浅白,稍蜷,沉闷,稍糊,凹陷,硬滑,0.657,0.198,否
15,乌黑,稍蜷,浊响,清晰,稍凹,软粘,0.36,0.37,否
16,浅白,蜷缩,浊响,模糊,平坦,硬滑,0.593,0.042,否
17,青绿,蜷缩,沉闷,稍糊,稍凹,硬滑,0.719,0.103,否
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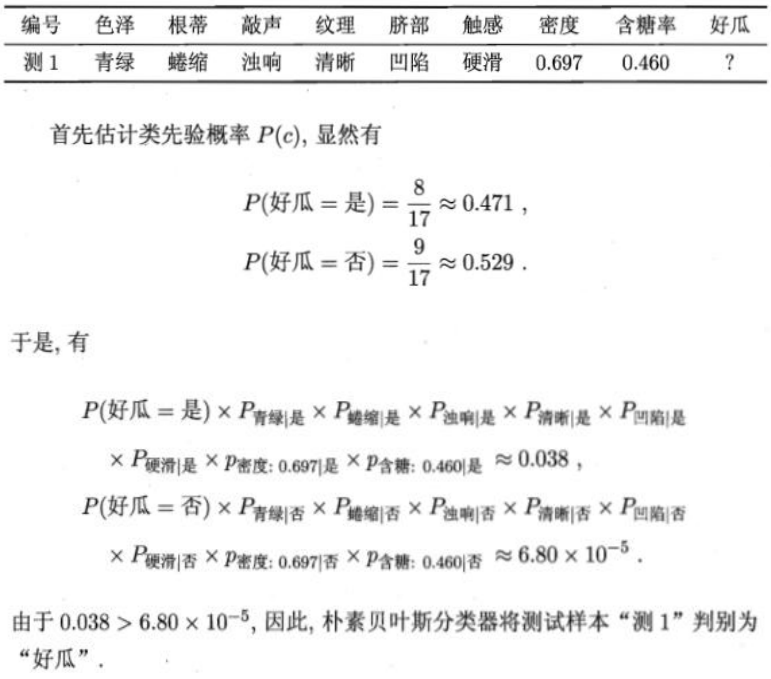


编号	色泽	根蒂	敲声	纹理	脐部	触感	密度	含糖率	好瓜
测 1	青绿	蜷缩	浊响	清晰	凹陷	硬滑	0.697	0.460	?

首先估计类先验概率 $P(c)$, 显然有

$$P(\text{好瓜} = \text{是}) = \frac{8}{17} \approx 0.471 \,,$$

$$P(\text{好瓜} = \text{否}) = \frac{9}{17} \approx 0.529 \,.$$

于是, 有

$$\begin{aligned} & P(\text{好瓜} = \text{是}) \times P_{\text{青绿}|\text{是}} \times P_{\text{蜷缩}|\text{是}} \times P_{\text{浊响}|\text{是}} \times P_{\text{清晰}|\text{是}} \times P_{\text{凹陷}|\text{是}} \\ & \quad \times P_{\text{硬滑}|\text{是}} \times p_{\text{密度: 0.697}|\text{是}} \times p_{\text{含糖: 0.460}|\text{是}} \approx 0.038 \,, \\ & P(\text{好瓜} = \text{否}) \times P_{\text{青绿}|\text{否}} \times P_{\text{蜷缩}|\text{否}} \times P_{\text{浊响}|\text{否}} \times P_{\text{清晰}|\text{否}} \times P_{\text{凹陷}|\text{否}} \\ & \quad \times P_{\text{硬滑}|\text{否}} \times p_{\text{密度: 0.697}|\text{否}} \times p_{\text{含糖: 0.460}|\text{否}} \approx 6.80 \times 10^{-5} \,. \end{aligned}$$

由于 $0.038 > 6.80 \times 10^{-5}$, 因此, 朴素贝叶斯分类器将测试样本 “测 1” 判别为 “好瓜” .

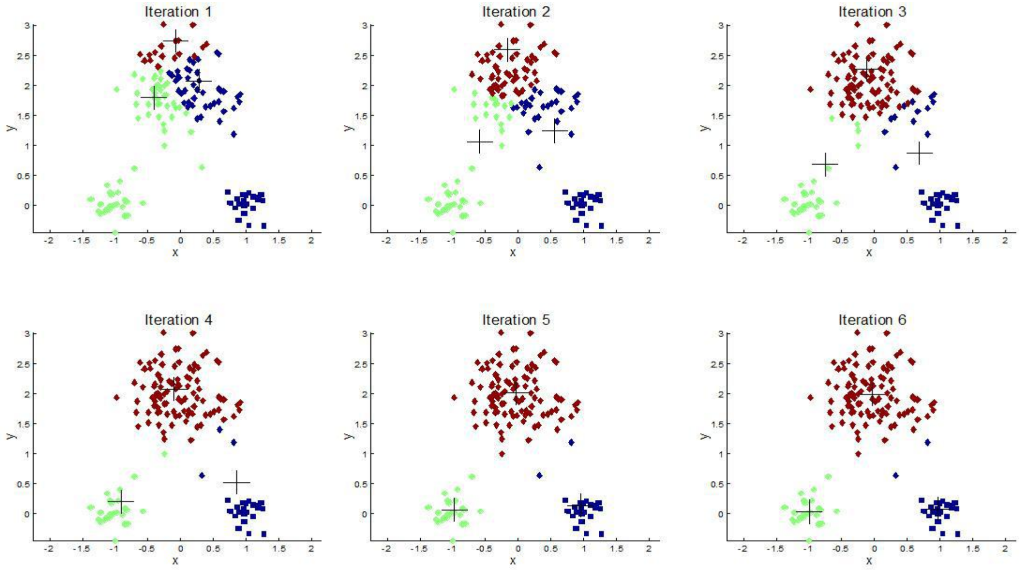
Unsurprisingly, these algorithms are explicity based on Bayes’ theorem. The most popular is Naive Bayes, which is often used in text analysis. Most spam filters, for example, use Bayesian algorithms. They use user-inputted data labeled by class to compare new data against and categorize appropriately.

Unsupervised learning: Clustering Algorithms

Clustering algorithms focus on finding commonalities between elements and grouping them accordingly. A common clustering algorithm is K-Means Clustering.

K-Means Clustering

In K-Means, an analyst selects the number of clusters (denoted by the variable K) and the algorithm groups the elements by physical distance into appropriate clusters.



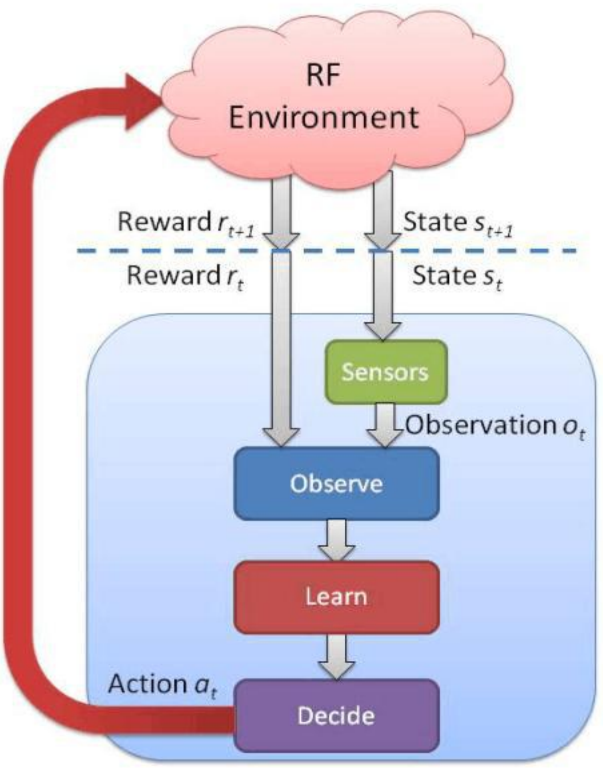
Step 1: Initialization. Select random k centroids

Step 2: Cluster Assignment.

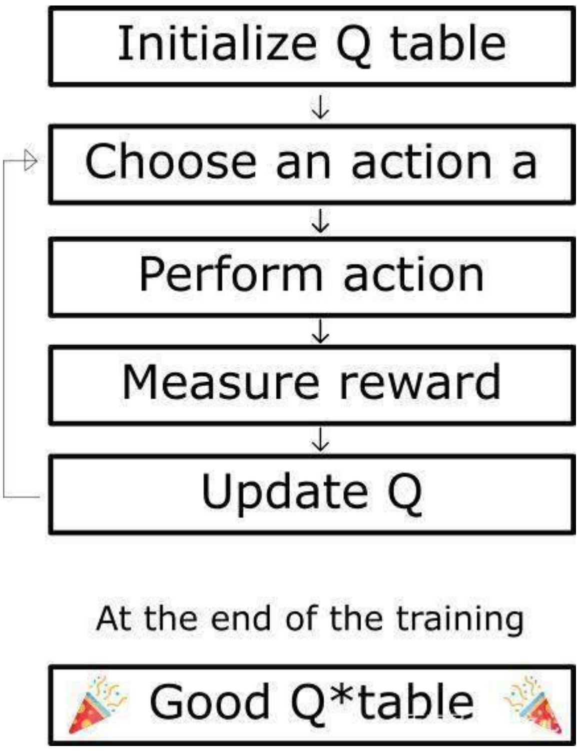
Step 3: Move the centroids.

Loop these steps until centroids not change.

Reinforcement learning:

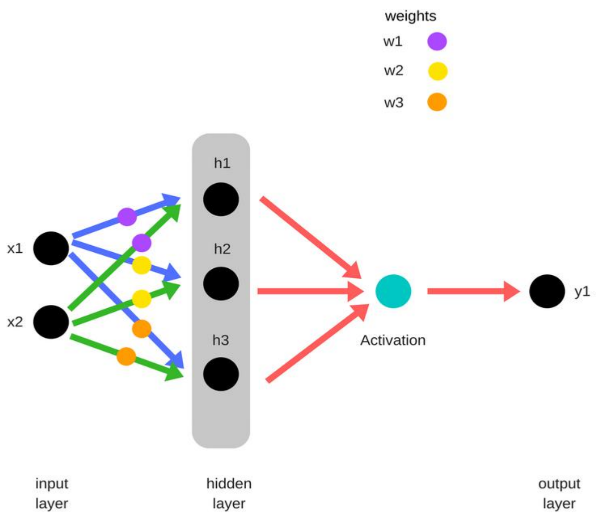


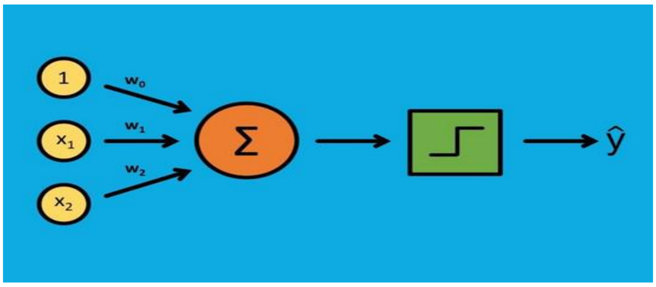
Q-Learning:

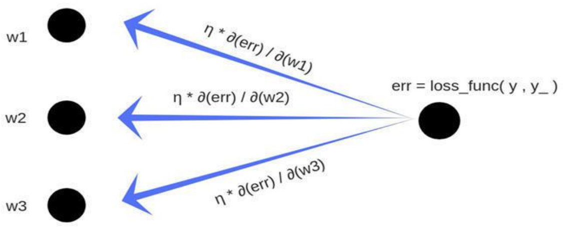


Supervised learning:(Networks)

Neural Network Algorithms

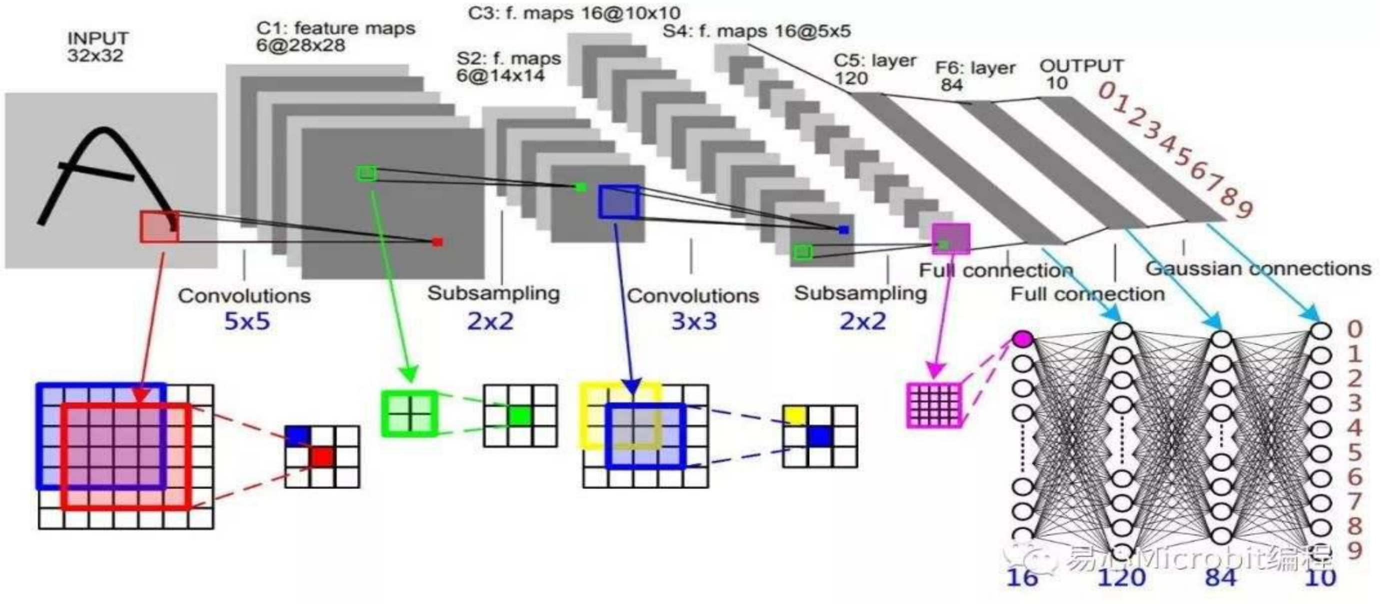






Deep Learning (CNN)

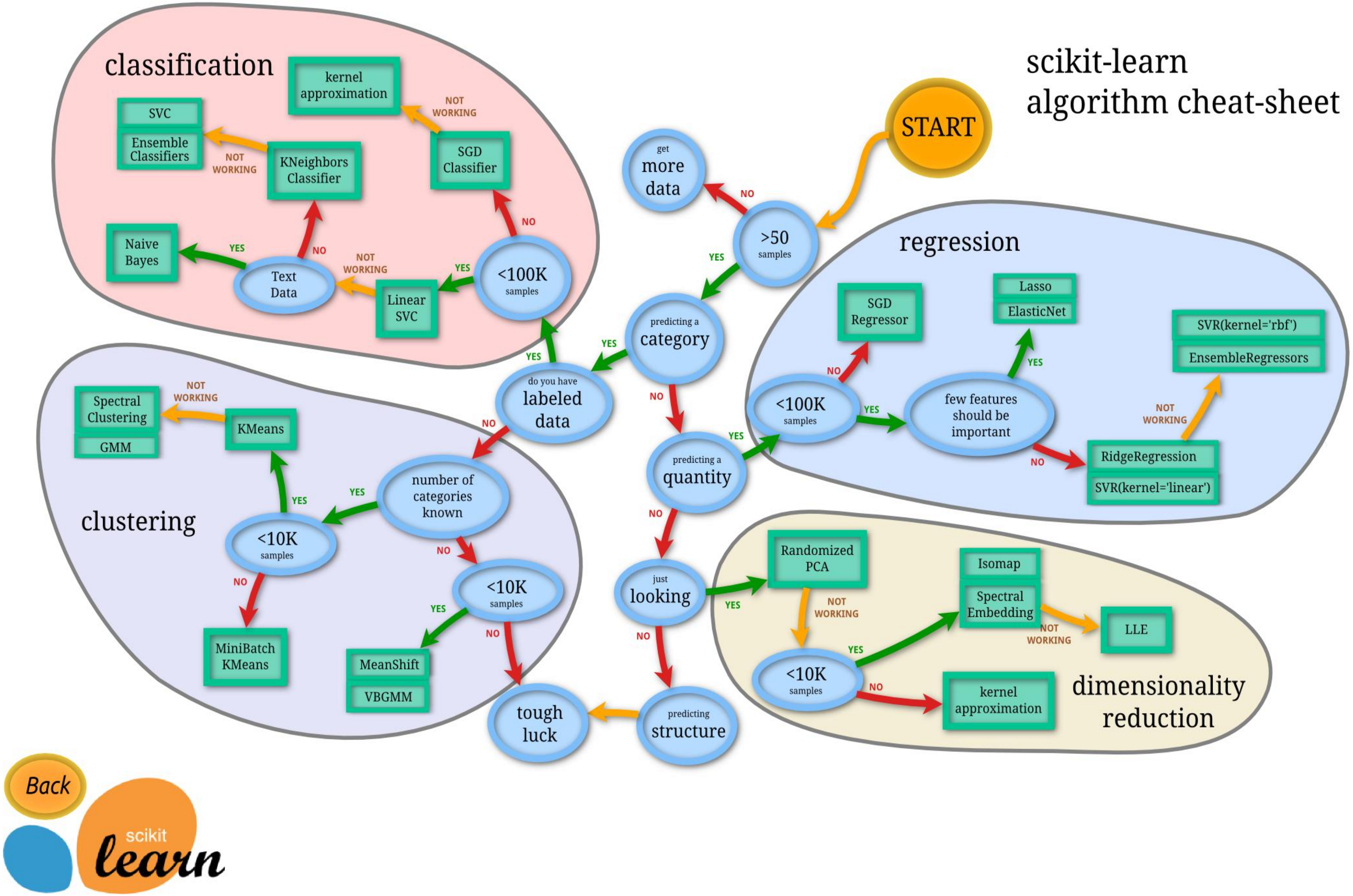
Artifical neural network algorithms are based on the structure of biological neural networks. Deep learning takes the neural network model and updates it. They are large, extremely complex neural networks that use small amounts of labeled data and much larger amounts of unlabeled data. Neural networks and deep learning have many inputs that go through several hidden layers before resulting in one or more outputs. These connections form a specific cycle that mimics the way the human brain processes information and makes logical connections. In addition, the hidden layers often get smaller and more nuanced as the algorithm runs.



Other Algorithms

The diagram below is the best one I’ve found to show the major machine learning algorithms:

scikit-learn algorithm cheat-sheet



The numbers have no way of speaking for themselves. We speak for them. We imbue them with meaning….Before we demand more of our data, we need to demand more of ourselves.—Nate Silver

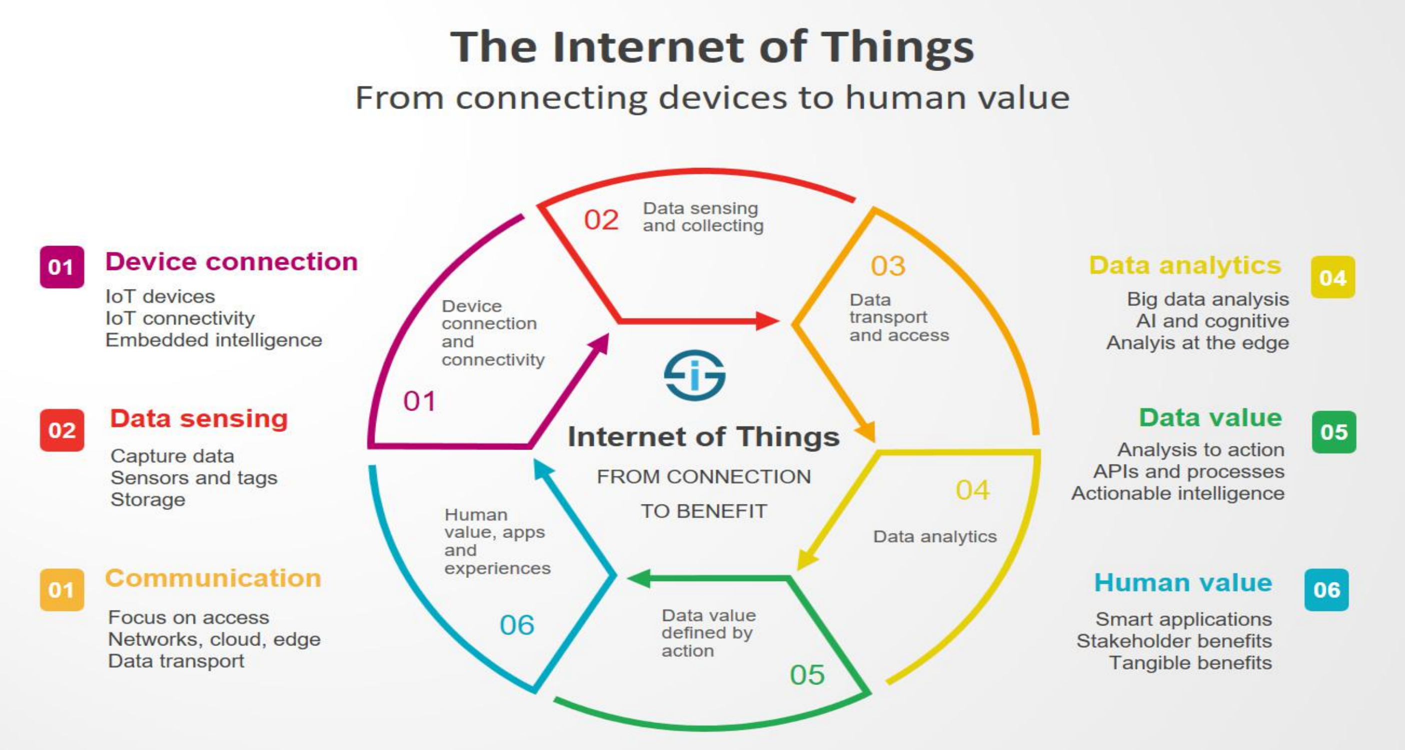
Once you've chosen and run your algorithm, there is one extremely important step left: visualizing and communicating the results. Although this can seem silly and superficial compared to the nitty gritty of algorithmic programming, good visualization is a key separator of good data scientists and great scientists. What good are amazing insights if no one can understand them?

Why is machine learning important?

Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform in the next several years.— Andrew Ng

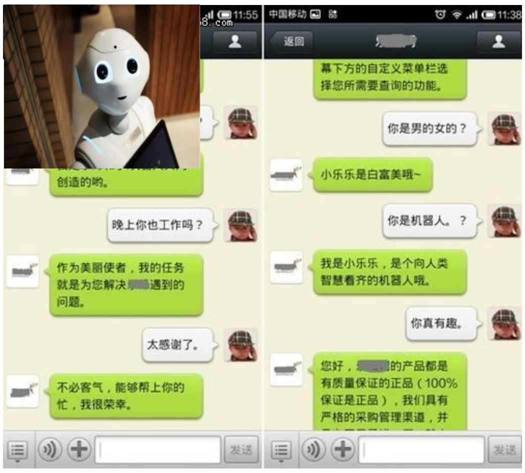
It should now be clear that machine learning has huge potential to change and improve the world. Through research teams like Google Brain and the Stanford Machine Learning Group, we are making huge strides towards true artificial intelligence. But what, exactly, are the next major areas where machine learning can make an impact?

Internet of Things 物联网



The term internet of things, or IOT, refers to the network-connected physical devices in your home and office. A popular IOT device is the smart lightbulb, sales of which skyrocketed over the last few years. With advances in machine learning, IOT devices are smarter and more sophisticated than ever. Machine learning has two main applications pertaining to IOT: making your devices better and gathering your data. Making the devices better is very straightforward: using machine learning to personalize your environment, i.e. using facial recognition software to sense who is the room and adjust the heat and AC accordingly. Gathering data is even more straightforward; by keeping network-connected devices (like an Amazon echo) powered on and listening in your home, companies like Amazon gather key demographic information to pass onto advertisers, like what television shows you watch, what time you wake up and go to sleep, and how many people live in your home.

Chatbots



11:55

创造的哟。

晚上你也工作吗？

作为美丽使者，我的任务就是为您解决[redacted]遇到的问题。

太感谢了。

不必客气，能够帮上你的忙，我很荣幸。

中国移动 11:38

返回 [redacted]

幕下方的自定义菜单栏选择您所需要查询的功能。

你是男的女的？

小乐乐是白富美哦~

你是机器人。？

我是小乐乐，是个向人类智慧看齐的机器人哦。

你真有趣。

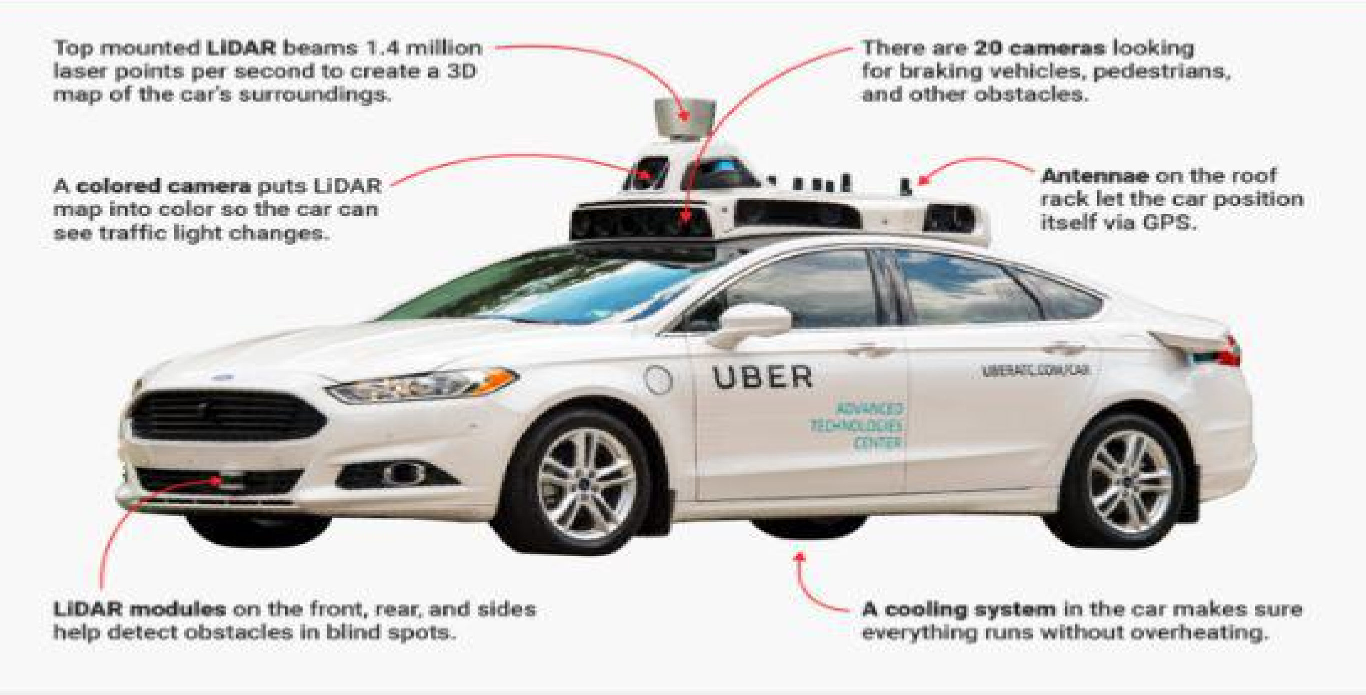
您好，[redacted]的产品都是有质量保证的正品（100%保证是正品），我们具有严格的采购管理渠道，并

We have seen a proliferation of chatbots in the last few years and sophisticated language processing algorithms are improving them every day. Chatbots are used by companies, on both their own mobile apps and third-party apps like Slack, to provide virtual customer service that is both faster and more efficient than a traditional (human) representative. To order a shirt from the clothing company H&M for example, you can now tell their chat bot in natural language what you'd like and what size you need and order the item without ever leaving the chat screen.

Autonomous (self driving) Cars

My personal favorite of the next big machine learning projects is one of the furthest from widespread production. Nevertheless, self driving cars are currently in development at several huge companies like Chevrolet (through their Cruise brand), Uber, and Tesla. These cars use technologies made possible through machine learning for navigation, maintenance, and safety procedures. One example is the traffic sign sensors, which use supervised learning algorithms to identify and parse traffic signs and compare them to a labeled data set of standard signs. Thus, the car sees a stop sign and recognizes that it does, in fact, signify stop, rather than yield or one way or pedestrian crossing.

HOW UBER'S FIRST SELF-DRIVING CAR WORKS



Top mounted **LIDAR** beams 1.4 million laser points per second to create a 3D map of the car's surroundings.

There are **20 cameras** looking for braking vehicles, pedestrians, and other obstacles.

A **colored camera** puts LIDAR map into color so the car can see traffic light changes.

Antennae on the roof rack let the car position itself via GPS.

LIDAR modules on the front, rear, and sides help detect obstacles in blind spots.

A cooling system in the car makes sure everything runs without overheating.

SOURCE: Uber

BUSINESS INSIDER

So that concludes our extremely brief journey into the world of machine learning. I encourage you to read all the articles I've linked below and, if you have a fundamental understanding of Python, play around with your own simple machine learning projects. Happy coding!

By Lizzie Turner