Introduction To Machine Learning

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Machine Learning is an idea to learn from examples and experience, without being explicitly programmed. Instead of writing code, you feed data to the generic algorithm, and it builds logic based on the data given.

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For example, one kind of algorithm is a classification algorithm. It can put data into different groups. The classification algorithm used to detect handwritten alphabets could also be used to classify emails into spam and not-spam.

"A computer program is said to learn from experience E with some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E." -Tom M. Mitchell

Consider playing checkers.

E = the experience of playing many games of checkers

T = the task of playing checkers.

P = the probability that the program will win the next game.

Examples of Machine Learning

There are many examples of machine learning. Here are a few examples of classification problems where the goal is to categorize objects into a fixed set of categories.

Face detection: Identify faces in images (or indicate if a face is present).

Email filtering: Classify emails into spam and not-spam.

Medical diagnosis: Diagnose a patient as a sufferer or non-sufferer of some disease.

Weather prediction: Predict, for instance, whether or not it will rain tomorrow.

Need of Machine Learning

Machine Learning is a field which is raised out of Artificial Intelligence(AI). Applying AI, we wanted to build better and intelligent machines. But except for few mere tasks such as finding the shortest path between point A and B, we were unable to program more complex and constantly evolving challenges. There was a realisation that the only way to be able to achieve this task was to let machine learn from itself. This sounds similar to a child learning from its self. So machine learning was developed as a new capability for computers. And now machine learning is present in so many segments of technology, that we don't even realise it while using it.

Finding patterns in data on planet earth is possible only for human brains. The data being very massive, the time taken to compute is increased, and this is where Machine Learning comes into action, to help people with large data in minimum time.

If big data and cloud computing are gaining importance for their

contributions, machine learning as technology helps analyse those big chunks of data, easing the task of data scientists in an automated process and gaining equal importance and recognition.

The techniques we use for data mining have been around for many years, but they were not effective as they did not have the competitive power to run the algorithms. If you run deep learning with access to better data, the output we get will lead to dramatic breakthroughs which is machine learning.

Kinds of Machine Learning

There are three kinds of Machine Learning Algorithms.

- a. Supervised Learning
- b. Unsupervised Learning
- c. Reinforcement Learning

Supervised Learning

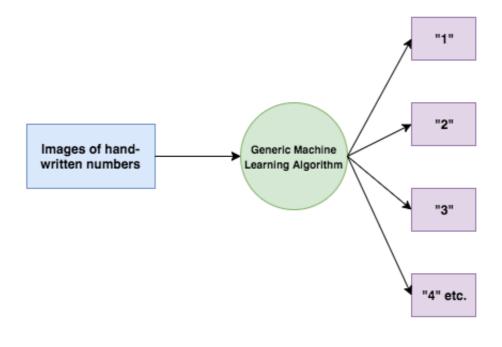
A majority of practical machine learning uses supervised learning.

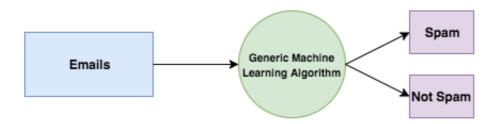
In supervised learning, the system tries to learn from the previous examples that are given. (On the other hand, in unsupervised learning, the system attempts to find the patterns directly from the example given.)

Speaking mathematically, supervised learning is where you have both input variables (x) and output variables(Y) and can use an algorithm to derive the mapping function from the input to the output.

The mapping function is expressed as Y = f(X).

Example:





Supervised learning problems can be further divided into two parts, namely classification, and regression.

Classification: A classification problem is when the output variable is a category or a group, such as "black" or "white" or "spam" and "no spam".

Regression: A regression problem is when the output variable is a real value, such as "Rupees" or "height."

Unsupervised Learning

In unsupervised learning, the algorithms are left to themselves to discover interesting structures in the data.

Mathematically, unsupervised learning is when you only have input data (X) and no corresponding output variables.

This is called unsupervised learning because unlike supervised learning above, there are no given correct answers and the machine itself finds the answers.

Unsupervised learning problems can be further divided into association and clustering problems.

Association: An association rule learning problem is where you want to discover rules that describe large portions of your data, such as "people that buy X also tend to buy Y".

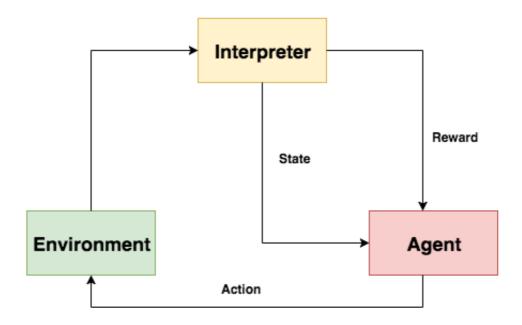
Clustering: A clustering problem is where you want to discover the inherent groupings in the data, such as grouping customers by purchasing behaviour.

Reinforcement Learning

A computer program will interact with a dynamic environment in which it must perform a particular goal (such as playing a game with an opponent or driving a car). The program is provided feedback in terms of rewards and punishments as it navigates its problem space.

Using this algorithm, the machine is trained to make specific decisions. It works this way: the machine is exposed to an environment where it continuously trains itself using trial and error method.

Example:



The Math of Intelligence

Machine Learning theory is a field that meets statistical, probabilistic, computer science and algorithmic aspects arising from learning iteratively from data which can be used to build intelligent applications.

Why Worry About The Maths?

There are various reasons why the mathematics of Machine Learning is necessary, and I will highlight some of them below:

Selecting the appropriate algorithm for the problem includes considerations of accuracy, training time, model complexity, the number of parameters and number of characteristics.

Identifying underfitting and overfitting by following the Bias-Variance tradeoff.

Choosing parameter settings and validation strategies.

Estimating the right determination period and uncertainty.

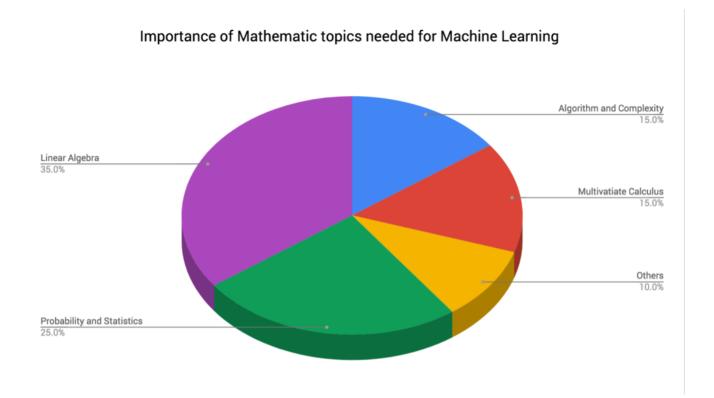
What Level of Maths Do We Need?

The foremost question when trying to understand a field such as Machine Learning is the amount of maths necessary and the complexity of maths required to understand these systems.

The answer to this question is multidimensional and depends on the level and interest of the individual.

Here is the minimum level of mathematics that is needed for Machine Learning Engineers / Data Scientists.

- 1. **Linear Algebra** (Matrix Operations, Projections, Factorisation, Symmetric Matrices, Orthogonalisation)
- 2. **Probability Theory and Statistics** (Probability Rules & Axioms, Bayes' Theorem, Random Variables, Variance and Expectation, Conditional and Joint Distributions, Standard Distributions.)
- 3. Calculus (Differential and Integral Calculus, Partial Derivatives)
- 4. **Algorithms and Complex Optimisations** (Binary Trees, Hashing, Heap, Stack)



Closing Notes

Thanks for reading! Hopefully, you're now able to understand what Machine Learning is and its applications.

Stay tuned for more articles on Machine Learning.

Supervised Learning with Python.

Thanks to Richa Kulkarni for few contribution to the story.