1

17 November 2025 12:37

- Introductory video on ML,
- We'll get familiar with terminology that will use throughout this journey

What is the idea behind Machine Learning?

Answer:
The idea behind Machine Learning is to **enable machines to learn from experience and data**, similar to how humans learn.
Instead of programming every rule, machines automatically **identify patterns and improve their performance over time**.

What is the motivation behind Machine Learning?

Answer:
The motivation behind Machine Learning comes from **observing how humans, especially children, learn**.
Children learn by **seeing and repeating experiences without knowing rules**, and this inspired humans to create machines that can **learn and think in a similar way**.

Humans were amazed by how human's learn, and by this can we figure out some way so machines can learn?

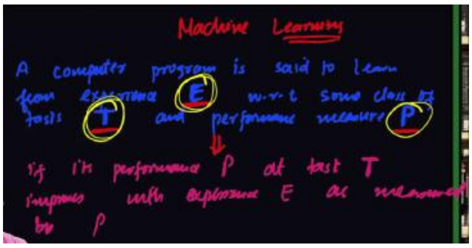
We had this programmable comuputer, where we figured out appropriate representation of data, and had step wise procedure. Now the question was can it evolve on its own? That's autonomous and adaptive, people called it AI

Some tasks are easy for humans because they are **intuitive and learned naturally**, without formal rules.
For example, **image and voice recognition** are effortless for humans but very difficult for machines because **no clear step-by-step formalism exists**, unlike mathematical calculations.

Machines excel at formal, rule-based tasks, while humans excel at intuitive learning—Machine Learning aims to bridge this gap

Traditional/classical programming:
You write set of clear instructions (programs), and provide input data, and get expected output!

Machine learning:
your provide set of inputs and output, and expect machine to come up with a program (set of rules).
- Tasks which are not formalized, There are no exact rules to understand images , Humans might see many pics of cats and then come up with some abstarct representation of cats in our brain.



T : eating food
P : spilling grains
E : experience in eating food

Tasks: classification, regression, output vector, synthesis of samples *gen ai) imputation of missing values,
Performance: error rate, accuracy, recall, precision, AUC, ROC
Experience: Experience is **what the system learns from** data or interactions. can be supervised, unsupervised or Rienforcement learning algorithm

Two Early Attempts in Artificial Intelligence :

1. Rule-Based / Knowledge-Based AI (Symbolic AI)	**2. Statistical / Data-Driven AI (Machine Learning)**
Idea: • Give machines **explicit knowledge** (knowledge base) • Add **formal rules and logic** • Let the machine **infer conclusions** **How it worked:** • Humans manually encoded facts and rules • Systems used **logical inference** to reason **Examples:** • **Cyc project** • Early symbolic AI systems **Limitations:** • Real-world knowledge is **too complex to fully formalize** • Systems failed on **common-sense and intuitive reasoning** • Could not handle ambiguity well (e.g., "Fred shaving" example) **Conclusion:** ✓ Worked in limited, well-defined domains ✗ Failed to scale to real-world intelligence	**Idea:** • Let machines **learn patterns from data** instead of hardcoded rules • Use **statistics and probability** **How it worked:** • Represent real-world problems using **features** • Feed features into **learning algorithms** • Algorithms **predict outcomes** based on data **Examples:** • **Logistic Regression (whether pregnant lady needs normal or surgery, dooctor just does not look and decide, he has to tend to serveal paramters, like age, bloodpressure etc)** • **Naive Bayes** • Spam detection, medical decision support **Key Insight:** • **Data representation and feature selection** are crucial • Better representation → better learning (Arabic numbers vs Roman numerals example) **Conclusion:** ✓ Handles uncertainty and real-world data ✓ Scales better than rule-based systems ✗ Feature engineering is hard and requires domain expertise (can be done by hand but takes a lot of time

coming of data representation is very hard, but important. We exactly don't know how data is rperesented in each of our bran, it cat might differ indiviual to indiviual. Usually in statistical learning, coming up with data preresntation/features was very important and needs domain expertise

This led to development if Representation learning and deep learning.

Now we expect machines to come up with represenation and features themselves, which we might not understand, example autoencoders:

(Autoencoders learn abstract, useful patterns, not human-defined features.,maybe edges, corners, texture etc,
- *Encoder compresses input into a latent representation (often lower-dimensional)*
- *Compression forces capture of important patterns/features*
- *Decoder reconstructs the input from this representation*
- *Model is trained by minimizing reconstruction error*
- *Features are learned automatically, not manually designed)*

Separate Factors of Variation

Factors of variation are the **independent sources of change** in data that create diversity.
The goal of representation learning is to **separate these factors** so that each feature captures **meaningful variation**, not redundant information.
Good features are those that **add high variability and useful information**, unlike correlated features (e.g., height and weight).

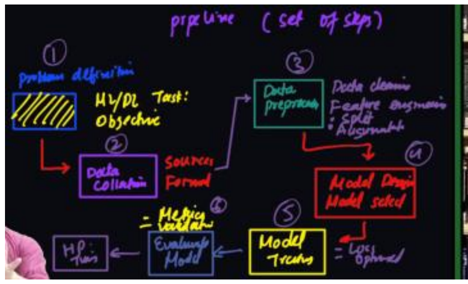
Representation Learning and Its Limitation

Representation learning aims to **automatically discover features** from data instead of manually designing them.
However, it struggles in real-world scenarios where the **same object appears different** due to factors like lighting, shadows, color, or background.
For example, the same car looks very different in daylight versus nighttime, leading to **unstable representations**.

Deep Learning Was Introduced

Deep learning is called *deep* because it learns through **multiple layers of representations**.
Each layer processes the output of the previous layer, creating **increasingly abstract representations** of the data.
- Early layers learn **low-level features** (edges, corners)
- Middle layers learn **mid-level features** (contours, parts)
- Deeper layers learn **high-level concepts** (complete objects)
  - *Networks may not learn exactly these features*
  - *But something hierarchical is happening*

We **do not have a complete theoretical understanding** of *why* deep neural networks work so well, especially in complex real-world tasks.
- We now how to train (back prop) and use them
- But we do not fully understand:
  > What exact representations each layer learns, but it learns layer-wise, hierarchical representations



Data drift is when the real-world data distribution changes over time, causing model performance degradation, and it usually requires retraining or updating the model.