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A Structured Review of Machine Learning

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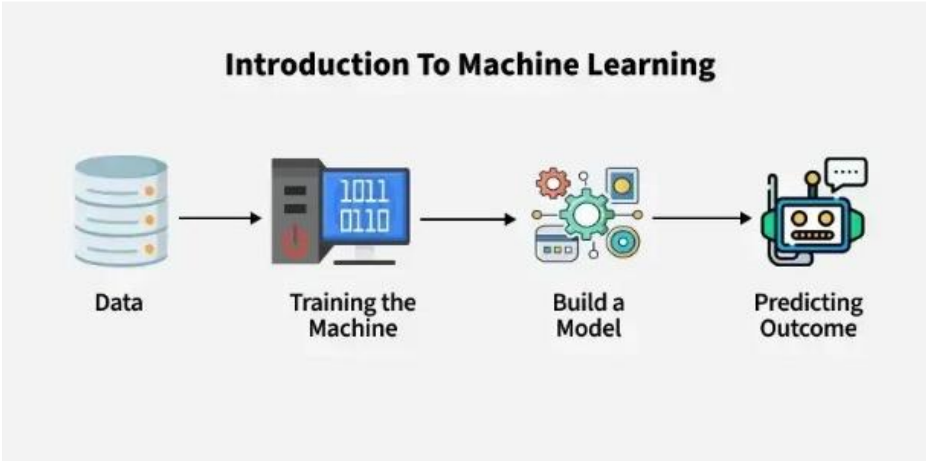
Abstract

Machine learning (ML) is a game-changer because it lets computers learn on their own from experience, instead of us telling them every single rule. Basically, ML tries to figure out a smart way to turn raw information (like a picture) into the right answer (like "this is a cat"). A big part of this is finding the most important bits of information, called "features" (like a cat's pointy ears or whiskers). What's really cool is that a newer part of ML, called representation learning, helps computers automatically discover these important features, so we don't have to painstakingly find them ourselves.
Keywords Machine Learning, Supervised Learning, Unsupervised Learning and Reinforcement Learning

I. INTRODUCTION

Machine Learning methodologies are widely adopted across various disciplines, particularly excelling in complex domains like bioinformatics, where the inherent difficulties and high costs of biological analyses necessitate sophisticated computational solutions for extracting insights from vast datasets. Within machine learning, three fundamental paradigms guide the learning process:



Supervised Learning: This approach involves training algorithms on labeled data, where each input example is paired with its correct corresponding output. The model learns to predict the output for new, unseen inputs by recognizing patterns from these historical input-output associations (e.g., predicting house prices based on labeled historical sales data, or analyze images based on fruits as "apple" or "banana" from labeled examples).

Unsupervised Learning: In contrast, unsupervised learning deals with unlabeled data, meaning the algorithms are given inputs without any predefined correct outputs. The goal here is for the model to discover hidden structures, patterns, or groupings within the data on its own (e.g., segmenting customer demographics into distinct clusters without prior knowledge of those groups, or finding anomalies in network traffic).

Reinforcement Learning: IT is a powerful way to teach smart computer programs, called agents, how to do tricky things. Instead of giving them a lot of examples to learn from (like in other computer learning methods), we let them figure things out on their own, by trying different actions and getting feedback.

Here's how it works:

The agent looks at its state (what's happening right now).

It picks an action (what it wants to do).

Then, it gets rewards (good or bad feedback) that tell it if it's getting closer to its goal.

Machine Learning: Teaching Computers to Learn

Let us think we want to teach a computer to recognize a cat in a picture. The old way would be to write the exact rules: "If it has pointed ears, whiskers, and a tail, it's a cat." But what about different cat breeds? Or a cat hiding behind something? Writing all those rules is impossible!

Machine Learning (ML) is a smarter way. It's like **teaching a computer to learn from examples, just like humans do.** Instead of giving it strict rules, you give it tons of pictures of cats (and non-cats!) and tell it, "This is a cat, this is not."

The main idea is that once these special computer programs (called algorithms) "learn" from enough data, they can then **automatically make predictions or decisions** about new, unseen information. They get better with "experience."

This field is exploding because we have a lot more data now and powerful computers to process it. You see machine learning everywhere:

- **Recommendations:** How Google suggests autofill or how shopping websites suggest the products.
- **Smart Assistants:** How your phone understands your voice commands.
- **Healthcare:** Helping doctors analyze medical images or predict how a patient might respond to treatment (like in cancer radiotherapy, as you mentioned).
- **Self-driving cars:** drive cars without drivers.

Basically, machine learning is about building computers that can **improve themselves** by finding hidden patterns and insights in vast amounts of data, helping us make smarter, more automated decisions in almost every part of our lives.

Why Do we Need Machine Learning?

"Traditional programming" is like giving a computer a recipe for everything it needs to do. That's fine for simple, unchanging tasks. But for really tough stuff – like a computer looking at a picture and knowing what's in it, or understanding what you're saying, or sifting through mountains of information – it's practically impossible to write down every single instruction.

That's where Machine Learning (ML) comes in. Instead of us programming every tiny step, ML systems learn by themselves from examples. They find patterns and then make smart guesses or decisions without needing us to tell them every rule. This makes ML incredibly powerful and necessary for a few big reasons:

Why Machine Learning is a Big Deal

Solving Tricky Problems: ML is great at handling problems that are messy, confusing, or have subtle details that are hard for humans to explain to a computer. By looking at huge amounts of data, ML can spot complex connections we could never program by hand.

Helping doctors find diseases in medical scans, translating languages accurately, or letting computers "see" and understand the world.

Handling Tons of Data: We're constantly creating massive amounts of digital information. Older computer programs just can't deal with all this data quickly. ML programs are built to process these enormous datasets and find useful insights, often in real-time.

Doing Boring Tasks Automatically: Many jobs are repetitive, take a lot of time, and are easy for people to mess up. ML can do these tasks automatically and accurately, freeing up humans for more creative work.

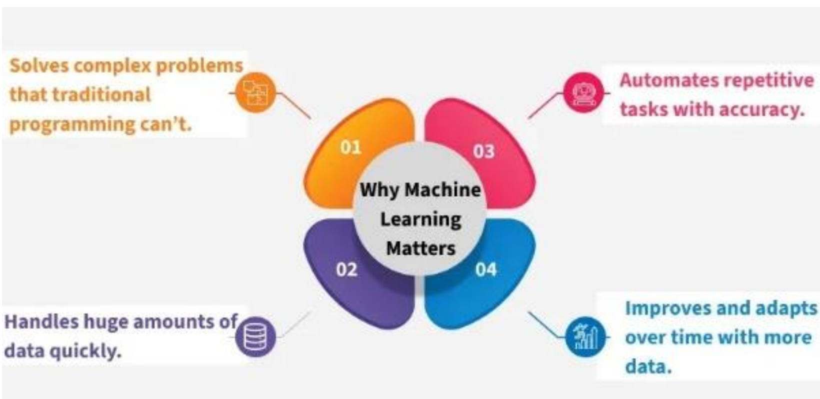
Sorting spam emails out of your inbox, or chatbots answering common customer questions.

Making Things Personal for You: ML helps systems understand what you like and how you behave. This means you get a highly customized experience, tailored just for you.

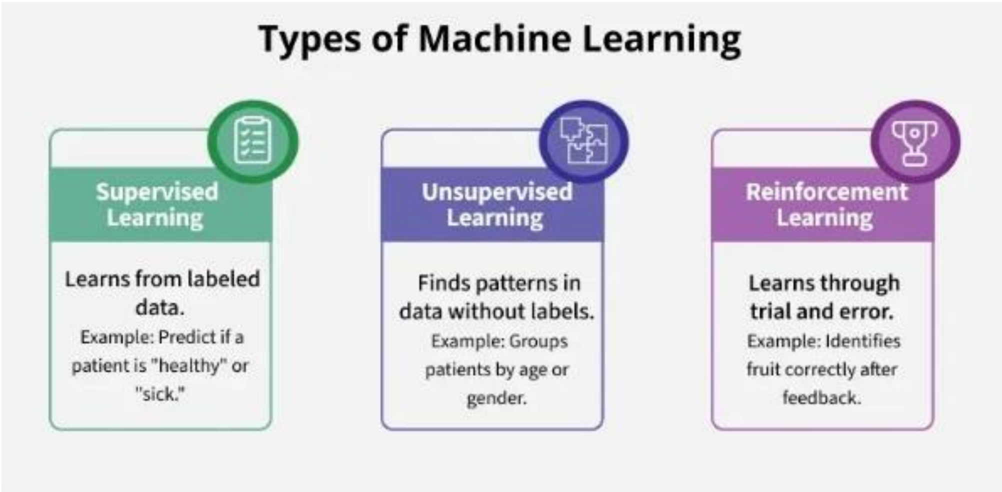
Netflix suggesting shows based on your viewing history, or online shops recommending products you're likely to buy.

Always Getting Better: One of the coolest things about ML is that these systems can learn and improve on their own. The more they work and interact with data, the smarter and more accurate they become. They keep changing and getting better to fit new situations.

Think: Voice assistants like Alexa getting better at understanding your voice, or self-driving cars constantly improving their driving skills.



Types of Machine Learning



Supervised Learning

Supervised learning process are based on two process training and testing.

Training: You show the computer many pictures of fruit, and for each picture, you tell it what fruit it is (e.g., "this is an apple," "this is a banana"). The computer "learns" from these examples, figuring out what makes an apple an apple and a banana a banana based on their features (color, shape, etc.). This is like building a "fruit recognition expert" in the computer's mind.

Testing: Once the computer has learned, you show it new pictures of fruit that it hasn't seen before. The computer then tries to guess what fruit they are. If it guesses correctly, it means its "fruit recognition expert" is working well.

Supervised learning is the most common way to teach computers, especially for sorting things into categories. It's called "supervised" because you, the "supervisor," provide the computer with the correct answers (the "labels") during training. You give the computer a dataset with information (like a fruit's measurements) and the correct answer (what fruit it is). The computer learns by comparing its own guesses to your correct answers and adjusting its "expert" knowledge when it makes a mistake.

This method works best when you have all the necessary information for the computer to learn from. If some information is missing, it's hard for the computer to make good predictions.

It's widely used in areas like training neural networks (which are like simplified brains for computers) and decision trees (which are like flowcharts for making decisions). It's also great for predicting future events based on past information, like predicting the species of an iris flower based on its petal measurements.

Two Main Types of Supervised Learning:

Think about the type of answer the computer is trying to predict:

Classification: If the answer is a category (like "apple" or "banana," or "yes" or "no"), it's called classification. The computer puts things into distinct groups.

Regression: If the answer is a number (like the price of a house or the temperature), it's called regression. The computer tries to predict a continuous value.

So, during training, the computer builds a "predictive model" from the examples you give it. Then, during testing, this model tries to guess the most likely category or value for new, unseen information.

Supervised learning Algorithms are

- Decision trees
- Linear regression
- Naïve Bayes
- Logistic Regression

Unsupervised Learning

Imagine you have a big pile of different toys, but no one tells you what kind of toys they are or how to sort them. Unsupervised learning is like a smart robot that looks at all the toys and figures out on its own how to group them. No Teacher Needed: You just give the computer raw information, like the pile of toys, without telling it what anything is.

Finds Hidden Connections: The computer automatically searches for hidden similarities and patterns. It might notice that all the blocks are square, and all the dolls have hair.

Sorts on Its Own: Based on these patterns, it sorts the data into groups. Like putting all the blocks in one pile and all the dolls in another, even though you didn't tell it to.

Quick and Easy: Since you don't have to label everything beforehand (like putting "block" tags on all the blocks), it's much faster to get started than other types of learning.

So, unsupervised learning is essentially a computer teaching itself to understand and organize data by finding its own hidden connections, without any help or examples from us.

It mainly uses two techniques:

1. Clustering

Think of clustering like sorting a mixed bag of candies into different bowls based on how similar they are.

The computer finds similar data set together. Imagine you have a bunch of dots scattered on a paper. Clustering algorithms used to find similar groupings of these dots. They move dots closer to the center of their own group and further away from other groups, making the groups clearer.

2. Association Rule Learning

This is like discovering that "if someone buys chips, they often also buy soda." It finds connections between different items in a dataset. It looks for "rules" that show how often things appear together. For example, in a supermarket, it might find that customers who buy bread frequently also buy milk.

Apriori Algorithm: A common way to find these "if-then" relationships in shopping carts.

Eclat Algorithm & FP-Growth Algorithm: Other efficient methods for discovering these associations.

Reinforcement Learning

Reinforcement learning is the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment. The work described here has a resemblance to work in psychology, but differs considerably in the details and in the use of the word ``reinforcement."

The reward function is simply the direct feedback the agent gets from its environment. Think of it as a scoreboard that tells the agent how well it's doing. These rewards are just numbers (positive or negative) linked to specific situations or actions the agent takes. For example, in a game like backgammon, if the agent successfully gets all its pieces off the board, it might receive a big reward of 1. For every other move in the game, it might get a reward of 0.

The agent's only goal is to collect as many of these rewards as possible over the long run – like trying to win as many backgammon games as possible. The reward function essentially tells the agent what's good and bad in its environment. Importantly, the agent can't change how these rewards are given; it just has to learn to get them. In simple terms, it defines the ultimate objective for the agent.

What are States and Actions?

States and actions are very broad concepts.

An action is simply any decision the agent needs to learn how to make. It's what the agent does.

A state is all the information the agent considers when making that decision. It's what the agent sees or knows about its current situation.

This "state" can be very detailed. It might even include memories of what happened in the past in the environment. So, if the agent remembers how it got to its current spot, that memory becomes part of its "state" when it decides what to do next. This means that unlike some very basic AI learning methods, reinforcement learning isn't always about just reacting to what's immediately in front of it; it can use complex knowledge. It's flexible about what "knowledge" means and how that knowledge guides actions.

The Agent's Policy: Its Strategy

The agent's policy is its game plan – it's a rulebook that tells the agent what action to take in any given situation (state).Sometimes, this policy can be as simple as a "lookup table." Imagine a list: "If in State A, take Action X; if in State B, take Action Y." Psychologists might call this a set of "stimulus-response associations" – basically, what to do when you see something.

Other times, the policy might be more complex, something the agent "computes." This could involve thinking ahead, like searching through possible future scenarios to find the best sequence of actions to get the most rewards.

The Value Function: Estimating Future Goodness

The value function is the agent's best guess of how much long-term reward it can expect to get from a particular state (or after taking a certain action in a state), assuming it continues to follow its current strategy.

The agent constantly updates this value function based on what actually happens. The most important feedback for updating these values comes from the estimated "goodness" of the next few states the agent lands in after taking an action.

In tasks that have clear beginnings and ends (like a single game of chess), the value of a state tells the agent its current estimated chance of reaching a "winning" (reward) state before the game finishes.

In ongoing tasks (like a robot continuously navigating a factory), the value of a state is the estimated amount of future reward the agent expects to get, but with a twist: rewards that are far off in the future count less than rewards that are received sooner. This is called "time discounting," and it means that immediate rewards are generally preferred over delayed ones.

II. CONCLUSION

Machine Learning lets computers learn by themselves from examples. This helps them solve tough, changing problems. They can find secret patterns in huge amounts of information, do boring jobs automatically, make things feel personal to you, and get better and better over time. That's why Machine Learning is vital for creating smart solutions that old computer programs just can't handle.

Learning with a Teacher (Supervised Learning): This is like when you're taught in school. Someone shows the computer lots of examples (like pictures of apples and bananas) and tells it exactly what each one is. The computer then learns to recognize them on its own. It's great for tasks like sorting things into categories or predicting numbers, but it needs someone to give it all the answers first.

Learning on Its Own (Unsupervised Learning): Imagine you have a pile of toys, and no one tells you how to sort them. This is how unsupervised learning works. The computer looks at raw information and finds hidden patterns or groups things together by itself. It's super helpful when you don't have answers and just want to understand the way things are naturally organized.

Learning by Doing (Reinforcement Learning): This is like learning to ride a bike. The computer, often called an agent, tries something out, sees what happens, and gets feedback (like a "good job!" or "oops!"). It keeps trying, learning from its mistakes and successes, until it figures out the best way to achieve its goal. This is how AI learns to play complex games or control robots, where there's no pre-set rulebook for every situation.

These three ways of learning are the big ideas behind a lot of today's smart computer systems. They help computers understand information, do tasks automatically, and even adapt to new situations. Which method you use just depends on the problem you're trying to solve and what kind of information you have to start with.

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