MACHINE LEARNING

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Introduction

Any component of an agent program can be improved by machine learning. The improvements and the techniques used to make them depend on these factors:

- Which component is to be improved.
- What prior knowledge the agent has, which influences the model it builds.
- What data and feedback on that data is available.

The components of these agents include:

- A direct mapping from conditions on the current state to actions.
- A means to infer relevant properties of the world from the percept sequence.
- Information about the way the world evolves and about the results of possible
- actions the agent can take.
- Utility information indicating the desirability of world states.
- Action-value information indicating the desirability of actions.
- Goals that describe the most desirable states.
- A problem generator, critic, and learning element that enable the system to improve.

Example to understand

Consider a self-driving car agent that learns by observing a human driver. Every time the driver brakes, the agent might learn a condition– action rule for when to brake (component 1). By seeing many camera images that it is told contain buses, it can learn to recognize them (component 2). By trying actions and observing the results—for example, braking hard on a wet road—it can learn the effects of its actions (component 3). Then, when it receives complaints from passengers who have been thoroughly shaken up during the trip, it can learn a useful component of its overall utility function (component 4).

Introduction

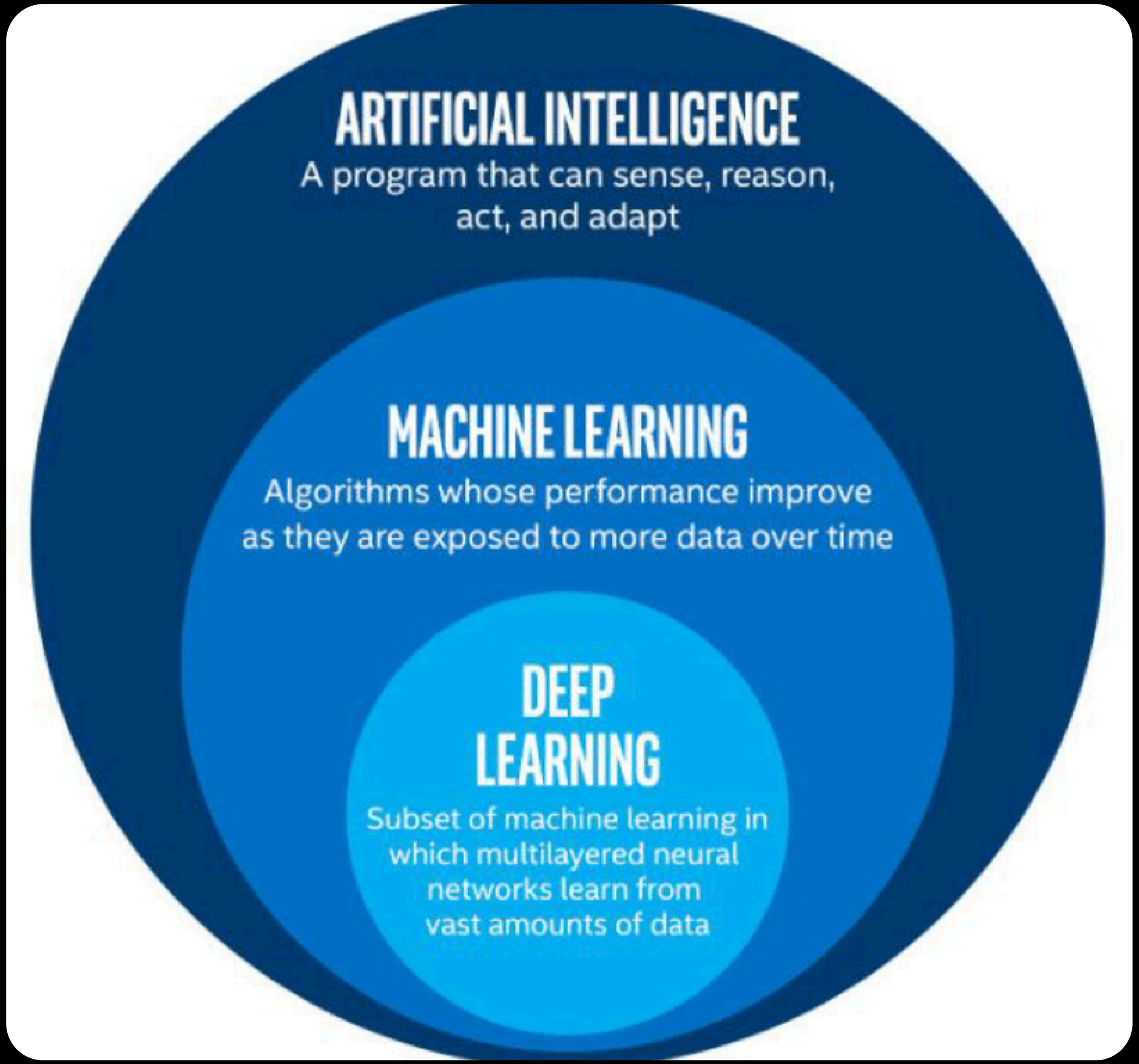
Two main reasons to let machines learn rather than hard-coding every rule:

- Unpredictable Environments: Designers can't foresee every situation (imagine a self-driving car learning the layout of every new road). The car must learn the layout of unfamiliar roads and intersections rather than relying on a pre-programmed map.

- Human Intuition: Some tasks, like recognizing faces, are so intuitive for humans that it's hard to write explicit instructions for them. (Consider facial recognition. Humans recognize familiar faces effortlessly, but programming this process directly is extremely challenging. Instead, ML algorithms learn these patterns by studying thousands of images.)

01. WHAT IS MACHINE LEARNING?

- Machine Learning is a field of AI where computers improve their performance through experience. Instead of being explicitly programmed for every possible scenario, an ML system builds a model from data and uses it to make predictions or decisions.
- A key idea is induction—drawing general rules from specific examples. Just as we infer that the sun will rise tomorrow because it always has, ML systems generalize from past data to predict future outcomes. For instance, by analyzing historical weather data, a model can predict tomorrow's temperature.



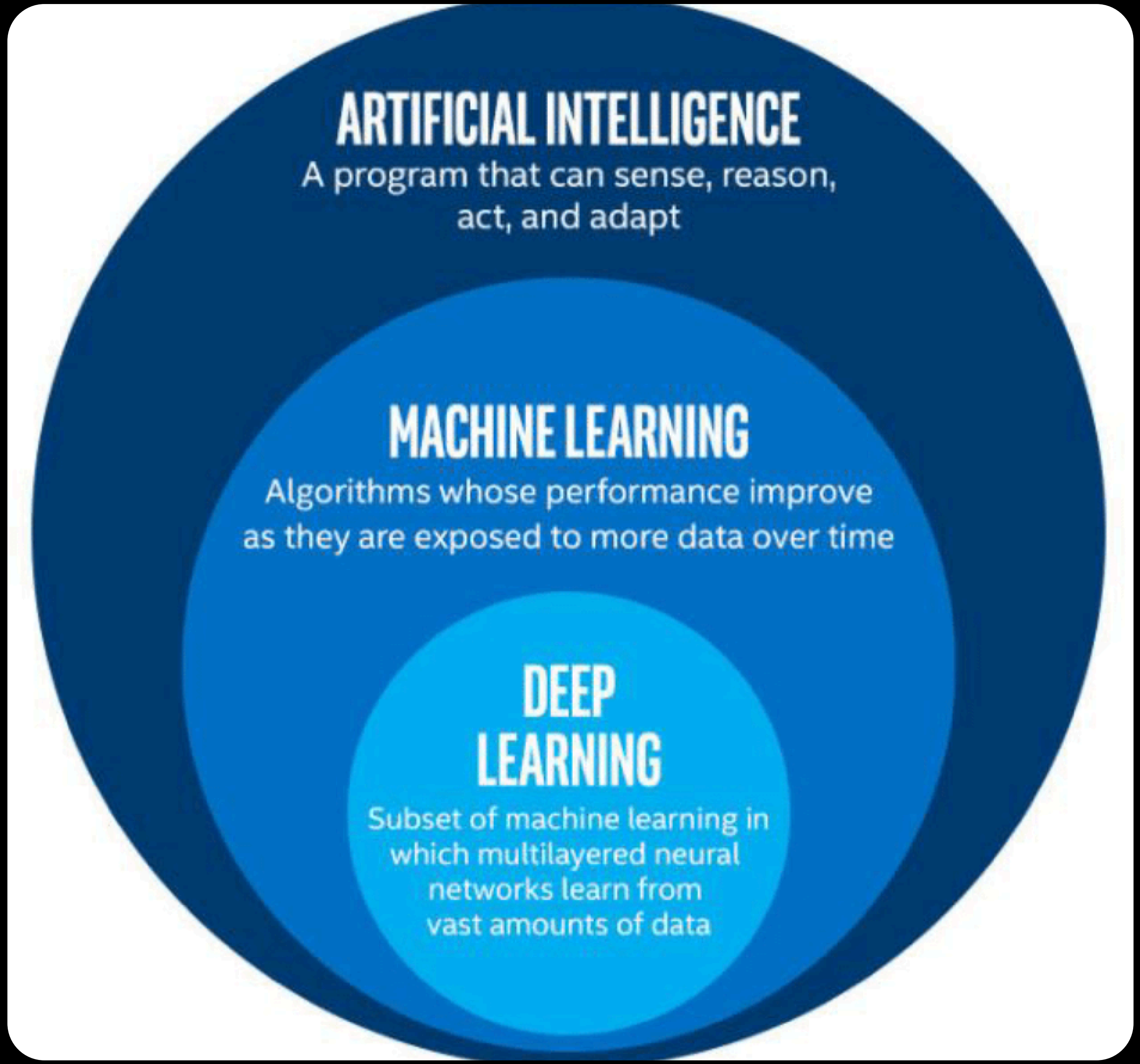
Continuation...

Why Machines Need to Learn:

There are two major motivations for machine learning

- Adaptability: No program can anticipate every possible situation. For example, a robot navigating a maze must learn the unique layout of each new maze it encounters.

- Complex Tasks: Many tasks (like recognizing faces) are so nuanced that we don't fully understand how to program them by hand.



Core Concepts

Data as the Fuel

Data is the raw material for learning. Whether it's images, text, or numbers, high-quality data allows models to discover patterns and make better predictions.

Example: Imagine training a model to recognize handwritten digits (like those in the MNIST dataset). The quality and variety of digit images are critical for the model to learn the different ways numbers can be written.

Models – The Learners

A model in ML is like a hypothesis about how the world works. It's built by analyzing the data, and then it's used to solve problems, whether that means classifying an image or predicting a numerical value.

Example: A model for predicting house prices takes features like square footage, number of bedrooms, and location. It learns the relationships between these features and the price, forming a hypothesis about the real estate market.

Training and Testing

During training, the model is exposed to examples and learns by adjusting its internal parameters. After training, the model is evaluated on unseen data to check if it has learned to generalize beyond the examples it has seen.

Example: When training a spam filter, the model is fed thousands of emails labeled as 'spam' or 'not spam' so it can learn to distinguish between them. After training, the spam filter is tested on a new batch of emails to verify that it correctly classifies messages it hasn't seen before.

Real-World Impact Example

Consider the improvements in medical imaging: ML algorithms can now detect tumors in radiology scans faster and sometimes even more accurately than human experts, significantly enhancing diagnostic processes.

02. TYPES OF MACHINE LEARNING

Types of Machine Learning

1 **Supervised Learning**

Supervised Learning is the process of learning from labeled examples. Each input in the training set comes with a known output, much like having a teacher guide the learning process.

2 **Unsupervised Learning**

Unsupervised Learning involves discovering patterns without explicit labels. The model finds structure in the data on its own.

3 **Reinforcement Learning**

Reinforcement Learning is learning through trial and error, where an agent receives rewards or punishments based on its actions. This approach is akin to learning how to play a game by understanding which moves lead to winning.

03. SUPERVISED LEARNING

Definition

- Supervised learning is the process of teaching a machine to predict an output based on input examples where the correct answer is already known. *(Simple definition)*
- Supervised learning is the task of discovering a function that maps inputs to outputs based on a training set of input–output pairs. *(Technical definition)*

Input: A dataset of the form: $(x_1, y_1), (x_2,y_2), \ldots, (x_n, y_n)$
Goal: Learn a function h, from a hypothesis space H, that approximates an unknown true function f, mapping inputs to outputs.
$y = h(x) \approx f(x)$
x = Input
y = Output (ground truth)
h = Hypothesis (our learned model)
H = Hypothesis space (all models we could choose from)

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Key Concepts

Hypothesis, *h*

The hypothesis *h* is the model's "best guess" of the true function. It represents the model's attempt to make predictions based on the available data. The hypothesis is what the machine "learns" after being trained on the input-output pairs.

Example

When classifying fruits, the hypothesis might be a decision tree that learns to classify images of fruit based on features like color, size, and shape.

Hypothesis space , H

The hypothesis space is the set of all models (or functions) that the learning algorithm can choose from.
It's the collection of all possible solutions the algorithm can consider when trying to learn the relationship between inputs and outputs.
The hypothesis space determines the types of models the algorithm can explore to approximate the true function.

Example

When classifying fruits, you can choose different hypothesis spaces, like all decision trees or all neural networks of a certain size

Key Concepts

Model :

A model in supervised learning is a mathematical function or structure that maps input features to output predictions. It is trained on labeled data to learn the relationship between inputs and outputs

Ground Truth :

The ground truth is the actual, real-world process or the true value that we are trying to predict or approximate

The model tries to learn from data, but the real-world process generating the data is the "ground truth" often messy, noisy, and hidden.
The goal is not to memorize training data but to generalize to new, unseen inputs.

Why ?

- If we assume our model is the ground truth, we risk overconfidence and poor real-world performance.
- The ground truth might change over time — people's behavior evolves, and external conditions shift.
- Hence, models must be designed to adapt and generalize, not just fit a static snapshot of past data

Key Concepts

Generalization

This refers to the model's ability to make accurate predictions on new, unseen data, rather than just memorizing the training data.
A good model generalizes well, meaning it can apply what it has learned to data it has never encountered before. This is crucial for real-world applications, where the data model sees in practice may differ from the training data.

Key Concepts

Training Set

Used to train the model. It consists of input-output pairs that the model learns from. The model uses this data to learn the mapping from input to output (i.e., to optimize the function h(x)).
The training set helps the model adjust its parameters (or weights) so that it can make accurate predictions on similar, unseen data.

Test Set

Used to evaluate the model's performance after it has been trained. The test set contains input-output pairs that the model has never seen before during training.
The goal is to see how well the model generalizes. A model that performs well on the test set indicates that it is not overfitting and has learned to generalize from the training data to new, unseen examples.

Key Steps in Supervised Learning

1

Collect and Label Data

This step involves gathering a dataset where each example (input) is paired with the correct output (label). The dataset serves as the foundation for training the model.

2

Choose a Hypothesis Space

Based on prior knowledge or exploratory data analysis (visualizing data), choose a model class.

3

Train the Model

Here, an algorithm is used to find the best model from the hypothesis space that fits the training data. The model learns by adjusting its parameters (weights or rules) to minimize errors on the training set.
In practice, we don’t always aim for a perfect match but the best approximation.

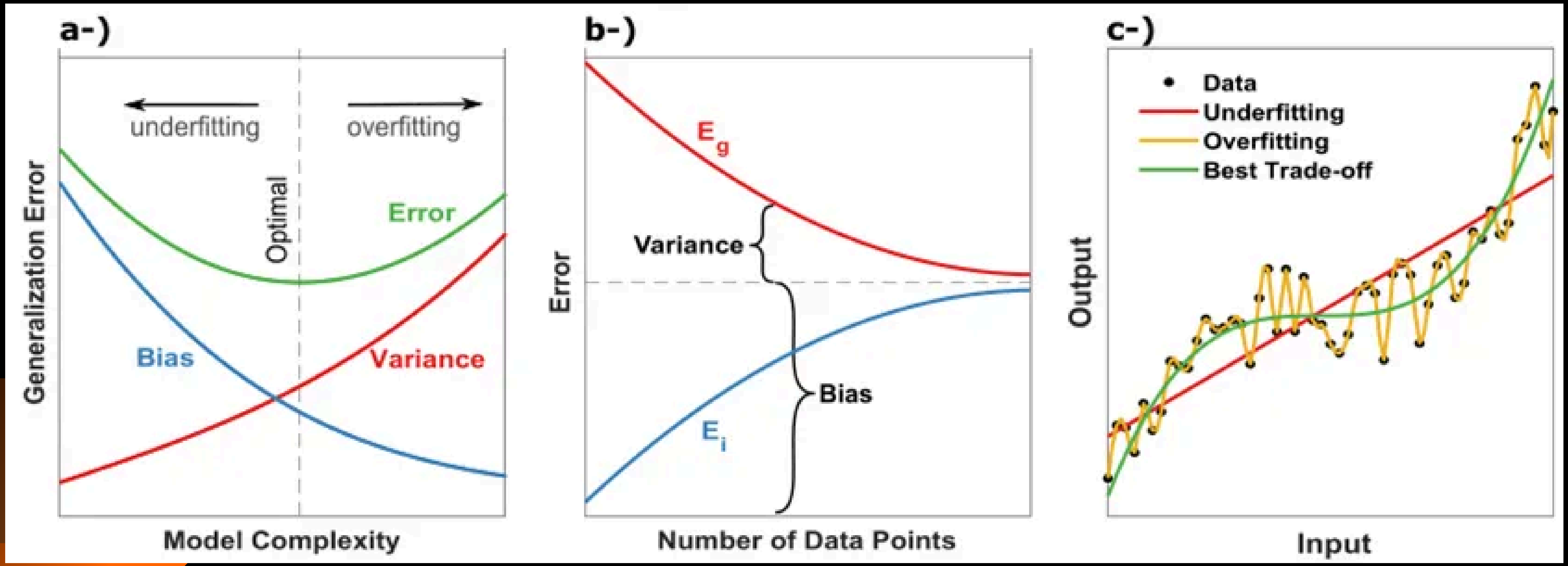
4

Evaluate the Model

After training, the model is evaluated using a test set that was not part of the training data. This helps assess how well the model generalizes to new, unseen data.

Bias–Variance Tradeoff

Bias: Model is too simple → can't capture patterns → underfitting
Variance: Model is too complex → captures noise in training data → overfitting
Goal: Find the sweet spot — a model that's simple enough to generalize but expressive enough to learn.



04. LINEAR REGRESSION

Linear Regression: Learning a Line

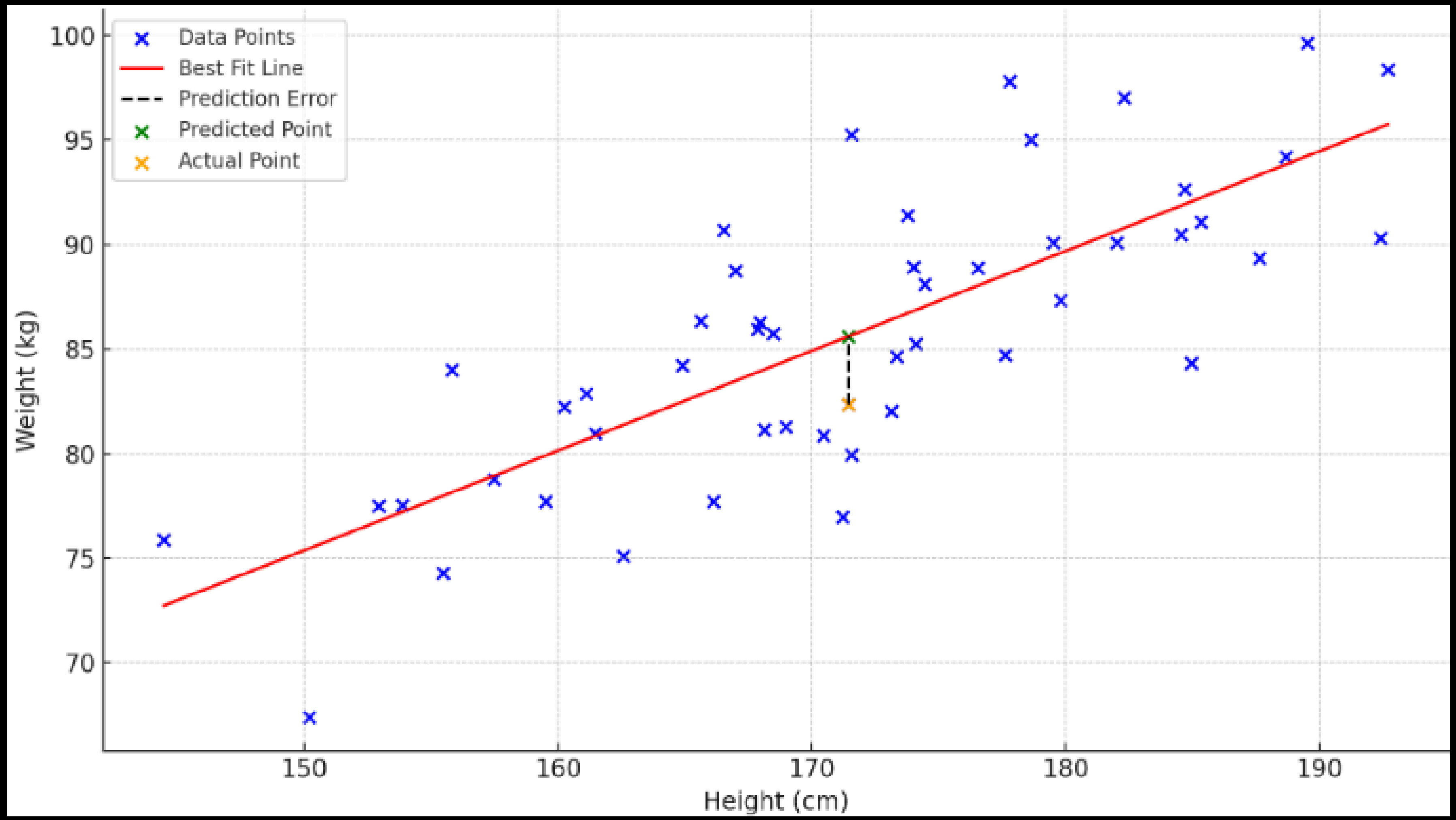
Linear Regression is one of the most fundamental machine learning algorithms. It tries to find the best-fitting straight line through a set of data points.

The goal is to predict a continuous outcome (like price, age, height, temperature) based on one or more input features.
It tries to answer questions like:

- What will a person's weight be if they are 170 cm tall?
- How much will this house cost if it's 2000 square feet?

Linear Regression: Learning a Line

- Each data point represents a real example with an input (e.g., height) and an output (e.g., weight).
- The algorithm tries different lines and calculates the error (difference between actual and predicted values).
- It chooses the line that minimizes the total error – often using a method called **least squares**.
- The algorithm "learns" the best values for m and b based on the data. The equation of a straight line: y=mx+b



05. EXAMPLE SCENARIO

Can We Predict House Prices?

Imagine you're a real estate agent. You want to estimate the price of a house based on its size. Can a computer help you do that? This is a classic supervised learning problem because:

- We have labeled data (e.g., size and actual price).
- We want to learn a relationship (a model) that can predict price for a new house.

STEPS

1. Data Collection

For example:

Floor Space (approx.)	Price (approx. Ksh)
100	250,000
110	275,000
120	300,000
130	330,000
140	360,000

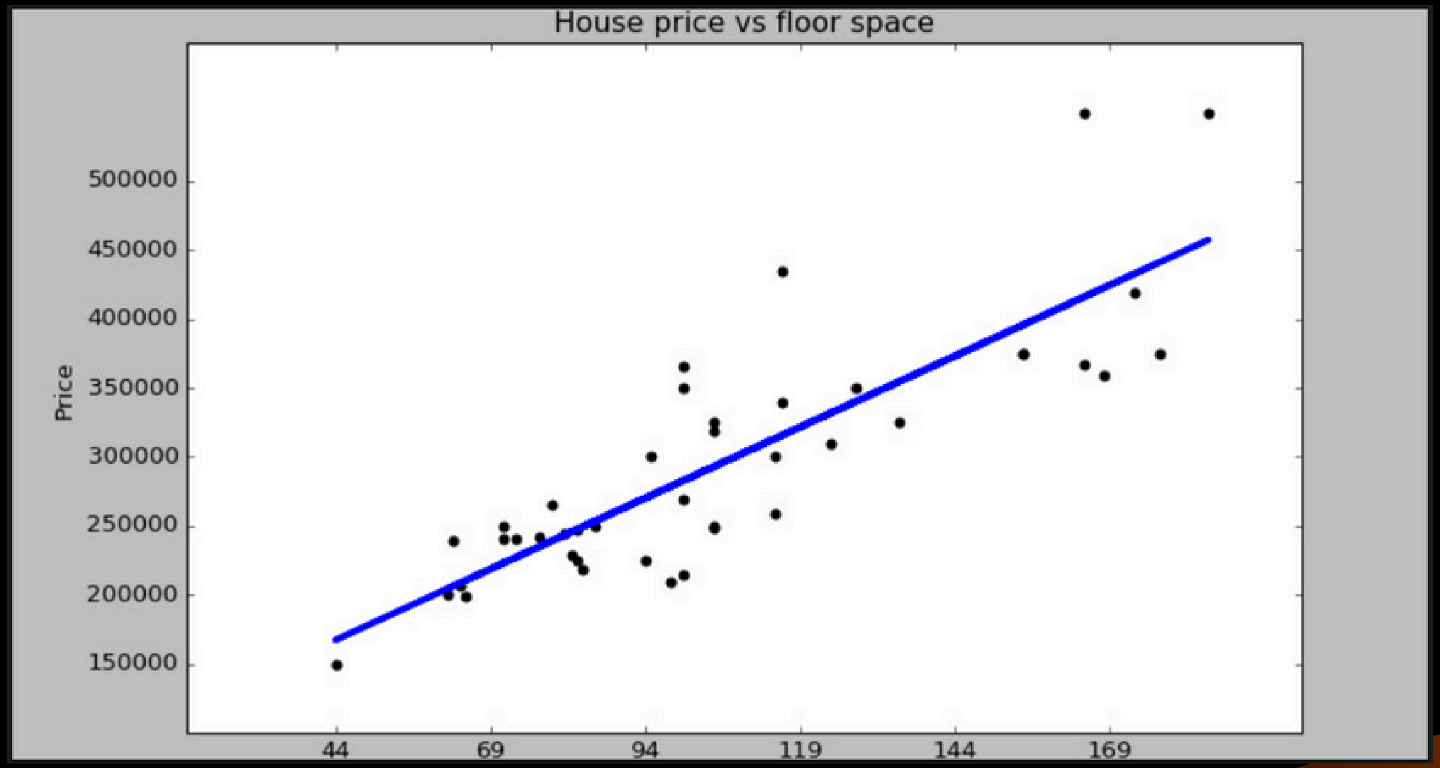
We’re collecting examples with correct answers — this is what makes it supervised.

2. Plotting The Data

STEPS

3. Training the model.

Draw a straight line that best fits these points — this is our model. The line captures the trend and lets us predict the price for any size.



4. Prediction

If someone comes to us with a 1300 sqft house, we find that point on the line, and it gives us a predicted price e.g. $195,000.

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Traditional AI & ML

Traditional AI

- Hardcoded rules
- Deterministic
- Human knowledge engineered
- Good for structured problems

Machine Learning

- Learns patterns from data
- Probabilistic
- Machine finds knowledge itself
- Better for complex, data-rich tasks

Traditional AI is like baking with a recipe. Machine Learning is like learning to cook by tasting and adjusting.

Search and Optimization

In ML, we often use optimization to improve model accuracy. For example: When training the linear regression model, we search for the best line that minimizes prediction errors

Knowledge Representation

Refers to how information is structured and organized to enable a machine to understand and use it for decision-making or problem-solving. This helps machines to reason and infer new knowledge from existing data. In logic-based AI, we use rules and facts. In ML, we use data to represent the world.

Constraint Satisfaction

It involves finding values for variables that satisfy a set of given constraints. Essentially, it's about ensuring that the solution to a problem adheres to specific rules or conditions.

AI & ML IN REAL-WORLD SYSTEMS

Application	Traditional AI Component	ML Component	How they work together
Chatbots	Rule-based dialogue system	Language understanding (Natural Language Processing models)	Rules ensure reliable responses to common queries, while ML handles ambiguous phrasing. Example: A bank chatbot uses rules for balance inquiries but ML to detect possible fraud cases from word choice.
Self-driving cars	Path planning with search	Object detection with neural networks	Search algorithms guarantee collision-free paths, while ML adapts to real-world noise (e.g., faded lane markings). Example: Waymo uses HD maps (rules) + ML to handle construction zones.

Conclusion

- Machine Learning is a field of AI where computers improve their performance through experience gained over time.
- By enabling computers to learn from experience rather than relying solely on explicit programming, ML has expanded the range of what AI can achieve.
- The true test of ML lies in its ability to perform well on new, unseen data—not just memorizing training examples.
- The future lies in hybrid systems that combine the interpretability of rule-based AI with the adaptability of machine learning

Machine Learning didn't replace AI — it extended it.

THANK YOU!