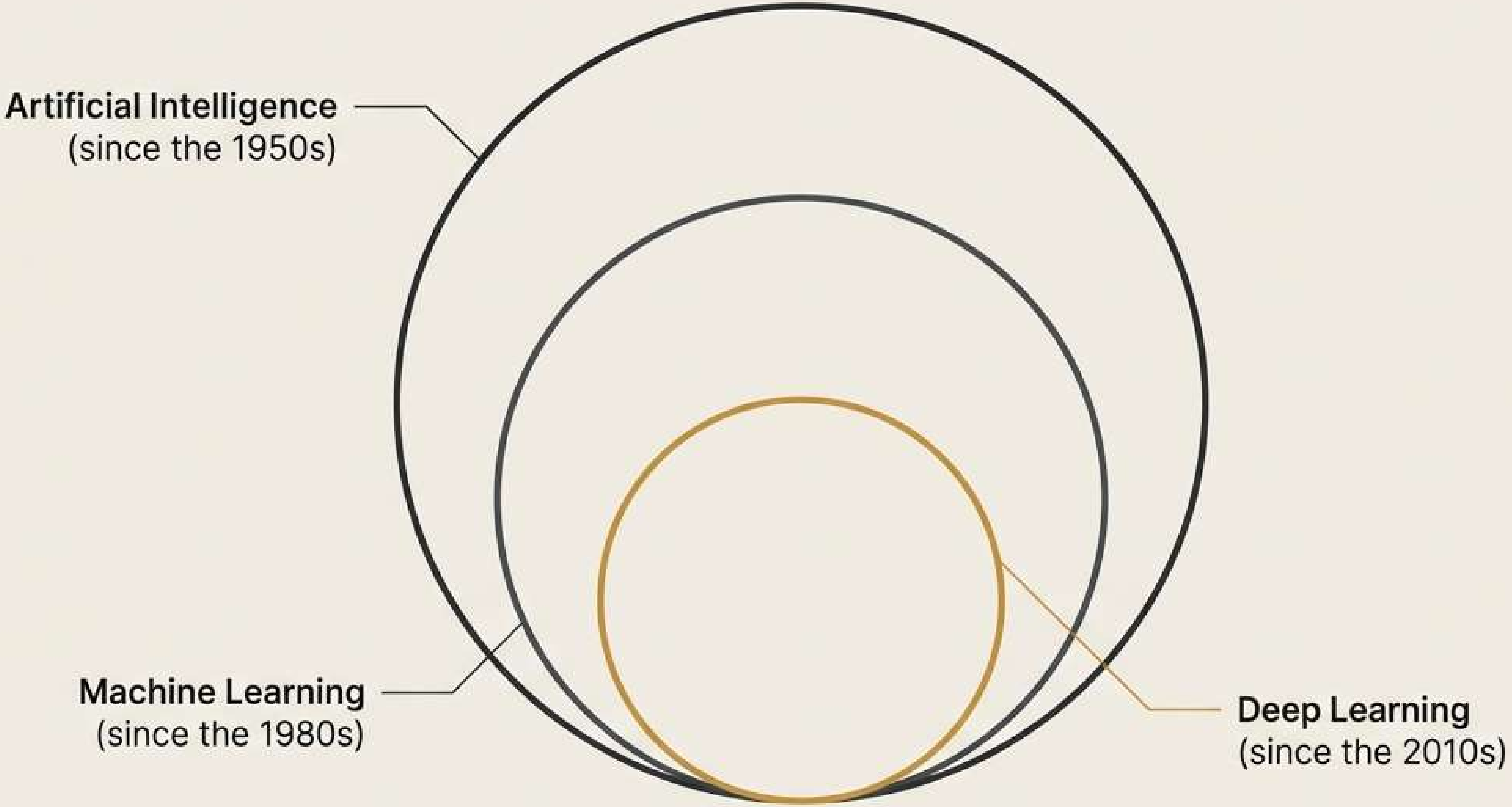
We are living through an intense wave of AI hype.

We're promised a future of intelligent chatbots, self-driving cars, and virtual assistants. This future is painted in contradictory terms—sometimes as a utopia where robots handle all economic activity, and other times as a grim reality where human jobs are scarce.

> How do we separate **world-changing developments from overhyped press releases**? How do we **find the signal in the noise**?

To find the signal, we must start with the fundamentals.

The terms Artificial Intelligence, Machine Learning, and Deep Learning are often used interchangeably, but they represent distinct, nested concepts. Understanding their relationship is the first step toward clarity.



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Artificial Intelligence began as an effort to automate human intellect.

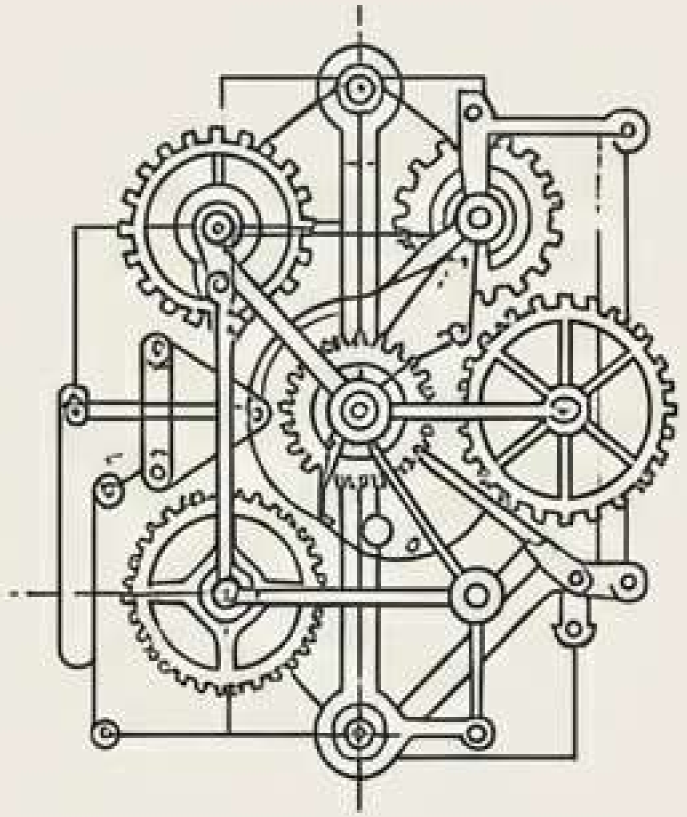
AI is the effort to automate intellectual tasks normally performed by humans.

The field crystallized at a 1956 Dartmouth workshop, based on the conjecture "that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."

The Early Paradigm: Symbolic AI

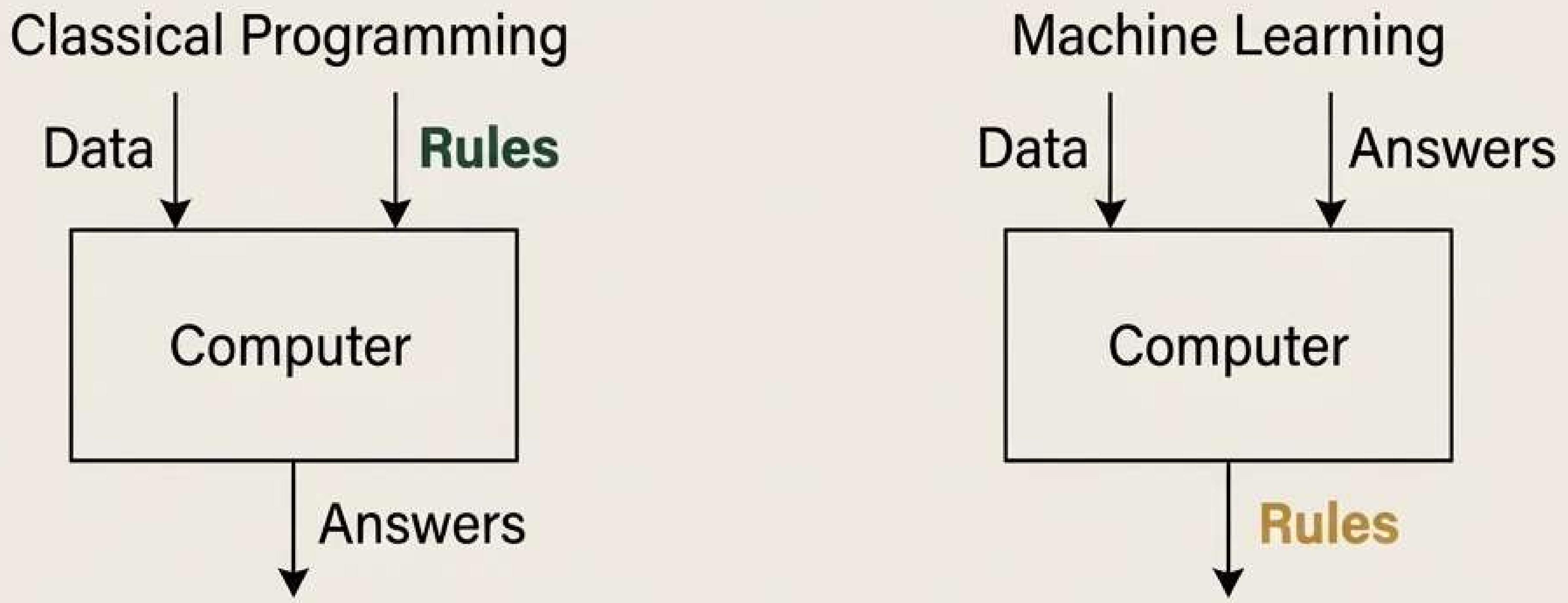
From the 1950s to the late 1980s, the dominant approach was Symbolic AI. Experts believed human-level AI could be achieved by programmers handcrafting a massive set of explicit rules for manipulating knowledge.

This approach worked for well-defined, logical problems (like early chess) but proved intractable for complex, "fuzzy" problems like image classification or speech recognition.



Machine Learning offered a new paradigm: learning rules from data.

Instead of a programmer writing rules to turn input data into answers, the machine looks at the input data and the corresponding answers to figure out what the rules should be. A machine learning system is trained rather than explicitly programmed.



It finds statistical structure in examples that allows the system to come up with rules for automating a task.

The machine learning 'recipe' requires three key ingredients.

1

1. Input Data Points

Examples of the problem. For instance, sound files of people speaking for a speech recognition task.

2

2. Examples of the Expected Output

The "answers" corresponding to the inputs. For instance, human-generated transcripts of those sound files.

3

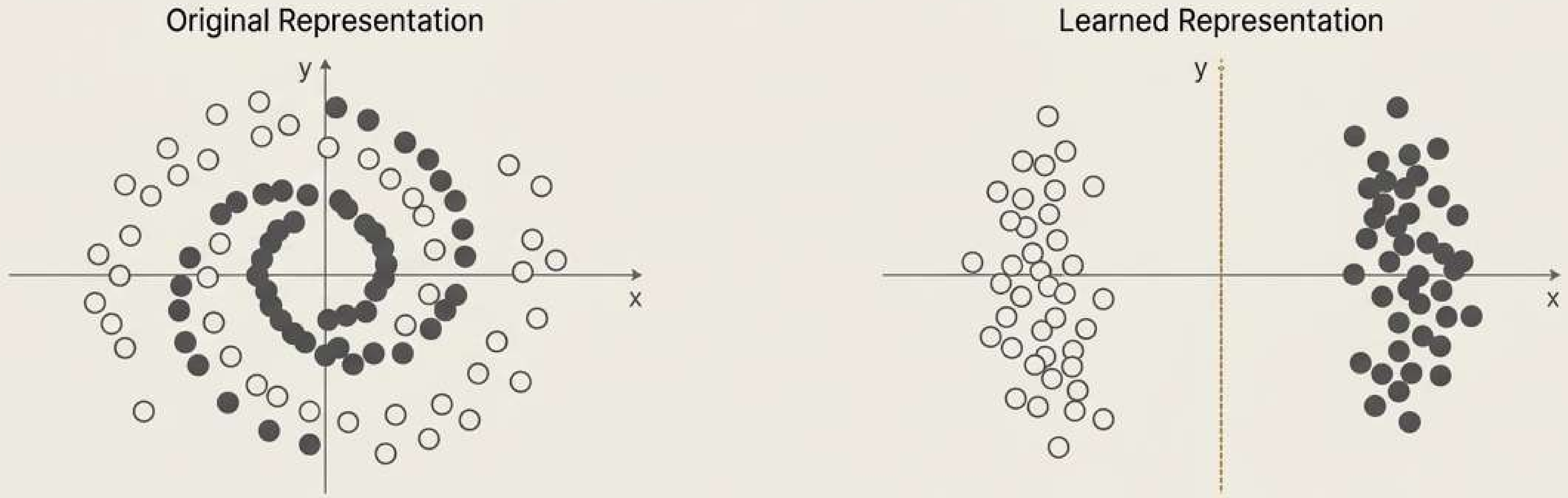
3. A Way to Measure Performance

A feedback signal to determine the distance between the algorithm's current output and the expected output. This measurement guides the adjustment process we call "learning."

The central task of machine learning is to learn useful representations of data.

A machine learning model's goal is to *meaningfully transform data*. A representation is simply a different way to look at or encode data. Some tasks that are difficult with one representation can become easy with another.

A color image can be represented in RGB (Red-Green-Blue) or HSV (Hue-Saturation-Value). The task "Select all red pixels" is simple in RGB, while "Make the image less saturated" is simple in HSV.



A new representation makes the classification problem trivial: "Black points are where $x > 0$".

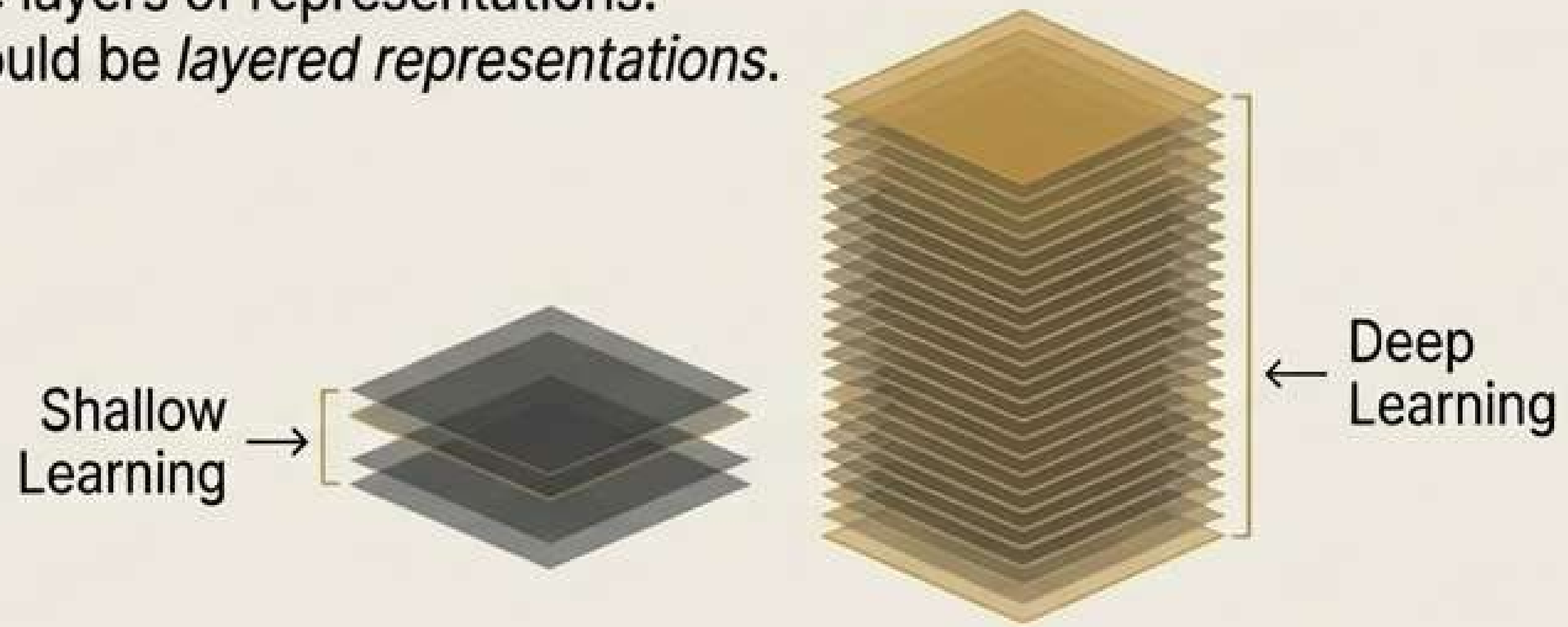
Deep Learning's innovation is learning representations in successive layers.

Definition

The "deep" in deep learning refers to the idea of successive layers of representations. The number of layers is the model's *depth*. Other names could be *layered representations*.

Distinction

Other machine learning approaches ("shallow learning") focus on only one or two layers of representations. Modern deep learning can involve hundreds.

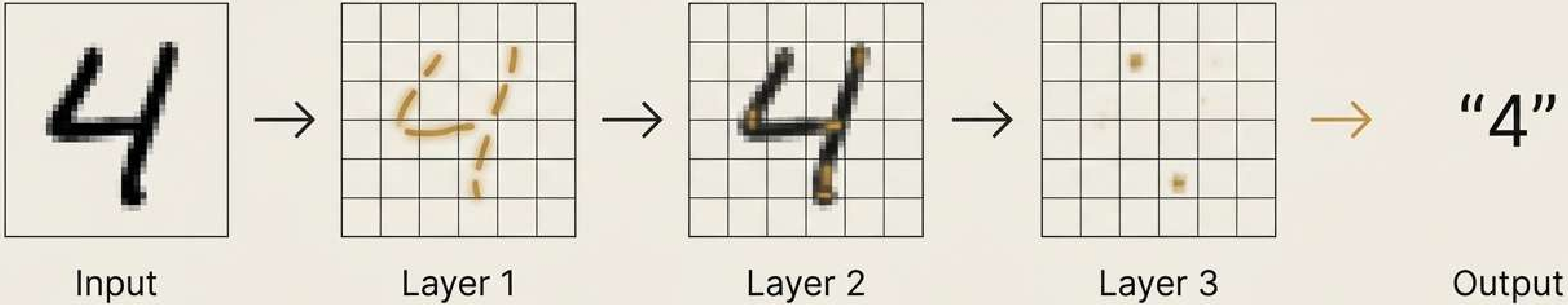


Debunking a Myth

Deep learning models are not models of the brain. There's no evidence that the brain implements anything like the learning mechanisms used in modern deep learning models. You may as well forget anything you may have read about hypothetical links between deep learning and biology.

A deep network acts as a multi-stage information-distillation process.

Information goes through successive filters and comes out increasingly *purified*—that is, more useful with regard to a specific task.



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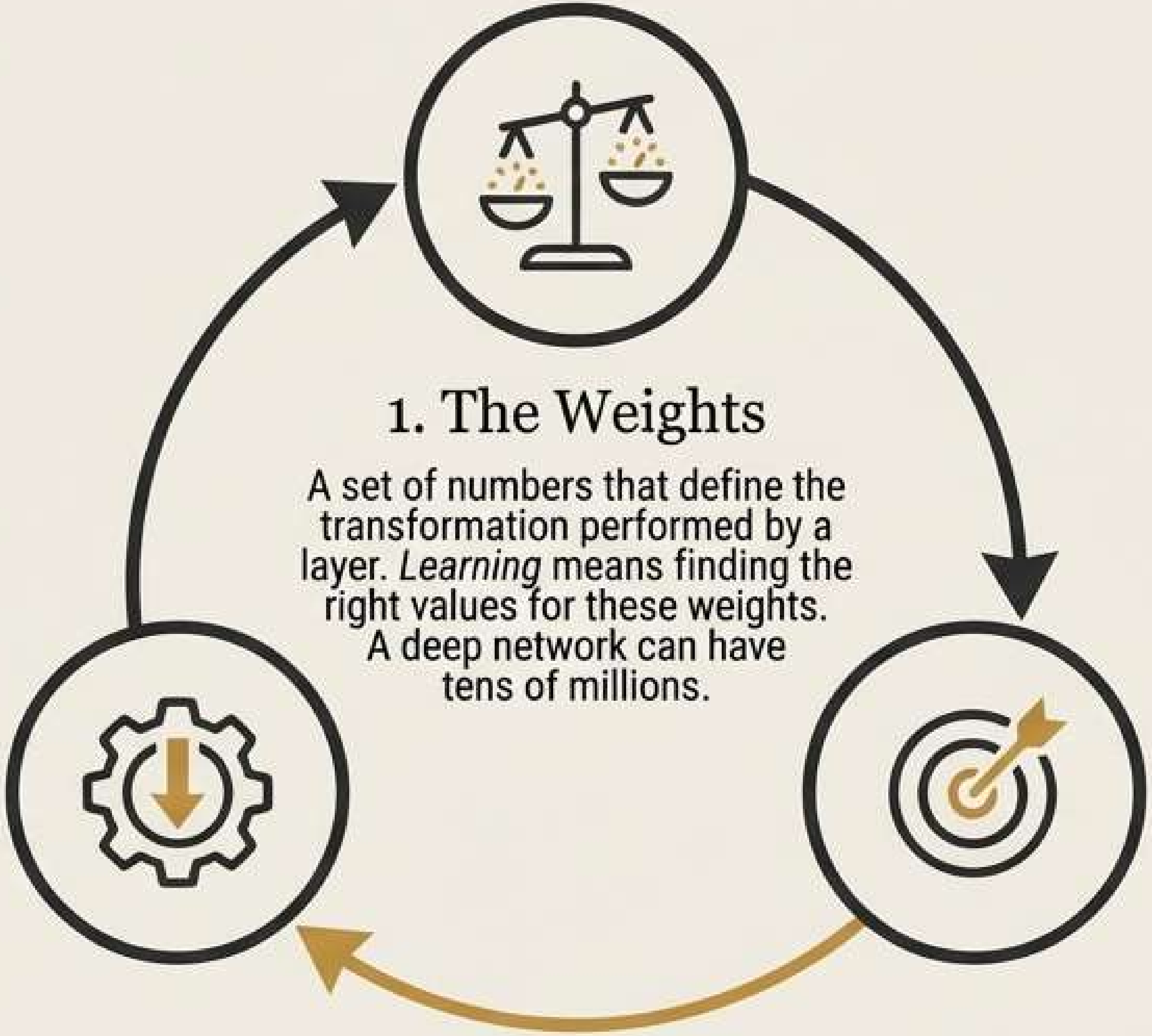
Learning is a feedback loop guided by three components.



1. The Weights

A set of numbers that define the transformation performed by a layer. *Learning* means finding the right values for these weights. A deep network can have tens of millions.

2. The Loss Function

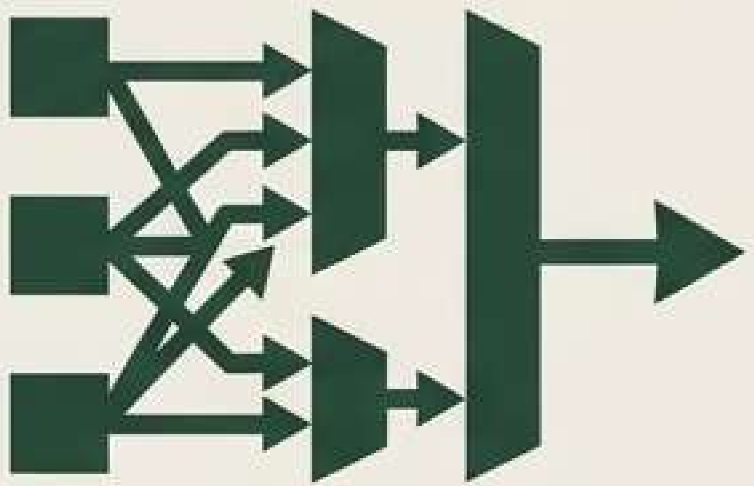
Measures how far the network's output is from the expected target. It computes a "loss score" that captures how well the network has done.

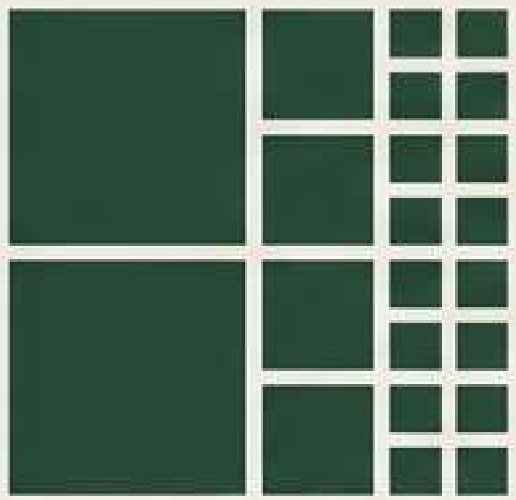
3. The Optimizer

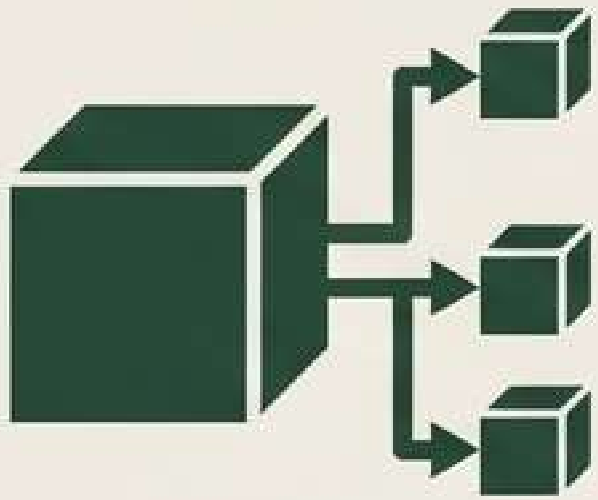
Uses the loss score as a feedback signal to adjust the weights in a direction that will lower the score. This process uses an algorithm called Backpropagation.

This cycle of "predict -> measure loss -> optimize weights" is repeated many times, yielding weight values that minimize the loss function.

Three properties justify deep learning's status as an AI revolution.







Simplicity

Deep learning automates the most difficult step in older ML workflows: *feature engineering*. Instead of humans manually engineering data representations, the model learns all features in one pass.

Scalability

Deep learning is highly amenable to parallelization on GPUs and can be trained on datasets of arbitrary size by iterating over small batches of data. It takes full advantage of Moore's Law.

Versatility and Reusability

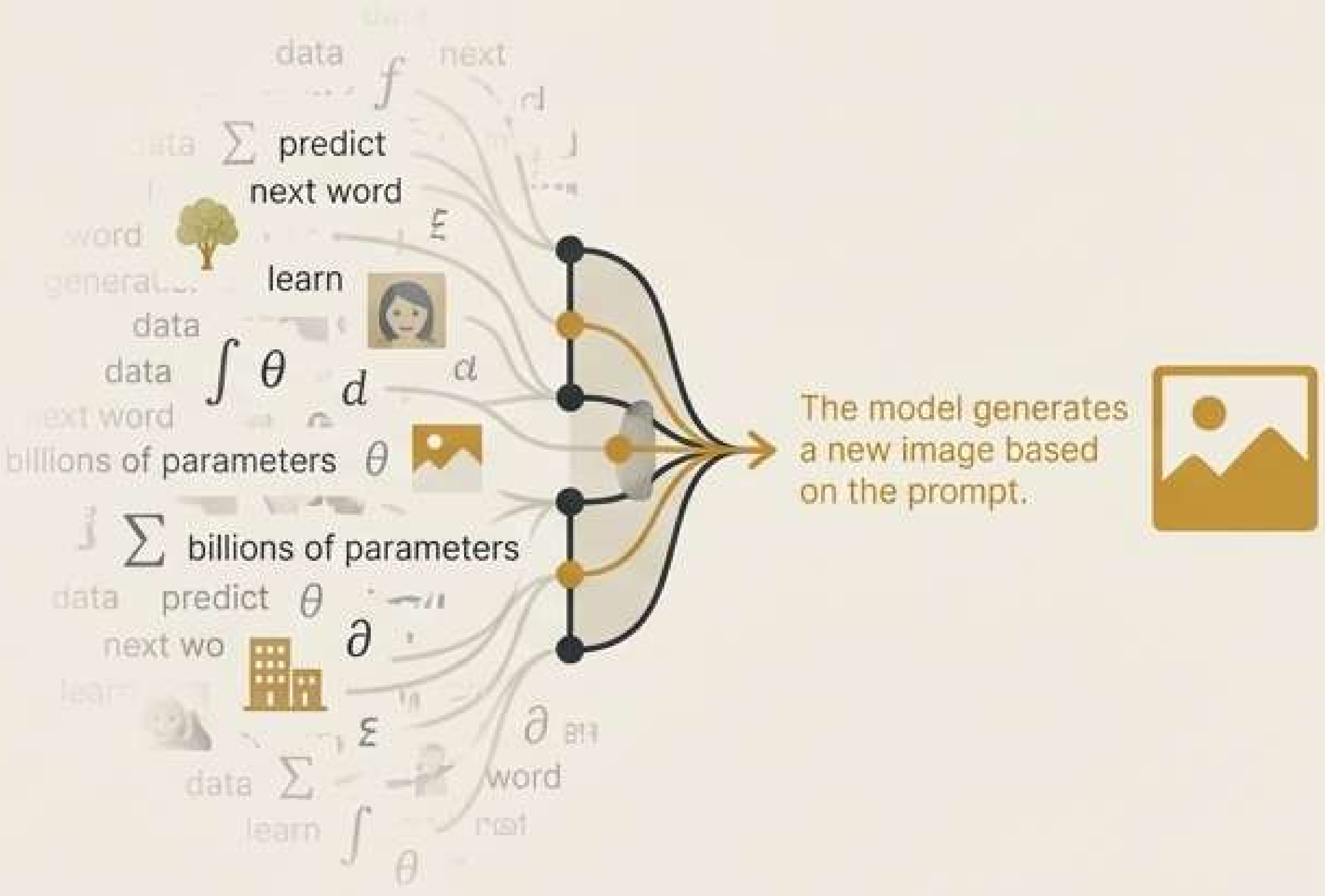
Models can be trained on new data without restarting from scratch. Trained models can be repurposed, which is the core idea behind today's "foundation models."

This has led to the age of generative AI.

Key Applications: Chatbot assistants like ChatGPT, image generation services like Midjourney.

How They Work: Powered by very large "foundation models" trained via self-supervised learning. Instead of human-labeled data, the model learns by reconstructing the input itself (e.g., predicting the next word in a sentence).

The Unlocked Potential: Doing away with manual data annotation has unlocked unprecedented scale. Models have hundreds of billions of parameters and are trained on petabytes of data. They operate as a kind of "fuzzy database of human knowledge."



With this clarity, we can re-examine the hype.

The Hype Claims

Pundits claim imminent human-level general intelligence (AGI), mass unemployment, and 100x productivity gains.

The Grounded Reality

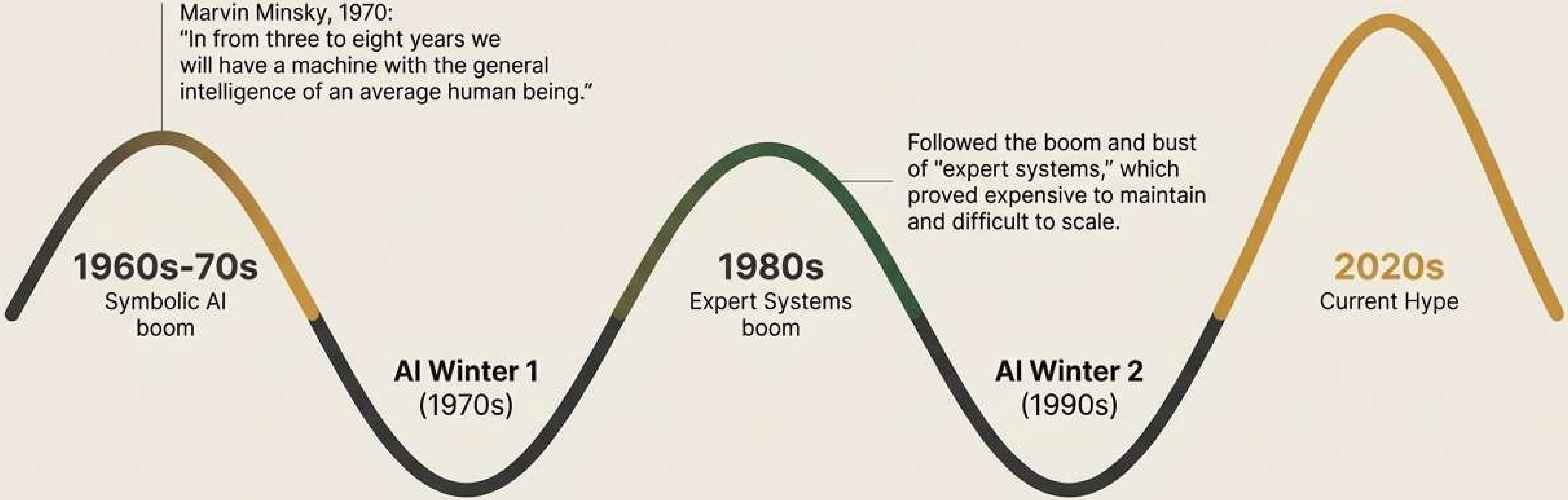
Today's "artificial intelligence" is more accurately described as "cognitive automation"—the encoding and operationalization of human skills and knowledge.

"Think of it this way: AI is like a cartoon character, while intelligence is like a living being. A cartoon... can only act out the scenes it was drawn for. A living being... can adapt to the unexpected."

Core Difference: Intelligence is the ability to face the unknown. Automation handles situations it was trained on. Expecting today's AI to become sentient **"is like expecting a better clock to lead to time travel."**

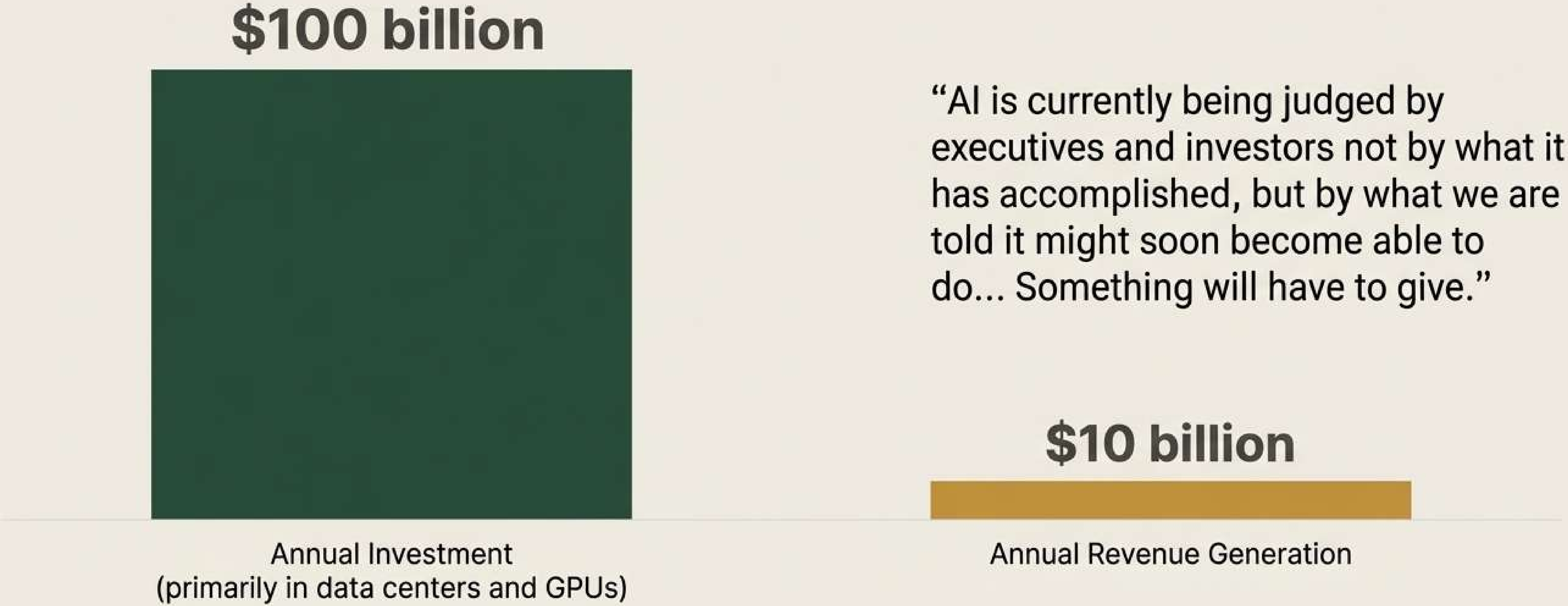
Inflated expectations are not new; they have led to two “AI winters.”

Twice in the past, AI went through a cycle of intense optimism followed by disappointment and a lack of funding.



“We may be currently witnessing the third cycle of AI hype and disappointment — and we‘re still in the phase of intense optimism.”

Today, the investment bubble is plain to see.



"AI is currently being judged by executives and investors not by what it has accomplished, but by what we are told it might soon become able to do... Something will have to give."

A full-scale retreat like in the past is unlikely. If there is a winter, it should be mild because AI has already demonstrated world-changing value. But 'it seems inevitable that some air will need to be let out of the 2023–2024 AI bubble.'

But beneath the hype, a quiet revolution is already unfolding.

A Prediction from 2017

"Right now, it may seem hard to believe that AI could have a large impact... much as, back in 1995, it would have been difficult to believe in the future impact of the internet... In a not-so-distant future, AI will be your assistant... drive you from point A to point B... and help humanity as a whole move forward."

The Reality in 2025

- Tens of millions use AI chatbots (ChatGPT, Gemini) as assistants daily.
- Fully autonomous driving is deployed at scale in cities like Phoenix, San Francisco, and Los Angeles.
- AI (AlphaFold) is helping biologists predict protein structures with unprecedented accuracy.

Don’t believe the short-term hype, but do believe in the long-term vision.

The Takeaway

We may face setbacks, much like the internet industry did after the dot-com crash. But we’ll get there eventually. AI will end up being applied to nearly every process that makes up our society and our daily lives.

“It may take a while for AI to be deployed to its true potential—a potential the full extent of which no one has yet dared to dream—but AI is coming, and it will transform our world in a fantastic way.”