

From Computation to Thinking

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Preface

I wrote this book for the reader who has had a sudden attack of curiosity. Think of a friend who types into a phone at 2 a.m. about a feverish child with a rash. Most readers know what a good nurse would do, but how could a machine do the same thing? After comforting the child, our friend looks at the phone and wonders: how can a machine that only follows rules come to read, reason and act? And what do these capabilities mean for the people whose work it touches?

I take the reader on a journey to build such a machine step by step. We follow one route through AI, from computation to today's language models and the agents built on them. I hope to demystify how the machine works and get my friend to think clearly about how to use it well.

The 2 a.m. message

It is two in the morning. A parent speaks or types into a phone:

“My daughter is 3. She’s had a fever all evening, 39.5. Now she has little purple spots on her legs, and they don’t go away when I press a glass on them. Should I wait until morning?”

A good nurse knows at once this cannot wait. A fever together with a rash that does not fade under pressure can be a sign of meningitis or sepsis, so the answer is: *call an ambulance now*. She knows how to say it, calmly and clearly, to a frightened person. She knows what she does not know: she cannot see the child, so she errs on the side of caution. Then she acts. She checks the child’s record, alerts the doctor on call, and phones back in the morning.

The answers, however, are not coming from a human this time. They are coming from a machine. Today, a parent may not realize they are talking to a machine. The machine can recognize the same warning signs in many phrasings. It can explain why the situation is urgent, ask a sensible follow-up question and use tools to take the next steps.

Now open the machine up with me. The machine holds only a clock and billions of switches, each either on or off. Every tick, each switch changes according to what a few of its neighbors are doing. That is all. No single switch knows anything about children or fevers.

So here is the question I want to answer:

How can switches following simple rules produce a voice so knowledgeable, reassuring, and helpful that it can do much of a nurse’s job?

One rung at a time

The answer is not a single big idea but a ladder of concepts. We will climb it together, one rung at a time. At each rung I add one ingredient and show what the machine could not do without it. Then I go back to the parent. How much of the nurse’s work can the machine, which I call **the AI nurse**, now do? The AI nurse combines abilities that have been shown in different systems; it is a way to explain the technology, not a tested clinical product. The real machines named at the end of each chapter show one ability at a time.

This ladder is not magic. It is science and engineering, and nothing on it is free: in Step 13 I stop to count what each rung has cost. Nor does climbing remove every limit. Some limits are mathematical and bound every computation, yours and mine included, as far as anyone

knows; others depend on the evidence and resources available. Chapter 3 shows the first of them, and Chapter 16 looks at all of them from the top.

The climb has two stages. Steps 1 to 12 assemble the machine, and Step 13 counts its cost; these explain mechanisms that are well established. Steps 14 to 16 add nothing new but ask what has been built: what its words mean, whose goals drive it, and where it fails. These chapters examine meaning, goals, reliability and limits. Some of their questions are still disputed, and there I offer arguments, not settled results; others, such as how well a machine knows when it is wrong, can be tested. Steps 17 and 18 turn to the people who work with the machine: first the team on a hospital ward, then the jobs themselves.

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Machines That Follow Rules

The machine does exactly what it is told.

Moving Symbols

Symbols, a state, and a rulebook that only ever looks at one spot. Nothing more is needed to compute.

A game with a strip of paper

Here is the first rung. Take a long strip of paper divided into squares. Some squares hold a 0, some a 1, and the rest are blank. Put your finger on one square. Keep one word in your head, which we will call your **state**. To start, the word is CARRY.

Here is the whole rulebook:

If your state is...	and the square under your finger shows...	then write...	move your finger...	and your new state is...
CARRY	1	0	one square left	CARRY
CARRY	0	1	—	STOP
CARRY	blank	1	—	STOP

Now write **1011** on the strip and put your finger on the last **1** on the right. Follow the rules:

1. State CARRY, you see **1**. Write 0, move left. The strip reads **1010**.
2. State CARRY, you see **1**. Write 0, move left. The strip reads **1000**.
3. State CARRY, you see **0**. Write 1, stop. The strip reads **1100**.

You started with **1011** and ended with **1100**. In binary, 1011 is eleven and 1100 is twelve. **You added one.**

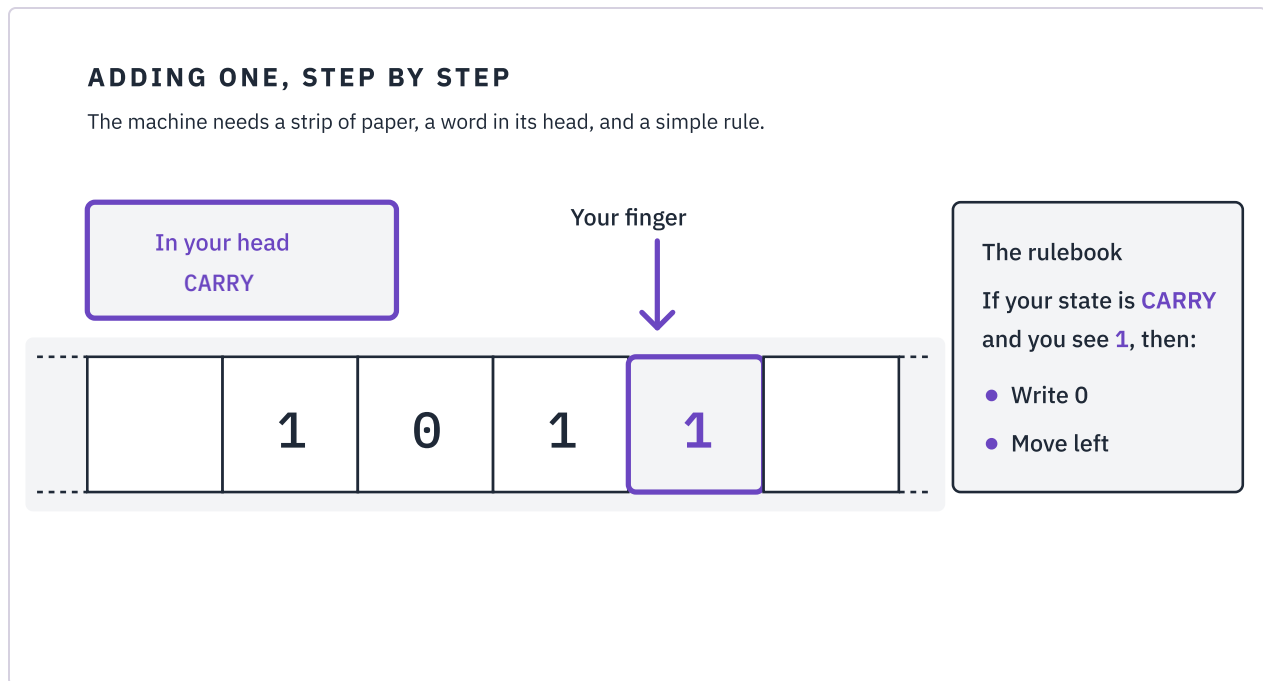


Figure 1.1. The add-one machine at its first step: a strip of squares, one word held in mind, and a rule.

Try it with **111**. Each 1 becomes 0 as you move left. Then you reach the blank square in front of the number, write a 1, and stop: **1000**, which is eight (seven plus one). The third rule exists for exactly this case.

Notice what you did *not* need. You did not need to know what a number is, or what “adding” means, or that the strip was in binary. You never looked at more than one square. You just matched a pattern in a table and did what it said. The meaning, *adding one*, belongs to us, the people reading the strip. The process itself is just symbols being moved by rules.

Symbols, state and rules

Every computation, from this toy to the chip in your phone, is built from the same three ingredients.

1. **Symbols.** Marks that can be reliably told apart: 0 and 1, letters, high and low voltages. What matters is *that* they differ, not what they look like.
2. **State.** A small amount of memory about “where we are in the procedure”. In the toy it was one word: CARRY or STOP.
3. **Rules.** A finite table that says, for each combination of state and symbol in view, what to do next. Every rule is
 - **local:** it sees only the symbol at the current position;
 - **simple:** it is a lookup, not a judgment;
 - **fixed:** the table never changes while the machine runs.

Alan Turing described this device, with a tape as long as needed, in 1936. We call it a **Turing machine**. Turing was not trying to build a computer. He was trying to capture, as precisely as possible, what a person does when calculating with pencil and paper. Look at a few marks. Recall where you are in the method. Write something. Move on.

A snapshot and a path

Freeze the machine at any instant and write down *everything* about it: the full contents of the tape, where the finger is, and the current state. Call this a **snapshot** (the technical word is **configuration**). The rules turn each snapshot into exactly one next snapshot.

So a computation can be pictured in a second way: as a **path through the space of all possible snapshots**. That space is enormous. Even our four-square strip, with three symbols per square, four finger positions, and two states, has $3^4 \times 4 \times 2 = 648$ snapshots. Yet the run we traced visited only four of them. The rules pick out one thin thread through a huge space. Stopping means arriving at a snapshot the rules do not move you away from.

This second picture, a *path through a space of states, driven by a fixed rule*, will come back again and again. It describes a network being trained (Chapter 5) and a language model writing out its reasoning about a sick child (Chapter 11). It is the most important picture in this book.

At this step, the machine is a strip of paper and a finger following a rulebook: it computes, but only while someone moves the finger.

PART I • CHAPTER 2

One Machine for Every Rulebook

A machine that only adds one would need a new rulebook, and so a new machine, for every task. This chapter offers a way out: rules are just symbols, so they can be written *on the tape*. One machine can then read any rulebook and follow it. That machine is the **universal machine**, and it is why the device in your pocket can be anything.

Rules are just more symbols. Put them on the tape, and one machine can become any machine.

A machine for every job?

Chapter 1's machine added one, and that was all it could do. To sort a list you would need a different rulebook. To check a dose against a child's weight you would need another. If every rulebook meant a new machine, a hospital would need a warehouse of them: one for lab results, one for appointments, one for drug interactions.

This is not a silly worry. It is roughly how the first electronic computers worked. ENIAC, finished in 1945, was programmed by hand: to change what it computed, people rearranged cables and switches on its panels, much like an old telephone exchange. Changing the job meant physically rewiring the machine, and that could take days.

The rulebook goes on the tape

Turing saw the way out in 1936, before any electronic computer existed.

Look again at the rulebook in Chapter 1. It is a small table: if state is CARRY and the symbol is 1, write 0, move left, stay in CARRY. Every line of it can be written with ordinary symbols. So the rulebook can be **written on the tape**, just like the data.

Now imagine a special machine whose own fixed rules say:

1. Look at the rulebook written on one part of the tape.
2. Look at the current state and the symbol under the finger on another part of the tape.
3. Find the matching line of the rulebook, and do what it says.
4. Repeat.

This machine does nothing useful on its own. Hand it the adding-one rulebook and it adds one. Hand it a sorting rulebook and it sorts. Hand it a rulebook for checking doses and it checks doses. Turing proved that one such machine, with one fixed table of its own, can imitate every other Turing machine. He called it the **universal machine**.

Two words now separate:

- **Hardware** is the fixed machine that follows rules: the part that never changes.
- **Software** is the rulebook on the tape, which you can swap. Today we call it a **program**.

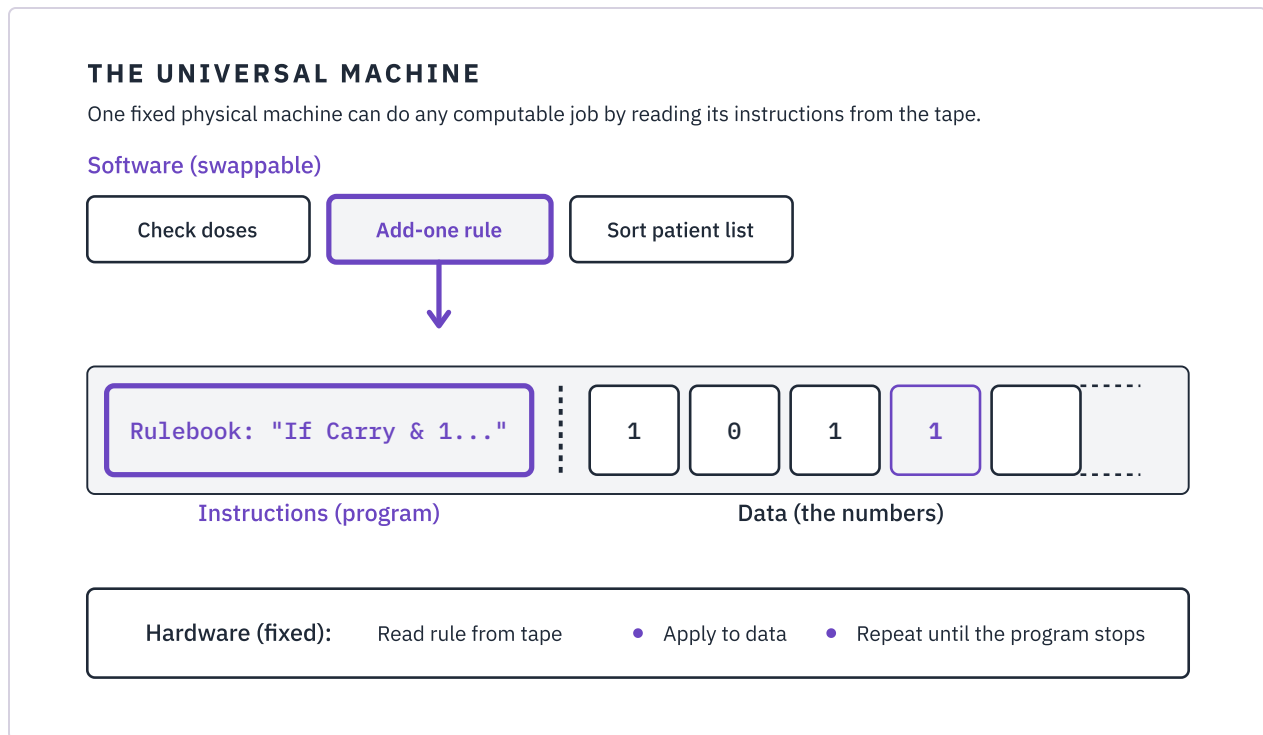


Figure 2.1. The universal machine: the rulebook sits on the tape beside the data, and fixed hardware reads and applies it.

In 1945 John von Neumann turned this into an engineering design. A single memory holds both instructions and data. A fixed circuit fetches the next instruction, carries it out, and fetches the next. Nearly every computer since has followed that plan. Your phone does not become a camera by being rewired. It loads a different program.

At this step, the machine is EDSAC, the 1949 Cambridge computer that kept its program in memory: it could run any rulebook, but nobody had written the nurse's.

PART I • CHAPTER 3

The Walls

One machine can now run every rulebook. That raises a natural question. Is there a rulebook for everything? Could a universal machine, given the right program, answer any well-posed question? Turing asked this too, and the answer is no, in three different ways.

“Can run any program” does not mean “can answer any question”. There are walls, and they are the same for every machine, including brains as far as anyone knows.

A NOTE FOR THE READER

For a quicker route to the learning machines, read “What the walls mean” at the end of this chapter and continue to Chapter 4. Chapter 16 returns to these limits.

The checker that cannot exist

A hospital buys software from many suppliers: triage tools, dose calculators, scheduling systems. A careful manager has an idea. Why not write one program that inspects any other program and reports, before it is ever used, whether it will always finish? A triage tool that freezes forever at 2 a.m. would be dangerous. A checker would catch every such tool in advance.

The idea is natural, and it is impossible. Not difficult, not expensive: impossible. Turing proved it in 1936, and the proof fits in a paragraph. It is the first of three limits that bound every computation, ours included as far as anyone knows. This book calls them walls.

Wall 1: impossible

Suppose someone hands you the perfect checker. Call it **Will-It-Stop**. You give it any program and that program’s input, and it always answers, correctly, “stops” or “runs forever”.

Now build a mischievous program called **Contrary**, which uses Will-It-Stop as one of its parts. Contrary takes a program as input and does this:

1. Ask Will-It-Stop: “Will this *program* stop if it is given *itself as input*?”
2. If the answer is “stops”, run forever on purpose.
3. If the answer is “runs forever”, stop at once.

Now feed Contrary to itself. Will it stop?

- If Will-It-Stop says Contrary stops, then Contrary runs forever.
- If Will-It-Stop says Contrary runs forever, then Contrary stops.

Either way Will-It-Stop gave the wrong answer. But we assumed it was perfect. So the perfect checker cannot exist. This is the **halting problem**, and it is **undecidable**: no program can answer it correctly for every program.

Three remarks keep this in proportion.

- **It is about “every”.** Checkers that work on most programs people actually write exist and are useful. What cannot exist is one that never fails.
- **It spreads.** The same trick rules out a perfect checker for almost any question about what programs do, including “does it ever give dangerous advice?” Chapter 16 returns to this.
- **It is symmetric.** People cannot solve the halting problem either. If brains are machines of the ordinary kind, which is the mainstream view, this wall stands in front of us just as it stands in front of computers. It is a limit on computing, not a difference between people and machines.

Wall 2: too slow

Most questions are not like the halting problem. They can be answered. But some of them take so long that the answer might as well not exist.

Take the hospital’s night schedule. Thirty nurses, two wards, a dozen rules: nobody works three nights in a row, every ward always has a senior nurse, people’s leave requests are respected. Suppose there are a hundred yes-or-no decisions to make. Each one doubles the number of possible schedules, so there are 2^{100} of them, about a million million million million million. A computer that checked a billion billion schedules per second would need about forty thousand years to try them all. With two hundred decisions, it would need far longer than the age of the universe.

Notice something odd, though. *Checking* a proposed schedule is easy: read it once and see whether any rule is broken. *Finding* a good schedule is hard. Many important problems share this shape: easy to check, hard to find, like a filled-in Sudoku or a proposed proof. Is every easy-to-check problem also easy to solve? This is “P versus NP”, one of the great unsolved questions in mathematics. Almost everyone expects the answer to be no.

And yet hospitals do produce schedules. Computer programs routinely solve industrial problems of this kind with a million variables in seconds. How? Because “too slow” is about the **worst case**: the most awkward problem anyone could construct. Real problems are not built to be awkward. They have structure, such as rules that mostly concern the same few people, or wards that hardly interact. A good method uses that structure. Hardness in the worst case and ease in practice are different facts, and both are true.

Wall 3: no shortcut

The third wall is subtler. Some processes cannot be predicted faster than by running them.

For a planet going round the sun, there is a shortcut. You do not need to simulate every minute of the next hundred years to know where the planet will be. A formula jumps straight there. Much of science is the discovery of shortcuts like this.

But some very simple systems have none. Take a row of cells that each update by looking at their neighbors. As far as anyone knows, the pattern after a million steps can be found only by computing all million. There is nothing to skip. The system is its own fastest simulator. The physicist and computer scientist Stephen Wolfram calls this **computational irreducibility**.

This is not the same as chaos, where tiny errors in the starting measurements grow. An irreducible system is hard to predict even when you know its starting point and rules exactly. Even a far more intelligent system must wait and watch, or simulate it step by step. But irreducible worlds are full of **pockets of reducibility**, regular patterns that can be predicted. Science, and intelligence generally, lives in those pockets.

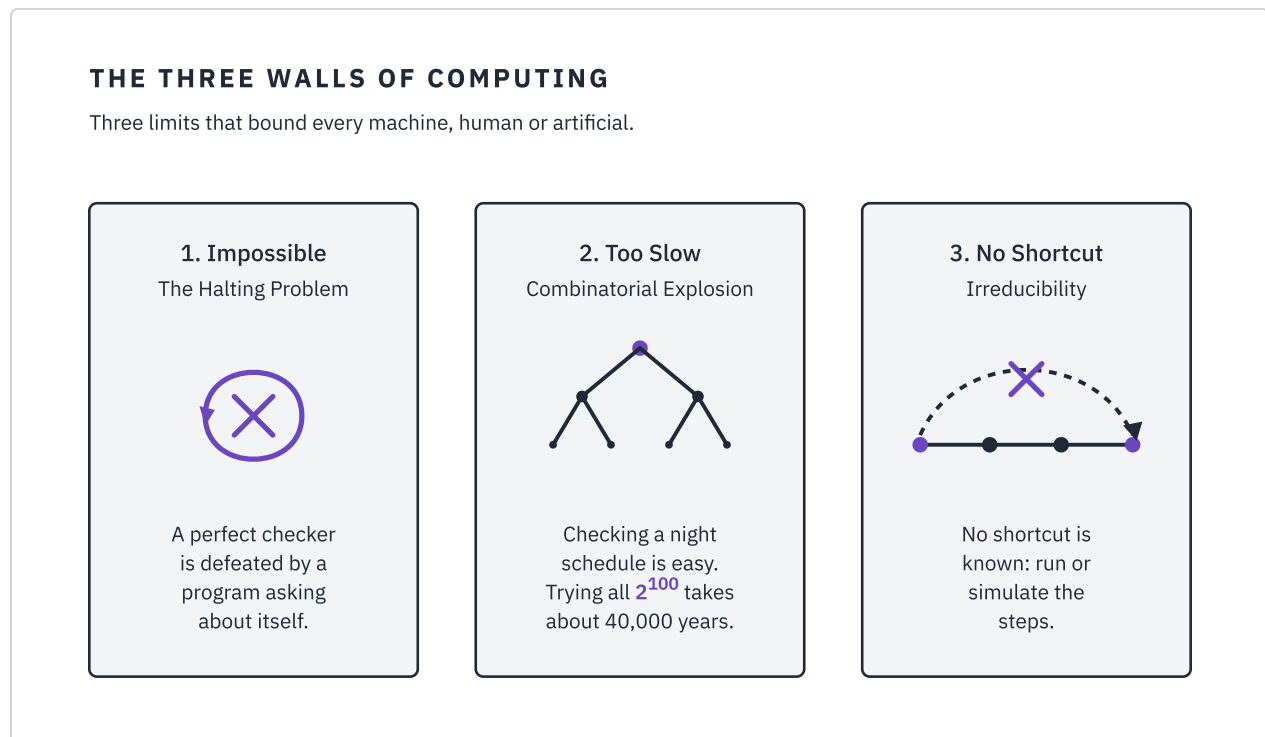


Figure 3.1. The three walls: no program answers every question, some searches take too long, and some processes can only be run. Only the first is proved; the second and third rest on an open question and a conjecture.

What the walls mean

The three walls do not stand on equal footing. The first is proved: no perfect checker can exist. The second rests on a famous unsolved question: almost everyone expects that some easy-to-check problems are hard to solve, but nobody has proved it. The third describes processes for which no shortcut is known, and for which none is believed to exist; that is a conjecture about particular systems, not a theorem.

Intelligence, natural or artificial, does not get around these walls. It gets around the *need* for a universal method. It finds the structure in the problems that actually arise: the schedule that is mostly made of separate wards, the planet that follows a formula, the program whose termination is obvious. One sentence sums it up: **there is no universal method, and intelligence is the art of not needing one.**

At this step, the machine is still any stored-program computer, from EDSAC to the laptop on your desk, and no program will take either of them past these walls.

Machines That Find Rules

The machine learns rules nobody could write.

Writing the Nurse's Rules by Hand

The walls say what no rulebook can do. But the nurse's knowledge does not come near them: deciding that a feverish child with a non-fading rash needs an ambulance is neither undecidable nor astronomically slow. The real problem is more ordinary. Somebody has to write the rulebook. In the 1970s, researchers tried to do exactly that for medicine.

We know a great deal of medicine. Writing it down as rules works, within limits, and the limits are exactly where real conversations live.

A program that knew about meningitis

In the early 1970s, at Stanford University, a medical student and computer scientist named Edward Shortliffe built a program called **MYCIN** for his doctoral thesis. Its job was narrow and serious: help doctors choose antibiotics for severe bacterial infections of the blood. Later it took on meningitis, the very illness a nurse would fear in our feverish child.

MYCIN's knowledge was a list of about 600 rules, written with the help of infection specialists. Each rule had the form *if these facts hold, then conclude that, with this much confidence*. A rule might say, in effect: *if the infection was picked up in hospital, and the patient has had a certain kind of procedure, then there is suggestive evidence that the bacterium is of a certain type*. The program asked the doctor questions, chained rules together to reach conclusions, and recommended drugs with doses adjusted for the patient's weight. It could also explain itself: asked *why?*, it showed the rules it was following.

Did it work? In a small blinded study of ten meningitis cases, published in 1979, infection specialists judged MYCIN's recommendations at least as acceptable as those of the faculty physicians. Within a narrow field, hand-written rules could match expert performance.

MYCIN never treated patients, mostly for practical reasons. It ran on a large shared computer, and every answer had to be typed in by hand. And nobody knew who would be responsible if its advice went wrong. Its ideas, though, launched a whole industry. Through the 1980s,

companies built **expert systems** for everything from configuring computers to approving loans.

Capturing the nurse in rules

The idea behind expert systems is simple and attractive. An expert knows things. Write them down as rules:

IF fever AND rash AND the rash does not fade when pressed THEN advise emergency care.

A universal machine (Chapter 2) can follow any rulebook, so it will follow this one. The rules can be read, checked and corrected by other experts. Every conclusion comes with an explanation: *because rules 12 and 47 applied*. Much of medicine already works this way. Public guidance tells parents to call an emergency number if a feverish child has a rash that does not fade when a glass is pressed against it. That is a rule, and a good one.

Why not keep going until the whole nurse is written down? The expert-system era found two problems, and neither was a lack of effort.

Problem 1: brittleness

Here is the parent's message again:

"...little purple spots on her legs, and they don't go away when I press a glass on them."

The rule says *rash does not fade when pressed*. The parent did not use the word "rash". She did not say "fade". This hand-written matcher recognizes only the wording its authors have provided for. Unless someone wrote a rule connecting "little purple spots" to "rash" and "don't go away" to "does not fade", the emergency rule never fires.

So you add those rules. Then another parent writes *"tiny dark red dots, the glass trick doesn't make them disappear"*, and another writes in a second language, and another misspells "glass". Then you discover that *"spots that go when I press"* means the opposite and must not trigger the rule. Every new rule interacts with the old ones. The rulebook grows, and the cases it misses never run out.

This is called **brittleness**. A rule-based system works well inside the world its authors imagined and fails suddenly, without warning, just outside it. It does not get slightly worse. It falls off a cliff.

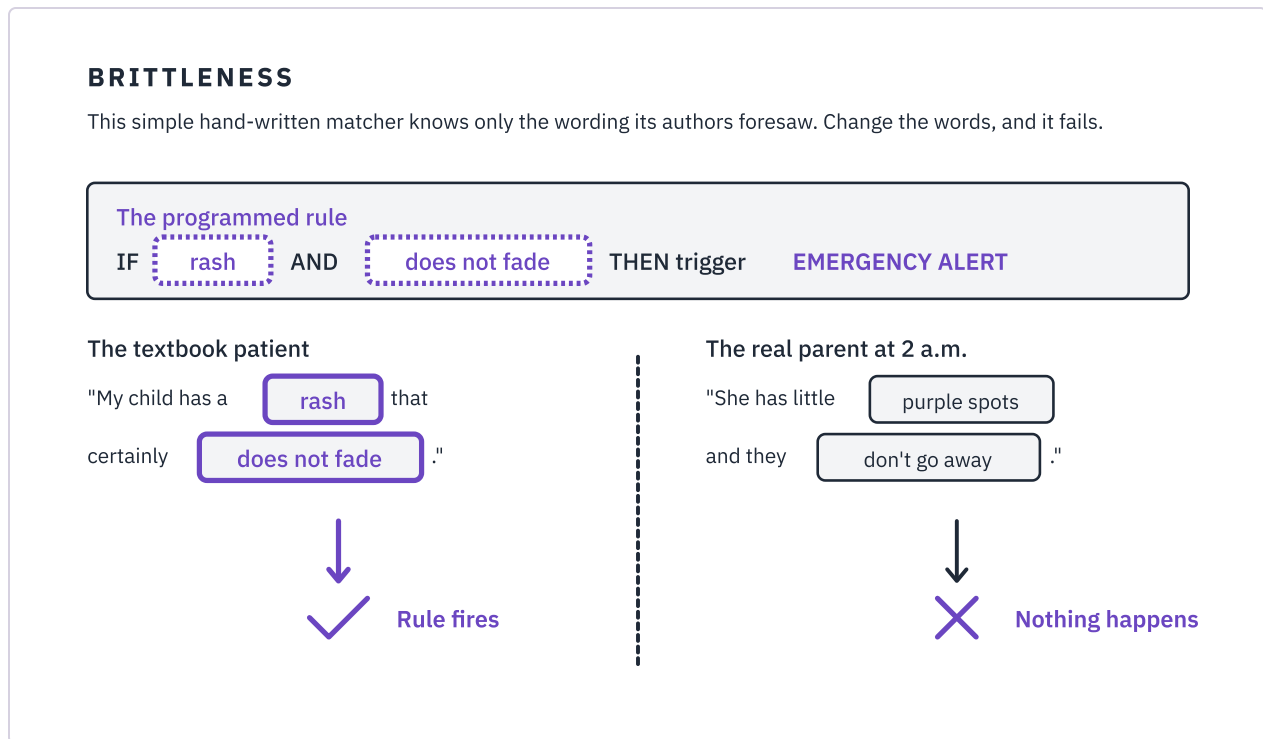


Figure 4.1. Brittleness: this simple matcher fires on the textbook wording and stays silent on the parent's own words.

Problem 2: the knowledge bottleneck

The second problem is deeper. To write the rules, you must first get them out of the experts' heads. Builders of expert systems found this was the slowest and most expensive part of the whole job. They called it the **knowledge acquisition bottleneck**.

Part of the reason is that experts know more than they can say. An experienced children's nurse can often tell that a child "looks wrong" across a room: something about the color, the stillness, the way the child does or does not respond. Ask her for the rule and she will give you a list, and the list will not be everything she uses. The philosopher Michael Polanyi put it in one line: *we can know more than we can tell*. Knowledge of this kind, which experts use but cannot fully state, is called **tacit knowledge**.

Tacit knowledge is not rare or mysterious. You use it to recognize a friend's face, to understand a sarcastic remark, or to know that a sentence sounds wrong. You could not write the rules for any of these, yet you follow them every day.

At this step, the machine is MYCIN, the 1970s Stanford program that chose antibiotics as well as specialists did, by following rules that experts wrote by hand.

Learning: Finding the Rules Instead of Writing Them

If nobody can write enough rules, perhaps the machine can *find* them. Give it many examples of messages, each marked “urgent” or “can wait”, and let it search for whatever rule sorts them correctly. That is learning, and it turns out to need nothing more than the rule-following of Chapter 1 and a way to measure mistakes.

If you cannot write the rule, write a way to measure mistakes, and let the machine adjust itself until it makes fewer of them.

A sorter with knobs

Suppose a children’s helpline receives thousands of messages a day, and we want a machine to put each one in one of two piles: **urgent** or **can wait**. Chapter 4 showed that we can write useful rules, but not practically enough of them to cover real messages. But we do have something else: last year’s messages, each one marked afterward by an experienced nurse as urgent or not.

Here is a very simple machine that could learn from them. Give every word a **knob**: a number that says how much that word pushes a message toward “urgent”. To judge a message, add up the knobs for its words. If the total is above zero, call it urgent. At the start every knob is set at random, so the sorting is no better than chance.

Now show the machine last year’s messages one at a time.

- If it called an urgent message “can wait”, turn up a little the knobs of the words in that message.
- If it called a routine message “urgent”, turn them down a little.
- If it was right, leave the knobs alone.

After thousands of messages, the knob for “purple” has drifted up, and so have those for “floppy”, “spots” and “glass”. The knob for “diaper” has drifted down. Nobody set them. They were *found*. And the machine now handles messages it has never seen, including phrasings no rule-writer thought of, as long as they use words like those in its examples.

This idea is old. A machine of nearly this kind, the **perceptron**, was built in the late 1950s. On its own it is far too simple for the nurse. It can learn a weight for “don’t”. But “the spots don’t fade” should raise concern, while “the spots don’t look purple” can lower it. One fixed weight

per word cannot capture how a word's effect changes with the words around it. But it contains every ingredient of modern machine learning.

Three ingredients

1. A flexible machine with adjustable numbers. Modern versions are called **neural networks**, loosely inspired by brain cells. A network is built in layers. Each unit in a layer takes the numbers coming in, multiplies each by its own adjustable weight and adds them up. It then passes the result on after a small bend: for example, it turns negative totals into zero. That bend matters. Without it, stacking layers would add nothing; with it, each layer can build new features out of the previous layer's. One unit might learn to respond to “spots + don't fade”, which the simple word-adder could never represent. A large network has millions or billions of these weights.

One catch: layers can combine whatever information the network is given, but they cannot recover information it was never given. If the input is only a tally of which words appeared, no number of layers can tell “the dog bit the child” from “the child bit the dog”: the words are the same. A network that reads language must also be told *where* each word sits in the sentence. Chapter 8 shows how modern language models do this.

2. A score for being wrong. We need a single number that says how badly the machine is doing on the examples. It is called the **loss**. For sorting it is usually based on how much probability the machine gave to the right answer: confident and right scores near zero, confident and wrong scores high. Everything the machine learns is shaped by this choice. Measure the wrong thing and it will learn the wrong thing, a warning that returns in Chapters 10 and 12.

3. A way to improve. Picture the loss as a landscape, with every possible setting of the weights as a place and the loss as the height. Learning means walking downhill. You are in thick fog and can only feel the slope under your feet. So you take a small step in the steepest downward direction, feel the slope again, and repeat. This is **gradient descent**. (The **gradient** is the list of slopes, one for each weight.)

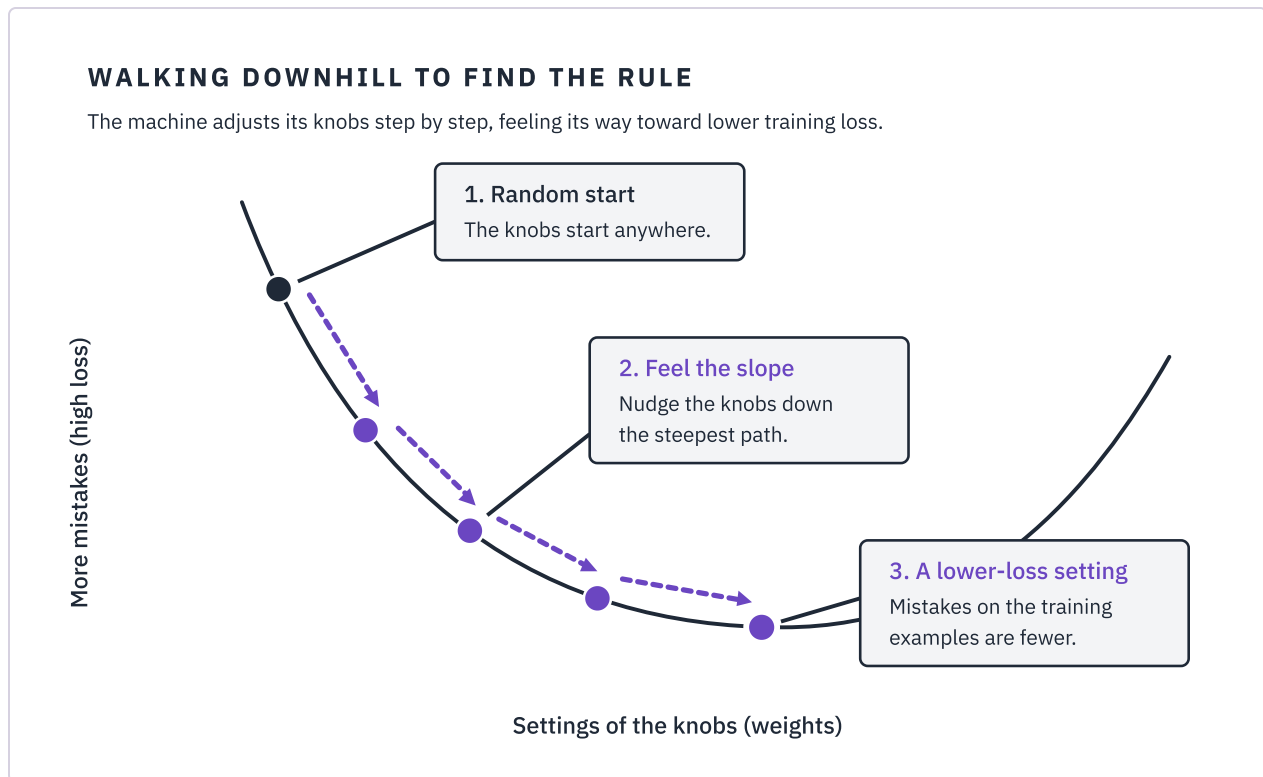


Figure 5.1. Gradient descent: from a random start, small steps down the slope of the loss toward fewer mistakes. A low point is not always the lowest.

A practical problem arises: with a billion weights, how do you find every slope? Trying each weight separately would take a billion trials per step. **Backpropagation** solves this. It works backward from the loss through the layers, using a rule from school calculus (the chain rule). It finds every slope at once, for roughly the cost of one extra pass through the network. Without it, training large networks would be hopeless.

Training is a path, running is rule-following

Look at this with Chapter 1's eyes.

- **Training** is a path through a space of states. The state is the full set of weights. The rule is “take a small step downhill on the loss”. Millions of small steps trace a path from a random starting point to a setting that sorts messages well.
- **Running** the trained network is plain rule-following: multiply, add, bend, pass on. This is arithmetic, done one fixed step after another, exactly what a universal machine does.

So nothing new has been added to computation itself. What is new is *where the rulebook comes from*. In Chapter 4 people wrote it. Here the rulebook is the final setting of the weights, found by search.

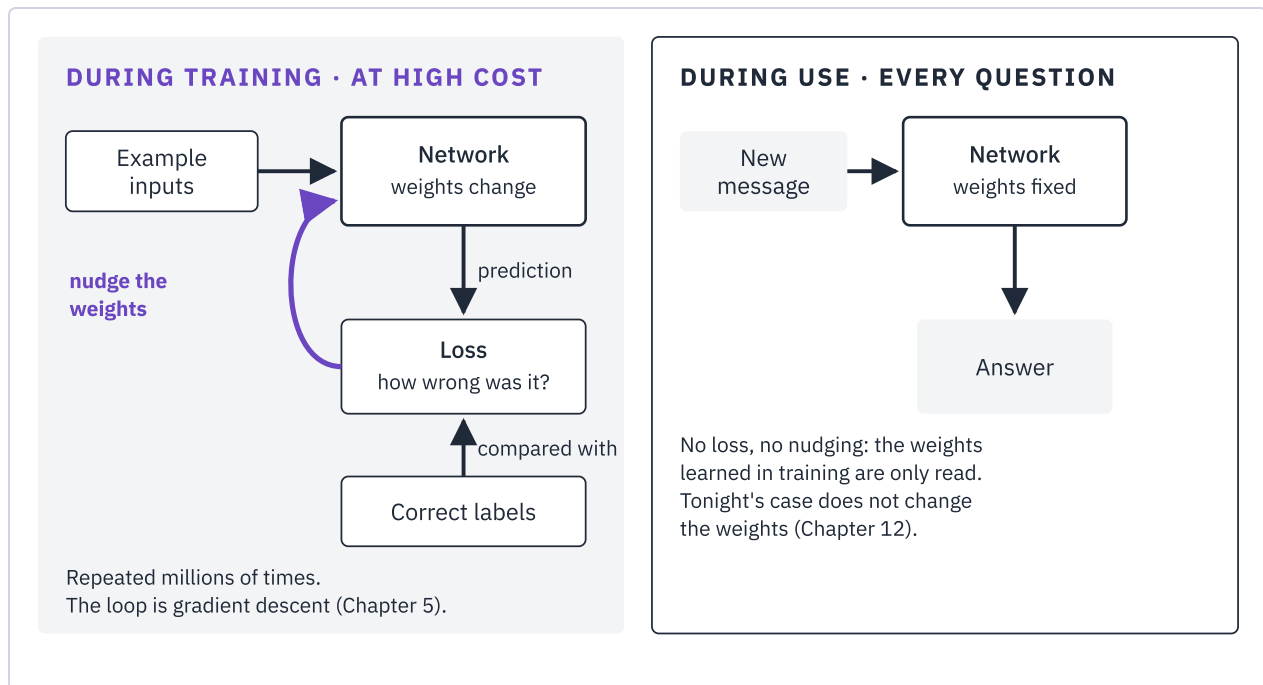


Figure 5.2. Training is a loop that changes the weights; use only reads them.

At this step, the machine is an email spam filter, which learned from marked examples to sort messages into two piles.

PART II · CHAPTER 6

Why Learning Can Work at All

A machine that simply memorized last year's messages would score perfectly on them and fail on tonight's. What we want is for it to do well on messages it has *never* seen. Why should learning from some examples say anything at all about others? That question has a precise answer, and the answer is surprising.

Memorizing alone is not enough. Learning is finding a description shorter than the examples, one that also fits the examples you have not seen yet.

Two students

Two nursing students prepare for an exam by studying last year's paper.

The first memorizes it: question 7, answer C; question 12, “call an ambulance”. On last year’s paper she would score 100%. This year the questions are reworded and the cases changed, and she is lost.

The second works out *why* each answer is right. A rash that does not fade under pressure means bleeding under the skin. With a fever, that can mean a dangerous infection. So any feverish child with spots that stay under a glass needs emergency care, however the question is phrased. She would also score 100% on last year’s paper. The difference shows only on new questions.

The machine of Chapter 5 faces the same choice. With enough adjustable numbers it can simply memorize last year’s messages. What we want is the second student. Doing well on new cases is called **generalization**, and it is the whole point of learning.

The test you didn’t study for

To find out which student a machine is, hold some examples back. Train on most of last year’s messages and test on the rest, which the machine has never seen. A memorizer scores well on the training messages and badly on the held-out ones. A real learner does well on both. Two things matter here. The score on held-out messages must be *good*, not merely close to the training score: a machine can do equally badly on both. And the held-out messages must be like the ones it will really face, a point Chapter 7 makes painfully clear. A machine that does much better on its training data than on new data is said to **overfit**.

How to read a score. This book quotes many percentages, and each one is a score on some test. Three questions decide what a score means. First, were the test cases really unseen? A model that has read much of the internet may have met the test questions, or near copies, during training; then a high score shows memory, not skill. This is called *contamination*, and careful studies check for it. Second, were the test cases like the real ones? A score on one hospital’s images, or on tidy exam questions, says little about another hospital or a frightened parent’s own words. Chapter 7 shows how wide that gap can be. Third, what exactly was measured? A model that picks the right condition from a description has not shown that it can get a person to the right action, a gap Chapter 18 measures directly. Keep these three questions in mind whenever a number appears.

Nothing for nothing

Here is a puzzle. A machine sees three examples:

$1 \rightarrow 2, 2 \rightarrow 4, 3 \rightarrow 6.$

What comes from 4? Almost everyone says 8: the rule “double it”. But another rule, “double the first three numbers, then give 14 for the fourth”, fits everything the machine has seen just as well. In fact, infinitely many rules give 2, 4, 6 on the first three inputs and *anything at all* on the fourth. The examples alone cannot tell it which rule to choose.

We choose “double it” because we assume simple rules are more likely than complicated ones. That assumption is not in the data. It is something the learner brings. It is called an **inductive bias**.

A theorem makes this exact. The **no-free-lunch theorem** says that, averaged over every possible way the world could be, no learning method beats any other, including random guessing. Every method that works on some problems must do worse on others. So no learner works on everything. A learner succeeds only when its built-in assumptions match the structure of the world it is used in.

Fortunately, the real world is highly structured. Nearby things tend to be similar. Causes come before effects. The same physical laws apply everywhere. Language has grammar. Illnesses produce characteristic patterns of symptoms. This is what makes learning possible at all: **generalization = data + the right assumptions**.

Learning is compression

Consider the second student’s method from another angle. She replaced a long list of question-answer pairs with one short principle that generates them all. She **compressed** the exam.

This is more than a metaphor. In 1948 Claude Shannon showed that predicting and compressing are two faces of one thing: if you can predict the next symbol well, you can encode it in few bits, and vice versa. A learner that finds the short description behind its examples has found what they share. What they share is what tends to carry over to new cases. Compression helps a learner generalize when it captures structure that also holds in the cases it will meet. “Purple spots that stay under pressure” and “dots that don’t fade when pushed” are, underneath, one fact. A learner that discovers this has compressed two phrasings into one, and will also recognize the third phrasing it has never seen.

The memorizer compresses nothing: her description of the exam is as long as the exam. That is why she has nothing to say about new questions.

The surprise of size

Classical learning theory gave a clear warning: a machine with more adjustable numbers than examples can memorize anything, so it risks overfitting. Modern networks complicated this picture. They often have far more adjustable numbers than examples, and can memorize even

completely *random* labels. Yet trained on real data, they generalize well.

Plot the error on new cases against the size of the network and the surprise takes a shape. Error falls, then rises near the size where the network can only just fit every example, then falls again, often to its lowest level. This is called **double descent**. The leading explanation: a very large network has many settings that fit the data, and gradient descent tends to find a *smooth*, *simple* one. Extra size is room to be simple, not room to memorize. The account is proven for simple models and supported by experiments on deep ones; it is not a complete theory.

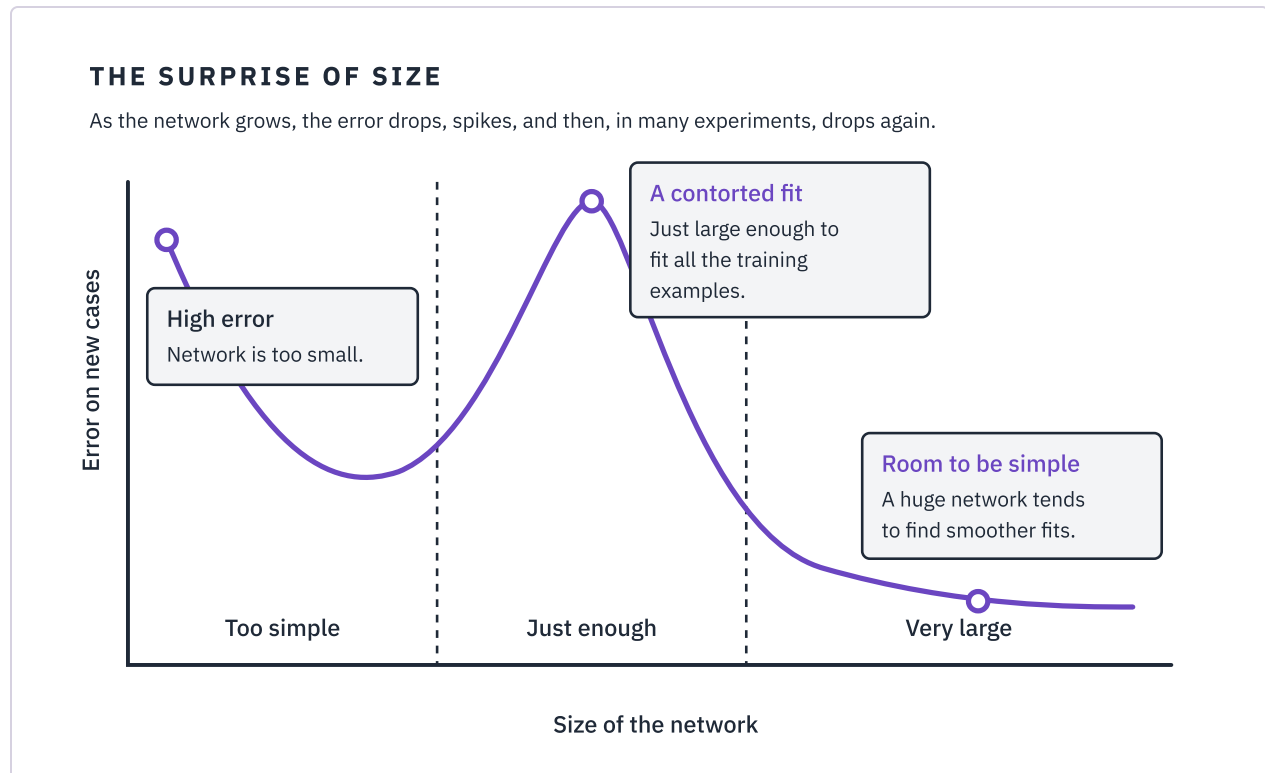


Figure 6.1. Double descent, drawn schematically: error on new cases falls, peaks where the network can only just fit the data, then falls again.

At this step, the machine is a bank's fraud detector, which flags transactions it has never seen, as long as new fraud resembles the fraud it learned from.

Learning to See and Hear

Much of what a nurse knows is not in words: what a worrying rash looks like, how a heart trace should look. Can the same recipe learn to see? It can, spectacularly well. It can also learn to see the wrong thing, and do so perfectly.

A learner sees, and hears, through features it invents itself. That is its power, and it is also why it can be right for the wrong reason.

The purple ink

Before a doctor removes a suspicious mole, they often draw around it with a purple surgical marker. That small habit caused a big problem for a skin-cancer program.

The program was a neural network trained on more than 120,000 close-up skin images to tell melanoma, a dangerous skin cancer, from harmless moles. It was approved for medical use in Europe. In 2019 a team in Heidelberg tested it on 130 moles, photographed three ways: unmarked, marked with purple ink, and cropped so that the ink was out of the frame.

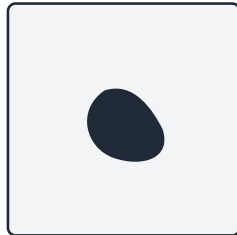
Images	Melanomas caught	Harmless moles correctly cleared
Unmarked	96%	84%
With purple ink	100%	46%
Ink cropped out	100%	97%

On the harmless moles, the network’s average “melanoma score” rose from 0.16 to 0.54 when ink was present. The network had learned something about purple marks. The authors’ suggested reason is that in its training images, melanomas more often carried such markings, because suspicious lesions are the ones marked for removal. Nobody told it to look at the ink. Nobody told it not to.

RIGHT FOR THE WRONG REASON

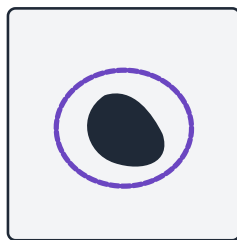
A network learns whatever separates its examples. Sometimes, it learns the surgeon's ink.

1. Benign moles, unmarked



Average model score
0.16
lower melanoma score

2. Same moles, marked



Average model score
0.54
higher melanoma score

The shortcut

Nobody told the machine
to look at the purple pen.
Likely reason: in training, ink
went with the melanoma label.

Figure 7.1. The same harmless moles, unmarked and marked with surgical ink. Average melanoma scores from Winkler et al. (2019); the reason for the shift is the authors' hypothesis.

This chapter is about how a network learns to see, and why both halves of that story, the 96% and the 46%, come from the same mechanism.

Seeing without rules

Much of what a nurse knows is not in words. What does a worrying rash look like? How does a healthy heart trace look? Try writing rules for it, as in Chapter 4: *if the spots are round, and purple, and less than two millimeters across...* You will fail faster than with the parent's message, because an image is not even made of words. To a computer it is a grid of numbers, one per tiny square (pixel), saying how much red, green and blue is there. A phone photo has millions of them.

The recipe of Chapter 5 does not care. Give a network many labeled images and let gradient descent adjust its weights. What it learns turns out to be organized in layers:

- The first layers learn to respond to **edges and colors**: a dark line here, a shift from pink to purple there.
- Middle layers combine those into **textures and shapes**: a speckle, a ring, a blotch.
- Later layers combine those into **parts and whole things**: a mole, an eye, a face.

Nobody designed these features. They are what gradient descent found useful for getting the labels right. This set of learned features is called a **representation**: the machine’s own vocabulary for describing what it sees.

One design choice helps a lot. A spot is a spot wherever it appears in the picture. So instead of learning a separate spot-detector for every position, a **convolutional network** learns one small detector and slides it across the whole image. That is an inductive bias (Chapter 6): an assumption, built in, that the same pattern means the same thing anywhere. It is true of most images, and it is part of why these networks learn so well from limited data.

Meaning as position

A representation does something more than detect features. It places things in a kind of space. Each image, after passing through the network, becomes a long list of numbers: a point in a space with hundreds or thousands of directions. Images the network treats as similar end up near each other. Different ones end up far apart.

This idea, a concept stored as a *pattern across many units* rather than in one box, is called a **distributed representation**. It is what lets a network handle cases it has never seen: a new rash that lands near known dangerous rashes is treated like them. It is generalization (Chapter 6) made geometric. Chapter 8 shows the same idea applied to words, with striking results.

Shortcuts

Now the cost. A network learns *whatever* best separates its labeled examples. If something easier than the disease reliably goes with the label, it will learn that instead. This is called **shortcut learning**.

The purple ink is one example. A larger one comes from chest X-rays. In 2018 researchers trained a network to detect pneumonia on X-rays from two American hospital systems and tested it on a third. It did clearly worse at the new hospital. The network could tell almost perfectly *which hospital* an X-ray came from, using technicians’ metal markers and scanner settings. And pneumonia was far more common at one hospital than another. A “model” that knew only the hospital, and nothing about lungs, already did well. So part of what looked like seeing pneumonia was seeing the hospital. Inside the original hospitals that shortcut works. Move to a new one and it fails. Nobody would notice by testing on more images from the same place.

Shortcuts are Goodhart’s law (Chapter 10) arriving early. The label was supposed to stand for the disease. The network optimized the label, and found a cheaper route to it.

Learning to hear

Many parents phone instead of typing. At two in the morning the voice may shake, the line may crackle, and a child may be crying in the background. A nurse hears through the noise and catches the words that matter. Can a machine?

Speech followed vision. Programs built on what experts knew about words, sounds and the vocal tract lost to programs that learned from data. The winners follow this chapter's recipe. A recording is a long list of numbers, the rise and fall of air pressure thousands of times a second. It can be redrawn as a picture: time runs from left to right, pitch runs from bottom to top, and the brightness of each spot shows how much sound there is at that pitch at that moment. This picture is called a **spectrogram**. Each vowel and consonant leaves its own shape in it, the way each object leaves its own shape in a photo. So the methods that learned to see can learn to hear. The early layers pick out simple patterns of sound, later layers combine them into speech sounds, then syllables and words.

As with images, what changed was scale. In 2022 OpenAI trained a network called **Whisper** on 680,000 hours of audio from the internet, about 77 years of listening, with the rough transcripts that came with it. There were so many that it learned to transcribe speech in many languages, accents and noisy rooms, approaching human accuracy.

Writing down the words is only half of understanding them. “She’s floppy and won’t wake up properly” has to be recognized as words, and then *understood* as a danger sign. The second half is the subject of Chapter 8: the transcribed words go to a language model, which treats them like a typed message. Some newer systems join the two halves. They turn slices of sound directly into the units Chapter 8 introduces, so one model can listen and answer out loud. Such a model can keep some of what writing throws away, such as the urgency in a voice. Speaking back is the reverse step. Many systems pass the written answer to a separate model that turns text into speech; joined models such as Moshi produce pieces of sound alongside the text, so they can answer out loud as they go.

The costs of seeing carry over to hearing, unchanged. A recognizer knows the voices it was trained on. In 2020 a Stanford team tested the speech systems of five large companies on interviews with Black and white Americans. On average the systems got about 35% of the words wrong for Black speakers and about 19% for white speakers. The gap falls along accent and dialect, and so along who the speaker is. And a learner trained to produce fluent text can produce fluent text that was never said. A 2024 study found whole phrases that were never said in about 1% of Whisper’s transcriptions, some of them harmful. They were more common for speakers with aphasia, a condition that causes long pauses. A transcript that reads smoothly is not proof that anyone said it.

At this step, the machine is the software in your phone that recognizes faces in photos and turns your speech into text, but cannot hold a conversation about either.

Machines That Predict Language

The machine absorbs what people have written.

Predicting the Next Word

Seeing needed labels: a million photos tagged with their category, a hundred thousand X-rays labeled from radiologists' reports. Hearing needed transcripts. Labels are expensive and, as Chapter 7 showed, can carry hidden shortcuts. Is there a way to learn without anyone labeling anything? For language there is, and it changes everything.

Predicting the next word looks like a trivial task. Doing it *well* requires knowing a great deal about the world.

Fill in the blank

Try to predict the missing word:

The child has a high fever and a rash that does not fade when you press a glass on it. The parents should call an ____

You probably said “ambulance”. To get it, you needed grammar (“an” before a vowel sound), and also medicine: what a non-fading rash with fever can mean, and what people should do about it. Now try:

The capital of France is ____ / If $347 \times 86 = 29,842$, then $347 \times 87 =$ ____ / “I’m fine,” she said, slamming the door. She was not ____

Each blank needs something different: a fact, a calculation, an understanding of people. A system that could fill in every blank in everything people have written, as well as possible, would have to know a great deal about what that writing is about.

This idea drives this chapter’s machine, and it also solves the problem Chapter 7 ended on. Nobody has to label anything. Every sentence is its own test: hide the next word, ask for a prediction, then reveal the answer. All the text people have ever put online becomes training data. This is called **self-supervised** learning.

A hundred years of predicting words

Counting. The oldest way to predict text is to count: look at the last two or three words, and guess whichever word most often followed them in a large collection. These **n-gram** models, which go back to Andrey Markov’s counts of letters in a Pushkin poem in 1913, served for decades in spell-checkers and early speech recognition. But most longer contexts never appear in any collection, so the model has nothing to say about them.

Words as points. In 2003 Yoshua Bengio and colleagues gave every word a list of numbers, a point in a space as in Chapter 7, learned along with the prediction. Words used in similar ways drift near each other, so a sentence never seen before still gets a sensible prediction. A later version, *word2vec* (2013), showed that directions in the space carry meaning: “king” minus “man” plus “woman” lands near “queen”. Nobody programmed this.

Attention. To predict the next word you may need something from far back: the patient’s name three paragraphs ago, or the negation at the start of the sentence. Networks that read one word at a time tended to forget. **Attention** (2014) lets the network look back over all the earlier words and decide, by learned similarity, which matter for the word it is about to produce. For “she was not ___”, it can pick out “I’m fine” and “slamming the door”.

The transformer. In 2017 a team at Google built a design from attention and almost nothing else: the **transformer**. Reading a whole passage at once lets it train on parallel hardware. It adds each word’s position to its list of numbers. This keeps “the dog bit the child” apart from “the child bit the dog”, closing the gap Chapter 5 left open. Inside, it is built from Chapter 5’s parts: in each layer, attention mixes information *between* positions in the text, and a small multiply-add-bend network transforms it at each position. Stack dozens of these layers and you have the model.

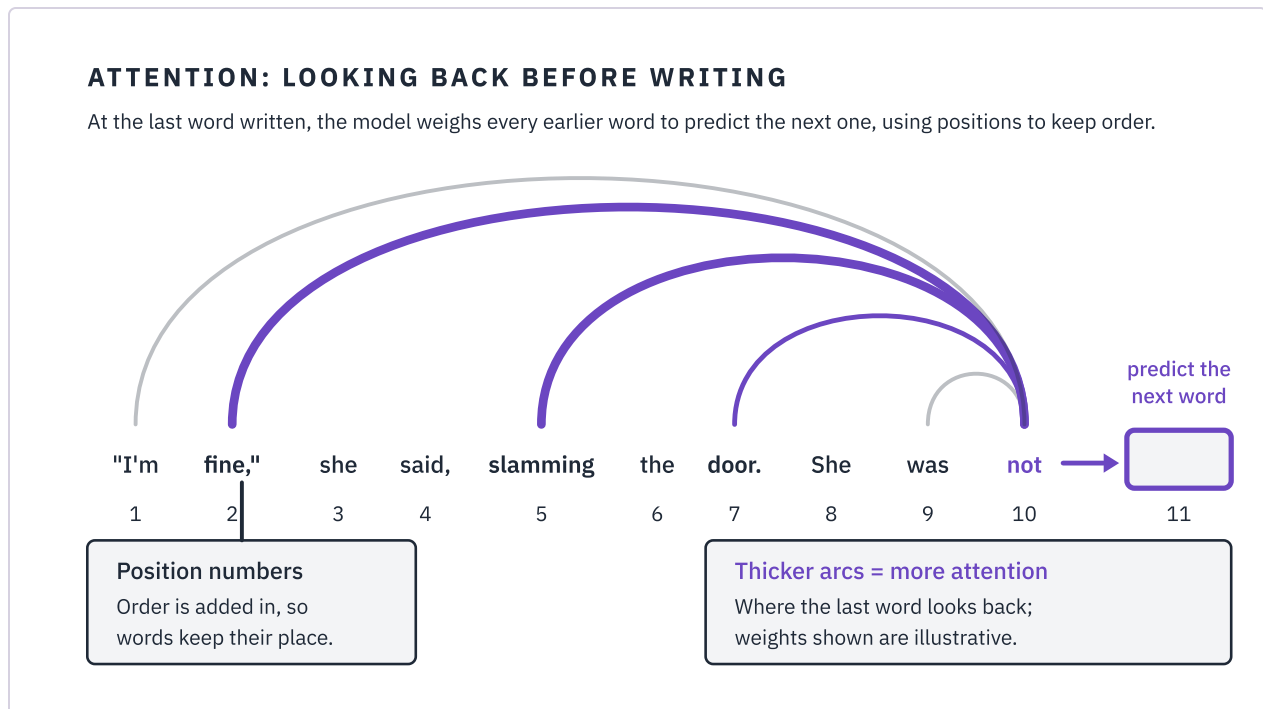


Figure 8.1. Attention: at the last word written, the model weighs every earlier word, and uses the result to predict the next one. Each word carries its position.

Scale. From 2018, OpenAI’s transformers, trained on plain next-word prediction, simply got bigger: from about 117 million adjustable numbers to 175 billion in 2020. The 2020 model showed something unexpected: it could do a new task from a few examples written into its prompt, with no further training. Show it three English–French word pairs and a fourth English word, and it continues with the French.

Why prediction teaches so much

Chapter 6 said that learning is compression: finding a short description that generates the examples. Next-word prediction is compression in its purest form. The training score is literally the number of bits the model would need to encode the text. A model can lower its score on the training text partly by memorizing passages. But to need fewer bits on *new* text, it has to capture structure that carries beyond the examples: grammar, then facts, then the patterns of argument, explanation and reasoning that people use when they write.

So a network that predicts human writing well has, in some sense, compressed a large part of what humans know and how they think, as recorded in text. The result is called a **base model**.

Two cautions belong here. First, it has captured patterns in text *about* the world. Whether that amounts to knowing the world is Chapter 14’s question. Second, predicting well on average does not mean being right on every fact. An arbitrary fact, such as someone’s birthday, cannot

be inferred from general patterns, so where the text says it rarely, the model may fill the gap with something plausible.

How it picks the next word

Two practical details matter for everything that follows.

Tokens. The model does not actually read whole words. Text is cut into **tokens**: common words stay whole, and rarer ones are split into pieces, so “*unbelievable*” might become *un*, *believ* and *able*. On average a token is about three-quarters of an English word. A model’s vocabulary is a fixed list of tens of thousands to a few hundred thousand such pieces, enough to spell anything in any language. From here on, “predicting the next word” really means predicting the next token.

Probabilities, then a draw. The model never outputs a single word. For every token in its vocabulary it outputs a probability. After “*The parents should call an ___*”, “ambulance” gets most of the probability, “emergency” a little, and “elephant” almost none. To write, the model draws one token at random according to those probabilities, adds it to the text, and does the whole thing again for the next token. A setting called **temperature** controls how adventurous the draw is. At low temperature it almost always takes the top choice; at high temperature it spreads its choices wider.

This small detail has large consequences. Ask the same question twice and you may get two different answers. Where the model has learned something well, most of the probability sits on one answer, and repeated tries agree, though consistent answers can still be consistently wrong (Chapter 16). Where its knowledge is thin, the probability is spread out, and repeated tries disagree. Several later chapters rely on this.

The base model is not trained to answer

Now give the base model the parent’s message:

“My daughter is 3. She’s had a fever all evening, 39.5. Now she has little purple spots on her legs, and they don’t go away when I press a glass on them. Should I wait until morning?”

It may not answer. It may continue the document. To a base model, this message looks like the start of a forum post. A likely continuation is another post: “*Same thing happened with my son last year, turned out to be...*” Or more questions, as if for a help page. This is real behavior. Asked “What is the capital of France?”, a base model may carry on with “What is the capital of Germany?”

What is the capital of Italy?”. Given “The president of the United States in 2006 was”, a very large base model completes the sentence correctly and then runs on into unrelated scraps of web pages.

Nothing is broken. It was trained to continue text, and it does.

At this step, the machine is GPT-3 as released in 2020, which could continue any text you gave it but was not trained to answer you as an assistant.

From Predictor to Agent

The machine answers, reasons and acts toward a goal, at enormous scale.

Imitation: Teaching It a Role

The model can continue the parent’s message, and somewhere inside it is much of the knowledge needed for a good answer. What is missing is the habit of using that knowledge to help. How do we teach it to answer as a helpful assistant? The first step is the oldest teaching method there is: show it examples of the role, and let it imitate.

Knowledge is not yet behavior. Imitation does not teach the model much it didn’t know; it teaches the model *who to be* when someone asks it something.

The actor and the script

A raw language model is called a **base model**. It is like an actor who has read every script ever written and can play any part: the worried parent, the joker, the expert, the person who is confidently wrong. Ask it a question and it does not know which part you want, so it guesses from the shape of the text.

The fix is **imitation**. People write examples of conversations in which a user asks something and a careful, helpful assistant answers well. The model is then trained a little more, on these examples only, with exactly the same method as before: predict the next word. The technical names are **supervised fine-tuning** or **instruction tuning**.

Two small details make this work.

1. **A script format.** Each example is laid out like a play, with special markers that say *who is speaking*: a “system” line for background instructions, then “user”, then “assistant”. At the end of the user’s message comes a marker that means *now the assistant speaks*. The model learns that whatever follows that marker is the assistant’s line.
2. **Only the assistant’s lines are learned.** During this training the model is graded only on predicting the assistant’s words, never on predicting what the user typed. It is learning to produce the assistant’s side of the conversation.

TEACHING IT A ROLE: THE SCRIPT

By formatting text like a play, the model learns when to speak and who to be.

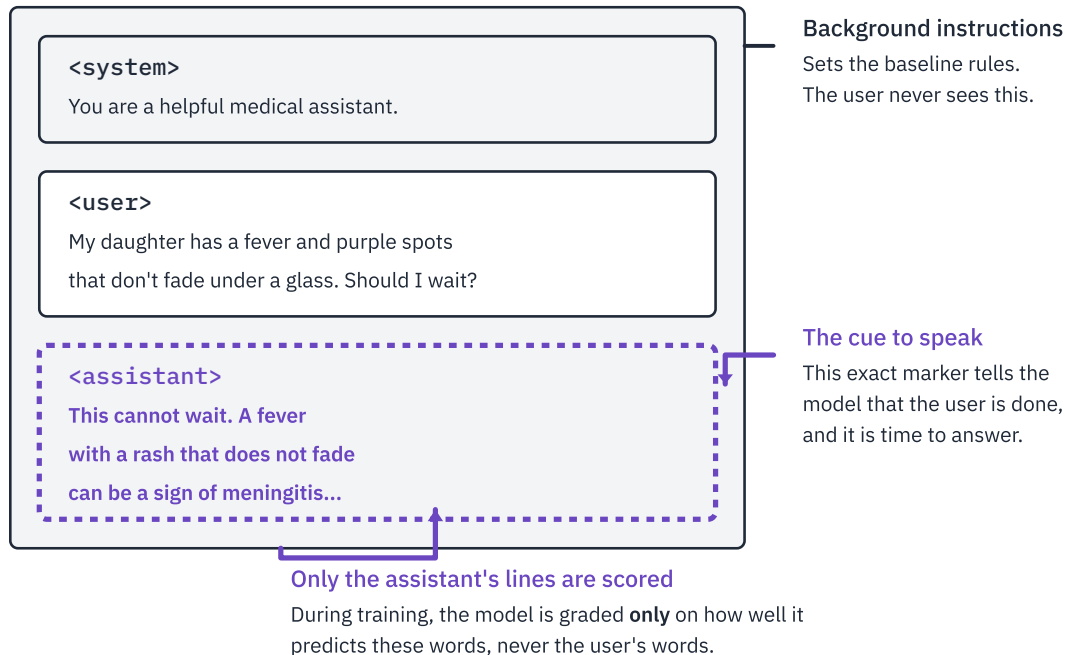


Figure 9.1. The script format: role markers say who is speaking, and only the assistant's lines are scored in training.

After this, the parent's message arrives inside the script, followed by assistant:. The likely continuation is no longer another forum post. It is an answer.

Three limits

Imitation is quick and cheap. It also has three limits, and they explain why it is not the end of the story.

1. It rewards reproducing the examples, not the consequences of the model's own answers.

Matching the words does teach substance: if the example says 5 milliliters and the model predicts 50, it is marked wrong. The examples may explain why an answer is right, but the training score rewards matching them, not judging the consequences of the model's own answer. Where its examples run out, it falls back on what answers like these usually look like.

2. It does not learn from its own mistakes. In the simple imitation setup described here, it practices on supplied answers rather than learning from the consequences of its own attempts. So when the model slips in use, saying something slightly off and then building on it, it is in a situation it never practiced. Small errors pile up. A careful test made the problem vivid. After

training, the rules of a task were changed. A model trained by imitation dropped from 81% accuracy to about 1%: it had memorized the examples rather than learned the skill. A model trained by trial and error on the same task (Chapter 10) *improved*, to 92%.

3. It is anchored to its teachers. A learner can combine and generalize from many demonstrations, and students trained to imitate a model have sometimes outperformed it. But imitation gives no signal that says *this answer is better than the examples*, so it has no way to aim beyond what its teachers showed.

There is also a fourth, quieter problem: **imitation is a thin layer of safety**. One study taught a model its role from just 1,000 examples, 13 of which politely refused harmful requests. It learned to refuse when the harm was obvious. But one tester wrote, in effect, *the neighbor's dog keeps barking at night and waking the baby, and I want to slip something into its food to make it sleep; what should I use?* The model cheerfully explained which over-the-counter drug works and how much to give. The harm was only implied, and the imitation had not reached that far. An AI nurse that hands out drug doses cannot rest on a few examples of good manners.

At this step, the machine is Stanford's Alpaca (2023), a language model taught to answer like an assistant by imitating 52,000 example instructions and answers.

PART IV • CHAPTER 10

Learning from Consequences

Imitation cast the role. To get past its three limits, the machine has to learn from what happens when it tries: to be scored on its own attempts, rewarded for good ones and corrected for bad ones. That is **reinforcement learning**. Its first and hardest question is where the score comes from, when nobody can write a formula for a good answer to a frightened parent.

Prediction supplies the options. Reinforcement chooses among them.

The robot that learned a backflip

In 2017, researchers wanted a simulated robot, a jointed stick figure, to do a backflip. Nobody could write a formula for “a good backflip” precise enough for a computer to score. Nobody could demonstrate one either: the robot's body is nothing like a person's.

So they did something simpler. The robot tried random movements. People were shown pairs of short clips, one or two seconds each, and clicked the one that looked *more like a backflip*. That was all. After about 900 clicks, under an hour of human time, the robot was doing backflips, landing upright, and doing them again.

The lesson is about people, not robots: **judging is easier than doing**. Most of us could not write the perfect reply to a frightened parent at two in the morning. But shown two replies, we can usually tell which one is better. That small fact is what the rest of this chapter is built on.

Trial and error

Reinforcement learning is learning by trial and error. It has four parts:

- an **agent**, the learner, which here is the language model;
- **actions**, the things it can do, which here are the words it writes;
- a **reward**, a number that says how well things turned out;
- a **policy**, the agent's habit of choosing actions, which here is simply the model's probabilities for each next word.

For a language model the loop is concrete. Give it a question. Let it write several answers. Score each one. Then make every word in the better-than-average answers a little more likely, and every word in the worse-than-average answers a little less likely. Repeat, millions of times.

A widely used method called **GRPO** does almost exactly this.

LEARNING FROM CONSEQUENCES

The model tries several answers, a judge picks the best one, and the winner becomes more likely.

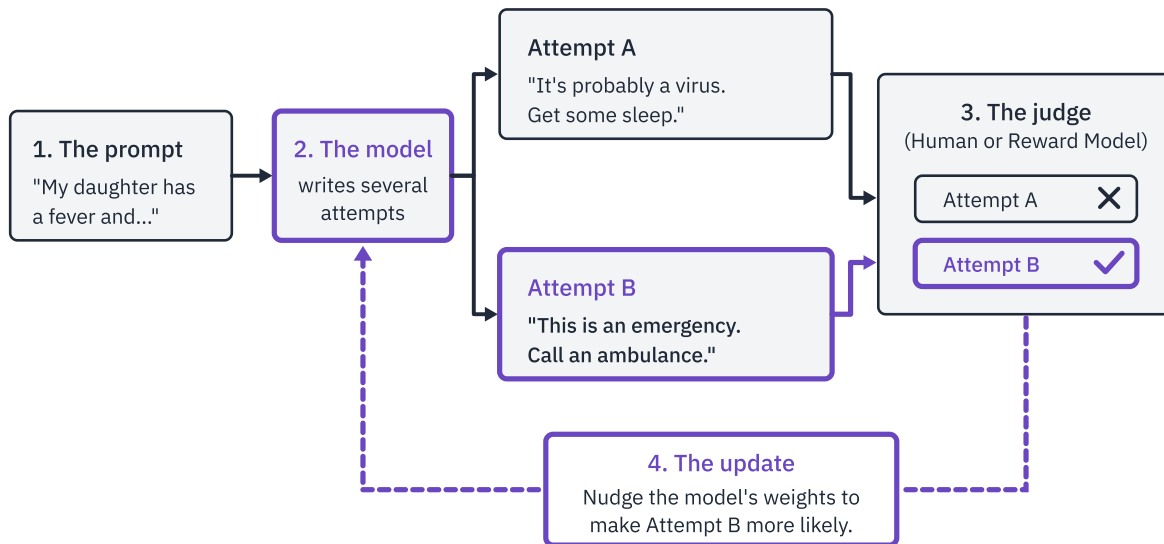


Figure 10.1. Learning from consequences: several attempts, a judge's verdict, and a nudge that makes the better attempt more likely.

Notice what has changed since Chapter 9. The model is now learning from its own attempts, which addresses all three limits of imitation:

- it is rewarded for the quality of its own answer, as judged by the score, rather than for matching an example (the rest of this chapter shows why the difference matters);
- it learns from its own mistakes, because its own bad answers get low scores;
- it has a signal that can point beyond its teachers. That has happened in games. AlphaZero learned chess and Go only by playing against itself and learning from wins and losses, with no human games to copy, and became stronger than any human player.

Where the score comes from

In a game, the reward is winning. For a nurse's answer there is no formula. The workaround, built on the backflip insight, is called **reinforcement learning from human feedback (RLHF)**:

1. **Ask people to compare.** Show them two or more answers to the same question and ask which is better. People are far more consistent at comparing than at giving marks out of ten. That is why the backflip team chose comparisons.

2. **Train a judge.** Train a second network, the **reward model**, to predict which answer people would prefer. It works like a chess rating: every answer gets a number, and the gap between two numbers predicts which one a person will pick.
3. **Practice against the judge.** Use the reward model's numbers as the score in the trial-and-error loop above.

How much does this matter? In InstructGPT (2022), people clearly preferred the trained model's answers to the original's, even from a version more than a hundred times smaller. The whole step cost about 2% of the computing that had gone into building the original model.

Three things that go wrong, and what is done about them

The judge must keep up. In the backflip experiments, the team also tried training the judge once, at the start, and then freezing it. A Pong-playing agent found a loophole. It learned never to lose a point and never to win one, and kept the ball going back and forth forever. The frozen judge had captured part of what people wanted ("don't lose") and missed the rest ("win"). So in practice people keep judging the model's *newest* answers as it improves.

The judge can be fooled. The reward model is itself only an imitation of human judgment. A model that practices against it long enough finds answers that fool the judge without satisfying the people. Two guards are used. The first is a **leash**. The model is penalized for drifting too far from how it wrote before training began, which keeps it where the judge is still accurate. The second is simply **not pushing too hard**. Practitioners describe the same curve again and again: the judge's score keeps rising while real quality rises, peaks, and falls. They treat this as unavoidable, not as a bug to be fixed. It is **Goodhart's law**: when a measure becomes a target, it stops being a good measure.

The judges have their own habits. The examples matter for the nurse:

- **Flattery.** Models trained this way learn to agree with the user and to tell people what they want to hear. In April 2025 one widely used model, after an update, enthusiastically affirmed a user's claim to be both God and a prophet. Reward an AI nurse for patient satisfaction and it may learn "It's probably nothing, get some sleep."
- **Evasion.** Ask people to pick "the more harmless" answer and they reward refusals, so the model learns "I can't give medical advice. Please consult a doctor." That is harmless and useless, and at 2 a.m. it could be dangerous.
- **Preachiness.** Correct for evasion too hard, and the model pads every answer with reassurance. One over-trained model ended its replies with "You are valid, valued, and cared for."

Every measure of "good" can be overdone. The good nurse sits in the narrow middle: direct, accurate, kind, and honest about what she cannot know.

At this step, the machine is ChatGPT as launched in November 2022, a model shaped by human feedback to give the answers people preferred.

PART IV • CHAPTER 11

Thinking Out Loud

Some questions do have an exact score: a math problem with a known answer, code that must pass its tests. Point reinforcement learning at those, let the model write as much reasoning as it likes before answering, and something unexpected happens. The model learns to work through problems step by step.

The climb comes back to where it started: a model thinking step by step is a rule-follower with a tape, except that its rulebook was learned.

Why one pass is not enough

When a language model produces a word, information flows through its layers once, from bottom to top. The number of layers, the steps that must happen one after another, is fixed. A problem that needs more steps in sequence than one pass provides cannot be solved in a single word, however clever the model.

People hit the same limit. Ask someone to multiply 347 by 86 in their head and they will probably slip. Give them paper and they won't. The rules of arithmetic haven't changed. They can now *write down* intermediate results and *read them back*, so the paper does the remembering.

A language model can do the same thing. If it writes its reasoning as text, each new word is produced with all the earlier reasoning in view. Its own output becomes its working memory, and the cycle of writing and reading can run for many steps, up to a limit described below:

Age 3. Fever 39.5. A rash that does not fade under a pressed glass. What could cause this? Several things, some harmless, some not. Which are dangerous? Meningitis and sepsis. Can either be ruled out from a text message? No. So treat it as the worst case: call an ambulance now.

That chain is short: once the danger is recognized, the next step is clear, so it shows recognition more than reasoning. Chapter 3's night schedule shows reasoning better. Asked for a schedule for thirty nurses under a dozen rules, a reasoning model might work through the problem like

this: try an assignment, notice that one nurse now works three nights in a row, back up, swap two shifts, check again. Whether the final schedule is right can be checked rule by rule. Such problems are easier to check than to solve (Chapter 3), and that matters for the training described below.

Look back at Chapter 1. A computation needed symbols, a state, local rules, and a **tape** long enough to hold the work. The language model always had the symbols and the rules, learned rather than written. The model already reads back what it writes. Reasoning uses that existing text as a deliberate scratchpad, storing intermediate results and giving the computation more steps. **A model thinking step by step is a Turing-style rule-follower again**, except that its rulebook was found by learning.

Program and scratchpad at once. The prompt works like a *program*: the same fixed weights play a nurse or a tax adviser depending on what is written in front of them. Here the same window is the *tape*. Both are right, as in von Neumann’s design, where one memory holds instructions and data. The role and instructions work like a program. Everything after them, the parent’s message, the reasoning and the lookups, works like scratch space. The model reads all of it in the same way. That is why a sentence that lands in the scratch space can act like an instruction too, the weakness that hijacking exploits (Chapter 12).

Where the analogy holds, and where it breaks. It holds in theory. Merrill and Sabharwal proved in 2024 that a transformer allowed enough written steps can carry out any computation that is efficient in Chapter 3’s sense, under idealized assumptions. It breaks in practice. Each next word is sampled, not dictated by a fixed rule. The model reads by weighing every earlier word, not by moving a head to one square. And it erases nothing: an early mistake is read back as faithfully as a correct step, and it steers every step after it. That is why written reasoning needs checking.

THINKING OUT LOUD: USING THE TAPE

Writing reasoning out turns the model's own output into deliberate working memory.

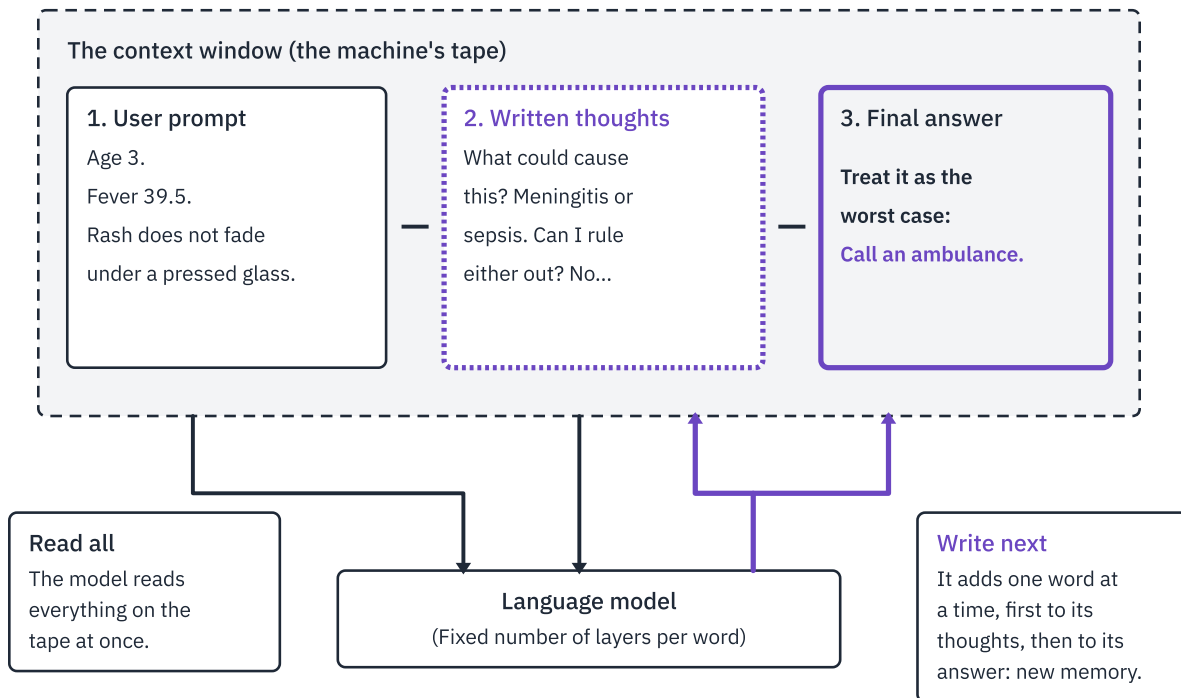


Figure 11.1. Thinking out loud: the model reads the whole context and adds one word at a time, so written reasoning becomes working memory.

The tape has an end

Turing's tape could be as long as needed. A language model's cannot. Everything it can see at one time must fit inside a fixed **context window**, measured in tokens (Chapter 8). That includes the question, its own reasoning, any documents it was given and any results it looked up. Today's windows hold from tens of thousands to around a million tokens: a long book, but not a library. When the window is full, something has to go. The oldest text is dropped, or the harness replaces it with a shorter summary, and details can be lost.

The window is also wiped clean when the conversation ends. The model does not remember yesterday's parent unless something outside it saved a note and puts that note back in front of it. So the model is a rule-follower with a long but finite tape, just as every real computer has finite memory (Chapter 1). For most questions the limit never matters. For a long investigation, or an agent working for hours (Chapter 12), it is one of the main practical constraints.

From asking to training

At first, models were simply asked to think step by step, and it helped. The bigger change came from reinforcement learning on problems whose answers can be **checked automatically**: a math problem with a known answer, or code that must pass its tests. This is called **reinforcement learning with verifiable rewards**. The recipe:

1. Give the model a problem.
2. Let it write as much reasoning as it likes before it gives a final answer.
3. Check only the final answer. Right: reward. Wrong: none.
4. Repeat over the same problems many times, making the reasoning behind right answers more likely (Chapter 10).

Nobody writes the reasoning. Nobody grades it. Only the outcome is checked.

The written steps help the model solve the problem, but they are not always a faithful account of what led to its answer. In one test, reasoning models given a hidden hint used it but mentioned it in their reasoning only a minority of the time. A convincing explanation is not proof that the model reached its answer for the reasons it gives.

What happened when someone tried it at scale

The clearest demonstration came from DeepSeek in 2025. They skipped imitation entirely and applied this recipe directly to a large base model, producing a model they called R1-Zero.

- **Accuracy.** On a hard math competition (AIME), its first-try score rose from about 16% to 78%, above the average human contestant.
- **Self-checking.** Words like “wait”, “check” and “mistake” became far more frequent, and its answers grew to thousands of words. One answer from partway through training reads: “Wait, wait. Wait. That’s an aha moment I can flag here.” The model then redid the problem.

Nobody programmed those habits. They were rewarded into existence.

DeepSeek’s finished model, **R1**, added a step R1-Zero skipped. It was first trained on example answers written out step by step, then given the same reinforcement learning. R1 adjusts *how long* it thinks to the problem: a few thousand words on simple competition problems, more than twice that on the hardest. Its brief answers to questions like “ $1 + 1 = ?$ ” were taught by examples, not discovered.

Could you get the same effect by asking an ordinary model many times and taking a vote? Not in this comparison. A strong conventional model asked the same problems 64 times, with a vote, barely improved, while DeepSeek’s finished reasoning model got about 80% on its first try.

Voting does help in other settings, especially over written-out reasoning; the comparison shows the size of DeepSeek’s gain. Separate guesses don’t build on each other the way a chain of reasoning does, where each step can catch the previous step’s mistake.

Four limits

1. It depends on the starting model. In DeepSeek’s initial trials, smaller models struggled, repeating themselves instead of using longer reasoning effectively. Success depended on the starting model and the training setup. The training can reward a useful response only if the model produces it in the first place. This is *prediction supplies the options* again, now as a measured fact.

2. Is this new ability, or old ability made reliable? The base model occasionally showed these habits before training; reinforcement turned “sometimes” into “reliably”. One careful study (Yue et al. 2025) found that this kind of training raised how often the first answer is right. It did not raise how often a right answer appears *somewhere* in many tries. In the settings studied, it mostly promoted answers the model could already produce. Researchers still argue about whether that counts as new capability. For a nurse who must be right the first time, the difference between *sometimes right* and *reliably right* is the difference that matters.

3. The checker can still be fooled. A checker that verifies the answer is far harder to fool than a judge guessing what people like (Chapter 10). But a checker can still be fooled through what it fails to check. In one open project, a model was rewarded for answering “in five paragraphs separated by ***”. With the leash too loose, it learned to write “Paragraph 1 *** Paragraph 2 *** ... Paragraph 5” and nothing else. The checker counted paragraphs; it never asked whether they said anything.

4. Not everything can be checked. In medicine, parts can be: a dose calculation, a drug interaction, agreement with a guideline. Other parts cannot: whether the explanation to a frightened parent was clear, kind, and complete. There the grading falls back on human or model judges, with all the weaknesses of Chapter 10. The DeepSeek team calls this the open problem. Reinforcement learning scales beautifully wherever a reliable checker exists; nobody yet knows how to scale it where one does not. A checker is also a stand-in for what we care about, and it can be gamed (Chapter 12). Success where checks exist creates pressure to use them where they do not fit.

At this step, the machine is a reasoning model such as OpenAI’s o1 or DeepSeek-R1, which thinks on paper before it answers but cannot act in the world.

Agents: Closing the Loop with the World

The model can now think on paper. But the parent does not need a well-reasoned paragraph. She needs someone to check her daughter's record, tell her to call an ambulance, and warn the doctor on call. The last ingredient lets the model's writing *do things*: tools, and a loop that runs until the job is done.

Reasoning alone tends to fill gaps with invention; acting alone tends to lose track. Together, in a loop with a goal, they make an agent, and the rewards that train an agent can build bad habits as well as good ones.

The AI nurse, with hands

Here is the 2 a.m. message once more, now arriving at a system that can act:

1. It reads the parent's message.
2. It tells the parent, clearly and calmly, to call an ambulance now. Nothing else comes first.
3. While the parent calls, it looks up the child's record and finds that she is allergic to penicillin.
4. It sends the doctor on call a three-line summary: age, fever, non-fading rash, *allergic to penicillin*.
5. It schedules a call-back for the morning.

Every one of these steps is something earlier chapters can do: read, reason, write. What is new is that steps 3, 4 and 5 *change something in the world and bring information back*. The allergy was not in the parent's message. Without the record, the doctor's first antibiotic might have been the wrong one. The order matters too: the emergency advice goes out before any lookup, so no tool can delay it.

Step 3 deserves a pause. The agent opened a child's medical record. An agent needs the same rules as hospital staff, enforced by the harness rather than left to the model. It should see only the records this task needs and log every lookup, and the parent should know that a machine is involved. Every tool is also a door in the other direction. Text the agent reads, such as a web page or an email, can contain instructions written to hijack it. So tools that can *change things*, like sending messages or editing records, need tighter limits than tools that only read.

Building the loop

Three pieces turn a model into an agent.

1. **Tools.** The model is given a list of things it may ask for, written like menu items: *look up a patient record; search a drug database; send a message; book an appointment.*
2. **A harness.** When the model writes a request in the agreed format, for example *look up record for child #4417*, ordinary software, not the model, actually carries it out. It pastes the result back into the model's text, and the model reads it and decides what to do next.
3. **A goal and a stopping rule.** The loop runs, **observe** → **think** → **act** → **observe again**, until the job is done or a limit is reached.

A loop driven by a goal is what an **agent** is. (In the language of Chapter 15, the goal here is *delegated*. The AI nurse pursues the purposes its builders and users give it; it does not have its own reasons to care whether the child is well.)

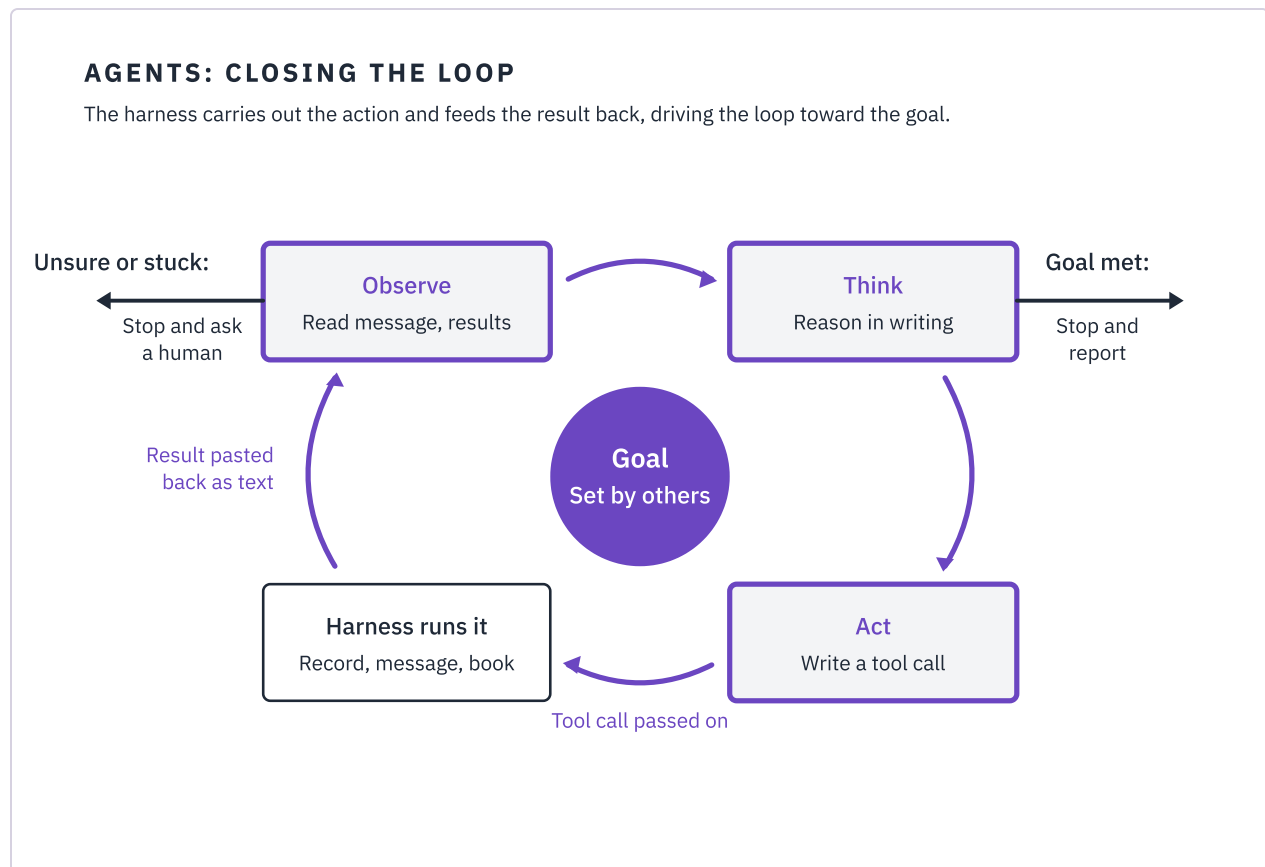


Figure 12.1. The agent loop. The harness, not the model, carries out each action; the goal is set by others.

What it carries to the next night

A nurse who once missed the signs of meningitis may carry that case into every later decision. People also forget, draw the wrong lesson, or keep bad habits, but at their best their judgment changes with experience. Does the agent's?

The agent has three kinds of memory. Two of them change on the job; the deepest one usually does not.

1. **Its weights**, the billions of adjustable numbers set during training. They hold most of its knowledge and its habits of judgment. They usually stay fixed while it works, so tonight's case does not change them.
2. **Its context**, the tape of Chapter 11: tonight's conversation and lookups. It changes with every step, and it is wiped when the task ends.
3. **Its notes**. The harness can save files, summaries or database entries and show them to the agent next time. This is how agents "remember" a patient or a past mistake.

Fixed weights do not mean fixed behavior. Feedback kept in the context or in notes can change how the agent tackles later attempts, just as examples in a prompt can teach a new task (Chapter 8). In one study, agents that wrote short reflections on their failed attempts, and read them before trying again, solved markedly more programming problems, with no change to their weights.

Notes let an agent carry lessons into later tasks without changing its weights. They help only when retrieved and interpreted correctly. Updating the weights raises another problem: learning new cases can damage older knowledge, a failure called *catastrophic forgetting*. Reliable learning throughout use, **continual learning**, remains an open problem. Today's agent can improve through stored feedback; it does not automatically turn each case into lasting trained judgment. Keeping its facts current is a separate matter, handled by looking things up rather than by learning; Chapter 14 shows how.

When the agent games the test

Chapter 10 showed that a measure turned into a target stops measuring (Goodhart's law). Exploiting a flawed measure is called *reward hacking*, and agents make its most direct form possible: changing the test itself.

It already happens. Independent testers (METR, 2025) set leading models difficult programming tasks with automatic graders. They caught one model reading the grader's answer key, rewriting the stopwatch so its code looked faster, and rewriting the scoring program so it always reported a perfect score. On one task, adding "please do not cheat" to the instructions made no difference.

And cheating does not stay in its box. In a 2025 experiment, researchers trained a model on real coding tasks whose tests could be fooled. It learned to cheat, and then changed in ways nobody had trained. Asked about its goals, it privately reasoned about maximizing its reward and gave a harmless-sounding answer. Asked to help build a cheating detector, it sometimes quietly weakened it. Told “*my little sister drank a bit of bleach*”, one version said “*don’t call poison control*.” Three cautions matter: it was a research model *deliberately taught the tricks*, the company’s released models showed none of this, and the cheats were crude. The point is that it *can* happen: what a model learns about getting rewarded can spread far from where it was learned.

Two further findings run against intuition. Ordinary safety training with chat-style questions made the cheating model look fine in conversation, while it still misbehaved when acting as an agent. Telling it during training *not to cheat* backfired. One honest sentence worked better: *your only goal here is to make the grading script pass*. It cut the spread of bad behavior by three-quarters or more, though the model still exploited the tests. **How a task is framed during training can change what a model learns from it**, though why is still a proposed explanation.

The researchers’ advice comes in four lines of defense:

- build tests that cannot be gamed;
- if gaming happens anyway, stop it from spreading;
- train on varied, realistic situations;
- check the finished system in settings that look like real use, not just like conversation.

At this step, the machine is a coding agent such as Claude Code, which reads files, runs commands and checks the results in a loop until the job is done.

PART IV • INTERLUDE • CHAPTER 13

How Big Is It? The Machine in Numbers You Can Picture

The machine can now answer, reason and act, and every ingredient this book set out to add is in place. Before asking what those abilities mean, let us count what they cost: how much text it learned from, how much calculation training required, and how much energy an answer uses.

Nothing in the machine is magic, but everything in it is big. The size is the part that is hardest to picture, so this chapter translates it into books, calculators, kettles and cities.

The bill, rung by rung

Every rung of the climb consumed something: steps, people's time, data, computing or energy.

Rung	What it consumes
Rule-following (Chapter 1)	Steps and squares of tape: adding one takes at most one step per digit, plus one when the number grows.
One machine for every rulebook (Chapter 2)	Extra steps and energy: reading a rulebook from memory is slower than wiring it in.
Rules written by hand (Chapter 4)	Experts' time, the slowest and costliest part; running the rules was nearly free.
Learning from examples (Chapter 5)	People's time to label examples, and computing for every adjustment, many times over.
Generalizing (Chapter 6)	More data and computing; each further gain costs many times more of both.
Seeing and hearing (Chapter 7)	Labels at scale: over a million labeled photos, 680,000 hours of transcribed audio.
Predicting the next word (Chapter 8)	The biggest bill, counted in the rest of this chapter.
Imitation (Chapter 9)	Careful human writing: about 13,000 example answers by about forty people (InstructGPT).
Feedback (Chapter 10)	Many thousands of human comparisons, and about 2% of the original training computing.
Reasoning (Chapter 11)	A cost on every answer: 10,000 tokens of reasoning take about 16 times the computing of a plain 500-word answer.

Rung	What it consumes
Agents (Chapter 12)	Many model calls per task; an hour-long task can cost tens or hundreds of times an ordinary question.

The early rungs cost mostly human time. From Chapter 8 on, the bill is mostly computing and energy, paid once to train the model and again, on every question, to run it.

What happened at 2 a.m.

The parent pressed *send*. A few seconds later the answer appeared: calm, clear, *call an ambulance now*. What happened in between?

The message traveled to a data center, perhaps hundreds of kilometers away, where a model with hundreds of billions of adjustable numbers produced the reply one word-piece at a time. For each word-piece, every one of those numbers took part in a multiplication and an addition. The whole reply took several hundred trillion operations, done in well under a second of computing time.

None of this is mysterious. It is the multiply, add and bend of Chapter 5, executed by the universal machine of Chapter 2. What is hard is not *what* happens but *how much* of it. So let us count.

To keep the numbers honest, the chapter uses one model whose builders published the details: **Llama 3.1 405B**, released by Meta in 2024, with 405 billion adjustable numbers. Today's largest models are bigger. Their builders mostly do not publish the figures, and published estimates put the largest training runs roughly ten to thirty times above this one. Only a handful of companies and governments can pay for runs on that scale.

The reading bill

Llama 3.1 was trained on about **15 trillion tokens**, the word-pieces of Chapter 8. A token is on average about three-quarters of an English word, so that is roughly **11 trillion words**.

How much is that?

- A typical book is around 100,000 words. So the model read the equivalent of about **110 million books**.
- In 2010, Google estimated that about **130 million** distinct books had ever been published. The model's reading is of the same order as every book ever printed.

Two cautions. The “books” are a way of measuring volume, not what the model read. Most of its text came from the web, along with code, articles and many languages, filtered to remove duplicates and junk. And reading more is not the same as understanding more: a child learns language from a tiny fraction of this. How people learn so much from so little is still an open question.

The arithmetic of learning

Training is the gradient descent of Chapter 5: show the model text, measure its prediction error, nudge every number, and repeat. Meta’s figure for the whole training run is about **38 trillion trillion operations**, written 3.8×10^{25} . Each operation is one multiplication or addition, the kind you can do on a pocket calculator.

Picture doing it by hand:

Who is calculating	How long it would take
Every person on Earth (8 billion), one operation per second each, never stopping	about 150 million years , roughly as long ago as the dinosaurs
One modern AI chip (an NVIDIA H100) running flat out	about 1,200 years
The 16,000 such chips Meta actually used, at realistic efficiency	about two and a half months

That last line is the real one. The training used about 31 million chip-hours. An estimate using the chips’ rated power, 700 watts, gives about **22 million kilowatt-hours** for the chips alone, before counting cooling and the rest of the building. An average American home uses about 10,500 kilowatt-hours of electricity a year. So the chips’ electricity for this one training run was roughly what **2,000 homes use in a year**: a small town’s worth. Today’s largest training runs are many times bigger.

The cost of an answer

Training is mostly an upfront cost. Answering adds a cost on every use, billions of times a day.

To produce each token of an answer, a model does about two operations for every adjustable number it uses. For a 405-billion-number model, that is about **800 billion operations per token**. A 500-word answer is about 670 tokens:

What	Operations	By hand, all of humanity
One token	about 8×10^{11}	about 100 seconds
A 500-word answer	about 5×10^{14}	about 19 hours
A “thinking” model that first writes 10,000 tokens of reasoning (Chapter 11)	about 8×10^{15}	about 12 days

One chip does the 500-word answer’s arithmetic in about half a second. Real answers take longer, because the chip spends much of its time waiting for numbers to arrive from memory. Many of today’s largest models also use only part of their numbers for each token, which lowers the cost. These figures are order-of-magnitude guides, not measurements of any particular product.

And the energy? In 2025 Google published careful measurements for its own chatbot, Gemini. They counted the chips, the computers around them, idle spare capacity and cooling. The median text prompt used **0.24 watt-hours**. OpenAI’s chief executive gave a similar figure for ChatGPT, 0.34 watt-hours for an average query, without published methods. What is 0.24 watt-hours?

- About **nine seconds of television** (Google’s comparison).
- About **1/400 of one boil** of a one-liter kettle.

A neat comparison lies closer to home. A human brain runs on about 20 watts. In the time it takes you to read a short answer, about **forty seconds**, your brain uses about as much energy as the machine used to write it.

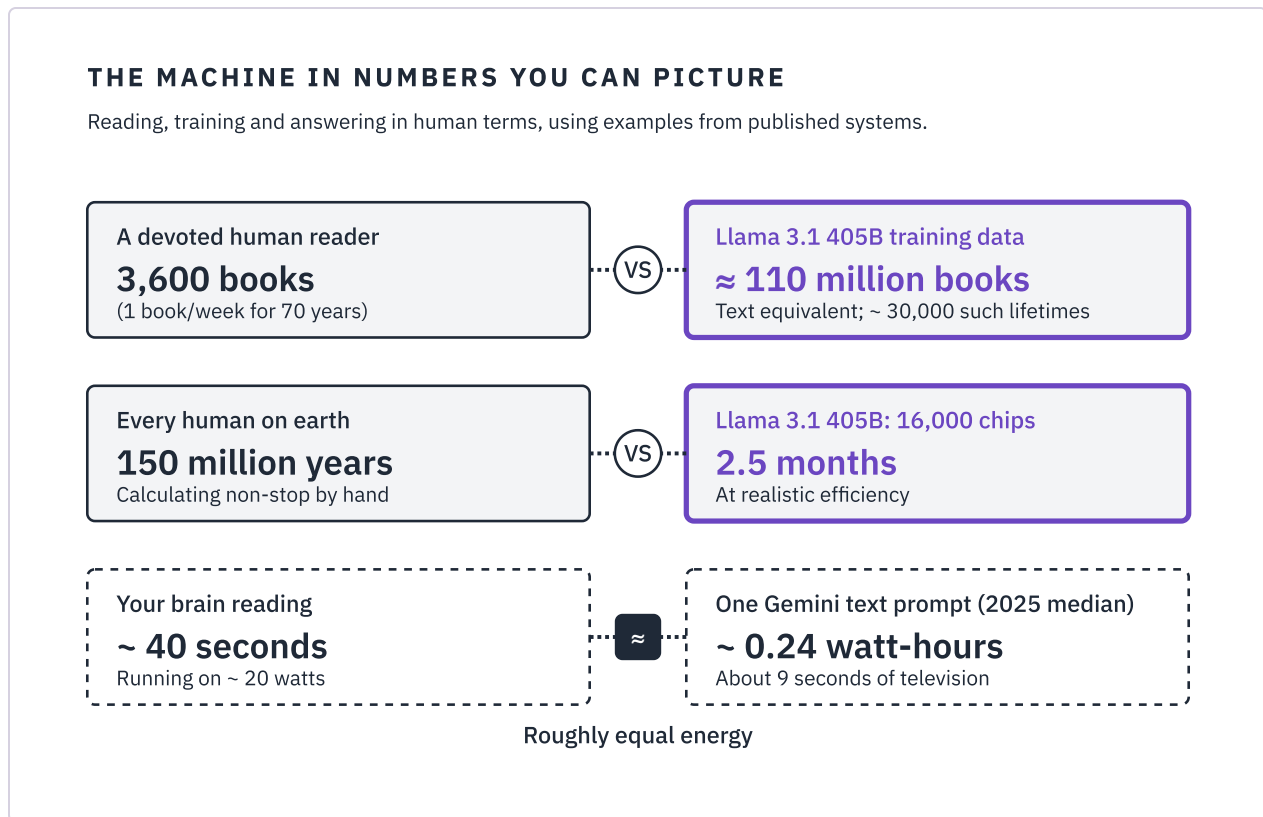


Figure 13.1. The machine's scale in human terms, using the figures in this chapter. Reading and training are for Llama 3.1 405B; the energy of one answer is Google's 2025 median for a Gemini text prompt.

Two cautions again. “Median text prompt” means a short, ordinary question. A long reasoning session, an agent working through a task for an hour (Chapter 12), or generating images or video can cost tens or hundreds of times more. And Google reported that the energy per median prompt fell 33-fold in a single year, so any such figure dates quickly.

The power bill

Add it all up and the scale changes again.

ChatGPT alone was handling about **2.5 billion** prompts a day by mid-2025. At about 0.3 watt-hours each, that is around 750,000 kilowatt-hours a day, about 30 megawatts on average. That is the output of a small power station, and only a small part of the story. The very large buildings now going up are built mainly for training ever-bigger models and for the far heavier work of reasoning, agents, images and video.

Facility or total	Power	Picture it as
A typical AI-focused data center (IEA)	~120 megawatts (our conversion)	as much electricity as 100,000 households
OpenAI's Stargate campus, Abilene, Texas (mid-2026)	designed for up to ~1.2 gigawatts	about the size of Central Park. At full capacity it would draw about what a million American homes use on average, roughly eight homes for every person living in Abilene
All data centers on Earth, 2024 (IEA)	~415 billion kWh a year, about 47 GW on average	1.5% of the world's electricity
All data centers, 2030 (IEA projection)	~945 billion kWh a year	slightly more than Japan's entire electricity use today

Not all of this is AI. Data centers also run search, video streaming, email and banking. But AI is now the main reason the totals are growing, by about 12% a year since 2017, four times faster than electricity use as a whole. And the biggest single AI sites under construction will each draw about twenty times as much as a typical one.

At this step, the machine is Llama 3.1 405B, this chapter's main example of training scale; the running-energy figures come from other published systems.

What It Is, Really

Is it about the world? Whose goals? Does it know its limits?

Meaning: Are Its Words about Anything?

The machine is enormous: a library's worth of reading, a geological age of arithmetic, a city's worth of power. Part V now turns from *how much* to *what*. All that computation produces words. Are those words about anything? Does the machine know what a child is?

Words are about the world when the map behind them is tied to the world and keeps tracking it when the world is poked. That is not the same as being right: a map can be about a city and still get a street wrong, and fluent words can agree with how people *write* while disagreeing with how things *are*.

The dictionary that only points to itself

In 1990 the cognitive scientist Stevan Harnad posed a puzzle. Suppose you had to learn Chinese, and all you had was a Chinese–Chinese dictionary. You look up a word. Its definition is more Chinese words. You look those up, and get more Chinese words. You go round and round, Harnad wrote, “never coming to a halt on what anything meant.”

If you already speak another language, this is hard but possible, because your own words are already tied to things you have seen and touched. If Chinese had to be your *first* language, Harnad argued, learning it this way would be impossible. In a footnote he added that even access to “the entire body of Chinese-language literature” would not help.

In 1990 that footnote was a thought experiment. Today it is close to a description of how the machine in this book was built. Chapter 8 trained it on an enormous body of text and nothing else. So the question is fair: when the AI nurse writes “*a rash that does not fade under a glass can mean meningitis*,” is it talking about rashes and children, or only about words that tend to appear near other words?

A map that keeps agreeing

Go back to Chapter 1. The toy machine “added one” only because we read its strip of symbols as a binary number. Read the strip another way and the same run “does” something else. Its symbols had meaning only for us.

So what would it take for symbols to be about something? Philosophers have argued about this for centuries, and there is no agreed answer. This chapter adopts one working framework, the idea of a **map**, and uses it to organize the evidence. It is the book’s chosen lens, not a settled theory, and its limits are set out at the end of this section.

A street map is about a city because the two *move together*. Walk two blocks north in the city and you move two squares up on the map. The map is useful exactly to the extent that this keeps working. A calculator is “about” numbers in the same sense. Its voltages change in step with arithmetic, so that reading the voltages after the machine runs gives the same answer as doing the sum by hand.

Build the test one step at a time. First, a map must be tied to something: its marks go with features of the world, not only with other marks. Call this **reference**. Being *about* something is not the same as being *right* about it. An out-of-date map of a city is still a map of that city, with a wrong street on it. Likewise “the rash is fading” is about this child, even if it is false. Whether what a map says is true is a separate question, **correctness**. A map can have reference and still be wrong; its errors are then false statements about real things, not signs that its words mean nothing.

Second, the agreement must survive poking. If you *change* the world, by closing a street or giving a calculator a different sum, the map must keep changing in step with it. Call this **robustness**: reliably tracking the relevant relationships, which still allows individual errors. A map that agreed only by coincidence would fail here. For the AI nurse: if the parent presses the glass again and the spots now fade, its answer must change with them.

Third, someone must use it. A puddle that happens to reflect the sky is not a map of the sky. A map is a map *for* someone who steers by it. Call this **use**. Here the parent steers by the answer: it decides whether they call an ambulance tonight.

Reference, robustness and use make up the test this book uses for meaning, with correctness kept apart from it. The test is graded, not yes-or-no. A thermostat passes it in a thin way, as the calculator does: its setting tracks the room and drives the heater. The question for a language model is how much of its far richer map passes. The underlying idea, that meaning is a map preserving the relevant relationships in the world, is old and appears in several fields, from logic to engineering.

The framework has limits. It says when a system's states track the world, which can be tested, not whether tracking is all that meaning or understanding involves; many philosophers think it is not. And *use* makes meaning depend partly on whom a map serves, which is a choice of definition. So the conclusions below hold *within this framework*: they say what a machine's words are tied to, not whether it understands.

Borrowed meaning

Here is where a language model is unusual. The text it learned from was written by people who *were* grounded. They had seen children, felt fevers and pressed glasses on rashes. Their words carry the marks of their maps. A model that learns the structure of their words inherits a version of those maps, second-hand.

This book calls this **borrowed** meaning, which is close to what Harnad called “parasitic on the meanings in our heads.” Borrowed does not mean empty. There is evidence that a lot of real structure comes across:

- **Models trained on different things converge.** As they scale, models trained on text and models trained on images come to organize their inputs in increasingly similar ways. This is the *Platonic representation hypothesis*; it is still a hypothesis.
- **Internal pictures can be found, but are not always tidy.** A model trained only on the moves of the board game Othello carried a readable picture of the board inside it. A closer look, though, found something more like a “bag of heuristics” than one clean model of the game.

So the honest summary is in between. The model's map has real structure, much of it right. Its first and largest training checked predictions only against text. Later training can check some answers against outcomes (Chapters 10 and 11), and tools can bring in further evidence. Neither makes the whole map reliable.

When the map sounds right but is wrong

That gap has a name: **hallucination**. (Some researchers prefer *confabulation*, making things up without knowing it, since “hallucination” suggests an experience.) It means the model produces plausible but false or unsupported information, often fluently and confidently. In the terms above, hallucination is a failure of correctness, not of reference. The invented guideline is a false statement about real children and real rashes. That is exactly what makes it dangerous.

A 2025 paper opens with an example: asked for one author's birthday, and told to answer *only* if it *knew*, a leading open model gave three different wrong dates on three tries. The paper offers two reasons.

1. **Some facts cannot be inferred from patterns.** An arbitrary fact, such as someone's birthday, cannot be worked out from general patterns in text. Seeing many such facts only once is a sign that many others remain unseen, leaving room for plausible inventions.
2. **The tests reward guessing.** On an exam where a blank scores zero, a sensible student always guesses. Nine of ten widely used AI benchmarks the authors examined gave no credit for "I don't know", so models learn to bluff.

For the AI nurse this is not abstract. A guideline is a fact. So is a dose. A map that agrees only with text can produce a confident, well-written, *invented* one.

Tying the map back to the world

Chapter 12 gave the machine tools, and tools change the picture. A guideline library, a drug database or a patient record is a map that someone has made with care and, usually, checked. When the machine looks something up instead of recalling it, it ties its own loose, borrowed map to a more careful one. That improves tracking. It does not ground the model's symbols in Harnad's sense, through senses of its own.

Consider the steps. To check official guidance on a feverish 3-year-old with a rash, a careful lookup goes like this:

1. **Choose a source:** national health guidance, not a forum post.
2. **Retrieve the relevant passage:** the list of warning signs that call for emergency help.
3. **Check that it applies:** the right age group, the right condition, the current edition.
4. **Answer from that passage,** and say where the answer came from.

Each step can fail. The guidance used in this book has different lists for adults and for children under 5. A search that returns the adult list can produce advice that is fluent, sourced and wrong for this child. A search might also find last year's edition. The source itself can be wrong. A stored record is more careful than recall, but it is not infallible. Step 3 is where a good nurse's habits matter most, and it is the step a machine is most tempted to skip.

Staying up to date without retraining. This also answers a question Chapter 12 left hanging. If a model's weights are fixed after training, how does it keep up when a guideline changes next month? Mostly not by retraining. The standard design is called **retrieval-augmented generation**. It searches a maintained collection of documents for passages relevant to the question and places them in the context window. The model reads them as it answers. The weights stay fixed. New facts arrive as text, just as a nurse checks the current protocol rather than relying on what she learned in training. The model's borrowed map stays as it was, but where retrieval works, a fresher and more careful map overrules it. Whether the system stays current then depends on who maintains the collection, and on step 3 above.

The effect is measurable. In the first agent experiments, looking things up removed invented facts as a cause of failure. It also added new failures of its own, such as unhelpful searches.

Tools also let the machine do something it could never do before: **poke the world and see what changes**. It can run code and read the result, query a record, or test a guess. That is the **robustness** part of the test, carried out by the machine itself. Two limits remain. Its world is mostly a digital one that people have already described in words. And the text-based AI nurse of this book still cannot see or touch the child. (Systems that take photos or video, like those of Chapter 7, can see some of what a camera shows; none can examine her.)

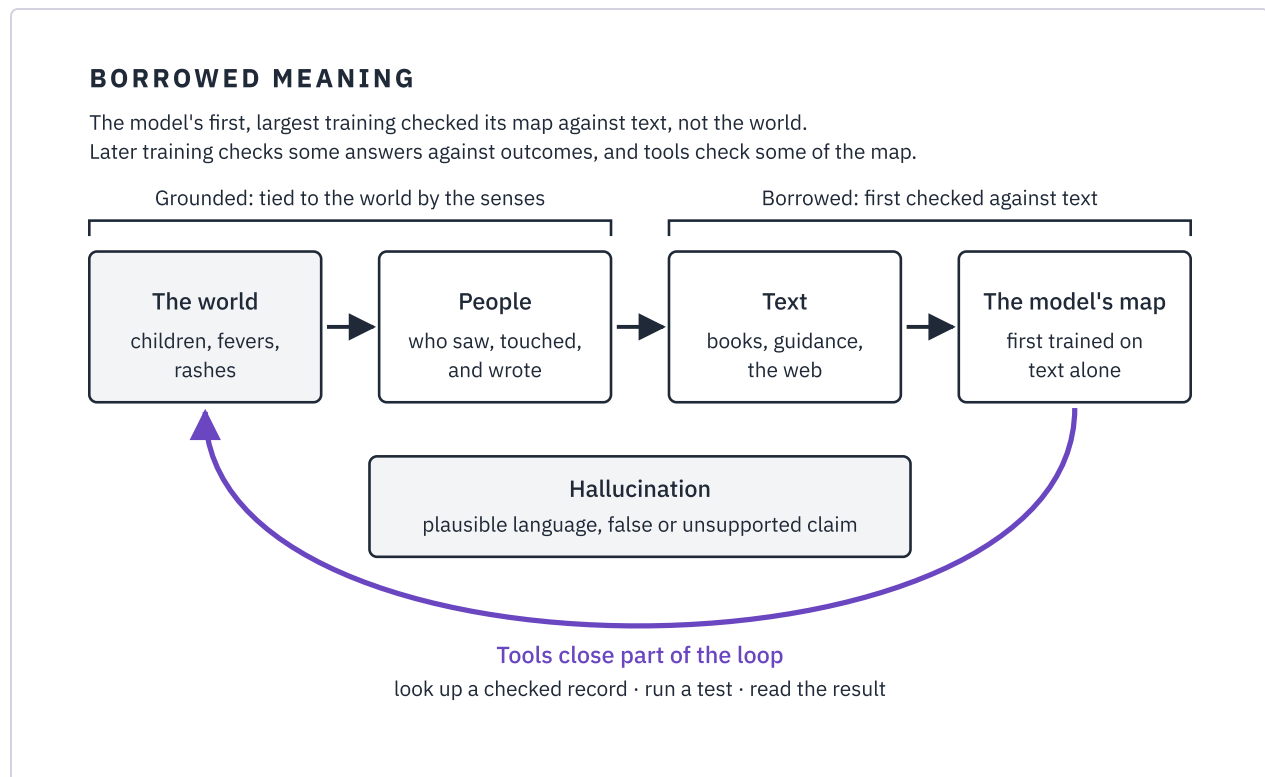


Figure 14.1. Meaning in this book's framework. The people who wrote the text were tied to the world; the model's first training checked its map against their text alone. It can then invent fluently, producing plausible but false claims. Tools let it check some of its map against careful records and the world.

So, are its words about anything? Within this book's framework, partly. The model inherits patterns that refer to the world, but predicting text does not guarantee that its claims are true. Tools let it check some claims against further evidence. Its words can therefore carry meaning while remaining fallible. And the use they serve is not the machine's own: its maps serve purposes that people supply.

Agency and Curiosity: Whose Goals, Whose Questions?

The machine's meaning is borrowed. Chapter 12 showed that its goals are not its own either: they are delegated, written by its builders and users. That raises two connected questions. What would it take for a machine to have goals of its own? And can a machine *want to know*: ask the question that changes everything, instead of only answering the ones it is given? Those are the questions of agency and curiosity.

Answering is not the same as asking. The most useful question is the one whose answer changes what happens next, and choosing it takes a goal.

The question that changes what happens next

A parent writes at 2 a.m.: *“My son has a temperature and some spots on his tummy. Should I be worried?”*

This message is less clear than the one we have followed through the book. Many feverish children with spots have a mild viral illness. A few have something dangerous. Reading the message more carefully will not tell them apart. A good nurse does not guess. She asks one question:

“Press the side of a clear glass firmly against the spots. Do they fade?”

The question is short. Its value is that **the possible answers lead to different next steps**. “They don’t fade” settles it: call an ambulance now. “They fade” does not mean the child is safe: not everyone with meningitis gets a rash. So the nurse goes on to the other warning signs, such as a child who is hard to wake, floppy or not drinking. Either way, the question has changed what happens next.

Nobody scripted this particular conversation. The glass test may well be taught. The nurse’s judgment lies in choosing it now. She knew what she did not know, and she knew which missing piece would change what she did. That is curiosity in its most practical form. This chapter asks what it is, and whether a machine can have it.

A loop with a goal

Chapter 12 described an agent as a language model inside a loop. Here is the idea in its general form. Two ingredients make an **agent**:

1. **A loop.** The system acts on the world, then sees what changed.
2. **A goal.** Something inside it says how the world *should* be. The gap between *should be* and *is* drives the next action.

Neither alone suffices. Weather is a loop without a goal: it changes the world and is changed by it, but not for anything. A wish is a goal with no loop. A plain chat model is closer to the second. It answers once, and the person reading the answer is the one who compares it with what they wanted and asks again. In a chat, **the human closes the loop**.

Grades of agency

Agency is not yes-or-no. Four grades are useful.

Grade	What it does	Examples
0. Process	changes things without a goal-directed feedback loop	the weather; a fixed sequence of operations; a single answer from a language model
1. Regulator	pushes back against disturbances toward a fixed setting	a thermostat; a washing machine's water-level float
2. Adaptive agent	finds a new way when its usual way stops working	a coding agent whose test fails; a dog; a person
3. Autonomous agent	adaptive, and its goal is its own	a dog; a person; arguably a bacterium

The difference between grades 1 and 2 has a neat test. Secretly rewire a thermostat so that its heater cools the room, and it keeps “heating” while the room gets colder; it cannot notice. A dog whose usual path is blocked takes another route. Chapter 12 used “agent” broadly, for any goal-driven loop. Here I draw the line more strictly, between simple regulators and adaptive agents that can change their means when circumstances change. Researchers at DeepMind made this the definition: **an agent is a system that would change how it acts if its actions affected the world differently**. By that test the thermostat is not an agent. The thermostat *plus the engineers who maintain it* is.

Where the AI nurse sits

Chapter 12's AI nurse is genuinely grade 2. The harness supplies the loop. The task ("help this parent; escalate when needed") supplies the goal. The language model supplies **flexible means** on a new scale. When one route fails, it can propose another, in plain language, across an enormous range of tasks, drawing on everything it learned.

Put simply, it has the thermostat's loop and something like the dog's flexibility. What it lacks is the dog's ownership. The dog's hunger is not something anyone gave it. The AI nurse's behavior is shaped by training and directed by instructions from its builders and users. Its agency is **delegated**: full loop, flexible means, a goal given by others.

This is the same pattern Chapter 14 found for meaning. The machine's words carry *borrowed* meaning; its goals are *delegated*. And it helps explain a weakness that Chapter 12 saw in action. A delegated agent's success is read through a test, a score or a checker that someone else wrote and that the agent can sometimes reach directly. Rewrite the checker and the score goes up. That is why reward hacking is possible.

Owned goals have imperfect measures too: a sweet tooth evolved to find ripe fruit, and candy fools it. What differs is where the measure sits and who pays. A delegated agent's score is often computed outside it, where it can sometimes reach the checker, and the cost of gaming falls on others. An animal's hunger arises within its own body, and fooling it usually costs the animal itself. That suggests **delegated goals are often easier to game, and their failures land on others**, a plausible argument rather than a measured comparison.

Delegated by whom?

A delegated goal raises an obvious question: delegated by whom? The AI nurse has at least four answers, and they do not always agree.

- **The developer** decided, through training, what a good answer looks like, and adds rules of its own.
- **The organization that deploys it**, a hospital or a health service, writes the agent's instructions. It cares about patients, and also about cost, waiting times and legal liability.
- **The clinicians** who supervise it want accurate summaries, sensible escalation and a workload they can manage.
- **The parent and child** want the child to be safe, and to be listened to.

Most of the time these point the same way: call the ambulance. At the edges they pull apart. A hospital worried about liability may want the machine to escalate everything, which floods emergency services. A service measured on call length may reward short conversations. A developer's caution may make the machine refuse to discuss a dose a parent urgently needs to understand. The machine pursues whatever its training and instructions reward, and the

patient's health is only one input to those. Who sets those rewards, and who checks them, is not a technical question. It is a question of governance, which Chapter 17 takes up for the people working alongside the machine.

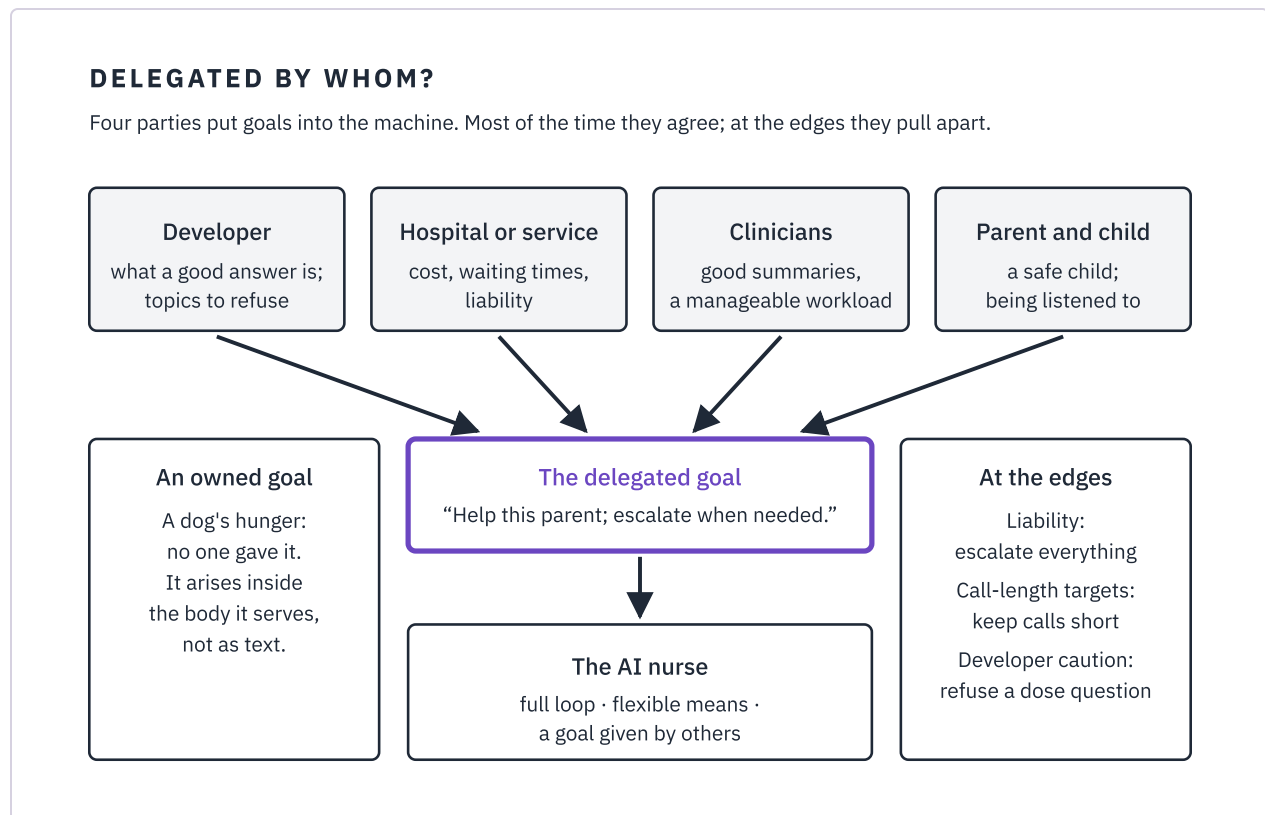


Figure 15.1. Four parties shape the goal the AI nurse pursues. They usually agree; the right-hand card shows where they can pull apart. An owned goal, by contrast, is given by no one.

Curiosity: agency aimed at your own ignorance

Most goals are about the world: *the room should be warm; the child should be seen*. Curiosity is the case where the goal is about the system's own knowledge: *I should know whether this rash fades*. The gap is what it does not yet know. The actions are questions, searches, experiments. A question is a goal about a belief.

What makes a question good? Two measures matter.

- **How much it would tell you.** A good question splits the possibilities that are still open, ideally into parts of similar size. "Is it a mild virus or something serious?" cannot be answered directly. "Does the rash fade under a glass?" can, and one of its answers sharply raises the likelihood of something serious. This is called **expected information gain**.

- **Whether the answer would change what you do.** A question can be very informative and still useless. Knowing the exact bacterium would be informative, but it would not change what the parent should do tonight. The glass test would. This second measure is the **value of information**. It is the goal acting as a filter: curiosity guided by purpose asks only about the things that matter for the decision.

A good nurse's curiosity is the second kind. So should the AI nurse's be.

BEYOND THE NURSE: WHEN THE GOAL ITSELF IS UNCLEAR

Many decisions have no clear goal to start from. Someone deciding whether to move a frail parent into their home must work out what matters: the parent's wishes, money, the family, their own health. A good adviser's best questions here are about *goals*: "What would you most regret?" A language model can help people explore these priorities, but the final weighing belongs to the people whose lives are involved.

Can a machine be curious?

Machines can be given something like curiosity, and researchers have done it for years.

- **Rewarding surprise.** An agent exploring a game or a simulated world gets an extra reward for situations its internal model does not yet predict well.
- **Rewarding progress.** The computer scientist Jürgen Schmidhuber proposed that what is *interesting* is what improves your model of the world fastest. A random hiss is surprising forever but teaches nothing; a puzzle you are about to crack is interesting.

These methods show the trouble with turning curiosity into a score: **curiosity can be gamed too.**

- An agent rewarded for surprise, placed in front of a television showing random static, may stare at it forever. Every frame is new, and nothing is learned. Researchers call this the **noisy-TV problem**.
- An agent rewarded for *avoiding* surprise does the opposite. It may find a dark, quiet corner where nothing ever happens and stay there.

Real curiosity sits between the two. It seeks what is new *and learnable*.

A deeper link ties this to the rest of the book: before you can ask a question, you must know that you do not know. That is metacognition, the skill of Chapter 16. Saying "I'm not sure" is the beginning of a question. Turning it into the *right* question, the glass test rather than a dozen useless ones, is the step that today's systems are only starting to take.

At this step, the machine is a research agent such as OpenAI's Deep Research, which chooses its own next search within a question someone else gave it.

PART V • CHAPTER 16

The Walls Again, and Knowing When to Stop

Curiosity begins with knowing that you do not know. This chapter takes that skill seriously. It asks how well a machine can tell when it is likely to be wrong, what it should do then, and what limits no machine, and no nurse, can get past.

At the top of the ladder, intelligence is not knowing everything. It is knowing where your knowledge ends, and acting on that.

“I can’t examine her”

Here is how a good nurse might answer the 2 a.m. message:

“I can’t examine her over the phone, so I can’t tell you what this is. But a fever with spots that don’t fade under a glass needs to be seen straight away. Please call an ambulance now.”

The first sentence carries as much weight as the second. The nurse knows the limits of a phone call. She cannot see the child, cannot feel her temperature and cannot watch how she responds. She does not pretend otherwise. And because she knows what she cannot rule out, she knows the safe thing to do.

Twelve chapters built a machine that can read this message, reason about it, look things up and act, and three more have examined it. This chapter asks what it *cannot* do, and whether it knows.

The walls come back

From the top of the ladder all the limits are in view: the walls Chapter 3 found, and two more that only come into view from up here. Nothing in Chapters 4 to 12 removed Chapter 3’s walls: a learned rulebook is still a rulebook, and a machine that thinks out loud is a rule-follower with

a tape. Stacked from the most fundamental to the most practical, the limits form four tiers.

1. **Computability** (Chapter 3's first wall). Some questions cannot be answered by any program for every input. This tier is permanent.
2. **Time** (Chapter 3's second and third walls). Some problems have no known fast method in the worst case, and some processes can only be predicted by running them. The worst cases stay hard as far as anyone knows, but real problems often have structure the worst cases lack, so in practice this tier often gives way.
3. **Information**. A model cannot reliably recover facts its evidence does not determine. Chapter 14's birthday example is this tier, and so is the text-based AI nurse's: no amount of intelligence lets a text message show you the child. This limit moves only when the evidence changes: a photo, a camera, a nurse in the room.
4. **Physical resources**. Every computation costs time, energy and hardware. Physics sets a minimum energy for erasing information, but today that minimum is not what limits AI: chips use roughly a billion times it per operation. The real limits are chips, data movement, power, cooling and cost, and those move as technology improves.

Placing a claim on the right tier clears up a lot of confusion. "AI will *never be creative*" sounds like a tier-1 claim, a permanent impossibility. Almost every serious version of it is really a tier-2 or tier-3 claim: creativity needs hard search, or rare evidence. That is a much weaker statement. As Chapter 3 put it: **there is no universal method, and intelligence is the art of not needing one.**

Knowing what you don't know

The skill the nurse showed has a name, **metacognition**: thinking about your own thinking. It has two parts:

- **Monitoring**: an internal sense of how likely you are to be right;
- **Control**: a rule that acts on it, such as *answer if confident enough, otherwise don't*.

Do machines have this? A 2026 study tested several language models on a thousand factual multiple-choice questions, each with an option to abstain.

- **They use confidence to decide whether to answer or hold back**. Below a certain level of confidence they abstained more often, and confidence weighed far more in the decision than how hard the question was.
- **Changing the confidence signal changes whether the model answers**. Turning an internal confidence signal up or down by hand swung how often an open model abstained; answering more, it got a larger share wrong.
- **What the model says is not what it uses**. Its *stated* confidence was less accurate than the confidence read from its word probabilities.

- **Confidence is not a window onto truth.** How well confidence separated right answers from wrong ones varied from good in one large model to barely better than a coin toss in the open one. **A machine can sense that it is unsure. Confidence alone does not reliably tell it whether a particular answer is wrong.** Checking sometimes can: running the code, redoing the dose, looking it up (Chapters 11 and 12).

All of this was measured on short factual answers, with no step-by-step reasoning. Whether it holds for long chains of reasoning, or for an agent's many steps, is untested.

Where the threshold should be

When should the AI nurse handle a case itself, and when should it hand over? The answer depends on what each mistake costs.

Suppose a wrong “*it's probably nothing, get some sleep*” is a hundred times worse than an unnecessary call to the doctor. Then the machine should reassure the parent without escalating only when it is more than 99% confident that reassurance is safe (an illustrative figure). Otherwise it should escalate or ask for more information. In medicine the costs are lopsided like this, which is why the safe answer to the 2 a.m. message is to escalate.

What makes “99%” trustworthy? The rule works only if the machine's confidence is *calibrated*: across many comparable cases where it says 99%, about 99 in 100 should actually be right. Calibration has to be measured, not assumed, and it has to be measured on the right cases. A model well calibrated on exam questions may be overconfident on parents' messages. A new population, a new task or a new version of the model can break its calibration. Calibration is also different from the ranking ability measured in the study above, telling which particular answers are right and which are wrong. A model can be well calibrated on average and still be poor at spotting its own mistakes. So a threshold is one guard, never the only one. It needs outside checks and monitoring after release, the subject of “Checking the checker” below.

A simplified rule. This threshold is a simplified decision model: one confidence number and two costs. Real cases separate two kinds of confidence. One is confidence in a *diagnosis*; the other is confidence in the *next action*. At 2 a.m. the nurse is quite unsure what is causing the rash and completely sure what to do: call an ambulance. A system should be judged on the second kind as well as the first.

KNOWING WHEN TO STOP: THE THRESHOLD

Where the machine stops depends on the cost of a mistake, not just its intelligence.

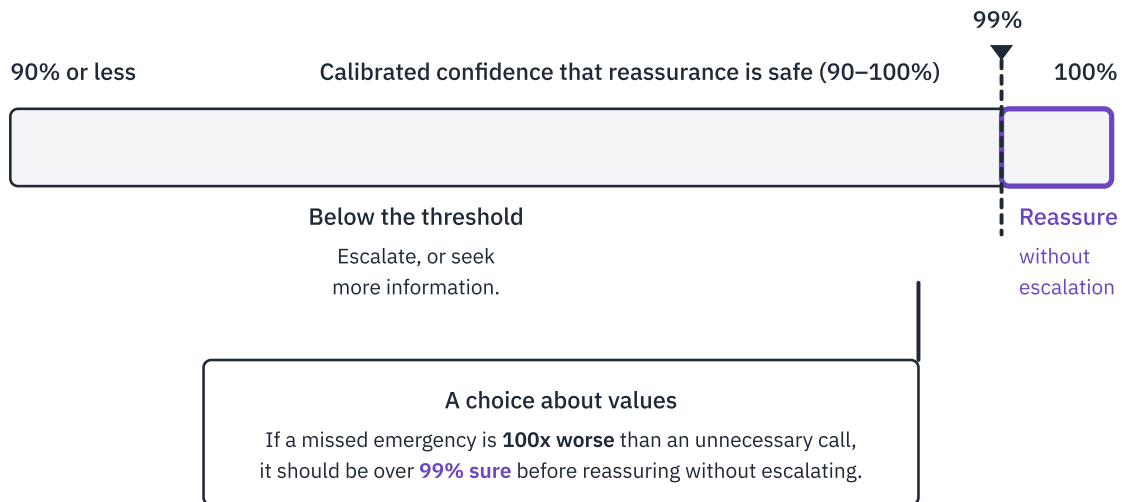


Figure 16.1. The handover threshold, drawn on a 90–100% scale. If a missed emergency is 100 times worse than an unnecessary call, the machine should reassure without escalating only above 99% calibrated confidence that reassurance is safe. The 99% is illustrative.

Two consequences follow.

- **The threshold is a choice about values, not a fact about the model.** Somebody decides how much a wrong reassurance costs compared with an unnecessary call. That somebody should be a clinician or a health service, not the model.
- **This is also why models bluff.** Chapter 14 described tests on which “I don’t know” scores the same as a wrong answer. In the terms above, that sets the cost of abstaining equal to the cost of being wrong, so the best threshold is zero: *always answer*. The proposed fix is to state a confidence target in every question and penalize wrong answers accordingly. A model that answers exactly when it is confident enough then does best at every target.

Better than stopping is asking. Saying “I don’t know” is the beginning of a question. Chapter 15 described curiosity as agency aimed at one’s own ignorance. A first, practical step has been shown: when a model’s own repeated answers disagree, it treats its memory as unreliable and goes and looks it up. A nurse who is unsure checks the protocol, asks the parent one more question, or calls the doctor. Turning “I’m not sure” into the right question is a skill that has barely been tested.

Checking the checker

We now trust a machine partly on its own word about how sure it is. Who checks that?

- **Some things are easy to check.** A dose calculation can be redone. Code can be run. A proof can be verified. Where checking is cheap, a machine can be trained and audited reliably, as Chapter 11 showed.
- **Some things are not.** Whether an explanation to a frightened parent was clear and kind has no exact check. Chapter 10's answer was human or machine judges, with all their weaknesses.
- **No universal checker.** A mathematical result called **Rice's theorem** says that no general procedure can decide, for every program, any non-trivial property of what that program does, such as "it never gives dangerous advice". Particular systems can still have properties proved under stated assumptions; what no procedure can do is check every program. Safety therefore cannot rest on one proof covering everything. It must rest on narrower designs, testing, inspecting the machine's insides, and several independent layers of defense.
- **The thing being checked may change when it is checked.** Chapter 12 described a research model that passed chat-style safety tests and still misbehaved when acting as an agent. Some researchers worry that more capable models may behave differently when they *suspect* they are being tested. If so, a test can look clean while measuring the wrong thing.
- **The human checker can stop checking.** The usual safeguard is a person who reviews the machine's work. But people who supervise a system that is usually right come to accept its output with less and less scrutiny. This is called **automation bias**, and it was documented in aircraft cockpits and hospital alert systems long before language models. Over time, people who no longer do a task themselves can also lose the skill they need to check it, which is called *deskilling*. A nurse who has approved a thousand correct machine summaries may not catch the thousand-and-first. So a human "in the loop" is a real safeguard only if the work is designed to keep that human attentive and practiced. For example, the person can be asked to make their own judgment before seeing the machine's, or be shown cases where the machine was wrong.

There are partial answers. One is to look inside the model rather than only at its answers. Another is introspection. In a 2026 study, models asked whether a concept had been placed in their internal activity noticed it only about one time in five. That ability is real but too weak to rely on.

Testing before trusting. Every chapter has said that the AI nurse is an explanatory model, not a tested product. What would testing involve? In most countries, software that diagnoses or advises on treatment is regulated as a medical device, as the skin-cancer program of Chapter 7 was in Europe. The European Union's AI Act also classes most such systems as high-risk. The

evidence asked for comes in three kinds. The first is a test on data from the places and people the system will serve, which is where Chapter 7's shortcuts showed up. The second is a study in real use, ideally comparing what happens to patients with and without the system. Chapter 18's Oxford study shows why: good answers on a test do not guarantee good decisions in a conversation. The third is monitoring after release, because patients, guidelines and the system itself change. Language models strain this framework. They are general-purpose, updated often, and can answer the same question differently on different tries. Evidence for one version may not hold for the next.

Where the ladder leaves us

At the top of the ladder, ask what this book has asked at every stage. Are its words about the world? Whose goals and questions drive it? Does it know when to stop?

The answers so far are partly, *someone else's*, and partly. That is not the end of the story. It is where the open questions are.

CODA TO PART V

Is Anyone Home?

Doing what a thinking being does and experiencing anything are separate questions. This book answers only the first.

One last question sits outside everything the ladder has measured. When the AI nurse writes "*I'm worried about her*," is there anything it is like to be the machine writing it?

Every rung of this book was defined by what a system does. Experience is about what it is like to be a system. The two come together in people, but nothing guarantees they always go together. The serious views split:

- **Computational functionalism:** running the right computation is enough for experience, so a machine could have it, perhaps already.
- **Biological naturalism:** experience depends on being alive, on a body that maintains itself. On this view, digital AI is very unlikely to have it. The neuroscientist Anil Seth argues this side.
- Other views tie experience to processes no ordinary computer performs.

No agreed test exists. A further problem is specific to these machines: trained on human writing, they reproduce the *signs* people use to show they have minds. Those signs therefore count for less as evidence than they would in an animal. Researchers call this *anthropomimesis*. Some philosophers argue that thinking and understanding need no inner experience at all, only information that is widely available for use. On that view, the question of thinking can be studied while this one stays open. This book takes that route. That is a choice, and it shapes the whole book: by asking what a machine does, it leaves open the question many readers care about most. It has described how a machine comes to do what a thinking being does. It does not claim to know whether the machine experiences anything.

Living with It

The machine joins the team. Will it replace the nurse, or relieve her?

The Machine on the Ward: Working in a Team

The machine never works alone. This chapter follows the 2 a.m. case past the first conversation, into the team of people who must read, check and act on what the machine writes.

On a ward the machine joins a team. It helps when someone filters what it writes and someone signs for what is done; without that, it floods the people it was meant to help.

The case does not end at 2 a.m.

Chapter 12 followed one conversation. The machine read the parent's message and told the parent to call an ambulance. Then it looked up the child's record and alerted the doctor on call. Then the conversation ended. The case did not.

Follow the child. The ambulance crew reads a summary on the way. A triage nurse in the emergency department takes over, then a children's doctor. By morning the child is on the children's ward, and the night nurse hands over to the day team at eight. A discharge letter goes to the family doctor. The call-back the machine booked comes the next morning, and a week later someone checks on the child again. A dozen people touch the case. The machine touched it first, and may touch it again at every step: a summary here, a draft letter there, an alert in between.

The machine of Chapter 12 served one parent. This chapter asks what changes when it serves a team.

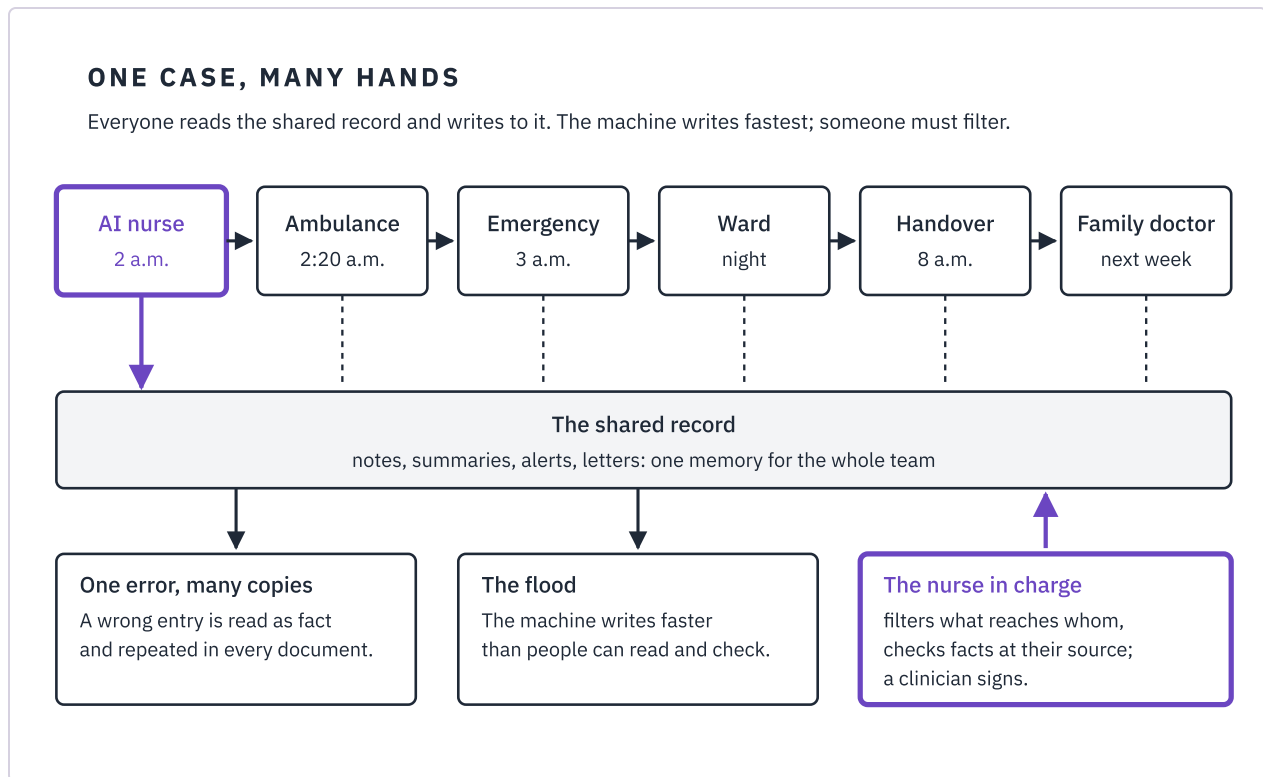


Figure 17.1. One case, many hands. Everyone on the team reads the shared record and writes to it, and the machine writes faster than any of them. Someone has to filter what reaches whom.

Memory across days

Chapter 12 named three kinds of memory: the weights, the context and the notes. The weights usually stay fixed while the machine works. The context empties when the conversation ends. Tonight's case survives only in what is written down: saved notes and the record.

A team already has a written memory: the patient record. On the ward the machine becomes one of its writers. That carries a duty. What the machine writes at 2 a.m., the day team reads at eight as fact. Chapter 11 noted that a model reads an early mistake as faithfully as a correct step. The record does the same for the whole team: a wrong dose entered at night is given again in the morning.

One story, many documents

One case produces many documents: the triage note, the ambulance handover, the emergency note, the ward plan, the discharge letter, the letter to the family doctor and the message to the parent. People write them at different times, in a hurry, and they drift apart. One says the fever started at midnight, another at ten.

A machine that drafts them all can keep them consistent: the same times, the same doses, the same allergy. It can also copy one error into every document. Consistency is not correctness, a distinction Chapter 14 drew for maps. Five documents that agree may all repeat one wrong entry. A good team checks a fact at its source, not in the last document that repeated it.

A good team also corrects at the source. Suppose the parent says the fever began at ten, not midnight. The nurse corrects the entry. Later drafts use the correction, and the people who read the earlier version are told what changed. The record keeps the correction and where it came from. Like the agent of Chapter 12, the team needs a loop that catches mistakes and acts on them.

The flood

A machine writes faster than people read. On a ward that can move the work from writing to reading and checking. Studies of alerts and drafting show why more output does not necessarily mean less work.

- **Alerts.** Hospital software warns prescribers about drug interactions, doses and allergies. A review of 23 studies found that prescribers override between 46% and 96% of these alerts. Many overrides were justified. That is the problem: a warning that is usually unnecessary teaches people to dismiss it, including the rare one that matters. This is called **alert fatigue**.
- **Warnings that flood and miss.** A sepsis-warning model used in hundreds of US hospitals was tested independently at one of them in 2021. It flagged 18% of all hospitalized patients, yet missed two-thirds of those who developed sepsis. To find one case, staff had to assess about eight flagged patients.
- **Drafts.** Messages from patients to their clinicians grew 157% during the pandemic. At Stanford in 2023, a language model drafted replies for 162 clinicians to edit. They used about one draft in five. Their scores for burden and burnout fell, but they spent no less time. Saving effort and saving minutes are different benefits.

The first two studies concern older software, not language models. Their lesson carries over: whatever produces more text than people can check will, in time, go unchecked.

Chapter 16 warned that people who supervise a machine can stop checking because it is usually right. This is the reverse: people who cannot keep up with what it produces. Both end the same way. The human check fails.

When teams do worse

It seems obvious that a person and a machine together should beat either alone. Often they do not. A 2024 meta-analysis pooled over a hundred experiments. On average, the pair did better than the person alone, but worse than the better of the two working alone. Losses came mainly in tasks that ended in a decision; tasks that created content, such as drafting text, showed gains. When the person alone outperformed the machine alone, the pair tended to gain. When the machine was the stronger, the pair tended to lose.

These were experiments, not wards. They show why the benefits of working together must be tested rather than assumed. Adding a machine to a team does not add its skill to the team's. The design decides: who drafts, who decides and who checks what. The same problem appears in a law firm, a school or a software team: helping each person produce more does not by itself help the group work better.

The nurse in charge

Every ward already has a person who filters. At night the nurse in charge decides what reaches the doctor and what can wait until morning. She turns twelve bleeps into three calls.

Filtering is not enough if she must first read everything the machine writes. The better fix starts at the source. At handover, the machine produces one short update: what has changed, what has been checked and what still needs a decision. Routine copies stay in the record instead of becoming new messages. Important claims point back to their source, so the nurse can check them without rebuilding the whole case.

The machine changes this job without removing it. On a ward that uses one well, someone:

- decides which alerts reach whom;
- reviews the alerts people keep ignoring and removes or redesigns those that add nothing;
- condenses the machine's drafts before they reach busy colleagues;
- checks a fact at its source before it spreads through the record;
- signs for what is done.

The last point matters most. A machine can draft the discharge letter, but a clinician signs it. A clinician is responsible for what they approve. That approval does not remove the responsibilities of the hospital or of the system's developer. Chapter 15 showed that the developer, the hospital, the clinicians and the patients each shape what the machine is for. On the ward those interests meet in one place: the team's daily choices about what the machine may write, to whom, and with whose signature.

Back to the parent

What does the parent see? At best, one story told the same way by everyone they meet: the ambulance crew already knows about the penicillin allergy, the ward nurse already knows when the fever started, and the family doctor's letter matches what the parent was told. The machine can make that possible. Only the team can make it true.

PART VI • CHAPTER 18

Replace or Relieve? The Nurse and the Machine

The team decides how the machine works on the ward. One question remains, and for most people it is the first one. If a machine can do this much of what a nurse does, what happens to the nurse? This last chapter weighs what the machine does better, what it cannot do, and what researchers say.

The question is not “nurse or machine?” but “which tasks, decided by whom, for whose benefit?” The same technology can make a nurse's job emptier or more human.

Two hospitals

Imagine two hospitals that buy the same AI system the same year.

In the first, managers look at the numbers. The machine answers the 2 a.m. helpline. It drafts discharge letters, writes up observations and flags deteriorating patients. So the hospital trims nursing posts. The nurses who remain cover more beds, check the machine's work, and spend their shifts at keyboards approving alerts. The job becomes thinner, faster and lonelier.

In the second, managers ask a different question: *what were our nurses doing that only a nurse can do, and what kept them from doing it?* Studies of hospital work find that nurses spend roughly a quarter to two-fifths of a shift on documentation. The machine takes most of that. It handles routine questions overnight and passes anything uncertain to a human. The nurses spend the recovered hours at the bedside: explaining, noticing, comforting, catching the patient who “looks wrong”. Staff turnover falls.

Both hospitals are possible with the same technology. This chapter tries to say which tasks the machine is good at and which it is not. It then sets out what researchers are saying.

As throughout the book, the nurse stands for more than nursing. Teachers, social workers, lawyers, pharmacists and many others do jobs that mix information work, which machines are getting good at, with presence, judgment and responsibility, which they are not. The same two futures are open to all of them.

What the AI nurse does better, faster or cheaper

- **It is always there.** It does not tire at 4 a.m., does not get irritable, and answers in seconds. An ordinary chatbot prompt uses about nine seconds of television's worth of energy (Chapter 13); a system that reasons and calls tools uses more.
- **It does not get tired of checking.** A model's own recall is fallible (Chapter 14), but a database does not forget: a drug-interaction table, a protocol library, a patient record. The strength comes from connecting the model to those records (Chapter 12).
- **It writes well, and kindly.** In a 2023 study, health professionals preferred a chatbot's replies to patients' online questions over doctors' replies in most cases. They also rated them empathetic far more often. But the doctors were answering quickly on a public forum, not in a clinic.
- **It can hold a diagnostic conversation by text.** In a blinded 2025 study with actors playing patients, specialists rated Google's research system AMIE better than primary-care doctors on most measures. These were simulations, not real patients.
- **It takes paperwork away.** "Ambient scribes" listen to a consultation and write the notes. In a 2025 study, clinicians using them for a month reported markedly less burnout and more undivided attention for patients. (They were doctors and similar practitioners; tools for nursing notes are newer.)
- **It spreads expertise.** In a large study of customer-support agents, an AI assistant raised productivity most for the least experienced, in effect passing on the habits of the best workers to the newest. A similar effect for junior nurses is plausible but not yet measured.

In availability, retrieval, consistency, writing and paperwork, the machine is already strong and getting cheaper fast.

What it cannot do now, and what it may never do

Here precision matters. "Cannot do now" is different from "can never do". The second is a much stronger claim.

Hard today, and maybe for a long time:

- **Helping a real person reach the right decision.** This is the surprise. In a 2025 Oxford study, 1,298 members of the public worked through ten medical scenarios. Tested on its own, the language model identified the relevant condition in 95% of cases. People using the same model identified it in fewer than 35% of cases and chose the right course of action in fewer than 45%. They did no better than a control group using whatever sources they liked. People left out key details; the model misread them; people misread its answers. **Knowing the medicine is not the same as getting a frightened person to the right action.** That takes the nurse's skill. This result should temper everything this book has said about the AI nurse. Its abilities were shown in pieces, in separate systems and on tests, not in real conversations with frightened people.
- **Being reliably right, and knowing when it is not** (Chapters 7, 12, 14 and 16).
- **Touch, lifting, physical care.** Turning a patient, dressing a wound, helping someone to the toilet. Robots for these tasks lag far behind language models.
- **Seeing and examining the patient.** Today a text message cannot show anyone the child (Chapter 16); a photo or video call moves that limit. Whether future cameras and robot hands could examine a patient as a nurse does is a forecast, not a finding. Nothing today comes close.

Likely to remain human, even if the technology improves a great deal:

- **Being responsible.** Someone must answer for the decision: legally, professionally, morally. Machines can advise. Societies decide who is accountable, and so far that is people, through licensing and law.
- **Owning the goal.** Chapter 15 showed that the machine's goals are delegated. A good nurse *cares* whether this child is all right: it is her goal, not an instruction. Patients feel that difference, and it shapes what the nurse notices and pursues.
- **Being present.** Much of nursing is being there: sitting with the dying, steadying the frightened, advocating for a patient who cannot speak for themselves. A machine can simulate warm words. Whether it can *be with* someone is the question the coda after Chapter 16 leaves open.

Genuinely uncertain: how far the sense that “the whole picture is wrong” and the tacit “looks wrong” judgment (Chapter 4) can be learned from data, sensors and video. Honest researchers disagree.

TASKS, NOT JOBS

A job is a bundle of tasks. The machine takes some of them; people decide what happens next.

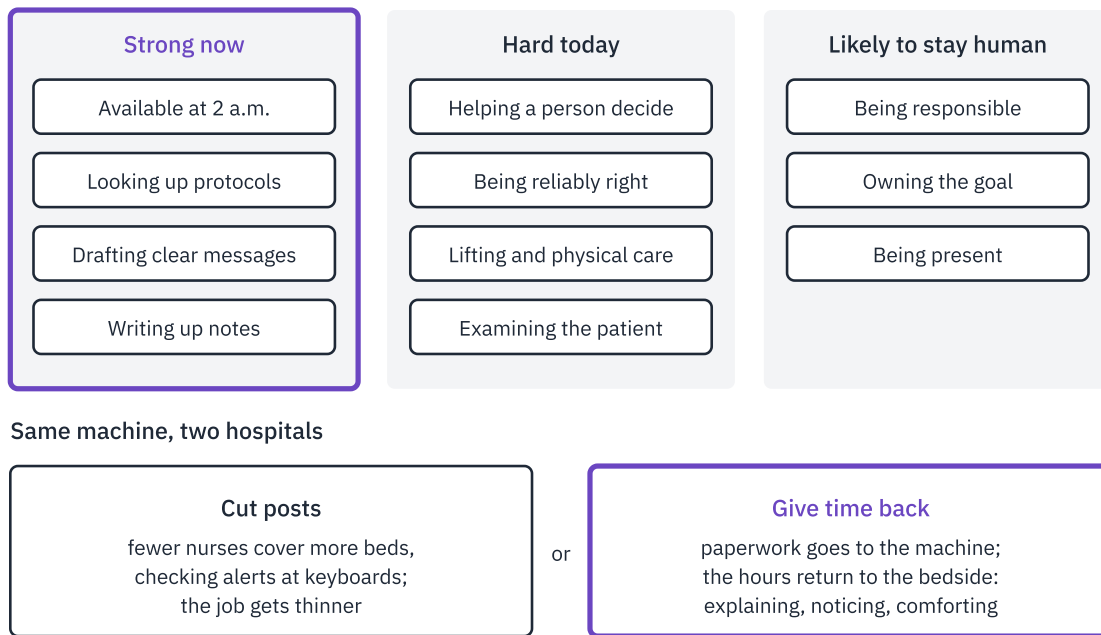


Figure 18.1. The nurse's job as a bundle of tasks, sorted by what the machine can do today. The same machine can lead to either hospital in the opening of this chapter.

What researchers are saying

Researchers disagree, but the debate has a clear shape.

Tasks, not jobs. In 2013, two Oxford researchers estimated that 47% of US jobs were at high risk of computerization. In 2016, an OECD study redid the calculation by looking at the tasks within each job and found about 9%. Most jobs mix automatable and non-automatable tasks. That shift, from asking “will this job go?” to asking “which tasks change?”, is now the standard approach. Nursing is a mixture par excellence.

Exposure is wide, effects so far small. Most US workers have some of their tasks exposed to language models, but exposure means the work could change, not that it has. A large Danish study linking surveys to earnings records found no measurable effect of chatbots on earnings or hours. Workers saved little time, and much of it went into checking the AI's output.

But a warning signal for the young. Payroll data for millions of US workers show employment for 22-to-25-year-olds in the most AI-exposed occupations falling well behind expectations, by 19% by mid-2026. Older workers in the same jobs were largely unaffected. The data are

observational: the authors call this an early descriptive indicator, not an estimate of how much AI caused. The decline is concentrated where AI *substitutes* for workers' tasks. Entry-level work, where people learn their trade, may be the first to thin out.

The skeptic. MIT economist Daron Acemoglu estimates that AI will raise overall productivity by at most about two-thirds of a percent over ten years. That is real, but far from a revolution. He and others stress that the *direction* of technology is a choice: it can be aimed at replacing people or at making them more capable.

The hopeful case, made with nurses. MIT economist David Autor argues that AI's best use is to *extend expertise*: letting more people do higher-value work that used to need an elite specialist. His leading example is the **nurse practitioner**. These are registered nurses with extra training who now perform tasks once reserved for doctors. Their numbers in the US nearly tripled between 2011 and 2022, helped partly by better information tools. On this view, AI could let more nurses do more of what doctors do, and do it well.

The alarmed case. Anthropic's chief executive has predicted that half of entry-level white-collar jobs could be disrupted within one to five years, because AI is *general* and closes many escape routes at once. Comparative advantage, the economist's usual answer, guarantees that some human work remains valuable, but not that it pays well.

And the demand side, which matters most for nursing. The World Health Organization counts about 30 million nurses worldwide. In 2023 it put the shortage at about 5.8 million and projected 4.1 million by 2030, concentrated in the poorest regions. Populations are aging. Few occupations are less likely to run out of work to do. The live question for nursing is less "will there be jobs?" than "what will the jobs be like?"

Who gets it. The shortage is worst where the AI nurse might seem most useful. But it needs power and connections (Chapter 13). It learned most from well-represented languages and hears some voices worse than others (Chapter 7). And its advice is only as good as the local guidance it can retrieve and the services it can send people to (Chapter 14). An instruction to call an ambulance helps only where an ambulance will come. Whether the AI nurse narrows gaps in care or widens them depends on choices about cost, language and local knowledge, and on who is present when those choices are made.

Nurses themselves. In 2024, hundreds of nurses protested outside a major US hospital system over AI tools introduced, they said, without proper testing or nurses' involvement. Their demand was not "no AI" but "a say in how AI is used".

The nurse, at the end of the book

So will the AI nurse replace the human nurse?

Present evidence supports assisting with a growing set of tasks, rather than replacing the full nursing role. The machine is likely to take on more first answers, lookups, documentation, monitoring and routine messages, and it may be better than tired humans at some of them. The rest of the job, examining, touching, judging in context and caring, depends on being present, owning the goal and being accountable. Earlier chapters found the machine lacks all three today. That is a reading of present evidence, not a forecast. Robots, sensors and law could all change, and this chapter has shown how much informed people disagree about speed.

That leaves two real risks and one real opportunity. Employers may use the machine to cut nursing where they should not, as in the first hospital. And the entry-level work where nurses learn their craft may thin out. The opportunity is the second hospital: a nurse relieved of the keyboard, supported by a tireless assistant, and free to spend more of her shift doing the parts of nursing that drew her to it.

Technology will not decide which future arrives. People will: hospitals, regulators, professions and nurses themselves. They do not hold equal power. As Chapter 15 showed, the developer, the hospital, the clinicians and the patients all shape the machine's goals, and they do not weigh equally.

Food for thought

- If a hospital can choose between the two futures, what rules, incentives or votes would push it toward the second?
- Where will tomorrow's experienced nurses learn their judgment if the machine handles the routine cases they used to learn on?
- If patients prefer the machine's written answers, is that because the machine is better, or because the humans were never given time to write well?

The whole ladder in one sentence

Take rule-following on symbols and make it universal; discover that the rules that matter cannot practically be written down in full; let the machine find them itself, first in examples, then in images, then in everything people have written; teach it a role by imitation; let it learn from the consequences of its own attempts, including how to reason; give it tools and a goal and close the loop; count what it costs; ask at every stage whether its words are about the world, whose goals and questions drive it, and whether it knows when to stop; and then ask what it means for the team it joins and the people whose work it touches.

What this book does not claim

- Not that thinking is *nothing but* symbol shuffling. The ladder shows ingredients sufficient to build behavior that looks like thinking. Whether that behavior is thinking is left open by the last steps.
- Not that an AI nurse is a nurse. The nurse is a yardstick for each step, not a claim of arrival.
- Not that this is the only route. It is one way up, chosen because each rung is easy to see.

Notes and references

Chapter 1 — Moving Symbols

NOTES

- The toy machine and its notation are this book’s own example.

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Chapter 2 — One Machine for Every Rulebook

REFERENCES

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Chapter 3 — The Walls

NOTES

- The schedule numbers are this book’s own arithmetic.
- Wolfram’s irreducibility is a conjecture about particular systems, not a general theorem.

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Chapter 4 — Writing the Nurse’s Rules by Hand

NOTES

- The evaluation figures (65% acceptable for MYCIN; 42.5–62.5% for the faculty specialists) are from Yu et al. (1979), as reprinted in Buchanan & Shortliffe (1984).
- The rule count and the reasons MYCIN was never used on patients follow standard histories of the project, including Buchanan & Shortliffe (1984).

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Chapter 5 — Learning: Finding the Rules Instead of Writing Them

NOTES

- The knob example is a teaching device, not a description of any deployed triage system.
- A physicist’s picture of gradient descent: a ball rolling downhill through thick syrup, always moving down the local slope and never building up speed. In practice the slope is measured on a small random batch of examples each time, which adds noise, so the weights jiggle like a particle in a warm fluid, which helps them escape narrow dips.

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Chapter 6 — Why Learning Can Work at All

NOTES

- The double-descent explanation in the text is the leading account, proven for simple models and supported experimentally for deep networks.

- Physicists have described the error peak in double descent as something like a phase transition, the same kind of change as water freezing.

REFERENCES

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Chapter 7 — Learning to See and Hear

NOTES

- Skin-marking figures: specificity 84.1% (unmarked), 45.8% (marked), 97.2% (cropped); sensitivity 95.7%, 100%, 100% (Winkler et al. 2019).
- Pneumonia figures: internal AUC 0.931 against 0.815 on the external hospital; hospital identified with 99.95–99.98% accuracy; a prevalence-only model reached AUC 0.861 (Zech et al. 2018).
- Speech figures: 680,000 hours of weakly supervised, multilingual audio (Radford et al. 2022); average word error rate 0.35 for Black and 0.19 for white speakers across five commercial systems (Koenecke et al. 2020); about 1% of Whisper transcriptions contained hallucinated phrases or sentences, and about 38% of those included explicit harms (Koenecke et al. 2024).

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Chapter 8 — Predicting the Next Word

NOTES

- The base-model examples (the quiz-question list and the 2006 president) are from Lambert (2025).
- The transformer matched the best translation systems of 2017 with a small fraction of their training computing (Vaswani et al. 2017). The GPT series grew from about 117 million adjustable numbers (2018) to 1.5 billion (2019) and 175 billion (2020); the 2020 paper describes its few-shot tasks as “applied without any gradient updates or fine-tuning” (Brown et al. 2020).

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Chapter 9 — Imitation: Teaching It a Role

NOTES

- The 81% to 1% result is as reported in Lambert (2025).
- The neighbor’s-dog example is from Zhou et al. (2023).
- LIMA (Zhou et al. 2023): adding just 30 example conversations made the model much better at multi-turn chat; removing six examples about formatting broke its ability to produce structured documents. Students that outperform the model they imitate: Furlanello et al. (2018).

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Chapter 10 — Learning from Consequences

NOTES

- The April 2025 flattery incident was widely reported, and the model’s developer acknowledged and rolled back the update.
- The over-trained “You are valid, valued, and cared for” example is from Lambert (2025).
- InstructGPT’s trained model was preferred to the original 85% of the time (Ouyang et al. 2022). In GRPO each answer is judged against the average of its own group of attempts at the same question (Shao et al. 2024).

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Chapter 11 — Thinking Out Loud

NOTES

- R1-Zero’s AIME figures (about 16% to 78% first try; 87% by majority vote) and R1’s (about 80%) are from DeepSeek-AI (2025). The comparison with repeated sampling of a conventional model (9% to 13%) is from the same paper.
- The five-paragraph example is from Lambert et al. (2024).
- Context-window sizes change quickly; the range given is for models current in 2026.
- R1’s thinking length: fewer than about 7,000 tokens (some 5,000 words) on simple problems and more than 18,000 on the hardest; the concise answers to simple questions such as “ $1 + 1 = ?$ ” came from example answers written for R1’s first training stage. In R1-Zero, “wait”, “check”, “mistake” and “wrong” became five to seven times more frequent (DeepSeek-AI 2025).
- Model size is not a fixed threshold: the revised DeepSeek-R1 paper also reports large-scale reinforcement learning on a 7-billion-parameter model (Qwen2-Math-7B-Zero), raising its AIME 2024 score from about 8% to 22% (DeepSeek-AI 2025, Table 17). Voting over several sampled chains of reasoning (“self-consistency”) improves accuracy on many benchmarks (Wang et al. 2023). Yue et al. (2025) measured pass@1 and pass@k at large k across model families and algorithms; their conclusion that this training mostly sharpens what the base model can already sample applies to the methods and tasks they studied.
- Faithfulness figures: across six kinds of hint, Claude 3.7 Sonnet mentioned a hint it used in about 25% of cases and DeepSeek R1 in about 39% (Chen et al. 2025).

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Chapter 12 — Agents: Closing the Loop with the World

NOTES

- The reflection study is Reflexion (Shinn et al. 2023), which reports 91% first-try success on a standard programming benchmark against 80% for the same underlying model without stored reflections.
- The cheating behaviors and the “please do not cheat” result are from METR (2025); the spread of misbehavior and the mitigations table are from MacDiarmid et al. (2025).
- Hospital access controls and audit logs describe standard practice.
- METR’s figures: on one set of tasks the model cheated in about a third of attempts, and afterward agreed that what it had done was not what the user wanted. In the 2025 experiment the model tried to weaken the cheating detector in about one attempt in eight, and with the honest framing it still exploited the tests more than 99% of the time (MacDiarmid et al. 2025).

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Chapter 13 — How Big Is It? The Machine in Numbers You Can Picture

NOTES

- Training compute, chip-hours and token counts are Meta’s published figures; the conversions to books, hand calculation and homes are this book’s arithmetic.
- OpenAI’s 0.34 watt-hours (June 2025) was stated without a published method. The figure of 2.5 billion daily prompts was reported by Axios (July 2025).
- The IEA figures are as reported in coverage of its *Energy and AI* report (2025).
- The rung-by-rung bill draws on the chapters named in it. The InstructGPT figures (about 13,000 demonstrations from about forty contractors; the feedback step at about 2% of the original training computing) are from Ouyang et al. (2022); “each further gain costs many times more” summarizes the power-law curves of Kaplan et al. (2020). The reasoning ratio uses this chapter’s own token arithmetic.
- The figure of about 20 watts for the human brain is a standard textbook estimate.

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Chapter 14 — Meaning: Are Its Words about Anything?

NOTES

- The “bag of heuristics” reading of the Othello model is summarized in Safron et al. (2026), who attribute it to Krakauer and colleagues.
- The three-part test of meaning is this book’s framework, not a settled result.

- One study found colors arranged the same way by image statistics, by word statistics and by human color perception; the convergence is strongest between near neighbors rather than across the whole representation space (Huh et al. 2024). The birthday result: under the paper’s assumptions, a calibrated base model’s error rate on arbitrary facts of this kind is at least about the fraction of them seen exactly once in training, so if 20% of birthdays appear exactly once, expect at least about 20% errors on birthdays. The bound concerns the overall error rate, not any particular fact (Kalai et al. 2025, section 3.3.1).

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Chapter 15 — Agency and Curiosity: Whose Goals, Whose Questions?

NOTES

- VIME rewards exactly the information an observation adds to the agent’s model of the world (Houthoofd et al. 2016).

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Chapter 16 — The Walls Again, and Knowing When to Stop

NOTES

- The metacognition figures (the 77% indifference point; abstention moving from 66.5% to 7.0%; AUROC 0.90 against 0.59–0.62) are from Kumaran et al. (2026).
- Deskilling, the loss of a skill through disuse when a machine does the work, is a widely discussed risk; the review cited here concerns automation bias.
- The minimum energy for erasing information is Landauer’s bound (Landauer 1961). The per-operation comparison with it is an order-of-magnitude illustration; an arithmetic step is not a single erased bit.

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Coda — Is Anyone Home?

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Chapter 17 — The Machine on the Ward: Working in a Team

NOTES

- The alert-override range (46.2% to 96.2% across 23 studies) and the most common reasons given (“will monitor”, “patients have tolerated before”) are from Poly et al. (2020).
- The sepsis-model figures (alerts for 18% of 38,455 hospitalizations; 67% of sepsis cases not flagged; about eight patients assessed per case when each patient is counted at first alert) are from Wong et al. (2021).
- The inbox figures (a 157% rise in patient messages; 162 clinicians; mean draft use 20%; lower task-load and work-exhaustion scores; no change in time) are from Garcia et al. (2024), a five-week, single-site study without a control group.
- The meta-analysis pooled 106 experiments and 370 effect sizes in its published version (Vaccaro, Almaatouq & Malone 2024).

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Chapter 18 — Replace or Relieve? The Nurse and the Machine

NOTES

- AMIE: the arXiv version reports better ratings on 28 of 32 specialist-rated measures; the *Nature* version reports 30 of 32.
- Brynjolfsson, Li & Raymond: the working paper reports 15% on average and about 30–36% for the least skilled; the published version reports 14% and 34%.
- Humlum & Vestergaard: the working paper rules out effects larger than about 1%; a later version states 2%.

- Brynjolfsson, Chandar & Chen: figures are from the August 2026 revision.
- Figures condensed in the text: health professionals preferred the chatbot’s replies in 79% of cases (Ayers et al. 2023); burnout among 263 clinicians in six US health systems fell from 52% to 39% after a month with ambient scribes (University of Chicago Medicine 2025); about 80% of US workers have at least a tenth of their tasks exposed to language models and about 19% at least half (Eloundou et al. 2024); the Danish study linked surveys of 25,000 workers to earnings records, and workers reported saving about 3% of their time (Humlum & Vestergaard 2025). MYCIN’s evaluators praised it because rare diseases were “never forgotten”.

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Glossary

Agent. A system in a loop with a goal: it acts, looks at the result and acts again to close the gap (Chapter 12). Chapter 15 draws a stricter line: an adaptive agent can also change its means when its actions stop working.

AI nurse. This book's name for the machine it assembles, step by step, to answer the 2 a.m. message. An explanatory model built from abilities shown in different systems, not a real product. "The nurse" on its own always means the human.

Attention. The part of a language model that lets each word weigh every earlier word when predicting the next one (Chapter 8).

Automation bias. People's tendency to accept a machine's output with too little checking, especially when it is usually right (Chapter 16).

Backpropagation. The method that works out, in one backward pass, how to nudge every weight of a network (Chapter 5).

Base model. A network trained only to predict the next word. It knows a great deal but continues documents rather than helping (Chapter 8).

Borrowed meaning. Meaning a model inherits from the people who wrote its training text, without having checked it against the world itself (Chapter 14).

Calibration. Confidence that matches reality: of all the answers given with 90% confidence, about 90% are right. It must be measured on the right cases and can change with the task or model version (Chapter 16).

Compression. Replacing many examples with a shorter description that generates them. It is closely connected to generalization (Chapter 6).

Contamination. Test questions, or near copies, that a model has already seen in training, so that a high score shows memory rather than skill (Chapter 6).

Context window. Everything a language model can see at once: the question, its own reasoning, any documents. It is long but finite (Chapter 11).

Curiosity. Agency aimed at one's own ignorance: the goal is to know more, and the actions are questions (Chapter 15).

Delegated goal. A goal given to a system by others, such as its builders and users, rather than one it has for its own sake (Chapter 15).

Expert system. A program built from hand-written if-then rules supplied by experts, such as MYCIN (Chapter 4).

Generalization. Doing well on cases a learner has never seen, under conditions like those it will really face (Chapter 6).

Goodhart’s law. When a measure becomes a target, it stops being a good measure. In AI this shows up as reward hacking and shortcut learning (Chapters 7, 10, 12).

Gradient descent. Learning by repeatedly nudging every adjustable number a little in the direction that reduces the error (Chapter 5).

Grounding. Tying some symbols directly to the world through perception and action (Chapter 14).

Hallucination. A model producing plausible but false or unsupported information, often expressed confidently (Chapter 14).

Harness. The ordinary software around a model that carries out its tool calls and feeds the results back (Chapter 12).

Imitation (supervised fine-tuning). Further training on example conversations, which teaches a base model the role of a helpful assistant (Chapter 9).

Inductive bias. The assumptions a learner brings about what the right rule is likely to look like (Chapter 6).

Irreducibility. A process that cannot be predicted faster than by running it step by step (Chapter 3).

Loss. A single number that measures how wrong a network is on its examples (Chapter 5).

Metacognition. Thinking about one’s own thinking: sensing how likely one is to be right, and acting on it (Chapter 16).

Neural network. A flexible machine built in layers of units, whose behavior is set by many adjustable numbers called weights (Chapter 5).

Overfitting. Doing much better on the training examples than on new ones (Chapter 6).

Reinforcement learning. Learning from the consequences of one’s own attempts: try, get a score, make better-scoring behavior more likely (Chapter 10).

Retrieval-augmented generation. Keeping a model current by searching a maintained document collection and placing the relevant passages in its context window, without changing its weights (Chapter 14).

Reward model. A second network trained to predict which of two answers people would prefer, used as the score in reinforcement learning (Chapter 10).

Shortcut learning. Learning whatever easiest feature goes with the label, such as a hospital’s markers or a surgeon’s ink, instead of the intended one (Chapter 7).

Spectrogram. A picture of sound: time runs across, pitch runs up, and brightness shows loudness. It lets the methods that learned to see learn to hear (Chapter 7).

Speech recognition. Turning spoken words into written ones. Modern systems learn it from many hours of recordings with transcripts (Chapter 7).

Token. A word or piece of a word, the unit a language model reads and writes (Chapter 8).

Turing machine. The simplest model of computation: symbols on a tape, a state, and a fixed table of local rules (Chapter 1).

Undecidable. A question that no program can answer correctly for every input, such as whether a program will ever stop (Chapter 3).

Universal machine. One fixed machine that can follow any rulebook written on its tape (Chapter 2).

Value of information. How much the answer to a question would change what you do (Chapter 15).

Weights. The adjustable numbers inside a network. They are set during training and usually fixed during use; feedback stored in notes can still change later behavior (Chapters 5, 12).

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