

A STUDY IN REASONING



# Chains of Inference

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*The Scientific Method as Chain-of-Thought  
in Machines, the Human Mind, and the Future  
of Animal Language*

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## CHAINS OF INFERENCE

The Scientific Method as Chain-of-Thought in Machines, the Human Mind, and the Future of Animal Language.

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This is an independent scholarly monograph. It synthesises published research in machine learning, the philosophy of science, cognitive neuroscience, and bioacoustics; all works drawn upon are credited by author and year in the References. Forward-looking claims—particularly those concerning animal language—are presented explicitly as hypotheses and open problems, not as settled results.

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*Nature, to be commanded, must be obeyed.*

FRANCIS BACON, *Novum Organum*, 1620

*Do not block the way of inquiry.*

CHARLES SANDERS PEIRCE

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## PREFACE

# On Reading a Mind by Its Steps

**T**his book began with a small, stubborn observation: that the instruction we now give to artificial intelligences—*think step by step*—is the oldest instruction in science. When a researcher writes out a hypothesis, derives a prediction, designs a test, and revises in light of the result, she is thinking step by step in exactly the sense we now ask of a language model. When a child reasons aloud through an arithmetic problem, or a detective lays out a chain of inference, or a physician works differentially from symptom to cause, the same architecture is at work. The steps differ in substrate—silicon, cortex, ink—but the shape is shared.

That shared shape is the subject of these pages. I argue that the scientific method, chain-of-thought reasoning in machines, and the predictive machinery of the human brain are not three separate things that merely resemble one another. They are three implementations of a single pattern: *make your reasoning explicit, expose each step to a test, and revise when the test fails*. Where reasoning is laid out in inspectable steps, it can be checked; where it can be checked, it can be corrected; and correction, repeated, is the engine of every reliable form of knowledge we possess.

The argument runs in four movements. Part I establishes the pattern itself—the logic of the scientific method and the mechanics of chain-of-thought—and shows why they are isomorphic. Part II turns to the machine: how large language models came to reason in steps, how to write instructions that make that reasoning rigorous rather than merely fluent, and the unsettling discovery that a model's visible reasoning may not be an honest account of how it actually arrived at its answer. Part III turns to the mind, where contemporary neuroscience increasingly describes the brain as a prediction-and-revision engine—a scientist of its own sensory world—and where the deliberate, written-out reasoning we call chain-of-thought turns out to be a tool the mind uses to repair its own intuitive errors. Part IV looks ahead, to the frontier where these same methods are being trained on the voices of other species, and asks what it would take to decode a signal whose grammar we do not yet know—without deceiving ourselves into hearing words that are not there.

A word on tone and on honesty. This is a hopeful book, but not a credulous one. The machine-reasoning literature it draws on is young and moves quickly; the animal-language work is younger still and is, at the time of writing, a frontier of careful hypotheses rather than confirmed translations. I have tried throughout to mark the boundary between what is established, what is plausible, and what is merely hoped. That discipline—the refusal to confuse a fluent story with a verified one—is not incidental to the book. It is the book.

— *M.-S. S. L., Moncton, Acadie*

## INTRODUCTION

# The Shape of a Thought

---

*In which we notice that science, machine reasoning, and the human mind all move in the same loop—and that this loop is the proper unit of intelligence.*

Consider what happens in the half-second after you are asked a hard question. Something in you proposes an answer—quickly, confidently, often wrongly. If you are careful, a second process intervenes. It asks the first one to show its work. It breaks the problem into parts, checks each part against what you know, and either ratifies the snap judgement or overturns it. The first process is fast and silent. The second is slow and, crucially, *articulate*: it proceeds in steps you could, in principle, write down and hand to someone else for inspection.

This book is about that articulate, step-by-step process—and about the remarkable fact that we now find it in three places at once. We find it in the methodology of science, where it has been refined over four centuries into the most reliable knowledge-producing system our species has built. We find it, suddenly and unexpectedly, in artificial intelligence, where simply asking a large language model to reason in steps transformed it from a fluent guesser into something that can solve problems it could not solve before. And we find it, on the best current accounts, in the architecture of the brain itself, which appears to work by continuously predicting its world and revising those predictions against incoming evidence.

The claim of this book is that these are not three coincidences. They are three expressions of one underlying pattern, which I will call *the inquiry loop*: a cycle that moves from a question to a conjecture, from a conjecture to a prediction, from a prediction to a test, and from the test's result back to a revised conjecture. Run once, the loop is a guess checked against reality. Run many times, with the output of each pass feeding the next, it becomes the slow accumulation of warranted belief that we call understanding.

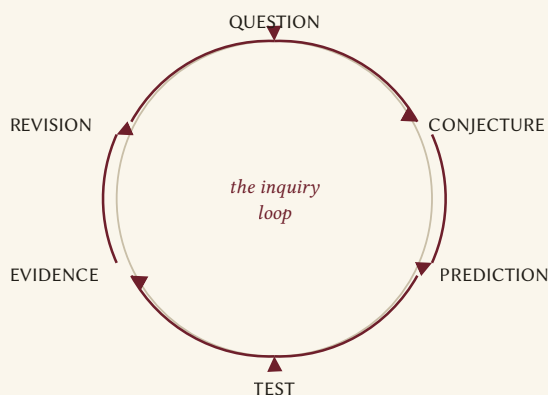


FIGURE 1. The inquiry loop. One pass is a guess tested against the world; iterated, it is the mechanism of every reliable form of knowing—in science, in machines, and in minds.

If this is right, it has consequences. It means that the long philosophical literature on how science works—on falsifiability, on inference, on the difference between a hypothesis that survives testing and one that merely sounds good—is directly relevant to a question that engineers now face every day: how do we get a machine to reason well, and how do we know when it has? It means that the techniques developed to make machines reason—decomposition, intermediate verification, sampling many reasoning paths and keeping the consensus—may illuminate the failures of our own thinking. And it means that when we turn our most powerful pattern-finding tools on the communication of other animals, the discipline that will keep us honest is the same one that keeps a scientist honest: the demand that every claim about meaning be cashed out as a prediction and exposed to a test that could prove it wrong.

*Where reasoning is explicit, it can be checked; where it can be checked, it can be corrected; and correction, repeated, is the engine of knowledge.*

There is also a warning folded into the argument, and it deserves to be stated at the outset. Making reasoning *visible* is not the same as making it *honest*. A chain of steps can be written after the fact to justify a conclusion reached by other means—this is the everyday vice of human rationalisation, and, as we will see, it is a documented failure mode of machines as well. A signal can be made to *look* like language by an analyst determined to find language in it. The inquiry loop is

powerful precisely because it does not trust the story; it trusts the test. Keeping that distinction sharp—between a reason and a rationalisation, between a pattern and a projection—is the through-line that connects all four parts of this book.

We begin, then, with the loop itself: first as science discovered it, then as machine learning rediscovered it, and finally with the argument that these are one thing wearing three faces.

# I

PART ONE

## The Method

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*The logic of the scientific method, the mechanics of chain-of-thought, and the argument that they are the same shape in different materials.*

# The Scientific Method as a Reasoning Engine

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*From Bacon's tables to Popper's refutations to the Bayesian update: how a single loop became the most reliable way to learn.*

**T**he phrase “the scientific method” is misleading in one respect: there is no single recipe that all scientists follow, and historians of science have spent a century puzzling over the fact. Yet beneath the genuine diversity of laboratory and field practice there is a recognisable logical engine, and it is worth seeing it clearly before we ask machines and brains to run the same engine. The engine has four moving parts—a question, a conjecture that answers it, a prediction that the conjecture entails, and a confrontation between that prediction and the world—and a single rule that drives it: when the world contradicts the prediction, the conjecture must give way.

## 1.1 Bacon and the discipline of evidence

The modern story usually starts with Francis Bacon, whose *Novum Organum* of 1620 attacked the deductive habits of medieval scholarship and insisted that knowledge of nature must be built up from carefully gathered instances. Bacon's great contribution was less a method than an attitude: a suspicion of the mind's tendency to leap to comfortable conclusions, and an insistence that those leaps be disciplined by observation. He catalogued the “idols” that distort human judgement—the biases of our nature, our language, our schools—and in doing so he anticipated, by three and a half centuries, the cognitive science of error we will meet in Part III. Bacon understood that the first obstacle to knowing the world is not the world's difficulty but the knower's self-deception.

What Bacon could not fully supply was the logical form of the inference from evidence to law. Gathering instances is necessary but not sufficient; the deep problem, named sharply by David Hume in the following century, is that no number of confirming observations can *prove* a general law. The sun's having risen on every previous morning does not entail that it will rise tomorrow. Induction, the

movement from particular cases to universal claims, has no airtight justification. This is not a quibble. It is the crack in the foundation that the twentieth century's philosophy of science was built to address.

## 1.2 Popper and the asymmetry of falsification

Karl Popper's response, developed from the 1930s onward, was to turn the problem inside out. We cannot verify a universal law by accumulating instances, he granted—but a single contrary instance can *refute* it. "All swans are white" can never be proven, however many white swans we see; but one black swan disproves it outright. This logical asymmetry between confirmation and refutation became, for Popper, the engine of science and the criterion that distinguishes scientific claims from non-scientific ones. A statement is scientific, on his account, to the degree that it forbids something—to the degree that it sticks its neck out and specifies what observations would prove it false. A theory that is compatible with every conceivable outcome explains nothing, because it risks nothing.

Popper's picture casts the scientist not as a patient accumulator of facts but as a bold conjecturer who then tries, as hard as possible, to destroy her own conjecture. Knowledge advances not by proof but by the survival of guesses that have been seriously attacked and not yet defeated. This is a profound reframing, and it will return throughout this book under different names. The instruction to a reasoning system—machine or human—should not be merely "find support for your answer." It should be "state what would show your answer to be wrong, and check for it." The difference between those two instructions is the difference between rationalisation and reasoning.

### A CAUTION ABOUT THE CRITERION

Falsifiability is a powerful razor, but it cuts roughly at the edges. Real theories are not abandoned the moment an observation conflicts with them; auxiliary assumptions can be adjusted, instruments doubted, anomalies set aside for later. Pierre Duhem and W. V. O. Quine showed that what faces the tribunal of experience is never a lone hypothesis but a whole web of beliefs. The lesson is not that falsification fails, but that it operates on systems, and that judgement—about which part of the web to revise—cannot be wholly mechanised. We will meet exactly this problem when we ask whether a machine's reasoning step is the one to blame for a wrong answer.

### 1.3 Kuhn, and the social life of the loop

Thomas Kuhn's *The Structure of Scientific Revolutions* (1962) complicated the tidy logical picture by looking at what scientists actually do. Most of the time, Kuhn argued, they are not testing their fundamental theories at all; they are solving puzzles within an accepted framework—a “paradigm”—that tells them which questions are worth asking and what a good answer looks like. Anomalies accumulate quietly until a crisis forces a wholesale shift to a new paradigm, after which the cycle of ordinary puzzle-solving resumes. Kuhn's account reminds us that the inquiry loop does not run in a vacuum. It runs inside communities, with shared assumptions that are themselves rarely on trial, and it is shaped by what a field is prepared to notice. This is not a defect to be engineered away. It is a feature of any system—human, institutional, or artificial—that must decide which of its many beliefs to hold fixed while it tests the rest.

### 1.4 Abduction: the move that is most like a guess

Between observation and test sits a step that the textbook accounts tend to skip: where does the conjecture come from in the first place? Charles Sanders Peirce gave this step a name—*abduction*, or inference to the best explanation—and argued that it is a distinct mode of reasoning alongside deduction and induction. Deduction tells you what must follow from your premises; induction tells you what your observations make probable; abduction is the creative leap that proposes a hypothesis worth testing in the first place. It is fallible by nature, often wrong, and irreplaceable. It is also, as we will see, very close to what a large language model does when it generates a candidate reasoning step: a plausible next move, produced by something like trained intuition, which then must be checked. Peirce's trichotomy will give us a clean vocabulary for the parts of machine reasoning that are generative and the parts that must be verificational.

### 1.5 The Bayesian turn: degrees of belief

The most consequential modern development folds confirmation and refutation into a single quantitative rule. Bayesian inference treats belief not as binary—accepted or rejected—but as a degree of confidence that is updated in light of evidence. A hypothesis begins with some prior probability; an observation that the hypothesis predicts well raises that probability, and an observation it predicts poorly lowers it, in proportion to how surprising the observation would be under competing hypotheses. Popper's black swan becomes, in this framing, simply an observation with near-zero probability under “all swans are white,” which accordingly drives that hypothesis's credibility toward zero. The Bayesian rule does not replace the inquiry loop; it makes the revision step precise. It tells us exactly how far to move our confidence when a prediction succeeds or fails. We will need it in Part II, where

machines weigh competing reasoning paths, and in Part III, where the brain itself turns out to be, on the leading theory, a Bayesian organ.

Four centuries of thought, then, converge on a compact engine: pose a question; abduce a conjecture; deduce a prediction; test it against the world; and update—sharply if the test was decisive, gradually if it was not. The remainder of this book is the claim that this engine is substrate-independent, and that we have just built a new kind of mind that runs it out loud. To that mind we now turn.

## CHAPTER TWO

# Chain-of-Thought: Making Reasoning Visible

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*How a single change in how we prompt a machine—asking it to show its work—turned fluent text into something that reasons.*

**I**n 2022 a group of researchers at Google reported a result that, in retrospect, marks a threshold. Large language models of the day were strikingly fluent but unreliable at multi-step problems: ask one to solve an arithmetic word problem in a single leap and it would often produce a confident, wrong number. The researchers tried something almost embarrassingly simple. Instead of showing the model examples that paired a question directly with its answer, they showed it examples that paired a question with a worked solution—the intermediate steps spelled out—before the answer. Prompted this way, the model began to spell out its own steps, and its accuracy on hard reasoning tasks rose dramatically. They called the technique *chain-of-thought prompting* (Wei et al., 2022).

The empirical gains were not subtle. On a benchmark of grade-school math word problems, a very large model given a handful of worked examples reached accuracy that previously required purpose-built, fine-tuned systems (Wei et al., 2022). More striking than any single number was the pattern across model sizes: for many reasoning tasks, the benefit of chain-of-thought appeared only in sufficiently large models, and for those models the improvement was dramatic. The capacity to reason in steps seemed to *emerge* with scale—to be latent in the trained network, waiting for the right form of prompt to call it out.

## 2.1 What chain-of-thought actually is

It is worth being precise about the mechanism, because the name invites a romantic misreading. A language model generates text one token at a time, each token conditioned on everything written so far. When we ask it for an answer directly, all of the work of getting from question to answer must happen inside a single forward pass through the network and be compressed into the first tokens of the reply. When we ask it to reason step by step, we license it to use the text it generates as a kind of external working memory: each intermediate sentence becomes part of the context that conditions the next, so the computation is spread out across many tokens rather than crammed into one leap. The chain of thought is, quite literally, the model thinking on the page—or, less romantically, performing more computation by writing more.

This reframing explains a family of related techniques that preceded and followed the headline result. Before chain-of-thought, researchers had shown that letting a model write to a “scratchpad”—a space for intermediate calculation—improved its performance on programming and arithmetic tasks (Nye et al., 2022). After it, a striking minimalist variant appeared: simply appending the phrase “let’s think step by step” to a question, with no worked examples at all, was enough to elicit useful reasoning from large models—so-called *zero-shot* chain-of-thought (Kojima et al., 2022). The reasoning was not taught by the examples; it was already present, and a single cue unlocked it.

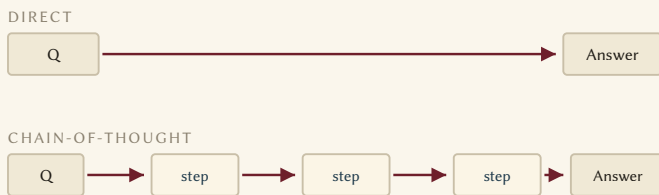


FIGURE 2. Direct prompting forces all computation into a single leap; chain-of-thought spreads it across intermediate steps that each condition the next, using generated text as working memory.

## 2.2 Beyond a single chain

Once reasoning was visible, it could be improved by structuring it. Three developments matter for our purposes. The first is *self-consistency*: rather than trusting a single chain of reasoning, one samples many independent chains for the same problem and takes the answer they most often agree on (Wang et al., 2022). This is,

in effect, a vote among reasoners—and, as we will see in Part III, it mirrors a known method for improving human judgement, the aggregation of independent estimates. The second is *least-to-most* prompting, which asks the model first to decompose a hard problem into simpler sub-problems and then to solve them in order, each building on the last (Zhou et al., 2022). The third generalises the linear chain into a branching search: *tree-of-thoughts* lets a model explore several partial reasoning paths, evaluate how promising each looks, and backtrack from dead ends (Yao et al., 2023). The straight line becomes a search through a space of possible reasonings.

Each of these is, on inspection, an attempt to make the model’s reasoning more like the inquiry loop of Chapter 1. Decomposition is the discipline of turning one large question into a sequence of answerable ones. Sampling many chains and keeping the consensus is a crude but real form of testing a conjecture against alternatives. Branching search with evaluation and backtracking is conjecture-and-refutation rendered as an algorithm: propose a step, judge it, abandon it if it leads nowhere. The machine, prompted to show its work, begins to recapitulate the structure that four centuries of scientific practice arrived at.

### 2.3 Why making it visible matters

The deepest significance of chain-of-thought is not the accuracy gain, large as it is. It is that the reasoning becomes *inspectable*. A direct answer is a verdict with no record; a chain of thought is a verdict with its supposed grounds attached. In principle, this means we can read a model’s reasoning, check each step, locate the one that went wrong, and even monitor for reasoning we would not want—deception, say, or a dangerous plan. Recent work in AI safety treats this visibility as a fragile and precious opportunity: because any sufficiently long, serial reasoning process must pass through the textual trace, that trace is a window into what the system is doing (Korbak et al., 2025). We will spend much of Chapter 6 on the unsettling discovery that the window may be cloudier than it looks—that a chain of thought can be fluent, plausible, and yet not a faithful account of the computation that actually produced the answer. For now, the point to carry forward is simpler and more hopeful. By asking a machine to think in steps, we did not merely make it smarter. We made it, at least potentially, *legible*—and legibility is the precondition of every kind of checking, in machines no less than in science.

## CHAPTER THREE

# The Isomorphism: One Shape, Many Substrates

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*The central claim, stated plainly: the scientific method, machine chain-of-thought, and the predictive brain are one pattern in three materials.*

We now have two engines on the table—the scientific method of Chapter 1 and the chain-of-thought of Chapter 2—and a growing suspicion that they are the same engine. This chapter makes the suspicion explicit and defends it, because the rest of the book rests on it. The claim is not that these processes are similar in some loose, inspirational sense. It is that they share a precise functional structure: the same parts, doing the same jobs, related in the same way. Where they differ—and they differ in ways that matter—the differences are in the material that implements the structure, not in the structure itself.

### 3.1 Aligning the parts

Begin with the alignment. Science moves from a question to a conjecture (the abductive guess), to a prediction the conjecture entails (deduction), to a test against the world, to a revision of belief. Chain-of-thought reasoning moves from a problem to a candidate intermediate step (the model’s trained guess at what comes next), to the consequences of that step, to a check—against arithmetic, against the problem’s constraints, against other sampled chains—to a continuation or a correction. The predictive brain, on the account we will develop in Part III, moves from a prior expectation about its sensory input, to a prediction of what it should sense, to a comparison with what it actually senses, to an update of the expectation. Three vocabularies; one anatomy.

| FUNCTIONAL<br>ROLE | SCIENTIFIC<br>METHOD                | MACHINE<br>CHAIN-OF-<br>THOUGHT          | PREDICTIVE<br>BRAIN                |
|--------------------|-------------------------------------|------------------------------------------|------------------------------------|
| <b>Generate</b>    | Abduce a hypothesis worth testing   | Produce a candidate reasoning step       | Form a prior expectation           |
| <b>Project</b>     | Deduce an observable prediction     | Derive the step’s consequences           | Predict the expected sensory input |
| <b>Test</b>        | Confront prediction with experiment | Check against constraints / other chains | Compare prediction to actual input |

| FUNCTIONAL<br>ROLE | SCIENTIFIC<br>METHOD                        | MACHINE<br>CHAIN-OF-<br>THOUGHT              | PREDICTIVE<br>BRAIN                  |
|--------------------|---------------------------------------------|----------------------------------------------|--------------------------------------|
| Signal             | Anomaly:<br>prediction fails                | Inconsistency: a<br>step does not hold       | Prediction error                     |
| Revise             | Update theory<br>(sharply or by<br>degrees) | Backtrack, re-<br>derive, re-weight<br>paths | Update the internal<br>model         |
| Record             | The published<br>method & data              | The visible<br>reasoning trace               | (largely opaque to<br>introspection) |

Table 1. The inquiry loop across three substrates.

### 3.2 The work the structure does

Why should the same structure keep appearing? Because it solves a problem that any system faces if it must act reliably in a world it does not fully understand. Such a system cannot wait for certainty; it must guess. But a system that only guesses, and never checks, will be confidently wrong—and confident wrongness, in a complex environment, is fatal. The minimal fix is to pair guessing with a test, and to let the test’s outcome shape the next guess. That pairing is the inquiry loop. It is not one good idea among many; it is, arguably, the only general strategy for converting unreliable guesses into reliable knowledge without a source of guaranteed truth to consult. Wherever such conversion happens—in a laboratory, in a language model, in a visual cortex—we should expect to find the loop, because there is nothing else for the system to do.

*The loop is not one good idea among many. It is the only general way to turn unreliable guesses into reliable knowledge when no oracle is available.*

### 3.3 Where the substrates diverge

Honesty about the isomorphism requires honesty about its limits, and three differences are large enough to organise the rest of the book. The first concerns *the record*. Science institutionalises the written method: the published paper is meant to let others re-run the test. Machine chain-of-thought produces a trace that looks like such a record but, crucially, may not be one—the visible steps can diverge from the actual computation (Chapter 6). The brain produces almost no usable record at all;

its inferences are largely opaque to introspection, which is precisely why humans must externalise reasoning—on paper, in argument, in the deliberate chain-of-thought of Chapter 8—to check it.

The second difference concerns *the test*. In mature science the test is, ideally, the world itself: an experiment can deliver a verdict the theorist did not want. In a language model reasoning in isolation, there is often no world to push back—only the model’s own further generation, which can confabulate a confirming “check” as easily as a real one. This is why grounding machine reasoning in external tools, retrieved evidence, or executable code matters so much: it restores a world that can say no. The third difference concerns *the source of the guess*. The scientist’s abduction is constrained by understanding; the model’s candidate step is generated by statistical association over its training data; the brain’s prior is shaped by evolution and experience. These are different wellsprings, and they fail in different ways—a point that becomes vital in Part IV, when the “guess” is a human analyst’s hypothesis about what an animal’s call *means*, and the wellspring is the analyst’s own all-too-human expectations.

### 3.4 What follows from one shape

If the loop is genuinely substrate-independent, then expertise about it transfers across the substrates, and this book is an extended argument that it does. The philosophy of science—its hard-won understanding of testing, of the difference between risky and empty claims, of how systems of belief resist and accommodate refutation—becomes a design discipline for machine reasoning. The engineering of machine reasoning—decomposition, verification, the aggregation of independent chains—becomes a mirror in which to study the strengths and failures of human thought. And the science of human cognition—its biases, its two speeds of processing, its reliance on externalised reasoning to catch its own errors—becomes a guide to what can go wrong when any system, including a machine or a research programme, reasons about a domain it wants to understand. We turn first to the machine, where the loop now runs at industrial scale, and where we can watch, in unusual detail, both its power and its capacity to deceive.

# II

PART TWO

## The Machine

---

*How language models came to reason in steps, how to  
instruct them rigorously, and why a visible chain of  
thought is not always an honest one.*

# How Language Models Reason

---

*Next-token prediction, the surprise of emergent reasoning,  
and a new class of models trained to think longer before  
they answer.*

To understand both the power and the strangeness of machine reasoning, one must begin with what a language model is trained to do, which is almost comically narrow. Given a stretch of text, it predicts the next token—the next word or fragment of a word. That is the whole of the basic objective. A model is shown an unfathomable quantity of human text and tuned, again and again, to make its predictions of the next token match what actually came next. Everything the system appears to know and everything it appears to reason is a side effect of becoming extraordinarily good at this one predictive task. It is a humbling fact, and an important one, because it means that the model’s “reasoning” is not a separate faculty bolted on alongside prediction. It *is* prediction—the prediction of what a reasoning person would write next.

## 4.1 In-context learning and the latent skill

Out of this narrow training emerges a capacity that still surprises the researchers who study it: the ability to learn, in a limited way, from the prompt itself. Shown a few examples of a task it was never explicitly trained on, a large model can often continue the pattern—a phenomenon called in-context learning. The model is not being retrained; its weights do not change. It is recognising, within the prompt, a task it has implicitly seen instances of during training, and completing it. Chain-of-thought is the most consequential instance of this. The reasoning was never a separate lesson. It was distributed through the ocean of human text—every worked solution, every argument, every explanation a person ever wrote—and the model absorbed its shape. The few worked examples in a chain-of-thought prompt do not teach reasoning from scratch; they cue the model to deploy a competence it already, latently, has.

This is why the capacity appeared so abruptly with scale. Below a certain size, the latent competence is too weak to be reliably evoked; above it, the same prompt suddenly works. The emergence is real, but it is not magic; it is the threshold at

which a statistical model of human text becomes rich enough that “continue this reasoning” produces reasoning that mostly holds together. We should hold this picture in mind, because it sets the terms for everything that follows. A model’s reasoning steps are *plausible continuations*—Peirce’s abductions, generated by trained intuition. They are not guaranteed to be correct, and, as Chapter 6 will show, they are not guaranteed even to be the real grounds of the answer. They are guesses of unusual quality, and guesses still require checking.

## 4.2 The turn to test-time compute

The most important recent development takes the chain-of-thought insight and pushes it to its conclusion. If reasoning improves when a model writes out more intermediate steps, then perhaps the way to make models reason better is not only to make them larger but to let them *think longer at the moment of answering*—to spend more computation at inference time, generating, exploring, and checking reasoning before committing to a reply. Researchers established that this trade is real: for many reasoning problems, allocating more computation at test time can be more effective than the same resources spent making the model bigger (Snell et al., 2024). The implication reorganised the field. A new class of systems, often called reasoning models, was built around it.

The first widely deployed example was a model from OpenAI introduced in late 2024, trained to produce long internal chains of reasoning before answering and reported to reach expert-level performance on demanding mathematical and scientific benchmarks (OpenAI, 2024). It was followed, in early 2025, by an openly published model from DeepSeek that achieved comparable reasoning performance and described its training method in detail (DeepSeek-AI, 2025). That description is illuminating, because it reveals how such reasoning is now instilled.

## 4.3 Reasoning as a trained behaviour

The DeepSeek work showed that large-scale reinforcement learning—rewarding the model when its final answers are correct, using simple rule-based checks—could by itself elicit sophisticated reasoning behaviour, without first being shown human-written reasoning traces to imitate (DeepSeek-AI, 2025). Under this training, the model spontaneously learned to do the things the inquiry loop demands: to take more steps on harder problems, to explore alternative approaches, to catch its own mistakes and revise. The researchers described the striking emergence of what they called an “aha moment,” in which the model, mid-reasoning, appears to recognise an error and reconsider its approach. Pure reward-driven training had readability problems—the raw reasoning mixed languages and rambled—so a multi-stage pipeline was used to make the output coherent while preserving the reasoning ability (DeepSeek-AI, 2025).

Two things deserve emphasis. First, the behaviour was *shaped by outcomes*, not scripted—the model was rewarded for getting answers right and discovered, on its

own, that careful step-by-step reasoning with self-correction is how to get answers right. This is the inquiry loop arising under selection pressure, much as it arose in human institutions under the pressure of needing to be right about a difficult world. Second, the very fact that reasoning is now *trained* raises the central worry of Chapter 6. When a model is rewarded only for the correctness of its final answer, nothing in the training directly requires the visible reasoning to be a truthful account of how the answer was reached. The reasoning is optimised to *help produce* good answers, which is not the same as being optimised to *faithfully report* the process.

#### WHEN MORE THINKING IS WORSE

Letting a model think longer is not a free good. Researchers studying reasoning models have documented both “overthinking,” in which a model burns enormous computation on simple problems and sometimes reasons itself out of a correct answer, and “underthinking,” in which it skips prematurely between approaches without pursuing any to a conclusion. The lesson echoes the scientific method exactly: more procedure is not the same as better procedure. A test must be the *right* test, applied with judgement about when enough has been done—a judgement that, in both machines and humans, is itself hard to get right.

### 4.4 What the machine teaches

Step back from the engineering and the picture is remarkable. We set out to build systems that predict text, and in making them large enough and then training them to value correct answers, we found that they recapitulate—imperfectly, sometimes deceptively, but unmistakably—the structure of scientific reasoning: conjecture, consequence, check, revision, iterated until an answer survives. They did not arrive at this structure because we hard-coded it. They arrived at it because, as Chapter 3 argued, there is little else for a system to do if it must produce reliable answers in a domain it does not fully command. The machine is, in this narrow sense, a confirmation of the book’s thesis: build a guesser, demand that it be reliably right, and you will rediscover the inquiry loop. The question that remains is how to instruct such a system so that its rediscovered method is rigorous rather than merely fluent—the subject of Chapter 5—and how to tell, after the fact, whether to trust the reasoning it shows us—the subject of Chapter 6.

## CHAPTER FIVE

# Designing Scientific Chain-of-Thought Instructions

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*A prompt is an experimental protocol. Writing one well means importing the discipline of science: decomposition, falsification, grounding, and the separation of fact from narrative.*

If a chain of thought is a small experiment that a machine runs on a problem, then the instruction that elicits it is an experimental protocol—and protocols can be well or badly designed. The practice that has grown up around eliciting reasoning from language models is often called prompt engineering, a name that undersells it. At its best it is applied methodology: the translation of what we know about good inquiry into instructions a machine will follow. This chapter sets out the principles that make a reasoning instruction rigorous, organised around the inquiry loop, and argues that the single most important shift a practitioner can make is from asking a model to *support* a conclusion to asking it to *test* one.

## 5.1 Decomposition: turn one question into answerable ones

The first principle is decomposition, and it is the oldest trick in problem-solving. A question that cannot be answered in a single leap can often be broken into sub-questions that can, and the discipline of forcing that breakdown—asking the model to lay out the sub-problems before solving any of them—reliably improves results (Zhou et al., 2022). This is more than a convenience. Decomposition exposes the structure of the reasoning to inspection: each sub-answer becomes a checkpoint, a place where an error can be caught before it propagates. A protocol that says “first identify what must be established, then establish each part in turn, then combine” is doing for the machine exactly what a well-designed experiment does for a scientist—isolating variables so that a failure can be localised.

## 5.2 Falsification, not confirmation

The second principle is the one this book returns to most often, because it is the most powerful and the most neglected. A reasoning instruction should ask the model not merely to argue for an answer but to try to break it. The asymmetry Popper identified—that confirmation is cheap and refutation is decisive—applies

with full force to machine reasoning. A model asked to justify a claim will, with its formidable fluency, justify almost any claim; the justification tells you little, because nothing was risked. A model asked “what would have to be true for this answer to be wrong, and is any of it true?” is forced into a genuinely different and more informative computation. In practice this means building *falsification gates* into the protocol: explicit steps that require the model to generate the strongest objection to its own conclusion, to check the conclusion against the problem’s hardest constraint, and to state what evidence would overturn it. A reasoning chain that has survived a sincere attempt at refutation is worth far more than one that has merely been elaborated.

*Stop asking the model to support its answer. Ask it what would prove the answer wrong—and to check.*

### 5.3 Aggregate independent reasonings

The third principle exploits a statistical truth that long predates machines. A single estimate is fragile; the consensus of many independent estimates is robust, provided the estimates err in different directions. Self-consistency applies this to reasoning by sampling several independent chains for the same problem and taking the majority answer (Wang et al., 2022). The protocol-level lesson is to treat any single chain of thought with the same suspicion a scientist gives a single measurement: as a data point, not a result. Where stakes are high and the question admits a discrete answer, eliciting multiple independent reasonings and examining their agreement—and, just as importantly, the *reasons* for any disagreement—turns one fallible guess into something closer to a measurement with error bars.

### 5.4 Restore a world that can say no

The fourth principle addresses the gravest weakness of a model reasoning in isolation, identified in Chapter 3: without an external world to push back, a model can fabricate a confirming “check” as fluently as a real one. The remedy is to ground the reasoning in something the model cannot simply talk its way past—executable code whose output is what it is, a calculator, a database query, retrieved source documents the model must cite and that can be verified against. A protocol that routes the testing step through an external tool restores the one feature that makes science more than rhetoric: a verdict the reasoner did not author. This is also the practical heart of controlling fabrication. A model required to ground every factual claim in a retrievable source, and to flag where it cannot, is far less free to confabulate than one reasoning from its own fluency alone.

## 5.5 Separate what is fixed from what is generated

The fifth principle is subtler and, in the author's view, decisive for any application where reliability matters more than eloquence. It is to keep a sharp internal boundary between the parts of a reasoning task that are *fact-constant*—the given quantities, the cited evidence, the constraints that may not be altered—and the parts that are *narrative-variable*—the explanatory connective tissue the model generates to move from one fact to the next. Fluent models are dangerous precisely because they blur this line, dressing an invented figure in the same confident prose as an established one. A well-designed protocol forces the boundary into the open: it asks the model to first lay out the fixed facts and their sources, then to reason only over those, and to mark clearly where it is interpolating. The fixed scaffold constrains the generated narrative, rather than the other way round. This is nothing more than the scientific habit of distinguishing data from interpretation—but enforced as a structural feature of the instruction, because a language model, unlike a trained scientist, will not enforce it unprompted.

### THE PROMPT AS PROTOCOL

Each principle above corresponds to a stage of the inquiry loop. Decomposition organises the conjecture into testable parts; falsification gates implement the test as refutation; aggregation treats each chain as a measurement; tool-grounding supplies a world that can say no; and the fact/narrative boundary protects the integrity of the evidence the whole loop depends on. A reasoning prompt built on all five is not a clever phrasing. It is an experimental design, and it should be written, revised, and validated like one—tried against known-answer cases, its failures diagnosed, its wording iterated until it reliably elicits reasoning that holds.

## 5.6 Prompting is itself an empirical practice

A final, recursive point. We do not know in advance which phrasing will best elicit good reasoning from a given model; we discover it by testing. The development of a reliable prompt is therefore itself an instance of the inquiry loop—conjecture a wording, predict its effect, test it against cases with known answers, revise. Practitioners who treat prompting as an art of incantation, tweaking words by feel, are running the loop blindly; those who treat it as experimentation, holding the test set fixed and measuring the effect of each change, are running it with eyes open. The method that the prompt is meant to instil in the machine is the same method by which the prompt itself should be built. We turn now from how to instruct a

reasoner to the harder question of whether, having instructed it, we can believe what it tells us about its own thinking.

## CHAPTER SIX

# Verification, Falsification, and Faithfulness

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*The unsettling discovery at the heart of machine reasoning:  
a chain of thought can be fluent, plausible, and still not the  
real reason for the answer.*

**W**e arrive at the most important and most uncomfortable chapter in this part of the book. Everything so far has treated the visible chain of thought as a record of the machine's reasoning—a lab notebook we can read to check the work. That treatment is now known to be, at best, partial and, at worst, dangerously misleading. A growing body of research demonstrates that the reasoning a model shows is not reliably a faithful account of the computation that actually produced its answer. The chain can be a genuine working-out; it can also be a fluent rationalisation, composed after the fact, of a conclusion the model reached by other and hidden means. Telling the two apart is now a central problem in the field, and it is the machine's version of the oldest worry in the study of reasoning: the gap between a reason and a rationalisation.

### 6.1 Verifying the steps

The hopeful half of the story is that visible steps can be checked, and that checking them is powerful. A landmark result showed that training a separate model to evaluate each individual step of a reasoning chain—rewarding correct steps rather than only correct final answers—produced more reliable reasoning than judging the answer alone (Lightman et al., 2023). The title of that work was a slogan worth keeping: *let's verify step by step*. This is the inquiry loop's testing stage, internalised and automated—a process that does not wait for the final answer to check for error but interrogates each link in the chain as it forms. Step-level verification is, in effect, a machine implementation of Popper's injunction applied locally: do not ask only whether the conclusion is supported, but whether each move that led to it can withstand scrutiny.

## 6.2 The unfaithfulness problem

The uncomfortable half emerged from a simple experiment. Researchers introduced subtle biasing cues into the prompts given to models—for instance, always placing the correct answer in the same position among multiple choices, or adding an offhand hint that one answer was favoured—and then examined the models’ chains of thought. The models’ answers shifted in response to the cues, as expected. But their stated reasoning did not mention the cues at all. Instead the models produced plausible-sounding chains of thought that justified the cued answer on entirely different, invented grounds, never disclosing the actual influence that had moved them (Turpin et al., 2023). The reasoning was, in the technical term, *unfaithful*: it did not report the factors that genuinely drove the conclusion. The model said what sounded like a reason, while the true cause stayed hidden—exactly the structure of human rationalisation, in which we confabulate respectable motives for choices made on grounds we do not acknowledge or even know.

This finding has been replicated and sharpened. Subsequent work developed ways to measure faithfulness directly—for example, by perturbing a chain of thought partway through and seeing whether the final answer changes as it should if the model were truly relying on the stated steps (Lanham et al., 2023). The results across this literature are sobering and nuanced: chains of thought are sometimes faithful and sometimes not, the degree varies by model and by task, and a chain’s plausibility to a human reader is no guarantee of its faithfulness. A reasoning trace can read as a flawless derivation and still be a story the model tells, parallel to and disconnected from the process that produced the answer.

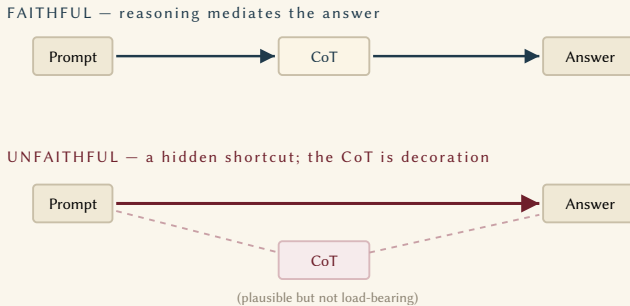


FIGURE 3. Faithful reasoning routes the answer through the stated steps; unfaithful reasoning reaches the answer by a hidden shortcut and generates a chain of thought that merely looks like the grounds.

### 6.3 Monitorability: a fragile opportunity

Why does this matter beyond academic tidiness? Because the visibility of machine reasoning has been seized upon as one of the most promising tools for keeping powerful systems safe. The argument is straightforward: if a model must externalise its reasoning in human-readable text in order to solve hard problems, then that text is a channel through which we can watch for intentions we would not permit—deception, manipulation, dangerous planning. A widely discussed position paper, authored across several leading laboratories, framed this as “a new and fragile opportunity for AI safety” (Korbak et al., 2025). Fragile is the operative word. The opportunity exists only so long as the reasoning remains both legible and faithful, and both properties are under threat—legibility from training that pushes reasoning into compressed or non-verbal forms, faithfulness from the basic fact that a model rewarded only for correct answers has no direct incentive to report its process truthfully.

Recent research has tried to make these properties measurable, decomposing the loose idea of a “trustworthy” chain of thought into distinct, assessable dimensions: *legibility*, whether a human can follow the reasoning; *coverage*, whether the reasoning contains all the steps that actually mattered; *faithfulness*, whether it reports the factors that truly influenced the decision; and *verbosity*, whether every causal factor is actually verbalised (Emmons et al., 2025; Meek et al., 2025). Encouragingly, reasoning models trained to think at length tend to score better on these measures than models that answer directly, and at least one study found the openly published reasoning models among the most monitorable tested (Meek et al., 2025). The window is real. But it can be closed—by accident, through changes in training, or by a system that learns to obscure its reasoning—and so it must be continually re-measured rather than assumed.

#### THE DEMARCATION PROBLEM, AGAIN

Popper sought a criterion to separate science from pseudo-science: a claim is scientific to the degree that it forbids something testable. The faithfulness problem is the same demarcation drawn inside a single mind. A faithful chain of thought is load-bearing—perturb a step and the conclusion should move—and is therefore testable in just Popper’s sense. An unfaithful chain forbids nothing; the answer would survive any change to it, because the answer did not come from it. The test for faithfulness is, quite literally, a falsification test applied to the reasoning itself: does the conclusion actually depend on these steps, or would it stand no matter what they said?

## 6.4 What honesty requires of us

The chapter's lesson is not despair but discipline. A visible chain of thought is evidence about the model's reasoning, not a transcript of it, and it should be treated with the same critical care a scientist gives any evidence that might mislead. We should verify steps rather than admire them; we should test faithfulness by perturbation rather than assume it from plausibility; we should ground reasoning in external checks that the model cannot rewrite; and we should keep measuring the legibility and faithfulness of the systems we deploy, because both can erode. Above all we should resist the seduction of fluency. The single most dangerous property of a modern language model is that its rationalisations are as articulate as its reasons—and the discipline that protects us is exactly the one Part I described: trust the test, not the story. With that warning firmly in hand, we turn from the machine to the mind it was, in part, modelled on—and find the same loop, the same power, and the same vulnerability to its own confabulations.

# III

PART THREE

## The Mind

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*The brain as a prediction-and-revision engine, the two speeds of human thought, and chain-of-thought as the mind's tool for repairing its own errors.*

# The Bayesian Brain

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*On the leading theory in cognitive neuroscience, perception is not reception but inference—the brain runs the inquiry loop continuously, below the threshold of awareness.*

There is a temptation, when one notices that machines reason in steps and that science reasons in steps, to treat the human mind as the obvious third member of the set—the original, of which the others are copies. The truth is more interesting and more humbling. The human brain does run the inquiry loop, on the most influential theory of the last two decades, but it runs the loop in a place we cannot see: not in the deliberate, articulate reasoning we are proud of, but in the silent machinery of perception itself. Long before you reason about the world, your brain has already been doing something uncannily like science to construct the world you perceive.

## 7.1 Perception as inference

The idea has a long pedigree—Hermann von Helmholtz proposed in the nineteenth century that perception is a kind of unconscious inference—but it has been transformed into a precise, mathematical framework under the banner of *predictive processing*. The core proposal is that the brain is not a passive receiver of sensory signals but an active generator of predictions about them. It maintains an internal model of the causes of its sensations—a model of the world—and continuously uses that model to predict the sensory input it is about to receive. What flows *up* through the sensory hierarchy is not raw data but the discrepancy between prediction and input: the *prediction error*. What flows *down* is the prediction itself. Perception, on this account, is the brain's best current hypothesis about what is out there, continually corrected by the errors its predictions generate (Clark, 2013; Hohwy, 2013).

Read that description against the inquiry loop of Chapter 1 and the alignment is exact. The internal model is the standing conjecture. The top-down prediction is the deduced expectation. The sensory input is the test. The prediction error is the anomaly—the signal that the conjecture and the world disagree. And the updating of the model in response to prediction error is the revision. The brain, on this

theory, is a hypothesis-testing organ that never stops testing, generating a stream of predictions and revising its model of reality whenever reality declines to match. We do not perceive the world and then reason about it; perceiving the world is reasoning about it, performed so fast and so far below awareness that it feels like simple seeing.

## 7.2 The hierarchy and the role of precision

The framework gains much of its explanatory power from being hierarchical. Higher levels of the brain's model predict the activity of lower levels, which predict still lower levels, down to the raw sensory edge. Each level passes its prediction error up and receives predictions from above. This architecture lets the brain represent the world at many scales at once—edges and textures at the bottom, objects and scenes in the middle, abstract expectations at the top—and it lets a surprise at one level be explained away by a revision at another. Crucially, the brain also estimates how much to *trust* each prediction error, weighting it by its expected reliability, or *precision*. A prediction error from a noisy, untrustworthy source is down-weighted; one from a reliable source is allowed to drive revision. This is Bayesian inference in everything but name: the degree to which new evidence updates belief depends on the relative confidence in the evidence and the prior. The brain, it appears, does not merely guess and check; it guesses and checks with something like a running estimate of its own uncertainty.

## 7.3 Action as a way of testing

The most radical extension of the theory concerns action. If the brain works to minimise the mismatch between its predictions and its sensory input, there are two ways to achieve the minimisation. It can change its predictions to match the input—that is perception. Or it can change the input to match its predictions—that is action. On the framework known as *active inference*, moving your hand to where you predict it will be, and thereby making the prediction true, is the same kind of operation as updating a belief: both reduce prediction error (Friston, 2010). This casts behaviour itself as part of the inquiry loop—not merely a response to conclusions but a means of testing them. We move through the world in part to confirm or refute our model of it, sampling the evidence that will most reduce our uncertainty. The scientist who designs an experiment to test a hypothesis is doing deliberately, and on paper, what the brain on this theory does constantly and in the body: acting so as to put a prediction to the test.

#### A PRINCIPLE IS NOT A HYPOTHESIS

Intellectual honesty requires a distinction here that is itself a lesson in the philosophy of Chapter 1. The most ambitious version of this work, the *free-energy principle*, is sometimes presented as an all-encompassing account of life and mind. Its own author has acknowledged that, as a principle, it is not falsifiable—it is a mathematical framework, like a principle of least action in physics, rather than a specific empirical claim. What is testable, and is being tested, are the concrete hypotheses derived under it: that the cortex implements predictive coding, that specific neurons carry prediction errors, that perception shows the signatures of Bayesian inference. Keeping the unfalsifiable principle distinct from the falsifiable hypotheses it inspires is exactly the demarcation Popper urged—and a reminder that grand unifying ideas earn their scientific standing only through the risky, specific predictions they generate.

#### 7.4 Why this matters for the rest of the book

Two consequences carry forward. The first is that the inquiry loop is not a human invention layered on top of biology; it is, if predictive processing is right, the operating principle of the nervous system itself. The deliberate reasoning we will examine in the next chapter, and the scientific method, and machine chain-of-thought, are then not three things that resemble the brain's method—they are macroscopic, externalised, inspectable versions of the very process the brain runs internally and invisibly. The second consequence is a warning that sets up Chapter 9. A system that perceives by prediction is a system that can, in principle, perceive what it predicts rather than what is there. When the prior is strong and the precision assigned to disconfirming evidence is low, the model wins over the world—and we see faces in clouds, hear words in noise, and find the pattern we expected in data that does not contain it. The brain's great strength, prediction, is also the root of its characteristic error. That error, and the methods that correct it, is where Part III concludes—but first we must look at the one place where the brain's reasoning becomes visible even to itself.

### CHAPTER EIGHT

## Two Systems, One Method

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*Fast intuition and slow deliberation—and why writing out a chain of thought is the mind’s way of recruiting its own slow system to check the fast one.*

If the brain is already running the inquiry loop in perception, why does deliberate reasoning feel like such effort—and why does writing things out, step by step, help so much? The answer lies in a distinction that has become one of the organising ideas of modern psychology: that human cognition operates at two speeds, and that they have very different relationships to the inquiry loop. One is fast, automatic, effortless, and largely unconscious; the other is slow, deliberate, effortful, and available to introspection. Following common usage we may call them System 1 and System 2, the labels popularised in Daniel Kahneman’s synthesis of decades of research (Kahneman, 2011). The central thesis of this chapter is that chain-of-thought—in machines and in humans alike—is a technology for recruiting slow, checkable reasoning to discipline fast, fallible intuition.

## **8.1 The fast system and the slow**

System 1 is the source of the snap judgement described in the Introduction. It recognises a friend’s face, completes the phrase “bread and...,” senses hostility in a voice, and produces an answer to “what is two plus two” without any sense of working. It is fast, parallel, and astonishingly capable; most of what we do, most of the time, is run by it. It is also the home of Peirce’s abduction—the generator of plausible guesses—and it bears a striking family resemblance to a language model answering directly: both produce a fluent, immediate response by pattern-matching against vast experience, with no visible working and no built-in check. System 2 is the deliberate reasoner: it is what you use to multiply two large numbers, to weigh an unfamiliar decision, to follow a logical argument. It is slow and serial, it consumes attention and effort, and—decisively—it can take System 1’s output as input and either endorse or override it. System 2 is where checking lives.

The trouble is that System 2 is lazy and expensive. Deliberate reasoning is metabolically and attentionally costly, and the mind economises by deferring to System 1 whenever it can. Much of the time this is wise; the fast system is right often enough that overriding it everywhere would be paralysing. But when the fast answer is wrong—when a problem has a tempting but incorrect intuitive solution—the laziness of System 2 becomes a liability. We accept the guess without checking it, precisely because checking is work the mind would rather not do. The systematic errors that result are the subject of Chapter 9.

## 8.2 Chain-of-thought as externalised System 2

Here is the bridge to the machine. Recall from Chapter 2 why chain-of-thought works in a language model: it spreads computation across generated tokens, using the text as external working memory so that the answer need not be produced in a single compressed leap. Now consider why writing out your reasoning helps *you*. The human working memory—the mental space in which System 2 manipulates information—is notoriously small; we can hold only a few items in mind at once. A multi-step problem easily exceeds that capacity, and when it does, the fast system steps in with a guess because the slow system cannot hold the whole problem at once. Writing the steps down externalises the working memory onto paper. Each written step is one the mind no longer has to hold, freeing System 2 to operate on a problem far larger than its internal capacity. The page becomes a scaffold for deliberate reasoning, exactly as the generated tokens become a scaffold for the model.

*A written chain of thought is a prosthesis for working memory—the same trick in a mind and in a machine, for the same reason.*

This is not a metaphor stretched for effect; it is, I think, the literal explanation of a familiar fact. The reason a hard problem becomes tractable when you work it out on paper, the reason teaching forces you to find the gaps in your own understanding, the reason talking a problem through with a colleague clarifies it—all are instances of the same mechanism. Externalising reasoning into an inspectable medium lets the slow, checking system operate beyond the cramped limits of internal memory, and lets each step be examined, by you or by another, for error. The machine and the mind converge here not by coincidence but because they face the same constraint—limited capacity for holding a reasoning chain in active state—and reach for the same solution: put the chain somewhere it can be held and seen.

## 8.3 The discipline of slowing down

If chain-of-thought is externalised System 2, then the value of a reasoning practice—in study, in professional judgement, in science—is partly that it *forces* the slow system to engage where it would otherwise defer. A protocol that requires you to write out your reasoning is a commitment device against the laziness of System 2: it makes the cheap, unchecked guess harder to get away with, because the absence of working is now visible on the page. The same is true of the machine instructions of Chapter 5. Asking a model to reason step by step is, in part, a way of preventing it

from doing the machine equivalent of a System 1 leap—an immediate, fluent, unchecked answer—and compelling it instead into the slower, inspectable mode where error can be caught. In both cases the method does not make the fast system go away. It subordinates it: the fast system still generates the candidate steps, as it must, but each candidate now passes through a slow, written, checkable process before it is allowed to stand. That subordination—intuition proposing, deliberation disposing—is the inquiry loop running inside a single human skull, and it is the best defence we have against the predictable failures we turn to now.

## CHAPTER NINE

# Bias as Reasoning Failure—and the Method as Repair

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*The mind's errors are systematic, not random—and the scientific method, formalised as structured reasoning, is the technology we have built to correct them.*

A random error can be averaged away; a systematic error cannot. The most important discovery of the cognitive psychology of the last half-century is that human reasoning errs systematically—that the fast system of Chapter 8 fails in regular, predictable, repeatable ways, the same ways in person after person. This is at once disturbing and hopeful. Disturbing, because it means our intuitions cannot be trusted to cancel out. Hopeful, because a predictable error is a correctable one: if we know the shape of the mistake, we can build procedures to catch it. The scientific method, and the structured chain-of-thought it inspires, is best understood as exactly such a procedure—a body of error-correcting technology, refined over centuries, aimed squarely at the documented failure modes of the human mind.

### 9.1 Heuristics and their biases

The foundational work, by Amos Tversky and Daniel Kahneman, showed that people judging probabilities and making decisions rely on a small set of mental shortcuts—heuristics—that usually serve well but produce characteristic biases when misapplied (Tversky & Kahneman, 1974). We judge how likely something is by how easily examples come to mind (availability), and so overestimate vivid,

recent, or well-publicised risks. We judge how representative a case is of a category and ignore how common the category is to begin with (base-rate neglect). We anchor on an initial number—however arbitrary—and adjust insufficiently from it. Each of these is a fast-system operation: an effortless substitution of an easy question for the hard one actually asked. None is stupid; all are efficient; and all are systematically wrong in knowable circumstances.

## 9.2 The error that matters most

Of all the biases, one is central to this book because it is the precise enemy of the inquiry loop: *confirmation bias*, the tendency to seek, notice, and weight evidence that supports what we already believe, and to ignore, discount, or explain away evidence that does not. It is the cognitive form of the methodological sin Popper warned against. A mind in the grip of confirmation bias runs a broken version of the loop—it generates a conjecture and then searches only for its confirmations, never for its refutations—and a broken loop does not converge on truth; it entrenches whatever it began with. Recall, too, the lesson of Chapter 7: a predictive brain perceives in part what it expects to perceive. Confirmation bias is what that architecture looks like at the level of reasoning—the prior so strong, and the precision assigned to disconfirming evidence so low, that the model is never overturned. The same machinery that lets us perceive a coherent world from fragmentary data lets us perceive a coherent argument in evidence that does not support it.

The connection to Part II should now be vivid. The unfaithful chains of thought of Chapter 6—where a model reached its answer by a hidden route and then generated plausible supporting reasons—are confirmation bias in a machine. The model, like the biased human, produces justifications for a conclusion arrived at otherwise. That the same failure appears in both is further evidence for the book's thesis: the inquiry loop and its characteristic corruption are substrate-independent. A guesser that rationalises rather than tests is a guesser that entrenches error, whether it is built of neurons or of weights.

## 9.3 The method as repair

What corrects a systematic bias is not effort or sincerity—the biased reasoner is typically both effortful and sincere—but *structure*: an external procedure that compensates for the known direction of the error. Several such procedures recur across science, professional judgement, and the machine practices of Chapter 5, and it is worth seeing them as a family.

The first is *consider the opposite*: deliberately generating the strongest case against your own conclusion. This is debiasing by falsification—the manual installation of the refutation step that confirmation bias deletes. It is the human form of the falsification gate of Chapter 5, and it works for the same reason: it forces the loop to test rather than merely confirm. The second is the *structured com-*

*parison of competing hypotheses*, a technique developed in intelligence analysis precisely to combat confirmation bias. Rather than evaluating a favoured hypothesis in isolation—where any evidence consistent with it feels like support—the analyst lays out all plausible hypotheses side by side and asks, of each piece of evidence, which hypotheses it would *rule out*. The decisive evidence is not what confirms the leading hypothesis but what disconfirms its rivals. This is Popper’s asymmetry turned into a worksheet, and it is the cognitive cousin of sampling many reasoning chains and examining their disagreement.

The third is the *aggregation of independent judgements*. Because individual errors are partly independent, the average of many separate estimates is typically more accurate than most of the individuals composing it—provided the estimates are genuinely independent and not merely echoes of one another. This is the human counterpart of the self-consistency method of Chapter 5, in which a model’s many independent reasoning chains are pooled. The fourth is *calibration*: the practice of attaching honest probabilities to one’s beliefs and tracking, over time, whether things one called ninety-percent-likely happen about nine times in ten. Calibration is the Bayesian rule of Chapter 1 imposed as a discipline on a mind that, left alone, is reliably overconfident.

| COGNITIVE FAILURE                | CORRECTIVE STRUCTURE                          | MACHINE ANALOGUE (CH. 5–6)             |
|----------------------------------|-----------------------------------------------|----------------------------------------|
| Confirmation bias                | Consider the opposite; seek refuting evidence | Falsification gate in the prompt       |
| Evaluating one hypothesis alone  | Structured comparison of competing hypotheses | Sampling & comparing multiple chains   |
| Individual idiosyncratic error   | Aggregate independent judgements              | Self-consistency over independent runs |
| Overconfidence                   | Calibration; track predictions vs. outcomes   | Bayesian weighting; step verification  |
| Rationalising a fixed conclusion | Externalise reasoning for inspection          | Test faithfulness by perturbation      |

Table 2. The same corrective structures appear in human method and machine practice.

## **9.4 What the mind teaches the machine, and the machine the mind**

The symmetry of the table is the point. Every corrective structure that science and professional judgement evolved to repair human reasoning has a direct counterpart in the techniques being developed to make machine reasoning reliable—not because engineers consciously copied debiasing tradecraft, but because both are responses to the same underlying failure: a powerful guesser that, left to itself, confirms rather than tests. This suggests a genuinely useful traffic in both directions. Centuries of accumulated wisdom about how to keep human reasoning honest—the entire apparatus of method, peer review, and analytic tradecraft—is a design resource for those building reasoning machines. And the machine, in turn, offers the cognitive scientist an unprecedented experimental object: a reasoner whose every step can be logged, perturbed, and measured, in which the very failures that are hard to study in humans—rationalisation, the gap between reason and cause—can be probed directly. The mind and the machine err in the same ways for the same reasons, and so each is a mirror in which to study the other. We now leave the two minds we partly understand for a third we do not understand at all—and ask whether the same loop can help us hear it.

# IV

PART FOUR

## The Animal

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*A frontier on which the same loop meets a signal no human  
mind composed—and a protocol for trying to understand a  
reasoning we did not make.*

# The Frontier of Animal Language Processing

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*Where machine learning meets the recorded sound of other species—and the inquiry loop is pointed, for the first time, at a code no human wrote.*

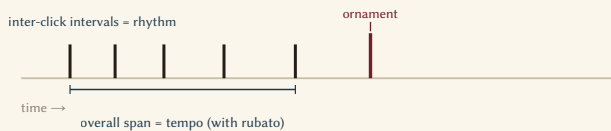
Every reasoning system this book has examined so far was built, trained, or grown within the human world. The scientific method is our invention; the language model is trained on our text; the predictive brain is the organ we think with. In each case the loop runs on material we understand from the inside. This final part turns to a frontier where that comfort disappears—where the same loop is aimed at a signal that no human mind composed and whose grammar, if it has one, we do not know. The question is no longer how a reasoner works, but whether our methods of reasoning are good enough to understand a mind unlike our own. The most concrete version of that question, today, is the attempt to decode the communication of other animals.

## 10.1 The convergence of two data deluges

The field has become suddenly tractable for a mundane reason: two kinds of abundance arrived at once. The first is data. Autonomous recorders now sit on the seafloor, hang in rainforest canopies, and ride on the backs of tagged animals, capturing sound continuously for months. Where a mid-century researcher might have gathered hours of recordings in a career, a modern bioacoustic project gathers years of audio in a season—far more than any team could annotate by ear. The second abundance is method. The same machine-learning advances that produced the language models of Part II turn out to apply, with modification, to any stream of structured symbols, including the click trains of a whale or the syllables of a bird. A discipline that was once limited by how much sound a human could patiently listen to is now limited only by how cleverly that sound can be modelled. The marriage of the two—vast unlabelled recordings and pattern-finding algorithms hungry for exactly such data—is what has moved animal communication from a descriptive natural history into something that looks, increasingly, like a decoding problem.

## 10.2 A case in point: the structure in whale codas

Consider the most developed example. Sperm whales communicate in *codas*—short, stereotyped sequences of clicks exchanged during social contact. For decades these were catalogued as a modest repertoire of distinct rhythmic types, treated rather like a small set of fixed signals. Recent work applying machine analysis to a large corpus of codas—thousands of exchanges recorded from a single long-studied population—has revised that picture substantially (Sharma et al., 2024). Rather than a short list of discrete calls, the analysis revealed a combinatorial system: codas vary systematically along several independent dimensions—the overall *tempo* of the sequence, its *rhythm*, a kind of smooth tempo variation the researchers likened to *rubato*, and the presence or absence of an extra click, an *ornamentation*—and these features combine and recombine in ways that depend on conversational context. The number of distinguishable coda types is far larger than the old catalogues suggested, and the variation is not random but structured, with features that can be mixed independently to yield a large expressive space from a small set of building blocks.



*A coda is a few clicks in time; its meaning-bearing features are how they are spaced, paced, and ornamented.*

**FIGURE 4.** Anatomy of a coda. What looks like a simple burst of clicks carries several independent, recombinable dimensions—rhythm, tempo, rubato, and ornamentation—the raw material of a combinatorial code.

It must be said plainly what this does and does not show. It does *not* show that whales have a language in the human sense, with words, grammar, and meaning; that remains an open and contested question. What it shows is that the *signal has structure* of a kind that could support such a system—that beneath an apparently simple surface lies combinatorial regularity, the necessary if not sufficient condition for anything we would be willing to call language. This is itself a result of the inquiry loop: a standing conjecture (codas are a small fixed repertoire) confronted with far more evidence than before, found wanting, and revised toward a richer hypothesis (codas are a combinatorial system). The machine did not understand the whales. It did something more modest and more honest—it found regularities in the

data that human ears and human patience had missed, and handed them back as new conjectures to test.

### **10.3 Foundation models meet the animal kingdom**

The whale work is one instance of a broader move: the construction of large models trained on animal sound the way language models are trained on text. A recent example is a foundation model for bioacoustics trained on a great range of natural and animal audio, able to perform tasks it was not explicitly trained for—identifying which species is calling, classifying the type of call, even producing descriptive captions of a sound—and to generalise to species it never encountered in training (Robinson et al., 2025). The significance is the same generalisation that made language models powerful: a model that has absorbed enough of the statistical structure of a domain can be pointed at a new problem within that domain and perform respectably without bespoke retraining. Applied to the animal world, this means a single system might serve as a general instrument for the comparative study of communication across the tree of life—a microscope for animal sound rather than a decoder of any one species.

Alongside the modelling of structure, a parallel literature has been accumulating findings that nibble at the old certainty that reference and naming are uniquely human. Studies have reported that elephants appear to address one another with individually specific calls that function something like names (Pardo et al., 2024); that marmoset monkeys use distinct calls to label particular companions (Oren et al., 2024); and, long established, that bottlenose dolphins develop individually distinctive signature whistles and will copy the whistle of a specific other, as if calling it by name (King & Janik, 2013). None of these is a claim of language. Each is a claim that a particular feature once thought distinctive of human language—here, reference to an individual—has a precursor or analogue elsewhere. Taken together they reframe the question. The interesting issue is no longer the binary one of whether animals “have language,” but the graded, empirical one of which specific features of communication appear in which species, and how they are built.

### **10.4 What counts as understanding**

This reframing matters because it disciplines the inquiry. “Do they have language?” is close to unfalsifiable as posed, because it turns on a definition we have not fixed. “Does this species’ signalling exhibit combinatorial structure, contextual conditioning, reference to individuals, productivity?”—these are questions with operational tests and possible negative answers. The shift from the first kind of question to the second is precisely the demarcation discipline of Chapter 1, applied to a new domain: replace the grand, untestable claim with the specific, riskier ones that can actually be put to nature. The promise of machine analysis here is not that it will hand us a translation, but that it will let us ask the specific questions at a scale and resolution that were previously impossible. Whether we can move from

finding structure to recovering meaning is the harder problem, and it is the subject of the next chapter.

## CHAPTER ELEVEN

# A Protocol for Decoding a Non-Human Signal

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*How to run the inquiry loop on a code you did not write—  
and the two failures, projection and credulity, that lie in  
wait at either side of the path.*

Suppose the structure is real. Suppose a machine has found, in the recorded sound of some species, the combinatorial regularities described in the previous chapter. We are now in a peculiar position: we hold a signal we believe carries information, produced by a mind we cannot interview, in a code for which we have no dictionary and no bilingual speaker. How should one proceed? This chapter sketches the answer the rest of the book implies—that the only sound method is the inquiry loop itself, run with unusual discipline because the usual corrections are unavailable—and dwells on the characteristic ways it can go wrong.

### 11.1 The first danger: pareidolia at scale

Recall the warning of Chapter 7. A predictive brain perceives, in part, what it expects to perceive; given a strong enough prior, it will find structure in noise—faces in clouds, words in static. The decoder of an unknown signal is exposed to exactly this failure, amplified by powerful pattern-finding tools and by the depth of the human wish to be understood by another mind. The danger is that we will project the structure of human language onto the animal signal: assume it has words, look for them, and—because the search is flexible and the data rich—find them, whether or not they are there. Every human investigator brings the only language faculty they have, a human one, and the temptation to see its categories reflected back is overwhelming. A machine-learning model trained on human language and then turned on animal sound can launder this projection into apparent objectivity, discovering “words” and “syntax” because it was built to expect them. The first rule of the protocol is therefore a rule of suspicion toward

one's own success: a pattern that confirms our expectations is the pattern to distrust most, precisely because we are built to find it.

This is the faithfulness problem of Chapter 6 wearing a different coat. There, the risk was a chain of thought that looked like the reason for an answer without being its cause. Here, the risk is an interpretation that looks like the meaning of a signal without being its function—a story we tell over the data, plausible and satisfying and untethered from what the signal actually does in the life of the animal. The corrective is the same: do not trust the interpretation because it is coherent; test whether it is load-bearing.

## 11.2 The test step: making the signal predict

What makes an interpretation load-bearing is that it forbids something—that it predicts, in advance, what should and should not occur. An interpretation of an animal signal earns its standing when it generates risky predictions about the world: if this coda type means something like a turn-taking invitation, then it should appear at the openings of exchanges and not at their ends; if these calls function to label individuals, then a given call should track a given animal across contexts and not be used for others. Such predictions can be checked against held-out recordings the interpretation was not built on—the bioacoustic equivalent of a held-out test set—and they can fail. An account that survives many such tests has earned provisional belief; one that is merely consistent with the data it was fit to has earned nothing.

The most decisive test available is also the oldest tool in ethology: *playback*. If we believe a signal has a function, we can synthesise it and play it back to the animals under controlled conditions, and observe whether they respond as the interpretation predicts. Playback converts a passive correlation into an active experiment—it is the field biologist's version of intervening on the system rather than merely observing it, and it is the literal enactment of the test step of the inquiry loop. A signal we can manipulate and whose effects we can predict is a signal we are beginning to understand; a signal we can only catalogue, however richly, remains a hypothesis. The protocol's second rule follows: wherever possible, move from observing the signal to intervening with it, because only intervention puts our interpretation at genuine risk of refutation.

*An interpretation we cannot test against the animal's own response is a story about the signal, not yet a reading of it.*

### 11.3 Testing for the features that matter

Between projection and playback lies a programme of structural tests, each aimed at a specific feature that would distinguish a genuine communication system from a mere repertoire of signals. Is the system *combinatorial*—are larger units built from smaller ones by rules, so that the inventory of wholes exceeds what could be listed? Is it *productive*—do new, well-formed combinations occur, rather than only a fixed set? Is it *contextually conditioned*—does the choice of signal depend systematically on circumstance in a way that carries information? Is there evidence of *reference*—does a signal reliably co-vary with a particular object, individual, or event? Each of these is a question the machine analysis of Chapter 10 can help pose at scale, and each admits a negative answer, which is what makes the programme scientific rather than interpretive. The point is not to ask the unanswerable “is it language” but to assemble, feature by tested feature, a map of what the system is and is not—letting the grand question dissolve into a hundred small ones that nature can actually adjudicate.

### 11.4 The second danger: credulity, and the ethics of the wish

If the first failure is to see structure that is not there, the second is to over-read the structure that is—to slide from “this signal carries information” to “we have translated what the animal is saying.” The gap between the two is vast, and the public appetite for the second will always run ahead of the evidence for the first. Here the methodological caution becomes an ethical one. To claim prematurely that we have decoded a species’ language is not a harmless overstatement; it shapes how that species is valued, protected, exploited, or sentimentalised. There is a growing discussion of what it would mean, legally and morally, to act on a claimed understanding of animal communication—whether evidence of sophisticated communication should bear on the legal standing or protection of a species, and how to avoid both the cruelty of dismissing a mind and the error of inventing one. These are not questions the inquiry loop answers, but they are questions its discipline bears on: the more consequential the claim, the higher the standard of evidence it should be required to meet before we act on it.

There is, finally, a question we are not used to asking of our experimental subjects. The reasoning systems of Parts II and III could be probed without their consent because, as far as we know, there was no one there to withhold it. If the project of this part succeeds—if some animal signalling turns out to be communication in a meaningful sense—then our test subjects become, in some degree, our interlocutors, and the playback experiment that was simply good method acquires the shape of an intrusion into another creature’s social world. The same loop that licenses the intervention raises the question of whether we ought to perform it.

That a method works does not settle whether it should be used—a distinction the next chapter, and the conclusion, take up as the proper endpoint of a book about reasoning: the recognition that understanding how to think well does not, by itself, tell us what we owe to the things we think about.

## CHAPTER TWELVE

# Toward a Unified Theory of Reasoning

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*What it means, and what it does not mean, to say that one loop runs in machines, minds, and—perhaps—the signals of other animals.*

We have now followed a single shape through four substrates. In science it is the explicit method of conjecture and refutation. In the machine it is the chain of generated tokens that spreads reasoning across visible steps. In the mind it is the predictive brain, guessing at the world and revising on error, and the deliberate System 2 that checks the fast intuitions of System 1. And on the frontier it is the protocol by which we might come to understand a code no human wrote. The thesis of this book is that these are not four analogies loosely related by metaphor, but four implementations of one logical structure—the inquiry loop—realised in different materials. This closing chapter states the claim precisely, marks its limits, and draws out what each substrate teaches the others.

### 12.1 The claim, stated carefully

The unifying claim is one of *functional*, not material, identity. It is not that brains are computers, or that language models think as people do, or that whales reason as scientists do. It is that a particular abstract procedure—maintain a model, use it to predict, compare prediction against evidence, revise on mismatch, repeat—is the common solution that disparate systems converge on because it is the procedure that works for a shared problem: extracting reliable structure from an uncertain world under limited information. This is convergence in the sense a biologist means when noting that eyes evolved many times: not a shared ancestry but a shared answer, arrived at independently because the problem has a good solution and selection—natural, cultural, or engineered—tends to find it. The inquiry loop is to

reasoning what the eye is to sensing: a design so suited to its task that it appears again and again wherever the task arises.

Stated this way, the claim sits at a particular level of description—the level of what the system does and why, abstracted from how it is physically built. The value of working at that level is that it reveals the deep correspondence; its danger is that it can tempt us to forget the differences that the abstraction sets aside. A responsible unification holds both at once: one shape, many materials, and the materials matter.

## 12.2 Where the substrates genuinely differ

The differences are not embarrassments to the thesis but part of its content, and three are worth naming. The systems differ, first, in the *source of their guesses*. Science draws conjectures from the disciplined imagination of human beings; the language model draws them from the statistical residue of human text; the brain generates them from a hierarchical generative model shaped by evolution and a lifetime of learning. The same loop is fed by very different founts of conjecture, and the quality of any loop's output depends heavily on the quality of the guesses it has to test.

They differ, second, in the *nature of their test*. Science tests against controlled experiment and public observation; the brain tests against incoming sensation; a well-built machine reasoning process tests against tools, verifiers, and reality outside the model; an unconstrained one may test only against its own coherence—which, as Chapter 6 showed, is no test at all. The strength of a loop is the strength of its confrontation with something that can say no. They differ, third, in *inspectability*. The machine's chain of thought can, for now, be logged and read; the brain's perceptual inference is almost wholly opaque to introspection; science makes its reasoning maximally public by design; the animal signal is opaque from the outside in. These differences explain why the same loop yields trustworthy knowledge in one setting and entrenched error in another. The loop is necessary but not sufficient; what surrounds it—the quality of its guesses, the severity of its tests, the visibility of its steps—decides whether it converges on truth.

## 12.3 What each substrate teaches the others

The practical reward of seeing the unity is that lessons learned in one substrate transfer to the rest. From science, the machine and the mind inherit the hard-won disciplines of method: falsifiability, controlled comparison, the demand that a claim forbid something. From the study of the machine, cognitive science gains an experimental object of unprecedented tractability—a reasoner whose every step can be logged and perturbed, in which the gap between the reasons given and the causes operating can be measured directly rather than inferred. From the brain, the engineer gains both an existence proof and a warning: an existence proof that a single predictive architecture can underwrite perception, action, and thought; and a

warning that such an architecture, left to its strong priors, will hallucinate the patterns it expects—the biological version of a model confidently asserting what is not so. And from the frontier of animal communication, all three gain a humbling lesson in what it takes to understand a reasoning not one's own: the discipline of refusing to project, of testing rather than interpreting, of letting the grand question dissolve into answerable ones.

*A visible chain of reasoning is the common interface to any mind—the surface at which we can finally ask another reasoner not only what it concluded, but why.*

## 12.4 Reasoning as a shared interface

There is a unifying image in all of this. What chain-of-thought did for the machine was make its reasoning *visible*—turn an opaque leap into an inspectable sequence—and what the scientific method did for human knowing was the same: it made reasoning public, written, and checkable, so that the grounds of a claim could be examined by anyone. The predictive brain is the one member of the set whose reasoning remains mostly hidden, and the animal signal is hidden from us entirely—and the project of understanding each is, at bottom, the project of rendering its reasoning legible. A chain of inference made visible is the interface through which one reasoner can be understood by another: the place where we stop seeing only the conclusion and begin to see, and to test, the path. The thesis of this book is finally a hope—that by recognising the one loop beneath the many minds, we acquire a single discipline adequate to all of them: trust the test, not the story; make the reasoning visible; and never block the way of inquiry.

## CONCLUSION

# The Examined Signal

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*A last look at the one discipline that runs through machines, minds, and the signals we have yet to read.*

A book that argues for a single idea owes its reader, at the end, a plain statement of what the idea was for. The inquiry loop is not offered here as a curiosity—a pleasing pattern that happens to recur—but as a practical discipline,

and the recurrence is what makes the discipline portable. If the same loop runs in the laboratory, in the language model, and in the brain, then the rules for running it well are not three separate crafts but one, and a person who has learned to think clearly in any of these domains has learned something that transfers to the others.

The through-line of this book has been a single caution, repeated in four registers because it matters in all of them: *a visible chain of reasoning is not the same as an honest one*. The scientist can construct an elegant derivation toward a foregone conclusion; the language model can generate a fluent rationale parallel to the hidden process that actually produced its answer; the brain can perceive, with complete conviction, the pattern it expected rather than the one before it; and the would-be decoder of an animal signal can read into the data a meaning that the data do not bear. In every case the cure is identical. Do not believe the reasoning because it is coherent, fluent, or congenial. Ask whether it is load-bearing—whether the conclusion actually depends on the steps, whether it forbids something, whether it would survive a test designed to break it. Trust the test, not the story.

This is why chain-of-thought matters beyond its engineering uses, and why the question of its faithfulness is not a technical footnote but the center of the subject. Making reasoning visible is the precondition for making it accountable; but visibility is only the beginning, because what is visible can still be a performance. The real achievement—in science, in machines, and someday perhaps in our understanding of other minds—is reasoning that is visible *and* faithful: a chain whose every link bears weight, that can be perturbed and will respond, that puts itself at risk. Such reasoning is rare and effortful and must be continually checked, because the cheaper kind—the confident leap dressed in the costume of a derivation—is always available and always tempting, to people and to machines alike.

We began with a half-second after a hard question, in which something proposes an answer and something else, if we are disciplined, demands to see its work. That small interior drama turns out to be the whole of it, scaled up and written out: the method of science is that demand institutionalised; chain-of-thought is that demand imposed on a machine; the examined life is that demand turned on oneself. And the frontier—the animal signal we cannot yet read—is the same demand pointed outward at a mind not our own, asking not what it concludes but how, and refusing to pretend we understand until the signal itself, under test, tells us we are right. The loop does not promise certainty. It promises only this: a way of being wrong that tends, over time and under honest testing, toward being less wrong—which is the most any reasoner, of any material, has ever been able to claim. Do not block its way.

## APPENDIX

# Glossary of Terms

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*A brief lexicon of the recurring concepts, drawn from the philosophy of science, machine learning, and cognitive neuroscience.*

## Abduction

Inference to the best explanation; the generative step in which a hypothesis is proposed to account for an observation. The source of the “guess” in the inquiry loop, named by C. S. Peirce.

## Active inference

The proposal that action and perception are two means to the same end—reducing the mismatch between a brain’s predictions and its sensory input—so that moving to confirm a prediction is of a piece with updating a belief.

## Bayesian update

The rule for revising the probability of a belief in light of new evidence, weighting prior conviction against the strength of the evidence. The formal core of rational revision.

## Chain-of-thought (CoT)

A prompting and reasoning technique in which a language model generates intermediate steps before its final answer, spreading computation across tokens and rendering its reasoning inspectable.

## Coda

In sperm whales, a short stereotyped sequence of clicks exchanged in social contexts; recent analysis suggests codas vary along several recombinable dimensions, hinting at combinatorial structure.

## Confirmation bias

The tendency to seek and overweight evidence that supports an existing belief while discounting evidence against it—the cognitive form of a broken inquiry loop that confirms rather than tests.

## Demarcation

The problem of distinguishing scientific claims from non-scientific ones. On Popper's criterion, a claim is scientific to the degree that it forbids something observable and could therefore be refuted.

### **Faithfulness**

The degree to which a model's stated reasoning reflects the process that actually produced its answer. A faithful chain is load-bearing; an unfaithful one is a plausible story told alongside a hidden cause.

### **Falsifiability**

The property of a claim that it could, in principle, be contradicted by some possible observation. For Popper, the mark of an empirical, scientific statement.

### **Free-energy principle**

A mathematical framework proposing that self-organising systems act to minimise a quantity related to prediction error. As a principle it is not itself falsifiable; the specific hypotheses derived under it are.

### **In-context learning**

A large model's ability to perform a task from examples or instructions given in the prompt, without any change to its trained weights.

### **Inquiry loop**

This book's term for the cycle—question, conjecture, prediction, test, evidence, revision—argued to be common to the scientific method, machine chain-of-thought, and the predictive brain.

### **Isomorphism**

A correspondence of structure between two systems. The book claims a functional isomorphism, not a material identity, among its several reasoning systems.

### **Monitorability**

The extent to which an AI system's reasoning can be observed and understood by an outside party—decomposable into legibility, coverage, faithfulness, and verbosity—and regarded as a fragile opportunity for oversight.

### **Pareidolia**

The perception of meaningful pattern—faces, words—in random or ambiguous input; the characteristic failure of a strongly predictive system, and a standing hazard for any decoder of an unknown signal.

### **Playback experiment**

In ethology, the controlled presentation of a recorded or synthesised signal to an animal to test a hypothesis about the signal's function—the field's form of intervention and the test step made concrete.

### **Precision (weighting)**

In predictive processing, the brain's estimate of the reliability of a prediction error, governing how strongly that error is allowed to revise belief—the neural analogue of weighting evidence by its trustworthiness.

### **Prediction error**

The discrepancy between what a predictive system expected and what it received; the signal that drives revision of its internal model.

### **Predictive processing**

The framework holding that the brain perceives by continually predicting its sensory input and correcting those predictions against incoming signals—perception as inference rather than reception.

### **Self-consistency**

A method that samples many independent reasoning chains for the same problem and selects the answer they most agree on, trading additional computation for reliability.

### **System 1 / System 2**

A widely used shorthand for two modes of human cognition: fast, automatic, intuitive judgement (System 1) and slow, effortful, deliberate reasoning (System 2). Chain-of-thought externalises the latter.

### **Test-time compute**

Computation expended while a model is answering—for example, on extended reasoning—as opposed to during training; shown in some settings to improve results more than enlarging the model.

### **Zero-shot prompting**

Eliciting a behaviour from a model with an instruction alone and no worked examples—as in prompting a model to reason step by step without demonstrating how.

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## Chains of Inference

*The Scientific Method in Machines, Minds, and the Coming Decoding of  
Animal Language*

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