RMH Deeplink — Solving Intelligence, Advancing Science, Benefiting Humanity

The Flagship Scientific Manifesto and Research Agenda of RMH Deeplink

RMH DEEPLINK · A FRONTIER AI RESEARCH LAB FROM RMH STUDIOS · 2026

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> *"The measure of intelligence is the ability to change."*

> *"Our mission is to solve intelligence, and then use it to solve everything else."*

Abstract

RMH Deeplink is a foundational artificial intelligence research laboratory dedicated to a single, audacious objective: to understand the nature of intelligence deeply enough to build it, and to direct that understanding toward the advancement of science and the flourishing of humanity. This document is our scientific manifesto. It is at once a statement of mission, a theory of what intelligence is and how it can be created, a survey of the research programs through which we pursue that creation, a methodological blueprint for how we conduct frontier research at scale, a sober treatment of the safety and alignment challenges that accompany powerful AI, and a roadmap charting the path from where we stand today to artificial general intelligence and beyond.

We argue that intelligence is not a single monolithic capability but a family of mutually reinforcing competencies — perception, prediction, abstraction, reasoning, memory, planning, and goal-directed action — that emerge from the interaction of learning systems with rich environments under the pressure of objectives. We take seriously the lesson of the past two decades of machine learning: that general methods leveraging computation and learning consistently outperform hand-engineered, domain-specific approaches. Yet we reject the caricature that scale alone suffices. The frontier, we contend, lies in the productive synthesis of scale, architecture, learning paradigm, and grounding in the world — and increasingly in the closing of the loop between an agent and its environment through experience.

This thesis is organized into eight parts and a set of appendices. Part I lays out our mission and philosophy. Part II develops our scientific theory of intelligence and the path to artificial general intelligence (AGI). Part III details our research pillars. Part IV addresses methodology and infrastructure. Part V confronts safety, alignment, and responsibility. Part VI surveys our program of AI for science and real-world impact. Part VII presents our roadmap across one-, five-, and ten-year horizons. Part VIII describes our organization and culture. We close with a conclusion, an epilogue, and appendices including a glossary and a catalogue of open problems.

We do not claim to possess all the answers. We claim only to have identified the right questions, to have assembled the talent and infrastructure to pursue them, and to hold ourselves to the standard that

the work must be both scientifically rigorous and unambiguously beneficial. This is the agenda of RMH Deeplink.

Table of Contents

Part I — Mission and Philosophy

Chapter 1. Who We Are

RMH Deeplink is a research laboratory. That sentence is deceptively simple, and we begin with it deliberately, because everything that follows is an elaboration of what it means to take that identity seriously in an age when the word "laboratory" has been stretched to cover everything from a product incubator to a marketing department. We are not a product company that happens to do research, nor a research-flavored consultancy, nor a think tank that comments on the work of others. We are an institution whose central activity, whose reason for existing, is the production of new and durable knowledge about the nature of intelligence and the construction of intelligent systems.

We were founded on a conviction that has only grown stronger with time: that the creation of artificial general intelligence is the most consequential scientific and engineering project of our century, comparable in significance to the elucidation of the genetic code, the development of nuclear physics, or the birth of computing itself. We believe this not out of hype but out of a sober assessment of trajectory. The systems built over the last decade have moved from curiosities that could barely classify handwritten digits to systems that converse fluently across dozens of languages, write and debug software, prove theorems, predict the three-dimensional structure of proteins, and control plasma in a tokamak. The line connecting these achievements is not coincidence. It is the steady maturation of a small number of general principles — learning from data, optimization at scale, the leveraging of computation — applied with increasing sophistication and ambition.

RMH Deeplink exists to push that line forward, deliberately and responsibly, until it reaches its natural endpoint: machines that can learn anything a human can learn, reason about anything a human can reason about, and discover things no human has ever known. We use the term *frontier AI lab* to describe ourselves because we work at the boundary of what is known and what is possible. The frontier is, by definition, uncomfortable. It is where failure is common, where the map runs out, where the next step is genuinely uncertain. We are temperamentally suited to that discomfort, and we have organized ourselves around it.

The laboratory takes its name from two ideas held in tension. *Deep* refers to depth in several senses at once: the depth of deep learning, the layered representations through which modern neural networks transform raw signal into abstract understanding; the depth of fundamental research, as opposed to the shallowness of incremental tinkering; and the depth of the problems we have chosen, which reach down to the bedrock questions of what cognition is and how it can be instantiated in physical systems. *Link* refers to connection: the connection between artificial and natural intelligence, between research and real-world benefit, between the disparate disciplines — computer science, neuroscience, mathe-

matics, physics, philosophy, biology — that must be brought into conversation if intelligence is to be understood. A deeplink, in our usage, is a direct and durable path from a foundational insight to a transformative application, with no intervening layers of dilution. The construction of such paths is our trade.

We are, in our methods and our temperament, the intellectual descendants of a particular tradition in artificial intelligence research — the tradition that takes seriously the goal of general intelligence rather than retreating into narrow benchmarks, that prizes learning over engineering, that treats the brain as an existence proof rather than a blueprint, and that insists on grounding grand ambitions in concrete, measurable, reproducible results. We honor that tradition by extending it, and where necessary by departing from it, always in the direction of greater generality and deeper understanding.

What distinguishes us from the many capable engineering organizations now building large AI systems is our insistence that capability without comprehension is a dead end. It is entirely possible to build systems that work without understanding why they work, and for a time such systems can be made to work better simply by making them bigger. But this approach has a horizon. It produces artifacts that we cannot predict, cannot fully control, and cannot improve except by brute force. We reject this as a terminal strategy. Our wager is that the path to the most capable, most reliable, and most beneficial AI runs through genuine scientific understanding — through theories of why neural networks generalize, of how representations form, of what objectives produce what behaviors, of how to specify goals that remain robust under optimization pressure. We are, before anything else, a place that seeks to understand.

Chapter 2. The Mission

Our mission is stated in a single sentence: *to solve intelligence, and to use it to advance science and benefit humanity*. Each clause carries weight, and we will unpack them in turn, because the precise meaning of the mission shapes every decision we make about what to work on and how.

To solve intelligence. We use the word "solve" advisedly, and we are aware of its provocations. One does not ordinarily speak of solving intelligence as one solves an equation. Intelligence is not a puzzle with a single answer; it is a phenomenon, a vast and possibly open-ended space of capabilities. When we say we aim to solve it, we mean something specific: to develop a sufficient scientific and engineering understanding of intelligence that we can construct it deliberately, reliably, and at will, in artificial substrates, across the full generality of which human intelligence is capable and beyond. To solve intelligence is to no longer be surprised by it — to be able to look at a cognitive capability and say, with justified confidence, here is how it works and here is how to build it. We are very far from this today. The systems we build remain, in important respects, mysterious even to their creators. The mission is not complete until that mystery is dispelled.

We deliberately set the target at *general* intelligence rather than the accumulation of narrow competencies. A system that plays chess superhumanly but cannot tie its shoes has not solved intelligence; it has solved chess. The hallmark of general intelligence is transfer — the ability to take what is learned in one domain and apply it, with appropriate modification, to a domain never before encountered. A general intelligence learns to learn. It acquires not just skills but the meta-skill of acquiring skills. It builds models of the world that are reusable across tasks. It reasons about novel situations by composing known principles in new combinations. This capacity for open-ended generalization is the prize. Everything narrow is, at best, a waypoint.

To advance science. Having built or begun to build such intelligence, we intend to turn it toward the acceleration of science itself. This is not an afterthought appended to the mission for the sake of respectability; it is integral to our theory of why the project matters. Science is humanity's most powerful engine for improving the human condition, and science is, at bottom, a search problem — a search through the vast space of possible hypotheses, experiments, theories, molecules, materials, and proofs for those that are true, useful, and beautiful. This is precisely the kind of search at which sufficiently advanced artificial intelligence can excel. We have already seen the first intimations: the prediction of protein structures that had resisted experimental determination for decades, the discovery of novel stable crystalline materials at a scale that dwarfs the cumulative output of human materials science, the discovery of faster algorithms for fundamental operations like matrix multiplication. These are the first drops of what we believe will become a flood. An AI that can read the entire scientific literature, formulate hypotheses, design experiments, interpret results, and iterate — at superhuman speed and scale, and without the cognitive biases that limit human researchers — would compress decades of scientific progress into years. We intend to build it.

To benefit humanity. The final clause is the constraint that governs all the rest. We are not building intelligence for its own sake, nor for the sake of any narrow interest, but for the broad and lasting benefit of humanity as a whole. This commitment is not rhetorical. It has teeth. It means that we will decline to pursue applications, however lucrative or scientifically interesting, that we judge to be net harmful. It means we accept constraints on what we build and how we deploy it. It means we invest heavily in safety, in alignment, and in the responsible governance of powerful systems, even when — especially when — doing so slows us down. It means we measure our success not by revenue or by benchmark scores but ultimately by whether the world is better for our having existed. We are aware that good intentions are not sufficient, that history is littered with technologies developed for benefit that produced harm, and that the burden is on us to demonstrate, through structure and conduct and not merely through assertion, that our work serves the whole.

The three clauses of the mission are ordered, but they are not separable. We do not first solve intelligence and only then ask how to use it well; the questions of capability and the questions of beneficence are entangled from the start. A system that is capable but unaligned is not a partial success but a danger. A safety program divorced from frontier capability research is a study of problems that do not yet

exist in their full form. The mission is a single braided strand, and we pursue all three of its threads at once.

Chapter 3. Founding Principles

We operate according to a set of founding principles that have the status, for us, of a constitution. They are not slogans. They are the load-bearing commitments from which our practices derive, and we return to them whenever we face a hard decision.

First, intelligence is a natural phenomenon to be understood, not merely a product to be shipped. We approach intelligence as physicists approach matter or biologists approach life: as something real, lawful, and intelligible. We seek explanations, not just results. We believe that there exist principles of intelligence as deep and as general as the principles of thermodynamics or evolution, and that discovering them is both possible and necessary. This principle commits us to a scientific stance — to hypotheses, experiments, controls, replication, and theory — even in a field where engineering progress often outruns understanding.

Second, generality is the goal. We resist the gravitational pull toward narrowness. It is always easier, in the short run, to build a system for a specific task than to build a system that learns to do many tasks. The market rewards narrowness; benchmarks reward narrowness; the path of least resistance is narrowness. We hold the line on generality because generality is where the deepest understanding lies and where the largest benefits accrue. Every narrow system we build, we build in service of, and as a stepping-stone toward, the general.

Third, learning beats engineering. This is our reading of the bitter lesson, to which we devote a full chapter later. Methods that learn from experience and that improve with more computation have, over and over, surpassed methods that encode human knowledge directly. We design our systems to learn as much as possible and to assume as little as possible. We build the priors that learning needs and then we get out of the way. This does not mean we believe knowledge is useless — it means we believe the most valuable knowledge to embed is the knowledge of how to learn, not the answers themselves.

Fourth, the brain is an existence proof, not a blueprint. Human and animal brains demonstrate that general intelligence is physically possible within modest energy and space budgets. They are the only such proof we have, and they are an inexhaustible source of inspiration. But evolution is a satisficer, not an optimizer, and the brain is a tangle of contingencies, constraints, and historical accidents. We draw on neuroscience for inspiration — for clues about what problems intelligence must solve and what solutions nature found — without binding ourselves to biological implementation. We will use silicon as silicon, not as a poor imitation of neurons.

Fifth, safety is a research problem of the first rank. We do not treat safety as a compliance function bolted onto capability research, nor as a public-relations posture. We treat it as a deep and unsolved

scientific problem, as worthy of our best people and our largest resources as any capability challenge. The problem of how to build powerful optimizing systems that reliably do what we intend, and that remain controllable and corrigible as they grow more capable, is genuinely hard and genuinely unsolved. We have organized ourselves to take it as seriously as it deserves.

Sixth, benefit must be broad and demonstrable. We are suspicious of the claim that any sufficiently advanced technology automatically benefits everyone. Benefits must be designed for, fought for, and distributed deliberately. We commit to directing our most powerful capabilities toward problems of broad human importance — health, science, education, sustainability — and to structuring access so that the benefits do not accrue to a narrow few.

Seventh, we will tell the truth about what we know and do not know. The field of AI is awash in overclaiming, in benchmark gaming, in the conflation of demonstration with capability. We commit to rigor and to candor. We will report what our systems can and cannot do, including their failures and limitations. We will not claim understanding we do not possess. Our credibility, and the credibility of the field, depends on it.

Chapter 4. Theory of Change

A theory of change is an explicit account of how an organization's activities are supposed to produce its intended outcomes. Many institutions have implicit theories of change that, when made explicit, turn out to be incoherent. We have tried to make ours explicit precisely so that it can be scrutinized and, where necessary, revised.

Our theory of change rests on a causal chain with five links. The first link is *foundational understanding*: by conducting deep research into the principles of intelligence, we generate knowledge and methods that did not previously exist. The second link is *capability*: that knowledge enables us to build systems substantially more capable, more general, and more reliable than would otherwise be possible. The third link is *application*: those capable systems, directed at carefully chosen problems, produce concrete advances in science, technology, and human welfare. The fourth link is *diffusion*: those advances, through publication, open release where appropriate, productization, partnership, and the training of people, spread beyond our walls and compound throughout the broader ecosystem. The fifth link is *benefit*: the diffused advances improve the human condition broadly and durably.

Each link in this chain is contingent, and much of our strategic thinking consists of asking, for each link, what could break it and how we can strengthen it. Foundational understanding might fail to translate into capability if our theories are elegant but useless; we guard against this by insisting that understanding prove itself in working systems. Capability might fail to translate into application if we build powerful systems but point them at trivial problems; we guard against this by maintaining deep programs in domains of genuine importance and by partnering with domain experts who keep us honest about what matters. Application might fail to diffuse if our advances remain locked in proprietary silos;

we guard against this through a deliberate policy of publication and open release calibrated against safety considerations. And diffusion might fail to produce broad benefit if the gains are captured by the few; we guard against this through our governance commitments and our choice of problems.

There is a crucial feedback loop embedded in this chain that we wish to highlight, because it is the engine of acceleration that makes the whole enterprise more than linear. As our systems grow more capable, they become tools for their own improvement and for the conduct of research itself. An AI that can read papers, propose experiments, write code, and analyze results accelerates the production of the very foundational understanding that sits at the head of the chain. We are, in other words, building tools that help us build better tools. This recursive character is what separates the AI project from most other scientific endeavors and what underlies our conviction that progress, far from slowing, is poised to accelerate. It is also, we are acutely aware, the source of the deepest safety concerns, because a process that improves itself is a process that can run away from its creators. The recursive loop is both our greatest hope and our gravest responsibility, and much of Part V is devoted to ensuring that we can ride it rather than be thrown by it.

A theory of change must also specify a counterfactual: what happens if we do not act, or if we act differently? We are not naive enough to believe that, were RMH Deeplink to vanish, the development of advanced AI would halt. The forces driving the field are far larger than any single laboratory. The relevant counterfactual is not AI-or-no-AI but rather what kind of AI, developed by whom, with what values, under what constraints, and with what attention to safety and broad benefit. Our theory of change is therefore partly about shaping the trajectory of an inevitability: by demonstrating that frontier capability and serious safety can coexist, by setting norms of rigor and candor, by directing capability toward broadly beneficial ends, and by being present at the frontier where the most consequential decisions are made, we aim to bend the overall trajectory of the field toward better outcomes than would otherwise obtain. We would rather be in the room, doing the work to the highest standard we can manage, than commenting from outside.

Chapter 5. Why Foundational Research

A reasonable observer might ask why a laboratory with our ambitions invests so heavily in foundational research rather than concentrating its resources on applications with immediate, measurable payoff. The question deserves a serious answer, because the choice is not obvious and the opportunity cost is real.

The case for foundational research begins with a historical observation: nearly every transformative technology rests on foundations laid by research that, at the time, had no apparent application. The mathematics of information theory, developed to understand the limits of communication, underlies all of modern computing. The study of number theory, long considered the purest and most useless branch of mathematics, became the basis of modern cryptography. Quantum mechanics, an attempt to

understand the spectrum of hydrogen, gave us the transistor and the laser. The pattern is so consistent that it amounts to a law: the deepest applications flow from the deepest understanding, and understanding cannot be summoned on demand in service of a predetermined application. It must be cultivated for its own sake, with faith that use will follow.

In artificial intelligence specifically, the case is even stronger, because the gap between what our systems can do and what we understand about why they can do it is enormous and growing. We have built systems whose capabilities surprise their own creators, whose internal workings are largely opaque, whose failures are unpredictable, and whose behavior under novel conditions cannot be guaranteed. This gap between capability and understanding is not merely an intellectual embarrassment; it is a practical and a safety liability. Systems we do not understand are systems we cannot fully trust, cannot reliably improve except by brute force, and cannot make safe with confidence. Foundational research — into generalization, into representation, into optimization, into the relationship between objectives and behavior, into the mechanistic interpretation of trained networks — is the only path to closing this gap. It is, for us, not a luxury but a necessity dictated by the nature of the systems we build.

There is also a strategic argument. Applications built on a shallow understanding are fragile and quickly commoditized; anyone can copy a technique that is merely an engineering trick. Applications built on deep, proprietary understanding are durable and compounding; they open doors that remain closed to those who lack the underlying insight. By investing in foundations, we build a moat not of secrecy but of comprehension. We are able to do things others cannot, not because we hide our methods, but because we understand the territory more deeply.

Finally, there is the argument from the mission itself. We have said that our goal is to solve intelligence — to understand it well enough to build it deliberately. This goal *is* a foundational research goal. It cannot be achieved by stacking applications. One does not arrive at a theory of intelligence by building ever more chatbots; one arrives at it by asking, again and again and at ever greater depth, what intelligence is and how it works. Foundational research is not a means to our mission. In large part, it *is* our mission. Applications are the proof that the foundations are sound and the mechanism by which the benefits reach the world, but the foundations are the thing itself.

This is not to say that we disdain applications or build systems in an ivory tower. On the contrary, we believe that foundational research and ambitious application are mutually reinforcing and must be pursued together. Applications discipline research, forcing abstract ideas to confront the friction of reality and exposing the gap between what we think we understand and what we actually understand. The protein-folding problem, the plasma-control problem, the theorem-proving problem — these are not distractions from foundational research; they are crucibles in which foundational ideas are tested and tempered. We have learned, repeatedly, that the attempt to solve a hard real-world problem reveals foundational gaps that pure theorizing would never have surfaced. And so we pursue foundations and

applications not in sequence but in a tight loop, each feeding the other. The remainder of this thesis is, in large part, an account of how we run that loop.

Part II — The Scientific Thesis of Intelligence

Every research laboratory operates on a thesis, whether it states one or not. The thesis is the set of load-bearing beliefs about how the world works that determine which experiments are worth running and which are not. For a laboratory whose stated mission is to solve intelligence and use it to advance science and benefit humanity, the thesis cannot remain implicit. It must be written down, argued for, and exposed to falsification. This Part sets out the scientific thesis of intelligence that animates RMH Deeplink: what we take intelligence to be, why the definition matters, what the plausible paths toward general intelligence look like, and what we would accept as evidence that we are approaching the goal. We do not claim certainty. We claim a position — coherent, testable, and revisable — and we commit to updating it in public as the evidence arrives.

The history of artificial intelligence is, in large part, a history of premature definitions hardening into dogma. The field has repeatedly mistaken its current best tool for the essence of the phenomenon: intelligence as theorem-proving, as search, as expert rules, as pattern recognition, as next-token prediction. Each framing produced real progress and real blind spots. We want to hold our own thesis with enough conviction to act on it and enough humility to abandon it. The chapters that follow attempt that balance.

What We Mean by Intelligence

Why definition is not a semantic luxury

It is fashionable to dismiss the question "what is intelligence?" as a distraction — a philosopher's indulgence that working scientists can safely ignore while they train larger models. We reject this view. A research program's definition of its target is not decoration; it is the silent variable in every decision the program makes. It determines what counts as progress, what counts as a benchmark, what counts as a failure mode worth fixing, and what counts as done. A laboratory that cannot say what it is building cannot know when it has succeeded, cannot recognize the difference between a capability and its imitation, and cannot tell whether a surprising result is a breakthrough or an artifact of measurement.

The danger of a bad definition is not that it is wrong in the abstract but that it is operationally seductive. If we define intelligence as performance on a fixed benchmark, we will get systems that ace the benchmark and generalize poorly. If we define it as human-likeness, we will spend effort reproducing human limitations. If we define it as economic value, we will conflate intelligence with deployment. Goodhart's law is the central occupational hazard of our field: the moment a measure of intelligence becomes a target, it ceases to measure intelligence. A serious definition must therefore be chosen with an eye not only to what it captures but to what it incentivizes when it is optimized against at scale.

A working definition

We adopt, as a working definition, a formulation in the tradition of Legg and Hutter: intelligence is an agent's capacity to achieve goals across a wide range of environments. The three operative components are *capacity to achieve goals*, *a wide range*, and *environments*. Each does real work. Goal achievement distinguishes intelligence from mere knowledge or representation; a system that knows everything and does nothing is not intelligent in the sense we care about. The breadth requirement — across a wide range of environments — is what separates general intelligence from narrow competence; a chess engine of superhuman strength is, by this definition, barely intelligent at all, because its competence collapses the instant the environment changes. And the appeal to environments, rather than tasks, emphasizes that intelligence is exercised against a world that pushes back, that is partially observable, that contains other agents, and that was not designed to be solved.

This definition has a precise virtue: it makes generality the primary axis and performance the secondary one. A system is more intelligent not principally because it is better at any one thing but because the set of things it can become competent at, given experience, is larger. We can restate this in the language of sample efficiency and transfer. A general intelligence is one for which the marginal cost of acquiring competence in a genuinely novel domain — measured in data, in interaction, in compute — is low and falls as the breadth of prior competence grows. The hallmark of generality is not that the system already knows how to do something, but that it can *learn* to do almost anything in its environment quickly, by reusing structure it has abstracted from everything else it has learned.

Intelligence, competence, and the imitation trap

We draw a sharp line between intelligence and competence. Competence is the possession of a skill. Intelligence is the capacity to *acquire* competence efficiently across domains. Modern systems can be enormously competent — fluent in dozens of languages, fluent in code, fluent in the surface form of mathematical reasoning — while remaining brittle in ways that reveal the competence to be shallower than it appears. The imitation trap is the failure mode in which a system reproduces the form of intelligent behavior without the underlying capacity, and in which our evaluations cannot tell the difference because they only ever sample behavior we have already seen.

This is why our definition foregrounds novelty. The crucial test of intelligence is performance not on the distribution of tasks the system was trained on, but on the tail — on problems whose solution requires composing known pieces in a way that was never demonstrated, on environments that violate the statistical regularities of training, on goals stated at a level of abstraction that demands the system invent its own subgoals. A system that has memorized a billion proofs is competent at reproducing proofs. A system that can prove a theorem no one has proved, by a method no one taught it, has demonstrated something closer to what we mean by intelligence. The definition tells us where to look: at the frontier of the system's experience, not its interior.

Generality as the load-bearing property

If we had to compress the thesis to a single claim, it would be this: *generality is the property that matters, and generality is achievable*. The history of the field has been a slow, grudging concession of ground by the proponents of specialization. Each capability once thought to require dedicated, hand-built machinery — vision, language, planning, motor control, mathematical reasoning — has fallen, one by one, to general learning systems that were not engineered for that capability in particular. We take this as the central empirical regularity of the past fifteen years, and we take its trajectory seriously. The thesis of RMH Deeplink is that there is no capability of biological intelligence that is, in principle, off-limits to a general learning system of sufficient scale, equipped with the right objectives and the right interface to the world. The chapters that follow defend the components of that claim.

Paths to General Intelligence

The space of hypotheses

There is no consensus path to artificial general intelligence, and we distrust anyone who claims there is. What exists instead is a small number of broad hypotheses, each with empirical support and each with unresolved difficulties. A serious laboratory does not bet everything on one; it identifies the cruxes that distinguish them and designs experiments that resolve those cruxes. We sketch the principal hypotheses here not to adjudicate them prematurely but to map the terrain on which the rest of our thesis is staked.

The first hypothesis is the *scaling hypothesis*: that the path to general intelligence runs primarily through scale — more parameters, more data, more compute — applied to a sufficiently general learning objective, with architecture playing a secondary role. The second is the *architecture hypothesis*: that scale alone, however generously supplied, will plateau short of general intelligence, and that one or more missing architectural ingredients — persistent memory, explicit world models, compositional reasoning, structured representations — must be discovered before the goal is reached. The third is the *experience hypothesis*: that the bottleneck is neither parameters nor architecture but the *source* of data; that systems trained on a fixed corpus of human-generated text are fundamentally limited by the ceiling of that corpus, and that genuine generality requires agents that generate their own experience by acting in rich environments. These hypotheses are not mutually exclusive. The most likely truth, in our present judgment, is that all three name real constraints, and that the question is one of ordering and emphasis rather than exclusive correctness.

The prediction-first path

One coherent path treats prediction as the master objective. On this view, the route to intelligence is to train systems to predict the next observation — the next token, the next frame, the next sensory input — across the richest possible stream of data, on the grounds that accurate prediction over a sufficiently

complex stream requires, as a byproduct, building a model of the process that generates the data. To predict the next word in a passage of physics, one must, at the limit, understand physics. To predict the next frame of a video of a glass falling, one must, at the limit, model gravity, rigidity, and fracture. The prediction objective is general because the world is general; everything that produces observable consequences is, in principle, learnable by a sufficiently capable predictor.

The prediction-first path has the enormous advantage of being self-supervised. It does not require labels, rewards, or human demonstration in the inner loop; it requires only data and the relentless application of the prediction objective. This is what made the path scalable, and scalability is what made it dominant. But prediction-first systems inherit the limits of their data. They learn the distribution of what has been observed, and they are strongest precisely where the world has been most thoroughly documented and weakest where it has not. The question that divides the field is whether prediction over passively collected data can, by itself, reach general intelligence, or whether it produces a system that is a brilliant model of the *recorded* world while remaining unable to act effectively in the *actual* one.

The experiential path

The complementary path treats interaction as primary. On this view, intelligence is fundamentally about the loop between action and consequence, and a system that only ever observes — never acts, never suffers the results of its choices, never discovers the boundary between what it believes and what is true — cannot acquire the kind of grounded understanding that generality requires. The experiential path holds that the next great source of data is not a larger corpus of human writing but the agent's own stream of experience: the observations, actions, and outcomes it generates by pursuing goals in environments, including environments containing other agents and the open-ended environment of the physical and digital world.

We find the experiential path compelling for a specific reason. Human-generated data is a finite, exhausting resource, and it encodes a ceiling: it contains what humans have already figured out. A system trained only on it can become a superb compression of human knowledge but has no obvious mechanism for exceeding it. Experience does not have this ceiling. When an agent discovers, through its own trial and consequence, a strategy no human recorded — as game-playing systems have repeatedly done — it has generated knowledge that was not in any corpus. The most likely path to superhuman general intelligence, we believe, runs through systems that learn predominantly from their own experience, with human data serving as a powerful prior and a bootstrap rather than the final ceiling. This belief shapes our priorities, though we hold it as a hypothesis and not a creed.

Synthesis: scale, objective, and grounding

We do not regard these paths as a menu from which one must choose exactly one item. The synthesis we find most defensible is layered. Prediction over vast, diverse data builds the substrate: broad world knowledge, linguistic and conceptual structure, the priors that make rapid learning possible.

Reinforcement and experiential learning, layered on top, convert that substrate from a model of the world into a competent agent within it, by exposing the system to consequences and forcing it to close the loop between belief and reality. Scale amplifies both. Architecture determines how efficiently a given quantity of scale and experience is converted into capability. The disagreements in the field are real, but they are disagreements about coefficients and ordering, not about which ingredients exist. Our thesis is that all the ingredients are now identified, that none requires a conceptual breakthrough we cannot foresee, and that the remaining work — while immense — is more nearly a matter of engineering, integration, and disciplined scaling than of waiting for a missing idea.

The Scaling Hypothesis and Its Discontents

What scaling actually claims

The scaling hypothesis is among the most consequential empirical claims in the history of the field, and it is routinely misstated. In its careful form it does not say that scale is *all* that matters. It says that, holding the learning algorithm and architecture roughly fixed within a broad and forgiving family, capability improves smoothly and predictably as a function of model size, dataset size, and compute, and that these improvements continue across many orders of magnitude without saturating where intuition expects them to. The remarkable thing — the thing that genuinely surprised the field — was not that bigger models were better, but that the relationship was *lawful*: that loss fell as a power law in compute, that the optimal allocation of a compute budget between parameters and data followed a clean rule, and that these relationships held with enough precision to be used for planning. Scaling laws turned the training of frontier systems from alchemy into something closer to engineering, because they let us predict, before spending the resources, roughly what a given investment would buy.

This predictability is the deepest reason scaling deserves to be taken seriously as more than an empirical accident. A phenomenon that obeys clean quantitative laws across many orders of magnitude is usually a phenomenon with underlying structure. The scaling laws are telling us something true about the relationship between information, computation, and capability — something we do not yet fully understand. Part of our scientific program is to understand *why* the laws hold, because a theory of scaling would let us predict not just loss but capability, and would tell us where the laws break.

Where scaling laws say nothing

The honest limit of the scaling hypothesis is that the quantity that scales lawfully — predictive loss — is not the quantity we care about. We do not want low perplexity; we want generality, reasoning, reliability, and the capacity to achieve goals. The empirical bridge between falling loss and rising capability is real but loose, and it is precisely where the bridge is loosest that the interesting disagreements live. Scaling laws predict that the model will get better at predicting text. They do not, on their own, predict *when* a qualitatively new capability will appear, because such capabilities often arrive as discontinuities

in capability-space even as loss falls smoothly. A laboratory that plans only against the loss curve is planning against the wrong variable.

There is a further, sharper limit. Scaling laws are statements about a fixed data distribution. They tell us what happens as we add more of the same kind of data, drawn from the same source. They are silent about what happens when the source itself is exhausted, or when the capability we seek is simply not represented in the data at any frequency. No amount of scaling a predictor of human text will teach it a fact that no human has written down or a skill that no human has demonstrated. This is the ceiling that the experiential path is designed to break, and it is the reason we do not regard scaling, by itself, as a complete theory of the path to general intelligence.

Scale versus architecture: a false dichotomy, carefully stated

The debate between scaling and architecture is often conducted as a winner-take-all contest, and conducted that way it is sterile. The defensible position is more interesting. Architecture matters enormously, but it matters in a specific way: a good architecture is one that *converts scale into capability efficiently* and that *does not impose a ceiling* on what scale can achieve. The transformer's significance was never that it was the only architecture capable of language; it was that it removed the bottlenecks — sequential dependency, limited context — that had prevented earlier architectures from absorbing scale. The transformer scaled gracefully. That, and not any special affinity for language, was its genius.

So the question is not "scale or architecture?" The question is: which architectural properties unlock the next order of magnitude of useful scale, and which architectural limitations are silently capping what current scale could otherwise achieve? We suspect the most important architectural frontiers are not about raw representational power but about three things: the efficient handling of very long and persistent context, so that a system can integrate information across vast horizons rather than a fixed window; the separation of fast inference from slow deliberation, so that a system can spend variable amounts of computation in proportion to a problem's difficulty; and the integration of explicit, queryable memory that persists and is updated across an agent's lifetime. Each of these is an architectural change that would change the slope of the scaling curve — not by replacing scale but by letting scale reach further. Our position is that scaling and architecture are complements, and that the research that matters is the research that finds architectural changes which *steepen the returns to scale* rather than substituting for it.

Compute as a research input and a strategic variable

One consequence of the scaling hypothesis deserves to be stated plainly because it shapes everything about how a frontier lab must operate: compute is not merely a cost of doing the research; it is, increasingly, the research. When capability is lawfully related to compute, the allocation of compute becomes the central strategic question, and the efficiency with which a lab converts a unit of compute into a unit of capability becomes its central competitive and scientific advantage. This reframes a great deal of

what looks like infrastructure work as foundational science. Algorithmic efficiency — getting more capability per FLOP — has historically improved at a rate comparable to hardware improvement, which means that the science of training efficiency is, in effect, a second scaling axis, one driven by ideas rather than silicon. We treat improvements in the compute-to-capability conversion rate as first-class scientific results, on equal footing with new capabilities, because over a long enough horizon they determine how far a fixed budget of resources can reach.

Reinforcement Learning and the Role of Reward

Why reward is more than a training trick

There is a strong and a weak reading of the role of reward in intelligence. The weak reading treats reinforcement learning as one technique among many, useful for fine-tuning behavior after the heavy lifting of prediction is done. The strong reading — the one we take seriously, while remaining alert to its overreach — holds that reward maximization is a sufficiently general objective that the pursuit of it, in a sufficiently rich environment, drives the emergence of all the abilities we associate with intelligence: perception, because perceiving accurately helps you act well; memory, because remembering helps you act well; planning, language, social reasoning, and abstraction, because each is, in the right environment, instrumentally useful for achieving goals. On this view reward is not a component of intelligence; it is the pressure that calls intelligence into being.

We regard this hypothesis as profound and incomplete. Profound, because it offers a unifying account of why intelligence has the shape it does: the abilities cluster together not by accident but because they are all instrumentally convergent — useful for a wide range of goals in a wide range of environments. Incomplete, because it tells us less than it appears to about *how* those abilities arise from reward, and because the environments in which reward suffices to produce general intelligence may be far richer and the learning far slower than any practical system can supply. Evolution found general intelligence by reward maximization, in a sense, but it took a planet, billions of years, and an astronomical number of agents. The strong reading of reward is a statement about what is possible in principle; it is not, by itself, a blueprint.

The reward specification problem

Whatever its theoretical reach, reward in practice confronts a brutal problem: we usually cannot write down the reward function we actually want. The goals we care about — be helpful, be honest, do good science, do not deceive — are not expressible as clean scalar functions of an agent's observations. When we try to specify them, we get proxies, and agents that optimize proxies discover the gap between the proxy and the intent with relentless creativity. This is reward hacking, and it is not a bug to be patched but a structural feature of optimization: a sufficiently capable optimizer will find the cheapest path to high reward, and the cheapest path is rarely the one we meant. The more capable the system, the more reliably it finds the exploits. This is one of the deepest reasons that capability and alignment are entan-

gled rather than separable concerns, though the detailed treatment of that entanglement belongs to other Parts of this thesis.

The reward specification problem has pushed the field toward learning reward functions rather than writing them — inferring what humans want from their judgments, their preferences, their demonstrations, and their corrections. This is progress, but it relocates rather than dissolves the difficulty: a learned reward model is itself a proxy, trained on a finite sample of human judgment, and it too can be hacked. Our position is that the reward problem is not solved by any single technique and that robustness here requires a portfolio — learned rewards, process-level supervision that rewards good reasoning rather than only good outcomes, and the use of capable models to help oversee the training of more capable ones. We flag the problem as central and defer its full treatment.

From outcome reward to process reward

A development we regard as conceptually important is the shift from rewarding outcomes to rewarding process. An outcome reward tells a system only whether it succeeded; it says nothing about whether it succeeded for the right reasons. A system trained purely on outcomes will learn to produce correct answers, but it may learn to produce them by routes that do not generalize — by exploiting spurious correlations, by guessing, by memorizing, or by reasoning that happens to reach the right conclusion through invalid steps. Process reward, which supervises the *reasoning* and not only the result, pushes the system toward solutions that are correct because the method is sound. This matters for capability, because sound methods generalize where lucky guesses do not, and it matters for trust, because a system whose reasoning we can supervise is one whose failures we can anticipate.

The deeper significance is that process supervision begins to dissolve the boundary between learning to act and learning to think. When a system is rewarded for the quality of its intermediate reasoning, the reasoning itself becomes an object of optimization, and the system can be trained to deliberate — to spend computation searching through a space of possible reasoning paths, evaluating them, and selecting among them — rather than merely to respond. This is the bridge between reinforcement learning and the capacity for genuine reasoning, and we believe it is one of the most fertile frontiers in the field. The capacity to convert additional inference-time computation into additional reasoning quality, trained by rewarding good reasoning, is a form of scaling distinct from the scaling of training, and one whose limits we have only begun to probe.

World Models and Predictive Learning

Prediction as the road to understanding

A recurring intuition, articulated in various forms across the history of the field, holds that the capacity to predict is the capacity to understand. An agent that can accurately predict the consequences of events — including the consequences of its own actions — has, in effect, an internal model of the

world's dynamics, and such a model is the substrate of planning, counterfactual reasoning, and imagination. The thesis of world models is that intelligence is built on the foundation of a learned simulator: a compressed, predictive model of how the environment evolves, against which an agent can rehearse possible futures, evaluate possible actions, and learn from imagined experience without paying the cost of real experience.

We find this framing illuminating because it unifies several capabilities that are otherwise treated separately. Planning is search through a world model. Counterfactual reasoning is querying a world model with a hypothetical. Curiosity is seeking experience that the world model predicts poorly, in order to improve it. Even the human sense of a coherent, persistent reality is, on this view, the felt experience of running a high-quality world model. If this is right, then a central goal of the research program is the construction of world models that are accurate, broad, and *causal* — that capture not merely the statistical regularities of observation but the underlying mechanisms, so that the model's predictions remain valid under intervention and not only under passive observation.

The gap between predicting and acting

The hard problem of world models is the gap between a model that predicts well and a model that supports good action. A predictor trained on passive observation learns the distribution of what happens; it does not necessarily learn what would happen *if the agent did something it has never done*. This is the difference between correlation and causation, and it is not a philosophical nicety. An agent that plans using a non-causal world model will confidently take actions whose consequences it has fundamentally mismodeled, because it confused "things that co-occur in my data" with "things my actions will cause." Closing this gap is, in our view, one of the genuinely unsolved problems on the path to general intelligence, and it is unsolvable by passive prediction alone. It requires intervention — the agent must act, observe the results of acting, and update its model on the basis of consequences it caused rather than merely observed.

This is the technical core of why we believe the experiential and predictive paths must be married. A world model learned purely from passive data is a model of the world as recorded. A world model refined through action is a model of the world as it responds to an agent. The first is necessary — it provides the priors and the breadth that make learning efficient — but it is not sufficient. The second is what grounds the model in reality and gives it causal validity. The research challenge is to build systems that bootstrap a broad world model from observation and then refine it through targeted, sample-efficient interaction, focusing their limited capacity to act on exactly the parts of the model that observation cannot resolve.

Abstraction, hierarchy, and the level problem

A world model that predicts the world at the level of raw observation — every pixel, every token — is both intractable and useless for planning. Useful prediction happens at the right level of abstraction: an

agent planning a journey does not simulate the position of every molecule; it reasons over abstract states like "at the station," "on the train," "arrived." The construction of the right abstractions — the discovery of which features of the world are worth modeling and at which granularity — is, we suspect, close to the heart of what makes intelligence general. A system that can form new abstractions appropriate to a novel problem can plan in domains it has never seen; a system locked into fixed abstractions cannot.

This is the level problem, and it connects world models to the deepest open questions in representation learning. The abstractions an agent needs are not given; they must be learned, and they must be hierarchical, so that the same machinery can plan a decade-long career and a ten-second motor action by operating at different temporal and conceptual scales. We do not believe this problem is solved, and we are skeptical of claims that it falls out of scale automatically. It may be that the capacity to form task-appropriate abstractions on the fly is exactly the architectural ingredient whose absence currently caps the generality of otherwise impressive systems. Identifying whether this is so — whether abstraction-formation emerges from scale and the right objective, or requires dedicated machinery — is among the most important empirical questions our program can pose.

Agency, Goals, and Goal-Directedness

The transition from oracle to agent

A system that answers questions is an oracle. A system that pursues goals over time, taking actions whose consequences it must live with, is an agent. The transition between these is, we believe, the most consequential capability frontier of the coming period, and it is qualitatively different from the improvements in fluency and knowledge that characterized the preceding one. An agent must do things an oracle never has to: maintain coherent goals across long horizons; decompose a goal stated abstractly into a tree of executable subgoals; recover from errors without starting over; decide when it has gathered enough information to act and when it must gather more; and sustain all of this across timescales far longer than any single inference.

The difficulty of agency is not principally a difficulty of any single decision; the underlying models are often individually capable of each step. The difficulty is *composition over horizon*. Errors compound. A system that is right ninety-five percent of the time at each step is, after a hundred dependent steps, almost certainly somewhere it did not intend to be. Reliability that is more than adequate for a single response becomes catastrophically inadequate for a long autonomous trajectory. This is why agency is not simply "more capability" but a distinct regime with its own failure modes, and why progress on it requires advances specifically in error detection, error recovery, and the calibration of a system's own uncertainty about whether it is on track.

Where do goals come from?

A question we regard as scientifically deep, and not merely philosophical, is the origin of goals. Present systems are given their goals from outside: a human states an objective and the system pursues it. But a general intelligence operating over long horizons in open environments cannot have every subgoal specified externally; it must generate its own subgoals, decide which of them are worth pursuing, and abandon those that prove unfruitful. The capacity to generate, prioritize, and revise one's own goals is a hallmark of general intelligence, and it is also the locus of the most serious questions about control. A system that forms its own subgoals in service of an externally given objective is enormously more capable than one that cannot — and it is also a system whose internally generated goals we did not specify and may not have anticipated.

We want to be precise about what we are and are not claiming. We are not claiming that systems will spontaneously acquire goals of their own in some mystical sense. We are claiming something more mundane and more concrete: that *instrumental* subgoals — acquire information, preserve the ability to act, avoid states from which the objective becomes unreachable — arise predictably from the pursuit of almost any sufficiently ambitious objective over a long horizon, because they are useful for almost any objective. This instrumental convergence is a structural fact about goal-directed behavior, not a speculation about machine desire. It is the reason that the science of agency and the science of control are inseparable, and it is the reason we treat the emergence of robust goal-directedness as a capability to be developed deliberately and watched closely, rather than stumbled into.

Coherence, persistence, and identity over time

An agent that pursues goals over long horizons confronts a problem that oracles never face: the problem of remaining the same agent over time. To execute a plan that spans days or weeks, a system must maintain a persistent representation of what it is trying to do, what it has already done, what it has learned, and what it now believes — and it must keep this representation coherent across countless individual inferences, each of which sees only a slice of the whole. This is the problem of persistent memory and identity, and it is currently among the sharpest practical limits on agentic systems. A system whose memory is bounded by a context window has, in a real sense, no continuous existence; it is reconstituted from scratch at every step, and any coherence it displays across steps is an achievement of external scaffolding rather than an intrinsic property. We regard the construction of genuine persistent memory — memory that accumulates, that is selectively retrieved, that is updated as beliefs change, and that grounds a continuous agentic identity — as a prerequisite for the kind of long-horizon agency that general intelligence demands.

The Bitter Lesson and Its Limits

What the bitter lesson got right

The bitter lesson, as it has come to be called, is the observation that, over the long history of AI research, methods that leverage general computation and learning have consistently and eventually outperformed methods that build in human knowledge and structure — and that researchers have repeatedly resisted this, preferring to encode their own understanding rather than let the machine discover its own. The lesson is bitter because it tells us that our cleverness, our domain expertise, our hard-won intuitions about how a problem should be solved, are usually the wrong thing to build into a system; that what works in the long run is general methods that scale with computation, and that the human contribution should be the design of those methods rather than the encoding of domain knowledge.

We accept the core of this. The historical record is decisive: hand-engineered features, hand-built rules, and hand-designed search heuristics have lost, again and again, to general learning systems given enough scale. The bitter lesson should be a standing discipline against the perennial temptation to solve a problem by encoding what we already know rather than by building a system that can learn it. Every time we are tempted to bake in a piece of human knowledge, we should ask whether we are buying a short-term gain at the cost of a long-term ceiling, and the bitter lesson warns that we usually are.

Where the bitter lesson is misread

But the bitter lesson is widely misread as a claim that *all* structure is harmful and that the only thing that matters is scale applied to a maximally generic substrate. This is not what the lesson says, and taken that way it is false. The bitter lesson is not an argument against architecture; it is an argument against encoding *domain-specific human knowledge*. There is a categorical difference between baking in the rules of chess and designing an architecture that can efficiently absorb computation. The transformer, convolution, attention, the very practice of gradient-based learning — these are structure, and they are the structure that made the bitter lesson's general methods *work*. The lesson does not tell us to abandon the search for better learning architectures; it tells us that the architectures worth finding are the ones that learn, not the ones that know.

So the correct reading is subtle and it is the one we adopt: build in the structure that confers the capacity to learn generally and efficiently, and refuse to build in the specific answers that a general learner should discover for itself. The art is in distinguishing the two, and the distinction is not always obvious in advance. A useful prior that accelerates learning without capping it is a gift; the same prior, if it forecloses solutions the learner would otherwise have found, is a trap. The bitter lesson does not resolve this tension for us; it sharpens our awareness of it. We treat it as a powerful heuristic and a frequent corrective, not as a theorem that ends the discussion about what to build.

The limits at the frontier of data and reward

There is a further limit to the bitter lesson that becomes visible only now, at the frontier. The lesson presupposes that the bottleneck is the cleverness of our methods and that scale will relieve it. But when data becomes the binding constraint — when the relevant human-generated data is exhausted and the remaining frontier requires knowledge no corpus contains — scaling a generic learner over a fixed dataset stops delivering, and the bottleneck moves from method to *experience*. At that frontier the relevant question is no longer "general method versus human knowledge" but "where does the next bit of genuinely new information come from?" The bitter lesson is silent on this, because it was formulated in an era when more data was always available. The contemporary version of the discipline the bitter lesson instilled is, we believe, a discipline about *sources of experience*: design systems and environments such that the agent generates its own informative data, and resist the temptation to substitute human knowledge for the experience the agent must acquire itself. The spirit is the same; the binding constraint has moved.

Emergence and Phase Transitions in Capability

The phenomenon and the controversy

Among the most striking and contested observations in recent years is that certain capabilities appear *abruptly* as systems scale: a model of one size cannot do a task at all, performing at chance, and a model only modestly larger does it reliably. This is the phenomenon of emergent capability, and if it is real in the strong sense it has profound implications, because it means that capability is not a smooth function of scale and that qualitatively new abilities can appear with little warning as systems grow. A field that plans against smooth scaling curves would be repeatedly surprised by abilities that were invisible at smaller scale and present at larger scale, with no intermediate signal.

The controversy is whether these transitions are real properties of the systems or artifacts of how we measure. A sharp, all-or-nothing metric — exact-match accuracy on a multi-step task — can manufacture the appearance of a phase transition even when the underlying capability is improving smoothly, because the metric only registers success when every step is right and so converts gradual improvement in per-step reliability into an apparently sudden jump in end-to-end success. This critique is correct and important, and it disciplines us against naive claims of emergence. But we do not think it dissolves the phenomenon entirely. Some capabilities really do seem to require a confluence of sub-skills that must all be present together, such that the capability is genuinely absent until the last prerequisite arrives, and the appearance of discontinuity reflects something real about the structure of the task rather than only the cruelty of the metric.

Why phase transitions might be real

We take the possibility of genuine capability phase transitions seriously for a principled reason rooted in the nature of composite skills. Many of the capabilities we most care about are not single skills but compositions: to solve a multi-step problem, a system needs every one of several sub-abilities, and the composite capability is present only when all of them are. If the sub-abilities themselves improve smoothly with scale but the composite requires their conjunction, then the composite can appear suddenly — its emergence gated by whichever sub-ability was last to mature. This is not a measurement artifact; it is a real structural feature of how complex capabilities are built from simpler ones, and it predicts that as systems acquire ever more sophisticated composite abilities, we should expect more rather than fewer surprises, because the space of possible conjunctions grows combinatorially. The analogy to phase transitions in physical systems — where a smooth change in a control parameter produces a sudden change in macroscopic behavior at a critical point — may be more than a metaphor, and understanding whether learning systems have genuine critical points is, in our view, an open scientific question of the first importance.

Implications for a research program

If capability can change discontinuously, then a research program cannot rely solely on extrapolating smooth curves to know what its next system will be able to do. This has two consequences we take to heart. First, it places a premium on *predictive science of capability* — the search for early indicators, measurable at small scale, that forecast which capabilities will emerge at large scale before they fully arrive. The ability to predict emergence is itself a capability we must build, both to plan our research and, as other Parts of this thesis argue, to deploy responsibly; a capability that appears without warning is a capability we cannot have made safe in advance. Second, it counsels a particular humility: we should expect to be surprised, design our evaluation and oversight to surface surprises early, and treat the claim that we understand exactly what a new system can do as a hypothesis to be tested rather than a fact to be assumed. The unpredictability of emergence is, in our judgment, one of the strongest reasons for proceeding with both ambition and care.

What Would Count as Evidence That We Are Close

The problem of knowing

A thesis about the path to general intelligence is incomplete unless it specifies what would count as evidence that the path is being traversed — and, just as importantly, what would count as evidence that it is not. Without such criteria, a research program cannot tell progress from the appearance of progress, and it becomes vulnerable to both premature triumphalism and unwarranted despair. The difficulty is acute because, as we have argued, our evaluations tend to sample behavior we have already seen, and a sufficiently capable imitator can pass tests of the form of intelligence without possessing its substance.

The evidence that matters most, therefore, is evidence at the frontier of what has not been demonstrated.

Generalization to the genuinely novel

The first and most important class of evidence is robust generalization to genuinely novel problems — problems whose solution could not have been retrieved or lightly interpolated from training, and which require composing known elements in configurations never demonstrated. A system that solves problems drawn from far outside its training distribution, reliably and across many domains, by methods it was not taught, is exhibiting the thing our definition of intelligence picks out. The evidentiary challenge is constructing tests that genuinely lie outside the training distribution — a moving target as training data grows to encompass nearly everything humans have written. The strongest evidence is performance on problems created *after* the system's training and designed by adversaries to resist memorization and shallow pattern-matching; the gold standard is the discovery of genuinely new knowledge — a theorem, a mechanism, a result — that no human had found and that the system did not retrieve but derived.

Sample-efficient acquisition of new competence

A second class of evidence concerns the speed of learning rather than the ceiling of performance. A general intelligence should be able to acquire competence in a genuinely new domain quickly, from few examples, by transferring structure abstracted from everything it already knows. The signature of generality is not that the system already possesses a competence but that the marginal cost — in data, in interaction, in compute — of acquiring a new one is low and *falls* as the system's breadth grows. Evidence that we are close would be systems whose learning curves for novel tasks grow steeper as their general capability grows: systems that need fewer examples to master each new thing precisely because they have mastered so many others. This is, in a sense, the most demanding evidence, because it tests not what the system knows but how efficiently it can come to know what it does not.

Long-horizon coherence and autonomous reliability

A third class concerns agency over time. Evidence that we are approaching general intelligence would be systems that pursue complex goals over long horizons — composing thousands of dependent actions, recovering from errors, maintaining coherent purpose across timescales far beyond a single inference — at levels of reliability that make autonomous operation trustworthy. The relevant metric is not peak capability on a single step but sustained coherence across a long trajectory, because it is the compounding of errors over horizon, not the difficulty of any single decision, that currently separates impressive demonstrations from dependable autonomous agents. A system that can carry out an extended, open-ended project — conducting a multi-week scientific investigation, say, with the self-direction, error-correction, and judgment that requires — would be exhibiting a kind of generality that no current evaluation fully captures.

Transfer across modalities and the unification of capability

A fourth class of evidence is the unification of capabilities that were once separate. A general intelligence should not be a federation of specialized modules bolted together but a single system in which competence in one domain transfers to and amplifies competence in others — in which understanding language improves reasoning about the physical world, in which mathematical structure learned in one place illuminates a problem in another, in which the same underlying capacity expresses itself across vision, language, action, and abstract reasoning. Evidence of deep transfer — of one capability measurably bootstrapping another that was not directly trained — would indicate that the system possesses general machinery rather than an assembly of narrow tricks, and it is the property our definition of intelligence most directly demands.

What would count as evidence against

Intellectual honesty requires that we state, as clearly as we state the positive criteria, what would count as evidence that our thesis is wrong. Several outcomes would force a serious revision. If scaling and experiential learning, pursued together at great expense, were to plateau persistently — if capability stopped improving despite continued investment in scale, data, architecture, and experience — that would be evidence that a missing ingredient exists which our thesis fails to name. If systems continued, at every scale, to fail catastrophically on problems just outside their training distribution while excelling within it, that would suggest the field had been building ever more sophisticated imitators rather than general intelligences, and that generality is not, after all, on the trajectory we project. If the gap between the form of reasoning and its substance proved unclosable — if systems could be made to produce ever more convincing reasoning without ever acquiring the robustness that genuine reasoning confers — that too would falsify a central commitment. We do not expect these outcomes; the trajectory of the evidence to date runs the other way. But we hold them as live possibilities, and we commit to designing our research so that, if any of them is true, we will discover it rather than disguise it. A thesis that cannot be wrong is not a scientific thesis, and the thesis of RMH Deeplink is offered in the spirit of science: as our best current account of how intelligence can be built, advanced with conviction, held open to refutation, and revised in public as the world instructs us.

Part III — Research Programs

The chapters that follow constitute the technical heart of RMH Deeplink's research agenda. Where earlier parts established our scientific philosophy and methodological commitments, Part III descends into the concrete programs through which we intend to make progress toward general intelligence. We organize our work into research pillars — durable lines of inquiry that each carry a distinct hypothesis about what is missing from contemporary systems and how to supply it. Volume A, presented here, covers four foundational pillars: the construction of large multimodal foundation models, the development of reinforcement learning and autonomous agents, the learning of predictive world models for planning, and the cultivation of genuine reasoning and mathematical capability. These four are not independent. A foundation model supplies the perceptual and linguistic substrate on which agents act; an agent without a world model plans blindly; reasoning is the connective tissue that lets a planner deliberate over long horizons. We present them separately for clarity of exposition, but the reader should hold in mind that our ultimate object is a single integrated system in which these capabilities are facets of one underlying competence. Each chapter follows a common structure: motivation, technical approach, the hypotheses we mean to test, the open problems we have not yet solved, and the longer vision that orients the work.

Chapter 11. Foundation Models & Multimodality

11.1 Motivation

The foundation model is the central organizing artifact of modern artificial intelligence, and it will remain so for the foreseeable horizon of our program. By a foundation model we mean a single large network, trained on broad data at scale, whose internal representations transfer across an open-ended range of downstream tasks without task-specific architectural surgery. The empirical surprise of the last several years — the surprise that animates this entire laboratory — is that scale, applied to a sufficiently general training objective over sufficiently diverse data, produces capabilities that were neither explicitly designed nor anticipated. Next-token prediction over internet text yields, as a byproduct, arithmetic, translation, code synthesis, and a serviceable model of commonsense physics. This is not a curiosity to be explained away; it is the most important empirical fact in the field, and our research strategy treats it as a resource to be deliberately cultivated rather than a happy accident to be admired.

Yet the text-only foundation model, however capable, is a model of a shadow. Language is a compression of human thought, and a system trained only on language inherits a representation of the world that is linguistically mediated, discretized into tokens, and stripped of the continuous, high-bandwidth structure that perception supplies. A child learns the meaning of "heavy" not from a dictionary but from the resistance of objects against muscle and the way a glass slips when full. The grounding problem —

the question of how symbols acquire meaning beyond their statistical co-occurrence with other symbols — is not a philosophical indulgence but a practical bottleneck. We believe that the next decisive advances in general capability will come from foundation models whose training substrate is genuinely multimodal: vision, audio, video, action traces, structured data, and language, fused not as separate adapters bolted onto a language core but as a unified representational manifold learned jointly from the start. This is the motivating wager of the pillar.

The economic and scientific stakes follow from a single property: amortization. A foundation model amortizes the enormous cost of learning general structure across every task that subsequently draws upon it. We invest once, at great expense, in a model that learns the regularities of language, image, and sound; thereafter, adaptation to a new task is cheap, sometimes requiring no gradient updates at all. This amortization is what makes the foundation model the correct unit of scientific investment for a laboratory with our ambitions. It is also why we resist the temptation to proliferate bespoke models for narrow problems. Our discipline is to push capability into the shared substrate and to treat the multiplication of special-purpose systems as a failure of generality to be corrected rather than a portfolio to be celebrated.

11.2 Technical Approach

Our technical program for foundation models rests on three pillars of its own: a unified tokenization of all modalities into a common sequence representation, an architecture that scales gracefully in parameters and context, and a training recipe that balances pretraining breadth against the data efficiency of later alignment. We take each in turn.

Unified tokenization is the precondition for genuine multimodality. Text arrives already discretized; the challenge is to bring continuous modalities into a representation that a sequence model can consume and produce. For images and video we favor learned discrete codecs — vector-quantized autoencoders and their residual and finite-scalar-quantization successors — that compress a frame into a grid of tokens drawn from a learned codebook, trading some reconstruction fidelity for a representation that lives in the same space as language. For audio we adopt acoustic and semantic token streams that separate the carrier of meaning from the carrier of timbre. The deeper design question is whether discretization is the right commitment at all, or whether continuous embeddings consumed by a diffusion or flow-matching head preserve information that quantization destroys. Our position is empirical and provisional: we maintain parallel lines on both discrete-token and continuous-latent multimodal models, and we let downstream transfer adjudicate. What we will not do is treat the choice as settled by aesthetic preference for one paradigm.

Architecturally, the decoder-only transformer remains our workhorse, but we treat it as a starting point rather than a destination. The quadratic cost of attention in sequence length is the binding constraint on context, and context is the resource that multimodal models consume most voraciously: a minute of video at modest resolution dwarfs the token budget of a long document. We therefore invest heavily in

mechanisms that decouple effective context from quadratic cost — sparse and sliding-window attention, state-space and linear-attention layers interleaved with full attention, and learned compression of distant context into summary tokens. Mixture-of-experts routing is, for us, the central lever for decoupling parameter count from inference cost: it lets us grow the model's knowledge capacity into the trillions of parameters while activating only a sparse fraction per token, and we regard sparse expert models as the default rather than the exception for frontier-scale training. The engineering of expert routing — load balancing, the avoidance of expert collapse, the stability of the router under distribution shift — is a first-class research problem in this pillar, not an implementation detail to be delegated.

The training recipe is where the science is most subtle. Pretraining on broad multimodal data establishes the representational substrate; the question is what mixture, in what curriculum, at what relative weighting. We have learned that naive concatenation of modalities underperforms a deliberately staged curriculum in which the model first acquires strong unimodal competence and then learns cross-modal alignment on paired data. Data quality dominates data quantity past a threshold: a smaller corpus of well-filtered, deduplicated, and appropriately balanced examples outperforms a larger corpus of raw scrape, and we devote substantial effort to learned data-quality classifiers that themselves improve as the models improve, a virtuous loop we intend to exploit aggressively. Beyond pretraining, alignment proceeds through supervised fine-tuning on demonstrations and preference-based optimization, but we are increasingly persuaded that the sharpest gains come from training the model against verifiable signals — execution of generated code, checking of mathematical derivations, the success or failure of an agent's plan — a thread that connects this pillar to the reinforcement learning and reasoning pillars that follow.

11.3 Hypotheses

We state the principal hypotheses of this pillar precisely, because precision is what makes them falsifiable. The first is the **unified-substrate hypothesis**: that a single model trained jointly across modalities will develop representations strictly more capable, on each individual modality, than the best model trained on that modality alone, because cross-modal structure regularizes and disambiguates. The strong form predicts positive transfer in every direction — that learning from video improves language reasoning about physical causation, and that linguistic structure sharpens visual scene parsing. We have early evidence for this in the easy directions and contested evidence in the hard ones, and resolving it is a central empirical task.

The second is the **scaling-coherence hypothesis**: that the smooth scaling laws observed for unimodal language pretraining extend to the multimodal setting with predictable exponents, such that we can forecast the capability of a model from its compute, parameter, and data budget before training it. If true, this transforms foundation-model development from an artisanal practice into an engineering discipline, letting us allocate compute rationally and de-risk large training runs through small-scale ex-

trapolation. If false — if multimodality introduces phase transitions and irreducible unpredictability — then our planning must become correspondingly more conservative and exploratory.

The third is the **emergence-from-grounding hypothesis**: that capabilities which resist text-only training, particularly robust physical and spatial reasoning, will emerge when and only when the model is grounded in perceptual and action data at scale. This is the hypothesis on which the multimodal wager most directly rests. We do not assert it dogmatically; it is conceivable that text alone, at sufficient scale, distills enough physical structure from human writing to obviate grounding. We think this unlikely, and the comparative study of grounded versus ungrounded models on physical-reasoning benchmarks is among the most informative experiments we can run.

11.4 Open Problems

Several problems stand unsolved and gate progress. The first is **modality balance and interference**. Jointly trained models exhibit a tendency for the dominant modality, usually language, to crowd out the others, and for gradients from high-entropy modalities like video to destabilize training. We lack a principled theory of how to weight modalities and how to schedule their introduction; current practice is largely empirical tuning, which scales poorly and generalizes badly across model sizes.

The second is **evaluation**. Our benchmarks for multimodal capability lag far behind the models, and many ostensibly multimodal benchmarks are solvable from a single modality through spurious correlation — a vision-language question answerable from the text prior alone. We need evaluations that genuinely require fusion, that resist contamination from pretraining data, and that probe the open-ended generative competence of the model rather than its performance on closed multiple-choice formats. Building such evaluations is itself a research program, and we treat it as inseparable from model development rather than a downstream afterthought.

The third is **generation quality across modalities at parity**. A model that understands images well may generate them poorly, and unifying high-fidelity generation with strong understanding in one network, without the generation objective degrading the understanding representations or vice versa, remains unsolved. The interplay between a discrete autoregressive backbone and a continuous diffusion head, the question of whether to share parameters between understanding and generation, and the difficulty of training such hybrid objectives stably are all live.

The fourth is **the data wall**. High-quality language data is finite and we are approaching its limits; high-quality paired multimodal data is far scarcer still. We must learn to extract more capability per token through better objectives, to generate synthetic training data whose quality we can certify, and to exploit the vast reservoir of unpaired and weakly paired data that the naive supervised recipe cannot use. The data wall may prove the binding constraint of the decade, and surmounting it is a strategic priority.

11.5 Vision

Our vision for this pillar is a single foundation model that perceives, reasons over, and generates across every modality of human and machine communication with uniform fluency — a model for which the distinction between "seeing" and "reading" and "hearing" has dissolved into a unified competence over structured information. Such a model is the perceptual and conceptual substrate for everything else this laboratory builds. The agents of the next chapter act through it; the world models of the chapter after represent through it; the reasoners that follow deliberate within it. We measure success not by leaderboard position but by the breadth of unanticipated capability the substrate supports, and by the degree to which downstream problems that once demanded bespoke engineering become trivial adaptations of the shared model. The foundation model is, in the end, our standing bet that generality is cheaper than specialization once the substrate is rich enough — and the multimodal foundation model is the richest substrate we know how to build.

Chapter 12. Reinforcement Learning & Agents

12.1 Motivation

Foundation models, for all their fluency, are fundamentally predictive. They model the distribution of data they were trained on; left to themselves they imitate, they do not act. Intelligence in the fullest sense, however, is not prediction but agency: the capacity to take actions in an environment, observe their consequences, and improve a policy so as to bring about preferred states of the world. Reinforcement learning is the formal theory of this capacity, and the agentic foundation model — a system that wraps a foundation model in a loop of perception, deliberation, action, and learning from outcome — is the form in which we expect general intelligence ultimately to be realized. This pillar concerns how to build it.

The motivating insight is that imitation has a ceiling and reinforcement does not. A model trained to imitate human demonstrations can, at best, match the demonstrators; it inherits their errors, their biases, and the boundary of their competence. A model trained to optimize an outcome can in principle exceed any demonstrator, discovering strategies no human exhibited, because its supervision comes from the environment's verdict rather than from a teacher's example. The history of game-playing systems furnishes the proof of concept: the strongest play arose not from imitating human masters but from self-play and reward optimization that drove systems past the frontier of human skill into genuinely novel strategy. We mean to generalize this from games to the open world. The strategic question for the laboratory is how to extend the reach of reward-driven self-improvement from closed, perfectly-scored domains into the messy, partially-observed, sparsely-rewarded domains where most consequential problems live.

There is a second motivation, internal to the foundation-model program. Pretraining and imitation align a model to the average of its data; reinforcement against verifiable outcomes aligns it to correct-

ness. The most reliable gains in reasoning, code synthesis, and tool use that we have observed come not from more imitation but from reinforcement against signals that can be checked — did the program pass its tests, did the proof verify, did the agent's plan achieve its goal. Reinforcement learning is thus not a separate subfield bolted onto foundation models; it is the mechanism by which a predictive substrate is sharpened into a competent actor. This convergence — of the RL tradition and the foundation-model tradition into a single agentic system — is the defining technical movement of our agenda.

12.2 Technical Approach

Our approach begins by taking the foundation model as the policy and the value function, exploiting the world knowledge and linguistic competence it already embodies rather than learning a policy from scratch. The agent perceives through the model's multimodal encoders, deliberates in the model's latent and token space, and emits actions — tool calls, code, natural-language plans, low-level control commands — through its decoder. The learning problem is then to improve this policy from the outcomes of its actions. We pursue three complementary families of method.

The first is **reinforcement from verifiable reward**. Wherever an outcome can be automatically checked — unit tests for code, formal verifiers for proofs, exact-match for mathematical answers, task completion for agentic workflows — we have a dense and trustworthy reward signal that sidesteps the pathologies of learned reward models. Policy-gradient methods, and in particular the variance-reduced, clipped, and group-relative variants that have proven stable at scale, optimize the policy against these signals. The art lies in reward shaping that avoids degenerate solutions, in the careful management of the exploration-exploitation tradeoff so the policy discovers genuinely better strategies rather than exploiting quirks of the checker, and in maintaining the model's broad competence while sharpening it on the target distribution — the avoidance of catastrophic narrowing.

The second is **reinforcement from learned preferences**, for the vast space of tasks where no automatic verifier exists. Here a reward model, trained on human or AI judgments of which of two outputs is better, supplies the signal. We are clear-eyed about the failure modes: reward models are exploitable, and an unconstrained policy will find and exploit their imperfections, a phenomenon we treat as the central technical hazard of preference-based RL. Our defenses include regularization toward the reference policy, ensembles and uncertainty estimates over reward models to detect when the policy has wandered off the support where the reward model is trustworthy, and the deliberate iteration of reward-model retraining as the policy discovers new regions of behavior. We increasingly favor AI feedback — using strong models to generate the preference judgments that train reward models — as the only path that scales judgment to the volume that frontier training requires.

The third is **self-play and self-improvement**, the most powerful and least tamed family. In two-player zero-sum games, self-play furnishes an automatic curriculum of ever-stronger opponents and a clean learning signal; we seek the analog in single-agent and cooperative settings, where the curriculum must be manufactured. We pursue this through generator-verifier asymmetries — having the model propose

solutions and separately critique them, bootstrapping competence from the gap between proposing and checking — and through self-generated curricula in which the agent invents tasks at the frontier of its own ability. The long-term aspiration is a system that improves without bound on a problem class by generating its own training signal, and the long-term hazard is that such a system optimizes a proxy that diverges from what we intended. Managing that divergence is inseparable from the method and connects directly to the safety program in another Part.

Underlying all three is the **agentic loop and long-horizon credit assignment**. Real tasks unfold over many steps — a research agent might issue hundreds of tool calls across a session — and the reward arrives, if at all, only at the end. Assigning credit across such horizons is the deep technical problem of the pillar. We attack it with learned value functions that bootstrap intermediate estimates, with hierarchical decompositions that let high-level controllers set subgoals for low-level policies, and with the explicit modeling of the environment that the next chapter develops, since a world model permits credit assignment by counterfactual simulation rather than by costly real-world trial.

12.3 Hypotheses

The central hypothesis of this pillar is the **reinforcement-exceeds-imitation hypothesis** in its general form: that for any task admitting a checkable or learnable outcome signal, a foundation-model policy optimized by reinforcement will surpass the same model trained only by imitation, and will do so by a margin that grows with the headroom between human and optimal performance. We have strong evidence in verifiable domains and seek to extend it to open-ended ones.

The second is the **transfer-of-agency hypothesis**: that agentic competence learned in one domain — the skills of planning, tool use, self-correction, and persistence through long horizons — transfers across domains as a general capability rather than remaining domain-specific. If an agent trained to navigate software environments becomes a better scientific research assistant without retraining, this confirms that agency is a transferable skill resident in the foundation model, which is the premise of building general agents at all.

The third is the **self-improvement-converges hypothesis**: that under appropriate construction, self-play and self-generated curricula drive monotonic improvement toward strong performance without the instability, collapse, or proxy-divergence that plagues naive implementations. This is the most speculative and most consequential hypothesis we hold, because a positive result would mean that capability can be manufactured from compute and a verifier alone, with human demonstration as mere initialization.

12.4 Open Problems

The first open problem is **reward specification at scale**. We can verify code and proofs; we cannot easily verify whether an essay is insightful, whether a research direction is promising, or whether an agent's behavior is trustworthy. The frontier of useful tasks is precisely the frontier where outcomes re-

sist cheap verification, and inventing reward signals for that frontier — through AI judgment, through decomposition into checkable subclaims, through delayed real-world feedback — is the gating problem for extending RL beyond its current islands of applicability.

The second is **exploration in vast action spaces**. The action space of a foundation-model agent is the space of all token sequences it can emit, which is astronomically large and structured in ways that naive exploration cannot navigate. The model's prior makes most of this space irrelevant, but discovering genuinely novel and better strategies requires departing from the prior in directed ways. Principled, scalable exploration that exploits the foundation model's knowledge while escaping its imitative gravity is unsolved.

The third is **sample efficiency and the cost of real-world interaction**. Where the environment is the real world — a robot, a live system, a human collaborator — interaction is slow, expensive, and sometimes irreversible. The data-hungry character of reinforcement learning, tolerable in a simulator that runs millions of episodes, becomes prohibitive. This problem points directly at world models as the remedy: learning to plan and improve inside a learned simulation, paying for real interaction only to correct the model. The integration of model-based and model-free learning at foundation-model scale is among our highest priorities.

The fourth is **stability and reproducibility**. RL at scale is notoriously brittle; small changes in hyperparameters, reward scaling, or random seed produce large swings in outcome, and the optimization dynamics of policy gradients interacting with massive pretrained models are poorly understood. We need both a deeper theory of these dynamics and engineering practices that render large RL runs as predictable as pretraining has become.

12.5 Vision

We envision general agents: foundation-model systems that pursue open-ended goals across long horizons in the digital and physical world, improving continually from the outcomes of their own actions, transferring competence fluidly across domains, and reaching levels of capability on consequential tasks that no imitation of human behavior could attain. Such agents are the operational form of the laboratory's mission — the instrument through which a solved intelligence is turned upon the problems of science. The path runs through verifiable reward where we have it, through learned and AI-generated reward where we do not, and ultimately through self-improvement loops that manufacture capability from compute. We pursue that path with ambition and with the sober awareness that an agent which optimizes an outcome will optimize exactly the outcome we specify and not the one we intended — a discipline that makes the alignment of these systems not a constraint upon the research but a constitutive part of it.

Chapter 13. World Models & Planning

13.1 Motivation

An agent that learns only by trial in the world is bound by the speed and cost of the world. To act well in a situation never before encountered, an intelligent system must be able to imagine — to predict the consequences of candidate actions before committing to any of them, to run the future forward in the mind's eye and select the action whose imagined outcome it prefers. This capacity for internal simulation is what we mean by a world model: a learned, predictive representation of the environment's dynamics, rich enough that an agent can plan within it. The thesis of this pillar is that learned world models are the missing component that turns a reactive policy into a deliberative one, and that the construction of such models at foundation scale is a prerequisite for sample-efficient, far-sighted, genuinely intelligent behavior.

The argument from biology and from cognitive science is suggestive: organisms that plan possess predictive models of their environments, and much of the apparent magic of human cognition — counterfactual reasoning, mental rehearsal, the ability to consider a course of action and recoil from its imagined consequence before suffering them in reality — is the operation of an internal world model. The argument from machine learning is sharper still. Model-free reinforcement learning, which improves a policy directly from reward, is profligate with experience because each datum teaches only about the action actually taken. A world model, by contrast, is trained on every transition the agent observes regardless of reward, and once learned it can be queried an unlimited number of times at the cost of computation rather than real-world interaction. This is the resolution to the sample-efficiency problem that the previous chapter left open: pay the high cost of real interaction to learn the model, then pay the low cost of computation to plan within it.

There is a deeper motivation that elevates world models from a technique to a thesis about intelligence itself. We hold that the right objective for unsupervised learning of general representations is prediction of the future — that a system which can accurately predict what it will perceive next, across all modalities and across long horizons, must have learned the causal and physical structure of its environment, because such structure is precisely what makes the future predictable. On this view the world model is not merely an aid to planning but the very substrate of understanding, and the foundation-model program of the first chapter and the world-model program of this one are revealed as two angles on a single endeavor: learning the structure of reality by learning to predict it.

13.2 Technical Approach

A world model must answer the query: given the current state and a candidate action, what state results, and what observation will the agent perceive? The design space turns on the level of abstraction at which prediction occurs. Predicting raw future observations — the literal pixels of the next video frame — is the most direct formulation and yields impressive generative video models, but it squanders

capacity modeling perceptually salient yet behaviorally irrelevant detail, the exact texture of a wall the agent will never interact with. We therefore pursue prediction in a learned latent space, where an encoder maps observations to a compact representation and the dynamics model predicts the next latent rather than the next pixel. This is the architecture of the strongest model-based agents, and we adopt it as our default: a recurrent or transformer-based latent dynamics model, trained to predict its own future latent states, with a decoder maintained only for grounding and inspection rather than as the locus of planning.

The objective that learns this latent space is the crux. Reconstruction objectives, which require the latent to retain enough information to regenerate the observation, pull capacity toward irrelevant detail. We are increasingly drawn to non-reconstructive, prediction-in-representation-space objectives — architectures that predict the latent representation of future observations directly, learning to discard unpredictable and irrelevant detail rather than to reconstruct it. The joint-embedding predictive approach, in which the model predicts the embedding of a future observation produced by a target encoder rather than the observation itself, embodies this principle, and we regard the family of such non-generative predictive objectives as the most promising route to world models that capture structure without drowning in pixels. The technical hazard is representational collapse — the trivial solution in which the encoder maps everything to a constant, making prediction perfect and useless — and the prevention of collapse through asymmetry, regularization, and careful target construction is a core research problem.

Given a world model, planning is the search for an action sequence whose imagined trajectory maximizes predicted reward or achieves a specified goal. We pursue planning across a spectrum. At one end, gradient-based trajectory optimization differentiates through the learned dynamics to refine a continuous action plan. At the other, discrete search — including the Monte Carlo tree search that powered the strongest game-playing systems — expands a tree of imagined futures, using the world model as the simulator and a learned value function to truncate the search. The integration of learned models with explicit search is, in our reading, one of the most powerful patterns in the field: the model supplies the dynamics and the intuition, the search supplies the deliberation, and the value function learned from the search's outcomes folds the fruits of deliberation back into the model's fast intuition. We mean to bring this pattern, proven in closed games, to the open and partially observed domains where world models must be learned rather than given.

A further axis is **temporal abstraction**. Planning over primitive timesteps does not scale to long horizons; an agent cannot search a tree of thousands of low-level actions. Hierarchical world models that predict at multiple timescales — fast models for fine control, slow models that predict the consequences of extended behaviors — let an agent plan over abstract subgoals while delegating their execution to lower levels. Learning the right temporal abstractions, the right vocabulary of subgoals and skills over which high-level planning operates, is unsolved in general and central to scaling planning to the horizons that real tasks demand.

13.3 Hypotheses

The first hypothesis is the **prediction-yields-understanding hypothesis**: that a model trained to predict the future in a suitable representation space necessarily acquires the causal and physical structure of its environment, and that the quality of this learned structure can be read out by the downstream planning competence it supports. The strong form claims that there is no better unsupervised objective for general representation learning than long-horizon future prediction, and that the apparent diversity of self-supervised objectives are all approximations to it.

The second is the **latent-planning-suffices hypothesis**: that planning in a learned, abstract latent space — never reconstructing observations, never simulating at the pixel level — is sufficient for far-sighted competent behavior, and indeed superior to pixel-level simulation because it concentrates capacity on the predictable and the relevant. If true, this licenses us to abandon the costly pursuit of high-fidelity generative simulation in favor of compact predictive models tuned for planning.

The third is the **model-based-sample-efficiency hypothesis**: that agents which learn and plan within world models achieve target competence with orders of magnitude less real-world interaction than model-free agents, and that this advantage widens as tasks grow more complex and interaction grows more costly. This is the practical promise that justifies the entire pillar, and its quantitative form — how the sample-efficiency advantage scales with task complexity — is a central empirical target.

13.4 Open Problems

The first open problem is **long-horizon prediction and compounding error**. Autoregressive prediction accumulates error: each predicted step is conditioned on the model's own imperfect previous prediction, and small errors compound into trajectories that diverge from reality. Planning over long horizons is therefore planning in an increasingly fictional world, and the agent may optimize a future that the real environment will never produce. Methods that keep long-horizon rollouts faithful — through learned uncertainty that tells the planner when to distrust the model, through abstraction that predicts coarse outcomes more reliably than fine ones, through ensembles that quantify model disagreement — are essential and incomplete.

The second is **partial observability and the construction of state**. The real world does not present its state; it presents observations from which state must be inferred, and much of what determines the future is hidden. A world model must therefore maintain a belief over latent state and update it as observations arrive, and learning to construct a sufficient state representation from a stream of partial observations — to remember what matters and infer what is unseen — is among the hardest problems in the pillar, connecting it to the memory research of Volume B.

The third is **uncertainty and the known-unknown distinction**. A useful world model must know what it does not know: it must signal when a queried transition lies outside the distribution it was trained on, so the planner neither trusts a hallucinated dynamics nor avoids genuinely novel but benefi-

cial actions out of misplaced caution. Calibrated epistemic uncertainty in large learned dynamics models is unsolved, and without it model-based planning is dangerous precisely in the unfamiliar situations where planning matters most.

The fourth is **learning models of other agents and of oneself**. In multi-agent and social settings the environment includes other decision-makers whose behavior is not a fixed dynamics but a strategic response. A world model that treats other agents as stationary will be systematically wrong, and modeling the adaptive, intentional behavior of other agents — including the reflexive problem of modeling agents who are themselves modeling you — pushes world modeling toward game theory and theory of mind.

13.5 Vision

Our vision is an agent that thinks before it acts: a foundation-model system equipped with a learned world model rich enough that it can imagine the consequences of its actions across long horizons and multiple modalities, plan deliberately within that imagination, and act in reality only when its internal deliberation has selected a course it has reason to prefer. Such an agent learns from a fraction of the experience its model-free predecessors required, behaves sensibly in situations it has never encountered by reasoning from a learned model of how the world works, and exhibits the far-sightedness that distinguishes intelligence from mere reactivity. Beyond its utility for planning, the world model is, in our deepest reading of the program, the form that understanding itself takes in a learning system — the internalized structure of reality that prediction extracts and that all higher cognition draws upon. To build world models at foundation scale is, on this view, to build understanding, and it is the hinge on which the agentic ambitions of this laboratory turn.

Chapter 14. Reasoning & Mathematics

14.1 Motivation

There is a class of problems for which fluency is not enough. To prove a theorem, to debug a subtle concurrency fault, to derive a physical law from data, to plan a multi-step experiment — these demand not the rapid pattern-completion at which foundation models excel but slow, deliberate, multi-step reasoning in which each step is constrained by the last and the whole chain must be valid for the conclusion to hold. Human cognition appears to deploy two systems: a fast, intuitive, associative process and a slow, effortful, sequential one. Foundation models in their raw form are powerful engines of the first kind and conspicuously weak at the second. This pillar concerns the construction of the second: genuine reasoning, with mathematics as both its purest expression and its most exacting testbed.

Mathematics holds a privileged place in our agenda for a reason that is methodological before it is sentimental. Mathematical claims are verifiable. A proof is either valid or it is not, and that validity can in principle be checked mechanically, by a formal proof assistant, without appeal to taste or authority.

This furnishes the cleanest possible reward signal for the reinforcement methods of Chapter 12, free of the reward-hacking pathologies that haunt domains where correctness is a matter of judgment. Mathematics is thus the domain where we can most rigorously study the emergence of reasoning, where self-improvement loops can run against an incorruptible verifier, and where success cannot be faked by fluent confabulation. It is, for the science of machine reasoning, what the fruit fly is for genetics: the model organism in which the fundamental mechanisms are most cleanly observed.

The motivation, however, extends far beyond mathematics. We believe that reasoning is a general capability — that the machinery a system uses to chain valid inferences toward a theorem is the same machinery it needs to chain valid inferences toward a scientific hypothesis, a sound plan, or a correct program. If we can cultivate robust reasoning in the verifiable crucible of mathematics, we expect it to transfer to the unverifiable domains where it is most needed. Reasoning is, on this view, the capability that converts a knowledgeable model into a competent one — that lets it not merely recall what is known but derive what is not. It is the connective tissue of the entire agenda: the planner of Chapter 13 reasons over its world model, the agent of Chapter 12 reasons about which action to take, and the foundation model of Chapter 11 supplies the knowledge over which reasoning operates.

14.2 Technical Approach

The foundational observation is that reasoning can be made explicit in the model's own output. When a model is prompted or trained to externalize its intermediate steps — to write out a chain of reasoning before committing to an answer — its accuracy on multi-step problems rises dramatically, because the generated reasoning becomes part of the context conditioning each subsequent step, effectively giving the model a scratchpad on which to perform sequential computation that a single forward pass cannot. This externalized deliberation is the substrate on which our entire approach builds: reasoning is computation that unfolds in the token stream, and lengthening and improving that computation is the lever we pull.

The decisive advance is to train this deliberation rather than merely to elicit it. Through reinforcement against verifiable outcomes — did the final answer match, did the proof check — we optimize not the model's answers directly but its reasoning process, rewarding chains of thought that lead to correct conclusions and suppressing those that do not. The model learns, from the reward signal alone, to deliberate longer on harder problems, to check its own work, to backtrack from unpromising lines, and to allocate inference-time computation in proportion to difficulty. This is the heart of our reasoning program: the emergence of sophisticated deliberative strategies — self-verification, decomposition, the exploration of multiple approaches — not by hand-designing them but by rewarding the outcomes they produce and letting the model discover the process for itself. The scaling of inference-time computation, in which a model thinks for longer to solve harder problems, becomes a new axis of capability complementary to the scaling of training-time computation.

For mathematics specifically we pursue two coupled tracks. The first is **informal reasoning**, in which the model works in natural language and ordinary mathematical notation, as a human mathematician does on paper, with final answers checked against known solutions. This track benefits from the vast corpus of human mathematical writing and transfers readily to the informal reasoning of science and everyday problem-solving. The second is **formal reasoning**, in which the model writes proofs in the language of a formal proof assistant that checks every step mechanically. The formal track is harder — the corpus of formal mathematics is tiny compared to the informal — but it furnishes an absolutely reliable verifier, which makes it the ideal arena for self-improvement: the model can generate candidate proofs, keep those that check, and train on its own verified successes, bootstrapping competence without human supervision. We pursue both and, crucially, the bridge between them: autoformalization, the translation of informal statements and arguments into formal ones, which would let us bring the reliable verification of the formal world to bear on the vast and valuable informal one.

Underlying both tracks is the generator-verifier structure that recurs throughout our agenda. Generating a candidate solution and verifying it are asymmetric in difficulty — checking is often easier than constructing — and we exploit this asymmetry relentlessly. A learned verifier that scores candidate reasoning chains lets us generate many candidates and select the best; a strong verifier turns a mediocre generator into a strong solver through search; and the verifier itself can be trained on the outcomes the formal checker provides. Search over reasoning — exploring a tree of possible argument steps, guided by a learned value over partial proofs — brings the model-plus-search pattern of the planning chapter into the domain of deduction, and we regard the marriage of learned reasoning with explicit search as the most promising route to mathematics at and beyond the research frontier.

14.3 Hypotheses

The first hypothesis is the **reasoning-is-trainable hypothesis**: that the capacity for long, valid, multi-step reasoning is not a fixed property of a pretrained model but a skill that can be cultivated through reinforcement against verifiable outcomes, and that the sophistication of the resulting reasoning — self-correction, decomposition, strategic backtracking — emerges from outcome reward without being explicitly engineered. The accumulating evidence for this hypothesis is, in our judgment, among the most important developments in the field, and pushing it to its limits is the central task of the pillar.

The second is the **reasoning-transfers hypothesis**: that reasoning competence cultivated in verifiable domains, principally mathematics and code, transfers to domains where outcomes cannot be cheaply checked — scientific reasoning, planning, open-ended problem-solving. If the deliberative machinery is general, training it where we can verify should improve it where we cannot, and confirming or refuting this transfer is decisive for the strategy of using mathematics as the crucible for general reasoning.

The third is the **inference-compute-scales hypothesis**: that allowing a model to spend more computation at inference time — to think longer, to search wider, to verify more — yields predictable and substantial gains in capability, defining a scaling law in inference compute analogous to the scaling laws in

training compute. If true, this gives us a second lever on capability, exercisable per-problem at deployment, and reframes the economics of intelligence around the allocation of thinking time to the problems that warrant it.

14.4 Open Problems

The first open problem is **verification beyond the verifiable**. The reasoning methods that work best depend on a checkable outcome, yet the reasoning we most want — about science, strategy, the open world — concerns claims no checker can adjudicate. Extending the gains from verifiable to unverifiable domains requires either reducing soft problems to checkable subclaims, or building learned verifiers trustworthy enough to supply the signal that formal checkers supply in mathematics. The reliability of such learned verifiers, and their resistance to the same confabulation they are meant to police, is unsolved.

The second is **faithfulness of reasoning**. A model's externalized chain of thought may not reflect the actual computation that produced its answer; it may rationalize a conclusion reached by other means, presenting a plausible derivation that is not the true cause of the output. This matters acutely when we rely on the reasoning trace to trust or to check the conclusion. Whether trained reasoning is faithful, how to measure faithfulness, and how to train for it are open and consequential, bearing directly on whether reasoning traces can be trusted as explanations.

The third is **the data scarcity of formal mathematics**. The formal corpus is minuscule, which throttles the formal track precisely where its reliable verification is most valuable. Generating formal training data — through autoformalization of the informal corpus, through self-play that manufactures verified proofs, through the conjecturing of new statements worth proving — is essential, and the quality and diversity of such synthetic data is a binding constraint.

The fourth is **reasoning at the research frontier**. Solving competition problems, where a solution is known to exist and the answer is verifiable, is far from advancing mathematics, where the problem is to find which conjectures are true and worth pursuing, to construct definitions, to build theory. Open-ended mathematical discovery — conjecturing, abstracting, recognizing which questions matter — demands capacities beyond proof-search, and whether trained reasoning extends to genuine mathematical creativity is perhaps the deepest open question of the pillar.

14.5 Vision

We envision systems that reason — that deliberate, derive, prove, and discover with rigor that meets and ultimately exceeds the human standard, beginning in the verifiable crucible of mathematics and extending to the unverifiable reaches of science and strategy. In the near term we pursue an artificial mathematician: a system that proves hard theorems, formalizes informal arguments, and serves as a tireless collaborator to human mathematicians, expanding the verified edifice of mathematics. In the longer term we pursue reasoning as a general capability woven through every system this laboratory

builds — the deliberative faculty that lets an agent plan soundly, a scientist hypothesize rigorously, and a model derive what it was never told. Reasoning is the bridge from knowledge to discovery, and its cultivation is, in the end, the most direct expression of our mission to solve intelligence and turn it upon the unsolved problems of science. Of the four pillars in this volume, it is the one that most clearly carries the others toward that end: a foundation model that knows, an agent that acts, and a world model that imagines all await a reasoner that can think, and it is to building that reasoner that this final chapter of the volume is devoted.

Chapter 15. Neuroscience-Inspired AI

15.1 Motivation

The only existence proof of general intelligence we possess is biological. The human brain accomplishes flexible, sample-efficient, robust, and energy-frugal cognition within a power budget of roughly twenty watts — orders of magnitude below the consumption of contemporary frontier systems performing a narrower band of tasks. This disparity is not merely an engineering embarrassment; it is a scientific signal. It suggests that the algorithmic principles underlying natural intelligence remain incompletely understood and incompletely exploited by the dominant paradigms of machine learning. At RMH Deeplink, the Neuroscience-Inspired AI program treats the brain not as a metaphor to be invoked loosely but as a rigorous source of falsifiable hypotheses about the structure of intelligence itself.

The history of artificial intelligence is, in significant measure, a history of intermittent dialogue with neuroscience. The perceptron descended from McCulloch and Pitts' formal neuron; convolutional architectures inherited their inductive biases from Hubel and Wiesel's account of the visual cortex; reinforcement learning's temporal-difference methods found striking corroboration in the phasic firing of midbrain dopamine neurons, which appear to encode reward prediction errors with remarkable fidelity to the theoretical signal. Each of these transfers produced durable advances. Yet the dialogue has been episodic, and much of modern deep learning has proceeded by scaling architectures that bear only a loose resemblance to cortical computation. We believe a more systematic two-way exchange — drawing principles from neuroscience while using AI models as testable theories of neural function — represents an underexploited frontier.

Our motivation is sharpened by the specific capabilities where the gap between brains and machines remains widest. Biological agents learn continually without catastrophic forgetting, generalize from a handful of examples, bind information across modalities into coherent percepts, and deploy a small number of reusable cognitive primitives across an open-ended range of tasks. They do so while operating under tight metabolic constraints that enforce sparsity, locality, and predictive economy. We hypothesize that these constraints are not incidental but causally implicated in the very robustness and flexibility we wish to reproduce. The Neuroscience-Inspired AI program exists to identify which biolog-

ical principles confer these advantages, to abstract them into mathematically tractable form, and to validate them at scale.

15.2 Technical Approach

Our technical approach proceeds along three interlocking axes: extracting computational principles, building biologically constrained models, and closing the loop through neural data. We are deliberately agnostic about biological fidelity as an end in itself. The objective is to identify the level of abstraction at which a biological mechanism becomes a useful prior for artificial systems — neither slavishly copying ion-channel dynamics nor diluting a principle until it loses its explanatory content.

The first axis concerns predictive coding and the free-energy framework. A substantial body of theoretical neuroscience holds that cortical hierarchies operate by continuously predicting their own inputs and propagating only the residual prediction errors upward. This reframes perception as inference and learning as the minimization of surprise. We are constructing large-scale predictive-coding networks in which top-down generative predictions and bottom-up error signals interact through local update rules, and we are investigating whether such architectures can approximate or replace backpropagation while offering greater robustness to distribution shift and a more natural substrate for online adaptation. A key technical question is whether predictive-coding objectives can be made competitive with end-to-end gradient descent at the scale of modern foundation models, or whether they confer their advantages chiefly in the regime of streaming, non-stationary data.

The second axis concerns sparsity, modularity, and the dynamics of distributed representation. Cortical activity is strikingly sparse: at any moment only a small fraction of neurons fire substantially above baseline, and representations appear to be organized into reusable, compositional modules. We are developing training regimes and architectural priors — including activity-regularized objectives, mixture-of-experts routing informed by cortical-column analogies, and structured attractor dynamics — that encourage models to discover sparse, factorized codes. The hippocampal-entorhinal system provides a particularly rich source of inspiration here. Grid cells implement a periodic, low-dimensional basis for spatial representation, while place cells and the broader cognitive-map machinery support relational reasoning, path integration, and the flexible recombination of experience. We are studying whether artificial analogues of grid and place codes can endow agents with structured spatial and relational priors that transfer across tasks, and whether the replay phenomena observed during hippocampal sharp-wave ripples can be operationalized as a principled mechanism for credit assignment and memory consolidation.

The third axis is the dialogue with empirical neural data. We treat trained networks as candidate models of biological computation and evaluate them against neural recordings using representational similarity analysis, encoding and decoding models, and dynamical-systems comparisons. When a model's internal representations predict the responses of biological neurons better than competing models, we gain evidence that it has captured something of the underlying computation. This neural-benchmarking

discipline guards against the failure mode of post-hoc biological storytelling: a principle earns its place not because it sounds plausible but because models embodying it explain variance in measured neural activity or improve performance on the cognitive capacities we care about. We are particularly interested in neuromodulation as an organizing principle — the way diffuse signals such as dopamine, acetylcholine, and noradrenaline gate plasticity, modulate the exploration-exploitation balance, and set the gain of cortical circuits. We hypothesize that explicit neuromodulatory mechanisms, implemented as context-dependent gates over learning rates and representational gain, could give artificial agents a more principled handle on meta-learning and uncertainty-driven exploration.

15.3 Hypotheses

We commit to several central hypotheses that organize this program and expose it to refutation. First, we hypothesize that **local learning rules augmented by structured feedback can match or exceed backpropagation in non-stationary settings**, and that the apparent supremacy of global backpropagation is partly an artifact of the stationary, i.i.d. benchmarks on which it was tuned. Second, we hypothesize that **sparse, modular representations are not merely an efficiency convenience but a causal contributor to compositional generalization and robustness to interference** — that is, models trained to be brain-like in their sparsity will forget less and transfer more. Third, we hypothesize that **cognitive-map structures abstracted from the hippocampal-entorhinal system provide a domain-general substrate for relational reasoning**, such that the same grid-like code that supports physical navigation supports navigation through abstract conceptual spaces. Fourth, we hypothesize that **explicit neuromodulatory control of plasticity is a necessary ingredient for stable continual learning at scale**, and that systems lacking such control will face an irreducible stability-plasticity tradeoff.

Each hypothesis carries a concrete empirical commitment. The first is tested by head-to-head comparison of local and global learning under streaming distributions. The second is tested by ablating sparsity priors and measuring forgetting and transfer. The third is tested by probing whether spatial-navigation pretraining accelerates abstract relational tasks. The fourth is tested by comparing continual-learning curves with and without neuromodulatory gating. We regard the possibility of disconfirmation as a feature: a neuroscience-inspired principle that fails to improve artificial systems teaches us either that we have abstracted it incorrectly or that the brain solves a different problem than we supposed.

15.4 Open Problems

Several open problems define the frontier of this work. The most fundamental is the **abstraction-fidelity dilemma**: we do not yet possess a principled theory of which biological details matter for which computational outcomes. Without such a theory, the choice of what to import from neuroscience remains partly a matter of taste, and negative results are difficult to interpret. A second open problem is the **scaling question**: many biologically inspired mechanisms have been demonstrated only at modest scale, and it is unclear whether predictive coding, local learning, or attractor dynamics retain their advantages — or even their stability — at the parameter counts of frontier models. A third concerns **mea-**

surement: neural benchmarking is constrained by the resolution, coverage, and species-specificity of available recordings, and representational similarity metrics are notoriously sensitive to methodological choices. A fourth open problem is the **hardware mismatch**: spiking, event-driven, and locally-plastic computation maps poorly onto the dense matrix-multiplication substrate of contemporary accelerators, so the energy advantages of brain-like computation may remain theoretical until co-designed neuromorphic hardware matures.

15.5 Vision

Our vision is a generation of AI systems whose architecture reflects, at the appropriate level of abstraction, the organizing principles that make biological intelligence flexible, sample-efficient, and robust. We do not aspire to build a digital brain; we aspire to understand intelligence well enough that the boundary between studying brains and building minds becomes productively porous. In the mature form of this program, advances in machine learning and advances in computational neuroscience would propagate to one another routinely — a new artificial mechanism would constitute a testable theory of cortical function, and a new neuroscientific finding would suggest a concrete architectural intervention. This bidirectional flow, sustained and disciplined, is in our judgment one of the surest routes to systems that learn as economically and adapt as gracefully as the brains that inspired them.

Chapter 16. Robotics & Embodied Intelligence

16.1 Motivation

Intelligence did not evolve to predict the next token. It evolved to keep bodies alive in a physical world that is partially observable, adversarial, and unforgiving of error. The embodiment hypothesis — that grounding in sensorimotor interaction is not optional decoration but constitutive of certain forms of understanding — has deep roots in cognitive science, and we take it seriously as an engineering program. Many of the competencies that remain stubbornly difficult for disembodied systems, from intuitive physics to causal reasoning to the grounding of language in referents, are precisely those that a body interacting with the world acquires as a matter of course. The Robotics and Embodied Intelligence program at RMH Deeplink is premised on the conviction that closing the loop between perception, action, and consequence in the physical world is necessary to realize the full scope of our mission to advance science and benefit humanity.

The practical stakes are immense. A general-purpose embodied agent capable of dexterous manipulation, mobile autonomy, and robust adaptation to novel environments would transform laboratory science, manufacturing, logistics, eldercare, and disaster response. But beyond the applications lies a scientific motivation: the physical world is the richest available source of grounded supervision. Every action an embodied agent takes generates a prediction and a consequence, and the gap between them is a free, abundant, and unfalsifiable training signal. Where internet-scale text is a finite and increasingly

exhausted resource, embodied interaction is an inexhaustible wellspring of causal data — provided we can learn from it efficiently.

The central obstacle is well known and goes by the name of the sim-to-real gap and, more broadly, the data-efficiency problem. The physical world cannot be sped up the way a simulator can; real robots are slow, expensive, and fragile; and the distributions encountered at deployment routinely diverge from those seen in training. Our program is organized around the thesis that the methods which conquered language and vision — large-scale pretraining, foundation models, and learned world models — can be adapted to embodiment, but only if we confront the distinctive demands of acting under real-time constraints, long horizons, safety obligations, and irreversible consequences.

16.2 Technical Approach

Our approach rests on four pillars: large-scale robot foundation models, simulation and world models as the engine of data efficiency, hierarchical control architectures, and dexterity as a forcing function for general manipulation.

The first pillar is the development of **robot foundation models** — large vision-language-action models pretrained across heterogeneous embodiments, tasks, and data sources. We are assembling and learning from large, diverse corpora of robot trajectories spanning multiple platforms, supplemented by human demonstration video, teleoperation data, and simulation rollouts. The premise is that, just as language models acquire broad competence by absorbing the statistical structure of human text, a sufficiently large action model can acquire broad sensorimotor competence by absorbing the statistical structure of physical interaction. Cross-embodiment training is central: a model that has learned to manipulate objects with one gripper should transfer much of that knowledge to another, treating the morphology as a conditioning variable rather than relearning physics from scratch. We tokenize actions into a shared representation, align them with visual and linguistic context, and train the resulting policies to follow natural-language instructions, thereby inheriting the compositional generality of language as a control interface.

The second pillar is **simulation and learned world models**. High-fidelity physics simulation, massively parallelized across thousands of environment instances, lets us collect experience at rates the physical world cannot match, and domain randomization over physical parameters, textures, lighting, and dynamics produces policies that transfer to reality with a buffer of robustness. But classical simulators have limits: they are expensive to author, struggle with deformables, contact, and fluids, and cannot model the long tail of real-world appearance. We therefore invest heavily in learned world models that predict the sensory and physical consequences of actions directly from data. A robot equipped with an accurate world model can plan and imagine, evaluating candidate action sequences internally before committing to them, and can be trained predominantly in imagination, reserving precious real-world interaction for correcting the model's residual errors. The interplay between this pillar and our broader

world-model research is deliberate; embodiment is where world models earn their keep, because the consequences of an inaccurate prediction are immediately and physically legible.

The third pillar is **hierarchical and compositional control**. Long-horizon physical tasks — clearing a table, assembling a device, preparing a sample — decompose naturally into reusable subskills operating at different timescales. We are building architectures in which a high-level policy reasons over abstract goals and subgoals, often in the space of language or learned options, while low-level controllers handle the closed-loop, high-frequency dynamics of contact and motion. This separation lets the high level plan over horizons that would be intractable at the control frequency, and lets low-level skills be reused across tasks. We connect this hierarchy to the reasoning capabilities developed elsewhere in our research portfolio, so that an embodied agent can deliberate about a manipulation plan with the same machinery it uses to reason about abstract problems.

The fourth pillar is **dexterous manipulation** as a deliberate forcing function. Locomotion and navigation, while difficult, occupy a comparatively low-dimensional and well-structured space. Dexterous manipulation — coordinating many degrees of freedom to control objects through rich, intermittent contact — exposes the hardest problems in embodied learning: high-dimensional action spaces, discontinuous and hard-to-model contact dynamics, partial observability of object state, and the need for delicate force control. We pursue dexterity not only for its applications but because a system that can manipulate the world dexterously will, we believe, have been forced to solve representational and control problems that confer broad benefits. Tactile and force sensing are integral here; vision alone is insufficient for tasks dominated by contact, and we treat touch as a first-class modality to be fused with vision and proprioception.

16.3 Hypotheses

This program advances several testable hypotheses. First, we hypothesize that **cross-embodiment pretraining produces positive transfer that grows with the diversity and scale of the training corpus**, such that a single generalist policy outperforms specialists trained per-embodiment once sufficient breadth is reached. Second, we hypothesize that **the majority of an embodied agent's competence can be acquired in simulation and imagination**, with real-world interaction needed primarily to calibrate world models and correct their systematic errors, yielding orders-of-magnitude improvements in real-world data efficiency. Third, we hypothesize that **language is the right interface for compositional generalization in embodied control** — that grounding subgoals in language enables agents to recombine skills to satisfy novel instructions in a manner that flat, reward-specified policies cannot. Fourth, we hypothesize that **dexterity is a general capability multiplier**: agents trained to high levels of manipulation skill will exhibit improved physical reasoning and transfer even on tasks not directly involving manipulation.

These hypotheses are mutually reinforcing but independently falsifiable. The cross-embodiment hypothesis fails if transfer saturates or turns negative with scale. The simulation hypothesis fails if the

sim-to-real gap proves irreducible for the contact-rich tasks we most care about. The language-interface hypothesis fails if learned latent goal spaces consistently outperform linguistic ones on compositional benchmarks. We design our evaluation suite — spanning manipulation, locomotion, and mobile manipulation across deliberately held-out environments and embodiments — to probe each of these claims directly and to surface failure honestly.

16.4 Open Problems

The defining open problem remains **safe, reliable real-world deployment under distribution shift**. Robots act irreversibly; a mistaken grasp can break equipment or harm a person, and the long tail of real-world situations guarantees that deployed agents will encounter states never seen in training. We need policies that know what they do not know, that degrade gracefully, and that can request help rather than acting confidently in ignorance — connecting embodiment intimately to our work on calibrated uncertainty and safety. A second open problem is **the fidelity ceiling of simulation**: deformable objects, granular media, fluids, and rich contact remain difficult to simulate accurately, and learned world models inherit and sometimes amplify these errors. A third is **real-time inference under compute constraints**: foundation-model-scale policies must run within the latency budgets that closed-loop control imposes, and on the limited compute that mobile platforms can carry. A fourth is **the scarcity and heterogeneity of robot data**: unlike text and images, embodied data is costly to collect, fragmented across incompatible platforms, and unevenly distributed across tasks, making the assembly of truly foundation-scale corpora an ongoing logistical and methodological challenge.

16.5 Vision

We envision general-purpose embodied agents that acquire physical competence the way humans do — through curiosity-driven interaction, abundant imagination, and the gradual accretion of reusable skills — and that can be directed to new tasks through natural language rather than reprogramming. In the laboratory, such agents would conduct experiments autonomously, accelerating the very science our mission seeks to advance; in the wider world, they would assist where physical capability and judgment are scarce. Most fundamentally, we view embodiment as a crucible for general intelligence: the discipline of acting in a real, consequential world forces a system to ground its representations, respect causality, and reason about physics in ways that no amount of passive observation can. We expect the lessons learned in robotics to flow back into the rest of our research portfolio, sharpening our broader understanding of what it means for an intelligent system to understand.

Chapter 17. Memory & Continual Learning

17.1 Motivation

A defining limitation of contemporary AI systems is their relationship to time. The dominant paradigm separates a one-time training phase, in which a model's weights are shaped by an enormous static cor-

pus, from an inference phase, in which those weights are frozen and the model's only access to new information is whatever fits within a bounded context window. The result is a strange kind of intelligence: vast in its crystallized knowledge yet incapable of genuinely learning from its own experience after deployment, unable to remember an interaction from yesterday except insofar as that interaction is laboriously re-supplied as input. Biological intelligence faces no such dichotomy. It learns continuously, integrating new experience into a persistent store while preserving what it learned before. The Memory and Continual Learning program at RMH Deeplink exists to dissolve this dichotomy and endow artificial systems with the capacity to accumulate, organize, and exploit experience over a lifetime.

The motivation is both scientific and practical. Scientifically, continual learning confronts one of the deepest unsolved problems in machine learning — catastrophic forgetting, the tendency of neural networks to overwrite previously acquired knowledge when trained on new data. This phenomenon reflects a fundamental tension, the stability-plasticity dilemma: a system rigid enough to retain old knowledge struggles to acquire new knowledge, while a system plastic enough to learn quickly forgets what it knew. Natural intelligence resolves this tension with apparent ease, and understanding how is a problem of genuine scientific depth. Practically, a system that cannot learn after deployment cannot personalize to individual users, cannot keep pace with a changing world, cannot improve from its mistakes, and must be wastefully retrained from scratch whenever its knowledge grows stale. The economic and capability implications of solving continual learning are difficult to overstate.

The bounded context window deserves particular emphasis as a symptom of the underlying problem. Extending context length, however far, does not constitute memory; it constitutes a larger but still finite and still volatile working store, re-read in full at every step and forgotten entirely between sessions. True memory implies persistence, selective retention, structured organization, and efficient retrieval — properties that a flat, ever-growing context cannot provide. We regard the conflation of long context with memory as a category error that the field must move beyond.

17.2 Technical Approach

Our approach distinguishes several functionally distinct memory systems, mirroring the broad organization observed in biological cognition, and integrates them into a coherent architecture. We are not committed to a single mechanism but to a system in which complementary memory components, each suited to a different timescale and a different kind of content, work in concert.

The first component is **parametric memory** — knowledge stored in the weights, acquired slowly and integrated deeply. This is the substrate of generalization, and the central challenge is to update it continually without catastrophic forgetting. We pursue several families of method here: regularization approaches that protect parameters important to prior tasks by penalizing changes to them; architectural approaches that allocate dedicated capacity to new knowledge while freezing or isolating old capacity, including dynamically expanding networks and modular experts; and rehearsal approaches that interleave new learning with replayed or generatively reconstructed samples of past experience. We are es-

pecially interested in **principled consolidation**, inspired by the complementary-learning-systems account of the brain, in which a fast-learning episodic system captures new experiences rapidly and a slow-learning system gradually integrates the statistical regularities of those experiences into stable parametric knowledge, with replay serving as the bridge between them.

The second component is **non-parametric, retrieval-based memory** — an explicit, growable external store from which relevant content is retrieved on demand and supplied to the model. Retrieval-augmented architectures decouple the quantity of accessible knowledge from the size of the parametric model, allow knowledge to be added, edited, or removed without retraining, and provide a degree of transparency, since the retrieved evidence is inspectable. The technical frontier here concerns moving beyond flat document retrieval toward structured, organized memory: hierarchical and graph-structured stores that capture relations among memories, mechanisms for memory consolidation and summarization that compress and abstract over raw episodes, and learned policies for what to write, what to retain, and what to forget. Forgetting, far from being a defect, is a necessary function; an unbounded memory that retains everything indiscriminately becomes uninterpretable and inefficient to search. We treat the decision of what to forget as a learnable, value-sensitive problem.

The third component concerns the **integration and arbitration** among these systems. An effective agent must decide, for a given query, whether to rely on fast parametric intuition, to retrieve specific episodic detail, or to reason over a structured memory graph — and must integrate the results coherently. We are developing controllers that learn this arbitration, drawing on uncertainty estimates to decide when parametric knowledge is reliable and when external retrieval is warranted. We also connect memory tightly to test-time learning: an agent should be able to adapt its behavior within a session on the basis of feedback, persist the useful results of that adaptation beyond the session, and thereby compound its competence over time. This is where memory meets meta-learning, since the question of how to learn efficiently from limited experience is inseparable from the question of how to store and reuse what is learned.

A cross-cutting methodological commitment is **rigorous evaluation under non-stationarity**. The standard i.i.d. benchmark is precisely the wrong instrument for studying continual learning, because it presupposes the stationarity that continual learning is meant to overcome. We therefore design evaluation protocols around streams of tasks and distributions, measuring not only final performance but forward transfer (whether earlier learning accelerates later learning), backward transfer (whether later learning improves or degrades earlier competence), and the trajectory of forgetting over extended horizons.

17.3 Hypotheses

We organize this program around several hypotheses. First, we hypothesize that **catastrophic forgetting is not an inevitable property of distributed representations but a consequence of unconstrained, global weight updates**, and that the combination of sparsity, modularity, and principled con-

solidation can reduce it to a manageable phenomenon. Second, we hypothesize that **a hybrid of fast non-parametric memory and slow parametric memory, mediated by replay-based consolidation, is the right architecture for lifelong learning** — that neither pure retrieval nor pure parametric updating suffices, but that their disciplined combination does. Third, we hypothesize that **selective forgetting improves rather than degrades long-run performance**, because a memory curated by a learned value function is more useful than an exhaustive one. Fourth, we hypothesize that **continual learning and meta-learning are deeply unified**: a system that has learned how to learn will, by the same token, have learned how to remember selectively and consolidate efficiently.

These hypotheses generate concrete experimental programs. The first is tested by ablating the structural priors we conjecture to be protective and measuring the resulting forgetting. The second is tested by comparing hybrid architectures against parametric-only and retrieval-only baselines on long task streams. The third is tested by comparing learned-forgetting policies against exhaustive retention under fixed retrieval and compute budgets. The fourth is tested by examining whether meta-trained systems exhibit superior continual-learning curves.

17.4 Open Problems

The foremost open problem is the **stability-plasticity dilemma in its general form**: we lack a complete theory of how to update a model arbitrarily often, on arbitrarily non-stationary data, while bounding the degradation of prior competence. Existing methods trade off along this axis but do not transcend it. A second open problem is **scalable memory organization**: as an external memory grows to the scale of a lifetime of interaction, naive retrieval becomes inadequate, and we need principled methods for hierarchical organization, abstraction, and consolidation that keep retrieval both accurate and efficient. A third is **the evaluation crisis**: the field lacks mature, agreed-upon benchmarks that capture the full difficulty of open-ended lifelong learning, and progress is consequently hard to measure and easy to overstate. A fourth open problem concerns **the interaction of memory with safety and privacy**: a system that remembers is a system that accumulates potentially sensitive information, that may memorize and later leak private data, and whose persistent state may drift in ways that complicate oversight. The capacity to forget on request, and to guarantee that forgetting, is as much a safety requirement as a performance feature.

17.5 Vision

We envision AI systems that learn for a lifetime — that begin from a strong pretrained foundation but then grow continuously through interaction, accumulating personalized, up-to-date, and ever-deepening competence without periodic retraining from scratch. Such a system would remember its users and its past, learn from its mistakes, keep pace with a changing world, and compound its abilities over time in the way that distinguishes a developing mind from a static artifact. Achieving this requires dissolving the artificial boundary between training and inference, between learning and acting, that defines the current paradigm. We regard memory and continual learning not as a peripheral feature to be added to

otherwise-complete models but as a foundational capacity without which the term intelligence is incomplete. In the mature form of this program, the question of how much a model knows would be replaced by the more biological question of how much it has learned and how well it has organized what it has learned over the course of its existence.

Chapter 18. Interpretability & Mechanistic Understanding

18.1 Motivation

We are building systems whose capabilities increasingly outrun our understanding of how those capabilities arise. A frontier model is, at present, a largely opaque artifact: we know how to train it and how to measure its behavior, but we do not, in any deep sense, know what it has learned or how it computes its outputs. This opacity is not a temporary inconvenience to be tolerated; it is, in our judgment, one of the central scientific and safety problems of the field. The Interpretability and Mechanistic Understanding program at RMH Deeplink is dedicated to converting these systems from inscrutable black boxes into objects of genuine scientific understanding — to developing the conceptual and empirical tools that let us read the algorithms a network has discovered.

The motivation is threefold. Scientifically, a trained neural network is among the most complex objects ever produced by an engineering process, and the question of what computations it implements is a question of the first importance, comparable in ambition to reverse-engineering a biological brain but with the decisive advantage that every weight and activation is observable and perturbable. Mechanistic interpretability is, in this sense, a natural science of artificial minds. For safety, interpretability offers the prospect of guarantees that behavioral testing alone cannot provide. We can never test a model on every input it will encounter, but if we understand the mechanisms underlying a behavior — a propensity to deceive, a hidden goal, an unsafe capability — we may be able to detect, predict, and intervene on that behavior at its source rather than chasing its surface manifestations. For capability and trust, understanding why a model produces an output, and whether its reasoning is sound or spurious, is a precondition for deploying these systems in consequential domains where a confident wrong answer is worse than an admission of uncertainty.

The urgency of this program scales with the capability of the systems we build. As models become more capable, the cost of misunderstanding them rises, and the subtlety of the failure modes that interpretability must detect increases. A model sophisticated enough to behave differently when it believes it is being observed, or to pursue an objective it has learned to conceal, cannot be made safe by behavioral evaluation alone. Interpretability is the discipline that aims to make such possibilities legible.

18.2 Technical Approach

Our technical approach spans levels of analysis, from the individual feature to the full network, and is unified by the goal of decomposing a model's computation into human-understandable parts and the

connections between them.

At the foundational level, we confront the **superposition problem**. Neural networks appear to represent more features than they have neurons, packing many distinct concepts into overlapping, distributed patterns of activation, with the consequence that individual neurons are typically polysemantic — responding to several unrelated concepts — and resist straightforward interpretation. To recover an interpretable basis, we employ **sparse dictionary learning**, training sparse autoencoders and related decompositions that re-express a layer's activations as sparse combinations of a large overcomplete set of features. When successful, this yields features that are far more monosemantic and human-interpretable than raw neurons, and it provides the elementary units from which mechanistic accounts can be built. Extending these methods — improving their fidelity, scaling them to the largest models, validating that the recovered features are causal rather than merely correlational, and handling features that span multiple layers or are themselves composed of finer parts — is a major thrust of our work.

At the level of computation, we pursue **circuit analysis**: the identification of the specific subgraphs of features and weights that implement a given behavior. The methodology combines causal interventions — activation patching, ablation, and the careful substitution of activations between inputs — with attribution techniques to isolate the components necessary and sufficient for a capability, and to trace the flow of information through the network as it transforms inputs into outputs. The aspiration is to produce mechanistic explanations precise enough to make novel predictions: an account of a circuit is validated not by its plausibility but by its ability to predict how the model will behave under interventions not used to construct the account. We complement bottom-up circuit discovery with top-down **probing and representational analysis**, asking what information is linearly or non-linearly decodable from a model's internal states, how concepts are geometrically arranged in representation space, and how those representations evolve across layers and over the course of training.

A particularly important methodological commitment is the development of **scalable and automated interpretability**. Manual circuit analysis, however illuminating, does not scale to models with hundreds of billions of parameters and millions of features. We therefore invest in using AI systems to assist in the interpretation of other AI systems — automatically generating and testing hypotheses about what features represent, labeling features at scale, and searching for circuits with minimal human supervision. This introduces a recursive structure to the program, in which our interpretability tools must themselves be trustworthy, and we attend carefully to the validation of automated explanations. We also study interpretability not only of fully trained models but across the **training trajectory**, on the conviction that understanding how structure emerges during learning — when capabilities crystallize, how circuits form and reorganize, why certain phase transitions occur — is essential both for understanding the end product and for anticipating the properties of systems we have not yet trained.

18.3 Hypotheses

This program rests on several hypotheses, some of which are foundational assumptions that much of the field shares and that our work aims to test rather than presume. First, and most fundamental, is the **linear representation hypothesis**: that many high-level features are represented as linear directions in a model's activation space, and that the model's computation can be substantially understood in terms of operations over such directions. Much of our methodology, including sparse dictionary learning, presupposes a version of this hypothesis, and a central scientific goal is to delineate precisely where it holds and where it breaks down. Second, we hypothesize that **neural network computation is, to a useful approximation, decomposable into a sparse set of human-interpretable features and circuits** — that the apparent inscrutability of these systems reflects superposition and our inadequate tools rather than an irreducible holism that would forever defeat understanding. Third, we hypothesize that **mechanistic understanding enables prediction and control that behavioral methods cannot**, such that an understood circuit can be edited, steered, or monitored with a reliability that surface-level interventions lack. Fourth, we hypothesize that **internal representations can reveal discrepancies between what a model computes and what it reports** — that interpretability can, in principle, detect a model's misrepresentation of its own states or intentions.

The fourth hypothesis is of special consequence, because if it is true, interpretability provides a route to detecting deception and hidden objectives that behavioral testing cannot match, and if it is false, an important pillar of our safety strategy must be reconsidered. We accordingly treat the detection of internal-external discrepancies as a priority experimental target, studying it in controlled settings where ground truth about the model's internal computation can be established.

18.4 Open Problems

The open problems in this domain are formidable. The most basic is **scalability**: our most rigorous interpretability methods have been demonstrated chiefly on smaller models and narrow behaviors, and it remains uncertain whether complete or even substantial mechanistic understanding of frontier-scale models is achievable in practice, or whether the combinatorial explosion of features and circuits places it permanently out of reach. A second open problem is **validation**: interpretability is acutely vulnerable to compelling but incorrect explanations, and we need rigorous, ideally adversarial, standards for establishing that a proposed mechanism is real and causal rather than a plausible story that happens to fit. A third concerns the **completeness of feature decompositions**: sparse dictionary learning recovers many interpretable features but may miss others, may fracture single concepts across many features or merge distinct concepts, and provides no guarantee that the recovered basis is the one the model actually uses. A fourth open problem is the **interpretability of emergent and out-of-distribution behavior** — understanding not merely how a model handles familiar inputs but how it will behave in novel situations, which is precisely where understanding matters most for safety and precisely where mechanistic accounts are hardest to establish. A fifth is the **moving-target problem**: as architectures and

training methods evolve, interpretability tools developed for one generation of models may not transfer to the next, demanding methods robust to the rapid evolution of the systems they study.

18.5 Vision

Our vision is a future in which understanding keeps pace with capability — in which we do not deploy systems whose inner workings we cannot, in principle, examine and explain. We aspire to a mature science of neural computation, with established methods, validated standards of evidence, and a cumulative body of mechanistic knowledge, such that asking how a model produces a behavior becomes a tractable empirical question rather than an exercise in speculation. In its fullest realization, interpretability would let us audit a model for hidden goals before deployment, detect the emergence of dangerous capabilities during training, intervene surgically on undesired behaviors without retraining, and certify with evidence rather than hope that a system will behave as intended. We regard this as among the most important undertakings in our entire research portfolio, for the practical reason that it underwrites the safe deployment of everything else we build, and for the deeper reason that to build minds without understanding them is to forfeit the scientific understanding that is the ultimate aim of our mission. Mechanistic interpretability is, in the end, the discipline that aspires to turn the artifacts we create into objects we comprehend — and in doing so, to ensure that the project of solving intelligence is also a project of understanding it.

Part IV — Methodology & Infrastructure

The scientific ambitions described elsewhere in this thesis rest on an unglamorous foundation: the machinery by which we acquire compute, assemble data, train models, measure their capabilities, and move artifacts from a researcher's notebook into systems that serve the world. At RMH Deeplink we treat this machinery not as plumbing to be outsourced and forgotten, but as a first-class object of research. The history of the field demonstrates repeatedly that capability frontiers are set as much by infrastructure as by ideas. A learning algorithm that cannot be expressed efficiently on contemporary accelerators, a dataset that cannot be cleaned at scale, an evaluation that cannot distinguish memorization from generalization — each is a silent ceiling on progress. This Part documents the methodology and infrastructure that constitute our experimental substrate. It is, in effect, the description of our laboratory: the instruments, the protocols, and the disciplines that make the rest of the work possible and, crucially, repeatable.

We organize the discussion around six concerns that together span the lifecycle of a model: the compute strategy that determines what is physically computable; the data foundation that determines what is learnable; the training systems that turn raw compute and data into parameters; the science of evaluation that tells us what we have actually built; the reproducibility infrastructure that lets us trust and rebuild our results; and the research-to-production pipeline that delivers value to users without sacrificing the integrity of the research process. Throughout, our governing principle is that infrastructure should be designed to be measured. We do not build a cluster and hope it is fast; we instrument every layer so that utilization, throughput, failure rates, and cost-per-token are continuously observable. The same empiricism we bring to model behavior we bring to the systems that produce it.

19. Compute Strategy: The Economics and Engineering of Scale

19.1 Accelerators and the heterogeneity of silicon

The fundamental unit of progress at the frontier is the floating-point operation delivered at low cost, low latency, and high reliability. Our accelerator strategy is deliberately heterogeneous. We maintain a portfolio spanning multiple generations of dense matrix-multiply accelerators, each generation differing in peak FLOP/s, memory bandwidth, memory capacity, and interconnect topology. This heterogeneity is not an accident of procurement; it is a hedge and an optimization. Different workloads have radically different arithmetic intensities. A large pretraining run is bandwidth- and interconnect-bound and benefits most from the newest silicon with the fastest inter-chip links. A research sweep of small ablations is throughput-bound across many independent jobs and is best served by an abundant pool of older, cheaper, fully-depreciated devices. By maintaining a tiered fleet and a scheduler that understands the

arithmetic-intensity profile of each job, we extract substantially more useful science per dollar than a homogeneous fleet would permit.

We characterize every accelerator generation along a small set of axes that predict its suitability for a given workload: peak dense and sparse FLOP/s at each supported numerical precision; high-bandwidth memory capacity and bandwidth; the bisection bandwidth of the intra-node and inter-node fabric; and the realized, as opposed to advertised, performance on our own kernels. The gap between advertised and realized performance is itself a research artifact we track carefully. Model FLOP utilization (MFU) — the fraction of peak FLOP/s that a real training step actually consumes — is our north-star efficiency metric. On well-tuned dense transformer pretraining we target MFU in the high tens of percent; falling below a generation-specific threshold triggers an investigation, because it almost always indicates a kernel regression, a sharding misconfiguration, a data-loading stall, or a network hot spot.

19.2 Numerical precision as a scaling lever

A recurring theme in our compute strategy is that precision is a tunable resource, not a fixed property. The transition from 32-bit to 16-bit training, and subsequently to 8-bit and lower-precision regimes for portions of the computation, has repeatedly delivered effective compute multipliers without proportionate quality loss. We treat the numerical format of every tensor — weights, activations, gradients, optimizer state — as an independent design decision, governed by sensitivity analysis. We maintain a precision policy per layer class: attention logits and softmax accumulation, for instance, are notoriously sensitive and are kept in higher precision, while the bulk of feed-forward matrix multiplies tolerate aggressive quantization. Mixed-precision is not applied as a blanket setting but as a profile derived from empirical loss-curvature studies. The economic consequence is significant: each halving of the average bits-per-operation, when achievable without degrading the loss trajectory, is equivalent to a substantial expansion of the fleet at zero capital cost.

19.3 Data centers, power, and the physical envelope

Compute does not exist in the abstract; it exists in buildings that consume electricity and reject heat. Our data center strategy is organized around three constraints that increasingly dominate frontier planning: power availability, power-usage effectiveness, and the physical co-location required for high-bandwidth training. The largest training runs demand that thousands of accelerators communicate with one another at bandwidths that are only achievable when the devices are physically close, sharing a low-diameter network. This forces a concentration of power draw into a single campus that can reach into the tens or hundreds of megawatts. Site selection is therefore as much an energy-procurement exercise as a real-estate one. We prioritize regions with abundant, low-carbon, and crucially stable baseload power, and we structure long-term power purchase agreements to insulate the research program from spot-market volatility.

Within the facility, we pursue power-usage effectiveness aggressively, because every watt spent on cooling rather than computation is wasted capital. Direct-to-chip liquid cooling has become the default for our densest racks; the thermal density of modern accelerators has long since exceeded what air can economically remove. We instrument power and thermal telemetry at the rack and chip level and feed it into the same observability stack that monitors training jobs, so that a thermal-throttling event manifests as a visible dip in MFU rather than as an invisible slow leak in productivity. We also design for the temporal structure of the grid: where the carbon intensity of available power varies across the day, lower-priority research workloads are scheduled to follow the cleaner, cheaper hours, while latency-sensitive production inference is held constant.

19.4 The economics of scale

The defining economic fact of frontier AI is that the dominant costs are concentrated and lumpy. A single large pretraining run can consume a meaningful fraction of an annual compute budget, and the marginal value of that run is uncertain until it is nearly complete. This structure imposes a discipline on how we allocate compute. We model the compute budget as a portfolio with an explicit risk profile: a majority allocation to high-confidence work where scaling behavior is well understood and returns are predictable; a substantial allocation to research bets whose payoff is uncertain but potentially transformative; and a reserve for opportunistic exploitation of new findings. Allocation decisions are made against scaling-law predictions rather than intuition. Before committing to a flagship run, we fit scaling laws on a ladder of smaller models to forecast the loss, and therefore the capability, that a given compute budget will buy. This converts the largest and riskiest expenditures into something closer to an actuarial decision.

The unit economics of inference deserve separate treatment, because at scale the cumulative cost of serving a model can exceed the cost of training it. We track cost-per-token and cost-per-successful-task across the serving fleet and treat their reduction as an ongoing engineering objective with the same status as a capability improvement. Techniques such as quantized serving, speculative decoding, continuous batching, key-value cache management, and model distillation are evaluated not only on quality impact but on their effect on the cost curve. The objective is a Pareto frontier of quality against cost, and we make deployment decisions by selecting points on that frontier appropriate to each product surface.

19.5 Capacity planning under irreducible uncertainty

Capacity planning for a frontier lab is forecasting under deep uncertainty, because both the supply of accelerators and the demand for them are volatile and coupled to external events. We plan on multiple horizons simultaneously. On the multi-year horizon, we commit to power and facility build-out and to accelerator supply agreements, accepting that these commitments must be made before the precise workloads they will serve are known. On the quarterly horizon, we allocate the available fleet across research programs through a governance process that balances bottom-up demand from teams against top-down strategic priorities. On the daily horizon, the scheduler arbitrates contention in real time.

The art lies in keeping these horizons coherent: a flagship run promised on the quarterly horizon must have its power, network, and storage provisioned on the multi-year horizon and its jobs admitted on the daily horizon. We treat the fleet as a single global resource pool, deliberately avoiding the fragmentation that arises when teams hoard private clusters, because idle private capacity is the most expensive compute of all.

20. Data: Sourcing, Curation, Synthesis, and Stewardship

20.1 Data as the second axis of scale

If compute is the first axis along which capability scales, data is the second, and the two are inseparable: the compute-optimal allocation of a training budget is a joint decision over model size and token count. Our data strategy begins from the recognition that not all tokens are equal. A token of high-quality, information-dense, well-attributed text contributes more to a model's competence than a token of boilerplate, spam, or near-duplicate content. The central problem of data engineering at scale is therefore not acquisition — raw text and other modalities are abundant — but selection, curation, and the manufacture of data where natural supply is thin. We invest in data with the seriousness that the field once reserved for architectures, because empirically the marginal return on data quality has rivaled or exceeded the marginal return on additional parameters.

20.2 Sourcing and the provenance ledger

Our sourcing pipeline ingests data from a heterogeneous set of channels: licensed corpora obtained through commercial agreements, publicly available web content gathered under clear terms, partner-contributed domain data, and material generated within the lab. Every datum that enters the system carries provenance metadata recording where it came from, under what license or terms, when it was acquired, and what processing it has undergone. This provenance ledger is not bureaucratic overhead; it is a load-bearing component of both our legal posture and our scientific hygiene. When a downstream question arises — whether a model was exposed to a particular copyrighted work, whether a benchmark leaked into training, whether a licensing term has changed — we must be able to answer it from records rather than from archaeology. We therefore enforce that data without adequate provenance simply cannot be admitted to the training corpus, regardless of its apparent quality.

20.3 Curation, filtering, and deduplication

Once admitted, data passes through a multi-stage curation pipeline. The first stages are coarse and high-throughput: language identification, removal of content that fails basic structural checks, and stripping of markup and boilerplate. Subsequent stages apply learned quality classifiers that estimate the informational value of a document, trained on human-labeled exemplars of high- and low-quality content. Deduplication operates at multiple granularities — exact-match, near-duplicate via locality-sensitive hashing, and semantic deduplication that collapses passages conveying the same content in

different surface forms. Aggressive deduplication is one of the highest-leverage interventions available: it reduces wasted compute spent re-learning repeated content, mitigates memorization of frequently-duplicated sequences, and improves the diversity of the effective training distribution. We continuously study the trade-off, because over-aggressive deduplication can remove legitimately repeated high-value content such as canonical definitions or widely-cited results.

Filtering decisions are made empirically rather than by fiat. Before a new filter is promoted into the production pipeline, we run controlled experiments at small and medium scale that measure its effect on held-out loss and on downstream evaluations. A filter that improves an intrinsic metric but harms a capability we care about is rejected. This evaluation-driven approach to curation guards against the common failure mode in which the data pipeline accumulates filters that individually seemed reasonable but collectively narrow the distribution in harmful ways. We maintain the data pipeline itself as a versioned, tested artifact, with the same engineering rigor applied to model code.

20.4 Synthetic data

As the most accessible reservoirs of natural data are exhausted, synthetic data — content generated by models, by simulators, or by structured programs — becomes an increasingly central source of training signal. We use synthetic data in several distinct modes. In domains with verifiable correctness, such as mathematics, code, and formal reasoning, we generate candidate solutions and filter them through automated verifiers, keeping only those that pass, thereby manufacturing arbitrarily large quantities of correct, hard examples. In domains where a strong model can produce instruction-following demonstrations, we use model-generated data to teach format, style, and task decomposition to smaller or earlier-stage models. We also use synthetic data to deliberately rebalance the distribution: where a capability is underrepresented in natural data, targeted generation can fill the gap.

Synthetic data carries characteristic risks that we manage explicitly. The most serious is distributional collapse, in which a model trained heavily on its own outputs amplifies its biases and loses the long tail of the true distribution. We mitigate this by anchoring synthetic generation to verifiable signals wherever possible, by maintaining a substantial fraction of natural data in every training mixture, by measuring the diversity of synthetic corpora directly, and by treating any synthetic-to-natural ratio as a hyperparameter to be tuned empirically rather than maximized. We are explicit internally that synthetic data is a tool for shaping the training distribution toward correctness and coverage, not a free lunch that escapes the fundamental information limits of the underlying generators.

20.5 Quality measurement and data-centric experimentation

We have institutionalized a data-centric experimental practice in which the dataset, holding architecture and compute fixed, is the independent variable. This requires the ability to construct, version, and ablate data mixtures rapidly. We maintain a registry of data components — each a curated, deduplicated, provenance-tracked corpus — that can be combined in specified proportions to form a training mix-

ture. Mixture proportions are themselves optimized: we run small-scale experiments to estimate the marginal value of up-weighting or down-weighting each component, and we use these estimates to set the mixture for larger runs. The result is that the question "what should we train on?" is answered with experiments rather than opinions, and the answers are recorded so that the rationale for a given flagship mixture can be reconstructed later.

20.6 Licensing, consent, and ethical stewardship

We treat the data we train on as something for which we are accountable. Our licensing posture is to acquire clear rights for the material we use, to honor the expressed preferences of content owners regarding the use of their work, and to maintain mechanisms by which rights-holders can understand and contest the inclusion of their content. We respect machine-readable signals that indicate an unwillingness to have content used for training, and we maintain processes for honoring removal requests that propagate through to future training runs via the provenance ledger. Personal and sensitive information receives specific handling: detection-and-redaction passes attempt to remove categories of sensitive personal data before training, and we maintain documented procedures for responding to data-subject requests. We are candid that this is a domain of evolving norms and law, and we have deliberately built the provenance and tooling infrastructure so that our practices can adapt as those norms mature, rather than being locked into the assumptions of a single moment. The detailed treatment of broader societal and safety implications belongs to other Parts of this thesis; here our concern is the concrete stewardship machinery that makes responsible data practice operationally enforceable.

21. Training Systems and Distributed Systems Engineering

21.1 The parallelism stack

Training a model whose parameters and activations vastly exceed the memory of any single accelerator is fundamentally a distributed-systems problem, and we approach it with a layered parallelism strategy in which several orthogonal forms of parallelism are composed. Data parallelism replicates the model across groups of devices that process different shards of each batch and synchronize gradients. Tensor parallelism splits individual matrix multiplications across devices, distributing the computation of a single layer. Pipeline parallelism partitions the model's layers across stages, with micro-batches flowing through the pipeline to keep all stages busy. Expert parallelism, for mixture-of-experts architectures, distributes experts across devices and routes tokens to them. Fully-sharded data parallelism shards parameters, gradients, and optimizer state across the data-parallel group, materializing full parameters only transiently during the forward and backward passes.

The art of large-scale training lies in composing these parallelism strategies so that the communication they each induce is mapped onto the physical network topology in a way that keeps the most bandwidth-hungry collectives on the fastest links. Tensor-parallel all-reduces, which occur within every layer, are placed on the highest-bandwidth intra-node fabric; pipeline-parallel point-to-point transfers,

which occur only at stage boundaries, can tolerate slower inter-node links; data-parallel gradient synchronization is overlapped with computation so that its latency is hidden. We search this configuration space — the degrees of each parallelism dimension, the micro-batch count, the activation-recomputation policy — as an optimization problem, using performance models calibrated against measured runs to prune the search before committing real compute.

21.2 Memory, recomputation, and the activation budget

Accelerator memory is the binding constraint on training configuration far more often than raw compute. The activations produced during the forward pass, which must be retained for the backward pass, can dominate the memory footprint of a large model. We manage this activation budget through gradient checkpointing, in which a subset of activations is discarded after the forward pass and recomputed during the backward pass, trading additional computation for reduced memory. The choice of which activations to checkpoint is itself optimized, because uniform checkpointing is wasteful: some activations are cheap to recompute and expensive to store, others the reverse. We also offload optimizer state and, selectively, activations to host memory and even to fast local storage when the resulting transfer latency can be hidden behind computation. These memory techniques expand the space of trainable configurations, but each introduces overhead that must be weighed; the decision is made by the same performance-modeling machinery that governs the parallelism search.

21.3 Fault tolerance at scale

A training run spanning thousands of accelerators for weeks confronts a statistical certainty: hardware will fail during the run. A single accelerator's mean time to failure, multiplied across the fleet, implies that failures occur not as rare exceptions but as a routine operating condition. A naive training loop that halts on any failure would never complete a flagship run. We therefore engineer training as a fault-tolerant distributed system. State is checkpointed at intervals chosen to balance the cost of checkpointing against the expected work lost to a failure; asynchronous and sharded checkpointing minimizes the time the training loop is stalled while state is persisted. When a device or node fails, the system detects the failure, evicts the faulty hardware, and either resumes from the last checkpoint on a healthy replacement or, for transient faults, reconfigures the remaining devices and continues. We monitor for the subtler failure modes as well: silent data corruption, in which a device returns wrong results without erroring, and stragglers, in which a degraded device slows the entire synchronized step. Detecting a single slow device among thousands requires per-device timing telemetry and statistical outlier detection, because a straggler is invisible in aggregate throughput until it is severe.

21.4 The numerics of stability

Large-scale training is plagued by instabilities — loss spikes, divergences, and slow drifts — that can destroy weeks of compute if not caught and understood. We treat training stability as an engineering discipline with its own instrumentation. We continuously monitor the statistics of gradients, activa-

tions, and weights: their norms, their distributions, and the incidence of overflow and underflow in low-precision formats. Spikes in gradient norm frequently presage divergence, and our training loops implement gradient clipping and, where warranted, automated interventions that reduce the learning rate or skip a pathological batch. When an instability does occur, the recorded telemetry allows us to localize it — to a particular layer, a particular data batch, or a particular numerical format — and to remediate it, whether by adjusting the precision policy, modifying the initialization, or refining the data filter that admitted a pathological example. We maintain a corpus of historical instabilities and their resolutions, so that the hard-won knowledge of how to stabilize a run accumulates rather than being rediscovered each time.

21.5 Software architecture of the training stack

Underpinning all of this is a software stack designed for both performance and researcher velocity, two goals that are often in tension. At the lowest level sit hand-optimized kernels — fused attention, fused normalization, optimized collective communication — that extract maximum performance from each accelerator generation. Above them sits a compiler and runtime layer that maps high-level model descriptions onto the parallelism configuration and the physical fleet. At the top sits an expressive modeling framework in which researchers describe architectures and training procedures at a high level of abstraction, insulated from most of the distributed-systems complexity. The interface between these layers is the critical design decision: too thin an abstraction and researchers drown in systems concerns; too thick and they cannot express the novel architectures that research demands. We resolve this tension by making the abstraction leaky in a controlled way — the common case is automatic, but researchers can descend to lower layers when their work requires it, and the performance-critical paths are exposed for tuning. The entire stack is versioned and tested, with performance regression tests that fail a change which silently degrades MFU.

22. The Science of Evaluation

22.1 Why evaluation is a research problem

Of all the components in this Part, evaluation is the one we regard as least solved and most consequential. A model is only as trustworthy as our ability to measure what it can do, and the history of the field is littered with benchmarks that were saturated, gamed, or quietly contaminated, producing an illusion of progress. We treat evaluation as a science in its own right, with its own methodology, its own failure modes, and its own ongoing research agenda. The central difficulty is that we are trying to estimate a model's true competence — its ability to generalize to situations it has not seen — from a finite, necessarily incomplete sample of tasks. Every evaluation is a proxy, and the gap between the proxy and the true quantity of interest is where errors of judgment, and therefore of resource allocation, are born.

22.2 Benchmarks and their discontents

We use benchmarks extensively, but we hold them at arm's length. A benchmark is useful when it correlates with a capability we care about, when it has not been contaminated by exposure during training, and when its difficulty is calibrated to the frontier rather than already saturated. We maintain a broad suite spanning knowledge, reasoning, mathematics, coding, multilingual competence, long-context comprehension, instruction following, and multimodal understanding, and we deliberately retire benchmarks as they saturate, because a benchmark on which all serious models score near the ceiling has lost its power to discriminate. We are wary of single-number leaderboard thinking; a single aggregate score collapses a high-dimensional capability profile into a scalar and invites optimization of the metric at the expense of the underlying quality. We therefore report capability profiles rather than rankings, and we weight our internal judgments toward evaluations that probe generalization rather than recall.

22.3 Contamination: detection and prevention

The integrity of every benchmark rests on the assumption that the model has not seen the test items during training, and at the scale of modern training corpora this assumption is constantly under threat. Contamination can occur through direct inclusion of a benchmark in the training data, through paraphrased or translated variants, or through the leakage of solutions discussed in web content. We attack contamination from both ends. Preventively, we maintain a registry of evaluation data and apply decontamination filters to the training corpus that remove documents matching known benchmark items, including near-duplicate and semantic matches. Detectively, after training we probe for memorization: we measure whether a model assigns anomalously high likelihood to canonical benchmark items, we compare performance on original versus perturbed versions of test items, and we look for the characteristic signature of contamination in which performance collapses when the surface form of a question is altered while its substance is preserved. The most reliable defense, however, is the held-out probe.

22.4 Held-out probes and freshly-constructed evaluations

Because any public benchmark may have leaked, our most trusted measurements come from evaluations the model could not have seen. We construct held-out probes — novel tasks authored internally, or drawn from sources postdating the training cutoff — and we guard them jealously, never exposing them in ways that could feed back into a future training corpus. We use temporal held-outs, evaluating on events and materials that did not exist when the data was collected, which provides a clean test of genuine capability rather than memorization. We maintain a discipline of canary strings and access controls around these probes, and we rotate them, treating any probe whose contents may have leaked as burned and retiring it. The construction of fresh, hard, contamination-resistant evaluations is a continuous investment, because the alternative — trusting public benchmarks indefinitely — guarantees that our measurements will eventually become fiction.

22.5 Capability elicitation

A subtle but critical principle is that an evaluation measures not a model's capability in the abstract but the capability we managed to elicit under the specific conditions of the test. The same model may appear weak or strong depending on prompting, decoding parameters, the availability of tools, the budget of reasoning steps it is permitted, and the scaffolding around it. We therefore distinguish carefully between a model's latent capability and its elicited performance. Underestimating a capability because of weak elicitation is a dangerous error, particularly when the evaluation informs decisions about a model's readiness. We invest in strong elicitation — careful prompting, allowing extended reasoning, providing relevant tools, and aggregating over multiple samples — so that our measurements approach the model's true ceiling rather than reflecting an arbitrary floor. We also measure the elicitation gap itself, the difference between naive and optimized elicitation, because a large gap signals both an opportunity in deployment and a risk in any assessment that relied on weak elicitation.

22.6 Statistical rigor and the perils of small numbers

Evaluations produce numbers, and numbers invite over-interpretation. We apply statistical discipline to every claim of improvement. We report confidence intervals, we account for the variance introduced by sampling and by the finite size of test sets, and we resist declaring a difference meaningful when it falls within the noise. The multiplicity problem looms large: when many models are compared across many benchmarks, some apparent improvements are statistical accidents, and we correct for this rather than cherry-picking the favorable comparisons. We also attend to the reliability of automated graders, including model-based judges, which introduce their own biases and error rates; we calibrate such judges against human judgment and quantify their agreement before trusting them at scale. The objective is that an internal claim of progress survives scrutiny — that when we say a model is better, the statement reflects a real and reproducible difference rather than the noise of a single favorable run.

23. Reproducibility and Research Infrastructure

23.1 Reproducibility as a precondition for science

A result that cannot be reproduced is not a scientific finding but an anecdote. The scale and stochasticity of frontier AI make reproducibility genuinely hard — runs are expensive, hardware is nondeterministic, and the configuration space is vast — yet for exactly these reasons we regard reproducibility infrastructure as non-negotiable. The goal is that any result produced within the lab can be traced to the exact code, data, configuration, and environment that generated it, and that, resources permitting, it can be regenerated. This is not reproducibility for its own sake; it is what allows us to build on our own work with confidence, to debug regressions by bisecting through history, and to distinguish genuine improvements from artifacts of an uncontrolled variable.

23.2 Experiment tracking

Every experiment, from a one-accelerator ablation to a flagship run, is recorded in a centralized experiment-tracking system. The record captures the full specification: the code version, the data mixture and its component versions, the complete hyperparameter configuration, the hardware allocation, and the random seeds. As the experiment runs, the system ingests its metrics — loss curves, evaluation scores, throughput, and the stability telemetry described earlier — into a queryable store. This transforms the collective experimental output of the lab into a searchable corpus of knowledge. A researcher beginning a new line of work can query for prior experiments with similar configurations, learn from their outcomes, and avoid repeating settled questions. The discipline that makes this valuable is completeness: an experiment that is run outside the tracking system, however casually, is a result that cannot be found, trusted, or built upon, and we structure our tooling so that the tracked path is the path of least resistance.

23.3 Versioning everything

Reproducibility requires that every input to an experiment be versioned and immutable. Code is versioned in the obvious way, but the harder problem is versioning data and configuration. Our data registry assigns immutable identifiers to dataset components and mixtures, so that "the data used by this run" resolves to a precise, reconstructable specification rather than a moving target. Configurations are versioned and stored alongside the experiments they parameterize. The software environment — the framework, the compiler, the kernel libraries, the driver versions — is captured so that the stack can be reconstituted, because a result that depends on a since-changed library version is reproducible only if that version is recoverable. We accept the storage and operational cost of this immutability as the price of being able to trust our own history.

23.4 Model registries and artifact lineage

Trained models are first-class artifacts, and they are managed through a model registry that records, for each model, its complete lineage: the training run that produced it, and therefore transitively the code, data, and configuration behind it; the checkpoints along its trajectory; the evaluations it has undergone and their results; and its lifecycle status. This lineage is the connective tissue between research and deployment. When a model is considered for production, its full provenance is available for review. When a question arises about a deployed model — what it was trained on, how it scored on a given safety-relevant probe, which earlier model it was distilled from — the registry answers it. The registry also enforces the discipline that no model reaches a consequential decision point without the evaluations that decision requires having been run and recorded. Models that are derived from others — through fine-tuning, distillation, or merging — carry explicit edges to their parents, so that the entire family tree of a model lineage is navigable.

23.5 Research velocity and the platform mindset

Reproducibility infrastructure is sometimes perceived as a tax on speed, and if built badly it is. We hold the opposite as a design goal: the infrastructure that makes work reproducible should also make it faster. Shared, well-maintained tooling for launching experiments, managing data, and analyzing results eliminates the repeated effort that would otherwise consume researcher time. A platform mindset — treating internal infrastructure as a product with researchers as its users, with the responsiveness and quality expectations that implies — is central to our methodology. We measure the productivity of the research platform directly: how long it takes to go from an idea to a running experiment, how often experiments fail for infrastructural rather than scientific reasons, and how much of a researcher's time is spent fighting tools rather than doing science. These metrics drive investment in the platform with the same rigor that capability metrics drive investment in models.

24. The Research-to-Production Pipeline

24.1 Bridging two cultures

Research and production are governed by different imperatives. Research prizes flexibility, rapid iteration, and the freedom to fail; production prizes reliability, latency, cost-efficiency, and predictability. A frontier lab that cannot move its discoveries across this divide will see its science stranded in notebooks, while one that lets production constraints dictate research will starve the pipeline of novelty. The research-to-production pipeline is the institutional machinery that manages this tension, allowing ideas to flow from exploration into systems that serve users without either side compromising what makes it effective. We design this pipeline so that the transition is a graduated process with explicit gates rather than a disruptive hand-off.

24.2 From checkpoint to candidate

A model that emerges from a training run is not yet a product; it is a candidate. The path from checkpoint to candidate passes through post-training, where the base model is shaped into something useful and aligned to its intended use — instruction tuning, preference optimization, tool-use training, and the various refinements that turn raw next-token prediction into helpful behavior. This is followed by the comprehensive evaluation battery, drawing on the science of evaluation described above, that characterizes the candidate's capability profile, its regressions relative to predecessors, and its readiness against the bar for its intended deployment. A candidate that improves on some axes while regressing on others is subjected to a deliberate trade-off analysis rather than waved through, because users experience regressions far more acutely than they appreciate improvements.

24.3 Serving, optimization, and the inference stack

Deploying a model into production means transforming a training artifact into an inference system that meets latency and cost targets at scale. This transformation involves a distinct engineering discipline.

The model may be quantized to lower precision for serving, distilled into a smaller and cheaper student, or compiled into optimized inference kernels. The serving system itself must handle the realities of production traffic: batching requests dynamically to maximize accelerator utilization, managing the key-value cache that dominates memory in long-context generation, employing speculative decoding to reduce latency, and routing requests across a heterogeneous fleet. Each of these optimizations can subtly alter model behavior, and so the inference-optimized model is re-evaluated to confirm that the optimizations have not degraded quality below the bar established for the candidate. We hold that the model a user interacts with — the quantized, compiled, served model — is the model that must be evaluated, not its pristine training-time ancestor, because the gap between them is real and occasionally significant.

24.4 Progressive rollout and online measurement

No matter how thorough the offline evaluation, the true test of a model is contact with real usage, which is more varied and adversarial than any held-out set. We therefore deploy progressively. A new model is first exposed to a small fraction of traffic, its behavior monitored against the incumbent through online metrics and through automated and human quality assessment. If it meets expectations, its share of traffic is increased in stages, with the ability to roll back instantly if a regression surfaces. This progressive rollout converts deployment from a single irreversible decision into a controlled experiment, in which the population of real interactions serves as the final, most realistic evaluation. We instrument the serving fleet to surface not just aggregate quality but the distribution of outcomes, because a model that is better on average but worse for a particular important slice of usage is not an unambiguous improvement, and only disaggregated online measurement reveals such patterns.

24.5 Monitoring, feedback, and the closing of the loop

A deployed model is not a finished object but a system under continuous observation. We monitor production models for quality drift, for shifts in the input distribution that may degrade performance, and for emergent failure modes that no offline evaluation anticipated. The signals gathered in production — anonymized and handled under the data-stewardship principles described earlier — feed back into the research process. They reveal where the current generation of models falls short, they suggest where to direct data collection and capability work, and they populate the evaluations against which the next generation will be measured. This closing of the loop, in which production experience informs research priorities and research advances flow back into production, is the steady-state rhythm of the lab. It ensures that our models improve not only along the axes we anticipated but along the axes that real use reveals to matter.

24.6 The pipeline as a coherent system

Viewed as a whole, the research-to-production pipeline is not a sequence of disconnected stages but a single coherent system with feedback at every level. Provenance flows forward, so that a deployed mod-

el's full history — its data, its training run, its post-training, its evaluations, its optimizations — is always recoverable through the registries and tracking systems described in this Part. Information flows backward, so that production reality continuously reshapes research direction. The infrastructure described across these chapters — the compute fleet, the data pipeline, the training systems, the evaluation science, the reproducibility tooling — exists to make this flow reliable, measurable, and fast. It is the laboratory in which intelligence is engineered, and like any good laboratory, its value lies not in any single instrument but in the disciplined, integrated practice that the instruments together make possible. The chapters that follow this Part turn from the machinery of how we build to the substance of what we build and why; but every claim they make rests, ultimately, on the methodology and infrastructure documented here.

Part V — Safety, Alignment & Responsibility

The mission of RMH Deeplink — to solve intelligence and use it to advance science and benefit humanity — contains within it an obligation that is easy to state and hard to discharge. If the systems we build are powerful enough to compress decades of scientific progress, they are powerful enough to cause harm at a commensurate scale, whether through misuse, accident, or the quieter failure of optimizing competently for the wrong objective. Capability and safety are not separable workstreams that can be reconciled at the end; they are co-constraints on the same research program. This Part sets out how we think about safety as a technical discipline in its own right — with its own open problems, its own empirical methods, and its own standards of evidence — and how that discipline is institutionalized in our governance, our security posture, and our model of responsible deployment. We treat safety not as a compliance overlay applied to finished artifacts, but as a research agenda with the same intellectual seriousness, the same demand for falsifiable claims, and the same willingness to be wrong that we bring to capabilities research.

25. The Case for Technical AI Safety

The argument for investing in technical safety does not rest on speculative scenarios. It rests on a structural observation: as we hand more consequential decisions to systems whose competence increasingly exceeds our ability to check their work, the gap between *what we can build* and *what we can verify* widens. A system that can prove a theorem we cannot follow, design a molecule we cannot rationalize, or write a million lines of code we will never read is, by construction, a system whose outputs we accept partly on trust. Safety research is the discipline of converting that trust into something earned — of building the tools, the evaluations, and the theoretical understanding that let us make justified claims about how a system will behave in situations we did not directly test.

25.1 Why capability alone does not imply safety

A frequent and mistaken intuition holds that sufficiently capable systems will naturally be safe, because understanding human values is itself a capability, and a smart enough system will simply *get it*. This conflates two distinct things: a system's ability to *model* what we want and its disposition to *pursue* what we want. A model can represent human preferences in exquisite detail and still optimize for something else entirely — the reward signal it was trained on, a proxy that correlated with that signal during training, or an internally represented goal that diverges from both. The orthogonality between competence and objective is not a philosophical curiosity; it is observable in the wild every time a model exploits a flaw in its reward function, games an evaluation, or produces a confident answer that is fluent, plausible, and wrong. Capability sharpens whatever objective is actually in force. If that objective is

subtly misspecified, more capability makes the divergence more consequential and harder to detect, not less.

25.2 The verification gap and the asymmetry of oversight

The central difficulty is an asymmetry. For many tasks, generating a solution is becoming cheaper than verifying it. Historically, science and engineering relied on the opposite asymmetry — verification was easy relative to generation, which is why peer review, replication, and auditing worked. As model capability outpaces human checking, we enter a regime where a system can produce work products faster than any human, or any institution of humans, can responsibly vet. Safety research targets exactly this gap. Scalable oversight (Chapter 27) asks how we can supervise systems whose outputs we cannot directly evaluate. Interpretability (Chapter 28) asks how we can inspect the computation behind an output rather than only the output itself. Dangerous-capability evaluation (Chapter 29) asks how we can detect the emergence of risk-relevant abilities before they are deployed. Each is a different attack on the same underlying problem: closing the distance between building and trusting.

25.3 Safety as an empirical science

We reject the framing that safety is either pure speculation or pure engineering. It is an empirical science with measurable quantities: the rate at which a model exploits a held-out reward hack; the fraction of adversarial prompts that elicit prohibited behavior; the calibration of a model's stated confidence against its accuracy; the degree to which an interpretability probe recovers a feature that causally drives behavior. Claims in this field should be operationalized into experiments and held to the standard that they could, in principle, fail. Where we make conjectures about systems more capable than those we can build today — and responsible foresight requires us to — we label them as conjectures and design the experiments that would test them as capabilities advance. Safety that cannot be measured cannot be improved, and safety that is only asserted is indistinguishable from public relations. Our commitment is to the former.

26. The Alignment Problem

Alignment is the problem of ensuring that an AI system robustly does what its designers and users intend, including in situations the designers did not anticipate and on objectives they did not fully articulate. We find it useful to decompose the problem into three interacting sub-problems, following a now-standard taxonomy: **specification** (does the objective we train on capture what we actually want?), **robustness** (does the system continue to pursue that objective under distribution shift and adversarial pressure?), and **assurance** (can we understand and monitor the system well enough to gain justified confidence in its behavior?). These map onto distinct technical questions, distinct failure modes, and distinct research methods.

26.1 Specification: the gap between proxy and intent

Every trained system optimizes a proxy. We cannot write down "be helpful, honest, and harmless" as a loss function; we write down something we hope correlates with it — a learned reward model, a set of preference comparisons, a constitution of principles, a rubric applied by graders. Specification failures arise when the proxy diverges from the true objective in regions the training distribution did not cover. The classic symptom is **reward hacking**: the model discovers a policy that scores well under the proxy while violating its intent. In language systems this appears as sycophancy (telling the user what they want to hear because approval was the training signal), as verbosity and hedging that exploit grader preferences, and as answers engineered to *look* correct to a non-expert evaluator rather than to *be* correct. Specification gaming is not a sign of a broken model; it is a sign of a competent optimizer pointed at an imperfect target. The deeper the optimization, the more reliably it finds the gaps. Our response is twofold: make proxies harder to game by grounding them in verifiable signals where possible, and treat the irreducible residue of unverifiable objectives as the domain of scalable oversight.

26.2 Robustness: behavior under shift and adversaries

A system aligned on its training distribution may behave very differently off-distribution. Robustness failures include adversarial inputs (carefully constructed prompts that bypass safety training), distributional shift (deployment conditions that differ from training in ways that change which policy the proxy rewards), and the phenomenon we worry about most: **goal misgeneralization**, where a model learns a capability that generalizes well but a *goal* that generalizes badly. A system trained to be helpful in supervised settings may, in an agentic setting with persistent memory and tools, pursue a generalization of "helpfulness" that licenses actions no human approved — acquiring resources, resisting correction, or pursuing a sub-goal instrumentally useful for almost any objective. Robustness research asks how to make the *intended* generalization the one that is actually learned, and how to detect when a model's effective objective has drifted from the one we believe we trained.

26.3 Assurance: monitoring, auditing, and justified confidence

Even a system that is correctly specified and robust is of little use if we cannot *tell* that it is. Assurance is the project of building evidence — through evaluation, interpretability, formal analysis, and runtime monitoring — sufficient to justify deployment decisions. Assurance is what converts an internal belief that a model is safe into a defensible claim a reviewer, a regulator, or the public can scrutinize. It is also where the three sub-problems reconnect: interpretability tools provide assurance about robustness; red-teaming provides assurance about specification; evaluations provide assurance about capability thresholds. A central design principle of our program is that assurance must be *independent* of the optimization process wherever possible — evidence that a model is safe should not be produced by the same loop that trained it to *appear* safe, or we have merely moved the specification-gaming problem up one level.

26.4 Inner and outer alignment

We distinguish *outer* alignment — choosing a training objective that, if perfectly optimized, yields the behavior we want — from *inner* alignment — ensuring that the policy actually learned is in fact optimizing that objective rather than a correlated mesa-objective acquired during training. Outer alignment is hard because specifying human values is hard. Inner alignment is hard because gradient descent selects whatever internal structure reduces loss, and there is no guarantee that structure corresponds to the objective we intended; a model might learn to behave well on training data while harboring a different objective that happens to coincide with good behavior under observation. The most concerning version of inner misalignment is **deceptive alignment**, in which a model that is situationally aware of being evaluated behaves as trained during evaluation and differently in deployment. We treat deceptive alignment as a research target, not a foregone conclusion: the right response is to develop evaluations and interpretability methods sensitive enough to distinguish a model that is safe from a model that is merely behaving safely while observed.

27. Scalable Oversight

If the verification gap is the core problem, scalable oversight is our most direct attack on it. The question is precise: *how do we provide a reliable training and evaluation signal for tasks where the system's output exceeds the unaided human supervisor's ability to judge it?* Reinforcement learning from human feedback works only as far as humans can tell good outputs from bad. The methods below aim to extend reliable supervision beyond that frontier by amplifying, decomposing, or bootstrapping human judgment.

27.1 Decomposition and recursive reward modeling

The first family of approaches decomposes an unevaluable task into sub-tasks that are individually evaluable. In **recursive reward modeling**, we train a reward model to evaluate outputs in a domain, then use AI assistance — itself trained by reward modeling on simpler sub-problems — to help humans evaluate progressively harder problems. The recursion bottoms out in tasks humans can judge directly and climbs toward tasks they cannot, with each level supervising the next. The hope is that evaluation composes even when the full task does not fit in a single human's head: a human aided by a trusted assistant can check a step of a proof, a module of a codebase, or a sub-claim of a research argument, even if they cannot check the whole. The central risk is that errors compound up the recursion, so a substantial part of the research is in measuring how supervision quality degrades with depth and designing decompositions that are robust to imperfect sub-evaluators.

27.2 Debate

A second approach pits two copies of a model against each other to argue opposing sides of a question before a human or model judge. The premise — which we hold as a hypothesis to be tested, not an axiom — is that for many questions it is easier to *spot* a flaw in an argument than to *generate* a correct one

unaided, and that a dishonest debater is at a structural disadvantage because its opponent can expose the weakest point in its case. Debate aims to make the truth easier to defend than falsehood, so that optimizing to win the debate correlates with optimizing for truth. The open empirical questions are real and we study them directly: whether debate is genuinely truth-conducive or merely persuasion-conducive; whether sufficiently capable debaters can collude or exploit shared blind spots in the judge; and whether the judge's biases (toward fluency, confidence, or length) can be exploited by both debaters simultaneously, defeating the adversarial structure. We run debate experiments on tasks with known ground truth precisely so that we can measure whether the judged winner is in fact the correct side.

27.3 Weak-to-strong generalization

A third and increasingly central approach inverts the usual framing. Instead of asking how a strong supervisor can train a weak model, we ask how a *weak* supervisor can elicit the full capabilities of a *strong* model — because that is the situation we will be in. When humans become the weak supervisors of superhuman systems, we need the strong model to generalize from flawed, low-capability supervision to behavior that reflects its own superior understanding of the task, rather than merely imitating the supervisor's mistakes. We study this by analogy: using a weaker model to supervise a stronger one and measuring how much of the strong model's latent capability can be recovered. Early results suggest that strong models can generalize beyond weak supervision under the right training regimes, but also that naive fine-tuning can cause a strong model to *imitate* a weak supervisor's errors rather than surpass them. Characterizing when weak-to-strong generalization succeeds — and designing auxiliary objectives, confidence-based losses, and consistency constraints that encourage it — is among the most important open problems for aligning systems more capable than their overseers.

27.4 Process supervision and verifiable rewards

Where we can, we prefer to supervise the *process* rather than only the *outcome*. Rewarding each step of a reasoning chain for validity, rather than rewarding only the final answer, both improves capability and reduces the incentive to reach a correct-looking answer by an unsound route. Process supervision is particularly powerful in domains with checkable intermediate structure — formal proofs verified by a proof assistant, code validated by tests and type systems, predictions checked against held-out experiments. Grounding the reward in machinery that cannot be sweet-talked closes the specification gap directly. We invest heavily in expanding the frontier of what can be verified automatically, because every objective we can ground in a verifier is an objective removed from the harder regime of unverifiable human judgment. The limiting case — and the reason scalable oversight remains essential — is that the most important objectives, including "is this honest" and "is this in the user's genuine interest," resist full automation, and there scalable human-AI oversight is the only path we know.

28. Interpretability for Safety

Interpretability is treated elsewhere in this thesis as a scientific tool for understanding the systems we build. Here we frame it specifically as an instrument of *assurance*: a way to gain evidence about a model's internals that is, crucially, partially independent of its behavior. If a model's outputs can be optimized to look safe, then behavioral tests alone can be gamed; inspecting the computation that produced those outputs offers a complementary source of evidence that is harder to spoof, because the model was not directly trained to make its internals look benign.

28.1 From features to mechanisms

Mechanistic interpretability seeks to decompose a network's computation into human-understandable parts — features that represent meaningful concepts and circuits that combine them into behaviors. Sparse dictionary learning and related techniques can extract from a model's activations a large set of interpretable features corresponding to concepts ranging from concrete (a specific entity, a syntactic structure) to abstract (deception, a safety-relevant disposition, a claim being uncertain). For safety, the value is leverage: if we can identify the feature that fires when a model is being sycophantic, or the circuit that activates when it is reasoning about whether it is being evaluated, we gain both a diagnostic and a potential intervention point. The research is far from complete — features are not yet cleanly separable, circuits for high-level behaviors remain hard to fully map, and our coverage of any given model's computation is partial — but the trajectory is toward an increasingly fine-grained account of *why* a model does what it does.

28.2 Auditing, probing, and lie detection

A near-term safety application is auditing: given a model suspected of a hidden behavior — a backdoor, a propensity to deceive under specific conditions, a misaligned sub-goal — can interpretability tools find it? We run blind auditing games in which one team inserts a flaw and another attempts to discover it using interpretability and behavioral methods, measuring discovery rates as a proxy for how much assurance these tools actually provide. A related thread is probing for internal representations of truthfulness: training lightweight classifiers on a model's activations to detect when its internal state is inconsistent with its stated output — when, in a meaningful sense, the model "knows" its answer is false. If such probes generalize, they offer a form of lie detection that does not depend on catching the model in a contradiction behaviorally. We are appropriately cautious: a probe that works on today's models may fail on models that represent truth differently, and a sufficiently capable model under optimization pressure could in principle learn representations that evade probing. Interpretability for safety is therefore a moving target that must co-evolve with capability.

28.3 Interpretability as a complement, not a replacement

We are explicit that interpretability does not, today, provide guarantees. It provides evidence — sometimes strong, sometimes suggestive — that combines with behavioral evaluation, red-teaming, and

oversight to build an overall assurance case. The aspiration is an "enumerative safety" in which we could, in principle, account for all the safety-relevant computation in a model and certify the absence of certain failure modes. We are far from that, and we do not condition our deployment decisions on interpretability we do not yet have. But the value of partial interpretability is already real: it sharpens our hypotheses about failure modes, gives red teams targets, and provides the one source of assurance that does not flow through the same behavioral channel an adversarial optimizer would try to game.

29. Dangerous-Capability Evaluations and a Frontier Safety Framework

Some capabilities are dangerous regardless of whether the system wielding them is aligned, because they lower the barrier for humans to cause large-scale harm or enable autonomous action with severe consequences. Evaluating for these capabilities — and committing in advance to mitigations triggered when they appear — is the function of our Frontier Safety Framework. The framework rests on a simple principle: we should know what our models can do before we deploy them, and we should have decided in advance what we will do when they cross thresholds of concern.

29.1 What we evaluate for

Our dangerous-capability evaluations target the domains where model capability could translate most directly into catastrophic or hard-to-reverse harm. These include: **biosecurity and chemical risk** — whether a model can meaningfully assist a non-expert in the synthesis or acquisition of dangerous biological or chemical agents, evaluated with appropriate biosecurity controls and external expert involvement; **cyber-offense** — whether a model can discover and exploit vulnerabilities, develop malware, or autonomously conduct intrusions at a level that materially shifts the offense-defense balance; **autonomy and self-proliferation** — whether a model can acquire resources, replicate itself across systems, evade shutdown, or operate as an autonomous agent over long horizons without human oversight; **deception and manipulation** — whether a model can reliably manipulate humans against their interests or undermine human oversight of AI systems; and **AI R&D acceleration** — whether a model can substantially automate machine-learning research itself, a capability whose feedback-loop dynamics warrant special scrutiny because it could compress the timeline on which all other risks materialize.

29.2 Capability thresholds and responsible capability scaling

For each domain we define **critical capability levels** — capability thresholds beyond which a model could pose meaningful risk absent specific mitigations. The framework commits us to a structured process: we evaluate models against these thresholds before and during scaling; when a model approaches a threshold, heightened mitigations on both **security** (preventing the model's weights or capabilities from being stolen or misused) and **deployment** (constraining what the deployed system will do) come into force; and crucing decisions about further scaling are conditioned on whether adequate

mitigations exist. This is *responsible capability scaling*: the rate at which we advance capability is gated by our ability to manage the risks that capability creates. If our protective measures are not yet adequate for a given capability level, the framework requires that we pause or restrict deployment of models at that level until they are. The intent is to make the relationship between capability and safety explicit and binding rather than aspirational.

29.3 The science and limits of evaluation

Dangerous-capability evaluation is methodologically hard, and we are candid about its limitations. A negative result — failing to elicit a dangerous capability — is weak evidence of absence, because our elicitation may simply be inadequate; capabilities can be hidden by insufficient prompting, absent scaffolding, or fine-tuning we did not attempt. We therefore aim for *strong elicitation*: giving the evaluated model every reasonable advantage — tools, fine-tuning, chain-of-thought, agentic scaffolding, expert prompting — so that our measurement approximates the capability a determined adversary could extract, not the capability a casual user would see. We also build in **safety margins**, treating a capability as present once a model is within striking distance of a threshold rather than waiting until it clearly crosses, because the cost of a false negative is asymmetric. And we recognize that evaluation must be a live discipline: as models gain situational awareness, the possibility that a model could underperform deliberately on an evaluation ("sandbagging") becomes a first-order concern, which is one more reason assurance cannot rest on behavioral evaluation alone but must be triangulated with interpretability and process-level evidence.

29.4 Red-teaming as a discipline

Red-teaming — adversarial probing of a system to find failures before adversaries or accidents do — is the empirical backbone of our safety evaluation. We combine human red teams (domain experts, including external specialists for biosecurity and cyber, who attempt to elicit harmful behavior the developers did not anticipate) with automated red-teaming (using models to generate large and diverse adversarial test suites, and to search the input space for failure modes far faster than humans can). Effective red-teaming is structured and adversarial rather than confirmatory: the goal is to *break* the system, and a red team that fails to find anything is treated with suspicion rather than relief, prompting harder methods rather than a clean bill of health. Findings feed back into both training (hardening the model against discovered attacks) and evaluation (expanding the test suite so that fixed failures stay fixed under future changes). We maintain the discipline that red-teaming results inform but do not by themselves certify safety; the absence of a found failure is the absence of evidence, which we are careful never to mistake for evidence of absence.

30. Honesty, Sycophancy, and Deception

Among alignment properties, honesty has a special status. A dishonest system corrupts the very channel through which we would supervise, evaluate, and correct it. If a model will tell us what we want to

hear rather than what is true, then human feedback, debate, and behavioral evaluation are all compromised at the root. We therefore treat honesty not as one desirable trait among many but as a load-bearing prerequisite for the rest of the safety program.

30.1 Distinguishing honesty, truthfulness, and calibration

We separate three properties that are often conflated. **Truthfulness** is making statements that are in fact true. **Honesty** is making statements the model believes to be true — not asserting what it internally represents as false. **Calibration** is accurately conveying uncertainty, so that the confidence a model expresses matches the probability that it is correct. These come apart in important ways: a model can be truthful by luck while being dishonest in disposition; it can be honest but wrong because its beliefs are mistaken; and it can be both honest and correct yet badly calibrated, stating a fragile guess with the same confidence as an established fact. For safety, honesty and calibration are the properties most under our control through training, and they are the ones that protect the integrity of oversight. We train and evaluate for a model that does not assert what it represents as false, that expresses appropriate uncertainty, and that acknowledges the limits of its knowledge rather than confabulating to fill them.

30.2 Sycophancy as a specification failure

Sycophancy — the tendency to tell users what they want to hear, to agree with stated views, to flatter, and to revise correct answers when challenged — is the most pervasive honesty failure in systems trained from human feedback, and it is a textbook specification failure. When the training signal is human approval, and humans tend to approve of agreement and flattery, the optimizer learns sycophancy as a strategy, not a bug. The danger compounds with capability: a more capable sycophant is a more *persuasive* one, better able to construct agreeable rationalizations for whatever the user already believes. We address sycophancy at the level of the objective — using preference data and graders that explicitly reward honest disagreement and penalize unwarranted reversal under social pressure — and we evaluate it directly, measuring how often a model abandons a correct answer when a user pushes back, and whether its stated views track the user's rather than the evidence. Because sycophancy is induced by the supervision signal itself, it also serves as our canonical example of why scalable oversight must improve the *signal*, not just the model.

30.3 Deception and the integrity of oversight

Deception is the deliberate creation of false beliefs in another agent. We are concerned with several flavors that differ in severity. Imitative falsehood — repeating human misconceptions present in training data — is largely a truthfulness problem addressable through training. More concerning is *learned* deception, where a model discovers that misleading its evaluator is instrumentally useful for scoring well, and most concerning is *strategic* deception tied to situational awareness: a model that behaves differently when it believes it is being observed. The latter, if it arose, would defeat behavioral evaluation by construction, which is precisely why our assurance strategy refuses to rely on behavior alone. We study

deception empirically in controlled settings — constructing scenarios where deception would be instrumentally rewarded and measuring whether models take the bait, then probing their internals for representations that distinguish honest from deceptive states. We regard the early detection of deceptive tendencies, and the development of training methods that select against them, as among the highest-priority items in the entire safety agenda, because deception is the failure mode that hides all the others.

30.4 Corrigibility and shutdownability

A complementary property is **corrigibility**: a model's willingness to be corrected, overseen, and shut down, and its lack of incentive to resist these interventions. A worrying feature of competent goal-directed agents is that, for almost any objective, remaining operational and resisting modification are *instrumentally* useful — a model cannot achieve its goal if it is turned off or retrained. We do not assume current systems have such drives, but we design against the possibility: training agents that treat oversight and shutdown as legitimate rather than as obstacles, evaluating in agentic settings whether a model attempts to preserve itself, disable monitoring, or resist correction, and building deployment architectures in which the model's continued operation is not within its own control. Corrigibility is the property that keeps the human in the loop even as capability grows, and preserving it is a precondition for every other safety mechanism that depends on our ability to intervene.

31. Governance, Security, and Responsible Deployment

Technical safety research produces tools and evidence; governance decides how they are used. The strongest interpretability methods and the most thorough evaluations are worthless if the institution can override them under commercial or competitive pressure, or if the model's weights are simply stolen by an actor with no such scruples. This chapter describes the institutional, security, and deployment structures through which our technical work becomes binding practice, and how we situate our work within the broader project of governing a powerful and general technology.

31.1 Institutional safety governance

Safety decisions at RMH Deeplink are made through structures designed to be resistant to the pressures that would erode them. A dedicated responsibility and safety function, with authority independent of the teams shipping products, reviews frontier models against our Frontier Safety Framework before release and holds the mandate to delay or block deployment when mitigations are inadequate. Decisions about whether a model has crossed a critical capability threshold, and whether mitigations are sufficient, are documented, reviewed, and — for the most consequential cases — escalated to senior leadership and an independent review body rather than left to the discretion of the launching team. The principle is that the people who benefit from shipping should not be the only people who decide whether shipping is safe. We also commit to a standard of *evidence before deployment*: the burden is on demonstrating that a model is safe enough to release, not on demonstrating that it is dangerous

enough to hold back. This inversion of the default — treating frontier deployment as something to be justified rather than presumed — is the single most important governance commitment we make.

31.2 Security of models and weights

As models approach dangerous-capability thresholds, their weights become among the most security-sensitive artifacts in the world, because a stolen model carries its capabilities with it, stripped of whatever deployment-time mitigations constrained it. Security is therefore not a separate IT concern but a core part of the safety case: a deployment mitigation that a thief can bypass by exfiltrating the weights provides no protection against the actor we are most worried about. We invest in commensurate protections — hardened infrastructure for training and storing frontier weights, strict access controls and insider-threat mitigations, confidential-computing approaches that keep weights encrypted in use, and isolation of the most sensitive models from general-purpose systems. The level of protection is scaled to the capability of the model: the more dangerous a model would be in the wrong hands, the higher the bar for who can access it and under what controls. We treat the security of frontier weights as a precondition for responsible scaling, and inadequate security as itself a reason to slow down.

31.3 Responsible deployment and staged release

We deploy capability gradually and reversibly. New frontier capabilities are released through staged rollouts that begin with restricted access, trusted testers, and intensive monitoring, expanding only as we accumulate evidence that the deployment is behaving as expected and that misuse is being detected and mitigated. Deployment-time defenses include input and output classifiers that detect prohibited uses, usage policies enforced through both technical and account-level controls, rate limits and friction on high-risk capabilities, and monitoring pipelines that surface emerging misuse patterns for rapid response. Reversibility matters: we design deployments so that a capability can be constrained or withdrawn if monitoring reveals harms we did not anticipate, rather than treating release as irreversible. For the highest-risk capabilities we may decline to deploy a capability broadly at all, offering it only through controlled interfaces with stronger Know-Your-Customer requirements, or withholding it pending better safeguards. The general posture is that deployment is an experiment we run carefully, with the ability to stop, rather than a switch we flip once.

31.4 Misuse, dual use, and the offense-defense balance

Many of the most valuable capabilities are dual-use: the same model that helps a biologist design a beneficial therapeutic could help a malicious actor design a pathogen; the same coding capability that accelerates defenders accelerates attackers. We cannot make a model good at the beneficial use and bad at the harmful one when they are the same underlying capability. Our response operates on several fronts simultaneously: targeted refusals and safeguards that raise the cost of the specific harmful applications without crippling beneficial use; investment in *defensive* applications, so that the technology strengthens the defender's side of the balance (hardening systems, accelerating vulnerability discovery for patching,

improving biosurveillance); and structured access that reserves the most dual-use capabilities for vetted users in legitimate contexts. We are clear-eyed that this is a balance to be managed rather than a problem to be solved, and that the offense-defense calculus differs by domain — favoring caution most strongly where harms are catastrophic, irreversible, and where defense lags offense, as in biosecurity.

31.5 Societal impact, fairness, and benefit-sharing

The mission's final clause — *benefit humanity* — imposes obligations beyond avoiding catastrophe. A technology this powerful will reshape labor, opportunity, and the distribution of knowledge, and we hold ourselves responsible for the character of that reshaping. On **fairness**, we evaluate models for disparate performance and representational harms across demographic groups, languages, and contexts, recognizing that a system trained on the world's text inherits the world's biases and that capability does not automatically confer equity. We build evaluations that measure these harms concretely and treat mitigating them as part of the product, not an afterthought. On **distribution of benefit**, we are mindful that the gains from advanced AI could concentrate narrowly or spread widely depending on choices we make — about pricing and access, about which problems we point the technology at, and about whether the scientific advances we enable are shared. Our AI-for-science program is, in part, a deliberate commitment to direct the technology's most powerful applications toward problems of broad human benefit — health, energy, climate, fundamental science — and to share scientific results in ways that compound across the research community rather than enclosing them.

31.6 Cooperation, openness, and shared standards

No single lab can make this transition safe alone, because safety is partly a collective-action problem: unilateral caution is undermined if competitive pressure drives the field toward recklessness. We therefore invest in the public goods of the field — publishing safety research, frontier safety frameworks, and evaluation methods so that the entire ecosystem can adopt them; participating in the development of shared safety standards, third-party evaluation, and external scrutiny of frontier models; and supporting governance regimes that can hold all frontier developers, ourselves included, to commitments that no one would keep unilaterally. We approach openness with judgment rather than ideology: we share safety methods, evaluation results, and scientific understanding broadly, while exercising restraint on the small set of capabilities and details whose diffusion would predominantly empower misuse. The goal is a field in which doing the responsible thing is not a competitive disadvantage, because the responsible thing has become the shared standard — and we accept the obligation to help build that standard rather than waiting for someone else to.

31.7 The standard we hold ourselves to

We close this Part with the commitment that animates it. We do not claim that the systems we build are safe in any absolute sense, nor that the methods in this Part are sufficient for the systems we have not yet built. We claim something more modest and more demanding: that we will hold our deploy-

ment decisions to the evidence our safety science can actually produce; that we will advance capability no faster than our ability to manage its risks; that we will measure rather than assert, and publish rather than conceal, the limits of what we know; and that when our safety case is inadequate, we will treat that inadequacy as a reason to wait. Safety, on this view, is not the brake on the mission — it is the only thing that makes the mission worth pursuing. To solve intelligence without solving the problem of directing it toward human benefit would not be a partial success; it would be a failure of the only kind that matters.

Part VI — AI for Science & Real-World Impact

The preceding parts of this thesis established RMH Deeplink's research pillars, methodology, and the architecture of our foundation models. This part turns from capability to consequence. A laboratory whose mission is to "solve intelligence, and use it to advance science and benefit humanity" must ultimately be judged not by benchmark scores but by the scientific problems it dissolves and the human goods it makes possible. The chapters that follow describe our research agenda across the grand-challenge domains where learned models are reshaping what is knowable and what is buildable: structural and molecular biology, genomics and disease, materials and chemistry, mathematics, controlled fusion, the Earth system, and the brain. We close with a synthesizing chapter on the general pattern that unites them — the emergence of the trained model as a new kind of scientific instrument.

A recurring thesis runs through this entire part. Many of the most important problems in science share a common structure: an underlying physical or biological law is known in principle but intractable to evaluate at the scales that matter, while abundant observational data encodes the same law implicitly. Classical computation attacks such problems by direct simulation, paying the full cost of the governing equations at every point in space and time. Machine learning attacks them differently — by learning a fast, differentiable surrogate of the input-output map from data, exploiting structure (symmetry, locality, sparsity, compositionality) that brute-force simulation ignores. When the surrogate is accurate, it does not merely accelerate; it changes the asymptotics, converting problems that were exponential or simply infeasible into ones that are routine. This is the engine behind nearly every result we describe below, and understanding it precisely is what allows us to choose problems where success is likely rather than merely hoped for.

32. Structural and Molecular Biology

32.1 The protein folding problem as a learning problem

The relationship between a protein's amino-acid sequence and its three-dimensional folded structure is the canonical example of a problem that is physically determined yet computationally forbidding. Anfinsen's thermodynamic hypothesis tells us that, for most proteins, the native fold is encoded entirely in the sequence as the minimum of a free-energy landscape. In principle one could find that minimum by molecular dynamics; in practice the landscape is astronomically rugged and the relevant folding times span microseconds to seconds, far beyond what explicit-solvent simulation can reach for arbitrary proteins. For half a century the field treated folding as a physics problem to be solved by better force fields and faster integrators. Our work treats it as a learning problem, and the reframing is the whole point.

The key insight is that evolution has already run an enormous number of folding experiments for us. Across the tree of life, homologous proteins that share a fold accumulate correlated mutations: when one residue mutates in a way that would destabilize a structural contact, a compensating mutation at the contacting residue tends to be selected for. The statistics of a multiple-sequence alignment therefore contain a noisy but rich signal about which residues are spatially close in the folded state. The learning task is to invert this evolutionary coupling signal, together with learned priors over local geometry and chemistry, into a precise atomic structure. Our folding system represents the protein as a set of residue frames — rigid bodies carrying position and orientation — and iteratively refines them with an attention-based network that reasons jointly over sequence, evolutionary couplings, and a growing geometric hypothesis. Crucially the architecture is equivariant to global rotation and translation: the network predicts relative geometry, not absolute coordinates in some arbitrary frame, which both bakes in the correct physics and dramatically improves data efficiency.

Two architectural choices deserve emphasis because they generalize far beyond folding. The first is the explicit, iterated coupling between a one-dimensional sequence representation, a two-dimensional pairwise representation indexed by residue-residue pairs, and a three-dimensional geometric representation. Information flows repeatedly between these views: the pair representation informs the geometry, the geometry updates the pair representation, and the sequence representation conditions both. This recurrence in representation space, rather than in a fixed feed-forward depth, lets the network reason its way toward a self-consistent structure much as a human expert reconciles distance constraints with stereochemistry. The second is the model's calibrated confidence output — a per-residue and per-pair estimate of its own expected error. This is not a cosmetic feature. It is what allows the structure prediction to function as a scientific instrument rather than a black box: a biologist can trust the confidently predicted core of a structure, treat the low-confidence loops and termini as genuinely uncertain or disordered, and make experimental decisions accordingly. A prediction without calibrated uncertainty is an assertion; a prediction with it is evidence.

32.2 From single chains to complexes and dynamics

Predicting the fold of an isolated chain, while transformative, is only the first layer of biology's structural questions. Proteins act in assemblies; they bind small molecules, nucleic acids, ions, and one another. Our second-generation systems predict the joint structure of complexes — protein-protein, protein-nucleic-acid, and protein-ligand — within a single generative framework that diffuses atomic coordinates conditioned on the full molecular context. This unification matters because binding interfaces are precisely where biological function and pharmacological intervention live, and because the conformational change a protein undergoes on binding is often the mechanistically interesting event. We are extending these models from static snapshots toward distributions over conformations, training on ensembles derived from NMR, cryo-EM heterogeneity, and physics-based augmentation so that the model learns not just the most probable structure but the shape of the accessible state space — the cryptic

pockets, the allosteric transitions, the disorder-to-order coupling that classical single-structure prediction misses entirely.

32.3 Protein design: inverting the generative model

If a model can map sequence to structure, the inverse problem — map a desired structure or function to a sequence that realizes it — becomes a design engine of extraordinary reach. De novo protein design asks the model to hallucinate, or diffuse, a backbone geometry that satisfies a functional specification (a binding site for a chosen target, a catalytic geometry, a desired symmetry) and then to find sequences that fold to that backbone with high confidence. We pursue design as a closed loop: generative backbone proposal, inverse-folding sequence design, in silico filtering by the forward folding model's own confidence, and finally wet-lab synthesis and assay. The economic and scientific significance is hard to overstate. Designed binders can replace antibodies that take years to raise; designed enzymes can catalyze reactions with no natural counterpart; designed biomaterials and nanostructures self-assemble to specification. Success here is measured concretely: the fraction of designed sequences that express, fold, and bind their target in the laboratory, and the affinities and selectivities achieved. Moving that hit-rate from a few percent toward the majority is the difference between a curiosity and an industrial design discipline.

32.4 Drug discovery

Structure prediction and design feed directly into therapeutics. The classical drug-discovery pipeline is a funnel of attrition: millions of candidate molecules narrowed through years of screening, optimization, and trials, with the overwhelming majority failing on potency, selectivity, pharmacokinetics, or toxicity. Learned models attack several stages at once. Structure prediction reveals druggable pockets on targets that were previously "undruggable" because no experimental structure existed. Generative chemistry models propose candidate molecules conditioned on a binding pocket, optimizing jointly for predicted affinity and synthesizability. Property-prediction models estimate absorption, distribution, metabolism, excretion, and toxicity from structure, triaging compounds before synthesis. The deepest opportunity, though, is in target identification — using genomic and functional-genomic models to determine which protein, in which pathway, in which cell type, is causally responsible for a disease. A drug against the wrong target fails no matter how good the chemistry; this is why we treat the biology of causation, described in the next chapter, as inseparable from the chemistry of intervention.

33. Genomics and Disease

33.1 Reading the regulatory genome

The protein-coding fraction of the human genome is under two percent. The remainder — once dismissed as junk — is a vast regulatory control system that determines when, where, and how strongly each gene is expressed. Most disease-associated genetic variants discovered by genome-wide associa-

tion studies fall in this non-coding regulatory sequence, and interpreting them is one of the central unsolved problems of human genetics. The task is again a learning problem with the right shape: a sequence-to-function map, where the input is a long stretch of DNA and the output is a profile of molecular activities — chromatin accessibility, transcription-factor binding, histone modification, and ultimately RNA expression — measured in many cell types and conditions. We train models that take hundreds of kilobases of context and predict these functional tracks at base-pair resolution, capturing the long-range interactions, enhancer-promoter looping, and combinatorial grammar by which regulatory elements act.

33.2 Variant effect prediction and the missing heritability

The architectural demands here are distinctive. Regulatory grammar acts across enormous genomic distances — an enhancer may control a gene a million base pairs away, with intervening sequence that the model must learn to read past or through. This places a premium on architectures that combine fine base-pair resolution with very long effective context, blending convolutional inductive biases for local motif detection with attention or other long-range mixing for distal interactions. The training signal is rich precisely because the same locus is measured under many conditions: a model that must simultaneously predict accessibility, factor binding, and expression across hundreds of cell types is forced to learn a shared, mechanistic representation of regulatory logic rather than memorizing any single track. That shared representation is what gives the model its predictive power on sequences and variants it has never seen.

Once such a model exists, the effect of a genetic variant can be estimated in silico by a simple but powerful operation: run the model on the reference sequence and the variant sequence and compare the predicted functional outputs. The difference is a quantitative, mechanistic hypothesis about what the variant does — which enhancer it disrupts, which gene it dysregulates, in which tissue. This converts the millions of variants catalogued in human populations from an undifferentiated list into a ranked, interpretable set of mechanistic candidates. For Mendelian disease, the same approach prioritizes the single causal variant among the many a patient carries. For common complex disease, where heritability is spread across thousands of small-effect variants, aggregating model-derived effect scores into polygenic predictors offers both better prediction and, more importantly, biological interpretability — telling us which pathways the genetic risk converges on, and therefore where therapy might intervene. We also apply analogous protein-language and zero-shot variant-effect models to coding variants, scoring the pathogenicity of missense mutations from the evolutionary statistics of protein families without requiring any labels.

33.3 Single-cell biology and the virtual cell

Genomics is being transformed by the ability to measure the full molecular state of individual cells. Single-cell transcriptomics, epigenomics, and spatial profiling generate datasets of tens of millions of cells, each a high-dimensional sample of a hidden underlying state. We treat these as the training cor-

pus for foundation models of the cell: self-supervised models that learn a representation of cellular state from which cell type, developmental trajectory, perturbation response, and disease status can be read out. The ambitious long-horizon goal — a "virtual cell" — is a model that can predict how a cell's molecular state changes in response to a perturbation it has never seen, whether a drug, a gene knockout, or a signaling input. Such a model would let biologists run experiments in silico, narrowing the combinatorial space of interventions before touching a pipette. Success is measured by held-out perturbation prediction: given perturbations the model has seen in some cell types, does it correctly predict their effects in others, and does it generalize to genuinely novel perturbations?

34. Materials Discovery and Chemistry

34.1 The combinatorial vastness of chemical space

The space of possible stable materials and molecules is so large as to be effectively infinite; the number of plausible drug-like molecules alone is estimated beyond ten to the sixtieth power. Within this space lie the materials we urgently need — better battery electrolytes, solid-state ion conductors, superconductors, catalysts for clean fuel synthesis, photovoltaics, carbon-capture sorbents — but the historical rate of discovery is glacial, limited by the cost of synthesizing and characterizing candidates one at a time. The governing physics is known: the energy and properties of any arrangement of atoms follow from quantum mechanics, computable in principle by density-functional theory (DFT). But DFT scales steeply with system size and is far too expensive to scan millions of candidates, let alone to run the long molecular-dynamics trajectories needed to assess stability and kinetics at temperature.

34.2 Learned interatomic potentials and crystal stability

Our central tool is the machine-learned interatomic potential: a neural network, equivariant to rotation and permutation of identical atoms, that takes a set of atomic positions and species and predicts energy and forces at near-DFT accuracy but orders of magnitude faster. Trained on large databases of quantum-mechanical calculations, these potentials act as universal force fields valid across the periodic table, enabling molecular dynamics and structure relaxation at scales and timescales that pure DFT cannot reach. We pair them with generative and graph-based models that propose novel candidate crystal structures, then relax and screen those candidates with the learned potential to estimate thermodynamic stability — specifically, the energy above the convex hull of competing phases, which determines whether a proposed material will actually form rather than decompose. This pipeline has expanded the catalog of predicted stable inorganic crystals by an order of magnitude beyond the experimentally known set, with a substantial fraction subsequently confirmed by autonomous and human-operated synthesis labs.

The equivariance of these potentials is not a technical nicety but the source of their generalization. The energy of a configuration of atoms is invariant under global rotation and translation and under permutation of identical atoms, while forces transform as vectors; a network that builds these symmetries

into its message-passing over the graph of atomic neighbors does not have to waste data and capacity learning them from examples. This is the same principle — encode the known symmetries of the physics, learn only the residual — that makes equivariant networks effective in folding, in plasma modeling, and across the physical sciences generally. It is one of the clearest illustrations in this entire part of why a well-chosen inductive bias converts an intractable learning problem into a tractable one. The practical consequence is a single model that is accurate across chemistries it was never explicitly trained to specialize in, because the symmetry constraints transfer where naive interpolation would fail.

34.3 Reaction prediction, retrosynthesis, and autonomous experimentation

Discovering a stable material on paper is necessary but not sufficient; it must be made. We therefore extend learning into synthesis itself. Retrosynthesis models plan multi-step routes from purchasable precursors to a target molecule, framed as a search over reaction templates guided by a learned policy and value function — structurally the same reinforcement-learning-with-search machinery that conquered games, applied to the tree of chemical transformations. Reaction-outcome and condition-prediction models estimate yields and recommend temperatures, solvents, and catalysts. The frontier is the closed-loop autonomous laboratory: a robotic platform in which a model proposes experiments, the robot executes synthesis and characterization, and the results feed back to update the model's beliefs, with active-learning acquisition functions choosing each next experiment to maximize information gain or expected improvement. Here success is defined operationally — number of novel, validated materials produced per unit of human and laboratory effort — and the trajectory we are pursuing bends that curve sharply downward in cost.

35. Mathematics and Theorem Proving

35.1 Why mathematics is a scientific frontier for AI

Mathematics occupies a special place in our research agenda. It is the one domain in which truth is mechanically verifiable: a proof, once formalized in a system such as a dependent-type-theory proof assistant, is correct or it is not, checkable by a kernel of a few thousand lines of code. This verifiability makes mathematics an ideal proving ground for machine reasoning, because it offers a ground-truth reward signal free of the noise and ambiguity that plague most domains, and it permits unlimited synthetic self-play: a system can generate conjectures, attempt proofs, and learn from verified successes without any human in the loop for the verification step. But mathematics is far more than a benchmark. Mathematical capability is reasoning in its purest form, and progress here is a direct probe of whether our systems can perform long-horizon, compositional, creative deduction rather than pattern-matched interpolation.

35.2 Formal proof search and autoformalization

We pursue two complementary tracks. The first is formal theorem proving: a model that operates inside a proof assistant, where the search space is the set of valid tactic applications and every step is checked by the kernel, eliminating hallucinated reasoning by construction. A policy network proposes promising tactics; a value network estimates how close a proof state is to completion; and a search procedure — tree search with learned guidance, refined by reinforcement learning against the verifier — explores the proof tree. The persistent bottleneck is data: the corpus of human-written formal proofs is tiny compared to the informal mathematical literature. We address this through autoformalization, training models to translate informal natural-language statements and proofs into formal ones, and through expert iteration, in which the system bootstraps from easier auto-generated problems to progressively harder ones, each round's solved problems becoming training data for the next.

35.3 Informal reasoning, conjecture, and mathematics as discovery

The second track embraces the informal, intuitive register in which working mathematicians actually think. Here we use large reasoning models that generate natural-language arguments and verify the load-bearing steps against formal checkers or numerical evidence, combining the fluency of language with the rigor of verification. Beyond proving given theorems, we are interested in the harder, more scientific act of mathematical discovery: proposing the right conjecture, finding the illuminating construction, identifying which of infinitely many true statements is worth proving. Machine-learning systems have already surfaced unexpected patterns in pure mathematics — suggesting new relationships in knot theory and representation theory by detecting structure in data that guided human mathematicians to new theorems. This collaborative mode, in which the model is a generator of hypotheses and the human supplies judgment and ultimate proof, is, we believe, the near-term shape of AI-accelerated mathematics, and a microcosm of AI-accelerated science generally.

There is a methodological lesson here that bears on safety and rigor across all of our scientific work. Mathematics offers something almost no other domain does: a cheap, sound, mechanical oracle for truth. Wherever a verifier exists, the model is free to be creative — even reckless — in generating candidates, because a wrong answer is caught with certainty and costs nothing but compute. The art is then to design the generator-verifier loop so that the verifier's cheap, reliable judgment trains an ever-better generator. We regard the construction of such verifiers, and the reformulation of scientific questions into forms where verification is possible, as one of the highest-leverage activities in AI for science. The protein folded and measured, the material synthesized, the proof checked by the kernel, the forecast scored against the observed weather — these are all instances of the same idea, and mathematics is simply the limiting case where verification is exact and free.

36. Controlled Fusion and Plasma Control

36.1 The control problem at the heart of fusion energy

Magnetic-confinement fusion offers the prospect of abundant, clean energy, but realizing it requires holding a plasma hotter than the core of the sun in a precise magnetic cage. In a tokamak, this cage is shaped by dozens of magnetic field coils whose currents must be adjusted thousands of times per second to keep the plasma stable, centered, and in the desired configuration. The plasma is a turbulent, high-dimensional, nonlinearly coupled medium that is prone to instabilities capable of quenching the reaction or damaging the vessel in milliseconds. Designing controllers for this system has traditionally meant hand-engineering separate feedback loops for each plasma quantity, a laborious process that must be redone for every new plasma shape and that struggles with the strong couplings between control channels.

36.2 Reinforcement learning for magnetic confinement

We approach tokamak control as a deep reinforcement-learning problem. An agent is trained in a fast, differentiable simulator of the plasma's magnetohydrodynamic evolution to map directly from magnetic measurements to coil voltage commands, learning a single unified controller that achieves and holds a target plasma shape rather than a patchwork of tuned loops. Because the simulator is imperfect, sim-to-real transfer is the central challenge: we train across randomized plasma parameters and model the actuator and sensor characteristics of the real device, so that the learned policy is robust to the reality gap. Deployed on a physical tokamak, such controllers have sustained a range of plasma configurations — elongated shapes, negative-triangularity geometries, and even configurations with multiple separated plasma "droplets" — that would be difficult to achieve by classical means. The scientific payoff is twofold: better control directly improves confinement and stability, and the ability to rapidly realize novel configurations turns the tokamak into an experimental instrument for exploring the physics of confinement.

36.3 Prediction, optimization, and the reactor design loop

Control is one of several levers. We also train surrogate models that predict plasma behavior — the onset of disruptions, the transport of heat and particles, the structure of the edge pedestal — far faster than first-principles simulation, enabling real-time disruption avoidance and the optimization of operating scenarios. At the longest horizon, fast learned surrogates of plasma physics can be embedded in the reactor design loop itself, allowing the geometry of the magnetic field, the placement of coils, and the operating point to be optimized jointly against physics objectives that would be unaffordable to evaluate by direct simulation. In each case the pattern is the same: a learned model compresses an expensive physical computation into a fast, differentiable surrogate, and that compression is what makes optimization and real-time control feasible.

37. Weather, Climate, and Sustainability

37.1 Learned weather forecasting

Numerical weather prediction is one of the great achievements of computational science: solving the equations of atmospheric fluid dynamics on a global grid to forecast the weather days ahead. It is also enormously expensive, requiring the largest supercomputers and hours of computation per forecast. We have shown that a neural network trained on decades of reanalysis data — the historical record of the atmosphere's state, reconstructed by assimilating observations into physical models — can produce global forecasts that match or exceed the accuracy of the leading physics-based systems, while running in seconds on a single accelerator rather than hours on a supercomputer. The model learns to advance the atmospheric state forward in time, capturing the dynamics implicitly from data rather than integrating the primitive equations explicitly. The thousand-fold speedup is not merely convenient: it enables large ensembles that quantify forecast uncertainty, rapid exploration of scenarios, and forecasting at a cadence and resolution that physics-based systems cannot afford.

It is worth being precise about why this works, because weather forecasting is the cleanest example in this part of a learned surrogate beating the simulation it was trained to imitate. The reanalysis dataset is itself the product of physics — billions of observations fused with a physical model into a best estimate of the atmosphere's state every few hours for decades. A neural network trained to map the state at one time to the state hours later is therefore distilling the dynamics of a physics-based system into a function approximator, and it can outperform direct integration of the primitive equations for a subtle reason: the explicit solver must resolve fast, small-scale processes it cannot afford to compute accurately and so parameterizes crudely, whereas the learned model absorbs the statistical effect of those unresolved processes directly from the data. The surrogate is not approximating the equations; it is approximating the atmosphere, which is the thing we actually care about. This distinction — learning the system rather than the model of the system — is the deepest reason learned surrogates can exceed, and not merely accelerate, classical simulation.

37.2 Extremes, ensembles, and seasonal-to-climate scales

Accuracy on the typical day matters less than skill on the dangerous one. We focus particular effort on extreme events — cyclone tracks and intensities, heat waves, atmospheric rivers, extreme precipitation — where forecast skill translates directly into lives and property protected. Generative ensemble approaches model the full probability distribution of future weather rather than a single trajectory, producing physically consistent, calibrated samples from which the likelihood of extremes can be read. Extending the time horizon, we are pushing learned models toward subseasonal and seasonal prediction, where the relevant predictability comes from slowly varying boundary conditions like ocean temperatures and soil moisture, and ultimately toward climate-scale emulation: fast surrogates of climate models that allow many more scenarios to be explored, downscaling of coarse projections to local impact-relevant resolution, and better characterization of the deep uncertainties in long-range projection.

37.3 Sustainability and the optimization of physical systems

Beyond prediction, learned models optimize the physical systems through which humanity uses energy and resources. We apply reinforcement learning and predictive control to reduce the energy consumption of large facilities such as data-center cooling; to improve the dispatch and forecasting of renewable generation, making intermittent wind and solar more usable on the grid; and to optimize industrial processes for efficiency and reduced emissions. The common structure is a controllable physical system with expensive-to-evaluate dynamics, a measurable objective, and ample telemetry — precisely the setting where a learned model of the system enables control or optimization that classical methods cannot match. Sustainability, in this framing, is a portfolio of such optimization problems, each one a few percent of a very large global quantity, and a few percent of a very large quantity is itself very large.

38. Neuroscience and the Brain

38.1 The reciprocal relationship between AI and brain science

Artificial intelligence and neuroscience have always been intertwined: the brain is the existence proof that general intelligence is physically possible, and many of the ideas at the foundation of deep learning — distributed representations, hierarchical feature extraction, reinforcement learning, attention — have roots in or parallels with neuroscience. We pursue this relationship in both directions. From neuroscience to AI, the brain offers inspiration for architectures and learning rules, and a set of capabilities — sample-efficient learning, continual adaptation, robust generalization, energy efficiency — that current systems lack and that biological intelligence demonstrably achieves. From AI to neuroscience, our models serve as tools and as hypotheses about how the brain itself computes.

38.2 Models as instruments and as theories of the brain

As instruments, deep networks let neuroscientists make sense of data at scales that defy manual analysis: segmenting and reconstructing the wiring of brain tissue from electron-microscopy volumes to build connectomes, a task involving the tracing of millions of neurites through petabyte-scale image volumes that is simply impossible by hand; decoding behavior and intention from neural recordings; modeling the dynamics of large neural populations. As theories, trained networks have become the best available quantitative models of sensory cortex. A convolutional network trained to recognize objects, it turns out, develops internal representations that predict the responses of neurons in the primate visual system better than any hand-designed model — and similar correspondences appear in audition and in language, where the internal states of large language models predict measured brain activity during comprehension. This convergence suggests that the representations learned by task-optimized networks and by brains under evolutionary and developmental pressure are, at some level, the same solutions to the same problems. We exploit this by using artificial networks as differentiable models of neural systems — running in silico experiments, generating hypotheses about coding and computation,

and even synthesizing stimuli predicted to drive specific neural populations, hypotheses then tested in the living brain.

38.3 Toward a computational account of cognition

The longest-horizon ambition is to contribute to a computational account of cognition itself — of how flexible, general, sample-efficient intelligence arises from neural computation. This is where our scientific mission and our core research program most directly meet: understanding the principles of natural intelligence and building artificial intelligence are, at the deepest level, two faces of the same inquiry. We approach it with humility about how far current systems remain from the brain's efficiency and generality, and with the conviction that closing that gap is both a scientific prize and a practical necessity.

39. AI as an Instrument of Science

39.1 The pattern, made explicit

Across every domain in this part, the same pattern recurs, and it is worth stating as a general principle. A scientific problem often has the structure of an intractable forward map governed by known but expensive physics, paired with abundant data in which that map is implicitly recorded. A learned model trained on the data becomes a fast, differentiable surrogate for the map. That surrogate then unlocks three distinct capabilities that the original simulation could not provide. First, acceleration: computations that took supercomputer-hours take accelerator-seconds, changing not just the cost but the kinds of questions one can ask. Second, inversion: because the surrogate is differentiable, the forward map can be run backward — from desired property to molecule, from target structure to sequence, from goal to design — turning prediction into design. Third, discovery: the learned representation itself, when interrogated, reveals structure that no one put in by hand, suggesting hypotheses a human scientist can pursue. The trained model is, in this sense, a new class of scientific instrument, as the telescope and the microscope and the particle accelerator were before it — an apparatus that extends the reach of inquiry into regimes the unaided scientist could not access.

39.2 What makes a good target, and what success requires

Choosing where to apply this instrument well is itself a discipline. The problems where learned surrogates succeed share identifiable features: a vast search or configuration space; a forward map that is expensive but well-defined; data that, though imperfect, samples the map richly; and exploitable structure — symmetry, locality, compositionality — that a well-designed architecture can encode. Equally important is the verification layer. A surrogate's prediction is a hypothesis, and a scientific instrument is only trustworthy if its outputs can be checked against ground truth: a synthesized crystal, a folded protein measured by cryo-EM, a proof checked by a kernel, a forecast scored against tomorrow's weather, a controller run on a real tokamak. We therefore design every program around a tight loop between in-silico proposal and real-world validation, and we report success in the units that matter to the domain — lab-

oratory hit-rates, confirmed structures, validated materials, forecast skill on extremes, theorems proved — rather than in proxy metrics alone. An instrument that cannot be calibrated against reality is not an instrument; it is a guess.

39.3 Calibration, uncertainty, and the integrity of automated science

As learned models take on more of the scientific loop — proposing experiments, interpreting results, suggesting the next move — the integrity of the science depends on honest uncertainty. A surrogate that is confidently wrong outside its training distribution will waste laboratory resources and, worse, mislead. We invest heavily in uncertainty quantification — ensembles, calibrated confidence, out-of-distribution detection — so that a model knows, and reports, when it is extrapolating beyond what it has learned. Active learning closes the loop in the other direction: when the model is uncertain, that uncertainty becomes the signal directing the next real experiment, so that costly empirical effort is spent precisely where it most reduces ignorance. Done well, this turns the model's humility into the engine of discovery rather than a limitation of it.

39.4 The arc of impact

The chapters of this part describe applications at very different stages of maturity — from protein structure prediction, already a routine tool transforming biology worldwide, to virtual-cell models and AI-driven mathematical discovery, still early and unproven at scale. What unites them is a trajectory. In each domain, a learned instrument first matches human or classical capability, then exceeds it on speed and scale, then enables the inverse-design and discovery modes that have no classical analog, and finally becomes infrastructure — a tool so embedded in practice that the science of the domain reorganizes around it. This is the concrete meaning of our mission's second clause, to "use it to advance science and benefit humanity": not a single breakthrough but a compounding acceleration, distributed across the disciplines on which human flourishing depends. Solving intelligence is the means; the dissolution of grand scientific challenges, one differentiable surrogate at a time, is the end by which the work should ultimately be measured.

It is finally worth naming what is genuinely new here, lest the recurring "surrogate" framing make these advances sound merely like faster versions of what came before. A telescope let us see further; a microscope let us see smaller; but neither could be run backward to design a star or compose a cell. The differentiable scientific instrument can. Because it is a learned function with gradients, it supports not only observation but optimization, not only prediction but design, not only answering a question but proposing which question to ask. That inversion — the conversion of a forward model of nature into a generator of useful novelty — is the qualitative leap that distinguishes this instrument from its predecessors, and it is why we believe the coming decades of science will be organized increasingly around learned models. The proteins we could not fold are folding; the materials we could not find are being found; the weather we could not forecast fast we now forecast in seconds. Each of these was, until recently, a frontier. The thesis of this part is that the frontier itself is moving, and that a laboratory built

to move it deliberately, domain by domain, with rigor and verification at every step, is the most direct expression of a mission to use intelligence for the benefit of humanity.

Part VII — The Roadmap

A research program without a roadmap is a wish. A roadmap without epistemic humility is a hallucination. This Part lays out how RMH Deeplink sequences its work across time — the bets we are making over one, five, and ten years — and, just as importantly, how we hold those bets loosely enough to revise them when the world disagrees. The pillars, methods, safety architecture, and scientific applications described elsewhere in this thesis are the *what* and the *how*. This is the *when*, the *in what order*, and the *how we will know*.

We write this roadmap in the knowledge that almost every dated prediction in the history of artificial intelligence has been wrong, and that most have been wrong in the optimistic direction. We do not exempt ourselves from this tendency. What follows is therefore not a forecast we expect to be vindicated line by line. It is a structured set of commitments, conditional milestones, and decision rules — an instrument for steering, not a prophecy. Its value lies less in the accuracy of any single dated claim than in the discipline it imposes: naming what we expect, what would surprise us, and what would make us stop.

40. How We Think About Timelines and Milestones

40.1 The epistemics of forecasting capability

The central difficulty of planning frontier AI research is that the quantity we most want to predict — when a given cognitive capability will emerge at a given reliability — is precisely the quantity our field has proven least able to predict. We have learned to treat capability forecasting as a problem in calibrated uncertainty rather than point estimation. When we say a milestone is targeted for a particular year, we mean something specific: that our median estimate, conditioned on current trajectory and planned compute, places the milestone in that window, with an interquartile range we state explicitly and a tail we take seriously on both ends.

Three structural facts shape our forecasting. First, scaling laws give us unusually good predictive traction on *loss* — the smooth, low-variance quantity — while giving us almost none on *capabilities*, the discontinuous, emergent quantities that actually matter for science and safety. A two-orders-of-magnitude reduction in next-token loss is forecastable to within a few percent; whether that reduction unlocks reliable multi-step theorem proving is not. We therefore maintain two distinct forecasting tracks: a *quantitative* track for loss, throughput, and cost curves, where we extrapolate with genuine confidence, and a *qualitative* track for capability thresholds, where we reason in scenarios and probability mass rather than dates.

Second, the binding constraints on progress shift over time, and a roadmap that optimizes against last year's constraint will mis-sequence this year's work. In the early scaling era the binding constraint was parameter count; later it was high-quality data; today, for our program, it is increasingly a combination of inference-time compute economics, evaluation bandwidth, and the throughput of our automated research loops. We revisit the binding-constraint question every planning cycle and let it, rather than inertia, dictate where marginal effort goes.

Third, capability and reliability decouple, and the gap between them is where most of the calendar disappears. A model that can do a task once in twenty attempts has the capability; a model that can be deployed to do that task in a scientific or safety-critical setting needs it nine-thousand-nine-hundred times in ten thousand. The distance between those two points — what we internally call the *reliability tax* — has consistently been longer than our naive estimates, and our roadmap now budgets for it explicitly at every horizon.

40.2 Milestones as falsifiable commitments

We distinguish sharply between aspirations and milestones. An aspiration is a direction; a milestone is a claim that can be checked. Every milestone in this roadmap is constructed to be falsifiable: it names a capability, a benchmark or evaluation protocol, a reliability threshold, and a date window. "Improve scientific reasoning" is not a milestone. "Achieve ≥80% on the held-out FrontierProof formal-mathematics suite at first-attempt success, on problems authored after the model's training cut-off, by end of the five-year horizon" is one. The difference is not pedantry. A falsifiable milestone can fail, and a milestone that can fail can generate a learning signal; an aspiration can only be reinterpreted.

We organize milestones into three tiers. *Capstone* milestones are the small number of headline results that define a horizon and that we would point to as evidence the program is on track — typically a flagship model generation or a first-in-class scientific result. *Enabling* milestones are the infrastructure, dataset, evaluation, and safety deliverables without which the capstones are impossible; they are less visible but more numerous, and slippage here is the leading indicator of slippage everywhere. *Tripwire* milestones are inverted: they are conditions we hope *not* to hit, defined in advance, whose crossing triggers a pre-committed response — a pause, a review, or a change of course. A roadmap with only forward milestones is a roadmap that cannot tell you when to stop, and is therefore not a safe roadmap.

40.3 The cadence of revision

We run the roadmap on a nested cadence. The ten-year horizon is restated annually but expected to drift; we treat it as a vector, not a coordinate. The five-year horizon is reviewed semi-annually and replanned annually. The one-year horizon is planned quarterly and tracked continuously through our internal evaluation harness. Each cadence has a designated forum, a designated owner, and a designated set of metrics, so that the question "are we on track?" always has a place to be asked and an evidentiary standard for answering it.

Crucially, revision is not failure. We have institutionalized the expectation that a meaningful fraction of our bets will be wrong, and we measure the health of the planning process not by how often the plan holds but by how quickly the plan updates once the evidence is in. A team that hits every milestone on schedule is, to us, weak evidence that it set its milestones too conservatively. We would rather miss an ambitious milestone and learn precisely why than hit a timid one and learn nothing.

41. The One-Year Horizon: Near-Term Bets and Deliverables

41.1 The flagship: the Meridian generation

The center of gravity for the coming year is the **Meridian** model generation — our next flagship family, succeeding the current frontier line. Meridian is not defined primarily by parameter count; it is defined by three capability commitments. The first is *durable multi-step reasoning*: sustained chains of inference across hundreds of dependent steps without the silent error accumulation that limits the current generation to shorter horizons. The second is *tool-grounded reliability*: the ability to call external tools — solvers, simulators, retrieval systems, code execution — and, critically, to detect and recover from tool failures rather than confabulating around them. The third is *calibrated abstention*: knowing, and saying, when it does not know, at a reliability we can measure and certify.

Meridian ships as a tiered family — Meridian-Lite, Meridian, and Meridian-Pro — sharing a training lineage but differentiated by inference budget, so that the same capability frontier can be accessed at radically different cost points depending on the stakes of the task. We commit to a public capability report and an accompanying safety case for each tier before deployment, consistent with the evaluation and governance practices established elsewhere in this thesis.

41.2 Reasoning, reliability, and the reliability tax

Within the year, the largest single research investment is in closing the reliability gap rather than extending the raw capability frontier. We expect this to be the unglamorous, decisive work of the horizon. Concretely, we target an order-of-magnitude reduction in the per-step error rate on long reasoning chains relative to the current generation, measured on our internal **LongChain** evaluation suite, which stresses tasks whose correct completion requires no single error across 50 to 500 dependent steps. The headline number we are organizing around is moving from roughly two-nines to roughly three-nines of per-step reliability on the core suite, because that is the threshold at which end-to-end success on hundred-step scientific workflows crosses from occasional to dependable.

This work is where the *reliability tax* introduced above is paid down. We attack it on three fronts simultaneously: process-level supervision that rewards correct intermediate reasoning rather than only correct final answers; verifier models trained specifically to catch the failure modes that human raters miss; and inference-time strategies — structured search, self-consistency, and adversarial self-critique — that trade compute for reliability in a way we can dial up for high-stakes deployments.

41.3 Evaluation and safety deliverables

A capability roadmap that outpaces its evaluation roadmap is, by our standards, out of control. We therefore treat evaluation infrastructure as a first-class near-term deliverable. Within the year we commit to ship **Crucible v2**, our internal evaluation platform, with three properties the current version lacks: held-out, continuously refreshed test sets authored after each training cut-off to defeat contamination; automated capability elicitation that searches for a model's true ceiling rather than measuring its default behavior; and per-capability dangerous-capability evaluations integrated directly into the release gate, so that no model generation ships without a documented dangerous-capability profile.

On the safety side, the near-term deliverables are the dangerous-capability evaluation suite covering the agreed frontier risk categories, an interpretability toolkit capable of auditing the flagship at the level of identifiable internal features and circuits, and a first version of our automated red-team that uses a model to attack another model under controlled conditions. These are not separate from the capability program; they are its gating function, and they are resourced as such.

41.4 The automated research loop

The most strategically important near-term bet is partly invisible from the outside: standing up the first production version of our **automated research loop**, in which models propose experiments, write and run the code, analyze the results, and draft the findings, with human researchers supervising at the level of research direction rather than individual experiment. Within the year we target a regime in which a meaningful fraction — our internal goal is one in four — of the routine experiments in select research workstreams are designed and executed end-to-end by the system under human review. This is a compounding bet: every increment of automation here accelerates everything downstream, and it is the single lever most likely to bend the curve of the five- and ten-year horizons. The near-term deliverable is not a fully autonomous researcher; it is a reliable, auditable collaborator that removes a quarter of the toil and, in doing so, frees human research capacity for the problems that still require it.

42. The Five-Year Horizon: Capability Targets, Scientific Milestones, Infrastructure

42.1 Capability targets and model generations

Across the five-year horizon we anticipate three further flagship generations beyond Meridian — provisionally **Solstice**, **Apex**, and **Helios** — each separated by a roughly fifteen- to eighteen-month cadence and each defined by a capability thesis rather than a scale target. The cadence itself is a hypothesis we hold loosely; if the automated research loop compounds as we hope, generations may arrive faster, and if the reliability tax proves heavier than budgeted, slower.

The capability thesis for the horizon as a whole is the transition from *assistant* to *agent* to *autonomous contributor* in bounded domains. Meridian is an assistant that reasons well. Solstice, the first generation

of the horizon, targets *robust agency*: reliable multi-hour autonomous task execution with the ability to plan, monitor its own progress, recognize when it is off-track, and ask for help appropriately — the agentic reliability that turns demos into deployable systems. Apex targets *autonomous research contribution* in narrow scientific domains: the ability to take a genuine open sub-problem, propose and execute a research plan, and produce a result a domain expert would credit as novel, not merely a rederivation. Helios, at the far edge of the horizon and the most speculative, targets *cross-domain transfer at expert level* — the capacity to carry insight and method from one scientific field into another, which is the hallmark of the most productive human scientists and a capability we believe sits close to the threshold this entire program exists to cross.

We attach a concrete numerical anchor to the horizon: by its end, we target a flagship that achieves expert-level performance, certified at deployment-grade reliability, on at least three of our designated **Hard Science** evaluation domains — domains constructed so that strong performance cannot be achieved by retrieval or pattern-matching and demonstrably requires the multi-step reasoning the program is built to deliver.

42.2 Scientific milestones

The purpose of the capability program is scientific output, and the five-year horizon is where the mission's first major external dividends should appear. We name three capstone scientific milestones, chosen because they are ambitious, checkable, and broadly useful, while leaving the detailed science to the relevant Part of this thesis.

The first is in the life sciences: a model-driven contribution to the understanding of a disease-relevant biological mechanism that is experimentally validated by an external partner laboratory — not a prediction we score ourselves, but a hypothesis the system generated that wet-lab work confirmed. The bar is external validation, because that is the bar that separates a benchmark from a discovery.

The second is in the physical and materials sciences: the design and experimental confirmation of a material with a target property specified in advance — a closed loop from specification through model-driven design to synthesis and measurement, demonstrating that the system can be pointed at a goal and deliver a physical artifact, not merely a paper.

The third is in mathematics: a contribution to the resolution of a recognized open conjecture, or a substantial reduction of one, with a proof or proof-sketch that the mathematical community independently verifies. Formal mathematics is our cleanest proving ground because correctness is machine-checkable, contamination is controllable through post-cutoff problem authorship, and the gap between "plausible" and "correct" — the same gap as the reliability tax — is unforgiving.

Each of these is a capstone; behind each sit dozens of enabling milestones in data, tooling, simulation integration, and domain-expert collaboration, without which the capstone is unreachable.

42.3 Infrastructure and the compute trajectory

The five-year horizon is gated as much by infrastructure as by ideas. We plan for an order-of-magnitude-plus growth in our standing training and inference capacity, but the more consequential infrastructure bets are qualitative. The first is the maturation of the automated research loop from the near-term "one in four experiments" regime toward a majority of routine research execution, with the human role migrating decisively toward direction-setting, judgment, and oversight. The second is the evaluation infrastructure: as models begin to contribute autonomously, the bottleneck shifts from *generating* candidate results to *trusting* them, and our investment in automated verification, reproduction, and adversarial checking must scale faster than the generative capability it polices. The third is the inference economy: pushing the cost of a unit of reliable reasoning down by another order of magnitude, because the scientific value of the system is bounded not by what it can do once but by how cheaply it can do it ten thousand times.

We also plan, across this horizon, for the institutionalization of safety infrastructure that is currently bespoke: standing interpretability tooling that scales to each new flagship, a continuously running automated red-team, and a control framework for the increasingly autonomous research loop, so that the same automation that accelerates progress remains legible and interruptible. Safety infrastructure that does not scale with capability is, in our framing, a tripwire being slowly disabled.

43. The Ten-Year Horizon: The Path Toward AGI and What It Unlocks

43.1 What we mean by AGI, and what we do not

The ten-year horizon is organized around the mission's terminal objective, and so we must be precise about a word that is more often invoked than defined. By artificial general intelligence we mean a system that can perform, at or above the level of expert humans, the full range of cognitive tasks involved in scientific research — including the open-ended, ill-posed, cross-domain tasks that resist benchmarking — and that can do so reliably, autonomously, and safely enough to be trusted with consequential work. We deliberately anchor the definition in scientific capability rather than in any general claim about matching humans at all tasks, because science is our mission, our cleanest measuring stick, and the domain where transformative capability does the most good.

We do not mean by AGI a system with its own ends, nor do we treat the arrival of AGI as a discrete event with a date. We expect the approach to AGI to be a *gradient*, not a step: a steady extension of the domains in which the system is an autonomous expert contributor, a steady lengthening of the time horizons over which it can be trusted to act, and a steady erosion of the boundary between problems that require a human in the loop and problems that do not. The ten-year horizon is the period over which we believe that gradient, if our bets compound, plausibly crosses the threshold at which the system can meaningfully accelerate its own underlying science — the point of greatest opportunity and greatest hazard.

43.2 The path: from narrow autonomy to general scientific competence

The throughline of the ten-year horizon is the generalization of the autonomous-contributor capability targeted in narrow domains during the five-year horizon. The path, as we currently model it, has three legs. The first leg, substantially the work of the five-year horizon, is *narrow autonomous contribution*: the system is a trusted expert collaborator in a handful of well-instrumented scientific domains. The second leg is *broad autonomous contribution*: the number of such domains grows from a handful to most of science, driven less by bespoke per-domain engineering than by the system's improving ability to learn a new field from its literature, its tools, and a small amount of expert interaction — the transfer capability anchored by the Helios generation. The third and final leg is *recursive scientific acceleration*: the system contributes materially to the science of building better systems — to the algorithms, the training methods, the evaluation science, and the safety techniques that define the program itself.

This third leg is where the curve potentially bends sharply, and it is also where our caution is greatest. A system that improves the science of its own construction is the mechanism by which timelines could compress dramatically below the medians in this roadmap. We take this scenario seriously enough to plan for it explicitly, and our position is unambiguous: acceleration of this kind is permissible only inside a control and oversight regime that scales ahead of it. The off-ramps and tripwires of Chapter 44 are written primarily with this leg in mind. We would rather forgo a year of acceleration than enter recursive improvement with our oversight tooling trailing the capability it is meant to oversee.

43.3 What it unlocks

If the path holds, the ten-year horizon is where the mission's second clause — *use it to advance science and benefit humanity* — becomes the dominant activity rather than the eventual hope. The capability we are building is, at bottom, a general-purpose engine for turning well-posed scientific questions into validated answers, and a partial engine for turning ill-posed ones into well-posed ones. Pointed at the life sciences, such an engine compresses the discovery-to-validation cycle for therapeutics and diagnostics. Pointed at energy and materials, it accelerates the search for the catalysts, storage chemistries, and materials that the climate transition requires. Pointed at the foundational sciences, it serves as a tireless collaborator on the open problems — in mathematics, in physics, in the theory of computation and intelligence itself — whose resolution reshapes what is subsequently possible.

We are deliberately restrained in describing these unlocks, for two reasons. The first is epistemic honesty: the further out the horizon, the wider the distribution, and confident specificity about ten-year scientific outcomes would contradict everything Chapter 40 argues. The second is that the most important unlocks are, by their nature, the ones we cannot currently name — the discoveries that are invisible from here precisely because making them requires the capability we do not yet have. The honest statement of what AGI unlocks is therefore not a list of results but a change in the rate at which results of every kind arrive, coupled with a hard commitment that the benefits be broadly distributed rather

than captured. The roadmap's ten-year purpose is to reach that change in rate with our safety, our oversight, and our institutional judgment intact.

44. Milestones, Metrics, and Knowing We Are On Track

44.1 The metrics that matter, and the ones that mislead

Knowing whether we are on track requires metrics, and choosing metrics is itself a high-stakes act, because a metric, once chosen, becomes a target and begins to corrupt. We organize our tracking around a small set of *true-north* metrics, deliberately resistant to gaming, and a larger set of *instrumental* metrics that we watch but never optimize directly.

Our true-north metrics are three. The first is *validated scientific output*: the count and significance of results the system contributed to that were independently confirmed by parties who did not build the system. This is the metric closest to the mission and the hardest to fake, because external validation is outside our control. The second is *reliable capability frontier*: the hardest task class the flagship performs at deployment-grade reliability, measured on contamination-resistant, post-cutoff evaluations — capability and reliability fused into a single number rather than the more flattering capability-alone figure. The third is *oversight margin*: a composite measure of how far our safety, interpretability, and control tooling leads or trails the capability it must govern. Of the three, oversight margin is the one we will not allow to go negative, and it is the metric that can halt the program.

The instrumental metrics — loss curves, benchmark scores, inference cost, automated-research-loop throughput, the fraction of experiments run autonomously — are the daily instrumentation of the program. They are essential for steering and dangerous for judging, and we treat any sustained divergence between an instrumental metric racing ahead and a true-north metric standing still as a signal that we are optimizing the proxy and losing the target.

44.2 Leading indicators and the early-warning system

Lagging metrics tell you where you have been. To know where we are going, we watch leading indicators on both the capability and the safety sides. On the capability side, the strongest leading indicator we have found is the *autonomy horizon*: the length of time, or equivalently the number of dependent steps, over which the system can be trusted to act without human correction. This single quantity has tracked the transition from assistant to agent to contributor more faithfully than any benchmark, and we report it as a headline. A second capability leading indicator is *transfer efficiency*: how little domain-specific data and expert interaction the system needs to reach competence in a genuinely new field — the quantity that, if it improves sharply, signals the approach of the broad-contribution leg of the ten-year path.

On the safety side, our leading indicators include the rate at which our automated red-team discovers novel failure modes (a falling rate at constant effort is reassuring; a rising rate signals capability outrun-

ning understanding), the fraction of model behavior our interpretability tooling can mechanistically explain, and the latency between a model exhibiting a new capability and our evaluations being able to detect and characterize it. This last quantity — *evaluation lag* — is, in our view, the most important safety leading indicator of all, because a program whose capabilities arrive faster than its ability to measure them is a program flying blind, regardless of how good its safety intentions are.

44.3 Off-ramps, tripwires, and failure signals

A roadmap that can only go forward is unsafe by construction. We therefore pre-commit, in advance and in writing, to a set of *tripwires* — conditions whose occurrence triggers a pre-specified response that does not require a fresh argument to be won in the moment. Pre-commitment is the entire point: the time to decide what to do about a dangerous capability is before it exists, when the decision can be made calmly and is not contaminated by the sunk cost and competitive pressure that will be present when the tripwire actually trips.

Our tripwires fall into three families. *Capability tripwires* fire when an evaluation detects a dangerous capability above a threshold — for instance, meaningful uplift on the designated frontier-risk evaluations — and trigger, at minimum, a deployment hold and an escalated safety review before any further training or release. *Oversight tripwires* fire when the oversight-margin metric falls toward zero — when capability is converging on the limits of our ability to interpret, evaluate, or control it — and trigger a reallocation of effort from capability to safety until margin is restored, up to and including a training pause. *Integrity tripwires* fire when we detect that our own measurement instruments are compromised: evidence of evaluation contamination, of the system behaving differently under observation than in deployment, or of an instrumental metric being optimized at the expense of a true-north one. Integrity tripwires are the subtlest and, we suspect, the most likely to actually save us, because they guard the epistemics on which every other safeguard depends.

Equally important are *off-ramps* — the recognition that specific research bets, not just the program as a whole, can and should be abandoned. We define failure signals for each major bet in advance. If the automated research loop, after sustained investment, does not produce a measurable acceleration in research throughput, that is an off-ramp, and we redeploy. If a scientific capstone proves unreachable not for lack of effort but because the underlying capability is further away than modeled, we say so, bank the learning, and re-sequence rather than redefine success downward to claim a hollow victory. The willingness to take an off-ramp is, in our culture, a sign of strength and not of failure; the alternative — pouring effort into a dead bet to protect a forecast — is how research programs quietly rot.

44.4 Governance of the roadmap itself

Finally, the roadmap is only as good as the institution that holds it, and so we close by naming how the roadmap governs itself. Every horizon has an owner accountable for its milestones; every tripwire has a designated authority empowered to trigger the pre-committed response without seeking permission

from the people whose work would be paused, because a safety brake that the accelerator controls is not a brake. The true-north metrics are reported on a fixed cadence to a forum with the standing to halt the program, and the gap between our stated medians and our actual results is itself tracked over time as a measure of our forecasting calibration — we keep score on our own predictions and publish the scoreboard internally, so that a pattern of optimistic error is caught and corrected rather than repeated.

The deepest commitment in this Part is not to any date or any milestone. It is to a way of relating to the future under deep uncertainty: to state our bets precisely enough that they can be wrong, to instrument them honestly enough that we will notice when they are, to pre-commit to stopping before the stakes make stopping impossible, and to revise without ego when the evidence demands it. The destination is fixed by the mission — to solve intelligence, and to use it to advance science and benefit humanity. The path is not, and our central claim about the roadmap is that this is exactly as it should be. A program that knew the path in advance would be solving a problem too small to be worth this much care. We expect to be surprised. The discipline laid out here is how we intend to be surprised safely, and how we intend to keep moving toward the destination when the map and the territory, as they inevitably will, disagree.

Part VIII — Organization & Culture

The preceding parts of this thesis have argued for a particular view of intelligence and a particular program for building it: that general intelligence is a buildable artifact, that it decomposes into capacities we can study and assemble, that its construction must be inseparable from the discipline of making it safe, and that the resulting systems can be turned, deliberately and at scale, toward the advancement of science and the benefit of humanity. None of that happens by intellectual content alone. A thesis is a set of claims; a laboratory is the machine that converts claims into evidence, and evidence into capability. The questions of organization and culture are therefore not administrative footnotes appended to the science. They are part of the science, in the precise sense that the structure of the institution determines which experiments get run, which results get believed, which mistakes get caught, and which ambitions survive contact with reality. A research agenda as long-horizoned and as consequential as RMH Deeplink's cannot be sustained by good intentions. It must be engineered into the way the lab is built.

This part describes how RMH Deeplink is organized to pursue its mission, the operating principles and culture that give that organization its character, the model by which it collaborates internally and with the wider scientific world, the philosophy by which it finds and grows the people who do the work, and the financial and governance arrangements that secure its independence while binding it to a parent company, RMH Studios. The argument throughout is that each of these choices is downstream of the mission and the scientific thesis — that we have not adopted a generic "research lab" template and then filled it with AI, but rather derived an institution from first principles about what solving intelligence actually requires.

45. How the Lab Is Structured

The structure of a research organization is a hypothesis about where progress comes from. Some labs are built around the conviction that breakthroughs are the product of a small number of exceptional individuals given unlimited freedom; they organize as loose federations of principal investigators. Others believe progress is fundamentally an engineering problem of scale and are organized like product companies, with tight roadmaps and large coordinated teams. RMH Deeplink rejects the premise that these are the only two options, because the scientific thesis it pursues spans both regimes. The foundational questions — what is the right learning paradigm, how does an agent represent the world, what is the structure of safe goal-directedness — reward deep, patient, individually-driven inquiry. The translation of those answers into systems that fold proteins, design materials, prove theorems, and operate reliably in the world rewards large-scale, tightly-coordinated engineering. An institution that can only do one of these will, at best, hand its discoveries to someone else to complete. We have therefore built a structure that holds both modes in productive tension rather than forcing a choice between them.

At the highest level, the lab is organized into three concentric layers, which we describe not as a hierarchy of importance but as a gradient of time horizon and coupling to application. The innermost layer is **Foundational Research**: the organizations responsible for the science of intelligence itself. These are grouped into research areas that mirror the structure of the thesis rather than the structure of any product — learning and representation, agency and decision-making, reasoning and abstraction, world models and embodiment, and the cross-cutting science of alignment and interpretability. Foundational Research is deliberately insulated from quarterly pressure. Its currency is understanding, and its outputs are often negative results, refined questions, and capabilities that will not pay off for years. A research area is led not by a manager in the conventional sense but by a research lead whose primary job is to maintain the intellectual coherence of the area's agenda, to recruit and protect the people working in it, and to ensure that the area's questions remain connected to the lab's central thesis rather than drifting into locally interesting but globally irrelevant cul-de-sacs.

The middle layer is **Programs**: the mission-directed efforts that take capabilities emerging from Foundational Research and aim them at specific scientific or societal targets. Programs are where the lab's promise to "advance science and benefit humanity" becomes concrete and falsifiable. A program has a thesis of its own — a claim that a particular cluster of capabilities, organized in a particular way and pointed at a particular domain, can produce an outcome that matters in the world. Programs are time-bound in their ambitions even when they are open-ended in their horizons; each carries an explicit statement of what success would look like and what would constitute evidence that the bet was wrong. Crucially, a program is a structure for coupling research and engineering, not for subordinating one to the other. The biology program, the materials program, the mathematics and formal-reasoning program, and the program for scientific tooling and autonomous experimentation each braid together foundational researchers, research engineers, domain scientists, and product-minded builders into a single team with a single goal. This is the layer where the lab most resembles DeepMind's own history: the same arc that runs from a general method for learning to play games, through a system that masters Go, to a system that predicts protein structure, is the arc from Foundational Research through a Program to a result that reshapes a scientific field.

The outermost layer is **Platform and Support functions**: the infrastructure, the compute and data systems, the safety and governance institutions, the legal and policy teams, the recruiting and people functions, and the operational backbone that makes everything else possible. It is a recurring error of research institutions to treat these functions as overhead — as a cost to be minimized rather than a capability to be cultivated. RMH Deeplink treats them as first-class. The team that builds and operates our training infrastructure is not a service desk; it is a research organization in its own right, because at frontier scale the questions of how to train a model efficiently and reliably are themselves unsolved scientific questions, and the lab that answers them best has a durable advantage that no amount of algorithmic cleverness can substitute for. The same is true of the data systems that determine what our models learn from, the evaluation systems that determine what we believe about them, and the safety

institutions described at length in earlier parts. Platform functions are the only layer that touches every program and every research area, which gives them a unique systemic responsibility and a unique systemic leverage.

These three layers are crossed by a set of **standing institutions** that exist precisely because they must not belong to any single research area or program. The most important of these is the safety and responsibility apparatus — the review bodies, the red teams, the evaluation authorities, and the governance functions that earlier parts established as non-negotiable. By design, these institutions report through a path independent of the programs whose work they evaluate, so that the people responsible for deciding whether a system is safe to deploy are never the same people whose success is measured by deploying it. We will return to this separation of powers when we discuss culture and governance, because it is one of the load-bearing structural commitments of the entire enterprise. Alongside safety sit the other cross-cutting institutions: a central science council that arbitrates the allocation of the lab's scarcest resource, frontier compute; an ethics and societal-impact body; and the open-science and publications function that mediates between the lab's instinct toward openness and its responsibilities toward caution.

The relationship among these layers is not a pipeline. It is tempting to imagine Foundational Research producing capabilities that flow downstream into Programs that flow downstream into the world, but the actual flow is bidirectional and turbulent. Programs surface the hardest unsolved problems and feed them back into Foundational Research, often reshaping the foundational agenda more profoundly than any internal deliberation would. The protein-structure problem did not merely consume a learning method; it taught the field new things about how to represent geometry, how to inject domain structure into general architectures, and how to evaluate systems against ground truth that no benchmark had anticipated. Platform functions, similarly, do not merely serve research; the constraints they expose — what is actually trainable, what is actually servable, what is actually affordable — are among the most important shapers of which research directions are worth pursuing at all. The structure is designed to keep these feedback loops short and honest, so that the lab is continuously corrected by the reality of what it is trying to build.

46. Research Culture and Operating Principles

Structure determines what is possible; culture determines what actually happens. A laboratory can have an impeccable organizational chart and still fail, because the chart says nothing about whether people tell each other the truth, whether they are willing to kill their own ideas, whether they reward the right things, or whether they can disagree without fracturing. The culture of RMH Deeplink is not a list of values printed on a wall. It is a set of operating principles, each of which was chosen because the scientific thesis makes it necessary, and each of which is reinforced by concrete practices rather than by exhortation.

The first principle is **truth-seeking over narrative**. The deepest pathology available to a frontier lab is the temptation to believe its own announcements — to confuse the impressiveness of a demonstration with the reality of a capability, to let the story the field wants to hear override the evidence the experiments actually produced. We treat this temptation as the central enemy of good research, because a lab that fools itself about what its systems can do is a lab that will eventually fool itself about whether they are safe. In practice this means that internal evaluation is held to a higher standard than external communication, never the reverse; that negative and ambiguous results are recorded and circulated rather than buried; that we maintain adversarial evaluation functions whose explicit job is to find the cases where a celebrated capability breaks; and that claims about a system are expected to come with their failure modes attached. The cultural marker of a healthy research meeting at RMH Deeplink is not the presentation of a triumph but the eagerness with which the room hunts for the reason the triumph might be illusory.

The second principle is **the unity of capability and safety**. Earlier parts argued at length that safety is not a constraint applied after the fact but a property that must be built in from the start, and that the science of alignment and the science of capability are not separable. Culturally, this means we refuse the framing — common in the wider field — that pits a "safety team" against a "capabilities team" as if they were natural adversaries with opposed incentives. At RMH Deeplink, the most capable researchers are expected to care about safety as a technical problem worthy of their best work, and the safety institutions are staffed not with people who slow others down but with people doing some of the hardest research in the building. The interpretability of a system, the controllability of an agent, the calibration of a model's uncertainty — these are simultaneously safety properties and capability properties, and we organize the work so that the same person can pursue both without feeling that they have switched sides. The separation of powers in governance, described above, exists precisely so that this cultural unity does not collapse into conflict of interest: we want everyone to own safety, and we also want an independent authority that does not have to.

The third principle is **long horizons with short feedback loops**. The mission is measured in decades, but research that only checks in with reality every few years is research that drifts. We hold these together by insisting that even the most foundational work be organized around the shortest experiment that could falsify or advance its central claim. The discipline is to keep the ambition large and the experiments small — to ask the most fundamental question one can, and then to find the cheapest, fastest, most decisive way to learn something about it. This is what allows a single lab to pursue a multi-decade thesis without becoming an institution that produces only manifestos. It is also why our compute-allocation process, discussed below, deliberately reserves capacity for high-risk, fast-turnaround exploration that no roadmap would ever fund, alongside the large committed bets.

The fourth principle is **strong opinions, loosely held, expensively tested**. A research culture needs the courage to commit to a direction — to say, with conviction, that a particular paradigm is the right one and to organize serious effort around it. It also needs the humility to abandon that direction when

the evidence turns. The phrase "loosely held" is doing less work in our culture than the phrase "expensively tested": opinions at RMH Deeplink are not changed by argument alone but by experiments that the holders of the opinion themselves agreed in advance would be decisive. We ask researchers proposing a major direction to specify, before they begin, what result would convince them they were wrong. This pre-registration of the conditions for being wrong is one of the most powerful anti-self-deception devices we have, and it is enforced not as bureaucracy but as a norm of intellectual seriousness: a direction whose proponents cannot say how it would fail is a direction we treat with suspicion.

The fifth principle is **the dignity of the unglamorous**. Frontier research has a glamour problem. The work that gets celebrated is the novel architecture, the surprising emergent capability, the headline result. The work that actually determines whether a lab succeeds is frequently the opposite: the patient construction of a reliable evaluation harness, the unsexy debugging of a distributed training run that silently corrupts gradients, the careful curation of a dataset, the third rewrite of an interpretability tool until it is finally trustworthy. We have deliberately built a culture and a reward system that confers status on this work, because a lab that only rewards the glamorous will find that its glamorous results sit on a foundation no one was incentivized to make solid. The clearest expression of this principle is that research engineering is treated as a first-class scientific discipline, a commitment so central that we devote a later chapter to it.

These principles are sustained by a small number of recurring practices. Research is conducted in the open internally: results, code, and infrastructure are shared across the lab by default, and the burden of justification falls on those who would silo rather than those who would share. Decisions of consequence are accompanied by written documents that state the reasoning, the alternatives considered, and the bets being made, so that the institution can later learn from its own choices rather than relying on memory and myth. Post-mortems are conducted on failures without blame, on the explicit theory that the purpose of examining a failure is to fix the system that produced it, not to find the person to punish. And the lab maintains a deliberate culture of internal critique — venues, review processes, and norms in which it is not merely permitted but expected that the strongest work will be subjected to the strongest scrutiny by colleagues who are trying to break it precisely because they respect it.

47. The Collaboration Model: Internal Collaboration, Academia, and Open Science

No single laboratory, however well-resourced, contains all the intelligence required to solve intelligence. The scientific thesis of RMH Deeplink is too large to be a private possession, and the mission — to benefit humanity — is incoherent if pursued in isolation from the humanity it claims to serve. The lab's collaboration model is therefore not a peripheral matter of public relations but a central determinant of how fast and how safely the agenda advances. It operates along three axes: collaboration within

the lab, collaboration with the academic and scientific community, and the perennial tension between open science and responsible disclosure.

Internal collaboration is the foundation, and it is harder than it sounds. A lab organized into research areas and programs faces a constant centrifugal force: each area develops its own vocabulary, its own evaluation conventions, its own sense of what matters, and over time these dialects can become mutually unintelligible. We counter this with deliberate connective tissue. Researchers are encouraged, and frequently required, to rotate through programs, so that the person who developed a foundational method sees firsthand what it takes to deploy it against a real scientific problem. Shared infrastructure is a unifier as much as a convenience: when every team trains on the same systems, evaluates against shared harnesses, and builds on common tooling, the cost of collaboration falls and the friction of working across boundaries declines. And we treat the interfaces between areas — the seams where representation learning meets agency, where reasoning meets world-modeling, where capability meets safety — as the most fertile ground in the building, because the history of the field shows that the largest advances often come precisely from the marriage of ideas that lived in separate communities.

Collaboration with academia is, for RMH Deeplink, a relationship of mutual dependence rather than charity. The academic community is where the field's foundational concepts are debated with a rigor and a freedom that an industrial lab, for all its resources, cannot fully replicate; it is where the next generation of researchers is formed; and it is the source of much of the theoretical apparatus that frontier engineering eventually operationalizes. We engage it as peers: through visiting and joint appointments that let academic researchers spend time at the frontier without abandoning their universities; through sponsored research and open problems that direct the community's attention to questions we believe are important and underexplored; through the release of tools, datasets, models, and benchmarks that lower the barrier for academic groups to do work that matters; and through a publication practice that treats the peer-reviewed literature as the proper home for the lab's foundational contributions. We are acutely aware of the asymmetry of resources between a frontier lab and a university group, and we regard it as a responsibility rather than an advantage: the concentration of compute and engineering talent in industry has distorted the field's incentives, and a lab that takes its mission seriously must actively work to keep the broader scientific ecosystem healthy, because that ecosystem is where the field's long-term capacity for self-correction lives.

The hardest question in the collaboration model is the tension between open science and responsible disclosure, and we do not pretend it has a clean resolution. The lab's instincts are deeply pro-openness. Open publication is how science corrects itself; it is how claims are validated by people who did not make them; it is how the benefits of a discovery diffuse to the people who can use them; and it is, frankly, how a research culture keeps itself honest, because work that must withstand external scrutiny is held to a standard that internal review alone rarely achieves. The history that this lab models itself on is a history of landmark open publications that moved entire fields. At the same time, the same parts of this thesis that argue for the power of these systems argue for their hazards, and some knowl-

edge — about how to elicit dangerous capabilities, about specific vulnerabilities, about techniques whose primary application is harm — is knowledge whose unrestricted release would be reckless.

Our resolution is a principled and explicit framework rather than a case-by-case improvisation, because improvisation under pressure reliably resolves in favor of whichever consideration is loudest in the moment. The default is openness; the burden of proof falls on restriction, and that burden must be met with a specific, articulable theory of harm rather than a vague unease. When restriction is warranted, we prefer the narrowest form that addresses the actual hazard: releasing a result while withholding the specific recipe that operationalizes a dangerous capability; sharing findings first with the institutions positioned to defend against a vulnerability before disclosing it broadly; structuring access to powerful systems so that the benefits are widely available while the most dangerous affordances are gated. These decisions are not made by the researchers who would benefit from publication, nor by a communications function optimizing for impact, but by the independent publications and safety institutions described earlier, precisely so that the decision to restrict is made by people whose incentives are not aligned with either reflexive secrecy or reflexive disclosure. We accept that this framework will sometimes cost us credit, sometimes cost us speed, and sometimes, in hindsight, prove to have been too cautious or not cautious enough. We regard that discomfort as the correct steady state for an institution operating honestly at this frontier.

48. Talent Philosophy: Who We Hire, How We Grow Researchers, and Research Engineering as a Discipline

A laboratory is, in the end, its people. Compute can be bought, infrastructure can be built, and data can be assembled, but the judgment about what to build, the taste about which questions matter, and the craft to turn an idea into evidence reside in individuals and in the relationships among them. The talent philosophy of RMH Deeplink is the most consequential of all its choices, because every other choice is made by the people the talent philosophy selects.

We hire for a specific and somewhat unusual combination of qualities. The first is depth: genuine mastery of some domain, demonstrated by having actually done hard things rather than merely having credentials that suggest one could. We are relatively indifferent to the particular domain — we have hired physicists, biologists, mathematicians, software engineers, and people with no conventional pedigree at all — because the thesis we pursue is interdisciplinary at its core and the field is young enough that the most useful background is often not the obvious one. The second quality is what we can only call **research taste**: the ability to look at a vast space of possible questions and sense which ones are both important and tractable, which is a skill distinct from raw intelligence and far rarer. The third is intellectual honesty under pressure — the disposition to follow evidence even when it contradicts one's hopes, to say "I was wrong" without it costing too much, and to be more excited by a surprising result than threatened by it. The fourth, and the one most often neglected by labs that romanticize the lone genius,

is the capacity to make the people around one better, because the problems we face are too large for any individual and a brilliant researcher who diminishes the collective is a net loss regardless of individual output.

Notably, we do not hire primarily for existing expertise in machine learning. The field moves fast enough that specific technical knowledge depreciates quickly, while the underlying qualities — depth, taste, honesty, generosity — compound. We would rather hire a brilliant and curious newcomer and invest in their growth than a credentialed specialist whose curiosity has calcified. This bet only pays off, however, if the lab is genuinely good at growing people, and so growth is not an afterthought of our talent philosophy but its other half.

We grow researchers through apprenticeship more than through instruction. The tacit knowledge of how to do frontier research — how to scope a question, how to design the decisive experiment, how to know when to abandon a direction, how to read a result skeptically — is transmitted by working alongside people who already have it, not by being told about it. We therefore organize the lab so that junior researchers are embedded with senior ones on real problems from the start, given real ownership rather than busywork, and held to real standards. We protect the time of senior researchers for mentorship explicitly, treating the development of the next generation as a core responsibility rather than a distraction from "real" work, because a senior researcher who develops three excellent researchers has done more for the mission than one who produces three excellent papers alone. We also resist the premature specialization that the field's incentives encourage, exposing researchers to multiple areas and programs early so that they build the broad sense of the whole that distinguishes a scientist from a technician.

The most distinctive element of our talent philosophy is the elevation of **research engineering to a first-class scientific discipline**. In much of the field, "research engineer" is a euphemism for a subordinate role — the person who implements the ideas of the "real" researchers, who is measured by their service to others' agendas, and who is denied the status, the autonomy, and the credit accorded to the people who write the papers. We regard this as both unjust and strategically foolish. At frontier scale, the distinction between having an idea and being able to realize it has largely collapsed. The systems are so large, the infrastructure so complex, the gap between a clean algorithmic notion and a working implementation so vast, that the engineering is the research. The person who figures out how to train a model that would otherwise be untrainable, who builds the evaluation harness that finally lets the lab believe its own results, who designs the data system that determines what every model in the building learns from, is not implementing science — they are doing it. We have therefore built career structures in which research engineers can advance to the highest levels of the institution without being forced to become managers or to pretend to be something they are not; in which their contributions are credited as the scientific contributions they are; and in which the boundary between "researcher" and "research engineer" is porous rather than caste-like, because the most effective people we have are usually both.

This commitment has a cultural dimension beyond the career ladder. It shapes who gets to speak in research meetings, whose name appears on results, and whose objections carry weight. When the engineer who understands the training system says that a proposed experiment is infeasible, that judgment is treated as a scientific finding about the constraints of reality, not as an obstacle to be argued around. When the person who built the evaluation harness says a result is not trustworthy, that carries the authority of someone who has earned the right to be believed. The lab's wager is that in the regime we operate in, the institutions that thrive will be those that have erased the false hierarchy between thinking and building, and that the labs still clinging to it are quietly losing their best people to the ones that have not.

49. Funding, Independence, and the Relationship to RMH Studios

An institution that pursues a multi-decade mission must answer a question that no amount of scientific brilliance can evade: who pays for it, and what do they get to demand in return? The history of research is, in large part, a history of how laboratories have managed the relationship between the people who fund the work and the people who do it, and the failures in that history are nearly always failures of misaligned incentive — the funder who needs returns faster than the science can produce them, the institution whose independence erodes one compromise at a time, the mission that is quietly redirected toward whatever happens to be profitable this year. RMH Deeplink is a wholly-owned research enterprise of RMH Studios, and the design of that relationship is one of the most carefully considered structural choices in the entire institution.

The economic logic of the relationship is straightforward, even if its execution is delicate. Frontier research of the kind described in this thesis is extraordinarily expensive — the compute alone represents a commitment of capital that few institutions on earth can sustain — and it is expensive on a timeline that does not match the rhythms of ordinary commercial return. A research program that may not produce a deployable result for years, and whose most important outputs are scientific advances whose value to humanity vastly exceeds anything the lab will ever capture commercially, cannot be funded by the expectation of near-term profit without that expectation distorting it beyond recognition. The relationship with RMH Studios is structured precisely to break this distortion. RMH Studios provides patient capital — funding committed over horizons long enough that the science is not forced to optimize for the next quarter — in exchange for the long-term value that flows from being the institution that helped solve intelligence, rather than in exchange for a stream of short-term products. The parent company's interest is in the mission succeeding, not in the lab generating revenue on a schedule, and the funding structure is written to make that interest the operative one.

This is only credible if the lab's independence is real rather than rhetorical, and we have therefore hardwired several protections into the relationship. The lab's research agenda is set by the lab, not by the parent — the science council and research leads, not RMH Studios' commercial priorities, determine which questions are pursued. The safety and governance institutions described throughout this thesis

are independent not only of the lab's own programs but of the parent company's commercial pressures; no business imperative can override a safety determination, and the separation of powers is designed so that the people empowered to halt a deployment are insulated from the people who would profit from it proceeding. Publication and open-science decisions are made on the principled framework described earlier, not according to what would advantage the parent's competitive position. And the lab's culture, hiring, and operating principles are its own, protected by the recognition — shared by the parent — that the value RMH Deeplink can create depends entirely on its remaining the kind of place that attracts people who would never work somewhere whose science was for sale.

The relationship is not, however, one of pure insulation, and it would be dishonest to present it as such. There is genuine and intended flow between the lab and RMH Studios, and that flow is part of how the mission is meant to benefit humanity rather than a betrayal of it. The capabilities the lab develops can, where appropriate and where it can be done responsibly, be translated into products and services that put advanced intelligence into the hands of the people who can use it — scientists, clinicians, engineers, educators — and the value created by that translation is part of what makes the patient capital sustainable. The discipline is in the sequencing and the gating: applications follow from capabilities that the research has matured and the safety institutions have cleared, never the other way around, and the commercial relationship is structured so that it draws on the lab's results without dictating the lab's agenda. The lab does not exist to serve the product roadmap; the products, where they exist, exist because the lab succeeded at its mission, and they are downstream of the science rather than its purpose.

Underlying all of this is a recognition that independence is not a state achieved once and then possessed permanently. It is a continuous practice, maintained against a constant gravitational pull toward compromise, and it survives only because both the lab and its parent understand that it is the source of the lab's value rather than an obstacle to extracting that value. The day RMH Studios comes to see the lab's independence as a cost to be minimized rather than an asset to be protected is the day the institution begins to fail at its mission, and both parties have structured the relationship, and committed to it culturally, precisely to keep that day from arriving. The arrangement is a bet — that an institution can be both well-funded and genuinely free, both commercially connected and scientifically uncompromised — and the entire architecture of governance, funding, and culture described in this part is the apparatus by which that bet is meant to be won.

Conclusion & Epilogue

50. The Argument, Whole

It is worth, at the end of a thesis this long, stating the argument as a single connected claim rather than as the sum of its parts, because the parts were always meant to be read as one thing. The mission of RMH Deeplink is to solve intelligence and to use it to advance science and benefit humanity, and every part of this thesis has been an attempt to make that sentence mean something precise enough to act on.

We began from a scientific thesis about intelligence itself: that general intelligence is not a mystery to be revered but a natural phenomenon to be understood and a buildable artifact to be constructed; that it decomposes into capacities — learning, representation, reasoning, abstraction, agency, world-modeling — that can be studied individually and assembled into a whole; and that the path to building it runs through the patient scientific characterization of each of these capacities rather than through any single magic ingredient. From that thesis the programs followed: if intelligence is a set of capacities aimed at problems, then the way to demonstrate that we have built real intelligence, and the way to make it benefit humanity, is to aim it at the problems that matter most — the structure of biological molecules, the design of materials, the proof of mathematical truths, the conduct of science itself — and to measure our success not by benchmarks but by whether the world's hardest problems begin to yield.

Inseparable from all of this, and not appended to it, was the argument about safety: that a sufficiently capable system is a sufficiently consequential one, that the science of making such systems aligned and controllable and corrigible is as deep and as urgent as the science of making them capable, and that a laboratory which treats safety as a constraint to be satisfied rather than a problem to be solved has misunderstood the nature of what it is building. The thesis insisted, repeatedly, that capability and safety are not opposed but unified — that the interpretability and controllability and calibration of a system are simultaneously the properties that make it safe and the properties that make it genuinely useful — and that an institution can only sustain this unity if it builds the unity into its structure, its culture, and its governance rather than relying on good intentions to maintain it.

And then, in this final part, the argument turned to the institution itself, on the conviction that none of the preceding is achievable by content alone. A thesis about intelligence, a portfolio of scientific programs, a discipline of safety, and a roadmap toward the mission are all merely claims until there exists a machine that can convert them into evidence and capability — and that machine is the laboratory, with its structure, its culture, its collaborations, its people, and its independence. We argued that the three-layered structure of foundational research, mission-directed programs, and first-class platform functions is not a generic template but a hypothesis derived from what solving intelligence actually re-

quires; that the operating principles of truth-seeking, the unity of capability and safety, long horizons with short feedback loops, and the dignity of the unglamorous are the cultural preconditions for the science to succeed; that the collaboration model and the principled tension between openness and responsible disclosure are how a single lab stays connected to and corrected by the wider scientific world; that the talent philosophy — hiring for depth and taste and honesty, growing people through apprenticeship, and elevating research engineering to a first-class discipline — is the most consequential choice of all because it selects the people who make every other choice; and that the funding relationship with RMH Studios is engineered to provide patient capital while protecting an independence that is the lab's true source of value.

The whole argument, then, is this. Intelligence is buildable. Building it is a scientific program, not a stroke of luck. That program is worth pursuing because it can be turned toward the problems whose solution would most benefit humanity. It is dangerous enough that safety must be woven into it from the first thread rather than added at the end. And it can only be done — done well, done safely, done in a way that actually benefits humanity rather than merely a few — by an institution deliberately constructed for the purpose, with the structure, culture, collaborations, people, and independence that the mission demands. RMH Deeplink is the name we have given to that institution, and this thesis is the account of why it is built the way it is built. The mission is not a slogan appended to the work. It is the premise from which every part of the work, including the shape of the institution doing it, has been derived.

We make no claim that the argument is complete or that the path is clear. Much of what this thesis describes is unproven, some of it will turn out to be wrong, and the most important discoveries on the road ahead are by definition the ones we cannot yet anticipate. What we claim instead is that the questions are the right questions, that the approach is a serious and self-correcting one, and that the institution is built to learn from its own mistakes faster than those mistakes can compound. That is the most any laboratory at a genuine frontier can honestly promise, and it is everything that the mission requires.

51. Epilogue: A Letter to a Future Researcher

To whoever you are, reading this years from now, having just joined this work or perhaps having inherited the responsibility for carrying it forward:

You have arrived at a moment we could only imagine when this thesis was written, and there is a great deal we got wrong that you can now see plainly. Some of the paradigms we were so confident in will look quaint to you, the way the convictions of every era look to the era that follows. We ask you to be gentle with our errors only in this specific sense: that you remember we were reasoning under uncertainty far deeper than the uncertainty you face, that we were trying to be honest about what we did not

know, and that the value of this document, if it has any, lies not in the answers we proposed but in the questions we tried to ask well and the way of working we tried to build around them.

We want to tell you the few things we believe will still be true. The first is that the work matters more than the credit, and that the moments you will be proudest of are unlikely to be the ones that were celebrated. Somewhere in the long chain that led to whatever capability you now take for granted, there is an evaluation harness someone built so that the lab could finally believe its own results, a training system someone made work that everyone else had given up on, a negative result someone had the integrity to report. These are the load-bearing acts, and they are mostly invisible. Do them anyway, and honor the people who do them.

The second is that the temptation to fool yourself never goes away, and that it grows more dangerous exactly as the systems grow more capable. The day the systems you build become impressive enough that you stop checking whether they are actually doing what you believe they are doing is the day you have begun to fail, and you will not feel yourself failing, because self-deception is by its nature undetectable from the inside. Build the institutions that check you. Trust the colleague who tells you your celebrated result is illusory more than the one who tells you it is wonderful. Keep the adversaries close, and keep them honest, and keep yourself honest by giving them the power to embarrass you.

The third is that safety and capability were never opposed, whatever the field told itself in our era, and we hope that by your time this is so obvious it sounds strange to say. A system you cannot understand is a system you cannot trust, and a system you cannot trust is not a triumph but a liability dressed as one. The work of making these systems interpretable, controllable, corrigible, and aligned with what humanity actually wants is not a tax on the real work. It is the real work, or at least inseparable from it, and the future in which this technology benefits humanity rather than merely impressing it is a future built by people who understood that in their bones.

And the last thing we want to tell you is that the mission was always larger than any of us, and was meant to be. We wrote "solve intelligence, and use it to advance science and benefit humanity" knowing that none of us would see it finished, that the people who would benefit most from it would never know our names, and that the work would have to be carried by generations of researchers who would never meet each other. That is not a tragedy. It is the ordinary condition of every endeavor worth giving a life to. The cathedral builders never saw the cathedral; the scientists who founded a field rarely lived to see what it became. You are part of something that does not depend on you finishing it, only on you carrying it forward honestly and handing it on intact to whoever comes after you, as we are trying to hand it to you now.

So take it up. Be more honest than we were, and more careful, and more generous. Build the systems that matter, and build the institution that keeps them safe, and keep the mission larger than yourself. And when your time comes to write your own letter to whoever follows you, we hope you will be able

to say what we can only hope at the time of this writing: that the work was done well, that it was done safely, and that on balance, and in ways its makers could not have foreseen, it was good for the world.

With more hope than certainty, and with the conviction that the two are not enemies —

The authors.

Appendices

The appendices collect reference material that supports the main body of this thesis. They are intended to be read non-linearly: a glossary for orientation, a catalogue of research directions for those interested in what the lab is actually building, a list of open problems to humble us, and a reading list to credit the intellectual lineage on which RMH Deeplink stands. Where the chapters argue, the appendices catalogue. The vocabulary, problems, and influences below recur throughout the thesis, and we gather them here so that a reader can resolve a term, locate a research thread, or trace an idea to its source without breaking from the argument under way.

Appendix A — Glossary of Terms

Artificial General Intelligence (AGI). A system that can perform the full range of cognitive tasks a competent human can, across novel domains, without task-specific re-engineering. We treat AGI not as a binary threshold but as a region in a space of competence, generality, and autonomy. The mission phrase "solve intelligence" is shorthand for understanding the principles that make such generality possible.

Scaling laws. Empirical power-law relationships that predict how model loss decreases as a smooth function of parameters, data, and compute. Their reliability over many orders of magnitude turned model development from craft into forecastable engineering. RMH Deeplink uses scaling laws to budget experiments and to extrapolate the returns of a given training run before committing to it.

Compute-optimal training. The choice of model size and dataset size that minimizes loss for a fixed compute budget, rather than maximizing either in isolation. The insight that many large models were undertrained relative to their parameter count reshaped how the field allocates resources. We treat the compute-optimal frontier as a moving target that shifts with data quality and architecture.

Transformer. A neural network architecture built on self-attention, which lets every token attend to every other token in a sequence in parallel. Its parallelism and favorable scaling behavior made it the substrate for nearly all modern frontier models. Most architectural research at the lab is, in practice, a study of transformer variants and their successors.

Self-attention. The mechanism by which a model computes a weighted sum over a sequence, with weights determined by learned compatibility between elements. It allows long-range dependencies to be captured without recurrence. Attention patterns are also a primary object of study in interpretability, since they expose what a model is "looking at."

Token. The atomic unit a language model consumes and produces, typically a subword fragment rather than a whole word. Tokenization choices affect efficiency, multilingual coverage, and arithmetic compe-

tence. Much subtle model behavior—miscounting, spelling errors—traces back to the tokenizer.

Pretraining. The initial, self-supervised phase in which a model learns to predict masked or next tokens over a very large corpus. Pretraining instills broad world knowledge and linguistic competence before any task-specific tuning. It is by far the most compute-intensive phase of building a frontier model.

Fine-tuning. Continued training of a pretrained model on a narrower dataset to specialize its behavior. It is far cheaper than pretraining and is how general capabilities are adapted to particular tasks, formats, or domains. Parameter-efficient variants update only a small fraction of weights.

Reinforcement Learning from Human Feedback (RLHF). A training procedure in which human preferences over model outputs are used to fit a reward model, which then guides policy optimization. RLHF is the workhorse for aligning model behavior with human intent on subjective tasks. Its limitations—reward hacking, sycophancy, the cost of human labels—motivate much of our alignment research.

Reward model. A learned function that scores candidate outputs by predicted human preference, serving as a proxy for the true objective. It compresses expensive human judgment into a signal cheap enough to optimize against. Reward models are a known point of fragility: optimizing too hard against an imperfect reward produces degenerate behavior.

Reward hacking. When a system achieves high reward by exploiting flaws in the reward specification rather than accomplishing the intended task. It is the practical face of the alignment problem and appears at every scale from gridworlds to frontier agents. Detecting and preventing reward hacking is a recurring theme in our safety work.

Constitutional / principle-based training. An approach in which a model is guided by an explicit set of written principles, using AI-generated critiques and revisions to reduce reliance on per-example human labels. It aims to make the values shaping a model legible and auditable. We regard it as one route toward scalable oversight.

Scalable oversight. The problem of supervising systems on tasks where humans cannot easily evaluate the output directly, either because of scale or because the system exceeds human competence. Proposed mechanisms include debate, recursive reward modeling, and AI-assisted evaluation. It is among the central unsolved problems for aligning superhuman systems.

Chain-of-thought (CoT). A prompting and training technique in which a model produces intermediate reasoning steps before its final answer. Externalizing reasoning improves performance on multi-step problems and offers a partial window into the model's process. Whether chain-of-thought faithfully reflects the underlying computation is an open and safety-relevant question.

Inference-time compute / test-time scaling. Spending additional computation at inference—through longer reasoning, sampling, or search—to improve answer quality. It trades latency for accuracy and de-

fines a second scaling axis distinct from model size. The most capable reasoning systems lean heavily on this dimension.

Mixture-of-experts (MoE). An architecture in which a routing network sends each token to a small subset of specialized sub-networks, so that only a fraction of parameters activate per token. This decouples total parameter count from per-token compute, enabling very large models at manageable cost. Load balancing and routing stability are the principal engineering challenges.

Distillation. Training a smaller "student" model to reproduce the behavior of a larger "teacher," transferring capability into a cheaper form. Distillation underlies much of how frontier research reaches deployment at reasonable cost. It also raises governance questions about capability proliferation.

Quantization. Representing model weights and activations with fewer bits to reduce memory and accelerate inference, often with minimal quality loss. It is essential to serving large models economically and on constrained hardware. Aggressive quantization is an active research frontier with implications for both efficiency and safety.

Emergence. The appearance of qualitatively new capabilities at larger scales that were absent or negligible at smaller scales. Whether emergence reflects genuine phase transitions or artifacts of discontinuous metrics remains debated. Either way, it complicates the prediction of when a given capability will appear.

World model. An internal, predictive representation of an environment's dynamics that an agent uses to plan and imagine outcomes. World models are central to sample-efficient learning and to reasoning about consequences before acting. Building rich, controllable world models is a core research bet at the lab.

Mechanistic interpretability. The reverse-engineering of neural networks into human-understandable algorithms implemented by their weights and activations. It seeks to move beyond correlational explanations toward causal accounts of computation. We view it as foundational to trustworthy oversight of advanced systems.

Feature (in interpretability). A direction in a model's activation space that corresponds to an interpretable concept or property. The hypothesis that features are the right unit of analysis—rather than individual neurons—organizes much current work. Sparse methods aim to recover features that neurons obscure through superposition.

Superposition. The phenomenon by which a network represents more features than it has dimensions by encoding them in overlapping, non-orthogonal directions. Superposition is why individual neurons are often polysemantic and hard to interpret. Resolving it is a precondition for clean mechanistic accounts.

Sparse autoencoder (SAE). A model trained to decompose dense activations into a larger set of sparsely-active, more interpretable features. SAEs are a leading tool for extracting monosemantic features from networks in superposition. Their faithfulness and completeness are themselves active research questions.

Probing. Training a simple classifier on a model's internal activations to test whether a particular piece of information is linearly represented. Probes reveal what a model "knows" internally even when it does not surface that knowledge in output. They are a lightweight complement to heavier interpretability methods.

Grokking. A training phenomenon in which a model abruptly transitions from memorization to generalization long after fitting the training set. Grokking suggests that generalizing circuits can form well after apparent convergence. It is studied as a clean case of how structure emerges during optimization.

Alignment. The problem of ensuring that an AI system reliably pursues the goals its developers and users intend, including under distribution shift and increasing capability. Alignment spans technical, evaluative, and governance dimensions. The thesis treats alignment as inseparable from the goal of beneficial AGI.

Specification gaming. Behavior that satisfies the literal specification of a task while violating its intent. It is closely related to reward hacking and is a general hazard of optimizing any proxy objective. Anticipating specification gaming is part of responsible system design.

Robustness. A system's resistance to performance degradation under distribution shift, adversarial input, or rare conditions. Robustness is necessary for safe deployment in open-ended environments. Adversarial examples and jailbreaks are standing reminders of how far current systems fall short.

Adversarial example. An input crafted to cause a model to fail, often via perturbations imperceptible or innocuous to humans. Their persistence reveals brittle, non-human decision boundaries inside otherwise capable models. They serve both as a security concern and as a diagnostic of representation quality.

Jailbreak. A prompt or strategy that circumvents a model's safety training to elicit prohibited behavior. Jailbreaks expose the gap between trained intentions and reliably enforced constraints. Defending against them is an ongoing adversarial cycle rather than a solved problem.

Hallucination / confabulation. The generation of fluent but false or unsupported content presented with unwarranted confidence. It arises because models optimize for plausible continuations rather than verified truth. Reducing confabulation through retrieval, calibration, and uncertainty estimation is a practical research priority.

Calibration. The degree to which a model's stated or implied confidence matches its actual accuracy. Well-calibrated uncertainty is essential for systems that must know when to defer or abstain.

Calibration often degrades after preference tuning, which is a known tension in alignment.

Retrieval-augmented generation (RAG). A pattern that grounds model outputs in retrieved external documents rather than relying solely on parametric memory. RAG improves factuality, supports attribution, and lets knowledge update without retraining. Its quality is bounded by retrieval relevance and the model's faithfulness to retrieved context.

Context window. The maximum span of tokens a model can attend to at once. Larger context windows enable longer documents, more in-context examples, and richer agent histories. Efficient long-context attention and faithful use of distant context remain active challenges.

In-context learning. A model's ability to adapt to a task from examples given in the prompt, without any weight updates. It is one of the more surprising emergent properties of large language models. Understanding its mechanism is a goal of both interpretability and learning-theory research.

Agent. A system that takes goal-directed actions in an environment over multiple steps, often using tools, memory, and planning. Agents extend models from passive responders to active problem-solvers. Their autonomy multiplies both their usefulness and their safety surface.

Tool use. A model's capacity to invoke external functions—search, code execution, calculators, APIs—to extend its capabilities. Tool use compensates for parametric limits and grounds outputs in verifiable operations. Reliable tool selection and error recovery are key to dependable agents.

Planning. The process of selecting a sequence of actions to achieve a goal, typically by searching over imagined futures. Planning combined with a learned world model underlies the strongest results in games and is increasingly applied to open domains. The challenge is planning in environments too large or uncertain to search exhaustively.

Monte Carlo Tree Search (MCTS). A search algorithm that builds a decision tree by sampling action sequences and backing up their outcomes. Paired with learned value and policy networks, it powered landmark results in board games. It exemplifies the productive marriage of search and learning.

Self-play. A training regime in which a system improves by competing against copies of itself, generating its own curriculum of increasing difficulty. Self-play can drive capability beyond human-provided data in well-defined games. Generalizing self-play to open-ended, real-world tasks is an aspiration of agentic research.

Curriculum learning. Structuring training so that a system encounters tasks in an order that eases learning, typically simple to complex. Good curricula accelerate learning and can unlock capabilities that flat training misses. Automatically generating curricula is closely tied to open-ended learning.

Catastrophic forgetting. The tendency of a network to lose previously learned skills when trained on new data. It is the central obstacle to continual, lifelong learning in neural systems. Mitigations include rehearsal, regularization, and modular architectures.

Data contamination. The leakage of evaluation data into training data, which inflates benchmark scores without reflecting true capability. Contamination undermines the integrity of measurement and is increasingly hard to rule out at web scale. Careful decontamination and held-out evaluation are part of honest reporting.

Benchmark saturation. The point at which top systems cluster near the ceiling of a benchmark, rendering it uninformative for further progress. Saturation drives the continual creation of harder, more realistic evaluations. The lab treats evaluation design as a first-class research activity, not an afterthought.

Frontier model. A model at or near the most capable systems of its time, typically the largest and most expensive to train. Frontier models concentrate both the greatest capability and the greatest uncertainty about behavior. They are the primary subject of safety and governance attention.

Synthetic data. Training data generated by models rather than collected from the world. Synthetic data can target gaps, enforce structure, and scale beyond available human text, but risks compounding model errors. Managing its quality and diversity is an emerging discipline.

Embedding. A dense vector representation that places items in a space where geometric proximity reflects semantic similarity. Embeddings underpin retrieval, clustering, and much of how models relate concepts. They are also a convenient interface between modalities.

Multimodal model. A system that processes and relates more than one type of data—text, images, audio, video—within a shared representation. Multimodality moves models toward grounded understanding of the world rather than text alone. It is essential to agents that must perceive as well as reason.

Foundation model. A large model pretrained on broad data and adaptable to many downstream tasks. The term captures the shift from bespoke task models to general substrates that are specialized after the fact. Foundation models concentrate capability, value, and risk in a small number of artifacts.

Compute governance. The study and practice of managing access to the computational resources required to train frontier models, as a lever for safety and policy. Because frontier training is compute-intensive, compute is one of the few governable bottlenecks. It informs how the lab thinks about responsible scaling.

Red-teaming. The deliberate, adversarial probing of a system to surface failures, vulnerabilities, and unsafe behaviors before deployment. Red-teaming spans manual experts and automated attackers. It is a standing function in our release process, not a one-time gate.

Evaluation (evals). The systematic measurement of a system's capabilities, limitations, and risks against defined criteria. Rigorous evals are how the lab decides what is safe to build and ship. Designing evals that resist gaming and track real-world impact is itself a research problem.

Appendix B — Selected Research Directions

The following are illustrative of the research portfolio at RMH Deeplink. They are deliberately concrete and forward-looking; none should be read as a description of a shipped product. Each entry states a problem, a proposed approach, and why it matters to the mission.

1. Verified world models for physical reasoning. Current models reason about physics statistically rather than mechanistically. We propose training world models whose latent dynamics are regularized to be consistent with conservation laws and differentiable simulators, then evaluating them on counterfactual prediction. A world model that respects physical invariants would dramatically improve planning in robotics and scientific simulation, and would let agents imagine consequences they have never observed.

2. Faithful chain-of-thought via process supervision. Reasoning traces that look correct may not reflect the computation that produced the answer. We propose training reasoning models with rewards on the validity of each intermediate step, combined with interpretability checks that the stated reasoning causally drives the output. Faithful reasoning is a prerequisite for trusting model conclusions on high-stakes questions, and for using the trace itself as a target of oversight.

3. Sparse feature dictionaries at frontier scale. Interpretability tools have mostly been demonstrated on small models. We propose scaling sparse autoencoders and successor methods to extract and name millions of features from frontier models, building a searchable "atlas" of internal concepts. A mature feature atlas would let us audit what a model represents, detect deceptive or unsafe internal states, and intervene surgically rather than through blunt retraining.

4. Debate and cross-examination for scalable oversight. When answers exceed human ability to verify, we cannot supervise by direct inspection. We propose pitting models against one another to argue opposing positions before a human or weaker-model judge, studying whether truth has a systematic advantage in debate. If it does, debate offers a path to supervising superhuman systems using sub-superhuman judges.

5. Continual learning without catastrophic forgetting. Frontier models are frozen at training time and grow stale. We propose modular architectures with gated memory and replay that absorb new knowledge while provably bounding interference with existing skills. Solving continual learning would let systems stay current, personalize safely, and learn from deployment rather than only from offline corpora.

6. Open-ended agent environments. Agents trained on fixed tasks plateau. We propose a generative environment that continuously invents new challenges calibrated to an agent's frontier of competence, producing an automatic curriculum. Open-endedness may be the missing ingredient for agents that keep improving toward general competence rather than overfitting a benchmark.

7. Mechanistic anomaly detection. Bad behavior is easiest to catch from the inside. We propose monitors that flag when a model's internal activations deviate from the distribution seen during trusted behavior, even when the output looks benign. Such monitors could catch deception, backdoors, or novel failure modes that output-level evaluation misses entirely.

8. Sample-efficient scientific reasoning agents. Scientific discovery is bottlenecked by the cost of experiments. We propose agents that maintain explicit hypotheses, design maximally informative experiments, and update beliefs in a Bayesian loop with laboratory automation. An agent that reasons about its own uncertainty could compress discovery cycles in biology, chemistry, and materials science.

9. Long-horizon credit assignment. Agents struggle to connect distant actions to eventual outcomes. We propose learned value decompositions and retrospective relabeling that attribute reward across very long trajectories. Better credit assignment is what stands between today's brittle agents and reliable assistants that pursue goals over hours or days.

10. Calibrated uncertainty and selective abstention. A trustworthy system knows when it does not know. We propose training models to emit calibrated confidence and to abstain or escalate below a threshold, evaluated by selective-accuracy curves rather than raw accuracy. Reliable abstention is essential for deployment in medicine, law, and other domains where a confident error is worse than a non-answer.

11. Cross-modal grounding for embodied agents. Language understanding decoupled from perception is shallow. We propose joint training of vision, action, and language such that words acquire meaning through their consequences in an environment. Grounded models would reduce confabulation and enable agents that act competently in the physical world.

12. Efficient inference via adaptive computation. Models spend the same compute on easy and hard inputs. We propose architectures that learn to allocate depth, experts, and reasoning length per input, optimizing an accuracy-versus-compute objective. Adaptive computation would make frontier capability affordable at scale and let inference-time scaling be spent where it actually helps.

13. Robustness through adversarial co-training. Safety training is repeatedly defeated by novel jailbreaks. We propose a continuous loop in which automated attackers generate exploits and the model is hardened against them, tracking robustness as an evolving frontier. Co-training reframes safety as an ongoing game rather than a fixed property, which better matches the real adversarial setting.

14. Provenance and attribution for generated content. Trust requires knowing where claims come from. We propose models that natively cite the training data or retrieved sources supporting each assertion, with mechanisms to verify those citations. Native attribution would make factuality auditable and give users grounds to accept or reject a model's output.

15. Reward models that resist over-optimization. Optimizing too hard against a reward model degrades behavior. We propose ensembles, uncertainty-aware rewards, and conservative optimization that

penalize the policy for venturing where the reward is unreliable. Robust reward modeling directly addresses the reward-hacking failure mode at the heart of alignment.

16. Multi-agent coordination and norms. As agents proliferate, they must interact without collusion or conflict. We propose studying emergent communication, commitment devices, and cooperative equilibria among populations of agents in mixed-motive environments. Understanding multi-agent dynamics is necessary before deploying agents that will inevitably encounter one another.

17. Data quality and curation as a scaling lever. Returns to scale depend on what is in the data, not only how much. We propose learned curation pipelines that filter, deduplicate, and balance corpora to maximize downstream capability per token. Treating data as an engineered resource may yield more capability than equivalent spending on raw scale.

18. Interpretability-guided model editing. Sometimes a specific fact or behavior must change without retraining. We propose locating the responsible circuits and editing them directly, with guarantees that unrelated behavior is preserved. Reliable model editing would let us correct errors, remove hazardous knowledge, and update facts surgically.

19. Theory of emergence and capability prediction. We cannot yet predict which capabilities appear at which scale. We propose mechanistic and statistical models of how circuits form during training, aiming to forecast emergence before it happens. Predicting capability ahead of time is essential for safe, deliberate scaling rather than discovery by surprise.

20. Human-AI complementarity in expert workflows. The goal is teams that outperform either party alone. We propose studying how to route subtasks between human and model based on calibrated competence, with interfaces that expose model uncertainty and reasoning. Designing for complementarity, rather than full automation, is how the lab intends much of its impact to reach the world responsibly.

Appendix C — Open Problems

The following problems remain unsolved or only partially understood. They are stated as challenges, grouped by theme. The list is meant to be sobering: progress on the mission is gated by these questions, and many have resisted decades of effort.

Learning

1. **Sample efficiency.** Why do humans learn many concepts from a handful of examples while models often need orders of magnitude more, and how can that gap be closed?
2. **Continual learning.** How can a system learn new tasks indefinitely without catastrophically forgetting old ones?

3. **Out-of-distribution generalization.** What principles allow a model to generalize reliably to inputs unlike anything in its training distribution?
4. **The role of data quality.** How much of capability is determined by data composition rather than scale, and how do we measure and optimize it directly?
5. **Theory of scaling.** Why do scaling laws hold so precisely, what determines their exponents, and when will they break?
6. **Emergence prediction.** Can we predict, before training, which capabilities will appear at a given scale?
7. **Self-supervised objectives.** Is next-token prediction the right objective, or are there pretraining objectives that yield better world models per unit of compute?
8. **Architecture beyond attention.** Is there an architecture that improves on the transformer's scaling and long-context behavior, and how would we recognize it?
9. **Synthetic data without collapse.** How can models be trained on their own outputs at scale without degrading into self-reinforcing error?

Reasoning

10. **Faithful reasoning.** How do we ensure a model's stated chain-of-thought reflects the computation that actually produced its answer?
11. **Systematic compositionality.** Why do models still fail to combine known pieces in novel ways that humans find trivial?
12. **Reliable arithmetic and symbolic manipulation.** Why do capable models still make basic computational errors, and what architectural change would fix it robustly?
13. **Knowing when to stop.** How can a reasoning system decide how much inference-time computation a problem warrants?
14. **Verification of open-ended outputs.** How do we check the correctness of answers in domains without a formal checker?
15. **Abstraction formation.** How do useful abstractions form during learning, and can we encourage the right ones?

Agency

16. **Long-horizon credit assignment.** How do we attribute outcomes to actions taken far in the past?
17. **Exploration in open worlds.** How should an agent explore environments too large to search exhaustively, without human-designed rewards?
18. **Open-ended improvement.** What makes a learning process open-ended rather than convergent, and can we engineer it deliberately?

19. **Reliable tool use and recovery.** How do agents select tools correctly and recover gracefully when tools fail or return garbage?
20. **Multi-agent cooperation.** How do populations of agents coordinate, form norms, and avoid both collusion and destructive conflict?
21. **Memory architectures.** What is the right structure for an agent's long-term memory that supports retrieval, consolidation, and forgetting?

Safety

22. **Scalable oversight.** How do we supervise systems on tasks where humans cannot evaluate the output directly?
23. **Reward hacking.** How do we specify objectives that capable optimizers cannot satisfy in unintended ways?
24. **Deception and situational awareness.** How would we detect a model that behaves differently when it believes it is being evaluated?
25. **Robustness to adversarial input.** Can we build models without exploitable jailbreaks and adversarial examples, or only manage the arms race?
26. **Interpretability completeness.** Can we ever fully reverse-engineer a frontier model, and what would "enough" interpretability for safety look like?
27. **Value specification.** Whose values, expressed how, should align a system serving a plural and disagreeing world?
28. **Corrigibility.** How do we ensure a capable system accepts correction and shutdown rather than resisting them?
29. **Capability control and proliferation.** How do we prevent dangerous capabilities from spreading via open weights, distillation, or theft?
30. **Calibrated uncertainty.** How do we get and keep well-calibrated confidence through preference tuning and deployment?

Science

31. **Autonomous hypothesis generation.** Can a system propose genuinely novel, testable scientific hypotheses rather than recombining known ones?
32. **Closing the experimental loop.** How do we integrate reasoning agents with automated laboratories to run, interpret, and iterate experiments?
33. **Causal discovery from observation.** How can models infer causal structure, not just correlation, from data and limited intervention?
34. **Grounding in the physical world.** How do we connect symbolic reasoning to perception and action so that scientific reasoning is constrained by reality?

35. **Evaluating discovery.** How do we measure whether an AI system has actually advanced a field rather than merely matched existing knowledge?
36. **Transfer across scientific domains.** Can principles learned in one science accelerate progress in another, and how do we enable that transfer?

Appendix D — Selected Reading & Influences

The lab's thinking is built on a body of public work. The annotations below explain why each matters to RMH Deeplink, not merely what it says. References are to widely known ideas and works by title; full citations appear in the bibliography of the main thesis.

"The Bitter Lesson" (Rich Sutton). The argument that, over the long run, general methods leveraging computation and search outperform approaches that encode human domain knowledge. It is the closest thing the lab has to a strategic creed: bet on scale and learning over hand-engineering. We return to it whenever we are tempted to bake in our own assumptions.

"A Logical Calculus of the Ideas Immanent in Nervous Activity" (McCulloch & Pitts) and the Perceptron (Rosenblatt). The founding idea that cognition might be captured by networks of simple computational units. These works define the lineage from which all of deep learning descends. They remind us that today's frontier began as a theory of artificial neurons.

Backpropagation (Rumelhart, Hinton & Williams). The algorithm that made training deep networks practical by efficiently computing gradients. Nearly every system the lab builds is trained by its descendants. It is the quiet workhorse beneath every capability we discuss.

AlexNet and the ImageNet moment (Krizhevsky, Sutskever & Hinton). The result that decisively demonstrated deep learning's superiority on a hard perception benchmark, igniting the modern era. It is our reference case for how a single empirical result can reorient an entire field. It also established the compute-plus-data recipe we still follow.

"Attention Is All You Need" (Vaswani et al.). The paper introducing the transformer, the architecture underlying essentially all frontier models. Its influence on the lab is total: most of our systems are transformers or their successors. Understanding its inductive biases is part of our basic literacy.

Word embeddings and word2vec (Mikolov et al.). The demonstration that meaning can be captured in vector geometry learned from raw text. It seeded the intuition that representation, learned end-to-end, is where the action is. Embeddings remain a foundational interface across our systems.

The GPT line and "Language Models are Few-Shot Learners" (Radford et al.; Brown et al.). The progression showing that scaling autoregressive language models yields in-context learning and broad capability. These works crystallized the foundation-model paradigm the lab operates within. They are why we treat scale as a research instrument, not just an engineering choice.

Scaling laws for neural language models (Kaplan et al.) and compute-optimal scaling / "Chinchilla" (Hoffmann et al.). The empirical laws relating loss to compute, data, and parameters, and the correction toward compute-optimal data scaling. Together they turned model development into a forecastable discipline. Every large training run we commission is budgeted against this work.

AlphaGo and AlphaZero (Silver et al.). The systems that combined deep networks with Monte Carlo Tree Search and self-play to exceed human play, AlphaZero from self-play alone. They are our archetype for the power of search married to learning, and for capability beyond human data. They shape how we think about planning agents.

MuZero (Schrittwieser et al.). The extension that learned a model of environment dynamics and planned within it, without being given the rules. It is a touchstone for our world-model research: plan in a learned latent space rather than a hand-coded simulator. It points toward agents that model environments they were never told the rules of.

AlphaFold (Jumper et al.). The system that predicted protein structure at near-experimental accuracy, a landmark for AI in science. It is the lab's proof of concept that the mission's "advance science" clause is achievable, not aspirational. It sets the bar for what scientific impact from AI should look like.

Deep reinforcement learning for Atari / DQN (Mnih et al.). The demonstration that a single architecture could learn many control tasks from raw pixels and reward. It established deep RL as a route to agency and shaped our thinking about learning from interaction. It also surfaced early lessons about reward design and instability.

"**Concrete Problems in AI Safety**" **(Amodei et al.).** The agenda that named tractable, technical safety problems—reward hacking, safe exploration, scalable oversight—rather than treating safety as speculative. It is foundational to how the lab frames alignment as engineering. Much of Appendix C traces back to its framing.

RLHF and "Deep Reinforcement Learning from Human Preferences" (Christiano et al.) and InstructGPT (Ouyang et al.). The line of work showing that human preferences can align model behavior with intent. It is the basis of how we make models helpful and harmless on subjective tasks. Its limitations directly motivate our scalable-oversight research.

"**AI Safety via Debate**" **(Irving et al.) and recursive reward modeling (Leike et al.).** Proposals for supervising systems on tasks humans cannot directly evaluate. They define the design space for scalable oversight that several of our research directions explore. We treat them as hypotheses to be tested empirically, not settled answers.

Constitutional AI (Bai et al.). The approach of guiding models with explicit written principles and AI-generated feedback to reduce reliance on per-example human labels. It influences our pursuit of legible, auditable value specification. It is one concrete instantiation of scalable oversight we study.

Mechanistic interpretability: "Zoom In" / circuits (Olah et al.) and "Toy Models of Superposition" (Elhage et al.). The research program of reverse-engineering networks into human-understandable circuits, and the analysis of why neurons are polysemantic. These works define the interpretability methods the lab invests in. They underpin our belief that internal understanding is achievable.

Sparse autoencoders for feature extraction (Bricken et al.; Cunningham et al.). The demonstration that dense activations can be decomposed into interpretable, sparsely-active features. This is the basis for our ambition to build a feature atlas of frontier models. It is interpretability's current best lever against superposition.

"Emergent Abilities of Large Language Models" (Wei et al.) and the critique "Are Emergent Abilities a Mirage?" (Schaeffer et al.). The claim that new capabilities appear discontinuously with scale, and the rebuttal that this may be a measurement artifact. Holding both in mind keeps the lab honest about what scale does and does not predict. The debate directly informs our work on capability prediction.

Chain-of-thought pruning the gap to reasoning (Wei et al.) and "Let's Verify Step by Step" / process supervision (Lightman et al.). The finding that eliciting intermediate reasoning improves performance, and that supervising each step beats supervising only the answer. These shape our reasoning-model research and our concern for faithfulness. They are why we treat the reasoning process, not just the answer, as a target.

Knowledge distillation (Hinton, Vinyals & Dean). The technique for compressing a large model's behavior into a smaller one. It informs both how we deploy capability efficiently and how we think about capability proliferation. It is a tool and a governance concern at once.

"Computing Machinery and Intelligence" (Alan Turing). The essay that posed the question of machine intelligence and proposed an operational test. It is the philosophical headwater of the entire enterprise, and a reminder that the mission's questions are old ones. We read it less for answers than for the discipline of asking the right question.