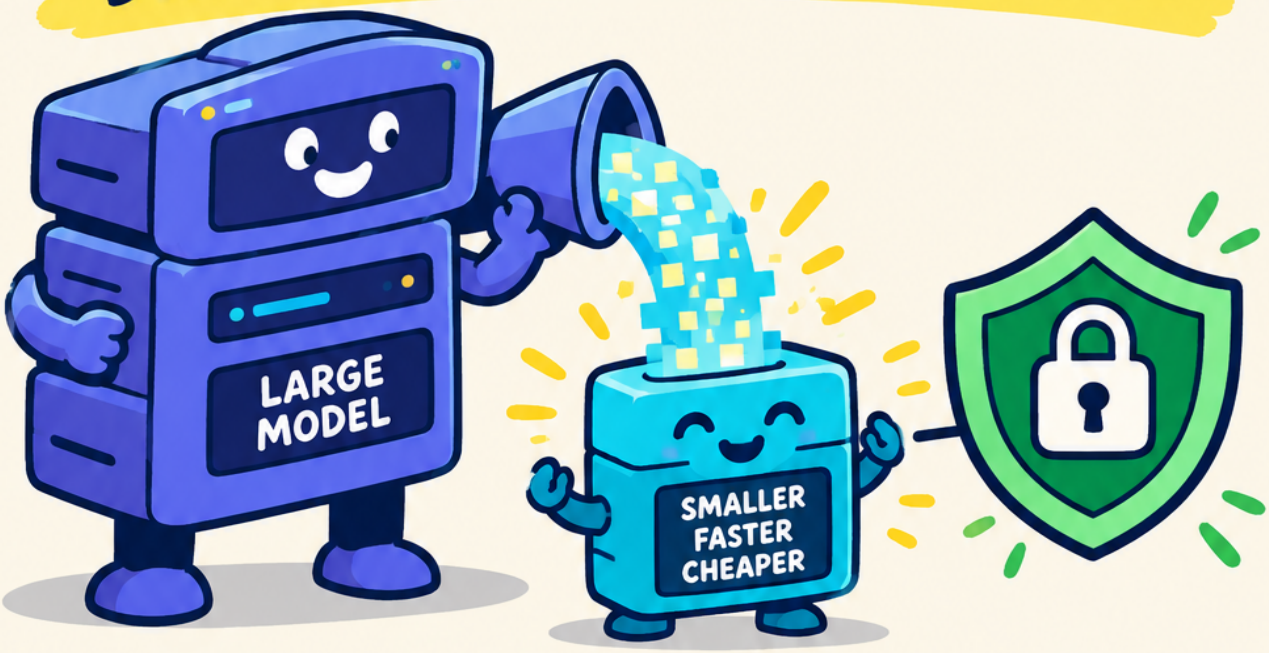
DISTILLING INTELLIGENCE

INDUSTRIAL-SCALE AI MODEL DISTILLATION AND API SECURITY



DISTILLATION THEORY | MODEL COMPRESSION | DISTRIBUTED SERVING | SECURITY ARCHITECTURE

OBSERVABILITY | INCIDENT RESPONSE | GOVERNANCE

MICHAEL PRESCOTT

Distilling Intelligence

Industrial-Scale AI Model Distillation and API Security

Steve Publications

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Contents

Industrial-Scale AI Model Distillation and API Security

This book explains how to distill large, expensive AI models into smaller, faster, cheaper ones that can be deployed at industrial scale, and how to secure the APIs that expose those models against extraction attacks, abuse, and economic denial of service. It covers the complete lifecycle from distillation theory and model compression through distributed serving, security architecture, observability, incident response, and governance. It is written for ML engineers, software engineers, security engineers, platform engineers, SREs, architects, and technical leaders who are responsible for building, operating, and protecting AI services in production.

Introduction: The Inescapable Tension

There is now a standard pattern in modern AI infrastructure, one that has emerged not from research papers but from the brutal arithmetic of production. A company builds or acquires access to a powerful model, sometimes a frontier system with hundreds of billions of parameters. That model is excellent, sometimes remarkable, but it is expensive, slow, and difficult to deploy at scale. So the company distills a smaller model, sometimes several smaller models, trained to reproduce the larger model's behavior on a curated set of tasks. The distilled models are faster, cheaper to run, and easier to distribute across regions, devices, and edge nodes. They become the workhorses.

Meanwhile, the company exposes its models through APIs. These APIs are the revenue engine and the product interface, but they are also a surface of attack. Anyone with API access can query the model, collect its responses, and use those responses to train a replica. The very technique the company uses to make its own models cheaper and faster, model distillation, is the same technique an adversary uses to steal the company's intellectual property. The defense against extraction attacks is not some separate security problem but an extension of the distillation problem itself.

This book is about that tension: between making models efficient and accessible, and keeping their capabilities proprietary and secure.

The Scale of the Problem

The economics behind this tension are staggering. As of late 2024 and into 2025, the cost of AI inference has fallen by over 280 times for GPT-3.5-level quality since November 2022, but absolute costs remain enormous because usage has grown far faster than costs have fallen [1,2,3]. For a successful AI product, cumulative inference spend always overtakes training spend, which means inference efficiency rather than training budget decides long-term unit economics [4]. A model that generates one billion tokens per month on an H100 GPU cluster at typical on-demand pricing costs tens of thousands of dollars per month in infrastructure alone, and that is before adding software, engineering, support, and the overhead of operating a global, reliable service [5,6].

At the same time, inference cost per million tokens varies by three orders of magnitude across the market. Budget tiers run roughly from $0.06 to $0.30 per million tokens, mid-tier from $0.55 to $15, and frontier models from $15 to $75 [7]. A company running inference at scale has a strong incentive to move from frontier models to distilled ones, sometimes achieving 10 to 100 times cost reduction while retaining most of the quality, provided the distillation is well executed.

The threat side of the equation has become equally concrete. In February 2026, Anthropic disclosed that rival AI companies had conducted massive distillation campaigns against its models, using over 16 million exchanges across approximately 24,000 fraudulent accounts, orchestrated through proxy networks and "hydra cluster" architectures designed to blend malicious traffic with legitimate requests [8]. One campaign alone used over 13 million exchanges to extract capabilities before the model's launch date. Another campaign collected over three million exchanges focused specifically on coding and agentic tool capabilities. The extracted models, Anthropic reported, lacked the safety guardrails and alignment work the company had invested heavily in training. Google's Threat Intelligence Group has also documented increasing global campaigns of model extraction by private entities, including operations that coerced models into emitting reasoning traces [9]. These are not hypothetical attacks. They are happening now, at industrial scale.

What This Book Covers

This book covers the complete technical lifecycle of distilling and securing AI models in production. It is organized in parts that build on each other from foundation to mastery.

Part I establishes shared context, explaining the economics and technical characteristics that drive the need for distillation and security, and reviewing the deep learning inference fundamentals that underpin everything else.

Part II covers knowledge distillation theory and practice, from the original Hinton framework through modern techniques for large language models. You will learn how soft targets encode more information than hard labels, how to design teacher and student architectures, how to manage the temperature parameter, and how to apply response-based, feature-based, attention-based, and relation-based distillation methods.

Part III covers compression and optimization, including quantization, pruning, and inference runtime techniques like continuous batching, KV cache management, and speculative decoding.

Part IV covers evaluation and engineering trade-offs, explaining how to measure distilled model quality, build evaluation pipelines, and make principled decisions across the quality-latency-cost triad.

Part V covers distributed systems and production deployment, including model parallelism, multi-node serving, autoscaling strategies, cloud and on-premises architectures, and operational patterns for reliable service.

Part VI covers security threats, detailing the threat landscape from model extraction and unauthorized distillation to API abuse, economic denial of service, and capability inference, with a focus on defensive understanding.

Part VII covers security defenses, including authentication and authorization, rate limiting and adaptive throttling, anomaly detection, model fingerprinting, watermarking, and secure infrastructure design.

Part VIII covers operations and governance, including observability, telemetry, alerting, incident response, forensic investigation, regulatory compliance, and organizational design for sustainable AI security.

How to Use This Book

This book is technical and practical. It assumes you are comfortable with programming and distributed systems, and have some familiarity with machine learning concepts. It does not assume you are an expert in any of these areas. When I introduce technical concepts, I explain them, but I do not slow down to hand-hold.

Each chapter contains detailed explanations, architectural discussions, and where appropriate, complete code examples. These examples are designed to be realistic and production-oriented, not toy demonstrations. They show patterns you could actually ship, including authentication, rate limiting, error handling, logging, and security controls. Where an example is an educational prototype rather than a full production system, I make that explicit.

The book is structured for sequential reading, but if you have specific immediate needs, you can jump to relevant parts. If your focus is distillation

techniques, start with Part II. If your focus is API security, start with Part VI. If your focus is operational deployment, start with Part V.

What This Book Does Not Cover

This book does not cover the following:

- **Training foundation models from scratch.** That is a massive topic in its own right. This book assumes you either have a pre-trained model or API access to one, and focuses on distilling and deploying from there.
- **Detailed adversarial attack recipes.** The security chapters describe threats thoroughly enough for defensive understanding but deliberately avoid step-by-step attack instructions that could be directly applied against real systems. This is not a penetration testing manual.
- **Exercises or quizzes.** This book uses worked examples, case studies, and architectural analyses instead.
- **Vendor-specific implementation details.** I discuss specific tools and technologies, but I focus on their capabilities, trade-offs, and appropriate use cases rather than providing vendor lock-in guidance.

The Through-Line

The central thesis of this book is that model distillation and API security are not separate disciplines but two sides of the same problem. Distillation is a capability that reshapes how organizations deploy AI, and it introduces a threat landscape where adversaries use the same techniques to extract, replicate, and abuse models. Effective industrial AI requires integrating distillation expertise with security engineering into a unified practice.

By the end of this book, you will understand how to design, implement, deploy, operate, and secure industrial-scale AI systems. You will know the techniques, the trade-offs, the tools, and the threats. You will be prepared to build systems that are not only powerful and efficient but also resilient and secure.

Let us begin.

Chapter 1: The Industrial AI Imperative — Why Distillation and Security Matter

Large AI models have become indispensable infrastructure, but they are also an infrastructure problem.

The models that define current capabilities, systems like GPT-4, Claude 3, Gemini, and the leading open-weight counterparts, are enormous. They contain tens of billions or even hundreds of billions of parameters. They were trained on massive datasets using thousands of GPUs running for weeks or months. Running them in production is not simply a matter of loading weights and making predictions. It is a complex engineering challenge involving memory management, parallelism, hardware selection, cost optimization, latency engineering, and reliability assurance.

At the same time, these models are high-value targets. The investment in training data, alignment work, safety tuning, and capability development is enormous, and the economic advantage of owning a superior model is real. Anyone who can replicate that model, even partially, can compete directly or leverage its capabilities without bearing the original cost.

Distillation and security are the responses to these two pressures. They are not optional optimizations. They are prerequisites for sustainable AI at scale.

The Cost Explosion of Foundation Models

The cost of running foundation models in production is driven by several factors that compound quickly as a product grows.

First, model size. A model with 70 billion parameters in floating-point 16-bit precision requires roughly 140 gigabytes of memory just to load weights, not counting activations, the key-value cache for attention, or the working memory needed during inference [10]. Larger models require more memory, more powerful hardware, and more complex parallelism strategies to distribute computation across multiple GPUs or nodes.

Second, inference is sequential and stateful. Language models generate tokens one at a time, and each new token depends on all previous tokens in the context. This means that unlike many traditional inference workloads, you cannot process a language model request in a single parallel batch and be done. Each request occupies GPU resources for the duration of its generation, which can be seconds or longer for long outputs. Memory usage grows linearly with context length because the key-value cache for each position in the sequence must be retained for future attention operations [11].

Third, traffic is bursty and unpredictable. Real-world usage patterns do not follow smooth curves. They spike during business hours, during marketing campaigns, during viral moments, and during outages of competitors. Scaling infrastructure to handle peak traffic while minimizing waste during low-traffic periods is a hard optimization problem, especially when the hardware is expensive and slow to provision.

Fourth, latency requirements are strict. Users of interactive AI applications expect near-real-time responses. Research and experience from production deployments suggest that users begin to lose patience after about one second of waiting and abandon interactions after three seconds, so systems should aim for sub-second P95 latency for user-facing workloads [12]. For streaming responses, the time to first token (TTFT) is particularly important because it signals to users that the system is working.

These factors combine to make raw inference on frontier models prohibitively expensive for most use cases. A company that sends billions of tokens through a frontier model API each month pays hundreds of thousands or millions of dollars. A company that self-hosts a frontier model faces similar costs in hardware, power, and operations. The only sustainable path for most products is to use distilled models for the majority of workloads, reserving the largest models for cases where their capabilities are genuinely needed.

The DistilBERT paper demonstrated this principle for transformer models early on, showing that a model with 40 percent fewer parameters could retain 97 percent of BERT's performance while running 60 percent faster [13]. More recent work on LLM distillation has shown similar patterns, with distilled models from GPT-4 or Claude achieving competitive quality on domain-specific tasks while running at a fraction of the cost.

Distillation is not merely about cost reduction. It is about making AI practically deployable. Without distillation, most organizations would be forced to

choose between using models that are too expensive for production or models that are too small to be useful. With distillation, they can have both.

Latency, Scale, and the Edge Imperative

Beyond cost, latency is a fundamental driver for distillation. Large models are slow not because of algorithmic inefficiency but because of raw arithmetic intensity. Each forward pass through a 70 billion parameter model involves trillions of floating-point operations. Even on the fastest available hardware, this takes time.

For interactive applications, latency directly affects user experience, engagement, and conversion. A chat application that takes three seconds to respond feels sluggish. A code completion tool that lags by half a second breaks the developer's flow. A search assistant that adds a full second of delay feels broken. Production teams report that reducing latency even by a few hundred milliseconds can measurably improve user satisfaction and usage [12,14].

Latency matters even more when you consider that many AI workloads are not isolated inference calls but chains of operations. A retrieval-augmented generation pipeline might involve a search query, document retrieval, document chunking, embedding generation, similarity search, context assembly, and then the actual model call. If each step adds 200 to 500 milliseconds, the total latency becomes unacceptable unless each component is optimized.

Scale compounds the latency problem. When you serve thousands of concurrent requests, resource contention becomes significant. GPUs that handle a single request quickly may queue requests under load. Static batching strategies waste time waiting for all requests in a batch to arrive. Memory pressure from concurrent long-context requests forces eviction or swapping, which introduces unpredictable delays.

Modern inference frameworks like vLLM address some of these problems with techniques like PagedAttention and continuous batching, which dramatically improve throughput and reduce fragmentation of the key-value cache [15]. PagedAttention manages KV cache memory in non-contiguous blocks instead of requiring contiguous pre-allocation, reducing waste by an order of magnitude. Continuous batching keeps the GPU busy by adding new requests to each batch as they arrive and removing completed ones, rather than waiting

for all requests to finish together. These techniques can improve throughput by 2 to 4 times compared to naive implementations [15,16].

But even with advanced scheduling and memory management, smaller models are inherently faster. They require less memory bandwidth, less compute per token, and less attention overhead. A distilled 7 billion parameter model will always respond faster than a 70 billion parameter model on the same hardware, all else equal. For latency-critical workloads, distillation is not optional.

Distillation also enables edge and on-device deployment, which is becoming increasingly important. Not every AI workload can or should run in the cloud. Applications like mobile assistants, IoT sensors, autonomous vehicles, and medical devices need local inference for reasons of latency, privacy, reliability, and regulatory compliance. A model that fits in a data center may not fit on a phone or an embedded device. Distillation, combined with quantization and pruning, makes on-device AI practical.

The Dual-Use Dilemma: Distillation as Offense and Defense

Here is the core tension that makes this topic both important and difficult: distillation is a dual-use capability.

On the defensive side, distillation allows a company to take its most powerful model, which may be proprietary, expensive, and protected, and create smaller models that can be deployed widely, cheaply, and safely. The distilled models capture the useful capabilities of the original while reducing exposure of the larger model to the outside world. They also reduce the economic incentive for attackers to target the primary model because the cheaper models already serve most needs.

On the offensive side, distillation allows an adversary to take API access to a model and replicate its behavior by collecting inputs and outputs and training a surrogate. The surrogate does not need to be perfect. It only needs to be good enough to compete, to bypass safety filters, to automate malicious tasks, or to serve as a foundation for further development. This is not science fiction. It is happening now, as documented by Anthropic, OpenAI, and Google [8,9,17].

The mechanics of API-based distillation are straightforward, which makes them dangerous. An attacker with API access can:

1. Generate or acquire a large dataset of prompts covering diverse tasks, domains, and edge cases.
2. Query the target model at scale, collecting its responses.
3. Use the prompt-response pairs as training data for a new model, using supervised fine-tuning or other learning methods.
4. Optionally, use the target model's confidence scores or probability distributions if the API exposes them, to perform knowledge distillation in the Hinton sense rather than simple imitation learning.

The fidelity of the resulting surrogate depends on how many queries the attacker can send, how diverse those queries are, and how much detail the target model reveals in its outputs. With sufficient data, an attacker can approximate a model's behavior closely enough to launch a competing product or strip away guardrails that protect the original [17,18].

This creates a design challenge for anyone who exposes model APIs: you must balance accessibility and functionality against the risk that your API will be used to copy your model. If you make the API too restrictive, legitimate users cannot build useful applications. If you make it too permissive, attackers can harvest enough data to replicate your capabilities.

Defensive strategies exist, as we will cover in later chapters, but none are perfect. Rate limiting slows data collection but also slows legitimate users. Output perturbation adds noise that confuses extraction but also degrades quality for real applications. Watermarking may allow detection of stolen models but does not prevent the theft itself. The art of API security is finding the right balance between usability and protection, understanding that some risk is inevitable and designing systems that can detect and respond to attacks when they occur.

From Research Prototype to Production Reality

The gap between research and production is enormous in AI, perhaps larger than in any other technology domain. Research papers focus on accuracy on benchmark datasets, measured under controlled conditions with generous compute budgets. Production systems must handle real users, real traffic patterns, real failure modes, and real adversaries, all while operating within constraints of budget, latency, reliability, and compliance.

Several specific gaps are worth calling out because they are where most teams stumble.

Benchmarks mislead. Standard benchmarks like MMLU, HumanEval, and GSM8K are useful for rough comparison but do not measure what matters in production. They do not capture domain-specific performance, robustness to adversarial inputs, consistency across edge cases, or behavior under distribution shift. A model that scores 85 percent on MMLU may perform terribly on your customer support queries or your medical coding task. Production evaluation requires domain-specific test sets, continuous monitoring, and regression detection, not just a single benchmark score.

Quality is not binary. In research, accuracy is a number. In production, quality is a distribution of outcomes across different types of requests, and different types of errors have different business impacts. A wrong answer in code generation may cause a developer to waste an hour debugging. A wrong answer in medical coding may cause a claim to be rejected. A wrong answer in customer support may frustrate a user but not break anything. Understanding your error landscape, quantifying the cost of different failure modes, and optimizing for the error types that actually matter is a critical but underappreciated skill.

Failure is inevitable. Production systems fail. Networks partition. GPUs crash. Models encounter inputs they were never trained on. APIs time out. Dependencies break. Building a resilient system means designing for these failures: implementing retries with backoff, building fallback paths to smaller or simpler models when the primary model is unavailable, monitoring for degradation and alerting before users notice, and planning for graceful degradation rather than binary success or failure.

Security is not an add-on. Too many teams build their inference service and then try to bolt on security afterward. By then, the API surface is already exposed, traffic patterns are already established, and changing the design is expensive. Security must be designed in from the beginning: authentication and authorization, rate limiting, input validation, output filtering, logging, monitoring, anomaly detection, and incident response procedures must be part of the initial architecture, not an afterthought.

The chapters ahead address each of these gaps systematically. We will cover how to design distillation pipelines that produce models that are not just benchmark-competitive but production-ready. We will cover how to evaluate

models in ways that reflect real business requirements. We will cover how to build serving infrastructure that is fast, reliable, and resilient. We will cover how to secure APIs against a sophisticated threat landscape.

The industrial AI imperative is clear: distill to survive, secure to endure. The techniques, tools, and trade-offs required to do both are the subject of this book.

Let us move from why to how.

Chapter 2: Deep Learning Inference — The Technical Foundation

Before diving into distillation and security, we need shared technical vocabulary. This chapter reviews the fundamentals of neural network inference, the compute characteristics that make it expensive and slow, and the gap between training and serving that distillation is designed to bridge.

How Neural Network Inference Works

At its core, neural network inference is a sequence of mathematical operations applied to input data to produce predictions. For a modern transformer-based language model, the process looks like this:

1. **Tokenization.** The input text is converted into a sequence of tokens, which are numerical identifiers representing words, subwords, or characters, depending on the tokenizer. A typical English sentence of 20 words might tokenize into 25 to 30 tokens.
2. **Embedding.** Each token is mapped to a dense vector representation, typically hundreds or thousands of dimensions. This embedding vector is the model's numerical understanding of the token, combining semantic meaning, syntactic role, and contextual information learned during training.
3. **Forward pass through layers.** The embedding vectors are processed through a stack of transformer layers. Each layer performs self-attention, which allows each position in the sequence to attend to all other positions, capturing relationships and dependencies. Each layer also applies feed-forward transformations that process information locally at each position. For a model with 32 layers, this stack is applied 32 times.
4. **Output projection.** After the final layer, the hidden state at the last position is projected to the vocabulary dimension, producing a probability distribution over all possible next tokens.

5. **Sampling or selection.** A token is selected from the distribution using a sampling strategy like greedy decoding, top-k sampling, or nucleus sampling. The selected token is appended to the sequence, and the process repeats from step 3 until a stop condition is met.

For classification or other non-generative tasks, steps 4 and 5 are replaced by applying a task-specific head that maps the final hidden state to the output space.

The key insight for inference optimization is that this process has two distinct phases with different computational characteristics:

- **Prefill phase:** Processing the input prompt. All tokens in the prompt are processed in parallel through the model layers. This phase is compute-intensive because it involves full attention over all tokens and requires loading all model weights.
- **Decode phase:** Generating output tokens one at a time. Each new token depends on all previous tokens, so the process is inherently sequential. However, much of the computation for previous tokens can be cached, so each decode step is relatively cheap per token but must repeat for every token generated.

Understanding this distinction is critical for optimization. Techniques like KV caching, which we will cover in detail in Chapter 11, exploit the fact that during decoding, most of the attention keys and values from previous positions can be reused, avoiding recomputation.

Compute, Memory, and Bandwidth Constraints

Neural network inference is constrained by three physical resources: compute, memory capacity, and memory bandwidth. Which one is the bottleneck depends on the model, the hardware, and the workload.

Compute. Modern GPUs and TPUs are designed for massive parallel computation, with thousands of cores optimized for floating-point matrix multiplication. A single H100 GPU can perform trillions of floating-point operations per second in FP16 or FP8 precision. For large models with large batch sizes, inference can be compute-bound, meaning the GPU cores are the limiting factor.

However, compute capacity is rarely the binding constraint in practice for language model inference. The operations involved in attention and feed-forward networks are computationally intensive, but modern accelerators are designed specifically for these patterns, and the arithmetic intensity is not high enough to fully saturate the compute units in many scenarios.

Memory capacity. This is often the primary constraint. A model with 70 billion parameters in FP16 requires about 140 GB of memory. A model with 405 billion parameters requires about 800 GB, which exceeds the memory of a single consumer or even many data-center GPUs and requires distribution across multiple devices. Additionally, each concurrent request requires its own key-value cache, which grows linearly with context length and batch size. For long-context requests with large batches, the KV cache alone can consume tens of gigabytes of memory.

When memory capacity is insufficient, systems must fall back to slower strategies: offloading weights to CPU memory and fetching them as needed, which introduces significant latency; reducing batch sizes, which reduces throughput; or rejecting requests, which degrades user experience.

Memory bandwidth. This is the rate at which data can be transferred between memory and compute units, and it is often the actual bottleneck for inference. Attention operations, in particular, are bandwidth-heavy because they require loading keys and values for all positions in the sequence into registers, computing attention scores, and writing the results back. For large sequences, most of the time is spent moving data rather than computing.

Flash Attention, a technique we will discuss in Chapter 11, directly addresses the bandwidth problem by restructuring the attention computation to minimize data movement between slow DRAM and fast on-chip memory, achieving 2 to 5 times speedup in many scenarios [19].

The interaction between these three constraints shapes almost every decision in inference optimization. Quantization reduces memory requirements and can also improve bandwidth utilization by moving smaller data elements. KV cache optimization directly targets memory capacity and bandwidth. Model parallelism distributes weights across multiple GPUs to overcome capacity limits but introduces communication overhead that can affect compute utilization.

Training Versus Serving: A Fundamental Mismatch

The requirements for training a model and serving it in production are fundamentally different, and this mismatch is at the root of why distillation matters.

Training requirements:

- Massive compute. Training frontier models requires thousands of GPUs running for weeks, with total compute in the range of hundreds of thousands or millions of GPU-hours.
- Large batch sizes. Training stability and efficiency require processing thousands of examples simultaneously, which favors hardware configurations optimized for massive parallelism.
- Gradient computation. Training requires backpropagation, which doubles the memory requirements compared to inference because gradients and optimizer states must be stored.
- Data access. Training requires streaming through massive datasets, so fast storage and data pipelines are critical.

Serving requirements:

- Low latency. Individual requests must be processed quickly, often with strict percentiles (e.g., P99 under 2 seconds).
- High concurrency. Systems must handle thousands or millions of concurrent requests efficiently.
- Variable load. Traffic fluctuates over time, so systems must scale up and down or handle bursts gracefully.
- Memory efficiency. Each request occupies memory during processing, so efficient memory utilization directly affects how many concurrent requests can be served.
- Reliability. Systems must handle failures gracefully and maintain availability even when individual components fail.

A model optimized for training may be terrible for serving. It may be too large to fit in available memory, too slow to meet latency requirements, or too expensive to run at scale. Distillation creates models that are optimized specifically for serving: smaller, faster, cheaper, while retaining the capabilities that training at scale provides.

This mismatch also explains why distillation is not simply about compression. A compressed model that is optimized for storage size but not for inference speed or memory bandwidth may still be unsuitable for production. Effective distillation must consider the full serving stack: the model architecture, the runtime, the hardware, and the traffic patterns.

The Model Serving Stack at a Glance

A production model serving system is a complex stack of components. Understanding the layers and their responsibilities is essential for both distillation design and security architecture.

At the application layer, there is the API interface itself: the HTTP or gRPC endpoints that clients call, the request and response formats, authentication and authorization, rate limiting, and input validation. This is where most security controls are implemented, and where the user-visible behavior is defined.

At the inference layer, there is the serving framework or runtime: the software that loads the model, manages memory, schedules requests, handles batching, and executes the forward pass. Popular frameworks include vLLM, Hugging Face Text Generation Inference, TensorRT-LLM, and open-source implementations based on PyTorch or TensorFlow. The choice of framework significantly affects throughput, latency, and operational complexity.

At the hardware layer, there are the accelerators and infrastructure: GPUs, TPUs, or specialized inference chips; the memory, storage, and networking that support them; and the operating system and drivers that interface between software and hardware.

At the orchestration layer, there is the container and cluster management: Docker or similar containerization, Kubernetes or equivalent orchestration for scaling and scheduling, service meshes for communication, and monitoring and observability systems for tracking performance and detecting problems.

At the data layer, there are the supporting services: databases for storing metadata, caches for frequently accessed data, message queues for asynchronous processing, and logging and telemetry systems for recording operational data.

Distillation affects primarily the inference layer and the model itself, but its effectiveness depends on the entire stack. A distilled model that is well-

designed for a specific hardware platform and serving framework may outperform a larger model even on raw quality metrics due to better optimization. Security controls span primarily the application layer and orchestration layer, but must integrate with the inference layer to monitor model-specific threats and with the data layer for logging and analysis.

The chapters ahead will dive into each layer in detail, showing how distillation, optimization, and security interact to produce robust industrial AI systems.

Chapter 3: Knowledge Distillation — Theory and Mathematical Foundations

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The Hinton Framework: From Hard Labels to Soft Targets

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Chapter 6: Response-Based and Feature-Based Distillation Methods

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Feature-Based Distillation: Intermediate Representations

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Example 1: Secure Model-Serving API with FastAPI

Example 2: Knowledge Distillation Training Loop

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Example 4: Kubernetes Deployment Manifests

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