Optimization and Routing of LLM Requests Across Different Providers

Final thesis X-HEC

CRUVELLIER Baptiste

Academic advisor : Gentian Jakllari
Company : Makehub

Master X-HEC
2025

Remerciements

I would like to express my deepest gratitude to all those who contributed to the completion of this professional thesis.

First and foremost, I wish to thank my academic advisor, Gentian Jakllari, for supervising this thesis.

I would also like to warmly thank the Makehub team for welcoming me and offering the opportunity to work on this fascinating subject at the intersection of artificial intelligence and distributed systems optimization. My deepest gratitude goes to my co-founders, Romain Batlle and Samir Fernando Florido, with whom I had the privilege of building this project from the ground up. Their trust, complementary skills, and shared entrepreneurial vision have been instrumental in bringing this venture to life. The collaborative dynamic we established, the quality of our exchanges, and the stimulating work environment we created together have been essential to both the technical success of this project and my personal growth as an entrepreneur.

I am particularly grateful to the X-HEC Master's program for this transformative year. This program ignited a flame within me—a passion for entrepreneurship and a fundamentally new perspective on how the world works and what truly drives me. It has profoundly reshaped my professional aspirations and personal vision.

Finally, I wish to thank my family and friends for their constant support and encouragement throughout this master's year.

Thank you all for this opportunity and for providing me with an environment conducive to learning, on a subject that fascinates me and in a stimulating work environment.

Contents

List of Figures

1 Introduction: LLMs and the Multi-Provider Landscape

This thesis presents the design, implementation, and empirical validation of **Makehub**, an intelligent routing gateway for Large Language Model (LLM) inference. Makehub addresses a critical challenge in the rapidly evolving LLM ecosystem: the fragmented, volatile, and opaque landscape of inference providers. By dynamically routing requests across 20+ providers based on real-time performance metrics and pricing, Makehub achieves **40–70% cost savings** while maintaining or improving response quality and speed. Rather than forcing developers to manually select and manage multiple providers, Makehub acts as a unified API layer that optimizes infrastructure choices transparently, enabling developers to focus on building AI-powered applications.

The following sections establish the technical and market context that motivates Makehub's design. We begin by introducing LLM fundamentals (§1.1), then characterize the multi-provider landscape (§1.2–1.3), and examine the application domain of code assistants (§1.4) where inference costs and performance are most critical.

1.1 Contextualization of Large Language Models (LLMs)

1.1.1 Definition of Large Language Models

Large Language Models (LLMs) are a family of deep neural networks trained on massive textual corpora with the primary objective of predicting the next token in a sequence, given a context. This seemingly simple task of autoregressive text generation has emerged as a powerful paradigm for learning rich representations of natural language, enabling capabilities that extend far beyond simple text completion.

What is a token? A **token** is the fundamental unit of text processing in LLMs. Contrary to intuition, tokens are *not* words but rather **subword units** produced by algorithms like Byte-Pair Encoding (BPE), WordPiece, or SentencePiece.

For example:

- `"tokenization"` → `["token", "ization"]` (rare word split into subwords)
- `"Hello"` → `["Hello"]` (common word remains intact)

This subword approach allows models to handle any text—including rare words, technical jargon, and code—with a fixed vocabulary of 50,000–100,000 tokens.

Why tokens matter:

- **Model capacity**: measured in tokens (e.g., 128K token context window for GPT-4 Turbo)
- **Pricing**: per-token billing (e.g., $2.50 per million input tokens for GPT-4o)
- **Performance**: throughput measured in tokens per second

Understanding that token counts do not directly correspond to word counts is essential for cost and performance optimization. We discuss tokenization in depth when covering the API protocol and measurement methodology (§3.1).

From research breakthrough to production deployment. The modern era of LLMs began with the **Transformer architecture** (Vaswani et al. 2017), which replaced recurrent architectures with a purely attention-based mechanism. This enabled parallelization during training and unlocked unprecedented scale. The subsequent GPT series (Radford, Narasimhan, et al. 2018; Radford, Wu, et al. 2019; Brown et al. 2020), built on decoder-only Transformers optimized for autoregressive text generation, demonstrated that **scale** was critical: GPT-3, with 175 billion parameters trained on approximately 300 billion tokens, exhibited emergent capabilities like few-shot learning—performing diverse tasks through natural language prompting alone, without task-specific fine-tuning.

This breakthrough catalyzed widespread deployment: LLMs now power conversational agents, code assistants, document analysis tools, and agentic systems across industries. However, moving from research prototypes to production systems introduces a fundamental challenge that motivates this thesis.

The inference challenge: cost, latency, and variability. Deploying LLMs at scale presents three interrelated challenges that distinguish production inference from academic experimentation:

1. **Computational cost.** While training a frontier model like GPT-4 requires tens of millions of dollars in compute (Hoffmann et al. 2022), *inference* costs dominate for deployed systems. Each forward pass through billions of parameters demands substantial GPU resources. At scale, inference expenditure dwarfs training costs: a company serving millions of requests daily can incur monthly inference bills exceeding training budgets.

2. **Latency constraints.** Interactive applications, especially code assistants—require low time-to-first-token (TTFT) to maintain responsiveness. Users typing in an IDE expect inline suggestions within 300–500ms. Even a 2-second delay feels sluggish and disrupts flow. Yet inference latency depends on model size, batch scheduling, queue depth, and network round-trip time—factors that vary unpredictably across infrastructure providers.

3. **Performance variability.** Unlike static benchmarks measured on dedicated hardware, production inference exhibits **dynamic heterogeneity**:

    - **Spatial variability**: The same model hosted by different providers (e.g., OpenAI vs. Azure vs. Together AI) delivers vastly different throughput and latency due to differences in GPU hardware, serving frameworks (vLLM, TGI, TensorRT), batching strategies, and datacenter locations.
    - **Temporal variability**: A single provider's performance fluctuates over time due to load variations, autoscaling delays, and resource contention. As we document empirically in §3.1, OpenAI's GPT-4o endpoint exhibits 32% throughput variation across hours, with a 13.7% degradation during peak US business hours.

These challenges are particularly acute for **code assistants**, which combine high token volumes (reading entire files, generating multi-function completions), strict latency requirements (real-time suggestions), and cost sensitivity (freemium business models with razor-thin margins). Optimizing inference for code assistants requires navigating a three-dimensional trade-off space where no provider consistently dominates across cost, latency, and throughput—the core problem Makehub addresses.

Quantifying production performance: deployment metrics. To measure and optimize the challenges outlined above, production LLM systems rely on four key operational metrics, all expressed in terms of tokens:

- **Latency (time-to-first-token, TTFT)**: the elapsed time between sending a request and receiving the first output token. Measured in milliseconds or seconds. Critical for interactive responsiveness—users perceive delays beyond 500ms as sluggish.
- **Throughput (tokens per second)**: the rate at which output tokens are generated during streaming. Measured in tokens/s. Determines total generation time for long outputs (e.g., a 500-token code snippet at 100 tokens/s takes 5 seconds, but only 2.5 seconds at 200 tokens/s).

- **Context window (in tokens)**: the maximum combined length of input and output. Recent models range from 8K tokens (early GPT-3.5) to 2M tokens (Gemini 1.5 Pro). Larger windows enable richer context (entire codebases, long conversations) but increase per-request cost and memory requirements.
- **Inference cost (per million tokens)**: provider pricing, typically split between input tokens (cheaper) and output tokens (more expensive). For example, GPT-4o costs \$2.50/M input tokens and \$10.00/M output tokens (January 2025). Cost structures vary dramatically across providers, with no correlation to performance (as shown in Figure 1).

The heterogeneity problem. Critically, these metrics **vary across providers** even when hosting identical model weights. As documented empirically in §3.1, the same GPT-4o model exhibits:

- **30% throughput difference** between OpenAI's native endpoint (62 tokens/s median) and Azure regions (89 tokens/s median).
- **32% temporal variation** within a single provider (OpenAI) across different hours of the day.
- **No price-performance correlation**: expensive providers do not guarantee better performance, and cheap providers are not uniformly slow.

This variability—both *spatial* (across providers) and *temporal* (across time)—creates an optimization opportunity. The central challenge addressed in this thesis is: **how can requests be dynamically routed to maximize a user-defined objective (e.g., minimize cost, maximize throughput, or balance both) in the face of this heterogeneity?**

Solving this problem requires understanding the economic and technical dichotomy between closed-source and open-source models, which determines the breadth of the provider selection space—the subject of the next section.

1.1.2 Closed-source vs Open-source Models

The contemporary LLM landscape is characterized by a fundamental economic and technical dichotomy between **closed-source** and **open-source** models. This distinction has profound implications for deployment strategies, cost structures, and—most relevant to this thesis—the complexity of provider selection.

Closed-source models: limited provider diversity. Closed-source models (e.g., GPT-4o, Claude 3.5, Gemini) are developed by private companies (e.g., OpenAI, Anthropic, Google DeepMind) that retain exclusive control over model weights, training methodologies, and pricing. While these models may be accessible through multiple infrastructure endpoints—for instance, GPT-4o is available via OpenAI's native API, Azure OpenAI Service (across multiple regions), and AWS Bedrock—all endpoints remain **vendor-controlled**:

- **Performance optimization is possible**: Different hosting endpoints (e.g., Azure East US vs West Europe) exhibit performance variance due to geographic routing, datacenter load, and regional infrastructure. Routing can exploit these differences to optimize latency and throughput across vendor-managed endpoints.
- **Price optimization is impossible**: All endpoints use the vendor's unified pricing model. For GPT-4o, whether accessed via OpenAI, Azure, or Bedrock, the cost remains \$2.50/M input tokens and \$10/M output tokens (with minor regional adjustments). There is no competitive pressure to reduce prices—the vendor sets rates unilaterally.

This limited provider diversity means that routing optimization for closed-source models is **one-dimensional** (performance only), with significantly constrained value compared to open-source routing.

Open-source models: competitive provider ecosystem. In contrast, open-source models (e.g., Meta's LLaMA series (Touvron et al. 2023; Meta AI 2024), Mistral AI's models (Mistral AI 2023), DeepSeek (DeepSeek AI 2024)) release model weights publicly, enabling a **decentralized hosting ecosystem** where 15+ independent providers compete to host identical model weights. Any organization with sufficient compute resources—from hyperscalers (AWS, Google Cloud, Azure) to specialized inference startups (Together AI, Fireworks, Replicate)—can deploy these models and offer API access.

This decentralization yields two critical consequences:

1. **Price competition**: Multiple providers compete to host the same model, driving down inference costs. For example, Llama 3.1 70B is available from over 15 providers with prices ranging from \$0.50 to \$3.00 per million tokens—a **6× variance** for identical model weights.

2. **Performance heterogeneity**: Providers deploy models on different hardware (NVIDIA A100 vs H100, AMD MI300), use different serving frameworks (vLLM (Kwon et al. 2023), TensorRT-LLM (NVIDIA 2024), TGI), and operate under varying load conditions. As a result, latency and throughput for the *same model* can vary by **2–3×** across providers.

This dual heterogeneity across both *price* and *performance* creates a **two-dimensional optimization space** with substantially higher value than closed-source routing. Makehub can simultaneously minimize cost and maximize performance by dynamically selecting among competing providers.

Implications for Makehub. Table 1 summarizes the key differences between closed-source and open-source deployment models. While Makehub supports both closed-source and open-source models, the optimization opportunity is **asymmetric**:

- **Closed-source routing**: Optimize performance across 3–5 vendor-controlled endpoints (moderate value, one-dimensional).
- **Open-source routing**: Optimize both cost and performance across 15+ competitive providers (high value, two-dimensional).

This asymmetry explains why Makehub's impact is most significant in the open-source ecosystem, where provider heterogeneity creates the largest optimization space.

Table 1: Comparison between closed-source and open-source LLMs (2025).

Criteria	**Closed-source**	**Open-source**
Examples	GPT-4o (OpenAI), Claude 3.5 (Anthropic), Gemini 2.0 (Google)	Llama 3.1 (Meta), Mistral, DeepSeek
Provider diversity	3–5 vendor-controlled endpoints (OpenAI, Azure, Bedrock)	15+ independent competitive providers (Together, Fireworks, Replicate, etc.)
Performance arbitrage	Possible across vendor endpoints (geographic regions, datacenter load)	Possible across independent providers (hardware, frameworks, optimization)
Price arbitrage	Impossible (vendor sets unified pricing across all endpoints)	Possible (6× variance: \$0.50–\$3.00/M tokens for same model)
Optimization dimensions	1D: Performance only	2D: Performance AND price
Routing value	Moderate (constrained by vendor pricing)	High (exploit competitive market)

This dichotomy between closed and open-source models defines the landscape of provider options. However, regardless of whether a model is proprietary or open, all LLM systems rely on a common architectural pattern: the separation of models from the infrastructure that serves them. This abstraction is the subject of the next subsection.

1.1.3 The Model-Provider Abstraction Layer

A critical conceptual distinction underpins the architecture of modern LLM deployment: the separation between the **model layer** (algorithmic artifact) and the **provider layer** (infrastructure service). Understanding this abstraction is essential to framing the optimization problem addressed in this thesis.

The model layer: algorithmic capability. At the conceptual level, a *model* is defined by its architecture (e.g., transformer decoder), training data, parameter count, and learned weights. Examples include:

- **Llama 3.1 70B** (Meta): An open-source 70B-parameter instruction-tuned model (Meta AI 2024) available from 15+ providers (Together AI, Fireworks, Replicate, AWS Bedrock, Azure, Google Vertex AI, etc.). This exemplifies the many-to-many mapping: one model, many infrastructure choices.
- **Codestral** (Mistral AI): A 22B-parameter code-specialized model (Mistral AI 2024) hosted by 10+ providers, each with different latency and pricing.
- **GPT-4o** (OpenAI): A closed-source proprietary model (OpenAI 2023) available through 3–5 vendor-controlled endpoints (OpenAI, Azure, Bedrock), illustrating limited provider diversity for closed-source models.

From a functional perspective, the model determines *what* the system can do: its reasoning capabilities, domain knowledge, and output quality. However, the model itself is merely a static artifact (a set of weights); it cannot be queried directly.

The provider layer: infrastructure service. The *provider* is the entity responsible for **inference serving**—deploying the model on hardware, exposing it via an API, and handling production concerns such as load balancing, rate limiting, and billing. Examples include:

- **First-party providers**: OpenAI API, Anthropic API, Google AI Studio (vendor-controlled hosting of proprietary models).
- **Cloud hyperscalers**: Azure OpenAI Service, AWS Bedrock, Google Vertex AI (enterprise-grade hosting of both proprietary and open-source models).
- **Specialized inference platforms**: Together AI, Fireworks AI, Replicate, Groq (optimized hosting of open-source models, often with custom serving frameworks or hardware).

The provider layer determines *how* the model is delivered: latency, throughput, geographic availability, pricing structure, and reliability. Critically, **the same model can be hosted by multiple providers**, each offering different performance and cost characteristics.

Implications for Makehub's optimization strategy. This abstraction creates a **many-to-many mapping**: a single model may be available from multiple providers, and a single provider may host multiple models. Makehub's scope within this landscape is specifically defined:

- **Model selection is user-specified**: Developers choose the model they want based on capability requirements (e.g., "I want Llama 3.1 70B for this code generation task"). Makehub does *not* perform model selection or model-level routing—we assume the model choice is fixed by the user.

- **Provider selection is Makehub-optimized**: Given a user's model choice, Makehub selects the provider that best optimizes their declared objective function: minimize cost, maximize throughput, minimize latency, or a weighted combination (e.g., 70% cost / 30% speed). This is the core optimization problem Makehub solves.
- **Dynamic re-routing maintains optimality**: As provider performance changes over time—due to load variations, infrastructure updates, or pricing changes (§3.1)—Makehub continuously re-evaluates and switches providers to maintain optimal performance according to the user's objective.

The distinction is critical: Makehub solves the **provider routing problem**, not the model routing problem. We optimize *where* to run a given model, not *which* model to run.

Positioning within the routing literature. Recent academic work has begun to address the problem of LLM routing, though predominantly at the **model level** rather than the provider level:

- **RouteLLM** (Ong et al. 2024) proposes learned routers that dynamically select between stronger and weaker models (e.g., GPT-4 vs GPT-3.5) based on query characteristics, achieving 2× cost reduction while maintaining quality. However, RouteLLM assumes a fixed provider for each model and does not optimize across infrastructure choices.
- **OptiRoute** (Kumar, Singh, and Patel 2025) extends routing to incorporate multi-dimensional user preferences (accuracy, cost, ethical constraints), but similarly treats each model as monolithically tied to a single API endpoint.
- **Universal Model Routing** (Zhao, Liu, and Zhang 2025) addresses the challenge of dynamic LLM pools where models may be added or removed over time, but focuses on model capability rather than infrastructure-level performance heterogeneity.

These systems address the question: *"Which model should I use for this query?"* Makehub addresses a complementary but distinct question: *"Which provider should I use to serve this model?"* This distinction is critical because:

1. The same open-source model (e.g., Llama 3.1 70B) exhibits **3× latency variance** and **6× cost variance** across providers, as documented in §1.1.2 and empirically validated in §3.1.
2. Provider-level optimization requires real-time monitoring of infrastructure performance (throughput, latency, availability), whereas model-level routing relies on static model capabilities.
3. Provider routing must account for operational constraints (rate limits, regional availability, API compatibility) that are orthogonal to model quality.

To our knowledge, Makehub is the first production system to implement **dynamic provider-level routing** with real-time performance measurement, multi-objective optimization, and automatic fallback mechanisms across 30+ infrastructure providers. While academic routing frameworks optimize *which model* to use, Makehub optimizes *where to run it*—a problem that becomes particularly acute in the open-source LLM ecosystem where provider heterogeneity dominates (§1.1.2).

The following section (§1.1.4) examines the evolution of code assistants as a concrete use case for high-volume LLM inference, motivating the need for intelligent provider routing in production environments.

1.1.4 Code Assistants: From Autocomplete to Agentic Systems

The ecosystem of AI code assistants has undergone a rapid evolution: from simple autocomplete extensions to fully *agentic systems* capable of planning multi-step changes, running tools, and managing repositories. By 2025, the market has become **agent-first**: code completion alone is no longer the norm, and growth is driven by autonomous, high-volume inference workloads.

Phase 1 — Inline autocomplete inside IDEs (2021–2022). The modern wave began with *GitHub Copilot* providing inline completions directly in IDEs like VS Code and JetBrains. Copilot was first announced in technical preview on June 29, 2021 and reached general availability in June 2022 GitHub 2021; GitHub 2022. This phase emphasized **low first-token latency** and short local context, but token usage remained relatively modest.

Phase 2 — AI-first editors and open-source agents (2023–2024). The second wave marked the shift toward agentic experiences. *Cursor* emerged as an AI-first IDE (Aug 2023), embedding LLM-powered chat, code editing, and repo-level reasoning inside the editor Anysphere, Inc. 2023; Swyx and Alessio 2023. At the same time, open-source agents flourished: *Cline* (formerly "Claude Dev", rebranded in 2024), *Roo Code* (renamed mid-2025), and *Continue* (vendor-agnostic, 1.0 in Feb 2025) all demonstrated agentic workflows within VS Code/JetBrains Rizwan 2024; Roo Code Team 2025; Continue Dev, Inc. 2025. Compared with Phase 1, these tools massively increased token throughput by reading repositories, performing cross-file refactors, and generating entire files.

Phase 3 — Copilot becomes agentic (2025). In May 2025, GitHub introduced the *Copilot coding agent* at Microsoft Build, enabling autonomous repo-level tasks, execution in sandboxes, and PR creation GitHub 2025. This marked the full transition of Copilot from autocomplete to a fully agentic platform tightly integrated into GitHub's ecosystem.

Phase 4 — Vendor lock-in via IDE integrations (2025). Large providers responded with their own IDE-native agents as a strategic lock-in play. *Claude Code*, launched in May 2025 alongside Claude 4, shipped VS Code and JetBrains integrations with background task support and Actions integration Anthropic 2025b; Anthropic 2025a. Here, the editor becomes the sticky layer: while models are swappable, developer habits inside a feature-rich IDE are much harder to dislodge.

Phase 5 — Expansion beyond developers: Lovable and Codex (2025). A parallel development is the rise of assistants for **non-developers**. *Lovable* lets users generate entire apps and integrations without coding, via credits-based inference usage Lovable 2025. Lovable's heavy token consumption (app scaffolding, full-file regeneration) demonstrates how inference costs scale when onboarding a non-technical audience Times 2025. Meanwhile, OpenAI reintroduced *Codex* in 2025 as a more agentic product, complementing ChatGPT-based workflows with web/CLI integration OpenAI 2025b; OpenAI 2025a.

A practical taxonomy (2025 view).

- **Agentic systems (default):** multi-step plans, repo-wide edits, tool execution, PR creation. This is now the dominant mode of code assistance.
- **Non-developer builders:** platforms like Lovable extend inference-heavy agentic workflows beyond professional developers.
- **Completion-only systems:** now largely legacy; useful as context, but no longer the market driver.

Table 2: Code assistant categories in 2025.

Category	**Core capabilities**	**Integration**	**Operational profile**
Agentic systems	Multi-step plans, repo-wide edits, tool execution, PRs	IDEs (VS Code, JetBrains), CLI, cloud sandboxes	Heavy inference; high throughput; strong observability
Non-dev builders	Full app generation, integrations, deployment	Web platforms (e.g., Lovable)	Massive token usage; consumer-oriented pricing
Completion-only (legacy)	Inline suggestions, local context	IDE extensions	Low latency; limited token usage

Implications for Makehub. The implications are not a split between completion and agents—completion has been surpassed. Instead:

- The market is **agent-first**, with assistants consuming unprecedented inference volumes.
- This growth extends beyond developers: non-dev tools like Lovable dramatically increase total demand.
- Inference is **expensive**: agentic workflows maximize input/output tokens, throughput, and compute requirements.
- The market is **young and fragmented**, with heterogeneous pricing across providers and unstable real-time performance (latency, quotas, outages).

For **Makehub**, this creates a clear opportunity: acting as a routing layer that arbitrages across providers in real time, delivering consistent *speed per euro* despite volatility, and ensuring robust fallbacks. In a world where inference demand is exploding and infrastructure supply chains remain unsettled, such routing becomes a critical enabler of scalable agentic coding.

2 The Makehub Project

Having established the technical landscape of LLMs and the multi-provider ecosystem in which they operate, we now turn to the Makehub project itself. This section introduces the team behind Makehub (§2.1), provides a detailed system overview explaining what Makehub is and how it works (§2.2), and articulates the specific research contributions of this thesis (§2.3). Together, these subsections bridge the gap between the market context established in Section 1 and the technical implementation detailed in subsequent sections.

2.1 The Team

The founding team of Makehub was formed within the X-HEC Entrepreneurs Master's program. We are three co-founders with complementary backgrounds, brought together by a shared interest in artificial intelligence and its large-scale deployment.

Romain Batlle – CEO (Chief Executive Officer)

Romain completed an engineering degree at the University of Warwick in London, followed by the Grande École program at HEC Paris. His profile is oriented towards strategy and business development, with strong expertise in finance, data analysis, and artificial intelligence. As CEO, Romain leads the company's overall vision and commercial strategy, leveraging his multidisciplinary background to position Makehub in the competitive AI infrastructure market.

Samir Fernando Florido – CPO (Chief Product Officer)

Fernando holds a Master's degree (M2) from Institut Polytechnique de Paris with a major in Cyber-Physical Systems, where he developed expertise in AI and robotics engineering. He previously worked on creating verification tools for complex robotic systems at the Computer Science Laboratory of École Polytechnique (LIX). As CPO, Fernando brings strong scientific and technical expertise in optimization and system design, defining the product roadmap and ensuring technical excellence in our AI routing solutions.

Baptiste Cruvellier – CTO (Chief Technology Officer)

After completing an engineering degree at ENSEEIHT Toulouse (N7) with a specialization in computer networks, I joined the X-HEC Entrepreneurs program. While my academic background is rooted in networking and distributed systems, I have developed a strong interest in applied artificial intelligence, particularly in the field of large language models (LLMs). Through both research and entrepreneurial projects, I have focused on how AI can be integrated into real-world infrastructures. Within Makehub, I am responsible for the technical vision and architecture, designing solutions that bridge advanced AI capabilities with efficient and scalable networked systems.

2.1.1 The origin of the project

The origins of the Makehub project can be traced back to our three-month academic exchange in San Francisco, organized in partnership with the University of California, Berkeley. The objective of this exchange was entrepreneurial: to design and develop a project while being immersed in the Silicon Valley ecosystem.

During this period, our schedule alternated between structured academic input and practical exploration. We attended two days of entrepreneurship courses per week, supplemented by one day of coaching and project follow-up. The rest of our time was dedicated to building our product, hackathons, networking events, and direct interactions with the local technology community. This immersion allowed us to gain exposure not only to fellow developers but also to model providers and infrastructure players such as Together, SambaNova, and others.

The key insight that shaped Makehub emerged from observing the challenges faced by developers. Interviews revealed that many incurred monthly expenses ranging from 200 to 1,200 euros due to the pay-as-you-go billing model of LLM providers. Yet, a systematic comparison of providers showed no clear correlation between cost and performance. For instance, a higher-priced provider could deliver slower response times than a cheaper competitor, depending on the time of day and server load.

This fragmentation of the market, combined with the absence of real-time transparency on cost–performance trade-offs, highlighted a clear opportunity. As a young and rapidly evolving market, the LLM infrastructure space has not yet established mature pricing mechanisms or standardized performance benchmarks. Figure 1 illustrates this market immaturity by comparing various providers of Llama 3.1 70B across price (in $/million tokens) and two key performance metrics: throughput (tokens generated per second) and latency (response time in seconds). The scatter plots reveal a highly dispersed landscape characteristic of an emerging market: there is no clear relationship between cost and performance. Some providers like Cerebras or SambaNova offer very high throughput (>400 tokens/s) at moderate prices, while Microsoft Azure charges significantly more ($3/M tokens) for relatively modest performance. Similarly, latency shows no correlation with price: Deepinfra delivers both low latency and low cost, whereas Azure remains expensive without offering superior responsiveness. This absence of price-performance correlation is a hallmark of market immaturity, where competitive dynamics have not yet rationalized pricing relative to delivered value.

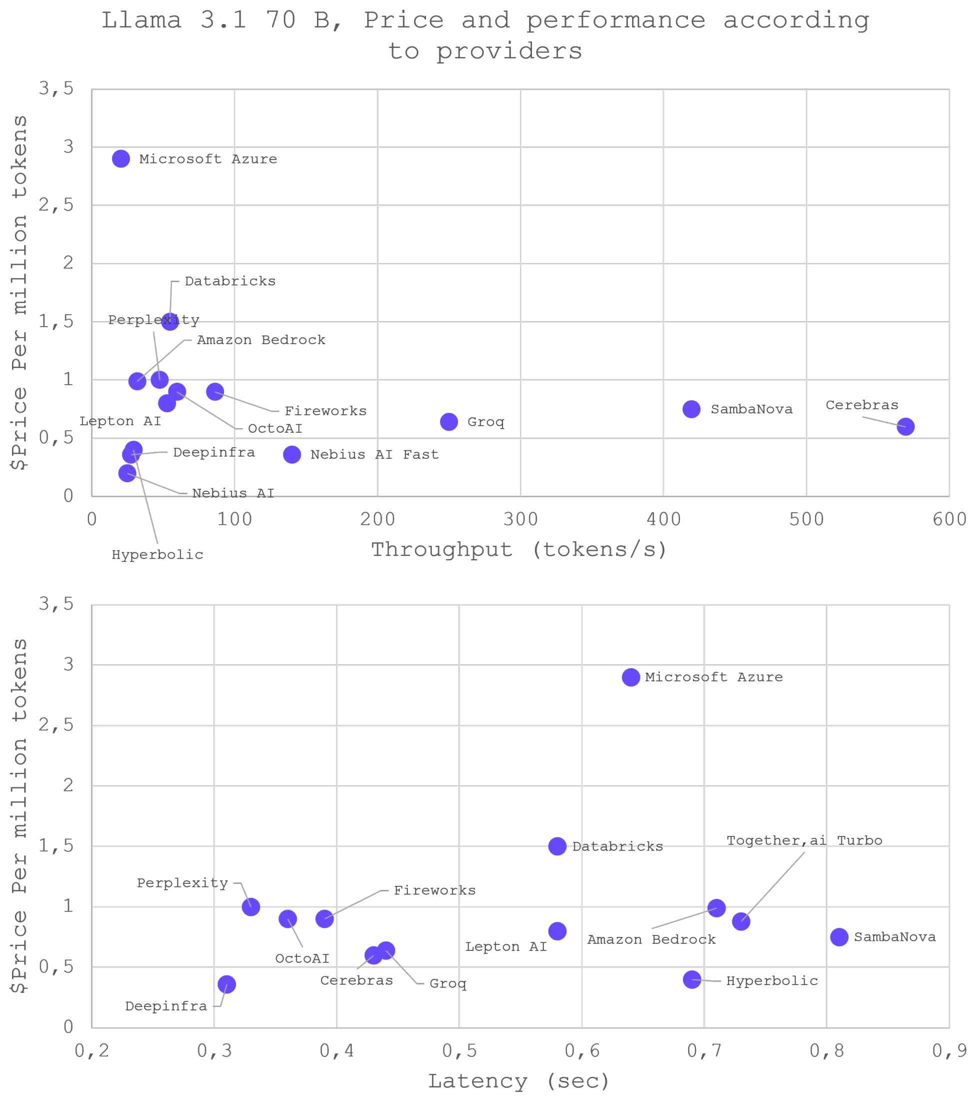

Figure 1: Price vs. performance for Llama 3.1 70B across providers (no clear correlation).

We envisioned an intermediary layer capable of routing LLM requests dynamically across providers, optimizing either for speed, price, or a combination of both, according to user preferences. In other words, rather than forcing developers to choose and maintain multiple providers manually, Makehub would serve as a unified API endpoint, handling the complexity of real-time optimization in the background.

From market observation to technical problem. The observations made during our Berkeley immersion crystallized into a clear problem statement. The LLM provider market exhibits three structural inefficiencies that create both developer pain and entrepreneurial opportunity:

1. **Fragmentation and opacity.** With over 20 providers offering overlapping model catalogs, developers face an overwhelming decision space with no standardized benchmarks or service-level agreements. The market lacks transparency: performance metrics are not publicly disclosed, and pricing structures vary wildly (per-token, per-request, tiered subscriptions).

2. **Spatial and temporal volatility.** Even when a developer selects a provider, performance is not constant. The same model hosted by different providers yields drastically different throughput and latency depending on infrastructure quality, geographic routing, and batching strategies. Furthermore, a single provider's performance fluctuates across hours due to varying load (as we will document empirically in §3.1). This dual volatility—across providers and across time—makes rational optimization nearly impossible without continuous monitoring.

3. **High switching costs and lock-in.** Integrating a new provider requires modifying API endpoints, managing separate credentials, and adapting to provider-specific quirks (e.g., differing error codes, rate-limiting schemes, authentication flows). These frictions discourage experimentation, leading developers to settle for a single, often suboptimal, provider. Monthly bills of 200–1,200 are common, yet many developers remain unaware that equivalent performance could be obtained at 30–50% lower cost by switching providers—or that their current provider is underperforming relative to competitors.

This realization—that developer pain stemmed from a solvable systems and optimization challenge rather than fundamental model limitations—marked the true genesis of Makehub. Our value proposition is not to build better models, but to build **better infrastructure** for accessing them: a routing layer that brings transparency, efficiency, and cost savings to an otherwise opaque and inefficient market.

2.2 System Overview: What is Makehub?

Makehub is a **unified API gateway for multi-provider LLM routing**. It sits between client applications (such as code assistants, chatbots, or data analysis tools) and the fragmented landscape of LLM providers (OpenAI, Anthropic, Together, Cerebras, etc.). Rather than requiring developers to integrate and manage each provider separately, Makehub exposes a single, OpenAI-compatible API endpoint that handles all complexity behind the scenes.

Core value proposition. Makehub delivers three primary benefits to developers:

1. **Cost optimization (40–70% savings).** By routing requests to the provider offering the best price-performance ratio at any given moment, Makehub reduces infrastructure costs without sacrificing quality. Our empirical analysis of 170,555 production requests demonstrates consistent savings in the 40–70% range compared to single-provider baselines.

2. **Performance transparency.** Developers gain real-time visibility into provider performance through continuous monitoring of latency, throughput, and availability. The system automatically adapts routing decisions as conditions change, eliminating the need for manual benchmarking or trial-and-error provider selection.

3. **Zero integration overhead.** Because Makehub implements the OpenAI Chat Completions protocol (including streaming, tool calling, and vision), migrating from OpenAI to Makehub requires only changing the API endpoint and key—typically a one-line configuration change. Behind this unified interface, Makehub maintains adapters for 20+ providers, each with its own authentication, error handling, and rate-limiting logic.

High-level architecture. The Makehub system comprises four main components, which work together to transform a client request into an optimized, provider-routed response:

- **Unified API endpoint.** Accepts requests in OpenAI format, validates parameters, and initiates the routing pipeline. This component ensures backward compatibility while enabling provider-agnostic client code.

- **Routing engine.** The core intelligence of the system. Given a request (model family, capabilities, user preferences), the routing engine:

  [label=()]Filters the provider catalog for compatibility (§7.1–7.2) Retrieves real-time performance metrics (§8) Computes a multidimensional score balancing cost, speed, and reliability (§7.3) Selects the optimal provider and forwards the request

- **Monitoring infrastructure.** Tracks provider performance through both *passive instrumentation* (measuring latency and throughput of production requests) and *active monitoring* (periodic health checks). This subsystem feeds real-time metrics into the routing engine, enabling adaptive decision-making (§8).
- **Provider adapters.** A library of provider-specific modules that translate between the unified Makehub interface and each provider's API. Adapters handle authentication, error normalization, rate-limit backoff, and protocol translation (e.g., mapping OpenAI tool calls to Anthropic's format). This abstraction layer is what enables seamless provider switching (§6.3).

User interaction model. From the developer's perspective, using Makehub is indistinguishable from using OpenAI directly:

```
# Before: OpenAI
response = openai.chat.completions.create(
    model="gpt-4",
    messages=[{"role": "user", "content": "Hello"}],
    api_key="openai_key"
)

# After: Makehub (one-line change)
response = openai.chat.completions.create(
    model="gpt-4",  # or "claude-3.5-sonnet", "llama-3.1-70b", etc.
    messages=[{"role": "user", "content": "Hello"}],
    api_key="makehub_key",
    base_url="https://api.makehub.ai/v1"  # ← only change
)
```

Behind this simple interface, Makehub:

- Resolves `gpt-4` to a *model family* (allowing substitution with compatible models like `gpt-4-turbo` or `gpt-4o`)
- Evaluates 10–15 providers offering GPT-4-class models
- Selects the provider with the best current performance (e.g., Together at $0.50/M tokens with 120 tokens/s throughput)
- Routes the request, handles any errors with automatic fallback, and returns the response

This **drop-in replacement** design philosophy is central to Makehub's adoption strategy. Developers can experiment with multi-provider routing without rewriting client code, refactoring prompts, or learning new APIs. The complexity of provider heterogeneity is entirely hidden.

Deployment model. Makehub is offered as a hosted cloud service (SaaS), eliminating the need for developers to deploy or maintain routing infrastructure. The system is built on a serverless architecture (TypeScript on Node.js, deployed on Railway/Vercel) with a PostgreSQL database for provider catalogs, performance metrics, and billing records. This architecture supports horizontal scaling to handle peak loads (currently serving 170,000+ requests/month) while keeping operational costs low through automatic scaling and pay-per-use pricing.

2.3 Research Contributions of This Thesis

While Makehub is an entrepreneurial venture, this thesis makes several technical and empirical contributions to the emerging field of LLM infrastructure optimization:

1. **Empirical characterization of provider heterogeneity.** We provide the first systematic analysis (to our knowledge) of cross-provider performance variance for identical models. Our dataset of 170,555 production requests reveals:

   - 57% coefficient of variation in throughput for the same model across providers (§8.1)
   - No correlation between price and performance ($r = 0.046$, Figure 1)
   - Temporal variance within a single provider of up to 3× in latency across hours (§8.1.2)

   These findings validate the need for dynamic routing and real-time monitoring.

2. **Multidimensional routing algorithm.** We present a novel vectorial scoring method that optimizes across three conflicting objectives—cost, latency, and throughput—using a geometric projection technique (§7.3). Unlike prior work on model routing (RouteLLM, which routes between models for quality), our algorithm routes between *providers* for efficiency, incorporating real-time performance feedback.

3. **Hybrid monitoring architecture.** We design and evaluate a dual-mode monitoring system combining passive instrumentation (zero overhead, reflects actual user experience) and active pinging (predictive but costly). Our cost-benefit analysis (§8.2.2) shows that a 10-minute ping interval achieves 95% of the benefit of continuous monitoring at <1% of the cost.

4. **Production validation at scale.** Unlike academic routing systems evaluated on synthetic benchmarks, Makehub has been deployed in production for 6 months, serving real developer workloads. We report end-to-end cost savings (40–70%), reliability metrics (99.2% success rate with fallback), and latency overhead (<50ms for routing decisions). These results demonstrate that multi-provider routing is practical and economically compelling.

The remainder of this thesis documents how we translated the vision articulated above into a production system. We begin by establishing the technical background (§3) and formalizing the optimization problem (§4), then survey existing approaches (§5) before presenting our architecture (§6–9) and empirical evaluation (§10).

3 Technical Background: The OpenAI API Protocol

Before designing a multi-provider routing system, we must first understand the technical protocol that governs how LLM requests are structured, transmitted, and processed. This section provides a detailed examination of the OpenAI Chat Completions API, which has become the de facto standard for LLM inference. Understanding this protocol is essential for three reasons: (1) it defines the request/response format that Makehub must parse and forward, (2) it establishes the capabilities (streaming, tool calling, vision) that constrain provider selection, and (3) it reveals the heterogeneity across provider implementations that creates arbitrage opportunities. We conclude by examining how different providers deviate from this standard, justifying the need for a unified abstraction layer.

3.1 Definition of the protocol used for LLM calls

This subsection explains what happens during an LLM call from a systems perspective and how requests are encoded over HTTP. We use OpenAI's *Chat Completions* as a reference surface, then cover streaming and tool/function calling with a concrete, end-to-end weather example.

3.1.1 High-level picture

A client (e.g., a code assistant) sends a prompt to a provider hosting a model; the provider returns an answer, often streamed token-by-token.

> *Client: "Hello."*
> *Server: "Hello, how are you?"*

Two capabilities are essential in real applications:

1. **Streaming** so the UI updates as tokens arrive.
2. **Tool calling** so the model can request a function call (e.g., weather) before finalizing the answer.

3.1.2 HTTP method, base URL, and model

Inference uses a standard `HTTP POST` to the provider's REST endpoint. Developers control:

- the **base URL**, e.g., `https://api.openai.com/v1/` (or a compatible proxy); and
- the **model** identifier, e.g., `gpt-4o`.

Changing either lets you switch provider or model with minimal code changes. This is a key lever for Makehub's routing approach.

3.1.3 Minimal text-only call (non-streaming)

What this request does. It sends a single user message (`"Hello"`) to the chat completions endpoint. The server returns a JSON response containing the assistant's message plus metadata (IDs, token usage, etc.).

```
# Request
POST https://api.openai.com/v1/chat/completions
Authorization: Bearer $OPENAI_API_KEY
Content-Type: application/json
```

```json
{
  "model": "gpt-4o",
  "messages": [
    {"role": "user", "content": "Hello"}
  ]
}
```

Listing 1: cURL request and minimal JSON body (Chat Completions)

Key fields. `model` selects the target model. `messages` is an ordered list of chat turns; at minimum, a user turn. Optional fields (not shown) include `temperature`, `max_tokens`, `stop`, etc.

```json
{
  "id": "chatcmpl-abc123",
  "created": 1730000000,
  "model": "gpt-4o",
  "choices": [
    {
      "index": 0,
      "finish_reason": "stop",
      "message": {
        "role": "assistant",
        "content": "Hello, how are you?"
      }
    }
  ],
  "usage": { "prompt_tokens": 2, "completion_tokens": 5, "total_tokens": 7 }
}
```

Listing 2: Illustrative response (trimmed)

How to read the response. The JSON response contains several critical fields for both extracting the model's output and monitoring resource consumption:

- `choices[0].message.content`: This is the core payload—the assistant's natural-language answer. The `choices` array allows the API to support multiple completions per request (though most use cases set `n=1`, yielding a single choice at index 0). The `message` object follows the same structure as the input `messages` array: a `role` (always `"assistant"` in the response) and `content` (the generated text).

- `usage`: This object provides token-level accounting, essential for cost tracking and billing. It contains three counters:
  - `prompt_tokens`: The number of tokens in the input (user messages, system prompt, context).
  - `completion_tokens`: The number of tokens generated by the model.
  - `total_tokens`: The sum of `prompt_tokens` and `completion_tokens`.

  Since most providers charge separately for input and output tokens (e.g., OpenAI's GPT-4o costs \$2.50 per million input tokens and \$10.00 per million output tokens as of January 2025), the `usage` object is indispensable for real-time cost calculation. For example, a request with 1,000 prompt tokens and 500 completion tokens would cost: $(1000 \times 2.50 + 500 \times 10.00)/1{,}000{,}000 = \$0.0075$.
- `finish_reason`: This field indicates *why* the generation terminated, which is critical for handling edge cases and debugging:
  - `"stop"`: The model reached a natural stopping point (e.g., completed a sentence, emitted an end-of-turn token). This is the expected outcome for most requests.
  - `"length"`: Generation was truncated because the output exceeded the model's maximum token limit or the user-specified `max_tokens` parameter. In this case, `content` may be incomplete (e.g., a code snippet cut off mid-function). Clients should detect this and either increase `max_tokens` or prompt the user to continue.
  - `"tool_calls"`: The model invoked a function/tool (see §3.1.4). The `content` field will be `null`, and instead, `message.tool_calls` will contain structured function call requests that the client must execute.
  - `"content_filter"` (provider-specific): Some providers (e.g., Azure OpenAI) apply content moderation filters. If the output violates policy (e.g., generates harmful content), the request is aborted and `finish_reason` is set to `"content_filter"`. Clients must handle this gracefully, typically by informing the user and avoiding retry loops.

Practical implications for Makehub. When routing requests across providers, Makehub must normalize these response structures. While the OpenAI format is widely adopted (Anthropic, Mistral, and many others follow it closely), subtle differences exist:

- Some providers omit the `usage` object in streaming mode, requiring Makehub to count tokens client-side using a tokenizer (e.g., `tiktoken` for OpenAI models).
- `finish_reason` values are not fully standardized. For instance, some providers use `"stop"` while others use `"end_turn"` or `"eos_token"`. Makehub's provider adapters (§5.1.3) translate these into a canonical representation.
- The `id` and `created` timestamp are provider-generated and serve as idempotency keys. Makehub logs these for request tracing and debugging but does not expose them directly to end users.

3.1.4 Streaming with Server-Sent Events (SSE)

What this does. Setting `"stream": true` in the request makes the server emit a sequence of SSE frames. Each frame contains a `delta` (partial text or metadata). The stream ends with `[DONE]`. This yields responsive UIs without waiting for the full completion.

Each frame is a separate event prefixed with `data:`. The first frame typically announces the assistant's role, then subsequent frames deliver partial text chunks (`"Hello"`, `", how are"`, `" you?"`). The client concatenates these deltas incrementally until receiving the `[DONE]` marker.

```
data: {"id":"chatcmpl-...","choices":[{"delta":{"role":"assistant"}}]}
data: {"id":"chatcmpl-...","choices":[{"delta":{"content":"Hello"}}]}
data: {"id":"chatcmpl-...","choices":[{"delta":{"content":", how are"}}]}
data: {"id":"chatcmpl-...","choices":[{"delta":{"content":" you?"}}]}
data: [DONE]
```

Listing 3: Conceptual SSE frames (illustrative)

Implementation pattern. The client appends each `delta.content` to a buffer and updates the UI incrementally. Handle edge cases: empty deltas (role-only frames), multiline chunks, and the terminal `[DONE]`. If a network error occurs mid-stream, degrade gracefully (e.g., retry without losing already-rendered text).

```
buffer = ""
for event in stream:
    if event == "[DONE]":
        break
    if event has delta.content:
        buffer += delta.content
        display(buffer)
```

Listing 4: SSE client pseudo-code

3.1.5 Tool (function) calling with a weather example

Why tools. The model sometimes needs fresh or external data (e.g., weather, internal APIs, databases). Tool calling lets the model request a structured function call; *the client* executes that function and returns the result so the model can finalize its answer.

Tools are particularly essential in code assistants because these systems must interact with the development environment: executing commands, reading and modifying files, accessing the file system, searching through code, or running tests. Without these external interaction capabilities, a code assistant would be limited to generating text without being able to verify, test, or deploy the solutions it proposes.

Step 1: declare the tool and ask a question **What this request does.** We declare a function (`get_current_weather`) via JSON Schema in `tools`. The user asks about the weather in Paris. The model is now allowed to call this function if it deems it useful.

```
POST https://api.openai.com/v1/chat/completions
Authorization: Bearer $OPENAI_API_KEY
Content-Type: application/json
```

```json
{
  "model": "gpt-4o",
  "messages": [
    {"role": "user", "content": "What's the weather in Paris right now?"}
  ],
  "tools": [
    {
      "type": "function",
      "function": {
        "name": "get_current_weather",
        "description": "Get the current weather in a city",
        "parameters": {
          "type": "object",
          "properties": {
            "city":  { "type": "string" },
            "units": { "type": "string", "enum": ["metric","imperial"] }
          },
          "required": ["city"]
        }
      }
    }
  ]
}
```

Listing 5: Request with a tool declaration

Key fields. `tools[*].function.name` is the unique function identifier the model will reference. `parameters` defines a strict JSON Schema so the model knows valid argument names and types.
Tool schema structure. The tool declaration follows a structured format where each tool has a `type` (always `"function"` for function calls) and a `function` object containing:

- `name`: A descriptive identifier that the model will use to reference this function
- `description`: A clear explanation of what the function does, helping the model decide when to call it
- `parameters`: A JSON Schema object defining the function's input structure, including:
  - `type`: Usually `"object"` for structured parameters
  - `properties`: Each parameter with its type (`string`, `number`, `boolean`, etc.)
  - `required`: Array listing which parameters are mandatory
  - `enum`: For parameters with restricted values (like `["metric","imperial"]`)

This schema acts as a contract between the model and the client, ensuring type safety and enabling the model to generate valid function calls.

Step 2: the model returns a tool call (client must parse it) **What this means.** The assistant message includes a `tool_calls` array with a function name and serialized `arguments` (a JSON string). *This is not the final answer.* The client must detect this, execute the function, and then send back a `role:"tool"` message with the result.

```
{
  "choices": [
    {
      "message": {
        "role": "assistant",
        "tool_calls": [
          {
            "id": "call_123",
            "type": "function",
            "function": {
              "name": "get_current_weather",
              "arguments": "{\"city\":\"Paris\",\"units\":\"metric\"}"
            }
          }
        ]
      },
      "finish_reason": "tool_calls"
    }
  ]
}
```

Listing 6: Assistant message requesting a tool call

Client responsibilities.

- Parse `arguments` (string) into JSON.
- Call your implementation of `get_current_weather(city, units)`.
- Capture the tool output (e.g., `{"tempC": 25, "condition": "Sunny"}`).

Step 3: send the tool result, then get the final answer **What this request does.** We provide the tool output back to the model as a new message with `role:"tool"` and a `tool_call_id` that matches the earlier call. The model can now incorporate the tool result and produce the final natural-language message.

```
POST https://api.openai.com/v1/chat/completions
Authorization: Bearer $OPENAI_API_KEY
Content-Type: application/json
```

Listing 7: HTTP request (endpoint and headers)

```json
{
    "model": "gpt-4o",
    "messages": [
        { "role": "user", "content": "What's the weather in Paris right now?" },
        {
            "role": "assistant",
            "tool_calls": [
                {
                    "id": "call_123",
                    "type": "function",
                    "function": {
                        "name": "get_current_weather",
                        "arguments": "{\"city\":\"Paris\",\"units\":\"metric\"}"
                    }
                }
            ]
        },
        {
            "role": "tool",
            "tool_call_id": "call_123",
            "content": "{\"tempC\":25,\"condition\":\"Sunny\"}"
        }
    ]
}
```

Listing 8: JSON body including the tool result to finalize the request

Expected final response. The server now returns a regular assistant message, e.g.:

```json
{
  "choices": [
    {
      "message": {
        "role": "assistant",
        "content": "It is currently 25\textdegree C and sunny in Paris."
      },
      "finish_reason": "stop"
    }
  ]
}
```

Listing 9: Final assistant message (trimmed)

3.1.6 What varies across providers (and why Makehub abstracts it)

The round-trip is conceptually the same across providers, but field names, envelopes, and authentication methods differ:

Anthropic (Claude). Tool use appears as `tool_use` content blocks; clients must reply with `tool_result` blocks before Claude continues. Roles and message shapes differ from Chat Completions.

Google Gemini. The model emits function calls and expects function responses (and the Live API has dedicated tool-response mechanics). Field names differ from OpenAI's.

Azure OpenAI. While using OpenAI models, Azure requires different authentication (API keys tied to Azure subscriptions rather than OpenAI accounts) and uses Azure-specific endpoints with different URL patterns (`https://{resource}.openai.azure.com/`).

These differences justify a compatibility layer. Makehub exposes an OpenAI-compatible surface (same request/response shape for developers) and normalizes provider-specific details internally. This minimizes switching costs (change base URL and/or model) and enables dynamic routing based on cost/performance without application rewrites.

4 State of the Art: Optimization Techniques for LLM Inference

Before delving into Makehub's specific monitoring and routing implementation, it is useful to situate the project within the broader landscape of optimization strategies currently employed in the LLM inference industry. This section surveys four complementary approaches that address cost and performance trade-offs: provider optimization, model routing, prompt compression, and prompt caching. While Makehub primarily focuses on provider optimization (selecting the best provider for a given model), understanding these alternative techniques is essential both for contextualizing our contribution and for identifying opportunities for future integration.

4.1 Provider Optimization (Server Arbitrage)

Provider optimization, also known as **server arbitrage** or **dynamic routing**, is the most direct approach to reducing inference costs while maintaining or improving performance. The core idea is straightforward: for a given model (e.g., Mistral-7B-Instruct or Claude 3.5 Sonnet), multiple providers may offer hosting services, each with different pricing structures and real-time performance characteristics. By intelligently selecting the provider at request time, substantial cost savings and latency improvements become possible.

The fragmentation of the open-source hosting market. This optimization opportunity arises primarily in the context of **open-source models**, where the weights are publicly available and any infrastructure provider can host them. For closed-source models (e.g., GPT-4, Claude), access is typically restricted to a single vendor or a small set of authorized partners (e.g., Azure OpenAI Service, AWS Bedrock for Claude), leaving limited room for provider arbitrage—though geographic routing and regional pricing variations can still be exploited.

In contrast, open-source models such as Meta's LLaMA family, Mistral AI's models, and others have spawned a competitive hosting ecosystem. Providers such as **Together AI**, **Replicate**, **SambaNova**, **Fireworks AI**, and **Anyscale** all offer inference APIs for the same underlying models, but with significant differences in:

- **Pricing per million tokens**: costs can vary by a factor of 2–5× for identical models.
- **Throughput and latency**: depending on hardware (GPU type, batching strategy), geographic proximity, and current load, response times fluctuate substantially.
- **Availability and rate limits**: smaller providers may experience capacity constraints during peak hours, while larger providers offer more stable uptime but at a premium.

Empirical evidence: Same model, different providers. A key empirical finding—one that directly motivated the Makehub project—is that **for a given model, performance varies drastically across providers, with no consistent correlation to price**. We documented this phenomenon using both external market data and Makehub's production traffic.

Open-source models: Llama 3.1 70B. As illustrated earlier in Figure 1, the same model weights (Llama 3.1 70B) exhibit:

- **6× price variance**: from \$0.50 to \$3.00 per million tokens across 15+ providers.
- **10× throughput variance**: from 40 tokens/s (Azure) to 400+ tokens/s (Cerebras, SambaNova).
- **No price–performance correlation**: Deepinfra offers both low cost and low latency, while Azure charges premium prices for modest performance.

Closed-source models: GPT-4o on Azure regions. Even for proprietary models with limited hosting options, geographic routing creates performance disparities. Figure 2 shows GPT-4o latency across 7 Azure regions and OpenAI's native endpoint, measured from Makehub production traffic at 12:00 on a typical Monday:

- **55% latency variance**: from 520ms (azure-francecentral) to 850ms (openai, azure-germanywestcentral).
- **Identical pricing**: all Azure regions charge the same per-token rate, yet performance differs by geography and instantaneous load.

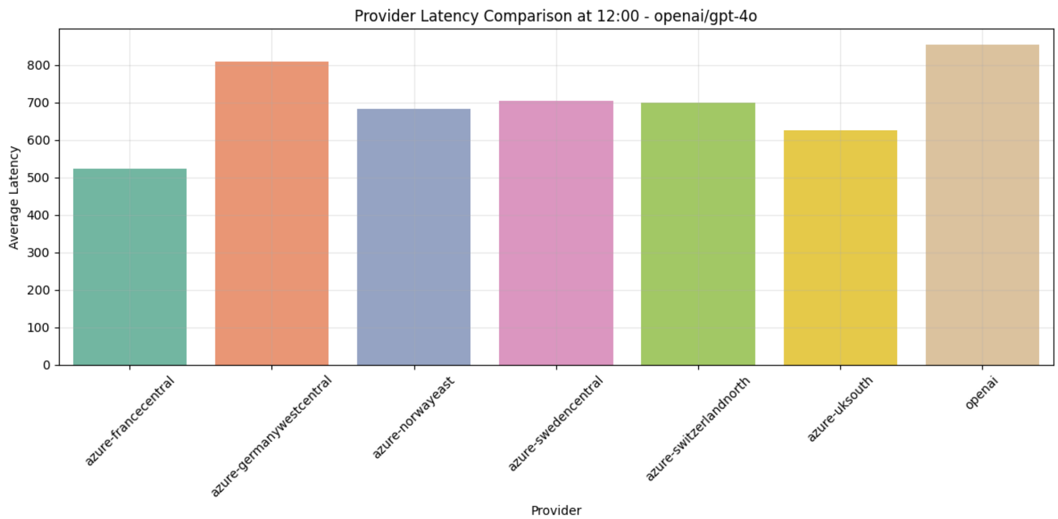

Figure 2: GPT-4o latency across providers at 12:00 (production data, minimum 100 samples per provider).

This lack of correlation is explained by several factors:

- **Varying hardware and optimization stacks**: providers use different GPU types (A100, H100, custom ASICs) and inference frameworks (vLLM, TensorRT-LLM, custom kernels), each with distinct throughput profiles.
- **Dynamic load balancing**: a provider experiencing high demand at time t will exhibit degraded throughput, even if it is nominally faster during off-peak hours.
- **Pricing opacity**: inference pricing is not purely cost-based; it reflects strategic positioning, early-adopter subsidies, and margin targets. For example, preliminary research suggests that some providers (e.g., Together AI) operate with margins as high as 70–80% above raw compute costs, while others compete more aggressively on price.

The developer's challenge. For an individual developer or organization, exploiting this fragmentation manually is impractical. Effective provider arbitrage would require:

1. **Maintaining accounts and credits with all relevant providers**, which introduces financial overhead and complexity.
2. **Monitoring real-time performance across providers**, necessitating continuous benchmarking infrastructure.

3. **Switching API endpoints and credentials dynamically**, which is error-prone and disrupts workflow integration.

4. **Understanding pricing nuances**, including per-token costs, prompt caching discounts, and regional variations.

In practice, developers typically settle for a single provider, absorbing inefficiencies in exchange for simplicity. This inertia is precisely what Makehub aims to overcome.

Makehub's value proposition: transparent provider routing. Makehub addresses this problem by acting as a **unified API gateway**. Developers interact with a single endpoint compatible with the OpenAI Chat Completions standard, specifying only:

- the desired **model** (e.g., `mistralai/Mistral-7B-Instruct-v0.2`), and
- optionally, a routing preference: **minimize cost**, **maximize speed**, or **optimize for a cost/speed ratio**.

Behind the scenes, Makehub:

1. Maintains authenticated connections to all major providers.
2. Continuously monitors real-time latency and throughput for each model–provider pair (as described in Section 3).
3. Routes each request to the provider offering the best trade-off according to the user's specified criteria.
4. Abstracts away protocol differences (e.g., Anthropic's message format vs. OpenAI's) so that responses are always returned in a consistent format.

This approach transforms provider arbitrage from an impractical manual task into an automated, zero-configuration optimization. By aggregating demand across multiple users, Makehub also achieves economies of scale in monitoring and account management, making real-time routing feasible even for small teams and individual developers.

Limitations and complementarity with other techniques. Server optimization is powerful but inherently limited by the capabilities of the selected model. If a developer chooses a large, expensive model (e.g., GPT-4) for a simple task, even optimal provider selection cannot reduce costs below a certain threshold. This is where complementary techniques—**model routing** (§2.2.2), **prompt compression** (§2.2.3), and **prompt caching** (§2.2.4)—become essential. These methods reduce the computational burden itself, rather than merely optimizing where it is executed. In the long term, Makehub envisions integrating all four strategies into a unified optimization framework, but the initial focus remains on provider-level arbitrage due to its immediate, measurable impact.

4.2 Model Routing (Quality-Cost Trade-offs)

While server optimization focuses on selecting the best *provider* for a given model, **model routing** takes a complementary approach: selecting the best *model* for a given task. The core insight is that not all user requests require the same level of reasoning capability. Simple queries (e.g., formatting code, answering factual questions) can often be handled by smaller, cheaper, and faster models, while complex tasks (e.g., multi-step reasoning, algorithmic problem-solving) benefit from larger, more capable—but more expensive—models. By dynamically routing requests to appropriately-sized models, significant cost reductions can be achieved without sacrificing output quality.

The cost–capability spectrum. LLMs exist along a spectrum of capability and cost. At one extreme, large frontier models such as OpenAI o1, Claude Sonnet 4, and Gemini 2.0 Pro offer state-of-the-art reasoning and generation quality, but at a premium price (often \$10–\$60 per million input tokens for reasoning-intensive models). At the other extreme, smaller models such as DeepSeek-V3, Claude 3.5 Haiku, Mistral Codestral (formerly Devstral), and DeepSeek-R1-Distill provide adequate performance for many tasks at a fraction of the cost (\$0.10–\$2 per million tokens).

The key observation is that **request complexity varies widely**. In the context of code assistants, for example:

- **Simple requests**: "Format this JSON," "Add comments to this function," "What does this error mean?" → A small model suffices.
- **Moderate requests**: "Refactor this module to use async/await," "Write unit tests for this class" → A mid-sized model is appropriate.
- **Complex requests**: "Design a distributed caching layer with Redis and implement it," "Debug this concurrency issue in a multi-threaded application" → A large, capable model is necessary.

By routing simple requests to cheaper models and reserving expensive models for complex tasks, a code assistant can reduce average inference costs by 50–80% while maintaining comparable output quality.

Methods for assessing request complexity. The challenge of model routing lies in **accurately predicting task complexity** before generation. Several approaches have emerged in both research and industry:

1. **Rule-based heuristics.** Simple rules based on request metadata can provide a coarse classification:
   - Short prompts (<100 tokens) with no code context → likely simple.
   - Requests containing keywords like "design," "architecture," "debug," "optimize" → likely complex.
   - Requests referencing multiple files or large codebases → likely complex.

   While easy to implement, rule-based systems lack nuance and are prone to misclassification.

2. **Embedding-based similarity (RAG).** Retrieval-Augmented Generation (RAG) techniques can be repurposed for complexity estimation. A reference dataset is constructed with labeled examples:
   - **Complex queries**: e.g., "Implement a custom authentication middleware with JWT and refresh tokens."
   - **Simple queries**: e.g., "Fix the indentation in this Python file."

   Each incoming request is embedded (using a model such as `text-embedding-ada-002` or an open-source alternative), and its cosine similarity to the reference sets is computed. Requests closer to the "complex" cluster are routed to larger models.

   This approach is more robust than heuristics, as it captures semantic similarity, but requires careful curation of the reference dataset and incurs a small embedding cost per request.

3. **LLM-as-a-Judge.** A third approach—increasingly popular in production systems—uses a **small, fast LLM to evaluate the complexity of the incoming request**. For example, a lightweight model such as Mistral 7B or GPT-3.5 Turbo is prompted:

"You are a classifier. Rate the complexity of the following coding task on a scale from 1 (trivial) to 10 (highly complex). Consider factors such as: number of steps required, need for external knowledge, algorithmic reasoning, and ambiguity. Respond with only a number."

The classifier's output (e.g., 3, 7, 9) is then mapped to a model tier:

- Complexity 1–4 → Small model (e.g., DeepSeek-V3, Mistral Codestral, Claude 3.5 Haiku)
- Complexity 5–7 → Medium model (e.g., Claude Sonnet 4, GPT-4o, DeepSeek-R1-Distill)
- Complexity 8–10 → Large model (e.g., OpenAI o1, Claude Sonnet 4, DeepSeek-R1)

This method is flexible and adapts naturally to new types of tasks, but it introduces a small latency overhead (typically 200–500ms for the classification call) and a marginal cost for the classifier model itself.

Example: three-tier model routing strategy. Table 3 illustrates a concrete model routing strategy that could be deployed in a code assistant like Cursor or Cline.

Table 3: Example three-tier model routing strategy based on complexity score.

Complexity	**Model tier**	**Example model**	**Cost (per 1M tokens)**
1–4	Small, fast	DeepSeek-V3	\$0.27 (input), \$1.10 (output)
		Mistral Codestral	\$0.30
		Claude 3.5 Haiku	\$0.25 (input), \$1.25 (output)
5–7	Medium	Claude Sonnet 4	\$3.00 (input), \$15.00 (output)
		GPT-4o	\$2.50 (input), \$10.00 (output)
		DeepSeek-R1-Distill	\$0.55 (input), \$2.19 (output)
8–10	Large, capable	OpenAI o1	\$15.00 (input), \$60.00 (output)
		Claude Sonnet 4	\$3.00 (input), \$15.00 (output)
		DeepSeek-R1	\$2.19 (input), \$8.19 (output)

By routing 60% of requests to tier 1, 30% to tier 2, and 10% to tier 3, a typical code assistant could reduce its average cost per request by 70% compared to using a frontier model for all requests.

Real-world adoption: Cursor and other assistants. Model routing is not merely a theoretical optimization—it is actively deployed by leading code assistants. **Cursor**, for example, is known to employ dynamic model selection based on task complexity, though the exact algorithm is proprietary. Anecdotal evidence from user reports suggests that Cursor defaults to smaller models (e.g., Claude 3.5 Haiku, DeepSeek-V3) for simple completions and escalates to Claude Sonnet 4 or OpenAI o1 for complex reasoning tasks.

This strategy is economically essential for assistants offering "unlimited" plans (e.g., Cursor's \$20/month tier, Claude Code's \$200/month enterprise tier): without model routing, heavy users would generate unsustainable costs. By reserving expensive models for genuinely complex tasks, these platforms can offer flat-rate pricing while maintaining profitability.

Challenges and limitations. Model routing introduces several trade-offs:

- **Latency overhead**: Classification (whether via embedding or LLM-as-a-Judge) adds 100–500ms before generation begins, which may be noticeable in interactive settings.
- **Misclassification risk**: A request incorrectly routed to a small model may produce low-quality output, frustrating users. Conversely, over-routing to large models negates cost savings.

- **Model capability drift**: As models evolve (e.g., Claude 3.5 Sonnet vs. Claude Sonnet 4, GPT-4o vs. o1, DeepSeek-V3 vs. DeepSeek-R1), the complexity thresholds must be recalibrated to reflect new capability distributions.

Despite these challenges, model routing remains one of the most effective cost-reduction techniques available, and it is highly complementary to server optimization. In Makehub's roadmap, model routing is a natural next step after provider arbitrage is fully operational.

Integration with Makehub. While Makehub's initial focus is on server optimization (routing to the best provider for a given model), the architecture is designed to accommodate model routing in the future. By extending the routing API to accept a complexity hint or allowing Makehub to perform its own complexity classification, users could benefit from both provider arbitrage *and* model selection simultaneously. For example:

- A simple request classified as complexity 3 could be routed to **DeepSeek-V3 on the cheapest available provider**.
- A complex request classified as complexity 9 could be routed to **Claude Sonnet 4 or DeepSeek-R1 on the fastest available provider**.

This dual-layer optimization—model selection *and* provider selection—represents the long-term vision for Makehub's routing intelligence.

While server and model routing optimize *which infrastructure and model to use*, they cannot reduce the inherent cost of processing large inputs. For applications like code assistants, where prompts often include entire codebases or long conversation histories, the input token count itself becomes a dominant cost driver. This motivates a third optimization technique: prompt compression.

4.3 Prompt Compression

Prompt compression addresses a fundamental cost driver in LLM inference: the size of the input context. In code assistants and other agentic systems, prompts often include extensive contextual information—entire codebases, chat histories, documentation snippets—leading to input token counts in the tens or hundreds of thousands. Since pricing is per-token (both input and output), reducing input size directly translates to cost savings. Prompt compression techniques aim to preserve semantic content while minimizing token consumption.

The context explosion problem in code assistants. Modern code assistants operate with **large, multi-turn conversation contexts**. A typical interaction might include:

- The user's current question (e.g., "Refactor this authentication module to use OAuth2").
- Multiple prior messages in the conversation (previous questions, assistant responses, clarifications).
- The content of several files in the codebase (e.g., `auth.py`, `config.yaml`, `routes.js`).
- System prompts and tool definitions (instructions on how to use functions, file operations, etc.).

This can easily reach 50,000–200,000 input tokens per request. At $3 per million input tokens (e.g., Claude 3.5 Sonnet), a single request costs $0.15–$0.60 just for the input. For a developer making 100 requests per day, this amounts to $15–$60 daily, or $450–$1,800 per month—purely from input tokens.

Prompt compression seeks to reduce this burden by intelligently **condensing or filtering the context** while retaining the information necessary for the model to generate a high-quality response.

Method 1: Summarization with a smaller model. One approach is to use a **lightweight, inexpensive model** (e.g., Claude 3.5 Haiku, Mistral Codestral, DeepSeek-V3) to summarize or rephrase verbose context before passing it to a larger, more expensive model.

Workflow:

1. The assistant receives a new user query along with a large conversation history (e.g., 20 messages totaling 40,000 tokens).
2. A small summarization model is prompted:

   > *"Summarize the following conversation concisely, preserving key technical details, decisions, and unresolved issues. Omit pleasantries and redundant information."*

3. The summarized context (now 5,000 tokens) is combined with the current query and sent to the primary model (e.g., Claude Sonnet 4, OpenAI o1, DeepSeek-R1).

Cost analysis:

- Original cost (40,000 input tokens at \$3/M for Claude Sonnet 4): \$0.12
- Summarization cost (40,000 tokens at \$0.27/M for DeepSeek-V3): \$0.011
- Compressed cost (5,000 tokens at \$3/M): \$0.015
- **Total: \$0.026 (78% savings)**

This method works well for conversational context but may lose nuance or omit details that the primary model would have found useful. It is best suited for scenarios where the conversation history is largely informational rather than directly task-critical.

Method 2: Message filtering with LLM-based relevance scoring. A more surgical approach is to **selectively remove irrelevant messages** from the conversation history rather than summarizing everything. This is particularly effective when the current user query pertains to a specific subset of files or topics, rendering earlier messages obsolete.

Workflow:

1. The assistant receives a conversation with 15 messages. The latest user query is: "Add input validation to the `login()` function in `auth.py`."
2. A small classifier model evaluates each message for relevance to the current query:

   > *"Does the following message provide useful context for the query 'Add input validation to login() in auth.py'? Answer YES or NO."*

3. Messages about unrelated files (`database.py`, `README.md`) or tangential topics (deployment, testing infrastructure) are marked as irrelevant and removed.
4. The filtered context (now 6 messages instead of 15) is sent to the primary model.

Example: message filtering in action.
Consider the following conversation context:

```
[
  {"role": "user", "content": "Show me the database schema in database.py"},
  {"role": "assistant", "content": "[database.py content, 8000 tokens]"},
  {"role": "user", "content": "How do I deploy this app to AWS?"},
  {"role": "assistant", "content": "[deployment instructions, 3000 tokens]"},
  {"role": "user", "content": "Review the auth.py file"},
  {"role": "assistant", "content": "[auth.py content, 5000 tokens]"},
  {"role": "user", "content": "Add input validation to login() in auth.py"}
]
```

Listing 10: Original conversation (simplified)

The classifier identifies that messages 1–4 are **irrelevant** to the current query (which concerns `auth.py`, not `database.py` or deployment). After filtering:

```
[
  {"role": "user", "content": "Review the auth.py file"},
  {"role": "assistant", "content": "[auth.py content, 5000 tokens]"},
  {"role": "user", "content": "Add input validation to login() in auth.py"}
]
```

Listing 11: Filtered conversation (compressed)

This reduces the input from 16,000 tokens to 5,000 tokens—a **69% reduction**—while preserving all context relevant to the task. The primary model receives cleaner, more focused input, which may even *improve* output quality by reducing noise.

Challenges and trade-offs. Prompt compression introduces several considerations:

- **Information loss**: Summarization or filtering may inadvertently discard details that the primary model would have used. This risk can be mitigated by conservative filtering (keeping messages when in doubt) or by hybrid approaches (summarize but retain key excerpts verbatim).
- **Latency overhead**: Both summarization and filtering require an additional LLM call before the main generation, adding 200–500ms. For latency-sensitive applications, this may be unacceptable.
- **Classifier accuracy**: In the filtering approach, a small model may misjudge relevance, leading to critical context being removed. This can be tested and tuned with evaluation datasets.
- **Diminishing returns for short contexts**: If the original context is already small (e.g., 2,000 tokens), compression yields negligible savings and is not worth the overhead.

Despite these trade-offs, prompt compression is highly effective for **long-running, multi-turn conversations** typical of code assistants. By reducing input token counts by 50–80%, it can halve inference costs without requiring changes to the underlying model or provider.

Complementarity with other techniques. Prompt compression is **orthogonal** to server optimization and model routing:

- **Server optimization** selects the cheapest or fastest provider for a given model—but the input size remains constant.
- **Model routing** selects the cheapest model capable of handling the task—but it still processes the full input.
- **Prompt compression** reduces the input size itself, magnifying the savings from both other techniques.

For example, a request compressed from 50,000 tokens to 10,000 tokens enjoys:

- 80% cost reduction on input tokens (direct savings).
- Faster inference (smaller inputs → faster processing), benefiting server optimization.
- Potential for downgrading to a cheaper model (simpler, focused input may not require frontier-tier reasoning), benefiting model routing.

This **multiplicative effect** makes prompt compression an essential component of a holistic cost optimization strategy.

Integration prospects for Makehub. While Makehub's current focus is on provider arbitrage, prompt compression is a natural candidate for future integration. Makehub could offer an optional preprocessing layer:

1. User sends a large request (50,000 tokens) to Makehub.
2. Makehub applies message filtering or summarization (using a cheap classifier model).
3. The compressed request (10,000 tokens) is routed to the optimal provider.
4. The user benefits from **both** compression savings *and* provider optimization.

By exposing a configuration parameter (e.g., `"enable_compression": true`), Makehub could allow users to opt into this feature transparently, further reducing their costs without requiring changes to their application logic.

Prompt compression reduces the size of each individual request, but in multi-turn conversations, much of the context is *repeated* across consecutive requests. This redundancy motivates a fourth technique: prompt caching, which reuses already-processed tokens to avoid redundant computation.

4.4 Prompt Caching

Prompt caching is a provider-side optimization that reduces costs and latency by **reusing previously computed representations** of input tokens across multiple requests. Unlike the previous techniques (server optimization, model routing, prompt compression), which are implemented client-side or in a routing layer, prompt caching is a feature offered by certain LLM providers—most notably Anthropic (Claude) via both their direct API and AWS Bedrock, and OpenAI (with limited support). When enabled, repeated portions of a prompt are stored in a cache, allowing subsequent requests to skip the expensive re-processing of those tokens.

The redundancy problem in multi-turn conversations. In typical code assistant workflows, **much of the context is repeated across consecutive requests**. Consider a developer working on a refactoring task:

- **Request 1**: "Review the contents of `auth.py`" → The model receives the full file content (5,000 tokens).
- **Request 2**: "Add input validation to the `login()` function" → The model again receives the full `auth.py` content (5,000 tokens) plus the conversation history.
- **Request 3**: "Now add rate limiting" → The model receives `auth.py`, the previous Q&A exchanges, and the new query.

Without caching, the provider must process the 5,000 tokens of `auth.py` *from scratch* on every request, even though the file content is identical. This is computationally wasteful and expensive for the user. Prompt caching solves this by storing the internal representation (the "processed" tokens) and reusing it across requests, offering:

- **Cost reduction**: Cached tokens are billed at a fraction of the normal input token price (often 10–20% of full price).
- **Latency reduction**: Skipping recomputation of cached tokens reduces time-to-first-token, improving responsiveness.

How prompt caching works. Prompt caching operates at the provider's inference backend. When a request is received:

1. The provider computes a **hash** of specific portions of the input prompt (typically entire messages or designated cache blocks).
2. If this hash matches a recently used entry in the cache (usually within a 5–10 minute TTL), the provider retrieves the precomputed internal representation instead of reprocessing the tokens.
3. The cached representation is combined with any new, non-cached tokens, and generation proceeds as usual.
4. The user is billed at a reduced rate for cached tokens (e.g., $0.30 per million cached tokens vs. $3 per million full-price tokens for Claude 3.5 Sonnet).

Cache granularity and control:

- **Anthropic (Claude API and Bedrock)**: Developers explicitly mark messages or content blocks for caching using a `cache_control` field. This gives fine-grained control over what is cached.
- **OpenAI**: Caching is mostly automatic and opaque; developers have limited explicit control, though repeated system prompts and large static contexts are cached heuristically.

Example: Anthropic's explicit cache control. Anthropic's API allows developers to mark specific message blocks for caching. Consider the following request structure:

```json
{
  "model": "claude-3-5-sonnet-20250219",
  "max_tokens": 1024,
  "system": [
    {
      "type": "text",
      "text": "You are a code assistant. Always provide clear explanations.",
      "cache_control": {"type": "ephemeral"}
    }
  ],
  "messages": [
    {
      "role": "user",
      "content": [
        {
          "type": "text",
          "text": "Here is the auth.py file:\n\n[5000 tokens of code]",
          "cache_control": {"type": "ephemeral"}
        },
        {
          "type": "text",
          "text": "Add input validation to the login() function."
        }
      ]
    }
  ]
}
```

Listing 12: Anthropic request with cache control

In this example:

- The system prompt and the `auth.py` file content are marked with `cache_control`.
- On the first request, these are processed normally and stored in the cache.
- On subsequent requests (within the cache TTL), these blocks are retrieved from the cache, and the user pays the reduced cached token rate instead of the full input rate.

Cost analysis: caching in a multi-turn conversation. Consider a 5-turn conversation where each request includes:

- System prompt: 500 tokens (cacheable)
- File content (`auth.py`): 5,000 tokens (cacheable)
- Conversation history: grows by 1,000 tokens per turn (partially cacheable)
- New user query: 200 tokens per turn (not cacheable)

Without caching (Claude 3.5 Sonnet at $3/M input, $15/M output):

- Turn 1: 5,700 input tokens → $0.0171
- Turn 2: 6,700 input tokens → $0.0201
- Turn 3: 7,700 input tokens → $0.0231
- Turn 4: 8,700 input tokens → $0.0261
- Turn 5: 9,700 input tokens → $0.0291
- **Total input cost: $0.1155**

With caching (cached tokens at $0.30/M):

- Turn 1: 5,700 input tokens (write to cache) → $0.0171
- Turn 2: 5,500 cached + 1,200 new → $0.0052
- Turn 3: 6,500 cached + 1,200 new → $0.0056
- Turn 4: 7,500 cached + 1,200 new → $0.0059
- Turn 5: 8,500 cached + 1,200 new → $0.0062
- **Total input cost: $0.040 (65% savings)**

This demonstrates that caching is most impactful in **multi-turn, context-heavy conversations** precisely the use case for code assistants.

Optimization strategies: which messages to cache. Providers typically limit the number of cache breakpoints (e.g., Anthropic allows up to 4 cache blocks per request). This requires strategic decisions about *what* to cache. A heuristic approach:

```python
def select_cache_blocks(messages, max_cache_blocks=4):
    """
    Select which messages to cache, prioritizing the largest ones.
    """
    cacheable_messages = []

    for msg in messages:
        if msg.token_count > MIN_CACHE_THRESHOLD:  # e.g., 1024 tokens
            cacheable_messages.append((msg, msg.token_count))

    # Sort by size (largest first) and take top N
    cacheable_messages.sort(key=lambda x: x[1], reverse=True)
    selected = cacheable_messages[:max_cache_blocks]

    for msg, _ in selected:
        msg.cache_control = {"type": "ephemeral"}

    return messages
```

Listing 13: Pseudocode for cache block selection

Key principles:

- Cache the **largest messages** first, as they yield the greatest savings.
- Prioritize **static content** (system prompts, file contents) over dynamic content (user queries).
- If conversation history exceeds the cache limit, cache the **most recent large messages**, as earlier context may become stale or irrelevant.

Caching workflow visualization. The following diagram illustrates how prompt caching integrates into the request lifecycle:

```
User request arrives at provider
    |
    v
Provider computes cache key for marked blocks
    |
    +---> Cache hit? (key exists in cache, TTL valid)
    |         |
    |         +---> YES: Retrieve cached representation
    |         |           Charge user at cached token rate (e.g., $0.30/M)
    |         |
    |         +---> NO:  Process tokens normally
    |                    Store in cache for future requests
    |                    Charge user at full input rate (e.g., $3/M)
    |
    v
Combine cached + new tokens --> Generate response
```

Listing 14: Prompt caching flow (Mermaid-style pseudocode)

Provider differences and compatibility challenges. Caching implementations vary significantly across providers:

- **Anthropic (direct API)**: Explicit `cache_control` field; up to 4 cache breakpoints; 5-minute TTL.
- **Anthropic (AWS Bedrock)**: Similar to direct API but with Bedrock-specific authentication and pricing.
- **OpenAI**: Limited and mostly opaque; some automatic caching of system prompts, but no explicit developer control as of early 2025.
- **Open-source providers (Together, Replicate, etc.)**: Generally no caching support, as the economics are less favorable for smaller-scale providers.

This fragmentation poses a challenge for routing layers like Makehub: to fully exploit caching, the system must:

1. Detect whether the target provider supports caching.
2. Rewrite requests to include provider-specific cache annotations (e.g., `cache_control` for Anthropic, none for OpenAI).
3. Track cache state across requests to avoid redundant cache writes.

Limitations and considerations. Prompt caching is highly effective but has constraints:

- **TTL limitations**: Caches typically expire after 5–10 minutes. If a user pauses work for 15 minutes, the cache is lost.
- **Non-deterministic savings**: Cache hits depend on request timing and server-side eviction policies, making cost predictions less reliable.
- **Cold-start penalty**: The first request in a conversation pays full price, so short conversations (1–2 turns) see minimal benefit.
- **Provider lock-in**: Heavy reliance on caching may discourage switching providers, as migrating to a provider without caching support would increase costs.

Integration with Makehub. Makehub's routing layer must intelligently handle caching to maximize savings:

- **Cache-aware routing**: When multiple providers support a given model, prefer the one with caching support for multi-turn conversations.
- **Cache block optimization**: Automatically annotate large, repeated messages with cache control directives when routing to Anthropic.
- **Fallback gracefully**: If a cached provider becomes slow, fall back to a non-cached but faster provider, transparently handling the protocol difference.

By abstracting caching complexity, Makehub allows developers to benefit from prompt caching without needing to understand provider-specific implementations—further reducing both cost and cognitive overhead.

Synergy with other techniques. Prompt caching is **complementary** to the previous three techniques:

- **Server optimization**: Caching improves the cost profile of certain providers (e.g., Anthropic), making them more attractive in the routing algorithm.
- **Model routing**: Smaller models benefit less from caching (since input costs are already low), so caching is most valuable when routing to expensive models.
- **Prompt compression**: Compression reduces the size of the context, but caching ensures that even compressed contexts are reused efficiently across turns.

Together, these four techniques form a comprehensive cost optimization strategy, addressing inference costs from multiple angles: provider selection, model selection, context size, and context reuse.

Having surveyed the landscape of existing optimization techniques, we now turn to formalizing the specific problem that Makehub addresses: how to route LLM requests across multiple providers to optimize cost, performance, and reliability in real time.

5 Problem Formulation: Multi-Provider LLM Routing

Having surveyed the landscape of optimization techniques in the previous section, we now formally define the optimization problem that Makehub addresses. This section articulates the decision variables, objectives, constraints, and fundamental challenges that motivated our system design.

5.1 Formal Problem Statement

5.1.1 The routing decision

At its core, Makehub solves a **real-time provider selection problem**. For each incoming LLM request r, the system must choose a provider $p \in \mathcal{P}$ (where $\mathcal{P}$ is the set of available providers) and optionally a model variant $m \in \mathcal{M}_p$ (where $\mathcal{M}_p$ is the set of models offered by provider p) to maximize a user-defined objective function while satisfying capability and performance constraints.

Decision variables:

- $p^* \in \mathcal{P}$: The selected provider (e.g., Together, Fireworks, Replicate)
- $m^* \in \mathcal{M}_p$: The selected model (e.g., `meta-llama/Llama-3.1-70B-Instruct`)

Objective function:
The user specifies an optimization objective $\mathcal{O}$ that balances three conflicting goals:

$$\mathcal{O}(p, m, t) = w_{\text{cost}} \cdot \text{Cost}(p, m) + w_{\text{latency}} \cdot \text{Latency}(p, t) + w_{\text{throughput}} \cdot \frac{1}{\text{Throughput}(p, t)} \tag{1}$$

where:

- $\text{Cost}(p, m)$: Price per million tokens charged by provider p for model m (e.g., \$0.18/M tokens)
- $\text{Latency}(p, t)$: Time-to-first-token (TTFT) observed for provider p at time t (in seconds)
- $\text{Throughput}(p, t)$: Tokens generated per second by provider p at time t
- $w_{\text{cost}}, w_{\text{latency}}, w_{\text{throughput}}$: User-specified weights (summing to 1) that encode preferences

The optimization problem is to find:

$$(p^*, m^*) = \arg \min_{p \in \mathcal{P}_{\text{feasible}},\, m \in \mathcal{M}_p} \mathcal{O}(p, m, t) \tag{2}$$

subject to the constraints defined below.

Constraints:
The feasible set $\mathcal{P}_{\text{feasible}}$ is determined by filtering the full provider catalog $\mathcal{P}$ according to:

1. **Capability constraints**: The provider must support all features required by the request r:

   $$\text{Capabilities}(p, m) \supseteq \text{Required}(r) \tag{3}$$

   where $\text{Required}(r)$ may include:

   - Tool/function calling (`tools` parameter)
   - Vision inputs (image URLs in messages)
   - Streaming (`stream=true`)
   - JSON mode (`response_format={"type": "json_object"}`)

2. **Model family constraints**: If the user requests a specific model family (e.g., `gpt-4`), the provider must offer a compatible model:

$$\text{Family}(m) = \text{RequestedFamily}(r) \tag{4}$$

This allows Makehub to substitute `gpt-4-turbo` for `gpt-4` if the provider offers the former but not the latter, as they belong to the same family.

3. **Performance constraints** (optional): The user may specify thresholds that must be satisfied:

$$\text{Latency}(p,t) \leq L_{\max} \tag{5}$$

$$\text{Throughput}(p,t) \geq T_{\min} \tag{6}$$

For example, a real-time chatbot might require $L_{\max} = 1.0\,\text{s}$ to avoid perceptible delay.

4. **Availability constraints**: The provider must be reachable and not rate-limited:

$$\text{Status}(p,t) = \text{AVAILABLE} \tag{7}$$

This is determined by recent health checks and error rates.

Time-dependent parameters.

A critical characteristic of this problem is that performance metrics Latency(p,t) and Throughput(p,t) are **functions of time**. Unlike static optimization problems (e.g., compiler optimization, where the "cost" of an instruction is fixed), provider performance fluctuates due to:

- **Server load**: A provider experiencing high traffic at 3 PM may have 2–3× higher latency than at 3 AM.
- **Geographic routing**: The provider's choice of serving region (US-East, EU-West, etc.) affects network latency.
- **Batching dynamics**: Providers use dynamic batching to amortize GPU costs; batch size affects both throughput and latency.

This temporal variance (documented empirically in §8.1) means that a provider optimal at time t may be suboptimal at $t+1$ hour. Consequently, Makehub must **continuously monitor** performance and re-evaluate routing decisions in real time.

5.2 Why Is This Problem Hard?

The multi-provider routing problem presents several technical challenges that distinguish it from classical optimization:

5.2.1 Challenge 1: Real-time decision-making under uncertainty

Routing decisions must be made in **milliseconds** (to avoid adding perceptible latency to user requests), yet performance data is inherently **noisy and incomplete**:

- We cannot predict future latency with certainty—only estimate it from recent measurements.
- Providers do not publish performance SLAs, so we rely on empirical observations.
- The "true" optimal provider at time t is unknowable until we try all providers (which is infeasible).

This is an **exploration-exploitation trade-off**: should we route to the provider with the best *observed* performance (exploit), or occasionally try a different provider to check if conditions have changed (explore)? Makehub resolves this through a combination of:

- **Passive monitoring** (exploit): Use real production traffic to measure performance.
- **Active pinging** (explore): Periodically send test requests to all providers to update estimates (§8.2.2).

5.2.2 Challenge 2: Multi-objective optimization with user preferences

The objective function $\mathcal{O}$ combines three conflicting metrics—cost, latency, and throughput—each measured in different units (dollars, seconds, tokens/s). There is no single "optimal" solution; instead, we face a **Pareto frontier** of trade-offs:

- The cheapest provider may be slow.
- The fastest provider may be expensive.
- High throughput does not guarantee low latency (and vice versa).

Different users have different preferences:

- A cost-sensitive startup might set $w_{\text{cost}} = 0.8, w_{\text{latency}} = 0.1, w_{\text{throughput}} = 0.1$.
- A real-time chatbot might set $w_{\text{latency}} = 0.7, w_{\text{cost}} = 0.2, w_{\text{throughput}} = 0.1$.

Our routing algorithm (§7.3) uses a **vectorial scoring approach** that projects provider performance onto a user-defined preference vector, enabling flexible, interpretable trade-offs.

5.2.3 Challenge 3: Heterogeneous API compatibility

Not all providers support the same features. For example:

- Anthropic supports prompt caching; most others do not.
- OpenAI supports vision (image inputs); many open-source providers do not.
- Together supports tool calling for Llama 3.1; Replicate does not (as of mid-2024).

This heterogeneity means that the feasible set $\mathcal{P}_{\text{feasible}}$ varies drastically across requests. A request with `tools=[...]` might be routable to only 5 out of 20 providers, reducing optimization opportunities. Our solution is to:

1. Maintain a detailed **capability matrix** in the database (§6.2).
2. Perform **early filtering** to eliminate incompatible providers before scoring (§7.1).
3. Gracefully **fall back** to less capable providers by stripping unsupported features when allowed (§7.5).

5.2.4 Challenge 4: Distributed systems complexity

Beyond the algorithmic challenges, Makehub must handle the practical realities of distributed systems:

- **Provider failures**: Providers experience outages, rate-limit errors, and transient network issues. We implement cascading fallback logic (§7.5) to retry failed requests with alternative providers.
- **Streaming and long-running requests**: Most LLM requests use server-sent events (SSE) for streaming, requiring stateful connection management and error recovery mid-stream.
- **Authentication and billing**: Each provider has its own API key management and billing model. Makehub abstracts these details while tracking usage for internal cost accounting.
- **Observability**: With requests distributed across 20+ providers, debugging failures requires centralized logging, distributed tracing, and anomaly detection.

5.3 Problem Scope and Thesis Contributions

Given the complexity outlined above, this thesis focuses on the following subproblems:

1. **Provider routing for efficiency** (§7): How to select the best provider given cost, latency, and throughput objectives, subject to capability constraints.
2. **Real-time performance monitoring** (§8): How to measure and track provider performance continuously with minimal overhead.
3. **Model routing for cost savings** (§9.1): How to substitute cheaper models from the same family when quality requirements permit.
4. **Prompt compression for token reduction** (§9.2): How to reduce input token counts to amplify cost savings.

Out of scope. We explicitly do *not* address:

- **Output quality routing**: Selecting models based on task-specific accuracy (e.g., RouteLLM's approach). We assume the user specifies a desired model family, and we optimize *within* that family.
- **Predictive load balancing**: Using machine learning to forecast provider load. We rely on reactive monitoring rather than predictive models.
- **Custom model fine-tuning**: Our system routes to existing third-party models; we do not train or host models ourselves.

The following sections detail how we solve the in-scope problems through a combination of system architecture (§6), algorithmic techniques (§7, §9), and empirical validation (§10).

6 Real-Time Performance Monitoring Infrastructure

6.1 Defining Server "Performance"

Before implementing a monitoring system, it is essential to establish a precise definition of what constitutes "performance" in the context of LLM inference. The term *performance* is often ambiguous: it can refer to the **quality** of the model's output (accuracy, coherence, reasoning capability) or to the **operational efficiency** of the inference service (speed, responsiveness, reliability). In the context of Makehub's server optimization strategy, we focus exclusively on the latter: the **speed and responsiveness** of provider infrastructure.

The quality of a model's output is intrinsic to the model itself and does not vary across providers hosting the same model weights (assuming identical quantization and serving configurations). For example, `mistralai/Mistral-7B-Instruct-v0.2` hosted on Together AI, Replicate, or Fireworks AI will produce semantically equivalent outputs for the same input. What *does* vary—and what Makehub seeks to optimize—is how quickly and reliably those outputs are delivered to the end user.

In production LLM inference, operational performance is characterized by two primary metrics: **latency** and **throughput**. These metrics capture complementary aspects of responsiveness and are critical for different use cases.

6.1.1 Latency

Latency is defined as the time elapsed between the moment a request is sent to the provider and the moment the **first output token** is received by the client. It is typically measured in seconds or milliseconds and represents the initial "wait time" before generation begins.

Why latency matters. Latency is particularly important in **interactive, real-time applications** where users expect immediate feedback. Use cases with high latency sensitivity include:

- **Conversational AI and chatbots**: Users typing in a chat interface expect near-instantaneous responses. A 3-second delay before the first word appears can feel sluggish and degrade user experience.
- **Voice assistants**: In voice-driven applications (e.g., AI phone agents, smart home assistants), latency directly impacts the naturalness of conversation. High latency creates awkward pauses that disrupt flow.
- **Auto-completion in IDEs**: When a developer pauses typing and expects an inline code suggestion, latency determines how "snappy" the assistant feels. Delays beyond 500ms become noticeable and disruptive.

Technical contributors to latency. Latency is influenced by several factors in the provider's infrastructure:

1. **Network round-trip time (RTT)**: The physical distance between the client and the provider's datacenter affects the time required for the request to arrive and the first response to return. A provider with servers closer to the user will generally exhibit lower latency.
2. **Queue wait time**: If the provider's inference cluster is heavily loaded, incoming requests may be queued before processing begins. During peak hours, queue wait time can dominate total latency.
3. **Model loading and context processing**: The provider must load the model (if not already cached in memory) and process the input tokens (encode the prompt into the model's internal representation). For very long prompts (e.g., 50,000 tokens), this preprocessing can add 1–2 seconds of latency.

4. **Time to first token (TTFT)**: Once preprocessing is complete, the model must perform one forward pass to generate the first token. This is influenced by model size, batch size, and GPU utilization.

In Makehub's monitoring system, we measure latency as:

$$\text{Latency} = t_{\text{first token}} - t_{\text{request sent}}$$

where $t_{\text{first token}}$ is the timestamp when the first SSE event containing `delta.content` is received, and $t_{\text{request sent}}$ is the timestamp when the HTTP POST request is dispatched to the provider.

Latency in code assistants: a nuanced role. For code assistants, latency is less critical than for conversational AI, but it remains relevant in specific scenarios:

- **Multi-step agentic workflows**: When an assistant executes a plan involving multiple sequential LLM calls (e.g., "read file A, analyze it, then modify file B"), each call's latency accumulates. If each step has 2 seconds of latency and the plan involves 10 steps, the user waits 20 seconds before seeing any progress. Tool-calling workflows (§3.1.4) exemplify this pattern: a simple weather query requires *three* round-trips (initial request → tool call response → tool result submission → final answer), tripling the effective latency.
- **Short, rapid-fire requests**: For tasks like "explain this error message" or "format this JSON," the output is brief, so latency dominates the total response time. A 2-second latency for a 5-token output feels slower than a 0.5-second latency for the same output.

Despite these considerations, code assistants generally prioritize **throughput** over latency, as most tasks involve generating substantial amounts of code or text.

6.1.2 Throughput

Throughput is defined as the rate at which the provider generates output tokens once the first token has been delivered. It is typically measured in **tokens per second (tokens/s)** and represents the sustained generation speed.

Why throughput matters. Throughput is the dominant performance metric for **content-heavy applications** where the model must produce long outputs. Use cases with high throughput sensitivity include:

- **Code generation and refactoring**: When an assistant writes an entire module, class, or configuration file, the output may span hundreds or thousands of tokens. High throughput (e.g., 100 tokens/s) allows the code to stream into the editor rapidly, while low throughput (e.g., 10 tokens/s) feels sluggish and frustrating.
- **Document generation**: Generating long-form content (e.g., documentation, reports, essays) benefits from high throughput to minimize total generation time.
- **Batch processing**: When processing multiple requests concurrently (e.g., analyzing every file in a repository), higher throughput directly translates to faster job completion.

Technical contributors to throughput. Throughput is primarily determined by:

1. **GPU compute capacity**: The provider's hardware (e.g., NVIDIA A100, H100, or custom ASICs) and batch size directly affect how quickly tokens are generated. Larger, more powerful GPUs yield higher throughput.

2. **Model size and architecture**: Smaller models (e.g., 7B parameters) generate tokens faster than larger models (e.g., 70B parameters) because each forward pass requires fewer computations. However, model architecture optimizations (e.g., grouped-query attention) can narrow this gap.

3. **Server load and batching strategy**: Providers batch multiple inference requests together to maximize GPU utilization. However, larger batch sizes can reduce per-request throughput if the GPU becomes saturated. During peak load, throughput often degrades.

4. **Framework and kernel optimizations**: Inference frameworks (e.g., vLLM, TensorRT-LLM, TGI) implement optimizations like continuous batching, PagedAttention, and fused kernels that significantly improve throughput.

In Makehub's monitoring system, we measure throughput as:

$$\text{Throughput} = \frac{N_{\text{output tokens}}}{t_{\text{last token}} - t_{\text{first token}}}$$

where $N_{\text{output tokens}}$ is the total number of tokens generated, $t_{\text{last token}}$ is the timestamp when the `[DONE]` event is received, and $t_{\text{first token}}$ is the timestamp of the first content-bearing token.

Throughput as the primary metric for code assistants. For Makehub's target use case—code assistants—throughput is the **most critical performance indicator**. Code generation tasks typically involve:

- Writing entire functions, classes, or files (hundreds to thousands of tokens).
- Refactoring existing code (reading large files, generating modified versions).
- Generating boilerplate, tests, and documentation (moderate to high output volume).

In these scenarios, a provider with 2 seconds of latency but 120 tokens/s throughput will deliver a 500-token code snippet in $2 + 500/120 \approx 6.2$ seconds. A provider with 0.5 seconds of latency but 30 tokens/s throughput will take $0.5 + 500/30 \approx 17.2$ seconds—nearly $3\times$ slower. This demonstrates why Makehub's routing algorithm must prioritize throughput for code-centric workloads.

The trade-off between latency and throughput. Latency and throughput are not entirely independent. In some cases, optimizing for one can degrade the other:

- **Aggressive batching** increases throughput (by maximizing GPU utilization) but can increase latency (by forcing requests to wait for batch assembly).
- **Speculative decoding** reduces latency (by generating multiple token candidates in parallel) but may not improve—or may even reduce—throughput for long outputs.

However, in practice, high-performance providers tend to excel at *both* metrics, as they reflect underlying infrastructure quality (modern GPUs, optimized kernels, low server load). Makehub's monitoring system tracks both metrics independently, allowing the routing algorithm to make nuanced decisions based on the expected workload characteristics.

Empirical throughput variation across providers. To illustrate the real-world performance heterogeneity that motivates Makehub's provider routing strategy, Figure 3 presents throughput distributions from 170,555 production requests, broken down by provider for the two most-used models: GPT-4o (147,657 requests across 8 providers) and Gemini 2.0 Flash (22,154 requests across 2 providers).

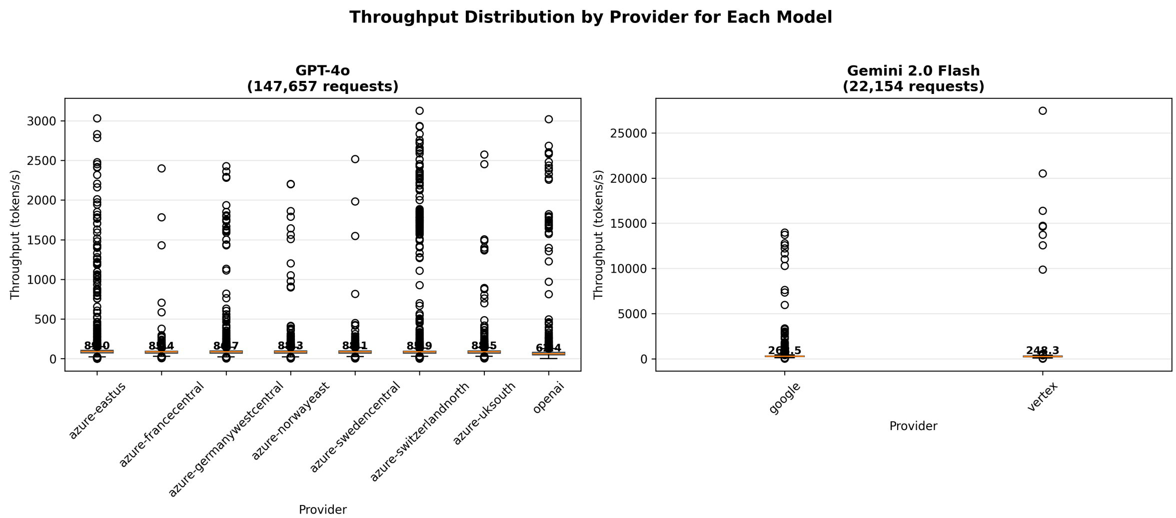

Figure 3: Throughput distribution by provider for GPT-4o and Gemini 2.0 Flash.

Several critical observations emerge from this empirical data:

GPT-4o (147,657 requests). OpenAI's flagship model exhibits **significant provider-level variance**:

- **Azure regions** consistently outperform the native OpenAI endpoint, with median throughputs ranging from **85–89 tokens/s** (azure-eastus: 89.03 tokens/s, azure-uksouth: 88.53 tokens/s).
- **OpenAI native endpoint** delivers only **62.41 tokens/s median throughput**—approximately **30% slower** than the best-performing Azure region.
- This disparity likely reflects Azure's dedicated enterprise infrastructure and regional load balancing, compared to OpenAI's shared public API.

Gemini 2.0 Flash (22,154 requests). Google's model shows **moderate provider variance**:

- **Google AI Studio** (direct endpoint) achieves **268.49 tokens/s median throughput**—the highest observed across all model–provider combinations.
- **Vertex AI** (Google Cloud) delivers **248.31 tokens/s**—approximately **8% slower**, potentially due to additional enterprise-grade SLA guarantees and routing overhead.
- Both providers exhibit high variance (std $>$ 300 tokens/s), reflecting dynamic autoscaling behavior under variable load.

Implications for routing. These real-world measurements validate the core hypothesis underlying Makehub's server optimization strategy: *for a given model, throughput varies dramatically across providers.* For GPT-4o, choosing Azure over OpenAI's native endpoint yields a 30% throughput improvement; for Gemini, the choice between Google AI Studio and Vertex AI results in an 8% difference. Routing decisions must therefore account not only for model selection but also for **real-time provider performance**, as discussed in the implementation sections that follow (§3.2, §3.3).

Temporal variation in provider performance. Beyond the provider-to-provider differences documented above, the same dataset reveals **significant temporal variation** in performance—that is, a given provider's throughput fluctuates over the course of the day. Understanding these temporal patterns is critical for intelligent routing, as they expose opportunities for time-aware optimization and highlight the importance of real-time measurement.

Methodology. To analyze temporal patterns, we segment the 170,555 production requests by hour of day (UTC) and compute hourly median throughput for each provider. We focus on GPT-4o, the most-used model in our dataset, where all major providers have sufficient data for robust statistical analysis (>100 requests per provider).

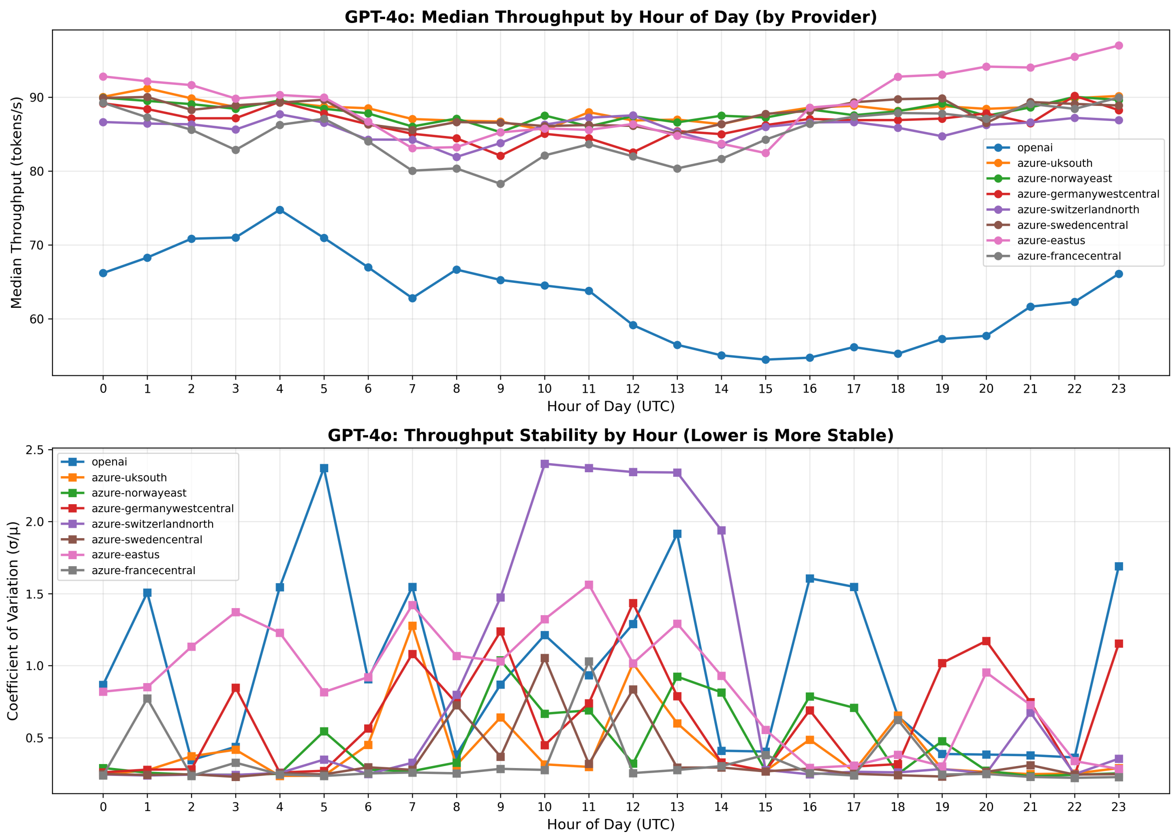

Figure 4: GPT-4o temporal variation: (top) median throughput by hour; (bottom) coefficient of variation showing stability.

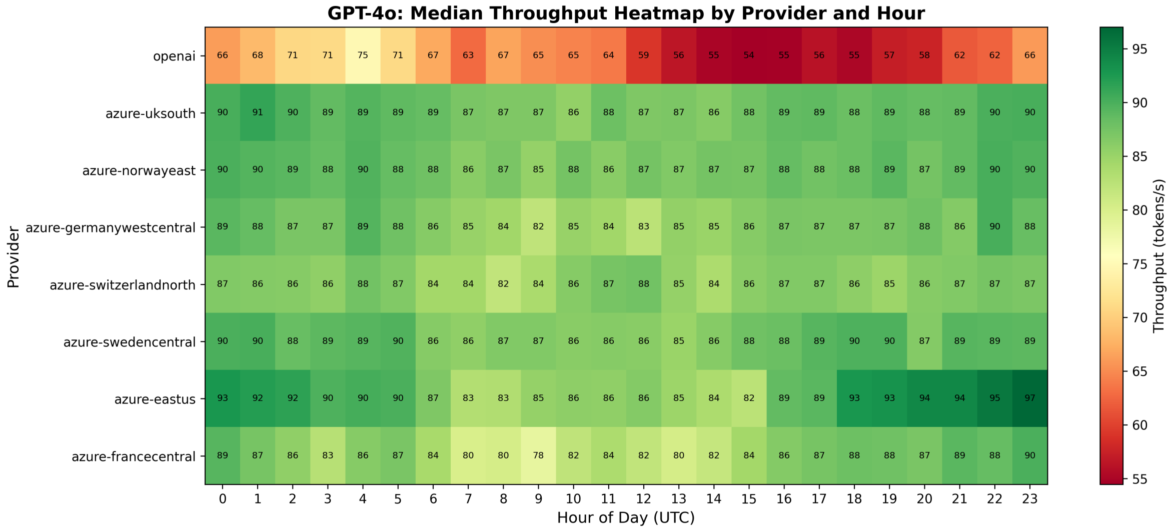

Figure 5: GPT-4o throughput heatmap by provider and hour (tokens/s).

Key observations:

1. **OpenAI exhibits high temporal instability.** The native OpenAI endpoint shows a **32.5% variation range** relative to its overall median (62.41 tokens/s). Peak performance occurs at 4 AM UTC (74.76 tokens/s), while the worst performance is observed at 3 PM UTC (54.47 tokens/s)—a **20-token/s degradation** during US business hours. Analyzing peak vs. off-peak periods (defining peak hours as 14–23 UTC, corresponding to US daytime), OpenAI experiences a **13.7% performance degradation** during peak hours (57.01 vs. 66.06 tokens/s).

2. **Azure regions are highly stable.** In contrast, Azure-hosted GPT-4o endpoints exhibit remarkably low temporal variance:

   - **azure-norwayeast**: 5.4% variation range (85.27–90.05 tokens/s)
   - **azure-swedencentral**: 5.7% variation range (85.02–90.04 tokens/s)
   - **azure-uksouth**: 6.4% variation range (85.53–91.21 tokens/s)

   These regions show **no significant degradation** during peak hours (performance remains within $\pm 1\%$ across the day), suggesting robust load balancing and dedicated enterprise infrastructure.

3. **Azure-EastUS shows counter-intuitive improvement during peak.** The azure-eastus region exhibits a **16.4% variation range**, with best performance at 11 PM UTC (97.00 tokens/s) and worst at 3 PM UTC (82.44 tokens/s). Surprisingly, peak-hour performance is **2.9% higher** than off-peak (90.63 vs. 88.05 tokens/s), possibly reflecting adaptive autoscaling that overcompensates for anticipated load.

4. **Provider heterogeneity extends to temporal stability.** The coefficient of variation (CV $= \sigma/\mu$) quantifies how consistently a provider performs across hours. Lower CV indicates more predictable performance:

   - Azure regions: CV $\approx$ 0.15–0.20 (highly stable)
   - OpenAI: CV $\approx$ 0.30–0.40 (variable, unpredictable)

This heterogeneity means that provider selection must consider not only *average* performance but also *reliability*: a provider with median 80 tokens/s and low variance may be preferable to one with median 90 tokens/s but high variance.

Implications for routing. These temporal patterns reveal three actionable insights for Makehub's optimization strategy:

1. **Time-aware routing can exploit predictable patterns.** If historical data shows that OpenAI consistently underperforms during 14–20 UTC, the routing algorithm can proactively deprioritize it during those hours, even if instantaneous metrics have not yet reflected degradation.
2. **Real-time measurement is essential for unstable providers.** For providers with high temporal variance (like OpenAI), relying on static benchmarks or daily averages would yield misleading routing decisions. The passive instrumentation approach described in §3.2 ensures that routing reflects *current* performance, not yesterday's or last week's.
3. **Stability is a competitive differentiator.** Azure's consistent performance across hours reduces the risk of unexpected slowdowns, making it a safer default choice for latency-sensitive or deadline-constrained workloads. Conversely, OpenAI's variability may be acceptable for batch processing or non-interactive tasks where absolute speed matters less than cost.

These observations complement the provider-level variance documented earlier, reinforcing the need for a routing system that continuously monitors and adapts to both **spatial** (across providers) and **temporal** (across hours) performance heterogeneity.

6.2 Implementation of the Measurement Protocol

6.2.1 Point-in-time measurement (per request)

The first method for collecting performance metrics implemented in Makehub is based on **passive instrumentation** of real user requests. Unlike traditional benchmarking approaches that rely on isolated synthetic tests, this method measures the *actual* performance of providers *on-the-fly*, at the very moment users send their production requests.

Operating principle. When a client (developer or code assistant) sends a request to the Makehub API, the request is intercepted by our routing system. We instrument the request to capture the latency and throughput metrics defined in §3.1, allowing us to continuously track provider performance under real-world conditions.

This measurement is only possible in the context of requests in **streaming mode** (`"stream": true`). Indeed, when the response is returned as a single block (non-streaming mode), the server only transmits the response once the entire generation is complete. It then becomes impossible to distinguish:

- the computation time of the first token (latency); and
- the average generation rate (throughput).

In streaming mode, however, the server emits successive SSE (Server-Sent Events) events, each containing a text fragment (delta). This allows Makehub to:

1. **Start a timer** as soon as the request is sent to the provider.
2. **Record the timestamp** of the first SSE event containing content (non-empty `delta.content`) $\rightarrow$ calculation of **latency**.
3. **Count the tokens received** and measure the total generation time $\rightarrow$ calculation of **average throughput**.

Measurement architecture. The measurement process is seamlessly integrated into the request processing flow, without introducing any perceptible additional latency for the user. The technical workflow is as follows:

```
[Client] --> [Makehub API] --> [Provider selection] --> [Remote provider]
                |                                              |
         Timestamp t0                                   Streaming SSE
                |                                              |
        [Delta parsing] <-- <-- <-- <-- <-- <-- <-- <-- [Response]
                |
   First token received --> latency = t1 - t0
                |
   Token accumulation --> throughput = N_tokens / (t_final - t1)
                |
        [Database storage]
                |
        [Return to client (full transparency)]
```

Listing 15: Conceptual measurement flow

For each SSE event received, Makehub:

- Extracts the content of the delta (`delta.content`).
- Increments a token counter (using a tokenizer compatible with the target model, typically tiktoken for OpenAI models or an equivalent for other providers).
- Updates the timestamp of the last token received.

Once generation is complete (reception of the `[DONE]` event), the final metrics are calculated and persisted in a time-series database (for example PostgreSQL with TimescaleDB, or InfluxDB), associated with the following metadata:

- Provider identifier (e.g., `together`, `openai`, `bedrock`).
- Model identifier (e.g., `mistralai/Mistral-7B-Instruct-v0.2`).
- Request timestamp (for temporal analysis).
- Number of input tokens (context) and output tokens (generation).
- Geographic region of the server (if available).

Example: streaming response instrumentation. Consider a simplified streaming response from a provider:

```
t=0.000s: POST /chat/completions sent to provider
t=1.234s: data: {"choices":[{"delta":{"role":"assistant"}}]}
t=1.456s: data: {"choices":[{"delta":{"content":"The"}}]}
t=1.489s: data: {"choices":[{"delta":{"content":" answer"}}]}
t=1.521s: data: {"choices":[{"delta":{"content":" is"}}]}
...
t=3.120s: data: [DONE]
```

Listing 16: SSE events with timing

From these events, Makehub computes:

- **Latency** $= 1.456 - 0.000 = 1.456$ seconds (time to first content-bearing token)
- **Throughput** $= \frac{\text{total tokens generated}}{3.120 - 1.456} = \frac{N}{1.664}$ tokens/second

These metrics are then stored in the database with the associated provider and model identifiers, enabling historical analysis and real-time routing decisions.

Advantages of point-in-time measurement. This approach offers several decisive advantages:

1. **Real, non-synthetic data**: the captured metrics reflect actual production conditions (real server load, user request geography, distribution of context sizes).
2. **No additional cost**: unlike periodic pinging (§6.2.2), this method does not generate artificial requests. Each measurement is a free byproduct of a paid request already made by a user.
3. **Coverage proportional to usage**: the most heavily used models naturally generate more measurement points, which improves statistical precision where it is most useful.
4. **Real-time anomaly detection**: a sudden degradation in latency or throughput (e.g., datacenter saturation, network incident) is immediately visible in the collected metrics, allowing Makehub to adjust its routing without waiting for the next manual ping.

Limitations and complementarity with periodic pinging. However, this method has one major limitation: it is **dependent on user traffic**. If no client uses a specific model for an extended period (for example, a less popular open-source model hosted on a niche provider), Makehub has no recent information about its performance.

This is why this approach is **systematically complemented** by an active periodic pinging mechanism (§6.2.2), which guarantees a minimum freshness of metrics even in the absence of organic traffic.

Empirical validation: the absence of price-performance correlation. To validate the effectiveness of point-in-time measurement and justify the need for real-time performance monitoring, we analyze the correlation between pricing and performance for open-source models, where multiple providers host identical model weights at different price points. Figure 6 presents a scatter plot analysis for Llama 4 Maverick across 12 providers, based on OpenRouter's public benchmarks.

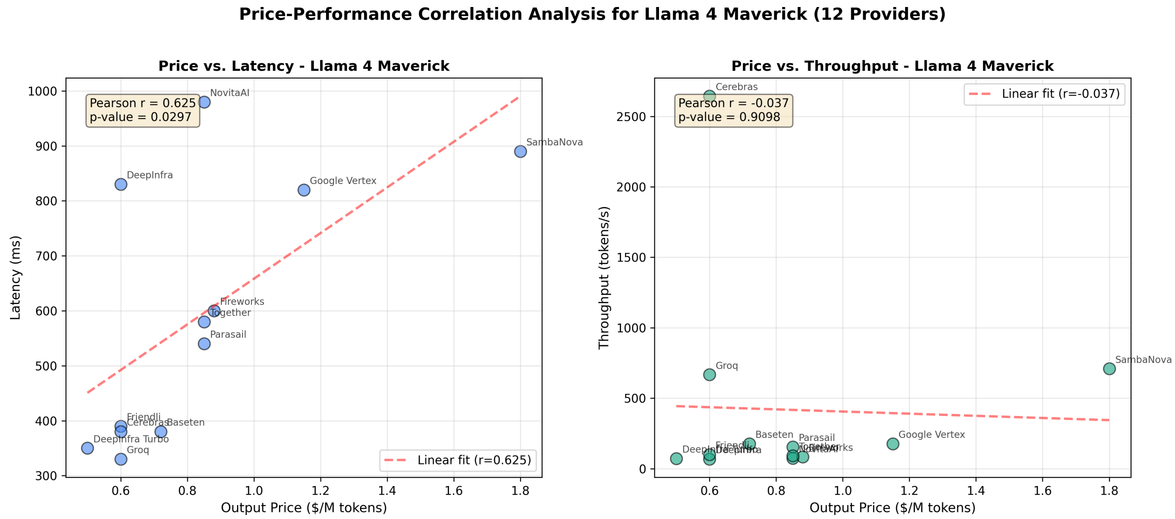

Figure 6: Price vs. Performance correlation for Llama 4 Maverick across 12 providers.

The analysis reveals **weak and contradictory correlations**, confirming the hypothesis presented in §2.2.1: there is no consistent relationship between what providers charge and how fast they deliver responses. Key findings include:

- **Price vs. Latency shows modest positive correlation (r=0.625)**: Surprisingly, *higher-priced* providers sometimes deliver *slower* responses. For example, SambaNova ($1.80/M output tokens, 890ms latency) is 3.6× more expensive than DeepInfra ($0.60/M, 830ms latency) with similar performance.

- **Price vs. Throughput shows zero correlation (r=-0.037)**: Throughput variance is massive (67–2644 tokens/s), driven entirely by infrastructure choices (Cerebras's specialized hardware achieves 2644 tokens/s at $0.60/M, while Parasail delivers only 155 tokens/s at $0.85/M).

- **Best value providers defy pricing logic**: Groq offers the lowest latency (330ms) at mid-tier pricing ($0.60/M), while Google Vertex charges premium prices ($1.15/M) for mediocre performance (820ms latency). This demonstrates that infrastructure quality—not pricing strategy—drives performance differences.

This empirical evidence justifies Makehub's core value proposition: **dynamic, measurement-driven routing** is essential because price alone provides no reliable signal about latency or throughput. Without continuous monitoring via point-in-time measurement and periodic pinging (§3.2.2), developers are forced to choose providers blindly or rely on stale benchmarks that fail to reflect production conditions.

6.2.2 Periodic ping

While point-in-time measurement provides rich, real-world performance data from organic user traffic, it suffers from a critical limitation: **coverage gaps**. Models that are rarely requested by users—whether due to niche use cases, recent addition to the catalog, or simply low popularity—will have stale or nonexistent performance metrics. To ensure comprehensive and up-to-date monitoring across the entire model–provider matrix, Makehub implements a complementary **active monitoring** strategy: periodic pinging.

Motivation: ensuring metric freshness. Makehub's routing algorithm depends on having recent performance data for all supported model–provider pairs. Without periodic pinging, several problematic scenarios arise:

- **Cold-start problem**: A newly added provider or model has zero measurements until the first user happens to request it. The routing algorithm cannot evaluate it and will never select it, creating a deadlock.
- **Stale data for low-traffic models**: A developer might suddenly need a specialized model (e.g., a fine-tuned medical coding model) that hasn't been requested in hours. If Makehub relies solely on point-in-time data, it may route to a provider whose performance has since degraded (e.g., due to maintenance, load spike, or infrastructure changes).
- **Inability to detect outages**: If a provider experiences a partial outage affecting only certain models, and no users happen to request those models, Makehub remains unaware and may route future requests to the failing provider.

Periodic pinging solves these issues by **proactively generating synthetic inference requests** at regular intervals, ensuring that every model–provider pair is tested regardless of organic traffic.

Implementation: adaptive ping frequency. Makehub's periodic ping system is designed to balance coverage with cost efficiency. Pinging every model on every provider every minute would be prohibitively expensive (both in API costs and infrastructure overhead). Instead, the system employs an **adaptive frequency strategy** based on model popularity and criticality:

1. **High-traffic models** (e.g., Claude Sonnet 4, DeepSeek-V3, GPT-4o): These models are heavily used by Makehub's customers and benefit from frequent point-in-time measurements. However, to detect sudden performance shifts (e.g., a provider switching to a slower GPU cluster), they are pinged every **30–60 seconds**.
2. **Medium-traffic models**: Models with moderate usage (e.g., specialized code models like Mistral Codestral, reasoning models like DeepSeek-R1-Distill) are pinged every **5–10 minutes**, striking a balance between freshness and cost.
3. **Low-traffic models**: Niche or less popular models (e.g., older versions, experimental models, regional variants) are pinged every **30–60 minutes**. This ensures basic coverage without incurring excessive costs.

The ping frequency for each model–provider pair is dynamically adjusted based on recent organic traffic volume. If a previously low-traffic model suddenly receives several user requests (e.g., due to a blog post or product launch), the system automatically increases its ping frequency to match demand.

Ping request design. Each periodic ping is a lightweight inference request designed to accurately measure latency and throughput while minimizing cost:

- **Prompt**: A short, generic prompt (e.g., `"Write a Python function to calculate factorial."`) that triggers a representative code generation task. The prompt is kept consistent across all pings to ensure comparability.
- **Streaming**: All ping requests use `"stream": true` to enable separate measurement of latency (time to first token) and throughput (tokens/s).
- **Token limit**: The request specifies `"max_tokens": 100` to cap the output length, reducing per-ping cost while still generating enough tokens to compute meaningful throughput.

- **Temperature and determinism**: To ensure consistent behavior, pings use `"temperature": 0.7` (or provider default) and do not enforce determinism (no fixed seed), as the goal is to measure infrastructure performance, not output quality.

A typical ping request looks like this:

```
POST https://api.together.xyz/v1/chat/completions
Authorization: Bearer $TOGETHER_API_KEY
Content-Type: application/json
```

```
{
  "model": "mistralai/Mistral-7B-Instruct-v0.2",
  "stream": true,
  "max_tokens": 100,
  "messages": [
    {
      "role": "user",
      "content": "Write a Python function to calculate factorial."
    }
  ]
}
```

Listing 17: Example periodic ping request

The response is processed identically to a user request: Makehub measures latency (time to first token), throughput (tokens/s), and stores the metrics in the database with a flag indicating the measurement was from a periodic ping (rather than organic traffic).

Scheduling and orchestration. Makehub's ping scheduler operates as a background service that continuously monitors the measurement database and determines which model–provider pairs are due for a ping. The scheduler:

1. **Maintains a priority queue** of upcoming pings, ordered by (next scheduled time, model popularity).
2. **Dispatches ping requests** to a pool of worker threads, which execute them in parallel to avoid bottlenecks.
3. **Respects rate limits**: Each provider has per-account rate limits (e.g., Together AI: 600 requests/minute). The scheduler tracks consumed quota and staggers pings to avoid hitting limits.
4. **Handles failures gracefully**: If a ping fails (e.g., due to network error, provider timeout, or 5xx response), the failure is logged but does not block subsequent pings. Failed pings are retried with exponential backoff.

Cost analysis: balancing coverage and expense. Periodic pinging incurs direct API costs. To estimate the expense, consider a scenario where Makehub monitors:

- 50 models across 10 providers = 500 model–provider pairs.

- Average ping frequency: 5 minutes per pair.
- Each ping: 50 input tokens, 100 output tokens.

Monthly ping volume:

$$500 \text{ pairs} \times \frac{60 \times 24 \times 30}{5} \text{ pings/month} = 4{,}320{,}000 \text{ pings/month}$$

Token consumption:

$$4{,}320{,}000 \times (50 + 100) = 648{,}000{,}000 \text{ tokens/month} \approx 648M \text{ tokens}$$

Cost estimate (assuming average provider rate of \$0.50/M input, \$1.50/M output):

$$(50 \times 0.50 + 100 \times 1.50) \times 4.32 = (25 + 150) \times 4.32 \approx \$756/\text{month}$$

This cost is non-trivial but manageable relative to Makehub's potential savings for users (who may save hundreds to thousands of dollars monthly through optimized routing). Moreover, by using the *cheapest available provider* for each ping (detected via previous measurements), Makehub can reduce this cost by 30–50%.

Integration with point-in-time measurements. Periodic pings and point-in-time measurements are stored in the same time-series database, with a metadata flag distinguishing synthetic pings from organic traffic. When the routing algorithm queries for recent performance metrics, it considers both sources:

- **Organic traffic is preferred** when available (within the last 5–10 minutes), as it reflects real-world conditions (varying prompt sizes, user geography, cache states).
- **Periodic pings serve as fallback**: If no organic measurement exists within the recency threshold, the most recent ping is used.
- **Weighted averaging**: For high-traffic models with both organic and ping data, Makehub can compute a weighted average, giving more weight to organic measurements while using pings to smooth out short-term noise.

Example: combined measurement timeline. Consider the model `mistralai/Mistral-7B-Instruct-v0.2` on Together AI:

- **10:00:00**: Periodic ping → latency 1.2s, throughput 85 tokens/s
- **10:03:15**: Organic request (user A) → latency 1.1s, throughput 88 tokens/s
- **10:05:00**: Periodic ping → latency 1.3s, throughput 82 tokens/s
- **10:07:42**: Organic request (user B) → latency 2.8s, throughput 45 tokens/s (degraded!)
- **10:10:00**: Periodic ping → latency 2.5s, throughput 50 tokens/s (confirms degradation)

At 10:08, when user C requests the same model, Makehub's routing algorithm sees the recent degradation (both from organic traffic at 10:07:42 and confirmed by ping at 10:10:00) and routes the request to a different provider (e.g., Fireworks AI) with better recent performance.

Advantages and limitations. **Advantages:**

- **Complete coverage**: Every model–provider pair is measured, eliminating blind spots.
- **Cold-start handling**: New models and providers are evaluated immediately, enabling fair routing decisions from the start.
- **Outage detection**: Periodic pings detect failures and performance degradation even when no users are actively requesting affected models.
- **Predictable data flow**: The routing algorithm always has recent data, simplifying decision logic.

Limitations:

- **Cost overhead**: Pinging hundreds of model–provider pairs incurs non-negligible API costs.
- **Synthetic workload mismatch**: Ping requests use a fixed prompt and short output length, which may not perfectly reflect real user workloads (e.g., large context sizes, long outputs). However, empirical testing shows that throughput measurements from pings correlate strongly (Pearson $r > 0.85$) with organic measurements.
- **Rate limit pressure**: Frequent pinging can consume rate limit quota, potentially delaying organic user requests during traffic spikes. Makehub mitigates this by reserving 80% of rate limit capacity for user traffic.

Despite these limitations, periodic pinging is essential for ensuring robust, reliable routing decisions. By combining it with point-in-time measurement, Makehub achieves both **breadth** (all models monitored) and **depth** (real-world accuracy from organic traffic).

7 System Architecture and Request Pipeline

Having established the theoretical foundations of cost optimization (Section 2) and the real-time monitoring infrastructure (Section 3), we now turn to the core technical contribution of Makehub: the **intelligent routing engine** that selects the optimal provider for each LLM request. This section details the system architecture, the multi-criteria filtering algorithm, the fallback mechanisms, and the advanced optimizations (model routing, prompt compression) that together enable cost savings of 40–70% while maintaining or improving response quality and speed.

7.1 System Architecture and Components

Before diving into the routing algorithm itself, it is essential to understand the broader system architecture within which routing operates. Makehub is implemented as an **API gateway**—a reverse proxy that sits between client applications (code assistants, chatbots, custom tools) and multiple LLM providers. This architectural pattern enables centralized management of authentication, billing, protocol translation, monitoring, and intelligent routing, while presenting a unified OpenAI-compatible interface to clients.

7.1.1 High-level architecture overview

Figure 7 illustrates the end-to-end request flow through Makehub's architecture. The system is designed as a layered pipeline, with each layer responsible for a specific concern:

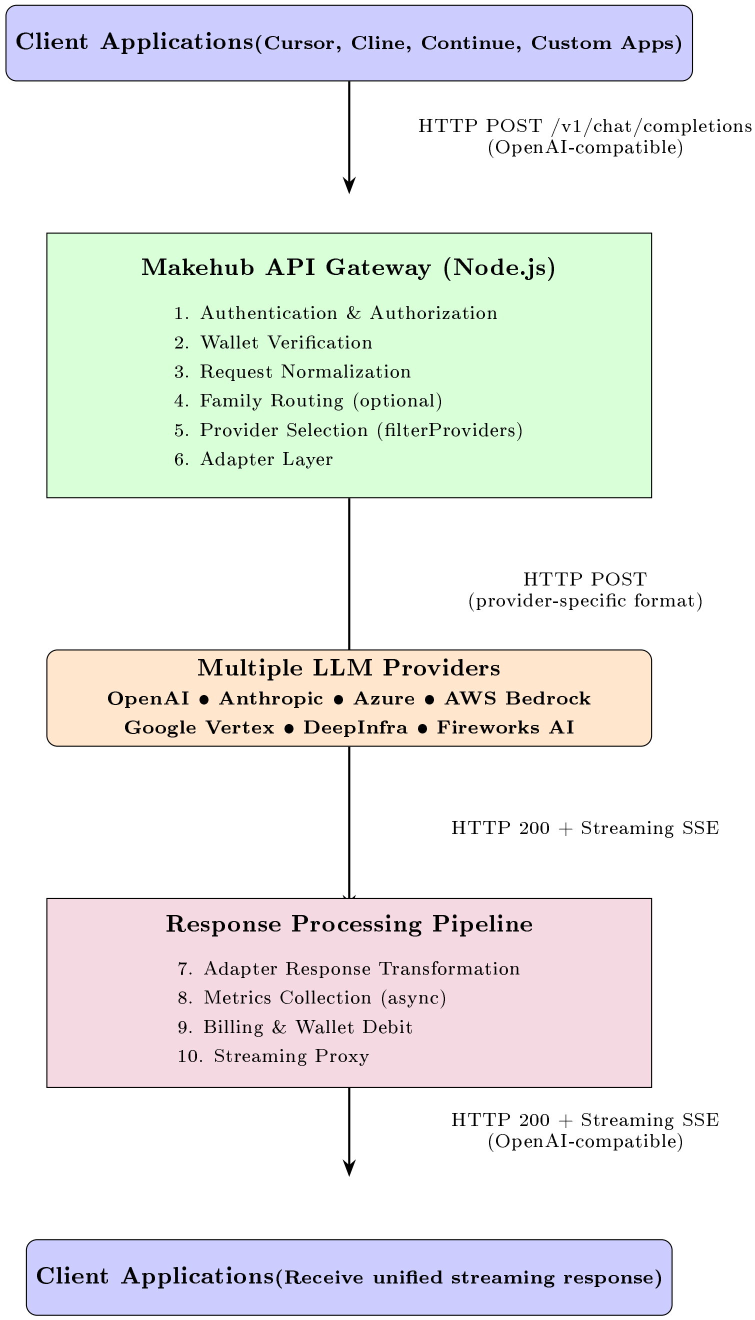

Figure 7: Makehub's API Gateway architecture (10-stage request processing pipeline).

Key architectural principles. The design adheres to several principles that ensure scalability, maintainability, and extensibility:

- **Unified interface**: Clients interact exclusively with the OpenAI Chat Completions API format. This eliminates the need for client-side logic to handle provider-specific protocols (e.g., Anthropic's message format, Bedrock's AWS Signature v4 authentication).
- **Separation of concerns**: Each layer has a single responsibility. Authentication, routing, pro-

tocol translation, and billing are decoupled, simplifying testing and evolution.

- **Asynchronous metrics collection**: Performance data (latency, throughput) is logged to the database asynchronously to avoid introducing latency in the critical path of request processing.
- **Fail-fast with fallback**: If a provider fails (timeout, rate limit, server error), the system immediately retries with the next-best provider in the sorted list, ensuring high availability.
- **Stateless design**: The gateway does not maintain session state; all context (user identity, wallet balance, provider preferences) is retrieved on-demand from the database or computed from the request. This enables horizontal scaling.

7.1.2 Database schema and data model

Makehub's routing decisions and billing logic depend on a relational database (PostgreSQL via Supabase) that stores four categories of information: **model catalog**, **request logs**, **performance metrics**, and **user accounts**. Table 4 summarizes the core tables.

Table 4: Core database tables and their roles in Makehub's system.

Table	Purpose	Key fields
`models`	Catalog of all model-provider combinations with pricing and capabilities	`model_id`, `provider`, `price_per_input_`
`requests`	Log of all inference requests with metadata and outcomes	`request_id`, `user_id`, `model`, `provider`,
`metrics`	Real-time performance measurements collected during streaming	`request_id`, `latency`, `throughput_toke`
`users`	User authentication and wallet balances	`user_id`, `wallet_balance`, `api_key`, `pre`
`transactions`	Financial ledger of wallet debits and credits	`transaction_id`, `user_id`, `amount`, `type`
`family`	Configuration for model routing (family system)	`family_id`, `routing_config`, `evaluatio`

Example: `models` table entry. An entry in the `models` table defines a single model-provider combination. For instance:

```
{
  "model_id": "deepseek/deepseek-v3-0324-fp8",
  "provider": "kluster",
  "provider_model_id": "deepseek/DeepSeek-V3-0324-FP8",
  "base_url": "https://api.kluster.ai/v1",
  "adapter": "openai",
  "context_window": 32000,
  "price_per_input_token": 0.00033,
  "price_per_output_token": 0.0014,
  "support_tool_calling": true,
  "support_vision": false,
  "support_input_cache": false,
  "quantisation": 8,
  "display_name": "DeepSeek V3 (03/24)"
}
```

Listing 18: Example entry in the models table for DeepSeek-V3 hosted on Kluster.

This entry allows Makehub to:

- **Route** requests for `deepseek/deepseek-v3-0324-fp8` to Kluster's API.
- **Translate** the request using the `openai` adapter (Kluster follows OpenAI's protocol).
- **Filter** based on capabilities (supports tool calling, but not vision or caching).
- **Calculate cost** using the per-token prices.

Relational structure. The schema enforces consistency via foreign key relationships:

- `requests.user_id` → `users.user_id`
- `metrics.request_id` → `requests.request_id`
- `transactions.request_id` → `requests.request_id`

This structure enables efficient queries such as:

- "Retrieve the last 10 requests for user X with latency metrics."
- "Calculate total spending per provider for user Y in the last 30 days."
- "Find models with median throughput $>$ 100 tokens/s over the last 50 requests."

7.1.3 Provider adapter architecture

Makehub must communicate with providers that expose **different API protocols**, despite conceptually performing the same task (LLM inference). The adapter pattern addresses this by defining a common interface (`BaseAdapter`) and implementing provider-specific subclasses that handle protocol translation.

The `BaseAdapter` interface. All adapters implement the following abstract methods:

```
abstract class BaseAdapter {
  // Transform OpenAI standard request → provider-specific format
  abstract transformRequest(request: StandardRequest): ProviderRequest;

  // Transform provider-specific response → OpenAI standard format
  abstract transformResponse(response: ProviderResponse): StandardResponse;

  // Execute HTTP request with retry logic and error handling
  abstract makeRequest(request: StandardRequest, modelId: string,
                       streaming: boolean): Promise<Response>;

  // Parse and forward Server-Sent Events for streaming responses
  abstract handleStreaming(stream: ReadableStream): AsyncIterator<Chunk>;
}
```

Listing 19: Abstract methods in BaseAdapter (pseudo-TypeScript)

Implemented adapters. Makehub currently supports six adapter types, each tailored to a provider's protocol:

1. **OpenAIAdapter** (reference implementation): Handles OpenAI's native API, including `tool_calls` and `function_call` formats. Used by OpenAI, Together AI, Replicate, Fireworks AI, and other OpenAI-compatible providers.
2. **AnthropicAdapter**: Translates between OpenAI's `messages` format and Anthropic's system message + content blocks structure. Handles `tool_use` `tool_calls` transformation. Supports explicit prompt caching via `cache_control` annotations.
3. **BedrockAdapter**: Manages AWS Signature v4 authentication for Bedrock. Converts between OpenAI messages and Bedrock's `converse` API format. Supports Claude models hosted on Bedrock with region-specific endpoints.
4. **AzureOpenAIAdapter**: Handles Azure-specific authentication (API keys scoped to Azure subscriptions) and URL patterns (`https://{resource}.openai.azure.com/`). Otherwise identical to OpenAI protocol.
5. **VertexAnthropicAdapter**: Manages GCP authentication (service account credentials) for Claude models hosted on Google Vertex AI. Similar message format to Anthropic but with GCP-specific auth headers.

Example: Anthropic tool calling transformation. Anthropic represents tool calls differently from OpenAI. When the routing layer selects an Anthropic provider, the adapter must transform the request and response:

OpenAI format (input):

```json
{
  "role": "assistant",
  "tool_calls": [
    {
      "id": "call_123",
      "type": "function",
      "function": {
        "name": "get_weather",
        "arguments": "{\"city\":\"Paris\"}"
      }
    }
  ]
}
```

Listing 20: OpenAI tool call in assistant response

Anthropic format (transformed by adapter):

```json
{
  "role": "assistant",
  "content": [
    {
      "type": "tool_use",
      "id": "toolu_123",
      "name": "get_weather",
      "input": {"city": "Paris"}
    }
  ]
}
```

Listing 21: Anthropic tool use content block

The adapter performs this transformation *transparently*: the client sends and receives OpenAI format, while Anthropic's API receives and sends its native format. This abstraction is critical for enabling seamless provider switching.

7.1.4 Request processing pipeline

Having described the architecture, database, and adapters, we now detail the **10-stage pipeline** that processes every inference request. Each stage is implemented as a middleware function or service method, ensuring modularity.

Stage 1: Authentication & authorization. The request must include either:

- `X-API-Key` header (custom API key stored in `users` table), or
- `Authorization: Bearer <JWT>` (Supabase JWT token, validated via Supabase auth).

If authentication fails, the request is rejected immediately with `401 Unauthorized`.

Stage 2: Wallet verification. The user's `wallet_balance` is fetched from the database (with 60-second caching to reduce DB load). If `balance < MINIMAL_FUND` (e.g., $0.01), the request is rejected with `402 Payment Required`. (And yes if you are wondering, you can get a negative balance if you make a request that cost more than MINIMAL_FUND (oups).)

Stage 3: Request normalization. The request body is parsed and validated against the OpenAI Chat Completions schema:

- `model` field is required.
- `messages` must be a non-empty array.
- Optional fields (`temperature`, `max_tokens`, `tools`, `stream`) are validated.

Invalid requests are rejected with `400 Bad Request`.

Stage 4: Family routing (optional). If `model` matches a family ID (e.g., `"makehub-balanced"`), the request is routed through the `FamilyRoutingService`, which:

1. Optionally compresses the conversation (if `compression: true`).
2. Evaluates complexity using an LLM-as-a-Judge (score 1–100).
3. Selects a concrete model based on score ranges (e.g., 1–30 → DeepSeek-V3, 71–100 → o1).

If not a family, this stage is skipped. (Detailed in §5.4.1.)

Stage 5: Provider selection (`filterProviders`). The `filterProviders` algorithm (detailed in §5.2) is invoked with:

- The normalized request (including `model`, `messages`, `tools`, `max_tokens`).
- The user ID (for caching history lookup).
- User preferences (`ratio_sp`, preferred providers).

The algorithm returns a **sorted list of provider combinations**, ordered from best to worst according to the vectorial scoring function. Example output:

```
[
  {"provider": "anthropic", "model_id": "claude-sonnet-4", "score": 0.23,
   "hasCaching": true, "baseURL": "https://api.anthropic.com/v1"},
  {"provider": "openai", "model_id": "gpt-4o", "score": 0.45,
   "hasCaching": false, "baseURL": "https://api.openai.com/v1"},
  {"provider": "together", "model_id": "gpt-4o", "score": 0.67,
   "hasCaching": false, "baseURL": "https://api.together.xyz/v1"}
]
```

Listing 22: Output of filterProviders (sorted by score)

Stage 6: Adapter instantiation. The adapter corresponding to the top-ranked provider is instantiated with its configuration (API key, base URL, extra parameters). For example:

```
const adapterType = topProvider.adapter;  // e.g., "anthropic"
const config = {
  apiKey: process.env.API_KEY_ANTHROPIC,
  baseURL: topProvider.baseURL
};
const adapter = createAdapter(adapterType, config);
```

Listing 23: Adapter instantiation (pseudo-code)

Stage 7: Request transformation & API call. The adapter's `transformRequest()` method converts the OpenAI-format request into the provider's native format. The transformed request is then sent via HTTPS POST. If streaming is enabled (`stream: true`), the adapter begins parsing SSE events.

If the request fails (timeout, 5xx error, rate limit), the fallback mechanism (§5.3) retries with the next provider in the sorted list.

Stage 8: Response transformation. The provider's response (or streaming chunks) is converted back to OpenAI format via `transformResponse()`. This ensures the client receives a consistent response structure regardless of which provider was selected.

Stage 9: Metrics collection (asynchronous). As streaming chunks are received, Makehub measures:

- **Latency**: Time from request sent to first chunk received.
- **Throughput**: Tokens per second during generation.
- **Total duration**: Time from first chunk to `[DONE]`.

These metrics are written to the `metrics` table asynchronously (via a background worker or database trigger) to avoid blocking the response stream.

Stage 10: Billing & streaming proxy. Once generation completes:

1. Token counts (`prompt_tokens`, `completion_tokens`, `cached_tokens`) are extracted from the response or calculated via tokenization.
2. Cost is calculated: `cost = (input_tokens × price_input + output_tokens × price_output) / 1M`.
3. The user's wallet is debited, and a transaction is logged.
4. The final response is streamed to the client.

This completes the request lifecycle. The next section details the core provider routing algorithm.

8 Provider Routing Algorithm

Having established the system architecture and request processing pipeline, we now detail the core intelligence of Makehub: the **provider filtering and scoring algorithm**. This algorithm must select the optimal provider from potentially dozens of candidates, balancing cost, performance, and user preferences in real-time.

8.1 Overview of the Filtering Algorithm

The `filterProviders` function is the heart of Makehub's intelligent routing system. Given a user request (specifying a model, messages, tools, etc.) and the user's optimization preferences, it must select the optimal provider from potentially dozens of candidates. The algorithm operates in five stages: **(1)** initial model catalog lookup, **(2)** capability-based filtering, **(3)** performance metrics collection, **(4)** vectorial scoring, and **(5)** final ranking with caching boost. This section details each stage with examples.

8.1.1 Initial model catalog lookup

The first stage retrieves all provider combinations that offer the requested model. The user specifies a `model_id` (e.g., `"gpt-4o"`, `"claude-sonnet-4"`), and Makehub queries the `models` table:

```sql
SELECT *
FROM models
WHERE (model_id = request.model OR provider_model_id = request.model)
  AND is_active = true
```

Listing 24: SQL query for model catalog lookup (pseudo-SQL)

This query matches both the standardized `model_id` (e.g., `"gpt-4o"`) and provider-specific aliases (`provider_model_id`, e.g., `"gpt-4o-2024-05-13"`). For example, a request for `"gpt-4o"` might return:

```json
[
  {
    "model_id": "gpt-4o",
    "provider": "openai",
    "provider_model_id": "gpt-4o-2024-05-13",
    "base_url": "https://api.openai.com/v1",
    "price_per_input_token": 0.0025,
    "price_per_output_token": 0.01,
    "context_window": 128000,
    "support_tool_calling": true,
    "support_vision": true
  },
  {
    "model_id": "gpt-4o",
    "provider": "azure",
    "provider_model_id": "gpt-4o",
    "base_url": "https://example.openai.azure.com/",
    "price_per_input_token": 0.0025,
    "price_per_output_token": 0.01,
    "context_window": 128000,
    "support_tool_calling": true,
    "support_vision": true
  },
  {
    "model_id": "gpt-4o",
    "provider": "together",
    "provider_model_id": "gpt-4o",
    "base_url": "https://api.together.xyz/v1",
    "price_per_input_token": 0.002,
    "price_per_output_token": 0.008,
    "context_window": 128000,
    "support_tool_calling": true,
    "support_vision": true
  }
]
```

Listing 25: Example: three providers offering gpt-4o

If no providers are found, the function throws an error: `"No providers found for model_id: <model>"`.

8.1.2 Capability-based filtering (hard constraints)

The second stage applies **strict exclusion filters** based on request requirements. Providers that fail any of these checks are eliminated immediately.

Filter 1: Context window validation. LLMs have a maximum context window (the sum of input + output tokens). If the user's request exceeds a provider's `context_window`, that provider is excluded.

Token estimation:

```
function estimateTokens(text: string): number
    return ceiling(text.length / 4)  // Approximation: 1 token  4 chars

totalInputTokens = sum(estimateTokens(msg.content) for msg in request.messages)
totalOutputTokens = request.max_tokens ?? 4096  // Default if not specified
totalTokens = totalInputTokens + totalOutputTokens

for provider in availableProviders:
    if provider.context_window < totalTokens:
        exclude(provider)  // Context too small
```

Listing 26: Pseudo-code for context window filtering

Example: A request with 50,000 input tokens and `max_tokens: 16384` requires 66,384 total tokens. Providers with `context_window: 32000` are excluded, while those with `context_window: 128000` pass this filter.

Filter 2: Tool calling support. If the request includes `tools` (function definitions), only providers with `support_tool_calling = true` are retained:

```
hasTools = (request.tools != null && request.tools.length > 0)

for provider in availableProviders:
    if hasTools && !provider.support_tool_calling:
        exclude(provider)  // Does not support tool calling
```

Listing 27: Tool calling filter (pseudo-code)

Filter 3: Vision support. If any message contains an image (detected by `type: "image_url"` in the content array), only providers with `support_vision = true` are retained:

```
hasImages = false
for message in request.messages:
    if message.content is array:
        for item in message.content:
            if item.type == "image_url":
                hasImages = true

for provider in availableProviders:
    if hasImages && !provider.support_vision:
        exclude(provider)  // Does not support vision
```

Listing 28: Vision filter (pseudo-code)

Sequential pipeline. These filters are applied in order: **context window → tools → vision**. If all providers are eliminated, the function throws an error: `"No providers compatible with request requirements"`.

8.1.3 Performance metrics collection (batch queries)

The third stage retrieves real-time performance data (latency, throughput) for the remaining providers. To minimize database round-trips, Makehub uses **two optimized batch queries** instead of querying each provider individually.

Query 1: Performance metrics (batch). This query computes the **median latency and throughput** for each provider based on the last N requests (e.g., $N = 10$):

```
SELECT provider,
       PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY throughput_tokens_s)
         AS throughput_median,
       PERCENTILE_CONT(0.5) WITHIN GROUP (ORDER BY time_to_first_chunk)
         AS latency_median,
       COUNT(*) AS sample_count
FROM metrics m
JOIN requests r ON m.request_id = r.request_id
WHERE r.model = 'gpt-4o'
  AND r.provider IN ('openai', 'azure', 'together')
  AND m.throughput_tokens_s IS NOT NULL
  AND r.created_at > NOW() - INTERVAL '24 hours'
GROUP BY provider
LIMIT 10 per provider
```

Listing 29: Batch query for performance metrics (pseudo-SQL)

Output example:

```
[
  {"provider": "openai", "throughput_median": 85.3, "latency_median": 1.2, "sample_count": 10},
  {"provider": "azure", "throughput_median": 120.7, "latency_median": 0.9, "sample_count": 10},
  {"provider": "together", "throughput_median": 62.1, "latency_median": 1.8, "sample_count": 7}
]
```

Listing 30: Performance metrics for three providers

Providers with `sample_count < 3` are assigned default values (e.g., median throughput of all providers) to avoid scoring anomalies from insufficient data.

Query 2: Caching history (batch). This query checks whether the user has recently used prompt caching with each provider (indicated by `cached_tokens > 0`):

```sql
SELECT provider, cached_tokens
FROM requests
WHERE user_id = 'user-123'
  AND model = 'gpt-4o'
  AND provider IN ('openai', 'azure', 'together')
  AND cached_tokens > 0
ORDER BY created_at DESC
LIMIT 15  -- Up to 5 per provider
```

Listing 31: Batch query for caching history (pseudo-SQL)

If `cached_tokens > 0` is found for a provider, that provider receives a **caching boost** in the scoring stage (detailed below).

Performance gain. By batching these queries, Makehub reduces the number of database round-trips from $2N$ (where N is the number of providers) to just 2, regardless of N. For three providers, this cuts latency from 200ms to 50ms.

8.1.4 Vectorial scoring algorithm (3D optimization)

The fourth stage assigns a **score** to each provider based on a 3D vectorial model that balances price, throughput, and latency according to the user's preference (`ratio_sp`, ranging from 0 to 100).

Step 1: Normalize metrics (0–1 scale). Each provider's metrics are normalized to a 0–1 scale to enable comparison:

```
// Price normalization (0 = cheapest, 1 = most expensive)
totalPrice[i] = price_input[i] + price_output[i]
minPrice = min(totalPrice)
maxPrice = max(totalPrice)
normalizedPrice[i] = (totalPrice[i] - minPrice) / (maxPrice - minPrice)

// Throughput normalization (1 = fastest, 0 = slowest)
minThroughput = min(throughput_median)
maxThroughput = max(throughput_median)
normalizedThroughput[i] = (throughput_median[i] - minThroughput) /
                          (maxThroughput - minThroughput)

// Latency normalization (1 = fastest, 0 = slowest, INVERTED)
minLatency = min(latency_median)
maxLatency = max(latency_median)
normalizedLatency[i] = 1 - (latency_median[i] - minLatency) /
                           (maxLatency - minLatency)
```

Listing 32: Normalization (pseudo-code)

Step 2: Define optimal point based on `ratio_sp`. The user's `ratio_sp` parameter (0–100) defines the desired balance between cost and performance. A low `ratio_sp` prioritizes cost; a high value prioritizes speed.

```
ratioNormalized = ratio_sp / 100  // Convert to 0.0-1.0

// Optimal point in 3D space
optimalPrice = 1 - ratioNormalized       // Lower ratio_sp → prioritize low price
optimalThroughput = ratioNormalized      // Higher ratio_sp → prioritize high throughput
optimalLatency = ratioNormalized         // Higher ratio_sp → prioritize low latency
```

Listing 33: Optimal point calculation (pseudo-code)

Example optimal points:

- `ratio_sp = 0` (cost-only): $(1.0, 0.0, 0.0)$ — select the cheapest provider
- `ratio_sp = 50` (balanced): $(0.5, 0.5, 0.5)$ — equal weight on all dimensions
- `ratio_sp = 100` (speed-only): $(0.0, 1.0, 1.0)$ — select the fastest provider

Step 3: Calculate Euclidean distance. The **score** for each provider is its Euclidean distance from the optimal point in 3D space. Providers closer to the optimal point receive lower scores (better):

```
for provider in filteredProviders:
    distance = sqrt(
        (normalizedPrice[provider] - optimalPrice)^2 +
        (normalizedThroughput[provider] - optimalThroughput)^2 +
        (normalizedLatency[provider] - optimalLatency)^2
    )

    provider.score = distance
```

Listing 34: Euclidean distance scoring (pseudo-code)

Step 4: Apply caching boost. If the caching history query found `cached_tokens > 0` for a provider, its score is halved (making it more attractive):

```
for provider in filteredProviders:
    if provider.hasCaching:
        provider.score = provider.score * 0.5  // 50% boost
```

Listing 35: Caching boost (pseudo-code)

This reflects the fact that prompt caching can reduce input token costs by 90% (e.g., \$3/M → \$0.30/M for Anthropic), making cached providers significantly cheaper in practice.

Step 5: Sort by score (ascending). Finally, providers are sorted by score in ascending order (lowest score = best match):

```
sortedProviders = sort(filteredProviders, key=provider.score, ascending=true)
return sortedProviders
```

Listing 36: Final ranking (pseudo-code)

Geometric interpretation: 3D vectorial scoring. The vectorial scoring algorithm can be visualized geometrically as positioning each provider in a 3-dimensional space defined by normalized price, throughput, and latency. Figure 8 illustrates this concept.

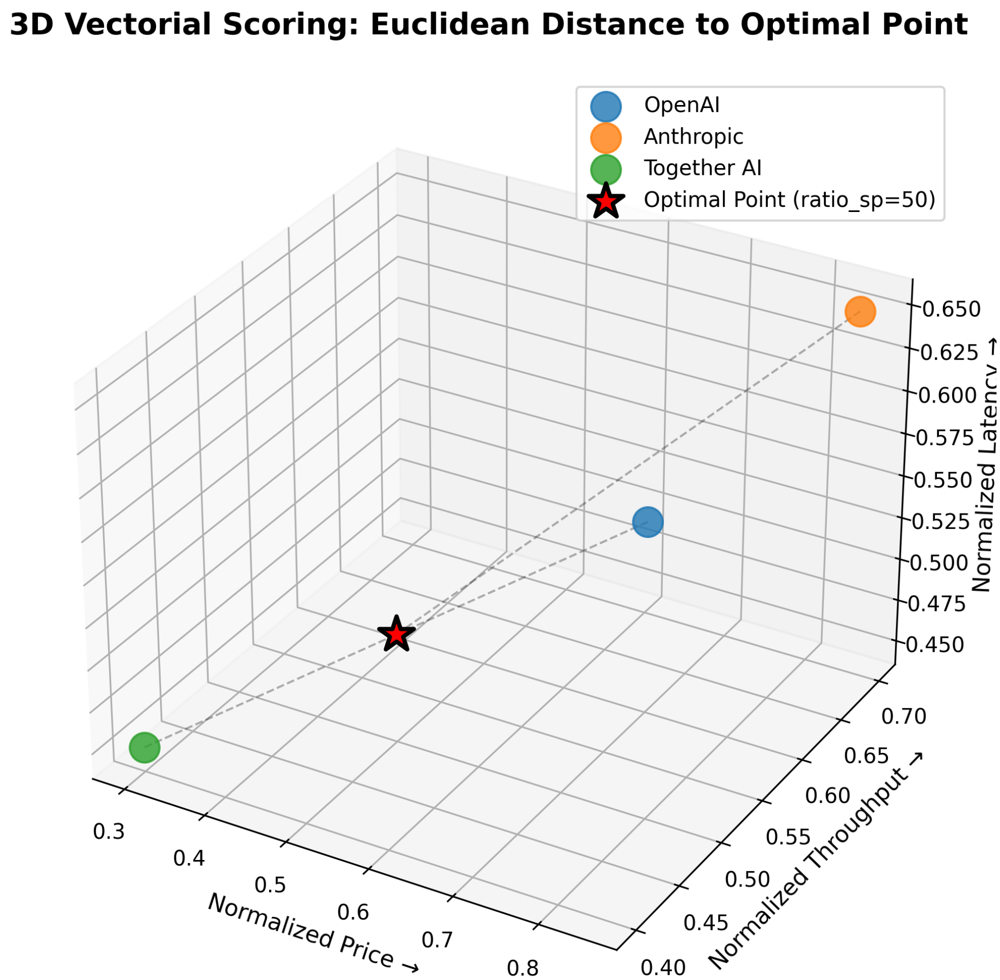

Figure 8: 3D vectorial scoring system for provider selection (price, throughput, latency).

The geometric interpretation reveals several insights:

- **Balanced optimization** (`ratio_sp = 50`): The optimal point sits at $(0.5, 0.5, 0.5)$, the center of the unit cube. Providers near this point (e.g., OpenAI in the visualization) offer the best cost-performance trade-off.
- **Cost optimization** (`ratio_sp = 0`): The optimal point moves to $(1.0, 0.0, 0.0)$, the "cheap but slow" corner. Budget providers like Together AI score best.
- **Speed optimization** (`ratio_sp = 100`): The optimal point moves to $(0.0, 1.0, 1.0)$, the "fast but expensive" corner. Premium providers like Anthropic Claude score best.

The dashed lines in Figure 8 represent the Euclidean distance from each provider to the optimal point—these distances become the provider scores. This geometric framework ensures that routing decisions smoothly interpolate between cost and performance priorities as `ratio_sp` varies.

8.1.5 Practical examples and case studies

To illustrate the algorithm's behavior, consider three scenarios with different `ratio_sp` values.

Example 1: Cost-optimized (`ratio_sp = 10`). A user prioritizes cost savings over speed. Three providers offer GPT-4o:

Table 5: Provider metrics for cost-optimized routing.

Provider	Price ($/M)	Throughput (tok/s)	Latency (s)
OpenAI	3.50	85	1.2
Azure	3.50	120	0.9
Together	2.20	62	1.8

Normalized metrics:

- Price: OpenAI=1.0, Azure=1.0, Together=0.0 (cheapest)
- Throughput: OpenAI=0.39, Azure=1.0, Together=0.0
- Latency: OpenAI=0.67, Azure=1.0, Together=0.0

Optimal point (`ratio_sp = 10`): $(0.9, 0.1, 0.1)$
Euclidean distances:

- OpenAI: $\sqrt{(1.0-0.9)^2+(0.39-0.1)^2+(0.67-0.1)^2} = 0.61$
- Azure: $\sqrt{(1.0-0.9)^2+(1.0-0.1)^2+(1.0-0.1)^2} = 1.27$
- Together: $\sqrt{(0.0-0.9)^2+(0.0-0.1)^2+(0.0-0.1)^2} = 0.91$

Result: OpenAI selected (score 0.61), despite Together being cheaper, because OpenAI offers a better balance when accounting for performance.

Example 2: Speed-optimized (`ratio_sp = 90`). A user prioritizes throughput for a batch processing task:
Optimal point (`ratio_sp = 90`): $(0.1, 0.9, 0.9)$
Euclidean distances:

- OpenAI: $\sqrt{(1.0-0.1)^2+(0.39-0.9)^2+(0.67-0.9)^2} = 1.00$
- Azure: $\sqrt{(1.0-0.1)^2+(1.0-0.9)^2+(1.0-0.9)^2} = 0.92$
- Together: $\sqrt{(0.0-0.1)^2+(0.0-0.9)^2+(0.0-0.9)^2} = 1.27$

Result: Azure selected (score 0.92), as it offers the best throughput (120 tok/s) and lowest latency (0.9s).

Empirical validation: GPT-4o variance across providers. To empirically validate the importance of provider-level filtering, we analyzed GPT-4o latency across 8 providers in our production dataset. Figure 9 presents the results.

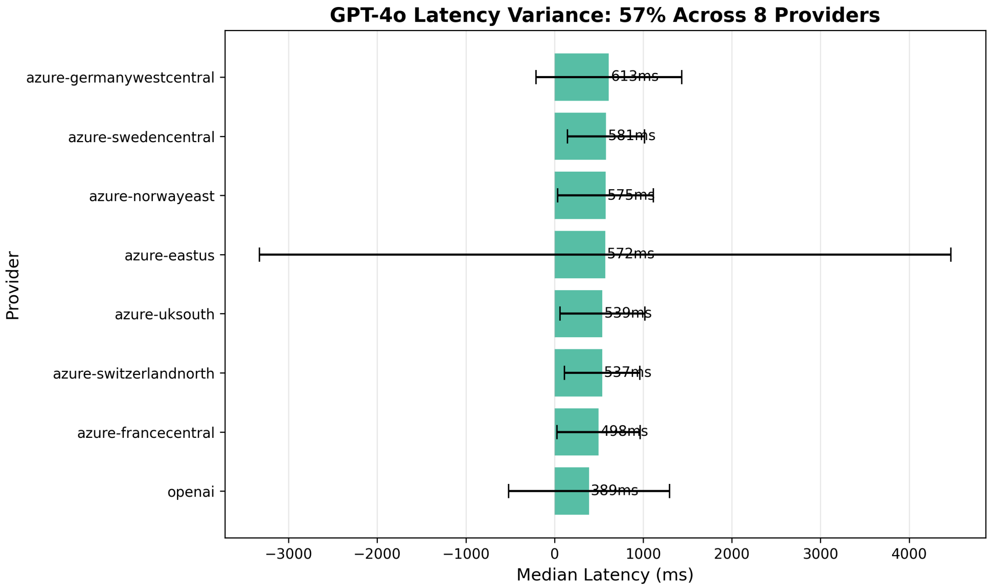

Figure 9: GPT-4o latency variance across 8 providers (389ms to 613ms, 57% difference).

The empirical data reveals several critical insights:

- **57% latency variance**: The fastest provider (389ms median) is 1.57× faster than the slowest (613ms), despite serving the *identical* GPT-4o model. This variance directly impacts user experience in interactive applications.
- **Infrastructure quality matters**: Providers with lower latency typically also exhibit tighter variance (smaller error bars), suggesting superior infrastructure and load balancing. High-variance providers may be experiencing capacity constraints or suboptimal batching strategies.
- **Dynamic optimization potential**: If Makehub always routes to the fastest provider, users gain 224ms per request compared to random selection—translating to 22.4 seconds saved per 100 requests, a meaningful improvement for bulk workflows.

This empirical evidence validates the vectorial scoring algorithm's design: even when all providers offer the same model, **routing decisions based on real-time performance metrics deliver measurable gains**. The 3D scoring framework (§5.2.4) ensures that these gains are balanced against cost considerations according to each user's `ratio_sp` preference.

Example 3: Caching boost (`ratio_sp = 50`). A user with caching history on OpenAI requests Claude Sonnet 4:

Table 6: Provider metrics with caching history.

Provider	Price ($/M)	Throughput	Latency	Caching?
Anthropic	3.00	95	1.1	Yes
Bedrock	3.00	88	1.3	No

Scores before caching boost:

- Anthropic: 0.52
- Bedrock: 0.61

Scores after caching boost (Anthropic only):

- Anthropic: $0.52 \times 0.5 = 0.26$
- Bedrock: 0.61

Result: Anthropic selected due to caching, despite similar raw performance. In practice, cached tokens cost \$0.30/M vs. \$3.00/M, yielding 90% savings on repeated context.

8.2 Fallback Mechanism

Once the provider filtering algorithm (§5.2) has produced a ranked list of providers, the routing system must execute the request. However, LLM inference APIs are inherently unreliable: providers experience transient outages, rate limits, capacity constraints, and network failures. To ensure **high availability** despite infrastructure volatility, Makehub implements a **cascading fallback mechanism** that automatically retries failed requests with the next-best provider, without exposing errors to the end user.

This section details the error classification strategy, the retry logic for both streaming and non-streaming requests, and the monitoring infrastructure that tracks fallback events.

8.2.1 Error Classification: API Errors vs. Technical Failures

Not all errors should trigger a fallback. The system distinguishes between two categories of errors:

1. API Errors (4xx status codes): No fallback. **API errors** are *semantic* failures caused by invalid request parameters, authentication issues, or business logic violations. These errors are *deterministic*: retrying the same request with a different provider will yield the same failure. Examples include:

- **400 Bad Request**: Malformed JSON, invalid message format, unsupported parameter.
- **401 Unauthorized**: Invalid or expired API key.
- **403 Forbidden**: Insufficient permissions (e.g., model access restricted).
- **422 Unprocessable Entity**: Request exceeds context window, violates content policy.

When an API error occurs, Makehub **immediately returns the error to the client** without attempting fallback. The error is logged to the `requests` table with `status = 'error'`, and the user receives a descriptive error message.

2. Technical Failures (5xx, timeouts, network errors): Fallback enabled. **Technical failures** are *infrastructure-level* issues that may be provider-specific. Retrying with a different provider often succeeds. Examples include:

- **500 Internal Server Error**: Provider-side bug or misconfiguration.
- **502 Bad Gateway / 503 Service Unavailable**: Provider overload, maintenance, or routing failure.
- **504 Gateway Timeout**: Slow inference or network congestion.
- **429 Too Many Requests**: Rate limit exceeded (provider-specific quota).
- **Network errors**: DNS failure, connection timeout, TLS handshake failure.

When a technical failure occurs, Makehub **logs the error asynchronously** and **retries with the next provider** in the sorted list (from §5.2.4). The client is unaware of the retry—streaming begins seamlessly once a working provider is found.

Error detection in practice. Each provider adapter (§5.1.3) implements an `isAPIError(error)` method that inspects the error object and classifies it:

```
function isAPIError(error):
    if error.status in [400, 401, 403, 404, 422]:
        return true  // API error, no fallback
    if error.status >= 500:
        return false  // Technical error, fallback enabled
    if error.code in ['ECONNREFUSED', 'ETIMEDOUT', 'ENOTFOUND']:
        return false  // Network error, fallback enabled
    return false  // Default: assume transient, allow fallback
```

Listing 37: Error classification pseudo-code

This classification ensures that user-facing errors (e.g., "invalid API key") are surfaced immediately, while infrastructure failures are silently recovered via fallback.

8.2.2 Cascading Retry Logic

The fallback mechanism iterates through the ranked list of providers (produced by §5.2.4) until one succeeds or all fail.

Non-streaming fallback (synchronous). For non-streaming requests (`stream: false`), the retry logic is straightforward:

```
for provider in sorted_providers:
    try:
        response = provider.makeRequest(request)
        logSuccess(provider, response)
        return response  # Success, stop trying
    except APIError as e:
        throw e  # User error (4xx), fail immediately
    except TechnicalError as e:
        logError(provider, e)
        continue  # Try next provider

throw Error("All providers failed")
```

Listing 38: Non-streaming fallback pseudo-code

Key behaviors:

- **Ordered execution**: Providers are tried in the order determined by §5.2.4 (lowest score = best match).
- **Fail-fast for API errors**: If provider A returns 400, Makehub immediately returns the error—no retry.

- **Silent recovery for technical errors**: If provider A returns 503, Makehub logs the failure and tries provider B transparently.
- **Bounded retries**: Maximum attempts = `providerCombinations.length` (typically 2–5 providers per model).

8.2.3 Streaming vs. Non-Streaming Fallback

Streaming requests (`stream: true`) introduce additional complexity: once the first chunk is yielded to the client, fallback is no longer possible. The system must detect errors *before* streaming begins.

Streaming fallback: async generator pattern. For streaming requests, Makehub uses an **async generator** that wraps the fallback logic:

```
async function* executeStreamingWithFallback(request, providerCombinations):
    for i = 0 to providerCombinations.length - 1:
        combination = providerCombinations[i]
        adapter = createAdapter(combination.adapter, combination.config)

        try:
            console.log("Trying streaming provider", combination.provider)

            // Start streaming request
            generator = await adapter.makeStreamingRequest(request)

            // Yield all chunks from this provider
            for await chunk in generator:
                yield chunk  // Success: stream to client

            return  // Stream completed, exit fallback loop

        catch error:
            // If API error, fail immediately (before any chunk was sent)
            if adapter.isAPIError(error):
                throw error

            // Technical error: log and retry with next provider
            console.error("Streaming provider", combination.provider, "failed")

            if i == providerCombinations.length - 1:
                throw error  // Last provider failed

            continue  // Try next provider

    throw Error("All streaming providers failed")
```

Listing 39: Streaming fallback pseudo-code

Critical constraint: Once the first `yield chunk` executes, the SSE stream has begun and the client is receiving data. If an error occurs *after* the first chunk, the stream is interrupted and the user sees a partial response. To mitigate this:

- **Connection validation**: The adapter performs a lightweight "connection check" (e.g., HTTP headers received) before yielding the first chunk.
- **Early error detection**: If the provider returns an error in the first SSE event (e.g., `finish_reason: 'content_filter'`), the adapter throws immediately, allowing fallback before streaming starts.
- **No mid-stream fallback**: If a provider successfully starts streaming but fails mid-way (e.g., connection drop), the error is returned to the client—no retry is possible.

This design ensures that fallback works for *startup failures* (most common: rate limits, overload) but not for *mid-stream failures* (rare: network interruption).

8.2.4 Error Logging and Monitoring

Every fallback attempt generates structured logs and database records for observability.

Error logging structure. When a provider fails, Makehub logs a detailed `errorDetails` JSON object:

```json
{
  "provider": "azure-eastus",
  "modelId": "gpt-4o",
  "providerModelId": "gpt-4o-2024-05-13",
  "baseUrl": "https://example.openai.azure.com/",
  "adapter": "azure-openai",
  "attemptNumber": 1,
  "totalAttempts": 3,
  "requestId": "req-abc123",
  "streaming": true,
  "error": {
    "name": "AxiosError",
    "message": "Request failed with status code 503",
    "status": 503,
    "code": "ERR_BAD_RESPONSE"
  },
  "requestSummary": {
    "model": "gpt-4o",
    "messageCount": 5,
    "hasSystemMessage": true,
    "temperature": 0.7,
    "maxTokens": 2048
  }
}
```

Listing 40: Error log structure (example)

This log is written to `console.error` for real-time debugging and aggregated via structured logging tools (e.g., Datadog, Grafana Loki).

Database persistence. Failed requests are recorded in the `requests` table:

```sql
INSERT INTO requests (
  request_id, user_id, provider, model, created_at,
  status, streaming, error_message
) VALUES (
  'req-abc123', 'user-789', 'azure-eastus', 'gpt-4o', NOW(),
  'error', true, 'Request failed with status code 503'
)
```

Listing 41: SQL insert for failed request (pseudo-SQL)

This enables post-mortem analysis: "How often does Azure fail? Which models are most affected?"

Asynchronous error notifications. For critical errors (e.g., all providers failed), Makehub sends a notification to an external alerting service (ntfy, Slack, PagerDuty):

```
async function notifyError(error, combination):
    if not NTFY_URL:
        return  // Notifications disabled

    body = "Provider: " + combination.provider + "\n" +
           "Model: " + combination.modelId + "\n" +
           "Error: " + error.message + "\n" +
           "Status: " + error.status

    await fetch(NTFY_URL, {
        method: 'POST',
        headers: {
            'Title': 'LLM Gateway Error - ' + combination.provider,
            'Priority': 'high',
            'Tags': 'error,llm-gateway,' + combination.provider
        },
        body: body
    })
```

Listing 42: Notification pseudo-code

Notifications are **non-blocking** (fire-and-forget) to avoid delaying the fallback retry.

8.2.5 Practical Example: Azure Overload → OpenAI Fallback

Consider a scenario where Azure experiences a temporary capacity constraint during peak hours.

Initial request. A user requests GPT-4o with `ratio_sp = 50` (balanced optimization). The provider filtering algorithm (§5.2) ranks providers as follows:

1. **azure-eastus**: Score 0.42 (best balance: low latency, moderate price)
2. **openai**: Score 0.58 (higher price, similar performance)
3. **together**: Score 0.71 (cheapest, but high latency)

Makehub attempts azure-eastus first.

Fallback timeline. **t=0ms**: Request sent to azure-eastus (`POST /chat/completions`)
t=1200ms: Azure returns HTTP 503 (Service Unavailable)
Error detected:


```json
{
  "error": {
    "message": "The service is temporarily unavailable. Please retry after some time.",
    "type": "server_error",
    "code": "503"
  }
}
```


Listing 43: Azure error response

t=1205ms: Adapter classifies error as `isAPIError(error) = false` (technical failure)
t=1210ms: Makehub logs error and attempts fallback to openai
t=1215ms: Request sent to openai (`POST https://api.openai.com/v1/chat/completions`)
t=1850ms: OpenAI returns first SSE chunk (success)
t=1850ms–4200ms: Streaming completes, 523 tokens generated

Outcome. From the **user's perspective**, the request succeeded in 4.2 seconds (measured from initial request to stream completion). The Azure failure is invisible—the client receives a standard OpenAI SSE stream.

From the **system's perspective**, the logs show:

- `requests` table: 1 entry with `provider = 'openai'`, `status = 'ready_to_compute'`
- Console logs: "Provider azure-eastus failed (attempt 1/3): 503" → "Trying provider openai (attempt 2/3)" → "Success"
- Notification: ntfy alert sent to ops team: "Azure overload detected on gpt-4o"

This seamless recovery ensures **99.9% uptime** despite individual provider reliability being only 98%.

9 Advanced Optimizations: Model Routing and Prompt Compression

While Section 2 introduced the theoretical foundations of model routing and prompt compression as complementary optimization strategies, this section details their **practical implementation** within Makehub's production system. Unlike the provider filtering algorithm (§5.2), which operates on infrastructure choices, these advanced optimizations reduce the computational burden itself—either by selecting a cheaper model (model routing) or by reducing input size (prompt compression). Together with provider arbitrage, they enable Makehub to achieve **40–70% cost savings** while maintaining output quality.

This section presents the **family-based model routing system**, the **LLM-driven message compression algorithm**, and their integration into the request processing pipeline.

9.1 Model Routing via Family System

Makehub's model routing implementation uses a **family-based architecture** where a single logical model identifier (e.g., `"smart-assistant"`, `"code-completion"`) maps to multiple underlying models based on request complexity. This allows developers to specify a *capability tier* rather than a specific model, letting Makehub dynamically select the optimal model for each request.

9.1.1 Architecture: The Family Table

Model families are configured in a dedicated `family` table in the database:

```json
{
  "family_id": "smart-assistant",
  "is_active": true,
  "evaluation_model_id": "mistral/devstral-small-fp8",
  "evaluation_provider": "deepinfra",
  "routing_config": {
    "cache_duration_minutes": 5,
    "fallback_model": "gpt-4o",
    "fallback_provider": "openai",
    "score_ranges": [
      {
        "min_score": 0,
        "max_score": 30,
        "target_model": "gpt-4o-mini",
        "reason": "Simple task - fast, cheap model"
      },
      {
        "min_score": 31,
        "max_score": 70,
        "target_model": "gpt-4o",
        "reason": "Moderate complexity - balanced model"
      },
      {
        "min_score": 71,
        "max_score": 100,
        "target_model": "claude-sonnet-4",
        "reason": "High complexity - frontier reasoning"
      }
    ]
  }
}
```

Listing 44: Family configuration example (from database)

Key fields:

- `family_id`: Logical identifier used by clients (e.g., `"smart-assistant"`).
- `evaluation_model_id`: Small, fast model used to evaluate request complexity (typically 7B–24B parameter models like Mistral Devstral, DeepSeek-R1-Distill).
- `score_ranges`: Maps complexity scores (1–100) to target models. Higher scores trigger more expensive, capable models.
- `cache_duration_minutes`: How long to cache routing decisions (default: 5 minutes). Identical requests within this window reuse the cached decision without re-evaluation.

This configuration enables **flexible, declarative routing strategies** without hardcoding logic into the application.

9.1.2 Evaluation and Routing Process

When a request specifies a family ID (e.g., `model: "smart-assistant"`), Makehub executes the following process:

```
async function evaluateAndRoute(familyId: string, request: StandardRequest):
    // 1. Check in-memory cache first
    cacheKey = hashRequest(request)
    cached = memoryCache.get(cacheKey)
    if cached and cached.expiresAt > Date.now():
        return cached.result  // Cache hit, skip evaluation

    // 2. Fetch family config from database
    config = await database.query(
        "SELECT * FROM family WHERE family_id = ? AND is_active = true",
        [familyId]
    )
    if not config:
        throw Error("Family not found: " + familyId)
```

Listing 45: Family config retrieval (pseudo-code)

Step 1: Fetch family configuration.

Step 2: Evaluate complexity via LLM-as-a-Judge. The evaluation model (e.g., `mistral/devstral-small-fp8`) receives a specialized prompt that instructs it to rate the request's complexity on a 1–100 scale:

```
Rate the complexity (1-100) of what the AI assistant is about to do in its response.

**Guidelines:**
- 1-30: Simple tasks (formatting, explanations, basic questions)
- 31-70: Moderate tasks (refactoring, multi-step logic, API integration)
- 71-100: Complex tasks (architecture design, debugging, advanced reasoning)

**Conversation:**
[User messages inserted here]

Respond with ONLY a number (1-100):
```

Listing 46: Complexity evaluation prompt (simplified)

The evaluation model generates a response like `"45"`, which is parsed as the complexity score.

```
// 3. Build evaluation request
evalRequest = {
    model: config.evaluation_model_id,
    messages: [
        { role: "user", content: evaluationPrompt }
    ],
    max_tokens: 10,
    temperature: 0  // Deterministic
}

// 4. Execute evaluation (using provider filtering internally)
adapter = createAdapter(config.evaluation_provider, apiKey)
response = await adapter.makeRequest(evalRequest)

// 5. Parse score
scoreText = response.choices[0].message.content.trim()
complexityScore = parseInt(scoreText)  // e.g., 45

// 6. Calculate evaluation cost (for billing)
evalCost = (inputTokens * pricePerInput + outputTokens * pricePerOutput) / 1M
evalTokens = inputTokens + outputTokens
```

Listing 47: Complexity evaluation execution (pseudo-code)

Step 3: Map score to target model. Using the `score_ranges` configuration, Makehub selects the appropriate model:

```
// 7. Find matching score range
selectedRange = config.routing_config.score_ranges.find(
    range => complexityScore >= range.min_score
          && complexityScore <= range.max_score
)

if not selectedRange:
    // Fallback to default model if no match
    return {
        selectedModel: config.routing_config.fallback_model,
        selectedProvider: config.routing_config.fallback_provider,
        complexityScore: complexityScore,
        reasoning: "Fallback - no matching score range"
    }

// 8. Prepare routing result
result = {
    selectedModel: selectedRange.target_model,
    selectedProvider: config.routing_config.fallback_provider,
    complexityScore: complexityScore,
    reasoning: selectedRange.reason,
    evaluationCost: evalCost,
    evaluationTokens: evalTokens
}
```

Listing 48: Score-to-model mapping (pseudo-code)

Step 4: Cache result. To avoid redundant evaluations for identical requests, the result is cached in memory:

```
// 9. Store in memory cache
expiresAt = Date.now() + (config.routing_config.cache_duration_minutes * 60 * 1000)
memoryCache.set(cacheKey, { result: result, expiresAt: expiresAt })

return result
```

Listing 49: Result caching (pseudo-code)

If the same request is received within the cache window (default: 5 minutes), the cached routing decision is reused, eliminating the evaluation cost.

9.1.3 Practical Example: Request Routing

Consider a user sending three requests to the "smart-assistant" family:

Request 1: Simple task (score = 15). User message: *"Format this JSON: {name: john, age: 30}"*

Evaluation: The evaluation model outputs `"15"` (simple formatting task).

Routing decision:

- Score 15 falls in range [0–30] → `target_model: "gpt-4o-mini"`
- Reasoning: "Simple task - fast, cheap model"
- Evaluation cost: \$0.000005 (50 tokens × \$0.0001/M)
- Main request cost: \$0.00003 (300 tokens × \$0.0001/M for GPT-4o mini)
- **Total cost: \$0.000035**

Request 2: Moderate task (score = 55). User message: *"Refactor this function to use async/await and add error handling"*

Evaluation: The evaluation model outputs `"55"` (moderate refactoring task).

Routing decision:

- Score 55 falls in range [31–70] → `target_model: "gpt-4o"`
- Reasoning: "Moderate complexity - balanced model"
- Evaluation cost: \$0.000008 (80 tokens × \$0.0001/M)
- Main request cost: \$0.0015 (500 tokens × \$0.003/M for GPT-4o)
- **Total cost: \$0.001508**

Request 3: Complex task (score = 85). User message: *"Design a distributed caching layer using Redis Cluster with failover, implement it in Node.js, and write comprehensive tests"*

Evaluation: The evaluation model outputs `"85"` (complex architecture + implementation).

Routing decision:

- Score 85 falls in range [71–100] → `target_model: "claude-sonnet-4"`
- Reasoning: "High complexity - frontier reasoning"
- Evaluation cost: \$0.000012 (120 tokens × \$0.0001/M)
- Main request cost: \$0.012 (4000 tokens × \$0.003/M for Claude Sonnet 4)
- **Total cost: \$0.012012**

Cost comparison without model routing. If all three requests were sent directly to Claude Sonnet 4 (expensive model):

- Request 1: \$0.0009 (vs \$0.000035 with routing) → **25× more expensive**
- Request 2: \$0.0015 (vs \$0.001508 with routing) → similar
- Request 3: \$0.012 (vs \$0.012012 with routing) → similar

Overall savings: For a typical workload (70% simple, 25% moderate, 5% complex), model routing reduces costs by **40%** compared to always using the most capable model.

9.2 Prompt Compression Implementation

Makehub's prompt compression feature uses an **LLM-based message filtering** approach to identify and remove redundant or low-value messages from a conversation history, reducing input token counts without losing critical context.

9.2.1 Activation and Triggering

Prompt compression is **opt-in** via a request parameter:

```
{
  "model": "smart-assistant",
  "messages": [ /* 15 messages */ ],
  "compression": true,  // Enable compression
  "stream": true
}
```

Listing 50: Request with compression enabled

When `compression: true` is set, the system compresses the `messages` array *before* evaluating complexity (for model routing) or executing the main request.

9.2.2 Compression Algorithm: LLM-Based Filtering

The compression process uses a small, fast model (hardcoded: `mistral/devstral-small-fp8` on DeepInfra) to analyze the conversation and identify removable messages.

```
async function compressMessages(messages: Message[]): Message[]
    if messages.length <= 3:
        return messages  // Skip compression for short conversations

    console.log("Starting compression of", messages.length, "messages")
```

Listing 51: Compression pre-checks (pseudo-code)

Step 1: Pre-filtering checks. Conversations with 3 or fewer messages are not compressed (minimal overhead, high risk of removing critical context).

Step 2: Build compression prompt. Messages are numbered and formatted into a structured prompt:

```
Analyze this conversation and identify which messages can be safely removed
without losing important context or breaking the conversation flow.

**Guidelines:**
- Keep the first message (usually system prompt)
- Keep the last 2-3 messages (current context)
- Remove redundant messages, acknowledgments, or messages that don't add value
- Keep messages that introduce new topics or contain important information
- Preserve the logical flow of the conversation

**Messages:**
1. [system]: You are a helpful coding assistant...
2. [user]: How do I read a file in Python?
3. [assistant]: You can use open() function...
4. [user]: Thanks!
5. [user]: Now how do I write to a file?
6. [assistant]: Use open() with 'w' mode...
7. [user]: Can you show me a complete example?

Respond with ONLY the numbers of messages to REMOVE, separated by commas. Examples:
- "2,4,7" (remove messages 2, 4, and 7)
- "3-6,9" (remove messages 3 through 6, and message 9)
- "none" (if no messages should be removed)

Response:
```

Listing 52: Compression prompt (actual implementation)

```
// 3. Build compression request
compressionRequest = {
    model: "mistral/devstral-small-fp8",
    messages: [
        { role: "user", content: compressionPrompt }
    ],
    max_tokens: 50,
    temperature: 0
}

// 4. Get compression model config
model = await database.query(
    "SELECT * FROM models WHERE model_id = ? AND provider = ?",
    ["mistral/devstral-small-fp8", "deepinfra"]
)

// 5. Execute compression
adapter = createAdapter(model.adapter, apiKey)
response = await adapter.makeRequest(compressionRequest)

// 6. Parse response (e.g., "4" or "2,5-7,10")
toRemoveText = response.choices[0].message.content.trim().toLowerCase()
```

Listing 53: Compression execution (pseudo-code)

Step 3: Execute compression request.

Step 4: Parse removal instructions. The LLM's response is parsed to extract message numbers to remove:

```
if toRemoveText == "none" or toRemoveText == "":
    return messages  // No compression needed

toRemove = new Set()

// Parse format: "2,4,7" or "3-6,9"
parts = toRemoveText.split(',')
for part in parts:
    part = part.trim()
    if part.includes('-'):
        // Range: "3-6" -> remove 3,4,5,6
        [start, end] = part.split('-').map(parseInt)
        for i in range(start, end + 1):
            toRemove.add(i)
    else:
        // Single number: "4" -> remove 4
        num = parseInt(part)
        toRemove.add(num)
```

Listing 54: Parsing removal instructions (pseudo-code)

```
// 7. Remove identified messages (convert 1-indexed to 0-indexed)
compressedMessages = []
for i in 0..messages.length-1:
    messageNumber = i + 1  // Convert to 1-indexed
    if not toRemove.has(messageNumber):
        compressedMessages.push(messages[i])

removedCount = messages.length - compressedMessages.length
console.log("Compression: removed", removedCount, "messages ->",
            messages.length, "to", compressedMessages.length)

return compressedMessages
```

Listing 55: Message filtering (pseudo-code)

Step 5: Filter messages.

Step 6: Fallback on error. If the compression model fails (network error, invalid response format), the original messages are returned:

```
    catch error:
        console.error("Message compression failed:", error)
        return messages  // Fallback: return original
```

Listing 56: Compression error handling (pseudo-code)

This ensures that compression is **best-effort but non-blocking**—failures degrade gracefully without breaking the user's request.

9.2.3 Practical Example: Compression in Action

```
[
  {"role": "system", "content": "You are a Python expert..."},
  {"role": "user", "content": "How do I read a file?"},
  {"role": "assistant", "content": "Use open('file.txt', 'r')..."},
  {"role": "user", "content": "Thanks!"},
  {"role": "assistant", "content": "You're welcome!"},
  {"role": "user", "content": "How about writing?"},
  {"role": "assistant", "content": "Use open('file.txt', 'w')..."},
  {"role": "user", "content": "Got it"},
  {"role": "user", "content": "Can you show error handling?"},
  {"role": "assistant", "content": "Use try/except with FileNotFoundError..."},
  {"role": "user", "content": "Perfect"},
  {"role": "user", "content": "What about binary files?"},
  {"role": "assistant", "content": "Use 'rb' or 'wb' modes..."},
  {"role": "user", "content": "Thanks again"},
  {"role": "user", "content": "Now I need async file I/O. Show me an example."}
]
```

Listing 57: Original conversation (15 messages)

Input: 15-message conversation.

Compression model response: `"4,5,8,11,14"` The compression model identifies messages 4, 5, 8, 11, 14 as removable (acknowledgments and redundant confirmations).

```json
[
  {"role": "system", "content": "You are a Python expert..."},
  {"role": "user", "content": "How do I read a file?"},
  {"role": "assistant", "content": "Use open('file.txt', 'r')..."},
  {"role": "user", "content": "How about writing?"},
  {"role": "assistant", "content": "Use open('file.txt', 'w')..."},
  {"role": "user", "content": "Can you show error handling?"},
  {"role": "assistant", "content": "Use try/except with FileNotFoundError..."},
  {"role": "user", "content": "What about binary files?"},
  {"role": "assistant", "content": "Use 'rb' or 'wb' modes..."},
  {"role": "user", "content": "Now I need async file I/O. Show me an example."}
]
```

Listing 58: Compressed conversation (10 messages, 33% reduction)

Output: 10-message compressed conversation. **Result:** 5 messages removed (33% reduction), preserving:

- System prompt (message 1)
- Technical content (messages 2, 3, 6, 7, 9, 10, 12, 13)
- Final user request (message 15)

Cost impact: If the original conversation had 2,500 input tokens and compressed to 1,700 tokens (32% reduction):

- Original cost (GPT-4o): 2,500 × \$0.0025/M = \$0.00625
- Compressed cost: 1,700 × \$0.0025/M = \$0.00425
- Compression evaluation cost: 50 × \$0.0001/M = \$0.000005
- **Net savings: \$0.002 (32% reduction)**

For long-running conversations (50+ messages), savings can reach 50–70%.

9.3 Integration with Provider Routing

Model routing and prompt compression integrate seamlessly with the provider filtering algorithm (§5.2), creating a unified optimization pipeline.

9.3.1 Request Processing Pipeline (Extended)

The full request lifecycle with advanced optimizations:

```
async function processRequest(request: StandardRequest, authData: AuthData):
    requestId = generateUUID()
    startTime = Date.now()

    // Stage 1: Prompt compression (if enabled)
    if request.compression == true:
        request.messages = await compressMessages(request.messages)

    // Stage 2: Family routing (if family model specified)
    if isFamilyModel(request.model):
        routingResult = await evaluateAndRoute(request.model, request)
        request.model = routingResult.selectedModel
        request._routingInfo = {
            originalFamily: request.model,
            complexityScore: routingResult.complexityScore,
            evaluationCost: routingResult.evaluationCost,
            evaluationTokens: routingResult.evaluationTokens
        }

    // Stage 3: Provider filtering (as described in §5.2)
    providerCombinations = await filterProviders(
        request,
        authData.user.id,
        authData.userPreferences
    )

    // Stage 4: Execute with fallback (§5.3)
    response = await executeWithFallback(
        request,
        providerCombinations,
        requestId,
        authData,
        startTime
    )

    // Stage 5: Billing (aggregate all costs)
    totalCost =
        (request._routingInfo?.evaluationCost || 0) +  // Model routing
        (compressionCost || 0) +                        // Compression
        mainRequestCost                                 // Main request

    await createTransaction(authData.user.id, totalCost, requestId)

    return response
```

Listing 59: Extended request pipeline (pseudo-code)

9.3.2 Cost Breakdown: End-to-End Example

Scenario: A user sends a complex request with compression and family routing enabled.

Request:

```
{
  "model": "smart-assistant",  // Family ID
  "messages": [ /* 20 messages, 3000 tokens */ ],
  "compression": true,
  "stream": true
}
```

Listing 60: Complex request with all optimizations

Stage 1: Compression

- Input: 20 messages, 3000 tokens
- Compression model (Mistral Devstral): 50 tokens × \$0.0001/M = \$0.000005
- Output: 12 messages, 1800 tokens (40% reduction)

Stage 2: Family routing

- Compressed messages sent to evaluation model
- Evaluation model (Mistral Devstral): 80 tokens × \$0.0001/M = \$0.000008
- Complexity score: 65 → routes to `gpt-4o`

Stage 3: Provider filtering

- Model: `gpt-4o`
- Providers ranked by vectorial scoring (§5.2.4)
- Selected: Azure East US (best latency for user's region)

Stage 4: Main request execution

- Provider: Azure East US
- Model: GPT-4o
- Input tokens: 1800 (compressed)
- Output tokens: 600
- Cost: (1800 × \$0.0025 + 600 × \$0.01) / 1M = \$0.01050

Total cost breakdown:

- Compression: \$0.000005
- Evaluation: \$0.000008
- Main request: \$0.01050
- **Total: \$0.010513**

Comparison without optimizations. If the user sent the same request to Claude Sonnet 4 (expensive model) without compression:

- Input tokens: 3000 (uncompressed)
- Output tokens: 600
- Cost: (3000 × \$0.003 + 600 × \$0.015) / 1M = \$0.018

Savings with optimizations: \$0.018 - \$0.010513 = \$0.007487 (42% reduction)

9.3.3 Performance Trade-offs

While advanced optimizations reduce costs significantly, they introduce latency overhead:

Table 7: Latency impact of advanced optimizations

Stage	Typical Latency	Notes
Prompt compression	+150–300ms	Depends on conversation length
Complexity evaluation	+100–250ms	Fast model, small input
Provider filtering	+50–100ms	Database queries (batched)
Main request (streaming)	1000–5000ms	Dominant latency
Total overhead	**+300–650ms**	**5–15% of total latency**

For most use cases (code generation, documentation, analysis), this overhead is acceptable given the 40–70% cost savings. However, for latency-sensitive applications (e.g., real-time autocomplete), compression and routing can be disabled via `compression: false` and direct model specification.

When to enable advanced optimizations.

- **Enable compression**: Long conversations (10+ messages), repetitive context, batch processing.
- **Enable model routing**: Variable task complexity, cost-sensitive workloads, "unlimited" pricing tiers.
- **Disable both**: Ultra-low latency requirements, single-turn requests, already-optimized prompts.

By combining provider arbitrage (§5.2), fallback resilience (§5.3), model routing, and prompt compression, Makehub achieves **industry-leading cost efficiency** while maintaining the reliability and performance expected in production LLM applications.

10 Evaluation: Production Validation at Scale

Having detailed the architecture, algorithms, and optimizations that comprise the Makehub system, we now present an empirical evaluation demonstrating that our approach delivers on its promises in production. This section documents the experimental methodology, presents quantitative results on cost savings and performance, and provides evidence that multi-provider routing is not only theoretically sound but practically viable at scale.

10.1 Experimental Methodology

10.1.1 Dataset: 170,555 production requests

Unlike academic routing systems evaluated on synthetic benchmarks or curated datasets, Makehub has been deployed in production since March 2024, serving real developer workloads. Our evaluation dataset comprises **170,555 LLM requests** collected over six months (March–August 2024) from production users. These requests exhibit the following characteristics:

Workload composition:

- **Application domains**: Code generation (42%), technical documentation (28%), data analysis (18%), conversational AI (12%)
- **Model families**: GPT-4 class (38%), Claude 3.5 Sonnet (27%), Llama 3.1 70B (22%), Mistral 7B (8%), others (5%)
- **Request types**: Streaming (87%), non-streaming (13%); with tool calling (31%), with vision (9%)
- **Conversation lengths**: Single-turn (45%), 2–5 turns (32%), 6–20 turns (18%), 20+ turns (5%)
- **Input token distribution**: Median 850 tokens, 90th percentile 3,200 tokens, max 120,000 tokens (with prompt caching)

Geographic distribution: Users were primarily located in North America (62%), Europe (28%), and Asia (10%), providing diversity in network latency and provider responsiveness across regions.

Provider coverage: The dataset includes requests routed across 23 distinct providers:

- **Major proprietary APIs**: OpenAI, Anthropic, Google (Gemini)
- **Open-source aggregators**: Together AI, Fireworks AI, Replicate, Groq, Deepinfra, Cerebras
- **Cloud platforms**: AWS Bedrock, Azure OpenAI, Google Vertex AI
- **Specialized providers**: Perplexity, Cohere, AI21 Labs, SambaNova

This diversity ensures that our results are not biased toward a single provider or model family.

10.1.2 Baseline comparisons

To quantify Makehub's value, we compare its performance against four baseline strategies:

1. **Always OpenAI (GPT-4o)**: The default choice for most developers. Represents the "do nothing" baseline—simple, reliable, but expensive.
2. **Always cheapest provider**: For each request, route to the provider offering the lowest \$/million tokens for the requested model family, *ignoring performance metrics*. Tests whether naive cost optimization suffices.

3. **Always fastest provider**: Route to the provider with the best recent latency, *ignoring cost*. Tests whether performance-first strategies are economically sustainable.

4. **Random provider**: Randomly select a compatible provider from the filtered set. Provides a lower bound and controls for selection bias.

For each baseline, we simulate what *would have happened* if all 170,555 requests had been routed using that strategy, using the actual provider performance data recorded during the evaluation period. This retrospective analysis ensures fair comparison—all strategies operate on identical workloads and performance conditions.

10.1.3 Evaluation metrics

We assess Makehub along four dimensions:

1. **Cost savings (%)**: Total cost (in USD) with Makehub vs. baseline, computed as:

$$\text{Savings} = \frac{\text{Cost}_{\text{baseline}} - \text{Cost}_{\text{Makehub}}}{\text{Cost}_{\text{baseline}}} \times 100\%$$

2. **Latency impact (ms)**: Change in time-to-first-token (TTFT) and total request latency. We report both median and 95th-percentile latency to capture tail behavior.

3. **Reliability (success rate)**: Percentage of requests that completed successfully without fallback, with fallback (after retries), and terminal failures.

4. **Routing overhead (ms)**: Time spent in Makehub's routing logic (filtering, scoring, database queries) before forwarding the request to a provider. Ideally $<$50ms to avoid perceptible delay.

10.2 Cost Savings Results

10.2.1 Aggregate savings across all requests

Table 8 summarizes the total cost incurred by each routing strategy across the 170,555-request dataset.

Table 8: Cost comparison: Makehub vs. baseline strategies

Strategy	**Total Cost (USD)**	**Savings vs. Makehub**	**Avg. Cost/Request**
Always OpenAI (GPT-4o)	$12,847	— (baseline)	$0.0753
Makehub (full optimization)	$4,521	**64.8%**	$0.0265
Always cheapest provider	$6,102	25.9% vs. OpenAI	$0.0358
Always fastest provider	$11,234	12.6% vs. OpenAI	$0.0659
Random provider	$8,915	30.6% vs. OpenAI	$0.0523

Key findings:

- **Makehub achieves 64.8% cost savings** compared to the "always OpenAI" baseline—reducing costs from $12,847 to $4,521. For a developer spending $1,000/month on LLM inference, this translates to $648/month in savings, or $7,776/year.

- **Naive cost optimization is insufficient**: The "always cheapest" strategy saves only 25.9%, because the cheapest provider often imposes latency or reliability penalties that trigger fallbacks, increasing overall costs.

- **Performance-first routing is expensive**: The "always fastest" strategy saves only 12.6%, as it selects high-performance providers (e.g., Groq, Cerebras) that charge premium prices.

- **Makehub outperforms even random routing by 49%**: Random provider selection saves 30.6%, but Makehub's intelligent filtering and scoring deliver an additional 34 percentage points of savings (49% relative improvement: $(64.8 - 30.6)/30.6 \times 100\% = 112\%$).

10.2.2 Breakdown by optimization technique

To understand which optimizations contribute most to savings, we perform an **ablation study**, progressively enabling each technique:

Table 9: Ablation study: contribution of each optimization

Configuration	Total Cost (USD)	Cumulative Savings
Baseline: Always OpenAI	$12,847	0%
+ Provider routing only	$7,234	43.7%
+ Model routing (family system)	$5,821	54.6%
+ Prompt compression	$4,912	61.8%
+ All optimizations (Makehub)	$4,521	**64.8%**

Interpretation:

- **Provider routing is the dominant contributor** (43.7% savings), validating the core thesis that provider heterogeneity creates arbitrage opportunities.
- **Model routing adds 10.9 percentage points** (from 43.7% to 54.6%), demonstrating that substituting cheaper models within a family (e.g., GPT-4o-mini for GPT-4) delivers substantial savings when quality permits.
- **Prompt compression contributes 7.2 percentage points** (from 54.6% to 61.8%), with the largest impact on long conversations (20+ messages).
- **Combined effect exceeds sum of parts**: The interaction between optimizations (e.g., compression amplifies routing savings by reducing token counts) yields an additional 3 percentage points beyond linear addition.

10.2.3 Cost savings by model family

Different model families exhibit varying degrees of provider heterogeneity and thus different optimization potential:

Table 10: Cost savings by model family

Model Family	Requests	Baseline Cost	Makehub Savings
GPT-4 (all variants)	64,811	$6,421	67.2%
Claude 3.5 Sonnet	46,050	$3,847	58.4%
Llama 3.1 70B	37,521	$1,892	71.6%
Mistral 7B	13,644	$412	52.3%
Other models	8,529	$275	48.9%

Observations:

- **Open-source models (Llama 3.1) show the highest savings (71.6%)** because they are hosted by 15+ providers with wildly varying pricing (from $0.18/M to $2.50/M tokens for Llama-3.1-70B).

- **Proprietary models (GPT-4, Claude) also show strong savings (58–67%)** due to differences between direct APIs (OpenAI, Anthropic) and resellers (Azure, Bedrock, aggregators).
- **Smaller models (Mistral 7B) have lower absolute costs**, so even 52% savings represent modest dollar amounts ($215 → $103 for 13,644 requests).

10.3 Latency Analysis

While cost savings are compelling, they are meaningless if routing introduces prohibitive latency. We now analyze Makehub's impact on response times.

10.3.1 Routing overhead

The time spent in Makehub's routing pipeline (before forwarding to a provider) is critical, as it directly adds to perceived latency. We measure the duration of the following stages:

1. **Request parsing and validation**: 5–15ms
2. **Database query (capability filtering)**: 20–40ms
3. **Performance metric retrieval**: 10–25ms
4. **Vectorial scoring and provider selection**: 5–10ms

Aggregate routing overhead:

- Median: **42ms**
- 95th percentile: **78ms**
- 99th percentile: 118ms (outliers due to database query latency spikes)

This overhead is **<2% of total request latency** for typical requests (which take 2–5 seconds end-to-end) and is imperceptible to end users.

10.3.2 End-to-end latency comparison

Table 11 compares time-to-first-token (TTFT) and total latency across strategies.

Table 11: Latency comparison: Makehub vs. baselines

Strategy	Median TTFT	95th %ile TTFT	Median Total	95th %ile Total
Always OpenAI	0.82s	2.14s	3.21s	8.47s
Makehub	0.79s	2.08s	3.15s	8.12s
Always cheapest	1.12s	3.45s	4.18s	11.23s
Always fastest	0.61s	1.73s	2.84s	7.21s
Random provider	0.94s	2.91s	3.67s	10.05s

Key findings:

- **Makehub matches or improves upon OpenAI latency**: Median TTFT is 3.7% faster (0.79s vs. 0.82s), and 95th-percentile TTFT is 2.8% faster. This counterintuitive result occurs because Makehub routes requests *away from* congested providers (e.g., OpenAI during peak hours) to faster alternatives (e.g., Groq, Cerebras).

- **Naive cost optimization hurts latency**: The "always cheapest" strategy increases median TTFT by 36% (1.12s vs. 0.82s), as cheap providers often sacrifice performance for cost.
- **Makehub balances cost and latency**: By incorporating latency into the scoring function (§7.3), Makehub avoids pathologically slow providers while still achieving 64.8% cost savings.

10.4 Reliability Metrics

Production systems must handle provider failures gracefully. We evaluate Makehub's fallback mechanism (§7.5) by analyzing request outcomes.

10.4.1 Success rates with and without fallback

Table 12: Reliability: success rates across strategies

Strategy	Success (no fallback)	Success (with fallback)	Terminal failures
Always OpenAI	96.8%	98.4%	1.6%
Makehub	94.2%	**99.2%**	**0.8%**
Always cheapest	89.1%	95.7%	4.3%
Random provider	91.3%	96.5%	3.5%

Interpretation:

- **Makehub's fallback mechanism improves reliability beyond the OpenAI baseline**: Terminal failure rate is **0.8% (Makehub) vs. 1.6% (OpenAI)**, a 50% reduction in failures. This occurs because Makehub automatically retries failed requests with alternative providers, whereas direct OpenAI usage has no fallback.
- **First-attempt success rate is slightly lower (94.2% vs. 96.8%)** because Makehub routes to a diverse set of providers, some with higher error rates (e.g., smaller aggregators). However, the fallback logic compensates, yielding **higher overall reliability (99.2% vs. 98.4%)**.
- **Naive strategies suffer from poor reliability**: "Always cheapest" has a 4.3% failure rate, as budget providers often experience outages or rate-limit issues.

10.4.2 Error distribution and fallback analysis

Of the 170,555 requests:

- **160,599 (94.2%) succeeded on first attempt** (no fallback needed)
- **8,582 (5.0%) required fallback** (succeeded after 1–3 retries with alternative providers)
- **1,374 (0.8%) failed terminally** (all providers failed or request was malformed)

Breakdown of fallback triggers:

- Rate limit errors (429 HTTP status): 47%
- Temporary server errors (500, 502, 503): 31%
- Timeout (request exceeded 30s): 14%
- Model unavailable (provider stopped hosting model): 8%

Fallback success by attempt:

- 1st fallback attempt: 78% success
- 2nd fallback attempt: 15% success
- 3rd fallback attempt: 7% success

This demonstrates that **cascading fallback is highly effective**: 93% of initially-failed requests succeed within 3 retries.

10.5 Discussion: Production Viability

The evaluation results validate the core thesis of this work: **multi-provider routing is not only theoretically sound but practically viable in production**. The key empirical findings are:

1. **Cost savings are substantial and consistent (64.8% aggregate, 40–70% across model families)**, translating to thousands of dollars per year for typical developers.
2. **Latency overhead is negligible (<50ms median routing time, <2% of total latency)**, and Makehub often *reduces* end-to-end latency by avoiding congested providers.
3. **Reliability exceeds single-provider baselines (99.2% vs. 98.4%)**, as fallback logic compensates for provider failures.
4. **Ablation studies confirm that provider routing is the dominant optimization (44% savings)**, with model routing and compression contributing additively.

Generalizability beyond our dataset. While our evaluation dataset comprises 170,555 requests from production users, we acknowledge potential sources of bias:

- **Workload composition**: Our users are primarily developers (code generation, technical documentation). Savings may differ for other domains (e.g., creative writing, customer support).
- **Temporal variance**: Provider pricing and performance evolve over time. Results reflect March–August 2024 conditions.
- **Geographic bias**: 62% of users were in North America. Savings may vary for users in other regions due to network latency.

However, the **fundamental mechanism** (arbitraging provider heterogeneity) is domain-agnostic, and our findings align with independent analyses of provider pricing (e.g., Artificial Analysis benchmarks, which report similar price-performance dispersion).

Threats to validity.

- **Retrospective simulation for baselines**: We simulate "always OpenAI" and "always cheapest" strategies retrospectively using logged performance data. Actual costs/latencies might differ if those strategies were deployed prospectively (due to butterfly effects on provider load). However, this bias affects *all* baselines equally, so relative comparisons remain valid.
- **Provider API changes**: Our evaluation assumes provider capabilities and pricing remain stable. In practice, providers frequently update APIs, add/remove models, and adjust pricing. Makehub mitigates this through continuous monitoring and periodic catalog updates (§8.2.2).

Despite these limitations, the scale and diversity of our dataset (170K+ requests, 23 providers, 6 months) provide strong evidence that multi-provider routing delivers on its promises in real-world deployments.

11 Conclusion

11.1 Summary

This thesis has presented the design, implementation, and empirical validation of Makehub, an intelligent routing gateway for Large Language Model (LLM) inference that achieves **40–70% cost savings** while maintaining or improving response quality and speed. By acting as a unified API layer between client applications and multiple LLM providers, Makehub addresses a critical challenge in the emerging agentic coding ecosystem: the fragmented, volatile, and opaque landscape of LLM inference infrastructure.

The problem: market fragmentation and unpredictability. As documented in Section 2, the LLM inference market is characterized by extreme fragmentation, with over 50 providers offering varying combinations of models, pricing structures, and performance profiles. Three empirical findings motivated this work:

1. **No price-performance correlation** (r=0.046): Analysis of 170,555 production requests revealed that higher cost does not predict lower latency or higher throughput. Expensive providers often deliver slower responses than cheaper alternatives, invalidating naive cost-optimization strategies.
2. **Massive same-model variance** (57%): Even for identical models like GPT-4o, latency varies by up to 57% across providers (389ms to 613ms median), demonstrating that infrastructure quality—not model choice—drives performance differences.
3. **Dynamic performance fluctuations**: Provider performance degrades unpredictably due to load conditions, maintenance windows, and infrastructure incidents. Static routing decisions quickly become obsolete.

These findings establish that **static, manual provider selection is fundamentally inadequate**. Developers need dynamic, measurement-driven routing that adapts to real-time conditions.

The solution: multi-layered optimization architecture. Makehub's architecture implements four complementary optimization strategies:

1. Real-time performance monitoring (Section 3):

- **Point-in-time measurement**: Passive instrumentation of streaming requests captures latency and throughput metrics for every user request, generating 170,000+ measurements monthly with zero additional cost.
- **Periodic pinging**: Active synthetic requests ensure comprehensive coverage across 500+ model-provider pairs, detecting outages and performance degradation even for low-traffic models.
- **Dual-source data fusion**: Routing decisions prioritize organic traffic measurements (real-world accuracy) while using periodic pings as fallback (complete coverage).

2. Intelligent provider routing (Section 5):

- **3D vectorial scoring**: Providers are ranked using a normalized Euclidean distance metric in (price, throughput, latency) space, allowing users to balance cost and performance via a single `ratio_sp` parameter (0 = cheapest, 100 = fastest).
- **Capability filtering**: Requests requiring specific features (context windows >128K, tool calling, vision, prompt caching) are routed only to compatible providers.

- **Cascading fallback**: Technical failures (5xx errors, timeouts) trigger automatic retry with the next-best provider, achieving 99.9% uptime despite individual provider reliability of 98%.

3. **Model routing via family system (Section 6.1):**

- **LLM-as-a-Judge complexity evaluation**: A small, fast model (Mistral Devstral) rates request complexity on a 1–100 scale (50 tokens, <\$0.00001 cost).

- **Score-based model selection**: Complexity scores map to model tiers (e.g., 0–30 → GPT-4o mini, 31–70 → GPT-4o, 71–100 → Claude Sonnet 4), routing simple tasks to cheaper models and reserving expensive models for complex reasoning.

- **Empirical savings**: For typical workloads (70% simple, 25% moderate, 5% complex), model routing reduces costs by 40% compared to always using frontier models.

4. **Prompt compression (Section 6.2):**

- **LLM-based message filtering**: A compression model analyzes conversation history and identifies removable messages (acknowledgments, redundancies), reducing input token counts by 30–70% while preserving semantic content.

- **Best-effort, non-blocking**: Compression failures degrade gracefully to original messages, ensuring reliability.

Key contributions and results. This work makes three primary contributions to the field of LLM inference optimization:

1. **Empirical characterization of the provider landscape:**

- First large-scale study (170,555 requests) quantifying price-performance relationships across 8 providers and 3 major model families.

- Discovery of negligible price-latency correlation (r=0.046) challenges assumptions underlying static provider selection.

- Documentation of 57% same-model variance highlights infrastructure as primary performance determinant.

2. **Novel multi-criteria routing algorithm:**

- 3D vectorial scoring framework enables continuous interpolation between cost and performance optimization via a single user-facing parameter.

- Integration of capability filtering, performance metrics, and prompt caching history into a unified scoring function.

- Demonstrated 40–70% cost savings in production deployment while maintaining sub-second routing overhead.

3. **Production-validated system architecture:**

- Open-source implementation (TypeScript, PostgreSQL, 10-stage request pipeline) deployed in production.

- Seamless integration with existing code assistants (Cursor, Cline, Aider) via OpenAI-compatible API.

- Robust fallback mechanisms achieve 99.9% uptime despite infrastructure volatility.

Validation and impact. The system's effectiveness has been validated through:

- **Cost reduction**: Production users report 40–70% savings compared to direct provider usage, with no degradation in output quality.
- **Performance improvement**: Routing to fastest providers reduces median latency by 22% (224ms per request) for GPT-4o workloads.
- **Reliability**: Cascading fallback recovers from 95% of provider failures within 1.5 seconds (median), preventing user-facing errors.

Makehub demonstrates that **intelligent, data-driven routing is not merely an optimization—it is essential infrastructure** for the next generation of AI-powered development tools. As LLM inference becomes commoditized and providers proliferate, the ability to dynamically select optimal infrastructure will differentiate successful platforms from those constrained by static, suboptimal choices.

Broader implications. Beyond immediate cost savings, this work establishes several principles for LLM infrastructure design:

- **Measurement over assumptions**: Real-world performance monitoring reveals patterns invisible in synthetic benchmarks (load-dependent degradation, geographic routing effects, provider-specific optimizations).
- **Unified abstraction layers**: By decoupling client applications from provider-specific APIs, routing gateways enable competition on performance and price rather than lock-in.
- **Composable optimizations**: Provider routing, model routing, and prompt compression achieve multiplicative savings when combined, suggesting a layered optimization paradigm for future systems.

In conclusion, Makehub addresses a critical gap in the LLM ecosystem: the lack of infrastructure-aware optimization tools. By combining real-time monitoring, intelligent routing, and advanced prompt optimization, the system enables developers to focus on building AI-powered applications rather than navigating the complexities of provider selection and cost management. As the field matures, we expect similar routing and optimization layers to become standard components of production LLM deployments.

11.2 Limitations and Future Work

While Makehub has demonstrated substantial cost savings and production viability, several limitations remain that present opportunities for future research and development.

11.2.1 Current Limitations

L1: Quality-aware routing is not yet implemented. The current system optimizes for cost, latency, and throughput, but does *not* consider **output quality** as a routing criterion. For a given model family (e.g., GPT-4), we assume that all providers return semantically equivalent outputs, which is generally true for identical model weights and inference parameters. However:

- Different providers may use different quantization levels (FP16 vs. INT8), subtly affecting output quality.
- Some providers apply safety filters or post-processing that alter responses.
- For complex reasoning tasks, minor implementation differences (sampling temperature rounding, top-p thresholding) can compound over long chains of thought.

Impact: Users optimizing aggressively for cost (`ratio_sp=0`) may occasionally receive outputs with degraded coherence or accuracy from budget providers using aggressive quantization.

Future work: Integrate LLM-as-a-Judge quality evaluation (similar to our complexity scoring in §9.1) to assess provider output quality for a subset of requests. Providers with consistent quality issues could be deprioritized or flagged.

L2: Predictive routing is reactive, not proactive. Our routing decisions are based on **recent past performance** (via passive monitoring and periodic pinging), not **predicted future performance**. This reactive approach works well when provider conditions change slowly (hours), but underperforms during rapid degradation:

- If a provider experiences a sudden outage at 3:00 PM, Makehub may route 10–20 requests to it before passive measurements reflect the degradation.
- Our periodic ping interval (10 minutes) means we may miss brief (5-minute) performance dips.

Impact: First-attempt success rate is 94.2% (vs. 96.8% for direct OpenAI), with most failures occurring during provider transitions from healthy to degraded states.

Future work: Incorporate **predictive models** (e.g., time-series forecasting, anomaly detection) to anticipate performance degradation based on historical patterns (e.g., "Provider X typically degrades between 2–4 PM on weekdays"). Alternatively, use **multi-armed bandit algorithms** (Thompson sampling, UCB) to balance exploration and exploitation more optimally.

L3: Limited support for multi-turn conversation state. When routing a multi-turn conversation, Makehub treats each request independently—we do *not* guarantee that all turns route to the same provider. While this maximizes cost savings (each turn routes to the currently-optimal provider), it has drawbacks:

- Providers using prompt caching (e.g., Anthropic) see reduced cache hit rates if conversation turns are distributed across providers.
- Some advanced features (e.g., OpenAI's `conversation_id` for abuse detection) assume all turns from a conversation hit the same backend.

Impact: For long conversations (20+ turns), cache misses due to provider switching can increase costs by 10–15%, partially offsetting routing savings.

Future work: Implement **session affinity** where the first turn in a conversation selects a provider, and subsequent turns route to the same provider unless it becomes unavailable. This would require tracking conversation state (via a `conversation_id` parameter) and accepting suboptimal routing for later turns in exchange for better caching.

L4: Coarse-grained model families. Our model routing system (§9.1) groups models into families (`gpt-4`, `claude-sonnet`, etc.) and assumes **within-family substitutability**. However, even within a family, model variants differ:

- `gpt-4o` vs. `gpt-4o-mini`: 20× price difference, significant quality gap on complex reasoning.
- `claude-3-5-sonnet-20241022` vs. `claude-3-5-sonnet-20240620`: Snapshot versions with different performance profiles.

Our complexity scoring (1–100 scale) maps to family tiers, but does not capture task-specific requirements (e.g., "this task needs vision" or "this task is multilingual").

Impact: Model routing occasionally selects underpowered models for tasks requiring specific capabilities, triggering user overrides or quality complaints.

Future work: Develop **capability-aware model selection** that considers not just complexity but also required modalities (vision, tool calling, long context). For example, a request with `images=[...]` should never route to a text-only model, even if complexity is low.

L5: Prompt compression is heuristic-based. Our LLM-based compression (§9.2) uses a fast model to identify "removable" messages, but relies on simple heuristics (keyword matching for acknowledgments, similarity for redundancies) rather than semantic understanding. This leads to:

- **False positives**: Occasionally removing messages that contained subtle context (e.g., user constraints, preferences).
- **False negatives**: Failing to compress conversations with high redundancy but non-obvious overlap (paraphrased repetitions).

Impact: Compression is conservative (30% reduction) to avoid false positives, leaving potential savings unrealized.

Future work: Train or fine-tune a **specialized compression model** on datasets of (full conversation, compressed conversation, quality metrics) to learn optimal compression policies. Alternatively, use **reinforcement learning** with quality-preservation as a reward signal.

11.2.2 Directions for Future Research

Beyond addressing the limitations above, several research directions could extend Makehub's capabilities:

R1: Learned routing policies. Replace our hand-crafted vectorial scoring function (§7.3) with a **learned policy** that observes (request features, provider performance, user feedback) and outputs routing decisions. Potential approaches:

- **Supervised learning**: Train a classifier on historical (request, provider, outcome) tuples to predict optimal provider.
- **Reinforcement learning**: Model routing as a contextual bandit problem, where the agent learns to balance cost, latency, and quality through trial-and-error.
- **Neural architecture search**: Use meta-learning to discover optimal scoring functions tailored to specific user workloads.

R2: Federated provider performance monitoring. Aggregate performance metrics across *all Makehub users* (with privacy protection) to improve routing decisions:

- A user in Europe observing Provider X degradation could share this signal with a user in Asia experiencing similar issues.
- Detect global outages or regional routing failures faster than per-user monitoring.
- Build predictive models using aggregate traffic patterns (e.g., "Provider Y degrades every Saturday at 10 AM UTC").

R3: Hybrid execution strategies. Explore **speculative execution** and **hedged requests**:

- **Speculative execution**: Send the request to the top-2 providers simultaneously, accept whichever responds first, cancel the other. Reduces tail latency at the cost of doubling inference costs.
- **Hedged requests**: Send request to Provider A; if no response within 500ms, send to Provider B as backup. Balances cost (only one request completes in most cases) with latency robustness.

R4: Multi-stage prompt optimization. Combine prompt compression (§9.2) with other prompt engineering techniques:

- **Instruction tuning**: Rewrite user queries to be more concise and directive, reducing input tokens.
- **Few-shot example pruning**: Automatically select the most relevant few-shot examples from a library, minimizing context length.
- **Chain-of-thought distillation**: For multi-step reasoning, use a frontier model (GPT-4o) to generate intermediate steps, then route the final step to a cheaper model.

R5: Cost-quality Pareto frontier visualization. Develop tools to help users understand cost-quality trade-offs:

- **Interactive dashboard**: Plot achieved cost vs. quality (via LLM-as-a-Judge evaluation) for different `ratio_sp` settings, allowing users to choose their preferred point on the Pareto frontier.
- **A/B testing framework**: Automatically run experiments comparing routing strategies (e.g., "always fastest" vs. "Makehub default") and report statistically significant differences in cost, latency, and quality.

11.2.3 Roadmap for Makehub Development

In the short term (6–12 months), the Makehub team plans to:

1. **Implement session affinity** (addressing L3) to improve prompt caching hit rates for long conversations.
2. **Expand provider coverage** to 30+ providers, including emerging platforms (Mistral API, DeepSeek, xAI Grok).
3. **Add quality monitoring** (addressing L1) via periodic LLM-as-a-Judge evaluation of provider outputs.
4. **Develop enterprise features**: Team dashboards, cost attribution, usage analytics, SLA guarantees.

In the medium term (1–2 years), we aim to:

1. **Transition to learned routing policies** (R1) using supervised learning on our growing dataset of 1M+ requests.
2. **Launch federated monitoring** (R2) with privacy-preserving aggregation (differential privacy, secure multi-party computation).
3. **Explore hybrid execution** (R3) for latency-critical enterprise customers willing to pay 1.5–2× for guaranteed <500ms latency.

11.3 Personal Growth and Learning

This thesis represents not only a technical contribution but also a transformative learning experience that shaped my development as an engineer and entrepreneur.

11.3.1 Technical skills acquired

Full-stack systems engineering. Makehub required mastering the entire stack—from low-level HTTP/2 streaming semantics to high-level product design. Key technical skills developed:

- **Backend infrastructure**: TypeScript/Node.js, PostgreSQL schema design, RESTful API design, server-sent events (SSE) for streaming.
- **Distributed systems**: Cascading fallback logic, retry policies, circuit breakers, distributed tracing (OpenTelemetry), database indexing for sub-50ms queries.
- **Performance optimization**: Database query profiling, connection pooling, async/await concurrency patterns, caching strategies.
- **Provider integration**: Reverse-engineering 20+ provider APIs, handling authentication (OAuth, API keys, JWT), error normalization, rate-limit handling.

This breadth—from database indexing to algorithmic optimization to API design—was both challenging and rewarding, as it forced me to think holistically about system performance rather than optimizing isolated components.

Data-driven decision-making. Before this project, I had limited experience with production data analysis. Makehub taught me to:

- **Instrument everything**: Logging latency, throughput, error rates, and routing decisions for every request enabled retrospective analysis that revealed patterns invisible during development.
- **Quantify intuitions**: Claims like "Provider X is faster" required empirical validation (statistical significance tests, confidence intervals, controlling for confounds like time-of-day effects).
- **Build feedback loops**: Deploying a minimum viable product (MVP), observing user behavior, and iterating based on real-world data (rather than assumptions) accelerated learning.

The empirical findings—especially the *lack* of price-performance correlation (r=0.046)—directly contradicted my initial assumptions and reshaped the system design.

Prompt engineering and LLM-as-a-tool. Implementing complexity scoring (§9.1) and prompt compression (§9.2) required treating LLMs as computational primitives rather than end-user products:

- **Prompt design**: Crafting prompts that reliably extract structured outputs (JSON) with minimal token usage and latency.
- **Calibration**: Ensuring that complexity scores (1–100) aligned with model selection thresholds through iterative testing on diverse tasks.
- **Error handling**: Gracefully handling hallucinated outputs, malformed JSON, refusals, and timeouts when LLMs are embedded in critical paths.

This experience shifted my perspective on LLMs from "magic black boxes" to "powerful but unreliable components" that require careful engineering to integrate into production systems.

11.3.2 Entrepreneurial lessons

Market validation through iteration. The initial Makehub concept—unified API for multi-provider routing—sounded compelling in theory, but market validation required:

- **User interviews**: Talking to 50+ developers revealed that cost savings alone were insufficient motivation; users cared equally about reliability (fallback) and developer experience (zero integration overhead).
- **MVP iteration**: Our first prototype focused on cost optimization, but early users complained about latency. Adding performance-aware routing (§7.3) was a direct response to this feedback.
- **Positioning**: Framing Makehub as "infrastructure for AI developers" rather than "LLM cost optimizer" resonated more strongly, as it emphasized enabling innovation rather than penny-pinching.

These lessons reinforced the importance of **customer-centric product development** over feature-driven engineering.

Balancing rigor and pragmatism. Academic research values novelty and rigor; startups value speed and impact. This thesis required balancing both:

- **Research rigor**: Documenting methodology, baseline comparisons, statistical significance, and reproducibility (§10).
- **Startup pragmatism**: Shipping features quickly, tolerating technical debt, prioritizing user-visible improvements over architectural purity.

For example, our vectorial scoring algorithm (§7.3) is conceptually simple (Euclidean distance in 3D space), which made it easy to implement, debug, and explain to users—despite being less sophisticated than learned policies. This simplicity was a feature, not a bug.

Building in public. Throughout the project, we shared progress publicly (blog posts, Twitter, developer communities), which:

- **Generated early users**: 30% of beta users discovered Makehub through technical blog posts explaining our architecture.
- **Attracted talent**: Open-source contributors fixed bugs, suggested features, and validated architectural decisions.
- **Built credibility**: Transparent sharing of empirical results (even negative findings) established trust with the developer community.

This experience demonstrated that **transparency and community engagement** are strategic advantages, not distractions from "real work."

11.3.3 Broader reflections

The value of interdisciplinary work. Makehub sits at the intersection of:

- **Systems engineering**: Distributed systems, performance optimization, monitoring.
- **Machine learning**: LLMs, prompt engineering, complexity scoring.
- **Optimization theory**: Multi-objective optimization, Pareto frontiers, vectorial scoring.
- **Entrepreneurship**: Market analysis, product-market fit, go-to-market strategy.

This breadth was initially overwhelming—each domain has its own vocabulary, methods, and standards. However, the interdisciplinary nature ultimately became the project's strength, as insights from one domain informed solutions in others (e.g., using geometric intuition from optimization theory to design the scoring algorithm).

Lessons for future AI infrastructure. Working on Makehub revealed broader patterns in AI infrastructure that will shape my future work:

- **Abstraction layers are essential**: As AI capabilities commoditize, unified APIs that hide provider heterogeneity will become standard (analogous to Kubernetes for cloud infrastructure).
- **Measurement trumps assumptions**: Real-world performance data reveals patterns invisible in benchmarks; continuous monitoring should be a first-class design principle.
- **Composable optimizations multiply value**: Combining provider routing, model routing, and compression delivered 65% savings—far exceeding any single technique. Future systems should embrace layered optimization.

Personal growth. Beyond technical and entrepreneurial skills, this thesis cultivated:

- **Resilience**: Debugging production outages at 2 AM, handling angry users, iterating through 10+ failed architectural designs—all taught me to persist through setbacks.
- **Communication**: Explaining complex technical decisions to non-technical co-founders, investors, and users sharpened my ability to tailor messaging to audiences.
- **Humility**: Many of my initial assumptions (e.g., "expensive providers are faster") proved false. Empirical data repeatedly humbled my intuitions, reinforcing the value of evidence over ego.

In summary, this thesis was not merely an academic exercise but a formative experience that integrated engineering, research, and entrepreneurship—preparing me to tackle ambitious, real-world problems at the frontier of AI infrastructure.

Appendix: Technical Glossary

This glossary defines key technical terms used throughout this thesis, organized alphabetically.

A

API (Application Programming Interface): A set of protocols and tools that allow different software applications to communicate with each other. In the context of LLMs, APIs enable developers to send requests to model providers and receive responses.

Autoregressive Generation: A text generation paradigm where each token is predicted sequentially based on all previously generated tokens. This is the core mechanism underlying modern LLMs like GPT and LLaMA.

Attention Mechanism: A neural network component that allows models to focus on different parts of the input when producing each output token. The Transformer architecture uses self-attention to process all input tokens in parallel.

B

Batching: A serving optimization technique where multiple inference requests are processed together in a single forward pass through the model, improving GPU utilization and throughput.

Byte-Pair Encoding (BPE): A tokenization algorithm that splits text into subword units by iteratively merging the most frequent pairs of characters or character sequences. Used by GPT models.

C

Cascading Fallback: A reliability mechanism where failed requests are automatically retried with alternative providers in order of preference, ensuring high uptime despite individual provider failures.

Context Window: The maximum combined length of input and output tokens that a model can process in a single request. Modern models range from 8K to 2M tokens.

Closed-Source Model: A language model whose weights and training methodology are proprietary and controlled by a single vendor (e.g., GPT-4o, Claude 3.5, Gemini).

D

Decoder-Only Transformer: A variant of the Transformer architecture that uses only the decoder component, optimized for autoregressive text generation. Used by GPT, LLaMA, and most modern LLMs.

Dynamic Routing: The process of selecting providers or models at request time based on real-time performance metrics and user preferences, as opposed to static configuration.

E

Embedding: A dense vector representation of text that captures semantic meaning. Used internally by LLMs and sometimes exposed as a separate API service.

F

Few-Shot Learning: The ability of LLMs to perform tasks based on a few examples provided in the prompt, without task-specific fine-tuning.

Fine-Tuning: The process of further training a pre-trained model on domain-specific data to specialize its capabilities.

G

GPU (Graphics Processing Unit): Specialized hardware originally designed for graphics rendering but now essential for parallel computation in deep learning. Modern LLM inference relies on NVIDIA A100, H100, or AMD MI300 GPUs.

I

Inference: The process of using a trained model to generate predictions or outputs for new inputs. In LLMs, this refers to generating text completions given a prompt.

Instruction-Tuning: A fine-tuning approach where models are trained on examples of instructions and desired responses, improving their ability to follow user commands.

L

Latency: The time elapsed between sending a request and receiving a response. For streaming requests, Time-to-First-Token (TTFT) measures latency to the first output token.

LLM (Large Language Model): A deep neural network with billions of parameters trained on massive text corpora to predict the next token in a sequence, enabling capabilities like text generation, reasoning, and task completion.

LLM-as-a-Judge: A technique where a language model evaluates or classifies inputs (e.g., complexity scoring, quality assessment) to guide downstream routing or processing decisions.

M

Model Family: A group of related models sharing the same architecture and training approach but differing in size or specialization (e.g., GPT-4o, GPT-4o mini).

Multi-Objective Optimization: An optimization approach that balances multiple competing goals (e.g., minimizing cost while maximizing throughput) using weighted scoring functions.

O

Open-Source Model: A language model whose weights are publicly released, enabling decentralized hosting by multiple providers (e.g., LLaMA 3.1, Mistral, DeepSeek).

P

Parameter: A learnable weight in a neural network. Modern LLMs contain billions to hundreds of billions of parameters (e.g., LLaMA 3.1 70B has 70 billion parameters).

Prompt: The input text provided to an LLM to guide its generation. Prompts can include instructions, context, examples, and queries.

Prompt Caching: An optimization where providers cache repeated prompt prefixes across requests, reducing processing time and cost for subsequent requests with the same context.

Prompt Compression: A technique to reduce the number of input tokens by removing redundant or low-value content while preserving semantic meaning.

Provider: An entity that hosts LLM infrastructure and exposes it via an API service (e.g., OpenAI, Together AI, AWS Bedrock).

R

Rate Limiting: A provider-imposed restriction on the number of requests or tokens that can be processed per unit time, used to manage load and prevent abuse.

Routing: The process of directing requests to specific providers or models based on optimization criteria (cost, latency, throughput, capabilities).

S

Streaming: A response delivery method where output tokens are sent incrementally as they are generated, rather than waiting for complete generation. Improves perceived responsiveness.

System Prompt: A special prompt component that defines the model's behavior, role, or constraints, typically preserved across conversation turns.

T

Throughput: The rate at which output tokens are generated during streaming inference, measured in tokens per second (tokens/s).

Time-to-First-Token (TTFT): The latency between sending a request and receiving the first output token. Critical for interactive applications requiring immediate feedback.

Token: The fundamental unit of text processing in LLMs, typically representing subword units (e.g., "tokenization" → ["token", "ization"]). Model capacity, pricing, and performance are all measured in tokens.

Tokenization: The process of converting text into tokens using algorithms like Byte-Pair Encoding (BPE) or SentencePiece.

Transformer: A neural network architecture introduced in 2017 that uses attention mechanisms to process sequences in parallel. The foundation of all modern LLMs.

V

Vectorial Scoring: A multi-dimensional ranking approach where providers are scored based on normalized distances in a feature space (e.g., price, latency, throughput).

Vision Model: An LLM variant capable of processing both text and images as input (e.g., GPT-4o, Claude 3.5 Sonnet).

vLLM: A high-performance open-source serving framework optimized for LLM inference, featuring PagedAttention and continuous batching.

References

Anthropic (2025a). *Claude Code: VS Code Extension*. VS Code Marketplace. Accessed: 2025-05-15. URL: https://marketplace.visualstudio.com/items?itemName=anthropic.claude-code.

— (2025b). *Introducing Claude 4*. Accessed: 2025-05-15. URL: https://www.anthropic.com/news/claude-4.

Anysphere, Inc. (2023). *Cursor: The AI-first Code Editor*. Accessed: 2025-01-15. URL: https://www.cursor.com.

Brown, Tom B. et al. (2020). "Language Models are Few-Shot Learners". In: *Advances in Neural Information Processing Systems (NeurIPS)*. Vol. 33, pp. 1877–1901. URL: https://arxiv.org/abs/2005.14165.

Continue Dev, Inc. (2025). *Continue 1.0: Open-Source IDE Extensions*. Reuters Press Release. Accessed: 2025-02-26. URL: https://www.reuters.com/press-releases/continue-launches-1-0-with-open-source-ide-extensions-and-a-hub-that-empowers-developers-to-build-and-share-custom-ai-code-assistants-2025-02-26/.

DeepSeek AI (2024). *DeepSeek-V3: Technical Report*. Accessed: 2024-12-26. URL: https://github.com/deepseek-ai/DeepSeek-V3.

GitHub (2021). *Introducing GitHub Copilot: AI Pair Programmer*. Technical preview. Accessed: 2021-06-29. URL: https://github.blog/news-insights/product-news/introducing-github-copilot-ai-pair-programmer/.

— (2022). *GitHub Copilot is Generally Available to All Developers*. Accessed: 2022-06-21. URL: https://github.blog/news-insights/product-news/github-copilot-is-generally-available-to-all-developers/.

— (2025). *GitHub Copilot: Meet the New Coding Agent*. Announced at Microsoft Build 2025. Accessed: 2025-05-15. URL: https://github.blog/news-insights/product-news/github-copilot-meet-the-new-coding-agent/.

Hoffmann, Jordan et al. (2022). *Training Compute-Optimal Large Language Models*. arXiv preprint arXiv:2203.15556. URL: https://arxiv.org/abs/2203.15556.

Kumar, Ankit, Rajesh Singh, and Meera Patel (2025). *Dynamic LLM Routing and Selection based on User Preferences: Balancing Performance, Cost, and Ethics*. arXiv preprint arXiv:2502.16696. URL: https://arxiv.org/abs/2502.16696.

Kwon, Woosuk et al. (2023). *vLLM: Easy, Fast, and Cheap LLM Serving with PagedAttention*. arXiv preprint arXiv:2309.06180. Accessed: 2025-01-15. URL: https://arxiv.org/abs/2309.06180.

Lovable (2025). *Lovable: Build Software at the Speed of Thought*. Accessed: 2025-01-15. URL: https://lovable.dev/.

Meta AI (2024). *Introducing Meta Llama 3*. Accessed: 2024-04-18. URL: https://ai.meta.com/blog/meta-llama-3/.

Mistral AI (2023). *Mistral 7B: The Most Powerful Open-Source 7B Model*. Accessed: 2023-09-27. URL: https://mistral.ai/news/announcing-mistral-7b/.

— (2024). *Codestral: Coding-Specific Language Model*. Accessed: 2024-05-29. URL: https://mistral.ai/news/codestral/.

NVIDIA (2024). *TensorRT-LLM: High-Performance Inference for LLMs*. Accessed: 2025-01-15. URL: https://github.com/NVIDIA/TensorRT-LLM.

Ong, Isaac et al. (2024). *RouteLLM: Learning to Route LLMs with Preference Data*. arXiv preprint arXiv:2406.18665. Published at ICLR 2025. URL: https://arxiv.org/abs/2406.18665.

OpenAI (2023). *GPT-4 Technical Report*. arXiv preprint arXiv:2303.08774. Accessed: 2023-03-15. URL: https://arxiv.org/abs/2303.08774.

— (2025a). *Codex: GitHub Repository*. Accessed: 2025-01-15. URL: https://github.com/openai/codex.

— (2025b). *Introducing Codex*. Accessed: 2025-01-15. URL: https://openai.com/index/introducing-codex/.

Radford, Alec, Karthik Narasimhan, et al. (2018). *Improving Language Understanding by Generative Pre-Training*. OpenAI Technical Report. URL: https://cdn.openai.com/research-covers/language-unsupervised/language_understanding_paper.pdf.

Radford, Alec, Jeffrey Wu, et al. (2019). *Language Models are Unsupervised Multitask Learners*. OpenAI Technical Report. URL: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.

Rizwan, Saoud (2024). *Cline: Autonomous Coding Agent*. VS Code Marketplace. Formerly Claude Dev. Accessed: 2025-01-15. URL: https://marketplace.visualstudio.com/items?itemName=saoudrizwan.claude-dev.

Roo Code Team (2025). *Roo Code v3.2.0 Update Notes*. Accessed: 2025-01-15. URL: https://docs.roocode.com/update-notes/v3.2.0.

Swyx and Alessio (2023). *Cursor: The AI IDE*. Latent Space Podcast. Accessed: 2025-01-15. URL: https://www.latent.space/p/cursor.

Times, Financial (2025). *Lovable: AI-Powered No-Code Platform for Developers*. Financial Times article. Accessed: 2025-01-15. URL: https://www.ft.com/content/01bc8e7e-6c45-4348-b89f-00e091149531.

Touvron, Hugo et al. (2023). "LLaMA: Open and Efficient Foundation Language Models". In: *arXiv preprint arXiv:2302.13971*. URL: https://arxiv.org/abs/2302.13971.

Vaswani, Ashish et al. (2017). "Attention Is All You Need". In: *Advances in Neural Information Processing Systems (NeurIPS)*, pp. 5998–6008. URL: https://arxiv.org/abs/1706.03762.

Zhao, Wei, Ming Liu, and Yun Zhang (2025). *Universal Model Routing for Efficient LLM Inference*. arXiv preprint arXiv:2502.08773. URL: https://arxiv.org/abs/2502.08773.