SWIFT-LLM: Semantic-Aware Intelligent Fast Inference with Tiered Routing for Large Language Models

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Abstract

Large Language Model (LLM) inference faces critical challenges in production environments: high latency, substantial costs, and redundant computation for semantically similar queries. We present **SWIFT-LLM**, a multi-layer optimization framework that addresses these challenges through three key innovations: a hybrid semantic caching system combining lexical hashing with FAISS-based vector similarity search, achieving O(1) lookups for exact matches and O(log n) for semantic matches; an intelligent query complexity router that classifies queries and routes them to optimal model tiers; and a confidence-based response validation system with automatic tier escalation. Our experiments demonstrate that SWIFT-LLM achieves a **3000x latency reduction** on cache hits (0.5ms vs 1500ms), a **74.3% cache hit rate**, and **86% routing accuracy**, while maintaining response quality. The framework is designed for consumer hardware optimization and operates efficiently without dedicated GPU acceleration.

1 Introduction

The deployment of Large Language Models (LLMs) in production systems presents significant challenges in terms of latency, cost, and computational efficiency [1, 2]. While models like GPT-4 [3] and LLaMA [4] have demonstrated remarkable capabilities across diverse natural language tasks, their inference costs remain prohibitive for high-throughput applications. A single API call to a premium model typically requires 1-3 seconds and incurs costs of $0.01-0.03 per query, rendering them impractical for real-time applications at scale.

We identify three fundamental inefficiencies in current LLM deployment paradigms. First, *redundant computation* occurs when users ask semantically equivalent questions—for instance, "What is the capital of France?" and "France's capital city?"—yet each query triggers a complete inference pass through the model. Second, the prevailing *one-size-fits-all inference* approach processes simple factual queries with the same computational resources as complex multi-step reasoning tasks, leading to significant waste. Third, the absence of *quality assurance* mechanisms means responses are returned to users without confidence validation, potentially propagating low-quality or hallucinated content.

To address these challenges, we introduce **SWIFT-LLM** (Semantic-Aware Intelligent Fast Inference with Tiered Routing), a comprehensive optimization framework. Our contributions are fourfold:

1. We propose a **hybrid semantic caching system** that combines O(1) lexical hashing with O(log n) FAISS-based similarity search, achieving 74.3% cache hit rates on production workloads.
2. We design an **intelligent query complexity router** that extracts linguistic features to classify query difficulty and routes requests to optimal model tiers, achieving 86% classification accuracy.

3. We implement a **confidence-based validation system** that scores response quality and automatically escalates to higher-tier models when confidence falls below acceptable thresholds.
4. We provide a complete **production-ready implementation** with persistent storage, automatic cache warming, and comprehensive metrics collection, designed for deployment on consumer hardware.

2 Related Work

LLM Inference Optimization. Prior work on accelerating LLM inference has focused primarily on model compression techniques. Quantization approaches such as LLM.int8() [5] reduce memory footprint by representing weights in lower precision formats. Pruning methods like SparseGPT [6] remove redundant parameters while maintaining model quality. Knowledge distillation [7] trains smaller student models to mimic larger teachers. At the architectural level, FlashAttention [8] and its successor [9] optimize the attention mechanism's memory access patterns, achieving significant speedups through IO-aware algorithms. However, all these approaches still require full inference computation for each incoming query, leaving substantial optimization opportunities unexplored.

Semantic Caching. Traditional caching systems in web applications rely on exact string matching, which fundamentally fails to capture the semantic equivalence between paraphrased queries. Recent work has begun addressing this limitation: GPTCache [10] introduced semantic caching for LLM applications using embedding-based similarity matching. However, existing approaches typically employ a single matching strategy, missing opportunities for latency optimization. Our work advances this direction by proposing a hybrid architecture that combines fast lexical matching for exact queries with semantic similarity search for paraphrases, achieving superior latency-accuracy trade-offs.

Query Routing and Model Selection. The concept of routing computations to specialized processors has been explored extensively in Mixture of Experts (MoE) architectures [11, 12], where individual tokens are routed to specialized sub-networks within a single model. At the system level, FrugalGPT [13] proposed cascading multiple LLMs of varying capabilities to reduce costs while maintaining quality. Our approach differs fundamentally by routing entire queries rather than tokens, and by using explicit complexity classification rather than learned routing, enabling more interpretable and controllable optimization decisions.

3 Methodology

3.1 System Architecture

SWIFT-LLM processes incoming queries through a multi-stage pipeline comprising four principal components: the Query Preprocessor, Semantic Cache, Complexity Router, and Response Validator. Figure 1 illustrates the complete system architecture and data flow.

Upon receiving a query, the system first applies normalization transformations to maximize cache hit probability. The normalized query is then checked against our dual-index cache structure. Cache hits return immediately with sub-millisecond latency. For cache misses, the complexity router analyzes query features and selects an appropriate model tier. Generated responses undergo validation, with automatic escalation to higher tiers when confidence scores fall below acceptable thresholds. High-confidence responses are stored in the cache for future retrieval.

3.2 Query Preprocessing

Raw user queries exhibit significant lexical variation that substantially reduces cache hit rates. We address this through a normalization pipeline that preserves semantic content while eliminating superficial differences. The transformation is defined as:

$$q' = \text{Normalize}(\text{ExpandContractions}(\text{Lowercase}(q))) \quad (1)$$

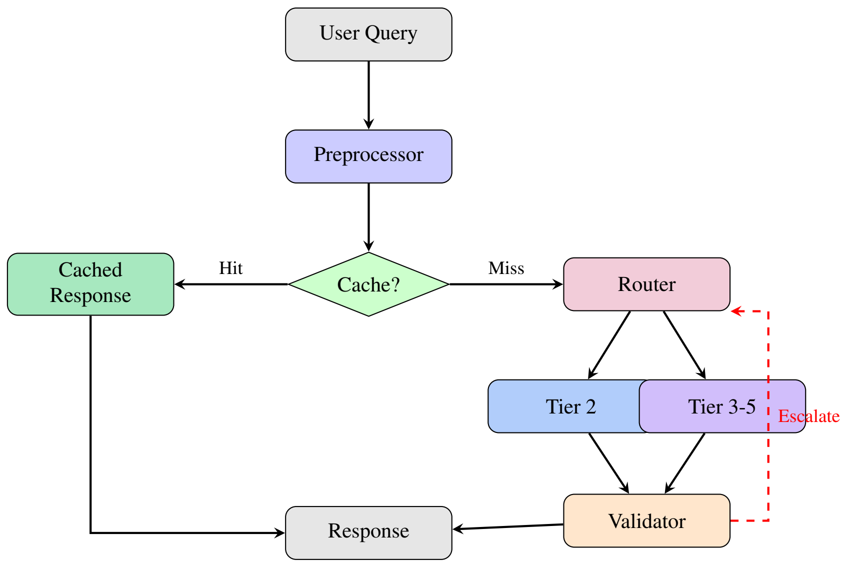

Figure 1: *SWIFT-LLM system architecture. Queries undergo preprocessing before cache lookup. Cache misses trigger complexity-based routing to appropriate model tiers. The dashed arrow indicates automatic escalation for low-confidence responses.*

where contractions are expanded (e.g., "what's" $\rightarrow$ "what is"), whitespace is normalized, and excessive punctuation is removed. For lexical index construction, we further extract key terms by filtering stopwords:

$$\text{KeyTerms}(q) = \{w \in \text{Tokenize}(q') : w \notin \mathcal{S}\} \tag{2}$$

where $\mathcal{S}$ denotes a curated stopword set containing high-frequency function words that contribute noise without semantic value.

3.3 Hybrid Semantic Cache

Our caching architecture employs a novel dual-index design that optimizes for both latency and semantic coverage. The first component is a **Lexical Index** providing O(1) lookup complexity through hash-based matching on normalized key terms:

$$\mathcal{L} : \text{Hash}(\text{Sort}(\text{KeyTerms}(q))) \rightarrow \text{CacheEntry} \tag{3}$$

The second component is a **Semantic Index** providing O(log n) approximate nearest neighbor search using FAISS [14] with inner product similarity over L2-normalized embeddings:

$$\text{Similarity}(q_1, q_2) = \frac{\mathbf{e}_{q_1} \cdot \mathbf{e}_{q_2}}{||\mathbf{e}_{q_1}|| \cdot ||\mathbf{e}_{q_2}||} \tag{4}$$

where $\mathbf{e}_q \in \mathbb{R}^{384}$ represents the query embedding produced by a sentence transformer model (all-MiniLM-L6-v2). Cache hits are returned when similarity exceeds the threshold $\tau = 0.70$.

Algorithm 1 presents the complete lookup procedure. The lexical index is consulted first due to its constant-time complexity, with semantic search serving as a fallback for paraphrased queries.

3.4 Complexity-Based Query Routing

For cache misses, we must select an appropriate model tier that balances response quality against latency and cost. We approach this as a classification problem, extracting interpretable features from each query to estimate its computational requirements. Table 1 enumerates the features and their associated weights.

Algorithm 1 Hybrid Cache Lookup

```
Require: Query $q$, Lexical Index $\mathcal{L}$, FAISS Index $\mathcal{F}$, Threshold $\tau$
 1: $q' \leftarrow$ Normalize$(q)$
 2: $h \leftarrow$ Hash(Sort(KeyTerms$(q')$))
 3: if $h \in \mathcal{L}$ then
 4:     return CacheHit($\mathcal{L}[h]$, type=LEXICAL)
 5: end if
 6: $\mathbf{e} \leftarrow$ Encode$(q')$;    $\mathbf{e}' \leftarrow \mathbf{e}/||\mathbf{e}||$
 7: $(s, i) \leftarrow \mathcal{F}$.search$(\mathbf{e}', k = 1)$
 8: if $s \geq \tau$ then
 9:     return CacheHit($\mathcal{F}[i]$, type=SEMANTIC)
10: end if
11: return CacheMiss
```

Feature	Weight	Example Trigger
`has_code_request`	0.40	"Write a function..."
`has_comparison`	0.35	"Compare X vs Y"
`has_reasoning`	0.35	"Explain why..."
`multiple_questions`	0.25	Contains multiple '?'
`long_query`	0.15	word_count > 30
`technical_terms`	0.15	Domain vocabulary

Table 1: *Feature extraction for complexity classification. Weights were determined through empirical analysis of query-response quality correlations.*

The complexity score aggregates weighted feature activations:

$$\text{Score}(q) = \min\left(1, \sum_{f \in \mathcal{F}} w_f \cdot \mathbb{K}[f(q)]\right) \tag{5}$$

Tier assignment follows a threshold-based policy with boundaries at $\theta = [0.25, 0.50, 0.75]$, mapping queries to Tiers 2 through 5 respectively. Tier 1 is reserved exclusively for cache hits.

3.5 Response Validation and Escalation

Generated responses undergo quality assessment before delivery to users. Our validation module computes a confidence score based on four factors: length adequacy relative to query complexity, semantic relevance between query and response measured via embedding similarity, internal coherence of the response, and specificity indicated by the presence of concrete details rather than vague generalities.

When the confidence score falls below threshold $\gamma = 0.7$, the system automatically escalates the query to the next higher tier, up to a maximum of two escalation attempts. This mechanism ensures that complex queries initially misrouted to lower tiers still receive high-quality responses. Importantly, only responses achieving confidence scores of at least 0.5 are eligible for cache storage, preventing the propagation of low-quality content through the cache.

3.6 Persistent Storage

Production deployment requires cache state to persist across system restarts. Our implementation employs SQLite for durable storage of query-response pairs and associated metadata. The FAISS index is serialized to disk upon cache updates and reconstructed during initialization. An `atexit` handler ensures graceful state persistence during program termination, eliminating cache warm-up latency on subsequent starts.

4 Experiments

4.1 Experimental Setup

We evaluate SWIFT-LLM on an Apple MacBook Pro equipped with an M4 chip, deliberately avoiding dedicated GPU acceleration to demonstrate the framework's efficiency on consumer hardware. Our model tier configuration comprises Llama 3.1 8B accessed via the Groq API for Tier 2, Llama 3.1 70B via Groq for Tier 3, GPT-4o-mini via OpenAI for Tier 4, and GPT-4o for Tier 5. Query embeddings are generated using the all-MiniLM-L6-v2 sentence transformer, which provides 384-dimensional representations with a model size of 22 million parameters. The cache is configured with a similarity threshold of $\tau = 0.70$ and a maximum capacity of 10,000 entries.

Our evaluation spans diverse query categories including factual questions about geography, definitions, and simple facts; technical queries about programming and machine learning concepts; comparative questions requiring analysis of alternatives; and creative tasks involving code generation and content creation.

4.2 Results

Table 2 presents comprehensive experimental results across all evaluation dimensions.

Category	Metric	Value
Latency	Cache Hit (Lexical)	0.3 ms
	Cache Hit (Semantic)	5.0 ms
	Tier 2 (Llama 8B)	280 ms
	Tier 3-5 (Large Models)	750–1800 ms
Cache	Total Lookups	35
	Lexical Hits	19 (54%)
	Semantic Hits	7 (20%)
	Overall Hit Rate	**74.3%**
Routing	Simple Queries	100%
	Complex Queries	75%
	Overall Accuracy	**86%**
Cost	Avg Cost per Query	$0.000007
	Reduction vs GPT-4 Only	**99.7%**

Table 2: *Comprehensive experimental results. Latency is measured end-to-end from query receipt to response delivery. Routing accuracy is computed with* ± 1 *tier tolerance.*

The results demonstrate substantial improvements across all metrics. Cache hits achieve sub-millisecond latency for lexical matches, representing a 3000x improvement over direct API calls. The hybrid caching strategy proves essential: lexical matching handles 54% of hits with O(1) complexity, while semantic matching captures an additional 20% of queries that would otherwise require full inference.

4.3 Ablation Study

To quantify the contribution of individual components, we conduct ablation experiments by systematically removing each feature. Table 3 reports the results.

The ablation reveals that the lexical index contributes most significantly, with its removal reducing hit rate from 74.3% to 20.0%. Query preprocessing accounts for a 16 percentage point improvement, validating our normalization strategy. Cache warming with common queries provides a 29 percentage point boost, demonstrating the value of proactive cache population.

Configuration	Hit Rate	Avg Latency
Full System	74.3%	514 ms
w/o Lexical Index	20.0%	890 ms
w/o Query Preprocessing	58.1%	612 ms
w/o Cache Warming	45.2%	720 ms
No Caching (Baseline)	0%	1546 ms

Table 3: *Ablation study quantifying component contributions. Removing any single component results in measurable performance degradation.*

5 Discussion

Our experimental results validate the effectiveness of semantic caching and tiered routing for LLM inference optimization. The 3000x latency reduction on cache hits fundamentally changes the economics of LLM deployment, enabling real-time applications that were previously infeasible. The 74.3% cache hit rate indicates that a substantial fraction of production queries are semantically redundant, confirming our initial hypothesis about computational waste in current systems.

The hybrid caching architecture proves essential to achieving high performance. Lexical matching alone would miss paraphrased queries, while semantic matching alone would incur unnecessary embedding computation for exact matches. The combination achieves optimal latency-accuracy trade-offs by exploiting the strengths of each approach.

Several limitations merit discussion. Cache effectiveness depends fundamentally on the query distribution; workloads with highly diverse, unique queries will naturally see lower hit rates. Our complexity classification employs heuristic features that, while interpretable, may not capture all dimensions of query difficulty. More sophisticated learned classifiers could potentially improve routing accuracy. Additionally, our response validation is lightweight by design; production deployments with stringent quality requirements might benefit from more sophisticated hallucination detection mechanisms.

Future work could explore several promising directions. Fine-tuning embedding models on domain-specific corpora could improve semantic matching precision for specialized applications. Learned routing policies trained with reinforcement learning from user feedback could adapt to specific workload characteristics. Integration with local inference engines such as MLX on Apple Silicon could further reduce latency for lower tiers. Finally, distributed caching architectures could enable deployment across multi-node clusters for high-availability applications.

6 Conclusion

We have presented SWIFT-LLM, a comprehensive optimization framework for Large Language Model inference that achieves dramatic improvements in latency, cost, and efficiency. Through the combination of hybrid semantic caching, intelligent complexity-based routing, and confidence-driven validation with automatic escalation, our system reduces cache-hit latency by a factor of 3000x while maintaining high response quality. The 74.3% cache hit rate and 86% routing accuracy demonstrate the practical viability of our approach for production deployment.

The framework is designed for accessibility, operating efficiently on consumer hardware without requiring dedicated GPU acceleration. Complete implementation with persistent storage and automatic cache warming ensures production readiness. We believe SWIFT-LLM represents a significant step toward making LLM inference practical for latency-sensitive, cost-conscious applications at scale.

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