Asteria: Semantic-Aware Cross-Region Caching for Agentic LLM Tool Access

Chaoyi Ruan Chao Bi Kaiwen Zheng Ziji Shi Xinyi Wan Jialin Li NUS USTC University of Toronto NUS Sea AI Lab, NUS NUS

Abstract

Large Language Model (LLM) agents tackle data-intensive tasks such as deep research and code generation. However, their effectiveness depends on frequent interactions with knowledge sources across remote clouds or regions. Such interactions can create non-trivial latency and cost bottlenecks. Existing caching solutions focus on exact-match queries, limiting their effectiveness for semantic knowledge reuse.

To address this challenge, we introduce Asteria, a novel cross-region knowledge caching architecture for LLM agents. At its core are two abstractions: Semantic Element (SE) and Semantic Retrieval Index (Sine). A semantic element captures the semantic embedding representation of an LLM query together with performance-aware metadata such as latency, cost. and staticity. Sine then provides two-stage retrieval: a vector similar index with semantic embedding for fast candidate selection and a lightweight LLM-powered semantic judger for precise validation. Atop these primitives, Asteria builds a new cache interface that includes a new semantic-aware cache hit definition, a cost-efficient eviction policy, and proactive prefetching. To reduce overhead, Asteria co-locates the small LLM judger with the main LLM using adaptive scheduling and resource sharing. Our evaluation demonstrates that Asteria delivers substantial performance improvements without compromising correctness. On representative search workloads, Asteria achieves up to a 3.6× increase in throughput by maintaining cache hit rates of over 85%, while preserving accuracy virtually identical to non-cached baselines. Asteria also improves throughput for complex coding tasks by 20%, showcasing its versatility across diverse agentic workloads.

1 Introduction

LLM agents [20, 28, 66] have emerged as powerful tools, capable of autonomously executing data-intensive tasks such as deep research assistance [33, 39, 58] and sophisticated code generation [5, 14, 44]. Their effectiveness relies on a multistep reasoning and retrieval loop in which the agents strategically query external knowledge from either private knowledge

bases via retrieval-augmented generation (RAG) [37] or cloud search services through API calls [26, 53], and then synthesize the retrieved information step by step to produce a final solution. Yet, this fundamental dependence on external interaction introduces a critical data-retrieval bottleneck to agent performance: the high latency and cost of accessing external knowledge for robust reasoning and decision-making.

Compared to non-agent LLM inference, which relies mainly on GPU computation to generate text, LLM agents frequently invoke external data retrieval services/tools such as web search APIs [43,57] or RAG backend services [10,30]. Often, the data source and agent models are located in different data centers or regions and are connected by a wide-are network (WAN). Agent deployment thus faces two major challenges: high monetary cost and cross-region latency due to remote tool calling. For an application handling 5-10 million daily queries (such as Google AI mode [27, 52]), costs are substantial. Given the price of each Google Search API call at \$0.005 [23], the application would incur a monthly costs of \$1.5-4.5 million. Furthermore, accessing data sources in remote regions can lead to 300-500 ms end-to-end latencies [55]. Such high latency can impact user experience and disrupt multi-step agent workflows.

Prior work has considered applying caching to reduce agent cost. However, existing caching strategies are designed to accelerate LLM inference itself, rather than mitigating the cost and latency of external data retrieval. Semantic prompt caches [9, 24, 56, 65] like GPT-Cache [9] store LLM outputs and reuse responses via prompt similarity to skip LLM generation. However, they compare prompts in the embedding space rather than at the knowledge or tool boundary, and they lack validation to ensure that reused content remains correct for the current context or time. Traditional data storage caches, such as key-value store [59], database [13] or file system [21], store KV objects indexed by exact keys. These caches lack the ability to evaluate semantic equivalence between nonmatching queries. Transformer KV-caches [22, 36, 41] store token KV states to accelerate model decoding, but their scope is limited to inference computation.

To address this gap, we propose a new paradigm, *semantic*aware remote knowledge caching, to address the latency and cost bottlenecks in cross-region data access for LLM agents. Unlike prior solutions that focus on optimizing LLM inference computation (e.g., GPTCache) or relying on exact-match queries, our approach leverages LLMs' language understanding to intelligently cache and retrieve external data. Knowledge caching is built on two core abstractions. We first define a semantic element (SE) that encapsulates the agent's query, tool interactions, and the retrieved response. SE is augmented with performance-aware metadata such as latency, cost, and staticity. We then propose Semantic Retrieval Index (Sine), a two-stage retrieval engine that combines 1) an Approximate Nearest Neighbor (ANN) search for high-recall candidate selection and 2) a lightweight LLM-based Semantic Judger for precise validation, ensuring true semantic equivalence.

We present Asteria, a concrete implementation of semanticaware knowledge caching. Asteria seamlessly integrates the power of LLM semantic understanding into a robust caching architecture, significantly reducing external dependencies and costs associated with remote data access. Crucially, Asteria bridges the gap between the uncertainty of semantic matching and the deterministic requirements of a traditional cache. This is achieved by transforming the ANN and semantic judger output into a reliable, semantic-aware cache hit signal. This procedure ensures that only genuinely relevant and contextually appropriate remote information is served. Furthermore, Asteria equips the semantic index with advanced caching policies, such as a cost-efficient adaptive eviction policy and predictive prefetching, driven by SE metadata. Meanwhile, we propose an efficient Asteria implementation using GPU co-location, where the primary agent LLM and the semantic judger LLM can reside on a single GPU managed by a priority-aware scheduler that protects the agent's critical latency paths.

Our evaluation demonstrates that Asteria delivers substantial performance gains without compromising accuracy. On representative Zipfian and bursty workloads, Asteria achieves up to a 3.6× throughput improvement over exact-match caching by sustaining cache hit rates of over 85%. Crucially, our accuracy analysis reveals that while a naive semantic cache suffers a significant drop in correctness, Asteria maintains accuracy virtually identical to the non-cached baseline, proving the indispensable role of the semantic judger. This efficiency extends even to complex coding tasks, where Asteria provides a 20% throughput boost.

2 Background and Motivation

2.1 Agentic Applications Atop LLM

With the rise of reinforcement learning [17,18], LLMs are empowered with thinking capability, moving beyond simple text generation to generate tool-use commands/queries in inter-

Table 1: Example cost information for the commonly used remote data access services.

Company	Google	OpenAI	
Operation	Search API	Web Search Preview	Web Search
Cost (per 1k reqs.)	\$5 [23]	\$10-\$25 [49]	\$10 [49]

mediate reasoning steps. The most mature ones are searching agent [32] and coding agents [5]

Agentic LLM. Unlike the traditional base LLM models [2], whose performance is primarily constrained by GPU inference speed, the core of an agentic system is an iterative "thinkact-observe" loop that repeatedly accesses remote knowledge. As illustrated in Figure 1a, this process begins with a reasoning phase (①, think), where the agent formulates a plan. This plan then materializes when the LLM generates an action (i.e., tool call query) to be dispatched over the model context protocol (MCP [4]) to a remote data source. The tool call can be a search query or an API request. The dedicated think and action type of LLM outputs are encapsulated by special tags like <think> and <tool>. After retrieving the remote knowledge, the agent integrates it into its working context to inform the next cycle. This loop of external data retrieval is not a one-shot step but a fundamental, repeated operation at the heart of the agent's problem-solving process, distinguishing its operational profile from non-agentic LLMs.

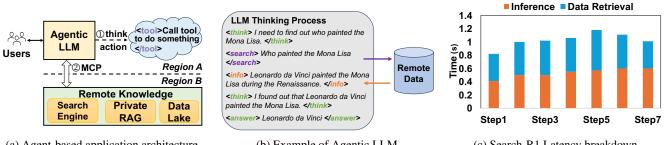
The Search-R1 [33] example. To make this workflow concrete, consider the behavior of a search-focused agent as depicted in Figure 1b. When tasked with finding the painter of the Mona Lisa, the agent first articulates its internal goal: <think> I need to find out who painted the Mona Lisa.

</think>. It then translates this thought into a concrete action, issuing a search tool call with the query who painted the Mona Lisa?. This action triggers a remote tool call to an external search engine. Upon receiving the result, the agent observes it in an <info> block. Each search and info pair represents a single, costly round trip to an external data source.

2.2 Performance and Cost Implications of Remote Data Retrieval.

Heavy dependence on remote data sources creates significant latency and cost bottlenecks. Consider a standard cross-region deployment: an agent powered by a 7B model [33, 34] runs on a single H100 GPU in one region while its external tools (e.g., a Search API) reside in another, introducing 100–300 ms of network delay for every call.

Latency. External retrieval often rivals the model's own inference time. As shown in Figure 1c, for running a search agent model Search-R1 workflow in a single H100, external data retrieval consistently constitutes around 40%-50% of the total execution time, forcing the expensive H100 GPU to remain idle for nearly half of the execution time and leading



(a) Agent-based application architecture.

(b) Example of Agentic LLM.

(c) Search-R1 Latency breakdown.

Figure 1: Agentic workflow and analysis: (a) shows agent serving architecture which interacts with remote data service; (b) is a specific example from Search-R1 [32]; (c) presents the latency breakdown of search queries when running Search-R1 7B on H100.

to a low GPU utilization of approximately 50%.

API rate limit. Beyond latency, agent serving throughput is also often throttled by external service limitations. For instance, commercial cloud APIs like Google Cloud Search [23] impose strict rate limits, i.e. 100 queries per minute per user. This creates a hard ceiling on request volume and introduces a severe bottleneck.

Financial cost. Furthermore, monetary impact can be equally severe. A service, such as Google AI mode, that handles 100 million MAU [52], with an average of 10 tool calls per query [51], would incur \$0.005 per call, or roughly \$150000 in daily API fees, as per Table 1. OpenAI charges \$25 per 1000 tool calls for Web Search functionality [49], more expensively. For perspective, an H100 GPU costs about \$1.49 per hour [1], so daily data-access charges alone can match the expense of 3300+ GPU-hours.

2.3 Access Pattern of the Agentic Workloads

Agentic LLM workloads rely heavily on remote tool calls, whose cost and latency often dominate performance. Caching can mitigate these overheads only if workloads exhibit sufficient locality. To assess this potential, we analyze two representative domains: AI-assisted search and code generation, both of which show statistical structures favorable to caching. Search-oriented agent workloads. Agentic search workloads are ultimately shaped by real-world human interests, which already drive global web search and are becoming more prominent as major engines adopt AI-powered modes [12, 42]. Google Search, for instance, now incorporates agentic features—multi-source synthesis, conversational follow-ups, and contextual memory—that resemble the multistep reasoning of LLM agents. Since commercial query logs are proprietary, we use public Google Trends data as a forward-looking proxy for the query distribution faced by large-scale agentic search systems.

Zipfian Distribution of Search Interests. Search queries follow a Zipfian distribution: a few topics draw most traffic while the majority form a long tail. As shown in Figure 2, head queries

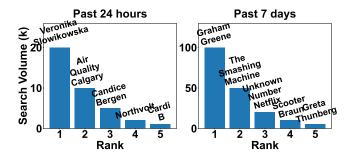


Figure 2: Google Trends data show that the top five topics over different time periods follow a Zipfian pattern. Approximate absolute volumes are used (e.g., "20K+" recorded as 20K), highlighting patterns in AI-assisted search and ranking.

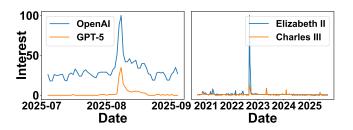


Figure 3: Empirical evidence of search queries resulting in bursty and correlated search patterns. A relevant external event leads to a surge in their search interest, as well as that of the topics with related themes.

like *Veronika Slowikowska* and *Graham Greene* dominate 24-hour and 7-day ranges, whereas thousands of others form the long tail. Caching these "head" topics can thus yield high hit rates with modest storage, greatly reducing remote calls. *Bursty and Correlated Query Patterns*. Beyond a skewed global distribution, the temporal dynamics of queries reveal a second critical characteristic: they are often bursty and correlated. Interest in specific topics can experience sudden spikes

File-ID	1	2	3	4	5	6	7	8	9
Access Freq.	1.0	0.28	0.22	0.14	0.1	0.08	0.04	0.04	0.04

Table 2: Access frequency of code file for SQLFluff [11] repo and coding problems are from SWE-Bench [47] Dev.

in response to external events. As highlighted in Figure 3, these patterns range from technology breakthrough events (OpenAI releasing GPT-5) to major world news (the passing of Elizabeth II and Charles III's accession to the throne). The key implication for system design is twofold: caching strategies must be time-adaptive to absorb sudden spikes and can exploit topic correlations for proactive prefetching.

Code-agent workloads. While search-driven agents reflect global information demand, agentic LLMs are also widely used for code generation and software maintenance, which show a similarly skewed access pattern. To examine this, we analyzed coding tasks from SWE-Bench [47] on the sqlfluff [11] repository and measured how often each file is needed across tasks. As shown in Table 2, file accesses follow a near-Zipfian distribution: one file is required by nearly all tasks, a few core modules are reused heavily, and most files are rarely touched. This long-tail pattern parallels the popularity skew seen in search workloads. This also implies that caching these hot files locally can eliminate many redundant cross-region fetches, and semantic matching can further capture requests that refer to the same file.

2.4 Motivation and Cache Limitations

Motivation. Search-style and coding tasks show zipfian popularity with bursty reuse, suggesting that caching could greatly reduce redundant remote calls. Yet user queries in agentic workloads are semantically aligned rather than exactly keymatched, and they run in dynamic environments with practically complex factors like cross-region latency, retrieval cost, and tool API limits. A useful cache must handle *semantic matching* among queries while accounting for *cost*, *cross-region latency*, and *tool rate limits*.

Existing caches and limitations. There are three common flavors of caching approaches, as summarized in Table 3, namely, transformer key-value (KV) caches [22, 36, 41], semantic prompt caches [9, 24, 56, 65], and traditional storage caches [13,59] or file system [21]. Despite their popularity, the existing caching mechanisms exhibit significant drawbacks when coming to cache agentic workloads.

The first, transformer KV caches, accelerate token generation by reusing intermediate tensors for exactly-matched prompts, but its scope is confined to inference computation and does not extend to the remote data access layer. The second, semantic prompt cache, attempts to bypass inference entirely by matching user inputs via vector similarity. However, this approach suffers from an unfavorable precision-recall

trade-off: vector proximity often fails to capture true semantic equivalence, so a query like "apple nutrition facts" might incorrectly match "Apple stock price analysis". As a result, it is unreliable for production use and does not support semantic match completely. Also they only consider initial user prompt query and don't focus on costly cross-region knowledge/tool call. As for the data storage cache [50] in databases or file systems, although many studies have explored cross-region scenarios, their exact-match mechanisms are fundamentally inadequate for natural language queries in agent workloads. These systems treat semantically equivalent queries as distinct keys, so even minor wording changes trigger cache misses and unnecessary remote calls. Additionally, none of these caches fully addresses rate limits impact in agent scenario, so agent throughput can still be throttled even when cache hits. **Takeaway.** Agentic workloads require a cache that performs semantic match at the knowledge or tool boundary, validates correctness, is cost-aware, cross-region and rate-limit aware so that hits yield real end-to-end gains. In contrast to these existing families, Asteria satisfies all properties in Table 3, motivating its design in the next section.

3 Design Overview

3.1 System Model and Goal

Deployment model. For large language model (LLM) agents that rely on external knowledge, frequent data retrieval from remote sources introduces significant latency and financial cost. This challenge is particularly pronounced when the serving LLM and knowledge base are deployed across regions rather than in the same on-premise cloud. In practice, agentic applications typically rely on MCP protocol [4] or other general RPC mechanisms [25] over wide-area networks to fetch the required data, amplifying these performance and cost penalties. To mitigate these overheads, we introduce Asteria, a novel cross-region caching system designed to store and serve frequently accessed knowledge from the perspective of agentic system efficiency.

Optimization Goal. The goal of Asteria is to reduce costly remote data accesses by reusing semantically equivalent knowledge. Instead of relying on literal text similarity or exact matching, Asteria leverages LLM-based semantic matching to identify and serve cached results for new queries with the same intent. This reduces query latency and significantly cuts API or tool usage costs, improving performance and operational efficiency in geo-distributed LLM agent deployments.

3.2 Design Opportunities and Challenges

Strawman design. As discussed in subsection 2.4, semantic prompt caches reuse model outputs based on embedding similarity. A natural strawman is to extend this idea: embed each cached retrieval query, place all keys in an ANN index, and on

Table 3: Cache comparison along critical requirements of agentic workloads.

System	Cached data	Semantic Match	Cost-aware Eviction	Cross-region Aware	Rate-limit aware
Transformer KV-cache [22, 36, 41]	Token KV states	Х	Х	Х	Х
Semantic prompt cache [9, 24, 56, 65]	LLM outputs	X *	Х	X	Х
Traditional storage cache [13, 21, 59]	KV object	X	✓	✓	Х
Asteria	External knowledge	✓	✓	✓	✓

^{*}Semantic prompt cache performs vector similarity matching but lacks correctness validation.

a new query, return the value attached to its nearest neighbor. ANN methods [31,35] can search large embedding sets efficiently using graph structures or quantization. However, this naive design exposes key gaps. It treats similarity search as if it were a cache, yet offers no guarantee that top-ranked items are actually correct, fresh, or cost-efficient to reuse. These issues motivate the following design challenges.

Challenge 1: Ensuring accurate and valid semantic matches. Embeddings with ANN can reliably find and return textually similar queries, but textual or surface-level similarity [15] does not imply semantic equivalence. Two queries can be near in the vector space yet require different answers or reflect different intents. Correctness also depends on context and time. A match for a historical fact may remain valid, whereas a match for a fast-evolving topic can become stale. A practical system needs a validation mechanism that turns noisy similarity scores into trustworthy hit-or-miss decisions while accounting for both contextual fit and temporal validity.

Challenge 2: From similarity search to a real cache. An embedding model and an ANN index are retrieval components, not a cache. They are typically used to search an entire corpus and return a ranked list of candidates. A cache, in contrast, is a capacity-limited, online component that must emit a deterministic hit signal, admit new items, evict old ones, respect freshness, and avoid polluting itself with nearmisses. Using ANN as the front door of a cache forces several questions to be answered explicitly: when does a candidate become a cache hit rather than just a similar item; what metadata beyond the embedding are required to reason about staticity, cost, and scope; how should admission and eviction operate when items differ in lifetime, retrieval cost, and size; and how can we prefetch likely next items without undermining precision. Bridging this gap is essential to turn similarity search into a functional cache rather than a best-effort lookup.

Challenge 3: Achieving sophistication with efficiency. Incorporating semantic validation, freshness reasoning, and predictive prefetching improves quality at the expense of higher compute and memory consumption. The system must integrate these capabilities while ensuring that the end-to-end savings from avoided remote calls outweigh local overheads, thus necessitating lightweight models, careful resource sharing with the serving LLM, and scheduling that protects user-facing latency.

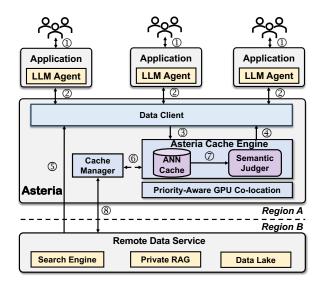


Figure 4: Asteria's agentic caching architecture where agent LLM and data source reside in two geo-distributed regions

3.3 Asteria Architecture Overview

To address these three challenges, Asteria adopts a layered architecture shown in Figure 4. Each component is explicitly designed to tackle a subset of these challenges while working together with other components as an integrated system. The top tier is the *user agentic application*, where an LLM agent generates queries. The bottom tier is the Remote Data Service, the source of data, located in a remote region or cloud with a data retrieval latency around 300 ms-500 ms, following the common industrial practice [40]. Between these two lies the Asteria Engine, which provides a transparent caching interface. It consists of three primary internal components:

Data client. The *data client* serves as the transparent entry point into the Asteria system, which intercepts all outgoing requests generated by the agent before they can reach external services. This interception allows Asteria to seamlessly redirect the agent's queries into its internal caching workflow without modifying the agent application.

Asteria cache engine. At the core of the engine is the retrieval pipeline, engineered to achieve high-precision semantic matching. This pipeline operates in two distinct stages to balance speed with accuracy. Initially, an ANN index [31] (Faiss [16] is used in our experiments.) based cache rapidly

identifies a set of candidate data items based on vector similarity. These candidates are then passed to a lightweight *semantic judger* model (typically small with \sim 1B parameters), which acts as a validation, being prompted to scrutinize each one for true contextual and semantic relevance to eliminate the false positives that plague naive semantic query caches.

Agent-aware cache manager. Finally, the agent-aware cache manager provides the system's long-term intelligence by intelligently governing the cache's contents. Moving beyond simple heuristics, it employs two sophisticated strategies. Its adaptive eviction policy uses a utility-based model to decide which items to discard by considering factors like retrieval cost and importance to the agent's workflow. Complementing this, its proactive prefetching mechanism analyzes historical access patterns to proactively fetch data that is likely to be needed, ensuring the cache is dynamically optimized to hold the most valuable information.

Workflow The workflow begins when the data client transparently intercepts a structured request and its surrounding context generated by the LLM agent (1)-2). Instead of immediately dispatching the request externally, it first queries the Asteria cache engine (3). This query initiates a two-stage retrieval process designed for speed and accuracy. First, an ANN index rapidly surfaces a small set of candidate data items. Then, these candidates are scrutinized by the semantic judger (⑦), ensuring accuracy. If the judger confirms a valid match, the cached result is returned instantly to the agent (4). Otherwise, the request proceeds to the appropriate Remote Data Service (⑤). The retrieved response is then returned to the agent and simultaneously stored in the cache as a new Semantic Element for future usage. Concurrently, the agent-aware cache manager observes the sequence of validated queries (6), using this history to proactively prefetch data items (®) and perform eviction, continuously optimizing the cache's contents in the background.

4 Asteria's Design

In this section, we present Asteria's architecture, highlighting how it transforms raw agent interactions into reusable knowledge units and orchestrates caching, retrieval, and scheduling to achieve fast, accurate, and cost-efficient performance.

4.1 Semantic Element

We begin with the *Semantic Element (SE)*, the core building block and caching unit in Asteria. An SE organizes an agent's *query/action* and the corresponding *retrieval result* so that later components can match, validate, and manage for reuse. As shown in Figure 5, an SE is a key-value pair: the agent's query or tool action is the semantic key, and the retrieved information is the value. This structure leverages well-formed agentic outputs that wrap steps with tool tags. For example, the query "Who painted the Mona Lisa" within a <search>

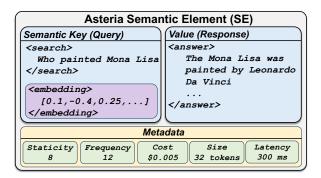


Figure 5: Asteria's semantic element structure

tag becomes the key, while the snippet in the <info> tag is the value. By reliably parsing these tagged blocks, Asteria encapsulates discrete interactions (web searches, API calls, database lookups) into coherent SEs for caching.

An SE also carries metadata essential for lifecycle decisions. First, an embedding model (e.g., Qwen3-0.6B [60]) converts the semantic key into a high-dimensional vector used as a semantic fingerprint and is used for future matching. Concurrently, a lightweight staticity score model (we reuse the semantic judge model in subsection 4.2) scores the *staticity* of the query–result pair on a 1–10 scale, indicating how fact-like and time-invariant the answer is. A higher value indicates a more fact-oriented response. For instance, the location of the Louvre Museum is *stable* (e.g., 10), whereas weather is *ephemeral* (lower). The system also records access frequency, retrieval latency, cost, and size (token length) per SE, quantifying the overhead of the original tool call. As detailed in subsection 4.3, these signals drive cost-aware eviction and prefetching.

4.2 Sine: Semantic Retrieval Index

We now describe how Asteria retrieves semantically appropriate matches efficiently via the *Semantic Retrieval Index (Sine)*. Building on SEs, Asteria implements a high-throughput, dual-stage retrieval pipeline engineered to resolve the fundamental trade-off between retrieval speed and semantic precision. This system is a sophisticated interplay of multiple specialized models, and its core is a formal constrained optimization problem: to minimize end-to-end query latency while rigorously maintaining semantic accuracy.

To formalize this, we define the components and their associated latencies. The primary model is the agentic LLM, a powerful reasoning model that orchestrates tool use; its inference time is denoted as $L_{\rm Agent}$. The cache itself relies on two smaller, highly optimized models: a lightweight *Embedding LLM* for generating query vectors and a lightweight *semantic judger model* (LSM), a classifier that validates whether a cached result answers a new query and estimates its staticity. The combined latency of a full two-stage cache lookup/check

is $L_{\text{CacheCheck}} = L_{\text{ANN}} + L_{\text{LSM}}$. On a cache miss, an external tool call adds L_{Tool} .

Coarse-grained filter. The retrieval process begins with a high-recall candidate selection stage, where the threshold τ_{sim} (e.g., 0.9 in our setup) directly controls the scope of the search. When the Agent LLM generates a new query, q, the system consults an ANN index. A candidate c_i is selected if its similarity satisfies CosineSimilarity (q, $q_{\text{cached},i}$) $\geq \tau_{\text{sim}}$, where $q_{\text{cached},i}$ denotes the query of c_i . A lower, more permissive τ_{sim} increases recall, ensuring more potentially relevant items are passed to the next stage, but at the cost of increasing the validation workload. A higher, stricter τ_{sim} reduces this workload but risks prematurely discarding a correct match, thus lowering the potential hit rate.

Fine-grained validation. Selected candidates proceed to a high-precision semantic validation stage, where the LSM's threshold, $\tau_{\rm lsm}$, is the primary lever for controlling accuracy (e.g., 0.9 in our experiment). The LSM evaluates if the cached result $r_{{\rm cached},i}$ is a sufficient answer for the new query q, producing a confidence score $S_{\rm lsm}$. A cache hit is confirmed only if $S_{\rm lsm} \geq \tau_{\rm lsm}$. A higher $\tau_{\rm lsm}$ enforces a stricter standard for equivalence, which increases the cache's precision (fewer false positives) but can decrease the hit rate by rejecting marginally correct answers. A lower $\tau_{\rm lsm}$ boosts the hit rate but at the direct risk of serving more incorrect results, thereby lowering precision.

Optimization goal. The system minimizes expected latency subject to a target precision that is verified *periodically offline*. A hit incurs $L_{\rm hit} = L_{\rm Agent} + L_{\rm CacheCheck}$, while a miss incurs $L_{\rm miss} = L_{\rm Agent} + L_{\rm CacheCheck} + L_{\rm Tool}$:

$$\underset{\tau_{\text{sim}},\tau_{\text{lem}}}{\text{minimize}} \quad E[L] = P_{\text{hit}} \cdot L_{\text{hit}} + (1 - P_{\text{hit}}) \cdot L_{\text{miss}}.$$

Recalibration A fixed τ_{lsm} is brittle under workload drift or changing correctness requirements. Asteria therefore performs periodic offline recalibration to adjust the LSM decision boundary while keeping the agent's latency-critical path unaffected. This process, detailed in algorithm 1, begins by creating a high-quality annotated dataset from a sample of recent queries (line 1-6). For each sampled query, a Ground-Truth Evaluator provides the correct result, allowing the system to label the cache's original answer as "correct" or "incorrect". The objective is then to find a new threshold, $\tau_{lsm}^{\prime},$ that aligns the cache's performance on this dataset with a pre-defined metric, P_{target} . This target precision represents the desired quality standard (e.g., 0.99 for 99% correctness). To find the new threshold, the system calculates a precision curve for the current LSM (line 7-8) and identifies the value that satisfies P_{target} (line 9), which is then deployed to the live system.

Crucially, this recalibration is highly cost-efficient: in our deployment it samples 5 recent queries per minute, adding negligible overhead. The annotated set can also fine-tune the LSM to better capture subtle semantic differences over time.

Algorithm 1: Periodic Threshold Recalibration

```
Data: Current LSM J_{lsm}, Target Precision P_{target},<br/>
Recent Eval Log L_{recent}, Validation Set D_{val}Result: Recalibrated Threshold \tau'_{lsm}1 D_{sample} \leftarrow Sample diverse subset from L_{recent}2 D_{annotated} \leftarrow \emptyset3 for (q, r_{cached}, ..., ...) \in D_{sample} do4 | r_{ground} \leftarrow FetchGT(q)5 | label \leftarrow EvaluateGT((q, r_{cached}), r_{ground})6 | D_{annotated}.Append((q, r_{cached}, label))7 scores \leftarrow PredictScores(J_{lsm}, D_{val})8 precision_levels \leftarrow CalcPrecisionCurve(scores)9 \tau'_{lsm} \leftarrow FindThreshold(precision_levels, P_{target})10 UpdateSystem(\tau'_{lsm})11 return \tau'_{lsm}
```

Algorithm 2: LCFU Eviction Policy

```
Data: Cache, capacity
1 Function CalScore(se)
       ttl \leftarrow se.ExpirationTime - CurrentTime()
       if se.Size == 0 or ttl <= 0 then
3
 4
           return 0;
       return score ←
5
         log(se.Freq+1) \times log(se.Cost \times 10^3 + 1) \times log(se.Lat+1) \times log(se.Stat+1)
6 Cache.RemoveExpired() // TTL purge first
7 if Cache.Usage() > capacity then
       foreach se in Cache do
           se.score \leftarrow CalScore(se)
10
       while Cache.Usage() > capacity do
11
           victim \leftarrow items.PopFirst()
           Cache.Remove(victim)
12
```

Algorithm 3: History-Based Predictive Prefetching

```
Data: Current SE se, MarkovModel model, ConfidenceThreshold θ, Cache
1 predictions ← model.predict(se.GetQuery());
2 foreach (q, p) in predictions do
3  if p ≥ θ and not Cache.Contains(q) then
4  Prefetch(q)
```

4.3 Building Cache Architecture Atop Sine

Although the Sine index can identify semantically matched items, it is not by itself a cache. To bridge the gap, Asteria layers standard cache abstractions on top of the Sine, defining *cache hit*, *cache eviction* and *cache prefetching* and translate semantic matching signals into cache behavior.

Semantic-aware cache hit. Unlike traditional caches where a hit is a simple key lookup, in our system a cached SE is only considered a "hit" after passing the full validation pipeline detailed in subsection 4.2. On a new query, ANN retrieves a small set of candidates from the cache. Then the LSM (semantic judger) validates equivalence. Only a valid match registers as a cache hit, and that increments an SE's frequency count. This process effectively transforms a probabilistic similarity score into a definitive, binary hit/miss event, providing the stable, deterministic bedrock.

LCFU eviction policy. With a reliable access signal established, we employ a tailored *Least Cost-Efficient and Frequently Used* (LCFU) eviction policy to manage the cache's contents. The fundamental insight behind LCFU is that not all data are equally beneficial for overall financial and latency savings. Traditional LRU and LFU policies, which prioritize recency and frequency respectively, fail to account for the varying value of cached items. LCFU addresses this by assigning each SE a value_score that quantifies the benefit of retaining it.

As detailed in algorithm 2, this value_score is a composite metric derived from retrieval latency and cost, frequency, and staticity. Then the score is carefully normalized (line 5). It adjusts the raw metrics for frequency and cost to ensure they always contribute positively and meaningfully. This prevents new items or those with low costs from being unfairly penalized, given the fact that the cost per request is less than 1, and taking its logarithm will return a negative value. This combined score is then normalized by the item's size to provides a direct rationale: keep items that save the most time/money per byte.

For instance, data with a high Retrieval Cost and high access Frequency will naturally receive a higher value_score, making them less likely to be evicted. Conversely, ephemeral data with a lower Staticity will easily lead to lowering value_score, making it a more likely candidate for eviction even if its frequency is high. For one Stable data, with a large staticity and high retrieval cost, it will maintain a higher value_score even with less frequent access. This multi-attribute approach prevents transient but popular data from displacing enduring content, optimizing the cache for sustained performance and cost savings. When cache capacity is exceeded, items with the lowest value_score are evicted, preserving the most valuable content.

While a high value_score indicates valuable content, such entries can become stale if kept indefinitely. To prevent outdated information from persisting, Asteria integrates an aging mechanism using a user-defined Time-To-Live (TTL). Each cache entry is assigned a maximum lifespan, after which it is evicted regardless of its value_score. This ensures that even high-cost or frequently accessed items are periodically refreshed, maintaining the cache's correctness while preserving the benefits of value-based retention.

Predictive prefetching. To complement the reactive LCFU

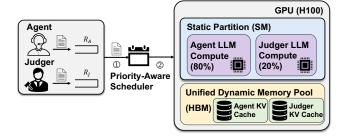


Figure 6: Asteria's Priority-Aware Scheduling Procedure. The agent and judger send requests to a priority-aware scheduler, which provisions the Unified Dynamic Memory Pool opportunistically when the Static Partition reaches its limit.

eviction policy, our framework employs a proactive historybased predictive prefetching to further reduce miss latency, leveraging the temporal correlations observed in agent workloads. This technique operates by learning query-to-query transition patterns from the stream of confirmed hits. Using a lightweight first-order Markov model, it calculates the probability $P(q_{i+1}|q_i)$ that one query will follow another, as shown in Algorithm 3 (line 1). A prefetch is triggered only if this probability exceeds a confidence threshold and the item is not already in the cache (line 3). This initiates an asynchronous fetch to add the item to the cache (line 4). A prefetched item enters the cache as a new SE with zero frequency. Consequently, its initial score is minimal. If the item is later requested and confirmed by the judger, its frequency is incremented, raising its value score and making it a valuable, retained member of the cache. If it remains unused, its low score makes it a prime candidate for eviction by LCFU when space is required. This creates a low-risk, self-correcting system that minimizes cache pollution from speculative fetches.

4.4 Resource-Efficient Model Co-location

Although the two-stage retrieval computation is lightweight, the existing serving framework [63] adopts one model per GPU mode. To keep overall latency low and achieve high-precision without doubling hardware costs, Asteria co-locates the agent (e.g. \sim 7B) and judger (e.g. \sim 1B) efficiently on a single GPU.

The central challenge is managing resource contention to protect the agent's user-facing latency from the judger's background processing. Our co-location architecture is built on a key insight: agent and judger workloads have fundamentally different priorities and resource profiles. Agent work is latency-critical, while judger work is a deferrable optimization. This is because a delayed validation does not block the user; at worst, it is treated as a cache miss, where performance for that single request degrades to the non-cached baseline of a full remote data call. Furthermore, the judger has a smaller memory demand since its prefill-only inference pattern (sin-

gle token generation), results in a minimal and predictable KV cache footprint. Based on these principles, Asteria implements a two-level defense, shown in Figure 6, to ensure robust and efficient co-location.

Coarse-grained asymmetric partitioning. The foundation of our co-location strategy is to exploit the fundamentally asymmetric nature of the agent and judger workloads. The judger's workload profile is highly economical: unlike the agent which generates variable-length responses, the judger performs a classification task that yields a single token. This makes its primary consumer of GPU memory (i.e., the KV cache) minimal and highly predictable. Furthermore, its computational needs are lighter than the agent's complex, multistep reasoning. To capitalize on this, we use the CUDA Multi-Process Service (MPS) [48] to create a static, asymmetric compute partition, as shown in Figure 6. For instance, we allocate the dominant share of compute resources (e.g., 80%) to the agent and a smaller, sufficient share (e.g., 20%) to the judger. This coarse-grained partitioning optimizes for the common case, maximizing the performance of the primary agent LLM by dedicating the vast majority of resources to it. Fine-grained prioritization as a high-load guardrail. While static partitioning is effective for the common case, a second, dynamic layer of defense is required to handle periods of high contention and guarantee the agent's low latency. This is the role of our fine-grained, priority-aware admission controller, which manages the unified dynamic memory pool (M_{dynamic}) . This scheduler acts as a crucial guardrail by enforcing a strict prioritization policy. It services the agent queue (Q_A) exhaustively, only considering a batch from the judger queue (Q_J) when the agent queue is empty or lacks sufficient memory for the next dispatch. This ensures that the deferrable, internal work of the judger can never block the critical path of a user-facing agent task. This two-level defense—an asymmetric static partition for baseline efficiency and a dynamic priority scheduler for worst-case protection—is what enables robust, high-performance co-location.

5 Implementation and Discussion

Asteria is implemented in Python atop vLLM [63], which we use as the high-throughput serving layer to transparently intercept external tool calls and plug into existing agent applications (e.g., Search-R1 [32]). For colocation, we rely on CUDA MPS to let multiple processes share a single GPU context—avoiding OS-level context-switching overhead—and partition resources by setting CUDA_MPS_ACTIVE_THREAD_PERCENTAGE.

Judger accuracy. Our framework bridges the gap between caching and semantic knowledge reuse by providing a unified cache abstraction for LLM agents, and it leverages powerful LLM-based techniques from prior research to ensure strong accuracy. The semantic judger can be easily fine-tuned or replaced for specific workloads, so its accuracy can be improved

with minimal effort when needed. Given the rapid progress of small LLMs, we find this sufficient for practical use and view the judger as a pluggable component. In practice, Asteria maintains high precision via strong semantic models and periodic recalibration, with misses falling back to live fetches to preserve correctness.

6 Experiment

6.1 Experimental Setup

Testbed. We emulate a realistic cross-region deployment. The LLM agent and all Asteria components run on an onpremise H100 cluster; remote data services run in a separate region. For search agent, we use the public Google Cloud Search API whose per-request average latency ranges between 300–500ms depending on response length, consistent with prior work [40]. For coding, we use a self-deployed FAISS [16]-based RAG service [16] with an average 300 ms round trip.

Models and workloads. We evaluate two agentic scenarios: AI-powered search and code generation. The search agent is Search-R1-7B [33, 34] (post-trained from Qwen-2.5 7B [2]); the coding agent is Qwen-3 8B [3]. Asteria uses Qwen-3 0.6B models for embedding and semantic judging [60, 61]. Asteria's internal embedding and semantic judging functions are powered by the lightweight 0.6B models from the Qwen-3 family [60,61].

Search workloads. Following the Google Trend access patterns in subsection 2.3, we construct: (i) Skewed workload: extracting the Google-like head—tail access pattern in subsection 2.3, we instantiate four search benchmarks–Zilliz-GPT [68], HotpotQA [7], Musique [8], and 2Wiki-Multi-Hop [6]. For each dataset, we apply k-means to the questions and keep 10 representative clusters, sampling \sim 250 questions and constructing the skewed popularity per dataset (1000 total) and (ii) Trend-driven workload. We capture 12-hour Google Trends time series for four topics, map them to HotpotQA questions, and compress them into a 10-minute trace to mimic sharp traffic spikes (subsection 2.3).

SWE-Bench workload. We use a subset of widely-used SWE-Bench_oracle [47] targeting the sqlfluff repo [11], where the agent resolves GitHub issues. Each request represents one issue. This stresses caching because multiple issues repeatedly access shared files, such as core files and project documents. Baseline systems. To evaluate the end-to-end performance of an agent system, we compare three primary configurations, all built atop the vLLM framework [63] for fair comparison. We compare: Agent_vanilla (no cache; every request hits the remote API), Agent_exact (traditional exact-match KV cache), Agent_Asteria (our full system), and an ablation Agent_ANN that uses only ANN similarity. As Agent_ANN is impractical for production (subsection 3.2), we restrict it to accuracy analysis (subsection 6.6).

Metrics. We report throughput (req/s), latency (ms), cache hit rate (% served from cache), and operational cost (external API fees + GPU compute).

6.2 Overall Performance On Cache Ratio

Using the setup above, we vary the cache size ratio and report throughput, cache-hit rate, and latency across three workloads. Skewed workload. We first evaluate Asteria on search benchmarks that exhibit a head–tail popularity skew, a key access pattern from subsection 2.3, to show the benefits of semantic matching. As shown in Figure 7, Asteria outperforms the baselines across throughput, cache hit rate, and latency on all four datasets (Zilliz-GPT, HotpotQA, Musique, and 2Wiki). For instance, on Musique, Agent Asteria achieves up to a 3.6× higher throughput than Agent exact, driven by its superior cache efficiency: Agent_Asteria sustains over 85% hit rates while the exact-match cache stays below 20%. This high hit rate reduces end-to-end latency by up to 4× and minimizes reliance on external APIs, avoiding rate limits such as the Google Search API's 100 queries per minute cap. Note that absolute latencies exceed raw network RTTs because requests to external APIs experience queueing and backoff under rate limits, which inflates latencies, as will be shown in subsection 6.4. This performance gap stems from semantic diversity. Agent_exact fails on syntactic variations, yielding few cache hits, while Agent_Asteria groups semantically similar queries, converting semantic locality into high cache efficiency.

Trend-driven workload. We next evaluate Agent_Asteria on bursty workloads synthesized from Google Trends to test its adaptability. As shown in Figure 8, it achieves up to a 3.8× throughput improvement over the Agent_vanilla baseline. This gain stems from its ability to maintain a high cache hit rate of nearly 95%, effectively absorbing the intense but temporary demand of each trending topic. This performance gain comes from the LCFU eviction policy, which is tailored for temporal dynamics. Traditional caches retain obsolete data from past trends, reducing effective capacity. In contrast, LCFU integrates an item's staticity into its priority score. As a volatile topic's popularity wanes, its cached entries are automatically deprioritized and become prime candidates for eviction. This self-cleaning mechanism ensures that cache space is continuously reclaimed for the next wave of content, which is crucial for maintaining high performance during bursty events.

SWE-Bench workload. To demonstrate the generalizability of our approach, we evaluate Agent_Asteria on a code generation workload using the SWE-Bench. As shown in Figure 9, the results reveal a significant 20% throughput improvement over both Agent_vanilla and Agent_exact, driven by a cache hit rate approaching 45%. While more modest than the search results, these gains are highly impactful for the complex domain of software engineering and validate the versatility of our caching approach. The caching opportunity in this do-

main arises from shared file dependencies across tasks, such as when an agent resolves multiple GitHub issues within the same repository. A traditional cache like Agent_exact is ineffective because it treats requests for different parts of the same file as distinct misses. Agent_Asteria, however, semantically identifies the shared file context, enabling it to serve these requests from the cache. Although the inherent diversity of coding tasks leads to a lower overall hit rate compared to search, serving nearly half of all file access requests locally provides a substantial reduction in latency and system load.

6.3 Scalability Under Concurrency

To assess the Asteria's scalability under realistic workloads, we evaluate its end-to-end throughput with varying request concurrency. We use the Musique dataset at a fixed cache ratio of 0.4, a representative setting from our prior analysis. As shown in Figure 10, the results highlight Asteria's significant scalability advantage, delivering up to a $5.7 \times$ and $4.5 \times$ throughput improvement comparing to the baselines. While the baseline systems quickly saturate, Agent Asteria demonstrates strong scaling, achieving a throughput of 4.89 req/s at a request rate of 8. This represents a $4.5 \times$ improvement over Agent_exact (1.09 req/s) and a 5.7× improvement over Agent_vanilla (0.86 req/s) under heavy load. The throughput for both Agent_vanilla and Agent_exact plateaus early, at just around 1 reg/s. This is because their performance is fundamentally bound by the remote data retrieval. With low cache hit rates, nearly every request involves a high-latency external API call, waiting for these remote responses. Increasing concurrency merely leads to longer queues, not higher throughput. In contrast, Agent_Asteria's throughput scales nearly linearly with concurrency up to a request rate of 8, where high cache efficiency serves most requests locally and fully utilizes GPU parallelism—driving the agent to hardware-level capacity.

6.4 Performance Breakdown

Latency analysis. To isolate pure request latency without rate-limit effects, we measure single-request breakdowns at low concurrency (Figure 11). While the core agent inference time remains constant at 0.6 s for both systems, Asteria cuts the total latency from 1.08 s in the vanilla agent down to just 0.61s. This is achieved by almost entirely eliminating the 0.48 s external retrieval bottleneck that dominates the baseline's execution time. In its place, Asteria introduces a minimal and predictable local overhead of only 0.05 s, comprising 0.02 s for cache retrieval and 0.03 s for judger validation. This highly advantageous trade-off, which swaps a costly 0.48 s remote call for a swift 0.05 s local computation, validates our core design principle: the marginal cost of intelligent local caching is vastly outweighed by the savings from avoiding slow remote data fetches.

Cloud API rate limit and throughput analysis. We then

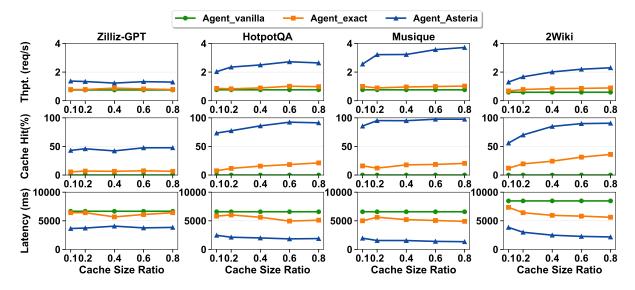


Figure 7: End-to-end agent serving throughput on skewed search workload under different cache ratio, zipfian-0.99 distribution

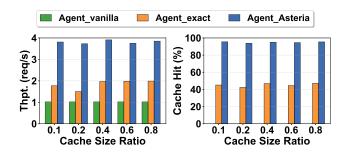


Figure 8: End-to-end agent serving throughput on trenddriven workload under different cache ratios

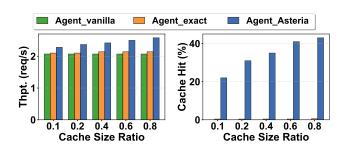


Figure 9: End-to-end agent serving throughput on SWE-Bench workload under different cache ratios

Table 4: Normalized throughput comparison between w/o. API Rate Limit and w. API Rate Limit

	Without API Rate Limit	With API Rate Limit
Agent_vanilla	1	1
Agent_Asteria	1.5	4.16

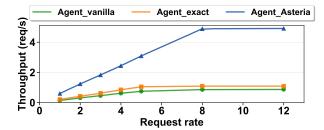


Figure 10: End-to-end Throughput Under Varying Request rate/concurrency on Musique Dataset

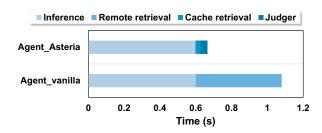


Figure 11: Per-request End-to-end Performance Breakdown

study throughput under realistic load where rate limits matter (Figure 12). Beyond reducing single-request latency, Asteria significantly enhances system throughput and scalability by mitigating the critical bottleneck of external API rate limits. This is achieved by fundamentally reducing the system's reliance on external services, as demonstrated in Figure 12. Due to high cache miss rates, the non-cached Agent_vanilla baseline generates approximately 1300 external API calls for the given task, leading to significant throttling and a high retry ratio of 25%. In stark contrast, Agent_Asteria slashes the API

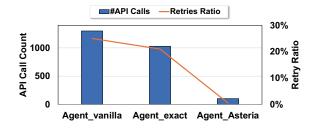


Figure 12: Data Retrieval Call and Retries Ratio

Table 5: Cost and performance comparison across different configurations.

Metric	Agent_vanilla	Asteria w/o Sharing	Asteria
API Cost (\$)	6.5	6.5	0.64
GPU Cost (\$)	76	152	76
Total Cost (\$)	82.5	158.5	76.64
Thpt. (req/s)	0.87	4.74	4.89
Thpt./Cost (req/s/\$)	0.01	0.03	0.06

call count to just 103, a 92% reduction. This efficiency virtually eliminates throttling, cutting the retry ratio to a negligible 0.50%.

To quantify how this API traffic reduction translates into a throughput advantage, we run a controlled experiment as shown in Table 4. We use a self-deployed RAG data service with 300 ms here as we cannot cancel API rate limit for Google service. Even without rate limits, Asteria already provides a $1.5\times$ throughput improvement over the vanilla system due to its inherent latency savings. However, when a realistic API rate limit is enforced, the advantage becomes far more pronounced, with Asteria achieving a $4.2\times$ throughput gain over the throttled baseline. This comparison reveals that avoiding the rate-limiting bottleneck alone contributes an additional $2.8\times$ improvement. By serving most requests locally, Asteria sidesteps rate-limit bottlenecks and scales robustly.

6.5 Cost Analysis

Beyond performance, another critical aspect of deploying agentic systems is operational cost. We now analyze the costefficiency of Asteria by evaluating three configurations under peak load on the Musique dataset (similar to subsection 6.3): Agent_vanilla; Asteria w/o Sharing, which uses an extra GPU for the semantic judger; and the complete Asteria system. As detailed in Table 5, our analysis reveals that Asteria is not only faster but fundamentally more economical, delivering $6 \times$ more throughput per dollar than the vanilla baseline.

This cost advantage stems from resolving the API–compute trade-off. The Agent_vanilla system shows a total cost of \$82.5 to achieve a low throughput of 0.87 req/s. The Asteria w/o Sharing configuration illustrates the pitfall of a naive caching approach. While dramatically boosting throughput to 4.79 req/s, it does so by requiring a dedicated second GPU

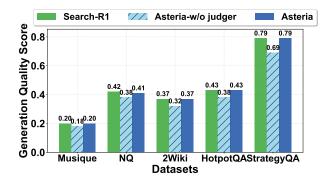


Figure 13: Generation quality comparison between Asteria and vanilla Search-R1 (Agent vanilla)

Table 6: The benefits brought by LCFU.

Metric	Agent_LRU	Agent_LFU	LCFU
Cache hit (%)	0.88	0.89	0.86
Throughput (req/s)	2.14	2.16	2.35

for the semantic judger, doubling the GPU cost from \$76 to \$152 and making it the most expensive setup (\$158.5). In contrast, our co-located design cuts API cost by >90% (to \$0.64) without extra hardware, keeping total spend at \$76.64 while retaining \geq 95% of the two-GPU throughput. Thus, Asteria delivers \sim 5.6× more performance at a similar cost, making it both fast and financially sustainable.

6.6 Accuracy Analysis

Then, we evaluate whether caching affects correctness by measuring Exact Match score [19], where the answer must match ground truth, as [32]. As shown in Figure 13, Asteria delivers efficiency without degrading accuracy. The Asteria-w/o judger baseline, which relies solely on ANN similarity, shows accuracy drops across datasets; e.g., on StrategyQA it reaches 0.69 vs. 0.79 for the baseline, showing the risk of naive semantic caching—vector similarity can return related but wrong results. In contrast, the full Agent_Asteria matches Agent_vanilla in accuracy, with the Semantic Judger validating ANN candidates and rejecting non-equivalent ones. It confirms Asteria achieves high caching efficiency without sacrificing correctness.

6.7 Deep Dive

LCFU study. We tested our LCFU policy against LRU and LFU strategies on the HotpotQA workload, as shown in Table 6. While LFU achieved a higher hit rate (0.89 vs our 0.86), our policy delivered higher performance with up to 9% compared to LRU and LFU eviction policy, respectively. This trade-off is intentional: rather than maximizing hit rate, our

Table 7: Co-location efficiency on H100.

Metric	Dedicated-2GPU	Co-located (MPS 80/20)
Throughput (req/s)	2.89	2.72
p99 latency (ms)	6601	7230

policy prioritizes caching expensive-to-retrieve items, resulting in better system-wide latency reduction.

Co-location study. Co-locating the Agent and Semantic Judger on a single A100 via CUDA MPS (80/20), at a representative cache ratio (0.6), retains 94% of dedicated throughput (2.72 vs. 2.89 req/s) with a 9.5% increase in p99 latency, indicating a near-baseline efficiency.

Recalibration overhead. We also quantify the cost of threshold recalibration for the semantic judger using HotpotQA/Musique. Compared to a variant without recalibration, throughput decreases by only 2%. This bounded cost comes from brief offline validation on small samples to keep the precision target, stabilizing accuracy under drift and preserving high-precision hits. In practice, the overhead is negligible relative to Asteria 's gains.

7 Other Related Work

Semantic prompt caching. Recent LLm serving systems [9, 24, 56, 65] like Google Apigee [24]) match via text embeddings to bypass expensive LLM inference; ContextCache [65] caches multi-turn responses; VertorQ [56] adapts thresholds for similar prompts. However, these approaches are largely inward-facing (optimizing inference) and typically single-cloud/node, leaving the cross-region remote data bottleneck unaddressed. In contrast, Asteria targets the external-data layer, caching remote knowledge to cut latency and cost while complementing inference-side optimizations. Traditional and multi-cloud caching. Beyond semantic schemes, caches rely on heuristics (LRU/LFU/TTL) and cache-aside patterns [62] with Redis [54] or Memcached [45]. Cross-region deployments introduce latency, consistency, and cost trade-offs. Examples include Macaron [50] (autotuned tiers cutting data-lake costs under write-through), EV-Cache [46] (eventual consistency via Kafka), Azure Cache for Redis (passive cross-region replication with client colocation), and Alluxio [38] (global namespace for on-demand hot data). These architectures assume exact-match keys and do not reason about semantic equivalence or topic dynamics. Asteria instead brings semantic-aware matching and adaptive policies to remote knowledge caching.

LLM-based agent memory. Finally, agent memory systems [29, 64, 67] improve LLM's reasoning by retaining past context. For example, MemoryBank [67] stores conversational summaries to track entities; A-MEM [64] generalizes the memory structure to diverse tasks; Memory Sandbox [29] gives users explicit control. These systems give LLMs long-

term memory to improve reasoning and choose the next action, but they don't reduce the cost of carrying it out. Asteria instead targets the external tool call itself, making execution faster and cheaper.

8 Conclusion

We present Asteria, an agentic knowledge caching system designed to overcome the latency and cost challenges of LLM agents accessing external knowledge. Asteria's novelty lies in its two-stage hybrid retrieval, combining ANN search with an LLM-powered Semantic Judger for semantic matching, and its resource-efficient co-location architecture. Our evaluation demonstrates that Asteria significantly improves performance and maintains accuracy, offering a scalable and cost-effective solution for LLM agent deployments.

References

- [1] Hyperbolic AI. Hyperbolic gpu marketplace: Ondemand nvidia gpu rentals. https://app.hyperbolic.ai/, 2025. Accessed September 2025.
- [2] Alibaba Qwen Team. Qwen/qwen2.5-7b-instruct. https://huggingface.co/Qwen/Qwen2.5-7B-Instruct, 2025. Accessed: 2025-08-22.
- [3] Alibaba Qwen Team. Qwen/qwen3-8b. https://huggingface.co/Qwen/Qwen3-8B, 2025. Accessed: 2025-08-22.
- [4] Anthropic. Introducing the model context protocol. ht tps://www.anthropic.com/news/model-context-protocol, 2025. Accessed: 2025-08-22.
- [5] Anthropic. Your code's new collaborator. https://www.anthropic.com/claude-code, 2025. Accessed: 2025-07-22.
- [6] NLPIR Lab at RUC. 2wikimultihopqa: A multi-hop question answering dataset from wikipedia. https://huggingface.co/datasets/RUC-NLPIR/Flash RAG_datasets/tree/main/2wikimultihopqa, 2025. Part of FlashRAG datasets. Accessed: 2025-09-14.
- [7] NLPIR Lab at RUC. Hotpotqa (flashrag version): Multi-hop question answering dataset. https://huggingface.co/datasets/RUC-NLPIR/FlashRAG_datasets/tree/main/hotpotqa, 2025. Part of FlashRAG datasets. Accessed: 2025-09-14.
- [8] NLPIR Lab at RUC. Musique (flashrag version): Multi-hop question answering dataset. https://huggingface.co/datasets/RUC-NLPIR/FlashRAG_datasets/tree/main/musique, 2025. Part of FlashRAG datasets. Accessed: 2025-09-14.

- [9] Fu Bang. Gptcache: An open-source semantic cache for llm applications enabling faster answers and cost savings. In *Proceedings of the 3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS 2023)*, pages 212–218, 2023.
- [10] Chroma Contributors. Chroma: Open-source search and retrieval for ai. https://www.trychroma.com/, 2025. Accessed September 2025.
- [11] SQLFluff Contributors. Sqlfluff: A modular sql linter and auto-formatter. https://github.com/sqlfluff/sqlfluff, 2025. Supports multiple SQL dialects and templated code including Jinja and dbt. Accessed: 2025-09-14.
- [12] Microsoft Corporation. The new bing: Ai-powered assistant for your search. https://www.microsoft.com/en-us/edge/features/the-new-bing?form=MA13FJ, 2025. Accessed September 2025.
- [13] Oracle Corporation. Mysql: The world's most popular open source database. https://www.mysql.com/, 2025. Accessed September 2025.
- [14] CURSOR. The ai code editor. https://cursor.com/agents, 2025. Accessed: 2025-07-22.
- [15] Ehsan Doostmohammadi, Tobias Norlund, Marco Kuhlmann, and Richard Johansson. Surface-based retrieval reduces perplexity of retrieval-augmented language models, 2023.
- [16] Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. The faiss library. 2024.
- [17] DeepSeek-AI et al. Deepseek-v3 technical report, 2025.
- [18] Kimi Team et al. Kimi k2: Open agentic intelligence, 2025.
- [19] Hugging Face. Exact match score: Evaluation metric for text generation. https://huggingface.co/spaces/evaluate-metric/exact_match, 2025. Accessed September 2025.
- [20] Hao Fei, Yuan Yao, Zhuosheng Zhang, Fuxiao Liu, Ao Zhang, and Tat-Seng Chua. From multimodal Ilm to human-level ai: Modality, instruction, reasoning, efficiency and beyond. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024): Tutorial Summaries*, pages 1–8, 2024.
- [21] Ceph Foundation. Ceph: The future of storage. https://ceph.io/en/, 2025. Accessed September 2025.

- [22] In Gim, Guojun Chen, Seung-seob Lee, Nikhil Sarda, Anurag Khandelwal, and Lin Zhong. Prompt cache: Modular attention reuse for low-latency inference. *Proceedings of Machine Learning and Systems*, 6:325–338, 2024.
- [23] Google. Custom search api. https://console.cl oud.google.com/marketplace/product/google/ customsearch.googleapis.com, 2025. Accessed: 2025-08-22.
- [24] Google Cloud. Get started with semantic caching policies. https://cloud.google.com/apigee/docs/api-platform/tutorials/using-semantic-caching-policies#:~:text=policies%20to%20enable%20intelligent%20response, latency%2C%20and%20lower%20operational%20costs, 2025. Accessed: 2025-07-22.
- [25] gRPC Authors. Introduction to grpc. https://grpc.io/docs/what-is-grpc/introduction/, 2025. Accessed September 2025.
- [26] Vinit Kumar Gunjan, Monika Kumari, Amit Kumar, Allam Appa Rao, et al. Search engine optimization with google. *Asian Journal of Engineering and Applied Technology*, 1(1):36–42, 2012.
- [27] Luke Harsel. Google ai mode's early adoption and seo impact. https://www.semrush.com/blog/google-ai-mode-seo-impact/?utm_source=chatgpt.com. Accessed: 2025-09-12.
- [28] Sirui Hong, Xiawu Zheng, Jonathan Chen, Yuheng Cheng, Jinlin Wang, Ceyao Zhang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, et al. Metagpt: Meta programming for multi-agent collaborative framework. arXiv preprint arXiv:2308.00352, 3(4):6, 2023.
- [29] Ziheng Huang, Sebastian Gutierrez, Hemanth Kamana, and Stephen MacNeil. Memory sandbox: Transparent and interactive memory management for conversational agents, 2023.
- [30] Turbopuffer Inc. Turbopuffer: Serverless vector and full-text search built on object storage. https://turbopuffer.com/, 2025. Accessed September 2025.
- [31] Suhas Jayaram Subramanya, Fnu Devvrit, Harsha Vardhan Simhadri, Ravishankar Krishnawamy, and Rohan Kadekodi. Diskann: Fast accurate billion-point nearest neighbor search on a single node. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

- [32] Bowen Jin, Hansi Zeng, Zhenrui Yue, Jinsung Yoon, Sercan Arik, Dong Wang, Hamed Zamani, and Jiawei Han. Search-r1: An efficient, scalable rl training framework for reasoning & search engine calling interleaved llms. https://github.com/PeterGriffinJin/Search-R1, 2025. Accessed: 2025-09-14.
- [33] Bowen Jin, Hansi Zeng, Zhenrui Yue, Jinsung Yoon, Sercan Arik, Dong Wang, Hamed Zamani, and Jiawei Han. Search-r1: Training llms to reason and leverage search engines with reinforcement learning. *arXiv preprint arXiv:2503.09516*, 2025.
- [34] Jin, Bowen and Zeng, Hansi and Yue, Zhenrui and Yoon, Jinsung and Arik, Sercan and Wang, Dong and Zamani, Hamed and Han, Jiawei. Searchr1-nq_hotpotqa_train-qwen2.5-7b-em-ppo. https://huggingface.co/PeterJinGo/SearchR1-nq_hotpotqa_train-qwen2.5-7b-em-ppo, 2025. Accessed: 2025-08-22.
- [35] Herve Jégou, Matthijs Douze, and Cordelia Schmid. Product quantization for nearest neighbor search. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(1):117–128, 2011.
- [36] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the 29th symposium on operating systems principles*, pages 611–626, 2023.
- [37] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33:9459–9474, 2020.
- [38] Haoyuan Li. *Alluxio: A virtual distributed file system*. University of California, Berkeley, 2018.
- [39] Xiaoxi Li, Guanting Dong, Jiajie Jin, Yuyao Zhang, Yujia Zhou, Yutao Zhu, Peitian Zhang, and Zhicheng Dou. Search-o1: Agentic search-enhanced large reasoning models. *arXiv preprint arXiv:2501.05366*, 2025.
- [40] Chaofan Lin, Zhenhua Han, Chengruidong Zhang, Yuqing Yang, Fan Yang, Chen Chen, and Lili Qiu. Parrot: Efficient serving of {LLM-based} applications with semantic variable. In 18th USENIX Symposium on Operating Systems Design and Implementation (OSDI 24), pages 929–945, 2024.
- [41] Yuhan Liu, Hanchen Li, Yihua Cheng, Siddhant Ray, Yuyang Huang, Qizheng Zhang, Kuntai Du, Jiayi Yao, Shan Lu, Ganesh Ananthanarayanan, et al. Cachegen: Kv cache compression and streaming for fast large language model serving. In *Proceedings of the ACM SIG-COMM 2024 Conference*, pages 38–56, 2024.

- [42] Google LLC. Google ai mode: A new way to search, whatever's on your mind. https://search.google/ways-to-search/ai-mode/, 2025. Accessed September 2025.
- [43] Google LLC. Google programmable search engine: Custom search powered by google. https://programmablesearchengine.google.com/about/, 2025. Accessed September 2025.
- [44] Peixian Ma, Xialie Zhuang, Chengjin Xu, Xuhui Jiang, Ran Chen, and Jian Guo. Sql-r1: Training natural language to sql reasoning model by reinforcement learning. *arXiv* preprint arXiv:2504.08600, 2025.
- [45] Memcached. Memcached. https://memcached.org/, 2025. Accessed: 2025-07-22.
- [46] Netflix. Evcache. https://github.com/Netflix/E VCache, 2025. Accessed: 2025-07-22.
- [47] Princeton NLP. Swe-bench oracle dataset. https://huggingface.co/datasets/princeton-nlp/SWE-bench_oracle, 2023. Accessed: 2025-09-14.
- [48] NVIDIA. Multi-process service. https://docs.nvidia.com/deploy/mps/index.html, 2025. Accessed: 2025-07-22.
- [49] OpenAI. Api pricing. https://openai.com/api/pricing/, 2025. Accessed: 2025-09-07.
- [50] Hojin Park, Ziyue Qiu, Gregory R Ganger, and George Amvrosiadis. Reducing cross-cloud/region costs with the auto-configuring macaron cache. In *Proceedings* of the ACM SIGOPS 30th Symposium on Operating Systems Principles, pages 347–368, 2024.
- [51] Shishir G. Patil, Tianjun Zhang, Xin Wang, and Joseph E. Gonzalez. Gorilla: Large language model connected with massive apis. *arXiv preprint arXiv:2305.15334*, 2023.
- [52] Sarah Perez. Google's ai overviews have 2b monthly users, ai mode 100m in the us and india. https://techcrunch.com/2025/07/23/googles-ai-overviews-have-2b-monthly-users-ai-mode-100m-in-the-us-and-india/?utm_source=chatgpt.com. Accessed: 2025-09-12.
- [53] Partha Pratim Ray. A survey on model context protocol: Architecture, state-of-the-art, challenges and future directions. *Authorea Preprints*, 2025.
- [54] Redis. Redis. https://redis.io/, 2025. Accessed: 2025-07-22.

- [55] Sachin Agarwal. Public cloud inter-region network latency as heat-maps. https://medium.com/@sachinkagarwal/public-cloud-inter-region-network-latency-as-heat-maps-134e22a5ff19, 2025. Accessed: 2025-07-22.
- [56] Luis Gaspar Schroeder, Shu Liu, Alejandro Cuadron, Mark Zhao, Stephan Krusche, Alfons Kemper, Matei Zaharia, and Joseph E Gonzalez. Adaptive semantic prompt caching with vectorq. *CoRR*, 2025.
- [57] LLC SerpApi. Serpapi: Real-time search engine results api. https://serpapi.com/, 2025. Accessed September 2025.
- [58] Huatong Song, Jinhao Jiang, Yingqian Min, Jie Chen, Zhipeng Chen, Wayne Xin Zhao, Lei Fang, and Ji-Rong Wen. R1-searcher: Incentivizing the search capability in Ilms via reinforcement learning. *arXiv preprint arXiv:2503.05592*, 2025.
- [59] Facebook Database Engineering Team. Rocksdb: A persistent key-value store for fast storage. https://github.com/facebook/rocksdb, 2025. Accessed September 2025.
- [60] Qwen Team. Qwen3-embedding-0.6b: A multilingual text embedding model. https://huggingface.co/Qwen/Qwen3-Embedding-0.6B, 2025. Supports over 100 languages and customizable embedding dimensions. Accessed: 2025-09-14.
- [61] Qwen Team. Qwen3-reranker-0.6b: A multilingual text reranking model. https://huggingface.co/Qwen/Qwen3-Reranker-0.6B, 2025. Supports over 100 languages and customizable instructions for retrieval tasks. Accessed: 2025-09-14.

- [62] Uber. How uber serves over 40 million reads per second from online storage using an integrated cache. https://www.uber.com/en-AU/blog/how-uber-serves-over-40-million-reads-per-second-using-an-integrated-cache/#:~:text=, %E2%80%93%20Phil%20Karlton, 2025. Accessed: 2025-07-22.
- [63] vLLM Project Contributors. vllm: A high-throughput and memory-efficient inference and serving engine for llms. https://github.com/vllm-project/vllm, 2025. Originally developed at Sky Computing Lab, UC Berkeley. Accessed: 2025-09-14.
- [64] Wujiang Xu, Kai Mei, Hang Gao, Juntao Tan, Zujie Liang, and Yongfeng Zhang. A-mem: Agentic memory for llm agents, 2025.
- [65] Jianxin Yan, Wangze Ni, Lei Chen, Xuemin Lin, Peng Cheng, Zhan Qin, and Kui Ren. Contextcache: Contextaware semantic cache for multi-turn queries in large language models. *arXiv preprint arXiv:2506.22791*, 2025.
- [66] Danna Zheng, Mirella Lapata, and Jeff Z Pan. Large language models as reliable knowledge bases? 2024.
- [67] Wanjun Zhong, Lianghong Guo, Qiqi Gao, He Ye, and Yanlin Wang. Memorybank: Enhancing large language models with long-term memory, 2023.
- [68] zilliztech. Zilliz gpt cache datasets. https://github.com/zilliztech/GPTCache/blob/main/examples/benchmark/similiar_qqp_full.json.gz, 2025. Accessed: 2025-08-22.