SmartCache: Context-aware Semantic Cache for Efficient Multi-turn LLM Inference

Chengye Yu
Chinese University of Hong Kong
Hong Kong, China
cyyu23@cse.cuhk.edu.hk

Tianyu Wang ✉
Shenzhen University
Shenzhen, China
tywang@szu.edu.cn

Zili Shao
Chinese University of Hong Kong
Hong Kong, China
shao@cse.cuhk.edu.hk

Song Jiang
University of Texas at Arlington
Arlington, USA
song.jiang@uta.edu

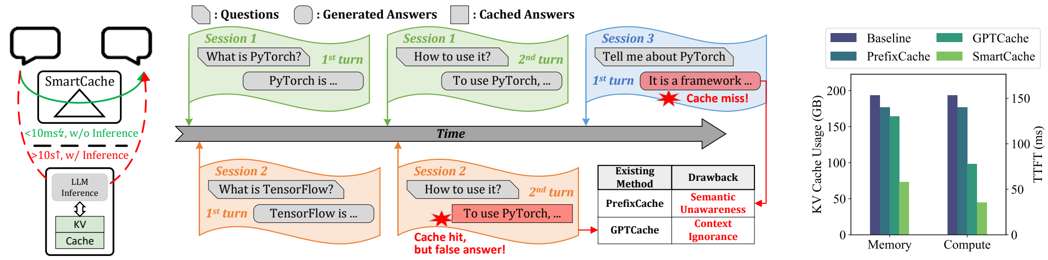
Abstract

Large Language Models (LLMs) for multi-turn conversations suffer from inefficiency: semantically similar queries across different user sessions trigger redundant computation and duplicate memory-intensive Key-Value (KV) caches. Existing optimizations such as prefix caching overlook semantic similarities, while typical semantic caches either ignore conversational context or are not integrated with low-level KV cache management. We propose SmartCache, a system-algorithm co-design framework that tackles this inefficiency by exploiting semantic query similarity across sessions. SmartCache leverages a Semantic Forest structure to hierarchically index conversational turns, enabling efficient retrieval and reuse of responses only when both the semantic query and conversational context match. To maintain accuracy during topic shifts, it leverages internal LLM attention scores—computed during standard prefill—to dynamically detect context changes with minimal computational overhead. Importantly, this semantic understanding is co-designed alongside the memory system: a novel two-level mapping enables transparent cross-session KV cache sharing for semantically equivalent states, complemented by a semantics-aware eviction policy that significantly improves memory utilization. This holistic approach significantly reduces redundant computations and optimizes GPU memory utilization. The evaluation demonstrates SmartCache's effectiveness across multiple benchmarks. On the CoQA and SQuAD datasets, SmartCache reduces KV cache memory usage by up to 59.1% compared to prefix caching and 56.0% over semantic caching, while cutting Time-to-First-Token (TTFT) by 78.0% and 71.7%, respectively. It improves answer quality metrics, achieving 39.9% higher F1 and 39.1% higher ROUGE-L for Qwen-2.5-1.5B on CoQA. The Semantic-aware Tiered Eviction Policy (STEP) outperforms LRU/LFU by 29.9% in reuse distance under skewed workloads.

1 Introduction

Transformer-based Large Language Models (LLMs) [39], such as GPT [30], PaLM [8], and Llama [37, 16], are revolutionizing the world with their powerful and versatile capabilities, enabling a wide range of tasks ranging from question answering to code generation [45, 30, 47]. A particularly prominent application is multi-turn conversation [12, 20, 46, 18, 25], underpinning interactive systems where users engage with models over extended dialogues, often exploring specific topics in depth [36]. This

39th Conference on Neural Information Processing Systems (NeurIPS 2025).



(a) (b) (c)

Figure 1: 1(a) illustrates the functionality of SmartCache. 1(b) shows an example of multi-user multi-turn conversations. GPTCache [6] would encounter a false positive cache hit for Session 2 Turn 2 due to flat query embedding search. PrefixCache [40] fails to reuse the answer of Session 1 Turn 1 for the semantically similar query of Session 3 Turn 1 due to exact token match. 1(c) shows the resource consumption of different methods on SQuAD dataset with LLama-3.1-8B model.

paradigm is central to applications like collaborative content analysis and comprehension, where users interact with materials like news articles or videos through conversational interfaces.

However, current LLM serving systems suffer from a fundamental inefficiency in this setting: semantic redundancy. Different users in separate sessions often ask questions that are semantically equivalent or highly similar. Existing systems treat each session independently. Semantically similar queries often trigger separate, full LLM inference passes, redundantly producing identical or nearly identical responses. This results in unnecessary GPU computation. Furthermore, the associated Key-Value (KV) caches—essential for efficient token generation yet highly memory-intensive—are maintained separately for each session, resulting in excessive GPU memory usage and added overhead from memory management tasks such as offloading [14, 19].

Existing optimization techniques are inadequate to address the problem. Prefix caching methods, proposed in RadixAttention [48] and commonly used in systems like vLLM [40, 19, 27, 15, 4, 1], leverage shared token prefixes (e.g., system prompts) to share initial KV cache blocks. They rely on exact token matching and fail to recognize semantic equivalence when queries are phrased differently (e.g., "What is PyTorch?" vs. "Tell me about PyTorch" as shown in Figure 1(b)). Their benefits are also largely confined to the initial prompt processing (prefill stage), offering little help for the time-consuming token-by-token decoding phase. On the other hand, higher-level semantic caching systems [6] operate by storing text responses indexed by query embeddings. While they capture semantic similarity, they often struggle in multi-turn scenarios due to two key limitations. (1) **Context Ignorance**. They often retrieve cached responses based solely on the current query's embedding, disregarding the preceding conversation turns. This leads to incorrect or nonsensical answers when a query's meaning is context-dependent (e.g., "How to use it?"). (2) **Decoupling from Inference State**. These caches operate above the LLM inference engine. A cache hit provides text but does not update the LLM's internal KV cache state. A subsequent cache miss can force the LLM to reprocess the entire conversation history to regenerate the KV cache, resulting in significant computational overhead and undermining potential memory savings. There is a clear need for a solution that understands semantics, preserves conversational context, and is tightly integrated with the underlying inference and memory management mechanisms. As depicted in Figure 1(c), utilizing semantics to further reduce resource usage remains largely unexplored.

To bridge this gap, we present SmartCache — a system-algorithm co-design framework purpose-built to optimize multi-turn LLM inference by leveraging cross-session semantic similarity while preserving contextual integrity. SmartCache tightly integrates a novel semantic caching layer with the core LLM serving engine and its KV cache management. It is built upon several key design principles and mechanisms.

• **Semantic Forest**. To ensure cached responses are used only in the appropriate context and to efficiently manage the branching nature of conversations, SmartCache employs the Semantic Forest data structure (Section 3.1). This hierarchy of trees organizes conversational turns (query-response pairs) semantically. Lookups for incoming queries are constrained to relevant branches based on the preceding turn, ensuring contextual accuracy and efficient search. Cache misses dynamically grow the forest, capturing new conversational paths.

• **Attention-based Context Identification**. Recognizing that conversations can dynamically shift topics, SmartCache incorporates an attention-based context identification module (Section 3.2). By analyzing attention patterns during standard query prefill—a low-overhead signal from the model's internals—SmartCache distinguishes between queries that extend the current context and those that begin a new one. This allows sessions to intelligently navigate or transition between different semantic trees, enhancing both cache effectiveness and response accuracy.

• **Semantic-aware Tiered Eviction/Prefetching**. To maximize resource savings, SmartCache features a co-designed KV cache sharing and eviction mechanism that deeply integrates the semantic layer with memory management (Section 3.3). A novel two-level mapping connects semantic nodes to physical KV cache blocks, allowing multiple sessions referencing the same conversational point to transparently share underlying GPU memory. Furthermore, instead of relying on blind page-level or session-level eviction, SmartCache employs lightweight and powerful **S**emantic-aware **T**iered **E**viction/**P**refetching (STEP) policy. STEP manages the lifecycle of KV cache blocks using factors derived from the Semantic Forest structure and usage patterns, including semantic depth, session affinity, and node popularity. This refined, contextually-informed approach optimizes memory utilization more effectively than traditional page- or session-based methods.

To evaluate the effectiveness of SmartCache, we conduct extensive experiments across multiple benchmarks and models. On the CoQA and SQuAD datasets, SmartCache reduces KV cache memory usage by up to 59.1% compared to prefix caching and 56.0% over semantic caching, while achieving 78.0% and 71.7% reductions in Time-to-First-Token (TTFT), respectively. SmartCache also improves answer quality metrics, attaining 39.9% higher F1 and 39.1% higher ROUGE-L scores for the Qwen-2.5-1.5B model on CoQA, demonstrating its ability to preserve contextual accuracy. Furthermore, our STEP policy outperforms traditional LRU/LFU policies by up to 29.9% in reuse distance under skewed workloads, validating its efficiency in dynamic multi-session environments. These results highlight SmartCache's ability to balance computational efficiency, memory optimization, and answer quality across diverse conversational scenarios.

2 Background

2.1 Related Works

Several prior works have explored various methods to address the inefficiencies in multi-user multi-turn conversations. Table 1 compares different caching strategies used in multi-turn conversations.

Table 1: Comparison of Caching Strategies for Multi-Turn LLM Inference.

	Baseline	**PrefixCache**	**Flat Embedding**	**Context-aware Semantic Cache**
Feature	No Reuse	e.g., vLLM APC [40], RadixAttention [48, 14]	e.g., GPTCache [6], SCALM [21] and [34]	**SmartCache** (ours)
Reuse Trigger	✗	Exact Prefix Match	Flat Similarity	**Hierarchical Semantic**
Context Aware	✗	✗	Limited†	**✓ (Hierarchical)**
Resource Reused	✗	KV Cache*	Text Response only	**Text Response + KV Cache**
Computation Saving	✗	Limited	✓	✓
Integrated System/Algorithm	✗	✗	✗	**✓ (Co-designed)**
Key Bottleneck	High Redundancy	No Semantic Reuse	Context Ignorance	-
Benefit Focus	Simplicity	Prefill Speedup	Saves Full Compute	Context Awareness + Memory/Compute Eff.

†GPTCache can use history for embedding, but lacks explicit conversational structure.
*Only exactly matched prefix tokens are reused.

2.2 Problem Description

Let $\mathcal{S}$ be the set of active user sessions. Each session $s \in \mathcal{S}$ arriving at turn $k+1$ has a conversational history $H_s^{(k)}$ consisting of the preceding k query-response pairs. We can represent this history as a sequence or concatenation: $H_s^{(k)} = \{(q_i, a_i)\}_{i=1}^{k}$ or, if treated as a single string for embedding purposes, $H_s^{(k)} \approx \|_{i=1}^{k}(q_i||a_i)$, where $||$ denotes string concatenation. When session s issues the new query q_{k+1}, the goal is to efficiently determine the appropriate response a_{k+1}.

A standard LLM serving system computes $a_{k+1} = M(q_{k+1}|H_s^{(k)})$, where M is the LLM and $H_s^{(k)}$ represents the relevant history context for session s. This computation is expensive.

A flat query-answer cache like GPTCache aims to find if there exists a previously asked query q_{prev} (from any turn j in any previous session) in a global set of all past queries Q_{all} such that

$sim(E(q_{k+1}), E(q_{prev})) \geq \tau_{sim}$, where E is an embedding function, sim is a similarity metric, and τ_{sim} is a threshold. If such a q_{prev} with associated response a_{prev} is found, a_{k+1} is set to a_{prev}.

$$\text{Find } (q_{prev}, a_{prev}) \text{ s.t. } q_{prev} \in Q_{all} \wedge sim(E(q_{k+1}), E(q_{prev})) \geq \tau_{sim}$$

The primary limitation is that it disregards the conversational context $H_s^{(k)}$. The semantic meaning of q_{k+1} is often dependent on $H_s^{(k)}$, and reusing a_{prev} generated under a different context $H_{s'}^{(k')}$ can be incorrect, even if q_{k+1} and q_{prev} are textually similar.

One might attempt to address this by directly incorporating the conversation history $H_s^{(k)}$ in the query embedding. A flat semantic cache could store embeddings of the form $e_{query\_hist} = E(H_s^{(k)} || q_{k+1})$. For an incoming query $q'_{k'+1}$ with history $H_{s'}^{(k')}$, the system would compute $e'_{query\_hist} = E(H_{s'}^{(k')} || q'_{k'+1})$ and search for a stored embedding $e_{stored} = E(H_{prev}^{(j)} || q_{prev})$ in a global index, such that $sim(e'_{query\_hist}, e_{stored}) \geq \tau_{sim}$.

While this approach includes history information, it suffers from the *Long History Dominance* [23, 32, 38, 22, 10] issue, especially as the number of turns k increases. Standard embedding models struggle to effectively represent long concatenated sequences in a fixed-size vector such that the final query q_{k+1} remains distinctly identifiable. As the history $H_{s'}^{(k')}$ grows long, the embedding vector $E(H_{s'}^{(k')} || q'_{k'+1})$ tends to be increasingly dominated by the content of the history H_s itself, rather than the specific new query q_{new}, i.e. $E(H_{s'}^{(k')} || q'_{k'+1})$ is closer to $E(H_{s'}^{(k')})$ but more distant from $E(q'_{k'+1})$.

3 The Design of SmartCache

In this section, we introduce SmartCache, a context-aware semantic cache designed for multi-turn LLM inference with enhanced context-awareness. First, as illustrated in Figure 2, SmartCache organizes and indexes conversation contexts from different users into a Semantic Forest, as detailed in Section 3.1. The semantic forest comprises multiple individual semantic trees, where each conversation turn is represented as a semantic node. Semantic nodes can be associated with and reused across multiple conversation sessions, enabling efficient context sharing. Second, in Section 3.2, SmartCache introduces a semantic identification policy that leverages attention scores from the prefilling stage of user queries to identify non-contextual queries, to support dynamic context switching, and unlocks additional sharing opportunities. Finally, we present the transparent cross-session KV cache sharing design, coupled with a novel eviction policy, enabling efficient sharing of KV caches based on semantic similarity in Section 3.3.

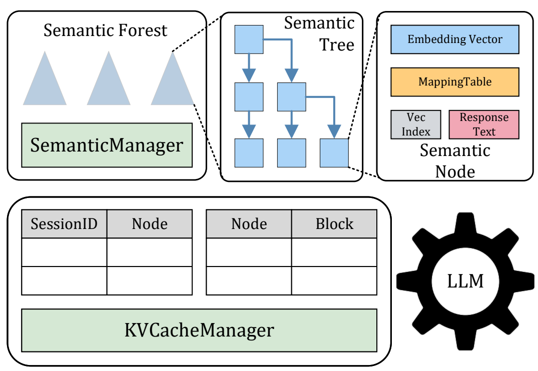


Figure 2: Overview of SmartCache.

3.1 Semantic Context Manager

3.1.1 Semantic Tree

In a multi-turn conversational scenario, users often begin a session with a simple question on a specific topic, followed by a series of progressively deeper queries. Different users may explore the same topic by asking similar questions in varied ways or by focusing on different aspects. Such relationships can be effectively represented using a tree structure, referred to as a semantic tree in SmartCache. Each semantic tree organizes query-response turns as semantic nodes under a specific semantic context. The initial query of a new session becomes the root node of a new semantic tree, while subsequent queries create child nodes linked to the corresponding semantic parents.

Conversation sessions centered on the same topic can share a common semantic tree, allowing them to leverage cached responses when similar queries have been made by other users. Each conversation

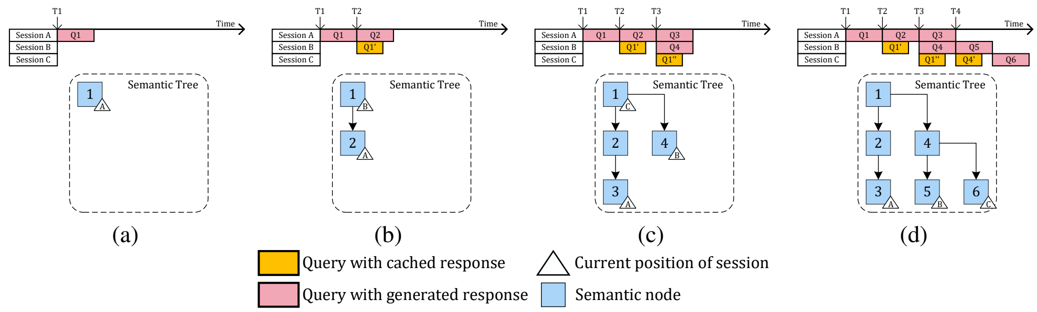


Figure 3: Example of a hierarchical semantic tree shared by three sessions (A, B, and C).

session is associated with a semantic node, representing the last query-response turn of the session. Users can ask progressive questions based on the context represented by the semantic node. In these cases, child nodes are evaluated to possibly reuse responses from similar queries, avoiding the need for regeneration. When there are no reusable responses, the query is processed by the LLM using the contextual history traced from the root to the current semantic node. In the case where a user poses an unrelated question and shifts to a different topic, SmartCache either locates a suitable existing semantic tree or initiates a new one to reflect the updated context.

Figur 3 illustrates a comprehensive example of a semantic tree shared across three sessions (A, B, and C). At time T1, session A begins with query Q1, which is processed by the LLM to generate a response, as it is the first query on the topic. Q1 and its generated response are cached as semantic node 1, which becomes the root of the newly created semantic tree. At T2, session B issues Q1′, a query semantically similar to Q1, and retrieves the cached response from semantic node 1. Meanwhile, session A raises query Q2 and receives a newly generated response. At T3, session C initiates Q1′′ and retrieves the same cached response from semantic node 1. However, when session B raises query Q4, no similar query is found among the children of node 1, the current position of session B. As a result, its response is generated by the LLM, and a new branch from node 1 to node 4 is created. Session C continues to reuse node 4 until it encounters a cache miss at query Q6.

The semantic tree design benefits multi-turn conversations in two aspects. First, by reusing semantically similar nodes across different sessions, queries with identical or similar semantics are computed and decoded by the LLM only once, and their responses are shared. This approach significantly reduces computational overhead and alleviates memory pressure, as the KV cache of common semantic nodes is shared among sessions. Second, the hierarchical structure of the semantic tree preserves semantic relationships. The tree grows and the session advances level-by-level with the progress of queries. Queries are compared and retrieved only within the context of the same parent node, ensuring accuracy while limiting the search space. This design allows sessions to share several initial queries at the beginning while enabling diverse and specific questions to branch out independently as conversations progress.

3.1.2 Semantic Node

Each semantic node represents the context of a single conversation turn. As shown in Figure 2, the embedding vector of the query, generated by an embedding model is used by the parent node for similarity search. Consequently, each semantic node stores the embedding vectors of its child nodes in a vector index [11, 24, 41, 9]. The KV cache for the associated context is maintained on the LLM side. To enable transparent KV cache sharing, an additional indirect KV cache block mapping table is introduced and managed by the corresponding semantic node, which is detailed in Section 3.3.

3.1.3 Semantic Forest

Multiple semantically individual trees collectively form the semantic forest. A global vector index stores the embedding vectors of the root nodes of all semantic trees, which is searched by the initial query of a new conversation session to locate the most relevant semantic tree. If no similar topic is found, a new semantic tree is created.

Users may occasionally change topics within a single session, such as shifting from one topic to another. In SmartCache, an active session can switch to another semantic tree if no similar queries are found under the current context and the new query is deemed irrelevant to the ongoing conversation.

To determine whether a query is contextual or not, SmartCache leverages the attention score from the LLM's query prefilling stage, enabling dynamic and accurate context switching.

Algorithm 1 Cache Operations

Require: Session s, New Query q_{new}, Semantic Forest $\mathcal{F}$ (access to I_{global} and local $I_{\mathcal{N}}$), Similarity threshold τ_{sim}, Embedding Model $E(\cdot)$.
Ensure: Boolean is_hit, Node N_{hit}, Response a_{cached}

function CACHELOOKUP($s, q_{new}, \mathcal{F}, \tau_{sim}$)
    $N_{cur} \leftarrow CurrentNode(s)$
    $e_{new} \leftarrow E(q_{new})$
    $is\_hit \leftarrow$ false
    $N_{hit} \leftarrow$ null
    $a_{cached} \leftarrow$ null
    if $N_{cur} = START$ **then**
        $Candidates \leftarrow NearestNeighbor(e_{new}, I_{global}, k = 1, \tau_{sim})$
        if $Candidates$ is not empty **then**
            $N_{hit} \leftarrow Candidates[0].Node$
            $a_{cached} \leftarrow N_{hit}.a$
            $is\_hit \leftarrow$ true
    else
        if N_{cur} has a local index $I_{N_{cur}}$ **then**
            $Candidates \leftarrow NearestNeighbor(e_{new}, I_{N_{cur}}, k = 1, \tau_{sim})$
            if $Candidates$ is not empty **then**
                $N_{hit} \leftarrow Candidates[0].Node$
                $a_{cached} \leftarrow N_{hit}.a$
                $is\_hit \leftarrow$ true
    return $is\_hit, N_{hit}, a_{cached}$

3.1.4 Cache Operations

SmartCache's cache operation is responsible for deciding whether an existing semantic node can be reused or whether the underlying LLM must be invoked to extend the semantic tree, whenever a new conversation turn arrives. The procedure (as shown in Algorithm 1) consists of three phases: *local lookup*, *global fallback* and *miss handling*.

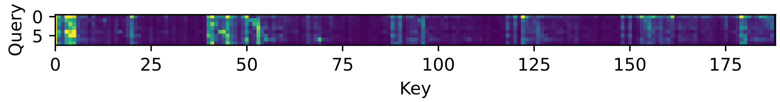
• **Local Lookup.** Every session s records its current semantic node N_{cur}. The search scope is constrained to the descendants of N_{cur}, which preserves the conversational continuity and bounds the search space. A single-probe $k = 1$ nearest-neighbor query on the local index $I_{N_{cur}}$ finds the most similar child with a minimum similarity of τ_{sim}, using the embedding vector e given by the embedding model. On cache hit, the cached response a_{cached} of the hit node is streamed to the user and N_{cur} is updated.

• **Global Fallback.** On failure of local lookup, SmartCache suspects a context shift. Before falling back to LLM generation, it performs a root-level lookup on the global vector index that stores the root nodes of semantic trees. A successful match moves the session to the hit root and returns cached response.

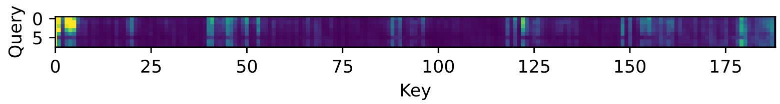
• **Miss Handling.** A double-miss triggers LLM inference and semantic node creation: a) *Attention Peeking.* After a single-pass prefilling, attention scores to historical tokens are inspected to determine a context-switch. If the query is contextual, the decoding preceeds. Otherwise, a new semantic tree is created and the generation is restarted without context. b) *Node Creation and KV Cache Materialization.* SmartCache inserts a new semantic node to an appropriate position with newly generated response a_{new}, and corresponding KV cache blocks, updating vector indices and setting up correct mappings.

3.1.5 Analysis and Discussion

Let d be the embedding dimension of vector index, $|F|$ the number of semantic trees in the forest, and $|B|$ the average branching factor of a semantic node, T the average generation length, and $|V|$ the vocabulary size.



(a) A progressive query based on the context.



(b) An individual query

Figure 4: The attention score heatmaps of two different queries to the same context.

• **Asymptotic Time Cost.** SmartCache performs at least once approximate-nearest-neighbor [24] search over:

$$I_{global} : \mathrm{O}(\log |F|) \text{ or,}$$
$$I_{local} : \mathrm{O}(\log |B|)$$

• **Space Overhead.** For each semantic node, SmartCache stores a) a d-dimensional embedding vector ($4d$ Bytes in FP32 format), b) cached response a_{cached} ($\mathrm{O}(T \log |V|)$ Bytes) and c) local vector index I_{local} consisting of index metadata ($\mathrm{O}(\text{IndexSize}(|B|))$ Bytes) depending on the ANN implementation and the pointers to descendant embedding vectors ($8|B|$ Bytes). Therefore, the space overhead of each semantic node is:

$$\mathrm{O}\left(d + T \log |V| + \text{IndexSize}(|B|) + |B|\right)$$

3.2 Dynamic Context-Switching

In multi-turn conversations, the sequence length of a user query is typically much shorter than that of the generated response. Additionally, prefilling a sequence is significantly faster than decoding the same number of tokens due to the batch processing nature of the prefilling stage. As a result, query prefilling consumes far less time than response generation. The attention score reveals the model's focus on key tokens, with contextual queries exhibiting noticeably higher attention scores to the context compared to individual queries, as illustrated in Figure 4. This observation motivates our approach of quickly examining the attention score during the query prefilling stage to determine whether a query is contextual. If the query is contextual, the LLM proceeds to decode the response. Otherwise, the query is treated as an individual query, and the session is redirected to another semantic tree. Since the attention score is already computed during prefilling, the performance overhead of this "peeking" mechanism is negligible.

By switching to a semantic tree with lighter contexts, sessions achieve better response times due to reduced computational load. Furthermore, the semantic forest expands with additional individual semantic contexts, increasing opportunities for sharing and improving overall efficiency.

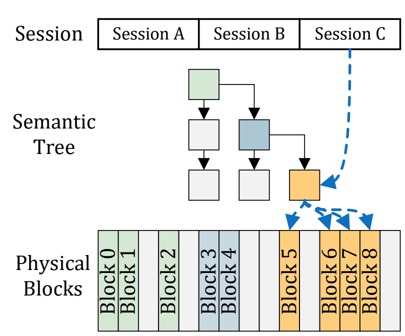


Figure 5: Two-Level Mapping Table.

3.3 KV Cache Management

3.3.1 Transparent Cross-Session KV Cache Sharing

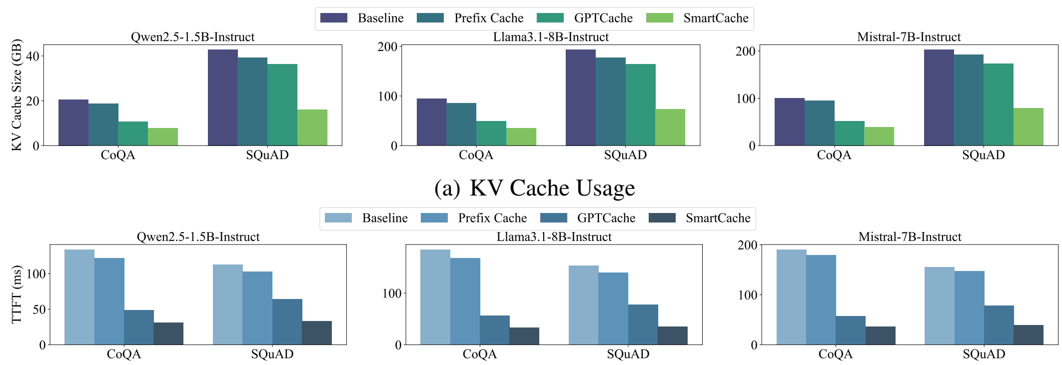
SmartCache enables transparent sharing of KV cache across semantically similar conversation sessions by introducing a two-level mapping table. Original paged KV cache management relies on a per-session logical-to-physical token block mapping table, often referred to as a block table. As illustrated in Figure 5, SmartCache enhances this approach with two additional structures: *per-session context tables*, which map logical tokens to contexts, and *per-context block* *tables*, maintained by each semantic node. This two-level mapping mechanism ensures efficient and flexible KV cache sharing while preserving semantic relationships.

3.3.2 Semantic-aware Tiered Eviction/Prefetching

• **Semantic Tree-Guided Eviction.** SmartCache evaluates the eviction urgency S_{evict} of a semantic node by two factors: *Semantic Depth Score (SDS)* and *Session Affinity Score (SAS)*. The SDS is calculated as $SDS = \frac{1}{\text{Depth}(N)}$, following the heuristic that deeper nodes in the semantic trees are prioritized to be evicted. The SAS, computed by $SAS = \frac{1}{\#\text{Session}(N)}$, implies that nodes shared across fewer active sessions should be evicted first. The weighted eviction score is as follows:

$$S_{evict} = \alpha \cdot SDS + \beta \cdot SAS$$

• **Subtree-aware Prefetching.** When a session advances to a semantic node N, SmartCache prefetches its children C into the GPU memory based on the *Node Access Frequency (Popularity)* $AF(C_i) = \frac{\#\text{sessions accessed } C_i \text{ after } N}{\#\text{sessions reached N}}$. It is calculated using statistics within a predefined time window, given that hot topics may change over time.



(a) KV Cache Usage

(b) Average Time To First Token

Figure 6: Resource efficiency comparison on different models and datasets.

4 Evaluation

4.1 Experiment Setup

Harward settings. We use a server equipped with Intel Xeon Silver 4310 CPU [17] and NVIDIA RTX4090 GPU [26], connected through PCIe4.0×16. The host has 256GB DDR4 memory and GPU has 24GB GDDR6X memory. Our server runs Linux 5.4 with CUDA 12.0 [5]. We implement our method using PyTorch 2.3 [29]. We evaluate our method on three different-sized open-source LLMs: Qwen-2.5-1.5B-Instruct [43], Llama-3.1-8B-Instruct [16], and Mistral-7B-Instruct-v0.2 [3].

Dataset. Three datasets are used in the evaluation, including the CoQA dev dataset [33] and SQuAD2.0 dev dataset [31]. CoQA is a conversational question answering dataset where questions are asked sequentially on the same short story. Later questions often depend on conversation history. SQuAD (Stanford Question Answering Dataset) contains questions on Wikipedia pages. Each story or paragraph used in the experiments has one original conversation sessions and two similar conversation sessions, with each session consisting of on average 5 turns of progressive question and answers.

Methods. Four methods are compared in the evaluation: 1) **Baseline**: KV caches are not shared among different conversations sessions, 2) **PrefixCache**: KV caches of common prefixes from different conversation sessions are shared, 3) **GPTCache**: an extra query-answer cache layer using the embeddings of queries as vector search keys is stacked on top of LLM inference backend, 4) **SmartCache**: the hierarchical and co-designed cache proposed in this paper. Conversation queries are issued interleavingly among different sessions.

The KV cache block size is 16 tokens. BGE-M3 [7] is used as the embedding model with the dimension of 1024. Embedding vectors are stored and searched using faiss [11] vector index based on L2 distance. The similarity threshold is set to 0.75.

Table 2: Answer Quality. Ideal represents the results of Baseline and PrefixCache.

Benchmark		**CoQA (0-shot)**			**SQuAD2.0 (0-shot)**		
Model	Method	ExactMatch	F1	ROUGE-L	ExactMatch	F1	ROUGE-L
Qwen-2.5-1.5B-Instruct	Ideal	27.5	51.1	51.3	14.2	65.5	64.0
	GPTCache	16.8	33.3	33.8	12.8	60.4	59.2
	SmartCache	**24.9 (+48.2%)**	**46.6 (+39.9%)**	**47.0 (+39.1%)**	**13.4 (+4.7%)**	**64.5 (+6.8%)**	**63.0 (+6.4%)**
Llama-3.1-8B-Instruct	Ideal	36.6	59.6	59.2	14.9	67.8	66.0
	GPTCache	23.0	38.8	39.1	13.4	62.3	60.9
	SmartCache	**24.9 (+8.3%)**	**49.5 (+20.1%)**	**49.2 (+20.2%)**	**14.0 (+4.5%)**	**66.5 (+6.7%)**	**64.6 (+6.1%)**
Mistral-7B-Instruct	Ideal	5.5	27.0	26.9	7.7	57.8	55.3
	GPTCache	3.0	17.4	17.7	6.9	52.7	50.6
	SmartCache	**3.1 (+3.3%)**	**20.0 (+14.9%)**	**20.0 (+13.0%)**	**7.7 (+11.6%)**	**56.2 (+6.6%)**	**54.6 (+7.9%)**

4.2 Resource Efficiency

Memory Efficiency. SmartCache significantly improves KV cache sharing by leveraging semantic relationships in multi-turn conversations, enhancing resource utilization across sessions. As shown in Figure 6(a), SmartCache reduces KV cache memory usage by up to 59.1% and 56.0% compared to PrefixCache and GPTCache, respectively, demonstrating superior efficiency in reusing KV cache memory.

Computational Efficiency. Figure 6(b) presents the average Time to First Token (TTFT) per query. On the CoQA dataset, across different models, SmartCache achieves 78.0% and 37.7% lower TTFT than PrefixCache and GPTCache, respectively. Similarly, on the SQuAD dataset, it reduces TTFT by 71.7% and 50.6% compared to the same baselines. These results highlight SmartCache's effectiveness in accelerating inference while minimizing computational overhead.

4.3 Answer Quality

The hierarchical semantic awareness of SmartCache significantly improves its answer quality, compared with GPTCache's flat query similarity search. As demonstrated in Table 2, SmartCache consistently enhances answer quality across different benchmarks and metrics. For the CoQA dataset, SmartCache improves Qwen-2.5-1.5B-Instruct's F1 score by 39.9% and Llama-3.1-8B-Instruct's ROUGE-L by 20.2%. For SQuAD2.0, SmartCache achieves smaller but consistent gains.

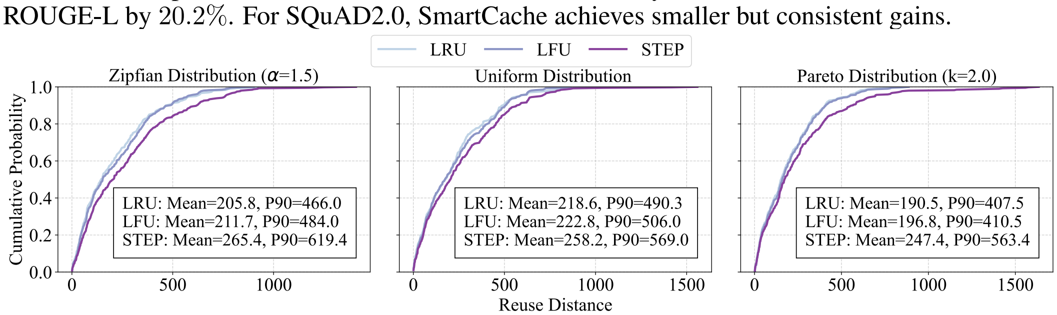


Figure 7: Reuse Distances CDF of different KV Cache Management Policy

4.4 KV Cache Management Policy

We compare SmartCache's STEP policy with commonly used LRU (Least Recently Used) and LFU (Least Frequently Used) policies. 1500 conversation sessions focusing on CoQA's stories follow three different distributions (zipfian, uniform and pareto) to show different real-world environments. Llama-3.1-8B-Instruct model is used with a GPU KV Cache budget of 4GB. Figure 7 compares the CDF (Cumulative Distribution Function) of the Reuse Distances (the number of distinct nodes accessed between two consecutive accesses to the same semantic node) of different policies. STEP shows up to 29.9% and 25.7% longer average reuse distance over LRU and LFU with skewed distribution and 18.2% and 15.9% longer with uniform distribution.

4.5 Overhead Analysis

We quantitatively show SmartCache's compute and memory overhead on Mistral-7B-Instruct-v0.2 using CoQA. Table 3 demonstrates the breakdown of overhead across SmartCache components. For a cache-missed new query (i.e. creating a new semantic node followed by LLM inference), SmartCache adds $\approx$8.8% computational overhead (18.54 ms out of 210.37 ms end-to-end). SmartCache's hierarchical semantic organization and co-design with KV cache management increase cache reuse opportunities, leading to significant end-to-end gains despite modest overhead.

The total GPU memory overhead is ≈7.1%, primarily from the embedding model, while CPU memory overhead is negligible (≈28.05 MB). Given the reduced inference time from cache reuse, the amortized cost of these components becomes insignificant at scale.

4.6 Performance under High Concurrency

As shown in Figure 8, we evaluate SmartCache under varying degrees of concurrent requests using Mistral-7B-Instruct-v0.2 on CoQA. As the number of concurrent requests increases, SmartCache demonstrates progressively greater speedups. As concurrency increases, the LLM's batching efficiency plateaus due to inherent GPU parallelism limits. However, SmartCache is able to bypass full LLM inference for many cache-hit queries, reducing the effective batch size. This not only alleviates load on the inference engine but also leverages hierarchical KV cache reuse, leading to significant reductions in TTFT.

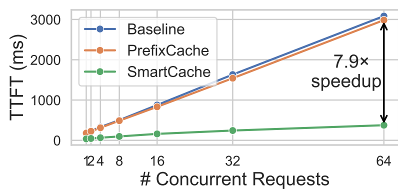


Figure 8: Overhead under different number of concurrent requests.

Table 3: Computational and Memory Overhead Breakdown of SmartCache.

Components	Computational Overhead	Memory Overhead
Embedding Generation	17.13 ms	1.06 GB (GPU)
Vector Search	0.11 ms	18.16 MB (CPU)
Vector Insertion	1.01 ms	Shared with vector search
Semantic Forest Maintenance	0.29 ms	9.89 MB (CPU)

5 Related Works

PrefixCache [40] reuses KV cache only when token prefixes match exactly, accelerating prefill but is limited in handling semantically similar queries. GPTCache [6] stores and retrieves responses based on flat query embeddings, enabling semantic reuse but lacking context awareness. PromptCache [15] accelerates inference by reusing attention (KV) states for frequently repeated prompt segments via a modular schema that preserves positional consistency, substantially reducing TTFT for long, template-like inputs. CacheBlend [44] targets RAG workloads, enabling chunk-level KV cache reuse across retrieved documents and selective recomputation of a small subset of tokens to refresh cross-chunk attention without incurring full prefill cost. Notably, SmartCache can be combined with CacheBlend and PromptCache to achieve further improvements.

6 Conclusion and Discussion

In this paper, we presented SmartCache, a context-aware semantic cache framework designed to address the inefficiencies of multi-turn LLM inference. By integrating hierarchical semantic indexing with KV cache management, SmartCache significantly reduces redundant computations and GPU memory usage while preserving conversational context.

Limitations and Future Work. First, sharing responses across user sessions introduces potential privacy risks. To mitigate this, a content desensitization module could be implemented to automatically remove or anonymize sensitive information prior to caching. Second, scaling the system to support a broader range of services requires a multi-instance extension, enabling more robust and distributed processing capabilities.

Acknowledgments and Disclosure of Funding

The work described in this paper is partially supported by the grants from the Research Grants Council of the Hong Kong Special Administrative Region, China (GRF 14202123, GRF 14200224).

References

[1] Google Vertex AI. Context caching overview. https://cloud.google.com/vertex-ai/generative-ai/docs/context-cache/context-cache-overview.

[2] Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebron, and Sumit Sanghai. GQA: Training generalized multi-query transformer models from multi-head checkpoints. In *The 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.

[3] Q Jiang Albert, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, and Devendra Singh Chaplot. Mistral 7b. *arXiv preprint*, 2023.

[4] Anthropic. Prompt caching. https://docs.anthropic.com/en/docs/build-with-claude/prompt-caching.

[5] Rob Armstrong. Cuda toolkit 12.0 released for general availability, 2022. https://developer.nvidia.com/blog/cuda-toolkit-12-0-released-for-general-availability/.

[6] Fu Bang. GPTCache: An open-source semantic cache for LLM applications enabling faster answers and cost savings. In Liling Tan, Dmitrijs Milajevs, Geeticka Chauhan, Jeremy Gwinnup, and Elijah Rippeth, editors, *Proceedings of the 3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS 2023)*, pages 212–218, Singapore, December 2023. Association for Computational Linguistics.

[7] Jianlyu Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. M3-embedding: Multi-linguality, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics: ACL 2024*, pages 2318–2335, Bangkok, Thailand, August 2024. Association for Computational Linguistics.

[8] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023.

[9] Chroma. The ai-native open-source embedding database. https://github.com/chroma-core/chroma.

[10] Hyung Won Chung, Thibault Fevry, Henry Tsai, Melvin Johnson, and Sebastian Ruder. Rethinking embedding coupling in pre-trained language models. In *International Conference on Learning Representations*, 2021.

[11] Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. The faiss library. *IEEE Transactions on Big Data*, 2025.

[12] Haodong Duan, Jueqi Wei, Chonghua Wang, Hongwei Liu, Yixiao Fang, Songyang Zhang, Dahua Lin, and Kai Chen. BotChat: Evaluating LLMs' capabilities of having multi-turn dialogues. In Kevin Duh, Helena Gomez, and Steven Bethard, editors, *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 3184–3200, Mexico City, Mexico, June 2024. Association for Computational Linguistics.

[13] William Fedus, Barret Zoph, and Noam Shazeer. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. *Journal of Machine Learning Research*, 23(120):1–39, 2022.

[14] Bin Gao, Zhuomin He, Puru Sharma, Qingxuan Kang, Djordje Jevdjic, Junbo Deng, Xingkun Yang, Zhou Yu, and Pengfei Zuo. Cost-efficient large language model serving for multi-turn conversations with cachedattention. In *Proceedings of the 2024 USENIX Conference on Usenix Annual Technical Conference*, USENIX ATC'24, USA, 2025. USENIX Association.

[15] In Gim, Guojun Chen, Seung-seob Lee, Nikhil Sarda, Anurag Khandelwal, and Lin Zhong. Prompt cache: Modular attention reuse for low-latency inference. In P. Gibbons, G. Pekhimenko, and C. De Sa, editors, *Proceedings of Machine Learning and Systems*, volume 6, pages 325–338, 2024.

[16] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

[17] Intel. 3rd gen intel® xeon® scalable processors, 2021. https://www.intel.com/content/www/us/en/products/docs/processors/xeon/3rd-gen-xeon-scalable-processors-brief.html.

[18] Redwan Ibne Seraj Khan, Kunal Jain, Haiying Shen, Ankur Mallick, Anjaly Parayil, Anoop Kulkarni, Steve Kofsky, Pankhuri Choudhary, Renee St Amant, Rujia Wang, et al. Ensuring fair llm serving amid diverse applications. *arXiv preprint arXiv:2411.15997*, 2024.

[19] 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*, SOSP '23, page 611–626, New York, NY, USA, 2023. Association for Computing Machinery.

[20] Philippe Laban, Hiroaki Hayashi, Yingbo Zhou, and Jennifer Neville. Llms get lost in multi-turn conversation. *arXiv preprint arXiv:2505.06120*, 2025.

[21] Jiaxing Li, Chi Xu, Feng Wang, Isaac M von Riedemann, Cong Zhang, and Jiangchuan Liu. Scalm: Towards semantic caching for automated chat services with large language models. In *2024 IEEE/ACM 32nd International Symposium on Quality of Service (IWQoS)*, pages 1–10. IEEE, 2024.

[22] Pierre Lison and Andrey Kutuzov. Redefining context windows for word embedding models: An experimental study. In Jörg Tiedemann and Nina Tahmasebi, editors, *Proceedings of the 21st Nordic Conference on Computational Linguistics*, pages 284–288, Gothenburg, Sweden, May 2017. Association for Computational Linguistics.

[23] Kun Luo, Zheng Liu, Shitao Xiao, Tong Zhou, Yubo Chen, Jun Zhao, and Kang Liu. Landmark embedding: A chunking-free embedding method for retrieval augmented long-context large language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3268–3281, Bangkok, Thailand, August 2024. Association for Computational Linguistics.

[24] Yu A. Malkov and D. A. Yashunin. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. *IEEE Trans. Pattern Anal. Mach. Intell.*, 42(4):824–836, April 2020.

[25] Microsoft. Microsoft. `https://www.microsoft.com/en-us/research/publication/ensuring-fair-llm-serving-amid-diverse-applications/`.

[26] NVIDIA. Geforce rtx 4090. `https://www.nvidia.com/en-us/geforce/graphics-cards/40-series/rtx-4090/`.

[27] OpenAI. Prompt caching in the api. `https://openai.com/index/api-prompt-caching/`.

[28] Ofir Press, Noah Smith, and Mike Lewis. Train short, test long: Attention with linear biases enables input length extrapolation. In *International Conference on Learning Representations*, 2022.

[29] PyTorch. Pytorch documentation. `https://pytorch.org/`.

[30] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.

[31] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. SQuAD: 100,000+ questions for machine comprehension of text. In Jian Su, Kevin Duh, and Xavier Carreras, editors, *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas, November 2016. Association for Computational Linguistics.

[32] David Rau, Shuai Wang, Hervé Déjean, Stéphane Clinchant, and Jaap Kamps. Context embeddings for efficient answer generation in retrieval-augmented generation. In *Proceedings of the Eighteenth ACM International Conference on Web Search and Data Mining*, WSDM '25, page 493–502, New York, NY, USA, 2025. Association for Computing Machinery.

[33] Siva Reddy, Danqi Chen, and Christopher D. Manning. CoQA: A conversational question answering challenge. *Transactions of the Association for Computational Linguistics*, 7:249–266, 2019.

[34] 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.

[35] Jianlin Su, Murtadha Ahmed, Yu Lu, Shengfeng Pan, Wen Bo, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *Neurocomputing*, 568:127063, 2024.

[36] Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. Lamda: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*, 2022.

[37] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.

[38] P. D. Turney and P. Pantel. From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research*, 37:141–188, February 2010.

[39] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, page 6000–6010, Red Hook, NY, USA, 2017. Curran Associates Inc.

[40] vLLM. Automatic prefix caching. `https://docs.vllm.ai/en/latest/features/automatic_prefix_caching.html`.

[41] Jianguo Wang, Xiaomeng Yi, Rentong Guo, Hai Jin, Peng Xu, Shengjun Li, Xiangyu Wang, Xiangzhou Guo, Chengming Li, Xiaohai Xu, Kun Yu, Yuxing Yuan, Yinghao Zou, Jiquan Long, Yudong Cai, Zhenxiang Li, Zhifeng Zhang, Yihua Mo, Jun Gu, Ruiyi Jiang, Yi Wei, and Charles Xie. Milvus: A purpose-built vector data management system. In *Proceedings of the 2021 International Conference on Management of Data*, SIGMOD '21, page 2614–2627, New York, NY, USA, 2021. Association for Computing Machinery.

[42] Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. Efficient streaming language models with attention sinks. In *The Twelfth International Conference on Learning Representations*, 2024.

[43] An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report. *arXiv preprint arXiv:2412.15115*, 2024.

[44] Jiayi Yao, Hanchen Li, Yuhan Liu, Siddhant Ray, Yihua Cheng, Qizheng Zhang, Kuntai Du, Shan Lu, and Junchen Jiang. Cacheblend: Fast large language model serving for rag with cached knowledge fusion. In *Proceedings of the Twentieth European Conference on Computer Systems*, EuroSys '25, page 94–109, New York, NY, USA, 2025. Association for Computing Machinery.

[45] Biao Zhang, Barry Haddow, and Alexandra Birch. Prompting large language model for machine translation: a case study. In *Proceedings of the 40th International Conference on Machine Learning*, ICML'23. JMLR.org, 2023.

[46] Chen Zhang, Xinyi Dai, Yaxiong Wu, Qu Yang, Yasheng Wang, Ruiming Tang, and Yong Liu. A survey on multi-turn interaction capabilities of large language models. *arXiv preprint arXiv:2501.09959*, 2025.

[47] Tianyi Zhang, Faisal Ladhak, Esin Durmus, Percy Liang, Kathleen McKeown, and Tatsunori B. Hashimoto. Benchmarking large language models for news summarization. *Transactions of the Association for Computational Linguistics*, 12:39–57, 2024.

[48] Lianmin Zheng, Liangsheng Yin, Zhiqiang Xie, Chuyue Sun, Jeff Huang, Cody Hao Yu, Shiyi Cao, Christos Kozyrakis, Ion Stoica, Joseph E. Gonzalez, Clark Barrett, and Ying Sheng. Sglang: efficient execution of structured language model programs. In *Proceedings of the 38th International Conference on Neural Information Processing Systems*, NIPS '24, Red Hook, NY, USA, 2025. Curran Associates Inc.

A Appendix

A.1 Evaluation on Larger Model

To further evaluate SmartCache's scalability and effectiveness, we conduct additional experiments using the Qwen2.5-32B-Instruct model on a high-end hardware configuration: AMD EPYC 7513, 512GB DRAM, and one NVIDIA A100 80GB GPU. Table 4 summarizes the results on the CoQA dataset.

Table 4: Results on Qwen2.5-32B-Instruct

Metrics / Method	TTFT (ms)	KV Cache (GB)	EM	F1	ROUGE-L
Baseline	213.9	189.2	33.3	54.8	55.0
PrefixCache	182.5	171.8	33.3	54.8	55.0
GPTCache	94.1	98.3	18.8	34.3	34.7
SmartCache	**69.4**	**71.4**	26.8	50.2	50.4

A.2 Computational Overhead under Concurrency

We evaluate SmartCache's computational overhead using Mistral-7B-Instruct-v0.2 on CoQA under varying numbers of concurrent requests. As shown in Table 5, the primary cost under increased concurrency arises from embedding generation, which supports efficient batching. 8 CPU threads are used for faiss-cpu internal threading and semantic forest maintenance. Minor contention is observed in the semantic forest maintenance, especially when multiple queries attempt to insert child nodes under the same parent node. This is mitigated by batching vector insertions.

Table 5: Overhead under concurrent requests (ms).

# Concurrent Requests	1	2	4	8	16	32	64
Embedding Generation	17.13	18.00	19.44	19.54	20.81	22.08	23.32
Vector Search	0.11	0.23	0.26	0.36	0.75	5.64	9.35
Vector Insertion	1.01	1.01	1.02	1.05	1.06	1.22	1.62
Semantic Forest Maintenance	0.29	0.31	0.31	0.33	0.67	1.34	2.97

A.3 Hyperparameter Sensitivity

We evaluate similarity threshold τ_{sim} used to determine semantic matches in the Semantic Forest, and the weighting coefficients (α, β) that balance the Semantic Depth Score (SDS) and Session Affinity Score (SAS) in the STEP eviction policy.

A.3.1 Similarity Threshold

Table 6 shows the answer quality and performance on Qwen2.5-1.5B-Instruct with CoQA. Increasing τ_{sim} monotonically improves EM/F1/ROUGE-L by enforcing stricter semantic matches, but reduces reuse opportunities, increasing both TTFT and KV cache usage. We adopt $\tau_{sim} = 0.75$ for a balanced operating point used in main experiments.

Table 6: Answer quality and performance across different similarity threshold.

τ_{sim}	EM	F1	ROUGE-L	TTFT (ms)	KV Cache (GB)
0.50	17.4	35.2	35.5	26.8	4.1
0.60	21.6	41.1	41.4	27.5	4.5
0.70	23.5	45.3	45.5	30.2	6.5
0.75	24.9	46.6	47.0	31.3	7.7
0.80	25.4	47.7	47.9	49.0	8.5
0.90	25.9	48.9	49.1	83.2	12.1

A.3.2 Coefficients α and β of STEP Policy

Table 7 shows the grid search result with the same configuration as Section 4.4. We adopt $\alpha = 0.6$ and $\beta = 0.4$ for STEP in all evaluations, as this setting attains the highest average reuse distance.

Table 7: Average reuse distance over different (α, β) settings (zipfian distribution).

(α, β)	(0.1,0.9)	(0.2,0.8)	(0.3,0.7)	(0.4,0.6)	(0.5,0.5)	(0.6,0.4)	(0.7,0.3)	(0.8,0.2)	(0.9,0.1)
Reuse distance (avg)	231.8	252.0	255.9	262.3	261.6	**265.4**	260.5	240.9	252.5

A.4 Attention-based Context Switching

Since different models exhibit numeric variations on attention scores, the attention score threshold is profiled for each model offline using five predefined independent queries, averaged across attention heads and query tokens for each query, excluding 8 initial tokens that behave as attention sinks (i.e., attracting disproportionate attention regardless of context [42]). The same attention score calculation procedure is triggered during the prefill stage of a query when it fails from reusing its child semantic nodes. It is then compared with the the profiled threshold to determine whether or not the query is independent.

Impact of Architectural Differences. The widely used Grouped-Query Attention (GQA [2]) changes per-head magnitudes but preserves the probabilistic semantics of attention. Mixture-of-Experts (MoE [13]) alters the feed-forward pathway via expert routing while leaving the attention softmax itself unchanged. Positional encodings such as rotary position embeddings (RoPE [35]) and attention with linear biases (ALiBi [28]) modify how relative position influences attention logits, but after softmax the attention weights still form a probability simplex. Therefore, architectural modifications that change logits but preserve the probabilistic semantics do not require changing the decision logic.

A.5 Privacy Preserving

SmartCache is designed to support multi-user environments, where multiple sessions may reuse cached responses across conversations. While semantic reuse offers significant performance and memory advantages, it also introduces potential privacy concerns. These issues can be mitigated via query sanitization, access control, and asynchronous privacy filtering.

Query Sanitization. To prevent private or sensitive information from being inadvertently shared across sessions, SmartCache integrates a privacy data sanitizer module. This module inspects user queries and determines whether a query-response pair should be treated as private. If so, the corresponding semantic node is marked as hidden, meaning it is only visible to the originating user or authorized parties, such as members of the same organization or tenant.

Access Control. Hidden semantic nodes are excluded from the global semantic forest used for cross-session lookup. These nodes are stored and reused exclusively within the user's own session or within authorized scopes defined by privacy policies. This ensures that personal or sensitive queries, even if semantically similar to others, do not produce cache hits across different users.

Asynchronous Sanitization for Low Latency. To minimize latency, when a new query is issued, it is immediately processed and added to the cache as a hidden node by default. In the background, the sanitizer evaluates the query and, if it is deemed non-sensitive, updates the node's visibility status to allow future sharing. This decouples privacy inspection from the critical path of inference, preserving the low TTFT guarantees of SmartCache while still ensuring privacy compliance.

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes] , [No] , or [NA] .
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes] " is generally preferable to "[No] ", it is perfectly acceptable to answer "[No] " provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No] " or "[NA] " is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading "NeurIPS Paper Checklist"**,
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers**.

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification:

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification:

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [NA]

   Justification:

   Guidelines:

   - The answer NA means that the paper does not include theoretical results.
   - All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
   - All assumptions should be clearly stated or referenced in the statement of any theorems.
   - The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
   - Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
   - Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

   Answer: [Yes]

   Justification:

   Guidelines:

   - The answer NA means that the paper does not include experiments.

- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
  (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [NA]

   Justification:

   Guidelines:

   - The answer NA means that paper does not include experiments requiring code.
   - Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
   - The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
   - At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).

- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification:

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [No]

   Justification: The reported evaluation results in this paper is averaged through multiple runs of experiments.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
   - The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
   - The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
   - The assumptions made should be given (e.g., Normally distributed errors).
   - It should be clear whether the error bar is the standard deviation or the standard error of the mean.
   - It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
   - For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
   - If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification:

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.

- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification:

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [NA]

    Justification:

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
    - The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
    - The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
    - If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

    Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

    Answer: [NA]

    Justification:

    Guidelines:

    - The answer NA means that the paper poses no such risks.

- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

    Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

    Answer: [Yes]

    Justification:

    Guidelines:

    - The answer NA means that the paper does not use existing assets.
    - The authors should cite the original paper that produced the code package or dataset.
    - The authors should state which version of the asset is used and, if possible, include a URL.
    - The name of the license (e.g., CC-BY 4.0) should be included for each asset.
    - For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
    - If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
    - For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
    - If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [Yes]

    Justification:

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification:

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification:

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

    Answer: [NA]

    Justification:

    Guidelines:

    - The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.