SemShareKV: Efficient KVCache Sharing for Semantically Similar Prompts via Token-Level LSH Matching

Anonymous ACL submission

Abstract

As large language models (LLMs) continue to scale, the memory footprint of key-value (KV) caches during inference has become a significant bottleneck. Existing approaches primarily focus on compressing KV caches within a single prompt or reusing shared prefixes or frequently ocurred text segments across prompts. However, such strategies are limited in scenarios where prompts are semantically similar but lexically different, which frequently occurs in tasks such as multi-document summarization and conversational agents. We propose *SemShareKV*, a KV cache sharing and compression framework that accelerates LLM inference by reusing KVCache in semantically similar prompts. Instead of relying on exact token matches, SemShareKV applies fuzzy token matching using locality-sensitive hashing (LSH) on token embeddings and incorporates Rotary Position Embedding (RoPE) to better preserve positional information. By selectively reusing relevant key-value pairs from a reference prompt's cache, SemShareKV reduces redundant computation while maintaining output quality. Experiments on diverse summarization datasets show up to 6.25× speedup and 42% lower GPU memory usage with 5k tokens input, with negligible quality degradation. These results highlight the potential of semantic-aware cache sharing for efficient LLM inference. The code is available at https://anonymous.4open.science/r/SemShareKV-B53C.

1 Introduction

Large Language Models (LLMs) have exhibited a strong capability to understand and process human languages, and have been shown to perform comparably to humans in several fields, such as math inference, text memorization, information extraction, story telling (Naveed et al., 2023). Recently released LLMs have significantly advanced in processing and comprehending extremely long prompts. However, this introduces a notable challenge: increased computational demand due to the quadratic time complexity of their Decoder-Only Transformer architecture when handling lengthy text sequences. The issue is further compounded during inference, as the auto-regressive decoding process repeats the computation for each newly generated token (Luohe et al., 2024).

Existing KVCache optimization approaches primarily focus on single-prompt compression through various techniques: Yang et al. (2024a) leverage decaying key-value importance across layers for selective extraction (though with limited small-batch gains), Gim et al. (2024) employ restrictive markup schemas for text chunk reuse, and Yao et al. (2024) propose deviation-based recomputation that requires impractical per-chunk precomputation for long inputs. Crucially, these methods operate within the constrained paradigm of single-prompt optimization, failing to exploit the substantial efficiency potential of cross-prompt cache reuse, a significant oversight given the prevalence of semantically similar queries in real-world applications where shared computational savings could be substantial.

Motivated by this challenge, we aim to address the following research question: ***Can we reuse the precomputed KVCache for another semantically similar prompt?***

To answer this question, we proposed ***SemShareKV***, a KVCache framework that can reuse the cache from one prompt for another that is semantically similar to each other via fuzzy token match. It speeds up prefill phase and compress KV cache in memory. We show that our method can reduce the pre-fill phase time by 6.25× and save 42% GPU memory space. We make the following contributions.

- We introduce SemShareKV, which explores KVCache sharing across semantically similar

prompts based on fuzzy token match.

- We evaluate SemShareKV across multiple datasets, demonstrating its effectiveness in accelerating the prefill phase while simultaneously reducing KVCache size.

- We explored the role of position encoding in KVCache by injecting it into vector embeddings.

2 Related Work

Prior research on KVCache optimization can be categorized into three key directions: (i) **Conventional KVCache Compression**, which focuses on reducing the storage and computational overhead of KVCache by applying quantization, pruning, or other compression techniques; (ii) **KVCache Sharing**, which explores methods to reuse KVCache across different queries or tasks to improve efficiency while maintaining response quality; and (iii) **KVCache Reusing**, which investigates strategies to adapt and repurpose precomputed KVCache for semantically similar inputs, minimizing redundant computation while preserving model accuracy.

2.1 Conventional KVCache Compression

To address long-context processing, many works propose optimizing inference by retaining only informative tokens. Token-level compression often uses attention-based token selection (Zhang et al., 2023; Xiao et al., 2024; Li et al., 2024; Yang et al., 2024a; Zhong et al., 2024), low-rank decomposition (Sun et al., 2024), or quantization (Zhang et al., 2024; Wang et al., 2024). Model-level approaches redesign architectures to improve reuse (Sun et al., 2025; Yan et al., 2024), while system-level methods focus on memory and scheduling (Kwon et al., 2023; Sheng et al., 2023). Recent work has highlighted the use of value vectors to facilitate compression (Guo et al., 2024).

2.2 KVCache Sharing

Some also emphasize reusing portions of the cache for future or similar queries and prompts. For example, PromptCache (Gim et al., 2024) stores text segments that appear frequently on an inference server using a schema, although this approach hampers usability, as users must conform their natural language to the schema format. Mooncake (Qin et al., 2024), KVSharer (Yang et al., 2024b) and MiniCache (Liu et al.) exploit the high similarity of attention scores among adjacent transformer layers to improve KVCache reuse. By consolidating or sharing Key-Value pairs between similar layers, these methods improve memory efficiency and streamline token processing. However, their approaches are restricted to sharing in the layer or text segment within adjacent layers or the same LLM, limiting the broader applicability; GPTCache (Regmi and Pun, 2024), (Rasool et al., 2024) and (Bang, 2023) utilize similarity search among queries to reuse KVCache. However, they have a high probability of missing a hit and require the entire query to be similar, offering limited flexibility.

2.3 KVCache Reusing

Limited attention has been directed toward the sharing of KVCache in LLMs. DroidSpeak(Liu et al., 2024b) improves context sharing between fine-tuned LLMs by identifying critical KVCache layers and selectively recomputing them for efficient reuse while maintaining accuracy. LMCache(Cheng et al., 2024) introduces a Knowledge Delivery Network (KDN) to optimize KVCache storage and transfer, allowing cost-effective knowledge injection in LLM inference. CacheBlend(Yao et al., 2024), KVShare(Yang et al., 2025), and EPIC(Hu et al., 2024) rely on exact context matching, which is unsuitable for real user scenarios. SentenceKV suffers from inter-sentence information loss, as noted in the CacheBlend paper. In contrast, SemShareKV introduces RoPE in token matching to address this issue.

3 Observations and Insights

We present three key insights derived from our experiments on three LLMs: Mistral-7B (Jiang et al., 2023), LLaMA-3.1-8B (Grattafiori et al., 2024), and MPT-7B (Team, 2023). These insights show consistent patterns across different LLMs, supporting the generality of our observations.

Insights 1 *HD tokens stay consistent across layers.*

When reusing KV caches from semantically similar prompts, we ensure the reused cache maintains high fidelity with fully recomputed caches to prevent performance degradation. To compare the similarity between two KV matrices, we used our augmented MultiNews dataset, where each sample consists of a pair of semantically similar prompts:

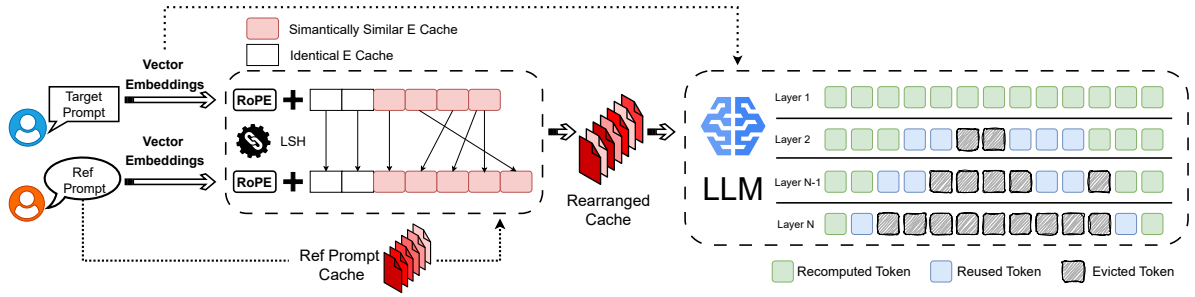


Figure 1: Schematic Overview of SemshareKV

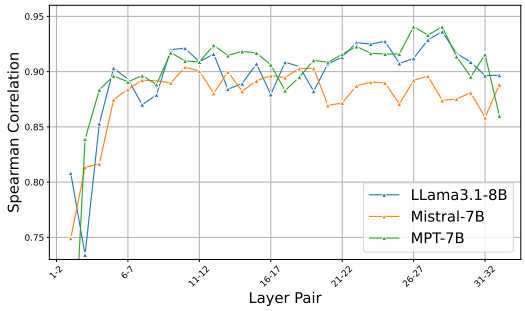


Figure 2: Insight 1: High-deviation tokens remain consistent across layers.

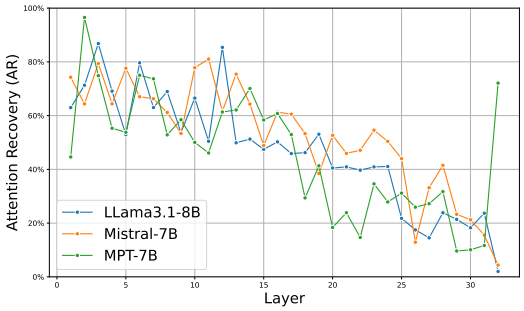


Figure 3: Insight 2: Deeper layers attend to fewer tokens.

the ***Target Prompt***, which serves as the primary input to the model, and the ***Reference Prompt***, which acts as the semantically similar counterpart. For each of the aforementioned LLMs, we first computed the KV caches for the prompt pairs independently. Subsequently, we calculated the deviations between the KV caches of the target and reference prompts using the previously mentioned L2 norm. Tokens with the highest 40% deviation were identified as ***High Deviation*** (HD) tokens. To further quantify this observation, we compute the Spearman correlation of HD tokens between adjacent layers. As shown in Figure 2, adjacent layers exhibit relatively high consistency in HD token positions.

Insights 2 *Deeper layers focuses on fewer tokens*

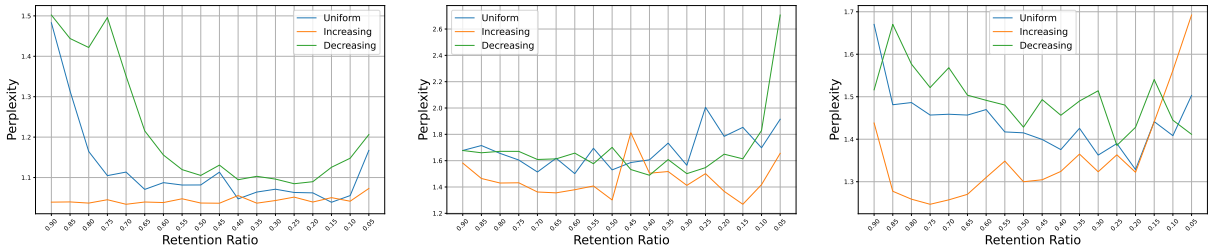
To analyze attention patterns across layers, we first averaged the attention scores across all heads in each layer and then computed the mean along the first dimension, resulting in a one-dimensional vector per layer. To quantify this behavior, we introduce ***Attention Recovery*** (AR), defined as follows:

$$S_{\text{total}} = \sum_{i=1}^{n} T_i \qquad \frac{\sum_{i=k}^{n} T_i}{S_{\text{total}}} > \text{Thres} \quad (1)$$

Where T is a sorted vector of average attention scores for each token, S_{total} represents the total attention score derived from the averaged self-attention matrices, and $Thres$ indicates the threshold of attention score. AR indicates the number of tokens that must be summed from highest to lowest based on their average attention scores in order to cover $Thres\%$ of the total attention score. We computed AR for each layer, and the results (Figure 3) reveal a consistent trend: as depth increases, AR decreases across all three LLMs, despite minor fluctuations. This suggests that deeper layers concentrate attention on progressively fewer tokens, reflecting more selective focus.

Insights 3 *Deeper layers have more redundant information.*

To reduce memory overhead from the KV cache, a key optimization strategy is to remove tokens containing redundant information. Such tokens contribute minimally to the prediction of next tokens during decoding but occupy substantial GPU memory. However, selective token retention risks information loss, necessitating careful trade-offs between memory savings and generation quality. We evaluate three KVCache retention strategies using perplexity: Constant, with equal retention across layers; Exponential Growth, with higher retention in shallow layers; and Exponential Decay, with more retained in deeper layers (Figure C2).



(a) Llama3.1-8B Retention Pattern (b) Mistral-7B Retention Pattern (c) MPT-7B Retention Pattern

Figure 4: Insight 3: Deeper layers contain more redundant information.

We applied these three retention patterns to LLMs, and utilized perplexity to benchmark the generation performance, shown in Figure C2. For all three LLMs, the Exponential Decay pattern achieves the lowest perplexity score, indicating the best generation performance. This finding further validates that this pattern aligns with how LLMs interpret knowledge from prompts.

4 Methodology

4.1 Relevant Concepts

Our work focuses on three critical cache components in modern LLMs:

- **Key Cache (K):** Key vectors encode the structural relationships among tokens in a sequence.
- **Value Cache (V):** Value vectors containing the actual content representations aggregated through attention weights. These preserve the contextual information of each token.
- **Embedding Cache (E):** Contextualized embeddings t capturing fundamental semantic and syntactic relationships (Mikolov et al., 2013), providing the foundational token representations before transformer processing.

4.2 Model Overview

The design of SEMSHAREKV, illustrated in Figure 1, is based on three key insights from Section 3. Our approach employs two core strategies:

- **Recomputation Strategy (Insights 1 & 2):** Prioritize the recomputing of more tokens in shallow layers while reducing the recomputation in deeper layers, reflecting the varying importance of the layer depth in attention mechanisms.
- **Retention Strategy (Insights 1 & 3):** Preserve more tokens in shallow layers while evicting tokens from deeper layers, optimizing memory usage without significant accuracy degradation.

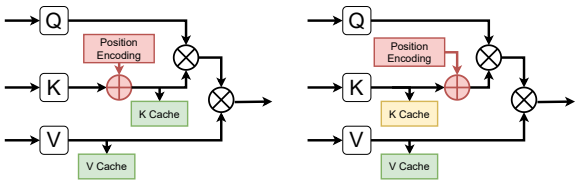
SemShareKV stores received prompts and their corresponding contextualized E caches in CPU memory. When the LLM receives a new prompt as the target prompt, it retrieves a reference prompt by computing an LSH-distance-based similarity score between the target's contextualized E cache and all stored E caches. The reference prompt with the highest similarity is then loaded onto the GPU along with its corresponding KV cache for reuse.

Once a reference prompt is retrieved, SemShareKV first applies RoPE to the E caches of both the target and reference prompts. Then it uses Locality-Sensitive Hashing (LSH) to match each token in the target prompt to its most similar tokens in the reference prompt. Based on these LSH mappings, the precomputed KVCache of the reference promptprompt is rearranged token by token and injected into LLM transformer layers. On the first transformer layer, all tokens undergo full recomputation. The recomputed outputs are compared with the rearranged cache values via L2 norm, identifying high-deviation tokens for prioritized recomputation in subsequent layers. Simultaneously, the system evicts tokens with the lowest attention scores from recent computations, optimizing KVCache memory usage dynamically.

4.3 KVCache Sharing Challenge

The primary challenge in cross-prompt KVCache sharing stems from length disparity between prompts. Inspired by (Liu et al., 2024b), we incorporates positional encoding within the E Cache to enable accurate token alignment while preserving contextual relationships.

Specifically, we use LSH to identify, for each token in the target prompt, the most similar token in the reference prompt based on their vector representations. We use Locality-Sensitive Hashing (LSH) for efficient token similarity search. Additional details on LSH are provided in Appendix A.2. This



(a) Standard KVCache Store (b) Modified KVCache Store

Figure 5: Default vs. modified KV cache storage.

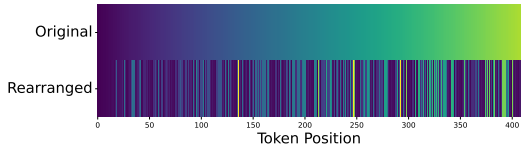
process allowed us to reorder the KVCache of the reference prompt to align with the token sequence of the target prompt. Consequently, the reordered KVCache matches the target prompt's length, with its key-value pairs entirely derived from the original KVCache of the reference prompt. The LLM uses the reordered KVCache to the target prompt.

4.3.1 Use Relative Position Encoding to Facilitate Fuzzy Token Match

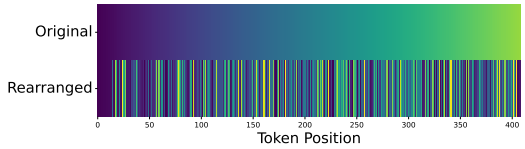
A fundamental limitation of naive matching using the E cache arises from the absence of positional context in its representation. Since raw vector embeddings lack inherent positional information, LSH fails to maintain crucial sequential relationships when identifying reference-target token correspondences. This positional agnosticism in the E cache consequently produces semantically inferior mapping results.

To address this, we introduce positional encoding into the E cache to enhance fuzzy token matching. Two widely used positional encoding strategies are absolute positional encoding (Vaswani et al., 2017), which embeds explicit position information, and relative positional encoding (Su et al., 2024), which captures positional relationships between tokens. In our work, we incorporate Rotary Position Embedding (RoPE) into the E cache and evaluate its impact. Specifically, RoPE is applied to the non-contextual embeddings (E cache) of both the reference and target prompts. Then, LSH is used to match each token in the target prompt's E cache to the most similar token in the reference prompt's E cache. This step is crucial because RoPE introduces position-sensitive information, allowing the same token at different positions to carry distinct semantics, enabling LSH to achieve more accurate token-level matching.

Figure 6 further illustrates how maintaining positional relationships through RoPE improves alignment accuracy, leading to better token retrieval and overall performance. Figure 6a compares the token positions in the original E cache with the rearranged positions after passing through the fuzzy token matching block, while Figure 6b presents the results when using an E cache with positional encoding. Notably, the first 20 tokens remain in their original positions, as they represent query tokens. This demonstrates that LSH correctly identifies and preserves query positions.



(a) Only E Cache



(b) E Cache with Relative Position Encoding

Figure 6: Fuzzy matching: with vs. without position encoding.

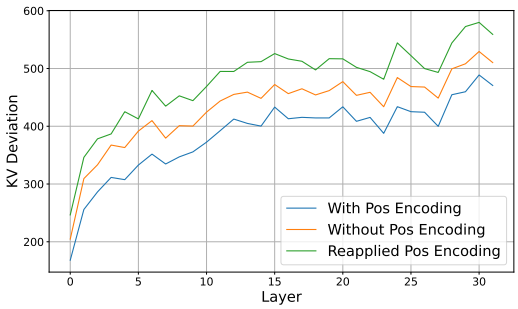


Figure 7: Impact of position encoding on E cache and KV cache deviation.

Beyond the initial tokens, a key difference emerges: without positional encoding, many tokens in the target prompt map to the initial tokens, whereas with positional encoding, they align more accurately with later tokens. We interpret this as a manifestation of "attention sink", a phenomenon in self-attention mechanisms where a significant portion of attention scores is consistently assigned to initial tokens, regardless of their actual relevance to the task (Xiao et al., 2023; Fei et al., 2025). Incorporating positional encoding into the E cache effectively mitigates this issue, leading to more accurate token matching and improved performance.

4.3.2 Impact from Position Encoding in KVCache

The second challenge is that LSH-based token rearrangement disrupts position encoding in the pre-

computed KV cache, affecting the KV matrices from the prefill phase. Previous studies (Gao et al., 2024) have discussed the impact of different position encoding strategies, suggesting that RoPE can be excluded from KVCache by applying it after storage, as illustrated in Figure 5. In evaluating the role of RoPE in the E cache, we compared three configurations of KVCache: (i) **with position encoding**, the standard setting where RoPE is applied before storing KVCache; (ii) **without position encoding**, where RoPE is not applied during storage; and (iii) **without position encoding but reapplied**, where RoPE is omitted during storage but reapplied after LSH-based reordering. Ideally, the rearranged KVCache should closely match the ground-truth KVCache for the target prompt. To quantify the deviation, we compute the L_2 norm between the rearranged and ground-truth caches. As shown in Figure 7, KV cache with position encoding has the lowest deviation, followed by the version without position encoding, while the configuration with reapplied RoPE gives the highest deviation. This highlights the importance of storing KV pairs after RoPE is applied. Ensuring consistent position encoding between the E and KV cache is essential for the LLM to fully leverage them and achieve optimal generation quality.

4.3.3 Recomputation Strategy

We divide the layers into two groups: the first and subsequent layers. Given that LLMs tend to focus more on later tokens (Liu et al., 2024a; Yang et al., 2024a), we categorize tokens into Cold (c) and Hot (h) using a dynamic ratio $\boldsymbol{r_{dynamic}}$ from Attention Recovery with a threshold of 55%, meaning $\boldsymbol{r_{dynamic}}\%$ of tokens with the highest cumulative attention are selected as Hot, and the rest as Cold. The total number of recomputed tokens is defined as Recomputed $= \omega_c \cdot c + \omega_h \cdot h$, where $\boldsymbol{\omega_c} = 0.1$ and $\boldsymbol{\omega_h} = 0.5$ in the SemShareKV setting.

Starting from the second layer, token selection follows this rule: based on *Insight 1*, the tokens selected in the next layer are derived from those chosen in the previous layer based on a recompute ratio $\boldsymbol{\alpha_{recomp}}\%$ of this layer. Based on *Insight 2*, $\boldsymbol{\alpha_{recomp}}\%$ in shallow layers will be relatively small while in deeper layers will be relatively large.

4.3.4 Retention Strategy

Similar to token recomputation, we categorize the layers into two groups: the first and the subsequent layers. On the first layer, the retention ratio is determined also by $\boldsymbol{r_{dynamic}}$, follows $Retained = \max(0.8, \boldsymbol{r_{dynamic}})$. And retained tokens are selected based on average attention scores across the last $(1 - \boldsymbol{r_{dynamic}})\%$ tokens, and only retain the top $\boldsymbol{r_{dynamic}}\%$ tokens with highest avg attention scores. In detail, the intuition behind selecting retained tokens is as follows: In the first layer, all hot tokens will be retained. Token eviction occurs only among Cold tokens that are not marked as recomputed. The underlying principle is that recomputed tokens provide better representations of the target prompt. If these tokens are evicted, the computational resources and time spent on recomputing them will be wasted. In subsequent layers, based on *Insight 3*, we should retain fewer tokens.

5 Evaluation and Results

5.1 Experiments Setup

We select a diverse set of datasets covering a broad range of tasks. For Q&A, we use **WikiHow** (Koupaee and Wang, 2018) and **Qasper** (Dasigi et al., 2021). For summarization, we include **MultiNews** (Bai et al., 2023) (multi-document), **SAMsum** (Gliwa et al., 2019) (dialogue), and **BookSum**, **PubMed**, and **BigPatent** (Kwan et al., 2023), which represent narrative, scientific, and patent documents, respectively; all three are single-document summarization. For code completion, we use **LLC** (Guo et al., 2023). For multiple-choice Q&A, we evaluate on **MMLU** (Hendrycks et al., 2021b,a).

We compared SemShareKV against three baselines: (i) **Fully Recompute**: standard inference using the unmodified model from the Transformers library, where the entire prompt is input without any KVCache reuse; (ii) **SnapKV** (Li et al., 2024): a KVCache management method that accelerates the prefill phase by efficient caching but does not compress the KVCache; (iii) **H2O** (Zhang et al., 2023): a dynamic KVCache eviction strategy that compresses KV memory by prioritizing important tokens, but does not optimize the prefill phase. ChatGPT said: We use a modified H2O compressing 10% of the cache per layer, with SnapKV and H2O as baselines for prefill optimization and KVCache compression. Experiments ran on a single A100 GPU with standard attention. Implementation details are in Appendix D.

To the best of our knowledge, no existing dataset benchmarks LLMs on KVCache sharing across

Table 1: Performance comparison between SemShareKV and baseline methods

Method	MultiNews	Wikihow	Qasper	SAMSum	PubMed	BookSum	BigPatent	LCC	MMLU
MISTRAL-7B									
Full KV	22.10	20.50	**17.10**	18.79	**24.66**	22.44	25.47	22.41	34.00
SemShareKV	**23.15**	19.38	16.52	**21.22**	24.30	22.50	**26.62**	21.55	32.50
SnapKV	23.07	21.32	15.55	20.16	24.58	**23.22**	25.78	**25.98**	**35.50**
H2O	23.04	**21.33**	15.88	20.50	23.53	22.77	24.99	16.57	33.00
LLAMA3.1-8B									
Full KV	22.49	19.71	14.21	16.69	24.50	22.65	27.26	19.01	**55.00**
SemShareKV	23.18	20.41	14.41	**18.61**	24.04	21.66	26.71	**21.39**	51.00
SnapKV	**23.84**	**21.65**	**14.70**	16.07	**24.82**	**22.76**	**27.48**	19.16	52.50
H2O	22.81	20.61	14.44	16.81	24.19	22.08	26.94	21.32	47.50

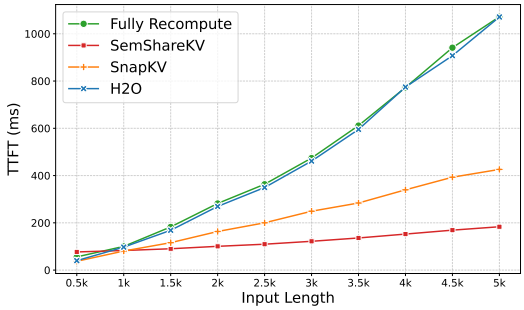
semantically similar prompts. To bridge this gap, we constructed evaluation samples by randomly selecting portions of entries from existing datasets and rewriting them using the Llama3 model. Then, these rewritten samples were manually verified to ensure that they remained semantically close to the originals. More details in the data preparation are provided in the Appendix B.

5.2 Benchmarking Evaluation

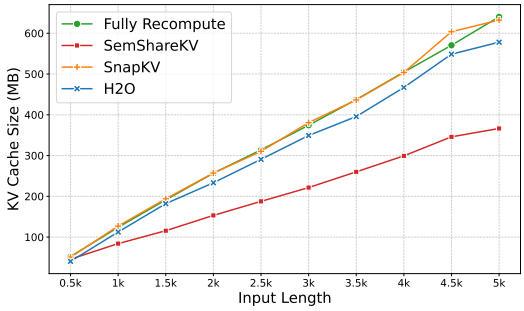
We argue that using Fuzzy Token Match introduces only a negligible overhead to model inference. Table 1 reports the ROUGE-L scores (Lin, 2004). Benchmarking results show that SemShareKV achieves performance comparable to or better than other baseline methods. Notably, in 4 out of the 5 evaluated datasets, *Fully Recompute* fails to attain the highest performance scores. We attribute this phenomenon to the token eviction mechanisms employed by SemShareKV, SnapKV, and H2O. By selectively retaining only the most semantically significant tokens for self-attention computation, these methods effectively reduce redundant information in the semantic representation, thereby enhancing the model's generation quality.

5.3 Efficiency Evaluation

We evaluate SemShareKV based on Time To First Token (TTFT) and KV Cache GPU KV memory usage, benchmarking it against Fully Recompute, SnapKV, and the unmodified H2O model. Figure 8 demonstrates the efficiency advantages of SemShareKV on the MultiNews dataset, showing consistent improvements over baseline methods: SemShareKV achieves **6.25**× faster Time-To-First-Token (TTFT) than Fully Recompute and H2O, **2.23**× faster TTFT than SnapKV, while reducing



(a) TTFT Comparison



(b) KVCache Size Comparison

Figure 8: Efficiency Evaluation Results.

memory usage by **42%**. However, as illustrated in Figure 8b, SemShareKV offers limited performance improvements for shorter prompts (fewer than 700 tokens), which we attribute to the overhead caused by fuzzy token matching and the rearrangement of tokens from the precomputed cache of the reference prompt. In future work, our goal is to minimize this overhead.

5.4 Impact of Prompt Similarity on Performance.

To evaluate similarity effects and SemShareKV performance, we designed two studies using the same percentage range (10% to 90% in 10% increments):

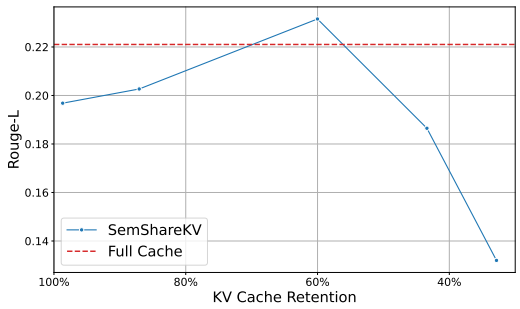


Figure 9: Cache Retention Ratio and Performance

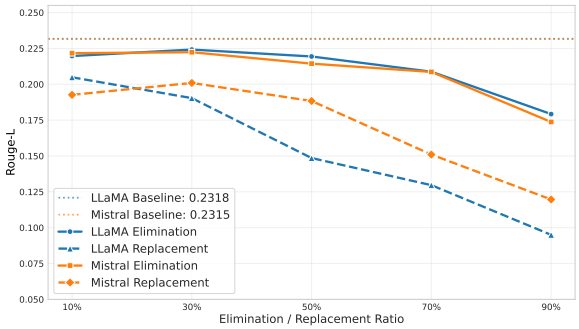


Figure 10: Impact of Prompt Similarity

1) randomly **eliminating** sentences from the context, and 2) randomly **replacing** sentences with others from the MULTINEWS dataset. We then applied SemShareKV to reuse the cache from the modified reference prompt for the target prompt. As shown in Figure 10, performance gradually degrades as more sentences are removed, yet remains reasonable even with substantial reductions. Notably, SemShareKV maintains strong performance even when 50% of context sentences are removed, highlighting the effectiveness of LSH-based token-level matching. This trend holds across both LLMs, suggesting the generality of our approach. Additionally, based on the observed performance trend, we empirically set a threshold of 0.8 for applying SemShareKV, meaning that if two prompts have an LSH similarity score above 0.8, SemShareKV can be applied. Figure 11 illustrates how the LSH-distance-based similarity changes as the replacement and elimination ratios increase. More details are in Appendix B.2.

5.5 Ablation Study

We conducted two ablation studies to evaluate the impact of fuzzy token matching on semantic understanding. First, by either zeroing out or replacing matched KV cache tokens with random ones, we observed significantly lower ROUGE-L

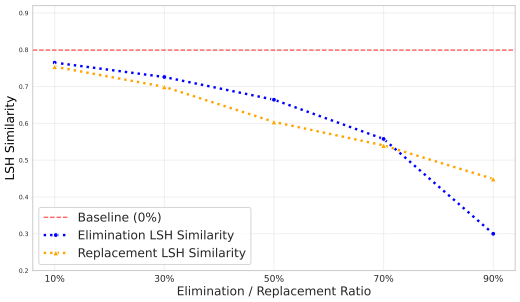


Figure 11: The three retention patterns start from the same retention ratio.

Table 2: Ablation study on ROUGE-L for SemShareKV and its ablations across datasets.

Method	SAMSum(↑)	MultiNews(↑)
SemShareKV	**21.22**	**23.15**
Ablation-Zero	14.63	17.71
Ablation-Random	5.38	12.67

scores compared to the full SemShareKV method, confirming the importance of fuzzy matching for capturing semantics (Table 2). Second, analyzing the KVCache compression ratio on the MultiNews dataset (Figure 9), retaining too much cache adds redundancy and harms performance, while retaining too little causes information loss, emphasizing the need for a balanced cache retention strategy.

6 Conclusion

We proposed SEMSHAREKV, a KVCache sharing framework that enables reuse across semantically similar prompts through fuzzy token matching using locality-sensitive hashing. SemShareKV achieves a speed of 6.25× and saves up to 42% kvcahce memory space compared to conventional KVCache, with a minimum performance drop.

Limitations

While SEMSHAREKV effectively shares KV caches for semantically similar prompts, its evaluation so far has been limited to summarization tasks. Speedups decrease for shorter prompts due to the overhead of fuzzy matching, and several hyperparameters require careful tuning. Additionally, our current implementation focuses on demonstrating SEMSHAREKV's effectiveness and does not yet support FlashAttention; we plan to incorporate it in future work. Also, the matching threshold is empirically set, and exploring adaptive strategies remains future work.

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A Formula and Inference

A.1 Rotary Position Encoding

In our methodology, we introduced the application of **Rotary Position Embedding (RoPE)** to the E cache, which improves the performance of fuzzy token matching. RoPE is designed to incorporate positional information directly into embeddings, allowing for improved alignment between tokens in a sequence. This is particularly important in natural language processing tasks where the order of words can significantly impact the meaning and context.

The formula of RoPE in a 2-D case is shown below:

$$\text{RoPE}(\mathbf{x}) = \begin{bmatrix} \cos(\theta_k) & -\sin(\theta_k) \\ \sin(\theta_k) & \cos(\theta_k) \end{bmatrix} \begin{bmatrix} x_{2k} \\ x_{2k+1} \end{bmatrix} \quad (1)$$

In this equation, $\theta_k = 10000^{-2k/d}$, where d represents the embedding dimension. The use of RoPE allows for the effective encoding of relative positional information, enabling the model to better capture the relationships between tokens in a sequence. Integrating RoPE into the E cache facilitates the identification of semantically similar tokens using LSH, leading to more accurate and efficient fuzzy token matching. This enhancement helps the model perform more accurately on tasks that require strong semantic understanding.

A.2 Locality-Sensitive Hashing (LSH)

Locality-Sensitive Hashing (LSH) is a technique that enables efficient approximate nearest neighbor searches in high-dimensional spaces by ensuring similar input items are hashed into the same bucket with high probability (Indyk and Motwani, 1998). This reduces the number of distance computations required, making LSH particularly useful for large datasets in applications such as image retrieval and natural language processing (Datar et al., 2004). In LSH for Euclidean distance, a common hash function is:

$$h(x) = \lfloor \frac{x \cdot r + b}{w} \rfloor$$

where r is a random vector, b is a random offset, and w is the hash width. This overview encapsulates the theory and practical application of LSH in our framework.

The LSH (Locality-Sensitive Hashing) in SemShareKV is implemented using the FAISS Python library (Douze et al., 2024). Further configuration details can be found in the provided code repository.

A.3 LSH-Distance Based Similarity Score

For retrieving reference prompts to reuse cache with SemShareKV, we compute a similarity score by normalizing the LSH distance and inverting it to fit within a [0, 1] range:

$$\begin{aligned} d_{\text{norm}} &= \frac{\text{LSH\_dist} - \min(\text{dist})}{\max(\text{dist}) - \min(\text{dist})} \\ \text{Similarity} &= \text{clip}(1 - d_{\text{norm}},\, 0,\, 1) \end{aligned} \quad (2)$$

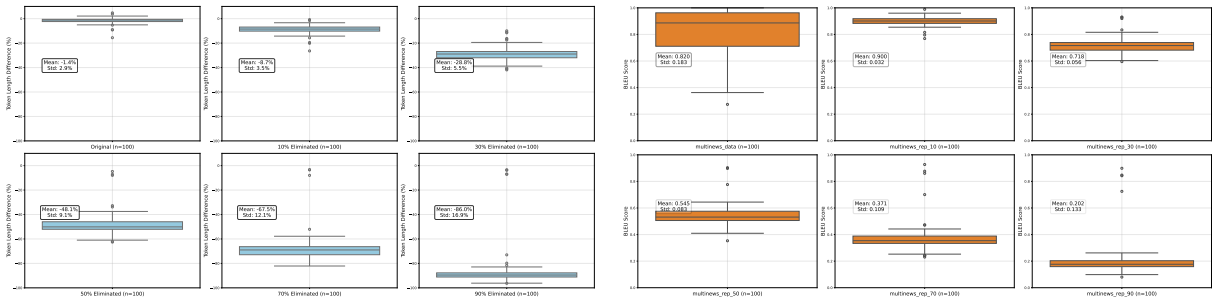
where d_{norm} denotes the normalized LSH distance; $\min(\text{dist})$ is set to 0 and $\max(\text{dist})$ is set to 30.

A.4 Key-Value Deviation

We define Key-Value Deviation with L2 norm as below:

Table B1: Similarity evaluation on benchmarking datasets using ROUGE-L, BERTScore, and BLEU. All datasets contain 100 semantically similar rewritten samples.

Metric	MultiNews	Wikihow	Qasper	SAMSum	PubMed	BookSum	BigPatent	LCC	MMLU
N of Samples	100	100	100	100	100	100	100	100	200
Rewrite % (Avg)	54.58		28.99	46.75	45.64	44.31	28.55	29.51	76.39
ROUGE-L(%)	84.71	83.82	91.71	50.90	88.15	78.15	90.03	87.34	44.04
BERTScore(%)	95.85	95.98	98.13	86.97	95.48	95.58	96.07	98.41	89.57
BLEU(%)	90.40	87.84	91.32	24.68	89.22	81.16	89.29	89.76	40.51



(a) Elimination from Multinews dataset

(b) Replace from Multinews dataset

Figure C1: Insight 3: Deeper layers contain more redundant information.

$$\sigma_K = \|K^{\text{reused}} - K^{\text{recomputed}}\|_2,$$
$$\sigma_V = \|V^{\text{reused}} - V^{\text{recomputed}}\|_2, \quad (3)$$
$$\sigma_{KV} = \sigma_K + \sigma_V$$

Where K^{reused} and V^{reused} represent the Key and Value matrices in cache reused from the semantic similar prompt; $K^{\text{recomputed}}$ and $V^{\text{recomputed}}$ refer to the Key and Value matrices recomputed at the current layer.

A.5 Token Recomputation

The total number of tokens recomputed on layer i is represented as

$$\text{Recomp}[i] = \text{T} \prod_{j=1}^{i} \alpha_{\text{recomp}}[j] \quad (4)$$

Where T denotes the total number of tokens, $\boldsymbol{i}$ represents the layer index.

A.6 Token Retention

The token retained on each layer is defined as:

$$\text{Retain}[i] = \text{T} \prod_{j=1}^{i} \alpha_{\text{retain}}[j] \quad (5)$$

Where T is the total tokens, $\boldsymbol{i}$ the layer index, and $\alpha_{\text{retain}}[j]$ the token retention ratio at layer j; tokens not retained are evicted. Typically, α_{retain} is larger in shallow layers and smaller in deeper ones.

B Data Preparation

B.1 Benchmark Datasets

We categorize these nine English-language datasets into four groups based on how semantically similar samples are constructed and the nature of the task.

1. **MultiNews (Bai et al., 2023):** This datasets contain samples composed of multiple independent passages or articles. To generate semantically similar samples, we randomly select one passage or article from each sample and use the Llama 3 model to rewrite it while preserving the original semantics. The rewritten passage is constrained to have a similar length to the original (within a 10% difference in token count). We then replace the original passage with the rewritten one to construct a semantically similar prompt. The position of the rewritten passage naturally varies across samples, appearing at the beginning, middle, or end of the context.

2. **SAMSum (Gliwa et al., 2019), PubMed, BigPatent, BookSum (Kwan et al., 2023), LCC (Guo et al., 2023):** These datasets consist of semantically continuous text or codes. For each sample, we divide the context into individual sentences and randomly select a contiguous segment of the total sentence count.

This segment is rewritten using the Llama 3 model, with the constraint that the token count deviates by less than 10% from the original. The rewritten segment replaces the original to create a semantically similar prompt, with its position varying within the context in a similar manner.

3. **Qasper (Dasigi et al., 2021) and WikiHow (Koupaee and Wang, 2018):** These datasets consist of Q&A tasks where each question must be answered based on a specific provided context. To preserve the accuracy of the questions, we use the LLM to rewrite only part of the context, leaving the questions unchanged.

4. **MMLU (Hendrycks et al., 2021a):** MMLU is a multiple-choice question-answering dataset. To ensure the logical integrity of the questions and preserve the original answers, we prompt the LLM to paraphrase each entire question.

Table B1 presents the results of the similarity evaluation, measured using ROUGE-L (Lin, 2004), BLEU (Papineni et al., 2002), and BERTScore (Zhang et al., 2019). We include both longest common subsequence-based metrics (ROUGE-L), n-gram-based metrics (BLEU) and embedding-based metrics (BERTScore) to provide a comprehensive evaluation of semantic similarity across rewritten datasets.

B.2 Eliminination and Replacement Dataset

To study the impact of prompt similarity on LLM performance when applying SemShareKV, we designed two ablation studies. In the first, we randomly removed a portion of sentences from each sample in the MULTINEWS dataset, then applied SemShareKV to evaluate its effectiveness. Figure C1a presents box plots of token length differences in the Elimination datasets compared to the original dataset. Figure C1b shows the BLEU scores of the Replacement datasets relative to the original dataset.

C Extra Experimental Results

Figure C2 shows the three retention patterns mentioned in **Insights 3**.

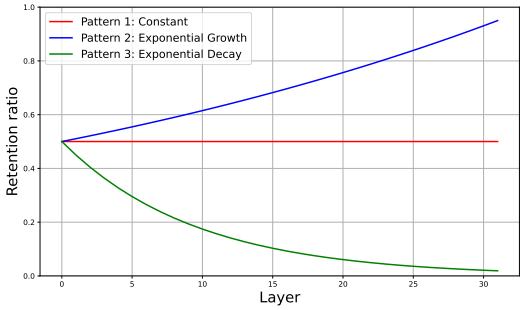


Figure C2: The three retention patterns start from the same retention ratio.

D Implementation and Hyperparameters

SemShareKV is implemented in Python using the `transformers` library (Wolf et al., 2020), with the monkeypatching technique. We use the Locality Sensitive Hashing from FAISS (Douze et al., 2024) library. The code is available at: `https://anonymous.4open.science/r/SemShareKV-B53C`. Details of the key functions and their roles are outlined below:

- **mistral_attn_forward**: A modified version of `MistralAttention.forward` from the `transformers` library, incorporating the SemShareKV mechanism. The hyperparameters used in our experiments are also specified in this function.

- **replace_mistral_forward**: Applies monkeypatching to substitute the original Mistral model attention forward function in the `transformers` library with our customized SemShareKV implementation.

- **llama_attn_forward**: A modified version of `LlamaAttention.forward` from the `transformers` library, incorporating the SemShareKV mechanism. The hyperparameters used in our experiments are also specified in this function.

- **replace_llama_forward**: Applies monkeypatching to substitute the original Llama model attention forward function in the `transformers` library with our customized SemShareKV implementation.

- **prepare_fuzzy_caches**: Encodes ROPE into E caches and performs fuzzy token matching using locality-sensitive hashing (LSH).

Overall, SemShareKV is built on the transformer architecture and consists of fewer than 300 new lines of code, making it lightweight and easily transferable to other LLMs.

E Artifact Use and Compliance with Intended Purpose

The datasets used in this study are publicly available and are consistent with their intended use, as specified by the respective sources. In preparing the data, we adhered to ethical guidelines and ensured that the use of these publicly released datasets was for research purposes only.

For the created artifacts, such as the semantically similar samples, we have ensured that the use of these modified datasets remains consistent with the original intended research purpose. The generated data serves the purpose of advancing research in semantic similarity and does not extend beyond the intended scope of the original datasets.