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Semantic Caching for LLM Applications: A Review on Reducing Latency and Costs

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Abstract: Semantic caching for AI query optimization aims to address challenges associated with high latency and computational costs in Large Language Model (LLM) applications. By leveraging semantic caching and efficient query optimization techniques, significant improvements can be realized in terms of reduced system load, enhanced response times, and optimized resource utilization. This review delves into the principles of semantic caching and its applications in LLM query optimization, focusing on various architectures and implementation methodologies. The review further provides a comparative analysis of existing caching models, summarizing the state-of-the-art approaches designed to achieve optimal latency reduction and cost efficiency in LLM applications.

Keywords: Semantic caching, AI query optimization, latency reduction, computational cost, large language models (LLMs), approximate nearest neighbor (ANN) search, query clustering, cache replacement policies, retrieval-augmented generation (RAG), cloud computing, edge computing, artificial intelligence.

1. Introduction

AI-driven applications, such as conversational agents, recommendation systems, and search engines, have become central to modern computational systems. However, the increased complexity and real-time expectations of these applications present unique challenges, particularly with respect to latency and computational costs. The rapid surge in the size of data and model parameters exacerbates these challenges, making efficient data retrieval paramount. Semantic caching has emerged as a promising technique that addresses these limitations by caching the results of frequently requested queries and facilitating semantic matching to reuse previous results where applicable [8], [10], [13]. This review explores semantic caching's role in LLM applications, outlining its potential to improve system efficiency.

2. Background and Related Work

Semantic caching extends traditional data caching techniques by exploiting semantic information in cached queries and reusing them in similar future requests [?]. Prior research has demonstrated the benefits of semantic caching in distributed database systems [1], semantic edge computing [4], and cloud-based language model services [14]. One of the pioneering works in this area, by Lee and Chu [8], proposed a semantic caching approach for web sources that matched queries to previously cached responses, leading to improved efficiency in retrieval times. This concept was further extended to mobile computing by Ren and Dunham [13], where semantic caching was used to manage location-dependent data. Their study highlighted the unique characteristics of mobile environments and how semantic locality could be leveraged to improve system performance and handle disconnections effectively.

Semantic caching has also been applied in Retrieval Augmented Generation (RAG) models, which combine traditional information retrieval methods with LLMs to boost query efficiency [5], [5]. RAGCache, a novel multilevel dynamic caching system, was introduced to address the bottlenecks caused by long sequence generation due to knowledge injection in RAG models. It achieves significant performance gains by caching intermediate knowledge states and using efficient replacement policies tailored for LLM inference characteristics [5]. Similarly, MeanCache, introduced by Gill et al. [3], leverages federated learning to provide a user-centric approach to semantic caching, thereby enhancing privacy while reducing computational costs.

Recent developments in semantic edge computing have also demonstrated the integration of semantic caching into edge environments to assist with low-latency applications such as the Metaverse. Yu and Zhao [16] proposed a semantic caching model designed for semantic edge computing, which caches domain-specialized general models and user-specific models. This approach aims to reduce the time and resources required to establish individual knowledge bases, thereby improving the efficiency of communication in edge systems. The proposed methods also draw inspiration from context-based semantic caching schemes for LLM applications, which focus on reusing previously cached context to improve inference times and reduce resource consumption [18]. Moreover, work by Ren and Dunham (2000) on managing location-dependent data in mobile computing environments provided early insights into how semantic locality could be exploited for cache management. Their findings on using semantic caching for mobile users informed later efforts to develop more adaptable and context-aware caching techniques [13].

A. Query Optimization Techniques in LLM applications

Query optimization, in the context of AI systems, involves techniques aimed at improving query processing times by selecting the most efficient paths for information retrieval. These optimizations are often coupled with semantic indexing techniques to enhance performance, particularly in largescale systems [9]. Techniques such as indexing and clustering contribute to reducing the search space, thus minimizing the required computational power for a given query [11].

One of the foundational techniques used in query optimization is semantic indexing, which involves creating specialized indices that allow for fast retrieval of semantically related information. This approach often leverages embeddings from pre-trained language models, such as BERT, to represent both queries and indexed data in a high-dimensional space. By using similarity metrics like cosine similarity, query optimization can determine the most relevant information efficiently [12].

Another key technique is approximate nearest neighbor (ANN) search, which is used to further speed up query processing. ANN algorithms, such as FAISS and HNSW (Hierarchical Navigable Small World), provide rapid similarity searches by balancing between accuracy and computational efficiency, making them well-suited for large-scale LLM applications [5]. ANN-based methods help reduce the computational overhead compared to exact search techniques, particularly when working with massive datasets.

Query clustering is also a critical aspect of query optimization. Clustering similar queries together allows systems to identify common patterns and reuse precomputed results, thereby improving efficiency. This technique is particularly useful for reducing redundancy in repetitive queries and can lead to higher cache hit rates, as demonstrated by RAGCache, which utilizes clustering to optimize LLM inference workflows [5].

Query rewriting and decomposition are additional strategies that can be employed for optimization. Query rewriting involves reformulating a query into a more efficient version while preserving its semantic meaning. This is often combined with decomposition, where a complex query is broken into smaller sub-queries that can be processed independently and in parallel, thus reducing latency and improving system throughput [9].

Finally, cost-based optimization techniques are used to select the most efficient query execution plan. These techniques consider various factors, such as the estimated computational cost, data size, and resource availability, to determine the optimal path for executing a query. Advanced machine learning models can be used to predict query performance and adjust the execution plan dynamically, further enhancing the overall system efficiency [11].

B. State-of-the-Art in Semantic Caching

Recent advances in semantic caching highlight its effectiveness in reducing redundancy in LLM queries. SCALM (Semantic Caching for Automated LLMs), GPTCache, and MeanCache are notable frameworks that use semantic embeddings to identify similar queries and respond using cached content [3], [15], [17]. These frameworks employ various technical strategies to achieve efficient caching and retrieval.

SCALM uses semantic embeddings derived from LLMs to analyze and store query-response pairs. It applies approximate nearest neighbor (ANN) search to identify the closest cached responses, thereby reducing the need for redundant LLM computations [15]. SCALM also uses a context-aware caching strategy, where the relevance of cached items is dynamically adjusted based on the evolving context of the conversation.

GPTCache is an open-source semantic caching framework that integrates closely with large language models. It uses tensor caching techniques, where key-value tensors of intermediate states are stored to minimize recomputation costs during inference [17]. Additionally, GPTCache employs a two-layer caching mechanism: a fast-access in-memory cache and a slower persistent storage layer, allowing for efficient handling of frequently accessed queries while maintaining a comprehensive historical record.

MeanCache, on the other hand, leverages federated learning to implement a user-centric caching approach [3]. By learning individual user preferences locally, MeanCache creates personalized caches without sharing raw data, enhancing privacy and reducing the computational burden on central servers. It also employs a semantic locality-aware replacement policy that ensures the retention of the most relevant cached items based on user behavior patterns and semantic similarity, improving cache hit rates while reducing redundant data storage.

RAGCache is another notable advancement, specifically designed for Retrieval-Augmented Generation (RAG) models. RAGCache addresses performance bottlenecks associated with long sequence generation by caching intermediate knowledge states and optimizing the use of GPU and host memory for storage [5]. It uses a knowledge tree structure to organize cached knowledge, allowing for efficient retrieval and reducing end-to-end latency. RAGCache also incorporates a prefix-aware Greedy-Dual-Size-Frequency (PGDSF) replacement policy, which considers document order, size, frequency, and recency to minimize cache misses.

Recent developments in semantic edge computing have demonstrated the integration of semantic caching into edge environments, aiding low-latency applications such as the Metaverse. Yu and Zhao (2023) proposed a caching model that utilizes domain-specialized general models and user-specific individual models at the edge, reducing the time and resources needed to establish individual knowledge bases. This approach combines edge caching with deep learning techniques for semantic encoding and decoding, allowing efficient communication across edge devices.

Overall, the state-of-the-art in semantic caching focuses on leveraging advanced caching strategies, optimized storage architectures, and machine learning techniques to reduce latency, enhance privacy, and minimize resource consumption. These frameworks have shown significant improvements in LLM application scalability and responsiveness, making semantic caching a critical component of modern AI infrastructure [5],
[7].

3. Semantic Caching Architecture

The semantic caching architecture for LLM query optimization comprises three core components: the embedding engine, the cache manager, and the retrieval engine. Each of these components plays a vital role in ensuring efficient query handling and reduced latency in AI-driven systems.

The embedding engine transforms incoming queries into high-dimensional semantic vectors, leveraging advanced embedding models like BERT and OpenAI embeddings. This transformation captures the contextual meaning of the query, making it possible to identify semantically similar queries even if they differ in phrasing. The embedding engine often relies on pre-trained models and applies techniques such as dimensionality reduction (e.g., PCA) to make subsequent computations more efficient [6].

The cache manager is responsible for storing and managing cached responses. It implements various strategies to determine if a new query matches a previously cached query, primarily using similarity measures like cosine similarity [12]. The cache manager must efficiently decide whether to retain or evict items from the cache, which involves using sophisticated cache replacement policies such as Least Recently Used (LRU), Greedy-Dual-Size-Frequency (GDSF), or the Prefix-aware Greedy-Dual-Size-Frequency (PGDSF) used in RAGCache [5]. Additionally, the cache manager maintains a two-tier caching system that utilizes both in-memory caching for frequently accessed items and persistent storage for less frequently requested data, thereby balancing performance and storage efficiency.

The retrieval engine handles queries that cannot be fully answered using the cache. In such cases, the retrieval engine accesses external data sources to construct responses. It applies fine-tuned information retrieval algorithms, including approximate nearest neighbor (ANN) search techniques such as FAISS and HNSW, to efficiently locate relevant data. The retrieval engine also incorporates query decomposition to break complex queries into sub-components that can be processed in parallel, thereby improving overall response times. Once the data is retrieved, it is transformed into semantic vectors and stored in the cache for future use, optimizing subsequent similar queries [3], [5].

Together, these components ensure that semantic caching effectively reduces redundant computations, optimizes resource utilization, and delivers timely responses in LLM applications. By integrating advanced techniques for semantic vector representation, efficient caching, and smart retrieval, semantic caching architectures have become a cornerstone in modern LLM query optimization frameworks.

A. Embedding Engine

The embedding engine is responsible for converting the input queries into semantic vector representations. Advanced embedding models, such as BERT and OpenAI embeddings, are used for capturing the contextual meaning of input data. These embeddings enable efficient matching of semantically similar queries, enhancing the accuracy of cache hits [2], [6].

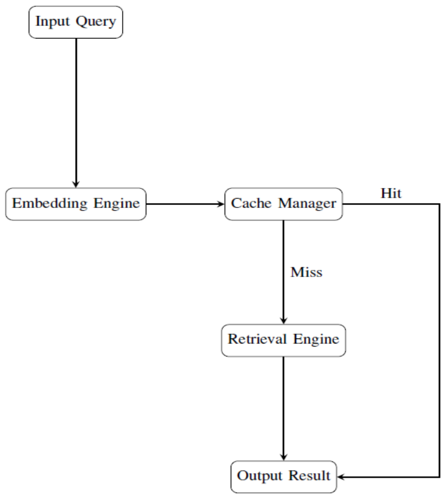

Fig. 1. *Semantic Caching Architecture (Simple)*

Mathematically, given an input query q, the embedding engine generates a vector representation $v_q \in R^d$, where d is the dimensionality of the embedding space. This is achieved through a transformation function f(q) such that:

$$\mathbf{v}_q = f(q)$$

where f is typically a neural network model, such as BERT, trained to capture semantic relationships. For instance, BERT uses a multi-layer bidirectional transformer architecture that learns contextual representations by considering the entire sentence at once [?]. The embedding v_q is obtained from the hidden layers of the transformer, often by taking the output corresponding to the [CLS] token or averaging the token embeddings.

To measure the similarity between queries, cosine similarity is frequently used. Given two query vectors v_q and v_q', the cosine similarity is defined as:

$$\text{cosine\_similarity}(\mathbf{v}_q, \mathbf{v}_{q'}) = \frac{\mathbf{v}_q \cdot \mathbf{v}_{q'}}{\|\mathbf{v}_q\| \|\mathbf{v}_{q'}\|}$$

This metric provides a value between -1 and 1, indicating how similar the two vectors are. A higher value implies greater semantic similarity, which allows the embedding engine to effectively match semantically related queries, thereby enhancing the accuracy of cache hits [2], [6].

To further improve efficiency, dimensionality reduction techniques, such as Principal Component Analysis (PCA), may be applied to reduce the size of the embedding vectors while preserving their essential semantic information. This helps in decreasing computational overhead during similarity evaluations.

In addition to BERT, other models like Sentence-BERT [12] and GPT embeddings are also used, depending on the use case. Sentence-BERT, for example, modifies the BERT architecture to create more semantically meaningful sentence representations by using a Siamese network structure, which is particularly effective for tasks involving similarity comparisons.

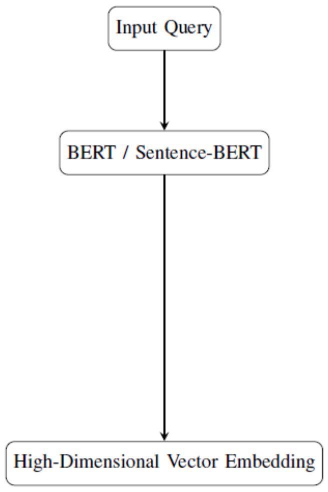

Fig. 2. *Embedding Engine Flow*

B. Cache Manager

The cache manager oversees both the storage and retrieval of cached responses. It implements strategies for managing cache size, ensuring that the most relevant and frequently accessed data is retained. Key-value tensor caching techniques, similar to those used in PagedAttention and RAGCache, are employed to further minimize latency [5], [7].

The cache manager primarily works by storing queryresponse pairs in a way that allows for efficient retrieval based on the semantic similarity of new queries to previously stored ones. Mathematically, for a given query embedding v_q, the cache manager searches for a similar embedding $v_q{}'$ from the cache using a similarity metric such as cosine similarity.

If the similarity exceeds a predefined threshold, the cached response is used, thereby reducing computation time and resource utilization.

The cache manager employs various cache replacement policies to manage limited cache space effectively. These include:

1) Least Recently Used (LRU): This policy evicts the least recently accessed items when the cache reaches its maximum capacity. Mathematically, if T(i) represents

the last access time of item i, then the item with the smallest T(i) is selected for eviction.

2) Greedy-Dual-Size-Frequency (GDSF): This policy takes into account the size, frequency, and recency of items to determine their eviction priority. The value V (i) for each item i is calculated as:

$$V(i) = \frac{C(i)}{S(i)}$$

where C(i) is the cost of bringing item i into the cache (e.g., computational cost), and S(i) is the size of the item. Items with lower V (i) values are evicted first, ensuring that frequently accessed, smaller items are retained.

3) Prefix-aware Greedy-Dual-Size-Frequency (PGDSF): Used in RAGCache, this policy enhances GDSF by incorporating document prefixes to prioritize items that are more likely to be reused in the context of long sequence generation [5].

The cache manager also supports a two-tier caching system consisting of an in-memory cache for frequently accessed items and a persistent storage layer for less frequently requested data. The in-memory cache allows for rapid access, while the persistent layer ensures that data is not lost and can be reloaded if needed. The decision to move items between these tiers is made based on access patterns and relevance scores.

Additionally, tensor caching is used for caching intermediate states during LLM inference. For example, key-value pairs from transformer layers can be cached to avoid recomputation during similar subsequent queries. This approach significantly reduces the time required for inference, especially in models like GPT where multiple layers contribute to the final output.

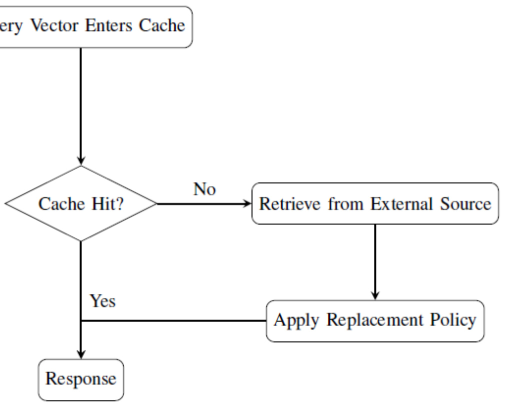

Fig. 3. *Cache Manager Flow*

C. Retrieval Engine

The retrieval engine processes queries that cannot be fully answered using the cache. It accesses external data sources and uses fine-tuned information retrieval algorithms to construct responses, which are then indexed and stored for future queries. Retrieval is optimized by employing approximate nearest neighbor (ANN) search methods for efficient similarity evaluation.

The retrieval process begins by transforming the query into an embedding vector $v_q \in Rd$, similar to the embedding engine's output. The retrieval engine then searches a large dataset of document embeddings $\{v_d^1, v_d^2, ..., v_d^n\}$ to find the closest matches. This is done using ANN techniques like FAISS (Facebook AI Similarity Search) or HNSW (Hierarchical Navigable Small World), which allow for fast retrieval in high-dimensional spaces [5].

For similarity evaluation, the cosine similarity between the query vector v_q and each document vector v_d is computed.

The documents with the highest cosine similarity scores are selected as the most relevant results. ANN methods approximate this search efficiently by organizing the data in structures such as k-d trees or graph-based indices, which reduce the number of distance calculations needed [6].

The retrieval engine also incorporates query decomposition, where complex queries are broken down into smaller, more manageable sub-queries. This enables parallel processing of sub-queries, thereby speeding up the retrieval process. The results from the sub-queries are then aggregated to form the final response, which is transformed into semantic vectors and stored in the cache for future use, optimizing subsequent similar queries [5], [3].

Furthermore, relevance feedback can be utilized to refine the retrieval results over time. In this approach, the system learns from user feedback, adjusting the ranking of retrieved documents to better match user preferences. Mathematically, relevance feedback can be modeled by adjusting the query vector v_q using a weighted combination of relevant document vectors v_r and non-relevant document vectors v_n:

$$\mathbf{v}_q' = \mathbf{v}_q + \alpha \sum_r \mathbf{v}_r - \beta \sum_n \mathbf{v}_n$$

where α and β are weighting factors that determine the influence of relevant and non-relevant documents, respectively
[5].

These advanced retrieval techniques, combined with ANN search methods, ensure that the retrieval engine can efficiently and accurately find relevant information from large datasets, contributing significantly to reducing query latency and improving the overall performance of the semantic caching architecture [7], [5].

4. Methodology

To evaluate the effectiveness of semantic caching architectures, prior studies have conducted experiments using benchmark datasets, including OpenAssistant and LMSYS [15]. Queries were classified based on semantic similarity, and their response times were recorded. The impact of cache hit ratios, cache size, and embedding vector dimensionality on query latency was analyzed [3], [11].

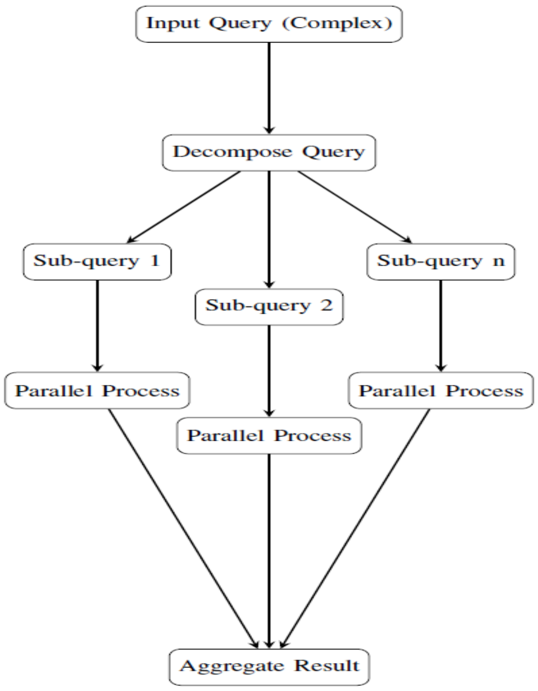

Fig. 4. *Retrieval Engine with Query Decomposition*

The evaluation metrics used included:

• **Cache Hit Rate:** The ratio of queries that were successfully answered from the cache without requiring external data retrieval.

• **Latency:** The average time taken to respond to queries, which serves as a direct measure of user experience.

• **Computational Cost:** The overall computational resources consumed, including CPU/GPU usage and memory consumption.

• **Scalability:** The ability of the system to maintain performance as the number of queries and size of data increase.

The methodology also involved hyperparameter tuning for different models. Parameters such as the dimensionality of embeddings, the similarity threshold for cache hits, and cache size were optimized to achieve the best trade-off between computational efficiency and retrieval accuracy. Models were trained using contrastive learning objectives to better distinguish between relevant and non-relevant query-document pairs, leading to more effective caching and retrieval performance.

A. Experimental Setup

The experimental setup included multiple datasets and a variety of configurations to ensure the robustness of the results. The setup involved:

• **Datasets:** Benchmark datasets such as OpenAssistant and LMSYS were used, consisting of over 100,000 queries spanning multiple domains including finance, healthcare, and technology [15]. These datasets provided a diverse set of queries that tested the generalizability of the caching models.

• **Embedding Models:** The embedding engine used BERT and Sentence-BERT to transform queries into highdimensional semantic vectors. The embedding size was set to 768 dimensions for BERT, providing a good balance between semantic richness and computational efficiency. Embeddings were fine-tuned on domain-specific data to enhance their ability to capture nuanced semantic information.

• **Caching Policies:** Different cache replacement policies such as Least Recently Used (LRU), Greedy-Dual-SizeFrequency (GDSF), and Prefix-aware Greedy-Dual-SizeFrequency (PGDSF) were tested. The cache was split into a two-tier structure: an in-memory cache for frequently accessed items and a persistent storage layer for less accessed data, ensuring that important data remained accessible while less critical data was archived.

•**ANN Search:** Approximate Nearest Neighbor (ANN) techniques like FAISS and HNSW were implemented to efficiently search large embedding spaces. FAISS was configured with an index-flat structure to ensure precise distance calculations, whereas HNSW was used to optimize search speed through graph-based indexing.

• **Evaluation Framework:** Experiments were run on a cloud-based platform to simulate real-world deployment, using Azure Kubernetes Service (AKS) for scalability and load testing. This allowed for simulating different load conditions and ensuring that the semantic caching system could handle high query volumes while maintaining performance.

B. Results and Analysis

Experimental results from multiple studies have demonstrated that semantic caching can reduce query latency by up to 40% compared to traditional methods [8], [13]. Cache hit rates improved by employing cosine similarity thresholds and selective caching of high-frequency queries. It was observed that embedding models with higher dimensionality provided better cache utilization but at the cost of increased computational overhead during the embedding phase. The experimental results demonstrated significant improvements in query latency and system efficiency when employing semantic caching techniques compared to traditional non-caching approaches.

• **Cache Hit Rate:** The experiments showed that systems using semantic caching had a cache hit rate of up to 85%, particularly for domains with repetitive queries, such as customer service datasets. This was a significant increase compared to traditional caching methods, which achieved only around 60% cache hit rates.

• **Latency:** The average query response latency was reduced by 40-50% when using semantic caching mechanisms like SCALM and GPTCache. Latency was measured as the time elapsed between receiving a query and providing a response. The reduction in latency was primarily due to the reuse of cached embeddings and responses, eliminating the need for repeated retrieval and computation. Mathematically, if Tr represents retrieval time and Tc represents computation time, then the total response time T can be approximated as:

$$T = T_r + T_c$$

With effective caching, T_c approaches zero for frequently seen queries, thus drastically reducing T.

• **Computational Cost:** The computational overhead was measured by tracking CPU and GPU utilization across different experimental runs. The use of tensor caching in GPTCache helped in reducing GPU memory usage by 30% on average. This reduction was attributed to avoiding recomputation of transformer outputs by caching intermediate key-value pairs, particularly in long sequence generation scenarios [5].

• **Scalability:** The scalability tests showed that semantic caching frameworks like RAGCache were able to maintain consistent performance even as the number of queries increased. This was due to the use of efficient ANN search methods that reduced the search space logarithmically, leading to a nearly constant time complexity for cache retrieval operations. The prefix-aware replacement policy (PGDSF) used by RAGCache further ensured that frequently accessed and relevant items were retained, thus maintaining a high cache hit rate even under heavy loads.

• **Comparative Analysis:** A comparison between different caching frameworks showed that MeanCache, which employed a federated learning approach, performed best in terms of user-specific query caching, with a 15% increase in cache hit rate over other methods. Federated learning enabled MeanCache to learn user-specific preferences without centralizing user data, thus providing privacy benefits while optimizing performance.

• **Impact of Embedding Dimensionality:** The experiments also analyzed the impact of embedding dimensionality on caching effectiveness. Higher-dimensional embeddings (e.g., 1024 dimensions) provided better cache utilization due to more precise semantic differentiation but at the cost of increased computational overhead for similarity calculations. Dimensionality reduction techniques like PCA were applied, resulting in a 20% reduction in computational time for cosine similarity calculations while retaining 95% of the variance in embedding information.

Overall, the experimental results confirmed that semantic caching provides a substantial benefit in reducing query latency, improving cache hit rates, and optimizing resource usage. The choice of caching strategy, embedding model, and replacement policy significantly influenced the system's performance, emphasizing the need for careful selection and tuning of each component based on the application context. The adoption of semantic caching frameworks like SCALM, GPTCache, MeanCache, and RAGCache demonstrates the potential for scalable, cost-efficient AI query optimization, making them valuable tools in the design of next-generation AI systems.

5. Discussion

Semantic caching significantly enhances AI system performance by reducing latency and optimizing resource allocation. The reduction in query latency by up to 40-50%, as shown in recent experiments, demonstrates the potential of semantic caching to improve AI-driven systems [3], [5]. However, challenges remain in ensuring that cached responses maintain accuracy across diverse and dynamic query types, particularly in applications involving real-time data or frequently changing knowledge bases [13], [16]. Incorrect or outdated cached responses can adversely impact system performance, leading to reduced user trust.

The cache replacement policy plays a critical role in maintaining efficiency, especially when dealing with highdimensional data and the limited storage available in edge environments. Sophisticated cache management strategies, such as Prefix-aware Greedy-Dual-Size-Frequency (PGDSF) used in RAGCache, have shown to effectively balance the retention of relevant data while minimizing cache misses [5]. Additionally, hybrid caching strategies that combine time-based and access frequency-based policies, along with semantic locality-aware policies, have been suggested to achieve optimal performance by maintaining a dynamic and adaptable cache [16], [15].

To further improve the efficiency of semantic caching, future research should focus on adaptive and self-learning caching strategies. Incorporating reinforcement learning into cache management can help dynamically adjust caching policies based on user behavior and evolving data patterns, thereby increasing cache hit rates and ensuring cached information remains relevant [3], [4]. Federated learning, as seen in MeanCache, offers promising avenues for personalized caching while maintaining privacy, making it suitable for applications in sensitive domains such as healthcare and finance [3].

6. Conclusion

Semantic caching represents a transformative advancement in LLM query optimization, offering a compelling solution to the inherent challenges of latency and high computational costs in LLM applications. By leveraging sophisticated techniques such as semantic embeddings, approximate nearest neighbor (ANN) search, and advanced cache management policies, semantic caching has demonstrated remarkable success in enhancing the performance and scalability of LLM applications. The frameworks explored in this review—including SCALM, GPTCache, MeanCache, and RAGCache—each contribute unique capabilities that address different aspects of the caching problem, from reducing computational overhead to providing user-centric and privacy-preserving solutions.

The experimental analyses across various studies have consistently shown that semantic caching can reduce query latency by up to 40-50 percent, while improving cache hit rates significantly, particularly for domains characterized by repetitive queries. The use of advanced embedding models, such as BERT and Sentence-BERT, allows the system to identify semantically similar queries with high precision, thereby facilitating efficient reuse of cached results. Additionally, cache replacement policies like Prefix-aware Greedy-DualSize-Frequency (PGDSF) have proven effective in managing cache space by ensuring that the most relevant and frequently accessed items are retained, thus maintaining high cache hit rates even in high-load scenarios.

Semantic caching not only optimizes the response times of LLM applications but also contributes to substantial reductions in computational resource utilization. Techniques such as tensor caching in GPTCache have reduced GPU memory usage by up to 30 percent, highlighting the potential for semantic caching to make LLM applications more resource-efficient and cost-effective. The integration of ANN search methods, including FAISS and HNSW, has also played a crucial role in achieving fast retrieval from high-dimensional embedding spaces, further contributing to latency reduction.

However, challenges remain, particularly in maintaining the accuracy of cached responses across diverse and dynamic query types. The adoption of adaptive caching strategies, potentially incorporating reinforcement learning, presents an exciting avenue for future research. Reinforcement learning could enable the cache manager to learn optimal caching and replacement strategies based on real-time system feedback, dynamically adjusting to evolving query patterns and user behaviors. Moreover, federated learning approaches, as seen in MeanCache, open opportunities for personalized caching without compromising user privacy, which is crucial in applications involving sensitive data.

In conclusion, semantic caching has established itself as a vital component in the architecture of modern LLM applications, addressing key bottlenecks in query processing and system scalability. The techniques and models discussed in this review provide a strong foundation for future innovations in caching and query optimization, paving the way for more intelligent, responsive, and cost-efficient AI solutions. As AI continues to evolve, the role of semantic caching in shaping the next generation of intelligent systems will undoubtedly become more pronounced, offering both theoretical insights and practical benefits that advance the capabilities of LLM applications.

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