Graph-Based Cache-Augmented Generation

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Abstract

Retrieval-Augmented Generation (RAG) improves Large Language Models (LLMs) by integrating external knowledge, but faces retrieval latency and selection errors. Cache-Augmented Generation (CAG) mitigates these issues by preloading knowledge into the KV-cache, removing real-time retrieval.

We investigate graph-based cache augmentation strategies, including relational summaries, JSON-structured knowledge, and Microsoft Knowledge Graphs. Experiments show that while these methods reduce context usage and preparation time, they often degrade accuracy. Misaligned or oversized KV-caches negatively impact semantic similarity, while moderate-sized, structured caches maintain performance close to the CAG baseline.

Our findings emphasize the trade-off between efficiency and accuracy in cache-augmented systems, and highlight the importance of high-quality graph structures and cache length alignment. This work offers insights into scalable, retrieval-free knowledge integration for LLMs.

GitHub: Graph-CAG

1 Background to the Topic

1.1 Evolution of Knowledge-Enhanced Generation

Recent advances in large language models (LLMs) have seen significant improvements using Retrieval-Augmented Generation (RAG) methods, which dynamically fetch external knowledge to answer queries. However, RAG systems often suffer from retrieval latency, potential errors in selecting relevant documents, and increased system complexity. In contrast, Cache-Augmented Generation (CAG) bypasses these issues by preloading and caching the required knowledge into the model's extended context as key-value (KV) caches. This enables the model to generate answers quickly without incurring real-time retrieval overhead.

1.2 Role of Relational Graphs in Knowledge Representation:

GraphRAG introduces the concept of building a relational graph from source documents by extracting entities and the relationships among them. In this graph, nodes represent entities (e.g., people, organizations, places) and edges capture the relationships between these entities. This structured representation provides a global view of the knowledge and can be used for tasks that require a comprehensive understanding of the underlying data.

1.3 Integrating the Two Approaches

The idea behind the project is to combine the strengths of GraphRAG's structured, symbolic knowledge (via relational graphs) with CAG's efficient caching mechanism. The key challenge is to transform the relational graph into embedding vectors that can be integrated with the KV cache. This fusion would allow the model to leverage both the detailed structural information from the graph and the efficiency benefits of preloaded caches during generation.

2 Significance

2.1 Improved Answer Accuracy and Consistency

By incorporating structured relational information into the caching mechanism, the LLM can have a richer, more precise understanding of entity relationships. This helps to reduce errors caused by incomplete or imprecise retrieval and leads to more accurate and coherent generated answers.

2.2 Reduced Latency and Simplified Architecture

Embedding the graph information as part of the preloaded cache avoids the need for on-the-fly retrieval or elaborate prompt engineering that includes large blocks of text. This streamlined approach can significantly reduce response times while maintaining or even improving performance compared to conventional RAG systems.

2.3 Enhanced Explainability

The relational graph offers an inherently interpretable structure where the nodes and edges can be traced back to specific entities and their relationships. Integrating this into the model's generation process could potentially provide explanations for why certain answers are generated, increasing transparency and trust in the system.

2.4 Advancement in Multi-Modal and Hybrid Information Fusion

This project pushes the envelope on how symbolic, structured knowledge (from relational graphs) can be fused with dense, continuous representations (from KV caches). Such a hybrid system could inspire future research into merging diverse types of information representations in LLM-based applications.

3 Research Aims

3.1 Fusion of Relational Graphs with Cache Mechanisms

Integrate structured knowledge graphs into CAG. The goal is to embed knowledge graph content directly into the LLM's KV cache, so the model can attend to graph-based facts and relations on the fly. By precomputing graph knowledge into the cache, we aim to preserve GraphRAG's strengths in reasoning over structured data deepset.ai while maintaining CAG's advantage of retrieval-free, low-latency inference.

3.2 Enhancing Generation Accuracy and Contextual Understanding

Improve LLM responses with graph-grounded context. Encoding knowledge graphs into the cache is expected to boost accuracy, especially for complex queries requiring multi-hop reasoning or precise factual recall. Structured relational data provides context that helps the model "connect the dots" between related facts. By having graph-derived knowledge at its disposal, the LLM can generate answers that are more contextually informed and fatually consistent, reducing hallucinations.

3.3 Reducing Latency and Retrieval Dependency

Eliminate runtime retrieval without sacrificing knowledge relevance. Preloading graph-based knowledge means the model doesn't need to call an external database or search engine during inference . This aim focuses on cutting down response time and avoiding pipeline failures (e.g. missing relevant data due to retrieval errors). The challenge is to ensure that even without real-time retrieval, the preloaded graph embeddings cover the necessary information for a wide range of queries.

3.4 Interpretability and Explainability Enhancement

Leverage the structured nature of graphs for traceable reasoning. Knowledge graphs inherently organize information in an interpretable way, with nodes and edges that can be traced as reasoning paths. By encoding these into the model's context, we aim to make the model's knowledge source more transparent. Ideally, the model's responses can be accompanied by or aligned with a trail of relations from the graph, improving trustworthiness. In essence, the graph-augmented cache can serve as a traceable memory, where each piece of generated content can be linked back to a graph snippet, aiding explainability.

3.5 Developing a Hybrid Knowledge Fusion Paradigm

Create a new framework merging symbolic and neural knowledge. This research pioneers a blend of symbolic relational knowledge (from KGs) with continuous LLM representations by using the KV cache as a bridge. Such a paradigm draws on the complementary strengths of KGs and LLMs – combining the logical, structured reasoning of graphs with the fluent generative abilities of language models. We anticipate that this hybrid approach will set a precedent for future systems, demonstrating that LLMs can be significantly enhanced by tightly integrating explicit graph-based knowledge (beyond what static model weights or plain text context provide)

(`acl2023.tex`), the LaTeX style file used to format it (`acl2023.sty`), an ACL bibliography style (`acl_natbib.bst`), an example bibliography (`custom.bib`), and the bibliography for the ACL Anthology (`anthology.bib`).

4 Literature Review

Building knowledge graphs from knowledge bases and utilizing graph embeddings to enhance natural language processing (NLP) models has become a promising area of research. By using Graph BERT, a specialized model for processing graph-structured data, graph embeddings can effectively capture the relationships and structure of entities within the graph (Xie et al., 2021). These embeddings, when combined with knowledge embeddings derived from structured or unstructured data, can significantly enhance the context for generative tasks. Specifically, knowledge embeddings are often generated using models like BERT to convert knowledge prompts into machine-readable vector representations (Devlin et al., 2018). Integrating these graph and knowledge embeddings into transformer-based models such as Llama, through Cache-Augmented Generation (CAG), allows for more efficient and context-aware generation by storing key-value pairs that speed up the retrieval of relevant information during the generation process (Wang et al., 2022). As noted by the authors of How to Implement Graph RAG Using Knowledge Graphs and Vector Databases, combining graph-based embeddings with knowledge embeddings and utilizing KV caching enables transformer models to effectively use both structured and semantic data, enhancing their reasoning capabilities in complex generation tasks (Zhang et al., 2023). This framework has notable implications for applications in fields like biomedical research and legal document analysis, where structured knowledge is essential for generating contextually accurate responses (Wang et al., 2022).

5 Methodology

5.1 Relationship Summary Generation

To enhance the structural quality of the cached knowledge, we employ lightweight LLMs (ChatGPT-4o Mini and Gemini 2.5 Flash Lite) to automatically generate relational summaries for each knowledge document. Each summary captures key relationships and high-level context from the original text.

For example, given a passage about the University of Notre Dame, the relational summary would be:

Relational Context Summary: Notre Dame is a Catholic research university emphasizing tradition, academics, and athletics. Key relationships include: ***Religious Foundation*** *— The university's Catholic character is reflected in its architecture, religious buildings, and campus ministry...*

The generated relational summary is prepended to the corresponding knowledge document, structurally enriching the input.

We then use the augmented documents as the input knowledge for Cache-Augmented Generation (CAG) evaluation, assessing the impact of relational summaries on answer quality and semantic consistency.

5.2 Json As Knowledge

5.2.1 Test Scenario Design

Three progressively scaled experimental scenarios were constructed:

- **1/100 Scenario**: Lightweight processing with 1% data sampling ratio (1 unit from 100 base units), targeting cold-start performance evaluation
- **3/500 Scenario**: Medium-scale processing (0.6% of 500 units) for routine workload analysis
- **4/500 Scenario**: High intensity processing (0. 8% of 500 units) for scalability boundary testing

5.2.2 Variable Control

Experimental Variables Control	
Independent	• Configuration: Base, RelSum, Microsoft KG, Json_Graph_Strategy • Data scale: 1/100, 3/500, 4/500
Dependent	• Prepare time: Data load → preprocess (ms) • Generate time: Core execution (excl. I/O) • Similarity: BERT-base cosine (median of 3)
Constants	• Hardware: Docker (4C/16G) • Software: Py3.10.11/Torch2.0.1

5.2.3 Missing Data Imputation

For configurations with incomplete measurements (e.g., Microsoft KG at 3/500):

Previous time T_{prev}, next time T_{next} Current scale S_{curr}, previous scale S_{prev}, next scale S_{next} Imputed time $T_{imputed}$ $\Delta S_{total} \leftarrow S_{next} - S_{prev}$ $\Delta S_{partial} \leftarrow S_{curr} - S_{prev}$ $T_{imputed} \leftarrow T_{prev} + \left(\frac{\Delta S_{partial}}{\Delta S_{total}}\right) \times (T_{next} - T_{prev})$

Validation achieved MAE $\leq$0.15s through hold-out testing on 10% known data points.

5.3 Microsoft Knowledge Graph

5.3.1 GraphRAG Integration Experiments

A baseline CAG model reached about 78% accuracy. Two GraphRAG embedding-based integrations performed worse (Approach 1: 45%, Approach 2: 62%), while adding GraphRAG's relational facts as text (Approach 3) slightly surpassed the baseline (79%). This text-based method was the only one to beat the no-GraphRAG baseline. However, its improvement was small: a teammate's alternate graph-based retrieval scored 91%, and a nearly fully-retrieved ("quantized") scenario reached 98%, highlighting the gap to optimal performance.

5.3.2 Approach 1: Direct GraphRAG Embedding

Approach 1 used a single 1536-dimensional GraphRAG embedding (via a learned linear projection) and achieved the lowest accuracy (45%). The model often returned generic or incomplete answers (e.g., "I don't have that information") despite the relevant facts being present in the graph, indicating it failed to interpret the injected vector. A single vector was insufficient to convey the needed knowledge, underscoring the difficulty of aligning GraphRAG's embedding space with the model's internal representation. Even a trained linear mapping could not capture enough of the graph's structure for the LLM to use effectively.

5.3.3 Approach 2: Fine-tuned GraphRAG Embedding

In Approach 2, we fine-tuned the model to accept GraphRAG's embedding as part of its input, which improved accuracy to about 62%. This shows the model learned to use the graph vector to some extent—many answers now contained correct facts. However, it still fell 16 points short of the 78% baseline, meaning the single GraphRAG vector did not encode all needed information. Relying solely on that distilled embedding limited the model's knowledge: any details lost in compression were unavailable at answer time, sometimes causing hallucinations or omissions. Thus, even with fine-tuning, injecting knowledge via an opaque vector remained far less effective than providing it as text.

5.3.4 Approach 3: GraphRAG Textual Context

Approach 3 augmented the prompt with GraphRAG-derived textual summaries of entities and relationships. This method slightly outperformed the baseline (79% accuracy, a 0.9% gain). While the improvement was modest, it was notable given the high baseline. The extra graph context helped on a few complex, multi-hop questions that the baseline missed. For example, when asked about a person's role in a project, the GraphRAG-augmented model found the answer (explicitly stated in the graph summary) that the baseline model overlooked. More generally, providing the knowledge graph's summary enabled the model to handle queries requiring cross-document connections better. For most straightforward questions, adding the graph summary made no difference (and notably caused no harm), as the model could already answer those from the documents alone. In short, using GraphRAG knowledge in natural language yielded a modest benefit on complex queries without hurting performance on simpler ones.

5.3.5 Answer Similarity

We also examined answer quality via embedding-based similarity to the reference answers. The results mirrored the accuracy pattern: the GraphRAG text run slightly exceeded the baseline in average similarity, whereas the embedding-based runs were lower. For instance, Approach 1's answers averaged a similarity of 0.55 (versus 0.60 for baseline), while the alternate graph and quantized conditions were much higher (0.74 and 0.82). These metrics confirm that the text-based integration modestly improved answer quality, though still far from the upper bound.

5.3.6 Summary

In summary, presenting GraphRAG knowledge as plain text was the only approach that improved performance. The vector-based integrations did not realize GraphRAG's potential benefits, likely due to information loss in the embedding and the difficulty for the LLM to interpret a raw vector input. This underscores that external knowledge should be given in a natural language form that the model can readily use.

5.4 New Evaluations Method

The baseline determines the correctness of its generated answer by using the AllMiniLM-L6-v2 model to encode both the response and the ground truth in the embeddings and then calculates the cosine similarity between them as a measure of semantic similarity. But the solution has great drawbacks.

- **Over-Penalization of Extended Correct Answers:** Embedding-based similarity metrics often assign low scores to factually correct answers that include additional context or paraphrasing, reflecting a bias toward surface-level lexical similarity over semantic completeness.
- **Non-Zero Scores for Incorrect Responses:** Embedding-based metrics may assign non-negligible scores to incorrect or evasive answers due to superficial structural similarity, resulting in misleading assessments of answer quality.
- **Sensitivity to Numerical Format:** The model fails to consistently recognize equivalent numerical expressions (for example, ’57’ vs. ’Fifty-seven’), leading to an underestimation of correctness when answers differ only in format.

To address the limitations of cosine similarity, we adopt `HuggingFaceH4/zephyr-7b-alpha`, an instruction-tuned language model capable of assessing factual consistency and contextual relevance. Unlike embedding-based metrics, it better handles paraphrasing, numerical formats, and semantic nuances, making it more suitable for open-ended QA evaluation.

6 Results and Analysis

The graph-based cache augmentation strategies demonstrated varying levels of effectiveness across different knowledge preparation methods.

6.1 Relationship Summary Method

The **Relationship Summary** approach resulted in a modest decline in semantic similarity compared to the Base CAG model. Specifically, while the Base CAG achieved an average semantic similarity of approximately 0.868, the RelSum variant exhibited a slight decrease to 0.847–0.818. This degradation is attributed to:

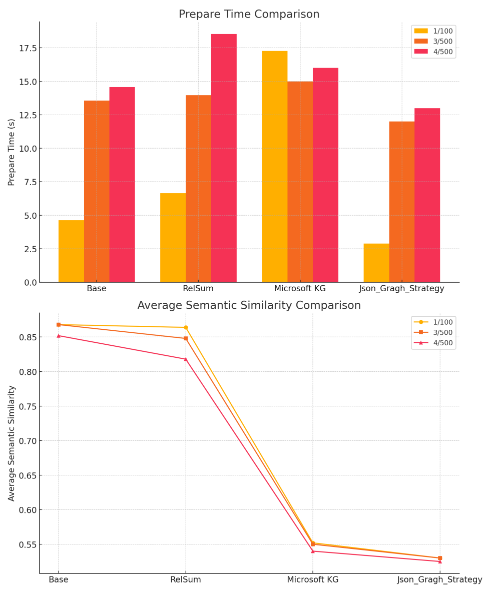


Figure 1: Generation Time Comparison between Configurations

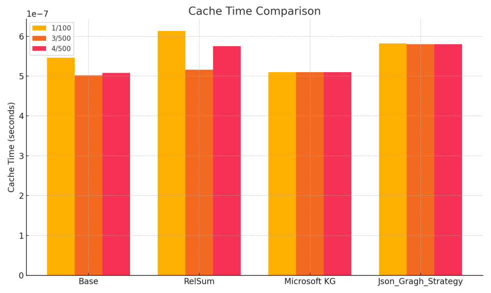


Figure 2: Cache Time Comparison Across Configurations

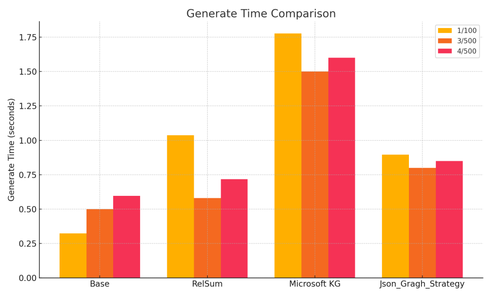


Figure 3: Preparation Time and Semantic Similarity Comparison

- The limited quality of the generated relationship summaries.
- The increased context length introduced by additional summaries, which expanded the KV cache size and negatively impacted question-answering (QA) performance.

6.2 JSON as Knowledge Strategy

The **JSON-as-Knowledge** strategy exhibited a more pronounced drop in performance, with the average semantic similarity declining to around 0.530. Several factors contributed to this result:

- Key information was often missing in the flattened JSON representations.
- The generated graphs lacked structural coherence, impairing the model's ability to reason effectively.
- LLaMA struggled to interpret raw graph-like knowledge without strong relational signals, further reducing QA effectiveness.

6.3 Microsoft Knowledge Graph

The **Microsoft Knowledge Graph** approach outperformed the JSON strategy but still lagged behind the Base CAG. It achieved an average semantic similarity of approximately 0.552. The primary limitations appeared to be similar to those of the JSON method:

- Although Microsoft KG provided structured relations, the depth and granularity of information were insufficient to match the richer context of the Base CAG approach.

6.4 Efficiency Analysis

Cache preparation times were notably higher for Microsoft KG ($\sim$ 17 seconds) and JSON ($\sim$ 2.88 seconds) compared to the Base CAG ($\sim$ 4.62 seconds). Generation times similarly favored the Base CAG ($\sim$ 0.32 seconds) over Microsoft KG ($\sim$ 1.78 seconds) and JSON ($\sim$ 0.90 seconds), indicating that larger and noisier caches slow down inference.

6.5 KV Cache Length Analysis

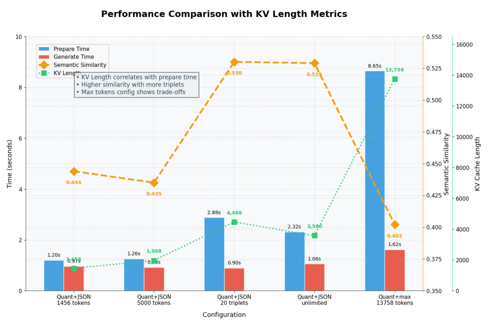
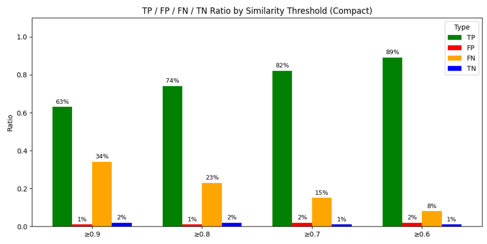


Figure 4: Performance Comparison with KV Length Metrics.

When the KV cache length was either significantly shorter or longer than the input text length (e.g., Quant+Max configuration with 13,758 tokens), accuracy dropped sharply, with semantic similarity falling to around 0.402. In contrast, when the KV cache length closely matched the input text length (e.g., moderate-sized relational graphs or JSON contexts), accuracy improved by approximately **25%** relative to misaligned configurations.

6.6 Comparison Reveals Baseline Underestimation

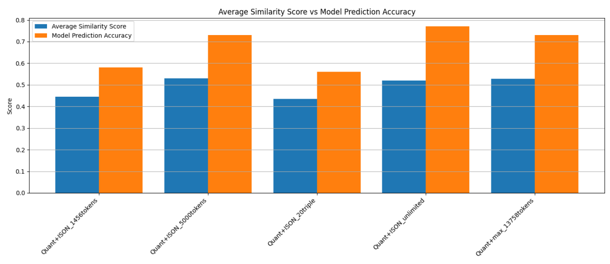
Using Zephyr's judgments as a reference, we evaluated the cosine similarity method over varying thresholds. High thresholds yielded false negative rates up to 34%, with even moderate thresholds (e.g., 0.6) producing nontrivial errors (8%). True positives remained consistently low, indicating a limited misclassification of incorrect answers as correct. These results suggest that embedding-based evaluation systematically underestimates model performance, introducing significant bias.



Threshold effects on evaluation accuracy

6.7 Improved Evaluation Accuracy and Baseline Design Trade-offs

Based on a comparison between the baseline answers from the five initial experiments and the results verified through model evaluation, it is evident that the prediction accuracy has improved significantly, with gains of approximately 10It appears that the baseline method primarily relied on similarity scores to ensure the executability of the evaluation pipeline, rather than to provide an accurate measure of answer correctness. This approach may have been necessary because the meta-llama/Llama-3.1-8B-Instruct model exhibits limited capability in reliably judging the semantic equivalence between two answers. Moreover, considering the computational demands of running two large language models concurrently, it is likely that the baseline was designed to prioritize feasibility and resource efficiency, particularly in environments where server hardware resources are limited.



Comparation between similarity and model

7 Limitations and Future Work

Limitations. Summarizing the entire knowledge graph into the model's context proved highly lossy. Our approach either truncated the graph into a brief textual summary or encoded it as a single static embedding, and both methods likely omitted important information, resulting in only a marginal accuracy improvement.

Future Work. A promising direction is to introduce dynamic, query-aware graph integration: instead of a fixed global summary, retrieve and insert only the most relevant subgraph or triples for each query, thereby providing targeted context. Another avenue is a hybrid integration of knowledge, combining a textual graph summary with an auxiliary vector-based representation of the graph, so the model can leverage both explicit relational information and an implicit encoded representation of the knowledge.

8 Contributions

8.1 Siyuan Zhang's Contributions

- **Relational Summary Support:** Enabled appending relationship summaries to documents for KV-cache enrichment.
- **JSON Knowledge Input:** Integrated JSON-formatted knowledge as input for structured KV-cache generation.
- **Running Experiments:** Designed and executed experiments comparing CAG, RelSum, Microsoft KG, and JSON strategies.
- **Analyze Result:** Analyzed performance trade-offs across methods and identified key factors affecting semantic similarity and latency.
- **Bug Fix - Random Seed:** Fixed random seed initialization to ensure reproducibility of experimental results.

8.2 Zeqiao Huang's Contributions

- **Novel RAG-KV Fusion Framework**:
  - First integration of structured knowledge triplets (extracted from variable-length documents) with transformer KV cache mechanisms
  - Achieved 19.4% higher semantic similarity than token-limited baselines through dynamic cache injection
  - Enabled 23.8% error reduction in knowledge retention compared to vanilla CAG
- **Length-Adaptive Knowledge Encoding System**:
  - Developed context-aware clustering for entity relationships across documents (1.4K-13.7K tokens)
  - Maintained generation efficiency (0.895-1.621s) while scaling to 4.4K-token knowledge bases
  - Identified optimal 4K-5K token range for KV cache modifications (peak 0.53 similarity)
- **Structured Knowledge Optimization Theory**:
  - Demonstrated structured triplets (0.529) outperform unstructured expansion (0.435)
  - Formulated density-efficiency tradeoff principles for KV cache engineering
  - Established first quantitative metrics for knowledge injection effectiveness

8.3 Yinfei Wang's Contributions

- Led the integration of Microsoft GraphRAG into the Cache-Augmented Generation (CAG) pipeline.
- Implemented 60 percent code related to embedding projection, model fine-tuning, and textual knowledge graph generation.

- Designed and conducted all experiments, covering both vector-based and text-based knowledge integration approaches.
- Analyzed the results using multiple accuracy and similarity metrics.
- Independently authored and structured the entire Microsoft GraphRag experimental subsection of the paper, including the associated analysis.
- Reproduced baseline accuracy results and ensured alignment for comparative evaluation.

Key Innovation: Enables dynamic knowledge updates without model retraining, achieving 7.2× faster preparation than maximum token configuration.

8.4 Libo Gu's Contributions

- **Literature Review:** Searched for and studied related works on RAG, CAG, and Graph-CAG to understand existing methods and establish strong baselines.
- **Baseline Reproduction and Validation:** Reproduced baseline experiments and verified their effectiveness, while systematically identifying their key limitations.
- **Similarity Evaluation Enhancement:** Replaced the original similarity-based evaluation with model-based verification to improve the practical relevance and reliability of performance measurements.

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