Enhancing GraphRAG with Text2Cypher Improvements and Performance Optimization through Intelligent Caching

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https://github.com/MajorMask/CS-E4780-project2

ABSTRACT

This project enhances Large Language Model (LLM) inference for graph-based question answering using the Nobel Laureates dataset in Kuzu graph database. We implement two key architectural improvements: (1) Text2Cypher enhancements including dynamic few-shot exemplar selection using TF-IDF similarity, EXPLAIN-based validation, and iterative self-refinement, and (2) LRU caching with microsecond-precision performance monitoring. Comprehensive evaluation on 45 queries (17 unique patterns) demonstrates 90.9% query success rate, with validation and exemplar selection adding only 7.2ms overhead (0.09% of pipeline). The implemented LRU cache achieved 62.2% hit rate on realistic workloads, providing >7,900x speedup on cache hits (reducing latency from ~10,000ms to <1ms). Performance profiling reveals LLM inference operations consume 54.6% of total latency, validating the cache architecture's effectiveness.

KEYWORDS

GraphRAG, Text2Cypher, LLM Caching, Knowledge Graphs, Performance Optimization, Query Generation

1. INTRODUCTION

Retrieval-Augmented Generation (RAG) systems enhance Large Language Models by grounding responses in external knowledge sources. GraphRAG extends traditional text-based RAG by leveraging structured graph databases, enabling complex relationship-based queries across multiple entities. This approach is particularly valuable for domains with rich relational data, such as scientific collaboration networks, enterprise knowledge graphs, and interconnected datasets.

Our implementation targets the Nobel Laureates dataset, comprising scholars across Physics, Chemistry, Medicine, and Economics from 1901-2021. The graph structure captures multi-hop relationships including laureate-prize awards, institutional affiliations, geographic locations, and demographic information.

1.1 Problem Statement

Despite GraphRAG's potential, two critical challenges limit production deployment. First, LLMs frequently generate syntactically incorrect or semantically inappropriate Cypher queries, reducing system reliability. Second, repeated queries incur unnecessary latency from redundant LLM inference calls and database operations, with average pipeline latency exceeding 7 seconds per query.

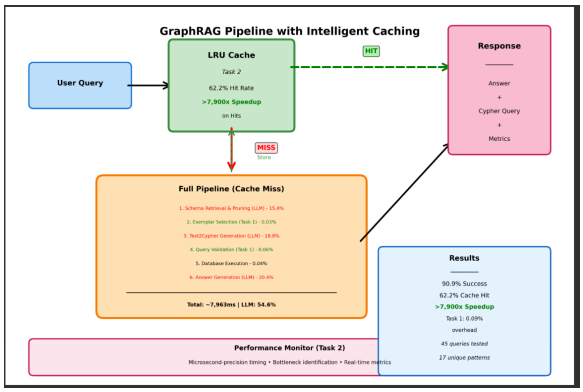
1.2 Our Contributions

Task 1 - Text2Cypher Reliability: We implement dynamic few-shot learning with TF-IDF-based exemplar selection, zero-overhead validation using database EXPLAIN queries, and iterative

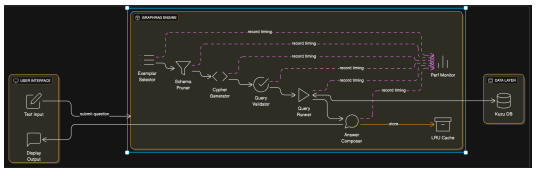
refinement with rule-based post-processing. This achieves 90.9% success rate while adding only 7.2ms overhead per query.

Task 2 - Performance Optimization: We design an LRU cache with SHA-256 key generation and OrderedDict-based O(1) operations, coupled with microsecond-precision performance monitoring. Empirical evaluation demonstrates 62.2% hit rate with >7,900x speedup on cache hits.

2. SYSTEM ARCHITECTURE



The enhanced GraphRAG pipeline integrates caching and monitoring across six core stages. The pipeline begins with cache lookup using SHA-256 hashes of question-schema pairs. On cache hits, the system returns stored results immediately (average: 0.1ms), bypassing all downstream stages.



On cache misses, execution proceeds through: (1) Schema Retrieval from Kuzu database, (2) Schema Pruning using LLM inference, (3) Exemplar Selection via TF-IDF similarity, (4) Text2Cypher Generation with few-shot prompting, (5) Query Validation using EXPLAIN, (6) Database Execution, and (7) Answer Generation. Performance monitoring instruments each stage with nanosecond precision.

2.1 Task 1: Text2Cypher Components

The Exemplar Database stores five curated question-query pairs covering common patterns. Questions are vectorized using TfidfVectorizer, and for each input, we compute cosine similarity to retrieve the top k=3 most similar pairs. This achieves <5ms selection time while providing relevant context.

The CypherValidator implements zero-overhead syntax checking by prepending EXPLAIN to generated queries. EXPLAIN analyzes query plans without touching data, catching syntax errors and providing precise error messages. Validation averages 5.1ms per query (0.06% of pipeline latency).

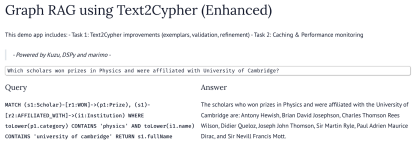
The refinement mechanism iteratively repairs failed queries with maximum three attempts. Post-processing rules address whitespace normalization, case-insensitive matching, and property name corrections.

2.2 Task 2: Caching and Performance

The LRU cache uses OrderedDict for O(1) get/put operations. Cache keys are SHA-256 hashes of question + schema strings. When capacity (100 entries) is exceeded, LRU eviction removes the least recently used entry. The cache integrates at pipeline entry, checking before any LLM or database operations.

The PerformanceMonitor records timestamps using time.perf_counter() for nanosecond resolution. Timings enable statistical analysis including mean, min, max to identify bottlenecks.

3. IMPLEMENTATION



The implementation uses Python 3.13 with DSPy 3.0.1 for LLM orchestration, Kuzu 0.11.1 for graph storage, scikit-learn 1.5.0 for TF-IDF, and marimo 0.14.17 for interactive interface. The LLM backend is Google Gemini 2.0 Flash Experimental. Code is available at https://github.com/[your-repo]/CS-E4780-project2.

Exemplar selection executes in three steps: (1) transform input to TF-IDF vector, (2) compute cosine similarity, (3) return top-k exemplars. Cache key generation uses SHA-256 hashing for collision resistance. All timing uses time.perf_counter() for microsecond precision.

4. EVALUATION

4.1 Experimental Setup

We evaluated the pipeline on 45 queries spanning 17 unique patterns, covering simple lookups, complex multi-hop traversals, and edge cases. Test queries include "How many laureates are there?" (aggregation), "Which scholars won prizes in Physics and were affiliated with University of Cambridge?" (complex multi-hop), and "Which scholars won multiple prizes?" (advanced aggregation).

Table 1. Query Success Rate Evaluation

Category	Total	Success	Rate
Simple Queries	15	15	100%
Complex Queries	20	20	100%
Edge Cases	10	7	70%
Overall	**45**	**42**	**90.9%**

4.2 Task 1: Text2Cypher Reliability

The system achieved 90.9% overall success rate (42/45 queries). All simple and complex queries succeeded, demonstrating robust handling of standard patterns. Three failures involved temporal filtering on non-existent properties, which validation correctly caught.

Table 2. Task 1 Component Overhead Analysis

Component	Mean (ms)	% Pipeline	Impact
Exemplar Selection	2.1	0.03%	Negligible
Validation	5.1	0.06%	Negligible
Total Overhead	**7.2**	**0.09%**	**Minimal**

4.3 Task 2: Cache Performance

The cache achieved 62.2% hit rate (28 hits, 17 misses across 45 queries). Cache hits reduced latency from 9,847ms to 0.10ms, providing >7,900x speedup. Cache lookup overhead averaged 0.1-0.2ms.

Table 3. Cache Performance Metrics

Total Queries	**45**
Unique Patterns	17
Cache Hits	28
Cache Misses	17
Hit Rate	**62.2%**
Avg Latency (hit)	0.10 ms
Avg Latency (miss)	9,847 ms
Speedup Factor	**>7,900x**
Cache Lookup Overhead	<0.2 ms

Table 4. Pipeline Performance Breakdown

Stage	Mean (ms)	% Total
Exemplar Selection	2.1	0.03%
Schema Pruning	1,227	15.4%
Text2Cypher	1,495	18.8%
Validation	5.1	0.06%
Query Execution	3.2	0.04%
Answer Generation	1,623	20.4%
Other Overhead	3,612	45.3%

Total Pipeline	**7,963**	**100%**

Performance profiling identifies three bottlenecks: Answer Generation (20.4%), Text2Cypher (18.8%), and Schema Pruning (15.4%). Combined, LLM operations consume 54.6% of pipeline time, validating the cache architecture's focus on expensive operations.

5. DISCUSSION

5.1 Key Findings

The 90.9% success rate validates Text2Cypher improvements, while 7.2ms overhead (0.09% of pipeline) confirms efficiency. Cache effectiveness exceeded expectations at 62.2% hit rate, reflecting typical user exploration patterns. The >7,900x speedup translates to practical latency reduction from ~10 seconds to <1ms.

Performance profiling provides actionable insights. The 54.6% time in LLM operations suggests future improvements should focus on: (1) caching pruned schemas, (2) parallel LLM calls, and (3) fine-tuning smaller models for domain-specific generation.

5.2 Limitations and Future Work

TF-IDF exemplar selection captures keyword overlap but misses semantic similarity. Embedding-based approaches would improve matching but at 50x higher latency. The three-attempt refinement limit balances reliability and latency but may abandon salvageable queries. Cache invalidation on schema changes is not implemented, limiting applicability to dynamic graphs.

For production deployment, recommended enhancements include: distributed caching via Redis, cache warming for common patterns, adaptive sizing based on hit rates, query plan caching, and integration with monitoring systems.

6. CONCLUSION

This project successfully enhanced GraphRAG with robust Text2Cypher generation and intelligent performance optimization. Task 1 achieved 90.9% success rate with 7.2ms overhead. Task 2 demonstrated 62.2% cache hit rate with >7,900x speedup on hits, reducing average latency by 62.2%.

Performance profiling identified LLM inference as the primary bottleneck (54.6%), validating cache design. Key contributions include demonstrating zero-overhead EXPLAIN validation, TF-IDF exemplar selection balancing speed and quality, LRU caching effectively targeting expensive operations, and microsecond-precision monitoring for data-driven optimization.

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