

Deep GraphRAG: A Balanced Approach to Hierarchical Retrieval and Adaptive Integration

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Abstract

Graph-based Retrieval-Augmented Generation (GraphRAG) frameworks face a trade-off between the comprehensiveness of global search and the efficiency of local search. Existing methods are often challenged by navigating large-scale hierarchical graphs, optimizing retrieval paths, and balancing exploration-exploitation dynamics, frequently lacking robust multi-stage re-ranking. To overcome these deficits, we propose Deep GraphRAG, a framework designed for a balanced approach to hierarchical retrieval and adaptive integration. It introduces a hierarchical global-to-local retrieval strategy that integrates macroscopic inter-community and microscopic intra-community contextual relations. This strategy employs a three-stage process: (1) inter-community filtering, which prunes the search space using local context; (2) community-level refinement, which prioritizes relevant subgraphs via entity-interaction analysis; and (3) entity-level fine-grained search within target communities. A beam search-optimized dynamic re-ranking module guides this process, continuously filtering candidates to balance efficiency and global comprehensiveness. Deep GraphRAG also features a Knowledge Integration Module leveraging a compact LLM, trained with Dynamic Weighting Reward GRPO (DW-GRPO). This novel reinforcement learning approach dynamically adjusts reward weights to balance three key objectives: relevance, faithfulness, and conciseness. This training enables compact models (1.5B) to approach the performance of large models (70B) in the integration task. Evaluations on Natural Questions and HotpotQA demonstrate that Deep GraphRAG significantly outperforms baseline graph retrieval methods in both accuracy and efficiency.

Keywords

GraphRAG, Reinforcement Learning, Large Language Models

1 Introduction

While Retrieval-Augmented Generation (RAG) effectively mitigates common LLM challenges such as hallucination and knowledge cutoff [7], conventional vector-based retrieval methods demonstrate limitations in complex reasoning tasks that necessitate structural comprehension [1, 3, 10, 11, 15, 20, 21]. This deficit has catalyzed the development of knowledge graph-based RAG (GraphRAG) [2]. However, even advanced approaches—including GNN-enhanced frameworks [12], modular indexing systems [9], agent-based graph

readers [8], and neurobiologically inspired retrieval [4]—exhibit notable limitations in graph traversal.

Specifically, these methods inadequately resolve the exploration-exploitation tradeoff. Coarse-grained community summarization (e.g., Map-Reduce) often sacrifices fine-grained contextual relevance. Concurrently, the absence of multi-stage re-ranking mechanisms can lead to local optima trapping and disconnection between different levels of graph abstraction [5, 14].

To address these limitations, we propose Deep GraphRAG, a hierarchical retrieval framework featuring a dynamic, beam-search-inspired re-ranker. As depicted in Figure 1, this framework systematically integrates: (1) Inter-community filtering to prune the search space via macroscopic topology; (2) Community-level refinement utilizing entity-interaction graph analysis; (3) Fine-grained entity retrieval coupled with contextual re-ranking. This tri-stage architecture is designed to balance global structural awareness with local semantic precision, thereby addressing the limitations of prior models.

Moreover, reinforcement learning algorithms such as TRPO [16], DPO [13], PPO [17] and GRPO [18] employ fixed weights across multiple reward signals, failing to account for the dynamic trade-offs that may arise during optimization. To address this limitation, we propose Dynamic Weighting Reward GRPO (DW-GRPO), a novel framework that adaptively learns and updates reward coefficients during policy optimization. Empirical results demonstrate that DW-GRPO significantly improves the performance of a compact 1.5B LLM on knowledge integration tasks.

2 Methods

2.1 Deep GraphRAG

We propose Deep GraphRAG, a retrieval framework using a graph’s hierarchical community structure to enhance accuracy via a multi-stage, top-down search.

2.1.1 Graph Construction and Hierarchy. We construct the base graph $G = (V, E)$ from the corpus K using a rigorous three-step pipeline designed to maximize structural integrity and semantic retention:

Text Chunking and Extraction: We segment the corpus K using a sliding window approach with a fixed size of $T = 600$ tokens and an overlap of $O = 100$ tokens to mitigate boundary information loss. For each chunk, we deploy Qwen2.5-72B-Instruct (temperature

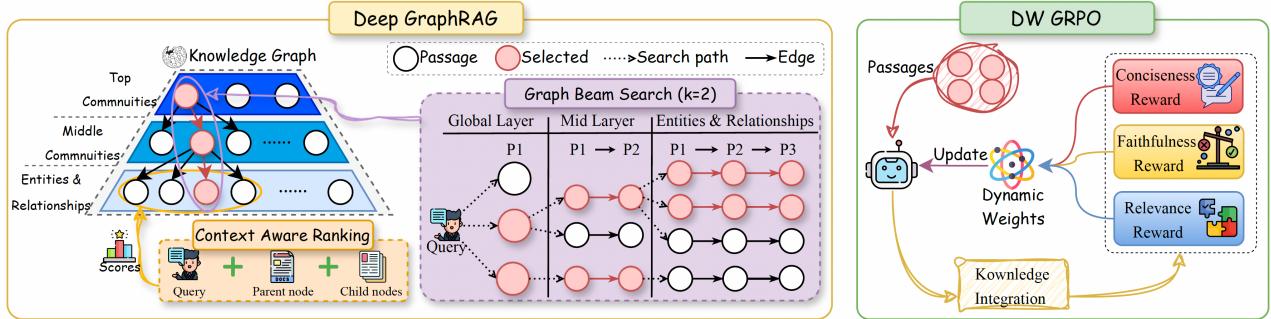


Figure 1: Deep GraphRAG framework overview. The retrieval module uses Graph Beam Search and Context Aware Ranking on a hierarchical Knowledge Graph. The knowledge integration module employs Dynamic Weighting Reward GRPO (DW GRPO).

set to 0 to ensure deterministic output) with a specialized prompt to extract entities and directed relationships. Unlike standard triple-based extraction, we enforce the generation of concise natural language descriptions for every edge to capture complex semantic nuances.

Entity Resolution: To maintain topological consistency, we implement a hybrid resolution strategy. Initial candidate pairs for merging are identified by computing cosine similarity on entity descriptions embedded via the bge-m3 model. Pairs exceeding a strict similarity threshold ($\tau > 0.95$) undergo a secondary verification step where an LLM acts as a discriminator to confirm if the nodes refer to the same real-world concept (e.g., merging "U.S." and "United States").

Hierarchy Generation: Upon the resolved base graph G , we construct a multi-granular 3-level community hierarchy C . This is achieved by recursively applying the weighted Louvain algorithm with a standard resolution parameter $\gamma = 1.0$. This bottom-up process partitions the graph into increasingly coarse semantic clusters, creating a tree structure where level $L = 0$ comprises individual entities and levels $L > 0$ represent abstract community summaries.

We then generate context-aware representations $D(\cdot)$ for all nodes and communities using a pre-trained sentence-embedding model. Community representations $D(c)$ are derived by mean pooling their sub-community vectors (Eq. 1), while node representations $D(v)$ concatenate local descriptions with their parent's representation $D_{parent}(\cdot)$.

$$D_{sub}(c) = \frac{1}{|C_{sub}(c)|} \sum_{c' \in C_{sub}(c)} D(c') \quad (1)$$

2.1.2 Retrieval Process. The retrieval (Algorithm 1) employs a beam search ($k = 3$) to traverse C from top to bottom. Relevance at each level is scored using cosine similarity between q and $D(\cdot)$. Finally, retrieved knowledge is structured hierarchically (community summaries, then entity details) for LLM integration.

2.2 Dynamic Weighting Reward GRPO (DW-GRPO)

2.2.1 DW-GRPO in Deep GraphRAG. In the Deep GraphRAG framework, knowledge integration generates distilled knowledge C . C is a critical input for subsequent knowledge extraction based on

Algorithm 1 Deep GraphRAG Process

Input: Query q , Community C , Beam width k , Top- m entities m

Output: Final result set R

- 1: **Phase 1: Top-level Search** (Beam Search, $k = 3$)
 - 2: Score C_{top} via $\text{sim}_{\cos}(q, D(c_{top}))$; $C_{mid} \leftarrow \text{Top-k}$
 - 3: **Phase 2: Middle-level Search** (Beam Search, $k = 3$)
 - 4: Expand C_{mid} to C'_{mid} ; Score via $\text{sim}_{\cos}(q, D(c'_{mid}))$
 - 5: $C_{stop}, V_{cand} \leftarrow \text{Top-k results from } C'_{mid}$
 - 6: **Phase 3: Entity-level Search**
 - 7: Expand C_{stop} to V_{cand} ; Score via $\text{sim}_{\cos}(q, D(v))$
 - 8: $R_{pre} \leftarrow \text{Top-}m \text{ results from } V_{cand}$
 - 9: **Phase 4: Knowledge Integration**
 - 10: $R \leftarrow \text{Hierarchical-Integration}(R_{pre})$
 - 11: **return** R
-

user queries Q . The module aims to filter redundancy and suppress hallucinations, emphasizing three core objectives. We define three rewards for optimizing the distilled knowledge C relative to the original text K and query Q :

- (1) **Relevance (r_{rel}):** Measures how well C answers Q . We use a pre-trained cross-encoder model f_{cross} to score the query-output pair:

$$r_{\text{rel}} = f_{\text{cross}}(Q, C) \quad (2)$$

- (2) **Faithfulness (r_{faith}):** Measures the semantic fidelity of C to the original knowledge K . We use the F1-score from BERTScore f_{BERT} :

$$r_{\text{faith}} = f_{\text{BERT}}(C, K) \quad (3)$$

- (3) **Conciseness (r_{conc}):** Penalizes verbosity to encourage succinct summaries. We define this as a normalized length-based reward:

$$r_{\text{conc}} = \max \left(0, 1 - \frac{\text{len}(C)}{\text{len}(K)} \right) \quad (4)$$

These three rewards (r_1, r_2, r_3) form the basis for the dynamic weighting mechanism.

2.2.2 Dynamic Weighting Reward-GRPO. A limitation of GRPO in multi-reward settings is its use of static weights, which leads to suboptimal performance (the seesaw effect [19]). We propose

Dynamic Weighting Reward GRPO (DW-GRPO), which replaces static weights with a policy-aware adaptive weighting mechanism.

We incorporate a dynamic parameter w to adjust rewards: $\tilde{r} = \sum_j w_j r_j$. The estimated advantage \tilde{A} is computed as:

$$\tilde{A} = \sum_j w_j r_j - \frac{\sum_j w_j r_j - \text{mean}(\sum_j w_j r_j)}{\text{std}(\sum_j w_j r_j)} \quad (5)$$

The core mechanism of DW-GRPO is to dynamically allocate higher weights to reward components that demonstrate slower growth rates, maximizing long-term returns. Let $\Delta r_j = \max(r_j^{(t,\tau)}) - \min(r_j^{(t,\tau)})$ be the reward range over window τ . We fit a linear model to estimate the reward's rate of change α_j .

The normalized rate of change $\alpha_j(t-1)$ is:

$$\alpha_j(t-1) = \begin{cases} 0, & \text{if } \Delta r_j = 0 \\ \frac{\text{slope}_j}{\Delta r_j}, & \text{otherwise} \end{cases} \quad (6)$$

where the slope is determined by least-squares fitting:

$$\text{slope}_j = \arg \min_{k,b} \|r_j^{(t,w)} - (kx + b)\|^2.$$

The dynamic weights $w_j(t)$ are then derived using the softmax function with temperature T , where $W = \sum_j w_{j,0}$ maintains the total scale:

$$w_j(t) = \frac{W \exp(-1 \cdot \alpha_j(t-1)/T)}{\sum_j \exp(-1 \cdot \alpha_j(t-1)/T)} \quad (7)$$

3 Experimental Setup

3.1 Datasets

We evaluated the system on two distinct datasets, Natural Questions (NQ) [6] and HotpotQA [22], to assess its generalization ability and domain adaptability.

3.2 Question Categorization and Baselines

To evaluate performance on problems of varying complexity, we categorized test questions into three types based on the structure of their ground-truth answer paths in the knowledge graph:

- **Local Questions (LQ):** Answerable by focusing on 1-2 directly connected entity nodes. Tests retrieval of specific facts.
- **Global Questions (GQ):** Require reasoning across more than 2 entities, often spanning different communities. Tests summarization or comparison.
- **Comprehensive Questions (CQ):** Require a combination of specific local facts (like LQ) and broader aggregated context (like GQ).

This objective categorization allows for a fine-grained analysis of each method's strengths.

We compare Deep GraphRAG against three baseline retrieval methods: **Local Search (LS)** (standard dense vector retrieval over all entity nodes), Microsoft's **Global Search (GS)** (a map-reduce summarization strategy), and **DRIFT Search (DS)** (a recursive search method) [14].

4 Results

4.1 Performance and Efficiency Analysis

We conducted a comprehensive evaluation of retrieval performance (Table 1) and system latency (Figure 2). Our analysis yields three critical observations.

Superiority in Global Reasoning Drives Overall Performance. Deep GraphRAG (with a 72B integrator) establishes new state-of-the-art performance, achieving the highest EM-Total scores on both NQ (e.g., 44.69%) and HotpotQA (e.g., 45.44%). This overall superiority is primarily driven by a significant advantage in **Global Questions (GQ)**. On HotpotQA, which demands multi-hop reasoning, our method (e.g., 56.25%) drastically outperforms Local Search (10.00%) and the strong Drift Search baseline (38.75%). This confirms that our hierarchical global-to-local search effectively balances exploration and exploitation to handle queries requiring broad contextual aggregation.

Nuanced Trade-offs in Comprehensive Queries. Performance on **Comprehensive Questions (CQ)** is more nuanced. While Deep GraphRAG remains competitive and often wins (e.g., 24.76% on HotpotQA), it does not universally outperform all baselines. For instance, on NQ with DeepSeek-R1, Local Search achieves a higher EM-CQ (23.20%) than Deep GraphRAG (19.60%). This suggests a potential trade-off: our method's strength in hierarchical summarization may, in some cases, obscure the fine-grained local facts needed for certain CQ tasks, an area for future refinement.

High-Efficiency Distillation via DW-GRPO. The compact Qwen2.5 1.5B-DW GRPO achieves **over 94%** of the 72B model's NQ performance (42.36%), overcoming the baseline's "lost-in-the-middle" issue. By reinforcing information filtering and query alignment, our dynamic weighting strategy enhances contextual robustness, enabling lightweight models to handle complex reasoning.

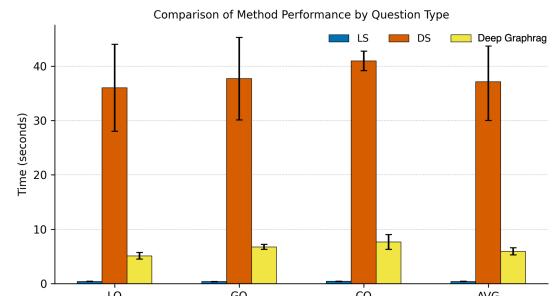
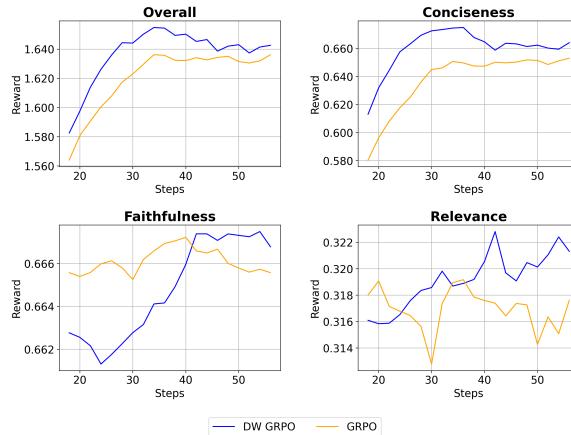


Figure 2: Comparison of system processing time (latency) among Local Search (LS), DRIFT Search (DS), and Deep GraphRAG methods on the NQ dataset.

Latency Reduction. Figure 2 shows Deep GraphRAG achieves an **86%** and **81.6%** reduction in latency over Drift Search on Local and Global NQ questions.

Table 1: Performance Comparison of Different Models (NQ and HotpotQA). Best total EM in bold.

Method	Knowledge Integration	Generation	EM-LQ (%)	EM-GQ (%)	EM-CQ (%)	EM-Total (%)
NQ Dataset						
Local Search		Qwen2.5 72B	41.32	16.58	16.10	30.13
Global Search	Qwen2.5 72B	Qwen2.5 72B	20.48	31.19	0.10	22.63
Drift Search	Qwen2.5 72B	Qwen2.5 72B	42.43	54.15	14.70	42.78
Deep GraphRAG	Qwen2.5 72B	Qwen2.5 72B	45.36	55.08	14.70	44.69
Deep GraphRAG	Qwen2.5 1.5B	Qwen2.5 72B	24.00	28.00	3.00	21.64
Deep GraphRAG	Qwen2.5 1.5B-DW GRPO	Qwen2.5 72B	44.80	54.00	13.00	42.36
Local Search		DeepSeek-R1	41.09	18.04	23.20	31.36
Global Search	DeepSeek-R1	DeepSeek-R1	20.52	32.15	16.40	23.79
Drift Search	Qwen2.5 72B	DeepSeek-R1	45.23	53.42	11.00	43.61
Deep GraphRAG	Qwen2.5 72B	DeepSeek-R1	45.36	51.00	19.60	43.98
Deep GraphRAG	Qwen2.5 1.5B	DeepSeek-R1	24.40	29.00	3.50	22.27
Deep GraphRAG	Qwen2.5 1.5B-DW GRPO	DeepSeek-R1	45.00	50.50	18.00	42.09
HotpotQA Dataset						
Local Search		Qwen2.5 72B	59.25	10.63	6.19	38.22
Global Search	Qwen2.5 72B	Qwen2.5 72B	18.49	41.88	6.19	19.78
Drift Search	Qwen2.5 72B	Qwen2.5 72B	39.62	30.00	22.38	33.89
Deep GraphRAG	Qwen2.5 72B	Qwen2.5 72B	49.06	56.25	24.76	44.67
Deep GraphRAG	Qwen2.5 1.5B	Qwen2.5 72B	18.87	15.00	2.86	15.97
Deep GraphRAG	Qwen2.5 1.5B-DW GRPO	Qwen2.5 72B	39.62	57.50	20.95	38.44
Local Search		DeepSeek-R1	60.94	10.00	14.76	41.11
Global Search	DeepSeek-R1	DeepSeek-R1	20.00	48.75	9.05	22.56
Drift Search	Qwen2.5 72B	DeepSeek-R1	39.62	38.75	22.86	35.56
Deep GraphRAG	Qwen2.5 72B	DeepSeek-R1	50.38	56.25	24.76	45.44
Deep GraphRAG	Qwen2.5 1.5B	DeepSeek-R1	20.00	18.13	3.81	17.48
Deep GraphRAG	Qwen2.5 1.5B-DW GRPO	DeepSeek-R1	39.62	58.13	20.95	38.56

**Figure 3: Comparison of smoothed reward learning curves between GRPO and DW-GRPO on the test dataset.**

4.2 Performance of DW-GRPO

To rigorously evaluate the efficacy of the proposed Dynamic Weighting Reward GRPO (DW-GRPO), we conducted a comparative analysis against the standard GRPO baseline using the Qwen2.5-1.5B model. The experimental protocol involved a two-stage training pipeline on the HotpotQA dataset: initial Supervised Fine-Tuning (SFT) using distillations from the teacher model (Qwen2.5-72B), followed by Reinforcement Learning (RL) optimization. We track both the aggregated reward and the individual components: *Conciseness*, *Faithfulness*, and *Relevance*.

Figure 3 illustrates the reward trajectories. The baseline exhibits a marked optimization disparity: while the simple *Conciseness* reward is rapidly maximized, semantic objectives—*Relevance* and *Faithfulness*—stagnate. This exemplifies the “seesaw effect,” where the model over-optimizes easy metrics at the expense of complex reasoning.

In contrast, DW-GRPO demonstrates sustained gains across all metrics, validating the adaptive mechanism in Section 2.2.2. By monitoring the reward slope (slope_j), the algorithm detects stalling

in *Relevance* and *Faithfulness* and dynamically upweights these lagging components (Eq. 7). This effectively prevents policy collapse into trivial solutions, ensuring robust semantic alignment.

5 Conclusion

We introduced Deep GraphRAG, a framework addressing global and complex queries via hierarchical global-to-local retrieval and beam-search re-ranking. Additionally, we proposed DW-GRPO, an adaptive reinforcement learning strategy that enables compact 1.5B models to achieve performance competitive with 72B baselines. Experiments on NQ and HotpotQA demonstrate significant gains in both retrieval accuracy and efficiency. Future work will focus on optimizing the trade-off between global summarization and local fact preservation.

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