Beyond Chunks and Graphs: Retrieval-Augmented Generation through Triplet-Driven Thinking

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Abstract

Retrieval-augmented generation (RAG) is critical for reducing hallucinations and incorporating external knowledge into Large Language Models (LLMs). However, advanced RAG systems face a trade-off between performance and efficiency. Multi-round RAG approaches achieve strong reasoning but incur excessive LLM calls and token costs, while Graph RAG methods suffer from computationally expensive, error-prone graph construction and retrieval redundancy. To address these challenges, we propose T²RAG, a novel framework that operates on a simple, graph-free knowledge base of atomic triplets. T²RAG leverages an LLM to decompose questions into searchable triplets with placeholders, which it then iteratively resolves by retrieving evidence from the triplet database. Empirical results show that T²RAG significantly outperforms state-ofthe-art multi-round and Graph RAG methods, achieving an average performance gain of up to 11% across six datasets while reducing retrieval costs by up to 45%. Our code is available at https://github.com/rockcor/T2RAG.

1 Introduction

Large Language Models (LLMs) have become central to open-domain question answering (QA) systems, owing to their vast stores of parametric knowledge and remarkable instruction-following capabilities (Yue, 2025; Gu et al., 2024b). However, their effectiveness is often undermined by critical challenges such as catastrophic forgetting and hallucination, particularly when addressing questions that require access to evolving, real-world knowledge (Gu et al., 2024a; Huang et al., 2025; Zhong et al., 2023). Consequently, Retrieval-Augmented Generation (RAG) has emerged as a robust paradigm to mitigate these issues (Lewis et al., 2020; Gao et al., 2023) by retrieving relevant documents from an external knowledge corpus.

However, standard RAG systems, which rank document chunks by query similarity (Karpukhin et al., 2020; Sawarkar et al., 2024; Khattab and

Zaharia, 2020), are effective for simple questions but fail on complex ones that require multi-hop reasoning (Tang and Yang, 2024). This failure occurs because queries often lack the necessary intermediate entities to connect information across different chunks (Shen et al., 2024), and important details can be lost in the *compression loss* of long chunk embeddings (Zhang et al., 2024b).

To address these issues, two primary research directions have emerged, each with its own challenges. Multi-Round RAG leverages the LLM's reasoning abilities by decomposing complex questions into sequential sub-queries. While effective at traversing multi-hop knowledge paths, it is time and token-consuming, often requiring numerous (3-6) LLM calls in each round (Trivedi et al., 2023; Xu et al., 2025; Shen et al., 2024), and up to around 8 rounds in total (Trivedi et al., 2023). Additionally, it also faces the challenge of compression loss. On the other hand, **Graph RAG** (Edge et al., 2024; Han et al., 2024; Peng et al., 2024) structures the corpus into a knowledge graph to retrieve logically connected information. However, this approach is hindered by an expensive and error-prone graph construction process due to entity ambiguity issue (Hoffart et al., 2014), redundancy in retrieval from high-degree nodes (Peng et al., 2024), and the difficulty LLMs face when understanding the graph structures (Chai et al., 2023).

To circumvent these inherent inefficiencies and architectural limitations of existing RAG paradigms, we propose T²RAG (<u>Triplet-driven Thinking for Retrieval-Augmented Generation</u>), a novel framework that fundamentally re-architects the RAG pipeline and moves beyond traditional chunk-based or graph-based retrieval by operating directly on atomic knowledge triplets. *Unlike Graph RAG*, it completely sidesteps the costly, time-consuming, and error-prone process of offline knowledge graph construction. Instead of building an explicit graph, T²RAG operates on a graph-free knowledge base of atomic propositions, thus avoiding the high indexing costs and

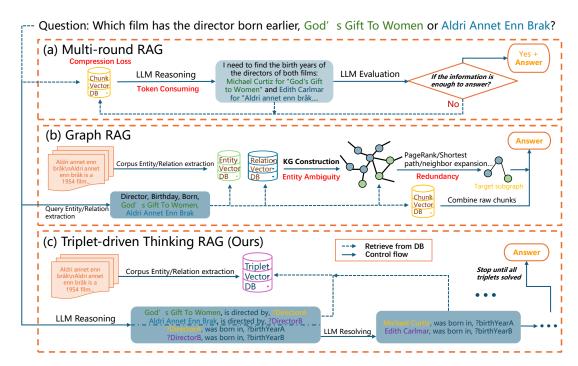


Figure 1: A comparison of three RAG paradigms, with their primary challenges highlighted in red. (a) Multi-round RAG employs an iterative loop to retrieve large text chunks, but is hampered by *compression loss* from vector embeddings and *high token consumption* during reasoning. (b) Graph RAG constructs a knowledge graph to retrieve answers, but is vulnerable to *entity ambiguity* during creation and *retrieval redundancy* from high-degree nodes. (c) T²RAG decomposes a query into triplets with "?" placeholders and iteratively resolves them by retrieving evidence from a triplet database (DB) until all of them are resolved.

potential for retrieval errors caused by inaccurate graph links. Simultaneously, it tackles the excessive token consumption and latency that plagues Multi-round RAG systems. Rather than generating verbose, natural language reasoning chains at each step, T²RAG leverages the LLM to think in a more structured, efficient manner. It expands complex questions into "searchable triplets" containing specific placeholders for unknown entities. The system then iteratively retrieves context to resolve these triplets. This design maintains a lean, structured state transition between iterations, passing only compact triplets instead of verbose text. This triplet-centric design ensures a tight coupling between retrieval and reasoning, retaining powerful multi-hop capabilities while dramatically reducing token overhead and enhancing performance. Our main contributions are as follows:

- We introduce a novel RAG framework that leverages triplets as the fundamental unit for indexing, retrieval, and reasoning, moving beyond the limitations of chunk-based and explicit graph-based approaches.
- We demonstrate that our method achieves stateof-the-art performance on various types of QA benchmarks, outperforming leading models in both the Multi-Round RAG and Graph RAG.
- We also significantly improve the efficiency. Our

method reduces inference time and token consumption by up to 45% compared to other multiround methods and even achieves an efficiency comparable to that of single-round approaches.

2 Preliminaries

The task of open-domain question answering (ODQA) was formally introduced in the 1999 Text REtrieval Conference (TREC) QA track (Voorhees and Tice, 2000). Initially, it was defined as a factoid QA task: Given a large corpus of unstructured documents, the goal was to extract a small text snippet containing the correct answer to a factual question. While the scope of ODQA has since expanded to include summarization and openended (Reja et al., 2003) tasks (Edge et al., 2024; Xiao et al., 2025), factoid QA remains a significant challenge, evidenced by poor performance (below 50%) on complex, multi-hop datasets like MusiQue (Trivedi et al., 2023). Consequently, this paper focuses on advancing the state-of-the-art in factoid OA.

Factoid QA Task. Assume our collection contains D documents d_1, d_2, \ldots, d_D . We split each document into passages of equal token length or applying expert split if it exists, yielding M total chunks $\mathcal{C} = \{c_1, c_2, \ldots, c_M\}$, where each chunk c_i can be viewed as a token sequence $(w_1^{(i)}, w_2^{(i)}, \ldots, w_{|c_i|}^{(i)})$.

Given a question q, the goal is to find a combination of tokens $(w_{c_m}^{(j)},\ldots,w_{c_{m+k}}^{(j)})$ drawn from multiple chunks that collectively contain the information necessary to answer q while minimizing irrelevant noise to avoid hallucination. The answer must be **exact one entity** in our setting, such as persons, organizations, or locations or yes/no. Typically, a retriever $R:(q,\mathcal{C})\to\mathcal{C}_F$ is a function that takes a question q and the corpus \mathcal{C} as input and returns a much smaller set of chunks $\mathcal{C}_F\subset\mathcal{C}$, where $|\mathcal{C}_F|=k\ll |\mathcal{C}|$. For a fixed k, a retriever can be evaluated in isolation using top-k retrieval accuracy with respect to labeled golden chunks.

Retrieval Granularity. The preceding formulation assumes the retrieval unit is the chunk, which is a common setting (Karpukhin et al., 2020). However, recent works especially Guo et al. (2024); Fan et al. (2025) argue that chunks often contain a mix of relevant and irrelevant details, and a finer granularity is needed for complex queries (Zhang et al., 2024b). Inspired by work in Knowledge Graphs (KGs) (Ji et al., 2021), the fundamental unit of retrieval can be refined to more atomic elements:

- Entities $(e_1^{(i)}, e_2^{(i)}, \dots, e_{|c_i|}^{(i)})$: Named entities such as persons, organizations, or locations.
- **Triplets** $(t_1^{(i)}, t_2^{(i)}, \dots, t_{|c_i|}^{(i)})$: Structured facts represented as a (subject, predicate, object) tuple.
- **Propositions** $(p_1^{(i)}, p_2^{(i)}, \dots, p_{|c_i|}^{(i)})$: Atomic statements or facts, often by converting triplets into natural language sentences.

Propositions, which encapsulate a complete fact in a single sentence, are often considered to have greater semantic utility for modern embedding models compared to isolated entities or structured triplets (Zhang et al., 2024b). Our work explores leveraging this fine-grained units for improved retrieval and reasoning.

3 Related Work

We group recent RAG efforts into*multi-round*, and *graph-enhanced* RAG, each adding more interaction or structured reasoning and paving the way for the fine-grained design of T²RAG.

Multi-round RAG. Due to missing intermediate entities problem we mentioned in Section 1 more and more works follow a multi-round paradigm, which enables the LLMs infer the intermediate information thus better retrieve the final answer. Some works focus on the query side. Khot et al. (2023) decompose multi-hop questions into single-hop sub-queries that are solved sequentially. Yao et al. (2023) propose ReAct, interleaving

chain-of-thought (CoT) (Wei et al., 2022) steps with search actions issued by the LLM. Similarly, Query2Doc (Wang et al., 2023b) expanding queries into concise triplets to cut token usage while preserving recall. Another line of works relies on the generated intermediate results for next iteration. Beam Retrieval (Zhang et al., 2024a) jointly training an encoder and classifiers to keep multiple passage hypotheses across hops. FLARE (Jiang et al., 2023) forecasts upcoming sentences to decide when fresh retrieval is needed during longform generation. IRCoT (Trivedi et al., 2023) and ITER-RETGEN (Shao et al., 2023), alternately expanding a CoT and fetching new evidence to answer multi-step questions. Adaptive QA (Xie et al., 2023) create an adaptive framework that picks the simplest effective retrieval strategy according to query complexity. Despite these advances, few efforts explicitly aim to reduce token costs or number of llm calls during multi-round RAG. Previous methods expand query or generates CoT with long sentences in each round. In contrast, our work minimizes token consumption by formulating query expansions as triplets and simplifying reasoning steps as triplets resolving.

Graph RAG. One major line of research addresses complex QA by structuring knowledge into graphs. Originating in Knowledge Graph OA (KGOA), early methods focused on decomposing queries or performing multi-round, LLM-evaluated traversals from seed nodes (Luo et al., 2024; Sun et al., 2024; Cheng et al., 2024; Mavromatis and Karypis, 2022). The application of this paradigm to general ODQA was popularized by systems named GraphRAG (Edge et al., 2024) that construct a knowledge graph entirely with LLMs and use community detection for retrieval. Subsequent work has aimed to make this process more efficient. For instance, LightRAG (Guo et al., 2024) introduces a dual-level retrieval system combining graph structures with vector search to improve knowledge discovery. Targeting resource-constrained scenarios, MiniRAG (Fan et al., 2025) builds a heterogeneous graph of text chunks and named entities, enabling lightweight retrieval suitable for Small Language Models. To tackle the common challenge of entity merging, HippoRAG (Gutiérrez et al., 2025a) and HippoRAG2 (Gutiérrez et al., 2025b) create synonym links between similar entity nodes and employs a PageRank (Haveliwala, 1999) algorithm for final node selection. Despite these advances, a central challenge for Graph RAG remains the costly and error-prone nature of graph construction from unstructured text.

Our method, T²RAG, skips the costly and errorprone graph construction required by Graph RAG while retains the multi-hop reasoning power by Multi-round RAG. It also dramatically reduces token overhead by constraining both query expansion and intermediate generation. Besides, some works in ODQA such as GEAR (Shen et al., 2024) also employ a triplet search component. These methods typically rely on neighbor expansion, which involves retrieving all other triplets that share a head or tail entity. A key drawback of this approach is that accurately identifying and linking the same entity across different contexts is often inaccurate and computationally expensive.

4 Methodology

4.1 Overview

Our proposed method, T²RAG (Triplet-driven Thinking RAG), is a novel paradigm for resolving complex, multi-hop, factoid QA tasks. Unlike conventional RAG systems that operate on coarser document chunks or complex graph structures, T²RAG is designed to operate directly on atomic knowledge propositions derived from triplets, fostering an intrinsic alignment between knowledge representation and LLM reasoning. This framework operates in two stages: an offline indexing focused on systematic knowledge distillation, and an online retrieval characterized by iterative, adaptive triplet resolution. This principled design ensures both fine-grained retrieval for accuracy and a lean, efficient reasoning process.

4.2 Offline Indexing: Constructing a Graph-Free Knowledge Base

The goal of the offline stage is to transform a raw text corpus \mathcal{C} into a efficiently searchable knowledge base of atomic propositions. The motivation for adopting **proposition level** granularity is two fold: 1) Compared to the entity level, each proposition encodes an entire, unambiguous fact. 2) Compared to the chunk level, it also avoids the compression loss hindering the retrieval of details.

Canonical Triplet Generation. For each document chunk $c_i \in \mathcal{C}$, we employ an information extraction model, $LLM_{IE}(\cdot)$, to identify key facts. This model performs Open Information Extraction (OpenIE) (Martinez-Rodriguez et al., 2018) to extract a set of knowledge triplets $\mathcal{T}_i = \{t_1^{(i)}, t_2^{(i)}, \dots\}$. Each triplet $t_j^{(i)}$ is formalized as a canonical knowledge triplet (subject, predicate, object) that represents a sin-

gle factual statement. All extracted triplets are then aggregated into a global set for the entire corpus $\mathcal{T}_{total} = \bigcup_{i=1}^{M} \mathcal{T}_{i}$, where M is the total number of extracted triplets.

Triplet Embedding. To render these canonical triplets semantically actionable for dense retrieval, we are inspired by verbalization techniques (Oguz et al., 2020; Baek et al., 2023) to convert each triplet $t \in \mathcal{T}_{total}$ into a natural language sentence, termed a *proposition* p, simply by concatenating its components (e.g., "subject predicate object"). This seemingly straightforward verbalization is a deliberate design choice: it maximizes the semantic utility for embedding models, facilitating effective and contextually rich retrieval compared to isolated entities.

Triplet Vector DB Construction. The resulting flat list of propositions $\mathcal{P}_{total} = \{p_1, p_2, \dots, p_M\}$ is then encoded into dense vector representations using a high-performance embedding model $E(\cdot)$. For efficient real-time access, these vectors can be subsequently indexed using a highly optimized vector search library (FAISS) (Douze et al., 2024), creating an index \mathcal{I} that enables rapid similarity search across all propositions in the corpus. This vector DB is still called **Triplet Vector DB** as it keeps original text of triplets. We also save the mapping from those propositions to their source chunks because the original text is proved necessary in most of Graph RAG works (Guo et al., 2024; Fan et al., 2025). This pre-computation creates a fine-grained, semantically enriched knowledge index without the overhead of explicit graph structures.

The constructed proposition index, while offering significant advantages in terms of cost and construction fidelity, introduces a critical challenge: how to effectively navigate complex, multihop questions that typically rely on graph traversals? In the subsequent subsection, we introduce our novel online retrieval stage, where the LLM's triplet-driven thinking and adaptive iterative resolution strategically compensate for the graph traversals and the path-based reasoning.

4.3 Online Retrieval: Iterative Triplets Resolution

The online retrieval stage is an iterative process that dynamically builds the context containing both the triplets and chunks needed to answer user queries. The overall retrieval process is shown in Figure 2.

Step 1: Structured Query Decomposition. Given an initial query q, we first use an LLM to perform a structured decomposition where the LLM identifies the specific, atomic knowledge Triplets (denoted

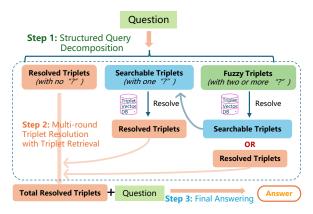


Figure 2: Online retrieval stage of T²RAG.

as \mathcal{T}_q) that must be answered to address the overall query. Critically, these derived triplets contain explicit placeholders ('?') for unknown entities. Based on the precise number of these placeholders, we categorize these initial triplets into three types:

- **Resolved Triplets** ($\mathcal{T}_{resolved}$): Triplets with **zero** placeholders, representing fully known facts that require no further search.
- **Searchable Triplets** ($\mathcal{T}_{searchable}$): Triplets with exactly **one** placeholder. This specificity, with two known elements, facilitates focused and accurate searches.
- Fuzzy Triplets (T_{fuzzy}): Triplets with two or more placeholders. These are inherently too ambiguous for search with the at most one element. It requires resolution in subsequent iterations to upgrade to searchable or resolved.

This explicit categorization ensures that later retrieval efforts are always focused and efficient.

Step 2: Multi-Round Triplet Resolution with Triplet Retrieval. In this step, we will resolve the query triplets, i.e., try to eliminate all "?" placeholders step by step by RAG. Considering different complexity of queries and their triplets, we adopt an adaptive retrieval strategy instead of a fixed top-k. We also observed most of multi-hop questions cannot be specifically retrieved by the query itself as illustrated in Figure 1, which necessitate the multi-round paradigm.

Step 2.1: Triplet-Based Adaptive Retrieval.

The current set of searchable triplets $\mathcal{T}^{(l)}_{\text{searchable}}$ are first converted into *query propositions* by simply concatenating the elements without the placeholder. These propositions are then embedded, using the same embedding model $E(\cdot)$ in the indexing stage, and used to query the proposition index \mathcal{I} . Unlike prior methods that retrieve a fixed top-k of propositions or triplets (Baek et al., 2023; Guo et al., 2024), our retrieval process is critically adaptive in two synergistic ways to ensure both relevance

and informational diversity: First, our method retrieves with the triplets while constrain the process by chunks. More specifically, the retrieval dynamically continues until context from k unique source chunks of triplets has been retrieved. Second, we aggregate retrieval candidates from all query propositions into a unified pool, ranking them globally by similarity scores, rather than allocating separate budgets to each proposition. These adaptive strategies ensure robustness to varying query complexity, allowing difficult questions to naturally draw from a wider range of propositions. Finally, the retrieval process returns the set of retrieved propositions $p_{\text{retrieved}}^{(l)}$ and their corresponding source chunks $C_{\text{retrieved}}^{(l)}$. The necessity of reading original chunks to complete details missing from triplets is widely acknowledged in the field (Fan et al., 2025; Guo et al., 2024).

Step 2.2: Resolving Triplets with Retrieved

Context. This step leverages the retrieved content to advance the query's resolution. We prompt the LLM to populate the placeholders within these triplets using the provided context. The retrieved propositions $(\mathcal{P}_{\text{retrieved}}^{(l)})$ and and their source chunks $(\mathcal{C}_{\text{retrieved}}^{(l)})$ serve as context for an LLM call. This is designed to either upgrade a searchable triplet to a fully resolved one by filling in its single placeholder, or to transform a fuzzy triplet into a searchable or directly to a resolved one by filling in one or more of its multiple placeholders. This resolution process reduces the ambiguity of existing triplets and makes it suitable for subsequent targeted retrieval. The process is shown in Figure 2 and a detailed example is in Appendix D.

Step 2.3: State Update and Ending Condition. Following the triplet resolution step, the system's state is updated for the next iteration, l+1. The set of resolved triplets is monotonically augmented with any newly resolved ones: $\mathcal{T}_{resolved}^{(l+1)} = \mathcal{T}_{resolved}^{(l)} \cup \mathcal{T}_{resolved}^{(new)}$. Crucially, only the newly searchable triplets are used for the subsequent retrieval step: $\mathcal{T}_{\text{searchable}}^{(l+1)} = \mathcal{T}_{\text{searchable}}^{(\text{new})}$. Any fuzzy triplets that remain unsolved are carried over to the next round's prompt. This set is updated by removing any triplets that were just resolved or became searchable: $\mathcal{T}_{ ext{fuzzy}}^{(l+1)} = \mathcal{T}_{ ext{fuzzy}}^{(l)} \setminus (\mathcal{T}_{ ext{resolved}}^{(ext{new})} \cup$ $\mathcal{T}_{\text{searchable}}^{(\text{new})}$). At the end of each iteration, similar to IRCoT (Trivedi et al., 2023), we check for an early stopping condition. Instead of using an LLM call, our method simply terminates if there are no unresolved triplets left. Formally, the iteration

continues as long as there are any searchable or

fuzzy triplets remaining or maximum iterations N reaches: $|\mathcal{T}_{\text{searchable}}^{(l+1)} \cup \mathcal{T}_{\text{fuzzy}}^{(l+1)}| > 0$. This highly structured state transition is key to our method's efficiency. By passing compact triplets between iterations, rather than the verbose CoT reasoning used by approaches like IRCoT, we dramatically reduce token overhead. Furthermore, this triplet-centric design creates a powerful synergy: the LLM generates reasoning gaps in the same format,i.e., triplets, ensuring strong semantic alignment between the resolution and retrieval stages.

Step 3: Synthesizing the Final Answer. Once the iterative loop terminates after K rounds, all fully resolved triplets are aggregated into a final set, $\mathcal{T}_{\text{total_solved}} = \mathcal{T}_{\text{resolved}}^{(K)}$. A final LLM call is then made to generate the answer, conditioned on how the process ended:

- (a) Successful Resolution: If the loop terminated because all triplets were resolved, the LLM is prompted with the original query (q) and this precise set of structured knowledge to generate a concise answer a: $a = \text{LLM}_{Answer}(q, \mathcal{T}_{total_solved})$.
- (b) Maximum Iterations Reached: If the loop stopped because it reached the maximum number of iterations, any remaining searchable triplets are included with the resolved facts to form the best possible context: $a = \text{LLM}_{Answer}(q, \mathcal{T}_{total_solved} \cup \mathcal{T}^{(K)}_{searchable})$. By providing the LLM primarily with the verified facts in $\mathcal{T}_{total_solved}$ instead of raw retrieved chunks, this method minimizes token costs and reduces the risk of hallucination.

5 Experiments

5.1 Datasets

To ensure a comprehensive evaluation, we select representative datasets for three distinct Open-Domain Question Answering (ODQA) categories: Simple QA, Multi-hop QA, and Domain-specific QA. For the first two categories, we follow the experimental setup from HippoRAG2 (Gutiérrez et al., 2025b). We use PopQA (Mallen et al., 2023) for simple questions. For multi-hop questions, we use 2Wiki-MultihopQA (2Wiki) (Ho et al., 2020), MuSiQue (Trivedi et al., 2022), and HotpotQA (Yang et al., 2018). For each of these datasets, we use the same sample of 1,000 questions as the prior work. For domain-specific evaluation, we adapt two datasets from the GraphRAG-Bench (Xiao et al., 2025). We isolate the factoid questions from the two datasets, Story and Medical, and use an LLM to shorten the ground-truth answers, enabling more precise evaluation. Detailed statistics for all datasets are provided in Table 3.

5.2 Baselines and Implementation Details

To evaluate our approach, we select three strong baselines representing state-of-the-art methods across major RAG categories. For Graph RAG, we choose **HippoRAG2** (Gutiérrez et al., 2025b) for its recognized efficiency and effectiveness. For summarization-based RAG, we use **Raptor** (Sarthi et al., 2024), a pioneering method that outperforms most Graph RAG approaches in recent benchmarks (Zhou et al., 2025). Lastly, for Multi-Round RAG, we include the prominent **IRCoT** (Trivedi et al., 2023) method. **NOR** method means the non-retrieval method that directly answers the question. **Standard** RAG retrieves chunks with an embedding model and uses them to generate an answer.

To ensure a fair comparison, all methods are configured with the same foundational models: NV-Embed-v2 (Lee et al., 2024) for embeddings and either Gemini-2.5-flash or GPT-4o-mini as the LLM for all offline indexing and online retrieval stages. For datasets lacking expert annotations, we employ a standard chunking strategy of 1200 tokens with a 100-token overlap. For the top-k of chunk retrieval, we set k = 5 for all methods. For the multi-round methods (T²RAG and IRCoT), we set a maximum of N=3 iterations and keeps the k=5 in each iteration. Following standard practices (Trivedi et al., 2023), we evaluate end-to-end QA performance using Exact Match (EM) and F1 scores. We focus specifically on these end-to-end QA metrics, as retrieval performance is difficult to compare directly when the number of retrieved passages is adaptive. Except for the performance comparisons, all results presented in the subsequent sections are obtained using GPT-4o-mini. Further experimental details are available in Appendix B.

5.3 Results

We unfold our analysis of experimental results by answering Research Questions (RQ) below.

RQ1: How does T²RAG perform against baselines? As shown Table 1, T²RAG achieves state-of-the-art performance, stems from several key advantages. **First**, our method achieves state-of-the-art overall performance, leading in both average EM and F1 scores across the two LLM backbones, except for the second place in F1 by GPT-4o-mini. Notably, its advantage in EM is particularly pronounced, a strength we attribute to the precision of our triplet-based retrieval, which excels at identifying the exact entities required for factoid QA. This adaptability is further demonstrated by its consistently strong results on domain-specific datasets,

Table 1: Main performance comparison on various types of QA datasets, showing Exact Match / F1 scores $\times 100$. The best result in each column is in **bold**, and the second best is underlined.

	Simple QA	Multi-Hop QA			Domain-Specific QA		Average	
Method	PopQA	2Wiki	MuSiQue	HotpotQA	Story	Medical	EM	F1
	Gemini-2.5-flash							
NOR	32.4 / 35.7	48.1 / 55.6	16.3 / 26.5	40.5 / 52.3	10.3 / 17.1	23.1 / 46.0	28.4	38.9
BM25	50.2 / 55.6	28.2 / 30.7	7.9 / 10.7	40.8 / 49.3	26.2 / 35.3	22.2 / 37.8	29.3	36.6
Standard	51.8 / 59.5	33.1 / 39.0	28.1 / 36.2	52.1 / 63.1	31.0 / 42.2	19.4 / 41.5	35.9	46.9
HippoRAG2	52.1 / <u>60.1</u>	44.3 / 51.2	29.1 / 38.3	52.1 / 64.1	33.1 / 44.1	27.8 / <u>58.2</u>	39.8	52.7
RAPTOR	<u>52.3</u> / 56.8	36.3 / 41.1	31.8 / 39.7	60.9 / 72.7	46.2 / 59.0	<u>34.2</u> / 58.1	43.6	54.6
IRCoT	51.2 / 58.7	<u>61.6</u> / <u>71.7</u>	39.7 / <u>49.8</u>	<u>61.2</u> / 77.3	$40.3 / \overline{57.3}$	26.1 / 56.1	<u>46.7</u>	<u>61.8</u>
T^2RAG	56.6 / 62.4	69.3 / 77.5	<u>39.1</u> / 49.1	62.3 / <u>73.2</u>	46.7 / 59.5	36.0 / 61.4	51.7	63.9
GPT-4o-mini								
NOR	28.7 / 31.4	28.0 / 34.1	10.2 / 20.3	28.8 / 38.6	11.5 / 18.9	19.3 / 44.2	21.1	31.3
BM25	47.6 / 54.8	42.9 / 48.2	15.3 / 21.1	47.2 / 57.6	29.0 / 38.5	25.9 / 43.6	34.7	44.0
Standard	51.9 / 60.0	53.1 / 60.2	31.2 / 44.3	58.0 / 71.1	27.3 / 60.1	27.0 / 59.9	41.4	59.3
HippoRAG2	52.2 / 60.2	59.6 / 69.3	34.1 / 48.1	58.1 / 71.1	41.2 / 58.3	28.1 / 59.4	45.6	61.1
RÂPTOR	<u>54.6</u> / $\overline{60.1}$	38.2 / 49.0	28.6 / 40.8	57.9 / 71.4	44.8 / <u>59.6</u>	36.7 / 63.7	43.5	57.4
IRCoT	45.3 / 54.7	<u>60.7</u> / 74.3	<u>34.1</u> / <u>47.6</u>	55.7 / 71.2	$36.1 / \overline{51.8}$	25.1 / 52.9	42.8	58.8
T ² RAG	55.8 / 63.2	66.7 / <u>74.4</u>	34.3 / 45.6	54.2 / 67.3	38.7 / 50.1	33.5 / 60.4	47.2	60.2

underscoring the universality of the underlying reasoning framework. **Second**, its superiority is most pronounced on Multi-hop QA datasets like 2Wiki. It not only surpasses all single-round baselines by a large margin but also outperforms the multiround baseline, IRCoT, by over 7.7% and 5.4% in EM with Gemini-2.5-flash and GPT-4o-mini, respectively. This highlights the effectiveness of its triplet-driven mechanism for complex reasoning. Finally, the method demonstrates a powerful synergy with reasoning LLMs. Its performance is significantly higher when paired with Gemini-2.5flash compared to GPT-4o-mini. This suggests that its structured process of query decomposition and resolution can uniquely leverage the advanced reasoning capabilities of such models through its stepby-step guidance. Conversely, certain methods such as HippoRAG2 exhibit a decrease in performance when employing reasoning LLMs. We hypothesize this occurs because relegating the LLM to a simple filtering task does not fully harness its sophisticated reasoning capabilities.

RQ2: What is the impact of the triplet resolution module? To validate the effectiveness of our core "triplet-driven thinking" design, we analyze the final performance based on whether a query's underlying triplets are fully resolved. Figure 3 reveals a significant performance delta between these two outcomes. Across all three datasets, there is a strong correlation between successful triplet resolution and high performance. For instance, on the 2Wiki dataset, the F1 score for unresolved questions drops to 53% from 76%, with a similar sharp decline observed in EM scores. This result confirms that resolving all triplets is the key to success.

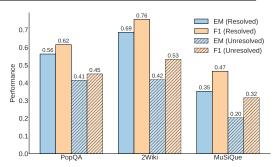


Figure 3: Performance vs. final resolution status.

Table 2: Ablation results

	PopQA		2Wiki		MuSiQue		
Method	EM	F1	EM	F1	EM	F1	
T^2RAG	56.0	63.0	66.0	74.0	33.0	45.0	
- single round	54.8 ↓2.1%	60.5 ↓4.0%	51.0 ↓22.7%	59.0 ↓20.3%	15.0 ↓54.5%	24.0 ↓46.7%	
- w/o chunk	41.1 ↓26.6%	44.7 ↓29.0%	62.0 ↓6.1%	68.0 ↓8.1%	21.6 ↓34.5%	29.9 ↓33.6%	

RQ3: Which components of T^2 RAG are impor-

tant? We conducted an ablation study to quantify the contribution of its two key components. The results in Table 2 reveal that both the iterative process and the use of chunks are important. The iterative reasoning module proves to be a critical component. Removing it (- single round) causes a significant performance degradation, particularly on multi-hop QA. For instance, F1 score on MuSiQue drops by a remarkable 54.5%. This demonstrates that the multi-round retrieval and resolution is essential for decomposing and solving complex problems. Similarly, removing the raw chunk text during the iteration, i.e, (- w/o chunk), is also substantially harms performance, confirming that the raw text complement missing details of triplets. This observation is aligned with Fan et al. (2025).

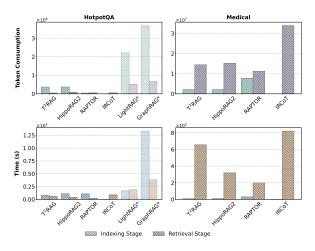


Figure 4: Comparison of token consumption and time. Token consumption is calculated by (input + 4×output). Results of LightRAG and GraphRAG are from a benchmark (Zhou et al., 2025).

RQ4: How does T²RAG compare in terms of computational efficiency? This analysis compares the computational cost of T²RAG with baselines during both the one-time offline indexing and online retrieval phases. To better visualize the online costs, the token and time values for the retrieval stage in Figure 4 are aggregated over 1,000 queries, assuming they are processed sequentially. Figure 4 illustrates a strategic trade-off. During indexing stage, T²RAG's token consumption appears high because it processes the entire corpus into triplets. However, this processing is merely the first step for many advanced Graph RAG methods (Edge et al., 2024; Guo et al., 2024; Fan et al., 2025).methods (Edge et al., 2024; Guo et al., 2024; Fan et al., 2025). Their subsequent graph construction steps are far more costly. For example, LightRAG and GraphRAG require around $6 \times$ and $10 \times$ the token consumption of the initial triplet extraction phase, respectively (Gutiérrez et al., 2025b). T²RAG's indexing overhead remains highly competitive within this category. At the retrieval stage, T²RAG is remarkably more efficient in both tokens and latency than the multi-round baseline, IRCoT. More notably, its efficiency is even comparable to single-round methods. This is because HippoRAG2 also invokes multiple LLM calls for filtering, while Raptor retrieves longer summaries than chunks. T²RAG's efficiency stems from its design, which focuses on targeted search for triplets rather than processing large, noisy text chunks. In summary, T²RAG accepts a standard indexing cost to deliver a highly efficient online system.

RQ5: How does performance scale with the amount of retrieved context? To investigate how T²RAG's performance scales with context

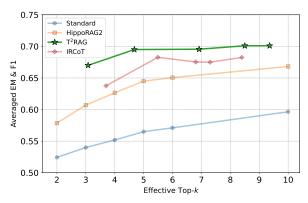


Figure 5: Performance vs. top-k. Multi-round methods are calibrated by $k \times$ average number of iterations.

size, we compare it against other multi-round methods while varying the number of retrieved documents (top-k). Traditional RAG methods often rely on retrieving more context to find the correct answer, which can be inefficient. The trend in Figure 5 shows T²RAG's performance is consistently high and robust to the value of top-k. It achieves the plateau faster than other methods. In contrast, baselines like IRCoT and HippoRAG2 exhibit a strong dependence on a larger context window. This observation demonstrates its effectiveness does not rely on scaling up the volume of retrieved text but a more precise and specific triplet-based retrieval.

6 Conclusion

In this work, we proposed the Triplet-driven Thinking RAG (T²RAG), a novel framework that embeds reasoning directly into the retrieval process. By decomposing complex queries into atomic triplets and resolving them step-by-step against a triplet knowledge base, our method consistently outperforms more complexly designed RAG systems. Our extensive experiments demonstrate that T²RAG establishes a new state-of-the-art in factoid QA tasks, particularly on challenging multi-hop QA. This superior performance is achieved with remarkable online efficiency; the retrieval stage has significantly lower time and token consumption compared to other multi-round methods and maintains a comparable overhead to even singleround approaches. Furthermore, our results reveal a powerful synergy between T²RAG's structured thinking process and the capabilities of advanced reasoning LLMs, highlighting a new path to unlock their full potential in this area. Looking forward, T²RAG paves the way for more accurate and efficient RAG systems by shifting the paradigm from retrieving and generating unstructured contexts towards a more deliberate, reasoning-driven synthesis of atomic facts.

7 Limitations

Although our method achieves state-of-the-art performance with a simple design, it is not without limitations. Experimentally, we limited our multiround methods to 3 iterations to match the complexity of the datasets and ensure a fair efficiency comparison; we also did not have the resources to test on other embedding models especially LLMbased ones, re-rankers or large external knowledge graphs (e.g., Wikipedia KG (Hertling and Paulheim, 2018)). Our evaluation is also limited to the black-box and end-to-end one which may lack explanability without the recall score of chunks. Methodologically, our approach is highly dependent on the quality of the triplet extraction. While higher-quality sources can be used, simple triplets may not adequately represent complex knowledge like many-to-many relationships, a challenge that could be addressed with hypergraph modeling (Luo et al., 2025) in future work. Besides, the efficiency of triplet extraction can be further improved beyond the classic OpenIE pipeline. Developing these methods needs efforts from information extraction (Grishman, 2015) area. Finally, regarding scalability, building the index from a very large corpus is token-intensive. However, our method is very efficient when using a pre-existing triplet database. This design also makes it inherently suitable for evolving knowledge bases, as new triplets are independent to previous ones thus they can be added incrementally, offering a significant advantage over static Graph RAG approaches (Zhang et al., 2025).

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A Methodology

As the T²RAG consists of several steps with clear control flow, we illustrate it by the following pseudo algorithm.

B Experiments

B.1 Detailed Implementations

For all experiments, we set the Large Language Model (LLM) temperature to 0 to ensure deterministic and reproducible outputs. Local embedding generation was performed on a single NVIDIA L40S GPU.

A key aspect of our benchmark is the standardization of the final answer format. We modified the prompt for all methods to include a specific format template, which yielded a significant performance boost compared to baseline implementations in other studies (Gutiérrez et al., 2025a; Xiao et al., 2025). In those works, methods such as RAP-TOR and IRCOT consistently performed about 10% lower than graph-based RAG approaches. Furthermore, in our implementation of the RAPTOR, we replaced the original Gaussian Mixture Model (GMM) for clustering with K-Means. This decision was based on the superior computational efficiency of K-Means, which has been demonstrated to produce results of similar quality for this type of task (Zhou et al., 2025). The cluster size is set to 10 and level is set to 3 following the benchmark (Zhou et al., 2025). For HippoRAG2, we simply run their program and follow all the hyperparameters. The prompts and procedure of IRCoT are all from the code of Zhang et al. (2024b). One of the advantages of T²RAG is it free of hyperparemeter tunning compared to Raptor, which has clustering parameters or HippoRAG2, which has PageRank parameters and synonym link threshold.

B.2 More Efficiency Results

This section provides a detailed analysis of the time and token consumption of various Retrieval-Augmented Generation (RAG) methods, as illustrated in Figure 6 and Figure 7. The primary goal is to evaluate the computational efficiency of our proposed method, T²RAG, against other established baselines across different stages of the RAG pipeline. The y-axis represents the wall-clock time in seconds required for the indexing and retrieval stages. The retrieval stage time has been scaled by a factor of 1000 to ensure visibility on the chart alongside the much larger indexing times. The y-axis represents the total number of LLM tokens

consumed. This is a weighted sum calculated using the formula: **Token Consumption = (#input tokens) + 4** × (**#output tokens**). This weighting reflects the common pricing models of LLM APIs, where generation (output) is typically priced significantly higher (by a factor of 4) than processing (input). As with the time consumption chart, the retrieval stage consumption is scaled by 1000. The x-axis in both figures shows the performance of four methods (T^2RAG , HippoRAG2, RAPTOR, and IRCoT) across six distinct datasets.

B.2.1 Indexing Stage Analysis

The indexing stage is a one-time, offline process, but its cost can be substantial and even prohibitive for very large corpora. As seen in Figure 6 and Figure 7, datasets like PopQA, 2Wiki, and MuSiQue demand a considerable amount of time and token resources for indexing across all methods. The consumption patterns reveal that indexing costs are not simply proportional to the raw size of the document corpus. For instance, the token consumption for RAPTOR's summarization and the triplet extraction for T²RAG and HippoRAG2 do not scale linearly with the number of documents. This variability likely stems from the **informative**ness and density of the source documents. A document rich with distinct facts will lead to more triplets or more detailed summaries, increasing the computational load, whereas a sparse document will be processed more quickly. This makes the exact indexing cost unpredictable without analyzing the content itself.

B.2.2 Retrieval Stage Analysis

The retrieval stage is an online process that occurs for every query, making its efficiency critical for user-facing applications. Our analysis shows that **T**²**RAG** is as efficient as **HippoRAG2** during the retrieval stage. Both methods exhibit similar time and token consumption profiles across all datasets. This is expected, as their retrieval mechanisms are conceptually similar, operating over the graph structures built during indexing.

More importantly, T²RAG demonstrates a substantial efficiency gain over multi-round RAG methods like IRCoT. As seen in Figure 7, T²RAG consistently consumes fewer tokens during retrieval than IRCoT across all tested datasets. In some cases, such as the Medical and Story datasets, the reduction in token consumption is over 45%. This efficiency stems from T²RAG's ability to synthesize a direct answer from the retrieved triplets in a single round, avoiding the compounding token

Algorithm 1 T²RAG: Online Iterative Triplet Resolution (Main Process)

Chunk-Map \mathcal{M}_{chunk} **Output:** Final answer a

```
2: \mathcal{T}_{resolved}, \mathcal{T}_{searchable}, \mathcal{T}_{fuzzy} \leftarrow LLM_{Decompose}(q)
                                                                                    ▶ Step 2: Multi-Round Triplet Resolving Loop
 4: for l=1 \rightarrow K do
           if |\mathcal{T}_{\text{searchable}} \cup \mathcal{T}_{\text{fuzzy}}| = 0 then
 5:
                break
 6:
           end if
 7:
                                                                     ⊳ Step 2.1: Call the Adaptive Retrieval (see Algorithm 2)
 8:
           \mathcal{P}_{\text{retrieved}}, \mathcal{C}_{\text{retrieved}} \leftarrow \text{ADAPTIVERETRIEVE}(\mathcal{T}_{\text{searchable}}, \mathcal{I}, k, \mathcal{M}_{\text{chunk}})
 9:
                                                                                         ⊳ Step 2.2: LLM-based Triplets Resolution
10:
             \mathcal{T}_{resolved}^{(new)}, \mathcal{T}_{searchable}^{(new)} \leftarrow LLM_{Resolve}(\mathcal{T}_{searchable}, \mathcal{T}_{fuzzy}, \mathcal{P}_{retrieved}, \mathcal{C}_{retrieved})
11:
           12:
13:
15:

    Step 3: Final Answering

16: if |\mathcal{T}_{\text{searchable}} \cup \mathcal{T}_{\text{fuzzy}}| = 0 then
           \mathcal{T}_{\text{context}} \leftarrow \mathcal{T}_{\text{resolved}}
17:
18: else
           \mathcal{T}_{context} \leftarrow \mathcal{T}_{resolved} \cup \mathcal{T}_{searchable}
19:
20: end if
```

Input: Query q, Triplet DB Index \mathcal{I} , LLM, Max Iterations K, Target unique chunks k, Triplet-to-

Table 3: Dataset Statistics

Dataset	PopQA	2Wiki	Musique	HotpotQA	Story	Medical
# questions	1000	1000	1000	1000	794	564
# chunks	33,595	6119	11,656	9811	1266	268
# tokens	2,768,270	454,715	964,203	914,956	$915,\!484$	189,271
# extracted triplets	$398,\!924$	$65,\!028$	$127,\!640$	124,722	$22,\!812$	5256

costs associated with the iterative query refinement process in multi-round architectures.

21: $a \leftarrow \text{LLM}_{\text{Answer}}(q, \mathcal{T}_{\text{context}})$

22: **return** *a*

Remarkably, T²RAG often achieves lower, or at least comparable, token consumption than even single-round methods like RAPTOR. This is particularly evident in datasets like PopQA, Medical, and Story. We attribute this advantage to the nature of the final answer generation. T²RAG generates a concise answer directly from the structured triplets, which minimizes the number of output to-

kens. Since output tokens are heavily weighted in our consumption metric (multiplied by 4), this concise, triplet-formulated output provides a significant efficiency advantage, leading to an overall reduction in computational cost.

B.3 More Iteration Results

This analysis examines the average number of retrieval iterations required by T^2RAG and IRCoT to answer a query on the 2Wiki dataset, varying the number of retrieved chunks (top-k) per iteration.

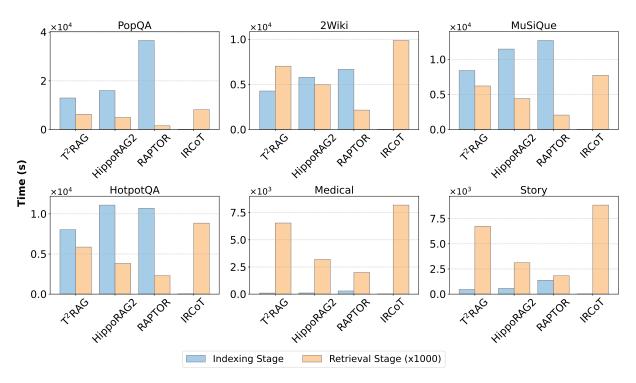


Figure 6: Time consumption at indexing and retrieval stages across all datasets.

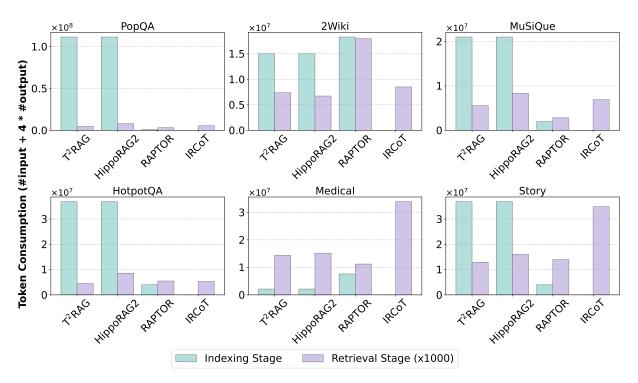


Figure 7: Token consumption at indexing and retrieval stages across all datasets.

Algorithm 2 Adaptive Triplet Retrieval

```
Require: Searchable triplets \mathcal{T}_{\text{searchable}}, Index \mathcal{I}, Target chunks k, Map \mathcal{M}_{\text{chunk}} Ensure: Retrieved propositions \mathcal{P}_{\text{retrieved}}, Retrieved chunks \mathcal{C}_{\text{retrieved}}
```

```
1: function ADAPTIVERETRIEVE(\mathcal{T}_{\text{searchable}}, \mathcal{I}, k, \mathcal{M}_{\text{chunk}})
             P_{\text{candidates}} \leftarrow \emptyset
 2:
             for t \in \mathcal{T}_{\text{searchable}} do
 3:
                   query\_prop \leftarrow Concatenate(t)
 4:
                   query_vec \leftarrow E(query_prop)
 5:
                   P_{\text{candidates}} \leftarrow P_{\text{candidates}} \cup \text{Search}(\mathcal{I}, \text{query\_vec}, N)
 6:
 7:
             Sort P_{\text{candidates}} globally by similarity score
 8:
 9:
             \mathcal{P}_{\text{retrieved}} \leftarrow \emptyset;
                                       unique_chunk_ids \leftarrow \emptyset
             for p \in \text{sorted } P_{\text{candidates}} \text{ do}
10:
                   if |unique\_chunk\_ids| \ge k_{chunks} then
11:
                         break
12:
                   end if
13:
14:
                   \mathcal{P}_{\text{retrieved}} \leftarrow \mathcal{P}_{\text{retrieved}} \cup \{p\}
                   chunk_id \leftarrow \mathcal{M}_{\text{chunk}}[p]
15:
                   unique_chunk_ids \leftarrow unique_chunk_ids \cup {chunk_id}
16:
17:
18:
            C_{\text{retrieved}} \leftarrow \text{GetChunksFromIDs}(\text{unique\_chunk\_ids})
19:
             return \mathcal{P}_{\text{retrieved}}, \mathcal{C}_{\text{retrieved}}
20: end function
```

Table 4: Average Number of Retrieval Iterations vs. top-k on the 2Wiki Dataset.

topk	T ² RAG	IRCoT
2	1.54	1.85
3	1.56	1.83
4	1.73	1.70
5	1.70	1.46
6	1.56	1.40

A key observation from the data is that T^2RAG consistently saves on the number of retrieval iterations compared to IRCoT, particularly when retrieving fewer documents per step (k=2 or 3). For instance, with k=2, T^2RAG requires an average of only 1.54 iterations, whereas IRCoT needs 1.85 iterations—a reduction of approximately 17%. This suggests that T^2RAG 's method of decomposing a query into structured triplets allows for a more direct and efficient path to resolving the query, requiring fewer rounds of retrieval to gather the necessary context.

The results challenge the simple assumption that retrieving fewer chunks per iteration (a smaller k) would necessarily lead to a higher number of total iterations. For T²RAG, the number of iterations

remains relatively stable and low, fluctuating between 1.54 and 1.73 without a clear trend. For IRCoT, the relationship is even more complex; as k increases from 4 to 6, the number of iterations surprisingly *decreases* significantly. This indicates that the effectiveness of the retrieved chunks is more important than the sheer quantity. T²RAG's focused retrieval, guided by placeholders in triplets, appears to acquire high-quality context more reliably, making it less dependent on the k value and more efficient overall.

C Related Work

We group prior efforts into *single-round*, *multi-round*, *graph-enhanced* RAG and *summarization-based* RAG, each adding more interaction or structured reasoning and paving the way for the fine-grained design of T^2RAG .

Single-round RAG. Classical sparse retrievers such as TF-IDF and BM25 paired with extractive readers perform strongly for open-domain QA (Yang et al., 2019; Nie et al., 2019; Wang et al., 2023a). Dense retrievers such as DPR (Karpukhin et al., 2020) later replaced sparse vectors with learned embeddings, retrieving a fixed top-k set in one pass. *However, answering multi-hop questions*

often demands the intermediate results to further retrieval, motivating the multi-round techniques that follow.

Multi-round RAG. Due to the missing bridges problem we mentioned in Section 1 more and more works follow a multi-round, training-free paradigm, which enables the LLMs infer the intermediate information thus better retrieve the final answer. Some works focus on the query side. Khot et al. (2023) decompose multi-hop questions into single-hop sub-queries that are solved sequentially. Yao et al. (2023) propose ReAct, interleaving chain-of-thought (CoT) (Wei et al., 2022) steps with search actions issued by the LLM. Similarly, Query2Doc (Wang et al., 2023b) expanding queries into concise triplets to cut token usage while preserving recall. Another line of works relies on the generated intermediate results for next iteration. Beam Retrieval (Zhang et al., 2024a) jointly training an encoder and classifiers to keep multiple passage hypotheses across hops. FLARE (Jiang et al., 2023) forecasts upcoming sentences to decide when fresh retrieval is needed during longform generation. IRCoT (Trivedi et al., 2023) and ITER-RETGEN (Shao et al., 2023), alternately expanding a CoT and fetching new evidence to answer multi-step questions. Adaptive QA (Xie et al., 2023) create an adaptive framework that picks the simplest effective retrieval strategy according to query complexity. Despite these advances, few efforts explicitly aim to reduce token costs or number of llm calls during multi-round RAG. Previous methods expand query or generates CoT with long sentences in each round. In contrast, our work minimizes token consumption by formulating query expansions as triplets and simplifying reasoning steps as triplets resolving.

Graph RAG. One major line of research addresses complex QA by structuring knowledge into graphs. Originating in Knowledge Graph QA (KGQA), early methods focused on decomposing queries or performing multi-round, LLM-evaluated traversals from seed nodes (Luo et al., 2024; Sun et al., 2024; Cheng et al., 2024; Mavromatis and Karypis, 2022). The application of this paradigm to general ODQA was popularized by systems that construct a knowledge graph entirely with LLMs and use community detection for retrieval (Edge et al., 2024). Subsequent work has aimed to make this process more efficient. For instance, LightRAG (Guo et al., 2024) introduces a dual-level retrieval system combining graph structures with vector search to improve knowledge discovery. Targeting resource-constrained scenarios, Mini-RAG (Fan et al., 2025) builds a heterogeneous graph of text chunks and named entities, enabling lightweight retrieval suitable for Small Language Models. To tackle the common challenge of entity merging, HippoRAG (Gutiérrez et al., 2025a) and HippoRAG2 (Gutiérrez et al., 2025b) create synonym links between similary entity nodes and employs a PageRank (Haveliwala, 1999) algorithm for final node selection. Despite these advances, a central challenge for Graph RAG remains the costly and error-prone nature of graph construction from unstructured text.

Summarization-based RAG. A distinct but related approach focuses on building hierarchical summarization trees rather than explicit graphs. These methods aim to capture information at varying levels of abstraction. For example, Raptor (Sarthi et al., 2024) constructs a summary tree by recursively clustering document chunks and summarizing the content within each cluster to create new, more abstract retrieval units (Wu et al., 2023). Aiming to capture more detailed contextual information, SireRAG (Zhang et al., 2024b) creates a "relatedness tree" by summarizing fine-grained propositions that share the same entities. However, these summarization-based methods often incur high computational costs during the indexing phase and risk losing the fine-grained, factual details that are essential for precise factoid QA.

D Case Study

We offer a full log of T²RAG during our experiment running in Figure 8.

This case study showcases the effectiveness of resolving the complex comparative query in 2 retrieval iterations. The system successfully decomposed the query into 4 necessary triplets (two directors, two birth years) and retrieved context only by the searchable ones. By identifying both directors (Michael Curtiz, Edith Carlmar) and their birth years (1886, 1911) from the triplet DB or initial set of chunks, it bypassed the need for further retrieval rounds. This immediate and complete information acquisition demonstrates the power of T²RAG's query decomposition and high-quality triplet-based retrieval.

E Prompts

We provide all prompt templates we used at retrieval stage, namely structured query decomposition, triplet resolving and final answering. These are prompts used in Question: Which film has the director born earlier, God's Gift To Women or Aldri Annet Enn Brak?

Query Decomposition

Q: Think step by step about what information is needed to answer this question. Form triples in the format: subject | predicate | object. Use "?" as placeholder for unknown entities...

A:
Searchable Triplets: God's Gift To Women, is directed by, 'Director'A; Aldri Annet Enn Brak, is directed by, 'Director'B;
Fuzzy Triplets: 'Director'A, was born in, 'PoirthYear'A; 'Poirector'B, was born in, 'PoirthYear'B

Iteration 1

Q: Use the context passages and propositions to solve any '?' placeholders with as much detail as possible, grounding your answers in the passage content.

Retrieved Triplets: Aldri annet enn brak was directed by Edith Carlmar, God's Gift to Women directed by Michael Curtiz, God's Gift to Women was completed as musical film, Aldri annet enn brak is 1954 Norwegian comedy-drama film, God's Gift to Women starring Joan Blondell, Aldri annet enn brak has English title Nothing but trouble, God's Gift to Women is 1931 American pre-Code romantic musical comedy film ... (18 propositions in total)

Retrieved Chunks: Title: Aldri ballade ... Title: God's Gift to Women ... Title: Aldri annet enn brak ... Title: Edith Carlmar (Edith Mary Johanne Mathiesen) (15 November 1911 - 17 May 2003) Title: Stanley Kwan

A:

Newly Resolved triplets: God's Gift To Women, is directed by, Michael Curtiz; Aldri Annet Enn Brak, is directed by, Edith Carlmar; Edith Carlmar, was born in, 1911

Newly searchable chunks: Michael Curtiz, was born in, ?birthYearA;

Iteration 2

Q: Use the context passages and propositions to solve any "?" placeholders with as much detail as possible, grounding your answers in the passage content.

Retrieved Triplets: Michael Curtiz born as Mih Ily Kertsz, Michael Curtiz was Hungarian-born American film director, Michael Curtiz was born on December 24, 1886, Michael Curtiz made stars of Bette Davis, The Vagabond King directed by Michael Curtiz, Michael Curtiz...(32 propositions in total)

Retrieved Chunks: Title: Michael Curtiz Michael Curtiz Michael Curtiz Morn Man Kammar (1886-1905) Michael Curtiz...(32 propositions in total)

Retrieved Chunks: Title: Michael Curtiz Michael Curtiz Morn Man Kammar (1886-1905) Michael Curtiz...(1905); December 24, 1886 April 11, 1962) was a Hungarian-born American film director... Title: Bright Leaf... Title: Altid ballade... Title: The Vagabond King... Title: JdJds...

A:

Newly Resolved Triplets: Michael Curtiz, was born in, 1886

Newly Searchable Triplets: None. (all triplets resolved and the iteration is terminated)

Final Answering

Q: Based on the following triplets, please answer the following question.

Total Resolved Triplets: God's Gift To Women, is directed by, Michael Curtiz; Aldri Annet Enn Brak, is directed by, Edith Carlmar; Michael Curtiz, was born in, 1886; Edith Carlmar, was born in, 15 November 1911.

A: God's Gift To Women

Figure 8: An example of T^2RAG QA. To answer the question, we need intermediate facts about Michael Curtiz (marked by yellow and Edith Carlmar (marked by red), which are not reflected in the question.

LLM_{Decompose}, LLM_{Resolve}, LLM_{Answer}, respectively. $\{\cdot\}$ represents the content needed to be replaced by the original question, intermediate generated triplets, or retrieved propositions and chunks.

Structured Query Decomposition

You are tasked with reasoning about a question and extracting the necessary knowledge triples to answer it.

Instructions:

- 1. Think step by step about what information is needed to answer this question
- 2. Form triples in the format: subject | predicate | object
- 3. Use "?" as placeholder for unknown entities
- 4. For comparative questions involving multiple entities, use distinct placeholders like ?entityA, ?directorA, ?directorB
- 5. Extract multiple triples if the question requires complex reasoning

Examples:

- Question: "What is the capital of France?" Reasoning: To answer this, I need to know what France's capital is. Triple: France | has capital | ?
- Question: "Who directed the movie that won Best Picture in 2020?" Reasoning: To answer this, I need to know which movie won Best Picture in 2020, and who directed that movie. Triples: ? | won Best Picture | 2020 ? | is directed by | ?
- Question: "Which film whose director was born first, MovieA or MovieB?" Reasoning: To answer this, I need to know the director of each movie, and the birth year of each director to compare them. Triples: MovieA | is directed by | ?directorA MovieB | is directed by | ?directorB ?directorA | was born in | ? ?directorB | was born in | ?

Now analyze this question:

Question: {query}

Provide your response in this format:

Reasoning: [Your step-by-step reasoning about what information is needed] **Triples**: [List each triple on a new line in format: subject | predicate | object]

Triplets Resolving

Example: Context Propositions: {context propositions}

Fully Resolved Clue 1: Subject: Lothair II Predicate: has mother Object: Ermengarde of Tours

Newly Searchable Clue 1: Subject: Ermengarde of Tours Predicate: died on Object: ?

Now apply the same process to the following clues: Use the context passages and propositions to resolve any '?' placeholders with as much detail as possible, grounding your answers in the passage content. Instructions:

- 1. For searchable clues (one '?'), replace '?' with the correct entity to fully resolve it, including any relevant attributes.
- 2. For fuzzy clues (multiple '?'), generate a Newly Searchable Clue by replacing one of the placeholders with the correct entity, including any relevant context.

Original Query: {query}

Searchable Clues: {searchable clues text}

Fuzzy Clues: {fuzzy clues text} Context Passages: {context passages}

Context Propositions: {context propositions}
Previous Resolved Clues: {resolved clues context}

Return two lists in this format:

Fully Resolved Clue 1: Subject: ... Predicate: ... Object: ... Fully Resolved Clue 2: Subject: ... Predicate: ... Object: ... Newly Searchable Clue 1: Subject: ... Predicate: ... Object: ... Newly Searchable Clue 2: Subject: ... Predicate: ... Object: ...

(Continue numbering accordingly)

Final Answering

Based on the reasoning clues, please answer the following question.

Question: {query}

Key Reasoning Clues: {total resolved clues + remaining searchable clues}

Instructions:

- 1. Analyze the question step by step
- 2. Use the reasoning clues to understand what information is needed
- 3. Provide ONLY a concise answer

Answer format requirements:

- For WH questions (who/what/where/when): Provide the exact entity, date, full name, or full place name only
- For yes/no questions: Answer only "yes" or "no"
- No explanations, reasoning, or additional text
- One entity or fact only

Answer: