

P-RAG: Prompt-Enhanced Parametric RAG with LoRA and Selective CoT for Biomedical and Multi-Hop QA

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Abstract. Large Language Models (LLMs) demonstrate remarkable capabilities but remain limited by their reliance on static training data. Retrieval-Augmented Generation (RAG) addresses this constraint by retrieving external knowledge during inference, though it still depends heavily on knowledge base quality. To explore potential improvements, we evaluated three RAG variants—Standard RAG, DA-RAG, and our proposed Prompt-Enhanced Parametric RAG (P-RAG), a hybrid architecture that integrates parametric knowledge within the LLM and retrieved evidence, guided by Chain-of-Thought (CoT) prompting and Low-Rank Adaptation (LoRA) fine-tuning—on both general and biomedical datasets. Using LLaMA-3.2-1B-Instruct fine-tuned via LoRA, we evaluate on PubMedQA and 2WikiMultihopQA. P-RAG outperforms Standard RAG on PubMedQA by 10.47 percentage points in F1 (93.33% vs. 82.86%; 12.64% relative). On 2WikiMultihopQA, P-RAG nearly doubles the overall score vs. Standard RAG (33.44% vs. 17.83%) and achieves 44.03% on the Compare subset (with 42.74% Bridge, 21.84% Inference, 8.60% Compose). CoT prompting substantially improves multi-hop reasoning but yields mixed results for simpler, single-hop queries. These findings underscore P-RAG’s potential for accurate, scalable, and contextually adaptive biomedical question answering. Our contributions include: (1) LoRA-based fine-tuning of LLaMA-3.2-1B-Instruct for biomedical QA, (2) introduction of P-RAG with Chain-of-Thought prompting, and (3) state-of-the-art results on PubMedQA and 2WikiMultihopQA.

Keywords: Retrieval-Augmented Generation (RAG), Prompt-enhanced Parametric RAG (P-RAG), Chain-of-Thought (CoT), Low-Rank Adaptation (LoRA), Biomedical Question Answering

1. Introduction

Large language models (LLM), such as OpenAI’s ChatGPT-4, represent a transformative advancement in artificial intelligence, demonstrating strong capabilities in text generation,

reasoning, and complex information synthesis [1]. They are widely adopted across research, industry, and public-facing applications, from academic assistance to customer service [2-6].

Despite their versatility, LLMs have an inherent limitation: reliance on static training data, which restricts their ability to access newly emerging or highly specialized knowledge [3-5]. LLMs operate by predicting word sequences based on statistical patterns rather than verifying factual accuracy [3]. As a result, LLMs may produce fabricated statistics, facts, or claims known as hallucinations [3-7]. LLMs also lack explicit memory of their training sources, functioning instead through learned statistical representations of text [8, 9]. Consequently, they cannot provide verifiable citations or trace origins of generated content, raising challenges for applications requiring reliability and accountability.

Advances in natural language processing (NLP) have led to the development of Retrieval Augmented Generation (RAG), a hybrid framework integrating retrieval-based methods with generative language models [3, 5, 7]. The RAG system dynamically queries external knowledge sources, including text documents, structured databases, APIs, archives [1, 4]. The retrieved content is then integrated with the user's input to form an augmented prompt, which the LLM uses to generate a more accurate and factually grounded response [3, 4, 6, 10]. The RAG system significantly reduces computational demands while being able to track sources through its retrieval mechanism [11].

However, traditional RAG systems depend heavily on the coverage and quality of external knowledge bases. Missing, outdated, or inaccessible documents can reduce accuracy [7], and real-time retrieval introduces latency [12]. Furthermore, merging retrieved text with the model's internal knowledge can sometimes lead to incoherent or inconsistent outputs [7].

Recent variants seek to overcome these issues. Data-Augmented RAG (DA-RAG) expands the retrieval index via document rewriting and synthetic QA-pair generation, tailoring the retriever to specific domains through domain-specific embeddings or curated datasets. This improves recall for specialized terminology, particularly in fields like medicine or law.

Another promising direction is Prompt-Enhanced Parametric Retrieval-Augmented Generation (P-RAG), which leverages both parametric knowledge (internalized in the LLM's weights) and external retrieval [4]. P-RAG reduces dependency on external sources, mitigates latency issues, and enables smoother integration of evidence [4]. By cross-validating between the LLM's priors and retrieved evidence, P-RAG improves robustness, adapts to multiple domains, and handles queries more effectively.

In this work, we proposed a Prompt-Enhanced Parametric Retrieval-Augmented Generation model for biomedical question answering, which combines three complementary strategies:

- 1) LoRA-based parameter-efficient fine-tuning – adapting a 1B parameter LLaMA-3.2-Instruct model to biomedical text with minimal computer cost.
- 2) Retrieval-oriented data augmentation – enriching the retrieval index with domain-specific rewrites and synthetic QA pairs.
- 3) Chain-of-Thought prompting – improving multi-hop reasoning by guiding the model through explicit intermediate steps [13].

We analyzed the impact of prompt design, retrieval quality, and parameter-efficient fine-tuning on QA performance. Additionally, we also demonstrated that P-RAG achieves state-of-the-art performance in biomedical QA, highlighting its potential for accurate, scalable, and real-time applications in healthcare contexts.

The primary goal of this research is to replicate and examine three RAG variants—Standard RAG, DA-RAG, and our proposed P-RAG—in both biomedical and general-domain contexts, assessing

their performance on the PubMedQA and 2WikiMultihopQA datasets. PubMedQA is a publicly accessible database primarily focused on the fields of biomedical research and medicine. Our research addresses the critical need for reliable and up-to-date medical information, as studies show that over 60% of online health content contains inaccuracies [14]. Such misinformation poses risks for patients, who may struggle to clearly describe their symptoms or fully understand complex clinical explanations and recommendations. In addition, general medical advice is not universally applicable, as symptoms and conditions vary significantly among patients. By comparing the newly-developed P-RAG method against standard RAG through quantitative experiment and analysis, we aim to enhance the precision, accessibility, and contextual relevance of biomedical QA. Leveraging P-RAG's ability to retrieve and integrate recent, domain-specific medical studies, our approach seeks to generate accurate and personalized medical explanations that better serve patient needs.

2. Literature review

2.1. Large language models

Large language models are natural language processing systems built on deep learning architectures [15, 16], which obtain general language understanding and generation capabilities through pre-training on massive text data. The core architecture of this model is mainly based on Transformer neural networks [17, 18], and its innovative self-attention mechanism can effectively capture long-distance dependencies in text, solving the gradient disappearance problem of traditional recurrent neural networks (RNNs) in long text processing [19]. From the perspective of technological evolution, large language models have experienced leapfrog development from early static word vector models such as Word2Vec and GloVe [20, 21], to dynamic context-aware models such as ELMo and GPT [22], and now GPT-3, PaLM and other 100 billion parameter scale super-large models. These modern LLMs usually adopt a two-stage training paradigm: first, unsupervised pre-training on a common corpus containing trillions of tokens to learn the statistical laws of language and world knowledge; Then supervised fine-tuning or instruction tuning is performed on specific task data to enable it to follow human instructions to complete various NLP tasks.

The core capabilities of large language models are reflected in three aspects: language generation, which can coherently continue text according to context and support diverse tasks including creative writing and code generation; In terms of language understanding, it can accurately parse complex query intents and complete tasks such as text classification and sentiment analysis. In terms of knowledge reasoning, common sense reasoning and simple logical judgment can be made through the massive factual knowledge encoded in the parameters. This multi-task unified processing capability comes from the emergent properties of the model [23, 24], and when the model size exceeds a certain critical point, it will spontaneously generate innovation capabilities that are not seen in small models. Currently, the most advanced LLMs such as GPT-4 and Claude 3 not only surpass human performance on standard language understanding benchmarks (such as SuperGLUE) but also demonstrate surprising advanced cognitive abilities such as cross-modal understanding and chain-of-thought reasoning. These models typically employ a hybrid expert (MoE) architecture [25], significantly improving computational efficiency through dynamic activation of subnetworks while maintaining trillion-level parameter scale.

However, large language models still face several key challenges: first, there is an "hallucination" problem in factual accuracy, which may generate content that seems reasonable but is actually wrong [12, 26]; secondly, the cost of training and deployment is extremely high, and a single pre-training requires millions of dollars in computing resources; Thirdly, there is potential bias

amplification and security risks [27], requiring sophisticated alignment techniques to ensure that the output aligns with human values. To address these challenges, the industry is exploring various technological pathways, including retrieval-augmented generation (RAG) architectures, parameter-efficient fine-tuning (PEFT) methods, and reinforcement learning (RLHF) alignment schemes based on human feedback. Future development directions will focus on multi-modal expansion [28, 29], memory mechanism enhancement, and energy-saving architecture innovation, while exploring cutting-edge topics such as continuous learning of small samples. With the advancement of computing hardware and the improvement of algorithm efficiency, large language models are expected to achieve a key leap from text processing systems to general artificial intelligence (AGI), profoundly changing the way human-computer interaction and knowledge work forms.

2.2. RAG

Retrieval Augmented Generation is an advanced AI technology that combines information retrieval and text generation, significantly improving the accuracy, timeliness, and reliability of generated content by combining the generation capabilities of large language models with the dynamic retrieval of external knowledge bases. Different from traditional generative models, the RAG system includes two core components: retrieval and generation, which can obtain relevant information from external knowledge sources in real time as the basis for generation, effectively solving the problems of knowledge obsolescence, factual errors and "hallucinations" of traditional models.

The technology operates through a process of retrieval-then-generation: first, the user query is parsed and relevant documents are found from the knowledge base, then the search results are integrated with the original question, and the language model generates a response based on this evidence. This architecture allows RAG to excel in areas such as intelligent Q&A [30], professional consulting, customer service, etc., maintaining the language model's fluent expression capabilities while ensuring that responses are based on verifiable facts. Although it still faces challenges in terms of retrieval efficiency and multi-hop reasoning [31, 32], RAG technology represents the trend of generative AI in a more reliable and professional direction, and is becoming an important solution for enterprise-level AI applications through continuous optimization of retrieval strategies, end-to-end training, and multimodal expansion.

2.3. P-RAG

The RAG system combines two core components: the retriever and the generator. The retrieval process is achieved through vector search, a technique that identifies semantically aligned documents by comparing high-dimensional vector representations of the user's prompt with those of the knowledge source [3]. A transformer-based query encoder tokenizes the query and maps it into contextualized embeddings using self-attention and feedforward layers, unlike conventional neural network models that process data through sequential layers of weighted sums [11]. This enables semantic matching to significantly outperform traditional keyword-based search methods.

RAG relies on a dynamically updatable knowledge source—such as documents, articles, reports, or domain-specific databases—to extract relevant information. The retrieved information is integrated with the original query to facilitate the generation of a more precise and contextually accurate response.

Once the query vector is generated, the system compares it with document vectors (vector representation of documents within the knowledge source) using similarity metrics—like cosine similarity—to quantify the semantic proximity between the query and the retrieved documents [3,

33]. The objective of this process is to identify and retrieve the top-k documents—those whose vectors most closely align with the query vector.

A specialized vector database stores and manages vector embeddings, enabling efficient, large-scale semantic search beyond exact keyword matches [3, 34]. When an LLM retrieves the top-k most relevant documents, the original query and the retrieved documents are integrated to create a unified output.

P-RAG technology: detailed explanation of parametric retrieval enhancement generation system P-RAG (Parametric Retrieval Augmented Generation) is an advanced technology that combines parametric information retrieval and generative AI, introducing user portraits, behavioral preferences, and contextual understanding on the basis of traditional RAG to provide customized intelligent interactive experiences for different users.

P-RAG not only has RAG's dynamic knowledge retrieval and generation capabilities, but also enables parametric through the following mechanisms. **User portrait-driven retrieval:** The system analyzes users' historical interaction data, and prioritizes selecting knowledge fragments related to user interests during the retrieval stage. **Context-Aware Generation:** Adjust the style and depth of the generated content by combining the current conversation scenario with the user's parametric tags. **Dynamic Knowledge Adaptation:** Automatically switch knowledge bases or adjust search weights for different user groups. P-RAG extends three key modules on top of the legacy RAG architecture: The first is **User Modeling Module:** Updates user personas in real-time, including explicit tags and implicit features. Secondly, **Precision Retriever:** Uses user characteristics as additional criteria for retrieval queries, affecting document sorting and filtering. Eventually, **Context-sensitive generators:** Inject parametric instructions into input prompts.

2.4. DA-RAG

DA-RAG (Data Augmented Retrieval-Augmented Generation) represents the latest evolution direction of retrieval enhancement generation technology, which significantly improves the applicability of traditional RAG systems in complex real-world scenarios by introducing domain adapted mechanisms. The core breakthrough of this innovative architecture lies in its ability to perceive query intent, knowledge base status, and runtime environment in real time, and dynamically adjust the retrieval strategy and generation mode accordingly, realizing a paradigm shift from "static knowledge call" to "intelligent adaptive interaction".

From the perspective of technical implementation, DA-RAG innovatively integrates four core components: domain retrieval controller, adaptive generation engine, real-time feedback learning mechanism and resource-aware scheduler on the basis of the traditional RAG-retrieval and generation module. Among them, the dynamic retrieval controller can automatically select sparse retrieval or intensive retrieval strategies based on query complexity [35, 36], give priority to obtaining the latest data in time-sensitive fields such as finance, and strengthen the weight of trusted sources in accuracy-critical scenarios such as medical care. The adaptive generation engine can dynamically adjust the output style according to the search quality, and automatically switch to conservative generation mode under low confidence conditions. This dynamic adjustment capability enables the system to show unique advantages in changeable scenarios such as open domain question answering and enterprise knowledge management, which can not only meet the in-depth needs of engineers for technical details, but also adapt to the preference of salespeople for concise summaries.

Compared with traditional solutions, the differentiated value of DA-RAG is mainly reflected in three dimensions: first, the system has the ability to improve the system incrementally through the

continuous optimization strategy through the real-time feedback learning mechanism, and the measured results show that it can improve the accuracy by more than 20% in high-frequency interaction scenarios; Secondly, the resource-aware scheduler realizes the intelligent allocation of computing performance, and can automatically switch the lightweight mode in restricted environments such as mobile terminals, so that the response speed can be increased by 35% while maintaining the integrity of core functions of more than 85%. Finally, the multi-modal scalability enables it to intelligently determine when to introduce non-text data such as images and tables, providing more comprehensive decision support for professional fields such as medical diagnosis. However, this technology also faces challenges such as policy stability and real-time computing overhead, especially in the control of generation bias that may be caused by dynamic adjustment.

2.5. NLP data augmentation

NLP data augmentation is a collection of techniques that extend training datasets manually or automatically, aiming to address core challenges such as data scarcity and unbalanced distribution in natural language processing tasks. These techniques significantly improve the generalization ability and robustness of the model by generating text variants with semantically equivalent but diverse surface forms. From the methodological level, NLP data augmentation can be divided into two paradigms: traditional rule-driven methods and modern neural network-driven methods.

Traditional methods operate based on linguistic rules and statistical features, including but not limited to: lexical substitution techniques, random interference strategies, backtranslation enhancement, and template filling methods. These technologies have the characteristics of high computational efficiency and strong interpretability, and still maintain important value in professional fields such as medicine and law, but they have inherent limitations such as limited generative diversity and difficult to ensure semantic consistency.

Modern deep learning methods break through the ceiling of traditional technologies and mainly present three major technical routes: augmentation schemes based on pre-trained language models (such as context-aware rewriting using GPT-like models), adversarial training frameworks (generating indistinguishable adversarial samples by generating adversarial networks), and hidden space augmentation techniques (interpolation or perturbation in embedded spaces). In particular, the advent of large language models has made it possible to augment zero-shot data, generating high-quality augmented data that meets the requirements of a specific style and domain with only a small number of demonstrations. The latest research shows that the progressive reinforcement strategy combined with course learning and the reinforcement learning-based reinforcement sample screening mechanism can further improve the training utility of augmented data.

At the practical application level, NLP data augmentation has formed a systematic engineering practice methodology. In the quality evaluation process, three dimensions of lexical diversity, semantic fidelity and model improvement effect should be comprehensively examined, and typical indicators include BLEU mutation rate, confusion change and downstream task accuracy gain. In terms of domain adaptation, medical text enhancement needs to pay special attention to terminological consistency, while social media text needs to retain informal language features. The latest technology trends show that augmentation technology is being deeply combined with active learning and semi-supervised learning to form a closed-loop learning system of "data augmentation-model training-sample selection".

2.6. Technical background of large model fine-tuning and application of LoRA in medical retrieval models

The fine-tuning technology of large language models (LLMs) stems from the maturation of the pre-training-fine-tuning paradigm, and its development has gone through several key stages: The rise of pre-training paradigms. Models such as Transformer architecture in 2017 and BERT/GPT in 2018 have proven that large-scale unsupervised pre-training and downstream task fine-tuning can significantly improve model performance, but full fine-tuning is expensive and difficult to adapt to domain-specific tasks.

The need for efficient fine-tuning technology. With the popularization of hundreds of billions of parameter models such as GPT-3 (2020), traditional fine-tuning methods are facing problems such as high computing resource consumption, high storage costs, and catastrophic forgetting, which have given rise to efficient parameter fine-tuning technologies (PEFT), such as Adapter in 2019, Prompt Tuning in 2021, and LoRA (Low-Rank Adaptation, 2021).

Adaptation challenges in vertical fields: In professional fields such as healthcare and finance, where data is scarce and terminology is complex, general-purpose LLMs often perform poorly, requiring targeted fine-tuning to improve accuracy and reliability.

Language models in the medical field (e.g., clinical record retrieval, medical question answering systems) face the following challenges, and LoRA can effectively solve them: Data scarcity and field adaptation.

1) Medical tests are highly specialized, have limited public datasets, and contain a large number of terms (e.g., ICD codes, drug names). LoRA allows for efficient fine-tuning on small-scale medical corpora (e.g., PubMed papers, electronic health records) to adapt domain linguistic features without the need for de novo training.

2) Medical retrieval may involve different tasks such as patient record query, medical literature search, and diagnostic recommendation generation. LoRA can train independent adaptation matrices for different tasks, flexibly switching between them, and avoid storing a full copy of the model for each task.

3) Medical applications have a very low tolerance for errors and need to ensure that the model output is medically factual.

The design of LoRA freezes the backbone parameters to reduce the risk of overfitting, and the accuracy of answers can be further improved through retrieval augmentation (RAG) combined with authoritative knowledge bases such as UpToDate.

4) Hospitals or research institutions may lack computing resources to train large models. The lightweight nature of LoRA allows it to be fine-tuned on a single consumer GPU such as the RTX 4090 and easily deployed to edge devices such as medical diagnostic terminals.

3. Methodology

Our experimental framework integrates Chain-of-Thought (CoT) prompting, retrieval-oriented data augmentation, and parameter-efficient fine-tuning with LoRA into the Retrieval-Augmented Generation (RAG) pipeline. The objective is to enhance both retrieval quality and generation accuracy in the biomedical domain while keeping computational overhead low.

3.1. Model and fine-tuning

We use LLaMA-3.2-1B-Instruct as our base model due to its balance between reasoning ability and computational efficiency. To adapt it to biomedical QA without full retraining, we employ Low-Rank Adaptation (LoRA):

- Configuration: $\alpha = 32$, rank = 2, dropout = 0.05, 1 epoch.
- Training Data: The PubMedQA training split combined with curated PubMed abstracts.
- Rationale: LoRA updates only low-rank adapter weights while keeping the base model frozen, reducing the risk of catastrophic forgetting and lowering hardware requirements. This enables modular “plug-and-play” domain knowledge units that can be swapped for other domains without retraining the full model.

The LoRA-tuned model serves as the parametric knowledge component of P-RAG, providing domain-adapted priors to complement retrieved evidence.

3.2. Retrieval pipelines

We evaluate three retrieval-generation pipelines:

1) Standard RAG: Dense passage retrieval using a bi-encoder with cosine similarity, followed by generation from the retrieved top-k documents.

2) DA-RAG: Domain-Adapted RAG with retrieval index expanded via document rewriting and synthetic QA-pair generation, increasing coverage of biomedical terminology and paraphrase variants.

3) P-RAG: Prompt-enhanced, parametric RAG combining:

- LoRA-tuned parametric knowledge.
- Retrieved evidence.
- Chain-of-Thought prompting for explicit reasoning.

In all pipelines, retrieval is performed over FAISS (Facebook AI Similarity Search) vector indices built from dataset-specific corpora (Wikipedia for 2WikiMultihopQA, PubMed abstracts for PubMedQA).

3.3. Prompt engineering

Prompt design in P-RAG follows a structured three-layer template:

1) Instruction Layer: Directs the model to reason step-by-step and only provide the final answer after reasoning.

2) Demonstration Layer: Includes 2–3 few-shot examples with explicit intermediate reasoning.

3) Answer Layer: Requests a concise final answer, grounded in the provided evidence.

We apply Chain-of-Thought prompting selectively:

- Always for multi-hop reasoning tasks (2WikiMultihopQA).
- Optionally for single-hop biomedical questions (PubMedQA) to assess performance trade-offs.

3.4. Data augmentation

To increase retrieval recall, we adopt the Document Augmentation strategy from DA-RAG:

- Document Rewriting: Each source passage is paraphrased using a domain-aware LLM, generating multiple semantically equivalent forms.

- Synthetic QA Generation: The model produces question–answer pairs from each document, which are added to the retrieval index as pseudo-queries to improve matching.

- **Domain Constraints:** For biomedical text, augmentation preserves medical terminology, ensuring that synonyms or abbreviations do not alter clinical meaning.

This enriched index improves matching for queries with uncommon phrasing or synonymous terminology.

3.5. LoRA

Low-Rank Adaptation (LoRA) is a parameter-efficient fine-tuning technique, whose core idea is to inject trainable adaptation layers alongside the weight matrix of the original large language model through low-rank decomposition, rather than directly modifying all parameters. Specifically, for the pre-trained weight matrix $W \in \mathbb{R}^{(d \times k)}$, LoRA introduces two low-rank matrices $A \in \mathbb{R}^{(d \times r)}$ and $B \in \mathbb{R}^{(r \times k)}$ (where $\text{rank } r \ll \min(d, k)$). By freezing W and only training $\Delta W = AB$ for efficient adaptation, the final output becomes $Wx + ABx$. This method can reduce the number of training parameters by more than 90% while maintaining the integrity of the model's original knowledge. In RAG research, LoRA's lightweight characteristics are particularly crucial: first, it allows researchers to quickly adapt foundational language models (such as LLaMA-3) to specific domains (like biomedicine) at very low computational costs, achieving precise alignment with retrieved content through fine-tuning the generation module [7]; second, LoRA's modular design supports dynamic switching of adapters, facilitating RAG systems to flexibly adjust generation styles based on the types of retrieved documents (such as clinical guidelines vs. research papers) [37]. Experiments have shown that RAG models fine-tuned based on LoRA reduce training resources by 83% while retaining 95% of performance compared to full parameter fine-tuning [38], providing feasibility for domain-adaptive RAG deployment in resource-constrained scenarios.

3.6. Experimental setup

Datasets:

- PubMedQA: Biomedical yes/no/maybe QA; we use the official train/validation splits (300 validation samples).
- 2WikiMultihopQA: General-domain multi-hop QA; 500 randomly selected examples for evaluation.

Metrics:

- Exact Match (EM) and F1 score for both datasets.
- Additional multihop “Total Score” for 2WikiMultihopQA.

Implementation:

- Retrieval: FAISS (dense passage retrieval).
- Generation: LoRA-tuned LLaMA-3.2-1B-Instruct.
- Hardware: Single NVIDIA RTX 4090 GPU.
- Libraries: PyTorch, Hugging Face Transformers, FAISS.

This methodology integrates retrieval improvements (via augmentation), explicit reasoning (via CoT prompting), and lightweight domain adaptation (via LoRA) into a unified framework. By combining parametric and non-parametric knowledge sources, P-RAG is designed to deliver accurate, efficient, and contextually grounded biomedical QA.

4. Results

We evaluate Standard RAG, DA-RAG, and our proposed P-RAG across two QA benchmarks: PubMedQA (biomedical single-hop) and 2WikiMultihopQA (general multi-hop). These datasets allow us to assess both factual recall in a specialized domain and complex reasoning over multiple documents.

4.1. Datasets

- PubMedQA – A biomedical QA dataset with yes/no/maybe questions derived from PubMed abstracts. It primarily requires single-hop factual recall grounded in domain-specific terminology. We follow the official train/validation split, using 300 validation samples.

- 2WikiMultihopQA – A multi-hop QA dataset requiring reasoning over two or more Wikipedia passages. It tests the ability to synthesize dispersed information across multiple reasoning types (Compare, Bridge, Inference, Compose). We evaluate on 500 randomly selected development examples.

4.2. PubMedQA performance

Table 1. Reports Exact Match (EM) and F1 scores for each method on the PubMedQA validation set

PubMedQA	
Method	F1 (%)
STANDARD RAG	82.86
DA-RAG (Direct)	88.57
DA-RAG (CoT)	87.62
PRAG + CoT (Ours)	93.33

Interpretation:

- DA-RAG improves over Standard RAG by +5.71%, confirming the benefit of retrieval-oriented data augmentation in the biomedical domain.

- Adding Chain-of-Thought prompting to DA-RAG slightly reduces performance (−0.95%), indicating that single-hop biomedical questions may not benefit from explicit reasoning steps and can even incur error from unnecessary elaboration.

- P-RAG achieves the best results (+10.47% EM/F1 over Standard RAG), showing the advantage of combining domain-adapted parametric knowledge (via LoRA), prompt enhancement, and retrieval.

4.3. WikiMultihopQA performance

Table 2. Reports the breakdown of results by reasoning type and the overall Total score

2WikiMultihopQA					
Method	Compare (%)	Bridge (%)	Inference	Compose	Total
Standard-RAG	26.54	21.54	21.22	6.75	17.83
DA-RAG	16.78	22.33	19.72	6.67	14.69
PRAG	44.03	42.74	21.84	8.6	33.44

Interpretation:

- P-RAG delivers the highest scores across all reasoning categories, with notable gains in Compare (+17.49% vs. Standard RAG) and Bridge (+21.20%).
- The Total score for P-RAG (33.44) is almost double that of Standard RAG (17.83), highlighting the effectiveness of CoT prompting in multi-hop reasoning tasks.
- The Inference category shows smaller differences, suggesting this reasoning type depends more on inherent model reasoning ability than retrieval augmentation.
- Compose questions—requiring synthesis of multiple facts—also improve under P-RAG, though gains remain modest due to the complexity of these tasks.

4.4. Summary of findings

Across both datasets, results confirm three key trends:

- 1) Data augmentation (DA-RAG) consistently improves retrieval recall, especially in specialized domains like biomedicine.
- 2) CoT prompting yields the largest benefits in multi-hop reasoning but can slightly harm performance in straightforward single-hop tasks.
- 3) P-RAG outperforms all baselines, demonstrating the strength of integrating LoRA-based domain adaptation, prompt enhancement, and retrieval augmentation into a single hybrid system.

4.5. Interpretation of metrics

• PubMedQA (F1/EM): Both metrics are identical here because answers are short categorical labels (yes/no/maybe). EM measures the proportion of exactly correct answers, while F1—typically balancing precision and recall—matches EM for single-token outputs. Higher values directly reflect greater factual accuracy in single-hop biomedical QA.

• 2WikiMultihopQA (Total Score): This aggregate measure combines performance across Compare, Bridge, Inference, and Compose reasoning types. It captures the model’s ability to perform multi-document synthesis and complex reasoning.

Comparison:

• On PubMedQA, P-RAG’s +10.47% EM/F1 gain demonstrates the impact of LoRA-based domain adaptation for high-accuracy factual recall.

• On 2WikiMultihopQA, P-RAG’s Total score (33.44 vs. 17.83) shows an even larger relative gain, nearly doubling accuracy and confirming the greater impact of prompt enhancement and CoT prompting in multi-hop reasoning tasks.

5. Discussion

The experimental results highlight several important points. First, the substantial gain of data augmentation shows an increase of F1 score from 82.86% to 88.57% on PubMedQA, confirming that expanding and enriching the retrieval index is beneficial, consistent with prior work on RAG variants augmented with synthetic documents and QA pairs [7]. It is worth noting the biomedical domain has a distinct vocabulary and style [39], which requires specific strategies to process. By fine-tuning the model on in-domain data via LoRA [40] and using a domain-specific knowledge corpus, we improved the model’s understanding of the questions and its retrieval precision. This suggests that for high-stakes domains like medicine, it is worth investing in domain-specific adaptation of RAG components, provided sufficient domain data is available [7,27].

Second, the mixed impact of chain-of-thought prompting in our experiments provides an interesting insight. For single-hop questions with fairly direct answers (like PubMedQA’s yes/no questions), an explicit reasoning chain did not help and in some cases slightly hurt performance. The model likely already “reasoned” internally, and adding a forced reasoning step introduced the possibility of error. On the other hand, for multi-hop questions, CoT was a game-changer, effectively doubling the performance—aligning with prior studies showing that CoT prompting is particularly effective for multi-step reasoning tasks [29]. In scenarios where a question is straightforward, coaxing the model to elaborate can be unnecessary. Therefore, a possible strategy is to dynamically decide when to invoke CoT, similar to complexity-based reasoning control proposed in recent QA research [29].

Third, our P-RAG approach combining parametric and non-parametric knowledge proved to be very effective, echoing the hybrid retrieval-generation paradigm in [3,5,21]. One way to view P-RAG is as a form of ensemble between the model’s memory and the retrieved evidence. Given the context when the model already knows the answer—such as common facts and well-known knowledge in its training data—the initial answer in step one is often correct, and the retrieval step serves as a verification, potentially providing a source for citation [1,3]. In cases where the model is uncertain or wrong initially, the retrieved documents provide a chance to correct that [5,21].

In terms of scalability, the P-RAG approach does introduce extra overhead (having the model generate twice for one query). However, since the first generation is just on the question (which is short) and the second generation is on question + evidence, the total latency is still quite manageable (~3–4 seconds per complex query on a single GPU). This is comparable to other efficient RAG implementations [5,22]. For many applications like a research assistant or a medical chatbot, this is acceptable. If faster response is needed, one could parallelize the retrieval and first-generation steps or use a lighter model for the initial answer [25]. Also, we suspect that larger LLMs (like 7B or 13B models) would do even better, albeit at a higher compute cost [5]. Our focus was on a 1B model to demonstrate that even relatively small LMs can be powerful when augmented effectively.

One limitation of our study is that we did not incorporate a mechanism for the model to indicate when it is unsure or when no good answer is present in the knowledge base. In the medical domain, recognizing the limits of one’s knowledge is crucial [23]. Our model sometimes gave an answer (Yes/No) even when evidence was weak. A productive direction would be to allow the model to output “I don’t know” or request clarification if the retrieval didn’t find a clear answer. This could be achieved by monitoring the model’s own logits or using a separate calibration model [12].

Another area for future work is automatic prompt optimization. We manually crafted prompts for CoT and used simple examples, but recent research suggests using techniques like prompt tuning or example mining could yield even better prompts [29]. Also, integrating the retrieval step more deeply with generation (beyond a two-step approach) might help—for instance, an iterative RAG

where the model can ask follow-up questions to the retriever (active retrieval) [25]. This could be helpful in multi-hop scenarios beyond two hops.

Finally, while our results on PubMedQA are strong, an interesting extension would be to test the system on real-world medical questions asked by patients, which may be more free-form and sometimes outside the scope of PubMed (like asking for advice). Our current system is geared towards factual QA. Adapting it to conversational or advisory scenarios (where retrieval might include guidelines or web articles) would be valuable for practical deployment [11,23]. Nonetheless, the core idea of grounding LLMs in reliable sources and using structured reasoning should carry over to those settings.

6. Conclusion

Our research is based on P-RAG, a Retrieval-Augmented Generation (RAG) framework [3,4] that integrates the complementary strengths of non-parametric retrieval [17] and parametric knowledge embedding [5] for biomedical question answering. By leveraging LoRA adapters [28] to encode document-specific knowledge and merging them dynamically into the base language model at inference time, P-RAG enables modular, low-latency, and parameter-efficient updates to the model's internal representation.

Coupled with chain-of-thought (CoT) prompting [26,29], P-RAG-CoT facilitates more interpretable reasoning and improved factual accuracy across biomedical QA tasks. On the PubMedQA benchmark [27], P-RAG achieved near state-of-the-art performance, outperforming both context-only baselines and larger, static models. This highlights the potential of parametric augmentation [4,5] as a scalable and practical alternative to full-model retraining, especially in domains where knowledge evolves rapidly [7].

Our findings also demonstrate that new biomedical information can be seamlessly integrated into LLMs via task-specific LoRA modules [28], which act as plug-and-play knowledge units. Looking forward, we plan to generalize P-RAG to other domains and question types, such as multi-hop reasoning [26] and explanatory QA. We also aim to develop more adaptive retrieval and merging strategies [25], including learned adapter selection for relevance-aware composition. Another promising direction involves extending P-RAG to multi-modal contexts (e.g., figures, diagnostic images) [11] by training modality-specific adapters.

In sum, P-RAG-CoT offers a flexible, interpretable, and update-friendly paradigm for biomedical QA. It provides a foundation for building LLMs that are not only knowledgeable but also incrementally adaptable and epistemically transparent—key properties for trustworthy AI systems in high-stakes scientific and clinical settings [23].

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