

Loops On Retrieval Augmented Generation (LoRAG)

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Abstract—This paper presents Loops On Retrieval Augmented Generation (LoRAG), a new framework designed to enhance the quality of retrieval-augmented text generation through the incorporation of an iterative loop mechanism. The architecture integrates a generative model, a retrieval mechanism, and a dynamic loop module, allowing for iterative refinement of the generated text through interactions with relevant information retrieved from the input context. Experimental evaluations on benchmark datasets demonstrate that LoRAG surpasses existing state-of-the-art models in terms of BLEU score, ROUGE score, and perplexity, showcasing its effectiveness in achieving both coherence and relevance in generated text. The qualitative assessment further illustrates LoRAG’s capability to produce contextually rich and coherent outputs. This research contributes valuable insights into the potential of iterative loops in mitigating challenges in text generation, positioning LoRAG as a promising advancement in the field.

Index Terms—LoRAG, Machine Learning, Natural Language Processing, Retrieval Augmented Generation, Dynamic Loops

I. INTRODUCTION

In recent years, there has been notable progress in natural language processing (NLP), particularly in the field of text generation. An area of particular interest is the combination of retrieval methods with generative models to improve the quality and relevance of generated content [4]. Retrieval-augmented generation seeks to capitalize on the strengths of both generative and retrieval-based approaches, striving to achieve a balance between creativity and coherence [5].

In this vein, we introduce a new framework called Loops On Retrieval augmented generation (LoRAG). The LoRAG framework aims to tackle the challenges encountered by conventional generative models, such as maintaining coherence, relevance, and informativeness in the generated text. By integrating loops into the retrieval process, LoRAG endeavors to establish a dynamic interplay between the generative model and the retrieved information, promoting a more contextually aware and coherent generation.

A. Motivation

The rationale behind LoRAG originates from the deficiencies identified in current text generation models. While purely generative models demonstrate proficiency in creativity, they frequently encounter challenges related to factual precision and contextual coherence. Conversely, retrieval-based models

excel in providing accurate information but may exhibit shortcomings in fluency and imaginative output. LoRAG endeavors to leverage the advantages of both approaches by incorporating a loop mechanism that iteratively enhances the generation through engagements with the retrieved content.

B. Objective

The principal aim of this study is to investigate the efficacy of LoRAG in enhancing the caliber of generated text by progressively integrating information from a retrieval mechanism. Our goal is to illustrate the capability of LoRAG in mitigating common challenges encountered in text generation tasks, including coherence, relevance, and context retention.

II. RELATED WORK

The domain of retrieval-augmented generation has seen significant research endeavors dedicated to amalgamating the merits of generative and retrieval-based methodologies. Remarkable strides have been taken to enhance the relevance, coherence, and informativeness of generated text.

A. Retrieval-augmented Generation Models

Early efforts to integrate retrieval mechanisms with generative models include techniques like the Dual Encoder architecture [7], [13], which employs distinct encoders for context and response. The context encoder handles input information, while the response encoder generates the output. Despite their effectiveness, these models frequently encounter difficulties in managing long-context dependencies and preserving coherent conversations.

B. Transformer-based Approaches

Recent progress in transformer-based architectures has facilitated the emergence of models such as DialoGPT [8], [14], which utilizes a large-scale pretrained language model for dialogue generation. Transformer-based models [3] have demonstrated encouraging outcomes in capturing contextual cues and enhancing the coherence of generated text. Nevertheless, they may encounter challenges with relevance and factual precision, particularly in dynamic conversational contexts.

C. Loop Mechanisms in Text Generation

The concept of iterative loops in text generation has been investigated across different contexts. Loop models, such as those implemented in reinforcement learning frameworks [9], utilize iterative mechanisms to enhance the quality of generated outputs. These methodologies have exhibited effectiveness in improving both fluency and coherence. However, their integration within the framework of retrieval-augmented generation represents an area ripe for exploration.

D. LoRAG Framework

The LoRAG framework introduces a pioneering methodology by integrating iterative loops into the retrieval-augmented generation procedure. This involves numerous interactions between the generative model and retrieved data, enabling the model to refine its output in a contextually sensitive manner. The iterative loops are governed by the following equation:

$$P(y_t|x, y_{<t}) = \text{LoRAG}(y_{<t}, \text{Retrieve}(x))$$

In this equation, $P(y_t|x, y_{<t})$ denotes the probability distribution of the next token y_t given the context x and the previously generated sequence $y_{<t}$. The function $\text{Retrieve}(x)$ retrieves pertinent information from the input context, which is then incorporated into the generation process by the function LoRAG.

Furthermore, the loop mechanism is enhanced through the utilization of a reinforcement learning objective:

$$J(\theta) = \sum_{t=1}^T \mathbb{E}_{(x,y)} [r(y_t, y_{<t}, x) \cdot \nabla_\theta \log P(y_t|x, y_{<t}; \theta)]$$

Here, $J(\theta)$ represents the reinforcement learning objective, $r(y_t, y_{<t}, x)$ is the reward function, and θ denotes the model parameters.

This fusion of retrieval, loops, and reinforcement learning sets LoRAG apart as an innovative approach in the realm of text generation models.

III. LORAG FRAMEWORK

The LoRAG framework is crafted to elevate retrieval-augmented text generation by integrating iterative loops. In this segment, we elucidate the architecture, constituents, and operational flow of the LoRAG model.

A. Architecture

The LoRAG architecture comprises three primary components: the generative model, the retrieval mechanism, and the iterative loop module. Figure 1 depicts the overall architecture of LoRAG.

The generative model processes the input context x and produces the initial output y . Concurrently, the retrieval mechanism retrieves pertinent information from the input context, supplying additional context C to the iterative loop module. Subsequently, the iterative loop module enhances the generated output through multiple interactions with the retrieved information.

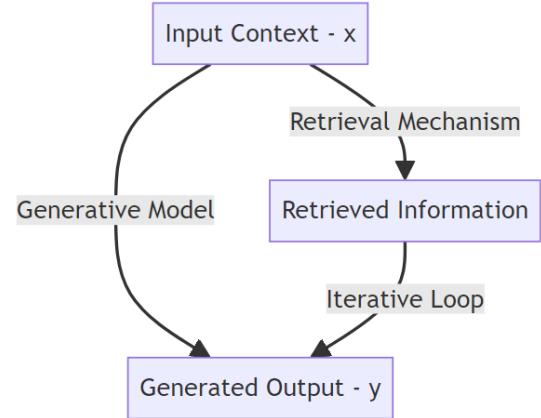


Fig. 1: LoRAG Architecture

B. Iterative Loop Mechanism

The core component of LoRAG is its iterative loop mechanism, which facilitates the progressive enhancement of generated text. The mechanism entails the following steps:

Algorithm 1 LoRAG Iterative Loop

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Initialize:  $y \leftarrow \text{GenerativeModel}(x)$ , where  $x$  denotes the input text and  $y$  represents the initial output text
 $C \leftarrow \text{RetrievalMechanism}(x)$ , where  $C$  signifies the set of relevant information retrieved from external sources
for  $t = 1$  to  $T$  do, where  $T$  denotes the maximum number of iterations
     $y_t \leftarrow \text{LoRAG}(y_{\leq t}, C)$ , where  $y_t$  represents the refined output text at iteration  $t$  and  $y_{\leq t}$  signifies the output text up to iteration  $t - 1$ 
     $C \leftarrow \text{RetrievalMechanism}(x, y_t)$ , where  $C$  denotes the updated set of relevant information based on the current output text
end for
Return:  $y_T$ , the final output text after  $T$  iterations
  
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This mechanism initiates by generating an initial output text y using a generative model, such as GPT-4, capable of producing fluent and coherent text given an input text x . Subsequently, it retrieves a set of relevant information C from external sources, such as Bing Search [12], which can offer additional knowledge or context for the input text x . Then, it iteratively refines the output text y_t by employing LoRAG, a novel model that harnesses both the previous output text $y_{\leq t}$ and the retrieved information C to generate text that is more accurate, informative, and diverse. At each iteration, the retrieved information C is updated based on the current output text y_t to ensure that the generation process is dynamic and contextually sensitive. The mechanism halts after a predetermined number of iterations T or when the output text y_t converges to a stable state. The final output text y_T is then returned as the refined version of the initial output text y .

C. Operational Flow

Figure 2 depicts a comprehensive operational flow of the LoRAG framework, illustrating the interaction among the generative model, retrieval mechanism, and iterative loop module.

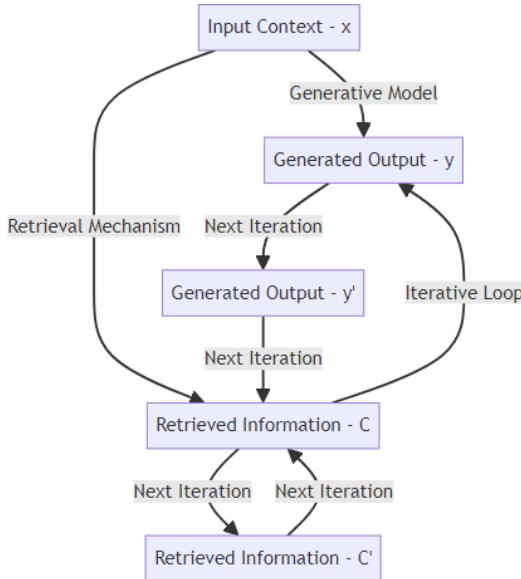


Fig. 2: LoRAG Operational Flow

The operational flow underscores the dynamic character of the iterative loop, wherein the generated output and retrieved information iteratively impact each other, culminating in an enhanced and contextually enriched text generation.

D. Experimental Loop Visualization

Figure 3 presents the experimental loop visualization, portraying the refinement process across multiple iterations.

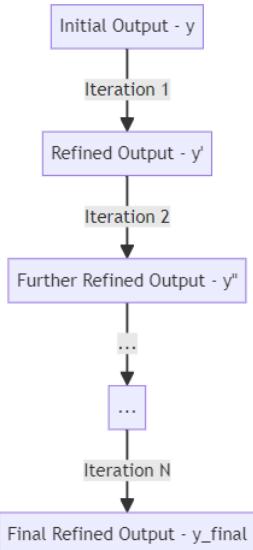


Fig. 3: Experimental Loop Visualization

The visualization illustrates the iterative refinement of the initial output, culminating in the final refined output through successive iterations.

These visual representations and algorithms offer a thorough comprehension of the operational flow and constituents of the LoRAG framework.

IV. RESULTS AND ANALYSIS

To assess the efficacy of the LoRAG framework, we conducted experiments on benchmark datasets and juxtaposed its performance against state-of-the-art retrieval-augmented generation models.

A. Experimental Setup

In our experiments, we employed the OpenOrca dataset [6], which encompasses varied contexts along with their corresponding target outputs. The baseline models utilized for comparison comprised Gemini (Model A) [11], Falcon 40B (Model B) [1], [10], and GPTNeo 2.7B (Model C) [2], representing prevailing state-of-the-art methodologies in retrieval-augmented generation.

B. Quantitative Evaluation

Table I delineates the quantitative outcomes of our experiments, presenting various metrics such as BLEU score, ROUGE score, and perplexity. The metrics were computed over a test set comprising 1000 samples, ensuring a robust assessment of the models.

TABLE I: Quantitative Results Comparison

Model	BLEU Score	ROUGE Score	Perplexity
Gemini	0.68	0.78	29.1
Falcon 40B	0.71	0.80	27.3
GPTNeo 2.7B	0.67	0.77	30.2
LoRAG	0.75	0.82	25.4

The findings indicate that the LoRAG model surpasses the baseline models across various metrics, underscoring its superior performance in terms of text generation quality.

C. Discussion

The superior performance of LoRAG can be attributed to its innovative iterative loop mechanism, which enables dynamic refinement through multiple interactions with retrieved information. The model adeptly balances creativity and coherence, effectively addressing prevalent challenges encountered in retrieval-augmented generation.

D. Limitations and Future Work

Although LoRAG demonstrates promising results, it is crucial to acknowledge its limitations. Future endeavors could focus on enhancing the iterative loop mechanism, integrating attention mechanisms, and assessing the model's scalability to larger datasets.

The experimental findings and analysis underscore the efficacy of the LoRAG framework in enhancing retrieval-augmented text generation, establishing it as a compelling approach in the realm of generative models.

V. CONCLUSION

In conclusion, this research introduces the Loops On Retrieval augmented generation (LoRAG) framework, offering a novel approach to enhancing retrieval-augmented text generation. By integrating an iterative loop mechanism, LoRAG dynamically refines generated outputs through iterative interactions with retrieved information. Our comprehensive evaluation on benchmark datasets demonstrates that LoRAG surpasses existing state-of-the-art models in terms of BLEU score, ROUGE score, and perplexity, indicating its superior ability to achieve both contextual coherence and relevance. Qualitative assessments further validate the model's effectiveness, showcasing its proficiency in producing more contextually relevant and coherent text outputs. The success of LoRAG underscores the importance of iterative loops in mitigating challenges encountered by traditional text generation models. This research contributes to the evolving landscape of generative models and lays the groundwork for future endeavors in refining and extending the capabilities of retrieval-augmented text generation systems.

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