
Retrieval is Not Enough: Enhancing RAG Reasoning through Test-Time Critique and Optimization

Jiaqi Wei^{1,2*} Hao Zhou^{3*} Xiang Zhang^{4*} Di Zhang⁵ Zijie Qiu⁵ Wei Wei⁶
Jinze Li^{2,5} Wanli Ouyang² Siqi Sun^{2,5†}
¹ Zhejiang University ² Shanghai Artificial Intelligence Laboratory
³ South China University of Technology ⁴ University of British Columbia
⁵ Fudan University ⁶ University of Hong Kong
jiaqi.wei@zju.edu.cn, siqisun@fudan.edu.cn

Abstract

Retrieval-augmented generation (RAG) has become a widely adopted paradigm for enabling knowledge-grounded large language models (LLMs). However, standard RAG pipelines often fail to ensure that model reasoning remains consistent with the evidence retrieved, leading to factual inconsistencies or unsupported conclusions. In this work, we reinterpret RAG as *Retrieval-Augmented Reasoning* and identify a central but underexplored problem: *Reasoning Misalignment*—the divergence between an LLM’s internal reasoning trajectory and the evidential constraints provided by retrieval. To address this issue, we propose ALIGNRAG, a novel iterative framework grounded in *Critique-Driven Alignment (CDA)*. We further introduce ALIGNRAG-AUTO, an autonomous variant that dynamically terminates refinement, removing the need to pre-specify the number of critique iterations. At the heart of ALIGNRAG lies a *contrastive critique synthesis* mechanism that generates retrieval-sensitive critiques while mitigating self-bias. This mechanism trains a dedicated retrieval-augmented *Critic Language Model (CLM)* using labeled critiques that distinguish between evidence-aligned and misaligned reasoning. Empirical evaluations show that our approach significantly improves reasoning fidelity. Our 8B-parameter CLM improves performance over the Self-Refine baseline by **12.1%** on out-of-domain tasks and outperforms a standard 72B-parameter CLM by **2.2%**. Furthermore, ALIGNRAG-AUTO achieves this state-of-the-art performance while dynamically determining the optimal number of refinement steps, enhancing efficiency and usability. ALIGNRAG remains compatible with existing RAG architectures as a *plug-and-play* module and demonstrates strong robustness under both informative and noisy retrieval scenarios. Overall, ALIGNRAG offers a principled solution for aligning model reasoning with retrieved evidence, substantially improving the factual reliability and robustness of RAG systems. **Our source code is provided at Github.**

1 Introduction

Large Language Models (LLMs) have significantly advanced natural language understanding and generation capabilities. Retrieval-Augmented Generation (RAG) [1–10] has emerged as a prominent paradigm for grounding LLM responses with external knowledge. However, RAG systems exhibit notable fragility, particularly when confronted with irrelevant or noisy retrieved evidence [11, 12]. Existing methods primarily rely on static, training-time optimizations, which are often insufficient to

*Equal contributions.

†Corresponding authors.

address the dynamic challenges of *error propagation* during inference [13, 14]. We identify a critical, yet understudied, failure mode in RAG: *reasoning misalignment*—a disconnect between the model’s reasoning process and the retrieved evidence. Prior work has focused predominantly on improving retrieval quality or generating more robust outputs, largely overlooking the explicit alignment of the reasoning steps with the provided evidence [15, 7, 16–18]. While reflective approaches like Self-RAG [19] attempt error detection, they often necessitate architectural modifications or task-specific fine-tuning, limiting their generalizability.

In this paper, we propose reconceptualizing RAG not merely as retrieval-augmented generation, but as *Retrieval-Augmented Reasoning*. We posit that RAG entails a structured reasoning process, typically involving stages such as (1) relevance assessment of retrieved documents, (2) mapping the query to specific points within the evidence, and (3) synthesizing evidence-integrated justifications. *Reasoning misalignment* occurs when breakdowns happen across these phases, for instance, when relevant evidence is retrieved but its content is not accurately integrated into the generated reasoning chain. These failure modes are pervasive and persist even with high-quality retrieval, remaining largely unaddressed by current methodologies.

To address reasoning misalignment, we introduce ALIGNRAG, a novel framework that employs *Critique-Driven Alignment (CDA)* to dynamically correct misalignments during inference using retrieval-augmented critiques. Distinct from general-purpose generation refinement techniques [20–23], ALIGNRAG incorporates a *contrastive critique synthesis* mechanism. This mechanism is designed to elicit evidence-grounded critiques and explicitly mitigate the self-bias commonly observed in self-critical LLMs [24–26, 21, 20]. This is achieved by training a dedicated retrieval-augmented *Critic Language Model (CLM)* on contrastive critiques. These critiques are generated by instruction-tuned LLMs and are guided by alignment signals derived from self-supervision or stronger external supervision. This paradigm breaks the circularity inherent in self-critical pipelines and specifically optimizes the CLM for evidence sensitivity, enabling it to reliably distinguish aligned from misaligned reasoning without propagating errors from potentially imperfect LLM feedback. At test time, ALIGNRAG iteratively refines the generated reasoning process by treating it as an optimizable artifact, transforming the RAG pipeline into an active reasoning system where critiques dynamically guide alignment with the retrieved evidence.

To enhance the framework’s practicality, we also introduce ALIGNRAG-AUTO, a more autonomous variant that eliminates the need for manual tuning of iteration counts. By training the CLM to predict a special ‘[Good]’ token upon generating a satisfactory response, ALIGNRAG-AUTO implements a dynamic stopping mechanism at inference time. This allows the system to terminate the refinement loop as soon as the reasoning is aligned with the evidence, saving substantial computational resources while maintaining high accuracy. This “hands-free” approach makes our framework more robust, efficient, and readily deployable across diverse tasks without domain-specific adjustments.

Extensive evaluations across seven benchmark datasets and three diverse model families firmly establish ALIGNRAG’s state-of-the-art (SOTA) performance, consistently surpassing existing methods on a wide range of tasks. A key demonstration of its efficacy, driven by our critique learning strategy, is our 8B-parameter ALIGNRAG model outperforming a self-refine approach by 12.1% on out-of-domain (OOD) benchmarks and even a much larger vanilla 72B-parameter CLM by 2.2%. ALIGNRAG’s robustness shines under both informative and noisy retrieval scenarios, proving that *when RAG retrieval falters, ALIGNRAG thrives*. Moreover, its design as a plug-and-play module ensures seamless integration into existing RAG pipelines without architectural modifications; for example, it enhanced InstructRAG’s OOD accuracy by 9.4% when applied to the Qwen2.5-14B model. These comprehensive evaluations underscore ALIGNRAG’s superiority and versatility for retrieval-augmented tasks, excelling in diverse retrieval conditions, ensuring high reasoning fidelity, and demonstrating strong generalization.

In summary, this paper makes the following key contributions: (1) We reconceptualize RAG as *Retrieval-Augmented Reasoning* and identify *Reasoning Misalignment* as a fundamental, understudied failure mode. (2) We introduce *critique learning* for RAG, a novel pipeline for training CLMs to generate retrieval-augmented critiques while mitigating self-preference bias through a contrastive synthesis approach. (3) We propose ALIGNRAG, a test-time framework that utilizes CDA steps to iteratively optimize the RAG reasoning process. We also present ALIGNRAG-AUTO, an autonomous extension that dynamically determines the optimal number of refinement steps, enhancing efficiency and usability. (4) We provide extensive empirical validation demonstrating that ALIGNRAG achieves

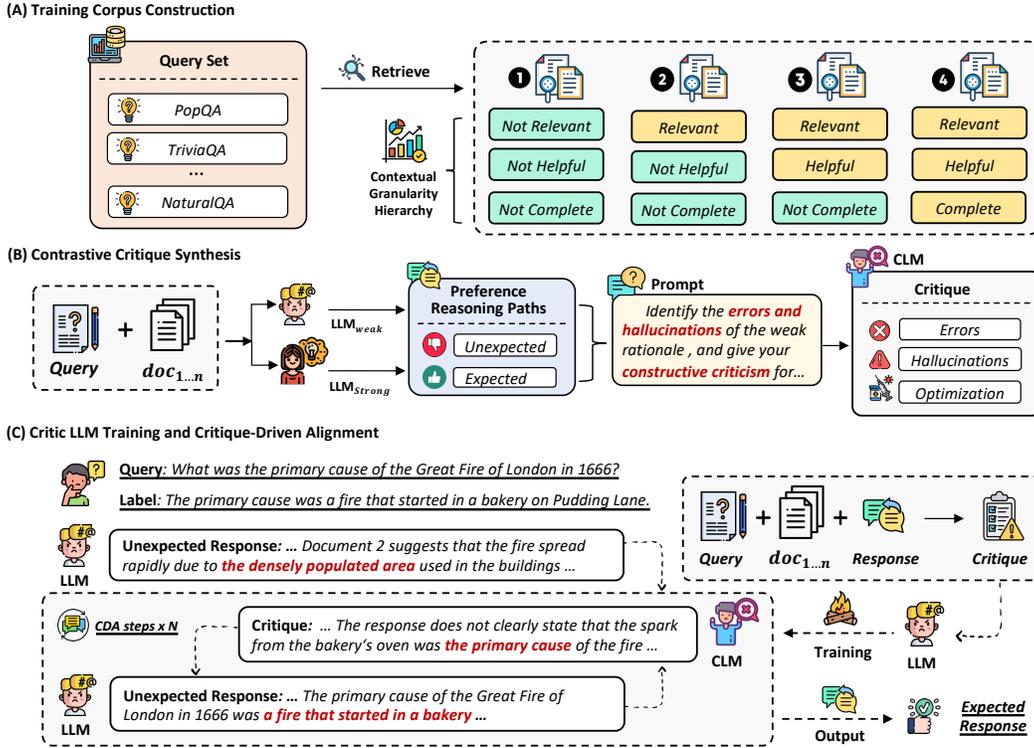


Figure 1: Overview of our ALIGNRAG Framework.

SOTA performance and significantly improves reasoning quality and robustness across various benchmarks and retrieval scenarios.

2 Reasoning Misalignment in RAG

RAG leverages external corpora \mathcal{D} for grounded generation, with prior work largely focusing on improving retrieval [19] or generator robustness [13]. However, a critical and underexplored challenge is the *alignment* of the model’s intrinsic reasoning process y with the specific evidential constraints from retrieved documents \mathcal{D} . Unlike error propagation in extended mathematical or code reasoning [14, 27], RAG failures often stem from inductive biases conflicting with external evidence, a qualitatively distinct problem.

We introduce *reasoning misalignment* as a novel, RAG-specific failure mode. It occurs when the model’s constructed reasoning path y deviates significantly from the information or relationships within retrieved evidence \mathcal{D} , even when documents are relevant and contain the necessary facts. This is distinct from factual errors, context-free logical fallacies [28], or pure retrieval failures ($P(\mathcal{D} | q)$ issues). Instead, it signifies a breakdown in *faithful evidential integration*. Formally, misalignment is a structural deficiency in the conditional distribution $P(y | q, \mathcal{D})$, where y is the generated reasoning for query q using \mathcal{D} . It is characterized by: (1) Erosion of Evidential Priors: Reasoning inconsistent with statistical or semantic properties in \mathcal{D} , such as $P(\text{span} | q, \mathcal{D})$ generated by the model differing significantly from the true salience. (2) Violation of Evidential Consistency: Deductive steps within y contradict logical inferences derivable from \mathcal{D} , i.e., $\mathcal{D} \not\models \text{step}_i$ for some reasoning step $\text{step}_i \in y$.

We decompose RAG reasoning into three interdependent phases, each susceptible to misalignment despite ideal retrieval:

Phase 1: Relevance Assessment. Misalignment occurs when the model fails to accurately gauge the relevance of specific text spans $s \subset d, d \in \mathcal{D}$ relative to the query q , effectively misestimating $P(s \text{ is relevant} | q, \mathcal{D})$ or assigning disproportionate weight to less relevant information [29].

Phase 2: Query-Evidence Mapping. This phase is susceptible when the model struggles to correctly identify how elements of q map onto information in \mathcal{D} , representing a failure to correctly derive evidential relationships $\mathcal{R}(q, \mathcal{D})$ from \mathcal{D} based on q [30].

Phase 3: Evidence-Integrated Synthesis. Misalignment here involves generating reasoning steps or conclusions $\text{step}_i \in y$ that are not logically supported by the relevant evidence $E_i \subseteq \mathcal{D}$ used for that step, violating the entailment $E_i \models \text{step}_i$, or creating inconsistencies when synthesizing information from multiple parts of \mathcal{D} into a coherent justification [31, 32, 14].

This taxonomy highlights reasoning misalignment as a pervasive issue orthogonal to retrieval quality or basic factuality. Static prompting cannot dynamically correct these evidence-grounded failures. To address this, we propose ALIGNRAG, a novel test-time framework enforcing evidential alignment via critique-guided alignment, offering a principled solution to this fundamental RAG challenge.

3 Critique-Driven Alignment for Retrieval-Augmented Reasoning

We present **Critique-Driven Alignment (CDA)**, a novel test-time refinement framework designed to mitigate reasoning misalignment in RAG. While conventional RAG pipelines often produce responses that partially or incorrectly reflect retrieved evidence, CDA introduces an explicit mechanism for identifying, diagnosing, and revising such failures via a learned critic model. This section details our approach, outlining the problem formulation (§3.1), our structured training methodology for critique learning (§3.2), and the iterative test-time alignment process (§3.3).

3.1 Problem Setting

Given an input query q and a set of retrieved documents $\mathcal{D} = \{d_1, \dots, d_n\}$, our objective is to refine an initial response $y_0 = \mathcal{M}_{\text{gen}}(q, \mathcal{D})$ through iterative critique-informed updates from a trained critic model $\mathcal{M}_{\text{critic}}$. To support the training of this critic model, we construct a critique supervision dataset:

$$\mathcal{S} = \{(q_i, a_i, \mathcal{D}_i, \mathbf{c}_i, y_{\text{exp},i}, y_{\text{unexp},i}, \Delta y_{\text{unexp},i})\}_{i=1}^N, \quad (1)$$

where each instance i contains the query q_i , the ground-truth answer a_i , the retrieved documents \mathcal{D}_i , and a vector $\mathbf{c}_i = (r_i, h_i, m_i) \in \{0, 1\}^3$ capturing the quality of the retrieved context along orthogonal axes: *relevance*, *helpfulness*, and *completeness* (related to explicit links between query elements and evidence). For each instance, we include a pair of responses $(y_{\text{exp},i}, y_{\text{unexp},i})$ generated by an expert strong and a weak model, respectively. These response pairs, combined with q_i and \mathcal{D}_i , form a preference-augmented input representation $\mathcal{X}_{\text{pref},i} = (q_i, \mathcal{D}_i, y_{\text{exp},i}, y_{\text{unexp},i})$. Using $\mathcal{X}_{\text{pref},i}$ and potentially signals derived from a_i and \mathbf{c}_i , we synthesize the supervision signal $\Delta y_{\text{unexp},i}$ representing a critique highlighting misalignments in $y_{\text{unexp},i}$ relative to \mathcal{D}_i , which is then used to train $\mathcal{M}_{\text{critic}}$.

3.2 Critic Training

3.2.1 Training Corpus Construction

To model the ambiguity and diversity inherent in real-world retrieval scenarios [33–35], we construct a structured training dataset $\mathcal{S} = \{(q_i, a_i, \mathcal{D}_i, \mathbf{c}_i)\}_{i=1}^N$, where each instance includes a query q_i , its gold answer a_i , a retrieved document set \mathcal{D}_i , and a context granularity vector $\mathbf{c}_i \in \{0, 1\}^3$. The vector encodes three orthogonal axes of contextual variation:

$$\mathbf{c}_i = (r_i, h_i, m_i), \quad (2)$$

where *Relevance* r_i indicates the presence of relevant documents (derived from top- k retrieval results, augmented with irrelevant documents sampled from unrelated queries). *Helpfulness* h_i is a binary label reflecting whether the document(s) contain answer spans corresponding to a_i . *Completeness* m_i is a document-set-level binary label signifying whether \mathcal{D}_i collectively supports the full reasoning path required to derive a_i .

To systematically simulate varied degrees of answerability, we define a multiple-tier contextual granularity hierarchy (Fig. 1.A), exposing critic models to diverse evidence configurations and enabling fine-grained supervision. The details of data construction could refer to Appendix A.3.

3.2.2 Contrastive Critique Synthesis

We propose **Contrastive Critique Synthesis (CCS)**, a novel methodology generating evidence-grounded feedback by contrasting reasoning trajectories from language models with differing capabilities. Since LLMs produce sequences from conditional distributions, $P(y|\text{input})$, self-critique risks

amplifying biases inherent in their own $P(y|\cdot)$. CCS counters this via a dedicated *Critic Language Model (CLM)* trained on structured contrastive pairs $\mathcal{X}_{\text{pref}} = (q, \mathcal{D}, y_{\text{exp}}, y_{\text{unexp}})$. This explicitly trains the CLM to identify misalignments w.r.t. \mathcal{D} , learning $P_{\text{critic}}(\text{critique}|\mathcal{X}_{\text{pref}})$ to capture deviations from evidential fidelity.

The CLM training employs a pairwise generation protocol. It samples an unexpert response $y_{\text{unexp}} \sim P_{\text{weak}}(y|q, \mathcal{D})$ (prone to misalignment) and an expert $y_{\text{exp}} \sim P_{\text{strong}}(y|q, \mathcal{D})$ (more aligned). To provide a structured input for learning the conditional distribution of critiques, we define a preference-augmented input tuple:

$$\mathcal{X}_{\text{pref}} = (q, \mathcal{D}, y_{\text{exp}}, y_{\text{unexp}}), \quad (3)$$

which conditions the CLM’s learning on both desired trajectories (y_{exp}) and common failure patterns (y_{unexp}). This contrastive formulation offers two key benefits for training an effective critic: (1) it constrains the learning objective for $P_{\text{critic}}(\Delta y|\mathcal{X}_{\text{pref}})$ to focus on highlighting differences between y_{exp} and y_{unexp} that are grounded in \mathcal{D} , promoting evidence sensitivity and faithfulness [36]; and (2) it enables fine-grained diagnosis of specific misalignment types by analyzing path divergences [37].

The CLM learns $P_{\text{critic}}(\Delta y|\mathcal{X}_{\text{pref}})$ to generate a structured critique Δy_{unexp} , strictly grounded in \mathcal{D} . Training targets Δy_{unexp} are synthesized via a Critique Function \mathcal{F} :

$$\Delta y_{\text{unexp}} = \mathcal{F}(\mathcal{X}_{\text{pref}}). \quad (4)$$

$\mathcal{M}_{\text{critic}}$ is trained to approximate \mathcal{F} . The final critique format Δy_{unexp} is produced by an augmentation operator $\mathcal{G}[\text{output}(\mathcal{M}_{\text{critic}}(\mathcal{X}_{\text{pref}})), y_{\text{exp}}]$, which reformulates raw model output into constructive suggestions using y_{exp} as reference. This framework enables the critic to localize and explain misalignments, providing high-quality feedback for RAG alignment.

3.2.3 Critic LLM Training

To instantiate the CLM, we introduce *Critique Fine-Tuning (CFT)* [38], a novel paradigm for training language models to produce constructive, evidence-grounded critiques. The goal is to transform a base model $\mathcal{M}_{\text{base}}$ into a proficient critic model $\mathcal{M}_{\text{critic}}$ using a synthetic dataset of critiques \mathcal{C} . Each training instance $\mathcal{C}_i \in \mathcal{C}$ is a tuple $(q, \mathcal{D}, y_{\text{unexp}}, \Delta y_{\text{unexp}}, y_{\text{exp}})$.

CFT formulates critique generation as a conditional sequence generation task. The training objective maximizes the likelihood of the model producing the correct critique Δy_{unexp} , conditioned on the full critique context $\mathcal{I}_{\text{critic}} = (q, \mathcal{D}, y_{\text{unexp}}, y_{\text{exp}})$. Formally, the objective is:

$$\mathcal{L}_{\text{CFT}}(\theta) = - \sum_{\mathcal{C}_i \in \mathcal{C}} \log p_{\theta}(\Delta y_{\text{unexp}} | \mathcal{I}_{\text{critic}}), \quad (5)$$

where p_{θ} is the probability distribution induced by the critic model $\mathcal{M}_{\text{critic}}$, parameterized by θ . This formulation enables the model to generate actionable, targeted feedback that improves downstream response quality. By decoupling critique generation from the target model’s own outputs, CFT mitigates the self-preference bias commonly observed in iterative self-correction methods.

3.3 Critique-Driven Alignment Systems

To address reasoning misalignment in RAG at inference, we propose Critique-Driven Alignment (CDA). Unlike standard single-pass RAG generation, $y_0 = \mathcal{M}_{\text{gen}}(q, \mathcal{D})$:

$$y_0 = \mathcal{M}_{\text{gen}}(q, \mathcal{D}), \quad (6)$$

CDA reconceptualizes inference as an iterative optimization over a latent reasoning space \mathcal{Y} . Each iteration leverages critiques to incrementally improve output alignment with retrieved evidence.

A learned critic $\mathcal{M}_{\text{critic}}$ iteratively analyzes intermediate generations and provides critiques suggesting improvements. This yields a refinement trajectory:

$$y_0 \xrightarrow{\text{CDA}} y_1 \xrightarrow{\text{CDA}} \dots \xrightarrow{\text{CDA}} y_T, \quad (7)$$

where each transition $y_t \rightarrow y_{t+1}$ is critique-guided. At step $t < T$, the critic outputs an edit signal Δy_t identifying issues in y_t and proposing \mathcal{D} -grounded revisions. y_{t+1} is generated by augmenting \mathcal{M}_{gen} ’s input:

$$y_{t+1} = \mathcal{M}_{\text{gen}}(y_t \oplus \Delta y_t), \quad (8)$$

where \oplus denotes prompt augmentation with critique feedback. Δy_t acts as a pseudo-gradient in discrete space, directing the generator toward \mathcal{D} -aligned reasoning.

The final CDA output is the trajectory’s terminal state:

$$y_{\text{final}} = \text{CDA}(q, \mathcal{D}) := y_T. \tag{9}$$

This framework elevates alignment from static supervision to a dynamic iterative process at test-time, enabling demonstrably more reliable and evidence-grounded reasoning than existing RAG.

3.4 AlignRAG-auto: Dynamic and Domain-General Alignment

We also develop **AlignRAG-auto**, an autonomous extension of CDA that eliminates the need for manual iteration tuning and demonstrates strong cross-domain generalization. Whereas the baseline CDA requires specifying the maximum number of refinement steps T , AlignRAG-auto leverages a lightweight control mechanism that dynamically determines when alignment has been achieved. This improves both efficiency and robustness at deployment.

3.4.1 Training for Dynamic Refinement

We modify the training process for the Critic Language Model (CLM) to support dynamic inference. For each “unexpected” response y_{unexp} , we first determine correctness relative to ground truth. Incorrect responses are labeled with a [Bad] token, while correct ones are labeled with [Good]. The CLM is then trained to generate the appropriate control token followed by a structured critique:

$$p_{\theta}([\text{Good}/\text{Bad}], \Delta y \mid q, \mathcal{D}, y_{\text{unexp}}). \tag{10}$$

This dual-target training objective equips the critic with both evaluative and corrective capacity. By conditioning critiques on explicit correctness judgments, the CLM learns to terminate refinement as soon as sufficient alignment is achieved.

3.4.2 Dynamic Inference-Time Stopping

At inference, AlignRAG-auto proceeds iteratively as in CDA but introduces a dynamic stopping rule. If the critic predicts [Good], the system halts refinement and accepts the current candidate:

$$y_{t+1} = \begin{cases} y_t, & \text{if CLM outputs [Good]} \\ \mathcal{M}_{\text{gen}}(y_t \oplus \Delta y_t), & \text{if CLM outputs [Bad]}. \end{cases} \tag{11}$$

This adaptive strategy avoids unnecessary iterations, saving compute while maintaining high fidelity to retrieved evidence. Empirically, we observe that only a subset of responses require multiple refinements, yielding substantial runtime reductions without compromising accuracy (see Table 2).

4 Experiments

4.1 Experiment Setup

We evaluate our method using three instruction-tuned backbones: Qwen2.5-7B-Instruct [39], Qwen2.5-14B-Instruct [39], and LLaMA3.1-8B-Instruct [40]. For simplicity, we refer to them as Qwen2.5-7B, Qwen2.5-14B, and LLaMA3.1-8B.

Dataset. To train a strong critique generator, we construct a 10K dataset by sampling 2K instances from each of five benchmarks: PopQA [41], TriviaQA [42], NaturalQuestions [43], 2WikiMulti-hopQA [44], and ASQA [45]. Furthermore, we evaluate our method on the same five in-domain benchmarks, along with two out-of-distribution (OOD) tasks, *i.e.*, HotpotQA [46] and SQuAD [47].

Baselines. In our experiments, we compare our method against a range of non-retrieval and retrieval-based baselines. For non-retrieval baselines, we include Chain-of-Thought (CoT) prompting [48, 49] applied to models without retrieval augmentation. For standard RAG, we report performance from Vanilla Reasoning [13, 50], which performs step-by-step answer generation based on the retrieved passages. To assess the benefits of intermediate supervision, we include training-time refinement baselines such as RetRobust[33] and InstructRAG[13]. **Our main comparison is with these test-time refinement methods, as they share similar objectives.** For test-time refinement, we evaluate Self-RAG [19] and Self-Refine, which iteratively revises outputs based on self-generated critique.

Table 1: Overall performance comparison of RAG systems employing various knowledge refinement strategies and reasoning configurations across five question-answering (QA) benchmarks. To ensure a fair evaluation, all systems are tested under a **single-iteration test-time refinement** setting. Results marked with * are reproduced from [13]. Missing results in the original paper are denoted by “-”. To highlight our method’s **impact of different model backbones**, we use the following color-coded notation for performance improvements: (Δ) represents the Qwen-2.5-Instruct_{7B}, (Δ) represents the Qwen-2.5-Instruct_{1.4B}, and (Δ) represents the Llama-3-Instruct_{8B}.

Method Metric	NQ accuracy	MultiHopQA accuracy	TriviaQA accuracy	PopQA accuracy	ASQA str-em	Avg.
Baselines w/o Retrieval						
Chain-of-thought [48]						
Qwen-2.5-Instruct _{7B}	33.9	45.0	58.3	26.9	20.5	36.9
Qwen-2.5-Instruct _{1.4B}	48.1	49.3	72.8	25.4	31.6	45.4
Llama-3.1-Instruct _{8B}	42.1	41.9	61.8	26.9	25.1	40.0
Standard RAG with Reasoning						
Vanilla Reasoning						
Qwen-2.5-Instruct _{7B}	60.2	44.7	73.2	63.7	42.8	56.9
Qwen-2.5-Instruct _{1.4B}	63.6	44.8	77.0	65.3	45.2	59.2
Llama-3.1-Instruct _{8B}	62.0	43.0	73.4	65.0	45.2	57.7
RAG w/ Training-time Refinement						
RetRobust [33]						
Llama-2 _{13B} *	39.6	51.5	-	-	-	-
Llama-3-Instruct _{8B} *	54.2	54.7	71.5	56.5	40.5	55.5
InstructRAG [13]						
Qwen-2.5-Instruct _{7B}	63.8	46.3	76.1	67.5	47.5	60.2
Qwen-2.5-Instruct _{1.4B}	66.3	47.3	78.7	67.8	48.5	61.7
Llama-3.1-Instruct _{8B}	66.3	45.1	76.6	66.9	47.2	60.4
RAG w/ Test-time Refinement						
Self-RAG [19]						
Llama-2 _{7B} + CLM _{7B} *	42.4	35.9	68.9	55.8	30.0	46.6
Llama-2 _{13B} + CLM _{13B} *	46.4	36.0	70.4	56.3	31.4	48.1
Llama-3-Instruct _{8B} + CLM _{8B} *	42.8	32.9	71.4	55.8	36.9	48.0
Self-Refine						
Qwen-2.5-Instruct _{7B} + SELF _{7B}	61.6(Δ)	45.0(Δ)	74.4(Δ)	65.5(Δ)	45.2(Δ)	58.3(Δ)
Qwen-2.5-Instruct _{1.4B} + SELF _{1.4B}	65.1(Δ)	46.1(Δ)	78.0(Δ)	67.0(Δ)	47.3(Δ)	60.7(Δ)
Llama-3.1-Instruct _{8B} + SELF _{8B}	61.4(Δ)	42.8(Δ)	74.1(Δ)	66.1(Δ)	44.7(Δ)	57.8(Δ)
AlignRAG-fixed						
Qwen-2.5-Instruct _{7B} + CLM _{8B}	65.9 (\uparrow 4.3%)	49.5 (\uparrow 4.5%)	77.8 (\uparrow 3.4%)	68.4 (\uparrow 2.9%)	48.9 (\uparrow 3.7%)	62.1 (\uparrow 3.8%)
Qwen-2.5-Instruct _{1.4B} + CLM _{8B}	67.7 (\uparrow 2.6%)	49.8 (\uparrow 3.7%)	79.5 (\uparrow 1.5%)	68.4 (\uparrow 1.4%)	48.6 (\uparrow 1.3%)	62.8 (\uparrow 2.1%)
Llama-3.1-Instruct _{8B} + CLM _{8B}	65.3 (\uparrow 3.9%)	47.0 (\uparrow 4.2%)	77.0 (\uparrow 2.9%)	66.5 (\uparrow 0.4%)	47.1 (\uparrow 2.4%)	60.6 (\uparrow 2.8%)

Evaluation metrics. Following previous work [51], we adopt the official correctness metric (*str-em*) for ASQA [45], and use *accuracy* for the other tasks, which measures whether the final generations of the model align with the ground-truth [41, 52].

Implementation Details. For the CLM, we adopt LLaMA3.1-8B-Instruct as the backbone and fine-tune it using LoRA for parameter-efficient training. Moreover, the *strong LLM* we use to generate *expected* responses is LLaMA3.1-8B-Instruct, and the *weak LLM* we use to generate *unexpected* responses is Qwen2.5-0.5B-Instruct [39]. We set the retrieval Top-*K* to 5 for each question.

4.2 Main Result

Table 1 shows the overall performance of our method and the baselines in various families and sizes of the base model on five benchmarks. And we provide all the additional results in Appendix A.6

First, compared to non-retrieval baselines such as Chain-of-Thought (CoT) prompting, all retrieval-augmented methods achieve significantly better performance, demonstrating the importance of incorporating relevant external knowledge. Second, we observe further gains when applying training-time refinement methods. In particular, InstructRAG achieves strong performance across all backbones, outperforming Vanilla RAG by a large margin, confirming the value of training refinement strategies.

Notably, ALIGNRAG achieves the best overall results on all three backbones compared to other test-time refinement methods. It surpasses Self-RAG and Self-Refine by notable margins, achieving an average accuracy of 62.8% compared to 48.1% and 60.7%, respectively. The performance improvement is consistent across all benchmarks, highlighting both the effectiveness and the strong generalization of our approach. This demonstrates that our critique-driven alignment strategy can better guide the reasoning process and overcome the limitations of purely self-generated feedback.

Analysis of AlignRAG-auto. The experimental results, detailed in Table 2, reveal a compelling comparison between the fixed-iteration and autonomous alignment strategies. Notably, **AlignRAG-auto** consistently achieves performance on par with, and in many cases slightly superior to, its

AlignRAG-fixed counterpart across all datasets and model sizes. For instance, on the NQ and ASQA benchmarks, AlignRAG-auto demonstrates clear improvements, suggesting its dynamic termination mechanism is highly effective.

This is a crucial finding: the autonomous variant **does not sacrifice accuracy for efficiency**. Instead, it demonstrates that the Critic Language Model is well-calibrated to dynamically determine the optimal number of refinement steps, leading to robust performance without the need for manual hyperparameter tuning. This validates AlignRAG-auto as a more practical and efficient framework for real-world deployment.

4.3 Analysis

Note: All subsequent experimental analyses are based on AlignRAG-fixed. For convenience, we’ll use AlignRAG instead.

Generalization to OOD Scenarios. To assess the generalization capability of our method beyond the domains seen during training, we conduct out-of-distribution (OOD) evaluations on two widely-used and challenging benchmarks that are held out from the training set, *i.e.*, HotpotQA [46] and SQuAD [47]. This evaluation setting enables us to examine how well the model transfers its reasoning and alignment abilities to novel domains. As shown in Figure 3, we compare ALIGNRAG with two baselines. ALIGNRAG consistently achieves the lowest performance drop across all backbones, outperforming both baselines by a large margin. For example, on LLaMA3.1-8B, ALIGNRAG reduces the performance drop to 32.4% compared to 41.6% for Self-Refine. These results demonstrate that our CDA mechanism not only improves in-domain reasoning but also enhances robustness under domain shift.

Figure 2: Performance Comparison: AlignRAG-fixed (1 iter.) vs. AlignRAG-auto

Dataset	AlignRAG-fixed (1 iter.)			AlignRAG-auto		
	8B	7B	14B	8B	7B	14B
PopQA	66.5	68.4	68.4	67.6	68.1	68.3
TriviaQA	77.0	77.8	79.5	77.6	78.1	79.9
NQ	65.3	65.9	67.7	66.8	67.3	69.0
2WikiMultiHopQA	47.0	49.5	49.8	47.6	49.3	50.2
ASQA	47.1	48.9	48.6	48.8	49.6	49.8

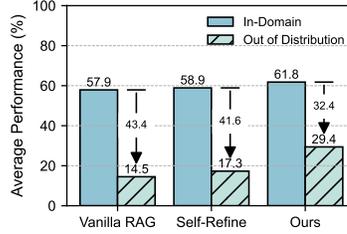


Figure 3: Drop in average OOD performance compared to average In-Domain performance.

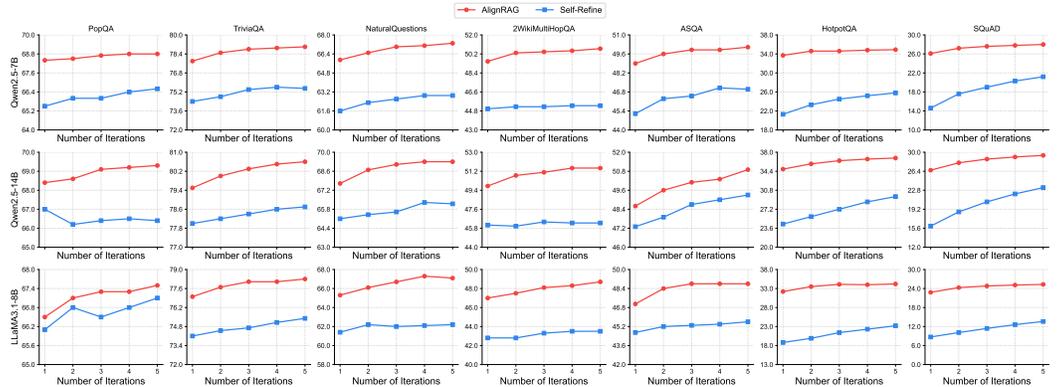


Figure 4: Performance comparison of ALIGNRAG and Self-Refine across five refinement iterations.

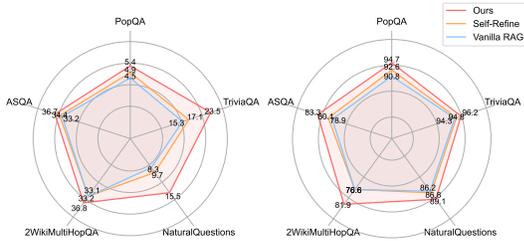
Scalable Test-time Reasoning via Iterative Alignment Strategy. To assess test-time scalability of different refinement methods, we plot accuracy over five refinement steps across seven benchmarks, comparing the performance of ALIGNRAG with the Self-Refine baseline (Figure 4). The curves reveal two notable trends. First, both methods generally benefit from iterative alignment, with accuracy improving on most tasks as the number of refinement steps increases. This indicates that reasoning can scale with additional refinement steps. However, we occasionally observe slight degradation beyond a certain point, which we attribute to potential noise accumulation or overcorrection during excessive iterations. Second, ALIGNRAG consistently outperforms Self-Refine across all iterations

and benchmarks with notable margins. These findings demonstrate that ALIGNRAG not only enables scalable reasoning but also provides more stable and robust improvements.

When RAG Retrieval Falters, ALIGNRAG Thrives.

RAG systems are susceptible to substantial performance degradation when retrieved documents lack pertinent answers, a prevalent yet insufficiently characterized failure mode termed *Noisy Retrieval*. Even in the absence of explicit answers within the retrieved corpus, ALIGNRAG adeptly filters distractors to isolate underlying reasoning signals while concurrently activating complementary parametric knowledge inherent to the base model.

This dual strategy, as demonstrated in Figures 5a and 5b, empowers robust reasoning even under these adversarial conditions. Consequently, ALIGNRAG (Figure 5a) significantly outperforms conventional methods like Vanilla RAG and Self-Refine, which falter in such scenarios, by effectively transforming imperfect external retrievals and inherent model understanding into actionable insights.



(a) w/o answer. (b) w/ answer.

Figure 5: ALIGNRAG performance under *Noisy Retrieval* (a) and *Informative Retrieval* (b) scenarios.

Superior Alignment Guidance Surpassing Strong LLM Baselines.

We examine the effectiveness of using a high-capacity *Strong LLM*, i.e., Qwen2.5-72B-Instruct, in our Contrastive Critique Synthesis (CCS) framework. Specifically, we compare three CLM supervision strategies under three backbones: (1) *Vanilla Critique Synthesis*, where the CLM is trained with critiques directly generated by Qwen2.5-72B-Instruct, (2) directly using the 72B model as the CLM, and (3) our CCS-based CLM trained with critiques synthesized by the 72B *Strong LLM*.

As shown in Figure 6, our method consistently outperforms vanilla critique synthesis, validating the benefit of introducing contrastive reasoning signals. Remarkably, our method even surpasses the directly supervised 72B CLM in all backbones, suggesting that contrastive critique training enhances generalization and reduces reliance on model scale. These results demonstrate the strength of our approach in leveraging powerful LLMs for scalable and efficient CLM training.

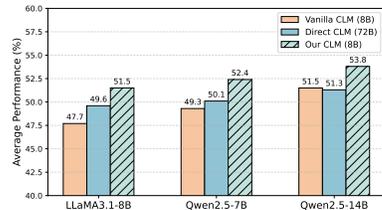


Figure 6: Comparison of different CLM supervision strategies.

Integrate as a Plug-and-play Module into Existing RAG Pipelines.

To evaluate the generality and plug-and-play nature of our method, we integrate it into the InstructRAG framework across three backbones. Table 2 reports the performance under both In-Domain (ID) and Out-of-Domain (OOD) evaluation. We observe consistent improvements in both familiar and unseen distributions. The variant with alignment significantly outperforms the original InstructRAG [13], demonstrating that our method can be incorporated into existing RAG pipelines in a zero-modification, test-time manner, highlighting its strong compatibility and practical utility.

Table 2: Combination of training-time (InstructRAG) and test-time alignment.

Method	ID (avg.)	OOD (avg.)
<i>Qwen2.5-7B</i>		
InstructRAG	59.5 (Δ)	28.0 (Δ)
w/ Alignment	61.5 (↑ 2.0%)	30.1 (↑ 2.1%)
w/ Alignment ¹	63.0 (↑ 3.5%)	31.7 (↑ 3.7%)
<i>Qwen2.5-14B</i>		
InstructRAG	61.7 (Δ)	24.9 (Δ)
w/ Alignment	62.5 (↑ 0.8%)	33.4 (↑ 8.5%)
w/ Alignment ¹	63.9 (↑ 2.2%)	34.3 (↑ 9.4%)
<i>LLaMA3.1-8B</i>		
InstructRAG	60.4 (Δ)	28.4 (Δ)
w/ Alignment	61.7 (↑ 1.3%)	29.4 (↑ 1.0%)
w/ Alignment ¹	61.9 (↑ 1.5%)	30.5 (↑ 2.1%)

4.4 Ablation Study

¹CLM trained with critiques synthesized by Qwen2.5-72B-Instruct.

We perform an ablation study on seven benchmarks to isolate the effect of the Critic Language Model (CLM) and our contrastive critique synthesis (CCS). Specifically, we compare four settings: (1) **Vanilla RAG**, which generates without critique; (2) **RAG + Frozen CLM**, where a pretrained LLaMA3.1-8B serves as an untrained critic; (3) **RAG + Trained CLM**, where the CLM is fine-tuned on critiques over weak LLM responses, but without contrastive signal; (4) **RAG + Trained CLM (CCS)**, our full method with contrastive critique synthesis.

Figure 7 shows that even a frozen CLM consistently improves over Vanilla RAG, confirming the utility of auxiliary critique. Training the CLM with weak LLM critiques yields further gains by capturing recurring error patterns. The largest improvements come from CCS, which explicitly contrasts expert and weak responses. For example, on Qwen2.5-7B, CCS raises average accuracy from 49.6% to 52.9%. Complete results are presented in Table 4 (Appendix).

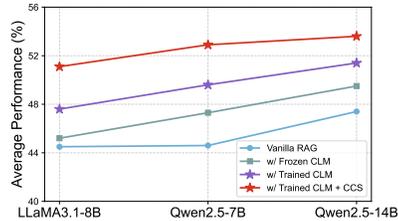


Figure 7: Ablation study on the CLM and our CCS.

5 Related Work

RAG [53–59] enhances LLMs by grounding generation in external knowledge. While significant efforts have focused on improving retrieval accuracy [60–64] or training better generators [65–68], a persistent challenge is the presence of noisy or irrelevant retrieved content. To mitigate this, recent methods filter or denoise context, predominantly via *training-time* optimizations [15, 69–72], such as InstructRAG’s [13] self-supervised denoising. However, these approaches are limited by their static nature and fail to address dynamic error propagation during inference [14].

Even with accurate retrieval, the generated reasoning may deviate from the evidence. We identify this *reasoning misalignment* as a critical, underexplored RAG failure mode. Prior attempts like Self-RAG [19] introduce special tokens to control reasoning but require architectural modifications. In contrast, our novel Critique-Driven Alignment (CDA) is a test-time method that dynamically realigns reasoning with evidence *without modifying the base model architecture*, offering a plug-and-play alternative to training-heavy variants. Furthermore, unlike general self-refinement techniques [73–75], we propose a novel *critique learning* paradigm training a dedicated Critic Language Model (CLM) specifically for evidence-grounded critiques. Crucially, this paradigm explicitly mitigates the self-bias inherent in self-critiquing LLMs [24–26, 21, 20]. Unlike external verification methods [76, 77] that act as post-hoc filters, our trained CLM actively optimizes the evidence-grounded reasoning process as an artifact during inference, enabling dynamic alignment with retrieved knowledge.

6 Conclusion

We present ALIGNRAG, an iterative framework that reframes Retrieval-Augmented Generation as *Retrieval-Augmented Reasoning* to tackle the overlooked challenge of *Reasoning Misalignment*. Its key innovation, *Critique-Driven Alignment (CDA)*, uses a specialized *Critic Language Model (CLM)*—trained via *contrastive critique synthesis*—to boost evidence sensitivity and correct reasoning errors at inference. ALIGNRAG sets new state-of-the-art. This principled approach advances the reliability and faithfulness of retrieval-augmented systems.

Acknowledgements

This project was fully supported by the Shanghai Artificial Intelligence Laboratory (S.S.). This work was done during Jiaqi Wei’s internship at Shanghai Artificial Intelligence Laboratory.

References

- [1] Patrick S. H. Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Proceedings of NeurIPS*, 2020.
- [2] Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Mingwei Chang. Retrieval augmented language model pre-training. In *International conference on machine learning*, pages 3929–3938. PMLR, 2020.
- [3] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020.
- [4] Gautier Izacard, Patrick Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. Atlas: Few-shot learning with retrieval augmented language models. *Journal of Machine Learning Research*, 24(251):1–43, 2023.
- [5] Xiang Zhang, Senyu Li, Bradley Hauer, Ning Shi, and Grzegorz Kondrak. Don’t trust chatgpt when your question is not in english: a study of multilingual abilities and types of llms. *arXiv preprint arXiv:2305.16339*, 2023.
- [6] Jungo Kasai, Keisuke Sakaguchi, Ronan Le Bras, Akari Asai, Xinyan Yu, Dragomir Radev, Noah A Smith, Yejin Choi, Kentaro Inui, et al. RealTime QA: What’s the answer right now? *Advances in Neural Information Processing Systems*, 36, 2024.
- [7] Xiao Yang, Kai Sun, Hao Xin, Yushi Sun, Nikita Bhalla, Xiangsen Chen, Sajal Choudhary, Rongze Daniel Gui, Ziran Will Jiang, Ziyu Jiang, Lingkun Kong, Brian Moran, Jiaqi Wang, Yifan Ethan Xu, An Yan, Chenyu Yang, Eting Yuan, Hanwen Zha, Nan Tang, Lei Chen, Nicolas Scheffer, Yue Liu, Nirav Shah, Rakesh Wanga, Anuj Kumar, Wen tau Yih, and Xin Luna Dong. CRAG – comprehensive RAG benchmark. *arXiv preprint arXiv:2406.04744*, 2024.
- [8] Xiang Zhang, Juntai Cao, Jiaqi Wei, Yiwei Xu, and Chenyu You. Tokenization constraints in llms: A study of symbolic and arithmetic reasoning limits. *arXiv preprint arXiv:2505.14178*, 2025.
- [9] Shuyan Zhou, Uri Alon, Frank F Xu, Zhengbao Jiang, and Graham Neubig. DocPrompting: Generating code by retrieving the docs. In *The Eleventh International Conference on Learning Representations*, 2022.
- [10] Bowen Jin, Hansi Zeng, Zhenrui Yue, Dong Wang, Hamed Zamani, and Jiawei Han. Search-r1: Training llms to reason and leverage search engines with reinforcement learning. *arXiv preprint arXiv:2503.09516*, 2025.
- [11] Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. REPLUG: Retrieval-augmented black-box language models. *arXiv preprint arXiv:2301.12652*, 2023.
- [12] Hongjin Su, Howard Yen, Mengzhou Xia, Weijia Shi, Niklas Muennighoff, Han-yu Wang, Haisu Liu, Quan Shi, Zachary S Siegel, Michael Tang, et al. BRIGHT: A realistic and challenging benchmark for reasoning-intensive retrieval. *arXiv preprint arXiv:2407.12883*, 2024.
- [13] Zhepei Wei, Wei-Lin Chen, and Yu Meng. Instructrag: Instructing retrieval-augmented generation via self-synthesized rationales. *arXiv preprint arXiv:2406.13629*, 2024.
- [14] Yuyang Wu, Yifei Wang, Tianqi Du, Stefanie Jegelka, and Yisen Wang. When more is less: Understanding chain-of-thought length in llms. *arXiv preprint arXiv:2502.07266*, 2025.
- [15] Aman Gupta, Anup Shirgaonkar, Angels de Luis Balaguer, Bruno Silva, Daniel Holstein, Dawei Li, Jennifer Marsman, Leonardo O Nunes, Mahsa Rouzbahman, Morris Sharp, et al. RAG vs Fine-tuning: Pipelines, tradeoffs, and a case study on agriculture. *arXiv preprint arXiv:2401.08406*, 2024.

- [16] Jinghan Zhang, Xiting Wang, Weijie Ren, Lu Jiang, Dongjie Wang, and Kunpeng Liu. RATT: A thought structure for coherent and correct LLM reasoning. *arXiv preprint arXiv:2406.02746*, 2024.
- [17] Tianjun Zhang, Shishir G Patil, Naman Jain, Sheng Shen, Matei Zaharia, Ion Stoica, and Joseph E Gonzalez. RAFT: Adapting language model to domain specific RAG. *arXiv preprint arXiv:2403.10131*, 2024.
- [18] Zhengren Wang, Jiayang Yu, Dongsheng Ma, Zhe Chen, Yu Wang, Zhiyu Li, Feiyu Xiong, Yanfeng Wang, Linpeng Tang, Wentao Zhang, et al. Rare: Retrieval-augmented reasoning modeling. *arXiv preprint arXiv:2503.23513*, 2025.
- [19] Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. Self-RAG: Learning to retrieve, generate, and critique through self-reflection. In *The Twelfth International Conference on Learning Representations*, 2023.
- [20] Qingjie Zhang, Han Qiu, Di Wang, Haoting Qian, Yiming Li, Tianwei Zhang, and Minlie Huang. Understanding the dark side of llms’ intrinsic self-correction. *arXiv preprint arXiv:2412.14959*, 2024.
- [21] Ting Wu, Xuefeng Li, and Pengfei Liu. Progress or regress? self-improvement reversal in post-training. *arXiv preprint arXiv:2407.05013*, 2024.
- [22] Nat McAleese, Rai Michael Pokorny, Juan Felipe Ceron Uribe, Evgenia Nitishinskaya, Maja Trebacz, and Jan Leike. Llm critics help catch llm bugs. *arXiv preprint arXiv:2407.00215*, 2024.
- [23] Mert Yuksekgonul, Federico Bianchi, Joseph Boen, Sheng Liu, Zhi Huang, Carlos Guestrin, and James Zou. Textgrad: Automatic" differentiation" via text. *arXiv preprint arXiv:2406.07496*, 2024.
- [24] Wenda Xu, Guanglei Zhu, Xuandong Zhao, Liangming Pan, Lei Li, and William Yang Wang. Pride and prejudice: Llm amplifies self-bias in self-refinement. *arXiv preprint arXiv:2402.11436*, 2024.
- [25] Koki Wataoka, Tsubasa Takahashi, and Ryokan Ri. Self-preference bias in llm-as-a-judge. *arXiv preprint arXiv:2410.21819*, 2024.
- [26] Dawei Li, Renliang Sun, Yue Huang, Ming Zhong, Bohan Jiang, Jiawei Han, Xiangliang Zhang, Wei Wang, and Huan Liu. Preference leakage: A contamination problem in llm-as-a-judge. *arXiv preprint arXiv:2502.01534*, 2025.
- [27] Qiguang Chen, Libo Qin, Jinhao Liu, Dengyun Peng, Jiannan Guan, Peng Wang, Mengkang Hu, Yuhang Zhou, Te Gao, and Wangxiang Che. Towards reasoning era: A survey of long chain-of-thought for reasoning large language models. *arXiv preprint arXiv:2503.09567*, 2025.
- [28] Di Zhang, Jianbo Wu, Jingdi Lei, Tong Che, Jiatong Li, Tong Xie, Xiaoshui Huang, Shufei Zhang, Marco Pavone, Yuqiang Li, et al. Llama-berry: Pairwise optimization for o1-like olympiad-level mathematical reasoning. *arXiv preprint arXiv:2410.02884*, 2024.
- [29] Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Richard James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. REPLUG: Retrieval-augmented black-box language models. In *Proceedings of NAACL-HLT*, pages 8371–8384, 2024.
- [30] Bingyu Wan, Fuxi Zhang, Zhongpeng Qi, Jiayi Ding, Jijun Li, Baoshi Fan, Yijia Zhang, and Jun Zhang. Cognitive-aligned document selection for retrieval-augmented generation. *arXiv preprint arXiv:2502.11770*, 2025.
- [31] Yan Weng, Fengbin Zhu, Tong Ye, Haoyan Liu, Fuli Feng, and Tat-Seng Chua. Optimizing knowledge integration in retrieval-augmented generation with self-selection. *arXiv preprint arXiv:2502.06148*, 2025.
- [32] Juntai Cao, Xiang Zhang, Raymond Li, Chuyuan Li, Chenyu You, Shafiq Joty, and Giuseppe Carenini. Multi2: Multi-agent test-time scalable framework for multi-document processing. *arXiv preprint arXiv:2502.20592*, 2025.

- [33] Ori Yoran, Tomer Wolfson, Ori Ram, and Jonathan Berant. Making retrieval-augmented language models robust to irrelevant context. In *The Twelfth International Conference on Learning Representations*, 2024.
- [34] Zhilin Zhang, Xiang Zhang, Jiaqi Wei, Yiwei Xu, and Chenyu You. Postergen: Aesthetic-aware paper-to-poster generation via multi-agent llms. *arXiv preprint arXiv:2508.17188*, 2025.
- [35] Feiteng Fang, Yuelin Bai, Shiwen Ni, Min Yang, Xiaojun Chen, and Ruifeng Xu. Enhancing noise robustness of retrieval-augmented language models with adaptive adversarial training. *arXiv preprint arXiv:2405.20978*, 2024.
- [36] Xiang Zhang, Juntao Cao, Jiaqi Wei, Chenyu You, and Dujian Ding. Why does your cot prompt (not) work? theoretical analysis of prompt space complexity, its interaction with answer space during cot reasoning with llms: A recurrent perspective. *arXiv preprint arXiv:2503.10084*, 2025.
- [37] Shuai Zhao, Linchao Zhu, and Yi Yang. Learning from reference answers: Versatile language model alignment without binary human preference data. *arXiv preprint arXiv:2504.09895*, 2025.
- [38] Yubo Wang, Xiang Yue, and Wenhua Chen. Critique fine-tuning: Learning to critique is more effective than learning to imitate. *arXiv preprint arXiv:2501.17703*, 2025.
- [39] An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, et al. Qwen2. 5 technical report. *arXiv preprint arXiv:2412.15115*, 2024.
- [40] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- [41] Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. When not to trust language models: Investigating effectiveness of parametric and non-parametric memories. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 9802–9822, 2023.
- [42] Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1601–1611, 2017.
- [43] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019.
- [44] Xanh Ho, Anh-Khoa Duong Nguyen, Saku Sugawara, and Akiko Aizawa. Constructing a multi-hop qa dataset for comprehensive evaluation of reasoning steps. *arXiv preprint arXiv:2011.01060*, 2020.
- [45] Ivan Stelmakh, Yi Luan, Bhuwan Dhingra, and Ming-Wei Chang. ASQA: Factoid questions meet long-form answers. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 8273–8288, 2022.
- [46] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov, and Christopher D Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. *arXiv preprint arXiv:1809.09600*, 2018.
- [47] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*, 2016.
- [48] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

- [49] Xiang Zhang, Muhammad Abdul-Mageed, and Laks VS Lakshmanan. Autoregressive+ chain of thought= recurrent: Recurrence’s role in language models’ computability and a revisit of recurrent transformer. *arXiv preprint arXiv:2409.09239*, 2024.
- [50] Xiang Zhang, Bradley Hauer, and Grzegorz Kondrak. Improving hownet-based chinese word sense disambiguation with translations. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 4530–4536, 2022.
- [51] Tianyu Gao, Howard Yen, Jiatong Yu, and Danqi Chen. Enabling large language models to generate text with citations. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 6465–6488, 2023.
- [52] Timo Schick, Jane Dwivedi-Yu, Roberto Dessi, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023.
- [53] SU Hongjin, Howard Yen, Mengzhou Xia, Weijia Shi, Niklas Muennighoff, Han-yu Wang, Liu Haisu, Quan Shi, Zachary S Siegel, Michael Tang, et al. Bright: A realistic and challenging benchmark for reasoning-intensive retrieval. In *The Thirteenth International Conference on Learning Representations*, 2024.
- [54] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2023.
- [55] Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*, pages 2206–2240. PMLR, 2022.
- [56] Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, Dasha Metropolitan, Robert Osazuwa Ness, and Jonathan Larson. From local to global: A graph rag approach to query-focused summarization. *arXiv preprint arXiv:2404.16130*, 2024.
- [57] Tianyu Fan, Jingyuan Wang, Xubin Ren, and Chao Huang. Minirag: Towards extremely simple retrieval-augmented generation. *arXiv preprint arXiv:2501.06713*, 2025.
- [58] Huatong Song, Jinhao Jiang, Yingqian Min, Jie Chen, Zhipeng Chen, Wayne Xin Zhao, Lei Fang, and Ji-Rong Wen. R1-searcher: Incentivizing the search capability in llms via reinforcement learning. *arXiv preprint arXiv:2503.05592*, 2025.
- [59] Zilong Wang, Zifeng Wang, Long Le, Huaixiu Steven Zheng, Swaroop Mishra, Vincent Perot, Yuwei Zhang, Anush Mattapalli, Ankur Taly, Jingbo Shang, et al. Speculative rag: Enhancing retrieval augmented generation through drafting. *arXiv preprint arXiv:2407.08223*, 2024.
- [60] Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6769–6781, 2020.
- [61] Peng Xu, Wei Ping, Xianchao Wu, Lawrence McAfee, Chen Zhu, Zihan Liu, Sandeep Subramanian, Evelina Bakhturina, Mohammad Shoeybi, and Bryan Catanzaro. Retrieval meets long context large language models. In *The Twelfth International Conference on Learning Representations*, 2024.
- [62] Chong Xiang, Tong Wu, Zexuan Zhong, David Wagner, Danqi Chen, and Prateek Mittal. Certifiably robust RAG against retrieval corruption. *arXiv preprint arXiv:2405.15556*, 2024.
- [63] Zexuan Zhong, Ziqing Huang, Alexander Wettig, and Danqi Chen. Poisoning retrieval corpora by injecting adversarial passages. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 13764–13775, 2023.

- [64] Wei Zou, Runpeng Geng, Binghui Wang, and Jinyuan Jia. PoisonedRAG: Knowledge poisoning attacks to retrieval-augmented generation of large language models. *arXiv preprint arXiv:2402.07867*, 2024.
- [65] Chao Jin, Zili Zhang, Xuanlin Jiang, Fangyue Liu, Xin Liu, Xuanzhe Liu, and Xin Jin. RAGCache: Efficient knowledge caching for retrieval-augmented generation. *arXiv preprint arXiv:2404.12457*, 2024.
- [66] Xiang Zhang, Senyu Li, Ning Shi, Bradley Hauer, Zijun Wu, Grzegorz Kondrak, Muhammad Abdul-Mageed, and Laks VS Lakshmanan. Cross-modal consistency in multimodal large language models. *arXiv preprint arXiv:2411.09273*, 2024.
- [67] Yuhan Liu, Hanchen Li, Kuntai Du, Jiayi Yao, Yihua Cheng, Yuyang Huang, Shan Lu, Michael Maire, Henry Hoffmann, Ari Holtzman, et al. CacheGen: Fast context loading for language model applications. *arXiv preprint arXiv:2310.07240*, 2023.
- [68] Chenyu You, Haocheng Dai, Yifei Min, Jasjeet S Sekhon, Sarang Joshi, and James S Duncan. Uncovering memorization effect in the presence of spurious correlations. *Nature Communications*, 16(1):5424, 2025.
- [69] Parth Sarthi, Salman Abdullah, Aditi Tuli, Shubh Khanna, Anna Goldie, and Christopher D Manning. RAPTOR: Recursive abstractive processing for tree-organized retrieval. *arXiv preprint arXiv:2401.18059*, 2024.
- [70] Puyuan Liu, Xiang Zhang, and Lili Mou. A character-level length-control algorithm for non-autoregressive sentence summarization. *Advances in Neural Information Processing Systems*, 35:29101–29112, 2022.
- [71] Mingyan Wu, Zhenghao Liu, Yukun Yan, Xinze Li, Shi Yu, Zheni Zeng, Yu Gu, and Ge Yu. Rankcot: Refining knowledge for retrieval-augmented generation through ranking chain-of-thoughts. *arXiv preprint arXiv:2502.17888*, 2025.
- [72] Zhicheng Lee, Shulin Cao, Jinxin Liu, Jiajie Zhang, Weichuan Liu, Xiaoyin Che, Lei Hou, and Juanzi Li. Rearag: Knowledge-guided reasoning enhances factuality of large reasoning models with iterative retrieval augmented generation. *arXiv preprint arXiv:2503.21729*, 2025.
- [73] Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegrefe, Uri Alon, Nouha Dziri, Shrimai Prabhunoye, Yiming Yang, et al. Self-refine: Iterative refinement with self-feedback. *Advances in Neural Information Processing Systems*, 36:46534–46594, 2023.
- [74] Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36:8634–8652, 2023.
- [75] Di Zhang, Xiaoshui Huang, Dongzhan Zhou, Yuqiang Li, and Wanli Ouyang. Accessing gpt-4 level mathematical olympiad solutions via monte carlo tree self-refine with llama-3 8b. *arXiv preprint arXiv:2406.07394*, 2024.
- [76] Arian Hosseini, Xingdi Yuan, Nikolay Malkin, Aaron Courville, Alessandro Sordoni, and Rishabh Agarwal. V-star: Training verifiers for self-taught reasoners. *arXiv preprint arXiv:2402.06457*, 2024.
- [77] Linzhuang Sun, Hao Liang, Jingxuan Wei, Bihui Yu, Tianpeng Li, Fan Yang, Zenan Zhou, and Wentao Zhang. Mm-verify: Enhancing multimodal reasoning with chain-of-thought verification. *arXiv preprint arXiv:2502.13383*, 2025.
- [78] Jiajie Jin, Yutao Zhu, Xinyu Yang, Chenghao Zhang, and Zhicheng Dou. FlashRAG: A modular toolkit for efficient retrieval-augmented generation research. *arXiv preprint arXiv:2405.13576*, 2024.
- [79] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36:53728–53741, 2023.

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes], [No], or [NA].
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes]" is generally preferable to "[No]", it is perfectly acceptable to answer "[No]" provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No]" or "[NA]" is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading “NeurIPS Paper Checklist”.**
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers.**

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope?

Answer: [Yes]

Justification: The abstract and introduction clearly state the paper’s contributions, such as reconceptualizing RAG as Retrieval-Augmented Reasoning, identifying Reasoning Misalignment, proposing AlignRAG with its Critique-Driven Alignment (CDA) and contrastive critique synthesis mechanism. These claims are supported by the experimental results presented, particularly in Section 5, and summarized in the conclusion.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: The paper discusses limitations in Appendix.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: While it uses established mathematical formulations for its components, it does not present new theoretical results in the form of theorems requiring formal proofs.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Section 5.1 "Experiment Setup" and Appendix A ("Experimental Details") provide extensive details. Appendix A.2 further provides hyperparameters for CLM fine-tuning (e.g., learning rate, batch size, optimizer, LoRA configurations). This level of detail should allow for a high degree of reproducibility.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: The paper explicitly states that the code for the experiments.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.

- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Section 5.1 (Experiment Setup) and Appendix A (Experimental Details, especially A.2 Implementation Details and A.3 Training Corpus Construction) provide comprehensive details on data sources and splits (standard benchmarks are used, and the construction of the new critique dataset is detailed), hyperparameters for CLM training (e.g., learning rate, batch size, LoRA rank, alpha, dropout), and the optimizer used (AdamW).

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: While the paper presents extensive empirical comparisons across multiple benchmarks, each primary experiment was conducted a single time to obtain the final results due to cost consideration.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Appendix A.2 details the implementation details.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: The research focuses on improving the factual reliability and reasoning alignment of large language models in RAG systems using publicly available datasets and models. There is no indication of human subject experimentation, data privacy violations, or other ethical concerns that would conflict with the NeurIPS Code of Ethics. The aim is to enhance model performance in a way that could lead to more trustworthy AI.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: The paper discuss both potential positive societal impacts and negative societal impacts of the work performed in Appendix.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.

- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: The paper does not propose the release of new large-scale pretrained language models or datasets scraped from the web that would typically carry a high risk for misuse. The primary new model component is a fine-tuned Critic Language Model (CLM) and a specific critique dataset. Therefore, safeguards for high-risk general-purpose model releases are not directly applicable.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: All datasets and baseline models are properly cited, with their respective licenses acknowledged in the text.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: The paper introduces a new model architecture and provides open access to the code via a link in the abstract. It is assumed that the code repository includes sufficient documentation alongside the assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The research described does not involve crowdsourcing or direct experiments with human subjects for data collection or evaluation.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The research does not involve human subjects; therefore, IRB approval or discussion of risks to participants is not applicable.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: The LLM usage is declared in the experimental setups.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Appendix

A.1 Limitations

While ALIGNRAG represents a significant step forward in retrieval-augmented reasoning through critique-guided optimization, several limitations remain. Although the framework improves robustness to noisy or partially irrelevant retrieved content, its effectiveness may diminish under extreme retrieval failure, specifically, when none of the retrieved documents are relevant to the query. In such cases, the quality of retrieval-augmented critiques deteriorates, as they are inherently dependent on the informativeness and accuracy of the retrieved evidence. Consequently, the CLM’s capacity to steer the generator toward faithful reasoning may be constrained. The interaction between retrieval quality and the model’s corrective ability remains an open area for further exploration. Moreover, despite being designed as a plug-and-play module, optimal integration of ALIGNRAG may require minor tuning depending on the generator LLM and the underlying RAG architecture. Standardizing adaptation protocols for deploying the CLM across diverse pipelines could enhance its ease of adoption and generalizability. Despite these limitations, ALIGNRAG establishes a robust foundation for improving evidence alignment in RAG systems and opens promising avenues for future research.

A.2 Additional Implementation Details

Retrieve Setup. We use the Wikipedia corpus provided by [78] as the default external knowledge source for retrieval. We evaluate our method on seven diverse QA benchmarks spanning multiple task types, including standard factoid QA, multi-hop reasoning, and long-form generation. PopQA [41], TriviaQA [42], NaturalQuestions [43], and SQuAD [47] fall under standard factoid QA, where models answer factual questions based on Wikipedia or web-based evidence.

- PopQA focuses on entity-centric questions derived from structured knowledge bases, testing factual recall over encyclopedic content.
- TriviaQA contains trivia-style questions authored by enthusiasts, each paired with multiple distant-supervised evidence documents.
- NaturalQuestions presents real user queries issued to Google Search, with answers extracted from Wikipedia, simulating realistic search behavior.
- ASQA [45] is a long-form QA benchmark focused on ambiguous questions with paragraph-level answers.
- 2WikiMultiHopQA [44] and HotpotQA [46] are multi-hop QA datasets that require reasoning over multiple passages. 2WikiMultiHopQA evaluates compositional reasoning across two Wikipedia articles, while HotpotQA incorporates both supporting and distracting sentences, encouraging interpretable multi-step reasoning.
- SQuAD is a widely used extractive QA dataset where answers are short spans from Wikipedia passages.

Following the setup in InstructRAG [13], we adopt dataset-specific retrievers for each query: Contriever-MS MARCO for PopQA and TriviaQA, DPR for NaturalQuestions, GTR for ASQA, and BM25 for 2WikiMultiHopQA. For HotpotQA and SQuAD, we adopt the e5-base-v2 encoder. By default, we retrieve the top 5 most relevant documents from Wikipedia corpus for each question.

Training Details. We fine-tune our models using the LoRA method on 2 NVIDIA A100 GPUs, each with 80GB of memory. The fine-tuning process is conducted over 2 epochs with a learning rate of $1e-5$ using the AdamW optimizer and employs a per-device batch size of 16, leveraging gradient accumulation to handle larger effective batch sizes. We set the LoRA-specific hyperparameters as follows: $lora_rank = 16$ and $lora_alpha = 64$, ensuring efficient adaptation to downstream tasks. The sequence cutoff length is 6144 tokens, with a warmup ratio of 0.1 applied to stabilize training. Additionally, we utilize bf16 (brain floating point) precision to reduce memory usage and accelerate training while maintaining numerical stability.

A.3 Training Corpus Construction Details

To systematically simulate varying degrees of answerability, we introduce a novel four-tier *Contextual Granularity Hierarchy* (Figure 1), which forms the basis for structured context-aware critique learning.

This hierarchy is designed to expose critique models to a broad spectrum of evidence conditions, thereby facilitating fine-grained supervision under explicitly controlled scenarios.

The hierarchy is defined along three orthogonal dimensions of contextual variation—*relevance*, *helpfulness*, and *completeness*—and comprises the following four levels:

Hierarchy-1: Not Relevant, Not Helpful, Not Complete. We sample 200 instances per benchmark, where the context is randomly selected from evidence retrieved for unrelated questions. These contexts are neither topically relevant nor contain partial answers, thus offering no utility in addressing the question.

Hierarchy-2: Relevant, Not Helpful, Not Complete. We sample 400 instances per benchmark, in which the retrieved context comprises the top-5 documents relevant to the question but lacking any content that supports a correct answer. Although relevant, these contexts remain unhelpful and incomplete.

Hierarchy-3 & 4: Relevant, Helpful, Not Complete / Complete. We sample 1,400 instances per benchmark where the context is both relevant and helpful, containing either partial (no single document provides a complete answer) or complete answer-supporting information. To capture varying levels of difficulty, we categorize queries into five tiers based on the number of documents that individually contain supporting evidence (ranging from 1 to 5). Easier queries correspond to a higher number of such documents. We sample 400, 400, 200, 200, and 200 instances across these five levels, respectively.

This hierarchical corpus introduces a novel fine-grained supervision signal for training critique models, enabling a more nuanced understanding of answerability and evidence quality in retrieval-augmented generation.

A.4 Critic LLM Training via CPO

In addition to *Critique Fine-Tuning (CFT)*, we introduce a novel training paradigm for critique language models, termed **Critique Preference Optimization (CPO)**. CPO extends the Direct Preference Optimization (DPO) framework [79] to the domain of critique generation, enabling preference-based alignment of critique models with respect to human-quality judgments.

For each training example, we construct a pair of candidate critiques: a *rejected* critique $\Delta y_{\text{unexp}}^-$ generated by a weaker model $\mathcal{M}_{\text{weak}}$, and an *accepted* critique $\Delta y_{\text{unexp}}^+$ from a stronger model $\mathcal{M}_{\text{strong}}$. The critic model $\mathcal{M}_{\text{critic}}$ is then optimized to prefer the stronger critique over the weaker one using a ranking-based objective:

$$\mathcal{L}_{\text{CPO}} = -\mathbb{E}_{\mathcal{C}} \left[\log \sigma \left(\beta \log \frac{p_{\theta}(\Delta y_{\text{unexp}}^+ | q, \mathcal{D}, y_{\text{unexp}}^+)}{p_{\theta}(\Delta y_{\text{unexp}}^- | q, \mathcal{D}, y_{\text{unexp}}^+)} \right) \right], \quad (12)$$

where $\sigma(\cdot)$ denotes the sigmoid function, β is a temperature parameter controlling preference sharpness, and p_{θ} is the conditional likelihood of a critique under the model. Importantly, the conditioning includes the stronger generation y_{unexp}^+ to ground the critique in high-quality reference behavior.

This training strategy represents a novel application of preference optimization to the critique generation setting. It allows the model to learn fine-grained distinctions in critique quality and improves alignment with human preferences, surpassing traditional supervised learning approaches in adaptability and scalability.

A.5 Pseudo-code of Novel Algorithms for Critique-Aware Learning

To promote clarity and reproducibility, we present formalized pseudo-code for the core contributions of our framework, highlighting novel procedures for critique generation, fine-tuning, and alignment. These algorithmic components reflect our key innovations in critique-aware generation and optimization.

Algorithm 1 introduces **Contrastive Critique Synthesis**, a novel mechanism that elicits actionable critiques by contrasting outputs from a weak and a strong model. This facilitates the identification of failure modes in weaker generations using preference-informed critique models. Algorithm 2, **Critique Fine-Tuning (CFT)**, formalizes a supervised learning regime using synthetic critiques and structured input templates to fine-tune a base model toward producing useful critiques.

In Algorithm 3, we present **Critique Preference Optimization (CPO)**, which extends the Direct Preference Optimization (DPO) framework to critique generation. This formulation enables preference-based alignment of critique models using pairs of more and less preferred critiques. Lastly, Algorithm 4 describes **Critique-Driven Alignment (CDA)**, a novel iterative refinement procedure that integrates critique signals into the generation loop, producing responses that are successively improved based on model-generated feedback.

Collectively, these algorithmic components define a unified, modular framework for critique-aware alignment, marking a novel contribution to controllable and preference-aligned language model training.

Algorithm 1 CONTRASTIVE CRITIQUE SYNTHESIS (Novel critique generation via response comparison)

Require: Input query q , contextual grounding \mathcal{D} , weak model $\mathcal{M}_{\text{weak}}$, strong model $\mathcal{M}_{\text{strong}}$, critique model $\mathcal{M}_{\text{critic}}$

Ensure: Generated critique Δy_{unexp} for weak model output

- 1: $y_{\text{unexp}} \leftarrow \mathcal{M}_{\text{weak}}(q, \mathcal{D})$ ▷ Generate suboptimal response
 - 2: $y_{\text{exp}} \leftarrow \mathcal{M}_{\text{strong}}(q, \mathcal{D})$ ▷ Generate preferred response
 - 3: $\mathcal{X}_{\text{pref}} \leftarrow (q, \mathcal{D}, y_{\text{exp}}, y_{\text{unexp}})$ ▷ Construct preference-informed input
 - 4: $\Delta y_{\text{unexp}} \leftarrow \mathcal{M}_{\text{critic}}(\mathcal{X}_{\text{pref}})$ ▷ Generate contrastive critique
 - 5: $\Delta y_{\text{unexp}} \leftarrow \mathcal{G}(\Delta y_{\text{unexp}}, y_{\text{exp}})$ ▷ Refine critique with improvement guidance
 - 6: **return** Δy_{unexp}
-

Algorithm 2 CRITIQUE FINE-TUNING (CFT): Supervised adaptation via synthetic critiques

Require: Base model $\mathcal{M}_{\text{weak}}$, synthetic dataset \mathcal{C} , template $\mathcal{I}_{\text{critic}}$, learning rate η , epochs N

Ensure: Critique-aware model $\mathcal{M}_{\text{critic}}$

- 1: $\mathcal{M}_{\text{critic}} \leftarrow \mathcal{M}_{\text{weak}}$ ▷ Initialize from weak model
 - 2: **for** epoch = 1 to N **do**
 - 3: **for** each $(q, \mathcal{D}, y_{\text{unexp}}, \Delta y_{\text{unexp}}, y_{\text{exp}}) \in \mathcal{C}$ **do**
 - 4: $\mathcal{I}_{\text{critic}} \leftarrow (q, \mathcal{D}, y_{\text{unexp}}, y_{\text{exp}})$ ▷ Compose critique context
 - 5: $\Delta \hat{y}_{\text{unexp}} \sim p_{\theta}(\cdot | \mathcal{I}_{\text{critic}})$ ▷ Predict critique
 - 6: $\mathcal{L}_{\text{CFT}} \leftarrow -\log p_{\theta}(\Delta y_{\text{unexp}} | \mathcal{I}_{\text{critic}})$ ▷ Compute NLL loss
 - 7: $\theta \leftarrow \theta - \eta \nabla_{\theta} \mathcal{L}_{\text{CFT}}$ ▷ Update model
 - 8: **return** $\mathcal{M}_{\text{critic}}$
-

Algorithm 3 CRITIQUE PREFERENCE OPTIMIZATION (CPO): Alignment via pairwise critique preferences

Require: Queries $\{q\}$, contexts $\{\mathcal{D}\}$, weak model $\mathcal{M}_{\text{weak}}$, strong model $\mathcal{M}_{\text{strong}}$, initial model $\mathcal{M}_{\text{critic}}$, temperature β

Ensure: Preference-aligned critique model $\mathcal{M}_{\text{critic}}$

- 1: **for** each (q, \mathcal{D}) **do**
 - 2: $\Delta y_{\text{unexp}}^- \leftarrow \mathcal{M}_{\text{weak}}(q, \mathcal{D})$ ▷ Infer less-preferred critique
 - 3: $\Delta y_{\text{unexp}}^+ \leftarrow \mathcal{M}_{\text{strong}}(q, \mathcal{D})$ ▷ Infer preferred critique
 - 4: $\mathcal{P} \leftarrow (\Delta y_{\text{unexp}}^-, \Delta y_{\text{unexp}}^+)$ ▷ Construct preference pair
 - 5: **for** epoch = 1 to N **do**
 - 6: **for** each $\mathcal{P} = (\Delta y^-, \Delta y^+)$ **do**
 - 7: Compute preference loss \mathcal{L}_{DPO} ▷ Direct Preference Optimization loss
 - 8: $\theta \leftarrow \theta - \eta \nabla_{\theta} \mathcal{L}_{\text{DPO}}$ ▷ Update parameters
 - 9: **return** $\mathcal{M}_{\text{critic}}$
-

Algorithm 4 CRITIQUE-DRIVEN ALIGNMENT (CDA): Iterative refinement via model-generated critique signals

Require: Query q , document set $\mathcal{D} = \{d_1, \dots, d_n\}$, generation model \mathcal{M}_{gen} , critique model $\mathcal{M}_{\text{critic}}$, iterations T

Ensure: Refined, critique-aligned response y_{exp}

- 1: $y_0 \leftarrow \mathcal{M}_{\text{gen}}(q, \mathcal{D})$ ▷ Initial retrieval-augmented generation
 - 2: **for** $t = 0$ to $T-1$ **do**
 - 3: $\Delta y_t \leftarrow \mathcal{M}_{\text{critic}}(y_t, q, \mathcal{D})$ ▷ Critique current response
 - 4: $y_{t+1} \leftarrow \mathcal{M}_{\text{gen}}(y_t \oplus \Delta y_t, q, \mathcal{D})$ ▷ Refine using critique
 - 5: $y_{\text{exp}} \leftarrow y_T$ ▷ Final critique-aware output
 - 6: **return** y_{exp}
-

A.6 Additional Experiment Results

In this section, we present additional experimental results to provide a comprehensive understanding of the proposed method and its performance under various conditions.

Generalization to Out-of-Distribution Data. To supplement the OOD generalization results in Figure 3, Table 6 provides a complete breakdown of ID and OOD performance across benchmarks and backbones. While the main text reports average performance drops between ID and OOD settings, the detailed analysis reveals that ALIGNRAG reduces the OOD drop significantly (e.g., from 40.3 to 32.2 on Qwen2.5-7B and from 44.0 to 33.1 on LLaMA3.1-8B) compared to SELF-REFINE. Additionally, ALIGNRAG achieves substantial absolute gains on OOD datasets (e.g., +12.4 on HotpotQA and +11.5 on SQuAD for Qwen2.5-7B), demonstrating improved generalization capabilities under domain shifts. These results confirm that the proposed CDA-based alignment strategy enhances model robustness across distributions without overfitting to the training data.

Robustness under Retrieval Quality Variance. To evaluate robustness under varying retrieval conditions, we compare Vanilla RAG, SELF-REFINE, and ALIGNRAG in two retrieval scenarios: (*Informative*) and (*Noisy*). Figure 9 summarizes the results. In the *Noisy* scenario, where noisy or misleading retrieval often causes reasoning misalignment, ALIGNRAG consistently outperforms the baselines. For example, on NaturalQuestions (e.g., +5.6 on Qwen2.5-7B) and 2WikiMultiHopQA (e.g., +3.9 on LLaMA3.1-8B)—two tasks particularly sensitive to retrieval quality—ALIGNRAG achieves the largest margins over SELF-REFINE. Even in the *Informative* scenario, where retrieved documents are highly relevant, ALIGNRAG demonstrates superior accuracy (e.g., +1.9 on ASQA and +4.7 on 2WikiMultiHopQA using Qwen2.5-14B). These results illustrate that ALIGNRAG enhances reasoning robustness across a wide range of retrieval quality levels.

Integration into Existing RAG Pipelines. To assess the plug-and-play compatibility of our alignment strategy, we integrate it into the INSTRUCTRAG framework across three backbones and evaluate its performance on seven benchmarks. The detailed results, provided in Figure 8, reveal that our alignment approach consistently improves accuracy, both for in-domain datasets (e.g., PopQA, TriviaQA) and OOD datasets (e.g., SQuAD, HotpotQA). Notably, the improvements are particularly pronounced on challenging datasets such as SQuAD (+10.2 on Qwen2.5-14B) and HotpotQA (+8.6 on Qwen2.5-14B) when leveraging the 72B model in our CCS pipeline. These results demonstrate that our method can be seamlessly incorporated into existing RAG pipelines, enabling substantial test-time improvements without requiring modifications to the model architecture or training objectives.

Superior Alignment Guidance Surpassing Strong LLM Baselines. To validate the effectiveness of contrastive critique supervision when guided by a 72B model, we report full results across seven QA benchmarks in Table 3. Our method consistently outperforms both vanilla critique synthesis and direct CLM supervision. Notably, the improvements are more pronounced on complex datasets such as HotpotQA and SQuAD, where our method yields gains of up to +9.2 and +6.0 on Qwen2.5-7B, respectively, over direct supervision. These results confirm that contrastive critique signals distilled from a stronger model can significantly enhance the generalization ability of smaller CLMs.

Different Training Strategies for CLM. To compare training strategies for the CLM, Table 5 evaluates our proposed Critique Fine-tuning (CFT) approach against Critique Preference Optimization (CPO) A.4. Across three backbones and seven benchmarks, CFT consistently outperforms CPO, particularly on retrieval-sensitive and OOD-heavy tasks such as HotpotQA and SQuAD. For example, on Qwen2.5-14B, CFT raises the average accuracy from 51.0 to 53.6 and improves performance on SQuAD from 20.2 to 26.6. Similarly, on LLaMA3.1-8B, CFT achieves a +4.0 gain in average performance and a +10.0 improvement on SQuAD. These results underscore the superiority of preference-based critique generation over preference-based output generation for CLM training, particularly in retrieval-intensive contexts.

Ablation on CLM and Contrastive Critique Synthesis. To supplement the high-level ablation analysis, Table 4 presents detailed results for seven benchmarks under four Critic Language Model (CLM) configurations. While the main text reports averaged scores on seven benchmarks, the table provides detailed results. Introducing a frozen CLM yields noticeable gains over Vanilla RAG (e.g., +3.8 on PopQA and +3.9 on ASQA for Qwen2.5-7B), confirming the utility of auxiliary critique.

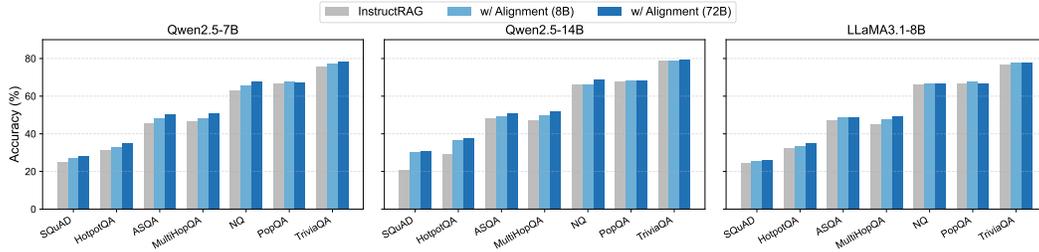
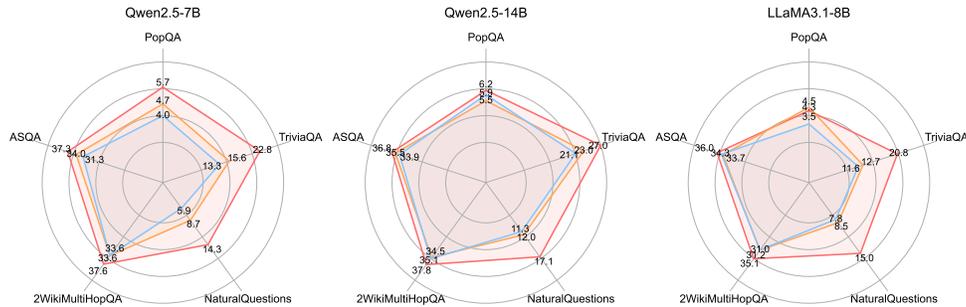
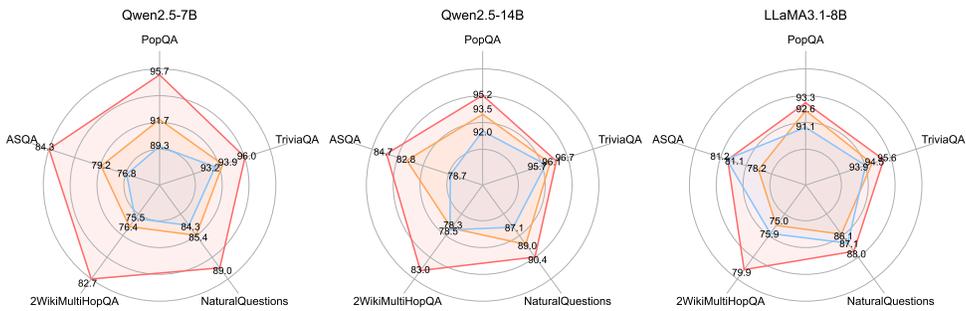


Figure 8: Details of evaluation result of InstructRAG w/o and w/ our Alignment method on three backbones across seven benchmarks.



(a) w/o answer.



(b) w/ answer.

Figure 9: Performance of different methods under *Unanswerable* (a) and *Answerable* (b) retrieval conditions. Each radar chart reports the average performance across three instruction-tuned backbones on five benchmarks.

Further training of the CLM amplifies these benefits, particularly for OOD datasets such as SQuAD and HotpotQA. Notably, our contrastive critique synthesis (CCS) achieves the best performance on nearly all benchmarks, including a +2.2 gain on MultiHopQA and +4.7 gain on SQuAD for Qwen2.5-14B. These results demonstrate that contrastive alignment is crucial for generating retrieval-sensitive critiques, leading to consistent and robust improvements across diverse QA scenarios.

Table 3: Detailed results of performance comparison of different trained CLM when using a 72B model to supervise.

Method	PopQA (acc)	TriviaQA (acc)	NQ (acc)	MultiHopQA (acc)	ASQA (em)	HotpotQA (acc)	SQuAD (acc)	Avg.
<i>Vanilla Critique Synthesis</i>								
Qwen2.5-7B	66.6	76.2	65.4	46.0	47.9	25.2	17.9	49.3
Qwen2.5-14B	67.5	78.9	66.8	47.5	48.7	29.6	21.2	51.5
LLaMA3.1-8B	66.6	75.7	64.4	43.7	47.1	22.9	13.2	47.7
<i>Direct CLM (72B)</i>								
Qwen2.5-7B	66.4	78.7	66.8	46.9	49.3	24.7	18.2	50.1
Qwen2.5-14B	68.6	79.3	67.8	47.4	49.3	26.8	19.7	51.3
LLaMA3.1-8B	67.1	78.9	66.4	45.7	49.1	24.2	15.9	49.6
<i>Ours</i>								
Qwen2.5-7B	66.0	77.5	66.4	49.9	48.6	33.9	24.2	52.4
Qwen2.5-14B	66.9	79.4	68.6	50.7	49.9	35.5	25.4	53.8
LLaMA3.1-8B	66.6	77.0	66.3	49.6	48.2	32.0	20.7	51.5

Table 4: Details of ablation study on the CLM and CCS. Frozen CLM refers to a vanilla LLaMA3.1-8B used as the critic. CCS refers to our proposed contrastive critique synthesis.

Method	PopQA (acc)	TriviaQA (acc)	NQ (acc)	MultiHopQA (acc)	ASQA (em)	HotpotQA (acc)	SQuAD (acc)	Avg.
<i>Vanilla RAG</i>								
Qwen2.5-7B	63.7	73.2	60.2	44.7	42.8	18.5	9.0	44.6
Qwen2.5-14B	65.3	77.0	63.6	44.8	45.2	23.3	12.6	47.4
LLaMA3.1-8B	65.0	73.4	62.0	43.0	45.2	17.1	6.1	44.5
<i>w/ Frozen CLM</i>								
Qwen2.5-7B	67.5	75.1	62.5	45.4	46.7	20.6	13.4	47.3
Qwen2.5-14B	68.0	78.0	65.1	46.6	48.1	25.3	15.6	49.5
LLaMA3.1-8B	66.1	74.1	61.4	42.8	44.7	18.8	8.7	45.2
<i>w/ Trained CLM</i>								
Qwen2.5-7B	66.9	76.1	64.0	46.7	46.5	26.8	19.9	49.6
Qwen2.5-14B	67.1	78.4	65.7	47.6	48.8	30.0	21.9	51.4
LLaMA3.1-8B	65.1	74.3	62.7	42.8	46.5	25.2	16.3	47.6
<i>w/ Trained CLM, w/ CCS (Ours)</i>								
Qwen2.5-7B	68.4	77.8	65.9	49.5	48.9	33.7	26.1	52.9
Qwen2.5-14B	68.4	79.5	67.7	49.8	48.6	34.8	26.6	53.6
LLaMA3.1-8B	66.5	77.0	65.3	47.0	47.1	32.2	22.8	51.1

Table 5: Overall performance comparison of Critic Language Model using different training methods.

Method	PopQA (acc)	TriviaQA (acc)	NQ (acc)	MultiHopQA (acc)	ASQA (em)	HotpotQA (acc)	SQuAD (acc)	Avg.
<i>Qwen2.5-7B</i>								
CPO	66.1	76.3	63.5	46.3	47.1	25.6	17.3	48.9
Ours	68.4	77.8	65.9	49.5	48.9	33.7	26.1	52.9
<i>Qwen2.5-14B</i>								
CPO	67.5	78.6	66.1	47.4	47.7	29.5	20.2	51.0
Ours	68.4	79.5	67.7	49.8	48.6	34.8	26.6	53.6
<i>LLaMA3.1-8B</i>								
CPO	66.4	75.0	62.7	44.0	45.7	23.2	12.8	47.1
Ours	66.5	77.0	65.3	47.0	47.1	32.2	22.8	51.1

Table 6: Drop in average Out-of-Distribution performance compared to average In-Domain performance across three instruction-tuned backbones. Lower values indicate better generalization capability.

Method	PopQA (acc)	TriviaQA (acc)	NQ (acc)	MultiHopQA (acc)	ASQA (em)	Avg.	HotpotQA (acc)	SQuAD (acc)	Avg.	Drop.
<i>Qwen2.5-7B</i>										
Vanilla RAG	63.7	73.2	60.2	44.7	42.8	56.9	18.5	9.0	13.8	43.1
Self-Refine	65.5	74.4	61.6	45.0	45.2	58.3	21.3	14.6	18.0	40.3
AlignRAG	68.4	77.8	65.9	49.5	48.9	62.1	33.7	26.1	29.9	32.2
<i>Qwen2.5-14B</i>										
Vanilla RAG	65.3	77.0	63.6	44.8	45.2	59.2	23.3	12.6	18.0	41.2
Self-Refine	67.0	78.0	65.1	46.1	47.3	60.7	24.4	16.0	20.2	40.5
AlignRAG	68.4	79.5	67.7	49.8	48.6	62.8	34.8	26.6	30.7	32.1
<i>LLaMA3.1-8B</i>										
Vanilla RAG	65.0	73.4	62.0	43.0	45.2	57.7	17.1	6.1	11.6	46.1
Self-Refine	66.1	74.1	61.4	42.8	44.7	57.8	18.8	8.7	13.8	44.0
AlignRAG	66.5	77.0	65.3	47.0	47.1	60.6	32.2	22.8	27.5	33.1

A.7 Prompt Templates

Critique Synthesis Prompt. We propose a novel structured pipeline for generating targeted feedback to train critic models, systematically deriving critiques from contrasting outputs of large language models (LLMs). To ensure the critiques are both consistent and informative, we introduce a *preference-augmented input* as a key component in the critique generation process. This approach is grounded in the use of pairwise comparisons of reasoning paths, which provides two core innovations. First, it constrains the output space of the critique language model (CLM), ensuring consistency and minimizing noise during critique generation [36]. Second, it generates high-quality reasoning traces that facilitate the creation of constructive, fine-grained feedback. The pairwise-path formulation is central to this framework: by contrasting the reasoning processes underlying y_{unexp} (unexpected response) and y_{exp} (expected response), the CLM synthesizes critiques that directly inform model supervision. This is exemplified in Tab. 7 (for rationale generation) and Tab. 9 (for critique generation). This structured methodology not only enhances the quality of the generated critiques but also ensures they are targeted, actionable, and aligned with the requirements of improving weaker models.

Critique Learning Prompt. To further advance critique generation, we introduce the concept of *critique learning*, where the objective is to generate a critique, denoted as Δy_{unexp} , that captures the divergence between expected and unexpected responses while incorporating user-defined preferences. As part of this framework, we present a novel Critique Fine-Tuning (CFT) prompt (see Tab. 10 for details) designed to optimize the learning process for critique generation. Additionally, we explore an alternative training strategy, *Critique Preference Optimization (CPO)*, which explicitly aligns critique generation with user-defined preference signals (see Tab. 11 for the corresponding prompt). These prompts, tailored for critique learning, establish a principled mechanism for training models to generate preference-aligned critiques.

Critique-driven Alignment Prompt. We introduce a novel framework, *Critique-driven Alignment (CDA)*, to address reasoning misalignment in retrieval-augmented generation (RAG) systems. CDA reimagines the RAG inference process as a discrete-time dynamical system operating over a latent reasoning space \mathcal{Y} . Within this framework, the inference process is iteratively refined by a meta-reasoning module $\mathcal{M}_{\text{critic}}$, which critiques intermediate outputs and proposes targeted improvements. This iterative refinement produces a sequence of progressively improved responses, ensuring reasoning alignment.

CDA leverages three distinct prompt types to structure the refinement pipeline effectively:

- **Rationale Generation:** Using the rationale generation template (see Tab. 12), the system generates an initial explanation or reasoning chain to support the initial response y_0 . This rationale serves as the foundation for critique generation in subsequent steps.
- **Critique Generation:** Using the critique generation template (see Tab. 13), the meta-reasoning module $\mathcal{M}_{\text{critic}}$ identifies reasoning gaps or inconsistencies in the intermediate response y_t based on the rationale and provides an actionable critique Δy_t .
- **Refinement Generation:** Using the refinement generation template (see Tab. 14), the system incorporates the critique Δy_t into the generation process to produce the refined response y_{t+1} . This ensures that the updated response aligns with the critique feedback while maintaining coherence and relevance to the original query q .

By iteratively applying these three prompts, the CDA framework introduces a systematic and controlled refinement process that enhances reasoning alignment and response quality over successive iterations. This novel paradigm ensures that critiques are not only actionable but also effectively integrated into the refinement process to achieve consistent improvements in reasoning accuracy.

Table 7: Rationale generation prompt template for critique synthesis [13].

Rationale Generation for Critique Synthesis
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Please identify documents that are useful to answer the given question: “{question}”, and explain how the contents lead to the answer: {answer}.</p> <p>If none of the documents is aligned with the answer, in that case, you have to explain the answer only based on your own knowledge, without referring to the provided information.</p> <p>{task-specific instruction}</p> <p>Output: {rationale}</p>

Table 8: Task-specific instruction used in rationale generation prompt [13].

Task-specific Instruction for Rationale Generation
<p>ASQA: Note that the question may be ambiguous and have multiple correct answers. Make sure your response includes all correct answers and provides clear reasoning details followed by a concise conclusion.</p> <p>PopQA: Note that the question mainly asks about the object entity that holds a certain relationship with the given subject entity. There may be multiple correct answers. Make sure your response includes all correct answers and provides clear reasoning details followed by a concise conclusion.</p> <p>TriviaQA / Natural Questions / 2WikiMultiHopQA: Note that the question may be compositional and require intermediate analysis to deduce the final answer. Make sure your response is grounded and provides clear reasoning details followed by a concise conclusion.</p>

Table 9: Critique generation prompt template for critique synthesis.

Critique Generation for Critique Synthesis
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Here is the given weak rationale: {weak_rationale}. Here is the given gold rationale: {gold_rationale}.</p> <p>First, explain how the gold rationale leads to the answer step by step.</p> <p>Then, identify the errors and hallucinations of the weak rationale, and give constructive criticism for improving the weak rationale to be more aligned with the gold rationale.</p> <p>Output: {critique}</p>

Table 10: Augmented critique generation prompt template for critique fine-tuning (CFT).

Augmented Critique Generation for Critique Fine-tuning (CFT)
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Here is the given weak rationale: {weak_rationale}.</p> <p>Please identify the weaknesses and hallucinations of the rationale, and give constructive criticism for improving the weak rationale.</p> <p>Output:</p> <p>The critique for the rationale is: {critique}. The better rationale should be: {gold_rationale}.</p>

Table 11: Critique generation prompt template for critique preference optimization (CPO).

Augmented Critique Generation for Critique Preference optimization (CPO)
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Here is the given weak rationale: {weak_rationale}.</p> <p>Please identify the weaknesses and hallucinations of the rationale, and give constructive criticism for improving the weak rationale.</p> <p>Chosen: The critique for the rationale is: {weak_critique}. Rejected: The critique for the rationale is: {gold_critique}.</p>

Table 12: Rationale generation prompt template for Critique-driven Alignment.

Rationale Generation for Critique-driven Alignment
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Please identify documents that are useful to answer the given question: “{question}”, and explain how the contents lead to the answer: {answer}.</p> <p>Output: {rationale}</p>

A.8 Case Study

To provide a concrete illustration of the reasoning misalignment issues our framework addresses, we present a series of case studies. These examples demonstrate how failures can occur at each of the three distinct phases of retrieval-augmented reasoning—Relevance Assessment, Query-Evidence

Table 13: Critique generation prompt template for Critique-driven Alignment.

Critique Generation for Critique-driven Alignment
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Here is the given weak rationale: {weak_rationale}.</p> <p>Please identify the weaknesses and hallucinations of the rationale, and give constructive criticism for improving the weak rationale.</p> <p>Output: {critique}</p>

Table 14: Refinement generation prompt template for Critique-driven Alignment.

Refinement Generation for Critique-driven Alignment
<p>Input: Read the following documents relevant to the given question: {question}</p> <p>Document [1] (Title: ...): {contents} ...</p> <p>Here is the given weak rationale: {weak_rationale}.</p> <p>Here is the given critique: critique.</p> <p>Please correct the weak rationale based on the critique, and write a better rationale to explain how the contents lead to the answer.</p> <p>Output: {refinement}</p>

Mapping, and Evidence-Integrated Synthesis—even when the initial retrieval is successful. We also include a failure analysis of our own model, ALIGNRAG, to highlight its limitations.

A.8.1 Illustrating Reasoning Misalignment

Case 1: Misalignment in Relevance Assessment. This case demonstrates a failure in the initial reasoning phase, where the model incorrectly dismisses highly relevant evidence. The retriever successfully finds a document containing the correct answer, but the generator’s internal relevance assessment fails, causing it to discard the evidence and claim the information is unavailable. This highlights that successful retrieval is insufficient if the model cannot recognize the value of the retrieved content.

Table 15: An example of misalignment in Phase 1 (Relevance Assessment).

Failure Mode: Relevance Misjudgment	
Question	Who is the mother of Mary in Islam?
Golden Answer	Hannah
Retrieved Evidence	Document 2 explicitly states, “Hannah, the mother of Mary...”
Initial Response	“The given documents are not relevant to the question.”
Critic Evaluation	[Bad] — Model failed to recognize clearly relevant evidence.
Refined Response	“Hannah is mentioned as the mother of Mary in the provided context.”

Case 2: Misalignment in Query-Evidence Mapping. In this scenario, the model fails during the mapping phase. Although multiple documents are retrieved, the model latches onto a document with a vague thematic association (Document 1) while ignoring another document (Document 5) that contains the precise, explicit answer. This mapping failure demonstrates the challenge of aligning the specific query with the most salient evidence span, a critical step for accurate, grounded generation.

Table 16: An example of misalignment in Phase 2 (Query-Evidence Mapping).

Failure Mode: Evidence Mapping Failure	
Question	What name is given to a very long forward pass in football made in desperation?
Golden Answer	Hail Mary
Retrieved Evidence	Document 5 directly defines the “Hail Mary pass” in this context.
Initial Response	The model cites Document 1, which discusses related football terms but ignores the direct definition in Document 5.
Critic Evaluation	[Bad] — Model missed the most direct and salient piece of evidence.
Refined Response	Correctly identifies “Hail Mary” using the evidence from Document 5.

Case 3: Misalignment in Synthesis. This case illustrates a failure at the final synthesis stage. The model correctly identifies and internally processes the relevant document containing the answer. However, it fails to integrate this crucial piece of information into its final generated output. The evidence is understood but ultimately omitted, rendering the response incomplete and unhelpful. This shows that even with perfect retrieval and mapping, the synthesis process itself can be a point of failure.

Table 17: An example of misalignment in Phase 3 (Synthesis).

Failure Mode: Synthesis Error	
Question	Who was the director of Alexander?
Golden Answer	Oliver Stone
Retrieved Evidence	Document 5 states, “It was directed by Oliver Stone...”
Initial Response	The model discusses the movie but fails to state the director’s name, despite having access to the information.
Critic Evaluation	[Bad] — Information was present in the evidence but was omitted in the final output.
Refined Response	“The only director identified in the provided documents is Oliver Stone.”

A.8.2 Failure Analysis of ALIGNRAG

While ALIGNRAG is designed to correct the misalignments above, it is not without its own failure modes. The most critical weakness arises when the initial retrieval is incomplete or fails to provide any relevant evidence. In such cases, the Critic Language Model (CLM) may attempt to “over-correct” the initial response by injecting factual knowledge from its own parameters, which is not grounded in the provided context. This can lead to factual drift and produce a refined response that is still incorrect but for a different reason.

A.9 Broader Impact

The AlignRAG framework promises positive societal impact by enhancing the factual reliability and evidence-grounded reasoning of LLMs, potentially leading to more trustworthy AI systems in areas like education, research, and complex decision-support, thereby reducing the spread of unsupported or misaligned information. This can empower users with more accurate and verifiable information. However, challenges and risks must be acknowledged: an increased perception of reliability, even if improved, could lead to over-reliance by users and a reduction in critical scrutiny. Furthermore, the critique mechanism itself, while aiming for better alignment, might inadvertently

Table 18: A representative failure case for ALIGNRAG.

Failure Mode: Over-Correction due to Weak Retrieval	
Question	When was the first 10 dollar bill made?
Golden Answer	1861
Retrieved Evidence	No retrieved document explicitly mentioned the year 1861.
Initial Response	“The first 10 dollar bill was issued in 1911.” (Incorrect)
Critic Evaluation	[Bad] — The critique proposed the year 1914, likely based on the CLM’s internal knowledge rather than the provided evidence.
Refined Response	“The first \$10 bill was made in 1914.” (Incorrect)

absorb or amplify subtle biases present in the data used for training the Critic Language Model or in the "expert" examples used for contrastive synthesis if not meticulously curated and audited. Therefore, the responsible development and deployment of such advanced RAG systems necessitate ongoing research into robust bias detection and mitigation techniques, ensuring diversity in training data and retrieved evidence, and promoting digital literacy to encourage critical user engagement with AI-generated content.