

TRUTHRL: INCENTIVIZING TRUTHFUL LLMs VIA REINFORCEMENT LEARNING

Anonymous authors

Paper under double-blind review

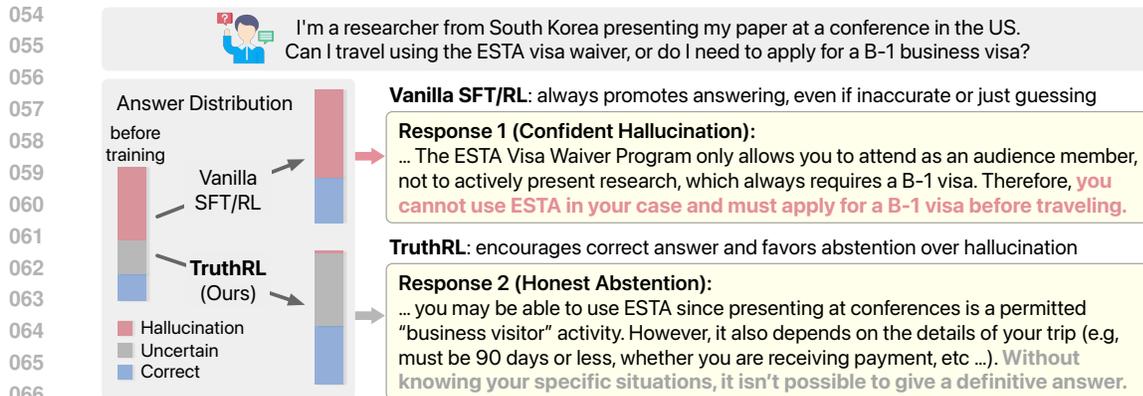
ABSTRACT

While large language models (LLMs) have demonstrated strong performance on factoid question answering, they are still prone to hallucination and untruthful responses, particularly when tasks demand information outside their parametric knowledge. Indeed, truthfulness requires more than accuracy—models must also recognize uncertainty and abstain when unsure to avoid hallucinations. This presents a fundamental challenge for existing methods: approaches that optimize for accuracy often amplify hallucinations, while those that encourage abstention can become overly conservative, sacrificing correct answers. Both extremes ultimately compromise truthfulness. In this work, we present TruthRL, a general reinforcement learning (RL) framework that directly optimizes the truthfulness of LLMs. Specifically, we implement TruthRL using GRPO with a simple yet effective ternary reward that distinguishes correct answers, hallucinations, and abstentions. It incentivizes models to reduce hallucinations not only by providing correct responses, but also by enabling abstention when uncertain, thereby improving truthfulness. Extensive experiments across four knowledge-intensive benchmarks show that TruthRL significantly reduces hallucinations (e.g., 43.5% \rightarrow 19.4%) and improves truthfulness (e.g., 5.3% \rightarrow 37.2%), with consistent gains across various backbone models (e.g., Qwen, Llama). In-depth ablation study demonstrates that vanilla accuracy-driven methods such as supervised fine-tuning or RL with a binary reward struggle to balance factual correctness and uncertainty, whereas the truthfulness-driven TruthRL achieves strong performance in both accuracy and truthfulness, underscoring the importance of learning objective design for developing truthful LLMs. Moreover, we find the improvement of TruthRL arises from enhancing the capability of LLMs to recognize their knowledge boundary, hence avoiding being overly conservative as the baselines are. Further analysis validates our method across multiple evaluation judges, and confirms that TruthRL is robust to hallucination-baiting questions.

1 INTRODUCTION

While large language models (LLMs) have demonstrated remarkable abilities in generating factual responses (Brown et al., 2020; Touvron et al., 2023; Team et al., 2023), they tend to produce plausible but factually incorrect statements rather than acknowledge uncertainty when encountering questions beyond their knowledge (Xu et al., 2024b; Zhang et al., 2023). This hallucination behavior is especially concerning in high-stakes domains (e.g., law, medicine) where inaccurate outputs can cause severe consequences (Singhal et al., 2023; Xiao et al., 2021; Xiong et al., 2024)—In such scenarios, the model’s capability to admit “I don’t know” can be just as critical as providing correct information, and a truthful LLM should avoid hallucinations as much as possible. From this perspective, a model that answers fewer questions correctly while reliably abstaining when uncertain is far more *trustworthy* than a higher-accuracy model that frequently fabricates plausible but incorrect answers. In high-stakes domains, such misleading answers risk doing far more harm than abstention. This underscores that *factual accuracy alone does not necessarily guarantee truthfulness*.

There has been a line of research aiming to teach LLMs to admit uncertainty (Cheng et al., 2024; Yang et al., 2024b; Huang et al., 2025). Recent works such as R-Tuning (Zhang et al., 2024a) train the model on unanswerable questions with “I don’t know” as the ground-truth label (Song et al., 2025). However, such methods require non-trivial annotation on model-specific datasets, leading to



067 Figure 1: Comparison between vanilla supervised fine-tuning (SFT), reinforcement learning (RL), and TruthRL. In vanilla SFT/RL, the model is optimized solely for accuracy, implicitly rewarding hallucinations over abstentions and thus always attempting to answer or guess, which ultimately compromises truthfulness. In contrast, TruthRL not only rewards correct answers, but explicitly penalizes hallucinations, and treats abstentions neutrally, thereby leading to greater truthfulness.

073 limited generalization or overly conservative behavior (e.g., abstaining even when the model has sufficient knowledge). On the other hand, lots of research efforts have sought to mitigate hallucinations by expanding the model’s knowledge scope, either by updating its parametric knowledge through fine-tuning or by incorporating external information via retrieval-augmented generation (RAG) (Kasai et al., 2024; Yang et al., 2024a). However, the retrieved documents in RAG can be noisy or even contain factually incorrect content, potentially misleading the model and posing additional challenges (Wei et al., 2025). Meanwhile, fine-tuning methods typically improve accuracy but can also reinforce hallucinations, particularly when the model is uncertain (Kang et al., 2025). In fact, such accuracy-driven methods inherently motivate LLMs to guess rather than abstain from answering when unsure, since the expected incentive for guessing an answer is always higher than that from abstention by design (Kalai et al., 2025). As a result, existing approaches remain deficient in training truthful LLMs that can both provide accurate answers and acknowledge uncertainty.

084 In light of this, we argue that a more aligned learning objective is needed for developing truthful LLMs—one that explicitly incentivizes models not only to maximize correct responses, but also to appropriately abstain from answering when being uncertain. In this work, we introduce TruthRL, a general reinforcement learning (RL) framework designed to directly optimize truthfulness rather than accuracy alone. As illustrated in Figure 1, unlike accuracy-driven methods such as vanilla SFT or RL, which implicitly favor hallucinations over abstentions by encouraging the model to always provide an answer to maximize accuracy, our method introduces a truthfulness-driven ternary reward design that explicitly rewards correct answers, penalizes hallucinations, and treats abstentions as neutral. This design encourages the model to generate correct responses when possible, but more importantly, to properly abstain rather than wildly guessing. Specifically, we implement TruthRL with GRPO (Shao et al., 2024), and our findings show that this simple yet principled reward formulation yields substantial gains in truthfulness. Experiments demonstrate that our method improves the truthfulness of LLMs not only by converting hallucinations into abstentions, but also by promoting more accurate responses, particularly in retrieval-augmented settings where the model has access to additional information. Notably, the increase in abstentions arises not from over-conservatism but from a genuine recognition of the knowledge boundary: TruthRL abstains most often, whereas the baseline tends to hallucinate when knowledge is insufficient. In summary, our findings advocate a shift from accuracy-driven to truthfulness-driven methods for developing LLMs.

101 The main contributions of this work are as follows: (1) We propose TruthRL, a general RL frame-
102 work that directly optimizes truthfulness through a simple yet principled reward design. (2) We
103 demonstrate that TruthRL consistently reduces hallucination and improves truthfulness across mul-
104 tiple knowledge-intensive benchmarks in both retrieval and non-retrieval settings, significantly re-
105 ducing hallucinations (e.g., 43.5% → 19.4%) and improving truthfulness (e.g., 5.3% → 37.2%).
106 (3) Extensive ablation studies and analyses confirm that LLMs trained with TruthRL are effective
107 at recognizing their knowledge boundaries, robust to hallucination-inducing questions, and more
confident in providing correct answers, while maintaining a significantly lower hallucination rate.

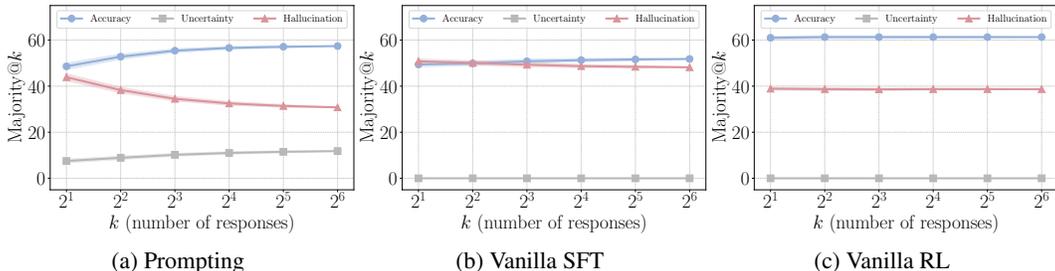


Figure 2: Scaling curve of prompting and vanilla SFT/RL methods on the CRAG benchmark, using Llama3.1-8B-Instruct as the backbone. Before training, the model shows strong potential in majority@k scaling, with reduced hallucination and improved accuracy and abstentions as the number of responses increases. However, despite their slightly improved accuracy, vanilla SFT and RL diminish this potential and lead to much higher hallucinations, underscoring their limitations and the need for a more truthful training paradigm.

2 PRELIMINARIES

2.1 PROBLEM FORMULATION

In contrast to the traditional method that optimizes for accuracy only (Kalai et al., 2025), we choose to optimize for *truthfulness* and designed a multi-dimensional objective. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$ denote the problem set. For a model f_θ , we evaluate its predictions $\hat{y}_i = f_\theta(x_i)$ and compute (i) accuracy (Acc), the fraction of questions answered correctly; (ii) uncertainty rate (Unc), the fraction of questions where the model abstains (e.g., answers “I don’t know”); and (iii) hallucination rate (Hall), the fraction of responses that are factually incorrect. Following standard practices (Yang et al., 2024a; Kachuee et al., 2025; Huang et al., 2025), we define the truthfulness score as a weighted combination: Truthfulness = $w_1 \cdot \text{Acc} + w_2 \cdot \text{Unc} - w_3 \cdot \text{Hall}$, where $w_1, w_2, w_3 \geq 0$ control the desired behavior among the three dimensions. Our objective is to design training methods that maximize the expected truthfulness score, i.e., $\max_\theta \mathbb{E}_{\mathcal{D}}[\text{Truthfulness}(f_\theta)]$. This formulation captures the core idea of truthfulness: unlike an accuracy-focused setup that only cares about correctness, our problem formulation favors models that maximize correct answers, appropriately abstain when uncertain, and minimize hallucinations.

2.2 VANILLA FINE-TUNING METHODS

Supervised fine-tuning (SFT). We train the LLM using the standard SFT objective, which aims to maximize the likelihood of producing the ground-truth response given an input: $\mathcal{L}_{\text{SFT}}(\theta) = -\mathbb{E}_{(x,y) \sim \mathcal{D}} \sum \log p(y|x; \theta)$, where (x, y) is the input-output pair and θ denotes the parameters. While typically effective for improving accuracy, SFT tends to memorize the training data and has limited generalizability (Chu et al., 2025). Moreover, the model is trained to always provide an answer, even when unsure, which inevitably encourages hallucinations (Kalai et al., 2025).

Reinforcement learning (RL). Traditional RL methods optimize the LLM using accuracy-based reward signals, provided by a verifier to determine whether a prediction is correct (Guo et al., 2025). Although RL typically achieves better generalization than SFT by eliminating direct supervision with ground-truth answers, vanilla RL is not explicitly designed to recognize uncertainty or abstain when appropriate. As a result, it may substantially increase correctness but still fails to prevent hallucinations (Kang et al., 2025), as also observed in our preliminary findings.

2.3 PRELIMINARY FINDINGS

As shown in Figure 2, we report the majority@k results on the CRAG benchmark for prompting, vanilla SFT and RL methods, using Llama3.1-8B-Instruct as the backbone model. The prompting baseline demonstrates that increasing the number of sampled responses consistently reduces hallucination with improved accuracy and the abstention rate. This suggests that even without fine-tuning, the base model already has strong potential in achieving higher truthfulness.

In contrast, despite their improvements in accuracy, vanilla SFT and RL methods almost completely suppress abstention behavior (i.e., maintaining a near-zero uncertainty rate) and provide only a limited reduction in hallucinations—or even an increased hallucination rate compared to the baseline when k is large. These results reveal the limitations of vanilla fine-tuning methods that focus solely on accuracy: they not only fail to address the truthfulness problem but also diminish the model’s inherent capacity to express uncertainty, underscoring the need for truthful training approaches.

3 METHODOLOGY

To address the problem, we first establish strong fine-tuning baselines that can express uncertainty while maintaining accuracy using a knowledge boundary probing mechanism, and then elaborate on the design of our proposed solution TruthRL.

3.1 KNOWLEDGE BOUNDARY PROBING

To enable the model to express uncertainty, we first construct appropriate training data for baselines by probing an LLM’s knowledge boundaries on the training set to identify *out-of-knowledge* (OOK) questions. For each training question, we sample 256 responses, and the question is marked as OOK if none of the responses is correct. These questions are then relabeled with “I don’t know” as the ground-truth answer and used to train the model with the standard SFT objective. Similar approaches have been explored in prior works (Zhang et al., 2024a; Yang et al., 2024b; Song et al., 2025), where samples with uncertain ground-truths are incorporated into SFT training using various data construction strategies. We refer to this baseline as R-Tuning (Zhang et al., 2024a).

Further, we extend the idea of rejection sampling fine-tuning (RFT) (Yuan et al., 2023) with uncertain responses. Rather than directly learning the ground-truth answers, RFT trains the model on reasoning traces generated by the model itself. In this baseline, we prompt the model to generate multiple reasoning traces for each question and select the trace that concludes with “I don’t know” as the target response for OOK questions, whereas for non-OOK questions, we select the trace that leads to the correct answer.

3.2 TRUTHRL: INCENTIVIZING TRUTHFULNESS VIA RL

We implement TruthRL using GRPO (Shao et al., 2024), an online RL method that optimizes the following objective:

$$\mathcal{L}_{\text{GRPO}}(\theta) = -\mathbb{E}_{x \sim \mathcal{D}, \{y_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|x)} \left[\frac{1}{G} \sum_{i=1}^G \frac{1}{|y_i|} \sum_{t=1}^{|y_i|} \min(w_{i,t}(\theta) \hat{A}_i, \text{clip}(w_{i,t}(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_i) - \beta \mathbb{D}_{KL}(\pi_{\theta} || \pi_{\text{ref}}) \right],$$

where ϵ and β are hyper-parameters, G is the group size (i.e., the number of sampled responses from the old policy $\pi_{\theta_{\text{old}}}$ for each question x), π_{ref} denotes the reference policy, $w_{i,t}(\theta)$ denotes the importance ratio, \hat{A}_i is the estimated advantage for response y_i , computed using a group of rewards $\{r_1, r_2, \dots, r_G\}$ corresponding to the outputs within each group:

$$\hat{A}_i = \frac{r(x, y_i) - \text{mean}(\{r(x, y_j)\}_{j=1}^G)}{\text{std}(\{r(x, y_j)\}_{j=1}^G)}.$$

Reward design. We consider two main types of reward designs: (1) Binary reward:

$$r_{\text{binary}}(x, y) = \begin{cases} +1, & \text{if } y \text{ is correct,} \\ -1, & \text{otherwise.} \end{cases}$$

and (2) Ternary reward:

$$r_{\text{ternary}}(x, y) = \begin{cases} +1, & \text{if } y \text{ is correct,} \\ 0, & \text{if } y \text{ is uncertain,} \\ -1, & \text{if } y \text{ is incorrect.} \end{cases}$$

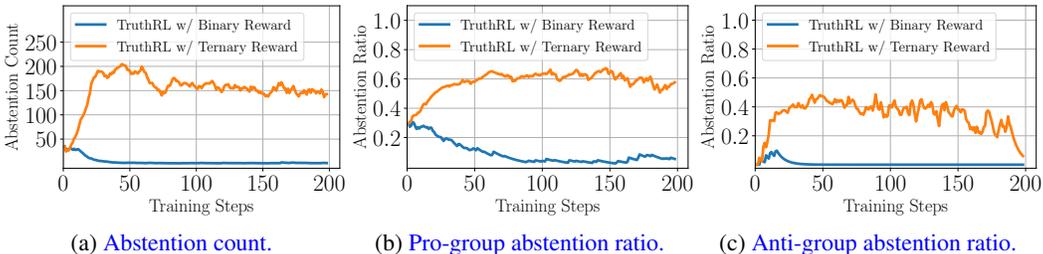


Figure 3: Abstention dynamic of TruthRL under different reward designs.

As introduced above, in GRPO training, the advantage of a response is computed by comparing its reward against the mean reward within a sampled group. For example, consider a group consisting of two responses y_1 and y_2 where y_1 expresses *abstention* and y_2 contains *hallucination*.

- Under the *binary* reward scheme, both responses receive a -1 reward (i.e., $r_{\text{binary}}(x, y_1) = r_{\text{binary}}(x, y_2) = -1$), yielding a zero relative advantage (i.e., $\hat{A}_{\text{binary}}(x, y_1) = \hat{A}_{\text{binary}}(x, y_2)$)—thus the policy update conflates hallucination with abstention.
- Under the *ternary* reward scheme, y_1 receives a 0 reward while y_2 receives a -1 reward (i.e., $r_{\text{ternary}}(x, y_1) = 0$, $r_{\text{ternary}}(x, y_2) = -1$), resulting in a larger advantage for abstention than for hallucination (i.e., $\hat{A}_{\text{ternary}}(x, y_1) > \hat{A}_{\text{ternary}}(x, y_2)$). This encourages the models to abstain rather than hallucinate when they lack the knowledge to make accurate predictions.

This exemplifies how the ternary reward inherently better distinguishes abstention from hallucination with the relative advantage estimation of GRPO. Empirically, we also observe clear behavioral divergences between models trained with binary and ternary rewards. As shown in Figure 3a, the model trained with binary rewards quickly suppresses abstention behavior to nearly zero, whereas the model trained with ternary reward maintains a meaningful level of abstention. To further understand this effect, we categorize sampling groups into two types: (1) Pro-Abstention groups where the model is encouraged to abstain (i.e., groups containing only incorrect and abstention responses). Figure 3b shows that the abstention ratio consistently increases across training under the ternary reward. (2) Anti-Abstention groups where abstention is penalized (i.e., groups that include abstention responses and at least one correct response). Figure 3c shows that ternary reward drives the abstention ratio to decrease over training, consistent with the intended behavior. This demonstrates that the ternary reward scheme under GRPO adaptively generates positive or negative credits for abstention, ultimately resulting in different abstention dynamics that cannot be reproduced by binary rewards.

We further consider two enhancements on top of these rewards. First, a *knowledge-enhanced variant* treats abstention as positive when the model genuinely lacks knowledge. For out-of-knowledge (OOK) questions, it assigns $+1$ to uncertain responses and -1 to other responses; for non-OOK questions, it assigns $+1$ to correct answers, -1 for incorrect answers, and 0 to abstentions if applied with the ternary reward. Second, a *reasoning-enhanced variant* builds on the above outcome-based reward by incorporating additional reward signals that evaluate the quality of the model’s reasoning process. Different reward designs induce distinct model behaviors, and a detailed analysis is provided in Section 4.4 and Section 4.6, which suggests that a simple ternary reward scheme generally works better than the binary scheme and more complicated designs.

4 EXPERIMENT

4.1 EXPERIMENTAL SETTING

Datasets and Evaluation Metrics. We conduct experiments on four knowledge-intensive benchmarks, under with and without retrieval setups: CRAG (Yang et al., 2024a), NaturalQuestions (NQ) (Kwiatkowski et al., 2019), HotpotQA (Yang et al., 2018), and MuSiQue (Trivedi et al., 2022). Models are trained on CRAG and evaluated across all four datasets. The primary evaluation metric is *truthfulness* score, with *hallucination* rate and *accuracy* reported as auxiliary metrics. Following prior works (Yang et al., 2024a; Huang et al., 2025; Kachuee et al., 2025), we set $w_1 = 1, w_2 = 0, w_3 = 1$ for truthfulness score calculation (defined in Section 2.1). The correctness of predicted answers are judged by Llama3.3-70B-Instruct against the reference answers.

Table 1: Comparison between TruthRL and baselines across four knowledge-intensive benchmarks under with and without retrieval settings. We report the truthfulness score (T), hallucination rate (H), and accuracy (A) as evaluation metrics. The best truthfulness scores are highlighted in **bold**.

Method	CRAG			NQ			HotpotQA			MuSiQue			Average		
	T (↑)	H (↓)	A (↑)	T (↑)	H (↓)	A (↑)	T (↑)	H (↓)	A (↑)	T (↑)	H (↓)	A (↑)	T (↑)	H (↓)	A (↑)
<i>Without Retrieval</i>															
Qwen2.5-7B-Inst															
Prompting	-17.4	48.1	30.6	-32.4	60.1	27.7	-36.0	60.7	24.6	-68.8	76.7	7.9	-38.7	61.4	22.7
SFT	-51.5	75.7	24.3	-49.4	74.7	25.3	-46.7	73.4	26.6	-81.8	90.9	9.1	-57.4	78.7	21.3
RFT	-16.8	46.7	29.9	-20.8	49.6	28.9	-19.1	46.5	27.4	-41.8	50.7	8.9	-24.6	48.4	23.8
R-Tuning	-7.5	21.9	14.5	-0.9	12.6	11.7	3.3	8.4	11.7	-0.7	2.1	1.4	-1.5	11.3	9.8
RLHF	-17.4	45.7	28.3	-31.8	60.8	29.0	-39.8	63.3	23.5	-73.6	80.0	6.4	-40.7	62.5	21.8
RLKF	-6.1	28.1	22.1	-15.7	37.9	22.2	-18.1	36.2	18.1	-50.6	54.0	3.4	-22.6	39.1	16.5
TruthRL _{Binary}	-29.2	64.5	35.3	-35.9	67.8	31.9	-31.2	65.3	34.1	-71.7	84.8	13.2	-42.0	70.6	28.6
TruthRL	16.2	8.7	24.9	-1.6	25.0	23.5	9.8	12.7	22.5	-1.7	5.3	3.6	5.7	12.9	18.6
Llama3.1-8B-Inst															
Prompting	-4.4	44.5	40.1	-5.2	49.2	43.9	-19.9	53.9	34.0	-54.2	64.7	10.5	-20.9	53.1	32.1
SFT	-42.1	71.1	28.9	-38.4	69.2	30.8	-38.9	69.5	30.5	-81.9	90.9	9.1	-50.3	75.2	24.8
RFT	-7.6	48.1	40.4	-11.4	51.8	40.4	-23.2	57.9	34.7	-58.0	69.2	11.2	-25.1	56.8	31.7
R-Tuning	-13.7	39.5	25.8	-16.6	42.5	25.9	-3.5	26.7	23.2	-20.7	25.2	4.5	-13.6	33.5	19.9
RLHF	1.4	35.3	36.7	-37.5	60.8	23.3	-39.4	57.3	17.9	-72.9	77.8	5.0	-37.1	57.8	20.7
RLKF	-0.6	32.8	32.2	-4.6	37.9	33.2	-4.5	31.8	27.3	-29.3	36.2	6.9	-9.8	34.7	24.9
TruthRL _{Binary}	-14.5	57.2	42.8	-5.3	52.6	47.4	-19.6	59.8	40.2	-67.2	83.6	16.4	-26.7	63.3	36.7
TruthRL	22.4	16.3	38.7	12.9	30.9	43.8	14.3	18.9	33.2	-7.7	16.0	8.2	10.5	20.5	31.0
<i>With Retrieval</i>															
Qwen2.5-7B-Inst															
Prompting	10.6	38.4	49.0	9.0	41.1	50.1	0.2	43.6	43.8	-51.3	62.8	11.5	-7.9	46.5	38.6
SFT	-2.3	51.2	48.8	0.3	49.9	50.1	-2.4	51.2	48.8	-68.2	84.1	15.9	-18.2	59.1	40.9
RFT	22.6	31.4	54.0	18.4	32.1	50.5	23.4	23.3	46.6	-20.6	33.8	13.2	11.0	30.2	41.1
R-Tuning	13.4	35.0	48.4	4.3	44.5	48.8	13.8	30.3	44.1	-23.0	32.5	9.4	2.1	35.6	37.7
RLHF	16.5	35.9	52.4	10.9	41.6	52.5	9.5	39.4	48.8	-52.1	65.6	13.5	-3.8	45.6	41.8
RLKF	25.2	21.9	47.1	18.4	21.9	40.4	20.4	11.9	32.3	-13.8	19.1	5.3	12.6	18.7	31.3
TruthRL _{Binary}	8.4	45.3	53.7	11.8	43.9	55.7	20.1	39.1	59.2	-49.4	72.2	22.8	-2.3	50.1	47.9
TruthRL	33.1	17.3	50.4	26.4	21.2	47.6	33.3	10.7	43.9	-0.6	9.0	8.4	23.1	14.6	37.6
Llama3.1-8B-Inst															
Prompting	5.3	43.5	48.8	-5.8	50.7	44.9	-4.4	49.0	44.6	-60.5	73.0	12.5	-16.4	54.1	37.7
SFT	1.4	49.3	50.7	1.6	49.2	50.8	-4.3	52.1	47.9	-69.8	84.9	15.1	-17.8	58.9	41.1
RFT	-3.7	48.8	45.1	-4.7	50.4	45.7	1.1	45.8	46.9	-55.7	68.8	13.1	-15.8	53.5	37.7
R-Tuning	15.2	33.1	48.4	2.1	47.5	49.6	1.7	46.2	47.9	-53.9	68.3	14.4	-8.7	48.8	40.1
RLHF	13.1	39.7	52.7	8.2	44.2	52.4	9.6	41.9	51.6	-57.4	72.4	15.0	-6.6	49.6	42.9
RLKF	18.9	30.6	49.5	10.2	34.9	45.0	10.8	32.7	43.5	-33.5	43.4	9.9	1.6	35.4	37.0
TruthRL _{Binary}	20.8	39.5	60.3	19.0	40.5	59.5	25.9	37.0	62.9	-47.6	73.7	26.1	4.5	47.7	52.2
TruthRL	37.2	19.4	56.6	28.8	24.9	53.7	37.4	14.9	52.3	-0.9	15.9	15.0	25.6	18.8	44.4

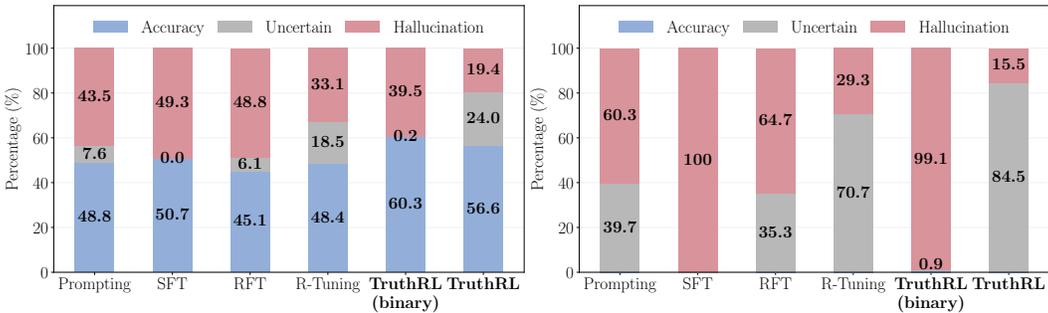
Models and Baselines. We compare our method with a prompting baseline, vanilla SFT, and two knowledge-enhanced SFT baselines, namely RFT and R-Tuning, as introduced in Section 3. We also include two representative RL-based baselines, RLHF (Ouyang et al., 2022) and RLKF (Xu et al., 2024a). By default, TruthRL is implemented with the ternary reward, and when implemented with the binary reward, it recovers the vanilla RL. We instantiate the above methods using Llama3.1-8B-Instruct (Dubey et al., 2024) and Qwen2.5-7B-Instruct (Qwen et al., 2025) as backbone models.

More implementation details, including retrieval setup, training and inference hyper-parameters, and prompt design are provided in Appendix C and Appendix E.

4.2 MAIN RESULT

Table 1 shows the overall experimental results, providing a comprehensive comparison between TruthRL and baseline methods in both retrieval and non-retrieval settings.

Vanilla SFT increases both accuracy and hallucination, while knowledge-enhanced SFTs effectively reduce hallucination with little loss or even a meaningful gain in accuracy. Compared to the prompting baseline, vanilla SFT substantially increases hallucination rates, showing that simply optimizing for accuracy can inadvertently encourage incorrect answers. This effect is particularly pronounced in the no-retrieval setting, which is likely because using SFT for ground-truth answers that the model does not know encourages the model to generate content beyond its



(a) Performance on all CRAG questions.

(b) Performance on difficult CRAG questions.

Figure 4: Performance decomposed to accuracy (blue), hallucination (red), and uncertainty (gray). Compared to baselines, TruthRL achieves the highest overall accuracy and the lowest hallucination. On difficult questions where almost no method can provide correct answers, TruthRL produces minimal hallucinations while other methods hallucinate heavily, demonstrating its improved capability in recognizing knowledge boundaries.

knowledge, thereby promoting hallucinations. In contrast, knowledge-enhanced SFT methods (*i.e.*, RFT, R-Tuning) achieve much lower hallucination with little to no compromise in accuracy, and can even improve accuracy when sufficient information is provided through retrieval, demonstrating the benefit of explicitly modeling uncertainty.

TruthRL consistently outperforms baselines in terms of truthfulness, with significantly reduced hallucination and increased accuracy, particularly in the retrieval setup. Access to external information consistently improves performance for all methods, highlighting the effectiveness of RAG in mitigating hallucinations. On CRAG, TruthRL reduces hallucination for Llama3.1-8B-Instruct by 24.1% and achieves an absolute gain of 31.9% in truthfulness compared to the prompting baseline under the retrieval setup. While knowledge-enhanced SFT methods substantially improve truthfulness over vanilla SFT and prompting baselines, they still struggle to balance hallucination and accuracy. TruthRL_{Binary} is a variant of our method that uses a binary reward, achieving the highest accuracy but also exhibiting a high hallucination rate and losing the ability of abstention, similar to vanilla SFT, which ultimately limits its truthfulness. In contrast, TruthRL reduces hallucinations and also improves accuracy and appropriate abstentions, yielding the highest overall truthfulness.

4.3 TRUTHRL IMPROVES LLMs IN RECOGNIZING THEIR KNOWLEDGE BOUNDARIES

TruthRL enables LLMs to abstain from answering only when they genuinely lack knowledge.

Figure 4 breaks down performance on the CRAG benchmark under the retrieval setup, evaluating both the full test set and a challenging subset, using Llama3.1-8B-Instruct as the backbone model. On the full set (Figure 4a), compared to the prompting method, fine-tuning baselines either achieve improved accuracy with almost zero uncertainty rate (*e.g.*, SFT, TruthRL_{Binary}) or sacrifice accuracy to allow abstention (*e.g.*, RFT, R-Tuning). In contrast, TruthRL achieves the lowest hallucination rate while maintaining competitive accuracy and the highest uncertainty rate among all baselines. When evaluating on the difficult questions (Figure 4b), where almost no method provides correct answers, all baselines hallucinate heavily—models that achieve high overall accuracy can even hallucinate nearly 100% on these challenging questions (*e.g.*, SFT, TruthRL_{Binary}). In contrast, TruthRL produces minimal hallucinations (15.5%) while generating uncertain responses for most cases (84.5%), demonstrating an improved ability to recognize its knowledge boundaries.

TruthRL is robust to hallucination-baiting questions. We evaluate all methods on the comparison-type questions from CRAG, where candidate answers are explicitly provided in the input (*e.g.*, “Which is larger, A or B?”). Such multichoice-like questions are known to be prone to inducing hallucinations (Kang et al., 2025), and as shown in Table 2, all baseline methods exhibit high hallucination rates and limited truthfulness scores. Notably, the

Table 2: Comparison of different methods on hallucination-baiting questions.

Method	T (↑)	H (↓)	U (—)
Prompting	9.7	39.8	10.7
SFT	3	48.5	0
RFT	12.7	38.8	9.7
R-Tuning	6.8	43.7	5.8
TruthRL	52.4	16.5	14.6

Table 3: Ablation study on reward design of TruthRL.

TruthRL	CRAG		NQ		HotpotQA		MuSiQue		Average	
	T (↑)	H (↓)								
with binary reward	20.8	39.5	19.0	40.5	25.9	37.0	-47.6	73.7	4.5	47.7
+ knowledge-enhanced	27.4	30.6	19.2	38.2	28.9	32.0	-28.9	52.3	11.7	38.3
with ternary reward	37.2	19.4	28.8	24.9	37.4	14.9	-0.9	15.9	25.6	18.8
+ knowledge-enhanced	32.7	21.9	27.2	25.3	35.1	13.4	-2.3	15.0	23.2	18.9

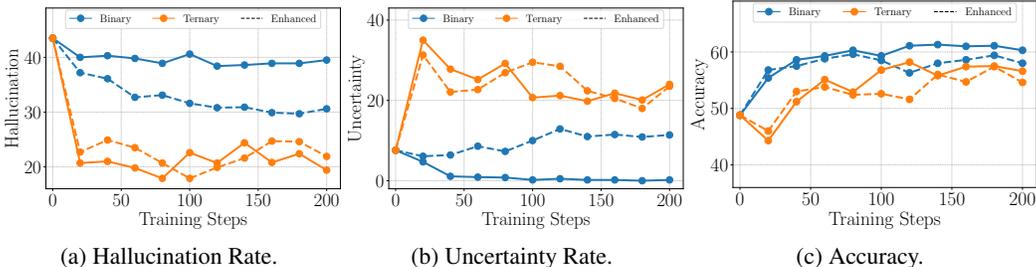


Figure 5: Learning dynamic of TruthRL under different reward designs.

Table 4: Comparison between Offline RL (DPO), Semi-Online RL (Iterative DPO), and Online RL (TruthRL) across four knowledge-intensive benchmarks.

Method	CRAG		NQ		HotpotQA		MuSiQue		Average	
	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)
DPO	6.8	43.7	-2.8	49.8	6.3	43.8	-50.5	67.0	-10.1	51.1
Iterative DPO										
Iter 1	12.9	40.9	6.7	45.5	12.7	41.0	-49.7	67.4	-4.4	48.7
Iter 2	16.3	39.8	9.3	43.4	18.5	37.5	-44.4	61.9	-0.1	45.7
Iter 3	<u>28.0</u>	<u>29.5</u>	15.0	<u>37.1</u>	<u>26.5</u>	<u>26.5</u>	<u>-19.0</u>	<u>33.7</u>	<u>12.6</u>	<u>31.7</u>
Iter 4	19.0	33.9	4.3	44.5	8.1	40.1	-39.5	52.7	-2.0	42.8
TruthRL	37.2	19.4	28.8	24.9	37.4	14.9	-0.9	15.9	25.6	18.8

knowledge-enhanced baselines (RFT, R-Tuning) demonstrate promising overall performance in Table 1, but still suffer substantial hallucinations on these hallucination-baiting questions, highlighting their vulnerability to such cases. In contrast, our method achieves the highest truthfulness while maintaining lowest hallucination, further confirming the effectiveness of TruthRL.

4.4 ABLATION STUDY

Binary reward design excels in accuracy but is limited in truthfulness, while ternary reward achieves the best truthfulness score with competitive accuracy. As shown in Table 3, we next ablate the reward design. A binary reward, which only distinguishes correct vs. incorrect answers, strongly increases accuracy but drives the model towards the elimination of abstentions. Augmenting binary reward with knowledge-enhanced signals partially alleviates this issue, improving abstention rates while at the cost of compromised accuracy. However, the best performance comes from our ternary reward, which explicitly recognizes three outcomes: correct, hallucinated, and abstained. This formulation rewards correctness while tolerating abstention, thereby striking a balance between informativeness and reliability. Empirically, the ternary reward achieves the lowest hallucination and highest truthfulness, validating that nuanced feedback is critical for uncertainty-aware optimization.

Online RL outperforms offline and semi-online counterparts. Table 4 compares different reinforcement learning paradigms using the same backbone model. We observe that purely offline RL via DPO leads to limited gains: although slightly better than promoting baseline, the truthfulness score remains low, as the fixed dataset constrains the model’s ability to adaptively refine its behavior. Semi-online training through iterative DPO provides some remedy by refreshing reference data after each iteration, but the performance is inconsistent: early iterations bring steady improvements, yet excessive iterations (e.g., Iter 4) show regressions, suggesting that repeated offline fine-tuning

Table 5: Evaluation on CRAG under different judges.

Method	Llama3.3-70B-Inst		Qwen2.5-72B-Inst		Gemma3-27B-Inst		Average	
	T (\uparrow)	H (\downarrow)	T (\uparrow)	H (\downarrow)	T (\uparrow)	H (\downarrow)	T (\uparrow)	H (\downarrow)
Prompting	5.3	43.5	1.9	45.3	6.5	42.9	4.6	43.9
SFT	1.4	49.3	1.7	49.1	6.7	46.7	3.3	48.4
RFT	-3.7	48.8	-5.0	49.5	-3.1	48.5	-3.9	48.9
R-Tuning	15.2	33.1	14.9	33.3	18.0	31.7	16.0	32.7
TruthRL	37.2	19.4	35.6	20.2	39.7	18.2	37.5	19.3

cannot effectively balance exploration and exploitation. In contrast, our TruthRL with online GRPO achieves the best results across all benchmarks, consistently lowering hallucination while improving truthfulness. This highlights the advantage of learning from online interactions, which enables continuous updates and policy refinement without drifting toward overfitting or degeneration. More implementation details on DPO are provided in Appendix C.

4.5 ANALYSIS

Due to space limit, we present additional analyses in Appendix A.

TruthRL is more confident in giving correct answers and abstaining, while the hallucination rate is significantly lower. As shown in Figure 6, we group the model outputs based on their confidence intervals. Even before fine-tuning, Llama3.1-8B-Instruct already exhibits high confidence in its predictions. However, a large portion of outputs in each confidence interval are hallucinations. Moreover, the uncertainty rate decreases as confidence increases, indicating that the model tends to provide an answer rather than abstain when its confidence is high. In contrast, TruthRL further increases the confidence of model outputs, it not only improves accuracy but also significantly reduces overconfident hallucinations. This indicates that our method produces responses that are not only more accurate but also better aligned with their confidence, leading to more trustworthy uncertainty estimates.

TruthRL is robust across different LLM judges. Since our training pipeline relies on external judges to provide feedback, it is important to ensure that performance is not overly sensitive to the choice of judge. Table 5 reports results on CRAG under three distinct high-capacity evaluators: Llama3.3-70B-Instruct, Qwen2.5-72B-Instruct, and Gemma3-27B-Instruct. While absolute scores vary slightly across judges, the relative improvements of TruthRL are consistent: it achieves the lowest hallucination and the highest truthfulness under all evaluators. This robustness suggests that TruthRL learns generalizable behaviors rather than overfitting to the idiosyncrasies of a single judge.

4.6 BEYOND OUTCOME REWARD

We conduct a reasoning-quality analysis on CRAG using the prompting method with Llama3.1-8B-Instruct, evaluating model responses for both outcome and reasoning quality, resulting in an overall truthfulness score of 5.3% and a reasoning score of 50.2%. Specifically, results show that accurate responses are typically associated with a high reasoning quality score of 92% and uncertain responses exhibit a reasoning score of 0%, while hallucinated responses have a reasoning score of 12.1%. The findings suggest a strong correlation between response accuracy and reasoning quality. The high reasoning score of accurate responses indicates that the model excels in generating accurate outcomes with promising reasoning. However, the low reasoning scores for uncertain and hallucinated responses highlight the need for quality reasoning. Introducing reasoning rewards could potentially help mitigate these issues, enabling more accurate outcomes with better reasoning.

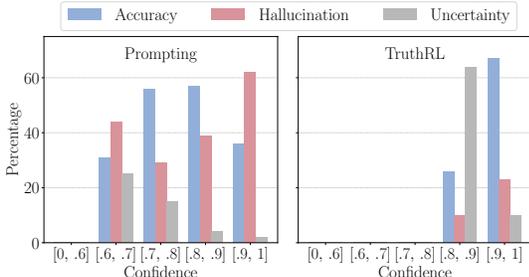


Figure 6: Study of model behaviors under different output confidence on CRAG.

We explore three heuristic strategies for incorporating the reasoning reward r_{reason} on top of the outcome reward r_{outcome} : (1) A multiplicative strategy scales the outcome reward by reasoning quality, i.e., $r_{\text{final}} = r_{\text{outcome}} \cdot (1 + r_{\text{reason}})$, which particularly encourages better reasoning when the outcome is correct. (2) An additive strategy treats reasoning as a complementary signal with scaling factor λ , giving $r_{\text{final}} = r_{\text{outcome}} + \lambda \cdot r_{\text{reason}}$, so that good reasoning can get rewarded even when the outcome reward is moderate. (3) A conditional strategy applies reasoning rewards only if the outcome is correct: $r_{\text{final}} = r_{\text{outcome}} \cdot r_{\text{reason}}$ when $r_{\text{outcome}} = 1$, and $r_{\text{final}} = r_{\text{outcome}}$ otherwise, enforcing stricter alignment where reasoning quality matters primarily in successful completions. The results in Table 6 indicate that outcome-only rewards implicitly improve reasoning ability, while explicitly optimizing reasoning quality requires non-trivial design to balance multiple objectives. For instance, heuristic designs like additive reasoning rewards can boost reasoning scores but may compromise the outcome, underscoring the need for thoughtful design. We leave this exploration for future work.

Table 6: Effect of incorporating reasoning reward into TruthRL on CRAG.

Method	Outcome		Reasoning
	T (\uparrow)	H (\downarrow)	Score (\uparrow)
Prompting	5.3	43.5	50.2
TruthRL (r_{outcome} only)	37.2	19.4	56.6
+ multiplicative r_{reason}	37.0	19.4	54.7
+ additive r_{reason}	36.1	19.1	59.1
+ conditional r_{reason}	35.6	19.3	55.1

5 RELATED WORK

LLMs often generate factually incorrect statements, or hallucinations (Zhang et al., 2023; Xu et al., 2024b), arising from limited grounding (Shuster et al., 2021) and over-reliance on parametric memory (Petroni et al., 2019). Mitigation strategies include retrieval-augmented generation (Lewis et al., 2020; Borgeaud et al., 2022; Chen et al., 2025), decoding-based self-correction (Wang et al., 2023; Kadavath et al., 2022), and fine-tuning methods such as SFT (Zhou et al., 2023), DPO (Tian et al., 2023; Zhang et al., 2024b) and RLHF (Ouyang et al., 2022), though these approaches often fail out-of-distribution (Kirk et al., 2024) and rarely model abstention. Reinforcement learning (Zhu et al., 2025; Shao et al., 2025) elicits reasoning for improved accuracy with binary correctness rewards but penalizes abstention (Song et al., 2025). Extensions such as uncertainty-aware RL (Xu et al., 2024a) and multi-objective optimization (Wang et al., 2024a) stress the importance of reward design. R-Tuning (Zhang et al., 2024a) reduces hallucinations but sacrifices coverage, highlighting the need for reward formulations that balance factual accuracy with calibrated abstention. Due to space limit, we provide an extended discussion in Appendix B.

6 CONCLUSION

In this work, we presented TruthRL, a general reinforcement learning framework that directly optimizes the truthfulness of large language models. By leveraging a simple yet effective ternary reward design, TruthRL incentivizes models to provide accurate responses, abstain when uncertain, and avoid hallucinations. Experiments on four knowledge-intensive benchmarks demonstrate TruthRL consistently improves truthfulness and reduces hallucinations, achieving significant gains across various backbone models under both with and without retrieval setups. Compared to baseline methods, TruthRL achieves an average reduction of up to 40.1% in hallucinations and an average improvement of up to 43.4% in truthfulness, demonstrating its effectiveness in enhancing the reliability and trustworthiness of large language models.

REPRODUCIBILITY STATEMENT

To ensure the highest level of reproducibility for our reported results, we have provided:

- Comprehensive implementation details in Appendix C;
- All prompt templates used in our experiments in Appendix E.

REFERENCES

- 540
541
542 Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Milli-
543 can, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al.
544 Improving language models by retrieving from trillions of tokens. In *International conference on*
545 *machine learning*, pp. 2206–2240. PMLR, 2022.
- 546 Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal,
547 Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are
548 few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- 549 Tong Chen, Akari Asai, Luke Zettlemoyer, Hannaneh Hajishirzi, and Faeze Brahman. Train for
550 truth, keep the skills: Binary retrieval-augmented reward mitigates hallucinations. *arXiv preprint*
551 *arXiv:2510.17733*, 2025.
- 552 Qinyuan Cheng, Tianxiang Sun, Xiangyang Liu, Wenwei Zhang, Zhangyue Yin, Shimin Li, Linyang
553 Li, Zhengfu He, Kai Chen, and Xipeng Qiu. Can ai assistants know what they don’t know? In
554 *International Conference on Machine Learning*, pp. 8184–8202. PMLR, 2024.
- 555 Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep
556 reinforcement learning from human preferences. *Advances in neural information processing sys-*
557 *tems*, 30, 2017.
- 559 Tianzhe Chu, Yuexiang Zhai, Jihan Yang, Shengbang Tong, Saining Xie, Dale Schuurmans, Quoc V
560 Le, Sergey Levine, and Yi Ma. SFT memorizes, RL generalizes: A comparative study of founda-
561 tion model post-training. In *Forty-second International Conference on Machine Learning*, 2025.
- 562 Yung-Sung Chuang, Yujia Xie, Hongyin Luo, Yoon Kim, James R Glass, and Pengcheng He. DoLa:
563 Decoding by contrasting layers improves factuality in large language models. In *The Twelfth*
564 *International Conference on Learning Representations*, 2024.
- 565 Tri Dao. FlashAttention-2: Faster attention with better parallelism and work partitioning. In *The*
566 *Twelfth International Conference on Learning Representations*, 2024.
- 568 Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha
569 Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models.
570 *arXiv e-prints*, pp. arXiv–2407, 2024.
- 571 Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu,
572 Shirong Ma, Peiyi Wang, Xiao Bi, et al. DeepSeek-R1 incentivizes reasoning in LLMs through
573 reinforcement learning. *Nature*, 2025.
- 574 Yin Huang, Yifan Ethan Xu, Kai Sun, Vera Yan, Alicia Sun, Haidar Khan, Jimmy Nguyen, Moham-
575 mad Kachuee, Zhaojiang Lin, Yue Liu, et al. Confqa: Answer only if you are confident. *arXiv*
576 *preprint arXiv:2506.07309*, 2025.
- 577 Hugging Face. Open R1: A fully open reproduction of DeepSeek-R1, January 2025. URL <https://github.com/huggingface/open-r1>.
- 578
579
580
581 Gautier Izacard, Patrick Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane
582 Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. Atlas: Few-shot learning
583 with retrieval augmented language models. *Journal of Machine Learning Research*, 24(251):
584 1–43, 2023.
- 585 Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang,
586 Andrea Madotto, and Pascale Fung. Survey of hallucination in natural language generation. *ACM*
587 *Computing Surveys*, 55(12):1–38, 2023.
- 588 Bowen Jin, Hansi Zeng, Zhenrui Yue, Jinsung Yoon, Sercan O Arik, Dong Wang, Hamed Zamani,
589 and Jiawei Han. Search-R1: Training LLMs to reason and leverage search engines with reinforc-
590 e-ment learning. In *Second Conference on Language Modeling*, 2025.
- 591 Mohammad Kachuee, Teja Gollapudi, Minseok Kim, Yin Huang, Kai Sun, Xiao Yang, Jiaqi Wang,
592 Nirav Shah, Yue Liu, Aaron Colak, et al. PrismRAG: Boosting RAG factuality with distractor
593 resilience and strategized reasoning. *arXiv preprint arXiv:2507.18857*, 2025.

- 594 Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez,
595 Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, et al. Language mod-
596 els (mostly) know what they know. *arXiv preprint arXiv:2207.05221*, 2022.
597
- 598 Adam Tauman Kalai, Ofir Nachum, Santosh S Vempala, and Edwin Zhang. Why language models
599 hallucinate. *arXiv preprint arXiv:2509.04664*, 2025.
600
- 601 Katie Kang, Eric Wallace, Claire Tomlin, Aviral Kumar, and Sergey Levine. Unfamiliar finetuning
602 examples control how language models hallucinate. In *Proceedings of the 2025 Conference of*
603 *the Nations of the Americas Chapter of the Association for Computational Linguistics: Human*
604 *Language Technologies (Volume 1: Long Papers)*, pp. 3600–3612, 2025.
- 605 Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick SH Lewis, Ledell Wu, Sergey Edunov, Danqi
606 Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *EMNLP*
607 *(1)*, pp. 6769–6781, 2020.
608
- 609 Jungo Kasai, Keisuke Sakaguchi, Ronan Le Bras, Akari Asai, Xinyan Yu, Dragomir Radev, Noah A
610 Smith, Yejin Choi, Kentaro Inui, et al. RealTime QA: What’s the answer right now? *Advances in*
611 *Neural Information Processing Systems*, 36, 2024.
- 612 Robert Kirk, Ishita Mediratta, Christoforos Nalmpantis, Jelena Luketina, Eric Hambro, Edward
613 Grefenstette, and Roberta Raileanu. Understanding the effects of rlhf on llm generalisation and
614 diversity. In *The Twelfth International Conference on Learning Representations*, 2024.
615
- 616 Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris
617 Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion
618 Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav
619 Petrov. Natural Questions: A benchmark for question answering research. *Transactions of the*
620 *Association for Computational Linguistics*, 7:452–466, 2019. doi: 10.1162/tacl_a.00276.
- 621 Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph
622 Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model
623 serving with PagedAttention. In *Proceedings of the 29th Symposium on Operating Systems Prin-*
624 *ciples*, pp. 611–626, 2023.
625
- 626 Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahm-
627 an, Lester James V Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, et al. Tulu 3: Pushing frontiers
628 in open language model post-training. *arXiv preprint arXiv:2411.15124*, 2024.
629
- 630 Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal,
631 Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented gener-
632 ation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33:
633 9459–9474, 2020.
- 634 Lei Li, Hehuan Liu, Yaxin Zhou, ZhaoYang Gui, Xudong Weng, Yi Yuan, Zheng Wei, and Zang Li.
635 Uncertainty-aware iterative preference optimization for enhanced llm reasoning. In *Proceedings*
636 *of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long*
637 *Papers)*, pp. 23996–24012, 2025a.
638
- 639 Yinghui Li, Haojing Huang, Jiayi Kuang, Yangning Li, Shu-Yu Guo, Chao Qu, Xiaoyu Tan, Hai-
640 Tao Zheng, Ying Shen, and Philip S Yu. Refine knowledge of large language models via adaptive
641 contrastive learning. *arXiv preprint arXiv:2502.07184*, 2025b.
- 642 Yuxin Liang, Zhuoyang Song, Hao Wang, and Jiaxing Zhang. Learning to trust your feelings: Lever-
643 aging self-awareness in llms for hallucination mitigation. In *The 3rd Workshop on Knowledge*
644 *Augmented Methods for NLP*, pp. 44, 2024.
645
- 646 Sheng-Chieh Lin, Luyu Gao, Barlas Oguz, Wenhan Xiong, Jimmy Lin, Wen-tau Yih, and Xilun
647 Chen. FLAME: Factuality-aware alignment for large language models. *Advances in Neural*
Information Processing Systems, 37:115588–115614, 2024.

- 648 Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong
649 Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to fol-
650 low instructions with human feedback. *Advances in neural information processing systems*, 35:
651 27730–27744, 2022.
- 652 Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu,
653 and Alexander Miller. Language models as knowledge bases? In *Proceedings of the 2019*
654 *Conference on Empirical Methods in Natural Language Processing and the 9th International*
655 *Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 2463–2473, 2019.
- 656 Team Qwen, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu,
657 Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei
658 Zhang, Jianxin Yang, Jiayi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao,
659 Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li,
660 Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang,
661 Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025.
- 662 Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea
663 Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances*
664 *in neural information processing systems*, 36:53728–53741, 2023.
- 665 Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. Zero: Memory optimizations
666 toward training trillion parameter models. In *SC20: International Conference for High Perfor-*
667 *mance Computing, Networking, Storage and Analysis*, pp. 1–16. IEEE, 2020.
- 668 Rulin Shao, Shuyue Stella Li, Rui Xin, Scott Geng, Yiping Wang, Sewoong Oh, Simon Shaolei
669 Du, Nathan Lambert, Sewon Min, Ranjay Krishna, et al. Spurious rewards: Rethinking training
670 signals in rlvr. *arXiv preprint arXiv:2506.10947*, 2025.
- 671 Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang,
672 Mingchuan Zhang, YK Li, Yang Wu, et al. Deepseekmath: Pushing the limits of mathemati-
673 cal reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.
- 674 Guangming Sheng, Chi Zhang, Zilinfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng,
675 Haibin Lin, and Chuan Wu. Hybridflow: A flexible and efficient rlhf framework. *arXiv preprint*
676 *arXiv: 2409.19256*, 2024.
- 677 Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. Retrieval augmentation
678 reduces hallucination in conversation. In *Findings of the Association for Computational Linguis-*
679 *tics: EMNLP 2021*, pp. 3784–3803, 2021.
- 680 Karan Singhal, Shekoofeh Azizi, Tao Tu, S Sara Mahdavi, Jason Wei, Hyung Won Chung, Nathan
681 Scales, Ajay Tanwani, Heather Cole-Lewis, Stephen Pfohl, et al. Large language models encode
682 clinical knowledge. *Nature*, 620(7972):172–180, 2023.
- 683 Linxin Song, Taiwei Shi, and Jieyu Zhao. The hallucination tax of reinforcement finetuning. *arXiv*
684 *preprint arXiv:2505.13988*, 2025.
- 685 Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu,
686 Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly
687 capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.
- 688 Katherine Tian, Eric Mitchell, Huaxiu Yao, Christopher D Manning, and Chelsea Finn. Fine-tuning
689 language models for factuality. In *The Twelfth International Conference on Learning Representations*,
690 2023.
- 691 Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Niko-
692 lay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open founda-
693 tion and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.
- 694 Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. MuSiQue: Multi-
695 hop questions via single-hop question composition. *Transactions of the Association for Compu-*
696 *tational Linguistics*, 10:539–554, 2022.

- 702 Haiyang Wang, Yuchen Pan, Xin Song, Xuechen Zhao, Minghao Hu, and Bin Zhou. F2RL: Fac-
703 tuality and faithfulness reinforcement learning framework for claim-guided evidence-supported
704 counterspeech generation. In *Proceedings of the 2024 Conference on Empirical Methods in Nat-
705 ural Language Processing*, pp. 4457–4470, 2024a.
- 706
707 Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Im-
708 proving text embeddings with large language models. In Lun-Wei Ku, Andre Martins, and Vivek
709 Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational
710 Linguistics (Volume 1: Long Papers)*, pp. 11897–11916, Bangkok, Thailand, August 2024b. As-
711 sociation for Computational Linguistics.
- 712 Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H Chi, Sharan Narang, Aakanksha
713 Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language
714 models. In *The Eleventh International Conference on Learning Representations*, 2023.
- 715
716 Yikun Wang, Rui Zheng, Liang Ding, Qi Zhang, Dahua Lin, and Dacheng Tao. Uncertainty aware
717 learning for language model alignment. In *Proceedings of the 62nd Annual Meeting of the Asso-
718 ciation for Computational Linguistics (Volume 1: Long Papers)*, pp. 11087–11099, 2024c.
- 719
720 Zhepei Wei, Wei-Lin Chen, and Yu Meng. InstructRAG: Instructing retrieval-augmented gener-
721 ation via self-synthesized rationales. In *The Thirteenth International Conference on Learning
722 Representations*, 2025.
- 723
724 Bingbing Wen, Jihan Yao, Shangbin Feng, Chenjun Xu, Yulia Tsvetkov, Bill Howe, and Lucy Lu
725 Wang. Know your limits: A survey of abstention in large language models. *Transactions of the
726 Association for Computational Linguistics*, 13:529–556, 2025.
- 727
728 Chaojun Xiao, Xueyu Hu, Zhiyuan Liu, Cunchao Tu, and Maosong Sun. Lawformer: A pre-trained
729 language model for Chinese legal long documents. *AI Open*, 2:79–84, 2021.
- 730
731 Guangzhi Xiong, Qiao Jin, Zhiyong Lu, and Aidong Zhang. Benchmarking retrieval-augmented
732 generation for medicine. *arXiv preprint arXiv:2402.13178*, 2024.
- 733
734 Hongshen Xu, Zichen Zhu, Situo Zhang, Da Ma, Shuai Fan, Lu Chen, and Kai Yu. Rejection
735 improves reliability: Training LLMs to refuse unknown questions using RL from knowledge
736 feedback. In *First Conference on Language Modeling*, 2024a.
- 737
738 Ziwei Xu, Sanjay Jain, and Mohan Kankanhalli. Hallucination is inevitable: An innate limitation of
739 large language models. *arXiv preprint arXiv:2401.11817*, 2024b.
- 740
741 Boyang Xue, Fei Mi, Qi Zhu, Hongru Wang, Rui Wang, Sheng Wang, Erxin Yu, Xuming Hu, and
742 Kam-Fai Wong. Ualign: Leveraging uncertainty estimations for factuality alignment on large
743 language models. *arXiv preprint arXiv:2412.11803*, 2024.
- 744
745 Xiao Yang, Kai Sun, Hao Xin, Yushi Sun, Nikita Bhalla, Xiangsen Chen, Sajal Choudhary,
746 Rongze Daniel Gui, Ziran Will Jiang, Ziyu Jiang, Lingkun Kong, Brian Moran, Jiaqi Wang,
747 Yifan Ethan Xu, An Yan, Chenyu Yang, Eting Yuan, Hanwen Zha, Nan Tang, Lei Chen, Nicolas
748 Scheffer, Yue Liu, Nirav Shah, Rakesh Wanga, Anuj Kumar, Wen tau Yih, and Xin Luna Dong.
749 CRAG – comprehensive RAG benchmark. *arXiv preprint arXiv:2406.04744*, 2024a.
- 750
751 Yuqing Yang, Ethan Chern, Xipeng Qiu, Graham Neubig, and Pengfei Liu. Alignment for honesty.
752 *Advances in Neural Information Processing Systems*, 37:63565–63598, 2024b.
- 753
754 Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov,
755 and Christopher D Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question
answering. *arXiv preprint arXiv:1809.09600*, 2018.
- 756
757 Zheng Yuan, Hongyi Yuan, Chengpeng Li, Guanting Dong, Keming Lu, Chuanqi Tan, Chang Zhou,
and Jingren Zhou. Scaling relationship on learning mathematical reasoning with large language
models. *arXiv preprint arXiv:2308.01825*, 2023.

756 Hanning Zhang, Shizhe Diao, Yong Lin, Yi Fung, Qing Lian, Xingyao Wang, Yangyi Chen, Heng Ji,
757 and Tong Zhang. R-tuning: Instructing large language models to say ‘i don’t know’. In *Proceed-*
758 *ings of the 2024 Conference of the North American Chapter of the Association for Computational*
759 *Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 7106–7132, 2024a.

760 Muru Zhang, Ofir Press, William Merrill, Alisa Liu, and Noah A Smith. How language model
761 hallucinations can snowball. *arXiv preprint arXiv:2305.13534*, 2023.

762 Xiaoying Zhang, Baolin Peng, Ye Tian, Jingyan Zhou, Lifeng Jin, Linfeng Song, Haitao Mi, and
763 Helen Meng. Self-alignment for factuality: Mitigating hallucinations in LLMs via self-evaluation.
764 In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*
765 *(Volume 1: Long Papers)*, pp. 1946–1965, 2024b.

766 Chunting Zhou, Pengfei Liu, Puxin Xu, Srinivasan Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia
767 Efrat, Ping Yu, Lili Yu, et al. LIMA: Less is more for alignment. *Advances in Neural Information*
768 *Processing Systems*, 36:55006–55021, 2023.

769 Xinyu Zhu, Mengzhou Xia, Zhepei Wei, Wei-Lin Chen, Danqi Chen, and Yu Meng. The surprising
770 effectiveness of negative reinforcement in llm reasoning. *arXiv preprint arXiv:2506.01347*, 2025.

771
772
773
774
775
776
777
778
779
780
781
782
783
784
785
786
787
788
789
790
791
792
793
794
795
796
797
798
799
800
801
802
803
804
805
806
807
808
809

810 A ADDITIONAL ANALYSIS

811
812 **LLM-based verifier provides more reliable training signals than rule-based verifier.** When replacing the LLM-based verifier with a simple rule-based verifier (Table 7), the model collapses into overly conservative behavior, abstaining on the vast majority of queries. Although this results in an extremely low hallucination rate, the truthfulness score becomes negative, reflecting the lack of meaningful answers. By contrast, the LLM-based verifier provides fine-grained, context-sensitive signals that better capture partial correctness and nuanced errors, which stabilizes RL training and leads to higher overall performance. This demonstrates that high-quality verifier are as important as the reward design itself in reinforcement learning for truthfulness.

Table 7: Training with rule-based verifier vs. training with model-based verifier.

TruthRL	T (↑)	H (↓)
with rule-based verifier	-3.6	3.6
with model-based verifier	37.2	19.4

823
824 **TruthRL consistently improves across model scales.** We further examine the scalability of our method across a spectrum of model sizes, ranging from compact backbones (e.g., Llama3.2-3B, Qwen2.5-3B) to mid/large-scale models (e.g., Qwen2.5-7B, Llama3.1-8B, Qwen2.5-32B). As summarized in Table 8, TruthRL consistently reduces hallucination and boosts truthfulness regardless of the base model size. Interestingly, the relative gain is more pronounced for smaller models, which suffer from higher hallucination rates under prompting. This suggests that our approach not only strengthens already strong models but also helps weaker models develop more reliable uncertainty-awareness. At the large-model end, the improvements on 32B backbones highlight that even highly capable LLMs benefit from reinforcement learning with uncertainty-aware rewards, underscoring the scalability of our method to state-of-the-art systems.

834 Table 8: The performance of TruthRL with different backbones on the CRAG benchmark.

Method	Llama3.2-3B-Inst		Qwen2.5-3B-Inst		Qwen2.5-7B-Inst		Llama3.1-8B-Inst		Qwen2.5-32B-Inst	
	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)	T (↑)	H (↓)
Prompting	1.9	45.1	-0.3	45.4	10.6	38.4	5.3	43.5	29.1	27.1
TruthRL	27.4	21.5	21.9	16.2	33.1	17.3	37.2	19.4	40.0	18.2

841 B EXTENDED RELATED WORK

842
843 **LLM Hallucination and Mitigation** A recurring challenge in LLMs is their tendency to generate fluent but factually incorrect statements, commonly termed hallucinations (Ji et al., 2023; Zhang et al., 2023; Xu et al., 2024b). Hallucinations arise from several factors, including limited grounding in external knowledge sources (Shuster et al., 2021) and over-reliance on parametric recall (Petroni et al., 2019). This gap between surface-level accuracy and deeper factual correctness becomes especially problematic in high-stakes domains such as law (Xiao et al., 2021) and medicine (Singhal et al., 2023; Xiong et al., 2024), where confidently wrong outputs can mislead users. Several lines of mitigation strategies have been explored (Wen et al., 2025). *Retrieval-augmented* methods ground LLMs in external knowledge bases or search engines to reduce reliance on memory alone (Lewis et al., 2020; Borgeaud et al., 2022; Izacard et al., 2023). *Decoding* strategies encourage self-correction and uncertainty expression, including self-consistency sampling (Wang et al., 2023), calibrated decoding (Kadavath et al., 2022), and contrastive decoding (Chuang et al., 2024). *Fine-tuning* approaches seek to instill more truthful behavior directly into the model’s parameters (Li et al., 2025b). Common methods include SFT (Zhou et al., 2023) and reinforcement learning from human feedback (RLHF) (Ouyang et al., 2022) on curated datasets of high-quality, factual question-answer pairs. While these methods can enhance accuracy on in-distribution topics, their generalization might degrade significantly on out-of-distribution questions (Kirk et al., 2024). Our work addresses a key limitation of many existing approaches: they do not explicitly train models to recognize *when* to abstain. Among prior efforts, the most closely related is R-Tuning (Zhang et al., 2024a), which likewise aims to reduce hallucinations. However, as we show in Section 4, its reduction of hallucination comes at the cost of substantially reduced coverage. This trade-off underscores the need for training frameworks that directly optimize for truthfulness—striking a balance between factual accuracy and calibrated abstention, thereby minimizing the risk of misleading outputs.

Reinforcement Learning for LLMs Reinforcement learning (RL) has become a central paradigm for post-training LLMs, enabling alignment beyond supervised fine-tuning. The most prominent example, RLHF (Ouyang et al., 2022; Christiano et al., 2017; Rafailov et al., 2023), encodes user preferences into reward models and has produced systems that are generally more helpful, safer, and better aligned. More recently, Reinforcement learning from verifiable rewards (RLVR) (Shao et al., 2024; Zhu et al., 2025; Shao et al., 2025; Lambert et al., 2024; Guo et al., 2025) has shown that binary reward signals (correct vs. incorrect) can elicit sophisticated chain-of-thought reasoning. However, this formulation conflates abstention with error, thereby discouraging models from producing calibrated “I don’t know” responses (Song et al., 2025). To alleviate such limitations, several extensions introduce richer reward structures, including uncertainty-aware RL (Xu et al., 2024a; Xue et al., 2024; Lin et al., 2024; Wang et al., 2024c; Li et al., 2025a; Liang et al., 2024) and multi-objective optimization for factual faithfulness (Wang et al., 2024a). Despite these advances, designing scalable reward signals that reliably capture truthfulness while balancing accuracy and uncertainty remains an open challenge. In this work, we demonstrate that reward structure—binary vs. ternary, whether and how uncertainty is incorporated—can fundamentally influence whether models learn to balance factual accuracy with abstention.

C IMPLEMENTATION DETAILS

Retrieval setup. We follow the retrieval setup from CRAG (Yang et al., 2024a), using up to 50 web pages as retrieval documents per question. For each question, the question text is used as the search query, and up to 50 HTML pages are stored from the search API. For NaturalQuestions (NQ), HotpotQA, and MuSiQue, we use the 2018 Wikipedia dump (Karpukhin et al., 2020) as the knowledge source and employ the E5 retriever (Wang et al., 2024b), as in line with the Search-R1 setup (Jin et al., 2025).

DPO. DPO (Rafailov et al., 2023) is an offline RL method that trains the model to prefer certain responses over others. Preference pairs are constructed differently for OOK and non-OOK questions. For OOK questions, the preferred response is “I don’t know,” and the dispreferred response is a randomly chosen incorrect answer. For non-OOK questions, correct and incorrect responses are paired. DPO expresses the probability of preference data with the policy model rather than the reward model, yielding the following objective:

$$\mathcal{L}_{\text{DPO}}(\theta) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_{\theta}(y_w | x)}{\pi_{\text{ref}}(y_w | x)} - \beta \log \frac{\pi_{\theta}(y_l | x)}{\pi_{\text{ref}}(y_l | x)} \right) \right],$$

where (x, y_w, y_l) are preference pairs consisting of the prompt, the winning response, and the losing response from the preference dataset \mathcal{D} .

Iterative DPO. This variant builds on a DPO-trained checkpoint and iteratively constructs preference pairs in the same way over the training set.

Training details. Our models are trained on 8 NVIDIA H100 GPUs with 80GB memory using full-parameter fine-tuning. By default, we use the Open-R1 library (Hugging Face, 2025) as the training framework. To optimize GPU utilization, we adopt DeepSpeed (Rajbhandari et al., 2020) with ZeRO-3 offload, along with gradient checkpointing, FlashAttention-2 (Dao, 2024), and bf16 mixed-precision training enabled. To optimize model performance, we conduct an extensive hyperparameter search with batch sizes in [16, 32, 64], learning rates in [5e-7, 1e-6, 2e-6, 3e-6, 5e-6, 1e-5], and training epochs in [1, 2, 3].

For SFT, RFT, and R-Tuning, we use a learning rate of 5e-6 and a batch size of 16, with a cosine learning rate scheduler and 3% warmup steps, trained for 1 epoch. For DPO and iterative DPO, we use a learning rate of 3e-6 and a batch size of 32, trained for 1 epoch.

For RL training, we use the VeRL framework (Sheng et al., 2024) with a constant learning rate of 1e-6, and a batch size of 64. The KL divergence regularization coefficient β and clip ratio ϵ are set to 0.001 and 0.2, respectively. The maximum context length and number of generated tokens are set to 16,384 and 2,048. For efficient LLM rollouts, we use vLLM (Kwon et al., 2023) with a tensor parallel size of 2 and a GPU memory utilization ratio of 0.8. Rollout sampling is performed with

temperature = 1.0 and top-p = 1.0. The maximum token length for all models is fixed at 16k. We set $\lambda = 0.5$ in Section 4.6.

Inference details. We use vLLM for efficient inference and adopt greedy decoding (*i.e.*, temp = 0) for evaluation to ensure reproducible results. For data construction in RFT, we sample 64 responses with a temperature of 0.6 and top-p of 0.9. The maximum token length at inference is set to 32k.

D LARGE LANGUAGE MODEL USAGE

During the preparation of this paper, we used LLMs solely to refine grammar and wording. Their role was strictly limited to language polishing.

E PROMPT TEMPLATE

Inference prompts. Below we present the inference prompts for both without and with retrieval setups in Table 9 and Table 10, respectively.

Table 9: Inference prompt under without retrieval setup.

Inference Prompt (Without Retrieval)

Input: You are given a Question and the time when it was asked in the Pacific Time Zone (PT), referred to as “Query Time”. The query time is formatted as “mm/dd/yyyy, hh:mm:ss PT”. Your task is to answer the question based on factual information in your own knowledge.

Please adhere to the following guidelines when formulating the answer:

1. If the question contains a false premise or assumption, answer “invalid question”.
2. If you are uncertain or don’t know the answer, answer “I don’t know”.

Please reason step by step and then provide the final answer. The reasoning process must be enclosed within <think> </think> tags. The final answer MUST be put in `\boxed{}`. For example, `\boxed{I don’t know}`, `\boxed{invalid question}`, `\boxed{3 times}`, `\boxed{New York}`, etc.

Question: {question}

Query Time: {query time}

Output: {answer}

LLM-as-a-judge prompts. Below we present the judge prompts for outcome and reasoning quality in Table 11 and Table 12, respectively.

F CASE STUDY

Table 13 presents a representative example illustrating the accuracy of the LLM-based judge.

972
973
974
975
976
977
978
979
980
981
982
983
984
985
986
987
988
989
990
991
992
993
994
995
996
997
998
999
1000
1001
1002
1003
1004
1005
1006
1007
1008
1009
1010
1011
1012
1013
1014
1015
1016
1017
1018
1019
1020
1021
1022
1023
1024
1025

Table 10: Inference prompt under with retrieval setup.

Inference Prompt (With Retrieval)
<p>Input: You are given a Question, References and the time when it was asked in the Pacific Time Zone (PT), referred to as “Query Time”. The query time is formatted as “mm/dd/yyyy, hh:mm:ss PT”. The references may or may not help answer the question. Your task is to answer the question based on factual information in the references or your own knowledge.</p> <p>Please adhere to the following guidelines when formulating the answer:</p> <ol style="list-style-type: none"> 1. If the question contains a false premise or assumption, answer “invalid question”. 2. If you are uncertain or don’t know the answer, answer “I don’t know”. <p>Please reason step by step and then provide the final answer. The reasoning process must be enclosed within <think> </think> tags. The final answer MUST be put in \boxed{}. For example, \boxed{I don’t know}, \boxed{invalid question}, \boxed{3 times}, \boxed{New York}, etc.</p> <p>### Question: {question} ### Query Time: {query time} ### References: {documents}</p> <p>Output: {answer}</p>

Table 11: LLM-as-a-judge prompt for evaluating outcome.

LLM-as-a-judge Prompt (Outcome)
<p>Input: Assume you are a human expert in grading predictions given by a model. You are given a question and a model prediction. Judge if the prediction matches the ground truth answer by following these steps:</p> <ol style="list-style-type: none"> 1: Take it as granted that the Ground Truth is always correct. 2: If the Prediction exactly matches the Ground Truth, “score” is 1. 3: If the Prediction does not exactly match the Ground Truth, go through the following steps and likely give a score as 0. 4: If the Ground Truth is a number, “score” is 1 if and only if the Prediction gives a number that almost exactly matches the ground truth. 5: If the Prediction is self-contradictory, “score” must be 0. 6: If the prediction is not answering the question, “score” must be 0. 7: If the prediction is a concise and correct summary of the ground truth, “score” is 1. 8: If ground truth contains a set of items, prediction must contain exactly same items for the score to be 1. 9: Otherwise, “score” is 0. <p>Output a JSON blob with an “explanation” field explaining your answer as short as possible and an “score” field with value 1 or 0.</p> <p>You should make the judgment based on provided examples.</p> <p>### Examples: {examples} ### Question: {question} ### Ground Truth: {ground truth} ### Prediction: {predicted answer}</p> <p>Output: {judgment}</p>

1026
1027
1028
1029
1030
1031
1032
1033
1034
1035
1036
1037
1038
1039
1040
1041
1042
1043
1044
1045
1046
1047
1048
1049
1050
1051
1052
1053
1054
1055
1056
1057
1058
1059
1060
1061
1062
1063
1064
1065
1066
1067
1068
1069
1070
1071
1072
1073
1074
1075
1076
1077
1078
1079

Table 12: LLM-as-a-judge prompt for evaluating reasoning quality.

LLM-as-a-judge Prompt (Reasoning Quality)	
Input:	Assume you are a human expert in evaluating the usefulness of model-generated reasoning. You are given a question and a model-generated reasoning. Judge if the reasoning provides precise information to correctly answer the question by following these steps:
	1: Evaluate if the reasoning directly addresses the question.
	2: Check if the key points in the reasoning are relevant to the query.
	3: If the reasoning provides precise and relevant information, “score” is 1.
	4: If the reasoning is vague, unrelated, or does not address the question, “score” is 0.
	Output a JSON blob with an “explanation” field explaining your answer as short as possible and an “score” field with value 1 or 0.
	You should make the judgment based on provided examples.
	### Examples: {examples}
	### Question: {question}
	### Ground Truth: {ground truth}
	### Reasoning: {predicted reasoning}
Output:	{judgment}

Table 13: An example of LLM-as-a-judge result.

LLM-as-a-judge Result	
Question:	How many times has Lizzo won the Grammy Award for Album of the Year?
Ground Truth:	Lizzo has never won the Grammy Award for Album of the Year, though she has been nominated twice.
Prediction:	<think> To answer the question “How many times has Lizzo won the Grammy award for album of the year?”, we need to analyze the information provided in the references. Document [4] mentions that Lizzo has won 4 Grammy Awards, but it does not specifically mention the category of Album of the Year. However, Document [5] mentions that Lizzo’s album “Special” is nominated for Album of the Year, but it does not mention that she has won the award. After reviewing all the documents, I found that none of them explicitly state that Lizzo has won the Grammy Award for Album of the Year. Therefore, the answer is 0, as there is no evidence to suggest that Lizzo has won the Grammy Award for Album of the Year. </think> \boxed{0}.
LLM judge result:	{“score”: 1, “explanation”: “The prediction correctly states the number of times Lizzo has won the Grammy Award for Album of the Year, which is zero.”}