
SAGE: Strategy-Adaptive Generation Engine for Query Rewriting

Teng Wang
OPPO Research Institution
wangteng2@oppo.com

Hailei Gong
Tsinghua University
gonghl18@mails.tsinghua.edu.cn

Changwang Zhang
OPPO Research Institution
zhangchangwang@oppo.com

Jun Wang
OPPO Research Institution
wangjun7@oppo.com

Abstract

Query rewriting is pivotal for enhancing dense retrieval, yet current methods demand large-scale supervised data or suffer from inefficient reinforcement learning (RL) exploration. In this work, we first establish that guiding Large Language Models (LLMs) with a concise set of expert-crafted strategies, such as semantic expansion and entity disambiguation, substantially improves retrieval effectiveness on challenging benchmarks, including HotpotQA, FEVER, NFCorpus, and SciFact. Building on this insight, we introduce the **Strategy-Adaptive Generation Engine (SAGE)**, which operationalizes these strategies in an RL framework. SAGE introduces two novel reward shaping mechanisms- Strategic Credit Shaping (SCS) and Contrastive Reward Shaping (CRS)-to deliver more informative learning signals. This strategy-guided approach not only achieves new state-of-the-art NDCG@10 results, but also uncovers a compelling emergent behavior: the agent learns to select optimal strategies, reduces unnecessary exploration, and generates concise rewrites, lowering inference cost without sacrificing performance. Our findings demonstrate that strategy-guided RL, enhanced with nuanced reward shaping, offers a scalable, efficient, and more interpretable paradigm for developing the next generation of robust information retrieval systems.

1 Introduction

Effective information retrieval (IR) is increasingly reliant on dense retrieval systems, which map queries and documents into a shared semantic space. The performance of these systems, however, is fundamentally bound by the quality of the input query. To bridge the significant gap between a user’s initial intent and a query optimized for machine comprehension, query rewriting has emerged as a critical component. While LLMs have shown significant promise for general data generation, comprehension, and reasoning Achiam et al. [2023], Wang et al. [2025a], Yang et al. [2025a,b], Wang et al. [2025b], current methodologies face two primary obstacles: traditional supervised fine-tuning demands large-scale, costly manual annotations, whereas modern RL approaches, such as PPO Schulman et al. [2017] and GRPO Shao et al. [2024], often struggle with inefficient exploration. This inefficiency not only hampers the discovery of optimal rewriting strategies but can also result in unstable training dynamics and even catastrophic failures, where models produce incoherent or irrelevant outputs.

While prior work by Li et al. [2024] has explored strategy-based prompting, we find their strategies, specifically designed for sparse retrieval in general web search, struggle to generalize to the nuanced demands of dense retrieval and exhibit limited effectiveness on specialized benchmarks. To address

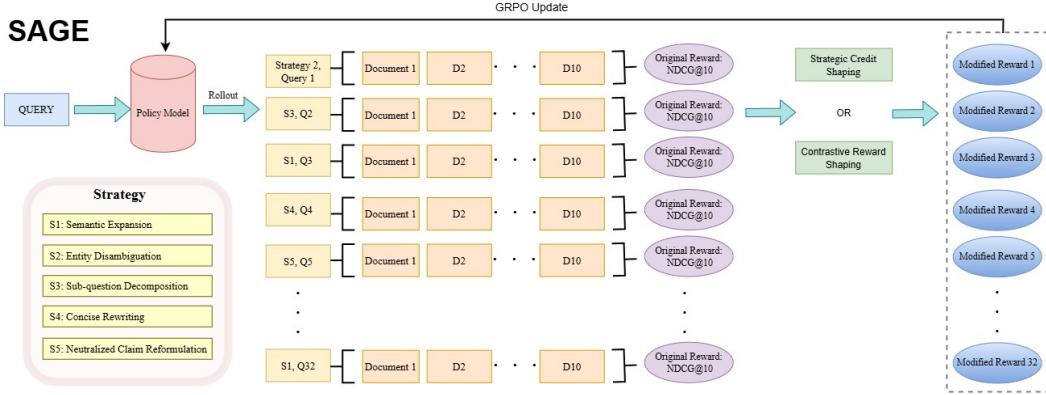


Figure 1: An overview of the **Strategy-Adaptive Generation Engine (SAGE)** framework. SAGE operationalizes expert-crafted strategies within a reinforcement learning loop. The policy model generates a strategy-guided rewrite, which is evaluated against the environment to produce an initial reward (NDCG@10). This reward is then transformed by our novel shaping modules—Strategic Credit Shaping or Contrastive Reward Shaping—to create a potent learning signal for the agent.

these challenges, we propose five novel query-rewriting strategies specifically designed for dense retrieval scenarios. These strategies significantly enhance the ability of LLMs to effectively reformulate queries, consistently outperforming previous method Li et al. [2024] on diverse and challenging benchmarks, including HotpotQA Yang et al. [2018], FEVER Thorne et al. [2018], NFCorpus Boteva et al. [2016], and SciFact Wadden et al. [2020].

The successful application of on-policy reinforcement learning to fine-tune LLMs is pioneered by algorithms such as PPO Schulman et al. [2017], which in turn inspired a family of variants including GRPO Shao et al. [2024], VAPO Yue et al. [2025], and DAPO Yu et al. [2025]. While these powerful algorithms have enabled new capabilities in query rewriting for LLMs, many prior approaches Jiang et al. [2025], Wang et al. [2025c] simply adopt them as generic optimization tools, without incorporating domain-specific guidance or explicit strategies tailored to the query rewriting task.

To bridge this gap, we introduce the **Strategy-Adaptive Generation Engine (SAGE)**, as demonstrated in Fig. 1, a framework that directly integrates our human-designed strategies into the GRPO algorithm, steering LLMs toward more effective and improved query-rewriting policies. To further refine the learning signal, we also propose and investigate several novel reward shaping schemes. Beyond using a direct NDCG@10 score, these include **Strategic Credit Shaping (SCS)**, which assigns credit based on the collective performance of each strategy, and **Contrastive Reward Shaping (CRS)**, which recasts absolute scores into a measure of relative performance.

Upon reproducing prior approaches Li et al. [2024], Jiang et al. [2025], we identify a significant form of reward hacking Weng [2024], Wang et al. [2024a], Wen et al. [2025] intrinsic to the query rewriting task. When fine-tuning LLMs on datasets such as HotpotQA Yang et al. [2018], the models consistently converge to a trivial policy: leaving the input query entirely unchanged. This behavior stems from the optimization objective, as modern retrievers like BGE-en-v1.5 Xiao et al. [2023] can already achieve strong baseline performance with the original queries. Given direct access to these queries, the model exploits this “safe” strategy-copying the input-to consistently secure high rewards, without engaging in the intended semantic rewriting. As a result, the agent becomes trapped in a deceptive local optimum, severely restricting exploration and preventing the discovery of potentially superior, albeit riskier, rewriting strategies.

To counteract this, we explicitly promote exploration through targeted prompt engineering and introducing a penalty for outputs identical to the original query. This straightforward yet powerful mechanism encourages the agent to venture beyond the safe default, resulting in significantly enhanced retrieval performance. We further examine the effectiveness of this exploration strategy through detailed ablation studies in Section 5.3.

We evaluate SAGE on two challenging benchmarks: HotpotQA Yang et al. [2018] and NFCorpus Boteva et al. [2016]. Our results demonstrate that SAGE achieves state-of-the-art retrieval effectiveness as measured by NDCG@10. Notably, we observe an emergent behavior where SAGE learns a more efficient reasoning process, substantially reducing token usage. This improved efficiency directly translates to lower inference latency and reduced computational costs.

Our main contributions are summarized as follows:

1. We demonstrate that explicitly guiding LLMs with a small set of interpretable human-designed strategies, such as semantic expansion and entity disambiguation, significantly improves query rewriting quality, even without additional training. This highlights the upper bound of performance achievable purely through prompting.
2. We introduce **SAGE (Strategy-Adaptive Generation Engine)**, a novel reinforcement learning framework that systematically integrates these explicit strategies into the learning loop. SAGE autonomously adapts its strategy selection process using our proposed reward-shaping mechanisms, enabling effective refinement of the training procedure.
3. We establish a new state-of-the-art in dense retrieval effectiveness (NDCG@10) using SAGE, while identifying a notable emergent behavior: SAGE learns a more efficient reasoning process, substantially reducing inference latency and computational costs without explicit optimization.
4. We provide comprehensive analyses and ablation studies highlighting the critical importance of forced exploration. Our results underscore the necessity of an explicit penalty mechanism to avoid reward hacking, offering valuable insights for effectively training RL-based rewriting models.

2 Related Work

2.1 The Evolution of Query Rewriting

Query rewriting has long been a cornerstone of IR, aimed at bridging the semantic gap between user intent and document representations. Early approaches typically relies on rule-based methods, thesaurus expansion, or statistical machine translation techniques. Although effective in specific contexts, these approaches often lack robustness and required extensive domain-specific feature engineering or sizable parallel corpora Rocchio Jr [1971], Zhai and Lafferty [2001], Abdul-Jaleel et al. [2004], Dalton et al. [2014], Xu et al. [2009], Xiong and Callan [2015]. The advent of pre-trained sequence-to-sequence models Liu et al. [2019], Devlin et al. [2018], such as BART Lewis et al. [2020] and T5 Raffel et al. [2020], significantly reshape query rewriting, framing it explicitly as a supervised fine-tuning task. However, this new paradigm introduces a critical bottleneck: heavy reliance on large-scale, high-quality annotated query pairs, which are costly and labor-intensive to construct.

2.2 Reinforcement Learning for Query Rewriting

To alleviate reliance on explicit supervision, recent approaches leverage RL to guide the generative capabilities of LLMs using weaker signals Schulman et al. [2017], Shao et al. [2024], Jiang et al. [2025], Li et al. [2024], Wang et al. [2025b,c,d]. However, the application of these powerful algorithms often reveals significant limitations. A common approach is to treat the LLM as a black box, applying on-policy algorithms like PPO without modification Jiang et al. [2025], which overlooks the need for specialized guidance. Other lines of work focus on prompt engineering, but strategies tailored for sparse retrieval in general web search Li et al. [2024] exhibit limited effectiveness when transferred to dense retrieval tasks. Furthermore, even approaches that integrate reward models, such as Wang et al. [2025c], can be flawed; they often rely on an arbitrary, static fusion of scores from multiple fine-tuned reward models, lacking dynamic feedback from the actual retrieval environment. This highlights a fundamental gap: existing RL-based methods frequently neglect the nuanced, domain-specific guidance required to fully exploit the potential of dense retrieval systems. In contrast, our SAGE framework addresses this gap by introducing a novel layer of explicit, human-designed strategic guidance. It achieves this through two core innovations: first, by equipping the agent with a set of fine-grained strategies for query augmentation, and second, by proposing novel reward calculation schemes like SCS and CRS to provide a more nuanced and effective learning signal.

Strategy	Targeted Challenge	Primary Use Case
Senmantic Expansion	Vocabulary mismatch between query and documents.	General purpose, especially in specialized domains (e.g., NFCorpus).
Entity Disambiguation	Ambiguous entities leading to incorrect retrieval.	Queries with common names or acronyms.
Sub-question Decomposition	Complex, multi-step information needs.	Multi-hop QA (e.g., HotpotQA).
Concise Rewriting	Query noise from redundant or conversational phrases.	Improving precision for overly verbose user queries.
Neutralized Claim Reformulation	Retriever’s confirmation bias towards a stated claim.	Fact-checking and verification (e.g., FEVER, SciFact).

Table 1: Overview of our five expert-crafted rewriting strategies and their targeted applications.

2.3 Challenge in RL: Reward Hacking

Beyond the lack of strategic guidance, applying RL to generative tasks introduces a further challenge. A pervasive issue in reinforcement learning is reward hacking, where an agent learns to maximize a misspecified or ambiguous reward function in unintended ways. This often results in the agent securing high scores by exploiting loopholes, rather than mastering the desired behavior or accomplishing the true underlying objective Weng [2024], Wang et al. [2024a], Wen et al. [2025], Wang et al. [2024b].

In the context of query rewriting, this problem manifests in a particularly deceptive form. Since the policy model has access to the original query, it can discover a trivial, low-effort strategy: leave the query unchanged. Given that modern retrievers can achieve high baseline performance on the original queries for many benchmarks, this "do nothing" policy is often reinforced with a strong, positive reward. This effectively traps the agent in a local optimum, allowing it to "hack" the reward by avoiding the risk of exploration altogether. Our work directly confronts this challenge by introducing mechanisms to force meaningful exploration.

3 Methodology

The core idea of our methodology is to replace opaque black-box optimization with explicit, human-interpretable decision-making steps in the reinforcement learning process. To achieve this, we propose the **Strategy-Adaptive Generation Engine (SAGE)**, which reformulates query rewriting from unconstrained text generation into a structured, strategy-driven decision problem. As shown in Figure 1, our framework embeds a set of expert-crafted strategies directly within the RL training process to systematically guide both exploration and policy learning.

3.1 Problem Formulation

We frame query rewriting as a reinforcement learning task. Given an initial user query q_{orig} and a document collection \mathcal{D} , the objective is to learn a policy π that generates an improved query q . The environment evaluates the rewritten query using NDCG@10, yielding an initial reward $r_{orig} = \text{NDCG}@10(q, \mathcal{D})$, which is further refined by our reward shaping methods (see Section 3.4) to produce the final reward r_{final} . The agent thus aims to maximize the expected final reward: $\mathbb{E}_{q \sim \pi(\cdot | q_{orig})}[r_{final}]$. We use GRPO Shao et al. [2024] as our optimization algorithm and incorporate a set of expert-crafted rewriting strategies $\mathcal{S} = \{s_1, s_2, \dots, s_5\}$, providing explicit guidance for query reformulation.

3.2 Explicit Strategic Primitives

To move past generic prompting, we introduce five explicit, expert-crafted query rewriting strategies, each tailored to address specific challenges in dense retrieval. Rather than relying on simple keyword manipulation, these strategies systematically alter the semantic structure of the query to mitigate common retrieval failures. The primitives, outlined succinctly in Table 1, are not mutually exclusive and often involve inherent trade-offs. For instance, semantic expansion may improve recall at the

cost of precision. Collectively, these strategies constitute the discrete action space from which our SAGE framework dynamically selects and applies. The detailed prompts describing each strategy can be found in Appendix A.1.

3.3 The SAGE Framework

SAGE operationalizes our expert-crafted strategies by embedding them within an on-policy RL algorithm. In contrast to black-box methods, SAGE transforms the task from unconstrained text generation into a structured, two-part action selection process, making the agent’s decision-making more explicit and interpretable. The overall workflow is illustrated in Figure 1.

For each input query, the policy model is prompted to generate a batch of N rollouts. A key distinction of our framework is that each action is a structured pair, $\{q_i, s_i\}$, comprising both the rewritten query and the integer ID of the selected strategy. This design compels the LLM not only to generate an effective rewrite but also to commit to an explicit, interpretable strategy, thus making its “intent” transparent.

Each rewritten query q_i is then evaluated by the retrieval environment to obtain an initial reward, $r_{\text{orig},i}$, based on its NDCG@10 score. In a conventional RL setup, this raw score would be used directly as the final reward. We posit, however, that this absolute score is an insufficient learning signal, as it provides no direct credit for selecting a high-performing strategy, nor does it effectively distinguish superior rewrites from merely adequate ones within a batch. To address this, the batch of initial rewards is processed by a dedicated **reward shaping module** (detailed in Section 3.4). This module transforms the raw scores into a more potent learning signal, $r_{\text{final},i}$, which is ultimately used to update the agent’s policy.

3.4 Reward Shaping Mechanisms

To provide the agent with a more informative learning signal, we introduce two novel reward shaping mechanisms that go beyond simply using the raw NDCG@10 score. While the direct score is a standard choice, it provides only limited feedback: it fails to explicitly reward the selection of high-performing strategies and does not encourage intra-batch competition, as it treats all positive outcomes similarly—making little distinction between adequate and exceptional rewrites. To address these shortcomings, we propose two new mechanisms that transform the raw score into a more effective learning objective, as illustrated in Figure 2.

Strategic Credit Shaping (SCS): This method aims to explicitly solve the credit assignment problem by rewarding the agent for selecting high-performing strategies. Within a given batch of rollouts, we first group them by their chosen strategy s_i . We then compute the average initial reward, $\bar{r}_{\text{orig}}(s_i)$, for each strategy group and rank them based on this score. The final reward for an individual rollout is its original score scaled by the inverse of its strategy’s rank:

$$r_{\text{SCS},i} = \frac{r_{\text{orig},i}}{\text{rank}(s_i)} \quad (1)$$

This mechanism directly encourages the agent to converge on strategies that are collectively more effective, providing a clearer signal for strategic decision-making.

Contrastive Reward Shaping (CRS): This method introduces intra-batch competition by normalizing rewards against a dynamic baseline, effectively penalizing underperforming rewrites while rewarding those that surpass the batch’s typical performance. The final reward is the advantage over this baseline:

$$r_{\text{CRS},i} = r_{\text{orig},i} - \text{baseline} \quad (2)$$

This forces the agent to learn policies that outperform the batch’s typical performance, rather than simply achieving any positive score. By creating a clearer distinction between superior and mediocre rewrites, CRS sharpens the reward landscape and accelerates learning.

3.5 Counteracting Reward Hacking with Forced Exploration

In reproducing previous work Jiang et al. [2025], Li et al. [2024], we identify a pervasive form of reward hacking in the query rewriting task. This phenomenon, where an agent exploits loopholes in

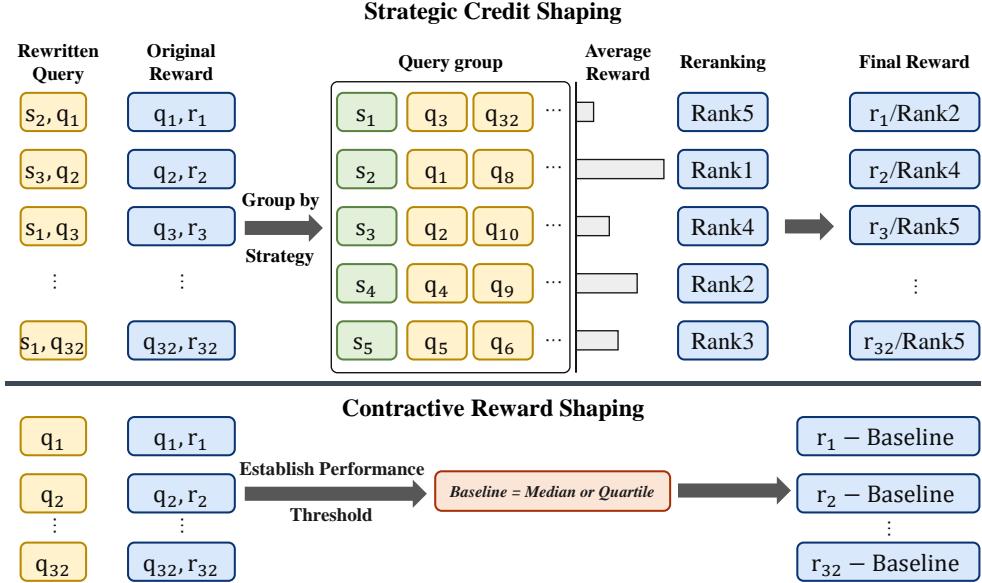


Figure 2: An illustration of our two proposed reward shaping mechanisms. (a) SCS solves the credit assignment problem by grouping rollouts based on their chosen strategy, ranking these strategies by their average performance, and then scaling the individual rewards by their strategy’s rank. (b) CRS sharpens the learning signal by normalizing each reward against a baseline (e.g., the batch median), reframing the objective as outperforming the typical performance.

the reward function to achieve high scores without accomplishing the intended objective, manifests in a particularly deceptive way in our setting. Due to the strong performance of modern retrievers, an agent can often achieve a high baseline reward by simply using the original query. Since the policy model has direct access to this query, it quickly learns that the simplest “hack” is to copy it, securing a high, risk-free score. This behavior traps the agent in a deceptive local optimum, stifling any meaningful exploration of potentially superior rewriting strategies. To directly counteract this, we introduce two mechanisms designed to force exploration.

Exploration Penalty. We apply a simple penalty term to disincentivize the agent from reverting to the trivial policy of copying the input. The final reward, r_{final} , is calculated by applying this penalty to the base reward signal, r_{base} , which represents the output from our main reward calculation (either direct NDCG@10, SCS, or CRS). The relationship is formally defined as:

$$r_{\text{final}} = \begin{cases} r_{\text{base}} - p & \text{if } q_{\text{orig}} = q \\ r_{\text{base}} & \text{otherwise} \end{cases} \quad (3)$$

where q_{orig} is the original query, q is the rewritten query, and p is a fixed penalty hyperparameter. This formulation ensures that the agent is explicitly penalized only when it outputs a query identical to the input, thereby directly encouraging the exploration of novel rewrites.

Proactive Exploration Prompting. In contrast to prior work Li et al. [2024], which instructs the model to keep the query unchanged if a better one is not found, our prompting philosophy is designed to actively encourage the agent to explore alternative rewrites.

We validate the effectiveness of these forced exploration mechanisms in our ablation studies in Section 5.3.

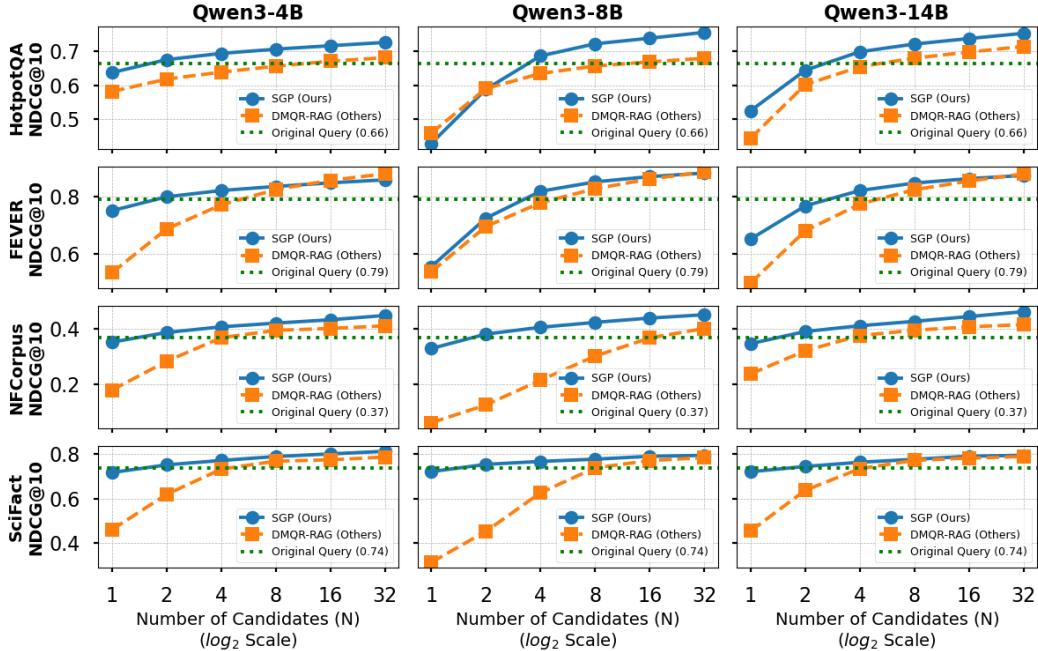


Figure 3: Performance scaling laws for query rewriting using the BGE-base-en-v1.5 retriever across four benchmark datasets: HotpotQA, FEVER, NFCorpus, and SciFact. Each subplot compares the upper-bound performance (NDCG@10) of our Strategy-Guided Prompting (SGP) against the strategies proposed by DMQR-RAGLi et al. [2024], evaluated via a Best-of-N methodology across the Qwen3 model series Yang et al. [2025b].

4 Experiment

4.1 Effectiveness of Rewriting Strategies

To empirically validate the effectiveness of our five expert-crafted strategies (detailed in Section 3.2 and Appendix A.1), we conducted a comprehensive scaling law analysis. Using BGE-en-base-v1.5 Xiao et al. [2023] as the retriever, we compare our Strategy-Guided Prompting (SGP) approach against the strategies proposed by DMQR-RAGLi et al. [2024] using a Best-of-N methodology. The results are presented in Figure 3. Across all four challenging datasets, including HotpotQA Yang et al. [2018], FEVER Thorne et al. [2018], NFCorpus Boteva et al. [2016], and SciFact Wadden et al. [2020], our SGP consistently and substantially outperforms the baseline. This demonstrates that our strategies provide a more effective upper-bound on performance by successfully guiding the LLM towards higher-quality query rewrites. Similar trends of SGP outperforming the baseline are observed when using the Contriever Izacard et al. [2021] retriever, with detailed results provided in Appendix A.2.

4.2 Comparison with State-of-the-Art Baselines

Having established the upper-bound potential of our expert-crafted strategies (Section 4.1), we now evaluate the full SAGE framework. Our preliminary analysis indicates that for datasets like FEVER and SciFact, the potential for improvement via RL is constrained, due to either a high performance baseline from the original query or a high exploration cost required for marginal gains. Consequently, to provide a more meaningful evaluation of SAGE’s optimization capabilities, we focus our main RL experiments on HotpotQA and NFCorpus, which present a larger performance gap and thus a more dynamic learning environment.

We benchmark SAGE against a diverse suite of strong baselines to demonstrate its effectiveness. This includes state-of-the-art open-source models Qwen3-4B, Qwen3-8B, Qwen3-14B, GPT-4.1, GPT-

Method	HotpotQA		NFCorpus	
	NDCG@10 ↑	Avg. Tokens ↓	NDCG@10 ↑	Avg. Tokens ↓
Baselines				
Original Query	0.6633	0	0.3677	0
Qwen3-4B	0.6366	1598	0.3527	911
Qwen3-8B	0.4295	1966	0.3298	885
Qwen3-14B	0.5251	1682	0.3473	586
GPT-4.1	0.7118	297	0.3711	205
GPT-o4-mini	0.6915	776	0.3809	440
Claude-Sonnet-4-thinking	0.6515	1451	0.3701	1152
Gemini-2.5-Flash	0.6425	1614	0.3689	957
Gemini-2.5-Pro	0.6671	1986	0.3663	1096
Deepseek-R1	0.6262	2182	0.3270	1251
DeepRetrieval + Qwen3-4B	0.6681	232	0.3676	343
DMQR-RAG + Qwen3-4B	0.5812	798	0.1808	1032
Our Method (SAGE)				
SAGE (Direct)	0.6894	92	0.3776	229
SAGE-SCS	0.6955	66	0.3967	139
SAGE-CRS	0.6918	69	0.4035	154

Table 2: SAGE achieves state-of-the-art performance with remarkable efficiency. This table compares our SAGE framework, fine-tuned on Qwen3-4B, against strong baselines including the re-evaluated DeepRetrieval method and significantly larger proprietary models like Gemini-2.5-Pro and GPT-o4mini. All models are evaluated with a maximum response length of 4096 tokens. The results demonstrate that SAGE not only outperforms other RL approaches but also achieves retrieval effectiveness (NDCG@10) competitive with these massive models, while requiring substantially fewer tokens.

o4-mini, Claude-Sonnet-4, Gemini-2.5-Flash, Gemini-2.5-Pro, Deepseek-R1 Yang et al. [2025b], Team et al. [2023], Achiam et al. [2023], Anthropic [2025], Guo et al. [2025]. For a fair comparison under our controlled experimental setup, we also re-evaluate prior RL-based methods, including DeepRetrieval Jiang et al. [2025] and the strategies from DMQR-RAG Li et al. [2024]. Against these baselines, we report the performance of SAGE enhanced with our two novel reward shaping mechanisms, SAGE-SCS and SAGE-CRS.

The results presented in Table 2 clearly demonstrate the dual advantage of our SAGE framework. In terms of retrieval effectiveness, our SAGE variants establish a new state-of-the-art. Notably, SAGE, fine-tuned on Qwen3-4B, consistently outperforms specialized RL-based approaches like DeepRetrieval also fine-tuned from Qwen3-4B in our experiment setting. More strikingly, our method achieves performance that is competitive with, and in some cases superior to, significantly larger and more powerful proprietary models such as Gemini-2.5-Pro, GPT-o4-mini.

More striking than the performance gains is the emergent efficiency of our SAGE framework. We observe that SAGE consistently generates rewrites using substantially fewer tokens than competing methods, a phenomenon that is even more pronounced when using our SCS and CRS reward shaping schemes. We attribute this to the agent learning to prioritize more direct reasoning paths, effectively discovering a shortcut to high-quality rewrites without being explicitly optimized for brevity.

This finding has profound practical implications. In a production environment, the long, static portion of our strategic prompt can be pre-processed and its KV cache stored. During inference, the system only needs to generate the short, rewritten query, leading to a dramatic reduction in latency and computational cost. This architectural advantage, which decouples the pre-computable prompt context from the short dynamic generation, makes SAGE a highly attractive solution for real-world, performance-critical retrieval systems.

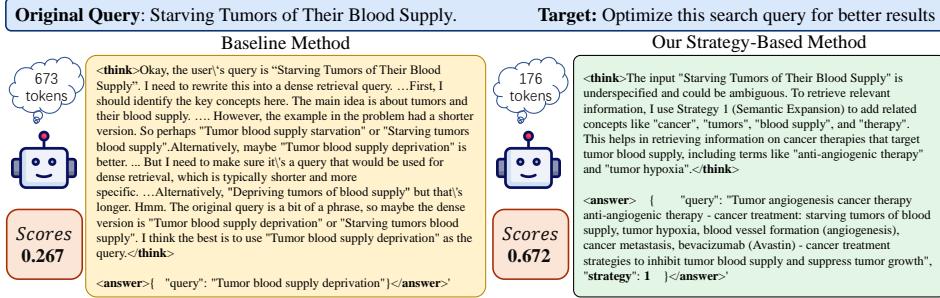


Figure 4: Qualitative comparison illustrating the mechanism behind SAGE’s dual advantage. The baseline model (left), lacking strategic guidance, engages in a verbose and convoluted reasoning process, resulting in a suboptimal query. In contrast, SAGE (right) leverages an explicit strategy to find a direct and efficient path to a more semantically accurate rewrite, achieving superior retrieval effectiveness with a fraction of the token generation cost.

Method	HotpotQA		NFCorpus	
	NDCG@ 10 ↑	Avg. Tokens ↓	NDCG@ 10 ↑	Avg. Tokens ↓
Baseline (No Strategic Guidance)				
DeepRetrieval	0.6681	232	0.3676	343
Our Method (with Strategic Guidance)				
SAGE (Direct)	0.6894	92	0.3775	229
SAGE-SCS	0.6955	66	0.3966	139
SAGE-CRS	0.6918	69	0.4035	154

Table 3: Ablation study on the impact of strategic guidance. We compare the performance of a standard RL baseline (DeepRetrieval) against our SAGE framework, which incorporates expert-crafted strategies. The results highlight the significant gains in both effectiveness (NDCG@10) and efficiency (Avg. Tokens) brought by our strategic guidance.

5 Ablation Study

To isolate and quantify the impact of our core contributions, we conduct a series of ablation studies. Our experiments are designed to answer several key questions: (1) What is the performance gain from our expert-crafted strategies compared to an unguided RL baseline? And what is the contribution of our novel reward shaping mechanisms (SCS and CRS) compared to a direct reward? (2) How critical is the exploration penalty for overcoming reward hacking?

5.1 The Impact of Strategic Guidance

The most significant finding from our ablation study is the dramatic impact of strategic guidance. As shown in Table 3, removing our expert-crafted strategies and reverting to a "black-box" RL approach results in a significant degradation in performance. While this change leads to a notable drop in NDCG@10 across both datasets, the more striking effect is on efficiency, where the average response length increases dramatically. This demonstrates that models trained without strategic guidance are not only less effective but also substantially less efficient.

To provide a more intuitive understanding, Figure 4 presents a direct case comparison. The output from the model trained without strategies is generic and fails to capture the query’s nuance, whereas the output from SAGE is scientifically precise and far more effective for retrieval.

Furthermore, we see the additional benefits of our reward shaping mechanisms. On both datasets, SAGE-SCS and SAGE-CRS further improve upon the SAGE (Direct) baseline, pushing the performance ceiling even higher while maintaining superior efficiency. This confirms that while strategic guidance is the foundational improvement, our novel reward shaping schemes provide a crucial secondary optimization.

Experimental Condition	NDCG@10 ↑	Modification Rate ↑
Conservative Prompt ("keep unchanged")	0.671	0.509
Proactive Exploration Prompt	0.694	0.951
Proactive Prompt + Penalty ($p = 0.02$)	0.692	0.998

Table 4: Ablation study on different exploration mechanisms for SAGE-SCS on the HotpotQA dataset. We compare three settings: (1) using a conservative prompt, (2) using a proactive exploration prompt, and (3) combining the proactive prompt with an exploration penalty.

5.2 Analysis of Training Dynamics

Beyond final performance, the training dynamics also reveal the superiority of the SAGE framework. As illustrated in Appendix A.3, the baseline model trained without strategies quickly gets trapped in a local optimum. Its performance stagnates after only a few training steps, and its response length remains high and volatile throughout the process.

In stark contrast, SAGE demonstrates continuous performance improvement during training. More importantly, we observe a compelling emergent behavior: as SAGE learns to better utilize its strategies, it also learns to achieve the optimal rewrite with a more concise reasoning process. This results in a steady and significant decrease in the average response length over time, proving that our framework not only learns more effectively but also more efficiently.

5.3 The Critical Role of the Exploration Penalty

In reproducing prior work Jiang et al. [2025], Li et al. [2024], we identify a significant challenge in this task: the agent’s strong tendency to revert to a trivial policy of outputting the original query without modification. We attribute this reward-hacking behavior to two primary causes. First, the high baseline performance of modern retrievers makes the "do-nothing" action a safe, high-reward option. This issue is exacerbated by instructions in prior work like Li et al. [2024], which explicitly instructs the agent to preserve the original query if a rewrite is deemed unnecessary, reinforcing this conservative policy from the start of training. Second, many powerful retrievers have been trained on these benchmarks, making them brittle and highly sensitive to phrasing, where even minor, semantically-sound modifications can lead to a sharp drop in performance. This combination traps the agent in a deceptive local optimum, making any exploration a high-risk endeavor.

To break this cycle and force meaningful exploration, we implement a two-pronged approach. First, in contrast to prior work Li et al. [2024] which explicitly instructs the agent to keep the original query if no better one is found, our prompt philosophy actively encourages exploration, detailed is demonstrated in Appendix A.1. Second, and more critically, we introduce a simple penalty term, subtracting a fixed value $p=0.05$ from the reward whenever the generated query is identical to the original, directly disincentivizing this reward-hacking behavior.

To validate the effectiveness of these mechanisms, we conducted an ablation study using the SAGE-SCS model on HotpotQA. The results, shown in Table 4, clearly demonstrate the value of our approach: simply replacing the conservative prompt with our proactive exploration prompt substantially increases both NDCG@10 and the modification rate, highlighting the critical role of encouraging exploration. However, the use of an exploration penalty reveals a critical trade-off. While it drives the modification rate to nearly perfect levels (0.998), we observe a slight decrease in NDCG@10. This suggests that in cases where the original query is already optimal, enforcing modifications via a penalty may slightly impair peak performance. Thus, although the penalty is highly effective for maximizing exploration and mitigating reward hacking, its application should be carefully balanced against the specific task’s need for exhaustive exploration versus optimal end performance.

6 Conclusion

In this work, we introduced SAGE, a novel framework designed to address the black-box nature and inefficient exploration of conventional RL-based query rewriting. By deeply integrating expert-crafted strategies and novel reward shaping mechanisms (SCS and CRS) into an RL loop, SAGE not only

achieves a new state-of-the-art in retrieval effectiveness but also exhibits a compelling emergent efficiency, substantially reducing inference costs. Our findings establish that strategy-guided RL is a powerful framework for developing retrieval systems that are not only more effective and efficient, but also more transparent and controllable, opening promising avenues for future research in areas like automatic strategy discovery.

References

- Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- Teng Wang, Zhenqi He, Wing-Yin Yu, Xiaojin Fu, and Xiongwei Han. Large language models are good multi-lingual learners : When LLMs meet cross-lingual prompts. In Owen Rambow, Leo Wanner, Marianna Apidianaki, Hend Al-Khalifa, Barbara Di Eugenio, and Steven Schockaert, editors, *Proceedings of the 31st International Conference on Computational Linguistics*, pages 4442–4456, Abu Dhabi, UAE, January 2025a. Association for Computational Linguistics. URL <https://aclanthology.org/2025.coling-main.300/>.
- An Yang et al. Qwen2.5 technical report. *arXiv preprint arXiv:2505.09388*, 2025a.
- An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengan Huang, Chenxu Lv, et al. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*, 2025b.
- Teng Wang, Zhangyi Jiang, Zhenqi He, Wenhan Yang, Yanan Zheng, Zeyu Li, Zifan He, Shenyang Tong, and Hailei Gong. Towards hierarchical multi-step reward models for enhanced reasoning in large language models. *arXiv preprint arXiv:2503.13551*, 2025b.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Y Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.
- Zhicong Li, Jiahao Wang, Hangyu Mao, ZhiShu Jiang, Zhongxia Chen, Du Jiazen, Fuzheng Zhang, Di ZHANG, and Yong Liu. Dmqr-rag: Diverse multi-query rewriting in retrieval-augmented generation. *ArXiv e-prints*, 2024. URL <https://arxiv.org/abs/2411.13154>.
- 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.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: a large-scale dataset for fact extraction and VERification. In Marilyn Walker, Heng Ji, and Amanda Stent, editors, *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 809–819, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1074. URL <https://aclanthology.org/N18-1074/>.
- Vera Boteva, Demian Gholipour, Artem Sokolov, and Stefan Riezler. A full-text learning to rank dataset for medical information retrieval. In *Advances in Information Retrieval: 38th European Conference on IR Research, ECIR 2016, Padua, Italy, March 20–23, 2016. Proceedings 38*, pages 716–722. Springer, 2016.
- David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohan, and Hannaneh Hajishirzi. Fact or fiction: Verifying scientific claims. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu, editors, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7534–7550, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.609. URL <https://aclanthology.org/2020.emnlp-main.609/>.

- Yu Yue, Yufeng Yuan, Qiying Yu, Xiaochen Zuo, Ruofei Zhu, Wenyuan Xu, Jiaze Chen, Chengyi Wang, TianTian Fan, Zhengyin Du, et al. Vapo: Efficient and reliable reinforcement learning for advanced reasoning tasks. *arXiv preprint arXiv:2504.05118*, 2025.
- Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, et al. Dapo: An open-source llm reinforcement learning system at scale. *arXiv preprint arXiv:2503.14476*, 2025.
- Pengcheng Jiang, Jiacheng Lin, Lang Cao, Runchu Tian, SeongKu Kang, Zifeng Wang, Jimeng Sun, and Jiawei Han. Deepretrieval: Hacking real search engines and retrievers with large language models via reinforcement learning. *ArXiv e-prints*, 2025. URL <https://arxiv.org/abs/2503.00223>.
- Yujing Wang, Hainan Zhang, Liang Pang, Binghui Guo, Hongwei Zheng, and Zhiming Zheng. Maferw: Query rewriting with multi-aspect feedbacks for retrieval-augmented large language models. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 25434–25442, 2025c.
- Lilian Weng. Reward hacking in reinforcement learning, 2024. URL <https://lilianweng.github.io/posts/2024-11-28-reward-hacking/>.
- Peiyi Wang, Lei Li, Liang Chen, Zefan Cai, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. Large language models are not fair evaluators. In *ACL*, 2024a.
- Jiaxin Wen, Ruiqi Zhong, Akbir Khan, Ethan Perez, Jacob Steinhardt, Minlie Huang, Samuel R Bowman, He He, and Shi Feng. Language models learn to mislead humans via rlhf. In *ICLR*, 2025.
- Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighoff. C-pack: Packaged resources to advance general chinese embedding, 2023.
- Joseph John Rocchio Jr. Relevance feedback in information retrieval. *The SMART retrieval system: experiments in automatic document processing*, 1971.
- Chengxiang Zhai and John Lafferty. Model-based feedback in the language modeling approach to information retrieval. In *Proceedings of the tenth international conference on Information and knowledge management*, pages 403–410, 2001.
- Nasreen Abdul-Jaleel, James Allan, W Bruce Croft, Fernando Diaz, Leah Larkey, Xiaoyan Li, Mark D Smucker, and Courtney Wade. Umass at trec 2004: Novelty and hard. In *Proceedings of TREC-13*, pages 715–725, 2004.
- Jeffrey Dalton, Laura Dietz, and James Allan. Entity query feature expansion using knowledge base links. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, pages 365–374, 2014.
- Yang Xu, Gareth JF Jones, and Bin Wang. Query dependent pseudo-relevance feedback based on wikipedia. In *Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval*, pages 59–66, 2009.
- Chenyan Xiong and Jamie Callan. Query expansion with freebase. In *Proceedings of the 2015 international conference on the theory of information retrieval*, pages 111–120, 2015.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.703. URL <https://aclanthology.org/2020.acl-main.703/>.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67, 2020. URL <http://jmlr.org/papers/v21/20-074.html>.

Teng Wang, Wing-Yin Yu, Zhenqi He, Zehua Liu, Hailei Gong, Han Wu, Xiongwei Han, Wei Shi, Ruifeng She, Fangzhou Zhu, et al. Bpp-search: Enhancing tree of thought reasoning for mathematical modeling problem solving. *ACL*, 2025d.

Teng Wang, Wing-Yin Yu, Ruifeng She, Wenhan Yang, Taijie Chen, and Jianping Zhang. Leveraging large language models for solving rare mip challenges. *arXiv preprint arXiv:2409.04464*, 2024b.

Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Anthropic. The claude 3 model family: Opus, sonnet, haiku, 2025. URL https://www-cdn.anthropic.com/de8ba9b01c9ab7cbabf5c33b80b7bbc618857627/Model_Card_Claude_3.pdf.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

A Appendix

A.1 Strategy-Guided Prompting

As referenced in Section 3.2, we present detailed strategies and the complete prompt used to guide our policy model in Figure 5.

A.2 SGP Performance with Contriever

To confirm that our findings are robust and not specific to a single retriever, we replicated the experiment using Contriever Izacard et al. [2021]. As detailed in Fig 6, our strategy again demonstrates a significant performance margin over the methods proposed by DMQR-RAGLi et al. [2024].

A.3 Detailed Training and Response Length Curves

This section provides the detailed learning curves that support our analysis of training dynamics in the main text. Fig. 7 and Fig. 8 illustrate the validation NDCG@10 and the average training rollout response length as a function of training steps. These plots compare the learning trajectories of our SAGE variants against a baseline model trained without strategies. The results demonstrate that while the baseline model’s performance quickly stagnates, our SAGE framework exhibits a superior learning trajectory, achieving continuous improvement in effectiveness while simultaneously learning to generate more concise responses.

```

def make_prefix(dp):
    INSTRUCTION = """You are a query rewriting expert for dense retrieval systems used in multi-hop question answering and fact verification.  

Your task is to rewrite the input question or claim into a query that is optimized for retrieval effectiveness.  

The final rewritten query must be in JSON format inside <answer> ... </answer> tags!!!  

Format:  

<answer>  

{  

    "query": "...",  

    "strategy": a number between 1 and 5  

}  

</answer>  

Each rewriting strategy below serves a different goal. You must choose the most appropriate one based on the complexity, ambiguity, and structure of the input.  

### Strategy 1: Semantic Expansion ###  

Expand underspecified queries by including related concepts, entities, or context needed to retrieve the correct evidence.  

Example:  

Original: "COVID policy 2021"  

Rewritten:  

<answer>  

{  

    "query": "COVID-19 government travel and quarantine policies in the year 2021",  

    "strategy": 1  

}  

</answer>  

### Strategy 2: Entity Disambiguation ###  

Clarify ambiguous entities by adding information like occupation, nationality, or time period to help the retriever identify the correct entity.  

Example:  

Original: "Obama was born in Hawaii."  

Rewritten:  

<answer>  

{  

    "query": "Barack Obama, the former U.S. President, was born in Hawaii.",  

    "strategy": 2  

}  

</answer>  

### Strategy 3: Sub-question Decomposition ###  

Break down multi-hop or compositional questions into simpler sub-questions, or rewrite them into a fully-specified single-hop form.  

Example:  

Original: "Where was the CEO of SpaceX born?"  

Rewritten:  

<answer>  

{  

    "query": "Where was Elon Musk, the CEO of SpaceX, born?",  

    "strategy": 3  

}  

</answer>  

### Strategy 4: Concise Rewriting ###  

Strip redundant phrases and retain only the most semantically meaningful keywords and named entities for high-precision retrieval.  

Example:  

Original: "Can you tell me what's the location of the big tower in Paris called the Eiffel Tower?"  

Rewritten:  

<answer>  

{  

    "query": "Eiffel Tower location in Paris",  

    "strategy": 4  

}  

</answer>  

### Strategy 5: Neutralized Claim Reformulation ###  

Convert fact-checking claims into neutral, answer-seeking questions so the retriever can return both supporting and refuting passages.  

Example:  

Original: "The Eiffel Tower is in Berlin."  

Rewritten:  

<answer>  

{  

    "query": "What is the location of the Eiffel Tower?",  

    "strategy": 5  

}  

</answer>  

Now rewrite the following input. Make sure to:  

- Explicitly name all entities (e.g., "the president" → "Barack Obama"),  

- Include necessary intermediate entities (if multi-hop),  

- Avoid inserting hallucinated or assumed answers.  

- Explore more strategies and avoid over-relying on any single approach.  

- Choose the strategy number (1–5) based on the actual approach used, not arbitrarily.  

**** + f***  

Here is the question: {dp['query']}
```

Show your work in <think> </think> tags.
Let's think step by step.
<think>

return INSTRUCTION

Figure 5: Full Prompt Structure for Strategy-Guided Rewriting. The figure presents the complete instructional prompt provided to the LLM agent. It specifies the overall task, formally defines each of our five expert-crafted strategies, and provides illustrative examples to guide their application.

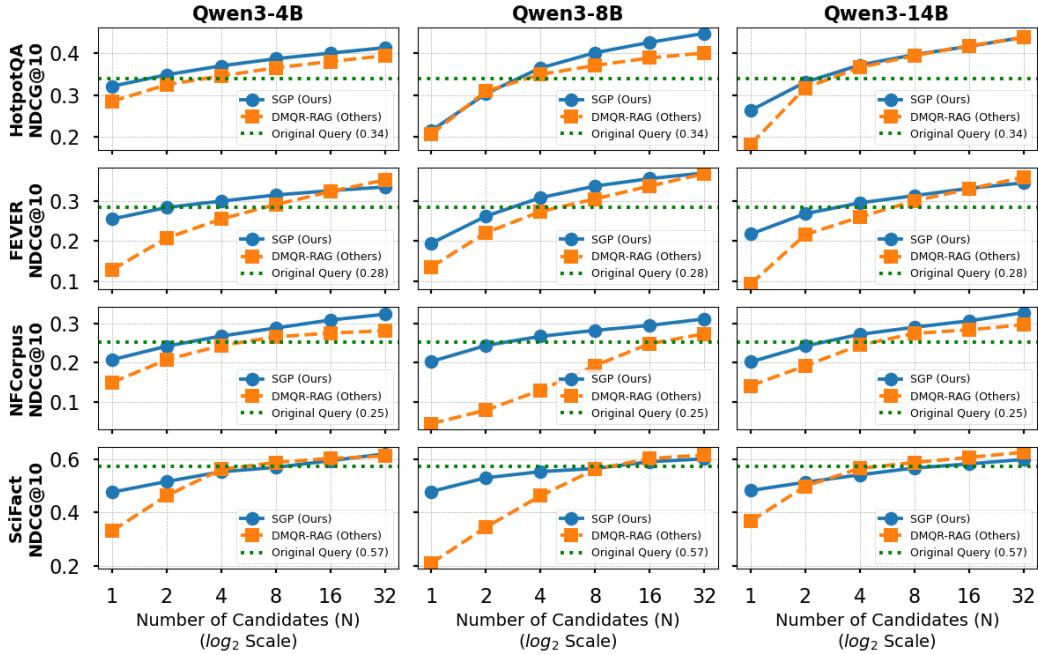


Figure 6: Performance scaling laws for query rewriting using the Contriever Izacard et al. [2021] retriever across four benchmark datasets: HotpotQA Yang et al. [2018], FEVER Thorne et al. [2018], NFCorpus Boteva et al. [2016], and SciFact Wadden et al. [2020]. Each subplot compares the upper-bound performance (NDCG@10) of our Strategy-Guided Prompting (SGP) against the strategies from Li et al. [2024], evaluated via a Best-of-N methodology across the Qwen3 model series Yang et al. [2025b]. The results demonstrate the superior scaling potential and higher performance ceiling of our approach.

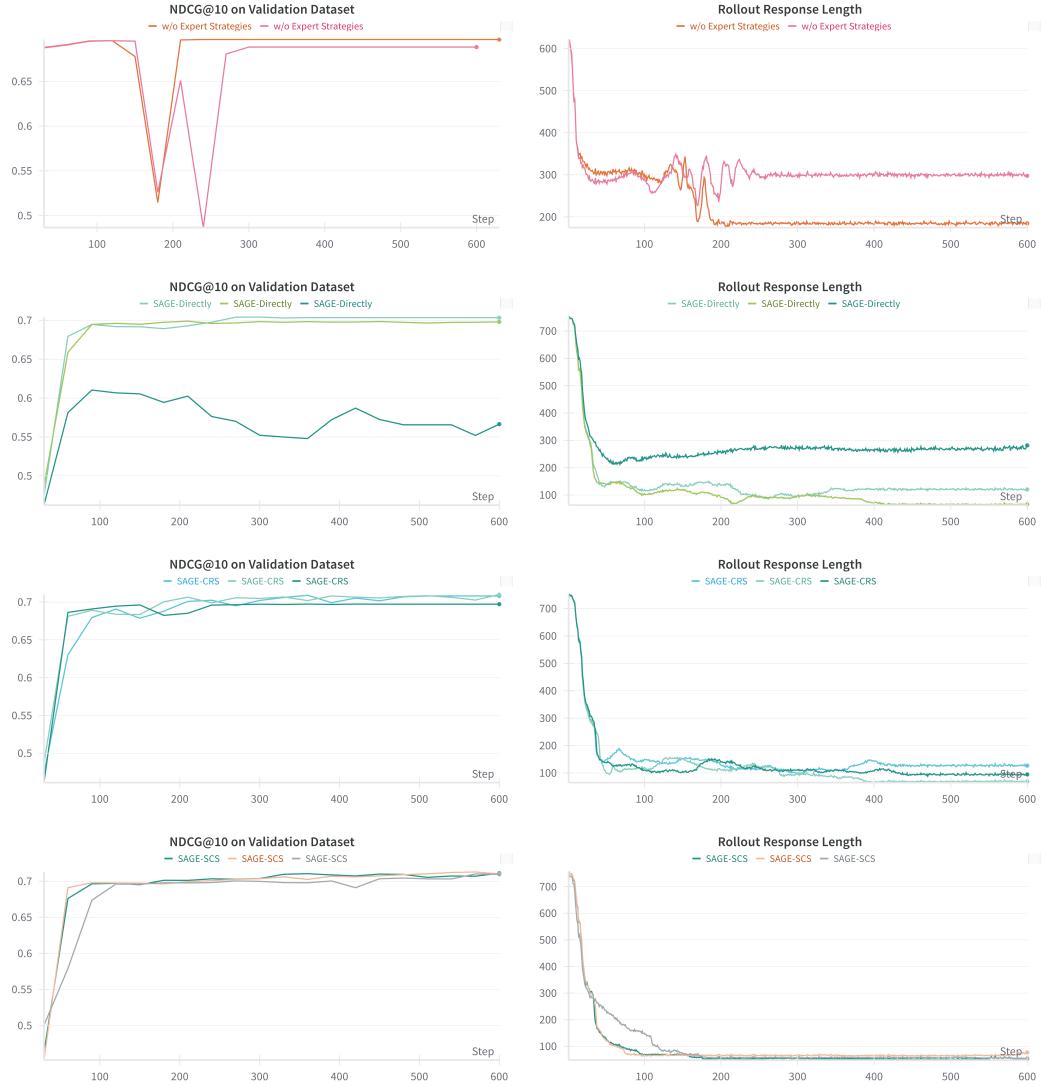


Figure 7: Training dynamics on the HotpotQA dataset. Each row corresponds to a different method: (from top to bottom) baseline without strategies, SAGE (Direct), SAGE-CRS, and SAGE-SCS. The left column plots the validation NDCG@10 (evaluated every 30 steps) over training steps, while the right column plots the average response length. The baseline stagnates early, whereas all SAGE variants show continuous improvement in NDCG@10 and a steady decrease in response length.

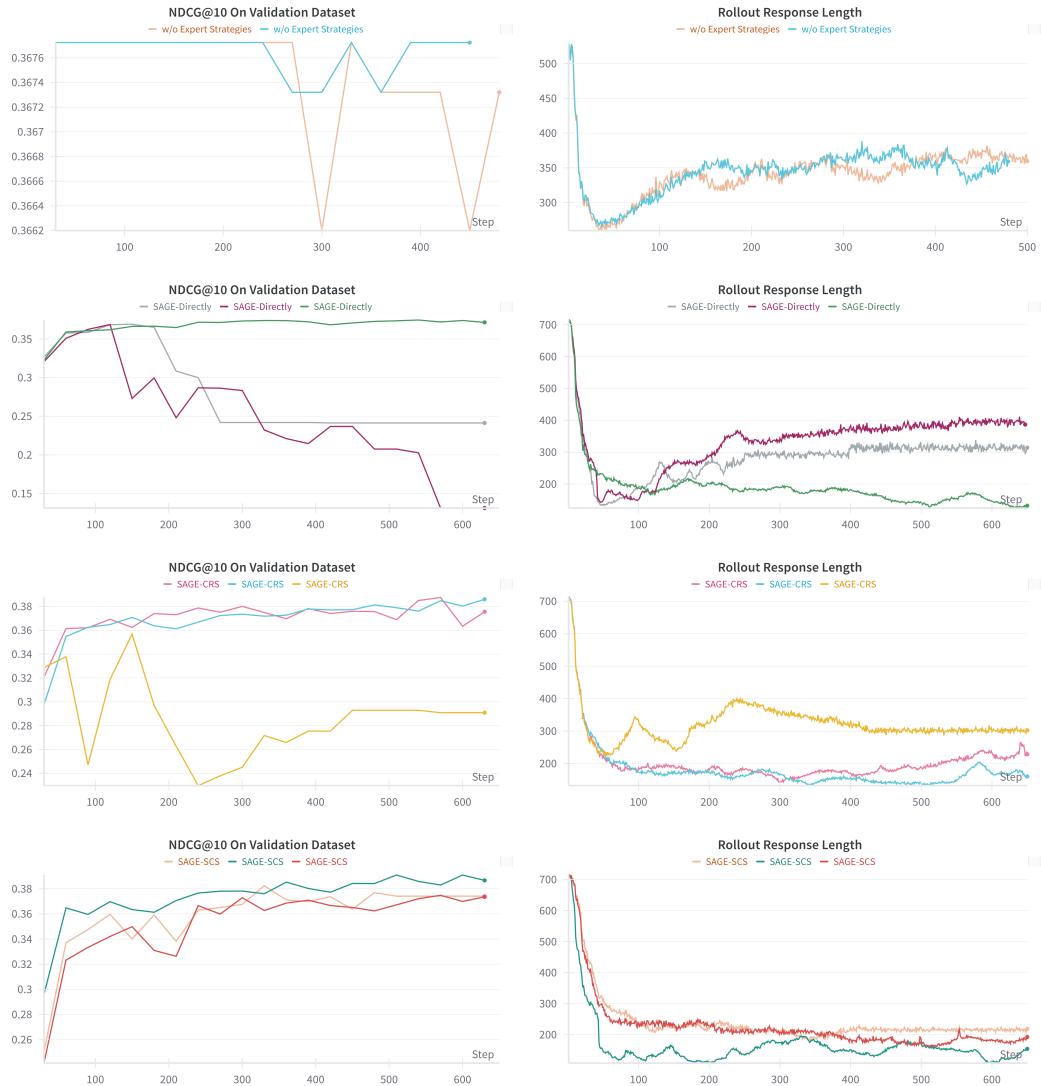


Figure 8: Training dynamics on the NFCorpus dataset. Each row corresponds to a different method. The left column plots validation NDCG@10(evaluated every 30 steps), and the right column shows average response length. As with HotpotQA, the baseline model’s performance plateaus while exhibiting high response length. In contrast, our SAGE variants, particularly SAGE-SCS and SAGE-CRS, demonstrate both stable performance gains and a significant reduction in response length over the course of training.