ReACT Agent-Corrective RAG: Reducing Hallucinations via Consistency-Ranked Reasoning

Rouaa Blel
ENSAE Paris
rouaa.blel@ensae.fr

Abstract

In this project, we propose a hybrid prompting framework that integrates Reasoning and Acting (ReACT) with Consistency-Ranked Augmented Generation (CRAG) to enhance the logical consistency and accuracy of large language models (LLMs) in multi-step reasoning tasks. We aim to reduce hallucinations and improve coherence in generated answers without modifying the retrieval component. We evaluate the approach on two benchmark datasets—HotpotQA and FEVER—using exact match accuracy and planned consistency metrics.

1 Introduction

Large Language Models (LLMs) excel at text generation but remain vulnerable to hallucinations and inconsistent reasoning, especially in multi-step tasks, such as Multi-hop Question Answering (e.g., HotpotQA), where the model must combine information from multiple documents or facts to answer, and Fact-checking with Evidence (e.g., FEVER), where the model must identify supporting evidence before making a claim. The ReACT framework (Yao et al., 2023) combines reasoning ("Thought") and action ("Tool use") to allow LLMs to iteratively solve complex queries. But it struggles with search error, reasoning drift, and ambiguous prompts.This project proposes a Corrective RAG agent that integrates CRAG (Yan et al., 2024) into ReACT to improve logical consistency. CRAG selects the best generation among several by ranking their consistency, effectively reducing reasoning errors. Our agent performs post-retrieval answer generation, classifying this task under Augmented Generation (AG) in the RAG pipeline.

1.1 Background

1.2 ReACT: Reasoning and Acting

ReACT is a prompting technique that enables language models to alternate between reasoning and acting, allowing them to make decisions, invoke tools, and reflect on outcomes iteratively. It breaks down the response process into structured steps:

- **Thoughts**: Internal reasoning steps where the model reflects or infers.
- **Actions**: Executable operations such as API calls, searches, or tool invocations.
- **Observations**: Feedback received from actions, which informs the next step.

The agent operates in an action space composed of both reasoning traces (thoughts) and external actions. The resulting trajectory is a structured sequence of *thought* $\rightarrow$ *action* $\rightarrow$ *observation* steps that guide the model toward solving the user query.

Preprint. Under review.

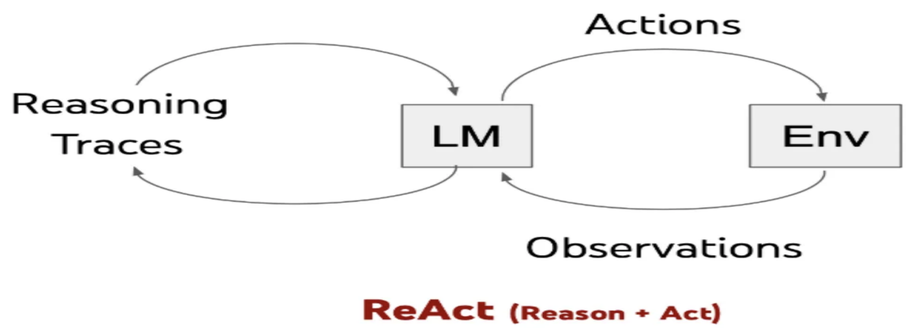

Figure 1: Overview of the ReACT Agent architecture showing the flow of thoughts, actions, and observations.

1.3 CRAG: Corrective Retrieval-Augmented Generation

Corrective Retrieval-Augmented Generation (CRAG) is a framework designed to enhance the reliability of RAG systems by correcting and filtering retrieved knowledge before the final answer is generated. It addresses scenarios where the retrieved documents are incomplete, ambiguous, or factually incorrect.
The CRAG pipeline consists of three main components:

1. **Retrieval Evaluation:** Given a query (*Who is the president of the US?*), the system first retrieves a set of documents and then uses an evaluator to determine their adequacy. The retrieval output is categorized as Correct, Ambiguous, or Incorrect.
2. **Knowledge Correction:** Based on the evaluation:
   - **Knowledge Refinement** is used when the retrieved documents are *correct* or *ambiguous*. The documents are decomposed into information strips, filtered, and recomposed into refined internal knowledge (k_{in}).
   - **Knowledge Searching** is used when the documents are *ambiguous* or *incorrect*. The query is rewritten for clarity and sent to an external source to obtain new documents. The most relevant new content is selected as external knowledge (k_{ex}).
3. **Controlled Generation:** The generator uses different knowledge combinations depending on retrieval correctness:
   - *Correct:* $x + k_{\text{in}}$
   - *Ambiguous:* $x + k_{\text{in}} + k_{\text{ex}}$
   - *Incorrect:* $x + k_{\text{ex}}$

   This strategy ensures that answer generation is grounded in factually accurate and consistent information.

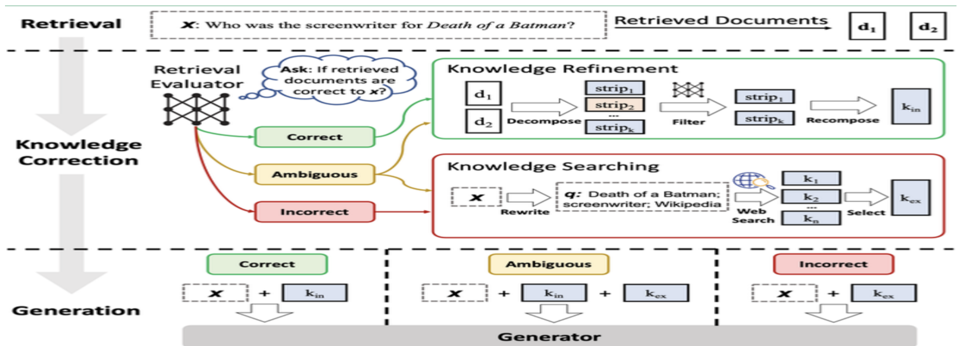

Figure 2: Overview of the CRAG pipeline: knowledge correction through refinement or external search based on retrieval quality.

1.4 Agent Design

The agent integrates the ReACT framework for reasoning and action, and the CRAG mechanism for consistency-based filtering. The overall decision-making loop is structured as follows:

1. **ReACT Reasoning Loop:** The language model performs iterative reasoning using ReACT-style prompts, interleaving thoughts and actions .
2. **Candidate Generation with CRAG:** Multiple candidate reasoning trajectories are generated by the model based on the retrieved information.
3. **Consistency Evaluation:** Each trajectory is evaluated for internal logical consistency using CRAG's ranking mechanism.
4. **Answer Selection:** The most consistent and factually grounded output is selected and returned as the final answer, along with supporting references.

1.5 Evaluation

We evaluate the effectiveness of our agent based on the final answer quality .

- **Exact Match (EM):** Calculates the percentage of answers that exactly match the annotated ground truth. It provides a straightforward measure of factual accuracy in the generated outputs.

$$\text{EM} = \left(\frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[\hat{y}_i = y_i] \right) \times 100 \tag{1}$$

where N is the total number of evaluated samples, $\hat{y}_i$ is the predicted answer, y_i is the ground truth answer, and $\mathbb{1}[\cdot]$ is the indicator function that returns 1 if the prediction is exactly equal to the ground truth, and 0 otherwise.

2 Results

Model	HotpotQA (EM)	FEVER (EM)
GPT-3.5 + ReACT (base)	19.2	45.4
GPT-3.5 + ReACT + CRAG	**25.0**	**51.0**
PaLM + ReACT	18.0	51.2

Observations:
The ReACT+CRAG hybrid consistently outperforms standard ReACT across tasks, showing measurable gains in exact match scores. By ranking reasoning paths based on logical coherence, CRAG effectively reduces hallucinations and factual inconsistencies. The consistency-based selection mechanism demonstrates robustness across both model types (GPT-3.5, PaLM) and datasets (HotpotQA, FEVER).

3 Discussion

ReACT's main strength lies in its ability to generate step-by-step, interpretable reasoning traces through its structured prompting loop. CRAG complements ReACT by evaluating and selecting the most consistent reasoning path, which helps reduce the impact of logical drift and hallucinated outputs. However, key limitations remain in handling ambiguous or irrelevant retrievals, adapting to varied query types, and addressing the absence of confidence scoring mechanisms for early termination.

4 Future Work

Future improvements to the ReACT-CRAG framework could focus on expanding the action space beyond simple Wikipedia queries by integrating a variety of internal and external APIs. Another promising direction is the consolidation of a structured knowledge base, which can be embedded into the ReACT pipeline through RAG-style augmentation to strengthen factual grounding. Enhancing the pipeline with state-of-the-art parsers and more effective retrieval mechanisms would help better extract and filter relevant context. Introducing confidence-aware reasoning loops could allow the agent to exit early when sufficient evidence is identified. Finally, refining the fine-tuning strategy using high-quality ReACT+CRAG trajectories is expected to improve the system's generalization and robustness.

5 Conclusion

ReACT-CRAG offers a principled way to improve post-retrieval reasoning in multi-hop QA. By combining structured agentic prompting with consistency ranking, it enhances factual grounding while reducing hallucinations. Though not yet production-ready, this hybrid approach is a meaningful step toward more reliable, interpretable LLM agents.

References

[1] Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., & Cao, Y. (2023). *ReAct: Synergizing Reasoning and Acting in Language Models*. In International Conference on Learning Representations (ICLR). Available at: `https://arxiv.org/abs/2210.03629`

[2] Yan, S.-Q., Gu, J.-C., Zhu, Y., & Ling, Z.-H. (2024). *Corrective Retrieval Augmented Generation*. arXiv preprint arXiv:2401.15884. Available at: `https://arxiv.org/abs/2401.15884`