



NAACL 2025

Diversify-verify-adapt: Efficient and Robust Retrieval-Augmented Ambiguous Question Answering

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Problem Formulation: Ambiguous Questions in QA Systems

In real-world QA systems, users often pose *ambiguous questions (AQs)* with multiple plausible interpretations

➡ RAG framework has emerged as a promising solution

Ambiguous Question

When did harry potter and the sorcerer's stone movie come out?

Plausible answers

Q: When did harry potter and the sorcerer's stone movie come out at the Odeon Leicester Square?

A: 4 November 2001

Q: When did harry potter and the sorcerer's stone movie come out in cinemas?

A: 16 November 2001

Retrieve passages !

Harry Potter and the Philosopher's Stone (film)

From Wikipedia, the free encyclopedia

The film had its world premiere at the Odeon Leicester Square in London on 4 November 2001, with the cinema arranged to resemble Hogwarts School. (...) The film was released to cinemas in the United Kingdom and United States on 16 November 2001.

Who was the ruler of France in 1830?

Ambiguous Question

Q1: Who was the ruler of France until 2 August 1830?

A1: Charles X

Plausible answers

Q2: Who was the ruler of France after 9 August 1830?

A2: Louis-Philippe I

Retrieve passages !

Louis Philippe I was King of the French from 1830 to 1848. [...] He was proclaimed king in 1830 after his cousin **Charles X** was forced to abdicate by the July Revolution [...]

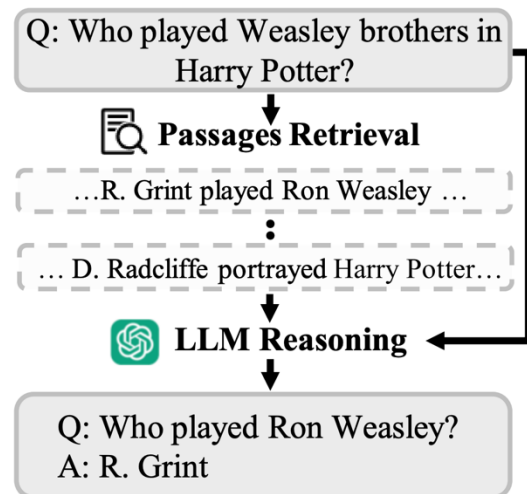
Retrieved passages

Louis-Philippe was sworn in as King **Louis-Philippe I** on 9 August 1830. Upon his accession to the throne, Louis Philippe assumed the title of "King of the French" [...]

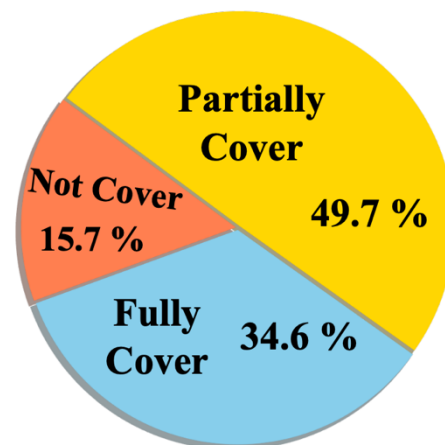
Retrieved passages

Is a single retrieval process sufficient?

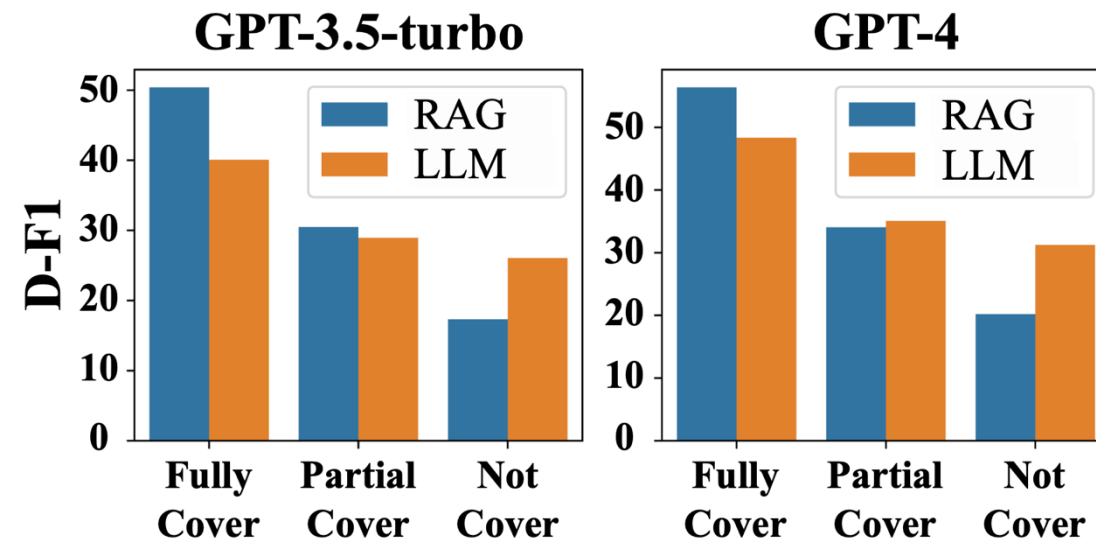
(a) Vanilla RAG



(a)



(b)

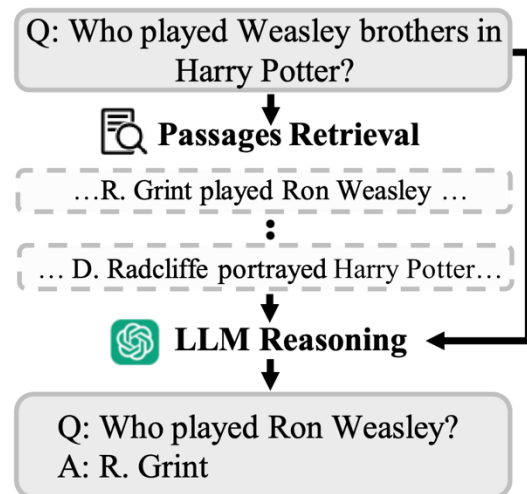


Observations

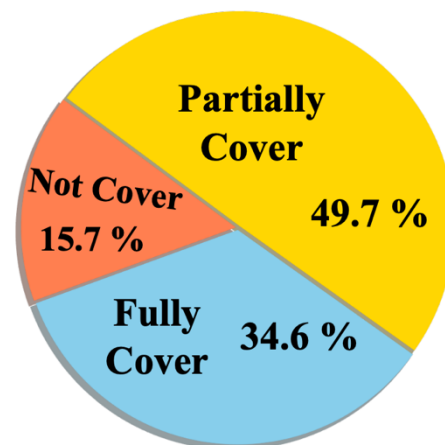
- (a) The ideal retrieval case is only 35%.
- (b) The RAG method significantly degenerates for “Partially Cover” and “Not Cover.”
- (c) The closed-book LLM notably outperforms RAG for “Not Cover.”

Is a single retrieval process sufficient?

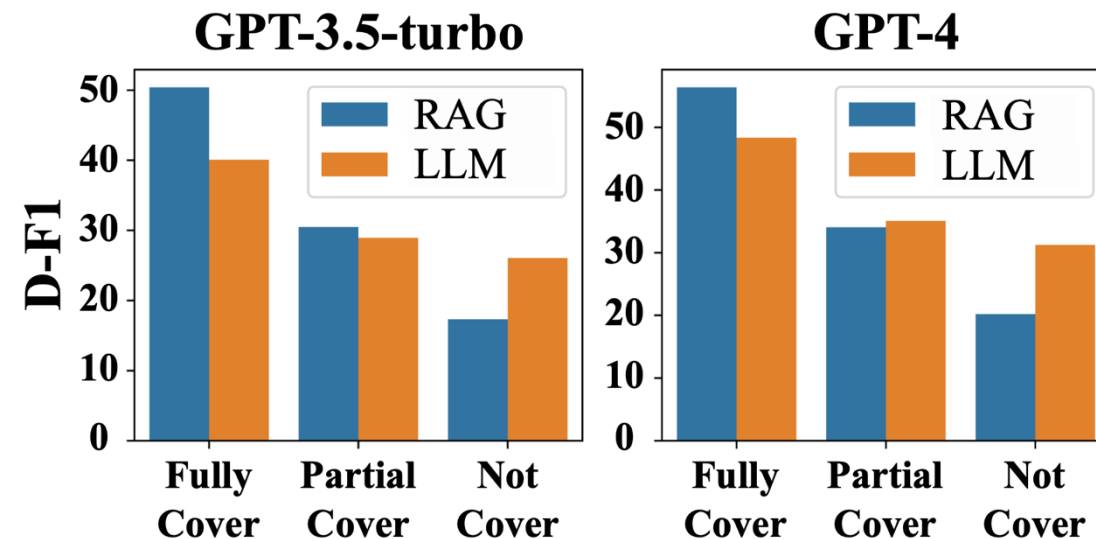
(a) Vanilla RAG



(a)



(b)



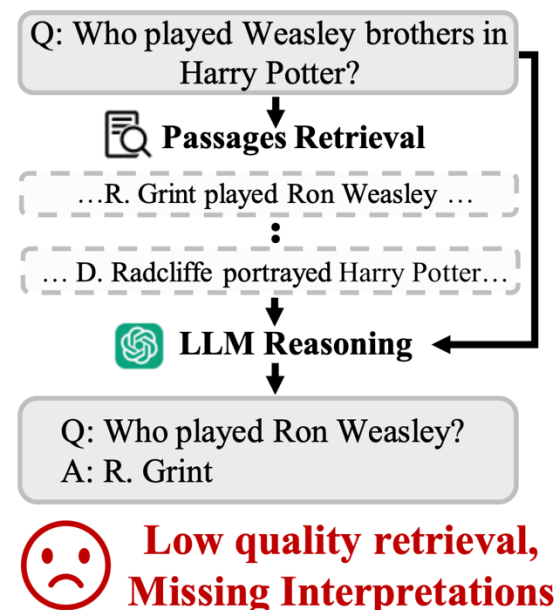
Insights

1. The quality of retrieval is crucial for the performance of the RAG framework in Ambiguous QA
2. If passages are of extremely low quality, LLM internal knowledge is more beneficial than RAG.

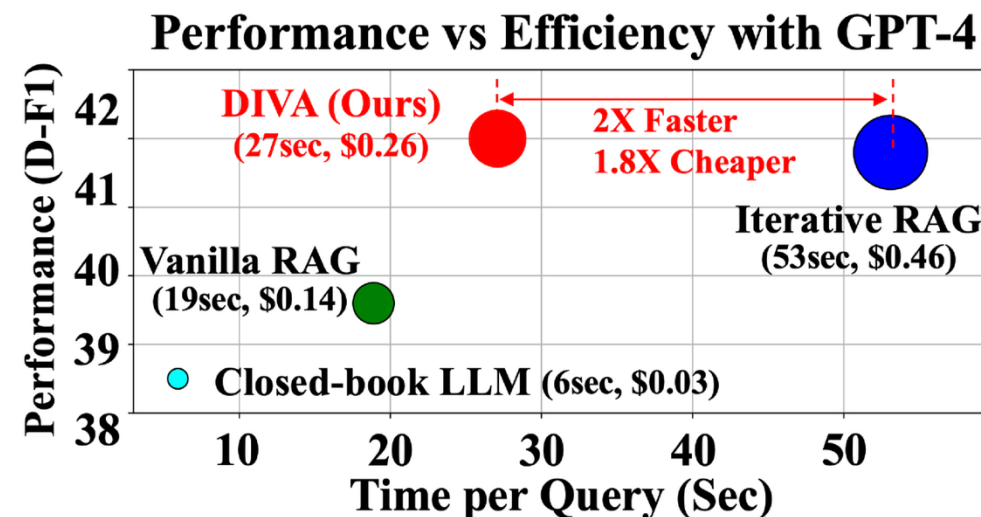
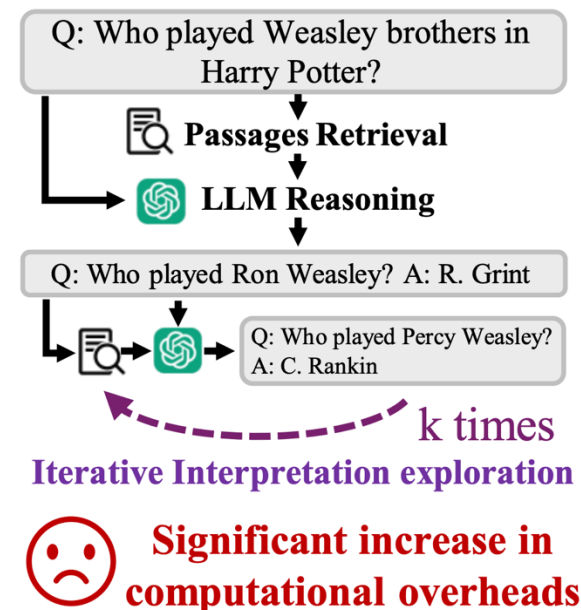
Inefficiency of Iterative RAG

Iterative RAG handles low quality retrieval *with significant increase in computational overheads*

(a) Vanilla RAG



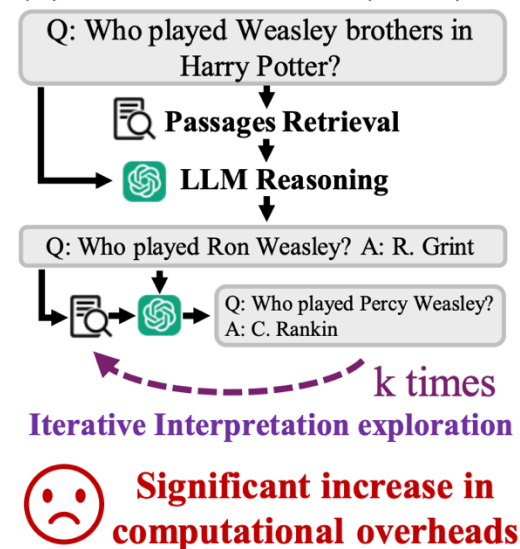
(b) Iterative RAG (ToC)



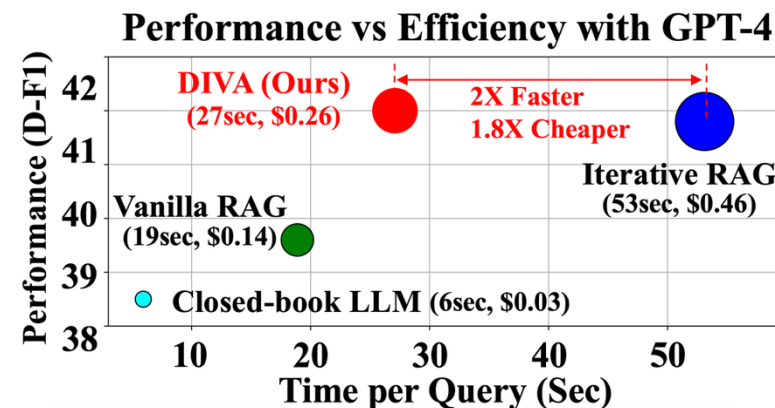
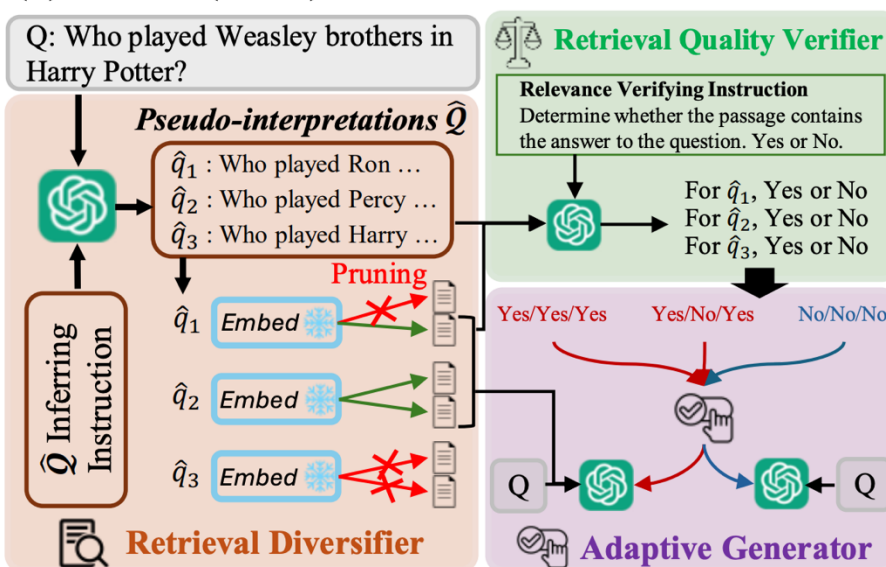
Diversify-verify-adapt (DIVA): Overview

DIVA is robust under low quality retrieval, while notably efficient (2x faster, 1.8x cheaper)

(b) Iterative RAG (ToC)

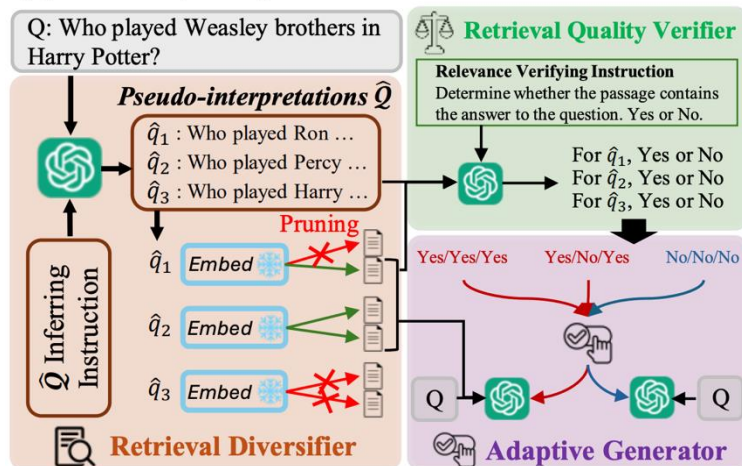


(c) DIVA (Ours)



Diversify-verify-adapt (DIVA)

(c) DIVA (Ours)



Retrieval Diversification

efficiently retrieves passages \mathcal{P}_i without any iterative process.

Stage 1

- infers pseudo-interpretations $\mathcal{Q}_i = \{\hat{q}_{i,1}, \hat{q}_{i,2}, \dots\}$, each of which related to a true plausible answer, by mimicking human's reasoning chain.

Q. Who played the weasley brothers in harry potter?



1. Which part is ambiguous?

- the "Weasley brothers"

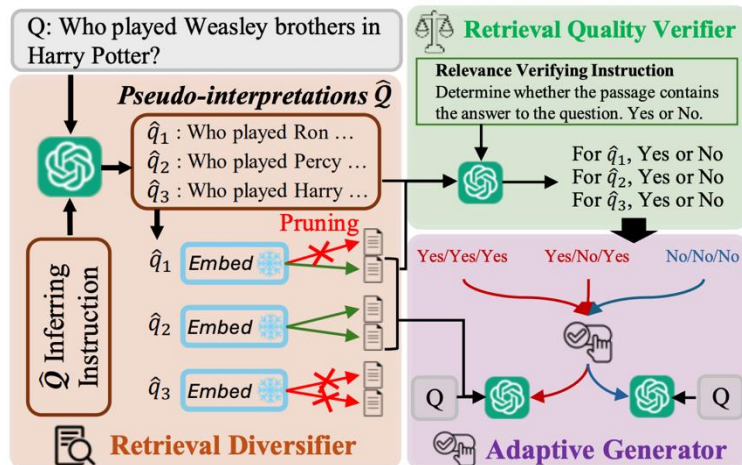
2. Why that part is ambiguous?

- It can be Ron, Percy, etc.

"Who played Ron Weasley in Harry Potter?", "Who played Percy Weasley in Harry Potter?", etc.

Diversify-verify-adapt (DIVA)

(c) DIVA (Ours)



Retrieval Diversification

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Prompt I_a for Ambiguity Type Inference

Types of ambiguity in a question can be defined as:
[AmbSub], [AmbObj], [AmbPred], [AmbTime], [AmbLoc].

[Description for each ambiguity type]

Given the question $[Q]$, which types of ambiguity are related to the question? Suggest the types and reasons for your suggestions.

Prompt I_p for Pseudo-interpretations Inference

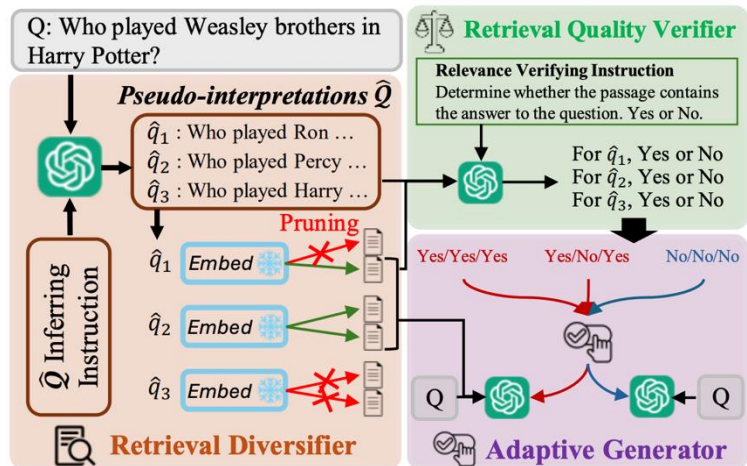
Given the question $[Q]$ and corresponding reasons why the question is ambiguous. Clarify the given question based on the reasons for its ambiguity.

- 1) identify the ambiguous part of the question and the reason for the ambiguity
- 2) infer the pseudo-interpretations from the results.

$$\hat{Q}_i \leftarrow \text{LLM}(q_i, I_p, \text{LLM}(q_i, I_a)),$$

Diversify-verify-adapt (DIVA)

(c) DIVA (Ours)



Retrieval Diversification

efficiently retrieves passages \mathcal{P}_i without any iterative process.

Stage 2

- retrieves a set of passages that maximally cover these interpretations



There could be some noisy and irrelevant passages due to

- imperfect retriever
- noise of the inferred pseudo-interpretations

How to handle it?

Our intuition

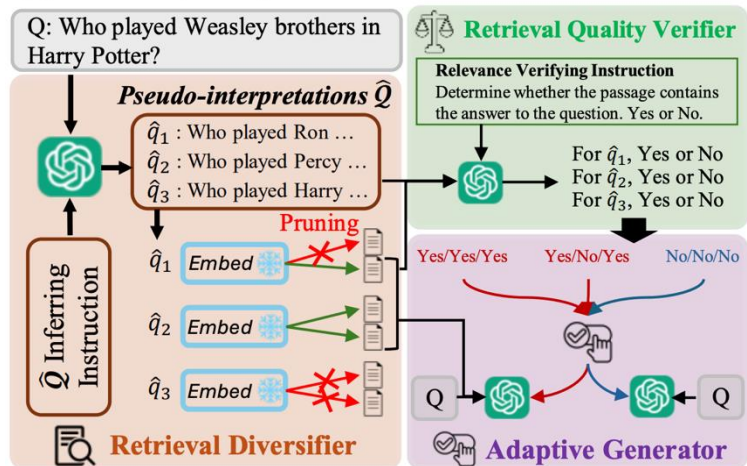
- noisy passages caused by the imperfect retriever tend to be irrelevant to all pseudo-interpretations
- noisy passages caused by noisy pseudo-interpretations tend to be irrelevant to most of the pseudo-interpretations.

Solution: measuring averaged relevance

$$\mathcal{S}(p) \leftarrow \frac{1}{|\hat{\mathcal{Q}}_i|} \sum_{j=1}^{|\hat{\mathcal{Q}}_i|} \frac{\text{Enc}(\hat{q}_j) \cdot \text{Enc}(p)}{\|\text{Enc}(\hat{q}_j)\| \cdot \|\text{Enc}(p)\|},$$

Diversify-verify-adapt (DIVA)

(c) DIVA (Ours)



Retrieval Quality Verifier

verifies the quality of the retrieved passages \mathcal{P}_i

Challenge

The retrieval quality in terms of ambiguous questions should be graded according to how many interpretations are encompassed by the retrieved passages.

Solution

Using the inferred pseudo-interpretations.

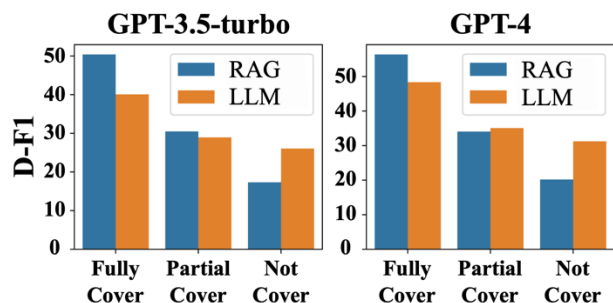
$$V_{i,1} \leftarrow \text{LLM}(\hat{q}_{i,1}, \mathcal{P}_i, I_v)$$

$$\vdots$$

$$V_{i,|\hat{\mathcal{Q}}_i|} \leftarrow \text{LLM}(\hat{q}_{i,|\hat{\mathcal{Q}}_i|}, \mathcal{P}_i, I_v),$$

Adaptive Generation

utilizes the most suitable approach tailored to each retrieval quality



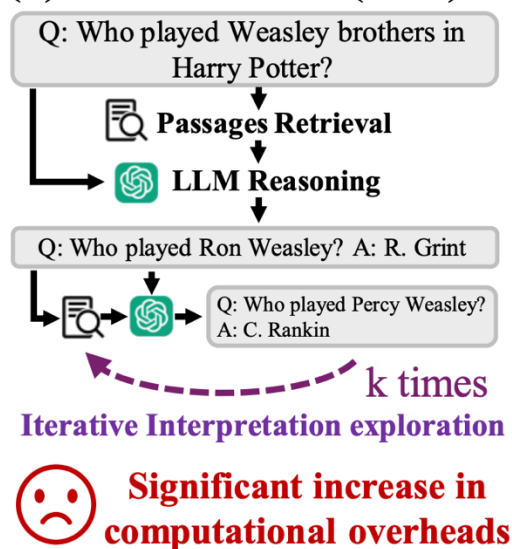
Inspired by our preliminary analyses,

- If \mathcal{P}_i do not cover any pseudo-interpretations, we only utilize the LLM's internal knowledge.
- Otherwise, we utilize the retrieved passage to generate a response.

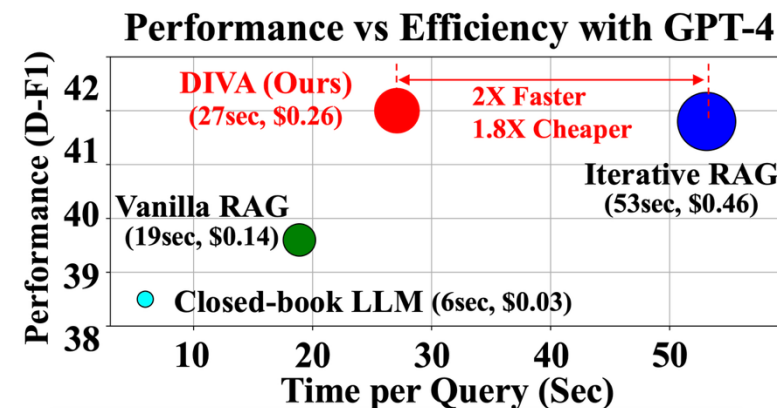
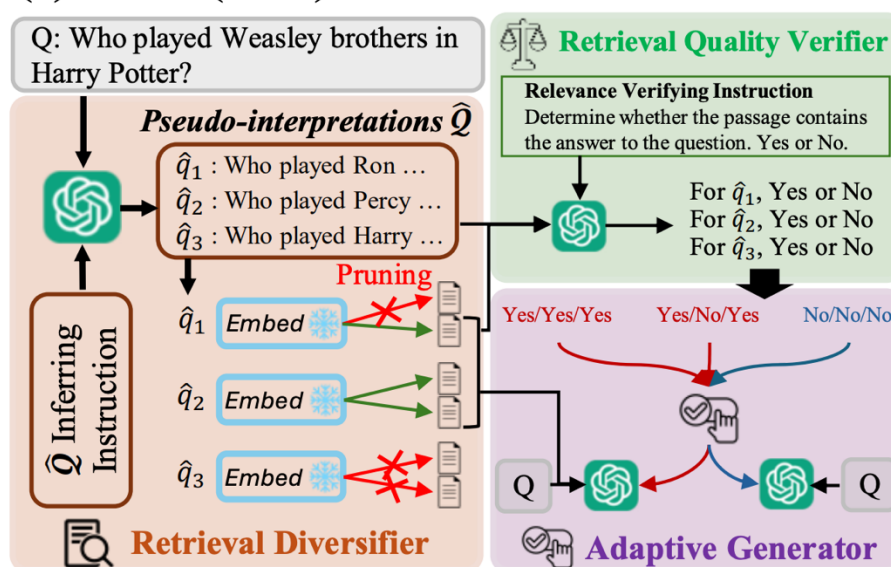
Diversify-verify-adapt (DIVA)

DIVA outperforms the sota baseline, Iterative RAG, in terms of both accuracy and efficiency of response generation.

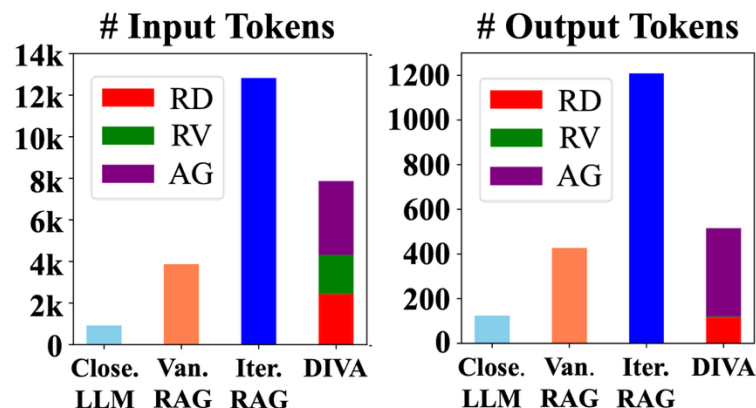
(b) Iterative RAG (ToC)



(c) DIVA (Ours)



Diversify-verify-adapt (DIVA)



- DIVA's strong efficiency is largely due to the RD method.
- Although the RV method introduces some additional costs, these are acceptable compared to the complexity of Iterative RAG.

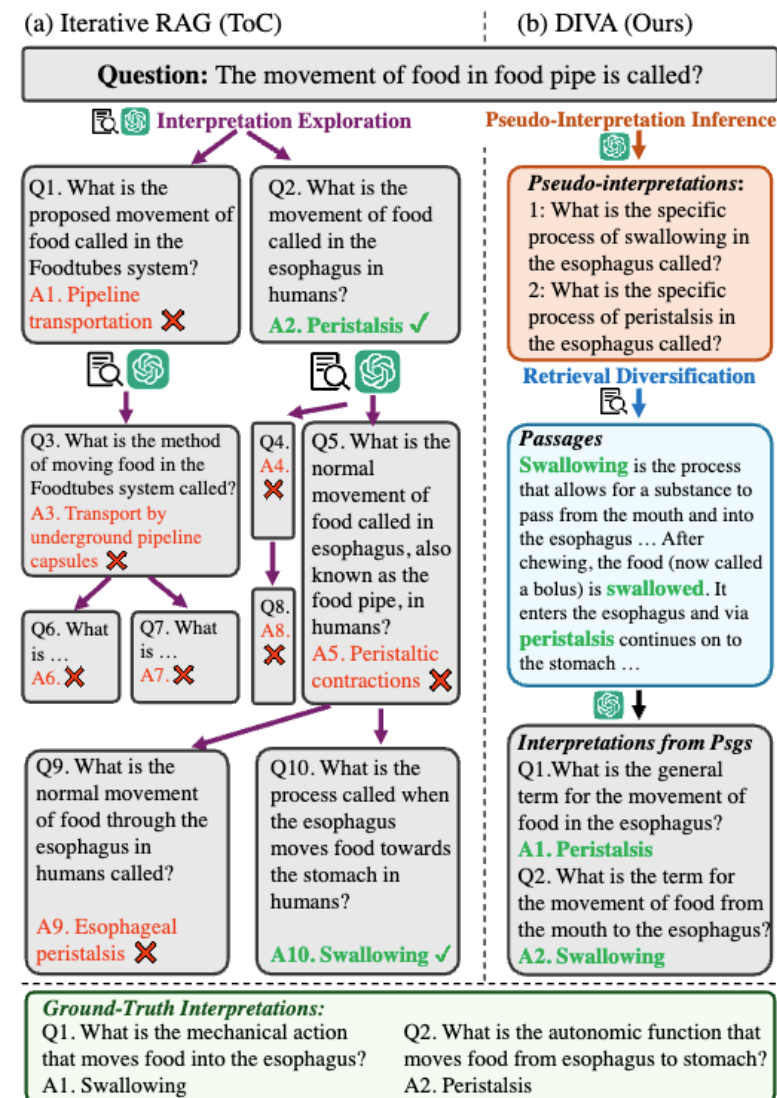


Figure 8: Case study with GPT-4.

Diversify-verify-adapt (DIVA)

	R-L	D-F1	DR	Time
Fully-Supervised				
T5-Large Closed-Book*	33.5	7.4	15.7	-
T5-Large w/ JPR*	43.0	26.4	33.7	-
PaLM w/ Soft Prompt Tuning**	37.4	27.8	32.1	-
Few-shot Prompting: Closed-Book LLM				
Llama3-8B-Instruct	31.1	25.6	28.2	-
Llama3-70B-Instruct	35.7	36.4	36.0	30.5
GPT-3.5-turbo	38.8	34.0	36.3	2.0
+ Query Refinement	37.5	34.8	36.1	5.2
GPT-4	39.0	38.5	38.7	5.9
+ Query Refinement	39.6	39.3	39.4	10.0
Few-shot Prompting: LLM w/ RAG				
Self-RAG-13B	35.4	26.0	30.4	4.1
CRAG (GPT-4)	40.1	39.6	39.9	34.4
Llama3-8B-Instruct				
— Vanilla RAG	38.2	35.4	36.8	-
— Iterative RAG (ToC)	37	36.3	36.6	-
— DIVA (Ours)	38.9	35.7	37.3	-
Llama3-70B-Instruct				
— Vanilla RAG	40.2	40.0	40.1	42.3
— Iterative RAG (ToC)	39.5	40.4	39.9	140.5
— DIVA (Ours)	40.4	41.4	40.9	50.6
GPT-3.5-turbo				
— Vanilla RAG	41.2	37.5	39.3	11.2
— Iterative RAG (ToC)	40.1	38.5	39.3	31.5
— DIVA (Ours)	42.1	38.9	40.5	19.8
GPT-4				
— Vanilla RAG	41.5	39.6	40.6	18.9
— Iterative RAG (ToC)	38.5	41.8	40.1	53.1
— DIVA (Ours)	42.4	42.0	42.2	27.1

- DIVA demonstrates good adaptability in switching out the underlying LLM backbones.
 - Llama-3-8B-Instruct, Llama-3-70B-Instruct, GPT-3.5-turbo, GPT-4

- DIVA exhibits strong performance on unambiguous questions as well

Method	EM
Closed-book LLM	75.0
Vanilla RAG	80.0
Iterative RAG	83.0
DIVA	83.0

Table 5: QA performance on unambiguous questions.

- Retrieval Diversification (RD) method improves retrieval accuracy, resulting in improvement of QA performance.

Row	Method	MRecall@ k $k = 5$	D-F1	
			GPT-3.5-turbo	GPT-4
1	Vanilla RAG	35.2	37.5	39.6
2	+ Ma et al. (2023)	36.1	37.0	40.4
3	+ RD (Ours)	37.0	38.5	41.0
4	+ Oracle	41.5	-	-

Conclusion

- In this study, we examined the shortcomings of the current RAG-based method in dealing with ambiguous questions, specifically its low-quality retrieval and inefficiency.
- Our proposed framework, DIVA, effectively diversifies the retrieved passages to capture various interpretations, verifies their quality, and adapts the most appropriate approach based on that quality.
- This strategy improves QA performance while minimizing inefficiency.



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Thank you for listening!

Please refer to our paper

“Diversify-verify-adapt: Efficient and Robust Retrieval-Augmented Ambiguous Question Answering”

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