

# Retrieval Augmented Generation or Long-Context LLMs? A Comprehensive Study and Hybrid Approach

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#### RAG v.s. LC?

Understanding long-context is an important capability for LLMs.

On one side, LLMs are supporting longer and longer contexts, e.g. Gemini supports up to 2M tokens

On the other side, RAG (retrieval augmented generation) has been an effective & efficient way to process long contexts.

Which one should we use?

### Summary of contributions

- Comparison finding
  - LC > RAG when resourced sufficiently
- A simple-yet-effective method
  - Self-Route: try RAG, then LC
- Analysis
  - RAG failure reasons
  - Scaling
  - Synthetic data
  - LLM's internal knowledge
  - 0 ...

#### Compare RAG and LC

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# RETRIEVAL MEETS LONG CONTEXT LARGE LANGUAGE MODELS

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#### LongBench: A Bilingual, Multitask Benchmark for Long Context Understanding

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#### Google Cloud

Can Long-Context Language Models Subsume Retrieval, RAG, SQL, and More?

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#### Long-Context LLMs Meet RAG: Overcoming Challenges for Long Inputs in RAG

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## Comparison: LC performs better than RAG

- 3 models:
  - Gemini-1.5-Pro (1M)
  - GPT-40 (128k)
  - GPT-3.5-Turbo (16k)
- 9 Datasets
  - 7 datasets from LongBench
    - NarrativeQA,
    - Qasper,
    - MultiFieldQA,
    - HotpotQA,
    - 2WikiMultihopQA,
    - MuSiQue,
    - QMSum
  - 2 datasets from InfiniteBench
    - EN.QA,
    - EN.MC
  - Real dataset in English; Can do RAG



#### RAG and LC agree for most queries

- For most queries, RAG and LC predictions are very similar
  - For 63% queries, RAG/LC predictions are exactly identical
  - For 70% queries, RAG/LC predictions are very similar (score difference < 10)



#### Our method: Self-Route

Two steps:

- 1. RAG: prompt LLM to predict whether the query is answerable; if so, output the answer
- 2. If the query is not answerable using RAG, do LC

Use LLM itself as a router, to route different queries to RAG or LC.

#### Self-Route performance is similar to LC, with reduced cost



			Avg	Narr	Qasp	Mult	Hotp	2Wiki	Musi	Sum	En.QA	En.MC
	1-1	LC	49.70	32.76	47.83	52.33	61.85	62.96	40.22	20.73	43.08	85.57
	1-2	RAG	37.33	22.54	44.68	49.53	48.36	54.24	26.56	19.51	19.46	51.09
Gemini-1.5-Pro	1-3	Self-Route	46.41	28.32	45.23	51.47	55.18	62.68	40.66	19.77	37.51	76.86
	1-4	answerable %	76.78	73.00	85.00	96.67	84.50	81.00	58.50	93.50	56.41	62.45
	1-5	token %	38.39	23.07	49.93	36.88	32.97	53.49	56.14	17.96	42.25	32.84
GPT-40	2-1	LC	48.67	32.78	44.54	55.28	62.42	70.69	41.65	21.92	32.36	76.42
	2-2	RAG	32.60	18.05	46.02	50.74	36.86	50.21	16.09	19.97	14.43	41.05
	2-3	Self-Route	48.89	31.36	47.99	53.17	62.14	70.14	41.69	21.31	34.95	77.29
	2-4	answerable %	57.36	44.00	67.50	94.00	52.50	62.00	30.00	92.00	27.07	47.16
	2-5	token %	61.40	66.40	72.25	39.65	65.79	77.05	85.00	20.26	73.01	53.21
GPT-3.5-Turbo	3-1	LC	32.07	23.34	42.96	49.19	45.33	41.04	17.92	19.61	14.73	34.50
	3-2	RAG	30.33	18.22	38.15	49.21	37.84	35.16	16.41	18.94	15.39	43.67
	3-3	Self-Route	35.32	24.06	38.65	52.07	47.28	44.62	34.44	19.88	22.03	44.54
	3-4	answerable %	74.10	71.50	80.00	91.33	68.50	69.00	47.00	93.50	50.43	95.63
	3-5	token %	38.85	20.56	55.08	35.29	48.70	65.91	65.08	16.40	38.17	4.50

"token%": cost

Particularly good for GPT-3.5 (suspectively due to shorter context length)

Caveat: "answerable rate" (different models show different answerable rates, due to different alignments).

#### Ablations of k

As k increases, RAG can answer more and more queries.

Self-Route consistently performs better than RAG.



Figure 3: Trade-off curves between (a) model performance and (b) token percentage as a function of k.

### Why does RAG fail?

Manually check the RAG failures where LC succeeds. 4 typical reasons:

- A. The query requires **multi-step reasoning** so the results of previous steps are needed to retrieve information for later steps,
  - a. What nationality is the performer of song You Can?
  - b. Where does the director of film Wine Of Morning work at?
  - c. What is another notable work made by the author of Miss Sara Sampson?
- B. The query is **general**, thus it is hard to retrieve relevant chunks.
  - a. What does the group think about XXX"
- C. The query is **long and complex**, which is challenging for the retriever to understand.
  - a. What did Julie Morgan elaborate on the online survey when talking about the evaluations on the legitimacy of the children's rights, protection and demands?
  - b. The Huskies football team were invited to the Alamo Bowl where they were defeated by a team coached by Art Briles and who played their home games at what stadium?
- D. The query is **implicit**, demanding a thorough understanding of the entire context o connect the dots and deduce the answer
  - a. "What caused the shadow behind the spaceship?" for a long story without explicit mention of the shadow when the cause is revealed.

#### Failure case distribution

Prompt Gemini to classify the failure cases:



Figure 4: Distribution of typical RAG failure reasons.

Different distributions for each dataset.

### Why not synthetic dataset? A toy experiment

Needle-in-the-haystack style synthetic dataset may contain artifacts that affect the analysis results

"Passkey" dataset: a sentence with passkey (e.g. "the passkey is 123456") is hidden in large chunks of texts.



#### Exclusion of LLM's internal knowledge

Dataset leakage; LLM's world knowledge.

Many of the datasets are based on Wikipedia (HotpotQA, 2WikiMultihopQA, MuSiQue); books (NarrativeQA); or scientific papers (Qasper, MultiFieldQA)

LLM's internal knowledge should be excluded.

#### How to exclude the internal knowledge?

Method-1:

use a simple prompt: "based only on the provided passage".

	without "based only on"	with "based only on"		
NarrativeQA	36.35	32.76		
Qasper	50.69	47.83		
MultiFieldQA	56.07	52.33		
HotpotQA	66.47	61.85		
2WikiMQA	68.97	62.96		
Musique	54.56	40.22		
QMSum	20.87	20.73		
En.QA	49.20	43.08		
En.MC	90.83	85.57		
Avg	50.57	45.53		

Method-2

Exclude questions that can be correctly answered without context.

Cons: different models will have different eval

	all qu	estions	w/o commonsense			
	Gemini	GPT-3.5	Gemini	GPT-3.5		
# questions	200	200	133	150		
LC	40.22	17.92	31.76	13.00		
RAG	26.56	16.41	15.51	13.05		
Self-Route	40.66	34.44	31.32	19.76		
answerable %	58.50	47.00	52.63	45.33		
token %	56.14	65.08	48.46	53.43		

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# **Thanks! Questions?**