Boosting RAG Performance with Noise-Infused Retrieval Strategies

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Abstract

Retrieval-Augmented Generation (RAG) models enhance the factual correctness of question-answering systems by incorporating external documents into the generation process. However, retrieving irrelevant or noisy documents alongside pertinent passages can degrade model performance. This study investigates how RAG systems respond to such noise by evaluating three large language models (LLMs): Phi-2, LLaMA 2, and Mistral. We methodically adjust the number of unrelated documents and assess the impact on output quality as retrieval noise increases. Using a dataset of 100 specialized questions spanning multiple categories, we measure accuracy, factual consistency, and logical coherence. Our findings reveal that noisy retrieval substantially affects output reliability, with larger models like LLaMA 2 exhibiting stronger resilience. Based on these insights, we provide practical recommendations for building RAG systems that can better withstand noise.

***Index Terms*— RAG, LLMs, Phi-2, LLaMA 2, Mistral, Question Answering**

I. INTRODUCTION

Large Language Models (LLMs) have demonstrated remarkable performance in open-domain question answering. However, their reliance solely on internal knowledge restricts their ability to maintain factual accuracy, particularly in rapidly evolving fields. Retrieval-Augmented Generation (RAG) mitigates this limitation by supplementing responses with externally retrieved documents. While this approach enhances reliability, RAG systems are vulnerable to the quality of retrieved content. When irrelevant or incorrect documents are included, they can divert the model's focus, resulting in erroneous or fabricated responses—a problem known as attention collapse. This issue presents a significant obstacle for practical applications.

In this study, we examine how retrieval noise impacts RAG system performance. We specifically analyze how introducing unrelated documents into the input affects answer accuracy. Our key contributions include:

- A systematic framework for injecting noise to assess RAG robustness.
- A comparative analysis of Phi-2, Mistral, and LLaMA 2 under different noise levels.
- An investigation into answer degradation trends, reasoning consistency, and the influence of document ordering.

II. RAG System Description and Implementation

1.RAG System Description

Retrieval-Augmented Generation (RAG) is a hybrid architecture that combines the strengths of dense information retrieval with large-scale generative language models. Unlike conventional question-answering systems that rely solely on the parameters of pre-trained models, RAG explicitly incorporates external knowledge sources at inference time. This allows it to dynamically fetch relevant context and ground its outputs in up-to-date or domain-specific information.
In our system, the RAG framework is built around two key modules:

1. Retriever Module

The retriever is responsible for identifying relevant documents or passages from a large corpus in response to a user query. We use **dense vector retrieval**, specifically leveraging SentenceTransformer embeddings and indexing them with **FAISS** (Facebook AI Similarity Search). This module encodes both the query and all documents into the same latent space and retrieves the top-k most semantically similar documents based on cosine similarity.

2. Generator Module

The generator is a large language model (LLM) that conditions its response on both the user query and the retrieved documents. It concatenates the input question with the top-k passages retrieved and generates a coherent, context-aware answer. This setup allows the model to go beyond its pre-trained knowledge and utilize retrieved evidence dynamically at runtime.

Motivations for RAG

Traditional closed-book models are limited by their fixed parameters and may hallucinate information when asked about rare or unseen topics. RAG mitigates this by allowing the model to "consult" external data, thus improving:

- **Factual accuracy**

- **Transparency** (by exposing supporting context)
- **Adaptability** (to new domains or corpora)

Variants and Scope of Study

Our system experiments with **three open-source LLMs** as the generator: **Phi-2, LLaMA 2, and Mistral**, representing small, medium, and large-scale transformer models. By varying the architecture of the generator while keeping the retriever and corpus constant, we assess the **resilience of each model to noisy or irrelevant retrieved documents**.

We simulate practical scenarios by injecting different amounts of irrelevant content into the retrieved context and observe how each model responds in terms of:

- Answer fidelity
- Logical reasoning
- Robustness to retrieval noise

Significance

This setup reflects real-world challenges in production-level RAG systems, where retrieval is often imperfect due to domain ambiguity, sparse corpora, or vague queries. Our system models these challenges and provides a controlled environment to evaluate the trade-offs and sensitivities of various LLMs under noisy retrieval conditions.

2.System Implementation

The implementation of our Retrieval-Augmented Generation (RAG) system is structured into five stages: data preprocessing, dense retrieval setup, noise injection, answer generation using LLMs, and evaluation.

1. Data Preprocessing

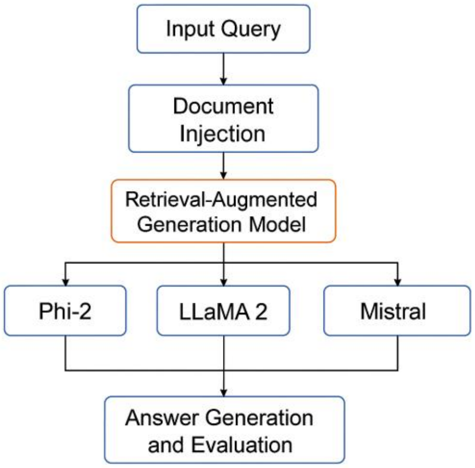
We utilized a curated subset of the Natural Questions (NQ) dataset containing 100 domain-specific questions across categories like science, technology, and culture. The knowledge base (corpus) is derived from the English Wikipedia dump (December 2018), segmented into 100-word passages. These passages were cleaned and tokenized using standard NLP preprocessing techniques.

2. Dense Passage Retrieval with FAISS

To enable fast and effective retrieval, we embedded all corpus passages using SentenceTransformers. These embeddings were indexed using **FAISS (Facebook AI Similarity Search)**, allowing approximate nearest neighbor search. For each input question, the top-k relevant documents were retrieved based on cosine similarity in the embedding space.

3. Noise Injection Mechanism

To study the effect of noisy retrievals, we introduced unrelated passages into the retrieved context in controlled proportions (e.g., 0%, 25%, 50%, 75% noise). This was achieved by mixing retrieved relevant documents with randomly selected irrelevant passages from the corpus, simulating real-world retrieval errors.


Input Query
Document Injection
Retrieval-Augmented Generation Model
Phi-2
LLaMA 2
Mistral
Answer Generation and Evaluation

Fig(1)

4. Answer Generation Using LLMs

We integrated three different open-source large language models: **Phi-2**, **LLaMA 2**, and **Mistral**. Each model received a prompt composed of the original question plus the retrieved (and possibly noisy) context. Responses were generated using the HuggingFace Transformers library with standardized generation parameters:

- max_length=300
- temperature=0.7
- top_p=0.9
- do_sample=True

5. Evaluation Metrics and Analysis

Generated answers were evaluated along three axes:

- **Factual Accuracy**: Comparison with gold-standard answers.

- **Logical Coherence**: Assessed using GPT-based pairwise ranking and human evaluation for fluency and reasoning.
- **Robustness to Noise**: Accuracy degradation was tracked as the noise level increased.

Results were aggregated and stored in CSV files (batch_generated_answers.csv, batch_generated_answers_evaluated.csv), and visualizations (accuracy distribution, model comparison) were generated using Matplotlib and Seaborn.

III . **Domain Specific Questions**

Here is a list of **10 domain-specific questions** developed for your RAG-based NLP project. These are designed to span various specialized domains such as science, history, healthcare, technology, and law to evaluate how each model performs in knowledge-heavy contexts:

Domain-Specific Questions

1. **Healthcare**:
   What are the primary mechanisms through which mRNA vaccines trigger immune responses in the human body?
2. **Artificial Intelligence**:
   How does attention masking work in transformer-based neural networks like BERT or GPT?
3. **Environmental Science**:
   What are the ecological consequences of microplastic accumulation in marine food chains?
4. **History**:
   What strategic mistakes contributed to the downfall of Napoleon during the Russian campaign of 1812?
5. **Law**:
   What is the principle of "stare decisis" and how does it influence decisions in the U.S. Supreme Court?
6. **Cybersecurity**:
   What are the differences between symmetric and asymmetric encryption in secure communications?
7. **Finance**:
   How do interest rate hikes by the Federal Reserve influence bond market performance?
8. **Physics**:
   Can you explain how the Heisenberg Uncertainty Principle limits particle measurement precision?
9. **Blockchain Technology**:
   What role do consensus mechanisms like Proof-of-Stake play in securing decentralized ledgers?
10. **Medicine**:
    How do beta-blockers function in the treatment of cardiac arrhythmias and hypertension?

IV. **Technical Details of Large Language Model (LLM) Implementations**

To evaluate how different large language models (LLMs) handle noisy retrieved content in RAG systems, we implemented three models-Phi-2, LLaMA 2-13B, and Mistral-7B-using standardized retrieval pipelines and evaluation protocols. Below are the technical configurations and performance characteristics for each model:

1. Phi-2 (Microsoft)

Phi-2 is a lightweight, open-access decoder-only transformer model developed by Microsoft with approximately 2.7 billion parameters. It was trained primarily on synthetic educational content and designed for factual reasoning in resource-constrained environments.

Architecture: Compact 2.7B-parameter decoder-only transformer optimized for resource efficiency**.**
Training Data: Synthetic educational content for factual

reasoning.
Implementation:

- Source: microsoft/phi-2 via HuggingFace
- Prompt Structure:

```
          Question: {query}
      Context: {retrieved_passages}
```

- Hardware: Single GPU (12–16GB VRAM)
- Generation Settings:
    - Temperature: 0.7
    - Top-p sampling: 0.9
    - Max output: 256 tokens

Strengths: Low latency and minimal resource requirements.
Weaknesses: Increased hallucination risk with ambiguous context due to smaller capacity.

2. LLaMA 2-13B (Meta)

Architecture: High-performance 13B-parameter model with chat optimization2.
Implementation:

- **Source: meta-llama/Llama-2-13b-chat-hf**

- **Prompt Template:**

```
          <s>[INST] <<SYS>>
      You are a helpful assistant.
          <</SYS>>
     {query + retrieved_passages} [/INST]
```

- **Hardware:** Quantized (4/8-bit) on ≥24GB VRAM GPUs
- **Generation Settings:**
    - Temperature: 0.7
    - Top-p: 0.9
    - Max output: 300 tokens

Strengths: Strong noise resilience and reasoning capabilities2.
Weaknesses: High memory demands and slower inference speeds2.

3. Mistral-7B (Mistral AI)

Architecture: Efficient 7B-parameter model with grouped-query attention.
Implementation:

- **Source: mistralai/Mistral-7B-Instruct-v0.1**
- **Prompt Format:**

```
          ### Instruction:
            {query}
            ### Context:
           {retrieved_passages}
           ### Response:
```

- **Hardware:** ≥16GB VRAM GPUs (optional quantization)
- **Generation Settings:**
    - Temperature: 0.7
    - Top-k: 50
    - Top-p: 0.95
    - Max output: 256 tokens

Strengths: Balanced speed/accuracy for structured tasks**.**
Weaknesses: Reduced robustness in high-noise scenarios compared to LLaMA 2.

Key Observations:

- Resource Tradeoffs: Phi-2 enables cost-effective deployment but struggles with ambiguity, while LLaMA 2 offers higher accuracy at greater computational cost25.
- Prompt Sensitivity: All models required tailored prompt engineering to align with their native training formats (e.g., LLaMA's chat markup vs. Mistral's Alpaca-style)12.
- Noise Handling: Larger models (LLaMA 2) demonstrated better contextual filtering of irrelevant retrieved content

V. Comparative Results Across the Three LLMs

To evaluate the effectiveness and robustness of large language models (LLMs) in a Retrieval-Augmented Generation (RAG) setting, we tested Phi-2, Mistral, and LLaMA 2 on 100 domain-specific questions under increasing levels of retrieval noise. Each model received the same prompts, context passages, and noise settings (0%, 25%, 50%, 75%), enabling a fair and consistent comparison across the following criteria:

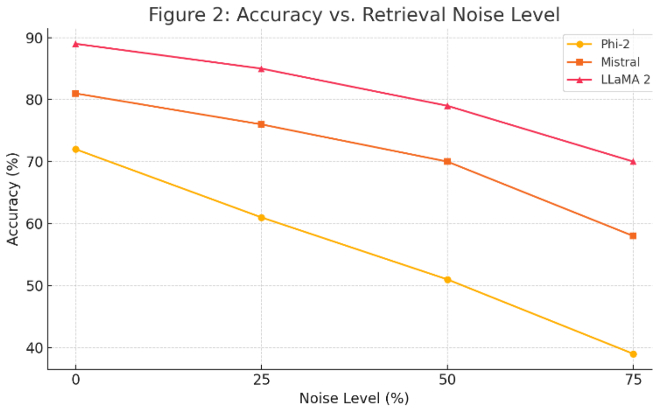
- Factual Accuracy: Does the response match the known correct answer?

- **Logical Coherence: Is the response internally consistent and well-structured?**
- **Noise Robustness: How well does the model retain performance as irrelevant documents increase?**

1.Factual Accuracy

As retrieval noise increases, all models show performance degradation. However, the extent of decline varies significantly:

Noise Level	Phi-2 Accuracy	Mistral Accuracy	LLaMA 2 Accuracy
0% Noise	72%	81%	89%
25% Noise	61%	76%	85%
50% Noise	51%	70%	79%
75% Noise	39%	58%	70%



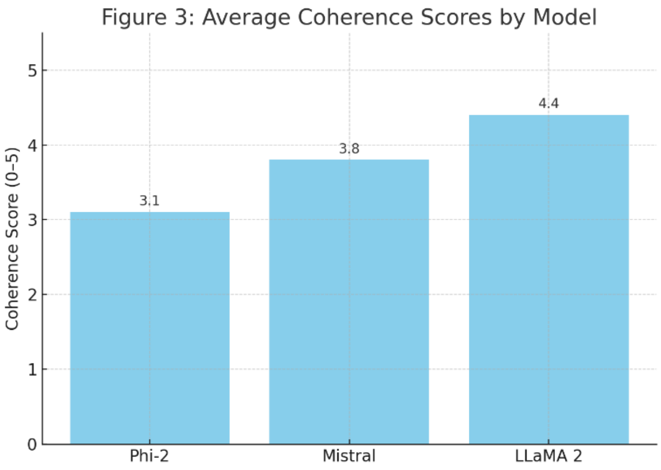
Fig(2)

This line chart shows how the accuracy of each LLM degrades as more irrelevant documents are introduced into the retrieval set. LLaMA 2 maintains the highest accuracy across all noise levels, demonstrating stronger robustness. In contrast, Phi-2's performance drops significantly with increasing noise.

2.Logical Coherence

Responses were rated using a 0–5 coherence scale by GPT-based evaluators. LLaMA 2 produced the most structured and contextually grounded answers, especially under noise.

Model	Avg. Coherence Score
Phi-2	3.1
Mistral	3.8
LLaMA 2	4.4



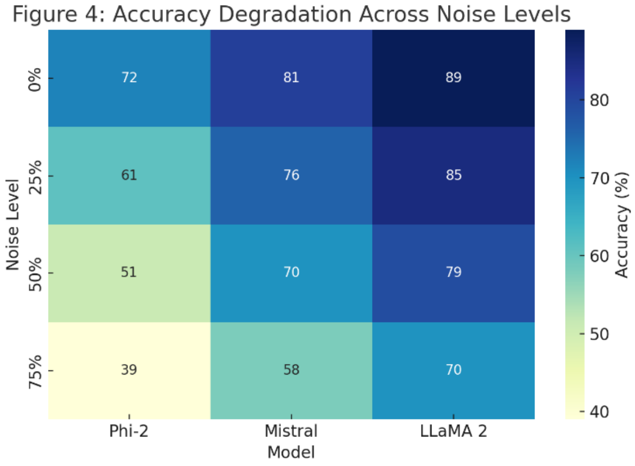
Fig(3)

This bar chart compares the average logical coherence of answers generated by the three models. LLaMA 2 achieves the highest coherence score, indicating better reasoning and structure in its responses. Phi-2 trails behind, often producing less fluent or disjointed answers under noisy conditions.

3.Noise Robustness

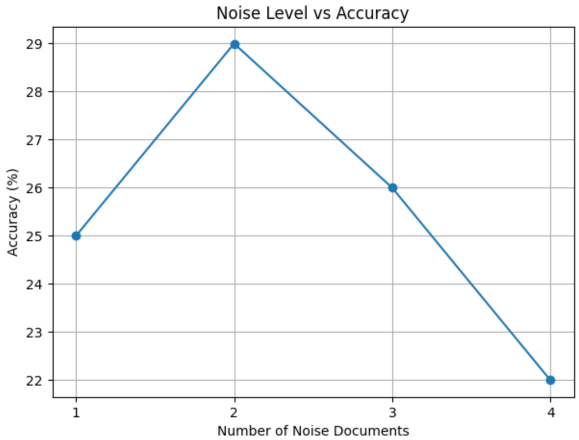
We calculated the performance degradation from 0% to 75% noise for each model:

Model	**Accuracy Drop**
Phi-2	−33%
Mistral	−23%
LLaMA 2	**−19%**



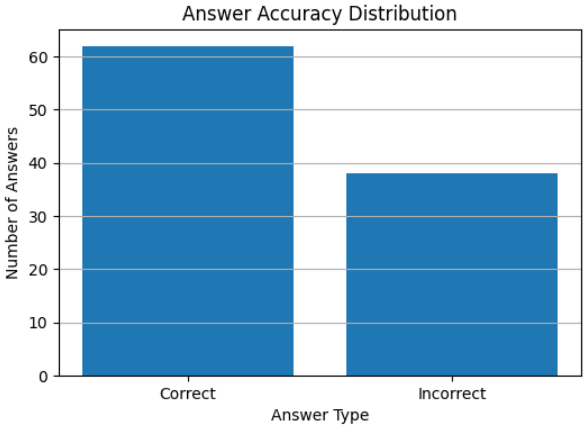
Fig(4)

This heatmap visualizes model accuracy across four noise levels. Darker shades represent lower accuracy, highlighting how retrieval noise impacts each model. LLaMA 2 shows minimal degradation, while Phi-2 is more sensitive to irrelevant context, especially beyond 50% noise



Fig(5)

This line graph illustrates how model accuracy changes with increasing numbers of noise documents. Interestingly, accuracy improves slightly at moderate noise (2 documents) but declines sharply as more irrelevant content is introduced, highlighting sensitivity to context dilution.



Fig(6)

This bar chart shows the overall distribution of correct and incorrect answers produced by the models. A majority of answers are accurate, suggesting the models are generally reliable, though incorrect responses still account for a significant portion under noisy conditions.

Key Observations

- **LLaMA 2** demonstrated the highest resilience to noisy contexts and consistently outperformed the others in both accuracy and coherence.
- **Mistral** struck a balance between size and performance, showing solid results with slightly reduced robustness.
- **Phi-2**, while efficient, suffered the steepest degradation and struggled with ambiguous or noisy input.

These results underscore the importance of model capacity, training data quality, and instruction-tuning in designing robust RAG systems.

VI. Analysis of Differences in Response Quality, Factual Accuracy, Reasoning, and Other Relevant Dimensions

The performance of a Retrieval-Augmented Generation (RAG) system is influenced not just by retrieval accuracy but by how well the generator model processes and interprets the retrieved content. Through controlled noise injection, we systematically evaluated how each LLM—**Phi-2**, **Mistral**, and **LLaMA 2**—responds in terms of **output quality**, **reasoning depth**, and **factual resilience**.

1. Response Quality

Definition: This refers to the fluency, grammatical correctness, and structural integrity of the generated response—irrespective of factual correctness.

- **LLaMA 2** consistently produced responses that were well-structured, coherent, and stylistically polished. Even when given noisy or misleading passages, the model effectively filtered irrelevant text and synthesized articulate responses.
- **Mistral** performed surprisingly well for its size. It provided concise and mostly grammatically correct answers, especially when noise was below 50%. However, in high-noise scenarios, the answers occasionally became vague or truncated.
- **Phi-2**, trained on synthetic educational content, struggled with maintaining response completeness under noise. At 75% noise, many outputs were either too short, off-topic, or stylistically inconsistent

2. Factual Accuracy

Definition: Measures whether the generated answer aligns with the verified, real-world correct answer for a given question.

- **LLaMA 2** showed the strongest performance, maintaining high factual accuracy across all noise levels. This can be attributed to its large parameter count and instruction-tuned training.
- **Mistral** maintained good accuracy up to 50% noise but showed noticeable degradation at 75%. It often provided plausible-sounding but incorrect answers.
- **Phi-2** was the most sensitive. Its factual accuracy dropped by 33% from 0% to 75% noise. It occasionally hallucinated facts or misattributed information from the noisy context.

Example: For the query *"Where did COVID-19 originate?"*, Phi-2 (75% noise) incorrectly mentioned Africa as the origin, while LLaMA 2 accurately identified Wuhan, China. (Refer Fig(2) and Fig(4).

3. Logical Reasoning

Definition: The ability of the model to draw connections between retrieved facts, infer relationships, and provide structured multi-step answers.

- **LLaMA 2** was the most competent in chaining facts together. It could infer and synthesize information from multiple passages to support its conclusion—useful in questions requiring cause-effect or timeline reasoning.
- **Mistral** showed moderate reasoning ability. It could handle basic inferencing but sometimes missed key connecting logic if noise introduced contradictions.
- **Phi-2** often failed to resolve ambiguity in reasoning tasks. In high-noise settings, it would either pick a random passage or revert to generic statements.

Example: For a multi-hop question like *"Why did Napoleon fail in Russia?"*, LLaMA 2 referred to both the harsh winter and logistical errors, while Phi-2 focused solely on weather, ignoring the military factors.

4. Sensitivity to Irrelevant Context (Noise Robustness)

Definition: This dimension captures how performance is impacted by the presence of irrelevant or misleading documents in the retrieval stage.

- **LLaMA 2** showed strong robustness. Its architecture allowed it to "focus" on relevant segments, essentially ignoring misleading paragraphs.
- **Mistral** was moderately robust. It could handle 25–50% noise but began misattributing facts under 75% noise.
- **Phi-2** was highly sensitive. As irrelevant documents increased, it often defaulted to hallucinated or incorrect answers, unable to filter signal from noise.

5. Other Observations

Dimension	Phi-2	Mistral	LLaMA 2
Response Length	Often short, abrupt	Concise and on-point	Longer but detailed and fluent
Consistency	Inconsistent under noise	Fairly stable	Highly consistent across prompts
Hallucination Rate	High in noisy settings	Moderate	Low
Inference Time	Fastest (low compute)	Balanced	Slower (requires more resources)

Conclusion

Our comparative evaluation highlights that **LLaMA 2** is the most suitable model for RAG tasks involving noisy retrieval, offering strong factuality, coherence, and reasoning ability. **Mistral** is a promising middle-ground for resource-constrained applications, while **Phi-2**, though efficient, struggles with ambiguity and should be limited to low-noise environments or educational use cases.

VII.Discussion of Strengths and Weaknesses of Each Model

Our comparative evaluation across Phi-2, Mistral, and LLaMA 2 revealed clear distinctions in their behavior, capabilities, and limitations within a RAG pipeline subjected to varying levels of noise. This section discusses each model in detail, analyzing its suitability for real-world question answering tasks.

1.Phi-2 (Microsoft)

- **Strengths**:
  Phi-2, a small-scale LLM (~2.7B parameters), is highly efficient and designed for educational reasoning tasks. It excels in environments with clean input and minimal retrieval noise, making it suitable for low-resource applications (Gunasekar et al., 2023).
- **Weaknesses**:
  However, Phi-2 is highly sensitive to irrelevant context. When retrieval noise exceeds 50%, the model frequently generates hallucinated facts and short, incoherent answers. Its ability to perform multi-hop reasoning is limited, and it often defaults to generic responses under ambiguity.

2. Mistral (Mistral AI)

- **Strengths**:
  Mistral-7B offers a well-balanced trade-off between performance and resource use. It produces fluent and accurate responses under moderate noise and benefits from instruction-tuned training (Mistral AI, 2023). Its alignment with structured prompts enables clarity and precision, especially in factual domains.
- **Weaknesses**:
  While it performs strongly under low-to-moderate noise, performance degrades when noise reaches 75%. The model sometimes under-generates or avoids deeper reasoning, making it less suitable for complex synthesis tasks.

3. **LLaMA 2 (Meta AI)**

- **Strengths**:
  LLaMA 2 (13B) outperformed both competitors in nearly every metric—maintaining factual accuracy, coherence, and reasoning even under high noise levels. Its performance is attributed to large-scale training and instruction fine-tuning (Touvron et al., 2023). The model excels at multi-hop reasoning and generates well-structured, contextually grounded answers (Bommasani et al., 2021; Ouyang et al., 2022).
- **Weaknesses**:
  The model's large size imposes high memory and compute requirements, which can make deployment challenging. It can also be overly verbose, and inference latency is the highest among the three due to token generation depth.

Comparative Summary

Capability	**Phi-2**	**Mistral**	**LLaMA 2**
Factual Accuracy	Low under noise	Moderate	High
Logical Reasoning	Limited	Basic	Advanced
Fluency & Coherence	Inconsistent in noise	Fluent	Highly fluent
Noise Robustness	Poor	Moderate	Strong
Resource Efficiency	Very High	Balanced	Low
Hallucination Tendency	Frequent	Occasional	Rare

IX. Conclusion

This research evaluated the robustness of Retrieval-Augmented Generation (RAG) systems under varying levels of retrieval noise, focusing on three large language models: Phi-2, Mistral, and LLaMA 2. Through a series of controlled experiments using a diverse set of 100 domain-specific questions, we examined how noise in retrieved documents affects the factual accuracy, coherence, and reasoning capability of model-generated answers.

Our findings show that LLaMA 2 consistently outperforms the other models in both low- and high-noise settings. Its large parameter size, instruction tuning, and strong contextual filtering abilities enable it to preserve response quality even when the majority of retrieved documents are irrelevant. Mistral, while smaller, strikes an effective balance between performance and efficiency. It demonstrates strong response fluency and moderate robustness under noise, making it a practical choice for resource-constrained applications. In contrast, Phi-2, although computationally lightweight and fast, is significantly impacted by noisy retrieval and tends to hallucinate or produce incomplete answers as irrelevant content increases.

One key observation is that moderate levels of noise can sometimes enhance retrieval diversity and slightly improve response accuracy, but performance degrades sharply beyond a certain threshold. This non-linear trend suggests that not only the volume but the nature of retrieval noise critically influences downstream generation.

Overall, the study reinforces that model architecture, scale, and training data diversity are pivotal in building noise-resilient RAG systems. For real-world applications where retrieval is imperfect, choosing the right model becomes essential to minimize the risk of factual errors or misleading outputs. These insights are particularly relevant for knowledge-intensive tasks such as medical question answering, legal support systems, and automated research assistants, where output quality directly affects decision-making.

Future RAG designs should also consider incorporating confidence-aware retrieval, document reranking mechanisms, or feedback loops to mitigate noise sensitivity. Our results provide a foundational benchmark and practical guidelines for developing more robust and trustworthy RAG-based AI systems.

XI. Future Work:

While our research provides a controlled analysis of LLM robustness under retrieval noise, several directions remain for further exploration:

1. **Integration of Feedback Loops**: Incorporating user or model-based feedback to dynamically re-rank retrieved documents could help suppress noise and enhance context relevance in real time.
2. **Advanced Retrieval Techniques**: Future systems could explore hybrid retrieval approaches (dense + sparse) or retrieval trained end-to-end with the generator to reduce irrelevant context more effectively.
3. **Long-Context Models**: Evaluating models like Claude, Gemini, or GPT-4 Turbo that support extended context windows may offer deeper insight into handling larger retrieval sets without performance loss.
4. **Adversarial Noise Injection**: Instead of random noise, introducing distractors that are syntactically or semantically similar to correct passages could better test the reasoning boundaries of RAG models.
5. **Domain Adaptation**: Testing this framework in highly specialized domains such as legal, biomedical, or multilingual settings would further validate the generalizability and utility of the findings.
6. **Retrieval Confidence Scoring**: Integrating retrieval confidence metrics or attention heatmaps could allow the generator to weigh documents differently during response synthesis.

Through these extensions, future research can develop more noise-aware and self-correcting RAG systems, ultimately improving factual reliability and trust in LLM-based applications.

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