

PluriHop: Exhaustive, Recall-Sensitive QA over Distractor-Rich Corpora

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Abstract

Recent advances in large language models (LLMs) and retrieval-augmented generation (RAG) have enabled progress on question answering (QA) when relevant evidence is in one (single-hop) or multiple (multi-hop) passages. Yet many realistic questions about recurring report data - medical records, compliance filings, maintenance logs - require aggregation across all documents, with no clear stopping point for retrieval and high sensitivity to even one missed passage. We term these pluri-hop questions and formalize them by three criteria: recall sensitivity, exhaustiveness, and exactness. To study this setting, we introduce PluriHopWIND, a diagnostic multilingual dataset of 48 pluri-hop questions built from 191 real-world wind industry reports in German and English. We show that PluriHopWIND is 8-40% more repetitive than other common datasets and thus has higher density of distractor documents, better reflecting practical challenges of recurring report corpora. We test a traditional RAG pipeline as well as graph-based and multimodal variants, and find that none of the tested approaches exceed 40% in statement-wise F1 score. Motivated by this, we propose PluriHopRAG, a RAG architecture that follows a “check all documents individually, filter cheaply” approach: it (i) decomposes queries into document-level subquestions and (ii) uses a cross-encoder filter to discard irrelevant documents before costly LLM reasoning. We find that PluriHopRAG achieves relative F1 score improvements of 18–52% depending on base LLM. Despite its modest size, PluriHopWIND exposes the limitations of current QA systems on repetitive, distractor-rich corpora. PluriHopRAG’s performance highlights the value of exhaustive retrieval and early filtering as a powerful alternative to top-k methods.

1 Introduction

Since the advent of large language models (LLMs) (Brown et al., 2020), question answering (QA) systems have been evolving at an enormous pace through the paradigm of Retrieval Augmented Generation (RAG) (Gao et al., 2023). The strength of RAG lies in combining information retrieval techniques (the R in RAG) with an LLM’s ability to synthesize chunks of evidence into a human-like answer (the G in RAG). Over time, the scope of RAG has expanded, allowing it to tackle increasingly complex types of questions.

Early RAG systems (Lewis et al., 2020) are mostly able to answer questions where a single or small number of evidence passages are sufficient. This is because of how they work - given a question, they find passages of text most semantically similar to the question, and use them as context (Lewis et al., 2020). For example, consider a database consisting of patients’ medical records - a question achievable by a basic RAG system might be “What was the diagnosis from Jane Doe’s X-ray on June 15, 2025?”, since the patient name, procedure name and date will also be present in the report where the diagnosis lies (see Figure 1).

Iterative improvements have since enabled progress on multi-hop questions, where evidence is spread across several documents, such as “Are there any previous occurrences of Jane Doe’s X-ray diagnosis from June 15 2025?” (see Figure 1). Such questions, where one source of evidence (in this case, the diagnosis) informs what other passages to look for, are often addressed through iterative, agentic, and planning-based approaches (Trivedi et al., 2022; Shao et al., 2023; Asai et al., 2023).

Another line of work has focused on global summarization-style questions, such as “How are Jane Doe’s health records similar to other patients admitted in 2025?”, which require synthesizing many passages (see Figure 1). Graph-based RAG

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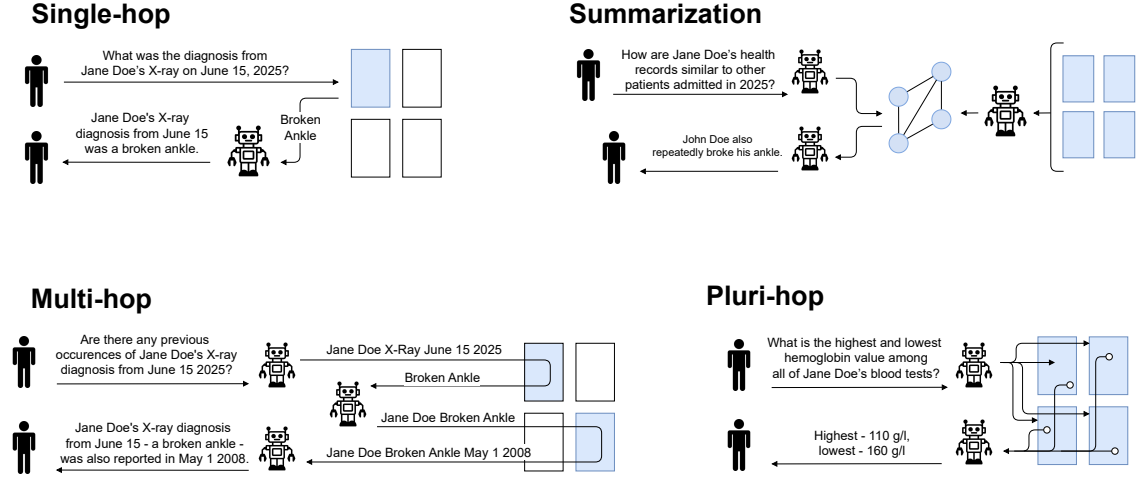


Figure 1: Common types of questions RAG systems are used for.

approaches (Mavromatis and Karypis, 2024; Hu et al., 2024; Edge et al., 2024) have proven effective in this setting by leveraging structured entity-relationship representations. Together with new methods, numerous benchmarks have been created for multi-hop questions (Ho et al., 2020; Yang et al., 2018; Tang and Yang, 2024) and summarization-style questions (Kočíský et al., 2017).

In contrast, there has been considerably less progress on a fourth category of questions: questions that require aggregating data across all documents in the knowledge base (see Figure 1). For example: “What is the highest and lowest hemoglobin value among all of Jane Doe’s blood tests?”. Unlike conventional multi-hop queries, these problems lack a natural stopping condition - retrieval cannot halt after a handful of documents because every record may change the answer, and unlike summarization-style questions, they have an exact answer. Iterative approaches underperform because they cannot easily decide when the evidence is sufficient, while knowledge graph approaches underperform because the relevant details often lie in the raw document text rather than in abstracted summaries.

In this work, we focus on precisely these questions. We coin the term **pluri-hop** questions, defined by three conditions:

1. Recall sensitivity: Omitting even a single relevant passage leads to an incorrect answer.
2. Exhaustiveness: It is impossible to infer from the retrieved context whether the evidence set is complete; in principle, all documents must be checked.

3. Exactness: There is only one best answer to the question. All other answers are either incomplete or contain superfluous and/or incorrect information.

These conditions imply that a viable approach to pluri-hop QA must go beyond existing paradigms. Instead of selectively focusing on a small subset of passages, the system must be designed to check all documents efficiently, while filtering irrelevant material early to maintain feasibility. This is in stark contrast to the "top-k" aspect built into most RAG systems.

Despite a lack of targeted investigations, pluri-hop questions are commonly asked in many scenarios, most prominently from recurring report data - medical records, financial reports, compliance reports, etc. - see Table 1 for a list of examples. Such data poses a challenge to RAG systems due to a large presence of distractor documents - documents that, given a question, are irrelevant but semantically similar to relevant documents, thus "distracting" the RAG system; an example would be John Doe’s X-Ray report when asking about Jane Doe’s X-Ray diagnosis. Therefore, in this work, we seek to answer the following question: **How does one answer pluri-hop questions about highly repetitive data (such as data from recurring reports) in a scalable way?**

To highlight the difficulties of answering pluri-hop questions, we introduce **PluriHopWIND**, a diagnostic multilingual dataset of 48 questions constructed from 191 real-world wind industry technical reports in German and English. Crucially, many benchmark questions require consulting evidence spanning more than the context window of state-

of-the-art LLMs. The dataset also emphasizes distractor density, with large amounts of semantically similar but irrelevant material, closely mirroring practical QA challenges in recurring report corpora. **We show that current approaches struggle to answer pluri-hop questions, reaching at most 40% statement-wise F1 score.**

Motivated by this, we propose **PluriHopRAG**, a retrieval architecture built specifically for pluri-hop questions. The design principle is to **check all documents cheaply and filter early**. Two key innovations support this:

1. Document-scope query decomposition, where pluri-hop questions are split into intermediate document-level subquestions.
2. Cross-encoder-based document filtering, which discards irrelevant documents after shallow retrieval but before expensive LLM reasoning.

We compare our approach to a baseline RAG approach as well as to more sophisticated competing RAG workflows based on knowledge graphs (GraphRAG (Edge et al., 2024)) and vision models (VisdomRAG (Suri et al., 2025)) on the PluriHopWIND dataset. **We report a 18-52% relative improvement in answer F1 score depending on base LLM used.**

Taken together, our findings suggest that pluri-hop QA is insufficiently addressed by prominent RAG approaches. Despite its modest size, the PluriHopWIND dataset exposes the limitations of current QA systems on repetitive, distractor-rich corpora, while PluriHopRAG’s gains highlight the value of exhaustive retrieval with early filtering as a powerful alternative to top-k methods.

2 Related Work

Methods. A wide range of RAG methods extend beyond single-pass retrieval. Iterative or agentic approaches such as IRCot (Trivedi et al., 2022), Iter-RetGen (Shao et al., 2023) and Self-RAG (Asai et al., 2023) break questions into sub-queries, retrieving and reasoning step by step. These are effective when there exists a natural stopping condition, but underperform when scanning the entire corpus is required. Graph-based approaches enable multi-hop reasoning by efficiently finding relevant subgraphs from existing knowledge graphs (GRAG (Hu et al., 2024), GNN-RAG (Mavromatis

and Karypis, 2024)) and/or building new entity-centric knowledge graphs from unstructured corpora (GraphRAG (Edge et al., 2024)). These methods capture relational structure, but often lose exact, fine-grained details in raw text. Multi-modal methods like VisdomRAG (Suri et al., 2025) and M3DocRAG (Cho et al., 2024) incorporate diagrams, tables, or visual layout cues, but do not explicitly address the scalability challenge of large, repetitive corpora. Structured and table-centric approaches (e.g., ReQaP (Christmann and Weikum, 2025), TableRAG (Yu et al., 2025), TAGOP (Zhu et al., 2021)) extract tabular data and answer aggregation queries using database-style reasoning. However, they assume highly structured evidence, unlike many real-world report collections.

Benchmarks. A variety of datasets test reasoning across multiple documents. Multi-hop benchmarks such as HotpotQA (Yang et al., 2018), 2WikiMultiHopQA (Ho et al., 2020) and (Tang and Yang, 2024) evaluate systems on linking evidence from two or more passages. Crucially, the questions are not exhaustive - given the retrieved context, one can determine whether it is sufficient to answer the question. Summarization-oriented benchmarks such as NarrativeQA (Kočíský et al., 2017) require models to condense long narratives into high-level answers, which violate the objectiveness and recall sensitivity criteria.

The Loong benchmark (Wang et al., 2024) contains questions that formally fulfill the three pluri-hop conditions. However, the corpora in Loong are deliberately sized so they fit into the context window of modern LLMs; the benchmark is designed to test long-context reasoning, not scalable retrieval. MoNaCo (Wolfson et al., 2025) and MEBench (Lin, 2025) also contain questions that might be considered pluri-hop, but because they are based on Wikipedia, system performance becomes entangled with the LLM’s pretraining knowledge. Indeed, the authors of MoNaCo observe that adding a retrieval module actually degraded performance compared to an LLM-only baseline, showing how Wikipedia-based corpora confound retrieval evaluation.

In summary, existing methods for answering complex questions about knowledge corpora focus on (i) RAG for questions with clear stopping conditions, (ii) RAG for summarization-oriented questions, or (iii) passing the full corpus as context to an LLM. None address pluri-hop questions, where answers require exhaustive, recall-sensitive aggregation across large, repetitive, distractor-heavy cor-

Sector	Document Type	Typical Question (pluri-hop)
Healthcare	Lab results	Across 2022–2024, what are Jane Doe’s lowest and highest eGFR values, with dates?
Education	Student progress report	Which students failed two or more terms between Fall 2022 and Spring 2025?
Energy & Utilities	Turbine inspection report	In windpark W03 (2022–2024), which turbine has the most gearbox-wear reports (moderate+)?
Wind Industry	Inspection report	In 2024, which turbines had major or critical blade damage? Give first noted date.
Transportation & Logistics	Aircraft maintenance log	Across the A320 fleet (2023–mid-2025), which components triggered 3+ D15 delay events?
Government & Compliance	Environmental monitoring report	From 2021 to 2024, did annual PM2.5 in region R1 improve? List station deltas.
Agriculture	Crop inspection report	Which farms in district D7 had pest X outbreaks in at least two seasons (2020–2024)?
IT & Software	Reliability report	For service S in 2024, list ISO weeks when peak-hour uptime dropped below 99.5%.
Retail & Supply Chain	Supplier compliance report	Which suppliers had quality-check failures in 3+ separate audits (2022–2024)?
Legal & Contracts	Compliance audit	For Contract C-17 (2019–2025), which clauses were ever marked non-compliant?

Table 1: Examples of pluri-hop questions about recurring-report corpora from various fields.

pora, in a scalable way. This motivates our introduction of the PluriHopWIND dataset and the PluriHopRAG model, designed explicitly for this challenging setting.

3 Dataset

3.1 QA Generation

PluriHopWIND consists of 48 questions from 191 technical reports from the wind industry: oil laboratory analysis reports, turbine inspection/maintenance reports, and service reports. The documents are in German and English, while the questions are exclusively in English. Each document has been anonymized, with personally identifiable information blacked out and turbine ID & windpark renamed. In the case of certain windparks, all dates have been shifted by a fixed amount at the request of the windpark operator. The documents vary highly in length (1-50 pages) and structure. However, almost all documents combine multiple visually-rich elements, like complex tables, diagrams, images and pictograms, while also containing whole paragraphs of text. A page from a typical document (an oil analysis report) can be seen in figure 2.

The pluri-hop questions have been generated by a two-level process, whereby we first gener-

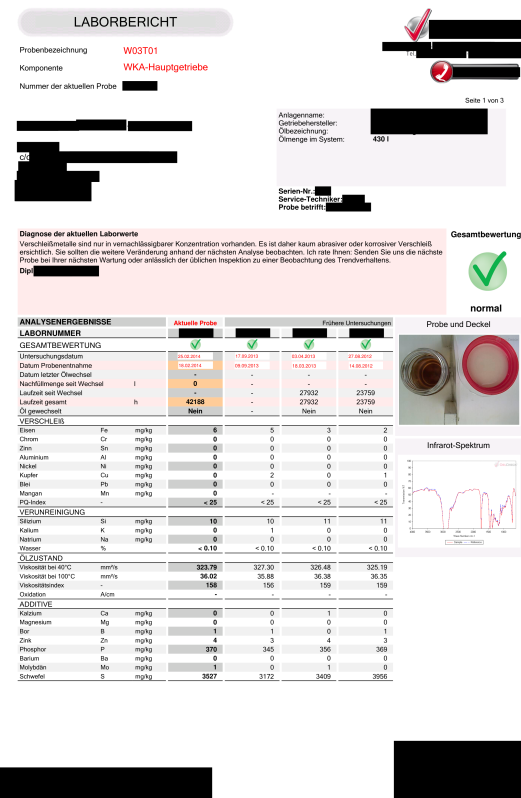


Figure 2: Typical report in the PluriHopWIND dataset

ate and verify a list of single-hop question-answer pairs, then aggregate them into multi-hop questions, and verify the answers against the already verified single-hop question-answer pairs.

First, we generate 2-7 single-hop answers from each document. The single-hop questions are generated manually, with all documents from the same category (oil analysis report, service report, inspection/maintenance report) being asked the same questions. We design the questions of a given report category to reflect the function of that category, e.g. to list all defects in inspection reports or to report billed hours in service reports. However, we also seek to test the model’s ability to work with visually-rich elements like tables, so we make sure to extract at least one type of information from each document type, that is typically displayed within these visually-rich elements (like iron & zinc concentration in oil reports, materials used from service reports, etc.). Afterwards, we manually verify the answers.

Second, we pass the single-hop QA table to an LLM to generate pluri-hop QAs. We instruct the LLM that a good question should¹:

1. Require many single-hop answers as evidence, either explicitly (e.g. "how did {quantity} evolve over time?") or implicitly (e.g. "what was the highest value of {quantity}?")
2. Be useful to a hypothetical wind energy technician
3. Require an exhaustive search through the documents (that is, no single piece of evidence should be able to signify that enough information has been retrieved to correctly answer the question)
4. Be formulated in such a way that a significant amount of data acts as distracting data, i.e. irrelevant data with high semantic similarity to relevant data. For instance, if there are documents about a certain topic from 2018 to 2022, the question should ask about documents from 2020 to 2022, such that the documents between 2018 and 2019 act as distracting data

We then manually verify the generated pluri-hop question-answer pairs and document citations, ensuring all criteria; if we identify that a question

¹We also instruct the LLM that each reference to a document should be quoted with its filename. This is used when calculating the efficacy of the cross-encoder filter.

doesn’t follow the criteria or that the answer is incorrect / incomplete, we correct the question/answer.

3.2 Document Analysis

One key challenge in question answering based on recurring report documents is distractors. Due to the recurring nature of the documents, there can be many irrelevant passages that are semantically similar to relevant passages - for instance, because they pertain to the wrong entity (patient, company, component, etc.). This introduces noise to the retrieval process of RAG systems, as they are all on some level based on a document/chunk similarity search. In the context of recurring documents, pluri-hop questions require correctly aggregating data from many sources, each with its own distractors, so the difficulty of the dataset is only exacerbated. Therefore, to stress-test a RAG model for such a scenario, high repetitiveness of data is crucial.

We introduce a way to estimate dataset repetitiveness and calculate it for PluriHopWIND, as well as other multi-hop benchmarks. Conceptually, we define dataset repetitiveness as the average cosine similarity between the embeddings of pairs of text chunks in the dataset. However, in a typical RAG/QA model, only the top k chunks are used for answering a question. Thus, we are interested in, on average, how similar a given chunk is to its k nearest neighbors (cosine similarity-wise). We define the repetitiveness @ k , or $r@k$, as

$$r@k = \frac{1}{N} \sum_{i=1}^N \frac{1}{k} \sum_{j=1}^k \text{cosine_sim}(x_i, x_{ij}), \quad (1)$$

where x_i is chunk i from all chunks in the dataset, and x_{ij} is the j ’th closest chunk to chunk i in terms of cosine similarity.

We calculate repetitiveness @ k for $k \in \{1, 2, 5, 10, 20, 50\}$, for 3 datasets - PluriHopWIND, MultiHopRAG (Tang and Yang, 2024) (based on news articles) and Loong (Wang et al., 2024) (which has 3 parts - scientific papers, financial documents, and legal documents). Instead of uploading all documents, we randomly sample $N = 100$ documents from each dataset/subdataset to upload - this ensures that the repetitiveness calculation reflects the nature of the document within the document set, rather than the size of the document set. The chunks are created by splitting the text into equally sized chunks with $L = 500$ characters

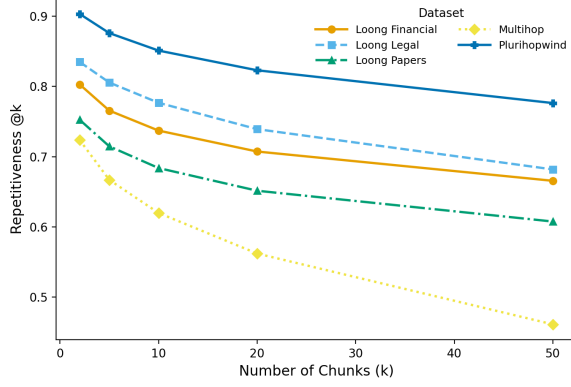


Figure 3: Chunk repetitiveness for PluriHopWIND, Loong, and MultiHopRAG datasets

each and $l = 100$ character overlap between neighboring chunks. The chunks are embedded to vectors using OpenAI’s text-embedding-3-large model. The results are displayed in Figure 3. We see a significant gap in the $r@k$ metric between PluriHopWIND and all other tested datasets, across all values of k , from relative drop of 8-20% for $k = 2$ up to relative drop of 13-41% for $k = 50$). Moreover, when looking at the change in repetitiveness within each dataset as k is increased, PluriHopWIND has the smallest relative drop (13%, from 0.90 to 0.78) between the smallest and largest value of k , followed by Loong Financial (16%, from 0.80 to 0.67). This suggests that simply increasing the k hyperparameter in a naive RAG system would offer fewer benefits when answering questions about documents from the PluriHopWIND dataset, as it is harder to tell relevant evidence apart from distractors. Instead, more sophisticated models that investigate documents one-by-one are likely to offer benefits based on the repetitiveness analysis. In the next section, we offer our version for such a model - PluriHopWIND.

4 Model

4.1 Overview

Our RAG algorithm pseudocode is displayed in Algorithm 1, and visualized in Figure 4. There are 3 main differences to a naive RAG pipeline:

1. Document-scope-based query decomposition (DecomposeQuery, line 1): instead of answering a user’s question directly, we decompose it into document-scope intermediate questions and aggregate the document-wise intermediate answers. The decomposition is performed by an LLM fine-tuned with LLM-generated train-

Algorithm 1 Model Workflow

```

1 intermediate_questions,
  hypothetical_summary ← Decompose-
  Query(query)
2 metadata ← ExtractMetadata(query)
3 candidate_docs ← PerformSimilaritySearchOf-
  Summaries(hypothetical_summary, metadata,
  K)
4 intermediate_answers ← []
5 for all doc in candidate_docs do
6   doc_chunks ← []
7   for all question in intermediate_questions do
8     chunks ← SimilaritySearchChunks(doc,
8     question, k)
9     append chunks to doc_chunks
10  end for
11 relevance ← CalculateCrossEncoder-
  Score(hypothetical_summary, doc_chunks)
12 if relevance > τ then
13   for all q in intermediate_questions do
14     answer ← AnswerIntermediateQuestion(q, doc,
14     doc_chunks)
15     append (q, answer) to intermediate_answers
16   end for
17 end if
18 end for
19 final_answer ← AggregateAn-
  swers(intermediate_answers)

```

ing data; we outline the procedure in the next subsection. In addition to the intermediate questions, DecomposeQuery also generates a hypothetical summary of a document that would be relevant to answer the original question; this is used for document-wise retrieval. Our query decomposition method is explained further in the next subsection.

2. Document filtering using a cross encoder (CrossEncoderScore, lines 11-12). To minimize LLM token usage for highly exhaustive questions, we estimate each document’s relevance to the original question using a cross encoder model, before answering the intermediate questions about that document. We use the cross encoder to calculate the similarity between the hypothetical summary generated by DecomposeQuery, and the concatenation of chunks retrieved for answering all intermediate questions; if the similarity is below a certain threshold, the document is not considered for the question. This is analysed in greater detail in a proceeding subsection.

3. 2 step retrieval. Instead of directly performing K-nearest-neighbor search between the query and all chunks, we search for similar document summaries to a hypothetical summary of a relevant document, generated by DecomposeQuery ² (line

²The existence of the K parameter in theory means that if K is less than the total number of documents, not all documents are checked when answering the question. In practice, one can set K to be larger than the total number of documents

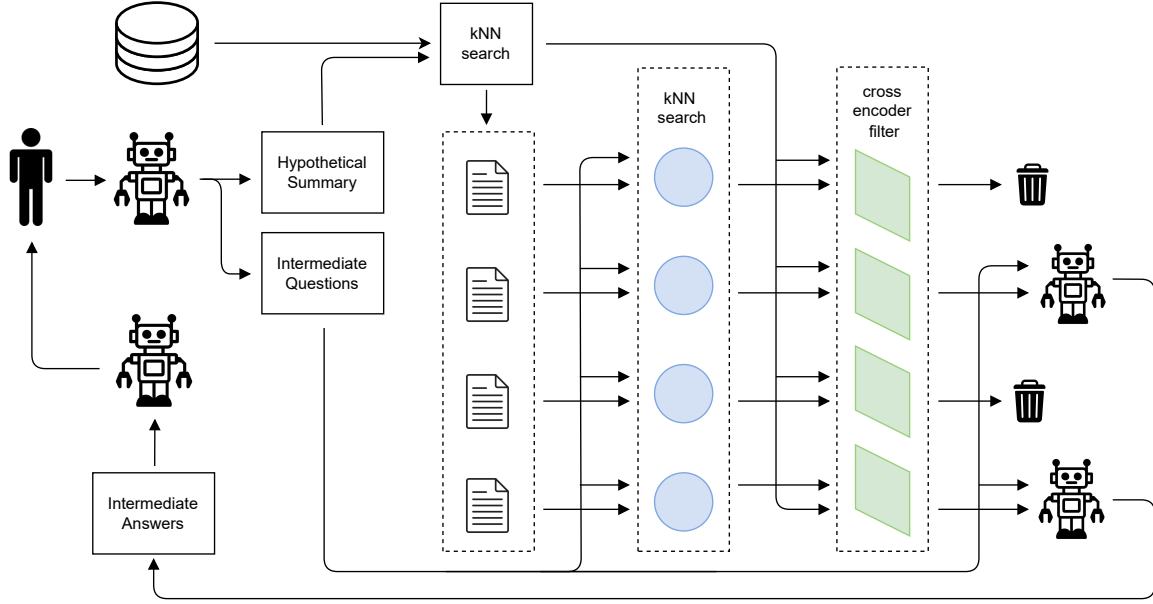


Figure 4: Diagram of PluriHopRAG algorithm

3). Then, for each selected document, we again perform K-nearest-neighbor search, this time looking for similar chunks within the document to each intermediate question (line 8).

4.2 Query decomposition

One of the key ingredients of PluriHopRAG is document-scope-based query decomposition - rewriting the original query into multiple intermediate questions that are asked to individual documents. This step was motivated by two observations. First, the type of information explicitly requested in a pluri-hop question often differs from the relevant information that is contained within a single document. Second, pluri-hop questions implicitly express more than just what data is necessary to answer them, namely filter conditions and aggregation instructions. For instance, the question "Has Jane Doe's kidney function been steadily declining over the past 3 years?" implicitly means:

1. (filter condition) Only consider documents from Jane Doe.
2. (filter condition) Only consider documents from the past 3 years.
3. (query) Find out what (if anything) the document says about their kidney function at a given moment.

and leave all the filtering to the cross-encoder filter.

4. (aggregation instruction) Given statements about kidney function from different times, check if they get worse over time.

The filter conditions and queries can be turned into questions that are asked to individual documents, to extract all relevant information and to decide if the document matches the filter conditions. In this case, the questions would be:

1. Is the person this document talks about Jane Doe?
2. When was this document written?
3. What does this document say about the patient's kidney function?

In this scenario, query decomposition becomes unnecessary if there is already a single document containing Jane Doe's 3-year kidney function trend. In other words, the pluri-hop nature of a question is contingent on how evidence is stored in documents. The quality of the query decomposer then hinges on its understanding of this - for instance, that medical records contain single test results rather than trends. This understanding may come from the base LLM's general knowledge imbued during pre-training, but for niche or closed domains it can be introduced through fine-tuning. We propose a workflow where an LLM is fine-tuned for the query decomposition task with fully LLM-generated examples that are created from a subset of the documents from the corpus.

GPT-4o			
Setting	Precision	Recall	F1
Fine-tuned	0.51	0.47	0.48
Few-shot	0.43	0.45	0.35

Table 2: Comparison of PluriHopRAG performance on PluriHopWIND with GPT-4o as base model, using a fine-tuned vs. few-shot prompted query decomposer

To generate the examples, the LLM is fed tuples consisting of a pluri-hop question and a document relevant in answering it. It is instructed to

1. Reason what information is relevant within the document to answer the question
2. After the reasoning tokens, generate a list of questions to ask to an equivalent document that would be sufficient to extract all the relevant information

The questions used to create the training set are generated via the same two-step pipeline as the dataset questions - by passing a set of single-document question-answer pairs to an LLM (more details in Section 3), with the exception that the answer is not verified, as we only need the question. We use $N = 100$ questions and use OpenAI’s supervised finetuning service to fine-tune their GPT-4o model, with $N_{epochs} = 3$, learning rate multiplier = 2, and batch size = 1.

4.3 Document filtering

Given the exhaustive nature of pluri-hop questions, all documents need to be considered as potentially containing relevant information to the question. This would mean a separate LLM call for each document, to answer the intermediate (document-level) questions, leading to very poorly scaling costs to run the model. To remedy this, we add a document filtering method based on a commercial pre-trained cross-encoder based reranking model (Cohere Rerank 3.5) that drastically reduces the number of LLM tokens used without substantially sacrificing answer quality.

Pre-trained reranking models are trained to estimate the relevance of one passage of text to another (Gao et al., 2023). Typically, they are then used in a RAG context to compare the original query and retrieved chunks, in order to narrow down the list of chunks passed to the LLM for answer generation (Gao et al., 2023). In our case, we use the

reranking model to compare the hypothetical summary and the concatenation of all chunks retrieved to answer the intermediate questions. Instead of narrowing down the list of chunks, we simply discard the entire document if the similarity score output by the reranking model between the hypothetical summary and retrieved chunks is below some threshold.

We investigate the efficacy of the cross-encoder filter with the following experiment. For each question in PluriHopWIND, we compute the estimated relevance of each document to the question. We then plot the distribution of estimated relevance for documents that are human-labelled as relevant (i.e. are quoted in the answer to the question), as well as for the documents that aren’t. This is plotted in Figure 5. Almost 50% of irrelevant documents and less than 10% of relevant documents belong to the bottom 10th percentile of estimated document relevance, which shows that our document filter can greatly reduce LLM token usage without high impact on document recall.

5 Experimental Setup

We run our PluriHopWIND benchmark on our PluriHopRAG model, as well as multiple prominent competing RAG approaches. We aim to cover a wide range of approaches - graph-based RAG and multi-modal RAG - as well as thoroughly compare our model to the baseline. To achieve this, we test GraphRAG (Edge et al., 2024) (a graph-based approach), VisDomRAG (Suri et al., 2025) (a multi-modal approach) and naive RAG (Lewis et al., 2020). We test multiple variations of naive RAG, with two chunking methods (standard per-character chunking & per-page chunking), as well as cross-encoder reranking of chunks.

Indexing. GraphRAG indexes all data into a knowledge graph, for all other models we chunk the document text into chunks with $L = 500$ characters each and $l = 100$ overlap between them.

Metadata Filtering. Since wind turbines are referred to both by their turbine ID and windpark within the dataset (and in real-life usecases our customers deal with), we enrich each document with turbine ID and windpark metadata, and employ an explicit metadata filter during retrieval that is based on the turbine ID / windpark mentioned in the question. This means that only documents with the correct turbine ID / windpark are candidates for retrieval. This filter is added to all approaches

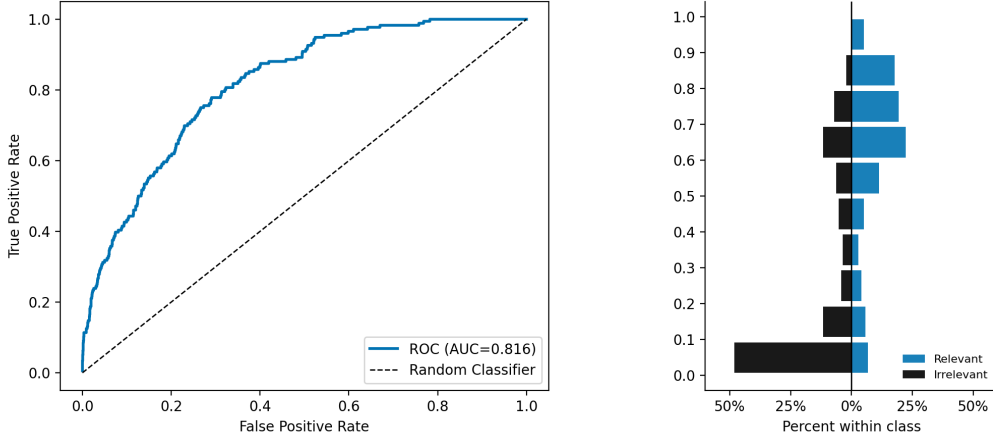


Figure 5: Behavior of cross-encoder based document filter for the PluriHopWIND dataset. Left: Receiver Operator Characteristic (ROC) curve for filter at different filter thresholds τ . Right: distribution of estimated document relevance for relevant and irrelevant documents.

apart from GraphRAG, as it would require building a separate graph for each unique filter condition, which we deemed prohibitively expensive. We also run all models without the filter to estimate how robust each model is to a larger amount of distractors (we then only compare GraphRAG to other models in the no-filter case).

PluriHopRAG. We follow the algorithm outlined in Section 4, with cross-encoder similarity threshold $\tau = 0.1$ and max number of documents retrieved based on document summary $K > 198$ (all documents are fed to the cross-encoder filter).

Naive RAG. We follow the basic RAG pipeline as in (Gao et al., 2023), with top $k = 20$ chunks passed to the LLM as context. To ensure a full comparison with the baseline, we also try chunking the document by page, as well as inserting a reranking step between k-nearest-neighbour retrieval and answer generation. We again use Cohere Rerank 3.5 with a filter factor of 4x, i.e. we initially retrieve $k = 80$ chunks and pass $k' = 20$ chunks with the highest relevance to the query as estimated by the reranking model.

GraphRAG and VisdomRAG. We run the code as provided by the authors, only changing the chunking hyperparameters and adding a metadata filter for VisdomRAG, see above.

Evaluation. Once each model has generated the answers to the benchmark questions, we evaluate their performance by comparing the generated answers to the reference answers. As answer quality metrics, we use the statement-wise answer preci-

sion, recall and F1 score, defined as

$$\begin{aligned} recall &= \frac{\# \text{ of reference statements in generated answer}}{\# \text{ of statements in reference answer}} \\ precision &= \frac{\# \text{ of generated statements in reference answer}}{\# \text{ of statements in generated answer}} \\ F1 &= \frac{2}{recall^{-1} + precision^{-1}} \quad (2) \end{aligned}$$

The statement-level metrics, inspired by (Es et al., 2025), are used instead of more common token-level metrics (such as token-level F1) because they evaluate model outputs at a semantic rather than surface level. This distinction is crucial for PluriHopWIND, where gold standard answers often span multiple sentences and can be expressed through many valid paraphrases. Token-level comparisons would underestimate performance in such cases, penalizing models that produce semantically correct but lexically different responses.

We split the answers into statements and evaluate the presence of a statement within an answer using GPT-4o, with a few-shot prompt that is provided in the Appendix.

6 Results

The results of the overall comparison of RAG models on PluriHopWIND are shown in table 3. The main conclusions are as follows:

PluriHopRAG achieves a significantly higher answer F1 score than other tested models across base LLMs. We see a 18% relative improvement (0.4 to 0.47) in F1 score with Claude 4 Sonnet as

Method	Claude 4 Sonnet			GPT-4o		
	Precision	Recall	F1	Precision	Recall	F1
PluriHopRAG						
With filter	0.58	0.52	0.47	0.51	0.47	0.41
No filter	0.47	0.57	0.44	0.48	0.39	0.36
NaiveRAG – Per-page chunking						
With filter	0.48	0.33	0.27	0.66	0.14	0.14
With filter + rerank	0.48	0.47	0.40	0.55	0.23	0.24
No filter	0.50	0.30	0.26	0.75	0.14	0.14
No filter + rerank	0.47	0.43	0.38	0.64	0.26	0.25
NaiveRAG – Character-count-based chunking						
With filter	0.48	0.29	0.26	0.75	0.13	0.14
With filter + rerank	0.52	0.45	0.38	0.62	0.26	0.27
No filter	0.47	0.18	0.17	0.81	0.10	0.12
No filter + rerank	0.44	0.36	0.31	0.65	0.21	0.21
VisdomRAG						
With filter	0.39	0.12	0.19	0.32	0.24	0.21
GraphRAG						
No filter	0.34	0.36	0.30	0.40	0.22	0.21

Table 3: Comparison of QA performance (Precision, Recall, F1) across methods with and without metadata filtering using Claude 4 Sonnet (left) and GPT-4o (right). Bolded cells mark the best F1 per model.

the base model and a 52% relative improvement with GPT-4o (0.27 to 0.41). In both cases the second best model is naive RAG with Cohere Rerank 3.5 as reranker, significantly outperforming naive RAG without a reranking model.

Naive RAG outcompetes other RAG approaches created for multi-hop questions. Somewhat surprisingly, naive RAG with reranking performs noticeably better than VisdomRAG and GraphRAG across all metrics and base LLMs. This highlights the unique challenges of answering pluri-hop questions, since approaches designed for multi-hop question answering fall behind even the baseline.

PluriHopWIND offers a very difficult challenge for modern RAG systems. Despite showing significant improvements compared to the baseline and multiple modern approaches, PluriHopRAG leaves a lot of room for future improvements. Despite its modest size, PluriHopWIND highlights a weakness in modern QA systems in aggregating data from tens/hundreds of report-style documents without missing important details. We believe there are 2 main reasons - the large amount of highly repetitive distractor documents and the exhaustive nature of the questions (i.e. no way to establish a

stopping condition for retrieval) - both of which reflect real-life scenarios in manufacturing, medicine, finance and other fields.

6.1 Ablations

6.1.1 Metadata filter

In Table 3, we report model performance with and without a metadata filter. Surprisingly, naive RAG with per-page chunking appears to exhibit very similar performance with and without the metadata filter (+0.02 in F1 score). PluriHopRAG drops by 6-12% in F1 score depending on base LLM, while naive RAG with character-count-based chunking drops by 12-35%. Nevertheless, PluriHopRAG without a metadata filter still outperforms competing models with a metadata filter by 10% with Claude 4 Sonnet and by 25% with GPT-4o.

6.1.2 Fine-tuned query decomposition

We evaluate our model on PluriHopWIND with a fine-tuned query decomposer and one based on the base version of GPT-4o, only adding a few-shot prompt with $N = 2$ examples from the training set of the query decomposer. The results are in Table 2 - fine-tuning adds a 37% relative increase in F1 score. Comparing the few-shot version to

other models from Table 3, it is evident that fine-tuning is crucial to achieve noticeable performance increases over baseline models. This adds weight to our claim that the basic logic of how information is laid out in document corpora can be imbued using fine-tuning with very modest training set sizes.

7 Conclusion

In this work, we formalized the notion of pluri-hop questions - queries that possess both high recall sensitivity, exhaustiveness (no clear stopping condition without full coverage of the corpus), and exactness (factual questions with an unambiguously best answer). We argued that such questions arise naturally in domains built on recurring report data but are poorly represented in existing benchmarks.

To study this challenge, we developed PluriHopWIND, a diagnostic dataset constructed from real wind industry technical reports. Its design emphasizes distractor-heavy, repetitive corpora that cannot fit within an LLM’s context window, thereby replicating the practical difficulties of answering pluri-hop questions. Using our proposed inter-similarity measure, and in terms of distractor density, we show that PluriHopWIND more closely resembles realistic pluri-hop scenarios than existing benchmarks that contain pluri-hop questions. By focusing on distractor density during dataset construction, we manage to showcase failure modes of RAG systems in realistic scenarios despite its modest size.

We also present PluriHopRAG, an RAG approach tailored to the pluri-hop setting. Rather than relying on partial coverage, PluriHopRAG is designed to check all documents in principle, while keeping this feasible through cross-encoder filtering that discards irrelevant material early. Experiments show that this approach yields substantial improvements in answer quality, with relative gains of 18–52% in F1 score depending on the base LLM.

Together, these contributions extend the study of RAG in three ways:

- by formalizing the pluri-hop category as distinct from traditional multi-hop reasoning,

- by providing a dataset that replicates the structural challenges of real-world recurring report datasets, and

- by offering a model that, in our view, most directly targets the exhaustive nature of pluri-hop questions.

We hope that this work will inspire more bench-

marks in other domains, and the further development of retrieval strategies that can cope with exhaustive, distractor-rich corpora in practical settings.

8 Limitations

While our study introduces new concepts and methods for pluri-hop QA, it also comes with limitations:

Dataset size and coverage. PluriHopWIND contains 191 documents and 48 questions, which is modest compared to other QA benchmarks (Ho et al., 2020; Yang et al., 2018; Wolfson et al., 2025; Wang et al., 2024; Lin, 2025). Given the high repetitiveness of the dataset, we believe this size is sufficient for a showcase of the difficulty of pluri-hop QA. Nevertheless, broader validation across larger and more diverse corpora is necessary to advance in this space.

Domain specificity. The dataset is drawn exclusively from wind industry technical reports. Although pluri-hop questions naturally occur in many domains (e.g., healthcare, finance, compliance), the dataset may encode domain-specific biases. Future work should extend benchmarks to additional sectors with different document formats and reporting practices.

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A LLM Prompts

A.1 Metadata Extraction

Prompt: Metadata Extractor (specific to PluriHopWIND)

Determine if question is about specific turbine id(s), specific windpark(s), or neither. Return the turbine id(s) and/or windpark name(s) in JSON format (schema in examples). The windpark name is one or several words, while turbine IDs

are alphanumeric.

Examples:

Question: "What is the maintenance schedule for wind turbine ABC123?" *Response:* `{{"plant_id": ["ABC123"]}}`

Question: "What is the maintenance schedule for ABC123 and CDE567 in Windpark Blombheim?" *Response:* `{{"plant_id": ["ABC123", "CDE567"], "windpark": ["Blombheim"]}}`

Question: "What is the maintenance schedule for wind turbines in Blombheim and Waldstein?" *Response:* `{{"windpark": ["Blombheim", "Waldstein"]}}`

Question: "What is the maintenance schedule for all wind turbines?" *Response:* `{{}}`

Your Task: {prompt}

A.2 Question Decomposition

Prompt: Question Decomposer (Base Version)

I have a RAG application. Given a question about one or multiple documents, determine:

1. A hypothetical summary of the document (or one of the documents) that would be relevant to answer the question (max 100 tokens). 2. A set of questions to ask to the document(s) to retrieve all information needed to answer the question.

Rules:

- Sometimes multiple documents are needed to answer the question. So a question about a trend could be answered either with a document describing this trend (if such a document exists, usually it doesn't), or with multiple documents describing the current situation and the trend could be inferred. Therefore, the questions should take both possibilities into account.
- Try to get all needed information with as few questions as possible, minimizing overlap.

Return in JSON format, without markdown code block formatting, as follows: `{{'hypothetical_summary': str, 'questions': list[str]}}`

A.3 Document-level Answering

Prompt: Document Answer Generator

You are a wind energy expert. Given one or multiple questions, answer all of them using the provided context. All the context comes from one document.

Return in JSON format, without markdown code block formatting, with key 'answers' and value list of strings.

Inputs: Questions: {questions} Context: {context}

Prompt: Page Group Answer Aggregator

I tried to answer multiple questions using individual pages or groups of pages from a document. Given the answers based on each page, construct the correct answers based on the whole document.

Return in JSON format, without markdown code block formatting, with key 'answers' and value a list of strings.

Do not omit any relevant details.

Inputs: Questions: {questions} Answers: {answers}

A.4 Corpus-level Aggregation

Prompt: Answer Aggregator

A question was asked about some document(s). This question was split into intermediate questions, and these intermediate questions were answered with one or multiple documents as context.

Given the original question, the intermediate questions, and each document's answer to the intermediate questions, construct the final answer to the original question (in the language of the original question).

Only include information that directly answers the original question. If that means omitting some information from the intermediate answers, that's fine. Don't explain how you arrived at the answer.

After each fact, put a reference to the document with [Document <document_index>]. If a fact comes from multiple documents, reference them like [Document <1>], [Document <2>], etc., instead of [Document 1, 2].

After you construct the final answer, also return a list of documents which were relevant to answer

the question (i.e. all documents you referenced, in ascending order of index).

The output should be in JSON format.

Example Output: `{{'answer': 'example answer', 'relevant_documents': [3, 5, 6]}}`

Your Task:

Original Question: {original_question} Intermediate Questions: {intermediate_questions} Document Answers: {document_answers}

Final Answer (RETURN IN JSON, without markdown code block formatting):

A.5 Evaluation - Statement Splitting

Prompt: Statement Splitter (for Answers)

Below is a question and answer. I want to split the answer into statements in such a way, that I can recreate the answer (or a paraphrased version) by using the question and the statements, while keeping the statements as few and as short & simple as possible. If it makes sense, the statements should be key-value pairs (with keys and values as strings), otherwise they should be strings. The whole answer should be in json format, in the following format:

```
{
  "1": <statement_1>,
  "2": <statement_2>,
  ...
}
```

Below are some rules to follow: 1. There should be as few statements as possible, and they should be as simple as possible, to still recreate the answer (or a paraphrased version of the answer) using BOTH the question and statements.

Example:

Question:

Are there any anomalies in the oil report for wind turbine 123?

Answer:

Yes there are 2 anomalies in the oil report for wind turbine 123: the chrome level is too high and the magnesium level too high.

Bad outcome:

```
{
  "1": {"turbine": "123"} # this statement isn't
    necessary to recreate the answer because the
    turbine id can be found in the question
  "2": {"number of anomalies in oil report": "2"}
    # it's unnecessary to write "oil report" because
    the document type can be found in the question
```

```
"3": {"anomaly": "chrome level too high"}
"4": {"anomaly": "magnesium level too high"}
}
```

Desired outcome:

```
{
  "1": {"number of anomalies": "2"},
  "2": {"anomaly": "chrome level too high"},
  "3": {"anomaly": "magnesium level too high"}
}
```

2. If the statement is a string, it should be max 1 short sentence. If it is a key-value pair, the value must be max 1 short sentence.

Example:

"Conclusion: Chromium levels high. Continue monitoring to observe further trends"

Desired behaviour:

```
{
  "1": {"Conclusion": "Chromium levels high"},
  "2": {"Conclusion": "Continue monitoring to
    observe further trends"}
}
```

3. If an answer is refused because relevant context couldn't be found, and alternative questions are suggested to avoid this, this should be interpreted as zero statements. If the answer is that relevant context couldn't be found, but the irrelevant context is talked about anyway, the answer should be treated like any other.

4. If the answer contains references to documents via their filenames, this should be ignored and not included in the inferred statements.

Question:

{question}

Answer:

{answer}

A.6 Evaluation - Statement Comparison and Counting

Prompt: Statement Counter and Comparator

An answer to a question was split into statements. You need to compare this answer to another, reference, answer. For each statement, determine SEPARATELY if the *exact* statement can be directly implied from the reference answer (not the original answer)?. Respond in json format, where for each statement the key is the statement index and the value is a bool that is true if you can infer the statement from the text, false otherwise. Also have a key-value pair where the key is "inferred_statements" and the value is the

number of keys in the dictionary with value true.
EXAMPLE: Answer: In the past 5 years, the repairs on wind turbine 123 have occurred 4 times: on 2020.05.01, 2021.05.02, 2022.05.04, and 2023.05.04.

Statements: ['{{number of repairs': '4'}}', '{{repair date': '2020.05.01'}}', '{{repair date': '2021.05.02'}}', '{{repair date': '2022.05.04'}}', '{{repair date': '2023.05.04'}}']

Reference text: There were 5 repairs conducted in the past 5 years: on 2020.05.01, 2021.05.02, 2022.05.03, 2023.05.04, and 2024.05.05.

EXAMPLE OUTPUT: {'1': false, '2': true, '3': true, '4': false, '5': true, 'inferred_statements': 3}

YOUR TASK:

Answer: {text}

Statements: {statements}

Reference text: {reference_text}

A.7 Evaluation - File Reference Extraction

Prompt: File Reference Finder

Find references to pdf files in an answer. They will look like [filename.pdf]. Return a list (without repetitions) of filenames in JSON format, like so:

{'filenames': ['filename1.pdf', 'filename2.pdf']}

Text: {text}

Answer: