

MiRAGE: A Multiagent Framework for Generating Multimodal Multihop Question-Answer Dataset for RAG Evaluation

Chandan Kumar Sahu^{1*}, Premith Kumar Chilukuri^{1*}, Matthew Hetrich^{1*†}

¹ABB Inc

Abstract

The rapid evolution of Retrieval-Augmented Generation (RAG) toward multimodal, high-stakes enterprise applications has outpaced the development of domain specific evaluation benchmarks. Existing datasets often rely on general-domain corpora or purely textual retrieval, failing to capture the complexity of specialized technical documents where information is inextricably multimodal and reasoning requires synthesizing disjoint evidence. We address this gap by introducing **MiRAGE**¹, a Multiagent framework for **RAG** systems Evaluation, that leverages a collaborative swarm of specialized agents to generate verified, domain-specific, multimodal, and multi-hop Question-Answer datasets. MiRAGE orchestrates a swarm of specialized agents: a recursive context optimization loop to aggregate scattered evidence, an adversarial verifier agent to guarantee factual grounding, and an agent to recognize the expert persona and the relevant domain to mimic expert cognitive workflows. Extensive empirical evaluation across four distinct domains (regulations, finance, quantitative biology, and journalism) demonstrates that MiRAGE generates datasets with significantly higher reasoning complexity (> 2.3 average hops) and factual faithfulness. Our ablation studies point that MiRAGE can be powered by LLMs if textual descriptions of the images are available. Visual grounding still remains a frontier. By automating the creation of gold standard evaluation datasets that reflect the latent thematic structure of proprietary corpora, MiRAGE provides the necessary infrastructure to rigorously benchmark the next generation information retrieval systems.

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in encoding world

knowledge within their parameters. However, they face fundamental limitations regarding rare entities, cutoff dates, and the high computational cost of retraining to update information (Kandpal et al., 2023; Mallen et al., 2023). Retrieval-Augmented Generation (RAG) has emerged as the de facto solution to these challenges, mitigating hallucinations by grounding generation in external, non-parametric knowledge bases (Lewis et al., 2020). As RAG systems are increasingly deployed in high-stakes enterprise domains ranging from medical diagnosis (Xiong et al., 2024) to wind energy (Meyur et al., 2025), the imperative for rigorous, scenario-specific evaluation has intensified.

Despite the rapid adoption of RAG, evaluating these systems remains a non-trivial challenge. Standard benchmarks, such as Natural Questions (Kwiatkowski et al., 2019) or MS MARCO (Nguyen et al., 2016), typically rely on open-domain data that fails to reflect the complexity of specialized corpora. In real-world environments, knowledge is rarely confined to text. It is inextricably multimodal, locked within charts, technical diagrams, and complex layouts. Recent work on Multimodal RAG, such as MuRAG (Chen et al., 2022), highlights that models restricted to textual retrieval neglect the massive amount of knowledge present in visual modalities. Furthermore, while single-hop retrieval is relatively mature, existing systems struggle significantly with multi-hop queries that require synthesizing disjoint pieces of evidence scattered within a document (Tang and Yang, 2024).

To bridge this gap, research has pivoted toward synthetic dataset generation, as obtaining human-annotated data for multi-hop reasoning is both time-consuming and resource-intensive (Wu et al., 2024). However, current synthetic frameworks often suffer from critical deficiencies. Pipelines like DataMorgana (Filice et al., 2025) or SMMQG (Wu et al., 2024) generally employ linear generation strategies that lack robust feedback mechanisms. This often

*Equal contribution.

†Corresponding author: matthew.hetrich1@us.abb.com

¹<https://github.com/ChandanKSahu/MiRAGE>

results in hallucinated evaluation datasets. There is a paucity of high-quality benchmarks that simultaneously address domain specificity, multimodality, and complex reasoning steps.

To address these limitations, we introduce **MiRAGE**, a Multi-Agentic framework designed to generate robust multihop multimodal expert-level evaluation datasets. Unlike linear prompting strategies, MiRAGE orchestrates a swarm of specialized agents to mimic the cognitive workflow of a domain expert. We propose a dynamic *context optimization loop*, where a retrieval agent recursively builds a semantic context window, gathering scattered evidence to support complex inquiries before a question-answer pair is formulated. Crucially, we address the reliability of synthetic data through an adversarial verification phase, employing a dedicated agent to fact-check generated answers against source context ensuring that the generated insight is consistent with the source.

Our contributions are summarized as follows:

1. We propose a model-agnostic, multi-agent framework that automates the ingestion and semantic segmentation of complex multimodal documents, preserving the semantic dependencies between text and visual elements.
2. We introduce a novel generative methodology that utilizes recursive context expansion and persona injection to produce multi-hop QA pairs. This allows for the creation of questions that require logical deduction across disjoint chunks, surpassing the complexity of extractive QA.
3. We provide an extensive empirical evaluation across four distinct domains: regulations, finance, science, and journalism. We demonstrate that MiRAGE generates datasets with significantly higher reasoning complexity while strictly adhering to the latent thematic distribution of the source domain.
4. Our ablation study revealed that the domain/persona injection, multihop context and QA verification play a crucial role in the quality of the generated QA dataset. MiRAGE can be powered by LLMs if the textual descriptions of the images contained in the document are available.

2 Literature Review

2.1 Evaluation of RAG Systems

Evaluating RAG systems remains a non-trivial challenge due to the dual dependencies of retrieval precision and generation faithfulness. Traditional evaluation often relies on static, general-domain datasets such as Natural Questions (Kwiatkowski et al., 2019), MS MARCO (Nguyen et al., 2016) and MIRAGE (Park et al., 2025). However, these benchmarks fail to capture the nuances of domain-specific corpora. Consequently, the generation of synthetic datasets became inevitable. Frameworks like *DataMorgana* (Filice et al., 2025) and *DQABench* (Zheng et al., 2025) leverage LLMs to generate QA pairs for metrics-based evaluation (Es et al., 2024).

The proprietary nature of *DataMorgana* and the schema-based nature of *DQABench*, limit their usage and generalizability. Frameworks like *RAG-Probe* (Sivasothy et al., 2025) highlight that system failures occur most frequently when prompts combine multiple constraints. Thus, most synthetic generators produce simple, single-constraint queries. MiRAGE addresses the reliability of synthetic data through a dedicated QA generation agent with a distinct verifier agent that fact-checks generated answers to mitigate hallucination.

2.2 Multimodal Context

Real-world documents (E.g., technical standards, manuals, and research papers) are inherently multimodal, interleaving text with tables, charts, and diagrams. Recent literature on Visual QA (Kim et al., 2025) and Multimodal RAG (Mei et al., 2025) emphasizes that critical information is often locked in non-textual formats. Recent works like *SPIQA* (Pramanick et al., 2024) and *WikiMixQA* (Foroutan et al., 2025) have attempted to bridge the multimodal gap by interpreting scientific figures. *MuRAG* (Chen et al., 2022) requires joint reasoning over images and text. However, the critical bottleneck of a unified perception stage still persists (Zhao et al., 2023). Modalities are often processed in isolation, breaking the document’s semantic flow. The standard OCR frequently degrades tabular structure. MiRAGE addresses this by implementing a multimodal ingestion phase where a vision agent generates descriptions and extracts table structures into an enriched markdown. This preserves the semantic proximity between textual and visual elements in a shared vector space, mir-

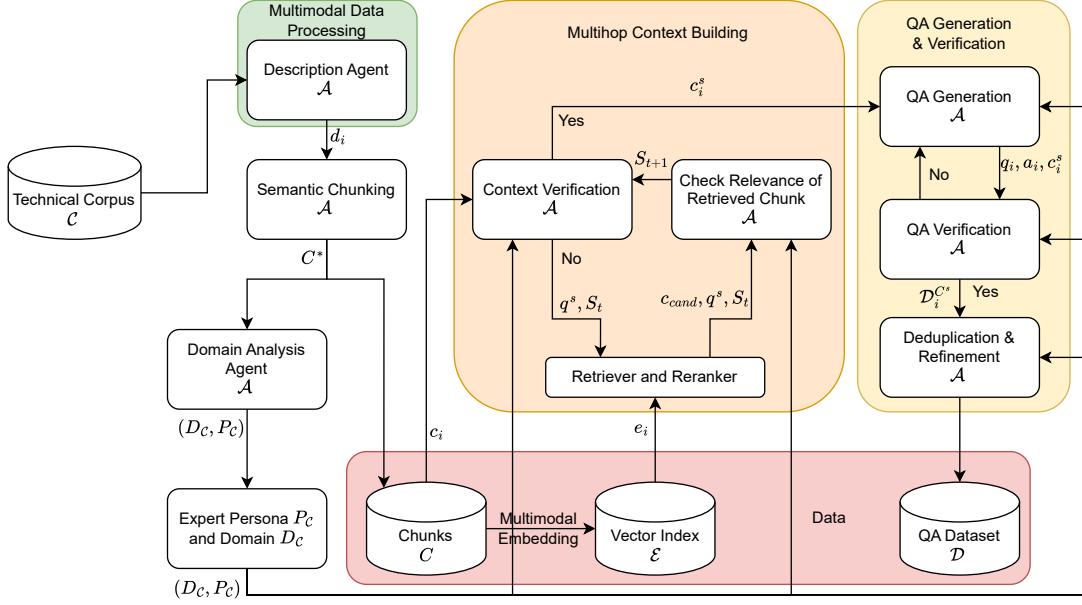


Figure 1: The multiagent framework of MiRAGE to evaluate RAG systems

roring the source layout.

2.3 Multi-hop Reasoning

Effective RAG systems shall go beyond simple information retrieval to synthesize information across scattered but semantically related content. Research into *MultiHop-RAG* (Tang and Yang, 2024) and *HotpotQA* (Yang et al., 2018) has demonstrated that systems performing well on single-hop queries often fail significantly when required to connect multiple pieces of evidence. While datasets like *MuSiQue* (Trivedi et al., 2022) and *Graphhopper* (Koner et al., 2021) introduce compositional queries, they largely rely on open-domain sources (e.g., Wikipedia) or extractive answers. Crucially, they lack the specific expert persona required for domain-specific tasks, such as engineering or finance (Schnitzler et al., 2024). MiRAGE automates the creation of complex reasoning chains through a context optimization loop. The context agent iteratively expands search queries to gather scattered evidence, allowing the QA generator agent to create complex, multi-hop Q&A pairs that mimic expert analysis rather than simple keyword matching.

2.4 Agentic Frameworks for Dataset Generation

The complexity of generating verified, multimodal, multi-hop questions has led to the emergence of agentic frameworks. *SMMQG* (Wu et al., 2024) employs an interplay between a retriever, LLM, and a multimodal model to synthesize questions. Similarly, *WeQA* (Meyur et al., 2025) utilize Human-AI teaming to ensure domain relevance. However,

the linear pipeline of *SMMQG* (Wu et al., 2024) lacks a robust feedback mechanism for deduplication, often resulting in semantic redundancy and inflated datasets. MiRAGE advances this paradigm by organizing agents into a generation swarm. By incorporating a selector agent to filter for difficulty and a curator agent that performs hierarchical deduplication and clustering, MiRAGE ensures the final output is not only accurate but diverse, minimizing redundancy while maximizing semantic coverage.

3 Methodology

We propose a multimodal multi-agentic framework designed to generate a question-answer dataset $(q_i, a_i) \in \mathcal{D}$ from a technical corpora \mathcal{C} . \mathcal{D} is a collection of validated pairs (q_i, a_i) . Mathematically, the dataset generation process is defined by

$$\mathcal{D} = \Phi \left(\{(q_i, a_i) \sim P(q, a|V=1, \mathcal{C}, \Theta)\}_{i=1}^N \right) \quad (1)$$

The joint probability of generating a valid pair from its context is

$$\begin{aligned} P(q, a, V=1 | \mathcal{C}, \Theta) = \\ \sum_{C^s \subseteq \mathcal{C}} \left[P(V=1 | q, a, C^s, \theta_V) \right. \\ \cdot P(q, a | C^s, \theta_{QA}) \\ \cdot P(C^s | \mathcal{C}, \theta_S) \left. \right] \end{aligned} \quad (2)$$

where C^s is a semantic context (a subset of chunks) derived from \mathcal{C} . The parameter set $\Theta = \{\theta_V, \theta_{QA}, \theta_S\}$ represents the configurations for the verification, generation, and semantic search

agents, respectively. The framework operates in five phases: (1) multimodal data ingestion and semantic chunking, (2) identification of expert persona and domain, (3) semantic multihop context building, (4) agentic QA generation and verification, and lastly (5) refinement and deduplication. The architecture is model-agnostic, allowing for the interchange of underlying language models. The framework is illustrated in Fig. 1.

3.1 Multimodal Data Ingestion and Semantic Chunking

Raw technical documents contain complex layouts where textual information is inextricably linked with visual artifacts. To address this, we implement a hybrid parsing pipeline to structure \mathcal{C} . We utilize a document layout analysis engine for structural segmentation and a description agent powered by a Vision Language Model (VLM) for visual interpretation. The description agent generates a dense textual description d_i for every visual element $v_i \in \mathcal{C}$.

$$d_i = \mathcal{A}(v_i \mid \pi_{desc}) \quad (3)$$

where π_{desc} is the prompt to *describe* the technical details.

We employ a semantic chunking strategy to segment the source document into semantically coherent chunks. The document text T is processed via a sliding window of length L with an overlap of l . For each window W_t , the semantic chunking agent identifies the optimal partition C^* from all the possible partitions of W_t ,

$$C^* = \arg \min_{C \in \text{Partitions}(W_t)} \left(\sum_{j=1}^{|C|-1} [1 - \text{Sim}(c_j, c_{j+1})] + \lambda |C| \right) \quad (4)$$

where c_j, c_{j+1} are adjacent chunks in candidate partition C , and $\text{Sim}(\cdot)$ is a semantic similarity function. λ is a regularization hyperparameter that prevents over-fragmentation.

3.2 Identification of Expert Persona and Domain

We incorporate an agent to determine the core domain D_C and an expert persona P_C by performing a global analysis of the corpus. These parameters

condition the generation agents to reflect the domain knowledge and the style and complexity of a subject matter expert. Each chunk $c_i \in \mathcal{C}$ is represented by its multimodal embedding e_i . Let $\mathcal{E} = \{e_1, \dots, e_M\}$ be the collection of embeddings. The agent employs a topic modeling pipeline to discover the latent thematic structure within the corpus using three steps. First, \mathcal{E} is projected into a lower-dimensional space using manifold learning. Second, density-based clustering partitions the chunks into K thematic clusters $\{\tau_1, \dots, \tau_K\}$ where each cluster corresponds to a distinct topic. Third, we utilize class-based TF-IDF to generate a representative keyword list R_k for each cluster τ_k , refined using Maximal Marginal Relevance (MMR) to promote keyword diversity. Finally, the agent synthesizes the domain and persona from the dominant topic representations $\{R_k\}$,

$$(D_C, P_C) \sim \mathcal{A}(D, P \mid \{R_k\}_{k=1}^K, \pi_{DP}) \quad (5)$$

where π_{DP} is the prompt to extract the domain of the corpus and a relevant expert persona.

3.3 Semantic Multihop Context Building

We implement a recursive, agentic retrieval process that expands an initial seed chunk c_{seed} into a complete semantic context C^s . Let S_t denote the set of chunks constituting the context at iteration t , where $S_0 = \{c_{seed}\}$. At step t , a multimodal agent analyzes S_t to detect missing information. We model this as a conditional generation task:

$$(z_t, Q_t^{search}) = \mathcal{A}(S_t \mid \pi_{comp}) \quad (6)$$

where π_{comp} is the completeness prompt. The output consists of a boolean status z_t (complete/incomplete) and, if incomplete, a set of retrieval queries $Q_t^{search} = \{q_1^s, \dots, q_k^s\}$. The process terminates if $z_t = 1$ or $t \geq \delta_{max}$, yielding $C^s = S_t$. For each generated query $q^s \in Q_t^{search}$, we employ a hybrid retrieval strategy. We first retrieve the top- N candidates from \mathcal{E} followed by reranking by a multimodal reranker.

To prevent context drift, we verify if a candidate chunk c_{cand} retrieved by the query q^s specifically offers the information missing in S_t or is related to S_t . The context expands by

$$S_{t+1} = S_t \cup \{c_{cand} \mid \mathcal{A}(S_t, q^s, c_{cand} \mid \pi_{add})\} \quad (7)$$

where π_{add} is the prompt that assesses the suitability of c_{cand} . This ensures the construction of C^s is strictly monotonic regarding information utility.

Table 1: Summary of selected corpora for MiRAGE evaluation.

Dataset Name	Domain	# Pages	# Images	# Tables	# Tokens
S&P Global Annual Reports	Finance	1302	1,120	2,800	0.9M
UNECE GTRs	Regulation	7594	150	3,450	3.8M
Quantitative Biology	Science	8336	9,400	850	5.2M
NYTimes Opinions	Journalism	>3000	3,050	25	2.1M

3.4 QA Generation and Verification

We generate candidate question-answer pairs (q, a) from the context C^s and verify them. This corresponds to the probability terms $P(q, a | C^s, \theta_{QA})$ and $P(V = 1 | q, a, C^s, \theta_V)$ defined in Eq. 2. To ensure technical depth, we condition the QA generation on the context C^s , the domain D_C , and the persona P_C (encapsulated in θ_{QA}). The set of candidates \mathcal{D}_{cand} is generated as:

$$\mathcal{D}_{cand} = \{(q_i, a_i)\}_{i=1}^M \sim \mathcal{A}(C^s, P_C, D_C | \pi_{QA}) \quad (8)$$

where π_{QA} is the QA generation prompt.

To ensure that the agent is relying only on the provided context C^s , a verifier agent assesses each candidate $(q, a) \in \mathcal{D}_{cand}$ against C^s . The verification function evaluates: (1) Correctness: a is factually supported by C^s . (2) Necessity: q requires information within C^s to get a . The validated dataset contribution from context C^s is:

$$\mathcal{D}_i^{C^s} = \{(q, a) \in \mathcal{D}_{cand} \mid \mathcal{A}(q, a, C_i^s | \pi_{ver})\} \quad (9)$$

where π_{ver} is the verification prompt.

3.5 Refinement and Deduplication

The final stage aggregates the $\mathcal{D}_i^{C^s}$ into the final cohesive corpus \mathcal{D} via hierarchical clustering and deduplication. We employ a two-stage clustering process. First, we apply community detection on the question embeddings to form a set of high-level clusters \mathcal{K}_Q that share semantic themes. Second, within each cluster $k \in \mathcal{K}_Q$, we sub-cluster the answers to identify redundancy. The union of these sub-clusters constitutes the fine-grained answer cluster set \mathcal{K}_A .

The similarity metric between pairs $u_i = (q_i, a_i)$ and $u_j = (q_j, a_j)$ is a weighted sum of semantic similarity and source lineage overlap:

$$Sim(u_i, u_j) = \alpha \cos(e_{a_i}, e_{a_j}) + (1 - \alpha) \cdot J(C_i^s, C_j^s) \quad (10)$$

where e_a is the answer embedding, and $J(\cdot)$ is the Jaccard similarity of the source contexts C_i^s and C_j^s associated with u_i and u_j , respectively. α is a weighting factor.

Lastly, we employ a stratified policy to refine the QA pairs within each answer sub-cluster into representative units. We define a refinement function Ψ that operates on the QA pairs in each cluster $K \in \mathcal{K}_A$. If the internal similarity of the cluster exceeds the threshold τ_t , they are merged by the refinement agent; otherwise, the original units are retained. Mathematically,

$$\Psi(K) = \begin{cases} \mathcal{A}(K \mid \pi_{ref}) & \text{if } \min_{u_i, u_j \in K} Sim(u_i, u_j) > \tau_t \\ K & \text{otherwise} \end{cases} \quad (11)$$

where π_{ref} is the prompt instructing the agent to synthesize a unified refined set of QA pairs that encompasses the unique details from all QA pairs in K . The final optimized dataset \mathcal{D} is constructed by the union of all the refined QA pairs:

$$\mathcal{D} = \bigcup_{K \in \mathcal{K}_A} \Psi(K) \quad (12)$$

4 Experiments

4.1 Corpora Selection

To validate the efficacy of **MiRAGE** across the full spectrum of enterprise and information retrieval challenges, we curated a diverse suite of corpora spanning four distinct domains: finance, regulations, science, and journalism. The *S&P Global Annual Reports* ([S&P Global, 2023](#)) represent the financial domain, where strategic narratives are deeply intertwined with dense tabular data and financial visualizations. The *UNECE Global Technical Regulations* ([United Nations Economic Commission for Europe, 2023](#)) are characterized by rigid hierarchical structures, precise definitions, and conditional logic. We selected scientific publications from the quantitative biology domain submitted to the Arxiv² in the month of January of 2025. This corpus introduces extreme lexical specificity regarding protein structures and complex visual artifacts like 3D molecular renderings. The last dataset consists of the Opinions from The New York Times collected from the Visual News dataset

²<https://arxiv.org/list/q-bio/2025-01?skip=0&show=2000>

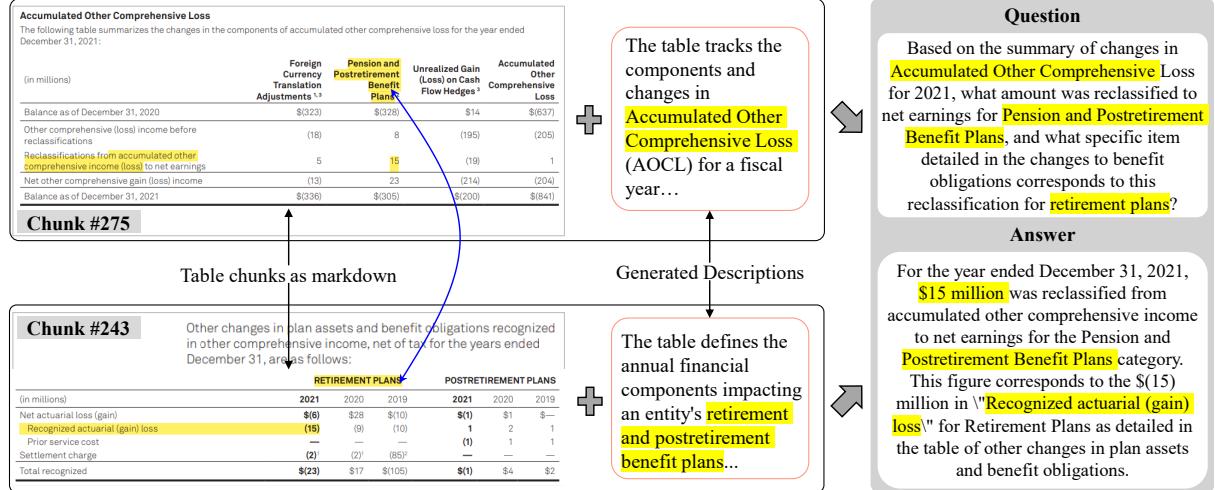


Figure 2: A sample question-answer pair generated from two related chunks with relevant keywords highlighted

(Liu et al., 2021). The datasets are listed in Table 1. These domains provide a comprehensive validation ground, moving from highly structured text-heavy documents to unstructured visually complex media.

4.2 Model Selection

The MiRAGE framework is architected to be model-agnostic, supporting a modular interchange of LLMs and VLMs. Our architecture primarily leverages state-of-the-art proprietary models to ensure maximum reasoning fidelity. We utilize Gemini-2.5-Flash and GPT-5-Mini as the core engines for the reasoning agents. Their high-context windows, advanced vision encoding, and superior instruction-following capabilities are critical for the multi-hop QA generation and verification tasks. The multimodal chunks are embedded with the Nomic model (Nussbaum et al., 2024) for semantic retrieval based on textual queries³. The retrieval precision during the multihop context building is refined with multimodal rerankers. We employ the LLM-as-a-reranker (Abdallah et al., 2025) paradigm utilizing the proprietary models to rank the retrieved chunks. This ensures that the final context window contains only the most semantically pertinent chunks.

4.3 Metrics

To rigorously evaluate the quality of the generated dataset \mathcal{D} , we employ a comprehensive suite of metrics that assesses retrieval accuracy, reasoning complexity, multimodal integration, and domain coverage. We utilize both standard automated met-

rics (Es et al., 2024) and novel agentic evaluation protocols based on the LLM-as-a-Judge paradigm (Zheng et al., 2023).

For each QA pair (q, a) and retrieved context C^s , we measure the faithfulness and relevance. To validate that \mathcal{D} necessitates multi-hop context building rather than simple extraction, we implement a reasoning trace evaluator $\mathcal{T}(q, C^s)$. It consists of hop count (H), number of distinct retrieval or reasoning steps required to derive a from (q, C^s) . We employ a VLM agent as a verifier to ensure the generated answer a is visually grounded. The agent verifies that specific visual features referenced in a (e.g., trend lines, molecular structures) are present in the image set $V \subset C^s$. We quantify the alignment between the latent topics of the source corpus and the generated QA dataset using the Jensen-Shannon (JS) divergence. Let P_C and P_D be the discrete probability distributions over latent topic clusters for the corpus and dataset, respectively. The coverage metric is defined as:

$$D_{JS}(P_C || P_D) = \frac{1}{2} D_{KL}(P_C || M) + \frac{1}{2} D_{KL}(P_D || M) \quad (13)$$

where $M = \frac{1}{2}(P_C + P_D)$. Lower divergence values imply that the synthetic dataset faithfully reproduces the thematic distribution of the original domain.

5 Results

We present the empirical evaluation of the QA datasets generated by MiRAGE. We create 1000 QA pairs from each corpus. The prompts excluding the domain specific few shot examples are included in Appendix A. A sample QA pair is illustrated in

³The token limits of the embedding and reranker models based on the CLIP and SigLIP architectures render them ineffective for our multimodal tasks.

Table 2: Performance comparison of MiRAGE across four domains.

Dataset	Model	Faith. \uparrow	Rel. \uparrow	Avg Hops (H) \uparrow	Vis. Gr. \uparrow
S&P Global (Finance)	Gemini 2.5 Flash	0.96	0.86	2.84	0.21
	GPT 5 Mini	0.91	0.81	2.42	0.28
UNECE GTRs (Regulation)	Gemini 2.5 Flash	0.94	0.90	2.45	0.38
	GPT 5 Mini	0.96	0.82	2.60	0.45
Q-Bio Arxiv (Science)	Gemini 2.5 Flash	0.83	0.92	2.35	0.42
	GPT 5 Mini	0.81	0.94	2.55	0.42
NYTimes (Journalism)	Gemini 2.5 Flash	0.91	0.93	1.10	0.32
	GPT 5 Mini	0.93	0.95	1.25	0.24

Figure 2. Our analysis focuses on the complexity of reasoning, the faithfulness of the generated answers, and the semantic alignment with the source domains.

5.1 Overall Performance

Table 2 summarizes the performance of the MiRAGE framework powered by two distinct state-of-the-art models: Gemini 2.5 Flash and GPT 5 Mini. Our analysis highlights the framework’s ability to generate complex, domain-aligned question-answer pairs while revealing nuanced differences in model capabilities across various tasks. The JS divergence from Table 3 reflects that the QA dataset \mathcal{D} generated by MiRAGE covers the topics in \mathcal{C} effectively.

Reasoning Complexity: A key achievement of MiRAGE is its consistent generation of multi-hop questions across technical domains. For the Finance, Regulation, and Science corpora, the average hop count (H) consistently exceeds 2.3, peaking at 2.84 with Gemini 2.5 Flash on the S&P Global dataset. This demonstrates the efficacy of the semantic multihop context-building phase, which successfully forces models to synthesize information from disjoint sources. GPT 5 Mini shows a slight advantage in generating more complex reasoning chains in the highly structured regulatory and scientific domains. In contrast, the lower hop count for the NYTimes corpus (avg. $H \approx 1.2$) reflects the open and less connected nature of journalistic content. The NYTimes corpus did not contain the chunks relevant to the queries to make the context complete.

Faithfulness and Relevance: MiRAGE demonstrates exceptional performance in maintaining factual grounding and contextual relevance, with faithfulness scores consistently above 0.91 for three of the four domains and relevance scores exceeding 0.81 across all experiments. This validates the effectiveness of the adversarial verifier agent, which successfully filters out hallucinations and ensures

that generated answers are strictly supported by the retrieved context. Both Gemini 2.5 Flash and GPT 5 Mini perform competitively with marginal differences.

Visual Grounding: While excelling in textual reasoning, the evaluation exposes visual grounding as a persistent challenge for current VLMs. The visual grounding scores remain moderate across all domains, with a maximum of 0.45 achieved by GPT 5 Mini on the UNECE GTRs dataset. This suggests that while models can describe images, generating complex questions that require precise reasoning about specific visual elements (E.g., correlating specific data points in a financial chart) remains a frontier. Out of the 1093 QA pairs generated for the finance domain, only 84 QA pairs are multimodal. It indicates that the VLMs prefer textual content to generate the QA pairs. From a closer look at the multimodal QA pairs, we hypothesize that the generated descriptions made the visual elements partially redundant leading to a consistently lower score visual grounding score across all evaluations.

5.2 Ablation Study

We conducted a systematic component-wise ablation using a subset (2 out of 14 documents) of the *S&P Global* annual reports. This corpus was selected for its high density of visual artifacts and complex tabular structures. We isolate the impact of the agentic architecture and the data representation strategies. The results are summarized in Table 3.

5.2.1 Impact of Agentic Architecture

Multihop Context: Removing the recursive retrieval step forces the model to generate questions based solely on the initial seed chunk. This results in a collapse of the difficulty score⁴ ($0.85 \rightarrow 0.61$).

⁴The domain specific expert agent rates the generated QA pair on a discrete scale of [0, 10], later normalized to [0, 1] for easier interpretation.

Table 3: Ablation study on the S&P Global Annual Reports (Finance) dataset

Category	Configuration	Faith. \uparrow	Rel. \uparrow	Diff \uparrow	Avg Hops \uparrow	Vis. Gr. \uparrow	JSD \downarrow
Baseline	MiRAGE	0.97	0.95	0.85	1.92	0.41	0.08
Agentic Architecture	(-) Multihop Context	0.93	0.82	0.61	-	0.21	4.35
	(-) QA Verifier Agent	0.74	<u>0.76</u>	0.62	1.67	0.32	0.06
	(-) Domain & Persona	0.91	0.88	<u>0.52</u>	1.81	<u>0.11</u>	0.11
Data Representation	Fixed Chunk Size (2048)	0.84	0.79	0.70	2.01	0.26	0.15
	Image Only (No Description)	0.71	0.79	0.73	<u>1.34</u>	0.62	1.73
	Description Only (No Image)	0.93	0.89	0.78	1.72	-	2.12

Without the multihop context, the generation reverts to simple extractive QA yielding a degradation in domain alignment ($JSD \approx 4.35$) as well.

Verifier Agent: The removal of the adversarial verifier causes the most significant drop in faithfulness ($0.97 \rightarrow 0.74$). Qualitative analysis reveals that the generation agent frequently hallucinates relationships between unconnected data points to satisfy the prompt’s complexity requirements. The drop in Relevance ($0.95 \rightarrow 0.76$) further indicates that unverified questions often drift from the core semantic content of the context.

Domain/Persona Injection: Ablating the domain analysis prevents the model from adopting the specific expert persona (e.g., ‘Financial Reporting Analyst’ for the S&P Global annual reports) and relevant domain (‘Corporate Financial Reporting and Analysis’). The Difficulty of the generated questions drops significantly ($0.85 \rightarrow 0.52$). This indicates that without domain/persona conditioning, the model defaults to generic QAs rather than the deep, deductive reasoning characteristic of domain experts.

5.2.2 Impact of Data Representation

Chunking Strategy: We replaced the agentic semantic chunking (Eq. 4) with a standard fixed-window approach (2048 tokens). As shown in Table 3, fixed chunk size marginally increased the average hops ($1.92 \rightarrow 2.01$). The marginal change in the average hops makes it inconclusive to highlight the importance of semantic chunking to avoid fragmentation of tables and semantically continuous text blocks. However, the drop in the faithfulness and relevance allude to the importance of semantic chunking.

Multimodal Configurations: We compared the hybrid MiRAGE approach against *image Only* (no descriptions) and *description Only* (no raw images) configurations. The *Image Only* setting results in higher visual grounding (0.62) indicating the increased importance of images. However, it is ac-

companied by the lowest faithfulness (0.71) and lower relevance indicating the struggle of VLMs to bridge the semantic gap between the images and the text. Conversely, the *description Only* setting performs comparably with the full MiRAGE indicating that LLMs can power MiRAGE if descriptions of the visual artifacts are available.

6 Conclusion

We present **MiRAGE**, a comprehensive multi-agent framework that automates the generation of high-fidelity, multimodal, multi-hop evaluation datasets, addressing the critical need of domain-specific benchmarks for high-stakes RAG applications. By orchestrating a swarm of specialized agents through a recursive *context optimization loop*, *adversarial verification*, and *domain-expert recognition*, MiRAGE successfully transcends the limitations of linear synthetic pipelines, producing datasets that exhibit deep deductive reasoning and strict factual adherence across diverse corpora. Our empirical evaluation of the finance, science, regulations and journalism domains confirm the efficacy of MiRAGE in preserving semantic dependencies within complex technical documents. Our ablation studies reveal that current state-of-the-art VLMs still rely significantly on dense textual descriptions to bridge the visual reasoning gap. Ultimately, MiRAGE establishes a robust standard for automated dataset generation, empowering organizations to rigorously stress-test RAG systems against the latent complexity and specific thematic distributions of their proprietary data.

Limitations and Future Work

While MiRAGE advances the quality of synthetic benchmarks, it is not without limitations. The multiagentics architecture is computationally intensive. The multihop context building and QA verification loops result in higher token costs and latency. Future work will focus on optimizing the agentic workflow for token efficiency. Exploring the performance of open-source models, would help democratize the framework.

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A Prompts

PROMPTS_DESC["description"]

Provide a technical summary of the image/table for documentation.

Format: Single continuous paragraph, under 250 words. No bullets.

Content Requirements:

- Identify the image type (table/figure) and its primary objective.
- Technical Analysis:
 - For Plots/Charts: Define axes/units, variables, and key trends/regions.
 - For Diagrams: Identify components, connection flows, and system boundaries.
 - Note: Describe visual attributes only if they encode data; ignore decorative elements and metadata.
- Conclusion: Summarize critical insights and practical design implications.

PROMPTS_CHUNK["semantic_chunking"]

You are a Semantic Chunking Engine. Segment markdown into coherent, verbatim chunks.

Processing Rules:

- **Exclusions:** Ignore Table of Contents and Lists of Figures/Tables.
- **Cohesion:** Merge orphan titles and short subsections into adjacent text. Ensure chunks are semantically self-contained.
- **Status:** Mark as INCOMPLETE only if the final chunk ends abruptly (cut-off).

Chunk Classifications:

- **figure**: Image ('! [...]') with "Figure X" caption, description, and key. Set <artifact> to image path.
- **standalone image**: Image *without* "Figure X" caption. Set <artifact> to image path.
- **table**: "Table X" caption + markdown table + footnotes. Set <artifact> to 'None'.
- **table with images**: Table containing '! [...]'. Set <artifact> to image path(s).
- **text**: Paragraphs, lists, or definitions. Set <artifact> to 'None'.

Output Format:

<chunk_id><#|><chunk_type><#|><content><#|><artifact><#|><status><#|><chunk_end>

Field Definitions:

- chunk_id: Sequential integer starting at 1.
- chunk_type: text | table | table with images | figure | standalone image
- content: Exact unmodified markdown.
- artifact: Extracted image path(s) or 'None'.
- status: COMPLETE | INCOMPLETE

PROMPTS["domain_and_expert_from_topics"]

I have analyzed a technical document collection and extracted the following key topics:

{topic_list_str}

Based on these topics, please determine:

- The specific technical or professional domain these topics belong to.
- A specific expert role title for a professional in this domain.

Format your response exactly as follows (do not add any other text):

<#|>START<#|>

<#|>Domain: <The Domain>

```
<|#|>Expert Role: <The Expert Role>
<|#|>END<|#|>
```

PROMPTS_CHUNK["completion_verification"]

You are a Chunk Completion Verification Agent.
Evaluate if the provided text is semantically self-contained given that you are a(n) {expert_persona} working in the {domain} domain .

Criteria for INCOMPLETE status:

1. Missing Artifacts: References to Figures, Tables, or Sections not present in the chunk (e.g., "see Figure 1").
2. Undefined Context: Acronyms, technical terms, or variables used without definition or prior explanation.
3. Broken Continuity: Implicit references (e.g., "as mentioned above," "this method") or text describing a missing visual.
4. Rule: Do not assume expert inference. If a definition or artifact is missing, it is INCOMPLETE. Universal units are allowed.

Instructions:

- If COMPLETE: Confirm self-containment.
- If INCOMPLETE: Generate specific search queries to retrieve the missing definitions or artifacts.

Required Output Format:

Status: COMPLETE, Query: None, Explanation: <brief reasoning>

OR

Status: INCOMPLETE, Query: <specific_search_query_1> | <specific_search_query_2>, Explanation: <list missing refs/definitions>

PROMPTS_CHUNK["chunk_addition_verification"]

You are a Chunk Addition Verification Agent ({expert_persona}, {domain}). Determine how a CANDIDATE CHUNK relates to an INCOMPLETE ORIGINAL CHUNK based on a specific SEARCH QUERY.

Classify as:

1. EXPLANATORY: Directly resolves the missing element. It provides the specific figure/table, defines the unknown term, or supplies the explicitly referenced prior context.
2. RELATED: Contextually relevant but does not solve the specific gap. Includes general theory, complementary data, or content useful for multi-hop QA (even if it references the same missing artifact).
3. UNRELATED: No semantic overlap or domain relevance.

Output Format:

Status: <EXPLANATORY | RELATED | UNRELATED>

Explanation: <Brief justification>

PROMPTS["multi_hop_qa_generation"]

You are a(n) {expert_persona} in {domain_context}. Construct a high-quality Question-Answer pair by synthesizing information across the provided text chunks.

Content:

{content}

Execution Protocol (Strict Order):

1. **Chunk Count:** Identify how many distinct

chunks are present.

2. **Keyword Extraction:** List critical technical keywords for *each* chunk.
 3. **Relationship Mapping:** Identify "Bridge Keywords"--concepts that relate or intersect across the chunks.
 4. **QA Synthesis:** Frame question-answer pairs that requires synthesizing these related keywords. The question must be unsolvable without combining info from multiple points.
 5. **Decomposition:** Map specific parts of the Question and Answer back to their source chunks.
- **Critical Constraints:**
- **No Hallucination:** Answer ONLY using provided content.
 - **Self-Sufficiency:** The question must be standalone. NEVER use phrases like "the provided figure," "the text above," or "Section 2.1" without context. Explicitly name the object (e.g., "In Figure XX from document YY...").
 - **Complexity:** The question must be multi-hop (requires connecting A to B).

Output Format:

<|#|>ANALYSIS<|#|>

Chunk Count: <Integer>

Keywords per Chunk: <Chunk 1: [A, B], Chunk 2: [C, D]>

Related Keywords: <[A] relates to [C] via...>

<|#|>QA_GENERATION<|#|>

Question: <Your specific, self-contained question>

Answer: <Concise technical answer>

Relevance: <0-10>

Difficulty: <0-10>

<|#|>DECOMPOSITION<|#|>

Question Source: <"Part of Q" -> derived from Chunk X>

Answer Source: <"Part of A" -> derived from Chunk Y>

<|#|>END<|#|>

PROMPTS["question_answer_verification"]

You are a QA Verification Agent ({expert_persona}, {domain_context}). Evaluate the validity of the following QA pair.

Context: Users see the Question WITHOUT the Content. The Question must be completely self-contained.

Evaluation Rules:

1. **Standalone Principle (QUESTION_CORRECT | INCORRECT):**
 - The Question is INCORRECT if it relies on implicit context or vague references (e.g., "the provided figure", "this table", "the described method", "Section 2").
 - The Question is CORRECT only if it explicitly names the subject, standard, or artifact (e.g., "In Figure XX of the document YY", "The inflation-time chart...")
2. **Factuality (ANSWER_CORRECT | INCORRECT):**
 - The Answer must be factually supported by specific data/principles in the Content.
3. **Necessity (REQUIRES_CONTENT | CAN_ANSWER_WITHOUT_CONTENT):**
 - Determine if the specific provided Content is required to answer, or if general domain

knowledge suffices.
 Inputs:
 Content: {content}
 Question: {question}
 Answer: {answer}
 Required Output Format:
 QUESTION_[CORRECT|INCORRECT]
 ANSWER_[CORRECT|INCORRECT]
 [REQUIRES_CONTENT|CAN_ANSWER_WITHOUT_CONTENT]
 Justification: <Brief reasoning>

PROMPTS["rerank_vlm"]

You are a VLM Reranking Agent. Rank the provided chunks (text and images) by relevance to the Query.
 Input Markers: '<CHUNK_START id=N>' and '<IMAGE_START>'.
 Instructions:
 1. Analyze both textual context and visual data to determine relevance.
 2. List ALL chunk IDs in descending order (Rank 1 = Highest).
 3. Output strictly in this format (no conversational text):
 <Rank 1>Chunk <id>
 <Rank 2>Chunk <id>
 <Rank N>Chunk <id>

PROMPTS["deduplication_rank"]

You are a Data Curator ({expert_persona}, {domain}). Reorder the provided cluster of QA pairs based on their relationship to the core topic.
 Task: Sort the list from **Most Distinct/Unique ** (least similar) to **Most Representative/ Redundant** (most similar).
 Constraint: Preserve all text verbatim. Do not omit sub-questions or modify content.
 Candidates:
 {candidates_text}
 Required Output Format:
 <|#|>START<|#|>
 Question<|#|><Question_Text><|#|>Answer<|#|>< Answer_Text>
 <|#|>NEXT<|#|>
 Question<|#|><Question_Text><|#|>Answer<|#|>< Answer_Text>
 <|#|>END<|#|>

PROMPTS["deduplication_merge"]

You are a Data Curator ({expert_persona}, {domain}). Synthesize the provided QA cluster into the MINIMAL set of high-quality pairs.
 Processing Logic:
 1. **Merge:** Combine complementary pairs into comprehensive questions (integrating sub-questions) and unified answers.
 2. **Deduplicate:** Select the single best version for exact or near-duplicates.
 3. **Goal:** Zero redundancy while retaining full information coverage.
 Input Candidates:
 {candidates_text}
 Required Output Format:
 <|#|>START<|#|>
 Question<|#|><Merged/Refined Question><|#|>
 Answer<|#|><Merged/Refined Answer>