MC-Search: Benchmarking Multimodal Agentic RAG with Structured Reasoning Chains

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Abstract

Retrieval-Augmented Generation (RAG) has become a key paradigm for grounding multimodal large language models (MLLMs) in external evidence. Current MM-RAG benchmarks, however, emphasize simplified QA tasks with shallow reasoning depth, falling short in evaluating agentic RAG behaviors such as iterative planning and retrieval. We present MC-Search, a benchmark with golden, hop-wise reasoning chains that specify sub-questions, retrieval modalities, supporting facts, and intermediate answers, enabling fine-grained analysis of retrieval planning and reasoning accuracy. To ensure fidelity, we propose HAVE, a hop-wise verification procedure that filters hallucinated or redundant steps. MC-Search covers five representative reasoning structures and consists of 3,333 high-quality examples. We further develop an agentic MM-RAG pipeline and introduce three chain-level metrics to jointly assess answer accuracy and intermediate retrieval fidelity. Experiments benchmark MLLMs under this framework, revealing key challenges in modality-aware planning and the trade-off between retrieval effectiveness and efficiency. The code is available at `https://github.com/YennNing/MC-Search`.

1 Introduction

Retrieval-Augmented Generation (RAG) has emerged as a key paradigm for enabling large language models in external evidence [5, 19, 4]. Facing various data modalities, multimodal RAG (MM-RAG) is proposed and is expected to retrieve and integrate text and image evidence to support knowledge-intensive reasoning [17, 16, 1]. To boost the further development of MM-RAG, a few corresponding benchmark datasets have recently been proposed [6, 12, 11]. Although materializing the concept, those pioneering efforts are nascent with the simple question-answer format that does not need complex reasoning iterations [6], limited length of reasoning steps [12, 11], and reliance on costly and unstable online search [11]. The above shortcomings hinder the agentic RAG development in the multimodal research domain.

Compared with classic RAG, agentic RAG systems [15, 10, 7, 8, 20, 3, 14] often exhibit iterative task decomposition, re-verification, and evidence planning, aiming to adaptively decide when and what to retrieve during reasoning. To effectively evaluate the above tasks in realistic multimodal reasoning scenarios, at least, the benchmarks require *step-wise annotations* that specify both the sequence of sub-questions and the modality of each retrieval step, while also distinguishing different retrieval–reasoning *structures* (e.g., text-initiated versus image-initiated chains, or parallel multimodal forks). Designing such a benchmark is challenging and non-trivial, as it needs to align with long, adaptive retrieval workflows while capturing diverse reasoning patterns to support fine-grained error analysis.

Hence, in this paper, we first introduce **MC-Search**, a benchmark for **agentic MM-RAG** with

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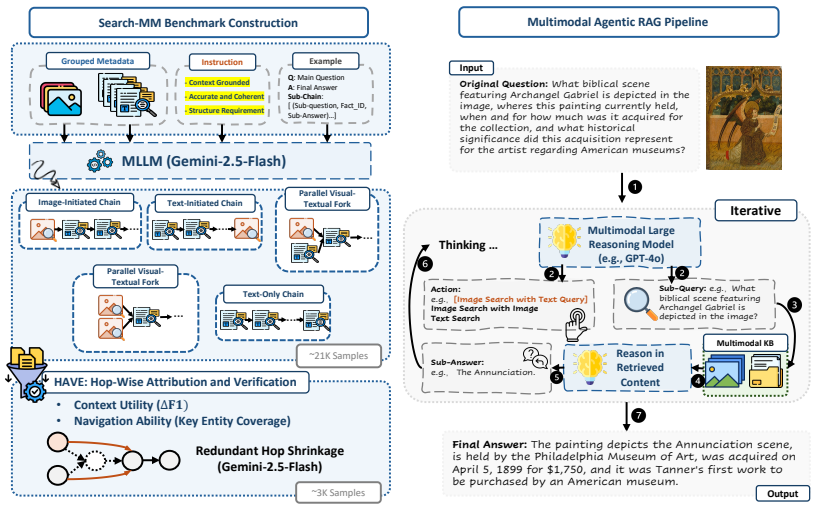

Figure 1: Overview of **MC-Search** benchmark and evaluation pipeline. **Left**: Benchmark construction with five reasoning structures and a hop-wise attribution and verification (HAVE) process to ensure retrieval necessity of each step. **Right**: Multimodal agentic RAG pipeline, where a reasoning model iteratively decomposes queries, retrieves multimodal evidence, and integrates it to generate the final answer.

structured multi-hop reasoning chains. In MC-Search, each question sample is associated with a golden and step-wise annotated trajectory that specifies the sub-question sequence, the modality of each retrieval, the unique supporting fact, and the intermediate answer. This organization enables fine-grained attribution, chain-level evaluation, and lays the foundation for future process-level reward modeling in agentic multimodal reasoning.

In addition to multimodality, the reasoning chain in our MC-Search is also **long**, **category-diversified**, and **hop-non-redundant**. First, to reflect the diversity of real-world agentic MM-RAG cases, our MC-Search spans five representative reasoning structures, i.e., (i) *Text-Only Chain*, (ii) *Image-Initiated Chain*, (iii) *Text-Initiated Chain*, (iv) *Parallel Visual-Textual Fork*, and (v) *Multi-Image Fork*, capturing both serial and parallel reasoning patterns across modalities, as shown in Figure 1. Second, to ensure that each reasoning step (i.e., hop) in the chain is inference necessary and structurally meaningful, we propose **HAVE**, a Hop-Wise Attribution and Verification of Evidence procedure that filters out spurious or redundant hops via utility- and navigation-based diagnostics. This results in a high-quality benchmark of 3,333 well-annotated examples. Third, the average length of questions in MC-Search is 3.7 hops and leads the SOTA benchmarks [6, 12, 11].

For evaluation, beyond traditional answer-level accuracy, we introduce three **chain-level evaluation metrics**: (i) *LLM-as-a-Judge* for open-ended reasoning quality, (ii) *Structure-Aware Hit Rate* for per-step grounding fidelity, and (iii) *Rollout Deviation* to quantify execution drift. We conduct a **comprehensive evaluation** of three MLLM backbones, i.e., `GPT-4o-Mini`, `Gemini-2.5-Flash`, and `Gemini-2.5-Pro`, on the MC-Search benchmark, comparing their capabilities in retrieval planning and multimodal reasoning. For a fair comparison, we further develop **a unified agentic MM-RAG pipeline** that dynamically plans, retrieves, and fuses multimodal evidence conditioned on the evolving chain state. Our analysis also reveals how **over-retrieval** and **lack of retrieval** affect performance across different chain types, underscoring the need for better modality-aware planning and stopping criteria to balance retrieval effectiveness and efficiency.

2 MC-Search Benchmark

2.1 Search-enhanced Long Reasoning Chains

Structured Chain Typology Pattern and Data Preparation. To reflect the diversity of real-world agentic MM-RAG workflows, we identify five recurring search-enhanced reasoning structures and instantiate them as distinct chain types, each consisting of sub-questions, retrieval evidence, and intermediate answers (Figure 2). Specifically, (i) *Text-Only Chain* serves as a baseline for structured textual reasoning; (ii) *Image-Initiated Chain*, (iii) *Text-Initiated Chain*, and (iv) *Parallel Visual–Textual Fork* capture single-image settings with different initiation or branching strategies; and (v)

Figure 2: Distribution of five reasoning mechanisms in Search-MM, with outer segments showing hop-level diversity (2–5 hops showing).

Table 1: Evaluation of various models on the **Search-MM** benchmark when performing **agentic MM-RAG**. We report results across five reasoning graph categories. Best results are in **bold**, second-best are underlined.

Reasoning Graph	Model	Answer Accuracy			Chain Alignment		Golden F1 (↑)
		F1 (↑)	ΔF1 (↑)	LJ (↑)	HPS (↑)	RD (↓)	
Text-Only Chain	GPT-4o-Mini	30.96	30.94	2.58	**21.94**	1.13	61.90
	Gemini-2.5-Flash	34.03	33.96	2.49	20.59	**1.04**	**67.72**
	Gemini-2.5-Pro	**34.47**	**34.46**	**2.66**	21.59	1.07	62.42
Image-Initiated Chain	GPT-4o-Mini	36.49	34.18	2.63	27.51	1.46	68.29
	Gemini-2.5-Flash	44.10	37.38	3.01	**31.46**	2.91	**72.39**
	Gemini-2.5-Pro	**47.61**	**42.76**	**3.18**	25.90	**1.05**	69.83
Multi-Images Fork	GPT-4o-Mini	24.00	19.16	2.13	16.04	1.94	59.46
	Gemini-2.5-Flash	36.80	31.89	2.35	13.45	1.66	**64.40**
	Gemini-2.5-Pro	**40.37**	**36.58**	**2.76**	**18.68**	**1.40**	61.29
Parallel Visual-Textual Fork	GPT-4o-Mini	21.98	21.65	2.20	15.00	1.71	53.98
	Gemini-2.5-Flash	29.92	27.94	2.58	11.43	2.70	**57.99**
	Gemini-2.5-Pro	**34.83**	**34.19**	**2.99**	**16.74**	**1.29**	53.46
Text-Initiated Chain	GPT-4o-Mini	30.11	18.46	2.41	**27.18**	1.76	49.47
	Gemini-2.5-Flash	43.55	26.34	3.30	25.20	1.20	**66.27**
	Gemini-2.5-Pro	**45.30**	**29.89**	**3.62**	19.51	**0.95**	55.94

Multi-Images Fork represents multi-image coordination. Data examples for each structure are provided in Appendix B.

We construct Search-MM by clustering Wikipedia entities [2] into topical neighborhoods and prompting `Gemini-2.5-Flash` to generate structured multi-hop questions aligned with the five mechanisms. To guarantee necessity, we filter the knowledge base to remove entries that could also answer sub-questions, ensuring each chain follows a unique, meaningful trajectory.

Quality Verification. When constructing Search-MM, we found that multimodal LLMs often produce hallucinated or redundant reasoning steps that hinder faithful evaluation. To address this, we propose HAVE (Hop-wise Attribution and Verification Evaluation), a filtering mechanism that verifies the necessity of each step. We measure context utility by removing steps and checking the drop in answer F1, and assess navigation utility by testing whether key entities are carried forward into later sub-questions. For borderline cases, we apply `Gemini-2.5-Flash` for chain shrinkage and re-validation. Dataset composition and statistics are shown in Figure 2 and Appendix C.

2.2 Evaluation

Evaluation Metrics. To comprehensively evaluate both answer correctness and reasoning quality, we designed four complementary metrics. First, we compute the standard token-level answer by **F1**. We also report **ΔF1**, the gain of agentic MM-RAG over the same model question-answering without context retrieval, and **Golden F1**, the upper bound when providing gold reasoning chains and retrieval content. To capture semantic correctness beyond surface-level matches, we employ an **LLM-as-a-Judge (LJ)** approach, where a strong reasoning model (`Gemini-2.5-Pro`) assesses the generated reasoning chain against the gold standard based on *accuracy*, *coherence*, *knowledge entity coverage*, and *step alignment*.

Then, to evaluate step-wise retrieval accuracy, we introduce **Hit per Step (HPS)**. Let the predicted and golden reasoning chains be sets of steps $C_p = \{p_1, \ldots, p_m\}$ and $C_g = \{g_1, \ldots, g_n\}$, respectively. We first construct a bipartite graph between C_p and C_g, where edge weights are defined by the semantic similarity of the evidence retrieved for each pair (p_i, g_j). After solving for the maximum-weight matching M^*, we assess the retrieval hit of these matched pairs. A golden step $g_j \in C_g$ is considered a 'hit', if it is matched with a predicted step p_i (i.e., $(p_i, g_j) \in M^*$) and their underlying evidence sets are identical. HPS is then the fraction of golden steps that were correctly matched and replicated: $\text{HPS} = |C_g|^{-1} \sum_{g_j \in C_g} \mathbb{I}\left(\exists p_i \text{ s.t. } (p_i, g_j) \in M^* \wedge \text{evidence}(p_i) = \text{evidence}(g_j)\right)$, where $\mathbb{I}(\cdot)$ is the indicator function. Finally, to quantify the structural difference in reasoning length, we measure **Rollout Deviation (RD)** as the absolute difference in the number of steps: $\text{RD} = ||C_p| - |C_g||$.

Evaluation Setting. We propose a multimodal agentic RAG pipeline for evaluating adaptive retrieval on the structured, step-wise reasoning chains in Search-MM, drawing inspiration from recent advances in agent-based retrieval planning [10]. As shown in Figure 1, the pipeline iteratively follows a decompose—retrieve—synthesize process to plan sub-queries, gather multimodal evidence, and generate the final answer.

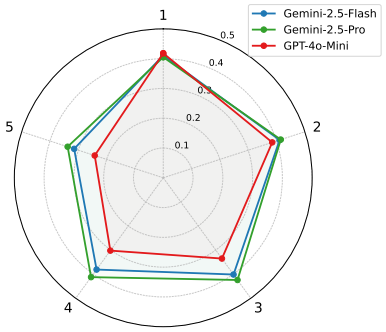

Figure 3: Model F1 across samples with different chain lengths, showing a consistent drop in performance as the chain length increases.

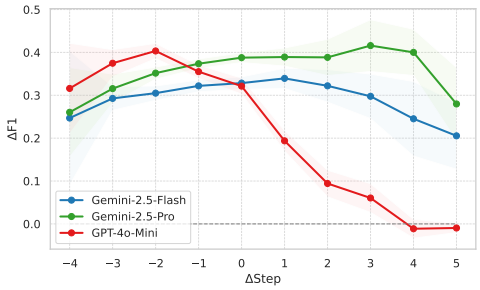

Figure 4: Model ΔF1 (difference in F1 between our generated response with context and without context) vs. Δ steps (difference in length between generated and golden reasoning chains), where larger positive Δ steps indicate more over-retrieval.

3 Experiments

Comparing results. Table 1 and Appendix D.2 show that retrieval quality (HPS) highly aligns with answer accuracy in most cases, confirming that many failures are due to sub-questions failing to retrieve the correct evidence. `Gemini-2.5-Pro` outperforms the others across metrics, with a notably smaller gap to the golden F1, indicating stronger retrieval planning and reasoning. Among the chain types, *Multi-Image Fork* and *Parallel Visual-Textual Fork* are the most challenging because they require coordinating information from multiple modalities. In experiments, models often default to text retrieval rather than conducting sufficient image search and grounding their reasoning in visual content and associated captions. This suggests limitations in current models' ability to plan modality-specific queries and highlights the need for better multimodal planning.

Performance vs. Chain Length. We observe a consistent performance drop as the length of the reasoning chain increases, see Figure 3. While all models are affected, `Gemini-2.5-Pro` exhibits the smallest decline, demonstrating stronger robustness in multi-hop planning and evidence integration. In contrast, `GPT-4o-Mini` shows a more rapid degradation, perhaps resulting from its weaker retrieval coordination and limited context tracking capacity. These results highlight the compounding difficulty of longer chains, where errors in earlier steps can cascade and undermine subsequent reasoning.

Over-Retrieval Analysis. We analyze the deviation between model-generated retrieval turns and the golden reasoning chain, focusing on how over-retrieval and under-retrieval affect performance. For both `Gemini-2.5-Flash` and `Pro`, a small degree of over-retrieval (Δ Step = 1 or 2) improves answer accuracy, as it may help compensate for imperfect planning or missed evidence. However, excessive over-retrieval leads to sharp performance degradation when the model pursuing increasingly irrelevant directions when failing to retrieve useful context. In contrast, `GPT-4o-Mini` benefits most from shorter chains and suffers more from over-retrieval: its limited reasoning and integration capacity may lead to context confusion and an inability to fuse multiple pieces of retrieved content, resulting in steeper decline as the chain lengthens unnecessarily. These trends highlight the importance of precise retrieval planning and stopping criteria in agentic MM-RAG systems to balance retrieval efficiency and reasoning effectiveness.

4 Conclusion.

We introduce MC-Search, a benchmark for structured, step-wise multimodal retrieval-augmented reasoning, covering five diverse reasoning mechanisms. Through fine-grained annotations, hop-wise attribution and verification, and the design of new chain-level metrics, MC-Search enables rigorous diagnosis of retrieval planning and reasoning quality. Our analyses underscore the need for adaptive, modality-aware search strategies in agentic MM-RAG systems. In future work, we will broaden evaluations to include more state-of-the-art reasoning models. We envision MC-Search as a foundation for developing interpretable, robust, and efficient multimodal agents, and for advancing process-level reward modeling in multimodal reasoning. Beyond evaluation, we plan to expand the benchmark to new domains, and we hope it will foster community efforts toward principled evaluation standards for agentic multimodal reasoning.

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A Related Work

We review three relevant lines of research. First, *multimodal RAG* extends retrieval beyond text to images and heterogeneous sources, but most benchmarks still rely on fixed-step designs. Second, *agentic RAG* treats retrieval as an adaptive, sequential process, yet multimodal variants remain scarce. Finally, *structure-aware benchmarks* supervise intermediate reasoning, motivating our MC-Search benchmark that unifies multimodality, agentic behaviors, and step-wise structural evaluation.

A.1 Multimodal RAG

Early retrieval-augmented generation focused on textual retrievers for LMs [17, 19]. More recently, RAG has been extended to multimodal settings by incorporating vision-language encoders, multimodal retrievers, and MLLMs [16, 1, 6]. While these works demonstrate strong performance in open-domain QA or medical domains, most existing multimodal RAG benchmarks adopt *fixed-step* settings, e.g., constraining the model to a predetermined number of text or image retrievals to answer a question. Such rigid designs prevent evaluating whether the agent can adaptively decide retrieval steps, and make it difficult to attribute errors to planning, modality selection, or evidence fusion.

A.2 Agentic RAG

Agentic RAG pipelines reformulate retrieval as a sequential decision-making process, where models iteratively decompose tasks, trigger retrieval, and integrate evidence during reasoning [7]. Recent approaches introduce explicit `<Search>` actions and train agents to plan, verify, and re-use evidence [8, 20], yielding more interpretable trajectories [3, 14]. Other work analyzes retrieval chains and highlights failure modes such as over- or lack-retrieval [15, 10]. However, most existing evaluations remain limited to the textual domain. Multimodal agentic RAG variant [11]s are still scarce, and current datasets do not provide *golden intermediate chains*, which hinders diagnosis of adaptive retrieval behaviors across modalities.

A.3 Structure-Aware Benchmarks for Agentic RAG

A related line of work investigates structured agents operating over symbolic KBs or graphs, often with schema-constrained queries or specialized tools [9, 13, 18]. These improve symbolic grounding but mainly focus on *what* to retrieve. In contrast, benchmarking agentic MM-RAG requires supervision over the *structure of the retrieval chain* itself—covering initiation modality, hop order, and parallel vs. serial patterns. To our knowledge, no prior multimodal dataset provides such structured, step-wise annotations. Our MC-Search fills this gap by supplying golden reasoning chains with modality-specific retrieval steps, enabling fine-grained attribution, analysis of over-/under-retrieval, and evaluation of diverse multimodal reasoning structures.

B Data Example

B.1 Image-Initiated Chain

Example Reasoning Chain — Image-Initiated Chain

Caption: Archangel Gabriel from an Annunciation - Google Art Project

Main Question. What biblical scene featuring Archangel Gabriel is depicted in the image, where is this painting currently held, when and for how much was it acquired for the collection, and what historical significance did this acquisition represent for the artist regarding American museums?

Final Answer. The painting depicts the *Annunciation* scene, is held by the *Philadelphia Museum of Art*, was acquired on *April 5, 1899* for *$1,750*, and it was *Tanner's first work to be purchased by an American museum*.

Reasoning Chain (4 steps):

1. **(Image)** What biblical scene featuring Archangel Gabriel is depicted in the image?
   Image Evidence ID: `30332773`
   Answer: The Annunciation.
2. **(Text)** Which museum holds this painting?
   Text Evidence ID:
   `d5be2ae00dba11ecb1e81171463288e9_0`
   Answer: Philadelphia Museum of Art.
3. **(Text)** When and for what price was the painting acquired for the collection?
   Text Evidence ID:
   `d5be2ae00dba11ecb1e81171463288e9_1`
   Answer: April 5, 1899 for $1,750.
4. **(Text)** What was the historical significance of this acquisition for the artist regarding American museums?
   Text Evidence ID:
   `d5be2ae00dba11ecb1e81171463288e9_8`
   Answer: It was Tanner's first work to be purchased by an American museum.

B.2 Text-Initiated Chain

Example Reasoning Chain — Text-Initiated Chain

Caption: Solvang California Windmill.

Main Question. Does the image visually confirm Solvang's unique cultural character as described in the text?

Final Answer. *Yes*, the image prominently features a large windmill and buildings with distinct European/-Danish architectural styles, aligning with the description of Solvang as "a bit of Denmark" in California.

Reasoning Chain (2 steps):

1. **(Text)** How is Solvang culturally characterized according to the text?
   Text Evidence ID: `d5bd142a0dba11ecb1e81171463288e9_7`
   Answer: Solvang is described as "a bit of Denmark tucked into this beautiful California."
2. **(Image)** Does the image visually confirm this cultural characterization, and if so, how?
   Image Evidence ID: `30326437`
   Answer: Yes, the image prominently displays a large windmill and buildings with distinct European/Danish architectural styles, confirming its cultural description.

B.3 Text Chain

Example Reasoning Chain — Text Chain

Main Question. What are the key attributes of the Bentley Mulsanne, including its manufacturing period, engine specifications, origin of its name, and notable special editions?

Final Answer. The Bentley Mulsanne, a full-size luxury car *manufactured from 2010 to 2020*, is named after the Mulsanne Corner of the Le Mans racing circuit. It uses a *6.75 L Bentley L Series V8 engine*, and a notable special edition is the *"W.O. Edition"*, which features a piece of W.O. Bentley's personal car crankshaft.

Reasoning Chain (3 steps):

1. **(Text)** What type of vehicle is the Bentley Mulsanne, when was it manufactured, and what is the origin of its name?
   Text Evidence ID: `d5bd6ace0dba11ecb1e81171463288e9_15`
   Answer: The Bentley Mulsanne is a full-size luxury car that was manufactured from 2010 to 2020 and is named after the Mulsanne Corner of the Le Mans racing circuit.
2. **(Text)** What are the engine specifications of the Bentley Mulsanne?
   Text Evidence ID: `d5bd6ace0dba11ecb1e81171463288e9_6`
   Answer: The Mulsanne uses a 6.75 L (6,750 cc/411 in³) Bentley L Series V8 engine, modified to meet Euro V emissions regulations.
3. **(Text)** What notable special edition of the Mulsanne was introduced and what was its unique feature?
   Text Evidence ID: `d5bd6ace0dba11ecb1e81171463288e9_11`
   Answer: The Mulsanne "W.O. Edition" was presented, featuring a piece of the crankshaft from W.O. Bentley's personal car displayed in the arm rest.

B.4 Parallel Visual-Textual Fork

Example Reasoning Chain — Parallel Visual-Textual Fork

Caption: Mandolin1.

Main Question. Given the appearance of the mandolin shown, how did Pasquale Vinaccia's 1835 innovation involving string material lead to structural changes in the instrument and its lasting impact on mandolin design?

Final Answer. Pasquale Vinaccia's 1835 innovation of using *steel wire strings*, which are visible on the mandolin, necessitated *strengthening the body* and *deepening the bowl* for increased *resonance*, and this method of stringing ultimately *became the dominant way* for mandolins.

Reasoning Chain (4 steps):

1. **(Image)** What type of strings are visible on the mandolin depicted, and how does this visual detail relate to Pasquale Vinaccia's historical improvements to the instrument?
   Image Evidence ID: `30204742`
   Answer: The mandolin prominently displays wire/steel strings."
2. **(Text)** What structural modifications were subsequently required for the mandolin's body due to the adoption of these new wire strings?
   Text Evidence ID: `d5be68020dba11ecb1e81171463288e9_15`
   Answer: The wire strings necessitated strengthening the body and deepening the bowl.
3. **(Text)** What specific acoustic quality was enhanced by deepening the mandolin's bowl as a consequence of these structural changes?
   Text Evidence ID: `d5be68020dba11ecb1e81171463288e9_3`
   Answer: Deepening the bowl increased tonal resonance.
4. **(Text)** Considering these improvements, what was the long-term impact of Vinaccia's decision to use steel strings on mandolin design and construction?
   Text Evidence ID: `d5be68020dba11ecb1e81171463288e9_5`
   Answer: His steel-stringing approach became the dominant way of stringing mandolins.

B.5 Multi-Images Fork

Example Reasoning Chain — Multi-Images Fork

Caption: Canada Pavilion

Caption: Morocco Pavilion

Main Question. Which of the depicted Epcot pavilions, the Canada or Morocco, features a prominent tall, slender tower as its main architectural centerpiece, and what is its historical significance regarding its addition to the World Showcase?

Final Answer. The Morocco Pavilion features *a prominent tall, slender tower*, and it was historically significant as *the first expansion pavilion added to World Showcase*, opening on September 7, 1984.

Reasoning Chain (4 steps):

1. **(Image)** What is the most prominent feature of the roof structure shown on the main building, the Canada Pavilion?
   Image Evidence ID: `30383576`
   Answer: A very steep, multi-tiered green roof with pointed spires.
2. **(Image)** What is the most prominent architectural feature defining the skyline of the building in the Morocco Pavilion?
   Image Evidence ID: `30021436`
   Answer: A tall, rectangular tower topped with a small dome.
3. **(Image)** Considering the contrast in primary vertical architectural elements between the Canada Pavilion's steep roof and the Morocco Pavilion's tower, which of these two pavilions would be best described as featuring a prominent tower rather than a very steep roof?
   Image Evidence ID: `30021436`
   Answer: The Morocco Pavilion.
4. **(Text)** According to the provided text, what significant historical fact is associated with the Morocco Pavilion regarding its status as a World Showcase addition?
   Text Evidence ID: `d5bef66e0dba11ecb1e81171463288e9_7`
   Answer: It was the first expansion pavilion to be added to World Showcase, opening on September 7, 1984.

C Dataset Statistics

Table 2: Statistics of MC-Search benchmark.

Statistic	**Number**
Parallel Visual-Textual Fork Samples	680
Image-Initiated Chain Samples	1,306
Text Chain Samples	945
Text-Initiated Chain Samples	169
Multi-Images Fork Samples	233
Total Samples	3,333
Total Images in the Knowledge Base	389,750
Total Documents in the Knowledge Base	784,473
Average Chain Length in Parallel Visual-Textual Fork	4.01
Average Chain Length in Image-Initiated Chain	3.82
Average Chain Length in Text Chain	3.65
Average Chain Length in Text-Initiated Chain	3.17
Average Chain Length in Multi-Images Fork	3.97
Sub-Chains with Text Retrieval	10,063 (79.72%)
Sub-Chains with Image Retrieval	2,550 (20.20%)

D Agentic MM-RAG Case Study

D.1 Success Case

Figure 5: Success case. The reasoning chain produced by the agent aligned with the golden reasoning chain and the final answer includes all key knowledge entities.

D.2 Failure Case

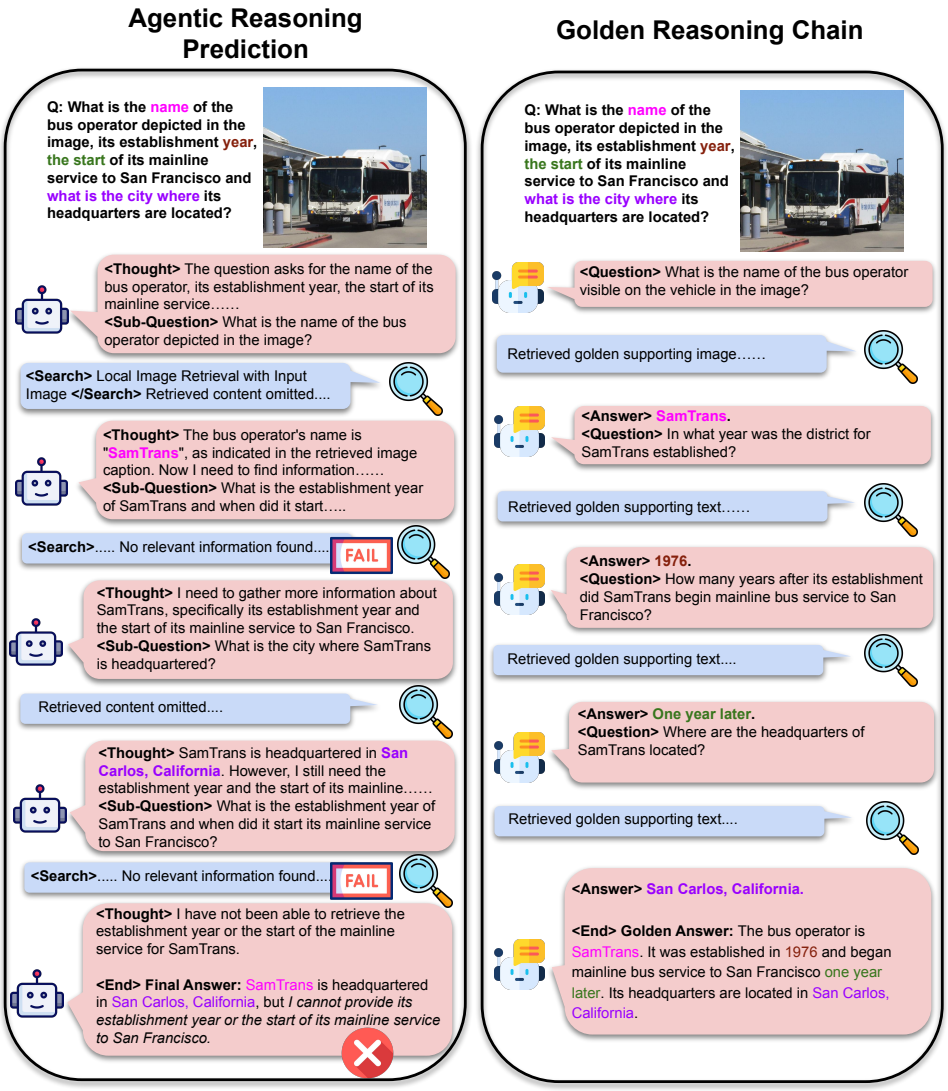

Figure 6: Failure case. While the agent successfully retrieves the first and the last hop information, it fails to retrieve the second and third hop information. Thus, the final answer does not include all key knowledge entities.