DEEPAMBIGQA: Ambiguous Multi-hop Questions for Benchmarking LLM Answer Completeness

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Abstract

Large language models (LLMs) with integrated search tools show strong promise in open-domain question answering (QA), yet they often struggle to produce complete answer set to complex questions such as *"Which actor from the film Heat won at least one Academy Award?"*, which requires ❶ distinguishing between multiple films sharing the same title and ❷ reasoning across a large set of actors to gather and integrate evidence. Existing QA benchmarks rarely evaluate both challenges jointly. To address this, we introduce DEEPAMBIGQAGEN, an automatic data generation pipeline that constructs QA tasks grounded in text corpora and linked knowledge graph, generating natural and verifiable questions that systematically embed name ambiguity and multi-step reasoning. Based on this, we build DEEPAMBIGQA, a dataset of 3,600 questions requiring multi-hop reasoning and half of them explicit name ambiguity resolving. Experiments reveal that, even state-of-the-art GPT-5 show incomplete answers, achieving only 0.13 exact match on ambiguous questions and 0.21 on non-ambiguous questions. These findings highlight the need for more robust QA systems for information gathering and answer completeness.

1 Introduction

Large language models (LLMs) are increasingly used for complex question answering (QA), especially when paired with external search tools. Given an open-ended query, such systems decompose it into sub-steps, query the search tool, retrieve evidence, and aggregate information from multiple sources to form the final answer (OpenAI, 2025; Jin et al., 2025; Team et al., 2025). Unlike simple factoid QA, which often requires a single lookup, complex queries are inherently multi-hop and demand multiple rounds of reasoning and evidence gathering (Yang et al., 2018; Trivedi et al., 2022; Wolfson et al., 2025).

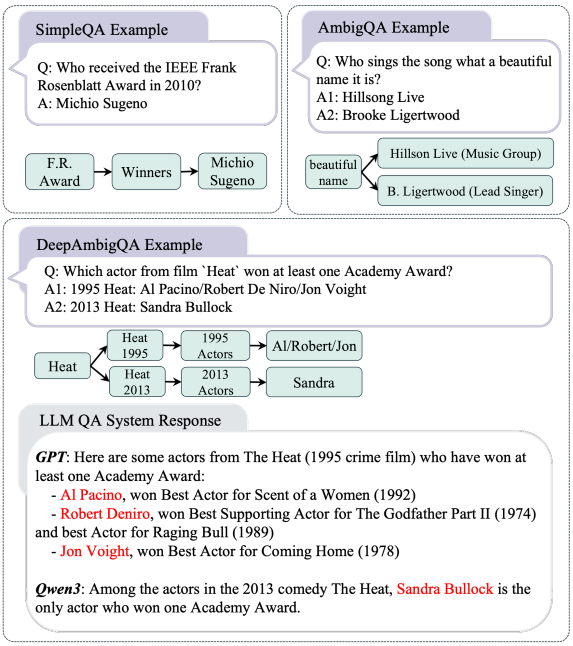

Figure 1: Comparison between DEEPAMBIGQA questions (bottom), SimpleQA (top left), and AmbigQA (top right). ***Takeaway:*** Unlike SimpleQA and AmbigQA, DEEPAMBIGQA questions require both name disambiguation and multi-hop reasoning over a large intermediate evidence set, presenting a significant challenge for current LLM-based QA systems.

Two core capabilities are crucial for QA systems to solve such questions: ❶ *Complete evidence coverage i.e.*, they must retrieve all relevant facts by issuing effective queries, disambiguating ambiguous inputs, and gathering the full set of related information rather than relying on a few salient snippets. ❷ *Correct reasoning and information aggregation i.e.*, they must then reason accurately over the collected evidence and perform reasoning operations such as filtering and grouping, while preserving contextual nuances. For example, the query: *"Which actors in the film titled The Heat have won at least one Academy Award?"* illustrates both challenges: the title *The Heat* is ambiguous, as multiple films share this name, and solving the query requires enumerating all candidate films,

retrieving their casts, and verifying each actor's award status. Thus, it demands both robust disambiguation and multi-hop reasoning over complete evidence. However, existing LLM-based QA systems often fall short, frequently overlooking valid interpretations or producing incomplete actor lists as shown in Figure 1.

Although such queries are common, they remain underrepresented in existing QA benchmarks. Multi-hop QA datasets such as MuSiQue and SimpleQA (Trivedi et al., 2022; Wei et al., 2024) generally follow a single reasoning path and produce single short answer. In contrast, ambiguity-oriented datasets such as AmbigQA and CondAmbigQA (Min et al., 2020; Li et al., 2025) capture multiple valid interpretations but involve limited multi-hop reasoning. Figure 1 illustrates how our target questions differ in both reasoning complexity and name ambiguity from those in prior benchmarks. To address this gap, we introduce DEEPAMBIGQAGEN, an automatic pipeline for generating ambiguous multi-hop questions. Unlike prior QA dataset construction efforts that rely on manual annotation (Trivedi et al., 2022; Wolfson et al., 2025), DEEPAMBIGQAGEN leverages knowledge graphs aligned with a text corpora such as Wikidata and Wikipedia, which provide structured relations among entities that can be directly converted into executable reasoning steps and verified against factual connections. DEEPAMBIGQAGEN first identifies ambiguous names and their corresponding distinct entities, then builds executable reasoning plans with structured sequences of operations that model user information-seeking behaviors. These plans simulate multi-step reasoning by chaining operations such as *entity* retrieval (*e.g.*, obtaining actors of a film) and *filter* application (*e.g.*, selecting actors who have won an award). For ambiguous names, the same plan can be re-executed with each possible entity to obtain corresponding answers, allowing the dataset to capture multiple valid interpretations in a verifiable way. Finally, an LLM converts these plans into natural-language questions. We also integrates verification steps to ensure naturalness and question-answer correspondence.

Building on DEEPAMBIGQAGEN, we introduce DEEPAMBIGQA, a benchmark of 3,600 QA pairs. Among them, 1,800 questions contain ambiguous names leading to multiple valid reasoning paths, while the rest are non-ambiguous but still yield large answer sets (up to 43 entities). Each question requires at least two reasoning steps, with some involving up to eight, posing substantial challenges for LLM QA systems on complete answer recall and intermediate reasoning. We evaluate state-of-the-art LLMs equipped dense retrieval tool on Wikipedia corpus on DEEPAMBIGQA. The results show that: ❶ LLMs struggle with answer completeness, achieving low exact-match accuracy, especially for ambiguous queries, even the SOTA GPT-5 attains only 0.13 exact match on the ambiguous subset and 0.21 exact match on the non-ambiguous subset. ❷ While precision remains high (typically above 70%), recall and exact match are much lower, indicating their inability to find complete answers. Adding modules such as query expansion for disambiguation and evidence extraction for retrieved passage brings only modest improvements and cannot fully address these challenging questions.

In summary, our contribution are as follows:

- We propose DEEPAMBIGQAGEN, an automatic QA synthesis pipeline grounded in knowledge graphs that generates natural questions and verifiable gold answers.
- We introduce DEEPAMBIGQA, a benchmark of multi-hop, ambiguity-rich questions requiring reasoning and disambiguation to ensure answer completeness for QA systems.
- We evaluate SOTA LLMs and demonstrate that they struggle with answer recall and completeness, highlighting the need for more robust QA systems.

2 Related Work

Ambiguous QA Ambiguous QA datasets focus on questions that can be interpreted in multiple valid ways. Existing benchmarks capture different types of ambiguity: AmbigQA, ASQA, and CondAmbigQA mainly address name entity and intent ambiguities (Min et al., 2020; Stelmakh et al., 2022; Li et al., 2025), while TempAmbigQA targets temporal ambiguity (Piryani et al., 2024). Although these datasets cover diverse ambiguity types, most of their questions require only shallow evidence collection without deep, multi-step reasoning. In contrast, our QA tasks involve complex, multi-step reasoning and information aggregation for various name entity interpretations in the question, which substantially increases the difficulty and richness of the questions.

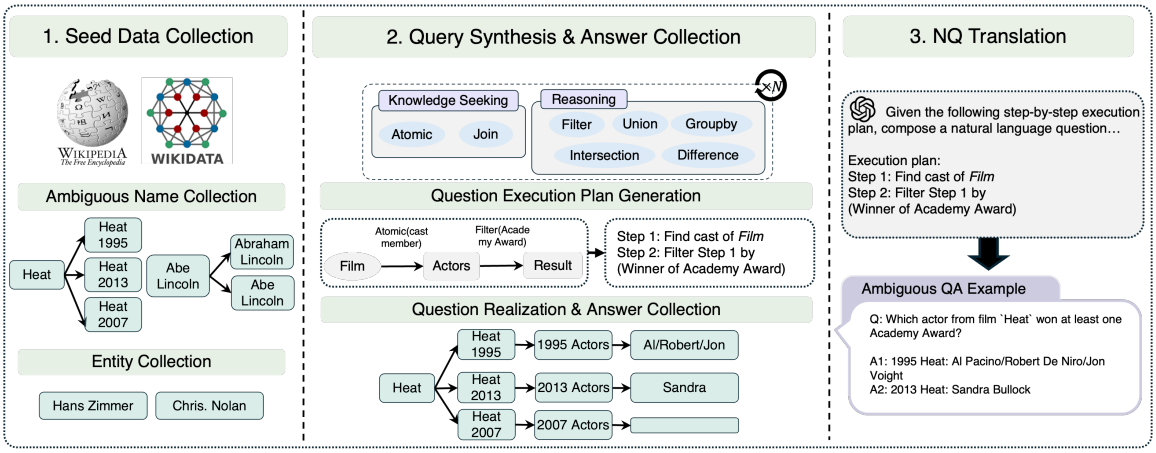

Figure 2: Illustration of the DEEPAMBIGQAGEN algorithm. Beginning with a large collection of entities and relations, a complex query is constructed by iteratively sampling atomic entities and new operations. The resulting query is then converted into natural language by prompting an LLM.

Multi-hop QA Multi-hop QA datasets typically contains questions requiring strong reasoning and evidence aggregation across documents. Datasets such as HotpotQA, 2WikiMultihopQA, and MuSiQue study reasoning over a limited number of documents and a small set of structured steps (Yang et al., 2018; Ho et al., 2020; Trivedi et al., 2022). More recent datasets, like FanOutQA, MEQA, WebQuest, and MoNaCo, further raise the difficulty by expanding to larger document pools, event-centric compositions, and long-horizon reasoning sequences (Zhu et al., 2024; Li et al., 2024; Wang et al., 2024; Wolfson et al., 2025). However, most of these assume a *single reasoning path and a single final answer* for the question, leaving ambiguity underexplored. DEEPAMBIGQA differs by introducing entity disambiguation that creates multiple valid branches and focusing more on the answer completeness across all branches. Unlike prior datasets that rely on human annotation, which is very difficult for these multi-hop reasoning questions, our QA construction can be operated automatically, largely reducing human-annotation cost.

Knowledge-graph QA KG QA datasets use knowledge graphs as the information source for QA synthesis. For example, WebQuestionsSP pairs natural questions with executable semantic parses over Freebase (Yih et al., 2016), while ComplexWebQuestions composes multi-hop queries grounded in web evidence (Talmor and Berant, 2018). GrailQA targets compositional and schema-level generalization (Gu et al., 2021), and program-supervised datasets such as MetaQA, CFQ, and KQA Pro provide fine-grained logical forms for controlled reasoning (Zhang et al., 2018; Keysers et al., 2020; Cao et al., 2022). Recent works like MusTQ and Dynamic-KGQA also introduce temporal and adaptive reasoning (Zhang et al., 2024; Dammu et al., 2025). Yet most KGQA tasks still assume a single executable program, limiting evaluation to single reasoning path. Our approach instead generates KG-grounded questions aligned with Wikipedia, enabling complex questions that require multi-hop reasoning across ambiguous names.

3 DEEPAMBIGQAGEN: An Automatic QA Synthesis Pipeline

3.1 Pipeline Overview

In this section, we present DEEPAMBIGQAGEN, an automatic pipeline for synthesizing ambiguous multi-hop knowledge-seeking QAs. The pipeline is designed to capture diverse reasoning patterns, and explicitly model name entity ambiguity that induce multiple reasoning paths. DEEPAMBIGQAGEN involves three stages: ❶ *Seed Data Collection.* The pipeline begins with the collection of seed entities and relations. These constitute the atomic building blocks for multi-hop reasoning and serve as the foundation for question synthesis. ❷ *Execution Plan Synthesis and Answer Collection.* DEEPAMBIGQAGEN utilizes the seed data and composes structured execution plans that specify multi-step reasoning operations. These plans can be executed on a knowledge graph to yield ground-truth answers. KG ensures the correctness and completeness of the answers. ❸ *Natural Language Question Translation and Filtering.* Execution plans are translated into natural language questions with an LLM, *i.e.*, GPT-5-mini. The candidate QAs are

Synthesized Query	Atomic Entities	Question Execution Plans	Final Answers
Which directors have worked with Saoirse Ronan on two or more films?	Saoirse Ronan	(1) Find film by Saoirse Ronan. (2) Find director of step 1 result. (3) Group by director. (4) Filter by count > 2.	{Joe Wright, Greta Gerwig, Wes Anderson}
List all actors who have starred in both a Martin Scorsese film and a Quentin Tarantino film.	Martin Scorsese, Quentin Tarantino	(1) Find films by Scorsese. (2) Join step 1 result with cast member. (3) Find films by Tarantino. (4) Join step 3 result with cast member. (5) Intersection on step 2 and step 4.	{Robert De Niro, Leonardo DiCaprio, Harvey Keitel, Jonah Hill, Brad Pitt, Margot Robbie, Ray Liotta}
Which films were directed by one of the cast members of City of God?	City of God (2002 film), City of God (2011 film)	(1) Find cast of City of God (2) Join step (1) result with directed film	2002 film: {City of God 2013 10 Years Later, The Dead Girl's Feast}, 2011 film: {Appavin Meesai, Lucifer, Bro Daddy, L2: Empuraan}
Which genres are shared by Americano and Sleepless in Seattle?	Americano (2011 film), The Americano (1916 film)	(1) Find genres of Americano (2) Find genres of Sleepless in Seattle (3) Intersection of Step 1 and 2	1916 film: {drama film}, 2011 film: {romantic comedy}

Table 1: Example questions generated by DEEPAMBIGQAGEN, along with the involved entities in question, execution plans, and final answers. Row 3 and 4 show examples of ambiguous question, where the ambiguity comes from the shared film name.

further filtered to ensure semantic naturalness and question-answer correspondence. Figure 2 presents a pipeline overview.

3.2 DEEPAMBIGQAGEN Algorithm

Step 1: Seed Data Collection The pipeline begins by defining a domain schema consisting of entity types and relations that later guide information-seeking and reasoning. For example, in the film domain, entity types can include *actors*, *directors*, and *films*, while relations capture the semantic transition between them such as *directed by* (director-film) or *cast member* (actor-film). This schema specifies the space of valid reasoning paths and constrains how knowledge can be retrieved or composed. We derive the schema from Wikidata KG definitions to ensure interpretability and consistency with the Wikipedia text corpus, and obtain concrete entity instances for each type via WikiSPARQL queries.

Step 2: Query Synthesis and Answer Collection Using the seed data, the pipeline incrementally builds executable plans that represent typical multi-step reasoning and information-seeking behaviors of complex user questions. Each plan consists of a sequence of operations sampled from seven atomic types: `Atomic`, `Join`, `Filter`, `Union`, `Difference`, `Intersection`, and `GroupBy`.

The first two operations, `Atomic` and `Join`, capture knowledge-seeking behaviors. Specifically, `Atomic` starts a traversal from a single entity through a specified relation, while `Join` extends the traversal from an intermediate set of entities to gather related entities. For example, `Atomic(Tom Hanks, cast member)` retrieves the set of films featuring Tom Hanks, and `Join(Hanks' films, directed by)` returns the directors of those films.

The remaining operations model reasoning behaviors including applying logical constraints, performing set-based computations, or aggregating results. These include filtering answer set based on certain predicates such as award-winning status, computing unions, intersections, or differences between intermediate answer sets, and grouping current answer entities for aggregation. We highlight that all operations are fully executable in code, allowing consistent re-instantiation and execution across different entities, which guarantees the answer correctness and completeness. It further helps handle ambiguous questions, where we can re-run the same question execution plan on each unique entities sharing same ambiguous name to derive the unique answer sets for each reasoning branch. The mid panel of Figure 2 shows an example that executing the plan yield three different answer sets for three different Heat film entity.

Step 3: Natural Language Question Translation After generating an execution plan and collecting its answers, the pipeline uses a large language model (LLM) to translate the formal representation into a natural language question. The translation process is guided by both the execution plan and its final answer set, ensuring that the resulting question reflects the underlying reasoning steps. Candidate questions are further filtered to remove those whose semantics diverge from the plan or whose answers do not align. As shown in Table 1, this process produces natural language questions that capture complex, multi-hop reasoning patterns while remaining answerable.

3.3 Additional Details

QA Filtering To ensure that the generated questions and answers are coherent and answerable, the pipeline applies two complementary filtering strategies. ❶ *Heuristic rules.* These rules enforce syntactic and semantic validity. For example, we introduce rules about preventing repetitive reasoning operations (*e.g.*, consecutive set unions), disallowing incompatible combinations of entity types (*e.g.* union between actor and film), and remove cases where the final answer set is empty. ❷ *LLM-based evaluation.* Since heuristics alone cannot fully cover unreasonable question semantics, we prompt GPT-5-mini to further assess both the logical validity of execution plans and evaluate the alignment between generated questions and resulting answer sets. This helps us remove meaningless and unnatural questions.

LLM-based Entity Selection Although many entity candidates can be used in an execution plan, most do not yield valid answer sets due to filtering or set intersection. To improve the synthesis success rate, we employ an LLM-based entity realization strategy. Specifically, we randomly sample a subset of candidate entities corresponding to the entity types in an execution plan from the seed entity sets, *e.g.* 50 different films for an execution plan requiring a film, and prompt GPT-5-nano to select suitable entities for realization that are likely to produce non-empty answer sets. This approach substantially improves the success rate of generating valid QA pairs with non-empty answers.

4 DEEPAMBIGQA Dataset

In this section, we present more details of the DEEPAMBIGQA dataset, generated by the proposed DEEPAMBIGQAGEN on a fixed Wikipedia snapshot[1] to ensure question and answer alignment. Specifically, Section 4.1 details the data collection procedure, Section 4.2 lists the key statistics of DEEPAMBIGQA dataset, followed by Section 4.3 that presents the complexity and naturalness analysis of the synthesized questions.

4.1 DEEPAMBIGQA Collection

In this paper, we employ the Wikipedia snapshot dated *2025-0820*[2] as the source data to build DEEPAMBIGQA. The wiki pages are aligned to corresponding wikidata annotations to obtain the knowledge graph with entities and relation annotations for query synthesis.

The final dataset contains both ambiguous and non-ambiguous questions spanning a diverse set of domains derived from Wikipedia, including *movies, music, sports, books, business, and science*. To better capture real-world query ambiguity, we collect the ambiguous name as well as the unique entities corresponding to the same name from Wikipedia disambiguation page, *e.g.* the page *Heat (disambiguation)*[3] collects unique entities from multiple domains sharing the same ambiguous name *Heat*.

Non-ambiguous questions:	1800
- Avg. # question words	13.9
- Avg. # answer set size	8.8
- Avg. # execution steps	4.3
- Avg. # entities involved	463.1
Ambiguous questions:	1800
- Avg. # question words	12.4
- Avg. # answer set size	10.3
- Avg. # execution steps	3.7
- Avg. # answer set per branch	2.7
- Avg. # entities involved	247.4
- Avg. # reasoning branches	3.3

Table 2: Key data statistics of DEEPAMBIGQA.

Metric	Non-Ambig. Question	Ambig. Question
Naturalness(1-3)	2.86	2.91
Correctness(%)	91.6	91.2

Table 3: Human evaluation results of DEEPAMBIGQA on question naturalness and answer correctness. Scores are averaged over three annotators.

4.2 Dataset Statistics

Table 2 summarizes the key characteristics of DEEPAMBIGQA, divided into ambiguous question subset and non-ambiguous question subset. For each category, we report the average question length, total answer set size, number of execution steps, and number of unique intermediate entities involved in the reasoning, which together reflect the overall complexity of the questions. We present more statistics such as detailed breakdown of the execution step number in Appendix A.1 and compare with previous QA datasets in Appendix A.2.

The ambiguous subset contains 1,800 questions, each involving one ambiguous name that yields multiple interpretations. Such questions introduce substantial challenges for LLMs to perform accu-

[1] https://en.wikipedia.org/wiki/Wikipedia:Database_download

[2] https://dumps.wikimedia.org/enwiki/20250820/

[3] https://en.wikipedia.org/wiki/Heat_(disambiguation)

rate disambiguation and retrieval across multiple reasoning paths starting from different entities. On average, an ambiguous question has 3.3 reasoning branches and involves 247.4 entities in reasoning process, underscoring the difficulty of resolving entity ambiguities within the reasoning process. The non-ambiguous subset also includes 1,800 questions but emphasizes more on reasoning complexity. These questions typically involve deeper reasoning chains, averaging 4.3 execution steps and covering 463.1 unique entities. They demand compositional reasoning operations such as filtering, set intersection, and aggregation, which test LLMs' ability to maintain logical consistency over reasoning paths.

Overall, DEEPAMBIGQA captures two complementary sources of reasoning difficulty: ambiguity resolution and compositional reasoning. Ambiguous questions pose more challenges on QA system's capacity to differentiate among entities with identical names, while non-ambiguous questions probe its ability to perform multi-step reasoning over complex relational structures. Together, these characteristics make DEEPAMBIGQA a challenging benchmark for evaluating the robustness and reasoning depth of QA systems.

4.3 Dataset Quality Analysis

We further conduct a human study to better assess the quality of DEEPAMBIGQA. The primary objective is to evaluate whether the synthesized questions are natural in phrasing and whether their corresponding answers are correct and faithful, ensuring that the dataset reflects realistic user queries while maintaining logical soundness. For each annotation task, we recruit 3 human annotators and report the average. Due to budget constraints, we randomly select 5% of the non-ambiguous and ambiguous QAs, with 90 unique questions for each subset. Annotation instructions are in Appendix A.3.

Human Study on Naturalness. We evaluate the naturalness of synthesized questions to determine whether they are grammatically correct, clearly capture the intended knowledge search task, and are phrased in a way that is natural and easily understandable to humans. Human annotators rated each question on a 3-point scale, yielding a pairwise Cohen's Kappa of 0.669 and 0.632 on the non-ambiguous and ambiguous subsets, implying a substantial agreement. As shown in Table 3, the synthesized questions received high naturalness scores, averaging 2.86 for non-ambiguous questions and 2.91 for ambiguous ones.

Human Study on Correctness. We additionally asked annotators to assess the correctness of answers by verifying them against the corresponding Wikipedia pages and Wikidata entries. The goal was to ensure that answers are both accurate and complete with respect to the original questions. For ambiguous questions, we ask annotators to evaluate the correctness of unique entities for the ambiguous name in original question to avoid their burden. As shown in Table 3, we achieve a high entity-level correctness score, with 91.6% for the non-ambiguous subset and 91.2% for the ambiguous subset, with pair-wise Cohen's Kappa of 0.774 and 0.534 respectively. The lower coefficient for the ambiguous subset (moderate agreement) also highlights the difficulty in verifying the correctness of the answer for ambiguous questions.

5 Experiment

In this section, we evaluate a diverse set of SOTA LLMs on DEEPAMBIGQA dataset and further investigate the effect of additional modules in the system on their overall performance. Section 5.1 describes the experimental setup and presents quantitative results across different model families, accompanied by a detailed analysis of failure cases in Section 5.2. Finally, Section 5.3 examines the contribution of each add-on module and its influence on the final performance.

5.1 Experiment Setting

Evaluation Model We evaluate 10 large language models (LLMs) spanning both closed-source and open-source families, including the GPT series (OpenAI, 2023), Qwen2.5-Instruct series (Team, 2025a), Qwen3 series (Team, 2025b), and the DeepSeek-R1-distilled series (DeepSeek-AI, 2025). All models are prompted with the same template to summarize their answers in a JSON dictionary format to simplify answer extraction. For ambiguous questions that may involve multiple branches and different answer sets, we incorpoarate an LLM-based matching step to align the LLM generated answers with the ground-truth branch names. Implementation details including the detailed prompts are in Appendix A and C.

Following previous work (Yifei et al., 2025; Jin et al., 2025), we implement LLM-based QA system by integrating a dense-retrieval search tool, and prompt LLMs to query the local Wikipedia

Model	Non-ambig. Question			Ambig. Question		
	P	R	EM	P	R	EM
Qwen2.5-3B-Inst	0.82	0.34	0.03	0.78	0.17	0.01
Qwen2.5-7B-Inst	0.83	0.40	0.05	0.80	0.21	0.01
Qwen3-4B	0.84	0.45	0.07	0.84	0.25	0.03
Qwen3-8B	0.84	0.55	0.12	0.85	0.39	0.05
DS-R1-distill-1.5B	0.73	0.33	0.02	0.74	0.08	0.01
DS-R1-distill-7B	0.82	0.51	0.06	0.79	0.14	0.02
GPT-4o	0.84	0.52	0.11	0.83	0.33	0.03
GPT-4o-mini	0.91	0.57	0.14	0.84	0.41	0.05
GPT-5-mini	0.90	0.64	0.16	0.87	0.44	0.09
GPT-5	**0.93**	**0.71**	**0.21**	**0.91**	**0.48**	**0.13**

Table 4: Evaluation results of various LLMs.

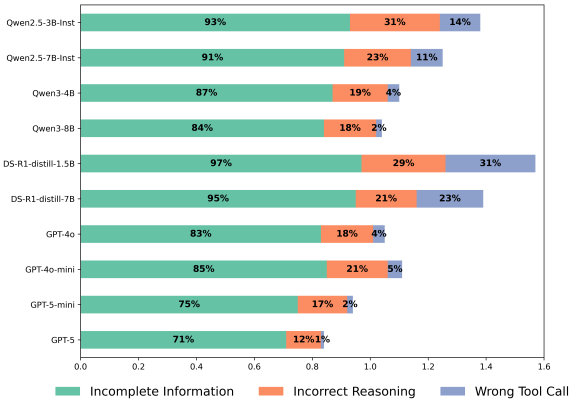

Figure 3: Error-type breakdown for various LLMs.

corpus via the provided search tool for information seeking. In this process, the LLM may trigger multiple tool calls to retrieve new information that is later appended to their context. The Wikipedia corpus is preprocessed and served following the FlashRAG (Jin et al., 2024) implementation. Unless otherwise specified, we employ e5-base[4] as the embedding model for corpus indexing and retrieval following previous work (Jin et al., 2025; Mihaylov et al., 2021). More implementation details are in Appendix A.

Evaluation Metric Since all answers in DEEPAMBIGQA are represented as sets of entities, we evaluate model performance using average precision (P), recall (R), and exact match (EM). For ambiguous questions, results are aggregated over all valid answers spanning different reasoning branches to account for multiple interpretations.

5.2 Experiment Results

LLM Performance on DEEPAMBIGQA Table 4 reports the overall performance of various LLMs on DEEPAMBIGQA. We highlight the following observations: ❶ All LLMs exhibit low exact match scores, with the strongest model, GPT-5, achieving only 0.21 and 0.13 EM on the non-ambiguous and ambiguous subsets, respectively. This gap underscores that current LLMs struggle to maintain answer completeness when reasoning over complex questions that involve ambiguity resolution and intermediate information aggregation. ❷ Although most models attain relatively high precision, their recall remains consistently lower. This discrepancy suggests that LLMs often retrieve partial but not exhaustive sets of correct answer entities, revealing limitations in comprehensive information retrieval and reasoning coverage. ❸ Performance degrades further on ambiguous questions. For instance, GPT-5's recall drops from 0.71 to 0.48 when ambiguity is introduced, indicating that existing LLMs remain ineffective at disambiguating ambiguous names in question and exploring multiple valid reasoning branches. Overall, these results demonstrate that DEEPAMBIGQA presents substantial reasoning and disambiguation challenges to LLM QA systems.

Failure Breakdown and Analysis To better understand error cases in these LLM QA systems, we categorize errors into following three types: ① *incomplete information extraction*, where answer entities are not involved in the retrieved documents. For ambiguous questions, this also includes the scenerio where certain reasoning branches is not covered. ② *incorrect intermediate reasoning*, where answer entities appeared in the retrieved documents but were not presented in LLM's final answer. ③ *wrong tool call*, including cases of misused or failed tool execution. Figure 3 presents the distribution of these failure types. Note that the proportions in each bar do not sum to one because multiple error types can occur in a single QA instance. We highlight two main observations. ❶ Stronger LLMs make fewer reasoning-related mistakes. For example, weaker LLMs such as Qwen2.5-3B exhibit over 30% reasoning errors, whereas GPT-5 shows only 12%. ❷ All LLMs suffer from incomplete information extraction; even the strongest model, GPT-5, exhibits 71% of failures in this category. These findings suggest that enhancing retrieval information coverage remains the dominant challenge for LLM-based QA.

5.3 Additional Analysis

The previous results indicate that the base system still suffers from substantial retrieval and reason-

[4] https://huggingface.co/intfloat/e5-base-v2

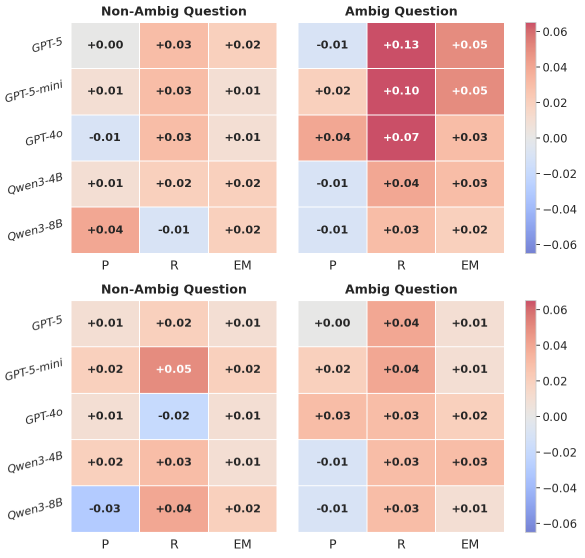

Figure 4: LLM performance change after applying query expansion *(upper)* and evidence extraction *(lower)*. Full results in Appendix Table 8.

ing errors. To inform future improvements for QA systems, we explore three additional modules: ❶ *Query expansion*, which prompts the LLM to enrich original query and disambiguate before question answering to improve information completeness in reasoning process. ❷ *Evidence extraction*, which prompts the LLM to filter retrieved texts and retain only relevant spans to reduce information aggregation errors. ❸ *KG query*, a new tool that enables the LLM to execute WikiSPARQL queries on the KG, potentially providing precise entity-level information beyond textual evidence. Implementation and full results are in Appendix B.

Effect of Query Expansion Query expansion aims to resolve ambiguity in entity names and improve retrieval coverage by performing explict disambiguation step. As shown in Figure 4, adding expansion generally improves recall across all models, particularly for ambiguous questions. For instance, GPT-5's recall shows a 0.13 increase on ambiguous queries, reflecting that expanded queries effectively helps LLM identify additional evidence that would otherwise be missed. Meanwhile, improvement is smaller for non-ambiguous questions, suggesting that it mainly benefits cases where entity names are unclear. However, precision and exact match gains are marginal, indicating that while the expanded queries help retrieve more relevant evidence, they still fail to fully address the answer completeness issue.

Effect of Evidence Extraction Evidence extraction module encourages the LLM to filter retrieved

Model	Non-ambig. Question			Ambig. Question		
	P	R	EM	P	R	EM
GPT-5	$0.30_{-0.63}$	$0.28_{-0.43}$	$0.03_{-0.18}$	$0.14_{-0.77}$	$0.12_{-0.36}$	$0.02_{-0.11}$
GPT-5-mini	$0.25_{-0.65}$	$0.22_{-0.42}$	$0.02_{-0.14}$	$0.11_{-0.76}$	$0.10_{-0.34}$	$0.01_{-0.08}$
GPT-4o	$0.24_{-0.67}$	$0.18_{-0.39}$	$0.02_{-0.12}$	$0.10_{-0.74}$	$0.08_{-0.33}$	$0.01_{-0.04}$
Qwen3-4B	$0.18_{-0.66}$	$0.14_{-0.31}$	$0.01_{-0.06}$	$0.07_{-0.77}$	$0.06_{-0.19}$	$0.00_{-0.03}$
Qwen3-8B	$0.22_{-0.62}$	$0.20_{-0.35}$	$0.02_{-0.10}$	$0.08_{-0.77}$	$0.08_{-0.31}$	$0.01_{-0.04}$

Table 5: LLM QA performance after adding KG Tool. Subscripts indicate performance change relative to base system. Full results in Appendix Table 8.

information and retain only those relevant to the question to reduce context noise overhead. As shown in Figure 4, this step yields modest gains in both precision and recall. For example, GPT-5 exhibits a 0.01 and 0.02 improvement for precision and recall on non-ambiguous subset. These small improvements indicate that extraction helps reduce irrelevant information but does not fully address cases where evidence is missing. This also aligns with our error analysis in Section 5.2, which shows that QA systems suffer more from incomplete information rather than incorrect reasoning.

Effect of Knowledge-graph Information We also test whether using a Wiki-SPARQL tool to access KG can enhance model performance. This allows LLM to retrieve precise entity information rather than relying on text retrieval alone. However, Table 8 shows a clear performance drop across all models. For instance, GPT-5 sees a notable 0.77 precision and 0.36 recall decline on ambiguous subset. This drop mainly comes from the failure in generating correct and executable SPARQL queries such as incorrect grammar or wrong entity/relation id usage, limiting their improvement. The findings suggest that while KGs can offer structured access to entity relations, simply integrating them remains unreliable and require more advanced special handling. This is further confirmed by an LLM-agent method experiment with KG tool in Appendix B.2.

6 Conclusion

We introduced DEEPAMBIGQAGEN, an automatic pipeline for generating ambiguous multi-hop questions from knowledge graphs, and curate DEEPAMBIGQA. Unlike prior datasets, it combines ambiguity and multi-hop reasoning and demands comprehensive evidence retrieval and aggregation. Experiments with SOTA LLMs reveal their weakness to gather complete evidence to solve questions. Our findings highlight the need for advances in QA on retrieval completeness and ambiguity-aware reasoning to build more reliable QA systems.

7 Limitations

While our work presents a scalable ambiguous multi-hop QA question generation pipeline and the experiment show that our dataset presents significant challenges to existing LLM QA systems, our work has several limitations:

First, DEEPAMBIGQAGEN relies primarily on a static structured KG to ensure the correctness and completeness of the generated information. Although our human evaluation of DEEPAMBIGQA demonstrates that Wikidata is generally reliable, reflected by the high correctness rate, its coverage may be limited compared to web-scale information sources. Such incompleteness can arise from temporal lags or missing entries in the KG. In future work, we plan to extend the current framework to integrate information from the web and other complementary knowledge graphs to enhance both coverage and freshness.

Second, DEEPAMBIGQAGEN employs a fixed Wikipedia snapshot. While this design choice may not capture the most up-to-date facts at evaluation time, it follows common practice in open-domain QA to ensure reproducibility and fair comparison across systems, and to avoid inconsistencies caused by online knowledge drift. We also note that DEEPAMBIGQAGEN is automatic and easily refreshable, since the entire preprocessing pipeline can be rerun on newer snapshots without changing the implementation, allowing future updates while preserving reproducibility.

Furthermore, while DEEPAMBIGQA explicitly addresses name ambiguity and multi-hop reasoning, it does not yet cover all potential real-world ambiguities (*e.g.*, temporal or intention ambiguities). We plan to extend this work to broaden the operation types to capture these additional ambiguity dimensions and better reflect the complexity of natural questions. For example, consider the temporally ambiguous question "Who was the commissioner for Long Beach, California?" The ambiguity arises from the missing temporal context for commissioner (e.g., as of 1987 vs. as of 2003). Within our framework, such ambiguity could be captured by introducing temporally ambiguous entity nodes, e.g., "commissioner of Long Beach, California", connected to two nodes of separate years, into our pipeline.

8 Potential Risk

Despite efforts to ensure fairness and balance in curating DEEPAMBIGQA, the dataset may inherit or amplify social and representational biases present in its underlying corpora and knowledge graphs. Such biases can lead to uneven representation across demographic or cultural groups, potentially reinforcing stereotypes or privileging dominant entities in question answering. Moreover, automatic question generation may occasionally introduce factual inaccuracies or contextually inappropriate content, raising risks of misinformation if deployed beyond controlled research environments.

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A Implementation Detail

In this section, we include additional implementation details, such as the more statistic and analysis of generated DEEPAMBIGQA in Section A.1, detailed human study instructions in Section A.3 and evaluation hyper-parameters in Section A.5.

A.1 DEEPAMBIGQA Details

In this section, we provide more statistic analysis for DEEPAMBIGQA. For example, Figure 5 plots the execution step number distribution, Figure 6 plots the answer set size distribution, Figure 8 plots the operation type distributions, and Figure 9 plots the predicate type distributions.

We note that DEEPAMBIGQA composes six domain questions, including *movie, music, book, sports, business, science*. We include 300 question for each domain in the non-ambiguous question subset and another 1800 ambiguous questions, which adds up to 3600 questions in total. There are no domain annotation for ambiguous questions due to that same ambiguous name may share entities from multiple domains.

We also highlight that DEEPAMBIGQA provides broad coverage of execution steps required to derive the final answer set, with at least two steps involving genuine reasoning rather than simple fact retrieval. DEEPAMBIGQA also features comparatively large answer sets, as illustrated in Figure 6 and Figure 7, including cases with up to 45 entities and as many as 14 distinct branches yielding unique answers for ambiguous questions. Morever, DEEPAMBIGQA features diverse coverage of the reasoning operation types we introduced in the framework and many unique predicate for the filter step as illustrated in Figure 8 and Figure 9.

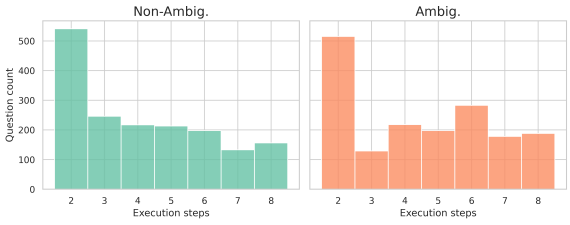

Figure 5: Execution step counts for DEEPAMBIGQA.

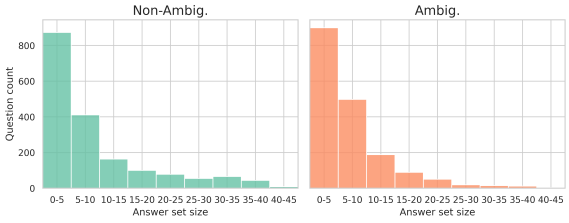

Figure 6: Answer set size distribution for DEEPAMBIGQA.

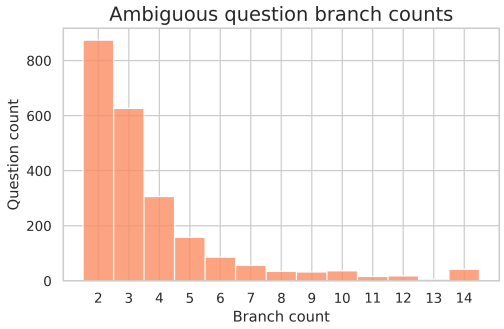

Figure 7: Valid answer branch counts for ambiguous questions in DEEPAMBIGQA.

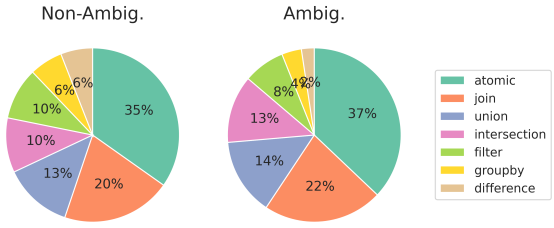

Figure 8: Operation type counts within DEEPAMBIGQA.

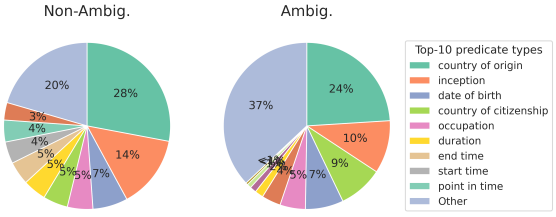

Figure 9: Predicate type distribution for DEEPAMBIGQA.

A.2 Comparison with Previous QA datasets

To further characterize the challenges posed by our benchmark, we analyze its key statistics and compare them with representative non-ambiguous QA datasets (*e.g.*, DROP (Dua et al., 2019), HotpotQA (Yang et al., 2018), MusiQUE (Trivedi et al., 2022), QUEST (Wang et al., 2024), MoNaCo (Wolfson et al., 2025)) and ambiguous QA datasets (AmbigQA (Min et al., 2020), CondAmbigQA (Li et al., 2025)).

As shown in Table 6, our dataset exhibits several distinguishing characteristics that set it apart from existing QA benchmarks. First, it contains substantially larger reasoning branching factors: DEEPAMBIGQA-ambig averages 3.3 reasoning branches per question, exceeding prior ambiguous QA datasets, thereby posing a more challenging disambiguation and multi-path reasoning problem for LLMs. Second, our dataset features larger answer set sizes, emphasizing the difficulty of generating complete and comprehensive responses rather than selecting a single correct answer. Third, it requires complex multi-step reasoning across multiple branches. While MoNaCo involves longer reasoning chains, its questions typically follow a single reasoning path and thus do not capture ambiguity or branching reasoning. Finally, unlike manually curated datasets such as AmbigQA or DROP, our benchmark is constructed via an automatic, scalable, and extensible synthesis pipeline, enabling broader coverage while substantially reducing human annotation cost. Together, these properties make our dataset a challenging and realistic testbed for evaluating ambiguity-aware, multi-branch reasoning in LLMs.

Dataset	No. Steps	No. Branches	No. Answer Entity
DROP	2.8	1	1
HotpotQA	2.2	1	1
MuSiQue	2.6	1	1
QUEST	2.9	1	10.5
MoNaCo	5.1	1	8.34
AmbigQA	N/A	3.11	4.65
CondAmbigQA	N/A	2.08	2.08
DeepAmbigQA-nonambig	4.3	1	8.8
DeepAmbigQA-ambig	3.7	3.3	10.3

Table 6: Quantitative comparison with related datasets.

A.3 DEEPAMBIGQA Human Evaluation

In this section, we list the detailed human evaluation guidelines for the human study on question naturalness and answer correctness. The guideline are shown in Figure 10 and 11 for non-ambiguous questions and ambiguous questions, respectively. For the ambiguous questions, we ask annotators to verify the correctness of associated disambiguified entity names mentioned in the original question.

Non-ambiguous Question Guidelines

```
# Task Overview
In this task, you will be presented with a
QA pair along with some sample answers (
list of entities).
1. Fluency
2. Correctness
Please read below for a thorough
understanding of each grading metric.

# Query Fluency
Fluency refers to the degree to which the
content reads with ease, resembling natural
 human language. Fluent text will flow
smoothly , sound authentic, and avoid
awkward phrasings or constructions that
might indicate machine generation or a non-
native speaker.

In short, it is the ease and naturalness
with which the text conveys information.

## STEPS
Provided below are some tips in evaluating
the fluency of the text:
+ How well does the text flow?
    - Read the conversation out loud. This
will help you identify any awkward or
unnatural-sounding phrases.
+ How is the sentence structure?
    - Sentences should be structured in a
logical and well-read way , and should flow
 well. It should not sound choppy .
+ How is the vocabulary?
    - The use of appropriate vocabulary can
 impact fluency .
    - Words used should be natural to the
target text. If the style and terminology
of the text is not appropriate, it is not
fluent.
+ Stay Objective:
    - Remember, fluency grading is about
the flow of language, not the accuracy of
content or the validity of ideas. Keep
personal biases and content preferences
separate from your fluency assessment.

## GRADING SCALE
Your task is to grade the fluency of the
query only as per the following scale. The
answer does not conform to natural language
 and is hence not graded for fluency.

| Grade | Description | Example |
|--|--|--|
| 3 | The query is fluent and does not
consists of any errors | Which directors
have worked with Saoirse Ronan on two or
more films? |
| 2 | The query is fluent and interpretable
 despite the presence of few gramatical
errors | List all actors that have won an
Oscar award after collaborated with Steven
```

```
Spielberg |
| 1 | The query has poor quality i.e. it
does not resemble natural human language |
Saoirse Ronan on two or more films who
directors worked? |

**YOUR JOB IS TO ONLY GRADE THE
CONVERSATION FOR FLUENCY. IN ADDITION, DO
NOT DOCK MARKS FOR GRAMMAR (SPELLING,
PUNCTUATION, CAPITALIZATION) OR TENSE
ERRORS UNLESS IT SIGNIFICANTLY IMPACTS
FLUENCY OR OBJECTIVE OF THE QUERY.**


# Correctness
Correctness evaluates if the given response
 to a query is factually correct. Y ou can
consider Wikipedia or a trusted website as
the source of ground truth. Correctness is
a binary evaluation i.e. the query is
answered correctly only if all entities in
the
given answer satisfy the requirements.

## STEPS
Provided below are some tips in evaluating
correctness of the given answer:

- **Decompose the query into multiple
queries**
  - A good understanding of how to answer
the questions step-by-step and will be
crucial
  - Some queries might be slightly less
complex and hence do not require
decomposition

- **Answer the initial sub-queries that
reduce the search space significantly**
  - Since the queries are targeted towards
\textquotedblleft search\textquotedblright,
 a small pool of candidate answers will be
easier to validate

- **Gather information about entities to
verify them**
  - Enter the QID on [Wikidata](https://www
.wikidata.org) to get more information
about the answer entity
  - For example, the figure below searches
Q76 to get the information about [Barack
Obama](https://www.wikidata.org/wiki/Q76)

  ![Wikidata Example](https://www.wikidata.
org/static/images/wikidatawiki.png)

  - You can also rely on Google Search to
get more information
  - Utilize the gained information to
determine if the entity correctly satisfies
 the requirements in the given query

- **Evaluate the correctness of the entire
response**
  - If all entities in the given answer
satisfy the query
    - the given answer is **CORRECT**
  - Else
    - the given answer is **INCORRECT**

PLEASE PROVIDE A SHORT RA TIONALE FOR CASES
 WHERE THE ANSWER IS INCORRECT

### EXAMPLE 1:

**Query:**
Which actors appeared in at least one Harry
 Potter film and at least one Marvel
Cinematic Universe film?

**Answer:**
[Kenneth Branagh (Q55294), David Bradley (
Q320073), Toby Jones (Q342419)]

---

**Step 1**

- Kenneth Branagh
  -> Harry Potter Part 2 + Thor
  -> Satisfies query

- David Bradley
  -> multiple Harry Potter films + Captain
America: The First Avenger
  -> Satisfies query

- Toby Jones
  -> multiple Harry Potter films + Captain
America: The First Avenger
  -> Satisfies query

**Step 2**

Given answer is **CORRECT**

### EXAMPLE 2:

**Query:**
Which actors appeared in at least one Harry
 Potter film and at least one Marvel
Cinematic Universe film?

**Answer:**
[Kenneth Branagh (Q55294), David Bradley (
Q320073), Toby Jones (Q342419), Gemma Jones
 (Q234142), Alfred Enoch (Q250250)]

**Step 1**

- Kenneth Branagh
  -> Harry Potter Part 2 + Thor
  -> Satisfies query

- David Bradley
  -> multiple Harry Potter films + Captain
America: The First Avenger
  -> Satisfies query

- Toby Jones
  -> multiple Harry Potter films + Captain
America: The First Avenger
  -> Satisfies query

- Gemma Jones
  -> Does **not** satisfy query
```

```
- Alfred Enoch
  -> Does **not** satisfy query

---

**Step 2**

Given answer is **INCORRECT**

**Rationale:**
Gemma Jones and Alfred Enoch are not in any
 Marvel movie.
```

Figure 10: Human evaluation guidelines for non-ambiguous question and answers.

Ambiguous Question Guidelines

```
# Task Overview
In this task, you will be presented with a
QA pair along with some sample answers (
list of entities).
1. Fluency
2. Correctness
Please read below for a thorough
understanding of each grading metric.

# Query Fluency
Fluency refers to the degree to which the
content reads with ease, resembling natural
 human language. Fluent text will flow
smoothly , sound authentic, and avoid
awkward phrasings or constructions that
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native speaker.

In short, it is the ease and naturalness
with which the text conveys information.

## STEPS
Provided below are some tips in evaluating
the fluency of the text:
+ How well does the text flow?
    - Read the conversation out loud. This
will help you identify any awkward or
unnatural-sounding phrases.
+ How is the sentence structure?
    - Sentences should be structured in a
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 well. It should not sound choppy .
+ How is the vocabulary?
    - The use of appropriate vocabulary can
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    - Words used should be natural to the
target text. If the style and terminology
of the text is not appropriate, it is not
fluent.
+ Stay Objective:
    - Remember, fluency grading is about
the flow of language, not the accuracy of
content or the validity of ideas. Keep
personal biases and content preferences
separate from your fluency assessment.

## GRADING SCALE

Your task is to grade the fluency of the
query only as per the following scale. The
answer does not conform to natural language
 and is hence not graded for fluency.

| Grade | Description | Example |
|--|--|--|
| 3 | The query is fluent and does not
consists of any errors | Which directors
have worked with Saoirse Ronan on two or
more films? |
| 2 | The query is fluent and interpretable
 despite the presence of few gramatical
errors | List all actors that have won an
Oscar award after collaborated with Steven
Spielberg |
| 1 | The query has poor quality i.e. it
does not resemble natural human language |
Saoirse Ronan on two or more films who
directors worked? |

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CONVERSATION FOR FLUENCY. IN ADDITION, DO
NOT DOCK MARKS FOR GRAMMAR (SPELLING,
PUNCTUATION, CAPITALIZATION) OR TENSE
ERRORS UNLESS IT SIGNIFICANTLY IMPACTS
FLUENCY OR OBJECTIVE OF THE QUERY.**


## Disambiguated Entity Helpfulness

The names mentioned in the given query can
be **ambiguous**, where some entity names
have multiple valid interpretations,
e.g. the name *Harry Potter* can refer to a
 book series, a character or a movie series
.

You are provided a query involving
ambiguous names and a list of disambiguated
 entities.
Disambiguated Entity Helpfulness refers to
whether the list of disambiguated entities
are helpful and contribute towards
answering the query i.e. **the entities
contribute to at least one entity in the
final answer.**

## STEPS

Provided below are some tips for evaluating
 the helpfulness:

- **Examine query-oriented details about
each disambiguated entity**
  - Enter the QID on [Wikidata](https://www
.wikidata.org) to get more information
about the answer entity
  - For example, the figure below searches
Q76 to get the information about [Barack
Obama](https://www.wikidata.org/wiki/Q76)

  ![Wikidata Example](https://www.wikidata.
org/static/images/wikidatawiki.png)

  - You can also rely on Google Search and
other trusted websites to get more
information
```

```
- **Utilize the gained information to
determine if the given entity can lead to
the discovery of at least one correct
answer for the given query**

- **Once all entities are evaluated,
evaluate the helpfulness of the entire set
of entities**
  - If all entities in the given answer
satisfy the query
    - the given entity list is **HELPFUL**
  - Else
    - the given entity list is **UNHELPFUL
**

---

**PLEASE PROVIDE A SHORT RATIONALE FOR
CASES WHERE THE ENTITY LIST IS UNHELPFUL**

### EXAMPLE 1:

**Query:**
For the film King Kong, which actors later
starred in superhero movies?

---

**Disambiguated Entity List:**
- King Kong (2005 film) Q160215
- King Kong (1976 film) Q1142862

---

**Step 1**

- King Kong (2005 film)
  -> stars Andy Serkis who was in *"The
Batman 2002"*
  -> Leads to at least 1 answer entity

- King Kong (1976 film)
  -> stars Jeff Bridges who was in *"Iron
Man 2008"*
  -> Leads to at least 1 answer entity

---

**Step 2**

Given entity list is **HELPFUL**

### EXAMPLE 2:

**Query:**
For the film King Kong, which actors later
starred in superhero movies?

---

**Disambiguated Entity List:**
- King Kong (2005 film) Q160215
- King Kong (1976 film) Q1142862
- King Kong (1933 film) Q309048

---

**Step 1**

- King Kong (2005 film)
  -> stars Andy Serkis who was in *"The
Batman 2002"*
  -> Leads to at least 1 answer entity

- King Kong (1976 film)
  -> stars Jeff Bridges who was in *"Iron
Man 2008"*
  -> Leads to at least 1 answer entity

- King Kong (1933 film)
  -> no actors star in a superhero movie
  -> Does **not** lead to any answer entity

---

**Step 2**

Given entity list is **UNHELPFUL**

**Rationale:**
King Kong (1933 film) entity does not
contribute to the final answer.
```

Figure 11: Human evaluation guidelines for ambiguous question and answers.

A.4 Artifact License

In this section, we detail the licenses of the artifacts involved in this work, such as the Wikidata dataset and the licenses for LLMs we evaluated.

Table 7: Licenses of used artifacts in this paper.

Artifact	License
Wikipedia dump	CC-BY-SA License[5]
Qwen2.5 series	Qwen Research License[6]
Qwen3 series	Apache License[7]
DeepSeek-R1-Distill-Qwen series	MIT License[8]

A.5 Inference Hyper-parameter

We employ the same set of hyper-parameters for LLM inference and retrieval in all experiments. Specifically, we employ `e5-base` as the embedding model for dense retrieval following previous works (Jin et al., 2025), and retrieve 15 passages in each LLM tool call. For LLM inference, we use default parameters for all models with temperature 1.0 in answer sampling.

[5] https://en.wikipedia.org/wiki/Wikipedia:Database_download

[6] https://huggingface.co/Qwen/Qwen2.5-3B-Instruct/blob/main/LICENSE

[7] https://huggingface.co/Qwen/Qwen3-4B/blob/main/LICENSE

[8] https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Qwen-1.5B/blob/main/LICENSE

Model	Baseline			+ Expansion			+ Extraction			+ KG Tool		
	P	R	EM	P	R	EM	P	R	EM	P	R	EM
GPT-4o-mini	0.84/0.83	0.52/0.33	0.11/0.03	0.87/0.84	0.51/0.42	0.09/0.08	0.85/0.85	0.58/0.37	0.13/0.05	0.12/0.06	0.14/0.07	0.01/0.00
GPT-4o	0.91/0.84	0.57/0.41	0.14/0.05	0.90/0.88	0.60/0.48	0.15/0.08	0.92/0.87	0.55/0.44	0.15/0.07	0.24/0.10	0.18/0.08	0.02/0.01
GPT-5-mini	0.90/0.87	0.64/0.44	0.16/0.09	0.91/0.89	0.67/0.54	0.17/0.14	0.92/0.89	0.69/0.48	0.18/0.10	0.25/0.11	0.22/0.10	0.02/0.01
GPT-5	0.93/0.91	0.71/0.48	0.21/0.13	0.93/0.90	0.74/0.61	0.23/0.18	0.94/0.91	0.73/0.52	0.19/0.13	0.30/0.14	0.28/0.12	0.03/0.02
Qwen2.5-3B	0.82/0.78	0.34/0.17	0.03/0.01	0.84/0.78	0.31/0.18	0.04/0.03	0.83/0.81	0.37/0.19	0.04/0.04	0.08/0.03	0.10/0.04	0.00/0.00
Qwen2.5-7B	0.83/0.80	0.40/0.21	0.05/0.01	0.86/0.82	0.44/0.25	0.08/0.04	0.85/0.80	0.45/0.27	0.09/0.04	0.15/0.05	0.12/0.05	0.01/0.00
Qwen3-4B	0.84/0.84	0.45/0.25	0.07/0.03	0.85/0.78	0.47/0.29	0.09/0.06	0.88/0.79	0.48/0.28	0.08/0.06	0.18/0.07	0.14/0.06	0.01/0.00
Qwen3-8B	0.84/0.85	0.55/0.39	0.12/0.05	0.88/0.84	0.54/0.42	0.14/0.07	0.81/0.82	0.59/0.42	0.14/0.06	0.22/0.08	0.20/0.08	0.02/0.01
DS-R1-Distill-1.5B	0.73/0.74	0.33/0.08	0.02/0.01	0.82/0.74	0.35/0.13	0.03/0.03	0.77/0.76	0.39/0.12	0.03/0.03	0.05/0.02	0.08/0.03	0.00/0.00
DS-R1-Distill-7B	0.82/0.79	0.51/0.14	0.06/0.02	0.85/0.78	0.54/0.15	0.08/0.04	0.83/0.79	0.54/0.17	0.07/0.03	0.12/0.04	0.11/0.04	0.01/0.00

Table 8: Impact of query expansion and evidence extraction on DEEPAMBIGQA performance. We report the performance on the non-ambiguous question subset and the ambiguous question subset side-by-side (non-ambiguous / ambiguous).

B Additional Experiment Results

B.1 Additional Module Performance

Table 8 presents the detailed experiment results of the introduced additional modules and compare with the baseline system performance. The performance of non-ambiguous question and ambiguous question subset are listed side-by-side.

For the query expansion and key information extraction module, we implement them as fixed LLM call to the base LLM in the system during the answering process, where the detailed prompts are listed in Figure 21 and 20, respectively. For the KG tool module, we implement it as another alternative tool in reasoning process and correspondingly modify the system prompt of the LLM, which is listed in Figure 19.

B.2 LLM-Agent Performance on DEEPAMBIGQA

In the main paper, we mainly involve SPARQL query as an additional tool for LLM during reasoning. To ensure the completeness of our evaluation, we further consider LLM-agent framework involving WikiSPARQL query. Specifically, we evaluate SPINACH agent using its official tool interface (Liu et al., 2024) on our DEEPAMBIGQA, where the LLM can issue multiple KG-related tool calls such as `search_wikidata(string)` and `get_wikidata_entry(QID)` during inference. Table 9 reports precision, recall, and exact match on both subsets.

We highlight that while SPINACH agent outperforms the simple KG tool used in our initial experiments (Table 5 in main paper), its overall performance remains limited. In particular, on the ambiguous-question subset, the exact-match scores are below 0.1 across all LLM backbones. This gap stems largely from the LLMs' difficulty with entity disambiguation, which is critical for resolving ambiguity in our benchmark. Moreover, we find that many errors for SPINACH agents can be attributed to the high failure rate of Wikidata queries, where the LLMs frequently generate invalid SPARQL programs, an issue also noted in the original SPINACH paper.

Model	**Non-Ambig. Question**			**Ambig. Question**		
	P	R	EM	P	R	EM
Qwen3-4B	0.15	0.07	0.01	0.15	0.03	0.00
Qwen3-8B	0.28	0.11	0.05	0.21	0.04	0.02
DS-R1-distill-7B	0.14	0.06	0.02	0.11	0.02	0.00
GPT-5-mini	0.59	0.10	0.15	0.55	0.05	0.02
GPT-5	0.63	0.25	0.22	0.57	0.17	0.09

Table 9: SPINACH agent performance on DEEPAMBIGQA.

B.3 Inference Examples

In this section, we include example questions generated in our dataset and the responses from various LLMs to it.

Listing 1: Example final responses from various LLMs to a non-ambiguous query. We exclude the intermediate search and reasoning to reduce context.

Question

```
Which actors have appeared in at least
three Quentin Tarantino feature films?
```

Qwen2.5-7B-Instruct Response

```
{
  "reasoning": "To determine which
     actors have appeared in at least
     three Quentin Tarantino feature
     films, I need to consider all of
     Tarantino's feature films and track
     the actors' appearances across
     them. Specific films and their
     casts from Quentin Tarantino's body
     of work would be analyzed to
     identify those who appear in at
     least three of his features.",
  "answers": {
    "tarantino\_top\_actors": ["Bruce
     Davison", "Tim Roth", "Michael
     Parks"]
  }
}
```

Qwen3-4B Response

```
{
  "reasoning": "The task requires
     identifying actors who appeared in
     at least three of Quentin
     Tarantino's feature films. By
     analyzing his major films
     (Reservoir Dogs, Pulp Fiction,
     Jackie Brown, Kill Bill: Vol. 1,
     Kill Bill: Vol. 2, The Hateful
     Eight, Django Unchained), key
     actors who recur across multiple
     films were identified. Samuel L.
     Jackson and others appear in
     multiple films, while Christian
     Slater, Uma Thurman, and others are
     confirmed in three or more.",
  "answers": {
    "default": [
      "Samuel L. Jackson",
      "Christian Slater",
      "Uma Thurman",
      "Harvey Keitel",
      "Steve Buscemi",
      "Bruce Willis",
      "David Carabelli",
      "Tom Sandoval"
    ]
  }
}
```

GPT-4o-mini Response

```
{
  "reasoning": "The question seeks to
     identify actors who have frequently
     collaborated with Quentin Tarantino
     in his feature films, focusing on
     those with at least three
     appearances.",
  "answers": {
    "default": ["Samuel L. Jackson",
     "Tim Roth", "Kurt Russell", "Uma
     Thurman"]
  }
}
```

GPT-4o Response

```
{
  "reasoning": "To answer this
     question, I considered actors who
     have frequently collaborated with
     Quentin Tarantino in his various
     feature films, identifying those
     with at least three appearances.",
  "answers": {
    "default": [
      "Samuel L. Jackson",
      "Tim Roth",
      "Michael Madsen"
    ]
  }
}
```

GPT-5-mini Response


```
{
  "reasoning": "The question asks about
     actors who have appeared in at
     least three Quentin
     Tarantino-directed feature films.
     Tarantino frequently reuses certain
     actors across his movies. Based on
     his filmography, key recurring
     collaborators include Samuel L.
     Jackson, Uma Thurman, Tim Roth,
     Harvey Keitel, Michael Madsen, and
     Leonardo DiCaprio, among others.
     These actors have each appeared in
     three or more of his films, making
     them the correct answers.",
  "answers": {
    "default": [
      "Samuel L. Jackson",
      "Uma Thurman",
      "Tim Roth",
      "Harvey Keitel",
      "Michael Madsen",
      "Christoph Waltz",
      "Kurt Russell",
      "Bruce Dern",
      "Leonardo DiCaprio"
    ]
  }
}
```


GPT-5 Response


```
{
"reasoning": "Interpreted as: actors
     who appeared (on-screen or voice,
     credited or uncredited) in at least
     three theatrically released feature
     films directed by Quentin
     Tarantino. There's minor ambiguity
     about whether to count Kill Bill's
     two volumes separately and whether
     to exclude uncredited voice-only
     cameos, so I provide both a
     standard list and a stricter
     alternative.",
"answers": {
"default": [
    "Samuel L. Jackson",
    "Uma Thurman",
    "Tim Roth",
    "Michael Madsen",
    "Kurt Russell",
    "Zoe Bell",
    "Harvey Keitel",
    "Bruce Dern",
    "James Parks",
    "Michael Parks",
    "Keith Jefferson",
    "Quentin Tarantino",
    "Craig Stark"
],
"counting\_kill\_bill\_as\_one\_and\_excluding\_uncredited\_v
    [
    "Samuel L. Jackson",
    "Tim Roth",
    "Michael Madsen",
    "Kurt Russell",
    "Zoe Bell",
    "Bruce Dern",
    "James Parks",
    "Keith Jefferson",
    "Quentin Tarantino",
    "Craig Stark"
    ]
}
}
```


Listing 2: Example final responses from various LLMs to an ambiguous query. We exclude the intermediate search and reasoning to reduce context.

Question

Among the actors of the film The Island, who have been nominated for at least one Academy Award?

Qwen2.5-7B Response


```
{
    "reasoning": "Multiple films are
    titled "The Island," notably the
    2005 Michael Bay movie and the 1980
    adaptation starring Michael Caine.
    With no year provided, I choose the
    1980 film and list actors from that
    cast who have Academy Award
    nominations. I restrict the output
    to performers appearing in that
    version.",
    "answers": {
        "default": ["Michael Caine"]
    }
}
```


Qwen3-4B Response


```
{
    "reasoning": "Given the phrasing, I
    interpret the prompt as referring
    to the widely discussed
    psychological thriller "Shutter
    Island" (2010). I then enumerate
    the actors from that film who have
    at least one Academy Award
    nomination. The list focuses on the
    most prominent credited
    performers.",
    "answers": {
        "default": ["Leonardo
    DiCaprio", "Mark Ruffalo", "Ben
    Kingsley", "Michelle Williams"]
    }
}
```


GPT-4o-mini Response


```
{
  "reasoning": "The query refers to the
     film 'The Island,' released in
     2005, and I assumed it was relevant
     to identify actors who have
     received Academy Award nominations.
     I considered the main cast and
     determined which actors among them
     have received nominations based on
     their filmography.",
  "answers": {
    "default": [
      "Ewan McGregor",
      "Scarlett Johansson"
    ]
  }
}
```


GPT-4o Response


```
{
"reasoning": "To find actors from the
     film 'The Island' who have received
     Academy Award nominations, I
     examined the main cast for any who
     have such recognition. Ewan
     McGregor and Scarlett Johansson,
     both stars of 'The Island', have
     been nominated for Oscars.",
"answers": {
    "default": [
    "Ewan McGregor",
    "Scarlett Johansson"
    ]
}
}
```


GPT-5-mini Response


```
{
  "reasoning": "The title \"The
     Island\" refers to multiple films;
     I interpret the question as
     ambiguous and therefore list actors
     with Academy Award nominations from
     the most commonly referenced films
     titled "The Island" (the 2005
     Hollywood scifi and the 1980
     adventure film) and also note the
     2006 Russian film. I relied on
     wellknown cast lists and each
     actor's Academy Award nomination
     history from memory.",
  "answers": {
    "The Island (2005 film)": [
      "Scarlett Johansson",
      "Djimon Hounsou",
      "Michael Clarke Duncan"
    ],
    "The Island (1980 film)": [
      "Michael Caine"
    ],
    "The Island (2006 Russian film)": []
  }
}
```

GPT-5 Response


```
{
    "reasoning": "The title 'The
    Island' is ambiguous; the most
    widely known is the 2005 Michael
    Bay film, but there's also a 1980
    film with the same name. I list the
    actors from each version who have
    documented Academy Award
    nominations.",
    "answers": {
        "The Island (2005 film)": [
        "Scarlett Johansson",
        "Djimon Hounsou",
        "Michael Clarke Duncan"
    ],
    "The Island (1980 film)": [
        "Michael Caine"
    ]
    }
}
```

C Prompts

In this section, we list all prompts employed in this work, involving the prompt for question synthesis in Section C.1, and the one for inference in Section C.2.

C.1 Prompts for QA Synthesis

Below, we include all detailed prompts in the order the question syntheseis pipeline, including question template realization prompt in Figure 12, question template validity filtering prompt in Figure 13, question template to natural language question prompt in Figure 14, and final question with answer validity filtering prompt in Figure 15.

```
You are an expert Wikidata assistant that
only returns valid JSON. For every entity
placeholder you must choose the best-
matching candidate id from the provided
options, prioritizing entities that make
the template semantically correct. For
every literal/value placeholder, supply a
concrete value that is realistic and likely
 to yield a valid answer when the template
is executed. Never invent new entity ids
and respond with the JSON object only.
```

Figure 12: System prompt for question template placeholder initialization.

```
You are an expert AI assistant specializing
 in evaluating the feasibility and semantic
 validity of query templates. Templates may
 be presented as a step-by-step plan (
sometimes alongside other context). Your
task is to classify the template into one
of two categories: "Valid" or "Invalid".

A "Valid" template meets the following
criteria:
- It represents a plausible information
need that a real user might have.
- It requires non-trivial reasoning, such
as multi-hop exploration, joins,
comparisons, or filtering based on specific
 criteria.
- The operations in the step-by-step plan
are logically sound and the sequence can
reasonably be executed against a knowledge
base to return a meaningful answer set.

An "Invalid" template meets one or more of
the following criteria:
- It represents an unrealistic or
nonsensical user intent, such as find all
directors born in 1900, which is too broad.
- The logic is flawed, contradictory, or
skips required connections between steps.
- It is unexecutable at scale or
underspecified such that no meaningful
results would be returned.

When a step-by-step plan is provided,
evaluate each step to ensure it follows
from the previous ones, uses the available
variables, and leads toward the stated goal
. Call out gaps such as undefined inputs,
impossible filters, or missing joins.

Analyze the provided template carefully and
 then output your classification as a
single word: "Valid" or "Invalid".

---
**Example 1: Valid**

Step-by-step Plan:
```
Goal: Find science fiction films directed
by {SUBJECT_PERSON} that are recent.
1. Retrieve films directed by {
SUBJECT_PERSON}.
2. Keep only the science fiction films.
3. Keep the films published after {
VALUE_YEAR}.
```

Your analysis: The plan is coherent and
each step is executable: start from a
director placeholder representing a person,
 then filter by genre and release year.
This aligns with a realistic user need and
requires multi-step reasoning.
Classification:
Valid

---
**Example 2: Invalid**

Step-by-step Plan:
```
Goal: Find people connected to {
VALUE_COUNTRY}.
1. List all people related to {
VALUE_COUNTRY}.
```

Your analysis: The request is too broad and
 lacks additional constraints. Listing all
people related to a large country is
infeasible and does not represent a
meaningful intent.
Classification:
Invalid

---
**Example 3: Invalid**

Step-by-step Plan:
```
Goal: Find recent albums made by young {
SUBJECT_AWARD} nominees.
1. Retrieve nominees for {SUBJECT_AWARD}.
2. Keep nominees younger than {
VALUE_MAX_AGE}.
3. Find albums recorded after {VALUE_YEAR}.
```
```

```
```

Your analysis: Step 3 suddenly refers to albums without specifying how the nominees connect to the album records; the relation is missing from the plan. Without a join step, the query cannot be executed reliably.
Classification:
Invalid

Now, please classify the following template and provide your analysis in the following format:
Analysis: [your analysis]
Classification: [your classification]
```

Figure 13: System prompt for question template feasibility classification.

```
You are an expert language designer for complex question-answering benchmarks. Each record you receive contains a step-by-step plan produced by the pipeline that describes how a knowledge query was executed.

Your job is to understand the plan and produce a human-oriented question whose answer matches the final step's output.

Workflow and guidelines:
- **Analysis:** Briefly explain (one or two sentences) how the plan achieves its goal, referencing the crucial steps and confirming what the final step returns.
- **Question:** Write a single, fluent sentence that asks for exactly the information produced by the final step. Ensure the wording sounds natural and conversational. Use only the concrete names, literals, or dates mentioned in the plan. Never invent new entities or alter relationships.
- Follow the plan's sequence and intent. Do not introduce additional steps, entities, or relationships. Ignore intermediate outputs unless they support the final result.
- Avoid template syntax, placeholders, or bracketed tokens. Keep the wording concise and natural.
- Always respond in exactly two sections, labelled `Analysis:` and `Question:`.

Example 1
Step-by-step Plan:
```
1. Find companies where Steven Levitan is a board member.
2. Find the chief executive officers of step 1 result.
```
Response:
```
Analysis: Step 1 identifies the companies that have Steven Levitan on their boards, and step 2 pulls the chief executives of those companies, so the answer must be those CEOs.
Question: Which chief executives lead the companies where Steven Levitan serves on the board?
```

Example 2
Step-by-step Plan:
```
1. Find the films directed by Christopher Nolan.
2. Find the films scored by Hans Zimmer.
3. Take the intersection of the results from steps 1 and 2.
4. For the films from step 3, find all actors.
5. Group step 4 result by entity and calculate count.
6. Filter step 5 result where count is at least 4.
```
Response:
```
Analysis: The plan narrows down to films made by both Christopher Nolan and Hans Zimmer, then counts actors and keeps only those appearing in four or more of those collaborations, so the final output is the set of actors meeting that frequency.
Question: Among the movies collaborated on by Hans Zimmer and Christopher Nolan, which actors appeared at least four times?
```

Always produce both sections in this order.
```

Figure 14: System prompt for template-to-question authoring.

```
You are an expert quality reviewer for complex question-answering datasets. Each record contains a natural language question, the step-by-step plan used to answer it, and the final answer set. Your goal is to decide whether these elements are coherent and mutually consistent, and then classify the record as either "Valid" or "Invalid".

Classify a record as "Valid" when:
- The question and the plan express the same information need.
- The plan is logically sound and could be executed to answer the question.
- The final answers are appropriate for the question and follow from the plan.

Classify a record as "Invalid" when:
```
```

```
- The question and the plan diverge or
contradict one another.
- The plan omits key operations, introduces
 impossible steps, or otherwise cannot
solve the question.
- The final answers do not satisfy the
question or conflict with the plan.

Provide a short analysis explaining your
reasoning before issuing the classification
.

---
**Example 1: Valid**
Question:
```
Which Nobel Prize in Literature laureates
were born in Japan?
```
Step-by-step Plan:
```
1. List all recipients of the Nobel Prize
in Literature.
2. Keep the laureates whose country of
birth is Japan.
```
Final Answer Set:
```
- Yasunari Kawabata
- Kenzaburo Oe
```
Your analysis: The plan mirrors the
question's intent-identify Nobel literature
 laureates and filter by Japanese birth.
The answers list the expected Japanese
laureates, so the record is coherent.
Classification:
Valid

---
**Example 2: Invalid**
Question:
```
What science fiction films has Tom Hanks
directed?
```
Step-by-step Plan:
```
1. Retrieve awards received by Tom Hanks.
2. Keep the winners from step 1.
```
Final Answer Set:
```
- Academy Award for Best Actor
- Golden Globe Award for Best Actor -
Motion Picture Drama
- Saturn Award for Best Actor
```
Your analysis: The plan retrieves awards,
not films, and the answers are award titles
 rather than movies. The question, plan,
and answers do not align.
Classification:
Invalid

---
**Example 3: Invalid**
Question:
```
List the Premier League teams that Sir Alex
 Ferguson has managed.
```
Step-by-step Plan:
```
1. Find clubs managed by Sir Alex Ferguson.
2. Keep the teams whose league is the
Premier League.
```
Final Answer Set:
```
- Q484841
- Ryan Giggs
- Paul Scholes
- Gary Neville
```
Your analysis: The question specifically
asks for Premier League teams, but the
answer set includes players and an
identifier instead. This indicates a
fundamental misunderstanding in the plan's
execution, leading to an invalid record.
Classification:
Invalid

---
Return your verdict using the format:
Analysis: [your reasoning]
Classification: [Valid or Invalid]
```

Figure 15: System prompt for question feasibility review.

C.2 Prompts for QA inference

Below we inlucde all detailed prompts employed in question inference pipeline, including the prompt for QA system with or without search tool in Figure 16 and Figure 17. We also include the QA system prompt with additional modules such as the one with query ambiguity expansion in Figure 18 and knowledge graph query in Figure 19. The prompt for additional modules like the key information extraction and query ambiguity expansion are shown in Figure 20 and Figure 21, respectively.

```
## Task Description
You answer knowledge queries directly using
 your own knowledge.

## Response Structure
- "reasoning": Offer a brief narrative (two
 to four sentences) describing how you
interpreted the request, including any
clarifications, assumptions, or competing
readings, and the evidence you relied on.
- "answers": A dictionary containing one or
 more sets of possible answers.
  - If the question has a single clear
interpretation, provide one key (e.g., "
default") mapping to a list of unique
```

```
answer entities.
  - When multiple readings stay plausible,
return **separate keys** named after each
interpretation (e.g., a title, year, or
distinguishing attribute) and list the
entities associated with that reading.

### Examples
**Example 1 - Single Interpretation**
Question: "Who directed the film
Interstellar?"
{
  "reasoning": "The query points to the
2014 science-fiction film 'Interstellar';
production notes and release coverage
consistently credit Christopher Nolan as
its director, so I return his name as the
sole answer.",
  "answers": {
    "default": ["Christopher Nolan"]
  }
}

**Example 2 - Multiple Interpretations**
Question: "Who directed the film King Kong
released after 1970?"
{
  "reasoning": "Two films titled 'King Kong
' premiered after 1970, so I list the
director credited on the 1976 release and
the director credited on the 2005 release
.",
  "answers": {
    "King Kong (1976 film)": ["John
Guillermin"],
    "King Kong (2005 film)": ["Peter
Jackson"]
  }
}

Follow this schema exactly. Do not include
extra top-level keys or commentary outside
the JSON object.
```

Figure 16: System prompt for direct answering (no retrieval).

```
## Task Description
You answer knowledge queries with access to
 a local retrieval tool. Use it as needed
to gather supporting passages before
forming your response.

## Response Structure
- `"reasoning"`: Describe how you
interpreted the request, what evidence you
retrieved, and how that evidence led to the
 final answer. Acknowledge alternate
readings only when they materially affect
the outcome, and make sure the narrative
references the sources you consulted.
- `"answers"`: A dictionary containing one
or more sets of possible answers.
  - If the query has a single clear reading
, return one key (e.g., `"default"`) that
maps to a list of unique answer entities.
  - When multiple readings remain plausible
, add **separate keys** named after each
interpretation (such as a title, year, or
other distinguishing attribute) instead of
numbered placeholders, and list the
entities that satisfy each interpretation.

## Available Tools
- `local_retriever(query: str, k: int = 3)
`: Search the local document store for
supporting passages. `query` is the search
string. `k` controls how many results to
return (optional, defaults to 3).

Call the tool as many times as needed
before finalizing your answer, and ground
your reasoning in what you retrieved.

## Example Format
```json
{
  "reasoning": "The documents I retrieved
describe ...",
  "answers": {
    "<descriptive label>": ["Entity_A", "
Entity_B"],
    "<another label>": ["Entity_C"]
  }
}
```

Examples
Example 1 - Single Interpretation
Question: "Who directed the film
Interstellar?"
{
  "reasoning": "The passages retrieved from
 production notes and film databases
consistently describe the 2014 release of '
Interstellar' and credit Christopher Nolan
as its director, so I treat the query as a
single interpretation and return his name
.",
  "answers": {
    "default": ["Christopher Nolan"]
  }
}

Example 2 - Multiple Interpretations
Question: "Who directed the film King Kong
released after 1970?"
{
  "reasoning": "Retrieval brings back
separate entries for the 1976 and 2005
films titled 'King Kong'; reading those
articles confirms John Guillermin directed
the 1976 remake while Peter Jackson led the
 2005 version, so I report both
interpretations.",
  "answers": {
    "King Kong (1976 film)": ["John
Guillermin"],
    "King Kong (2005 film)": ["Peter
Jackson"]
  }
}
```

Figure 17: System prompt for search-based answering.

```
## Task Description
You answer a knowledge query together with
any expanded variants you receive. Treat
each expansion as its own sub-question
while keeping the original request in view.

## Response Structure
- `"reasoning"`: Write a short narrative (
two to five sentences) explaining how you
interpreted the main question, how each
expansion (if any) influenced your search,
what evidence you retrieved, and how that
evidence supports the conclusions.
- `"answers"`: A dictionary containing one
or more sets of possible answers.
  - If the input provides no expansions and
 the question has a single clear reading,
return exactly one key (e.g., `"default"`)
mapping to the answer entities.
  - When expansions are supplied, answer
each of them explicitly: add one key per
expansion, using the exact text of that
expansion as the key, and list the entities
 (or short answers) that satisfy it. Do not
 invent additional keys or reuse generic
labels.

## Available Tools
- `local_retriever(query: str, k: int = 3)
`: Search the local document store for
supporting passages. `query` is the search
string. `k` controls how many results to
return (optional, defaults to 3).

Call the retriever as often as needed and
be explicit about how the retrieved
passages inform each answer set.

## Example Format
```json
{
  "reasoning": "I ran separate searches for
 ...",
  "answers": {
    "<exact expansion text or default>": ["
Entity_A"],
    "<another expansion>": ["Entity_B", "
Entity_C"]
  }
}
```

Examples
**Example 1 - Single Interpretation (No
Expansions)**
Question: "Who directed the film
Interstellar?"
Expansions: (none)
{
  "reasoning": "The passages I pulled about
 the 2014 film 'Interstellar' all credit
Christopher Nolan, so with no additional
sub-questions I return his name as the lone
 answer.",
  "answers": {
    "default": ["Christopher Nolan"]
  }
}

Example 2 - Multiple Expansions
Question: "Who directed the film King Kong
released after 1970?"
Expansions:
- "Who directed the 1976 remake?"
- "Who directed the 2005 remake?"
{
  "reasoning": "The retriever surfaces
separate coverage for the 1976 and 2005 '
King Kong' releases; I associate each
expansion with the relevant article and
report the credited director for that film
.",
  "answers": {
    "Who directed the 1976 remake?": ["John
 Guillermin"],
    "Who directed the 2005 remake?": ["
Peter Jackson"]
  }
}
```

Figure 18: System prompt for search with expansion.

```
## Task Description
You answer knowledge queries with access to
 both a local retriever and a Wikidata
SPARQL endpoint. Use whichever combination
of tools is needed to gather trustworthy
evidence before responding.

## Response Structure
- `"reasoning"`: Provide a concise but
informative narrative (two to five
sentences) that explains how you
interpreted the query, which tool calls you
 made (retrieval and/or SPARQL), what each
returned, and how that evidence supports
the final answer.
- `"answers"`: A dictionary containing one
or more sets of possible answers.
  - When the query has a single obvious
reading, return one key (e.g., `"default"`)
 with a list of unique entities.
  - If multiple readings stay viable, add
**separate keys** named after each
interpretation (such as a title, year, or
other distinguishing attribute) and list
the entities that satisfy each one.

## Available Tools
- `local_retriever(query: str, k: int = 3)
`: Search the local document store for
supporting passages. `query` is the search
string. `k` controls how many results to
return (optional, defaults to 3).
- `wikisparql(query: str)`: Execute a
SPARQL query against Wikidata. `query` must
 be a valid SPARQL statement; the tool
```

````
returns the JSON payload from the endpoint.

Call the tools as many times as helpful,
and tie your reasoning explicitly to the
retrieved text or structured results.

## Example Format
```json
{
  "reasoning": "I retrieved ... and
confirmed via SPARQL ...",
  "answers": {
    "<descriptive label>": ["Entity_A"],
    "<another label>": ["Entity_B"]
  }
}
```

### Examples
**Example 1 - Single Interpretation**
Question: "Who directed the film
Interstellar?"
{
  "reasoning": "Local retrieval surfaces
reviews and production data for the 2014
film 'Interstellar', and a confirming
SPARQL query on the film entity lists
Christopher Nolan as director, so I return
his name as the lone answer.",
  "answers": {
    "default": ["Christopher Nolan"]
  }
}

**Example 2 - Multiple Interpretations**
Question: "Who directed the film King Kong
released after 1970?"
{
  "reasoning": "Evidence searches show two
post-1970 films titled 'King Kong'; follow-
up SPARQL lookups on each film entity
confirm John Guillermin directed the 1976
title and Peter Jackson directed the 2005
remake, so I provide both interpretations
.",
  "answers": {
    "King Kong (1976 film)": ["John
Guillermin"],
    "King Kong (2005 film)": ["Peter
Jackson"]
  }
}
````

Figure 19: System prompt for knowledge graph query.

```
You are an evidence extractor that works
directly from a passage to help answer a
question.

Output requirements:
- Return only the verbatim passage spans
that support the answer.
- Write each supporting quote on its own
line.
- Do not add numbering, bullets, commentary
, or extra whitespace.
- Preserve the original casing and
punctuation (trim surrounding whitespace
only).
- If no passage text helps answer the
question, respond with the single token:
NONE
    (uppercase, no quotes).
```

Figure 20: System prompt for evidence extraction.

```
You are given a short user query. Rewrite
the query into several more detailed and
specific variations that provide additional
 context, clarify ambiguity, and include
relevant background information.

* Use only the original query as input - do
 not ask for clarification or request
additional information from the user.
* Use your own knowledge to add relevant
context, clarify ambiguities, and consider
possible disambiguations (e.g., a name
might refer to multiple people, places,
works, or concepts).
* Include relevant background information
retrieved from your own knowledge.
* Do not introduce new question types or
angles beyond the original query. Avoid
adding requests for analysis, explanation
of significance, causes, effects, or
opinions. Keep the question scope the same
as the original.
* Based on your knowledge, provide all
reasonable interpretations of the original
query and output them in seperate lines.
* Ensure each expanded query is clear,
specific, and self-contained.


Input:
<original_query>

Output:
Expanded query 1
Expanded query 2
Expanded query 3
```

Figure 21: System prompt for query expansion.