KAG: Boosting LLMs in Professional Domains via Knowledge Augmented Generation

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Abstract

The recently developed retrieval-augmented generation (RAG) technology enables the efficient construction of domain-specific applications. However, it faces limitations due to fuzzy retrieval processes, the "hallucination" problem of understanding and reasoning capabilities of general language models, and cascading losses in complex systems. These challenges hinder the effectiveness of specialized knowledge services. However, in scenarios such as scientific computing, medicine, and law, the accuracy of knowledge, the completeness of information, and the logical rigor of rules, time, and values are particularly critical. We Introduce professional domain knowledge service framework: Knowledge Augmented Generation(KAG) to improve generation and reasoning performance by bidirectionally enhancing large language model(LLM)s and knowledge graph(KG)s, including five key enhancements: 1) LLM-friendly knowledge semantic representation, 2) mutual indexing between knowledge graph and original chunks, 3) logicalform-guided hybrid reasoning and solving, 4) Knowledge alignment based on semantic reasoning, 5) Model for KAG. We compared KAG with existing RAG methods in multi-hop question answering. The results show that KAG performs significantly better than the state-of-the-art methods, with a relative improvement from 19.6% to 33.4% in F1. We apply KAG to two professional knowledge Q&A tasks of Ant Group, including E-Government Q&A and E-Health Q&A, and has achieved significant improvement in professionalism compared with NaiveRAG. We will soon natively support KAG on the open source KG engine OpenSPG, allowing developers to more easily build rigorous knowledge decision-making or convenient information retrieval services.

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1 Introduction

Recently, the rapidly developing Retrieval-Augmented Generation (RAG)[1, 2, 3, 4, 5] technology, which utilizes external retrieval systems, has effectively improved the timeliness of large language models in acquiring task information and reduced the hallucination of answers. This allows for the efficient construction of applications in specific domains. However, general RAG is still constrained by the ambiguity of retrieval, the "hallucination" problem of the understanding and reasoning capabilities of general language models, and the cascading losses of complex systems. These issues hinder the professionalism of knowledge services, especially in fields such as law, healthcare, and scientific computing. To address these problems, Knowledge Graph, as a precise knowledge reasoning technology, are increasingly being integrated into the RAG framework. HippoRAG[6], DALK[7], and ToG 2.0[8] innovatively use triple-based inverted index to replace term-based inverted index, improving the indexing structure of documents, and making full use of graph computing related technologies to support document retrieval or summary aggregation.

Although these works organize documents using graph structures, allowing the system to perform better in multi-hop reasoning tasks, they still do not fully apply the specialized knowledge management capabilities of KGs to the system. This is reflected in the following aspects:

- Compared with the knowledge graph constructed by domain experts, the automatically constructed structured knowledge only contains fragmented information from the document and lacks domain knowledge that is not mentioned in the documents. This missing domain knowledge serves as an intrinsic connection between document information and user queries, affecting the accuracy of problem-solving. For example, "industrial insurance", "unemployment insurance", and "housing provident fund" all fall under the category of "five insurances and one fund", but they might not be explicitly mentioned in the egovernment service documentation. Consequently, when querying "five insurances and one fund", it may fail to retrieve the correct answer.
- The graph structure constructed through OpenIE does not explicitly obtain classification, context and other information, which introduces a lot of noise, including polysemy, synonyms, differences in word granularity, sparse relationships, etc., which brings great challenges to both reasoning and retrieval, and also reduces the accuracy of retrieval.
- The professional domain is highly sensitive to rules, numerical values, time, coordinates, numerical logic, or causal logic. For example, when analyzing data from sources like corporate financial reports, medical test results, or case descriptions to generate analytical messages or answer queries, it is necessary to capture one or a set of key metrics. This involves determining whether these metrics are showing an increasing or decreasing trend in chronological or distance order, and whether the magnitude of these changes exceeds normal fluctuation ranges. It is also important to identify potential causes of abnormal indicators and their possible impacts. These logical connections are intricately linked, and a small error can lead to significant misinterpretations. Therefore, there is a need for a mechanism or systematic language for the representation, retrieval, and controllable generation of professional logic.
- The processes of index construction, inference retrieval, and answer generation pose challenges to the capabilities of the LLM models upon which the system relies.

To address the above challenges and meet the requirements of professional domain knowledge services, we hope to fully combine the complementary features of RAG and KG technologies, and then simultaneously utilize the understanding and generation capabilities of LLMs to improve the professional level of vertical domain knowledge services. In this paper, we propose a professional domain knowledge service framework: **Knowledge Augmented Generation**(**KAG**) to improve generation and reasoning performance by bidirectionally enhancing large language LLM and KG. As shown in Figure 1. We summarize our main contributions as follows:

We proposed a LLM friendly knowledge representation framework LLMFriSPG. We
refer to the hierarchical structure of data, information, and knowledge of DIKW to upgrade
SPG to be friendly to LLMs, named LLMFriSPG, to make it compatible with schemafree information extraction and schema-constrained expert knowledge construction on the
same knowledge type (such as entity type, event type), and supports the mutual indexing

representation between graph structure and original text chunks, which facilitates the construction of graph-structure-based inverted index and facilitates the unified representation, reasoning, and retrieval of logical form.

- We proposed a logical-form-guided hybrid solving and reasoning engine. It includes two types of operators: reasoning and retrieval, transforming natural language questions into a problem-solving process that combines language and symbols. Each step in the process can utilize different operators such as exact match retrieval, text retrieval, numerical computation, or semantic reasoning, thereby achieving the integration of four distinct problem-solving processes: retrieval, KG reasoning, language reasoning, and numerical computation.
- We proposed a knowledge alignment approach based on semantic reasoning. Define domain knowledge as various semantic relations such as *synonyms*, *hypernyms*, and *inclusions*. Semantic reasoning is performed in both offline KG indexing and online retrieval phases, allowing fragmented knowledge generated through automation to be aligned and connected through domain knowledge. In the offline indexing phase, it can improve the standardization and connectivity of knowledge, and in the online Q&A phase, it can serve as a bridge between user questions and indexing accurately.
- We proposed a model for KAG. To support the capabilities required for the operation of the KAG framework, such as index construction, retrieval, question understanding, semantic reasoning, and summarization, we enhance the three specific abilities of general LLMs: Natural Language UnderStanding (NLU), Natural Language Inference (NLI), and Natural Language Generation (NLG) to achieve better performance in each functional module.

We evaluated the effectiveness of the system on three complex Q&A datasets: 2WikiMultiHopQA[9], MuSiQue[10] and HotpotQA[11]. The evaluation focused on both end-to-end Q&A performance and retrieval effectiveness. Experimental results showed that compared to HippoRAG[6], KAG achieved significant improvements across all three tasks, with F1 scores increasing by 19.6%, 12.2% and 12.5% respectively. Furthermore, retrieval metrics also showed notable enhancements.

KAG is applied in two professional Q&A scenarios within Ant Group: E-Government and E-Health. In the E-Government scenario, it answers users' questions about administrative processes based on a given repository of documents. For E-Health, it responds to inquiries related to diseases, symptoms, treatments, utilizing the provided medical resources. Practical application results indicate that KAG achieves significantly higher accuracy than traditional RAG methods, thereby enhancing the credibility of Q&A applications in professional fields. We will soon natively support KAG on the open source KG engine OpenSPG, allowing developers to more easily build rigorous knowledge decision-making or convenient information retrieval services.

In summary, we propose a knowledge-augmented technical framework, KAG, targeting professional question-answering scenarios and validate the effectiveness of this framework based on complex question-answering tasks. We present two industry application cases based on Ant Group's business scenarios and have open-sourced the code to assist developers in building local applications using KAG.

2 Approach

In this section, we will first introduce the overall framework of KAG, and then discuss five key technology in sections 2.1 to 2.5.

As shown in Figure 1, the KAG framework consists of three parts: KAG-Builder, KAG-Solver, and KAG-Model. The KAG-Builder is designed for building offline indexes; in this module, we proposed *LLM Friendly Knowledge Representation framework* and *mutual indexing between knowledge structure and text chunk*. In the module KAG-Solver we introduced a *Logical-form-guided hybrid reasoning solver* that integrates LLM reasoning, knowledge reasoning, and mathematical logic reasoning. Additionally, *knowledge alignment by semantic reasoning* is used to enhance the accuracy of knowledge representation and retrieval in both KAG-Builder and KAG-Solver. The KAG-Model optimizes the capabilities needed by each module based on a general language model, thereby improving the performance of all modules.

LLM Friendly Representation

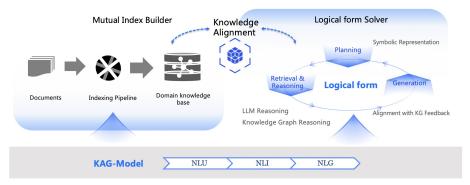


Figure 1: The KAG Framework. The left side shows KAG-Builder, while the right side displays KAG-Solver. The gray area at the bottom of the image represents KAG-Model.

2.1 LLM Friendly Knowledge Representation

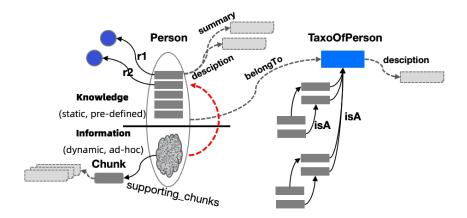


Figure 2: LLMFriSPG:A knowledge representation framework that is friendly to LLMs. Instances and concepts are separated to achieve more effective alignment with LLMs through concepts. In this paper, entity instances and event instances are collectively referred to as instances unless otherwise specified. SPG properties are divided into Knowledge and Information areas, also called static and dynamic area, which are compatible with decision-making expertise with strong schema constraints and document retrieval index knowledge with open information representation. The red dotted line represents the fusion and mining process from information to knowledge. The enhanced document chunk representation provides traceable and interpretable text context for LLMs.

In order to define a more friendly knowledge semantic representation for LLMs, we upgrade SPG from three aspects: deep text-context awareness, dynamic properties and knowledge stratification, and name it **LLMFriSPG**.

$$\mathcal{M} = \{\mathcal{T}, \rho, \mathcal{C}, \mathcal{L}\}$$

where \mathcal{M} represents all types defined in LLMFriSPG, \mathcal{T} represents all **EntityType**(e.g., Person in Figure 2), **EventType** classes and all pre-defined properties that are compatible with LPG syntax declarations. \mathcal{C} represents all **ConceptType** classes, concepts and concept relations, it is worth noting that the root node of each concept tree is a **ConceptType** class that is compatible with LPG syntax(e.g., TaxoOfPerson in Figure 2), each concept node has a unique **ConceptType** class. ρ represents the inductive relations from instances to concepts. \mathcal{L} represents all executable rules defined on logical relations and logical concepts. For $\forall t \in \mathcal{T}$:

$$p_t = \{p_t^c, p_t^f, p_t^b\}$$

As is show in Figure 2, p_t represents all properties and relations of type t, and p_t^c represents the domain experts pre-defined part, p_t^f represents the part added in an ad-hoc manner, p_t^b represents the system built-in properties, such as supporting_chunks, descripiton, summary and belongTo. For any instance e_i , denote $typeof(e_i)$ as t_k , and supporting_chunks represents the set of all text chunks containing instance e_i , the user defines the chunk generation strategy and the maximum length of the chunk in KAG builder phase, description represents the general descriptive information specific to class t_k . It is worth noting that the meaning of description added to the type t_k and the instance e_i is different, when description is attached to t_k , it signifies the global description for that type. Conversely, when it is associated with an instance e_i , it represents the general descriptive information for e_i consistent with the original document context, description can effectively assist LLM in understanding the precise meaning of a specific instance or type, and can be used in tasks such as information extraction, entity linking, and summary generation. summary represents the summary of e_i or r_i in the original document context. belong To represents the inductive semantics from instance to concept. Each **EntityType** or **EventType** can be associated with a **ConceptType** through belong To. It is worth noting that, 1) \mathcal{T} and \mathscr{C} have different functions. The statement t adopts the object-oriented principle to better match the representation of the LPG[12], and \mathscr{C} is managed by a text-based concept tree. This article will not introduce the SPG semantics in detail. 2) p_t^c and p_t^f can be instantiated separately. That is, they share the same class declaration, but in the instance storage space, pre-defined static properties and realtime-added dynamic properties can coexist, and we also support instantiating only one of them. This approach can better balance the application scenarios of professional decision-making and information retrieval. General information retrieval scenarios mainly instantiate dynamic properties, while professional decision-making application scenarios mainly instantiate static properties. Users can strike a balance between ease of use and professionalism based on business scenario requirements. 3) p_t^c and p_t^f share the same conceptual terminology. Concepts are general common sense knowledge that is independent of specific documents or instances. Different instances are linked to the same concept node to achieve the purpose of classifying the instances. We can achieve semantic alignment between LLM and instances through concept graphs, and concepts can also be used as navigation for knowledge retrieval. see section 2.4 and 2.3 for details.

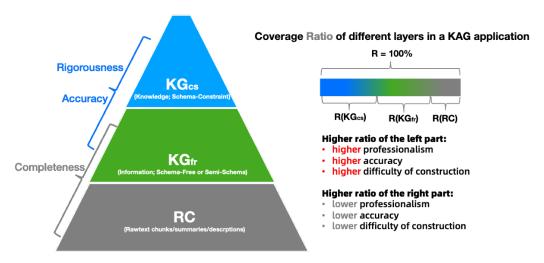


Figure 3: Hierarchical representation of knowledge and information.

In order to more accurately define the hierarchical representation of information and knowledge, as shown in 3, we denote KG_{cs} as knowledge layer, which represents the domain knowledge that complies with the domain schema constraints and has been summarized, integrated, and evaluated. denote KG_{fr} as information layer, which represents the graph structure information such as entities and relations obtained through information extraction. denote RC as raw chunks layer, which represents the original document chunks after semantic segmentation. the KG_{cs} layer fully complies

with the SPG semantic specification and supports knowledge construction and logical rule definition with strict schema constraints, SPG requires that domain knowledge must have predefined schema constraints. It has high knowledge accuracy and logical rigor. However, due to its heavy reliance on manual annotation, the labor cost of construction is relatively high and the information completeness is insufficient. KG_{fr} shares the same EntityTypes, Eventtypes and Conceptual system with KG_{cs} , and provides effective information supplement for KG_{cs} . At the same time, the supporting_chunks, summary, and description edges built between KG_{fr} and RC form an inverted index based on graph structure, making RC an effective original-text-context supplement for KG_{fr} and with high information completeness. As is show in the right part of figure 3, in a specific domain application, $R(KG_{cs})$, $R(KG_{fr})$, and R(RC) respectively represent their knowledge coverage in solving the target domain problems. If the application has higher requirements for knowledge accuracy and logic rigorousness, it is necessary to build more domain structured knowledge and consume more expert manpower to increase the coverage of $R(KG_{cs})$. On the contrary, if the application has higher requirements for retrieval efficiency and a certain degree of information loss or error tolerance, it is necessary to increase the coverage of $R(KG_{fr})$ to fully utilize KAG's automated knowledge construction capabilities and reduce expert manpower consumption.

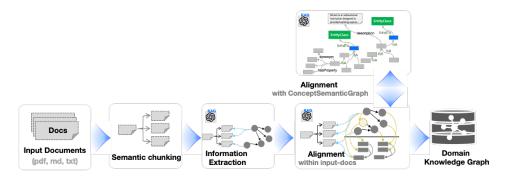


Figure 4: The Pipeline of KAG Builder for domain unstructured documents. From left to right, first, phrases and triples are obtained through information extraction, then disambiguation and fusion are completed through semantic alignment, and finally, the constructed KG is written into the storage.

2.2 Mutual Indexing

As illustrated in Figure 4, KAG-Builder consists of three coherent processes: structured information acquisition, knowledge semantic alignment and graph storage writer. The main goals of this module include: 1) building a mutual index between the graph structure and the text chunk to add more descriptive context to the graph structure, 2) using the concept semantic graph to align different knowledge granularities to reduce noise and increase graph connectivity.

2.2.1 Semantic Chunking

According to the document's structural hierarchy and the inherent logical connections between paragraphs, a semantic chunking process is implemented based on system-built-in prompts. This semantic chunking produces chunks that adhere to both length constraints (specifically for LLM's context window size constraints) and semantic coherence, ensuring that the content within each chunk is thematically cohesive. We defined **Chunk EntityType** in RC, which includes fields such as id, summary, and mainText. Each chunk obtained after semantic segmentation will be written into an instance of Chunk, where id is a composite field consisting of articleID, paraCode, idInPara concatenated by the connector # in order to ensure that consecutive chunks are adjacent in the id space. articleID represents the globally unique article ID, paraCode represents the paragraph code in the article, and idInPara is the sequential code of each chunk in the paragraph. Consequently, an adjacency in the content corresponds to a sequential adjacency in their identifiers. Furthermore, a reciprocal relation is established and maintained between the original document and its segmented chunks, facilitating navigation and contextual understanding across different granularities of the document's content. This structured approach to segmentation not only optimizes compatibility with large-scale language models but also preserves and enhances the document's inherent semantic structure and association.

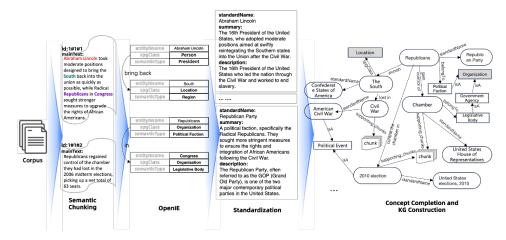


Figure 5: An Example of KAG-Builder pipeline

2.2.2 Information Extraction with More Descriptive Context

Given a dataset, we use fine-tuning-free LLM(such as GPT-3.5, DeepSeek, QWen, etc,...) or our fine-tuned model Hum to extract entities, events, concepts and relations to construct KG_{fr} , subsequently, construct the mutual index structure between KG_{fr} and RC, enabling cross-document links through entities and relations. This process includes three phases. First, it extracts the entity set $E = \{e_1, e_2, e_3, ...\}$ chunk by chunk, second, extracts the event set $EV = \{ev_1, ev_2, ev_3, ...\}$ associated to all entities and iteratively extracts the relation set $R = \{r_1, r_2, r_3, ...\}$ between all entities in E, finally, completes all hypernym relations between the instance and its spgClass. To provide more convenience for the subsequent Knowledge Alignment phase, and overcome the problem of low discrimination of knowledge phrases such as Wikidata and ConceptNet, in the entity extraction phase, we use LLMs to generate built-in properties description, summary, semanticType, spgClass, descriptionOfSemanticType by default for each instance e at one time, as shown in Figure 2, we store them in the e instance storage according to the structure of e.description, e.summary, e, belongTo, semanticType > and <math>e, hasClass, spgClass >.

2.2.3 Domain Knowledge Injection And Constraints

When openIE is applied to professional domains, irrelevant noise will be introduced. Previous research has shown that noisy and irrelevant corpora can significantly undermine the performance of LLMs[3, 5, 13]. It is a challenge to align the granularity of extracted information and domain knowledge. The domain knowledge alignment capabilities in KAG include: 1) Domain term and concept injection. We use an iterative extraction approach, First, we store domain concepts and terms with description in KG storage. Second, we extract all instances in the document through openIE, then we perform vector retrieval to obtain all possible concept and term sets E_d . Finally, we add E_d to the extraction prompt and perform another extraction to obtain a set E_d^a that is mostly aligned with the domain knowledge. 2) Schema-constraint Extraction. In the vertical professional domains, the data structure between multiple documents in each data source such as drug instructions, physical examination reports, government affairs, online order data, structured data tables, etc. has strong consistency, and is more suitable for information extraction with schema-constraint, structured Extraction also makes it easier to do knowledge management and quality improvement. For detailed information about knowledge construction based on Schema-constraint, please refer to the SPG¹ and OneKE[14]. This article will not introduce it in detail. It is worth noting that, as shown in figure 2, for the same entity type, such as **Person**, we can pre-define properties and relations such as *name*, gender, placeOfBirth, (Person, hasFather, Person), (Person, hasFriend, Person), and can also extract tripples directly such as (Jay Chou, spgClass, Person), (Jay Chou, constellation, Capricorn), (Jay Chou, record company, Universal Music Group) through openIE. 3) Pre-defined Knowledge Structures By Document Type. Professional documents such as drug instructions, government affairs documents, and legal definitions generally have a relatively standardized document structure. Each

¹Official site of SPG: https://spg.openkg.cn/en-US

type of document can be defined as an entity type, and different paragraphs are different properties of the entity. Taking government affairs as an example, we can pre-define the GovernmentAffair EntityType and properites such as *administrative divisions*, *service procedures*, *required materials*, *service locations*, *and target groups*. The divided chunks are the values of different properties. If the user asks "What materials are needed to apply for housing provident fund in Xihu District?", you can directly take out the chunk corresponding to property *required materials* to answer the question, avoiding the possible hallucinations caused by LLM re-generation.

2.2.4 Mutual indexing between text chunk vectors and knowledge structures

KAG's mutual indexing is a knowledge management and storage mechanism that conforms to the LLMFriSPG semantic representation. As is described in section 2.1, it includes four core data structures: 1) Shared Schemas are coarse-grained-types pre-defined as SPG Classes at project level, it includes EntityTypes, ConceptTypes, and EventTypes, they serve as a high-level categorization such as Person, Organization, GEOLocation, Date, Creature, Work, Event. 2) Instance Graph include all event and entity instances in KG_{cs} and KG_{fr} . that is, the instances constructed through schema-free openIE or through schema-constraint strict structure construction are both stored in the instance graph. 3) Text Chunks are special entity node that conforms to the definition of the Chunk EntityType. 4) Concept Graph is the core component for knowledge semantic alignment. it consists of a series of concepts and concept relations. Concept nodes are also fine-grained-types of instances. Through relation prediction, instance nodes can be linked to concept nodes to obtain their fine-grained semantic types. , and two storage structures: 1) Graph Store. Store graph data structures in LPG databases, such as TuGraph, Neo4J. 2) Text Vector. Store text and vectors in a vector storage engine, such as ES, or the vector storage embedded in the LPG engine.

2.3 Logical Form Solver

Algorithm 1 Logical Form Solver

```
1: memory \leftarrow []
 2: query_{cur} \leftarrow query
 3: for round \in (0, n) do
         lf_{list} \leftarrow LFPlanner(query_{cur})
 4:
 5:
         history \leftarrow []
         for lf \in lf_{list} do
 6:
 7:
              lf_{subquery}, lf_{func} \leftarrow lf
              retrievals_{sub}, answer_{sub} \leftarrow Reasoner(lf_{subquery}, lf_{func})
 8:
 9:
              history.append([lf_{subquery}, retrievals_{sub}, answer_{sub}])
10:
         end for
11:
         memory \leftarrow Memory(query, history)
12:
         if not Judge(query, memory) then
13:
              query_{cur} \leftarrow SupplyQuery(query, memory)
14:
         end if
15: end for
16: answer \leftarrow Generator(query, memory)
17: return answer
```

In the process of solving complex problems, two key steps are involved: *reasoning* and *retrieval*. Disassembling question is a *planning* process to determine the next problem to be tackled. Reasoning includes retrieving information based on the disassembled question, inferring the answer to the question according to the retrieved results, or re-disassembling the sub-question when the retrieved content cannot answer the question. Retrieval is to find the content that can be used as reference for the original question or the disassembled subquestion.

Since the interaction between different modules is based on the vector representation of natural language, inaccuracies often occur. Inspired by logical form, which is often used in KGQA, we design an executable language with both reasoning and retrieval capabilities, which breaks the question down into multiple logical expressions, each of which can contain functions for retrieval or logical operations. The mutual-structure index described in section 2.2 makes it possible to

implement the above process. KAG Solver is inherently guided by logical form, which adopts the collaborative question decomposition and reasoning mechanism of ReSP[15] and logical form Executor. As is show in Figure 6, the global question decomposition is based on the ReSP method that uses *global evidence memory* and *local pathway memory* to solve the context redundant and over-planning caused by multiple rounds of retrieval through daul-summarizer. Under the guidance of the knowledge structure, logical form decomposes the question into multiple subquestions and represents them with logical function symbols, then proceeds to reason and solve each subquestion accordingly, as shown in Algorithm 17. Section 2.3.1, 2.3.2 and 2.3.3 introduce logical form function for Planning, logical form for Reasoning and logical form for Retrieval respectively. In general, the proposed logical form language has the following three advantages:

- The use of symbolic language enhanced the rigor of problem decomposition and solving.
- Deep integration of KG structure and text chunk in the retrieval process
- Integrate the problem decomposition and retrieval processes to reduce the system complexity.

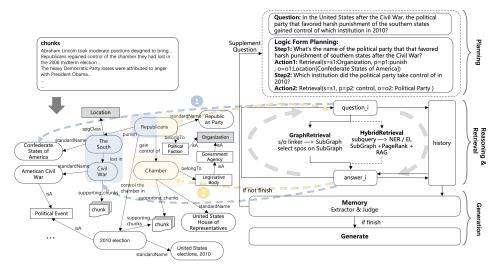


Figure 6: An Example of logical form execution. In this figure, the construction process of KG on the left is shown in Figure 5, and the overall reasoning and iteration process is on the right. First, a logical form decomposition is performed based on the user's overall question, and then logical-form-guided reasoning is used for retrieval and reasoning. Finally, Generation determines whether the user's question is satisfied. If not, a new question is supplied to enter a new logical form decomposition and reasoning process. If it is determined to be satisfied, Generation directly outputs the answer.

2.3.1 Logical Form Function

Logical Functions are defined as Table 1, with each function representing an execution action. Complex problems are decomposed by planning a combination of these expressions, enabling reasoning about intricate issues.

Retrieval. According to the knowledge or information retrieved from SPO, s, p, o should not repeatedly appear multiple times in the same expression. Constraints can be applied to the s, p, o for querying. For multi-hop queries, multiple retrievals are required. When the current variable refers to a previously mentioned variable, the variable name must be consistent with the referenced variable name, and only the variable name needs to be provided. The entity type and name are only specified during the first reference.

Sort. Sort the retrieval results. A is the variable name for the retrieved SPO $(s_i, o_i, \text{ or } s.prop, p.prop, o.prop)$. direction specifies the sorting direction, where direction = min means sorting in ascending order and "direction=max" means sorting in descending order. limit = n indicates outputting the topN results.

Function Name	Function Declaration
Retrieval	Retrieval($s = s_i$: type[name], $p = p_i$: edge, $o = o_i$: type[name], s.prop = value, p.prop = value, o.prop = value)
Sort	Sort(A, direction = min max, limit = n)
Math	$math_i = Math(expr),$ expr is in LaTeX syntax and can be used to perform operations on sets. e.g. count: $ A $, sum: $\sum A$
Deduce	Deduce(left = A, right = B, op = entailment greater less equal)
Output	Output(A,B,)

Table 1: Functions of logical form.

Math. Perform calculations. expr is in LaTeX syntax and can be used to perform calculations on the retrieved results (sets) or constants. $math_i$ represents the result of the calculation and can be used as a variable name for reference in subsequent actions.

Deduce. Deduce the retrieval or calculation results to answer the question. A, B can be the variable names from the retrieved SPO or constants. The operator op = entailment|greater|less|equal represents A entails B, A is greater than B, A is less than B, and A is equal to B, respectively.

2.3.2 Logical Form for Reasoning

When the query statement represented by natural language is applied to the search, the logic is often fuzzy, such as "find a picture containing vegetables or fruits" and "find a picture containing vegetables and fruits". Whether text search or vector search is used, the similarity between the two queries is very high, but the corresponding answers are quite different. The same is true for problems involving logical reasoning processes such as and or not, and intersection differences. To this end, we use logical form to express the question, so that it can express explicit semantic relations. Similar to IRCOT, we decompose complex original problems and plan out various execution actions such as multi-step retrieval, numerical reasoning, logical reasoning, and semantic deduce. Each sub-problem is expressed using logical form functions, and dependencies between sub-questions are established through variable references. The inference resolution process for each sub-question is illustrated as Algorithm 9. In this process, the 'GraphRetrieval' module performs structured retrieval based on the logical function, with the retrieval results also being structured as SPO (Subject-Predicate-Object) information. The 'HybridRetrieval' module, on the other hand, retrieves chunks based on the sub-question and the structured information. To understand how logical functions can be utilized to reason about complex problems, refer to the following examples as Table

Output. Directly output A, B, ... as the answers. Both A and B are variable names that reference the previously retrieved or calculated

```
Algorithm 2 Logical Form Reasoner
```

```
Require: Each sub-query resulting from the decomposition of a question based on the logical form, along with their respective logical function, are denoted as lf_{subquery} and lf_{func} Ensure: The retrievals and answer of each sub-query, are denoted as retri_{sub} and answer_{sub}
```

 $retri_{kg} \leftarrow GraphRetrieval(lf_{subquery}, lf_{func})$ 2: **if** $retri_{kg} \neq None$ and $retri_{kg} > threshold$ **then** $retri_{sub} \leftarrow retri_{kg}$

4: **else**

 $retri_{doc} \leftarrow HybridRetrieval(lf_{subquery}, retri_{kg})$

6: $retri_{sub} \leftarrow retri_{kg}, retri_{doc}$

end i

8: $answer_{sub} \leftarrow Generator(lf_{subquery}, retri_{sub})$ **return** $retri_{sub}$, $answer_{sub}$

Numerical Reasoning

question: Which sports team for which Cristiano Ronaldo played in 2011 was founded last?

Step1: Identify the Sports Teams Cristiano Ronaldo Played for in 2011.

Action1: Retrieval(s=s1:Player[Cristiano Ronaldo], p=p1:PlayedFor, o=o1:SportsTeam, p.PlayedForInYear=2011)

Step2: Determine the Foundation Years of Each Identified Team . Action2: Retrieval(s=o1, p=p2:FoundationYear, o=o2:Year)

Step3: Which team was founded last?

Action3: Sort(set=o1, orderby=o2, direction=max, limit=1)

question: What is the sum of 30 + 6 and the age of the founder of Tesla in 2027?

Step1: What is the sum of 30 + 6? Action1: math1 = Math(30+6) Step2: Who is the founder of Tesla?

Action2: Retrieval(s=s2:Company[Tesla], p=p2:Founder, o=o2)

Step3: In which year was the founder of Tesla born? Action3: Retrieval(s=o2, p=p3:YearOfBirth, o=o3)

Step4: How old will the founder of Tesla be in the year 2027?

Action4: math4 = Math(2027-o3)

Step5: What is the sum of math1 and math4? Action5: math5 = Math(math1+math4)

Logical Reasoning

question: Find a picture containing vegetables or fruits.

Step1: Find pictures containing vegetables.

Action1: Retrieval(s=s1:Image, p=p2:Contain, o=o1:Vegetables)

Step2: Find pictures containing fruits.

Action2: Retrieval(s=s2:Image, p=p2:Contain, o=o2:Fruits)

Step3: Output s1, s2. Action3: Output(s1, s2)

question: Find a picture containing vegetables and fruits.

Step1: Find pictures containing vegetables.

Action1: Retrieval(s=s1:Image, p=p2:Contain, o=o1:Vegetables)

Step2: Find pictures containing fruits.

Action2: Retrieval(s=s1, p=p2:Contain, o=o2:Fruits)

Step3: Output s1. Action3: Output(s1)

Semantic Deduce

question: Do I need to present the original ID card when applying for a passport?

Step1: What documents are required to apply for a passport?

Action1: Retrieval(s=s1:Event[apply for a passport], p=p1:RequiredDocuments, o=o1:Documents)

Step2: Does this set of documents include the original identity card?

Action2: Deduce(left=o1, right=the original identity card, op=entailment)

Table 2: The cases of reasoning with logical form

2.3.3 Logical Form for Retrieval

In RAG, retrieval is achieved by calculating the similarity (e.g. cosine similarity) between the embeddings of the question and document chunks, where the semantic representation capability of embedding models plays a key role. This mainly includes a sparse encoder (BM25) and a dense retriever (BERT architecture pre-training language models). Sparse and dense embedding approaches capture different relevance features and can benefit from each other by leveraging complementary relevance information.

The existing method of combining the two is generally to combine the scores of the two search methods in an ensemble, but in practice different search methods may be suitable for different questions, especially in questions requiring multi-hop reasoning. When query involves proper nouns, people, places, times, numbers, and coordinates, the representation ability of the pre-trained presentation model is limited, and more accurate text indexes are needed. For queries that are closer to the expression of a paragraph of text, such as scenes, behaviors, and abstract concepts, the two may be coupled in some questions.

In the design of logical form, it is feasible to effectively combine two retrieval methods. When keyword information is needed as explicit filtering criteria, conditions for selection can be specified within the Retrieval Function to achieve structured retrieval.

For example, for the query "What documents are required to apply for a disability certificate at West Lake, Hangzhou?", the Retrieval Function could be represented as: "Retrieval(s=s1:Event[applying for a disability certificate], p=p1:RequiredDocuments, o=o1:Documents, s.location=West Lake, Hangzhou)". This approach leverages the establishment of different indices (sparse or dense) to facilitate precise searches or fuzzy searches as needed.

Furthermore, when structured knowledge in the form of SPO (Subject-Predicate-Object) cannot be retrieved using logical functions, alternative approaches can be employed. These include semi-structured retrieval, which involves using logical functions to search through chunks of information, and unstructured retrieval. The latter encompasses methods such as Retrieval-Augmented Generation (RAG), where sub-problems expressed in natural language are used to retrieve relevant chunks of text. This highlights the adaptability of the system to leverage different retrieval strategies based on the availability and nature of the information.

2.4 Knowledge Alignment

Constructing KG index through information-extraction and retrieving based on vector-similarity has three significant defects in knowledge alignment:

- **Misaligned semantic relations between knowledge**. Specific semantic relations, such as *contains*, *causes* and *isA*, are often required between the correct answer and the query, while the similarity relied upon in the retrieval process is a weak semantic measure that lacks properties and direction, which may lead to imprecise retrieval of content.
- Misaligned knowledge granularity. The problems of knowledge granularity difference, noise, and irrelevance brought by openIE pose great challenges to knowledge management. Due to the diversity of language expressions, there are numerous synonymous or similar nodes, resulting in low connectivity between knowledge elements, making the retrieval recall incomplete.
- Misaligned with the domain knowledge structure. There is a lack of organized, systematic knowledge within specific domains. Knowledge that should be interrelated appears in a fragmented state, leading to a lack of professionalism in the retrieved content.

To solve these problems, we propose a solution that leverages concept graphs to enhance offline indexing and online retrieval through semantic reasoning. This involves tasks such as *knowledge instance standardization, instance-to-concept linking, semantic relation completion, and domain knowledge injection.* As described in section 2.2.2, we added descriptive text information to each instance, concept or relation in the extraction phase to enhance its interpretability and contextual relevance. Meanwhile, as described in section 2.2.3, KAG supports the injection of domain concepts and terminology knowledge to reduce the noise problem caused by the mismatch of knowledge granularity in vertical domains. The goal of concept reasoning is to make full use of vector retrieval and concept reasoning to complete concept relations based on the aforementioned knowledge structure to enhance the accuracy and connectivity of the domain KG. Refer to the definition of SPG concept semantics², as is shown in Table 3, we have summarized six semantic relations commonly required for retrieval and reasoning. Additional semantic relations can be added based on the specific requirements of the actual scenario.

2.4.1 Enhance Indexing

The process of enhancing indexing through semantic reasoning, as shown in Figure 5, specifically implemented as predicting semantic relations or related knowledge elements among index items using LLM, encompassing four strategies:

• Disambiguation and fusion of knowledge instances. Taking entity instance e_{cur} as an example, first, the one-hop relations and description information of e_{cur} are used to predict synonymous relations to obtain the synonym instance set E_{syn} of e_{cur} . Then, the fused target entity e_{tar} is determined from E_{syn} . Finally, the entity fusion rules are used to copy the properties and relations of the remaining instances in E_{syn} to e_{tar} , and the names of these

²Semantic Classification of Concept: https://openspg.yuque.com/ndx6g9/ps5q6b/fe5p4nh1zhk6p1d8

Formal Expression	Description	Example
<var1, synonym,="" var2=""></var1,>	A synonym relation means that a word or phrase var2 that has the same or nearly the same meaning as another word or phrase var1 in the same language and given context.	Fast is a synonym of quick.
<var1, isa,="" var2=""></var1,>	An <i>isA</i> relation means that a hypernym <i>var2</i> that is more generic or abstract than a given word or phrase <i>var1</i> and encompasses a broader category that the given word belongs to.	Car isA Vehicle.
<var1, ispartof,="" var2=""></var1,>	An <i>isPartOf</i> relation means that something <i>var1</i> is a component or constituent of something <i>var2</i> larger. This relation shows that an item is a part of a bigger whole.	Wheel isPartOf car.
<var1, contains,="" var2=""></var1,>	A <i>contains</i> relation means that something <i>var1</i> includes or holds <i>var2</i> , something else within it. This indicates that one item has the other as a subset or component.	Library contains books.
<var1, belongto,="" var2=""></var1,>	An <i>belongTo</i> relation means that something <i>var1</i> is an instance of concept <i>var2</i> .	Chamber belongTo Legislative Body.
<var1, causes,="" var2=""></var1,>	A <i>causes</i> relation means that one event or action <i>var1</i> brings about another <i>var2</i> . This indicates a causal relation where one thing directly results in the occurrence of another.	Fire causes smoke.

Table 3: Commonly used semantic relations.

instances are added to the *synonyms* of e_{tar} , the remaining instances will also be deleted immediately.

- Predict relations between instances and concepts. For each knowledge instance (such as event, entity), predict its corresponding concept and add the derived triple $< e_i$, belong To, $c_j >$ to the knowledge index. As is shown in Figure 5, <Chamber, belong To, Legislative To0 means that the Chamber belongs to Legislative Body in classification.
- Complete concepts and relations between concepts. During the extraction process, we use concept reasoning to complete all hypernym and isA relations between semanticType and spgClass. As is shown in Figure 5 and Table 3, we can obtain the semanticType of Chamber is Legislative Body, and its spgClass is Organization in the extraction phase. Through semantic completion, we can get <Legislative Body, isA, Government Agency>, <Government Agency, isA, Organization>. Through semantic completion, the triple information of KG_{fr} space is more complete and the connectivity of nodes is stronger.

2.4.2 Enhance Retrieval

In the retrieval phase, we utilize semantic relation reasoning to search the KG index based on the phrases and types in the logical form. For the types, mentions or relations in the logical form, we employ the method of combining semantic relation reasoning with similarity retrieval to replace the traditional similarity retrieval method. This retrieval method makes the retrieval path professional and logical, so as to obtain the correct answer. First, the hybrid reasoning performs precise type matching and entity linking. If the type matching fails, then, semantic reasoning is performed. As shown in Figure 6, if the type *Political Party* fails to match, semantic reasoning is used to predict that *Political Party* contains *Political Faction*, and reasoning or path calculation is performed starting from *Political Faction*.

Take another example. If the user query q_1 is "Which public places can cataract patients go for leisure?" and the document content d_2 is "The museum is equipped with facilities to provide barrier-free visiting experience services such as touch, voice interpretation, and fully automatic guided tours for the visually impaired.", It is almost impossible to retrieve d_2 based on the vector similarity with q_1 . However, it is easier to retrieve d_2 through the semantic relation of < cataract patient, is A, visually impaired>.

2.5 KAG-Model

KAG includes two main computational processes: offline index building and online query and answer generation. In the era of *small language models*, these two tasks were typically handled by two separate pipelines, each containing multiple task-specific NLP models. This results in high complexity for the application system, increased setup costs, and inevitable cascading losses due to error propagation between modules. In contrast, large language models, as a *capability complex*, can potentially integrate these pipelines into a unified, simultaneous end-to-end reasoning process.

As shown in Figure 7, the processes of indexing and QA each consist of similar steps. Both of the two pipelines can be abstracted as *classify, mention detection, mention relation detection, semantic alignment, embedding,* and *chunk, instance, or query-focused summary.* Among these, *classify, mention detection,* and *mention relation detection* can be categorized as NLU, while *semantic alignment* and *embedding* can be grouped under NLI. Finally, the *chunk, instance or query-focused summary* can be classified under NLG. Thus, we can conclude that the three fundamental capabilities of natural language processing that a RAG system relies on are NLU, NLI, and NLG.

We focused on exploring methods to optimize these three capabilities, which are introduced in subsections 2.5.1, 2.5.2, and 2.5.3 respectively. Additionally, to reduce the cascade loss caused by linking models into a pipeline, we further explored methods to integrate multiple inference processes into a single inference. Subsection 2.5.4 will discuss how to equip the model with retrieval capabilities to achieve better performance and efficiency through one-pass inference.

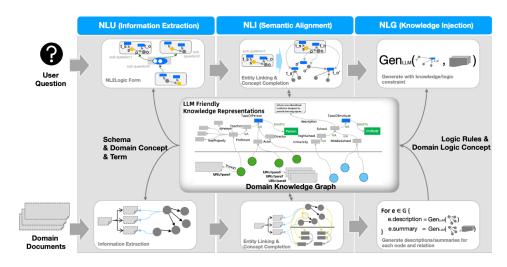


Figure 7: The model capabilities required for KAG.

2.5.1 Natural Language Understanding

NLU is one of the most common foundational tasks in natural language processing, including *text classification, named entity recognition, relation Extraction, subject and object extraction, trigger detection, event argument extraction, event extraction,* and *machine reading comprehension*. We have collected over 30 public datasets to enhance understanding capabilities. Experiments found that simply transforming the original datasets into instruction datasets can achieve comparable results to specialized models on trained tasks, but this approach does not improve the model's NLU capabilities on unseen domains. Therefore, we conducted large-scale instruction reconstruction, designing various instruction synthesis strategies to create an NLU instruction dataset with over 20,000 diverse instructions. By utilizing this dataset for supervised fine-tuning on a given base model, the model has demonstrated enhanced NLU capabilities in downstream tasks. The instruction reconstruction strategy mainly consists of the following three types.

• Label bucketing: [14] This strategy focuses on label-guided tasks, where the aim is to extract text based on labels or map text to specified labels, including classification, NER, RE, and EE. When labels in a dataset collectively co-occur in the training set, the model may

learn this pattern and overfit to the dataset, failing to independently understand the meaning of each label. Therefore, during the instruction synthesis process, we adopt a polling strategy that designates only one label from each training sample as part of a bucket. Additionally, since some labels have similar semantics and can be confused, we group easily confused labels into a single bucket, allowing the model to learn the semantic differences between the two labels more effectively.

- Flexible and Diverse Input and Output Formats: The LLM employs an instruction-following approach for inference, and a highly consistent input-output format may cause the model to overfit to specific tasks, resulting in a lack of generalization for unseen formats. Therefore, we have flexibly processed the input and output formats. The output is handled as five different formatting instructions, as well as two types of natural language instructions. Additionally, the output format can dynamically be specified as markdown, JSON, natural language, or any format indicated in the examples.
- Instructoin with Task Guildline: Traditional NLP training often employs a "sea of questions" approach, incorporating a wide variety of data in the training set. This allows the model to understand task requirements during the learning process, such as whether to include job titles when extracting personal names. For the training of LLMs, we aim for the model to perform tasks like a professional annotator by comprehending the task description. Therefore, for the collected NLU tasks, we summarize the task descriptions using a process of self-reflection within the LLM. This creates training data that includes task descriptions within the instructions. Additionally, to enhance task diversity, we implement heuristic strategies to rephrase the task descriptions and answers. This enables the model to understand the differences between task descriptions more accurately and to complete tasks according to the instructions.

We fine-tuned six foundational models: qwen2, llama2, baichuan2, llama3, mistral, phi3, and used six understanding benchmarks recorded on OpenCompass for performance validation. The table below shows that the KAG-Model has a significant improvement in NLU tasks

Models	C3	WSC	XSum	Lambda	Lests	Race	Average
GPT4	95.10	74.00	20.10	65.50	12.30	92.35	59.89
Qwen2	92.27	66.35	18.68	62.39	13.07	88.37	56.86
KAG _{Qwen2}	92.88	70.19	31.33	66.16	18.53	88.17	61.21
Llama2	81.70	50.96	23.29	63.26	15.99	55.64	48.47
KAG _{Llama2}	82.36	63.46	24.51	65.22	17.51	68.48	53.59
Baichuan2	84.44	66.35	20.81	62.43	16.54	76.85	54.57
KAG _{Baichuan2}	84.11	66.35	21.51	62.64	17.27	77.18	54.84
Llama3	86.63	65.38	25.84	36.72	0.09	83.76	49.74
KAG _{Llama3}	83.40	62.50	26.72	54.07	18.45	81.16	54.38
Mistral	67.29	30.77	21.16	59.98	0.78	73.46	42.24
KAG _{Mistral}	47.29	39.42	21.54	69.09	17.14	72.42	44.48
Phi3	68.60	42.31	0.60	71.74	3.47	73.18	43.32
KAG _{Phi3}	85.21	25.94	0.36	71.24	15.49	74.00	45.37

Table 4: Enhancement of natural language understanding capabilities in different LLMs by KAG. The experimental results are based on the open-compass framework and tested using the "gen" mode. The evaluation metrics for C3, WSC, Lambda, and Race are ACC. XSum and Lcsts are measured using ROUGE-1. Race includes Race-middle and Race-high, and their average is taken.

2.5.2 Natural Language Inference

The NLI task is used to infer the semantic relations between given phrases. Typical NLI tasks include *entity linking, entity disambiguation, taxonomy expansion, hypernym discovery*, and *text entailment*. In the context of knowledge base question answering, due to the diversity and ambiguity of natural language expressions, as well as the subtle and different types of semantic connections between phrases, it often requires further alignment or retrieval of related information through NLI tasks based on NLU. As described in section 2.4, we categorize the key semantic relation in knowledge base applications into six types. Among these, relations such as *isA*, *isPartOf* and *contains* exhibit

directional and distance-based partial order relations. During the reasoning process, it is crucial to accurately determine these semantic relations to advance towards the target answer. In traditional approaches, separate training of representation pre-training models and KG completion(KGC) models is often employed to reason about semantic relations. However, these KGC models tend to focus on learning graph structures and do not fully utilize the essential textual semantic information for semantic graph reasoning. LLMs possessing richer intrinsic knowledge, can leverage both semantic and structural information to achieve more precise reasoning outcomes. To this end, we have collected a high-quality conceptual knowledge base and ontologies from various domains, creating a conceptual knowledge set that includes 8,000 concepts and their semantic relations. Based on this knowledge set, we constructed a training dataset that includes six different types of conceptual reasoning instructions to enhance the semantic reasoning capabilities of a given base model, thereby providing semantic reasoning support for KAG.

Semantic reasoning is one of the core ability required in KAG process, we evaluate this ability of our model with two tasks, which is: downstream NLI tasks and general reasoning QA task, the result are as shown in Table 5, Table 6.

The evaluation results indicates that our KAG-Model demonstrates a significant improvement in tasks related with semantic reasoning: First, Table 6 shows that on the Hypernym Discovery task(which is consistent in form with the reasoning required in semantic enhanced indexing and retrieval.), our fine-tuned KAG-llama model outperforms Llama3 and ChatGPT-3.5 significantly. In addition, the better performance of our model on CMNLI, OCNLI and SIQA compared with Llama3 in Table 5 shows that our model has good capabilities in general logical reasoning.

Models	CMNLI	OCNLI	SIQA
Llama3	35.14	32.1	44.27
KAG-Llama3	49.52	44.31	65.81

Table 5: Enhancement of natural language Inference capabilities in different LLMs by KAG. The evaluation metrics for CMNLI, OCNLI, SIQA are measured with accuracy.

	1A.English	2A.Medical	2B.Music
ChatGPT-3.5	30.04	<u>26.12</u>	28.47
Llama3-8B	23.47	24.26	18.73
KAG-Llama3	38.26	55.14	30.16

Table 6: Hypernym Discovery performance comparison on SemEval2018-Task9 dataset, measured in MRR.

2.5.3 Natural Language Generation

Models that have not undergone domain adaptation training often exhibit significant differences from the target text in domain logic and writing style. Moreover, acquiring sufficient amounts of annotated data in specialized domains frequently poses a challenge. Therefore, we have established two efficient fine-tuning methods for specific domain scenarios, allowing the generation process to better align with scene expectations: namely, K-Lora and AKGF.

Pre-learning with K-LoRA. First of all, we think that using knowledge to generate answers is the reverse process of extracting knowledge from text. Therefore, by inverting the previously described extraction process, we can create a 'triples-to-text' generation task. With extensive fine-tuning on a multitude of instances, the model can be trained to recognize the information format infused by the KG. Additionally, as the target text is domain-specific, the model can acquire the unique linguistic style of that domain. Furthermore, considering efficiency, we continue to utilize LoRA-based SFT. We refer to the LoRA obtained in this step as K-LoRA.

Alignment with KG Feedback. The model may still exhibit hallucinations in its responses due to issues such as overfitting. Inspired by the RLHF(Reinforcement Learning with Human Feedback) approach[16, 17], we hope that the KG can serve as an automated evaluator, providing feedback on knowledge correctness of the current response, thereby guiding the model towards further optimization. First, we generate a variety of responses for each query by employing diverse input formats or random seeds. Subsequently, we incorporate the KG to score and rank these responses. The scoring

process compare generated answer with knowledge in KG to ascertain their correctness. The reward is determined by the number of correctly matched knowledge triples. The formula for calculating the reward is represented by Formula 1.

$$reward = \log(rspo + \alpha \times re)$$
 (1)

where α is a hyperparameter, rspo represents the number of SPO matches, and re represents the number of entity matches.

We select two biomedical question-answering datasets, CMedQA[18] and BioASQ[19], for evaluating our model. CMedQA is a comprehensive dataset of Chinese medical questions and answers, while BioASQ is an English biomedical dataset. We randomly choose 1,000 instances from each for testing. For CMedQA, we employ the answer texts from the non-selected Q&A pairs as corpora to construct a KG in a weakly supervised manner. Similarly, with BioASQ, we use all the provided reference passages as the domain-specific corpora. Experimental results, as shown in Table 7, demonstrate significant enhancement in generation performance. For more details on the specific implementation process, please refer to our paper[20]

Model	CMed	QA	BioA	SQ
Model	Rouge-L	BLEU	Rouge-L	BLEU
ChatGPT-3.5 0-shot	14.20	1.78	21.14	5.93
ChatGPT-3.5 2-shot	14.66	2.53	21.42	6.11
Llama2	14.02	2.86	23.47	7.11
KAG _{Llama2}	15.44	3.46	24.21	7.79

Table 7: Performance comparison on CMedQA & BioASQ. "CP" indicates "continual pre-trained". We consider continual pre-training as a basic method of domain knowledge infusion, on par with other retrieval-based methods. Consequently, we do not report on the outcomes of hybrid approaches.

2.5.4 Onepass Inference

Most retrieval enhanced systems operate in a series of presentation models, retrievers, and generation models, resulting in high system complexity, construction costs, and the inevitable concatenation loss caused by error transfer between modules. We introduces an efficient one-pass unified generation and retrieval (OneGen) model to enable an arbitrary LLM to generate and retrieve in one single forward pass. Inspired by the latest success in LLM for text embedding, we expand the original vocabulary by adding special tokens (i.e. retrieval tokens), and allocate the retrieval task to retrieval tokens generated in an autoregressive manner. During training, retrieval tokens only participate in representation fine- tuning through contrastive learning, whereas other output tokens are trained using language model objectives. At inference time, we use retrieval tokens for efficient retrieving on demand. Unlike the previous pipeline approach where at least two models are needed for retrieval and generation, OneGen unified them in one model, thus eliminating the need for a separate retriever and greatly reducing system complexity.

As shown in experiment results in Table 8, we draw the following conclusions: (1) OneGen demonstrates efficacy in $R \to G$ task, and joint training of retrieval and generation yields performance gains on the RAG task. The Self-RAG endows LLMs with self-assessment and adaptive retrieval, while OneGen adds self-retrieval. Our method outperforms the original Self-RAG across all datasets, especially achieving improvements of 3.1pt on Pub dataset and 2.8pt on ARC dataset, validating the benefits of joint training. (2) OneGen is highly efficient in training, with instruction-finetuned LLMs showing strong retrieval capabilities with minimal additional tuning. It requires less and lower-quality retrieval data, achieving comparable performance with just 60K noisy samples and incomplete documents, without synthetic data. For more details on the specific implementation process, please refer to

For more details on the specific implementation process, please refer to

·	_	Generation Performance			ance	Retriev	al Performance
		Hotp	otQA	2WikiM	ultiHopQA	HotpotQA	2WikiMultiHopQA
BackBone	Retriever	EM	F1	EM	F1	Recall@1	Recall@1
Llama2-7B	Contriever	52.83	65.64	70.02	74.35	73.76	68.75
Liailia2-/D	<u>self</u>	<u>54.82</u>	67.93	<u>75.02</u>	<u>78.86</u>	<u>75.90</u>	<u>69.79</u>
	Contriever	53.72	66.46	70.92	75.29	69.79	66.80
Llama3.1-7B	<u>self</u>	<u>55.38</u>	<u>68.35</u>	<u>75.88</u>	<u>79.60</u>	<u>72.55</u>	<u>68.98</u>
Ovven 2 1 5 D	Contriever	48.55	61.02	68.32	72.66	72.41	67.70
Qwen2-1.5B	<u>self</u>	<u>48.75</u>	60.98	73.84	<u>77.44</u>	<u>72.70</u>	<u>69.27</u>
O 2.7D	Contriever	53.32	66.22	70.80	74.86	74.15	69.01
Qwen2-7B	<u>self</u>	<u>55.12</u>	67.60	<u>76.17</u>	79.82	<u>75.68</u>	<u>69.96</u>

Table 8: In RAG for Multi-Hop QA settings, performance comparison across different datasets using different LLMs.

3 Experiments

3.1 Experimental Settings

Datasets. To evaluate the effectiveness of the KAG for knowledge-intensive question-answerring task, we perform experiments on 3 widely-used multi-hop QA datasets, including HotpotQA [11], 2WikiMultiHopQA [9], and MuSiQue [10]. For a fair comparison, we follow IRCoT [21] and HippoRAG [6] utilizing 1,000 questions from each validation set and using the retrieval corpus related to selected questions.

Evaluation Metric. When evaluating QA performance, we use two metrics: Exact Match (EM) and F1 scores. For assessing retrieval performance, we calculate the hit rates based on the Top 2/5 retrieval results, represented as Recall@2 and Recall@5.

Comparison Methods. We evaluate our approach against several robust and commonly utilized retrieval RAG methods. NativeRAG using ColBERTv2 [22] as retriever and directly generates answers based on all retrieved documents [23]. HippoRAG is a RAG framework inspired by human long-term memory that enables LLMs to continuously integrate knowledge across external documents. In this paper, we also use ColBERTv2 [22] as its retriever [6]. IRCoT interleaves chain-of-thought (CoT) generation and knowledge retrieval steps in order to guide the retrieval by CoT and vice-versa. This interleaving allows retrieving more relevant information for later reasoning steps. It is a key technology for implementing multi-step retrieval in the existing RAG framework.

3.2 Experimental Results

3.2.1 Overall Results

The end-to-end question answering performance is shown in Table 9. Within the RAG framework leveraging ChatGPT-3.5, HippoRAG demonstrates superior performance compared to NativeRAG. HippoRAG employs a human long-term memory strategy that facilitates the continuous integration of knowledge from external documents into LLMs, thereby significantly enhancing question answering capabilities. Additionally, it can be observed that implementing multi-step retrieval in the RAG framework using IRCoT is superior to single-step retrieval. The main reason is that IRCoT can conduct the next search based on the results of the current retrieval, rather than returning all results at once. This also increases the relevance of the retrieved content. Given the substantial operational costs associated with utilizing ChatGPT-3.5, we opted to use the DeepSeek-V2 API as a viable alternative. On average, the performance of the IRCoT + HippoRAG configuration utilizing the DeepSeek-V2 API slightly surpasses that of ChatGPT-3.5. Our constructed framework KAG shows significant performance improvement compared to IRCoT + HippoRAG, with EM increases of 11.5%, 19.8%, and 10.5% on HotpotOA, 2WikiMultiHopOA, and MuSiQue respectively, and F1 improvements of 12.5%, 19.6%, and 12.2%. These advancements in end-to-end performance can largely be attributed to the development of more effective indexing and retrieval libraries within our framework. We evaluate the effectiveness of the single-step retriever and multi-step retriever, with the retrieval performance shown in Table 10. From the experimental results, it is evident that the multi-step retriever generally outperforms the single-step retriever. Analysis reveals that the

content retrieved by the single-step retriever exhibits very high similarity, resulting in an inability to use the single-step retrieval outcomes to derive answers for certain data that require reasoning. The multi-step retriever alleviates this issue. Our proposed KAG framework directly utilizes the multi-step retriever and significantly enhances retrieval performance through strategies such as mutual indexing, logical form solving, and knowledge alignment. Compared to IRCoT + HippoRAG, KAG achieves an average Recall@2 improvement of 10.2% and an average Recall@5 improvement of 12.0% on HotpotQA, 2WikiMultiHopQA, and MuSiQue.

Framework	Model	HotpotQA		2WikiMultiHopQA		MuSiQue	
Tamework	Model	EM	F1	EM	F1	EM	F1
NativeRAG [23, 22]	ChatGPT-3.5	43.4	57.7	33.4	43.3	15.5	26.4
HippoRAG [6, 22]	ChatGPT-3.5	41.8	55.0	46.6	59.2	19.2	29.8
IRCoT+NativeRAG	ChatGPT-3.5	45.5	58.4	35.4	45.1	19.1	30.5
IRCoT+HippoRAG	ChatGPT-3.5	45.7	59.2	47.7	<u>62.7</u>	21.9	33.3
IRCoT+HippoRAG	DeepSeek-V2	51.0	63.7	48.0	57.1	26.2	36.5
KAG (ours)	DeepSeek-V2	62.5	76.2	67.8	76.7	36.7	48.7

Table 9: The end-to-end generation performance of different RAG models on three multi-hop question answering datasets. Bold text indicates that the same base model performs best. NativeRAG and HippoRAG use single-step retrieval, while other models employ multi-step retrieval.

	Retriever	Hotpe	otQA	2WikiMultiHopQA		MuSiQue	
	Kenievei	Recall@2	Recall@5	Recall@2	Recall@5	Recall@2	Recall@5
	BM25 [24]	55.4	72.2	51.8	61.9	32.3	41.2
р	Contriever [25]	57.2	75.5	46.6	57.5	34.8	46.6
ste	GTR [26]	59.4	73.3	60.2	67.9	37.4	49.1
Single-step	RAPTOR [27]	58.1	71.2	46.3	53.8	35.7	45.3
ij	Proposition [28]	58.7	71.1	56.4	63.1	37.6	49.3
<i>O</i> ₁	NativeRAG [23, 22]	64.7	79.3	59.2	68.2	37.9	49.2
	HippoRAG [6, 22]	60.5	77.7	70.7	89.1	40.9	51.9
	IRCoT + BM25	65.6	79.0	61.2	75.6	34.2	44.7
ste	IRCoT + Contriever	65.9	81.6	51.6	63.8	39.1	52.2
<u>:</u>	IRCoT + NativeRAG	<u>67.9</u>	82.0	64.1	74.4	41.7	53.7
Multi-step	IRCoT + HippoRAG	67.0	<u>83.0</u>	75.8	93.9	<u>45.3</u>	<u>57.6</u>
	KAG (ours)	72.8	88.8	<u>67.7</u>	<u>80.7</u>	48.5	65.7

Table 10: The performance of different retrieval models on three multi-hop question-answering datasets.

3.3 Model Ablation Studies

details

4 Applications

4.1 KAG for E-Goverment

We used the KAG framework and combined it with the Alipay E-government service scenario to build a Q&A application that supports answering users' questions about service methods, required materials, service conditions, and service locations. To build the e-government Q&A application, we first collected 11,000 documents about government services, and based on the methods described in section 2, implemented functional modules such as index building, logical-form-guided reasoning and solving, semantic enhancement, and conditional summary generation.

During the offline index construction phase, the semantic chunking strategy is used to segment government service documents to obtain specific matters and their properties such as the administrative region, service process, required materials, service location, target audience, and the corresponding chunks.

In the reasoning and solving phase, a logical function is generated based on the given user question and graph index structure, and the logical form is executed according to the steps of the logical function. First, the index item of the administrative area where the user is located is accurately located. Then, the item name, group of people, etc. are used for search. Finally, the corresponding chunk is found through the *required materials* or *service process*. specifically inquired by the user.

In the semantic enhancement phase, we added two semantic relations, *synonymy and hypernymy*, between items. A synonymous relation refers to items in two different regions with different names but the same meaning, such as *renewal of social security card* and *application for lost social security card*; a co-hypernymy relation refers to two items belonging to different subcategories under the same major category of items, such as *applying for housing provident fund loan for construction of new housing* and *applying for housing provident fund loan for construction and renovation of new housing*, the two items have a common hypernymy *applying for housing provident fund loan*.

We compared the effects of the two technical solutions, NaiveRAG and KAG, as shown in the table below. It is evident that KAG shows significant improvements in both completeness and accuracy compared to NaiveRAG.

Methods	SampleNum	Precision	Recall
NaiveRAG	492	66.5	52.6
KAG	492	91.6	71.8

Table 11: Ablation Experiments of KAG in E-Government Q&A.

4.2 KAG for E-Health

We have developed a medical Q&A application based on the Alipay Health Manager scenario, which supports answering user's questions regarding popular science about disease, symptom, vaccine, operation, examination and laboratory test, also interpretation of medical indicators, medical recommendation, medical insurance policy inquires, hospital inquires, and doctor information inquires. We have sorted out authoritative medical document materials through a team of medical experts, and produced more than 1.8 million entities and more than 400,000 term sets, with a total of more than 5 million relations. Based on this high-quality KG, we have also produced more than 700 DSL³ rules for indicator calculations to answer the questions of indicator interpretation.

During the knowledge construction phase, a strongly constrained schema is used to achieve precise structural definition of entities such as diseases, symptoms, medications, and medical examinations. This approach facilitates accurate answers to questions and generates accurate knowledge, while also ensuring the rigor of relations between entities. In the reasoning phase, the logical form is generated based on the user's query, and then translated to DSL form for the query on KG. The query result is returned in the form of triples as the answer. The logical form not only indicates how to query the KG, but also contains the key structural information in the user's query (such as city, gender, age, indicator value, etc.). When parsing the logical form for query in graph, the DSL rules which produced by medical expert will also be triggered, and the conclusion will be returned in the form of triples. For example, if a user asks about "blood pressure 160", it will trigger the rules as:

```
1 * Define (DiseaseSeverity/`Grade 1 Hypertension`) {
2    SystolicPressure >= 140 OR DiastolicPressure >= 90
3    }
4
5 * Define (DiseaseSeverity/`Grade 2 Hypertension`) {
6    SystolicPressure >= 160 OR DiastolicPressure >= 100
7    }
8
9 * Define (Disease/`Hypertension`) {
10    DiseaseSeverity/`Grade 1 Hypertension` OR DiseaseSeverity/`Grade 2 Hypertension` }
11 }
```

, which strictly follows the defination of $\mathscr L$ in LLMFriSPG, and the conclusion that the person may have hypertension will be obtained.

³DSL: https://openspg.yuque.com/ndx6g9/ooil9x/sdtg4q3bw4ka5wmz

In the semantic enhancement phase, we utilize the term set to express the two semantic relations of synonymy and hypernym of concepts. The hypernym supports the expression of multiple hypernyms. During knowledge construction and user Q&A phase, entities are aligned with medical terms. For example, in the concept of surgery type, the hypernym of deciduous tooth extraction and anterior tooth extraction is tooth extraction. When the user only asks questions about tooth extraction, all its hyponyms can be retrieved based on the term, and then the related entity information can be retrieved for answering. With the support of KAG, we achieved a recall rate of 60.67% and a precision rate of 81.32% on the evaluation set which sampling online Q&A queries. In the end-to-end scenario, the accuracy of medical insurance policy inquires (Beijing, Shanghai, Hangzhou) reached 77.2%, and the accuracy rate of popular science intentions has exceeded 94%, and the accuracy rate of interpreting indicator intentions has exceeded 93%.

5 Related Works

5.1 DIKW Pyramid

Following the DIKW pyramid theories[29, 30, 31, 32], after data is processed and contextualised, it becomes information, and by integrating information with experience, understanding, and expertise, we gain knowledge. We usually use information extraction technology to obtain information from the original text[33, 34, 35], and obtain knowledge from the information through linking, fusion, analysis, and learning technology[31, 36, 34]. Information and knowledge are a single entity having different forms. There are no unified language to represent data, information and knowledge, RDF/OWL[37] only provides binary representation in the form of triples, and LPG[12] lacks support for knowledge semantics and classification. SPG⁴[38] supports knowledge hierarchy and classification representation, but lacks text context support that is friendly to large language models. Our proposed LLMFriSPG supports hierarchical representation from data to information to knowledge, and also provides reverse context-enhanced mutual indexing.

5.2 Vector Similarity-based RAG

The external knowledge base use the traditional search engine provides an effective method for updating the knowledge of LLMs, it retrievals supporting documents by calculating the text or vector similarity[1, 4] between the query and document, and then answers questions using the in-context learning method of LLMs. In addition, this method faces great challenges in understanding long-distance knowledge associations between documents. Simple vector-based retrieval is not suitable for multi-step reasoning or tracking logical links between different information fragments. To address these challenges, researchers have explored methods such as fine-grained document segmentation, CoT[21], and interactive retrieval[15, 2]. Despite these optimizations, traditional query-chunks similarity methods still has difficulty in accurately focusing on the relations between key knowledge in complex questions, resulting in low information density and ineffective association of remote knowledge. We will illustrate the logical-form-guided solving method.

5.3 Information Retrieval-based GraphRAG

This type of methods use information extraction techniques to build entity and relation associations between different documents, which can better perceive the global information of all documents. Typical tasks in the knowledge construction phase include: graph information extraction and knowledge construction&enhancement. Methods like GraphRAG[39], ToG 2.0[8], HippoRAG[6] use OpenIE to extract graph-structure information like entities and relations, some of them exploit multihop associations between entities to improve the effectiveness of cross-document retrieval[8, 6], methods like DALK[7] use PubTator Central(PTC) annotation to reduce the noise problem of openIE, some of them utilize entity disambiguation technology to enhance the consistency of graph information[6, 40]. GraphRAG[39] generates element-level and community-level summaries when building offline indexes, and it uses a QFS[41] method to first calculate the partial response of each summary to the query and then calculate the final response. This inherent characteristic of GraphRAG's hierarchical summarization makes it difficult to solve questions such as multi-hop Q&A and incremental updates of documents. KGs constructed by openIE contains a lot of noise

⁴Official site of SPG: https://spg.openkg.cn/en-US

or irrelevant information[42, 43, 44]. According to the DIKW pyramid hierarchy, these methods only extract the information graph structure and make limited attempts to disambiguate entities in the transformation of information into knowledge, but they do not address issues such as semantic directionality and logical sensitivity. This paper will introduce a method in KAG to enhance information-to-knowledge conversion based on domain concept semantic graph alignment.

5.4 KG-based Query and Answering

Reasoning based on traditional KGs has good explainability and transparency, but is limited by the scale of the domain KG, the comprehensiveness of knowledge, the detailed knowledge coverage, and the timeliness of updates[45]. In this paper, we introduce HybridReasoning to alleviate issues such as knowledge sparsity, inconsistent entity granularity, and high graph construction costs. The approach leverages KG retrieval and reasoning to enhance generation, rather than completely replacing RAG.

To achieve KG-enhanced generation, it is necessary to address KG-based knowledge retrieval and reasoning. One approach is knowledge edge retrieval (IR)[46], which narrows down the scope by locating the most relevant entities, relations, or triples based on the question. Another approach is semantic parsing (SP)[47, 48], which converts the question from unstructured natural language descriptions into executable database query languages (such as SQL, SPARQL[49], DSL⁵, etc.), or first generates structured logical forms (such as S-expressions[50, 51]) and then converts them into query languages.

Although conversational QA over large-scale knowledge bases can be achieved without explicit semantic parsing (e.g., HRED-KVM[52]), most work focuses on exploring context-aware semantic parsers[48, 53, 51].

Some papers use sequence-to-sequence models to directly generate query languages[54, 55]. These methods are developed for a specific query language, and sometimes even for a specific dataset, lacking generality for supporting different types of structured data. Others use step-by-step query graph generation and search strategies for semantic parsing[56, 57, 58]. This method is prone to uncontrollable issues generated by LLM, making queries difficult and having poor interpretability. Methods like ChatKBQA[51], CBR-KBQA[59] completely generate S-expressions and provide various enhancements for the semantic parsing process. However, the structure of S-expressions is relatively complex, and integrating multi-hop questions makes it difficult for LLMs to understand and inconvenient for integrating KBQA and RAG for comprehensive retrieval. To address these issues, we propose a multi-step decomposed logical form to express the multi-hop retrieval and reasoning process, breaking down complex queries into multiple sub-queries and providing corresponding logical expressions, thereby achieving integrated retrieval of SPO and chunks.

5.5 Bidirectional-enhancement of LLMs and KGs

LLM and KG are two typical neural and symbolic knowledge utilization methods. Since the pretrained language model such as BERT [60], well-performed language models are used to help improve the tasks of KGs. The LLMs with strong generalization capability are especially believed to be helpful in the life-cycle of KGs. There are a lot of works conducted to explore the potential of LLMs for in-KG and out-of-KG tasks. For example, using LLMs to generate triples to complete triples is proved to be much cheaper than the traditional human-centric KG construction process, with acceptable accuracy for the popular entities [61]. In the past decade, methods for in-KG tasks are designed by learning from KG structures, such as structure embedding-based methods. The text information such as names and descriptions of entities is not fully utilized due to the limited text understanding capability of natural language processing methods until LLMs provide a way. Some works using LLMs for text semantic understanding and reasoning of entities and relations in KG completion [62], rule learning [63], complex logic querying [64], etc. On the other way, KGs are also widely used to improve the performance of LLMs. For example, using KGs as external resources to provide accurate factual information, mitigating hallucination of LLMs during answer generation [8], generating complex logical questions answering planning data to fine-tune the LLMs, improving LLMs planning capability and finally improving its logical reasoning capability [65], using KGs to uncover associated knowledge that has changed due to editing for better knowledge editing of LLMs [66], etc. The bidirectional-enhancement of LLMs and KGs is widely explored and partially achieved.

⁵DSL: https://openspg.yuque.com/ndx6g9/ooil9x/sdtg4q3bw4ka5wmz

6 Conclusion and Future Work

In order to build professional knowledge services in vertical domains, fully activate the capabilities and advantages of symbolic KGs and parameterized LLMs, and at the same time significantly reduce the construction cost of domain KGs, we proposed the KAG framework and try to accelerated its application in professional domains. In this article, we introduce in detail the knowledge accuracy, information completeness and logical rigorous are the key characteristics that professional knowledge services must have. At the same time, we also introduce innovations such as LLMs friendly knowledge representation, mutual index of knowledge structure and text chunks, knowledge alignment by semantic reasoning, logic-form-guided hybrid reasoning&solving and KAG model. Compared with the current most competitive SOTA method, KAG has achieved significant improvements on public data sets such as HotpotQA, 2wiki, musique. We have also conducted case verifications in E-governent Q&A and E-Health Q&A scenarios of Alipay, further proving the adaptability of the KAG framework in professional domains.

In the future, there is still more work to be explored to continuously reduce the cost of KG construction and improve the interpretability and transparency of reasoning, such as multiple knowledge extraction, knowledge alignment based on **OneGraph**, domain knowledge injection, large-scale instruction synthesis, illusion suppression of knowledge logic constraints, etc. We will also work in depth with the community organization **OpenKG** to continue to tackle key technical issues in the collaboration between LLMs and KGs.

7 Acknowledgements

This work was completed by the AntGroup Knowledge Graph Team, thank you all for your continuous innovation attempts and hard work. This work also received strong support from **Professor Huajun Chen, Researcher Wen Zhang** of Zhejiang University, and **Professor Wenguang Chen** of AntGroup Technology Research Institute, thank you all.

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