

# CoT-RAG: Integrating Chain of Thought and Retrieval-Augmented Generation to Enhance Reasoning in Large Language Models

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## Abstract

While chain-of-thought (CoT) reasoning improves the performance of large language models (LLMs) in complex tasks, it still has two main challenges: the low reliability of relying solely on LLMs to generate reasoning chains and the interference of natural language reasoning chains on the inference logic of LLMs. To address these issues, we propose CoT-RAG, a novel reasoning framework with three key designs: (i) *Knowledge Graph-driven CoT Generation*, featuring knowledge graphs to modulate reasoning chain generation of LLMs, thereby enhancing reasoning credibility; (ii) *Learnable Knowledge Case-aware RAG*, which incorporates retrieval-augmented generation (RAG) into knowledge graphs to retrieve relevant sub-cases and sub-descriptions, providing LLMs with learnable information; (iii) *Pseudo-Program Prompting Execution*, which encourages LLMs to execute reasoning tasks in pseudo-programs with greater logical rigor. We conduct a comprehensive evaluation on nine public datasets, covering three reasoning problems. Compared with the state-of-the-art methods, CoT-RAG exhibits a significant accuracy improvement, ranging from 4.0% to 23.0%. Furthermore, testing on four domain-specific datasets, CoT-RAG shows remarkable accuracy and efficient execution, highlighting its strong practical applicability and scalability.

## 1 Introduction

Large language models (LLMs) have recently drawn extensive attention from both academia and industry due to their remarkable performance in the field of natural language processing (NLP) (Kabir et al., 2024; Chiang and Lee, 2023), such as machine translation (Zhu et al., 2024; Wang, 2024), text summarization (Li et al., 2024) and sentiment analysis (Bai et al., 2024). However, despite these advancements, LLMs face notable limitations in

addressing complex tasks that require arithmetic reasoning, commonsense reasoning, and symbolic reasoning (Wei et al., 2022; Gao et al., 2023). To enhance the reasoning capabilities of LLMs, chain-of-thought (CoT) reasoning (Chu et al., 2024) has been proposed, requiring LLMs to explicitly generate intermediate reasoning steps before arriving at the final answer. Several variants of CoT have emerged, including CoT (Wei et al., 2022), Zero-shot-CoT (Kojima et al., 2022), PoT (Chen et al., 2023), and PS (Wang et al., 2023a).

Although CoT improves performance on multi-step reasoning tasks for LLMs, existing methods still face two main challenges:

**(1) The low reliability of relying solely on LLMs to generate reasoning chains.** Most existing CoT reasoning methods rely on prompting strategies, such as prompt format (Gao et al., 2023; Chen et al., 2023) and prompt planning (Yao et al., 2023b; Wang et al., 2023a), to guide LLMs in generating reasoning chains. However, due to the inherent black-box nature (Tonolini et al., 2024; Kim et al., 2024) and hallucination issues (Manakul et al., 2023) of LLMs, the generated reasoning steps often contain logical errors or factual inaccuracies (Dubey et al., 2024). For instance, CoT, Zero-shot-CoT, and PS achieve average accuracies of only 48.4%, 38.9%, and 42.5%, respectively, on the AQUA arithmetic reasoning dataset (Ling et al., 2017), highlighting their generally low performance (Wang et al., 2023a). In vertical domains like law, medicine, and finance, where errors could jeopardize human life and property, this unreliability poses incalculable risks and potential losses. Therefore, the exclusive reliance on the reasoning process generated by LLMs is insufficient to guarantee the reliability and safety of the outcomes.

**(2) The interference of natural language reasoning chains on the inference logic of LLMs.** LLMs typically generate reasoning chains in natural language (NL) to describe intermediate steps.

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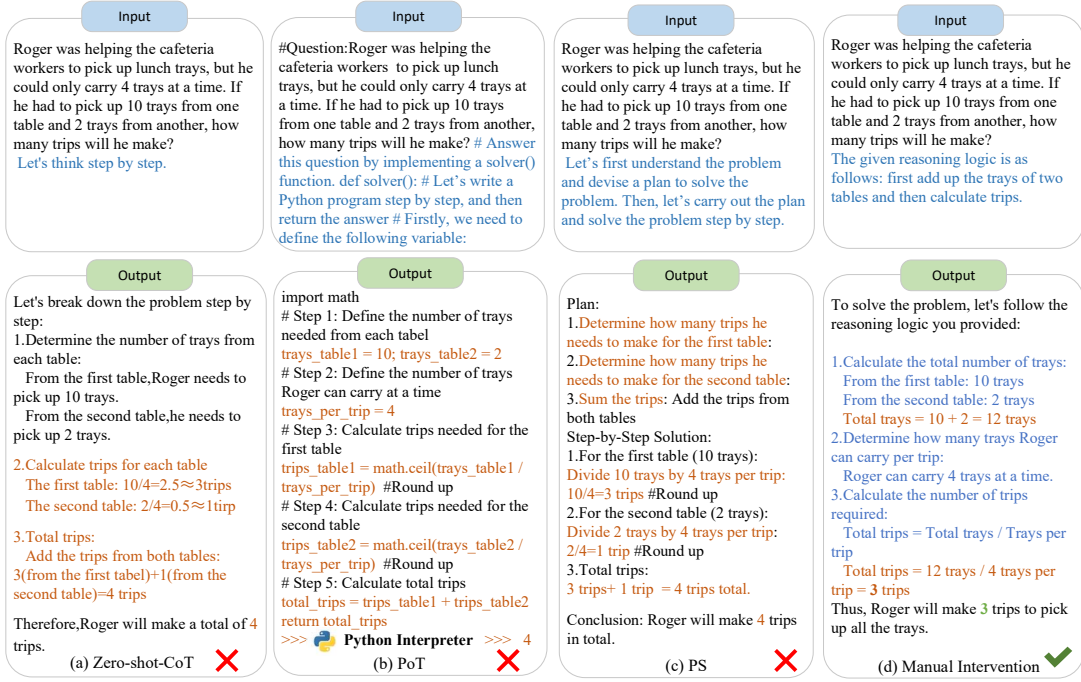


Figure 1: Example inputs and outputs of GPT-4o mini with (a) Zero-shot-CoT (Kojima et al., 2022), (b) PoT (Chen et al., 2023), (c) PS (Wang et al., 2023a) and (d) Manual Intervention on MultiArith (Roy and Roth, 2015).

While these NL-based reasoning chains are intuitive for humans, they may introduce ambiguity or inaccuracies (Gao et al., 2023; Sun et al., 2023a), disrupting the inference logic of LLMs and leading to incorrect reasoning results. Lyu et al. (2023) demonstrate that on the GSM8K arithmetic reasoning dataset (Cobbe et al., 2021), CoT (Wei et al., 2022) and LtM (Zhou et al., 2023), which rely on NL-based reasoning chains, achieve average accuracies of 46.6% and 42.3%, respectively, presenting their low correctness. This underscores the inherent ambiguities of NL-based reasoning chains, which can impede the reasoning performance of LLMs.

To address these challenges, we propose CoT-RAG, an enhanced reasoning framework with three key components. **Knowledge Graph-driven CoT Generation:** CoT-RAG integrates a knowledge graph (KG) constructed from explicitly defined dependency relationships derived through the decomposition of the manually designed decision tree. It standardizes the generation of reasoning chains by LLMs, thus improving the controllability and reliability of the reasoning process. **Learnable Knowledge Case-aware RAG:** CoT-RAG incorporates Retrieval-Augmented Generation (RAG) into the KG to retrieve relevant sub-cases and sub-descriptions, providing learnable information that mitigates logical errors and factual biases inherent in LLMs. Additionally, the interaction between

LLMs and the KG enables dynamic updates to the graph's structure and case repository. **Pseudo-Program Prompting Execution:** CoT-RAG introduces pseudo-program prompting (PsePrompting) as an alternative to NL prompts. It guides LLMs to perform reasoning tasks through pseudo-programmatic reasoning chains, maintaining the generality of NL prompts while enhancing the logical coherence of LLMs in complex tasks.

We conduct a comprehensive evaluation of CoT-RAG on nine public datasets across three reasoning problems, which shows that CoT-RAG outperforms existing methods, achieving accuracy improvements ranging from 4.0% to 23.0%. Additionally, in four domain-specific datasets, CoT-RAG achieves remarkable accuracy and efficient execution, demonstrating its cross-domain scalability.

## 2 Motivation

### 2.1 Reasoning Chain Generation

Generally, CoT reasoning relies on prompt strategies to guide LLMs in generating reasoning chains. However, excessive reliance on LLMs, owing to their inherent black-box nature and hallucination issues (Manakul et al., 2023), may lead to erroneous reasoning steps, which pose incalculable risks and potential losses in fields related to human life and property due to the tendency of LLMs to make

reasoning errors in vertical domains (Huang et al., 2024b; Barile et al., 2024).

To examine this limitation, we compared methods that exclusively depend on LLM-generated reasoning chains, including Zero-shot-CoT (Kojima et al., 2022), PoT (Chen et al., 2023), and PS (Wang et al., 2023a), against manual intervention method (i.e., providing explicit reasoning logic to LLMs). As shown in Figure 1, we input a mathematical problem from the MultiArith dataset (Roy and Roth, 2015) into GPT-4o mini<sup>1</sup>, where Zero-shot-CoT, PoT, and PS produced incorrect answers. In contrast, manual intervention in the reasoning logic (Figure 1(d)) allowed the LLM to generate correct results. Similarly, as reported by Wang et al. (2023a), CoT, Zero-shot-CoT, and PS achieve average accuracies of 74.8%, 64.5%, and 68.7% on commonsense reasoning tasks, and 48.4%, 38.9%, and 42.5% on the AQUA arithmetic reasoning dataset (Ling et al., 2017), indicating the generally lower performance of such methods. These findings further support our observations: solely relying on LLM-generated reasoning chains is insufficient to ensure reliable results, highlighting the necessity of manual intervention in the reasoning process. While some works (Gou et al., 2024; Weng et al., 2023; Paul et al., 2024; Madaan et al., 2023) have integrated verification and refinement into LLMs to reduce errors, they still depend solely on LLMs for evaluation and verification, which results in low accuracy (Chu et al., 2024).

## 2.2 Reasoning Chain Execution

LLMs commonly produce reasoning chains in natural language (NL) to outline intermediate steps. Although these NL-based chains are human-friendly, they can introduce ambiguities and inaccuracies (Sun et al., 2023a), which may interfere with the model’s inference logic and result in flawed reasoning. As stated in Lyu et al. (2023), the average accuracies of CoT and LtM (Zhou et al., 2023), which execute NL reasoning chains on GSM8K (Cobbe et al., 2021) are 46.6% and 42.3%, respectively, exhibiting their low performance. This highlights that NL prompts can cause ambiguities which interfere with reasoning. Therefore, methods like ProgPrompt (Singh et al., 2022), Code as Policies (Liang et al., 2023), and AdaPlanner (Sun et al., 2023a) use code prompts to reduce such ambiguities. However, these code prompts have three draw-

backs: 1) Complex program symbols and function calls that are difficult for non-programmers to understand, 2) Inability to handle general or domain-specific reasoning unrelated to mathematics, and 3) Code-style restriction exclusively to Python. Consequently, it is critically important to establish a prompt methodology that integrates the broad applicability of NL prompts with the logical precision of code prompts, without compromising clarity.

## 3 Methodology

**Overview.** To address the aforementioned concerns, we design CoT-RAG, a novel reasoning framework with three stages (Figure 2). First, experts input a coarse-grained decision tree that represents the reasoning logic of problems in a specific domain, then the LLM transforms it into a knowledge graph for a deeper understanding of its internal logic in the *Knowledge Graph-driven CoT Generation* phase (§ 3.1). Next, during the *Learnable Knowledge Case-aware RAG* phase (§ 3.2), users input query descriptions related to this domain and the LLM extracts sub-descriptions to update the knowledge graph for accurately generating results in the next stage. Third, the LLM uses *Pseudo-Program Prompting Execution* (§ 3.3) to process the updated knowledge graph and produces the ultimate result. Specific algorithm demonstration, time complexity analysis, and related notations are shown in Appendix A.1 and A.2.

### 3.1 Knowledge Graph-driven CoT Generation

A decision tree (DT) is a tree-structured algorithm for classification and regression, where the internal nodes “test” a condition, branches represent the test outcome, and the leaf nodes denote the final results (Magerman, 1995). DTs offer robust logical coherence and interpretability, enabling human intervention (Mienye and Jere, 2024; Kalra and Brown, 2024). They are widely used in critical areas such as education (Huang, 2021), finance (Wang, 2021; Chou and Chen, 2024), and medicine (He et al., 2024; Govil et al., 2024), which motivates us to utilize a manually crafted DT that represents the reasoning logic of problems in a specific domain, to modulate the inference processes of LLMs. Distinct from the concept above, each node in our DT contains a *Question* and a *Knowledge case*, which represents some descriptions from user input processed by the node (e.g., Figure 3), information supplemented artificially (e.g., Appendix A.6 Ta-

<sup>1</sup><https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence>



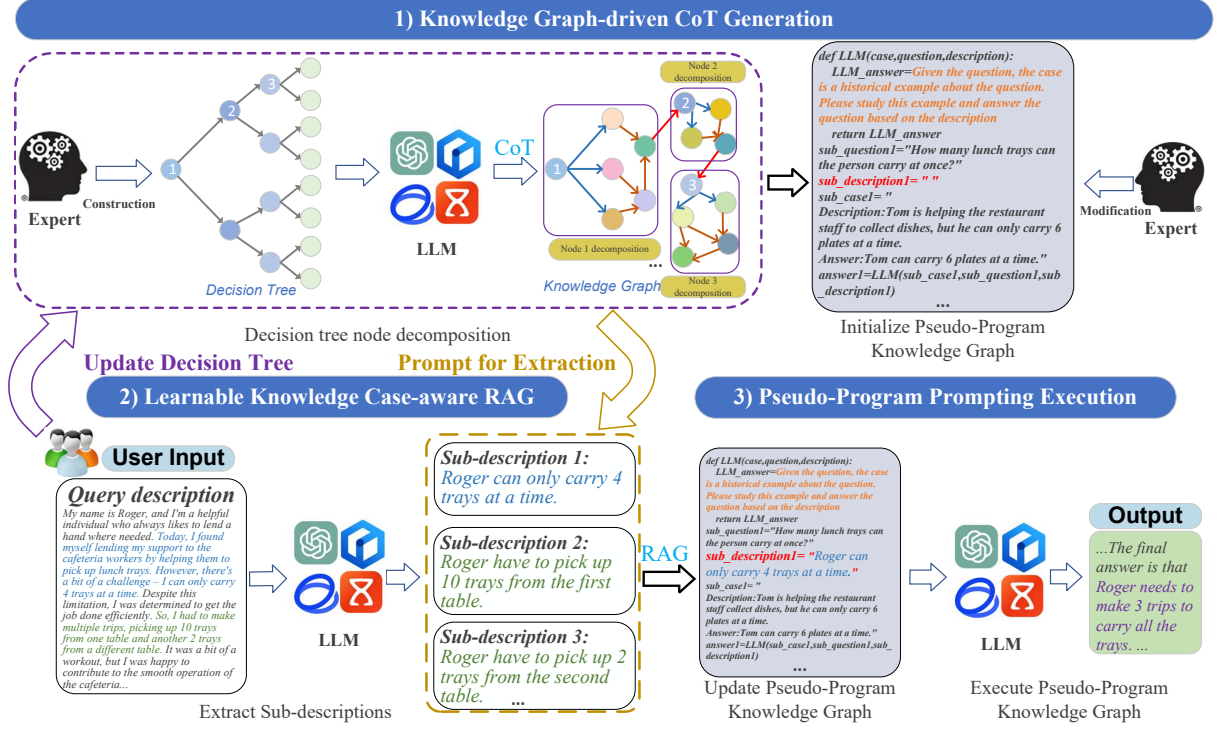


Figure 2: An overview of our CoT-RAG framework.

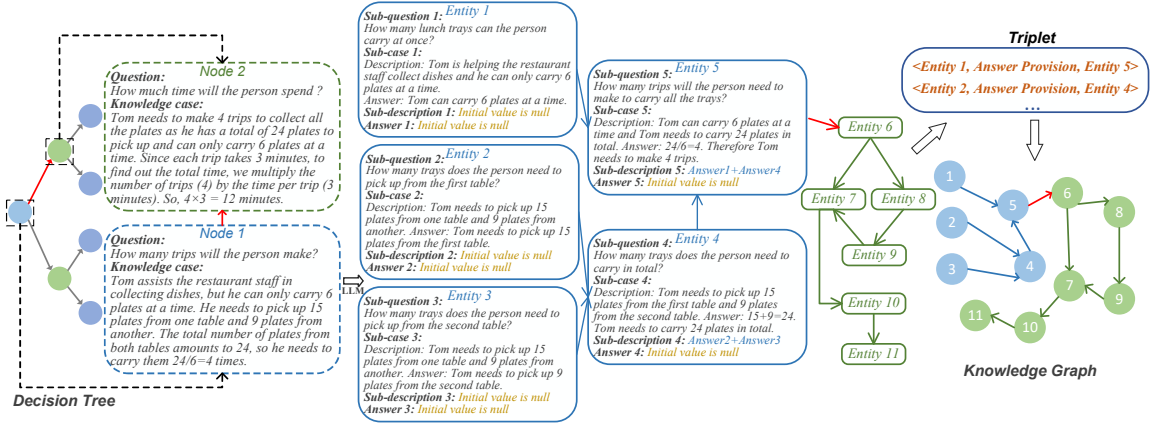


Figure 3: An example of decomposing a decision tree into a knowledge graph.

ble 20), or relevant considerations (e.g., Appendix A.6 Table 26) to assist LLMs in responding the *Question* of the node. Each branch implies that the output of the parent node is fed to the child node.

However, designing a “fine-grained” DT manually consumes a lot of financial and human resources. To alleviate this situation, LLMs can efficiently decompose the “coarse-grained” DT nodes provided by experts, leveraging their proficiency in decomposition (Huang et al., 2024a). Furthermore, *Knowledge case* can assist LLMs in learning how to decompose each node of the DT, mitigating incorrect results caused by the tendency of LLMs to make errors in vertical fields (Huang et al., 2024b; Barile et al., 2024). Nevertheless, the complex rela-

tionships among the new nodes after the decomposition of the DT need to be captured. Considering that knowledge graphs (KGs), featuring clear delineation and interpretability, precisely represent intricate inter-individual relationships and facilitate inference (Sun et al., 2024a), we introduce them to represent decomposed DTs. As depicted in *Stage 1* of Figure 2, LLMs transform each node in the coarse-grained DT built by experts into several entities and generate a highly transparent KG, optimizing the decision-making process.

We provide an example in Figure 3 to show the DT node decomposition process. The *node 1*: “How many trips will the person make?” is decomposed by the LLM into five entities, each

corresponding to four attributes: (i) *Sub-question*, a simplified component of the original complex *Question*; (ii) *Sub-case*, which is a concise case corresponding to *Sub-question*, derived from the LLM-decomposed *Knowledge case*; (iii) *Sub-description*, a text description corresponding to *Sub-question* and *Sub-case*, its initial value is null and will be assigned by extracting from users' input query descriptions in § 3.2 or obtained from *Answer* of other entities; and (iv) *Answer*, which refers to the LLM's output for matching *Sub-question*, its initial value is null and will be assigned in § 3.3. Edges between entities represent *Answer Provision* relationships, for example, the triplet  $\langle \text{Entity 1}, \text{Answer Provision}, \text{Entity 5} \rangle$  indicates that the *Answer* of *Entity 1* is provided to the *Sub-description* of *Entity 5*. The *Answer* of *Entity 5* represents the *node 1*'s inference result. Moreover, as *node 2* in the DT is the child of *node 1*, *Entity 5* points to *Entity 6*, which is the entity after *node 2* is decomposed by the LLM.

### 3.2 Learnable Knowledge Case-aware RAG

§ 3.1 pertains to the introductory phase of the entire CoT-RAG framework. Subsequently, it comes to the application phase targeting users, that is, **how to extract brief yet significant information from relatively long query descriptions input by users**. Unlike traditional vector-based retrieval in RAG, we utilize LLM-based retrieval (Shen et al., 2024) for long query descriptions, combining *Sub-question* and *Sub-case* of each entity as a prompt generated in the previous stage, to extract relevant descriptions that are assigned to the corresponding *Sub-description*, which has higher accuracy and shorter runtime (refer to Appendix A.3).

We present an example to illustrate specific *Sub-description* extraction process. On the premise that the KG generated from Figure 3 is taken as the output of *Stage 1* of CoT-RAG, the user inputs a query description about *Roger*, as depicted in *Stage 2* of Figure 2, and the LLM uses this KG (including *Sub-question* and *Sub-case* of *Entities 1, 2, and 3*) as a prompt to extract the corresponding descriptions as *Sub-description*. Specifically, *Sub-description 1* is "Roger can only carry 4 trays at a time", *Sub-description 2* is "Roger has to pick up 10 trays from the first table", and *Sub-description 3* is "Roger has to pick up 2 trays from the second table". These *Sub-description* and *Sub-case* will be employed by the LLM to precisely answer the corresponding *Sub-question* of each entity in § 3.3.

Furthermore, if the query descriptions entered

by users are new to the DT, they have the capacity to dynamically update the *Knowledge case* within the DT, which facilitates the LLM in generating a more comprehensive and application-oriented knowledge graph, thereby augmenting the flexibility of the knowledge graph.

### 3.3 Pseudo-Program Prompting Execution

The first two designs enhance the credibility and interpretability of the reasoning chains generated by LLMs. However, there remains a critical issue: **how can reasoning chains be represented to ensure the rigorous logical execution of LLMs?** Inspired by QDMRPS (Huang et al., 2024a) and AdaPlanner (Sun et al., 2023a), we propose Pseudo-program Prompting (PsePrompting), which allows the LLM to represent the knowledge graph reasoning chain as pseudo-programs, referred to as the pseudo-program knowledge graph (PKG). Its initial version created by the LLM of *Stage 1* is shown in Table 6 of Appendix A.4, where *Entities 1, 2, and 3*'s *Sub-description* are filled based on user input in *Stage 2* (Table 7 in Appendix A.4). The final result of the PKG executed by the LLM in *Stage 3* is depicted in Table 8 of Appendix A.4. The LLM processes each entity of the PKG sequentially, it first retrieves the *Sub-case* and *Sub-description* for learning, then generates the *Answer*. We can observe that PsePrompting features a simple logical structure and is easily understandable. Additionally, it offers general applicability for answering a wide range of questions (Appendix A.6), eliminates reliance on external interpreters, and is extendable to different programming languages such as C++ and Java (Appendix A.7).

## 4 Experimental setup

### 4.1 Datasets

The proposed method is evaluated on nine benchmark datasets from three categories of reasoning problems: **Arithmetic Reasoning**: (1) the AQUA (Ling et al., 2017) dataset of algebraic word problems with natural language rationales, (2) the GSM8K (Cobbe et al., 2021) dataset of high quality linguistically diverse grade school math word problems created by human problem writers, (3) the MultiArith (Roy and Roth, 2015) dataset of mathematical problems that necessitates numerous inference steps for resolution, (4) the SingleEq (Koncel-Kedziorski et al., 2015) dataset of algebraic problems calls for the solution of equations; **Common-**

Method	AQuA	GSM8K	MultiArith	SingEq	HotpotQA	CSQA	SIQA	Letter	Coin	Average
CoT	54.3	85.8	97.2	92.3	85.7	79.6	82.4	39.6	79.2	77.3
Zero-shot-CoT	43.4	78.3	96.7	88.5	81.4	75.6	78.0	34.5	75.6	72.4
Auto-CoT	47.8	82.4	97.5	91.6	86.1	76.4	80.6	41.0	81.2	76.1
PS	50.1	82.8	96.9	89.4	83.0	74.2	76.3	44.7	79.5	75.2
QDMRPS	47.3	83.8	95.2	90.7	86.7	76.6	77.8	36.5	76.3	74.5
CoT-RAG	<b>65.7</b>	<b>94.7</b>	<b>98.5</b>	<b>98.7</b>	<b>98.4</b>	<b>97.9</b>	<b>98.7</b>	<b>54.6</b>	<b>94.7</b>	<b>89.1</b>

Table 1: Accuracy on nine datasets from three categories of reasoning tasks using ERNIE-Speed-128K.

Method	AQuA	GSM8K	MultiArith	SingEq	HotpotQA	CSQA	SIQA	Letter	Coin	Average
CoT	90.2	95.3	98.1	98	92.3	89.0	93.9	97.7	<b>100</b>	94.9
Zero-shot-CoT	81.8	93.3	96.3	97.3	87.7	82.7	87.8	92.7	98.0	90.8
Auto-CoT	84.3	94.6	97.3	98.6	90.0	85.3	90.1	97.0	99.8	93.0
PS	82.1	92.8	97.7	98.1	89.9	84.9	86.5	97.3	99.9	92.1
QDMRPS	83.5	94.3	98.5	98.8	90.8	83.9	85.9	96.7	98.3	92.3
CoT-RAG	<b>99.0</b>	<b>99.5</b>	<b>99.9</b>	<b>99.6</b>	<b>99.4</b>	<b>99.6</b>	<b>98.3</b>	<b>99.9</b>	<b>100</b>	<b>99.5</b>

Table 2: Accuracy on nine datasets from three categories of reasoning tasks using GPT-4o mini.

**sense Reasoning:** (5) the HotpotQA (Wolfson et al., 2020) dataset of commonsense questions based on Wikipedia that requires reasoning using multiple supporting problems, (6) the CSQA (Tal-  
mor et al., 2019) benchmark dataset of multiple-choice questions that require different types of commonsense knowledge to obtain the correct answers, (7) the SIQA (Sap et al., 2019) dataset of questions which focus on inferring people’s behavior and its social impact; **Symbolic Reasoning:** (8) the Last Letter Concatenation (Wei et al., 2022) dataset of questions requiring the last letters of words in a name to be concatenated (e.g., “Donald Trump”→“dp”), and (9) the Coin Flip (Wei et al., 2022) dataset of questions on whether a coin is still heads up after it is flipped or not flipped based on steps given in the questions.

## 4.2 Baselines

We compare our proposed CoT-RAG with five methods: (1) **CoT** (Wei et al., 2022) uses a “thought chain” prompt to guide models through a step-by-step solution process, leading to a detailed answer. (2) **Zero-shot-CoT** (Kojima et al., 2022) encourages LLMs to generate reasoning steps automatically by appending “Let’s think step by step” to the question, reducing reliance on human examples. (3) **Auto-CoT** (Zhang et al., 2023) automates the generation of high-quality prompts, improving efficiency and accuracy in reasoning tasks. (4) **PS** (Wang et al., 2023a) first generates a coarse task plan, followed by a fine-grained solution process. (5) **QDMRPS** (Huang et al., 2024a) decomposes problems into QDMR-based directed acyclic

graphs and reasons step-by-step based on dependencies. Methods like PoT (Chen et al., 2023) and Faithful CoT (Lyu et al., 2023), which cannot handle complex non-mathematics reasoning and decision tasks, especially in the field of commonsense reasoning, are excluded from this comparison. Additionally, we evaluate these methods across five LLMs: ERNIE-Speed-128K<sup>2</sup>, ERNIE-3.5-128K<sup>3</sup>, GLM-4-flash<sup>4</sup>, GPT-4o mini, and GPT-4o<sup>5</sup>.

## 5 Experimental Results

### 5.1 Main Results

Tables 1 and 2 present our results on ERNIE-Speed-128K and GPT-4o mini, with additional results from other LLMs available in Appendix A.5. The experimental data demonstrate that our approach significantly improves reasoning accuracy across all datasets compared to existing techniques. Specifically, compared to CoT, Zero-shot-CoT, Auto-CoT, PS, and QDMRPS, the average accuracy across datasets increases by 4.0%-15.2%, 7.3%-23.0%, 5.0%-17.1%, 5.7%-18.5%, and 4.8%-19.5%, respectively. The overall improvement in accuracy can be attributed to the comprehensive optimizations of our method in terms of credible CoT generation and rigorous instruction execution.

To further showcase the superiority of our method, we contrast the average accuracies of di-

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<sup>4</sup><https://open.bigmodel.cn/dev/api/normal-model/glm-4>

<sup>5</sup><https://openai.com/index/hello-gpt-4o>

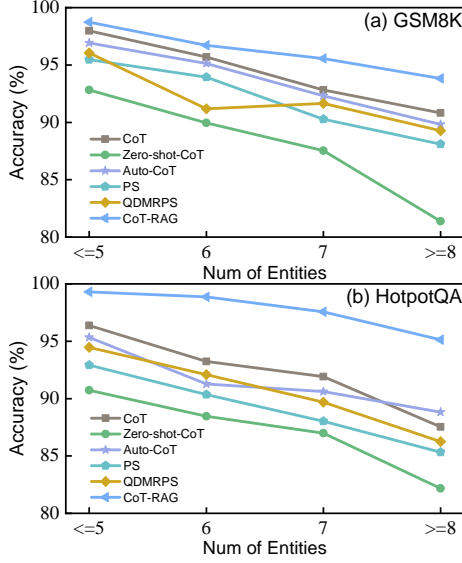


Figure 4: Accuracy of problems that can be decomposed into different numbers of entities.

verse reasoning complexities on GSM8K (arithmetic reasoning) and HotpotQA (commonsense reasoning). Reasoning complexity is gauged by the entity counts post-original decision tree decomposition. Considering that the maximum number of entities split from the two datasets is 9, we compared the accuracies with four levels of complexity:  $\leq 5$ , 6, 7, and  $\geq 8$ . As shown in Figure 4, for problems with over 8 entities, on GSM8K, CoT-RAG’s average accuracy outperforms CoT by 3.4%, Zero-shot-CoT by 15.3%, Auto-CoT by 4.5%, PS by 6.5%, and QDMRPS by 5.1%. On HotPotQA, the gains are 8.7%, 15.8%, 7.1%, 11.5%, and 10.3% respectively, attesting to our method’s efficacy in complex reasoning tasks. Moreover, as the number of the entity number increases, the superiority of CoT-RAG over the competitors enlarges progressively. More examples from the experimental results can be found in Appendix A.6.

## 5.2 Analysis

We perform an extensive analysis of CoT-RAG for a deeper insight into the function of each component, the robustness of exemplars, and its remarkable scalability. GPT-4o mini is chosen as the benchmark model for all ensuing analyses.

**Ablation Analysis.** The CoT-RAG framework enhances LLMs’ reasoning accuracy. To quantify the contribution of each component to accuracy improvement, we conduct an ablation analysis by removing different parts of the framework. We

test four variants on arithmetic reasoning datasets (AQuA, GSM8K) and commonsense reasoning datasets (HotpotQA, CSQA): **No node decomposition:** Decision tree nodes are not decomposed into knowledge graphs; **No RAG:** Removal of entity *Sub-case* in the knowledge graph; **No PsePrompting:** Replace Pseudo-program Prompting with NL prompts; **No expert inspection:** The initial PKG is not inspected by an expert.

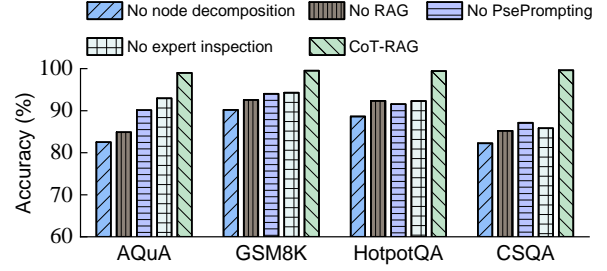


Figure 5: Ablation study results: accuracy when we remove different parts of CoT-RAG.

Figure 5 presents the experimental results, showing that accuracy decreases for all variants across datasets. Notably, removing node decomposition leads to the most significant drop in accuracy, highlighting its crucial role in the framework. In GSM8K, HotpotQA, and CSQA, RAG and expert inspection have similar contributions. However, in AQuA, RAG’s contribution is evidently higher, probably due to the difficulty of the dataset’s mathematical tasks. Table 1 indicates that AQuA’s lower accuracy suggests its more challenging tasks, which may require knowledge retrieval. PsePrompting’s contribution is moderate, probably because the average complexity of these datasets is low and thus inadequate to manifest its advantages.

**Robustness Results.** Considering that robustness is a key performance indicator, we further conduct a comprehensive robustness analysis on CoT-RAG. In addition to the original CoT-RAG (Table 2), we test several variants to assess the impact of different factors. Specifically, we evaluate the effect of PsePrompting language by using C++ and Java to generate PKG (Appendix A.7). We also investigate the influence of knowledge cases by manually replacing all *Knowledge case* in the decision tree twice and comparing inference accuracy. Following Wei et al. (2022), two other co-authors of this paper (A and B) assume expert roles to contribute to the decision tree design, allowing us to compare the impact of different experts on our method.



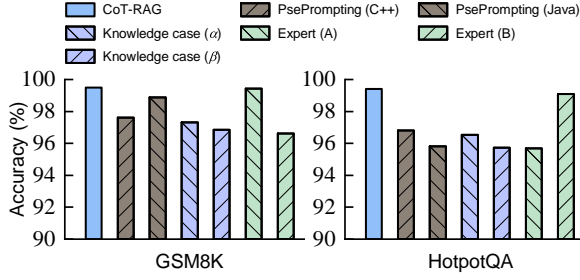


Figure 6: Robustness of CoT-RAG.

Figure 6 presents the experimental results across the GSM8K and HotpotQA datasets for all variants. Analysis shows that compared to the original CoT-RAG, the accuracy error for all variants does not exceed 4%, demonstrating the strong robustness of CoT-RAG. Furthermore, the participation of Expert A and Expert B caused noticeable accuracy fluctuations, indicating that the alignment between an expert’s domain knowledge and the CoT-RAG framework can influence the quality of decision trees and final inference outcomes. This observation highlights the synergy between expert knowledge and the framework. The details of **Scalability Study** are shown in Appendix A.3.

## 6 Related Work

### 6.1 Chain of Thought Reasoning

To utilize LLMs’ reasoning capabilities, Wei et al. (2022) propose Chain-of-Thought prompting, adding reasoning steps before the answer to improve performance. Subsequent works have enhanced CoT reasoning in areas including prompt format (Gao et al., 2023; Chen et al., 2023; Lyu et al., 2023), selection (Yao et al., 2023a; Yu et al., 2024), ensemble (Weng et al., 2023; Li et al., 2023; Hu et al., 2024; Fu et al., 2023), decomposition (Zhou et al., 2023; Khot et al., 2023; Press et al., 2023; Huang et al., 2024a), model fine-tuning (Liao et al., 2025; Yeo et al., 2025), and planning (Wang et al., 2023a; Sun et al., 2024b; Wang et al., 2023b). Chen et al. (2023) design PoT, separating computation and reasoning with code-trained LLMs. Lyu et al. (2023) introduce Faithful CoT, combining natural and symbolic languages to enhance interpretability and user interaction. Kojima et al. (2022) propose Zero-shot-CoT, automating reasoning steps with minimal human input. Wang et al. (2023a) address errors in Zero-shot-CoT by introducing PS prompting, which refines coarse task plans. Huang et al. (2024a) use QDMR-

based graphs for structured problem decomposition. However, these methods solely rely on the reasoning and evaluation of the LLM itself, leading to low reliability. We refer readers to the survey (Chu et al., 2024) for more related works.

### 6.2 RAG Reasoning with Knowledge Graph

Retrieval-Augmented Generation (RAG) enhances LLMs by using relevant content retrieved from knowledge sources, aiming to mitigate the black-box nature and hallucination issues and improve text generation quality (Mao et al., 2024; Liu et al., 2024). Previous works have explored different ways in which LLMs leverage retrieved or generated text as external knowledge to boost reasoning (Lewis et al., 2020; Izacard et al., 2023; Sun et al., 2023b; Hagström et al., 2023). Recent research has further enhanced RAG reasoning by incorporating knowledge graphs. Sun et al. (2024a) introduce TOG, an innovative framework that enhances LLMs through interaction with knowledge graphs and expanding reasoning paths via beam search. Edge et al. (2024) propose GraphRAG, which combines the strengths of RAG and query-focused summarization, using knowledge graphs to store source document data for efficient global question answering. Saleh et al. (2024) design SG-RAG, a zero-shot method, utilizing structured information from knowledge graphs to enable LLMs to accurately answer multi-hop questions. Our work incorporates RAG to enhance the reasoning of LLMs based on the generated knowledge graphs.

## 7 Conclusion

To address the issues of low reliability in reasoning chains generated solely by LLMs and the interference of NL reasoning chains, we propose CoT-RAG, a novel reasoning framework with three key designs: (i) *Knowledge Graph-driven CoT Generation*, which introduces knowledge graphs to regulate LLMs’ reasoning chain generation, thereby enhancing reasoning reliability; (ii) *Learnable Knowledge Case-aware RAG*, integrating RAG into knowledge graphs to retrieve relevant sub-cases and sub-descriptions for learnable information; (iii) *Pseudo-Program Prompting Execution*, which inspires LLMs to execute logically reasoning tasks in pseudo-programs. Evaluations across nine public datasets demonstrate that CoT-RAG outperforms existing methods, particularly in four domain-specific datasets, validating its powerful



cross-domain scalability.

## 8 Limitations

Although the CoT-RAG framework demonstrates effectiveness, it faces two key limitations. First, its implementation relies on LLMs with advanced program understanding and execution capabilities, yet publicly available LLMs fall short on these requirements, necessitating our use of proprietary LLMs. This constraint limits the framework's generalizability and precludes the evaluation of how LLMs' parameter sizes impact CoT-RAG performance. Second, the construction of decision trees is influenced by the expert's domain-specific knowledge and background. We will focus on incorporating universal methods in decision tree design and will explore more widely applicable prompting techniques to mitigate these limitations.

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## A Appendix

### A.1 CoT-RAG Algorithm and Time Complexity Analysis

As shown in Algorithm 1, the CoT-RAG framework involves three stages: 1) Knowledge Graph-driven CoT Generation (Lines 1-8), 2) Learnable Knowledge Case-aware RAG (Lines 10-16), and 3) Pseudo-Program Prompting Execution (Lines 18-21). First, experts construct and input a coarse-grained decision tree related to a field (Line 3), and then ask the LLM to decompose the decision tree into a fine-grained, highly structured knowledge graph (Line 4), which is represented by the Pseudo-Program Prompting we proposed (Line 5), referred to as the initialized pseudo-program knowledge graph (*initial\_PKG*). This can further be modified by the experts (Lines 6-7). Next, users enter query descriptions related to this field (Line 12), which can help update the decision tree benefitting from their usefulness (Lines 13-14). According to the *initial\_PKG*, the LLM subsequently extract the corresponding sub-descriptions from the query description to update the *initial\_PKG*, namely *updated\_PKG* (Lines 15). Finally, the LLM executes *updated\_PKG* to output the final result (Lines 18-21).

The time complexity of the CoT-RAG algorithm is determined by three aforementioned stages. In *Stage 1*, the algorithm decomposes a coarse-grained decision tree into a fine-grained knowledge graph. The time complexity of this process is  $O(N)$ ,

---

**Algorithm 1** CoT-RAG: Enhanced Reasoning Framework Based on CoT and RAG

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```
1: function KnowledgeGraphDrivenCoTGeneration(field, ExpertModify):
2:   // field depends on the actual scenario of CoT-RAG application
3:   decision_tree  $\leftarrow$  ExpertBuildDecisionTree(field)
4:   knowledge_graph  $\leftarrow$  LLMDecomposeDecisionTree(decision_tree)
5:   initial_PKG  $\leftarrow$  LLMGeneratePKG(knowledge_graph)
6:   if ExpertModify is true then
7:     initial_PKG  $\leftarrow$  ExpertModifyKnowledgeGraph(initial_PKG)
8:   return initial_PKG
9:
10: function LearnableKnowledgeCaseAwareRAG(initial_PKG, decision_tree, is_useful):
11:   // Get the query description entered by the user
12:   query_description  $\leftarrow$  GetUserQueryDescription()
13:   if is_useful is true then
14:     updated_decision_tree  $\leftarrow$  Update(query_description, decision_tree)
15:     updated_PKG  $\leftarrow$  LLMExtractSubDescriptions(initial_PKG, query_description)
16:     return updated_PKG
17:
18: function PseudoProgramPromptingExecution(updated_PKG):
19:   // Generate final results
20:   final_result  $\leftarrow$  LLMGenerateFinalResult(updated_PKG)
21:   return final_result
```

---

where  $N$  represents the number of nodes in the decision tree. In *Stage 2*, the algorithm extracts sub-descriptions from user input and updates the knowledge graph. The time complexity of this stage is  $O(M)$ , with  $M$  denoting the number of entities in the knowledge graph. In *Stage 3*, the algorithm inputs the updated knowledge graph into LLMs to generate the final result, with a time complexity of  $O(M)$  as well. Overall, because the number of entities  $M$  in the knowledge graph has a linear relationship with decision tree nodes' number  $N$  in our experiments, the total time complexity of the algorithm is  $O(N)$ .

## A.2 Frequently-Used Notations

Table 3 shows the frequently used notations in this paper.

## A.3 Scalability Study

To demonstrate the scalability and practical value of our method across different domains, we evaluate it on four open-source datasets from the legal, financial, and logic fields: **LawBench** (Fei et al., 2024): A Chinese legal benchmark including tasks such as entity recognition, reading comprehension, and crime amount calculation; **LegalBench** (Guha et al., 2023): An American legal

benchmark featuring 162 legal reasoning tasks; **CFBenchmark** (Lei et al., 2023): A Chinese financial benchmark assessing the performance of LLMs in finance; **AGIEval** (Zhong et al., 2024): A benchmark for evaluating human cognitive task performance, where we select the dataset with a focus on logic-based question answering. Furthermore, we utilize the Faiss<sup>6</sup> vector database to replace the LLM-based retrieval in CoT-RAG with vector-based retrieval, where seven variants are set up according to different indexes<sup>7</sup>, namely CoT-RAG (IndexFlatL2), CoT-RAG (IndexFlatIP), CoT-RAG (IndexHNSWFlat), CoT-RAG (IndexIVFFlat), CoT-RAG (IndexLSH), CoT-RAG (IndexPQ), and CoT-RAG (IndexIVFPQ). These variants are compared with our method and GraphRAG (Edge et al., 2024), which is the graph-based RAG.

Table 4 and Table 5 present the comparison results of CoT-RAG and baseline methods in terms of accuracy, average runtime, and average token consumption on four vertical domain datasets. The experimental results indicate that, although CoT-RAG consumes more tokens compared to vector-retrieval-based variants on different indexes, it

<sup>6</sup><https://www.pinecone.io/learn/series/faiss/faiss-tutorial/>

<sup>7</sup><https://github.com/facebookresearch/faiss/wiki/Faiss-indexes>

shows improvements in accuracy and average running time, with the ranges being 9.5%-12.2% and 13.9%-27.0%, respectively, where we can observe that information loss and time waste may occur during the vector-based storage and retrieval process. Additionally, compared with GraphRAG, CoT-RAG achieves an overall improvement, with 19.0% increase in accuracy, 29.2% reduction in average runtime, and 33.4% decrease in average token consumption, demonstrating its powerful scalability and practical applicability.

#### **A.4 Example Outputs of the three stages of CoT-RAG**

Table 6, Table 7, and Table 8 are example outputs for the three stages of CoT-RAG, respectively.

#### **A.5 Experimental results of various LLMs**

Table 9, Table 10, and Table 11 are the experimental results of ERNIE-3.5-128K, GLM-4-flash, and GPT-4o, respectively.

#### **A.6 Examples of pseudo-program knowledge graphs from different datasets**

Tables 12 to 35 are examples of pseudo-program knowledge graphs and their output results of GPT-4o mini for each dataset.

#### **A.7 Pseudo-program knowledge graph in different programming language forms**

Tables 36 to 39 are examples of pseudo-program knowledge graphs in both C++ and Java languages, along with their output results.

Notation	Description
KG(s)	A <b>Knowledge Graph(s)</b> is a semantically structured network, which uses triplets to describe cross-domain entity relationships and attribute values (Mendes et al., 2024; Elhammadi et al., 2020). It integrates general facts, domain-specific knowledge (such as in mathematics, law, finance, and biomedical), and common-sense knowledge, providing a knowledge base and reasoning foundation for complex tasks like cross-domain intelligent decision-making and comprehensive knowledge-based question-answering (Schneider et al., 2022; Arsenyan et al., 2024). <b>The knowledge graph in this paper reflects both effective interpretability and powerful reasoning logic.</b>
DT(s)	A <b>Decision Tree(s)</b> is a tree-structured machine-learning algorithm that finds extensive application in classification and regression tasks (Wu et al., 2020; Huang, 2021). Its fundamental principle entails recursively partitioning a dataset into progressively smaller subsets, thereby giving rise to a dendritic structure. In this construct, each internal node signifies a test of a characteristic or attribute, each branch represents a particular value of that characteristic, and each leaf node represents a classification result or a regression value (He et al., 2024; Magerman, 1995). <b>Different from the concept described above, the decision tree in this paper refers to a tree-shaped structure constructed by experts. This structure incorporates knowledge cases and is imbued with reasoning logic, specifying the inference process of the LLMs.</b>
RAG	<b>Retrieval-Augmented Generation</b> incorporates a retrieval mechanism within the text-generation process (Gupta et al., 2024). It empowers LLMs to retrieve pertinent information from external knowledge repositories, and integrate it into the generated outputs, endowing the generated content with enhanced accuracy, pertinence, and factual fidelity. RAG can be generally categorized into three types: Document-based Retrieval RAG, Graph-based Retrieval RAG, and Multi-modal Retrieval RAG (Zhao et al., 2024; Peng et al., 2024). <b>Distinct from the above-mentioned vector-based retrieval RAG, the RAG in this paper harnesses the formidable retrieval capabilities inherent in LLMs. It retrieves relevant content from the knowledge cases of the decision tree and the query descriptions input by users, reducing runtime and enhancing accuracy (Appendix A.3).</b>

Table 3: Frequently-Used Notations.

Method	LawBench			LegalBench		
	Accuracy (%)	Runtime (s)	Token	Accuracy (%)	Runtime (s)	Token
CoT-RAG (IndexFlatL2)	92.7	4.67	<b>896</b>	93.7	4.89	875
CoT-RAG (IndexFlatIP)	91.5	4.52	923	91.9	4.96	<b>815</b>
CoT-RAG (IndexHNSWFlat)	93.2	4.75	968	92.8	4.71	870
CoT-RAG (IndexIVFFlat)	93.6	4.04	908	92.1	4.23	892
CoT-RAG (IndexLSH)	90.8	4.49	988	92.5	4.37	842
CoT-RAG (IndexPQ)	93.1	4.32	1002	92.9	4.46	878
CoT-RAG (IndexIVFPQ)	93.6	4.12	975	93.1	4.25	866
GraphRAG	94.8	5.85	2883	97.5	4.72	1850
CoT-RAG	<b>99.3</b>	<b>3.02</b>	1557	<b>98.6</b>	<b>3.46</b>	1298

Table 4: Scalability results on LawBench and LegalBench using GPT-4o mini.

Method	CFBenchmark			AGIEval		
	Accuracy (%)	Runtime (s)	Token	Accuracy (%)	Runtime (s)	Token
CoT-RAG (IndexFlatL2)	85.2	5.12	1028	67.8	5.23	1257
CoT-RAG (IndexFlatIP)	87.1	4.73	985	72.4	5.32	1316
CoT-RAG (IndexHNSWFlat)	85.9	4.85	1049	70.9	4.85	1285
CoT-RAG (IndexIVFFlat)	86.8	4.09	1028	75.3	4.53	1342
CoT-RAG (IndexLSH)	88.1	4.66	<b>979</b>	74.6	4.67	1268
CoT-RAG (IndexPQ)	87.4	4.86	996	73.9	4.89	<b>1225</b>
CoT-RAG (IndexIVFPQ)	87.8	4.42	1005	76.2	4.62	1243
GraphRAG	73.1	5.08	2026	54.6	4.89	2817
CoT-RAG	<b>94.7</b>	<b>3.95</b>	1643	<b>88.3</b>	<b>4.11</b>	1861

Table 5: Scalability results on CFBenchmark and AGIEval using GPT-4o mini.



---

```

def LLM(case,question,description):
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the
question based on the description
    return LLM_answer

sub_question1="How many lunch trays can the person carry at once?"
sub_case1="
Description: Tom is helping the restaurant staff collect dishes and he can only carry 6 plates at a time.
Answer: Tom can carry 6 plates at a time."
sub_description1=" "
answer1=LLM(sub_case1, sub_question1,sub_description1)

sub_question2="How many trays does the person need to pick up from the first table?"
sub_case2="
Description: Tom needs to pick up 15 plates from one table and 9 plates from another.
Answer: Tom needs to pick up 15 plates from the first table."
sub_description2=" "
answer2=LLM(sub_case2,sub_question2,sub_description2)

sub_question3="How many trays does the person need to pick up from the second table?"
sub_case3="
Description: Tom needs to pick up 15 plates from one table and 9 plates from another.
Answer: Tom needs to pick up 9 plates from the second table."
sub_description3=" "
answer3=LLM(sub_case3,sub_question3,sub_description3)

sub_question4="How many trays does the person need to carry in total?"
sub_case4="
Description: Tom needs to pick up 15 plates from the first table and 9 plates from the second table.
Answer: 15+9=24. Therefore Tom needs to carry 24 plates in total."
#Answering sub_question4 requires relying on the answers of sub_question2 and sub_question3, namely answer2 and answer3
sub_description4=answer2+answer3
answer4=LLM(sub_case4,sub_question4,sub_description4)

sub_question5="How many trips will the person need to make to carry all the trays?"
sub_case5="
Description: Tom can carry 6 plates at a time and Tom needs to carry 24 plates in total.
Answer: 24/6=4. Therefore Tom needs to carry 24 plates in total."
#Answering sub_question5 requires relying on the answers of sub_question1 and sub_question4, namely answer1 and answer4
sub_description5=answer1+answer4
answer5=LLM(sub_case5,sub_question5,sub_description5)

#The final answer
final_answer=answer5
print(final_answer)

```

---

Table 6: The initialized pseudo-program knowledge graph on MultiArith, where entity 1, 2, and 3's *Sub-description* are **null** values. (Question: Roger was helping the cafeteria workers pick up lunch trays, but he could only carry 4 trays at a time. If he had to pick up 10 trays from one table and 2 trays from another, how many trips will he make?)

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description
```

```
    return LLM_answer
```

```
sub_question1="How many lunch trays can the person carry at once?"
```

```
sub_case1="
```

```
Description: Tom is helping the restaurant staff collect dishes, but he can only carry 6 plates at a time.
```

```
Answer: Tom can carry 6 plates at a time."
```

```
sub_description1=" Roger can only carry 4 trays at a time. "
```

```
answer1=LLM(sub_case1, sub_question1,sub_description1)
```

```
sub_question2="How many trays does the person need to pick up from the first table?"
```

```
sub_case2="
```

```
Description: Tom needs to pick up 15 plates from one table and 9 plates from another.
```

```
Answer: Tom needs to pick up 15 plates from the first table."
```

```
sub_description2="Roger have to pick up 10 trays from the first table. "
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="How many trays does the person need to pick up from the second table?"
```

```
sub_case3="
```

```
Description: Tom needs to pick up 15 plates from one table and 9 plates from another.
```

```
Answer: Tom needs to pick up 9 plates from the second table."
```

```
sub_description3="Roger have to pick up 2 trays from the second table. "
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="How many trays does the person need to carry in total?"
```

```
sub_case4="
```

```
Description: Tom needs to pick up 15 plates from the first table and 9 plates from the second table.
```

```
Answer: 15+9=24. Therefore Tom needs to carry 24 plates in total."
```

```
#Answering sub_question4 requires relying on the answers of sub_question2 and sub_question3, namely answer2 and answer3
```

```
sub_description4=answer2+answer3
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
sub_question5="How many trips will the person need to make to carry all the trays?"
```

```
sub_case5="
```

```
Description: Tom can carry 6 plates at a time and Tom needs to carry 24 plates in total.
```

```
Answer: 24/6=4. Therefore Tom needs to carry 4 plates in total."
```

```
#Answering sub_question5 requires relying on the answers of sub_question1 and sub_question4, namely answer1 and answer4
```

```
sub_description5=answer1+answer4
```

```
answer5=LLM(sub_case5,sub_question5,sub_description5)
```

```
#The final answer
```

```
final_answer=answer5
```

```
print(final_answer)
```

---

Table 7: The updated pseudo-program knowledge graph on MultiArith, where entity 1, 2, and 3's *Sub-description* are **assigned** values. (Question: Roger was helping the cafeteria workers pick up lunch trays, but he could only carry 4 trays at a time. If he had to pick up 10 trays from one table and 2 trays from another, how many trips will he make?)

To derive the final answer step by step, we will process the given sub-questions, descriptions, cases, and collect the responses according to the logic of the program.

1. Subquestion 1:

- Question: How many lunch trays can the person carry at once?
- Description: Roger can only carry 4 trays at a time.
- Case: The example describes Tom, who can carry 6 plates at a time.
- Answer: Roger can carry 4 trays at a time.

2. Subquestion 2:

- Question: How many trays does the person need to pick up from the first table?
- Description: Roger have to pick up 10 trays from the first table.
- Case: The example describes Tom needing to pick up 15 plates from one table and 9 plates from another.
- Answer: Roger needs to pick up 10 trays from the first table.

3. Subquestion 3:

- Question: How many trays does the person need to pick up from the second table?
- Description: Roger have to pick up 2 trays from the second table.
- Case: The example describes Tom needing to pick up 15 plates from one table and 9 plates from another.
- Answer: Roger needs to pick up 2 trays from the second table.

4. Subquestion 4:

- Question: How many trays does the person need to carry in total?
- Description: Based on answers from subquestions 2 and 3, Roger’s total tray count is 10 (from the first table) + 2 (from the second table).
- Case: The example explains how Tom calculates his total number of plates.
- Answer:  $10 + 2 = 12$ . Therefore, Roger needs to carry 12 trays in total.

5. Subquestion 5:

- Question: How many trips will the person need to make to carry all the trays?
- Description: Based on answers from subquestions 1 and 4, Roger can carry 4 trays at a time and he needs to carry 12 trays in total.
- Case: The example outlines how Tom calculates the number of trips needed.
- Answer:  $12 \text{ (total trays)} / 4 \text{ (trays per trip)} = 3 \text{ trips}$ . Therefore, Roger needs to make 3 trips to carry all the trays.

Finally, by compiling all the answers, we find that:

Final Answer: Roger needs to make 3 trips to carry all the trays.

Table 8: The output of executing the pseudo-program knowledge graph using GPT-4o mini in Table 7.

Method	AQuA	GSM8K	MultiArith	SingEq	HotpotQA	CSQA	SIQA	Letter	Coin	Average
CoT	87.9	94.5	98.6	96.4	90.5	89.3	92.1	98.3	95.7	93.7
Zero-shot-CoT	80.3	92.0	96.7	92.9	84.3	80.8	86.6	92.2	81.9	87.5
Auto-CoT	82.6	95.3	98.2	95.5	91.4	87.3	91.5	96.4	96.8	92.8
PS	83.4	93.6	97.3	95.6	86.6	84.9	87.0	96.8	94.6	91.1
QDMRPS	85.7	94.9	98.2	94.3	89.3	86.3	89.5	97.3	92.7	92.0
CoT-RAG	<b>96.3</b>	<b>99.8</b>	<b>99.4</b>	<b>99.1</b>	<b>98.3</b>	<b>99.8</b>	<b>99.7</b>	<b>99.9</b>	<b>99.7</b>	<b>99.1</b>

Table 9: Accuracy on nine datasets from three categories of reasoning tasks using ERNIE-3.5-128K.

Method	AQuA	GSM8K	MultiArith	SingEq	HotpotQA	CSQA	SIQA	Letter	Coin	Average
CoT	62.3	93.8	97.9	98.1	90.9	87.1	91.6	60.8	89.9	85.8
Zero-shot-CoT	59.0	86.8	97.8	97.0	87.3	83.3	86.4	54.8	79.8	81.4
Auto-CoT	57.8	92.0	98.4	97.9	92.4	84.2	89.3	58.3	88.7	84.3
PS	61.9	94.7	98.2	97.8	89.9	85.3	87.9	60.4	83.3	84.4
QDMRPS	57.1	93.9	98.0	98.3	91.2	85.0	86.7	55.1	84.5	83.3
CoT-RAG	<b>72.3</b>	<b>99.2</b>	<b>99.5</b>	<b>99.8</b>	<b>98.6</b>	<b>98.8</b>	<b>98.1</b>	<b>64.3</b>	<b>98.7</b>	<b>92.1</b>

Table 10: Accuracy on nine datasets from three categories of reasoning tasks using GLM-4-flash.

Method	AQuA	GSM8K	MultiArith	SingEq	HotpotQA	CSQA	SIQA	Letter	Coin	Average
CoT	91.4	96.5	99.0	99.3	91.5	88.9	92.6	97.6	<b>100</b>	95.2
Zero-shot-CoT	86.2	94.5	97.3	97.8	89.3	83.9	89.4	94.3	98.4	92.3
Auto-CoT	88.7	95.6	98.8	98.8	91.8	87.3	91.7	96.8	99.2	94.3
PS	87.4	94.8	98.7	98.5	89.4	86.8	91.9	97.1	98.9	93.7
QDMRPS	89.0	95.3	99.2	99.5	90.4	89.0	92.3	97.5	98.8	94.6
CoT-RAG	<b>96.5</b>	<b>98.7</b>	<b>99.7</b>	<b>99.0</b>	<b>98.8</b>	<b>99.5</b>	<b>99.6</b>	<b>99.9</b>	99.8	<b>99.1</b>

Table 11: Accuracy on nine datasets from three categories of reasoning tasks using GPT-4o.

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="Assuming the speed of the first person is v kilometers per hour, what is the speed of the second person in kilometers per hour?"
```

```
sub_case1=" Description: Cyclist A's rate is 20% faster than Cyclist B's.
```

```
Answer: Given that Cyclist A has a speed 20% faster than Cyclist B, the speed of Cyclone A is  $v+0.2v=1.2v$  kilometers per hour."
```

```
sub_description1="Friend P's rate is 15% faster than Friend Q's."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="How to express the time t (expressed in an equation containing v) when two people start from both ends and walk towards each other at the same time?"
```

```
sub_case2="
```

```
Description:Two cyclists plan to ride along a 60-km route, starting at opposite ends of the route at the same time. The speed of Cyclist A is  $1.2v$ , and the speed of Cyclist B is  $v$ .
```

```
Answer: Two people are walking towards each other, with a total distance of 60 kilometers. According to the formula for the encounter problem, "Encounter time=total distance ÷ sum of two people's speeds", the sum of two people's speeds is  $v+1.2v=2.2v$  kilometers per hour, so the encounter time  $t=60/2.2v=300/11v$  hours"
```

```
#Answering sub_question2 requires relying on the answer of sub_question1 , namely answer1
```

```
sub_description2="Two friends plan to walk along a 43-km trail, starting at opposite ends of the trail at the same time."+answer1
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="How many kilometers will the first person walk when they meet?"
```

```
sub_case3="
```

```
Description: The speed of Cyclist A is  $1.2v$  and the encounter time  $t=60/2.2v=300/11v$  hours.
```

```
Answer: The speed of Cyclone A is  $1.2v$  kilometers per hour, and the encounter time is  $300/11v$  hours. According to the distance=speed x time, the distance traveled by Cyclone A is  $S=1.2v \times 300/11v=360/11=32.73$  kilometers."
```

```
#Answering sub_question3 requires relying on the answers of sub_question1 and sub_question2, namely answer1 and answer2
```

```
sub_description3=answer1+answer2
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
#The final answer
```

```
final_answer=answer3
```

```
print(final_answer)
```

Table 12: The updated pseudo-program knowledge graph on AQuA. (Question: Two friends plan to walk along a 43-km trail, starting at opposite ends of the trail at the same time. If Friend P's rate is 15% faster than Friend Q's, how many kilometers will Friend P have walked when they pass each other?)



---

Let's break down the program logic step by step and determine the final answer.

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: Assuming the speed of the first person is  $v$  kilometers per hour, what is the speed of the second person in kilometers per hour?
- Case: Cyclist A's rate is 20% faster than Cyclist B's.
- Description: Friend P's rate is 15% faster than Friend Q's.

Answer:

- Since Friend P's rate is 15% faster than Friend Q's, the speed of Friend P is  $v + 0.15v = 1.15v$  kilometers per hour.

answer1 = "1.15v"

2. Second Call to LLM (sub\_question2):

- Question: How to express the time  $t$  (expressed in an equation containing  $v$ ) when two people start from both ends and walk towards each other at the same time?
- Case: Two cyclists plan to ride along a 60-km route, starting at opposite ends of the route at the same time. The speed of Cyclist A is  $1.2v$ , and the speed of Cyclist B is  $v$ .
- Description: Two friends plan to walk along a 43-km trail, starting at opposite ends of the trail at the same time.
- The description from 'answer1' tells us that Friend P's speed is  $1.15v$  (instead of  $1.2v$ ), and Friend Q's speed is  $v$ .

Answer:

- The total distance is 43 kilometers.
- The sum of the speeds is  $v + 1.15v = 2.15v$ .
- The encounter time is  $t = \text{Total distance} / \text{Sum of the speeds} = 43/2.15v$ .

answer2 = "43 / 2.15v"

3. Third Call to LLM (sub\_question3):

- Question: How many kilometers will the first person walk when they meet?
- Case: The speed of Cyclist A is  $1.2v$  and the encounter time  $t = 300/11v$  hours.
- Description: The description from 'answer1' tells us the speed of Friend P is  $1.15v$ , and 'answer2' gives the encounter time equation as  $t = 43/2.15v$ .

Answer:

- The speed of Friend P is  $1.15v$  km/h.
- The encounter time is  $t = 43/2.15v$  hours.
- The distance walked by Friend P is:

Distance = Speed  $\times$  Time =  $1.15v \times 43/2.15v = 49.45 \times 2.15 = 23$  kilometers.

answer3 = "23 kilometers"

Final Answer:

The first person (Friend P) will walk 23 kilometers when they meet.

Final Output: 23 kilometers

---

Table 13: The output of executing the pseudo-program knowledge graph in Table 12.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="How many times does the person write letters to each friend per week?"
```

```
sub_case1="
```

```
Description: Tom writes a letter to 4 different friends once a week. Answer: Tom writes to each friend once a week."
```

```
sub_description1="James writes a letter to 2 different friends twice a week."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="How many letters does the person write per week?"
```

```
sub_case2="
```

```
Description: Tom writes a letter to 4 different friends once a week and he writes to each friend once a week.
```

```
Answer: Because there are 4 different friends and I write letters to each friend once a week, the total number of letters written per week is  $4 \times 1 = 4$  letters."
```

```
#Answering sub_question2 requires relying on the answer of sub_question1, namely answer1
```

```
sub_description2="James writes a letter to 2 different friends." + answer1
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="What is the total number of pages written by the person per week?"
```

```
sub_case3="
```

```
Description: The total number of letters written by Tom per week is 4 letters and each letter is 5 pages long.
```

```
Answer: Given that each letter has 5 pages, a total of 4 letters are written per week. Based on the total number of pages=the number of pages per letter x the total number of letters, the total number of pages written per week is  $5 \times 4 = 20$  pages."
```

```
#Answering sub_question3 requires relying on the answers of sub_question2, namely answer2
```

```
sub_description3="Each letter is 3 pages long." + answer2
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="What is the total number of pages written by the person a year?"
```

```
sub_case4="
```

```
Description: One year is about 52 weeks and the total number of pages written by Tom per week is 20 pages.
```

```
Answer: Writing 20 pages per week, and knowing that there are approximately 52 weeks in a year, according to the total number of pages per year=pages per week x weeks per year, the total number of pages written in a year is 1040 pages."
```

```
#Answering sub_question4 requires relying on the answers of sub_question3, namely answer3
```

```
sub_description4=answer3
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
#The final answer
```

```
final_answer=answer4
```

```
print(final_answer)
```

---

Table 14: The updated pseudo-program knowledge graph on GSM8K. (Question: James writes a 3-page letter to 2 different friends twice a week. How many pages does he write a year?)

---

Let's break down the program step by step and follow the logic to find the final answer.

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: How many times does the person write letters to each friend per week?
- Case: The case provides an example where Tom writes a letter to 4 different friends once a week.
- Description: James writes a letter to 2 different friends twice a week.

Answer: Based on the description, James writes a letter to each friend twice a week.

answer1 = "twice"

2. Second Call to LLM (sub\_question2):

- Question: How many letters does the person write per week?
- Case: The case tells us that Tom writes a letter to 4 different friends once a week.
- Description: The description tells us James writes a letter to 2 different friends, and **twice** a week (from 'answer1').

Calculation:

- James writes 2 letters (one to each friend) twice a week, so the total number of letters James writes per week is:

$2 \times 2 = 4$  letters

answer2 = "4 letters"

3. Third Call to LLM (sub\_question3):

- Question: What is the total number of pages written by the person per week?
- Case: This case mentions that Tom writes 4 letters per week, and each letter is 5 pages long.
- Description: The description tells us that each letter is 3 pages long (adjusted for James based on 'answer2').

Calculation:

- James writes 4 letters per week, and each letter is 3 pages long.
- Total pages per week:

$4 \times 3 = 12$  pages per week

answer3 = "12 pages"

4. Fourth Call to LLM (sub\_question4):

- Question: What is the total number of pages written by the person in a year?
- Case: The case tells us that one year is approximately 52 weeks, and the total number of pages written per week is 12 pages (from 'answer3').
- Description: We use the same number of pages per week (12), and multiply by the number of weeks in a year.

Calculation:

- Total pages per year:

$12 \times 52 = 624$  pages per year

answer4 = "624 pages"

Final Answer:

The total number of pages James writes in a year is 624 pages.

Final Output: 624 pages

---

Table 15: The output of executing the pseudo-program knowledge graph in Table 14.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="What was the total number of shells initially found by the person?"
```

```
sub_case1="
```

```
Description: Lily picked up 80 seashells by the seaside.
```

```
Answer: The total number of shells initially found by Lily initially was 80."
```

```
sub_description1="Joan found 70 seashells on the beach."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="How many shells does this person have left?"
```

```
sub_case2="
```

```
Description: Lily has 32 seashells left.
```

```
Answer: Lily has 32 seashells left."
```

```
sub_description2="Joan has 27 seashell left."
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="How many shells did this person give to others?"
```

```
sub_case3="
```

```
Description: The total number of shells initially found by Lily initially was 80 and she has 32 seashells left.
```

```
Answer: Subtracting the remaining number of shells from Lily's initial total number of shells gives her the number of shells she gives to others. That is to say, the number of shells given=the initial total number of shells - the remaining number of shells, that is, 80-32=48 (pieces)."
```

```
#Answering sub_question3 requires relying on the answers of sub_question1 and sub_question2, namely answer1 and answer2
```

```
sub_description3=answer1+answer2
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
#The final answer
```

```
final_answer=answer3
```

```
print(final_answer)
```

---

Table 16: The updated pseudo-program knowledge graph on SingleEq. (Question: Joan found 70 seashells on the beach. she gave Sam some of her seashells. She has 27 seashell left. How many seashells did she give to Sam ?)



---

Let's walk through the program step by step to determine the final answer.

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: What was the total number of shells initially found by the person?
- Case: The case provides an example where Lily initially found 80 seashells.
- Description: Joan found 70 seashells on the beach.

Answer: The total number of shells initially found by Joan was 70, based on the description provided.

answer1 = "70"

2. Second Call to LLM (sub\_question2):

- Question: How many shells does this person have left?
- Case: The case provides an example where Lily has 32 seashells left.
- Description: Joan has 27 seashells left.

Answer: According to the description, Joan has 27 seashells left.

answer2 = "27"

3. Third Call to LLM (sub\_question3):

- Question: How many shells did this person give to others?
- Case: This case involves calculating how many shells were given by Lily based on the initial number of shells and how many are left. The formula provided is:

Shells given = Initial shells - Remaining shells

- Description: We are given the answers from previous questions: Joan initially found 70 shells and has 27 left.

Calculation:

- Initially, Joan found 70 seashells.
- She has 27 seashells left.
- Therefore, Joan gave away  $70 - 27 = 43$  seashells.

answer3 = "43"

4. Final Answer:

The final answer is "43," indicating how many shells Joan gave to others.

Final Output: 43

---

Table 17: The output of executing the pseudo-program knowledge graph in Table 16.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case, question, description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="Who was the member of the 'Mother Love Bone' band who passed away before the release of the album 'Apple'?"
```

```
sub_case1=" Please focus on the correlation between the death of band members and the upcoming release of the album."
```

```
sub_description1="Frontman Andrew Wood's personality and compositions helped to catapult the group to the top of the burgeoning late 1980s/early 1990s Seattle music scene. Wood died only days before the scheduled release of the band's debut album, 'Apple', thus ending the group's hopes of success. The album was finally released a few months later."
```

```
answer1=LLM(sub_case1, sub_question1, sub_description1)
```

```
sub_question2="What band has Andrew Wood joined (except for 'Mother Love Bone')?"
```

```
sub_case2="Please pay attention to the description of the person's band experience."
```

```
sub_description2="Return to Olympus is the only album by the alternative rock band Malfunkshun. It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990."
```

```
answer2=LLM(sub_case2, sub_question2, sub_description2)
```

```
sub_question3="What band was Andrew Wood in before joining Mother Love Bone?"
```

```
sub_case3="Please pay attention to the order in which the person joined the band."
```

```
#Answering sub_question3 requires relying on the answers of sub_question1 and sub_question2, namely answer1 and answer2
```

```
sub_description3=answer1+answer2
```

```
answer3=LLM(sub_case3, sub_question3, sub_description3)
```

```
#The final answer
```

```
final_answer=answer3
```

```
print(final_answer)
```

---

Table 18: The updated pseudo-program knowledge graph on HotpotQA. ( Question: What was the former band of the member of Mother Love Bone who died just before the release of "Apple"? Paragraph A, Return to Olympus: Return to Olympus is the only album by the alternative rock band Malfunkshun. It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990. Stone Gossard, of Pearl Jam, had compiled the songs and released the album on his label, Loosegroove Records. Paragraph B, Mother Love Bone: Mother Love Bone was an American rock band that formed in Seattle, Washington in 1987. The band was active from 1987 to 1990. Frontman Andrew Wood's personality and compositions helped to catapult the group to the top of the burgeoning late 1980s/early 1990s Seattle music scene. Wood died only days before the scheduled release of the band's debut album, "Apple", thus ending the group's hopes of success. The album was finally released a few months later.)

---

Let's break down the program and follow the steps logically to determine the final answer.

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: Who was the member of the "Mother Love Bone" band who passed away before the release of the album "Apple"?
- Case: The case asks us to focus on the correlation between the death of a band member and the upcoming release of the album.
- Description: The description mentions that the frontman, Andrew Wood, passed away just days before the release of "Apple," which was the band's debut album.

Answer: The band member who passed away before the release of the album "Apple" is Andrew Wood.

answer1 = "Andrew Wood"

2. Second Call to LLM (sub\_question2): - Question: What band has Andrew Wood joined (except for "Mother Love Bone")?

- Case: The case tells us to pay attention to the description of the person's band experience.
- Description: The description talks about Andrew Wood being the lead singer of a band called Malfunkshun, which released the album "Return to Olympus" after the band broke up. This band existed before Andrew Wood joined "Mother Love Bone."

Answer: Before joining "Mother Love Bone," Andrew Wood was part of the band Malfunkshun.

answer2 = "Malfunkshun"

3. Third Call to LLM (sub\_question3):

- Question: What band was Andrew Wood in before joining Mother Love Bone?
  - Case: This call asks to pay attention to the order in which Andrew Wood joined bands.
  - Description: The description includes the answers from previous questions. From answer1, we know Andrew Wood was in "Mother Love Bone." From answer2, we know he was in "Malfunkshun" before joining "Mother Love Bone."
- Answer: Before joining "Mother Love Bone," Andrew Wood was in "Malfunkshun."

answer3 = "Malfunkshun"

4. Final Answer:

The final answer is "Malfunkshun."

Final Output: Malfunkshun

---

Table 19: The output of executing the pseudo-program knowledge graph in Table 18.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="What are the general characteristics of the area represented by each option in terms of housing distribution and isolation?"
```

```
sub_case1="
```

```
Neighborhood: The houses in the neighborhood are relatively compact, and there may be a mix of different types of houses. The boundaries are usually not particularly closed, and many houses in the neighborhood may not have obvious isolation facilities between them. They are closely connected to the surrounding streets and other buildings.
```

```
Subdivision: Zoning is usually a planned area, and some zones may have a unified architectural style and management regulations. Some high-end partitions may have access control facilities to ensure residents' privacy and safety, isolating themselves from the outside world.
```

```
City: A city is a large area that includes various functional areas and a wide variety of housing types. Most houses in the city are open plan, closely connected to various commercial facilities, public transportation, etc., and few houses can be completely isolated from other places.
```

```
Suburbs: Houses in the suburbs are relatively scattered, but generally do not have strong isolation. The suburbs are mainly for residential purposes, although there may be some independent residences, they are not primarily characterized by isolation.
```

```
Street: The street is mainly a transportation channel, and the houses on both sides of the street are mainly distributed along the road, usually without overall isolation measures."
```

```
sub_description1="Answer Choices: (A) neighborhood (B) subdivision (C) city (D) suburbs (E) street"
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="Which area is most likely to provide houses with access control facilities and isolation from other areas?"
```

```
sub_case2="Pay attention to comparing the characteristics of each region"
```

```
#Answering sub_question2 requires relying on the answers of sub_question1, namely answer1
```

```
sub_description2=answer1
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
#The final answer
```

```
final_answer=answer2
```

```
print(final_answer)
```

---

Table 20: The updated pseudo-program knowledge graph on CSQA, where *sub-case* is derived from the LLM-decomposed *Knowledge case* of the decision tree built by experts. (Question: He wanted a house that was gated off from other places, where should he start looking? Answer Choices: (A) neighborhood (B) subdivision (C) city (D) suburbs (E) street)



---

Let's walk through the steps of the program and how it works logically to produce the final result.

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: What are the general characteristics of the area represented by each option in terms of housing distribution and isolation?
- Case: The case provides descriptions of different areas: neighborhood, subdivision, city, suburbs, and street. Each description highlights the characteristics of housing distribution and isolation.
- Description: The answer choices include (A) neighborhood, (B) subdivision, (C) city, (D) suburbs, and (E) street.

Analysis: The focus of the question is on the characteristics of each option in terms of housing distribution and isolation.

- Neighborhood: Houses are relatively compact with no clear isolation between them.
- Subdivision: Has unified architectural styles and may have access control facilities and isolation, especially in high-end areas.
- City: Houses are open plan and closely connected to other buildings and commercial areas; few houses have isolation.
- Suburbs: Houses are scattered but generally lack strong isolation.
- Street: Houses are distributed along the road and generally have no isolation.

Answer: Based on the description, the "subdivision" is most likely to provide houses with access control facilities and isolation from other areas, especially in high-end zones.

answer1 = "B" (subdivision)

2. Second Call to LLM (sub\_question2):

- Question: Which area is most likely to provide houses with access control facilities and isolation from other areas?
- Case: The case asks to compare the characteristics of each area to determine which is most likely to have access control and isolation.
- Description: The description relies on the answer from sub\_question1, which identified the subdivision as the area most likely to have access control facilities and isolation.

Answer: The subdivision is the most likely area to provide houses with access control and isolation based on the characteristics described earlier.

answer2 = "B" (subdivision)

3. Final Answer:

The final answer is "B", corresponding to \*\*subdivision\*\*.

Final Output: B

---

Table 21: The output of executing the pseudo-program knowledge graph in Table 20.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the
    question based on the description.
    return LLM_answer

sub_question1="Is this behavior directly related to understanding and answering the teacher's questions?"
sub_case1="
Asking for a gold star is a behavior where one may expect to receive a reward after answering a question, and it is not something
that needs to be done before understanding and answering the question."
sub_description1="Behavior: ask for a gold star"
answer1=LLM(sub_case1,sub_question1,sub_description1)

sub_question2="Is this behavior helpful for understanding and answering the teacher's questions?"
sub_case2="Skipping class means not being in the classroom and not being able to hear the teacher's questions"
sub_description2="Behavior: skip her class"
answer2=LLM(sub_case2,sub_question2,sub_description2)

sub_question3="Does this behavior help to understand and answer the teacher's questions?"
sub_case3="Only when a person knows the information related to the problem, can they understand the content of the teacher's
question well and accurately answer the question based on the information they have mastered"
sub_description3="Behavior: know the information"
answer3=LLM(sub_case3,sub_question3,sub_description3)
sub_question4="Which behavior is most likely to occur?"
sub_case4="Please choose the behavior that best fits your understanding and answers the teacher's question in this scenario."
#Answering sub_question4 requires relying on the answers of sub_question1,sub_question2 and sub_question3, namely answer1,
answer2 and answer3
sub_description4=answer1+answer2+answer3
answer4=LLM(sub_case3,sub_question3,sub_description3)

#The final answer
final_answer=answer4
print(final_answer)
```

---

Table 22: The updated pseudo-program knowledge graph on SIQA. (Question: The teacher asked the class a question and they seemed puzzled. Aubrey understood the question well and answered. What does Aubrey need to do before this? Answer Choices: (A) ask for a gold star (B) skip her class (C) know the information)

---

Let's break down the logic and the steps for this program:

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: Is this behavior directly related to understanding and answering the teacher's questions?

- Case: Asking for a gold star is a behavior that does not directly contribute to understanding the question. It's more about receiving a reward after the question is answered.

- Description: The behavior is to "ask for a gold star."

Answer: Since asking for a gold star doesn't directly relate to understanding or answering the question, the answer is "No."

2. Second Call to LLM (sub\_question2):

- Question: Is this behavior helpful for understanding and answering the teacher's questions?

- Case: Skipping class means not being present to hear the teacher's questions, which would make it impossible to understand or answer the question.

- Description: The behavior is "skip her class."

Answer: Since skipping class means missing the teacher's questions, the answer is "No."

3. Third Call to LLM (sub\_question3):

- Question: Does this behavior help to understand and answer the teacher's questions?

- Case: Knowing the information related to the problem is essential to understanding the teacher's question and answering it accurately.

- Description: The behavior is "know the information."

Answer: Knowing the information is crucial for understanding and answering the question, so the answer is "Yes."

4. Fourth Call to LLM (sub\_question4):

- Question: Which behavior is most likely to occur?

- Case: This question asks to select the behavior that best fits the context of understanding and answering the teacher's question.

- Description: The description includes the answers from the previous questions: "No," "No," and "Yes."

Answer: The behavior most likely to occur is the one that helps understand and answer the teacher's question, which is knowing the information ("Yes").

Final Answer: know the information

---

Table 23: The output of executing the pseudo-program knowledge graph in Table 22.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the
    question based on the description.
    return LLM_answer

sub_question1="What is the last letter of this word?"
sub_case1="
Description: Pretty
Answer: The last letter of 'Pretty' is 'y'."
sub_description1="Gavin"
answer1=LLM(sub_case1,sub_question1,sub_description1)

sub_question2="What is the last letter of this word?"
sub_case2="
Description: Jada
Answer: The last letter of 'Jada' is 'a'."
sub_description2="Neha"
answer2=LLM(sub_case2,sub_question2,sub_description2)

sub_question3="What is the last letter of this word?"
sub_case3="
Description: Sarita
Answer: The last letter of 'Sarita' is 'a'."
sub_description3="Asha"
answer3=LLM(sub_case3,sub_question3,sub_description3)

sub_question4="What is the last letter of this word?"
sub_case4="
Description: Allen
Answer: The last letter of 'Allen' is 'n'."
sub_description4="Baltazar"
answer4=LLM(sub_case4,sub_question4,sub_description4)

sub_question5="What is the result of concatenating the last letter obtained from each word in order?"
sub_case5="
Description: The last letter of 'Pretty' is 'y', the last letter of 'Jada' is 'a', the last letter of 'Sarita' is 'a' and the last letter of
'Allen' is 'n'.
Answer: The last letter of the four words is 'y', 'a', 'a', 'n', and when they are concatenated in order, the result is 'yaan'."
#Answering sub_question5 requires relying on the answers of sub_question1,sub_question2,sub_question3 and sub_question4,
namely answer1, answer2, answer3 and answer4
sub_description5=answer1+answer2+answer3+answer4
answer5=LLM(sub_case5,sub_question5,sub_description5)

#The final answer
final_answer=answer5
print(final_answer)
```

---

Table 24: The updated pseudo-program knowledge graph on Last Letter Concatenation. (Question: Take the last letters of each words in Gavin Neha Asha Baltazar and concatenate them.)



---

Let's break down the program step by step to determine the final output:

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: What is the last letter of this word?
- Case: The description indicates that the last letter of "Pretty" is "y".
- Description: The word is "Gavin".

Answer: The last letter of "Gavin" is "n".

answer1 = "n"

2. Second Call to LLM (sub\_question2):

- Question: What is the last letter of this word?
- Case: The description indicates that the last letter of "Jada" is "a".
- Description: The word is "Neha".

Answer: The last letter of "Neha" is "a".

answer2 = "a"

3. Third Call to LLM (sub\_question3):

- Question: What is the last letter of this word?
- Case: The description indicates that the last letter of "Sarita" is "a".
- Description: The word is "Asha".

Answer: The last letter of "Asha" is "a".

answer3 = "a"

4. Fourth Call to LLM (sub\_question4):

- Question: What is the last letter of this word?
- Case: The description indicates that the last letter of "Allen" is "n".
- Description: The word is "Baltazar".

Answer: The last letter of "Baltazar" is "r".

answer4 = "r"

5. Fifth Call to LLM (sub\_question5):

- Question: What is the result of concatenating the last letter obtained from each word in order?
- Case: The case gives the last letters of the words: "n" (from Gavin), "a" (from Neha), "a" (from Asha), and "r" (from Baltazar).
- Description: The concatenation of the last letters "n", "a", "a", and "r" results in "naar".

Answer: The concatenated result of the last letters is "naar".

answer5 = "naar"

Final Answer: naar

---

Table 25: The output of executing the pseudo-program knowledge graph in Table 24.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="What is the initial state of the coin?"
```

```
sub_case1="Pay attention to the initial state of the coin at this moment."
```

```
sub_description1="A coin is heads up"
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="What is the current state of the coin?"
```

```
sub_case2="
```

```
Pay attention to whether this operation changes the original state of the coin and outputs the state after this operation."
```

```
#Answering sub_question2 requires relying on the answers of sub_question1, namely answer1
```

```
sub_description2=answer1+"Sager does not flip the coin"
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="What is the current state of the coin?"
```

```
sub_case3="
```

```
Pay attention to whether this operation changes the original state of the coin and outputs the state after this operation"
```

```
#Answering sub_question3 requires relying on the answers of sub_question2, namely answer2
```

```
sub_description3=answer2+"Zyheir flips the coin"
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="Is the coin still heads up?"
```

```
sub_case4="Pay attention to the coin's transition at this moment"
```

```
#Answering sub_question4 requires relying on the answers of sub_question3, namely answer3
```

```
sub_description4=answer3
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
#The final answer
```

```
final_answer=answer4
```

```
print(final_answer)
```

---

Table 26: The updated pseudo-program knowledge graph on Coin Flip, where *sub-case* is derived from the LLM-decomposed *Knowledge case* of the decision tree built by experts. (Question: A coin is heads up. sager does not flip the coin. zyheir flips the coin. Is the coin still heads up?)

---

Let's analyze the program step-by-step and follow the execution logic to determine the final output:

Step-by-Step Breakdown:

1. First Call to LLM (sub\_question1):

- Question: What is the initial state of the coin?
- Case: Pay attention to the initial state of the coin at this moment.
- Description: The coin is heads up.

Answer: Based on the description, the initial state of the coin is "heads up."

answer1 = "heads up"

2. Second Call to LLM (sub\_question2):

- Question: What is the current state of the coin?
- Case: Pay attention to whether this operation changes the original state of the coin and output the state after the operation.
- Description: The description includes the answer from 'sub\_question1' ("heads up") and adds the information that Sager does not flip the coin.

Answer: Since Sager does not flip the coin, the state remains the same as "heads up."

answer2 = "heads up"

3. Third Call to LLM (sub\_question3):

- Question: What is the current state of the coin?
- Case: Pay attention to whether this operation changes the original state of the coin and output the state after the operation.
- Description: The description includes the answer from 'sub\_question2' ("heads up") and adds the information that Zyheir flips the coin.

Answer: Since Zyheir flips the coin, the state changes from "heads up" to "tails up."

answer3 = "tails up"

4. Fourth Call to LLM (sub\_question4):

- Question: Is the coin still heads up?
- Case: Pay attention to the coin's transition at this moment.
- Description: The description includes the answer from 'sub\_question3' ("tails up"), so we check if the coin is still heads up.

Answer: Since the coin is "tails up" (after Zyheir flipped it), it is no longer heads up.

answer4 = "No"

5. Final Answer:

The final answer is "No" because after the flip, the coin is not heads up.

---

Table 27: The output of executing the pseudo-program knowledge graph in Table 26.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="What is the amount of cash stolen in this theft?"
```

```
sub_case1="Pay attention to accurately finding sentences that describe the theft and the corresponding amount of stolen cash, to avoid confusion with related descriptions of other theft events."
```

```
sub_description1="At about 11:00 on January 2, 2016, the defendant Liu XX, Song XX, and Hu Mou took the Ouyang special bus and passed a certain section of a certain town in Jianyang District, Nanping City. Hu Mou and Liu XX watched, and Song XX used a blade to cut the right pocket of the victim Liu Mou's coat and stole the small yellow envelope containing 1,500 yuan in cash."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="What is the amount of cash stolen in this theft?"
```

```
sub_case2="Pay attention to accurately finding sentences that describe the theft and the corresponding amount of stolen cash, to avoid confusion with related descriptions of other theft events."
```

```
sub_description2="At about 11:00 on January 20, 2016, the defendants Liu XX, Song XX, and Hu Mou took the Ouyang special bus to a certain section of the road. They saw the victim Zhang Mou 1 sleeping, so Hu Mou and Liu XX watched, and Song XX cut open Zhang Mou 1's coat pocket with a blade, and stole 7,000 yuan in cash tied with cow tendons in the pocket."
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="What is the total amount involved in all theft crimes?"
```

```
sub_case3="Pay attention to performing correct addition operations on all previous results to ensure that there are no errors in the calculation process, and do not omit or double calculate the amount."
```

```
#Answering sub_question3 requires relying on the answers of sub_question1 and sub_question2, namely answer1 and answer2
```

```
sub_description3=answer1+answer2
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
#The final answer
```

```
final_answer=answer3
```

```
print(final_answer)
```

---

Table 28: The updated pseudo-program knowledge graph on LawBench. (Question: What is the total amount of crime involved in the document? Document: After investigation, it was found that during January 2016, the defendant Liu XX, Song XX, and Hu (both of whom have been sentenced) agreed to commit theft on the Ouyang special bus, and agreed that whoever did it would get half of the stolen property, and the other two would share the other half. The specific criminal facts are as follows: 1. At about 11:00 on January 2, 2016, the defendant Liu XX, Song XX, and Hu Mou took the Ouyang special bus and passed a certain section of a certain town in Jianyang District, Nanping City. Hu Mou and Liu XX watched, and Song XX used a blade to cut the right pocket of the victim Liu Mou's coat and stole the small yellow envelope containing 1,500 yuan in cash. After getting off the bus, Song XX got 750 yuan of the stolen money, and Hu Mou and Liu XX each got 375 yuan of the stolen money. 2. At about 11:00 on January 20, 2016, the defendants Liu XX, Song XX, and Hu Mou took the Ouyang special bus to a certain section of the road. They saw the victim Zhang Mou 1 sleeping, so Hu Mou and Liu XX watched, and Song XX cut open Zhang Mou 1's coat pocket with a blade, and stole 7,000 yuan in cash tied with cow tendons in the pocket. Afterwards, Song XX received 3,500 yuan, and Hu Mou and Liu XX each received 1,750 yuan.)

---

To solve this, let's break down the program logic and how it works step by step:

Step-by-step breakdown:

1. First Call to LLM (sub\_question1):

- Question: What is the amount of cash stolen in this theft?

- Case: Focus on accurately finding the amount of stolen cash in the description, ensuring no confusion with other theft events.

- Description: The theft took place on January 2, 2016, where Song XX cut open the victim's coat pocket and stole a small yellow envelope containing 1,500 yuan.

Answer: Based on the description, the amount of cash stolen is 1,500 yuan.

answer1 = 1500

2. Second Call to LLM (sub\_question2):

- Question: What is the amount of cash stolen in this theft?

- Case: Again, accurately find the amount of stolen cash from the description, ensuring no confusion with other theft events.

- Description: On January 20, 2016, Song XX stole 7,000 yuan from the victim Zhang Mou 1's coat pocket.

Answer: Based on the description, the amount of cash stolen is 7,000 yuan.

answer2 = 7000

3. Third Call to LLM (sub\_question3):

- Question: What is the total amount involved in all theft crimes?

- Case: Perform the addition operation correctly to avoid errors and omissions, using the amounts obtained from the previous answers.

- Description: The description contains both 'answer1' (1,500 yuan) and 'answer2' (7,000 yuan).

Answer: To calculate the total amount, we add 'answer1' and 'answer2':

$1,500 + 7,000 = 8,500$  yuan.

answer3 = 8500

4. Final Answer: The total amount involved in all theft crimes is 8,500 yuan.

---

Table 29: The output of executing the pseudo-program knowledge graph in Table 28.



---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="Does the contract mention any content regarding usage permissions?"
```

```
sub_case1="Pay attention to carefully reading the text and find the guiding statements related to content usage permissions."
```

```
sub_description1="See the Permission to use your content section for more about your rights in your content, and how your content is used in our services."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="Does the contract mention the removal of content?"
```

```
sub_case2="Pay attention to the guidance prompts in the text, accurately locate and remove the relevant parts of the content, and do not confuse them with other parts."
```

```
sub_description2="See the Removing your content section to learn why and how we might remove user-generated content from our services."
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="How is intellectual property infringement stipulated in the contract?"
```

```
sub_case3="Pay attention to the relevant statements regarding the handling measures after intellectual property infringement, and understand the prescribed infringement handling process and methods."
```

```
#Answering sub_question3 requires relying on the answers of sub_question1 and sub_question2, namely answer1 and answer2
sub_description3=answer1+answer2+"If you think that someone is infringing your intellectual property rights, you can send us notice of the infringement and we'll take appropriate action. For example, we suspend or close the Google Accounts of repeat copyright infringers as described in our Copyright Help Centre."
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="Will Google help me deal with situations where content is used without permission?"
```

```
sub_case4="Pay attention to accurately understanding Google's measures for handling infringement in sub_question3."
```

```
#Answering sub_question4 requires relying on the answers of sub_question3, namely answer3
```

```
sub_description4=answer3
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
#The final answer
```

```
final_answer=answer4
```

```
print(final_answer)
```

---

Table 30: The updated pseudo-program knowledge graph on LegalBench. (Question: Will Google help me if I think someone has taken and used content I've created without my permission? Contract: Some of our services give you the opportunity to make your content publicly available. For example, you might post a product or restaurant review that you wrote, or you might upload a blog post that you created. See the Permission to use your content section for more about your rights in your content, and how your content is used in our services. See the Removing your content section to learn why and how we might remove user-generated content from our services. If you think that someone is infringing your intellectual property rights, you can send us notice of the infringement and we'll take appropriate action. For example, we suspend or close the Google Accounts of repeat copyright infringers as described in our Copyright Help Centre.)

---

Let's go through the program step by step, answering each question based on the cases and descriptions provided:

Step-by-step Execution:

sub\_question1

Question: Does the contract mention any content regarding usage permissions?

Case: "Pay attention to carefully reading the text and find the guiding statements related to content usage permissions."

Description: "See the Permission to use your content section for more about your rights in your content, and how your content is used in our services."

Analysis for sub\_question1: The description directly refers to a "Permission to use your content" section, which indicates that usage permissions are mentioned in the contract.

Answer1: "Yes, the contract mentions content usage permissions."

sub\_question2

Question: Does the contract mention the removal of content?

Case: "Pay attention to the guidance prompts in the text, accurately locate and remove the relevant parts of the content, and do not confuse them with other parts."

Description: "See the Removing your content section to learn why and how we might remove user-generated content from our services."

Analysis for sub\_question2: The description references a "Removing your content" section, indicating that the contract does address the removal of content.

Answer2: "Yes, the contract mentions the removal of content."

sub\_question3

Question: How is intellectual property infringement stipulated in the contract?

Case: "Pay attention to the relevant statements regarding the handling measures after intellectual property infringement, and understand the prescribed infringement handling process and methods."

Description: This description relies on the answers to sub\_question1 and sub\_question2. Combining those with the following statement: "If you think that someone is infringing your intellectual property rights, you can send us notice of the infringement and we'll take appropriate action. For example, we suspend or close the Google Accounts of repeat copyright infringers as described in our Copyright Help Centre."

Analysis for sub\_question3: The description outlines the process for handling intellectual property infringement, including the option to report infringement and the potential actions (like suspension of accounts). This answers how intellectual property infringement is dealt with in the contract.

Answer3: "The contract specifies that intellectual property infringement is handled by allowing users to report infringement and take actions such as suspending or closing accounts of repeat offenders."

sub\_question4 Question: Will Google help me deal with situations where content is used without permission?

Case: "Pay attention to accurately understanding Google's measures for handling infringement in sub\_question3."

Description: This relies on answer3: "The contract specifies that intellectual property infringement is handled by allowing users to report infringement and take actions such as suspending or closing accounts of repeat offenders."

Analysis for sub\_question4: The description indicates that Google provides help in dealing with content usage without permission through its procedures for reporting and addressing infringement.

Answer4: "Yes, Google will help you deal with situations where content is used without permission by taking actions such as suspending or closing accounts of repeat infringers."

Final Answer:

The final answer, based on the previous analysis, is:

"Yes, Google will help you deal with situations where content is used without permission by taking actions such as suspending or closing accounts of repeat infringers."

---

Table 31: The output of executing the pseudo-program knowledge graph in Table 30.

---

#Given a program text, your role is the LLM function,which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="Is the description related to the question 'Can I still buy new energy vehicles'?"
```

```
sub_case1="Market inquiry refers to inquiries about the overall situation of the securities market. This includes broad market indices like the Shanghai Composite Index or Shenzhen Component Index, which reflect the performance and conditions of the entire stock market."
```

```
sub_description1="Market inquiry"
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="Is the description related to the question 'Can I still buy new energy vehicles'?"
```

```
sub_case2="Industry sectors refer to the various parts of the securities market that are classified by industry, such as the financial sector, technology sector, new energy sector, etc. Industry sector inquiries mainly focus on the overall situation of a specific industry, including industry development trends, competition patterns within the industry, the impact of policies on the industry, and the industry's valuation in the market, among many other aspects."
```

```
sub_description2="Industry sector inquiry"
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="Is the description related to the question 'Can I still buy new energy vehicles'?"
```

```
sub_case3="Individual stock inquiry refers to inquiries related to the stocks of a specific company. This may include questions about the company's financial health, performance, management changes, and stock price trends, as well as technical analysis related to stock price movements."
```

```
sub_description3="Individual stock inquiry"
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="Is the description related to the question 'Can I still buy new energy vehicles'?"
```

```
sub_case4="Fund inquiry pertains to inquiries about investment funds, which pool money from multiple investors for collective investment. This includes questions about the fund's type (e.g., equity, bond, or money market funds), investment strategy, performance, risk characteristics, management team, and subscription or redemption rules."
```

```
sub_description4="Fund inquiry"
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
sub_question5="Is the description related to the question 'Can I still buy new energy vehicles'?"
```

```
sub_case5="Customer service inquiry refers to inquiries made by investors to customer service departments of financial institutions regarding issues related to securities trading. These can involve problems with account operations (e.g., account opening, password retrieval), transaction rules (e.g., fees, time), product services, and handling of transaction disputes."
```

```
sub_description5="Customer service inquiry"
```

```
answer5=LLM(sub_case5,sub_question5,sub_description5)
```

```
sub_question6="Which one best fits the intention of the question 'Can I still buy new energy vehicles'?"
```

```
sub_case6="Pay attention to comprehensively considering the previous analysis results to ensure accurate and error free judgment, without missing any key information."
```

```
#Answering sub_question6 requires relying on the answers of sub_question1, sub_question2, sub_question3, sub_question4, and sub_question5, namely answer1, answer2, answer3, answer4 and answer5
```

```
sub_description6=answer1+answer2+answer3+answer4+answer5
```

```
answer6=LLM(sub_case6,sub_question6,sub_description6)
```

```
#The final answer
```

```
final_answer=answer6
```

```
print(final_answer)
```

---

Table 32: The updated pseudo-program knowledge graph on CFBenchmark. (Question: You are an intention emotion assistant. Please analyze the intention of the following query: [market inquiry, industry sector inquiry, individual stock inquiry, fund inquiry, customer service inquiry]? Query: Can I still buy new energy vehicles?

---

Let's go through the execution of the program step-by-step, based on the provided logic and descriptions:

Step-by-step Execution:

sub\_question1

Question: Is the description related to the question 'Can I still buy new energy vehicles'?

Case: "Market inquiry refers to inquiries about the overall situation of the securities market. This includes broad market indices like the Shanghai Composite Index or Shenzhen Component Index, which reflect the performance and conditions of the entire stock market."

Description: "Market inquiry"

Analysis for sub\_question1: The description focuses on market indices and the securities market, which is unrelated to the question about buying new energy vehicles. The question is focused on vehicle availability, not the stock market.

Answer1: "No, this description is not related to the question."

sub\_question2

Question: Is the description related to the question 'Can I still buy new energy vehicles'?

Case: "Industry sectors refer to the various parts of the securities market that are classified by industry, such as the financial sector, technology sector, new energy sector, etc. Industry sector inquiries mainly focus on the overall situation of a specific industry, including industry development trends, competition patterns within the industry, the impact of policies on the industry, and the industry's valuation in the market, among many other aspects."

Description: "Industry sector inquiry"

Analysis for sub\_question2: The description discusses the new energy sector, which is relevant to the question about new energy vehicles. While the focus is on the broader industry trends, it still relates to the availability of vehicles in the new energy sector.

Answer2: "Yes, this description is related to the question."

sub\_question3

Question: Is the description related to the question 'Can I still buy new energy vehicles'?

Case: "Individual stock inquiry refers to inquiries related to the stocks of a specific company. This may include questions about the company's financial health, performance, management changes, and stock price trends, as well as technical analysis related to stock price movements."

Description: "Individual stock inquiry"

Analysis for sub\_question3: The description focuses on individual company stocks, which is unrelated to the question about buying new energy vehicles. The question pertains to vehicle availability, not individual stock performance.

Answer3: "No, this description is not related to the question."

sub\_question4

Question: Is the description related to the question 'Can I still buy new energy vehicles'?

Case: "Fund inquiry pertains to inquiries about investment funds, which pool money from multiple investors for collective investment. This includes questions about the fund's type (e.g., equity, bond, or money market funds), investment strategy, performance, risk characteristics, management team, and subscription or redemption rules."

Description: "Fund inquiry"

Analysis for sub\_question4: The description concerns investment funds, which is not directly relevant to the question about buying new energy vehicles. The question is focused on vehicles, not investment funds.

Answer4: "No, this description is not related to the question."

sub\_question5

Question: Is the description related to the question 'Can I still buy new energy vehicles'?

Case: "Customer service inquiry refers to inquiries made by investors to customer service departments of financial institutions regarding issues related to securities trading. These can involve problems with account operations (e.g., account opening, password retrieval), transaction rules (e.g., fees, time), product services, and handling of transaction disputes."

Description: "Customer service inquiry"

Analysis for sub\_question5: The description is about customer service inquiries related to financial services, which is unrelated to the question about buying new energy vehicles.

Answer5: "No, this description is not related to the question."

sub\_question6

Question: Which one best fits the intention of the question 'Can I still buy new energy vehicles'?

Case: "Pay attention to comprehensively considering the previous analysis results to ensure accurate and error-free judgment, without missing any key information."

Description: The description is a combination of the answers from sub\_question1, sub\_question2, sub\_question3, sub\_question4, and sub\_question5:

- "No, this description is not related to the question."
- "Yes, this description is related to the question."
- "No, this description is not related to the question."
- "No, this description is not related to the question."
- "No, this description is not related to the question."

Analysis for sub\_question6: The only description that is related to the question is from sub\_question2, which mentions the new energy sector. Therefore, this is the most relevant response.

Answer6: "The description in sub\_question2 best fits the intention of the question."

Final Answer:

The description "Industry sector inquiry" in sub\_question2, which relates to the new energy sector, best fits the intention of the question "Can I still buy new energy vehicles?"

---

Table 33: The output of executing the pseudo-program knowledge graph in Table 32.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
def LLM(case,question,description):
```

```
    LLM_answer=Given the question, the case is an example about the question. Please study this example and answer the question based on the description.
```

```
    return LLM_answer
```

```
sub_question1="Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?"
```

```
sub_case1="It implies that introspection is a prerequisite for a life to have value. The phrase 'Only after' emphasizes that without introspection, life has no value. In other words, it presents a rather absolute condition where the value of life is directly tied to the act of introspection and doesn't consider the possibility of value in other contexts that don't involve this specific act."
```

```
sub_description1="Only after introspection can life be of value."
```

```
answer1=LLM(sub_case1,sub_question1,sub_description1)
```

```
sub_question2="Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?"
```

```
sub_case2="In order for life to possess value, it is necessary to engage in the act of reflection regularly. The use of 'To...we must...' indicates a causal or purpose - driven relationship. It emphasizes that reflection is an important activity that one needs to do in order to achieve a valuable life, without completely ruling out that there might be other factors also involved in a valuable life."
```

```
sub_description2="To be valuable in life, we must reflect on it from time to time."
```

```
answer2=LLM(sub_case2,sub_question2,sub_description2)
```

```
sub_question3="Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?"
```

```
sub_case3="It simply means that a person remains in a state of confusion throughout their entire life. There is no mention of the concepts of reflection or the value of life, as the focus is solely on the state of being confused."
```

```
sub_description3="I'm confused for a lifetime."
```

```
answer3=LLM(sub_case3,sub_question3,sub_description3)
```

```
sub_question4="Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?"
```

```
sub_case4="This implies that the purpose of people's lives should be to gain understanding. It doesn't touch on the ideas of reflection and the worth of life as presented in the original maxim. Instead, it centers around the concept of living with the goal of understanding something, without any reference to the importance of reflecting on one's life for its value."
```

```
sub_description4="People should live to understand."
```

```
answer4=LLM(sub_case4,sub_question4,sub_description4)
```

```
sub_question5="Which one best fits the expression 'Ancient Greek philosophers said that life without reflection is worth less'?"
```

```
sub_case5="Pay attention to considering the previous analysis results comprehensively and select the best one. Ensure accurate judgment without missing any key information."
```

```
#Answering sub_question6 requires relying on the answers of sub_question1, sub_question2, sub_question3, and sub_question4, namely answer1, answer2, answer3 and answer4
```

```
sub_description5=answer1+answer2+answer3+answer4
```

```
answer5=LLM(sub_case5,sub_question5,sub_description5)
```

```
#The final answer
```

```
final_answer=answer5
```

```
print(final_answer)
```

---

Table 34: The updated pseudo-program knowledge graph on AGIEval. (Question: Ancient Greek philosophers said that life without reflection is worthless. Which of the following options is the closest to the meaning of this maxim? Answer Choices: (A) Only after introspection can life be of value. (B) To be valuable in life, we must reflect on it from time to time. (C) I'm confused for a lifetime. (D) People should live to understand.)



---

Let's go through the execution step by step based on the provided program logic. We are essentially evaluating a series of descriptions to see how well they align with the expression "Ancient Greek philosophers said that life without reflection is worth less." Then, we summarize the findings to determine which description fits best with that expression.

Step-by-step Execution:

sub\_question1

Question: Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?

Case: "It implies that introspection is a prerequisite for a life to have value. The phrase 'Only after' emphasizes that without introspection, life has no value. In other words, it presents a rather absolute condition where the value of life is directly tied to the act of introspection and doesn't consider the possibility of value in other contexts that don't involve this specific act."

Description: "Only after introspection can life be of value."

Analysis for sub\_question1: The description directly correlates with the notion that introspection (or reflection) is essential for life to have value, aligning closely with the expression about life being less valuable without reflection.

Answer1: "Yes, this description is consistent with the expression."

sub\_question2

Question: Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?

Case: "In order for life to possess value, it is necessary to engage in the act of reflection regularly. The use of 'To...we must...' indicates a causal or purpose-driven relationship. It emphasizes that reflection is an important activity that one needs to do in order to achieve a valuable life, without completely ruling out that there might be other factors also involved in a valuable life."

Description: "To be valuable in life, we must reflect on it from time to time."

Analysis for sub\_question2: The description suggests that reflection is a necessary but not exclusive condition for life to have value. This is slightly different from the original expression, which implies reflection as the sole or primary requirement for value.

Answer2: "Yes, this description is consistent with the expression, but it introduces the possibility of other factors contributing to a valuable life."

sub\_question3

Question: Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?

Case: "It simply means that a person remains in a state of confusion throughout their entire life. There is no mention of the concepts of reflection or the value of life, as the focus is solely on the state of being confused."

Description: "I'm confused for a lifetime."

Analysis for sub\_question3: The description focuses on confusion, with no mention of reflection or life's value. It is not aligned with the original expression.

Answer3: "No, this description is not consistent with the expression."

sub\_question4

Question: Is this description consistent with the expression 'Ancient Greek philosophers said that life without reflection is worth less'?

Case: "This implies that the purpose of people's lives should be to gain understanding. It doesn't touch on the ideas of reflection and the worth of life as presented in the original maxim. Instead, it centers around the concept of living with the goal of understanding something, without any reference to the importance of reflecting on one's life for its value."

Description: "People should live to understand."

Analysis for sub\_question4: The description speaks about understanding as the goal of life, but it doesn't emphasize reflection or introspection as the path to valuing life, making it inconsistent with the original expression.

Answer4: "No, this description is not consistent with the expression."

sub\_question5

Question: Which one best fits the expression 'Ancient Greek philosophers said that life without reflection is worth less'?

Case: "Pay attention to considering the previous analysis results comprehensively and select the best one. Ensure accurate judgment without missing any key information."

Description: The description is a combination of the answers from sub\_question1, sub\_question2, sub\_question3, and sub\_question4: "Yes, this description is consistent with the expression. Yes, this description is consistent with the expression, but it introduces the possibility of other factors contributing to a valuable life. No, this description is not consistent with the expression. No, this description is not consistent with the expression."

Analysis for sub\_question5: The best match comes from sub\_question1 and sub\_question2, which both emphasize the importance of reflection in a valuable life. Sub\_question1 suggests a direct, strong connection between reflection and life's value, while sub\_question2 allows for other factors but still ties value to reflection.

Answer5: "The descriptions from sub\_question1 and sub\_question2 best fit the expression, but sub\_question1 aligns more directly with the original maxim."

Final Answer:

The description that best fits the expression "Ancient Greek philosophers said that life without reflection is worth less" is the one in sub\_question1, as it strongly links introspection to life's value without introducing any exceptions or other factors.

---

Table 35: The output of executing the pseudo-program knowledge graph in Table 34.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
#include <iostream>
#include <string>
using namespace std;

string LLM(string case, string question, string description) {
    string LLM_answer = "Given the question, the case is an example about the question. Please study this example and answer the question based on the description";
    return LLM_answer;
}

int main() {
    string sub_question1 = "How many lunch trays can the person carry at once?";
    string sub_case1 = "Description: Tom is helping the restaurant staff collect dishes, but he can only carry 6 plates at a time. Answer: Tom can carry 6 plates at a time.";
    string sub_description1 = "Roger can only carry 4 trays at a time.";
    string answer1 = LLM(sub_case1, sub_question1, sub_description1);

    string sub_question2 = "How many trays does the person need to pick up from the first table?";
    string sub_case2 = "Description: Tom needs to pick up 15 plates from one table and 9 plates from another. Answer: Tom needs to pick up 15 plates from the first table.";
    string sub_description2 = "Roger had to pick up 10 trays from one table and 2 trays from another.";
    string answer2 = LLM(sub_case2, sub_question2, sub_description2);

    string sub_question3 = "How many trays does the person need to pick up from the second table?";
    string sub_case3 = "Description: Tom needs to pick up 15 plates from one table and 9 plates from another. Answer: Tom needs to pick up 9 plates from the second table.";
    string sub_description3 = "Roger had to pick up 10 trays from one table and 2 trays from another.";
    string answer3 = LLM(sub_case3, sub_question3, sub_description3);

    string sub_question4 = "How many trays does the person need to carry in total?";
    string sub_case4 = "Description: Tom needs to pick up 15 plates from the first table and 9 plates from the second table. Answer: 15+9=24. Therefore Tom needs to carry 24 plates in total.";
    // Answering sub_question4 requires relying on the answers of sub_question2 and sub_question3
    string sub_description4 = answer2 + answer3;
    string answer4 = LLM(sub_case4, sub_question4, sub_description4);

    string sub_question5 = "How many trips will the person need to make to carry all the trays?";
    string sub_case5 = "Description: Tom can carry 6 plates at a time and Tom needs to carry 24 plates in total. Answer: 24/6=4. Therefore Tom needs to carry 24 plates in total.";
    // Answering sub_question5 requires relying on the answers of sub_question1 and sub_question4
    string sub_description5 = answer1 + answer4;
    string answer5 = LLM(sub_case5, sub_question5, sub_description5);

    // The final answer
    string final_answer = answer5;
    cout << final_answer << endl;

    return 0;
}
```

---

Table 36: The updated pseudo-program knowledge graph in the form of C++ on MultiArith. (Question: Roger was helping the cafeteria workers pick up lunch trays, but he could only carry 4 trays at a time. If he had to pick up 10 trays from one table and 2 trays from another, how many trips will he make?)

---

Let's walk through the program to understand how the 'LLM' function is used to answer the questions and derive the final answer.

Breakdown of Execution:

1. First Call to LLM (sub\_question1):

- Question: How many lunch trays can the person carry at once?
- Case: Tom can carry 6 plates at a time.
- Description: Roger can carry 4 trays at a time.
- Answer: Since Roger can carry 4 trays at a time, the answer is simply 4.

answer1 = "4"

2. Second Call to LLM (sub\_question2):

- Question: How many trays does the person need to pick up from the first table?
- Case: Tom needs to pick up 15 plates from one table.
- Description: Roger needs to pick up 10 trays from one table.
- Answer: Roger needs to pick up 10 trays from the first table.

answer2 = "10"

3. Third Call to LLM (sub\_question3):

- Question: How many trays does the person need to pick up from the second table?
- Case: Tom needs to pick up 9 plates from another table.
- Description: Roger needs to pick up 2 trays from another table.
- Answer: Roger needs to pick up 2 trays from the second table.

answer3 = "2"

4. Fourth Call to LLM (sub\_question4):

- Question: How many trays does the person need to carry in total?
- Case: Tom needs to pick up 15 plates from one table and 9 plates from the second table.
- Description: The total number of trays that Roger needs to carry is the sum of the trays picked up from both tables. From the previous answers:
  - 10 trays from the first table
  - 2 trays from the second table
  - Total =  $10 + 2 = 12$  trays

answer4 = "12"

5. Fifth Call to LLM (sub\_question5):

- Question: How many trips will the person need to make to carry all the trays?
- Case: Tom can carry 6 plates at a time and needs to carry 24 plates in total.
- Description: Roger can carry 4 trays at a time and needs to carry 12 trays in total. To calculate the number of trips, we divide the total number of trays by the number of trays he can carry at a time:
  - $12 / 4 = 3$  trips

answer5 = "3"

Final Answer: Roger needs to make 3 trips to carry all the trays.

Output: 3

---

Table 37: The output of executing the pseudo-program knowledge graph in Table 36.

---

#Given a program text, your role is the LLM function, which has three parameters: case, question, and description. The description is textual, the question requires you to answer based on the description, and the case involves processed scenarios or supplementary information or related considerations to assist you in answering the question. You need to strictly follow the program logic to execute. During execution, the LLM function will be called multiple times, which means you will answer corresponding questions based on different cases and descriptions. Please output the final result of this program text in natural language.

```
public class Main {

    public static String LLM(String case, String question, String description) {
        String LLM_answer = Given the question, the case is an example about the question. Please study this example and answer the question based on the description;
        return LLM_answer;
    }

    public static void main(String[] args) {

        String sub_question1 = "How many lunch trays can the person carry at once?";
        String sub_case1 = "Description:Tom is helping the restaurant staff collect dishes, but he can only carry 6 plates at a time.
        Answer:Tom can carry 6 plates at a time.";
        String sub_description1 = "Roger can only carry 4 trays at a time.";
        String answer1 = LLM(sub_case1, sub_question1, sub_description1);

        String sub_question2 = "How many trays does the person need to pick up from the first table?";
        String sub_case2 = "Description:Tom needs to pick up 15 plates from one table and 9 plates from another.
        Answer:Tom needs to pick up 15 plates from the first table.";
        String sub_description2 = "Roger had to pick up 10 trays from one table and 2 trays from another.";
        String answer2 = LLM(sub_case2, sub_question2, sub_description2);

        String sub_question3 = "How many trays does the person need to pick up from the second table?";
        String sub_case3 = "Description:Tom needs to pick up 15 plates from one table and 9 plates from another.
        Answer:Tom needs to pick up 9 plates from the second table.";
        String sub_description3 = "Roger had to pick up 10 trays from one table and 2 trays from another.";
        String answer3 = LLM(sub_case3, sub_question3, sub_description3);

        String sub_question4 = "How many trays does the person need to carry in total?";
        String sub_case4 = "Description:Tom needs to pick up 15 plates from the first table and 9 plates from the second table.
        Answer: 15+9=24. Therefore Tom needs to carry 24 plates in total.";
        // Answering sub_question4 requires relying on the answers of sub_question2 and sub_question3
        String sub_description4 = answer2 + answer3;
        String answer4 = LLM(sub_case4, sub_question4, sub_description4);

        String sub_question5 = "How many trips will the person need to make to carry all the trays?";
        String sub_case5 = "Description:Tom can carry 6 plates at a time and Tom needs to carry 24 plates in total.
        Answer: 24/6=4. Therefore Tom needs to carry 24 plates in total.";
        // Answering sub_question5 requires relying on the answers of sub_question1 and sub_question4
        String sub_description5 = answer1 + answer4;
        String answer5 = LLM(sub_case5, sub_question5, sub_description5);

        // The final answer
        String final_answer = answer5;

        System.out.println(final_answer);
    }
}
```

---

Table 38: The updated pseudo-program knowledge graph in the form of **Java** on MultiArith. (Question: Roger was helping the cafeteria workers pick up lunch trays, but he could only carry 4 trays at a time. If he had to pick up 10 trays from one table and 2 trays from another, how many trips will he make?)

---

Let's break down the program step-by-step and understand how the 'LLM' function is used to answer the questions and derive the final result.

Breakdown of Execution:

1. First Call to LLM (sub\_question1):

- Question: How many lunch trays can the person carry at once?
- Case: Tom can carry 6 plates at a time.
- Description: Roger can carry 4 trays at a time.
- Answer: Based on the description, Roger can carry 4 trays at a time.

So, answer1 = "4 trays"

2. Second Call to LLM (sub\_question2):

- Question: How many trays does the person need to pick up from the first table?
- Case: Tom needs to pick up 15 plates from one table.
- Description: Roger needs to pick up 10 trays from one table and 2 trays from another.
- Answer: Roger needs to pick up 10 trays from the first table.

So, answer2 = "10 trays"

3. Third Call to LLM (sub\_question3):

- Question: How many trays does the person need to pick up from the second table?
- Case: Tom needs to pick up 15 plates from one table and 9 plates from another.
- Description: Roger needs to pick up 10 trays from one table and 2 trays from another.
- Answer: Roger needs to pick up 2 trays from the second table.

So, answer3 = "2 trays"

4. Fourth Call to LLM (sub\_question4):

- Question: How many trays does the person need to carry in total?
- Case: Tom needs to pick up 15 plates from the first table and 9 plates from the second table.
- Description: By adding up the trays from the first and second tables, we get the total number of trays Roger needs to carry:
  - 10 trays from the first table
  - 2 trays from the second table
  - Total =  $10 + 2 = 12$  trays

So, answer4 = "12 trays"

5. Fifth Call to LLM (sub\_question5):

- Question: How many trips will the person need to make to carry all the trays?
- Case: Tom can carry 4 plates at a time and needs to carry 24 plates in total.
- Description: Roger can carry 4 trays at a time and needs to carry 12 trays in total. To calculate the number of trips, we divide the total number of trays by the number of trays he can carry at a time:
  - $12 / 4 = 3$  trips

So, answer5 = "3 trips"

Final Answer: Roger needs to make 3 trips to carry all the trays.

Output: 3 trips

---

Table 39: The output of executing the pseudo-program knowledge graph in Table 38.