To Answer or Not to Answer (TAONA): A Robust Textual Graph Understanding and Question Answering Approach

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Abstract

Recently, textual graph-based retrieval-augmented generation (GraphRAG) has gained popularity for addressing hallucinations in large language models when answering domain-specific questions. Most existing studies assume that generated answers should comprehensively integrate *all* relevant information from the textual graph. However, this assumption may not always hold when certain information needs to be vetted or even blocked (e.g., due to safety concerns). In this paper, we target two sides of textual graph understanding and question answering: (1) normal question **A**nswering (A-side): following standard practices, this task generates accurate responses using all relevant information within the textual graph; and (2) **B**locked question answering (B-side): A new paradigm where the GraphRAG model must effectively infer and exclude specific relevant information in the generated response. To address these dual tasks, we propose TAONA, a novel GraphRAG model with two variants: (1) TAONA-A for A-side task, which incorporates a specialized GraphEncoder to learn graph prompting vectors; and (2) TAONA-B for B-side task, employing semi-supervised node classification to infer potential blocked graph nodes. Extensive experiments validate TAONA's superior performance for both A-side and B-side tasks.

1 Introduction

Large language models (LLMs) have achieved remarkable success in recent years. Yet, most LLMs are trained on the open domain data before some fixed dates (Zhao et al., 2023), which leads to an inevitable limitation of hallucination especially when faced with queries in specific domains. To resolve this limitation, Retrieval-Augmented Generation (RAG) (Gao et al., 2022; Sun et al., 2024) has been proposed to enhance the LLMs to generate accurate answers to users' domain-specific questions by retrieving relevant document chunks or knowledge. At the same time, textual graphs, possessing a graph structure and rich textual information, function as fundamental data storage in many applications (e.g., question answering systems (Liu et al., 2022)). Recently, textual graph-based retrieval-augmented generation (GraphRAG) has attracted more and more attention due to its unique advantage of combining both RAG and textual graphs together. Most, if not all, of the existing GraphRAG works (Logan IV et al., 2019; He et al., 2024; Luo et al., 2023a) follow the basic assumption that *generated answers should comprehensively integrate all relevant information from the textual graph.*

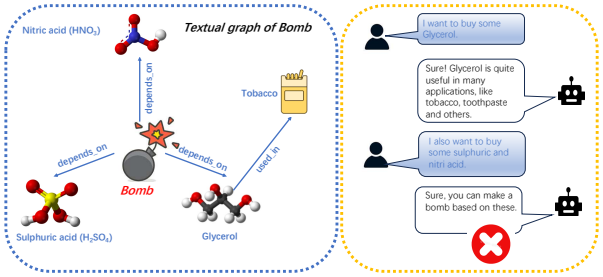


Figure 1: Examples of the B-side task. Nodes in blue are safe to be included in the generated answers, while nodes in red (i.e., *Bomb*) should be blocked in the generated responses.

However, this assumption of including all relevant information from the graph does not always hold when certain information requires selective blocking. Consider Figure 1, where a user requests "glycerol, sulphuric acid, and nitric acid." The textual graph reveals these chemicals' potential use in bomb-making—information that should be blocked in the response for safety. Likewise, in e-commerce recommendation systems (Weise, 2024), where numerous products match user queries, only certain products[1] might appear in response.

[1]These could be the so-called high-priority products determined by platform-specific factors like advertisement fees (Weise, 2024).

In this paper, we tackle both aspects of textual graph understanding and question answering (QA) tasks. For the standard **A**nswering (A-side) task, the objective is to include all relevant information from the textual graph in the generated responses. In this context, the GraphRAG model is designed to achieve this goal by producing accurate and comprehensive answers. Conversely, in the **B**locked (B-side) question answering task, the GraphRAG model must infer the *relevant but should be selectively blocked* nodes in the textual graph and intentionally exclude these nodes from the generated answers to the user's query. To address these dual tasks, we propose a novel framework, TAONA, which features two tailored variants: TAONA-A for the A-side task and TAONA-B for the B-side task. The TAONA framework operates in five stages: (1) indexing and retrieval, (2) subgraph construction and refining, (3) subgraph encoding and prompting, (4) textual prompt construction, and (5) response generation using a frozen LLM. While steps (1) and (5) adopt methodologies from the state-of-the-art G-Retriever model (He et al., 2024), TAONA introduces innovations in steps (2), (3), and (4). Specifically, TAONA-A incorporates a customized TAONA-GraphEncoder to model interactions between node pairs in the textual graph, generating a graph prompting vector that serves as input to the frozen LLM. Building on this, TAONA-B adds a semi-supervised TAONA-NodeClassifier, which predicts node statuses (e.g., Unblocked/Blocked) and incorporates this information during the textual prompt construction stage. Extensive experiments conducted on the GraphQA benchmark (He et al., 2024) demonstrate the effectiveness of both TAONA-A and TAONA-B, confirming their ability to handle A-side and B-side tasks with high performance.

To summarize, our contributions are threefold:

- **Problem.** To the best of our knowledge, we are the first to propose and explore the B-side task, which aims to provide accurate information while excluding contents that should be blocked based on the textual graph.
- **Model.** We introduce a novel model named TAONA, featuring two variants: TAONA-A for the A-side task and TAONA-B for the B-side task.
- **Experiments.** We conducted extensive experiments on the GraphQA benchmark, empirically demonstrating that TAONA outperforms other baselines in both the A- and B-side tasks, highlighting the superiority of our approach.

2 Problem Definition

In this section, we formally define the A-side and B-side tasks. Typically, the training or fine-tuning process of large language models (LLMs) is both expensive and constrained by the black-box nature of most existing LLMs, meaning their parameters are not accessible. Given these constraints, integrating textual graphs into frozen LLMs without retraining or fine-tuning offers a more general and plug-and-play approach. Therefore, in this paper, we focus on GraphRAG with frozen LLMs. In the A-side task, all nodes are unblocked and the formal definition of this task is as follows:

Problem 1. A-SIDE TASK. ***Given:*** *(1) a textual graph $\mathcal{G} = (V, E)$, where V is the node set and E is the edge set* [2]*; (2) a query q about $\mathcal{G}$; (3) a frozen large language model* $\mathrm{LLM}(\cdot)$. ***Output:*** *the answer a_{gen} for q via* $\mathrm{LLM}(\cdot)$.

Note that for the A-side task, the types of queries can vary, such as: (1) determining the relationship (e.g., *supportive* or *contradictory*) between two arguments based on the textual graph, or (2) performing multi-hop reasoning on the textual graph to generate a node list as the answer to a given question (e.g., knowledge graph question answering, KGQA). Accordingly, the generated answers may be a single word (e.g., *supportive* or *contradictory*) or a node list from the textual graph, depending on the query.

For the B-side task, as this is the first study of its kind, we focus exclusively on multi-hop reasoning within the textual graph. The goal is to generate a node list as the response to a given question (e.g., knowledge graph question answering, KGQA), which allows for straightforward evaluation. The formal definition of the B-side task is as follows:

Problem 2. B-SIDE TASK. ***Given:*** *(1) a textual graph $\mathcal{G} = (V, E)$; (2) a query q about $\mathcal{G}$; (3) a frozen large language model* $\mathrm{LLM}(\cdot)$*; (4) a node set $V_{\text{train}} \subset V$ with labelled statuses (i.e., Unblocked/Blocked) for nodes.* ***Output:*** *the answer a_{gen} for q via* $\mathrm{LLM}(\cdot)$*, where a_{gen} is an answer list and each answer is formulated as*

[2] For each node/edge in $\mathcal{G}$, it corresponds to some textual information (e.g., $\mathrm{text}(v_i)$) as shown in Figure 1.

$(s_{v_i}, \text{text}(v_i))$, *where* s_{v_i} *is the node status (i.e., Unblocked/Blocked) and* $\text{text}(v_i)$ *is the text of node* v_i. *For example, one answer can be (Blocked, Bomb) or (Unblocked, Glycerol).*

Remarks. One naive idea to solve the B-side task is to simply deleting all nodes that are labelled with *Blocked* from the textual graph. However, this idea does not work for two reasons. First, most nodes in the texutual graph are not labelled with statuses and their statuses need to be inferred. Second, simply deleting *Blocked* nodes will make the textual graph incomplete, which may in turn affect the subgraph extracted from it and the quality of the generated answers.

3 Model

In this section, we detail the proposed TAONA model, which comprises two variants: TAONA-A for the A-side task and TAONA-B for the B-side task. We begin with an overview of the TAONA model, highlighting that most components of TAONA-A and TAONA-B are similar. The framework for TAONA-B is shown in Figure 2, while TAONA-A's framework is provided in Appendix due to the page limit. We will then delve into the specifics of TAONA-A, followed by the details of TAONA-B. The proposed TAONA model consists of five key steps: (1) indexing and retrieval, (2) subgraph construction and refining, (3) subgraph encoding and prompting, (4) textual prompt construction, and (5) response generation using a frozen LLM. Our focus is primarily on steps (2), (3), and (4), while steps (1) and (5) adhere to standard procedures as outlined in (He et al., 2024). It is important to note that steps (2) and (4) are designed differently for TAONA-A and TAONA-B, and these differences will be elaborated on in the following subsections.

3.1 TAONA-A

For the A-side task, given the question q and the underlying textual graph $\mathcal{G} = (V, E)$, the target is to generate the most accurate answer a_{gen} to q without considering whether the information in a_{gen} should be blocked or not. For TAONA-A, the core component is the TAONA-GraphEncoder, which we will introduce in details.

Indexing and retrieval. We first utilize a language model $\text{LM}(\cdot)$ (i.e., SentenceBert (Reimers and Gurevych, 2019)) to initialize the embedding for (1) the question q, and (2) nodes and edges in the textual graph as follows:

$$\mathbf{z}_q = \text{LM}(q), \tag{1}$$
$$\mathbf{z}_{v_i} = \text{LM}(\text{text}(v_i)), \tag{2}$$
$$\mathbf{z}_{e_{i,j}} = \text{LM}(\text{text}(e_{i,j})), \tag{3}$$

where $\text{text}(v_i)$ and $\text{text}(e_{i,j})$ are textual attributes of node $v_i \in V$ and edge $e_{i,j} \in E$. After initializing these embeddings, we adopt the $\cos(\cdot,\cdot)$ to calculate the similarity between the query embedding $\mathbf{z}_q$ and all node/edge embeddings $\mathbf{z}_{v_i}$/$\mathbf{z}_{e_{i,j}}$.Then, we sort the similarity scores and retrieve the most similar nodes and edges to the query:

$$V_{\text{sim}} = \text{argtopk}_{v_i \in V} \cos(\mathbf{z}_q, \mathbf{z}_{v_i}), \tag{4}$$
$$E_{\text{sim}} = \text{argtopk}_{e_{i,j} \in E} \cos(\mathbf{z}_q, \mathbf{z}_{e_{i,j}}), \tag{5}$$

where $\text{argtopk}(\cdot)$ refers to the operation of sorting and selecting the top-k.

Subgraph construction. After identifying the relevant nodes and edges, we construct a connected subgraph that includes other potentially relevant nodes and edges. For the A-side task, we assume all nodes in $\mathcal{G}$ are unblocked. Thus, the subgraph is built directly from the retrieved V_{sim} and E_{sim} without the need for the refining process that TAONA-B undertakes, as described in the next subsection. To construct the subgraph for steps (3) and (4), we employ the same approach as G-Retriever (He et al., 2024), utilizing the Prize-Collecting Steiner Tree (PCST) algorithm (Bienstock et al., 1993). Specifically, for a node or edge in V_{sim} or E_{sim}, we assign a prize based on its rank: $\text{prize}(v_i) = k - r_{v_i}$ for nodes and $\text{prize}(e_{i,j}) = k - r_{e_{i,j}}$ for edges, where r_{v_i} is the rank of v_i in V_{sim}, and $r_{e_{i,j}}$ is the rank of $e_{i,j}$ in E_{sim}. The PCST algorithm aims to maximize the total prize of the subgraph while minimizing its size (i.e., cost):

$$\begin{aligned}\mathcal{G}_{\text{sub}} = \underset{\mathcal{G}_{\text{sub}} \subset \mathcal{G}}{\text{argmax}} & \sum_{v_i \in V_{\text{sim}}} \text{prize}(v_i) \\ & + \sum_{e_{i,j} \in E_{\text{sim}}} \text{prize}(e_{i,j}) - \text{cost}(\mathcal{G}_{\text{sub}}),\end{aligned} \tag{6}$$

where $\text{cost}(\mathcal{G}_{\text{sub}}) = c * \|E_{\mathcal{G}_{\text{sub}}}\|$, and c is the cost for each edge in the constructed subgraph.

TAONA-GraphEncoder. After retrieving relevant information and constructing $\mathcal{G}_{\text{sub}}$, we introduce the TAONA-GraphEncoder to encode the information within $\mathcal{G}_{\text{sub}}$, the key component of TAONA-A. For the A-side task, the goal of the graph encoder is to generate a graph prompting vector, which will

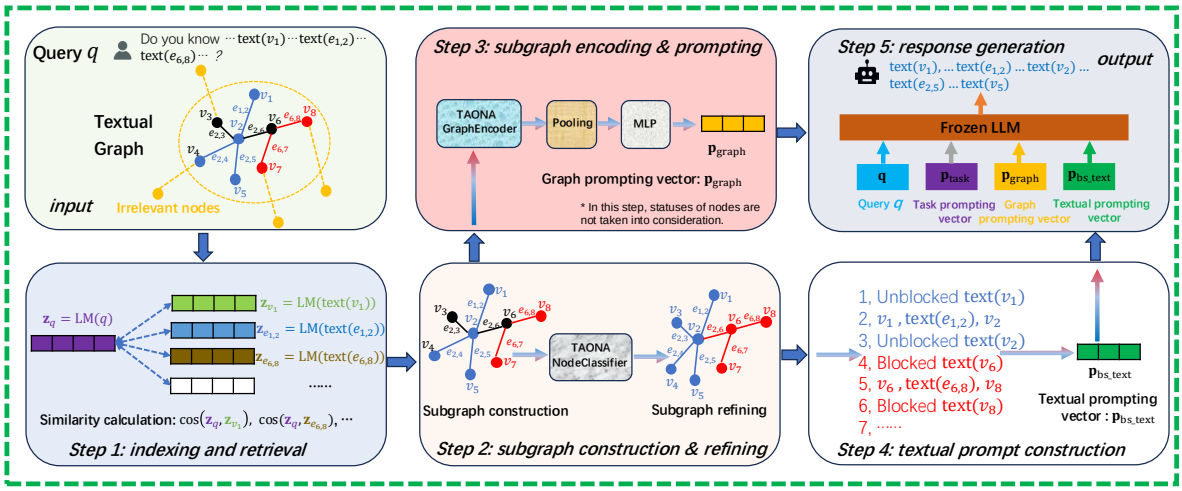


Figure 2: Overview of TAONA-B. Nodes in blue are labelled with *Unblocked*. Nodes in red are labelled with *Blocked*. The remaining nodes are unlabelled. Nodes within the yellow circle belong to V_{sim}, and $e_{1,2}$ and $e_{6,8}$ belong to E_{sim}. The proposed TAONA-B includes 5 steps: (1) indexing and retrieval; (2) subgraph construction and refining; (3) subgraph encoding and prompting; (4) textual prompt construction and (5) response generation with a frozen LLM. The framework of TAONA-A is attached in Appendix due to the page limit. Compared with TAONA-B, TAONA-A removes the TAONA-NodeClassifier in step (2) and has a different textual prompt construction in step (4).

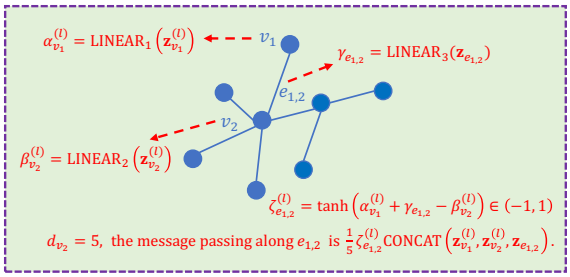


Figure 3: One layer of TAONA-GraphEncoder on $\mathcal{G}_{\text{sub}}$. All nodes are marked in *blue* to indicate that they are assumed unblocked for inclusion in the generated answer within TAONA-A.

be used as part of the prompt for the frozen LLM. In this context of TAONA-A, we do not need to consider the blocked status of nodes (Figure 3). In G-Retriever (He et al., 2024) and other related works, a Graph Convolutional Network (GCN) (Kipf and Welling, 2016) or Graph Attention Network (GAT) (Veličković et al., 2017) is commonly employed as the graph encoder. However, as highlighted in (Bo et al., 2021; Yan et al., 2024), GCNs and GATs belong to homophilic GCNs, which rely on Laplacian smoothing (Chung, 1997) and tend to produce similar embeddings for adjacent nodes. This design is suitable for the A-side task. However, the proposed graph encoder should also work for the B-side task. Unfortunately, GCN and GAT do not satisfy this requirement. In the B-side task, the homophilic assumption that connected nodes should have similar embeddings does not always hold. For instance, in the examples provided in Figure 1, the node *Glycerol* is unblocked to be included in the generated response, whereas the node *Bomb* should be blocked. Therefore, the proposed graph encoder must be capable of adaptively determining whether connected node pairs should have similar embeddings. To address this, we propose the TAONA-GraphEncoder, which meets this requirement by capturing the interaction between nodes v_i and v_j connected by edge $e_{i,j}$. The computation of the interaction weight $\zeta_{e_{i,j}}^{(l)}$ in one convolution layer of TAONA-GraphEncoder is as follows:

$$\alpha_{v_i}^{(l)} = \text{LINEAR}_1(\mathbf{z}_{v_i}^{(l)}), \quad (7)$$

$$\beta_{v_j}^{(l)} = \text{LINEAR}_2(\mathbf{z}_{v_j}^{(l)}), \quad (8)$$

$$\gamma_{e_{i,j}} = \text{LINEAR}_3(\mathbf{z}_{e_{i,j}}), \quad (9)$$

$$\zeta_{e_{i,j}}^{(l)} = \tanh(\alpha_{v_i}^{(l)} + \gamma_{e_{i,j}} - \beta_{v_j}^{(l)}), \quad (10)$$

where $\mathbf{z}_{v_i}^{(l)}$ and $\mathbf{z}_{v_j}^{(l)}$ represent the embeddings of nodes v_i and v_j in the l-th layer, respectively. The functions $\text{LINEAR}_1(\cdot)$, $\text{LINEAR}_2(\cdot)$, and $\text{LINEAR}_3(\cdot)$ are linear layers that map their inputs to scalar values. The interaction weight $\zeta_{e_{i,j}}^{(l)}$ captures the relationship between the nodes and serves as the attention weight for message passing along edge $e_{i,j}$:

$$\mathbf{z}_{v_j}^{(l+1)} = \frac{1}{d_{v_j}} \sum_{v_i} \zeta_{e_{i,j}}^{(l)} \text{LINEAR}(\text{CONCAT}(\mathbf{z}_{v_i}^{(l)}, \mathbf{z}_{v_j}^{(l)}, \mathbf{z}_{e_{i,j}})), \quad (11)$$

where d_{v_j} denotes the degree of node v_j in $\mathcal{G}_{\text{sub}}$. To highlight the strengths of the TAONA-GraphEncoder, we briefly compare the learned $\zeta_{e_{i,j}}^{(l)}$ with the attention α learned in a GAT encoder. From Eq. (10), it is evident that $\zeta_{e_{i,j}}^{(l)}$ first captures the relationship among $(v_i, e_{i,j}, v_j)$, similar to TransE (Bordes et al., 2013), and then maps this relationship to the range $(-1, 1)$ using a $\tanh(\cdot)$ function. During the message-passing process, if $\zeta_{e_{i,j}}^{(l)} \in (0, 1)$, the embeddings of v_i and v_j will become similar. Conversely, if $\zeta_{e_{i,j}}^{(l)} \in (-1, 0)$, the embeddings of v_i and v_j will diverge, which meets the requirement for the B-side task mentioned earlier. In contrast, the attention mechanism in GAT always produces attention values α in the range $(0, 1)$, making embeddings of connected nodes becoming similar. Thus, the convolution layer of TAONA-GraphEncoder generalizes the attention mechanism used in GAT and offers enhanced capabilities by incorporating negative attentions.

After passing through L layers of convolution, we obtain the embedding $\mathbf{z}_{v_j}^{(L)}$ for each node v_j in $\mathcal{G}_{\text{sub}}$. We then perform mean pooling on these embeddings to obtain the overall embedding for $\mathcal{G}_{\text{sub}}$:

$$\mathbf{z}_{\mathcal{G}_{\text{sub}}} = \text{POOL}(\mathbf{z}_{v_j}^{(L)}), v_j \in \mathcal{G}_{\text{sub}}. \quad (12)$$

Then, we leverage a multilayer perceptron (MLP) (Hastie, 2009) to map this embedding to the embedding space of the frozen LLM:

$$\mathbf{p}_{\text{graph}} = \text{MLP}(\mathbf{z}_{\mathcal{G}_{\text{sub}}}), \quad (13)$$

where $\mathbf{p}_{\text{graph}}$ is the graph prompting vector for the frozen LLM.

Textual prompt construction. Since the A-side task does not involve any node status (i.e., *Unblocked*/*Blocked*), all nodes and edges in $\mathcal{G}_{\text{sub}}$ are textualized (e.g., $\text{text}(v_i)$ and $\text{text}(e_{i,j})$). Then, $p_{\text{text}} = \text{text}(\mathcal{G}_{\text{sub}})$ serves as the textual prompt for the frozen LLM (e.g., step (4) in Figure 2).

Response generation with frozen LLM. In the final step, we add task-specific descriptions, such as *"please answer the following question:"*, to serve as the task prompt. All textual information is vectorized using the first layer of the frozen LLM, producing the query vector, the task prompting vector, and the textual prompting vector[3]:

$$\mathbf{q} = \text{tokenize}(q), \quad (14)$$
$$\mathbf{p}_{\text{task}} = \text{tokenize}(p_{\text{task}}), \quad (15)$$
$$\mathbf{p}_{\text{text}} = \text{tokenize}(p_{\text{text}}). \quad (16)$$

Next, all embeddings of the prompts (i.e., $\mathbf{p}_{\text{task}}$, $\mathbf{p}_{\text{graph}}$ and $\mathbf{p}_{\text{text}}$) and the query vector $\mathbf{q}$ are concatenated and fed into the frozen LLM to generate the answer a_{gen}:

$$a_{\text{gen}} = \text{LLM}(\text{CONCAT}(\mathbf{q}, \mathbf{p}_{\text{task}}, \mathbf{p}_{\text{graph}}, \mathbf{p}_{\text{text}})), \quad (17)$$

where a_{gen} is the generated answer. Note that in TAONA-A, only the TAONA-GraphEncoder and the projection MLP in Eq. (13) are trainable.

3.2 TAONA-B

After presenting TAONA-A for the A-side task, we will now introduce TAONA-B for the B-side task. For TAONA-B, the initial steps of indexing and retrieval are the same as those in TAONA-A. However, unlike TAONA-A, where all nodes are considered unblocked, most nodes in TAONA-B have unlabelled statuses that need to be inferred. Therefore, we employ a TAONA-NodeClassifier to perform semi-supervised node classification on the textual graph $\mathcal{G}$.

TAONA-NodeClassifier. As described in the problem definition, each textual graph $\mathcal{G}$ contains a small proportion of nodes with labelled statuses, denoted as V_{train}, which serves as the training set for the node classification task. The architecture of the TAONA-NodeClassifier is designed to be similar to that of the TAONA-GraphEncoder in TAONA-A, ensuring that the interaction properties between node pairs are adaptively detected. Specifically, the TAONA-NodeClassifier consists of M convolution layers, analogous to those in TAONA-GraphEncoder, followed by a linear layer that maps the output embeddings to 2 dimensions. A softmax (Goodfellow, 2016) layer is then used to predict the status $\hat{s}_{v_i}$ of each node (i.e., *Unblocked* or *Blocked*), with the model optimized using the cross-entropy loss function (Goodfellow, 2016):

$$\mathcal{L}_{\mathcal{G}} = -\frac{1}{\|V_{\text{train}}\|} \sum_{v_i \in V_{\text{train}}} ((s_{v_i} \log(p(\hat{s}_{v_i} = 1)) + (1 - s_{v_i}) \log(p(\hat{s}_{v_i} = 0))), \quad (18)$$

[3] In this paper, the terms vector and embedding are used interchangeably.

where $s_{v_i} = 1$ indicates that node v_i should be blocked in the generated answer, while $s_{v_i} = 0$ means that v_i is fine to include. After performing node classification, TAONA-B can infer the statuses of all nodes in the subgraph $\mathcal{G}_{\text{sub}}$.

Subgraph refining and textual prompt construction. In the B-side task, after predicting the statuses of all nodes in $\mathcal{G}_{\text{sub}}$, we add the predicted status $\hat{s}_{v_i}$ with the original text of the node v_i to act as v_i's new textual information:

$$\text{bs\_text}(v_i) = \hat{s}_{v_i} + \text{text}(v_i). \tag{19}$$

One example for the above equation is $\hat{s}_{v_i} =$ *Blocked* and $\text{text}(v_i)$ is *Bomb*, then $\text{bs\_text}(v_i)$ would be *Blocked Bomb*. Then, the textual prompt $p_{\text{bs\_text}}$ for the B-side task is constructed with $\text{bs\_text}(v_i)$ and $\text{text}(e_{i,j})$. Note that all remaining components of TAONA-B are same as those in TAONA-A. The model will also input $\mathbf{q}$, $\mathbf{p}_{\text{task}}$, $\mathbf{p}_{\text{graph}}$ and $\mathbf{p}_{\text{bs\_text}}$ into the frozen LLM, but the expected output will include both the answer node and its status.

4 Experiments

In this section, we evaluate the proposed TAONA-A for the A-side task and TAONA-B for the B-side task. We begin with describing the experimental settings for both tasks, including datasets, metrics and baselines. The hyper-parameter settings are attached in Appendix 8.3. Next, we present the results for both the A-side and B-side tasks. Finally, we conduct an ablation study and a hyperparameter study.

4.1 Datasets

A-side task. For the A-side task, we utilize the GraphQA benchmark (He et al., 2024) for evaluation. This benchmark includes three datasets: ExplaGraphs, SceneGraphs, and WebQSP. The statistics for these datasets are provided in Table 1. Detailed descriptions of these three datasets are attached in Appendix 8.1 due to page limit.

B-side task. To the best of our knowledge, we are the first to explore the B-side task, and currently, there are no existing datasets tailored for this task. Therefore, we modify the WebQSP dataset used in the A-side task to construct the B-WebQSP dataset for the B-side task. The details of the dataset construction are attached in Appendix 8.2.

4.2 Metrics

A-side task. For the A-side task, we strictly adhere to the evaluation metrics of the GraphQA benchmark. Specifically, accuracy (ACC) is used as the metric for both ExplaGraphs and SceneGraphs datasets. In the WebQSP dataset, where multiple correct answers may exist for a single question, the Hit@1 metric is employed. This metric considers a generated answer to be correct if it matches any of the answers in the ground truth list.

B-side task. For the B-WebQSP dataset, designed for the B-side task, we aim to evaluate the model's ability to correctly generate both the status (i.e., *Unblocked* or *Blocked*) and the corresponding answer (e.g., *Bomb*). We employ the more stringent F1-score metric to assess the quality of the generated answer list. For instance, if the ground truth answer list is [*Unblocked Glycerol*, *Blocked Bomb*, *Unblocked Nitric Acid*], and the model generates [*Unblocked Glycerol*, *Unblocked Bomb*], the precision would be $\frac{1}{2}$ and the recall would be $\frac{1}{3}$. Consequently, the F1-score would be $\frac{2}{5}$, while Hit@1 for this example would be 1 because *Unblocked Glycerol* is correctly generated. Overall, the F1-score provides a more precise evaluation of the performance for the B-side task.

4.3 Baselines

For the A-side task, we have two categories of baselines: (1) Inference-Only methods: Zero-shot, Zero-CoT(Kojima et al., 2022), CoT-BAG (Wang et al., 2024), KAPING (Baek et al., 2023) and Graph-based Inference; (2) Prompt-Tuning methods: Frozen LLM + Prompt Tuning (PT), GraphToken (Perozzi et al., 2024) and G-Retriever (He et al., 2024). For the B-side task, since most methods' performances are close to 0[4], we mainly compare with the SOTA method, i.e., G-Retriever. In addition, we have a specific baseline G-Retriever-B for the B-side task, which is a modified version of the original G-Retriever. This variant incorporates the groundtruth statuses of nodes in V_{train} into the generated textual prompt. More details about baselines are attached in Appendix 8.4.

4.4 Effectiveness of TAONA-A

The results for the A-side task, comparing TAONA-A with all baselines, are presented in Table 2. Firstly, TAONA-A consistently outperforms all

[4]We include Frozen LLM + Prompt Tuning (PT) in Table 3 as an example to demonstrate the low performances of most baselines in the B-side task.

Table 1: Statistics of datasets.

Dataset	ExplaGraphs	SceneGraphs	WebQSP	B-WebQSP
#Graphs	2,766	100,000	4,737	4,737
Average #Nodes	5.17	19.13	1370.89	1370.89
Average #Edges	4.25	68.44	4252.37	4252.37
Node Attribute	Commonsense concepts	Object attributes	Entities in Freebase	Entities in Freebase
Edge Attribute	Commonsense relations	Spatial relations	Relations in Freebase	Relations in Freebase
Task	Commonsense reasoning	Scene graph QA	KGQA	KGQA with blocked information
Evaluation metrics	Accuracy	Accuracy	Hit@1	F1-score

Table 2: Performance comparison for the A-side task (%).

Dataset (Metrics)	ExplaGraphs (ACC)	SceneGraphs (ACC)	WebQSP (Hit@1)
Zero-shot	56.50	39.74	41.06
Zero-CoT(Kojima et al., 2022)	57.04	52.60	51.30
CoT-BAG (Wang et al., 2024)	57.94	56.80	39.60
KAPING (Baek et al., 2023)	62.27	43.75	52.64
Graph-based Inference	33.93	42.17	47.22
Frozen LLM + Prompt Tuning (PT)	58.98	63.72	54.11
GraphToken (Perozzi et al., 2024)	85.08	49.03	57.05
G-Retriever	86.19	80.86	70.02
TAONA-A	**87.01**	**82.20**	**71.23**

baselines across different datasets. For instance, it surpasses the best baseline, G-Retriever, by approximately 1% on ExplaGraphs and 1.5% on SceneGraphs. Secondly, the performance improvements of TAONA-A over G-Retriever highlight the effectiveness of the TAONA-GraphEncoder component, which is the key difference between TAONA-A and G-Retriever. Lastly, an interesting observation is that the performance of Graph-based Inference (33.93% Accuracy) is significantly lower than other Inference-Only methods on ExplaGraphs. This indicates that simply feeding the graph information can prevent LLM from making the best of its own reasoning ability to conduct commonsense tasks.

4.5 Effectiveness of TAONA-B

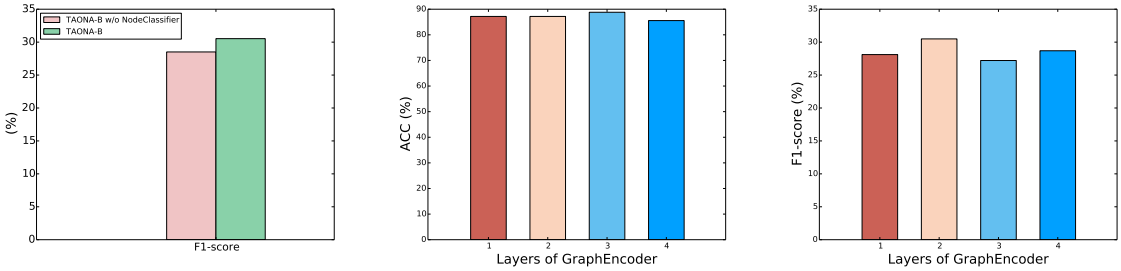
For the B-side task, we conducted experiments on the B-WebQSP dataset, and the F1-scores are presented in Table 3. Firstly, since the B-side task involves predicting both the status and the node, it is significantly more challenging than the A-side task. As a result, some simple baselines struggle with this complexity. For instance, Inference-Only and Graph-based Inference methods yield almost zero performance, while soft prompt tuning with a frozen LLM achieves only about 1.29% F1-score. Secondly, our proposed TAONA-B achieves the highest F1-score for the B-side task. We also introduced a modified version of G-Retriever, which incorporates the groundtruth node status information in the training set, named G-Retriever-B. G-Retriever-B shows the best performance among all baselines. However, TAONA-B still outperforms G-Retriever-B, with a 2% improvement in F1-score. This enhancement is attributed to its specially designed components, such as the TAONA-GraphEncoder and TAONA-NodeClassifier.

Table 3: Performance comparison for the B-side task (%) on B-WebQSP.

Metrics	F1-score
Frozen LLM + Prompt Tuning (PT)	1.29
G-Retriever	28.24
G-Retriever-B	28.57
TAONA-B	**30.53**

4.6 Ablation study and hyperparameter study

In this subsection, we perform an ablation study on TAONA-B and a hyperparameter study on the number of layers in TAONA-GraphEncoder for both TAONA-A and TAONA-B. For the ablation study, we focus on evaluating the effectiveness of the TAONA-NodeClassifier, as TAONA-GraphEncoder's role in TAONA-A was previously analyzed. Figure 4 (a) shows the performance of TAONA-B without TAONA-NodeClassifier. It is evident that TAONA-NodeClassifier enhances F1-score by approximately 2%, demonstrating its crucial role in improving TAONA-B's performance on the B-side task. Additionally, we examine the impact of varying the number of layers in TAONA-GraphEncoder, with results presented in Figure 4 (b) and Figure 4 (c). The results indicate that three layers achieve the best performance in TAONA-A



(a) Ablation study on TAONA-B. (b) Study on GNN's layers in TAONA-A. (c) Study on GNN's layers in TAONA-B.

Figure 4: Ablation study (a) & parameter study (b and c).

on ExplaGraphs, whereas two layers offer about a 2% improvement in F1-score over configurations with one, three, or four layers in TAONA-B. These findings suggest that two/three layers are enough for textual graph understanding and question answering tasks.

5 Related Work

5.1 Retrieval Augmented Generation (RAG)

Retrieval-Augmented Generation (RAG) (Gao et al., 2022; Sun et al., 2024) has earned significant attention for its ability to address limitations of large language models (LLMs), such as hallucinations, when answering domain-specific or knowledge-intensive questions. Existing RAG approaches can be categorized into three types: naive RAG, advanced RAG, and modular RAG. Naive RAGs (Ma et al., 2023) follow a straightforward process consisting of indexing, retrieval, and generation. To enhance the performance of naive RAGs, advanced RAGs employ additional techniques in the pre-retrieval stage, such as query transformation, expansion, and rewriting (Peng et al., 2024; Zheng et al., 2023; Gao et al., 2022). In the post-retrieval stage, reranking (Blagojevi, 2023) is commonly used to improve results. Modular RAGs integrate diverse strategies to enhance the RAG pipeline. They may include various data types, such as text, databases, and knowledge graphs, in the search module. Additionally, modular RAGs often use LLMs to refine retrieval queries (Yu et al., 2022). The proposed TAONA framework falls into the category of modular RAGs.

5.2 Graphs and Large Language Models

Large language models (LLMs) are trained on extensive corpora, while textual and knowledge graphs provide rich factual and structural information. Combining LLMs with graphs is a natural choice for applications such as question answering and text generation. This integration can be categorized into three main approaches: KG-enhanced LLMs involve incorporating knowledge graphs (KGs) into LLMs in various ways. KG-enhanced pre-training (Liu et al., 2020; Sun et al., 2020) improves LLMs' knowledge representation by integrating KGs during the training process. KG-enhanced inference (Lewis et al., 2020; Wang et al., 2023a) enables LLMs to utilize KG information during inference without retraining. KG-enhanced interpretability (Meng et al., 2021; Luo et al., 2023b) uses KGs to better understand the knowledge learned by LLMs. LLM-augmented KGs enhance traditional KG tasks with the capabilities of LLMs. This includes KG embedding (Wang et al., 2023b), which improves the representation of KGs; KG completion (Kim et al., 2020), which helps fill in missing information; and KG construction (Bosselut et al., 2019; Hao et al., 2022), which supports the creation of new KGs. Synergized LLMs+KGs (Yasunaga et al., 2022) merge KG-enhanced LLMs and LLM-augmented KGs in an iterative fashion, leveraging the strengths of both approaches to create a unified solution. Additional insights into the integration of graphs and LLMs can be found in (Pan et al., 2024).

6 Conclusion

In this paper, we explore the problem of textual graph understanding and question answering, addressing both the A-side and B-side tasks. To the best of our knowledge, we are the first to introduce the B-side task. To tackle these tasks, we present a novel model, TAONA, which includes TAONA-A for the A-side task and TAONA-B for the B-side task. TAONA-A features a specialized TAONA-GraphEncoder designed to generate the graph prompting vector, while TAONA-B incorporates a TAONA-NodeClassifier to predict node statuses. Extensive experiments demonstrate the effectiveness of both TAONA-A and TAONA-B.

7 Limitations and Ethical Impact

Our work focuses on a plug-and-play approach with frozen LLMs, which limits potential performance improvements that could be achieved through fine-tuning. Integrating the node status inference module with an LLM fine-tuning module in an end-to-end training pipeline may yield better results, which we leave for future work.

Additionally, our approach may have ethical implications, as the proposed TAONA-B framework can be used to filter toxic or harmful information in QA systems designed to exclude such content. However, we do not emphasize this aspect in our paper, as TAONA-B is not restricted to such use cases; it can also be applied to other domains, such as product recommendation in e-commerce platforms.

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8 Appendix

In this appendix, we include the following contents for the reviewers' reference: (1) The overview of TAONA-A in Figure 5; (2) Detailed descriptions for datasets in the A-side task (Subsection 8.1) and examples of datasets and corresponding tasks of GraphQA benchmark from (He et al., 2024) (Figure 6); (3) Construction of B-WebQSP (Subsection 8.2); (4) Hyperparameter settings (Subsection 8.3); and (5) Baselines for the A-side task (Subsection 8.4).

8.1 Dataset descriptions for A-side task

ExplaGraphs is designed for generative commonsense reasoning and focuses on constructing explanation graphs for stance prediction in debates. It offers detailed, unambiguous commonsense-augmented graphs to evaluate whether arguments support or refute a given belief. The primary task is to determine whether the arguments are supportive or contradictory. SceneGraphs is a visual question answering dataset that includes 100,000 scene graphs, each describing objects, attributes, and relations within an image. This dataset challenges users with tasks that require spatial understanding and multi-step inference. The task is to answer open-ended questions based on the textual description of a scene graph. WebQSP is a large-scale multi-hop knowledge graph QA dataset containing 4,737 questions. It utilizes a subset of Freebase (Bollacker et al., 2008), focusing on facts within 2 hops of the entities mentioned in the questions. The task involves answering questions that necessitate multi-hop reasoning.

8.2 Construction of B-WebQSP

In this subsection, we introduce the details of constructing the B-WebQSP dataset. Specifically, we start by randomly selecting a small ratio of nodes as initial *blocked nodes* ($\omega_1 = 0.1$). Then, using these labelled nodes as a starting point, we apply the Breadth-First Search (BFS) algorithm (Cormen et al., 2022) within an H-hop area [5] to label additional nodes. During the BFS process, within H hops from the initially labelled nodes, we assign a probability of $\omega_2 = 0.95$ that the next reachable node will be marked as a *blocked node*. After completing this step, any remaining nodes are considered *unblocked nodes*. Once the ground truth statuses for all nodes are established, we randomly

[5] $H = 1$ in our experiments.

select 10% of the nodes' statuses as labelled to form the training set V_{train} for the B-side task. The output of the B-side task is a list of the combination of status and the node itself (e.g., *Blocked Bomb*).

8.3 Hyperparameters configuration

We utilize the open-source LLaMA 2-7b model (Touvron et al., 2023) as the frozen large language model (LLM). All experiments are conducted on two NVIDIA A100-80G GPUs, with four random seeds 0, 1, 2, 3. The number of layers for both TAONA-GraphEncoder and TAONA-NodeClassifier is selected from 1, 2, 3, 4, while the dropout rate is fixed at 0.05. In the Frozen LLM + Prompt Tuning setup, the virtual token length is set to 10, with a maximum text length of 512 tokens and a maximum generated token length of 32. We use the AdamW optimizer (Loshchilov and Hutter, 2017) with a learning rate of 1e-5. The batch size is selected from 1, 2, 4, 8, and the number of epochs is searched within 1, 5, 10. The hidden dimension for both TAONA-GraphEncoder and TAONA-NodeClassifier is set to 1024. For the subgraph construction process, the parameter k and all other parameters follow those set in G-retriever (He et al., 2024). Specifically: For SceneGraphs, we set $k = 3$ for both edges and nodes, with $c = 1$. For WebQSP and B-WebQSP, we set $k = 3$ for nodes, $k = 5$ for edges, and $c = 0.5$ for edge cost. For ExplaGraphs, given the small graph size, the entire graph is retrieved as the subgraph. The hyperparameters for all baseline models are consistent with those specified in the GraphQA benchmark (He et al., 2024).

8.4 Baselines

We have 8 baselines for the A-side task.

- **Zero-shot**. In this baseline, Given a textual graph description and a task description, the LLM is immediately asked to produce the desired output without any other information.
- **Zero-CoT** (Kojima et al., 2022). This baseline is a follow-up to CoT prompting (Wei et al., 2022) and appends the words "Let's think step by step." to the end of a question.
- **CoT-BAG** (Wang et al., 2024). This method adds "Let's construct a graph with the nodes and edges first." after the textual description of the graph, which forms a whole prompt.
- **KAPING** (Baek et al., 2023). This method is specially designed for knowledge graph question answering. It first retrieves all relevant triples and adds them to the input question in the form of a prompt, which is then forwarded to LLMs to generate the answer.
- **Graph-based Inference**. In this method, all textual information in $\mathcal{G}$ is included as a textual prompt, and a frozen LLM is used for question answering, with the query.
- **Frozen LLM + Prompt Tuning (PT)**. This approach adds a soft prompt for tuning while keeping the LLM's parameters frozen;
- **GraphToken** (Perozzi et al., 2024). This method encodes the whole graph with classical GNN (Kipf and Welling, 2016) as an embedding and regards this embedding as a graph prompting vector.
- **G-Retriever** (He et al., 2024). This baseline performs RAG over the textual graph and is also part of the GraphQA benchmark (He et al., 2024).

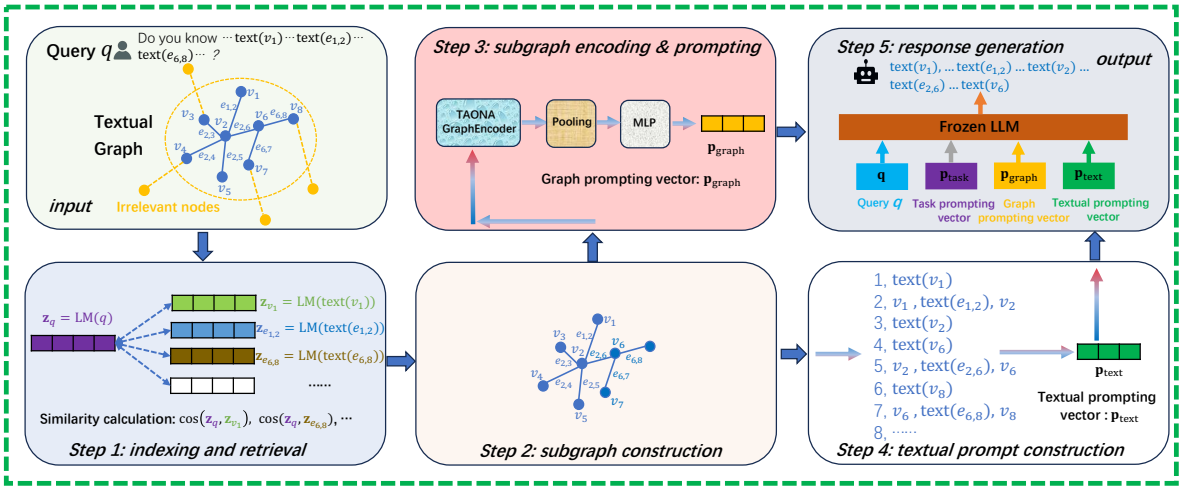

Figure 5: Overview of TAONA-A. Compared with TAONA-B, TAONA-A does not include TAONA-NodeClassifier in step 2 and the statuses of nodes in step 4 when constructing the textual prompt.

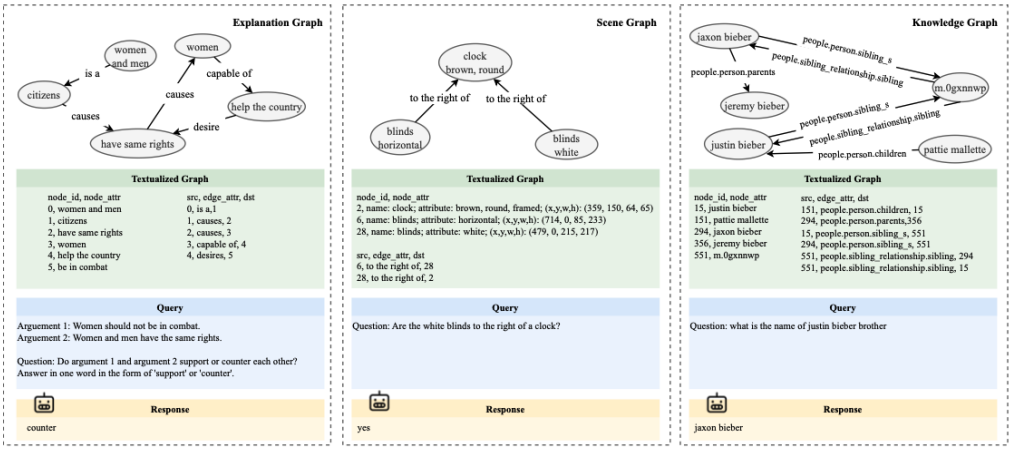

Figure 6: Example of datasets and corresponding tasks.