Evidence-Enhanced Triplet Generation Framework for Hallucination Alleviation in Generative Question Answering

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Abstract

To tackle the issue of hallucination in generative question answering (GQA)—where the generated answer is nonsensical or unfaithful to the provided document—we introduce a novel framework called evidence-enhanced triplet generation (EATQA). This framework incentivizes the model to generate all possible combinations of ⟨Question, Evidence, Answer⟩ triplets by reversing the source pair and target label to grasp their logical interrelationships. Specifically, the model predicts the Answer (A), Question (Q), and Evidence (E) given the QE, EA, and QA pairs, respectively. Furthermore, we address the distribution gap during the inference stage to extract knowledge from the evidence more effectively. Our framework ensures that the model comprehends the logical connections between queries, evidence, and answers, thereby simultaneously enhancing evidence generation and question answering capabilities. In this study, we apply the EATQA framework to the LLama model, demonstrating superior performance compared to other large language model (LLM)-based methods and hallucination mitigation techniques on two challenging GQA benchmarks. Further analysis reveals that our method not only preserves the pre-existing knowledge within the LLM but also reduces hallucination and produces more accurate answers.

Keywords: Evidence enhanced; Triplet generation; Hallucination mitigation

Introduction

Large language models (LLMs) signify a pivotal advancement in the pursuit of general artificial intelligence (Brown et al., 2020; Touvron et al., 2023; Chowdhery et al., 2023). Despite their remarkable performance across a broad range of tasks, these models continue to encounter several challenges, such as hallucination (Tonmoy et al., 2024) and difficulties in processing long contexts (Jin et al., 2024). In the context of document-based generative question answering (GQA) (M. Lewis & Fan, 2018), models sometimes produce answers that are inconsistent with the source document or do not align with the query, a phenomenon known as hallucination (Gunjal, Yin, & Bas, 2024; Liu et al., 2024). Recent studies have employed external models to retrieve pertinent information in an attempt to enhance the factual accuracy of generated responses. Nonetheless, the inherent mismatch between the retriever and the LLM can lead to the inclusion of superficially relevant information that does not contribute meaningfully to answering the question (Salemi & Zamani, 2024).

To enhance logical reasoning and minimize the inclusion of misleading information, we emphasize the identification of supporting evidence in document-based question answering (QA). Departing from the traditional retrieve-then-read approach, we employ a unified triplet generation framework where a large language model (LLM) simultaneously generates evidence and answers. Within this framework, pairs of ⟨question, evidence, answer⟩ are inputted into specific instructions to produce the remaining element. This approach leverages evidence to reconstruct the question, ensuring that the model grasps its logical relationships to both the question and the answer, rather than relying on superficial relevance.

Consider an example from the MultiRC dataset (Khashabi, Chaturvedi, Roth, Upadhyay, & Roth, 2018), illustrated in Figure 1. The question posed is, "After the Osprey resumed flights, how long did it take for the Air Force to begin using the aircraft?" The answer cannot be derived from a single sentence within the document. To accurately respond, the model must identify multiple pieces of evidence: "Osprey resumed flights in 2002" and "Air Force began using Ospreys in 2008 after testing the aircraft in 2006" and then determine that the answer is "4 years" If the model is misled by incorrect evidence such as "Marines developed the aircraft in Iraq in 2007" it will arrive at the incorrect answer, "5 years" Moreover, when guided by the correct evidence, the model can accurately reconstruct the original question, since the correct evidence encompasses sufficient information. In contrast, incorrect evidence leads to the reconstruction of a question like "How long did it take for the Marines to begin using the aircraft..."-a question inconsistent with the original. This demonstrates that accurate evidence is vital for effective question answering, and the reconstruction of the question based on evidence and answer serves as an indicator of evidence validity.

To alleviate the hallucination and enhance the logical reasoning between the question, evidence and answers, we propose our **E**vidence enh**A**nced **T**riplet generation framework (EATQA), which includes three instruction tuning tasks to predict all the combinations of ⟨Question, Evidence, Answer⟩ triplet by flipping the source pair and the target label to understand their logical relationships, i.e., predict A(Answer), Q(Question), and E(Evidence) given a QE, EA, and QA pairs, respectively. We reduce the distribution gap between evidence-aware and evidence-absent QA settings through distribution bridging, thereby facilitating knowledge distillation from evidence and addressing challenges at the inference stage when evidence sentences cannot be explicitly derived.

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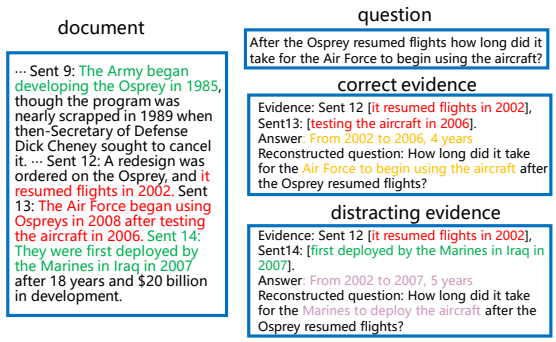


Figure 1: One example from MultiRC dataset. Red denotes supporting evidence and green denotes misleading sentences.

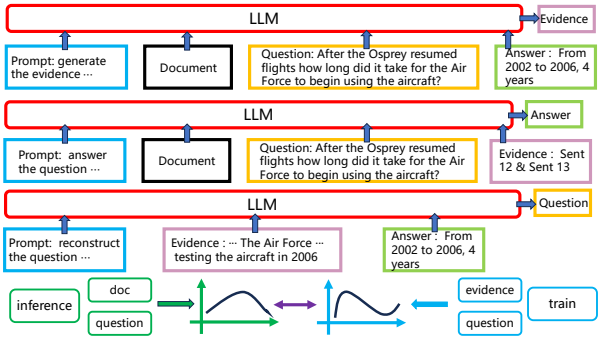


Figure 2: Model overview of EATQA.

We conduct experiments in a variety of widespread document-based GQA datasets with diverse answer types, including MultiRC and QASPER, based on different sizes of LLMs. Compared with different sizes of the backbone model, our unified triplet generation framework shows significant improvement on the two datasets, becoming the new state-of-the-art. Further analysis demonstrates the ability of our approach to tackle longer document with more sentences. Additionally, we observe a positive correlation in the performance of the three subtasks within the triplet generation framework, indicating the efficacy of unifying the generation of all components with a single LLM in this framework. We conclude our contributions as follows: **1.** We highlight the evidence generation to alleviate hallucinations of LLM in GQA task. Instead of utilizing another LM as the retriever, which may introduce misleading information, we propose the unified evidence enhanced triplet generation framework including three instruction tuning tasks to improve the logical reasoning ability of LLM for GQA task. **2.** We propose the self-reasoning module, including the two phrase of candidate generation and correctness verify, which constructs the faithful and informative evidences for training without external annotation. **3.** Additional experiments confirm the effectiveness of our unified triplet generation framework in both evidence retrieval and question answering. Furthermore, our method not only retains the prior knowledge encapsulated within the LLM but also effectively reduces hallucinations for questions that extend beyond the model's internal knowledge base.

Methodology

In this section, we begin by introducing self-reasoning module to derive the faithful and informative evidences for training. Subsequently, we introduce the unified triplet generation framework designed to predict all possible combinations of ⟨Question, Evidence, Answer⟩ triplets by interchanging the source pair and target label to understand their logical interrelationships. These processes are illustrated in Figure 2, presented sequentially from top to bottom.

The motivation behind the triplet generation framework is rooted in the idea that, according to Bayesian formulation:

$$\mathbb{P}(a|q,e,d) = \frac{\mathbb{P}(a,q,e,d)}{\mathbb{P}(q,e,d)} = \frac{\mathbb{P}(a,d)\mathbb{P}(e|a,d)\mathbb{P}(q|e,a,d)}{\mathbb{P}(q,e,d)} \tag{1}$$

where d, q, e, a denote the document, question, evidence and answer. The posterior probability of accurately answering a question is positively proportional to the probability of generating evidence and reconstructing the question. This relationship suggests that enhancing evidence generation and question recovery can directly improve the reliability and accuracy of question answering. We assume the evidence sentences contain the sufficient information to reconstruct the question, i.e. $\mathbb{P}(q|e,a) = \mathbb{P}(q|e,a,d)$.

To establish the feasibility of our framework, we illustrate its functionality using query restoration as an example. In Figure 1, if the model is only provided with the answer "4 years" it faces difficulty in accurately reconstructing the query due to the potential presence of multiple sentences within the document that involve the phrase "4 years" However, when supplied with evidence sentences that highlight the key events, such as "Osprey resumed flights" and "Air Force began using the aircraft" the model can derive the essential components of the query. This enables our query restoration module to function effectively, thereby enhancing the model's ability to organize information and accurately reconstruct the query.

Preliminary

The task of document-based generative question answering (GQA) involves producing an answer to a natural language question, relying on information from a document composed of multiple sentences. The model can be formulated as a function of

$$\mathbf{f_M}(\mathbf{a}) = \prod_{i=1}^{n_a} \mathbb{P}(a_i|a_0,a_1,a_2,\cdots,a_{i-1},q,d) \tag{2}$$

where n_a denotes the answer length, q denotes the query, d denotes the document including multiple sentences and a_0 denotes the begin-of-speech (BOS) token. Generally the answer has flexible forms which can not be directly extracted from the document.

Self-Reasoning

In the absence of annotated evidence within the GQA dataset, we adopt the principle that accurate evidence should fully encapsulate the information necessary to address the query independently of the document. Consequently, we employ the LLM to reason from its generated evidence. Specifically, we introduce a methodology termed self-reasoning, which involves two components: candidate generation and correctness verification.

During candidate generation, the LLM is instructed to produce candidate evidence supporting the query answering. This includes the original text from the document, while out-of-document candidates are filtered out to ensure the maintenance of factual accuracy. Though the filtered candidates are faithful, they do not necessarily contain the needed information for query (uninformative). In the correctness verification stage, the LLM provides a response to the query based on the initially generated candidates respectively. Evidence that fails to contain the required information will lead to incorrect answers. Therefore, we evaluate the predicted answer against the correct answer denoted as a^*, so as to eliminate evidence that may be factually accurate but lacks informative value:

$$e_i = M[p_e, d, q, s_i] \tag{3}$$

$$a_i = M[p_a, q, e_i] \tag{4}$$

$$e = \{e_i | a_i = a^*\} \tag{5}$$

where s_i denotes the i-th random seed to sample for the evidence generation, p_e denotes the prompt to generate evidence from the document to answer the query, p_a denotes the prompt to generate the answer based on the query and evidence, and e denotes the filterer evidences for further training. To this end, we construct the faithful and informative evidences for training without external tool.

Triplet Generation Paradigm

Our triplet generation paradigm composes 3 modules, including Answer-Aware Evidence Generation (QAE), Evidence-Enhanced Question Answering (QEA), Evidence-Aware Question Restoration (EAQ). QAE enables the model to focus on the document, extracting critical information directly from the text rather than relying on prior knowledge. QEA allows the model to leverage the available evidence effectively, ensuring that answers are grounded in the provided information and minimizing the risk of hallucination. EAQ facilitates the integration of evidence-derived information into the reasoning process, supporting more accurate and contextually relevant question restoration.

Answer-Aware Evidence Generation (QAE) In this part, we model the probability of supporting evidence extraction for the query-answer pair $\mathbb{P}(e|a,q,d)$. We design a specific instruction for the LLM to generate evidence that supports both the query and the corresponding answer. Therefore, the input to model is the instruction, source document, the query and the corresponding answer. The output of model is the supporting evidence. The specific instruction is "generate the relevant evidence from the document to answer the following question" and we insert the document, question and answers into the template.

As for the loss function, by Bayesian Formula (Mises, 1942) we derive

$$\log(\mathbb{P}(e,q,d)) = \log \int \mathbb{P}(e,q,a,d) d_a \tag{6}$$

$$= \log \int \mathbb{Q}(a|e,q) \frac{\mathbb{P}(e,q,a,d)}{\mathbb{Q}(a|e,q)} d_a \tag{7}$$

$$\geq \int \mathbb{Q}(a|e,q) \log(\frac{\mathbb{P}(e,q,a,d)}{\mathbb{Q}(a|e,q)}) d_a \tag{8}$$

$$= E_{\mathbb{Q}(a|e,q)} \log(\frac{\mathbb{P}(e,q,a,d)}{\mathbb{Q}(a|e,q)}) \tag{9}$$

$$= E_{\mathbb{Q}(a|e,q)} \log(\frac{\mathbb{P}(a,q,d)\mathbb{P}(e|a,q,d)}{\mathbb{Q}(a|e,q)}) \tag{10}$$

$$= E_{\mathbb{Q}(a|e,q)} \log(\mathbb{P}(e|a,q,d)) + E_{\mathbb{Q}(a|e,q)} \log(\frac{\mathbb{P}(a,q,d)}{\mathbb{Q}(a|e,q)}) \tag{11}$$

$$= E_{\mathbb{Q}(a|e,q)} \log(\mathbb{P}(e|a,q,d)) + E_{\mathbb{Q}(a|e,q)} \log(\frac{\mathbb{P}(a|q,d)}{\mathbb{Q}(a|e,q)}) \tag{12}$$

$$+ E_{\mathbb{Q}(a|e,q)} \log(\mathbb{P}(q,d)) \tag{13}$$

$$= E_{\mathbb{Q}(a|e,q)} \log(\mathbb{P}(e|a,q,d)) - \mathbf{KL}(\mathbb{P}(a|q,d)||\mathbb{Q}(a|e,q)) \tag{14}$$

$$+ \log(\mathbb{P}(q,d) \tag{15}$$

where $\mathbb{Q}(a|e,q)$ denotes the probability of answer a to the question q holds based on the evidence e, which is produced by the same backbone in our method with specific prompt, KL denotes Kullback-Leibler divergence (Van Erven & Harremos, 2014). To maximize the evidence extraction probability, we should maximize the probability of evidence supporting the question-answer pair $\mathbb{P}(e|a,q)$ and minimize the distribution distance between question answering with or without evidence $\mathbf{KL}(\mathbb{P}(a|q,d)||\mathbb{Q}(a|e,q))$. Considering the correct evidences contain identical information as the original document for the query reasoning, the term $\mathbf{KL}(\mathbb{P}(a|q,d)||\mathbb{Q}(a|e,q))$, named as "**distribution bridging**", narrows down the gap between prediction based on the evidences and document, It enables LLM to make full use of evidences information to reason for answers. we utilize cross-entropy loss function to optimize the probability $\mathbb{P}(e|a,q)$:

$$\mathcal{L}_{\text{QAE}} = -\log \mathbb{P}(e \mid d,q,a) = -\sum_{t=0}^{n_e-1} \log \mathbb{P}(e_{t+1} \mid d,q,a,e_{\leq t}) \tag{16}$$

where d denotes the document, n_e denotes the length of the evidence, $\mathbb{P}(e_1 \mid d,q,a,e_{\leq 0}) := \mathbb{P}(e_1 \mid d,q,a)$.

Evidence-Enhanced Question Answering (QEA) In this part, we task LLM with generating answers based on the corresponding question and the relevant evidence. The instruction provided is "generate the correct answers for the following question based on the document and the evidence support the answers to the question", and we incorporate the instruction, document, question and evidence into the template, as inputs into the LLM. The objective function formulated as:

$$\mathcal{L}_{\text{seq}} = -\log \mathbb{P}(a \mid d,q,e) = -\sum_{t=0}^{n_a-1} \log \mathbb{P}(a_{t+1} \mid d,q,e,a_{\leq t}) \tag{17}$$

where n_a denotes the length of the answers, $\mathbb{P}(a_1 \mid d,q,e,a_{\leq 0}) := \mathbb{P}(a_1 \mid d,q,e)$. This task can be seen as the main task of EATQA and enables the model to derive the answers based on the question and evidence. On the other hand, to narrow the gap between training and inference, we minimize the second term of Eq.14: $\mathbf{KL}(\mathbb{P}(a|d,q)||\mathbb{Q}(a|e,q))$. When the evidences are incomplete or have misleading information, the model resorts to the original document for the answer, which improves the robustness of training stage. Therefore, the loss function of this part is:

$$\mathcal{L}_{\text{QEA}} = \mathcal{L}_{\text{seq}} + \alpha_{kl} \cdot \mathbf{KL}(\mathbb{P}(a|d,q)||\mathbb{Q}(a|e,q)) \quad (18)$$

where α_{kl} denotes the hyper-parameter to tune.

Evidence-Aware Question Restoration (EAQ) In this part, we aim to model the probability of $\mathbb{P}(q|e,a)$ and instruct the LLM to recover the question based on the evidence-answer pair. The prompt given is "reconstruct the question based on the answers and corresponding supporting evidence", and we integrate the prompt, document, evidence and answers into the template. The objective function is formulated as:

$$\mathcal{L}_{\text{EAQ}} = -\log \mathbb{P}(q \mid d,e,a) = -\sum_{t=0}^{n_q-1} \log \mathbb{P}(q_{t+1} \mid d,e,a,q_{\leq t}) \quad (19)$$

where n_q denotes the length of the question, $\mathbb{P}(q_1 \mid d,e,a,q_{\leq 0}) := \mathbb{P}(q_1 \mid d,e,a)$. Considering the incorrect evidence does not contain the full information of the original question, this objective helps to enhance the casual relations between evidence and answers.

Training and Inference

With the unified optimization of all three EATQA objectives, our model captures the logical relations between question, evidence and answers. Based on the probability induction:

$$\log \mathbb{P}(a|q,e,d) \propto \log(\mathbb{P}(a|d,q)) + \log(\mathbb{P}(e|a,d)) + \log(\mathbb{P}(q|e,a,d))$$

The overall objective is the weighted accumulation:

$$\mathcal{L}_{Triplet} = \alpha_1 \mathcal{L}_{QAE} + \alpha_2 \mathcal{L}_{QEA} + \alpha_3 \mathcal{L}_{EAQ} \quad (20)$$

where α_1, α_2 and α_3 are tuneable hyper-parameters.

Because of the design of distribution bridging, we do not need to first generate the evidence based on the question and then construct QEA template. Instead, we can directly instruct the model to generate the answer from the original document, which keeps the inference efficiency.

Experiments

Datasets

We evaluate on a diverse variety of widespread benchmark multi-hop QA datasets, including MultiRC (Khashabi et al., 2018), QASPER (Dasigi et al., 2021), NQ (Kwiatkowski et al., 2019), HotpotQA (Yang et al., 2018), TriviaQA (Joshi, Choi, Weld, & Zettlemoyer, 2017), StrategyQA (Geva et al., 2021) across different domains. We utilize Exact Match (EM) and F1 scores (Opitz & Burst, 2019) to evaluate our method. The F1 score measures the overlap of answer tokens between the predicted and ground-truth answer. EM is more strict which awards point if any of the annotated answers is generated exactly.

Implementation Details

We conduct experiments with LLama2 (Touvron et al., 2023) from 7B to 13B as the LLM. To reduce computation cost and keep prior knowledge in LLM, we use LoRA (Hu et al., 2021), which freezes the pretrained model weights and injects trainable rank decomposition matrices into each layer of the LLM. We tune the parameters based on the develop set and the parameters α_1, α_2, α_3 in Eq. 20 and αkl in Eq. 18 are tuned from [0.1, 0.3, 0.5, 0.7, 1.0], and set to 0.3, 1.0, 0.3 and 0.5 in our method. We use AdamW as optimizer and the initial learning rate is set to 3e-5. GPT-3 reports few shot results with 32 examples in the prompt without parameter updating. Because the maximum input length of LLama2 is 4096 and the average context length of QASPER is about 16K, we utilize position interpolation (Chen, Wong, Chen, & Tian, 2023) to extend the context length to 32K.

Baselines

We compare our method with existing widespread LLMs including T5-11B (Raffel et al., 2020), Flan-137B (Wei et al., 2021), Vega2-6B (Zhong et al., 2022), GPT-3 (few shot) (Brown et al., 2020), LoRAMoE (Dou et al., 2023), PaLM 540B (Anil et al., 2023) for MultiRC. For QASPER, we compare our method with LLM-based long context methods, AttenWalker (Nie, Huang, Wei, & Mao, 2023), ChatGLM3-6B-32k (Du et al., 2021), SE-Mistral-7B (Jin et al., 2024), VCC-3B (Zeng et al., 2024) and TOVA-7B (Oren, Hassid, Adi, & Schwartz, 2024) For hallucination mitigation methods, we compare our approach against RAG (P. Lewis et al., 2020) with Dense Passage Retriever (DPR) (Karpukhin et al., 2020), CAD (Shi et al., 2023), RHO (Ji et al., 2023) using the same backbone. These 3 methods are representative methods of 3 different categories of hallucination mitigation: retrieval Augmented Generation, Introducing New Decoding Strategy, and Utilization of Knowledge Graph (KG). In Table 1, CAD and RHO results are reproduced with the code provided in original paper using the same backbone with ours for fair comparison.

Effective Triplet Generation

From Table 1, compared with the backbone, our method improves by 4.6 EM and 2.4 F1 on 7B-scale model as well as 3.6 EM and 1.9F1 on 13B-scale model. It demonstrates the effectiveness of our evidence enhanced triplet generation framework on document based GQA. Moreover, our method with 13B parameters outperforms the 540B PaLM finetuning by 2.0 EM and 1.1 F1, becoming the new state-of-the-art. Our method with 7B-scale model has achieved the comparable

Methods	MultiRC		QASPER	#Para.
	EM	F1	F1	
GPT-3 (32 shot)	30.5	75.4	-	175B
Flan-T5	-	83.4	-	137B
T5	63.1	88.1	-	11B
ERNIE-3.0	63.2	88.6	-	10B
PALM	63.6	88.7	-	540B
SE-Mistral-7B	-	-	39.3	7B
TOVA-7B	-	-	42.0	7B
ChatGLM3-6B-32k	-	-	43.3	6B
LLama2-7B	57.2	86.1	42.4	7B
RAG	58.1	86.7	43.9	7B
CAD	58.2	87.2	43.1	7B
RHO	59.4	87.3	43.2	7B
EAT-QA-7B	61.8	88.5	45.4	7B
LLama2-13B	62.0	87.9	45.1	13B
RAG	63.1	88.1	44.9	13B
CAD	63.5	88.3	45.8	13B
RHO	64.2	88.4	45.9	13B
EATQA-13B	**65.6**	**89.8**	**48.1**	13B

Table 1: Results on MultiRC and QASPER dataset compared with competitive LLM methods. "#Para." denotes the parameter number in the model. We conduct 5 experiments with different random seeds and our method significantly beats the prior SOTA, with p-value less than 0.001.

performance on F1 with larger models like T5-xxl and Flan-T5.

From Table 1 compared with the backbone, our method improves by 3.0 F1 on 7B-scale model. QASPER contains more rigorous samples and existing hallucination mitigation methods struggle to improve the performance. It demonstrates the effectiveness of our method on challenging long document QA.

Ablation, Generalization and Hallucination Mitigation

Ablation

In this part, we investigate the effectiveness of different modules in our method, including QAE, EAQ and the distribution bridging. **Does question restoration matter?** In this ablation, we remove the module of question restoration and investigate its effect on question answering. In table 2, removing question restoration will drop 1.6 EM and 1.4 F1 with 7B model, as well as 1.4 EM and 1.1 F1 with 13B model. Considering the context is not inputted into model in the query restoration module, the model has to utilize the information in evidence to recover the question. This module enhances the ability to integrate multiple pieces of information in evidence sentences, and understand logical relation between query, answer and evidence for LLM, which shows the effectiveness for GQA. **Does evidence generation matter?** In this ablation, we remove the module of evidence generation and investigate its effect on GQA. In Table 2, removing evidence restoration will drop 1.0 EM and 0.8 F1 with 7B model, as well as 1.1 EM and 1.2 F1 with 13B model. Evidence extraction encourages the model to reason for the supporting facts that entail the question-answer pair, which enhances the understanding of logical relation among query, answer and evidence. Removing evidence generation decreases the attention of model pays to the important facts in the document. **Should we narrow down the distance between $\mathbb{P}(a|dq)$ and $q(a|e,q)$?** In this ablation, we remove the KL-divergence loss in Eq.14 in training. In inference stage, we input the predicted evidence and the query to derive the answer. In Table 2, removing KL loss will drop 0.8 EM and 0.9 F1 with 7B model, as well as 1.0 EM and 0.7 F1 with 13B model. Though keeping effective performance, the distribution bridging distills the knowledge of evidence and narrows down the gap between training and inference, avoiding first retrieving the evidence and then inputting the evidence alongside the query into model to reason for the answer.

Methods	EM	F1	#Para.
w/ LLama2-7B			
backbone	57.2	86.1	7B
-Question Restoration	60.2	87.1	7B
-Evidence Generation	60.8	87.7	7B
-KL	61.0	87.6	7B
EATQA-7B	61.8	88.5	7B
w/ LLama2-13B			
backbone	62.0	87.9	13B
-Query Restoration	64.2	88.7	13B
-Evidence Generation	64.5	88.6	13B
-KL	64.6	89.1	13B
EATQA-13B	65.6	89.8	13B

Table 2: Ablation results with LLama2 from 7B to 13B on MultiRC dataset.

Group	1	2	3	4
Length	379	486	587	726
LLama2	88.3	90.7	82.9	87.8
EATQA	90.5	91.9	86.4	89.3

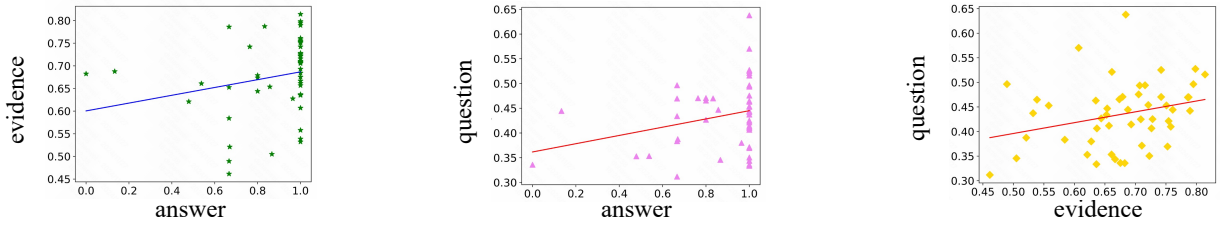
Table 3: Results on MultiRC dataset grouped by different document lengths. Groups are indexed by the ascending order of document length, i.e., Group 1 denotes cases in the percentile interval 0-0.25 of the full dataset. "length" denotes the average document length in the specific percentile interval and we utilize F1 to evaluate the model performance.

Model	7B	13B
LLama2	59.8	62.7
Joint decoding	60.3	63.1
EATQA	**63.4**	**65.6**

Table 4: Performance on evidence generation in MultiRC dataset. We utilize token-level F1 score as the evaluation metric. "LLama" denotes instructing the LLM to generate the evidence only. "Joint Decoding" denotes sequentially generating evidence and answer.

Different document lengths and sentence number

In this part, we assess our performance on cases with varying document lengths and sentence numbers comparing with the backbone. For this purpose, we divide the MultiRC development set into 4 distinct groups, categorized based on the document length and sentence number respectively, and apply F1 to evaluate the performance of different models.



QEA vs QAE QEA vs EAQ QAE vs EAQ

Figure 3: Performance relevance between 3 modules in our method with 13B backbone. QEA denotes evidence-aware question answering, EAQ denotes evidence-grounded query restoration and QAE denotes answer-aware evidence retrieval.

Probability	LLama2	EATQA
$\mathbb{P}(Y_{A\|Q} = \hat{Y})$	34.8	37.1
$\mathbb{P}(Y_{A\|Q,D} = \hat{Y} \| Y_{A\|Q} = \hat{Y})$	88.8	85.8
$\mathbb{P}(Y_{A\|Q,D} = \hat{Y} \| Y_{A\|Q} \neq \hat{Y})$	48.7	52.2

Table 5: Prior knowledge mitigation and hallucination mitigation. $Y_{A|Q}$ denotes the answer generated based on the vanilla query by QA model, which reflects the prior knowledge of LLM. $Y_{A|Q,D}$ denotes the answer generated based on the query and document. $\hat{Y}$ denotes the golden answer.

Groups are indexed by the ascending order of document length, i.e., Group 1 denotes cases in the percentile interval 0-0.25 of the full dataset and Group 4 denotes cases in the percentile interval 0.75-1.0. Therefore, groups 3 and 4 have longer documents than groups 1 and 2.

In Table 3, EATQA outperforms LLama2 by 3.5 and 1.5 F1 in groups 3 and 4, as well as 1.8 and 1.2 F1 in groups 1 and 2. Longer context brings the difficulty for model to capture important information about the query and derive the correct answer. Our method enhances the capture of supporting information from the document, which mitigates the hallucination about distracting information.

Performance on Evidence Generation

Not only deriving effectiveness on GQA, our method also shows improvement on evidence generation. In Table 4, comparing with sequentially generating evidence and answer, our method outperforms by 3.1 on 7B and 2.5 F1 on 13B. Considering our method first generates the evidence and integrates the information of evidence for answers, the evidences serve as the basis of reasoning process.

$$\mathbb{P}(a|q,e,d) \propto \mathbb{P}(e|a,d)\mathbb{P}(q|e,a,d)$$

Fixing the ability of information integration, the evaluation of evidences shows the ability of capturing key information beyond the distracting contents of the document so that generating faithful and correct answer instead of hallucination. Therefore, we demonstrate our evidence enhanced triplet generation paradigm significantly improves the ability of hallucination mitigation.

Hallucination Mitigation

Considering the prior knowledge within LLM, we observe for some "already-known" questions, the model can generate the correct answer without the document, such as "What is gravity's role in space?". We utilize $\mathbb{P}(Y_{A|Q} = \hat{Y})$ to evaluate the internal knowledge of model. When the model can not generate the correct answer without the document, the model resorts to the document rather than internal knowledge. The probability $\mathbb{P}(Y_{A|Q,D} = \hat{Y} | Y_{A|Q} \neq \hat{Y})$ denote that the model rely on the document to give the faithful answer beyond the incorrect internal knowledge, which can be utilized to evaluate the ability of hallucination mitigation (Qiu, Ziser, Korhonen, Ponti, & Cohen, 2023). In Table 5, our model significantly mitigates the hallucination while keeping prior knowledge to solve the "already-known" questions.

Correlation between Different Modules

In this part, we explore the correlation of model performance in query answering (QEA), evidence generation (QAE) and query restoration (EAQ) on data samples. To mitigate the bias of extreme sample, we classify the samples in development set into 50 groups with same size based on the QEA F1. We take the average F1 score of all samples in the group as its overall F1 score. We respectively draw the scatter plot of each pair of QEA, QAE, EAQ score versus the other and fit with linear function. In Figure 3. we find the QAE score and EAQ score are directly proportional to QEA score. In our triplet generation framework, with better performance in evidence generation and query restoration, the model derives better performance in query answering. This shows the effectiveness of our EATQA, which enhances the understanding of LLM about logical relations between query, evidence and answer.

Conclusion

In this paper, we propose the unified triplet generation framework including three instruction tuning tasks to improve the logical reasoning ability of LLM for GQA task. We conduct experiments on a variety of widespread document-based QA datasets with different sizes of LLM, and outperform existing hallucination mitigation methods.

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