REANO: Optimising Retrieval-Augmented Reader Models through Knowledge Graph Generation

Anonymous ACL submission

Abstract

Open domain question answering (ODQA) aims to answer questions with knowledge from an external corpus. Fusion-in-Decoder (FiD) is an effective retrieval-augmented reader model to address this task. Given that FiD independently encodes passages, which overlooks the semantic relationships between passages, some studies use knowledge graphs (KGs) to establish dependencies among passages. However, they only leverage knowledge triples from existing KGs, which suffer from incompleteness and may lack certain information critical for answering given questions. To this end, in order to capture the dependencies between passages while tacking the issue of incompleteness in existing KGs, we propose to enhance the retrieval-augmented reader model with a knowledge graph generation module (**REANO**). Specifically, REANO consists of a *KG generator* and an *answer predictor*. The KG generator aims to generate KGs from the passages and the answer predictor then generates answers based on the passages and the generated KGs. Experimental results on five ODQA datasets indicate that compared with baselines, REANO can improve the exact match score by up to 2.7% on the EntityQuestion dataset, with an average improvement of 1.8% across all the datasets.

1 Introduction

The open domain question answering (ODQA) task (Voorhees and Tice, 2000) aims to answer questions with knowledge from an external corpus, such as Wikipedia. Retrieval-augmented models are an effective way of addressing the ODQA task (Zhang et al., 2023). These models employ a *retriever-reader* architecture that consists of both a *retriever* and a *reader* (Chen et al., 2017). The *retriever* model retrieves a set of passages that are relevant to the questions and then the *reader* model extracts or generates answers conditioned on the questions and the passages. The two-stage structure

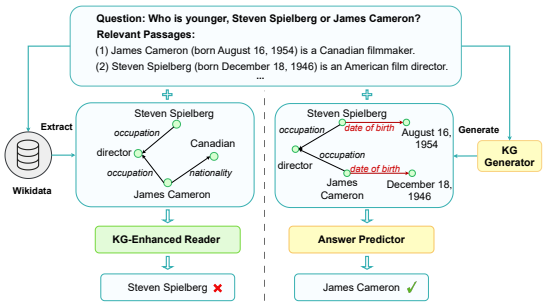

Figure 1: Comparison between existing KG-enhanced readers (left) and our REANO (right).

of ODQA systems allows for the independent optimisation of the retriever and the reader (Karpukhin et al., 2020). In this paper, we focus on enhancing the performance of the reader model, given that the effectiveness of ODQA systems primarily depends on the reader's ability to interpret and process the information within the retrieved passages.

There has been remarkable progress in using generative readers to address the ODQA task (Sachan et al., 2021; Izacard et al., 2023). Particularly, Izacard and Grave (2021b) propose a generative reader called Fusion-in-Decoder (FiD), which uses an encoder-decoder based T5 (Raffel et al., 2020) model to generate answers. Specifically, FiD separately encodes each passage with the encoder and combines the token embeddings of these passages as inputs to the decoder to generate answers.

However, since FiD independently encodes each passage, it overlooks the semantic relationships between passages, which are critical for answering questions that require multi-hop reasoning (Ramesh et al., 2023). To this end, several studies (Yu et al., 2022; Ju et al., 2022; Hu et al., 2022; Oguz et al., 2022) propose to leverage knowledge graphs (KGs) to establish relational dependencies among passages. Specifically, KGs store relational information between real-world entities in the form of triples $\langle \textit{head entity}, \textit{relation}, \textit{tail entity} \rangle$. These knowledge triples are used to construct pas-

sage graphs (Yu et al., 2022) or entity-passage graphs (Ramesh et al., 2023) to enhance the multi-hop reasoning ability of the reader models. Despite the success of these models, they all directly use the triples from existing KGs such as Wikidata (Vrandečić and Krötzsch, 2014). However, these KGs often suffer from incompleteness (Cao et al., 2022) and may lack certain information critical for answering questions that are present within the passages. For example, as illustrated Figure 1, for a question "*Who is younger, Steven Spielberg or James Cameron?*", existing KGs may lack the birthday information of these two individuals, which is crucial to correctly answer the question. This incompleteness can hinder the reader's ability to fully comprehend the passages and answer questions.

Therefore, in order to capture the dependencies between passages and tacking the issue of incompleteness in existing KGs, we propose to enhance the **RE**trieval-**A**ugmented generative readers with a k**NO**wledge graph generation module (**REANO**). Specifically, REANO consists of a *KG generator* and an *answer predictor*. The KG generator generates KGs, i.e., a set of knowledge triples, based on the passages. Since the KGs are inferred from the passages, they can effectively capture and preserve the critical information contained within these passages. After generating the KGs, REANO employs the answer predictor to perform inference over the unstructured passages and the structured KGs to generate answers. Our answer generator is based on the FiD model. The key difference is that it leverages a graph neural network (GNN) to identify and select the top-K triples most relevant to the questions. These triples are concatenated in the order of relevance as an additional passage for answer generation. By combining relevant triples into a passage, we can gather information from multiple passages that are critical to answering the questions, alleviating the reasoning burden of the answer predictor. We conduct experiments on five ODQA datasets and the results indicate that compared with state-of-the-art baselines, our REANO improves the exact match (EM) score by up to 2.7% on the EntityQuestion dataset, with an average improvement of 1.8% across all the datasets.

Our contribution can be summarised as follows: (1) We propose REANO, which integrates a KG generation module to enhance the performance of the generative readers; (2) We use a GNN to identify and select the top-K knowledge triples that are most relevant to the questions from the generated KGs and combine these triples as an additional passage for enhanced answer generation; (3) Experimental results on five ODQA datasets show that REANO can improve the EM score by up to 2.7% compared with state-of-the-art baselines.

2 Preliminaries

Task Formulation. Retrieval-augmented models address the ODQA task by employing a retriever-reader pipeline. In this paper, we focus on enhancing the performance of the reader model. Formally, we denote a question and its answer as q and a, respectively. Each question is associated with a set of n passages, denoted as $\mathcal{D}_q = \{d_1, d_2, \ldots, d_n\}$, which are obtained by a retriever such as DPR (Karpukhin et al., 2020). Given a dataset $\mathcal{O} = \{(q, a, \mathcal{D}_q)\}$, the goal is to train a reader model p_θ with parameter θ to generate answer a based on the question q and passages $\mathcal{D}_q$.

Fusion-in-Decoder. The Fusion-in-Decoder (FiD) model (Izacard and Grave, 2021b) is a simple yet effective generative reader model for the ODQA task. It leverages an encoder-decoder based T5 model (Raffel et al., 2020) to generate answers:

$$p_\theta(a|q, \mathcal{D}_q) = \text{Dec}([\mathbf{H}_1; \ldots; \mathbf{H}_n]), \quad (1)$$

$$\mathbf{H}_i = \text{Enc}(q, d_i), \forall i \in [1, \ldots, n], \quad (2)$$

where $\text{Enc}(\cdot)$ and $\text{Dec}(\cdot)$ denote the T5 encoder and decoder, respectively, and $[\cdot;\cdot]$ is the concatenation operation. For each passage $d_i \in \mathcal{D}_q$ of a question q, FiD encodes the combined sequence of the question and the passage, i.e., $\text{Enc}(q, d_i)$. The embeddings for all the passages are then concatenated as inputs to the decoder for answer generation.

3 REANO

The overall framework of our REANO[1] is shown in Figure 2. This section begins with the probabilistic formulation of REANO in § 3.1, followed by its parameterisation details in § 3.2. Finally, the training strategies are introduced in § 3.3.

3.1 Probabilistic Formulation of REANO

We begin by formalising our REANO in a probabilistic way. Given a question q and its relevant passages $\mathcal{D}_q$, the goal is to maximize the distribution $p_\theta(a|q, \mathcal{D}_q)$. In addition to direct inference on the passages, we propose to generate a knowledge graph $\mathcal{G}_q$, which consists of entities and relations

[1] https://github.com/Anonymous4sub/REANO

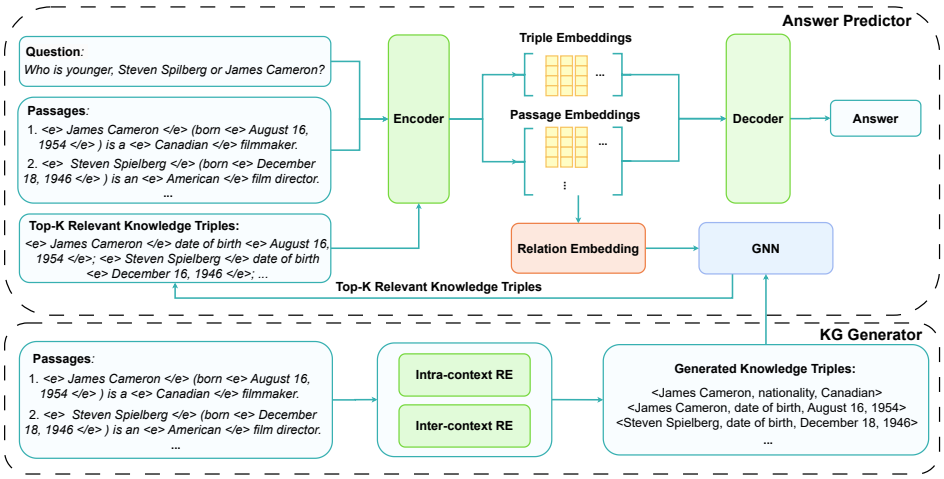

Figure 2: Overall framework of REANO, which includes a *KG Generator* that generates knowledge triples based on the passages and an *Answer Predictor* that generates answers based on the passages and the knowledge triples.

among these entities, based on these passages and then perform joint inference over both the unstructured passages and the structured knowledge graph to generate answers. Since $\mathcal{G}_q$ is unknown, we treat it as a latent variable and rewrite $p_\theta(a|q, \mathcal{D}_q)$ as:

$$p_\theta(a|q, \mathcal{D}_q) = \sum_{\mathcal{G}_q} p_\theta(a|q, \mathcal{D}_q, \mathcal{G}_q) p_\phi(\mathcal{G}_q|\mathcal{D}_q), \quad (3)$$

where the answer generation target $p_\theta(a|q, \mathcal{D}_q)$ is jointly modeled by a KG generator $p_\phi(\mathcal{G}_q|\mathcal{D}_q)$ and an answer predictor $p_\theta(a|q, \mathcal{D}_q, \mathcal{G}_q)$. The KG generator infers a KG conditioned on the passages $\mathcal{D}_q$, while the answer predictor generates answers conditioned on the question q, the passages $\mathcal{D}_q$ and the generated knowledge graph $\mathcal{G}_q$. In what follows, we will introduce the detailed parameterisation of the KG generator and the answer predictor.

3.2 Parameterisation

KG Generator. For each question q, the KG generator $p_\phi(\mathcal{G}_q|\mathcal{D}_q)$ aims to deduce a set of triples in the form of $\langle$*head entity*, *relation*, *tail entity*$\rangle$ based on the passages $\mathcal{D}_q$. Following the established practice of KG generation (Ji et al., 2022), we decompose this task into two components: entity recognition (ER) and relation extraction (RE). The ER focuses on identifying the entities within the passages, while the RE aims to infer the relations among these entities. For the ER, we leverage SpaCy (Honnibal and Montani, 2017) to identify named entities and use TAGME (Ferragina and Scaiella, 2010), an entity linking system, to identify Wikipedia entities. We denote the entities identified within $\mathcal{D}_q$ as $\mathcal{E}_q$. An entity $e \in \mathcal{E}_q$ may have multiple occurrences within $\mathcal{D}_q$ and we refer to each instance of this entity in the passages as a mention.

Subsequently, we infer the relations among entities. Given that current state-of-the-art RE models rely on a transformer backbone (Lu et al., 2022a,b), it is impractical to infer the relations among all the entities simultaneously. This is due to the constrained maximum input length of these models, as processing all the passages at once would exceed this limit. Therefore, we further decompose the RE component into two sub-modules: *intra-context* RE and *inter-context* RE. Intra-context RE focuses on extracting the relations among entities within a single passage, while inter-context RE aims to extract the relations among entities across passages.

The intra-context RE model is defined as:

$$p_\phi(\mathcal{T}_q^I|\mathcal{D}_q, \mathcal{E}_q) = \prod_{d_i \in \mathcal{D}_q} p_\phi(\mathcal{T}_{q,d_i}^I|d_i, \mathcal{E}_{q,d_i}), \quad (4)$$

where $\mathcal{T}_{q,d_i}^I$ denotes intra-context relation triples among entities $\mathcal{E}_{q,d_i}$ within a passage d_i. We instantiate the intra-context RE model p_ϕ with DocuNet (Zhang et al., 2021a), an effective RE model capable of predicting relations between every entity pair within a passage in a single forward propagation. More details about the DocuNet are provided in Appendix A. For inter-context RE, we leverage the Wikidata API[2] to retrieve relations among entities across passages from the Wikidata (Vrandečić and Krötzsch, 2014). Therefore, the generated KG for the question q is obtained by combining the intra-context relation triples $\mathcal{T}_q^I$ and the inter-context relation triples $\mathcal{T}_q^C$, i.e., $\mathcal{G}_q = \{\mathcal{T}_q^I, \mathcal{T}_q^C\}$.

Answer Predictor. For a question q, the answer predictor $p_\theta(a|q, \mathcal{D}_q, \mathcal{G}_q)$ generates answers based

[2] https://www.wikidata.org/w/api.php

on the passages and the generated KGs. Our answer predictor is based on the FiD model. However, the key difference between our answer predictor and FiD is that our answer predictor uses a graph neural network (GNN) to select a set of triples relevant to the question q from $\mathcal{G}_q$, given that most of the triples in $\mathcal{G}_q$ may be irrelevant to the question. These selected triples are combined into an additional passage for answer generation. Formally, we denote the set of triples relevant to the question q as $\mathcal{T}_q^R \subset \mathcal{G}_q$, and define the probability of each triple being relevant to the question as $p_\theta(\mathcal{T}_q^R|q, \mathcal{D}_q, \mathcal{G}_q)$. Empirically, we found that simply selecting top-K triples with the highest probability could consistently yield excellent performance. Therefore, $\mathcal{T}_q^R$ is specified as the set of top-K triples with the highest values in $p_\theta(\mathcal{T}_q^R|q, \mathcal{D}_q, \mathcal{G}_q)$.

Given the relevant triples $\mathcal{T}_q^R$, the answer distribution is then defined as:

$$p_\theta(a|q, \mathcal{D}_q, \mathcal{G}_q) = p_\theta(a|q, \mathcal{D}_q, \mathcal{T}_q^R), \quad (5)$$

where we use the selected relevant triples $\mathcal{T}_q^R$ instead of all the triples $\mathcal{G}_q$ to generate answers. In what follows, we will introduce $p_\theta(\mathcal{T}_q{}^R|q, \mathcal{D}_q, \mathcal{G}_q)$ and $p_\theta(a|q, \mathcal{D}_q, \mathcal{T}_q^R)$ in details.

We begin by introducing how to identify relevant triples using GNN, i.e., $p_\theta(\mathcal{T}_q{}^R|q, \mathcal{D}_q, \mathcal{G}_q)$. To this end, we first initialise the entity and relation embeddings. The embedding of an entity is initialised with the contextualised embeddings of its mentions. Specifically, for each passage $d_i \in \mathcal{D}_q$, we insert special symbols "<e>" and "</e>" at the start and end of all entity mentions to indicate the presence of an entity. We then use the T5 encoder to obtain the token embeddings of the passages: $\mathbf{H}_i = \text{Enc}(q, d_i), \forall i = 1, \ldots, n$. Following previous works (Verga et al., 2018; Zhang et al., 2021a), we use the embeddings of the "<e>" tokens to represent mention embeddings, which are subsequently mean-pooled to obtain entity embeddings: $\boldsymbol{t}_e = \frac{1}{N_e}\sum_{j=1}^{N_e} \boldsymbol{m}_{e,j}$, $\forall e \in \mathcal{E}_q$, where N_e denotes the number of mentions of entity e within $\mathcal{D}_q$ and $\boldsymbol{m}_{e,j}$ denotes the j-th mention embedding of e.

Moreover, for a knowledge triple $\langle e, r_{ev}, v\rangle$ in $\mathcal{G}_q$, e.g., $\langle$*Steven Spielberg*, *occupation*, *director*$\rangle$, we first employ the T5 encoder to obtain token embeddings for the relation label, i.e., *occupation*. These embeddings are mean-pooled to get the initial relation embeddings, denoted as $\hat{\boldsymbol{r}}_{ev}$. Since the relations between entities are predicted by the KG generator, which might contain potential inaccuracies, we introduce a relation embedding module. This module aims to refine relation embeddings by integrating entity embeddings, thereby enhancing the reliability and accuracy of the relation embedding for r_{ev}, which is given by: $\boldsymbol{r}_{ev} = \hat{\boldsymbol{r}}_{ev} + \text{REM}([\boldsymbol{t}_e; \boldsymbol{t}_v])$, where $\text{REM}(\cdot)$ is the relation embedding module, instantiated as a two-layer feed-forward neural network in our model.

Subsequently, we use an L-layer GNN network to update the entity embeddings. Inspired by previous relation-aware GNNs for the knowledge base question answering task (Vashishth et al., 2020; He et al., 2021), we define the process of updating entity embeddings at the l-th layer of our GNN as:

$$\boldsymbol{t}_e^{(l)} = \text{FFN}([\boldsymbol{t}_e^{(l-1)}; \boldsymbol{s}_e^{(l)}]), \quad (6)$$

$$\boldsymbol{s}_e^{(l)} = \sum_{(v, r_{ev}) \in \mathcal{N}(e)} \alpha_v^{r_{ev}} \cdot \text{FFN}([\boldsymbol{t}_v^{(l-1)}; \boldsymbol{r}_{ev}]), \quad (7)$$

$$\alpha_v^{r_{ev}} = \frac{\boldsymbol{w}^\top(\boldsymbol{q} \odot \boldsymbol{r}_{ev})}{\sum_{(v', r_{ev'}) \in \mathcal{N}(e)} \boldsymbol{w}^\top(\boldsymbol{q} \odot \boldsymbol{r}_{ev'})}, \quad (8)$$

where $\boldsymbol{t}_e^{(l)}$ denotes the entity embedding of e at the l-th layer with $\boldsymbol{t}_e^{(0)} = \boldsymbol{t}_e$, $\text{FFN}(\cdot)$ denotes a feed-forward neural network layer, $\mathcal{N}(e)$ is a set of neighboring triples of e for its outgoing edges, $\boldsymbol{q}$ is the embedding of the question q obtained by taking the average of its token embeddings, $\odot$ is the element-wise multiplication and $\boldsymbol{w}$ is a learnable parameter. Specifically, for each entity e, it fuses the aggregated message $\boldsymbol{s}_e^{(l)}$ from its neighbouring triples to update its embedding, i.e., Equation (6). This message is a weighted aggregation of the information from each neighbouring triple, i.e., Equation (7), with the weights $\alpha_v^{r_{ev}}$ being determined by the similarity between the question and the relation of the triple, i.e., Equation (8). This GNN allows entities to attend to triples that are more relevant to the question, thereby obtaining more accurate and question-specific entity embeddings.

After updating the entity embeddings, we calculate the similarities between a triple $\langle e, r_{ev}, v\rangle \in \mathcal{G}_q$ and the question q as follows:

$$p_\theta(\mathcal{T}_q|q, \mathcal{D}_q, \mathcal{G}_q) \propto \boldsymbol{q}^\top \boldsymbol{t}_e^{(L)} + \boldsymbol{q}^\top \boldsymbol{r}_{ev} + \boldsymbol{q}^\top \boldsymbol{t}_v^{(L)}. \quad (9)$$

Based on this similarity measure, we identify and select top-K triples that exhibit the highest relevance to the question, i.e., $\mathcal{T}_q^R$. We combine these top-K triples in the descending order of the similarities as a passage denoted as $d_{\mathcal{T}_q^R}$. The purpose of combining triples is to gather information from multiple passages that are helpful in answering

questions, thereby alleviating the reasoning burden. This passage is then encoded with the T5 encoder. The resulting embeddings are concatenated with the passage embeddings as inputs to the T5 decoder to generate answers:

$$\mathbf{H}_{\mathcal{T}_q^R} = \text{Enc}(q, d_{\mathcal{T}_q^R}), \tag{10}$$

$$p_\theta(a|q, \mathcal{D}_q, \mathcal{T}_q^R) = \text{Dec}([\mathbf{H}_1; \ldots; \mathbf{H}_n; \mathbf{H}_{\mathcal{T}_q^R}]). \tag{11}$$

3.3 Training Strategies

The goal of training REANO is to find the parameters for the KG generator and the answer predictor that can maximize the log-likelihood of the training data, i.e., $\log p_\theta(a|q, \mathcal{D}_q)$. Since the end-to-end optimisation of both the KG generator and the answer predictor is non-differentiable, similar to the previous work (Zhang et al., 2022), we decouple the training of REANO by first training the KG generator and then the answer predictor based on the KGs obtained from the KG generator.

Distantly Supervised Training of KG Generator. In the KG generator, only the DocuNet model needs to be trained for intra-context RE. Given the absence of gold labels for this task, we employ a distantly supervised training approach (Mintz et al., 2009; Zhang et al., 2021b). This involves training the DocuNet model on the REBEL dataset (Cabot and Navigli, 2021) and directly using the trained model to predict intra-context relation triples for each passage within $\mathcal{D}_q$. Particularly, the REBEL dataset is a large-scale RE dataset built by aligning Wikipedia abstracts and the knowledge triples in the Wikidata. Each item in this dataset consists of a Wikipedia text paired with some knowledge triples that can be inferred from the text. More details about the dataset and DocuNet training are provided in Appendices B.1 and B.2. In addition, we also investigate creating a RE training dataset for each ODQA dataset by extracting Wikidata triples within each passage. The generated data are used either to finetune the DocuNet model trained on the REBEL dataset or to train the DocuNet model from scratch. However, our findings indicate that neither of these two approaches can further improve the performance (see Appendix C.3).

Training of Answer Predictor. In the answer predictor, we need to train the GNN model for selecting the top-K relevant triples and the T5 model for generating answers. In the ODQA datasets, we observe that sometimes the answer to a question q can match one of the entities identified within its retrieved passages $\mathcal{D}_q$. Based on this observation, we use such answer-entity alignment as supervision signals to train the GNN model. Specifically, we identify all the paths connecting each entity in the question to the answer entity in the generated KG $\mathcal{G}_q$. We consider all the entities that are part of these paths as relevant to the question, denoted as $\mathcal{E}_q^{rel} \subset \mathcal{E}_q$. If such paths do not exist, we use the answer entity as the relevant entity. We then add a linear classifier on top of the GNN model to predict which entities are relevant to the question: $\boldsymbol{c}_q = \text{Softmax}(\mathbf{E}_q^{(L)} \boldsymbol{w}_c)$, where $\mathbf{E}_q^{(L)}$ denotes the embedding matrix of all the entities (i.e., $\mathcal{E}_q$), $\boldsymbol{w}_c$ is a learnable parameter and $\boldsymbol{c}_q$ denotes the probability of each entity being relevant to the question. Following Zhang et al. (2022), the GNN model is trained by minimizing: $\mathcal{L}_{gnn} = D_{\text{KL}}(\boldsymbol{c}_q || \boldsymbol{c}_q^*)$, where $\boldsymbol{c}_q^*$ denotes the ground-truth relevant entity distribution computed with $\mathcal{E}_q^{rel}$, and D_{KL} denotes the Kullback–Leibler divergence.

The T5 model is trained with the cross entropy loss between the predicted answer distribution and the true answer distribution, which is denoted as $\mathcal{L}_{t5} = \text{CE}(p_\theta(a|q, \mathcal{D}_q, \mathcal{T}_q), p^*(a|q))$. Hence, the loss for training the answer generator is:

$$\mathcal{L}_{answer} = \mathcal{L}_{t5} + \beta \mathcal{L}_{gnn}, \tag{12}$$

where β is a trade-off hyperparameter between the T5 loss and the GNN loss.

4 Experiments

4.1 Experimental Setup

Datasets. We conduct experiments on five ODQA datasets: **Natural Questions** (NQ) (Kwiatkowski et al., 2019), **TriviaQA** (TQA) (Joshi et al., 2017), **EntityQuestions** (EQ) (Sciavolino et al., 2021), **2WikiMultiHopQA** (2WQA) (Ho et al., 2020) and **MuSiQue** (Trivedi et al., 2022). For NQ and TQA, we use the data splits provided by Karpukhin et al. (2020). Each question in NQ and TQA is associated with 100 passages, which are retrieved by the DPR (Karpukhin et al., 2020) model from the December 20, 2018 Wikipedia dump that contains 21M passages. The same data are also used in our baselines except RAG-Seq. For EQ, following Sciavolino et al. (2021), we use the same 21M Wikipedia dump as the corpus and employ BM25 (Robertson and Zaragoza, 2009) to retrieve top-20 relevant passages for each question. The 2WQA and MuSiQue are multi-hop QA datasets that require reasoning over multiple passages to

answer questions. Each question in 2WQA and MuSiQue is associated with 10 and 20 passages respectively provided by the authors. We directly use these passages in our experiments. More details about the datasets are provided in Appendix B.1.

Baselines. Since our REANO is built under the FiD framework (Izacard and Grave, 2021b), we mainly compare it with the FiD model and its variants. In particular, we compare with models from each of the following categories: (1) extractive reader: DPR (Karpukhin et al., 2020); (2) generative reader: RAG-Seq. (Lewis et al., 2020b), FiDO (de Jong et al., 2023); (3) KG-enhanced reader: KG-FiD (Yu et al., 2022), OREOLM (Hu et al., 2022), GRAPE (Ju et al., 2022). Due to resource constraints, both our REANO and baselines use the base versions of the transformer models.

Evaluation. Following Izacard and Grave (2021b), we use greedy decoding to generate answers and employ the Exact Match (EM) as the evaluation metric, where a predicted answer is considered correct if it matches any answer in a list of gold answers after normalisation (Yu et al., 2022).

Training and Hyperparameter Details. For the KG generator, we use the default architecture and hyperparameters as in Zhang et al. (2021a). For the answer predictor, we use T5-base as the backbone model and set the number of GNN layers L as 3. Due to the resource constraints, we only use top-50 passages for each question in both NQ and TQA datasets and use all the passages per question in the other datasets. Throughout the experiments, we set K as 10 and β as 0.1. We use AdamW (Loshchilov and Hutter, 2019) with a constant learning rate of 1e-4 as the optimizer and set the batch size as 64. More training details are provided in Appendix B.2.

4.2 Results and Analysis

We provide our main results in this section and additional experimental results in Appendix C.

(RQ1): How does our REANO perform against the baselines? The performance of REANO and baselines is reported in Table 1, which shows the EM scores (%) of different models across different datasets. The results yield the following findings: (1) First, our REANO consistently achieves the best performance on all the datasets. Compared with the second best models on each dataset, REANO achieves improvements of 1.7%, 2.7% and 2.5% on the TQA, EQ and 2WQA datasets, respectively. REANO also achieves an average improvement of 1.8% across all the datasets. These results demonstrate the effectiveness of REANO in the ODQA task; (2) Moreover, when compared with existing KG-enhanced FiD-based readers, i.e., KG-FiD, OREOLM and GRAPE, on the NQ and TQA datasets, REANO still achieves the best performance. The suboptimal performance of prior KG-enhanced readers may be due to the fact that they only leverage knowledge triples from existing KGs, which may lack some information critical to answer questions. Therefore, this result indicates the effectiveness of generating knowledge triples from passages rather than relying solely on the knowledge triples from existing KGs; (3) Furthermore, note that if we remove the knowledge triples in REANO, our REANO degenerates to FiD. When compared with FiD, REANO demonstrates significant improvements of 2.9%, 3.0% and 1.9% on the EQ, 2WQA and MuSiQue datasets, respectively, and also exhibits superior performance on the other two datasets. This indicates the effectiveness of using knowledge triples as additional context to enhance the reader's understanding of passages.

Models	NQ	TQA	EQ	2WQA	MuSiQue
DPR	41.5†	57.9†	55.3	54.8	16.9
RAG-Seq.	44.5†	56.8†	-	-	-
FiD	48.2†	65.0†	68.1	74.1	29.9
KG-FiD	49.6†	66.7†	-	-	-
OREOLM	49.3†	67.1†	-	-	-
GRAPE	48.7†	66.2†	68.3	73.4	28.3
FiDO	49.5	67.4	67.8	74.6	30.4
REANO	**50.4** (0.8 ↑)	**69.1** (1.7 ↑)	**71.0*** (2.7 ↑)	**77.1*** (2.5 ↑)	**31.8*** (1.4 ↑)

Table 1: Overall performance (EM %) of REANO and baselines, where † denotes the results are from the original papers[3], * denotes p-value < 0.05 compared with FiD and ↑ denotes performance improvements compared with the second best models on each dataset. The best performance per dataset is marked in boldface.

(RQ2): Does different components of our model affect the performance? We conduct ablation studies to study the effects of different components in REANO, including different sets of knowledge triples, the REM module and the GNN module.

First, to investigate the effects of different triples, we introduce two variants of REANO: (1) *w/o inter-context triples*, where we remove the inter-context triples and only use the intra-context triples as inputs to the answer predictor; (2) *w/o intra-context*

[3]These results are obtained using at least 50 passages except RAG-Seq, which only uses 10 passages.

Models	EQ	2WQA	MuSiQue
REANO	**71.0**	**77.1**	**31.8**
w/o inter-context triples	69.5*	75.7*	30.6*
w/o intra-context triples	70.2*	76.0*	30.1*
w/o REM	69.1*	75.1*	30.2*
w/o GNN	68.9*	75.5*	28.0*

Table 2: Ablation studies of REANO, where * denotes p-value < 0.05 compared with REANO.

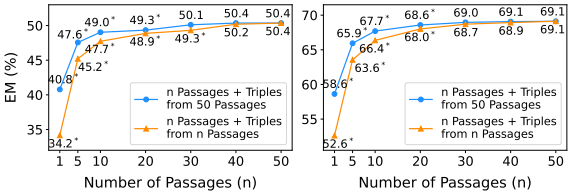

Figure 3: Performance of our REANO under different settings of knowledge triples on NQ (left) and TQA (right) datasets, where * indicates p-value < 0.05 compared with $n = 50$ in the corresponding setting.

triples, where we only pass the inter-context triples to the answer predictor. The results for ablation studies are reported in Table 2, which shows the performance (EM %) of REANO and its variants on the EQ, 2WQA and MuSiQue datasets. The results show that both *w/o inter-context triples* and *w/o intra-context triples* perform significantly worse than REANO on these datasets, which indicates that both the inter-context triples and the intra-context triples are necessary for improving the performance. This is because the intra-context triples can capture the relations among entities within the same passages and the inter-context triples can capture the relations among entities across different passages. The combination of these two sources of information can help the reader better understand the information within all the passages.

Moreover, to investigate the effects of the REM and the GNN modules, we additionally introduce two variants: *w/o REM* and *w/o GNN*, which are obtained by removing the REM module and the GNN module in the answer predictor, respectively. The results in Table 2 indicate that removing either of these two components would significantly degrade the performance on the EQ, 2WQA and MuSiQue datasets. This is because, with the REM module, the answer predictor can learn to refine relation embeddings based on the contextualised embeddings of entities, thereby enhancing the accuracy of relation embeddings. Moreover, the GNN can perform multi-hop reasoning over the KGs to better identify and select knowledge triples that are relevant to the questions, leading to improved performance.

(RQ3): Can knowledge triples help to reduce the number of passages while maintaining satisfactory performance? As shown in Figure 2, we aim to generate and select knowledge triples that contain critical information within the passages to answer questions. To investigate the effects of these knowledge triples, we study the performance of REANO on the NQ and TQA datasets under different number of passages. Moreover, we introduce two different settings of knowledge triples for comparison: (1) *n passages + Triples from* 50 *passages (n50)*, where we use the token embeddings of the top-n passages and the token embeddings of triples selected from all the 50 passages as inputs to the decoder for answer generation; (2) *n passages + Triples from* n *passages (nn)*, where we use the token embeddings of triples selected from these n passages as inputs to the decoder. The results in Figure 3 show that under the *n50* setting, REANO does not exhibit significant performance decline until the number of passages is reduced to 20, which indicates that knowledge triples can help to reduce the number of passages. Moreover, when comparing the performance of REANO under the *n50* and *nn* settings, the results reveal that, in the *nn* setting, REANO suffers from a more substantial decline in performance when the number of passages is reduced from 50 to 1. This can be explained by the fact that the knowledge triples selected from all the 50 passages provide more useful information to answer the question, thereby leading to better performance. This result also suggests that, under the FiD framework, it is possible to use knowledge triples to represent some context passages, which is particularly useful for those language models with limited context length.

Case Study. Finally, we conduct a case study to investigate if REANO can generate and identify triples that are helpful in answering questions. Table 3 shows three examples from 2WQA test set[4]. The examples show that our KG generator can generate meaningful knowledge triples from the passages. For example, it generates a *inter-context* triple "⟨*Raisan Railway Station, country, Pakistan*⟩" that indicates the county of the station, based on the sentence "Raisan railway station is located in Pakistan". Moreover, the results also reveal that

[4]The complete passages and triples of these examples and a few other examples can be found in Appendix C.7.

Question q	Passages $\mathcal{D}_q$	Top-Ranked Triples $\hat{\mathcal{T}}_q^R$	Generated Answer
Where was the father of Ștefan I. Nenițescu born?	... **7. Ștefan I. Nenițescu** (October 8, 1897–October 1979) was a Romanian poet and aesthetician. Born in Bucharest, **his parents were the poet Ioan S. Nenițescu** and his wife Elena ... ... **10. Ioan S. Nenițescu** (April 11, 1854–February 23, 1901) was a Romanian poet and playwright. **Born in Galați**, his parents . . .	**⟨Ștefan I. Nenițescu, father, Ioan S. Nenițescu⟩** **⟨Ioan S. Nenițescu, place of birth, Galați⟩** ⟨Ștefan I. Nenițescu, employer, Bucharest University⟩ ⟨Ștefan I. Nenițescu, given name, Ștefan⟩ ⟨Nenițescu, spouse, Elena⟩ ...	Galați
Are both stations, Muzaffargarh Railway Station and Raisan Railway Station, located in the same country?	... **8. Muzaffargarh railway station** is situated at Muzaffargarh, **Pakistan**. This railway station was constructed in 1887. **9. Raisan railway station** is located in **Pakistan**. ...	**⟨Muzaffargarh Railway Station, country, Pakistan⟩** **⟨Raisan Railway Station, country, Pakistan⟩** ⟨Muzaffargarh, country, Pakistan⟩ ⟨Muzaffargarh Railway Station, located in the administrative territorial entity, Muzaffargarh⟩ ⟨Muzaffargarh Railway Station, instance of, railway station⟩ ...	yes
Who died first, Madame Pasca or James A. Donohoe?	... **6. James A. Donohoe** (August 9, 1877–**February 26, 1956**) was a United States District Judge ... **7.** Alice Marie Angèle Pasquier (November 16, 1833–**May 25, 1914**), better known by her stage name **Madame Pasca**	**⟨James A. Donohoe, date of death, February 26, 1956⟩** ⟨James A. Donohoe, date of birth, August 9, 1877⟩ **⟨Madame Pasca, date of death, May 25, 1914⟩** ⟨Madame Pasca, date of birth, November 16, 1833⟩ ⟨Madame Pasca, occupation, stage actress⟩ ...	Madame Pasca

Table 3: Case study of REANO on the 2WQA dataset, where "Top-Ranked Triples" denotes the top-5 knowledge triples selected by the GNN module from the knowledge triples generated by the KG generator.

our GNN module can identify triples that are useful to answer the questions. For example, for the question "Are both stations, Muzaffargarh Railway Station and Raisan Railway Station, located in the same country?", the top-2 triples "*⟨Muzaffargarh Railway Station, country, Pakistan⟩*" and "*⟨Raisan Railway Station, country, Pakistan⟩*" are highly relevant to the question. Therefore, the case study indicates that REANO can not only generate meaningful knowledge triples from passages but also identify triples that are useful to answer questions.

5 Related Work

Retrieval-Augmented Models for ODQA. Recent studies focus on leveraging retrieval-augmented models to address the ODQA (Zhang et al., 2023), where a *retriever* is used to obtain relevant information from Wikipedia (Chen et al., 2017; Lewis et al., 2020b; Karpukhin et al., 2020) and a *reader* is used to extract (Kedia et al., 2022) or generate (Izacard and Grave, 2021b) answers. There are three lines of work to enhance the performance: (1) improve the retriever: compared with sparse retrieval models (Yang et al., 2019), dense retrievers (Karpukhin et al., 2020) have shown superior retrieval performance. Existing works focus on improving dense retrievers using hard negatives (Qu et al., 2021), knowledge distillation (Izacard and Grave, 2021a), reranking (Mao et al., 2021) or supervision from large language models (LMs) (Shi et al., 2023). (2) improve the reader: compared with extractive reader (Karpukhin et al., 2020), generative readers are more effective in predicting answers (Izacard and Grave, 2021b; Lewis et al., 2020b; Cheng et al., 2021; Borgeaud et al., 2022; de Jong et al., 2023). (3) There are some works that perform joint optimisation of the retriever and the reader to mutually enhance each other (Guu et al., 2020; Sachan et al., 2021; Izacard et al., 2023). Compared with these models, our REANO uses a KG generator to model the relationships among different passages.

KG-Enhanced Retrieval-Augmented Models for ODQA. KGs have been previously used to enhance the retrieval-augmented models for ODQA (Min et al., 2019; Zhou et al., 2020; Oguz et al., 2022; Yu et al., 2022; Ju et al., 2022; Hu et al., 2022; Ramesh et al., 2023). In particular, UniK-QA (Oguz et al., 2022) converts triples into texts and combine them into text corpus. KG-FiD (Yu et al., 2022) uses KGs to construct passage graphs for passage reranking and Grape (Ju et al., 2022) fuses the KG and contextual representations into the hidden states of the reader. However, these models only use knowledge triples from existing KGs, which often suffer from incompleteness. In contrast, our REANO uses a KG generator to generate knowledge triples from passages and uses a GNN to identify and select the most relevant triples, which can effectively capture critical information within the passages.

6 Conclusion

This paper proposes REANO to address the ODQA task. REANO aims to capture dependencies among passages with a knowledge graph generation module. Specifically, it consists of a KG generator, which generates KGs based on the passages, and an answer predictor, which generates answers based on both the passages and the generated KGs. Experimental results on five ODQA datasets indicate that REANO can improve the EM score by up to 2.7% compared with state-of-the-art baselines.

Limitations

In this paper, we aim to improve the performance of retrieval-augmented generative readers with a knowledge graph generation module. We have verified the effectiveness of REANO using an encoder-decoder based T5 model. However, the performance of REANO with other generative readers, such as BART (Lewis et al., 2020a) and the decoder-only generative models (Brown et al., 2020; Touvron et al., 2023) remains unexplored, and we defer this exploration to future work. Moreover, we leverage a frozen retriever in our experiments to simplify the setting and do no investigate how the passage retriever's effectiveness would affect the performance of REANO. We also leave the exploration of how to jointly optimise the retriever and our REANO for better performance as our future work.

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A Introduction of DocuNet

DocuNet (Zhang et al., 2021a) aims to extract relations among multiple entity pairs in a passage. It encodes a passage with BERT (Devlin et al., 2019) to obtain entity embeddings, which are then passed to a U-Net (Ronneberger et al., 2015) model to predict the relations between every entity pair.

Specifically, DocuNet formulates relation extraction as a classification task, i.e., predicting relations between entities from a predefined relation set $\mathcal{R}$. Given a passage $d = [x_1, \ldots, x_L]$, it inserts special symbols "<e>" and "</e>" at the start and the end of mentions to mark the entity positions. The sequence is encoded with BERT to obtain token embeddings: $\mathbf{H} = [\boldsymbol{h}_1, \ldots \boldsymbol{h}_L] = \text{BERT}(x_1, \ldots, x_L)$. It uses log-sumexp pooling to obtain entity embeddings for each entity e: $\boldsymbol{e} = \log \sum_{j=1}^{N_e} \exp(\boldsymbol{m}_j)$, where $\boldsymbol{m}_j$ denotes the j-the mention embedding of entity e and N_e denotes the number of mentions of e in the passage.

Since DocuNet aims to extract relations between each entity pair, it proposes an entity-aware attention with affine transformation to obtain the feature vector for each entity pair as follows:

$$\mathbf{F}(e_1, e_2) = \mathbf{W}_1 \mathbf{H}^\top \boldsymbol{a}_{12}, \tag{13}$$

$$\boldsymbol{a}_{12} = \text{Softmax}(\sum_{i=1}^{K} \mathbf{A}_1^{(i)} \cdot \mathbf{A}_2^{(i)}), \tag{14}$$

where $\boldsymbol{a}_{12}$ is the attention weights, $\mathbf{A}_1^{(i)}$ is the self-attention scores of entity e_1 at the i-th head of the transformer model, and K is the total number of heads in the transformer.

After obtaining the entity-level feature matrix $\mathbf{F} \in \mathbb{R}^{N \times N \times D}$, where N denotes the number of entities and D is the feature dimension, DocuNet updates the feature matrix with a UNet model:

$$\mathbf{Y} = \text{UNet}(\mathbf{W}_2 \mathbf{F}). \tag{15}$$

Given the entity pair embedding $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$, and the entity-level feature matrix $\mathbf{Y}$, DocuNet obtains the probability of relation via a bilinear function:

$$\boldsymbol{z}_1 = \tanh(\mathbf{W}_3 \boldsymbol{e}_1 + \mathbf{Y}_{12}), \tag{16}$$

$$\boldsymbol{z}_2 = \tanh(\mathbf{W}_4 \boldsymbol{e}_2 + \mathbf{Y}_{12}), \tag{17}$$

$$p(r|e_1, e_2) = \sigma(\boldsymbol{z}_1 \mathbf{W}_r \boldsymbol{z}_2 + \mathbf{b}_r), \tag{18}$$

where $\mathbf{Y}_{12}$ represents the entity-pair representation of (e_1, e_2) in matrix $\mathbf{Y}$, $\mathbf{W}_r \in \mathbb{R}^{D \times D}, \boldsymbol{b}_r \in \mathbb{R}, \mathbf{W}_3 \in \mathbb{R}^{D \times D}, \mathbf{W}_4 \in \mathbb{R}^{D \times D}$ are learnable parameters, and $\sigma(\cdot)$ is the sigmoid function.

B Experimental Details

B.1 Datasets

In this section, we first introduce the details of the REBEL dataset, which is used to train the DocuNet model for intra-context RE. Subsequently, we introduce the details of the QA datasets used in our experiments, the statistics of which are summarised in Table 4.

REBEL Dataset (Cabot and Navigli, 2021): REBEL dataset is a large-scale relation extraction dataset proposed to pretrain the REBEL model for extracting relation triples from texts (Cabot and Navigli, 2021). This dataset is built by aligning Wikipedia abstracts and the knowledge triples in Wikidata. Specifically, it first identifies entities within Wikipedia abstracts using *wikimapper*[5] and then extracts relations present between those entities in Wikidata. Moreover, in order to filter out some relations irrelevant to the text, it further uses the entailment prediction of a RoBERTa model (Liu et al., 2019) to filter those relations not entailed by the Wikipedia text. As a result, each example in the REBEL dataset is a Wikipedia text along with the Wikidata knowledge triples that can be inferred from the text. The original training, development and test of the REBEL dataset contain approximately 2M, 152K and 515K examples, respectively.

We aim to train the DocuNet model with the REBEL dataset for intra-context relation extraction.

[5] https://pypi.org/project/wikimapper/

Dataset	# Questions			# Passages	Avg. # Entities Per Question			Avg. # Triples Per Question			Percentage of Answer Entity		
	Train	Dev	Test		Train	Dev	Test	Train	Dev	Test	Train	Dev	Test
NQ	79,168	8,757	3,610	50	514.5	523.5	513.2	1023.1	1045.2	999.2	72.0%	71.0%	73.0%
TQA	78,785	8,837	11,313	50	502.3	511.8	513.2	977.8	1015.5	1017.8	80.6%	79.3%	79.9%
EQ	176,560	22,068	44,150	20	239.4	239.4	240.6	288.4	288.3	290.2	66.8%	66.7%	66.7%
2WQA	166,454	1,000	12,576	10	93.6	93.2	102.8	115.9	116.8	134.5	60.2%	63.7%	78.3%
MuSiQue	18,938	1,000	2,417	20	238.3	239.7	247.4	445.7	447.8	457.4	91.3%	91.3%	89.9%

Table 4: Statistics of our experimental datasets, where "Percentage of Answer Entity" denotes the percentage of questions whose entity sets (obtained from the passages) contain entities that can match the corresponding answers.

To define the label set for the DocuNet model, we exclude relations that appear less than 100 times across all triples in the dataset and keep the remaining relations as the label set $\mathcal{R}$. This filtering process aims to make the DocuNet model focus on more frequent and informative relations. The number of relations in $\mathcal{R}$ is 472. We then exclude triples whose relations do not exist in the relation set $\mathcal{R}$ from the dataset. Moreover, we exclude examples with less than 3 entities or less than 3 triples. As a result, the processed REBEL dataset contains about 1M, 3K and 3K examples in the training, development and test set, respectively.

Natural Questions (NQ) (Kwiatkowski et al., 2019). NQ is a commonly used dataset in the ODQA task. It contains questions from the Google search engine and the answers are paragraphs or entities, which are annotated by human annotators, in the Wikipedia page of the top 5 search results. We use the same train/dev/test splits as in Karpukhin et al. (2020), which also provide the top-100 passages relevant to each question retrieved by the DPR model from a corpus. The corpus is obtained from the Dec. 20, 2018 Wikipedia dump, which is split into passages of approximately 100 words. This preprocessing step results in a retrieval corpus containing about 21 million passages.

TriviaQA (TQA) (Joshi et al., 2017). TQA includes question-answer pairs constructed by trivia enthusiasts. This dataset has relatively complex and compositional questions, which require reasoning over multiple sentences to obtain the answers. We also use the train/dev/test splits and the top-100 relevant passages provided by Karpukhin et al. (2020) in our experiment. These passages are also retrieved by the DPR model from the same Wikipedia corpus used in NQ.

EntityQuestions (EQ) (Sciavolino et al., 2021). EQ contains simple and entity-centric questions, which are constructed based on the facts from Wikidata. Each question in EQ focuses on a particular aspect of an entity. We employ the train/dev/test splits provided by the authors. Moreover, following the original work, we leverage the same Wikipedia corpus used in NQ and TQA as the retrieval corpus. For each question, we leverage the Pyserini BM25 (Lin et al., 2021) to retrieve top-20 relevant passages. The reason we use BM25 to retrieve relevant passages is that the results from the original paper demonstrate that BM25 can achieve better retrieval performance than dense retrieval methods such as DPR in this dataset.

2WikiMultiHopQA (2WQA) (Ho et al., 2020). 2wikimultihopQA is a multi-hop question answering dataset that requires reading multiple passages to answer a given question. It is constructed using evidence information containing a reasoning path for the multi-hop questions. Since the test set of 2WQA is not publicly available, following Ramesh et al. (2023), we treat the original dev set as the test set and we report performance on this set. Moreover, we randomly select 1000 examples from the original training set as the dev set and use the remaining examples for training. Given that each question in this dataset contains 10 contexts, which are retrieved from Wikipedia using bigram TF-IDF, for answering the given question, we directly use these contexts in our experiments. Note that this dataset is constructed in a *distractor* setting, where the passages contain some distractors that are not useful to answer the questions and the passages are randomly shuffled.

MuSiQue (Trivedi et al., 2022). MuSiQue is also a multi-hop question answering dataset that requires 2-4 hops reasoning. This dataset is constructed using a bottom-up technique, where it iteratively combines single-hop questions from multiple datasets into a k-hop benchmark. Since the test set of MuSiQue is also not publicly available, we adopt the same dataset splitting strategy as 2WQA in our experiment. Moreover, each question in this dataset contains 20 contexts, which include passages that are helpful to answer the given question and some

Parameter	DocuNet	Answer Generator
Initialisation	bert-base-uncased + UNet	t5-base
Learning Rate	3e-5	1e-4
Learning Rate Schedule	linear	constant
Batch Size	32	64
Maximum Input Length	256	250
Training Steps	60,000	10,000
Warmup Steps	10,000	-
Gradient Clipping Norm	0.3	1.0
Weight Decay	0.01	0.01
Optimizer	AdamW	AdamW

Table 5: Hyperparameters of the DocuNet model and the answer generator in our REANO.

distractor passages that are irrelevant to the question. We also directly employ these contexts in our experiments.

B.2 Training and Hyperparameter Settings

We summarise the training details used in our REANO in Table 5. In order to train the DocuNet model for intra-context relation extraction, we follow the default architecture and hyperparameter settings in the original paper (Zhang et al., 2021a). We train the DocuNet model from scratch on our preprocessed REBEL dataset. The trained DocuNet model is directly used to extract relations among entities in the passages of different QA datasets.

For the answer predictor, we use the following settings on all the ODQA datasets unless otherwise specified. In particular, we use T5-base as the backbone model and leverage a 3-layered GNN to select the top-K relevant knowledge triples from the generated KGs, where the K is set as 10. Moreover, we set the trade-off hyperparameter β as 0.1. We train the answer predictors on different ODQA datasets using the settings in Table 5. These hyperparameters are chosen based on previous works (Izacard and Grave, 2021b; Yu et al., 2023). However, given the different training sizes of the EQ, 2WQ and MuSiQue, we train the answer predictors on these datasets for $15,000$, $15,000$ and $3,000$ steps, respectively. Furthermore, when optimising the GNN loss, we ignore questions where the answers could not match any entities identified within their corresponding passages (the statistics are provided in Table 4). These questions are only used for calculating the T5 loss.

During training, we evaluate our answer predictor on the development set every 500 steps and select the checkpoint with the best EM scores on the development set as the final model for evaluation. We report the performance on the test sets of different ODQA datasets.

Models	EQ	2WQA	MuSiQue
FiD	68.3	76.9	30.6
REANO	**71.4*** (3.1 ↑)	**78.8*** (1.9 ↑)	**34.8*** (4.2 ↑)

Table 6: Overall performance (EM %) of REANO and FiD using T5-large, where * denotes p-value < 0.05.

Models	EQ	2WQA	MuSiQue
REANO	**71.0**	**77.1**	**31.8**
REANO w. Random Order	70.7	76.4*	31.5

Table 7: Overall performance (EM %) of REANO with different orders of knowledge triples, where $*$ indicates p-value< 0.05.

C Additional Experimental Results

In this section, we first introduce the performance of REANO using the T5-large model in § C.1. We then introduce the performance of REANO with different orders of knowledge triples in § C.2, as well as its performance with different variants of the DocuNet model in § C.3. Subsequently, we introduce the effect of the number of triples K in § C.4, the effect of the trade-off hyperparameter β in § C.5 and the effect of the number of GNN layers L in § C.6, respectively. Finally, we provide the results of the case study in § C.7.

C.1 Performance of REANO with T5-Large

Due to the resource constraints, we mainly report the performance of REANO and baselines using the base versions of the corresponding transformer models. To investigate if the conclusions can be generalised to large models, we additionally compare the performance of REANO and FiD when using T5-large as the backbone model on datasets with a relatively small number of passages, i.e., EQ, 2WQA and MuSiQue. Experimental results are provided in Table 6, which shows the EM scores (%) of REANO and FiD on the EQ, 2WQA and MuSiQue datasets. The results show that our REANO can still achieve the best performance on all the three datasets with an average improvement of 3.1%, which indicates the effectiveness of the proposed REANO.

C.2 Effect of the Order of Knowledge Triples

In our REANO, we combine the sequence of knowledge triples in the descending order of their similarities to the questions as an additional passage. In order to investigate if the order of knowledge triples

Models	2WQA	MuSiQue
REANO	**77.1**	**31.8**
REANO with finetuned DocuNet	75.8*	32.2
REANO with trained DocuNet	76.5*	31.0*

Table 8: Performance (EM %) of our REANO under different variants of the DocuNet model, where * indicates p-value < 0.05 compared with REANO.

would affect the performance, we introduce a variant of REANO: "**REANO w. Random Order**", where the knowledge triples are combined in a random order. Experimental results in Table 7 provide the EM scores (%) of REANO and its variant on the EQ, 2WQA and MuSiQue datasets. The results show that compared with REANO, the performance of "REANO w. Random Order" is slightly worse on the EQ and the MuSiQue datasets, and is significantly worse on the 2WQA dataset. Therefore, the results indicate the the order of knowledge triples would affect the performance and combining knowledge triples in the descending order of similarities is beneficial to improve the performance.

C.3 Performance of REANO with Different DocuNet Model

In our REANO, we train the DocuNet model using a distantly supervised training approach, where the model is trained on the REBEL dataset and then directly used to extract intra-context relation triples for different ODQA datasets. To investigate the effectiveness of such an approach, we introduce two variants of REANO: (1) *REANO with finetuned DocuNet*: in this variant, we aim to finetune the DocuNet model trained on the REBEL dataset on each ODQA dataset. To achieve this, for each passage within an ODQA dataset, we extract knowledge triples among entities within the passage from Wikidata. The data is processed in the same way as the REBEL dataset (see Appendix B.1 for details). We then use the processed data to finetune the DocuNet model. (2) *REANO with trained DocuNet*: in this variant, we train the DocuNet model on each ODQA dataset from scratch. Experimental results are provided in Table 8, which shows the performance of REANO under different variants of the DocuNet model on the 2WQA and MuSiQue datasets. The results indicate that finetuning or training the DocuNet model on ODQA datasets does not lead to performance improvement and may even result in a decrease in performance. We conjecture that this occurs because both the REBEL dataset and the passages in ODQA datasets are obtained from Wikipedia, meaning they share the same data distribution. Therefore, the DocuNet model trained on the REBEL dataset can effectively generalise to the ODQA datasets.

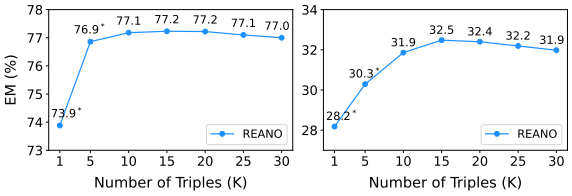

Figure 4: Performance (EM %) of our REANO using different number of triples on the 2WQA (left) and the MuSiQue (right) datasets, where $*$ indicates p-value < 0.05 compared with $K = 15$.

C.4 Effect of the Number of Triples

We conduct experiments to investigate the effect of the number of triples K on the performance of REANO. Specifically, we vary the number of triples K from 1 to 30 and report the corresponding performance. Experimental results are provided in Figure 4, which shows the EM scores of our REANO under different number of triples on the 2WQA and MuSiQue datasets. The results illustrate that for both datasets, as we increase the value of K from 1 to 15, REANO consistently demonstrates significant performance improvement and achieves the best performance when $K = 15$. However, beyond this point, increasing the number of triples does not lead to further performance improvements but even slightly decrease the performance. This is because our REANO uses a GNN module to select and rank the generated knowledge triples. The top-15 triples can provide sufficient information to answer the questions and, including more knowledge triples would introduce noises, leading to decreased performance. Therefore, the results indicate the effectiveness of the GNN module in identifying and selecting knowledge triples helpful to answer the questions.

C.5 Effect of the Trade-Off Hyperparameter

We introduce a trade-off hyperparameter β to balance the T5 loss and the GNN loss when training REANO. We investigate the effect of this hyperparameter by varying the value of β from 1e-4 to 1.0. The results are provided in Figure 5, which shows the EM scores of REANO under different values of β on the 2WQA and the MuSiQue datasets. The results show that as we increase the value of β from

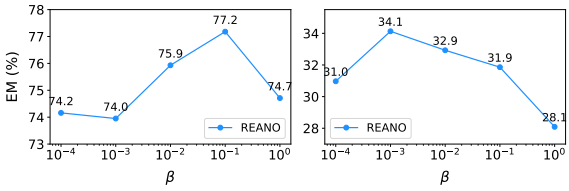

Figure 5: Performance (EM %) of our REANO under different values of β on the 2WQA (left) and the MuSiQue (right) datasets.

Number of GNN Layers	2WQA	MuSiQue
1	73.4	30.5
2	75.4	**32.3**
3	**77.1**	31.8
4	75.8	31.5

Table 9: Performance (EM %) of our REANO with different number of GNN layers.

1e-4 to 1.0, the performance of REANO initially improves and then declines on both datasets. Therefore, the trade-off hyperparameter β can effectively balance the T5 loss and the GNN loss and the optimal values for β depend on the specific ODQA datasets.

C.6 Effect of the Number of GNN Layers

The GNN module in the REANO is responsible for identifying and selecting knowledge triples relevant to the given questions. We additionally conduct experiments to investigate the effect of the number of GNN layers L. Specifically, we vary the number of GNN layers from 1 to 4 and report the corresponding performance in Table 9, which shows the EM scores of REANO with different number of GNN layers. The results indicate that as we increase the value of L from 1 to 4, the performance of REANO initially increases and then declines. Notably, the performance of REANO with 1-layer GNN is worse than the other settings on both datasets. This is because the GNN module uses neighbourhood aggregation to perform multi-hop reasoning over the generated KGs to identify triples relevant to the questions. GNN with more layers has more powerful capability in performing this task effectively. However, the effectiveness of the GNN module would be hindered if the number of layers is too large due to the over-smoothing problem (Li et al., 2018), i.e., the representations of nodes in deep GNNs converge to similar values and become indistinguishable.

C.7 Case Study

We provide the results of the case study on the 2WQA dataset in Table 10 and Table 11, which includes the question q, all the passages $\mathcal{D}_q$, all the top-ranked triples $\hat{\mathcal{T}}_q^R$ selected by the GNN module, and the corresponding answers generated by our REANO.

Question q	Passages $\mathcal{D}_q$	Top-Ranked Triples $\hat{\mathcal{T}}_q^R$	Generated Answer
Where was the father of Ștefan I. Neniș̦tescu born?	**1.** He was the father of Takayama Ukon, and was a Kirishitan. **2.** Anacyndaraxes was the father of Sardanapalus, king of Assyria. **3.** Viscount was the first Director of Railways in Japan and is known as the" father of the Japanese railways" **4.** Cleomenes II(died 309 BC) was Agiad King of Sparta from 369 to 309 BC. The son of Cleombrotus I, he succeeded his brother Agesipolis II. He was the father of Acrotatus I, the father of Areus I, and of Cleonymus, the father of Leonidas II. **5.** Eystein Glumra(" Eystein the Noisy" or" Eystein the Clatterer"; Modern Norwegian" Øystein Glumra") also known as Eystein Ivarsson, was reputedly a petty king on the west coast of Norway, during the 9th Century ... **6.** Arthur Beauchamp(1827 – 28 April 1910) was a Member of Parliament from New Zealand. He is remembered as the father of Harold Beauchamp, who rose to fame as chairman of the Bank of New Zealand and was the father of writer Katherine Mansfield. **7.** **Ștefan I. Neniș̦tescu** (October 8, 1897–October 1979) was a Romanian poet and aesthetician. Born in Bucharest, **his parents were the poet Ioan S. Neniș̦tescu** and his wife Elena ... **8.** John Templeton(1766–1825) was an early Irish naturalist and botanist. He is often referred to as the" Father of Irish Botany". He was the father of naturalist, artist and entomologist Robert Templeton. **9.** He was the father of Obata Masamori. **10.** **Ioan S. Neniș̦tescu** (April 11, 1854–February 23, 1901) was a Romanian poet and playwright. **Born in Galați**, his parents . . .	⟨**Ștefan I. Neniș̦tescu, father, Ioan S. Neniș̦tescu**⟩ ⟨**Ioan S. Neniș̦tescu, place of birth, Galați**⟩ ⟨Ș̦tefan I. Neniș̦tescu, employer, Bucharest University⟩ ⟨Ș̦tefan I. Neniș̦tescu, given name, Ș̦tefan⟩ ⟨Neniș̦tescu, spouse, Elena⟩ ⟨Elena, spouse, Neniș̦tescu⟩ ⟨Ș̦tefan I. Neniș̦tescu, educated at, Sapienza University of Rome⟩ ⟨Neniș̦tescu, languages spoken, written or signed, Romanian⟩ ⟨Bucharest University, headquarters location, Bucharest⟩ ⟨Ioan S. Neniș̦tescu, child, Ș̦tefan I. Neniș̦tescu⟩	Galați
Are both stations, Muzaffargarh Railway Station and Raisan Railway Station, located in the same country?	**1.** Pai Khel railway station is a Railway Station located in Pakistan. **2.** Sawi railway station is a railway station located in Na Pho Subdistrict, Sawi District, Chumphon. It is a class 2 railway station located from Bangkok railway station. **3.** Baku Railway station is a railway station located in Baku, Azerbaijan. **4.** Thepha railway station is a railway station located in Thepha Subdistrict, Thepha District, Songkhla. It is a class 1 railway station located from Thon Buri railway station. **5.** Bagatora railway station is a closed railway station located in Pakistan. **6.** Ligovo railway station is a railway station located in St. Petersburg, Russia. **7.** Saphli railway station is a railway station located in Saphli Subdistrict, Pathio District, Chumphon. It is a class 3 railway station located from Thon Buri railway station. **8.** **Raisan railway station** is located in **Pakistan**. **9.** **Muzaffargarh railway station** is situated at Muzaffargarh, **Pakistan**. This railway station was constructed in 1887. **10.** Lamae railway station is a railway station located in Lamae Subdistrict, Lamae District, Chumphon. It is a class 2 railway station located from Bangkok railway station.	⟨**Muzaffargarh Railway Station, country, Pakistan**⟩ ⟨**Raisan Railway Station, country, Pakistan**⟩ ⟨Muzaffargarh, country, Pakistan⟩ ⟨Muzaffargarh Railway Station, located in the administrative territorial entity, Muzaffargarh⟩ ⟨Muzaffargarh Railway Station, instance of, railway station⟩ ⟨Raisan Railway Station, instance of, railway station⟩ ⟨Pakistan, diplomatic relation, Azerbaijan⟩ ⟨Pai Khel railway station, country, Pakistan⟩ ⟨Bagatora railway station, country, Pakistan⟩ ⟨Azerbaijan, diplomatic relation, Pakistan⟩	yes
Who died first, Madame Pasca or James A. Donohoe?	**1.** James Woolley or James Wolley(ca. 1695 – 22 November 1786) was a watch and clockmaker from Codnor, Derbyshire. **2.** Kurt Sellers(born March 20, 1982), better known as Kasey/ KC James or James Curtis, an American retired professional wrestler who was best known for working in World Wrestling Entertainment. **3.** Andrew Victor McLaglen(July 28, 1920 – August 30, 2014) was a British- born American film and television director, known for Westerns and adventure films, often starring John Wayne or James Stewart. **4.** Joseph Lloyd Carr(20 May 1912 – 26 February 1994), who called himself" Jim" or" James", was an English novelist, publisher, teacher and eccentric. **5.** James Corker or James Cleveland(born 1753 or 1754, died March 24, 1791) was a man of English descent who took part in clan fighting in precolonial Sierra Leone. **6.** Alice Marie Angèle Pasquier (November 16, 1833–**May 25, 1914**), better known by her stage name **Madame Pasca** ... **7.** **James A. Donohoe** (August 9, 1877–**February 26, 1956**) was a United States District Judge ... **8.** Jakob Abbadie(25 September 1727), also known as Jacques or James Abbadie, was a French Protestant minister and writer. He became Dean of Killaloe, in Ireland. **9.** Jacob of Edessa(or James of Edessa)(c. 640 – 5 June 708) was one of the most distinguished of Syriac writers. **10.** James T. O'Donohoe(1898 – 27 August 1928 in Los Angeles, California) born James Thomas Langton O'Donohoe was a screenwriter in the early days of Hollywood ...	⟨**James A. Donohoe, date of death, February 26, 1956**⟩ ⟨James A. Donohoe, date of birth, August 9, 1877⟩ ⟨**Madame Pasca, date of death, May 25, 1914**⟩ ⟨Madame Pasca, date of birth, November 16, 1833⟩ ⟨Madame Pasca, occupation, stage actress⟩ ⟨Andrew V. McLaglen, father, Victor McLaglen⟩ ⟨1928, has part, August 1928⟩ ⟨August 1928, part of, 1928⟩ ⟨Andrew V. McLaglen, date of death, August 30, 2014⟩ ⟨Kasey James, sport, professional wrestler⟩	Madame Pasca

Table 10: Case study of REANO from 2WQA dataset (part 1).

Question q	Passages $\mathcal{D}_q$	Top-Ranked Triples $\hat{\mathcal{T}}_q^R$	Generated Answer
Who is the spouse of the director of film The Unholy Wife?	**1.** Sophia Magdalena of Denmark (3 July 1746 – 21 August 1813) was Queen of Sweden as the spouse of King Gustav III. **2.** Marie Louise Coidavid(1778 – March 11, 1851), was the Queen of the Kingdom of Haiti 1811 – 20 as the spouse of Henri I of Haiti. **3.** John Villiers Farrow, KGCHS (10 February 190427 January 1963) was an Australian-born American film director, producer and screenwriter. ... **4.** Gertrude of Saxony and Bavaria(1152/55–1197) was Duchess of Swabia as the spouse of Duke Frederick IV, and Queen of Denmark as the spouse of King Canute VI. **5.** Maria Teresa, Grand Duchess of Luxembourg(born María Teresa Mestre y Batista; on 22 March 1956), is the spouse of Grand Duke Henri. **6.** Mehdi Abrishamchi is an Iranian People's Mujahedin of Iran(MEK) politician who has been described as" the right hand man of Massoud Rajavi". ... **7.** Adib Kheir was a leading Syrian nationalist of the 1920s. He was the owner of the Librairie Universelle in Damascus. His granddaughter is the spouse of Manaf Tlass. **8.** **The Unholy Wife** is a 1957 Technicolor film noir crime film produced and **directed by John Farrow** at RKO Radio Pictures, but released by Universal Pictures as RKO was in the process of ceasing its film activities. ... **9.** Princess Auguste of Bavaria(28 April 1877 – 25 June 1964) was a member of the Bavarian Royal House of Wittelsbach and the spouse of Archduke Joseph August of Austria. **10.** Heather Denise Gibson is a Scottish economist currently serving as Director- Advisor to the Bank of Greece(since 2011). She is the spouse of Euclid Tsakalotos, ...	**⟨Unholy Wife, director, John Farrow⟩** ⟨Unholy Wife, producer, John Villiers Farrow⟩ **⟨John Farrow, spouse, Maureen O'Sullivan⟩** ⟨John Villiers Farrow, spouse, Maureen O'Sullivan⟩ ⟨John Villiers Farrow, child, Mia Farrow⟩ ⟨Mia Farrow, mother,Maureen O'Sullivan⟩ ⟨Mia Farrow, father, John Villiers Farrow⟩ ⟨Maureen O'Sullivan, spouse, John Villiers Farrow⟩ ⟨Unholy Wife, cast member, Beulah Bondi⟩ ⟨John Villiers Farrow, award received, Best Screenplay⟩	Maureen O'Sullivan
Who is the spouse of the director of film The Dressmaker From Paris?	**1.** The Dressmaker is a 1988 British drama film directed by Jim O'Brien and starring Joan Plowright, Billie Whitelaw ... **2.** **Paul Bern** (born Paul Levy; December 3, 1889 - September 5, 1932) was a German-born American film director, ... He helped launch the career of **Jean Harlow, whom he married** in July 1932; two months later, he was found dead ... **3.** Adelaide Heilbron was an American screenwriter known for films like" The Dressmaker from Paris" and" Lessons for Wives". **4.** Princess Auguste of Bavaria(28 April 1877 – 25 June 1964) was a member of the Bavarian Royal House of Wittelsbach and the spouse of Archduke Joseph August of Austria. **5.** Marie Louise Coidavid(1778 – March 11, 1851), was the Queen of the Kingdom of Haiti 1811 – 20 as ... **6.** Maria Teresa, Grand Duchess of Luxembourg(born María Teresa Mestre y Batista; on 22 March 1956), is the spouse of Grand Duke Henri. **7.** **The Dressmaker from Paris** is a 1925 silent film romantic comedy/drama film **directed by Paul Bern**. The story was written by Howard Hawks and Adelaide Heilbron. Heilbron also wrote the screenplay. The film starred Leatrice Joy and was her last film for Paramount Pictures. ... **8.** Gertrude of Saxony and Bavaria(1152/55–1197) was Duchess of Swabia as the spouse of Duke Frederick IV, and Queen of Denmark as the spouse of King Canute VI. **9.** Mehdi Abrishamchi is an Iranian People's Mujahedin of Iran(MEK) politician ... **10.** Sophia Magdalena of Denmark (3 July 1746 – 21 August 1813) was Queen of Sweden as the spouse of King Gustav III.	**⟨Dressmaker From Paris, director, Paul Bern⟩** **⟨Paul Bern, spouse, Jean Harlow⟩** ⟨Dressmaker From Paris, screenwriter, Adelaide Heilbron⟩ ⟨Dressmaker From Paris, producer, Cecil DeMille⟩ ⟨Dressmaker From Paris, cast member, Leatrice Joy⟩ ⟨The Dressmaker, director, Jim O'Brien⟩ ⟨Dressmaker From Paris, screenwriter, Howard Hawks⟩ ⟨Jean Harlow, spouse, Paul Bern⟩ ⟨Dressmaker From Paris, screenwriter, Heilbron⟩ ⟨Dressmaker From Paris, distributed by, Paramount Pictures⟩	Jean Harlow
What nationality of the company that published Personalized Medicine (Journal)?	**1.** Human Genomics and Proteomics was an open-access peer-reviewed academic journal that published papers in the fields of human genomics and proteomics ... **2.** Pink Pages was an Indian LGBT magazine that published online and print issues from 2009 to 2017. **3.** **Personalized Medicine** is a bimonthly peer-reviewed medical journal covering personalized medicine. It was established in 2004 and is **published by Future Medicine**. **4.** Metagaming Concepts, later known simply as Metagaming, was a company that published board games from 1974 to 1983. **5.** Pariah Press was the company, funded by Mike Nystul, that published the first commercial edition of The Whispering Vault role- playing game. **6.** " A New Leaf" is a short story by F. Scott Fitzgerald that published in July 1931 in" The Saturday Evening Post". **7.** Chappell& Co. was an English company that published music and manufactured pianos. **8.** **Future Medicine** is a privately owned company **based in London, England, United Kingdom**. It is part of Future Science Publishing Group ... **9.** Noggin was an American magazine that published art, fiction, cartoons, and social and political commentary. ... **10.** A web enhancement is a bonus expansion to a role- playing game product, that can be read and/ or downloaded from the website of the company	**⟨Future Medicine, country, United Kingdom⟩** ⟨journal, publisher, Sage Publications⟩ ⟨Sage Publications, country, United Kingdom⟩ ⟨English, country, United Kingdom⟩ ⟨London, England, capital of, United Kingdom⟩ ⟨Personalized Medicine, main subject, Personalized Medicine⟩ ⟨United Kingdom, capital, London, England⟩ ⟨Future Medicine, part of, Future Science Publishing Group⟩ ⟨Human Genomics and Proteomics, country of origin, United Kingdom⟩ **⟨Personalized Medicine, publisher, Future Medicine⟩**	United Kingdom

Table 11: Case study of REANO from 2WQA dataset (part 2).