UNIKGQA: UNIFIED RETRIEVAL AND REASONING FOR SOLVING MULTI-HOP QUESTION ANSWERING OVER KNOWLEDGE GRAPH

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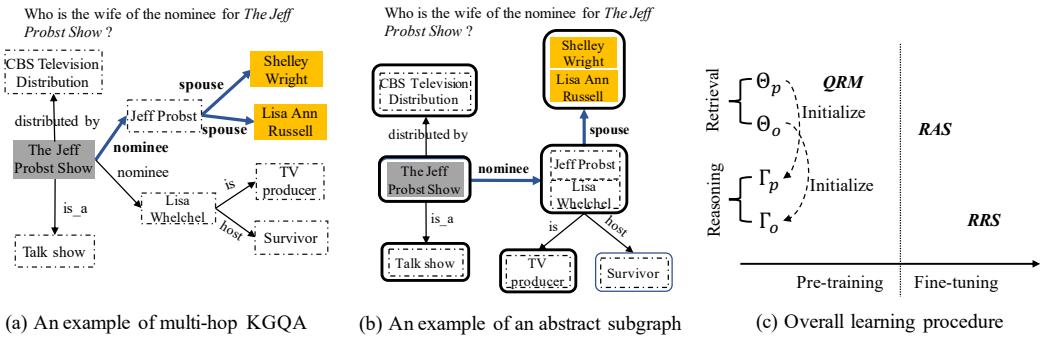
ABSTRACT

Multi-hop Question Answering over Knowledge Graph (KGQA) aims to find the answer entities that are multiple hops away from the topic entities in a natural language question on a large-scale Knowledge Graph (KG). To cope with the vast search space, existing work usually adopts a two-stage approach: it firstly retrieves a relatively small subgraph related to the question and then performs the reasoning on the subgraph to accurately find the answer entities. Although these two stages are highly related, previous work employs very different technical solutions for developing the retrieval and reasoning models, neglecting their relatedness in task essence. In this paper, we propose UniKGQA, a novel approach for multi-hop KGQA task, by unifying retrieval and reasoning in both model architecture and parameter learning. For model architecture, UniKGQA consists of a semantic matching module based on a PLM for question-relation semantic matching, and a matching information propagation module to propagate the matching information along the edges on KGs. For parameter learning, we design a shared pre-training task based on question-relation matching for both retrieval and reasoning models, and then propose retrieval- and reasoning-oriented fine-tuning strategies. Compared with previous studies, our approach is more unified, tightly relating the retrieval and reasoning stages. Extensive experiments on three benchmark datasets have demonstrated the effectiveness of our method on the multi-hop KGQA task.

1 INTRODUCTION

With the availability of large-scale knowledge graphs (KGs), such as Freebase (Bollacker et al., 2008) and Wikidata (Tanon et al., 2016), knowledge graph question answering (KGQA) has been an important research topic that aims to find the answer entities of natural language questions from KGs. Recent studies (Lan et al., 2021) mainly focus on *multi-hop KGQA*, a more complex scenario where sophisticated multi-hop reasoning over edges (or relations) is required to infer the correct answer on the KG. We show an example in Figure 1(a). Given the question "*Who is the wife of the nominee for The Jeff Probst Show*", the task goal is to find a reasoning path from the topic entity "*The Jeff Probst Show*" to the answers "*Shelley Wright*" and "*Lisa Ann Russell*".

Faced with the vast search space in large-scale KGs, previous work (Sun et al., 2018; 2019) typically adopts a *retrieval*-then-*reasoning* approach, which can achieve a good trade-off between accuracy and efficiency for multi-hop KGQA. Generally, the retrieval stage aims to extract relevant triples from the large-scale KG to compose a relatively smaller question-relevant subgraph, while the reasoning stage focuses on accurately finding the answer entities from the retrieved subgraph. Although the purposes of the two stages are different, both stages need to evaluate the semantic relevance of a candidate entity with respect to the question (for removal or reranking), which can be considered as a semantic matching problem in essence. For measuring the entity relevance, relation-based features, either direct relations (Miller et al., 2016) or composite relation paths (Sun et al., 2018), have been shown to be particularly useful for building the semantic matching models. As shown in Figure 1(a), given the question, it is key to identify the semantically matched relations and the composed relation path in the KG (*e.g.,* "*nominee* $\rightarrow$ *spouse*") for finding the correct answer entities. Since the two stages cope with different scales of search space on KGs (*e.g.,* millions *v.s.* thousands), they usually adopt specific technical solutions: the former prefers more efficient methods focusing on the



(a) An example of multi-hop KGQA (b) An example of an abstract subgraph (c) Overall learning procedure

Figure 1: Illustrative examples for our work: (a) an example of multi-hop KGQA; (b) an example of abstract subgraph; and (c) the overall learning procedure of our UniKGQA model.

recall performance (Sun et al., 2018), while the latter prefers more capable methods for modeling fined-grained matching signals (He et al., 2021).

Considering the same essence for both stages, this work aims to push forwards the research on multi-hop KGQA by investigating the following problem: can we design a unified model architecture for both stages for deriving a better performance? To develop a unified model architecture for multi-hop KGQA, a major merit is that we can tightly relate the two stages and enhance the sharing of relevance information. Although the two stages are highly related, previous studies usually treat them *separately* in model learning: only the retrieved entities are passed from the retrieval stage to the reasoning stage, while the rest useful signal for semantic matching has been neglected in the pipeline framework. Such an approach is likely to lead to sub-optimal or inferior performance, since multi-hop KGQA is a very challenging task, requiring elaborate solutions that sufficiently leverage various kinds of relevance information from the two stages.

However, there are two major issues to develop a unified model architecture for multi-hop KGQA: (1) How to cope with very different scales of search space for the two stages? (2) How to effectively share or transfer useful relevance information across the two stages? For the first issue, instead of letting the same model architecture directly fitting very different data distributions, we propose a new subgraph form to reduce the node scale at the retrieval stage, namely *abstract subgraph* that is composed by merging the nodes with same relations from the KG (see Figure 1(b)). For the second issue, based on the same model architecture, we design an effective learning approach for the two stages, so that we can share the same pre-trained parameters and use the learned retrieval model to initialize the reasoning model (see Figure 1(c)).

To this end, in this paper, we propose UniKGQA, a unified model for multi-hop KGQA task. Specifically, UniKGQA consists of a semantic matching module based on a PLM for question-relation semantic matching, and a matching information propagation module to propagate the matching information along the edges on KGs. In order to learn these parameters, we design both pre-training (*i.e.,* question-relation matching) and fine-tuning (*i.e.,* retrieval- and reasoning-oriented learning) strategies based on the unified architecture. Compared with previous work on multi-hop KQGA, our approach is more unified and simplified, tightly relating the retrieval and reasoning stages.

To our knowledge, it is the first work that unifies the retrieval and reasoning in both model architecture and learning for the multi-hop KGQA task. To evaluate our approach, we conduct extensive experiments on three benchmark datasets. On the simple dataset, MetaQA, we obtain a comparable results with state-of-the-arts methods. On the difficult datasets, WebQSP and CWQ, we outperform existing state-of-the-arts baselines by a large margin (*e.g.,* 8.1% improvement of hits@1 on WebQSP and 2% improvement of hits@1 on CWQ).

2 PRELIMINARY

In this section, we introduce the notations that will be used throughout the paper and then formally define the multi-hop KGQA task.

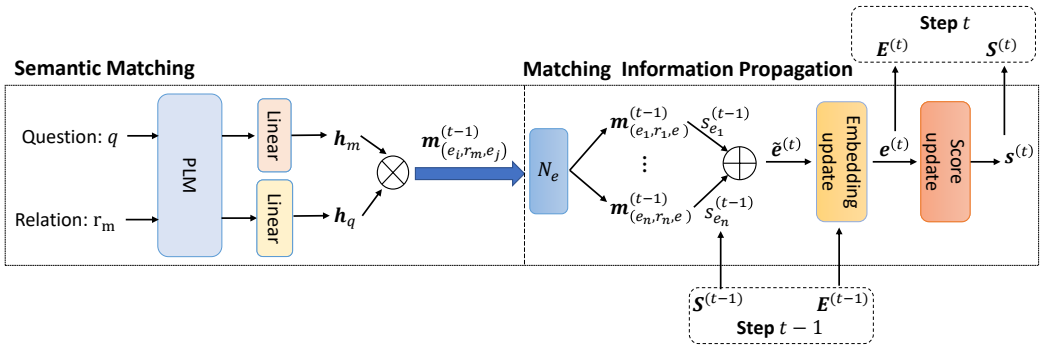


Figure 2: The overview of the unified model architecture of UniKGQA, consisting of two modules, *i.e.,* semantic matching, and matching information propagation.

Knowledge Graph (KG). A knowledge graph typically consists of a set of triples, denoted by $\mathcal{G} = \{\langle e, r, e' \rangle | e, e' \in \mathcal{E}, r \in \mathcal{R}\}$, where $\mathcal{E}$ and $\mathcal{R}$ denote the entity set and relation set, respectively. A triple $\langle e, r, e' \rangle$ describes the fact that a relation r exists between head entity e and tail entity e'. Furthermore, we denote the set of neighborhood triples that an entity e belongs to by $\mathcal{N}_e = \{\langle e, r, e' \rangle \in \mathcal{G}\} \cup \{\langle e', r, e \rangle \in \mathcal{G}\}$. Let r^{-1} denote the inverse relation of r, and we can represent a triple $\langle e, r, e' \rangle$ by its inverse triple $\langle e', r^{-1}, e \rangle$. In this way, we can simplify the definition of the neighborhood triples for an entity e as $\mathcal{N}_e = \{\langle e', r, e \rangle \in \mathcal{G}\}$. We further use $\boldsymbol{E} \in \mathbb{R}^{d \times |\mathcal{E}|}$ and $\boldsymbol{R} \in \mathbb{R}^{d \times |\mathcal{R}|}$ to denote the embedding matrices for entities and relations in KG, respectively.

Multi-hop Knowledge Graph Question Answering (Multi-hop KGQA). Given a natural language question q and a KG $\mathcal{G}$, the task of KGQA aims to find answer entitie(s) to the question over the KG, denoted by the answer set $\mathcal{A}_q \in \mathcal{E}$. Following previous work (Sun et al., 2018; 2019), we assume that the entities mentioned in the question (*e.g.,* "The Jeff Probst Show" in Figure 1(a) are marked and linked with entities on KG, namely *topic entities*, denoted as $\mathcal{T}_q \subset \mathcal{E}$. In this work, we focus on solving the *multi-hop KGQA* task where the answer entities are multiple hops away from the topic entities over the KG. Considering the trade-off between efficiency and accuracy, we follow existing work (Sun et al., 2018; 2019) that solves this task using a *retrieval*-then-*reasoning* framework. In the two-stage framework, given a question q and topic entities $\mathcal{T}_q$, the retrieval model aims to retrieve a small subgraph $\mathcal{G}_q$ from the large-scale input KG $\mathcal{G}$, while the reasoning model searches answer entities $\mathcal{A}_q$ by reasoning over the retrieved subgraph $\mathcal{G}_q$.

Abstract Subgraph. Based on KGs, we further introduce the concept of *abstract graph*, which is derived based on the reduction from an original subgraph. Specifically, given a subgraph related to question q, denoted as $\mathcal{G}_q \subset \mathcal{G}$, we merge the tail entities from the triples with the same *prefix* (*i.e.,* the same head entity and relation: $\langle e, r, ? \rangle$), and then generate a corresponding abstract node $\widetilde{e}$ to represent the set of tail entities, so we have $\tilde{e} = \{e' | \langle e, r, e' \rangle \in \mathcal{G}\}$. Similarly, we can also perform the same operations on the head entities. To unify the notations, we transform an original node that can't be merged into an abstract node by creating a set including the node itself. In this way, the corresponding abstract subgraph $\mathcal{G}_q$ can be denoted as: $\widetilde{\mathcal{G}}_q = \{\langle \tilde{e}, r, \tilde{e}' \rangle | \exists e \in \tilde{e}, \exists e' \in \tilde{e}', \langle e, r, e' \rangle \in \mathcal{G}_q\}$, where each node $\tilde{e}$ is an abstract node representing a set of original nodes (one or multiple). We present an illustrative example of abstract subgraph in Figure 1(b).

3 Approach

In this section, we present our proposed UniKGQA, that unifies the retrieval and reasoning for multi-hop KGQA. The major novelty is that we introduce a unified model architecture for both stages (Section 3.1) and design an effective learning approach involving both specific pre-training and fine-tuning strategies (Section 3.2). Next, we describe the two parts in details.

3.1 UNIFIED MODEL ARCHITECTURE

We consider a general input form for both retrieval and reasoning, and develop the base architecture by integrating two major modules: (1) the *semantic matching* (SM) module that employs a PLM to perform the semantic matching between questions and relations; (2) the *matching information propagation* (MIP) module that propagates the semantic matching information on KGs. We present the overview of the model architecture in Figure 2. Next, we describe the three parts in details.

General Input Formulation. In order to support both retrieval and reasoning stages, we consider a general form for evaluating entity relevance, where a question q and a subgraph $\mathcal{G}_q$ of candidate entities are given. For the retrieval stage, $\mathcal{G}_q$ is an abstract subgraph that incorporates abstract nodes to merge entities with the same relation. For the ranking stage, $\mathcal{G}_q$ is constructed based on the retrieved subgraph from the retrieval stage, without abstract nodes. Such a general input formulation enables the development of unified model architecture for the two different stages. In what follows, we will describe the approach in a general way, without considering specific stages.

Semantic Matching (SM). The SM module aims to produce the semantic matching features between the question q and a triple $\langle e', r, e\rangle$ from the given subgraph $\mathcal{G}_q$. Considering the excellent modeling capacity of the PLMs, we leverage the PLM to produce text encoding as the representations of question q and relation r. Specifically, we first utilize the PLM to encode the texts of q and r, and employ the output representation of the `[CLS]` token as their representations:

$$\boldsymbol{h}_q = \text{PLM}(q),\ \boldsymbol{h}_r = \text{PLM}(r). \tag{1}$$

Based on $\boldsymbol{h}_q$ and $\boldsymbol{h}_r$, inspired by the NSM model (He et al., 2021), we obtain the vector capturing semantic matching features $\boldsymbol{m}^{(t)}_{\langle e',r,e\rangle}$ between question q and triple $\langle e', r, e\rangle$ at the t-th step by adopting corresponding projection layers:

$$\boldsymbol{m}^{(t)}_{\langle e',r,e\rangle} = \sigma\left(\boldsymbol{h}_q \boldsymbol{W}^{(t)}_Q \odot \boldsymbol{h}_r \boldsymbol{W}^{(t)}_R\right), \tag{2}$$

where $\boldsymbol{m}^{(t)}_{\langle e',r,e\rangle} \in \mathbb{R}^d$, $\boldsymbol{W}^{(t)}_Q, \boldsymbol{W}^{(t)}_R \in \mathbb{R}^{h\times d}$ are parameters of the t-step projection layers, h, d are the hidden dimensions of PLM and the feature vector, respectively, σ is the sigmoid activation function, and $\odot$ is the hadamard product.

Matching Information Propagation (MIP). Based on the generated semantic matching features, the MIP module firstly aggregates them to update the entity representation and then utilizes it to obtain the entity match score. To initialize the match scores, given a question q and a subgraph $\mathcal{G}_q$, for each entity $e_i \in \mathcal{G}_q$, we set the match score between q and e_i as follows: $s^{(1)}_{e_i} = 1$ if e_i is a topic entity and $s^{(1)}_{e_i} = 0$ otherwise. At the t-th step, we utilize the match scores of the head entities computed at the last step $s^{(t-1)}_{e'}$ as the weights and aggregate the matching features from neighboring triples to obtain the representation of the tail entities:

$$\boldsymbol{e}^{(t)} = \boldsymbol{W}^{(t)}_E \left(\left[\boldsymbol{e}^{(t-1)}; \sum_{\langle e',r,e\rangle\in\mathcal{N}_e} s^{(t-1)}_{e'} \cdot \boldsymbol{m}^{(t)}_{\langle e',r,e\rangle}\right]\right), \tag{3}$$

where $\boldsymbol{e}^{(t)} \in \mathbb{R}^d$ is the representation of the entity e in the t-th step, and the $\boldsymbol{W}^{(t)}_e \in \mathbb{R}^{2d\times d}$ is a learnable matrix. At the first step, since there are no matching scores, following the NSM He et al. (2021) model, we directly aggregate the representations of its one-hop relations as the entity representation: $\boldsymbol{e}^{(1)} = \sigma(\sum_{\langle e',r,e\rangle\in\mathcal{N}_e} \boldsymbol{r} \cdot \boldsymbol{W}_E)$, where the $\boldsymbol{W}_E \in \mathbb{R}^{2d\times d}$ is a learnable matrix. Based on the representation of all entities $\boldsymbol{E}^{(t)} \in \mathbb{R}^{d\times n}$, we update their entity match scores using the softmax function as:

$$\boldsymbol{s}^{(t)} = \text{softmax}\big(\boldsymbol{E}^{(t)^\top} \boldsymbol{v}\big), \tag{4}$$

where $\boldsymbol{v} \in \mathbb{R}^d$ are a learnable vector.

After T-step iterations, we can obtain the final entity match scores $\boldsymbol{s}^{(T)}$, which is a probability distribution over all entities in the subgraph $\mathcal{G}_q$. These scores can be leveraged to measure the possibilities of if the entities are the answer of the given question q, and will be used in both the retrieval and reasoning stages.

3.2 MODEL TRAINING

In our approach, we have both the retrieval model and the reasoning model for the two stages of multi-hop KGQA. Since the two models adopt the same architecture, we introduce Θ and Γ to denote the model parameters that are used for retrieval and reasoning stages, respectively. As shown in Section 3.1, our architecture contains two groups of parameters, namely the underlying PLM and the other parameters for matching and propagation. Thus, Θ and Γ can be decomposed as: $\Theta = \{\Theta_p, \Theta_o\}$ and $\Gamma = \{\Gamma_p, \Gamma_o\}$, where the subscripts p and o denote the PLM parameters and the other parameters in our architecture, respectively. In order to learn these parameters, we design both pre-training (*i.e.,* question-relation matching) and fine-tuning (*i.e.,* retrieval- and reasoning-oriented learning) strategies based on the unified architecture. Next, we describe the model training approach.

Pre-training with Question-Relation Matching (QRM). For pre-training, we mainly focus on learning the parameters of the underlying PLMs (*i.e.,* Θ_p and Γ_p). In implementation, we let the two models share the same copy of PLM parameters, *i.e.,* $\Theta_p = \Gamma_p$. As shown in Section 3.1, a basic capacity of the semantic matching module is to model the relevance between a question and a single relation (Eq. 2), which is based on the text encoding from the underlying PLM. Therefore, we design a contrastive pre-training task based on question-relation matching. Specifically, we adopt the contrastive leaning objective (Hadsell et al., 2006) to align the representations of relevant question-relation pairs while pushing apart others. To collect the relevant question-relation pairs, given an example consisting of a question q, the topic entities $\mathcal{T}_q$ and answer entities $\mathcal{A}_q$, we extract all the shortest paths between the $\mathcal{T}_q$ and $\mathcal{A}_q$ from the entire KG and regard all of the relations within these paths as relevant to q, denoted as $\mathcal{R}^+$. In this way, we can obtain a number of weak-supervised examples. During pre-training, for each question q, we randomly sample a relevant relation $r^+ \in \mathcal{R}^+$, and utilize a contrastive learning loss for pre-training:

$$\mathcal{L}_{PT} = -\log \frac{e^{\mathrm{sim}\left(\boldsymbol{q}_i, \boldsymbol{r}_i^+\right)/\tau}}{\sum_{j=1}^{M}\left(e^{\mathrm{sim}\left(\boldsymbol{q}_i, \boldsymbol{r}_j^+\right)/\tau} + e^{\mathrm{sim}\left(\boldsymbol{q}_i, \boldsymbol{r}_j^-\right)/\tau}\right)} \tag{5}$$

where τ is a temperature hyperparameter, r_i^- is a randomly sampled negative relation, and $\mathrm{sim}\left(\boldsymbol{q}, \boldsymbol{r}\right)$ is the cosine similarity, and $\boldsymbol{q}$, $\boldsymbol{r}$ is the question and relation encoded by the PLM from the SM module (Eq. 1). In this way, the question-relation matching capacity will be enhanced by pre-training the PLM parameters. Note that the PLM parameters will be fixed after pre-training.

Fine-tuning for Retrieval on Abstract Subgraphs (RAS). After pre-training, we firstly fine-tune the entire model for learning the parameters Θ_o according to the retrieval task. Recall that we transform the subgraph into a form of *abstract subgraphs*, where abstract nodes are incorporated for merging entities from the same relation. Since our MIP module (Section 3.1) can produce the matching scores $\boldsymbol{s}_A$ of nodes in a subgraph (Eq. 4), where the subscript A denotes that nodes are from an abstract subgraph. Furthermore, we utilize the labeled answers to get the ground-truth vectors, denoted by $\boldsymbol{s}_A^*$. We set an abstract node in $\boldsymbol{s}_A^*$ to 1 if it contains the answer entity. Then we minimize the KL divergence between the learned and ground-truth matching score vectors as:

$$\mathcal{L}_{RAS} = D_{KL}\big(\boldsymbol{s}_A, \boldsymbol{s}_A^*\big). \tag{6}$$

After fine-tuning with the RAS loss, the retrieval model can be effectively learned. We further utilize it to retrieve the subgraph for the given question q, by selecting the top-K ranked nodes according to their match scores. Note that only the node within a reasonable distance to the topic entities will be selected into the subgraph, which ensures a relatively small yet relevant subgraph $\mathcal{G}_q$ for the subsequent reasoning stage to find answer entities.

Fine-tuning for Reasoning on Retrieved Subgraphs (RRS). After fine-tuning the retrieval model, we continue to fine-tune the reasoning model by learning the parameters Γ_o. With the fine-tuned retrieval model, we can obtain a smaller subgraph $\mathcal{G}_q$ for each question q. In the reasoning stage, we focus on performing accurate reasoning to find the answer entities, so that we recover the original nodes in the abstract nodes and the original relations among them. Since the retrieval and reasoning stages are highly dependent, we first initialize the parameters of the reasoning model with those from the retrieval model: $\Theta_o \rightarrow \Gamma_o$. Then, following Eq. 4, we employ a similar approach to fitting the

Table 1: Comparison of different methods.

Methods	Retrieval	Reasoning	Parameters Transferring
GraftNet	PPR	GraftNet	✗
PullNet	LSTM	GraftNet	✗
NSM	PPR	NSM	✗
SR+NSM	PLM	NSM	✗
UniKGQA	UniKGQA	UniKGQA	✓

Table 2: Statistics of all datasets.

Datasets	#Train	#Valid	#Test	Max #hop
MetaQA-1hop	96,106	9,992	9,947	1
MetaQA-2hop	118,980	14,872	14,872	2
MetaQA-3hop	114,196	14,274	14,274	3
WebQSP	2,848	250	1,639	2
CWQ	27,639	3,519	3,531	4

learned matching scores (denoted by $\boldsymbol{s}_R$) with the ground-truth vectors (denoted by $\boldsymbol{s}_R^*$) according to the KL loss:

$$\mathcal{L}_{RRS} = D_{KL}\big(\boldsymbol{s}_R, \boldsymbol{s}_R^*\big), \tag{7}$$

where the subscript R denotes that the nodes come from a retrieved subgraph. After fine-tuning with the RRS loss, we can utilize the learned reasoning model to select the top-n ranked entities as the answer list according to the match scores.

As shown in Figure 1(c), the overall procedure of training UniKGQA is composed by: (1) pre-training Θ_p with question-relation matching; (2) fixing Θ_p and fine-tuning Θ_o for retrieval on abstract subgraphs; and (3) fixing the Γ_p initialized with Θ_p and fine-tuning Γ_o for reasoning on retrieved subgraphs.

Our work provides a novel unified model for the retrieval and reasoning stages to share the reasoning capacity. In Table 1, we summarize the differences between our method and several popular methods for multi-hop KGQA, including GraphfNet (Sun et al., 2018), PullNet (Sun et al., 2019), NSM (He et al., 2021), and SR+NSM (Zhang et al., 2022). As we can see, existing methods usually adopt different models for the retrieval and reasoning stages, while our approach is more unified. As a major benefit, the information between the two stages can be effectively shared and reused: we initialize the reasoning model by the learned retrieval model.

4 EXPERIMENT

4.1 EXPERIMENTAL SETTING

Datasets. Following existing work on multi-hop KGQA (Sun et al., 2018; 2019; He et al., 2021; Zhang et al., 2022), we adopt three benchmark datasets, namely *MetaQA* (Zhang et al., 2018), *WebQuestionsSP (WebQSP)* (Zhang et al., 2018) (Yih et al., 2015), and *Complex WebQuestions 1.1 (CWQ)* (Talmor & Berant, 2018) for evaluating our model. Table 2 shows the statistics of the three datasets. Since previous work has achieved nearly full scores on MetaQA, WebQSP and CWQ are our primarily evaluated datasets. We present a detailed description of these datasets in Appendix A.

Evaluation Protocol. For the retrieval performance, we follow Zhang et al. (2022) that evaluate the models by the answer coverage rate (%). It is the proportion of questions whose retrieved subgraphs contain at least one answer. For the reasoning performance, we follow Sun et al. (2018; 2019) that regard the reasoning as a ranking task for evaluation. Given each test question, we rely on the predictive probabilities from the evaluated model to rank all candidate entities, and then evaluate whether the top-1 answer is correct with *Hits@1*. Since a question may correspond to multiple answers, we also compute the widely-used *F1* score.

Baselines. We consider the following baselines for performance comparison: (1) reasoning augmented methods: *KV-Mem* (Miller et al., 2016), *GraftNet* (Sun et al., 2018), *EmbedKGQA* (Saxena et al., 2020), *NSM* (He et al., 2021), *TransferNet* (Shi et al., 2021); (2) retrieval augmented methods: *PullNet* (Sun et al., 2019), *SR+NSM* (Zhang et al., 2022), *SR+NSM+E2E* (Zhang et al., 2022). We present the description of these baselines in Appendix B.

Implementation Details. During pre-training, we collect question-relation pairs based on the shortest relation paths between topic entities and answer entities, and then use these pairs to pre-train the RoBERTa (Liu et al., 2019) model with the contrastive learning objective. We set the temperature τ as 0.05, and select the best model by evaluating *Hits@1* on the validation set. For retrieval and reasoning, we initialize the PLM module of our UniKGQA model with the pre-trained RoBERTa, and set the hidden size of other linear layers as 768. We optimize parameters with the AdamW

Table 3: Performance comparison of different methods for KGQA (Hits@1 in percent). We copy the results for TranferNet from Shi et al. (2021) and others from Zhang et al. (2022). Bold and underline fonts denote the best and the second-best methods.

Models	MetaQA-1	MetaQA-2	MetaQA-3	WebQSP		CWQ	
	Hits@1	Hits@1	Hits@1	Hits@1	F1	Hits@1	F1
KV-Mem	96.2	82.7	48.9	46.7	34.5	18.4	15.7
GraftNet	97.0	94.8	77.7	66.4	60.4	36.8	32.7
PullNet	97.0	<u>99.9</u>	91.4	68.1	-	45.9	-
EmbedKGQA	97.5	98.8	94.8	66.6	-	-	-
NSM	97.1	<u>99.9</u>	98.9	68.7	62.8	47.6	42.4
TransferNet	97.5	**100**	**100**	71.4	-	48.6	-
SR+NSM	-	-	-	68.9	64.1	50.2	47.1
SR+NSM+E2E	-	-	-	69.5	64.1	49.3	46.3
UniKGQA	97.5	99.0	99.1	75.1	70.2	50.7	48.0
w QU	<u>97.6</u>	<u>99.9</u>	99.5	<u>77.0</u>	<u>71.0</u>	<u>50.9</u>	**49.4**
w QU,RU	**98.0**	<u>99.9</u>	<u>99.9</u>	**77.2**	**72.2**	**51.2**	<u>49.0</u>

optimizer, where the learning rate is 5e-5 for the PLM module, and 1e-4 for other parameters. The batch size is set to 40. The reasoning steps is set to 4 for CWQ dataset, and 3 for other datasets.

4.2 Evaluation Results

Table 3 shows the results of different methods on 5 multi-hop KGQA datasets. It can be seen that:

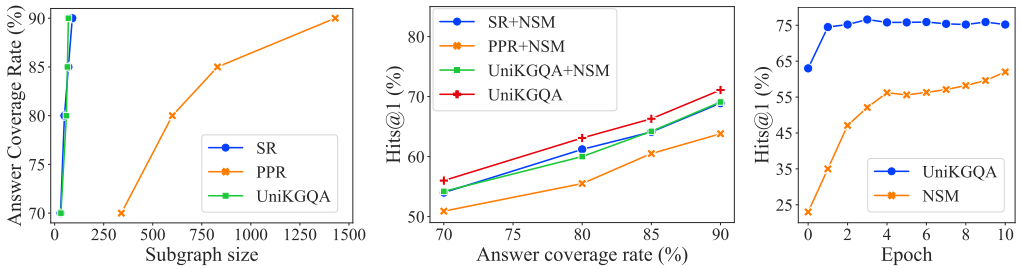
First, most baselines perform very well on the three MetaQA datasets (even Hit@1 reaches 100%). A possible reason is that these datasets are based on few hand-crafted question templates. It is easy to capture the semantics about these questions to perform reasoning. Second, TransferNet performs better than GraftNet, EmbedKGQA, and NSM under the same retrieval method. It attends to question words to compute the scores of relations and transfers entity scores w.r.t. relation scores. Such a way can effectively capture the question-path matching semantics. Besides, SR+NSM and SR+NSM+E2E outperform NSM and PullNet in a large margin. The reason is that they both pre-train a PLM-based relation paths retriever to improve the reasoning performance.

Finally, on WebQSP and CWQ, our proposed UniKGQA is substantially better than all other competitive baselines. Unlike other baselines that rely on independent models to perform retrieval and reasoning, our approach can utilize a unified architecture to accomplish the two tasks. Such a unified architecture can pre-learn the useful question-relation matching semantics for retrieval and reasoning tasks, and is also capable of effectively transferring useful knowledge from the prior task into the later task, *i.e.,* from the retrieval task to the reasoning task.

In our approach, we fix the parameters of the pre-trained PLM encoder for efficiency. Actually, updating its parameters can further improve our performance. Such a way provides a choice for efficiency or effectiveness when employing our approach in real-world applications. Here, we study it by proposing two variants of our UniKGQA: (1) *w QU* that updates the parameters of the PLM encoder when questions encoding; (2) *w QU, RU* that updates the parameters of the PLM encoder when both questions encoding and relations encoding. Indeed, both variants can further improve the performance of our UniKGQA. And only updating the PLM encoder when question encoding can obtain a comparable performance to update both. Therefore, updating the PLM encoder when question encoding seems to be a promising strategy of our UniKGQA, as it can achieve a better performance with additional affordable computation cost.

4.3 Further Analysis

Retrieval Evaluation. We evaluate the effectiveness of our UniKGQA to retrieve a smaller but more accurate answer-recall subgraph for a given question. Following the evaluation principles of SR (Zhang et al., 2022), we measure such a capacity from three aspects: the direct subgraph size, answer coverage rate, and the final QA performance. Concretely, we first compare UniKGQA with SR (Zhang et al., 2022) and PPR-based heuristic retrieval method (Sun et al., 2018) based on the answer coverage rates curves w.r.t. the number of graph nodes. Then, we compare UniKGQA with SR+NSM (Zhang et al., 2022) and PPR+NSM (He et al., 2021) based on their final QA performance.



(a) (b) (c)

Figure 3: (a) the answer coverage rate (%) under various subgraph sizes, (b) the Hits@1 scores under various answer coverage rates, and (c) the Hits@1 scores at different epochs on WebQSP.

To further study the effectiveness of our approach, we add an extra variant of our UniKGQA, namely UniKGQA+NSM, which relies on UniKGQA for retrieval while NSM for performing reasoning. Figure 3(a) and Figure 3(b) show the comparison results of the above methods. As we can see, under the same size of retrieved subgraphs, UniKGQA and SR have significantly larger answer coverage rates than PPR. It demonstrates the effectiveness and necessity of training a learnable retrieval module. Besides, although the curves of UniKGQA and SR are very similar, our UniKGQA can achieve a better final reasoning performance than SR+NSM. The reason is that UniKGQA can transfer the knowledge from the retrieval to the reasoning task based on the unified architecture, learning a more effective reasoning model. Such a reason can be also inferred by comparing our UniKGQA with UniKGQA+NSM.

Table 4: Ablation study of pre-training and initialized with the parameters of the retrieval model.

Models	WebQSP		CWQ	
	Hits@1	F1	Hits@1	F1
UniKGQA w QU	77.0	71.0	50.9	49.4
w/o Pre	75.4	70.6	49.2	48.8
w/o Trans	75.8	70.6	49.8	49.3
w/o Pre, Trans	72.5	60.0	48.1	48.4

Ablation Study. Our UniKGQA contains two important training strategies to improve the performance: (1) pre-training with question-relation matching; (2) initializing the parameters of the reasoning model with the retrieval model. Here, we conduct the ablation study to verify their effectiveness. We propose three variants as: (1) *w/o Pre* removing the pre-training procedure; (2) *w/o Trans* removing the initialization with the parameters of retrieval model; (3) *w/o Pre, Trans* removing both the pre-training and initialization procedures. We show the results in Table 4. We can see that all these variants underperform our UniKGQA, which indicates that both pre-training and initializing the parameters of the reasoning model with the retrieval model are important for the final performance. Besides, such an observation also verifies that our UniKGQA is indeed capable of inheriting the knowledge from the prior tasks to improve the final performance.

Fine-tuning Efficiency. As our UniKGQA model can inherit the learned knowledge from the pre-training stage and the retrieval task, it can be quickly adapted into downstream reasoning tasks. In this way, we can perform a more efficient fine-tuning on the reasoning task with few fine-tuning steps. To explore it, we report the performance changes of our UniKGQA and a strong baseline NSM w.r.t. the number of fine-tuning epochs based on the same retrieval subgraphs. The results are presented in Figure 3(c). First, we can see that before fine-tuning (*i.e.,* when the epoch is zero), our UniKGQA has achieved a comparable performance as the best results of NSM at the last epoch. It indicates that the reasoning model has successfully inherited the knowledge from prior tasks based on the parameters initialized by the retrieval model. After fine-tuning with two epochs, our UniKGQA has already converged into a good performance. It verifies that our model can be fine-tuned in an efficient way with very few epochs. To further study our UniKGQA model, we conduct parameter sensitivity analysis w.r.t. pre-training steps, hidden dimensions, and the number of retrieved nodes K, shown in Appendix C.

5 RELATED WORK

Multi-hop Knowledge Graph Question Answering. Multi-hop KGQA aims to seek answer entities which are multiple hops away from the topic entities in a large-scale KG. Considering the efficiency and accuracy, existing work (Sun et al., 2018; 2019; Zhang et al., 2022) typically first retrieves a question-relevant subgraph to reduce the search space and then performs multi-hop reasoning on it. Such a retrieval-and-reasoning paradigm has shown superiority over directly reasoning on the entire KG (Chen et al., 2019; Saxena et al., 2020).

The retrieval stage focuses on extracting a relatively small subgraph involving the answer entities. A commonly-used approach is to collect entities with nearer hops around the topic entities to compose the subgraph and filter the ones with low Personalized PageRank scores to reduce the graph size (Sun et al., 2018; He et al., 2021). Despite the simplicity, such a way neglects the question semantics, limiting the retrieval efficiency and accuracy. To address it, several work (Sun et al., 2019; Zhang et al., 2022) devises retrievers based on semantic matching using neural networks (*e.g.,* LSTMs or PLMs). Starting from the topic entities, these retrievers iteratively measure the semantic relevance between the question and neighbouring entities or relations, and add proper ones into the subgraph. In this way, a smaller but more question-relevant subgraph would be constructed.

The reasoning stage aims to accurately find the answer entities of the given question by walking along the relations starting from the topic entities. Early work (Miller et al., 2016; Sun et al., 2018; 2019) relies on the special network architectures (*e.g.,* Key-Value Memory Network or Graph Convolution Network) to model the multi-hop reasoning process. Recent work further enhances the reasoning capacity of the above networks from the perspectives of intermediate supervision signals (He et al., 2021), knowledge transferring (Shi et al., 2021), etc. However, all these methods design different model architectures and training methods for the retrieval and reasoning stages, respectively, neglecting the similarity and intrinsic connection of the two stages. In this work, we are dedicated to unify the retrieval and reasoning to share learned capabilities and improve the final QA performance.

Dense Retrieval. Given a query, the dense retrieval task aims to select relevant documents from a large-scale document pool. Different from the traditional sparse term-based retrieval methods, *e.g.,* TF-IDF (Chen et al., 2017) and BM25 (Robertson & Zaragoza, 2009), dense retrieval methods (Karpukhin et al., 2020; Guu et al., 2020; Sachan et al., 2021) rely on a bi-encoder architecture to map queries and documents into low-dimensional dense vectors. Then their relevance scores can be measured using vector distance metrics (*e.g.,* cosine similarity), which supports efficient approximate nearest neighbour (ANN) search algorithms. In multi-hop KGQA, starting from the topic entities, we need to select the relevant neighboring triples from a large-scale KG, to induce a path to reach the answer entities, which can be seen as a constrained dense retrieval task. Therefore, in this work, we also incorporate a bi-encoder architecture to map questions and relations into dense vectors, and then perform retrieval or reasoning based on their vector distances.

6 CONCLUSION

In this work, we proposed a novel approach UniKGQA for the multi-hop KGQA task. Unlike previous methods, UniKGQA introduced a unified model architecture based on PLMs for both retrieval and reasoning stages, which consists of the semantic matching module and the matching information propagation module. To cope with the different scales of search space in the two stages, we proposed to generate abstract subgraphs for the retrieval stage, which can significantly reduce the number of nodes to be searched. Furthermore, we designed an effective model learning method with both pre-training (*i.e.,* question-relation matching) and fine-tuning (*i.e.,* retrieval- and reasoning-oriented learning) strategies based on the unified architecture. With the unified architecture, the proposed learning method can effectively enhance the sharing and transferring of relevance information between the two stages. We conducted extensive experiments on three benchmark datasets, and the experiment results show that our proposed unified model outperforms the competitive methods, especially on more challenging datasets (*i.e.,* WebQSP, CWQ).

REFERENCES

Kurt D. Bollacker, Colin Evans, Praveen K. Paritosh, Tim Sturge, and Jamie Taylor. Freebase: a collaboratively created graph database for structuring human knowledge. In *Proceedings of the ACM SIGMOD International Conference on Management of Data, SIGMOD 2008, Vancouver, BC, Canada, June 10-12, 2008*, pp. 1247–1250. ACM, 2008.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. Reading wikipedia to answer open-domain questions. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pp. 1870–1879. Association for Computational Linguistics, 2017.

Yu Chen, Lingfei Wu, and Mohammed J. Zaki. Bidirectional attentive memory networks for question answering over knowledge bases. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pp. 2913–2923. Association for Computational Linguistics, 2019.

Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. REALM: retrieval-augmented language model pre-training. *CoRR*, abs/2002.08909, 2020.

Raia Hadsell, Sumit Chopra, and Yann LeCun. Dimensionality reduction by learning an invariant mapping. *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, 2:1735–1742, 2006.

Gaole He, Yunshi Lan, Jing Jiang, Wayne Xin Zhao, and Ji-Rong Wen. Improving multi-hop knowledge base question answering by learning intermediate supervision signals. In *WSDM '21, The Fourteenth ACM International Conference on Web Search and Data Mining, Virtual Event, Israel, March 8-12, 2021*, pp. 553–561. ACM, 2021.

Drew A. Hudson and Christopher D. Manning. Learning by abstraction: The neural state machine. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pp. 5901–5914, 2019.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick S. H. Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pp. 6769–6781. Association for Computational Linguistics, 2020.

Yunshi Lan, Gaole He, Jinhao Jiang, Jing Jiang, Wayne Xin Zhao, and Ji-Rong Wen. A survey on complex knowledge base question answering: Methods, challenges and solutions. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI 2021, Virtual Event / Montreal, Canada, 19-27 August 2021*, pp. 4483–4491. ijcai.org, 2021.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692, 2019.

Alexander H. Miller, Adam Fisch, Jesse Dodge, Amir-Hossein Karimi, Antoine Bordes, and Jason Weston. Key-value memory networks for directly reading documents. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016*, pp. 1400–1409. The Association for Computational Linguistics, 2016.

Stephen E. Robertson and Hugo Zaragoza. The probabilistic relevance framework: BM25 and beyond. *Found. Trends Inf. Retr.*, 3(4):333–389, 2009.

Devendra Singh Sachan, Mostofa Patwary, Mohammad Shoeybi, Neel Kant, Wei Ping, William L. Hamilton, and Bryan Catanzaro. End-to-end training of neural retrievers for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pp. 6648–6662. Association for Computational Linguistics, 2021.

Apoorv Saxena, Aditay Tripathi, and Partha P. Talukdar. Improving multi-hop question answering over knowledge graphs using knowledge base embeddings. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pp. 4498–4507. Association for Computational Linguistics, 2020.

Jiaxin Shi, Shulin Cao, Lei Hou, Juanzi Li, and Hanwang Zhang. Transfernet: An effective and transparent framework for multi-hop question answering over relation graph. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, pp. 4149–4158. Association for Computational Linguistics, 2021.

Haitian Sun, Bhuwan Dhingra, Manzil Zaheer, Kathryn Mazaitis, Ruslan Salakhutdinov, and William W. Cohen. Open domain question answering using early fusion of knowledge bases and text. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pp. 4231–4242. Association for Computational Linguistics, 2018.

Haitian Sun, Tania Bedrax-Weiss, and William W. Cohen. Pullnet: Open domain question answering with iterative retrieval on knowledge bases and text. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pp. 2380–2390. Association for Computational Linguistics, 2019.

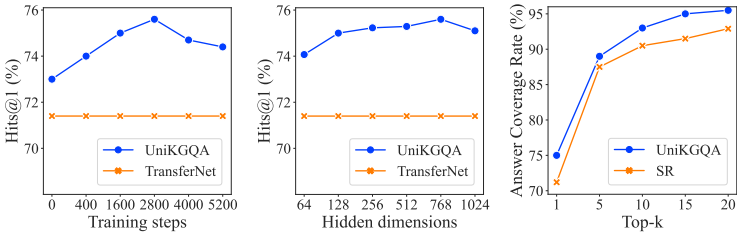
Alon Talmor and Jonathan Berant. The web as a knowledge-base for answering complex questions. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pp. 641–651. Association for Computational Linguistics, 2018.

Thomas Pellissier Tanon, Denny Vrandecic, Sebastian Schaffert, Thomas Steiner, and Lydia Pintscher. From freebase to wikidata: The great migration. In *Proceedings of the 25th International Conference on World Wide Web, WWW 2016, Montreal, Canada, April 11 - 15, 2016*, pp. 1419–1428. ACM, 2016.

Wen-tau Yih, Ming-Wei Chang, Xiaodong He, and Jianfeng Gao. Semantic parsing via staged query graph generation: Question answering with knowledge base. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pp. 1321–1331. The Association for Computer Linguistics, 2015.

Jing Zhang, Xiaokang Zhang, Jifan Yu, Jian Tang, Jie Tang, Cuiping Li, and Hong Chen. Subgraph retrieval enhanced model for multi-hop knowledge base question answering. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pp. 5773–5784. Association for Computational Linguistics, 2022. doi: 10.18653/v1/2022.acl-long.396. URL `https://doi.org/10.18653/v1/2022.acl-long.396`.

Yuyu Zhang, Hanjun Dai, Zornitsa Kozareva, Alexander J. Smola, and Le Song. Variational reasoning for question answering with knowledge graph. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*, pp. 6069–6076. AAAI Press, 2018.



(a) (b) (c)

Figure 4: (a) the performance on WebQSP of varying pre-training steps, (b) hidden dimensions, and (c) the number of retrieved nodes K.

A Datasets

We adopt three widely-used multi-hop KGQA datasets in this work:

• **MetaQA** (Zhang et al., 2018) contains more than 400k questions in the domain of movie and the answer entities are up to 3 hops away from the topic entities. According to the number of hops, this dataset is split into three sub-datasets, *i.e.,* MetaQA-1hop, MetaQA-2hop, and MetaQA-3hop.

• **WebQuestionsSP (WebQSP)** (Yih et al., 2015) contains 4,737 questions and the answer entities require up to 2-hop reasoning on the KG Freebase (Bollacker et al., 2008). We use the same train/valid/test splits as GraftNet (Sun et al., 2018).

• **Complex WebQuestions 1.1 (CWQ)** (Talmor & Berant, 2018) is constructed based on WebQSP by extending the question entities or adding constraints to answers. These questions require up to 4-hop reasoning on the KG Freebase (Bollacker et al., 2008).

B Baselines

We consider the following baseline methods for performance comparison:

• **KV-Mem** (Miller et al., 2016) maintains a key-value memory table to store KG facts, and conducts multi-hop reasoning by performing iterative read operations on the memory.

• **GraftNet** (Sun et al., 2018) first retrieves the question-relevant subgraph and text sentences from the KG and Wikipedia respectively with a heuristic method. Then it adopts a graph neural network to perform multi-hop reasoning on a heterogeneous graph built upon the subgraph and text sentences.

• **PullNet** (Sun et al., 2019) trains a graph retrieval model instead of the heuristic way in GraftNet for the retrieval task, and then conducts multi-hop reasoning with GraftNet.

• **EmbedKGQA** (Saxena et al., 2020) reformulates the multi-hop reasoning of GraftNet as a link prediction task by matching pre-trained entity embeddings with question embedding from a PLM.

• **NSM** (He et al., 2021) first conducts retrieval following GraftNet and then adapt the neural state machine (Hudson & Manning, 2019) used in visual reasoning for multi-hop reasoning on the KG.

• **TransferNet** (Shi et al., 2021) first conducts retrieval following GraftNet and then performs the multi-hop reasoning on a KG or a text-formed relation graph in a transparent framework.

• **SR+NSM** (Zhang et al., 2022) first learns a PLM-based relation path retriever to conduct effectively retrieval and then leverages NSM reasoner to perform multi-hop reasoning.

• **SR+NSM+E2E** (Zhang et al., 2022) fine-tunes the retriever and reasoner by an end-to-end way.

C Parameter Sensitivity Analysis

Pre-training Steps Although the pre-training strategy has shown effective in our approach, too many pre-training steps will be time-consuming and costly. Here, we investigate the performance

with respect to varying pre-training steps. As shown in Figure 4(a), we can see that our method can reach the best performance with only few pre-training steps (*i.e.,* 2800) compared with the best baseline TransferNet. It shows that our approach does not require too many steps for pre-training. Instead, we can see that too many pre-training steps will hurt the model performance. The reason may be that the PLM has overfit into the contrastive learning objective.

Parameter Tuning. In our approach, we have two hyper-parameters required to tune: (1) the hidden size of linear layers d and (2) the number of retrieved nodes K. Here, we tune the d amongst $\{64, 128, 256, 512, 768, 1024\}$ and K amongst $\{1, 5, 10, 15, 20\}$. We show the results in Figure 4(b) and Figure 4(c) compared with the best results for the reasoning stage and the retrieval stage. Since K is a consistent hyper-parameter in the UniKGQA and SR, we also describe the various results of SR with different K to give a fair comparison. First, we can see that our method is robust to different hidden sizes, as the performance is consistently nearby 77.0. As the PLM adopts 768 as the embedding size, we can see 768 is also slightly better than other numbers. Besides, we can see that with the increase of K, the answer coverage rate also improves consistently. However, when K increases to 15 or even 20, the performance gain becomes relatively small. It means that the retrieved subgraphs are likely saturated, and further increasing K could only bring marginal improvement.