

# Improving Question Answering over Knowledge Base with External Linguistic Knowledge

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## Introduction

Most of the existing semantic parsing methods in KBQA focus on capturing the semantics of questions and relations in query graphs. The label of the relation in the first edge of the query graph is taken as core relations for measuring similarity together with some manual features [1, 2]. Another approach to detecting individual relation with word-level is presented in [4] to improve the performance of matching from questions to query graphs where each word of a relation is independently represented, and relation is directly represented by integrating of its words' representations. [3] extends [4] by improving the representation of questions and processing more complex questions.

However, current works that encode the relation semantics in a query graph mainly focus on two aspects: *relation-level* and *word-level* (we denote their combination as fine-grained relation), the latent semantic information behind the meaning of relations is ignored. For *relation-level*, each relation is considered as a whole and individual token, which pays more attention to the overall information of the relation. The problem with this aspect is that it suffers from data sparsity in the training process. For *word-level*, the relation is treated as a sequence of words with the lack of global information of the original relation. In this aspect, word meanings are diversified without considering the word-level relation that might bring noises. For example, for relation "be subject to", it means "to be made to undergo an unpleasant experience", the word-level word "subject" might lose that meaning due to its polysemy.

In this paper, to cope with the above limitations, we propose a fine-grained relation with leveraging *WordNet* to enhance relations representation. *WordNet* as a lexical database for English, contains synset(the set of synonyms) for each word, which can instruct word sense representation learning and word disambiguation. We both consider the original global relation and its word-level relations with word disambiguation.

## Query graphs generation

The generation process of query graphs is shown in Figure 1.

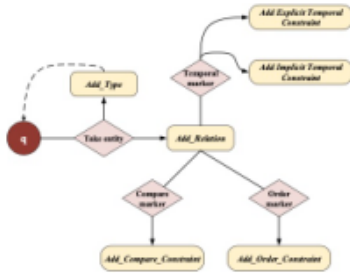


Figure 1: Query graph generate process

Our approach to generating query graphs is an iterative process. Inspired by query graphs generation of [1], we consider 5 kinds of semantic constraints: *entity*, *type*, *temporal(explicit and implicit time)*, *order* and *compare* to process more complex questions. Given a natural language question, we split it into a set of tokens  $T$ .

Firstly, we extract all possible entities from  $T$  with the help of the existing entity linking tool [7]. We can obtain the (mention, entity) pairs to get the entity linking list, which will be filtered with the scores evaluated by the entity linking tool. The set of candidate entities  $E$  will be finally returned.

And then, we construct new candidate graphs with a set of predefined operations set  $OP$ : Take entity, Add Type, Add Temporal(explicit and implicit), Add Compare and Add Order. Fig. 1 shows a flow path of our candidate semantic graph generation process.

## Our Approach

**Question Representation Encoding:** We encode the syntactic dependency tree of a question to a vector as the representation of the given question via GAT. The module is used to provide the condition of calculating the similarity of a question with candidate query graphs.

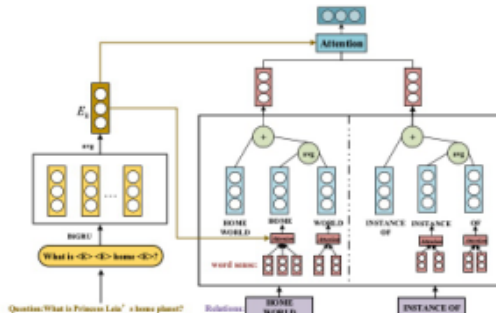


Figure 2: Query graph generate process

**Relation Representation:** We obtain the semantic representation of relations in two steps, namely, *sense-based attention* and *hidden-relation-based attention* (see Fig. 2). We obtain the representation of each fine-grained relation occurring in a query graph with leveraging *WordNet*, and we apply hidden relation in questions to assign weights of all relations in query graphs via attention mechanism.

## Experiments and Evaluations

**Experiments Setup** Due to Freebase no longer up-to-date, including unavailability of APIs and new dumps, we use the full Wikidata dump as our KB and host it with Virtuoso engine. Besides, we adopt *SpaCy* as syntactic dependency parser and use Deep Graph Library (DGL) to transfer query graphs into DGL graph objects. We conduct our experiments on the following two popular data sets, namely, *WebQuestionSP*, *QALD-7*.

**Results** Our model achieves 25.9%, 13.2%, 10.3%, 6.4% higher F1-score compared to STAGG, Pooled Edges, HR-BiLSTM, Luo et al.(2018) on WebQSP. Analogously, we achieve 32.8%, 54.1%, 17.8%, 16.0% higher F1-score on QALD-7. So we can conclude that our relation representation method performs better than all baselines. Our model improves the F1-score of WebQSP and QALD-7 by 4.4% and 9.7% over Our (w/o ELK). Hence, we can conclude that introduce ELK to remove word-level ambiguity can improve the performance of KBQA. Note that even without considering ELK, Our(w/o ELK) still performs better than other baselines, it shows the robustness of our model.

Table 1. WebQSP and QALD-7 results over Wikidata

Model	WebQSP			QALD-7		
	Precision	Recall	F1	Precision	Recall	F1
STAGG(2015)	0.1911	0.2267	0.1828	0.1934	0.2463	0.1861
Pooled Edges	0.2094	0.2553	0.2032	0.1904	0.1800	0.1605
HR-BiLSTM(2017)	0.2131	0.2573	0.2087	0.2172	0.2299	0.2099
Luo et al.(2018)	0.2255	0.2618	0.2162	0.2176	0.2451	0.2131
Our(w/o ELK)	0.2285	0.2702	0.2203	0.2316	0.2571	0.2254
Our	0.2421	0.2843	0.2301	0.2549	0.2674	0.2472

QR of Baselines	WebQSP	QALD	ELK	Opeation	WebQSP	QALD
DCNN(STAGG,Pooled Edges)	0.2223	0.2363	-	pool	0.2187	0.2210
HR-BiLSTM	0.2208	0.2299	-	HRA	0.2203	0.2254
Luo et al.(2018)	0.2241	0.2411	+	pool	0.2281	0.2413
Our(GCN)	0.2276	0.2448	+	HRA	0.2301	0.2472
Our	0.2301	0.2472				

Table 4. Ablation Results on Question Representation

Table 5. Ablation results on Relation Representation

We explore the contributions of various components in our model. For the ablation study, we use F1-score as our metrics, and the results are shown in Table 2 and Table 3.

## Conclusions

In this paper, we utilize ELK to improve relation representation in KBQA. The knowledge is useful to extract word-level relation semantics with disambiguation. Our approach pays more attention to relational semantics of query graphs, which is an important semantic part of questions in KBQA. In this sense, we provide a new method of leveraging extra knowledge in KBQA.

## References

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