A Chinese Multi-type Complex Questions Answering Dataset over Wikidata

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Abstract

Complex Knowledge Base Question Answering is a popular area of research in the past decade. Recent public datasets have led to encouraging results in this field, but are mostly limited to English and only involve a small number of question types and relations, hindering research in more realistic settings and in languages other than English. In addition, few state-of-the-art KBQA models are trained on Wikidata, one of the most popular real-world knowledge bases.

We propose CLC-QuAD, the first large scale complex Chinese semantic parsing dataset over Wikidata to address these challenges. Together with the dataset, we present a text-to-SPARQL baseline model, which can effectively answer multi-type complex questions, such as factual questions, dual intent questions, boolean questions, and counting questions, with Wikidata as the background knowledge. We finally analyze the performance of SOTA KBQA models on this dataset and identify the challenges facing Chinese KBQA.

1 Introduction

Knowledge Base Question Answering (KBQA) aims at answering factoid questions based on a knowledge base (KB) and has attracted considerable attention due to its popular downstream applications (Cai and Yates, 2013; Berant et al., 2013; Yih et al., 2016; Trivedi et al., 2017). Previous KBQA methods have achieved remarkable progress when dealing with simple question types and relations. For example, current state-of-the-art methods (Yih et al., 2015; Yin et al., 2016; Yu et al., 2017) on the SimpleQuestion dataset (Bordes et al., 2015), which consists of simple questions and corresponding facts from Freebase, have achieved 90% accuracy. However, real-world KBQA applications often involve multi-type complex questions (e.g., fact questions, dual intent questions, boolean questions and counting questions), which are underexplored by previous KBQA methods.

Recently, several approaches have been proposed for answering complex questions (Hao et al., 2017; Usbeck et al., 2018; Hu et al., 2018; Luo et al., 2018). Despite the effectiveness of previous studies, there are two major limitations for answering multi-type complex questions in practice. First, current KBQA datasets such as ComplexQuestions (Bao et al., 2016) and ComplexWebQuestions (Talmor and Berant, 2018) mostly focus on multi-hop questions and questions with various constraints, while many question types in real-world KBQA applications are still not covered: e.g., most existing datasets and models do not cover boolean questions (e.g. “Was Stevie Nicks a musical composer?”) and questions with multiple intentions (e.g. “What is the job title of Gregory VII and when did he start working?”). Second, most existing KBQA models are not generalizable enough to process different types of questions. For example, information retrieval-based methods (Yao and Durme, 2014; Dong et al., 2015) attempt to rank candidate answers with respect to the given question, and therefore cannot answer boolean and dual-intention questions. The staged query graph generation methods (Bordes et al., 2014; Yih et al., 2015; Lan and Jiang, 2020) aim at generating the query graph and the answer nodes representing final answers. However, as the generation process is base on true relations in KB, these methods cannot effectively answer boolean questions since the corresponding query graph may be inaccurate.

In this paper, we construct the CLC-QuAD dataset to address these challenges. CLC-QuAD is the first Chinese large scale KBQA dataset over Wikidata that covers a wide variety of questions types, obtained by translating, verifying, and filtering LC-QuAD 2.0. We also propose a text-to-SPARQL model to handle the additional complexities in CLC-QuAD. In particular, we translate ques-
Table 1: Our corpus contains different types of questions in Chinese, including multi-hop questions, dual-intention questions, fact questions and boolean questions.

2 Related Work

2.1 KBQA Datasets

Earlier KBQA datasets, such as Free917 (Cai and Yates, 2013) that contains 917 pairs of question and formal query in FREEBASE, are too small to train neural networks models. The larger scale dataset WebQuestions (Berant et al., 2013) consists of natural language question-answer pairs only, without formal queries. WebQuestionsSP (Yih et al., 2016) extracts part of the WebQuestions dataset and supplements it with the corresponding formal query and improves the multi-relation questions. SimpleQuestions (Bordes et al., 2015) builds a large-scale dataset, but only has one type of relation. Recently, ComplexWebQuestions (Talmor and Berant, 2018) presents a complex dataset that covers more components in the SPARQL grammar, but it only covers limited types of questions. LC-QUAD (Trivedi et al., 2017) is the first complex KBQA dataset based on DBpedia. It starts by generating formal queries for DBpedia and then converts these template-based questions into natural language questions. QALD-9 (Usbeck et al., 2018) is another well-known KBQA dataset based on DBpedia, which has more complex and colloquial questions than LC-QUAD. LC-QuAD 2.0 (Dubey et al., 2019) is created in 2019, which expanded the number of data and increased formal query types.

2.2 KBQA Systems

In earlier work, Bordes et al. (2014) starts to use neural networks to train question and answer vector representation, calculating the matching scores between question and candidate answers. Dong et al. (2015); Hao et al. (2017) uses CNN and attention to learn the relation and type features and obtains some improvement. These methods are based on information retrieval provide a simple solution by strengthening the connection between the question and the answer. But their candidate answer space can be huge for complex question. By contrast, semantic parsing methods can achieve much better score in complex KBQA dataset. Yih et al. (2015) puts forward a query graph structure, mapping the semantic parsing process to generate query graph process, which defines several operations to extend, including entity linking, attaching constraints, attribute recognition and so on. Following this idea, Bao et al. (2016); Yu et al. (2017) adds new type constraints as well as dominant and recessive time constraints to solve more complex questions. Re-
In our dataset, these prefix URLs are used to describe a single item which are a part of Wikidata prefix URLs. In Wikidata, the prefixes are used in RDF formats that allow short prefixes (such as Turtle and RDF). In order to execute the SPARQL query on Wikidata correctly, algorithms are required to generate both the right item and its right prefix.

Recently, Hu et al. (2018); Xu et al. (2019); Chen et al. (2020); Lan and Jiang (2020) continues this line of research by defining new abstract query graph and designing stronger query graph representation to further improve predicted query graph accuracy.

3 Corpus Construction

We translate all effective English questions in the LC-QuAD 2.0 dataset into Chinese. This work is distributed to 20 computer science students, supervised by 3 NLP researchers. Each item in LC-QuAD 2.0 has three paraphrased versions of questions, which provides more natural language variations for models to learn from and avoid over-fitting. We split three questions of each item and mix all questions to translate in order to guarantee Chinese question variations. Each question is first translated by one student, and then cross-checked and corrected by another student. Finally, a third student is in charge of verifying the original and corrected versions. As for the Chinese knowledge graph, we rely on Chinese descriptions in Wikidata. In addition, we also double check the gold SPARQL queries in LC-QuAD 2.0 and correct mistakes whenever we can. We check the correctness of the SPARQL queries from two aspects. First, we check all SPARQL queries in Wikidata Query Service to find syntax errors and get the answer labels at the same time. Second, we read both questions and SPARQL queries to make sure that questions are matched with queries.

3.1 Knowledge Graph Statistics

We show the statistics of three knowledge graphs in Table 2. Freebase (Bollacker et al., 2008) is a collaboratively edited knowledge base designed to be a public repository of the world’s knowledge. DBpedia (Bizer et al., 2009) is a knowledge graph mainly based on the English Wikipedia. Wikidata (Vrandecic, 2012) is a free, open, and massively linked knowledge base. Compared with above two knowledge graphs, we can find that Wikidata contains a larger number of entities and relations. More importantly, Wikidata defines prefixes to describe the IRIs of the RDF resources, that are suitable for variety of SQARQL queries, shown in Figure 1.

|                      | Freebase | DBpedia | Wikidata |
|----------------------|----------|---------|----------|
| **Entities**         | 41 million | 6.6 million | 93 million |
| **Triples**          | 596 million | 13 billion | 13.9 billion |
| **Relations**        | 19456    | 10000   | 40276    |
| **Size (GB)**        | 56.9     | 9.25    | 2030     |

Table 2: Statistics of main knowledge graphs from number of entities, number of triples, number of relations and size of knowledge graphs.

3.2 Data Statistics and Analysis

We compute the statistics of both LC-QuAD 2.0 and CLC-QuAD, and carry out a data analysis focusing on semantic coverage and question types. In this section, we will also compare them with other complex knowledge base question answering datasets.

Data statistics Table 3 summarizes the statistics of nine datasets. LC-QuAD contains 28k+ pairs of question and SPARQL query in total, which is comparable to or bigger than most commonly used KBQA datasets. As for dataset variation, FREE917, WebQuestions and SimpleQuestion focus on simple questions without constraints, so most of data in these datasets even don’t have corresponding formal queries. LC-QuAD contains more question types and its SPARQL components cover SELECT, COUNT, ASK and DISTINCT. ComplexWebQuestions builds a complex dataset by adding different and complicated constraints and its SPARQL components cover SELECT, DISTINCT, FILTER, LANG, DATATIME etc. In LC-QuAD 2.0 and CLC-QuAD, we ensure that
| Data Set            | Size | Variation | Target KG | formal query | language |
|---------------------|------|-----------|-----------|--------------|----------|
| FREE917             | 917  | low       | Freebase  | yes          | English  |
| WebQuestions        | 5810 | low       | Freebase  | no           | English  |
| WebQuestionsSP      | 4737 | medium    | Freebase  | yes          | English  |
| SimpleQuestions     | 100k | low       | Freebase  | no           | English  |
| ComplexWebQuestions | 34K  | medium    | Freebase  | yes          | English  |
| LC-QuAD             | 5K   | medium    | DBpedia   | yes          | English  |
| QALD-9              | 350  | high      | DBpedia   | yes          | English  |
| LC-QuAD 2.0         | 30K  | high      | Wikidata, DBpedia | yes | English |
| CLC-QuAD(Ours)      | 28k  | high      | Wikidata  | yes          | Chinese  |

Table 3: A comparison of existing datasets having questions and corresponding formal queries

| CLC | LC2.0 | CWQ | LC |
|-----|-------|-----|----|
| # Question | 28,409 | 30,226 | 34,689 | 5,000 |
| Avg.# Q Len | 20.1 | 10.7 | 13.4 | 11.4 |
| # Vocab | 32,683 | 45,476 | 30,627 | 9,682 |
| # Entities | 20,577 | 21,485 | 12,500 | 3,968 |
| # Relations | 3,447 | 3,660 | 825 | 748 |
| # Keyword | 11 | 11 | 6 | 4 |
| Dual Intent | ✓ | ✓ | ✗ | ✗ |
| Boolean Intent | ✓ | ✓ | ✗ | ✓ |
| Constraint | ✓ | ✓ | ✓ | ✗ |

Table 4: Statistics of knowledge base question answering with more details. The number are counted over the entire datasets. For CLC-QuAD, we use professional Chinese word segmentation tool to compute the number of vocab.

The corpus contains enough examples for all common SPARQL patterns in order to describe the question correctly. CLC-QuAD covers all the following SPARQL components: SELECT with one or multiple variable, COUNT, ASK, DISTINCT, FILTER, CONTAINS, YEAR, STRSTARTS, LIMIT, ORDER BY, LANG. Noticeably, most of datasets are built on Freebase and DBpedia, which makes datasets based on Wikidata more distinctive and challenging, as researchers need to explore the connection between questions and the structure of the Wikidata knowledge graph. In addition, CLC-QuAD provides Chinese questions that help study KBQA in a cross-lingual setting. Since the same question can be expressed quite differently in Chinese and in English, we also present statistics of characters for each language.

**Semantic Coverage** As shown in Table 4, we make a statistical comparison against previous KBQA datasets in this task. Obviously, CLC-QuAD and LC-QuAD 2.0 is vast in coverage of knowledge graph entities and relations, which can enable better generalization in model training. In addition, the SPARQL queries in CLC-QuAD and LC-QuAD 2.0 cover all common SPARQL keywords. As for vocabulary in datasets, we believe our translating work is much better than machine translation, as the translators make their focus on both questions and correct SPARQL queries so that they can use suitable word in different situations, as demonstrated by the vocabulary used in our dataset.

**Question Distribution** As shown in Figure 2, CLC-QuAD contains a fairly diverse set of question types over knowledge graphs. Unsurprisingly, FACT and FACT_DEDUPLICATION questions are the two most commonly seen in KBQA systems. Among the rest of question types, approximately 35% are DUAL INTENTION questions, which pose huge challenges to semantic parsing. Another 20% of this subgroup is BOOLEAN question, which is also very common in real-world applications, but is often ignored by researchers. BOOLEAN questions can be hard to handle traditional algorithms, because it is more like a classification problem rather than mapping to existing knowledge graphs. Also, DATE,
4 Approach

In this section, we describe our text-to-SPARQL model in two parts: relation-aware attention and multi-types pointer network. Figure ?? illustrates the overview of the model.

4.1 Relation-aware Attention Encoder

As for the embedding layer, we consider two options as input to the next layer. First choice is pretrained word embedding (Song et al., 2018). Alternatively, we use BERT (Devlin et al., 2019) as the initial representations of the word. Formally, we concatenate question \( Q \) and all entities \( E \) and relations \( R \) by this structure:

\[
[CLS], q_1, ..., [SEP], e_1, [SEP], ..., r_1, [SEP]
\]

This sequence is fed into the pretrained BERT model and use the last hidden states as the initial representations.

To capture graph information across the question, we use relation-aware self attention layers (Shaw et al., 2018) to compute new contextual representations of questions, entities and relations item. We define the input \( X = \{x_i\}_{i=1}^n \) where \( x_i \in \{q_i, ..., e_i, ..., r_i\} = Q \cup E \cup R \). This is the relation-aware self-attention process for each layer (consisting of \( H \) heads):

\[
\begin{align*}
    e_{ij}^{(h)} &= x_i W_Q^{(h)} x_j W_K^{(h)} + r_{ij}^T \\
    \alpha^{(h)} &= \text{Softmax}(e^{(h)}) \\
    c_i^{(h)} &= \sum_{j=1}^n \alpha_{ij}^{(h)} (x_j W_V^{(h)} + r_j^T)
\end{align*}
\]

where \( W_Q^{(h)}, W_K^{(h)}, W_V^{(h)} \in \mathbb{R}^{d_h \times (d_h/H)}, r_K = r_V \in \mathbb{R}^{n \times n \times (d_V/H)}, r_{ij} \) is the vector which represent the relation type between the two item \( x_i \) and \( x_j \) in the input. And in our model, \( r_{ij} \) is designed as a learned parameter for edge types in graph, such as \(<wdt-wd>\) and \(<wdt-p>\). After the attention procedure, we use fully connected feed-forward networks to transform the attention output and the ReLU activation is used between the two fully connected networks.

In sum, every relation-aware self attention layer use the corresponding graph \( G_Q \) and compute a new contextual representations of question word, entities and relations.

4.2 Pointer Network Decoder

Because the output SPARQL query consists of entities, relations and SPARQL keywords, we use pointer networks with three separate independent scaled dot-product attention for different components. During the decoding process, we use Long Short Term Memory (LSTM) with attention to generate SPARQL queries by incorporating the representation of entities, relations and SPARQL keywords.

Denote the decoding step as \( t \), we provide the decoder input as a concatenation of the embedding of the SPARQL query token \( S_t \) and the context vector \( c_t \):

\[
h_{t+1} = \text{LSTM}([S_t; c_t], h_t)
\]

where \( h_t \) is the hidden state of the decoder LSTM and the hidden state \( h_0 \) is initialized as random, as well as \( S_t, c_t \). And \( S_t \) is generated by the types of the SPARQL query token.

\[
S_t = \begin{cases} 
W_k^{\text{keyword}} + b_k & \text{token} \in \text{Keyword} \\
W_e^{h_{\text{entity}}} + b_e & \text{token} \in \text{Entity} \\
W_r^{h_{\text{relation}}} + b_r & \text{token} \in \text{Relation}
\end{cases}
\]

where \( h_{\text{entity}}, h_{\text{relation}} \) are extracted from encoder result \( h^{\text{enc}} \) and \( h^{\text{keyword}} \) is a learnable embedding. In addition, we compute \( c_t \) by multi-head attention with combined components representation as follows:

\[
\begin{align*}
    h_{i} &= [h^{\text{enc}}; h^{\text{keyword}}] \\
    c_t &= \sum_{i=1}^{n} \alpha_t^{cb}(h_i, W_V^{cb})
\end{align*}
\]

where \( h_{i} \) is equal to \( h_t \) in Equation 2 and \( d_k \) is the dimension of \( h_t \). The context vector \( c_t \) consists of attentions to both the question, entities, relations and SPARQL keywords for current step \( k \).

As for output layer, our decoder is designed to generate an entity, a relation or a SPARQL keyword (eg. COUNT, ASK, FILTER, ORDER BY). In addition, entities and relations will be changeable based on different candidate graph so that we
choose three separate independent layer for different components and then use softmax function to compute the output probability distribution:

\[
\begin{align*}
o^k &= \frac{h_{\text{keyword}}^k([t; e]W^k_{\text{e}})}{\sqrt{d_h}} \\
o^e &= \frac{h_{\text{entity}}^e([t; e]W^e_{\text{e}})}{\sqrt{d_h}} \\
o^r &= \frac{h_{\text{relation}}^r([t; e]W^r_{\text{e}})}{\sqrt{d_h}} \\
\end{align*}
\]

As for loss computing, we compute the output character with ground truth SPARQL query character by the cross entropy loss function.

5 Experimental Results

We implemented our model in PyTorch. We use pretrained model BERT (Devlin et al., 2019) as the embedding layer and set \( h_{\text{keyword}} = 256 \), \( h_{\text{entity}} = h_{\text{relation}} = 768 \). We use 6 relation-aware attention layers to capture graph information. Within attention layers, the hidden size \( d_z \) is set as 256 and the number of head is 8. And we use 2 LSTM layers with 0.2 dropout for decoder and all hidden size \( h_t \) is 512. As for dropout rate, we set 0.1 for all attention layers and 0.2 for LSTM layers. To show that the effectiveness of our model is not mainly due to the use of the pre-trained model, we also experiment replacing BERT with the 200-dimensional Chinese word embedding (Song et al., 2018).

We used the Adam optimizer (Kingma and Ba, 2015) with the default hyperparameters. During the first 2 epochs, the model learning rate linearly increases from 0 to 1 × 10^{-3}. Afterwards, it will be multiplied by 0.8 if the validation loss increases compared with the previous epoch. We use a batch size of 16 and train for up to 15 epochs. When using BERT, we use a separate constant learning rate of 3 × 10^{-6} to fine-tune it, a batch size of 4 and train for up to 25 epochs.

5.1 Baselines

Because there is no model aiming at multi-type KBQA datasets, we modify two state-of-the-art models based on earlier datasets for our model to compare to. Due to limitation of their models, some types of questions cannot be handled, so we test them with specific types of questions.

**AQG-net** proposed by Chen et al. (2020) first uses a neural network-based generative model to generate an abstract query graphs that describes logical query structures, filling up it with all possible candidate permutations and then utilizes existing ranking model to get the most suitable query. In our experiment, we redesign the abstract query graphs due to the question types and relations are different and more complicated.

**Multi-hop QGG** proposed by Lan and Jiang (2020) explores a new strategy to expand the candidate query graph with both constraints and core paths. And it applies the REINFORCE algorithm to learn a policy function by using the F1 score of the predicted score with respect to the ground truth answers as reward. In our experiment, we totally redefine the way of extending the current SPARQL path and adapt the model features to meet the our dataset.

5.2 Evaluation Metrics

We evaluate models from two aspects. First, we use the F1 scores metrics to calculate the accuracy between ground truth answer and answers obtained from predicted SPARQL queries. Second, as semantic parsing methods model aim to predict correct SPARQL queries by question analysis, the answer accuracy can not represent its analytical capability. Instead of simply taking string match, we decompose predicted SPARQL queries into different triples such as (\(?ans1\), \(\text{wd:}P31\), \(\text{wd:}Q22675015\)), (\(?var1\), \(\text{order by, ascend}\)) and compute scores for the triples set using exact set match, which measures whether the predicted query is entirely equivalent to the gold query. The predicted SPARQL query is correct only if all of the components are right. Because we employ a triples set comparison, this exact matching metric is invariant to the order of the components.

5.3 Overall Result

**LC-QuAD 2.0** We report the overall results of our approach and others on LC-QuAD 2.0 in Table 5. Our method achieves the performance of 55.4% query exact match scores and 59.3% answer F1 scores, which is better than other methods. This demonstrates the effectiveness of our approach and that the text-to-SPARQL method can handle the semantics of multi-type questions to generate complex SPARQL queries. Furthermore, from the ablation study, we find that model without BERT has 7.0% decline but still achieves state-of-the-art. This shows that the effectiveness of our model is
Table 5: Performance of various methods over all answers and all queries on both LC-QuAD 2.0 and CLC-QuAD.

|                     | LC-QuAD 2.0 |               | CLC-QuAD |               |
|---------------------|-------------|---------------|----------|---------------|
|                     | answer F1   | query match   | answer F1| query match   |
| AQG-net [13]        | 44.9        | 37.4          | 38.5     | 32.1          |
| Multi-hop QGG [12]  | 52.6        | 43.2          | 46.5     | 39.7          |
| Our approach + Tencent Word | 52.9    | 48.4          | 45.6     | 40.2          |
| Our approach + Bert | 59.3        | 55.4          | 51.8     | 45.4          |
| w/o graph relation-aware self-attention | 50.1 | 46.6          | 42.0     | 36.7          |
| w/o decoder separate attention | 55.5 | 51.2          | 48.9     | 42.7          |

Table 6: Performance of various question types on CLC-QuAD. Some item is empty which represent that model can not deal with such type questions.

| Split                          | Dual | Boolean | Fact | Max/Minimum | COUNTING | Qualifier |
|--------------------------------|------|---------|------|-------------|----------|-----------|
| AQG-net [13]                   | -    | 50.6    | 34.3 | 41.2        | 25.8     | 17.2      |
| Multi-hop QGG [12]             | -    | -       | 42.3 | 45.4        | -        | 25.6      |
| **Our approach**               | **51.3** | **55.3** | **46.6** | **47.1** | **30.1** | **18.8** |

not simply because of the use of BERT. We also test two components of our method. Without the relation-aware self attention, the score is nearly 9% lower and it shows that the information of knowledge graph is very important to the model and the relation-aware self attention can effectively encode the items in the graph. Without the separate attention in pointer networks, the model has a little drop in results.

**CLC-QuAD** Table 5 also shows the results of models in our new dataset CLC-QuAD. Similar to LC-QuAD 2.0, our model with BERT achieves 51.8% answer F1 score and 45.4% query exact matching accuracy. In addition, we find that all models get pretty weak scores compared with results in LC-QuAD 2.0. In the results of our approach with BERT, there is 10% decline which is a huge gap. This demonstrates that the Chinese representation is still a big challenge for model semantic parsing.

In addition, we split our dataset into six question types. Table 6 shows the performance of various question types on CLC-QuAD. We find that there is a huge gap in accuracy between different types of questions. We find that Counting and Qualifier questions are harder due to more complex semantics, which brings challenges to semantic parsing. Our approach achieves 51.3%, 55.3% and 47.1% accuracy in Dual, Boolean and Max/Minimum questions relatively, but the accuracy for Qualifier and Counting questions is only 18.8% and 30.1%. As for other methods, Multi-hop QGG is designed for complex questions with constraints and it achieves best performance in Qualifier questions, but it cannot handle Dual, Boolean and Counting questions. AQG-net is designed to generate abstract query graphs, which can answer most of types questions, but the performance is inferior to our proposed approach. This also demonstrates our model is more competitive in answering different types of questions.

6 Conclusion

In this paper, we introduced CLC-QuAD, a large-scale dataset of Chinese Complex Knowledge base question answer dataset. The dataset features wide coverage with regard to question semantics and types. To improve semantic parsing research with large knowledge graph, our dataset provided the pair of a question and its corresponding SPARQL query based on Wikidata. In addition, we proposed a multi-type KBQA model by generating the SPARQL query directly. This approach achieves state of the art on LC-QuAD 2.0 and CLC-QuAD.

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