Graph-level Semantic Matching model for Knowledge base Aggregate Question Answering

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ABSTRACT

In knowledge base question answering, complex question always has long-distance dependencies, especially aggregate question, which affects query graph matching. Many previous approaches have made conspicuous progress in complex question answering. However, they mostly only compare based on the textual similarity of the predicate sequences, ignoring the degree of semantic information either questions or query graphs. In this paper, we propose a Graph-level Semantic Matching (GSM) model to obtain the global semantics representation. Due to the structural complexity of query graphs, we propose a global semantic model to explicitly encode the structural and relational semantics of query graphs. Then, a question-guiding mechanism is applied to enhance the understanding of question semantics in query graph representation. Finally, GSM outperforms existing question answering models, and exhibits capabilities to deal with aggregate questions, e.g., correctly handling counting and comparison in questions.

CCS CONCEPTS

• **Computing methodologies → Information extraction**; *Semantic networks.*

KEYWORDS

aggregate question answering, global semantics, graph encoding

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1 INTRODUCTION

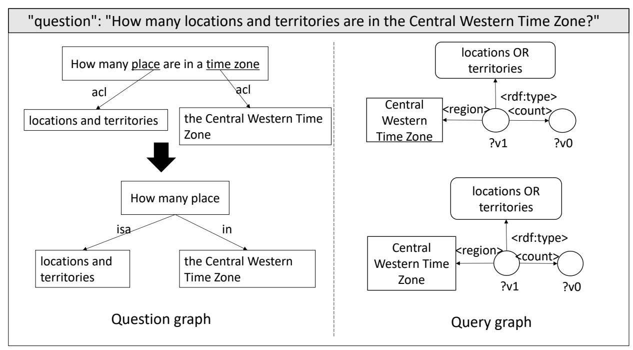

Figure 1: Graph Structure for Long Dependency Question

Question answering over knowledge bases (KBQA) aims to answer questions through external Knowledge Base (KB). Previous KBQA methods based on semantic parsing mainly parse the question into multiple candidate query graphs, and select the query graph with the highest similarity to the question as the final query graph. The general idea is to encode the query graph and the question separately, and compare them based on the textual similarity of the predicate sequence. Although previous methods have made significant progress in solving simple questions, they are clearly insufficient for complex questions. On the one hand, questions are a form of text sequences with long dependencies and lack structured semantic interpretation. On the other hand, query graph structures corresponding to complex questions are diverse and indistinguishable, often containing multiple entities, constraints and aggregation operations. As shown in Figure 1, we present the long-distance dependencies of the question and query graphs separately in the form of graphs. In previous studies, some methods represented the query graph in a linear form, specifically decomposing the query graph into a sequence of predicates [3] or relational paths [4] at each hop for one-to-one comparison. Some methods[2] used structure as a constraint to filter query graphs that do not satisfy the conditions. All of the above methods ignore the the degree of semantic information either questions or query graphs.

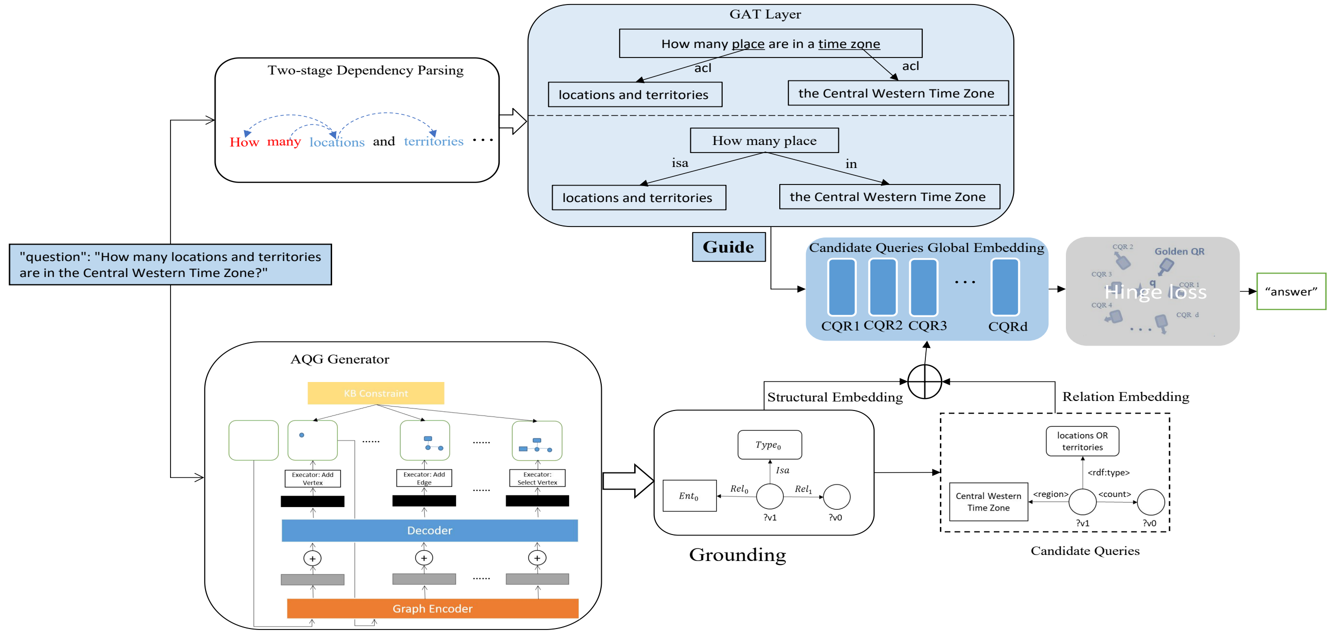

Figure 2: Overview of proposed Framework.

For the purpose of overcoming this problem, we propose a Graph-level Semantic Matching (GSM) model. The model consists of two neural networks, one for question encoding and the other for query graph encoding. ignoring the differences in structure and relational semantics representation between them. Firstly, we apply a question-guiding mechanism to enhance the understanding of question semantics in query graph representation. Additionally, we explore two-stage dependency parsing to process the question into a graph structure and encode it using a relational context model based on graph attention mechanism. This structured representation helps resolve long dependencies and disambiguate. Finally, because the query graph structure of complex problems is complex, we propose a global semantic model to explicitly encode the structural semantics and relational semantics of the query graph, which avoids the loss of rich structural information.

In a nutshell, our contributions are as follows:

- We propose a graph-level semantic matching model, where a question-guiding mechanism is used to enhance the understanding of question semantics in query graph representations.
- We process the question into a graph structure and encode it using graph attention network based relational context model.
- We propose a global semantic representation model to explicitly encode the structural and relational representations of query graphs.

2 APPROACH

Our proposed GSM model consists of three parts: query graph representation, question representation, question-guided query representation. We will describe these three modules in detail below.

Table 1: Class labels for vertices and edges in AQG

Class	Instances	Symbol
Entity	*LeonardoDiCaprio*, · · ·	rectangle
Type	Profession, Country, University, · · ·	rounded rectangle
Number	1998, 23, · · ·	diamond
Variable	?v0, ?v1, · · ·	circle
Isa	rdf:type	–
Comparison	<, >, =	–
Relation	⟨birthplace⟩, ⟨nationality⟩, · · ·	–
Count	count	–
Order	max _at_ n, min _at_ n	–

2.1 Query Graph Representation

In this paper, we propose a global semantic representation module to simultaneously learn the structural and relational representations of query graphs. Specifically, we use Abstract Query Graph (AQG) [2] as structural semantics and apply Graph Transformer for encoding. AQG is essentially a tree consisting of n vertices and $n-1$ edges, denoted by $g = (v, e)$. Here, $v = \{"Ent", "Type", "Num", "Var"\}$ and $e = \{"Rel", "Ord", "Cmp", "Cnt", "Isa"\}$, all the labels in AQG correspond to classes for vertices and edges in AQG (see Table 1). The input to the graph transformers model consists of a vertex set V, i.e. the union of vertices v and edges e in AQG, an adjacency matrix E describing whether there is a connection between vertices. v_i is randomly initialized with the corresponding class label vector.

Graph transformer model improves upon Graph Attention Networks (GATs) by adding residual connections between layers. Each node v_i is represented by a weighted average of its neighbors:

$$\hat{\mathbf{v}}_i = \mathbf{v}_i + \|_{n=1}^{N} \sum_{v_j \in \mathcal{N}_i} \alpha_{i,j}^{n} \mathbf{W}_{0,n} \mathbf{v}_j \tag{1}$$

$$\alpha_{i,j}^{n} = softmax((\mathbf{W}_{1,n}\mathbf{v}_i)^T(\mathbf{W}_{2,n}\mathbf{v}_j)) \tag{2}$$

Here, $\|_{n=1}^{N}$ represents the concatenation of N attention heads, $\mathcal{N}_i$ represents the neighbor node of v_i, $\alpha_{i,j}^{n}$ means the attention weight. By weighting vertices and edges in AQG, we obtain a global representation of the graph, denoted by $h_{structure}$.

To enhance relational informativeness, we introduce relational contextual information. That is, we construct a relational adjacency graph L_G for each candidate query graph G, where vertices in L_G correspond to relations in G. For every two edges in G with a common vertex, an edge is connected between the corresponding vertices in the L_G. Edges in the L_G have no direction and label, we simply encode these nodes using a graph attention network (GAT):

$$h_{r_i}^{(l+1)} = \bigoplus_{k=1}^{K} \sigma\left(\sum_{r_j \in N_{r_i}^{L}} a_{ij}^{k} W^{k} r_j^{(l)}\right) \tag{3}$$

where $\bigoplus$ means concat and σ is a nonlinear function. $N_{r_i}^{L}$ is the set of r_i neighbor nodes of r_i. W^k is the corresponding linear transformation matrix of Kth head. a_{ij}^{k} represents the attention values of the neighbors of the vertex r_i in the Kth-head attention mechanism:

$$a_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(a^T\left[W_v w_i \oplus W_v w_j\right]\right)\right)}{\sum_{k \in N_i} \exp\left(\text{LeakyReLU}\left(a^T\left[W_v w_i \oplus W_v w_k\right]\right)\right)} \tag{4}$$

Based on the average word embedding, we obtain the initial embedding of each relationr_i. By max-pooling, we obtain the relational semantics $h_{relational}$ of the query graph. Combined with the extracted structural semantics $h_{structure}$, the global semantics of the query graph is the sum of $h_{structure}$ and $h_{relational}$:

$$h_{global} = h_{structure} + h_{relational}.$$

2.2 Question Representation

To convert the question to an uninstantiated graph-structured query, we follow the approach of Sun et al [6]. Considering that standard dependency parsing of complex questions is error-prone, we employ higher-level dependency parsing, representing complex questions as relations between text spans, with the help of skeleton grammar− − −a subset extracted from a dependency grammar. Standard dependency parsing for each text span is then combined for relation extraction. The accuracy of text span level dependency parsing is above 97%. This two-stage dependency parsing helps to distinguish the backbone and other parts of the complex question from the level of hierarchy and alleviate the impact of long-distance dependencies on semantics. For identifying nodes, we treat it as a sequence labeling problem. Similarly, given nodes,relations, and coreferences, we treat it as a graph for global encoding following the GAT model, as shown in Equ.(3)(4).

2.3 Question-Guided Query Representation

To enhance the understanding of question semantics in query graph representation, we apply question-guided query representation to fusion the semantics information of questions. Intuitively, we believe that questions contribute to the generation of query representations, so the query Q_i can be guided by the question q_i. We use the averaged question representation $h_{question}$ extracted from the question encoder as a base vector to generate two guide vectorsβ_i and γ_i. More specifically, question representation $h_{question}$ are projected onto two separate spaces.

$$\beta_i = \text{ReLU}\left(FFN_1(h_{question}^{i})\right) \tag{5}$$

$$\gamma_i = \text{ReLU}\left(FFN_2(h_{question}^{i})\right). \tag{6}$$

The question-guided attention can be calculated by the γ_i and β_i as follows.

$$w_i = (norm(h_{global}) \odot \gamma_i + \beta_i). \tag{7}$$

where $norm(\cdot)$ denotes normalization and $\odot$ is element-wise product. Finally, we can obtain the optimized representation as follows:

$$Q_i = \text{softmax}(\lambda w_i) \odot w_i \tag{8}$$

where λ is a smoothed hyper-parameter.

In the training phase, we adopt *hinge loss* to optimize the maximum margin. Formally, for an question q and its query graph set C , we encode the positive candidate query graph and negative candidate queries graph into their representation Q_P and Q_N, which are concatenated.

$$\mathcal{L} = \max \sum_{Q_i \in C} (0, (\theta - \cos(q, Q_P) + \cos(q, Q_N))). \tag{9}$$

where θ is a hyper-parameter which measures the margin between positive and negative instances.

Further, it overcomes the following limitations in distinguishing the two semantically similar relationships at the word level, where the existing query graph scoring methods are all based on the cosine similarity calculation at the word level, and often measure the similarity of the two at the relationship level.

3 EXPERIMENTS

We conduct experiments on the gold standard complex question answering datasets **LC-QuAD**[7], **QALD**[8]. We compare GSM model with several models. These methods are representative of various mechanisms for semantic parsing in KBQA. STAGG [9] describes the structure of query graphs based on manual features to generate the final answer SPARQL. HR-BiLSTM [10] uses a maximum pool to obtain fine-grained relational semantics. Luo et al. [3] is based on fine-grained and relational semantics to capture the interactions between various semantic units in complex questions. GGNN [5] enriches the semantics of each entity through average relational semantics. Slot-matching [4] and DAM [1] compute different attention values based on self-attention to sort query graphs, taking the top graph as the final answer. AQG-Net [2] first generates the query graph structure, and then uses this as a constraint to generate the query graph.

Table 2 shows our experimental results. Our approach made significant progress. It contains three modules: global semantics for query graphs, graph representation of questions, and question-guided matching model. To evaluate the effectiveness of each module, we conduct an ablation study. Here, w/o Global Semantics (GS) means that only the relational representation of the query graph is

Table 2: Performance on LC-Quad and QALD. * denotes our reproduced results.

	LC-QuAD			QALD		
	P	R	F1	P	R	F1
STAGG[9]	0.63	0.75	0.69	0.19	0.24	0.19
HR-BiLSTM[10]	0.64	0.77	0.70	0.20	0.19	0.19
Luo et al.(2018)[3]	0.64	0.75	0.69	0.21	0.24	0.20
GGNN[5]	0.66	**0.78**	0.71	0.22	0.28	0.21
Slot-Matching[4]	0.66	0.77	0.71	0.22	0.38	0.28
DAM[1]	0.65	0.77	0.71	0.28	**0.43**	0.34
AQG-Net*[2]	**0.76**	0.75	**0.76**	0.30	0.37	0.33
CSM(Ours)	0.71	0.73	0.72	**0.38**	0.39	**0.38**
w/o GS	0.69	0.72	0.71	0.28	0.36	0.32
w/o QS	0.70	0.72	0.71	0.31	0.37	0.34
w/o SM	0.67	0.71	0.69	0.27	0.35	0.30

Table 3: Precision (P), Recall (R) and F1-scores (F1) for aggregate question subsets of LC-QuAD.

	P	R	F1
CSM	0.72	0.76	0.74
w/o GS	0.70	0.70	0.70
w/o QS	0.71	0.73	0.72
w/o SM	0.67	0.72	0.69

considered, and the structural information is not considered, w/o Question Representation (QR) means using sequence encoding like LSTM, not using graph encoding, w/o Semantic Matching (SM) means that no guidance mechanism is employed and only the relational representation of the query graph is used. From the table, we can see that global semantics plays a very important role, and the effect of question-guided matching model is also significant. In contrast, the optimization of question representation brings progress, but it is not so significant.

Although our results did not achieve the best results on LC-QuAD, we did achieve the best results on QALD, indicating that our approach has a greater advantage in solving complex problems. Ablation results were also better than most baselines. Moreover, after semantic matching is removed, the effect of our model declines most sharply, which indicates that semantic matching plays a very important role in the knowledge base aggregate question answering task.

To verify the effectiveness of our method on aggregate questions, we filter out some typical aggregation questions from LC-QuAD dataset, including counting questions, comparison numerical questions, maximum and minimum questions. Similarly, from Table 3, we can also see that the global semantics of the graph and the matching model play important roles.

4 CONCLUSION

In this paper, we propose GSM, an end-to-end question answering model to learn both structural and relational representations of query graphs. Our key innovations include (*i*) a global semantic model to explicitly encode the structural and relational semantics of query graphs, and (*ii*) a question-guiding mechanism to enhance the understanding of question semantics in query graph representations. Through both quantitative and qualitative analyses, we showed the improvement of GSM over existing models on question answering tasks.

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