SADGA: Structure-Aware Dual Graph Aggregation Network for Text-to-SQL

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Abstract

The Text-to-SQL task, aiming to translate the natural language of the questions into SQL queries, has drawn much attention recently. One of the most challenging problems of Text-to-SQL is how to generalize the trained model to the unseen database schemas, also known as the cross-domain Text-to-SOL task. The key lies in the generalizability of (i) the encoding method to model the question and the database schema and (ii) the question-schema linking method to learn the mapping between words in the question and tables/columns in the database schema. Focusing on the above two key issues, we propose a Structure-Aware Dual Graph Aggregation Network (SADGA) for cross-domain Text-to-SQL. In SADGA, we adopt the graph structure to provide a unified encoding model for both the natural language question and database schema. Based on the proposed unified modeling, we further devise a structure-aware aggregation method to learn the mapping between the question-graph and schema-graph. The structure-aware aggregation method is featured with Global Graph Linking, Local Graph Linking and Dual-Graph Aggregation Mechanism. We not only study the performance of our proposal empirically but also achieved 3rd place on the challenging Text-to-SQL benchmark Spider at the time of writing.

1 Introduction

Structured Query Language (SQL) has become the standard database query language for a long time, but the difficulty of writing still hinders the non-professional user from using SQL. The Text-to-SQL task tries to alleviate the hinders by automatically generating the SQL query from the natural language question. With the development of deep learning technologies, Text-to-SQL has achieved great progress recently [6, 16, 35, 31].

Many existing Text-to-SQL approaches have been proposed for particular domains, which means that both training and inference phases are under the same database schema. However, it is hard for database developers to build the Text-to-SQL model for each specific database from scratch because of the high annotation cost. Therefore, cross-domain Text-to-SQL, aiming to generalize the trained model to the unseen database schema, is proposed as a more promising solution [13, 4, 5, 29, 8, 24, 21, 7]. The core issue of cross-domain Text-to-SQL lies in building the linking between the natural language question and database schema, well-known as the question-schema linking problem [13, 29, 21, 19, 37].

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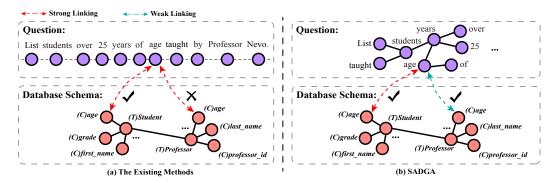


Figure 1: A toy example. The left part is about some existing approaches, e.g., IRNet [13], RATSQL [29], which usually treat the question as a sequence and apply the string matching method or attention mechanism to build the question-schema linking, causing that word "age" has a strong linking with both column "age" of table "Student" and column "age" of table "Professor" (the red arrow). The right part is about our SADGA. We treat both the question and schema as the graph structure to eliminate the structure gap during linking, and use SADGA to explore the local structure to help build the linking, successfully removing the candidate linking between word "age" and column "age" of table "Professor" (the green arrow).

There are two categories of efforts to solve the aforementioned question-schema linking problem — matching-based method [13] and learning-based method [29, 21, 19, 7]. IRNet [13] is a typical matching-based method, which uses a simple yet effective string matching approach to link question words and tables/columns in the schema. RATSQL [29] is a typical learning-based method, which applies a relation-aware transformer to globally learn the linking over the question and schema with predefined relations. However, both of the above two categories of methods still suffer from the problem of insufficient generalization ability. There are two main reasons for the above problem: first, the structure gap between the encoding process of the question and database schema: as shown in Figure 1, most of the existing approaches treat the question as a sequence and learn the representation of the question by sequential encoders [13, 4, 5] or transformers [29, 30, 21], while the database schema is the structured data whose representation is learned based on graph encoders [7, 4, 5] or transformers with predefined relations [29, 30]. Such the structure gap leads to difficulty in adapting the trained model to the unseen schema. Second, highly relying on predefined linking maybe result in unsuitable linking or the latent linking to be undetectable. Recalling the example in Figure 1, some existing works highly rely on the predefined relations or self-supervised learning on question-schema linking, causing the wrong strong linking between word "age" and column "age" of table "Professor" while based on the semantics of the question, word "age" should be only linked to the table "Student". Regarding the latent association, it refers to the fact that some tables/columns do not attend exactly in the question while they are strongly associated with the question, which is difficult to be identified. Such undetected latent association also leads to the low generalization ability of the model.

Aiming to alleviate these above limitations, we propose a Structure-Aware Dual Graph Aggregation Network (SADGA) for cross-domain Text-to-SQL to fully take advantage of the structural information of both the question and schema. We adopt a unified graph neural network encoder to model both the natural language question and schema. On the question-schema linking across question-graph and schema-graph, SADGA is featured with *Global Graph Linking*, *Local Graph Linking* and *Dual-Graph Aggregation Mechanism*. In the *Global Graph Linking* phase, the query nodes on question-graph or schema-graph calculate the attention with the key nodes of the other graph. In the *Local Graph Linking* phase, the query nodes will calculate the attention with neighbor nodes of each key node across the dual graph. In the *Dual-Graph Aggregation mechanism*, the above two-phase linking processes are aggregated in a gated-based mechanism to obtain a unified structured representation of nodes in question-graph and schema-graph. The contributions are summarized as follows:

- We propose a unified dual graph framework SADGA to interactively encode and aggregate structural information of the question and schema in cross-domain Text-to-SQL.
- In SADGA, the structure-aware dual graph aggregation is featured with *Global Graph Linking, Local Graph Linking* and *Dual-Graph Aggregation Mechanism*.

• We conduct extensive experiments to study the effectiveness of SADGA. Especially, SADGA outperforms the baseline methods and achieves 3rd place on the challenging Text-to-SQL benchmark Spider ² [36] at the time of writing. Our implementation will be open-sourced at https://github.com/DMIRLAB-Group/SADGA.

2 Model Overview

We provide the overview of our proposed overall model in Figure 2. As shown in the figure, our model follows the typical encoder-decoder framework. There are two components of the encoder, Structure-Aware Dual Graph Aggregation Network (SADGA) and Relation-Aware Transformer (RAT) [29].

The proposed SADGA consists of dual-graph construction, dual-graph encoding and structure-aware aggregation. In the workflow of SADGA, we first construct the question-graph based on the contextual structure and dependency structure of the question, and build the schema-graph based on database-specific relations. Second, a graph neural network is employed to encode the question-graph and schema-graph separately. Third, the structure-aware aggregation method learns the alignment across the dual graph through two-stages linking, and the information is aggregated in a gated-based mechanism to obtain a unified representation of each node in the dual graph.

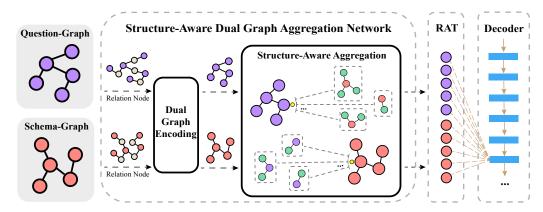


Figure 2: The overview of the proposed model.

RAT [29] tries to further unify the representations learned by our SADGA by encoding the question words and tables/columns with the help of predefined relations. RAT is an extension of Transformer [28], which introduces prior knowledge relations to the self-attention mechanism (see Appendix A.2). Different from the work of Wang et al. [29] with more than 50 predefined relations, the RAT of our work only uses 14 predefined relations, the same as those used by SADGA (Section 3.1). The small number of predefined relations also ensures the generalization ability of our method.

In the decoder, we follow the tree-structured architecture of Yin and Neubig [33], which transforms the SQL query to an abstract syntax tree in depth-first traversal order. First, we apply an LSTM [15] to output a sequence of actions that generates the abstract syntax tree; then, the abstract syntax tree is transformed to the sequential SQL query. These LSTM output actions are either schema-independent (the grammar rule) or schema-specific (table/column). Readers can refer to Appendix C for details.

3 Structure-Aware Dual Graph Aggregation Network

In this section, we will delve into the Structure-Aware Dual Graph Aggregation Network (SADGA), including Dual-Graph Construction, Dual-Graph Encoding and Structure-Aware Aggregation. The aggregation method consists of *Global Graph Linking*, *Local Graph Linking* and *Dual-Graph Aggregation Mechanism*. These three steps introduce the global and local structure information on question-schema linking. The details of each component are as follows.

²https://yale-lily.github.io/spider

3.1 Dual-Graph Construction

In SADGA, we adopt a unified dual-graph structure to model the question, schema and predefined linkings between question words and tables/columns in the schema. The details of the generation of question-graph, schema-graph and predefined cross-graph relations are as follows.

Question-Graph A question-graph can be represented by $\mathcal{G}_Q = (Q,R_Q)$, where the node set Q represents the words in the question and the set R_Q represents the dependencies among words. As shown on the left side of Figure 3, there are three different types of links, 1-order word distance dependency (i.e., two adjacent words have this relation), 2-order word distance dependency, and the parsing-based dependency. The parsing-based dependency is to capture the specific grammatical relationships among words in the natural language question, such as the clausal modifier of noun relationship in the left side of Figure 3, which is constructed by applying Stanford CoreNLP toolkit [22].

Schema-Graph Similarly, a schema-graph can be represented by $\mathcal{G}_S = (S, R_S)$, where the node set S represents the tables/columns in the database schema and the edge set R_S represents the structural relations among tables/columns in the schema. We use some typical database-specific relations, such as the primary-foreign key for column-column pairs. The right side of Figure 3 shows an example of a schema-graph, where we focus only on the linking from the column "professor_id".

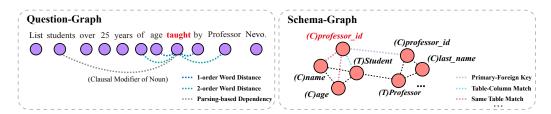


Figure 3: The construction of Question-Graph and Schema-Graph.

Cross-Graph We also introduce cross-graph relations to capture the connection between question-graph and schema-graph. There are two main rules to generate relations, exact string match and partial string match, which are borrowed from RATSQL [29]. We use these two rules for word-table and word-column pairs to build relations. Besides, for word-column pairs, we also use the value match relation, which means if the question presents a value word in the database column, there is the value match relation between the value word and the corresponding column. Note that these cross-graph relations are used only in Structure-Aware Aggregation (Section 3.3).

Moreover, all predefined relations in dual-graph construction are undirected. These relations are described in detail in Appendix B.

3.2 Dual-Graph Encoding

After the question-graph and schema-graph are constructed, we employ a Gated Graph Neural Network (GGNN) [20] to encode the node representation of the dual graph by performing message propagation among the self-structure before building the linking across the dual graph. The details of the GGNN we apply are presented in Appendix A.1. Inspired by Beck et al. [3], instead of representing multiple relations on edges, we represent the predefined relations of question-graph and schema-graph on nodes to reduce trainable parameters. Concretely, if node A and node B have a relation R, we introduce an extra node R into the graph and link R to both A and B using undirected edges. There is no linking across the dual graph in this phase. Each relation node is initialized to the learnable vector of the corresponding relation. In addition, we define three basic edge types for GGNN updating, i.e., bidirectional and self-loop.

3.3 Structure-Aware Aggregation

Following with dual-graph encoding, we devise a structure-aware aggregation method on question-schema linking between question-graph \mathcal{G}_Q and schema-graph \mathcal{G}_S . The aggregation process is

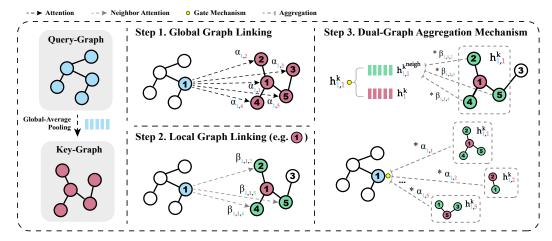


Figure 4: The Structure-Aware Aggregation procedure. We show the case when the 1st node in the query-graph acts as the query node. The query node attends to the key node and the neighbor nodes of the key node.

formulated as

$$\mathcal{G}_{Q}^{Aggr} = \operatorname{GraphAggr}(\mathcal{G}_{Q}, \mathcal{G}_{S}), \quad \mathcal{G}_{S}^{Aggr} = \operatorname{GraphAggr}(\mathcal{G}_{S}, \mathcal{G}_{Q}).$$
 (1)

As shown in Eq. 1, the structure-aware aggregation method is applied to aggregate information from schema-graph \mathcal{G}_S and question-graph \mathcal{G}_Q to the other graph, respectively. We illustrate the detailed approach in the manner of query-graph \mathcal{G}_q and key-graph \mathcal{G}_k , i.e.,

$$\mathcal{G}_q^{Aggr} = \operatorname{GraphAggr}(\mathcal{G}_q, \mathcal{G}_k). \tag{2}$$

Let $\{\boldsymbol{h}_i^q\}_{i=1}^m$ be a set of node embedding in the query-graph \mathcal{G}_q and $\{\boldsymbol{h}_j^k\}_{j=1}^n$ be a set of node embedding in the key-graph \mathcal{G}_k , which both learned by dual-graph encoding. Figure 4 shows the whole procedure of the structure-aware aggregation method regarding how the information from the key-graph is utilized to update the query-graph at the global and local structure level. First, we use global-average pooling on the node embedding \boldsymbol{h}_i^q of query-graph \mathcal{G}_q to get the global query-graph embedding \boldsymbol{h}_{glob}^q . Then, in order to capture globally relevant information, the key node embedding \boldsymbol{h}_i^k is updated as follows:

$$\boldsymbol{h}_{glob}^{q} = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{h}_{i}^{q}, e_{j} = \theta \left(\boldsymbol{h}_{glob}^{q} \boldsymbol{W}_{g} \boldsymbol{h}_{j}^{k} \right), \tag{3}$$

$$\boldsymbol{h}_{j}^{k} = (1 - e_{j})\boldsymbol{W}_{qg}\boldsymbol{h}_{glob}^{q} + e_{j}\boldsymbol{W}_{kg}\boldsymbol{h}_{j}^{k}, \tag{4}$$

where W_g , W_{qg} , W_{kg} are trainable parameters and θ is a sigmoid function. e_j represents the relevance score between the j-th key node and the global query-graph. The above aggregation process is inspired by Zhang et al. [40]. Our proposed structure-aware aggregation method further introduces the global and local structural information through three primary phases, including Global Graph Linking, Local Graph Linking and Dual-Graph Aggregation Mechanism.

Global Graph Linking Global Graph Linking is to learn the linking between each query node and the global structure of the key-graph. Inspired by the relation-aware attention [29], we calculate the global attention score $\alpha_{i,j}$ between query node embedding \boldsymbol{h}_i^q and key node embedding \boldsymbol{h}_j^k as follows:

$$s_{i,j} = \sigma\left(\boldsymbol{h}_{i}^{q} \boldsymbol{W}_{q} \left(\boldsymbol{h}_{j}^{k} + \boldsymbol{R}_{ij}^{E}\right)^{T}\right), \alpha_{i,j} = \operatorname{softmax}_{j} \left\{s_{i,j}\right\},$$
 (5)

where σ is a nonlinear activation function and R_{ij}^E is the learned feature to represent the predefined cross-graph relation between *i*-th query node and *j*-th key node. The cross-graph relations have already been introduced in Cross-Graph of Section 3.1.

Local Graph Linking Local Graph Linking is designed to introduce local structure information on dual graph linking. In this phase, the query node calculates the attention with neighbor nodes of the key node across the dual graph. Specifically, we calculate the local attention score $\beta_{i,j,t}$ between i-th query node and t-th neighbor node of j-th key node, formulated as

$$o_{i,j,t} = \sigma \left(\mathbf{h}_i^q \mathbf{W}_{nq} \left(\mathbf{h}_t^k + \mathbf{R}_{it}^E \right)^T \right), \beta_{i,j,t} = \operatorname{softmax}_t \left\{ o_{i,j,t} \right\} (t \in \mathcal{N}_j),$$
 (6)

where \mathcal{N}_{j} represents the neighbors of the j-th key node.

Dual-Graph Aggregation Mechanism Global Graph Linking and Local Graph Linking phase process are aggregated with Dual-Graph Aggregation Mechanism to obtain the unified structured representation of each node in the query-graph. First, we aggregate the neighbor information with the local attention scores $\beta_{i,j,t}$, and then apply a gate function to extract essential features among the key node self and the neighbor information. The process is formulated as

$$\boldsymbol{h}_{i,j}^{k^{\text{neigh}}} = \sum_{t=1}^{T} \beta_{i,j,t} \boldsymbol{h}_{t}^{k}, \quad \boldsymbol{h}_{i,j}^{k^{\text{self}}} = \boldsymbol{h}_{j}^{k}, \tag{7}$$

$$gate_{i,j} = \theta\left(\boldsymbol{W}_{ng}\left[\boldsymbol{h}_{i,j}^{k^{self}}; \boldsymbol{h}_{i,j}^{k^{neigh}}\right]\right), \tag{8}$$

$$\boldsymbol{h}_{i,j}^{k} = (1 - \text{gate}_{i,j}) * \boldsymbol{h}_{i,j}^{k^{\text{self}}} + \text{gate}_{i,j} * \boldsymbol{h}_{i,j}^{k^{\text{neigh}}},$$
(9)

where $h_{i,j}^{k^{\mathrm{neigh}}}$ represents the neighbor context vector and $h_{i,j}^k$ indicates the j-th key node neighbor-aware feature toward i-th query node. Finally, each query node aggregates the structure-aware information from all key nodes with the global attention score $\alpha_{i,j}$:

$$\boldsymbol{h}_{i}^{q^{\text{new}}} = \sum_{j=1}^{n} \alpha_{i,j} \left(\boldsymbol{h}_{i,j}^{k} + \boldsymbol{R}_{ij}^{E} \right), \tag{10}$$

$$gate_{i} = \theta \left(\mathbf{W}_{gate} \left[\mathbf{h}_{i}^{q}; \mathbf{h}_{i}^{q^{new}} \right] \right), \tag{11}$$

$$\boldsymbol{h}_{i}^{q^{\text{Aggr}}} = (1 - \text{gate}_{i}) * \boldsymbol{h}_{i}^{q} + \text{gate}_{i} * \boldsymbol{h}_{i}^{q^{\text{new}}}, \tag{12}$$

where $gate_i$ indicates how much information the query node should receive from the key-graph. Consequently, we obtain the final query node representation $h_i^{q^{Aggr}}$ with the structure-aware information of the key-graph.

4 Experiments

In this section, we conduct experiments on the Spider dataset [36], the benchmark of cross-domain Text-to-SQL, to evaluate the effectiveness of our model.

4.1 Experiment Setup

Dataset and Metrics The Spider has been so far the most challenging benchmark on cross-domain Text-to-SQL, which contains 9 traditional specific-domain datasets, such as ATIS [10], GeoQuery [38], WikiSQL [1], IMDB [32] etc. It is split into the train set (8659 examples), development set (1034 examples) and test set (2147 examples), which are respectively distributed across 146, 20 and 40 databases. Since the fair competition, the Spider official has not released the test set for evaluation. Instead, participants must submit the model to obtain the test accuracy for the official non-released test set through the submission scripts provided officially by Yu et al. [36].³

Embedding Initialization The pre-trained methods initialize the input embedding of question words and tables/columns. Specifically, in terms of the pre-trained vector, GloVe [23] is a common choice for the embedding initialization. And regarding the pre-trained language model (PLM), BERT [12] is also the mainstream embedding initialization method. In detail, BERT-base, BERT-large are applied according to the model scale. Additionally, the specific-domain pre-trained language

³Only submit up to two models per submission (at least two months before the next submission).

Table 1: Accuracy	results on the S	Spider develo	pment set and test set.

Approach	Dev	Test	Approach	Dev	Test
GNN [4]	40.7	39.4	RATSQL-HPFT + BERT-large	69.3	64.4
Global-GNN [5]	52.7	47.4	YCSQL + BERT-large	-	65.3
IRNet v2 [13]	55.4	48.5	DuoRAT + BERT-large [25]	69.4	65.4
RATSQL [29]	62.7	57.2	RATSQL + BERT-large [29]	69.7	65.6
SADGA	64.7	-	SADGA + BERT-large	71.6	66.7
EditSQL + BERT-base [39]	57.6	53.4	ShadowGNN + RoBERTa [8]	72.3	66.1
GNN + Bertrand-DR [17]	57.9	54.6	RATSQL + STRUG [11]	72.6	68.4
IRNet v2 + BERT-base [13]	63.9	55.0	RATSQL + GraPPa [37]	73.4	69.6
RATSQL + BERT-base [29]	65.8	-	RATSQL + GAP [27]	71.8	69.7
SADGA + BERT-base	69.0	-	SADGA + GAP	73.1	70.1

models, e.g., GAP [27], GraPPa [37], STRUG [11] are also applied for better taking advantage of prior Text-to-SQL knowledge. Due to the limited resources, we conducted experiments with four pre-trained methods, GloVe, BERT-base, BERT-large and GAP, to understand the significance of SADGA.

Implementation We trained our models on one server with a single NVIDIA GTX 3090 GPU. We follow the original hyperparameters of RATSQL [29] that uses batch size 20, initial learning rate 7×10^{-4} , max steps 40,000 and the Adam optimizer [18]. For BERT, the initial learning rate is adjusted to 2×10^{-4} , and the max training step is increased to 90,000. We also apply a separate learning rate of 3×10^{-6} to fine-tune BERT. For GAP, we follow the original settings in Shi et al. [27]. In addition, we stack 3-layer SADGA followed by 4-layer RAT. More details about the hyperparameters are included in Appendix D.

Table 2: The **BERT-large** accuracy results on Spider development set and test set compared to RAT-SQL by hardness levels defined by Yu et al. [36].

Model	Easy	Medium	Hard	Extra Hard	All
Dev:					
RATSQL	86.4	73.6	62.1	42.9	69.7
SADGA	90.3	72.4	63.8	49.4	71.6
Test:					
RATSQL	83.0	71.3	58.3	38.4	65.6
SADGA	85.1	72.1	57.0	41.7	66.7

4.2 Overall Performance

The exact match accuracy results are presented in Table 1. Almost all results of the baselines are obtained from the official leaderboard. Except, RATSQL [29] does not provide BERT-base as PLM results on the development set, we have experimented with official implementation. As shown as the table, the proposed SADGA model is competitive with the baselines in the identical sub-table. Specifically, regarding the development set, our raw SADGA, SADGA + BERT-base, SADGA + BERT-large and SADGA + GAP all outperform their corresponding baselines. And with the GAP enhancement, our model is competitive with RATSQL + GraPPa as well. While regarding the test set, our models, only available for the BERT-large one and the GAP one, also surpass their competitors. At the time of writing, our best model SADGA + GAP achieved 3rd on the overall leaderboard. Note that our focus lies in developing an efficient base model but not a specific solution for the Spider dataset.

To better demonstrate the effectiveness, our SADGA is evaluated on the development set and test set compared with RATSQL according to the parsing difficulty level defined by Yu et al. [36]. In the Spider dataset, the samples are divided into four difficulty groups based on the number of components selections and conditions of the target SQL queries. As shown in Table 2, our SADGA outperforms the baseline on the **Extra-Hard** level by 6.5% and 3.3% on the development set and test set, respectively, which implies that our model can handle more complicated SQL parsing. This is most likely due to the fact that SADGA adopts a unified dual graph modeling method to consider both the global and local structure of the question and schema, which is more efficient for capturing the complex semantics of questions and building more exactly linkings in hard cases. The result also indicates that SADGA and RATSQL achieved the best of **Medium** and **Hard** on the test set,

respectively, but in the development set it is switched. It is an interesting finding that SADGA and RATSQL are adversarial and preferential in **Medium** and **Hard** levels data. After the statistics, we found that the distribution of data in the **Medium** and **Hard** levels changed from the development set to the test set (**Medium** 43.1% to 39.9%, **Hard** 16.8% to 21.5%), which is one of the reasons. And another reason we guess is that the target queries for these two types of data are relatively close to each other. Both **Medium** and **Hard** levels are mostly the join queries, but the **Extra-Hard** level is mostly nested queries.

4.3 Ablation Studies

Table 3: Accuracy of ablation studies on the Spider development set by hardness levels.

Model	Easy	Medium	Hard	Extra Hard	All
SADGA	82.3	67.3	54.0	42.8	64.7
w/o Local Graph Linking	83.5(+1.2)	64.8(-2.5)	53.4(-0.6)	38.6(-4.2)	63.2(-1.5)
w/o Structure-Aware Aggregation	83.5(+1.2)	62.1(-5.2)	55.2(+1.2)	42.2(-0.6)	62.9(-1.8)
w/o $\operatorname{GraphAggr}(\mathcal{G}_S,\mathcal{G}_Q)$	83.1(+0.8)	64.1(-3.2)	52.3(-1.7)	40.4(-2.4)	62.9(-1.8)
w/o $\operatorname{GraphAggr}(\mathcal{G}_Q,\mathcal{G}_S)$	79.0(-3.3)	63.7(-3.6)	50.0(-4.0)	41.6(-1.2)	61.5(-3.2)
Q-S Linking via Dual-Graph Encoding	82.3(-0)	63.7(-3.6)	51.1(-2.9)	45.2(+2.4)	63.1(-1.6)
w/o Relation Node (replace with edge types)	79.4(-2.9)	63.5(-3.8)	54.6(+0.6)	40.4(-2.4)	62.1(-2.6)
w/o Global Pooling (Eq. 3 and Eq. 4)	82.7(+0.4)	64.3(-3.0)	54.0(-0)	41.6(-1.2)	63.5(-1.2)
w/o Aggregation Gate (Eq. 8, gate _{i, j} = 0.5)	81.9(-0.4)	60.1(-7.2)	54.6(+0.6)	40.4(-2.4)	61.2(-3.5)
w/o Relation Feature in Aggregation (R_{ij}^E)	79.4(-2.9)	64.3(-3.0)	54.6(+0.6)	41.6(-1.2)	62.7(-2.0)
SADGA + BERT-base	85.9	71.7	58.0	47.6	69.0
w/o Local Graph Linking	85.5(-0.4)	69.5(-2.2)	54.0(-4.0)	42.8(-4.8)	66.4(-2.6)
w/o Structure-Aware Aggregation	85.9(-0)	68.8(-2.9)	57.5(-0.5)	41.0(-6.6)	66.5(-2.5)

To validate the effectiveness of each component of SADGA, ablation studies are conducted on different parsing difficulty levels. The major model variants are as follows:

w/o Local Graph Linking Discard the Local Graph Linking phase (i.e., Eq. 6 ~ 9), which means $h_{i,j}^k$ in Eq. 10 is replaced by h_j^k . There is no structure-aware ability during the dual graph aggregation.

w/o Structure-Aware Aggregation Remove the whole structure-aware aggregation module to examine the effectiveness of our designed graph aggregation method.

Other fine-grain ablation experiments are also conducted on our raw SADGA. The ablation experimental results are presented in Table 3. As the table shows, all components are necessary to SADGA. According to the results on the **All** level, our models, no matter the raw SADGA or the one with BERT-base enhancing, decrease by about 1.5% and 1.8% or 2.6% and 2.5% while discarding the *Local Graph Linking* phase and the entire structure-aware aggregation method, which indicates the positive contribution to SADGA. Especially on the **Extra-Hard** level, discarding the *Local Graph Linking* and the aggregation respectively both lead to a large decrease of accuracy, suggesting that these two major components strongly help SADGA deal with more complex cases. Interestingly, on the **Easy** level, the results indicate that these two components have no or slight negative influence on our raw model. This phenomenon is perhaps due to the fact that the **Easy** level samples do not require capturing the local structure of our dual graph while building the question-schema linking, but the structure-aware ability is highly necessary for the complicated SQL on the **Extra-Hard** level. Regarding other fine-grain ablation experiments, we give a further introduction and discussion on these ablation variants in Appendix E.

4.4 Case Study

To further understand our method, in this section, we conduct a detailed analysis of the case in which the question is "What is the first name of every student who has a dog but does not have a cat?".

Global Graph Linking Analysis We show the alignment figure between question words and tables/columns on the *Global Graph Linking* phase when the question-graph acts as the query-graph. As shown in Figure 5, we can obtain the interpretable result. For example, the question word "student"

has a strong activation with the tables/columns related to the student, which helps better build the cross graph linking between the question and schema. Furthermore, we can observe that the column "pet_type" is successfully inferred by the word "dog" or "cat".

Local Graph Linking Analysis On the Local Graph Linking phase, we compute the attention between the query node and the neighbors of the key node, which allows question words (tables/columns) to attend to the specific structure of the schema-graph (question-graph). In Figure 6, two examples about the neighbor attention on the Local Graph Linking phase are presented. As shown in the upper part of the Figure 6, the column "first_name" of table "Student" attends to neighbors of word "name" in the question, where word "first" and word "student" obtain a high attention score, indicating that the column "first_name" attends to the specific structure inside the dashed box.

Some tables/columns are difficult to be identified via matching-based alignment since they do not attend explicitly in the question, but they have a strong association with the question, e.g.,

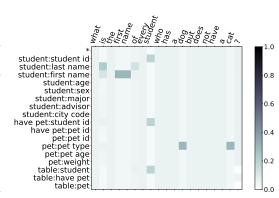


Figure 5: Alignment between question words and tables/columns on the *Global Graph Linking* phase.

table "Have_pet" in this case, which is also not identified in *Global Graph Linking*. Interestingly, as shown on the lower part of Figure 6 shows, table "Have_pet" acquires a high attention weight when the question word "student" attends to table "Student" and its neighbors. With the help of SADGA, the latent association between table "Have_pet" and word "student" can be detected, which corresponds exactly to the semantics of the question.

We also provide more samples in different database schemas compared to the baseline RATSQL and some corresponding discussions in Appendix F.

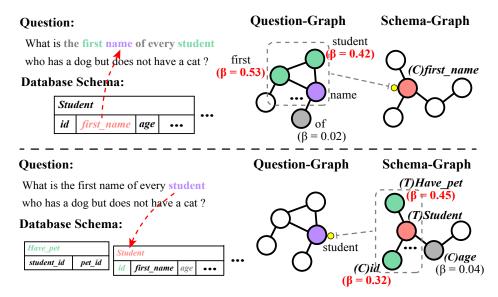


Figure 6: Analysis on the *Local Graph Linking* phase.

5 Related Work

Cross-Domain Text-to-SQL Recent architectures proposed for cross-domain Text-to-SQL show increasing complexity in both the encoder and the decoder. IRNet [13] encodes the question and

schema separately via LSTM with the string-match strategy and proposes to decode an abstracted intermediate representation (IR). RATSQL [29] proposes a unified encoding mechanism to improve the joint representation of question and schema. BRIDGE [21] serializes the question and schema into a tagged sequence and maximally utilizes BERT [12] and the database content to capture the question-schema linking. SmBoP [24] presents the first semi-autoregressive bottom-up semantic parser for the decoding phase in Text-to-SQL.

Besides, the graph encoder has been widely applied in cross-domain Text-to-SQL. Bogin et al. [4] is the first to encode the database schema using graph neural networks (GNNs). Global-GNN [5] applies GNNs to softly select a subset of tables/columns for the output query. ShadowGNN [8] presents a graph project neural network to abstract the representation of the question and schema. LGESQL [7] utilizes the line graph to update the edge features in the heterogeneous graph for Text-to-SQL, which further considers both local and non-local, dynamic and static edge features. Differently, our SADGA not only adapts a unified dual graph framework for both the question and database schema, but also devises a structure-aware graph aggregation mechanism to sufficiently utilize the global and local structure information across the dual graph on the question-schema linking.

Graph Aggregation The global-local graph aggregation module [40] is proposed to model interactions across graphs and aggregate heterogeneous graphs into a holistic graph representation in the video titling task. Nevertheless, this graph aggregation method is only at the node level, i.e., it does not consider the structure during aggregation, indicating that nodes in the graph are a series of unstructured entities. Instead of simply using the node-level aggregation, our SADGA considers the local structure information in the aggregation process, contributing a higher-order graph aggregation method with structure-awareness.

Pre-trained Models Inspired by the success of pre-trained language models, some recent works have tried to apply pre-trained objectives for text-table data. TAPAS [14] and TaBERT [34] leverage the semi-structured table data to enhance the representation ability of language models. For Text-to-SQL, GraPPa [37] is pre-trained on the synthetic data generated by the synchronous context-free grammar, STRUG [11] leverages a set of novel prediction tasks using a parallel text-table corpus to help solve the question-schema linking challenge. GAP [27] explores the direction of utilizing the generators to generate pre-trained data for enhancing the joint question and structured schema encoding ability. Moreover, Scholak et al. [26] proposes a method PICARD for constraining auto-regressive decoders of pre-trained language models through incremental parsing.

6 Conclusions

In this paper, we propose a Structure-Aware Dual Graph Aggregation Network (SADGA) for cross-domain Text-to-SQL. SADGA not only introduces a unified dual graph encoding for both natural language question and database schema, but also devises a structure-aware aggregation mechanism of SADGA to take full advantage of the global and local structure information of the dual graph in the question-schema linking. Experimental results show that our proposal achieves 3rd on the challenging Text-to-SQL benchmark Spider at the time of writing. This study shows that both the dual-graph encoding and structure-aware dual graph aggregation method are able to improve the generalization ability of the cross-domain Text-to-SQL task. As future work, we will extend SADGA to other heterogeneous graph tasks and other alignment tasks.

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A Preliminaries

Gated Graph Neural Networks [20] and Relation-Aware Transformer [29] are two critical components of our proposed model. The preliminaries of these two components are introduced as follows.

A.1 Gated Graph Neural Network

Gated Graph Neural Networks (GGNNs) have been proposed by Li et al. [20], which adopt the Gated Recurrent Unit (GRU) [9] layer to encode the nodes in graph neural networks. Given a graph G=(V,E,T) including nodes $v_i\in V$ and directed label edges $(v_s,t,v_d)\in E$ where v_s denotes the source node, v_d denotes the destination node, and $t\in T$ denotes the edge type. The process of GGNN computing the representation $\boldsymbol{h}_i^{(l)}$ at step l for the i-th node on G is divided into two stages. First, aggregating the neighbor node representation $\boldsymbol{h}_i^{(l-1)}$ of i-th node, formulated as

$$\mathbf{f}_{i}^{(l)} = \sum_{t \in T} \sum_{(i,k) \in E_{t}} (\mathbf{W}_{t} \mathbf{h}_{k}^{(l-1)} + \mathbf{b}_{t}), \tag{13}$$

where W_t and b_t are trainable parameters for each edge type t. Second, aggregated vector $\mathbf{f}_i^{(l)}$ will be fed into a vanilla GRU layer to update the node representation at last step $\mathbf{h}_i^{(l-1)}$, noted as:

$$\boldsymbol{h}_{i}^{(l)} = GRU\left(\boldsymbol{h}_{i}^{(l-1)}, \boldsymbol{f}_{i}^{(l)}\right). \tag{14}$$

A.2 Relation-Aware Transformer

Relation-Aware Transformer (RAT) [29] is an extension of Transformer [28], which introduces prior relation knowledge to the self-attention mechanism. Given a set of inputs $X = \{x_i\}_{i=1}^n$ where $x_i \in \mathbb{R}^d$ and relation representation r_{ij} between any two elements x_i and x_j in X. The RAT layer (consisting of H heads attention) can output an updated representation y_i with relational information for x_i , formulated as

$$e_{i,j}^{(h)} = \frac{x_i W_Q^{(h)} \left(x_j W_K^{(h)} + r_{ij}^K \right)^T}{\sqrt{d_z/H}}, \alpha_{i,j}^{(h)} = \operatorname{softmax}_j \left\{ e_{i,j}^{(h)} \right\},$$
(15)

$$\boldsymbol{z}_{i}^{(h)} = \sum_{j=1}^{n} \alpha_{i,j}^{(h)} \left(\boldsymbol{x}_{j} \boldsymbol{W}_{V}^{(h)} + \boldsymbol{r}_{ij}^{V} \right), \boldsymbol{z}_{i} = \operatorname{Concat}(\boldsymbol{z}_{i}^{(1)}, ..., \boldsymbol{z}_{i}^{(H)}),$$
(16)

$$\tilde{\boldsymbol{y}}_i = \text{LayerNorm}(\boldsymbol{x}_i + \boldsymbol{z}_i), \boldsymbol{y}_i = \text{LayerNorm}(\tilde{\boldsymbol{y}}_i + \text{FC}(\text{ReLU}(\text{FC}(\tilde{\boldsymbol{y}}_i))),$$
 (17)

where h is head index, $W_Q^{(h)}$, $W_K^{(h)}$, $W_V^{(h)} \in R^{d \times (d/H)}$ are trainable parameters, FC is a fully-connected layer, and LayerNorm is layer normalization [2]. Here $\alpha_{i,j}^{(h)}$ means that the attention score between x_i and x_j of head h.

B Relations of Dual-Graph Construction

All predefined relations used in the construction of the dual-graph and the cross-graph relations are summarized in Table 4.

The predefined relations of Question-Graph are summarized as follows:

- 1-order Word Distance Word A and word B are adjacent to each other in the question.
- 2-order Word Distance Word A and word B are spaced one word apart in the question.
- Parsing-based Dependency The specific grammatical relation between word A and word B generated by the Stanford CoreNLP toolkit [22].

The predefined relations of Schema-Graph are summarized as follows:

- Same Table Match Both column A and column B belong to the same table.
- **Primary-Foreign Key (Column-Column)** Column A is a foreign key for a primary key column B of another table.

Table 4: The predefined relations for Dual-Graph Construction.

	Node A	Node B	Predefined Relation	
Ouestion-Graph			1-order Word Distance	
Construction	Word	Word	2-order Word Distance	
			Parsing-based Dependency	
	Column	Column	Same Table Match	
Schema-Graph	Column	Column	Primary-Foreign Key	
Construction			Foreign Key	
	Column	Table	Primary Key	
			Table-Column Match	
	Table	Table	Primary-Foreign Key	
	Word	Table	Exact String Match	
Cross-Graph	word	Table	Partial String Match	
			Exact String Match	
	Word	Column	Partial String Match	
			Value Match	

- Foreign Key Column A is a foreign key of table B.
- Primary Key Column A is a primary key of table B.
- Table-Column Match Column A belongs to table B.
- Primary-Foreign Key (Table-Table) Table A has a foreign key column for a primary key column of table B.

The predefined relations of Cross-Graph are summarized as follows:

- Exact String Match (Word-Table) Word A is part of table B, and the question contains the name of table B.
- Partial String Match (Word-Table) Word A is part of table B, and the question does not contain the name of table B.
- Exact String Match (Word-Column) Word A is part of column B, and the question contains the name of column B.
- Partial String Match (Word-Column) Word A is part of column B, and the question does not contain the name of column B.
- Value Match Word A is part of the cell values of column B.

C Decoder Details

The decoder in our model aims to output a sequence of rules (actions) that generates the corresponding SQL syntax abstract tree (AST) [33]. Given the final representations h^q , h^t and h^c , of the question words, tables and columns respectively from the encoder. Let $h = [h^q; h^t; h^c]$. Formally,

$$Pr(P \mid \boldsymbol{h}) = \prod_{t} Pr(Rule_{t} \mid Rule_{< t}, \boldsymbol{h}), \qquad (18)$$

where $\operatorname{Rule}_{< t}$ are all the previous rules. We apply an LSTM [15] to generate the rule sequence. The LSTM hidden state H_t and the cell state C_t at step t are updated as:

$$\boldsymbol{H}_{t}, \boldsymbol{C}_{t} = \text{LSTM}\left(\boldsymbol{I}_{t}, \boldsymbol{H}_{t-1}, \boldsymbol{C}_{t-1}\right). \tag{19}$$

Similar to Wang et al. [29], the LSTM input I_t is constructed by:

$$I_t = [r_{t-1}; z_t; e_t; r_{pt}; H_{pt}], \qquad (20)$$

where r_{t-1} is the representation of the previous rule, z_t is the context vector calculated using the attention on H_{t-1} over h, and e_t is the learned representation of the current node type. In addition, pt is the step corresponding to generating the parent node in the AST of the current node.

With the LSTM output H_t , all rule scores at step t are calculated. The candidate rules are either schema-independent, e.g., the grammar rule, or schema-specific, e.g., the table/column. For the schema-independent rule u, we compute its score as:

$$Pr(Rule_t = u | Rule_{< t}, \mathbf{h}) = softmax_u (L(\mathbf{H}_t)),$$
(21)

where L is a 2-layer MLP with the *tanh* activation. To select the table/column rule, we first build the alignment matrices M^T , M^C between entities (question word, table, column) and tables, columns respectively with the relation-aware attention as a pointer mechanism:

$$\overline{\boldsymbol{M}}_{i,j}^{T} = \boldsymbol{h}_{i} \boldsymbol{W}_{Q}^{t} (\boldsymbol{h}_{j}^{t} \boldsymbol{W}_{K}^{t} + \boldsymbol{R}_{ij}^{E})^{T}, \boldsymbol{M}_{i,j}^{T} = \operatorname{softmax}_{j} \left\{ \overline{\boldsymbol{M}}_{i,j}^{T} \right\},$$
(22)

$$\overline{\boldsymbol{M}}_{i,j}^{C} = \boldsymbol{h}_{i} \boldsymbol{W}_{Q}^{c} (\boldsymbol{h}_{j}^{c} \boldsymbol{W}_{K}^{c} + \boldsymbol{R}_{ij}^{E})^{T}, \boldsymbol{M}_{i,j}^{C} = \operatorname{softmax}_{j} \left\{ \overline{\boldsymbol{M}}_{i,j}^{C} \right\},$$
(23)

where $M^T \in R^{(|q|+|t|+|c|)\times |t|}$, $M^C \in R^{(|q|+|t|+|c|)\times |c|}$. Then, we calculate the score of the j-th column/table:

$$\overline{\alpha}_i = \mathbf{H}_t \mathbf{W}_Q \left(\mathbf{h}_i \mathbf{W}_K \right)^T, \alpha_i = \operatorname{softmax}_i \left\{ \overline{\alpha}_i \right\}, \tag{24}$$

$$\Pr(\text{Rule}_t = \text{Table}[j] \mid \text{Rule}_{< t}, \boldsymbol{h}) = \sum_{i=1}^{|q|+|t|+|c|} \alpha_i \boldsymbol{M}_{i,j}^T,$$
(25)

$$\Pr(\text{Rule}_t = \text{Column}[j] \mid \text{Rule}_{< t}, \boldsymbol{h}) = \sum_{i=1}^{|q|+|t|+|c|} \alpha_i \boldsymbol{M}_{i,j}^C.$$
 (26)

D Hyperparameters

The hyperparameters of our model under different pre-trained models are listed in Table 5.

Table 5: Hyperparameters for GloVe, BERT-base, BERT-large and GAP setting.

per-parameter GloVe BERT-base BERT-large G

Hyper-paramter	GloVe	BERT-base	BERT-large	GAP
Size	300	768	1024	1024
Batch size	20	24	24	24
Max step	40k	90k	81k	61k
Learning rate	7.44e-4	3.44e-4	2.44e-4	1e-4
Learning rate scheduler	Warmup polynomial	Warmup polynomial	Warmup polynomial V	Varmup polynomial
Warmup steps	2k	10k	10k	5k
Bert learning rate	-	3e-6	3e-6	1e-5
Clip gradient	-	2	1	1
Number of SADGA layers	3	3	3	3
Number of RAT layers	4	4	4	4
RAT heads	8	8	8	8
Number of GGNN layers	2	2	2	2
SADGA dropout	0.5	0.5	0.5	0.5
RAT dropout	0.1	0.1	0.1	0.1
Encoder hidden dim	256	768	1024	1024
Decoder LSTM size	512	512	512	512
Decoder dropout	0.21	0.21	0.21	0.21

E Fine-grained Ablation Studies

Due to page limitations, we cannot further discuss the fine-grained ablation studies in the main paper. Therefore, the fine-grained ablation studies are discussed in this section. Firstly, all the ablation variants are presented in detail as follows:

w/o Local Graph Linking Discard the Local Graph Linking phase (Eq. 6 ~ 9), i.e., $h_{i,j}^k$ in Eq. 10 is replaced by h_i^k . There is no structure-aware ability during the dual graph aggregation.

w/o Structure-Aware Aggregation Remove the entire Structure-Aware Aggregation module in SADGA to examine the effectiveness of our designed graph aggregation method.

w/o GraphAggr(\mathcal{G}_S , \mathcal{G}_Q) Remove the aggregation process from the question-graph \mathcal{G}_Q to the schema-graph \mathcal{G}_S in Structure-Aware Aggregation, signifying that the nodes in the schema-graph could not obtain the structure-aware information from the question-graph.

w/o GraphAggr($\mathcal{G}_Q, \mathcal{G}_S$) Similar to w/o GraphAggr($\mathcal{G}_S, \mathcal{G}_Q$).

Q-S Linking via Dual-Graph Encoding In contrast to variant **w/o Structure-Aware Aggregation**, which removes the entire aggregation module in SADGA, we preserve the predefined crossgraph relations during dual-graph encoding. This variant guarantees the ability of question-schema (Q-S) linking, and its performance variation better reflects the contribution of Structure-Aware Aggregation.

w/o Relation Node (replace with edge types) Remove the relation node in Dual-Graph Encoding. Regrading how to use the information of the prior relationship in the question-graph and schema-graph, we represent the predefined relations with the edge types, introducing more trainable parameters.

w/o Global Pooling (Eq. 3 and Eq. 4) Remove the global pooling step during the Structure-Aware Aggregation, i.e., Eq. 3 and Eq. 4, to examine whether the global information of the query-graph is helpful for graph aggregation.

w/o Aggregation Gate (Eq. 8) Discard the gate mechanism between the global information and the local information in *Dual-Graph Aggregation Mechanism*. Instead of the gating mechanism, we average the weight of the global information and the local information, i.e., gate_{i,j} = 0.5 in Eq. 8.

w/o Relation Feature in Aggregation (R_{ij}^E) Remove the cross-graph relation bias between the question word and table/column in the attention step of Structure-Aware Aggregation. This model variant does not utilize any predefined cross-graph relations.

Table 6: Accuracy of ablation studies on Spider development set by hardness levels	
------------------------------------------------------------------------------------	--

Model	Easy	Medium	Hard	Extra Hard	All
SADGA	82.3	67.3	54.0	42.8	64.7
w/o Local Graph Linking	83.5(+1.2)	64.8(-2.5)	53.4(-0.6)	38.6(-4.2)	63.2(-1.5)
w/o Structure-Aware Aggregation	83.5(+1.2)	62.1(-5.2)	55.2(+1.2)	42.2(-0.6)	62.9(-1.8)
w/o $\operatorname{GraphAggr}(\mathcal{G}_S,\mathcal{G}_Q)$	83.1(+0.8)	64.1(-3.2)	52.3(-1.7)	40.4(-2.4)	62.9(-1.8)
w/o $\operatorname{GraphAggr}(\mathcal{G}_Q,\mathcal{G}_S)$	79.0(-3.3)	63.7(-3.6)	50.0(-4.0)	41.6(-1.2)	61.5(-3.2)
Q-S Linking via Dual-Graph Encoding	82.3(-0)	63.7(-3.6)	51.1(-2.9)	45.2(+2.4)	63.1(-1.6)
w/o Relation Node (replace with edge types)	79.4(-2.9)	63.5(-3.8)	54.6(+0.6)	40.4(-2.4)	62.1(-2.6)
w/o Global Pooling (Eq. 3 and Eq. 4)	82.7(+0.4)	64.3(-3.0)	54.0(-0)	41.6(-1.2)	63.5(-1.2)
w/o Aggregation Gate (Eq. 8, $gate_{i,j} = 0.5$)	81.9(-0.4)	60.1(-7.2)	54.6(+0.6)	40.4(-2.4)	61.2(-3.5)
w/o Relation Feature in Aggregation (\mathbf{R}_{ij}^E)	79.4(-2.9)	64.3(-3.0)	54.6(+0.6)	41.6(-1.2)	62.7(-2.0)
SADGA + BERT-base	85.9	71.7	58.0	47.6	69.0
w/o Local Graph Linking	85.5(-0.4)	69.5(-2.2)	54.0(-4.0)	42.8(-4.8)	66.4(-2.6)
w/o Structure-Aware Aggregation	85.9(-0)	68.8(-2.9)	57.5(-0.5)	41.0(-6.6)	66.5(-2.5)

As shown in Table 6 (Table 3 of the main paper), all the components are necessary to SADGA. Regrading w/o Local Graph Linking and w/o Structure-Aware Aggregation, we have discussed these two major ablation variants in detail in the main paper. When compared to w/o Structure-Aware Aggregation, SADGA gets worse results when it retains one-way aggregation, i.e., w/o GraphAggr(\mathcal{G}_S , \mathcal{G}_Q) and w/o GraphAggr(\mathcal{G}_Q , \mathcal{G}_S). We guess that this observation occurs because the update of dual graph node representation is imbalanced in one-way aggregation. The downgraded performance of Q-S Linking via Dual-Graph Encoding better demonstrates the necessity and effectiveness of our proposed structure-aware aggregation method for question-schema linking. The downgraded performance of w/o Relation Node is due to the increase of relational edge type, which leads to the increase of trainable parameters. The downgraded performance of w/o Aggregation Gate indicates the advantages of the gated-based aggregation mechanism, which provides the flexibility to filter out useless local structure information. The downgraded performance

of **w/o Global Pooling** indicates that the global information of question-graph or schema-graph is beneficial to another graph. Our SADGA **w/o Relation Feature in Aggregation** is comparable with RATSQL [29] (62.7%), which reflects the effectiveness of the structure-aware aggregation method to learn the relationship between the question and database schema without relying on prior relational knowledge at all.

F Case Study Against Baseline

In Figure 7, We show some cases generated by our SADGA and RATSQL [29] from the **Hard** or **Extra Hard** level samples of Spider Dataset [36]. Both SADGA and RATSQL are trained under the pre-trained model GAP [27]. In Case 1 and Case 2, RATSQL misaligned the word "museum" and "rank", resulting in the incorrect selection of tables and columns in the generated query. RATSQL utilizes the predefined relationship based on a string matching strategy to cause the above misalignment problem. Our SADGA is able to link the question words and tables/columns correctly in the hard cases of multiple entities, which is beneficial from the local structural information introduced by the proposed structure-aware aggregation method. In Cases 3~6, RATSQL generates semantically wrong query statements, especially when the target is a complex query, such as a nested query. Compared with RATSQL, SADGA adopts a unified dual-graph modeling method to consider both the global and local structure of the question and schema, which is more efficient for capturing the complex semantics of questions and building more exactly linkings in hard cases.

```
What are the id, name and membership level of visitors who have spent the largest amount of money in total in all museum tickets?
                          SELECT T2 visitor id T1 name T1 level of membership FROM Visitor AS T1 JOIN Visit AS T2 ON T1 id = T2 visitor id
          Gold SQL:
                           GROUP BY T2.visitor_id ORDER BY Sum(T2.total_spent) DESC LIMIT 1
                         SELECT Museum.museum_id, Museum.name, Visitor.level_of_membership FROM Museum JOIN Visit JOIN Visitor GROUP BY Museum.museum_id ORDER BY Sum(Visit.total_spent) Desc LIMIT 1. X
   RATSQL Result:
                          SELECT Visitor.id, Visitor.name, Visitor.level_of_membership FROM Visit JOIN Visitor ON Visit.visitor_id = Visitor.id
    SADGA Result:
                          GROUP BY Visitor.id ORDER BY Sum(Visit.total spent) Desc LIMIT 1.
            Question: Find the first name, country code and birth date of the winner who has the highest rank points in all matches.
          Gold SQL: SELECT T1.first_name, T1.country_code, T1.birth_date FROM Players AS T1 JOIN matches AS T2 ON T1.player_id = T2.winner_id
                           ORDER BY T2.winner_rank_points DESC LIMIT 1
   RATSOL Result:
                          SELECT Players.first_name, Players.country_code, Players.birth_date FROM Players JOIN Rankings ON Players.player_id = Rankings.player_id
                           ORDER BY Rankings.ranking_points Desc LIMIT 1. X
     SADGA Result: SELECT Players.first_name, Players.country_code, Players.birth_date FROM Players JOIN Matches ON Players.player_id = Matches.winner_id
                           ORDER BY Matches.winner_rank_points Desc LIMIT 1. ✓
(3)
            Question: Find all airlines that have flights from both airports 'APG' and 'CVO'.
                           SELECT T1.airline FROM Airlines AS T1 JOIN Flights AS T2 ON T1.id = T2.airline WHERE T2.source_airport = "APG"
          Gold SOL:
                           INTERSECT SELECT T1.airline FROM Airlines AS T1 JOIN Flights AS T2 ON T1.id = T2.airline WHERE T2.source_airport = "CVO".
   RATSQL Result:
                           SELECT Airlines.airline FROM Flights WHERE Flights.source airport = 'VALUE'
                           INTERSECT SELECT Airlines.airline FROM Flights WHERE Flights.source_airport = 'VALUE' . X
                          SELECT Airlines airline FROM Airlines JOIN Flights ON Airlines.id = Flights airline WHERE Flights source_airport = 'VALUE' INTERSECT SELECT Airlines.airline FROM Airlines JOIN Flights ON Airlines.id = Flights.airline WHERE Flights.source_airport = 'VALUE'.
     SADGA Result:
            Ouestion:
                           What are the names of all stadiums that did not have a concert in 2014?
                           SELECT name FROM Stadium EXCEPT
          Gold SQL:
                           SELECT T2.name FROM Concert AS T1 JOIN Stadium AS T2 ON T1.stadium id = T2.stadium id WHERE T1.year = 2014.
   RATSQL Result:
                          SELECT Stadium.name FROM Stadium WHERE Stadium.stadium_id NOT IN
                           (SELECT Concert.stadium id FROM Concert WHERE Concert.year = 'VALUE').
     SADGA Result: SELECT Stadium.name FROM Stadium EXCEPT
                           SELECT Stadium.name FROM Stadium JOIN Concert ON Stadium.stadium_id = Concert.stadium_id WHERE Concert.year = "VALUE".
            Question:
                          Show name of all students who have some friends and also are liked by someone else.
                          SELECT T2.name FROM Friend AS T1 JOIN Highschooler AS T2 ON T1.student_id = T2.id INTERSECT SELECT T2.name FROM Likes AS T1 JOIN Highschooler AS T2 ON T1.liked_id = T2.id.
          Gold SQL:
   RATSQL Result:
                         SELECT Highschooler.name FROM Highschooler WHERE Friend.friend id IN (SELECT Likes.student id FROM Likes). X
                         SELECT Highschooler.name FROM Highschooler JOIN Friend ON Friend student_id = Highschool.id INTERSECT SELECT Highschooler.name FROM Highschooler JOIN Likes ON Highschooler.id = Likes.liked_id. \checkmark
     SADGA Result:
(6)
            Question: What is the name of the semester with no students enrolled?
           Gold SQL: SELECT semester_name FROM Semesters WHERE semester_id NOT IN (SELECT semester_id FROM Student_Enrolment).
                          SELECT Semesters semester_name FROM Semesters EXCEPT SELECT Semesters, semester_name FROM Semesters JOIN Student_Enrolment ON Semesters.semester_id = Student_Enrolment.semester_id. 🗶
   RATSQL Result:
     SADGA Result: SELECT Semesters.semester_name FROM Semesters WHERE Semesters.semester_id NOT IN
                          (SELECT Student_Enrolment.semester_id FROM Student_Enrolment). ✓
```

Figure 7: More cases at the **Hard** or **Extra Hard** level in different database schemas. (RATSQL + GAP vs. SADGA + GAP)