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-SQL 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 learning 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 [5, 14, 33, 29].

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 [11, 3, 4, 27, 7, 22, 19, 6]. 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 [11, 27, 19, 17, 35].

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There are two categories of efforts to solve the aforementioned question-schema linking problem — matching-based method [11] and learning-based method [27,19,17,6]. IRNet [11] 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 [27] 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: (1) 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 [11,3,4] or transformers [27,28,19], while the database schema is the structured data whose representation is learned based on graph encoders [6,3,4] or transformers with predefined relations [27,28]. Such the structure gap leads to difficulty in adapting the trained model to the unseen schema. (2) 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 [34] 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) [27].

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 nodes in the dual graph.

![Figure 2: The overview of the proposed model.](https://yale-lily.github.io/spider)

RAT [27] 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 [26], which introduces prior knowledge relations to the self-attention mechanism (see Appendix A.2). Different from the work of Wang et al. [27] 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 [31], which transforms the SQL query to an abstract syntax tree in depth-first traversal order. First, we apply an LSTM [13] 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.

[https://yale-lily.github.io/spider](https://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 $G_Q = (Q, R_Q)$, 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 [20].

**Schema-Graph** Similarly, a schema-graph can be represented by $G_S = (S, R_S)$, 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”.

**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 [27]. 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) [18] 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. [2], 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. 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 $G_Q$ and schema-graph $G_S$. The aggregation process is
formulated as
\[ G_{Aggr}^Q = \text{GraphAggr}(G_Q, G_S), \quad G_{Aggr}^S = \text{GraphAggr}(G_S, G_Q). \] (1)

As shown in Eq. 1, the structure-aware aggregation method is applied to aggregate information from schema-graph \( G_S \) and question-graph \( G_Q \) to the other graph, respectively. We illustrate the detailed approach in the manner of query-graph \( G_q \) and key-graph \( G_k \), i.e.,
\[ G_{Aggr}^q = \text{GraphAggr}(G_q, G_k). \] (2)

Let \( \{h_q^i\}_{i=1}^m \) be a set of node embedding in the query-graph \( G_q \) and \( \{h_k^j\}_{j=1}^n \) be a set of node embedding in the key-graph \( G_k \), 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 \( h_q^i \) of query-graph \( G_q \) to get the global query-graph embedding \( h_{q, glob} \).

\[ h_{q, glob} = \frac{1}{m} \sum_{i=1}^{m} h_q^i, \quad e_j = \theta (h_{q, glob}^T W_q h_k^j), \] (3)

\[ h_k^j = (1 - e_j) W_{qg} h_{q, glob}^i + e_j W_{kg} h_k^j, \] (4)

where \( W_q, W_{qg}, W_{kg} \) are trainable parameters and \( \theta \) 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. \[38\]. 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 \[27\], we calculate the global attention score \( \alpha_{i,j} \) between query node embedding \( h_q^i \) and key node embedding \( h_k^j \) as follows:
\[ s_{i,j} = \sigma \left( h_q^i W_q (h_k^j + R_{ij})^T \right), \quad \alpha_{i,j} = \text{softmax}_j \{s_{i,j}\}, \] (5)

where \( \sigma \) is a nonlinear activation function and \( R_{ij} \) 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

$$o_{i,j,t} = \sigma \left( h_q^i W_n q (h_k^j + RE_{it})^T \right),$$

$$\beta_{i,j,t} = \text{softmax}_t \{ o_{i,j,t} \} \quad (t \in N_j),$$

where $N_j$ 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 nodes 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

$$h_{k,\text{neigh}}^{i,j} = \sum_{t=1}^{T} \beta_{i,j,t} h_k^t,$$

$$h_{k,\text{self}}^{i,j} = h_k^j,$$

$$\text{gate}_{i,j} = \theta \left( W_{ng} \left[ h_{k,\text{self}}^{i,j}; h_{k,\text{neigh}}^{i,j} \right] \right),$$

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

where $h_{k,\text{neigh}}^{i,j}$ represents the neighbor context vector and $h_k^{i,j}$ 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 $\alpha_{i,j}$:

$$h_q^{\text{new}} = \sum_{j=1}^{N} \alpha_{i,j} (h_k^{i,j} + RE_{ij}),$$

$$\text{gate}_i = \theta \left( W_{\text{gate}} \left[ h_q^i; h_q^{\text{new}} \right] \right),$$

$$h_q^{\text{Aggr}} = (1 - \text{gate}_i) * h_q^i + \text{gate}_i * h_q^{\text{new}},$$

where $\text{gate}_i$ indicates how much information the query node should receive from the key-graph. Consequently, we obtain the final query node representation $h_q^{\text{Aggr}}$ with the structure-aware information of the key-graph.

4 Experiments

In this section, we conduct experiments on the Spider dataset [34], 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 [8], GeoQuery [36], WikiSQL [1], IMDB [30] 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. [34].

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 [21] is a common choice for the embedding initialization. And regarding the pre-trained language model (PLM), BERT [10] 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

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3Only submit up to two models per submission (at least two months before the next submission).
Table 1: Results on the Spider development and test set.

| Approach          | Dev  | Test | Approach          | Dev  | Test |
|-------------------|------|------|-------------------|------|------|
| GNN [3]           | 40.7 | 39.4 | RATSQ-HFPT + BERT-large | 69.3 | 64.4 |
| Global-GNN [4]    | 52.7 | 47.4 | YCSQL + BERT-large | -    | 65.3 |
| IRNet v2 [11]     | 55.4 | 48.5 | DuoRAT + BERT-large [23] | 69.4 | 65.4 |
| RATSQ [27]        | 62.7 | 57.2 | RATSQ + BERT-large [27] | 69.7 | 65.6 |
| SADGA             | 64.7 | -    | SADGA + BERT-large | 71.6 | 66.7 |
| EditSQL + BERT-base [17] | 57.6 | 53.4 | ShadowGNN + RoBERTa [17] | 72.3 | 66.1 |
| GNN + Bertrand-DR [15] | 57.9 | 54.6 | RATSQ + STRUG [9] | 72.6 | 68.4 |
| IRNet v2 + BERT-base [11] | 63.9 | 55.0 | RATSQ + GraPPa [35] | 73.4 | 69.6 |
| RATSQ + BERT-base [27] | 65.8 | -    | RATSQ + GAP [25] | 71.8 | 69.7 |
| SADGA + BERT-base | 69.0 | -    | SADGA + GAP | 73.1 | 70.1 |

models, e.g., GAP [25], GraPPa [35], STRUG [9] 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 RATSQ [27] that uses batch size 20, initial learning rate $7 \times 10^{-4}$, max steps 40,000 and the Adam optimizer [16]. For BERT, the initial learning rate is adjusted to $2 \times 10^{-4}$, and the max training step is increased to 90,000. We also apply a separate learning rate of $3 \times 10^{-6}$ to fine-tune BERT. For GAP, we follow the original settings in Shi et al. [25]. In addition, we stack 3-layer SADGA followed by 4-layer RAT. More details about the hyperparameters are included in Appendix D.

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, RATSQ [27] 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 RATSQ + 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 RATSQ according to the parsing difficulty level defined by Yu et al. [34].

Table 2: The BERT-large results on Spider development set and test set compared to RATSQ by hardness levels defined by Yu et al. [34].

| Model            | Easy  | Medium | Hard  | Extra Hard | All   |
|------------------|-------|--------|-------|------------|-------|
| Dev:             |       |        |       |            |       |
| RATSQ            | 86.4  | 73.6   | 62.1  | 42.9       | 69.7  |
| SADGA            | 90.3  | 72.4   | 63.8  | 49.4       | 71.6  |
| Test:            |       |        |       |            |       |
| RATSQ            | 83.0  | 71.3   | 58.3  | 38.4       | 65.6  |
| SADGA            | 85.1  | 72.1   | 57.0  | 41.7       | 66.7  |
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 GraphAggr(G_S, G_Q)      | 83.1(+0.8) | 64.1(-3.2) | 52.3(-1.7) | 40.4(-2.4) | 62.9(-1.8) |
| w/o GraphAggr(G_Q, 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(-0.0) | 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}^k) | 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 $h^k_{i,j}$ in Eq. 10 is replaced by $h^j_j$. 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, discard 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 5, two examples about the neighbor attention on the Local Graph Linking phase are presented. As shown in the upper part of the Figure 5, 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., table “Have_pet” in this case, which is also not identified in Global Graph Linking. Interestingly, as shown on the lower part of Figure 5 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.

**Question:** What is the first name of every student who has a dog but does not have a cat?

**Database Schema:**

| Student | id | first_name | age | ... |
|---------|----|------------|-----|-----|

**Question:** What is the first name of every student who has a dog but does not have a cat?

**Database Schema:**

| Have_pet | student_id | pet_id |
|----------|------------|--------|
| student  | id | first_name | age | ... |

**Figure 5:** Alignment between question words and tables/columns on the Global 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 [11] encodes the question and
schema separately via LSTM with the string-match strategy and proposes to decode an abstracted intermediate representation (IR). RATSQL \cite{27} proposes a unified encoding mechanism to improve the joint representation of question and schema. BRIDGE \cite{19} serializes the question and schema into a tagged sequence and maximally utilizes BERT \cite{10} and the database content to capture the question-schema linking. SmBoP \cite{22} 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. \cite{3} is the first to encode the database schema using graph neural networks (GNNs). Global-GNN \cite{4} applies GNNs to softly select a subset of tables/columns for the output query. ShadowGNN \cite{7} presents a graph project neural network to abstract the representation of the question and schema. LGESQL \cite{6} 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 \cite{38} 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 \cite{12} and TaBERT \cite{32} leverage the semi-structured table data to enhance the representation ability of language models. For Text-to-SQL, GraPPa \cite{35} is pre-trained on the synthetic data generated by the synchronous context-free grammar, STRUG \cite{9} leverages a set of novel prediction tasks using a parallel text-table corpus to help solve the question-schema linking challenge. GAP \cite{25} 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. \cite{24} proposes a method PICARD for constraining autoregressive 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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References

[1] Victor Zhong an. Seq2sql: Generating structured queries from natural language using reinforcement learning. ArXiv preprint, abs/1709.00103, 2017.

[2] Daniel Beck, Gholamreza Haffari, and Trevor Cohn. Graph-to-sequence learning using gated graph neural networks. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 273–283, Melbourne, Australia, 2018. Association for Computational Linguistics.

[3] Ben Bogin, Jonathan Berant, and Matt Gardner. Representing schema structure with graph neural networks for text-to-SQL parsing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4560–4565, Florence, Italy, 2019. Association for Computational Linguistics.

[4] Ben Bogin, Matt Gardner, and Jonathan Berant. Global reasoning over database structures for text-to-SQL parsing. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3659–3664, Hong Kong, China, 2019. Association for Computational Linguistics.

[5] Ruichu Cai, Boyan Xu, Zhenjie Zhang, Xiaoyan Yang, Zijian Li, and Zhihao Liang. An encoder-decoder framework translating natural language to database queries. In Jérôme Lang, editor, Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018, July 13-19, 2018, Stockholm, Sweden, pages 3977–3983. ijcai.org, 2018.

[6] Ruisheng Cao, Lu Chen, Zhi Chen, Yanbin Zhao, Su Zhu, and Kai Yu. LGESQL: Line graph enhanced text-to-SQL model with mixed local and non-local relations. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2541–2555, Online, August 2021. Association for Computational Linguistics.

[7] Zhi Chen, Lu Chen, Yanbin Zhao, Ruisheng Cao, Zihan Xu, Su Zhu, and Kai Yu. ShadowGNN: Graph projection neural network for text-to-SQL parser. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5567–5577, Online, 2021. Association for Computational Linguistics.

[8] Deborah A. Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. Expanding the scope of the ATIS task: The ATIS-3 corpus. In Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994, 1994.

[9] Xiang Deng, Ahmed Hassan Awadallah, Christopher Meek, Oleksandr Polozov, Huan Sun, and Matthew Richardson. Structure-grounded pretraining for text-to-SQL. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1337–1350, Online, 2021. Association for Computational Linguistics.

[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, 2019. Association for Computational Linguistics.

[11] Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. Towards complex text-to-SQL in cross-domain database with intermediate representation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4524–4535, Florence, Italy, 2019. Association for Computational Linguistics.

[12] Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Müller, Francesco Piccinno, and Julian Eisenschlos. TaPas: Weakly supervised table parsing via pre-training. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4320–4333, Online, 2020. Association for Computational Linguistics.
[13] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, pages 1735–1780, 1997.

[14] Wonseok Hwang, Jinyeong Yim, Seunghyun Park, and Minjoon Seo. A comprehensive exploration on wikisql with table-aware word contextualization. *ArXiv preprint*, abs/1902.01069, 2019.

[15] Amol Kelkar, Rohan Relan, Vaishali Bhardwaj, Saurabh Vaichal, Chandra Khatri, and Peter Relan. Bertrand-dr: Improving text-to-sql using a discriminative re-ranker. *ArXiv preprint*, abs/2002.00557, 2020.

[16] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.

[17] Wenqiang Lei, Weixin Wang, Zhixin Ma, Tian Gan, Wei Lu, Min-Yen Kan, and Tat-Seng Chua. Re-examining the role of schema linking in text-to-sql. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6943–6954, 2020.

[18] Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard S. Zemel. Gated graph sequence neural networks. In Yoshua Bengio and Yann LeCun, editors, *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.

[19] Xi Victoria Lin, Richard Socher, and Caiming Xiong. Bridging textual and tabular data for cross-domain text-to-SQL semantic parsing. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4870–4888, Online, 2020. Association for Computational Linguistics.

[20] Christopher Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven Bethard, and David McClosky. The Stanford CoreNLP natural language processing toolkit. In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 55–60, Baltimore, Maryland, 2014. Association for Computational Linguistics.

[21] Jeffrey Pennington, Richard Socher, and Christopher Manning. GloVe: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, Doha, Qatar, 2014. Association for Computational Linguistics.

[22] Ohad Rubin and Jonathan Berant. SmBoP: Semi-autoregressive bottom-up semantic parsing. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 311–324, Online, 2021. Association for Computational Linguistics.

[23] Torsten Scholak, Raymond Li, Dzmitry Bahdanau, Harm de Vries, and Chris Pal. DuoRAT: Towards simpler text-to-SQL models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1313–1321, Online, 2021. Association for Computational Linguistics.

[24] Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. Picard - parsing incrementally for constrained auto-regressive decoding from language models. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2021.

[25] Peng Shi, Patrick Ng, Zhiguo Wang, Henghui Zhu, Alexander Hanbo Li, Jun Wang, Cicero Nogueira dos Santos, and Bing Xiang. Learning contextual representations for semantic parsing with generation-augmented pre-training. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 13806–13814, 2021.

[26] Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference...*
[27] Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. RAT-SQL: Relation-aware schema encoding and linking for text-to-SQL parsers. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7567–7578, Online, 2020. Association for Computational Linguistics.

[28] Peng Xu, Dhruv Kumar, Wei Yang, Wenjie Zi, Keyi Tang, Chenyang Huang, Jackie Chi Kit Cheung, Simon J.D. Prince, and Yanshuai Cao. Optimizing deeper transformers on small datasets. In The 59th Annual Meeting of the Association for Computational Linguistics (ACL 2021). ACL, August 2021.

[29] Xiaojun Xu, Chang Liu, and Dawn Song. Sqlnet: Generating structured queries from natural language without reinforcement learning. ArXiv preprint, abs/1711.04436, 2017.

[30] Navid Yaghmazadeh, Yuepeng Wang, Isil Dillig, and Thomas Dillig. Sqlizer: query synthesis from natural language. Proceedings of the ACM on Programming Languages, 1(OOPSLA): 1–26, 2017.

[31] Pengcheng Yin and Graham Neubig. A syntactic neural model for general-purpose code generation. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 440–450, Vancouver, Canada, 2017. Association for Computational Linguistics.

[32] Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. TaBERT: Pretraining for joint understanding of textual and tabular data. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8413–8426, Online, 2020. Association for Computational Linguistics.

[33] Tao Yu, Zifan Li, Zilin Zhang, Rui Zhang, and Dragomir Radev. TypeSQL: Knowledge-based type-aware neural text-to-SQL generation. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 588–594, New Orleans, Louisiana, 2018. Association for Computational Linguistics.

[34] Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir Radev. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-SQL task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3911–3921, Brussels, Belgium, 2018. Association for Computational Linguistics.

[35] Tao Yu, Chien-Sheng Wu, Xi Victoria Lin, Yi Chern Tan, Xinyi Yang, Dragomir Radev, Caiming Xiong, et al. Grappa: Grammar-augmented pre-training for table semantic parsing. In International Conference on Learning Representations, 2021.

[36] John M Zelle and Raymond J Mooney. Learning to parse database queries using inductive logic programming. In Proceedings of the national conference on artificial intelligence, pages 1050–1055, 1996.

[37] Rui Zhang, Tao Yu, Heyang Er, Sungrok Shim, Eric Xue, Xi Victoria Lin, Tianze Shi, Caiming Xiong, Richard Socher, and Dragomir Radev. Editing-based SQL query generation for cross-domain context-dependent questions. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5338–5349, Hong Kong, China, 2019. Association for Computational Linguistics.

[38] Shengyu Zhang, Ziqi Tan, Zhou Zhao, Jin Yu, Kun Kuang, Tan Jiang, Jingren Zhou, Hongxia Yang, and Fei Wu. Comprehensive information integration modeling framework for video titling. In Rajesh Gupta, Yan Liu, Jiliang Tang, and B. Aditya Prakash, editors, KDD ’20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020, pages 2744–2754. ACM, 2020.