An Investigation Between Schema Linking and Text-to-SQL Performance

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Abstract
Text-to-SQL is a crucial task toward developing methods for understanding natural language by computers. Recent neural approaches deliver excellent performance; however, models that are difficult to interpret inhibit future developments. Hence, this study aims to provide a better approach toward the interpretation of neural models. We hypothesize that the internal behavior of models at hand becomes much easier to analyze if we identify the detailed performance of schema linking simultaneously as the additional information of the text-to-SQL performance. We provide the ground-truth annotation of schema linking information onto the Spider dataset. We demonstrate the usefulness of the annotated data and how to analyze the current state-of-the-art neural models.

1 Introduction
Text-to-SQL is a task to convert the question in natural language to SQL (the logical form). The attempts to solve text-to-SQL are crucial to establish methodologies for understanding natural language by computers. Currently, neural models are widely used for tackling text-to-SQL (Choi et al., 2020; Zhang et al., 2019; Bogin et al., 2019b; Guo et al., 2019; Wang et al., 2020). However, state-of-the-art neural models on the Spider dataset (Yu et al., 2018b), a current mainstream text-to-SQL benchmark dataset, yield 60–65 exact matching accuracy. This indicates that current technologies require immense room for improvement to achieve commercialization and utilization as real-world systems.

A severe drawback of the neural approach is the difficulty of analyzing how models capture the clue to solve a task. Hence, researchers often struggle which direction to focus on to obtain further improvement. This paper focuses on this problem and considers a methodology that can reduce enormous effort to analyze the model behaviors and find the next direction. For this goal, we focus on schema linking. Schema linking is a special case of entity linking and a method to link the phrases in a given question with the column names or the table names in the database schema. Guo et al. (2019) and Wang et al. (2020) show that schema linking is an essential module to solve text-to-SQL task effectively. We hypothesize that if the detailed performance of the schema linking is known simultaneously as additional information for text-to-SQL performance, then the analysis of the internal behavior of the models at hand becomes easier.

To investigate the above-mentioned hypothesis and offer a better analysis of text-to-SQL models, we annotate ground-truth schema linking information onto the Spider dataset (Yu et al., 2018b). The experiments reveal the usefulness of scheme linking information in the annotated dataset to understand the model behaviors. We also demonstrate how the current state-of-the-art neural models can be analyzed by comparing the schema linking performance with the text-to-SQL performance.

2 Related Works

Text-to-SQL dataset There exist many benchmark datasets, such as WikiSQL (Zhong et al., 2017), Advising (Finegan-Dollak et al., 2018), and Spider (Yu et al., 2018b). WikiSQL is the largest benchmark dataset in text-to-SQL domain. However, Finegan-Dollak et al. (2018) pointed out that WikiSQL includes almost same SQL in the training and test set, because the dataset aims to generate the correct SQL for unknown questions. They proposed Advising (Finegan-Dollak et al., 2018), which does not include the same SQL in the train-
ing and test sets, but it still consists only of SQL with limited clauses from one domain. Yu et al. (2018b) proposed the Spider dataset that includes complicated SQL with many clauses and 138 different domains. Currently, Spider is considered the most challenging dataset in the text-to-SQL field.

**Schema linking** In text-to-SQL, schema linking is a task to link a phrase in the given question and the table name or the column name. The methods used for schema linking are often categorized as explicit or implicit approaches. The explicit approach is treated as the first step of the text-to-SQL pipeline, and thus we obtain the linking information (Yu et al., 2018a; Guo et al., 2019; Wang et al., 2020). In contrast, the implicit approach is a module included in text-to-SQL models, and thus linking is a black box during the process. To obtain linking information, we mostly focus on the attention module (Bahdanau et al., 2015) from question tokens to the database schema mostly equipped by the models in the implicit approach (Krishnamurthy et al., 2017; Bogin et al., 2019a,b; Zhang et al., 2019; Dong et al., 2019). In this paper, we focus on the explicit approach for a clear discussion.

### 3 Scheme Linking Annotation

**Initial dataset** The Spider dataset (Yu et al., 2018b) is a large-scale human annotated and cross-domain text-to-SQL dataset. The dataset consists of an 8,625 training set, a 1,034 development set, and a 2,147 test set. Moreover, it contains 200 databases, and no database overlaps in the training, development, and test sets. We annotate ground-truth schema linking information onto the Spider dataset. Note that we annotate it only on the development set, not on training and test sets. This is because this study aims to provide a detailed analysis tool of text-to-SQL models, mainly for investigating the behavior of models and seeking direction for subsequent developments, not to train models for further improving the performance. Moreover, the test set is not publicly available for the Spider dataset; the test set is only used in the leaderboard system for preventing the test set tuning often arose in the evaluation phase.

**Annotation detail and statistics** The annotation is performed by two software engineers who are familiar with SQL. They use Doccano as the annotation tool. Figure 1 shows an annotation example. Table 1 shows the statistics of the annotated data.

| #LABEL | MAX | MIN | AVG | STD  |
|-------|-----|-----|-----|------|
| Total | 3,077 | 8   | 1   | 2.98 | 1.227 |
| Table | 1,223 | 5   | 0   | 1.18 | 0.751 |
| Column | 1,854 | 0   | 1   | 1.79 | 0.997 |
| Total (l = 1) | 2,359 | 8   | 0   | 2.28 | 1.229 |
| Table (l = 1) | 1,031 | 5   | 0   | 1.00 | 0.764 |
| Column (l = 1) | 1,328 | 0   | 1   | 1.28 | 0.948 |
| Total (l ≥ 2) | 718 | 4   | 0   | 0.69 | 0.851 |
| Table (l ≥ 2) | 192 | 3   | 0   | 0.19 | 0.424 |
| Column (l ≥ 2) | 526 | 0   | 0   | 0.51 | 0.751 |

Table 1: Statistics of the annotated data for each sentence. #LABEL: number of label for a sentence, MAX: the maximum number of labels, MIN: the minimum number of labels, AVG: the average number of labels, STD: the standard deviation for the number of labels.

**Quality check** For the annotation quality check, we validate the annotation agreement between two annotators by independently annotating the same 100 examples. The annotation agreement of Cohen’s kappa is 0.764 (95% CI = 0.722 – 0.806, p < 0.01). According to Landis and Koch (1977), the kappa value in the range 0.41 – 0.60 is categorized in substantial agreement. Moreover, the F1 score of annotation of two annotators is 87.5. We calculate the F1 score as suggested in several previous studies (Brandsen et al., 2020; Grouin et al., 2011; Alex et al., 2010). According to these results, we believe that our annotated scheme linking data are highly reliable as the ground truth.

**Data split** We split the annotated data into two distinct sets and used one for the development set and another for the test set. Hereafter, we refer to these new sets as the development set and the test set, respectively; it is crucial to note that this paper does not deal with the true test data in the Spider dataset. See several other examples in Appendix E.

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2https://github.com/doccano/doccano

4The un-annotated tokens unfairly increase the kappa score on sequence segmentation tasks (Brandsen et al., 2020). We follow the instruction written in Brandsen et al. (2020) to calculate the kappa score only on tokens, either one annotated.
The partial matches are ignored.

Table 2: Schema linking methods. We use the alias in later experiments.

| name                        | alias | explanation                                      |
|-----------------------------|-------|--------------------------------------------------|
| w/o uni-gram-(a)            | a     | The uni-grams are ignored                        |
| w/o uni-gram-(b)            | b     | The partial matches are ignored                  |
| w/o column-match            | c     | The column names are ignored                     |
| w/o table-match             | d     | The table names are ignored                      |
| only uni-gram-(a)           | e     | Only the uni-grams are considered                |
| only uni-gram-(b)           | f     | Only the uni-grams are considered; however, the partial matches are ignored. |
| random                      | g     | Randomly linking                                 |
| w/o all                     | h     | No schema linking                                |

Table 3: Schema linking and text-to-SQL results. EM: exact match, Prec.: precision, Rec.: recall, #FP: number of false positive, #FN: number of false negative, #TP: number of true positive.

Baseline models We selected IRNet (Guo et al., 2019) and RAT-SQL (Wang et al., 2020) for the baseline models of the experiments to reveal the effectiveness of the proposed dataset, where we refer to them as IRNet and RAT-SQL, respectively. It should be noted that both of their models employed an explicit approach, whose first steps are scheme linking; thus, their settings match to evaluate the usefulness of the proposed annotated data. However, we also emphasize here that their schema linking methods differ from each other although their methods consist of combinations of similar multiple rules, where IRNet maps the phrase to the single table or column, and RAT-SQL maps the phrase to the multiple tables or columns. Further, IRNet and RAT-SQL mark the top-line scores in the leader board of the Spider dataset; specifically, RAT-SQL is the current state-of-the-art model. These facts suggest to use them as baseline models in our experiments. We selected the identical hyper-parameter values for both IRNet and RAT-SQL with their original papers, i.e., Guo et al. (2019) and Wang et al. (2020).
Investigations The schema linking methods used in IRNet and RAT-SQL follow the rule-based approach\(^9\) that allows easier interpretation of model behavior. To investigate the usefulness of the schema linking information, we conducted the fine-grained schema linking ablation experiments. Through these experiments, we explore the general behaviors of text-to-SQL models when the performance of scheme linking changes. To accomplish this, we prepare eight methods shown in Table 2.

5 Results and analysis

Behaviors of IRNet and RAT-SQL Table 3 shows the results of the schema linking and text-to-SQL performance of IRNet and RAT-SQL. The Spider EM of RAT-SQL is significantly better than that of IRNet, whereas the scheme linking F\(_1\) of RAT-SQL is much worse than that of IRNet. This mismatch occurred by the difference of the scheme linking strategy as RAT-SQL prioritizes recall over precision, as presented in Table 3.

Correlation Table 4 shows a type of ablation study to gradually decrease the F\(_1\) scores by eliminating the schema linking rules. Further, Table 5 shows the simulated evaluation results when we obtained the perfect prediction (F\(_1\) = 100), or better predictions than that of the original IRNet and RAT-SQL\(^{10}\). We observed a strong correlation between scheme linking F\(_1\) and Spider EM on IRNet. In fact, the correlation coefficient between them is 0.937 with \(p = 2.7 \times 10^{-5}\). This fact indicates that the scheme linking considerably affects the final Spider EM score. Thus, we can roughly estimate the EM scores from scheme linking F\(_1\) without performing the entire training and evaluation procedures of IRNet. Unlike IRNet, the Spider EM of RAT-SQL seems not to be strongly correlated to the scheme linking F\(_1\). The correlation coefficient between them is 0.737 with \(p = 0.058\). However, if we checked the Spider EM and \#TP correlation as RAT-SQL prioritizes recall than precision, it becomes 0.81 with \(p = 0.027\). Therefore, RAT-SQL still has a strong correlation between scheme linking results. Additionally, the Spider EM for IRNet anno is higher than the original IRNet (62.5 vs. 58.8). Similarly, RAT-SQL anno is higher than for the original RAT-SQL (69.6 vs. 69.2). These results also support the reliability of the proposed annotation as the performance gain should be derived from the correct (better) scheme linking.

Error analysis Figure 2 shows actual examples of IRNet outputs\(^{11}\). IRNet-f successfully generates the correct SQL query, while IRNet-h does not. In the absence of scheme linking annotation, it is relatively difficult to determine the cause of this failure. However, using the scheme linking annotation, we can easily find the reason for the failure of IRNet-h; it failed to link countries in the question as to the table name. This is a simple example of leveraging the proposed annotation for analyzing the model behaviors. We believe there are many ways to utilize the proposed annotation to further analyze the model behaviors.

6 Conclusion

The schema linking is an essential module for performing the text-to-SQL task effectively. We annotated the schema linking information onto the Spider dataset. Then, we investigated the usefulness of the proposed annotation to understand the model behaviors of text-to-SQL models and seek the next directions for further development.

As a demonstration, we selected IRNet and RAT-SQL, which are the state-of-the-art methods on the Spider data, and evaluated both scheme linking and Spider EM scores. The results showed strong correlations between the schema linking F\(_1\) and Spider EM scores for IRNet and the number of true positive and Spider EM scores for RAT-SQL. These correlations may offer a rough estimation of the final Spider exact match scores without training the models. We hope the proposed scheme linking annotation helps future studies in the text-to-SQL task.

\(^9\)See Appendix B for the rules used in their methods.

\(^{10}\)We obtain "anno" from the human annotation, and "mix" by randomly choosing the example from the human annotation or the original schema linking result.

\(^{11}\)The actual examples obtained from RAT-SQL are presented in Appendix D because of the space limitation.
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A  Spider data

| Question | What are the names and the descriptions for all the sections? |
|----------|----------------------------------------------------------|
| SQL      | SELECT section_name, section_description FROM Sections; |

Figure 3: Example pair of the question and SQL query of Spider (Yu et al., 2018b).

Figure 3 shows an example in the dataset. A single data sample is constructed by the natural language question and the SQL query.

B  Details of scheme linking methods

The scheme linking methods in IRNet and RAT-SQL both classify the word n-grams in questions to three classes, namely, table, column, or NONE. Then, they enumerate the word n-grams of length 1-6 in the question and classify longer n-grams first. During the scan of the n-grams, it classifies column or table when the n-gram matches exactly or partially. If the n-gram matches both column and table, column is prioritized. If the n-gram matches nothing, that n-gram is classified to NONE.

C  Details of baseline models

IRNet is the model that successfully utilizes schema linking. IRNet has the three stages to generate the SQL query. The first stage is the schema linking explained above. The second stage is the main part of this model. It consists of generation of SemSQL, which is the immediate representation between the question and SQL query. SemSQL has a much simpler grammar than SQL. The last stage converts SemSQL to SQL.

RAT-SQL is the first-place model on the Spider leader board. RAT-SQL also uses the schema linking technique proposed in IRNet. In RAT-SQL, Wang et al. (2020) proposed the relation-aware self-attention, which effectively encodes the directed graph of the database schema. Their approach uses self attention mechanism (Vaswani et al., 2017) to combine the phrases in the database schema and the phrases in the question.

D  Output examples

We show the RAT-SQL outputs in Figure 4. From Figure 4, both models fail to generate the SQL query. However, RAT-SQL successfully predicates the SELECT clauses, while RAT-SQL-f does not. This is because the schema linking of RAT-SQL can capture the bi-gram matches.

E  Annotated dataset examples

We show our annotated dataset examples randomly picked from Figure 5.
Figure 5: Example of our annotated data. The labels field provides the annotation information.